A Proposal for Incorporating Analogically Learned Constructions in a Feature Based Parsing Framework

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Abstract

Structure mapping theory is a computational model of analogy that has recently been used to learn FrameNet constructions from a small corpus of annotated text. This paper proposes an approach that uses constructions learned in this way to bootstrap the performance of an existing natural language understanding system with a more traditional feature-based chart parser, EA NLU. We examine the benefits of analogically learned constructions as well as the challenges involved in applying these generalizations to novel text.

Introduction

Construction grammar approaches share the principle that the fundamental building blocks of language are pairs of form and meaning called constructions (Goldberg, 2003). This runs counter to traditional approaches that treat language interpretation as a pipeline with discrete levels of analysis. Combining form and function allows construction grammar to explain many linguistic phenomena previously treated as peripheral such as partially productive idioms and other unusual linguistic patterns (e.g. Cullicover & Jackendoff, 1999). Furthermore, construction grammar provides a powerful tool for addressing linguistic creativity such as the use of denominal verbs (Kaschak & Glenberg, 2000).

Constructionist approaches typically view syntax as learnable without recourse to language-specific learning mechanisms (Goldberg, 2003). Tomasello (2003) has proposed that constructions are learned by generalizing from individual examples on a case by case basis using analogy (see also Namy & Gentner, 2006).

Indeed, there is evidence that comparison supports language learning and relational extraction in children. As an example, Christie & Gentner (2010) found that comparison improved relational abstraction in children as evidenced by the extension of novel spatial labels to new situations. Further, Namy & Gentner (2002) found that common labels can invite comparison. This facilitated children forming categories based on relational rather than perceptual similarities.

Recently, McFate & Forbus (2016) demonstrated that a computational model of analogical generalization could be used to generalize FrameNet (Fillmore *et al*, 2001) annotated sentences into constructions, and that constructions learned in this way could be applied to novel denominal verb sentences to produce the intended semantics.

In this paper, we propose that augmenting a chart parser with analogically learned constructions can potentially broaden coverage and increase adaptability. We start by summarizing the constructionist approach to argument structure. We continue with a description of the structure mapping theory of analogy and its computational implementation in the structure mapping engine (SME). We further examine how the SAGE model of analogical generalization, which uses SME, can be used to learn pairings of argument structure and semantics. We then propose a hybrid system that uses the output of a traditional feature-based semantic chart parser and analogical generalization to bootstrap the parser's performance on novel constructions. We conclude with an analysis of the challenges of learning constructions in this way, as well as a discussion of related work.

Background

Constructions

We take a construction to be a pairing of form and meaning where some aspect of the form or the meaning is not predictable from either its component parts or from another existing construction (Goldberg, 1995). Defined thusly, constructions capture all levels of linguistic analysis from morphemes to phrasal patterns. There is no strict distinction between words and syntax. We specifically

