Unsupervised Learning of Syntactic Structure

CS224N
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(borrowing slides from Dan Klein and Roger Levy)

Supervised training

- Standard statistical systems use a supervised paradigm.

Training:

Labeled training data → Statistics → Machine learning system → Prediction procedure

The real story

- Annotating labeled data is *labor-intensive!!!*

Training:

Human effort → Labeled training data → Statistics → Machine learning system → Prediction procedure

The real story (II)

- This also means that *moving to a new language, domain, or even genre can be difficult.*
- But unlabeled data is cheap!
- It would be nice to use the unlabeled data directly to learn the labelings you want in your model.
- Today we'll look at methods for doing exactly this for syntax learning.

Learning structured models

- Most of the models we look at in this class have been *structured*
  - Tagging
  - NER
  - Parsing
  - Role labeling
- The structure is *latent*
- With raw data, we have to construct models that will *be rewarded for inferring that latent structure*

A very simple example

- Suppose that we observe the following counts

A	9
B	9
C	1
D	1

- Suppose we are told that these counts arose from tossing two coins, each with a different label on each side
- Suppose further that we are told that the coins are not extremely unfair
- There is an intuitive solution; how can we learn it?

A very simple example (II)

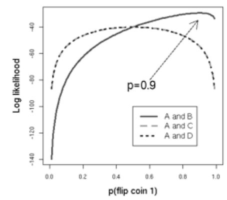
A	9
B	9
C	1
D	1

- Suppose we fully parameterize the model:
  - π :Probability of flipping coin 1
  - p_1 :Probability of coin 1 coming up "heads"
  - p_2 :Probability of coin 2 coming up "heads"
- The MLE of this solution is totally degenerate: it cannot distinguish which letters should be paired on a coin
  - Convince yourself of this!
- We need to specify more constraints on the model
  - The general idea would be to place priors on the model parameters
  - An extreme variant: force p_1=p_2=0.5

A very simple example (III)

A	9
B	9
C	1
D	1

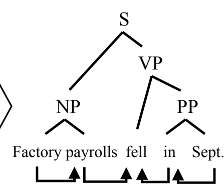
- An extreme variant: force p_1=p_2=0.5
- This *forces structure into the model*
- It also makes it easy to visualize the log-likelihood as a function of the remaining free para
- The intuitive solution is found!



What is Grammar Induction?

- Given:
  - lots of (flat, linear) text of a language
  - but no knowledge particular to that language
- Goal: to discover the natural units of text (constituents)
- Parsing assigns structures to sentences and shows semantic modification relationships

```
He was previously vice president
Pick a country any country
Factory payrolls fell in September
South Korea has different concerns
The Artist has his routine
He is his own man
One claims he 's pro-choice
...
...
...
...
...
Who 's telling the truth
```



Gold (1967)

- Gold: no superfinite class of languages (e.g., regular or context-free languages, etc.) is learnable without negative examples.
  - Certain conditions: nearly arbitrary sequence of examples; only constraint is that no sentence may be withheld from the learner indefinitely.
- Still regularly cited as bedrock for innatist linguistics
- Responses suggested by Gold:
  - Subtle, covert negative evidence ← Some recent claims
  - Innate knowledge shrinks language class ← Chomsky
  - Assumption about presentation of examples is too general ← e.g., probabilistic language model

Horning (1969)

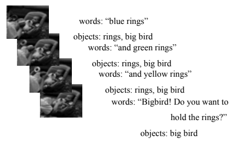
- If texts are generated by a stochastic process, how often something occurs can drive language acquisition
  - As time goes by without seeing something, we have evidence that it either doesn't happen or is very rare
  - Implicit negative evidence: can't withhold common stuff
- Horning: stochastic context-free languages are learnable* from only positive examples.
- But Horning's proof is enumerative, rather than providing a plausible grammar learning method
  (See, e.g., Rohde and Plaut 1999 for discussion)
- Here we provide two case studies:
  1. Phrase structure (and dependencies) learning
  2. Learning semantic roles underlying surface syntax

Motivations

- Natural Language Processing
  - Want to be able to make use of grammatical structure-based models for text domains and languages for which there are no treebanks (which is most of them)
  - There's much more data than annotated data
- Machine Learning
  - How can one learn structures, not just weights
- Linguistics/Cognitive Science
  - Unsupervised grammar learning can shed light on language acquisition and linguistic structure

Is this the right problem?

