Induction of Treebank-Aligned Lexical Resources LREC 2008

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Overview

- Goal: Induction of probabilistic treebank-aligned lexical resources.
- *Treebank-Aligned Lexicon*: a systematic correspondence between features of a probabilistic lexicon and structural annotation in a treebank.
- Features:
 - ♦ complex subcategorization frames for verbs or nouns.
 - ♦ attachment preference of adverbs



Overview

- Treebank PCFG and lexicon.
 - Unlexicalised Treebank PCFG : Clear division between grammar and lexicon.
 - ♦ Good performance (Klein and Manning, 2003)
- Large-scale lexicon: Unsupervised acquisition from unlabeled data.



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- A sophisticated PCFG that captures the same phenomena as more expressive formalisms.
 - \diamond Linguistic theory neutral.
 - \Diamond Focus on commonly observed phenomenon.



Treebank Transformation Framework

- Treebank Transformation : Johnson (1999), Klein and Manning (2003), etc.
- Training of PCFG on transformed treebank.



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- Methodology for transformation based on addition of linguistically motivated features, and feature-constraint solving.
- Database of Penn Treebank trees annotated with linguistic features as a resource.
- Components usable for transforming existing PTB-style treebanks, and building accurate PCFGs from them.



Feature Constraint Framework

- Bare-bones CFG extracted from Penn Treebank.
- A feature-constraint grammar is built by adding constraints on CF rules (YAP, Schmid (2000)).
- Each treebank tree converted into a trivial context-free shared forest.
- Constraints in the shared forest solved by YAP constraint solver.



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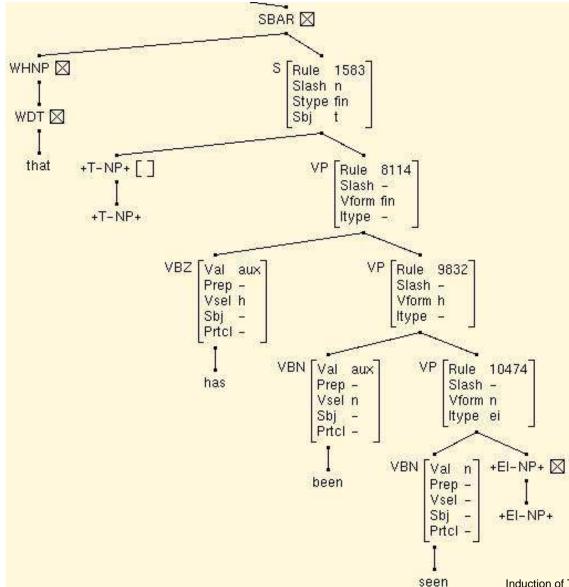
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Relative Clause

...that has been seen.





$VP \rightarrow VBD + EI-NP+ S$



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$$VP\{Vform = ns; \} \rightarrow VBD\{Val = ns; Sbj = x; Vsel = vf; \}$$

