The 22nd IEEE/WIC International Conference on Web Intelligence and Intelligent Agent Technology, October 26-29, 2023

Multi-behavior Recommendation with Action Pattern-aware Networks

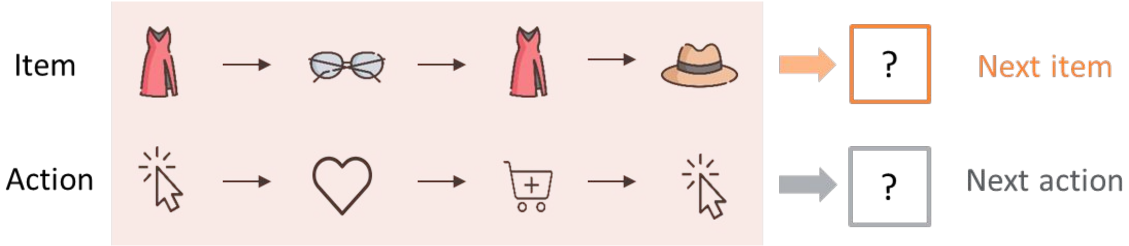
Chia-Ying Tsao Chih-Ting Yeh Jyh-Shing Jang
Yung-Yaw Chen Chuan-Ju Wang

Problem Statement

Given a multiplex behavior session s, which contains

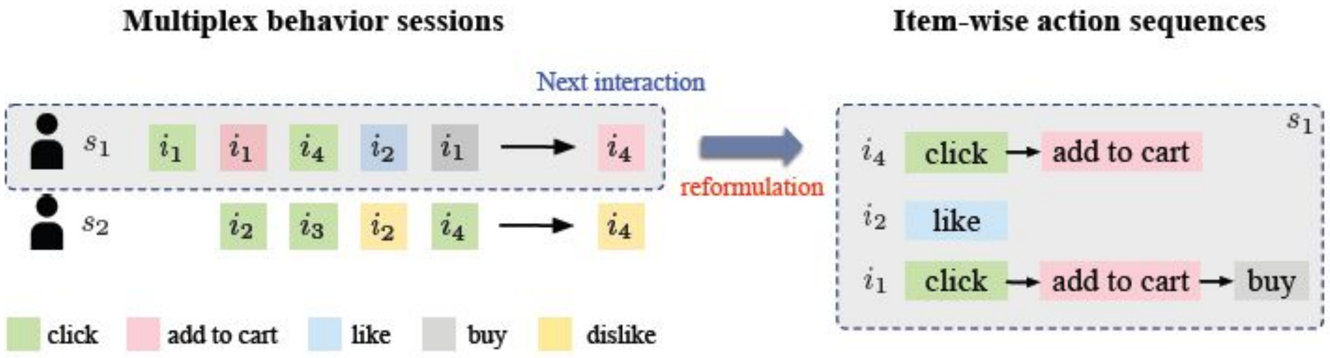
- Item sequence $[i_1, \ldots, i_t]$
- Action sequence $[a_1, \ldots, a_t]$

predict the next item $\hat{i}_{t+1}$ 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 $\mathcal{S}$, 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. $b_1 = [a_1, a_2]$