- Before proceeding…are we tackling the right problem?
  - We've already seen how the structures giving high likelihood to raw text may not be the structures we want
  - Also, it's fairly clear that kids don't learn language structure from linguistic input alone…



  - Real learning is *cross-modal*
- So why study unsupervised grammar induction from raw text?

Why induce grammars from raw text?

- I don't think this is a trivial question to answer. But there *are* some answers:
  - Practical: if unsupervised grammar induction worked well, it'd save a whole lot of annotation effort
  - Practical: we need tree structure to get compositional semantics to work
  - Scientific: unsupervised grammar induction may help us a place an *upper bound* on how much grammatical knowledge must be innate
  - Theoretical: the models and algorithms that make unsupervised grammar induction work well may help us with other, related tasks (e.g., machine translation)

Distributional clustering for syntax

- How do we evaluate unsupervised grammar induction?
- Basically like we evaluate supervised parsing: through bracketing accuracy
- But this means that we don't have to focus on inducing a *grammar*
- We can focus on inducing constituents in sentences instead

Distributional clustering for syntax (II)

- What makes a good constituent?
- Old insight from Zellig Harris (Chomsky's teacher): *something can appear in a consistent set of contexts*

  Sarah saw a dog standing near a tree.
  Sarah saw a big dog standing near a tree.
  Sarah saw me standing near a tree.
  Sarah saw three posts standing near a tree.
- Therefore we could try to characterize the space of possible constituents by the contexts they appear in
- We could then do clustering in this space

Distributional clustering for syntax (III)

- Clark, 2001: *k*-means clustering of common tag sequences occurring in context distributions
- Applied to 12 million words from the British National Corpus
- The results were promising:

(determiner)

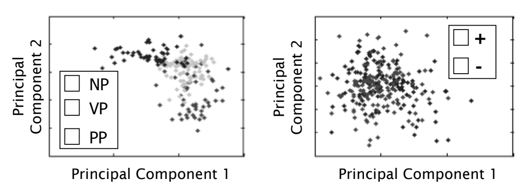
"the big dog"	AT0 AJ0 NN0	AJ0 AJ0
	AT0 AJ0 NN1	AJ0 CJC AJ0
	AT0 AJ0 NN2	AV0 AJ0
	AT0 AV0 AJ0 NN1	AV0 AV0 AJ0
"the very big dog"	AT0 NN0	ORD
"the dog"	AT0 NN1 PRP AT0 NN1	
"the dog near the tree"	AT0 NN1	

Problem: Identifying Constituents

Distributional classes are easy to find…

the final vote / two decades / most people — the final / the initial / two of the — of the / with a / without many — in the end / on time / for now — decided to / took most of / go with

… but figuring out which are constituents is hard.



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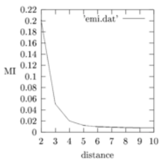
Distributional clustering for syntax (V)

- Clark 2001's solution:
  "with real constituents, there is high mutual information between the symbol occurring *before* the putative constituent and the symbol *after*…"
  - Filter out distituents on the basis of low mutual information
  - (controlling for distance between symbols)



	Cluster	Actual MI	Exp. MI	Valid
constituents	ATO NN1	0.11	0.04	Yes
	ATO NP0 NP0	0.13	0.02	Yes
	PRP AT0 NN1	0.06	0.02	Yes
	AV0 AJ0	0.27	0.1	Yes
distituents	NN1 AT0	0.008	0.02	No
	AT0 AJ0	0.02	0.03	No
	VBI AT0	0.01	0.02	No
	PRP AT0	0.01	0.03	No