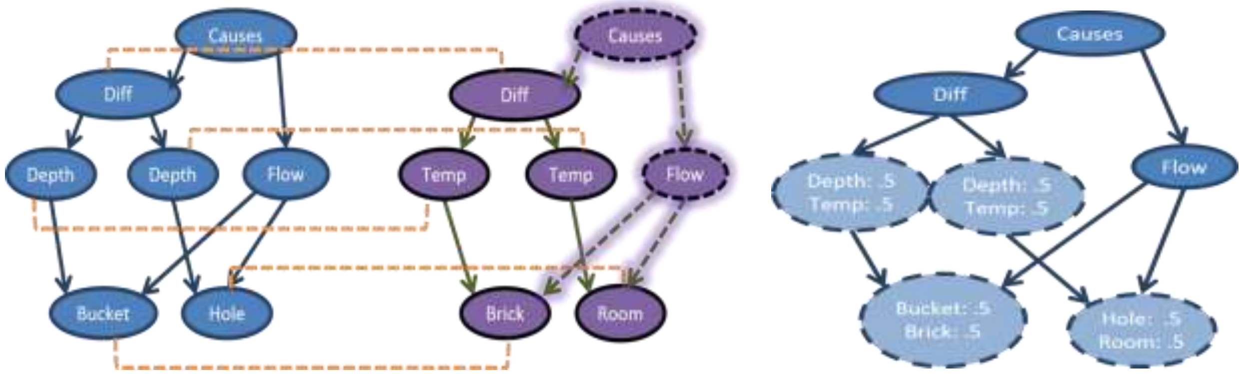

Figure 1: On the left-hand side, SME matches a predicate description of water flow from a bucket to a partial model of heat-flow from a brick to a room. The cause of the flow is the candidate inference (dashed lines). The right-hand side shows the resulting generalization of these two scenarios into a single prototypical flow event.

focus on argument structure constructions which define clauses in a language. An example would be the double object construction (NP-V-NP-NP).

Goldberg (1995;2006) proposes that argument structure constructions convey semantics and differentiates between semantic roles associated with the argument structure construction (*argument roles*) and those associated with the verb (*participant roles*). Both lexical items and argument structure constructions have *profiled* or salient roles. Which roles a verb profiles are lexically specified, while the profiled roles of the phrasal construction correspond to direct grammatical relations (SUBJ, OBJ_1, or OBJ_2). Interpretation of a verb in a construction then involves the fusion of these two sets of roles. Goldberg (1995;2006) argues that this fusion process obeys two primary principles.

- *The semantic coherence principle* allows roles to fuse only if one of the roles is an instance of the other.
- *The correspondence principle* enforces that, by default, profiled participant roles are fused with profiled argument roles. An exception to this rule would be verbs with three profiled roles, which allow one to be realized obliquely.

The reverse of the correspondence principle does not hold in that not all profiled argument roles need a profiled participant role. Thus the construction can contribute roles. As an example, consider the double object usage of the verb *kick* (e.g. "John kicked Mary the ball.") The double object is frequently analyzed as having the semantics of a transfer event with the argument roles of `agent`, `recipient`, and `patient` which align with the subject, object, and second object of the clause. *Kick* on the other hand has two profiled participant roles, a `kicker` and `kicked-object`. Semantically, the `kicker` is a subtype of `agent` and so the two can align. Similarly `kicked-object` is a sub-type of `patient`. This leaves the meaning of the first object to be contributed by the construction itself. The result is an interpretation where John transferred the ball to Mary through the means of a kick.

One important question is how argument roles become associated with phrasal constructions. One possibility is that they are generalized from individual item-specific examples through analogy. Next, we examine the structure mapping theory of analogy and how analogical generalization could result in argument roles.

Structure Mapping Theory & SME

Gentner's (1983) structure mapping theory views comparison as a process of alignment between hierarchical structured representations and proposes several constraints on the alignment process.

- *1-1 Mapping* limits each element in the base of a mapping to a single element in the target.
- *Parallel connectivity* ensures that if two elements are aligned, their children are aligned as well.
- *Tiered Identicality* imposes a preference for mapping between identical relations which prevents structurally similar but semantically anomalous mappings. Non-identical functions can match provided they are supported by larger shared structure and share an ontological parent (Falkenhainer, 1987).

Finally, the *systematicity* bias ensures a preference for mappings that preserve shared higher-order structure (e.g. causal structure). Clement & Gentner (1991) demonstrated this systematicity preference in humans with both match selection and prediction tasks. Furthermore, structure mapping proposes that aligned structure in the base can be projected onto the target as a form of inference.

As an example, consider the mapping in the left-hand side of Figure 1 which holds between a description of water flow and one of heat flow. In the base, on the left, a bucket containing water has a hole. A difference in the depth of the water causes the water to flow through the hole. Now consider the target, on the right, where a difference in temperature exists between a hot brick and a cool room. The difference relationships match and their children can be aligned. SME hypothesizes that the temperature difference will cause a flow process, which it does (heat flow).

