Applying Co-Training Methods to Statistical Parsing

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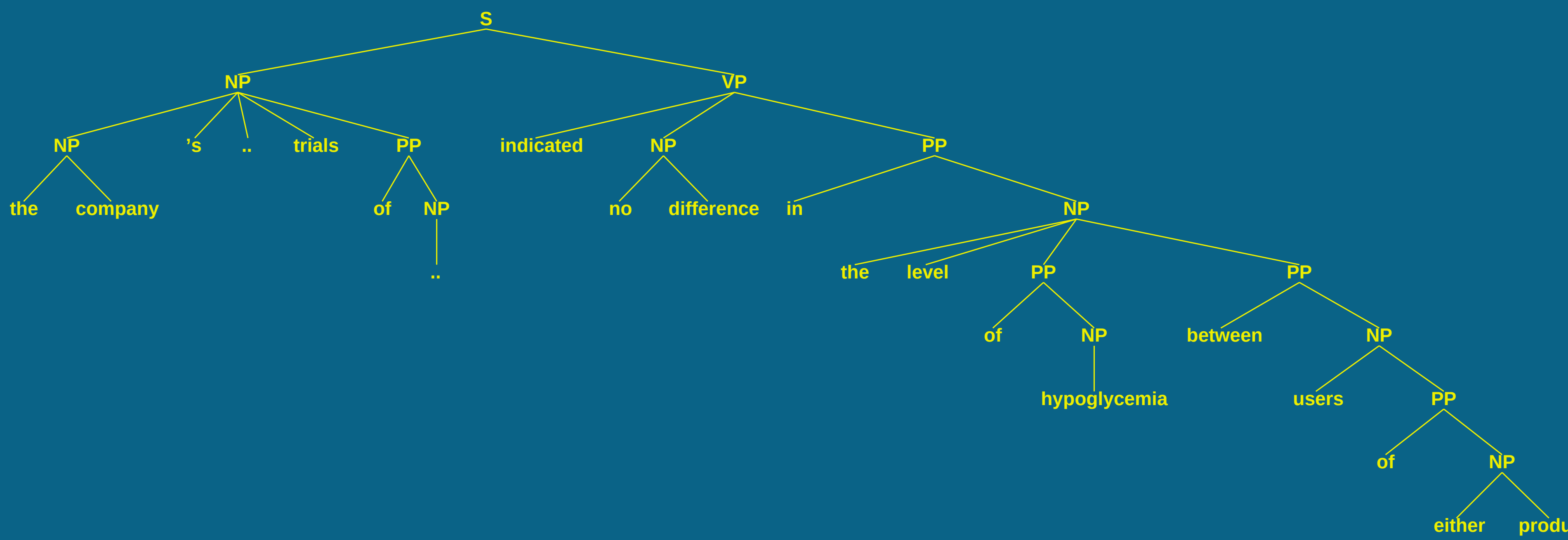
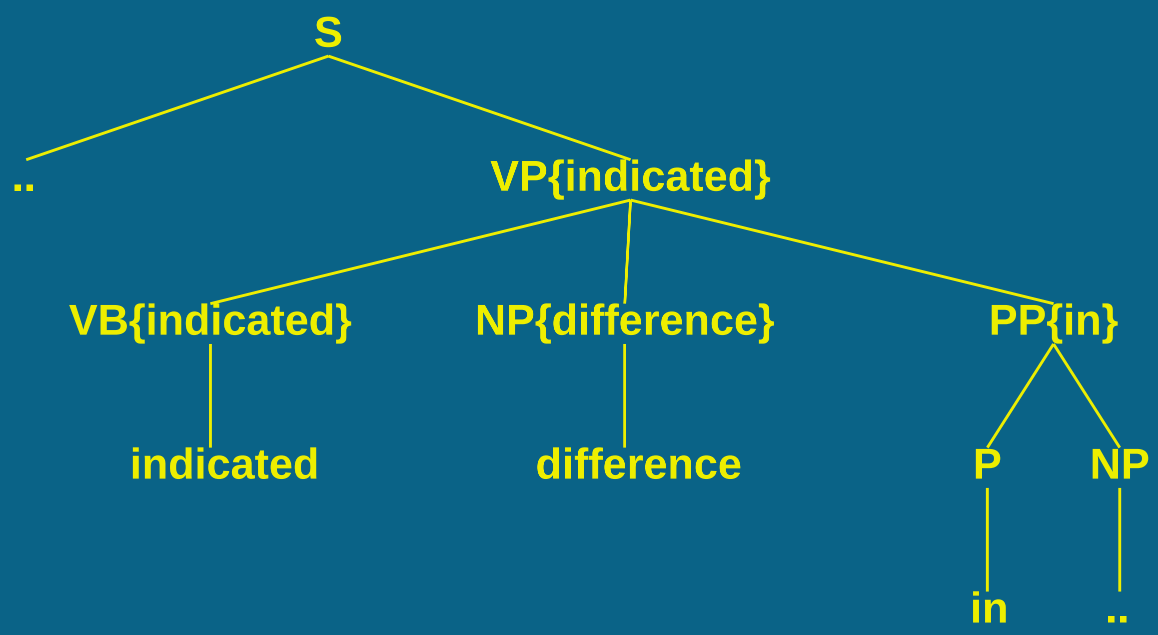
Statistical Parsing:

