Tree-Adjoining Grammar Parsing and Applications

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April 27, 2018

Outline

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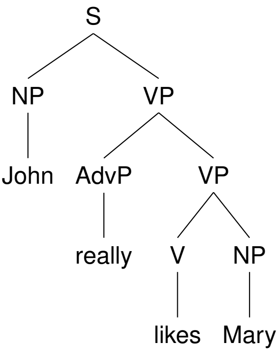
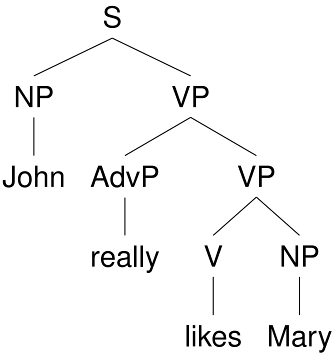
Syntactic Parsing



- Why do we need parsing?
- Does John love Mary? Does Mary love John?
- Understanding of a sentence depends on the structure

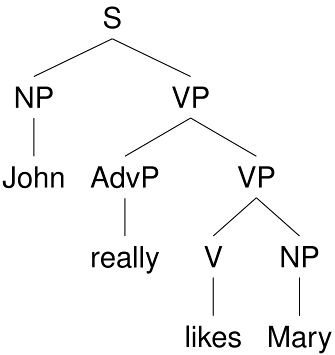
Context Free Grammars



$$S \rightarrow NP\ VP$$
$$VP \rightarrow AdvP\ VP$$
$$AdvP \rightarrow really$$
$$VP \rightarrow V\ NP$$
$$NP \rightarrow Mary$$
$$NP \rightarrow they$$
$$NP \rightarrow John$$
$$V \rightarrow like$$
$$V \rightarrow likes$$

- These production rules generate sentences

Context Free Grammars



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$$VP \rightarrow AdvP\ VP$$
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$$V \rightarrow like$$
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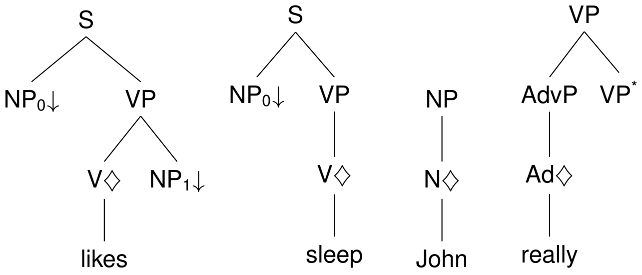
- **Fundamental problem**: constraints are distributed over separate rules
  How do we choose $V \rightarrow$ *like* or $V \rightarrow$ *likes*?

Tree-Adjoining Grammar

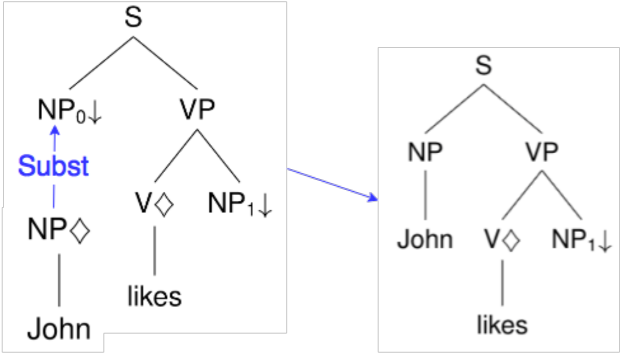
Tree-Adjoining Grammar (TAG) localizes grammatical constraints

- Finite set of lexicalized elementary trees
- Finite set of operations (Substitution and Adjunction) are used to combine elementary trees



