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A Psycholinguistically Motivated Version of TAG

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Abstract

We propose a psycholinguistically motivated version of TAG which is designed to model key properties of human sentence processing, viz., incrementality, connectedness, and prediction. We use findings from human experiments to motivate an incremental grammar formalism that makes it possible to build fully connected structures on a word-by-word basis. A key idea of the approach is to explicitly model the prediction of upcoming material and the subsequent verification and integration processes. We also propose a linking theory that links the predictions of our formalism to experimental data such as reading times, and illustrate how it can capture psycholinguistic results on the processing of either . . . or structures and relative clauses.

1 Introduction

Current evidence from psycholinguistic research suggests that language comprehension is largely incremental, i.e., that comprehenders build an interpretation of a sentence on a word-by-word basis. This is a fact that any cognitively motivated model of language understanding should capture. There is also evidence for full connectivity (Sturt and Lombardo, 2005), i.e., for the assumption that all words are connected by a single syntactic structure at any point in the incremental processing of a sentence. While this second point of full connectivity is more controversial, the model we are proposing here explores the implications of incrementality in its strict interpretation as full connectivity.

Furthermore, recent work on human sentence comprehension indicates that people make predictions of upcoming words and structures as they process language (Frazier et al., 2000; Kamide et al., 2003; Staub and Clifton, 2006). The concepts of connectedness and prediction are closely related: in order to assure that the syntactic structure of a sentence prefix is connected at every point in time, it can be necessary to include phrases whose yield has not been processed yet. This part of the structure needs to be generated by the parser in order to connect the words that have been seen so far, i.e., to achieve full connectivity (which in turn is required to build an incremental interpretation). This process has been formalized by (Lombardo and Sturt, 2002) using the notion of connection path.

In this paper, we explore how these key psycholinguistic concepts (incrementality, connectedness, and prediction) can be realized within a new version of tree-joining grammar (TAG), which we call Psycholinguistically Motivated TAG (PLTAG). We argue that TAG is better suited for this modeling task than other formalisms such as CCG or PCFGs and propose a linking theory that derives predictions of processing difficulty from aspects of the PLTAG formalism.

2 Related Work

A number of incremental versions of TAG have been proposed over the years (Shen and Joshi, 2005; Kato et al., 2004; Mazzei et al., 2007). The version proposed here differs from these approaches in a number of ways. Spinal LTAG (Shen and Joshi, 2005) does not implement full connectivity, and cannot easily be used to model prediction since it does not encode valencies. The proposals by (Mazzei et al., 2007) and (Kato et al., 2004) are more similar to our work, but are less well-suited for psycholinguistic modeling since they do not implement a verification mechanism, which is required to account for standard complexity results in the spirit of (Gibson, 1998). In addition, (Kato et al., 2004) do not distinguish between modifiers and arguments, since they operate on the Penn Treebank, where this information is not directly available.
Incremental parsers for other grammar formalisms include Roark’s (2001) for PCFGs, and Nivre’s (2004) for dependency grammars. Neither of these parsers implement strict incrementality, in the sense of always building connected structures. Furthermore, there are principled problems with PCFGs as a model of prediction difficulty, even if fully connected structures are built (see Section 7).

The main contributions in the version of TAG introduced in this paper is that it is incremental and respects full connectivity, while also modeling the verification and integration of syntactic material. Our main emphasis is on the modeling of prediction, which has been the subject of much recent research in psycholinguistics, as outlined in the previous section.

3 Incrementality and Prediction

We propose variant of TAG that incorporates two different types of prediction: prediction through substitution nodes in lexicon entries (e.g., if a verb subcategorizes for an object which has not yet been seen), and prediction via connection paths. The first type of prediction models the anticipation of upcoming syntactic structure that is licensed by the current input; the second type models prediction which is required to ensure that fully connected structures are built. We will discuss the mechanism for prediction due to connectivity first.

