# **Analogical Generalization of Linguistic Constructions**

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#### Abstract

Human language is extraordinarily creative in form and function, and adapting to this ever-shifting linguistic landscape is a daunting task for interactive cognitive systems. Recently, construction grammar has emerged as a linguistic theory for representing these complex and often idiomatic linguistic forms. Furthermore, analogical generalization has been proposed as a learning mechanism for extracting linguistic constructions from input. I propose an account that uses a computational model of analogy to learn and generalize argument structure constructions.

#### Introduction

Humans easily interpret novel uses of known linguistic items. Consider caused motion constructions or denominal verbs (Goldberg, 2003; Kaschak & Glenberg, 2000).

- 1 a) Pat sliced the carrots into the salad.
- b) Lyn crutched Tom her apple so he wouldn't starve. In 1a, we easily interpret the sentence such that slicing caused the carrots to fall into the salad, though one would hardly want to create a new sense of the word *slice* for this usage. Similarly, in 1b, the usage of *crutch* conveys that Lyn used a crutch to pass Tom the apple. Certainly this isn't a pre-defined semantics for *crutch*. Instead, construction grammar views the fundamental 'motion' and 'transfer' semantics of these sentences as properties of the grammatical forms, namely the transitive and dative constructions. Constructions pair form and meaning.

This approach is also useful in explaining more idiomatic constructions such as the comparative-coorelative ('The X-er, The Y-er) as in "The bigger they are, the harder they fall" (Cullicover & Jackendoff, 1999). In both examples, the structure of the sentence provides extra semantic meaning beyond that provided by the head verb. The semantics is enriched by the verb, not derived from it. This is one way construction grammar differs from traditional approaches. Additionally, construction grammar does not posit underlying grammatical transformations.

Finally, a core principle of construction grammar is that constructions are learnable from input. Indeed, Casenhiser Copyright © 2016, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.

& Goldberg (2005) demonstrate that children readily learn the semantics of novel argument structure constructions given few examples, and constructions have been invoked to explain a wide array of developmentary linguistic phenomena (Tomasello, 2003). One proposal for how humans learn these constructions is through analogical generalization.

#### **Analogical Generalization**

Our approach to analogical generalization is based on Gentner's (1983) structure mapping theory in which human similarity judgments are viewed as a process of alignment between hierarchical structured representations.

Falkenhainer et al's (1989) structure mapping engine (SME) is a computational implementation of structure mapping. SME takes a base and target case of structured representations and maps entities and relations. It prefers matches with a shared higher-order structure, so cases with high structural similarity but low feature similarity match. Relationships that are present in the base but not in the target can be hypothesized as candidate inferences.

SME provides the matching algorithm for the Sequential Analogical Generalization Engine (SAGE), a computational model of human analogical generalization that has been used in tasks such as learning concepts from maps (McLure et al, 2015). Given a new example and a case-library, SAGE compares it to existing examples using SME. If over threshold, the new example is added to an existing case to create a generalization with a probability distribution governing the features of mapped entities. Over time, SAGE produces schema-like constructs that still retains high-probability attributes and relationships.

# **Proposed Work and Progress**

My thesis has two goals: (1) support the claim that analogical generalization is a driving mechanism in construction learning. (2) Demonstrate that analogically learned constructions can improve language understanding.

## **Approach**

In pursuing the first goal, I plan to model several existing human studies. Casenhiser & Goldberg (2005) presented children with nonce verbs in a novel construction (S-O-V) which described videos of appearance scenarios. They found that children quickly applied the novel construction to new appearance scenarios and that this was facilitated when examples frequently shared a verb. This parallels a finding in the analogical generalization literature called *progressive alignment*, where highly similar cases pave the way for more difficult alignments, which SAGE models. The same phenomena explains the results of Childers and Tomasello (2001) who found that frequent pronoun usage in child-directed speech facilitated their production of a transitive construction for a nonce verb.

I aim to replicate these studies with my model. I will use SAGE to generalize over the syntactic surface forms of the utterances. For Casenhiser & Goldberg (2005), the semantics of the video will be automatically encoded through a series of drawings in the sketching software CogSketch (Forbus *et al*, 2011). Modeling these studies provides a framework for interactive construction learning. Secondly, replicating the progressive alignment effects supports the theory that analogy is used in human construction learning.

Furthermore, I plan to show that construction generalization can improve the linguistic competence of cognitive systems at scale. To do so, I will use SAGE to generalize semantic annotations from Fillmore *et al's* (2001) FrameNet. I will use the resulting representations to augment our NLU system. To assess performance, I plan to use Kaschak & Glenberg's (2000) denominal verb stimuli. Using these representations, it should produce a transfer interpretation of a sentence like 1b even though no such semantic frame exists for the verb *crutch*. This provides needed flexibility for an interactive cognitive system.

# Prior Work and Progress by 2/16

In McFate (2015) I used SAGE to learn pragmatic constraints on preposing constructions. However, the syntax was limited and the representation collapsed syntactic information.

I've also started generalizing constructions from FrameNet. Initial generalizations were made based on FrameNet annotations using a representation based on the ordering of phrase-level nodes.

My thesis makes use of several existing resources. CogSketch and SAGE are both existing systems, as is the EA NLU language understanding system (Tomai & Forbus, 2009). FrameNet provides a large corpus of semantic annotations. EA NLU uses the Research Cyc¹ ontology for semantic representations.

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By the date of the consortium I'll have a proof of concept version of our language system running which uses retrieval over FrameNet generalizations to guide interpretation. By this point, I also hope to have much of the framework in place for associating a linguistic form with a series of sketched events in CogSketch.

# **Future Work & Technical Challenges**

Much remains to be done. One crucial element is deciding on formalisms for representing linguistic input. This will be influenced by ongoing research into developmental language studies.

Additional challenges come from incorporating generalizations into an existing parsing pipeline, as well as integrating CogSketch into my existing framework. Finally, evaluating my model of Childers and Tomasello (2001) ideally involves a language generation mechanism which is still in development.

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<sup>1</sup> http://www.cyc.com/platform/researchcyc/