CS 4650/7650
Modern statistical parsers

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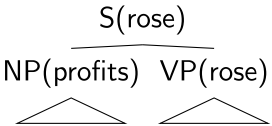
The Charniak parser

The Charniak (1997) parser gives a relatively straightforward way to lexicalize PCFGs.

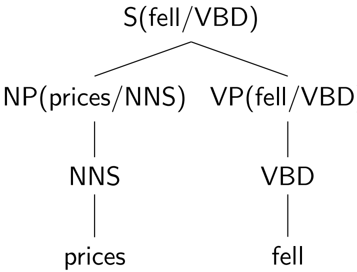
- Compute the head probability: $P(s_i | t_i, s_{p(i)}, t_{p(i)})$.
    - s_i is the head of constituent i
    - t_i is the syntactic category
    - $p(i)$ is the parent of node i
- Compute the rule probability: $P(r_i | t_i, s_i, t_{p(i)})$.
- Score each production by the product of the rule probability and the head probabilities.
- Apply standard CKY bottom-up parsing.



Head probabilities

The head probabilities capture "bilexical" phenomena, like the PP attachment (*President of Mexico*) example.

- $P(prices|NNS) = .013$
- $P(prices|NNS, NP) = .013$
- $P(prices|NNS, NP, S) = .025$
- $P(prices|NNS, NP, S, VBD) = .052$
- $P(prices|NNS, NP, S, VBD, fell) = .146$



Lexically conditioned rule probabilities

The rule probabilities capture phenomena like verb complement frames.

Local Tree	*come*	*take*	*think*	*want*
VP $\rightarrow$ V	9.5%	2.6%	4.6%	5.7%
VP $\rightarrow$ V NP	1.1%	32.1%	0.2%	13.9%
VP $\rightarrow$ V PP	34.5%	3.1%	7.1%	0.3%
VP $\rightarrow$ V SBAR	6.6%	0.3%	73.0%	0.2%
VP $\rightarrow$ V S	2.2%	1.3%	4.8%	70.8%
VP $\rightarrow$ V NP S	0.1%	5.7%	0.0%	0.3%
VP $\rightarrow$ V PRT NP	0.3%	5.8%	0.0%	0.0%
VP $\rightarrow$ V PRT PP	6.1%	1.5%	0.2%	0.0%

Data sparseness

- The Penn Treebank is still the main dataset for syntactic analysis of English.
- Yet 1M words is not nearly enough data to accurately estimate lexicalized models.
  - 965K constituents
  - 66 examples of WHADJP
  - only 6 of these aren't *how much* or *how many*
- Smoothing is absolutely critical for lexicalized parsers.

Smoothing the Charniak Parser

Head probability:

$$\begin{aligned}\hat{P}(s_i|t_i, s_{p(i)}, t_{p(i)}) =& \lambda_1 P_{mle}(s_i|t_i, s_{p(i)}, t_{p(i)}) \\ &+ \lambda_2 P_{mle}(s_i|t_i, \text{cluster}(s_{p(i)}), t_{p(i)}) \\ &+ \lambda_3 P_{mle}(s_i|t_i, t_{p(i)}) \\ &+ \lambda_4 P_{mle}(s_i|t_i)\end{aligned}$$

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\end{aligned}
$$

For example:

	$P(profit\|NP, rose, S)$	$P(corp.\|JJ, profit, NP)$
$P(s_i\|t_i, s_{p(i)}, t_{p(i)})$	0	.245
$P(s_i\|t_i, \text{cluster}(s_{p(i)}), t_{p(i)})$	.0035	.015
$P(s_i\|t_i, t_{p(i)})$	.00063	.0053
$P(s_i\|t_i)$	.00056	.0042

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We have to tune $\lambda_1 \ldots \lambda_4$, and an equivalent set of parameters for the rule probabilities.

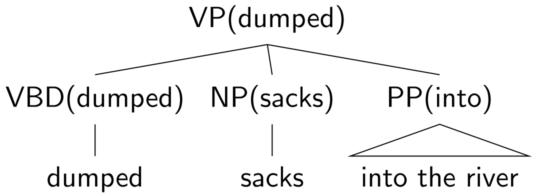
Smoothing the Charniak Parser

- The Charniak parser suffers from acute sparsity problems because it estimates the probability of entire rules.
- Another extreme would be to generate the children independently from each other.
  e.g., $P(S \rightarrow NP\ VP) \approx P_L(S \rightarrow NP)P_R(S \rightarrow VP)$
- The Collins (1999) and Charniak (2000) go for a compromise, conditioning on the parent and the head child.

