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Cross-lingual Entity Alignment with Incidental Supervision

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Understanding Relations Is Prominent In Practice

QA and Semantic Search

Google

mazda car that won 24 Hours of Le Mans

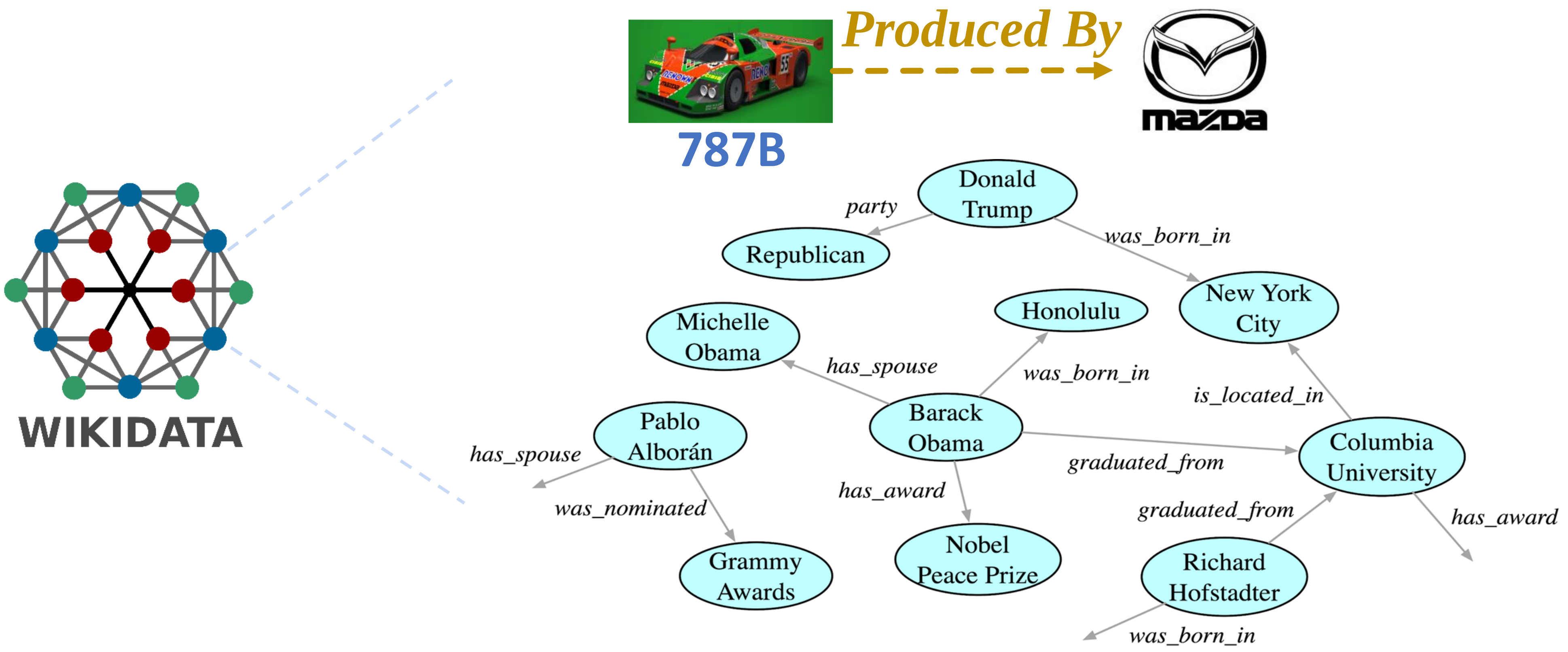
All Images News Shopping Videos More Settings Tools

About 34,600,000 results (1.04 seconds)

787B

(?car, ***produced by***, Mazda)
(?car, ***won***, 24 Hours of Le Mans)

