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.
  - Search and question answering.
  - Product info and 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

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

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

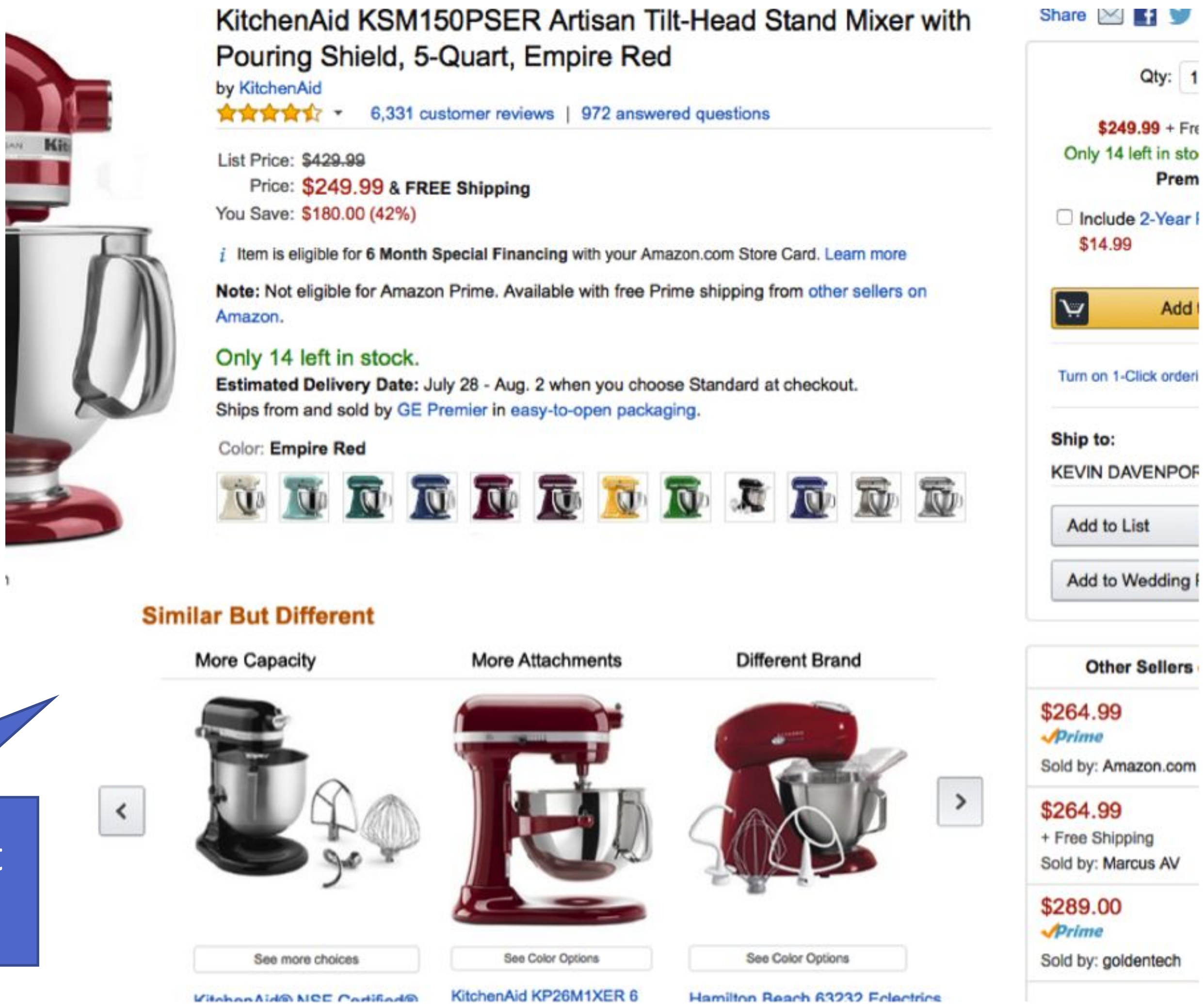
Size: **20 Count (Pack of 6)**

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

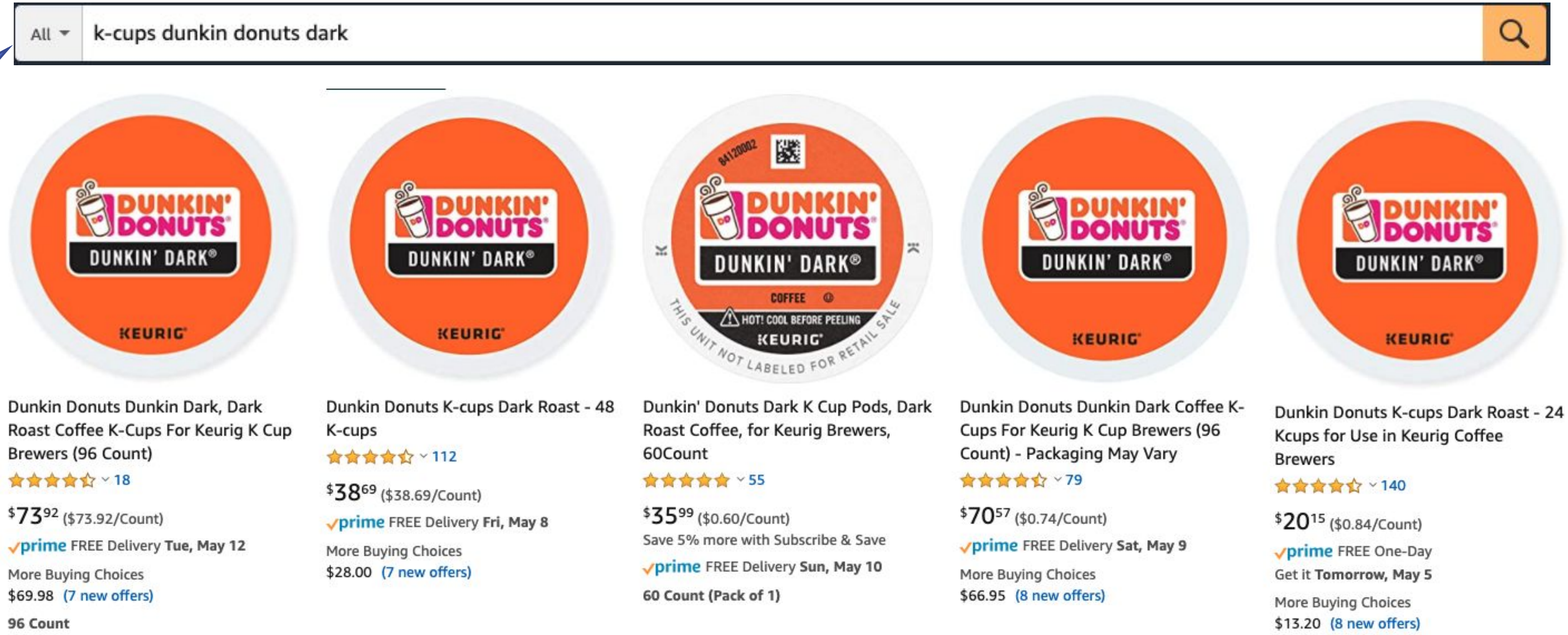
Making Use of the Graph Structure



Richer and deeper product recommendation

Making Use of the Graph Structure

Deeper product search



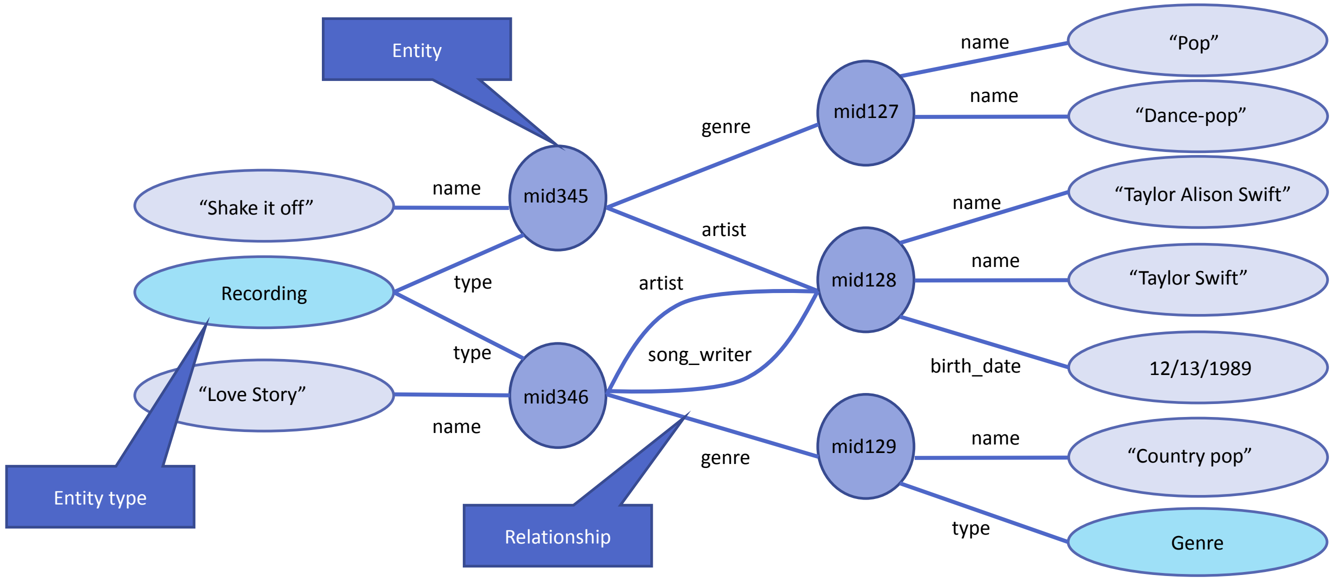
Product Knowledge Graph Embeddings

