



## Aims

### Current Aims

- **Predict prepositions** in native English text.
- For predictions, use a **purely surface-based**, “web-as-corpus” approach (e.g., Lapata & Keller, 2005).
- Determine the tradeoff between
  - **Informativeness** of context (→ the size of the context n-gram)
  - **Data-sparseness** (→ can we find the n-gram on the web?)

### Mid-Term Aims

- **Correct prepositions** in text written by **learners** of English.

## Related Work

Correct use of prepositions is a major problem for learners of English.

→ The computational analysis of preposition usage has attracted significant attention in recent years in the field of **Intelligent Computer Assisted Language Learning**.

(De Felice & Pulman, 2009; De Felice, 2008; Lee & Knutsson, 2008; Gamon et al., 2008; Chodorow et al., 2007; Tetreault & Chodorow, 2008a,b)

Most of the approaches first tackle the task of predicting prepositions in *native language* as a point of reference.

- The task is usually approached as a classification problem:
  - The classes are the prepositions.
  - The instances to be classified are the contexts.
  - Contexts are represented by a *rich set* of linguistic features (POS tags, PP attachment sites, WordNet classes of PP object and modified item, etc.).

## Our Approach

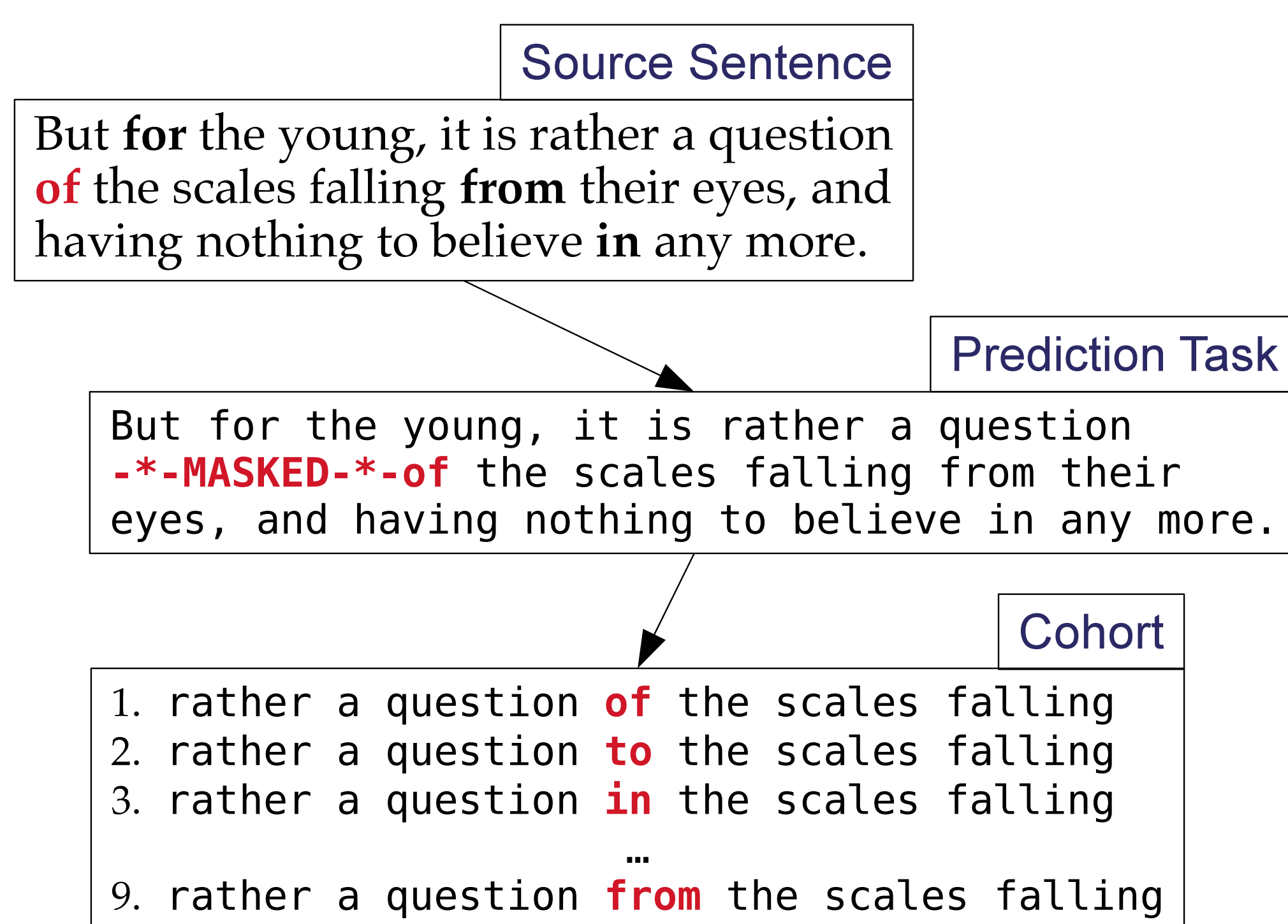
Using **purely surface-based predictions**, how much information can we find in the **immediate distributional context of the preposition**?

