

Home Page

Title Page

Contents



Page 1 of 48

Go Back

Full Screen

Close

Quit

State of the art NLParsing

Razvan Popescu

{popescu@di.unipi.it}

Computer Sciences Department, University of Pisa

25th May 2004

Home Page

Title Page

Contents



Page 2 of 48

Go Back

Full Screen

Close

Quit

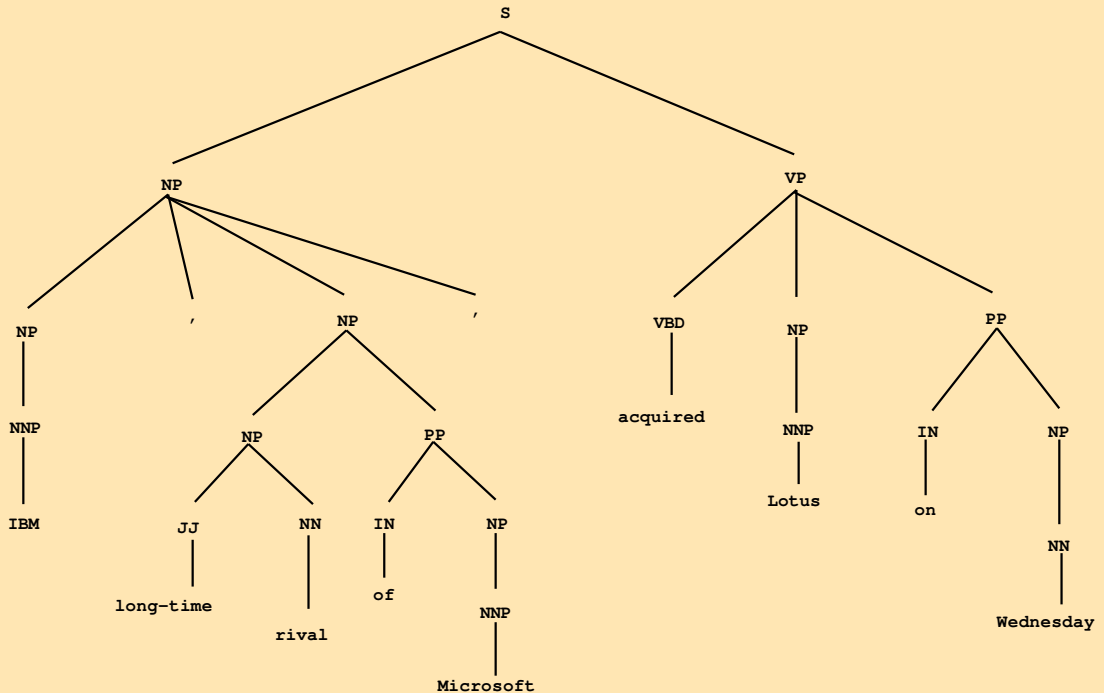
CONTENTS

- Introduction to NLParsing (Collins)
- "A statistical Model for Parsing and Word-Sense Disambiguation" (Bikel)
- "Multilingual Statistical Parsing Engine" (Bikel)
- References
- Appendix

PARSING

- Fundamental NLP problem
- Sentence \rightsquigarrow **Parser** \rightsquigarrow *ParseTree*
- State of the art NLParsing systems \equiv ML Probabilistic Parsing Techniques
 - Training sets $\equiv \{(Sentence1, Tree1); (Sentence2, Tree2); \dots; (SentenceN, TreeN)\} \Rightarrow$ Parameter estimates
 - Test sets \equiv *model evaluation*

PARSE TREE EXAMPLE



- POS
- ParseTree
- Applications \equiv Information Extraction/Retrieval, Machine Translation, Speech Recognition

Home Page

Title Page

Contents

◀

▶

◀

▶

Page 4 of 48

Go Back

Full Screen

Close

Quit

NL PARSING PROBLEMS

- Ambiguity
 - POS ambiguity (e.g. **saw** (verb) vs. **saw** (noun))
 - PP attachment ambiguity
 - Coordination btw different words in a sentence
- WSJ statistics
 - average sentence length: 23 words
 - sentences over 30 words: 26%
 - sentences over 40 words: 7%

APPROACHING THE NL PARSING PROBLEM

- Standard Approaches (Rule-Based)
 - hand-crafted grammar + lexically specific info
 - selectional restrictions (e.g. `eat & +fooda` and `apple` $\ni +food$) \rightsquigarrow disambiguation
 - problems with selectional restrictions
 - * vocabulary and grammar size (e.g. $\geq 24,444$ distinct words in 40,000 sentences of WSJ)
 - * theoretical problems
 - (MUC-6, 1995) – none of the five best systems used full-parsing