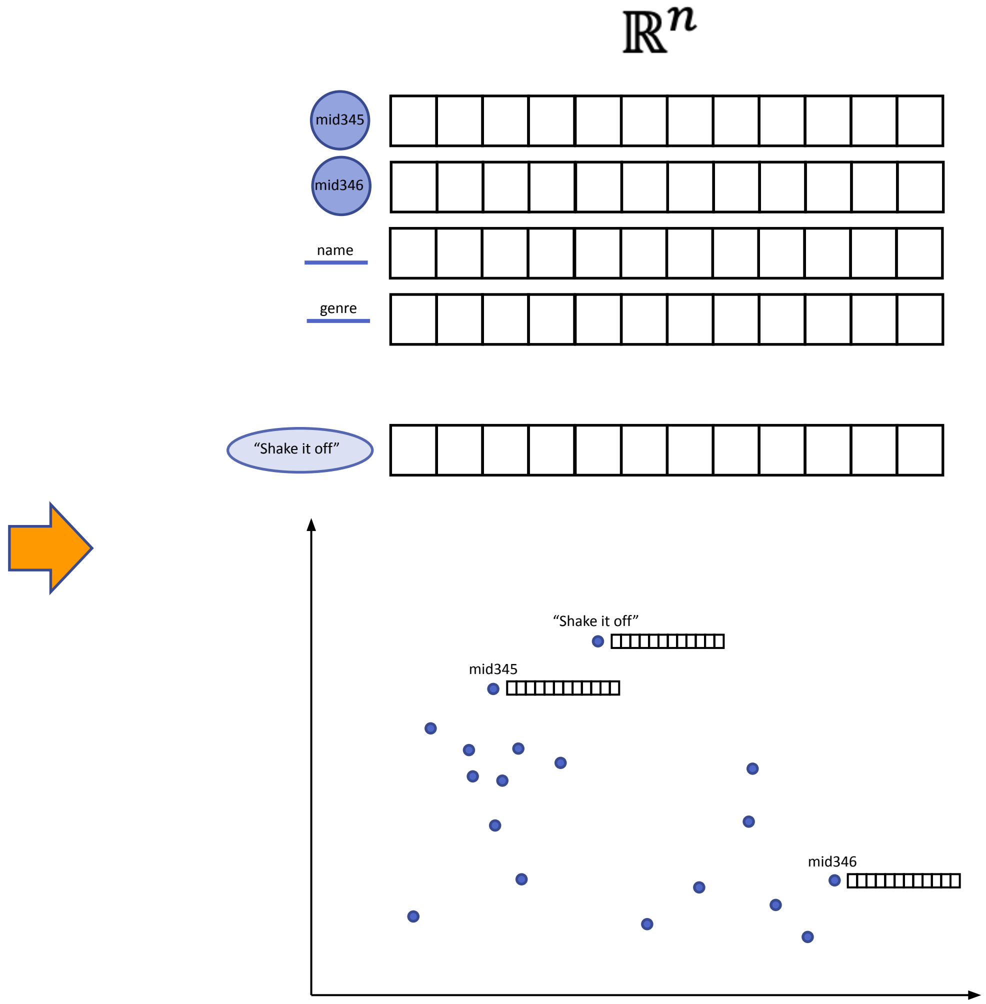
Overview, Definition, Applications

Knowledge Graph Embeddings

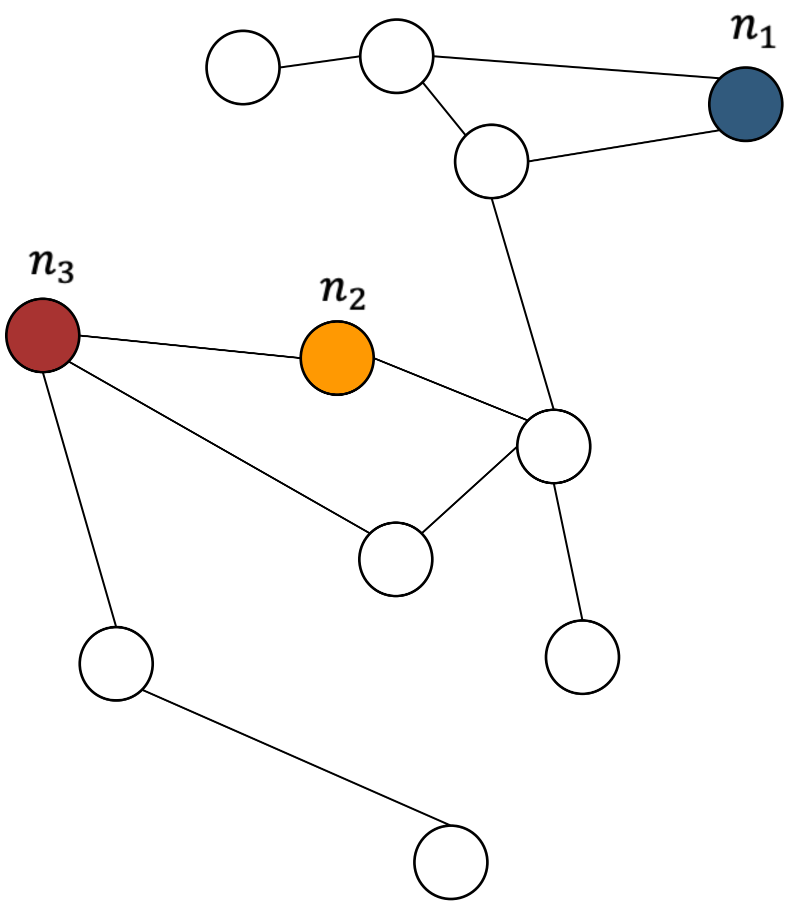
- The various KG applications make repeated use of knowledge graph embeddings (KGE).
- We will therefore recap the topic of KGE, then highlight the specificities of product knowledge graph embeddings (PKGE).
- KGE, and PKGE, also can have several standalone applications, that we highlight in this section.

Knowledge Graph Embedding





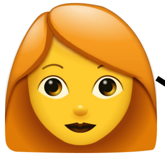
Node Classification

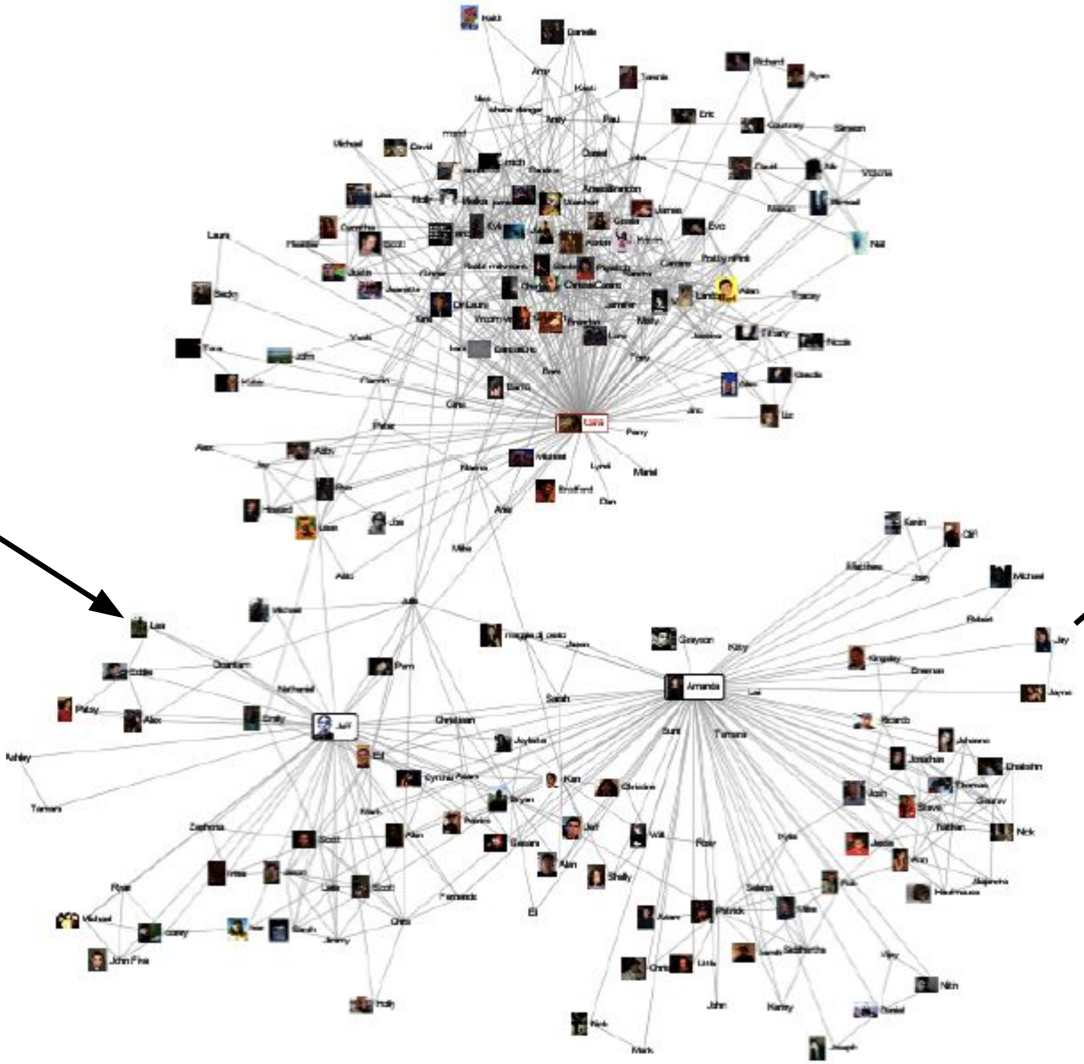


- If we know n1 is republican.
- And n3 is democrat.
- What can we say about n2?

