







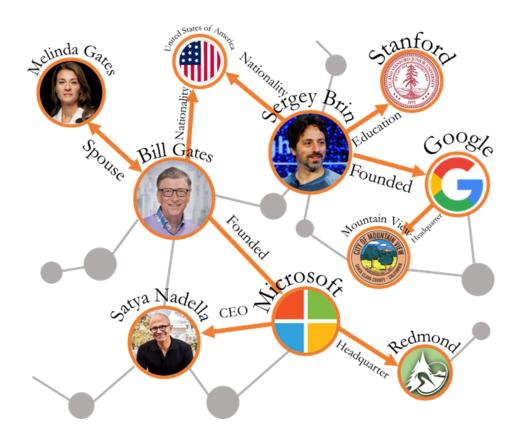
# Learning Relation Entailment with Structured and Textual Information

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Carnegie Mellon University<sup>1</sup>, Bosch Research North America<sup>2</sup>, Ohio State University<sup>3</sup> zhengbaj@cs.cmu.edu

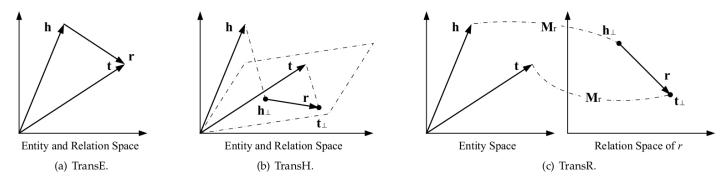
#### Motivation

• Relations among entities play a fundamental role in knowledge graphs.



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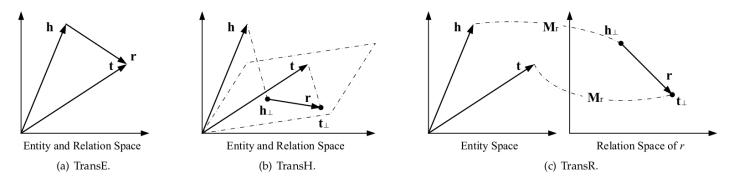
• However, relations are treated as independent.



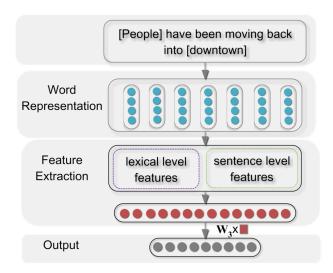
KG embedding: each relation is treated as an atomic unit with separate parameters.

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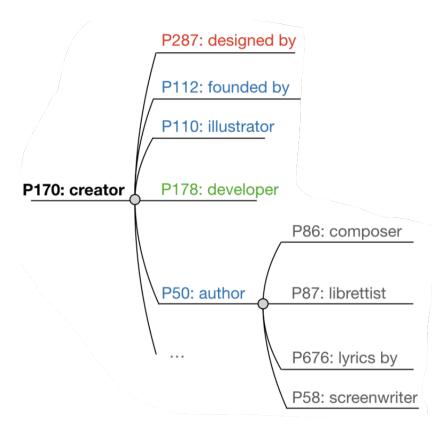
KG embedding: each relation is treated as an atomic unit with separate parameters.



Relation extraction: each relation is an independent class.

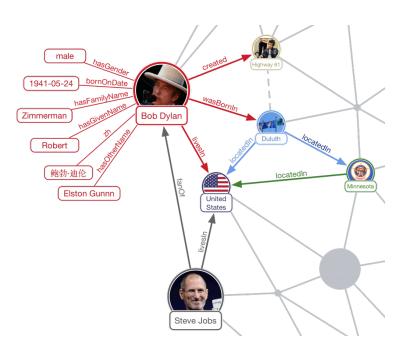
#### Meta-relation: Relations Between Relations

• Relation entailment: existence of one relation can entail the existence of another relation.



