

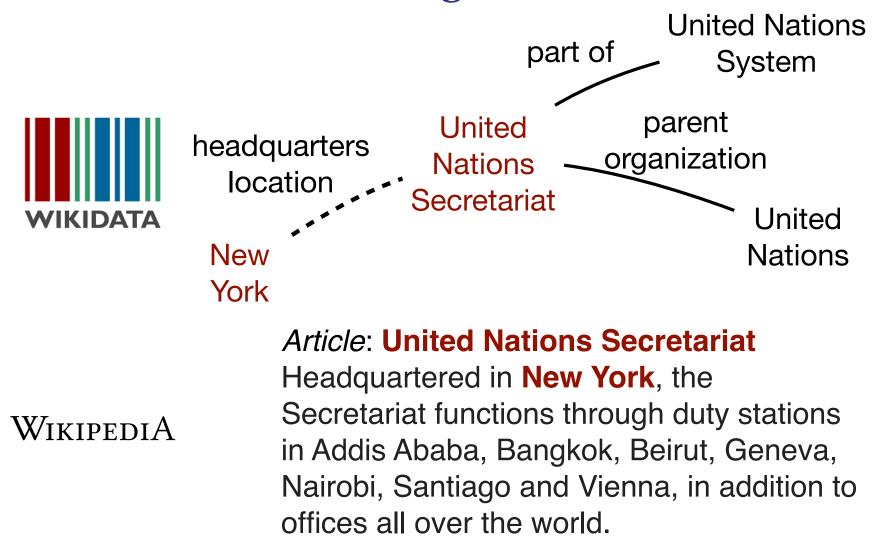
A Systematic Investigation of KB-Text Embedding Alignment at Scale



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Motivation

- Methods to separately embed KBs and text into a vector space(s) have been well-studied.
- Will aligning the KB and text vector spaces be an effective way to inject KB information into text embedding and vice versa?
- If so, what is the best alignment method?

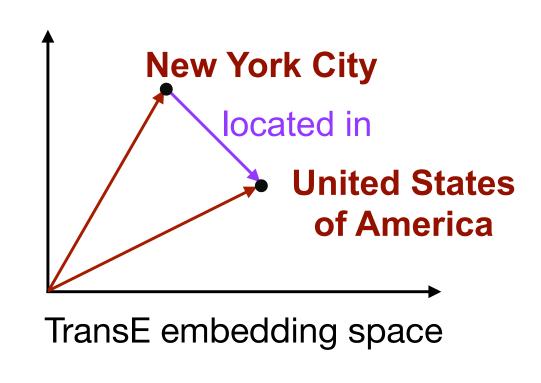


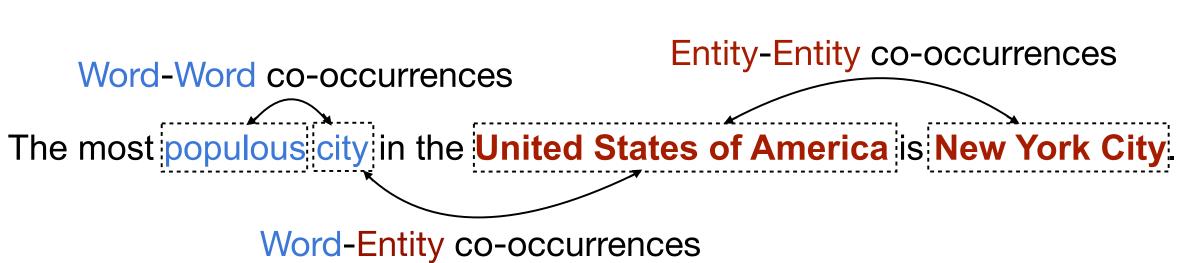
Key Contributions

- First systematic investigation on KB-text embedding alignment at scale.
 - Wikidata: 14.6M entities, 1.2K relations, 261M facts
 - Wikipedia: 8.2M articles, 2.1M words, 12.3M entities
- Evaluation framework with two tasks:
 - Few-shot link prediction: text → KB
 - Analogical reasoning: KB → text
- Release joint KB-text embeddings trained on the largest-scale data to date.

