A Generative Model of Words and Relationships from Multiple Sources

cBio@MSKCC

@__hylandSL

code and data:
https://github.com/corcra/bf2

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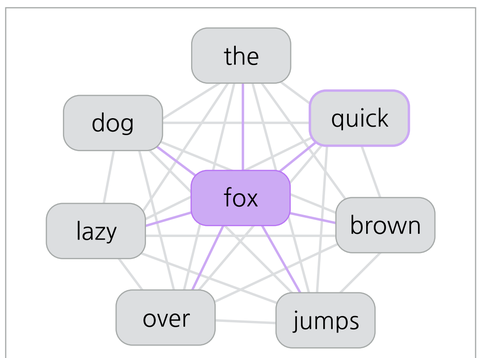
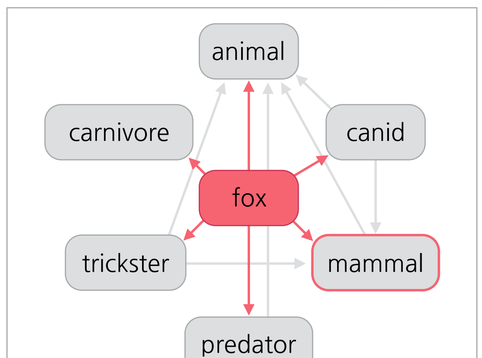
Introduction

- **Word embeddings:** useful semantic representations for downstream natural language processing tasks:
  - distance in embedding space ~ semantic distance
  - learn using **co-occurrence statistics**
- Notion of **similarity** is context-specific: each type of relationship defines new **similarity measure**
- Generalise co-occurrence to include structured data

unstructured text



structured knowledge



Model

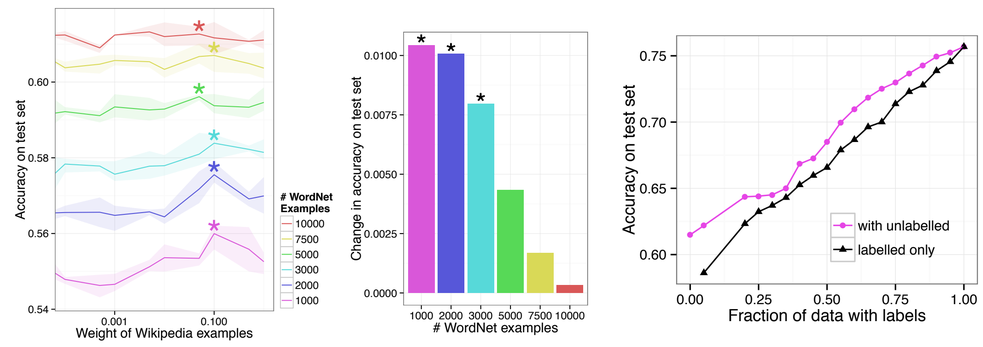
- Joint distribution over (**S, R, T**) triples, directed relationship **R** between source entity **S** and target entity **T**
- Words (**S** and **T**) represented by vectors, relationships **R** by **affine transformations** to allow relationship-specific similarity measure
- Energy function (cosine similarity): $\mathcal{E}(S,R,T|\Theta) = -\frac{\mathbf{v}_T \cdot G_R \mathbf{c}_S}{\|\mathbf{v}_T\| \|G_R \mathbf{c}_S\|}$
- Boltzmann distribution: $P(S,R,T|\Theta) = \frac{1}{Z(\Theta)} e^{-\mathcal{E}(S,R,T|\Theta)}$
- Missing labels can be summed over, e.g. to infer **latent relationships**

tamoxifen CAN_TREAT *breast_cancer*
dog APPEARS_IN_SENTENCE_WITH *fox*
brain IS_LOCATION_OF *glioma*
fox IS_HYPONYM_OF *carnivore*

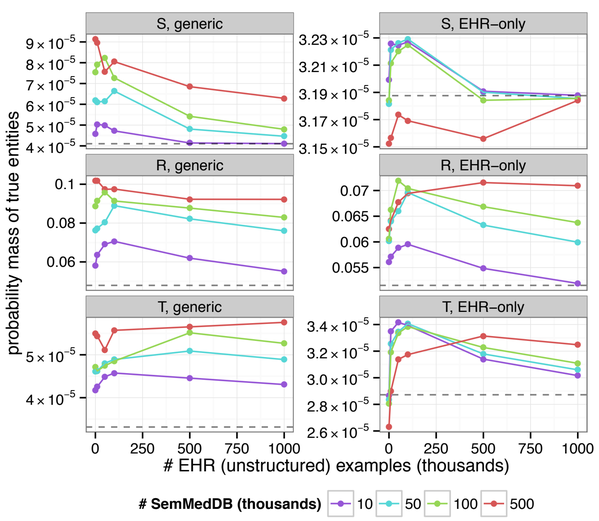
- Relationship is general: can combine **unstructured** (sentence co-occurrence) and **structured** (proximity in graph) sources
- Training: **stochastic maximum likelihood** (PCD) with Gibbs sampling

Experiments

- Triplet **classification**: predict if (**S, R, T**) is true/false: unstructured data helps when structured data is scarce, as does **unlabelled** unstructured data



Edge prediction: predict **R** given **S** and **T**, etc.: report total probability of all correct responses



Knowledge transfer: we can predict relationships between entities appearing **only** in the unstructured (EHR) data

Data

- **Generic English:** Wikipedia (unstructured), WordNet (structured)
  - 12 relationships (including APPEARS_IN_SENTENCE)
  - 112,581 WordNet training examples
- **Medical English**: electronic health records (EHR) from MSKCC (unstructured), SemMedDB (structured)
  - took top 20 relationships from SemMedDB
  - identified UMLS concepts in EHR

Conclusion

- Our model learns embeddings using both **distributional statistics** and **structured knowledge**
- Relationships between words are **affine transformations** of the space
- Combining data sources can improve the quality of embeddings
- We can predict relationships for **previously unobserved** entities

Kilicoglu *et al*. 2012. SemMedDB: a PubMed-scale repository of biomedical semantic predications. (*Bioinformatics)*
Mikolov *et al.* 2013. Distributed representations of words and phrases and their compositionality. (*NIPS)*
Tieleman, T. 2008. Training restricted Boltzmann machines using approximations to the likelihood gradient. *(ICML)*.
Socher *et al*. 2013. Reasoning with neural tensor networks for knowledge base completion. *(NIPS)*

paper: