# Word Representations & Dependency Parsing

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Background: Unsupervised Representation Learning

[Bengio+ 2003] [Collobert&Weston 2008] [Brown+ 1993] [Turian+ 2010] [Yu+ 2013]

Representations from large-scale unlabeled data are useful as task-independent features.

#### Neural Language Model

Score(Original) > Score(Corrupted) to learn weights & embeddings.

Score Score'
cat chills on a mat
Nara

Create a corrupted sentence by replacing a word.

Words with similar contexts are close to each other

Sophia
Paris<sub>Oslo</sub>

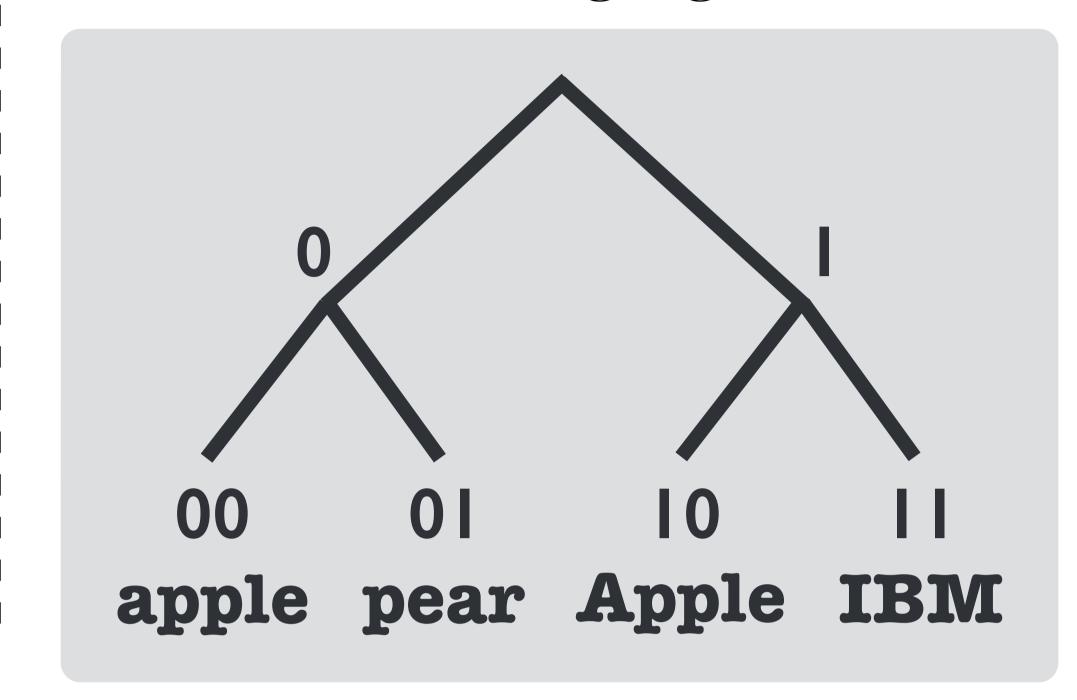
Nara
Seoul
Beijing
Beijing
China

Embedding
Real-value
dense vector

Baidu
Microsoft
Google

#### **Brown Clustering**

Hierarchical clustering based on class-based language model.



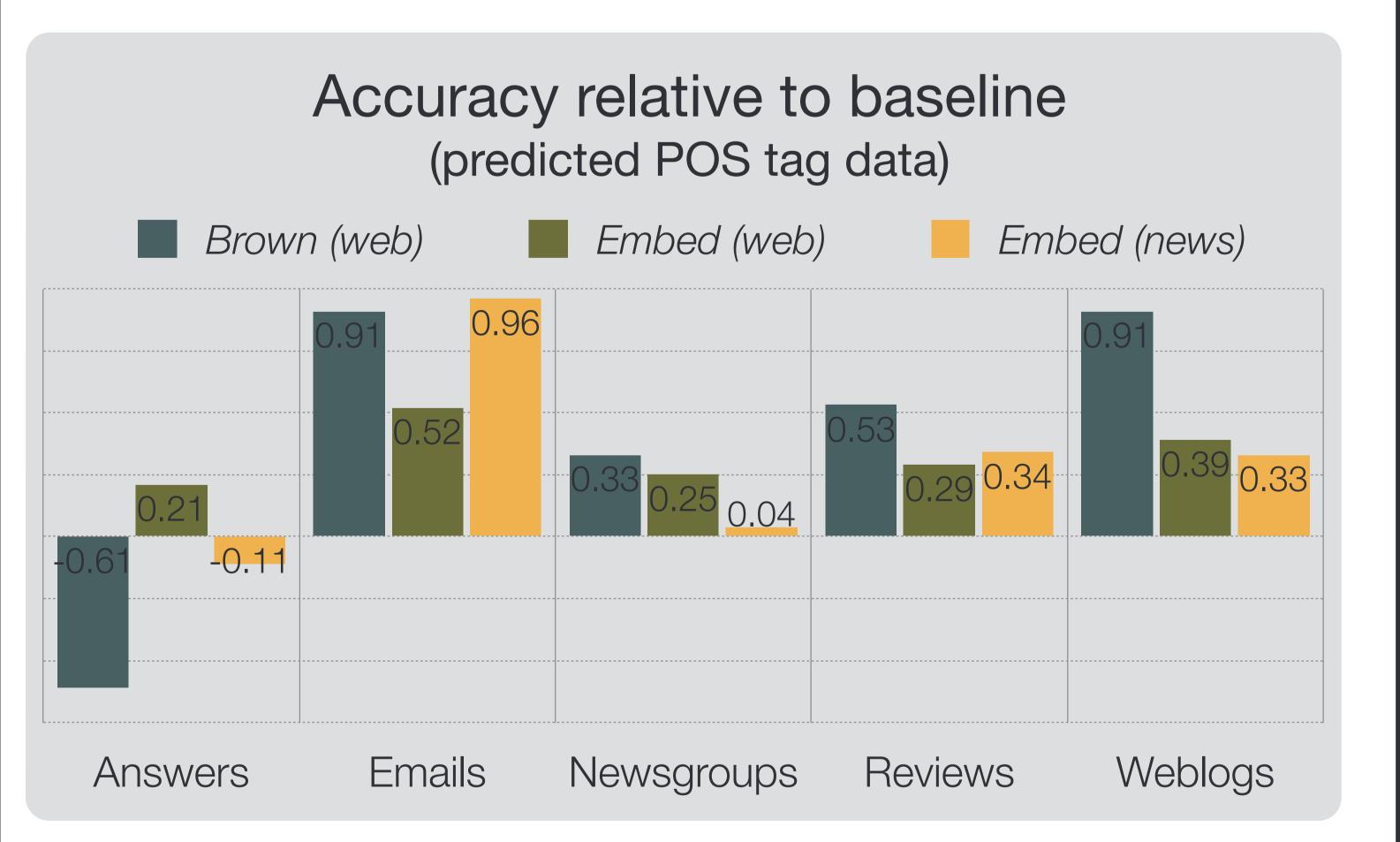
# Dependency Parsing with Word Representations

