Statistical Parsing Algorithms for Lexicalized Tree Adjoining Grammars

Dissertation Proposal Defense – 11/15/2000

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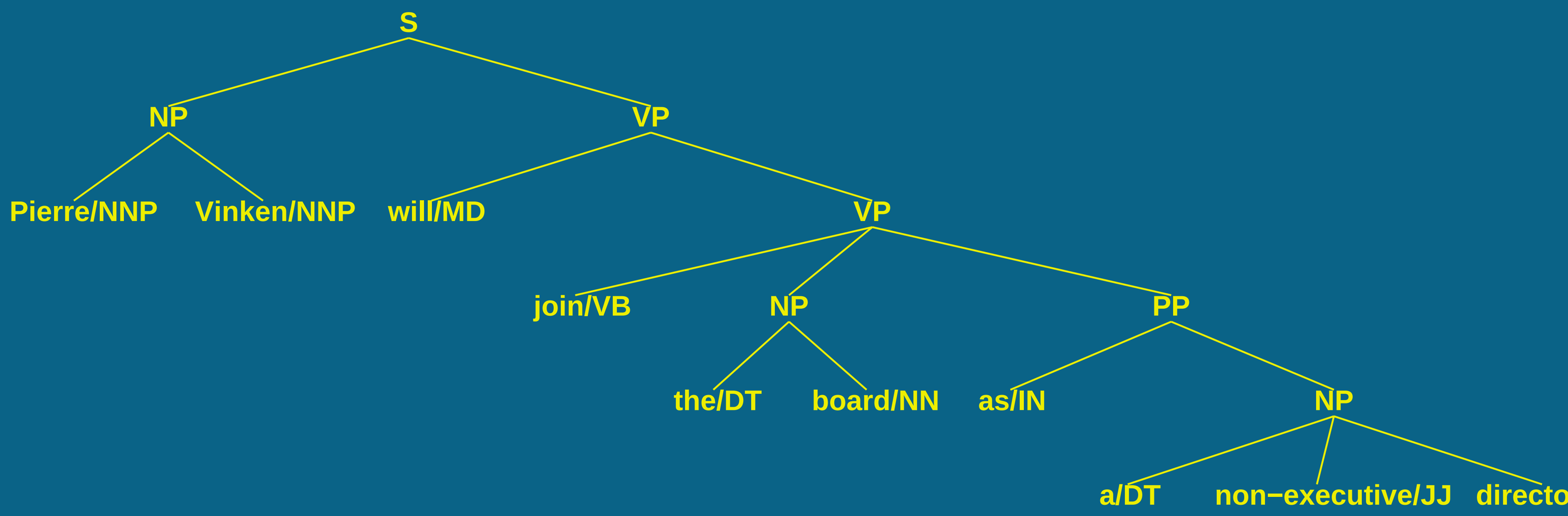
Overview

- Introduction
- Results
  - Determining if a probabilistic TAG is well-defined.
  - Computing inside probabilities: a statistical parser for TAGs.
  - Computing prefix probabilities.
  - Training a parser by combining labeled and unlabeled data.
- Proposed Work

Statistical Parsing

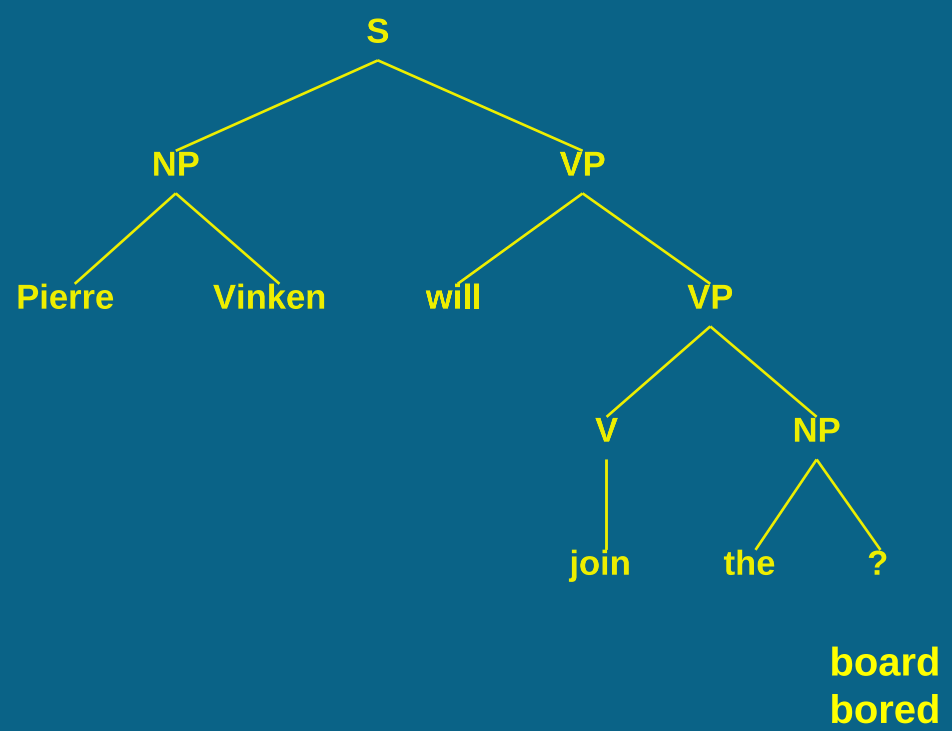
Pierre Vinken will join the board as a non-executive director



Language Modeling

Input: Pierre Vinken will join the . . .

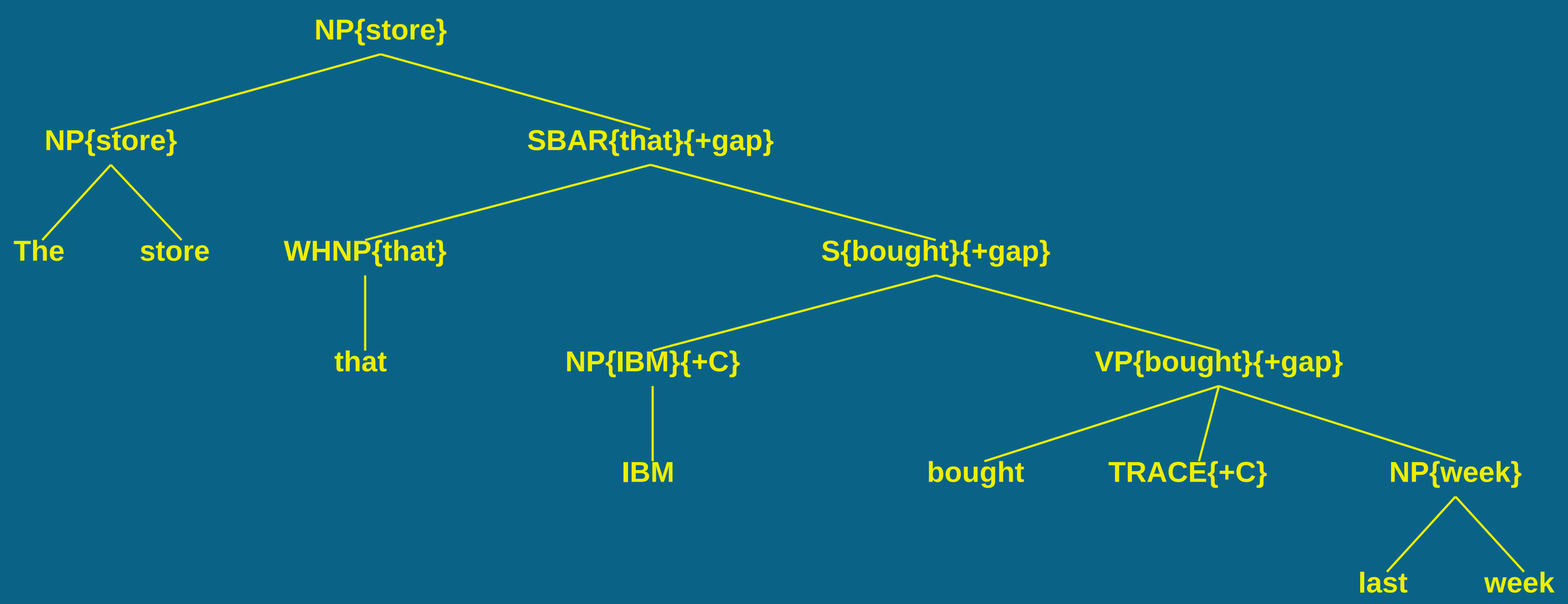
Word Prediction:



Tree Adjoining Grammars

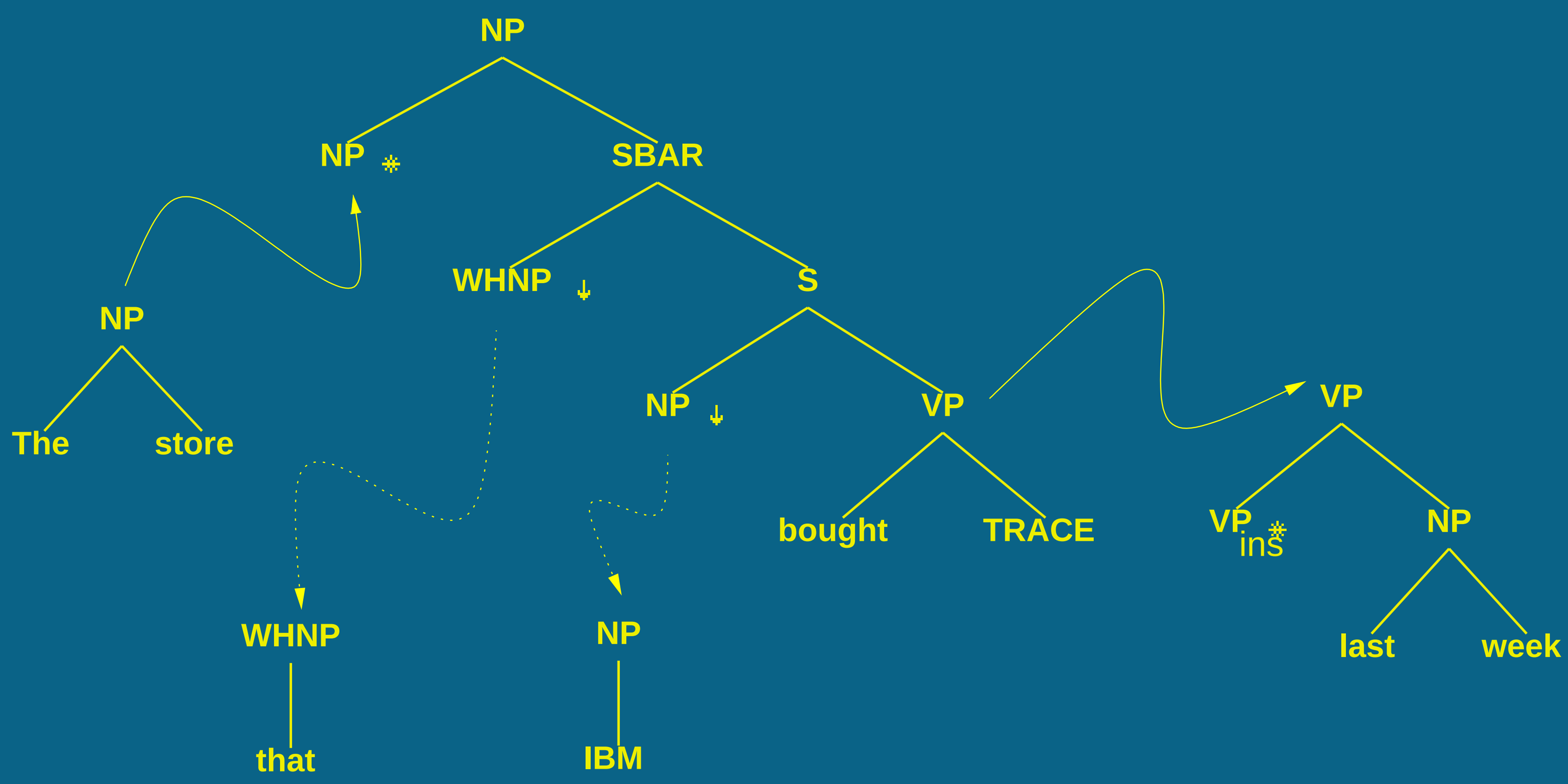
- The notion of predicate-argument structure is captured elegantly.
- Locality and independence assumptions.
- Simple and well-defined probability model.
- Parsing can be treated in two steps:
  1. Classification: structured labels (elementary trees) are assigned to each word in the sentence.
  2. Attachment: the elementary trees are connected to each other to form the parse.

Bilexical CFG with ‘features’ (Collins 1999)

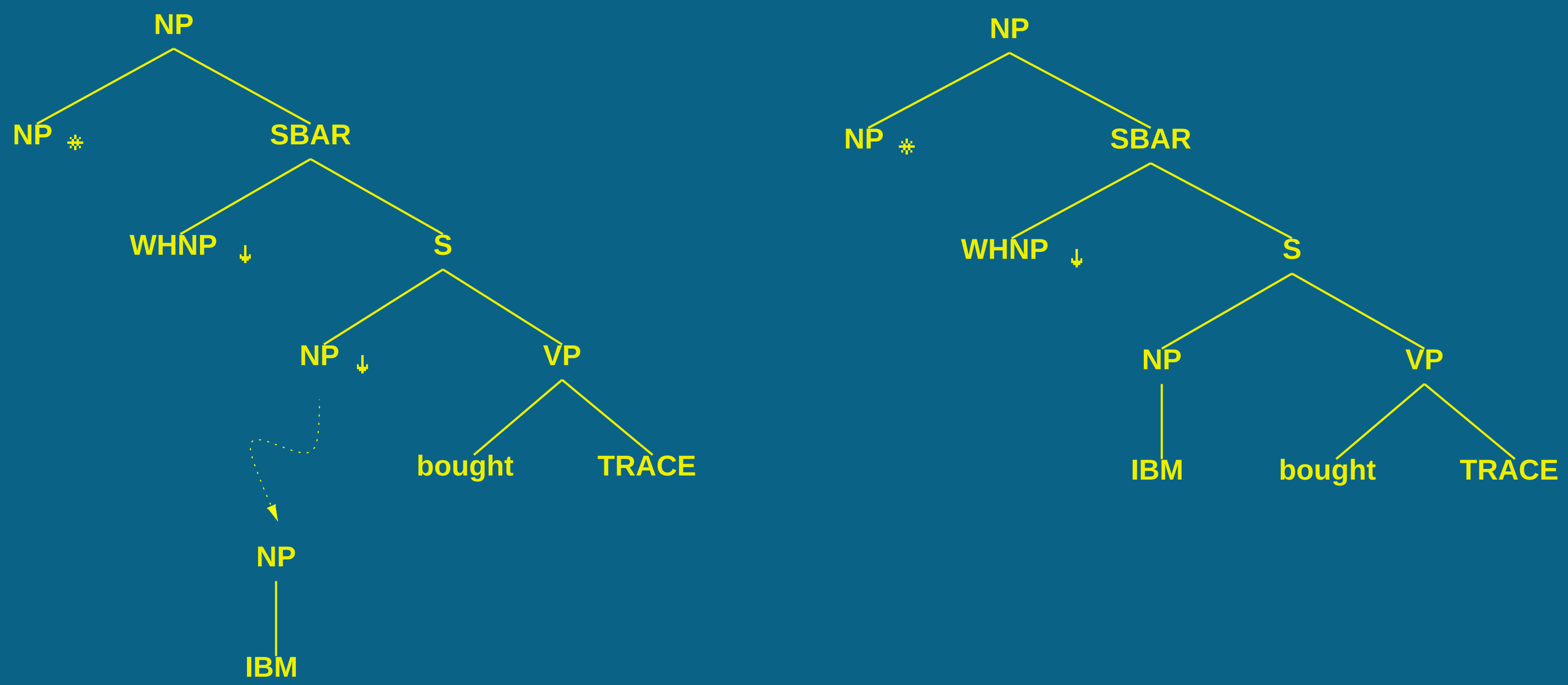


NP	$\rightarrow$	[	NP{+H}	SBAR{+gap}		]
SBAR{+gap}	$\rightarrow$	[	WHNP	S{+H}{+C}{+gap}		]
S{+gap}	$\rightarrow$	[	NP{+C}	SBAR{+H}{+gap}		]
VP{+gap}	$\rightarrow$	[	VB{+H}	TRACE{+C}	NP	]

