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An Analogical Account of Argument Structure Construction Acquisition and Application

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ABSTRACT

An Analogical Account of Argument Structure Construction Acquisition and Application

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This work presents a cognitive model of argument structure construction acquisition and application based on analogy. The claims of this model are that (1) constructions, pairings of form and meaning, are a productive unit of linguistic analysis that account for a broader range of phenomena than traditional approaches; (2) human acquisition of abstract argument structure constructions can be modeled as analogical generalization over individual examples; and (3) semantic interpretation can be modeled as the analogical integration of argument structure constructions and their constituents. In support of these claims, the primary contribution of this work is a computational model of argument structure acquisition and application that is built on top of the Structure Mapping Engine, a pre-existing computational model of analogy.

The model was evaluated via three cognitive experiments. First, the model was used to simulate semantic inferences from Kaschak & Glenberg's (2000) study of denominal verb interpretation which found that participants are influenced by argument structure when interpreting denominal verbs. The same model was also trained on child directed speech, with different parameters used to model conservative and liberal learners. The resulting constructions were analyzed for correctness and for an item-specific bias found in early language learning. Finally, the model was incorporated into the Analogical Theory of Mind model to simulate Hale & Tager-Flusberg's (2003) study on linguistic bootstrapping effects in theory of mind

acquisition. Taken together, these experiments provide evidence for an analogical approach to argument structure as a valid cognitive model.

Furthermore, it is also claimed (4) that the model has practical applications for natural language tasks such as question answering. To evaluate this claim, the model was extended as a domain-general semantic parser. The resulting system was used to achieve high performance on seven of Facebook's bAbI question answering tasks (Weston et al., 2015).

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1. Introduction

1.1 Motivation

Humans are incredibly creative with language. We interpret novel uses of familiar verbs, glean meaning based on context, and draw real world inferences from partial descriptions. As an example, consider the interpretation of denominal verbs (those derived from nouns) as in:

1. a) The boy *crutched* the angonoka the lettuce so he could watch it eat.

Most readers of a sentence like (1a) interpret it such that the boy used crutches to pass the angonoka the lettuce (Kaschak & Glenberg, 2000). However, it is unlikely that a reader has seen *crutch* as a verb before. Furthermore, a reader unfamiliar with the noun angonoka (a kind of tortoise) nevertheless interprets the sentence and may draw conclusions about the unknown entity (e.g. that it is an animal). (1a) may seem odd, but this kind of novel expression occurs frequently in real speech (consider the emergence of email as a verb).

In traditional linguistics, there is a common distinction between words, which have meanings (*lexical semantics*), and the rules that allow us to combine words into sentences (*syntax*). However, traditional accounts would typically require that the transfer meaning in (1a) be attached to the verb *crutch*, which, as we just examined, is unlikely to be known. The assumption that semantics originates solely in words is a hallmark of *lexicalism*, and it frequently extends even to more recent distributional models of semantics (e.g. Word2Vec (Mikolov et al., 2013)). Building on prior work, it is the claim of this dissertation that interpreting unrestricted natural language, in all of its creative complexity, requires moving beyond this assumption.

The driving motivation of this research has been to incorporate a richer notion of semantics into natural language interpretation, with the goals of addressing fundamental questions about how humans acquire and interpret language as well as increasing the ability of a computational agent to interpret text. In pursuing these goals, inspiration has come from a paradigm in cognitive linguistics called *construction grammar* as well as from related work on child language acquisition and interpretation. The following section outlines the claims of this research.

1.2 Statement of Claims

In construction grammar, words and syntax are both represented as a pairing of form and meaning called a *construction*. A word is a pairing of form (the letters G-I-V-E) and meaning (giving), but so too is the sentence in (1a), "[the boy]$_{np1}$ crutched$_{v}$ [the angonoka]$_{np2}$ [the lettuce]$_{np3}$". The syntactic pattern of this sentence (NP$_1$-Verb-NP$_2$-NP$_3$) is known as the double-object construction, and it is used to evoke a transfer of an object to a recipient (transfer-<(<donor>-<recipient>-<object>) (A. E. Goldberg, 2003; Kaschak & Glenberg, 2000). From a constructionist point of view, the transfer interpretation of the novel verb *crutch* in (1a) comes not from the word but rather from the syntactic construction it is used in. Following in the construction grammar paradigm, this work rests on the following first claim:

> *Claim 1: Constructions, pairings of form and meaning, are a productive unit of linguistic analysis that account for a broader range of phenomena than traditional approaches.*

As a joint representation for syntax and semantics, constructions provide a powerful mechanism for investigating many different linguistic phenomena (e.g. Culicover & Jackendoff, 1999; Fillmore, Kay, & Connor, 1988). More detailed support for this claim is given in Chapter 2. I argue that the construction grammar framework is also useful in designing cognitive systems that can learn from natural language. This work particularly focuses on the semantics provided by *argument-structure* (e.g. phrasal arguments to verbs).

Unlike traditional generative approaches (Chomsky, 1981; Lidz, Gleitman, & Gleitmanm, 2003; *inter alia*) construction grammar accounts do not posit an a priori universal grammar or language specific learning mechanisms (Goldberg, 2003). Thus, an important element of a constructionist approach is the mechanism whereby children acquire these constructions. One proposal has been that children acquire constructions through analogical generalization of individual examples (Gentner & Namy, 2006; Tomasello, 2009). There is abundant evidence that comparison of linguistic examples facilitates language learning and relational extraction (Christie & Gentner, 2010; Namy & Gentner, 2002, *inter alia*). I thus make the following claim:

Claim 2: Human acquisition of abstract argument structure constructions can be modeled as analogical generalization over individual examples.

In support of this claim, I implement a model of construction learning using a computational model of analogical generalization that is based on Gentner's (1983) Structure Mapping Theory of similarity (SMT). According to SMT, analogical comparison and in fact similarity judgements more broadly involve comparing structured representations pursuant to several constraints. SMT and evidence for the theory are described further in Chapter 3. This model of construction acquisition is described in Chapter 4 and evaluated in subsequent chapters.

I build on this model of acquisition to develop a model of how argument structure constructions integrate with verbs to generate interpretations. I model this integration as analogical alignment between a generalized argument structure construction and its constituents, the verb and its arguments. Thus, I claim:

Claim 3: Semantic interpretation can be modeled as the analogical integration of argument structure constructions and their constituents.

Finally, there are many tasks that require natural language understanding and many existing language interpretation systems. As an implemented model of language interpretation, I also claim that:

Claim 4: The model has practical applications for natural language tasks such as question answering.

1.3 Statement of Contributions

In support of the claims above, I present the following contributions.

Contribution 1: An implemented model of construction generalization and application by analogy.

The model utilizes the Sequential Analogical Generalization Engine (SAGE) (McLure, Friedman, & Forbus, 2015), a pre-existing model of analogical generalization, to generalize over individual sentences. SAGE aligns predicate calculus representations using Forbus et al.'s (2017) Structure Mapping Engine (SME), a computational model of Gentner's (1983) Structure Mapping Theory of analogy. SAGE then creates generalizations by producing probability distributions over aligned but different structure.

To model construction acquisition, SAGE generalizes over pairings of syntactic form and bound semantic roles. Interpretation is modeled as analogical alignment between a learned construction and its constituents. Given a syntactic representation of a sentence and a verb's possible semantic roles, generalized constructions can be retrieved using a pre-existing model of analogical retrieval called MAC/FAC (Forbus, Gentner, & Law, 1995). When the sentence and retrieved construction are aligned using SME, the semantic roles are assigned by analogical inference.

To evaluate this model, I simulate several cognitive phenomena. These experiments contribute an algorithmic account of important cognitive phenomena. They are as follows:

> *Contribution 2: A computational model of denominal verb interpretation based on argument structure that is used to simulate results from Kaschak & Glenberg's (2000) study*
>
> *Contribution 3: An analysis of constructions generated from child directed speech*
>
> *Contribution 4: A model of linguistic bootstrapping effects in theory of mind acquisition that is used to simulate results from Hale & Tager-Flusberg's* (2003) study

I first simulate the results of Kaschak & Glenberg's (2000) study regarding interpretation of denominal verbs (e.g. *crutched* as in 1a). I further train the model with annotated examples of child directed speech. Upon manual examination, the generalizations exhibit patterns similar to child learners. Finally, my approach to construction application by analogy is used as part of a model of how sentential complement training facilitates theory of mind development. These contributions are aimed at supporting the broader constructionist hypothesis that natural language constructions are acquired using domain independent learning mechanisms, and specifically that analogy plays a central role in the acquisition of abstract constructions.

I then adapt the model above for general purpose semantic parsing. The implemented system is evaluated on seven of the Facebook bAbI question answering tasks (Weston et al., 2015). Thus, this dissertation contributes:

> *Contribution 5: A construction-based model of language acquisition and interpretation that can be used to solve natural language tasks.*

1.4 Organization

Due to the breadth of topics covered in this dissertation, relevant background and related work is included throughout rather than in a single background chapter.

Chapter 2 provides an overview of construction grammar and outlines the syntactic and semantic representations from the linguistics literature that motivate this work. This chapter provides linguistic evidence of the claim that constructions underlie language representation.

Chapter 3 gives an overview of the psychological literature that motivates this work, specifically focusing on language acquisition. It also introduces the theory of analogy and computational models that underlie this work. This chapter provides psychological evidence of for my model of argument structure acquisition by analogical generalization.

Chapter 4 builds on the discussion in the previous chapters and introduces a computational cognitive model of construction acquisition and application by analogy. It describes the model in general terms while specific representations are discussed in the following chapters.

Chapter 5 describes a natural language representation based on Fillmore, Wooters, & Baker's (2001) FrameNet which the model uses to simulate Kaschak & Glenberg's (2000) study on denominal verb interpretation.

Chapter 6 builds on the work described in Chapter 5 and introduces a representation, called the *role alignment representation*, based on Goldberg's (1995) constructionist theory of argument structure. Both the FrameNet and role alignment representations are used to learn constructions from a corpus of child directed speech. These constructions are manually evaluated and the effects of each representation on the pattern of generalization are compared.

Chapter 7 uses the same general model of construction application as a part of a model of linguistic bootstrapping in theory of mind. The joint model is used to simulate results from Hale & Tager-Flusberg's (2003) theory of mind training study.

Chapter 8 adapts the cognitive model from the previous chapters for domain general semantic parsing. The approach uses FrameNet to generate semantic case frames for verbs. It uses the annotated corpus of child directed speech collected for the experiments in Chapter 6 as training data for construction acquisition. This corpus is manually extended with training examples from Facebooks bAbI training sets. The system is evaluated on seven of Facebook's bAbI question answering tasks (Weston et al., 2015)

Chapter 9 summarizes the claims and contributions of this manuscript in light of the previous chapters. It concludes with open questions and future work.

2. Natural Language Constructions

2.1 Linguistic Preliminaries

This section introduces relevant terminology from linguistics that is used throughout the paper. It also serves as a very brief introduction to traditional *Generative Grammar*, specifically the tradition of *Transformational Grammar*, from which *Construction Grammar* deviates.

The goal of a generative grammar is to include all and only the rules that produce syntactically well-formed sentences. The generative approach typically has a distinction between the rules which govern how words can be combined and how words contribute meaning to a sentence, *syntax* and *semantics*. In support of this distinction, Chomsky (1957) gives his famous example, “Colorless green ideas sleep furiously.”, a sentence which is syntactically correct but semantically inscrutable.

Under Chomsky’s account (and others), syntax allows words to form *constituents* which act as a single unit and participate in a hierarchical structure. One common kind of constituent is the *phrase*. An example is the basic noun phrase “the ball”. Constituency can be difficult to define formally and is frequently recognized based on how constituents travel together during movement operations (e.g. “[In the mountains] is [the man].” “[The man] is [in the mountains].”). Phrases are typically analyzed as having a *head* or nucleus which other constituents attach to. In a verb phrase this would be the verb. Phrases can take other phrases as constituents which results in the traditional syntax tree structure many people recognize from elementary school. Phrases are constructed by *phrase structure rules*. However, Chomsky also proposes *transformational rules* which operate over phrase structure to produce utterances.

Chomsky (1965) distinguishes between *deep* syntactic structure and *surface* syntactic structure which are related through these transformation rules. The idea is to relate semantically coherent but seemingly syntactically distinct sentences. A classic example of this would be fronting phenomena seen in (1 b,d):

1. a) The boy ate in the kitchen.
   b) In the kitchen, the boy ate.
   c) The boy will eat.
   d) Will the boy eat?

(1 a,b) are seemingly semantically identical, and at least they are true in the same logical world[1]. Similarly, the question (1d) is related to its declarative form (1c). Under a transformational account, 1(a,b) share the same underlying deep structure and 1(c,d) share the same underlying structure. In the transformational tradition, this deep structure is the level at which grammatical roles such as *subject* and *object* are assigned. While more modern "minimalist" approaches (see Chomsky, 1993) have done away with deep and surface structure specifically, the idea of sentences being derived from a different form remains an important part of these theories.

Chomsky (1965) is also one source for the concept of *subcategorization* which further constrains how predicates, usually verbs, can combine with constituent arguments and adjuncts. Syntactically, *arguments* to a predicate are constituents that are necessary to complete the predicate's meaning, while *adjuncts* are optional. As an example, consider (2):

2 a) I attained enlightenment in my sixth year.
  b) I attained enlightenment.
  c) *I attained.
  d) *I attained in my sixth year.

[1] Though, see Birner & Ward (1998) for an argument that non-canonical word order encodes information status.

The verb *attain* in (2a) appears with a noun phrase, *enlightenment*, and a prepositional phrase. The latter is optional (e.g. 2b) while the former is required for the sentence to make sense (2c,d). *Attain* subcategorizes for a direct object and is what is typically called a *transitive verb*. How constituents are expressed as arguments and adjuncts to predicates is called *argument structure*. Throughout this manuscript I make use of the following terms to refer to specific argument structure patterns:

Intransitive: One argument, e.g. *"He slept."*
Transitive: *Two arguments*, e.g. *"He attained enlightenment."*
Ditransitive: *Three arguments*, e.g. *"He gave me his possessions.*"

These patterns can combine with phrases in different ways yielding, for example:

Prepositional Transitive: "*He listened to them."*
Prepositional Ditransitive: "*He gave his possessions to me."*
Double Object Ditransitive: "*He gave me his possessions"*

The focus of this manuscript is the constructionist account of argument structure, specifically how argument structure constructions are acquired and the role argument structure plays in constructing semantic meaning.

With regard to the latter, the distinction in traditional approaches between syntax and semantics means that argument structure itself does not contribute semantics. As to how syntax is acquired, traditional generative approaches posit a *universal grammar* and language-specific learning mechanisms (e.g. Chomsky, 1981; Lidz, Gleitman, & Gleitmanm, 2003; *inter alia*). Arguments in favor of this approach typically make reference to the *poverty of the stimulus* argument which holds that children's linguistic environment is simultaneously too complex for linguistic patterns to be learned empirically and too limited to explain the incredible generative capacity of language. Instead, UG approaches typically claim that certain linguistic structures or cues are known a priori, and that language acquisition involves linking UG to the linguistic environment. In effect, there is a strong linguistic prior.

The following section describes the constructionist approach to linguistics which differs along all of the dimensions mentioned above. Unlike transformational grammar, construction grammar is not derivational. Constructionist approaches do not clearly divide syntax and semantics, and most adopt an empirical approach to language learning.

2.2 Introduction to Construction Grammar

Construction grammar is an emerging approach in linguistics that is both vastly different from the transformational approach and able to explain phenomena it does not. Construction grammar proposes that the fundamental building blocks of language are *constructions*, pairings of form and meaning where some aspect of the meaning is not strictly predictable from its component parts or another construction. Defined thusly, constructions cover all levels of linguistic description, from individual morphemes (e.g. -er, -ed) to complex phrase structure. In construction grammar, there is no typological distinction between words and syntactic constructions. To borrow from computer science, they are all the same data structure. This allows for an exceptional level of representational flexibility. As an example, consider Cullicover & Jackendoff's (1999) examination of the comparative-correlative construction as in:

3. The more I read, the less I understand.[2]

This statement implies an inverse correlation between reading and understanding, but no individual word encapsulates this meaning. Instead, the form of the construction itself guides the

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[2] A statement that hopefully won't be true of this dissertation

reader to this conclusion. As another example, consider Fillmore et al.*'s* (1988) analysis of the 'let alone' construction exemplified below:

4. a) I wouldn't live in Austin, let alone Houston.
   b) He couldn't run a mile, let alone a marathon.

An idiosyncratic property of the phrases following the commas is that they are required to begin with the lexical item, 'let alone', hence the name of the construction. However, the expression is not completely rigid as the phrases can vary widely subject to the restriction that they are comparable along the same dimension (e.g. goodness of city or distance). Construction grammar allows such mixed constructions and furthermore benefits from allowing syntactic forms to contribute semantics not easily attributable to a word.

Of course, not all meaning is specified by the syntax. Rather, a sentence interpretation arises from the integration of the semantic slots specified by the syntactic structure with those specified by the verb and pragmatic environment. Goldberg (1995, 2006) distinguishes between *argument roles* which are provided by the syntactic construction and *participant roles* which are provided by the verb. Individual verbs *profile* (make salient) specific participant roles. Sections 2.3 and 2.4 provide more information regarding lexical and constructional semantics.

Construction grammars differ from transformational approaches in another key way. They typically conform to the *surface generalization hypothesis*--that there is no distinction between surface form and a deep underlying syntactic format (Goldberg, 2003). Thus, while construction grammar is hierarchical, it is not derivational or transformational. Section 2.5 provides more detail on the interpretation and integration process.

Finally, constructionist approaches do not posit a universal grammar (Chomsky, 1981; Lidz et al., 2003; Lidz & Gleitman, 2004; *inter alia*) . Instead, constructions are hypothesized to be learnable on the basis of the input without recourse to language-specific mechanisms. Chapter 3 provides more detail about construction acquisition and the role of analogy[3] in particular.

2.3 Lexical Semantics

This section describes the approach to lexical semantics that has influenced the representations used throughout this thesis. Here, and in many constructionist approaches generally, we take a frame semantics approach to representing lexical semantics (Fillmore, 1967).

The frame semantic approach grew out of work on case grammar (Fillmore, 1967). Fillmore builds on the larger concept of *Case*, which refers to a system for marking dependent phrases for semantic or syntactic relationships, and he proposes an intermediate level of representation that bridges syntax and semantics called *deep case*s. Deep cases can be thought of as proto-semantic roles (e.g. `Agent`, `Object`, `Location` etc.), and each verb selects for certain sets of required and optional cases. Which deep cases a verb selects for is called its *case frame*. As an example, consider the verb *buy* which requires an `Agent` and an `Object` (e.g. I_{Agent} bought the $\text{pizza}_{\text{object}}$). Fillmore describes several ways in which deep case roles can be reflected in the surface form of a sentence, including the selection of prepositions and word ordering (Fillmore, 1967).

Note that a distinction is made between deep cases and the surface form. Deep cases reflect underlying syntactic structure which can be surfaced in a variety of ways. As an example, consider surface morphological case marking-- it is present in English pronouns which have different forms for the nominative (subject), accusative (object), and genitive (possessive) case:

[3] The term analogy is sometimes limited to comparisons of the form “A is to B as C is to D” where each item of comparison is a concept at the same level. However, throughout this thesis the term analogy is used more broadly to refer to the mapping of structured representations that may contain many concepts, including mappings between instances and generalizations as in later chapters.

i.e. I/he/she/they vs me/him/her/them vs mine/his/hers. An example of these differences is shown in (5).

5. a) I gave him the ball.
   b) *me gave he the ball.
   c) he gave me the ball.

The morphological case in (4ab), *I* vs *me*, reflects the deep distinction between `Agent` (*I*) and `Dative` (*me*). However, the same morphological case can cover multiple deep case assignments as in (6) where (me) is an `Instrument`.

6. a) He used me to hurt you.

Fillmore (1967, 1977) further proposes the existence of a case hierarchy which governs which phrases typically appear in subject position. While the principles have evolved and become more complex, it has been argued that a basic selection principle is that the subject is selected according to a case hierarchy:

Agent > Instrument > Object

That is to say that if a verb's case frame has both `Agent` and `Instrument` deep case, the `Agent` will canonically appear in subject position. If no `Agent` is present or the speaker wishes to de-emphasize its role, an `Instrument` takes subject position (see 6 a-b). Principles of subject selection can account for the ordering in (6c) when both an `Agent` and `Instrument` are present. Choosing to violate the case hierarchy (as in the passive) affects the form of the verb (e.g. 7 a,d)

7. a) John broke the window.
   b) A hammer broke the window.
   c) John broke the window with a hammer.
   d) The window was broken by John.

Under this account, the subject is a feature of the surface form of the sentence and is determined based on the underlying semantics (e.g. deep cases). This runs counter to Chomsky's

Standard Theory account (Chomsky, 1965) which posits surface and deep syntactic structure, and, while Fillmore does alter his account to reaffirm syntactic relations like subject and object, in many ways his approach foretells the Constructionist surface generalization hypothesis. For further evidence supporting this approach see Goldberg (1995, 2006).

Frame semantics provides the lexical-semantic framework for this work, and it builds on deep cases by addressing elements of meaning that they do not cover well. In developing frame semantics, Fillmore (1977) also attempts to limit the need for a proliferation of deep cases to cover all subtle aspects of meaning.

Fillmore (1977) suggests that the meaning of a word is understood relative to a cognitive schema that it brings into perspective. Which elements of a sentence are in perspective, in English, correspond to the arguments in the subject and direct object roles. Fillmore calls these the *nuclear elements* and proposes that which elements are selected as nuclear depend on which roles a verb foregrounds and general rules of salience. As an example, he suggests that human-like objects are more salient (see example 9 below).

Fillmore (1977) gives the classic example of a `Commercial_event` frame which might contain words such as *buy*, *sell*, and *pay*. Each of these words evokes the same background frame, but they represent different perspectives. The verb *buy* brings into focus the `purchaser` and the `goods`, while *pay* focuses on the `purchaser` and the `money`. As an example of how this effects the nuclear elements, see (8 a-d) below (Fillmore, 1977, p. 73).

8. a) I bought a dozen roses.
   b) I paid Harry five dollars.
   c) I bought a dozen roses from Harry for five dollars.
   d) I paid Harry five dollars for a dozen roses.

While each verb brings different elements into perspective, the other elements of the frame can be added on as adjuncts (8 c-d). Note that in (8c) the verb buy requires the goods to be a nuclear element, while in (8d) the money appears as nuclear. In neither case could one switch the object and oblique arguments and have a sensible sentence, but both sentences clearly express the same commercial transaction.

It's important to distinguish here between the roles of the cognitive schema that are evoked by the word, what we will call *frame elements* throughout, and the original deep cases which are far more generic. Fillmore proposes that arguments to the verb are brought into the foreground based on the salience of their frame elements, and that deep cases determine how they appear grammatically (e.g. in nuclear roles, subject and object).

Not all roles that a verb can bring into perspective appear in every construction. Rather a verb has a set of perspectives available. As an example, consider *hit*, which can perspectivize the `hitter` and `victim` roles, `hitter` and `instrument`, or just `instrument` and `victim` (9a-c) (Fillmore, 1977, p.75-6). Though when the object is itself animate there does seem to be a preference for appearing as a nuclear element, hence the awkwardness of (9e) which dehumanizes Harry.

9. a) I hit the fence with the stick.
   b) I hit the stick against the fence.
   c) The stick hit the fence.
   d) I hit Harry with the stick.
   e) ? I hit the stick against Harry[4].

[4] I don't interpret this as dehumanizing but rather as a repeated and non-harmful event. Perhaps this is because *against* typically implies that the hit object does not break. It sounds much better to me with the preposition "until …".

However, for some verbs certain roles are consistently in perspective. Compare *hit* to *beat* which is required to foreground the agentive role when transitive.

10. a) The stick hit the fence.
    b) *The stick beat the fence.

Interestingly, the semantic availability of certain information in a scene can bias recall towards verbs that perspectivize that information. Gentner (1981) found that participants were more likely to incorrectly recall a more specific verb appearing in a paragraph vs a general verb when the paragraph included extraneous information relevant to the more specific meaning. As an example, participants incorrectly recalled the verb *pay* (instead of the original verb, *give*) in a paragraph about money transfer when the money was *owed*.

To summarize, a verb in a syntactic construction puts into perspective certain elements of a broader frame, and individual verbs have certain frame elements that they obligatorily perspectivize. Langacker (1987) and Goldberg (1995) use the term *profile* to refer to the frame elements that a word obligatorily brings into perspective. Consistent with Goldberg, I will use the term profile in this way in the following sections.

Thus, nuclear elements of a sentence foreground elements of a semantic frame that is evoked by a word. These elements differ from deep cases, which are proto-semantic roles that apply to phrasal arguments and constrain which nuclear elements are assigned to which phrases.

2.4 Constructional Semantics

Goldberg builds frame semantics by allowing grammatical slots in a construction to carry semantic meaning (Goldberg, 1995). Goldberg calls the semantics that comes from these slots *argument roles* and distinguishes them from semantics that come from the verb, *participant roles*. Like Fillmore, Goldberg proposes that certain syntactic slots are salient (nuclear elements:

subject/object). The argument roles in these slots are *profiled*. Similarly, as described above, verbs *profile* elements of a semantic frame. These are profiled participant roles. Interpretation then proceeds as fusion of argument and participant roles pursuant to two constraints. This process is described in more detail in section 2.4. For now, let us consider an example from Goldberg (2006), the difference between the verbs *rob* and *steal*.

11. a. He stole the diamonds.
    b. *He robbed the diamonds.
    c. He robbed the banker.
    d. *He stole the banker.
    e. He stole the diamonds from the banker.
    f. He robbed the banker of his diamonds.

Both *rob* and *steal* entail a theft, but *steal* profiles the goods that were taken while *rob* profiles the victim of the crime. Thus, in 11a, it is acceptable to have the stolen diamonds in a profiled object position, while 1b is ungrammatical because the profiled victim is not present. The inverse is true for 11c,d. Furthermore, for both verbs the argument role assignment is consistent. The subject is the agent, and the direct object is the patient acted on. What Fillmore would identify as the deep case is the same but the profiled frame elements are different.

Note that both verbs can take the other's profiled role as an unprofiled adjunct as in (11 d-e) demonstrating that neither verb lacks the other's roles. Construction grammar thus provides a role for both specific verbal frame elements and an equivalent to Fillmore's deep cases. The deep cases correspond to the meaning brought by the construction and are tied to syntactic positions, the argument roles.

Argument roles attached to constructions allow many benefits. The first is one we have already discussed, the avoidance of hypothesizing preposterous word meanings like *crutch* in (1).

Another famous example of this is the caused motion construction exemplified in (12) below (Goldberg, 1995, P.152)

12. a) Sam helped him into the car.
    b) Frank sneezed the tissue off the table.
    c) They laughed the poor guy out of the room.
    d) *His cane helped him into the car.
    e) John asked Joe into the room.
    f) *John begged Joe into the room.

In each of the examples from (12) it is necessarily the case that the direct object of the sentence moves and that the subject is in some way causally responsible. Yet, (12 b-c) do not typically occur with a direct object, and the verb *help* certainly does not imply movement of the direct object by itself. Instead, Goldberg argues that the construction *coerces* the verb into a motion interpretation because the subject carries a `cause` argument role and the oblique argument caries a `goal` argument role. Note that the subject is required to be an agent or natural force since 12d is unacceptable. Furthermore, the construction only works when motion is implied as caused by the subject and not mediated by the object (e.g. 12f). These findings are compatible with a constructionist account but would be at odds with a lexicalist interpretation of the sentences.

Furthermore, it enables an independent analysis of a verbal predicate's arity. From a traditional perspective, one must say that a verb like *kicked* is a binary predicate based on the transitive form "X kicked Y". However, it can also be used as in "X kicked By the Z." Typical treatments assume *kick* is an n-ary predicate with n arguments only when they appear (which is in fact circular).[5] In a constructionist account, the verb itself has only a few senses, but these can

[5] Note that a Neo-Davidsonian or Frame Semantic treatment of the verb helps with this problem. In such an account, kick isn't a predicate at all but rather an event with binary frame elements that take it as an argument. Still, the question arises as to whether all the frame elements that it can appear with are actually "core" elements

be integrated into a construction (like the double object) to produce new kinds of meaning. Thus, the question of the arity of the predicate *kick* is simplified in that we no longer have to account for the constructional meaning. This also preserves some level of compositionality between verbs and syntax without positing undue semantics.

Goldberg (1995) proposes that interpretation involves the fusion of argument and participant roles and provides several criteria that govern the process. One contribution of my work is an algorithmic account of role fusion by analogy.

2.5 Language Interpretation and Role Integration

Goldberg puts forth two principles that govern fusion. The *semantic coherence principle* states that an argument and participant role may only *fuse* if one of the roles is an instance of the other. The *correspondence principle* states that, by default, profiled participant roles are fused with profiled argument roles. An exception is verbs with three profiled roles (e.g. *give*) which may have the least salient realized obliquely (e.g. as a prepositional attachment). When the correspondence and coherence principles are met, argument and patient roles lie in one-to-one correspondence.

These principles can explain the syntactic judgments in (11) (*steal* vs *rob*). In the ungrammatical examples (11 b,d) the lack of the profiled participant in the direct object violates correspondence. Note that it's not just the absence of the role as the sentences in (13) are also ungrammatical despite having all required arguments.

13. a) *He stole the banker of the diamonds.
    b) *He robbed the diamonds from the banker.

---

or not. Allowing for constructional semantics enables us to use the verb in novel ways without presupposing that the verb is a part of a particular frame.

The correspondence principle is not bidirectional. In a sentence like "X kicked Y the Z." there is no profiled or unprofiled role from *kick* corresponding to the Y recipient. That comes from the construction (a more obvious example is of course (1), *crutch*).

These principles govern canonical linguistic usage, but they can be violated with effect. A classic example of this is the passive construction in which the *agent* role is elided. Goldberg (1995) describes ways in which constructions can modify the role.

Shading occurs when a construction allows the most salient profiled argument to be unexpressed. An example is the passive construction (e.g. Mark was hit.) which elides the agent. Constructions can also *cut* roles entirely. The difference is that shading allows the role to be expressed as an adjunct (e.g. Mark was hit by Bill.) while cutting does not. An example of a cutting construction would be the English middle construction (e.g. The cheese cuts easily.) which does not allow the removed agent to be added as an adjunct.

Finally, Fillmore (1986) presents null instantiations which allow individual verbs to permit unexpressed roles. *Indefinite null complements* are required by the semantic frame but not syntactically. An example would be the *food* in the verb *eat* which can be used intransitively (Bill ate). These could be analyzed as optional unprofiled participant roles. Definite null complements however are more interesting and occur only when the elided argument can be recovered from context. An example would be the word *win* which can be used without a direct object (Bill won!) but only when what was won is inferable. Fillmore proposes that which roles can be null instantiated is verb-specific.

The focus of this work is on language usage that follows the *coherence* and *correspondence* principles (including when the verb lacks known roles as in *crutch*). I propose an account whereby fusion is achieved through analogical comparison (Chapter 3-4) and do not investigate cutting or shading.

2.6 Linguistic & Ontological Resources

This work makes use of several important resources. This section serves as an introduction to these resources.

2.6.1 Cyc Ontology

The Cyc ontology is the result of a multi-decade project to formalize the prerequisite background knowledge that an artificial intelligence would need to function independently in the world. The ontology language, CycL, is based on predicate calculus and includes higher-order predicates (e.g. quantification over predicates, modal logic) (Ramachandran, Reagan, & Goolsbey, 2005). Facts in Cyc are contextualized in hierarchical contexts called *microtheories* (Matuszek et al., 2006). Microtheories allow for contradictory expressions to exist in different contexts. For example, in the microtheory of real world facts, Peter Parker is a fictional character, but in the Marvel universe microtheory he both is real and has saved the world multiple times.

In Cyc, *collections* contain *individuals* or other collections that share certain properties. Membership in a collection is expressed with the predicate `isa` which is not transitive. Collections can inherit membership from parents via the transitive predicate `genls`. In addition to truth-conditional expressions, CycL allows *functions* which return new terms. For example, the expression `(spouseOf Clifton Suzanne)` is true in the world where Clifton and Suzanne are married. Suzanne could also be referred to using a function `(SpouseFn Clifton)` which returns the individual that is married to Clifton. Thus `(loves Clifton (SpouseFn Clifton))` and `(loves Clifton Suzanne)` are both true. CycL is the representation language used throughout this manuscript.

2.6.2 FrameNet

FrameNet is a computational compendium of semantic frames (Fillmore et al., 2001; Ruppenhofer, Ellsworth, & Petruck, 2006). In keeping with the central ideas of frame semantics, FrameNet links *lexical units* (words) to semantic frames which have core and non-core frame elements. As an example, see Figure 1, the entry for the `Giving` frame.

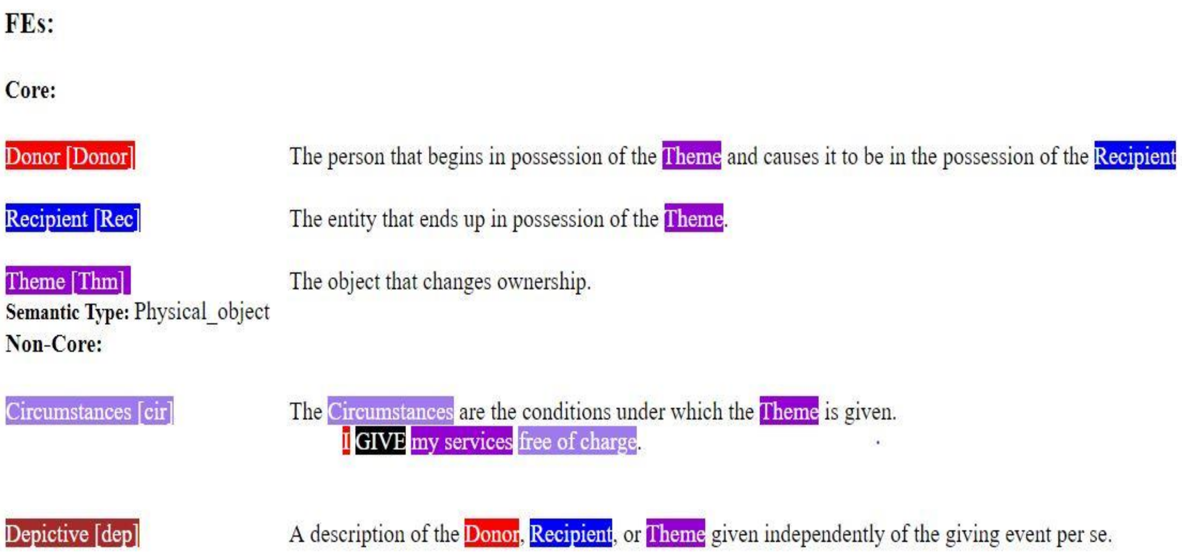

Figure 1: FrameNet Entry for the Giving frame

The `Giving` frame defines core frame elements for the `Donor`, `Recipient`, and `Theme` (the thing transferred). It also has non-core elements such as the `Circumstances` under which the event takes place. Core arguments are defined as those that are essential to the meaning of the frame. One prediction of coreness is that these are roles that are required to appear either explicitly in a construction or as a null complement. Non-core roles should appear primarily as adjuncts (e.g. prepositional phrases). Examples of typical non-core roles include place and manner.

Each frame contains lexical units that evoke it, and each lexical unit is annotated with syntactic patterns through which it instantiates the frame. These are called *valence patterns*. In “I gave him the tickets.”, the valence pattern is that the first noun phrase (I) is the Donor, the second noun phrase (him) is the Recipient, and the third (the tickets) is the Theme. In valence patterns, phrases that fill frame elements are also annotated with their grammatical function. Subjects are labeled <ext>, objects are labeled as <obj>, and oblique arguments and adjuncts are labeled as <dep>. Table 1 shows several valence patterns for the verb *give*. FrameNet explicitly marks indefinite null instantiated roles (INI), definite null instantiated roles (DNI), and null instantiations that are only licensed by a construction like the passive (CNI).

Table 1: Valence pattern examples

Donor	Recipient	Theme	Example: Give
NP<ext>	NP<ext>	NP<ext>	I gave him the tickets.
NP<ext>	PP[to]<dep>	NP<obj>	I gave the tickets to him.
CNI	NP<ext>	NP<obj>	He was given the tickets.

