

User Intention Inference Tsinghua-BST Joint Project

PIs: Peng Cui, Yingjie Zhang, Shiqiang Yang

Computer Science & Technology Department Tsinghua University

MOTIVATIONS

Social Context

User Intentions for Social Activities

Locational Context

Preference Context

DELIVERABLES

Data

2443 activities
5643 comments
20+ activity categories
27 testees

Algorithm

CF-based
Influence-based
Preference-based
Hybrid factor

System

Function completed Robust and stable Message encrypted Data flow efficient

DATA

Data

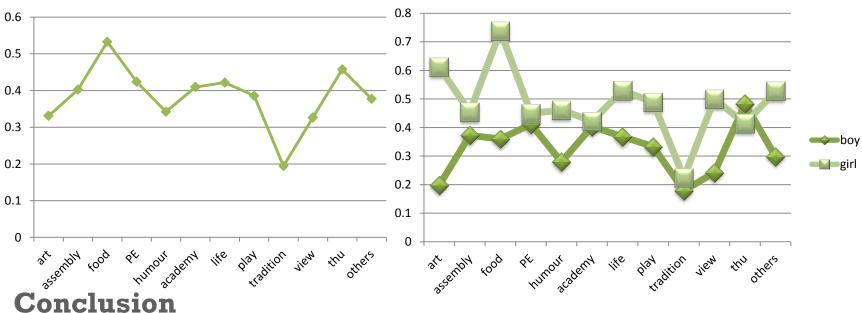
2443 activities 5643 comments 20+ activity categories 27 testees

Content

Preference Behavior

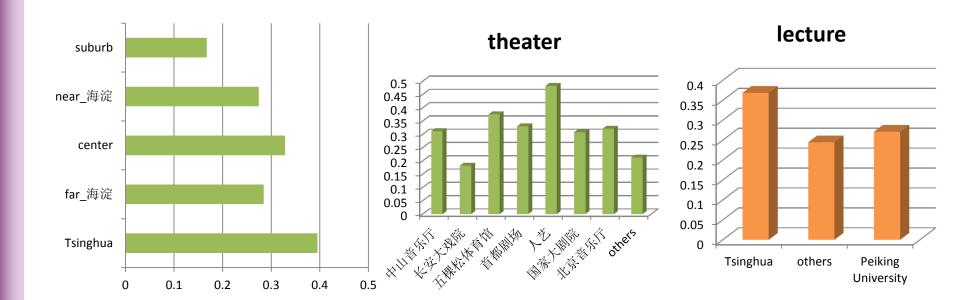
CONTENT





- 1, Students prefer activities in THU, which accounts for the common knowledge that people tend to choose familiar environment.
- 2, College students are more active in outside activities which is reflected in food and play peak.
- 3, Girls are more active in attending different kinds of activities.

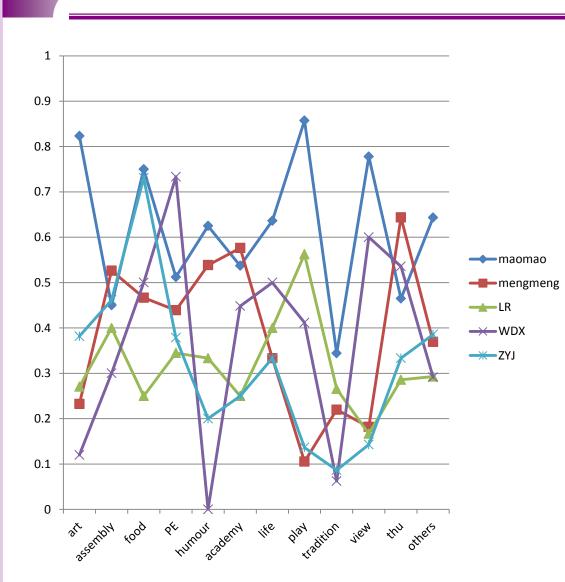
CONTENT (cont'd)



Conclusion

- 1, people sometimes prefer activities near their living or working places because of the less cost in distance.
- 2, but this is not always the case, not even a salient measure.
- 3, we can't use location as a simple rule for heuristic usage.