$$+ EI-NP+$$

$$S\{Sj = x; Vform = vf; \}$$

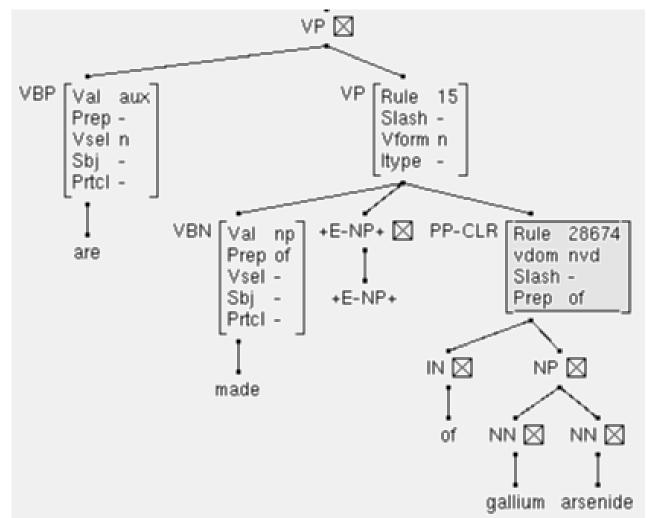


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Verbal Subcategorization

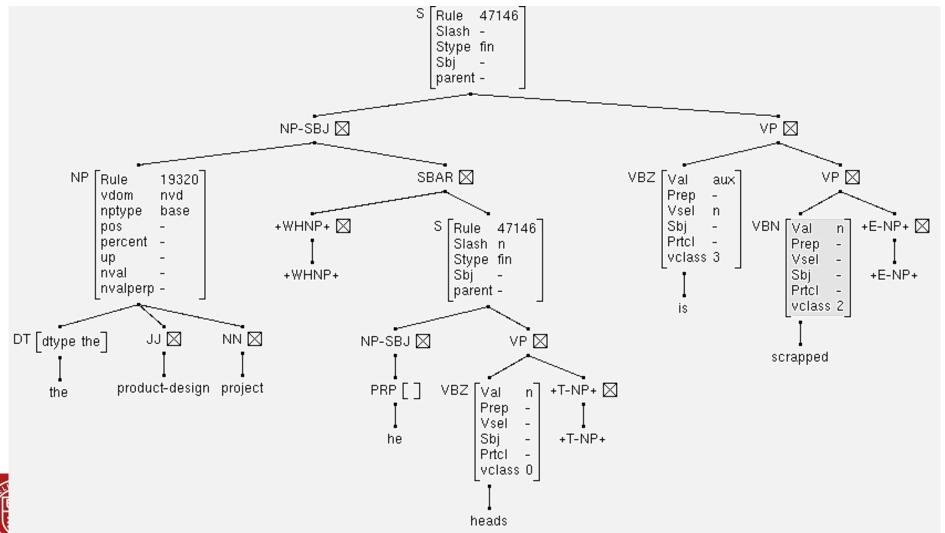
Structural information is projected onto lexical item: verbs, adverbs, nouns.





A feature-structure Treebank Tree

The product-design project he heads is scrapped



Treebank PCFG

- Frequencies collected from feature-annotated treebank database.
- Rule frequency table and frequency lexicon that can be used by a probabilistic parser.



Treebank grammar and lexicon

29092.0	ROOT	\rightarrow	S.finroot		
14134.0	S .fin	\rightarrow	NP-SBJ.nvd.base VP.fin		
13057.0	NP-SBJ.nvd.base	\rightarrow	PRP		
13050.0	PP.nvd.of.np	\rightarrow	IN.of NP.nvd.base		
tried	VBD.s.e.to 32.0 VBN.s.e.to 11.0 VBN.n 5.0				
VBD .z 1.0 VBD .n 1.0 VBD .s.e.g 1.0					
	VBN .z 1.0				
admired	VBD .n 1.0				
admit	VB .z 1.0 VB .n 1.0 VB .b 3.0				
	VBP .z 1.0 VBP	.p	1.0 VBP .b 2.0		
admonish	ing VBG .sto 1.0				



Treebank PCFG

• PCFG of variable granularity, based on attributes incorporated into the PCFG symbols.

PTB	No	Prep.	Prep.
Sec 23	Prepositions	on verbs	on nouns
Labeled Recall	86.5	86.11	85.98
Labeled Precision	86.7	86.50	86.3
Labeled F-score	86.6	86.31	86.14

Number of features on all categories: 19 Some structural features mostly linguistic features

Some structural features, mostly linguistic features.



