Combining Labeled and Unlabeled Data in Statistical Parsing

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Supervised Statistical Parsing on the Penn Treebank

System	$\leq 40 wds$ LP	$\leq 40 wds$ LR	$\leq 100 wds$ LP	$\leq 100 wds$ LR
Current	86.0	85.2		
(Chiang 2000)	87.7	87.7	86.9	87.0
(Charniak 99)	90.1	90.1	89.6	89.5
(Collins 00)	90.1	90.4	89.6	89.9
Voting (HB99)	92.09	89.18		

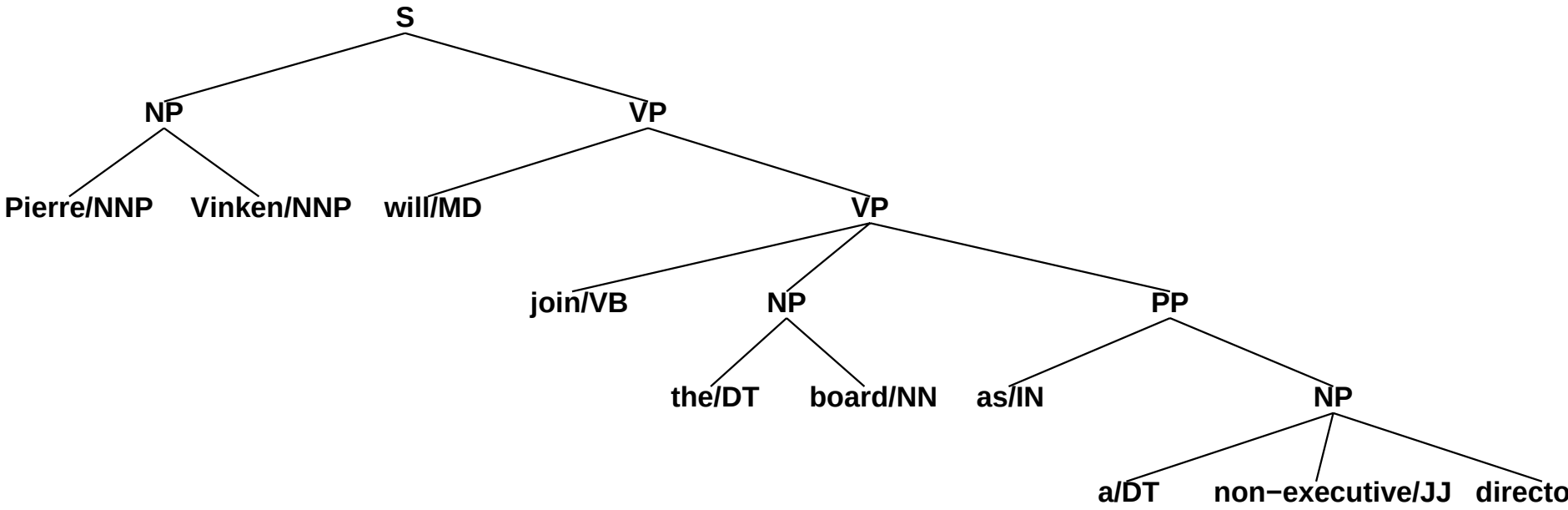
- Can we use less labeled data and still get reasonable performance?

- Can we use the full Treebank combined with (low-cost) unlabeled data to improve parsing?

