Analogical Generalization and Retrieval for Denominal Verb Interpretation

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Abstract

The creativity of natural language poses a significant theoretical problem. One example of this is denominal verbs (those derived from nouns) such as *spoon* in "She spooned me some sugar". Traditional generative approaches typically posit a unique entry in the lexicon for this usage, though this approach has difficulty scaling. Construction Grammar has evolved as a competing theory which instead allows the syntactic form of the sentence itself to contribute semantic meaning. However, how people learn syntactic constructions remains an open question. One suggestion has been that they are learned through analogical generalization. We evaluate this hypothesis using a computational model of analogical generalization to simulate Kaschak and Glenberg's (2000) study regarding interpretation of denominal verbs.

Keywords: Analogy; Construction Grammar; Linguistics; Analogical Generalization

Introduction

Linguistic creativity poses a theoretical problem for models of language learning and representation. One example of this is the use of denominal verbs (Clark & Clark, 1979) e.g.

1) a. She *spooned* me some sugar.
   b. The neighbor *hosed* the patio clean.

English speakers can easily interpret 1a as a transfer event involving sugar (with the spoon as instrument). Similarly 1b describes using the hose to wash a patio. How do we reach these interpretations? In many conventional theories the semantics of the sentence would be driven by the main verb. However, as Clark and Clark's (1979) analysis shows, the semantics of denominal verbs are highly context sensitive, and it certainly seems odd that *spoon* would independently have a transfer meaning in our lexicon. Construction grammar approaches present an alternative solution to this problem—that the interpretations are grounded in the argument structure itself (Goldberg, 2003).

Construction grammar proposes that the building blocks of language are *constructions*, pairings of form and meaning which are hierarchical and vary in both complexity and degree of fixedness. A morpheme is a kind of construction, as is the double-object (NP-V-NP-NP) pattern in 1a or the partially filled idiom "Jog X's memory" (Goldberg 2003).

An *expression* is a combination of non-contradictory constructions. In 1a, each of the NPs '*she*', '*me'*, and '*some sugar*' is an NP construction. They combine with the double-object construction (exemplified in 1) that specifies each NP's location and role. A construction can also specify general semantic meaning. For example, the double-object construction is associated with transfer events (Goldberg, 2003). With construction grammar, we don't need *spoon* to have a new lexical entry. Instead, the double-object construction imposes its meaning on the denominal verb.

Kaschak and Glenberg (2000) investigated how people interpret novel denominal verbs and found that, consistent with a constructionist approach, participants were sensitive to argument structure differences when interpreting textual entailment and selecting a meaning for the novel verbs. Specifically, participants were more likely to attribute a transfer interpretation to a double-object construction (like that in 1a). However, a significant unanswered question is how humans acquire and represent such constructions.

One proposal is that children use analogy processes to generalize abstract constructions from item-based examples (Tomasello, 2003). Under this account, language learners would map the structural form and communicative function of an utterance to other examples, thus gradually abstracting away individual features. The generalization associates a semantic function with the linguistic form and could be used to interpret novel verbs appearing in the same context.

Our goal is to provide computational evidence for the idea that analogical generalization and retrieval could result in constructions accounting for Kaschak and Glenberg's denominal interpretations. We evaluate this using SAGE (Mclure et al, 2015), a computational model of analogical generalization based on Gentner's (1983) structure-mapping theory. Using a computational model further allows us to investigate precisely what kinds of representations are needed for successful generalization.

We train SAGE over a small corpus of annotated sentences and use MAC/FAC, a model of analogical retrieval, to retrieve and apply the learned constructions to Kaschack & Glenberg's stimuli. For our semantic representation we use Fillmore *et al's* (2001) FrameNet, a frame-semantic resource for English. The result is a semantic role assignment that we can evaluate as consistent with either a transfer or transitive interpretation.

Background

Construction Grammar

Recently, several different constructionist approaches have emerged (e.g. Boas and Saag, 2012; Steels, 2011).

However, as Goldberg (2003) summarizes they generally have a few core principles in common.

