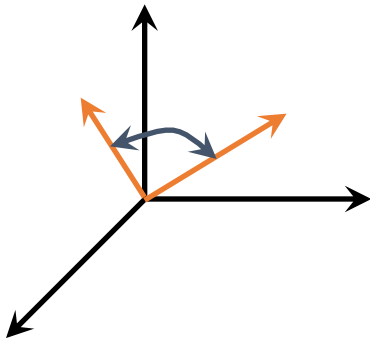


# Inducing Embeddings for Rare and Unseen Words by Leveraging Lexical Resources

Mohammad Taher Pilehvar

Nigel Collier

# Representation of rare words



# Representation of rare words

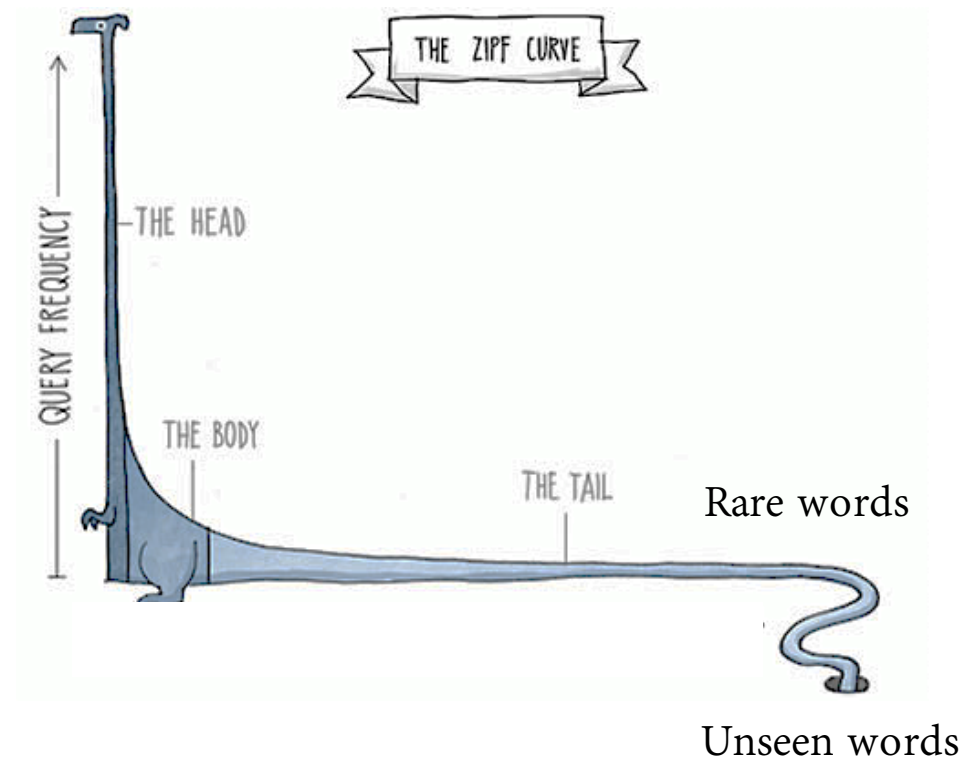
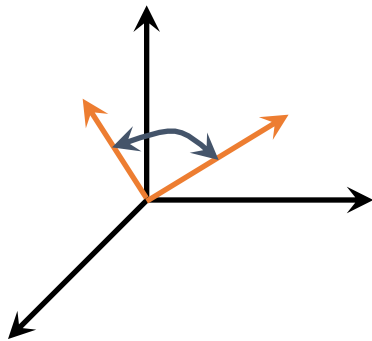


Illustration by Eva-Lotta  
[www.smashingmagazine.com](http://www.smashingmagazine.com)

