Invited Tech Talk

When Knowledge Graph Meets Product Recommendation

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Bio

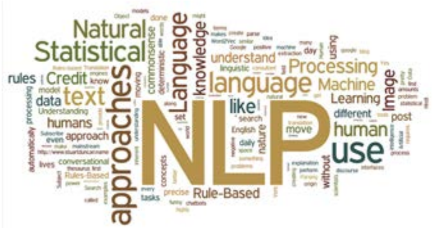
- Currently 5th-year Ph.D. candidate at UCLA co-advised by Yizhou Sun and Wei Wang in UCLA Data Mining Group.
- My research interests include knowledge graph, graph representation learning, KG-empowered applications (NLP, Bioinformatics, recommender systems, etc.).
- Before joining UCLA, I graduated in 2017 from Department of Automation, Tsinghua University.

Past Experiences

- Research Intern, Microsoft Research/MSAI, 2021
- PhD Research Intern, IBM, 2020
- Applied Science Intern, Amazon Product Graph, 2019
- Research Intern, NEC Labs America, 2018

Knowledge Graphs Are Important

- Foundational to knowledge-driven AI systems
- Enable many downstream applications (NLP tasks, QA systems, etc.)



Natural Language Processing

Sorry, I don't know that one.

QA & Dialogue systems

Knowledge Graphs

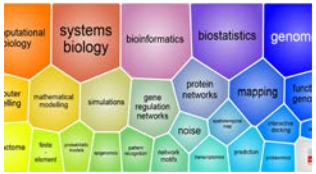
ebay

amazon

NETFLIX

Recommender Systems

P-Companion



Computational Biology

CIKM 2020 19-23 OCTOBER Online

UCLA Samueli Computer Science

product graph

CIKM Applied Research Paper

P-Companion: A Principled Framework for Diversified Complementary Product Recommendation

Junheng Hao, Tong Zhao, Jin Li, Xin Luna Dong,
Christos Faloutsos, Yizhou Sun, Wei Wang

Outline

- Background: Complementary Product Recommendation (CPR)
- Behavior-based Product Graphs (BPG)
- P-Companion Model
- Experiments & Case Study
- Summary & Future work

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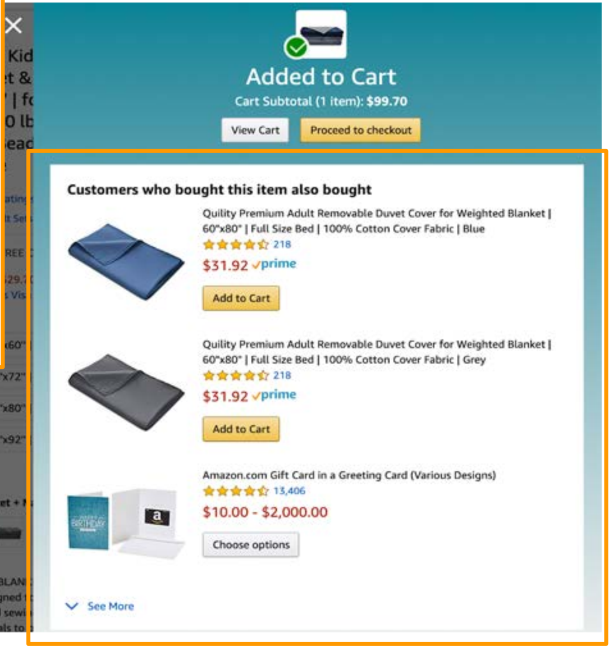
Products to purchase together?



Complementary Recommendation

Think about one customer who plans to buy a tennis racket (e.g., Head SpeedX Djokovic racket).

What would you recommend for him to purchase together?

- List 1: three more tennis rackets? → Sorry, we are not looking for substitutes!
- List 2: three sets of tennis balls? → Hmm, not bad, but only need one is good enough. Can we do better?
- List 3: one tennis ball pack, one bag and one headband? → Sound good this time!

Problem Definition

Given the input as catalog features (including item type) and customers behavior data, for a query item i, we recommend a set of items S(i) , aiming at optimizing their co-purchase probability and recommendation diversity.

Query item i

Related and diverse recommendation set S(i)

Key Challenges

- **C1:** Complementary relationship between products is not symmetric and complementary recommendation is not simply based on similarity measurement.
- **C2:** Besides relatedness, complementary recommendation also needs to consider diversity. Diversified recommendations can better fulfill customer’s need and significantly improve shopping experiences.
- **C3:** Complementary recommendation suffers in cold-start items. These items with low-resources on their features widely exist in e-commerce platform.
- *Some more challenges indeed…*

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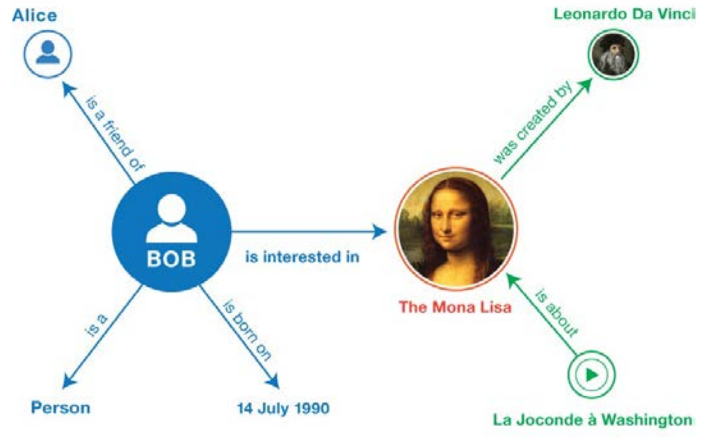
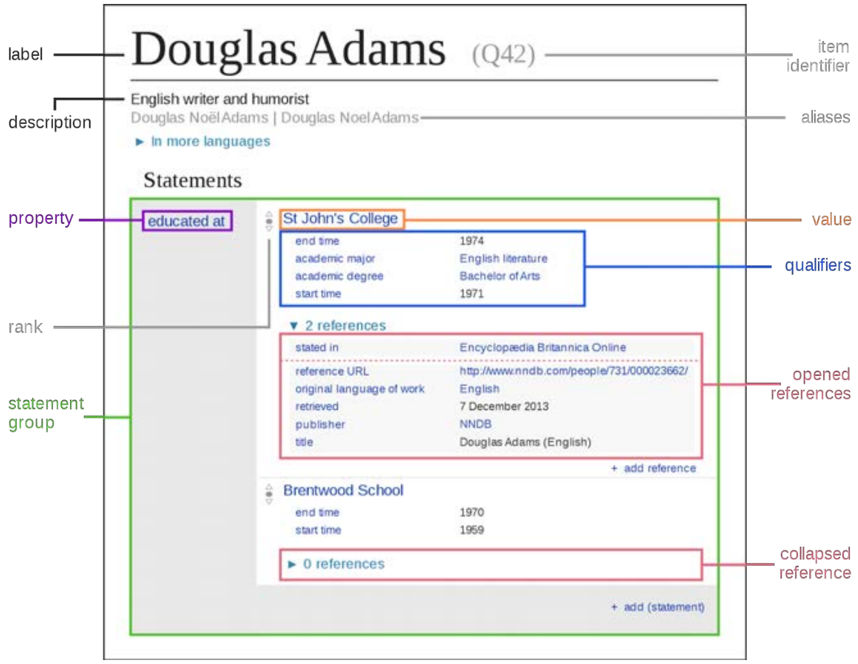
How are KGs structured or formatted?

