Arguments and Modifiers from the Learner’s Perspective

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Abstract
We present a model for inducing sentential argument structure, which distinguishes arguments from optional modifiers. We use this model to study whether representing an argument/modifier distinction helps in learning argument structure, and whether a linguistically-natural argument/modifier distinction can be induced from distributional data alone. Our results provide evidence for both hypotheses.

1 Introduction
A fundamental challenge facing the language learner is to determine the content and structure of the stored units in the lexicon. This problem is made more difficult by the fact that many lexical units have argument structure. Consider the verb put. The sentence, John put the socks is incomplete; when hearing such an utterance, a speaker of English will expect a location to also be specified: John put the socks in the drawer. Facts such as these can be captured if the lexical entry for put also specifies that the verb has three required arguments: (i) who is doing the putting (ii) what is being put (iii) and the destination of the putting.

The problem of acquiring argument structure is further complicated by the fact that not all phrases in a sentence fill an argument role. Instead, many are modifiers. Consider the sentence John put the socks in the drawer at 5 o’clock. The phrase at 5 o’clock occurs here with the verb put, but it is not an argument. Removing this phrase does not change the core structure of the PUTTING event, nor is the sentence incomplete without this phrase.

The distinction between arguments and modifiers has a long history in traditional grammar and is leveraged in many modern theories of syntax (Haegeman, 1994; Steedman, 2001; Sag et al., 2003). Despite the ubiquity of the distinction in syntax, however, there is a lack of consensus on the necessary and sufficient conditions for argumenthood (Schütze, 1995; Schütze and Gibson, 1999). It remains unclear whether the argument/modifier distinction is purely semantic or is also represented in syntax, whether it is binary or graded, and what effects argument/modifierhood have on the distribution of linguistic forms.

In this work, we take a new approach to these problems. We propose that the argument/modifier distinction is inferred on a phrase–by–phrase basis using probabilistic inference. Crucially, allowing the learner to separate the core argument structure of phrases from peripheral modifier content increases the generalizability of argument constructions. For example, the two sentences in Figure 1 intuitively share the same argument structures, but this overlap can only be identified if the prepositional phrase, “at 5 o’clock,” is treated as a modifier. Thus representing the argument/modifier distinction can help the learner find useful argument structures which generalize robustly.

Although, like the majority of theorists, we agree that the argument/adjunct distinction is fundamentally semantic, in this work we focus on its distributional correlates. Does the optionality of modifier phrases help the learner acquire lexical items with the right argument structure?

2 Approach
We adopt an approach where the lexicon consists of an inventory of stored tree fragments. These
tree fragments encode the necessary phrase types (i.e., arguments) that must be present in a structure before it is complete. In this system, sentences are generated by recursive substitution of tree fragments at the frontier argument nodes of other tree fragments. This approach extends work on learning probabilistic Tree–Substitution Grammars (TSGs) (Post and Gildea, 2009; Cohn et al., 2010; O’Donnell, 2011; O’Donnell et al., 2011).

To model modification, we introduce a second structure–building operation, adjunction. While substitution must be licensed by the existence of an argument node, adjunction can insert constituents into well–formed trees. Many syntactic theories have made use of an adjunction operation to model modification. Here, we adopt the variant known as sister–adjunction (Rambow et al., 1995; Chiang and Bikel, 2002) which can insert a constituent as the sister to any node in an existing tree.

In order to derive the complete tree for a sentence, starting from an S root node, we recursively sample arguments and modifiers as follows. For every nonterminal node on the frontier of our derivation, we sample an elementary tree from our lexicon to substitute into this node. As already noted, these elementary trees represent the argument structure of our tree. Then, for each argument nonterminal on the tree’s interior, we sister–adjoin one or more modifier nodes, which themselves are built by the same recursive process.

Figure 2 illustrates two derivations of the same tree, one in standard TSG without sister–adjunction, and one in our model. In the TSG derivation, at top, an elementary tree with four arguments – including the intuitively optional temporal PP – is used as the backbone for the derivation. The four phrases filling these arguments are then substituted into the elementary tree, as indicated by arrows. In the bottom derivation, which uses sister–adjunction, an elementary tree with only three arguments is used as the backbone. While the right-most temporal PP needed to be an argument of the elementary tree in the TSG derivation, the bottom derivation uses sister–adjunction to insert this PP as a child of the VP. Sister–adjunction therefore allows us to use an argument structure that matches the true argument structure of the verb “put.”