^aword feature

APPROACHING THE NL PARSING PROBLEM (cont'd)

- Machine-Learning Approaches (Statistical Methods)
 - **treebank**: {(sentence, parse-tree), ... }
 - PCFG systems \Rightarrow disappointing results
 - Other directions
 - * increased structural sensitivity models
 - * partially supervised training algs.
 - * probabilistic versions of lexicalised grammars
 - * history-based models
 - state of the art^a: SPATTER parser
 - * tested on WSJ
 - * no hand-crafted grammar; treebank trained
 - * 84.5/84.0% LP/LR – section 23 of the Penn WSJ treebank (non-lexicalised PCFGs \approx 72% avg. LP/LR)
 - * params conditioned on lexical information

^aMagerman, 1995



APPROACHING THE NL PARSING PROBLEM (cont'd)

- Machine-Learning Approaches (Statistical Methods^a)
 - D. Magerman's "Statistical decision tree models for parsing" (1995)
 - M. Collins' "Three generative lexicalised models for statistical parsing" (1997)
 - BBN's "SIFT" system (1998, derived from Model 2 of Collins)
 - M. Collins' "Head-Driven Statistical Models for Natural Language Parsing" (1999)
 - E. Charniak's "Maximum entropy-inspired parser" (2000)
 - D. Chiang's "Stochastic TAG parser" (2000)
 - LCC's parser (2002)
 - D. Bikel's "Multilingual Statistical Parsing Engine" (2002)
 - ...

^a1995 – nowadays

Home Page

Title Page

Contents



Page 9 of 48

Go Back

Full Screen

Close

Quit

A STATISTICAL MODEL FOR PARSING AND WORD-SENSE DISAMBIGUATION^a

- first attempt (2000)
- performance metrics: 84.0/67.3% LR/LP vs. 78.6% inter-annotator agreement (gold standard)

^athe core of Bikel's parser



MOTIVATION FROM EXAMPLES

1. [IBM bought [Lotus for \$200 million]].
2. Sony widened its product line [*PP* with personal computers].
3. The bank issued a check for \$100,000.
4. Apple is expecting [*NP* strong results].
5. IBM expected [*SBAR* each employee to wear a shirt and tie].

For 3.-5. syntactic context \rightsquigarrow word meanings

MOTIVATION FROM PREVIOUS WORK (PARSING)

- previous parsers success
 - computing machinery development
 - treebanks (e.g. Penn Treebank)
 - ML techniques for NLP (POS tagging and PP attachment)
 - **probabilistically modeled lexicalisation of grammar formalisms**
 - all recent successful parsers use "bilexical dependencies"
 - * attach probabilities to parser moves (Magerman 1997, Ratnaparkhi 1997)
 - * lexicalised PCFG variety (Collins 1997, Charniak 1997)
 - * involve "head-modifier relations"
 - * **[lexical head] semantics reduces parsing ambiguity!**
 - WordNet + hypernym structure ⇒ soft-clusters

Home Page

Title Page

Contents



Page 12 of 48

Go Back

Full Screen

Close

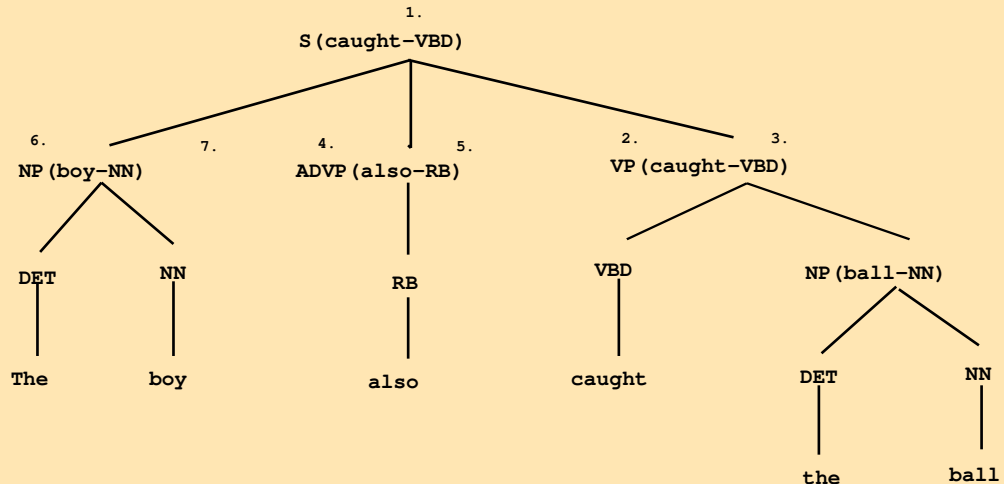
Quit

MOTIVATION FROM PREVIOUS WORK (WSD)

- syntactic context + dependency structures \Rightarrow WSD
- unsupervised WSD + WordNet based similarity heuristic \Rightarrow PP attachment (88.1%)
- head-driven bilexical dependencies + syntactic relations \Rightarrow generalised WSD (Stetina, 1998)

THE MODEL

- core \equiv BBN's SIFT



- generation order: head then L/R modifiers from the head outward^a
- recursive process
- many words are generated high up in the tree

^a(e.g. 1.-7.)