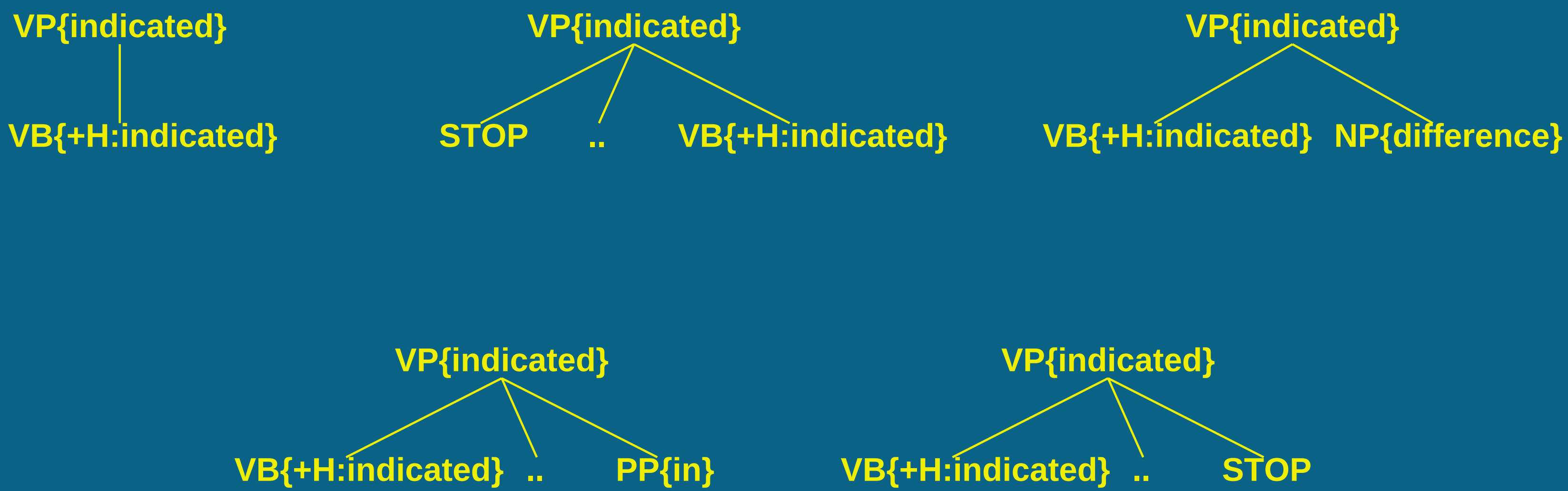
the company ’s clinical trials of both its animal and human-based insulins indicated no difference in the level of hypoglycemia between users of either product



Bilexical CFG (History-based parsers)

