CIKM Applied Research Paper

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

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Oct. 19-23, 2020 | Online Conference

Outline

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

What to buy together?

Frequently bought together

Total price: $149.67

Add all three to Cart

Add all three to List

One of these items ships sooner than the other. Show details

- [x] **This item:** HP OfficeJet 3830 All-in-One Wireless Printer, HP Instant Ink, Works with Alexa (K7V40A) $99.89
- [x] HP 63 | Ink Cartridge | Black | F6U62AN $20.89
- [x] HP 63 | Ink Cartridge | Tri-color | F6U61AN $28.89

Customers who bought this item also bought

Prometo	Pablo Alboran	Hotspot	Lighthouse, The
› Pablo Alborán	› Pablo Alborán	PET SHOP BOYS	Robert Pattinson
187	135	449	3,985
Audio CD	Audio CD	Audio CD	DVD
$16.41	$9.28	$11.19	$12.99
		prime FREE One-Day	prime FREE One-Day

Added to Cart

Cart Subtotal (1 item): $99.70

View Cart | Proceed to checkout

Customers who bought this item also bought

Quility Premium Adult Removable Duvet Cover for Weighted Blanket | 60"x80" | Full Size Bed | 100% Cotton Cover Fabric | Blue
218
$31.92 prime
Add to Cart

Quility Premium Adult Removable Duvet Cover for Weighted Blanket | 60"x80" | Full Size Bed | 100% Cotton Cover Fabric | Grey
218
$31.92 prime
Add to Cart

Amazon.com Gift Card in a Greeting Card (Various Designs)
13,406
$10.00 - $2,000.00
Choose options

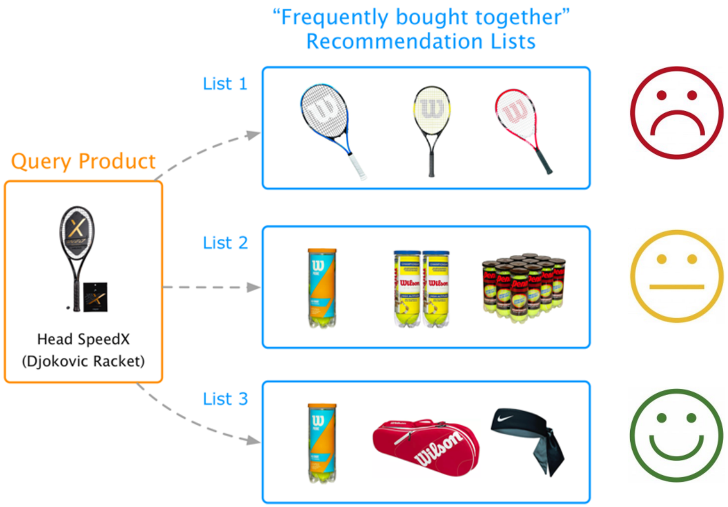
See More

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)**

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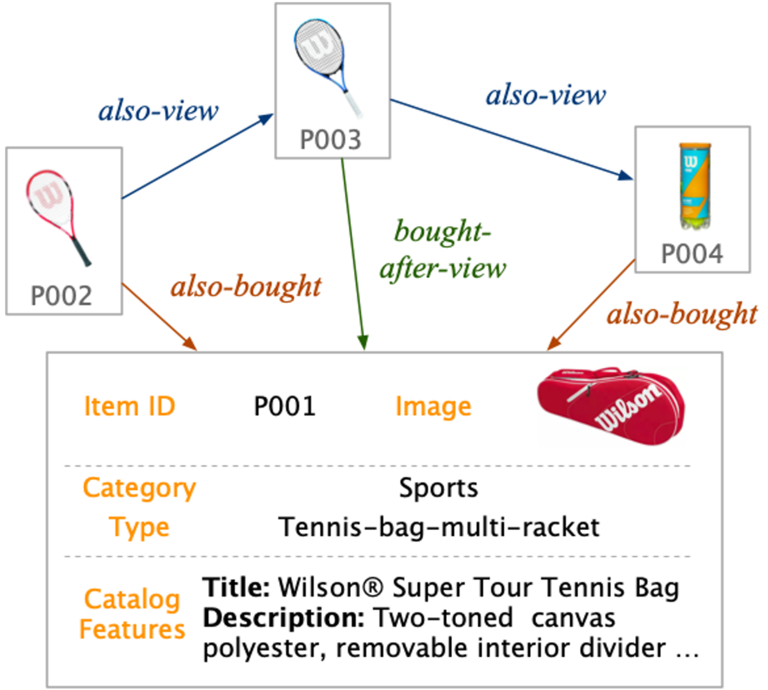
Behavior-based Product Graphs