Structure mapping theory has been implemented computationally in Forbus et al's (2016) structure mapping engine (SME). SME compares a base and target case of predicate calculus statements and generates a mapping, candidate inferences, and structural evaluation score.

Alignment proceeds in three phases. First, SME creates a 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. Candidate inferences can be projected based on aligned structure.

MAC/FAC and SAGE

SME provides the matching algorithm for the second stage of MAC/FAC, a model of analogical reminding (Forbus *et al*, 1995). MAC/FAC (which stands for many are called but few are chosen) is a model of recall that uses a cheap preliminary feature-vector match to return a pool of possible retrievals which are then evaluated by SME. This two phase process simulates human performance, demonstrating a retrieval bias towards feature-based retrieval but a preference for analogically related stories (Gentner *et* al, 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*, 2016). Given a new example and a library of existing examples, SAGE compares it to the existing examples using MAC/FAC. If over threshold, the new example is aligned with and added to an existing case to create a generalization with a probability distribution governing the specific attributes and relationships. Over time, SAGE produces schema-like constructs that still retain high-probability attributes. If SAGE were to generalize the cases in the left-hand side of Figure 1, it would result in the generalization on the right-hand side of Figure 1. It indicates that a difference in two quantities of the same type (depth or temperature) causes a flow process between the two entities that possess those quantities and provides a probability distribution representing what those entities are likely to be.

Analogical Learning of Argument Roles

McFate & Forbus (2016) demonstrate that SAGE can be used to generalize pairings of syntactic valence patterns and frame-semantics. These generalizations can be applied to novel sentences to produce constructional semantics by candidate inference.

Representations

McFate & Forbus (2016) generalize over sentences that were manually annotated in the style of Fillmore *et al*'s (2001) FrameNet. FrameNet is a lexical database that defines conceptual frames and their evoking lexical items. They further annotate how the roles of the frame (called frame elements) are instantiated in individual syntactic patterns (called valence patterns).

For example, the word *send* evokes the `Sending` frame which has required and optional frame elements such as a `Sender` and `Recipient`. The frame can be realized in a double object valence pattern as shown in example 1:

1) I saw John send the girl the letter.

With *send* as the target, the NP "John" would be annotated as the `Sender` of a giving frame. The NP, "*the girl*", would be the `Recipient`, and "*the letter*" would be the `Theme`. This annotation format only identifies the arguments to the target, ignoring other aspects of the sentence. The first NP in example 1 would be represented as follows, with explicit representation of the words in the constituent, the role relative to the target verb, and its argument order in the sentence (McFate & Forbus, 2016).

```
(isa NP1 NP)
(FE-Sender "send" NP1)
(wordMemberOf NP1 "John")
(loc1 sentence1 NP1)
```

Generalization

McFate & Forbus (2016) demonstrate that SAGE, operating over these forms, can create generalized pairings of syntactic structure and semantic roles. As an example, consider the generalization of the double object construction in Figure 2.

Two double object constructions (1 and 2) are represented with their FrameNet valence pattern and semantic annotation. SAGE creates a new generalization. The predicates are consistent, but the entities are turned into generalized entities where their instantiation is governed by a probability distribution. When a new example (3) comes in, its structure is slightly different as there is no explicit `donor`. Since it does not structurally match, it becomes a new ungeneralized example.

When a novel double object construction is given to the system without semantic annotation, SAGE is able to map to the generalization based on syntactic structure and apply the semantics of the double object as candidate inferences.