# Representation of rare words: past work

Recent work has mainly focused on  
morphologically complex rare words

intercommunicate

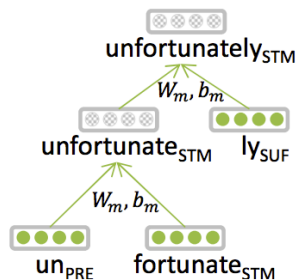
disturbances

postmodernism

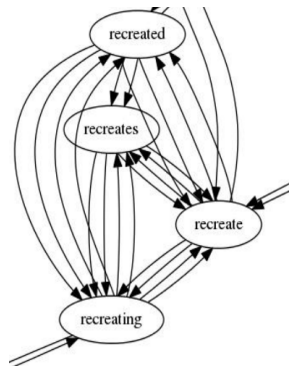
unconsciousness

corroding

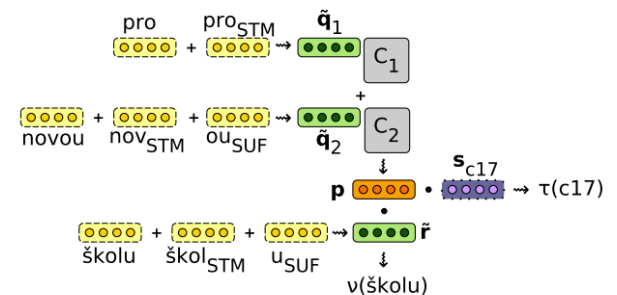
Luong et al. (2013)



Soricut and Och (2015)



Botha and Blunsom (2014)



# Representation of rare words

What about other (single morpheme) rare words?

Infrequent or domain-specific words

piquance

bronchomegaly

degust

abouphalia

hyperthreoninuria

enthuse

milphosis

schmetterlingswirbel

lieutenant

# Lexical resources to the rescue

Abundance of domain-specific lexical resources:  
ontologies, dictionaries, databases, etc.

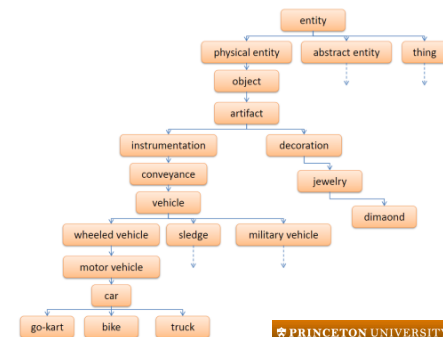


BabelNet

piquance  
bronchomegaly  
degust  
abouphalia

hyperthreoninuria

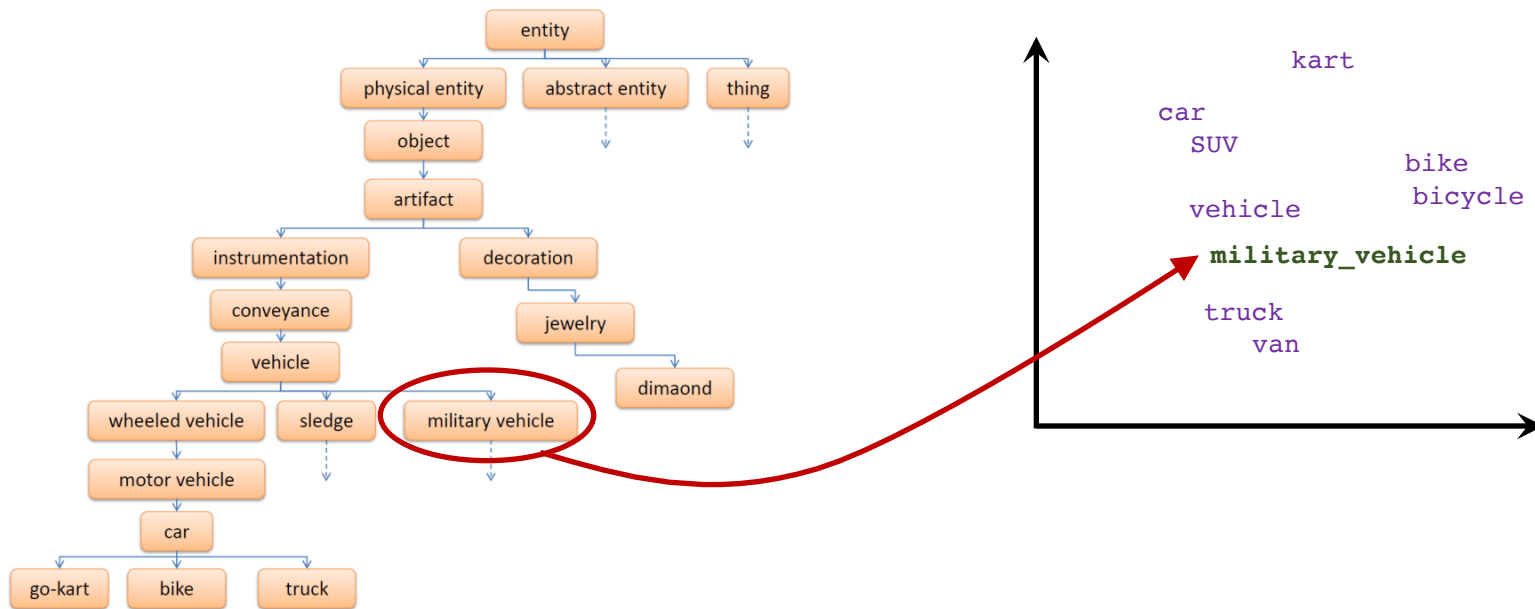
enthuse  
milphosis  
schmetterlingswirbel  
lieutenant



