Probabilistic parsing with a wide variety of features

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Joint work with Eugene Charniak (Brown) and Michael Collins (MIT)

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Talk outline

- Statistical parsing models
- Discriminatively trained reranking models
  - features for selecting good parses
  - estimation methods
  - evaluation
- Conclusion and future work

Approaches to statistical parsing

- Kinds of models: "Rationalist" vs. "Empiricist"
  - based on *linguistic theories* (CCG, HPSG, LFG, TAG, etc.)
    - typically use specialized representations
  - *models of trees* in a training corpus (Charniak, Collins, etc.)
- Grammars are typically *hand-written* or *extracted from a corpus* (or both?)
  - both methods *require linguistic knowledge*
  - each method is affected differently by
    - lack of linguistic knowledge (or resources needed to enter it)
    - errors and inconsistencies

Features in linear models

- (Statistical) features are *real-valued functions* of parses (e.g., in a PCFG, the number of times a rule is used in a tree)
- A model associates a *real-valued weight* with each feature (e.g., the log of the rule's probability)
- The *score* of a parse is the weighted sum of its feature values (the tree's log probability)
- Higher scoring parses are more likely to be correct
- Computational complexity of estimation (training) depends on *how these features interact*

Feature dependencies and complexity

- *"Generative models"* (features and constraints induce *tree-structured dependencies*, e.g., PCFGs, TAGs)
  - maximum likelihood estimation is computationally cheap (counting occurences of features in training data)
  - crafting a model with a given set of features can be difficult
- *"Conditional"* or *"discriminative models"* (features have arbitrary dependencies, e.g., SUBGs)
  - maximum likelihood estimation is computationally intractible (as far as we know)
  - *conditional estimation* is computationally feasible but expensive
  - features can be *arbitrary functions* of parses

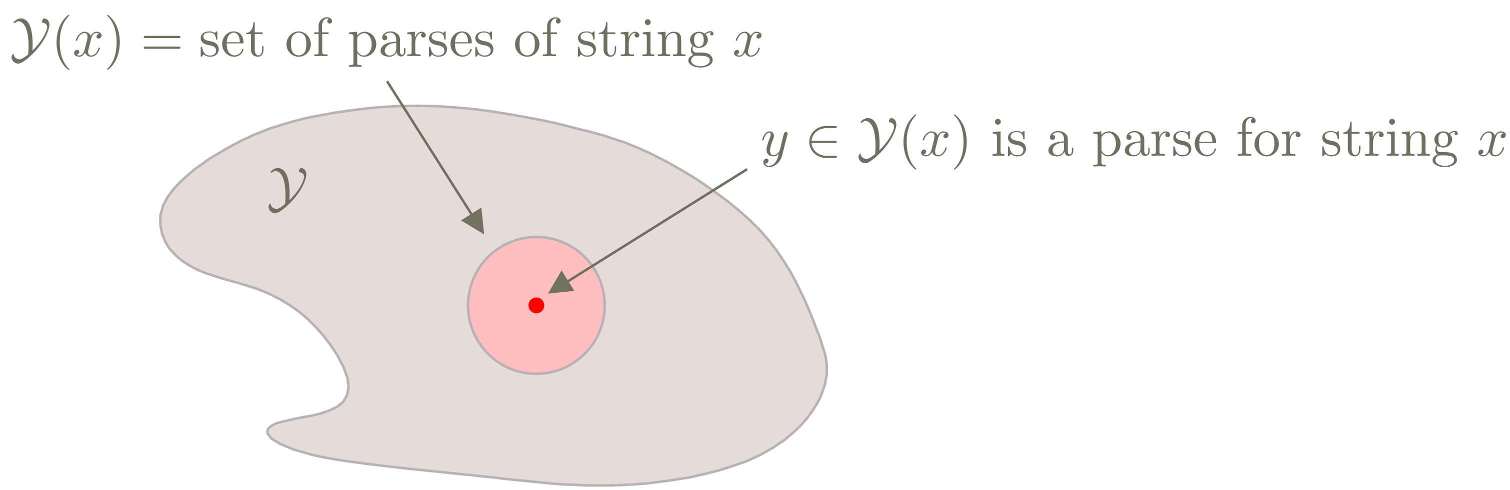
Why coarse-to-fine discriminative reranking?

- Question: *What are the best features for statistical parsing?*
- Intuition: *The choice of features matters more than the grammar formalism or parsing method*
- Are *global features* of the parse tree useful?

$\Rightarrow$ Choose a framework that makes experimenting with features as easy as possible

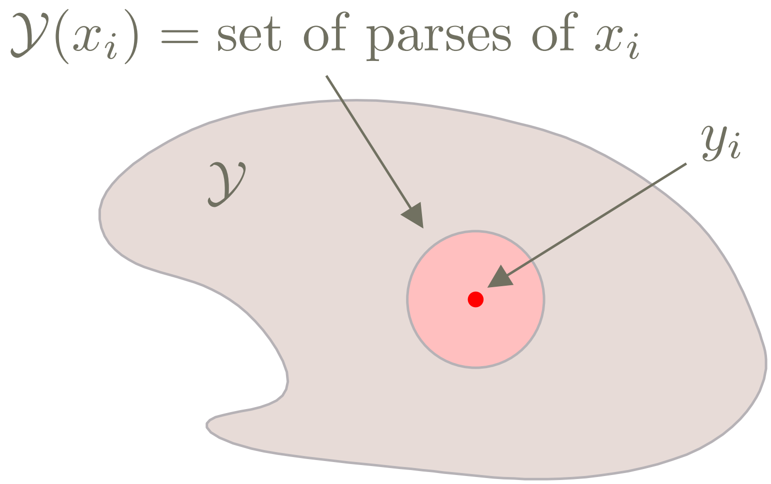
- *Coarse-to-fine discriminative reranking is such a framework*
  - features can be arbitrary functions of parse trees
  - computational complexity is manageable
- Why a Penn tree-bank parsing model?

The parsing problem



- $\mathcal{Y}$ = set of all parses, $\mathcal{Y}(x)$ = set of parses of string x
- $f = (f_1, \ldots, f_m)$ are real-valued *feature functions* (e.g., $f_{22}(y)$ = number of times an S dominates a VP in y)
- So $f(y) = (f_1(y), \ldots, f_m(y))$ is real-valued vector
- $w = (w_1, \ldots, w_m)$ is a *weight vector*, which we learn from training data
- $S_w(y) = w \cdot f(y) = \sum_{j=1}^{m} w_j f_j(y)$ is the *score* of a parse

Conditional training



- Labelled training data $D = ((x_1, y_1), \ldots, (x_n, y_n))$, where y_i is the correct parse for x_i
- Parsing: return the parse $y \in \mathcal{Y}(x)$ with the highest score
- Conditional training: Find a weight vector w so that the correct parse y_i scores "better" than any other parse in $\mathcal{Y}(x_i)$
- There are many different algorithms for doing this (MaxEnt, Perceptron, SVMs, etc.)

Another view of conditional training

	Correct parse's features	**All other parses' features**
sentence 1	$[1, 3, 2]$	$[2, 2, 3]$ $[3, 1, 5]$ $[2, 6, 3]$
sentence 2	$[7, 2, 1]$	$[2, 5, 5]$
sentence 3	$[2, 4, 2]$	$[1, 1, 7]$ $[7, 2, 1]$
...	...	...

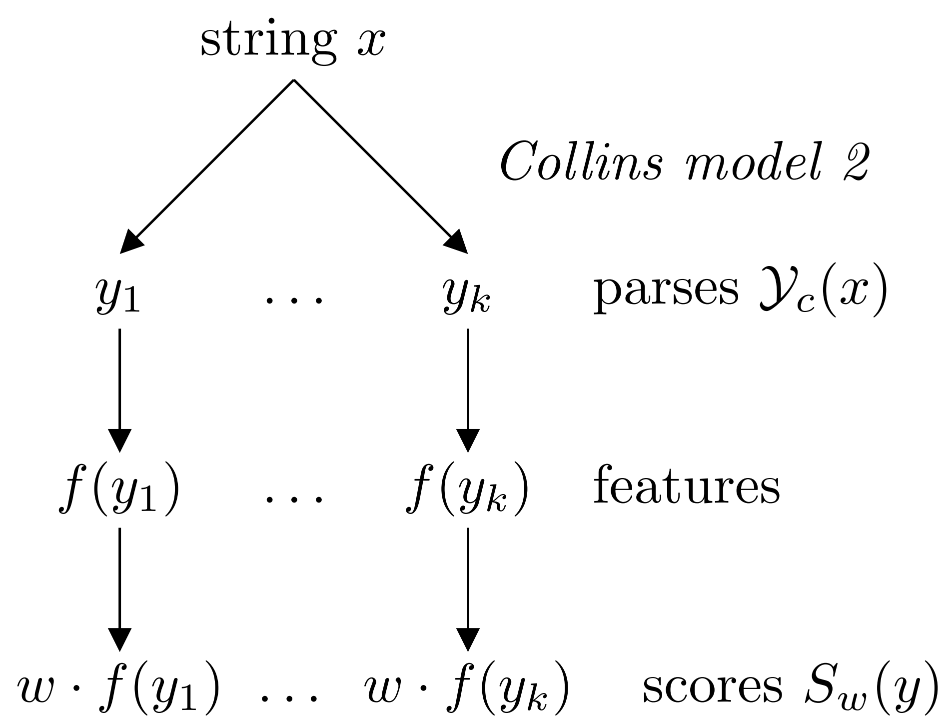
- Training data is *fully observed* (i.e., parsed data)
- Choose w to maximize score of *correct* parses relative to other parses
- Distribution of *sentences* is ignored
  - The models learnt by this kind of conditional training *can't be used as language models*
- *Nothing is learnt from unambiguous examples*