Knowledge Graphs: Precise But **Expensive** Knowledge Representation

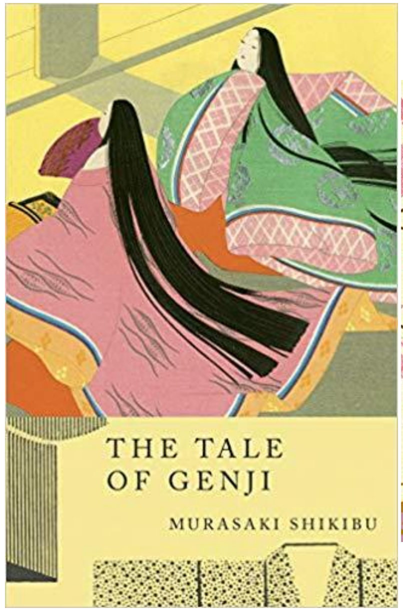


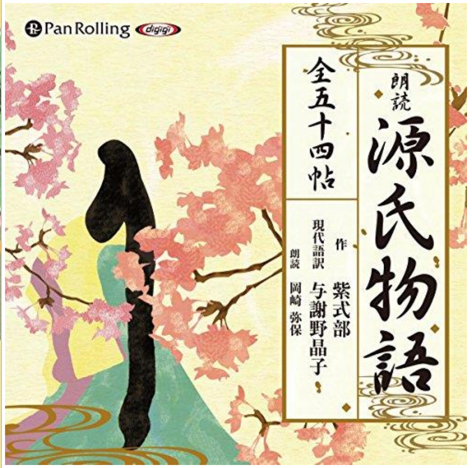
Obtaining the structural knowledge

- Is expensive (Avg $5.71 per triple **[Paulheim+, ISWC-18]** in open domain; higher cost in scientific domains).
- Has relied on massive human efforts.
- Has never been close to complete.

Knowledge Is Not Isolated

Different knowledge graphs can possess complementary knowledge





(The Tale of Genji, *Genre*, **?e**)

