Learning Verb Argument Structure from Minimally Annotated Corpora

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Classification of Verb Alternations

- Task: automatic classification of verbs based on their underlying thematic structure

- Verbs that take the same number and category of arguments but assign different thematic roles to them

- Payoff:
  - acquisition of lexical semantic knowledge;
  - improve disambiguation information for lexicalized probabilistic parsers

Classification of Verb Alternations: Application of SF Learning

Unergative

INTRAN: The horse raced past the barn. (NP_{agent} raced)

TRAN: The jockey raced the horse past the barn. (NP_{causer} raced NP_{agent})

Unaccusative

INTRAN: The butter melted in the pan. (NP_{theme} melted)

TRAN: The cook melted the butter in the pan. (NP_{causer} melted NP_{theme})

Object-Drop

INTRAN: The boy washed. (NP_{agent} washed)

TRAN: The boy washed the hall. (NP_{agent} washed NP_{theme})

(Stevenson and Merlo 1997)

The Hypothesis (Merlo and Stevenson 2001)

- All verbs in each class can occur with the same syntactic context as other verbs
- Statistical distributions of syntactic context can be distinguished for each verb
- Identify probabilistic features that pick out verb co-occurences with particular syntactic contexts and use for classification
- This work: application of SF learning to this kind of classifier to see if noisy data with less annotation can be used

Corpus tagged by Adwait Ratnaparkhi's tagger and then chunked using Steve Abney's chunker:

Pierre	NNP	nx	2
Vinken	NNP		
,	,		
61	CD	ax	3
years	NNS		
old	JJ		
,	,		
will	MD	vx	2
join	VB		
the	DT	nx	2
board	NN		
as	IN		
a	DT	nx	3
nonexecutive	JJ		
director	NN		
Nov.	NNP		
29	CD		
.	.		

Features used (cf. Merlo and Stevenson 2001)

1. simple past (VBD), and past participle(VBN)
2. active (ACT) and passive (PASS)
3. causative (CAUS)
4. animacy (ANIM)

New Features used

- POS features: part of speech of subject and object head noun
- SF features: transitive (TRAN) and intransitive (INTRAN)

Differences in data between current study and (Merlo and Stevenson 2001)

- (Merlo and Stevenson 2001) used an automatically parsed corpus of 65M words. Note that the parser was trained on 1M words of annotated data: the Penn Treebank

- However, not all their features exploited the parse tree structure
  (they used part-of-speech tags for features such as the causative feature)

- In our study we wanted to explore whether automatic subcat frame learning can replace the use of a full parser.

Learning Subcategorization Frames: TRAN and INTRAN features

- Discover valid subcategorization frames (SFs) for each verb

- Distinguish arguments from adjuncts

- Learning from data *not* annotated with SF information

Methods Used

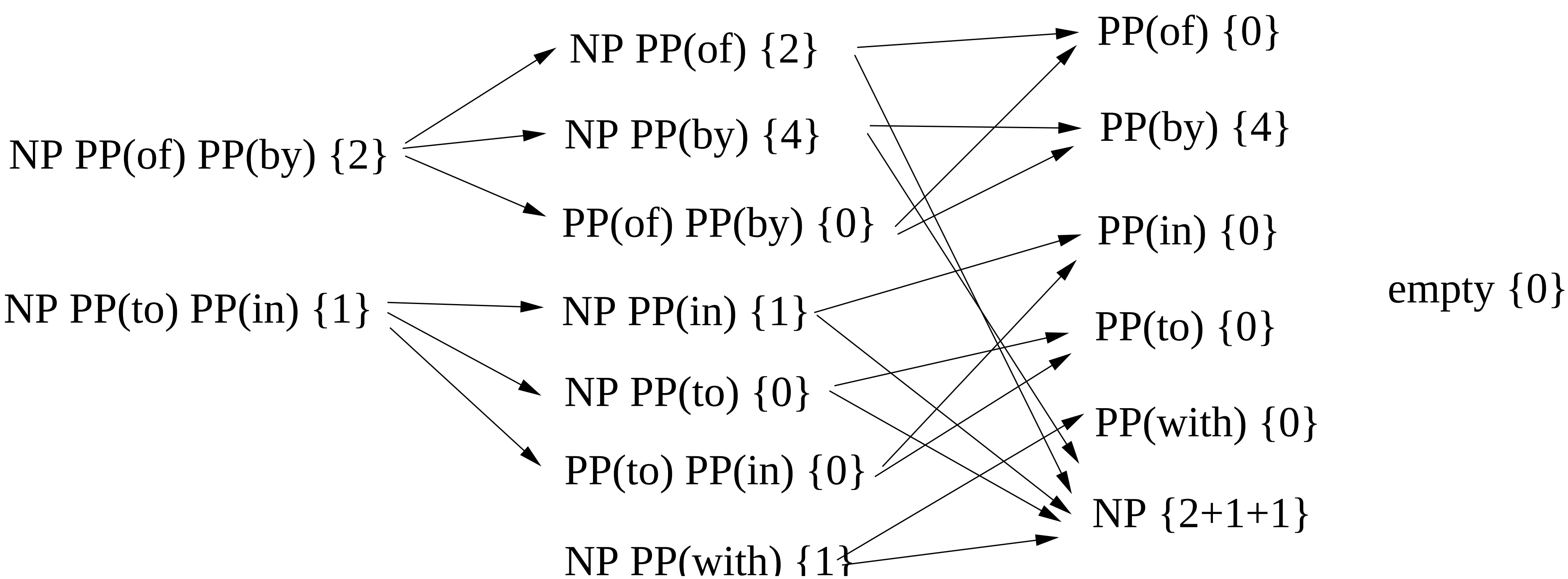
- Hypothesis Testing using:
  - Likelihood Ratio test
  - T-score test
  - Binomial models of miscue probabilities