Related Works
[Koo+ 2008]
[Wu+ 2013]

- Word reps as features for dependency parsing
- Web: small labeled data, large unlabeled data

### Experiment

- Data: Google Web Treebank
- Graph-based parser (1st-order)



- Cluster embeddings to use as features
- 1. Embed(news): trained with newswires
- 2. Embed(web): trained with g-web data

## Conclusion

Results improved with predicted POS tag data, but not with gold POS.

### **Future Works**

- Other ways to add embeddings?
- Accuracy vs. training time?

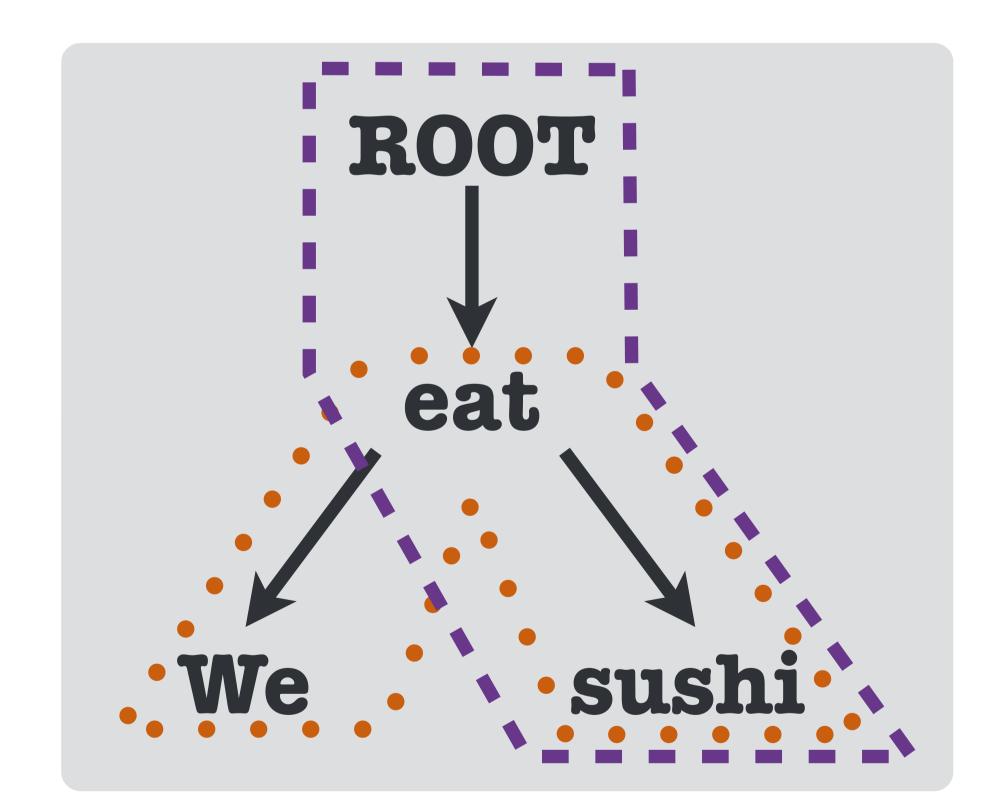
Learning Representations with Dependency Information

Related Works
[Bengio+ 2003]
[C&W 2008]

- NLM & Brown clustering use word sequences
- Can we learn better reps with dependency info?

### How to input dependency information?

- Tree paths?
- e.g. trigram
  - ancestors?
  - > siblings?



### How to make pseudo-negative examples?