i_2, i_3, i_2, i_2
a_1, a_3, a_2, a_3

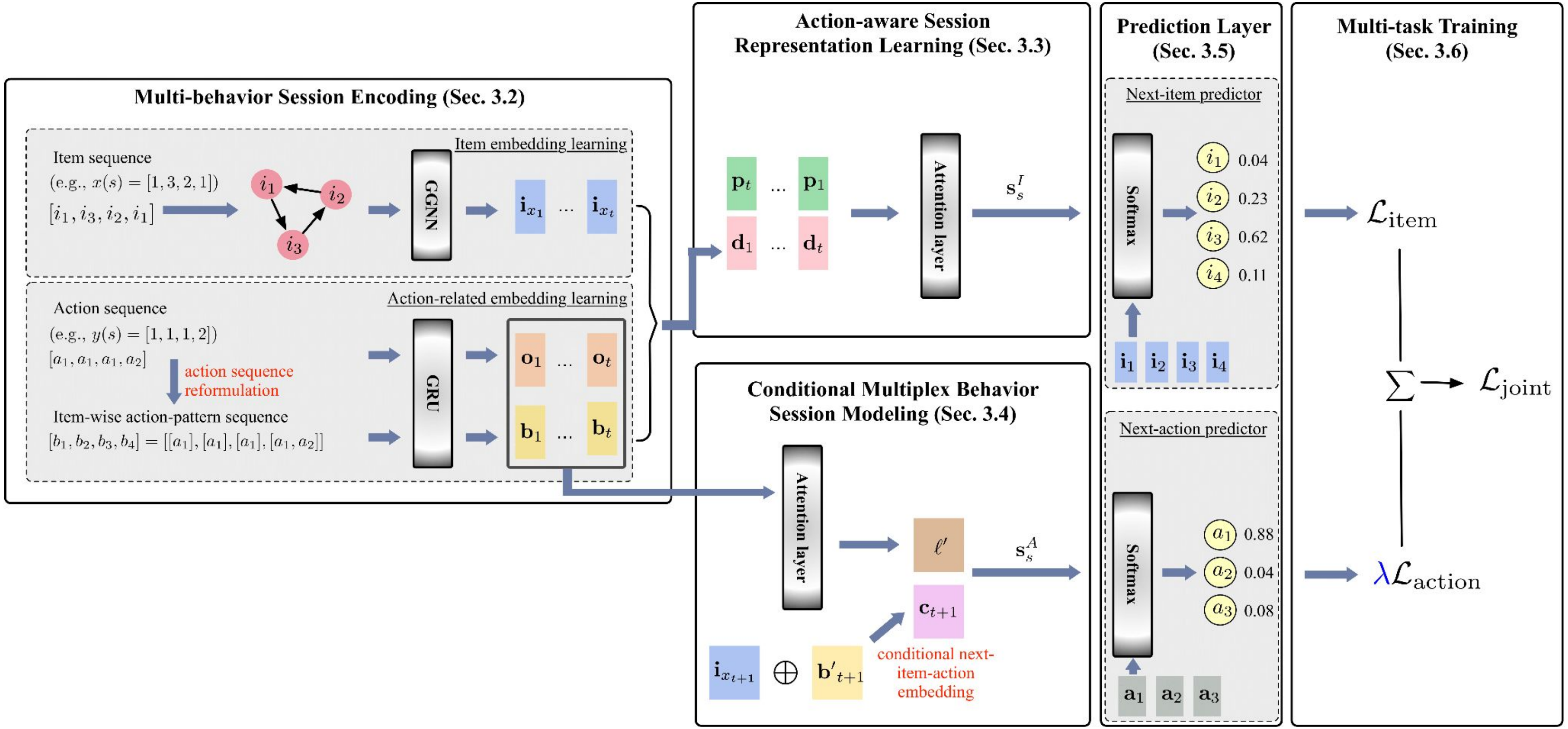
Action sequence

$\rightarrow$

$i_2 \quad i_3 \quad i_2 \quad i_2$
$[a_1] \quad [a_3] \quad [a_1, a_2] \quad [a_1, a_2, a_3]$

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

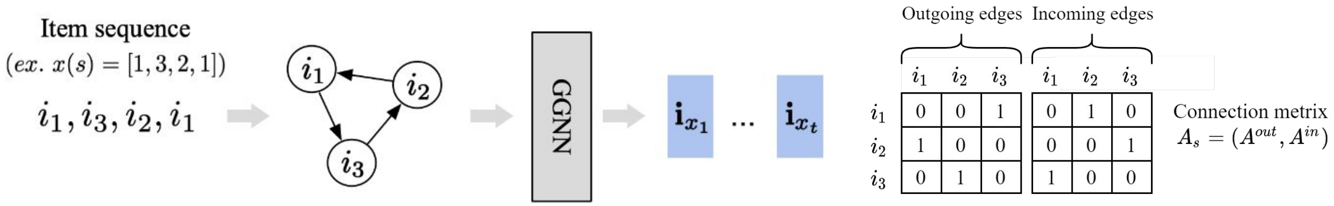
Next action prediction given specific item