Distributional clustering for syntax (VI)

- The final step: train an SCFG using vanilla maximum-likelihood estimation
- (hand-label the clusters to get interpretability)

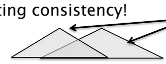
Ten most frequent rules expanding "NP"

Count	Right Hand Side
255793	AT0 NN1
104314	NP PP
103727	AT0 AJ0 NN1
73151	AT0 NN2
72686	DPS NN1
52202	AJ0 NN2
51575	DT0 NN1
35473	NP NP
34523	DT0 NN2
34140	AV0 NP

Structure vs. parameter search

- This did pretty well
- But the clustering-based structure-search approach is throwing out a hugely important type of information
- (did you see what it is?)
- …bracketing consistency!

both can't be a constituent at once

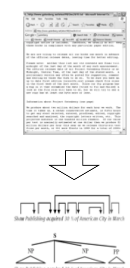


Sarah gave the big dog the most enthusiastic hug.

- Parameter-estimation approaches automatically incorporate this type of information
- This motivated the work of Klein & Manning (2002/2004)

Grammar induction: Klein and Manning (2004)

- Start with raw text, learn syntactic structure
- Some have argued that learning syntax from positive data alone is impossible:
  - Gold, 1967: Non-identifiability in the limit
  - Chomsky, 1980 : The poverty of the stimulus
- Many others have felt it should be possible:
  - Lari and Young, 1990
  - Carroll and Charniak, 1992
  - Alex Clark, 2001
  - Mark Paskin, 2001
  - … but it *is* a hard problem



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Idea: Lexical Affinity Models

- Words select other words on syntactic grounds

congress narrowly passed the amended bill

- Link up pairs with high mutual information
  - [Yuret, 1998]: Greedy linkage
  - [Paskin, 2001]: Iterative re-estimation with EM
- Evaluation: compare linked pairs to a gold standard

Method	Accuracy
Paskin, 2001	39.7

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Problem: Non-Syntactic Affinity

- Mutual information between words does not necessarily indicate syntactic selection.

congress narrowly passed the amended bill

expect brushbacks but no beanballs

a new year begins in new york

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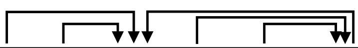
Idea: Word Classes

- Individual words like congress are entwined with semantic facts about the world.
- Syntactic classes, like NOUN and ADVERB are bleached of word-specific semantics.
- Automatic word classes more likely to look like DAYS-OF-WEEK or PERSON-NAME.
- We could build dependency models over word classes. [*cf*. Carroll and Charniak, 1992]



congress narrowly passed the amended bill

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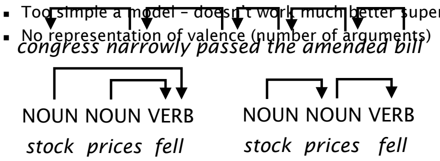
Problems: Word Class Models

Random	41.7	
Carroll and Charniak, 92	44.7	

- Issues:
  - Too simple a model – doesn't work much better supervised
  - No representation of valence (number of arguments)



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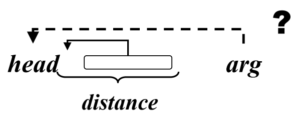
Bias: Using more sophisticated dependency representations



	Classes?	Distance	Local Factor
Paskin 01	✗	✗	$P(a \mid h)$
Carroll & Charniak 92	✓	✗	$P(c(a) \mid c(h))$
Our Model (DMV)	✓	✓	$P(c(a) \mid c(h), d)$

Adjacent Words	55.9	
Our Model (DMV)	63.6	

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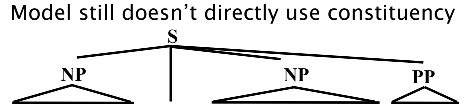
Constituency Parsing