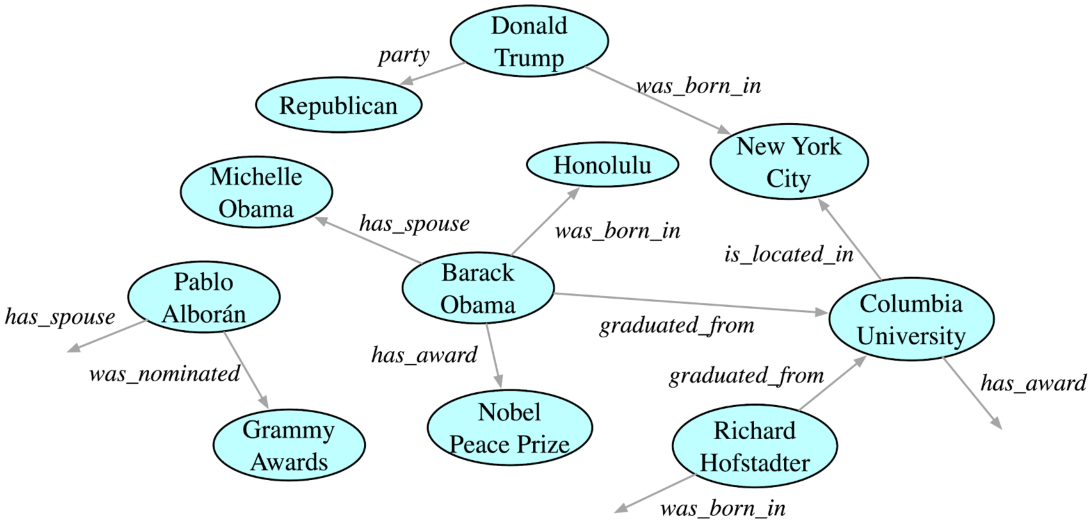
- **Triples (RDF)**
  - Represented by: a node for the subject, a node for the object, and an arc/node for the predicate.
  - Example: Semantic Web, medical ontologies, etc.



- **Label-property**
  - Entity, labels, properties, qualifiers, etc.
  - Example: Wikidata

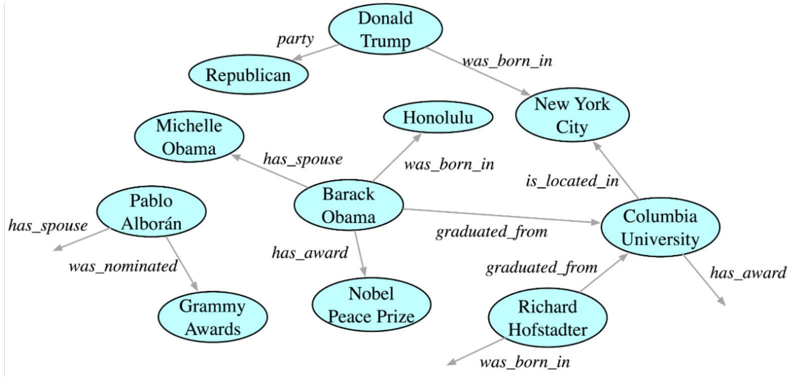


A KG Snapshot from YAGO, made with triples

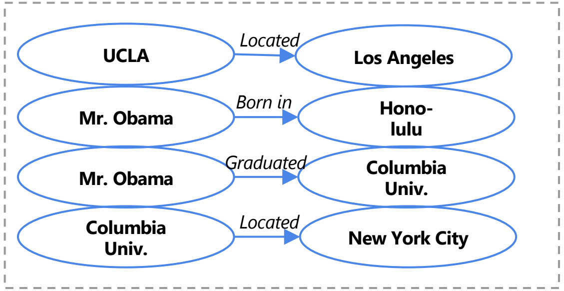


KG Embeddings From Triples

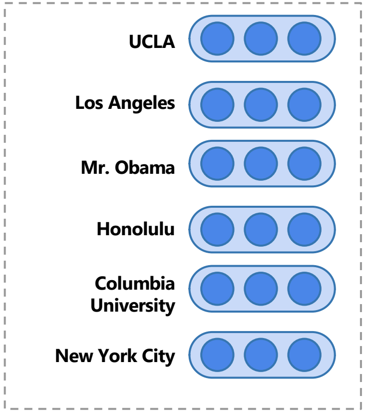
- Knowledge graph embeddings represent entities and relations as latent vectors or matrices and support effective relation learning and inference.
- **Input**: Relation facts (triples)
- **Output**: Embedding representations of objects and relations



Input

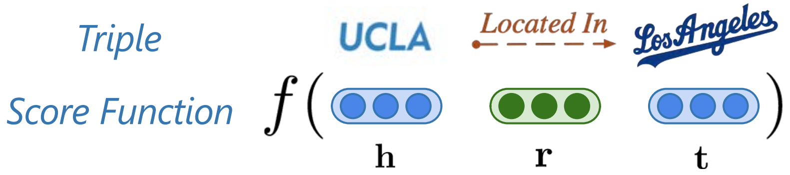


Output



Learning KG Embeddings

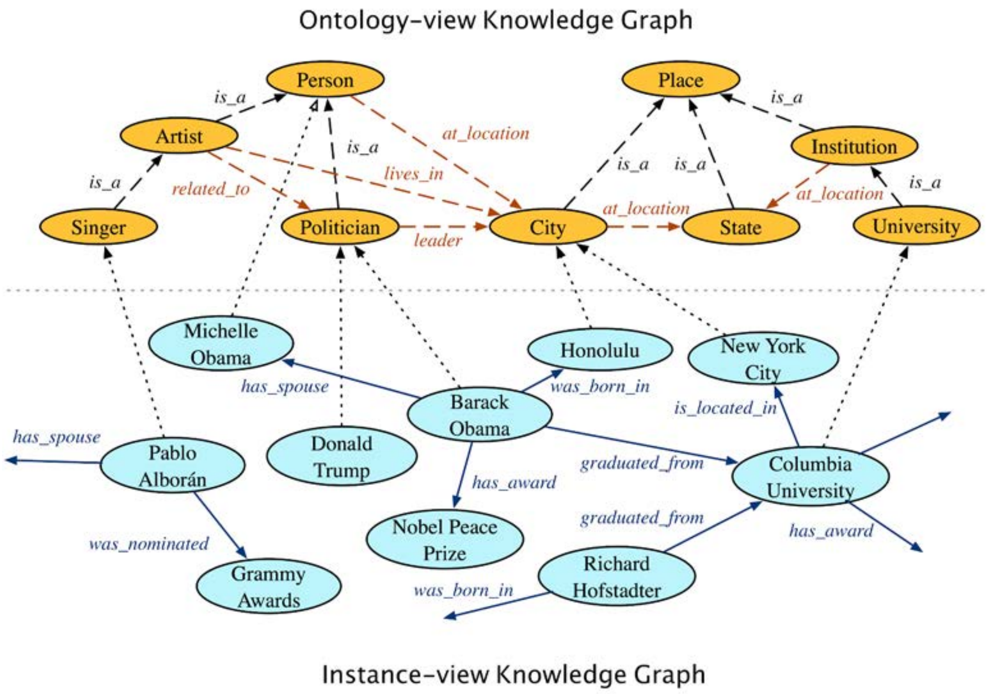
- Key of existing KG embedding methods: Triple score function



- Previous research employ various arithmetic methods to capture observed relations of entities in a single KG (for example, translational distance or similarity)

Model	Score Function	Embeddings
TransE (Bordes et al., 2013)	$-\|\|\mathbf{h}+\mathbf{r}-\mathbf{t}\|\|$	$\mathbf{h},\mathbf{r},\mathbf{t}\in\mathbb{R}^k$
TransX	$-\|\|g_{r,1}(\mathbf{h})+\mathbf{r}-g_{r,2}(\mathbf{t})\|\|$	$\mathbf{h},\mathbf{r},\mathbf{t}\in\mathbb{R}^k$
DistMult (Yang et al., 2014)	$(\mathbf{h}\circ\mathbf{t})\cdot\mathbf{r}$	$\mathbf{h},\mathbf{r},\mathbf{t}\in\mathbb{R}^k$
HolE (Nickel et al., 2016)	$(\mathbf{h}\star\mathbf{t})\cdot\mathbf{r}$	$\mathbf{h},\mathbf{r},\mathbf{t}\in\mathbb{R}^k$
ComplEx (Trouillon et al., 2016)	$\mathrm{Re}\langle\mathbf{r},\mathbf{h},\bar{\mathbf{t}}\rangle$	$\mathbf{h},\mathbf{r},\mathbf{t}\in\mathbb{C}^k$
ConvE (Dettmers et al., 2017)	$\langle\sigma(\mathrm{vec}(\sigma([\mathbf{r},\mathbf{h}]*\Omega))\mathbf{W}),\mathbf{t}\rangle$	$\mathbf{h},\mathbf{r},\mathbf{t}\in\mathbb{R}^k$
RotatE (Sun et al., 2019)	$-\|\|\mathbf{h}\circ\mathbf{r}-\mathbf{t}\|\|^2$	$\mathbf{h},\mathbf{r},\mathbf{t}\in\mathbb{C}^k,\ \|r_i\|=1$