In the vocabulary of Goldberg (1995), frame elements roughly correspond to participant roles. However, being a core frame element does not imply that it is a profiled participant role. Which core elements of the frame are profiled is specific to each evoking lexical unit, and it is implicit in the valence patterns that a word can participate in. Furthermore, not all verbs in a frame necessarily participate in the same set of valence patterns, and thus each lexical unit is annotated separately.

FrameNet also consists of a rich frame hierarchy in which frames can inherit from and be subframes of other frames (Baker, Fillmore, & Cronin, 2003). A frame that inherits from a parent has a corresponding frame element for each element in the parent, and it can introduce new frame elements. The subframe relation allows frames to act as ordered arguments to another frame, forming a kind of script. An example of this is the `Arraignment` frame which has subframes for the `Notification_of_charges`, `Entering_of_plea`, and `Bail_decision` which occur in that order. The `Arraignment` is itself a subframe of the larger `Criminal_process` frame. These subframes do not fill frame elements and in fact each has their own frame elements and lexical units. Rather they are ordered conceptual sub-events that occur as a part of the parent frame.

In this work, FrameNet provides the formalism for individual sentence semantics, and FrameNet annotated corpora are used in the construction learning experiments in Chapters 5 and 6. FrameNet is also used to generate case frames for the semantic parsing system in Chapter 8.

2.6.3 Dependency Parsing

In traditional phrase structure grammars, words form phrases which act as constituents to larger phrasal structures. The result is a *constituency parse* where words are constituents to intermediate phrases. Thus far, this work has approached language from a constituency perspective in assuming structures such as noun phrases and verb phrases. An alternative to a constituency representation is a *dependency parse*.

In a dependency parse, lemmas (words) are instead related to each-other using a fixed inventory of binary grammatical relations (e.g. Choi & Palmer, 2012; de Marneffe et al., 2014) . A dependency relation holds between the *head* and its *child* and is directed from head to child. A completed dependency parse is a directed graph containing all lemmas where all lemmas are the child of only one head and one node (the root) has only outgoing edges. This is frequently the main verb of the sentence. An example phrase structure parse and dependency parse are shown in Figure 2. Note that because the dependency parse does not introduce intermediate phrasal structures it has a flatter structure.

In the example in Figure 2, the word *boy* is the nominal subject of the root, *ate*. The *pizza* is its direct object. The determiners are the children of each noun through a determiner relationship. A number of dependency formats have been proposed. The most relevant to this work are the universal and CLEARStyle dependencies used by the spaCy[6] syntactic parser (Choi & Palmer, 2012; de Marneffe et al., 2014). For an extensive list of dependency relations covered by each, see the papers cited.

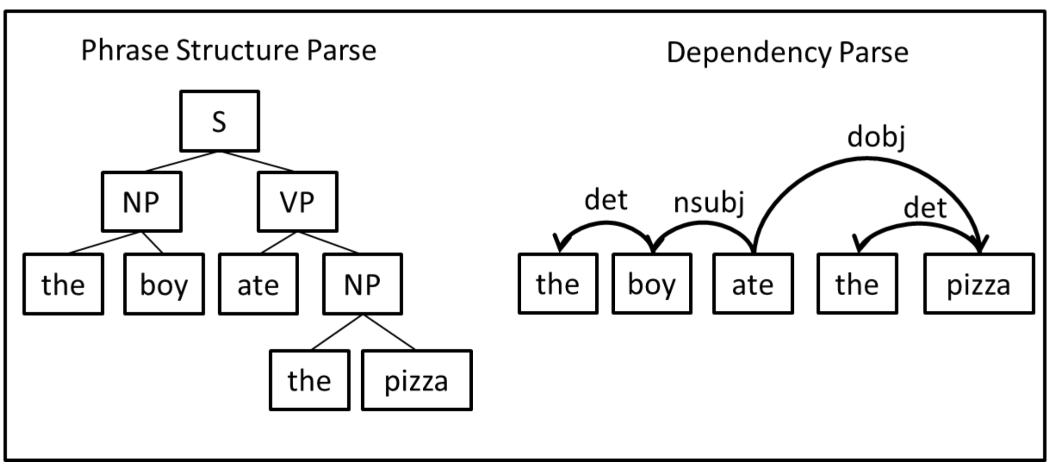

Figure 2: Parses for "The boy ate the pizza."

SpaCy is a natural language processing library that includes a statistical dependency parser and a number of trained language models. In this work, I use the SpaCy dependency

[6] https://spacy.io/api/annotation

parser and a language model trained on the OntoNotes corpus (Weischedel et al., 2013) and word embeddings trained on CommonCrawl[7] to provide a set of ordered dependencies as syntactic arguments to my argument structure constructions. This approach is described in Chapter 8.

2.7 Related Approaches

While this research has been most influenced by Goldberg's cognitive construction grammar (Goldberg, 1995, 2006), there are other approaches to construction grammar, some of which are also computationally implemented. This section describes these related approaches.

Goldberg (2006) describes several ways in which cognitive construction grammar differs from other constructionist paradigms. The first of these is what Goldberg identifies as Unification Construction Grammar (UCxG) (e.g. Fillmore et al., 1988; Kay & Fillmore, 1999). Like Head Driven Phrase Structure Grammar (Pollard & Sag, 1994), UCxG proposes a unification-based framework where each construction is an attribute value matrix. Pairs of attribute value matrices can be combined to form an expression or sub-part of an expression provided their attribute values do not conflict. The result of unification is a new attribute value matrix with the union of attributes and values from both constructions.

Sign based construction grammar (SBCG) aims to be a more rigorous formalism for unification based construction grammar (Boas & Sag, 2012). It includes a typed hierarchy of feature structures starting with the most general *sign* which includes words, lexemes and phrases. Including phrases, and thus grammar, as the same fundamental type as words marks it as a constructionist account and is a major departure from other unification grammars like HPSG.

[7] http://commoncrawl.org/

Fluid Construction Grammar (FCG) is also a unification-based construction grammar, however it takes a cognitive-functional approach in trying to model both syntactic correctness and linguistic processing (Steels, 2011). This differentiates it from purely generative models[8] of language. In FCG, constructions are represented as dyad feature structures with a semantics and a syntax side. This makes FCG constructions usable for both interpretation and language generation. The FCG formalism has been computationally implemented and used for experiments in robotic language evolution and human robot interaction (Spranger, 2016, 2017).

Embodied construction grammar (ECG) proposes that constructions link linguistic form to conceptual schemas which specify parameters for simulation (Bergen, Chang, & Narayan, 2004). This in turn results in inference and response. ECG also makes use of a unification-based framework but goes significantly further in its argument for the primacy of sensorimotor grounding.

With the possible exception of ECG, these unification based approaches are not necessarily intended to be cognitive models of language processing. Further, at least UCxG makes a distinction between grammatical representation and language use, and thus would not include information such as frequency in their construction representations. In contrast, Goldberg's approach, as well as other similar paradigms, focuses heavily on cognitive plausibility rather than on formalism design and algorithmic implementation. One goal of my research has been to provide a psychologically motivated formalism for and algorithmic account of construction acquisition and application based on this less formalized approach.

[8] This is not without objections. See (Müller, 2017) for an argument that FCG is in fact not so different from SBCG and other similar approaches.

Aside from Goldberg's work, there are a few other constructionist accounts that share the cognitive focus. Cognitive Grammar (Langacker, 1987, 1991) is one such approach that has many similarities with and heavily influences cognitive construction grammar (Goldberg, 2006). One way in which it differs from prior approaches is in its commitment to *image schemas* as semantic representations rather than propositional expressions. In this way it is more similar to ECG which uses embodied representations as well.

Another is Radical construction grammar (RCxG) (Croft, 2001). RCxG focusses on cross-linguistic differences to reject any kind of universal syntactic category or role and instead proposes that these are in fact construction-specific. This is in contrast to cognitive grammar which does at least posit some cognitive reality for parts of speech and other syntactic labels as prototypes.

Finally, the work in this dissertation does not completely conform to or cover all aspects of Goldberg's account. Of particular interest are the concepts of argument roles, participant roles, profiling, and role fusion. While I do address construction acquisition, I focus specifically on generalization and do not model relationships between constructions. Construction networks are a substantial contribution of prior work in linguistics and a significant area of interest for future work in extending my approach.

2.8 Conclusion

This chapter has summarized the core claims of construction grammar as well as the representational background that motivates a large portion of this work. It begins with deep cases which are proposed as a semantic layer that influences syntactic surface patterns. Deep cases can be thought of as very general semantic roles (e.g. `Agent`) that are selected by individual verbs. The set of deep cases that a verb selects for is its case frame (Fillmore, 1967).

Frame Semantics is introduced as a formalism in which verbs are interpreted relative to a cognitive schema that they provide a perspective on (Fillmore, 1967). Under a frame semantic account, verbs evoke a cognitive schema (such as giving) and profile specific roles of that schema in their nuclear syntactic positions. Frame elements come from underlying conceptual schemas, while deep cases are linguistic and control how profiled roles appear as subject and direct object.

Goldberg builds on Fillmore's approach, with deep cases playing the role of constructional semantics (argument roles) and frame elements as lexical semantics (participant roles) (Goldberg, 1995). Following Fillmore, constructions have profiled syntactic positions and words profile a specific subset of their participant roles. Goldberg proposes that interpretation involves fusing argument and participant roles pursuant to the constraints that the latter is an ontological specialization of the former and that the profiled participant roles appear in a construction's profiled syntactic slots (i.e. subject and direct objects).

The next chapter presents an argument for the role of analogical generalization in acquiring argument roles from individual example sentences as well as relevant psychological and computational background. Ultimately, I argue that argument structure constructions are acquired by a process of analogical generalization and that application can be modeled as analogical alignment between a syntactic construction and its arguments, including the participant roles of the verb.

3. Analogical Generalization of Constructions

3.1 Introduction

Given that constructionist approaches do not posit a universal grammar, an important question for these theories is how constructions and their associated argument roles are learned. This thesis draws inspiration from *usage-based* accounts to language learning which posit that language structure emerges from patterns of use, and that the process of language acquisition draws heavily on general cognitive pattern-finding processes (e.g. Tomasello, 2009). One suggestion has been that structured analogical comparison plays an important role in the acquisition of abstract constructions (Tomasello, 2009). This chapter describes the relevant background on language acquisition, analogy, and a summary of psychological evidence supporting the role of analogy in language acquisition.

3.2 Language Acquisition

Usage-based approaches promote the idea that language is learned using domain independent learning processes (Goldberg, 2003; Tomasello, 2009). Specifically, Tomasello has proposed that abstract constructions, such as the double object, are learned by generalizing over individual examples of them. The semantics associated with these constructions is thus a generalization over the semantics of the individuals. To put this in terms of Goldberg (1995), this would imply that argument roles emerge as generalizations over consistent alignments of syntax and participant roles.

Since constructions are learned from examples, this account predicts a pattern of development where competence is incremental and initially confined to contexts that appear frequently in the learner's environment. Tomasello marks out the learning trajectory in Figure 3 (Tomasello, 2009; Tomasello & Brooks, 1999).

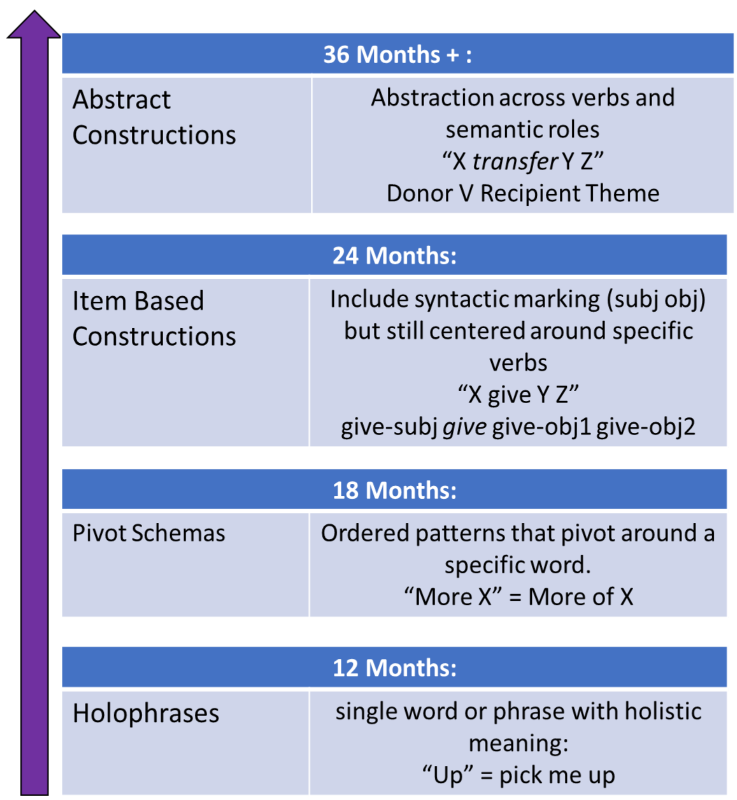

Figure 3: Developmental Trajectory of Grammar

Children begin with fixed holophrases which are single or multiword units that are invariant and have a consistent meaning. These are replaced by pivot schemas which allow variation around a fixed linguistic unit. Pivot schemas are followed by what Tomasello calls *item-based* constructions which include syntactic structure but are specific to the linguistic context they were acquired from. Children might acquire "X *gave* Y Z" and "X *sent* Y Z", but they have not yet generalized them into an abstract double object construction. It is this transformation from item-based to *abstract* constructions that is the primary focus of this dissertation.

This trajectory has been supported by an array of developmental evidence. For example, Maratsos et al. (1987) taught children a novel verb for a transitive action by using it in intransitive statements about the action (e.g. “The dough finally fudded” for putting playdough through a machine). The children were asked to repeat the action and asked what they were doing. This should prompt a transitive response (e.g. I’m fudding the dough). While older children (4.5-5.5 y.o.) were able to extend the intransitive usage to the transitive, 2-3 y.o. children were not as productive. This is despite the fact that the younger children could produce the transitive in other situations. This suggests that mastery and generalization of the transitive occurs incrementally, as expected if children learn and generalize from examples. Similarly, Theakston, Lieven, Pine, & Rowland (2001) found that children’s usage of a verb in a transitive or intransitive construction was predictable based on how frequently the verb appeared in that construction in the mother’s speech, again suggesting incremental learning.

Further evidence comes from an investigation of subject-auxiliary inversion errors (e.g. “*what he can ride in?” instead of “what can he ride in?”) in 2-4 y.o. children (Rowland & Pine, 2013). They found that children’s performance was entirely dependent on the specific lexical item, either 100% correct or incorrect. Again, this is expected if learning proceeds on an example by example basis.

Casenhiser & Goldberg (2005) taught children a novel construction (subject object verb) with nonce verbs pertaining to videos of appearance events. For example, a video of a rabbit appearing out of hat could be “The rabbit the hat *moopoed*”. After only sixteen examples (8 scenes repeated twice) children readily applied this construction to other appearance scenarios described with novel verbs. Furthermore, they examined how verb frequency affected the learning of constructions and found that, when the training examples were skewed such that individual nonce verbs appeared more often, children’s performance improved. This pattern of learning, specifically the benefit of skewed frequency, is again predicted by a usage-based account. One proposal as to why a skewed frequency is important is that it facilitates analogical generalization. This proposal is discussed further below.

Since it seems that children do in fact go through a phase where constructions are isolated to individual verbs, how then do language learners generalize item-based constructions? Tomasello (2009) proposes that analogical comparison could be used to align consistent syntactic structures and their associated lexical semantics. I claim that argument structure constructions arise from generalization of these analogically aligned item-based constructions. The section below describes the structure mapping theory of analogy, which motivates my work, as well as the computational model of analogy that is used throughout. Section 3.3 also discusses the developmental evidence that analogy plays a role in linguistic development.

3.3 Analogy

3.3.1 Structure Mapping

Structure Mapping Theory views analogical comparison, and similarity more broadly, as a process of alignment between cases of hierarchical structured representations (Gentner, 1983). As an example, consider the predicate calculus representations below of the subject from two double object sentences: “The dog gave the boy the ball.” and “the boy sent the dog the bone.” In both, there is a noun phrase that plays the role of subject to the verb. The same noun phrase has the semantic role of `donor` in the base (on the left). In each case, it is attached to different words using the predicate `wordMember`.

Base	**Target**
(donor np gave) (subject np gave) (isa np NounPhrase) (wordMember np "the") (wordMember np "dog") (headOf np "dog")	(subject np gave) (isa np NounPhrase) (wordMember np "the") (wordMember np "boy") (wordMember np "sent") (headOf np "boy")

Comparing these two cases proceeds according to several constraints. The *tiered identicality* constraint allows two expressions to match only if they share identical predicates. This constraint can be relaxed to allow mappings between expressions when one predicate is a close superordinate to the other. The *one-to-one* mapping constraint ensures that an entity or statement in one case can match to at most one in another. Thus, the subject noun phrase in the bae can match to at most one noun phrase in the target. The *parallel connectivity* constraint ensures that when two expressions are aligned, their arguments are also aligned. Thus, to align the two subject expressions, the noun phrases must align. Finally, *systematicity* is a preference for shared higher-order structure (e.g. the causal structure). Systematicity is highly predictive of human judgements. As an example, most people would say the sun is more similar to a light-bulb than a red rubber ball. Even though the ball may look more similar, the shared functional relationship, providing light, is what matters. Structure mapping is a psychological theory of similarity that allows for this kind of comparison.

Structure mapping theory has been implemented computationally in the structure mapping engine (SME) (Falkenhainer, Forbus, & Gentner, 1989; Forbus et al., 2017). SME compares a base and target case of predicate calculus statements like those above, which form a directed acyclic graph. Relationships that are present in the base but not the target that are connected to the mapping can be hypothesized as candidate inferences. As an example, consider the mapping in Figure 4 which holds between the two noun phrase subjects below.

As before, in the base on the left, we have a noun phrase subject that plays the donor role for the verb *give*. The target, on the right, has the same syntactic structure, a noun phrase subject. From there, SME hypothesizes that the donor relationship which holds in the base also holds in the target. This is a candidate inference.

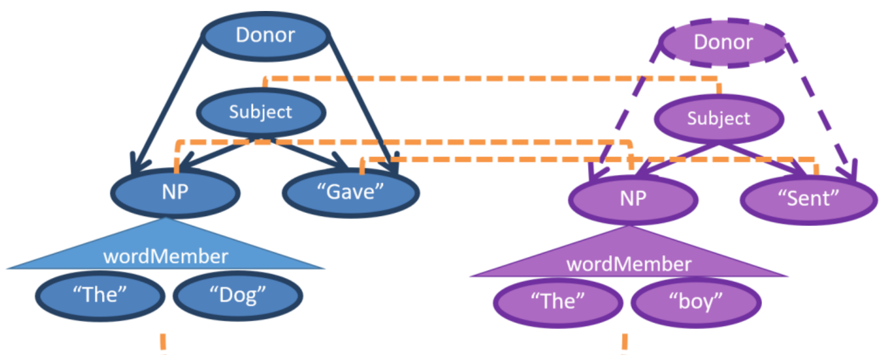

Figure 4: SME alignment between two subject NPs

The SME algorithm proceeds as follows. First, SME creates a match hypothesis network by proposing matches between all identical relations regardless of their structural consistency. Next, SME constructs sets of structurally consistent mappings (called kernels). The kernels are then scored by assigning a score to each match hypothesis in the kernel and allowing the score to trickle-down to sub-matches. This encourages systematicity. Finally, SME uses a greedy merge algorithm to combine compatible kernels based on their score. Candidate inferences are projected based on aligned structure.

There are a number of *control predicates* which can be used to modify how SME handles certain kinds of representations. The most relevant here is the declaration of a function as an `atomicAnalogyNat`. When thus declared, a function and its arguments are taken together as a single term for the purposes of identicality. As an example, consider a function `WordFn` which takes a single word and defines a predicate which applies the word as an attribute of its argument. Thus `((WordFn Dog-TheWord) dog1)` means that `dog1` has the attribute of being represented by `Dog-TheWord`. If not an `atomicAnalogyNat`, the same `WordFn` predicate could match to other `WordFn` predicates (e.g. `(WordFn Cat-TheWord)`). However, when it is an `atomicAnalogyNat`, it will match identically only with other expressions of the form `(WordFn Dog-TheWord)`.

3.3.2 Analogical Generalization

SME provides the matching algorithm for the model of analogical retrieval and generalization used in this work. MAC/FAC (which stands for "many are called but few are chosen") is a model of recall that uses a cheap preliminary feature-based match to return a pool of possible retrievals which are then evaluated by SME to find a structural match (Forbus et al., 1995). MAC/FAC takes a *probe case* which is a case of predicate calculus just as in SME. It retrieves the most similar case from a *case library* which contains cases, again in predicate calculus. This two phase process simulates human performance in a memory retrieval task over a set of cases, demonstrating a retrieval bias towards feature-based retrieval but a preference for analogically related stories (Gentner, Rattermann, & Forbus, 1993).

MAC/FAC is the retrieval mechanism in SAGE, the Sequential Analogical Generalization Engine, a computational model of how analogy is used in concept generalization

(Forbus et al., 2017; McLure et al., 2015). SAGE keeps generalizations in a *generalization pool* which is a case library that contains both examples (single cases) and generalizations. A

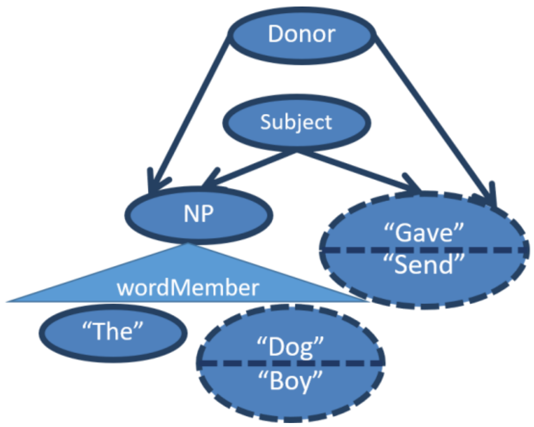

Figure 5: SAGE Generalization

generalization is a group of cases that are structurally aligned. Where they differ, SAGE replaces entities with *generalized entities* and accumulates frequency data about their bindings. A SAGE generalization also keeps a frequency distribution over expressions that are not present in all cases. As an example, Figure 5 shows a generalization of the two subject noun phrases above. From those two cases, SAGE has created a generalization for subject noun phrases that is consistent in its semantic role but which has a probabilistic distribution over the individual words. Of course, not all subject noun phrases are `donors`, rather this mapping should be viewed in the context of a mapping for the entire sentence which includes the rest of the double object syntactic structure. SAGE stores generalizations and ungeneralized examples in a case library called a *gpool*.

One claim of this work is that abstract constructions are acquired by analogical generalization over examples. Syntactic relationships (such as nuclear elements) provide the structure which SME generalizes over. Consistent semantic elements then emerge over time. The following section outlines existing psychological evidence that analogy plays a role in language acquisition.

3.4 The Role of Analogy in Construction Generalization

There is evidence that comparison facilitates the kind of abstraction and relational transfer needed to learn constructions. For example, Christie & Gentner (2010) taught preschoolers labels for novel spatial configurations. They then asked the preschoolers to extend the labels to one of two examples. One shared the same objects used in training while the other shared the same spatial relation. They found that children who were asked to explicitly compare the examples during training were significantly more able to transfer the label to the relational rather than object match. Further, Namy & Gentner (2002) found that common labels can invite comparison, facilitating the formation of categories based on relational rather than perceptual similarities.

More evidence that analogy plays a role in language acquisition comes from findings regarding a phenomenon called *progressive alignment* whereby comparison of examples with lower-order commonalities (e.g. attributes) facilitates extracting higher-order commonalities (Kotovsky & Gentner, 1996). Progressive alignment is predicted within the structure mapping literature, and SAGE has been used to model progressive alignment effects (Kandaswamy, Forbus, & Gentner, 2014). Recall from section 3.2 that Casenhiser & Goldberg (2005) demonstrated a facilitating effect of skewed verb frequency on construction acquisition. When a construction appears disproportionately with the same verb, it both invites comparison based on the shared linguistic item and facilitates progressive alignment due to the increased surface similarity (the same verb).

There is further evidence of progressive alignment effects in language development. For example, Goldwater, Tomlinson, Echols, & Love (2011) proposed a structure-mapping account of children's construction learning, as assessed by their linguistic *structural priming*. The phenomenon of priming in general is that conceptually related material is quicker and easier to access in memory, hence the ability to *prime* or bias retrievals using a priming example. Structural priming in language occurs when subsequent sentences repeat the sentence structure of utterances from earlier in the discourse. An example of this might be that an individual is more likely to use the double object construction (NP V NP NP) instead of the prepositional dative construction (NP V NP PP) to describe a giving event following the use of the double object in a previous utterance.

Goldwater et al. (2011) found that both 4- and 5-yr-old children showed linguistic structural priming, but 4-yr-olds required more semantically similar primes (e.g. sentences from the same domain) in order to show priming. Goldwater and Echols (2014) further found that 4-yr-olds primed with highly similar sentences could go on to show priming from less similar sentences—evidence for progressive alignment in learning constructions.

Haryu, Imai, & Okada (2011) also found a progressive alignment effect in a novel verb extension task. Verb learning requires extending verbs to new examples, but given a complex scene it is difficult for children to recognize the specific relation the verb refers to. Indeed, prior work found that children often fail to generalize novel verbs to new scenarios (e.g. Kersten & Smith, 2002). However, Haryu et al, (2011) found that verb extension was facilitated when children were exposed to repeated scenes with high object similarity. As expected with an analogical account, highly similar examples pave the way for relational extraction.

Furthermore, there is evidence that the language children hear is particularly well suited to learning by progressive alignment. In a constructionist analysis of a large corpus of child directed speech, several interesting patterns were found (Cameron-Faulkner, 2003). First, about one quarter of utterances were imperatives (commands) or were structured around the copula (be). These structures are highly canonical in English which increases surface similarity across examples. Furthermore, they found that over half of all utterances began with one of 52 item-specific frames and 45 percent began with one of only 17 words. Again, this suggests that child directed speech is highly surface similar across examples, which would facilitate learning by progressive alignment.

Additionally, recall from Section 2.2 that language can have morphological case marking, and that in English we see it with pronouns (e.g. me vs I). Explicit morphological marking makes it clearer what the syntactic and deep case semantic roles of an argument are, and in English repeated pronouns also provide highly surface similar examples that are useful for progressive alignment. As expected with a progressive alignment account, Childers & Tomasello (2001) found that the use of pronouns during training improved children’s ability to produce transitive utterances with a nonce verb.

Finally, there is evidence that the specific verbs that occur most frequently in a construction are both very general and alignable with the constructions’ eventual argument roles. This would facilitate acquisition if, as claimed here, argument roles are acquired via analogical alignment and generalization of verb specific roles. It has been hypothesized that such verbs form prototypical or basic templates that pave the way for more complex verbs to appear in a construction (Goldberg, Casenhiser, & Sethuraman, 2004; Ninio, 1999)

Ninio calls these early verbs “pathbreaking verbs” and analyzes their use in subject-verb-object (SVO) and verb-object (VO) constructions by Hebrew speaking children. She notes that these constructions often appear in the context of a single verb long before they appear with others, and that the verbs used tended to be general-purpose or “light” verbs (e.g. make/do, give, and want). Ninio further notes that children advance from this early phase and show rapid development, consistent with the idea that children extract a general syntactic pattern based on these early verbs which facilitates the acquisition of more specialized verbs.

Goldberg et al. (2004) build on this account, suggesting that these early verbs facilitate the acquisition of argument roles. Their account differs from Ninio’s in several ways. Ninio claims that pathbreaking verbs are “semantically more transitive” than others while Goldberg et al. propose a more significant role for word frequency. In their analysis these verbs are not necessarily the first verbs but rather the most prototypical. They support their claim with an analysis of the verb-locative (e.g. She went to the store.), verb-object-locative (e.g. She put the apple in the bag.), and the double object (He gave the dog a bone) constructions in child directed speech. As expected, they found that the first two constructions occurred most frequently with the generic verbs *go* and *put*. The double object occurred equally with both *give* and *tell*, though this might be an artifact of the corpus which was collected using a story reading task.

3.5 Conclusion

Construction grammar approaches typically take what is called a *usage-based* view of language acquisition, which proposes that all aspects of language are acquired incrementally based on patterns in the natural environment and by way of general cognitive mechanisms. This is in stark contrast to traditional views that propose an a priori universal grammar. This chapter has summarized evidence from developmental psychology that points to exactly such an incremental process.

If indeed children do acquire linguistic constructions incrementally, then an important question is how abstract constructions arise from individual examples. Tomasello (2009) has suggested that analogy plays a crucial role in aligning syntactic and semantic roles across utterances. Indeed, there seems to be ample evidence that analogy could be playing just such a role, and child directed speech seems especially tailored towards analogical learning.

In the following chapter, I propose a cognitive model of argument structure construction acquisition and generalization based on the structure mapping theory of analogy. I further model construction application as analogical inference.

4. Computational Model

4.1 Model Overview

This chapter presents a computational model that uses analogy to explain two important aspects of the constructionist approach. First, the model uses SAGE to generalize pairings of syntax and bound semantic roles in order to learn abstract argument structure constructions. Second, the model uses MAC/FAC to explain argument structure construction retrieval and the fusion of argument and participant roles. This section describes the model at an abstract level and provides related work. Chapters 5, 6, and 7 present the representations used in the model as well as cognitive evaluations. Chapter 8 extends the model for general semantic parsing.

Construction acquisition is modeled as generalization over pairings of syntactic relations and bound semantic roles. Bound means that the semantic roles have phrases as bound arguments. Each phrase can include the words it contains as attributes. When generalized, the result is a consistent alignment of syntactic and semantic roles with generalized entities replacing aligned but different arguments. During construction acquisition, each case is passed into SAGE to be generalized in a single Gpool, the *constructicon*. While constructionist approaches typically view the constructicon as a monolithic storage for all levels of constructions (e.g. morphemes on up), the approach presented here only focuses on argument structure constructions. This work does not attempt to model construction acquisition from the ground up (e.g. phrases), though possible extensions are discussed in Chapter 9.

Figure 6 shows an overview of the construction acquisition process. In the two training cases, there are syntactic relations that hold between a predicate (verb) and its two phrasal arguments (e.g. subject and object). The same phrasal arguments are bound to the verb’s participant roles (bound semantics). When generalized, the phrases become generalized entities with consistent syntactic-semantic bindings and a distribution over the bound semantic roles. In this model, these distributions become the semantics for argument roles. Throughout the following chapters, different representations are proposed and evaluated, however the fundamental model of acquisition remains the same.

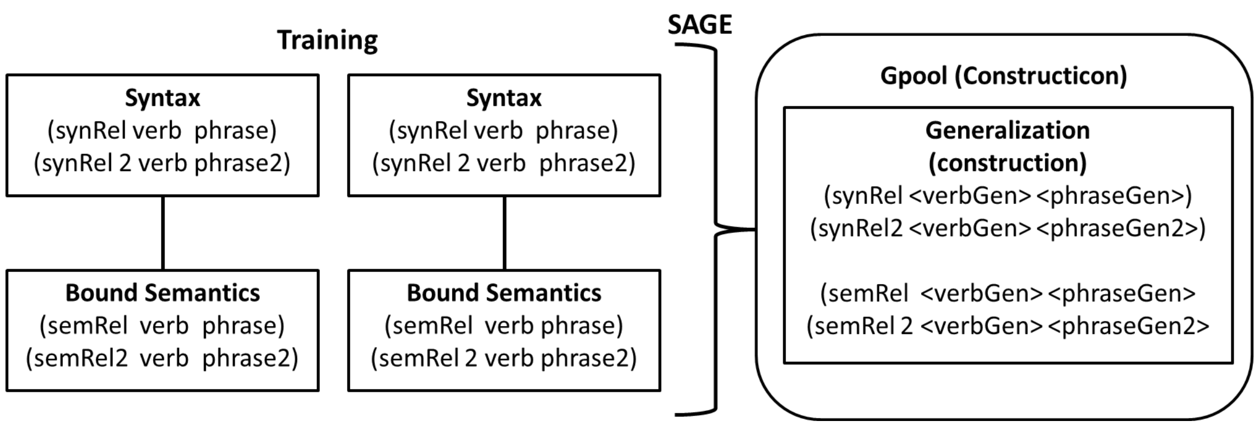

Figure 6: Overview of argument structure construction acquisition

When interpreting a novel utterance, the first step is to produce a case consisting of just the constituents of the construction. In Chapter 5, these are phrasal constituents. Chapter 6 extends the representation for known verbs to include a verb's case frame (profiled and unprofiled participants). Chapter 7 includes nested phrasal arguments (e.g. sentential complements). In this work, case frames are extracted from FrameNet.

MAC/FAC is used to retrieve an example or generalization (construction) from the gpool used during acquisition. The generalized argument roles of the construction align with the participant roles of the constituents case based on the shared syntactic representation. The binding of the participant role to its phrasal constituent and argument structure semantics are both analogically inferred. For novel verbs, there are no participant roles and the argument roles are applied by analogy based solely on aligned syntax. The verb then gets assigned the most likely semantics from the argument roles. Figure 7 shows an abstract overview of the construction interpretation process.

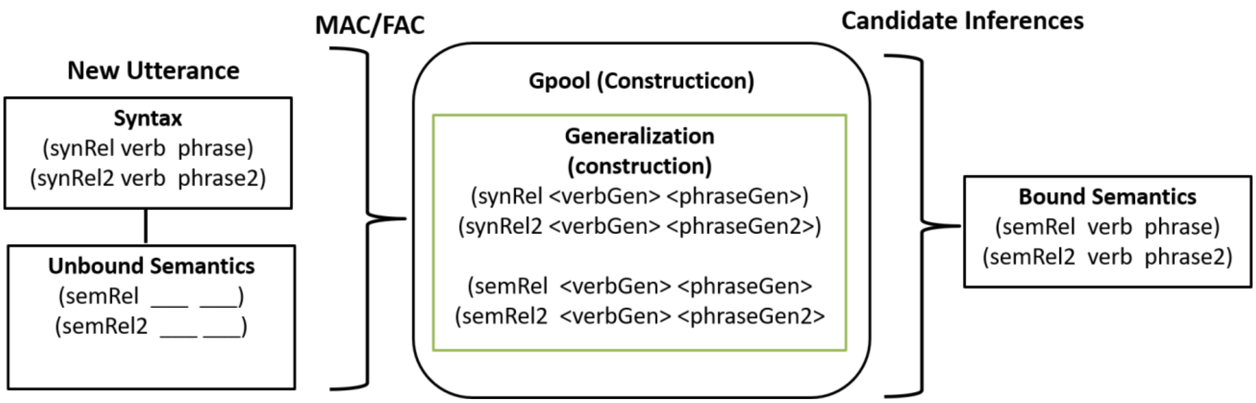

Figure 7: Overview of construction integration for interpretation

As a cognitive model, this approach makes several assumptions which are further refined depending on the representation used. The general assumptions are discussed here, while specific representational assumptions are discussed in the following chapters.

First, the model assumes some representation of grammatical packaging for a predicate and arguments. These relationships are possible at multiple levels of analysis, and so this approach flexibly adapts to model different theories of linguistic representation. Example argument representations include a phrase-based chunking, partial constituency parse, or dependency parse.

Second, the model treats argument roles as a statistical distribution over participant roles that have occurred in that construction. When interpreting a sentence, the participant roles of the verb align directly with an argument role from this distribution. An alternative approach would be to make the argument role a common superordinate predicate to the aligned participant roles.

Interpretation would then involve aligning argument and participant roles ontologically. The practical challenge with that approach is that it is unclear which level of superordinate predicates are appropriate. Furthermore, at least for the Cyc ontology, predicate hierarchies are not always uniformly distributed. Some areas, such as predicates for defining terrorist attacks, have rich hierarchies, while other common types of events jump immediately to very general predicates.

The generalized predicate approach would also require batch training, or else the superordinate predicate would need to be recalculated every time the construction occurs with a new verb. In contrast, the approach used here is incremental. It is also resistant to noise in that rare or erroneous occurrences of a verb in a construction do not unduly influence the total distribution.