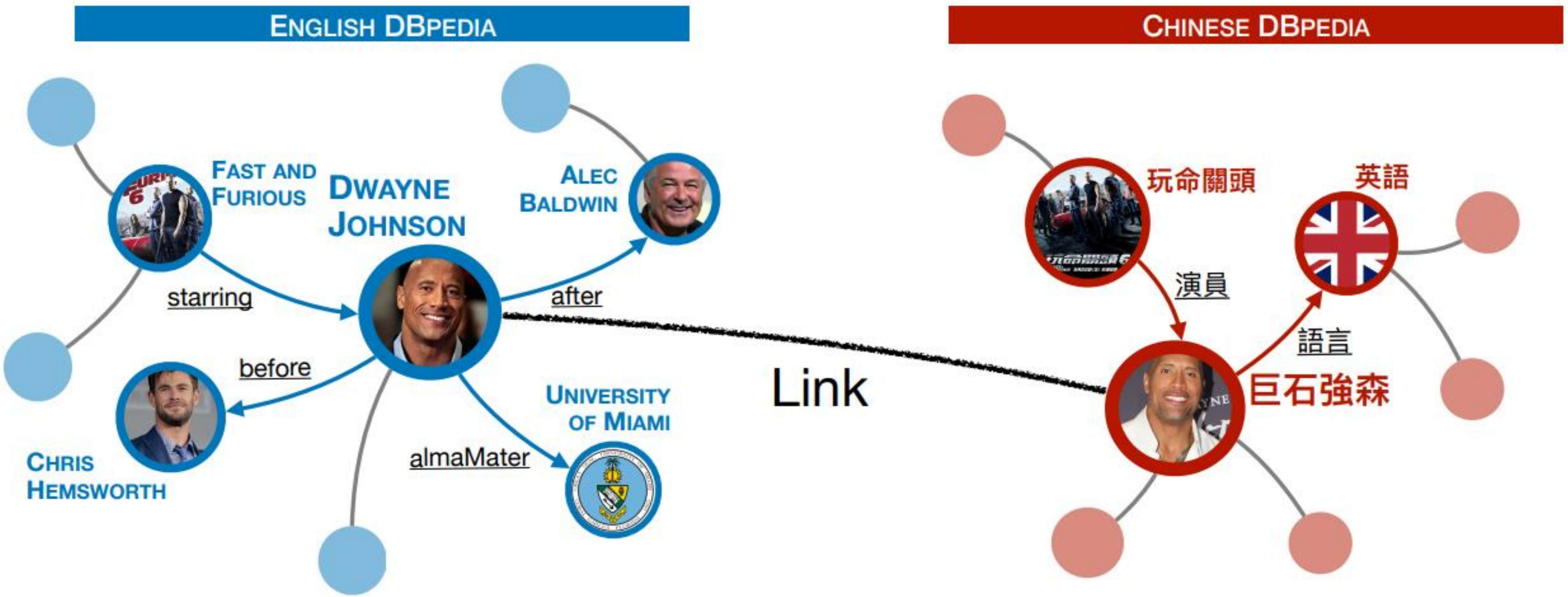
DBpedia

Novel

デビペディア

Monogatari (story)
Love story
Royal family story
Realistic novel
Ancient literature

Entity Alignment



Problem definition

- Given two (multilingual) KGs, identifying the same entity across them

Why important?

- Allows knowledge to be combined and synchronized in different KGs
- Helps with identifying trustworthy facts in KGs

What's New in This Work

Previous methods rely on (costly) direct supervision that is internal to KGs*

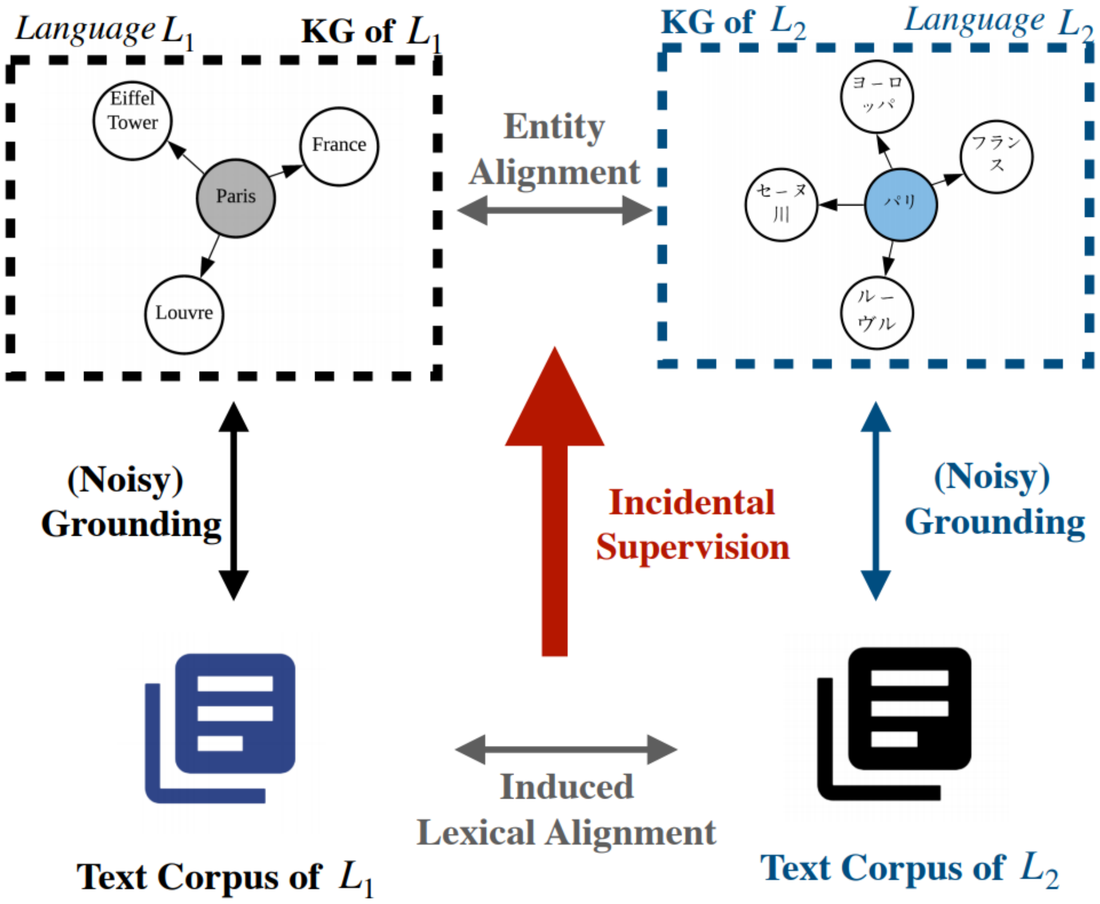
- Seed alignment labels
- Entity profiles: entity descriptions, attributes, etc.