Link Prediction

Does she know
Jay Leno?





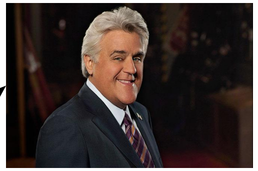


Figure adapted from Tang et al., 2017, Learning Representations of Large-Scale Networks, KDD17 Tutorial

PKGE, Compared to KGE

Text-heavy product description	● Descriptions provide a wealth of additional textual information. ● Requires explicit interaction of model with natural language.
User activity	● User activities, like product search, provide additional signals. ● Provide relations like product complement, co-view and substitute
Noise	● KGE facts are assumed to be well established and plausible. ● Facts in PKGE can be more noisy.
Hierarchical structure	● Hard to be embedded into Euclidean spaces. ● Can utilize hierarchical embeddings, like Poincaré embeddings.

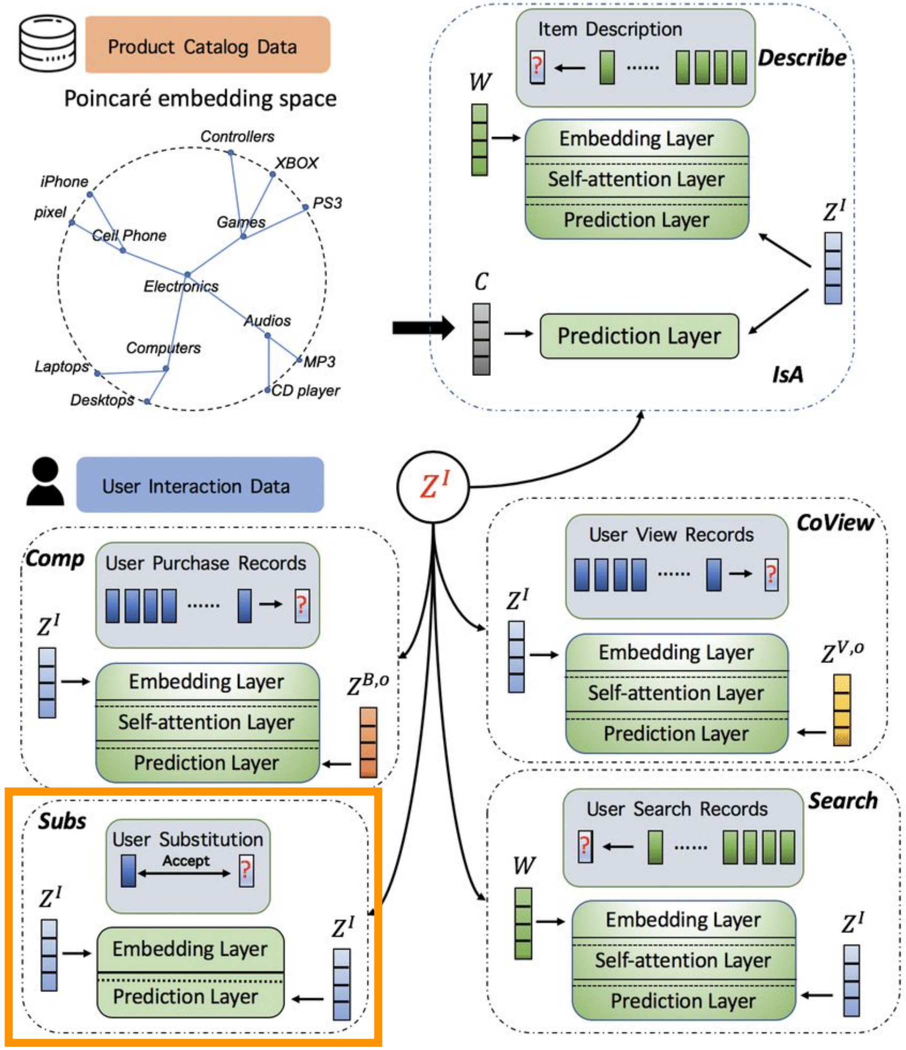
Product Knowledge Graph Embeddings

- Xu et al., 2020, presented a PKGE model, that is tailored to the specificities of the retail domain.
- Knowledge graph of products, words and category labels as entities and relations as edges
- Their embedding model showed improvement in tasks including:
  - Search ranking.
  - Recommendation.
  - Knowledge completion.

Xu, et al.,. 2020. Product Knowledge Graph Embedding for E-commerce. In WSDM '20.

Product Knowledge Graph Embeddings

- **Modelling substitute Relation**: Similar products should have similar embeddings.
  - Product substitute logs can represent such similarity.



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Product Knowledge Graph Embeddings

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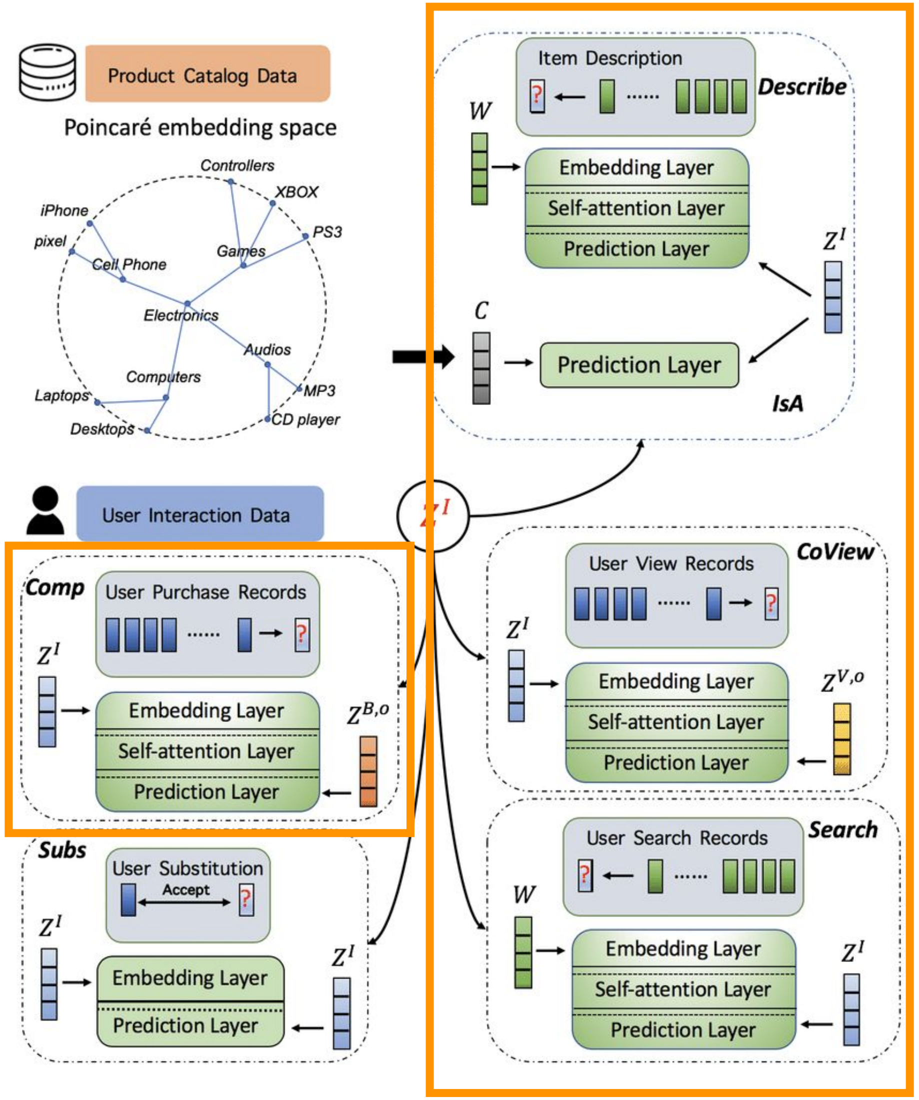
- **Self-attention mechanism** for noise-robust handling for complement, co-view, describe and search Relations.