One principle is that construction grammar allows argument structure to contribute semantic meaning. Also unlike generative approaches (e.g. Chomsky, 1981), differing syntactic expressions are not derived from underlying deep structures; rather each surface form is its own instantiation of a set of constructions.

Constructionist approaches have been especially useful in explaining more idiomatic constructions such as the comparative-correlative ('The X-er, The Y-er) as in "The bigger they are, the harder they fall" (Cullicover & Jackendoff, 1999). Here, the structure of the sentence provides extra semantic meaning beyond that provided by the head verb. It is enriched but not derived from the verb.

Perhaps most importantly, constructionist approaches view constructions as learnable using general cognitive mechanisms on the basis of input from the environment (Goldberg, 2003). There is no *universal grammar* (e.g. Chomsky, 1981; Lidz *et al*, 2003) Thus, a constructionist account naturally predicts piece-meal acquisition of language such that a child's early utterances are those that occur in its linguistic environment. There is considerable evidence for this pattern. For example, Rowland and Pine (2000) found that subject-auxiliary inversion errors in a child's speech were mostly specific to individual wh-word auxiliary pairs, and that the pairs the child produced correctly were those that occurred more frequently in the input. Similarly, Theakston *et al* (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.

More evidence of item-specific learning comes from Akhtar and Tomasello (1997) who found that older children (3;8) were able to use a transitive construction to interpret *agent* and *patient* roles for a novel verb while younger children (2;9) generally could not. However, both groups demonstrated understanding of transitive commands with known verbs. The older children had generalized a productive transitive construction while the younger children's understanding was verb specific.

However, if children's early language centers around item-based constructions, then an important question is how they develop more abstract syntactic knowledge.

Analogical Generalization

Analogy has been proposed as a mechanism for language learning and more specifically for generalizing from item-based constructions (Gentner & Namy 2006; Tomasello, 2003). There is abundant evidence that comparison facilitates language learning and relational extraction. Christie & Gentner (2010) found that comparison significantly improved relational abstraction in children when extending novel spatial labels to new situations. Further, Namy & Gentner (2002) found that common labels can invite comparison, facilitating the formation of categories based on relational rather than perceptual similarities.

Gentner's (1983) structure-mapping theory proposes that the process of comparison consists of aligning structured relational representations. The process is guided by constraints which prohibit many-to-one matches between entities and require matching parent relationships to have matching children. Further, structure-mapping proposes a bias towards systematicity, i.e. that people will prefer mappings that preserve higher-order (e.g. causal) structure. This preference has been demonstrated in humans with both match selection and prediction tasks (Clement & Gentner, 1991). Structure-mapping forms the theoretical basis for our model of analogical generalization. Forbus *et al*'s (2016) structure-mapping engine (SME) is a computational implementation of structure-mapping.

Our computational model of analogical generalization, SAGE (Mclure *et al*, 2015), is built on top of SME. SAGE operates over sets of predicate calculus representations called cases. Given a new (probe) case and a library of known cases, SAGE compares the case to ones in the library using a two-stage retrieval model, MAC/FAC (Forbus *et al*, 1995). The first stage compares flat feature-vector representations of the probe and case-library cases. While fast, this stage doesn't take into account structural similarity. The second stage operates over cases selected in the first phase and compares them using SME.

If the structural similarity score provided by SME is above a defined threshold[1], the new example will be combined with the retrieved case to create a generalization with a probability distribution governing features of the matched entities. Future examples can be added to the generalization or combine with other singletons to form a new generalization. If dissimilar to all, they join the case library as an ungeneralized example. Figure 1 shows the generalization process using representations from our experiment.

SAGE has been used in tasks such as learning concepts from maps (Mclure et al, 2015). Additionally, SAGE models a phenomenon from the analogy literature called *progressive alignment*, whereby highly-alignable cases pave the way for understanding less similar pairs, (Kotovsky and Gentner 1996; Kandaswamy *et al*, 2014).