This work leverages (cheap) incidental supervision from external free text

- Connecting entities with any available mentions in free text
- Contextual similarity and induced lexical alignment serve as indirect supervision for entity alignment
- Without the need of any additional labeled data

*>30 methods have been summarized in a recent survey: Sun, et al. A Benchmarking Study of Embedding-based Entity Alignment for Knowledge Graphs. **PVLDB**, vol. 13, ACM, 2020.

Incidental Supervision From Free Text



Three steps

1. ***(Noisy) grounding***: connecting KGs and text corpora
2. ***Embedding learning:*** embedding lexemes based on structures and text
3. ***Alignment induction***: self-learning for both entity and lexical alignment

Noisy Grounding

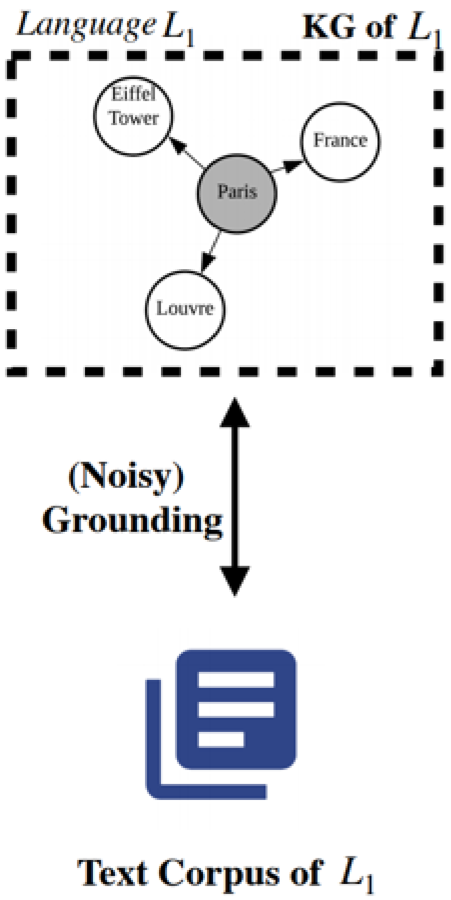
Combining two modalities of the same language

- KG and Free text

Two choices of techniques (without additional training labels)

- Off-the-shelf EDL models [Khashabi+ 2018]: NER + entity linking
- Surface form matching: longest prefix matching with a Completion Trie [Hsu+ 2013]