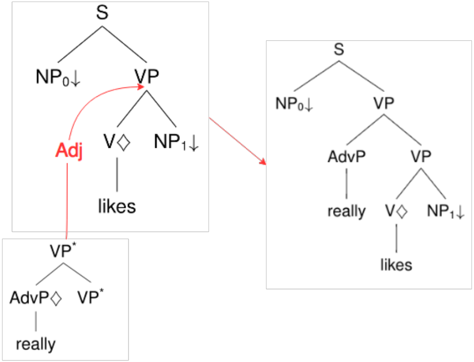
Tree-Adjoining Grammar

Substitution

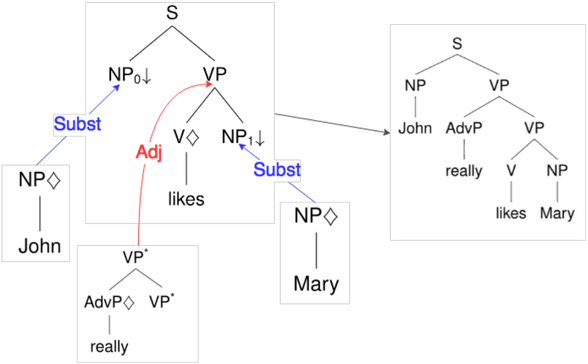


Tree-Adjoining Grammar

Adjunction



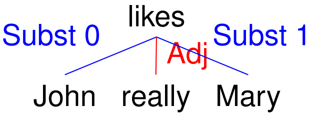
Tree-Adjoining Grammar

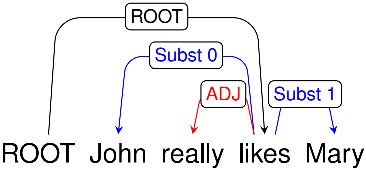


Adjunction allows for unbounded recursion while still enforcing agreement.
John smartly occasionally really only likes Mary...

Derivation Tree

Derivation tree records the operations.
Forms a dependency tree (each token has exactly one parent)

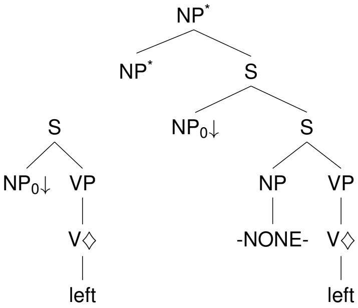




Two Steps in TAG Parsing

Now the reverse process.

- *Supertagging*
  Assign elementary trees (supertags) to each token. Similar to POS tagging.
- *Parsing*
  Predict operations on the elementary trees.



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Supertagging is a bottleneck

Supertagger	Parser	Stag Acc	UAS	LAS
Gold	Chart (MICA)	100.00	97.60	97.30
Maxent (MICA)	Chart (MICA)	88.52	87.60	85.80

- Supertagging is *almost parsing*
- There are about 5,000 supertags in the grammar
- About half of them occur only once in the training data (PTB WSJ Sections 1-22).

BiLSTM Supertagging

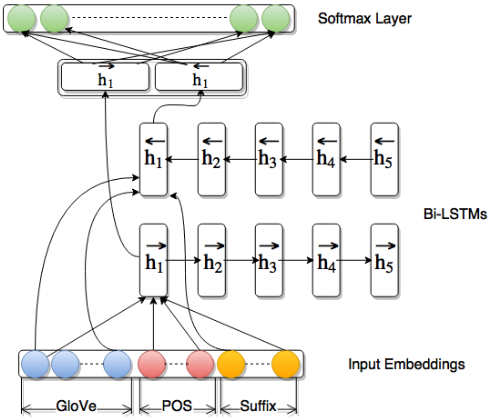

Figure: BiLSTM Supertagger Architecture.

Supertagging is still a bottleneck

Supertagger	Parser	Stag Acc	UAS	LAS
Maxent (MICA)	Chart (MICA)	88.52		
BiLSTM	Chart (MICA)	**89.32**		

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BiLSTM	Chart (MICA)	**89.32**	**90.05**	**88.32**

- We can compensate for supertagging errors by exploiting structural similarities across elementary trees.
- Similarities across supertags are not utilized by the chart parser.
- We use two alternative families of parsing algorithms

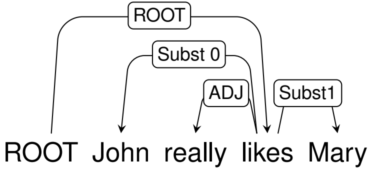
Outline

Parsing Models

- Prior Work: Unlexicalized Chart-Parser (MICA) [Bangalore et al., 2009]
- Unlexicalized Transition-based Parser [Kasai et al., 2017, Friedman et al., 2017]
- Graph-based Parser [Kasai et al., 2018]