### Data

- Random sample of section J of the BNC XML Edition (8060 sentences)
- We extract one **prediction task** for each occurrence of one of the top nine prepositions in the BNC *of, to, in, for, on, with, at, by, from*

→ Same corpus section and prepositions as used by De Felice (2008).

### Prediction Tasks



### Prediction of Prepositions Using Web Counts

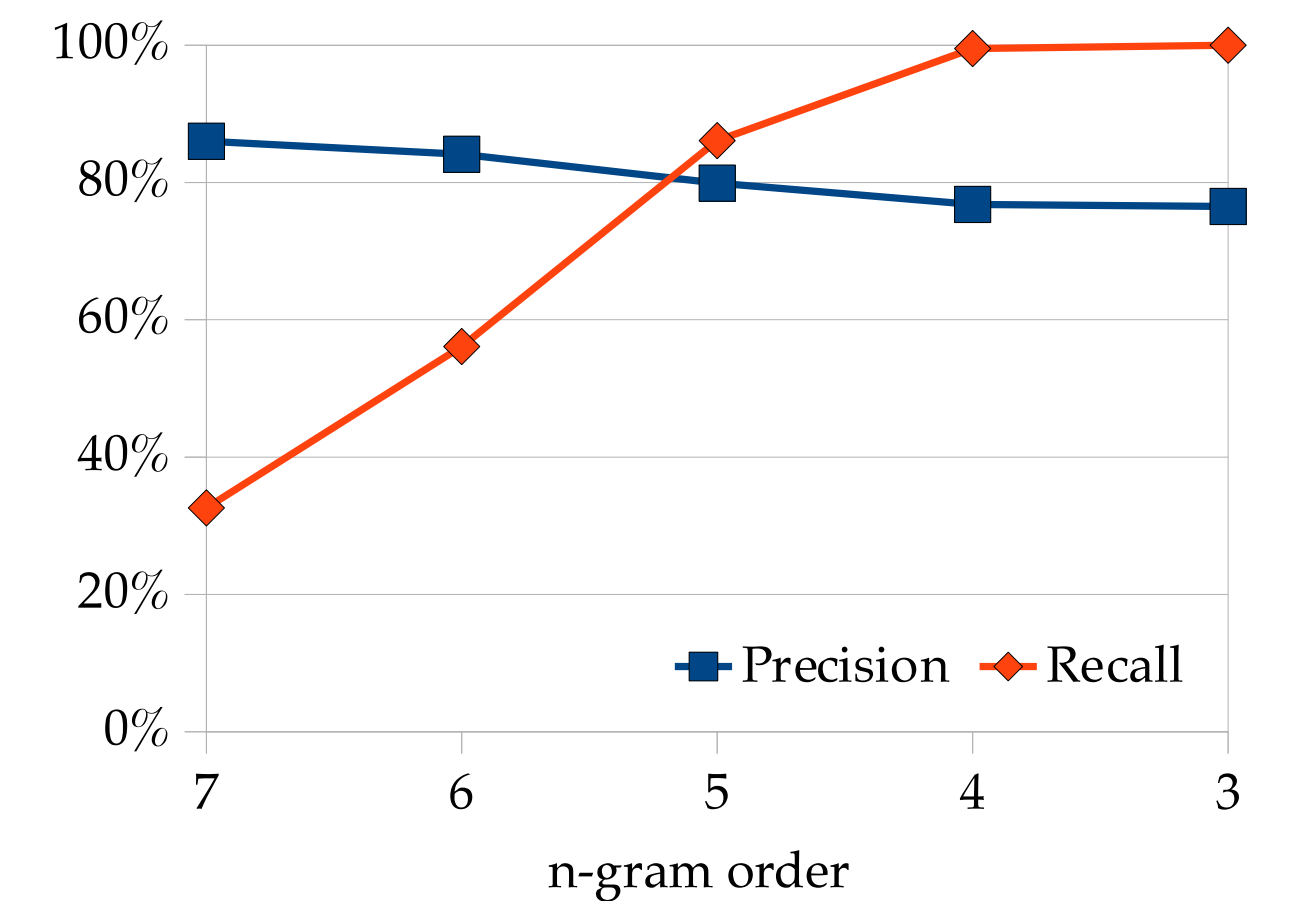
- Determine the **number of hits** for each 7-gram in a cohort using Yahoo’s BOSS service.
- Pick the preposition for which the **most hits** were found.
- In case of **no hits**, back off to **lower n-gram orders using overlap backoff**.