A coarse to fine approximation

- The set of parses $\mathcal{Y}(x)$ can be huge!
- Collins Model 2 parser produces a *set of candidate parses* $\mathcal{Y}_c(x)$ for each sentence x
- The score for each parse is $S_w(y) = w \cdot f(y)$
- The highest scoring parse

$$y^\star = \operatorname*{argmax}_{y \in \mathcal{Y}_c(x)} S_w(y)$$

is predicted correct



(Collins 1999 “Discriminative reranking”)

Advantages of this approach

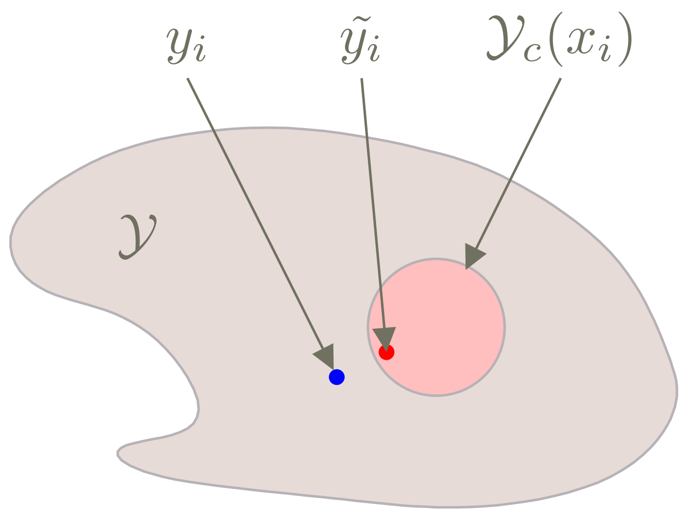
- The Collins parser only uses features for which there is a fast dynamic programming algorithm
- The set of parses $\mathcal{Y}_c(x)$ it produces is small enough that dynamic programming is not necessary
- This gives us almost complete freedom to formulate and explore possible features
- We're already starting from a good baseline ...
- ... but we only produce Penn treebank trees (instead of something deeper)
- and parser evaluation with respect to the Penn treebank is standard in the field

A complication

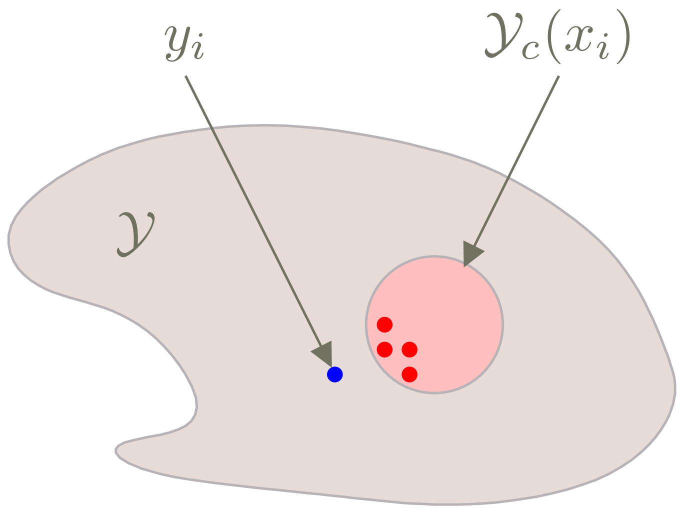
- Intuition: the discriminative learner should learn the common error modes of Collins parser
- Obvious approach: parse the training data with the Collins parser
- When parsed on the training section of the PTB, the Collins parser does much better on training section than it does on other text!
- Train the discriminative model from parser output on text parser was not trained on
- Use *cross-validation paradigm* to produce discriminative training data (divide training data into 10 sections)
- Development data described here is from PTB sections 20 and 21

Another complication

- Training data $((x_1, y_1), \ldots, (x_n, y_n))$
- Each string x_i is parsed using Collins parser, producing a set $\mathcal{Y}_c(x_i)$ of parse trees
- *The correct parse y_i might not be in the Collins parses $\mathcal{Y}_c(x_i)$*
- Let $\tilde{y}_i = \operatorname{argmax}_{y \in \mathcal{Y}_c(x_i)} F_{y_i}(y)$ be the *best Collins parse*, where $F_{y'}(y)$ measures parse accuracy
- Choose w to discriminate $\tilde{y}_i$ from the other $\mathcal{Y}_c(x_i)$



Multiple best parses



- There can be several Collins parses equally close to the correct parse: which one(s) should we declare to be the best parse?
- Weighting all close parses equally does not work as well (0.9025) as . . .
- picking the parse with the highest Collins parse probability (0.9036), but . . .
- letting the model pick its own winner from the close parses (EM-like scheme in Riezler '02) works best of all (0.904)

Baseline and oracle results

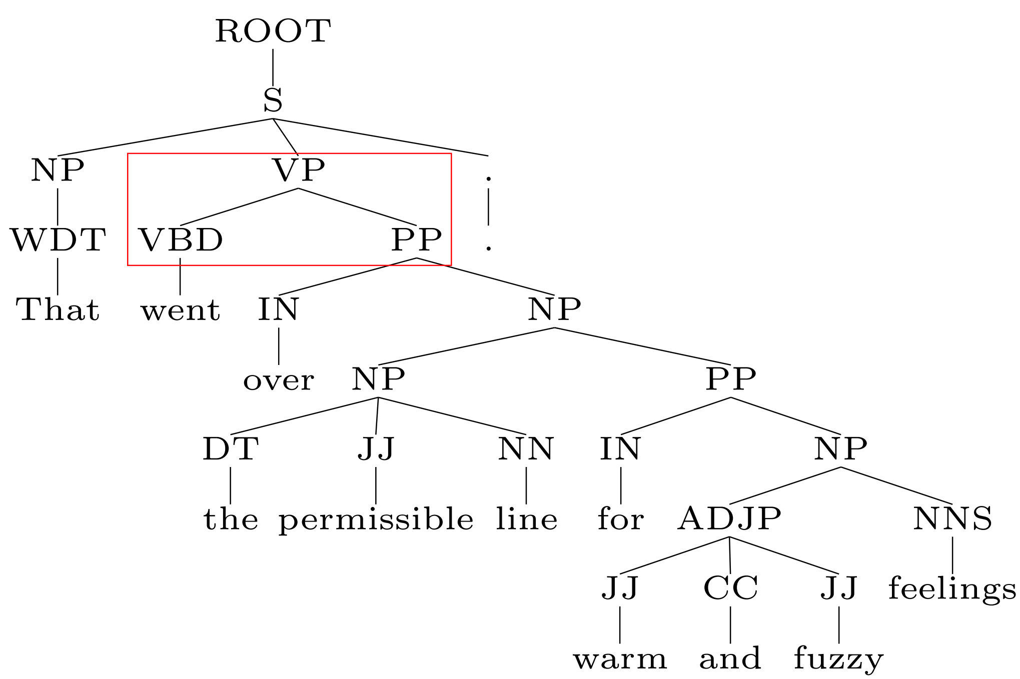
- Training corpus: 36,112 Penn treebank trees from sections 2–19, development corpus 3,720 trees from sections 20–21
- Collins Model 2 parser failed to produce a parse on 115 sentences
- Average $|\mathcal{Y}(x)| = 36.1$
- Model 2 f-score $= 0.882$ (picking parse with highest Model 2 probability)
- Oracle (maximum possible) f-score $= 0.953$ (i.e., evaluate f-score of closest parses $\tilde{y}_i$)

$\Rightarrow$ Oracle (maximum possible) error reduction 0.601

Expt 1: Only "old" features

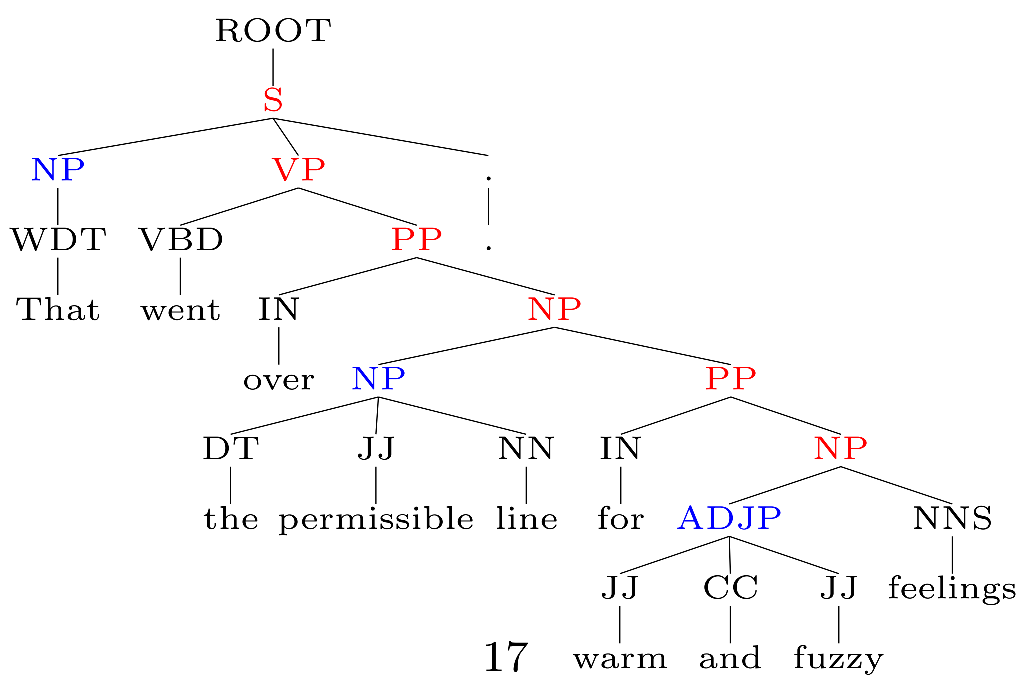
- Features: (1) *log Model 2 probability*, (9717) local tree features
- Model 2 already conditions on local trees!
- Feature selection: features must vary on 5 or more sentences
- Results: f-score $= 0.886$; $\approx 4\%$ error reduction