The Collins Parser

- The Charniak parser focuses on lexical relationships between children and parents.
- The Collins (1999) parser focuses on relationships between adjacent children of the same parent. It decomposes each rule as,
$$X \to L_i L_{i-1} \dots L_1 H R_1 \dots R_{j-1} R_j$$
- Each L and R is a child constituent of X, and they are generated from the head H outwards.
- The outermost elements of L and R are special $\bullet$ symbols.

Example



To model this rule, we would compute:

$$P(VP(dumped, VBD) \rightarrow \bullet\ VBD(dumped, VBD)\ NP(sacks, NNS)\ PP(into, P)\ \bullet)$$

Example

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- The rule probability is the product of these generative probabilities.
- **Horizontal Markovization**: we condition only on the head
- Collins parser also conditions on a "distance" of each constituent from the head.

Smoothing the Collins Parser

- Estimation is eased by factoring the rule probabilities, but smoothing is still needed.

$$\begin{aligned}\hat{P}(R_i(rw_i, rt_i)|p(i), hw, ht) =& \lambda_1 P_{mle}(R_i(rw_i, rt_i)|p(i), hw, ht)\\ &+ \lambda_2 P_{mle}(R_i(rw_i, rt_i)|p(i), ht)\\ &+ \lambda_3 P_{mle}(R_i(rw_i, rt_i)|p(i))\end{aligned}$$

- We set λ using Witten-Bell smoothing.
- Is it worth modeling bilexical dependencies?

The importance of bilexical dependencies

Back-off level	Number of accesses	Percentage
0	3,257,309	1.49
1	24,294,084	11.0
2	191,527,387	87.4
Total	219,078,780	100.0

- In general, bilexical probabilites are rarely available...

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- In general, bilexical probabilites are rarely available...
- ...but they are active in 29% of the rules in **top-scoring** parses.
- Still, they don't seem to play a big role in accuracy (Bikel 2004).

The complexity of lexicalized parsing

- Straightforward lexicalized parsing is $\mathcal{O}(N^5 G)$, where
  - N is the length of the sentence
  - G is the state space, equal to g^3 (cubic in the number of original non-terminals, because we condition on the head and the parent), times V^3 (cubic in the vocabulary size, for the same reason)
- Exhaustive search is totally infeasible; Collins and Charniak both use beam search to eliminate unpromising nodes from the chart.
- Eisner and Satta (2000, etc) give ways to parse more restricted classes of bilexical grammars in $O(N^4)$ or $O(N^3)$

Summary of lexicalized parsing

- Lexicalized parsing resulted in substantial accuracy gains from our original PCFG:

Vanilla PCFG	72%
Parent-annotations	80%
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- But the explosion in the size of the grammar required elaborate smoothing techniques and made parsing slow.
- Treebank syntactic categories are too coarse,
  but lexicalized categories may be too fine.
  Is there a middle ground?

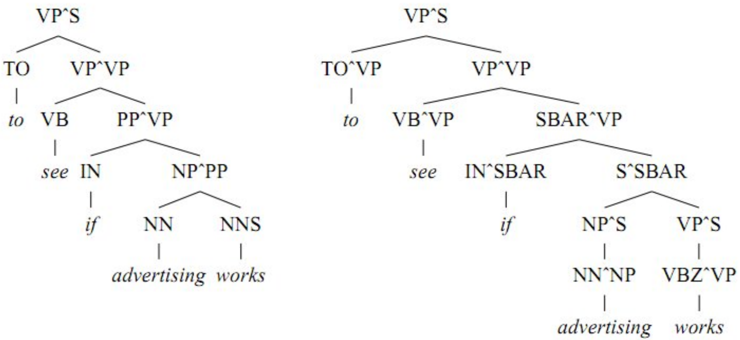
Accurate unlexicalized parsing (Klein and Manning 2003)

- Key idea is that the right level of linguistic detail is somewhere between treebank categories and individual words.
- For example, *on*/PP behaves differently from *of*/PP, but *cat*/N and *dog*/N do not.
- Approach: horizontal and vertical markovization, plus a series of linguistically-motivated splits to the Treebank categories.