THE MODEL (cont'd)

- formally
 - $P \rightarrow L_n L_{n-1} \dots L_1 H R_1 \dots R_{n-1} R_n$
 - P, H, L_i and R_i are lexicalised nonterminals of the form $X \langle w, t, f \rangle$:
 - * $X \equiv$ traditional CFG nonterminal
 - * $\langle w, t, f \rangle \equiv$ word - POS - word-feature (the head of X)
- $H \equiv$ head constituent of P
- $L_i/R_i \equiv$ left/right modifier constituents of P w.r.t. H

PROBABILITY STRUCTURE OF THE ORIGINAL MODEL

- p, l_i, r_i and $h \equiv$ unlexicalised nonterminals corresp. to P, L_i, R_i and H
- top-level generation probabilities^a
 - Probability of generating p as root:

$$P(p | +TOP+), e.g. P(S | +TOP+)^b \quad (1)$$

- Probability of generating a head node h with a parent p :

$$P(h|p), e.g. P(VP|S) \quad (2)$$

- Probability of generating a left-modifier l_i :

$$P_L(l_i | l_{i-1}, p, h, w_h), e.g. P_L(NP | ADV P, S, VP, caught)^c \quad (3)$$

- Probability of generating a right-modifier r_i :

$$P_R(r_i | r_{i-1}, p, h, w_h), e.g. P_R(NP | +BEGIN+, VP, VBD, caught)^d \quad (4)$$

^aomitting the smoothing details of BBN's model

^b+TOP+ \equiv the hidden root of all parse trees

^cwhen generating the NP for NP(boy-NN)

^dwhen generating the NP for NP(ball-NN); +BEGIN+ \equiv hidden nonterminal for determining the initial probability



PROBABILITY STRUCTURE OF THE ORIGINAL MODEL (cont'd)

- probabilities for generating lexical elements

1. for the POS tag of the head of the entire sentence t_h :

$$P(t_h|p) \quad (5)$$

2. for the POS tags of modifier constituents t_{l_i} and t_{r_i} :

$$P(t_{l_i}|l_i, t_h, w_h) \text{ and } P(t_{r_i}|r_i, t_h, w_h) \quad (6)$$

3. for the head word of the entire sentence w_h :

$$P(w_h|t_h, p) \quad (7)$$

- probabilities for generating lexical elements

4. for head words of modifier constituents w_{l_i} and w_{r_i} :

$$P(w_{l_i}|t_{l_i}, l_i, t_h, w_h) \text{ and } P(w_{r_i}|t_{r_i}, r_i, t_h, w_h) \quad (8)$$

5. for the word feature of the head of the entire sentence f_h :

$$P(f_h|w_h, t_h, p) \quad (9)$$

6. for the word features of the head words of modifier constituents f_{l_i} and f_{r_i} :

$$P(f_{l_i}|\text{known}(w_{l_i}), t_{l_i}, l_i, t_h, w_h) \text{ and } P(f_{r_i}|\text{known}(w_{r_i}), t_{r_i}, r_i, t_h, w_h)^a \quad (10)$$

- probability of the entire parse tree:

$$P(\text{parse_tree}) = \prod_{i \in I} P_i \quad (11)$$

, where $I \equiv$ the set of all elements of the *parse_tree*

- training data \Rightarrow maximum-likelihood estimates of the params

^a*known*(x) \Rightarrow *true* iff *observed*(x) ≥ 4 in the training data

WORD-SENSE EXTENSIONS TO THE LEXICAL MODEL

- parser output \equiv standard Treebank-style parse tree; (words + POS tags + WordNet synsets)
- **Q: synset is to be generated but WHEN?**
 - generation of $\langle w, t, f \rangle \equiv$ three steps \Rightarrow four possible computation points
 - soft clustering of synsets \Rightarrow add specificity to ambiguous lexical items + cluster lexical items with similar meanings
 - noun + vb synsets \Rightarrow *concept taxonomy* + hypernym \Rightarrow partial ordering over WordNet lemmas
- **A: after generating the POS tag, before generating the word**