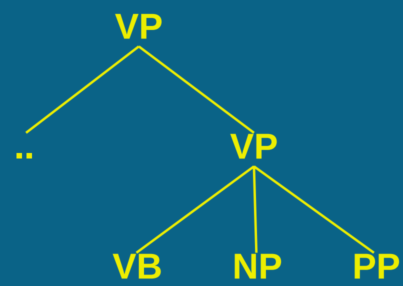


Bilexical CFG: VP{indicate} $\rightarrow$ VB{+H:indicate} NP{difference} PP{in}

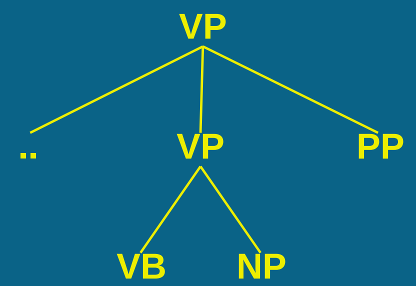


Independence Assumptions (Collins 99)

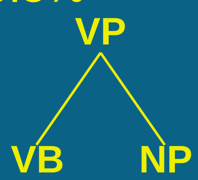
2.23%



0.06%



60.8%



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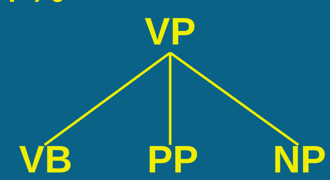
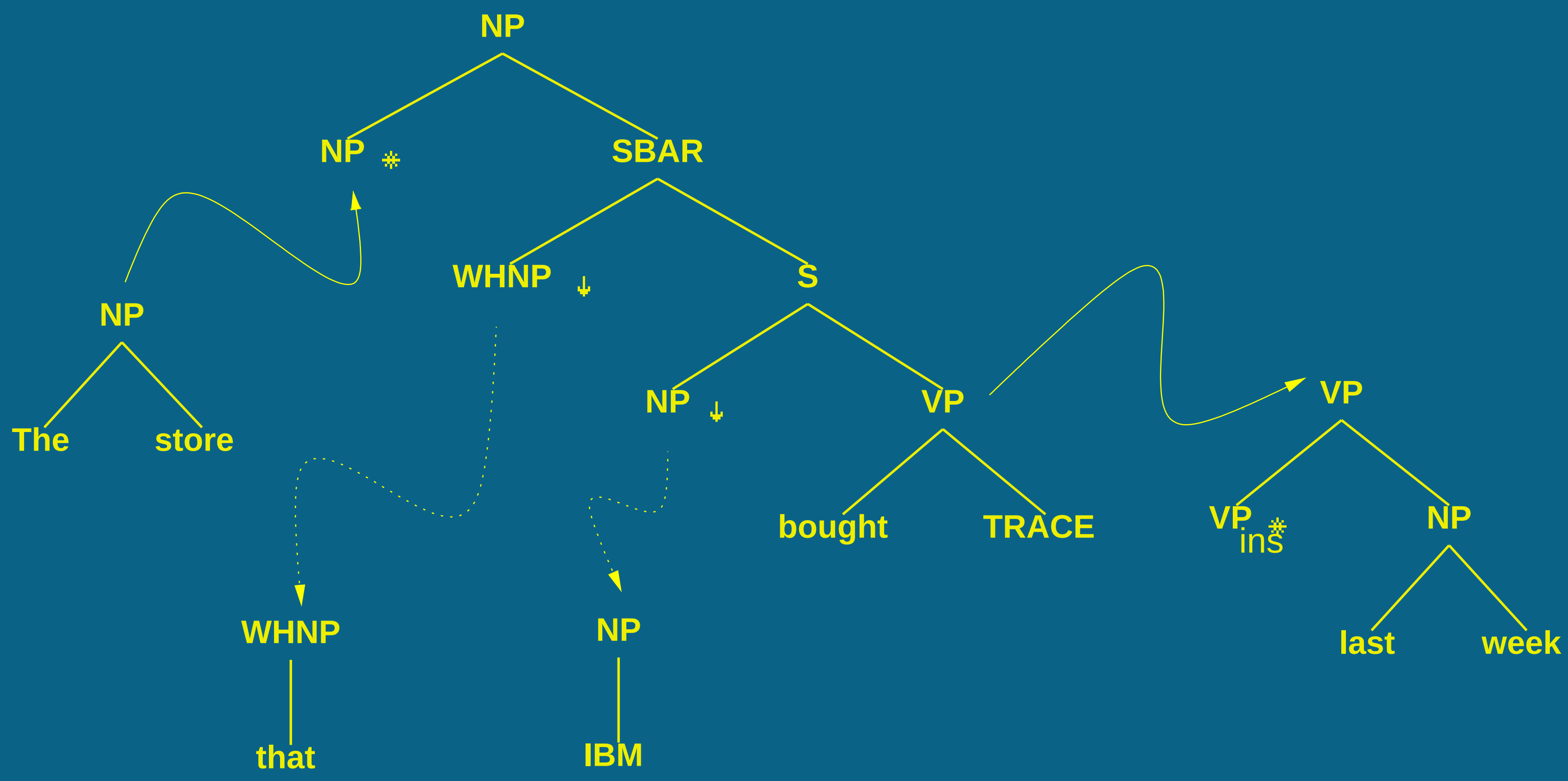
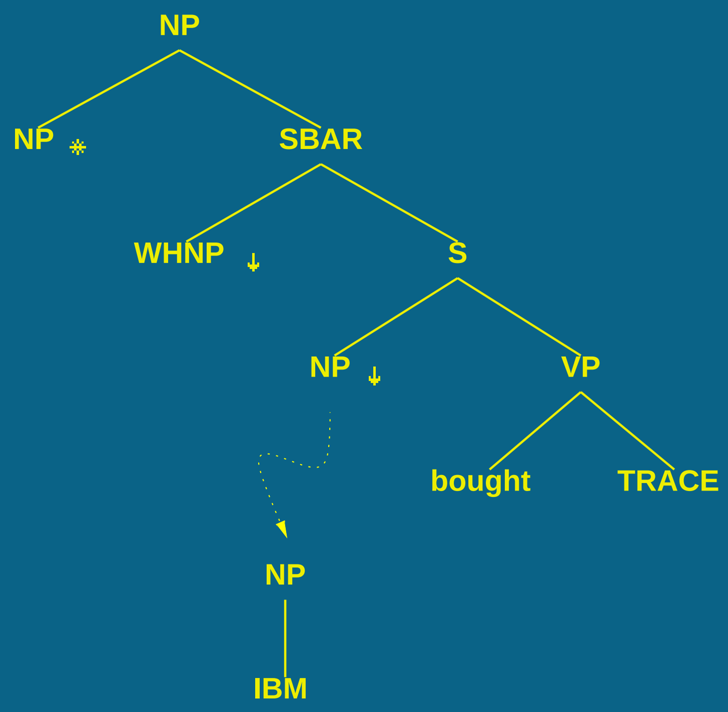
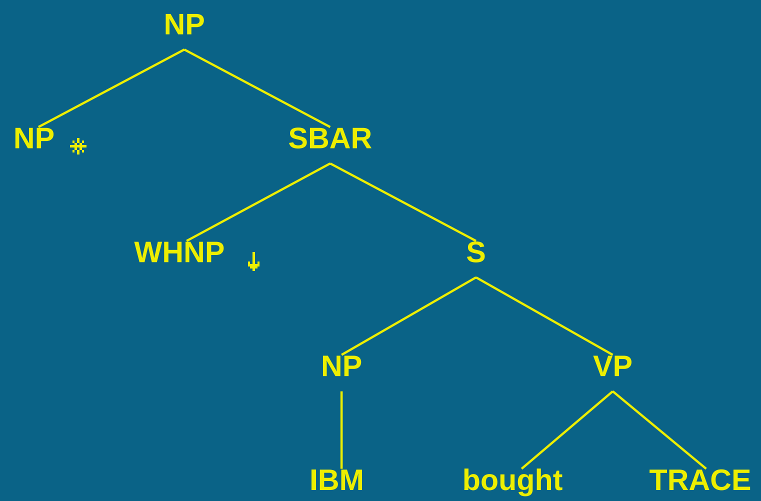