Markovization

Vertical Order		Horizontal Markov Order				
		$h=0$	$h=1$	$h\leq 2$	$h=2$	$h=\infty$
$v=1$	No annotation	71.27 (854)	72.5 (3119)	73.46 (3863)	72.96 (6207)	72.62 (9657)
$v\leq 2$	Sel. Parents	74.75 (2285)	77.42 (6564)	77.77 (7619)	77.50 (11398)	76.91 (14247)
$v=2$	All Parents	74.68 (2984)	77.42 (7312)	77.81 (8367)	77.50 (12132)	76.81 (14666)
$v\leq 3$	Sel. GParents	76.50 (4943)	78.59 (12374)	79.07 (13627)	78.97 (19545)	78.54 (20123)
$v=3$	All GParents	76.74 (7797)	79.18 (15740)	79.74 (16994)	79.07 (22886)	78.72 (22002)

Example



Annotating the IN tag with its parent causes it to prefer SBAR complements, resolving this error.

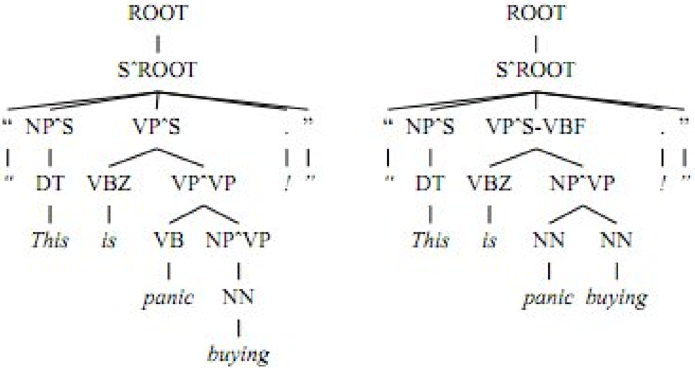
State-splitting

	Cumulative			Indiv.
Annotation	Size	F_1	Δ F_1	Δ F_1
Baseline ($v \leq 2, h \leq 2$)	7619	77.77	–	–
UNARY-INTERNAL	8065	78.32	0.55	0.55
UNARY-DT	8066	78.48	0.71	0.17
UNARY-RB	8069	78.86	1.09	0.43
TAG-PA	8520	80.62	2.85	2.52
SPLIT-IN	8541	81.19	3.42	2.12
SPLIT-AUX	9034	81.66	3.89	0.57
SPLIT-CC	9190	81.69	3.92	0.12
SPLIT-%	9255	81.81	4.04	0.15
TMP-NP	9594	82.25	4.48	1.07
GAPPED-S	9741	82.28	4.51	0.17
POSS-NP	9820	83.06	5.29	0.28
SPLIT-VP	10499	85.72	7.95	1.36
BASE-NP	11660	86.04	8.27	0.73
DOMINATES-V	14097	86.91	9.14	1.42
RIGHT-REC-NP	15276	87.04	9.27	1.94

Examples:

- BASE-NP: non-recursive NPs
- SPLIT-CC: distintinguish *and* and *but* from other CCs

Example



The original parse assigned a VP complement to a finite verb (is). Splitting the VP tag into finite and infinitival categories resolves this error.

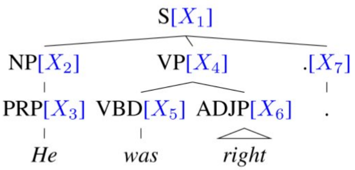
Automatic state-splitting

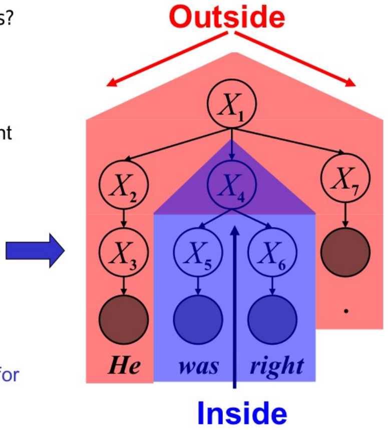
- The Klein and Manning unlexicalized parser requires substantial engineering.
- It would be a lot of work to apply this to a new language.
- Can we split the Treebank syntactic categories automatically?

State splitting through hidden variables (Petrov and Klein, 2007)

Can you automatically find good symbols?