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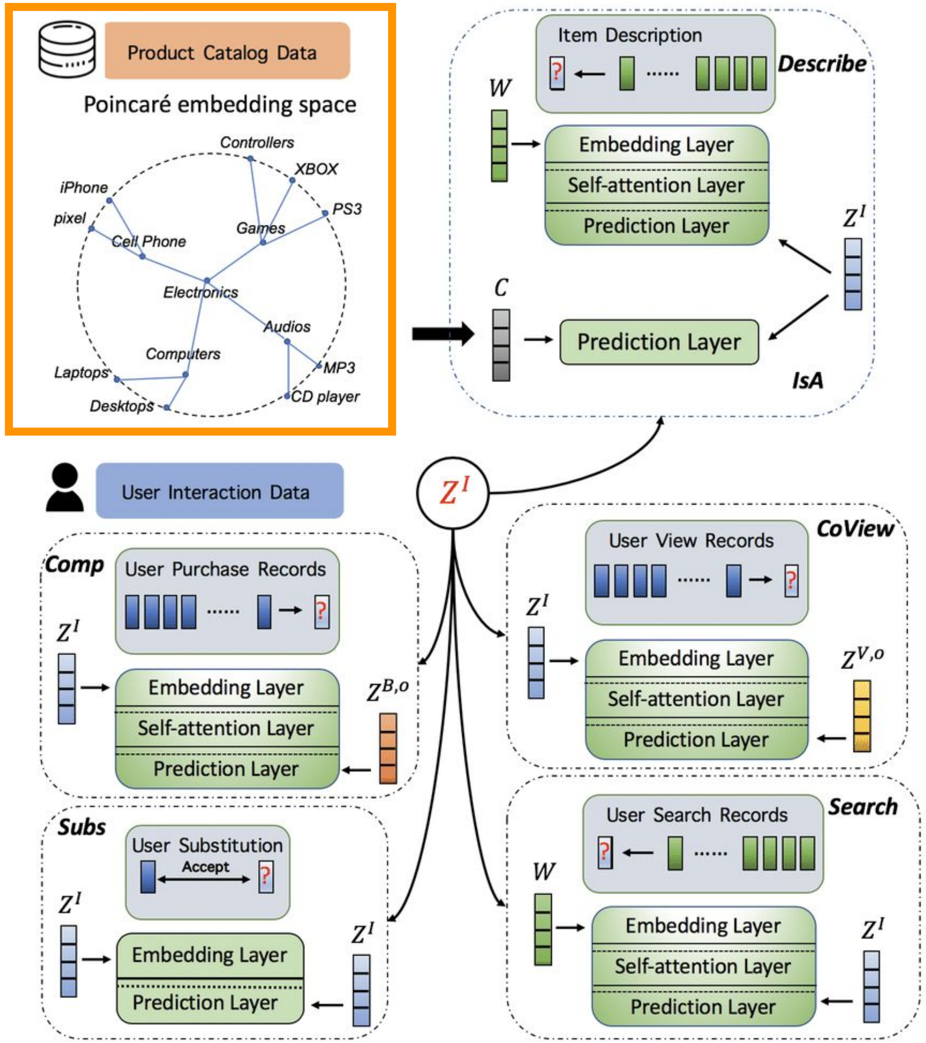
Product Knowledge Graph Embeddings

- **Modelling substitute Relation**: Similar products should have similar embeddings.
  - Product substitute logs can represent such similarity.
- **Self-attention mechanism** for noise-robust handling for complement, co-view, describe and search Relations.
- **Poincaré embedding** for the category hierarchy



Xu, et al.,. 2020. Product Knowledge Graph Embedding for E-commerce. In WSDM '20.

Product Knowledge Graph Applications

Recommendation Systems, Search and Question Answering

Recommendation Systems

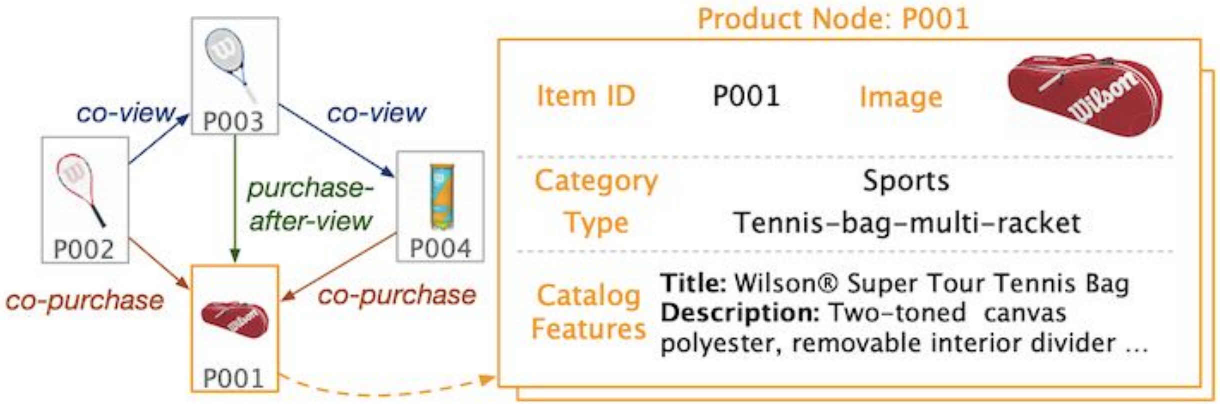
- Recommendation systems play a major role in eCommerce.
  - Enhance customer experience.
  - Drive revenue.
  - Maintain engagement.
  - Among others.

- PKGs play a big role in improving overall recommendation quality, in terms of:
  - Recommendation accuracy.
  - Recommendation diversity.
  - And recommendation explainability.

Product Recommendation Systems

- We can think of different variations of product recommendations:
  - Product substitutes.
  - Related products.
  - Complementary product recommendation.

- **Behavior-based Product Graph (BPG)**:
  - BPGs can be very useful for recommendation systems.
  - BPG is constructed with nodes as items with catalog features (type, etc) and edges as pairwise relations based on customer behavior.



Hao et al.,. 2020. P-Companion: A Principled Framework for Diversified Complementary Product Recommendation. Proceedings of the 29th CIKM conference.

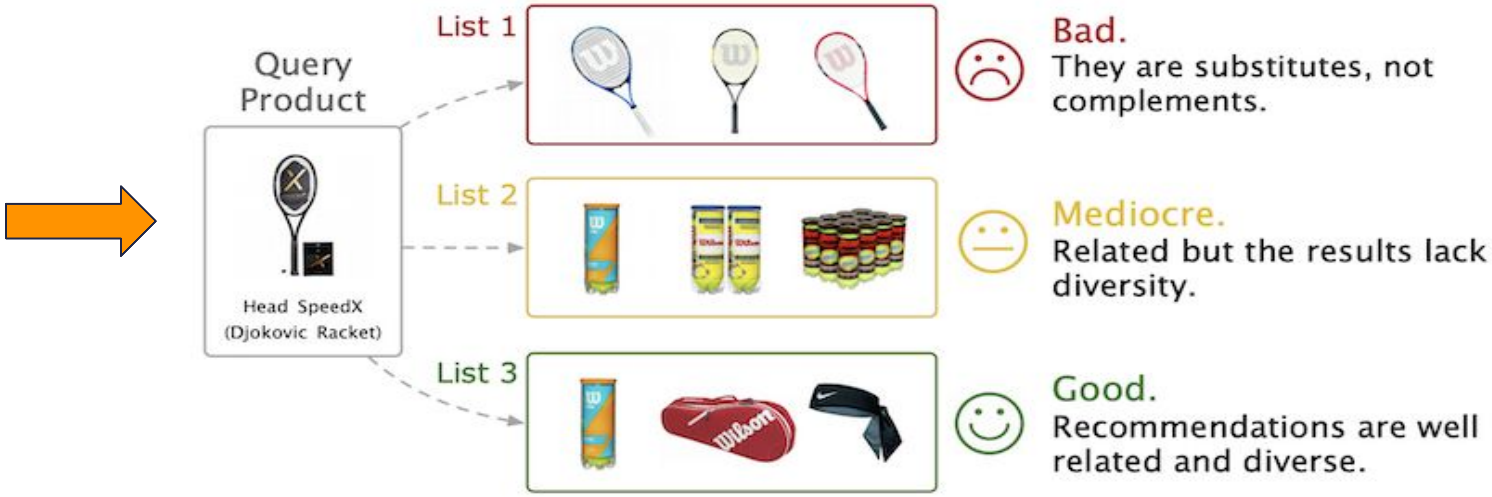
Specificities of Product Recommendation Systems

Recommendation diversity	• Recommendation diversity is critical for eCommerce. • Making related recommendations only is not enough.
Complementary recommendations	• Simple co-purchase patterns might not be enough. • Need semantic signal for complementary recommendations.
Recommendation interpretability	• Explicit paths in KGs provide a better explainability potential.
Hierarchical structure	• The product taxonomy and categories help in all previous issues.

Complementary Product Recommendation

- Complementary product recommendation (CPR) aims at providing product suggestions that are often bought together.
- Co-purchased products are not always complementary.