This figure illustrates how derivations in our model can have a greater degree of generalizability than those in a standard TSG. Sister–adjunction will be used to derive children which are not part of the core argument structure, meaning that a greater variety of structures can be derived by a combination of common argument structures and sister–joined modifiers. Importantly, this makes the learning problem for our model less sparse than for TSGs; our model can derive the trees in a corpus using fewer types of elementary trees than a TSG. As a result, the distribution over these elementary trees is easier to estimate.

To understand what role modifiers play during learning, we will develop a learning model that can induce the lexicon and modifier contexts used by our generative model.

3 Model

Our model extends earlier work on induction of Bayesian TSGs (Post and Gildea, 2009; O’Donnell, 2011; Cohn et al., 2010). The model uses a Bayesian non–parametric distribution—the Pitman-Yor Process, to place a prior over the lexicon of elementary trees. This distribution allows the complexity of the lexicon to grow to arbitrary size with the input, while still enforcing a bias for more compact lexicons.

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1Note that we depart from many discussions of argument structure in that we do not require that every stored fragment has a head word. In effect, we allow completely abstract phrasal constructions to also have argument structures.

2Our generative model is related to the generative model for Tree–Adjoining Grammars proposed in (Chiang, 2000)
For each nonterminal $c$, we define:

$$G_{c|a_c, b_c, P_E} \sim PYP(a_c, b_c, P_E(|c)) \quad (1)$$

$$e|c, G_{c} \sim G_{c}, \quad (2)$$

where $P_E(|c)$ is a context free distribution over elementary trees rooted at $c$, and $e$ is an elementary tree.

The context-free distribution over elementary trees $P_E(e|c)$ is defined by:

$$P_E(e|c) = \prod_{i \in I(e)} \left(1 - s_c\right) \prod_{j \in F(e)} s_{c_j} \prod_{c' \rightarrow \alpha \in e} P_{c'}(\alpha|c'),$$

where $I(e)$ is the set of internal nodes in $e$, $F(e)$ is the set of frontier nodes, $c_j$ is the nonterminal category associated with node $i$, and $s_c$ is the probability that we stop expanding at a node $c$. For this paper, the parameters $s_c$ are set to 0.5.

In addition to defining a distribution over elementary trees, we also define a distribution which governs modification via sister–adjunction. To sample a modifier, we first decide whether or not to sister–adjoint into location $l$ in a tree. Following this step, we sample a modifier category (e.g., a PP) conditioned on the location $l$’s context: its parent and left siblings. Because contexts are sparse, we use a backoff scheme based on hierarchical Dirichlet processes similar to the ngram backoff schemes defined in (Teh, 2006; Goldwater et al., 2006). Let $e$ be a nonterminal node in a tree derived by substitution into argument positions. The node $c$ will have $n \geq 1$ children derived by argument substitution: $d_0, ..., d_n$. In order to sister–adjoint between two of these children $d_i, d_{i+1}$, we recursively sample nonterminals $s_{i,1}, ..., s_{i,k}$ until we hit a STOP symbol:

$$P_a(s_{i,1}, ..., s_{i,k}, STOP|C_0) \quad (4)$$

$$= \prod_{j=1}^{k} P_a(s_{i,j}|C_j) \cdot (1 - P_{C_j}(STOP)) \cdot P_{C_{k+1}}(STOP)$$

where $C_j = d_1, s_{1,1}, ..., d_i, ..., s_{i,j-1}, c$ is the context for the $j$th modifier between these children. The distribution over sister–adjointed nonterminals is defined using a hierarchical Dirichlet process to implement backoff in a prefix tree over contexts. We define the distribution $G(q_1, ..., q_1)$ over sister–adjointed nonterminals $s_{i,j}$ given the context $q_1, ..., q_1$ by:

$$G(q_1, ..., q_1) \sim DP(\alpha, G(q_{l-1}, ..., q_1)). \quad (5)$$

The distribution $G$ at the root of the hierarchy is not conditioned on any prior context. We define $G$ by:

$$G \sim DP(\alpha, \text{Multinomial}(m)) \quad (6)$$

where $m$ is a vector with entries for each nonterminal, and where we sample $m \sim \text{Dir}(1,...,1)$.