Multi-task learning

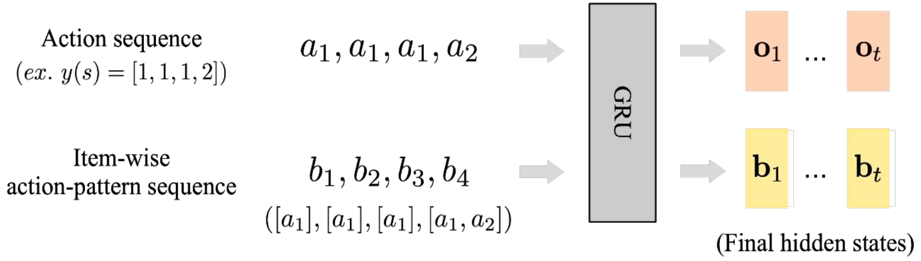
Optimize both item and action prediction simultaneously

Multi-behavior session encoding

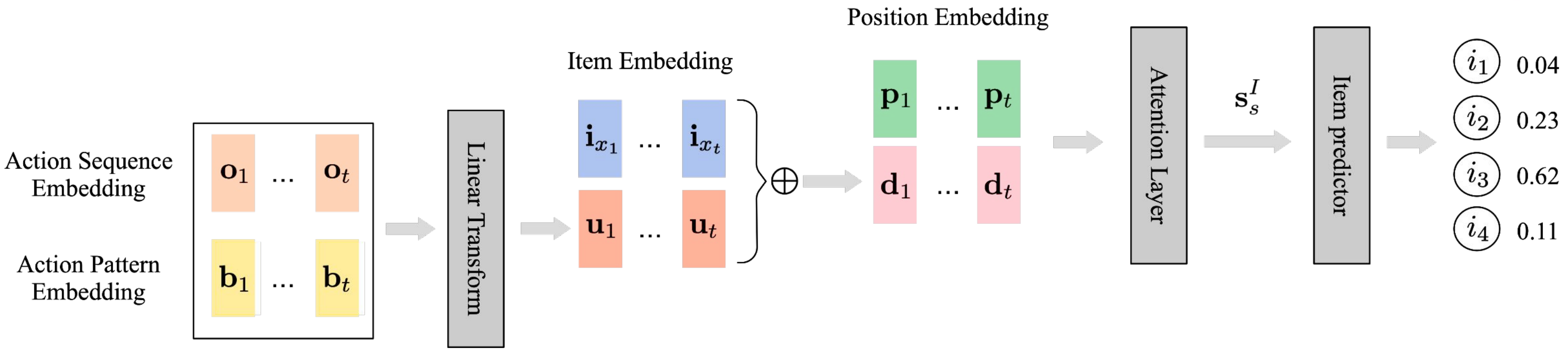
◎ Item embedding



◎ Action-related embedding learning



Action-aware Session Representation Learning for Next-item Prediction



1. Combine action embeddings

$$\mathbf{u}_k = dropout(RELU(\mathbf{o}_k \parallel \mathbf{b}_k)\mathbf{U}_4 + \mathbf{q}_3))$$

$$\mathbf{d}_k = \boldsymbol{i}_{x_k} + \mathbf{u}_k$$

2. Learn attention weights

$$\alpha_k = \mathbf{q}_5^{\mathsf{T}} \sigma(\mathbf{W}_{12}\mathbf{h}_k + \mathbf{W}_{13}\mathbf{s}' + \mathbf{q}_6)$$

$$\mathbf{h}_k = \tanh(\mathbf{d}_k \parallel \boldsymbol{p}_{t-k+1}\mathbf{U}_5 + \mathbf{q}_4)$$