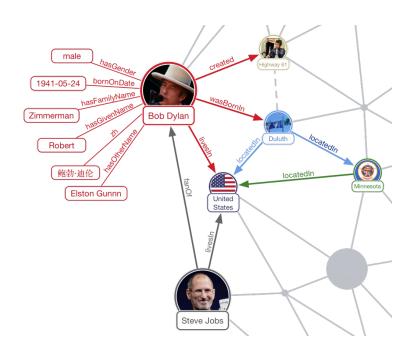
# Applications of Relation Entailment

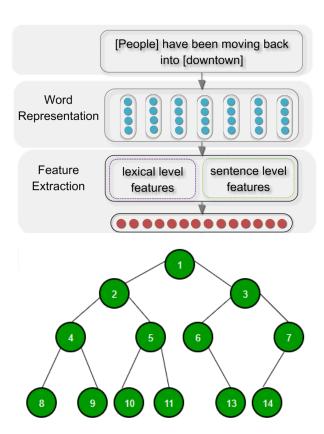
• Knowledge graph representation learning.



### Applications of Relation Entailment

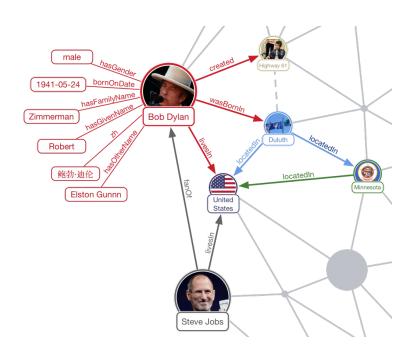
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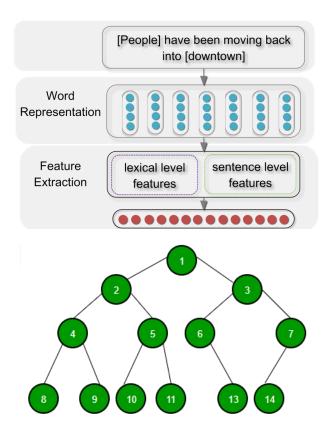


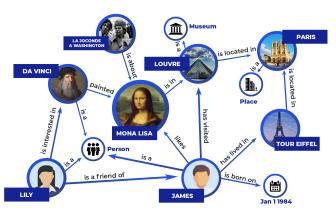


### Applications of Relation Entailment

- Knowledge graph representation learning.
- Relation extraction.
- KG-based question answering.



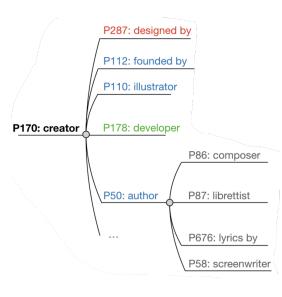




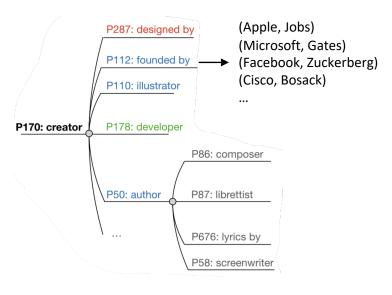


#### Relation Entailment Task Definition

- Notations
  - Head and tail entities  $h, t \in \mathcal{E}$ .
  - Relations  $r \in \mathcal{R}$ .
  - Instances of a relation  $C_r = \{(h, r, t)^{(i)}\}_i$ .
- Relation entailment
  - $r \models r'$  if and only if  $C_r \subseteq C_{r'}$ .
- Task of predicting relation entailment
  - Given a relation r, choose its (direct) parent  $r' \in \mathcal{L}$ .
  - A  $|\mathcal{L}|$ -way multi-class classification problem.