Transition-based Parsing

Arc-Eager System (MALT) [Nivre et al., 2006]



Transition-based Parsing

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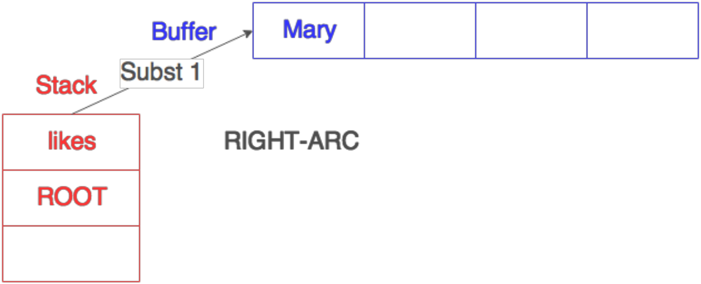
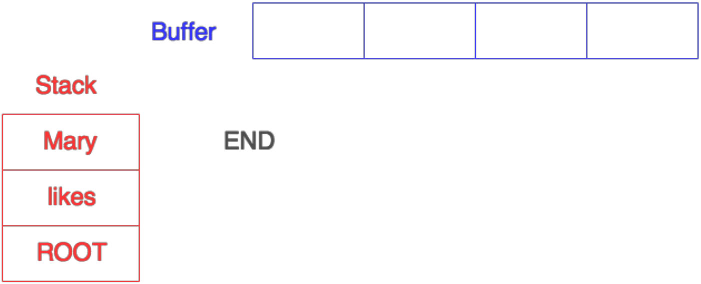


Transition-based Parsing



Transition-based TAG Parsing

How do we learn?

- Represent the configuration by the top k elements from stack and buffer: $\{s_i, b_i\}_{i=1}^{k}$ [Chen and Manning, 2014].
- Represent s_i (b_i) by the TAG elementary tree and the derived substitution operations performed into s_i.
- Encode the TAG elementary trees and the substitution operations with dense vectors.

NN Transition-based Parsing Model

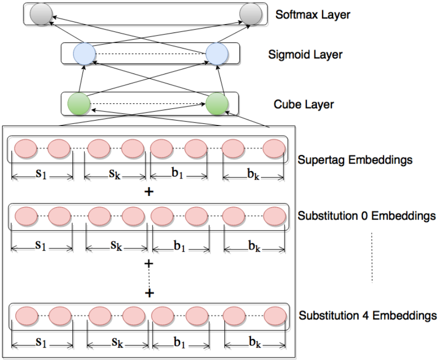
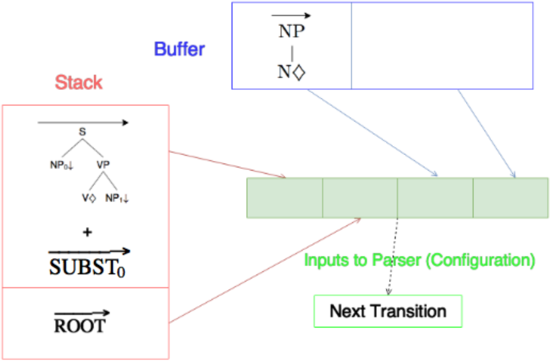


Figure: Transition-based Parser Neural Network Architecture.

Example

John really likes Mary

Stack	Buffer	Relations	Action
ROOT likes	Mary	$\{(ROOT, likes, ROOT), (likes, John, 0) \cdots\}$	RIGHT:1



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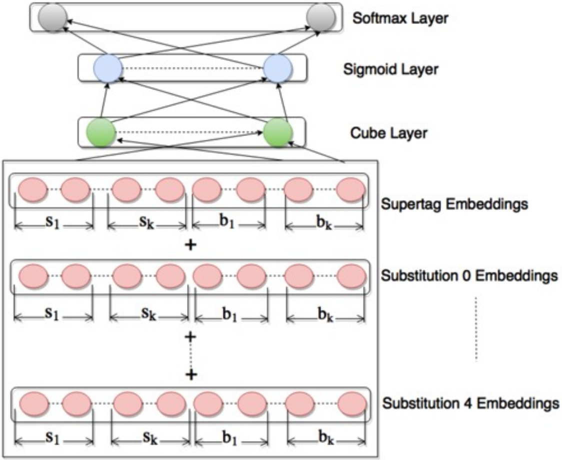
Embeddings for Elementary Trees