3.1 Prediction due to Connectivity

TAG elementary trees can not always be connected directly to a previously built syntactic structure. Examples are situations where two dependents precede a head, or where a grandparent and a child have been encountered, but the head of the parent node has not. For instance, in the sentence the horse seldom fell, the elementary tree of the horse cannot directly be combined with elementary tree of the adverbial modifier seldom, see Figure 1(a). The head fell which provides the intervening structure, has not been encountered at that point. Therefore, this intervening structure has to be predicted in order to connect the horse and seldom.¹ We use the substitution symbol ↓ to mark predicted structure. As a prediction mark, the substitution symbol can therefore also occur tree-internally. We assume that prediction is conservative, and only includes the structure as far as it is needed, i.e., only as far as it is included in the connection path (see Section 4 and Figure 3). It is important to bear in mind, however, that prediction grain size remains an open research question (for instance, we could predict the full elementary tree down to the lexical item, as proposed by (Mazzei et al., 2007), to even include the remaining subcategorized nodes or likely modifiers of that node).

Our minimal prediction method implies that adjunction must be possible at predicted nodes, as shown in Figure 1(a). When this happens, the head node of the auxiliary tree is marked as seen, while the foot node of the auxiliary tree takes over the prediction mark from the predicted connection structure, because we need to mark that we have not in fact yet seen the node that it adjoined to. If we marked both as non-predicted nodes, then we would not be able to guarantee that we can correctly keep track of what has been encountered in the input and what we have predicted.

We treat those connecting structures as special lexicon entries, where each predicted node is marked. A predicted node differs from the rest of the structure in that it needs to be verified, i.e., it has to be matched (through substitution of internal nodes) with later upcoming structure, as illustrated in Figure 1(b). A derivation of a sentence is only valid if all predicted nodes are matched. Our example shows how the tree structure for the horse seldom is connected with the elementary tree of fell. Each node of the new elementary tree can either be matched with a predicted node in the prefix tree, or it can be added (in Figure 1(b) when fell is integrated with The horse seldom, the S and VP nodes are matched against the predicted nodes, while the V node is added). It could therefore just as easily unify² with a transitive or ditransitive verb.

Issues arise in the verification process, e.g., how to unify structures after additional material has been adjoined. In our example, an additional VP node has been introduced by the adverb. The new nodes in the tree cannot unify with a random predicted node of the same category, but have to follow constraints of accessibility and have to have identical dominance relations. For example, consider a situation where we predict the structure between an object relative pronoun like whom and its trace (see

¹Because of the recursiveness of natural language, it is possible that there are infinitely many ways to connect two trees. Although embedding depth can be infinite in theory, we assume that it is finite and indeed very small due to limitations of human memory.

²Note that by unification we simply mean node matching and we will use these two terms interchangeably in this paper.
the top tree in Figure 4). If we encountered a verb next, we could match up the nodes of the verb elementary tree (S, VP, V) with the predicted nodes, and would still predict the subject noun phrase. If we then encountered a noun phrase, and again did not take into account any accessibility constraints (the substitution node is not accessible any more because filling it at this point would violate the linear order), we could substitute that noun into the subject position. That is, we would accept impossible RCs like whom thanked Peter, or misanalyze subject relative clauses as object relative clauses.

Figure 1: Example for prediction and verification of predictions

3.2 Prediction from Substitution Nodes

Another source for predictions are the lexicon entries themselves. Each substitution node that is to the right of the tree’s anchor naturally constitutes a predicted element during the parsing process. This means that we do not predict modifiers or any other kind of recursive structures, unless we have already seen a word that depends on the modifier (i.e., through connectivity, e.g., for a sentence prefix such as the horse very). Whether or not modifiers are predicted syntactically is currently an open research question. Preliminary evidence suggests that modifiers are predicted when they are required by the discourse context.

We also exploit TAG’s extended domain of locality in order to construct lexicon entries that are more appropriate for modeling psycholinguistic findings. An example is the either . . . or construction. Results by (Staub and Clifton, 2006) show that hearing the word either triggers prediction of or and the second conjunct: reading times on these regions were shorter in the either condition, and participants also did not misanalyze disjunctions at sentence level as noun disjunctions in the condition where either was present.