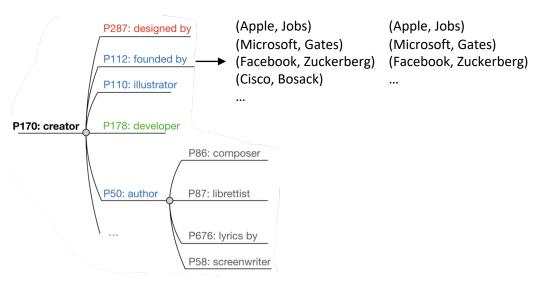


#### 1. Instances collection



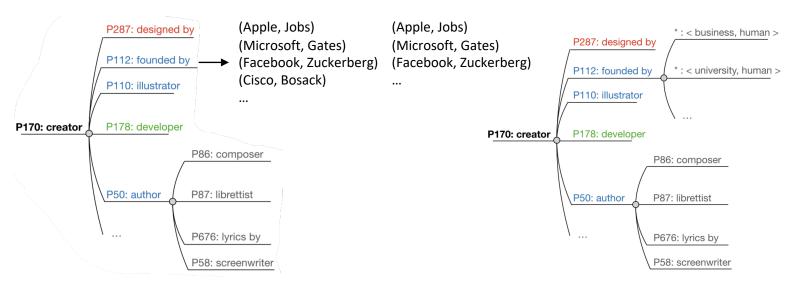
#### 1. Instances collection

#### 2. Downsampling



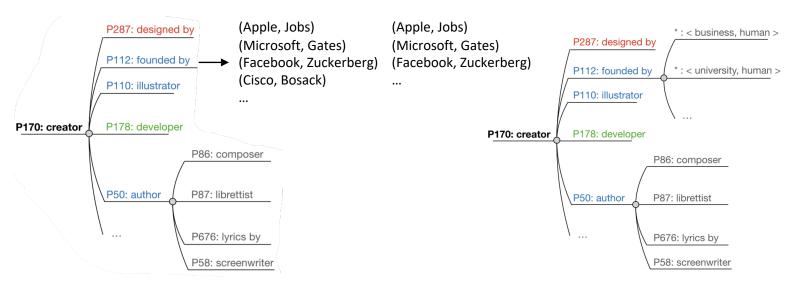
#### 1. Instances collection

#### 2. Downsampling 3. Relation expansion



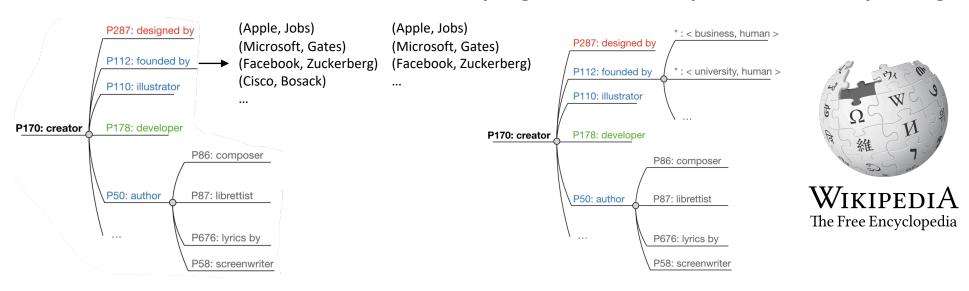
#### 1. Instances collection

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parent	Sub-relations
parent organization	<pre><laboratory, university="">, <airline, airline="">, <record label="" label,="" record="">,</record></airline,></laboratory,></pre>
architectural style	<railway architectural="" station,="" style="">, <church, architectural="" style="">,</church,></railway>
award received	<film, academy="" awards="">, <human, campaign="" medal="">, <human, scholarship="">,</human,></human,></film,>