Tree Adjoining Grammars: Different Modeling of Bilexical Dependencies



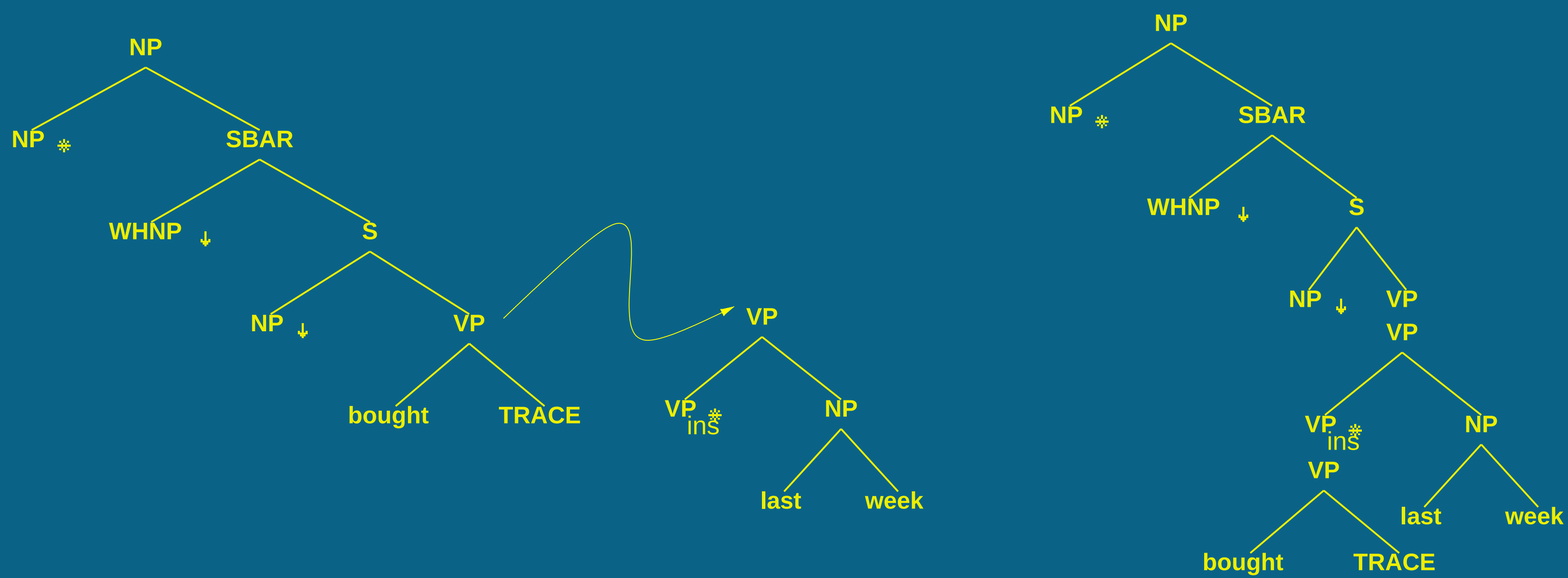
Probabilistic TAGs: Substitution





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

Probabilistic TAGs: Adjunction



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

Tree Adjoining Grammars

- Simple and well-defined model for parsing. (Schabes 92, Resnik 92, Sarkar 98) Performance(Chiang 2000): 86.9% LR 86.6% LP ($\leq$ 40 words)

- Locality and independence assumptions are captured elegantly.

- Parsing can be treated in two steps (Srinivas 97):

  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.

Training a Statistical Parser

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

- Several alternatives:

  - EM algorithm: Inside-Outside Algorithm (Schabes 92; Hwa 98)

  - Supervised training from a Treebank (Chiang 2000)

  - Parsing as Classification. Explore new machine learning techniques.

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

    * Conditional independence of features in the data.
      can we exploit this . . .

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 92; Della Pietra et al 94; de Marcken 95)

- 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. 92) The Xerox Tagger: used HMMs with hand-built tag dictionaries. High performance: 96% on Brown

- (Merialdo 94; Elworthy 94) used varying amounts of labeled data as seed information for training HMMs.