Embedding Methods

Knowledge Base embedding model: TransE Text embedding model: Skip-gram



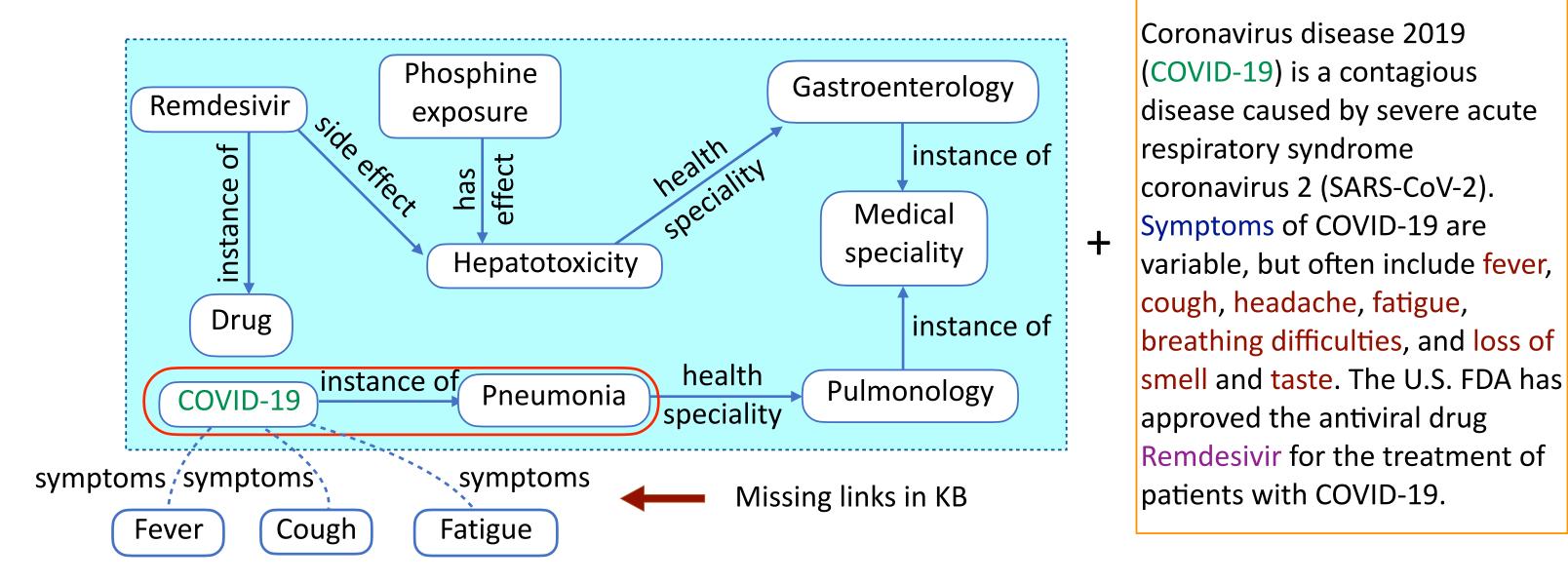


Alignment Methods Honolulu Honolulu (a) Alignment using Same Embedding **Knowledge Base** Alignment Loss Honolulu Barack Obama **Textual Corpus** (b) Alignment using Projection [Barack Obama] was born i born in [Honolulu]. Barack born_in Honolulu Barack born_in Honolulu Barack born_in Honolulu New edges in Honolulu (c) Alignment using Entity Names Original Entity-Word co-occurrences (Honolulu, was) (Honolulu, born) (Honolulu, in) Entity-Word co-occurrences for alignment (Honolulu), was) (Honolulu), born) (Honolulu), in) (d) Alignment using Wikipedia Anchors Textual Entity Node -- Tie Embedding [Entity Mention]: Wikipedia KB Entity Node Weights

