Applications

Overview and Introduction

Knowledge Extraction

Knowledge Cleaning

Q&A

Break

Ontology Mining

Applications **20 min**

Conclusion and Future Directions

Q&A

Product Knowledge Graph Applications

- Product knowledge graphs can have a plethora of applications in areas including:
  - Recommendation systems.
  - Question answering.
  - Search.
  - Product comparison.
  - Among others.

- Applications can make use of knowledge graphs through:
  - The structured factual information for each product.
  - The connections in the overall graph structure.

Making Use of Structured Information

	 Pro Air Fryer 5.8QT	 Pro II Air Fryer 5.8QT	 WIFI Air Fryer Oven 7QT	 Stainless Air Fryer 5.8QT
Included	100 Recipes	100 Recipes	30 Recipes&More Online Recipes	100 Recipes & Rack & 5 Skewers
Control	Digital	Digital	Digital/WIFI	Digital
Capacity	5.8QT	5.8QT	7QT	5.8QT
Color	Black/Red/White	Black	Black	Silver
Cooking Functions	13	12 (Customizable)	14	10
Shake Remind	✓	Customizable Shake Remind	✓	Customizable Shake Remind
Keep Warm	✓	✓	✓	-
Preheat	✓	✓	✓	✓
Power	1700W	1700W	1800W	1700W
Voltage	AC 120V	AC 120V	AC 120V	AC 120V

Facilitating structured product comparison

Making Use of Structured Information

Roll over image to zoom in

CeraVe Daily Moisturizing Lotion for Dry Skin | Body Lotion & Facial Moisturizer with Hyaluronic Acid and Ceramides | Fragrance Free | 19 Ounce

Visit the CeraVe Store

4.7 ★★★★½ 55,480 ratings | 321 answered questions

Amazon's Choice in Body Lotions by CeraVe

Price: $18.40 ($0.97 / Fl Oz) Get **Fast, Free Shipping** with Amazon Prime & FREE Returns

Get $50 off instantly: Pay $0.00 ~~$18.40~~ upon approval for the Amazon Rewards Visa Card. No annual fee.

Size: **19 Fl Oz (Pack of 1)**

12 Fl Oz (Pack of 1)	**19 Fl Oz (Pack of 1)**
$11.49 ($0.96 / Fl Oz)	**$18.40 ($0.97 / Fl Oz)**

Special Ingredients	Hyaluronic Acid
Item Form	Lotion
Brand	CeraVe
Skin Type	Dry
Age Range (Description)	Adult

Conveying structured product details and highlights

Making Use of Structured Information

Roll over image to zoom in

Taylors of Harrogate English Breakfast, 20 Count (Pack of 6)

Visit the Taylors of Harrogate Store

4.6 ★★★★½ 27,415 ratings | 161 answered questions

Climate Pledge Friendly

#1 Best Seller in Tea Samplers

Price: $31.43 ($0.26 / Count)

Get $50 off instantly: Pay $0.00 ~~$31.43~~ upon approval for the Amazon Rewards Visa Card. No annual fee.

Available at a lower price from other sellers that may not offer free Prime shipping.

Style: **Teabags**

Flavor Name:

English Breakfast

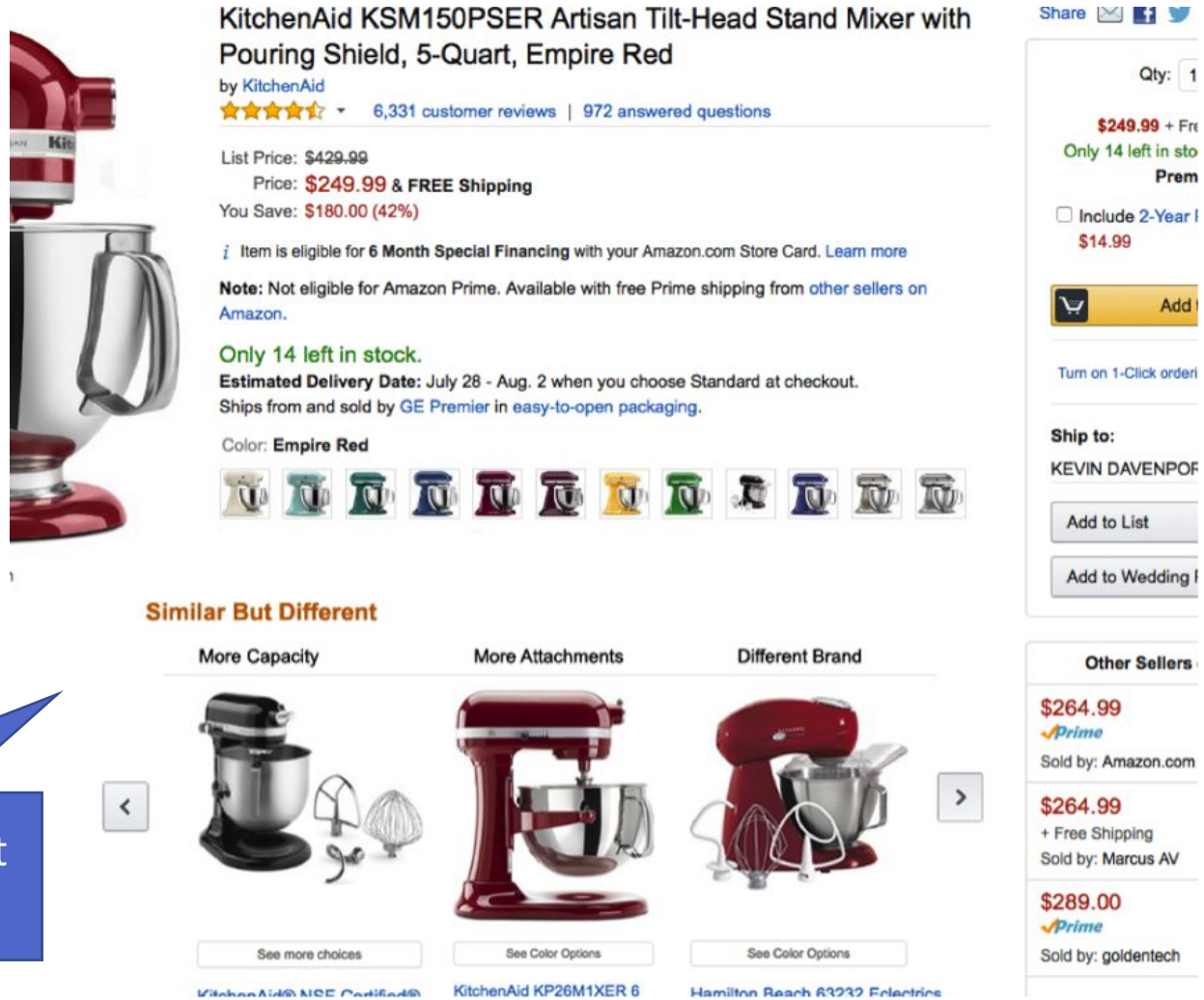
Size: **20 Count (Pack of 6)**

20 Count (Pack of 1) | **20 Count (Pack of 6)** | 48 Count (Pack of 1) | 100 Count (Pack of 1)

Brand	Taylors of Harrogate
Ingredients	Black African and Indian Teas
Flavor	English Breakfast
Item Form	Bagged

