Cross-lingual Entity Alignment with Incidental Supervision

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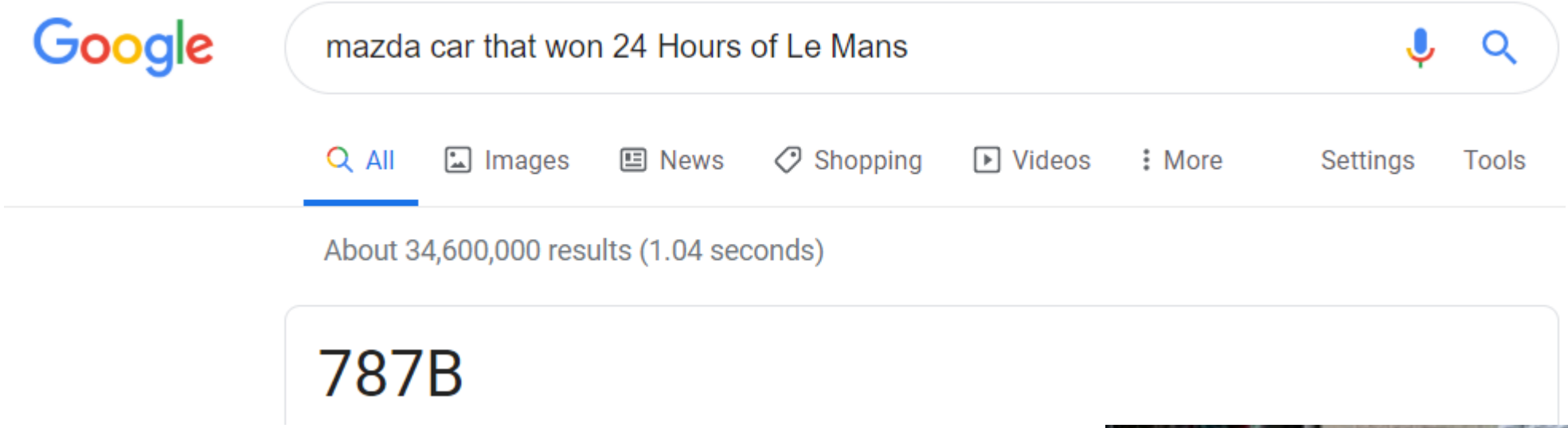
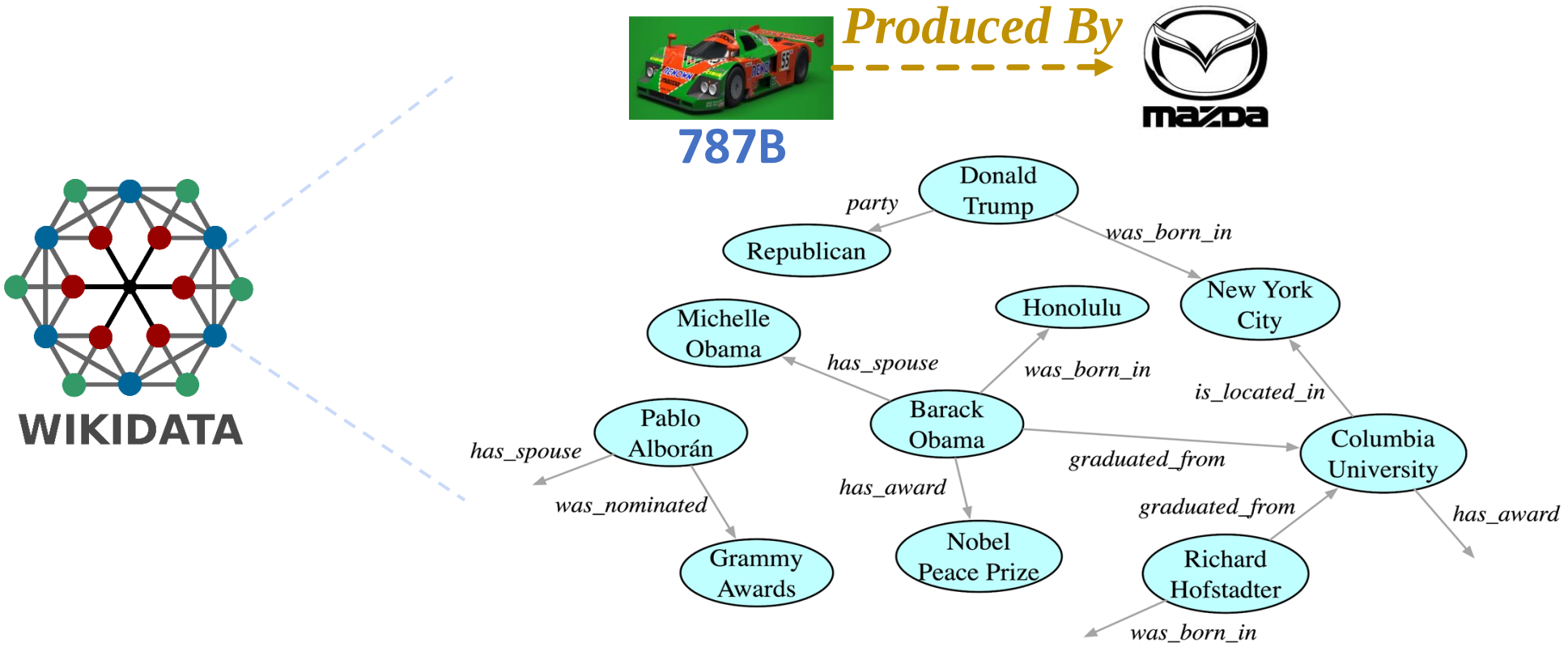
Understanding Relations Is Prominent In Practice