$\Rightarrow$ *discriminative training alone can improve accuracy*



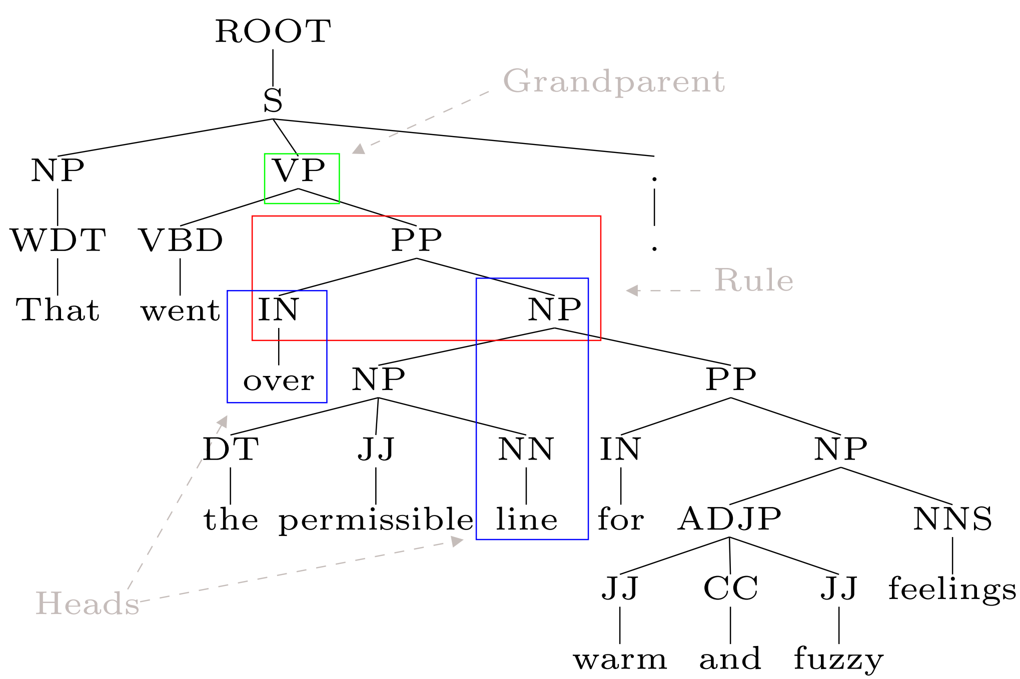
Expt 2: Rightmost branch bias

- The RightBranch feature's value is the number of nodes on the right-most branch (ignoring punctuation)
- Reflects the tendancy toward right branching
- LogProb + RightBranch: f-score = 0.884 (probably significant)
- LogProb + RightBranch + Rule: f-score = 0.889



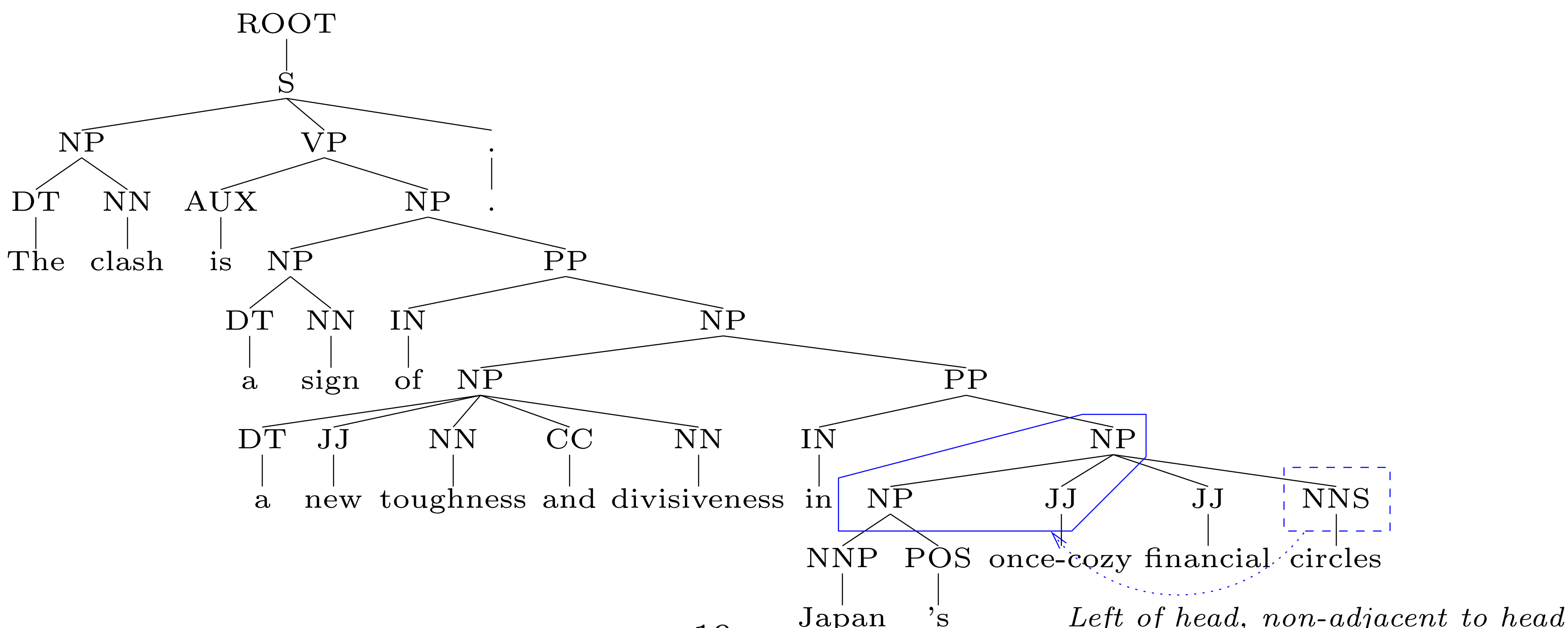
Lexicalized and parent-annotated rules

- *Lexicalization* associates each constituent with its head
- *Parent annotation* provides a little "vertical context"
- With all combinations, there are 158,890 rule features



n-gram rule features generalize rules

- Collects adjacent constituents in a local tree
- Also includes relationship to head
- Constituents can be ancestor-annotated and lexicalized
- 5,143 unlexicalized rule bigram features, 43,480 lexicalized rule bigram features

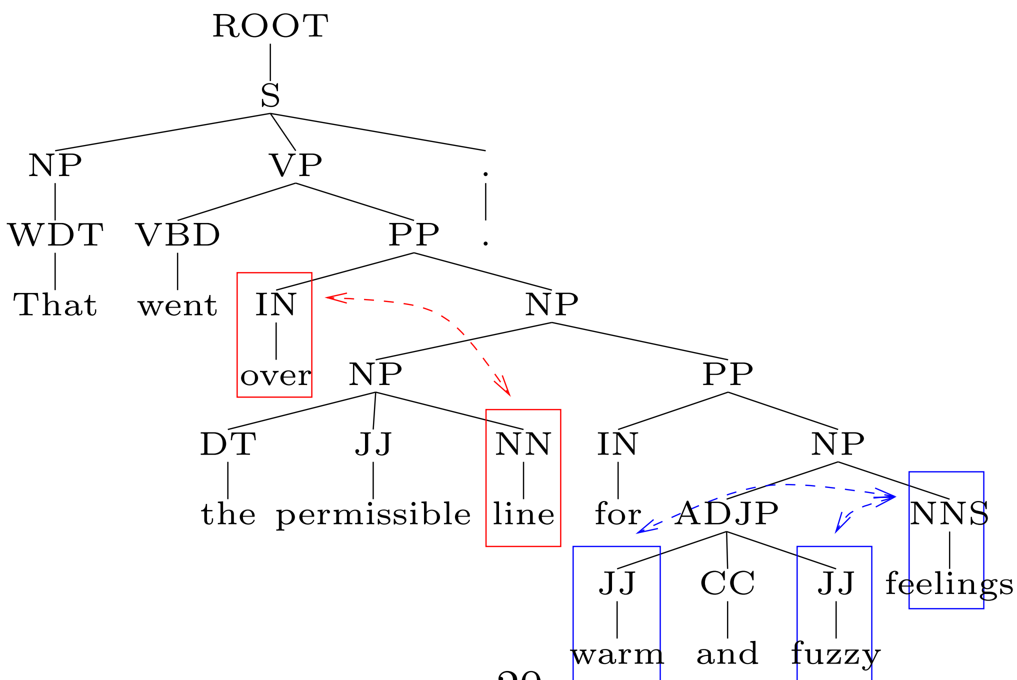


Head to head dependencies

- Head-to-head dependencies track the function-argument dependencies in a tree

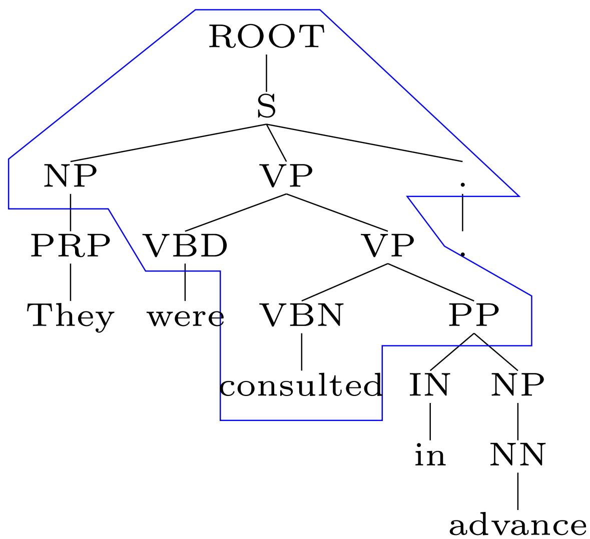
- *Co-ordination leads to phrases with multiple heads and arguments*