- Model still doesn't directly use constituency



Shaw Publishing acquired 30 % of American City in March

- Constituency structure gives boundaries

Information Extraction

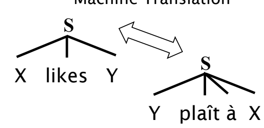
30 % of American City

~~*30 %*~~

~~*American City*~~

~~*30 % of American*~~

Machine Translation



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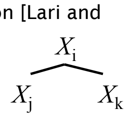
Idea: Learn PCFGs with EM

- Classic experiments on learning Probabilistic CFGs with Expectation-Maximization [Lari and Young, 1990]

$\{ X_1, X_2 \ldots X_n \}$



  - Full binary grammar over n symbols
  - Parse randomly at first
  - Re-estimate rule probabilities off parses
  - Repeat
- Their conclusion: it doesn't work at all!

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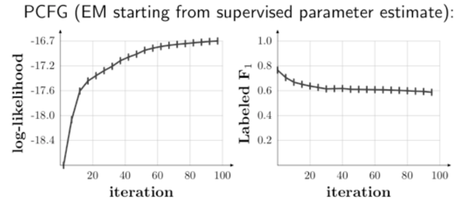
Can we just use PCFGs?

- Early approaches: Pereira & Schabes (1992), Carroll & Charniak (1994)
  - Initialize a simple PCFG using some "good guesses"

PCFG (EM starting from supervised parameter estimate):



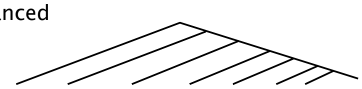
Other Approaches

- Other earlier work in learning constituency:
  - [Adrians, 99] Language grammars aren't general PCFGs
  - [Clark, 01] Mutual-information filters detect constituents, then an MDL-guided search assembles them
  - [van Zaanen, 00] Finds low edit-distance sentence pairs and extracts their differences
  - GB/Minimalism No empirical results
- Evaluation: fraction of nodes in gold trees correctly posited in proposed trees (unlabeled recall)

Adriaans, 1999	16.8	
Clark, 2001	34.6	
van Zaanen, 2000	35.6	

Right-Branching Baseline

- English trees tend to be right-branching, not balanced



they were unwilling to agree to new terms

- A simple (English-specific) baseline is to choose the right-branching structure for each sentence

van Zaanen, 00	35.6	
Right-Branch	46.4	

Inspiration: Distributional Clustering

♦ *the president said that the downturn was over* ♦

president	*the __ of*
president	*the __ said*
governor	*the __ of*
governor	*the __ appointed*
said	*sources __ ♦*
said	*president __ that*
reported	*sources __ ♦*

president governor

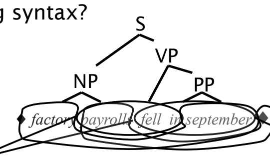
the a

said reported

[Finch and Chater 92, Schütze 93, Clark 01, many others]

Idea: Distributional Syntax?

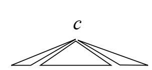
- Can we use distributional clustering for learning syntax?



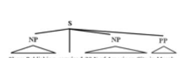
Span	Context
fell in september	*payrolls __ ♦*
payrolls fell in	*factory __ sept*

A Nested Distributional Model

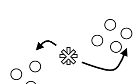
- We'd like a model that:
  - Ties spans to linear contexts (like distributional clustering)



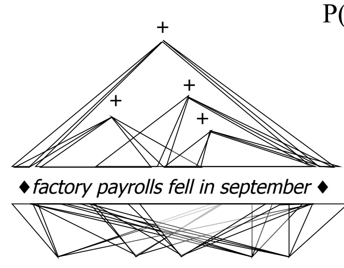
  - Considers only proper tree structures (like a PCFG model)



  - Has no symmetries to break (like a dependency model)



Constituent-Context Model (CCM)