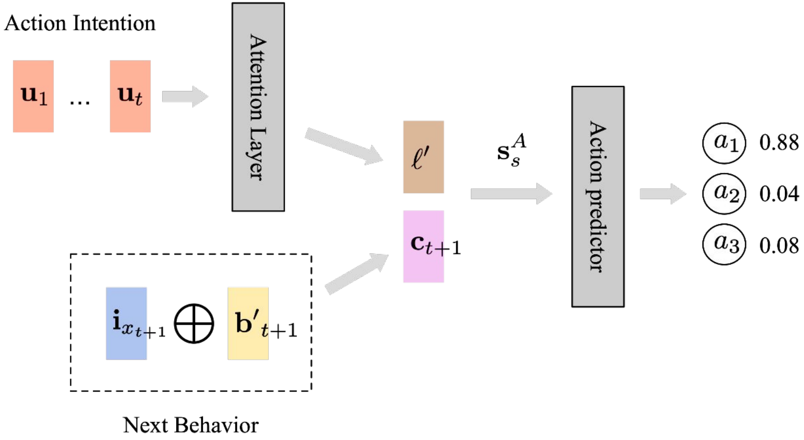
$$\mathbf{s}' = \sum_{i=1}^{t} \mathbf{d}_k / t$$

3. Compute item scores

$$\mathbf{s}_S^I = \sum_{i=1}^{t} \alpha_k \mathbf{d}_k$$

$$\hat{y}_j^I = softmax\left(\mathbf{s}_S^{I\,\mathsf{T}} \mathbf{i}_i\right)$$

Conditional Multiplex Behavior Session Modeling for Next-action Prediction



$\mathbf{i}_{x_{t+1}}$: *predicted next item embedding*

$\mathbf{b}'_{t+1}$: *action pattern embedding*

1. Learn session-level action intention

$$\mathbf{u}_k = RELU\big((\mathbf{o}_k \parallel \mathbf{b}_k)\mathbf{U}_6 + \mathbf{q}_7\big)$$

$$\beta_k = \mathbf{q}_8{}^T\sigma(\mathbf{W}_{14}\mathbf{u}_k + \mathbf{W}_{15}\mathbf{c}_{t+1} + \mathbf{q}_9)$$

$$\ell' = \sum_{k=1}^{t} \beta_k \mathbf{u}_k$$

2. Combine action intention & next behavior

$$\mathbf{c}_{t+1} = \mathbf{i}_{x_{t+1}} + \mathbf{b}'_{t+1} \qquad \mathbf{s}_s^A = \mathbf{U}_6(\ell' \parallel \mathbf{c}_{t+1})$$

3. Compute action scores

$$\hat{y}_j^A = softmax\left(\mathbf{s}_s^{A^\top}\mathbf{a}_i\right)$$

Multi-task Learning

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

$$\mathcal{L}_{action} = -\sum_{i=1}^{|I|} y_i^I \log(\hat{y}_i^I) + (1 - y_i^I)\log(1 - \hat{y}_i^I)$$

$$\mathcal{L}_{action} = -\sum_{i=1}^{|A|} \omega_i y_i^A \log(\hat{y}_i^A) + (1 - y_i^A)\log(1 - \hat{y}_i^A)$$