#### 1. Instances collection 2. Downsampling 3. Relation expansion 4. Entity linking

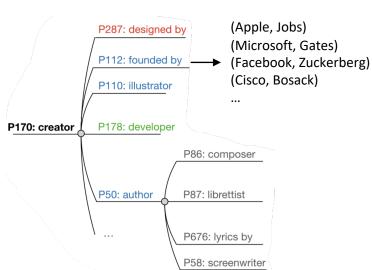


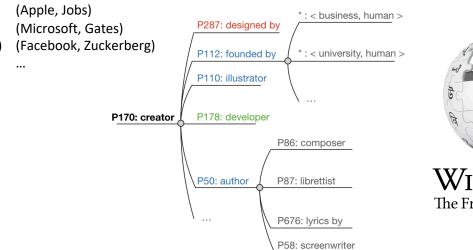
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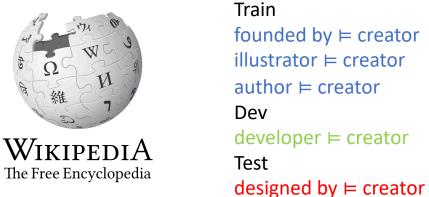
#### 1. Instances collection

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#### 5. Train/dev/test split

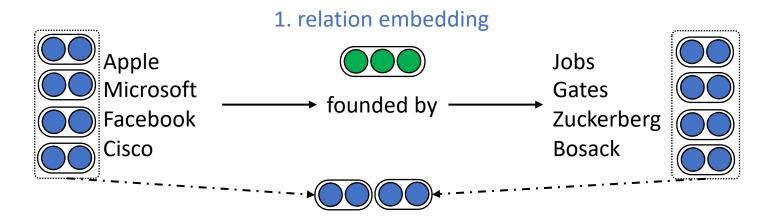




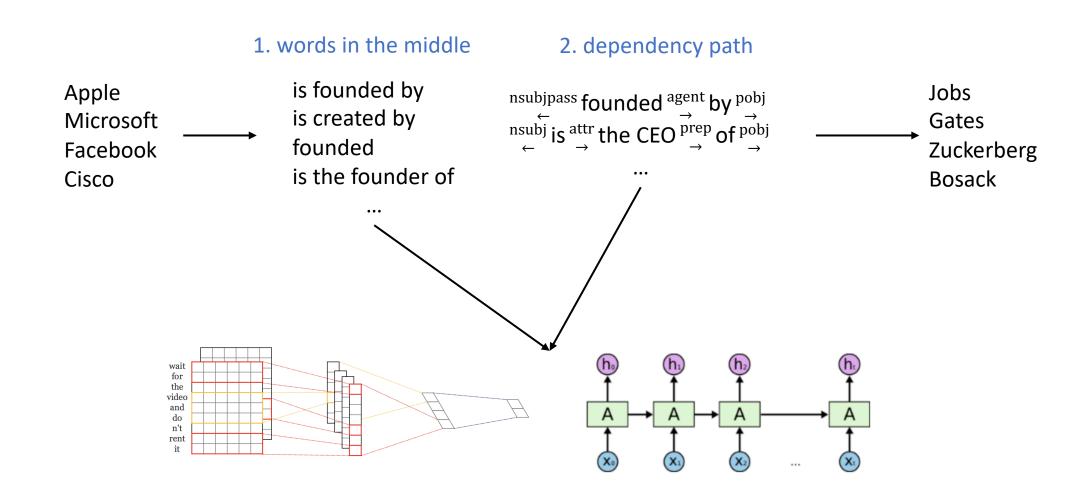


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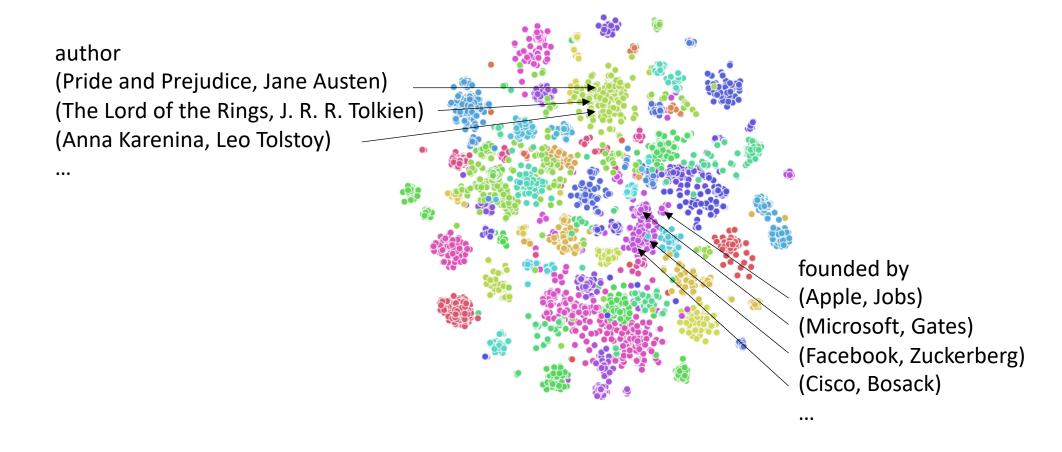
• With structured information



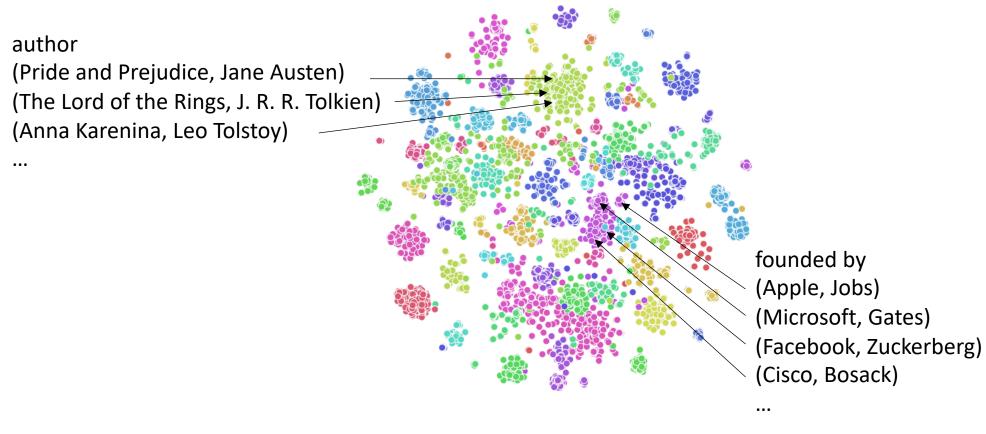
With textual information