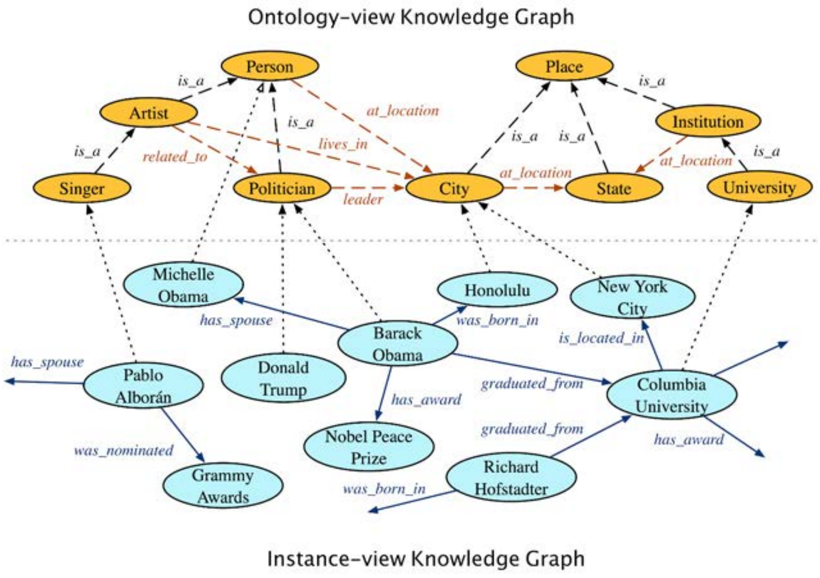
Before We Jump Into Product Graph

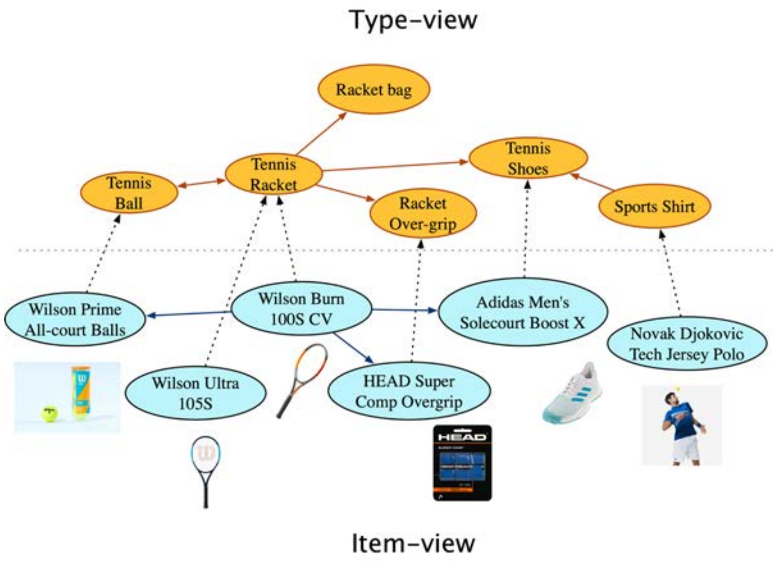


Terms

- Nodes/entities
- Relation, relation type
- Edges, triples
- Classes, types
- Ontology

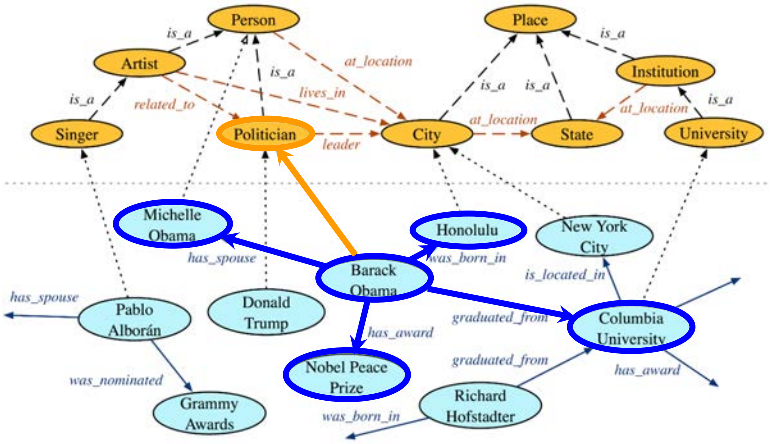
Before We Jump Into Product Graph





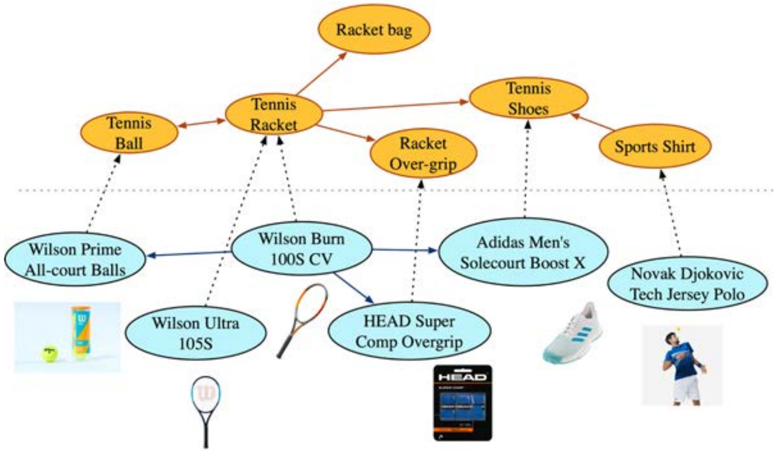
Before We Jump Into Product Graph

Ontology-view Knowledge Graph



Instance-view Knowledge Graph

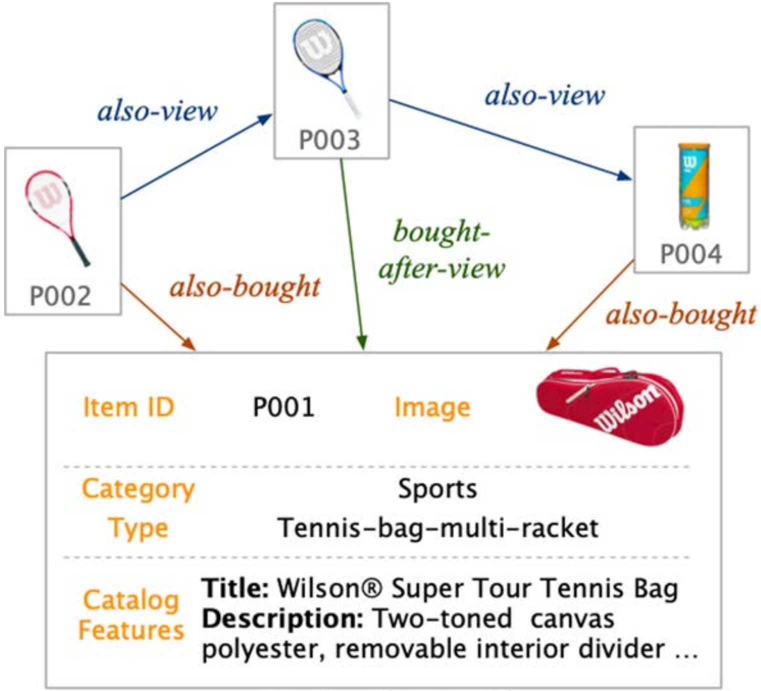
Type-view



Item-view

Behavior-based Product Graphs

- Behavior based product graph → Attributed heterogeneous information networks (KGs)
- Node: Product items with attributes (title, description, category, keywords)
- Edges: Customer browsing and purchase behaviors (such as also-bought, also-view, bought-after-view, as important indicators of substitutes or complements)
- Note that there are many alternative ways to construct product graphs.