High recall and noise-tolerant grounding



Embedding Learning

Jointly training two model components

$$S_L^E = S_L^K + S_L^T$$

KG Embedding

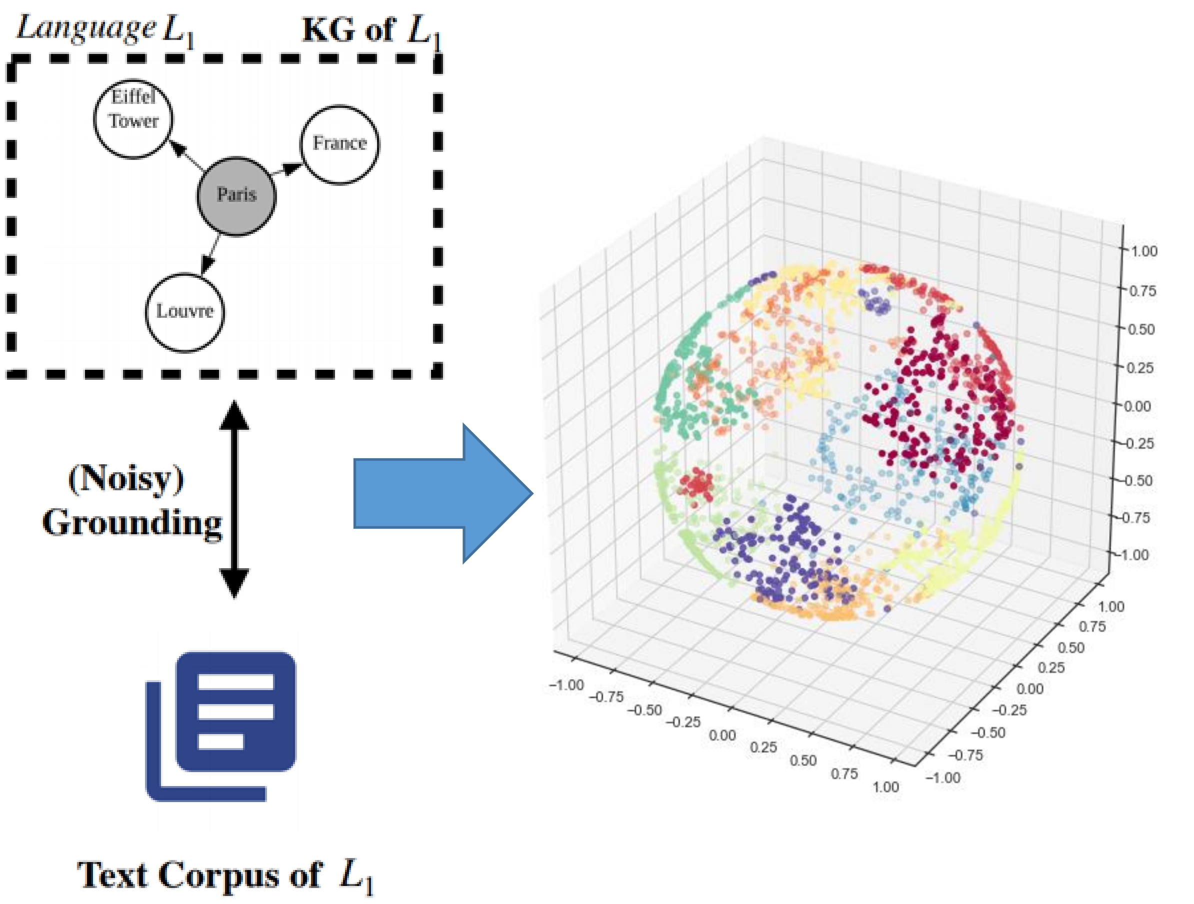
- l-layers of GCNs
- A translational learning-to-rank model

$$S_L^K = -\sum_{T \in G_L} \log \frac{\exp(b - |\boldsymbol{h} + \boldsymbol{r} - \boldsymbol{t}|)}{\sum_{\hat{T} \notin G_L} \exp(b - |\hat{\boldsymbol{h}} + \hat{\boldsymbol{r}} - \hat{\boldsymbol{t}}|)}$$

Text Embedding

- A Skip-Gram language model

$$S_L^T = -\sum_{x \in E_L \cup W_L} \sum_{x_c \in C_{x,D_L}} \log \frac{\exp(d(x, x_c))}{\sum_{x_n} \exp(d(x, x_n))}$$