- With all combinations, there are 121,885 head-to-head features



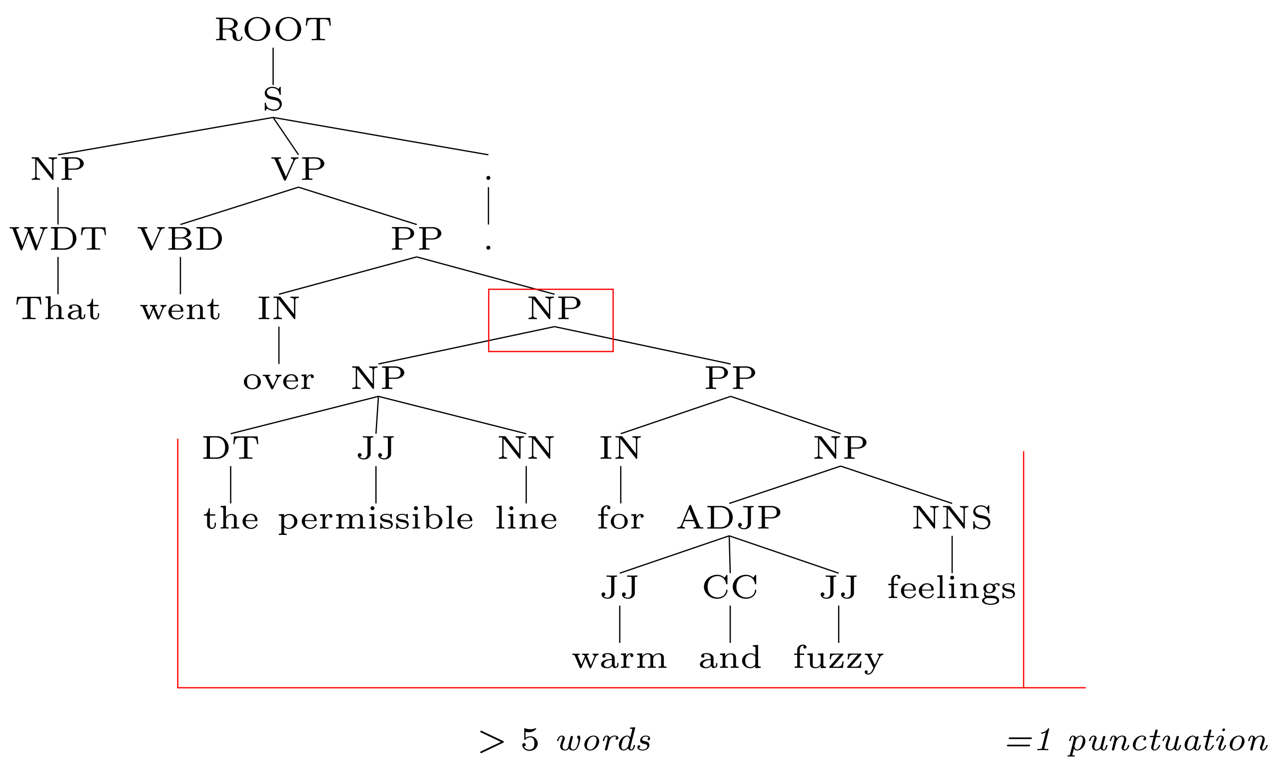
Head trees record all dependencies

- Head trees consist of a (lexical) head, all of its projections and (optionally) all of the siblings of these nodes
- These correspond roughly to TAG elementary trees



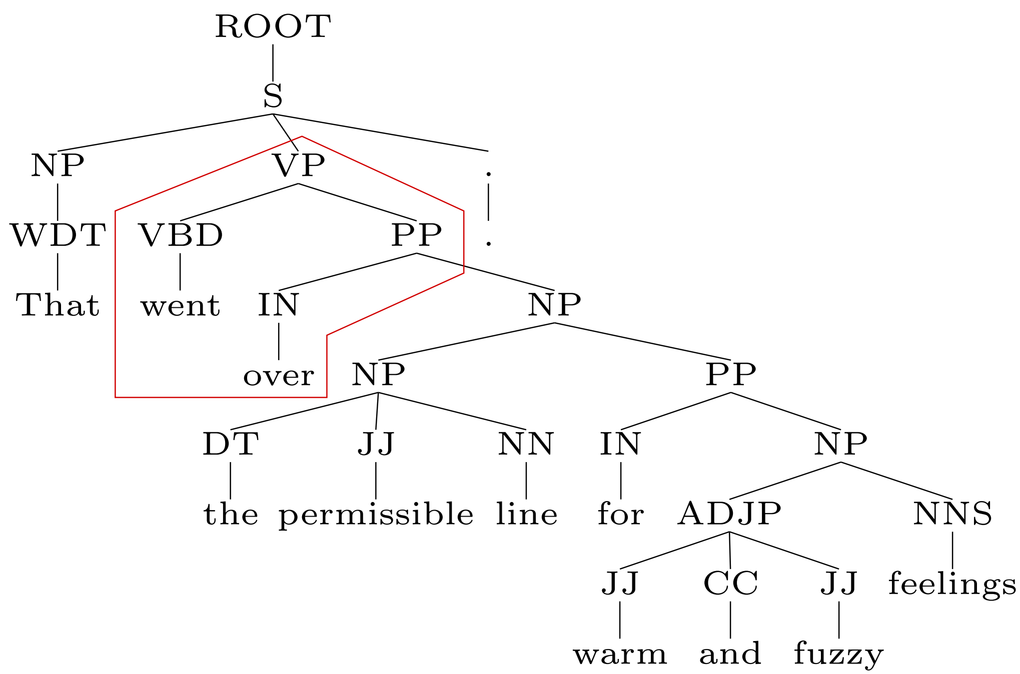
Constituent Heavyness and location

- Heavyness measures the constituent's category, its (binned) size and (binned) closeness to the end of the sentence
- There are 984 Heavyness features



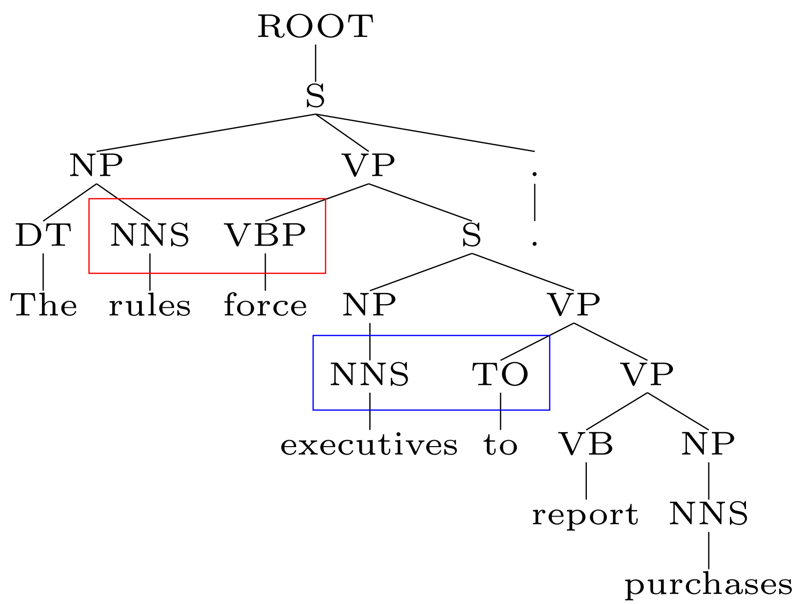
Tree n-gram

- A tree n-gram are tree fragments that connect sequences of adjacent n words
- There are 62,487 tree n-gram features



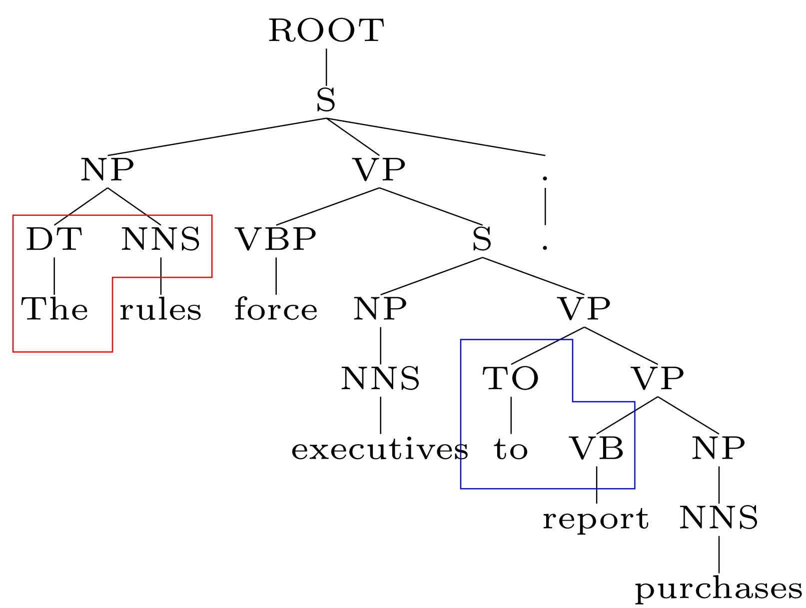
Subject-Verb Agreement

- The SubjVerbAgr features are the POS of the subject NP's lexical head and the VP's functional head
- There are 200 SubjVerbAgr features