- the probabilities for generating

1. the synset of the head of the entire sentence s_h :

$$P(s_h|t_h, p) \quad (12)$$

2. the head word of the entire sentence w_h becomes^a:

$$P(w_h|t_h, p) \quad (13)$$

3. synsets of modifier constituents s_{m_i} ^b:

$$\begin{aligned} \hat{P}(s_{m_i}|t_{m_i}, m_i, w_h, s_h) = & \quad (14) \\ & \lambda_0 \hat{P}(s_{m_i}|t_{m_i}, m_i, w_h, s_h) \\ & + \lambda_1 \hat{P}(s_{m_i}|t_{m_i}, m_i, s_h) \\ & + \lambda_2 \hat{P}(s_{m_i}|t_{m_i}, m_i, @^1(s_h)) \\ & + \dots \\ & + \lambda_{n+1} \hat{P}(s_{m_i}|t_{m_i}, m_i, @^n(s_h)) \\ & + \lambda_{n+2} \hat{P}(s_{m_i}|t_{m_i}, m_i) \\ & + \lambda_{n+3} \hat{P}(s_{m_i}|t_{m_i}) \end{aligned}$$

where $@^i(s_h)$ is the i^{th} hypernym of s_h

^a(7)++

^bcomplete with smoothing components

Home Page

Title Page

Contents



Page 20 of 48

Go Back

Full Screen

Close

Quit

UPDATED PROBABILITY STRUCTURES OF THE MODEL (cont'd)

- WordNet hypernym rels form DAG \Rightarrow uniformly-weighted mean over the probabilities conditioning on each of the hypernyms:

$$\hat{P}(s_{m_i}|t_{m_i}, m_i, @^j(s_h)) = \frac{1}{n} \sum_{k=1}^n \hat{P}(s_{m_i}|t_{m_i}, m_i, @_k^j(s_h)) \quad (15)$$

when $@^j(s_h) = \{@_1^j(s_h), \dots, @_n^j(s_h)\}$

UPDATED PROBABILITY STRUCTURES OF THE MODEL (cont'd)

- the probability for generating
 - head words of modifier constituents w_{m_i} ^a becomes^b:

$$\begin{aligned}
 \hat{P}(w_{m_i} | s_{m_i}, t_{m_i}, m_i, w_h, s_h) = & \quad (16) \\
 & \lambda_0 \hat{P}(w_{m_i} | s_{m_i}, t_{m_i}, m_i, w_h) \\
 & + \lambda_1 \hat{P}(w_{m_i} | s_{m_i}, t_{m_i}, m_i, s_h) \\
 & + \lambda_2 \hat{P}(w_{m_i} | s_{m_i}, t_{m_i}, m_i, @^1(s_h)) \\
 & \quad \quad \quad + \dots \\
 & + \lambda_{n+1} \hat{P}(w_{m_i} | s_{m_i}, t_{m_i}, m_i, @^n(s_h)) \\
 & + \lambda_{n+2} \hat{P}(w_{m_i} | s_{m_i}, t_{m_i}, m_i) \\
 & + \lambda_{n+3} \hat{P}(w_{m_i} | s_{m_i}, t_{m_i}) \\
 & + \lambda_{n+4} \hat{P}(w_{m_i} | s_{m_i})
 \end{aligned}$$

where $@^i(s_h)$ is the i^{th} hypernym of s_h

^acomplete with smoothing components

^b(8)++

Home Page

Title Page

Contents



Page 22 of 48

Go Back

Full Screen

Close

Quit

UPDATED PROBABILITY STRUCTURES OF THE MODEL (cont'd)

- observations

- train with [VP strike the target]; test with [VP attack the target] \Rightarrow **OK** (attack = **hypernym**(strike))
- **only** 2-4 back-off levels \rightsquigarrow negligible difference in parsing performance

A NEW APPROACH, A NEW DATASET

- Penn Treebank $\not\subseteq$ word-sense annotated corpus
- meet **SemCor**
 - + 455k word portion of the Brown Corpus
 - + every noun, verb, adjective, adverb + WordNet synset
 - Brown Corpus Treebank I style annotation
 - + part of Brown Corpus Treebank II style annotation
- $\{\text{Treebank II annotated Brown}\} \cap \{\text{SemCor}\} \approx 220\text{k words}$

