Deep Reinforcement Learning for Page-wise Recommendations

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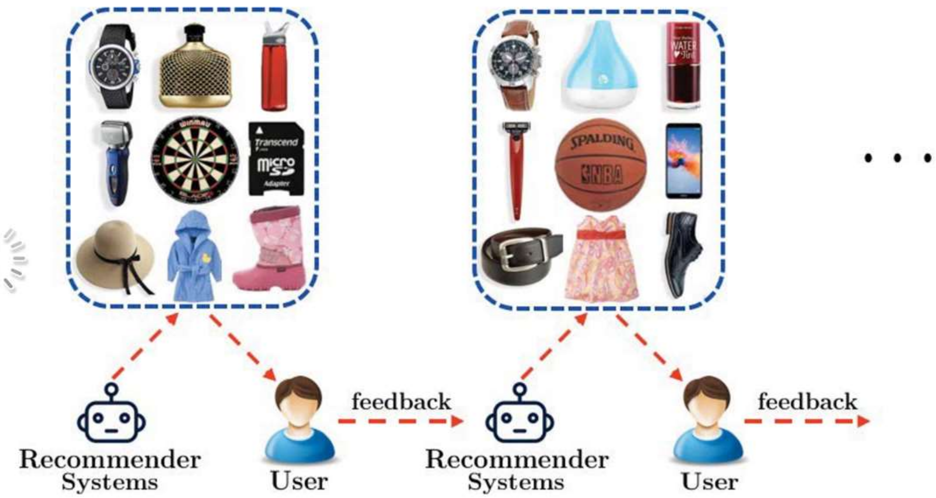
Recommendation Systems

Personalized suggestions

Two challenges:

- Updating suggestions based on feedback
- Properly displaying the suggestions



Previous Works

- Mostly greedy static processes
- Fail to continuously update their strategies
- Similar repeating suggestion sets
- Do no consider item placement in page

Our Work

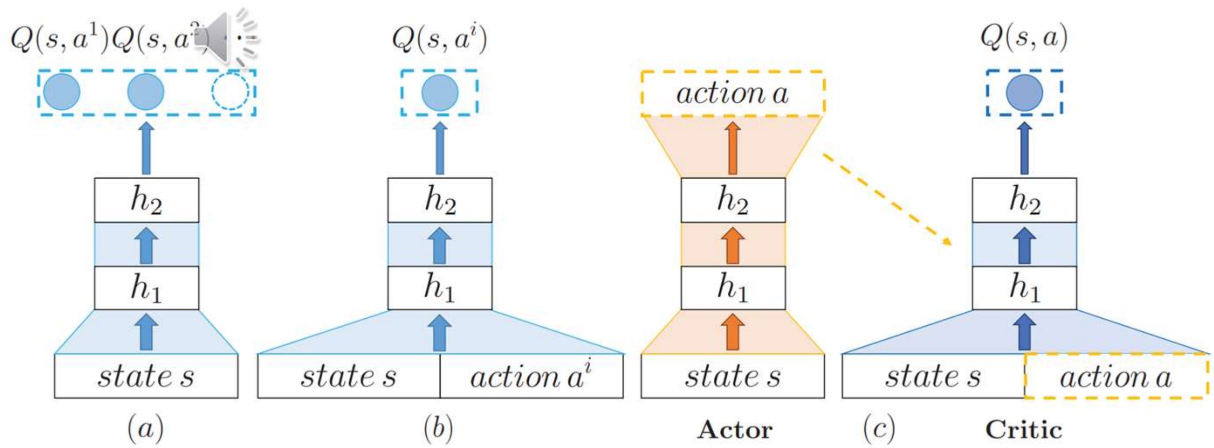
- Leveraging Deep Reinforcement Learning
- Capturing and utilizing users' real-time feedbacks
- Maximizing long-term rewards
- Bundling diverse and complimentary items
- Forming item display strategies for 2D pages