Scarcity of lexical data

In training sections of Penn Treebank, ~ 45000 sentences

- Total verb types: \sim 7450, tokens \sim 125000.
- ~ 2830 verb types with occurrence freq 1: 38% of all types,
 2.37% of all tokens.

admired	VBD .n 1.0
admit	VB .z 1.0 VB .n 1.0 VB .b 3.0
	VBP .z 1.0 VBP .p 1.0 VBP .b 2.0
admonishing	VBG .sto 1.0
adopted	VBN.aux.e.fin 2.0 VBD.n 15.0 VBD.np 1.0
	VBN .n 16.0



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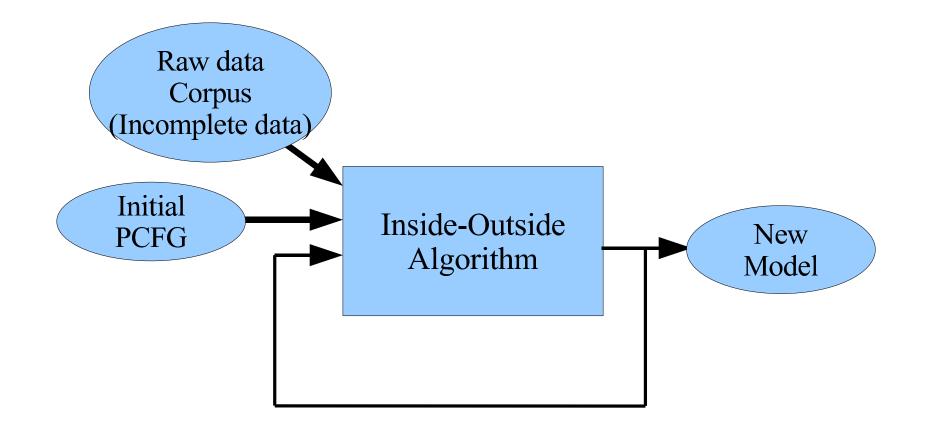
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- Focus on learning lexical parameters.
 - Lexical parameters obtained from re-estimated model and treebank.
 - ♦ Syntactic parameters obtained from treebank PCFG.

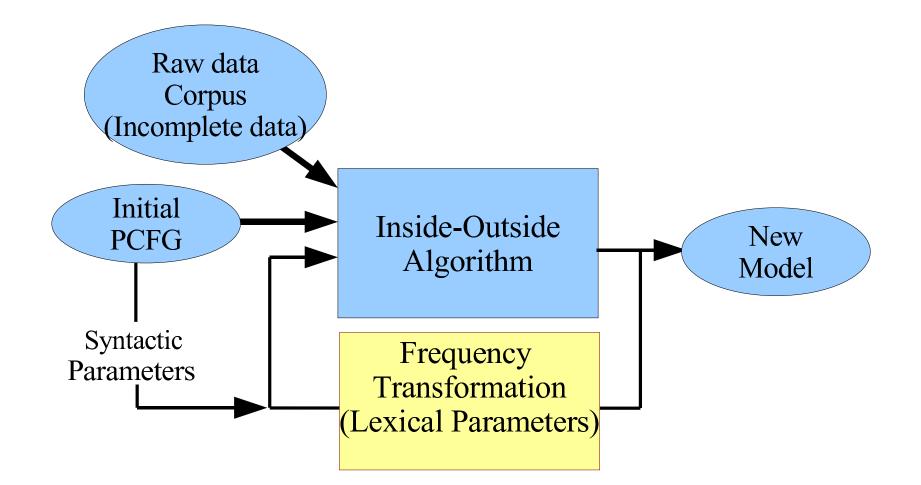


Inside-outside Re-estimation





Iterative Re-estimation





Lexical Transformation

- Constraint on re-estimated lexicons.
- Ensures that re-estimated lexicons are similar to treebank lexicon.
- Linear interpolation of the treebank and the re-estimated lexicons.

(1)
$$d_i(w,\tau,\iota) = (1-\lambda)t(w,\tau,\iota) + \lambda \bar{c}_i(w,\tau,\iota)$$

where

 w, τ, ι word, POS tag, incorporation sequence Scale Corpus frequencies:

$$\bar{c}_i(w,\tau,\iota) = \frac{t(\tau,\iota)}{c_i(\tau,\iota)} c_i(w,\tau,\iota)$$



• Non-novel words



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- Novel words:
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 - The re-estimation procedure is expected to acquire a word specific distribution.
- Words in the corpus (both novel and non-novel) get all possible incorporation values for the POS tag.