Embedding based on both structural and textual contexts

Alignment Induction

Iteratively inducing alignment

In each iteration

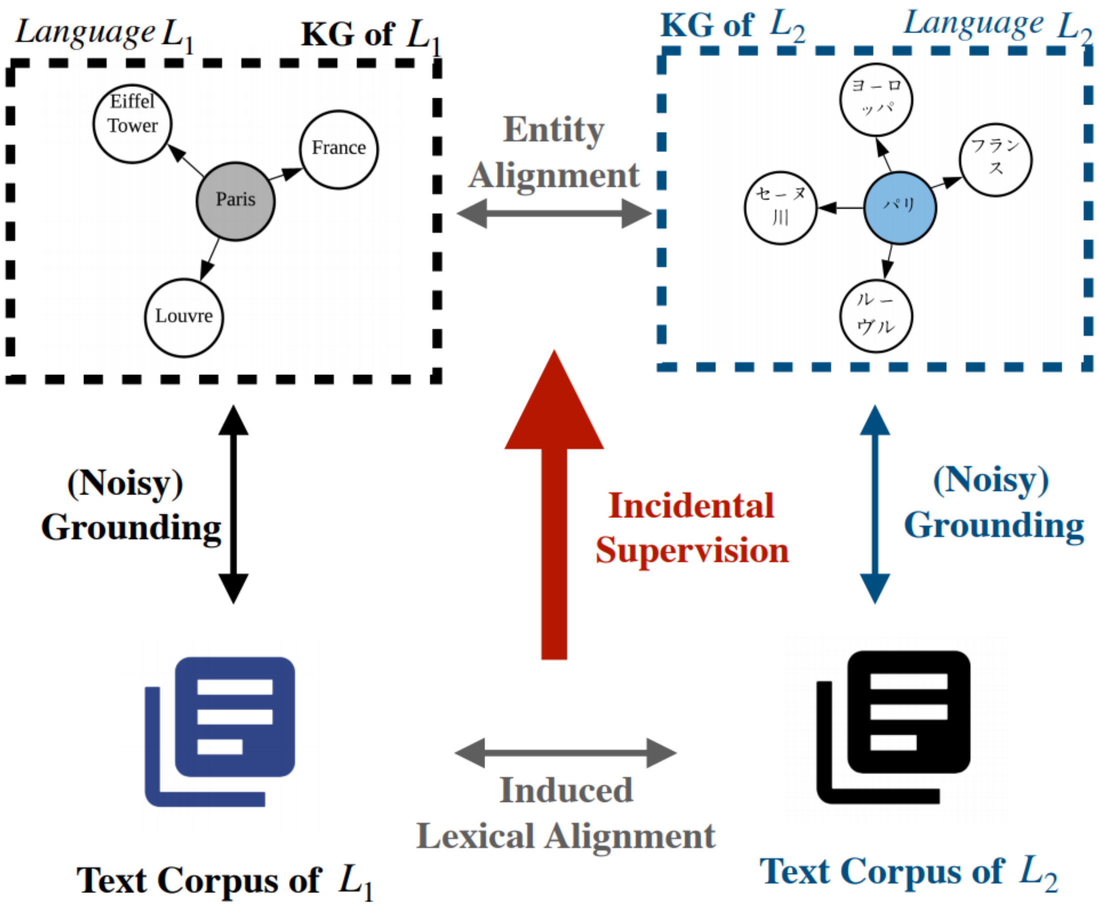
- Obtaining the closed-form Procrustes solution

$$S^{A}_{L_i,L_j} = \sum_{(x_i,x_j)\in I(L_i,L_j)} \left|\boldsymbol{M}_{ij}\boldsymbol{x}_i - \boldsymbol{x}_j\right|_2$$

- Propose new alignment pairs that are **mutual nearest neighbors (NN)**

- Continue until no mutual NNs are found

Lexical alignment serves as incidental supervision signals for entity alignment



Experiments

Datasets

- **DBP15k**: alignment between KGs of 4 languages (EN, FR, JA, ZH); ~30% seed alignment in training
- **WK3l**: alignment between KGs of 3 languages (DE, EN, FR); ~ 20% seed alignment in training