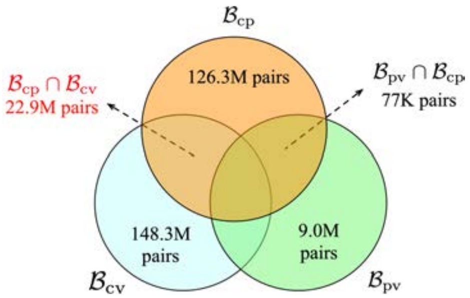


Product Node: P001

Data Analysis on BPG

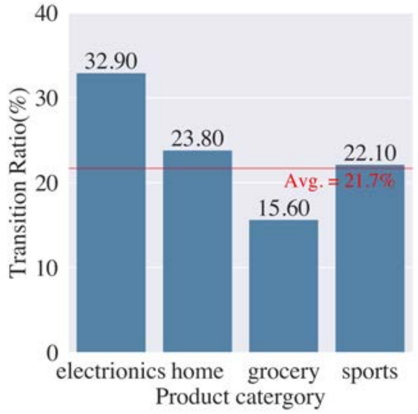
Two important observations:

1. Product pairs from co-purchase and co-view records are not disjoint, and the amount of overlap heavily depends on categories.
2. Complementary relation in products is often observed across multiple categories.



Solution: Distant Supervision Collection for Complementary Recommendation

1. We use a subset of co-purchase, i.e. $\mathcal{B}_{cp} - (\mathcal{B}_{pv} \cup \mathcal{B}_{cv})$ as labels for complementary products, which contains product pairs only in co-purchase records gives us the complement signals.
2. Removed the restriction of making recommendations within one category in and create a general dataset with multiple categories.



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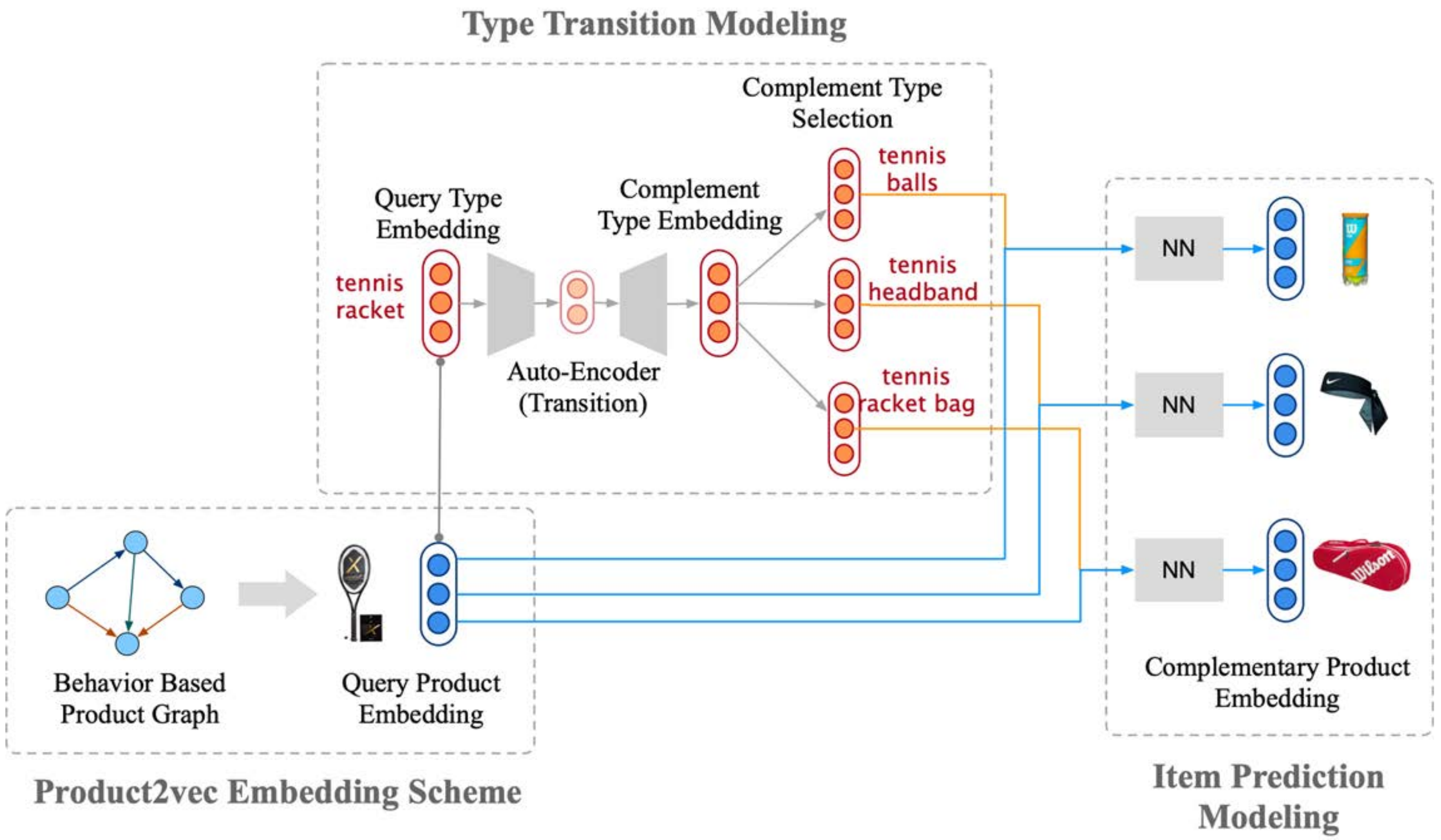
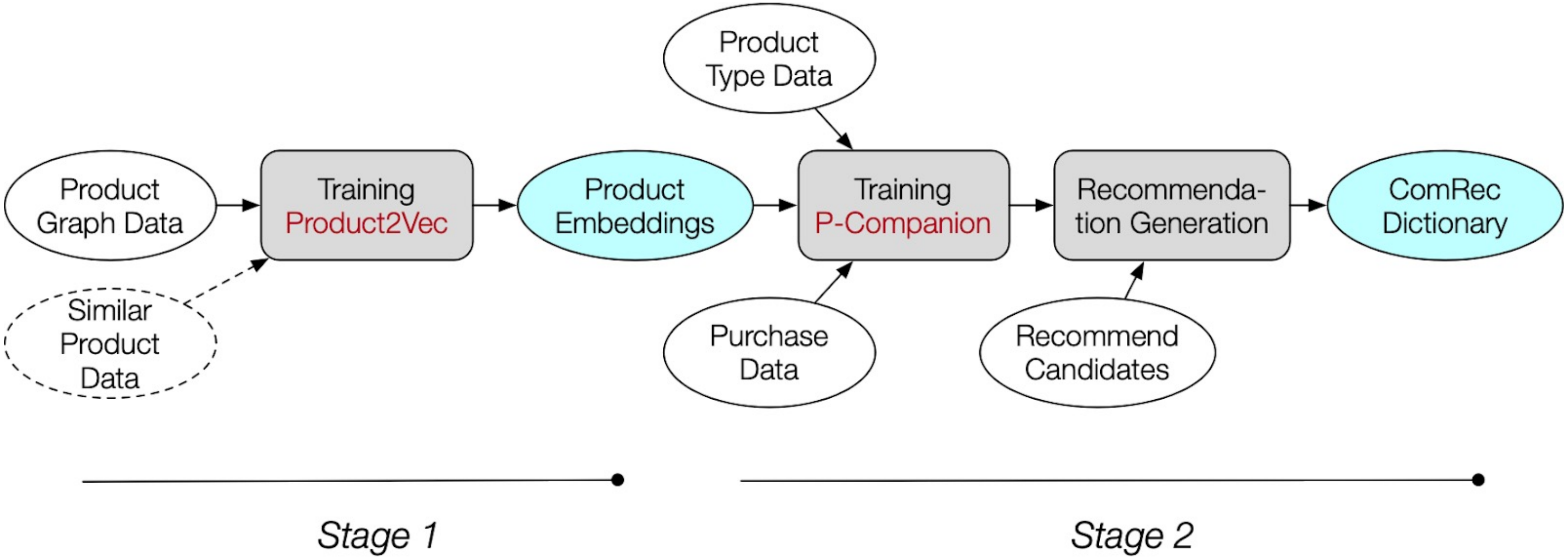
P-Companion: Overview

