电子科技大学
University of Electronic Science and Technology of China

Heterogeneous Network Related Recommendation

Wenbao Li

Data Mining Lab, Big Data Research Center, UESTC

Email：liwenbao930116@gmail.com

Outline

数据挖掘实验室

Data Mining Lab

- **Background**
- **Traditional Recommendation**
- **Heterogeneous Related Recommendation**
  - **With heterogeneous information(A)**
  - **In heterogenous network(B)**
- **Conclusion**

Outline

数据挖掘实验室

Data Mining Lab

- Background
- Traditional Recommendation
- Heterogeneous Related Recommendation
  - With heterogeneous information
  - In heterogenous network
- Conclusion

Background

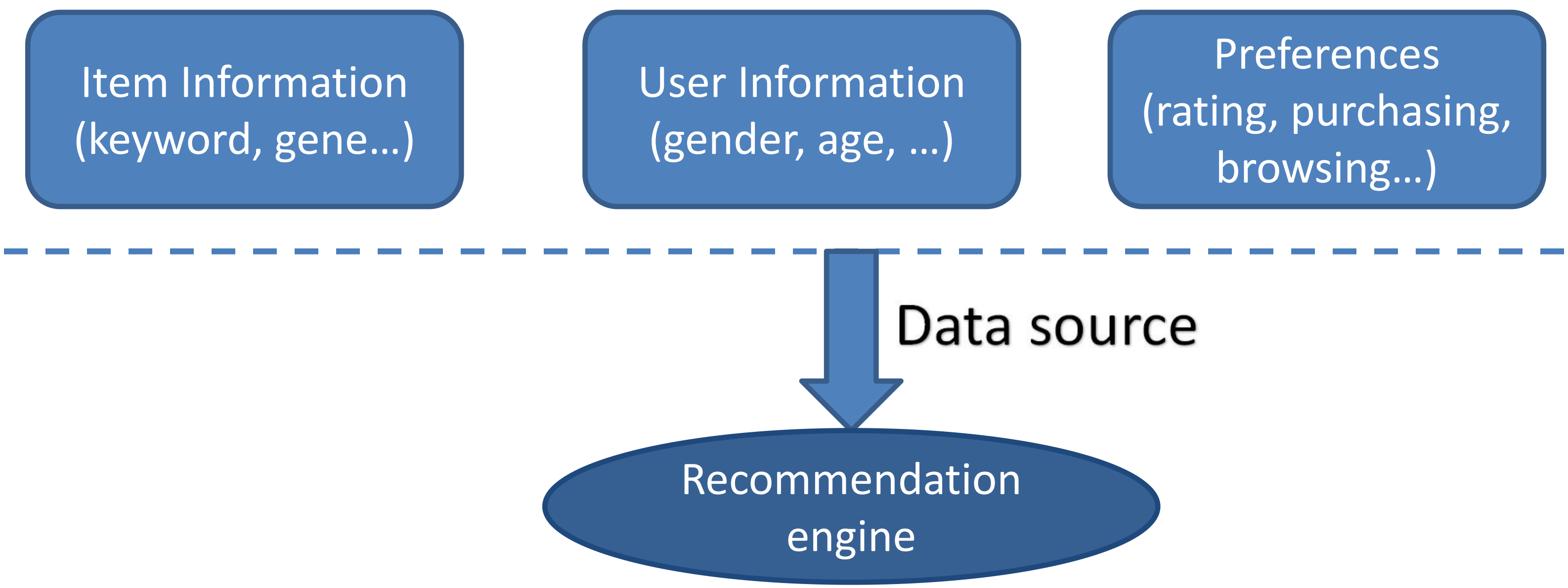
数据挖掘实验室

Data Mining Lab

- Many senarios

Background

- Recommendations can be as diverse as:
  - Products in e-commerce shops
  - Articles, infographics, and slide decks from brand publishers
  - News articles from media outlets
  - Brochures from different insurance types
  - Online educational materials for university students and alumni
- Target: people engaging with information and brands online.



