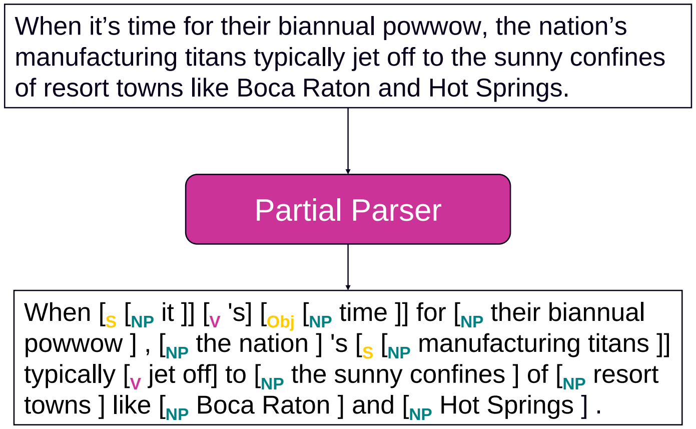
CS474 Natural Language Processing

- **Partial parsing / Chunking**
  - What is it?
  - Error-driven pruning of Treebank grammars
  - Comparison with other methods

Partial parsing



When it's time for their biannual powwow, the nation's manufacturing titans typically jet off to the sunny confines of resort towns like Boca Raton and Hot Springs.

When [$_{S}$ [$_{NP}$ it]] [$_{V}$'s] [$_{Obj}$ [$_{NP}$ time]] for [$_{NP}$ their biannual powwow] , [$_{NP}$ the nation] 's [$_{S}$ [$_{NP}$ manufacturing titans]] typically [$_{V}$ jet off] to [$_{NP}$ the sunny confines] of [$_{NP}$ resort towns] like [$_{NP}$ Boca Raton] and [$_{NP}$ Hot Springs] .

Why partial parsing?

- **Fast**
- **Supports a number of large-scale NLP tasks**
  - Information Extraction
  - Phrase identification for Information Retrieval
  - Question Answering

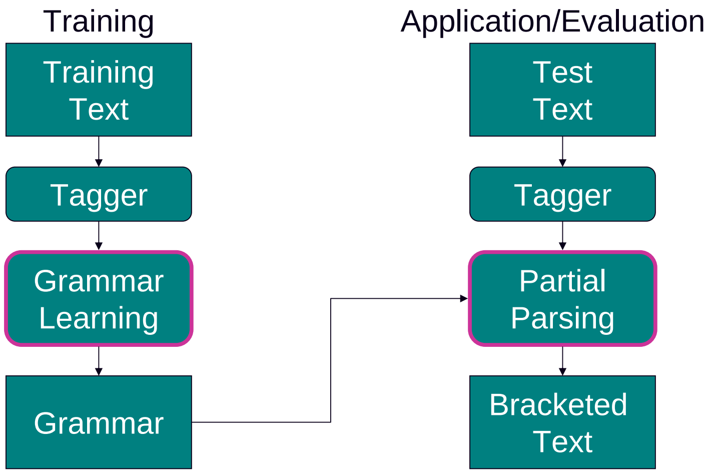
Inductive ML algorithm

- **Simple**

  base NP = any string having the same part-of-speech tag sequence as a base NP from the training corpus

- **Combines components of existing techniques**
  - Charniak (1996)
  - Brill (1995)
- **Achieves surprisingly high accuracies**

Partial parsing framework



Training

Training Text

Tagger

Grammar Learning

Grammar

Application/Evaluation

Test Text

Tagger

Partial Parsing

Bracketed Text

Rule extraction

rule = sequence of part-of-speech tags

Training Text

When/Adv **it**/**Pron** ’s/Pos **time**/**N** for/P **their**/**PosPron** **biannual**/**Adj** **powwow**/**N**, **the**/**Det** **nation**/**N** ’s/Pos **manufacturing**/V_g **titans**/N_{pl} typically/Adv jet/V off/P to/P **the**/**Det** **sunny**/**Adj** **confines**/N_{pl} of/P **resort**/**N** **towns**/N_{pl} like/P **Boca**/**Name** **Raton**/**Name** and/Conj **Hot**/**Name** **Springs**/**Name**.

NP Grammar

Pron
N
PosPron Adj N
Det N
V_g N_{pl}
Det Adj N_{pl}
N N_{pl}
Name Name

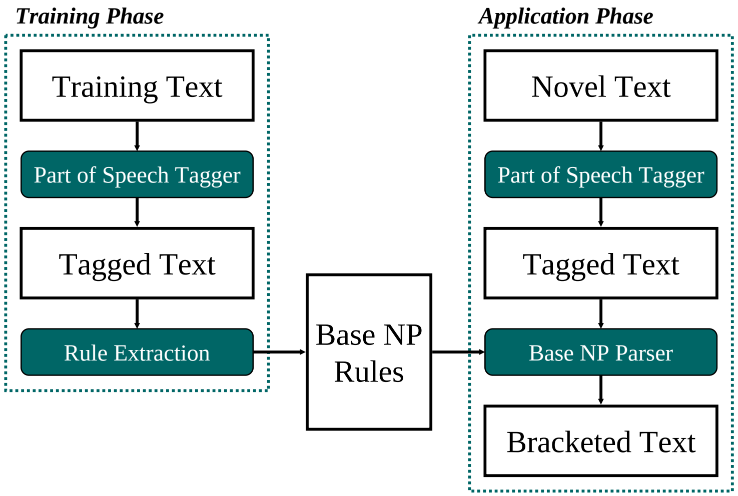
Partial parsing bracketer

- Left-to-right
- Longest-match

Det N? N?