There is evidence that progressive alignment contributes to language development. For example, Goldwater *et al* (2011) proposed a structure-mapping account of children's construction learning, as assessed by their syntactic priming (that is, by whether and to what extent they can re-use the syntactic form of a just-heard utterance when framing a new utterance). Goldwater et al. (2011) found that both 4- and 5-yr-old children showed syntactic priming, but (in keeping with our earlier discussion) 4-yr-olds were more concrete—the target had to be highly similar to the prime in order for them to show priming. Goldwater and Echols (2014) further

[1] An assimilation threshold of 1.0 means perfect identity would be required to merge, whereas a threshold of 0.0 means any two descriptions will be merged.

found that 4-yr-olds primed with high-similar sentences could go on to show priming from less similar sentences—evidence for progressive alignment in learning constructions (See also Childers & Tomasello, 2001).

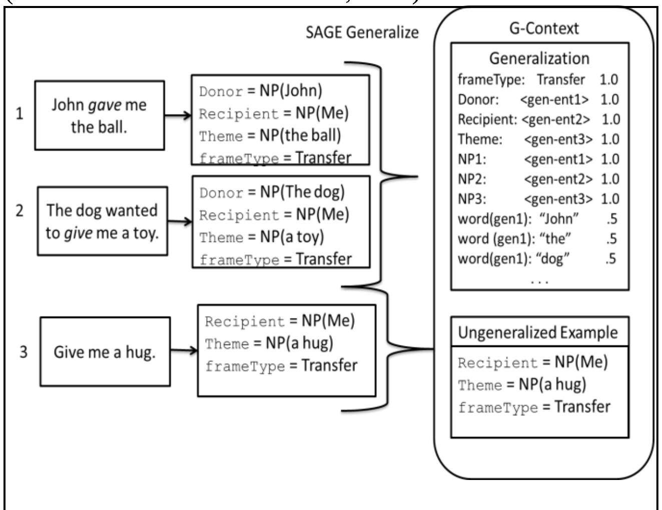

Figure 1: SAGE Generalization

Double-object sentences 1 and 2 are compared using SME. Since their similarity score is above threshold, their shared structure (semantic roles and phrase structure) is abstracted into a generalization with a probability distribution governing their variable features. Sentence 3, an imperative, is compared using MAC/FAC, but lacks a `Donor` FE and its `Theme` FE is in object position. It becomes an ungeneralized example.

Experiment

The first goal of the experiment is to evaluate whether analogical generalization can result in argument-structure constructions. The second is to evaluate whether these constructions can be used to interpret denominal verbs through analogical retrieval.

Simulation Target

Our target for simulation is the first experiment from Kaschak and Glenberg (2000). In Experiment 1, participants were presented with pairs of sentences (e.g. Figure 2) headed by either a conventional verb or a novel denominal verb. One was a double-object construction while the other was a transitive construction. Each also had an additional `Purpose` argument. This ensured both examples had the same number of entities, so readers must rely on structure.

Participants were evaluated on one of two tasks. In Task 1, participants were presented with one of two inferences. One was consistent with a transfer interpretation and the other a transitive action e.g. "Tom got the apple" vs "Lyn acted on the apple". They were then asked which example most strongly implied the inference. If they were influenced by the argument structure, then they should choose the double-object sentence for the transfer inference. In the inference task, participants overwhelmingly chose the double-object construction for transfer inferences (92% for conventional verbs and 80% for novel denominals).

1. Lyn crutched Tom her apple so he wouldn't starve. (double-object form)
2. Lyn crutched her apple so Tom wouldn't starve. (transitive form)

Figure 2: Example from Kaschak and Glenberg (2000)

In a second task, participants were shown each sentence independently and asked which of a pair of meanings e.g. "to act on using a crutch" or "to transfer using a crutch" best fit the denominal verb. If they were influenced by the argument structure, then they should select the transfer meaning for the double-object construction.

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).

Our simulation models the semantic classification of transfer vs transitive action. We trained SAGE on example sentences annotated with semantic frames and roles. For each double-object example from Kaschak and Glenberg (2000), the simulation should assign semantic roles consistent with a transfer frame. For each transitive example, it should label it with a transitive frame. Kaschak & Glenberg further claim that the full semantic meaning of the sentence is based on the affordances of the noun the denominal came from, a claim we do not examine.

