FedRec: Federated Recommendation with Explicit Feedback via User Averaging

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Introduction

Problem Definition

- **Privacy-aware** rating prediction with explicit feedback
  - Input: Some rating records \( R_u = \{(u, i, r_{ui}); i \in I_u\} \), where each user \( u \) has rated a set of items \( I_u \)
  - Goal: Predict the rating of user \( u \) to each item \( j \in I \setminus I_u \) without sharing the rating behaviors (i.e., \( I_u \))
Our Solution

User Averaging

In order to protect users’ privacy in rating prediction, in particular of what items user $u$ has rated (i.e., the rating behaviors in $\mathcal{I}_u$), we propose a simple but effective strategy, i.e., user averaging (UA). Specifically, we first randomly sample some unrated items $\mathcal{I}_u' \subseteq \mathcal{I} \setminus \mathcal{I}_u$ for each user $u$, and then assign a virtual rating $r'_{ui}$ to each item $i \in \mathcal{I}_u'$,

$$r'_{ui} = \bar{r}_u = \frac{\sum_{k=1}^{m} y_{uk} r_{uk}}{\sum_{k=1}^{m} y_{uk}},$$

where $\bar{r}_u$ denotes the average rating value of user $u$ to the rated items in $\mathcal{I}_u$. With the sampled items and their virtual ratings, we have a combined set of rating records for each user $u$, i.e., $\mathcal{R}_u' \cup \mathcal{R}_u$, where $\mathcal{R}_u' = \{(u, i, r'_{ui}), i \in \mathcal{I}_u'\}$. 
The server randomly **initialize** the model parameters.

Each client $u$ **downloads** the item-specific latent feature vectors.

Each client $u$ **conducts local training with user averaging**.

Each client $u$ **uploads** the gradients to the server.

The server **updates** the item-specific latent feature vectors.
## Results

<table>
<thead>
<tr>
<th>Style</th>
<th>Models</th>
<th>Framework</th>
<th>MAE Value</th>
<th>MD</th>
<th>STDR</th>
<th>RMSE Value</th>
<th>MD</th>
<th>STDR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Batch</td>
<td>PMF</td>
<td>Unfederated</td>
<td>0.7208 ± 0.0013</td>
<td>0.00%</td>
<td>0.34%</td>
<td>0.9123 ± 0.0014</td>
<td>0.01%</td>
<td>0.30%</td>
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<tr>
<td></td>
<td></td>
<td>Federated</td>
<td>0.7208 ± 0.0012</td>
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<td></td>
<td>0.9123 ± 0.0013</td>
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<tr>
<td>Stochastic</td>
<td>PMF</td>
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<td>0.46%</td>
<td>0.8701 ± 0.0021</td>
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<td>0.6829 ± 0.0012</td>
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<td></td>
<td>0.8700 ± 0.0015</td>
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<tr>
<td></td>
<td>SVD++</td>
<td>Unfederated</td>
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<td>0.33%</td>
<td>0.8493 ± 0.0013</td>
<td>0.01%</td>
<td>0.31%</td>
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<td>Federated</td>
<td>0.6620 ± 0.0012</td>
<td></td>
<td></td>
<td>0.8493 ± 0.0014</td>
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</tbody>
</table>

### Observations:

- MD < STDR (when $\rho = 0$): our FedRec is able to convert an unfederated model to a federated one equivalently ...

### More results:

- the recommendation performance decreases (i.e., the value of RMSE increases) with a larger value of $\rho$, which is expected because the averaging strategy will introduce some noise to the data ...
We follow a recent work on federated collaborative filtering (FCF) on item ranking with implicit feedback [Ammad-ud-din et al., 2019], and propose a generic federated recommendation (FedRec) framework for rating prediction with explicit feedback.

We propose a simple but effective strategy of user averaging to achieve a balance between communication/computational cost and privacy protection.

We federate some factorization-based models in both batch style and stochastic style to showcase the generality of our FedRec.