• Distribution-based



• Distribution-based



Kernel density estimation with a Gaussian kernel

#### Relation Entailment Prediction

cos( **()**, Unsupervised methods Supervised methods

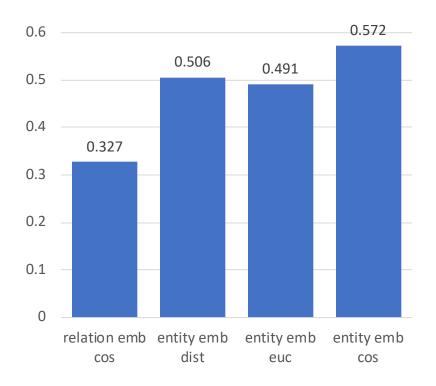
### Experimental Settings

- RelEnt Dataset
  - #Train, #Dev., #Test relations: 2055, 804, 692
  - #Classes: 498

- Evaluation Metrics
  - Accuracy@1, Accuracy@3, and mean reciprocal rank (MRR)

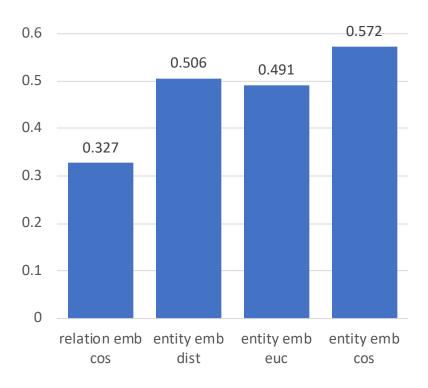
- Implementation Details
  - KG embedding methods: TransE, DistMult, ComplEx.
  - 50-dimensional GloVe embeddings.
  - BiLSTM with 64 hidden units, CNN with window size of 3 and 64 filters.