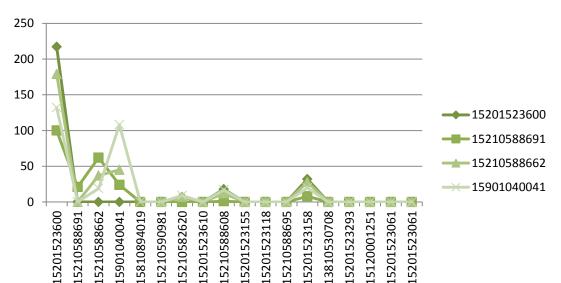
PREFERENCE



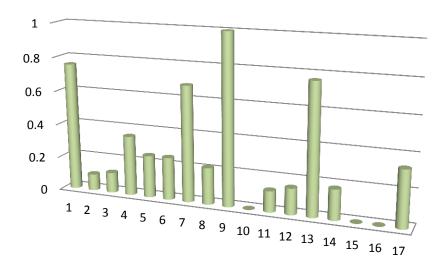
Conclusion

- 1, Different people has distinct predilection on activity topic choice.
- 2,People's comments, attend percent or refuse percent has a connection with their personal characteristics.

BEHAVIOR



ratio between preference and influence



Conclusion

- 1, The more activities a person takes part in, the more influence he/she has on others.
- 2, Different people are widely divergent in facing social influence.
- 3, In most cases, outgoing people would like to choose according to their personal preference.

ALGORITHM

Algorithm

Location-based

CF-based

Influence-based

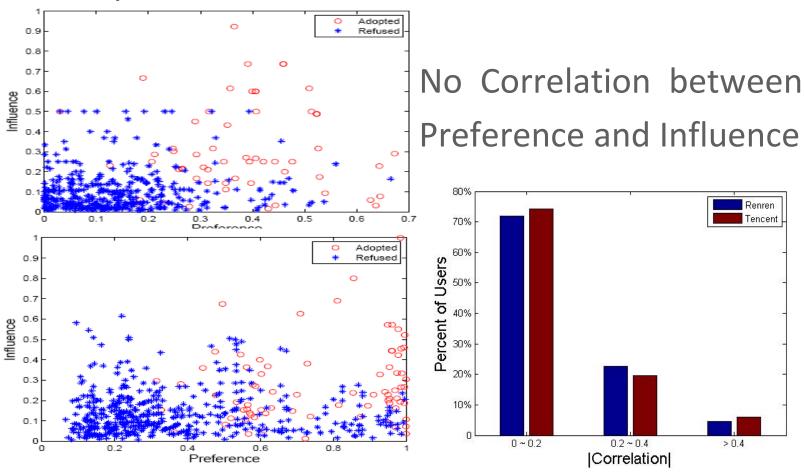
Preference-based

Hybrid factor

Preliminary Algorithm Evaluation

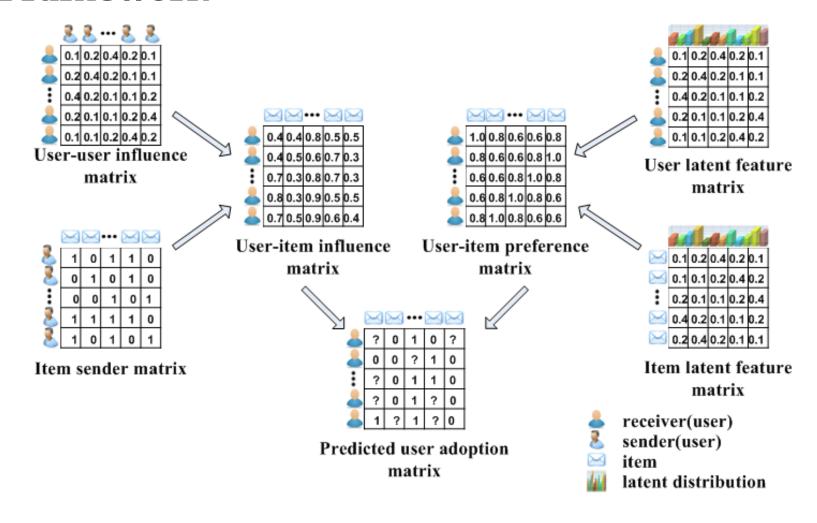
PRELIMINARY

Accepted > Refused on Preference and Influence



PRELIMINARY

Framework



ALGORITHM

Social Contextual Recommendation

$$P(\mathbf{R}|\mathbf{S}, \mathbf{U}, \mathbf{V}, \sigma_R^2) = \prod_{i=1}^{M} \prod_{j=1}^{N} \mathcal{N}(\mathbf{R}_{ij}|\mathbf{S}_i \mathbf{G}_j^\top \odot \mathbf{U}_i^\top \mathbf{V}_j, \sigma_R^2)$$