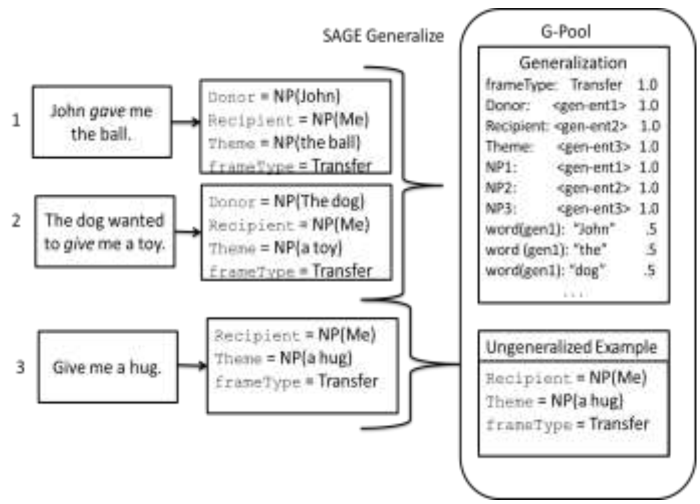

Figure 2: Construction Generalization (McFate & Forbus, 2016)

McFate & Forbus (2016) used this technique to interpret novel denominal verbs (e.g. Tom *crutched* Lyn the apple.) from Kaschak & Glenberg's (2000) denominal verb study. An example is shown in figure 3:

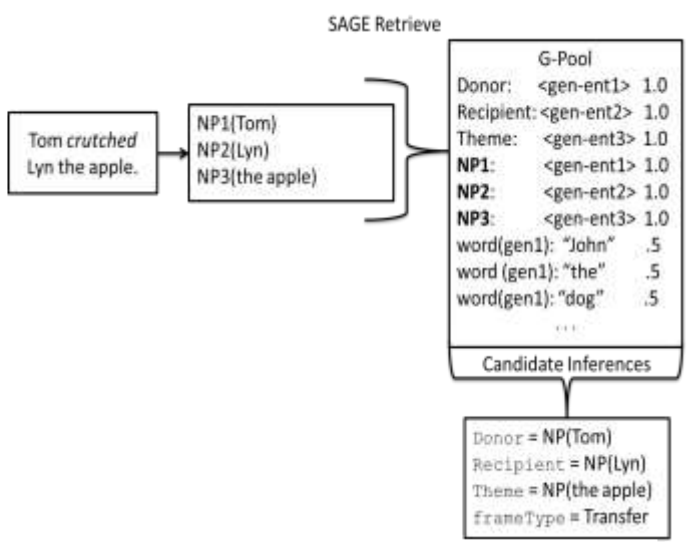

Figure 3: Construction Retrieval (McFate & Forbus, 2016)

One issue that naturally arises is that training cases may contain diverse verb-specific participant roles that align with the same argument structure. For example, many diverse verbs can appear in the intransitive construction.

In terms of acquisition, the linguistic environment itself might actually assist with this challenge. As Goldberg *et al*, (2004) note, individual constructions in child directed speech are frequently dominated by a single prototypical verb. That said, this approach generalizes across such diversity in one of two ways. One approach is to treat the potential predicates as a distribution and select the most likely, though a more sophisticated statistical approach is possible given that SAGE retains individual cases that support predicates in the generalization (McFate & Forbus, 2016). An alternative approach would be to look for a common shared ancestor and use that predicate for the argument role.

EA NLU

The Explanation Agent NLU system (Tomai & Forbus, 2009) is based on Allen's (1994) bottom-up feature-based chart parser. Rules in EA are augmented with features which constrain the kinds of constituents that can satisfy the right-side of a rule. An example feature would be agreement (singular vs plural). These features initially come from lexical entries for the words and are accumulated as the parser builds larger phrases. Furthermore, individual rules can add features to phrases. As an example, see Figure 4 where the subject of the sentence is added by a phrase-level grammar rule. It operates over Grishman *et al*'s (1993) COMLEX lexicon which includes lexical entries with annotated features.