Representations and Materials

We use Fillmore *et al's* (2001) FrameNet as our semantic representation. FrameNet defines frames that relate an evoking lexical item and its dependent structures to roles in a semantic description. For example, the word *Give* evokes the `Giving` frame which includes required an optional roles (frame elements) such as a `Donor` and `Recipient.` The realization of frame elements in a construction is called a valence pattern. Consider example (2) below:

2) I saw John *give* the teacher the apple.

With *give* as the target, the NP "John" would be annotated as the `Donor` of a giving frame. The NP, "the teacher", would be the `Recipient`, and "the apple" would be the `Theme`. This annotation format only identifies the arguments to the target, ignoring other aspects of the sentence.

The training set was created by manually annotating 21 sentences from a 6th grade reading comprehension workbook (Spectrum, 2007). Each training case consisted of a sentence and predicate calculus representations of its target verb, the arguments to that verb, their positions, their roles, and the words in each argument. For sentence 2, the first NP would be represented as follows:

```
(isa NP1 NP)
(FE-Donor "give" NP1)
(wordMemberOf NP1 "John")
(loc1 sentence1 NP1)
```

The test set was created by automatically chunking the stimuli from Kaschak and Glenberg (2005) into its valence pattern phrases using regular expressions. Each phrase was labeled with its phrase type as above, but no information about the evoked frame or the frame element was given. All 20 double-object examples from their experiment were used. We discarded one transitive example because its additional argument was not the same form as the rest of the examples. Thus, our total test set consisted of 39 examples.

Procedure

In the training phase, SAGE was given each of the training stimuli as an individual case for generalization (see Figure 1). The generalization threshold was set to .8. The training set consisted of nine sentences that evoked `Giving`. 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 `Transfer` sentences, only two illustrated the double-object in isolation. Six examples included an additional argument.

A hallmark of SAGE is its sensitivity to the order of the training stimuli, demonstrating progressive alignment. We first evaluated the model with a hand-made progressive alignment training order (PA-ordered) that clustered similar constructions and then with randomly generated orders.

In the evaluation phase, each example from our test set was used as a probe for analogical retrieval using MAC/FAC over the learned case-library. The top-scoring response is compared to the probe using SME. Structures in the base that are missing in the target are hypothesized as candidate inferences. These candidate inferences are the model's interpretation of the incoming sentence. This is shown in Figure 3.

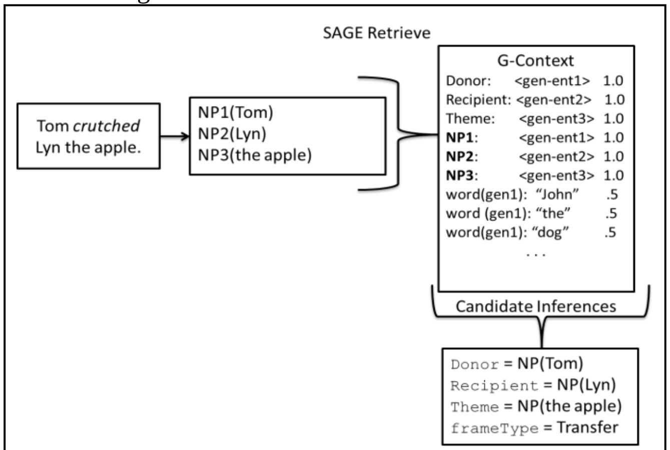

Figure 3: Retrieval and Interpretation of stimuli

Results

The results were evaluated based on the candidate inferences generated by the retrieval process. For the 20 double-object examples, a response was counted 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 and Glenberg (2000). An interpretation was judged incorrect if it over-assigned the three FEs which could happen if the double-object and prepositional ditransitives formed a single generalization.

For the transitive stimuli, we counted the interpretation 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.

We compared to two baselines. The first was a random baseline. For each example, we assume a random baseline system that 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.

PA-Ordered Training Set:

On 19 out of 20 examples, the model correctly interpreted the verb as evoking a `Giving` frame and correctly assigned all frame elements (`Donor, Recipient, Theme`).

On the transitive examples, the model correctly interpreted the event as non-transfer in 18 out of 19 examples. This gives us a total of 37 out of 39 (95%).