$$\mathcal{J} = ||\mathbf{R} - \mathbf{S} \mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}||_F + \alpha ||\mathbf{W} - \mathbf{U}^\top \mathbf{U}||_F$$

$$+\beta ||\mathbf{C} - \mathbf{V}^\top \mathbf{V}||_F + \gamma ||\mathbf{S} - \mathbf{F}||_F$$

$$+\delta ||\mathbf{S}||_F + \eta ||\mathbf{U}||_F + \lambda ||\mathbf{V}||_F$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{S}} = 2 \left(-\mathbf{R}(\mathbf{G} \odot \mathbf{V}^\top \mathbf{U}) + (\mathbf{S} \mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}) \mathbf{G} \right)$$

$$+\gamma (\mathbf{S} - \mathbf{F}) + \delta \mathbf{S}$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{U}} = 2 \left(-\mathbf{V} \mathbf{R}^\top + \mathbf{V}(\mathbf{G} \mathbf{S}^\top \odot \mathbf{V}^\top \mathbf{U}) - 2\alpha \mathbf{U} \mathbf{W} \right)$$

$$+2\alpha \mathbf{U} \mathbf{U}^\top \mathbf{U} + \eta \mathbf{U}$$

$$\frac{\partial \mathcal{J}}{\partial \mathbf{V}} = 2 \left(-\mathbf{U} \mathbf{R} + \mathbf{U}(\mathbf{S} \mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}) - 2\beta \mathbf{V} \mathbf{C} \right)$$

$$+2\beta \mathbf{V} \mathbf{V}^\top \mathbf{V} + \lambda \mathbf{V}$$

$$\frac{\partial \mathbf{J}}{\partial \mathbf{V}} = \frac{1}{2} \left(-\mathbf{U} \mathbf{R} + \mathbf{U}(\mathbf{S} \mathbf{G}^\top \odot \mathbf{U}^\top \mathbf{V}) - 2\beta \mathbf{V} \mathbf{C} \right)$$

$$+2\beta \mathbf{V} \mathbf{V}^\top \mathbf{V} + \lambda \mathbf{V}$$

Algorithm 1 Social Contextual Model Gradient Algorithm Require: $0 < \alpha_S^{(k)}, \alpha_U^{(k)}, \alpha_V^{(k)} < 1, k = 0$. Initialization
$$\begin{split} \mathcal{J}^{(0)} &= \mathcal{J}(\mathbf{S}^{(0)}, \mathbf{U}^{(0)}, \mathbf{V}^{(0)}).\\ \text{Ensure: } \mathcal{J}^{(0)} &\geq 0, \, \mathcal{J}^{(k+1)} < \mathcal{J}^{(k)} \end{split}$$
for $k = 1, 2, \cdots$ do Calculate $\frac{\partial \mathcal{J}^{(k-1)}}{\partial \mathbf{S}}$, $\frac{\partial \mathcal{J}^{(k-1)}}{\partial \mathbf{U}}$, $\frac{\partial \mathcal{J}^{(k-1)}}{\partial \mathbf{V}}$, $\mathbf{S}^{(k)} = \mathbf{S}^{(k-1)} - \alpha_S^{(k-1)} \cdot \frac{\partial \mathcal{J}^{(k-1)}}{\partial \mathbf{S}}$ $\mathcal{J}^{(k)} \leftarrow \mathcal{J}(\mathbf{S}^{(k)}, \mathbf{U}^{(k-1)}, \mathbf{V}^{(k-1)})$ $\mathbf{U}^{(k)} = \mathbf{U}^{(k-1)} - \alpha_U^{(k-1)} \cdot \frac{\partial \mathcal{J}}{\partial \mathbf{U}}^{(k-1)}$ $\mathcal{J}^{(k)} \leftarrow \mathcal{J}(\mathbf{S}^{(k)}, \mathbf{U}^{(k)}, \mathbf{V}^{(k-1)})$ $\mathbf{V}^{(k)} = \mathbf{V}^{(k-1)} - \alpha_{\mathbf{V}}^{(k-1)} \cdot \frac{\partial \mathcal{J}}{\partial \mathbf{V}}^{(k-1)}$ $\mathcal{J}^{(k)} \leftarrow \mathcal{J}(\mathbf{S}^{(k)}, \mathbf{U}^{(k)}, \mathbf{V}^{(k)})$

end for

ALGORITHM FOR APPLICATION

Complexity

Space O(M(M+N))