Third, role fusion is modeled as matching. The participant role aligns with the matching argument role based on syntactic and semantic relations, and this allows the model to label phrases with the relevant participant role. This works well for known verbs occurring in typical use and for novel verbs. However, one shortcoming of this model is that there is no added meaning from the fusion of the roles. Thus, it currently does not handle coercive usages of known verbs well. An example of this would be the use of the verb *smile* as a metaphorical motion causing verb in “The presenter smiled the comment away.” The current model would correctly label *the presenter* as the performer, but it would be left to guess at which frame-element from *smile* corresponds with *away* when none of the typical roles do. Interestingly, the model does apply the unmatched semantics of the argument roles as candidate inferences for the participant roles. While these are currently ignored, they could be used in the future to identify and perhaps interpret coercive metaphorical usages.

Furthermore, this is a model of argument structure construction acquisition and application. It does not attempt to model construction acquisition or application at the phrase or word level. One interesting possibility is that the constituents themselves should be represented as generalizations with their own internal structure. Given that the constructionist approach proposes constructions at every level of representation, this seems like a promising path forward.

Under this account, interpretation would involve multiple rounds of analogical construction application. However, given raw input it is difficult to determine which features of linguistic representation are important at each level. It is quite possible that recognizing phrases requires a far richer representation of the internal elements of words (e.g. morphology) than is investigated in this dissertation. Further complications arise in the composition of lower-level constructions and relations between them. One possibility is to learn different kinds of constructions in different gpools and then to use the candidate inferences from each layer as the input to the next layer. However, there seem to be some constructions, particularly idioms, which resist decomposition and thus are best understood as a whole. Future work will focus more on compositionality and relations between constructions, an area of active research in the construction grammar community (Goldberg, 2006).

Finally, the model assumes that analogical matching of constructions occurs naturally without an explicit invitation for comparison. Gentner & Hoyos (2017) provide a summary of several factors that support spontaneous comparison including: spatiotemporal proximity, high similarity, and common labels. As discussed in Chapter 3, child directed speech seems to naturally present sequential highly similar examples (progressive alignment) which would facilitate comparison. Future work should enrich the model with more restrictive conditions on when analogical generalization occurs. Interestingly, such a model suggests that language acquisition is dependent not so much upon volume of data but rather upon fortuitous and spontaneous confluences within the data (though volume may influence the likelihood of these fortunate events).

The remainder of this chapter describes related approaches both to grammar learning and language interpretation.

4.2 Related Work

The acquisition of linguistic constructions has been an active area of research in computer science. Connor, Gertner, Fisher, & Roth's (2008) Baby SRL system classified transitive agent and patient arguments using a linear classifier trained over a corpus of child directed speech. They investigated the theory that children use the number of nouns as a heuristic for classification, and they replicated child performance including over-generalization errors. Adding a feature for verb position greatly improved performance.

Baby SRL targets simpler constructions than those evaluated in the following chapters, and it does not use a phrasal representation. A fundamental difference between our approaches is that SAGE produces classifications for each phrase jointly (candidate inference), while theirs labels independently. This should affect error patterns, with independent labeling more likely to assign the same roles to multiple arguments. Furthermore, a linear classifier would not generally model progressive alignment.

Solan, Horn, Ruppin, & Edelman (2004) propose an incremental unsupervised algorithm which represents sentences as paths through a word-graph and identifies classes of equivalent words and patterns. Their model trained over a corpus of child directed speech and demonstrated intermediate performance on a 9th - grade ESL proficiency test. They did not include semantic roles as is necessary for the experiments above. A benefit of their approach is that constructions are learned hierarchically. One direction for future work could use hierarchical models of analogical generalization (Liang & Forbus, 2014).

There has also been adoption of constructionist approaches in the robotics community. Lucia translates embodied construction grammar constructions into SOAR production rules which allows a robot to acquire new skills and act on the world given linguistic input (Lindes & Laird, 2016, 2017). While successful, the ECG constructions are still manually constructed, and the project does not focus on language acquisition. Spranger (2017) generalized over interactions between robots to build Fluid Construction Grammar constructions for spatial prepositions. His approach did not use analogical generalization, though preliminary research suggests that the representations used are well suited for an analogical approach.

Perhaps the most comparable alternative computational model for construction acquisition is Alishahi & Stevenson's (2008) Bayesian account. A construction is represented as a cluster of frames. Given a verb in a frame (pairing of syntactic and semantic features), the frame is added to the lexical entry for the verb and clustered with its most likely construction. The clustering score is proportional to the prior probability of the construction and the conditional probability of the frame given the construction. The prior probability is determined by the number of frames a construction contains. The conditional probability of the frame as a member of the construction is the proportion of shared syntactic and semantic features. Interpretation then involves predicting the most likely semantic features given syntactic features, while production equates to predicting the most likely syntactic pattern given semantic features.

Their model was trained on automatically generated utterances created from a distributional analysis of child directed speech. Their model replicates a U-shaped learning curve in language acquisition, where early productions are exact replications followed by a period of over-generalization which eventually tapers off as erroneous uses become less probable. The model has also demonstrated sensitivity to verb frequency effects and was used to model children's acquisition of *desire* verbs before *belief* verbs (Barak, Fazly, & Stevenson, 2012, 2013).

Their account is similar to the model constructed in this work; they both treat constructions as having a probabilistic distribution over semantic features. One significant difference is that an analogical account can make use of more sophisticated structured syntactic representations, including syntactic dependencies and grammatical functions (e.g. subject/object). Another difference is that, in the following chapters, the analogical account represents words bound to phrases as attributes whereas their model does not retain individual words that appear in constructions. As such, the model would not predict progressive alignment effects from shared pronoun usage apart from the benefit from their semantic overlap.

That said, their model may be more resistant to noise in the syntactic representation since it does not draw conclusions based on structure. Thus, it might more flexibly accommodate missing syntactic or semantic features. This also may be why it is able to recover so effectively from a period of overgeneralization. One element of the Bayesian approach that would particularly benefit the SAGE model is an incorporation of prior probability of a construction (generalization) based on size or recent activation. In fact, in MAC/FAC retrieval, the score of a case is normalized to its size and so large, highly-variable, constructions can be less likely to attract new examples rather than more. Future work should examine a tighter integration of structural and feature-based measures of similarity for construction generalization.

5 Computational Model: Denominal Verb Interpretation

5.1 Introduction

This chapter presents an implemented version of the abstract model described in Chapter 4. The model uses representations that are based on FrameNet, and it is evaluated in a simulation of Kaschak & Glenberg's (2000) study of denominal verb interpretation. The following section presents the representations used in the experiment and provides examples of how the model operates with these representations.

5.2 Representations: FrameNet Based

As described in Section 2.6.1, FrameNet defines sematic frames that are evoked by lexical units. Frames have frame elements which are filled by phrases in a sentence. Consider the simple sentence, "I see it." The word *see* evokes the `Perception_experience` frame with frame elements such as `Perceiver_passive` and `Phenomenon`. In a sentence such as "I see it.", *I* would be the `Perceiver_passive` and *it* would be the `Phenomenon`.

Recall that frames are represented from the perspective of a target lexical unit. Thus, in a sentence like "I saw the man give the boy the ball." the entire clause "give the boy the ball" would be an argument when *see* is the target, specifically it would be the `Phenomenon`. This representation only identifies the arguments to the target, ignoring other aspects of the sentence. If *give* were the target, *I* would have no frame element with relation to the embedded clause.

The representation presented here modifies FrameNet to include absolute positions of phrases as well as an explicit representation of the words that are members of the phrase. As an example, the subject noun-phrase to *see* in "I saw it." would be represented as:

```
(isa NP1 NP)
(FE-Perceiver_passive see NP1)
(wordMemberOf NP1 I)
(loc1 clause1 NP1)
```

The pronoun, I, is the first phrase in the sentence (`loc1`) and it plays the role of `FE-Perceiver_passive`. Figure 8 illustrates an SME case constructed out of the predicate calculus representation for "I see it." Here, ovals represent relations and rectangles are individuals. Edges connect relations to their arguments and are labeled with their argument position. The relations in the top-half of the graph represent the syntactic arguments to the construction and the relations in the bottom-half are the semantics. The semantics and syntactic relations are both bound to phrases. `wordMemberOf` relations have been excluded for clarity.

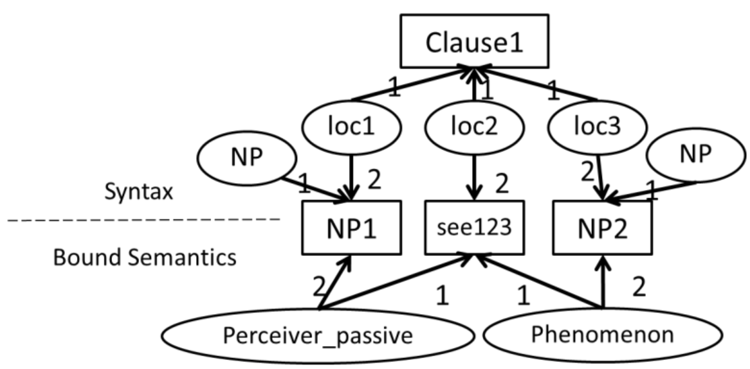

Figure 8: FrameNet style representation..

During construction acquisition, each construction is aligned and generalized using SAGE. Figure 9 illustrates a generalization for two transitive utterances, one with *see* and one with *look*. In the second, the direct object is an adverb (e.g. I looked there). When generalized, the entities become generalized entities, and the result is a construction where the direct object has a probability distribution governing its phrase type.

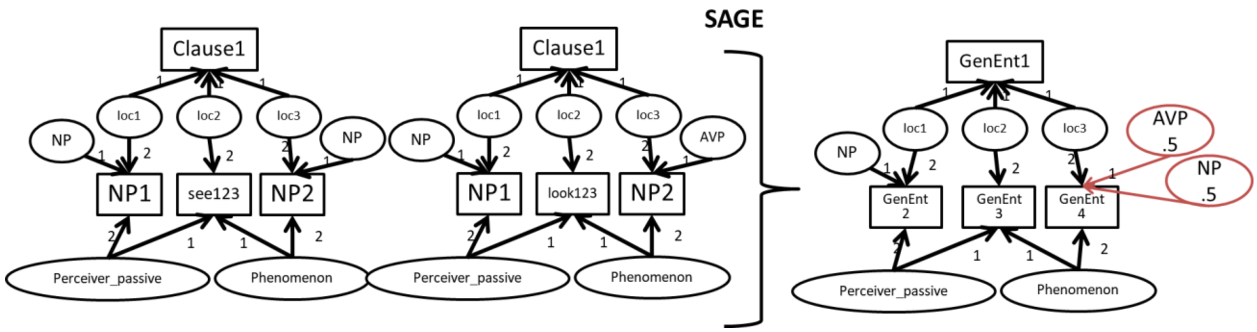

Figure 9: Example of construction generalization with FrameNet representation

After several examples, the gpool now contains several constructions, each one a generalization. Given a sentence unlabeled with semantic roles, they can be retrieved, and the roles applied by analogy. Figure 10 illustrates construction application by analogy.

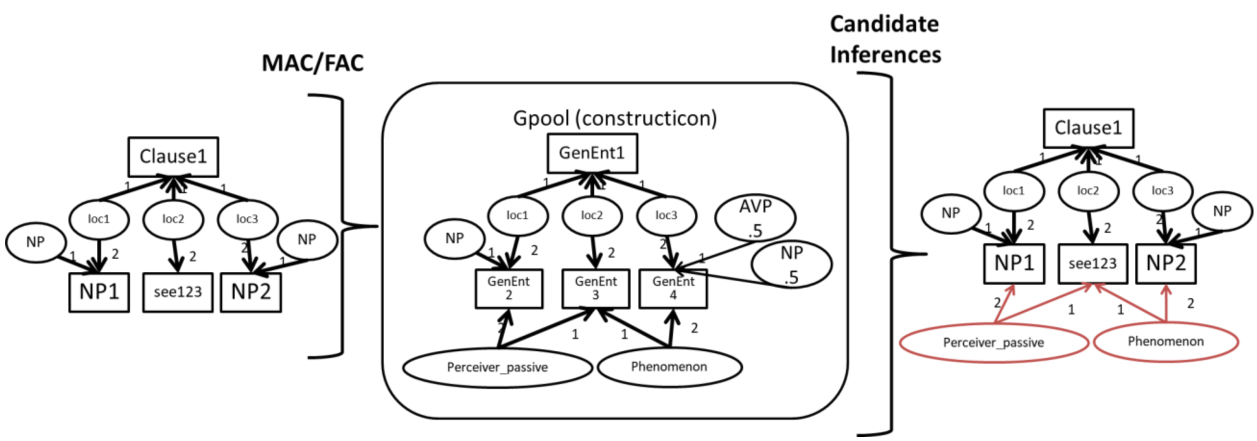

Figure 10: Application of construction by analogy

This model and representation are used to simulate denominal verb interpretation in McFate & Forbus (2016) which is summarized below.

5.3 Modeling Denominal Verb Interpretation

5.3.1 Simulation Target

Kaschak & Glenberg (2000) presented participants with denominal verbs (e.g. Mary *postcarded* her sister the good news) in a double-object (NP v NP NP) and a transitive (NP v NP) construction. Each had a PP attachment corresponding to the purpose (e.g. 'so he wouldn't starve') in order to regularize the number of entities in each sentence. In experiment 1, participants were given one of two tasks. In the sentence choice task, the participants were shown both sentences, the double-object and the transitive. They were then presented with a forced-choice task where they chose which sentence was consistent with a textual entailment of either a transfer event or a generic transitive action (see Figure 11). If they are influenced by the form of the construction, then participants should be significantly more likely to choose the double object sentence in the transfer entailment case.

In the second task (meaning-choice task), they presented one of the sentences and asked participants to choose between the two entailments. Again, a constructionist approach would expect the participants to be biased based on the form of the sentence. Thus, when presented with a double object construction they should chose the transfer entailment. An example of each condition is shown below with the expected answer highlighted in green.

In the sentence choice task, they evaluated using both conventional and novel denominal verbs. In both conditions, participants overwhelmingly chose the double-object construction for transfer inferences (92% for conventional verbs and 80% for novel denominals).

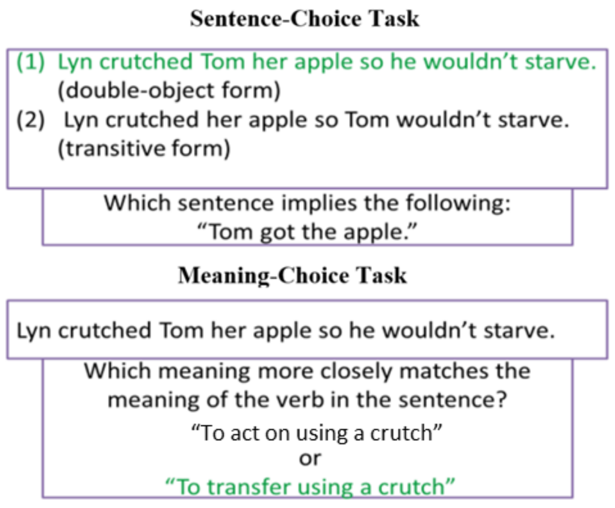

Figure 11: Experimental conditions from Kaschak & Glenberg (2000)

Participants in the meaning-choice task showed a weaker though still significant preference for the transfer definition when presented with the double-object construction (61% following double-object vs 42% following a transitive). Kaschak & Glenberg suggest that the weaker result may arise from the fact that both entailments were correct since transfer is a sub-relation of act on. Some participants may have just been conservative in their selection.

The goal in simulating this study is to provide computational evidence that analogical generalization could result in a generalized double-object with a 'transfer' semantics and to demonstrate that analogical retrieval of said construction could result in Kaschak & Glenberg's responses. Furthermore, using a computational model to simulate this experiment allows an investigation of what kinds of representations are needed for an analogical account.

5.3.2 Experiment

The training set was created by manually representing 21 sentences from a 6th grade reading comprehension workbook (Spectrum, 2007). The sentences were represented using the formalism in section 5.2. As a reminder, this was a FrameNet style representation modified to have explicit phrasal ordering e.g.:

```
(isa NP1 NP)
(FE-Donor give NP1)
(wordMemberOf NP1 the)
(wordMemberOf NP1 man)
(loc1 clause2 NP1)
```

The training set consisted of nine sentences that evoked the `Giving` frame. Seven examples were inheritors of the `Transitive_action` frame (e.g. `Cause_motion`) and four were distractor `Motion` frames. The training examples covered a wide range of constructions including examples with several prepositional attachments. Of the nine `Giving` sentences, only two illustrated the double-object in isolation. Six examples included an additional argument (e.g. a purpose).

The test set was created by using regular expressions to chunk each sentence from the Kaschak & Glenberg (2000) stimuli into its valence pattern. Each phrase was labeled with its phrase type as above (e.g. `(isa NP1 NP)`) and its location (e.g. `loc1`), but no information about the evoked frame or the frame element was included. All 20 double-object examples from their experiment were used. One transitive example was discarded because its additional argument was not the same form as the rest of the examples. Thus, the total test set consisted of 39 examples. The complete set is included in Appendix A.

In the training phase (see Figure 12), SAGE was given each of the training stimuli as an individual case for generalization. The generalization threshold was set to .8. Recall from section 3.2.2 that SAGE, being incremental, is sensitive to training order. This is in fact part of what allows it to model progressive alignment effects (Kandaswamy et al., 2014). Thus, the model was evaluated under two ordering conditions. In the first, the training stimuli were hand-ordered such that similar constructions were clustered together. This is called the progressive alignment training order (PA-ordered). The approach was also evaluated across 25 randomly generated orderings.

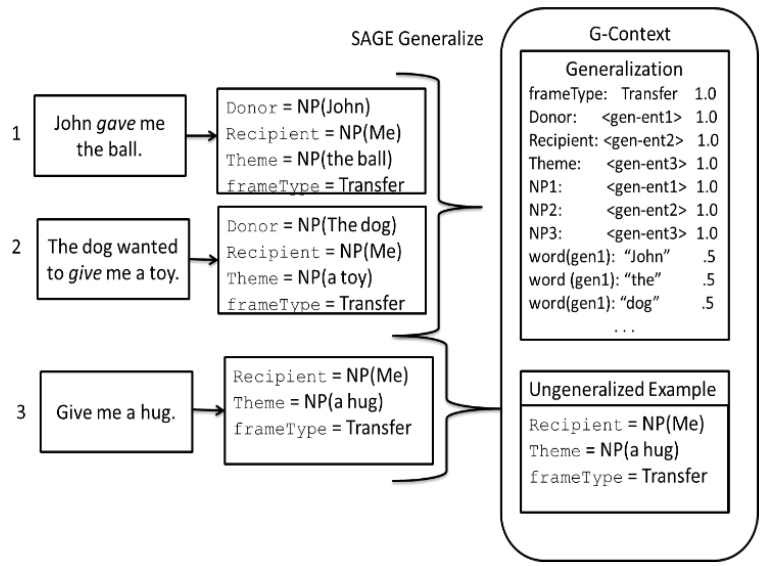

Figure 12: SAGE generalization of training sentences

In the evaluation phase (see Figure 13), each example from the test set was used as a probe for analogical retrieval by MAC/FAC over the learned gpool. The top-scoring response is compared to the probe using SME. Structures in the base that are missing in the target (i.e. the frame elements) are hypothesized as candidate inferences. These candidate inferences are the model's interpretation of the incoming sentence.

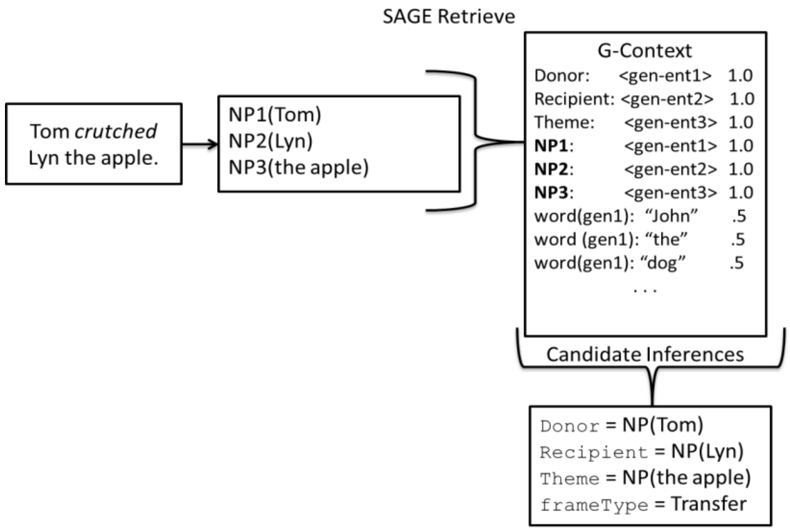

Figure 13: Interpreting a denominal verb

4.3.3 Results

The results were evaluated based on the candidate inferences generated by SME. For the 20 double-object examples, a response was counted as correct if it both correctly identified the frame-type of the verb (e.g. crutched = `Giving`) and if it correctly labeled the 3 NPs as `Donor`, `Recipient`, and `Theme`. This corresponds to a double-object response in Kaschak & Glenberg (2000). An interpretation was judged incorrect if it over-assigned the three FEs, which could happen if the double-object and prepositional ditransitive formed a single generalization.

For the transitive stimuli, the interpretation was correct if it chose an inheritor of `Transitive_action` or a generalization containing only those inheritors. Generic non-transitive `Motion`, for example, was incorrect. We did not evaluate the specific frame elements because a generic transitive action such as "Lyn acted on the apple" could be consistent with many different types of transitive action and the FEs vary across FN frames.

There were two baselines. The first was a random baseline. For each example, a random baseline system could label it Transfer, Transitive, or other (corresponding to the Motion distractors). Thus, it would have a 1/3 chance of classifying the frame-type correctly. For transfer classifications, it would further have to assign each FE correctly (1/6 at random). Thus, for the 19 transitives a random system would have a 1/3 chance of being correct. For the 20 transfer examples, random guessing would have a 1/18 chance of being correct. This gives a random baseline an overall mean of 7.4 (19%). The second was a baseline of guessing Transitive for each example. Under our evaluation measure, this would result in 19 correct answers (49%). We call these the random and choose-transitive baseline.

With the PA-Ordering for training, the model correctly interpreted the verb as evoking the `Giving` frame and correctly assigned all three frame elements on 19 out of 20 examples. On the transitive examples, the model correctly interpreted the frame as non-transfer in 18 out of 19 examples. This gives a total of 37 out of 39 (95%).

With a single manually (PA) determined training order, the model is deterministic. A Fisher's exact test demonstrated that the model significantly out-performs the expected performance of the random and choose transitive baselines ($P < .05$) on the test set.

Across 25 trials using random orders, the mean total correct dropped to 26.88 (68.9%). The double-object stimuli were most affected, dropping to a mean accuracy of 9.96. The max total accuracy across all 25 trials was 37 (95%) correct with 19 correct double-object classifications. The minimum accuracy was 19 (49%) correct classifications, with only 4 correct double-object classifications. A one-sample t-test demonstrated that the random order mean was a significant improvement over the random baseline t(24) = 16.05 P < .05. Its performance was also a significant improvement compared to the choose-transitive baseline t(24) = 6.49 P < .05.

As an additional evaluation, the generalizations created from PA-Order training were manually inspected. SAGE produced four generalizations. One was the simple double-object construction. Another contained two of the double-object with an additional modifier (e.g. purpose). The next contained two simple `Cause_motion` transitive sentences and the final generalization contained two examples of transitive actions with an additional argument.

Finally, recall that in the representation described above phrases were labeled with their phrase type (e.g. NP, PP). There is considerable disagreement about what kinds of grammatical categories exist if any, and so it is not ideal to make an ontological commitment to phrase types. Thus, performance was evaluated without phrase-type labels. Instead, the probe included the arguments to the verbs as unlabeled ‘chunks’. The model was trained with the PA-Ordering. In this condition the model correctly identified the `Giving` frame but consistently inferred a double-PP pattern, thus misaligning FEs. Without labels, it essentially only operates over the number of chunks and their size which isn’t enough to distinguish between examples. The theoretical implications of this are discussed below.

5.3.4 Discussion

After training, the model successfully applied the transfer and transitive semantics to the novel denominal verbs. The results of this model therefore support the claim that analogical generalization could be a mechanism for generalization and application of linguistic constructions. As predicted, receiving the examples in progressive alignment order led to the best results. This is consistent with the progressive alignment phenomenon seen in human learning.

The SAGE model of construction acquisition might thus predict that sequential comparison of canonical verbs would improve performance on the novel denominals. Kaschak & Glenberg (2000) do not evaluate this, though as described in Chapter 3 there is evidence that progressive alignment plays an important role in language acquisition. This is an interesting direction for future psychological research.

This simulation makes several representational assumptions. First, it assumes that humans are able to chunk sentences into arguments for a target verb. These phrases are explicitly ordered which is an important part of English syntax, however for languages that depend less on word order it would be possible to augment the representation with explicit case markers and other syntactic features. It is not claimed that these chunks are part of a specific larger parse structure, thus making this approach applicable to a broad subset of linguistic theories. The representation does have several shortcomings however. First, the method by which people identify verbal arguments is not addressed in this work. Additionally, the representation and thus the model is too dependent on phrase labels to identify constructions. A more structural approach that utilizes a richer grammatical representation is described in the following chapter.

5.4 Conclusion

This chapter has described an implemented cognitive computational model of construction acquisition and application based on the SAGE model of analogical generalization and retrieval. The model provides evidence for a central role of analogy in how language is acquired and interpreted, and to that end the general model has been evaluated with a simulation of a human-subjects experiment.

The model was used to simulate results from Kaschak & Glenberg's (2000) study regarding the interpretation of denominal verbs (e.g. “I crutched her the ball.”). Consistent with a constructionist account of language, they found that participants were significantly more likely to interpret a denominal verb as a transfer event when it occurred in the double object construction (NP V NP NP) than when it occurred transitively. In the work presented here, SAGE was trained over a corpus that was manually annotated with a semantic formalism similar to that used in FrameNet. Constructions emerged as generalizations over consistent syntactic structure and semantic roles, with distributions governing individual differences across examples. These constructions were applied by analogy (MAC/FAC) to interpret novel denominal verbs (e.g. *crutched*) which had syntactic but no semantic structure.

While the representations described in this chapter were appropriate for the simulation, there were several unresolved challenges. First, syntactic chunks for both the training and test stimuli were manually created. Second, the representation requires aligning frame elements, but there is no higher-order structure to suggest alignment when predicates are not identical. Both of these challenges are addressed in the representation discussed in the following chapter. Both the new representation and the FrameNet representation are evaluated with a manual analysis of constructions learned from a corpus of child directed speech.

6. Computational Model: Acquisition from Child Directed Speech

6.1 Representations Revisited: Role Alignment

The FrameNet representation (Section 5.2) enabled transfer of semantics to novel verbs, but there remained some serious problems that needed to be resolved. In the previous experiment, the argument roles were represented as a distribution over FEs that occurred with that construction. At least for the double-object, these roles are consistent. However, it was unclear which role should be assigned by candidate inference in the case of the transitive. As an example, consider the generalization in Figure 14 which is learned from examples with different subject frame elements (`Perceiver_passive` and `Perceiver_active`). There is no generalized entity for the frame elements; instead, each is equally likely to apply to the first noun phrase. Furthermore, the two aren't mutually exclusive.

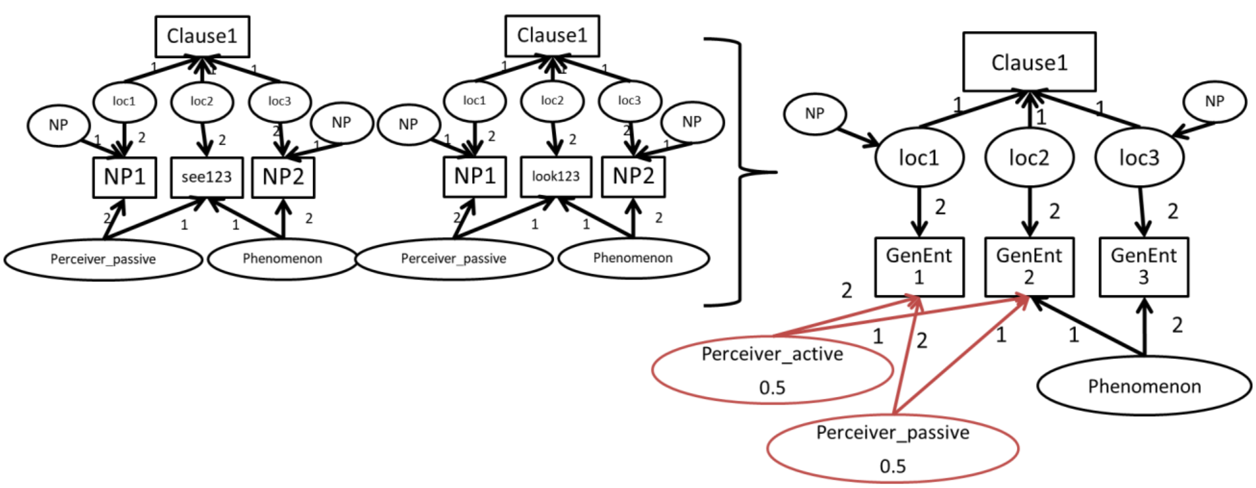

Figure 14: Generalization with different frame elements

One possible resolution would be to assign the most likely frame element for each syntactic location, but what should be done in the case of a known verb? It is unclear with the prior representation how to handle the unification of argument and participant roles. Imagine instead of a novel denominal verb like *crutch*, the system received a verb such as *send*. Interpretation should involve aligning the now known participant roles of the verb with the argument roles of the construction, but structurally there's no reason to match them unless they are identical. Even worse, the predicates must take arguments and so it is not possible in the prior representation to include unbound semantic roles in the constituents case.

Instead, this section proposes a different representation that reifies both the participant and argument roles, allowing them to be aligned structurally. Their particular semantics can then be separated out and given a distinct distribution. This formalism forms the basis of the system described in Chapter 8.

In what I call the *role alignment* representation, argument structure constructions and verbs are both represented as constructions with profiled and unprofiled roles (argument/participant). Each slot is accompanied with a predicate semantics as an external relation (e.g. an attribute). In the case of a learned argument structure construction, its argument roles are explicitly bound to a syntactic phrase (e.g. the subject of the sentence) using the predicate `constructRoleBinding`. These syntactic phrases are dependency parse relations and are contained in an n-ary higher-order predicate that enforces an absolute order on the phrases. Words in a phrase are represented as attributes. A graphical representation of the sentence "I see it." is shown in Figure 15, though word attributes have been removed for clarity.

As before, edges are labeled with their argument position. `syntacticOrder` is the n-ary ordering predicate which holds over the dependency relations `nsubj` and `dobj`. Both have the verb as the head and a phrase as their argument. The phrase is represented with its head using

`(HeadedPhraseFn <head>)`. These phrases are syntactically bound to argument roles by the binary `constructRoleBinding` predicate. The argument roles are represented with a function, `GrammaticalRoleFn`, which is atomic for analogy. `GrammaticalRoleFn` takes a dependency relation and an absolute location in the sentence. This allows for sentences that have multiple roles with the same type of grammatical function (e.g. multiple prepositions). Each argument role has its profile status attached as an attribute. The semantic predicate is attached using the function `HeadedPredFn` which takes the semantic role and returns a binary relation that relates the semantic role to the argument role and verb. It is atomic for analogy.

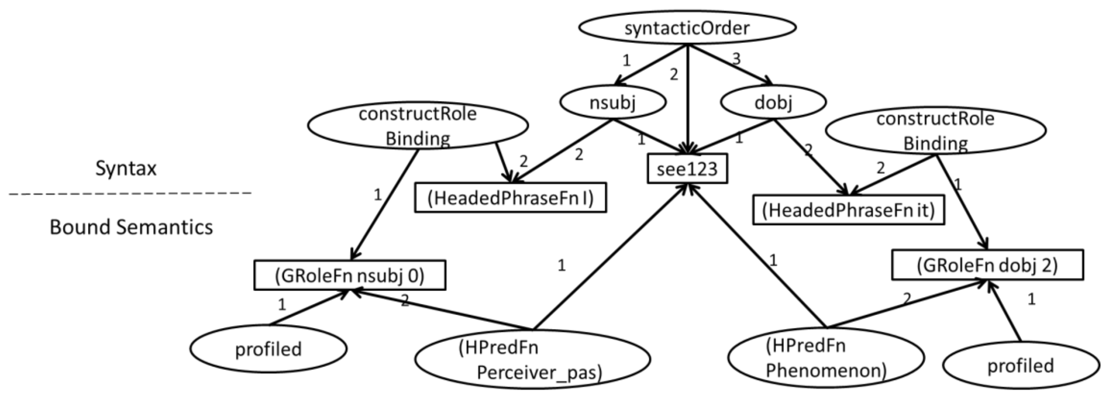

Figure 15: Argument structure representation of the basic transitive sentence "I saw it.".

While the example above includes only NP arguments, the representation of course handles other complement types as well. The one difference from traditional dependency representation is that prepositional phrases are represented as distinct predicates based on the specific preposition. Thus “in the table” and “on the table” would have different preposition dependencies. In practice, this was found to lead to more applicable generalizations and fewer generalization errors, though an alternative approach could treat the specific preposition as an attribute. This would result in more generic constructions, though perhaps at the cost of resolution in the representation.

During interpretation, a verb is represented as a set of participant roles which have their profile status and semantics attached in the same way as argument roles. The syntactic analysis of the verbal arguments is represented using the same ordered dependency parse representation. Because the participant role has been reified in the RA representation, it can have known semantics but unknown bindings. The `constructRoleBinding` is missing. This case represents the constituents of the argument structure construction.

Figure 16 shows an example constituents case for the sentence “I see it.” The dependency structure of the arguments is the same as in the argument structure construction. In this case, the verb *see* evokes participant roles from its semantic frame, `prole1` and `prole2`, both of which are profiled and both of which have an attached semantics (`Perceiver_passive/Phenomenon`). Neither is bound to their arguments.

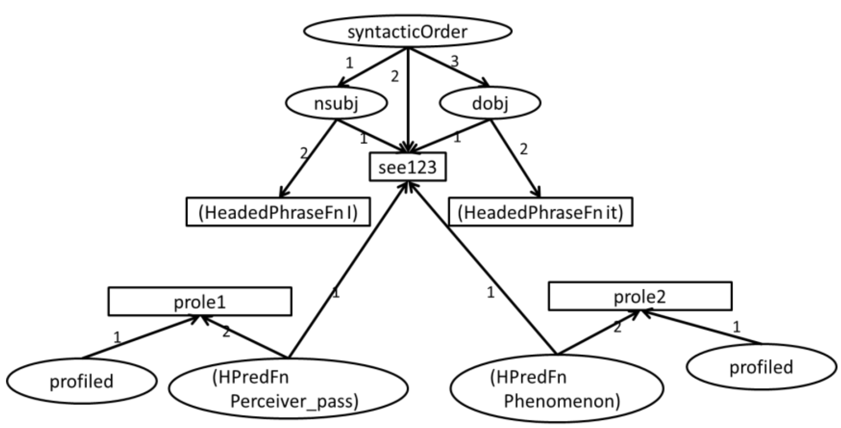

Figure 16: Constituents case for “I see it.”

As with the FrameNet based representation, construction acquisition is modeled as generalization. However, with the role alignment representation, the argument role remains a consistent entity with a distribution of semantic relations it can take. Figure 17 shows an example generalization for “I saw it” and “I looked there.” where the subject role for *look* is an active perceiver. As before, relations with a probability of less than one are highlighted in red.

