Latent-Variable Grammars and Natural Language Semantics

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Modern Natural Language Processing



1980s - rule based systems



1990s - statistical methods (frequentist?)



2000s - ... statistical methods (Bayesian analysis?)



2010s - continuous representations, deep learning

Grammar Models



Machine Learning



2 NLP

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Grammar Models



Machine Learning

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$$\begin{array}{l} \mathsf{S} \rightarrow \mathsf{NP} \; \mathsf{VP} \\ \mathsf{DT} \rightarrow \mathsf{the} \\ \cdots \end{array}$$

- Any problem in NLP that requires "understanding" text at some level
- Most prominently: requires lexical understanding (such as in lexical semantics)
 - By negation: anything that is not syntax! (or, goes beyond syntax?)

Syntax in Pictures





Semantics in Pictures



PCFGs with Latent States



- Latent states play the role of syntactic heads, as in lexicalization
- They are not part of the observed data in the treebank

We used latent-variable PCFGs to make progress on several problems:

- Syntactic parsing (the classic application of L-PCFGs)
- Machine translation
- Analyzing social media forums
- Open-domain question answering

• The probability of a tree is the product of rules with latent states:

$$p(t) = \prod p(a(h_1) \to b(h_2) c(h_3) \mid a(h_1))$$

- It is just a PCFG!
- However, we are interested in distributions over "skeletal" trees

$$p(\text{skeleton}(t)) = \sum_{h} \prod p(a(h_1) \to b(h_2) c(h_3) \mid a(h_1))$$

Distributions over skeletal trees are more expressive than PCFG

- Some variant of spectral learning for L-PCFGs (ACL, 2012)
- Based on the method of moments, with intuitive-to-understand variants (EMNLP, 2015)
- Performs pretty well on syntactic parsing problems
- Very (computationally) efficient
- Allows encoding information about the latent states directly (why is this important?)

- SVD variant: based on singular value decomposition of empirical count matrices (ACL, 2012; JMLR 2014)
- **Convex EM variant**: based on the so-called "anchor method" that identifies features that uniquely identify latent states (ACL, 2014)
- Clustering variant: a simplified version of the SVD variant that clusters low-dimensional representations to latent states (EMNLP, 2015)
- Simpler clustering variant: a further simplified version of the clustering variant (EMNLP, 2015b)

The (Simpler) Clustering Variant

1. For each node in a tree, create a context **feature vector**, as a function of the node and the nodes surrounding it

2. Cluster these vectors to m clusters using a clustering algorithm

3. Annotate each node with the cluster ID of its feature vector. Cluster ID = latent state



MoM: Set up equations involving moments and parameters

Then, solve with respect to the parameters

Recent use: finding the parameters of latent variables

Simplicity of estimation

Efficiency of estimation

Theoretical guarantees

Performance

With EM: local maximization of the log-likelihood function

If we could globally maximize the log-likelihood, estimation is likely to be "consistent"

With method of moments: sample complexity statements in the style of:

With n samples, the deviation between the estimated probability distribution and the "true" one is small if n is large. The error is a function of various elements, including n, some spectral elements of the moments and properties of the grammar.

Inside Features Used

Consider the VP node in the following tree:



The inside features consist of:

- The pairs (VP, V) and (VP, NP)
- The rule VP \rightarrow V NP
- The tree fragment (VP (V saw) NP)
- The tree fragment (VP V (NP D N))
- The pair of head part-of-speech tag with VP: (VP, V)

Outside Features Used



• The pair of head part-of-speech tag with D: (D, N)

Out-of-the-box accuracy of the clustering variant:

English: 86.48% German: 75.04%

Regular spectral algorithm (Cohen et al., 2013):

English: 88.53% German: 77.71%

- Models in the clustering variant are very compact
- Idea: create multiple models and combine them together
- Three ways to combine models together
- I will focus on MaxEnt reranking (Charniak and Johnson, 2005)

- Basic idea: noise the feature representations
- We used dropout and Gaussian noise (Wang et al., 2013)
- Dropout: zero randomly a small fraction of the features
- Gaussian noise: add random Gaussian noise to pre-clustered vectors

Oracle results:

English: 95.73% German: 90.12%

Regular spectral algorithm (Cohen et al., 2013):

English: 92.81% German: 83.45% Final results, MaxEnt reranking:

English: 90.18% German: 83.38%

Regular spectral algorithm (Cohen et al., 2013):

English: 89.06% German: 80.64% Each nonterminal a is associated with m_a latent states

Spectral learning gives a natural way to choose the number of latent states based on the number of non-zero singular vectors

This criterion does not take into account interactions between different nonterminals

Can we improve that?