  Conclusion: HMMs do not effectively combine labeled and unlabeled data

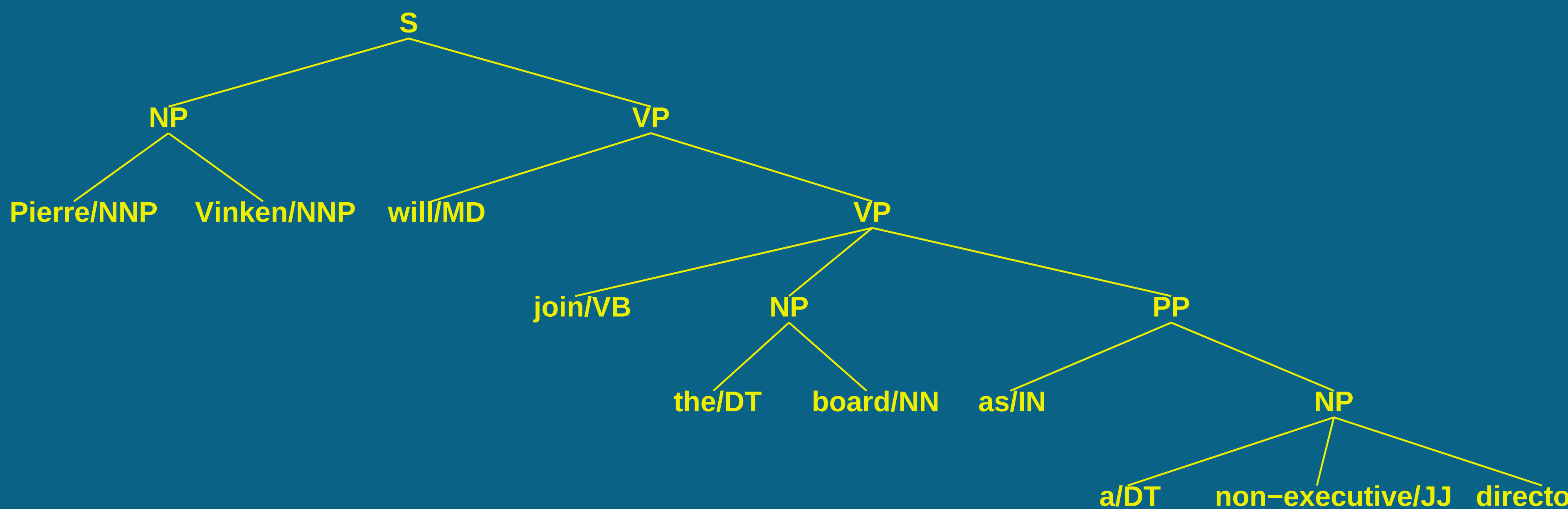
- (Brill 97) aggressively used tag dictionaries taken from labeled data to train an unsupervised POS tagger. c.f. text classification results

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

Co-Training (Blum and Mitchell 98; Yarowsky 95)

- Pick two “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 each model independently labels with high confidence. (Nigam and Ghani 2000)
- Pick confidently labeled examples.
  (Collins and Singer 99; Goldman and Zhou 2000); Active Learning
- Each model labels examples for the other in each iteration.

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)

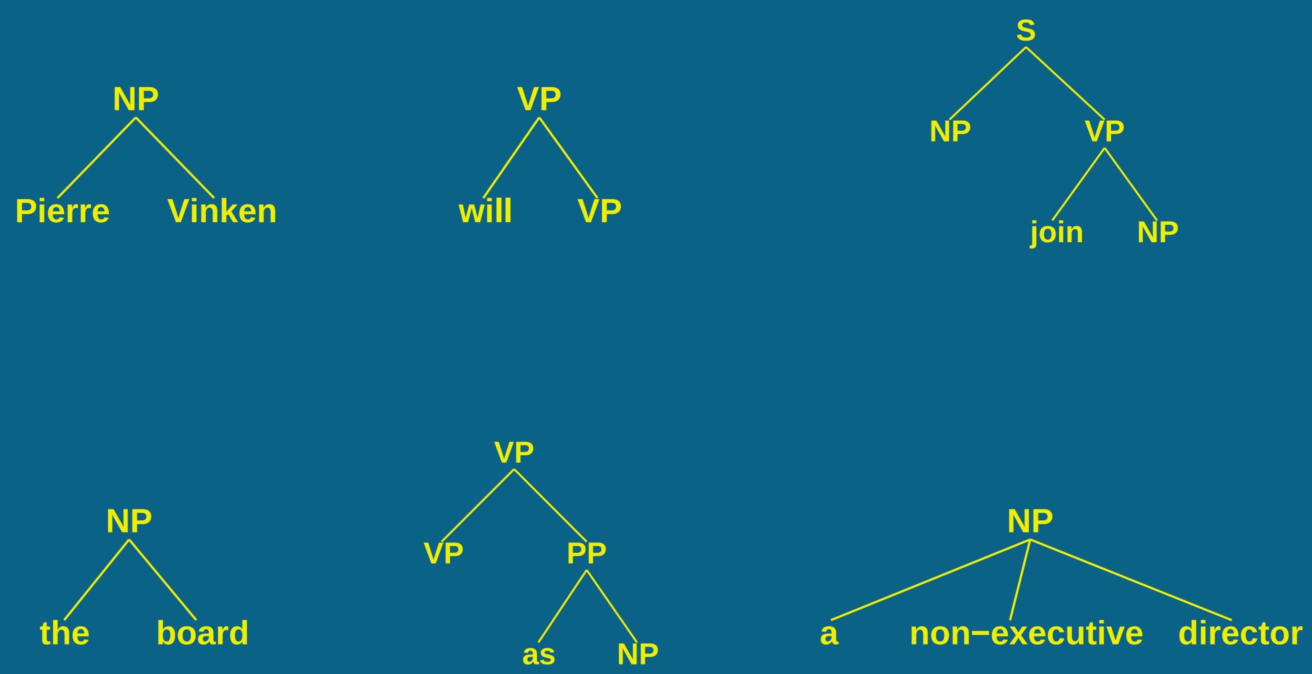
  NP(Vinken) $\rightarrow$ Pierre Vinken