Evaluation Framework

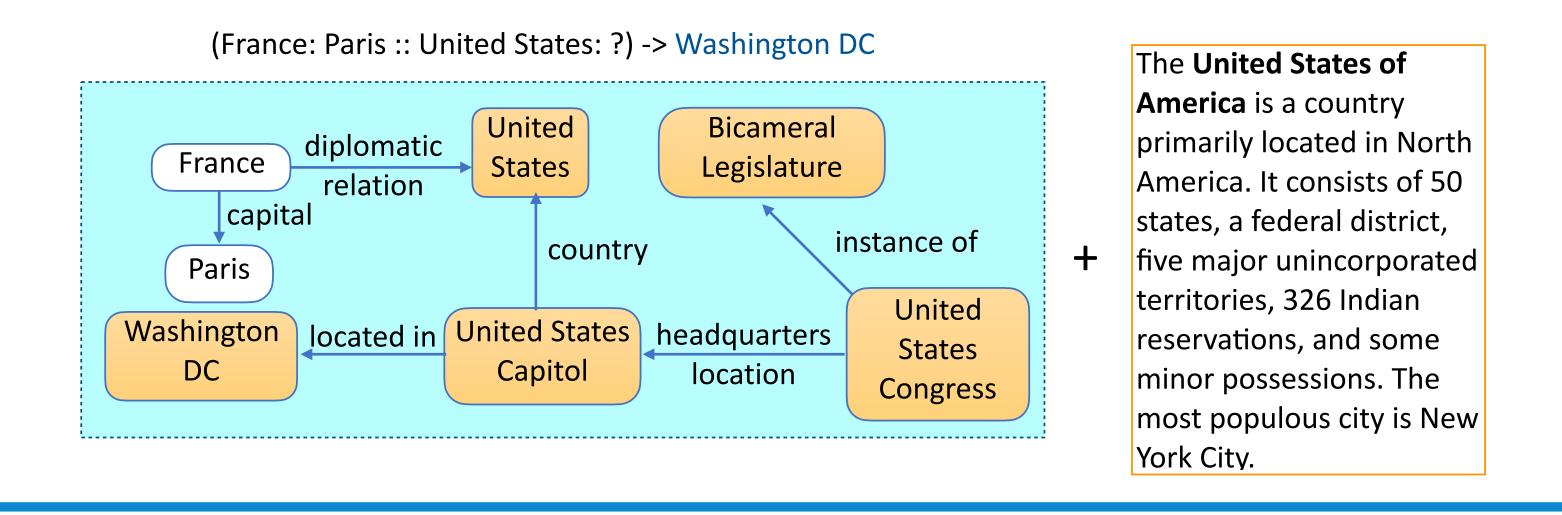
Few-shot link prediction

• Do link prediction for entities occurring rarely in the training set.



Analogical Reasoning

- Test the information flow from the knowledge-base embeddings to the skip-gram embeddings.
- $(h_1:t_1)::(h_2:?)$



Experiments

Overall Results

	Few-shot Link Prediction			Analogical Reasoning		
Model	MR	Hits@1	Hits@10	MR	Hits@1	Hits@10
TransE	187	20.3	40.4	_	_	_
Skip-gram	_	_	_	25	50.6	78.0
Projection	134	22.9	47.2	12	65.9	89.0
Same Embedding align.	102	30.7	51.8	11	60.7	87.5
Entity Name align.	116	23.1	46.7	8	66.5	91.0
Wikipedia Anchors align.	138	25.8	46.2	14	56.1	84.8

Table 1: Overall results for both evaluation tasks.

- Alignment methods significantly outperform the naive TransE and skip-gram baselines for few-shot link prediction and analogical reasoning respectively.
- Joint reasoning through alignment enhances both KB and text entity representations.
- The inductive bias of a particular alignment method can affect its performance on an evaluation task.

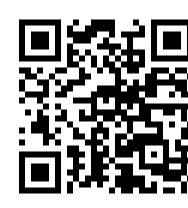
Case Study

- Knowledge base completion for COVID related relations using alignment models.
- Use the March 2020 Wikidata and December 2020 Wikipedia to train the alignment models.
- Evaluate on the difference of COVID related triples between March 2020 and December 2020 snapshots of Wikidata.
- Alignment methods outperform the TransE baseline in a majority of cases.

Relation	TransE	Projection	Same Embed.
Risk factor	312	261	153
Symptoms	37	36	39
Medical cond.	371	267	330
Cause of death	314	246	299

Table 2: Link Prediction results for COVID-19 case study (Mean Rank).

Contact Information





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