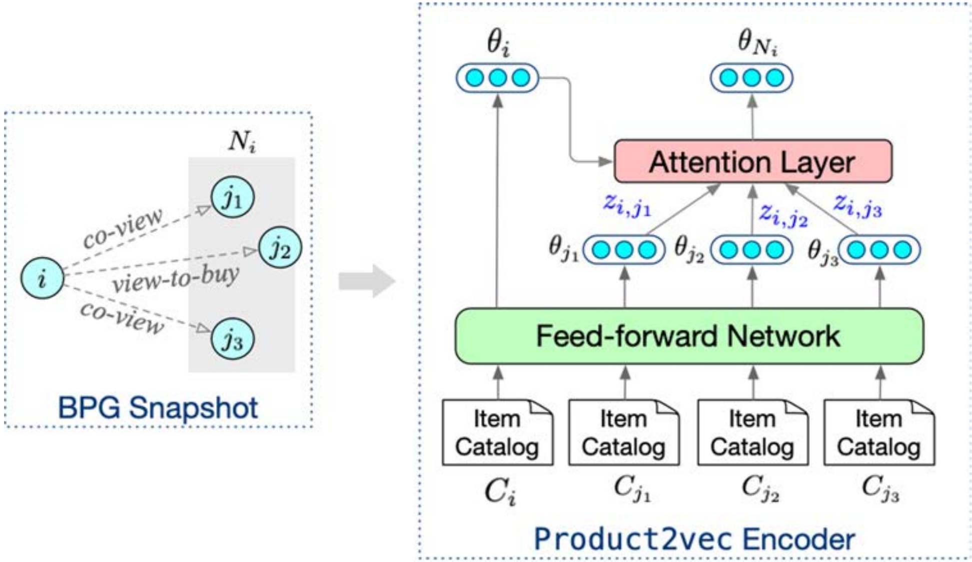


P-Companion: Workflow (Simplified Version)



Module 1: Product2Vec

- GNN-based representation learning framework for millions of products.
- FNN transforms the original item catalog features to embeddings and later aggregates the information from similar products selectively by the attention layer.
- After training, FNN can be applied to obtain product embeddings for millions of products, including cold-start ones, which are used for subsequent modules.



FNN Model:

$$\theta_i = FFN(C_j) = \sigma\left(\sigma\left(C_i W^{(1)} + b^{(1)}\right) W^{(2)} + b^{(2)}\right) W^{(3)} + b^{(3)}$$

Attention Weight:

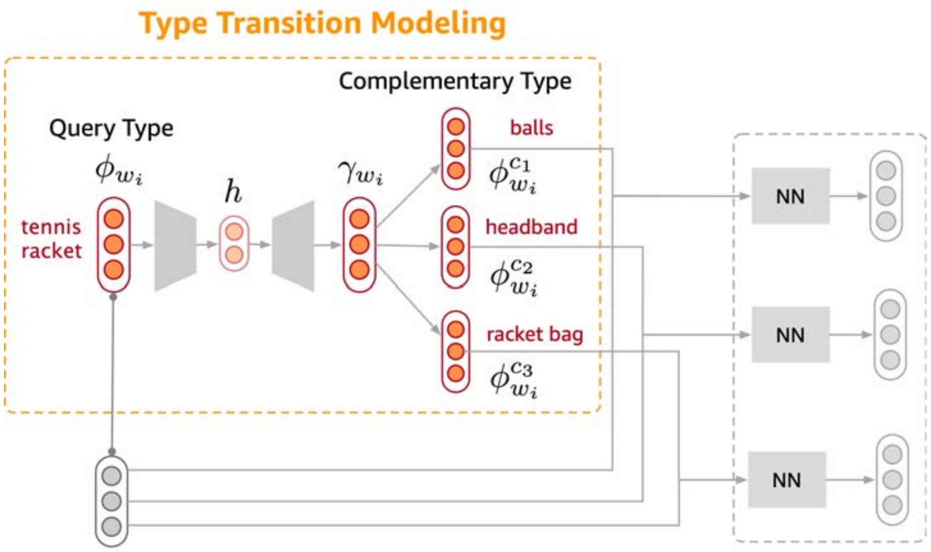
$$z_{i,j} = \mathrm{softmax}_j\left(\theta_i^T \theta_j\right) = \frac{\exp(\theta_i^T \theta_j)}{\sum_{j' \in N_i} \exp(\theta_i^T \theta_{j'})}$$

Product2Vec training loss:

$$L = \sum_{i \in \mathcal{I}} \sum_{y \in \{\pm 1\}} \left\{\max\left(\epsilon - y \cdot \left(\lambda - ||\theta_i - \theta_{N_i}||_2^2\right)\right)\right\}$$

Module 2: Complementary Type Transition

Goal: (1) Model the asymmetric relationship between query product type and complementary product types; (2) Generate diversified complementary product types for further item recommendation.



Auto-encoder based type transition model:

$$h = \text{Dropout}\left(\text{ReLU}\left(\phi_{w_i} W^{(4)} + b^{(4)}\right)\right)$$

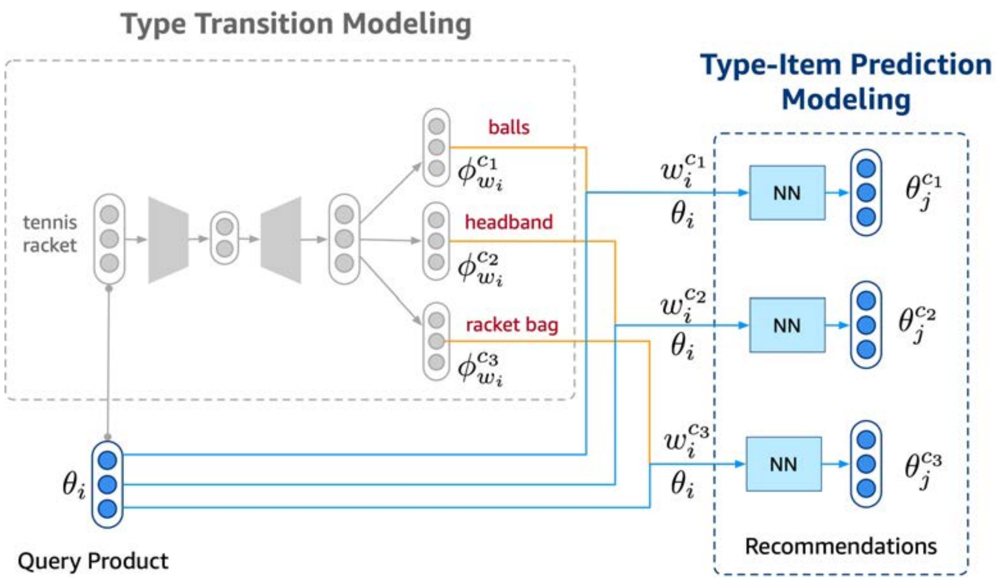
$$\gamma_{w_i} = hW^{(5)} + b^{(5)}$$

Training loss:

$$\min \sum_{i,j \in \mathcal{T}} \left(\max\left\{0, \epsilon_w - y_{i,j}\left(\lambda_w - \|\gamma_{w_i} - \phi_{w_j}^c\|_2^2\right)\right\}\right)$$

Module 3: Complementary Item Prediction

Goal: Output item recommendations given the embeddings of query product and inferred multiple complementary types.