Complementary recommendation systems



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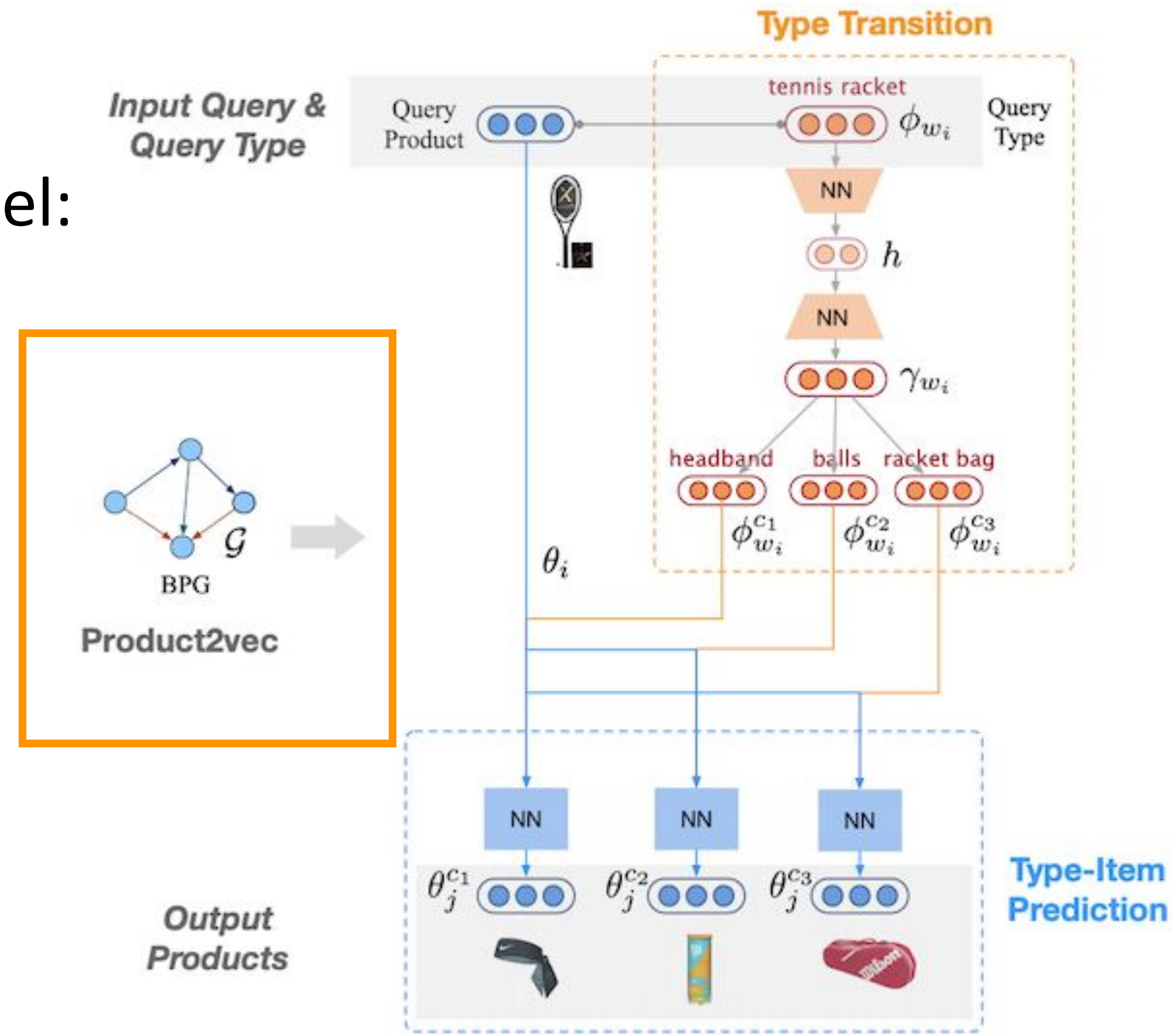
Product Complement Systems

Main components in Hao et al. 2020 complementary recommendation model:

- Product2vec: Pretrained product embeddings based on customer behavior data.



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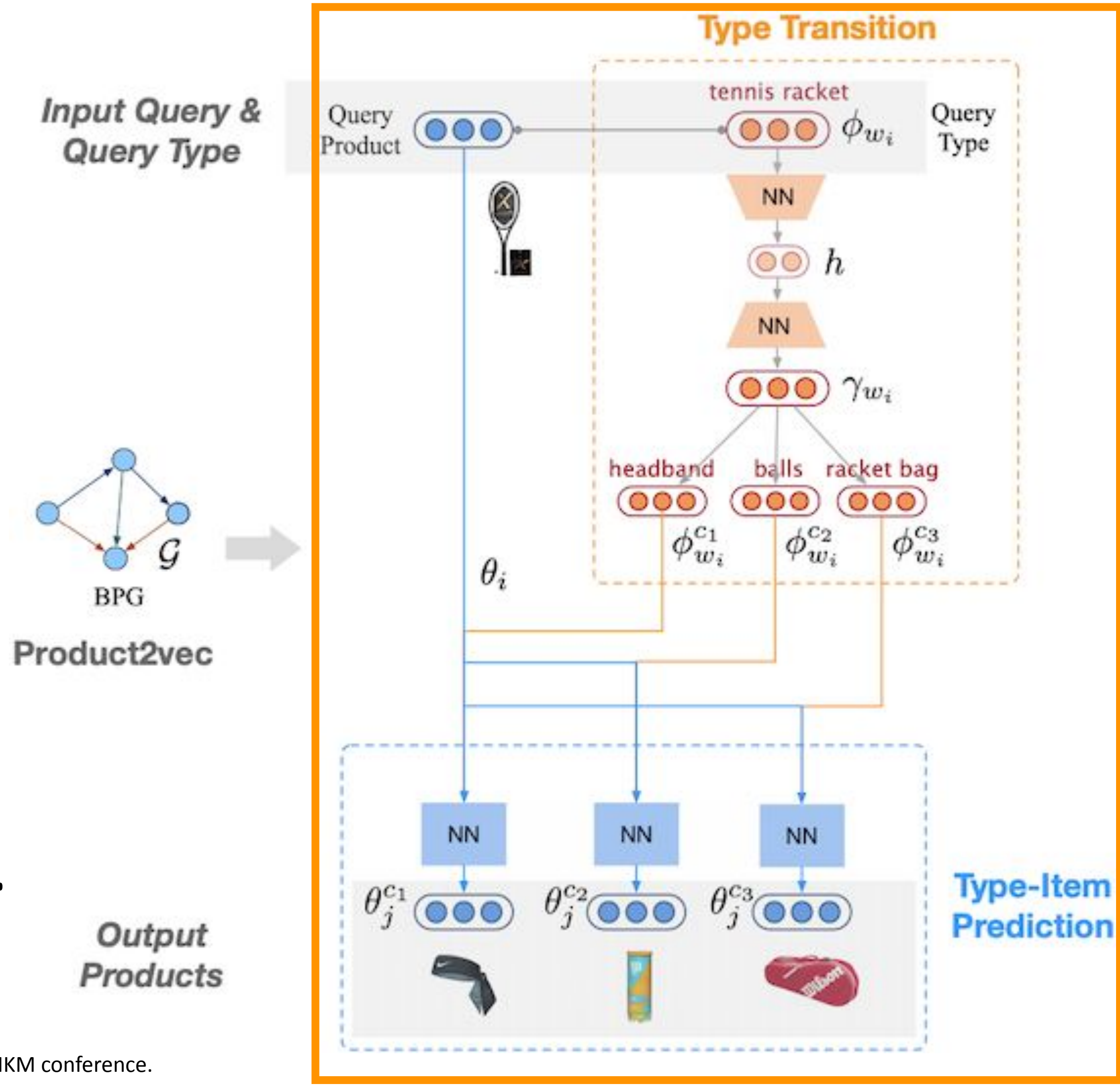
Product Complement Systems

Main components in Hao et al. 2020 complementary recommendation model:

- Product2vec: Pretrained product embeddings based on customer behavior data.
- Type transition: complementary product type prediction task (as opposed to actual products).
- Item prediction: Complementary product prediction from product type.



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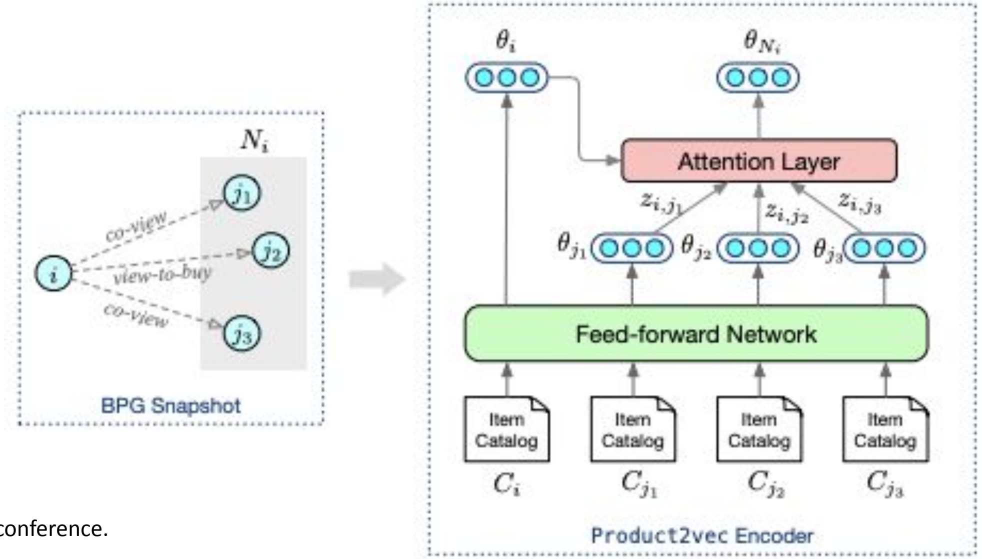
Product2Vec

- Just like the other “*2Vec” family. Learns pretrained representations for products that preserve similarities.
- Leverages user behavior logs, and the co-purchase relation in particular to build a graph, and use graph attention network.
- Very useful in cold-start products in many applications, especially recommendation systems.