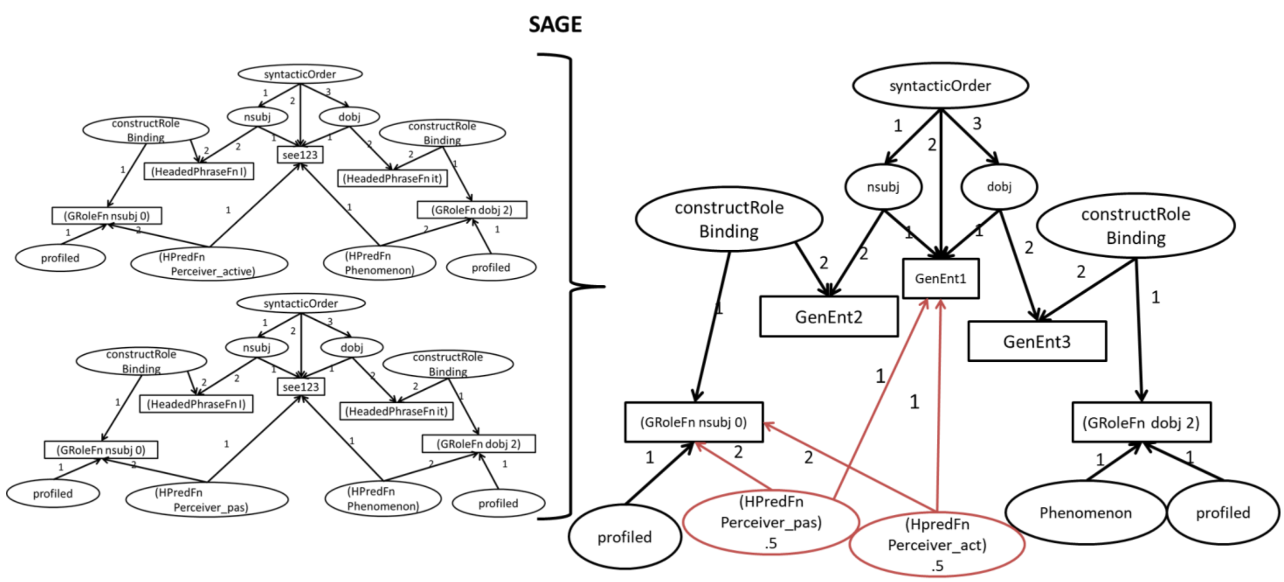

Figure 17: Example generalization with role alignment representation

When the sentence “I see it.” is interpreted, this constituents case becomes the probe for MAC/FAC retrieval. Just as before, the construction is retrieved and now, `constructionRoleBinding` is inferred by analogy. This connects the participant role with the semantics of `Perceiver_passive` to the phrase headed by *I*. The role of `Phenomenon` is connected to *it*.

When applied to a novel denominal verb (as in Section 4.3) there are no explicit participant roles. Instead, the syntactic parse aligns and the roles themselves are analogically inferred. Their semantic bindings are the most common semantic binding for that role, which tends to be a very general predicate (Goldberg, Casenhiser, & Sethuraman, 2004; Ninio, 1999).

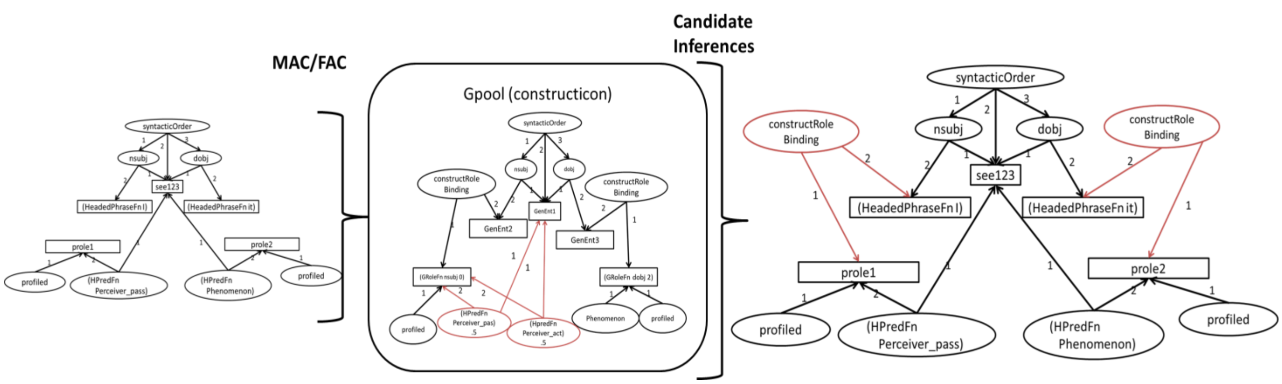

Figure 18: Interpretation with role alignment representation

Using this representation, the cognitive model makes slightly stronger assumptions. As before, it assumes that listeners are able to distinguish arguments to the verb, however it also assumes that these arguments are in typed relationships to the verb (e.g. nsubj/dobj). Dependency relations were chosen here because dependency parsing is a well-studied problem in computer science and it makes it easier to integrate the model with existing resources. However, in principle one need not assume the specific grammatical functions used here. An alternative representation might use $arg_1 \ldots arg_n$ and phrase-types to achieve a similar result.

Again, argument ordering is assumed, though in this representation the ordering predicate is higher-order. This predicts a significant role for argument order, which is true in English. For languages that rely less on word order, relations provided by explicit case-markers may play a similar role.

6.2 Learning from Child Directed Speech

In Chapter 5, the annotated training sentences were selected from a children's workbook and focused on a few specific constructions. This next experiment evaluates whether the model could learn from more naturalistic input by generalizing from annotated child directed speech. Initial findings using the FrameNet representations were presented in McFate , Klein, & Forbus (2017). An additional experiment generalizing over the role alignment representation is presented in section 6.2.3. The goal was to replicate patterns found in language acquisition and to compare the learning patterns of the two different representations.

6.2.1 Experiment

160 instances of child directed speech from the CHILDES Brown corpus (MacWhinney, 1996) were annotated with FrameNet frames and role elements. Each of the annotated examples contained one of 13 verbs that Alishahi & Stevenson (2008) previously identified as highly frequent in child directed speech. The verbs were *come, go, eat, fall, get, give, look, make, play, put, see, sit,* and *take*. This corpus was used to generate the training cases for experiments with both the FrameNet and role-alignment representations.

The first experiment with FrameNet representations used a similar formalism to the experiment in section 4.3 (McFate & Forbus, 2016). There were three differences. The first was that phrase labels (e.g. NP) included grammatical function (e.g. NP<ext>). Second, pronouns received a separate label (PRO vs NP). Finally, unlike in the previous experiment McFate et al. (2017) included null instantiations as an explicit grammatical role. Thus, a command such as "Sit there!" would have a null instantiation annotated for the `Agent` that the command is addressed to.

These did not appear in the prior experiment because neither the constructions in the training set nor test set contained null instantiations.

After the initial experiment, several annotation errors were discovered in the original corpus of 160 sentences. These were repaired for the following experiment which uses the role-alignment representation. The final set of annotated sentences is included in Appendix B. In the second experiment, there is no distinction between pronouns and noun phrases in general because, unlike the FrameNet representation, the role-alignment representation does not use explicit phrase labels. Table 2 summarizes the differences between each representation:

Table 2: Representation summary of differences

	Distinct Pronouns	Phrase Labels	Includes Nulls	Includes Words	Syntactic Representation
FrameNet Rep (McFate & Forbus, 2016)	No	Yes	No	Relation	Absolute Location Relations
FrameNet Rep (McFate et al., 2017)	Yes	Yes	Yes	Attribute	Absolute Location Relations
Role Alignment Rep (section 6.1)	No	No	No	Attribute	Ordered Syntactic Dependency Relations

In both experiments, the cases generated from the annotations were used as input to SAGE. The model was evaluated with different assimilation thresholds to simulate more liberal and more conservative learners. The training examples were ordered as they occurred in the corpus and the order was consistent across assimilation thresholds. The learned generalizations were manually examined both for correctness and as to whether the learned constructions demonstrated the item-specific bias evident in early language acquisition (Tomasello, 2009). A generalization was counted as incorrect when it misgeneralized constructions with incompatible syntactic orderings, e.g. one with and without a direct object. A construction was also incorrect if it generalized examples with the same syntactic pattern but different argument structure. An example would be a generalization that included a transitive with a prepositional argument and an intransitive with a prepositional adjunct (e.g. I went in the house. vs He died in May.). Note that one can remove the preposition in the second sentence (e.g. He died) but not in the first (*I went). With the role alignment representation this corresponds to generalizing a profiled and unprofiled role.

6.2.2 Results: FrameNet Representation

An analysis of the model's generalizations over the FrameNet representations is summarized in Table 3. With a generalization threshold of .8 SAGE creates 24 generalizations. The largest consisted of nine examples and was an item-specific construction for the common expression "Where are you going?". At this threshold SAGE is conservative, creating only two generalizations that weren't verb specific. These were two generalizations with the motion verbs *go*/*come*. The first contained examples with a prepositional Goal argument (e.g. "Go in the room."). The second was a generalization of one-word commands (e.g. "Go/Come")

Table 3: Results, FrameNet Representation

Generalization Threshold	Number of Generalizations	Average Examples per Generalization	Verb Specific Generalizations	Number of Misgeneralizations
.8	24	3.17	22	0
.7	28	4.32	19	3
.6	16	8.69	6	4

A threshold of .7 results in 28 generalizations and a less conservative learner. Eight of 28 generalizations include multiple verbs (mostly two). We see several interesting construction generalizations. There is a generalization for a locative construction (go *to* x) with verbs *come* and *go*. There also appears to be multi-word generalization for the instrumental construction centered on the preposition *with* (e.g. He played with the doll). At .7 there are several generalizations corresponding to a basic transitive construction (SVO) that are separated by types of verb (i.e. separate constructions for go/get/eat) as well as a more general transitive that collapses several verbs. Two verb-specific constructions capture questions fronted with WH-words (e.g. where). Other questions appear as transitive usages (e.g. "You see that"). This is a result of the FrameNet annotation format which does not mark for auxiliary verbs (e.g. *do*). For this experiment, there was no semantic difference represented for questions. We also see several imperative constructions (e.g. "Put it in the box.") that are verb specific.

At the .7 threshold we also begin to see misgeneralizations. Specifically, there is a generalization that wrongly generalizes several light verb constructions. There is also a faulty generalization of the transitive and intransitive for the verbs *see* and *play*.

At .6, there are 16 generalizations and 10 of them involve multiple verbs. However, at this threshold there are 4 misgeneralizations and each is quite large. There is a single misgeneralization for transitives and intransitives that consumes most of the separate constructions we see at .7.

6.2.3 Results: Role Alignment Representation

An analysis of the model's generalizations over the role alignment representations is summarized in the table below. The role alignment generalization seems to have markedly reduced the effect of the generalization threshold on the resulting generalizations. Given that at even at .8 there were now several verb-general constructions, a threshold of .95 was evaluated to examine item-specific constructions. Table 4 shows results for thresholds (.95/.8/.7). The threshold of .6 is not shown as there was no significant difference from .7.

Table 4: Results, role-alignment representation

Generalization Threshold	Number of Generalizations	Average Examples per Generalization	Verb Specific Generalizations	Number of Misgeneralizations
.95	23	3.39	23	0
.8	21	5.67	12	1
.7	21	5.76	11	1

A threshold of .95 represents a very conservative learner that results in exclusively item-specific constructions, similar to those of the .8 learner in the previous section. Again, there are multiple constructions for transitives, intransitives, and ditransitives, each separated by verb and whether the construction is interrogative, declarative, or imperative.

At a threshold of .8, there are significantly fewer item-specific constructions, and, while a misgeneralization does occur, it is more isolated than the errors with the FrameNet analysis. The largest of the learned constructions contains 31 examples and is a multi-verb construction for the basic transitive (NP V NP). Interestingly, the most frequently occurring verb in this construction was *get* (35% of examples) which occurred exclusively with pronominal subjects, frequently as an imperative (e.g. “You get it.”). In these constructions the subject `Recipient` role should be interpreted as an agentive participant (sometimes called accusative), and an analysis of the remaining examples reveals that they are consistent with an agentive subject and a direct object that is acted upon. This is consistent with prior analyses of the transitive.

The second largest generalization is an intransitive (NP V) construction that contains 15 examples. One interesting aspect of the construction is that the most common semantic roles applied to the subject are not agentive[9]. They are typically inanimate objects that are moving (40%). This captures that while an intransitive construction can include agentive participants (e.g. “He ran.”), they are standard for non-agentive verbs (e.g. “He died”) and in fact frequently the intransitive is used to remove agency by cutting the `Agent` (e.g. “I broke it.” vs “It broke.”).

Constructions with a prepositional argument are split based on the preposition (e.g. in the kitchen vs on the table) though several of them are not verb-specific. Interestingly this suggests an important role for both verbs and prepositions as islands around which initial constructions form. Indeed Fillmore (1967) presents prepositions as a kind of case marker, and it is possible that they play a similar role to pronouns in so far as they provide consistent alignable cues for comparison.

As with the FrameNet representation, there are WH-specific constructions, and several questions are spread out across transitive generalizations. This occurred again because there was no marking for auxiliaries or sentential function. However, there are two imperative constructions that contain multiple verbs, one with an adverbial argument (e.g. come here.) and a more generic one that just takes a noun phrase direct object (Get the napkin.).

At .8 there was one misgeneralization which aligns a prepositional argument and prepositional adjunct for the sentences for a caused motion and transitive motion construction

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[9] These kinds of verbs are frequently called unaccusative verbs. This is because, despite being non-volitional, their subjects are not marked by the accusative case.

(e.g. “I put them in there.” and “I went home in July.”). One borderline case not counted as incorrect is a generalization that makes no syntactic errors but generalizes two potentially distinct senses of the word *go*: “Where are you going.” and “Where does the ladder go?” It’s not clear that this is an error, as the latter sense of *go* as *belong* does seem to at least metaphorically refer to the motion frame.

At a threshold of .7, there is only one significant difference from .8. A formerly distinct example for *go* is merged with a construction for *come*. This covers one-word motion expressions such as “Come?” or “Go.”. The results remain the same at a threshold of .6, suggesting that the role-alignment representation is far more resistant to misgeneralizations than the original modified FrameNet representation.

6.2.4 Discussion

These experiments used SAGE to generalize across an annotated corpus of child directed speech. Different assimilation thresholds were used to model more conservative and liberal learners and to evaluate the effect that different representations had on generalization errors.

With the FrameNet representation previously used in McFate & Forbus (2016) there were significant differences in generalization patterns across three different generalization thresholds. As expected, a conservative threshold of .8 results in a learner that produces mostly item-specific constructions. This is consistent with the early phases of linguistic development in which competence with a construction is limited to individual verbs. With a slightly more liberal threshold we begin to see construction generalizations across verbs. While not completely general, they demonstrate that analogical generalization can result in complex constructions given individual examples. Finally, the most liberal setting retains several idiomatic constructions (e.g. where are you going) but begins to overgeneralize and confuse transitive and intransitive constructions.

While both representations are capable of capturing the verb-island phenomena, the FrameNet representation is more susceptible to the effects of the assimilation threshold. Furthermore, while generalizing over the FrameNet representation does produce multi-verb constructions, the vast majority of accurate generalizations are limited to two verbs; we never see a large single transitive construction without misgeneralizations of the intransitive. Note that at .8 there are 19 verb specific constructions for the FrameNet representation as opposed to 12 for role alignment. One reason for this is that labeling pronouns and noun phrases distinctly reduced overlap, however more important was that the location predicates (e.g. `loc1`) did not occur in a higher order relation and thus the structure of the representation was relatively flat.

By comparison, in the role-alignment representation, the syntactic dependency relations are arguments to the higher-order `syntacticOrder` predicate. This increases the importance of alignable syntactic structure relative to shared frame elements or words. This facilitates generalizing constructions across verbs with different semantic roles.

One interesting direction for future work is to consider sentential function (e.g. question, command) as an element of constructional semantics. There are distinct grammatical patterns for interrogatives and imperatives. Neither representation captured the former particularly well, though the role-alignment representation did capture imperatives. One step towards capturing interrogatives, and indeed more complex constructions in general, would be to include auxiliary verbs in the syntactic representation. Augmenting with sentential function would allow the system to apply the function of the utterance by analogy just like constructional semantics.

Furthermore, given the important role sociality is hypothesized to play in language acquisition, encoding the function of utterances could provide important cues for learning (Tomasello, 2009).

6.3 Conclusion

This chapter has presented a new representation of constructions and their arguments based on Goldberg's (1995) argument and participant role unification. This new representation addresses several problems with the FrameNet based representation used in the previous chapter. This new representation, called the role alignment representation, allows known verbs with unbound semantics to be bound to their arguments by analogy. It also can be used to apply argument roles to unknown verbs, as was done in the previous chapter.

Both representations were used to model construction acquisition from child directed speech. The learned constructions were manually analyzed for correctness and for learning patterns present in children. Different assimilation thresholds were used to model more conservative and liberal learners.

Both representations were able to generalize constructions with high accuracy, and both were able to demonstrate item-specific bias in learning at higher assimilation thresholds. That said, the role alignment representation proved more resistant to changes in assimilation threshold because of the use of a higher-order syntactic ordering predicate.

The following chapter presents a cognitive model of linguistic bootstrapping in theory of mind acquisition. This cognitive model uses my analogical account of construction application to create semantic cases for the AToM model of theory of mind (Rabkina, McFate, Forbus & Hoyos, 2017).

7. Computational Model: Linguistic Bootstrapping

7.1 Theory of Mind and Linguistic Bootstrapping

The final cognitive model in this manuscript explores how an analogical account of interpreting embedded clauses can explain *linguistic bootstrapping* effects in theory of mind acquisition. The work below appears in Rabkina, McFate, and Forbus (2018) and includes a simulation of results from Hale & Tager-Flusberg's (2003) study of bootstrapping in theory of mind tasks.

Theory of mind is the ability to reason about the beliefs of both oneself and others, including how they may differ from reality. Young children demonstrate remarkable failures in theory of mind, failing to predict others' beliefs and to even recognize their own prior beliefs when they had differed from reality. There is little debate that language acquisition affects the acquisition of Theory of Mind (ToM) (Milligan, Astington, & Dack, 2007). Instead, the debate has centered on the extent of the effects. This work focuses on the proposal that learning certain grammatical structures is a necessary prerequisite for gaining ToM reasoning abilities, and that children bootstrap ToM from these grammatical structures (de Villiers & Pyers, 2002; Hale & Tager-Flusberg, 2003; Lohmann & Tomasello, 2003). In particular, it has been argued that embedded clauses, for example the *eat* clause in "I saw him eat the apple.", play an important role because their nested sentence structure mirrors how beliefs are nested inside a person. Just as beliefs can be false, nested complements can be contradicted (e.g. He said he ran, but he walked), and linguistic bootstrapping theories propose that young children transfer what they learn about these syntactic structures to reasoning about mental states.

This work provides a computational model of linguistic bootstrapping from embedded clauses based on analogical construction application. There are two phases to the model. The first is that construction application by analogy results in a nested linguistic interpretation. This interpretation is activated in working memory, and then used by the AToM (Analogical Theory of Mind) model of ToM reasoning to make theory of mind judgements (Rabkina et al., 2017).

According to the AToM model, ToM reasoning involves analogical comparison of current situations to previous experiences. It is inspired by Bach's (2011) proposal that ToM reasoning and development occur via analogical reasoning, as well as Hoyos, Horton, & Gentner's (2015) findings that structural similarity aids ToM development. AToM assumes that most ToM reasoning occurs in working memory. Given a predicate calculus case that represents the situation being reasoned about, an analogous case is retrieved via a specialized version of SAGE that creates generalizations in a limited working memory and that is biased towards recent examples (SAGE-WM; Kandaswamy et al., 2014). In specific training situations, such as the training study modeled below, comparison cases are assumed to already be in working memory due to the near impossible task of modeling the contents of a full long-term memory. ToM predictions arise as inferences from the comparison of the two cases.

7.2 Modeling Linguistic Bootstrapping

7.2.1 Simulation Target

This work models a training study by Hale and Tager-Flusberg (2003). In their study children were placed into one of three training conditions. One group received training on sentential complements (SC; The boy said "…"). Another received training on relative clauses (RC; "The boy that jumped."), and the final group received training in false belief (FB) prediction. They found that SC training improved performance both in interpreting future SCs and in false belief reasoning. FB and RC training improved performance in their categories, but they did not demonstrate transfer across categories (e.g. improvement in RC and FB). This work particularly models the RC and SC training conditions and their effects on performance in the FB tests.

In Sentential Complements (SC) training, each child heard four stories about a boy's interaction with a *Sesame Street* character. Each story contained a sentential complement structure (e.g. "The boy said, 'I kissed Grover.'") which differed from reality (e.g. The boy kissing Big Bird). The child was then asked, "What did the boy say?". Regardless of the response the experimenter emphasized the difference between the contents of the embedded clause and reality, (e.g. "That's right/incorrect. The boy said, 'I kissed Grover,' but he really kissed Big Bird.")

In Relative Clause Training (RC) the children were told stories using the relative clause structure (e.g. "Bert hugged the girl who jumped up and down.") After each story, the child was asked about the contents of the clause (e.g. "Who did Bert hug?"). The relative clause structure was emphasized in the experimenter's response.

After training, the children were tested on three post-tests that each required false belief reasoning. The first was Location Change. Children were told a story about a boy and his mom. The boy and mother jointly put a cup in the dishwasher. The boy leaves and, while gone, his mom put the dishes away. The children were then asked whether he knows where the cup is, and where he will look for it.

The second test was an Appearance-Reality test. The children were shown a sponge that looked like a rock and asked what it looks like. They were then told to feel the object and encouraged to say that it feels like a sponge. Children were then asked what the object really was and what it looked like.

The third false belief test was an Unexpected Contents test. Children were shown a Band-Aid box and asked what they thought was in the box. They were then shown that there was actually a doll in the box. Test questions asked what the child had thought was in the box prior to looking inside, and what the child's friend would think was inside the box.

Scores on the post-test were calculated out of 6 points (2 per test; 1 per question). On average, children in the SC condition answered approximately 4.5 questions correctly[10]. Children in the RC condition averaged approximately 1 correct answer total.

7.2.3 Model and Experiment

Of interest are the syntactic representations that enable false belief reasoning. In the SC training condition, the crucial construction was of the form "X said Y, but really Z." This was represented using a nested phrase structure representation. Within the main clause, each constituent is represented as a headed phrase (e.g. NP and VP). When an argument to a construction contains a finite clause as a verbal argument (e.g. say "…"), the embedded clause is represented as being in the scope of the verb.

Figure 19 depicts the interpretation process. The SC construction ("X say Y but really Z") is on the far left. It is an argument structure construction that combines three arguments, a subject and unsatisfied verb, a finite clause argument to the verb, and an adverbial clause

[10] This was not significantly different from the children in the FB training condition.

adjunct. Critically, it implies that the nested clause is contradicted by the external clause ("but really Z").

Its constituents, in the middle, consist of the subject and verb, the SC argument to the verb *say,* and the adverbial clause at the end. When aligned, the system analogically transfers the structure of the construction to its constituents, including the semantics that the nested clause is contradicted by the outer adverbial clause.

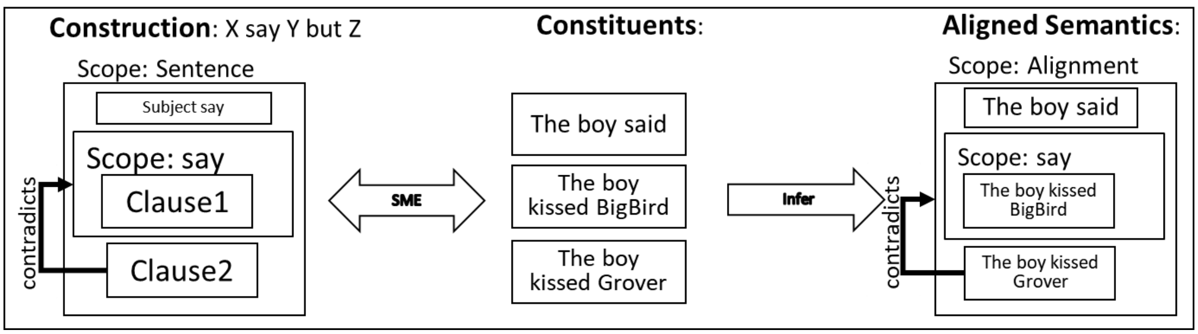

Figure 19: Analogical integration of the construction and its arguments results in nesting and contradiction

In the RC condition, the feedback contained a relative clause "X verb the Y that Z.". The same representation was used as in the RC condition. However, note that there is no nesting because the finite clause is not an argument to a verb. The construction is just a transitive construction; it combines an NP subject and a VP with a direct object. In this case the direct object contains a relative clause, but there is no nesting outside of the main clause.

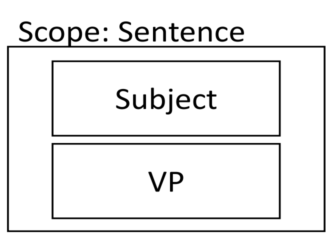

Figure 20: Argument structure construction for the relative clause feedback condition.

Table 5: The left column shows the representations for the SC argument structure construction, “X verb Y but Z” and the RC construction “X verb Y_{rel}”. Since the relative clause is a noun modifier, the RC is just a basic transitive construction.

SC & RC Constructions	Constituents	Aligned Semantics
Sentential Complement: (naryHoldsIn clause1 (situationConstituents clause1 NP-Subject) (naryHoldsIn say-clause (situationConstituents say-clause S-Comp)) (situationConstituents clause1 AVP-Clause)) ;; Construction Semantics (contradictory-Underspecified S-Comp AVP-Clause) Relative Clause: (naryHoldsIn clause1 (situationConstituents clause1 NP-Subject) (situationConstituents clause1 VP-Trans)	;; “The boy said” (situationConstituents arg1 (SituationSuchThatFn (communicatorOfInfo say92 boy1))) ;; “The boy kissed Grover.” (situationConstituents arg2 (SituationSuchThatFn (objectActedOn kiss1 Grover) (performedBy kiss1 boy1))) ;; “The boy kissed BigBird.” (situationConstituents arg3 (SituationSuchThatFn (objectActedOn kiss2 BigBird) (performedBy kiss2 boy1)))	(naryHoldsIn clause1 (situationConstituents arg1 (SituationSuchThatFn (communicatorOfInfo say92 boy1)) **(**naryHoldsIn **(skolem say-clause)** (situationConstituents (SituationSuchThatFn (objectActedOn kiss37 Grover) (performedBy kiss37 boy1))) (SituationSuchThatFn (objectActedOn kiss36 BigBird) (performedBy kiss36 boy1))) (**contradictory-Underspecified** (SituationSuchThatFn (objectActedOn kiss37 Grover) (performedBy kiss37 boy1)) (SituationSuchThatFn (objectActedOn kiss36 BigBird) (performedBy kiss36 boy1)))

A sample of the predicate calculus representations for the constructions and constituents is shown in the Table 5 above. The predicate `naryHoldsIn` is a variable arity predicate that takes expressions as arguments. It is used to define grammatical scope. Each argument is a constituent of the main clause (`situationConstituents`). In the construction, the sentential complement is embedded in an internal `naryHoldsIn` expression. The arguments are represented in a separate case where each is a `situationConstituents` relationship over the semantics of each constituent. The semantics inferred by analogy appear on the right of the table. The model infers that the situation of the second clause is nested in an internal context, and that it can contradict the external clause situation.

These representations differ from those in the previous sections, though the fundamental idea of a construction as a pairing of syntactic structure and argument semantics remains. The syntactic structure consists of the nested clauses, and the semantics are the contradiction that holds between the external and subordinate clause. The representation of the semantics is different in that it is not frame based (there is no *contradiction* frame with elements). Instead the clauses are related directly through the contradiction predicate.

To recast it in the role alignment representation, each constituent would participate in a frame (e.g. `Being_Contradictory`). The external clause fills the frame element `True_statement` and the subordinate fills a `False_statement` FE. The `naryHoldsIn` predicate plays a similar role to the `syntacticOrder` predicate in that it provides higher order structure, but there were no embedded clauses in the previous experiments. They could have been represented in the prior section by nesting `syntacticOrder` assertions.

Training stories consistent with Hale & Tager-Flusberg (2003) were semi-automatically encoded in predicate calculus using the EA NLU semantic parser (Tomai, 2009). Each training story is encoded as a case containing the critical argument structure construction and a case containing its arguments. Per the model described in Chapter 4, these are analogically aligned, and the resulting inference enters working memory. Per the AToM model, these training cases are generalized in working memory by SAGE-WM. It is assumed that the relevant generalization can be recalled to working memory during testing.

During testing, each test condition is represented as a case. Figure 21 shows the structure of the Unexpected Contents test. Here, the opinion that bandage boxes typically contain holds in reality. It is true in reality that the child has this belief, and it is also true in reality that the box actually contains a doll. In the predicate calculus representation, on the right, the events are wrapped in a containing function which returns the situation resulting from the events contained.


```
(naryHoldsIn reality39
;;;I hold opinions
 (situationConstituents reality39
     (hasBelief me123 opinions123))
;;;bandage boxes usually contain bandages
 (naryHoldsIn opinions52
   (situationConstituents opinions52
    (SituationSuchThatFn
     (implies
      (SituationSuchThatFn
       (isa box13 (ContainerContainingFn
        Box-Container Bandage)))
      (relationInstanceExists
        containedObject contain92 Bandage)))))
;;;really it contains a doll
 (situationConstituents reality39
  (SituationSuchThatFn
   (relationInstanceExists
     containedObject contain93 Doll)))
```

Figure 21: Unexpected contents test condition

Following the AToM model, false belief reasoning is accomplished by analogical comparison to a retrieved case in working memory. During testing, each case enters AToM’s working memory and a similar case is retrieved via SAGE-WM. The retrieved case was the aligned semantics. When a case was retrieved, any candidate inferences that came out of the best mapping were examined. A test was considered correct if a candidate inference implied that the true belief condition contradicted the false belief condition. For example, in the Unexpected Contents test, the fact that there was a doll in the box should contradict with the fact that bandage boxes usually contain bandages.

7.2.4 Results

As described above, in each of the training trials the inferred semantics from the syntax-semantic alignment entered AToM's working memory where they are generalized by SAGE-WM. The first case enters ungeneralized, and it forms a generalization with subsequent examples. After SC training, the working memory contained a single generalization. During testing, AToM has the generalization in working memory. AToM compares each test scenario to the contents of working memory. The nested structure within each false belief scenario aligned with the nested structure of the generalization and produced a single candidate inference. In each case, this candidate inference contained a contradiction between the true belief (e.g. there is a doll inside the bandage box) and the expected false belief (e.g. the box contains bandages). In the model, these candidate inferences predict correct responses to the false belief questions.

During RC training, a similar pattern emerged: the inferred semantics from each RC case were accumulated into a single generalization within WM. However, during testing, AToM was unable to align the learned generalization with the false belief stimuli. Therefore, it generated no correct inferences, ergo no correct responses. These results are consistent with the findings of Hale and Tager-Flusberg (2003): that sentential complement training bootstraps ToM, but relative clause training does not.

7.2.5 Discussion

An analogical approach to construction integration, paired with the AToM model of theory of mind, can account for linguistic bootstrapping effects in children's ToM development. This claim was evaluated by modeling Hale and Tager-Flusberg's (2003) study which demonstrated that children's ToM reasoning abilities improve with sentential complement training.

One criticism of the original study is that the contents of the sentential complement are false (Lohmann & Tomasello, 2003). That is, the boy tells a lie. The model's results however suggest that this is important—the contradiction between the contents of the *say* and the *really* drives the subsequent inference that belief/observation and reality may differ.

It is important to note, however, that the contradiction is not the only aspect of the SC training that leads to improved ToM reasoning in the model. The verbal nesting structure of SC sentences allows for structural alignment between the learned construction and the test cases. It is this alignment that leads to a candidate inference about a potential contradiction. Without the sentential complement, this inference would not be made.

Yet, without the contradiction, it is not clear what would be learned from the alignment. Lohmann & Tomasello (2003) report that children can improve in ToM reasoning abilities by bootstrapping from sentential complements that do not contain such a contradiction. Their SC training, however, included mental state verbs which may have a stronger priming effect. The question of how sentential complements might drive ToM development on their own deserves further research.

Finally, it is worth noting that while we represented the "X say Y but Z" construction as operating over un-nested arguments, an alternative representation exists. It is possible instead to interpret the construction as taking an already nested sentential complement (<X> <say Y> <but Z>). In such a case, the first argument would just be the NP subject. Representing the construction in this way would still result in the same final semantics, but the sentential complement would already be nested. Nesting and contradiction come from separate constructions as they are composed together.

7.3 Conclusion

This chapter has presented a cognitive model of linguistic bootstrapping in theory of mind acquisition that relies on analogical construction interpretation. In this model, a construction with nested argument structure (the sentential complement) is applied to its arguments by analogy, resulting in a representation where the nested facts contradicted with the external clause. These representations are generalized and retrieved as a part of the AToM model of theory of mind. They are applied by analogy to novel situations requiring false belief reasoning in which a person's beliefs (nested) contradict reality. The model was able to recognize when beliefs contradicted reality following training with the sentential complement but not with the relative clause construction, simulating developmental results (Hale & Tager-Flusberg, 2003).

The cognitive experiments in this and the prior two chapters provide evidence that analogical generalization model of construction acquisition and application can replicate human subjects findings. While we have thus far focused on models of human behavior, the following chapter describes how the same language model was used in broader natural language processing tasks.

8. Semantic Parsing with Constructions

8.1 Introduction

The previous chapters have presented a cognitive model of construction acquisition and application by analogy. The goal of this chapter is to extend the model for use in practical natural language understanding applications such as question answering. To that end, the extended model is described and evaluated on seven of Facebook's bAbI question answering tasks (Weston et al., 2015).

Section 6.1 introduced the role alignment representation which reifies argument and participant roles that are then associated with their semantics and profile status. In both the construction and its constituent case, the syntactic arguments are encapsulated in a predicate which provides an absolute order. The same representation is used throughout this chapter.

8.2 Approach

Interpretation arises from analogical alignment of an argument structure construction case and a case of its constituents (the verb, its arguments, and participant roles). The argument structure construction is learned by analogical generalization as in Chapter 6. In adapting the model for general semantic parsing and reasoning, there was one modification to the representation. Where possible, FrameNet frame elements were replaced with CycL predicates using a manually created mapping.

In the prior work, the constituents case was built from manually annotated corpora, but this is obviously not possible when parsing novel text. Instead, the constituents case is constructed from two sources. The first is a syntactic dependency parse of the sentence, which comes from the spaCy dependency parser. The second are case frames stored in the KB that list profiled and unprofiled participant roles for verbs. These were automatically constructed from FrameNet lexical units as described in Section 8.3. Figure 22 depicts the interpretation pipeline.