Tree Adjoining Grammars: Different Modeling of Bilexical Dependencies

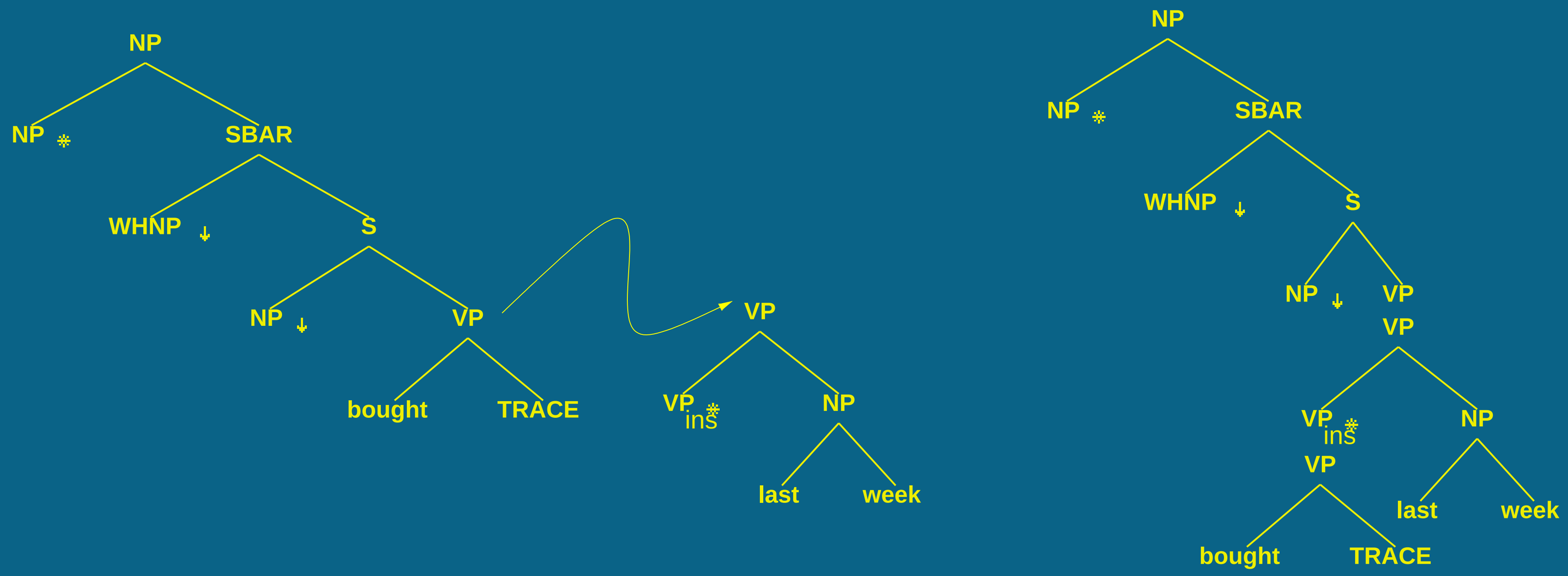


Probabilistic TAGs: Substitution



$$\sum_{t'} \mathcal{P}(t, \eta \rightarrow t') = 1$$

Probabilistic TAGs: Adjunction



$$\mathcal{P}(t, \eta \to NA) + \sum_{t'} \mathcal{P}(t, \eta \to t') = 1$$

Tree Adjoining Grammars

- Simpler model for parsing.
  Performance(Chiang 2000): 86.9% LR 86.6% LP ($\leq$ 40 words)

- Parsing can be treated in two steps:

  1. Classification: structured labels (elementary trees) are assigned to each word in the sentence.

  2. Attachment: Apply substitution or adjunction to combine the elementary trees to form the parse.

- Produces more than the phrase structure of each sentence.
  A more embellished parse in which phenomena such as predicate-argument structure, subcategorization and movement are given a probabilistic treatment.

Parsing as Classification and Attachment

- Assigning structured labels to each word results in an '*almost parse*'
  (Srinivas 1997)
  - A probabilistic treatment of classification: *SuperTagging*
  - A heuristic treatment of attachment: *Lightweight Dependency Analyzer*
- This work: a probabilistic treatment of both classification and attachment
- Extension to a more unsupervised approach
  (combining labeled and unlabeled data)

Theory and Practice of Probabilistic TAGs

- Applications of probabilistic grammars involve one or more of the following tasks, quoted from (Jelinek and Lafferty 1991):
  - What is the probability that a given string x is generated by a grammar? A probabilistic grammar is well-defined if:

$$\sum_{n=1}^{\infty} \sum_{w_1 w_2 \ldots w_n \in \mathcal{V}} \mathcal{P}(s \rightarrow w_1 w_2 \ldots w_n) = 1$$

  - What is the single most likely parse (or derivation) for x?
  - What is the probability that x occurs as a prefix of some string generated by the grammar?
  - How should the parameters (e.g., rule probabilities) be chosen?

Results: Overview

- A probabilistic grammar is well-defined if:

$$\sum_{n=1}^{\infty} \sum_{w_1 w_2 \ldots w_n \in \mathcal{V}} \mathcal{P}(s \rightarrow w_1 w_2 \ldots w_n) = 1$$

- What is the single most likely parse (or derivation) for x?
- What is the probability that x occurs as a prefix of some string generated by the grammar?
- How should the parameters (e.g., rule probabilities) be chosen?

Consistent Probabilistic TAGs

- A probabilistic grammar is well-defined if:

$$\sum_{n=1}^{\infty} \sum_{w_1 w_2 \ldots w_n \in \mathcal{V}} \mathcal{P}(s \rightarrow w_1 w_2 \ldots w_n) = 1$$

- Is it enough to have the following conditions?

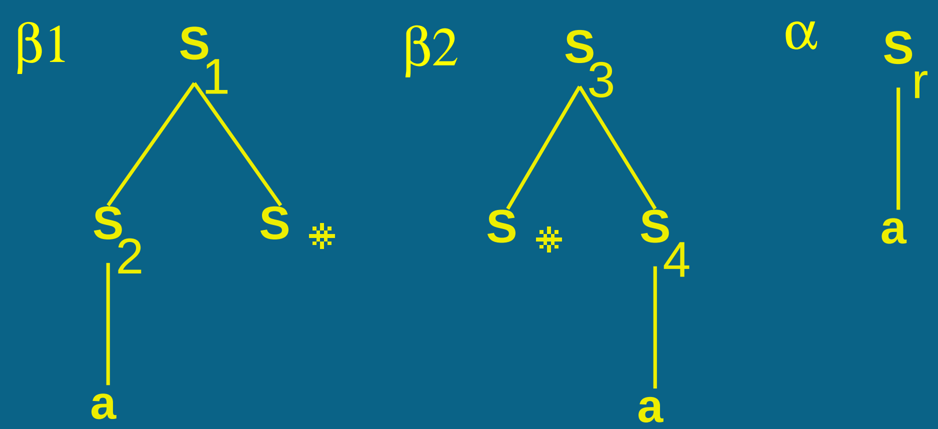
$$\begin{array}{rrcrcl} \textit{Substitution:} & & & \sum_{t'} \mathcal{P}(t, \eta \rightarrow t') & = & 1 \\ \textit{Adjunction:} & \mathcal{P}(t, \eta \rightarrow NA) & + & \sum_{t'} \mathcal{P}(t, \eta \rightarrow t') & = & 1 \end{array}$$

(a *proper* Probabilistic TAG)

Consistent Probabilistic TAGs

- In the PCFG: `(p = 0.99)`: $S \rightarrow S\,S$ and `(1-p)`: $S \rightarrow a$
- Let x_h be the total probability of all parses with height h.
- $x_{h+1} = 1 - p + p \cdot {x_h}^2$
- When $h \rightarrow \infty$: $x = 1 - p + p \cdot x^2$
- $x = (1/p) - 1$ since x_h is increasing.
- If $p > 1/2$ then all parses cumulatively get probability $x < 1$.
  Thus, the model is deficient.