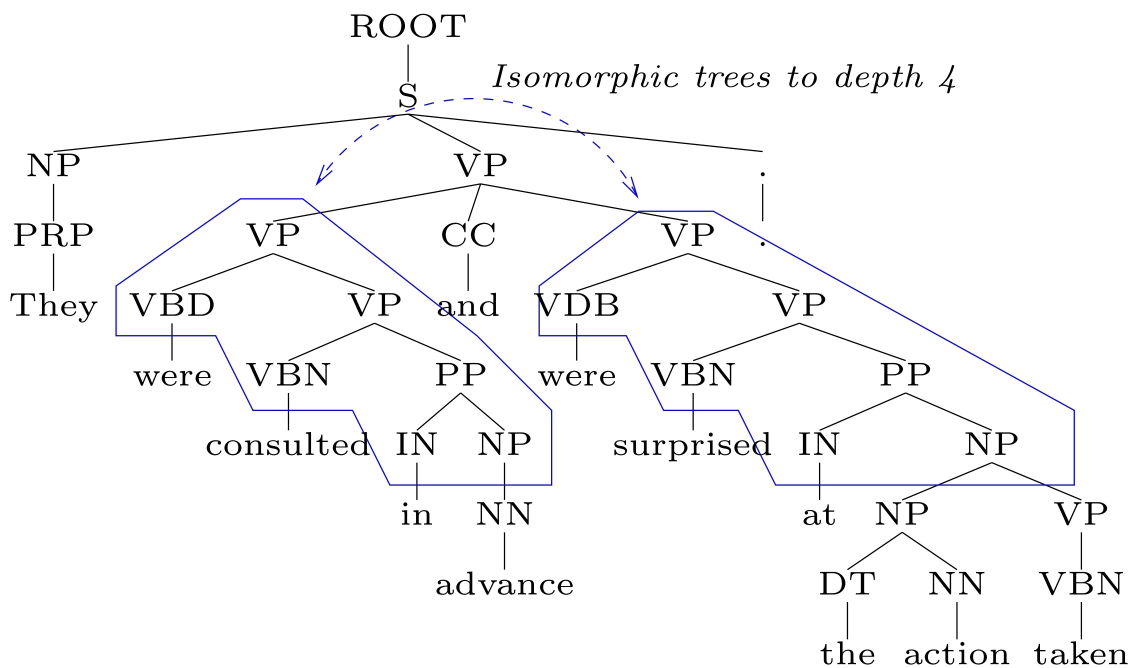
Functional-lexical head dependencies

- The SynSemHeads features collect pairs of functional and lexical heads of phrases (Grimshaw)
- This captures number agreement in NPs and aspects of other head-to-head dependencies
- There are 1,606 SynSemHeads features



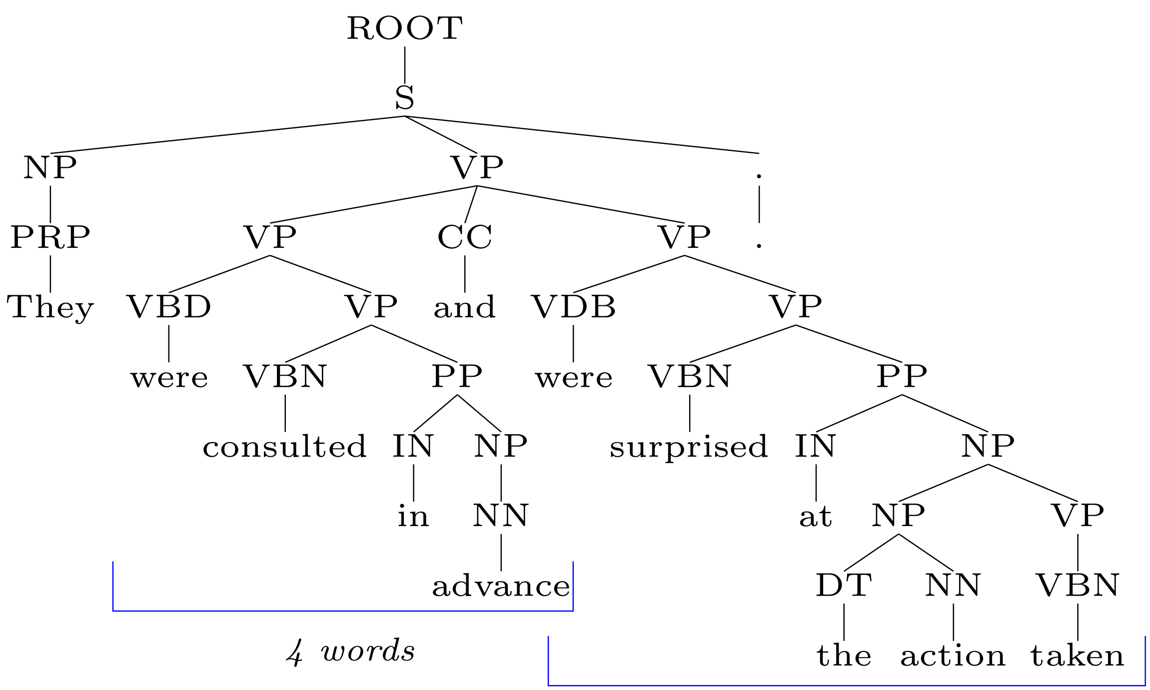
Coordination parallelism (1)

- The CoPar feature indicates the depth to which adjacent conjuncts are parallel
- There are 9 CoPar features



Coordination parallelism (2)

- The CoLenPar feature indicates the difference in length in adjacent conjuncts and whether this pair contains the last conjunct.
- There are 22 CoLenPar features



CoLenPar feature: (2,true)

Experimental results with all features

- Feature selection: features must vary on parses of at least 5 sentences in training data (a cutoff of 2 improves results)
- In this experiment, 883,936 features
- *log loss* with Gaussian regularization term: $11 \sum_j w_j^2$
  - dev set results: f-score = 0.903–0.904
  - *section 23 results: f-score = 0.9039 (≈20% error reduction), 47% of sentences have f-score = 1*
- *exp loss* with Gaussian regularization term: $50 \sum_j w_j^2$
  - dev set results: f-score = 0.902
- *averaged perceptron classifier* (very fast!)
  - dev set results: f-score = 0.902 (with feature class tuning)

Which kinds of features are best?

	# of features	f-score
Treebank trees	375,646	0.901
Correct parses	271,267	0.902
Incorrect parses	876,339	0.903
Correct & incorrect parses	883,936	0.903

- Features from incorrect parses characterize failure modes of Collins parser
- There are far more ways to be wrong than to be right!

Feature classes overview

# of feat.	av. value	s.d.	feat. class
1	0.416674	–	LogProb
2	-0.376498	0.000265398	RightBranch
9	0.117017	0.0371904	CoPar
22	0.0133718	0.0196021	CoLenPar
200	-0.000552325	0.00364032	SubjVerbAgr
984	-0.00118015	0.00613362	Heavy
1606	0.00145433	0.00196207	SynSemHeads
37068	0.000505719	0.000953109	Word
48623	6.68076e-05	0.00145942	NGram
122189	0.000623527	0.000679083	WProj
160582	0.00063112	0.000969829	Heads
203979	0.000393769	0.000832161	NGramTree
223354	0.000344003	0.000813581	Rule

Evaluating feature classes

Δ f-score	Δ $-\log$ CP	Δ correct	Δ best poss.	zeroed class
-0.00909743	3042.76	-123	-132	LogProb
-0.0034855	-107.341	17	-42	Rule
-0.00316443	120.551	-31	-64	NGram
-0.00292884	50.4752	-20	-44	Heads
-0.00248576	73.3785	-18	-25	Heavy
-0.00239372	251.753	-74	-27	RightBranch
-0.00208603	157.478	-19	-31	NGramTree
-0.00199449	130.832	-28	-36	WProj
-0.000761952	11.0709	5	-4	Word
-0.000422497	7.1691	6	-5	CoLenPar
-0.000368866	-14.2518	1	2	SynSemHeads
-0.000230322	11.3504	-9	-4	CoPar
-0.000100725	-14.7814	-2	0	SubjVerbAgr

Informal error analysis

- Manual examination of first 100 sentences of development data
- Preliminary classification of “type” of parser error
- Multiple errors per sentence were found

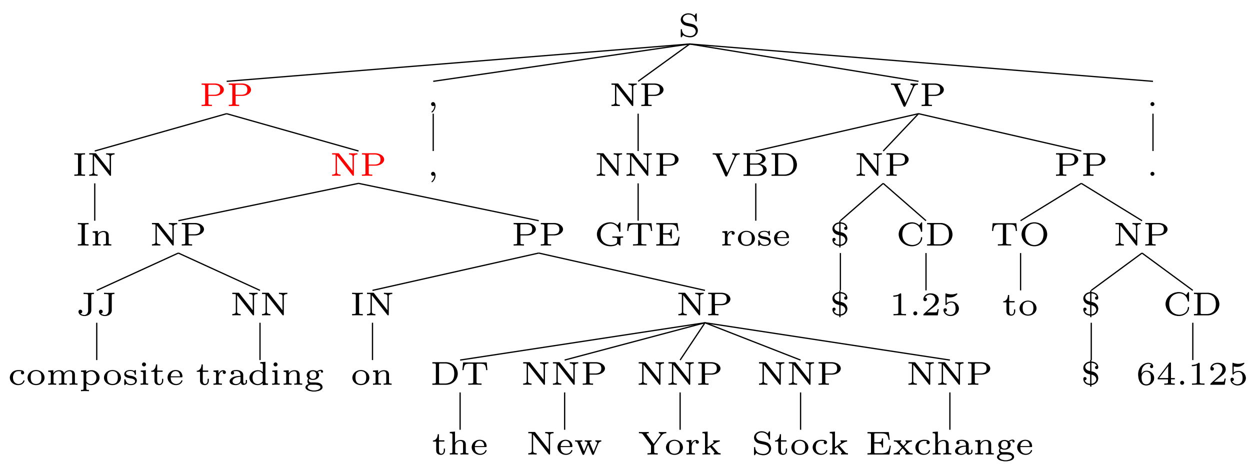
Error type	Reranker	Coarse parser
PP attach	19	3
Coordination	8	2
Category misanalysis	7	1
Other attachment	4	9
Compounding	2	3
Other errors	2	4

14 PTB errors, 7 PTB ambiguities

(Suggested by Yusuke Miyao)

Sample PP attachment error (1/2)

In composite trading on the New York Stock Exchange, GTE rose $1.25 to $64.125.