PRINCETON UNIVERSITY  
**WordNet**  
A lexical database for English

# Inducing embedding for unseen words

Leverage knowledge encoded in external lexical resources for inducing embeddings



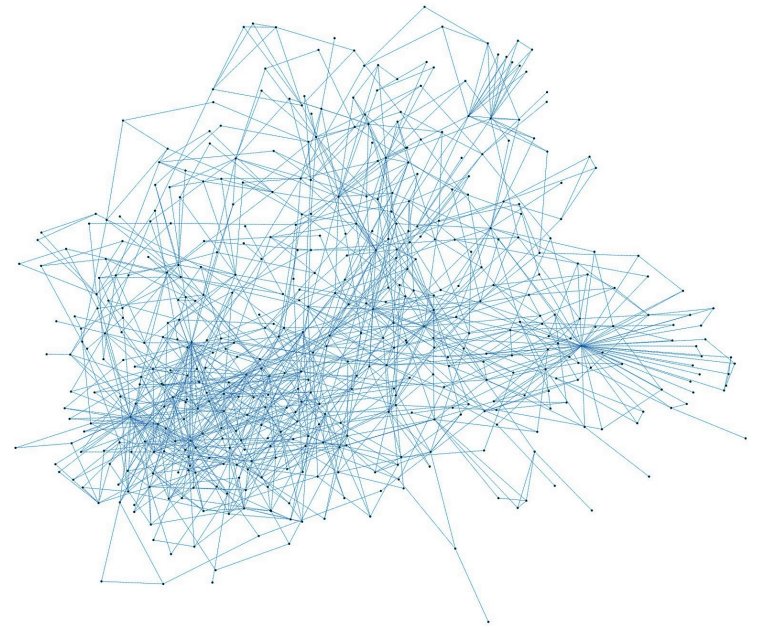
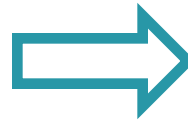
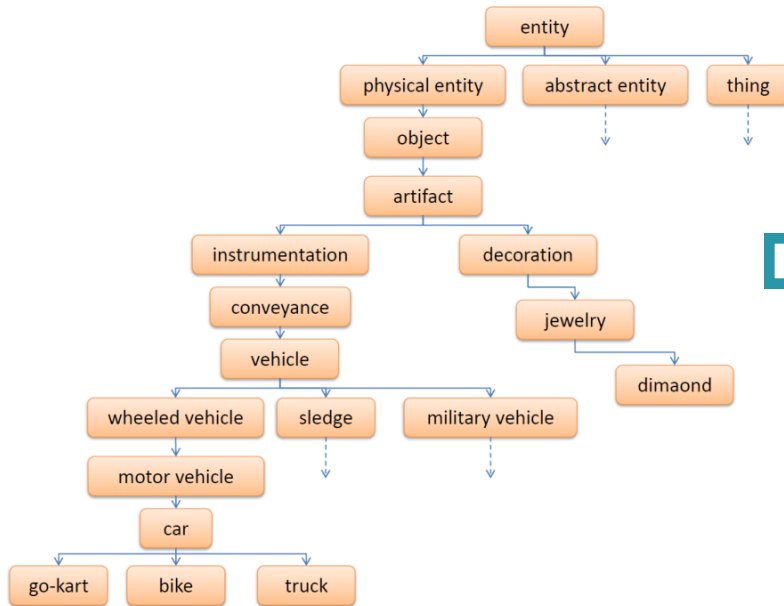
# Inducing embedding for unseen words