Choice of Framework Architecture

a) Conventional DQN methods do not support large action spaces

b) The time-complexity makes it impractical

c) Suitable for large and dynamic action spaces



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Architecture of Actor

Three challenges

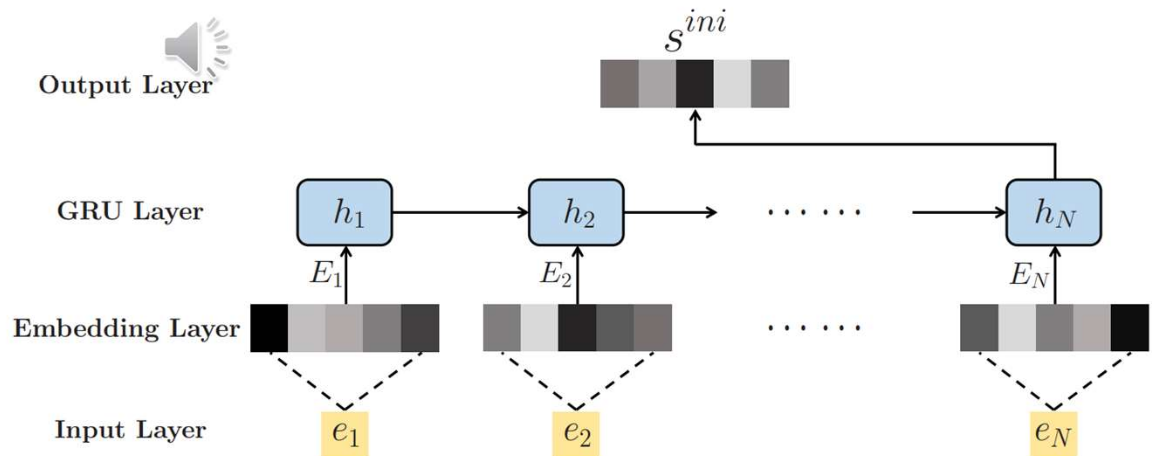
1. Setting an initial preference at the beginning of the session
2. Learning the real-time preferences in the current session
3. Jointly generating a set of recommendations and arranging them

Initial State Generation

Input Layer: user's last clicked/purchased items' representations

Embedding Layer: $E_i = \tanh(W_E e_i + b_E) \in R^{|E|}$

GRU: Gated Recurrent Units to capture users' sequential behavior



Real-time State Generation

Input Layer: x_i = (e_i = item rep., c_i = item cat., f_i = user feedback)

Embedding Layer:

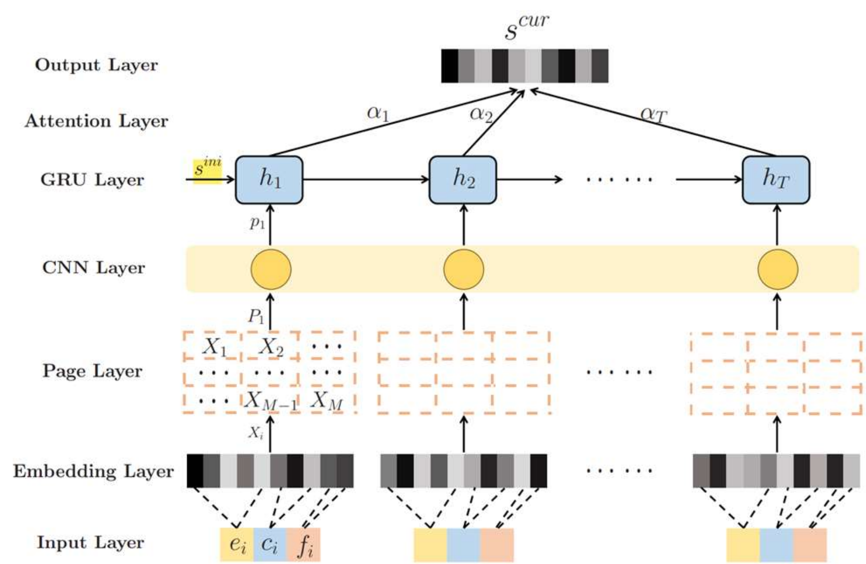
- $E_i = \tanh(W_E e_i + b_E) \in R^{|E|}$
- $C_i = \tanh(W_C c_i + b_C) \in R^{|C|}$
- $F_i = \tanh(W_F f_i + b_f) \in R^{|F|}$