Outline

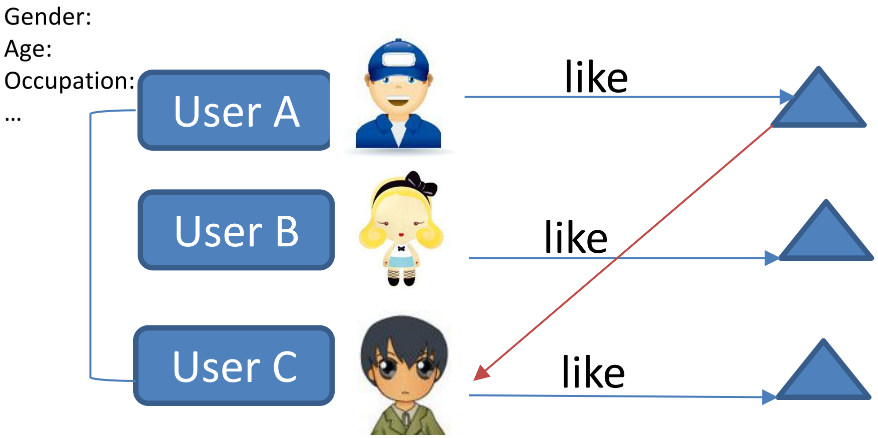
- Background
- Traditional Recommendation
- Heterogeneous Related Recommendation
  - With heterogeneous information(A)
  - In heterogenous network(B)
- Conclusion

Traditional Recommendation

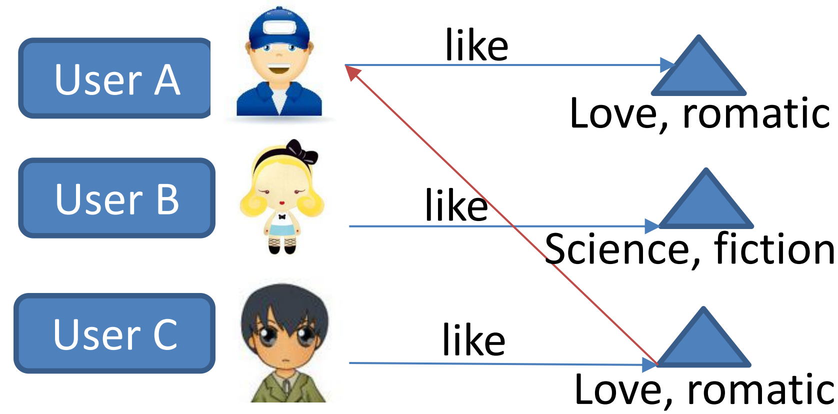
数据挖掘实验室

Data Mining Lab

Demography-based



Content-based



Collaborative filtering

A principle behind collaborative filtering assumes that **consumers are likely to enjoy items similar to those they've already purchased or downloaded, etc.** It then follows that they will also demonstrate similar patterns and take actions **consistent with the people that they are "the most like."**

Social based recommendation,

Hybrid recommendation

…

Some technologies for CF

- Neighborhood methods
  - By computing the relationships between items or, alternatively, between users. (euclidean distance or jaccard distance or others.)
- Latent factor models ~ matrix factorization
  - By characterizing both items and users on, say, 20 to 100 factors inferred from the ratings patterns. $\hat{r}_{ui} = p_u^T q_i$
    (p_u is the latent factor of user u, and q_i is the latent factor of item i)

$$\min_{q^*,p^*} \sum_{(u,i)\in\kappa} (r_{ui} - q_i^T p_u)^2 + \lambda(\|q_i\|^2 + \|p_u\|^2)$$

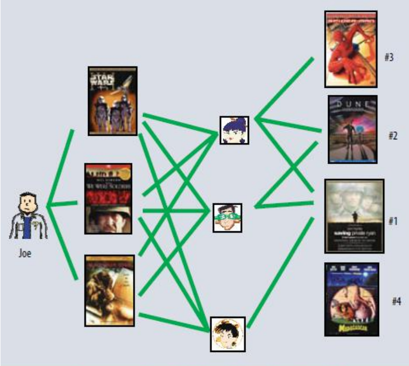


Figure 1. The user-oriented neighborhood method. Joe likes the three movies on the left. To make a prediction for him, the system finds similar users who also liked those movies, and then determines which other movies they liked. In this case, all three liked *Saving Private Ryan*, so that is the first recommendation. Two of them liked *Dune*, so that is next, and so on.

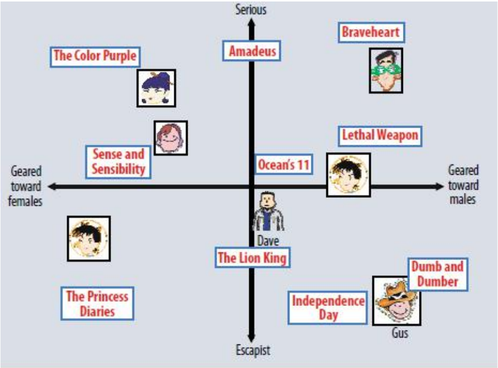


Figure 2. A simplified illustration of the latent factor approach, which characterizes both users and movies using two axes—male versus female and serious versus escapist.

