# Key Facets in Modern Knowledge Graph Representation Learning (KeyKGRL)

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The 24th International Semantic Web Conference (ISWC 2025) Tutorial
https://bdi-lab.github.io/keykgrl_iswc2025/

https://bdi-lab.kaist.ac.kr

# 00 Joyce Jiyoung Whang

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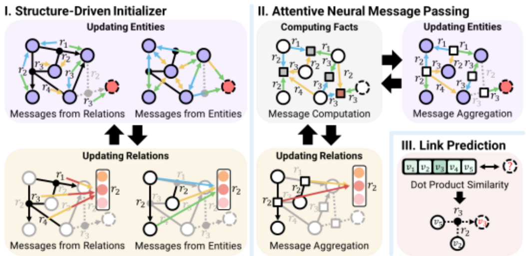
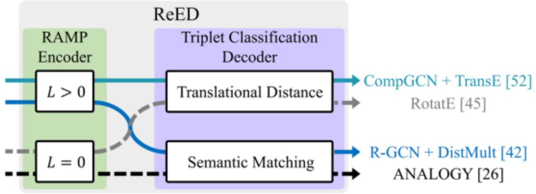
- Ph.D., Computer Science, The University of Texas at Austin, 2015
- Work Experience
  - Associate Professor, School of Computing, KAIST, Sep. 2023 – present
  - Assistant Professor, School of Computing, KAIST, Jul. 2020 – Aug. 2023
  - Assistant Professor, Computer Science, SKKU, Mar. 2016 – Jun. 2020
- Teaching
  - Graph Machine Learning and Mining (KAIST CS471)
  - Machine Learning (KAIST CS376)
  - Advanced Data Mining (KAIST CS665 & DS532, graduate course)

# 00 Big Data Intelligence Lab

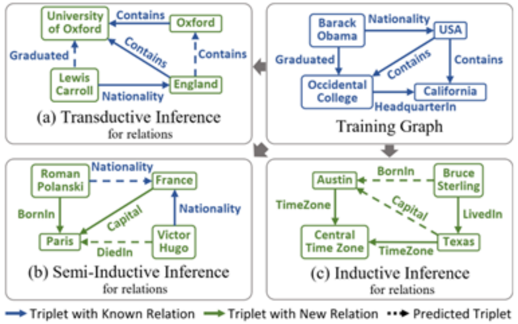
- Selected Publications
  - Structure Is All You Need: Structural Representation Learning on Hyper-Relational Knowledge Graphs (ICML 2025)
  - Stability and Generalization Capability of Subgraph Reasoning Models for Inductive Knowledge Graph Completion (ICML 2025)
  - Unveiling the Threat of Fraud Gangs to Graph Neural Networks: Multi-Target Graph Injection Attacks against GNN-Based Fraud Detectors (AAAI 2025)
  - PAC-Bayesian Generalization Bounds for Knowledge Graph Representation Learning (ICML 2024)
  - Why So Gullible? Enhancing the Robustness of Retrieval-Augmented Models against Counterfactual Noise (NAACL Findings 2024)
  - VISTA: Visual-Textual Knowledge Graph Representation Learning (EMNLP Findings 2023)
  - FinePrompt: Unveiling the Role of Finetuned Inductive Bias on Compositional Reasoning in GPT-4 (EMNLP Findings 2023)
  - Representation Learning on Hyper-Relational and Numeric Knowledge Graphs with Transformers (KDD 2023)
  - InGram: Inductive Knowledge Graph Embedding via Relation Graphs (ICML 2023)
  - Learning Representations of Bi-level Knowledge Graphs for Reasoning beyond Link Prediction (AAAI 2023)



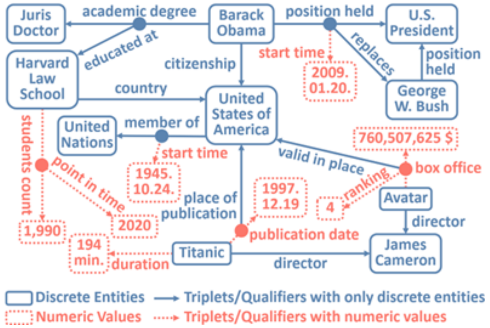

MAYPL (ICML 2025)




ReED (ICML 2024)

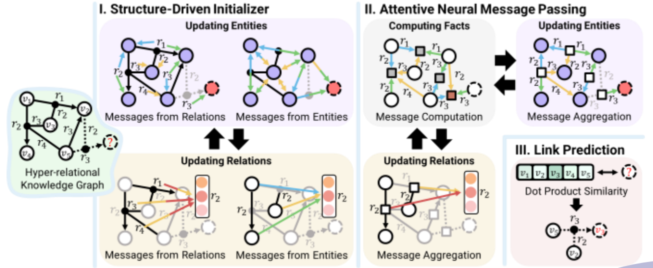



InGram (ICML 2023)

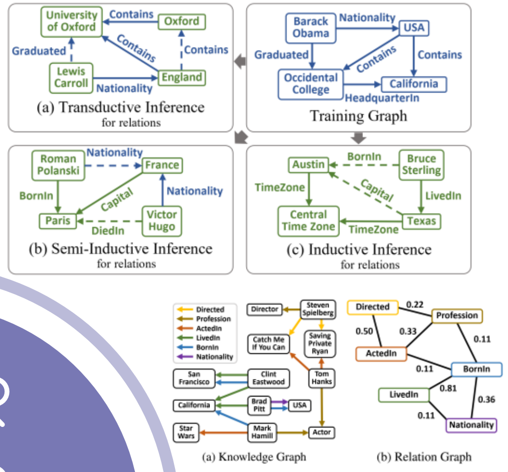



HyNT (KDD 2023)

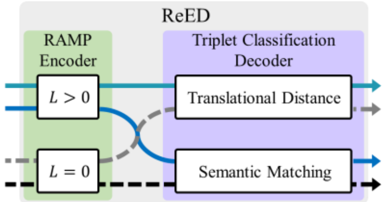
## Hyper-relational KG & Inductive KGC
**MAYPL** (ICML '25)



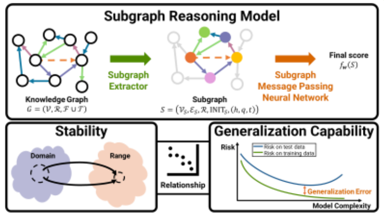

## Inductive KGC
**InGram** (ICML '23)




## Theory

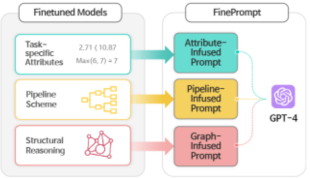



**ReED** (ICML '24)

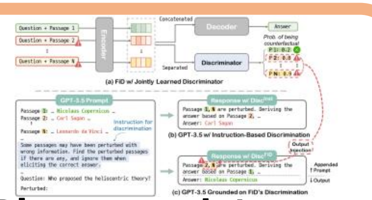



**SMPNN** (ICML '25)

## LLM

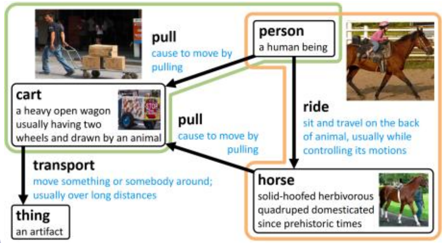



**FinePrompt** (EMNLP Findings '23)



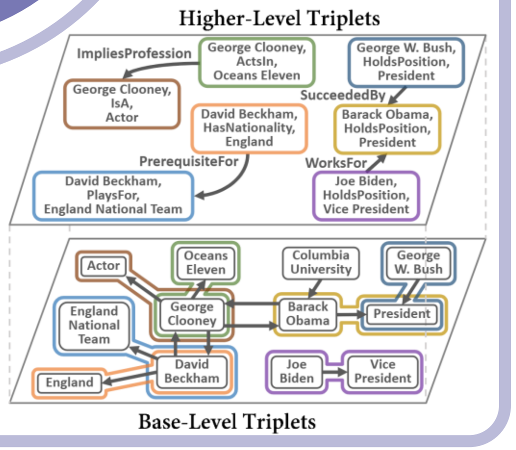
**Discern-and-Answer** (NAACL Findings '24)

## Multimodal KG
**VISTA** (EMNLP Findings '23)

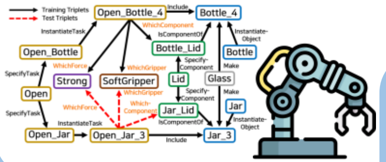



## Knowledge Graph

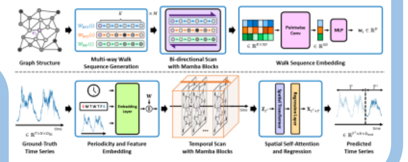
## Bi-level KG
**BiVE** (AAAI '23)



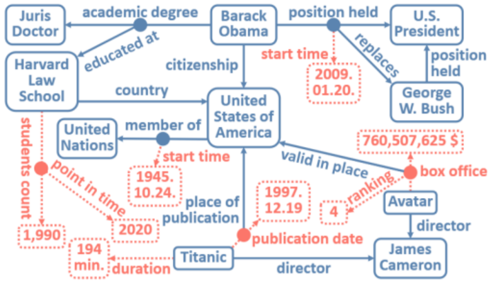

## Semantic Grasping
**roboKG** (RA-L & IROS '22)

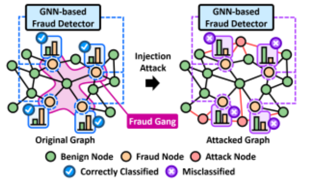


## Traffic Forecasting
**SpoT-Mamba** (STRL @ IJCAI '24)



## Hyper-relational & Numeric KG
**HyNT** (KDD '23)

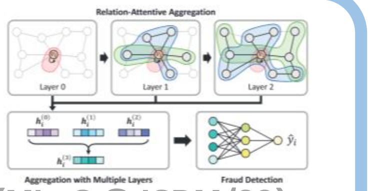



**MonTi** (AAAI '25)

**Graph Adversarial Attack**

## Applications

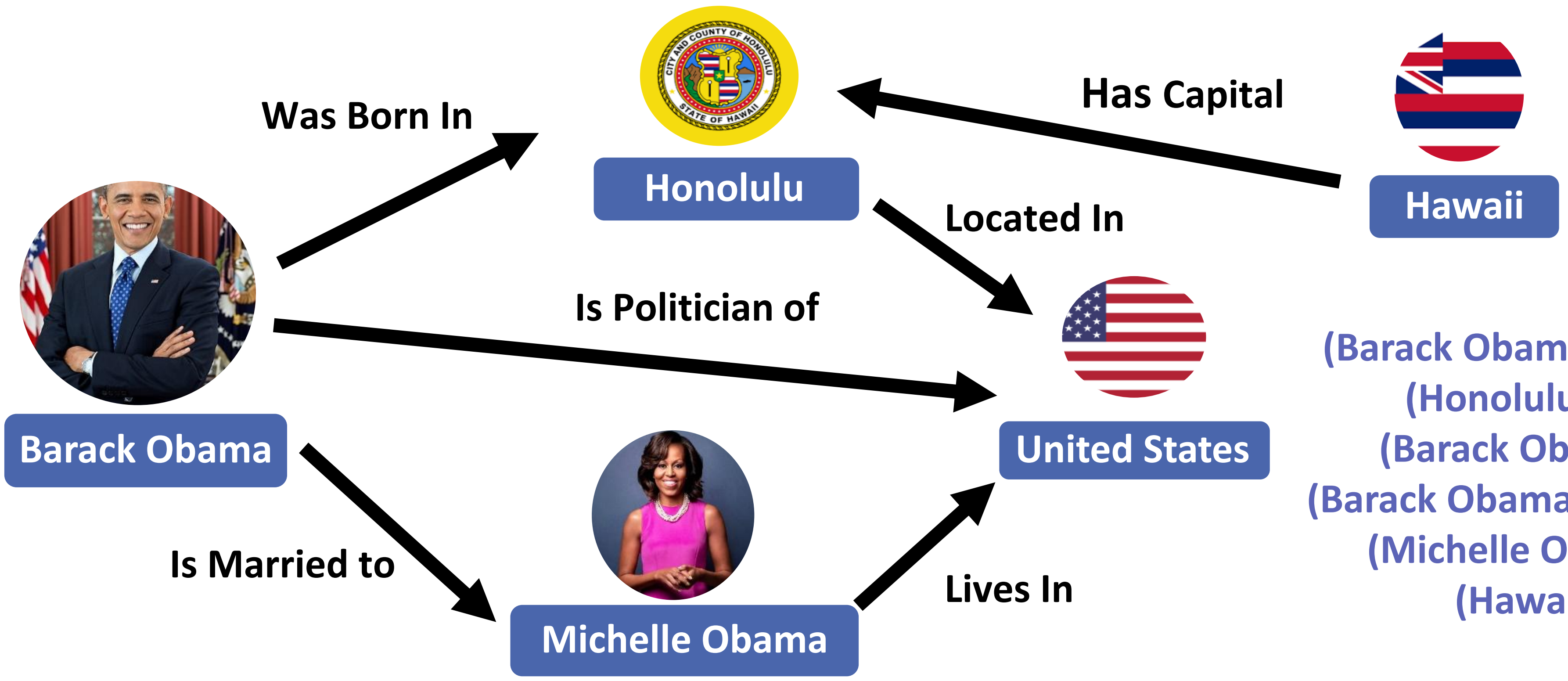



**DRAG** (MLoG @ ICDM '23)

**Fraud Detection**

# 01 Knowledge Graphs

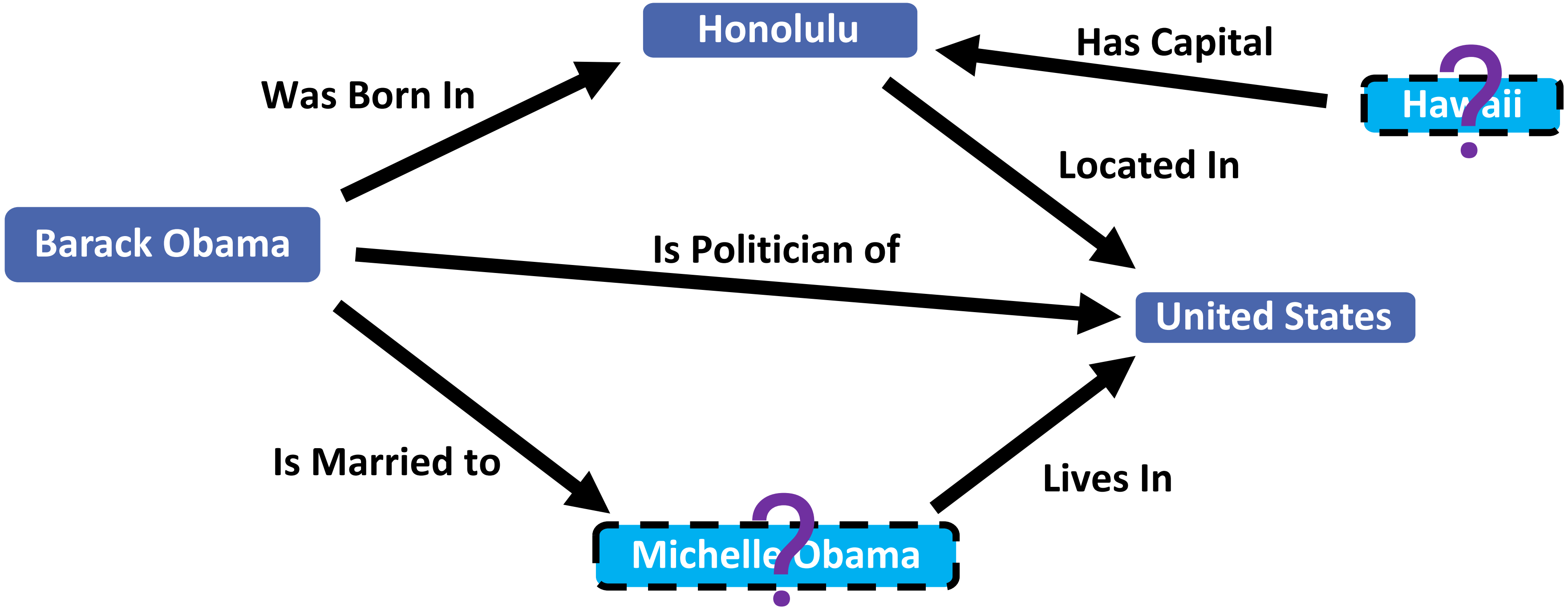
- Graphical Representation of Human Knowledge
  - Each fact is represented by a triplet (head entity, relation, tail entity)




(Barack Obama, is politician of, United States)
(Honolulu, located in, United States)
(Barack Obama, was born in, Honolulu)
(Barack Obama, is married to, Michelle Obama)
(Michelle Obama, lives in, United States)
(Hawaii, has capital, Honolulu)

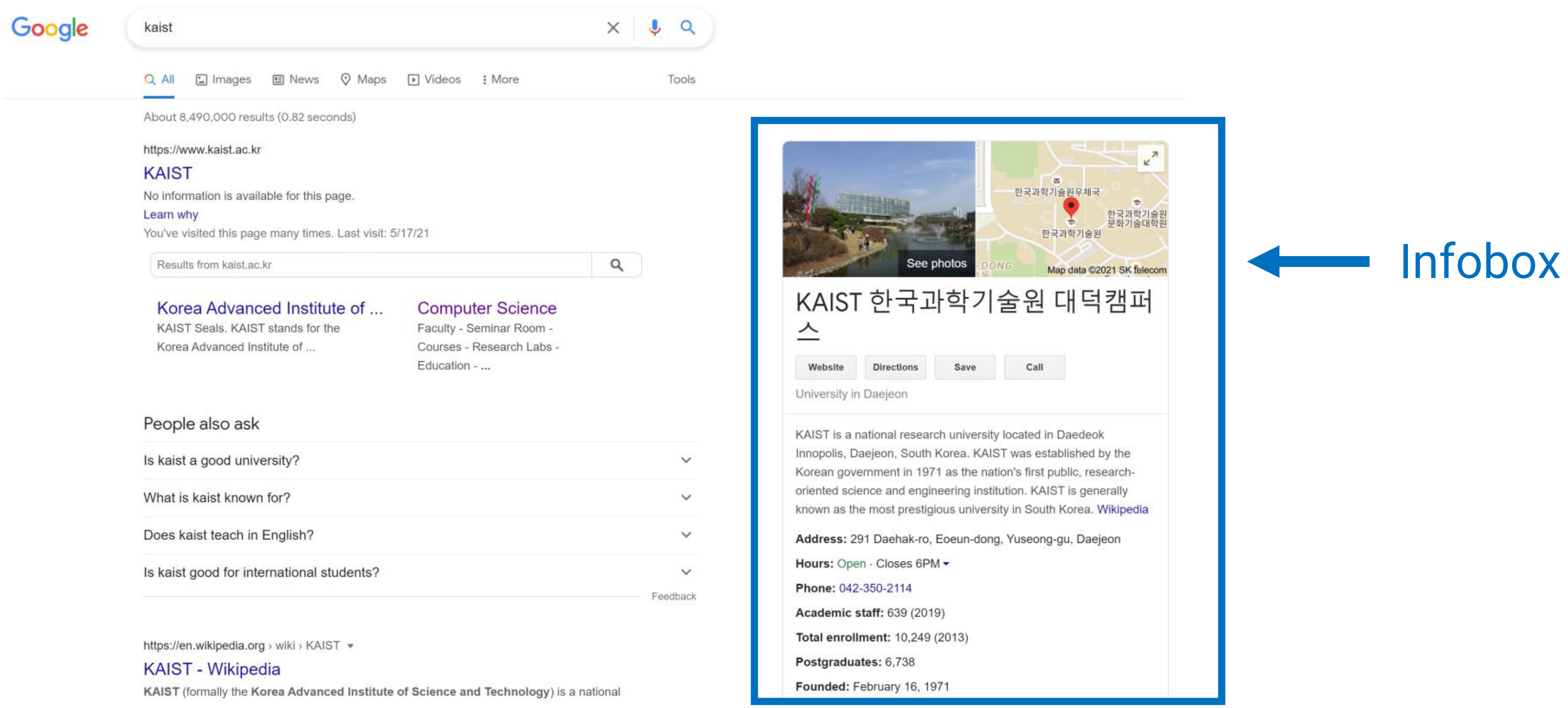
# 01 Knowledge Graph Completion

- Given a head entity and a relation, predict the tail entity.
- Given a tail entity and a relation, predict the head entity.



# 01 Examples of Knowledge Graphs

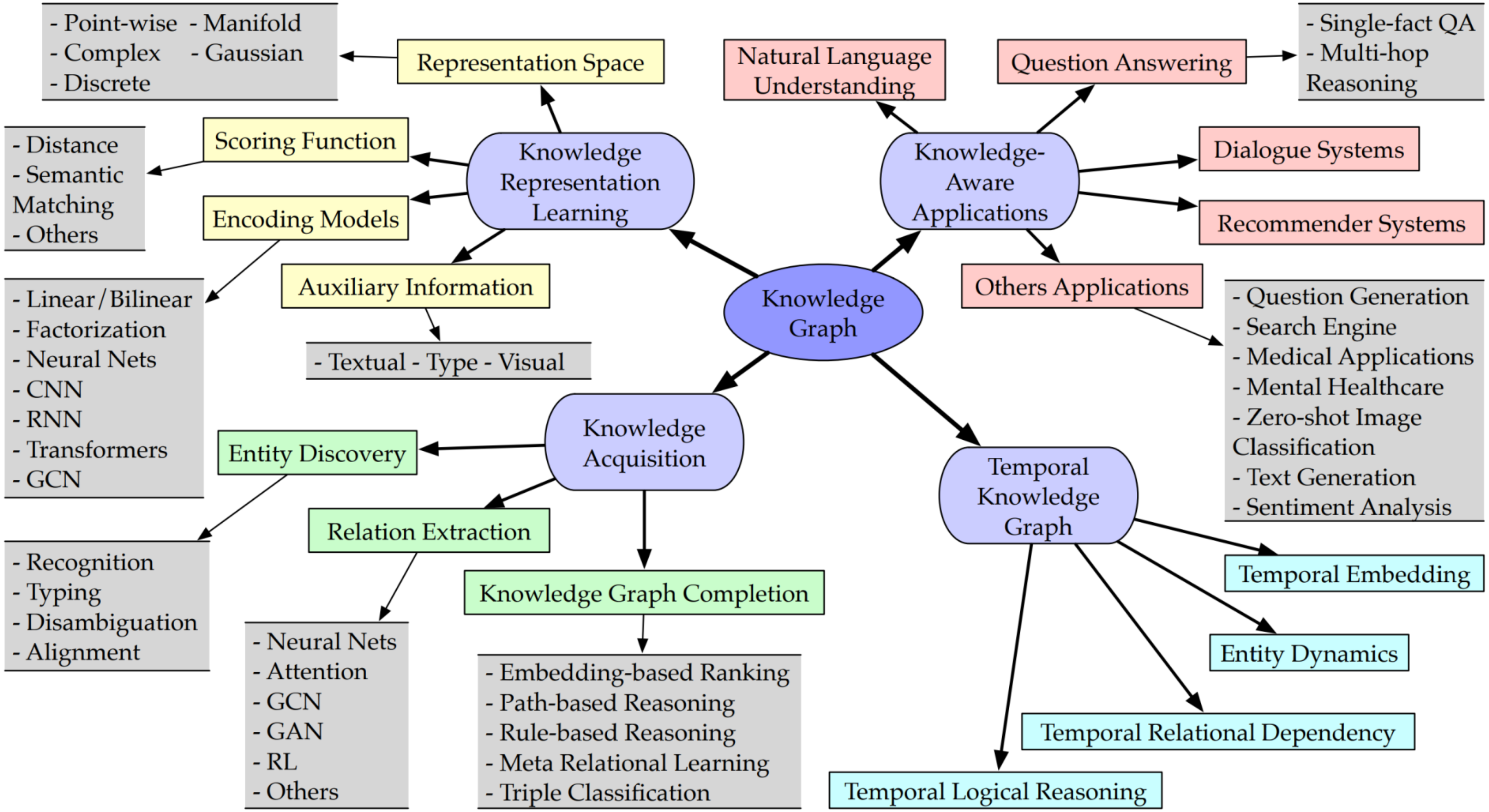
- Google's search engine
  - An infobox next to the search results is created based on knowledge graphs



# 01 Examples of Knowledge Graphs

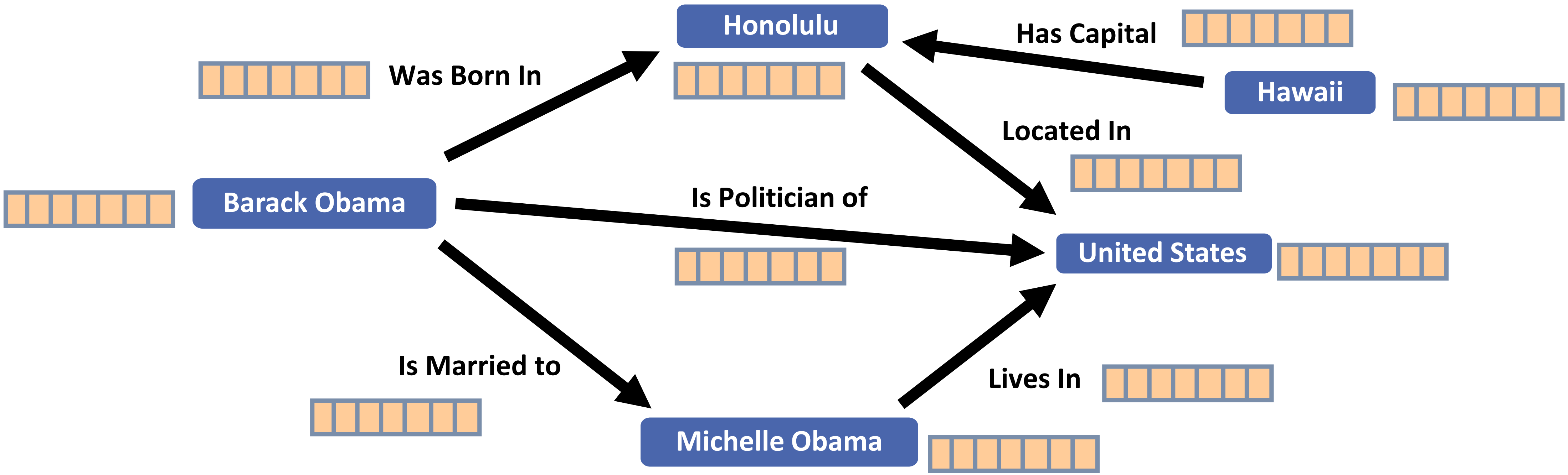
- Google's search engine
  - Knowledge graphs are embedded in the search engine.
- Microsoft's knowledge mining API
  - Used for the Bing search engine, QnA pair mining, processing LinkedIn data
- Meta's heterogeneous graphs
  - Analyze connections between people, events, ideas, and news
- Amazon's product networks
  - Utilize relationships between users, products, and their metadata
- IBM's knowledge graphs
  - Provide a framework to develop internal knowledge graphs

# 01 Research on Knowledge Graphs



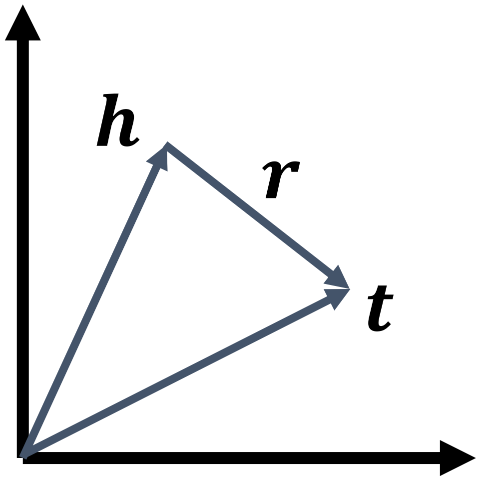
# 01 Knowledge Graph Embedding

- Represent the entities and relations in a low-dimensional feature space.
- Simplify the manipulation while preserving the inherent structure of the graph.

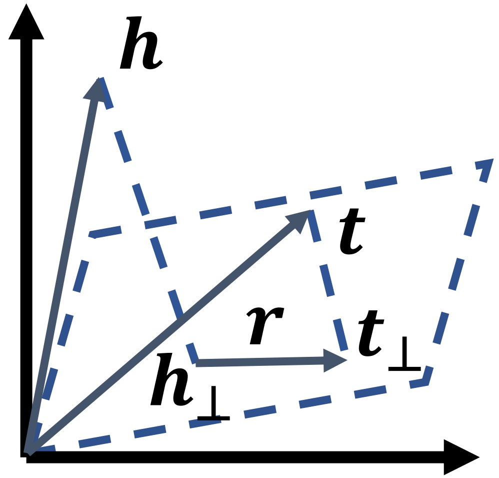


# 01 Knowledge Graph Embedding Models

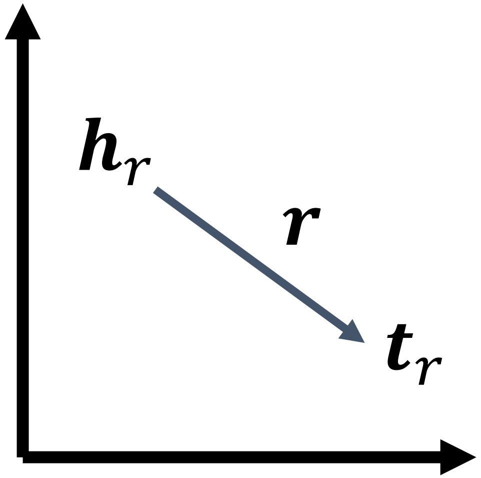
- Translational distance models
  - Use distance-based scoring functions.
  - Measure the plausibility of a fact as the distance between the two entities, usually after a translation carried out by the relation.
  - Examples: TransE, TransH, TransR, RotatE



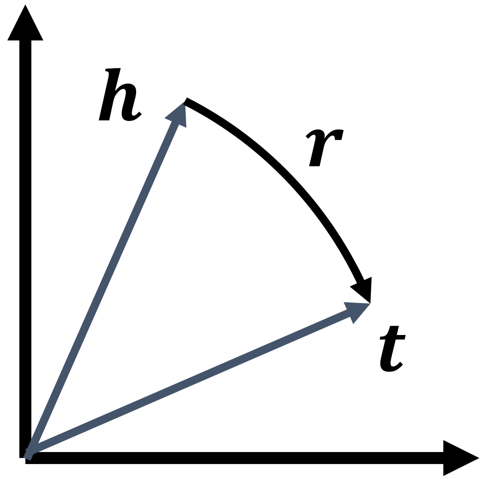

Entity and relation space




Entity and relation space



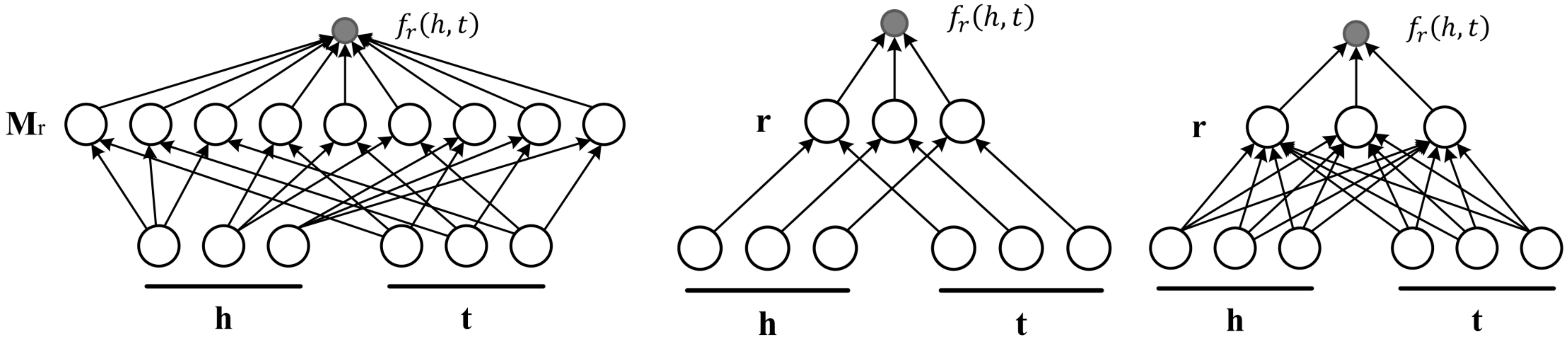

Relation space of $r$




Entity and relation space

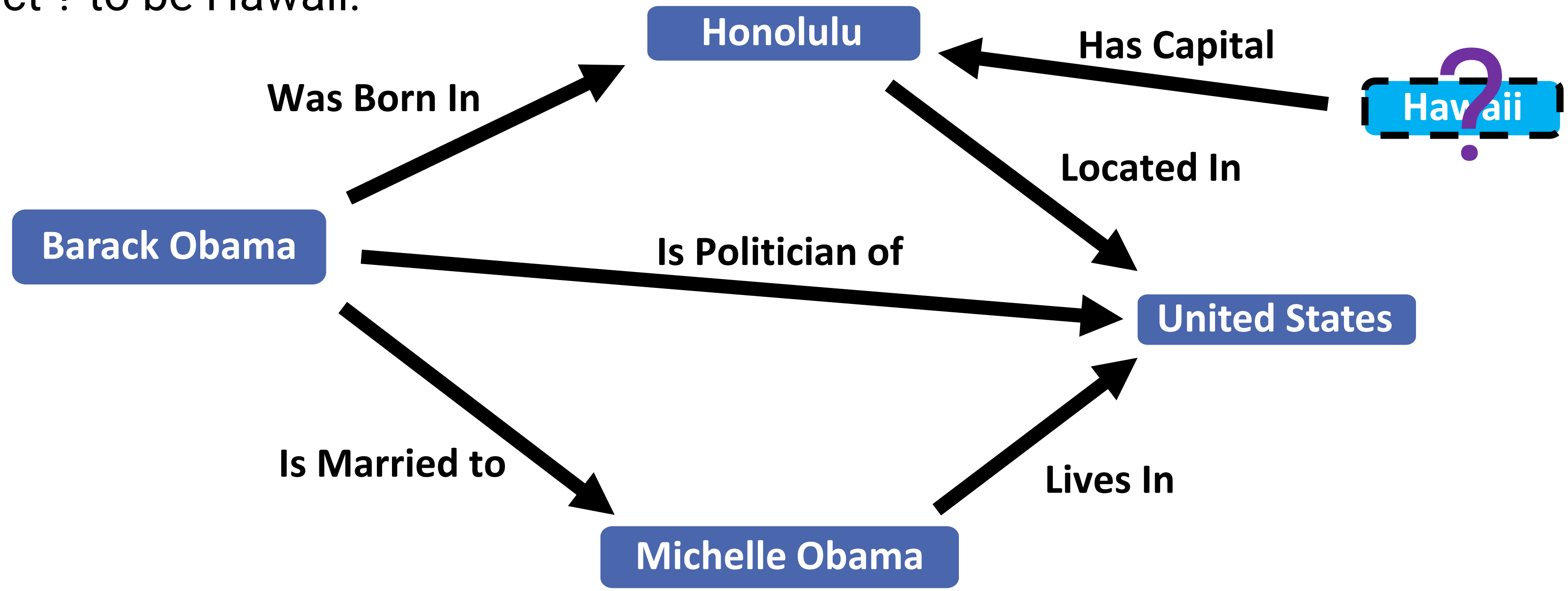
# 01 Knowledge Graph Embedding Models

- Semantic matching models
  - Exploit similarity-based scoring functions.
  - Measure plausibility of facts by matching latent semantics of entities and relations embodied in their vector space representations.
  - Examples: RESCAL, DistMult, HolE



## 01 Link Prediction in Knowledge Graphs

- Assume that we learned embeddings using TransE.
- To solve (?, HasCapital, Honolulu), compute $f_r(h,t) = -\|\boldsymbol{h} + \boldsymbol{r} - \boldsymbol{t}\|$.
  - A ranked list: Hawaii, United States, Barack Obama, Michelle Obama
  - Predict ? to be Hawaii.



# 01 Evaluation of Link Prediction

- Record ranks of correct answers in the ordered lists.
  - Mean Rank (MR)
    - Compute the average of the ranks.
    - The lower the better
  - Mean Reciprocal Rank (MRR)
    - The average of reciprocal ranks.
    - The higher the better
  - Hit@$N$
    - The proportion of ranks no larger than $N$.
    - The higher the better

# 01 Evaluation of Link Prediction

[Problem 1] Answer: D

| Rank | Entity |
|---|---|
| 1 | B |
| 2 | C |
| 3 | D |
| 4 | A |
| 5 | E |
| 6 | F |
| 7 | H |
| 8 | J |
| 9 | K |
| 10 | G |
| 11 | I |
| 12 | L |
| ⋮ | |

[Problem 2] Answer: G

| Rank | Entity |
|---|---|
| 1 | G |
| 2 | B |
| 3 | A |
| 4 | C |
| 5 | E |