Step 1 synchronising the 220k words

- hyphenates + word senses
 1. word sense of the head (e.g. `twelve-foot` \rightsquigarrow `foot_1`)
 2. if no clear head then word sense of the hypernym (e.g. `U.S.-Soviet` \rightsquigarrow `country_2`)
 3. if 1. & 2. fail, then split hyphenate in the Treebank II file
 4. if hyphenate $\in \{\text{"non-XYZ"}, \text{"anti-XYZ"}\}$, then annotate with the word sense of XYZ

Home Page

Title Page

Contents



Page 24 of 48

Go Back

Full Screen

Close

Quit

A NEW APPROACH, A NEW DATASET (cont'd)

Step 2 SemCor \cup Treebank II Brown issues

- keep only the first synset
- collocations^a: WordNet+, Treebank- \Rightarrow reanalyze collocations as a seq. of separate words with the same synset

^apatterns of words appearing together (e.g. "apple pie", "apple tree" – "apple" collocates with "pie" and "tree")

TRAINING AND DECODING

- the hypernym chain of the parent head used for the computation of back-off levels
- plug-'n'-play lexical model system
- top-down model, bottom-up parsing
- rank candidate parse trees
- (unextended parsing model) every possible tag t for a word $w \rightsquigarrow \langle w, t, f \rangle$ (f is computed deterministically) \Rightarrow 1st degree of ambiguity in decoding
- (WordNet extended model) every possible synset s for a word-tag pair $\rightsquigarrow \langle w, t, f, s \rangle$
- forms of pruning during decoding
 - parse tree ranking score \geq factor of e^{-k} of the top ranked parse
 - keep the n top-ranked subtrees
- "out-of-the-box" BBN ($k = -5$ and $n = 25$)
- Bikel's model ($k = -9$ and $n = 50$)

EXPERIMENTS AND RESULTS

- PARSING (1% of the 220K word corpus)

Test 1 the last 117 sentences (section "r")

– Disappointing results ← *"our initial test corpus was literally a joke"*²⁰

Test 2 sample every 100 sentences ⇒ 117 sentences

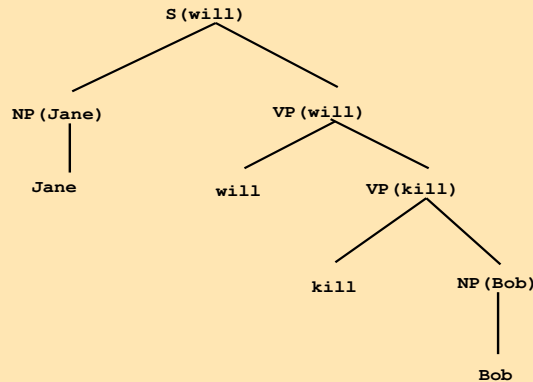
Model, test set	≤ 40 words				
	LR	LP	$\overline{\text{CB}}$	0CB	$\leq 2\text{CB}$
Norm, "r" ^a *	69.7	72.6	2.93	31.9	55.0
WN-ext, "r"	69.7	72.7	2.86	30.8	56.0
Norm, bal	83.1	85.0	0.82	75.9	85.7
WN-ext, bal	82.9	84.0	1.02	70.5	81.3
	All sentences				
	LR	LP	$\overline{\text{CB}}$	0CB	$\leq 2\text{CB}$
Norm, "r" ^a *	68.6	71.2	3.83	25.9	44.8
WN-ext, "r"	69.7	71.5	3.77	25.0	45.7
Norm, bal	82.0	84.4	1.00	73.5	83.8
WN-ext, bal	80.5	82.2	1.43	68.4	78.6

^ahumor writing section

EXPERIMENTS AND RESULTS (cont'd)

- PARSING OBSERVATIONS

- roughly similar results
- WN-ext \rightsquigarrow intermediate ambiguity during decoding
- trilexical/tertalexical dependencies \rightsquigarrow synset advantages
- [**bought** company [for **million**]] – no dependency
- soft clustering the synsets \rightsquigarrow offset the sparse data problem
- head rules are tuned for syntax, not semantics:



EXPERIMENTS AND RESULTS (cont'd)

- WORD SENSE DISAMBIGUATION

– results^a:

	Recall	Precision
Noun	86.5%	70.9%
Verb	84.0%	59.5%
Adj	80.2%	70.4%
Adv	78.5%	75.8%
Total	84.0%	67.3%

^aon the balanced test set

EXPERIMENTS AND RESULTS (cont'd)

- WSD OBSERVATIONS

Others distinguish homonyms

Bikel WordNet \Rightarrow fine-grained distinctions

Others disambiguate a small set of homonyms

Bikel attacks generalised WSD

- SemCor's inter-annotator agreement is 78.6% overall and 70% for words with polysemy $\geq 8 \Rightarrow$ **precision upper bound**

