Deep Recommender System: Fundamentals and Advances

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Tutorial website: https://deeprs-tutorial.github.io
Recommender Systems

Age of Information Explosion

Recommend item X to user

**Items** can be: Products, News, Movies, Videos, Friends, etc.
Recommender Systems

Recommendation has been widely applied in online services:
- E-commerce, Content Sharing, Social Networking ...

Product Recommendation

Frequently bought together

A + B + C

Total price: $208.9

Add all three to Cart
Add all three to List
Recommender Systems

Recommendation has been widely applied in online services:
- E-commerce, Content Sharing, Social Networking ...

News/Video/Image Recommendation

For you
Recommended based on your interests

This Research Paper From Google Research Proposes A 'Message Passing Graph Neural Network' That Explicitly Models Spatio-Temporal Relations
MarkTechPost - 2 days ago

Tested: Brydge MacBook Vertical Dock, completing my MacBook Pro desktop
YouTube - 23 hours ago
Recommender Systems

Recommendation has been widely applied in online services:
- E-commerce, Content Sharing, Social Networking...

Friend Recommendation
Problem Formulation

**INPUT**

Historical user-item interactions or additional side information (e.g., social relations, item’s knowledge, etc.)

**OUTPUT**

Predict how likely a user would interact with a target item (e.g., click, view, or purchase)
**Recommender Systems**

**Collaborative Filtering (CF) is the most well-known technique for recommendation.**
- Similar users (with respect to their historical interactions) have similar preferences.
- Modelling users’ preference on items based on their past interactions (e.g., ratings and clicks).

**Learning representations of users and items is the key of CF.**

**Task: predicting missing movie ratings in Netflix.**
Matrix Factorization

- Learn representations to describe users and items based on user-item rating matrix $R$.

User-item Rating Matrix $R$

<table>
<thead>
<tr>
<th>User</th>
<th>Spider Man</th>
<th>Captain America</th>
<th>Toy Story</th>
<th>Iron Man</th>
<th>Minions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lily</td>
<td>5</td>
<td>4</td>
<td>?</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>Peter</td>
<td>?</td>
<td>?</td>
<td>5</td>
<td>?</td>
<td>?</td>
</tr>
<tr>
<td>David</td>
<td>5</td>
<td>?</td>
<td>?</td>
<td>?</td>
<td>2</td>
</tr>
</tbody>
</table>

$n$ users

$m$ items (movies)

Items representations

$Q^T \in \mathbb{R}^{d \times m}$

User representations

$P \in \mathbb{R}^{n \times d}$

Predicted rating of item $j$ for user $i$:

$$\hat{r}_{ij} \approx p_i^T q_j = \sum_{k=1}^d p_{ik} q_{jk}$$
Objective with rating reconstruction error:

\[
\min_{\mathbf{P}, \mathbf{Q}} \sum_{i,j \in S} (r_{ij} - \hat{r}_{ij})^2 = \sum_{i,j \in S} (r_{ij} - \mathbf{p}_i^T \mathbf{q}_j)^2
\]

Given \( n \times m \) matrix \( \mathbf{R} \), the goal is to learn:

**Users/Items representations:** \( \mathbf{P} \in \mathbb{R}^{n \times d}, \mathbf{Q} \in \mathbb{R}^{m \times d} \)

Task: rating prediction in Netflix

- Observed user-item interactions (known): \( \mathbf{S} \)
Deep Learning is Changing Our Lives
Deep Recommender Systems

Fundamentals of Deep Recommender Systems

Reinforcement Learning (RL)
- Recommendation Policies
  - Offline optimization
  - Short-term reward

Graph Neural Networks (GNNs)
- Graph-structured Data
  - Information Isolated Island Issue: ignore implicit/explicit relationships among instances

Automated Machine Learning (AutoML)
- Manually Designed Architectures
  - Expert knowledge
  - Time and engineering efforts

Recommendation Policies
- Offline optimization
- Short-term reward
Agenda

- 9:00 – 9:10  Introduction to Recommender Systems (Jiliang Tang)
- 9:35 – 10:15 Reinforcement Learning for Recommendations (Xiangyu Zhao)

10:15 – 10:25  Coffee Break (10 mins)

- 10:25 – 11:00  Graph Neural Network for Recommendations (Wenqi Fan)
- 11:05 – 11:35 AutoML for recommendations (Xiangyu Zhao)
- 11:35 – 11:45  Conclusion and QA session