Parse tree

Sample PP attachment error (2/2)

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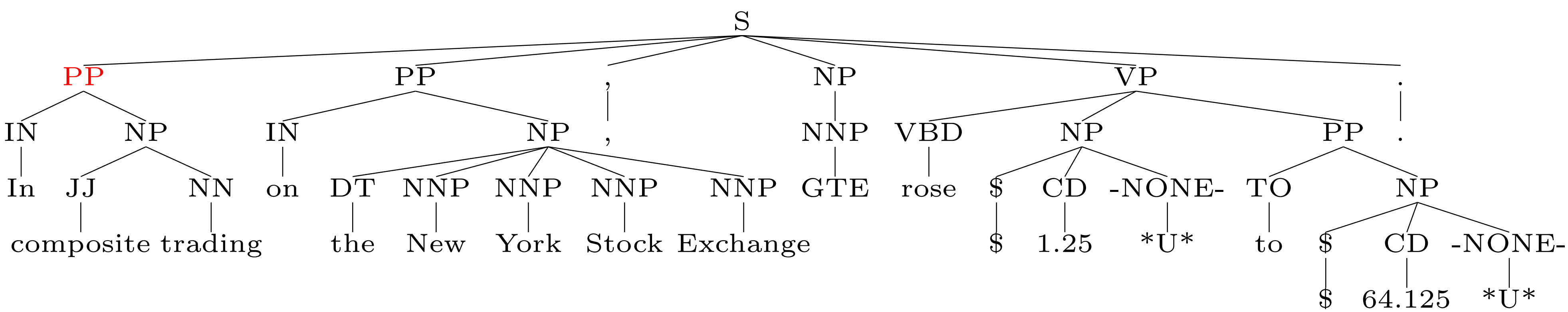
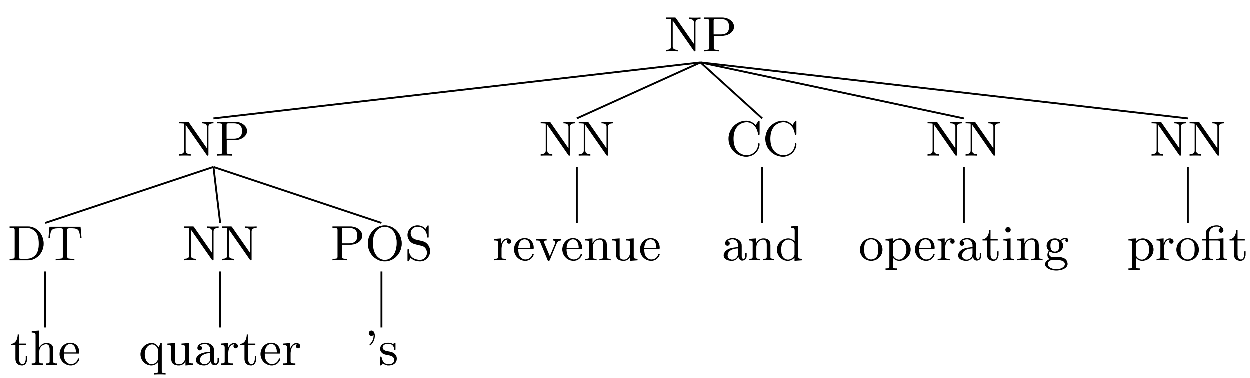


Gold (treebank) tree

Coordination error (1/2)

Earlier rate reductions in Texas and California reduced the quarter's revenue and operating profit $55 million; a year earlier, operating profit in telephone operations was reduced by a similar amount as a result of a provision for a reorganization.



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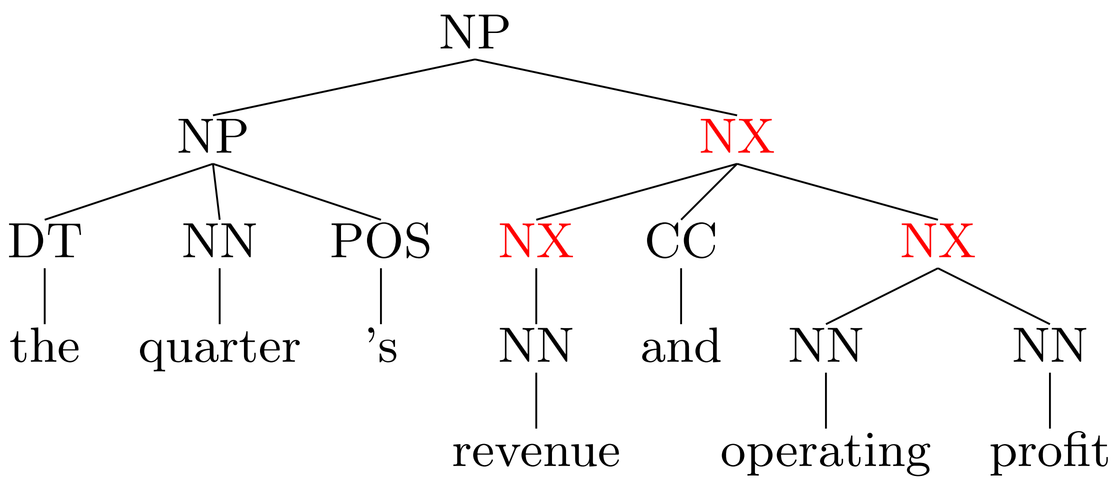
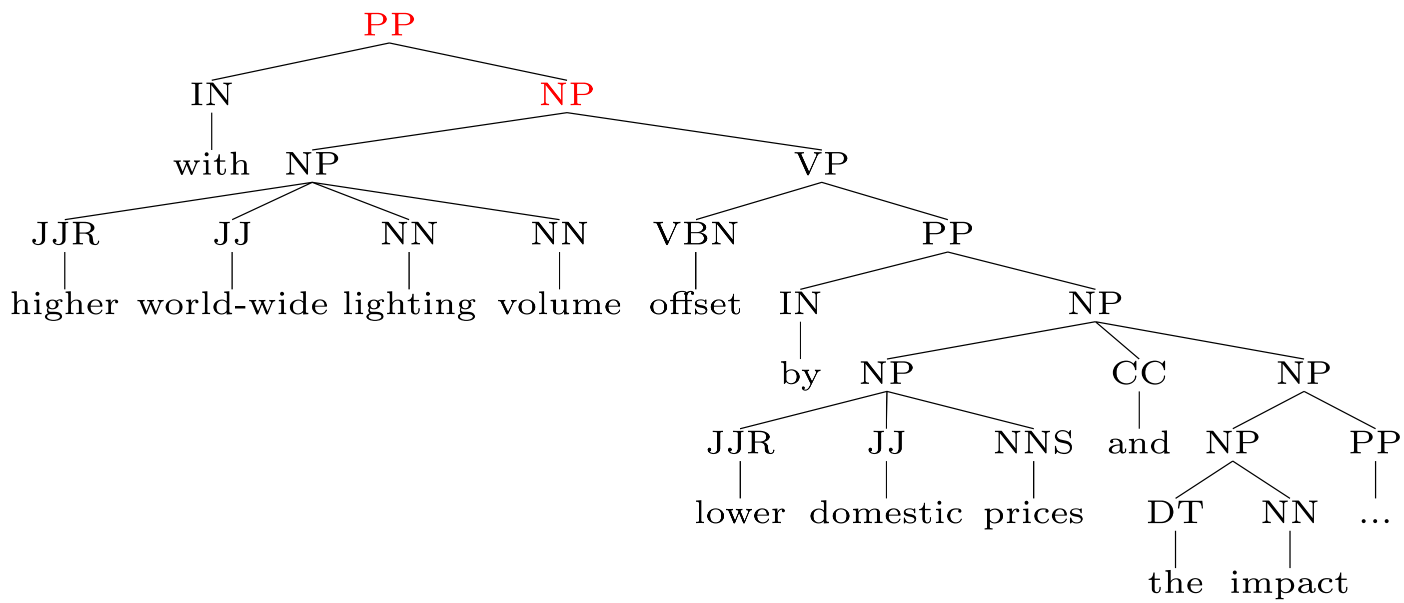


Gold (treebank) tree

Category misanalysis error (1/2)

Electrical products' sales fell to \$496.7 million from \$504.5 million with higher world-wide lighting volume offset by lower domestic prices and the impact of weaker currencies in Europe and South America.