One of the features in the grammar is a semantic field which consists of neo-Davidsonian semantic templates from the Cyc[1] ontology. These templates tie argument-structure roles (e.g. subject and object) to their semantic role in a particular construction. They are linked to individual lexical units and thus are verb specific. As an example, consider the double object entry for *give*:

```
(verbSemTrans Give-TheWord 0 Ditransitive
      (and (objectGiven :ACTION :OBJECT)
           (isa :ACTION GivingSomething)
           (giver :ACTION :SUBJECT)
           (givee :ACTION :OBLIQUE-OBJECT)))
```

After building a syntactic parse, the grammatical keywords in the frame are replaced with their referents. For example, "The boy gave the dog a ball" would end up as:

```
(and (isa give GivingEvent)
     (giver give boy)
     (give give dog)
     (objectGiven give ball))
```

Semantic ambiguity is represented in EA using disjunctive choice-sets. If "the apple" were added to the above example, it would have one option for a fruit and one for an Apple computer. Note that regardless of which is chosen, we don't need to create multiple versions for each possible noun assignment. The token *apple* is given, and it is a fruit or a computer.

This approach contrasts with the constructionist approach discussed in previous sections. Whereas a constructionist account seeks a tight integration between syntax and frame semantics, EA NLU relies on verbs to specify how semantic roles are assigned. That said, we

[1] http://www.cyc.com/platform/researchcyc/

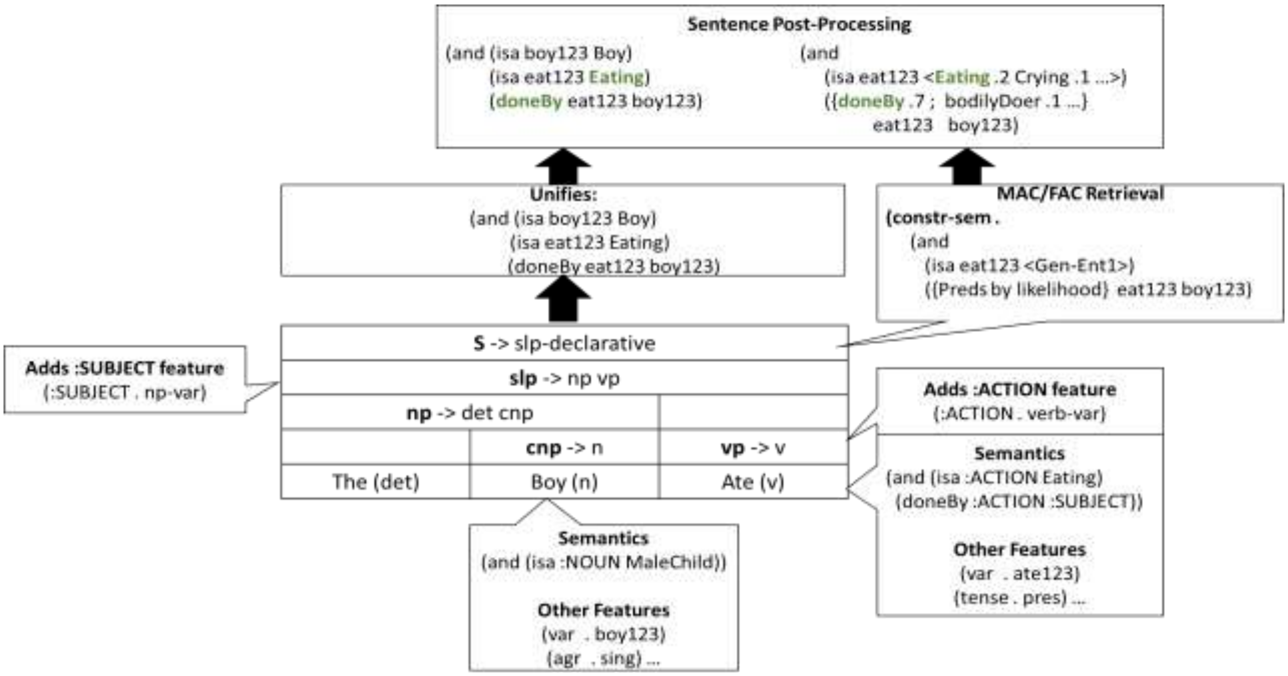

Figure 4: System Overview

believe that more traditional parsers like EA NLU could benefit from the incorporation of analogically learned constructions. We also propose that the output of traditional parsers could be used to bootstrap construction learning. We discuss a proposed hybrid system in the following section.

