Recommendation for Repeat Consumption from User Implicit Feedback (Extended Abstract)

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Motivations

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

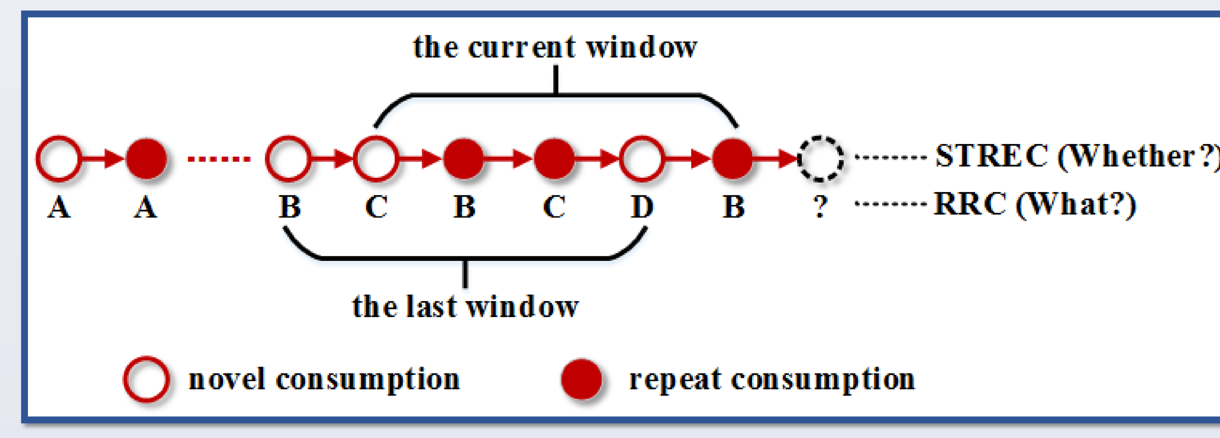
Contributions

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

RRC Problem

[1] Our AAAI-15 paper: Will you reconsume the near past? fast prediction on short-term reconsumption behaviors

- 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:

$$r_{uvt} = \mathbf{u}^\top \mathbf{v} + \mathbf{u}^\top \mathbf{A}_u \mathbf{f}_{uvt} = \mathbf{u}^\top(\mathbf{v} + \mathbf{A}_u \mathbf{f}_{uvt})$$

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

$$\begin{aligned} p(v_i >_{ut} v_j) &= \sigma(r_{uv_it} - r_{uv_jt}) \\ &= \sigma(\mathbf{u}^\top(\mathbf{v}_i + \mathbf{A}_u \mathbf{f}_{uv_it} - \mathbf{v}_j - \mathbf{A}_u \mathbf{f}_{uv_jt})) \\ &= \sigma(\mathbf{u}^\top(\mathbf{v}_i - \mathbf{v}_j + \mathbf{A}_u(\mathbf{f}_{uv_it} - \mathbf{f}_{uv_jt}))) \\ &= \frac{1}{1 + e^{-\mathbf{u}^\top(\mathbf{v}_i - \mathbf{v}_j + \mathbf{A}_u(\mathbf{f}_{uv_it} - \mathbf{f}_{uv_jt}))}}. \end{aligned}$$