QA and Semantic Search



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

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

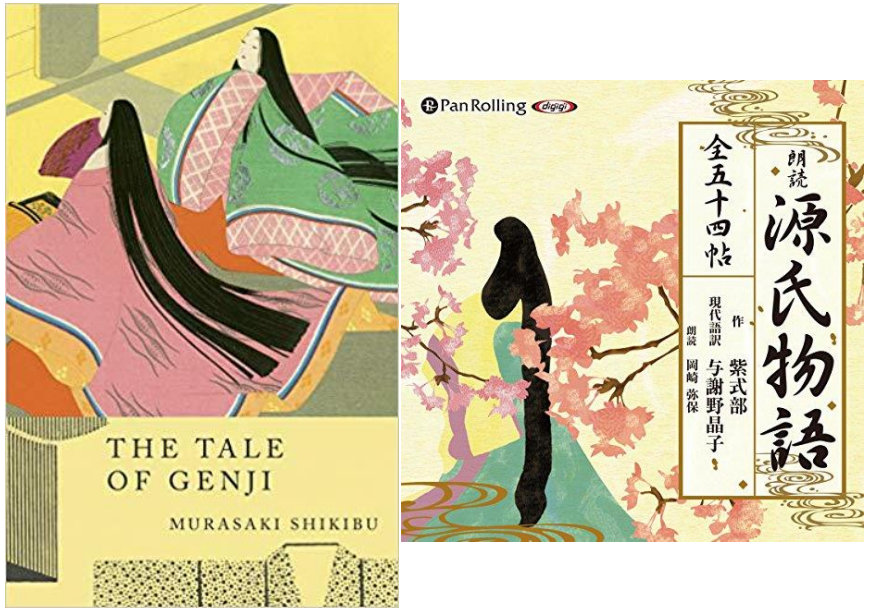


Obtaining the structural knowledge

- 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**)

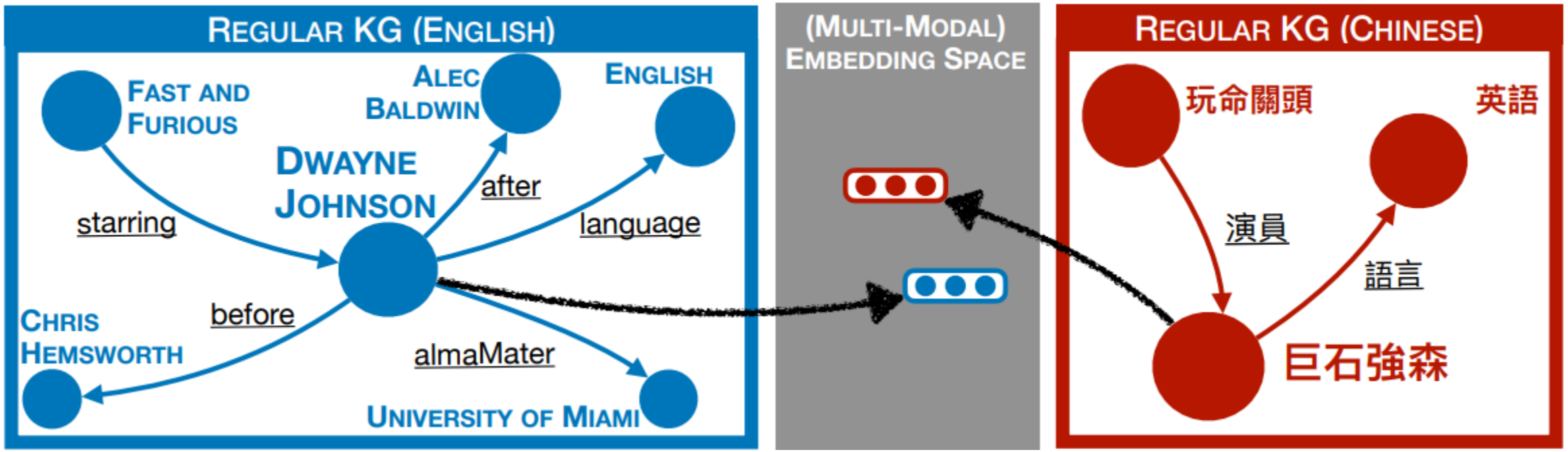
DBpedia

Novel

ヂビペディア

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*

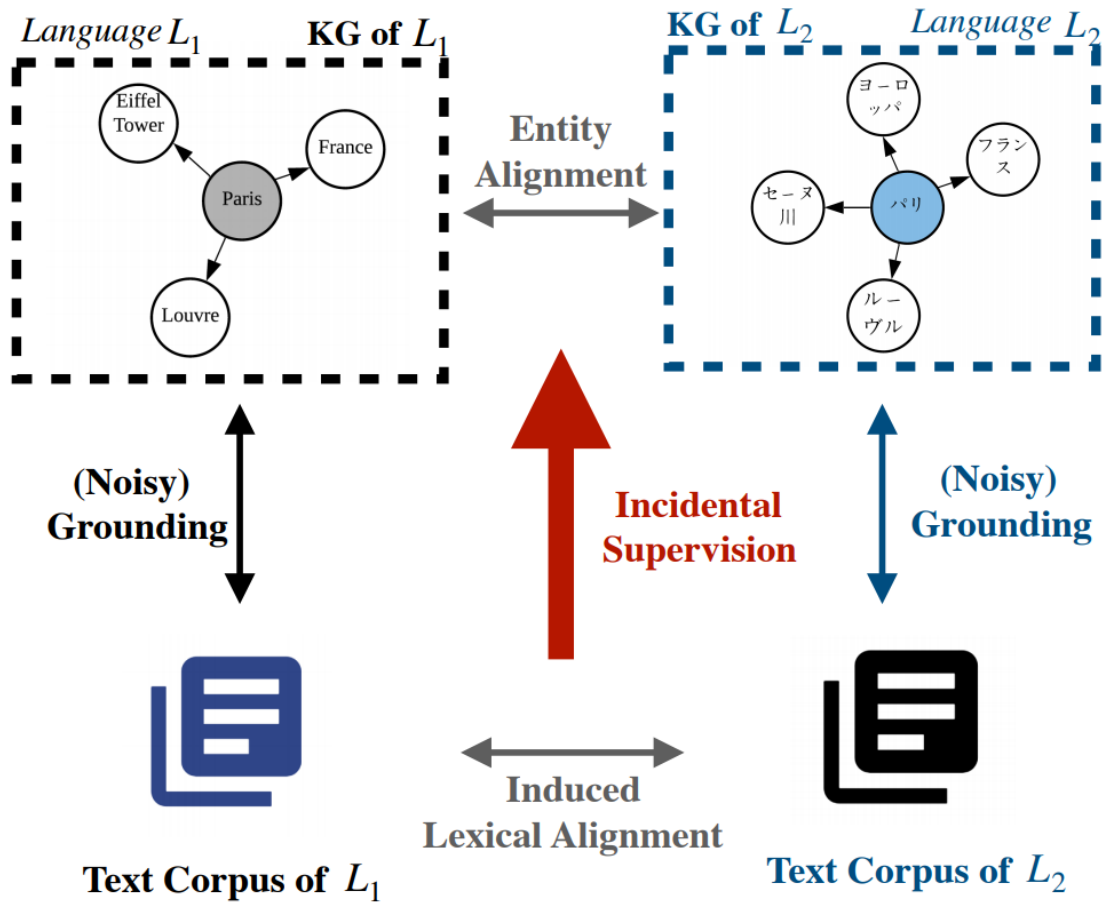
- Seed alignment labels
- Entity profiles: entity descriptions, attributes, etc.

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

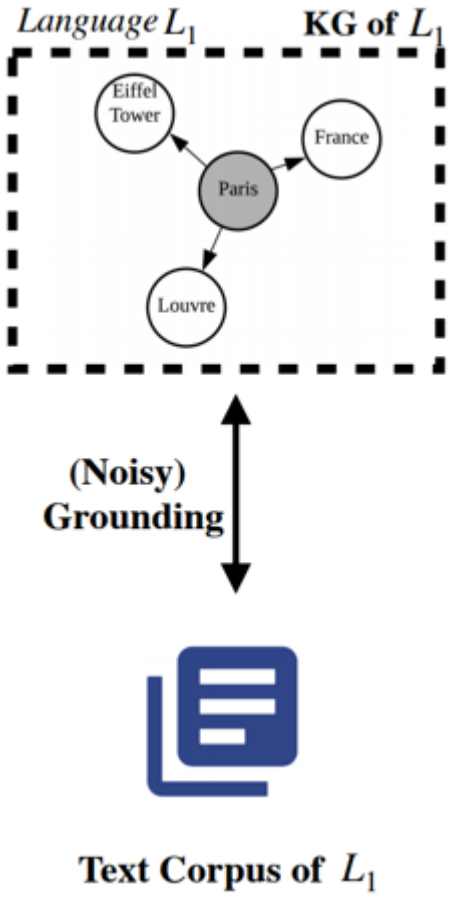
Combining two modalities of the same language

- 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

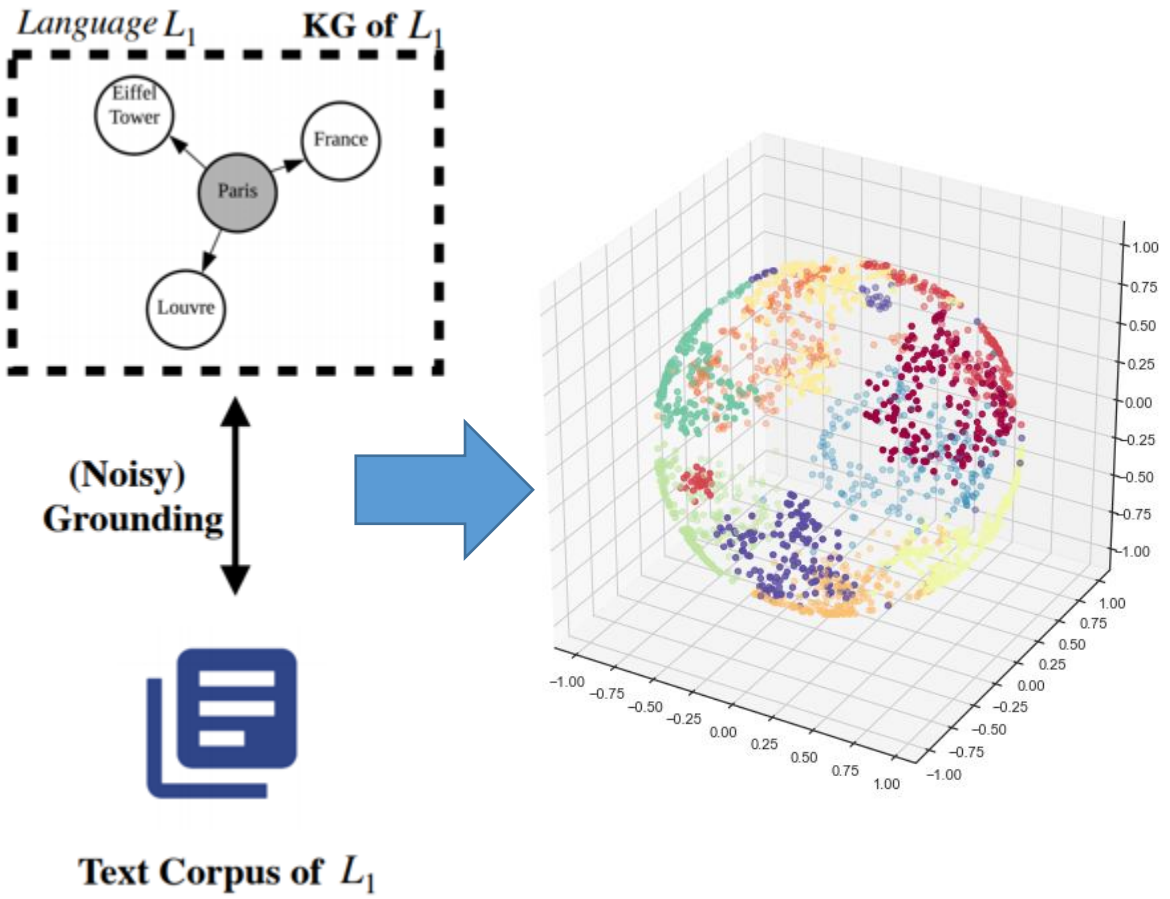
- l-layers of GCNs
- A translational learning-to-rank model

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

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

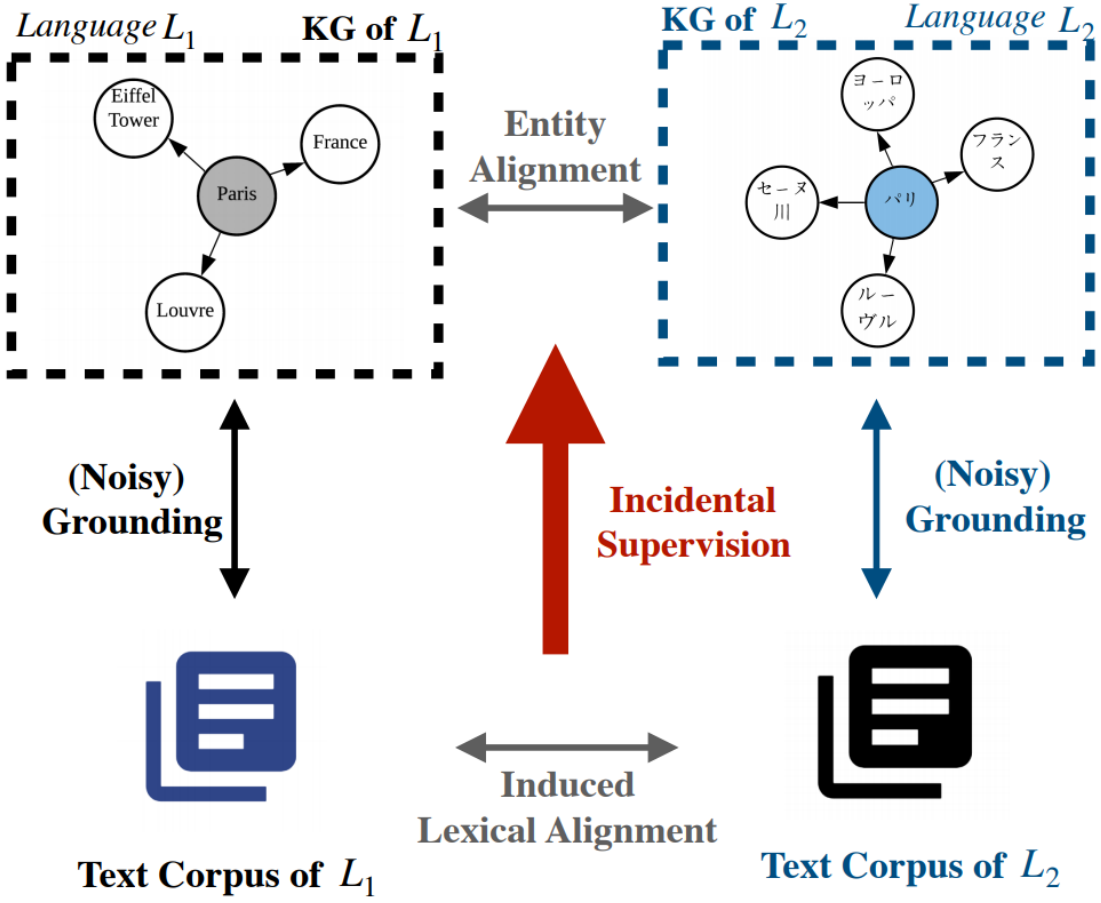
- Obtaining the closed-form Procrustes solution

