Motivations

- Repeat consumptions are more often than novel ones.
- Lack of study in repeat item recommendation.
- Temporal effect of implicit feedback is important.

Contributions

- Recommendation for repeat consumption (RRC).
- Time-sensitive personalized pairwise ranking model.
- Temporal behavioral feature extraction.

RRC Problem

- Given current window $W$, recommend items from $W$ to consume next.
- Preliminary: the next consumption is "known" to be repeat \[^1\].

Time-Sensitive Personalized Pairwise Ranking (TS-PPR) Model

Temporal preference:

$$r_{uvt} = u^\top v + u^\top A_{s} f_{uvt} = u^\top (v + A_{s} f_{uvt})$$

Probability: $u$ prefers $v_i$ more than $v_j$ at time $t$:

$$p(v_i > v_j) = \sigma(r_{uvt} - r_{uvt})$$

$$= \frac{\sigma(1 + (v_i + A_{s} f_{uvt} - v_j - A_{s} f_{uvt}))}{1 + e^{-1 + (v_i - v_j + A_{s} f_{uvt} - A_{s} f_{uvt})}}$$

Objective:

$$J = \sum_{(u,v_i,v_j)\in D} \ln p(v_i > v_j) + \frac{\lambda}{2} \sum_u \|A_u\|^2 + \frac{\gamma}{2} (\|U\|^2 + \|V\|^2)$$

Features:

- Normalized item popularity
- Normalized item reconsumption ratio
- Recency feature
- Dynamic familiarity

Feasibility: The extracted behavioral features are highly related to repeat consumptions!

In training, sample fixed number of negative $v_j$ for each $v_i$ w.r.t $u$ and $t$.

Train with SGD:

Algorithm 1. Parameter Inference Algorithm

Input:
- learning rate $\alpha$, regularization parameters $\gamma$, $\lambda$

Output:
- transform matrix $A_s$ for each user $u$, latent feature matrices $U$, $V$

1. initialize $A_s \sim N(0, M)$, $W_u$, $U$, $V \sim N(0, \gamma I)$
2. repeat
3. uniformly draw a user $u$ from user set $U$
4. uniformly draw a recommendation of $v_i$ w.r.t. item $v_i$ at time $t$
5. uniformly draw item $v_j (v_j \neq v_i)$ from the time window of $v_i$ at time $t$
6. $U' = (1 - \alpha) U + \alpha (1 - p(v_i > v_j)) \frac{1}{\|A_{s}\|} r_{uvt}$
7. $V' = (1 - \alpha) V + \alpha (1 - p(v_i > v_j)) \frac{1}{\|A_{s}\|} r_{uvt}$
8. $A'_{s} = (1 - \alpha) A_{s} + \alpha (1 - p(v_i > v_j)) \frac{1}{\|A_{s}\|} r_{uvt}$
9. $\text{until } J$ convergence
10. return $A$, $U$, $V$

Experiment

- Datasets: Gowalla (repeat check-ins), Lastfm (repeat song listening).
- Superior accuracy performance of TS-PPR compared to baselines.
- Accuracy drops after eliminating any of the four extracted features.
- About 1ms time cost for a single recommendation with TS-PPR.

Combine TS-PPR with our previous work \[^1\] towards a holistic recommender system for repeat consumptions.

Evaluation Combining STREC and TS-PPR

<table>
<thead>
<tr>
<th>Data Set</th>
<th>STREC</th>
<th>STREC (on STREC correct classification)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$\text{MAPE}_1$</td>
<td>$\text{MAPE}_2$</td>
</tr>
<tr>
<td>Gowalla</td>
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<td>0.1343</td>
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<tr>
<td>Lastfm</td>
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<td>0.0862</td>
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</tbody>
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