## Results

### Summary

Approach	Accuracy
Gamon et al. (2008)	62.32%
Tetreault and Chodorow (2008a)	79.00%
Bergsma et al. (2009)	75.50%
De Felice (2008) system	<b>70.06%</b>
Majority baseline ( <i>of</i> )	26.94%
Human agreement	88.60%
<b>This paper – surface-based approach</b>	<b>76.50%</b>

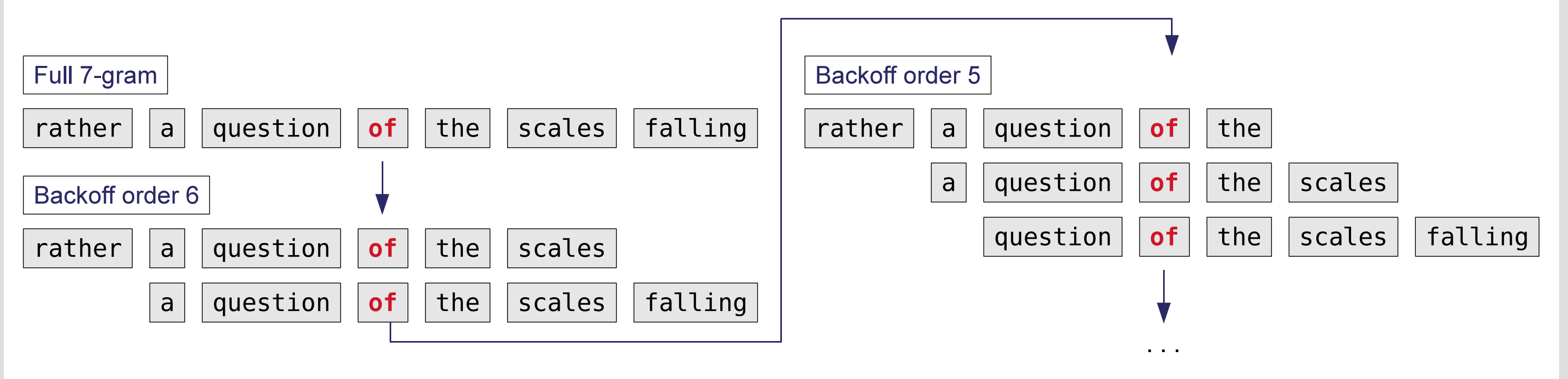
### Informativeness/Data Tradeoff



### Detailed Results

	Sum	7-grams (3 + prep + 3)	6-grams (truncated 7-gram)	5-grams (truncated 7-gram)	4-grams (truncated 7-gram)
<b>Total</b>	8060	6999	656	182	223
<b>Predictions</b>	2900	2195	379	119	207
correct	2495	1931	326	91	147
incorrect	405	264	53	28	60
<b>Requiring back-off</b>	5160	4804	277	63	16
<b>Precision</b>	86%	88%	86%	76.5%	71%
<b>Recall</b>	32.6%	28.7%	79.6%	59.1%	90.2%
<b>Back-off order 6</b>					
<b>Predictions</b>	2028	2028			
correct	1620	1620			
incorrect	408	408			
<b>Still requiring back-off</b>	2776	2776			
<b>Predict. orders 7+6</b>	4223	4223			
correct	3551	3551			
incorrect	672	672			
<b>Precision</b>	84.1%	84.1%			
<b>Recall</b>	56.1%	56.1%			
<b>Back-off order 5</b>					
<b>Predictions</b>	2180	2020	160		
correct	1542	1411	131		
incorrect	638	609	29		
<b>Still requiring back-off</b>	873	756	117		
<b>Predict. orders 7 – 5</b>	6782	6243	539		
correct	5419	4962	457		
incorrect	1363	1281	82		
<b>Precision</b>	79.9%	79.5%	84.8%		
<b>Recall</b>	86.1%	86.8%	79.6%		
<b>Back-off order 4</b>					
<b>Predictions</b>	905	743	106	56	
correct	488	382	68	38	
incorrect	417	361	38	18	
<b>Still requiring back-off</b>	31	13	11	7	
<b>Predict. orders 7 – 4</b>	7806	6986	645	175	
correct	5998	5344	525	129	
incorrect	1808	1642	120	46	
<b>Precision</b>	76.8%	76.5%	81.4%	73.7%	
<b>Recall</b>	99.5%	99.8%	97.9%	94.9%	
<b>Back-off order 3</b>					
<b>Predictions</b>	47	13	11	7	16
correct	21	5	7	3	6
incorrect	26	8	4	4	10