- Build a behavior-based product graph
- Nodes: 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)

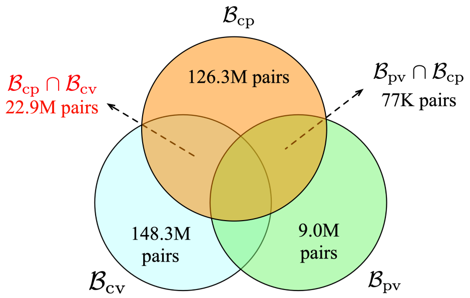


Product Node: P001

Data Analysis on BPG

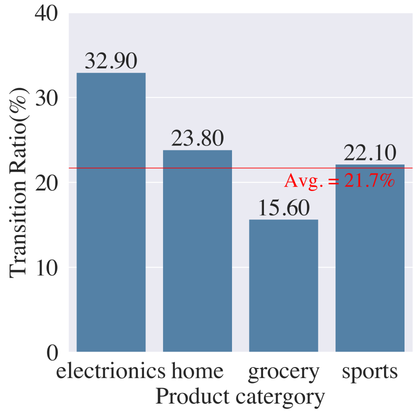
Two important observations:

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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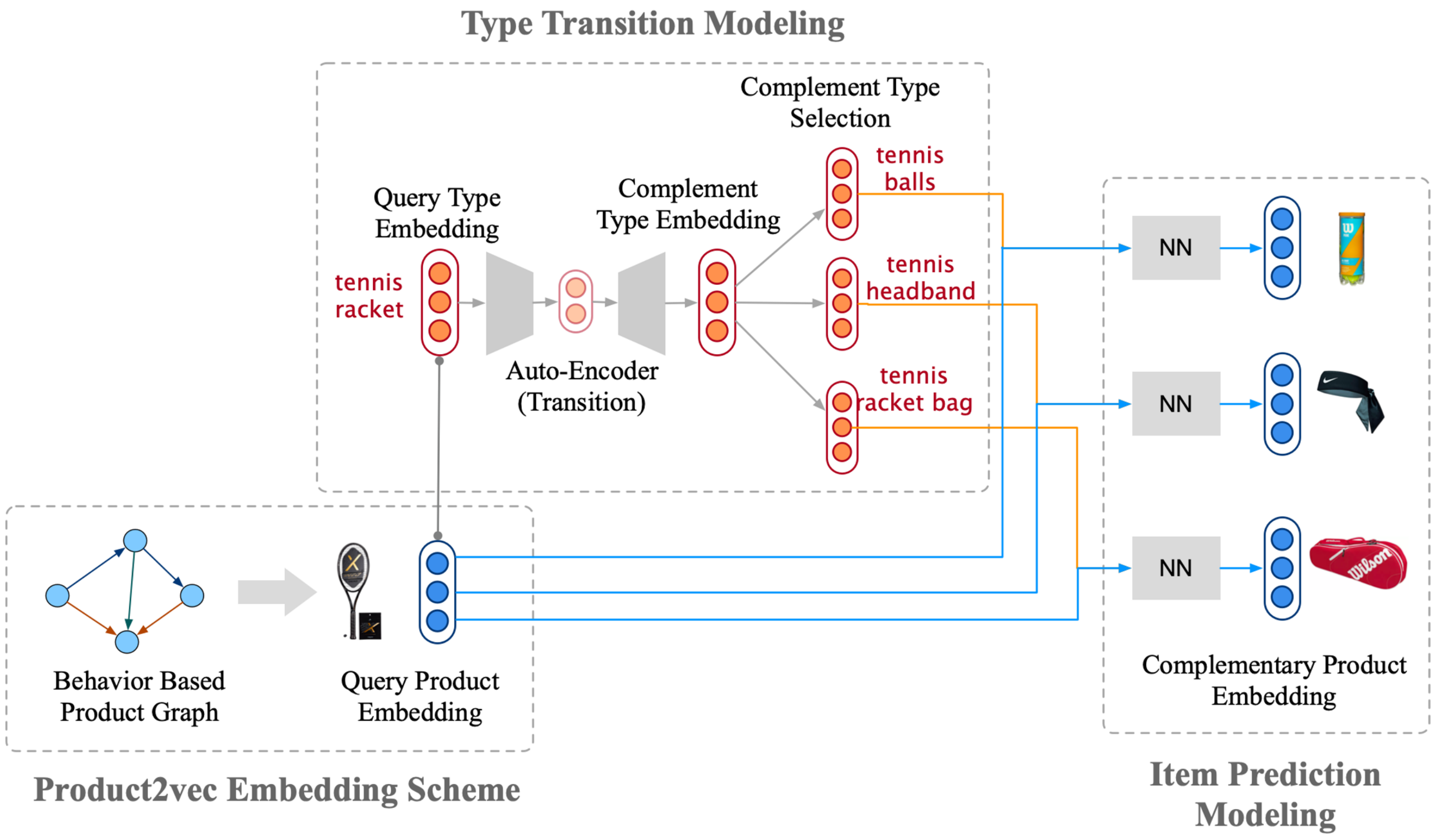
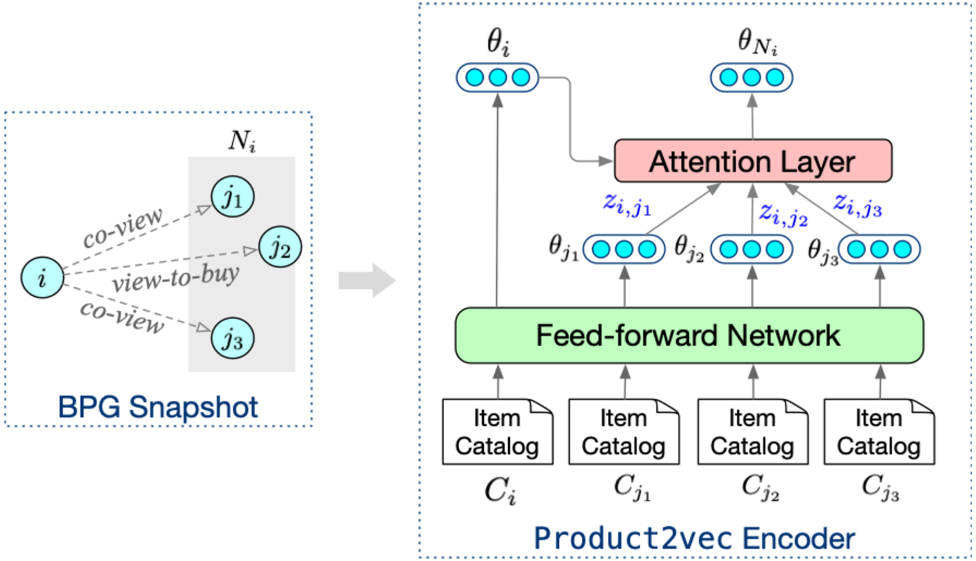
P-Companion: Overview