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

- 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

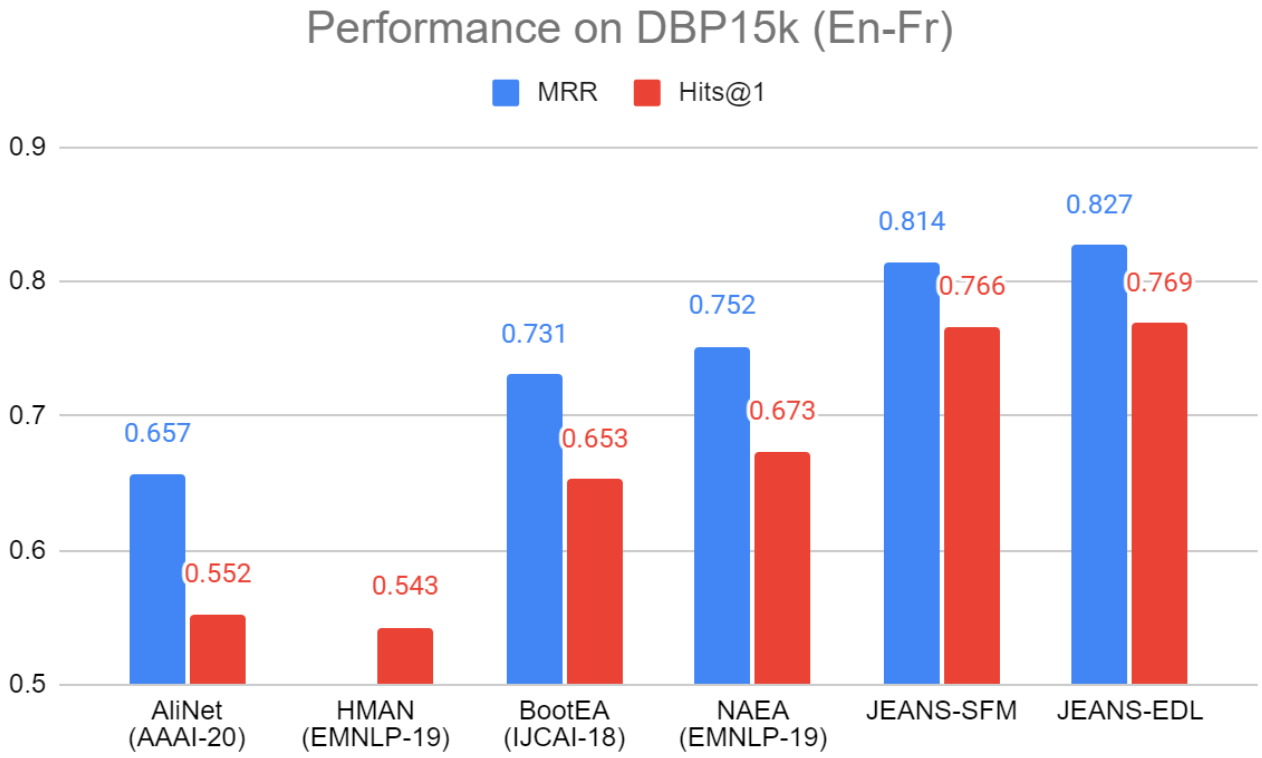
Metrics

- 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)