Item prediction neural model:

$$\theta_i^{w_c} = \theta_i \odot (\phi_{w_c}^c W^{(6)} + b^{(6)}),$$
$$s.t., \ ||\phi_{w_c}^c - \gamma_{w_i}||_2^2 \leq \beta$$

Training loss:

$$\min \sum_{i,j \in \mathcal{T}} \max \{0, \epsilon_i - y_{i,j} \left(\lambda_i - \|\theta_i^{w_c} - \theta_j\|_2^2\right)\}$$

Joint Training and Inference

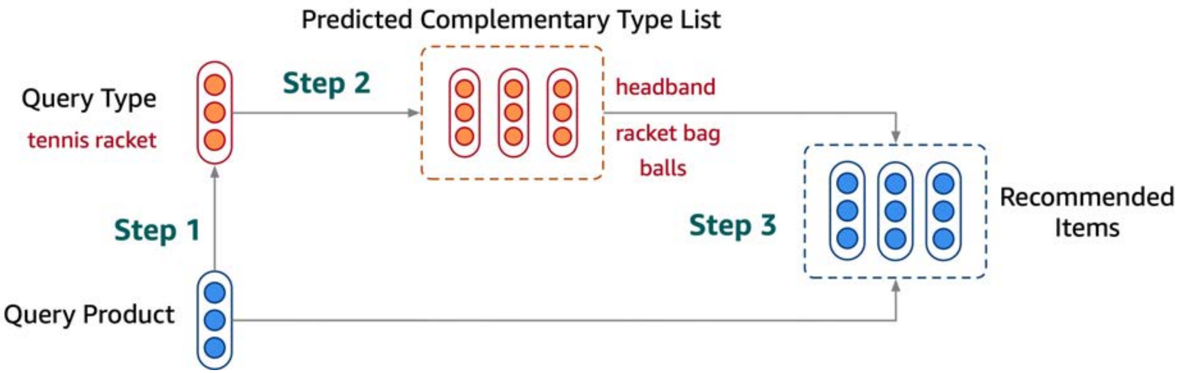
Joint training on type transition and item prediction:

$$\min \sum_{i,j \in \mathcal{T}} \alpha \boxed{\left(\max\left\{0, \epsilon_i - y_{i,j}\left(\lambda_i - \|\theta_i^{w_j} - \theta_j\|_2^2\right)\right)\right\}} + (1-\alpha) \boxed{\left(\max\left\{0, \epsilon_w - y_{i,j}\left(\lambda_w - \|\gamma_{w_i} - \phi_{w_j}^c\|_2^2\right)\right\}\right)}$$

Item prediction loss

Type transition loss

Inference stage:



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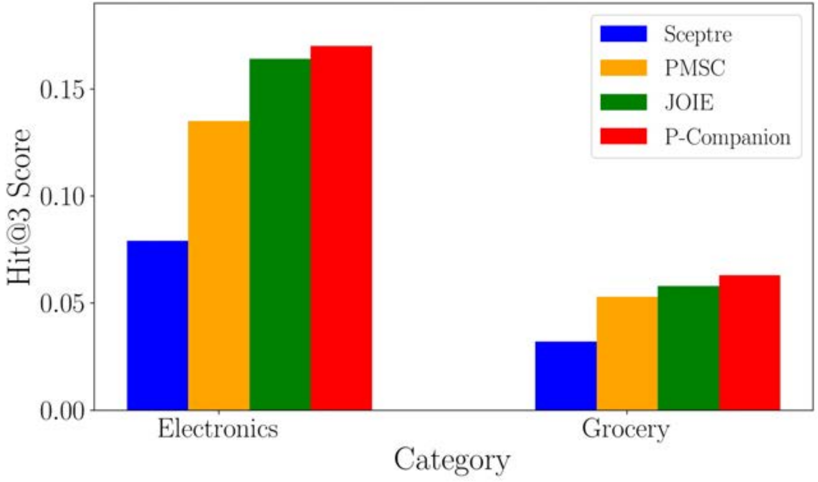
Evaluation: Dataset

- We evaluate P-Companion a real-world dataset obtained from Amazon.com, which includes over 24M of products with catalog features and customer behavioral data across 10+ product categories.
- For comparison with baselines, we also select grocery and electronics category as two subsets from Amazon.

Datasets	Electronics	Grocery	All Groups
# Items	97.6K	324.2K	24.54M
# Product Types	5.6K	6.5K	34.8K
# Co-purchase pairs	130.6K	804.1K	62.16M
# Co-view pairs	3.15M	8.96M	1154M
# purchase-after-view pairs	325.1K	1.10M	83.75M

Evaluation: From history purchase data

- Given a pair **(i , j)**, associated with type wi and wj, from co-purchase record as ground truth, we ask our model as well as all baselines to output recommendation list (with predicted complementary types), and consider the following:
  - whether item j is in the list. → ***Item level***
  - Whether type wj is in the predicted types → ***Type level***
- Metric: Hit@K score (both item level and type level, if applicable)
- Baselines: Sceptre, PMSC, JOIE



Dataset		Electronics	Grocery
Model & Setting		Hit@60	Hit@60
Sceptre		0.124	0.085
PMSC		0.179	0.139
JOIE		0.200	0.155
P-Companion	1 type × 60 items	0.138	0.088
	3 types × 20 items	0.198	0.153
	5 types × 12 items	0.222	**0.189**
	6 types × 10 items	**0.227**	0.187

Evaluation: Diversified Rec. Matters

- We can manually control the diversified configurations.
- Metric: Hit@K score (both item level and type level, if applicable)
- Baselines: Sceptre, PMSC, JOIE

Dataset		Electronics	Grocery
Model & Setting		Hit@60	Hit@60
Sceptre		0.124	0.085
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	3 types × 20 items	0.198	0.153
	5 types × 12 items	0.222	**0.189**
	6 types × 10 items	**0.227**	0.187

Evaluation: Cold-Start Items

- Cold-start items: Items without (many) FBT (Note: It still has complete product catalog features and type information, or inferred type)

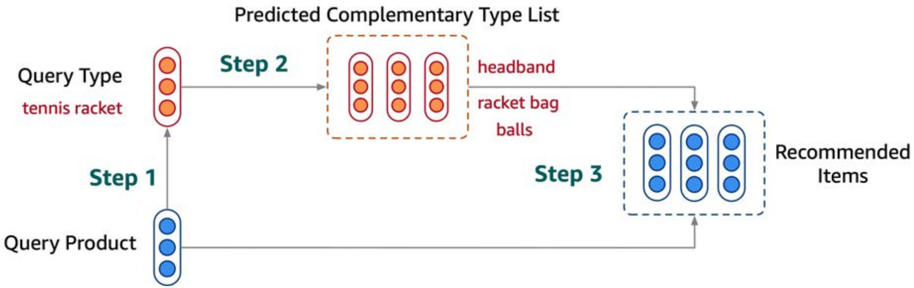

Table 8: Results on complementary recommendation on cold-start product items (H@k denotes Hit@k score).

Datasets	Electronics (*only cold-start items in testing*)			
Level	Item Hit score			Type Hit score
Metrics	H@1	H@3	H@10	H@3
Sceptre	0.049	0.065	0.081	n/a
PMSC	0.073	0.093	0.111	n/a
JOIE	0.107	0.136	0.157	0.138
P-Companion	**0.115**	**0.147**	**0.165**	**0.178**

Evaluation: From MTurk

- Historical co-purchase data is far from complete. It is possible that the products we recommend is reasonable but not observed in the past co-purchase data.
- MTurk: cross-source workers as human judgement by “questionnaire” on top-5 P-Companion generated recommendations.