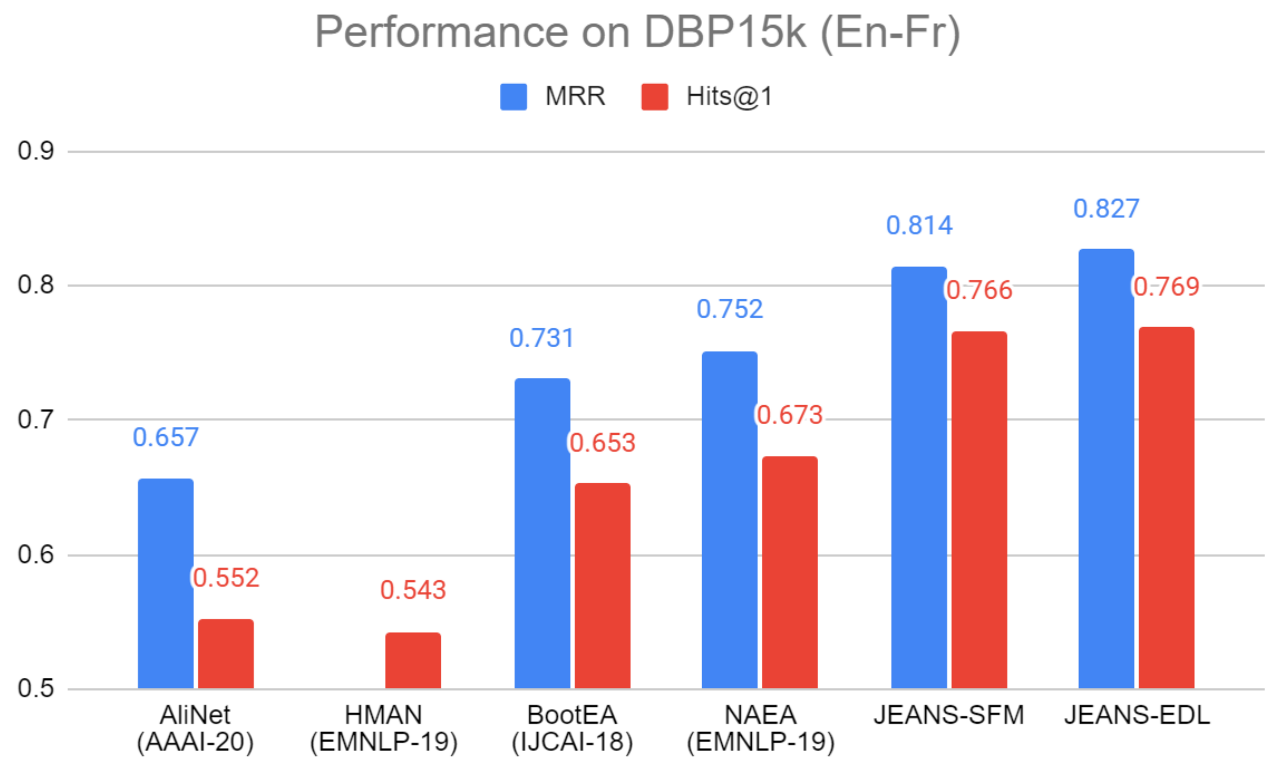
Metrics

- Ranking metrics including MRR, Hits@k (k=1, 10)

Baselines

- 10 supervised methods (**AliNet** [Sun+ 2020] is the best performing one)
- 3 based on auxiliary information (**HMAN** [Yang+ 2019] is the best performing one with entity descriptions)
- 5 semi-supervised methods (**BootEA** [Sun+ 2018] is the representative method, and **NAEA** [Zhu+ 2019] is the best performing one)

