



Outline

- Part I : A framework that will allow
 - addition of linguistically interesting features to existing treebank resulting in a more 'fine-grained' treebank
 - building statistical grammars parametrized on these features
- Part II : learn statistical tendencies of these features : connect to large amounts of data :
 - particularly relevant for phenomenon that is lexical in nature (e.g. valence)
 - ➡ evidence for these in treebank is sparse due to Zipfian distributions
- Evaluate utility of various features for learning

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Example of Lexical Scarcity in Treebank data

- Penn Treebank (1 million sentences) contains about 7450 verb types (125,000 tokens)
 - → 2830 have occurred only once (38% types)
 - ➡ 1034 have occurred twice (14% types)
- Thus not possible to obtain accurate statistical subcategorization tendencies for a large portion of lexicon

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Treebanks

- Collections of sentences hand-annotated with linguistic structure
- Penn Treebank (Marcus et. al., 1993): 40,000 Wall Street Journal sentences



Treebanks

- Treebank Grammar : extracted from a treebank
 - Both Symbolic and Probabilistic parts from Treebank
 - This talk : PCFGs (Probabilistic Context Free Grammars)



Treebanks

- Current treebanks contain coarse representations
 - Spurred research in statistical parsing
 - Allows for consistent and cheaper annotation
- Statistical grammars use coarse representations
 - statistics become very sparse if fine-grained
 - parsers even coarser than treebank
- For some aspects of linguistic research, and also high-end parsers
 - Fine-grained representations might be better
 - Overt representations of valence, agreement, and localising long-distance dependencies useful

Outline of Methodology for Treebank refinement

- I. Augment each node-label in tree with a feature-structure
 - → feature-structures contain (typed) features with (atomic) values
- 2. values of features incorporated into node-label of tree
 - → more fine-grained label





Step I : Tree augmented with feature-structures





Step II : Convert features into context-free symbols





Step II : Convert features into context-free symbols



mplementation

- Parsing treebank trees with a Feature-constraint grammar
 - Details of implementation in Schmid (2000), Deoskar & Rooth (2008), Deoskar (2009)
- Highlights
 - ➡ Reusable software for constraint-solving, and PCFG compilation
 - ➡ Robust : In case of ambiguities, unit freq of tree split into fractions
- Effort required for grammar-development : Feature-constraint grammar

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- Intuitive for linguists
- Difficult to manipulate existing parsers

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A control verb



A control verb





Performance

Treebank conversion

Coverage: > 98.5 % of Treebank trees

- Most ambiguities/failures due to remaining grammar bugs.
- PCFG
- Labelled bracketing f-score: 86.8 % on Section 23 of the Penn Treebank

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- Competitive performance for English
 - Best results for empty category detection (84.1 %)

Motivation for learning from unlabelled data

Most words have impoverished entries !!

attaches	VBZ.np 1.0			
attack	NN 22	VBP 1.0	VB.n 3.0	VB.z 1.0
abandon	VBZ.n 2.0			
abate	VB.z 1.0			

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Penn Treebank : 7450 verb types , 38% once, 14 % twice

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Learning from unlabelled data

How?

- Expectation Maximization (EM) (Dempster, et.al., 1977)
- good mathematical properties, convergence



Experimental Setup

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- ~ I Million words from Penn Treebank
- 4, 8, 12, 16 Million words of unlabeled text (Wall Street Journal, sentence length < 25 words)
- Evaluations by parsing held-out sentences from the Penn Treebank
 - Task: assigning correct valence to verbs that are *unseen* in the labeled data.

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- 118 novel verb types, 1200 tokens
- evaluated against the treebank tree

Learning from unlabelled data

Smoothed

Treebank Model

Parsing

Unlabeled Data

EM - based

Method

% Error

Reduction

Challenge : Unlabeled data tends to harm rather than help an already accurate model Constrain Unsupervised Model • Frequency transformations Deoskar(2008, 2009) • N copies of Labelled data + unlabelled data (To appear (2011), with Mylonakis, Sima'an) • More general method but worse results informatics 24 Valence Detection for Novel Verbs 4 M 8 M 12 M 16 M words words words words

Valence Error Percentages for Novel Verbs

29.86

27.8

25.89

12.76

29.86

27.8

25.18

15.67

29.86

27.8

24.7

17.5

29.86

27.8

27.08

9.31

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No verb specific

information

p<0.0001











Improvements in a variety of frame-types

Frame	% Error Reduction
transitive	21.52
intransitive	11.36
NP PP-CLR	7.14
PP-CLR	25
SBAR	0
s.e.to (control)	25
PRT NP	12.5
NP PP-DIR	14.28
NP NP	11.11

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Summary

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Other categories

- Improvements in Noun valence (but impoverished frames)
- Improvements in other lexico-syntactic dependencies: Adverb attachment to sentential, nominal, verbal nodes

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Summary

• Framework

- allows easy annotation of Treebank trees with feature-structures
- compilation of PCFG grammars containing features
- ➡ Effort required is in development of a feature-contraint grammar

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➡ PCFGs can be built containing various subsets of features

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 - → PCFGs can be built containing various subsets of features
- Connect to much larger data : Possible to improve the distributions of these features from unlabelled data (at least for some features, like valence)

Summary

- Framework
 - allows easy annotation of Treebank trees with feature-structures
 - compilation of PCFG grammars containing features
 - Effort required is in development of a feature-contraint grammar
 - ➡ PCFGs can be built containing various subsets of features
- Connect to much larger data : Possible to improve the distributions of these features from unlabelled data (at least for some features, like valence)
- Experiment with utility of various features for statistical grammar learning

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22 Future Work			
 Which features? Current grammar contains very few features: focus on features related to valence and constraining empty categories. Experiment with more features Finer divisions of clausal valence: S and SBAR Fine-grained Treebank grammars for other languages. 		Thank You!	
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