Bikel considers **exact synset matches** only

Others paradoxically Stetina reported 79.4% overall accuracy (1998)

Others Stetina ranks with heuristics

Bikel ranks with maximum-likelihood probability estimates

Bikel 50-odd Treebank vs. 4 WordNet POS \Rightarrow (output == synset, for a WordNet POS diff. from the gold file) \equiv **recall error**

[Home Page](#)

[Title Page](#)

[Contents](#)

◀ ▶

◀ ▶

Page 30 of 48

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

FUTURE WORK

- toward a state-of-the-art model (Collins' Model 2/3 based)
- experiment with radical model where nonterminals only have synsets as their heads and words are generated at the leaves
- add word-distance context to help WSD
- investigate unsupervised methods for WSD (e.g. Stetina's heuristics)

Bikel's "Multilingual Statistical Parsing Engine"

- limitations of previous parsers
 - fairly fixed probabilistic structure \Rightarrow re-coding
 - hard-coded English language features
 - hard-coded Penn Treebank features
 - designed for uniprocessor environment
- characteristics of Bikel's parser
 - head-driven, chart parsing engine
 - language/treebank portable
 - "plug-'n'-play" lexical probability structures
 - multiprocessor/multi-host support; multi-threaded sentence server \Rightarrow parallelism at the sentence level

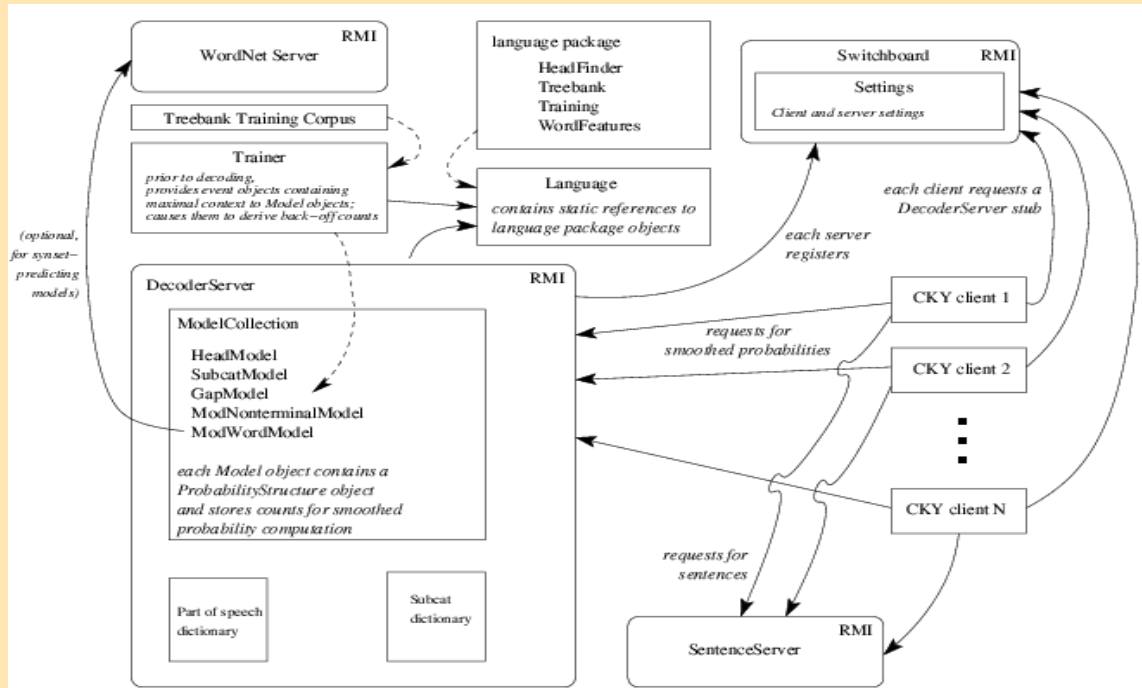
LANGUAGE INDEPENDENCE

- Testing
 - BBN's SIFT derived parser
 - Chiang's Stochastic TAG parser
- on English and Chinese
 - \approx 100k words of WSJ text from the English Penn Treebank
 - \approx 100k words of Xinhua text from the Chinese Treebank^a
- resulted in
 - Chiang's Stochastic TAG \Rightarrow 77%/78% LP/LR on Xinhua compared to 79%/80% on WSJ