The Berkeley parser has proved that coarse-to-fine techniques that carefully select the number of latent states are very useful

A beam search algorithm

The value in the queue is F_1 measure on a development set

We iterate through the nonterminals, and change the number of latent states, training, calculating accuracy and updating the queue

Major advantage: the training algorithm is relatively fast, so this is mangageable

Traversal of multidimensional vectors (latent state numbers), each giving an F_1 score



Results

Language	Berkeley	Spectral	Optimized	
Basque	74.7	79.6	80.5	*
French	79.9	78.0	78.1	
German	80.1	76.4	79.4	
Hebrew	87.0	86.5	89.0	*
Hungarian	85.2	86.5	88.4	*
Korean	78.5	76.5	80.0	*
Polish	86.7	90.5	91.2	*
Swedish	80.6	76.4	79.4	

Experiments: Language Modeling

Saul and Pereira (1997):

$$p(w_2|w_1) = \sum_{\boldsymbol{h}} p(w_2|\boldsymbol{h}) p(\boldsymbol{h}|w_1).$$



This model is a specific case of L-PCFG

Experimented with bi-gram modeling for the Brown corpus and Gigaword corpus

	Brown			NYT			
m	128	256	test	128	256	test	
bigram Kneser-Ney	408		415	271		279	
trigram Kneser-Ney	386		394	150		158	
EM	388 365		364	284	265	267	
iterations	98		504	35	32	207	
pivot	426 597		560	782	886	715	

Results: Perplexity

	Brown			NYT			
m	128	256	test	128	256	test	
bigram Kneser-Ney	408		415	271		279	
trigram Kneser-Ney	386		394	150		158	
EM	388	365	261	284	265	267	
iterations	9	8	304	35	32	207	
pivot	426	597	560	782	886	715	
pivot+EM	310	327	257	279	292	201	
iterations	1	1	557	19	12	201	

- Initialize EM with our algorithm's output
- EM converges in much fewer iterations
- Called "two-step estimation" (Lehmann and Casella, 1998)

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- Hierarchical phrase-based MT: use a synchronous grammar
- Rewrite pairs of phrases that are mutual translations
- There is a single nonterminal \boldsymbol{X}
- Example rule: $X \to \langle X \text{ good day } | X \text{ god dag } \rangle$

The Need for Context



Translate		
Italian Norwegian English English - detected ~	←	German English Spanish × Translate
The party takes place in this building	×	Die Partei in diesem Gebäude stattfindet
	(ا	☆ ■ / ・ ・

- Context in translation models is not sufficient for long sentences
- Solution: add latent variables to ${\rm X}$ ${\rm X}$ is now typed with a category that is not observed in data

Machine Translation



Synchronous L-PCFGs for hierarchical translation (Saluja et al., 2014)

System	BLEU score (test)			
Hiero	55.3			
EM, $m = 8$	49.8			
EM, $m = 16$	53.0			
Spectral, $m = 8$	53.6			
Spectral, $m = 16$	55.8			

Spectral grammars are much smaller

They use "minimal grammars" instead of "composed grammars"

Assume each pair of sentences has a single synchronous derivation

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Discussion Forums



Discussion Forums

cnet O US Edition Reviews Video How To Games Download TV HUYING GUIDE / OK, I have to guess that's the CPU thermal paste. by R. Proffitt @ / June 3, 2015 6:12 AM PDT In reply to: Cleaned computer, now runs games extremely slow? How about the GPU? For example those need love too. Example follows. http://www.tomshardware.com/reviews/radeon-r9-290x-thermal-paste-efficiency.3678.html REPLY / THIS WAS HELPFUL (0) GPU by Neoples871 / June 3, 2015 10:10 AM PDT Looking for a new TV? In reply to: OK, I have to guess that's the CPU thermal paste. We review tons of TVs here at CNET, but these are I am going to check out everything in my PC and make sure it's all plugged in correctly. I could have the ones that made the cut for best of 2015. bumped something without my knowledge but I feel like when I checked my information it would have told me that something was not working correctly whereas it says everything is working. I will SEE THE BEST TVS OF THE YEAR give an update once I do this, thanks, REPLY / . THIS WAS HELPFUL (0) But Bob's Right by itsdigger / June 3, 2015 12:38 PM PDT In reply to: GPU If your GPU is old or even new , you should apply new thermal paste . I have 2 brand new Nvidia 750 TI GPU's and right out of the box I removed and replaced with new **Bold.** Beautiful. Built for Business. thermal paste as from the factory I could see that it was way too thick . Take care of Rusiness at HP Store Digger

REPLY / THIS WAS HELPFUL (1)

- p_0 Bob: When I play a recorded video on my camera, it looks and sounds fine. On my computer, it plays at a really fast rate and sounds like Alvin and the Chipmunks!
- $p_1 \mbox{ Kate: } \mbox{ I'd find and install the machine's latest audio driver. }$
- p_2 Mary: The motherboard supplies the clocks for audio feedback. So update the audio and motherboard drivers.
- $p_3 \mbox{ Chris:}$ Another fine mess in audio is volume and speaker settings. You checked these?
- p_4 Jane: Yes, under speaker settings, look for hardware acceleration. Turning it off worked for me.
- $p_5~{\rm Matt:}~{\rm Audio~drivers}$ are at this $\underline{\rm link}.$ Rather than just audio drivers, I would also just do all drivers.

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Conversation Trees



A terminal node is a whole post now!