Consistent Probabilistic TAGs



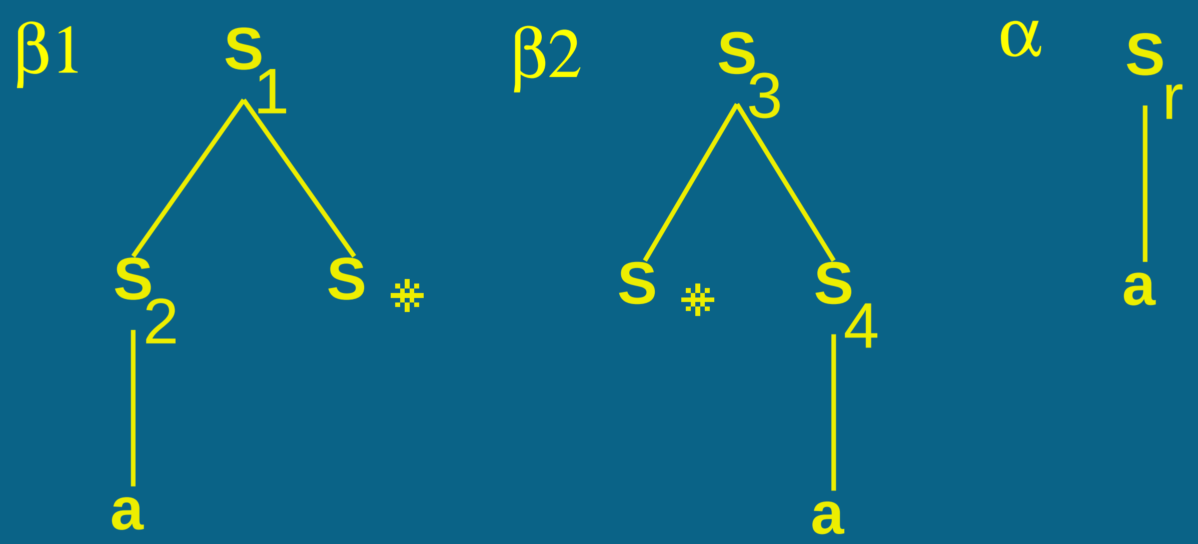
$$
\begin{array}{llll}
\mathcal{P}(S_r \to \beta_1) = .5 & & \mathcal{P}(S_r \to \beta_2) = .5 \\
\mathcal{P}(S_1 \to \beta_1) = .01 & & \mathcal{P}(S_1 \to \beta_2) = .98 \\
\mathcal{P}(S_2 \to \beta_1) = .98 & & \mathcal{P}(S_2 \to \beta_2) = .01 \\
\mathcal{P}(S_1 \to NA) = .01 & & \mathcal{P}(S_2 \to NA) = .01 \\
\mathcal{P}(S_3 \to \beta_1) = .01 & & \mathcal{P}(S_3 \to \beta_2) = .98 \\
\mathcal{P}(S_4 \to \beta_1) = .98 & & \mathcal{P}(S_4 \to \beta_2) = .01 \\
\mathcal{P}(S_3 \to NA) = .01 & & \mathcal{P}(S_4 \to NA) = .01
\end{array}
$$

Consistent Probabilistic TAGs

- First Result: An algorithm to decide whether a Probabilistic TAG is consistent
  - Describe TAG derivations as Markov branching processes.

    (described in proposal document)
  - Also can be shown by reducing Prob TAG grammar to a degenerate PCFG. (as suggested by Steve Abney)
  - Useful when we discuss the algorithm for computing prefix probabilities.

Consistent Probabilistic TAGs



$$
\begin{array}{lll}
\alpha & \rightarrow & S_r \\
\beta_1 & \rightarrow & S_1\, S_2 \\
S_1 & \rightarrow & \beta_1 \mid \beta_2 \mid \epsilon \\
S_2 & \rightarrow & \beta_1 \mid \beta_2 \mid \epsilon
\end{array}
\qquad
\begin{array}{lll}
S_r & \rightarrow & \beta_1 \mid \beta_2 \mid \epsilon \\
\beta_2 & \rightarrow & S_3\, S_4 \\
S_3 & \rightarrow & \beta_1 \mid \beta_2 \mid \epsilon \\
S_4 & \rightarrow & \beta_1 \mid \beta_2 \mid \epsilon
\end{array}
$$

Consistent Probabilistic TAGs

$$
\begin{aligned}
\mathcal{P}(\alpha \rightarrow S_r) &= 1.0 \\
\mathcal{P}(S_r \rightarrow \beta_1) &= .5 \\
\mathcal{P}(S_r \rightarrow \beta_2) &= .5 \\
\mathcal{P}(S_r \rightarrow \epsilon) &= 0 \\
\mathcal{P}(\beta_1 \rightarrow S_1\, S_2) &= 1.0 \\
\mathcal{P}(\beta_2 \rightarrow S_3\, S_4) &= 1.0 \\
\mathcal{P}(S_1 \rightarrow \beta_1) &= .01 \\
\mathcal{P}(S_1 \rightarrow \beta_2) &= .98 \\
\mathcal{P}(S_1 \rightarrow \epsilon) &= .01 \\
\mathcal{P}(S_2 \rightarrow \beta_1) &= .98 \\
\mathcal{P}(S_2 \rightarrow \beta_2) &= .01 \\
\mathcal{P}(S_2 \rightarrow \epsilon) &= .01
\end{aligned}
$$

Consistent Probabilistic TAGs

- Apply the PCFG result (Booth and Thompson 1973) on this grammar to check for consistency.

- Compute the expectation matrix $\mathcal{M}$ which contains expected values of observing a tree t when rewriting a node η.

- Check that the spectral radius $\rho(\mathcal{M}) < 1$. $\rho(\mathcal{M})$ is the modulus of the largest eigenvalue of $\mathcal{M}$.

Consistent Probabilistic TAGs

$$
\mathcal{M} = \begin{array}{c c}
 & \begin{array}{cccccccc} S_1 & S_2 & S_3 & S_4 & S_r & \alpha & \beta_1 & \beta_2 \end{array} \\
\begin{array}{c} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_r \\ \alpha \\ \beta_1 \\ \beta_2 \end{array} &
\left[\begin{array}{cccccccc}
0 & 0 & 0 & 0 & 0 & 0 & .01 & .98 \\
0 & 0 & 0 & 0 & 0 & 0 & .98 & .01 \\
0 & 0 & 0 & 0 & 0 & 0 & .01 & .98 \\
0 & 0 & 0 & 0 & 0 & 0 & .98 & .01 \\
0 & 0 & 0 & 0 & 0 & 0 & .5 & .5 \\
0 & 0 & 0 & 0 & 1.0 & 0 & 0 & 0 \\
1.0 & 1.0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1.0 & 1.0 & 0 & 0 & 0 & 0
\end{array}\right]
\end{array}
$$

- $\rho(\mathcal{M}) = 1.4071$. The input Prob TAG is correctly tagged as inconsistent.
- A condition for consistency and an algorithm for detecting deficiency.
- `http://www.cis.upenn.edu/~anoop/distrib/consist/`

Results: Overview

- A probabilistic grammar is well-defined if:

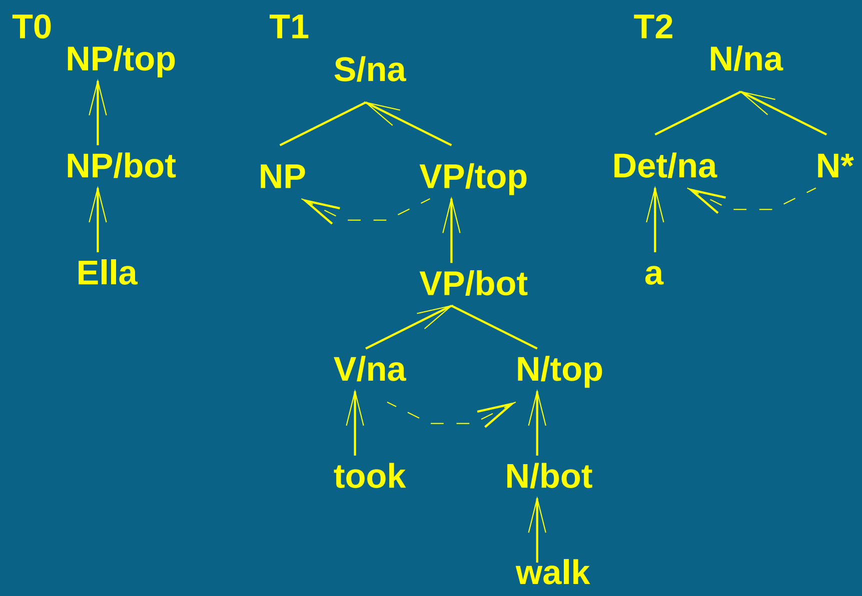
$$\sum_{n=1}^{\infty} \sum_{w_1 w_2 \ldots w_n \in \mathcal{V}} \mathcal{P}(s \to w_1 w_2 \ldots w_n) = 1$$

- What is the single most likely parse (or derivation) for x?

- What is the probability that x occurs as a prefix of some string generated by the grammar?

- How should the parameters (e.g., rule probabilities) be chosen?

Parser for Probabilistic TAGs



- Head corner chart parser for TAGs. Based on (van Noord 1990) head corner traversal
- Less average time/space complexity in practice compared to CKY for TAGs.
- Tree classification step reduces parsing time dramatically.
- `ftp://ftp.cis.upenn.edu/pub/xtag/lem/`

Results: Overview

- A probabilistic grammar is well-defined if:

$$\sum_{n=1}^{\infty} \sum_{w_1 w_2 \ldots w_n \in \mathcal{V}} \mathcal{P}(s \rightarrow w_1 w_2 \ldots w_n) = 1$$

- What is the single most likely parse (or derivation) for x?

- What is the probability that x occurs as a prefix of some string generated by the grammar?

- How should the parameters (e.g., rule probabilities) be chosen?

Prefix Probabilities: (with M.J. Nederhof and G. Satta)

- What is the probability that x occurs as a prefix of some string generated by the grammar?

- Language model: given a string $a_1, \ldots, a_{i-1}$, a_i can be any word in the vocabulary Σ, what is $P(a_i \mid a_1, \ldots, a_{i-1})$?

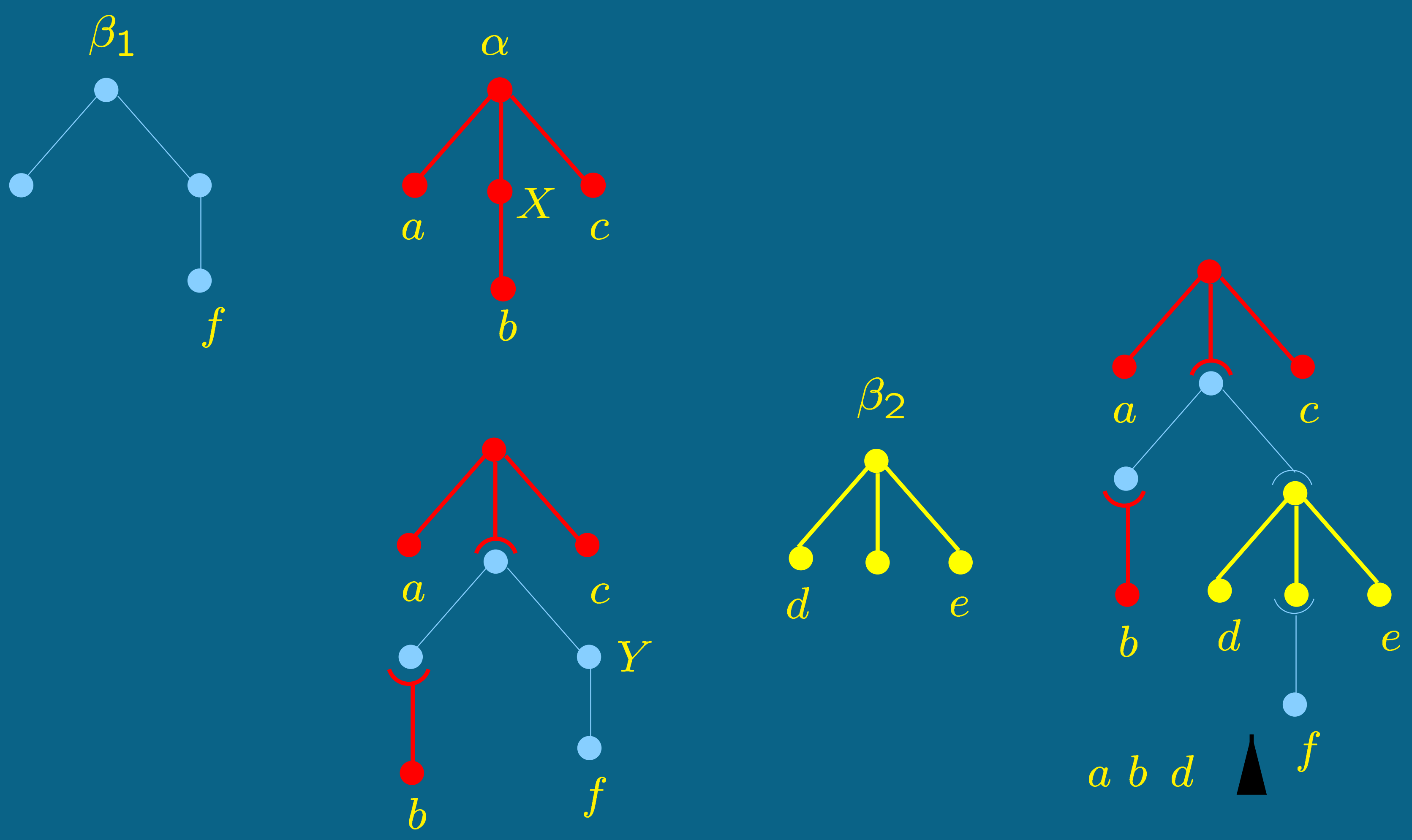
- Standard techniques use trigram models:

$$P(a_i \mid a_{i-2}, a_{i-1})$$

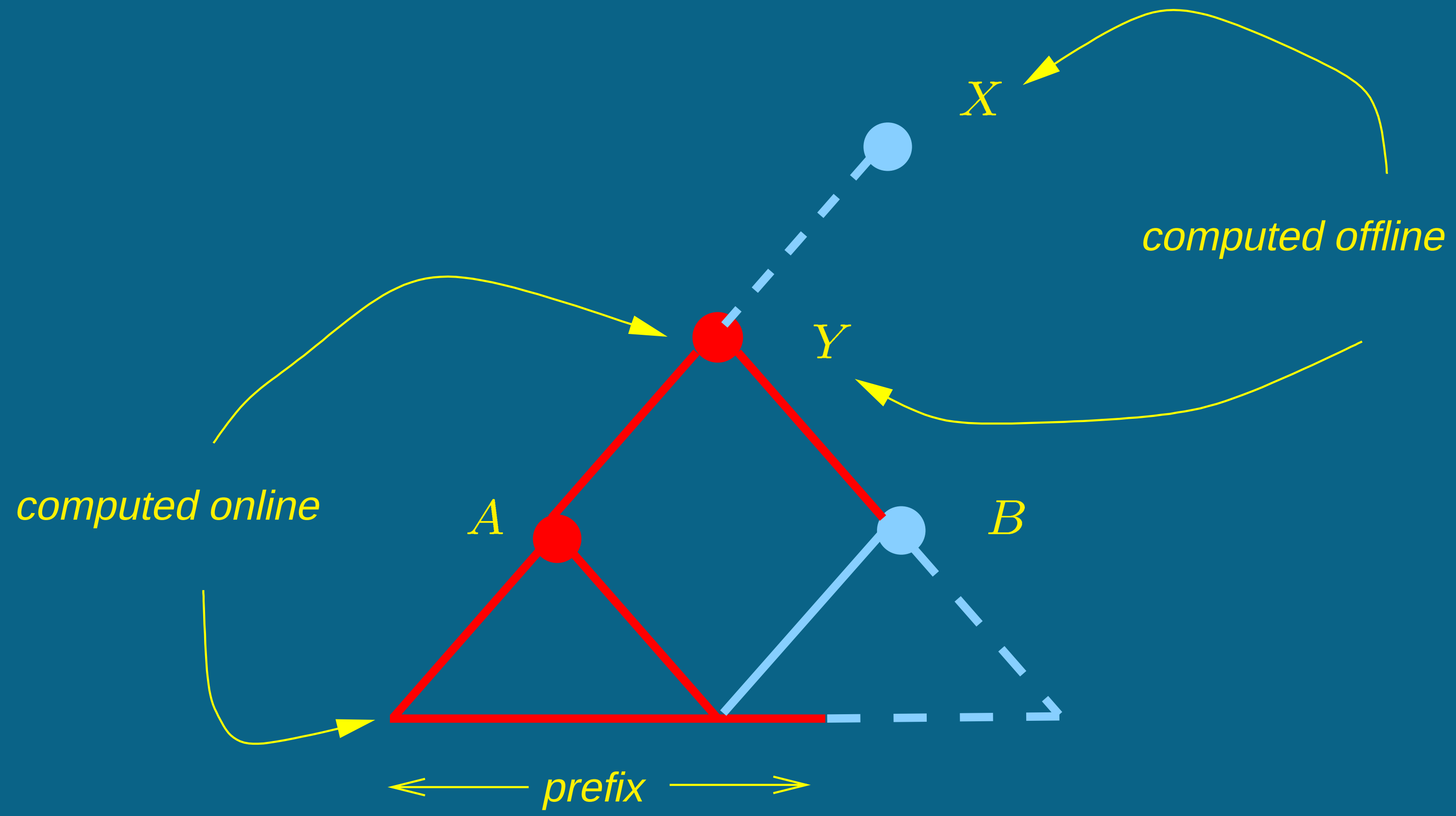
- A stochastic grammar can be used by computing the prefix probability:

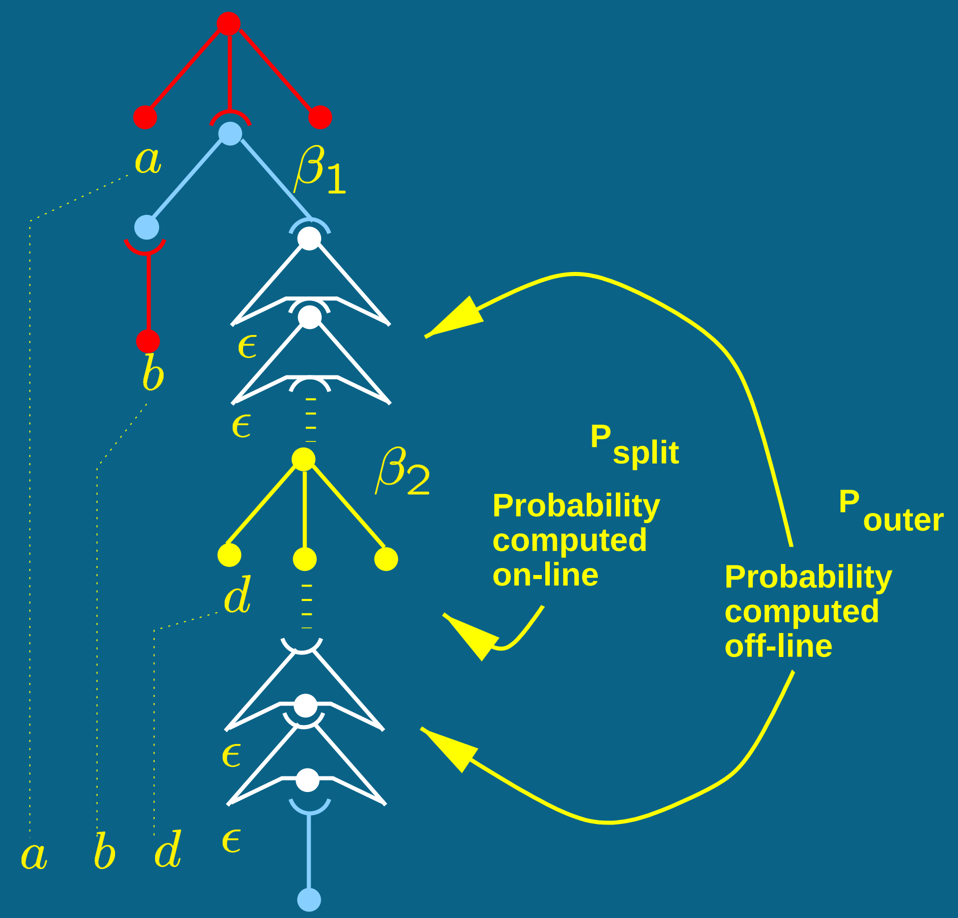
$$\sum_{w \in \Sigma^*} P(a_1, \ldots, a_i w)$$

Let prefix $= abd$



Prefix Probabilities for CFGs (Jelinek and Lafferty 1991)





$$\mathcal{P}([N_{\beta_1}, i, j, f_1, f_2]) = \sum_{\beta_2, f_1', f_2'} \mathcal{P}_{outer}([N_{\beta_1}, i, j, f_1, f_2], [\beta_2, f_1', f_2']) \times \mathcal{P}_{split}([R_{\beta_2}, i, j, f_1', f_2'])$$

Prefix Probabilities

- Derivations are a combination of two kinds of subderivations:

  1. potentially unbounded subderivations, independent of input

  2. bounded subderivations, depend on input symbols

- Problem: how to partition derivations uniquely into subderivations.

- Without unique partitions, algorithm will return incorrect probabilities.

Prefix Probabilities: Some Details

$$\sum_w \mathcal{P}(a_1 \dots a_n w) = \sum_{t \in \mathcal{I}} \mathcal{P}([t, 0, n, -, -])$$

$$\begin{aligned} &\mathcal{P}([N, i, j, -, -]) = \\ &\quad \mathcal{P}(N \to NA) \times \mathcal{P}([cdn(N), i, j, -, -]) + \\ &\quad \sum_{k,l} \mathcal{P}([cdn(N), k, l, -, -]) \times \sum_t \mathcal{P}(N \to t) \times \mathcal{P}([t, i, j, k, l]) \end{aligned}$$

$$\mathcal{P}([\alpha N, i, j, -, -]) = \sum_k \mathcal{P}([\alpha, i, k, -, -]) \times \mathcal{P}([N, k, j, -, -])$$

Prefix Probabilities: Some Details

$$\sum_w \mathcal{P}([\alpha N, i, j, -, -]) = \sum_k \mathcal{P}([\alpha, i, k, -, -]) \times \mathcal{P}([N, k, j, -, -])$$

$$\begin{aligned}
&\mathcal{P}_{outer}([\alpha N, i, j, -, -], [t, f_1', f_2']) = \\
&\quad \mathcal{P}_{outer}([\alpha, i, j, -, -]) \times \mathcal{P}([N, j, j, -, -]) + \\
&\quad \mathcal{P}([\alpha, i, i, -, -]) \times \mathcal{P}_{outer}([N, i, j, -, -], [t, f_1', f_2'])
\end{aligned}$$

Prefix Probabilities: Some Details

$$\sum_w \mathcal{P}([\alpha N, i, j, -, -]) = \sum_k \mathcal{P}([\alpha, i, k, -, -]) \times \mathcal{P}([N, k, j, -, -])$$

$$\begin{aligned}
&\mathcal{P}_{split}([\alpha N, i, j, -, -], [t, f_1', f_2']) = \\
&\quad (\sum_k \mathcal{P}([\alpha, i, k, -, -]) \times \mathcal{P}([N, k, j, -, -])) + \\
&\quad \mathcal{P}_{split}([\alpha, i, j, -, -]) \times \mathcal{P}([N, j, j, -, -]) + \\
&\quad \mathcal{P}([\alpha, i, i, -, -]) \times \mathcal{P}_{split}([N, i, j, -, -], [t, f_1', f_2'])
\end{aligned}$$