The proposed procedure:

1. View a lexical resource as a **semantic network**
2. Extract for an unseen word its set of **semantic landmarks**
3. **Induce** the embedding for the unseen word using its landmarks

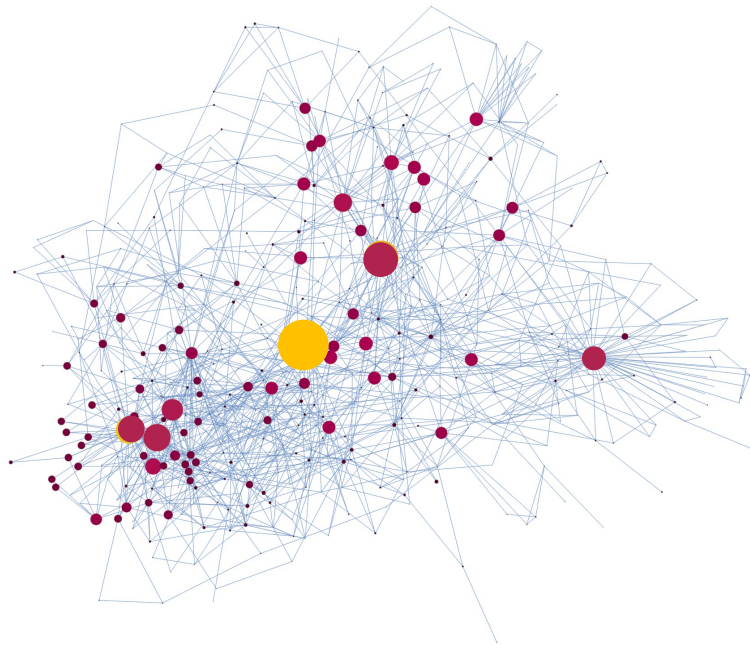
# Inducing embedding for unseen words

## 1. View lexical resource as a semantic network



# Inducing embedding for unseen words

## 2. Extract semantic landmarks



### **military\_vehicle**

---

vehicle  
military\_machine  
caisson  
tank  
humvee  
troop\_carrier  
pickup  
warplane  
Lorry  
Warship  
picket  
personnel

Using Personalized PageRank

# Inducing embedding for unseen words

## 3. Induce embeddings

$$\hat{\mathbf{d}}(w_r) = \theta \mathbf{d}(w_r^0) + \frac{1}{|\mathcal{L}_r|} \sum_{i=1}^{|\mathcal{L}_r|} e^{-i} \mathbf{d}(l_{i,r})$$

induced embedding for  $w_r$

semantic landmarks

embedding for the  $i$ -th landmark

# Inducing embedding for unseen words

## 3. Induce embeddings

$$\hat{\mathbf{d}}(w_r) = \theta \mathbf{d}(w_r^0) + \frac{1}{|\mathcal{L}_r|} \sum_{i=1}^{|\mathcal{L}_r|} e^{-i} \mathbf{d}(l_{i,r})$$