Proposed Approach

This paper proposes a method for using analogically learned constructions to enrich semantic interpretations in a more traditional parser like EA NLU. We propose a bootstrapping model whereby output from the semantic parser provides examples for generalization. The resulting generalizations are retrieved and applied using MAC/FAC during parsing to enrich the default semantic representations.

Training

For training, the system requires semantically parsed sentences. In EA NLU there are two ways to automatically disambiguate parses and semantics. One is with a series of domain-independent heuristics demonstrated in Barbella & Forbus (2013). Another is through the use of narrative functions which provide top-down guidance for individual reading domains (McFate *et al*, 2014). Alternatively, structure mapping generally requires very few training examples (see Kuehne *et al*, 2000; Liang & Forbus 2014), thus it may be feasible to manually disambiguate stimuli as a part of an active learning framework.

During training, cases from parsed examples would be fed to SAGE to form construction generalizations. Cases consist of a syntactic representation of the target clause and a neo-Davidsonian semantic representation. One possibility is to represent the syntax by extracting FrameNet style valence patterns from complete parses. However, a better approach may be to represent complete phrase-structure parses, treating each phrase as a functional predicate which results in a phrase and takes phrases as its arguments e.g.

```
(SentenceFn
  (NPFn
    (detFn "the") (nounFn "dog"))
  (VPFn
    (verbFn "ate")))
```

The challenge with this kind of representation is that SME requires its predicates to have the same number of arguments in order to match. Otherwise, the match would violate parallel connectivity. Thus, for example, a noun phrase with a determiner and one without would not match.

Preliminary experiments with this representation have enforced all phrases to be binary predicates, filling in empty slots with null variables, though this is obviously not a long-term solution.

Parsing

Once the system has generalized examples, it will use MAC/FAC to retrieve constructional semantics online during the parsing procedure. First it will retrieve constructions at the sentence-level, though in principal it is possible to learn semantics associated with smaller units of syntax. We propose that, just as in McFate & Forbus (2016) the retrieved construction can provide semantics via candidate inferences. We further propose that said semantics can be incorporated into the parse as a new feature, just as the parser currently adds features to phrase-level nodes. Figure 4 provides an overview of the system.

The input, “The boy ate.”, is tagged with potential parts of speech and input into the chart. From left to right, the parser extends the chart with completed constituents by applying feature-based rules. As described above, the assignment of semantic roles comes from Cyc lexical templates. They unify with keyword features (e.g. :SUBJECT, :OBJECT) which are inserted by grammar rules. For example, the neo-Davidsonian event, the :ACTION, is bound when constructing the verb phrase, while the :SUBJECT is bound at the sentence level phrase.

At the sentence level phrase, the parse so far is translated into its predicate representation and used as a probe-case for MAC/FAC which retrieves and applies the generalized construction by analogy. The semantic candidate inferences get added as a new feature value.

When the parse is complete, the constructional semantics will serve two roles. The first is that they will be used to constrain anomalous parses by providing semantic restrictions on the types of predicates allowed in a construction. The second is that constructional semantics can provide enriched semantics for creative uses of language. As an example, consider a sentence such as “He kicked her the ball.”

Cyc does not have a template for a double object usage of *kick*. Instead, EA produces the following semantics, leaving the role of the recipient unaccounted for:

```
(and (isa kick KickingEvent)
   (performedBy kick He)
   (objectActedOn kick ball)
```

However, the double object phrase structure would result in the retrieval of the double object construction which provides the following additional labels.

```
(and (giver kick He)
     (objectGiven kick ball)
     (givee kick her))
```

This allows for a more complete representation of the kicking event. Furthermore, the same technique can be used to handle novel verbs occurring in wild text.