Page Layer: original arrangement

CNN Layer: capture spatial correlations

GRU Layer: capture temporal correlations

Attention Layer: Weighted inputs



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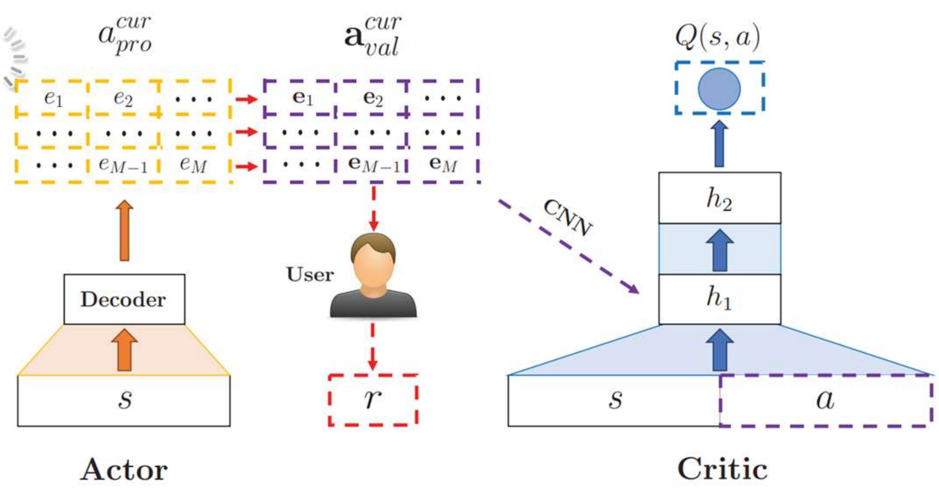
Action Generation

- Converts the vectors to 2D item lists
- Uses deconvolution neural networks (DeCNN)
- Output might need to be matched to actual items

Architecture of Critic

- Uses 2D-CNN to extract action vector from item page
- Action vector and state vector input to DQN



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Training

DDPG

Offline

- Pretrain agent with offline data
- Off-policy
- Fixed action data
- Minimize actor output and data difference:

$$\min_{\theta^\pi} \sum_{b=1}^{B} \left(\| a_{pro}^{cur} - \mathbf{a}_{val}^{cur} \|_F^2 \right)$$

Online

- On-policy
- Output matched through cosine similarity:

$$\mathbf{e}_i = \arg\max_{\mathbf{e} \in \mathcal{I}} \frac{e_i^\top \cdot \mathbf{e}}{\|e_i\| \|\mathbf{e}\|} = \arg\max_{\mathbf{e} \in \mathcal{I}} e_i^\top \cdot \frac{\mathbf{e}}{\|\mathbf{e}\|}$$

- Rewards based on actual user interactions

Training Algorithm

Critic

- Minimize loss function: $L(\theta^{\mu}) = \mathbb{E}_{s,a,r,s'}\left[\left(r + \gamma Q_{\theta^{\mu'}}(s', f_{\theta^{\pi'}}(s')) - Q_{\theta^{\mu}}(s, a)\right)^2\right]$
- Trained from samples in replay buffer

Actor

- Policy gradient update: $\nabla_{\theta^{\pi}} f_{\theta^{\pi}} \approx \mathbb{E}_s\left[\nabla_{\hat{a}} Q_{\theta^{\mu}}(s, \hat{a}) \nabla_{\theta^{\pi}} f_{\theta^{\pi}}(s)\right]$

Testing Procedure

Online testing

- Similar to transition generating stage during training

Offline testing

- Reranking items

Experiments

Database: 1M recommendation sessions

Initial state: 10 previous items

Recommendation page: 5 rows, 2 columns

Reward:

- Skipped: 0
- Clicked: 1
- Purchased 5

Embedding dimensions:

- $|E| = 50$
- $|C| = 35$
- $|F| = 15$

Offline metrics:

- Precision@20,
- Recall@20,
- F1-score@20,
- NDCG@20
- MAP

Online metrics:

- total sum of rewards

Results (Offline Test)