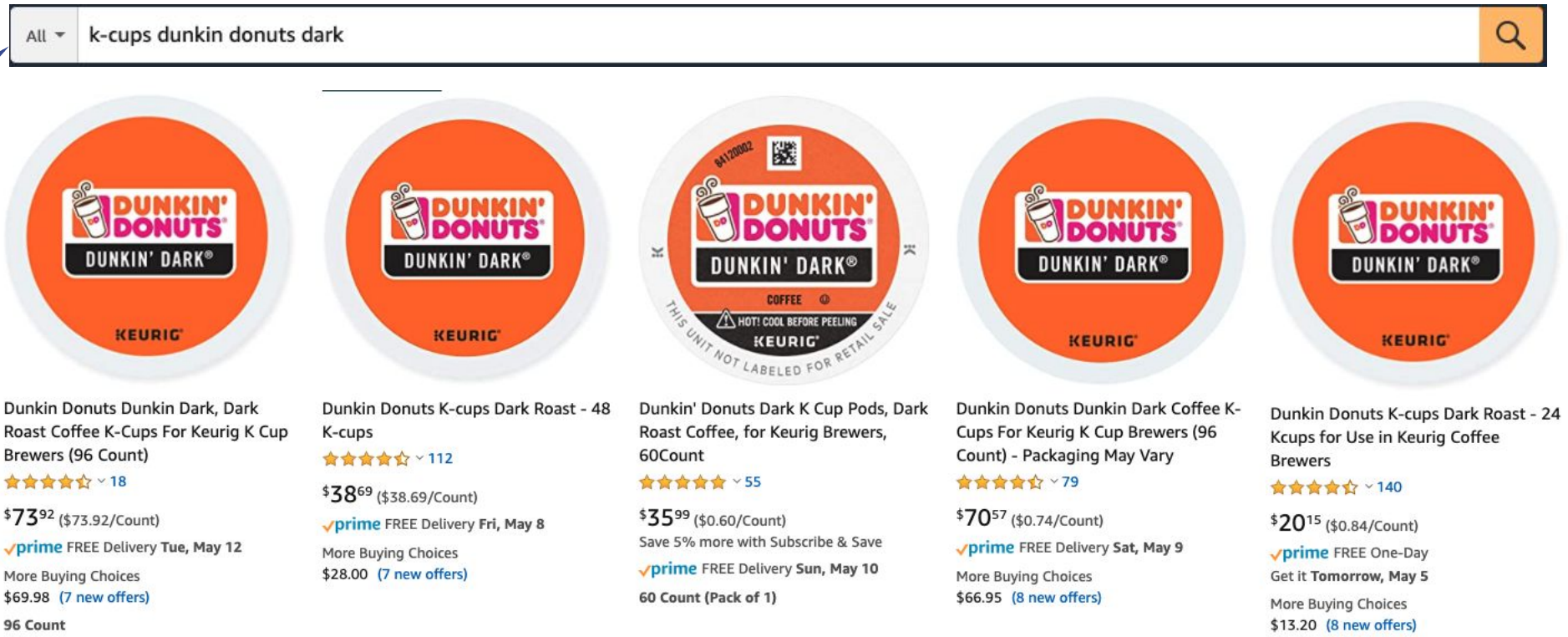
Providing product options

Making Use of Graph Structure



Making Use of Graph Structure

Product search



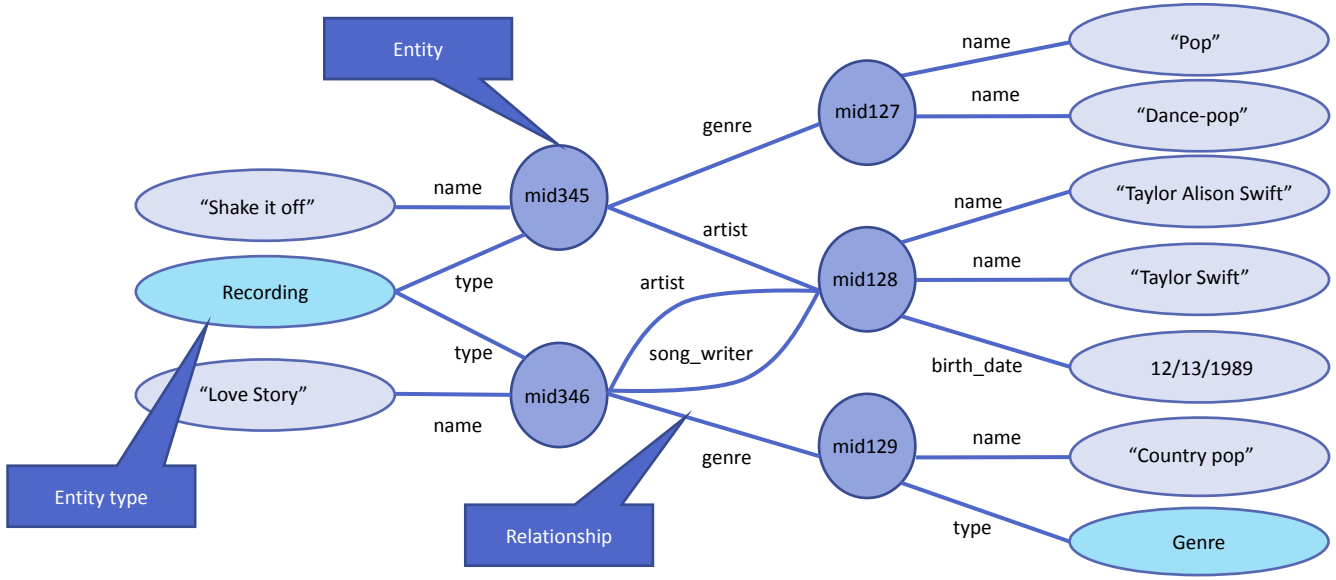
Knowledge Graph Embeddings

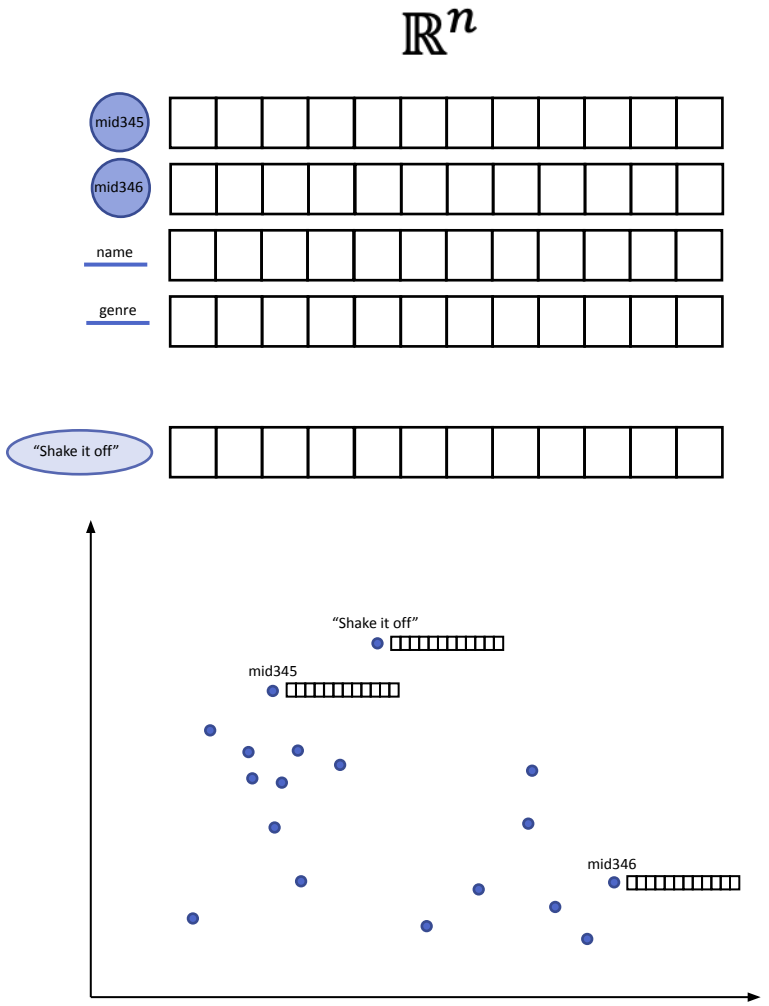
Overview, Definition, Applications

Knowledge Graph Embeddings

- The various application areas of knowledge graphs make repeated use of knowledge graph embeddings (KGE), in various configurations.
- We therefore thought of recapping the topic of KGE.
- KGE also can have several standalone applications, that we highlight in this section.

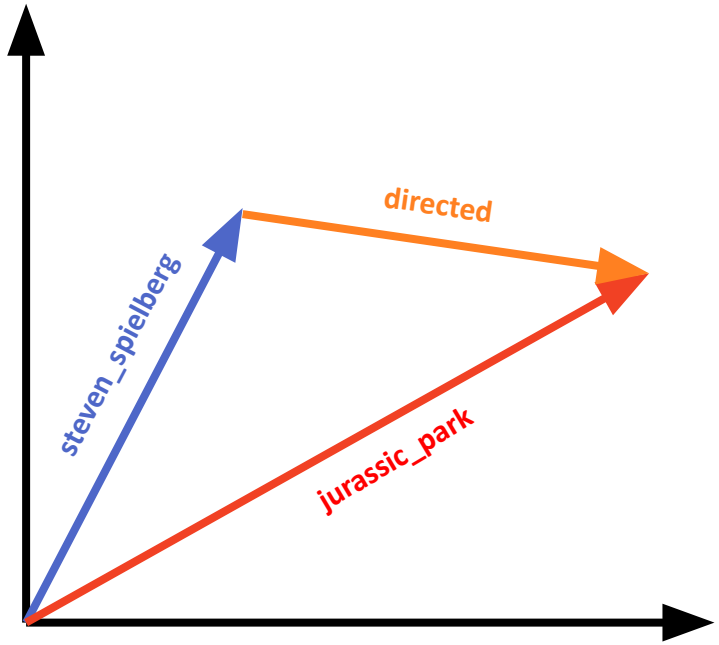
Knowledge Graph Embedding





Knowledge Graph Embedding

- Knowledge Graph Embedding (KGE): projections of entities and relations into a continuous low-dimensional space.
- Representing entities and relations as vectors can have strong expressive power.
- Plethora of downstream applications.
  - Node classification.
  - Link prediction.
  - Ranking.
  - And many other downstream applications.