Time $O(N^3T)$

Matrix Factorization

 $\mathbf{R} \leftarrow \mathbf{S} \mathbf{G}^{\mathrm{T}} \odot \mathbf{U}_{\mathbf{J}} \mathbf{V}^{\mathrm{T}}$

Practical

Linear Model

Space O(MN)

Time O(MN)

 $val(u, a) \neq \alpha \cdot val_{\substack{\textbf{itemCF}}}(u, a) + \beta \cdot val_{\substack{\textbf{preference}}}(u, a) + \gamma \cdot val_{\substack{\textbf{influence}}}(u, a) + \delta \cdot val_{\substack{\textbf{location}}}(u, a), \alpha, \beta, \gamma, \delta \in (0, 1)$

Hybrid: Item-based CF + Preference-based + Influencebased + Location-based Recommendation

EVALUATION

MAE (Mean Absolute Error), RMSE (Root Mean Square Error)

The lower, the better.

[0,1]

Kendall, Spearman (Ranking-based)

The higher, the better.

[-1, 1]

Prec@k (Precision at top-k)

The higher, the better.

[0, 100%]

	MAE	RMSE	Kendall	Spearman	Prec @5		Prec @15	Prec @20
Latest	0.995	1.148	0.006	0.008	40.4%	40.4%	40.7%	40.7%
Location	0.695	0.987	0.079	0.117	52.1%	50.3%	49.2%	48.7%
Hybrid	0.664	0.805	0.245	0.361	83.3%	80.5%	77.2%	74.5%

ALGORITHMIC TOOLSET

Location-based

User likes activities that are around him.

Mobile services. Restaurant, Café.

For user u and activity a,

$$val(u, a) = val(u, place(a)) = \sum_{a' \in Activities(u)} val(u, place(a'))$$

CF-based

User likes activities that his friends like.

E-commerce. Movie, music, phone, restaurant.

For user u and activity a,

$$val(u,a) = \sum_{v \in Friend(u)} val(v,a)$$

ALGORITHMIC TOOLSET

Influence-based

User likes activities from close relationships.

Social networks. Microblogging.

For user u and activity a,

$$val(u, a) = val(u, sender(a)) = \sum_{a' \in Activities(u)} val(u, sender(a'))$$

Preference-based

User likes activities that he always likes.

Web portal. News.

For user u and activity a,

$$val(u, a) = \sum_{a' \in Activities(u)} val(u, a')$$

DELIVERABLES

System

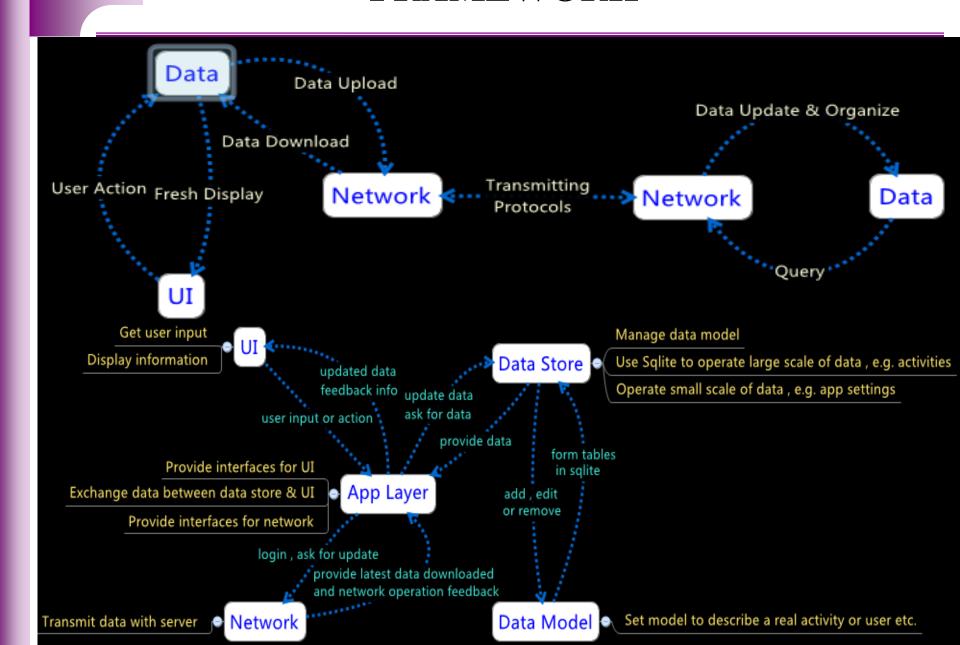
Function completed Robust and stable Message encrypted Data flow efficient