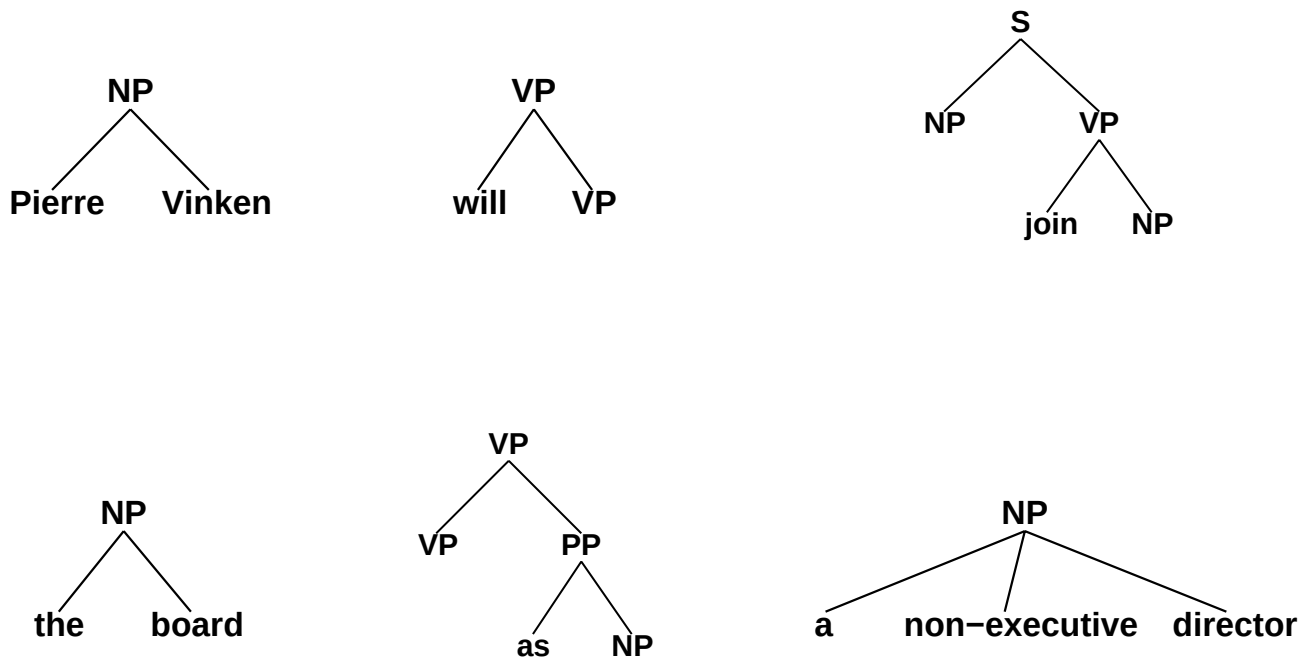
Co-Training (Blum and Mitchell 1998; Yarowsky 1995)

- 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 1999; 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

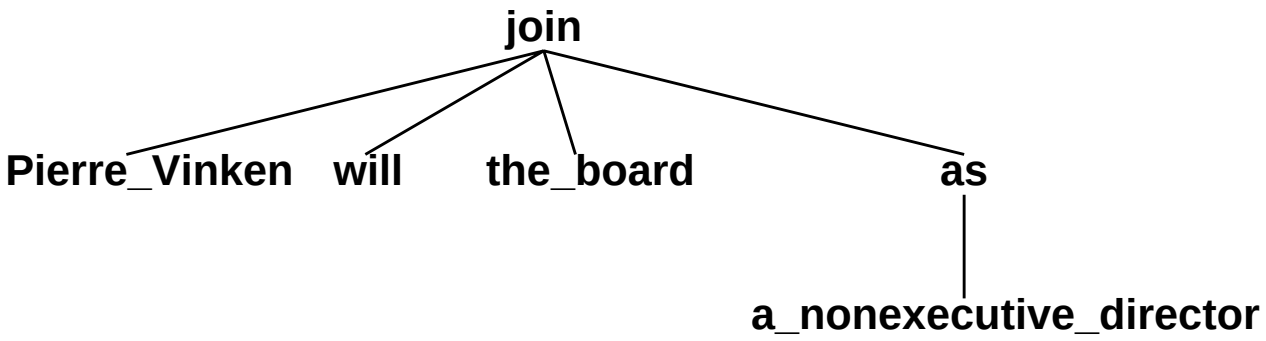


Parsing as n-best Tree Classification and Stapler: (Xia 2000; Srinivas 1997)



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

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 (stapled together) and add to *labeled*.
6. Pick most probable n from H2 and add to *labeled*
7. $n = n + k$; Go to Step 2