Sample KGE Models

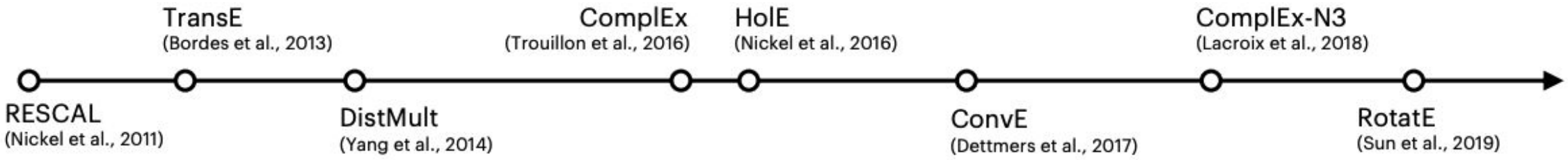
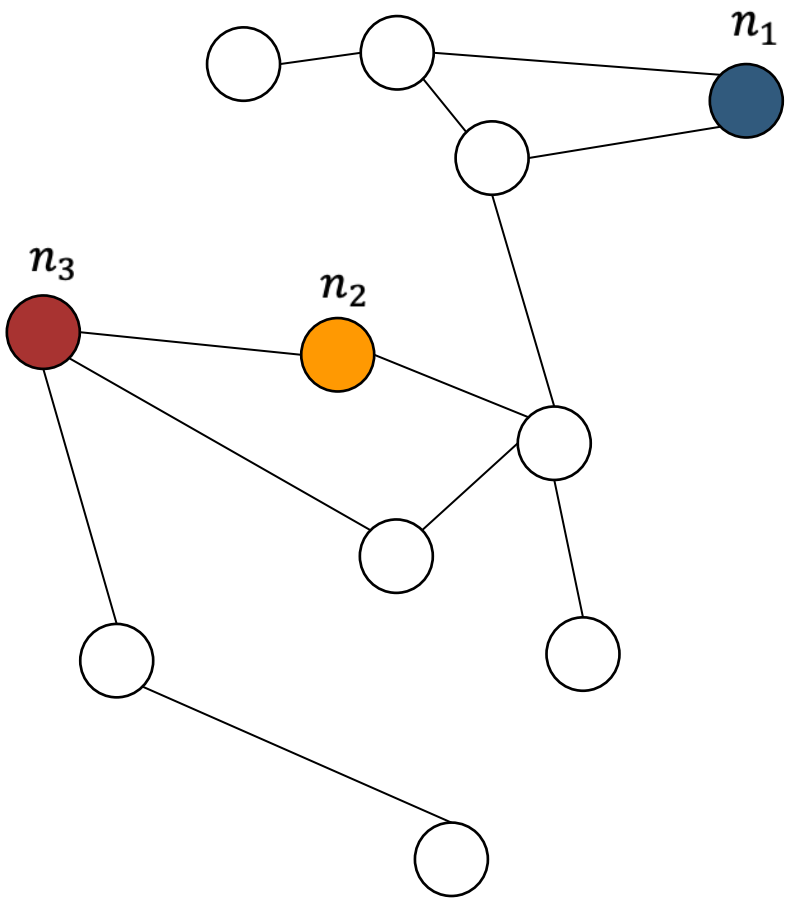


Figure from Costabello et al., Knowledge Graph Embeddings Tutorial: From Theory to Practice, KDD 2017 tutorial. https://doi.org/10.5281/zenodo.4268208