Example of MTurk Questionnaire

Question 2: Given you decide to purchase the base product, would you be interested in purchasing the recommended product together with the base product?

Base Product	Recommended Product	Answer
 Apple 13 Inch MacBook Pro / MD101LL/A / 2.5GHz Intel Core i5, 4GB RAM, 500GB HDD, Intel HD 4000 Graphics, DVDRW, WIFI Wireless, iSight Webcam	 MOSISO Laptop Sleeve Compatible 2018 MacBook Air 13 A1932 Retina Display/MacBook Pro 13 A1989 A1706 A1708 USB-C 2018 2017 2016/Surface Pro 6/5/4/3, Polyester Bag with Vertical Pocket, Wine Red	○ Yes, I am very likely to buy them together. ○ The recommendation inspires me the potential needs to purchase, but not this right one. ○ No, the recommendation is relevant but I am less likely to buy them together. ○ I do not think they are relevant.

Score Options:

Score-3: Perfect. → Yes, I am very likely to purchase them together!

Score-2: Inspiring. → The recommendation inspires the potential need, but just not the right one.

Score-1: Relevant. → The recommendation is relevant but I am not likely to buy them together.

Score-0: Failed. → Totally not relevant.

MTurk: P-Companion vs Co-purchase

- P-Companion achieves comparable average scores with co-purchase data.
- P-Companion can provide much more diversified recommendations from multiple product types, compared to the approach that simply relies on co-purchase.

Model	CP	P-Companion				
		Pos-1	Pos-2	Pos-3	Pos-4	Pos-5
% of Score 3	0.46	0.43	0.43	0.42	0.45	0.42
% of Score 2	0.25	0.27	0.27	0.27	0.26	0.27
% of Score 1	0.27	0.27	0.26	0.26	0.27	0.26
% of Score 0	0.02	0.02	0.04	0.04	0.03	0.04
Rel. Rate	0.98	0.97	0.96	0.95	0.97	0.96
Avg. Score	2.15	2.12	2.09	2.07	2.13	2.08

Case Study: Type Transition Prediction

Examples of Predicted Top-3 Complementary Type Predictions

Query Type	Predicted Complementary Types
camera-power-adapter	(1) sec-digit-card (2) micro-sd-card (3) hdmi-cable
cell-phone-battery	(1) cell-phone-screen-protect (2) battery-charge-case (3) flip-cell-phone-carry-case
roast-coffee-bean	(1) fridge-coffee-cream (2) whole-bean (3) white-tea
fly-fish-line	(1) fluorocarbon-fish-line (2) surf-fish-rod (3) fly-fish-reel

Case Study: Product Recommendation

Category	Query Item	Co-Purchase	Top-5 Recommendations from P-Companion				
Electronics							
Grocery							
All-Group (Pet home)		None					
All-Group (Fishing tools)		None					

Evaluation: Online Deployment

- After deploying P-Companion for online serving, we conduct online A/B testing on Amazon by splitting customer sessions randomly.
- For the control group, we use co-purchase datasets for the recommendation, while for the treatment group, we show recommendations from P-Companion.
- We observe relative **+0.23%** improvement on product sales, **+0.18%** improvement on profit gain, by considering both diversity and relevance in P-Companion.

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Extra Thoughts and Notes on *ComRec*

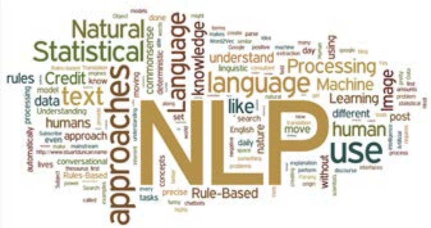
- Definition of *complementary product* for different product department (electronics, grocery, furniture, media/book, etc)
- Data sources and quality from noisy customer behavior
- Product type labeling scheme
- Adaptation and generalization for cold-start items
- Timestamp and separate orders in customer purchase → List/Bundle recommendation

Summary & Future Directions

- We present P-Companion, an end-to-end neural-based recommendation solution for diversified complementary product recommendation.
- We propose a novel schema to obtain improved distant supervision labels for better complementary model learning.
- Experimental evaluation has shown the effectiveness in recommending relevant and diversified complementary items over alternative approaches and demonstrated strong business values on our online production systems.
- Some future directions of P-Companion: (1) adaptive diversified recommendation for different categories; (2) leveraging temporal customer purchase history information to generate personalized complementary recommendations.

Knowledge Graphs Are Important

- Foundational to knowledge-driven AI systems
- Enable many downstream applications (NLP tasks, QA systems, etc.)