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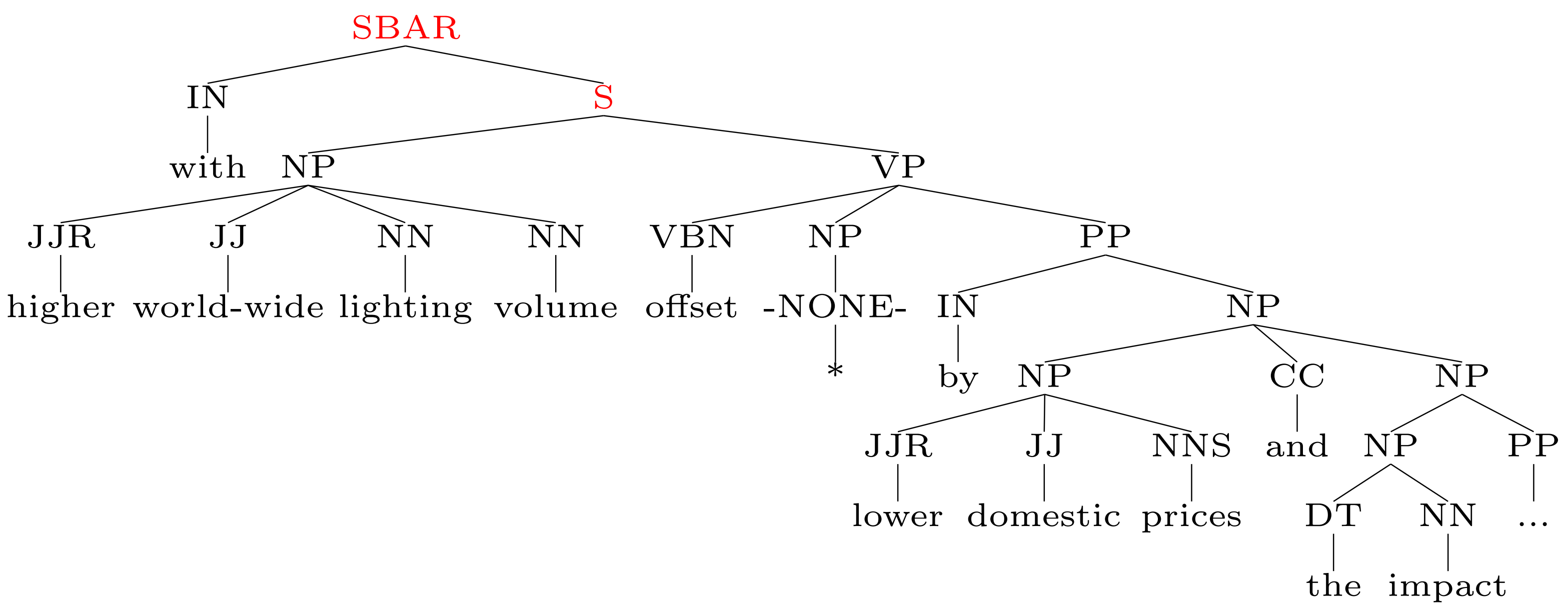
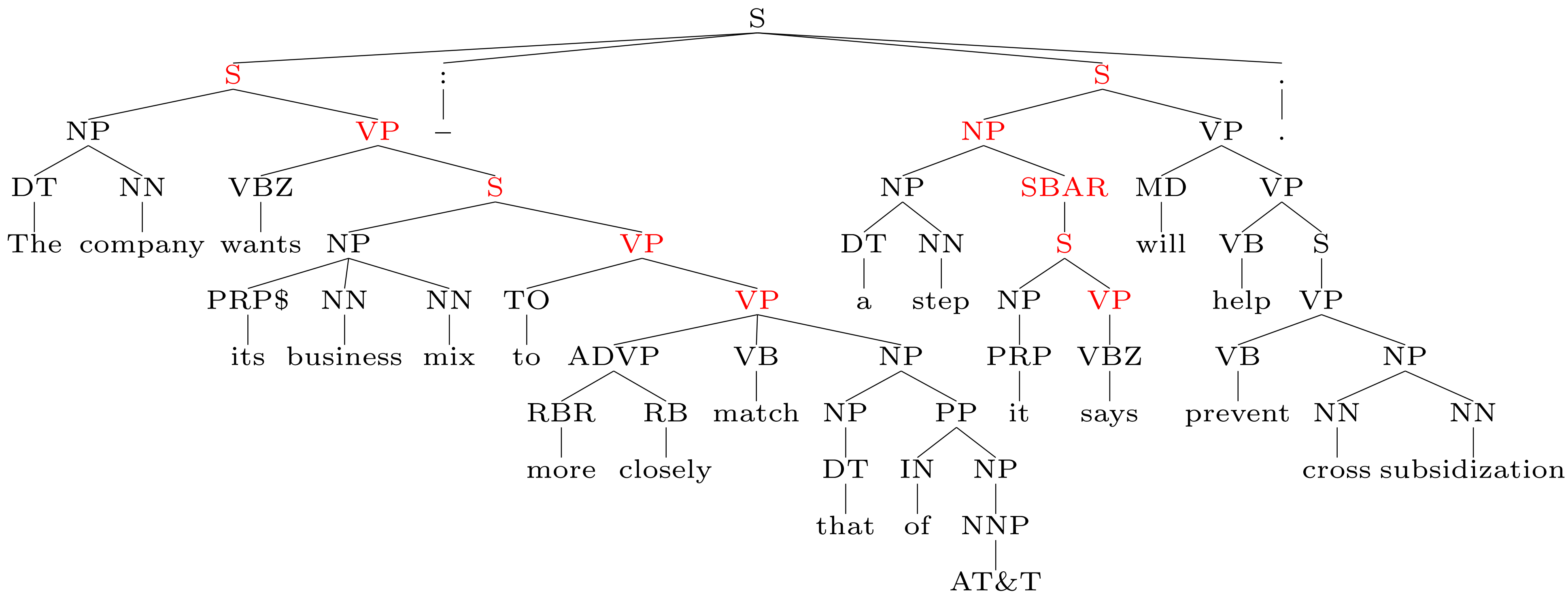


Gold (treebank) tree

Multiple attachment errors (1/3)

The company wants its business mix to more closely match that of AT&T – a step it says will help prevent cross subsidization.



Parse tree

Multiple attachment errors (2/3)

