# Partial Colexifications Improve Concept Embeddings

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# Introduction

***We learn meaningful, low-dimensional representations of concepts by applying graph embedding techniques on colexification networks.***

## Motivation

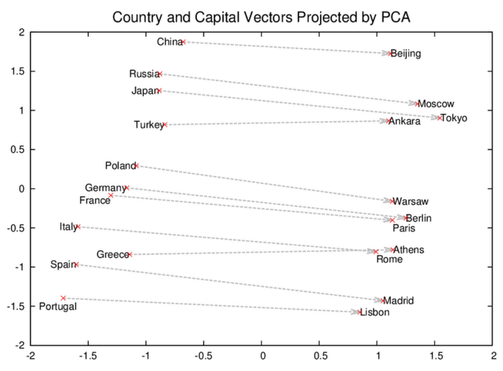
- State-of-the-art methods in computational historical linguistics are generally unable to model or reconstruct semantic change
- It is notoriously hard to quantify meaning cross-linguistically
- Modeling semantic relations between *concepts* reliably in a "computer-friendly" way could help bridging the gap

## Background

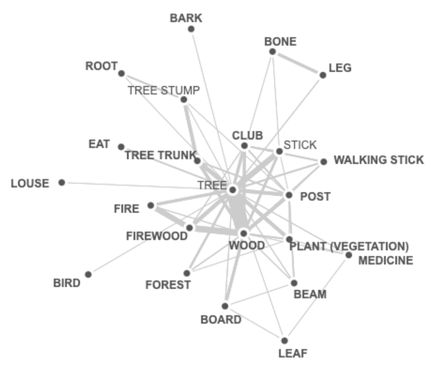
- **Word embeddings** have shown that various semantic relationships can be efficiently modeled in a low-dimensional vector space.
  - ...but since they embed words, they are not fit for wide cross-linguistic applications

- **Colexification networks** offer a cross-linguistic, concept-based approach on semantics, encoding common pathways of semantic shift
  - ...but their network structure can not readily be processed by downstream applications

**Using graph embedding techniques, we can learn embedded representations for concepts in colexification networks.**




(Mikolov et al., 2013)




(Rzymski et al., 2020)

# Materials and Methods

## Colexification Data

- Three types of colexification (List, 2023) inferred from the *Intercontinental Dictionary Series* (Key and Comrie, 2016):
  - full colexification
  - affix colexification
  - overlap colexification
- Colexification network for each type of colexification
- Concepts defined by the CLLD Concepticon (List et al., 2025)

## Graph Embedding Techniques

- ProNe (Zhang et al., 2019), Node2Vec (Grover and Leskovec, 2016) & SDNE (Wang et al., 2016)

## Training

- Train individual embeddings for each colexification network
- Combine embeddings from different colexification types as a post-processing step (concatenation + PCA)

# Experiments

## 1) Modeling Lexical Semantic Similarity

- Multilingual similarity ratings between word pairs, obtained from MultiSimLex (Vulić et al., 2020)
- Calculate cosine similarities between corresponding concept pairs
- Calculate Spearman's r between similarities

## 2) Predicting Semantic Change

- Obtain historically attested semantic changes from DatSemShift (Zalizniak et al., 2024)
- Negative sampling of random "changes"
- Train simple logistic regression classifier to tell apart true and false shifts, based on the respective concept similarities

## 3) Predicting Word Associations

- Obtain word association data from the Edinburgh Association Thesaurus (Kiss et al., 1973)
- Same experimental setup as previous task: Negative sampling, prediction with simple logistic regression classifier

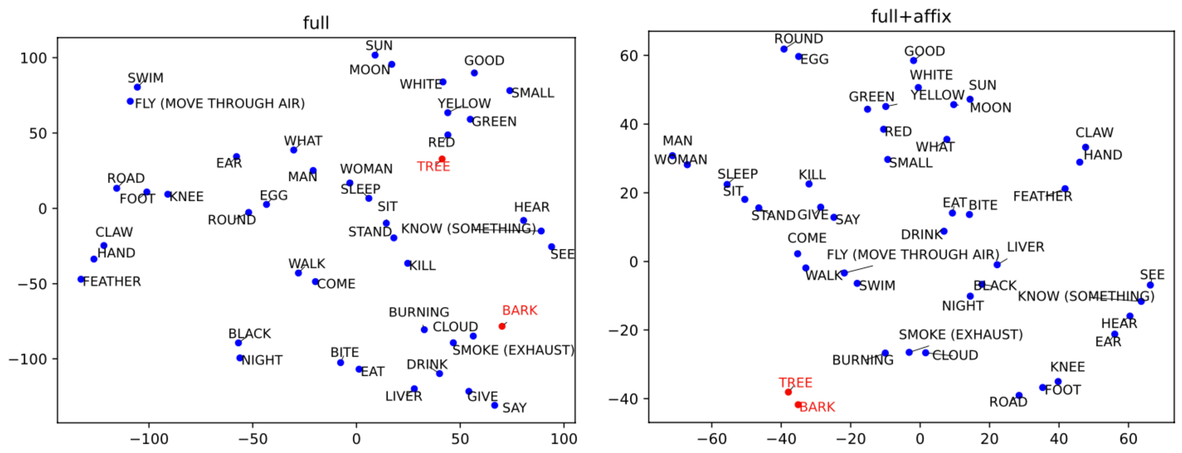
## Baselines

- Various similarity metrics inferred from the graph directly
- Multilingual fastText vectors (Grave et al., 2018)

# Results & Discussion

## Results

- Embeddings learned with ProNE perform the best on average, closely followed by Node2Vec; SDNE does not seem viable
- Concept embeddings outperform graph-based baselines in all three tasks, and fastText embeddings in 2 of 3 tasks
- Almost identical patterns between tasks 2 and 3
- Affix colexifications lead to better embeddings on all three tasks
- Overlap colexifications are beneficial for predicting semantic change and word association, but detrimental for modeling lexical similarity (the same pattern holds for fastText embeddings!)




## Discussion

- Partial colexifications can capture semantic relations that are rarely expressed by full colexification
- Affix colexification seems to capture a more direct relationship between concepts than overlap colexification

**Enriching embeddings with partial colexification data always leads to better results than relying on full colexification data alone!**

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