Not/Adv **this**/**Det** **year**/**N**. The/Det National/Name Association/Name of/P Manufacturers/Name settled/V_p on/P the/Det city/N of/P Indianapolis/Name for/P its/PosPron fall/N board/N meeting/N.

Overview of the method



Training Phase

Training Text

Part of Speech Tagger

Tagged Text

Rule Extraction

Base NP Rules

Application Phase

Novel Text

Part of Speech Tagger

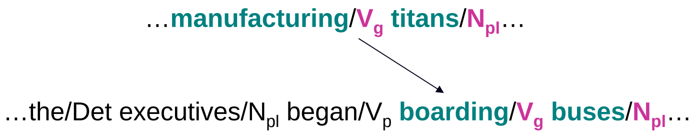
Tagged Text

Base NP Parser

Bracketed Text

Poorly performing rules

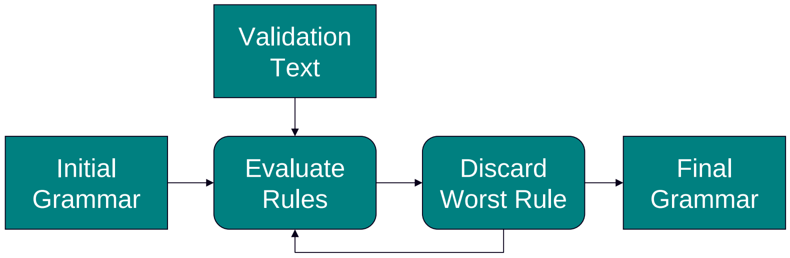
- **Sources of bad rules**
  - errors in training data
  - errors in part-of-speech tagging
  - irregular & ambiguous constructs



…**manufacturing**/V_g **titans**/N_{pl}…

…the/Det executives/N_{pl} began/V_p **boarding**/V_g **buses**/N_{pl}…

Grammar pruning



Validation Text

Initial Grammar

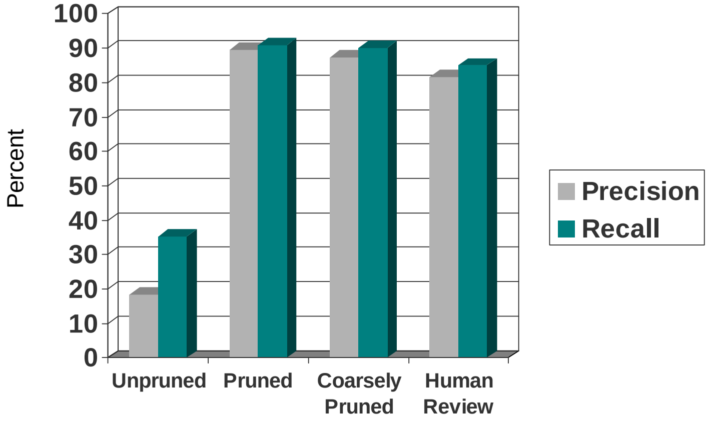
Evaluate Rules

Discard Worst Rule

Final Grammar

- score(r) = correct(r) - errors(r)
- stop when worst score is positive

Results

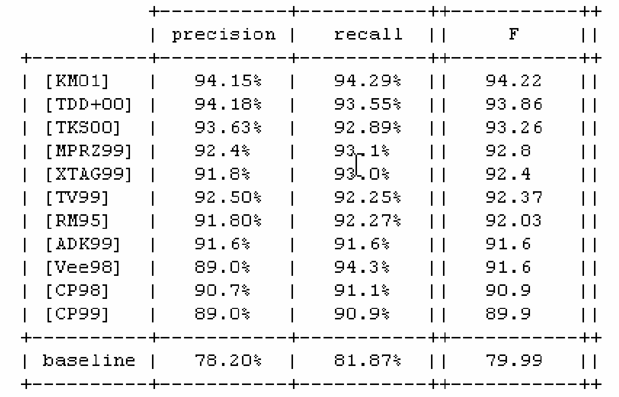


Results

	TBL results	Pierce & Cardie [98]	Difference
w/lexical templates	93.1P/93.5R		-3.7P/-2.6R
w/o lexical templates	90.5P/90.7R	89.4P/90.9R	-0.9P/+0.2R

- **TBL = transformation-based learning**
  - Results due to [Ramshaw & Marcus 1995, 1998]

State-of-the-Art



	precision	recall	F
[KM01]	94.15%	94.29%	94.22
[TDD+00]	94.18%	93.55%	93.86
[TKS00]	93.63%	92.89%	93.26
[MPRZ99]	92.4%	93.1%	92.8
[XTAG99]	91.8%	93.0%	92.4
[TV99]	92.50%	92.25%	92.37
[RM95]	91.80%	92.27%	92.03
[ADK99]	91.6%	91.6%	91.6
[Vee98]	89.0%	94.3%	91.6
[CP98]	90.7%	91.1%	90.9
[CP99]	89.0%	90.9%	89.9
baseline	78.20%	81.87%	79.99

- **ADK, CP98, CP99: no lexical information**
- **Baseline assigns most frequent chunk tag to each part of speech**

[table from Eric Tjong Kim Sang]

Advantages of the approach

- **Good performance**
- **Simple**
  - Easy to understand, implement
  - Produces intelligible grammar rules
  - Easy to update for new text genre
- **Efficient**
  - Fastest bracketing procedure
- **State of the art**
  - ~94% P/R for NP, VP, PP chunks
  - Using ensembles of SVM's (Kudo & Matsumoto, 2000) and Winnow as employed in Zhang et al. (2001)