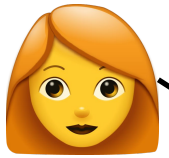
Node Classification

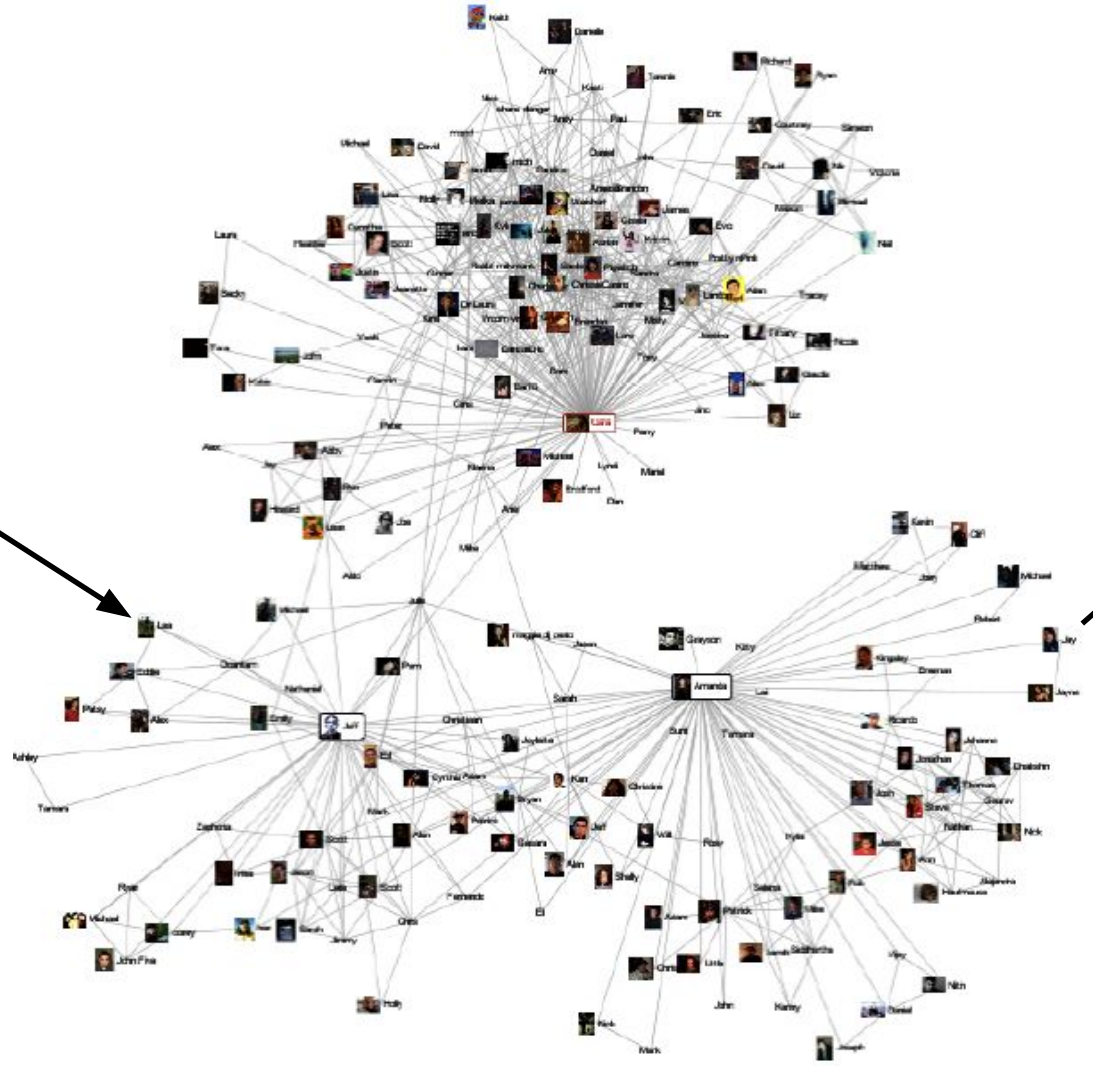


- If we know n_1 is republican.
- And n_3 is democrat.
- What can we say about n_2?

Link Prediction

Does she know
Jay Leno?





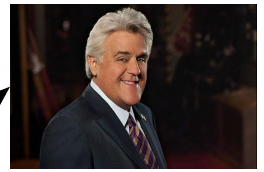


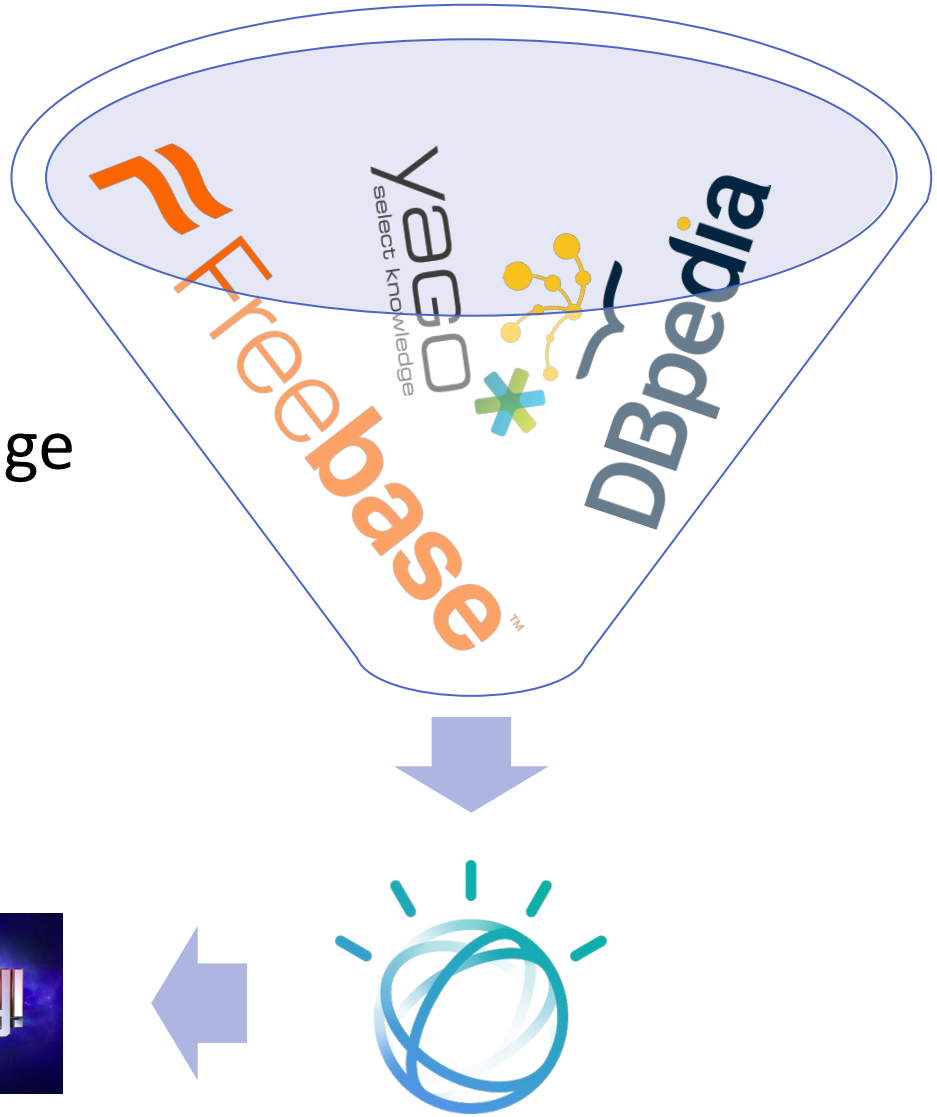
Figure from Tang et al., 2017, Learning Representations of Large-Scale Networks, KDD17 Tutorial

