

# Learning from History and Present: Next-item Recommendation via Discriminatively Exploiting User Behaviors

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## Abstract

In the modern e-commerce, the behaviors of customers contain rich information, e.g., consumption habits, the dynamics of preferences. Recently, session-based recommendations are becoming popular to explore the temporal characteristics of customers' interactive behaviors. However, existing works mainly exploit the short-term behaviors without fully taking the customers' long-term stable preferences and evolutions into account. In this paper, we propose a novel Behavior-Intensive Neural Network (BINN) for next-item recommendation by incorporating both users' historical stable preferences and present consumption motivations. Specifically, BINN contains two main components, i.e., Neural Item Embedding, and Discriminative Behaviors Learning. Firstly, a novel item embedding method based on user interactions is developed for obtaining a unified representation for each item. Then, with the embedded items and the interactive behaviors over item sequences, BINN discriminatively learns the historical preferences and present motivations of the target users. Thus, BINN could better perform recommendations of the next items for the target users. Finally, for evaluating the performances of BINN, we conduct extensive experiments on two real-world datasets, i.e., Tianshi and JD. The experimental results clearly demonstrate the effectiveness of BINN compared with several state-of-the-art methods.

## Motivation

- **Recommender system**, as an essential component of modern e-commerce websites, tries to predict what the most suitable products or services are of users, based on the users' preferences.
- In the modern e-commerce, the behaviors of customers contain rich information, e.g., consumption habits, the dynamics of preferences.
- That provide opportunities for smarter recommendations.



## Preference behaviors and Session behaviors:

- As a user's interactive behaviors naturally form a behavioral sequence over time, the user's historical preferences from the **long-term view** and present motivations or demands from the **short-term view** can be dynamically revealed.



## Problem

- Given a target user  $u$  with her sequential of interactive behaviors over items  $S_u = \{(x_1, b_1), (x_2, b_2), \dots, (x_T, b_T)\}$  and also all users' sequential interactions  $H = \{S_1, S_2, \dots, S_n\}$ , where  $|H| = n$  denotes the number of users. The personalized next-item recommendation task is to predict item  $x_{T+1}$  that the target user  $u$  is most likely to access in her next visit.

- **Input:** interactive behaviors of the target user
- **Input:** all users' sequential interactions
- **Output:** next-item candidates

## Challenges

- **Sparsity**
  - In e-commerce scenarios, data sparsity is a very common problem, i.e., only a small quantity of items bought by a few users. How to learn item similarities and user personalized strategies is a nontrivial problem.
- **Factors** affects the decision
  - Users' decision-making process is potentially affected by various factors, such as demands, prices, and preferences. To track and forecast the user's next potentially preferred item, how to model the effects of these factors in the decision making of item choosing is very challenging
- **Cold-start problem**
  - Cold start is a common problem of recommender systems that new users or items have not yet gathered sufficient information to recommend or be recommended, how to solve this problem is also a great challenge.

## Methodology: framework

- **Method Overview**
  - Item Representation: **Neural Item Embedding**
  - Personalized Sequential Strategy: **Discriminative Behaviors Learning**
    - ✓ Session Behaviors Learning
    - ✓ Preference Behaviors Learning

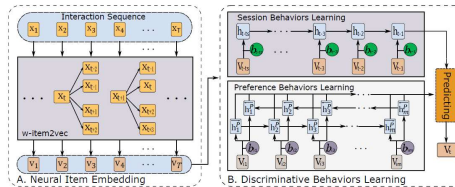


Figure 2: The overview of Behavior-Intensive Neural Network (BINN). A. Neural Item Embedding converts sequential items into a unified embedding space by w-item2vec. B. Discriminative Behaviors Learning constructs two alignments of user behaviors and discriminatively learns behavior information based on two LSTM-based architectures.

## Methodology: Neural Item Embedding

- **Neural Item Embedding:**
  - Traditional item representation:
    - ✓ 1-of-N encoding: may cost unaffordable time and always cannot to be optimized well because of the **high sparsity**.
    - ✓ Embedding layer: may make networks **lose performances** to some extent.
  - Goals:
    - ✓ Find an effective representation method to directly learn high-quality item vectors from the users' interaction sequences, with the result that items implied similar attractions tend to be close to each other.