P($S|T$) =

$\begin{cases} \text{P}(\textit{fpfis}|+) \\ \text{P}(\blacklozenge\_\_\blacklozenge|+) \end{cases}$

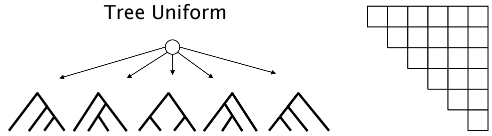
$\begin{cases} \text{P}(\textit{fp}|+) \\ \text{P}(\blacklozenge\_\_\ \textit{fell}|+) \end{cases}$

$\begin{cases} \text{P}(\textit{fis}|+) \\ \text{P}(\textit{p}\ \_\_\ \blacklozenge|+) \end{cases}$

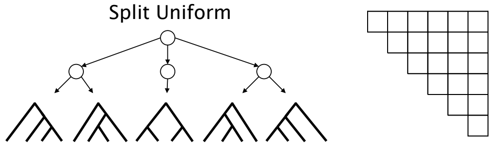
$\begin{cases} \text{P}(\textit{is}|+) \\ \text{P}(\textit{fell}\ \_\_\ \blacklozenge|+) \end{cases}$

Initialization: A little UG?

Tree Uniform



Split Uniform



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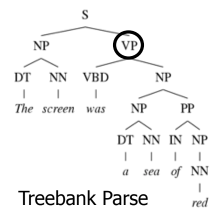
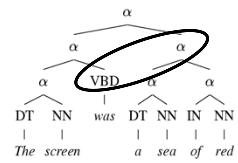
Results: Constituency

Right-Branch	70.0	



Treebank Parse



CCM Parse

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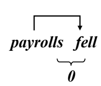
A combination model

- What we've got:
  - Two models of syntactic structure
  - Each was the first to break its baseline
- Can we combine them?
- Yes, using a product model
  - Which we also used for supervised parsing (Klein and Manning 2003)



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Combining the two models
[Klein and Manning ACL 2004]

Dependency Evaluation

Random	45.6	
DMV	62.7	
CCM + DMV	64.7	

Constituency Evaluation

Random	39.4	
CCM	81.0	
CCM + DMV	88.0	

!

- *Supervised* PCFG constituency recall is at 92.8
- Qualitative improvements
  - Subject-verb groups gone, modifier placement improved

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Crosslinguistic applicability of the learning algorithm

Constituency Evaluation

English (7422 sentences)		
Random Baseline	39.4	
CCM+DMV	88.0	

German (2175 sentences)		
Random Baseline	49.6	
CCM+DMV	89.7	

Chinese (2473 sentences)		
Random Baseline	35.5	
CCM+DMV	46.7	

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Most Common Errors: English

Overproposed Constituents

ADJ N	1022	*the [general partner]*
N-PROP N-PROP	447	*the [Big Board]*
DET N	398	*[an import] order*
ADJ N-PL	294	*six million [common shares]*
N-PL ADV	164	*[seats currently] are quoted*

Crossing Constituents

NUM NUM PREP NUM NUM	154	*rose to [# billion from # billion]*
N-PL ADV	133	*petroleum [prices also] surged*
N-PROP N-PROP N-PROP	67	*to [Hong Kong China] is*
ADJ N	66	*especially [strong growth]*

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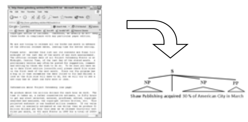
What Was Accomplished?

- Unsupervised learning:
  - Constituency structure
  - Dependency structure



- Constituency recall:

Random Baseline	39.4	
CCM + DMV	88.0	
Supervised PCFG	92.8	

- Why it works:
  - Combination of simple models
  - Representations designed for unsupervised learning

More recently…

- Quite a bit of other work has built on these results
  - Smith and Eisner 2005
  - Headden et al. 2009
  - Cohen and Smith 2009
  - Spitkovsky et al. 2010
- Improved performance (on longer sentences!) via a variety of techniques.