Knowledge Graph Applications

Question Answering, Recommendation, Retrieval

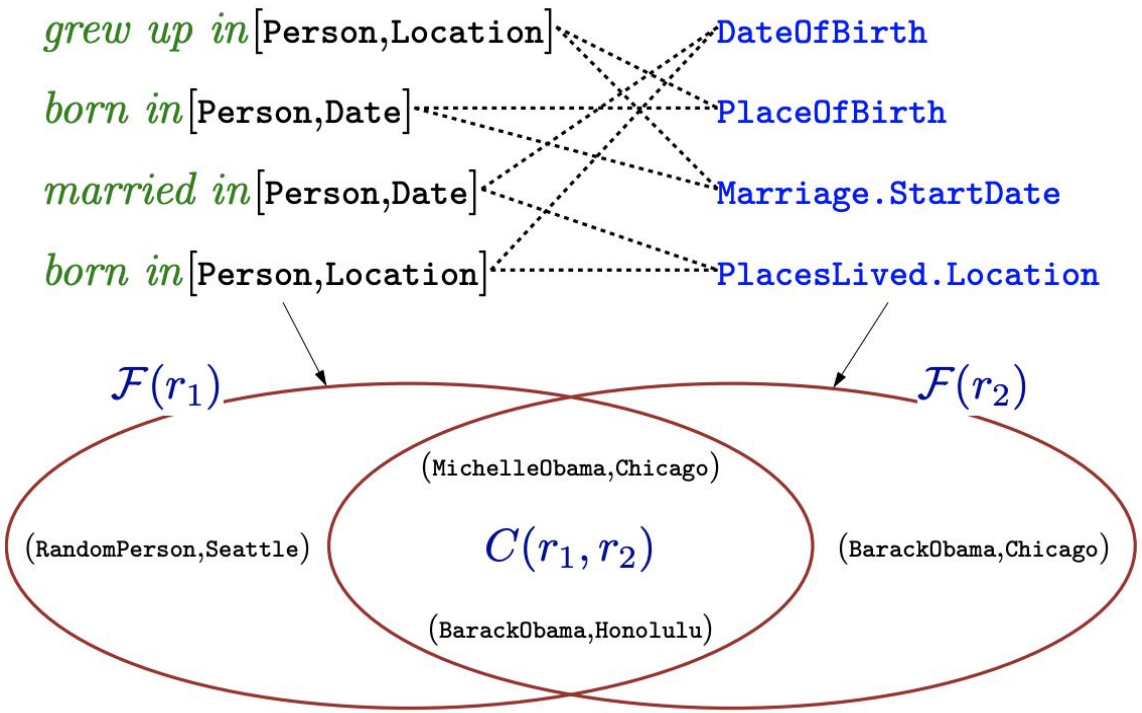
Question Answering

- Watson was a notable example of utilizing KGs in question answering.
- Overall approaches to incorporate knowledge graphs in question answering:
  - Semantic parsing and retrieval based
  - Embedding based
  - Deep Learning based



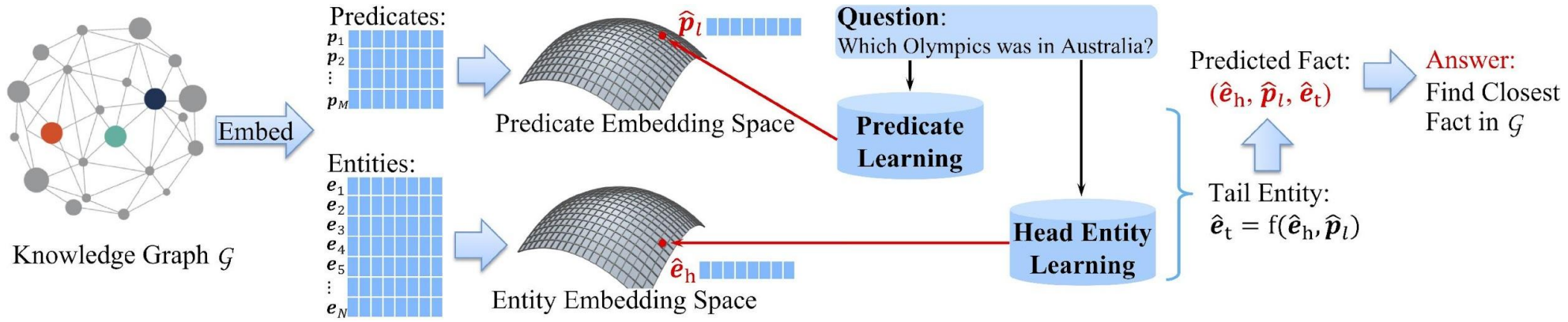
Semantic Parsing And Information Retrieval

- Map natural language phrases to logic forms.
  - Berant et al., 2013, use freebase to map against.
  - Parse forms to generate formal queries.
- Directly translate questions to queries.
  - Use KG to retrieve candidate answers.
  - Use various features to rank answers.
- Semantic parsing and retrieval approaches, however, requires expensive hand-crafted rules.

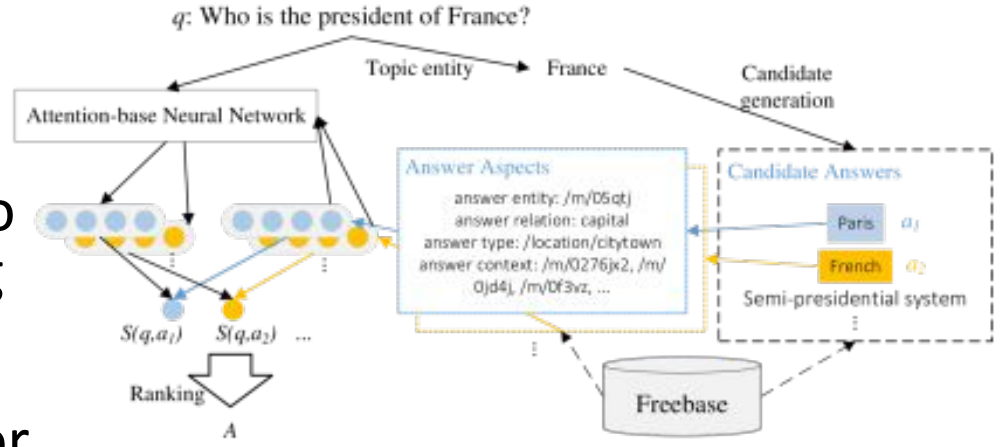


Embedding Based Question Answering

- Earlier contributions, like Bordes et al., 2014, use word embeddings
  - Embed words in question.
  - Embed KG entities from topic entity to answer.
  - Train embedding to score and rank answers.
- Huang et al., 2019, use KG embedding techniques
- Embedding based approaches work well for simple questions only.