PCA Plots of Vector Representations

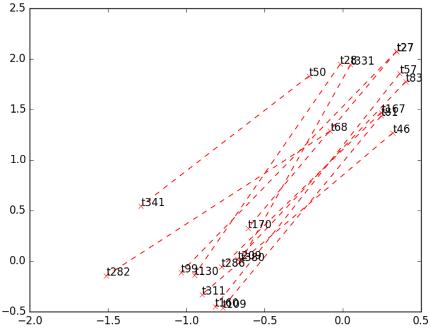


Figure: Declarative/subject relative alignment (Atomic embeddings)
ex: *the man* ***sneezed*** vs. *the man who* ***sneezed***

PCA Plots of Vector Representations

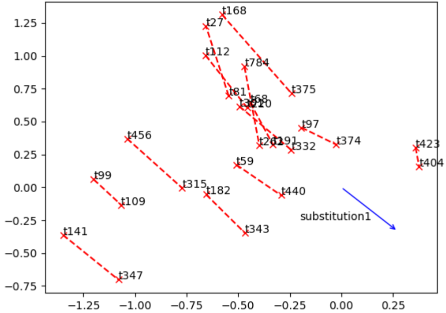


Figure: Transitive/intransitive alignment (Atomic embeddings).
ex: *the man who **devoured** the pizza* vs. *the man who **sneezed***

Analogy Test Results

n	# equations	% correct	Avg. position
300	246	50.40	7.98
4724	57220	4.62	289.48

Table: Analogy task results. (n is a number used to restrict which supertags are considered: For a given n, only equations for which all supertags are among the n most common supertags are considered.)

- **% correct**: Percent of equations for which the left hand side's closest cosine neighbor was the right hand side.
- **Avg. position**: The position of the correct right hand side in the list of supertag embeddings ranked by cosine distance from the left hand side.

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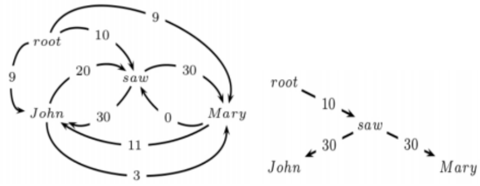
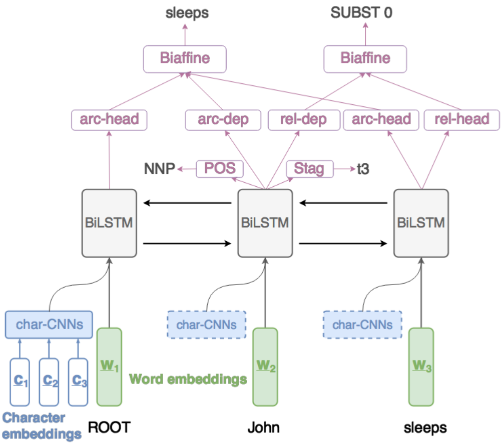
Graph-based Parsing



[McDonald et al., 2005]

- Score n^2 directed edges (n potential parents for each of the n tokens in a sentence) using features
- Find the maximum spanning tree (greedy + cycle fix)

Graph-based Parsing TAG Parsing



Comparison btw transition-based and graph-based

Rich feature representations with parse history v.s. global training/inference

- Transition-based parsers have parse history that naturally relates supertags that differ only by a certain operation (e.g. transitive/intransive)
- Transition-based parsers suffer from global error propagation
- Graph-based parsers assign scores independently
- Graph-based parser with BiLSTM feature representations (still no history)

New Results

Parser	UAS	LAS
MICA Chart	86.66	84.90
Transition-based Parsing	90.97	89.68
Joint Graph Parsing (POS+Stag)	**93.26**	**91.89**

Table: Parsing results on the test set.