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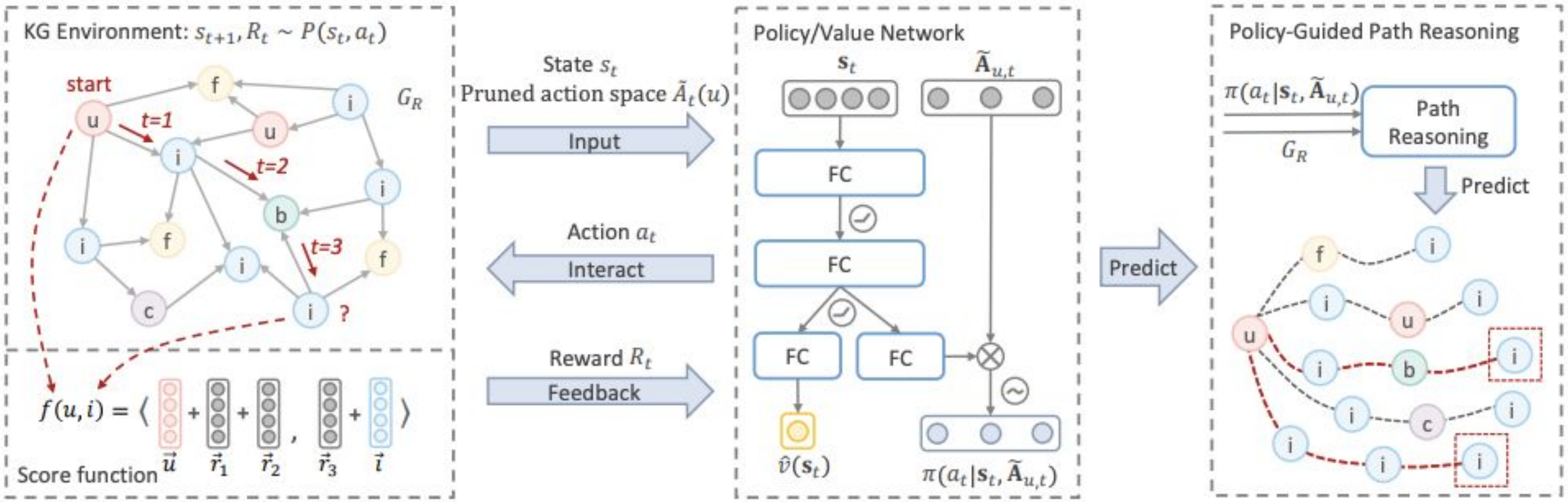
Explainable Product Recommendation

- The paths in PKGs also allow for explainable recommendation, through explicit reasoning.
- Xian et al., 2019, use reinforcement learning to identify recommendation paths from a user to product.



Xian et al., 2019. Reinforcement Knowledge Graph Reasoning for Explainable Recommendation. SIGIR’19

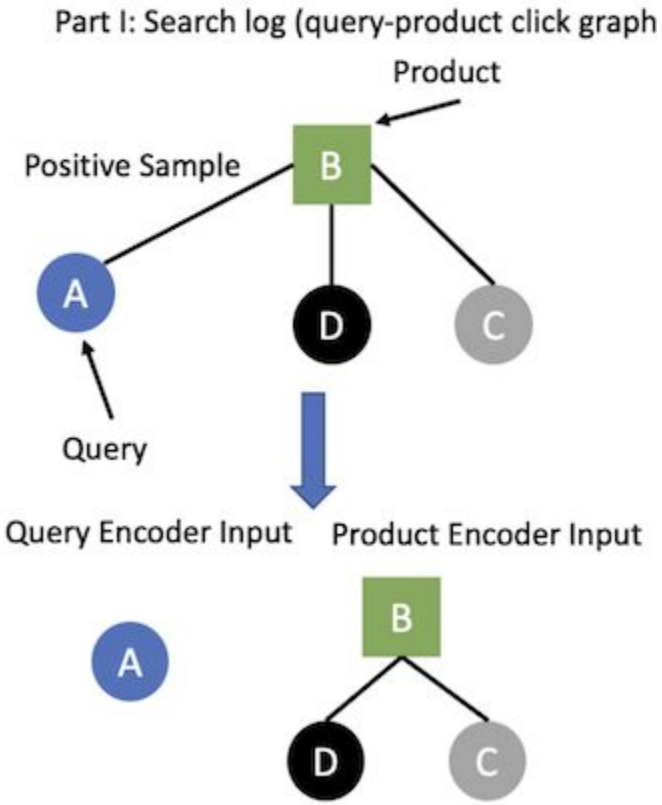
Product Search and Question Answering

User activity	• User search logs and purchases, product complements, co-view and substitute are very useful.
Multilingual search	• e-Commerce platforms serve many countries with several languages. • Ideally, should facilitate multilingual search to support scale.
Dynamic taxonomy	• Taxonomy enrichment and relation discovery.
Noise	• Facts in PKG can be noisy, which can affect results. • Importance of data cleaning.

Product Search

- Lu et al. 2020 presented a multilingual graph-based product search and retrieval model.
  - Transformer-based encoding.

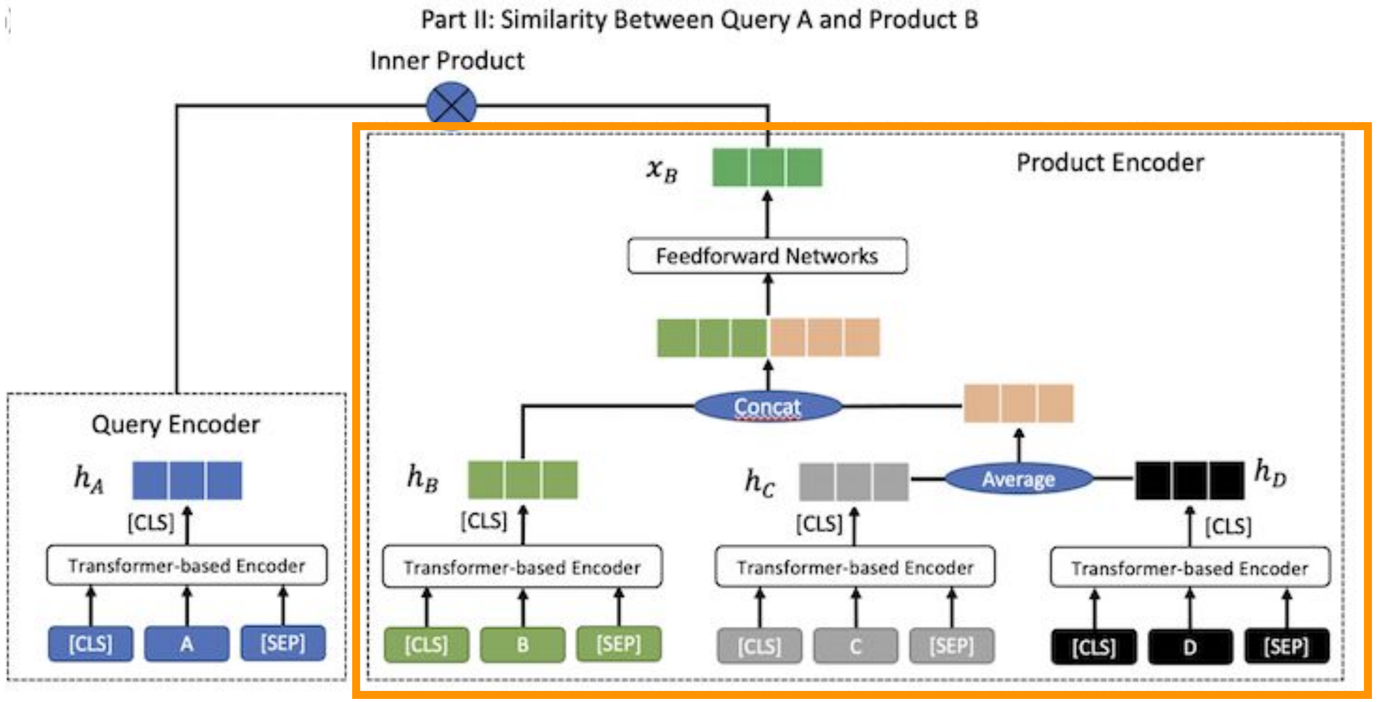
- Present query-to-product relationships as a bipartite graph.
  - Product (B) to query (A, C, and D) mapping.
  - Neighbouring queries (D, C) from search log.
  - A (positive sample) used to train query encoder.



Lu et al., 2021.. Graph-based Multilingual Product Retrieval in E-Commerce Search. NAACL’21.

Product Search

- Product encoder:
  - Takes product, and neighboring queries as input.
  - Transformer-based model.
  - Convolutional Graph Networks to learn representation.