- Methods: w-item2vec
  - ✓ Negative Sampling:  $p(x_j|x_i) = (\sigma^{\theta(x_i)}(w_i^T * v_j) \prod_k \sigma(-w_i^T * v_k))^{\theta(x_i)}$
  - ✓ Skip-gram:
 
$$\arg \max_{opt} = \frac{1}{K} \sum_{i=1}^K \sum_{j=1}^K \log p(x_j|x_i)$$

$$= \frac{1}{K} \sum_{i=1}^K \sum_{j \neq i}^K \theta(x_i) (\theta(x_i) * \log \sigma(w_i^T * v_j) + \sum_{k=1}^E \log \sigma(-w_i^T * v_k))$$

## Discriminative Behaviors Learning

- **Discriminative Behaviors Learning**
  - After obtaining item embeddings, Discriminative Behaviors Learning (DBL) could explore sequential behaviors as prior knowledge to recommend items that the target user is most likely to access in her next visit.
  - **Factors** affects the decision
    - Session Behaviors Learning for present motivates
    - Preference Behaviors Learning for historical preferences
- **Session Behaviors Learning:** is used to learn users' present consumption motivations from the short-term session behaviors.
  - Discrimination function:  $D_{DBL}(x_i, x_T) = \Phi((T - i) \leq T_s)$
  - Architecture:
 
$$i_t = \delta(W_{it}v_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + W_{bi}b_t + \tilde{b}_i)$$

$$f_t = \delta(W_{ft}v_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + W_{bf}b_t + \tilde{b}_f)$$

$$c_t = f_t c_{t-1} + i_t \tanh(W_{vc}v_t + W_{hc}h_{t-1} + W_{bc}b_t + \tilde{b}_c)$$

$$o_t = \delta(W_{to}v_t + W_{ho}h_{t-1} + W_{co}c_t + W_{bo}b_t + \tilde{b}_o)$$

$$h_t = o_t \tanh(c_t)$$
- **Preference Behaviors Learning:** is used to learn users' stable historical preferences from the preference behaviors in a long term.
  - Discrimination function:  $D_{PBL}(v_i, b_i) = \Phi(b_i \in P)$
  - Architecture:
 
$$h_i^p = \text{concatenate}(h_i^s, h_i^s)$$

$$\Psi_{PBL} = \text{average}(h_1^p, h_2^p, \dots, h_m^p)$$
- **Loss Function:**

$$\mathcal{L} = \frac{1}{|H|} \sum_{u \in H} \frac{1}{(|S_u| - ts - 1)} \sum_{t=ts+1}^{|S_u|} \xi(\tilde{v}_t, v_t)$$

## Experiments

- **Datasets:** Tianshi, JD
- **Metrics:** Recall@20, MRR@20
- **Comparison Methods:**
  - S-POP
  - BPR-MF
  - Item-KNN
  - GRU
  - HRNN

## Performance

Table 1: Statistics of datasets after pre-processing.

Statistics	Tianshi	JD
# of users	19,502	102,683
# of items	674,326	24,744
# of behaviors	8,799,273	37,664,992
# of behavior types	4	6
Avg. behaviors per user	451.30	369.94
Avg. behaviors per item	13.05	14.97.82
# of behaviors in training set	7,874,102	31,811,364
# of behaviors in test set	925,471	5,250,646

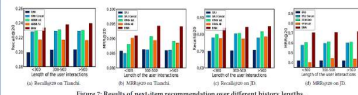


Figure 7: Results of next-item recommendation over different history lengths.

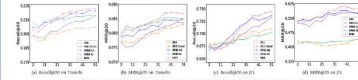


Figure 8: Recommendation performances of new users cold start on two datasets.

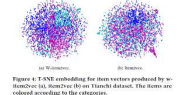


Figure 4: t-SNE embedding for item vectors produced by w-item2vec. (a) Embedding on Tianshi dataset. (b) Embedding on JD dataset. The items are colored according to the categories.

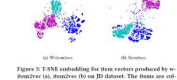


Figure 5: t-SNE embedding for item vectors produced by w-item2vec. (a) Embedding on Tianshi dataset. (b) Embedding on JD dataset. The items are colored according to the categories.

Table 2: Performance comparisons of BINN with baseline methods on two datasets (The improvements of RNN-based models over the best traditional method have been marked).

Methods	Tianshi		JD	
	Recall@20	MRR@20	Recall@20	MRR@20
P-POP	0.2262	0.0824	0.5854	0.2176
BPR-MF	0.0559	0.0165	0.1873	0.0664
Item-KNN	0.1964	0.0883	0.1246	0.0561
GRU4Rec	0.2025(-10.48%)	0.0861(-2.49%)	0.7034(-20.16%)	0.4198(+2.92%)
GRU4Rec-Concat	0.2307(+1.11%)	0.0899(+2.72%)	0.7934(+33.33%)	0.5052(+172.61%)
HRNN Init	0.2305(+1.09%)	0.0897(+1.59%)	0.8073(+37.91%)	0.6098(+180.23%)
HRNN All	0.2167(-4.20%)	0.0893(+1.13%)	0.7762(-32.59%)	0.4333(-99.22%)
BINN	0.2376(+5.04%)	0.0936(+6.08%)	0.8430(+44.00%)	0.7082(+223.46%)