As (Cristea and Webber, 1997) point out, there are a number of constructions with two parts where the first part can trigger prediction of the second part in, similar to either . . . or. A related form of prediction is syntactic parallelism; experimental findings by (Frazier et al., 2000) indicate that the second conjunct of a coordinate structure is processed faster if its internal structure is identical to that of the first conjunct. This can be seen as a form of prediction, i.e., the parser predicts the structure of the second conjunct as soon as it has processed the coordinator.

In the rest of this section, we will discuss in more detail how either . . . or prediction can be implemented our framework. Figure 2 shows an example of how the word either impacts parsing of the either . . . or disjunction in PLTAG, as opposed to a simple or disjunction: the lexicon entry for either predicts the occurrence of coordination with two entities of the same category, and requires or as a coordinator, see Figure 2(a). When either is not present, attachment of coordination in a sentence like Peter read a book (Figure 2(c)) is ambiguous at the coordinator or, because the or auxiliary tree can be adjoined either at the noun phrase level or at the sentence level (see Figure 2(b)).

The position of either enables humans to predict that a disjunction is coming up, and provides a cue indicating at which level to attach the coordinated phrase. These predictions enable humans to process the coordinator faster and make them less likely to misanalyzing S-level coordination as NP-coordination when either is present. In PLTAG, only one of the lexicon entries of or, namely the first in Figure 2(b) is compatible with the structure predicted at either. Using this way of analysing either, we can correctly predict processing speed-up for the case where either is present as opposed to coordination without either using the linking theory proposed in Section 5.

Note that the analysis of either shown in Figure 2(a) means that or does not provide any new information but only verifies previously predicted information, since it doesn’t introduce any new nodes into the tree, and that the auxiliary tree for or can-
Figure 2: Example for the use of TAG’s extended domain of locality to model expressions that trigger predictions, such as either . . . or

the auxiliary tree verifies the prediction as usual, while the foot node does not expand the node, but adopts the annotation of the node that it matches. Any substitution nodes in the or-auxiliary tree simply update the timestamp of the substitution node.

4 Treebank-based Lexicon Induction

We induce the lexicon needed for our incremental version of TAG from the Penn Treebank, complemented by Noun Phrase annotation (Vadas and Curran, 2007), Nombank (Meyers et al., 2004) and Propbank (Palmer et al., 2003), as well as Magerman’s head percolation table (Magerman, 1994). These additional resources help determine the elementary trees following procedures in (Xia et al. 2000) and distinguish arguments from modifiers. (Modifiers are not predicted unless they are needed for a connection path.) Figure 3 shows how a syntactic tree is composed out of elementary trees: each inner node is indexed with the number of the word that is its lexical anchor in order to show which parts of the syntactic tree belong to which lexicon entry.

Once the parsed trees have been segmented into elementary trees, we calculate connection paths for each prefix, as proposed by (Lombardo and Sturt, 2002). A connection path for words \( w_1 \ldots w_n \) is the minimal amount of structure that is needed to connect all words \( w_1 \ldots w_n \) into the same syntactic tree. The amount of structure needed at each word for the sentence the Italian people often vote Berlusconi is indicated in Figure 3 by the structure enclosed in the circles.

Figure 3: Generating lexicon entries from the Penn Treebank for an example sentence

We then use the connection paths and the canon-
ical elementary trees to determine which parts of
the structure are included in the connection path
for words $w_1 \ldots w_n$, but not part of any of the
elementary trees with feet $w_1 \ldots w_n$. In Figure 3, this
occurs twice: firstly when *Italian* has been read,
and the determiner and adjective can only be com-
bined by predicting that they must be part of the
same noun phrase, and secondly at *often*, when the
VP and S nodes have to be predicted.

By definition, all nodes of these connecting
structures are predicted nodes, and therefore anno-
tated as substitution nodes. We store these con-
necting structures as lexicon entries. They differ
from other lexicon entries in that all their nodes
are substitution nodes, and in that they are not lex-
cialized. The advantage of generating these sepa-
rate non-lexicalized entries over simply adding a
second predicted version of all lexicon entries is
that we retain a smaller lexicon, which reduces the
sparse data problem for training, and makes parsing
more efficient.