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Product Search

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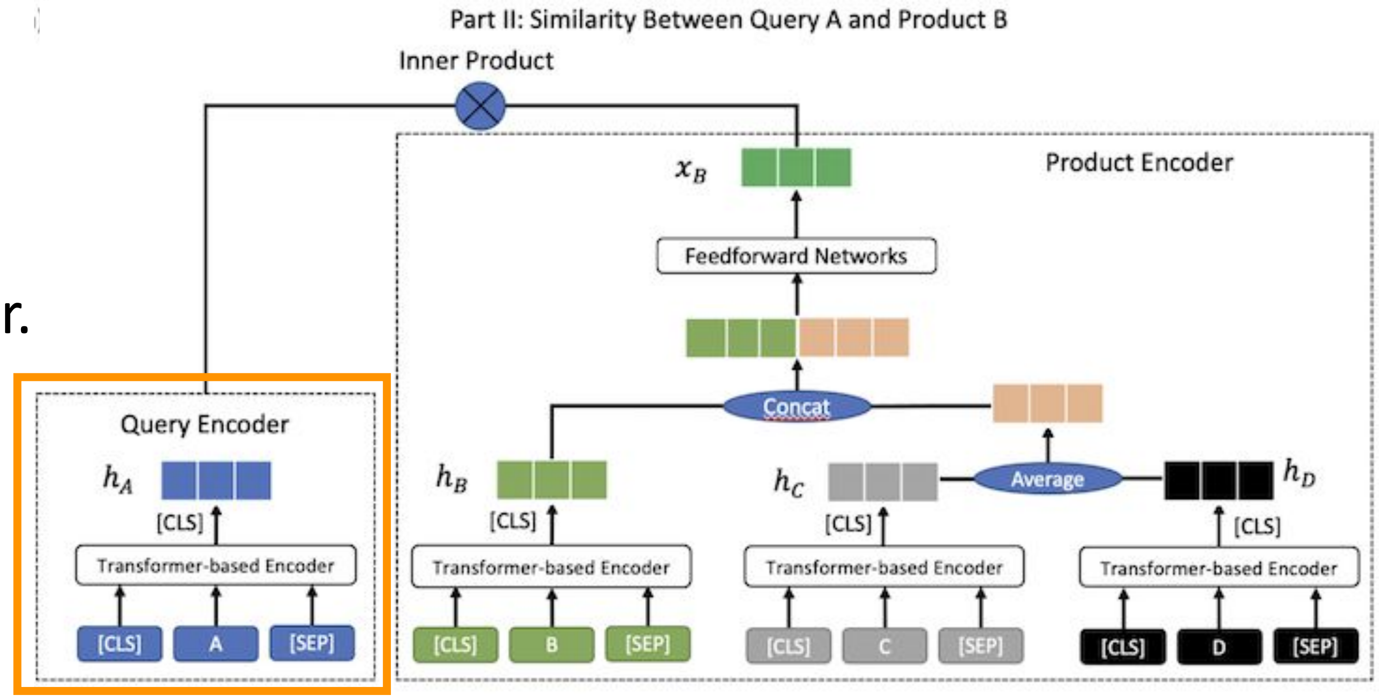
- Query encoder:
  - Transformer-based encoder. for the query text.



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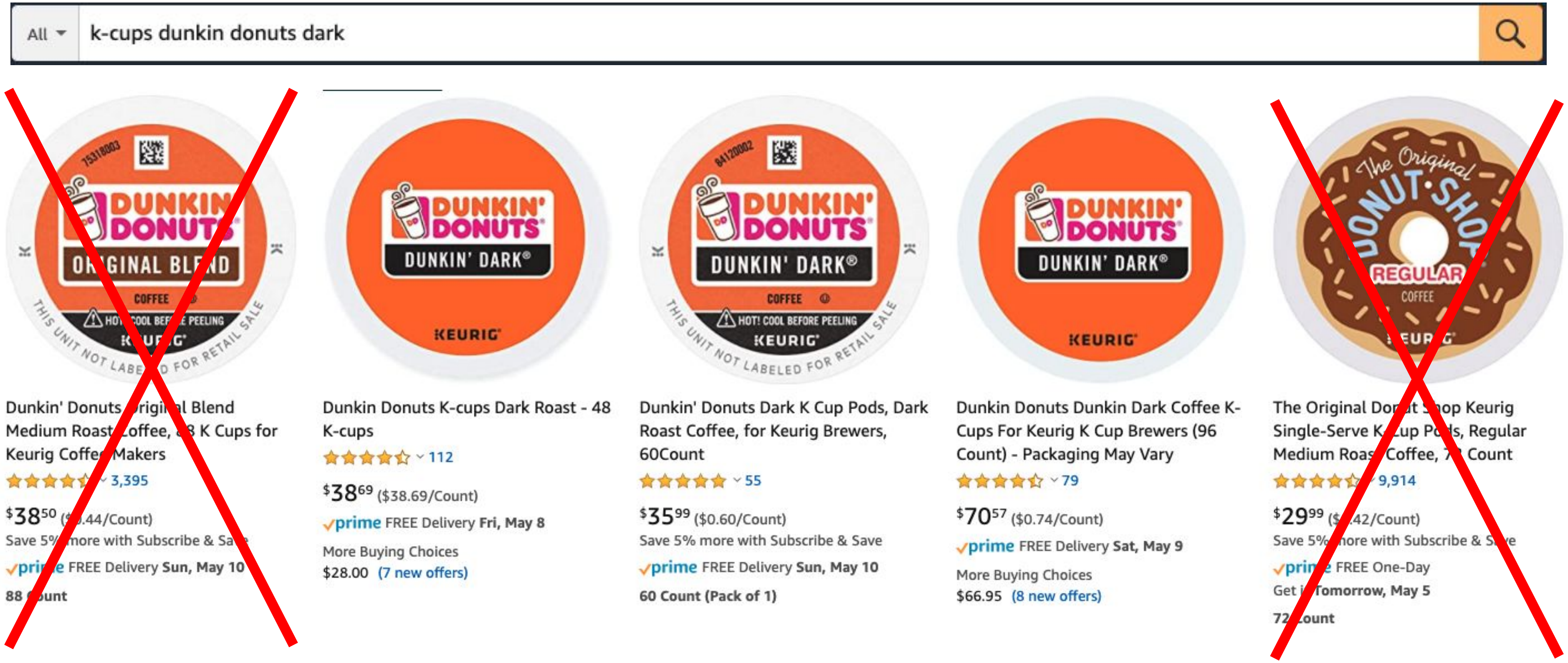
Product Search Challenges

- Exact match in search results, based on main query attributes, is very important in the product domain.
- Among the notable challenges facing product search is the incomplete taxonomy and overall factual knowledge.
- Completeness and scalability in PKGs help a lot on this regard. Direct access of product descriptions is also important.

Product Search Challenges



Conversational Product Search

- A natural extension to search and recommendation applications.
- Personal assistants are pervasive now, so inquiring about products, and asking for product recommendations, is a logical skill to add.
- Same setup as search techniques, with iterative turns, powered by product attributes, to further identify most relevant product.

Conclusions and Future Directions

What’s So Special about PKGs?

Primarily text heavy	● Textual product profiles. Other modalities complement text. ● Explicit natural language handling is critical.
Other modalities	● Product images can provide important additional signals.

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Dynamic taxonomy	● Constantly emerging product categories. ● Automatic taxonomy enrichment.

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Hierarchical structure	• The product taxonomy is mainly hierarchical in nature.
Dynamic taxonomy	• Constantly emerging product categories. • Automatic taxonomy enrichment.
User activity	• User search logs, product complement, co-view and substitute purchases can be very useful.

Knowledge Extraction Takeaways

- **Definition**: Find values for a given product and a set of attributes.
- **Recipe**: Sequence tagging.
- **Key to Success**: Scale up in different dimensions (#attributes, #categories).
- **Applicability to other domains**: Domains like finance, biomedical etc, where the “subject” is known.

Knowledge Cleaning Takeaways

- **Definition**: Finding wrong attribute values.
- **Recipe**: Identify data inconsistency column-wise, row-wise, source-wise and across sources.
- **Key to Success for Products**:
  - Leverage rich textual information of unstructured data as context
  - Solution with aware of taxonomy.
- **Applicability to Other Domains:** Domains like: medical, legal, etc.
  - Domains with heavy text data.
  - Rich taxonomy information.

Ontology Enrichment Takeaways

- **Definition**: discover relations between product categories and attributes.
  - Attribute Applicability: “Is an attribute applicable to one product category?”
  - Attribute Importance: “Is an attribute important when people are making their purchase decisions?”
- **Recipe**: Text Mining and Graph Mining.
- **Key to Success for Products**: Leverage both seller/customer inputs.
- **Applicability to other domains**:
  - An increasing variety of relationships or predicate diversity.
  - Quantify the relation strength.

Applications Takeaways

- Applications of product knowledge graphs can make use of:
  - The structured factual information for each product.
  - The product connections in the overall graph structure.
- The graph structure also allows the utilization of graph level constructs, like knowledge graph embeddings, which is useful for many applications.
- General applications of knowledge graphs include recommendation systems, search, among others.