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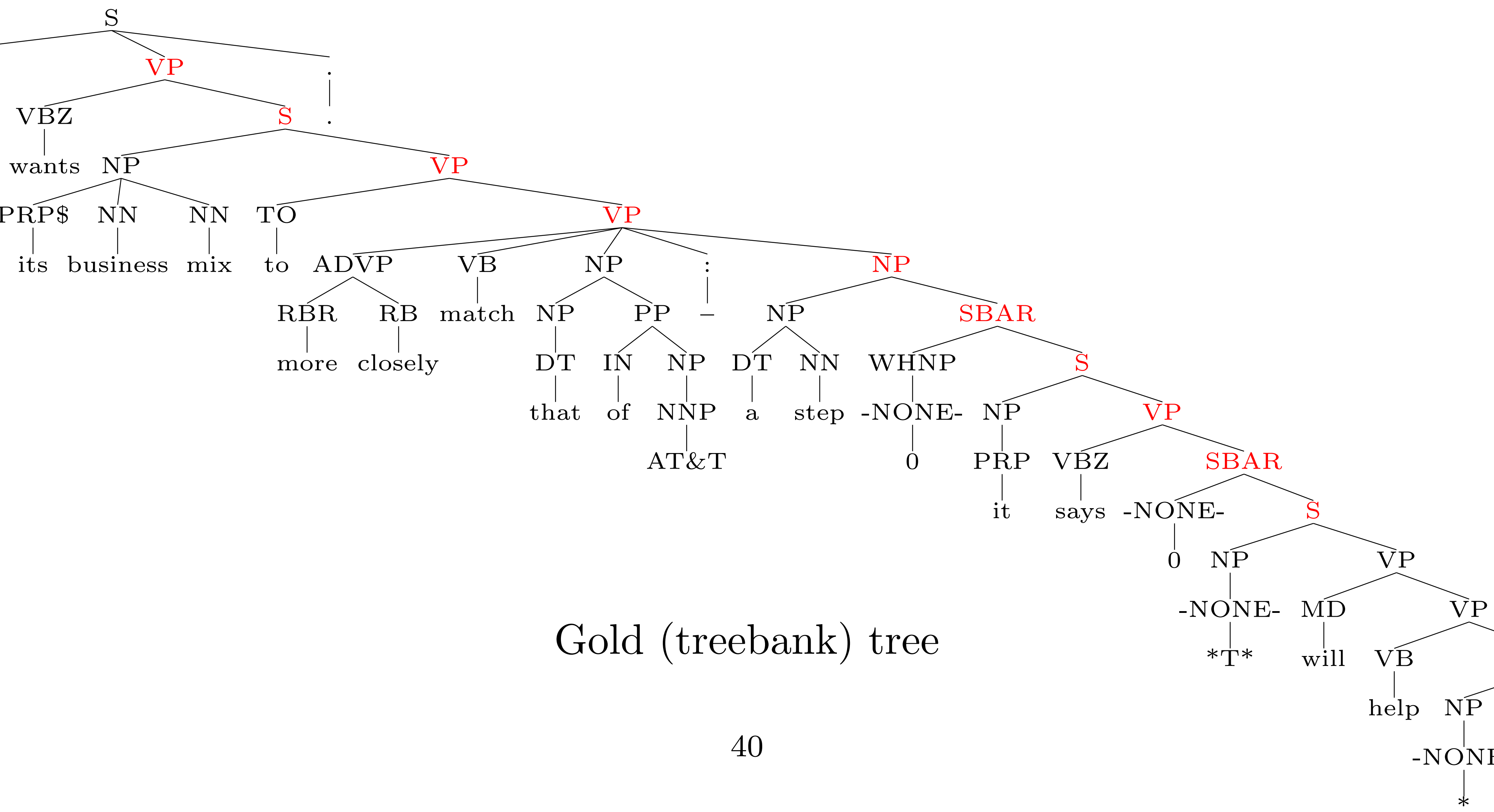
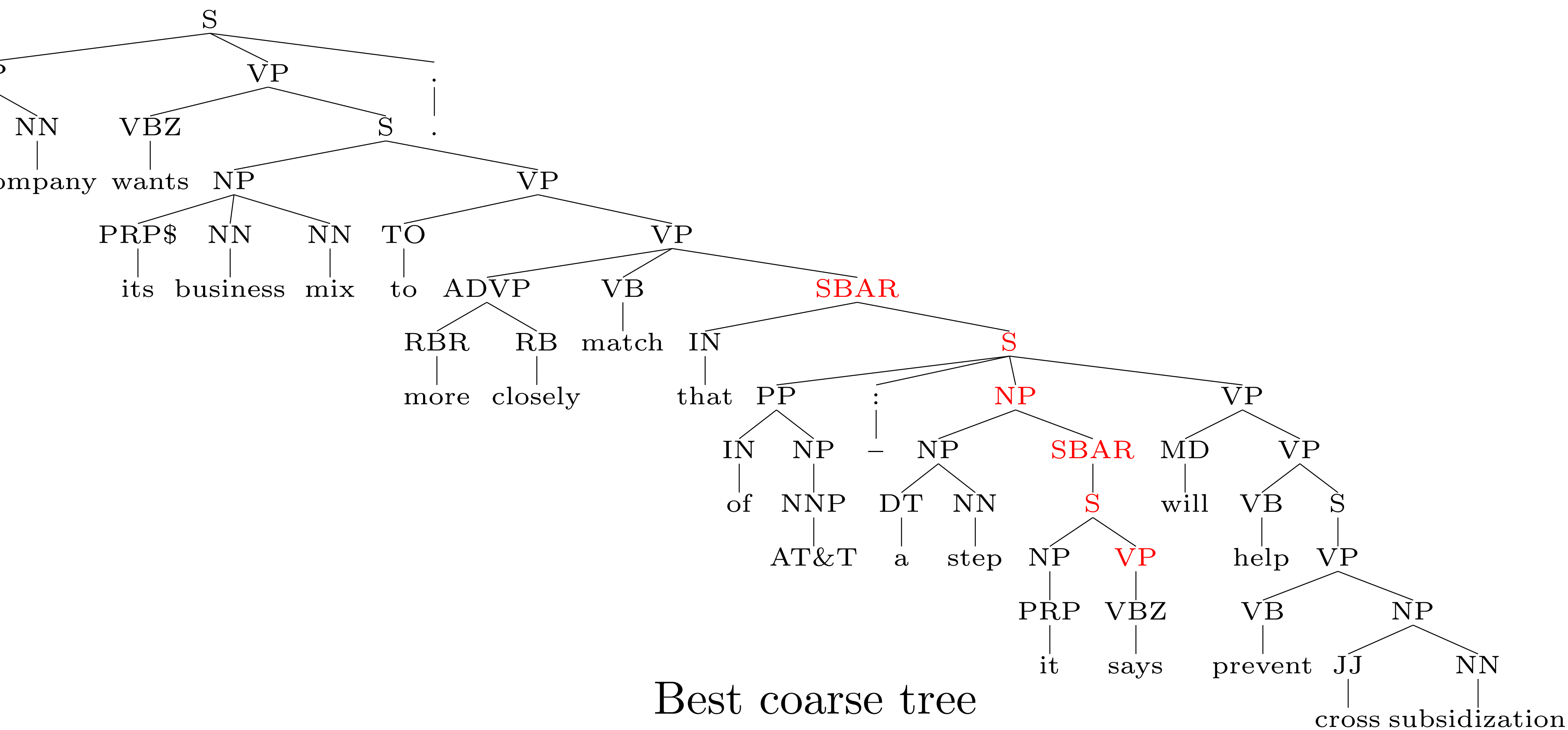


Gold (treebank) tree

Multiple attachment errors (3/3)

The company wants its business mix to more closely match that of AT&T – a step it says will help prevent cross subsidization.



Best coarse tree

Technical summary

- Generative and discriminative parsers both identify the likely parse y of a string x, e.g., by estimating $\mathrm{P}(y|x)$
- *Generative parsers also define language models*, estimate $\mathrm{P}(x)$
- *Discriminative estimation doesn't require feature independence*
  - suitable for models without tree-structured feature dependencies
- *Parsing is equally complex* for generative and discriminative parsers
  - *depends on features used*
  - *coarse-to-fine* approaches use one parser to narrow the search space for another
- *Estimation* is *computationally inexpensive for generative parsers*, but *expensive for discriminative parsers*
- Because a discriminative parser can use the generative model's probability estimate as a feature, *discriminative parsers almost never do worse* than the generative model, and often do substantially better.

Conclusions

- Discriminatively trained parsing models can perform better than standard generative parsing models
- *Features can be arbitrary functions of parse trees*
  - Non-local features can make a big difference!
  - Difficult to tell which features are most useful
  - Better evaluation (maybe requires real parsing applications?)
- Coarse-to-fine results in (moderately) efficient algorithms
- The parser's errors are often recognizable as certain types of mistakes
  - PP attachment is still a serious issue!

Future directions

- More features (fix those PP attachments!)
- Additional languages (Chinese)
- Richer linguistic representations (WH-dependencies)
- More efficient computational procedures for search and estimation
  - Dynamic programming, approximation methods (variational methods, best-first or beam search)
- Apply discriminative techniques to applications such as speech recognition and machine translation

Discriminative learning in other settings

- Speech recognition
  - Take x to be the acoustic signal, $\mathcal{Y}(x)$ all strings in recognizer lattice for x
  - Training data: $D = ((y_1, x_1), \ldots, (y_n, x_n))$, where y_i is correct transcript for x_i
  - Features could be n-grams, log parser prob, cache features
- Machine translation
  - Take x to be input language string, $\mathcal{Y}(x)$ a set of target language strings (e.g., generated by an IBM-style model)
  - Training data: $D = ((y_1, x_1), \ldots, (y_n, x_n))$, where y_i is correct translation of x_i
  - Features could be n-grams of target language strings, word and phrase correspondences, ...

Regularizer tuning in Max Ent models

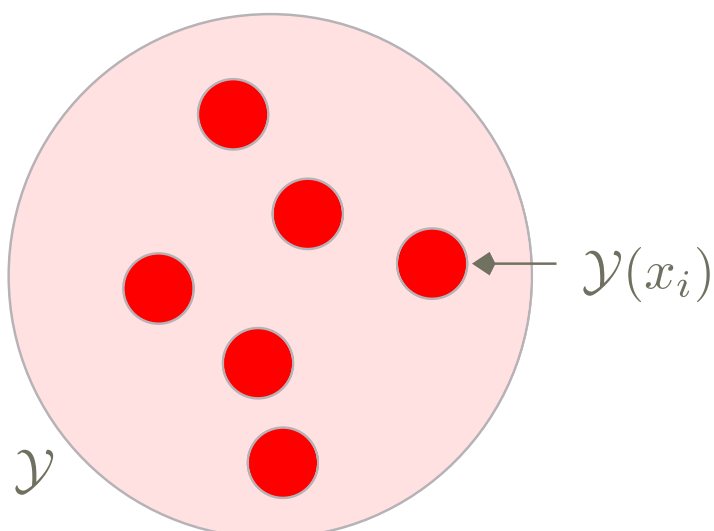
- Associate each feature f_j with bin $b(j)$
- Associate regularizer constant β_k with feature bin k
- Optimize feature weights $\alpha = (\alpha_1, \ldots, \alpha_m)$ on main training data M
- Optimize regularizer constants β on held-out data H

$$
\begin{aligned}
L_D(\alpha) &= \prod_{i=1}^{n} \mathrm{P}_\alpha(y_i|x_i), \text{ where } D = ((y_1, x_1), \ldots, (y_n, x_n)) \\
\hat{\alpha}(\beta) &= \operatorname*{argmax}_{\alpha} \log L_M(\alpha) - \sum_{j=1}^{m} \beta_{b(j)} \alpha_j^2 \\
\hat{\beta} &= \operatorname*{argmax}_{\beta} \log L_H(\hat{\alpha}(\beta))
\end{aligned}
$$

Expectation maximization for PCFGs

- Hidden training data: $D = (x_1, \ldots, x_n)$, where x_i is a string
- The Inside-Outside algorithm is an Expectation-Maximization algorithm for PCFGs

$$\begin{aligned} \hat{p} &= \operatorname*{argmax}_p L_D(p), \text{ where} \\ L_D(p) &= \prod_{i=1}^{n} \mathrm{P}_p(x_i) = \operatorname*{argmax}_p \prod_{i=1}^{n} \sum_{y \in \mathcal{Y}(x_i)} \mathrm{P}(y) \end{aligned}$$



Why there is no conditional ML EM

- Conditional ML conditions on the string x
- Hidden training data: $D = (x_1, \ldots, x_n)$, where x_i is a string
- The likelihood is the probability of predicting the string x_i given the string x_i, a *constant function*

$$\begin{aligned} \hat{p} &= \operatorname*{argmax}_p L_D(p), \text{ where} \\ L_D(p) &= \prod_{i=1}^{n} \mathrm{P}_p(x_i | x_i) \end{aligned}$$