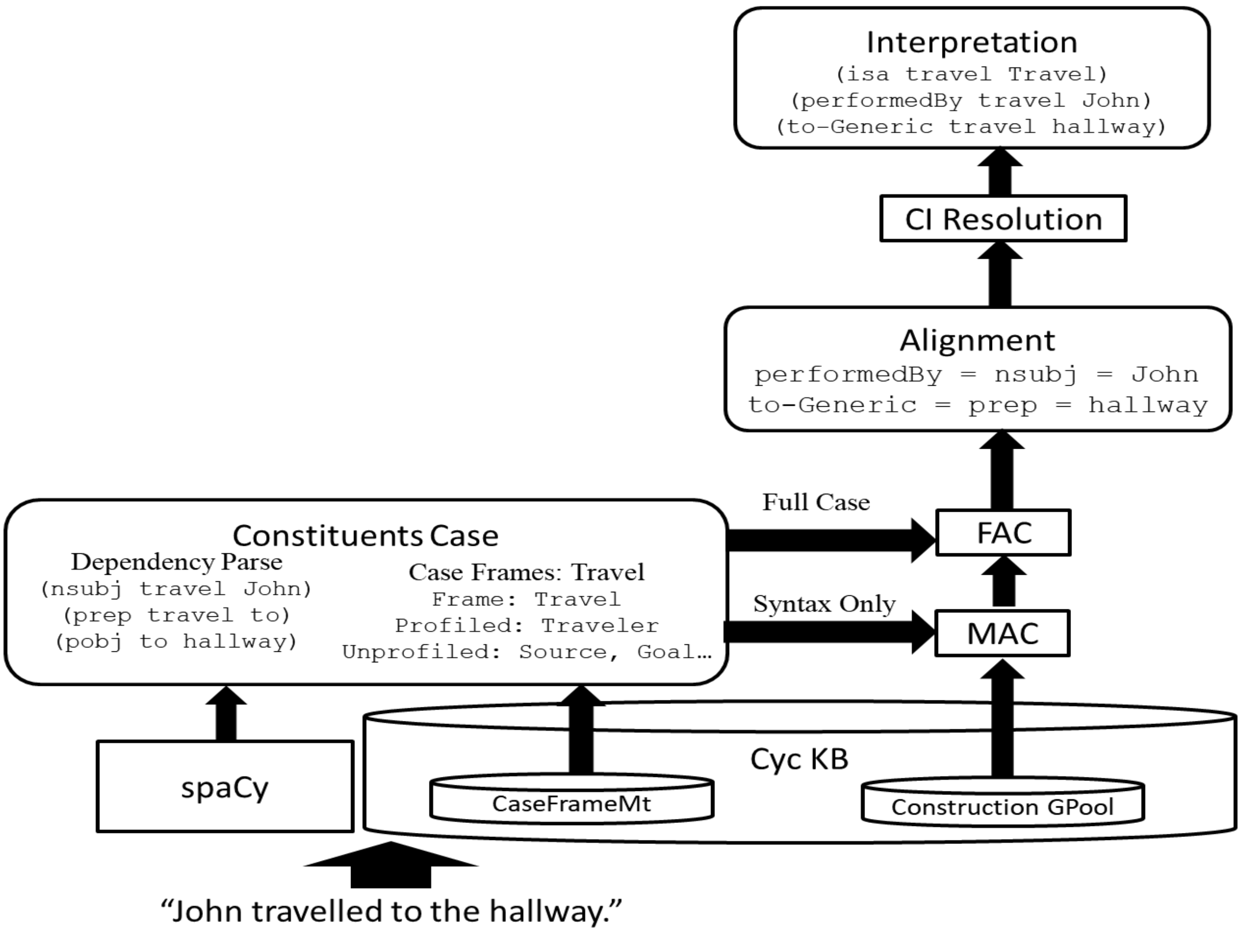

Figure 22: Analogical Interpretation Pipeline

First, the sentence is parsed by the spaCy dependency parser, and this dependency parse is pruned to contain only the verbal arguments. A verb's argument is represented as a headed phrase. For example, in the sentence in Figure 22, "John travelled to the hallway.", the phrase headed by *John* is given the dependency role `nsubj` relative to the verb *travel*. The dependencies are gathered into an absolute ordering, resulting in the following syntactic representation:

```
 (syntacticOrder
    (nsubj travelled5204 (HeadedPhraseFn John5203))
    travelled5204
    ((PrepFn to) travelled5204
     (HeadedPhraseFn hallway.5207))))
```

The second step is to retrieve the verb's case frames. Each case frame corresponds to a separate sense of the verb. A separate constituents case is created for each case frame by pairing the syntactic representation with the unbound frame elements of the case frame. In the completed case, FrameNet specific frame elements are mapped to CycL predicates using a manually constructed mapping. The case also contains word members of each phrase as attributes. An example constituent case is shown below:

```
(syntacticOrder
    (nsubj travelled5204 (HeadedPhraseFn John5203))
    travelled5204
    ((PrepFn to) travelled5204
     (HeadedPhraseFn hallway.5207))))

((RoleHasPredFn performedBy) travelled5204 performedBy))
(profiledLingRole performedBy)

((RoleHasPredFn to-Generic) travelled5204 to-Generic))
(profiledLingRole to-Generic)

((RoleHasPredFn dateOfEvent) travelled5204 dateOfEvent)
(unprofiledLingRole dateOfEvent)

((WordMemberFn hallway) (HeadedPhraseFn hallway))…
```

Participant roles are reified as their semantic relation for convenience (e.g. `performedBy`); however, as an entity in SME the form does not matter. The semantics comes from the functionally defined predicate `(RoleHasPredFn performedBy)` which is atomic for analogy.

The system then uses MAC/FAC for two phase retrieval. The first phase, MAC, operates only over the syntax. This is because including the entire case frame unduly favored verbs with large case frames whose potential participant roles overlapped with large generalizations (see Section 8.5 for more detail). The FAC phase of retrieval compares the complete constituents case to the argument structure constructions retrieved by MAC. During the FAC stage, SME generates role bindings by candidate inference.

These candidate inferences are then resolved to construct the final interpretation. With a known verb, CI resolution simply involves taking the bound participant role and formatting it in CycL syntax (e.g. performedBy <verb> <nsubj head>). For unknown verbs, the bindings introduce a skolem argument role for each phrasal argument. Each skolem is resolved with the most frequent semantic relation attributed to that role.

8.3 Experiment: bAbI Question Answering

8.3.1 The bAbI tasks

This system is evaluated on several of the Facebook bAbI question answering tasks (Weston et al., 2015). The bAbI tasks are each designed to test a specific aspect of language understanding and reasoning via questions about sequences of events. They are intended to provide simple perquisites for conversational agents.

Tasks are structured as a sequence of labeled lines. Each line is either a sentence that adds to a cumulative sequence of events or a question. When a line restarts at the label 1, a new sequence begins. An example from the bAbI-2 task is shown below. The final line gives the question, answer, and lines required to answer the question. In this case, answering the question requires knowing both that Sandra had the apple and that she is currently in bedroom.

```
1 Daniel went back to the hallway.
2 Sandra grabbed the apple there.
3 Mary went to the bedroom.
4 Sandra journeyed to the bedroom.
5 Where is the apple?   bedroom     3 4
```

Figure 23 illustrates sample text, questions, and answers from bAbI tasks 1-10 (Weston et al., 2015, p.4). The training, validation, and test sets are all automatically generated by the same world model.

Task 1: Single Supporting Fact
Mary went to the bathroom.
John moved to the hallway.
Mary travelled to the office.
Where is Mary? A:office

Task 2: Two Supporting Facts
John is in the playground.
John picked up the football.
Bob went to the kitchen.
Where is the football? A:playground

Task 3: Three Supporting Facts
John picked up the apple.
John went to the office.
John went to the kitchen.
John dropped the apple.
Where was the apple before the kitchen? A:office

Task 4: Two Argument Relations
The office is north of the bedroom.
The bedroom is north of the bathroom.
The kitchen is west of the garden.
What is north of the bedroom? A: office
What is the bedroom north of? A: bathroom

Task 5: Three Argument Relations
Mary gave the cake to Fred.
Fred gave the cake to Bill.
Jeff was given the milk by Bill.
Who gave the cake to Fred? A: Mary
Who did Fred give the cake to? A: Bill

Task 6: Yes/No Questions
John moved to the playground.
Daniel went to the bathroom.
John went back to the hallway.
Is John in the playground? A:no
Is Daniel in the bathroom? A:yes

Task 7: Counting
Daniel picked up the football.
Daniel dropped the football.
Daniel got the milk.
Daniel took the apple.
How many objects is Daniel holding? A: two

Task 8: Lists/Sets
Daniel picks up the football.
Daniel drops the newspaper.
Daniel picks up the milk.
John took the apple.
What is Daniel holding? milk, football

Task 9: Simple Negation
Sandra travelled to the office.
Fred is no longer in the office.
Is Fred in the office? A:no
Is Sandra in the office? A:yes

Task 10: Indefinite Knowledge
John is either in the classroom or the playground.
Sandra is in the garden.
Is John in the classroom? A:maybe
Is John in the office? A:no

Figure 23: Sample bAbI tasks 1-10 (Weston et al., 2015, p.4)

The bAbI tasks are relevant to this manuscript as a test of frame-semantic parsing. Each of the tasks requires correctly interpreting a string of events, with less room for error as questions begin to rely on multiple lines. For each task, a set of rules was created that would allow the system to answer the type of question in the task given a correct interpretation of the prior utterances.

The system was evaluated on bAbI tasks 1-3 and 5-8. Tasks 4, 9, and 10 were not attempted because the relevant semantics came from a lexical item other than the verb and its argument structure (e.g. 'north of').

8.3.2 Answering Questions

Questions in the bAbI corpus are about locations of people and objects. As such, the goal of interpretation was to construct a sequential history of events that could be used to answer questions deterministically.

Each line of the test corpus was read in order. If the line was a declarative sentence, it was parsed by the model and the semantic interpretation was stored in an event microtheory. Each line in a story is parsed into its own microtheory. A local task microtheory inherited each event specific microtheory. Each event was reified as a neo-Davidsonian event (e.g. `(isa give1 Giving)`), and each event was labeled with its line number. This enabled querying for ordering of events.

Questions were identified by regular expression. When a line contained a question, the relevant entity was extracted, and a task-specific query was constructed. Each query involved chaining backwards through events to find a satisfying solution. Queries were written as horn clauses. Appendix D contains the rule-set defined for the tasks. The table below shows the top-level query for each of the bAbI tasks and a description of its truth conditions.

Table 6: Top-level queries for bAbI tasks

Task	Predicate	Description
bAbI-1	`(isCurrentlyIn ?person ?place)`	True if a `?person` moves to a `?place` and does not move to another `?place2` in a subsequent event.
bAbI-2	`(isObjectCurrentlyIn ?object ?place)`	True if in some event a `?person` has obtained the `?object`, they did not subsequently lose the `?object`, and they are in `?place`. True if in some event a `?person` obtains the `?object`, they move to `?place`, they lose `?object`, and in no subsequent event does `?person2` obtain `?object`.
bAbI-3	`(wasInPlaceBefore ?object ?place ?placeBefore)`	True if in some event `?e` a `?person` moves to a `?place`, `?person` is holding `?object` in event `?e`, in some event `?e2` the `?person` moves to `?placeBefore`, `?e2` is before `?e1`, and in no event between `?e2` and `?e1` did `?person` move to `?place3`.
bAbI-5	`(giveTo ?e ?giver ?recipient ?object)`	True if in some event `?e` a `?giver` gives an `?object` to a `?recipient`.
	`(lastGiveTo ?e ?giver ?recipient ?object)`	True if `giveTo` holds and there is no other giving event `?e2` between `?giver` and `?recipient` following `?e`.
bAbI-6	`(isCurrentlyIn ?person ?place)`	See task 1
bAbI-7	`(CardinalityFn (isHoldingObject ?person ?object))`	True if in some event a `?person` has obtained the `?object`, they did not subsequently lose the `?object`
bAbI-8	`(SetOf ?object (isHoldingObject ?person ?object))`	See tasks 2,7

8.3.3 Construction Acquisition

Acquisition used the corpus of annotated child directed speech from Chapter 6. This corpus was modified with examples from the training sets of each task. For each task, unique constructions were identified. If they did not appear in the child-directed corpus or appeared with a novel verb frame, several examples were added for each unique verb frame that they appeared with. 33 total sentences were added to cover all 7 tasks. The number of training sentences added by task is shown below, Table 7. The added sentences are included in Appendix C.

8.3.4 Generating Case Frames

Case frames are generated from FrameNet. For each verb in FrameNet, a separate case frame is created for each semantic frame that verb evokes. Case frames also contain the profiling status of each of the frame elements. Recall from Section 2.5 that profiled roles are those that are canonically obligatory and that appear by default in profiled syntactic positions (e.g. subject and object). For each verb in a frame, an FE was considered profiled if it appeared in 80% or more of the example sentences in FrameNet.

8.3.5 Experiments

This manuscript reports results from four experiments. In all experiments, the gpool assimilation threshold during acquisition was set to .8. The probability cutoff was set to .2 for both acquisition and testing. All experiments were run over the bAbI test corpus of 1000 questions.

In experiment 1, MAC retrieved a maximum of 7 cases for each case frame during testing. The system assigned the semantic bindings of the mapping with the top base-normalized score. The base-normalized score is the score divided by the self-similarity score of the base. The base-normalized score was used because normalization involving the target (the case-frame) negatively affected verbs with larger frames despite all argument slots being filled. If two mappings had equal base-normalized scores, the highest target-normalized score was used as a tie-breaker.

During validation, several case frame errors were identified that reduced performance. First, the verb *pick* lacked an appropriate frame for the babi-2 corpus. Furthermore, the verbs *pass* and *grab* had frames with no profiled elements. This occurred when there were no FrameNet annotations for a verb in a semantic frame. These were corrected for experiment 2. In experiment 2, MAC retrieved a maximum of 10 cases for each case frame during testing.

Following experiments 1 and 2, further analysis of the validation set revealed that including words as attributes negatively impacted performance. The reason is that the bAbI corpus examples are drawn from a very limited vocabulary and thus the words are incredibly consistent. This consistency led to them having an undue effect on retrieval. In experiments 3 and 4, the word attributes were removed from cases used for acquisition and during application. Experiment 3 uses the same settings as experiment 1. Experiment 4 replicates experiment 2 but with a smaller maximum MAC output of 7 (instead of 10).

8.4 Results

Table 7 below provides a summary of the results on the bAbI test sets. Each test set contained 1000 questions. Results are discussed in the relevant subsections below.

Table 7: bAbI Experiment Summary

Task	Training Sentences Added	Case Frames Corrected	**Exp. 1** MAC = 7 Uncorrected	**Exp. 2** MAC = 10	**Exp. 3** No words MAC = 7 Uncorrected	**Exp. 4** No words MAC = 7
bAbI-1: Single Supporting Fact	3	0	81.6%	100%	100%	100%
bAbI-2: Two Supporting Facts	22	2	77.3%	99.8%	91.2%	99.8%
bAbI-3: Three Supporting Facts	0	0	32%	97.8%	51.6%	97.8%
bAbI-5: Three Argument Relations	5	1	93%	97.8%	93%	97.8%
bAbI-6: Yes/No Questions	3	0	89.6%	100%	100%	100%
bAbI-7: Counting Questions	0	0	87.8%	100%	87.8%	100%
bAbI-8: Lists/Sets	0	0	84.7%	100%	84.7%	100%

8.4.1 bAbI-1 Results

The bAbI-1 task consists of a series of individual movements followed by the question, "Where is X?" where X is an individual. This requires correctly interpreting the line containing the most recent movement of the individual. In experiment 1 the system achieved 81.6% accuracy which increased to 100% in experiment 2. The increase in experiment 2 came as a result of the increased MAC maximum window as none of the added case frames appeared in this task. The increased window was needed because of the distraction provided by word attributes as demonstrated by the 100% accuracy in experiments 3 and 4.

8.4.2 bAbI-2 Results

The bAbI-2 task consists of a series of movements, object retrieval, and object removal events. The questions are each of the form “Where is X?” where X is an object. This requires correctly interpreting who last picked-up the object and where they moved to. In experiment 1, the system achieved an accuracy of 77.3 % which increased to 99.8% in experiment 2. As the movement events in bAbI-2 are drawn from the same vocabulary as bAbI-1, the increased MAC window was partially responsible for the increase in performance in experiment 2. However, the addition of the *pick* case frame and correction of the *grab* case frame also contributed to the increase in performance. Again, we see that the increased MAC maximum output was largely needed because of the word attributes as performance in in experiment 3 (also uncorrected) only dropped to 91.2%. In experiment 4, the model achieved the same performance as in experiment 2 with the smaller MAC maximum output.

8.4.3 bAbI-3 Results

The bAbI-3 task consists of a series of movements, object retrieval, and object removal events. Each question is of the form “Where was X before Y?” where X is an object and Y is a location. The correct response is the location of the object immediately before Y, not all locations prior to Y. Objects are only moved by a person holding an object. Answering the question requires finding a movement event to the location when the person had the object and then checking the immediate prior location of the person. This combines the reasoning requirements from the prior bAbI tasks. In experiment 1, accuracy was 32% which increased to 97.8% in experiment 2. As these questions required multiple correct sentence interpretations, errors were more likely to result in incorrect answers. This lead to the significant decrease in performance in experiment 1. The increase in performance in experiment 2 is due to the same changes that were made for bAbI-2. Experiment 3 was a modest improvement over experiment 1 at 51.6%, demonstrating that removing word attributes did lead to improvement. Experiment 4 replicated the results of experiment 2 with the smaller MAC maximum output.

8.4.4 bAbI-5 Results

The bAbI-5 task consists of a series of movement events, object removal and retrieval events, and possession transfer events. Each question is about a possession transfer, asking who received an object, who gave it, or what the object was. Answering the question requires finding the most recent transfer event that holds for the participants. In experiment 1, the accuracy was 93% which increased to 97.8% in experiment 2. The increase in performance came from correcting the case frame for *pass*. Additional errors came from the spaCy parser which inconsistently assigned the *dative* or the *preposition* grammatical role to the oblique argument in ditransitive sentences like “Mary gave the football to Bill.” Interestingly, the impact of this error was minimized by the larger Childes corpus which included double-object constructions. While the syntactic order of the ditransitive and double-object are different, MAC/FAC retrieves and aligns the double-object based on the overlapping grammatical roles. The higher-order syntactic ordering relationship cannot be aligned, but semantic roles are attached on the basis of the grammatical roles. Experiments 3 and 4 replicated experiments 1 and 2 exactly.

8.4.5 bAbI-6 Results

The sequence of events in bAbI-6 was drawn from the same vocabulary as bAbI-1, however the questions were yes/no questions, e.g. “Is Mary in the kitchen?”. Answering the question requires the same reasoning as bAbI-1, but the person rather than the location is the question focus.

In experiment 1, accuracy was 89.6% which increased to 100% in experiment 2. Again, the increased MAC maximum output was responsible for the improved performance. As in task 1, the increased maximum output was needed because of the word attributes, as experiments 3 and 4 both achieved 100% accuracy.

8.4.6 bAbI-7 Results

The sequence of events in bAbI-7 was drawn from the combined vocabulary of the bAbI 1, 2, and 5 tasks. It differed in that people sometimes held multiple objects. Each question asked how many objects an individual carried. The same reasoning as bAbI-2 was used; however, the answer was now the cardinality of the set returned by the query. On this task, the system correctly answered 87.8% of questions in experiment 1 which increased to 100% in experiment 2. The increase resulted from the changes in prior experiments. Experiments 3 and 4 replicated experiments 1 and 2 identically.

8.4.7 bAbI-8 Results

The sequence of events in bAbI-8 shares the vocabulary with bAbI-2, however the task is to enumerate rather than count the objects carried by an individual. The same query was used as in the prior task, but the returned set of objects was compared to the answer set. On this task, the system correctly answered 84.7% of questions in experiment 1 which increased to 100% in experiment 2. The increase resulted from the changes made for the prior experiments. Experiments 3 and 4 replicated experiments 1 and 2 identically.

8.5 Discussion

The system performs well on all tasks with relatively few extensions to the training corpus. Weston et al. (2015) evaluate several models on the bAbI tasks with varying amounts of training data. This provides the current state of the art, though comparison is difficult because their intent was to learn a model that performs well on each QA task while the goal of this work was to create a general language model independent of the QA task.

Weston et al.'s top performing model was a variation on a memory neural network (Weston, Chopra, & Bordes, 2014). A memory network consists of a memory array which, in this case, contains a sequence of sentences. A trained controller neural network selects a slot from memory by chaining retrievals. The first retrieval is the memory slot with the maximum match score with the question, and subsequent retrievals depend on the slots retrieved thus far. In (Weston et al., 2014) this inference depth was set to 2. When inference stops, a scoring function selects an answer (word) from the retrieved memory. Weston et al. (2015) builds on this model with three improvements. The first allows the controller to perform another inference or stop at the current memory, thus allowing variable depth. The second was to use N-grams to represent the text of the sequences and questions. The third was to use a 2-layer tanh neural network in the matching function.

Their results on the relevant bAbI tasks are shown in Table 8. Columns 2 and 3 show two baselines, a standard LSTM model and a structured SVM model. Their top performing memory network is in column 3. Column 4 shows the number of training questions they needed to reach above 95% accuracy on each task (up to 1000). Column 6 shows the top performing analogical construction grammar systems (2 and 4). Again, the goals of the systems are different, but the analogical construction model outperforms the state of the art on tasks 7 and 8 and performs comparably on all other tasks (within 3%).

Table 8: bAbI results, comparison to state of the art

	LSTM	Structured SVM	Modified MemNN	Number of Training Questions	**Test Accuracy Experiment Corrected**
bAbI-1	50	99	100	250 ex	100%
bAbI-2	20	74	100	500 ex	99.8%
bAbI-3	20	17	100	500 ex	97.8%
bAbI-5	70	83	98	1000 ex	97.8%
bAbI-6	48	99	100	500 ex	100%
bAbI-7	49	69	85	1000 ex	100%
bAbI-8	45	70	91	1000 ex	100%

The corrections that were needed between experiments reveal interesting challenges for the analogical approach. The first source of improved performance was the increased MAC retrieval window in experiment 2. Why was this needed? In MAC, the similarity score is dot product of the two content vectors normalized by the magnitude of the two vectors. Given two vectors, *a* and *b*, the score would be calculated as:

$$\frac{\sum a_i b_i}{\sqrt{m(a)m(b)}}$$

where *m(x)* is the sum of the squares of the vector. The value for each relation in the content vector is its count in the case or, for a generalization, its probability. As more frequent relations in each case overlap, the MAC score increases. However, because of the normalization, having non-overlapping frequently occurring relations is costly. The constituents case contains just the syntactic information for the sentence, while the retrieved construction contains the bound argument roles. Since these can't overlap, more consistent, larger, constructions are dispreferred during MAC. Furthermore, grammatical relations are fairly uniform across sentences. Most have a subject and object. This means that their overlap loses discriminability.

However, if the constituents case were to contain the participant roles, generic roles such as *location* are likely to overlap with larger constructions even when, syntactically, there is no grammatical role for the constituent. For example, a constituents case for a verb in the transitive construction has a subject and an object (e.g. I ate the apple.). If it also includes all possible participant roles, it will include superfluous roles such as `location`. Now, given a transitive construction with an adjunct `location` (e.g. I ate the apple under the tree.), the transitive constituents case will be a better match to it based on the added semantic overlap. This is despite the fact that there is no evidence of a grammatical adjunct in the constituents case.

Thus, the syntax-only case for MAC comparison was chosen so as to avoid bindings for phantom adjuncts, but it did result in cases where, for smaller windows, MAC never found the appropriate construction. This problem was exacerbated by the artificial nature of the bAbI training sentences. Some constructions occurred with only one type of event and thus had completely consistent semantics and lexical attributes. This consistency meant that their absence hurt the MAC score more significantly. A more natural corpus would ameliorate this problem,

Another source of errors was incorrect case frames. For example, the *grab* and *pass* frames had no profiled roles because of a lack of annotated examples in FrameNet. Because profile status is syntactic for argument structure, it is consistent across examples. However, semantic roles vary between general and more specific predicates. Because of this, with diverse constructions, semantic roles are treated as less predictive than profile status. This resulted in the model choosing an incorrect sense of the verb for *grab* and *pass*.

It’s unclear whether this is undesired behavior since profile patterns essentially determine the subcategorization of a verb. Given a transitive construction, should the system prefer a verb sense that’s known to have two profiled roles or one that has better semantic overlap? I tend to lean towards the latter, and to some extent the system slightly prefers semantic overlap because the semantic bindings are represented as binary relations rather than as attributes. A stronger preference could be enforced by increasing the trickle-down multiplier in SME.

Both of these challenges could be resolved with a more robust shallow comparison measure. One idea, partially inspired by Alishahi & Stevenson (2008), would be to incorporate the size of the generalization into the MAC score so that generalizations that are consistent across many examples are more retrievable.

Ultimately, the results on these tasks are promising. Furthermore, while the approach does not learn how to answer the questions, the representations generated by the analogical model can be used in additional reasoning tasks and are not specific to the bAbI corpus. Future work should use the same approach to generate representations for different tasks either alone or as a part of a larger language system.

8.6 Future Work

An immediate next step would be to learn how to interpret and answer the questions given the linguistic output. First, the approach must be extended to include question constructions. These are already present and annotated in the child-directed speech corpus, but parts of speech such as auxiliaries are currently ignored. Incorporating these would allow the system to learn interrogative utterances. More challenging is learning how to answer the questions once interpreted.

One possible approach could build on Crouse, McFate, & Forbus' (2018) system which learned queries as paths in a connection graph between question and answer semantics. These queries were then applied by analogy for subsequent questions. However, this approach is complicated by the temporal reasoning needed to answer the questions. As an example, consider the following sequence:

```
Mary got the apple.
Fred got the ball.
Fred went to the kitchen.
Mary went to the bedroom.
Fred went to the bedroom.

Where was the ball before the bedroom? Kitchen
```

Answering the question requires connecting the entity *ball* to *kitchen* through bedroom. Assuming some ordering relation, e.g. Allen's (1983) temporal calculus, each event is related to the immediate following event. The following shortest path is then possible:

```
(moveTo e4 Fred bedroom)
(meets e4 e3)
(moveTo e3 Mary bedroom)
(meets e3 e2)
(moveTo e2 Fred kitchen)
(meets e2 e1)
(obtainedObject e1 Fred ball)
```

Crouse et al.'s (2018) approach could apply the same path to answer future questions with similar semantics. Unfortunately, these paths can be arbitrarily deep and so the same path cannot be used to answer a question with more irrelevant intermediate events. What is required is the ability to match sequences of relevant events despite length.

One possible solution comes from Friedman's (2015) psi compression technique. Psi compression operates over directed graphs and collapses the graphs by reifying paths of sequential relations. These paths are annotated with qualitative relationships that hold between each element in the sequence. Friedman (2015) gives the example of a ladder. Each rung monotonically increases in its vertical position. This path can be reified such that each of the rungs is a member of the path. Psi compression then asserts qualitative relationships that hold between each member in the path. For the ladder, this would be that, given a current rung, the value of its vertical position is increasing relative to the prior rung. Psi compression could identify the temporal sub-graph within the path shown above. The resulting compressed path might look as follows:

```
(orderedSequence path-1 e1 e2 e3 e4 e5)
(acyclicPath path-1)
(currentTerm path-1 cur-term)
(priorTerm path-1 prior-term)
(happensAfter cur-term prior-term)

(moveTo e4 Fred bedroom)
(obtainedObject e1 ball)
(moveTo e3 Fred kitchen)
…
```

Given a sequence of events, psi compression could be used to compress the events so that they match the learned path based on the properties of the sequence regardless of variance in path length. Given the terminal nodes of the learned path, irrelevant steps could be pruned by removing steps that don't include entities at either end of the path: *ball, Fred, and bedroom*. Then the question becomes, is there some subsequence of events in the psi-compressed case that matches all and only the pruned path and that maintains the same qualitative order as the relations in the query path.

The final query then is:

```
(sequence path-1 e1… eₙ)
(acyclicPath path-1)
(currentTerm path-1 cur-term)
(priorTerm path-1 prior-term)
(happensAfter cur-term prior-term)

(moveTo ?e4 ?Fred ?bedroom)
(moveTo ?e2 ?Fred ?kitchen)
(obtainedObject ?e1 ?Fred ?ball)

(> ?e4 ?e2 path-1)
(> ?e2 ?e1 path-1)
```

This approach would allow analogical application of a sequence query to novel sequences. However, it is not without flaws. The requirement of an exact match between the pruned query and a subsequence of events in the path means that the approach can ignore irrelevant interrupting events. However, irrelevant events that involve relevant entities would block application. Still, this is a promising approach and an important direction for future work.

8.7 Conclusion

This chapter has presented an implemented system that adapts the construction processing model from previous chapters for domain-general parsing. Using very few examples, the model achieves high performance on the semantic parsing needed for the bAbI question answering tasks. This demonstrates the efficacy of the model as a tool for NLP tasks above and beyond its contribution as a cognitive model.

9. Conclusion

9.1 Claims Revisited

I have argued that successfully modeling natural language understanding requires incorporating a more complex view of the interaction between argument structure and semantics. Specifically, I argue for a constructionist account of language understanding which, in contrast to traditional generative approaches, posits joint syntactic-semantic representations. Constructionist accounts further differ in that they do not posit a universal grammar or language-specific learning mechanisms. Because of this, they predict an incremental developmental pattern as individual examples are generalized into abstract constructions. In adopting the construction grammar framework I thus claimed that:

> *Claim 1: Constructions, pairings of form and meaning, are a productive unit of linguistic analysis that account for a broader range of phenomena than traditional approaches.*

Chapter 2 provided linguistic evidence that constructionist accounts can explain phenomena that traditional approaches consider peripheral. Chapter 3 provided psychological evidence supporting a constructionist account of language acquisition. To further support this claim, I used a construction grammar approach to model cognitive and linguistic phenomena. My cognitive model treats argument structure construction acquisition and application as analogical processes. I thus made the following two claims.

> *Claim 2: Human acquisition of abstract argument structure constructions can be modeled as analogical generalization over individual examples.*

> *Claim 3: Semantic interpretation can be modeled as the analogical integration of argument structure constructions and their constituents.*

In support of these claims, I first presented psychological evidence of analogical processes in language acquisition. I then presented my implemented computational model in Chapter 4. In the model, argument structure arises from generalization over item-specific examples. Argument roles are thus a distribution over participant roles that occur in a construction. The model relies on SAGE as its model of analogical generalization. Once learned, argument-structure constructions can then be retrieved and applied by analogy to interpret known and novel verbs.

To evaluate the cognitive model, I used it to simulate cognitive and linguistic phenomena. Chapter 5 presents a simulation of Kaschak & Glenberg's (2000) study on denominal verb interpretation. Denominal verbs present an interesting challenge for traditional accounts because the meaning of the verb is unlikely to exist in the lexicon. Kaschak & Glenberg (2000) found that, consistent with a constructionist account, participants in their study relied on argument structure to infer semantics for denominal verbs in transitive and double-object constructions.

In my simulation, constructions were acquired via analogical generalization over a small corpus annotated with FrameNet frame elements. Given phrasal arguments to a denominal verb, my model retrieved a generalized construction and inferred frame elements for each argument. This demonstrated that analogical generalization could result in generalized argument structure constructions and that these constructions could be productively applied to achieve human-like inferences.

To further support these claims, Chapter 6 presented an improved representation for constructions and their constituents that was inspired by Goldberg's (1995) account of role fusion. Called the role alignment representation, it reifies semantic roles for argument structure constructions and verbs. This allows their semantics to be attached as a distribution over externally connected predicates. Both the previous FrameNet based representation and the role alignment representation were used to model construction acquisition from child directed speech. The model used different assimilation thresholds to model more conservative and more liberal learners. With both representations the model learned highly accurate constructions and demonstrated item-specific generalization at higher thresholds. The role alignment representation proved more resilient to the effect of assimilation threshold. This demonstrated that the model was capable of producing human-like learning patterns from naturally occurring input.

Finally, the same approach to language interpretation was incorporated into a model of theory of mind reasoning to model linguistic bootstrapping effects. Hale & Tager-Flusberg (2003) found that children trained with sentential complement syntax improved on theory of mind tasks. Chapter 7 presented a cognitive model of this experiment based on the AToM model of ToM reasoning (Rabkina et al., 2017).

The Analogical Theory of Mind Model (AToM) is inspired by Bach’s (2011) proposal that ToM reasoning occurs by analogy to prior experiences, and that ToM development involves acquiring and generalizing these experiences. AToM uses a version of SAGE that creates generalizations in working memory, and ToM judgements are modeled as analogies to the contents of working memory. In our simulation, analogical construction application was used to apply nested syntactic structure and semantics to un-nested arguments. The resulting nested semantics, which included a contradiction between the internal and external clauses, were stored in working memory and applied by analogy to answer ToM questions.

Taken together, these experiments provide evidence for an analogical approach to argument structure as a valid cognitive model. However, I also argued that the model has practical uses for natural language applications.

Claim 4: The model has practical applications for natural language tasks such as question answering.

To support this claim, I extended my model for general semantic parsing and applied it to a subset of the bAbI question answering tasks. The model uses the role alignment representation from Chapter 6 and interprets text in three phases. First, a constituent case is constructed from a dependency parse and verb case frame. Case frames were automatically constructed from the FrameNet corpus. The syntax of the constituency parse is used as input to MAC to retrieve possible constructions from the constructicon gpool. During the FAC stage, each retrieval is compared to the constituent case using SME and the top mapping is kept. The top scoring mapping across all case frames is used as the interpretation.

The system was trained on a combination of the child directed speech corpus from Chapter 6 and manually annotated examples from the bAbI training set. The learned constructions were used to interpret the sequence of events in each task. These interpretations were used to answer questions about the sequences using hand-made rules. The system performed well on the seven bAbI tasks evaluated, demonstrating that the model is applicable to natural language applications more broadly.

9.2 Open Questions and Future Work

There remain many clear directions for future work. Several of these involve enriching how the model handles constituents below the level of argument structure (e.g. phrases). During acquisition, the current model has only been applied to learning abstract argument structure.

Furthermore, as a model of interpretation it operates over phrasal constituents. Analogy is not used to interpret text from the ground up.

As an example of the problems this can cause, consider the difference between sentences such as “She raised a hand.” and “She raised a child.” Both senses of the verb *raise* can occur transitively. The current model would likely pick the same sense for both, the sense of the verb with the most common transitive roles. In this case however, the sense is made clear by the semantic type of the complement. Clearly a richer representation for arguments is needed.

These problems are obviously connected, and a model of ground-up acquisition would require answering questions about intermediate levels of representation. A good place to start might be Tomasello’s ontogeny of language (see Figure 3: Developmental Trajectory of Grammar).

Children begin with single word holophrases which represent an entire fixed concept (e.g. Up = pick me up). These early constructions could arise as generalizations of linguistic context and semantic scenes. However, analogy requires structure, and it is unclear what representations should be used.

Some insight may come from the kinds of words that children acquire first. Gentner (1982) found a noun bias in early childhood language acquisition. Gentner & Boroditsky (2001) elaborate on this finding and propose that these initial words are easier to learn because they primarily refer to entities in the world while relational words require context for interpretation (e.g. syntactic arguments). Tomasello (2009) notes that while this finding is generally true, many early linguistic constructions are social words such as *hello* and *thank you* and argues that early constructions are those which have clear communicative intent more broadly. It is Tomasello’s claim that social-pragmatic cues (e.g. joint attention, prosodic emphasis) provide necessary constraints for early word acquisition.

It seems likely that both accounts are true in that many nouns are easier to learn because of their relative contextual independence and that social-pragmatic context plays an important role in structuring a chaotic scene. Said structure would facilitate acquisition by analogical generalization, with words that are consistently pragmatically marked becoming holophrases over a generalized scene. As vocabulary develops, elements of these scenes are isolated as individual linguistic constructions.

Beginning at around 18 months, children begin to produce word combinations (e.g. “cup” “juice” to refer to juice in a cup). What distinguishes these new productions is that they partition the scene. Around the same time children begin producing pivot schemas, constructions with a nucleus word and variable slots (e.g. “More ___”) (Tomasello, 2009). Given the ability to partition a scene into distinct words, pivot schemas could arise from analogical generalization over scenes with fixed relation holophrases (e.g. I want more = more) but variable entities (e.g. juice, milk). The generalized elements form primitive linguistic categories (e.g. things I want more of).

What is less clear is how to move from pivot schemas to the syntactic marking required for item-based constructions. Returning to the role alignment representation as an example, how does the transformation in Figure 24 occur?

```
Scene:
  (push ?X ?Y)
Pivot Schema:
     (order <Things that push> push <Things that are pushed>)
Item-based:
    (order ?X push ?Y)
    (binds ?X Role1)
    (binds ?Y Role2)
    ((RoleHasPredFn pusher) Role1)
    ((RoleHasPredFn pushee) Role2)
```

Figure 24: Re-representation from pivot schema to item-based construction

There is already a convergent strain of research in analogical accounts of conceptual change. Yan, Forbus, & Gentner (2003) propose an analogical theory of re-representation that uses the principles of structure mapping to identify opportunities and generate re-representation suggestions. Kandaswamy (2016) used some of these techniques in their model of comparison driven representational change. In their model, re-representation was triggered when two mutually-exclusive cases were found to be too similar by SME. It's possible that linguistic contrast could have a similar effect. Given a scene that a child thinks is describable by one construction, hearing it described with an alternative could trigger re-representation as a means of distinguishing between the new construction and the expected one.

Indeed, the role of comparison across and competition between constructions should be investigated in future versions of the analogical model. Of particular interest is statistical preemption, when one construction occurs where another might have been expected. Boyd & Goldberg (2011) found that participants were sensitive to preemptive contexts when producing novel adjectives with a distinct phonological feature. They further demonstrated that participants were sensitive to this context even when it was rendered uninformative by other elements of the sentence. Goldberg (2011) further provided a corpus analysis that suggests statistical preemption is a reliable cue for learning syntactic restrictions on alternating and non-alternating ditransitive verbs (e.g. give vs explain). It seems possible that preemption not only helps avoid overgeneralizations but also acts as a catalyst for representational change.