To perform inference, we developed a local Gibbs sampler which generalizes the one proposed by (Cohn et al., 2010).

4 Results

We evaluate our model in two ways. First, we examine whether representing the argument/modifier distinction increases the ability of the model to learn highly generalizable elementary trees that can be used as argument structures across a variety of sentences. Second, we ask whether our model is able to induce the correct argument/modifier distinction according to a linguistic gold–standard. We trained our model on sections 2–21 of the WSJ part of the Penn Treebank (Marcus et al., 1999). The model was trained on the trees in this corpus, without any further annotations for substitution or modification.

To address the first question, we compared the structure of the grammar learned by our model to a grammar learned by a version of our model without sister–adjunction (i.e., a TSG similar to the one used in Cohn et al.). Our model should find more common structure among the trees in the input corpus, and therefore it should learn a set of elementary trees which are more complex and more widely shared across sentences. We evaluated this hypothesis by analyzing the average complexity of the most probable elementary trees learned by these models. As Table 1 shows, our model discovers elementary trees that have greater depth and more nodes than those found by the TSG. In addition, our model accounts for a larger portion of the corpus with fewer rules: the top 50, 100, and 200 most common elementary trees in our model’s lexicon account for a greater portion of the corpus than the corresponding sets in the TSG.

Figure 3 illustrates a representative example from the corpus. By using sister–adjunction to separate the ADVP node from the rest of the sentence’s derivation, our model was able to use a common depth-3 elementary tree to derive the backbone of the sentence. In contrast, the TSG cannot give the same derivation, as it needs to include the ADVP
Most of those who left stock funds simply switched into money market funds.

![Figure 3: Part of a derivation found by our model.]

Table 1: This table shows the average depth and node count for elementary trees in our model and the TSG. The results are shown for the 50, 100, and 200 most frequent types of elementary trees.

| Model | Rank | Avg tree depth | Avg tree size | #Tokens |
|-------|------|----------------|---------------|---------|
| Modifier TSG | 50 | 1.39 | 3.42 | 97282 |
| | 50 | 1.38 | 2.98 | 88023 |
| Modifier TSG | 100 | 1.84 | 3.98 | 134205 |
| | 100 | 1.58 | 3.38 | 116404 |
| Modifier TSG | 200 | 1.97 | 4.27 | 170524 |
| | 200 | 1.77 | 3.84 | 146040 |

Table 2: This table shows precision and recall in identifying modifier nodes in the corpus.

| Model | Precision | Recall | #Guessed | #Correct |
|-------|-----------|--------|----------|----------|
| Random | 0.27 | 0.19 | 298394 | 82702 |
| Modifier | 0.62 | 0.15 | 108382 | 67516 |

We therefore calculated the probability that a node that was randomly initialized as a modifier was in fact a modifier, i.e. the precision of random initialization. Next, we looked at the precision of our model following training. Table 2 shows that among nodes that were labeled as modifiers, 0.27 were labeled correctly before training and 0.62 were labeled correctly after. This table also shows the recall performance for our model decreased by 0.04. Some of this decrease is due to limitations of the gold standard; for example, our model learns to classify infinitives and auxiliary verbs as arguments — consistent with standard linguistic analyses — whereas the gold standard classifies these as modifiers. Future work will investigate how the metric used for evaluation can be improved.

5 Summary

We have investigated the role of the argument/modifier distinction in learning. We first looked at whether introducing this distinction helps in generalizing from an input corpus. Our model, which represents modification using sister–adjunction, learns a richer lexicon than a model without modification, and its lexicon provides a more compact representation of the input corpus. We next looked at whether the traditional linguistic classification of arguments and modifiers can be induced from distributional information. Without supervision from the correct labelings of modifiers, our model learned to identify modifiers more accurately than chance. This suggests that although the argument/modifier distinction is traditionally drawn without reference to distributional properties, the distributional correlates of this distinction are sufficient to partially reconstruct it from a corpus. Taken together, these results suggest that representing the difference between arguments and modifiers may make it easier to acquire a language’s argument structure.

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