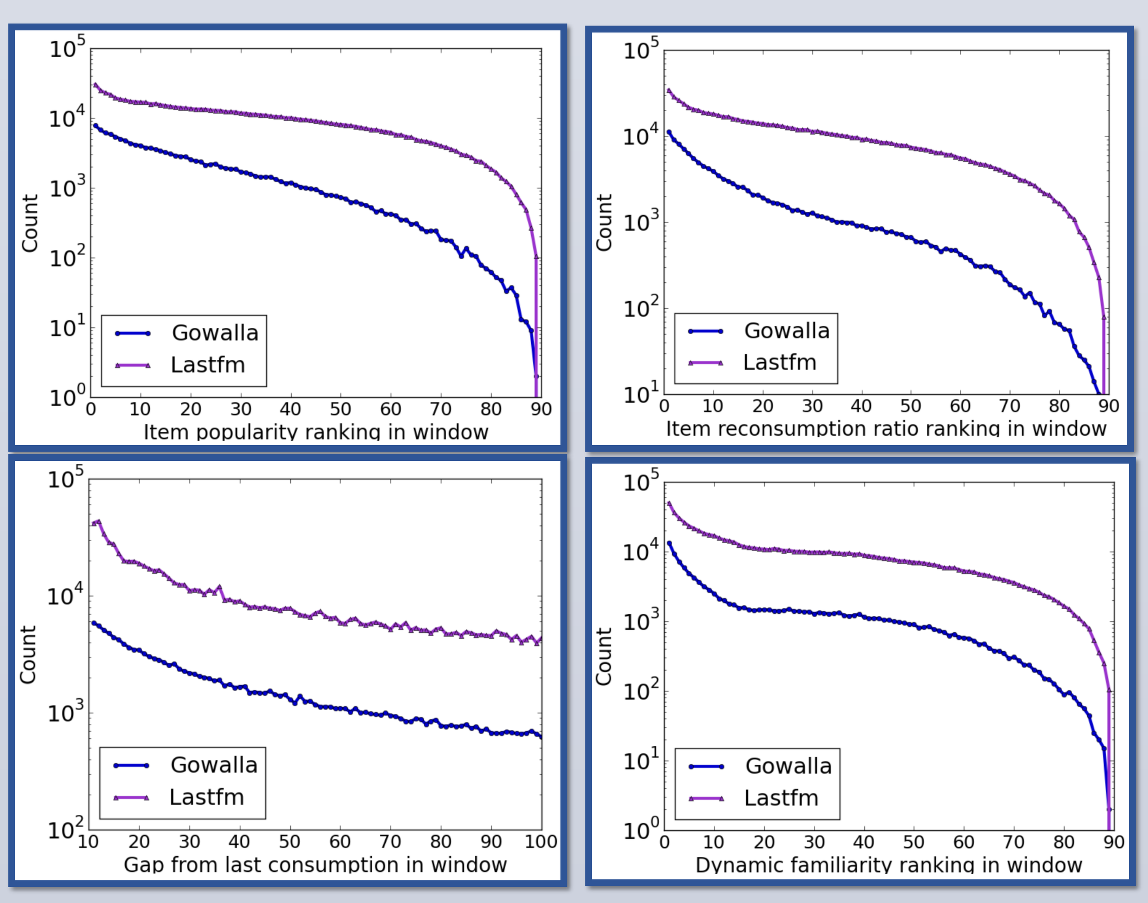
Objective:

$$\mathcal{J} = \sum_{(u, v_i, v_j, t) \in \mathcal{D}} -\ln p(v_i >_{u,t} v_j) + \frac{\lambda}{2} \sum_u \|\mathbf{A}_u\|_F^2 + \frac{\gamma}{2}(\|\mathbf{U}\|_F^2 + \|\mathbf{V}\|_F^2)$$

Features:

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

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 α, regularization parameters γ, λ.

Output:
transform matrix $\mathbf{A}_u$ for each user u,
latent feature matrices $\mathbf{U}, \mathbf{V}$.

```
initialize A_u ~ N(0, λI), ∀u, U, V ~ N(0, γI)
repeat
    uniformly draw a user u from user set 𝒰
    uniformly draw a repeat consumption of u w.r.t. item v_i at time t
    uniformly draw item v_j (v_j ≠ v_i) from the time window of u at time t
    u' ← (1 − αγ)u + α(1 − p(v_i >_ut v_j)) ∂/∂u (r_{uv_i t} − r_{uv_j t})
    v'_i ← (1 − αγ)v_i + α(1 − p(v_i >_ut v_j)) ∂/∂v_i (r_{uv_i t} − r_{uv_j t})
    v'_j ← (1 − αγ)v_j + α(1 − p(v_i >_ut v_j)) ∂/∂v_j (r_{uv_i t} − r_{uv_j t})
    A'_u ← (1 − αλ)A_u + α(1 − p(v_i >_ut v_j)) ∂/∂A_u (r_{uv_i t} − r_{uv_j t})
    u, v_i, v_j, A_u ← u', v'_i, v'_j, A'_u
until 𝒥 convergence
return A, U, V
```