An End-to-End Pipeline

Understand domain and attributes, and generate LOTS OF training data

Identify product taxonomy and attributes

Train and fine-tune models

Extraction Models

Postprocess extraction results to further improve data quality

Pre-publish evaluation as gatekeeper to guarantee high quality data

An End-to-End Pipeline

Automatic Training Data Generation

Distant supervision,
Data programming

Automatic Taxonomy Enrichment

Category classification,
attribute identification

Train and fine-tune models

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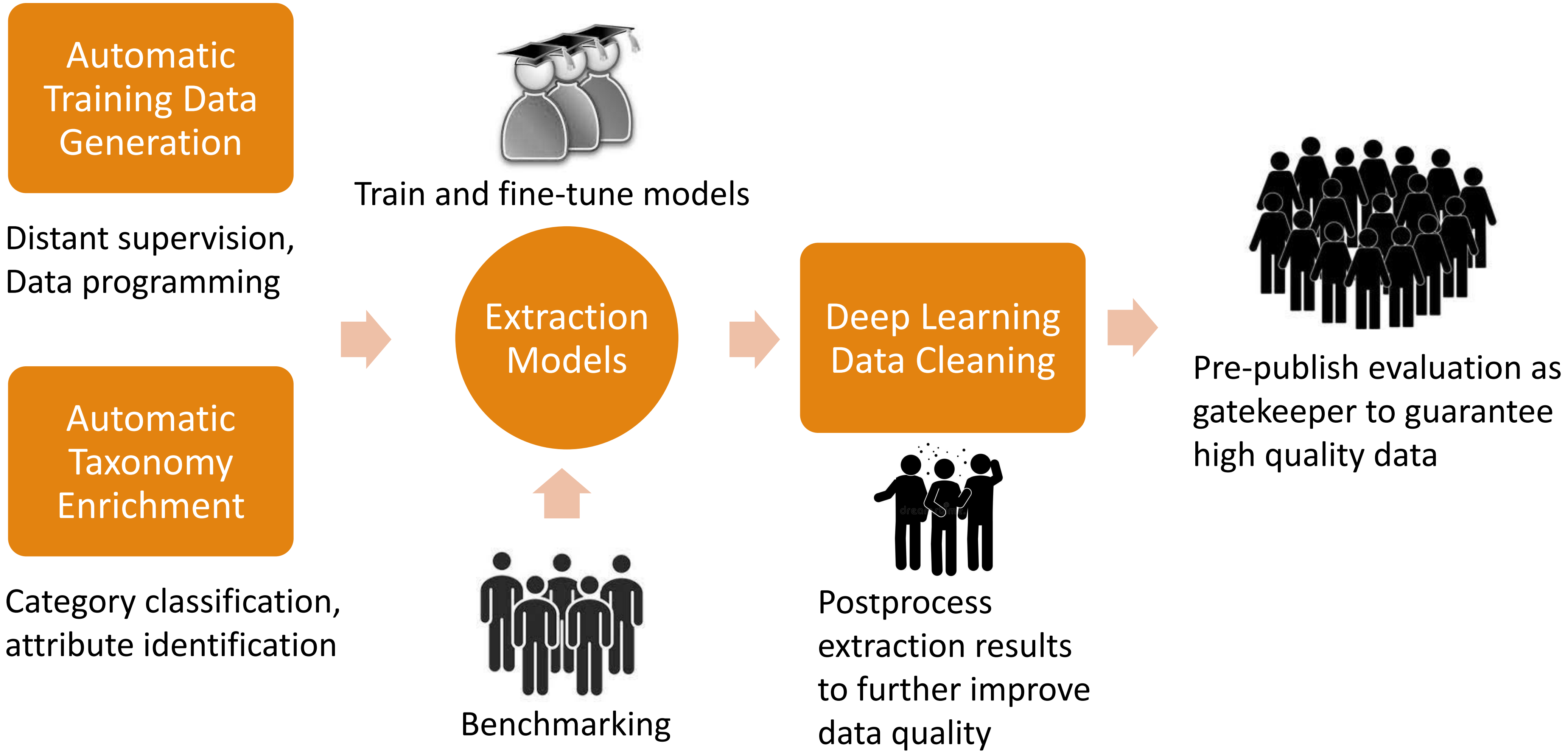

An End-to-End Pipeline

Automatic Training Data Generation

Distant supervision,
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Category classification,
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Train and fine-tune models

Extraction Models

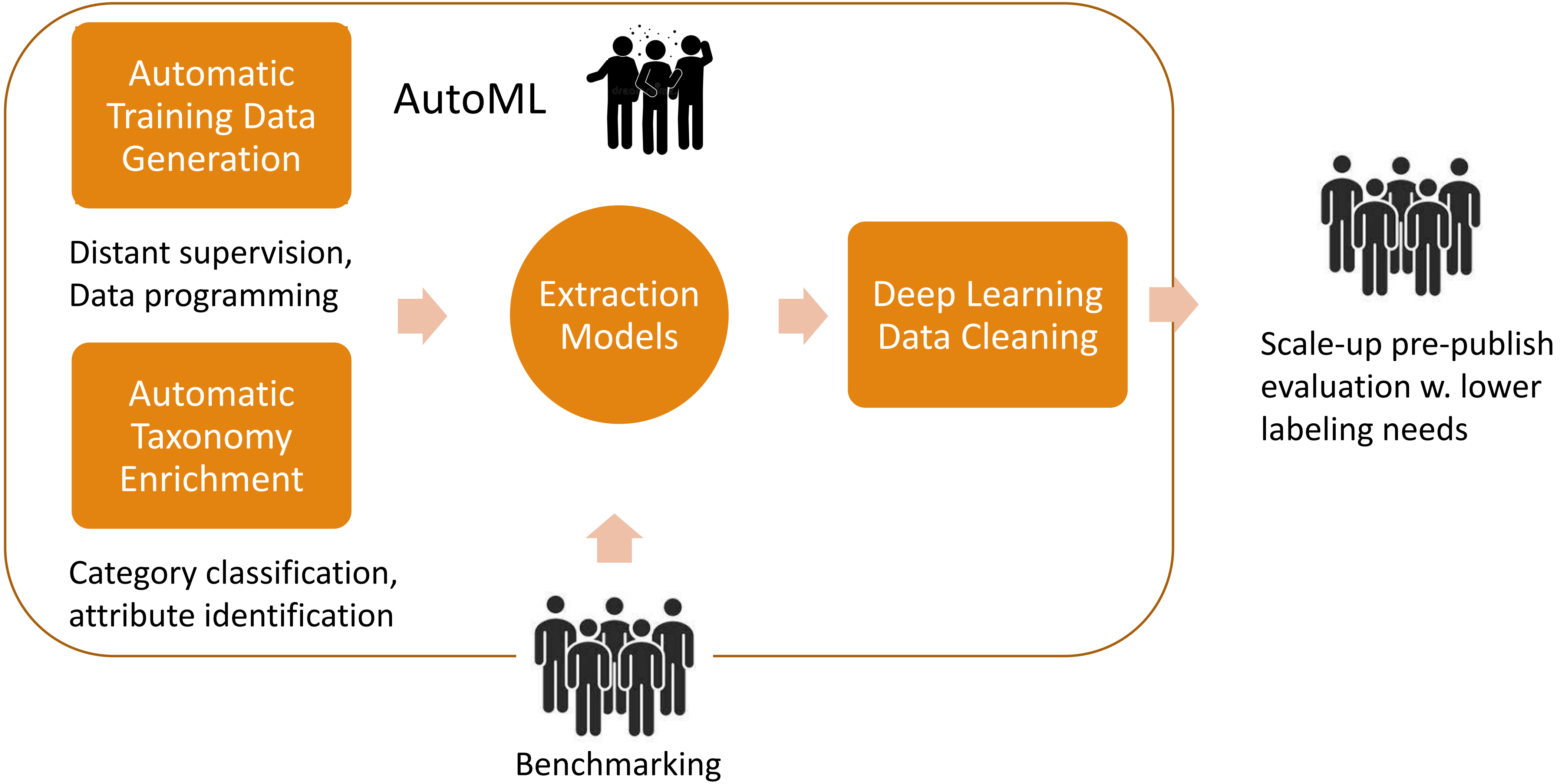
Benchmarking

Deep Learning Data Cleaning

Postprocess extraction results to further improve data quality

Scale-up pre-publish evaluation w. lower labeling needs

An End-to-End Pipeline



Practical Tips

- **Training data**
  - Mainly distant and weak supervision approaches.
  - Some manual rules to enhance quality is a good investment!
  - Check values distribution, and any outliers.

- **Evaluation:**
  - Two-step evaluation process:
    1. Annotate benchmarks to iterate while model training.
    2. Evaluate a predictions sample when model is ready.
  - Update model based on benchmarks.
  - Post-processing rules when manual intervention is unavoidable.

Practical Tips

- **Modeling scope**
  - Categorical classification: When target space is closed and small, and when handling implicit values.
  - Textual extraction: In open-world cases, and when target values tend to be mentioned explicitly.

- **Prediction confidence**
  - We set thresholds based on prediction confidence to filter out predictions, and balance precision and recall

Practical Tips

- **Human in the loop**
  - We strive for scale and automation, while maintaining accuracy.
  - Achievable, through balancing automation and human input, at the right place.
  - Empower humans with the right tools and analytics tools.

Applicability to other Domains

Media
(Music, movies, sports, etc)

- **Text heavy:** Moderate (entity-heavy)
- **User activity:** High
- **Noise:** High
- **Multimodal:** High
- **Dynamic ontology:** Moderate

Healthcare
(Records, Drs, medicine, etc)

- **Text heavy:** High
- **User activity:** Moderate
- **Noise:** Moderate
- **Multimodal:** Moderate
- **Dynamic ontology:** Moderate

Legal
(Cases, contracts, etc)

- **Text heavy:** High
- **User activity:** Low
- **Noise:** Moderate
- **Multimodal:** Low
- **Dynamic ontology:** Moderate

Future Directions

We identified the following themes for future directions:

- **Training data:**
  - Make better use of unlabeled and seed datasets.
  - Enhance data quality through better data programming methods.
- **Ensembling and multitask methods**:
  - Ensemble data cleaning methods, syntactic, semantic, graph, etc.
  - Ensembling tagging and classification methods.
  - Taxonomy Enrichment and Relation Discovery **in one shot.**

Future Directions

- **Multi-modal/multi-source signals**:
  - Better handling of multi-modal extraction.
  - Better utilization of user logs, like search, co-purchase, etc.
- **Personalization**
  - Better embedding users, venders, brands, etc.
  - Better connection with customer behavior.
- **Connect private to public data**
  - Incorporate common sense knowledge like ConceptNet to clean the data.

Questions