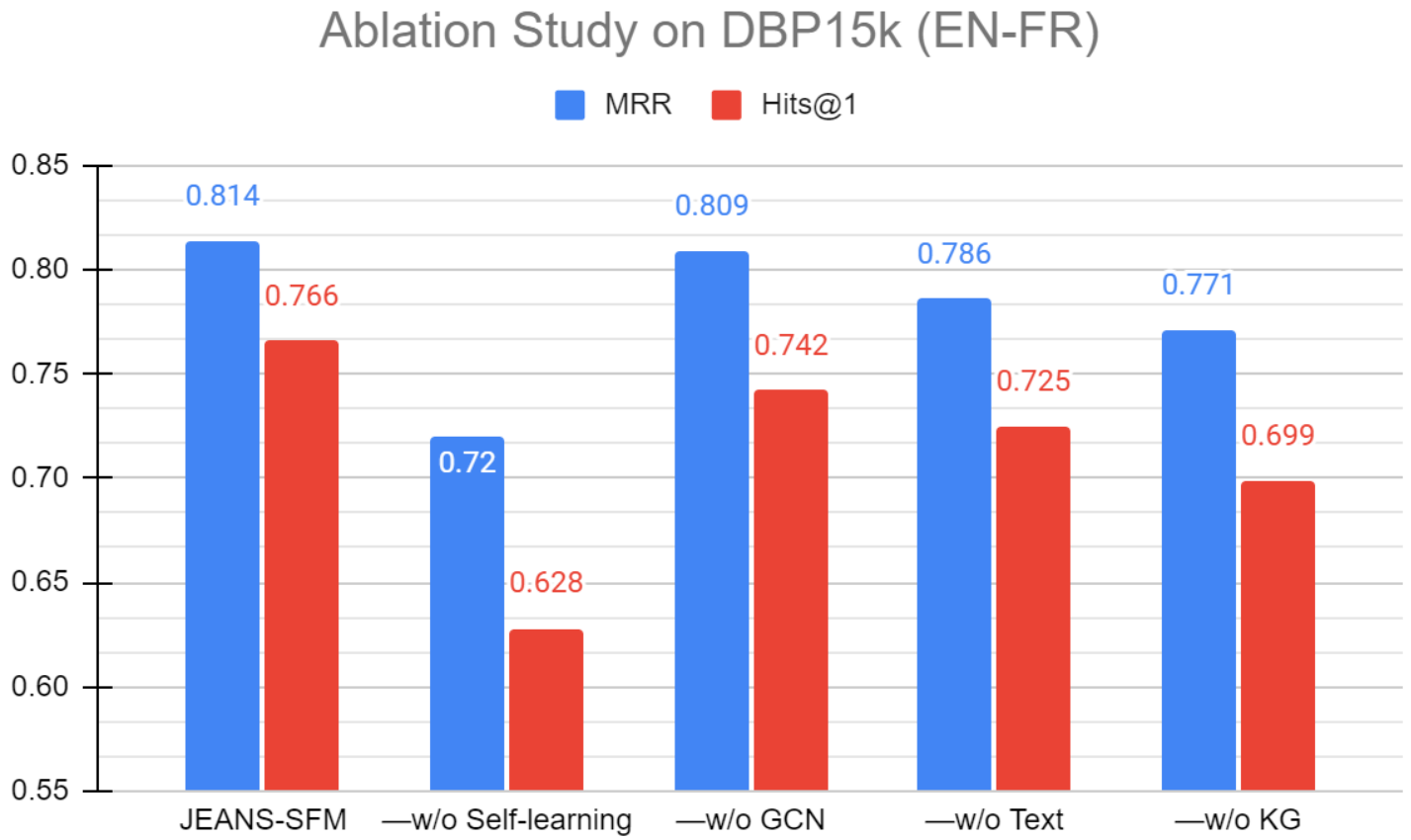
Experiments



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