Assuming re-representation can account for the emergence of syntactic representation; future work still needs to address semantic compositionality. The role-alignment representation allows for an interesting possibility. By reifying the constituent (e.g. `(HeadedPhraseFn pizza)`), the semantics of the phrase can be propagated as relations attached to it (e.g. `(headOf (HeadedPhraseFn pizza) pizza) (isa pizza (LargeFn Pizza)`). This gives a simple form of compositionality in that the result of each construction application is a reified construct with syntactic arguments and semantic roles about them. Interpretation could then be viewed as a series of analogies where the constituent case is built from constructions already applied and the semantic context. Questions remain however as to when and why phrasal constructions emerge. Do they develop as generalizations over argument structure constituents, or are they learned independently?

Finally, thus far the model has focused on argument-structure semantics that arise from generalization over verb-specific roles. However, clearly some semantics attached to argument structure comes from non-verbal constituents or even general pragmatic usage. As one example, Birner & Ward (1998) demonstrate that preposing constructions (e.g. On the counter sat the cat.) are only licensed when the preposed constituent (the counter) is already in the discourse or inferable from context. The relationship between how a sentence is structured relative to pragmatic constraints is called *information structure*, and future work should incorporate such non-lexical aspects of meaning.

References

Allen, James F. (1983). Maintaining knowledge about temporal intervals. *Communications of the ACM*. ACM Press: 832–843

Alishahi, A., & Stevenson, S. (2008). A computational model of early argument structure acquisition. *Cognitive Science*, *32*, 789–834.

Bach, T. (2011). Structure-mapping: Directions from simulation to theory. *Philosophical Psychology*, *24*(1), 23–51.

Baker, C. F., Fillmore, C. J., & Cronin, B. (2003). The structure of the FrameNet database. *International Journal of Lexicography*, *16*(3), 281–296.

Barak, L., Fazly, A., & Stevenson, S. (2012). Modeling the Emergence of an Exemplar Verb in Construction Learning, (2008), 1815–1820.

Barak, L., Fazly, A., & Stevenson, S. (2013). Acquisition of Desires before Beliefs: A Computational Investigation. *In Proceedings of the Seventeenth Conference on Computational Natural Language Learning, Sofia, Bulgaria, August 8-9 2013*, 231–240.

Bergen, B., Chang, N., & Narayan, S. (2004). Simulated action in an embodied construction grammar. *Proceedings of the Twenty-Sixth Annual Conference of the Cognitive Science Society*, 108–113.

Birner, B. J., & Ward, G. (1998). *Information Status and Noncanonical Word Order in English* (Vol. 40). John Benjamins Publishing.

Boas, H. C., & Sag, I. A. (2012). *Sign-based construction grammar*. CSLI Publications/Center for the Study of Language and Information.

Boyd, J. K., & Goldberg, A. E. (2011). Learning what not to say: The role of statistical preemption and categorization in a-adjective production. *Language*, 55-83.

Cameron-Faulkner, T. (2003). A construction based analysis of child directed speech. *Cognitive Science*, *27*(6), 843–873.

Casenhiser, D., & Goldberg, A. E. (2005). Fast mapping between a phrasal form and meaning. *Developmental Science*, *8*(6), 500–508.

Childers, J. B., & Tomasello, M. (2001). The role of pronouns in young children's acquisition of the English transitive construction. *Developmental Psychology*, *37*(6), 739–748.

Choi, J. D., & Palmer, M. (2012). Guidelines for the CLEAR Style Constituent to Dependency

Conversions. *Center for Computational Language and EducAtion Research University of Colorado Boulder Institute of Cognitive Science Technical Report 01-12*, 53.

Chomsky, (1957) *Syntactic Structures*. Walter de Gruyter

Chomsky, N. (1965). *Aspects of the Theory of Syntax*. MIT Press.

Chomsky, N. (1981). *Lectures on Government and Binding*. Foris Publications.

Chomsky, N. (1993). *A Minimalist Program for Linguistic Theory*. MIT occasional papers in linguistics no. 1.

Christie, S., & Gentner, D. (2010). Where Hypotheses Come From: Learning New Relations by Structural Alignment. *Journal of Cognition and Development*, *11*(3), 356–373.

Connor, M., Gertner, Y., Fisher, C., & Roth, D. (2008). Baby srl: Modeling early language acquisition. *Proceedings of the Twelfth Conference on Computational Natural Language Learning*, (August), 81–88.

Croft, W. (2001). *Radical construction grammar: Syntactic theory in typological perspective*. Oxford University Press on Demand.

Crouse, M., McFate, C.J., and Forbus, K.D. (2018). Learning from Unannotated QA Pairs to Analogically Disambiguate and Answer Questions. *Proceedings of AAAI 2018*.

Culicover, P. W., & Jackendoff, R. (1999). The View from the Periphery: The English Comparative Correlative. *Linguistic Inquiry*, *30*(4), 543–571.

de Marneffe, M.-C., Dozat, T., Silveira, N., Haverinen, K., Ginter, F., Nivre, J., & Manning, C. D. (2014). Universal Stanford Dependencies: A cross-linguistic typology. *In Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*

de Villiers, J. G., & Pyers, J. E. (2002). Complements to cognition: a longitudinal study of the relationship between complex syntax and false-belief-understanding. *Cognitive Development*, *17*(1), 1037–1060.

Falkenhainer, B., Forbus, K., & Gentner, D. (1989). The structure-mapping engine: Algorithm and examples. *Artificial Intelligence*, *41*(1), 1–63.

Fillmore, C. J. (1967). The Case for Case. *Texas Symposium on Language Universals*, 109.

Fillmore, C. J. (1977). The case for case reopened. *Syntax and semantics*, 8(1977), 59-82.

Fillmore, C. J. (1986). Pragmatically controlled zero anaphora. In *Annual Meeting of the*

Berkeley Linguistics Society (Vol. 12, pp. 95–107).

Fillmore, C. J., Kay, P., & Connor, M. C. O. (1988). Regularity and Idiomaticity in Grammatical Constructions: The Case of Let Alone Charles J. Fillmore; Paul Kay; Mary Catherine O'Connor.

Fillmore, C. J., Wooters, C., & Baker, C. F. (2001). Building a large lexical databank which provides deep semantics. In *Proceedings of the 15th Pacific Asia Conference on Language, Information and Computation* (pp. 3–26).

Forbus, K. D., Ferguson, R. W., Lovett, A., & Gentner, D. (2017). Extending SME to Handle Large-Scale Cognitive Modeling. *Cognitive Science*, *41*(5), 1152–1201.

Forbus, K. D., Gentner, D., & Law, K. (1995). MAC/FAC: A model of similarity-based retrieval. *Cognitive Science*, *19*(2), 141–205.

Friedman, S. E. (2015). Exploiting graph structure to summarize and compress relational knowledge. In *Proceedings of the 28th International Workshop on Qualitative Reasoning*. SIFT Minneapolis, MN.

Gentner, D. (1981). Integrating verb meanings into context. *Discourse processes,* 4(4), 349-375.

Gentner, D. (1982). Why nouns are learned before verbs: Linguistic relativity versus natural partitioning. *Center for the Study of Reading Technical Report; no. 257.*

Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive Science*, *7*(2), 155–170.

Gentner, D., & Boroditsky, L. (2001). Individuation, relativity, and early word learning. *Language acquisition and conceptual development*, 3, 215-256.

Gentner, D., & Hoyos, C. (2017). Analogy and abstraction. *Topics in cognitive science*, 9(3), 672-693.

Gentner, D., & Namy, L. L. (2006). Analogical processes in language learning. *Current Directions in Psychological Science*, *15*(6), 335 – 361.

Gentner, D., Rattermann, M. J., & Forbus, K. D. (1993). The roles of similarity in transfer: Separating retrievability from inferential soundness. *Cognitive Psychology*, *25*(4), 524–575.

Goldberg, A. E. (1995). *Constructions: A construction grammar approach to argument structure*. University of Chicago Press.

Goldberg, A. E. (2003). Constructions: a new theoretical approach to language. *Trends in*

Cognitive Sciences, *7*(5), 219–224.

Goldberg, A. E. (2006). *Constructions at work: The nature of generalization in language*. Oxford University Press on Demand.

Goldberg, A. E. (2011). Corpus evidence of the viability of statistical preemption. *Cognitive Linguistics*, 22(1), 131-153.

Goldberg, A., Casenhiser, D., & Sethuraman, N. (2004). Learning argument structure generalizations. *Cognitive Linguistics*.

Goldwater, M.B., & Echols, C. H. (2014) Structural priming as analogical mapping. Presented at the 13th ICSCL, Amsterdam

Goldwater, M. B., Tomlinson, M. T., Echols, C. H., & Love, B. C. (2011). Structural priming as structure-mapping: Children use analogies from previous utterances to guide sentence production. *Cognitive Science*, *35*(1), 156–170.

Hale, C. M., & Tager-Flusberg, H. (2003). The influence of language on theory of mind: A training study. *Developmental Science*, *6*(3), 346–359.

Haryu, E., Imai, M., & Okada, H. (2011). Object Similarity Bootstraps Young Children to Action-Based Verb Extension. *Child Development*, *82*(2), 674–686.

Hoyos, C., Horton, W. S., & Gentner, D. (2015). Analogical comparison aids false belief understanding in preschoolers. In *Proceedings of the 37th Annual Meeting of the Cognitive Science Society*. Cognitive Science Society.

Kandaswamy, S., Forbus, K. D., & Gentner, D. (2014). Modeling Learning via Progressive Alignment using Interim Generalizations. *Proceedings of the 36th Annual Conference of the Cognitive Science Society (CogSci 2014)*, 2471–2476.

Kandaswamy, S. (2016). Comparison driven representational change. Doctoral dissertation, Northwestern University, Department of Electrical Engineering and Computer Science, Evanston, Illinois.

Kaschak, M. P., & Glenberg, A. M. (2000). Constructing Meaning: The Role of Affordances and Grammatical Constructions in Sentence Comprehension. *Journal of Memory and Language*, *43*(3), 508–529.

Kay, P., & Fillmore, C. J. (1999). Grammatical constructions and linguistic generalizations: the What's X doing Y? construction. *Language*, 1–33.

Kipper, K., Korhonen, A., Ryant, N., & Palmer, M. (2006). Extending VerbNet with novel verb classes. In *Proceedings of LREC* (Vol. 2006, p. 1). Citeseer.

Kotovsky, L., & Gentner, D. (1996). Comparison and categorization in the development of relational similarity. *Child Development*, *67*(6), 2797–2822.

Langacker, R. W. (1987). *Foundations of cognitive grammar: Theoretical prerequisites* (Vol. 1). Stanford university press.

Langacker, R. W. (1991). Cognitive grammar. *Linguistic Theory and Grammatical Description*, 275–306.

Liang, C., & Forbus, K. (2014). Constructing hierarchical concepts via analogical generalization. In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 36).

Lidz, J., Gleitman, L., & Gleitmanm, H. (2003). Understanding how input matters: verb learning and the footprint of universal grammar. *Brain & Development*, *25*(4).

Lidz, J., & Gleitman, L. R. (2004). Yes, we still need Universal Grammar. *Cognition*, *94*(1), 85–93.

Lindes, P., & Laird, J. E. (2016). Toward Integrating Cognitive Linguistics and Cognitive Language Processing.\

Lindes, P., & Laird, J. (2017). Cognitive Modeling Approaches to Language Comprehension Using Construction Grammar. In *2017 AAAI Spring Symposium Series, Computational Construction Grammar and Natural Language Understanding.*

Lohmann, H., & Tomasello, M. (2003). The role of language in the development of false belief understanding: a training study. *Child Development*, *74*(4), 1130–44.

MacWhinney, B. (1996). The CHILDES system. *American Journal of Speech-Language Pathology*, *5*(1), 5–14.

Maratsos, M., Gudeman, R., Gerard-Ngo, P., and DeHart, G. 1987. A study in novel word learning: The productivity of the causative. In B. MacWhinney, ed., Mechanisms of language acquisition. Hillsdale, NJ: Erlbaum.

Matuszek, C., Cabral, J., Witbrock, M. J., & DeOliveira, J. (2006, March). An Introduction to the Syntax and Content of Cyc. *In AAAI Spring Symposium: Formalizing and Compiling Background Knowledge and Its Applications to Knowledge Representation and Question Answering* (pp. 44-49).

McFate, C. J., & Forbus, K. D. (2011). NULEX : An Open-License Broad Coverage Lexicon, 363–367.

McFate, C. J., & Forbus, K. D. (2016). Analogical Generalization and Retrieval for Denominal Verb Interpretation. Proceedings of Cogsci-2016.

McFate,C.J. Klein, J & Forbus, K. (2017). A Computational Investigation of Analogical Generalization of Linguistic Constructions. *Presented at Analogy-2017*

McLure, M. D., Friedman, S. E., & Forbus, K. D. (2015). Extending Analogical Generalization with Near-Misses. In *AAAI* (pp. 565–571).

Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient estimation of word representations in vector space. arXiv preprint arXiv:1301.3781.

Milligan, K., Astington, J. W., & Dack, L. A. (2007). Language and theory of mind: meta-analysis of the relation between language ability and false-belief understanding. *Child Development*, *78*(2), 622–46.

Müller, S. (2017). Head-Driven Phrase Structure Grammar, Sign-Based Construction Grammar, and Fluid Construction Grammar. *Constructions and Frames*, *9*(1), 139–173.

Namy, L. L., & Gentner, D. (2002). Making a silk purse out of two sow's ears: young children's use of comparison in category learning. *Journal of Experimental Psychology. General*, *131*(1), 5–15.

Ninio, A. (1999). Pathbreaking verbs in syntactic development and the question of prototypical transitivity. *Journal of Child Language*, *26*(3), 619–653.

Pollard, C., & Sag, I. A. (1994). *Head-driven phrase structure grammar*. University of Chicago Press.

Rabkina, I., McFate, C., Forbus, K. D., & Hoyos, C. (2017). Towards a Computational Analogical Theory of Mind. *In Proceedings of the 39th Annual Conference of the Cognitive Science Society* (pp. 2949-2954).

Ramachandran, D., Reagan, P., & Goolsbey, K. (2005). First-orderized ResearchCyc: Expressivity and efficiency in a common-sense ontology. *In AAAI Workshop on Contexts and Ontologies: Theory, Practice and Applications*.

Rowland, C. F., & Pine, J. M. (2013). Subject – auxiliary inversion errors and wh - question acquisition : ' what children do know ?,' (September 2000).

Ruppenhofer, J., Ellsworth, M., & Petruck, M. (2006). FrameNet II: Extended theory and practice. Retrieved from http://framenet2.icsi.berkeley.edu/docs/r1.5/book.pdf

Solan, Z., Horn, D., Ruppin, E., & Edelman, S. (2004). Unsupervised Context Sensitive Language Acquisition from a Large Corpus. *Advances in Neural Information Processing Systems 16*, 961–968.

Spectrum. (2007) Spectrum Reading Grade 6. School Specialty Publishing. Columbus, OH.

Spranger, M. (2016). *The Evolution of Grounded Spatial Language*. http://doi.org/10.17169/langsci.b53.183

Spranger, M. (2017). Usage-Based Grounded Construction Learning — A Computational Model, 245–250.

Steels, L. (2011). *Design patterns in fluid construction grammar* (Vol. 11). John Benjamins Publishing.

Theakston, a L., Lieven, E. V, Pine, J. M., & Rowland, C. F. (2001). The role of performance limitations in the acquisition of verb-argument structure: an alternative account. *Journal of Child Language*, *28*(1), 127–152.

Tomai, E., & Adviser-Forbus, K. (2009). *A pragmatic approach to computational narrative understanding*. Northwestern University.

Tomasello, M. (2009). *Constructing a language: A usage-based theory of language acquisition*. Harvard University Press.

Tomasello, M., & Brooks, P. J. (1999). Early syntactic development: A construction grammar approach. *The Development of Language*, 161–190.

Weischedel, Ralph, et al. OntoNotes Release 5.0 LDC2013T19. Web Download. Philadelphia: Linguistic Data Consortium, 2013.

Weston, J., Bordes, A., Chopra, S., Rush, A. M., van Merriënboer, B., Joulin, A., & Mikolov, T. (2015). Towards AI-Complete Question Answering: A Set of Prerequisite Toy Tasks.

Weston, J., Chopra, S., & Bordes, A. (2014). Memory Networks, 1–15.

Yan, J., Forbus, K. D., & Gentner, D. (2003). A theory of re-representation in analogical matching. *R. Alterman & D. Kirsh (Eds.), Proceedings of the 25th Annual Meeting of the Cognitive Science Society*, 1265–1270.

Appendix A: Training Corpus for McFate & Forbus (2016)

Below is the annotated training corpus for McFate & Forbus' (2016) simulation of Kaschak & Glenberg's (2000) denominal verb interpretation study. The sentences were taken from an elementary school reading comprehension textbook (Spectrum, 2007) and were manually annotated.

```
;;;;;;;;;;;;;;;;;Giving and Purchasing
(p6 "Maybe Mrs. Ito can give us some suggestions."
       (NP "Mrs. Ito" FN-Donor) (verb "give" target) (NP "us" FN-Recipient)
       (NP "some suggestions ." FN-Theme) (frameType "give" Giving))

(P74 "The snack gave them an energy boost, and just as they were about to get up,
three quails wandered into sight"
       (NP "The snack" FN-Donor) (verb "gave" target) (NP "them" FN-Recipient)
       (NP "an energy boost" FN-Theme) (frameType "gave" Giving))



(p48 "Olivia's mom gave me a backyard birdfeeder for my birthday."
       (Poss "Olivia's mom" FE-Donor) (verb "gave" target) (NP "Me" FE-Recipient)
       (NP "a backyard birdfeeder" FE-Theme)
       (PP[for] "for my birthday ." FN-Explanation)
       (frameType "gave" Giving))

(p36 "His parents had given him a camera as a gift."
       (Poss "His parents" FN-Donor) (verb "given" target) (NP "him" FN-Recipient)
       (NP "a camera" FN-Theme) (PP[as] "as a gift ."  FN-Explanation)
       (frameType "given" Giving))

(p30 "You might want to give them a bit of advanced warning if they're going to be
part of it."
       (NP "you" FN-Donor) (verb "give" target) (NP "them" FN-Recipient)
       (NP "A bit of advanced warning" FN-Theme)
       (PP[if] "if they're going to be part of it ." FN-Circumstances)
       (frameType "give" Giving))

(P96 "They are easier to paddle, and they catch waves more easily, which is good when
you are a beginner because it gives you more time to stand up."
       (NP "it" FN-Donor) (verb "gives" target) (NP "you" FN-Recipient)
       (NP "more time" FN-Theme) (VPto "to stand up ." FN-Imposed_Purpose)
       (frameType "gives" Giving))


(p6 " Mrs. Ito gave their order to the waitress."
       (NP "Mrs. Ito" FN-Donor) (verb "gave" target) (NP "their order" FN-Theme)
       (PP[to] "to the waitress ." FN-Recipient) (frameType "gave" Giving))

(p70 "Charley rinsed the dishes in a tub of clean water and then handed them to his
mom to be dried."
```

```
       (NP "Charley" FN-Donor) (verb "handed" target) (NP "them" FN-Theme)
       (PP[to] "to his mom" FN-Recipient) (VPto "to be dried ." FN-Imposed_Purpose)
       (frameType "handed" Giving))

(p8 "It may be passed down from one generation of a family to the next as a prized
possession."
       (NP "it" FN-Theme) (verb "passed_down" target)
       (PP[from] "from one generation of a family" FN-Donor)
       (PP[to] "to the next" FN-Recipient)
       (PP[as] "as a prized possession ."  FN-Explanation)
       (frameType "passed_down" Giving))



(p2 "In between innings, Mrs. Ito bought Alex and Emily a snack."
       (PP[in] "In between innings," FN-Time) (NP "Mrs. Ito" FN-Buyer) (verb "bought"
target)
       (NP "Alex and Emily" FN-Recipient) (NP "a snack ." FN-Goods)
       (frameType "bought" Commerce_buy))

;;;;;; Transitive_Actions = cause_motion, cause_to_be-Wet, creation

(p70 "Charley rinsed the dishes in a tub of clean water and then handed them to his
mom to be dried"
       (NP "Charley" FN-Agent) (verb "rinsed" target) (NP "the dishes" FN-Patient)
       (PP[in] "in a tub of clean water" FN-Liquid)
       (frameType "rinsed" Cause_to_be_wet))

(P30 "Dante's mom looked up in surprise and spilled some of the orange juice she was
pouring."
       (Poss "Dante's Mom" FN-Agent) (verb "spilled" target)
       (Sub "some of the orange juice she was pouring ." FN-Fluid)
       (frameType "spilled" Cause_fluidic_motion))

(p26 "The lighthouse was moved using the power of seven hydraulic jacks."
       (NP "The lighthouse" FN-Theme) (verb "moved" target)
       (VPIng "using the power of seven hydraulic jacks ." FN-Instrument)
       (frameType "moved" Cause_motion))

(P72 "In rain forests, bats drop plant seeds as they move, which allows new plants to
grow."
       (PP[in] "In rain forests ," FN-Area) (NP "bats" FN-Agent) (verb "drop" target)
       (NP "plant seeds" FN-Theme) (Sub "as they move ," FN-Path)
       (Sub "which allows new plants to grow ." FN-Result)
       (frameType "drop" Cause_motion))

(76 "Scientists believe that the water produced by the hot springs today is about
4,000 years old!"
       (NP "the water" FN-Created_entity) (verb "produced" target)
       (PP[by] "by the hot springs" FN-Creator) (Advb "today" FN-Time)
       (frameType "produced" Creation))

(92 "Well, it might sound funny, but I'm making a paste using meat tenderizer and
water."
       (NP "I" FN-Creator) (verb "making" target) (NP "a paste" FN-Created_entity)
       (VPIng "using meat tenderizer and water ." FN-Components)
       (frameType "making" Creation))

(94 "These contractions can push the jellyfish vertically through the water at a slow
pace."
```

```
       (NP "These contractions" FN-Agent) (verb "push" target)
       (NP "The Jellyfish" FN-Theme)
       (AdvP "vertically through the water" FN-Path)
       (PP[at] "at a slow pace ." FN-Manner)
       (frameType "push" Cause_motion))

;;;;;;;;;;;;;;;;;;;;;;;;;;;; Generic Motion
(p4 "To  make baseball even more popular , American teams regularly toured Japan in
the early 1900s and played exhibition games against the local amateurs"
       (PP[to] "To  make baseball even more popular ," FN-Purpose)
       (NP "American teams" FN-Traveller) (AdvP "regularly" FN-Frequency)
       (verb "toured" target) (NP "Japan" FN-Goal)
       (PP[in] "in the early 1900s" FN-Time)
       (frameType "toured" Travel))

(p52 "With long legs and a long neck extending out from their bodies, cranes create a
graceful sight as they glide across the sky."
       (PP[with] "With long legs and a long neck extending out from their bodies ,"
FN-Depictive)
       (NP "cranes" FN-Theme) (verb "glide" target)
       (AdvP "across the sky ." FN-Area)
       (frameType "glide" Motion))

(p66 "Sometimes plates move past one another without creating much of a disturbance."
       (NP "plates" FN-Theme) (verb "move" target)
       (PP[past] "past one another" FN-Path)
       (Sub "without creating much of a disturbance ." FN-Manner)
       (frameType "move" Motion))

(p4 "To  make baseball even more popular , American teams regularly toured Japan in
the early 1900s and played exhibition games against the local amateurs."
       (NP "American teams" FN-Participant_1) (AdvP "regularly" FN-Frequency)
       (verb "played" target) (NP "exhibition games" FN-Competition)
       (NP "the local amateurs ." FN-Participant_2) (frameType "played" Competition))
```

