Next-item Recommendation with Sequential Hypergraphs

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LinkedIn Inc.**
Next-item Recommendation

The goal is to infer the dynamic user preferences with sequential user interactions.

**Historic User-Item Interactions**

User A

- sofa
- bouquet
- wall decoration

User C

- Nintendo Switch
- iPhone 8
- iPhone XR

Historic User-Item Interactions Timeline:

- 2017
- 2018
- 2019
Next-item Recommendation

The goal is to infer the dynamic user preferences with sequential user interactions.

**Historic User-Item Interactions**

- User A: sofa, bouquet, wall decoration
- User C: Nintendo Switch, iPhone 8, iPhone XR

The next item?
How are items treated?
Items emerge and disappear

• From a **long-term** perspective, the relationships between items are unstable. ==&gt; **Short-term** relationships are critical for item modeling.

*More than 50% of the items become inactive shortly.*
The relationships change

- The relationships between items are changing along time.
- The variations are larger the longer time gap.

We capture the item co-occurrence with word2vec. Neighboring items change along time.
How are items treated?

For a certain time period, the meaning of an item can be revealed by the correlations defined by user interactions in the short term.
For a certain time period, the meaning of an item can be revealed by the correlations defined by user interactions in the short term.

iPhone 8 became a budget choice
Challenge 1

- High-order correlations
- Multiple-hop connections

A user may purchase multiple numbers of items in a certain time period.
Challenge 1

- High-order correlations
- Multiple-hop connections

Items connected by multiple-hop path are related.
Challenge 2

The semantics of an item can change **across users** and over time.

The same flower bouquet is linked to different purposes.

**September 2017**  --------------------------  **September 2019**
Challenge 2

The semantics of an item can change across users and over time.
Our proposal: HyperRec

A novel end-to-end framework with sequential Hypergraphs to enhance next-item recommendation.
Each hyperedge in a hypergraph can connect multiple nodes on a single edge, s.t.,

- Each node denotes an item; each hypedge can connect the set of items a user interacts within a certain short time period altogether.
Hypergraph

Hypergraph Convolutional Layers (HGCN)

Nodes —> Hyperedges  Hyperedges —>Nodes
Sequential Hypergraphs

Split user-item interactions based on the timestamps. Construct a series of short-term hypergraphs for different timestamps.
Sequential Hypergraphs

Residual Gating: Model the residual information among the consecutive timestamps.
Dynamic User Modeling

Short-term User Intent: Combining the items interacted by the user in the short-term period.

==> embeddings of hyperedges
Dynamic User Modeling

Fusion Layer: To generate the representation for a user-item interaction at timestamp $t$. 

(user, item, timestamp)
Dynamic User Modeling

Self-attention: Generate the dynamic user embedding
HyperRec

Dynamic User Modeling

Dynamic Item Embedding

HGCN

Layer L

Residual Gating

Fusion Layer

Self-attention

Dynamic User Preference

Predicted Score

Static Item Embedding

Sequential Hypergraphs

Dynamic Item Embedding

HGCN

Layer L

Residual Gating

HGCN

Layer L

Residual Gating

HGCN

Layer L

Residual Gating

Dynamic Item Embedding

Predicted Score

Static Item Embedding
# Experiments: Data

Three Datasets:

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#User</th>
<th>#Item</th>
<th>#User-User Interactions</th>
<th>Density</th>
<th>Cutting Timestamp</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Amazon</strong></td>
<td>74,823</td>
<td>64,602</td>
<td>1,475,092</td>
<td>0.0305%</td>
<td>Jan 1, 18</td>
</tr>
<tr>
<td><strong>Etsy</strong></td>
<td>15,357</td>
<td>56,969</td>
<td>489,189</td>
<td>0.0559%</td>
<td>Jan 1, 18</td>
</tr>
<tr>
<td><strong>Goodreads</strong></td>
<td>16,884</td>
<td>20,828</td>
<td>1,730,711</td>
<td>0.4922%</td>
<td>Jan 1, 17</td>
</tr>
</tbody>
</table>
Experiments: Metric

Leave-one-out Setting

• HIT@K: Hit Rate

• NDCG@K: Normalized Discounted Cumulative Gain

• MRR: Mean Reciprocal Rank

• K=1, 5
Experiments: Baselines

Compare with next-item recommendation frameworks:

- **PopRec**: Most Popular
- **TransRec**: Translation-based Recommendation *(RecSys 2017)*
- **GRU4Rec+**: Recurrent Neural Networks with Top-K Gains *(CIKM 2018)*
- **TCN**: Convolutional Generative Network for Next Item Recommendation *(WSDM 2019)*
Experiments: Baselines

Compare with attention-based recommendation frameworks:

• **HPMN**: Lifelong Sequential Modeling with Personalized Memorization *(SIGIR 2019)*

• **HGN**: Hierarchical Gating Networks for Sequential Recommendation *(KDD 2019)*

• **SASRec**: Self-attention Sequential Recommendation *(ICDM 2018)*

• **BERT4Rec**: Bidirectional Encoder Representations from Transformer for Sequential Recommendation *(CIKM 2019)*
HyperRec vs Baselines

• HyperRec can achieve the best performance for all of the evaluation metrics in the experiments.

• HyperRec outperforms all the baselines by 20.03%, 7.90% and 17.62% for Amazon, Etsy and Goodreads in NDCG@1/HIT@1.

• The outstanding performance of HyperRec in both e-commerce and information sharing platforms demonstrate that it can be generalized to various online platforms.
Impact of each component?

We conduct ablation tests to examine the effectiveness of each component.

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<td>0.4712</td>
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<td>0.1051</td>
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<tr>
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<tr>
<td>(5) (-) Dynamic Item Embedding</td>
<td>0.1131</td>
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<td>0.1147</td>
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<td>0.2709</td>
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<td>(7) (-) Dynamic in Prediction</td>
<td>0.1151</td>
<td>0.4703</td>
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Results under NDCG@1/HIT@1
Impact of each component?

It is essential to have dynamic item embedding revealing their change of semantic meanings with the sequential Hypergraphs.

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Modeling the residual information help to generate more informative item embeddings, leading to better performance.

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Results under NDCG@1/HIT@1
Impact of each component?

The design of our fusion layer can help in dynamic user preference elicitation.

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Results under NDCG@1/HIT@1
Conclusion

• We explore the dynamic meaning of items in real-world scenarios for next-item recommendation.

• We propose a novel recommendation framework empowered by sequential hypergraphs to incorporate the short-term correlations.

• The proposed HyperRec model can provide more accurate next-item recommendation for both E-commerce and information sharing platforms.

• The next step: Can we transfer the dynamic patterns across platforms or even across domains?
Please check our paper or contact jlwang@tamu.edu for more details.