Prefix Probabilities: Offline Computation

$$\mathcal{M} = \begin{array}{c} \\ S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_r \\ \alpha \\ \beta_1 \\ \beta_2 \end{array} \begin{array}{c} \begin{array}{cccccccc} S_1 & S_2 & S_3 & S_4 & S_r & \alpha & \beta_1 & \beta_2 \end{array} \\ \left[\begin{array}{cccccccc} 0 & 0 & 0 & 0 & 0 & 0 & .01 & .98 \\ 0 & 0 & 0 & 0 & 0 & 0 & .98 & .01 \\ 0 & 0 & 0 & 0 & 0 & 0 & .01 & .98 \\ 0 & 0 & 0 & 0 & 0 & 0 & .98 & .01 \\ 0 & 0 & 0 & 0 & 0 & 0 & .5 & .5 \\ 0 & 0 & 0 & 0 & 1.0 & 0 & 0 & 0 \\ 1.0 & 1.0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1.0 & 1.0 & 0 & 0 & 0 & 0 \end{array} \right] \end{array}$$

Prefix Probabilities: Offline Computation

- How to compute $\mathcal{P}_{outer}([N_{\beta_1}, i, j, f_1, f_2], [\beta_2, f_1', f_2'])$?

- $\mathcal{Q} = \mathcal{M} + \mathcal{M}^2 + \mathcal{M}^3 + \ldots$

- $\mathcal{Q} = \mathcal{M}[\mathcal{I} - \mathcal{M}]^{-1}$

- Compute $\mathcal{P}([\alpha, i, i, -, -])$ in a similar way.

Results: Overview

- A probabilistic grammar is well-defined if:

$$\sum_{n=1}^{\infty} \sum_{w_1 w_2 \ldots w_n \in \mathcal{V}} \mathcal{P}(s \rightarrow w_1 w_2 \ldots w_n) = 1$$

- What is the single most likely parse (or derivation) for x?

- What is the probability that x occurs as a prefix of some string generated by the grammar?

- How should the parameters (e.g., rule probabilities) be chosen?

Training a Statistical Parser

- How should the parameters (e.g., rule probabilities) be chosen?

- Several alternatives:
  - EM algorithm: Inside-Outside Algorithm (Schabes 1990; Hwa 1998)
  - Supervised training from a Treebank (Chiang 2000)
  - Parsing as Classification. Explore new machine learning techniques.

Open Issues in Lexicalized, Corpus-based Language Processing

- Adapting to new domains: training on one domain, testing (using) on another.

- Achieving higher performance when using limited amounts of annotated data.

- Separating structural (robust) aspects of the problem from lexical (sparse) ones.

  Explained in more detail later . . .

Statistical Parsing: Supervised vs. Unsupervised Methods

- “Stone soup” approaches to unsupervised learning of parsers cannot handle structurally rich parses found in the Penn Treebank.
  (Lafferty et al 1992; Della Pietra et al 1994; de Marcken 1995)

- A feasible technique: Combining Labeled and Unlabeled Data
  - Active Learning: Bet on which examples are the hardest.
    (and annotate them) (Hwa 2000)
  - Co-Training: Bet on which examples can be handled with high confidence. (use as labeled data)

Case Study in Unsupervised Methods: POS Tagging

- POS Tagging: finding categories for words
- *. . . the stocks* $\boxed{\textit{rose}}$*/V . . .* vs. *. . . a* $\boxed{\textit{rose}}$*/N bouquet . . .*
- Tag dictionary: $\boxed{\textit{rose}}$*: N, V*

  and nothing else

Case Study: Unsupervised POS Tagging

- (Cutting et al. 1992) The Xerox Tagger: used HMMs with hand-built tag dictionaries. High performance: 96% on Brown
- (Merialdo 1994; Elworthy 1994) used varying amounts of labeled data as seed information for training HMMs.

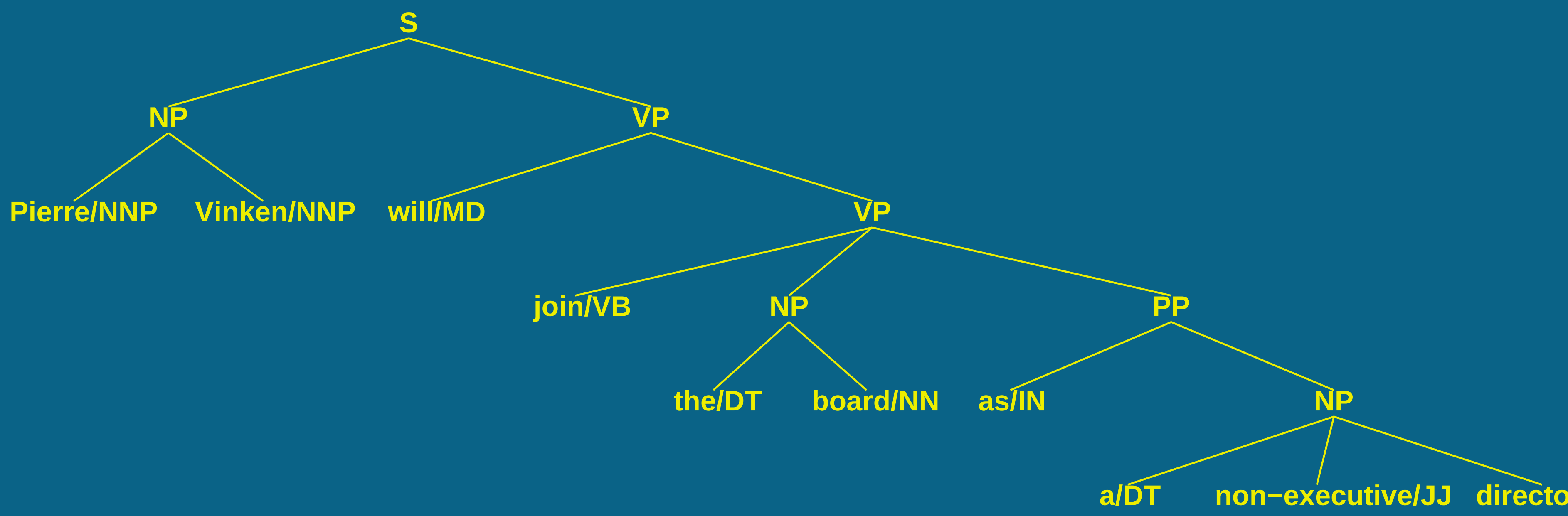
  Conclusion: HMMs do not effectively combine labeled and unlabeled data
- (Brill 1997) aggressively used tag dictionaries taken from labeled data to train an unsupervised POS tagger.

  Performance: 95% on WSJ. Approach does not easily extend to parsing: no notion of tag dictionary.

Co-Training (Blum and Mitchell 1998; Yarowsky 1995)

- Pick two (or more) “views” of a classification problem.
- Build separate models for each of these “views” and train each model on a small set of labeled data.
- Sample an unlabeled data set and to find examples that the models agree upon the most. Exploit the mutual constraints between the models
- Agreement can be computed as a simple product or in a more complex fashion. (Collins and Singer 1999; Goldman and Zhou 2000)
- Bet that these examples are good as training examples and iterate.