Appendix B: Annotated Corpus of Child Directed Speech

Below is the annotated training corpus derived from child directed speech. It was used in Chapters 6 and 8 as a training corpus.

```
;;;CHILDES
(adam01 175 "Do you want to play with them?"
       (target-verb play)
       (frame Intentionally_affect)     ;;found by searching "do"
       (pos-tag (mod"|"do pro-per"|"you v"|"want inf"|"to v"|"play prep"|"with pro-
obj"|"them ?))
       (syntax (PRO<ext> V PP[with]<dep>))
       (chunks ((PRO<ext> "you" FN-Agent) (verb "play" target) (PP[with]<dep> "with
them" FN-Patient)))
       (stype interrogative))

(adam01 235 "Why don't you look at some of the toys in the basket?"
       (target-verb look)
       (frame Perception_active)
       (pos-tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you cop"|"look prep"|"at
qn"|"some prep"|"of det-art"|"the n"|"toy-PL prep"|"in det-art"|"the n"|"basket.))
       (syntax (PRO<ext> V PP[at]<dep> PP[in]<dep>))
       (chunks ((PRO<ext> "you" FN-Perceiver_agentive) (verb "look" target)
(PP[at]<dep> "at some of the toys" FN-Phenomenon) (PP[in]<dep> "in the basket" FN-
Direction))) ;;;Does             this "in" count as a Direction?
       (stype imperative))

(adam01 288 "Let me put them together."
       (target-verb put)
       (frame Building)
       (pos-tag (v"|"let&ZERO pro-obj"|"me v"|"put&ZERO pro-obj"|"them
adv"|"together.))
       (syntax (PRO<ext> V PRO<obj> AVP<dep>)) ;;treating separated particles as a
modifier
       (chunks ((PRO<ext> "me" FN-Agent) (verb "put" target) (PRO<obj> "them" FN-
Components) (AVP<dep> "together" FN-Result))) ;;see FN Glue entry for chunk
       (stype declarative))

(adam01 460 "Where are you going?"
       (target-verb go)
       (frame Self_motion)
       (pos-tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP ?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))


(adam01 569 "If you look out the other window maybe you'll see it."
       (target-verb look)
       (frame Perception_active)
       (pos-tag (conj"|"if pro-per"|"you cop"|"look prep"|"out det-art"|"the
qn"|"other n"|"window adv"|"maybe pro-per"|"you~mod"|"will v"|"see pro-per"|"it.))
       (syntax (PRO<ext> V PP[out]<dep>))
       (chunks ((PRO<ext> "you" FN-Perceiver_agentive) (verb "look" target)
(PP[out]<dep> "out the window" FN-Direction)))
```

```
       (stype declarative))

(adam01 569 "If you look out the other window maybe you'll see it."
       (target-verb see)
       (frame Perception_experience)
       (pos-tag (conj"|"if pro-per"|"you cop"|"look prep"|"out det-art"|"the
qn"|"other n"|"window adv"|"maybe pro-per"|"you~mod"|"will v"|"see pro-per"|"it.))
       (syntax (AVP<dep> PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you'll" FN-Perceiver_passive) (verb "see" target) (NP<obj>
"it" FN-Phenomenon)))      ;;;Does "maybe" have an FE? Time? Manner?
       (stype declarative))

(adam01 580 "Did you see the truck?"
       (target-verb see)
       (frame Perception_experience)
       (pos-tag (v"|"do&PAST pro-per"|"you v"|"see det-art"|"the n"|"truck?))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you" FN-Perceiver_passive) (verb "see" target) (NP<obj>
"the truck" FN-Phenomenon)))
       (stype interrogative-do))

(adam01 586 "You didn't see."
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (pro-per"|"you mod"|"do&PAST~neg"|"not v"|"see pro-per"|"it.))
       (syntax (PRO<ext> V))
       (chunks ((PRO<ext> "You" FN-Perceiver_passive) (verb "see" target)))
       (stype declarative))

(adam01 589 "There goes one."
       (target-verb go)
       (frame Motion)
       (pos_tag (adv"|"there v"|"go-3S pro-indef"|"one.))
       (syntax (AVP<dep> V NP<ext>))
       (chunks ((AVP<dep> "There" FN-Goal) (verb "goes" target) (NP<ext> "one" FN-
Theme)))
       (stype declarative))

(adam01 613 "Put the truck where?"
       (target-verb put)
       (frame Placing)
       (pos_tag (v"|"put&ZERO det-art"|"the n"|"truck pro-rel"|"where ?))
       (syntax (V NP<obj> AVP<dep>))
       (chunks ((verb "put" target) (NP<obj> "the truck" FN-Theme) (AVP<dep> "where"
FN-Goal) (CNI " " FN-Agent)))
       (stype interrogative))

(adam01 619 "I think that one's too large to go in the window."
       (target-verb go)
       (frame Compatibility)
       (pos_tag (pro-sub"|"I v"|"think pro-dem"|"that pro-indef"|"one~cop"|"be&3S
adv"|"too n"|"large inf"|"to v"|"go prep"|"in det-art"|"the n"|"window.))
       (syntax (PRO<obj> AVP<dep> V PP[in]<dep>))
       (chunks ((PRO<obj> "that one" FN-Item_1) (AVP<dep> "too large" FN-Degree) (verb
"go" target) (PP[in]<dep> "in the window" FN-Item_2)))
       (stype declarative))

(adam01 627 "Tow truck come here?"
       (target-verb come)
       (frame Arriving)
```

```
        (pos_tag (n"|"tow n"|"truck v"|"come adv"|"here?))
        (syntax (NP<ext> V AVP<dep>))
        (chunks ((NP<ext> "Tow truck" FN-Theme) (verb "come" target) (AVP<dep> "here"
FN-Goal)))
        (stype interrogative))

(adam01 642 "There goes another one."
        (target-verb go)
        (frame Motion)
        (pos_tag (adv"|"there v"|"go-3S qn"|"another pro-indef"|"one.))
        (syntax (AVP<dep> V NP<ext>))     ;;; Is "another" a NP or PP? It's a
determiner.
        (chunks ((AVP<dep> "There" FN-Goal) (verb "goes" target) (NP<ext> "one" FN-
Theme)))
        (stype declarative))

(adam01 687 "I guess she might like to see that."
        (target-verb see)
        (frame Perception_active)
        (pos_tag (pro-sub"|"I v"|"guess pro-sub"|"she mod"|"might v"|"like inf"|"to
v"|"see pro-dem"|"that.))
        (syntax (PRO<ext> V PRO<obj>))
        (chunks ((PRO<ext> "she" FN-Perceiver_agentive) (verb "see" target) (PRO<ext>
"that" FN-Phenomenon)))
        (stype declarative))

(adam01 722 "Where have you seen a hat like that?"
        (target-verb see)
        (frame Perception_experience)
        (pos_tag (adv-int"|"where v"|"have pro-per"|"you part"|"see&PASTP det-art"|"a
n"|"hat prep"|"like pro-dem"|"that?))
        (syntax (AVP<dep> PRO<ext> V NP<obj> AVP<dep>))
        (chunks ((AVP<dep> "Where" FN-Place) (PRO<ext> "you" FN-Perceiver_passive)
(verb "seen" target) (NP<obj> "hat" FN-Phenomenon)))
        (stype interrogative))

(adam01 786 "I saw a tank truck."
        (target-verb see)
        (frame Perception_experience)
        (pos_tag (pro-sub"|"I v"|"see&PAST det-art"|"a n"|"tank n"|"truck.))
        (syntax (PRO<ext> V NP<obj>))
        (chunks ((PRO<ext> "I" FN-Perceiver_passive) (verb "saw" target) (NP<obj> "tank
truck" FN-Phenomenon)))
        (stype declarative))

(adam01 831 "Adam fall toy."
        (target-verb fall)
        (frame Motion_directional)
        (pos_tag (n-prop"|"Adam n"|"fall n"|"toy.))
        (syntax (NP<ext> V NP<obj>))
        (chunks ((NP<ext> "Adam" FN-Theme) (verb "fall" target)))
        (stype declarative))

(adam01 834 "You didn't fall that time."
        (target-verb fall)
        (frame Motion_directional)
        (pos_tag (pro-per"|"you mod"|"do&PAST~neg"|"not v"|"fall pro-dem"|"that
n"|"time.))
        (syntax (PRO<ext> V NP))   ;;; Is "that" a NP or PP? It's a determiner.
```

```
       (chunks ((PRO<ext> "You" FN-Theme) (verb "fall" target)))   ;;; Does "that
time" have an FE?
       (stype declarative))

(adam01 837 "You just sat down."
       (target-verb sit)
       (frame Change_posture)
       (pos_tag (pro-per"|"you adv"|"just v"|"sit&PAST adv"|"down.))
       (syntax (PRO<ext> AVP<dep> V ADV<dep>))
       (chunks ((PRO<ext> "You" FN-Protagonist) (AVP<dep> "just" FN-Manner) (verb
"sat" target) (AVP<dep> "down" FN-Goal)))
       (stype declarative))

(adam01 1001 "Why don't you take that over and show it to him."
       (target-verb take)
       (frame Bringing)
       (pos_tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you v"|"take pro-
dem"|"that adv"|"over coord"|"and v"|"show pro-per"|"it prep"|"to pro-obj"|"him.))
       (syntax (PRO<ext> V PRO<obj> PP[over]<dep>))
       (chunks ((PRO<ext> "You" FN-Agent) (verb "take" target) (PRO<obj> "that" FN-
Theme) (PP[over]<dep> "over" FN-Goal)))
       (stype imperative))

(adam01 1195 "Put pillow on the floor?"
       (target-verb put)
       (frame Placing)
       (pos_tag (v"|"put&ZERO n"|"pillow prep"|"on det-art"|"the n"|"floor?))
       (syntax (V NP<obj> PP[on]<dep>))
       (chunks ((verb "put" target) (NP<obj> "pillow" FN-Theme) (PP[on]<dep> "on the
floor" FN-Goal) (CNI " " FE-Agent)))
       (stype interrogative))

(adam01 1198 "You want Mommy to sit on the floor?"
       (target-verb sit)
       (frame Change_posture)     ;;; ;; ;;;; This "Change_posture" is for "sit"
       (pos_tag (pro-per"|"you v"|"want n-prop"|"Mommy inf"|"to v"|"sit prep"|"on det-
art"|"the 1200 n"|"floor ?))
       (syntax (PRO<ext> V NP<obj> V PP[on]<dep>))
       (chunks ((NP<obj> "Mommy" FN-Protagonist) (verb "sit" target) (PP[on]<dep> "on
the floor" FN-Goal)))
       (stype interrogative))

(adam01 1281 "Make mosquito?"
       (target-verb make)
       (frame Causation)
       (pos_tag (v"|"make n"|"mosquito?))
       (syntax (V NP<obj>))
       (chunks ((verb "make" target) (NP<obj> "mosquito" FN-Affected) (CNI " " FN-
Effect)))
       (stype interrogative))


(adam01 1294 "Don't take those out."
       (target-verb take)
       (frame Removing)
       (pos_tag (mod"|"do~neg"|"not v"|"take pro-dem"|"those adv"|"out.))
       (syntax (V NP<obj> PP[out]<dep>))
       (chunks ((verb "take" target) (NP<obj> "those" FN-Theme) (PP[out]<dep> "out"
FN-Source)))
       (stype imperative))
```

```
(adam01 1468 "You gave it to him."
       (target-verb give)
       (frame Giving)
       (pos_tag (pro-per"|"you v"|"give&PAST pro-per"|"it prep"|"to pro-obj"|"him.))
       (syntax (PRO<ext> V NP<obj> PP[to]<dep>))
       (chunks ((PRO<ext> "You" FN-Donor) (verb "gave" target) (NP<obj> "it" FN-Theme)
(PP[to]<dep> "to him" FN-Recipient)))
       (stype declarative))

(adam01 1492 "Go get what?"
       (target-verb get)
       (frame Getting)
       (pos_tag (v"|"go v"|"get pro-int"|"what?))
       (syntax (V PRO<obj>))
       (chunks ((verb "get" target) (PRO<obj> "what" FN-Theme)))
       (stype interrogative))

(adam01 1531 "Are you looking at the book?"
       (target-verb look)
       (frame Perception_active)
       (pos_tag (cop"|"be&PRES pro-per"|"you part"|"look-PRESP prep"|"at det-art"|"the
n"|"book?))
       (syntax (PRO<ext> V PP[at]<dep>))
       (chunks ((PRO<ext "you" FN-Perceiver_agentive) (verb "looking" target)
(PP[at]<dep> "at the book" FN-Phenomenon)))
       (stype interrogative))

(adam01 1710 "Look Adam."
       (target-verb look)
       (frame Perception_active)
       (pos_tag (co"|"look n-prop"|"Adam.))
       (syntax (V NP<ext>))
       (chunks ((verb "look" target) (NP<ext> "Adam" FN-Perceiver_agentive)))
       (stype imperative))


(adam01 1777 "Does your writing look like his?"
       (target-verb look)
       (frame Similarity)  ;; Found by searching "Resemble"
       (pos_tag (mod"|"do&3S det-poss"|"your n-gerund"|"write-PRESP cop"|"look
conj"|"like det-poss"|"his?))
       (syntax (NP<ext> V PP[like]<dep> PRO<obj>))
       (chunks ((NP<ext> "your writing" FN-Entity_1) (verb "look" target) (NP<obj>
"his" FN-Entity_2)))       ;;; Here, "look like" stands in for "resembles." Thus
"like" is a                particle of the verb and not a PP.
       (stype interrogative))

(adam01 1955 "Must go where?"
       (target-verb go)
       (frame Motion)
       (pos_tag (mod"|"must v"|"go adv-int"|"where?))
       (syntax (V AVP<dep>))
       (chunks ((verb "go" target) (AVP<dep> "where" FN-Goal) (CNI " " FN-Agent)))
       (stype interrogative))

(adam01 2093 "You don't have anything else to put in the box. Do you?"
       (target-verb put)
       (frame Placing)
```

```
       (pos_tag (pro-per"|"you mod"|"do~neg"|"not v"|"have pro-indef"|"anything
post"|"else inf"|"to v"|"put&ZERO prep"|"in det-art"|"the n"|"box v"|"do pro-
per"|"you?))
       (syntax (PRO<ext> NP<obj> AVP<dep> V PP[in]<dep>))
       (chunks ((PRO<ext> "You" FN-Agent) (NP<obj> "anything" FN-Theme) (verb "put"
target) (PP[in]<dep> "in the box" FN-Goal)))
       (stype declarative))

(adam01 2171 "You go get it."
       (target-verb get)
       (frame Getting)
       (pos_tag (pro-per"|"you v"|"go v"|"get pro-per"|"it.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "You" FN-Recipient) (verb "get" target) (NP<obj> "it" FN-
Theme)))
       (stype imperative))

(adam01 2195 "I'll go get it?"
       (target-verb get)
       (frame Getting)
       (pos_tag (pro-sub"|"I~mod"|"will v"|"go v"|"get pro-per"|"it.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "I" FN-Recipient) (verb "get" target) (NP<obj> "it" FN-
Theme)))
       (stype interrogative))

(adam01 2316 "Let's put the poor mailman's head back on."
       (target-verb put)
       (frame Placing)
       (pos_tag (v"|"let~pro-obj"|"us v"|"put&ZERO det-art"|"the adj"|"poor
n"|"+n"|"mail+n"|"man~poss"|"s v"|"head adv"|"back adv"|"on.))
       (syntax (V NP<obj> AVP[on]<dep>))
       (chunks ((PRO<ext> "us" FN-Agent)(verb "put" target) (NP<obj> "mailman's head"
FN-Theme) (AVP[on]<dep> "back on" FN-Goal)))
       (stype imperative))

(adam01 2321 "How can he see to deliver mail?" ;;;adverbial "to" - -
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (adv-int"|"how mod"|"can pro-sub"|"he v"|"see inf"|"to v"|"deliver
n"|"mail?))
       (syntax (PRO<ext> V VP2<dep>))
       (chunks ((PRO<ext> "he" FN-Perceiver_passive) (verb "see" target) (VP2<dep> "to
deliver mail" FN-Purpose) (CNI " " FN-Phenomenon)))    ;;;; "Purpose" does not actually
exist in FrameNet
       (stype interrogative))

(adam01 2381 "She's gone home."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (pro-sub"|"she~aux"|"be&3S part"|"go&PASTP n"|"home.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "She" FN-Self_mover) (verb "gone" target) (NP<obj> "home"
FN-Goal)))
       (stype declarative))

(adam01 2384 "She went home in July."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (pro-sub"|"she v"|"go&PAST adv"|"home prep"|"in n-prop"|"July.))
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	(syntax (PRO<ext> V NP<obj> PP[in]<dep>))
	(chunks ((PRO<ext> "She" FN-Self_mover) (verb "went" target) (NP<obj> "home"
FN-Goal) (PP[in]<dep> "in July" FN-Time)))
	(stype declarative))

(adam01 2405 "Why don't you come over here and play with the ball?"
	(target-verb come)
	(frame Arriving)
	(pos_tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you v"|"come adv"|"over
adv"|"here coord"|"and n"|"play prep"|"with det-art"|"the n"|"ball?))
	(syntax (PRO<ext> V PP[over]<dep>))
	(chunks ((PRO<ext> "you" FN-Theme) (verb "come" target) (PP[over]<dep> "over
here" FN-Goal)))
	(stype imperative))

(adam01 2405 "Why don't you come over here and play with the ball?"
	(target-verb play)
	(frame Intentionally_affect)	;;found by searching "do"
	(pos_tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you v"|"come adv"|"over
adv"|"here coord"|"and n"|"play prep"|"with det-art"|"the n"|"ball?))
	(syntax (PRO<ext> V PP[with]<dep>))	;;; add a NP<obj> for "the ball" if a
better "play" Frame is found
	(chunks ((PRO<ext> "you" FN-Agent) (verb "play" target) (PP[with]<dep> "with
the ball" FN-Patient)))
	(stype imperative))

(adam01 2416 "You can get it."
	(target-verb get)
	(frame Getting)
	(pos_tag (pro-per"|"you mod"|"can aux"|"get pro-per"|"it.))
	(syntax (PRO<ext> V NP<obj>))
	(chunks ((PRO<ext> "You" FN-Recipient) (verb "get" target) (NP<obj> "it" FN-
Theme)))
	(stype declarative))

(adam01 2422 "You go get it."
	(target-verb get)
	(frame Getting)
	(pos_tag (pro-per"|"you v"|"go v"|"get pro-per"|"it.))
	(syntax (PRO<ext> V NP<obj>))
	(chunks ((PRO<ext> "You" FN-Recipient) (verb "get" target) (NP<obj> "it" FN-
Theme)))
	(stype imperative))

(adam01 2434 "Did you get the ball?"
	(target-verb get)
	(frame Getting)
	(pos_tag (v"|"do&PAST pro-per"|"you v"|"get det-art"|"the n"|"ball?))
	(syntax (PRO<ext> V NP<obj>))
	(chunks ((PRO<ext> "you" FN-Recipient) (verb "get" target) (NP<obj> "the ball"
FN-Theme)))
	(stype interrogative-do))


(adam01 2514 "Let's see if there are any pictures in this book."
	(target-verb see)
	(frame Perception_active)
	(pos_tag (v"|"let~pro-obj"|"us v"|"see conj"|"if adv"|"there cop"|"be&PRES
qn"|"any n"|"picture-PL prep"|"in pro-dem"|"this n"|"book.))
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       (syntax (V Swhether PP[in]<dep>))       ;;; very uncommmon to have a full
clause nested
       (chunks ((PRO<ext> "us" FN-Perceiver_agentive) (verb "see" target) (Swhether
"if there are any pictures" FN-Phenomenon) (PP[in]<dep> "in this book" FN-Place)))
       (stype imperative))

(adam01 2671 "Record is playing?"
       (target-verb play)
       (frame Make_noise)
       (pos_tag (n"|"record aux"|"be&3S part"|"play-PRESP?))
       (syntax (NP<ext> V))
       (chunks ((NP<ext> "Record" FN-Sound_source) (verb "playing" target)))
       (stype interrogative))

(adam01 2677 "What does it do when it plays?"
       (target-verb play)
       (frame Make_noise)
       (pos_tag (pro-int"|"what mod"|"do&3S pro-per"|"it v"|"do conj"|"when pro-
per"|"it v"|"play-3S?))
       (syntax (PRO<ext> V))
       (chunks ((PRO<ext> "it" FN-Sound_source) (verb "plays" target)))
       (stype interrogative))

(adam01 2684 "Do you hear a horn playing?"
       (target-verb play)
       (frame Make-noise)
       (pos_tag (mod"|"do pro-per"|"you v"|"hear det-art"|"a n"|"horn part"|"play-
PRESP?))
       (syntax (NP<obj> V))
       (chunks ((NP<obj> "a horn" FN-Sound_source) (verb "playing" target)))
       (stype interrogative))

(adam01 2741 "What do you see in there?"
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (pro-int"|"what mod"|"do pro-per"|"you v"|"see adv"|"in adv"|"there?))
       (syntax (WHNP<obj> PRO<ext> V PP[in]<dep>))
       (chunks ((WHNP<obj> "What" FN-Phenomenon) (PRO<ext> "you" FN-Perceiver_passive)
(verb "see" target) (PP[in]<dep> "in there" FN-Place)))
       (stype interrogative))

(adam01 2799 "Where does the ladder go?"
       (target-verb go)
       (frame Compatibility)
       (pos_tag (adv-int"|"where v"|"do&3S det-art"|"the n"|"ladder v"|"go?))
       (syntax (AVP<dep> NP<ext> V))
       (chunks ((AVP<dep> "Where" FN-Item_2) (NP<ext> "the ladder" FN-Item_1) (verb
"go" target)))
       (stype interrogative))

(adam01 2805 "Can you put it on?"
       (target-verb put)
       (frame Dressing)
       (pos_tag (mod"|"can pro-per"|"you v"|"put&ZERO pro-per"|"it adv"|"on?))
       (syntax (PRO<ext> V PRO<obj>))
       (chunks ((PRO<ext> "you" FN-Wearer) (verb "put on" target) (PRO<obj> "it" FN-
Clothing)))
       (stype imperative))

(adam01 2811 "Can you put them in there?"
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       (target-verb put)
       (frame Placing)
       (pos_tag (mod"|"can pro-per"|"you v"|"put&ZERO pro-obj"|"them prep"|"in
adv"|"there?))
       (syntax (PRO<ext> V NP<obj> PP[in]<dep>))
       (chunks ((PRO<ext> "you" FN-Agent) (verb "put" target) (NP<obj> "them" FN-
Theme) (PP[in]<dep> "in there" FN-Goal)))
       (stype imperative))

(adam01 2833 "Shall I put this back there?"
       (target-verb put)
       (frame Placing)
       (pos_tag (mod"|"shall pro-sub"|"I v"|"put&ZERO det-dem"|"this adj"|"back
adv"|"there?))
       (syntax (PRO<ext> V NP<obj> PP[back]<dep>))
       (chunks ((PRO<ext> "I" FN-Agent) (verb "put" target) (NP<obj> "this" FN-Theme)
(PP[back]<dep> "back there" FN-Goal)))
       (stype interrogative))

(adam01 2901 "He's going out."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (pro-sub"|"he~aux"|"be&3S part"|"go-PRESP adv"|"out.))
       (syntax (PRO<ext> V PP[out]<dep>))
       (chunks ((PRO<ext> "He" FN-Self_mover) (verb "going" target) (PP[out]<dep>
"out" FN-Direction)))
       (stype declarative))

(adam01 2952 "You told her to sit there."
       (target-verb sit)
       (frame Change_posture)
       (pos_tag (pro-per"|"you v"|"tell&PAST pro-obj"|"her inf"|"to v"|"sit
adv"|"there.))
       (syntax (PRO<obj> V PP[there]<dep>))
       (chunks ((PRO<obj> "her" FN-Protagonist) (verb "to sit" target) (PP[there]<dep>
"there" FN-Goal)))
       (stype declarative))

(adam01 3062 "Did you see the sun?"
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (v"|"do&PAST pro-per"|"you v"|"see det-art"|"the n"|"sun ?))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you" FN-Perceiver_passive) (verb "see" target) (NP<obj>
"the sun" FN-Phenomenon)))
       (stype interrogative))

(adam01 3122 "Put water in it?"
       (target-verb put)
       (frame Placing)
       (pos_tag (v"|"put&ZERO n"|"water prep"|"in pro-per"|"it ?))
       (syntax (V NP<obj> PP[in]<dep>))
       (chunks ((verb "put" target) (NP<obj> "water" FN-Theme) (PP[in]<dep> "in it"
FN-Goal)))
       (stype interrogative))

(adam01 3185 "Where's your truck going?"
       (target-verb go)
       (frame Motion)
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       (pos_tag (adv-int"|"where~cop"|"be&3S det-poss"|"your n"|"truck part"|"go-
PRESP?))
       (syntax (AVP<dep> NP<ext> V))
       (chunks ((AVP<dep> "Where's" FN-Goal) (NP<ext> "your truck" FN-Theme) (verb
"going" target)))
       (stype interrogative))

(adam01 3275 "What did you see in the park this morning?"
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (pro-int"|"what mod"|"do&PAST pro-per"|"you v"|"see prep"|"in det-
art"|"the v"|"park pro-dem"|"this n"|"morning?))
       (syntax (WHNP<obj> PRO<ext> V PP[in]<dep>))
       (chunks ((WHNP<obj> "What" FN-Phenomenon) (PRO<ext> "you" FN-Perceiver_passive)
(verb "see" target) (PP[in]<dep> "in the park" FN-Place)))
       (stype interrogative))

(adam01 3336 "Daddy went to school."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (n-prop"|"Daddy v"|"go&PAST prep"|"to n"|"school.))
       (syntax (NP<ext> V NP<obj>))
       (chunks ((NP<ext> "Daddy" FN-Self_mover) (verb "went" target) (PP[to]<dep> "to
school" FN-Goal)))
       (stype declarative))

(adam01 3689 "Did you look in your basket?"
       (target-verb look)
       (frame Perception_active)
       (pos_tag (v"|"do&PAST pro-per"|"you cop"|"look prep"|"in det-poss"|"your
n"|"basket?))
       (syntax (PRO<ext> V PP[in]<dep>))
       (chunks ((PRO<ext> "you" FN-Perceiver_agentive) (verb "look" target)
(PP[in]<dep> "in your basket" FN-Direction)))
       (stype interrogative))

(adam01 3757 "Can you go with your bike?"
       (target-verb go)
       (frame Self_motion)
       (pos_tag (mod"|"can pro-per"|"you v"|"go prep"|"with det-poss"|"your
n"|"bike?))
       (syntax (PRO<ext> V PP[with]<dep>))
       (chunks ((PRO<ext> "you" FN-Self_mover) (verb "go" target) (PP[with]<dep> "with
your bike" FN-Cotheme)))
       (stype imperative))

(adam01 3826 "Don't take his head off."
       (target-verb take)
       (frame Removing)
       (pos_tag (mod"|"do~neg"|"not v"|"take det-poss"|"his n"|"head adv"|"off.))
       (syntax (V NP<obj> PP[off]<dep>))
       (chunks ((verb "take" target) (NP<obj> "his head" FN-Theme) (PP[off]<dep> "off"
FN-Source) (CNI " " FN-Agent)))
       (stype imperative))


(adam01 4011 "I can't see."
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (pro-sub"|"I mod"|"can~neg"|"not v"|"see.))
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        (syntax (PRO<ext> V))
        (chunks ((PRO<ext> "I" FN-Perceiver_passive) (verb "see" target)))
        (stype declarative))

(adam01 4026 "I can't see."
        (target-verb see)
        (frame Perception_experience)
        (pos_tag (pro-sub"|"I mod"|"can~neg"|"not v"|"see.))
        (syntax (PRO<ext> V))
        (chunks ((PRO<ext> "I" FN-Perceiver_passive) (verb "see" target)))
        (stype declarative))

(adam01 4263 "May I sit beside you?"
        (target-verb sit)
        (frame Change_posture)     ;;; ;; ;;;; This "Change_posture" is for "sit"
        (pos_tag (mod"|"may pro-sub"|"I v"|"sit prep"|"beside pro-per"|"you ?))
        (syntax (PRO<ext> V PP[beside]<dep>))
        (chunks ((PRO<ext> "I" FN-Protagonist) (verb "sit" target) (PP[beside]<dep>
"beside you" FN-Goal)))
        (stype interrogative))

(adam01 4427 "Let's see."
        (target-verb see)
        (frame Perception_experience)
        (pos_tag (v"|"let~pro-obj"|"us v"|"see.))
        (syntax (PRO<ext> V))
        (chunks ((PRO<ext> "us" Perceiver_passive) (verb "see" target)))
        (stype declarative))

(adam01 4537 "Don't sit on that."
        (target-verb sit)
        (frame Change_posture)
        (pos_tag (mod"|"do~neg"|"not v"|"sit prep"|"on pro-dem"|"that.))
        (syntax (V PP[on]<dep>))
        (chunks ((verb "sit" target) (PP[on]<dep> "on that" FN-Goal) (CNI " " FN-
Protagonist)))
        (stype imperative))

(adam01 4693 "You haven't seen Bozo in a long time (.) have you?"
        (target-verb see)
        (frame Perception_experience)
        (pos_tag (pro-per"|"you aux"|"have~neg"|"not part"|"see&PASTP n-prop"|"Bozo
prep"|"in det-art"|"a adj"|"long n"|"time v"|"have pro-per"|"you?))
        (syntax (PRO<ext> V NP<odj> PP[in]<dep>))
        (chunks ((PRO<ext> "you" FN-Perceiver_passive) (verb "seen" target) (NP<odj>
"Bozo" FN-Phenomenon) (PP[in]<dep> "in a long time" FN-Depictive)))
        (stype declarative))

(adam01 4713 "Are you sitting with me?"
        (target-verb sit)
        (frame Change_postire)
        (pos_tag (cop"|"be&PRES pro-per"|"you part"|"sit-PRESP prep"|"with pro-
obj"|"me?))
        (syntax (PRO<ext> V PP[with]<dep>))
        (chunks ((PRO<ext> "you" FN-Protagonist) (verb "sitting" target) (PP[with]<dep>
"with me" FN-Goal)))
        (stype interrogative))

(adam01 4896 "Yes (.) that does look like rain falling."
        (target-verb look)
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        (frame Give_impression)
        (pos_tag (co"|"yes pro-rel"|"that v"|"do&3S cop"|"look conj"|"like n"|"rain
part"|"fall-PRESP.))
        (syntax (NP<ext> V PP[like]<dep>))
        (chunks ((NP<ext> "that" FN-Phenomenon) (verb "look" target) (PP[like]<dep>
"like rain falling" FN-Characterization)))
        (stype declarative))

(adam01 4896 "Yes (.) that does look like rain falling."
        (target-verb fall)
        (frame Motion_directional)
        (pos_tag (co"|"yes pro-rel"|"that v"|"do&3S cop"|"look conj"|"like n"|"rain
part"|"fall-PRESP.))
        (syntax (NP<ext> V))
        (chunks ((NP<ext> "rain" FN-Theme) (verb "falling" target)))
        (stype declarative))

(adam01 5042 "You're going to give the kitty a ride in your wagon?"
        (target-verb give)
        (frame Giving)
        (pos_tag (pro-per"|"you~aux"|"be&PRES part"|"go-PRESP inf"|"to v"|"give det-
art"|"the n"|"kitty det-art"|"a n"|"ride prep"|"in det-poss"|"your n"|"wagon?))
        (syntax (PRO<ext> V NP<obj> NP))
        (chunks ((PRO<ext> "you" FN-Donor) (verb "give" target) (NP<dative> "the kitty"
FN-Recipient) (NP<obj> "a ride" FN-Theme)))
        (stype interrogative))


(adam01 5252 "Can you play it?"
        (target-verb play)
        (frame Cause_to_make_noise)
        (pos_tag (mod"|"can pro-per"|"you v"|"play pro-per"|"it?))
        (syntax (PRO<ext> V PRO<obj>))
        (chunks ((PRO<ext> "you" FN-Agent) (verb "play" target) (PRO<obj> "it" FN-
Sound_maker)))
        (stype imperative))

(eve01 49 "I took it."
        (target-verb take)
        (frame Taking)
        (pos_tag (pro-sub"|"I v"|"take&PAST pro-per"|"it.))
        (syntax (PRO<ext> V PRO<obj>))
        (chunks ((PRO<ext> "I" FN-Agent) (verb "took" target) (PRO<obj> "it" FN-
Theme)))
        (stype declarative))

(eve01 106 "Why don't you go in the room and kill a fly?"
        (target-verb go)
        (frame Self_motion)
        (pos_tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you v"|"go prep"|"in det-
art"|"the n"|"room coord"|"and v"|"kill det-art"|"a n"|"fly?))
        (syntax (PRO<ext> V PP[in]<dep>))
        (chunks ((PRO<ext> "you" FN-Self_mover) (verb "go" target) (PP[in]<dep> "in the
room" FN-Goal)))
        (stype imperative))

(eve01 111 "You go in the room and kill a fly."
        (target-verb go)
        (frame Self_motion)
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       (pos_tag (pro-per"|"you v"|"go prep"|"in det-art"|"the n"|"room coord"|"and
v"|"kill det-art"|"a n"|"fly.))
       (syntax (PRO<ext> V PP[in]<dep>))
       (chunks ((PRO<ext> "you" FN-Self_mover) (verb "go" target) (PP[in]<dep> "in the
room" FN-Goal)))
       (stype imperative))

(eve01 119 "You get a fly."
       (target-verb get)
       (frame Getting)
       (pos_tag (pro-per"|"you v"|"get det-art"|"a n"|"fly.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you" FN-Recipient) (verb "get" target) (NP<obj> "a fly" FN-
Theme)))
       (stype declarative))

(eve01 122 "You get one."
       (target-verb get)
       (frame Getting)
       (pos_tag (pro-per"|"you v"|"get pro-indef"|"one.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you" FN-Recipient) (verb "get" target) (NP<obj> "one" FN-
Theme)))
       (stype declarative))

(eve01 132 "Go and get your telephone."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (v"|"go))
       (syntax (V))
       (chunks ((verb "Go" target) (CNI " " FN-Theme)))
       (stype imperative))

(eve01 132 "Go and get your telephone."
       (target-verb get)
       (frame Getting)
       (pos_tag (v"|"go coord"|"and v"|"get det-poss"|"your n"|"telephone.))
       (syntax (V NP<obj>))
       (chunks ((verb "get" target) (NP<obj> "your telephone" FN-Theme) (CNI " " FN-
Recipient)))
       (stype declarative))

(eve01 135 "He gave you your telephone."
       (target-verb give)
       (frame Giving)
       (pos_tag (pro-sub"|"he v"|"give&PAST pro-per"|"you det-poss"|"your
n"|"telephone.))
       (syntax (PRO<ext> V PRO<obj> NP))
       (chunks ((PRO<ext> "He" FN-Donor) (verb "gave" target) (PRO<dative> "you" FN-
Recipient) (NP<obj> "your telephone" FN-Theme)))
       (stype declarative))

(eve01 269 "You want to sit on the stool and read the book?"
       (target-verb sit)
       (frame Change_posture)
       (pos_tag (pro-per"|"you v"|"want inf"|"to v"|"sit prep"|"on det-art"|"the
n"|"stool coord"|"and v"|"read&ZERO det-art"|"the n"|"book?))
       (syntax (PRO<ext> V PP[on]<dep>))
       (chunks ((PRO<ext> "You" FN-Protagonist) (verb "sit" target) (PP[on]<dep> "on
the stool" FN-Goal)))
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       (stype interrogative))

(eve01 293 "Did you eat it?"
       (target-verb eat)
       (frame Ingestion)
       (pos_tag (v"|"do&PAST pro-per"|"you v"|"eat pro-per"|"it?))
       (syntax (PRO<ext> V PRO<obj>))
       (chunks ((PRO<ext> "you" FN-Ingestor) (verb "eat" target) (PRO<obj> "it" FN-
Ingestibles)))
       (stype interrogative))

(eve01 296 "You ate it."
       (target-verb eat)
       (frame Ingestion)
       (pos_tag (pro-per"|"you v"|"eat&PAST pro-per"|"it.))
       (syntax (PRO<ext> V PRO<obj>))
       (chunks ((PRO<ext> "You" FN-Ingestor) (verb "ate" target) (PRO<obj> "it" FN-
Ingestibles)))
       (stype declarative))

(eve01 299 "I'll give you another."
       (target-verb give)
       (frame Giving)
       (pos_tag (pro-sub"|"I~mod"|"will v"|"give pro-per"|"you qn"|"another.))
       (syntax (PRO<ext> V PRO<obj> NP))
       (chunks ((PRO<ext> "I" FN-Donor) (verb "give" target) (PRO<dative> "you" FN-
Recipient) (NP<obj> "another" FN-Theme)))
       (stype declarative))

(eve01 332 "You xxx eat any more crackers."
       (target-verb eat)
       (frame Ingestion)
       (pos_tag (pro-per"|"you v"|"eat qn"|"any qn"|"more n"|"cracker-PL.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you" FN-Ingestor) (verb "eat" target) (NP<obj> "crackers"
FN-Ingestibles)))
       (stype declarative))

(eve01 388 "Where are you going?"
       (target-verb go)
       (frame Self_motion)
       (pos_tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))

(eve01 518 "Come see if we can find dolly's bottle."
       (target-verb come)
       (frame Self_motion)
       (pos_tag (v"|"come v"|"see conj"|"if pro-sub"|"we mod"|"can v"|"find n"|"doll-
DIM~poss"|"s n"|"bottle.))
       (syntax (V))
       (chunks ((verb "come" target) (CNI " " FN-Theme)))
       (stype imperative))

(eve01 518 "Come see if we can find dolly's bottle."
       (target-verb see)
       (frame Perception_active)
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       (pos_tag (v"|"come v"|"see conj"|"if pro-sub"|"we mod"|"can v"|"find n"|"doll-
DIM~poss"|"s n"|"bottle.))
       (syntax (V Swhether))
       (chunks ((verb "see" target) (Swhether "if we can find dolly's bottle" FN-
Phenomenon) (CNI " " FN-Perceiver_agentive)))
       (stype imperative))

(eve01 526 "Give dolly her bottle."
       (target-verb give)
       (frame Giving)
       (pos_tag (v"|"give n"|"doll-DIM det-poss"|"her n"|"bottle.))
       (syntax (V NP<obj> NP))
       (chunks ((verb "Give" target) (NP<dative> "dolly" FN-Recipient) (NP<obj> "her
bottle" FN-Theme) (CNI " " FN-Donor)))
       (stype imperative))

(eve01 736 "Do you wanna come up and sit on my lap?"
       (target-verb come)
       (frame Arriving)
       (pos_tag (mod"|"do pro-per"|"you v"|"want~inf"|"to v"|"come adv"|"up
coord"|"and v"|"sit prep"|"on det-poss"|"my n"|"lap?))
       (syntax (PRO<ext> V PP[up]<dep>))
       (chunks ((PRO<ext> "you" FN-Theme) (verb "come" target) (PP[up]<dep> "up" FN-
Goal)))
       (stype interrogative))


(eve01 736 "Do you wanna come up and sit on my lap?"
       (target-verb sit)
       (frame Change_posture)
       (pos_tag (mod"|"do pro-per"|"you v"|"want~inf"|"to v"|"come adv"|"up
coord"|"and v"|"sit prep"|"on det-poss"|"my n"|"lap?))
       (syntax (PRO<ext> V PP[on]<dep>))
       (chunks ((PRO<ext> "you" FN-Protagonist) (verb "sit" target) (PP[on]<dep> "on
my lap" FN-Goal)))
       (stype interrogative))

(eve01 827 "He wanted to see you."
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (pro-sub"|"he v"|"want-PAST inf"|"to v"|"see pro-per"|"you.))
       (syntax (PRO<ext> V PRO<obj>))
       (chunks ((PRO<ext> "He" FN-Perceiver_passive) (verb "see" target) (PRO<obj>
"you" FN-Phenomenon)))
       (stype declarative))

(eve01 854 "You sit in the corner and read."
       (target-verb sit)
       (frame Posture)
       (pos_tag (pro-per"|"you v"|"sit prep"|"in det-art"|"the n"|"corner coord"|"and
v"|"read&ZERO.))
       (syntax (PRO<ext> V PP[in]<dep>))
       (chunks ((PRO<ext> "you" FN-Agent) (verb "sit" target) (PP[in]<dep> "in the
corner" FN-Location)))
       (stype imperative))

(eve01 963 "Come?"
       (target-verb come)
       (frame Self_motion)
       (pos_tag (v"|"come?))
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       (syntax (V))
       (chunks ((verb "Come" target) (CNI " " FN-Theme)))
       (stype interrogative))

(eve01 966 "Where're you going?"
       (target-verb go)
       (frame Self_motion)
       (pos-tag (adv-int"|"where~aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "Where're" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))

(eve01 972 "The choo-choo is coming?"
       (target-verb come)
       (frame Arriving)
       (pos_tag (det-art"|"the n"|"+on"|"choo+on"|"choo aux"|"be&3S part"|"come-
PRESP?))
       (syntax (NP<ext> V))
       (chunks ((NP<ext> "The choo-choo" FN-Theme) (verb "coming" target)))
       (stype interrogative))

(eve01 1129 "Why don't you put Racketyboom back in the toy box?"
       (target-verb put)
       (frame Placing)
       (pos_tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you v"|"put&ZERO n-
prop"|"Racketyboom adv"|"back prep"|"in det-art"|"the n"|"toy n"|"box?))
       (syntax (PRO<ext> V NP<obj> PP[back]<dep>))
       (chunks ((PRO<ext> "you" FN-Agent) (verb "put" target) (NP<obj> "Racketyboom"
FN-Theme) (PP[back]<dep> "back in the toy box" FN-Goal)))
       (stype imperative))

(eve01 1161 "The man'll sit in the chair."
       (target-verb sit)
       (frame Change_posture)
       (pos_tag (det-art"|"the n"|"man~mod"|"will v"|"sit prep"|"in det-art"|"the
n"|"chair.))
       (syntax (NP<ext> V PP[in]<dep))
       (chunks ((NP<ext> "The man" FN-Protagonist) (verb "sit" target) (PP[in]<dep>
"in the chair" FN-Goal)))
       (stype declarative))

(eve01 1180 "Who's sitting?"
       (target-verb sit)
       (frame Posture)
       (pos_tag (pro-rel"|"who~aux"|"be&3S part"|"sit-PRESP ?))
       (syntax (AVP<dep> V))
       (chunks ((AVP<dep> "Who" FN-Protagonist) (verb "sitting" target)))
       (stype interrogative))

(eve01 1209 "Eve's sitting on the stool."
       (target-verb sit)
       (frame Posture)
       (pos_tag (n-prop"|"Eve~aux"|"be&3S part"|"sit-PRESP prep"|"on det-art"|"the
n"|"stool.))
       (syntax (NP<ext> V PP[on]<dep>))
       (chunks ((NP<ext> "Eve" FN-Protagonist) (verb "sitting" target) (PP[on]<dep>
"on the stool" FN-Goal)))
       (stype declarative))
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(eve01 1229 "Neil doesn't sit on the stool."
       (target-verb sit)
       (frame Posture)
       (pos_tag (n-prop"|"Neil mod"|"do&3S~neg"|"not v"|"sit prep"|"on det-art"|"the
n"|"stool.))
       (syntax (NP<ext> V PP[on]<dep>))
       (chunks ((NP<ext> "Neil" FN-Protagonist) (verb "sit" target) (PP[on]<dep> "on
the stool" FN-Goal)))
       (stype declarative))

(eve01 1241 "Get what?"
       (target-verb get)
       (frame Getting)
       (pos_tag (v"|"get pro-int"|"what?))
       (syntax (V NP<obj>))
       (chunks ((verb "Get" target) (NP<obj> "what" FN-Theme) (CNI " " FN-Recipient)))
       (stype interrogative))

(eve01 1247 "Get what?"
       (target-verb get)
       (frame Getting)
       (pos_tag (v"|"get pro-int"|"what?))
       (syntax (V NP<obj>))
       (chunks ((verb "Get" target) (NP<obj> "what" FN-Theme) (CNI " " FN-Recipient)))
       (stype interrogative))

(eve01 1342 "I'm making lunch."
       (target-verb make)
       (frame Cooking_creation)
       (pos_tag (pro-sub"|"I~aux"|"be&1S part"|"make-PRESP n"|"lunch.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "I" FN-Cook) (verb "making" target) (NP<obj> "lunch" FN-
Produced_food)))
       (stype declarative))

(eve01 1387 "Want to come up?"
       (target-verb come)
       (frame Arriving)
       (pos_tag (v"|"want v"|"come adv"|"up ?))
       (syntax (V PP[up]<dep>))
       (chunks ((verb "come" target) (PP[up]<dep> "up" FN-Goal) (CNI " " FN-Theme)))
       (stype interrogative))

(eve01 1452 "I'm going upstairs."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (pro-sub"|"I~aux"|"be&1S part"|"go-PRESP adv"|"upstairs.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "I" FN-Self_mover) (verb "going" target) (NP "upstairs" FN-
Goal)))
       (stype declarative))

(eve01 1487 "Can you get your chair?"
       (target-verb get)
       (frame Getting)
       (pos_tag (mod"|"can pro-per"|"you v"|"get det-poss"|"your n"|"chair?))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((Pro<ext> "you" FN-Recipient) (verb "get" target) (NP<obj> "your
chair" FN-Theme)))
       (stype imperative))
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(eve01 1490 "Give me the cheese."
       (target-verb give)
       (frame Giving)
       (pos_tag (v"|"give pro-obj"|"me det-art"|"the n"|"cheese.))
       (syntax (V PRO<obj> NP))
       (chunks ((verb "Give" target) (PRO<dative> "me" FN-Recipient) (NP<obj> "the
cheese" FN-Theme) (CNI " " FN-Donor)))
       (stype imperative))

(eve01 1562 "I'm going to the basement and I'll be right back."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (pro-sub"|"I~aux"|"be&1S part"|"go-PRESP prep"|"to det-art"|"the
n"|"basement coord"|"and pro-sub"|"I~mod"|"will cop"|"be adj"|"right n"|"back.))
       (syntax (PRO<ext> V PP[to]<dep>))
       (chunks ((PRO<ext> "I" FN-Self_mover) (verb "going" target) (PP[to]<dep> "to
the basement" FN-Goal)))
       (stype declarative))

(eve01 1658 "Give the man a cracker?"
       (target-verb give)
       (frame Giving)
       (pos_tag (v"|"give det-art"|"the n"|"man det-art"|"a n"|"cracker?))
       (syntax (V NP<obj> NP))
       (chunks ((verb "Give" target) (NP<dative> "the man" FN-Recipient) (NP<obj> "a
cacker" FN-Theme) (CNI " " FN-Donor)))
       (stype interrogative))

(eve01 1744 "You don't want anything else to eat?"
       (target-verb eat)
       (frame Ingestion)
       (pos_tag (pro-per"|"you mod"|"do~neg"|"not v"|"want pro-indef"|"anything
post"|"else inf"|"to v"|"eat?))
       (syntax (PRO<ext> NP<obj> V))
       (chunks ((PRO<ext> "You" FN-Ingestor) (NP<obj> "anything else" FN-Ingestibles)
(verb "to eat" target)))
       (stype interrogative))

(eve01 1762 "You may get down and eat the celery."
       (target-verb get)
       (frame Self_motion)        ;;; closest, since FrameNet does not have a "get
down" frame, as in get down from ur chair, or get down from the ladder
       (pos_tag (pro-per"|"you mod"|"may v"|"get adv"|"down coord"|"and v"|"eat det-
art"|"the n"|"celery.))
       (syntax (PRO<ext> V AVP<dep>))
       (chunks ((PRO<ext> "You" FN-Self_mover) (verb "get" target) (AVP<dep> "down"
FN-Goal)))
       (stype imperative))

(eve01 1762 "You may get down and eat the celery."
       (target-verb eat)
       (frame Ingestion)
       (pos_tag (pro-per"|"you mod"|"may v"|"get adv"|"down coord"|"and v"|"eat det-
art"|"the n"|"celery.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "You" FN-Ingestor) (verb "eat" target) (NP<obj> "the celery"
FN-Ingestibles)))
       (stype declarative))
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(eve01 1822 "The dolly eats his celery."
       (target-verb eats)
       (frame Ingestion)
       (pos_tag (det-art"|"the n"|"doll-DIM v"|"eat-3S det-poss"|"his n"|"celery.))
       (syntax (NP<ext> V NP<obj>))
       (chunks ((NP<ext> "The dolly" FN-Ingestor) (verb "eats" target) (NP<obj> "his
celery" FN-Ingestibles)))
       (stype declarative))
(eve01 1952 "You put that shoe on dolly."
       (target-verb put)
       (frame Dressing)
       (pos_tag (pro-per"|"you v"|"put&ZERO pro-dem"|"that n"|"shoe prep"|"on
n"|"doll-DIM.))
       (syntax (PRO<ext> V NP<obj> NP))
       (chunks ((PRO<ext> "You" FN-Dresser) (verb "put" target) (NP<obj> "that shoe"
FN-Clothing) (PP[on]<dep> "on dolly" FN-Wearer)))
       (stype declarative))

(eve01 2060 "Get the napkin."
       (target-verb get)
       (frame Getting)
       (pos_tag (v"|"get det-art"|"the n"|"napkin.))
       (syntax (V NP<obj>))
       (chunks ((verb "Get" target) (NP<obj> "the napkin" FN-Theme) (CNI " " FN-
Recipient)))
       (stype imperative))

(eve01 2284 "Let's put the books in the basket."
       (target-verb put)
       (frame Placing)
       (pos_tag (v"|"let~pro-obj"|"us v"|"put&ZERO det-art"|"the n"|"book-PL prep"|"in
det-art"|"the n"|"basket.))
       (syntax (PRO<ext> V NP<obj> PP[in]<dep>))
       (chunks ((PRO<ext> "us" FN-Agent) (verb "put" target) (PP[in]<dep> "in the
basket" FN-Goal)))
       (stype imperative))

(eve01 2299 "Could you get the other books?"
       (target-verb get)
       (frame Getting)
       (pos_tag (mod"|"could pro-per"|"you v"|"get det-art"|"the qn"|"other n"|"book-
PL?))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you" FN-Recipient) (verb "get" target) (NP<obj> "the other
books" FN-Theme)))
       (stype interrogative))

(eve01 2302 "You get the other books and we'll put them in the basket."
       (target-verb get)
       (frame Getting)
       (pos_tag (pro-per"|"you v"|"get det-art"|"the qn"|"other n"|"book-PL
coord"|"and pro-sub"|"we~mod"|"will v"|"put&ZERO pro-obj"|"them prep"|"in det-
art"|"the n"|"basket.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "you" FN-Recipient) (verb "get" target) (NP<obj> "the other
books" FN-Theme)))
       (stype imperative))

(eve01 2302 "You get the other books and we'll put them in the basket."
       (target-verb put)
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        (frame Placing)
        (pos_tag (pro-per"|"you v"|"get det-art"|"the qn"|"other n"|"book-PL
coord"|"and pro-sub"|"we~mod"|"will v"|"put&ZERO pro-obj"|"them prep"|"in det-
art"|"the n"|"basket.))
        (syntax (PRO<ext> V NP<obj> PP[in]<dep>))
        (chunks ((PRO<ext> "we'll" FN-Agent) (verb "put" target) (NP<obj> "them" FN-
Theme)(PP[in]<dep> "in the basket" FN-Goal)))
        (stype declarative))

(eve01 2320 "You look in the kitchen."
        (target-verb look)
        (frame Perception_active)
        (pos_tag (pro-per"|"you cop"|"look prep"|"in det-art"|"the n"|"kitchen.))
        (syntax (PRO<ext> V PP[in]<dep>))
        (chunks ((PRO<ext> "You" FN-Perceiver_agentive) (verb "look" target)
(PP[in]<dep> "in the kitchen" FN-Phenomenon)))
        (stype imperative))

(eve01 2388 "The coffee's coming."
        (target-verb come)
        (frame Arriving)
        (pos_tag (et-art"|"the n"|"coffee~aux"|"be&3S part"|"come-PRESP.))
        (syntax (NP<ext> V))
        (chunks ((NP<ext> "The coffee" FN-Theme) (verb "is coming" target)))
        (stype declarative))

(eve01 2521 "You fall?"
        (target-verb fall)
        (frame Motion_directional)
        (pos_tag (pro-per"|"you v"|"fall?))
        (syntax (PRO<ext> V))
        (chunks ((PRO<ext> "You" FN-Theme) (verb "fall" target)))
        (stype interrogative))

(eve01 2624 "I'm going to go to the basement."
        (target-verb go)
        (frame Self_motion)
        (pos_tag (pro-sub"|"I~aux"|"be&1S part"|"go-PRESP inf"|"to v"|"go prep"|"to
det-art"|"the n"|"basement.))
        (syntax (PRO<ext> V PP[to]<dep>))
        (chunks ((PRO<ext> "I" FN-Self_mover) (verb "go" target) (PP[to]<dep> "to the
basement" FN-Goal)))
        (stype declarative))

(eve01 2683 "Put this here on the floor."
        (target-verb put)
        (frame Placing)
        (pos_tag (v"|"put&ZERO pro-dem"|"this adv"|"here prep"|"on det-art"|"the
n"|"floor.))
        (syntax (V NP<obj> PP[on]<dep>))
        (chunks ((verb "Put" target) (NP<obj> "this" FN-Theme) (PP[on]<dep> "on the
floor" FN-Goal) (CNI " " FN-Agent)))
        (stype imperative))

(eve01 2780 "Look here."
        (target-verb look)
        (frame Perception_active)
        (pos_tag (cop"|"look adv"|"here.))
        (syntax (V AVP<dep>))
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       (chunks ((verb "Look" target) (AVP<dep> "here" FN-Direction) (CNI " " FN-
Perceiver_agentive)))
       (stype imperative))

(eve01 2881 "Gonna sit down?"
       (target-verb sit)
       (frame Change_posture)
       (pos_tag (part"|"go-PRESP~inf"|"to v"|"sit adv"|"down?))
       (syntax (V AVP<dep>))
       (chunks ((verb "sit" target) (AVP<dep> "down" FN-Goal) (CNI " " FN-
Protagonist)))
       (stype interrogative))

(eve01 2976 "Where are you going?"
       (target-verb go)
       (frame Self_motion)
       (pos_tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))

(eve01 2986 "You're gonna see Becky?"
       (target-verb see)
       (frame Perception_experience)
       (pos_tag (pro-per"|"you~aux"|"be&PRES part"|"go-PRESP~inf"|"to v"|"see n-
prop"|"Becky?))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "You" FN-Perceiver_passive) (verb "see" target) (NP<obj>
"Becky" FN-Phenomenon)))
       (stype interrogative))

(eve01 3001 "She's playing hard."
       (target-verb play)
       (frame Competition)
       (pos_tag (pro-sub"|"she~aux"|"be&3S part"|"play-PRESP adv"|"hard.))
       (syntax (PRO<ext> V AVP<dep>))
       (chunks ((PRO<ext> "She" FN-Participant_1) (verb "playing" target) (AVP<dep>
"hard" FN-Manner)))
       (stype declarative))

(eve01 3031 "Where are you going?"
       (target-verb go)
       (frame Self_motion)
       (pos_tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))

(eve01 3043 "You can see Becky later."
       (target-verb see)
       (frame Perception_experience)
       (pos_tag ())
       (syntax (PRO<ext> V NP<obj> AVP<dep>))
       (chunks ((PRO<ext> "You" FN-Perceiver_passive) (verb "see" target) (NP<obj>
"Becky" FN-Phenomenon) (AVP<dep> "later" FN-Time)))
       (stype declarative))

(eve01 3053 "Where are you going?"
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       (target-verb go)
       (frame Self_motion)
       (pos_tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))


(eve01 3068 "C'mon\, let's go in the room."
       (target-verb go)
       (frame Self_motion)
       (pos_tag (co"|"cmon beg"|"beg v"|"let~pro-obj"|"us v"|"go prep"|"in det-
art"|"the n"|"room.))
       (syntax (V PP[in]<dep>))
       (chunks ((PRO<ext> "us" FN-Self_mover) (verb "go" target) (PP[in]<dep> "in the
room" FN-Goal)))
       (stype imperative))

(eve01 3203 "It goes in the coffee."
       (target-verb go)
       (frame Motion)
       (pos_tag (pro-per"|"it v"|"go-3S prep"|"in det-art"|"the n"|"coffee.))
       (syntax (PRO<ext> V PP[in]<dep>))
       (chunks ((PRO<ext> "It" FN-Theme) (verb "goes" target) (PP[in]<dep> "in the
coffee" FN-Goal)))
       (stype declarative))

(eve01 3547 "He fell off the well."
       (target-verb fall)
       (frame Motion_directional)
       (pos_tag (pro-sub"|"he v"|"fall&PAST prep"|"off det-art"|"the adv"|"well.))
       (syntax (PRO<ext> V PP[off]<dep>))
       (chunks ((PRO<ext> "He" FN-Theme) (verb "fell" target) (PP[off]<dep> "off the
well" FN-Goal)))
       (stype declarative))

(eve01 3759 "You gonna play?"
       (target-verb play)
       (frame Make_noise)
       (pos_tag (pro-per"|"you part"|"go-PRESP~inf"|"to v"|"play?))
       (syntax (PRO<ext> V))
       (chunks ((PRO<ext> "You" FN-Agent) (verb "play" target)))
       (stype interrogative))

(eve01 3762 "you gonna play music for us?"
       (target-verb play)
       (frame Make_noise)
       (pos_tag (pro-per"|"you part"|"go-PRESP~inf"|"to n"|"play n"|"music prep"|"for
pro-obj"|"us?))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "You" FN-Agent) (verb "play" target) (NP<obj> "music" FN-
Sound)))
       (stype interrogative))

(eve01 3794 "Play the music."
       (target-verb play)
       (frame Make_noise)
       (pos_tag (v"|"play det-art"|"the n"|"music.))
       (syntax (V NP<obj>))
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       (chunks ((verb "play" target) (NP<obj> "the music" FN-Sound) (CNI " " FN-
Agent)))
       (stype imperative))

(eve01 3871 "Where are you going?"
       (target-verb go)
       (frame Self_motion)
       (pos_tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))


(eve01 3881 "Where are you going?"
       (target-verb go)
       (frame Self_motion)
       (pos_tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))

(eve01 3887 "Where are you going?"
       (target-verb go)
       (frame Self_motion)
       (pos_tag (adv-int"|"where aux"|"be&PRES pro-per"|"you part"|"go-PRESP?))
       (syntax (AVP<dep> PRO<ext> V))
       (chunks ((AVP<dep> "where" FN-Goal) (PRO<ext> "you" FN-Self_mover) (verb
"going" target)))
       (stype interrogative))

(eve01 3931 "Why don't you come in and sit in your chair?"
       (target-verb come)
       (frame Arriving)
       (pos_tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you v"|"come adv"|"in
coord"|"and v"|"sit prep"|"in det-poss"|"your n"|"chair end"|"end co"|"huh?))
       (syntax (PRO<ext> V PP[in]<dep>))
       (chunks ((PRO<ext> "you" FN-Theme) (verb "come" target) (PP[in]<dep> "in" FN-
Goal)))
       (stype imperative))

(eve01 3931 "Why don't you come in and sit in your chair?"
       (target-verb sit)
       (frame Change_posture)
       (pos_tag (adv-int"|"why mod"|"do~neg"|"not pro-per"|"you v"|"come adv"|"in
coord"|"and v"|"sit prep"|"in det-poss"|"your n"|"chair end"|"end co"|"huh?))
       (syntax (PRO<ext> V PP[in]<dep>))
       (chunks ((PRO<ext> "you" FN-Protagonist) (verb "sit" target) (PP[in]<dep> "in
your char" FN-Goal)))
       (stype imperative))


(eve01 3962 "I'll go get her."
       (target-verb get)
       (frame Getting)
       (pos_tag (pro-sub"|"I~mod"|"will v"|"go v"|"get pro-obj"|"her.))
       (syntax (PRO<ext> V PRO<obj>))
       (chunks ((PRO<ext> "I" FN-Recipient) (verb "get" target) (PRO<obj> "her" FN-
Theme)))
```

```
        (stype declarative))

(eve01 3993 "I see it."
        (target-verb see)
        (frame Perception_experience)
        (pos_tag (pro-sub"|"I v"|"see pro-per"|"it.))
        (syntax (PRO<ext> V PRO<obj>))
        (chunks ((PRO<ext> "I" FN-Perceiver_passive) (verb "see" target) (PRO<obj> "it"
FN-Phenomenon)))
        (stype declarative))

(eve01 4018 "Come here."
        (target-verb come)
        (frame Self_motion)
        (pos_tag (v"|"come adv"|"here.))
        (syntax (V AVP<dep>))
        (chunks ((verb "Come" target) (AVP<dep> "here" FN-Goal)))
        (stype imperative))

(eve01 4086 "Because I just put them on."
        (target-verb put)
        (frame Dressing)
        (pos_tag (conj"|"because pro-sub"|"I adv"|"just v"|"put&ZERO pro-obj"|"them
adv"|"on.))
        (syntax (PRO<ext> AVP<dep> V PRO<obj>))
        (chunks ((PRO<ext> "I" FN-Dresser) (AVP<dep> "just" FN-Time) (verb "put on"
target) (PRO<obj> "them" FN-Clothing) (CNI " " FN-Wearer)))
        (stype declarative))

(eve01 4108 "Come out here and play."
        (target-verb come)
        (frame Self_motion)
        (pos_tag (v"|"come adv"|"out adv"|"here coord"|"and n"|"play.))
        (syntax (V PP[out]<dep>))
        (chunks ((verb "come" target) (PP[out]<dep> "out here" FN-Goal) (CNI " " FN-
Theme)))
        (stype imperative))

(eve01 4108 "Come out here and play."
        (target-verb play)
        (frame Intentionally_affect)      ;;found by searching "do"
        (pos_tag (v"|"come adv"|"out adv"|"here coord"|"and n"|"play.))
        (syntax (V))
        (chunks ((verb "play" target) (CNI " " FN-Agent)))
        (stype imperative))

(eve01 4158 "Look on the floor."
        (target-verb look)
        (frame Perception_active)
        (pos_tag (cop"|"look prep"|"on det-art"|"the n"|"floor.))
        (syntax (V PP[on]<dep>))
        (chunks ((verb "look" target) (PP[on]<dep> "on the floor" FN-Direction) (CNI "
" FN-Perceiver_agentive)))
        (stype imperative))

(eve01 4249 "We can't go outside now."
        (target-verb go)
        (frame Self_motion)
        (pos_tag (pro-sub"|"we mod"|"can~neg"|"not v"|"go adv"|"outside adv"|"now.))
        (syntax (PRO<ext> V AVP<dep> AVP<dep>))
```

```
	(chunks ((PRO<ext> "we" FN-Self_mover) (verb "go" target) (AVP<dep> "outside"
FN-Goal) (AVP<dep> "now" FN-Time)))
	(stype declarative))

(eve01 4259 "We'll play outside later."
	(target-verb play)
	(frame Intentionally_affect)     ;;found by searching "do"
	(pos_tag (pro-sub"|"we~mod"|"will v"|"play adv"|"outside adv"|"later.))
	(syntax (PRO<ext> V AVP<dep> AVP<dep>))
	(chunks ((PRO<ext> "we" FN-Agent) (verb "play" target) (AVP<dep> "outside" FN-
Location) (AVP<dep> "later" FN-Time)))
	(stype declarative))

(eve01 4262 "Later we'll go outside."
	(target-verb go)
	(frame Self_motion)
	(pos_tag (adv"|"later pro-sub"|"we~mod"|"will v"|"go adv"|"outside.))
	(syntax (AVP<dep> PRO<ext> V AVP<dep>))
	(chunks ((AVP<dep> "Later" FN-Time) (PRO<ext> "we" FN-Self_mover) (verb "go"
target) (AVP<dep> "outside" FN-Goal)))
	(stype declarative))

(eve01 4271 "Later we'll go outside."
	(target-verb go)
	(frame Self_motion)
	(pos_tag (adv"|"later pro-sub"|"we~mod"|"will v"|"go adv"|"outside.))
	(syntax (AVP<dep> PRO<ext> V AVP<dep>))
	(chunks ((AVP<dep> "Later" FN-Time) (PRO<ext> "we" FN-Self_mover) (verb "go"
target) (AVP<dep> "outside" FN-Goal)))
	(stype declarative))

(eve01 4283 "We'll go outside later."
	(target-verb go)
	(frame Self_motion)
	(pos_tag (adv"|"later pro-sub"|"we~mod"|"will v"|"go adv"|"outside.))
	(syntax (PRO<ext> V AVP<dep> AVP<dep>))
	(chunks ((PRO<ext> "we" FN-Self_mover) (verb "go" target) (AVP<dep> "outside"
FN-Goal) (AVP<dep> "Later" FN-Time)))
	(stype declarative))

(eve01 4407 "We'll play with Sandy later."
	(target-verb play)
	(frame Intentionally_affect)     ;;found by searching "do"
	(pos_tag (pro-sub"|"we~mod"|"will v"|"play prep"|"with n-prop"|"Sandy
adv"|"later.))
	(syntax (PRO<ext> V PP[with]<dep> AVP<dep>))
	(chunks ((PRO<ext> "We" FN-Agent) (verb "play" target) (PP[with]<dep> "with
Sandy" FN-Patient) (AVP<dep> "later" FN-Time)))
	(stype declarative))

(eve01 4510 "I'm going to go in the basement."
	(target-verb go)
	(frame Self_motion)
	(pos_tag (pro-sub"|"I~aux"|"be&1S part"|"go-PRESP inf"|"to v"|"go prep"|"in
det-art"|"the n"|"basement.))
	(syntax (PRO<ext> V PP[in]<dep>))
	(chunks ((PRO<ext> "I" FN-Self_mover) (verb "go" target) (PP[in]<dep> "in the
basement" FN-Goal)))
	(stype declarative))
```

```
(eve01 4705 "You wouldn't eat a wiener if I fixed it for you."
       (target-verb eat)
       (frame Ingestion)
       (pos_tag (pro-per"|"you mod"|"will&COND~neg"|"not v"|"eat det-art"|"a
n"|"wiener conj"|"if pro-sub"|"I v"|"fix-PAST pro-per"|"it prep"|"for pro-per"|"you.))
       (syntax (PRO<ext> V NP<obj>))
       (chunks ((PRO<ext> "You" FN-Ingestor) (verb "eat" target) (NP<obj> "a weiner"
FN-Ingestibles)))
       (stype declarative))

(eve01 4899 "That's not for babies to play in."
       (target-verb play)
       (frame Intentionally_affect)
       (pos_tag (pro-dem"|"that~cop"|"be&3S neg"|"not prep"|"for n"|"baby-PL inf"|"to
v"|"play dv"|"in.))
       (syntax (NP<ext> V))
       (chunks ((NP<ext> "babies" FN-Agent) (verb "play" target)))
       (stype declarative))
```

