Multi-behavior Recommendation with Action Pattern-aware Networks

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Problem Statement

Given a multiplex behavior session $s$, which contains

- Item sequence $[i_1, \ldots, i_t]$
- Action sequence $[a_1, \ldots, a_t]$

predict the next item $i_{t+1}$ and its corresponding next action $\hat{a}_{t+1}$
Motivations

- Limitations of existing work
  - Concentrate on **single** action type of next item
  - Encode item and action sequences **separately** with similar algorithms
Contributions

◎ Propose an action-aware network multi-behavior recommender (APANet) to predict not only next item but also next action
◎ Identify the importance of modeling item-wise action sequences and propose a way to model such patterns
◎ Demonstrate effectiveness of methods in APANet by extensive experiments on three datasets
Notations

Given
- Session set \( S \), Item set \( I = \{i_1, \ldots, i_m\} \), Action set \( A = \{a_1, \ldots, a_n\} \)

Define
- Session \( S \) represented as index sequences \( [(x_1, y_1), (x_2, y_2), \ldots, (x_t, y_t)] \)
  - \( x_k \in \{1, 2, \ldots, m\}, y_k \in \{1, 2, \ldots, n\} \)
  - \( i_{x_k} \in I, a_{y_k} \in A \)
- Action pattern set \( B = \{b_1, b_2, \ldots, b_n\} \), e.g. \( b_1 = [a_1, a_2] \)

\[
\begin{array}{ccccc}
i_2, & i_3, & i_2, & i_2 & \rightarrow & i_2 & i_3 & i_2 & i_2 \\
a_1, & a_3, & a_2, & a_3 & & [a_1] & [a_3] & [a_1, a_2] & [a_1, a_2, a_3]
\end{array}
\]

Action sequence     Action pattern (accumulated action sequence per item)
Model: APANet
Proposed Methods

Multi-behavior session encoding
Item embedding learning
Action-related embedding learning

Action-aware session representation learning
Next item prediction considering the action pattern

Conditional multiplex behavior session modeling
Next action prediction given specific item

Multi-task learning
Optimize both item and action prediction simultaneously
Multi-behavior session encoding

Item embedding

Item sequence
(ex. $x(s) = [1, 3, 2, 1]$)

$\mathbf{i}_1, \mathbf{i}_3, \mathbf{i}_2, \mathbf{i}_1$ → $\mathbf{i}_{x1}$ → ... → $\mathbf{i}_{xT}$

Action-related embedding learning

Action sequence
(ex. $y(s) = [1, 1, 1, 2]$)

$a_1, a_1, a_1, a_2$ → $\mathbf{o}_1$ → ... → $\mathbf{o}_T$

Item-wise action-pattern sequence

$[a_1, [a_1], [a_1], [a_1, a_2]]$ → $\mathbf{b}_1$ → ... → $\mathbf{b}_T$

(Final hidden states)
Action-aware Session Representation Learning for Next-item Prediction

1. Combine action embeddings

\[ u_k = \text{dropout}(\text{ReLU}(o_k \parallel b_k) u_4 + q_3) \]
\[ d_k = i_x k + u_k \]

2. Learn attention weights

\[ \alpha_k = q_5^T \sigma(W_{12} h_k + W_{13} s' + q_6) \]
\[ h_k = \text{tanh}(d_k \parallel p_{t-k+1} u_5 + q_4) \]
\[ s' = \sum_{i=1}^{t} d_k / t \]

3. Compute item scores

\[ s_s^I = \sum_{i=1}^{t} \alpha_k d_k \]
\[ \hat{y}_j^I = \text{softmax}(s_s^I i_i) \]
Conditional Multiplex Behavior Session Modeling for Next-action Prediction

1. Learn session-level action intention

\[
\mathbf{u}_k = \text{RELU}( (\mathbf{o}_k \parallel \mathbf{b}_k) \mathbf{U}_6 + \mathbf{q}_7 )
\]

\[
\mathbf{\beta}_k = \mathbf{q}_{8}^T \sigma( \mathbf{W}_{14} \mathbf{u}_k + \mathbf{W}_{15} \mathbf{c}_{t+1} + \mathbf{q}_9 )
\]

\[
\ell' = \sum_{k=1}^{t} \mathbf{\beta}_k \mathbf{u}_k
\]

