Context Incorporation Techniques for Social Recommender Systems

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IEEE ICC 2021
14-23 June 2021, Virtual / Montreal

SAC-SN-2: AI and IoT for Social Networks
Agenda

- **Traditional Recommender Systems**
- **Context-Aware Recommender Systems: Background and Motivations**
- **Context Incorporation Algorithms**
  - Filtering Approaches
- **US-NCF: A prefiltering approach for a DL-based context incorporation**
- **US-NCF hybridization with social recommender systems**
- **Deployment**
  - Baselines
  - Testing setup
- **Results and Discussion**
  - BigDL: Engineered atop Apache Spark
- **Concluding remarks**
Recommender Systems

- **Recommender systems (RSs)** provide recommendations to users on items of interest.
- RSs work by calculating top ranking list of items recommended for users.
- A deep analysis of historical user-item interaction
  - Explicit: ratings (a.k.a. explicit feedback) or
  - Implicit: the time a user spends viewing a page of a specific item online.
- Collaborative Filtering (CF) remains the most predominant conventional RS.
Explicit Feedback

<table>
<thead>
<tr>
<th>User X Item</th>
<th>Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ibis Amman</strong></td>
<td><img src="U1" alt="Star Rating" /> <img src="I1" alt="Star Rating" /> <img src="I2" alt="Star Rating" /></td>
</tr>
<tr>
<td><strong>Mövenpick Hotel Amman</strong></td>
<td><img src="U2" alt="Star Rating" /> <img src="I1" alt="Star Rating" /> <img src="I2" alt="Star Rating" /></td>
</tr>
<tr>
<td><strong>W Amman Hotel</strong></td>
<td><img src="U3" alt="Star Rating" /> <img src="I1" alt="Star Rating" /> <img src="I2" alt="Star Rating" /></td>
</tr>
</tbody>
</table>

*NOTE: The table shows implicit feedback for three items (U1, U2, U3) with ratings assigned to each item (I1, I2).*
Are additional attributes helpful!

- Conventional RSs are not aware of the contextual information that may be served as additional information with the input data.
- Additional contextual information has a utility in improving the overall recommendation precision.
Context

• Any associated information that is useful for characterizing the situation of an object.
Context-aware interactions

- Contextual interaction is multidimensional
- Users X Items X Context $\rightarrow$ ratings

Incorporating Context Information into Recommender Systems

- Three approaches:
  
  ![Diagram showing three approaches:](image-url)
Item Splitting

• A dimensionality reduction: transforming a 3-dimensional rating interactions into a 2-dimensional counterpart.
User Splitting

• Same users show statistically significant feedback differences depending on various contextual conditions.
US-NCF: context incorporation for DL-based RSs
Using US-NCF with Online Social Networks

- Our context-aware recommender system can be used for supporting the operation of context-aware social recommender systems.

\[ \hat{r}_{uics} = p(v_i = r_c) \cdot \hat{r}_{uic} + (1 - p(v_i = r_c)) \cdot \hat{r}_{uis} \]
Experimental setup

• Evaluation metrics
  – average Mean Absolute Error (MAE) and validation loss
  – For ranking (i.e., top-N), we adopt an accuracy measure known as precision-in-top-N. We specifically have adopted ‘top-one-accuracy’ (a.k.a. P@1)

• Testbed
  – Cluster: our prototype over BigDL [9], which is coined over Apache Spark [10]. Therefore, taking advantage of the distributed running of the training models
  – Datasets:
    • two explicit feedback rating datasets
      – Movie rating dataset, Movielens 1M
      – trip planning website TripAdvisor
MAE of US-NCF Vs. baselines for all datasets

- Our model US-NCF significantly surpasses several baselines. On average, a gain that equals 1.8% was obtained compared to plain NCF, slightly better than that obtained when applying the state of the art CA-NCF.

- A higher gain is obtained when comparing US-NCF with conventional context-free model, specifically BiasedMF, where we obtain, on average, a gain that equals roughly 13.3%.
Validation loss of US-NCF Vs. NCF against ‘number of iterations’ on MovieLens 1M dataset.

+, averaged from 100 running sessions. On average, we got roughly 1.2% loss gain because of applying US-NCF instead of the stock version NCF.
Top1Accuracy US-NCF against baselines on all datasets

- US-NCF compares favorably to the baselines. We roughly obtain 4% and 90% when comparing US-NCF to the context-free plain NCF and BiasedMF, respectively. This signifies the importance of incorporating contexts in RSs. Also, it suggests that even context-free deep-learning based RSs perform better than traditional counterparts. The novel method US-NCF performs similarly when comparing it with the item-based state-of-art context-aware RS (CA-NCF).
Concluding remarks

- Incorporating context information into social recommender systems is important for generating more personalized recommendations.
- US-NCF is favorable over CA-NCF for social recommender systems. It is designed to model user’s contexts, whereas CA-NCF was designed to model item’s context.
- For SRSs, it is the relationships between the users that is the center of the analysis, not between items.
- The state-of-art method CA-NCF incorporates contexts with items of the plain NCF, thus recovering an item-based NCF, whereas the novel method US-NCF incorporates context into users, thus recovering a user-based version of NCF.
- A future work would include testing other pre-filtering approaches such as User-Item-Splitting, which combines the benefits of user-splitting and item-splitting.
Thanks for your attention!

Question's time...

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