The connection structure is non-lexicalized, and
therefore creates additional challenges for the
parser: the non-lexicalized structures can be trig-
gerated at any point in parsing, in particular when
simple substitution and adjunction are not success-
ful. They can also in principle be chained, i.e., sev-
eral non-lexicalized structures can be applied one
after the other, without ever applying any lexical-
ized rules. As a first approximation, we therefore
restrict these prediction rules to instances that we
encountered in the corpus, and do not only allow
several non-lexicalized rules in a row. This re-
striction means that there may be sentences which
this incremental parser cannot cover, even though
a non-incremental parser (or one without this re-
striction) can find an analysis for them. (CCG
has a similar problem with the application of type-
raising; in current CCG parsers, the search prob-
lem in type-raising is solved by lexicalizing type
raising.) Because of recursive rules in natural lan-
guage processing (strong incrementality with full
connectedness, prediction, ranked parallel process-
ing) which can be tested by linking an incremental
parser for this formalism with a theory of human
sentence comprehension.

The relation between the incremental parsing al-
gorithm and processing difficulty can be formal-
ized as follows: At each word, a set $E$ of syntac-
tic expectations $e$ is generated (they can be easily
read off the syntactic structure in the form of sub-
titution nodes). These expectations can be inter-
preted as denoting the categories needed to build
a grammatical sentence from the current input, and
are associated with probabilities $P(e)$, estimated by
the parser. Each structure also has a timestamp
or last activated. Based on this, decay is calculated,
under the assumption that recently-accessed struc-
tures are easier to access and integrate (decay is
weighted in during verification (substitution of in-
er nodes), regular substitution and adjunction).

In this model, processing difficulty is incurred
either when expectations are incompatible with the
current input (algorithmically, this corresponds to
the parser trying to substitute, adjoin, or verify a
new tree with the currently maintained structure,
but failing for all structures), or when successful in-
tegration takes place (i.e., unification of predicted
nodes and the elementary tree is successful, or a
node can be successfully adjoined). Intuitively, in-
tegration is costly because the parser has to bring
together the meaning of the matched categories.

Processing difficulty is proportional to the in-
verse probability of all integrated structures (less
activated structures are harder to integrate) plus the
probability of all deleted structures (more probable
structures are harder to discard), where both prob-
abilities weighted by recency:

$$D_w \propto \sum_{e \in E_i} f\left(\frac{1}{P(e)}\right) + \sum_{e \in E_d} f(P(e))$$

Here, $D_w$ is the difficulty at word $w$, and $E_i$ is the set
of expectations that could be integrated, while $E_d$ is
the set of expectations that have been discarded at
$w$. A decay is implemented by the function $f$.

6 Example

The following example aims to show how PLTAG
can explain increased processing difficulty at object
relative clauses (ORC) as opposed to subject relative
clauses (SRC). We chose this relative clause
example because there is evidence that object relative clauses are more difficult for humans to process from both experimental sources (King and Just, 1991; Gibson, 1998) and broad-coverage corpus data (Demberg and Keller, 2007).

Figure 4 shows two alternative structures for the phrase grand-parents who. The two analyses differ by whether they analyze who as an object relative pronoun or as a subject relative pronoun, and predict traces in different positions. Note the non-TAG-standard lexicon entry for the relative pronouns, which contains the RC phrase structure including the traces, and allow us to use the same lexicon entries for verbs in both main clauses and relative clauses. The decision of assigning the relative pronoun a more “eager” lexicon entry is based on the observation that encountering the object relative pronoun whom is sufficient to predict the argument structure of the relative clause (namely that there has to be a head for the relative clause, and that there has to be a subject, and a trace for the object). We plan to investigate in future work whether there is evidence that humans predict the whole structure given the relative pronoun.