2. Combine action intention & next behavior

\[
\mathbf{i}_{x_{t+1}}: \text{predicted next item embedding}
\]

\[
\mathbf{b}'_{t+1}: \text{action pattern embedding}
\]

\[
\mathbf{c}_{t+1} = \mathbf{i}_{x_{t+1}} + \mathbf{b}'_{t+1}
\]

\[
\mathbf{s}^A_s = \mathbf{U}_6 (\ell' \parallel \mathbf{c}_{t+1})
\]

3. Compute action scores

\[
\hat{y}^A_j = \text{softmax} \left( \mathbf{s}^A_s \mathbf{a}_i \right)
\]
Multi-task Learning

◎ Total loss: combination of the cross entropy loss of the two predictors

\[
L_{\text{action}} = - \sum_{i=1}^{||A||} y_i^l \log(\hat{y}_i^l) + (1 - y_i^l) \log(1 - \hat{y}_i^l)
\]

\[
L_{\text{action}} = - \sum_{i=1}^{||A||} \omega_i y_i^A \log(\hat{y}_i^A) + (1 - y_i^A) \log(1 - \hat{y}_i^A)
\]

\[
L_{\text{joint}} = L_{\text{item}} + \lambda L_{\text{action}}
\]

◎ Control parameters

\[\omega_i: \text{penalty weight of each type of action } a_i\]

\[\lambda: \text{multi-task learning weight}\]
Experiment Results: Next-Item Prediction

- APANet outperforms baseline models on 3 datasets
- All methods predict badly on KKBOX datasets due to its different data properties
- APANet achieves the most significant improvements for KKBOX, yielding 21.88% of HR@20 (KKBOX has 8 action types)
Next-best prediction is considered correct if **both the item and the action** match the ground truth.

The proposed APANet outperforms the compared methods (especially on KKBOX dataset).

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**Experiment Results: Next-Item and Next-Action Prediction**

- **IA_HR@20**
  - RetailRocket: [Graph 1]
  - Yoochoose: [Graph 1]
  - KKBOX: [Graph 1]

- **IA_MRR@20**
  - RetailRocket: [Graph 2]
  - Yoochoose: [Graph 2]
  - KKBOX: [Graph 2]
Ablation study: Effectiveness of APANet's components

Overall performance decline after discarding any individual component of the model, indicating the significance of these components in the design

<table>
<thead>
<tr>
<th>Model setting</th>
<th>KKBOX</th>
<th>RetailRocket</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HR@20</td>
<td>MRR@20</td>
</tr>
<tr>
<td>(1) W/o act_pattern_emb</td>
<td>9.813</td>
<td>2.065</td>
</tr>
<tr>
<td>(2) W/o act_seq_emb</td>
<td>10.201</td>
<td>2.411</td>
</tr>
<tr>
<td>(3) W/o pos_emb</td>
<td>7.430</td>
<td>2.040</td>
</tr>
<tr>
<td>(4) Next-action predictor</td>
<td>11.876</td>
<td>2.879</td>
</tr>
<tr>
<td>APANet</td>
<td>11.183</td>
<td>3.182</td>
</tr>
</tbody>
</table>
APANet Applications

For users:
Enhancing customer experience
- Predicting user’s next move
- E.g. gaming, shopping

For company:
Precision marketing
- Identifying potential customers
- Difference advertising
Conclusions and Future Work

Conclusions
- Propose a action-aware network multi-behavior recommender (APANet) that could predict not only the next-item but the next-action
- Design item-wise action pattern reformulation and a conditional network for action-intent generation
- Demonstrate the superior performance of the model by extensive experiments and ablation studies

Future work
- Introduce more side information such as item features
- Explore the importance to user intent of different action types
- Exploring interpretability aspects
Thank you!