Appendix C: Annotated bAbI Training Examples

The annotations below were derived from bAbI task training examples. They were added to the corpus used for construction acquisition in Chapter 8.

```
(manual 1 "Mary is in the bedroom."
       (target-verb be)
       (frame Being_located)
       (pos-tag ())
       (syntax (NP<ext> V PP[in]<dep>))
       (chunks ((NP<ext> "Mary" FN-Theme) (verb "is" target) (PP[in]<dep> "in the
bedroom" FN-Location)))
       (stype declarative))

(manual 2 "Daniel is in the hallway."
       (target-verb be)
       (frame Being_located)
       (pos-tag ())
       (syntax (NP<ext> V PP[in]<dep>))
       (chunks ((NP<ext> "Daniel" FN-Theme) (verb "is" target) (PP[in]<dep> "in the
hallway" FN-Location)))
       (stype declarative))

(manual 3 "Sandra went back to the hallway."
       (target-verb go)
       (frame Self_motion)
       (pos-tag ())
       (syntax (NP<ext> V AVP<dep>))
       (chunks ((NP<ext> "Sandra" FN-Self_mover) (verb "went" target) (AVP<dep> "back
to the hallway" FN-Goal)))
       (stype declarative))

(manual 4 "John went back to the garden."
       (target-verb go)
       (frame Self_motion)
       (pos-tag ())
       (syntax (NP<ext> V AVP<dep>))
       (chunks ((NP<ext> "John" FN-Self_mover) (verb "went" target) (AVP<dep> "back to
the garden" FN-Goal)))
       (stype declarative))

(manual 5 "Daniel went back to the kitchen."
       (target-verb go)
       (frame Self_motion)
       (pos-tag ())
       (syntax (NP<ext> V AVP<dep>))
       (chunks ((NP<ext> "Daniel" FN-Self_mover) (verb "went" target) (AVP<dep> "back
to the kitchen" FN-Goal)))
       (stype declarative))

(manual 6 "Daniel grabbed the milk there."
       (target-verb grab)
       (frame Taking)
       (pos-tag ())
       (synatx (NP<ext> V NP<obj> AVP<dep>))
```

```
	(chunks ((NP<ext> "Daniel" FN-Agent) (verb "grabbed" target) (NP<obj> "the
milk" FN-Theme) (AVP<dep> "there" FN-Source)))
	(stype declarative))


(manual 7 "Mary took the apple there."
	(target-verb take)
	(frame Taking)
	(pos-tag ())
	(synatx (NP<ext> V NP<obj> AVP<dep>))
	(chunks ((NP<ext> "Mary" FN-Agent) (verb "took" target) (NP<obj> "the apple"
FN-Theme) (AVP<dep> "there" FN-Source)))
	(stype declarative))

(manual 8 "John got the football there."
	(target-verb get)
	(frame Getting)
	(pos-tag ())
	(synatx (NP<ext> V NP<obj> AVP<dep>))
	(chunks ((NP<ext> "John" FN-Recipient) (verb "got" target) (NP<obj> "the
football" FN-Theme) (AVP<dep> "there" FN-Source)))
	(stype declarative))

(manual 9 "John got the milk there."
	(target-verb get)
	(frame Getting)
	(pos-tag ())
	(synatx (NP<ext> V NP<obj> AVP<dep>))
	(chunks ((NP<ext> "John" FN-Recipient) (verb "got" target) (NP<obj> "the milk"
FN-Theme) (AVP<dep> "there" FN-Source)))
	(stype declarative))

(manual 10 "Daniel got the milk there."
	(target-verb get)
	(frame Getting)
	(pos-tag ())
	(synatx (NP<ext> V NP<obj> AVP<dep>))
	(chunks ((NP<ext> "Daniel" FN-Recipient) (verb "got" target) (NP<obj> "the
milk" FN-Theme) (AVP<dep> "there" FN-Source)))
	(stype declarative))

;;;EXAMPLES BABI TASK 2

(manual 11 "John put down the apple."
	(target-verb put)
	(frame Placing)
	(pos-tag ())
	(synatx (NP<ext> V PRT<dep> NP<Obj>))
	(chunks ((NP<ext> "John" FN-Agent) (verb "put" target) (PRT<dep> "down" FN-
Manner) (NP<obj> "the apple" FN-Theme)))
	(stype declarative))

(manual 12 "Daniel put down the football."
	(target-verb put)
	(frame Placing)
	(pos-tag ())
	(synatx (NP<ext> V PRT<dep> NP<Obj>))
	(chunks ((NP<ext> "Daniel" FN-Agent) (verb "put" target) (PRT<dep> "down" FN-
Manner) (NP<obj> "the football" FN-Theme)))
	(stype declarative))
```

```
(manual 13 "John put down the milk there."
       (target-verb put)
       (frame Placing)
       (pos-tag ())
       (synatx (NP<ext> V PRT<dep> NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "John" FN-Agent) (verb "put" target) (PRT<dep> "down" FN-
Manner) (NP<obj> "the apple" FN-Theme) (AVP<dep> "there" FN-Goal) ))
       (stype declarative))

(manual 14 "Sandra put down the football there."
       (target-verb put)
       (frame Placing)
       (pos-tag ())
       (synatx (NP<ext> V PRT<dep> NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "Sandra" FN-Agent) (verb "put" target) (PRT<dep> "down" FN-
Manner) (NP<obj> "the football" FN-Theme) (AVP<dep> "there" FN-Goal) ))
       (stype declarative))

(manual 15 "Daniel picked up the apple there."
       (target-verb pick)
       (frame Taking)
       (pos-tag ())
       (synatx (NP<ext> V PRT<dep> NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "Daniel" FN-Agent) (verb "picked" target) (PRT<dep> "up" FN-
Manner) (NP<obj> "the apple" FN-Theme) (AVP<dep> "there" FN-Source) ))
       (stype declarative))

(manual 16 "Sandra picked up the football there."
       (target-verb pick)
       (frame Taking)
       (pos-tag ())
       (synatx (NP<ext> V PRT<dep> NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "Sandra" FN-Agent) (verb "picked" target) (PRT<dep> "up" FN-
Manner) (NP<obj> "the football" FN-Theme) (AVP<dep> "there" FN-Source) ))
       (stype declarative))

(manual 17 "John grabbed the football there."
       (target-verb grab)
       (frame Taking)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "John" FN-Agent) (verb "grabbed" target)  (NP<obj> "the
football" FN-Theme) (AVP<dep> "there" FN-Source) ))
       (stype declarative))

(manual 18 "John grabbed the apple there."
       (target-verb grab)
       (frame Taking)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "John" FN-Agent) (verb "grabbed" target)  (NP<obj> "the
apple" FN-Theme) (AVP<dep> "there" FN-Source) ))
       (stype declarative))

;;;Examples Task 3

(manual 19 "John took the apple."
       (target-verb take)
       (frame Taking)
```

```
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "John" FN-Agent) (verb "grabbed" target)  (NP<obj> "the
apple" FN-Theme)))
       (stype declarative))

(manual 20 "Daniel grabbed the football."
       (target-verb grab)
       (frame Taking)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "Daniel" FN-Agent) (verb "grabbed" target)  (NP<obj> "the
football" FN-Theme)))
       (stype declarative))

(manual 21 "Mary left the football."
       (target-verb leave)
       (frame Abandonment)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj>))
       (chunks ((NP<ext> "Mary" FN-Agent) (verb "left" target)  (NP<obj> "the
football" FN-Theme)))
       (stype declarative))

(manual 22 "Mary left the apple."
       (target-verb leave)
       (frame Abandonment)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj>))
       (chunks ((NP<ext> "Mary" FN-Agent) (verb "left" target)  (NP<obj> "Apple" FN-
Theme)))
       (stype declarative))

(manual 23 "Mary dropped the football."
       (target-verb drop)
       (frame Cause_Motion)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj>))
       (chunks ((NP<ext> "Mary" FN-Agent) (verb "dropped" target)  (NP<obj> "the
football" FN-Theme)))
       (stype declarative))

(manual 24 "Daniel dropped the football."
       (target-verb drop)
       (frame Cause_Motion)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj>))
       (chunks ((NP<ext> "Daniel" FN-Agent) (verb "dropped" target)  (NP<obj> "the
football" FN-Theme)))
       (stype declarative))


(manual 25 "Daniel dropped the football there."
       (target-verb drop)
       (frame Cause_Motion)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "Daniel" FN-Agent) (verb "dropped" target)  (NP<obj> "the
football" FN-Theme) (AVP<dep> "there" FN-Goal) ))
       (stype declarative))
```

```
(manual 26 "John dropped the apple there."
       (target-verb drop)
       (frame Cause_Motion)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "John" FN-Agent) (verb "dropped" target)  (NP<obj> "the
apple" FN-Theme) (AVP<dep> "there" FN-Goal) ))
       (stype declarative))

(manual 27 "John dropped the football there."
       (target-verb drop)
       (frame Cause_Motion)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> AVP<dep>))
       (chunks ((NP<ext> "John" FN-Agent) (verb "dropped" target)  (NP<obj> "the
football" FN-Theme) (AVP<dep> "there" FN-Goal) ))
       (stype declarative))


;;;Examples Task 5
(manual 28 "Bill gave the football to Fred."
       (target-verb give)
       (frame Giving)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> PP[to]<dep>))
       (chunks ((NP<ext> "Bill" FN-Donor) (verb "gave" target) (NP<obj> "the football"
FN-Theme) (PP[to]<dep> "to Fred" FN-Recipient)))
       (stype declarative))

(manual 29 "Fred handed the football to Bill."
       (target-verb hand)
       (frame Giving)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> PP[to]<dep>))
       (chunks ((NP<ext> "Fred" FN-Donor) (verb "handed" target) (NP<obj> "the
football" FN-Theme) (PP[to]<dep> "to Bill." FN-Recipient)))
       (stype declarative))

(manual 30 "Jeff handed the apple to Bill."
       (target-verb hand)
       (frame Giving)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> PP[to]<dep>))
       (chunks ((NP<ext> "Jeff" FN-Donor) (verb "handed" target) (NP<obj> "the apple"
FN-Theme) (PP[to]<dep> "to Bill." FN-Recipient)))
       (stype declarative))

(manual 31 "Jeff passed the milk to Bill."
       (target-verb pass)
       (frame Passing)
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> PP[to]<dep>))
       (chunks ((NP<ext> "Jeff" FN-Agent) (verb "passed" target) (NP<obj> "the milk"
FN-Theme) (PP[to]<dep> "to Bill." FN-Recipient)))
       (stype declarative))

(manual 32 "Bill passed the apple to Jeff."
       (target-verb pass)
       (frame Passing)
```

```
       (pos-tag ())
       (synatx (NP<ext> V NP<Obj> PP[to]<dep>))
       (chunks ((NP<ext> "Bill" FN-Agent) (verb "passed" target) (NP<obj> "the apple"
FN-Theme) (PP[to]<dep> "to Jeff." FN-Recipient)))
       (stype declarative))

(manual 33 "Sandra is in the office."
       (target-verb be)
       (frame Being_located)
       (pos-tag ())
       (syntax (NP<ext> V PP[in]<dep>))
       (chunks ((NP<ext> "Sandra" FN-Theme) (verb "is" target) (PP[in]<dep> "in the
office" FN-Location)))
       (stype declarative))
```

Appendix D: bAbI Rules

Below are the manual rules used to answer questions from the bAbI corpus. Results are presented in Chapter 8.

```
(<== (MovesTo ?event ?person ?place)
     (moverPred ?event ?person)
     (to-Generic ?event ?place))

(<== (moverPred ?event ?person)
     (performedBy ?event ?person))
(<== (moverPred ?event ?person)
     (objectMoving ?event ?person))

;;;;;;;;;;;;;;; Person Rules

;; Rule defining where a person currently is.
;; More than one MovesTo, find the MovesTo that has no other MovesTo after it
;;
(<== (isCurrentlyIn ?person ?place)
     (MovesTo ?event ?person ?place)
     (inferenceOnly (uninferredSentence (movesAfter ?event ?person ?place ?event2))))

(<== (movesAfter ?event ?person ?place ?event2)
     (MovesTo ?event2 ?person ?diff-place)
     (different ?event ?event2)
     (eventNumber ?event ?num1)
     (eventNumber ?event2 ?num2)
     (lessThan ?num1 ?num2))
     ;;;(cacheComplete (happensAfter ?event2 ?event)))


;;;;;;;;;;;;Person and Object Rules
(<== (obtainedObject ?event ?person ?object)
     (pickedUpObject ?event ?person ?object))

(<== (obtainedObject ?event ?person ?object)
     (giveTo ?event ?orig ?person ?object))

(<== (obtainedObject ?event ?person ?object)
     (gotObject ?event ?person ?object))

(<== (gotObject ?event ?person ?object)
     (objectOfPossessionTransfer ?event ?object)
     (toPossessor ?event ?person)
     (unknownSentence (from-Generic ?event ?place)))

(<== (lostObject ?event ?person ?object)
     (droppedObject ?event ?person ?object))
(<== (lostObject ?event ?person ?object)
     (giveTo ?event ?person ?anotherPerson ?object))

(<== (pickedUpObject ?event ?person ?object)
     (objectTaken ?event ?object)
     (performedBy ?event ?person))
```

```
(<== (droppedObject ?event ?person ?object)
     (discardPred ?event ?object)
     (performedBy ?event ?person))

(<== (droppedObject ?event ?person ?object)
     (isa ?event Cause_motion)
     (performedBy ?event ?person)
     (objectActedOn ?event ?object))

(<== (discardPred ?event ?object)
     (objectRemoved ?event ?object))
(<== (discardPred ?event ?object)
     (objectPlaced ?event ?object))
(<== (discardPred ?event ?object)
     (objectOfPossessionTransfer ?event ?object))

(<== (giveTo ?event ?place ?anotherPerson ?object)
     (transferObjPred ?event ?object)
     (toPossessor ?event ?anotherPerson)
     (fromPred ?event ?place))

(<== (fromPred ?event ?place)
     (from-Generic ?event ?place))

(<== (fromPred ?event ?place)
     (fromPossessor ?event ?place))

(<== (fromPred ?event ?person)
     (performedBy ?event ?person))

(<== (transferObjPred ?event ?object)
     (objectGiven ?event ?object))
(<== (transferObjPred ?event ?object)
     (objectOfPossessionTransfer ?event ?object))
(<== (transferObjPred ?event ?object)
     (objectActedOn ?event ?object))

;; Second case, person obtained the object and did not subsequently drop or give it
(<== (isHoldingObject ?person ?object)
     (obtainedObject ?event ?person ?object)
     (inferenceOnly (uninferredSentence (lostAfter ?event ?person ?object ?event2))))

(<== (lostAfter ?event ?person ?object ?event2)
     (lostObject ?event2 ?person ?object)
     (different ?event ?event2)
     (eventNumber ?event ?num)
     (eventNumber ?event2 ?num2)
     (lessThan ?num ?num2))

;;;;;;;;;;;;;;;;;;;;;;Object Rules

;; First case, someone is currently holding the object
(<== (isObjectCurrentlyIn ?object ?place)
     (inferenceOnly (isHoldingObject ?person ?object))
     (inferenceOnly (isCurrentlyIn ?person ?place)))

;; Second case, nobody is holding the object, find the last place it was dropped
;; find the location of the person who dropped it at that time
(<== (isObjectCurrentlyIn ?object ?place)
```

```
     (uninferredSentence (inferenceOnly (isHoldingObject ?person ?object)))
     (lostObject ?event ?person ?object)
     (inferenceOnly (uninferredSentence (lostAfter ?event ?person ?object ?event2)))
     (MovesTo ?event2 ?person ?place)
     ;;; MovesTo before the loss event
     (eventNumber ?event2 ?num2)
     (eventNumber ?event ?num)
     (lessThan ?num2 ?num)
     (uninferredSentence (MoveHappensBetween ?event2 ?event ?person)))

;;;happens after 2 before event
(<== (MoveHappensBetween ?event2 ?event ?person)
     (MovesTo ?event3 ?person ?place)
     (different ?event3 ?event2)
     (different ?event3 ?event)
     (eventNumber ?event ?num)
     (eventNumber ?event2 ?num2)
     (eventNumber ?event3 ?num3)
     (lessThan ?num3 ?num)
     (lessThan ?num2 ?num3))

(<== (lostBetween ?e1 ?person ?object ?e2)
     (lostObject ?e3 ?person ?object)
     (eventNumber ?e1 ?num)
     (eventNumber ?e2 ?num2)
     (eventNumber ?e3 ?num3)
     (different ?e3 ?e2)
     (different ?e3 ?e1)
     (lessThan ?num3 ?num)
     (lessThan ?num2 ?num3))
;; For the query : Where was the apple before the bathroom?
;; Get isCurrentlyIn
;;
;; If someone moves to a place while holding an object, the object was in the
;; last place that they were.
;; Objects are only moved by people.
(<== (wasInPlaceBefore ?object ?place ?placeBefore)
     (MovesTo ?move-event ?person ?place)
     (isHoldingObjectAtTime ?move-event ?person ?object ?obtained-event)
     (MovesTo ?move-event2 ?person ?place2)
     (different ?place ?place2)
     (eventNumber ?move-event2 ?num2)
     (eventNumber ?move-event ?num)
     (lessThan ?num2 ?num)
     (uninferredSentence (MoveHappensBetween ?move-event2 ?move-event ?person))
     (unifies ?place2 ?placeBefore))

;;X is holding Y at event E
;; if, in an event before E x picked-up Obj
;; if, since event has not dropped obj
(<== (isHoldingObjectAtTime ?time ?person ?object ?obtained-event)
     (obtainedObject ?prior-event ?person ?object)
     (eventNumber ?prior-event ?num1)
     (eventNumber ?time ?num2)
     (lessThan ?num1 ?num2)
     (uninferredSentence (lostBetween ?time ?person ?object ?prior-event))
     (unifies ?prior-event ?obtained-event))

;;;;;;;;;;;;;;;;;;Last give Rules
```

```
(<== (lastGiveTo ?event ?give-person ?receive-person ?give-object)
     (giveTo ?event ?give-person ?receive-person ?give-object)
     (uninferredSentence (givesAfter ?event ?give-object ?event2)))

(<== (givesAfter event ?give-object ?event2)
     (giveTo ?event2 ?give-person ?receive-person ?give-object)
     (eventNumber ?event ?num)
     (eventNumber ?event2 ?num2)
     (different ?event ?event2)
     (lessThan ?num ?num2))
```