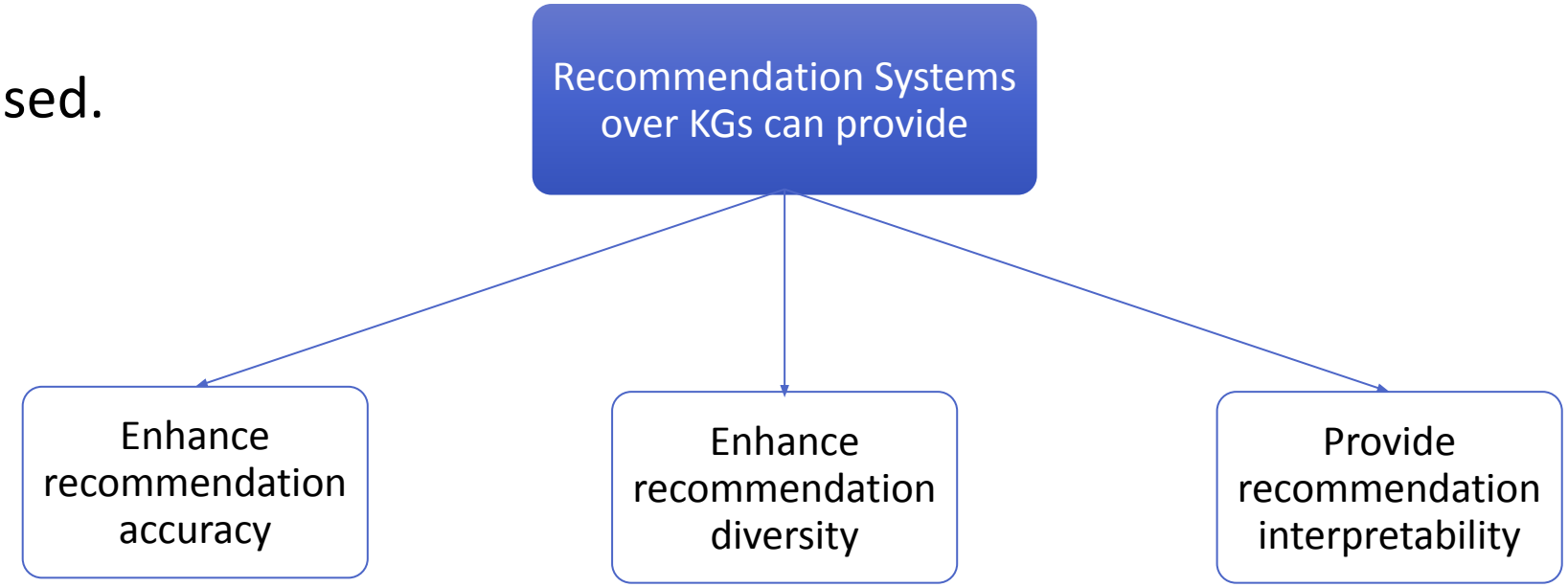
Deep Learning Based Question Answering



- Plethora of contributions:
  - Hao et al., 2017, Cross-attention mechanism to represent the questions dynamically according to the various candidate answer aspects.
  - Bauer et al., 2018 Generative pointer-generator decoder, with multi-attention to perform multiple hops of reasoning.
  - Do et al. 2021 use BERT to build BERT-based models for content and link classification, and traverse the KG to obtain answer paths.
  - Lukovnikov et al. 2021 also use BERT-based models, but for text to formal query translation as we presented earlier.
  - Among many others…

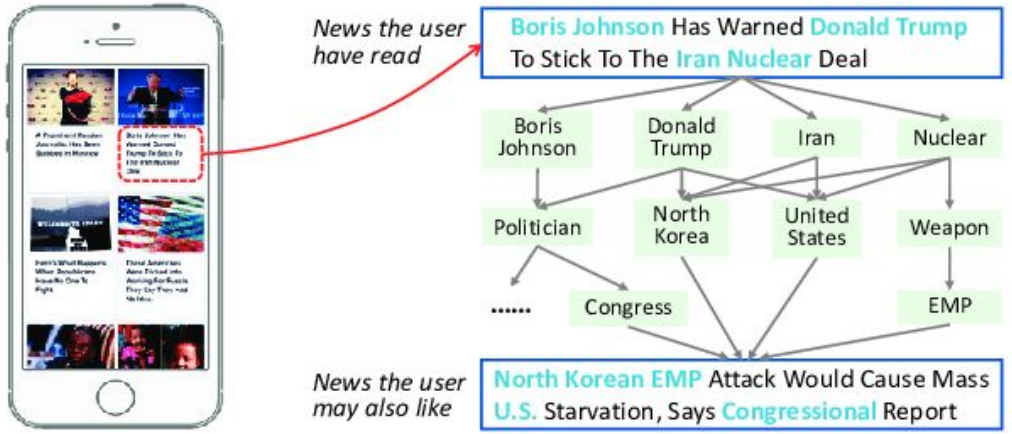
Recommendation Systems

- Recommendation systems have become cornerstones in all online content platforms, including eCommerce.
- Approaches:
  - Embedding-based.
  - Path-based.



Embedding-Based Recommendation

- Knowledge Graph Embeddings (KGE) have been utilized extensively in recommendation systems.
- Wang et al. 2018, associates word embeddings with corresponding KG entity embedding and uses multi-channel CNN to get news recommendations.