- Hypothesis: $\underbrace{p(f \mid v)}_{p_1} = \underbrace{p(f \mid !v)}_{p_2} = \underbrace{p(f)}_{p}$

Subsets of observed frames

- Iterative algorithm:
  - First use counts for the observed frame f in hypothesis testing
  - If f is rejected as true SF, produce all subsets of f
  - Select one subset of f as successor observed frame s which is updated with f's counts
  - Repeat for each s rejected by hypothesis testing

Subsets of observed frames



Successor Selection

1. Choose the successor frame that results in the strongest preference (lowest entropy across the corpus; exponential in num of frames)

2. Pick the successor frame with highest cumulative frequency at each step (greedy)

3. Random selection

$\rightarrow$ *Random selection works the best*

Experiment

- Data: 23M words of WSJ text chunked
- 76 verbs picked to balance frequency (classes from Levin)
- Learning subcategorization frames for these verbs (puts the verbs into either the TRAN or INTRAN class)

Experiment

- Trained a (decision stub) Boosting classifier and a Decision Tree classifier using C5.0
- Used a 90%-10% training-test split with 10-fold cross-validation
- Tried various combinations of features to find the most informative ones

Features	Average error rate from Rule Set	SE
TRAN, INTRAN, VBD, VBN, PASS, ACT	67.7%	0.9%
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS	40.8%	0.6%
TRAN, INTRAN, VBD, VBN, PASS, ACT, ANIM	36.9%	1.0%
TRAN, INTRAN, VBD, VBN, PASS, ACT, PART OF SPEECH	38.1%	1.1%
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS, ANIM	**33.9%**	**0.8%**
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS, PART OF SPEECH	37.1%	0.9%
TRAN, INTRAN, VBD, VBN, PASS, ACT, ANIM, PART OF SPEECH	35.9%	1.7%
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS, ANIM, PART OF SPEECH	38.3%	1.0%

Features	Average error rate from Decision Tree	SE
TRAN, INTRAN, VBD, VBN, PASS, ACT	49.4%	1.1%
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS	41.1%	0.8%
TRAN, INTRAN, VBD, VBN, PASS, ACT, ANIM	37.5%	0.8%
TRAN, INTRAN, VBD, VBN, PASS, ACT, PART OF SPEECH	39.2%	0.8%
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS, ANIM	**33.4%**	**0.7%**
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS, PART OF SPEECH	39.0%	0.7%
TRAN, INTRAN, VBD, VBN, PASS, ACT, ANIM, PART OF SPEECH	35.8%	1.3%
TRAN, INTRAN, VBD, VBN, PASS, ACT, CAUS, ANIM, PART OF SPEECH	39.5%	1.0%

Results

- Baseline: pick argument structure at random, ER = 65.5%

- (Merlo and Stevenson 2001) measure expert-based upper bound, ER = 13.5%

- (Merlo and Stevenson 2001) obtain ER = 30.2% with 65M words of automatically parsed WSJ text

- Current work: C5.0 classifier (using SF info), ER = 33.4% with 23M words of chunked text (SF info obtained by learning)

Conclusion

- Presented a technique which automatically identifies argument structure for a set of verbs

- This work shows that this task can be accomplished using only tagged and chunked data

- We also showed that a subcategorization frame learning algorithm can be applied to this task

- We achieved an error rate of 33.4% using chunked data which compares favorably with work that used automatically parsed data