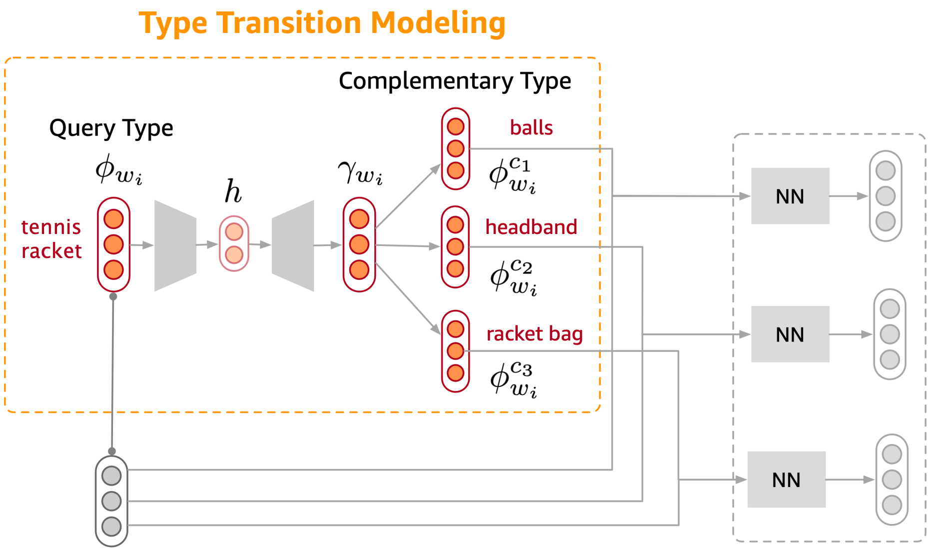
Module 1: Product2Vec

- 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.



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:

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

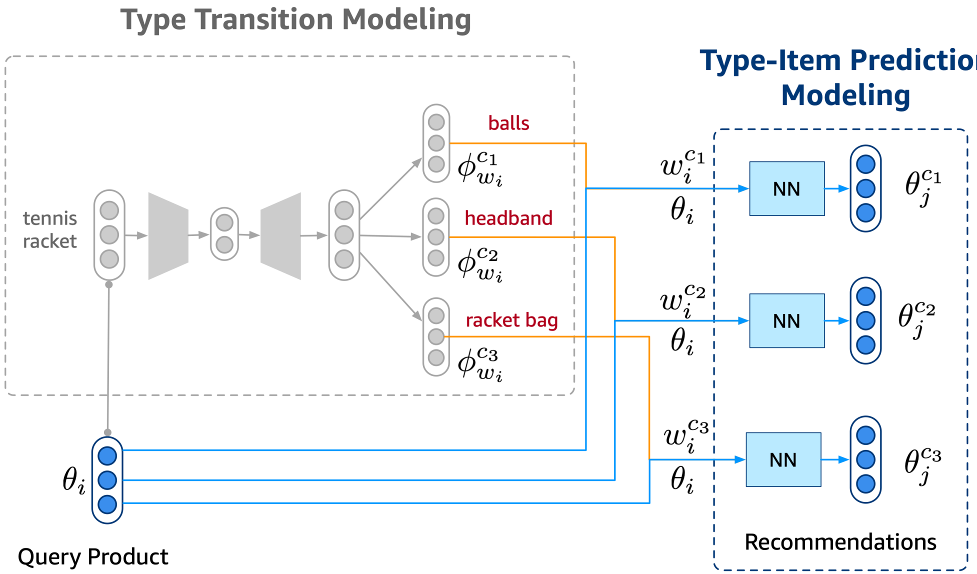
$$\gamma_{w_i} = hW^{(5)} + b^{(5)}$$

Training loss:

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

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:

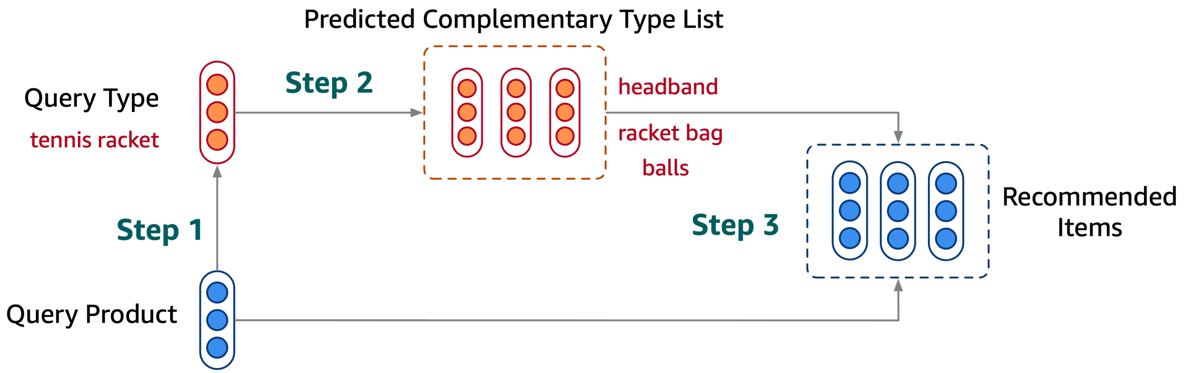
$$\min \sum_{i,j \in \mathcal{T}} \max \left\{0, \epsilon_i - y_{i,j} \left(\lambda_i - \|\theta_i^{w_c} - \theta_j\|_2^2\right)\right\}$$