Recommend by ranking with temporal preference r_{uvt}

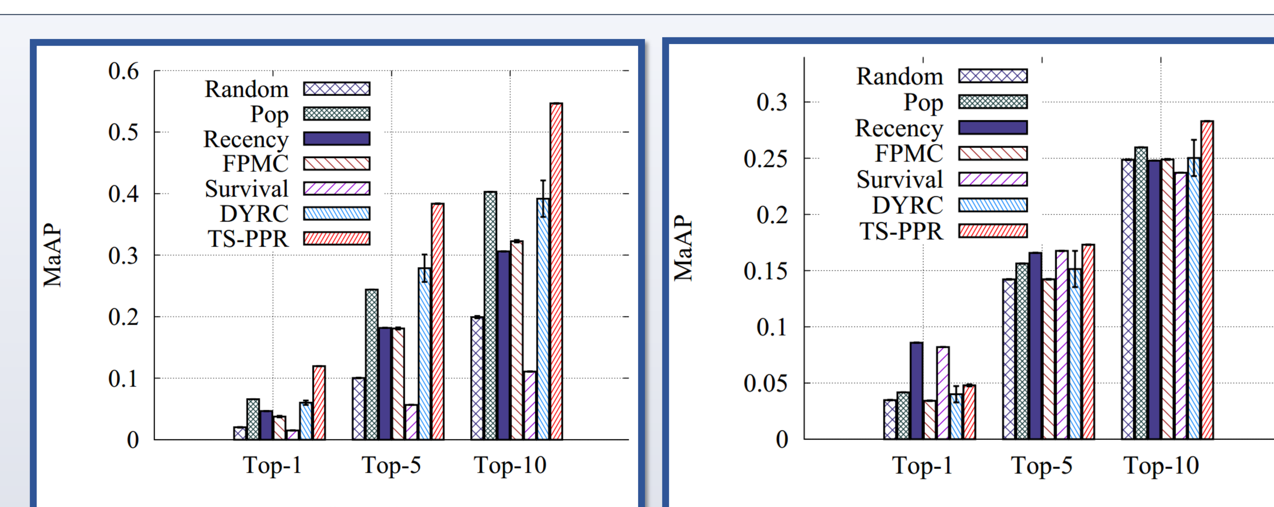
Experiments

- 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.

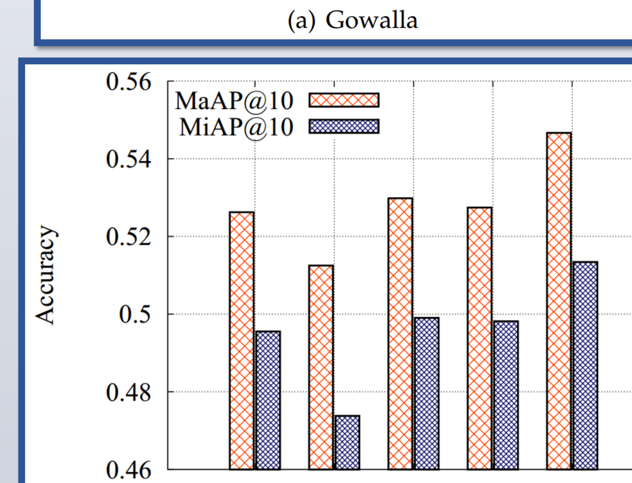
Combine TS-PPR with our previous work [1] towards a holistic recommender system for repeat consumptions.

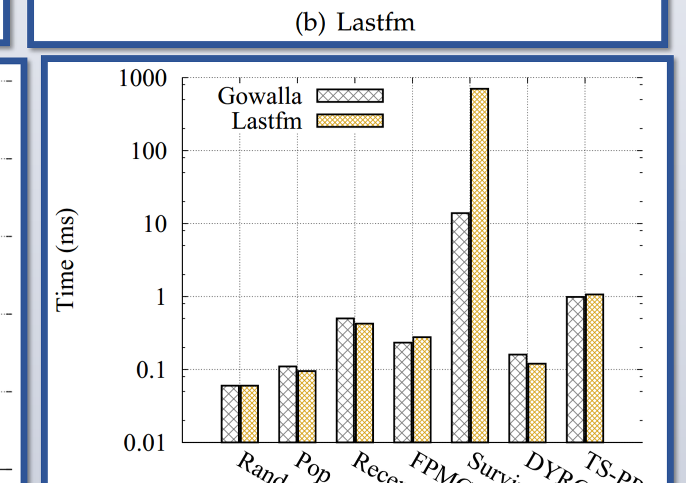
Evaluation Combining **STREC** and **TS-PPR**

Data Set	STREC	TS-PPR (on STREC correct classification) MaAP@1	MaAP@5	MaAP@10
Gowalla	0.6912	0.1343	0.4487	0.6314
Lastfm	0.8070	0.0862	0.2819	0.4336



(a) Gowalla (b) Lastfm





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