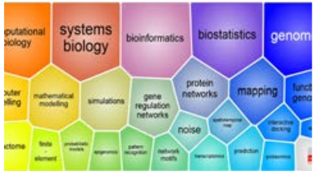


Natural Language Processing

Knowledge Graphs

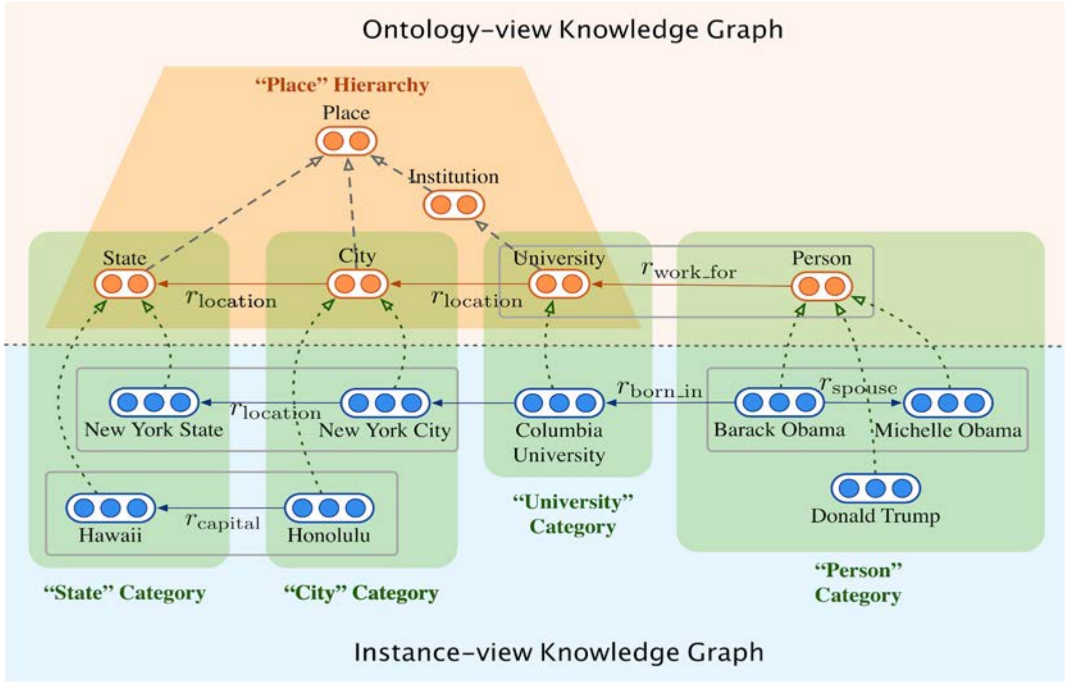
QA & Dialogue systems

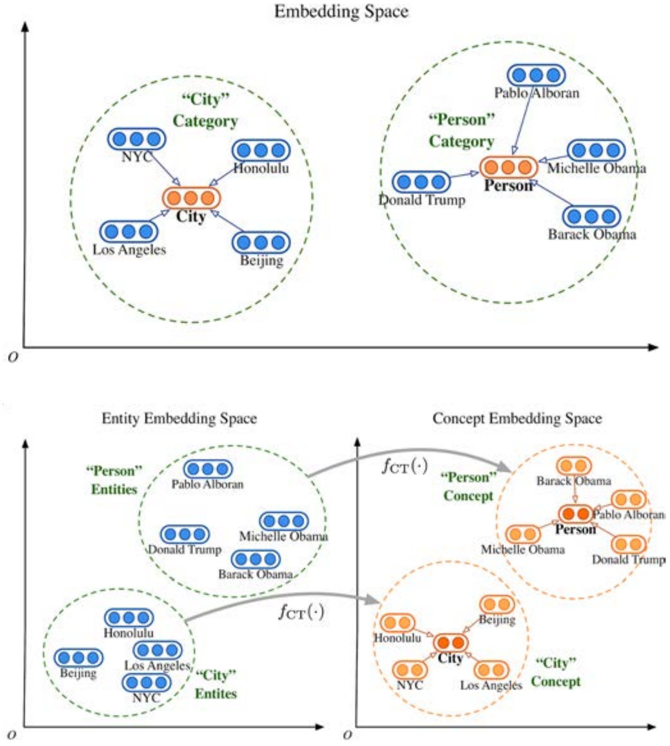
Recommender Systems



Computational Biology

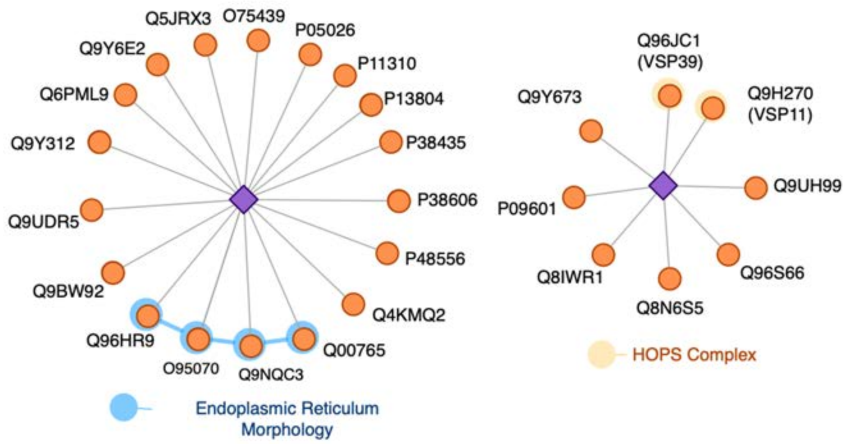
JOIE: Learning on Instance & Ontology View





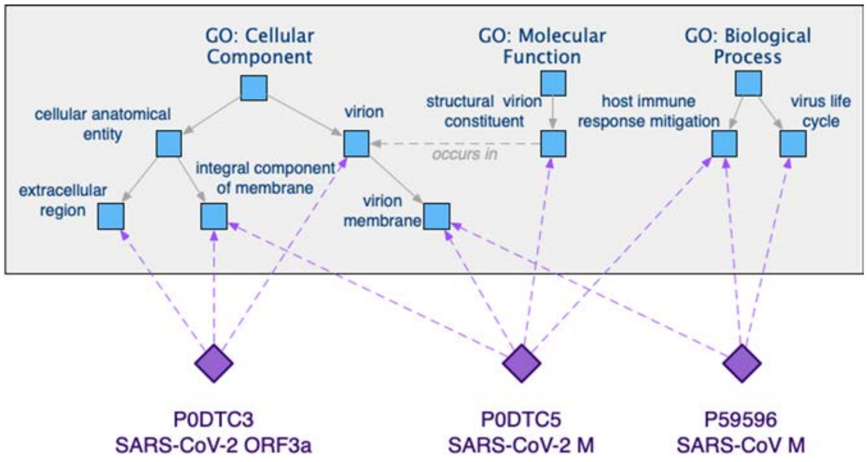
Similar Ontology-Instance Views in Bioinformatics

SARS-CoV-2 Human host interactions (Left) and SARS-CoV-2 Gene Ontology (GO) annotations (Right)

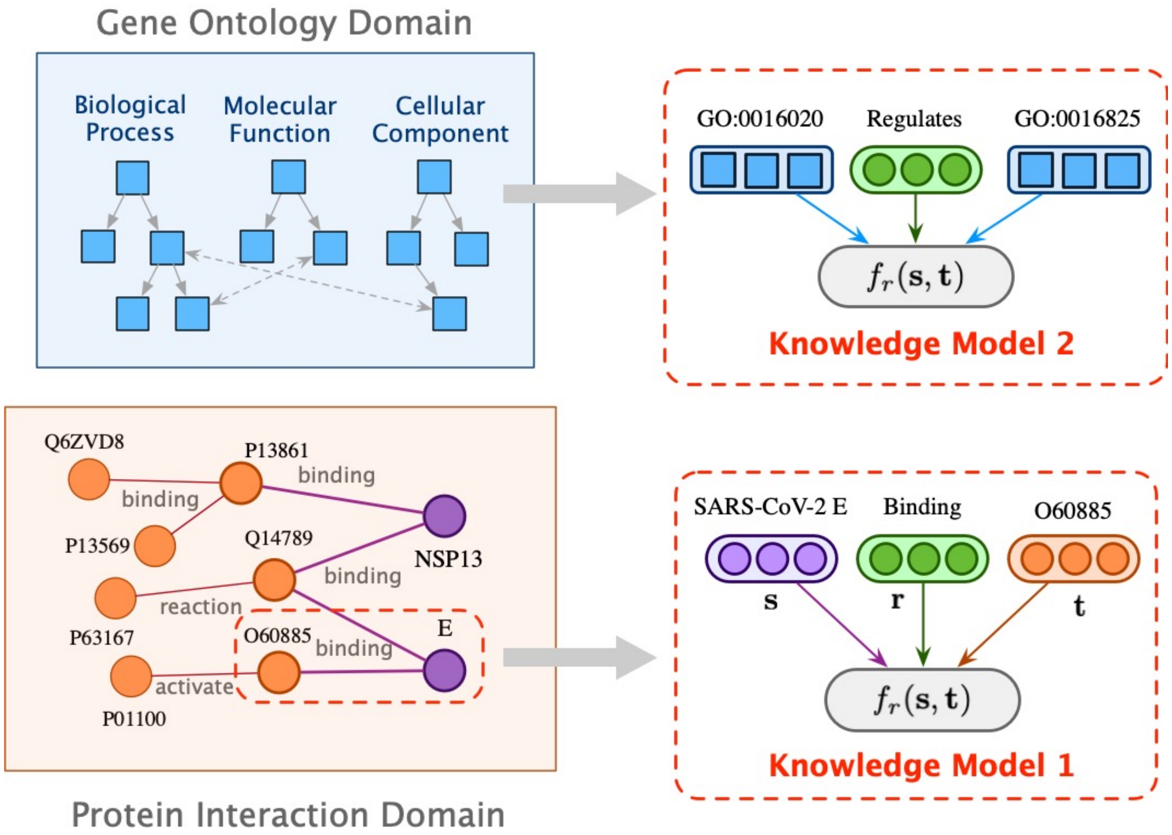


SARS-CoV-2 M Protein (P0DTC5)

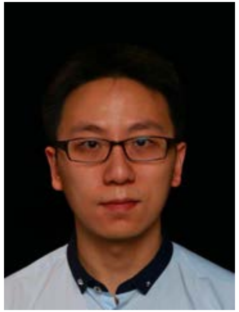
SARS-CoV-2 ORF 3a Protein (P0DTC3)



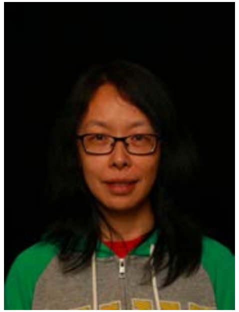
Bio-JOIE: Extension from JOIE



Collaborators



Tong Zhao
Amazon



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For more information, please check our paper and webpage!

Paper: https://dl.acm.org/doi/10.1145/3340531.3412732 (Video included)
Amazon Blog: https://www.amazon.science/blog/improving-complementary-product-recommendations

Thank you!

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