Framework

Stability

Flow Efficiency

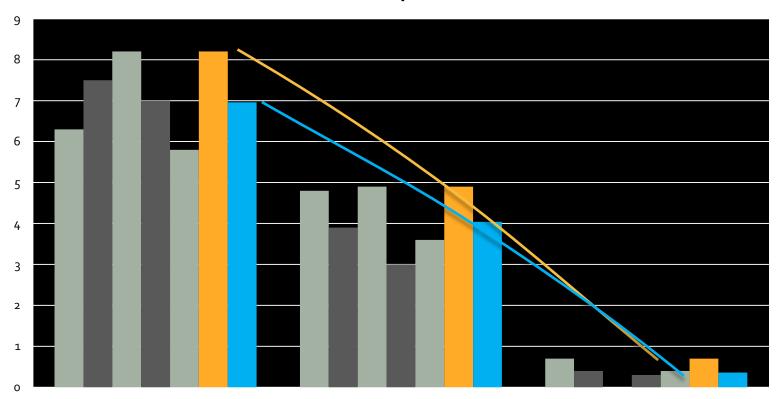
FRAMEWORK



STABILITY

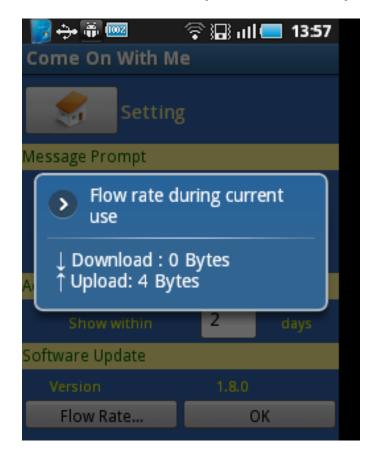
- The complex communication between server and client, and dynamic and intensive user behaviors make the system unstable.
- Now the system satisfy the requirement of practical use.

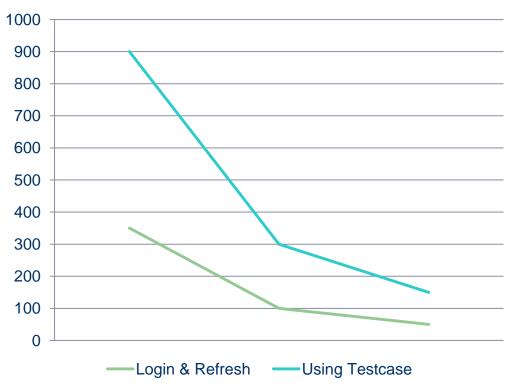
Frequency of abnormal exit (transformed into per 10 test cases)



FLOW EFFICIENCY

- The complex communication between server and client, and dynamic and intensive user behaviors make the system unstable.
- Now the system satisfy the requirement of practical use.





CONCLUSIONS

- The collected dataset is adequate to support following research:
 - ➤ User Modeling
 - ➤ Social Ties Inference
 - ➤ Intelligent Recommendation
- The algorithmic toolset includes:
 - ► Location-based Recommendation
 - ➤ Preference-based Recommendation
 - ➤ Collaborative Filtering
 - ► Influence-based Recommendation
 - ➤ Hybrid Factor Recommendation
- The system is adequate for further data collection and inner testing.

Merry Christmas and Happy New Year!