^aconsisting of 4185 sentences

PARSER DESIGN

- emulates BBN's SIFT & Model 2,3 of Collins



Arrow \equiv functional relationship

Solid arrow \equiv the direction of request from a client to a server

Dashed arrow \equiv the flow of information

Home Page

Title Page

Contents

Navigation arrows: left, right, double left, double right

Navigation arrows: left, right

Page 33 of 48

Go Back

Full Screen

Close

Quit

Home Page

Title Page

Contents



Page 34 of 48

Go Back

Full Screen

Close

Quit

LANGUAGE PACKAGE

- java package
- required classes
 - **Treebank** – data and methods specific to a particular treebank
 - **Training** – `—#—` to preprocessing training trees
 - **HeadFinder** – I: text file with head rules specific to a language treebank; O: head-finding method
 - **WordFeatures** – mapping of lexical items from a language to an orthographic/morphological word feature vectors
- unicode I/O files
- does not include WordNet
- **GOAL: creation of a new language package in 1-2 weeks**

Home Page

Title Page

Contents



Page 35 of 48

Go Back

Full Screen

Close

Quit

PROBABILITY STRUCTURE OBJECTS

- output element + [ProbabilityStructure object \equiv data objects representing the future and history of all possible back-off levels]
- TrainerEvent object \equiv history and future for a specified back-off level

PROBABILITY-LEVEL PARALLELISM

- **basic idea:** $(FILE, EXEC, HOST) \equiv (f_1, e_1, h_1), \dots, (f_n, e_n, h_n)$, where $FILE = f_1 \cup f_2 \cup \dots \cup f_n$, $EXEC = e_1 = e_2 = \dots = e_n$ and $HOST \rightsquigarrow h_1 \cup \dots \cup h_n$
- distributed computing parsing engine
- Sentence Server
- Separate parsers (clients) on each host
- Probability Server \equiv DecoderServer object + multi-proc + large RAM \Rightarrow smoothed top-level probability estimates to multiple small-chart parsing clients
- architecture features
 - load-balancing
 - fault-tolerant parsing engine w.r.t.
 - * DecoderServer
 - * Switchboard
 - Java RMI based architecture
 - copes with Solaris, Linux, Windows and MacOS X

Home Page

Title Page

Contents



Page 37 of 48

Go Back

Full Screen

Close

Quit

BUILT FOR SPEED

- parser optimizations
 - log-probability estimates and log-lambdas precomputing
 - hash maps
 - (new chart item == 0 probability)? **short-circuit decoding ops**
 - object pool
 - smaller optimizations based on profiling

[Home Page](#)

[Title Page](#)

[Contents](#)



Page 38 of 48

[Go Back](#)

[Full Screen](#)

[Close](#)

[Quit](#)

REPLICATING COLLINS' MODEL 2

Parser	≤ 40 words		≤ 100 words	
	LR	LP	LR	LP
Collins	89.75	90.19	88.47	89.30
Bikel	89.89	90.14	88.72	89.03

Tests carried out on Section 00 of the Penn Treebank

Home Page

Title Page

Contents



Page 39 of 48

Go Back

Full Screen

Close

Quit

DEVELOPING A LANGUAGE PACKAGE FOR CHINESE

- implementation time: **one and a half days!**
- state of the art results: On sentences ≤ 40 words \Rightarrow 77.0/81.6% LR/LP

REFERENCES

- Daniel M. Bikel. Design of a Multi-lingual, Parallel-processing Statistical Parsing Engine, HLT 2002 proceedings
- Daniel M. Bikel. A statistical model for parsing and word-sense disambiguation. In *Joint SIGDAT Conference on Empirical Methods in Natural Language Processing and Very Large Corpora*, Hong Kong, October 2000.
- Daniel M. Bikel and David Chiang. Two statistical parsing model applied to the Chinese Treebank. In Martha Palmer, Mitch Marcus, Aravind Joshi, and Fei Xia, editors, *Proceedings of the Second Chinese Language Processing Workshop*, pages 1-6, Hong Kong, 2000.
- Eugene Charniak. Statistical Parsing with a Context-free Grammar and Word Statistics. In *Proceedings of the Fourteenth National Conference on Artificial Intelligence*, Menlo Park. AAAI Press/MIT Press. 1997.
- Michael John Collins. *Head-Driven Statistical Models for Natural Language Parsing*. PhD thesis, University of Pennsylvania, 1999, Chapter 1, Pages 1-30.
- Mitchell P. Marcus, Beatrice Santorini, and Marry Ann Marcinkiewicz. Building a large annotated corpus of English: The Penn Treebank. *Computational Linguistics*, 19:313-330, 1993.
- George A. Miller, Richard T. Beckwith, Christiane D. Fellbaum, Derek Gross, and Katherine J. Miller. 1990. WordNet: An on-line lexical database. *International Journal of Lexicography*, 3(4):235-244.