Outline

Syntactically-oriented Textual Entailment

[Xu et al., 2017]

E.g. *The guy who left the room saw a squirrel*

$\Longrightarrow$ *The guy left the room*

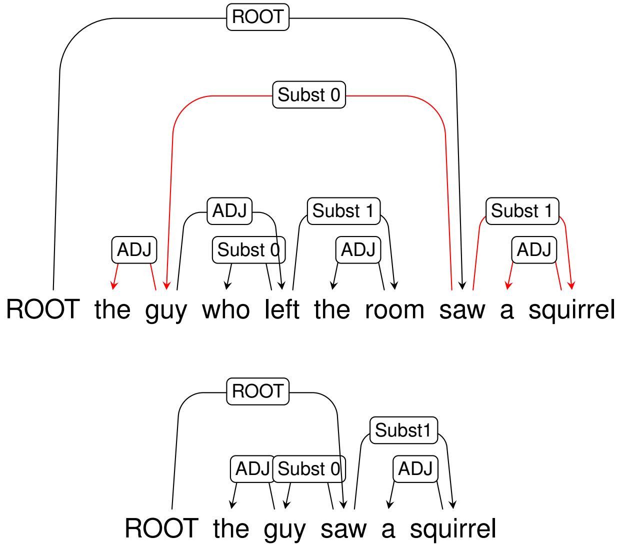
$\Longrightarrow$ *The guy saw a squirrel*

$\not\Longrightarrow$ *The room saw a squirrel*

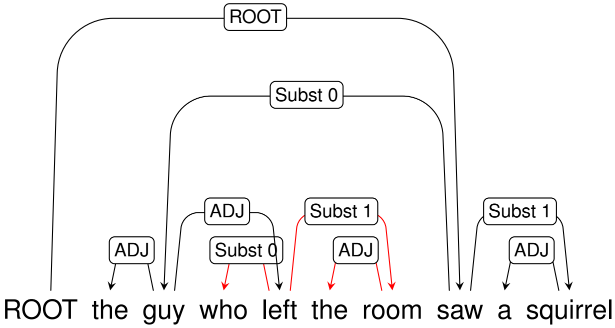
$\not\Longrightarrow$ *The guy saw an animal* (not pure syntactic)

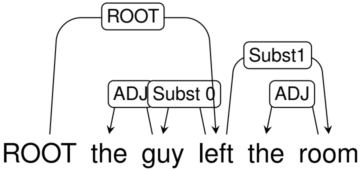
- Parse the original sentence and hypothesis
- Transform the parses using properties of supertags
- If the original sentence parse subsumes the hypothesis one, YES.

Syntactically-oriented Textual Entailment



Syntactically-oriented Textual Entailment



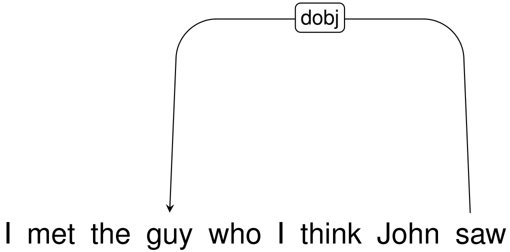


Syntactically-oriented Textual Entailment

System	%A	%P	%R	F1
[Rimell and Clark, 2010]	72.4	79.6	62.8	70.2
[Ng et al., 2010]	70.4	68.3	80.1	73.7
[Lien, 2014]	70.7	88.6	50.0	63.9
Transition-based TAG Parsing	72.4	85.4	56.4	68.0
Graph-based Method	**78.1**	86.3	68.6	**76.4**

Table: PETE test results. Precision (P), recall (R), and F1 are calculated for "entails."

Unbounded Dependency Recovery



System	obRC	obRd	sbRC	free	obQ	rnr	sbEm	Total
C&C	59.3	62.6	80.0	72.6	**72.6**	**49.4**	22.4	53.6
Enju	47.3	65.9	82.1	76.2	32.5	47.1	32.9	54.4
Stanford	22.0	1.1	74.7	64.3	41.2	45.4	10.6	38.1
MST	34.1	47.3	78.9	65.5	41.2	45.4	37.6	49.7
MALT	40.7	50.5	**84.2**	70.2	31.2	39.7	23.5	48.0
Joint	**72.5**	**78.0**	81.1	**85.7**	56.3	47.1	**49.4**	**64.9**

Acknowledgement

Thank you!

- Robert Frank, Dan Friedman, Tom McCoy, William Merrill, Alexis Nasr, Dragomir Radev, Owen Rambow, and Pauli Xu

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