<b>Still requiring back-off</b>	0	0	0	0	0
<b>Predict. orders 7 – 3</b>	8060	6999	656	182	223
correct	6166	5349	532	132	153
incorrect	1894	1650	124	50	70
<b>Precision</b>	76.5%	76.4%	81.1%	72.5%	68.6%
<b>Recall</b>	100%	100%	100%	100%	100%

## Overlap Backoff



## Future Work

- Use Google’s Web 1T 5-gram corpus data source instead of web counts.
- Explore backoff strategies based on linguistic generalizations.
- Vary the size of the context window based on **linguistic information**.
- Apply to **learner language** to identify and correct incorrect usage.

## References

Chodorow, M., J. Tetreault & N.-R. Han (2007). Detection of Grammatical Errors Involving Prepositions. In *Proceedings of the 4th ACL-SIGSEM Workshop on Prepositions*. Prague, Czech Republic: Association for Computational Linguistics.

De Felice, R. (2008). Automatic Error Detection in Non-native English. Ph.D. thesis, St Catherine’s College, University of Oxford.

De Felice, R. & S. Pulman (2009). Automatic Detection of Preposition Errors in Learner Writing. *CALICO* 26(3).

Gamon, M., J. Gao, C. Brockett, A. Klementiev, W. Dolan, D. Belenko & L. Vanderwende (2008). Using Contextual Speller Techniques and Language Modeling for ESL Error Correction. In *Proceedings of IJCNLP*. Hyderabad.

Lapata, M. & F. Keller (2005). Web-based Models for Natural Language Processing. *ACM Transactions on Speech and Language Processing* 2(1).

Lee, J. & O. Knutsson (2008). The Role of PP Attachment in Preposition Generation. In A. Gelbukh (ed.), *Proceedings of CILing 2008*. Haifa.

Tetreault, J. & M. Chodorow (2008a). Native Judgments of Non-Native Usage: Experiments in Preposition Error Detection. In *Proceedings of COLING-08*. Manchester.

Tetreault, J. & M. Chodorow (2008b). The Ups and Downs of Preposition Error Detection in ESL Writing. In *Proceedings of COLING-08*.