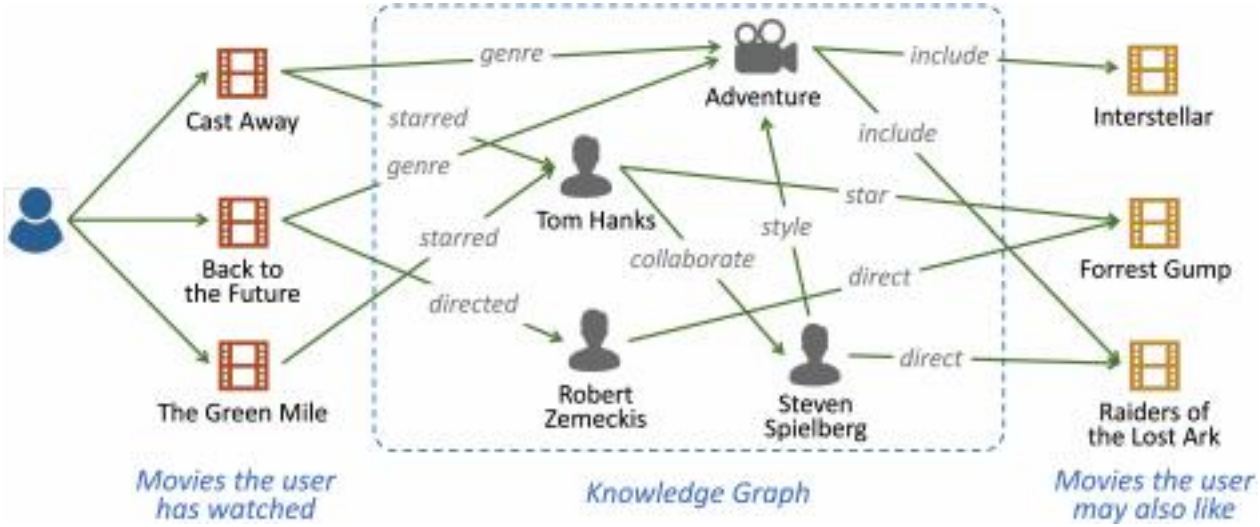


Path-Based Recommendation

- Path-based methods utilize the graph nature of the KG directly.
  - This can provide better explainability and reasoning capability.
  - But the over-reliance on the usually hand-crafted meta-paths can be constraining
- Zhao et al., 2017, use KG as a Heterogeneous Information Network (HIN).
  - Use meta-graph over the HIN to get semantic relations between homogenous entities.
  - Use matrix-factorization to get recommendations.
- Wang et al. 2018 model the sequential nature of paths using LSTMs.
  - Composing the semantics of entities and relations.
  - Training learns the associations of users to entities.

Path-Based Recommendation

- RippleNet, Wang et al. 2018, is an interesting approach that combines path-based and embedding-based methods.
  - Specifically to address cold-start filtering.
  - Previous user clicks are used to propagate preferences through the entities in a KG of movie knowledge, just like water “ripples”.
  - KGE updated through the preference propagation.

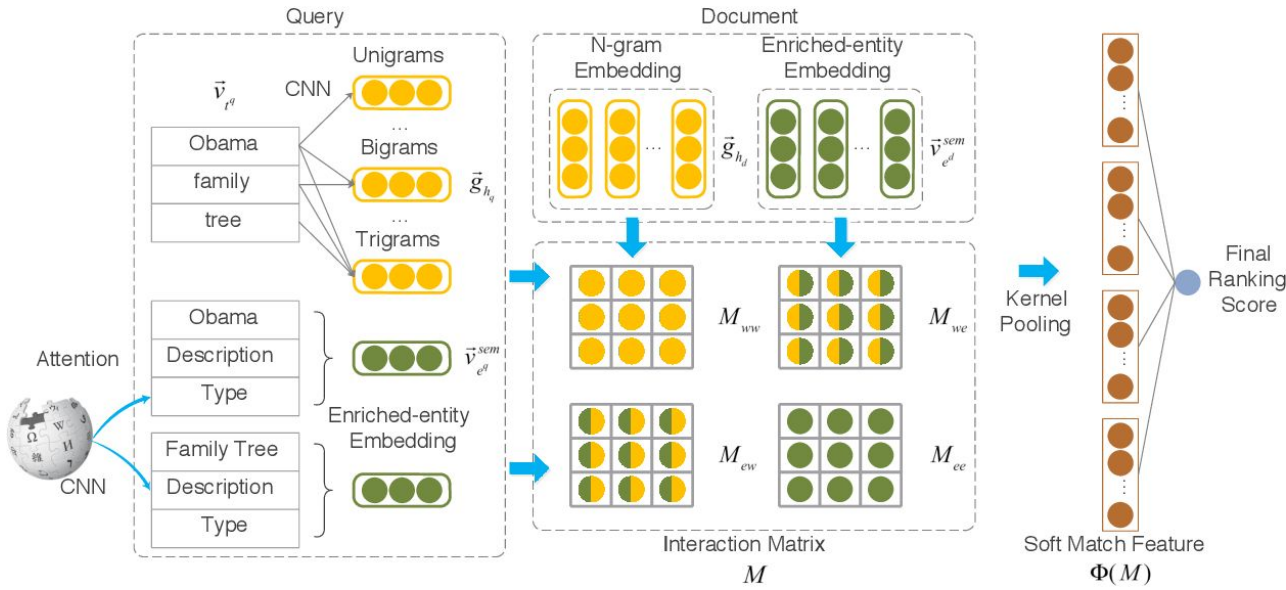


Search and Information Retrieval

- KGs have been utilized extensively in information retrieval applications.
  - Google Knowledge Graph to enhance search results.
  - Graph Search at Facebook.
  - Among others.
- We can identify several areas where KGs have been utilized to enhance information retrieval systems, including:
  - Ranking systems.
  - Document representation.
  - Query representation.

Ranking Systems

- Xiong et al., 2017, uses KGs for document ranking.
  - Word-level embeddings for the documents and queries.
  - KGE for the entities in the text that are covered by the KG.
  - Attention-based ranking system for the interaction between word-embeddings and KGE.
- Liu et al., 2018, use the same setup, but with neural-IR.
  - It uses interaction matrices between the various embeddings.
  - Then uses various neural layers for learning ranking scores.



Document Representation

- Incorporating KG in document-level representation primarily works by enriching document vector with KGE for entities.
- Raviv et al., 2016, use entity-based language models for document representation.
  - Use entity-linking tools to link mentions in document and queries to Wikipedia.
  - Use unigram language models for the linked entities.
- Ensan et al., 2017, use semantic-based language models.
  - Semantic-linking of concepts in documents to KGs.
  - Build graph representation of the concepts in document and query.
  - Probabilistic reasoning model for retrieval.

Query Representation

- The previous contributions for document representation also involve query representation efforts.
- Specific contributions for query representation mainly involve query expansion efforts.
- Dalton et al., 2014, use KGs to enrich queries with features from KG entities, including structured attributes and text.

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