With a single manually determined training order, the model is deterministic—there is no variance. Our model significantly out-performs the expected performance of the random baseline ($P < .05$). It is larger than the static *choose-transitive* baseline and thus out-performs that as well.

Random Training Orders:

We also evaluated our model using randomized training orders. 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 $t(24) = 6.49$ $P < .05$.

Generalizations:

We manually inspected the generalizations produced by the model trained on hand-ordered stimuli. SAGE produced four generalizations. One was the simple double-object construction. Another contained two of the double-object constructions with an additional modifier. The next contained two simple `cause_motion` transitive sentences and the final generalization contained two examples of transitive actions with an additional argument.

Without phrase labels:

We also evaluated performance without phrase type labels. Instead, the probe included the arguments to the verbs as unlabeled 'chunks'. The model was trained with the hand-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.

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. Indeed, the linguistic environment itself may facilitate this kind of learning, as Cameron-Faulkner *et al* (2003) found that 51% of child-directed speech began with one of 52 constructions, and 45% began with one of seventeen words. Future work demonstrating progressive alignment in language learning would support our model. We may predict that sequential comparison of canonical verbs would improve performance on the novel denominals. Kaschak & Glenberg (2005) do not evaluate this.

The model makes several representational assumptions. First, we assume that humans are able to chunk sentences into arguments for a target verb. We don't claim that these representations are part of a particular larger parse structure nor do we endorse a specific account of how humans form these arguments. Going from raw input to preliminary structures will be a significant focus of future work.

Our results also suggest the importance of both chunking a sentence into arguments and classifying sentence chunks. Without phrase-labels, performance dramatically decreased. One option is to include classification as a part of the chunking process. A two-phase model could use analogy to infer chunks from low-level features such as word order or dependency parse information.

Related Work

Semantic role labeling has been an active area of research in computational linguistics, though open-domain semantic parsing remains elusive. An example is Das *et al's* (2014) statistical SEMAFOR parser. Ovchinnikova's (2012) statistical abduction system additionally uses a knowledge-base extracted from WordNet and FrameNet. However, none of these systems focus on constructions. As far as we know, our model is the first use of a cognitive simulation to evaluate the analogical account of construction learning.

Connor *et al*'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 replicated child performance including over-generalization errors. Adding a feature for verb position greatly improved performance.

Baby SRL targets a simpler construction and uses a word-level representation, but they propose that the approach could be extended to use phrases. 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 *et al* (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 our task. A benefit of their approach is that constructions are learned hierarchically, where we currently learn a generalization for each valence pattern. One direction for future work could use hierarchical models of analogical generalization (Liang & Forbus, 2014).

Bergen, Chang, & Narayan (2000) propose Embodied Construction Grammar (ECG) in which constructions link linguistic form to conceptual schemas used to specify parameters for simulation. The simulation generates inference and prompts response. Their conceptual schemas are similar to our frames in specifying a predicate-argument mapping, though constructions in ECG also contribute additional simulation parameters such as perspective. While we don't incorporate simulation into our model of semantics, analogical generalization could support learning of ECG's conceptual-schemas.

Finally, Steels' (2011) Fluid Construction Grammar is a construction grammar formalism that was designed for work on human-robot interaction, though not necessarily as a cognitive model.

Conclusion & Future Work

Humans must adapt to an ever-shifting linguistic landscape. Constructionist accounts of language facilitate this by pairing semantic meaning and syntactic surface forms. Furthermore, constructionist theories view language as learnable using general cognitive abilities. We examine whether analogy could be a mechanism used in both the generalization of constructions and their application. We simulated experiment 1 of Kaschak and Glenberg's (2000) denominal verb study using a computational model of analogical generalization and retrieval, SAGE, which allowed for inspections of and concrete hypotheses about the representations used in construction building. Our model produced correct transitive and ditransitive semantics, supporting the role of analogy in language learning.

Much remains to be done. We explored only a handful of English constructions. Future work will focus on modeling other linguistic studies as well as applying these techniques to larger-scale problems. Finally, our system currently treats phrase-level chunking as a black box. Future work will involve building these representations from the ground up.

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