- The unlabelled corpus is tagged with POS tags in Penn Treebank style (Treetagger) and tokens of words and POS tags are tabulated to obtain a frequency table $g(w, \tau)$.
- Each frequency g(w, τ) is split among possible incorporations ι in proportion to a ratio of marginal frequencies in t₀

(2)
$$g(w,\tau,\iota) = \frac{t_0(\tau,\iota)}{t_0(\tau)}g(w,\tau)$$

The tagged corpus is merged with the treebank corpus

(3)
$$t(w,\tau,\iota) = (1-\lambda_{\tau,\iota})t_0(w,\tau,\iota) + \lambda_{\tau,\iota}g(w,\tau,\iota)$$



Experimental Setup

- Re-estimation: 4 Million words of unannotated Wall Street Journal Corpus (year 1994), sentence-length < 25 words
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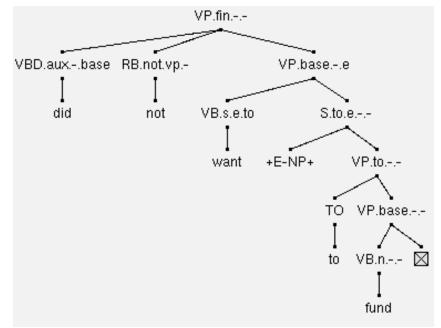
Evaluation: Acquiring subcategorization frames of novel verbs.

- 1360 tokens of 117 verb types: all occurrences heldout from treebank training data.
- Tokens of test verbs : preterminal (tag + incorporation sequence) extracted from Viterbi parse.
- Gold standard is the transformed treebank.



Subcat Frames

- Fine-grained subcategorization frames (81 subcategories)
- Intransitive, transitive, ditransitive, clausal, prepositional, etc.
- For clausal frames, the type and subject of clause.





Subcat. error % for Novel verbs

Iteration <i>i</i>	Interleaved Procedure	Standard Procedure
t_0	33.36	33.36
1	*24.40	28.69
2	*23.45	25.56
3	*23.05	27.86
4	*22.89	28.41
5	*22.81	_
6	22.83	_

10.55% absolute improvement and 31.6% error reduction



Evaluation

Overall Error reduction: 8.97% (16.8% overall error)



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Incorporating Prepositions into frame					
	Iteration <i>i</i>	Subcat Error	Subcat Error		
		(No Prep.)	(Prep. on verbs)		
	t_0	33.47	34.98		
	1	24.40	*25.52		
	2	23.45	*25.04		



Conclusions

- Framework for adding features to Treebank PCFG: features of interest can be added.
- PCFG formalism simple, and estimation methods well defined.
- Using a Treebank-aligned grammar makes standard and reliable evaluations of re-estimated grammars possible.
- Lexical information induced for novel items; also useful for low frequency items.



Noun Valence

- Three valences s, sbar, p
- NN and NNS (common nouns)

Iteration <i>i</i>	Noun valence Error
0	23.13
1	*20.35 (p < 0.0001)
2	21.49

Table 1: Noun Valence errors, with 4M words of training data.



Labeled Bracketing Evaluation

Iteration <i>i</i>	Interleaved Procedure	Standard Procedure
	f-score	f-score
t_0	86.55	86.55
1	86.83	86.96
2	*86.93	85.93
3	*86.92	84.87
4	*86.92	83.77
5	86.92	_
6	86.86	_



Larger Training Data

Iteration <i>i</i>	Subcat Error	Subcat Error
	4M words	8 M words
0	33.47	33.47
1	24.40	24.64
2	23.45	*22.26 (> 95% conf.)
3	23.05	22.34
4	22.89	23.05
5	22.81	-
6	22.83	–