induced embedding for  $w_r$

semantic landmarks

embedding for the  $i$ -th landmark

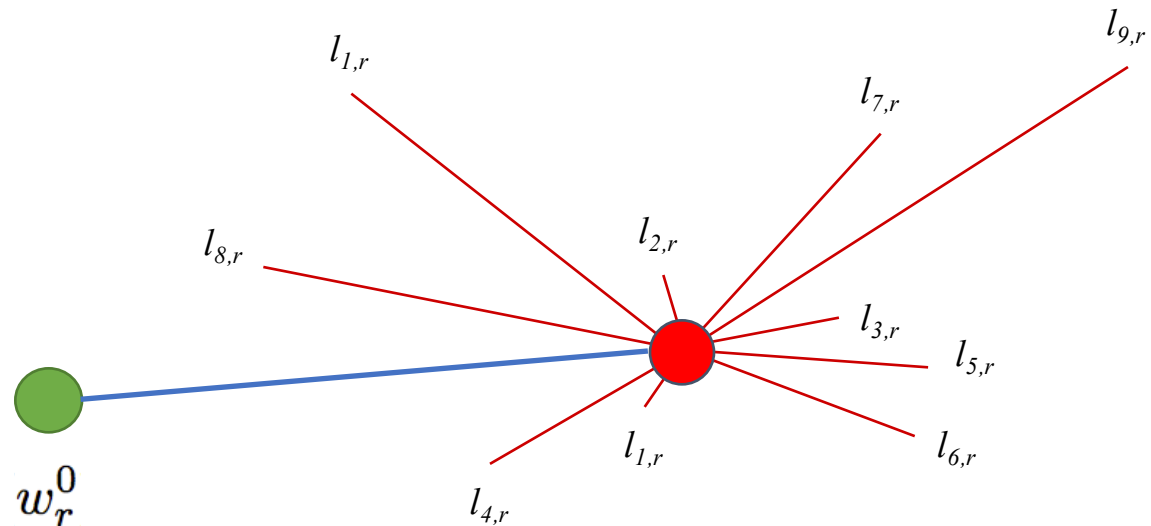
if there exists an initial (unreliable) representation  
for  $w_r$  which is to be improved

# Inducing embedding for unseen words

## 3. Induce embeddings

$$\hat{\mathbf{d}}(w_r) = \theta \mathbf{d}(w_r^0) + \frac{1}{|\mathcal{L}_r|} \sum_{i=1}^{|\mathcal{L}_r|} e^{-i} \mathbf{d}(l_{i,r})$$

induced embedding for  $w_r$       semantic landmarks      embedding for the  $i$ -th landmark



# Experiments

General domain setting

Rare Word similarity dataset

External lexical resource: WordNet

|          | Vanilla |      |        | +Induction |      |        |
|----------|---------|------|--------|------------|------|--------|
|          | OOV     | $r$  | $\rho$ | OOV        | $r$  | $\rho$ |
| GLOVE    | 11%     | 34.9 | 34.4   | 0%         | 38.6 | 39.7   |
| W2V-250K | 34%     | 31.0 | 25.9   | 0%         | 44.2 | 47.5   |
| W2V-GN   | 9%      | 43.8 | 45.3   | 0%         | 48.3 | 50.5   |

# Experiments

General domain setting  
Rare Word similarity dataset

| Approach                 | RW   |             | RG-65 |        |
|--------------------------|------|-------------|-------|--------|
|                          | OOV  | $\rho$      | OOV   | $\rho$ |
| Botha and Blunsom (2014) | NA   | 30.0        | NA    | 41.0   |
| Luong et al. (2013)*     | 0%   | 34.4        | 0%    | 65.5   |
| Soricut and Och (2015)*  | 0%   | 41.8        | 0%    | 75.1   |
| Our approach*            | 0%   | <b>43.3</b> | 0%    | 75.1   |
| <i>Number of pairs</i>   | 2034 |             | 65    |        |

Systems marked with \* are trained on the same corpus.

# Experiments

Specific domain setting (medical)

Datasets: MayoSRS (101 pairs) and UMNRSRS (566 pairs)

External lexical resource: Medical Subject Headings (MeSH)

|      |          | Vanilla |      |        | +Induction |      |        |
|------|----------|---------|------|--------|------------|------|--------|
|      |          | OOV     | $r$  | $\rho$ | OOV        | $r$  | $\rho$ |
| Mayo | GLOVE    | 16%     | 11.1 | 11.6   | 11%        | 36.7 | 26.1   |
|      | W2V-250K | 41%     | 1.2  | 2.9    | 21%        | 27.8 | 20.1   |
|      | W2V-GN   | 12%     | 15.5 | 14.0   | 10%        | 18.4 | 10.9   |
| UMN  | GLOVE    | 17%     | 31.6 | 24.4   | 6%         | 38.2 | 33.6   |
|      | W2V-250K | 38%     | 11.8 | 3.2    | 13%        | 27.8 | 20.1   |
|      | W2V-GN   | 17%     | 25.8 | 21.5   | 7%         | 32.8 | 32.4   |

# Conclusions

- A novel approach to inducing embeddings for unseen words

Based on the knowledge encoded in external lexical resources

- Improved performance on multiple benchmarks in general and specific domains
  - ❖ Extension to other domains and languages
  - ❖ New evaluation benchmarks

# Thank you!