Challenges

There are several challenges that we will have to tackle in adopting this approach more broadly. One challenge will be cases of constructional polysemy. As Goldberg (1995) argues, constructions share a set of related senses rather than one abstract sense. For example, the sentences in (2) are both ditransitive, but while (2a) implies that the recipient received the object no such implication holds for (2b) as evidenced by (2c,d).

2) a. Bill gave Mary a cake.
   b. Bill baked Mary a cake.
   c. ? Bill gave Mary a cake, but she didn’t get it.
   d. Bill baked Mary a cake, but she didn’t get it.

As described above, construction learning by analogy would result in a single abstract case. It is possible that if the implication were explicitly encoded it would form a separate generalization and thus a separate construction, but this does not fully capture the relationship between the generic sense and creation-verb specific sense of the construction.

The lack of relationship between generalizations also affects decisions regarding oblique arguments. How should one generalize two sentences like “John ate on a boat.” and “John ate with a fork.”? At a coarse level they share the same syntactic parse, and so one option is to generalize one NP-V-PP construction with a probability distribution over predicates that fulfill the oblique slot (e.g. `Place` vs. `Instrument`). Again, SAGE retains the initial cases that support each predicate and so similarity between the target construction and the case union of sentences that support each predicate could be used to determine which predicates apply. Alternatively, with a higher generalization threshold, SAGE would create multiple NP-V-PP generalizations with different PP predicates and prepositions (*with* vs *on*). Though again, in this case there would be no relation between prepositional constructions. Future work should explore hierarchical representations that allow constructions to inherit from more general parents. Liang & Forbus (2014) extended SAGE to create hierarchical concepts through agglomerative hierarchical clustering. The downside of this approach is that currently hierarchical generalization is a batch process rather than incremental.

Related Work

Our proposed system is not a construction-grammar parser per se. Rather, it will use constructions to improve an existing parser. Thus this approach could be applied to work in statistical semantic parsing (e.g. Das *et al’s* (2014) SEMAFOR). Our generalization mechanism operates over structured representations, which dovetails nicely with semantic parsing research more broadly.

Connor *et al*’s (2008) Baby SRL system was trained over annotated child directed speech and was able to correctly classify transitive agent and patient arguments. Their approach differs from ours in that they use word-level representations, though they propose that their approach could operate at the phrase level as well.

Livingston & Riesbeck’s Machine Reader uses an approach called direct memory access parsing (DMAP) (see also Riesbeck, 1986). The DMAP approach treats reading as the recognition of larger and larger conceptual structures in memory. This involves the unification of partially filled semantic patterns (e.g. Change-Event = "<variable> *are* <change>"). Analogical generalization could play a role in both the creation and retrieval of these patterns, though unlike our current approach DMAP specifically eschews argument structure.

There have been several computational approaches to construction grammar. For example, Schneider & Witbrock's (2015) semantic construction grammar uses partially filed semantic templates. In this approach, parsing can be thought of as analogous to filling partially-filled idioms. It seems likely that analogical generalization could play a role in learning the abstract semantic categories of these templates.

Bergen *et al*'s (2000) embodied construction grammar (ECG) proposes that constructions link linguistic form to conceptual schemas which specify parameters for simulation. This in turn results in inference and response. We don't incorporate simulation into our model of semantics, though it is possible that abstract conceptual schemas could be learned through generalization of previously seen situations.

Finally, Steels (2011) Fluid Construction Grammar (FCG) represents constructions as bidirectional feature-based rules. While our approach uses a feature-based grammar, it is not reversible and semantics are, for the most part, lexicalized. However, given their rich structure, FCG representations seem a promising formalism for learning by analogical generalization.

Conclusions

This paper has summarized how the SAGE model of analogical generalization can be used to create argument structure constructions from individual examples. We further propose a hybrid bootstrapping approach that uses an existing semantic parser to learn constructions and apply them to novel stimuli. While much work remains to be done, we believe this line of investigation to be promising.

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