- Brackets are known
- Base categories are known
- Induce subcategories
- Clever split/merge category refinement



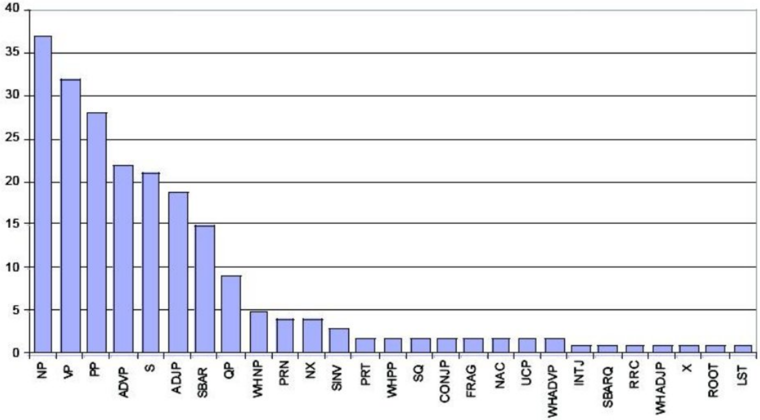


EM algorithm, like Forward-Backward for HMMs, but constrained by tree.

State splitting through hidden variables

- We'll talk more about latent variables next week.
- For now, think of it as structured clustering:
  - Assign a random subcategory to each node.
  - Learn a PCFG.
  - Apply the PCFG to relabel the nodes
    - subject to constraints of original annotations: VP3 can be relabeled as VP7, but not as an NP
  - Repeat

Number of phrasal subcategories



Examples

- Proper Nouns (NNP):

NNP-14	Oct.	Nov.	Sept.
NNP-12	John	Robert	James
NNP-2	J.	E.	L.
NNP-1	Bush	Noriega	Peters
NNP-15	New	San	Wall
NNP-3	York	Francisco	Street

- Personal pronouns (PRP):

PRP-0	It	He	I
PRP-1	it	he	they
PRP-2	it	them	him

Accuracy

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Lexicalized (Charniak 1997)	86%
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Lexicalized (Charniak 2000)	90.1%
State-splitting (Petrov and Klein 2007)	90.6%

Discriminative parsing

- Generative parsers assume observations are conditionally independent given the label.
- This prohibits redundant features like morphology and word clusters
- This made a big difference in sequence labeling (25% error reduction).
- Can it help in parsing?

Reranking

- Key idea: generate an N-best list of parses, learn a *ranking* function to score them (Collins, 2002)
- Advantage: can include arbitrary features.
- Can be as simple as perceptron
  - **Learning**
    $$w_n \leftarrow w_{n-1} + \eta(f(t, s) - f(\hat{t}, s)) \quad (1)$$
    where $f(t, s)$ are the features of the correct parse and $f(\hat{t}, s)$ are the features of the best-scoring parse.
  - **Decoding**: produce K parses from the generative model, return $\arg\max_k \mathbf{w}^\top f(t_k, s)$

Features

- **Conjoined** subtrees should have **similar depth and length**.
- English (and many other languages) have **right-branching** structure.
- Bigrams of horizontally neighboring tags
- Head-to-head dependencies, which can capture agreement
- “Heaviness” of non-terminals, and their proximity to the end of the sentence.

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Globally-normalized conditional models for parsing

The CFG-CRF model (Finkel et al., 2008):

$$P(t|s;\theta) = \frac{1}{Z_s} \prod_{r \in t} \phi(r|s;\theta)$$
$$Z_s = \sum_{t' \in \tau(s)} \prod_{r \in t'} \phi(r|s;\theta)$$

- Each parse t is a collection of productions $\{r\}$.
- Each production has a non-negative potential $\phi(r|s;\theta) = e^{\boldsymbol{\theta}^\top \mathbf{f}(r,s)}$.
- The unnormalized score for a parse is the product of its potentials.
- The *partition function* Z_s is the sum of the scores for all possible parses for a sentence s.

Decoding

- If the features are local in t, we can use CKY to decode.
- Features need not be local in s.
  (just like in discriminative sequence models)
- Just like CKY, but you multiply potentials ϕ rather than probabilities.
- We need only the unnormalized score $\prod_{r \in t} \phi(r|s;\theta)$.