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

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

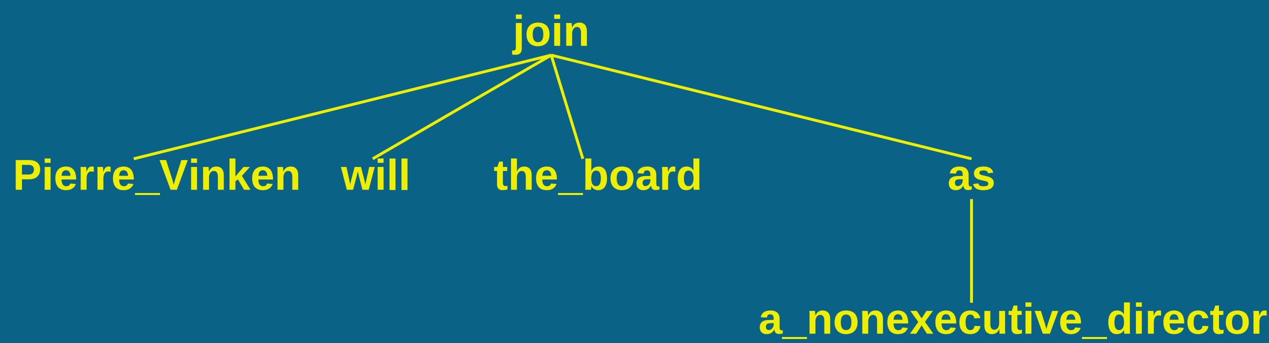
  $\ldots$

Parsing as Tree Classification and Attachment: (Srinivas 97; 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
   - Randomly select sentences from *unlabeled* and refill *cache*
   - If *cache* is empty; exit
3. Train models H1 and H2 using *labeled*
4. Apply H1 and H2 to cache.
5. Pick most probable n from H1 (run through H2) and add to *labeled*.
6. Pick most probable n from H2 and add to *labeled*
7. $n = n + k$; Go to Step **??**

Results

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

  Similar to the approach of (Brill 97)

  Novel trees were treated as unknown tree tokens

- The *cache* size was 3000 sentences.

Results

- Test set: Section 23

- Baseline Model was trained only on the *labeled* set: and Labeled Bracketing Precision = 72.23% Recall = 69.12%

- After 12 iterations of Co-Training:
  Labeled Bracketing Precision = 80.02% Recall = 79.64%

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.

Current Work

- Still needs human supervision to create the tree dictionary.
  For small datasets, this is unavoidable.

- Another application: use a large labeled dataset
  But improve performance using a much larger unlabeled dataset.

- Current expt: 1M words *labeled* and 23M words *unlabeled*.
  Tree dictionary is completely defined by the labeled set.

- Investigating the relationship between Co-Training and EM.

Co-Training and EM

	gradient descent over unlabeled	iterative selection from unlabeled
max output of a generative model	EM	co-EM*
select new examples independently	*Discriminative Objective Function*	Co-Training

* (Nigam and Ghani, 2000)