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 an 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.

Methodology: framework

Methodology: Neural Item Embedding

Challenges

- **Sparsity**
  - In e-commerce scenarios, data sparsity is a very common problem, i.e., only a small quantity of items have been 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: 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 motives
  - Preference Behaviors Learning for historical preferences.
- **Session Behaviors Learning**
  - is used to learn users’ present consumption motivations from the the short-term session behaviors.
  - Discrimination function: \(D_{\phi_0}(x, y) = \theta(\beta - \gamma \leq n_s)\)
  - Architecture: \(f_t = 9_1(W_1W_{h11} + W_{h12} + W_{h13} + b_1)\)
  - \(g_t = f_{t-1} + s_t + \alpha_{t-1}(W_2W_{h21} + W_{h22} + W_{h23} + b_2)\)
  - \(h_t = \tan h(c_0f_t + c_1g_t + c_2b_2)\)
  - \(D_{\phi_0}(x) = \theta(\phi_0(\beta) \leq 1)\)
  - Architecture: \(J = \text{concatenate}(J_1, J_2, J_3)\)
  - Loss Function:
    \[
    L = \frac{1}{|B|} \sum_{i=1}^{n} \left[ \frac{1}{\sum_{j=1}^{k} J_{i_j}} \sum_{j=1}^{k} (J_{i_j} - 1) \right]
    \]

Experiments

- **Datasets:** Tianchi, JD
- **Metrics:** Recall@20, MRR@20
- **Comparison Methods:**
  - S-Pop
  - RBF-MF
  - Item-KNN
  - GRU
  - HRNN
- **Performance**
  - Table 1: Statistics of datasets after preprocessing.
  - Table 2: Comparison of different metrics.
  - Table 3: Comparison of different methods.

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