Features

- standard PCFG stuff, with and without parent annotation
  (no need for complicated smoothing!)
- lexicon features over words and tags
  (including prev word and next word, and unknown word classes)
- bigrams and trigrams of *word classes* under each subtree

Learning

Just like logistic regression:

$$\mathcal{L} = \left[\sum_{(t,s)\in\mathcal{D}} \left(\sum_{r\in t} \sum_{i} \theta_i f_i(r,s) \right) - Z_s \right] + \sum_i \frac{\theta_i^2}{2\sigma^2}$$

$$\frac{\partial\mathcal{L}}{\partial\theta_i} = \left[\sum_{(t,s)\in\mathcal{D}} \left(\sum_{r\in t} \sum_{i} f_i(r,s) \right) - E_\theta[f_i|s] \right] + \frac{\theta_i}{\sigma^2}$$

- compute Z_s using the inside algorithm
- compute $E_\theta[f_i|s]$ using inside-outside

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- compute Z_s using the inside algorithm
- compute $E_\theta[f_i|s]$ using inside-outside
- But unfortunately, $\mathcal{O}(N^3 G)$ is still too slow.

Tricks

Chart prefiltering:

- Run a non-probabilistic CFG to prune away productions which do not lead to any valid parse.
- This saves time during inside-outside.

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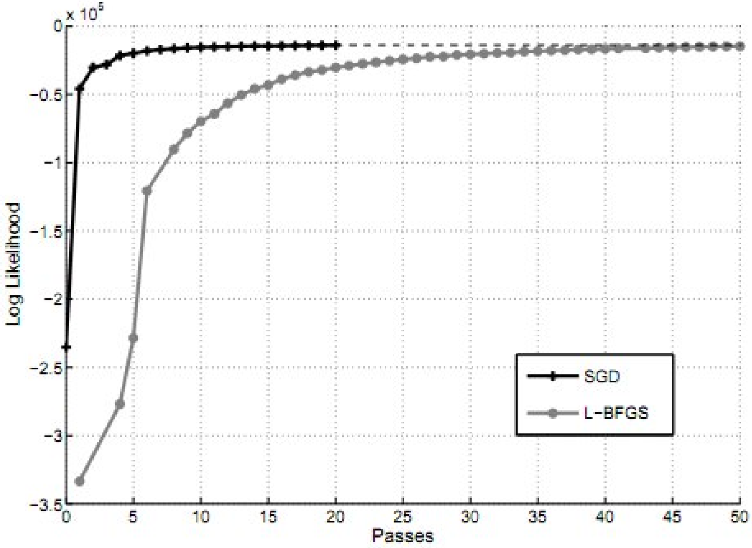
Parallelization via stochastic gradient descent:

- Let $\hat{\mathcal{L}}(\mathcal{D}_b^{(i)}; \boldsymbol{\theta})$ equal the likelihood computed from a "minibatch" of b examples.
- Then we can approximate the gradient, $\nabla\mathcal{L}(\mathcal{D}; \boldsymbol{\theta}) \approx \sum_i \nabla\mathcal{L}(\mathcal{D}_b^{(i)}; \boldsymbol{\theta})$.
- We can then parallelize the minibatches, and make stochastic gradient updates,

$$\theta_{k+1} = \theta_k - \eta_k \nabla\mathcal{L}(\mathcal{D}_b^{(i)}; \boldsymbol{\theta}),$$

where η_k is the learning rate after the k^{th} update.

Stochastic gradient



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- better than basic generative parsers, worse than reranking
- The key advantage of this approach is the simplicity:
  no need for complicated smoothing or backoff, just throw redundant information at the learner and let it sort things out
- Room for better features?

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Parent-annotations	80%
Lexicalized (Charniak 1997)	86%
Lexicalized (Collins 1999)	87%
State-splitting (Petrov and Klein 2007)	90.6%
Reranking (Charniak and Johnson 2005)	91.0%
CFG-CRF (Finkel et al 2008)	89.0

- better than basic generative parsers, worse than reranking
- The key advantage of this approach is the simplicity: no need for complicated smoothing or backoff, just throw redundant information at the learner and let it sort things out
- Room for better features?
- ... or better models? An alternative CRF based on tree-adjoining grammar, scored 91.1 (Carreras et al, 2008)

Recap

- A big part of parsing research has been figuring out the right level of description:
  - Unlexicalized PCFGs on treebank categories are too coarse.
  - Lexicalized parsers start with very rich probability models, and then apply smoothing for tractability.
  - State-splitting approaches start with the treebank categories and split as needed.
- Reranking approaches can learn rich feature representations, but can only apply them to a limited set of possible parses.
- Globally-normalized conditional parsers learn feature-based models and apply them to decode over the entire space of possible parses.