A Simple Convolutional Generative Network for Next Item Recommendation

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Session-based Recommendation

- Session-based recommendation Apps:
  Short-form mobile video (Tik Tok, Weishi, Yoo Video)
  Music (Tencent music, Yahoo! Music) & News
Static Recommendation

- Scenario: weak sequential property
- Ads recommendation, Google app store
• Related work:
  • **Markov chain**: Long long ago
  • **RNN/LSTM**: GRURec[1, 2] 2016, 2017
  • **CNN**: Caser [3], NextItNet [4] 2018
  • **Attention**: Transformer [5] 2017, 2018

[3] Personalized Top-N Sequential Recommendation via Convolutional Sequence Embedding. WSDM2018
[5] Next Item Recommendation with Self-Attention. ICDM2018
• **Session-based rec**: Top-n item recommendation
• **Offline**: NDCG, MRR, MAP, Pre@10, Rec@10
• **Online**: UV, VV, PV, CTR
Session-based Recommendation

- **RNN/LSTM**: GRURec[1]

pros: good for modelling seq
cons: bad for utilizing GPU

**Session-based Recommendation**

- **CNN:** Caser[1]

**Pros:** good for using GPU

**Cons:** max pooling loses much information, shallow layers

[1] Personalized Top-N Sequential Recommendation via Convolutional Sequence Embedding. WSDM2018
Session-based Recommendation

- **Attention[1]**

Pros: better for utilizing GPU
Cons: quadratic complexity, particularly for longer sequences

[1] Self-Attentive Sequential Recommendation. ICDM2018
Session-based Recommendation

- **CNN: NextItNet[1]**

**Pros:**
- CNN structure-model parallelism
- Residual block: deeper and stronger
- Dilated CNN: longer and better

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Session-based Recommendation

- **CNN**: NextItNet[1]

Pros: simple, no additional features, strong sequential property, remember longer, training faster

\[
\text{Caser/GRURec : } \{x_0, x_1, \ldots, x_{14}\} \Rightarrow x_{15} \\
\text{Ours : } \{x_0, x_1, \ldots, x_{14}\} \Rightarrow \{x_1, x_2, \ldots, x_{15}\}
\]

\[
\text{Caser/GRURec sub – session – 1 : } \{x_{-1}, x_0, \ldots, x_{13}\} \Rightarrow x_{14} \\
\text{Caser/GRURec sub – session – 2 : } \{x_{-1}, x_{-1}, \ldots, x_{12}\} \Rightarrow x_{13} \\
\ldots \ldots \\
\text{Caser/GRURec sub – session – 12 : } \{x_{-1}, x_{-1}, \ldots, x_2\} \Rightarrow x_{3}
\]
Session-based Recommendation

Residual blocks

- **CNN: NextItNet[1]**

![Diagram of the architecture of NextItNet](image)

![Diagram of residual blocks](image)
Session-based Recommendation

Mask Design

• **CNN:** NextItNet[1]
Session-based Recommendation

Experiments

- Weishi Data

<table>
<thead>
<tr>
<th></th>
<th>MostPop</th>
<th>Caser</th>
<th>NextItt</th>
</tr>
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<tbody>
<tr>
<td><strong>MRR@5</strong></td>
<td>0.005</td>
<td>0.055</td>
<td>0.080</td>
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<tr>
<td><strong>NDCG@5</strong></td>
<td>0.008</td>
<td>0.067</td>
<td>0.093</td>
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- Buying data, Lastfm music

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<tr>
<th>DATA</th>
<th>YOO</th>
<th>MUSIC_M5</th>
<th>MUSIC_L5</th>
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<th>MUSIC_L20</th>
<th>MUSIC_L50</th>
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<td>0.2920</td>
<td>0.2207</td>
<td>0.2214</td>
<td>0.1947</td>
<td>0.2060</td>
<td>0.2080</td>
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<td>0.2748</td>
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Table 2: Accuracy comparison. The upper, middle and below tables are MRR@5, HR@5 and NDCG@5 respectively.