$$\mathcal{L}_{joint} = \mathcal{L}_{item} + \lambda\mathcal{L}_{action}$$

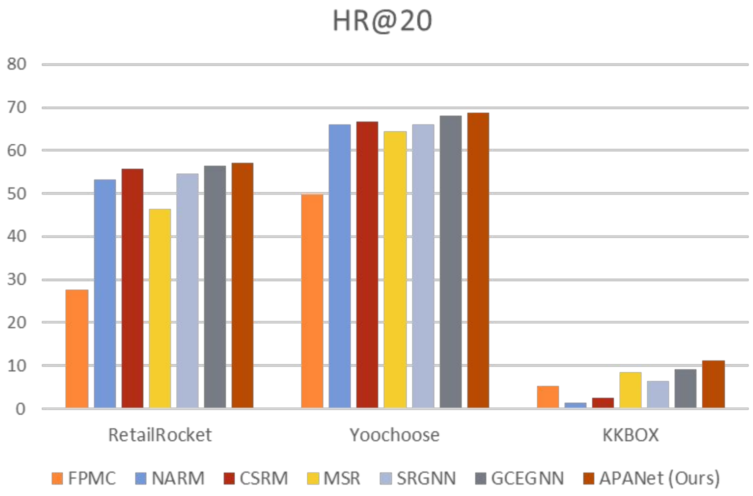
- Control parameters

ω_i: penalty weight of each type of action a_i

λ: multi-task learning weight

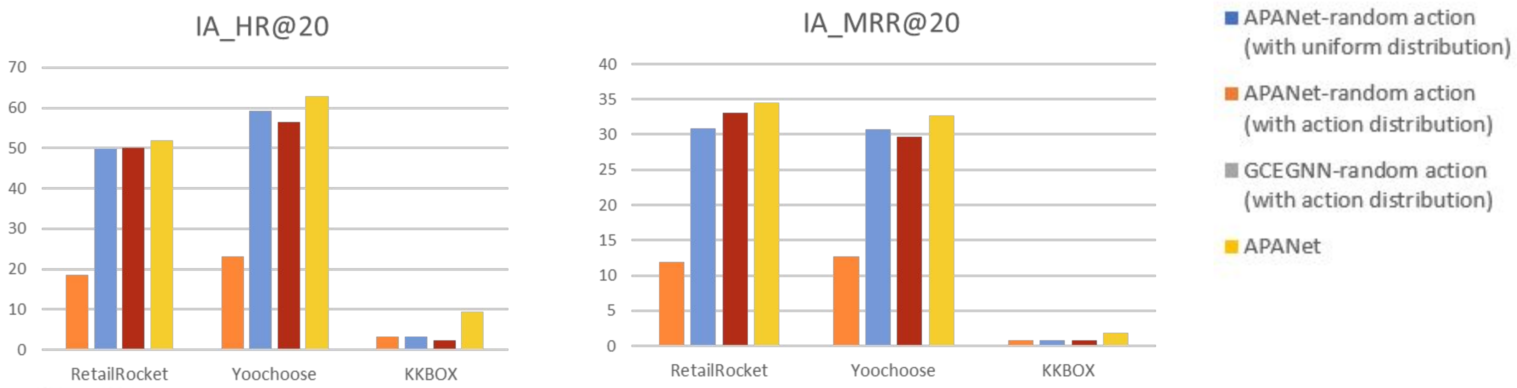
Experiment Results: Next-Item Prediction

- 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)



Experiment Results: Next-Item and Next-Action Prediction

- 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)



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

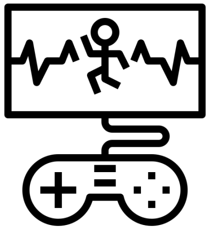
Model setting	KKBOX				RetailRocket			
	HR@20	MRR@20	IA_HR@20	IA_MRR@20	HR@20	MRR@20	IA_HR@20	IA_MRR@20
(1) W/o act_pattern_emb	9.813	2.065	6.853	1.395	55.211	37.933	49.886	30.634
(2) W/o act_seq_emb	10.201	2.411	8.830	1.864	56.419	38.025	51.137	33.240
(3) W/o pos_emb	7.430	2.040	5.149	1.079	54.905	37.881	49.183	30.271
(4) Next-action predictor	**11.876**	2.879	–	–	55.420	38.127	–	–
APANet	11.183	**3.182**	**9.446**	**1.881**	**57.001**	**38.735**	**51.790**	**34.475**

APANet Applications

For users:

Enhancing customer experience

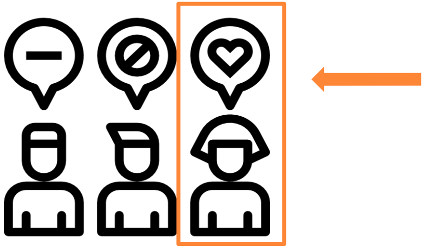
- Predicting user’s next move
- E.g. gaming, shopping

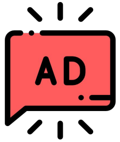


For company:

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!