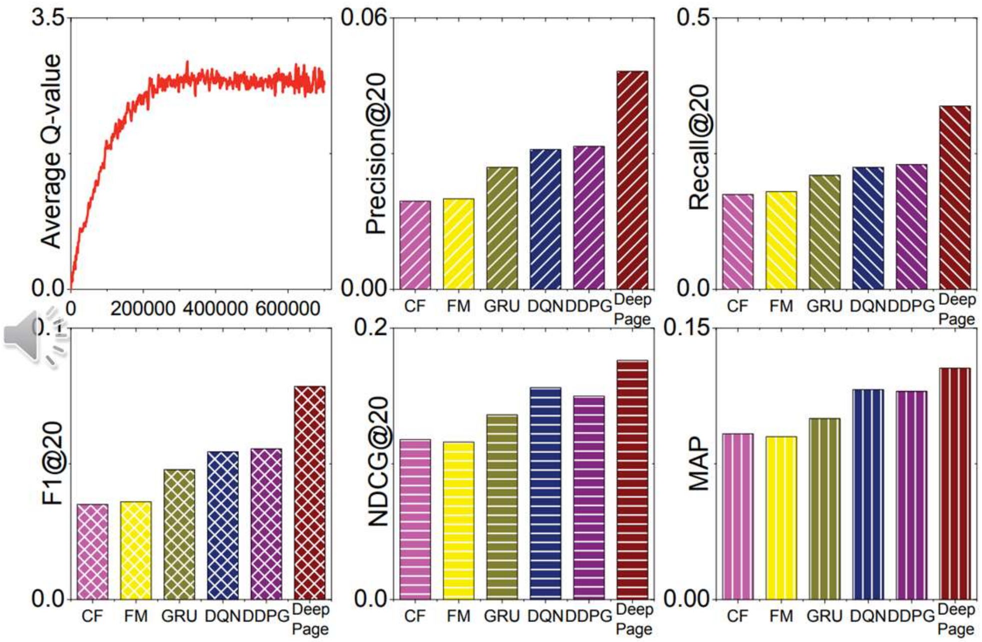
CF: Collaborative Filtering

FM: Factorization Machines

GRU: Click/purchase prediction

DQN: User history -> Recom. page

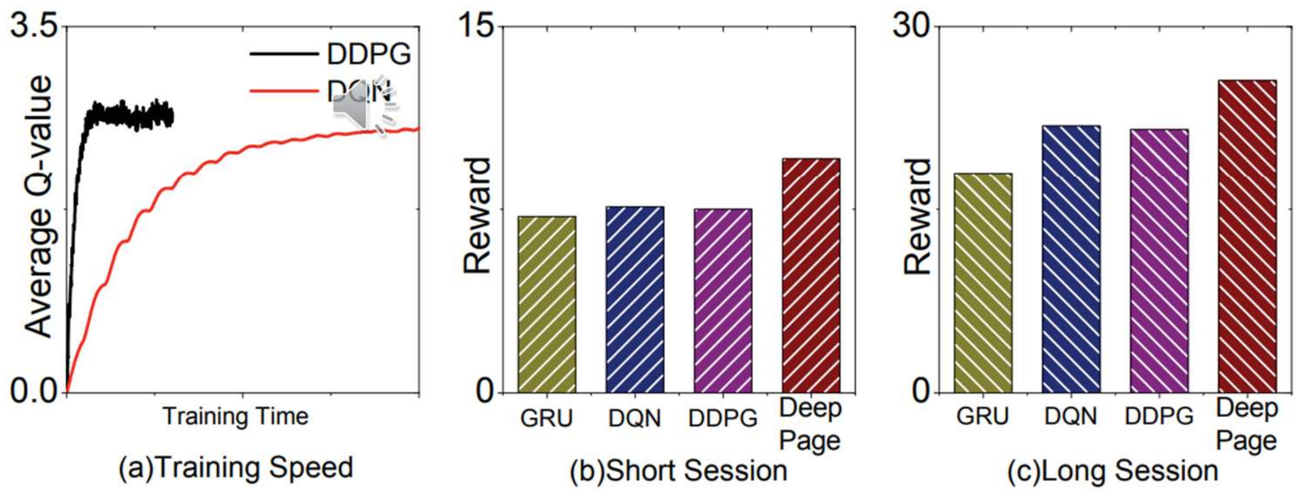
DDPG: Using 5 fully connected layers



Results (Online Test)

Short session: 10 recommendation pages

Long session: 50 recommendation pages



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Effectiveness of Components

1: remove embedding layers

2: remove categories and feedback

3: remove GRU in initial state

4: remove CNN

5: remove attention mechanisms

6: remove GRU in real-time state

7: replace DeCNN with FCL

Methods	Precision @20	Recall @20	F1score @20	NDCG @20	MAP
DeepPage-1	0.0479	0.3351	0.0779	0.1753	0.1276
DeepPage-2	0.0475	0.3308	0.0772	0.1737	0.1265
DeepPage-3	0.0351	0.2627	0.0578	0.1393	0.1071
DeepPage-4	0.0452	0.3136	0.0729	0.1679	0.1216
DeepPage-5	0.0476	0.3342	0.0775	0.1716	0.1243
DeepPage-6	0.0318	0.2433	0.0528	0.1316	0.1039
DeepPage-7	0.0459	0.3179	0.0736	0.1698	0.1233
DeepPage	**0.0491**	**0.3576**	**0.0805**	**0.1872**	**0.1378**

Conclusion

- Recommendation systems are complicated tasks
- Deep Reinforcement Learning proves necessary

Future work

- Reducing the temporal complexity of mapping output embeddings to actual items
- Handling multiple tasks in one reinforcement learning framework


That's all Folks!