In our example, the probability of the analyses at the relative pronoun is higher for the SRC (0.0003) than for the ORC (0.00004), since SRCs are more frequent (all probabilities in this example are fictitious and just for illustrative purposes). When the next word is encountered, that word may also be ambiguous, such as the word time in our example, whose probability is higher as a noun (0.08) than as a verb (0.02). All possible elementary trees for the new word have to be matched up with all prefix trees (analyses whose probability is below a certain threshold are ignored to limit the search problem and simulate memory limitations). In our example, the noun interpretation of time is compatible with the object relative clause interpretation, while the verb interpretation can be unified with the SRC analysis. The ORC structure still has lower probability than the SRC structure at this point, because 0.00003 · 0.08 < 0.0004 · 0.02. If an ORC verb was encountered next, we would correctly predict that this verb should be more difficult to process than the SRC verb, because five nodes have to be matched up instead of four, and the predicted nodes in the ORC analysis are one clock-cycle older than the ones in the SRC at the time of integrating the verb.

On encountering a disambiguating word, the processing difficulty proportional to the probability mass of all incompatible structures would be incurred. This means that higher processing difficulty occurs when the more probable structure (the SRC in our example) has to be discarded.

![Figure 4: Example of the interaction of lexical probabilities and verification cost in PLTAG](image)

7 Comparison with Other Grammar Formalisms

We decided to use tree-adjoining grammar instead of alternative formalisms like Combinatory Categorial Grammar (CCG) or Probabilistic Context Free Grammar (PCFG) because we felt that TAG
best met our requirements of strict incrementality with full connectivity.

In standard CCG with bottom-up parsing (Steedman, 2000), it is not possible to always find an incremental derivation. For example, in object relative clauses, the subject NP of the relative clause cannot be integrated in an incremental fashion because the category of the relative pronoun (\(N\backslash N\)/(S/NP)) is too abstract: it does not contain the category for the subject NP explicitly and the subject NP therefore has to connect with the verb first. Another example are coordinated clauses. The second conjunct can only be combined with the first conjunct when they both have the same category. However, (Sturt and Lombardo, 2005) show that human sentence processing is more incremental than the most incremental CCG derivation for a sentence like the pilot embarrassed John and put himself/herself in an awkward situation, where the c-command relation between the pilot and himself/herself is understood at the point of reading the reflexive pronoun, and not only after reading the full second conjunct, as CCG would predict under the assumption that the syntactic relation has to be established first in order to determine c-command relations.

Coordination in tree-adjoining grammar does not have this problem. It is not necessary that the end of the second conjunct must have been seen in order to connect the second conjunct to the beginning of the sentence, because the elementary tree for and is an auxiliary tree and adjoins into the previous structure. It is therefore connected to the preceding context right away, and himself can be substituted into a connected structure and will therefore be available for binding to the c-commanding phrase the pilot at an early processing stage.

Furthermore, pre- and post-modification is asymmetric for incremental derivations in CCG (and we are not aware of such an asymmetry in human sentence processing). CCG requires either type-raising at the head of a post-modified phrase, or non-connectivity. The reason for the asymmetry is that for pre-modification, e.g., an adjective before noun, there is no type-raising necessary in incremental processing (see Figure 5(b)). On the other hand, for post-modification it is necessary to type-raise the head before the post-modifier is processed (see Figure 5(d)). This asymmetry leads to the unintuitive situation of having an ambiguity for a noun when it is post-modified, but not when it is pre-modified. Alternatively, the structure either has to be undone once the modifier is encountered in order to allow for the composition (serial account), or the noun is explicitly ambiguous as to whether it will be modified or not (parallel account), or we cannot satisfy full connectivity. In both cases, post-modification requires more operations than pre-modification. This is not the case in TAG, because pre- and post-modification are adjoined into the tree in the same fashion (see Figure 5(a) and (c)).

![Figure 5: Comparision of pre- and post-modification in TAG and CCG](attachment:image.png)
Furthermore, PCFGs do not provide the extended domain of locality that we exploit in TAG.

8 Summary

We propose a framework for a new version of TAG which supports incremental, fully connected derivations, and makes explicit predictions about upcoming material in the sentence. This version of TAG can be combined with a linking theory to model human processing difficulty, and aims to account for recent findings on prediction and connectivity in human sentence comprehension.

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