Pierre Vinken will join the board as a non-executive director



Recursion in Parse Trees

- Usual decomposition of parse trees:

  S(join) $\rightarrow$ NP(Vinken) VP(join)

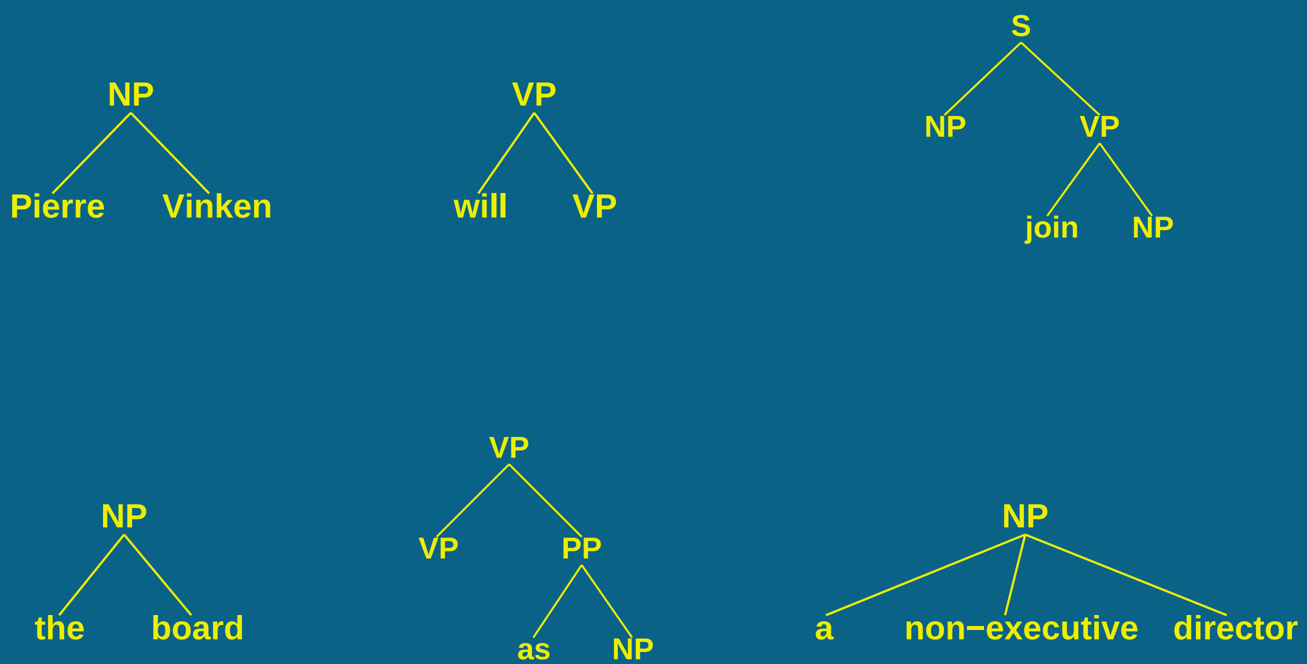
  NP(Vinken) $\rightarrow$ Pierre Vinken

  VP(join) $\rightarrow$ will VP(join)

  VP(join) $\rightarrow$ join NP(board) PP(as)

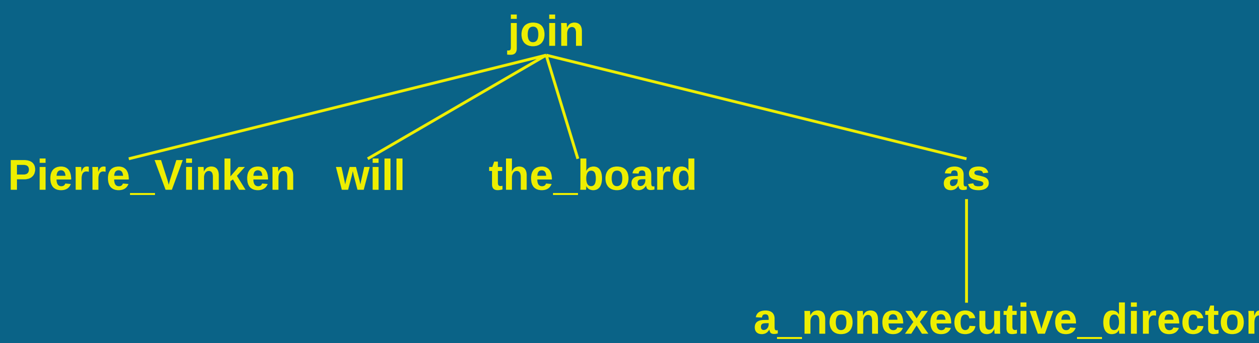
  ...

Parsing as Tree Classification and Attachment: (Srinivas 1997; Xia 2000)



Model H1: $\mathcal{P}(T_i \mid T_{i-2}T_{i-1}) \times \mathcal{P}(w_i \mid T_i)$

Parsing as Tree Classification and Attachment



Model H2: $\mathcal{P}(\text{TOP} = w, T) \times \Pi_i \mathcal{P}(w_i, T_i \mid \eta, w, T)$

The Co-Training Algorithm

1. Input: *labeled* and *unlabeled*
2. Update cache
   - If *unlabeled* is empty; exit
   - Randomly select sentences from *unlabeled* and refill *cache*
3. Train models H1 and H2 using *labeled*
4. Apply H1 to cache
5. Apply H2 to output of Step 4
6. Pick best n given overall score combining H1 and H2
7. Remove best n from *cache* and add to *labeled*
8. $n = 2n$; Go to Step 2

Preliminary Experiment

- *labeled* was set to Sections 02-06 of the Penn Treebank WSJ (9625 sentences)

- *unlabeled* was 30137 sentences (Section 07-21 of the Treebank stripped of all annotations).

- A TAG dictionary of all lexicalized trees from *labeled* and *unlabeled*.

  Similar to the approach of (Brill 1997)

  Novel trees were treated as unknown tree tokens

- The *cache* size was 3000 sentences.

Preliminary Experiment

- Test set: Section 0 (*development test set*)
- Baseline Model was trained only on the *labeled* set:
  Labeled Bracketing Precision = 67.43% Recall = 64.93%
- After 12 iterations of Co-Training:
  Labeled Bracketing Precision = 81.2% Recall = 78.94%
- NEW!: Evaluation of an unsupervised approach is directly comparable to other supervised parsers.

Summary

- Methods that combine labeled and unlabeled data provide a promising new direction towards unsupervised learning.
- Co-Training, previously used for classifiers with 2/3 labels, was extended to the complex problem of statistical parsing.
- Parsing treated as providing structured (tree) labels with attachments computed between these labels.
- Evaluation of a unsupervised method for parsing directly comparable with supervised approaches.

Proposed Work

- Evaluation of the Prefix Probability Parser.
- Further Evaluation of Co-Training.
- Learning Tag Dictionaries for Parsing.
- Integrate lexical knowledge acquisition into the Co-Training method.

Proposed Work: Evaluation of Prefix Probability Parser

- Modify existing parser to work from left to right.
- Note that we compute possible future contexts as well as histories. (unlike (Chelba and Jelinek 1998; Johnson and Roark 1999))
- Is it better to parse word graphs/lattices rather than parse left to right?
- Compare perplexity with a backed-off trigram model. Combining labeled and unlabeled data useful here.
- Compare word-error rate.

Proposed Work: Further Evaluation of Co-Training

- Current Work: Improve parser (better smoothing); Better combination of the models.

- Experiment with using a larger labeled (1M words) and unlabeled set (23M words).

- Experiment with smaller corpora, across domains and using Treebanks in other languages.

- Conjecture: Active Learning and Co-Training can be combined into a single framework.

Proposed Work: Learning Tag Dictionaries for Parsing

- Use machine learning techniques for learning the tag dictionary.
  - Subcategorization frame learning. (with D. Zeman)
    - Learnt 137 (lexicalized) subcat frames for Czech PDT.
    - Identified subcat frames in unseen data: 88% P, 74% R.
  - Learning Verb Classes. Pred-Argument structure (with W. Tripasai)
    - Classify V into $\mathtt{NP_0\ V\ NP_1;\ NP_1\ V;\ NP_0\ V}$
    - Using Decision Trees: Error Rate = 33.4%
- Integrate lexical knowledge acquisition into the Co-Training method.

Summary

- Results (Algorithms for . . .)
  - Determining if a probabilistic TAG is well-defined.
  - Computing inside probabilities: a statistical parser for TAGs.
  - Computing prefix probabilities.
  - Training a parser by combining labeled and unlabeled data.
- Proposed Work
  - Evaluation of the Prefix Probability Parser.
  - Further Evaluation of Co-Training.
  - Learning Tag Dictionaries for Parsing.
  - Integrate lexical knowledge acquisition into the Co-Training method.