Results

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

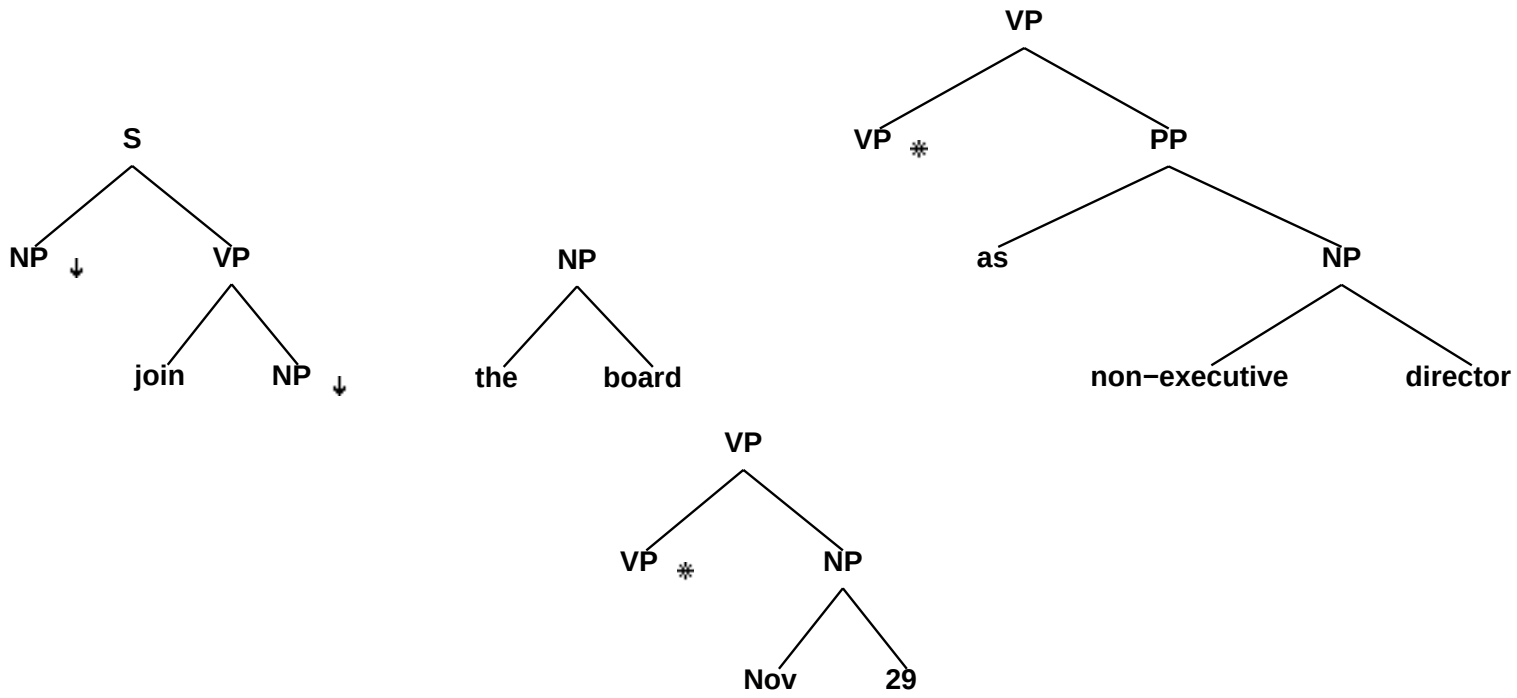
- *unlabeled* was 30137 sentences
  (Section 07-21 of the Treebank stripped of all annotations).

- A tree dictionary of all lexicalized trees. cf. (Brill 1997)

Results

- Test set: Section 23
- Baseline Model was trained only on the *labeled* set:
  Labeled Bracketing Precision = 72.23% Recall = 69.12%
- After 12 iterations of Co-Training:
  Labeled Bracketing Precision = 80.02% Recall = 79.64%
- Evaluation of an unsupervised approach is directly comparable to other supervised parsers (unlike previous work).

Co-training with two parsers



- Two different probability models for adjunction: single vs. multiple adjunction
- Non-overlapping lexicalized features: $\langle$*join, Nov_29*$\rangle$ vs. $\langle$*as, Nov_29*$\rangle$.

Co-training with two parsers

- Trained two parsers using these two models on sections 02-21 of the Penn Treebank.
- We then performed co-training using a larger set of WSJ unlabeled text (23M words).
- Even after 12 iterations of co-training, performance did not improve significantly over the baseline of LR 85.2% and LP 86%.
- Reason: Substantial overlap between the features used in each of the probability models;
  $\Rightarrow$ only 22% of the lexicalized features were different

Future Work in Exploiting Unlabeled Data for Parsing

- Co-training multiple parsers (JHU summer workshop 2002)
- Explicit search for conditionally independent features
- Exploiting voting methods: combining parsers to get a Maximum Constituents Parse (can bootstrap new rules)
- Conservatively change parameter values by exploiting the generative model