# Unsupervised Methods' Results

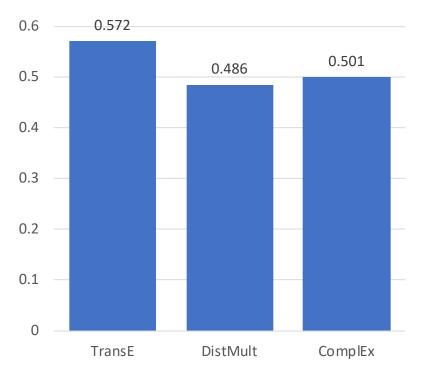


Acc@1 of different unsupervised methods with TransE.

### Unsupervised Methods' Results



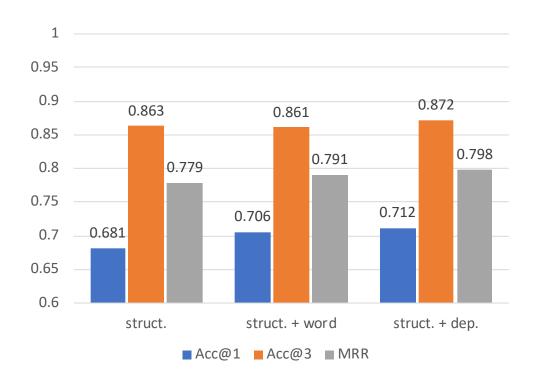
Acc@1 of different unsupervised methods with TransE.



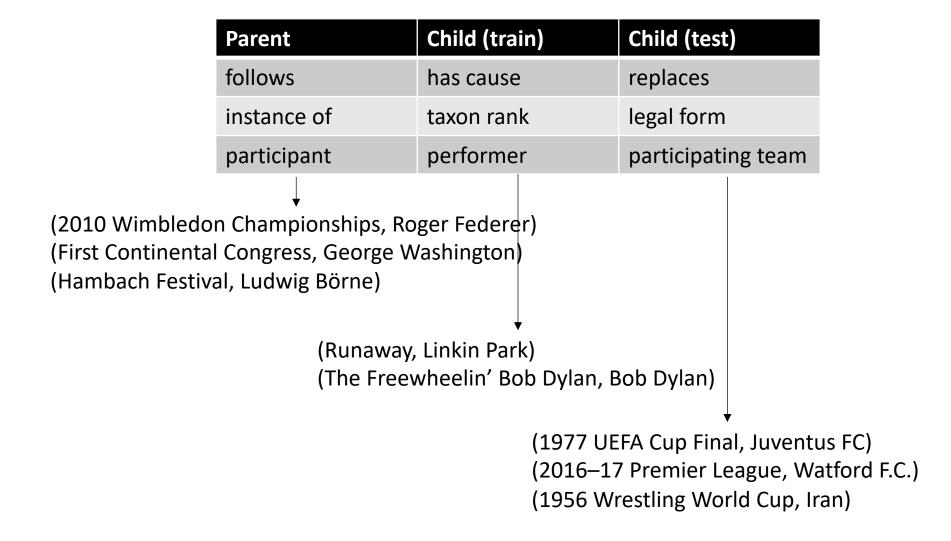
Acc@1 of entity embedding with cosine using different KG representations.

### Supervised Methods' Results

- Supervised > unsupervised.
- Textual information is complementary to structured information.



#### Error cases











#### Take away

- 1. Both structured and textual information contribute to relation entailment prediction.
- 2. Relation entailment prediction requires high-level abstraction.

Paper: <a href="https://openreview.net/pdf?id=ToTf">https://openreview.net/pdf?id=ToTf</a> MX7Vn

Code: <a href="https://github.com/jzbjyb/RelEnt">https://github.com/jzbjyb/RelEnt</a>