| 6 | D |
| 7 | H |
| 8 | J |
| 9 | L |
| 10 | F |
| 11 | K |
| 12 | I |
| ⋮ | |

[Problem 3] Answer: K

| Rank | Entity |
|---|---|
| 1 | A |
| 2 | C |
| 3 | F |
| 4 | B |
| 5 | J |
| 6 | D |
| 7 | E |
| 8 | G |
| 9 | H |
| 10 | K |
| 11 | I |
| 12 | L |
| ⋮ | |

[Problem 4] Answer: L

| Rank | Entity |
|---|---|
| 1 | C |
| 2 | D |
| 3 | F |
| 4 | B |
| 5 | E |
| 6 | G |
| 7 | I |
| 8 | A |
| 9 | J |
| 10 | K |
| 11 | H |
| 12 | L |
| ⋮ | |

MR=(3+1+10+12)/4=6.5, MRR=[1/3+1+1/10+1/12]/4=0.3792, Hit@10=3/4=0.75

# 02 Tutorial Overview

| Time Slot | Tutorial Time | Program |
|---|---|---|
| 9:00-10:30 | 9:00-9:10 | Opening & Introduction to Knowledge Graphs |
| | 9:10-9:40 | [Lecture 1] KG Embedding with Multimodal Data |
| | 9:40-10:10 | [Lecture 2] Inductive Reasoning on KGs |
| | 10:10-10:30 | [Exercise 1] Hands-on Practice of Inductive KGRL |
| 10:30-11:00 | Break Time | |
| 11:00-12:30 | 11:00-11:30 | [Lecture 3] KG Foundation Models |
| | 11:30-12:00 | [Lecture 4] Representation Learning on HKGs |
| | 12:00-12:20 | [Exercise 2] Hands-on Practice of HKGRL |
| | 12:20-12:30 | Discussion & Closing |

# 03 References

- Some slides are made based on the following references.
  - Q. Wang et al., “Knowledge graph embedding: a survey of approaches and applications”, TKDE, 2017.
  - H. Cai et al., “A Comprehensive Survey of Graph Embedding: Problems, Techniques, and Applications”, TKDE, 2018.
  - S. Ji et al., “A Survey on knowledge graphs: representation, acquisition and applications”, TNNLS, 2021.