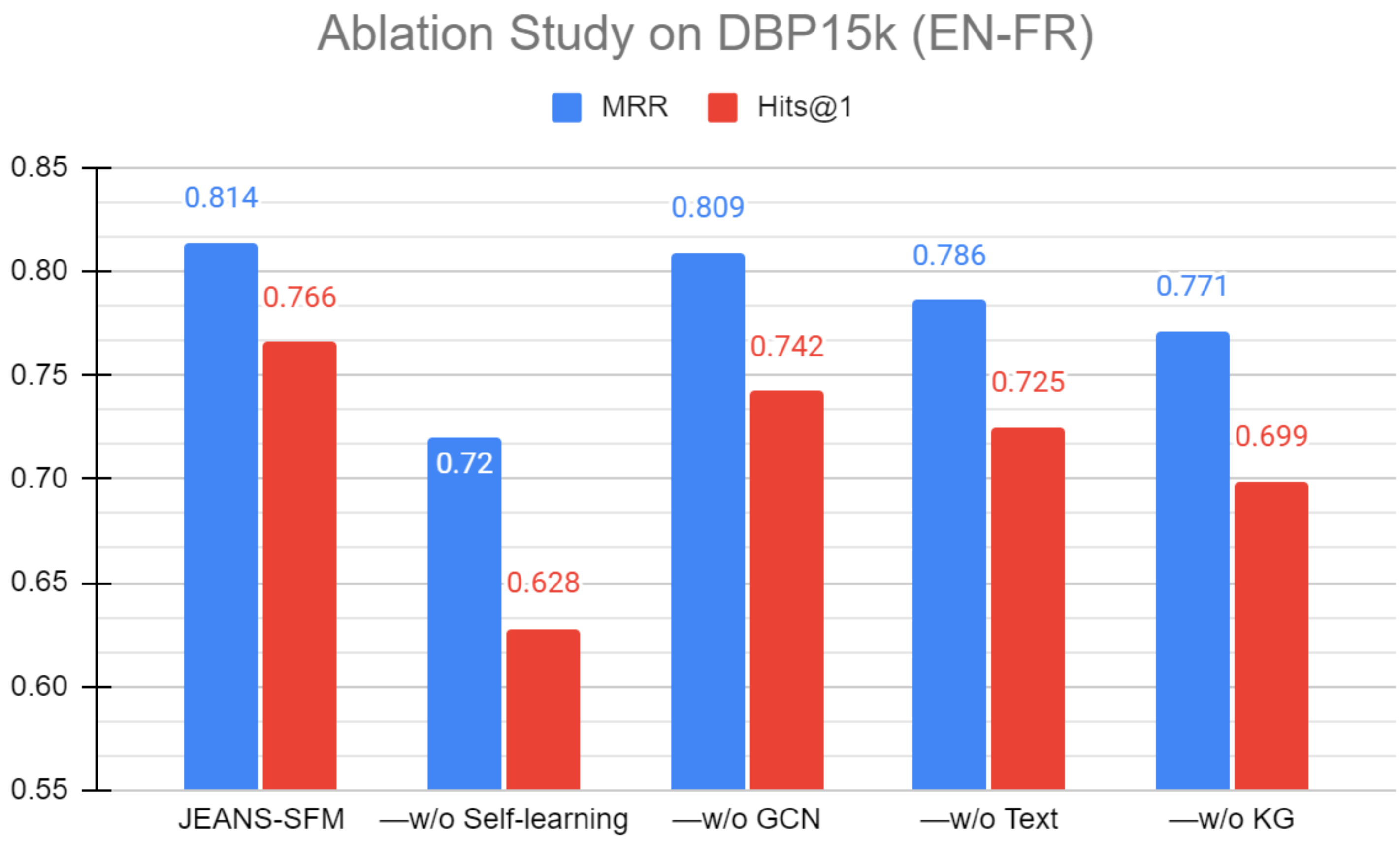
Experiments



Observations are consistent on all experimental settings

- Incidental supervision from free text effectively improve entity alignment on KGs
- Using pre-trained EDL or simple surface form matching (SFM) as grounding does not affect much the performance

Ablation Study



- Self-learning brings the most contribution
- Structural information from KGs is important
- Text information is a good addition

Conclusion

Contributions of this work

- An incidentally supervised method for entity alignment on KGs
- Instead of using (expensive) direct supervision from internal information of KGs, this work retrieves (cheap) supervision signals from external, unlabeled text
- New SOTA on benchmarks

Future directions

- Low-resource language KG construction and verification
- Application to low-resource scientific domains, e.g. pharmacy and genomics

References in the Slides

1. Paulheim, et al. How Much is a Triple? ISWC 2018
2. Khashabi, et al. Cogcompnlp: Your swiss army knife for nlp. LREC 2018
3. Hsu and Ottaviano. Space-efficient data structures for top-k completion. WWW 2013
4. Sun, et al. A benchmarking study of embedding-based entity alignment for knowledge graphs. PVLDB 2020
5. Sun, et al. Knowledge graph alignment network with gated multi-hop neighborhood aggregation. AAAI 2020
6. Zhu, et al. Neighborhood-aware attentional representation for multilingual knowledge graphs. IJCAI 2019
7. Yang, et al. Aligning cross-lingual entities with multi-aspect information. EMNLP-IJCNLP 2019

Thank You