Conversation Trees

We have grammar rules such as $S[11] \rightarrow T[3] X[5] X[12] X[5]$

Each latent state corresponds to a bag of words, a topic

The topic dominates the set of posts in the thread at the bottom



Linear ordering of posts: by time (PCFG not enough!)

Data and Task

- 13,352 threads of computer troubleshooting posts from cnet.com
- Number of posts per thread ranges from 1 to 394
- Threads are structured as dependency trees (reply structure)
- Convert the reply structure to a conversation tree
- Given a set of posts, we try to recover the thread structure



- The depth of a node
- Number of siblings
- Number of posts a node dominates
- Bag of words in dominated posts by a node
- ... and others

- Latent-variable context-free rewriting systems
- Allow discontinuous spans for a given nonterminal
- This allows us to have *non-projective* reply structure



Method	G-p	G-r	NG-p	NG-r	F (final score)
Right branching	35	100	100	0	0
All to root	100	0	56.8	87.6	0
Random	52.2	16.8	54.9	75.1	31.7
PCFG	39.4	58.3	48.8	36.1	45.0
PLCFRS	36.3	65.3	55.7	31.6	44.4

Bottom-line: PCFG does the best on average

Number of latent states used: a few dozens per nonterminal

Handling discontinuities does not help that much in total

Non-projective trees:

PCFG: 43.0%

PLCFRS: 44.1%

LCFRS help with non-projective trees

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- With the advent of new datasets, open-domain question answering has become a new challenge
- Current (industry) systems have relatively high precision, but really low recall
- The way a question is asked is very important
- What if it were asked in several different ways? What if we asked the same question more than once?

- 1. Take an input question q
- 2. Generate paraphrases for it: q_1, \ldots, q_m
- 3. Use the QA system to get answers a and a_1, \ldots, a_m
- Take a majority vote or another approach to synthesize an answer from a, a₁,..., a_m.

- L-PCFGs are a generative model
- Each latent state captures a summary of the tree below it
- Does the latent state capture enough information to generate a paraphrase of the tree below it?

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- Does the latent state capture enough information to generate a paraphrase of the tree below it?
- Unfortunately, the answer is no.

Lattice Constraints



- Constrain the generation to a lattice
- Original question: what language do people in Czech Republic speak?
- The lattice is created by taking words and phrases from the original sentence together with others from the Paraphrase Database

Generation of Question Paraphrases

- Paraphrases are generated from an L-PCFG while constraining them to the lattice
- A classifier filters "bad" paraphrases based on simple sentence statistics (such as BLEU score with respect to the original question)
- The classifier is learned from a small amount of manually annotated data with positive and negative examples of paraphrases
- The end result is a black-box that given a question, outputs paraphrases for that question
- The questions are syntactically diverse

- We use the Paralex corpus 18M paraphrase pairs with 2.4M distinct questions
- Parse the questions using the BLLIP parser
- Estimate an L-PCFG with 24 latent states
- How to capture semantic information?

Bi-Layered L-PCFGs

• Add another layer of latent states:



- The second layer has many more latent states (hundreds) and uses a different feature set
- Example feature: bag of words in the inside / outside trees

The basic system is from Reddy et al. (2014)

What language do people in Czech Republic speak?

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What language do people in Czech Republic speak?

What language do people in Czech Republic speak? What is Czech Republic's language? What language do people speak in Czech Republic? ... The basic system is from Reddy et al. (2014)

What language do people in Czech Republic speak?

What language do people in Czech Republic speak? What is Czech Republic's language? What language do people speak in Czech Republic? ... CCG

 $\lambda e.\text{speak.arg1}(e, \text{people})$ $\land \text{speak.arg2}(e, \text{language?})$ $\land \text{speak.in}(e, \text{CzechRepublic})$

Semantic Parsing Using Paraphrases

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Results

Algorithm	F_1 score
Berant and Liang (2014)	39.9
Bordes et al. (2014)	39.2
Dong et al. (2014)	40.8
Yao (2015)	44.3
Bao et al. (2015)	45.3
Bast and Haussmann (2015)	49.4
Berant and Liang (2015)	49.7
Yih et al. (2015)	52.5
Reddy et al. (2016)	50.3
PPDB	47.7
Bi-layered	48.1

- The method does not perform as well as state of the art
- It is partially because paraphrases are done at word level
- Now looking at doing this at a phrase level
- Starting to look more and more like an MT problem

Final Remarks

Another Example: Unsupervised Parsing



Latent structure is a bracketing (Parikh et al., 2014)

Similar in flavor to tree learning algorithms (e.g. Anandkumar, 2011)

Very different flavor from the four estimation algorithms

- Tensor decomposition for the reduction of grammar constant
- Can be used for L-PCFGs (Cohen and Collins, 2012)
- Can be used for PCFGs (Cohen et al., 2013)
- Turns a chart algorithm into linear in the number of nonterminals
- Related algorithm: Rabusseau et al. (2015)

Summary:

- Latent states + Grammars = Expressive, powerful formalism
- There are theoretically-motivated, efficient ways for estimation
- Various applications