Joint Training and Inference

Joint training on type transition and item prediction:

$$\min \sum_{i,j\in\mathcal{T}} \alpha \underbrace{\boxed{\left(\max\left\{0, \epsilon_i - y_{i,j}\left(\lambda_i - \|\theta_i^{w_j} - \theta_j\|_2^2\right)\right)\right\}}}_{\text{Item prediction loss}} + (1-\alpha) \underbrace{\boxed{\left(\max\left\{0, \epsilon_w - y_{i,j}\left(\lambda_w - \|\gamma_{w_i} - \phi^c_{w_j}\|_2^2\right)\right\}\right)}}_{\text{Type transition loss}}$$

Inference stage:



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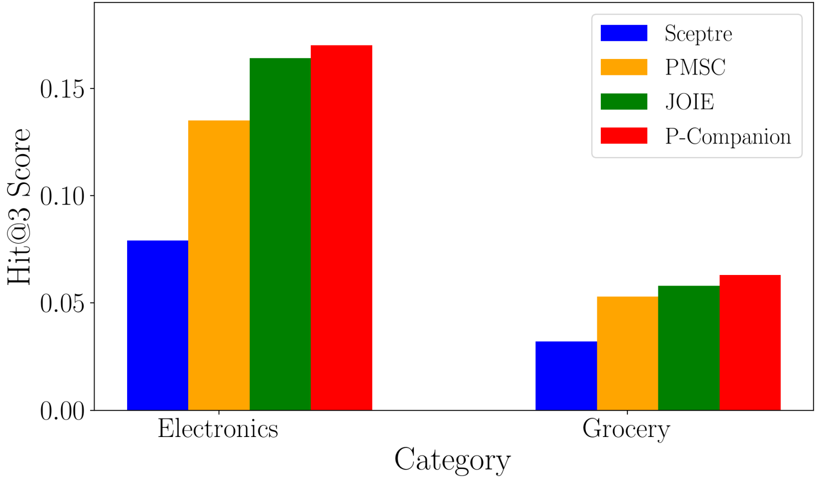
Evaluation: Dataset

- 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, 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

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

UCLA amazon

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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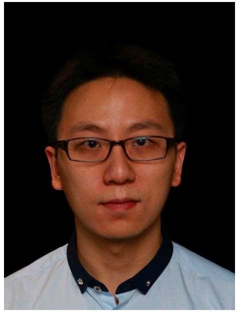
Summary & Future Directions

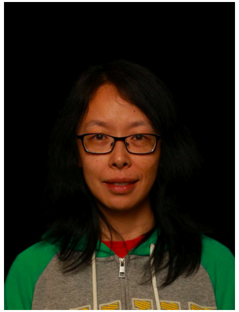
UCLA amazon

- **Model:** P-Companion, an end-to-end neural-based recommendation solution for diversified complementary product recommendation.
- **Data:** a novel schema to obtain improved distant supervision labels for better complementary model learning on multiple categories of products.
- **Performance:** 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.
- **Future directions of P-Companion:** (1) adaptive diversified recommendation for different categories; (2) leveraging temporal customer purchase history information to generate personalized complementary recommendations.

Acknowledgement

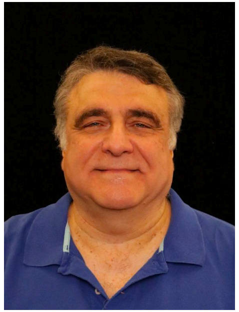


Tong Zhao
Amazon



Jin Li
Amazon

Luna Xin Dong
Amazon



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Thank you!

Q & A