Home Page

Title Page

Contents

◀▶

◀▶

Page 40 of 48

Go Back

Full Screen

Close

Quit

Home Page

Title Page

Contents



Page *41* of *48*

Go Back

Full Screen

Close

Quit

APPENDIX



TREEBANK – SAMPLE TAGGED TEXT^a

Battle-tested/NNP*/JJ industrial/JJ managers/NNS
 here/RB always/RB buck/VB*/VBP up/IN*/RP ner-
 vous/JJ newcomers/NNS with/IN the/DT tale/NN
 of/IN the/DT first/JJ of/IN their/PP\$ country-
 men/NNS*/FW warriors/NNS blown/VBN ashore/RB
 375/CD years/NNS ago/RB ./."/" From/IN the/DT
 beginning/NN ,/, it/PRP took/VBD a/DT man/NN
 with/IN extraordinary/JJ qualities/NNS to/TO
 succeed/VB in/IN Mexico/NNP ,/, "/" says/VBZ
 Kimihide/NNP Takimura/NNP ,/, president/NN of/IN
 Mitsui/NNS*/NNP group/NN 's/POS Kensetsu/NNP En-
 gineering/NNP Inc./NNP unit/NN ./.^b

^aafter correction

^b"" marks multiple POS tags

TREEBANK – SAMPLE BRACKETED TEXT^a

```

( (S
  (NP Battle-tested industrial managers
    here)
  always
  (VP buck
    up
    (NP nervous newcomers)
    (PP with
      (NP the tale
        (PP of
          (NP (NP the
            (ADJP first
              (PP of
                (NP their countrymen))))
            (S (NP *)
              to
              (VP visit
                (NP Mexico))))
          ,
          (NP (NP a boatload
            (PP of
              (NP (NP warriors)
                (VP-1 blown
                  ashore
                    (ADVP (NP 375 years)
                      ago))))
                (VP-1 *pseudo-attach*)))))))))

```

^aafter correction; simplified

Home Page

Title Page

Contents



Page 44 of 48

Go Back

Full Screen

Close

Quit

WORD FEATURE EXAMPLE

- **WordFeatures** \equiv orthographic and morphological features of words. It encodes:
 1. capitalization
 2. hyphenation
 3. inflection
 4. derivation
 5. numeric
- Example: "C3H0I0D3N0" stands for **Geography** (non-sentence-initial capitalised, no hyphenation, no inflection, "graphy" derivation and non-numeric)

BIKEL'S PARSER – PACKAGES



Packages	
danbikel.lisp	Provides classes to create, read and manipulate symbolic expressions (S-expressions), including interned symbols.
danbikel.parser	Provides the core framework of this extensible statistical parsing engine.
danbikel.parser.arabic	Provides language-specific classes necessary to parse Arabic.
danbikel.parser.chinese	Provides language-specific classes necessary to parse Chinese.
danbikel.parser.constraints	Provides interfaces and classes to allow constrain-parsing.
danbikel.parser.english	Provides language-specific classes necessary to parse English.
danbikel.parser.lang	Provides default abstract base classes for the required interfaces of a language package.
danbikel.parser.ms	Default package for model structure classes (subclasses of ProbabilityStructure).
danbikel.parser.util	Utility classes for displaying and manipulating parse trees.
danbikel.switchboard	Provides classes to implement a distributed client-server environment, with a central switchboard responsible for assigning clients to servers and for doling out objects to clients for processing.
danbikel.util	Provides some basic utility classes.
danbikel.util.proxy	Contains various <code>InvocationHandler</code> objects with static factory methods to provide <i>proxy instances</i> .

Home Page

Title Page

Contents



Page 46 of 48

Go Back

Full Screen

Close

Quit

BIKEL'S PARSER – LANGUAGE PACKAGE

Class Summary	
AbstractHeadFinder	Provides a default abstract implementation of the HeadFinder interface.
AbstractHeadFinder.HeadFindInstruction	Data structure for specifying a way to search for a head in a grammar production: a set of symbols to scan for and the direction of that scan.
AbstractTraining	Provides methods for language-specific preprocessing of training parse trees.
AbstractTreebank	A collection of mostly-abstract methods to be implemented by a language-specific subclass.
AbstractWordFeatures	Provides a default abstract implementation of the WordFeatures interface.

Home Page

Title Page

Contents



Page 47 of 48

Go Back

Full Screen

Close

Quit

IMPLEMENTATION METRICS

- 12 packages
- \approx 240 classes
- \approx 4800 methods !?!

Home Page

Title Page

Contents



Page 48 of 48

Go Back

Full Screen

Close

Quit

THANK YOU!