Outline

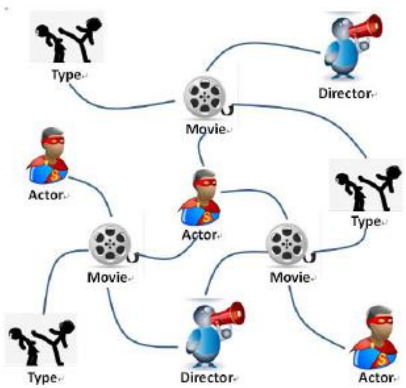
数据挖掘实验室
Data Mining Lab

- **Background**
- **Traditional Recommendation**
- **Heterogeneous Related Recommendation**
  - **With heterogeneous information(A)**
  - **In heterogenous network(B)**
- **Conclusion**

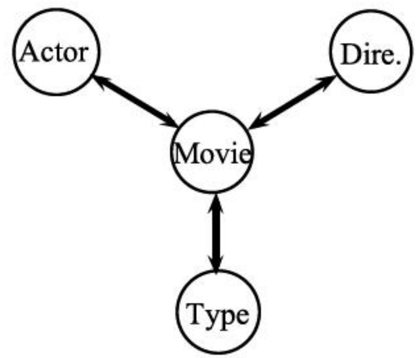
Heterogeneous (information)network

数据挖掘实验室

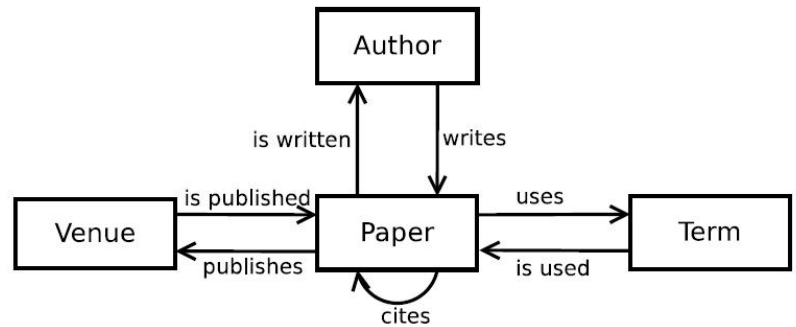
Data Mining Lab

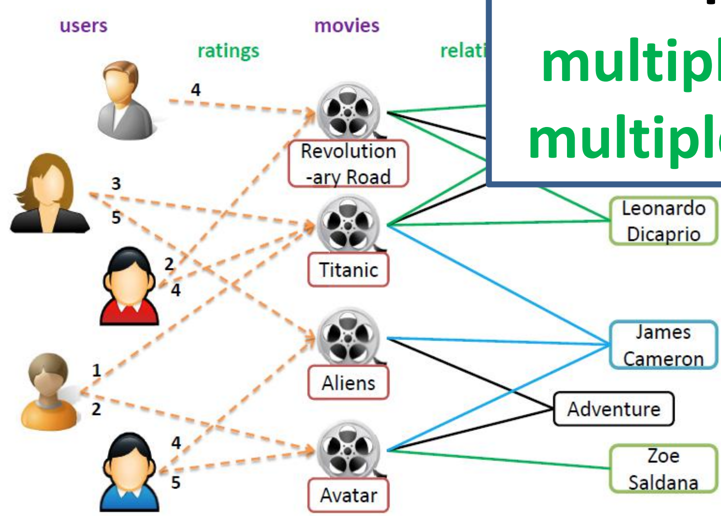


(a) Heterogeneous network of movie data



(b) Network schema

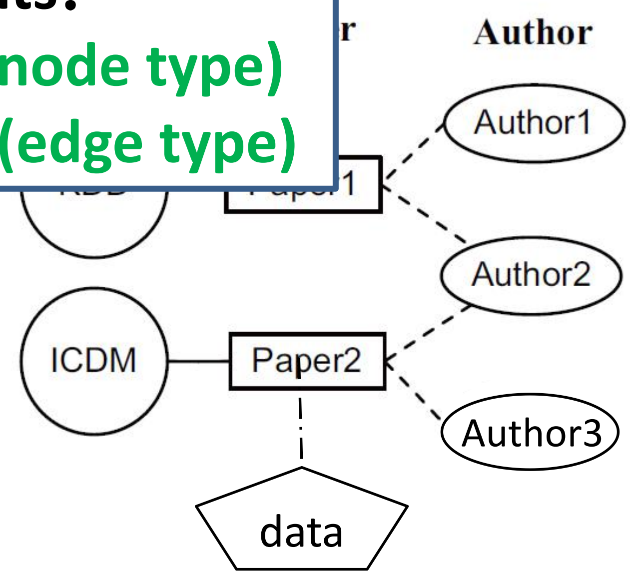




Key elements：

multiple entities(node type)

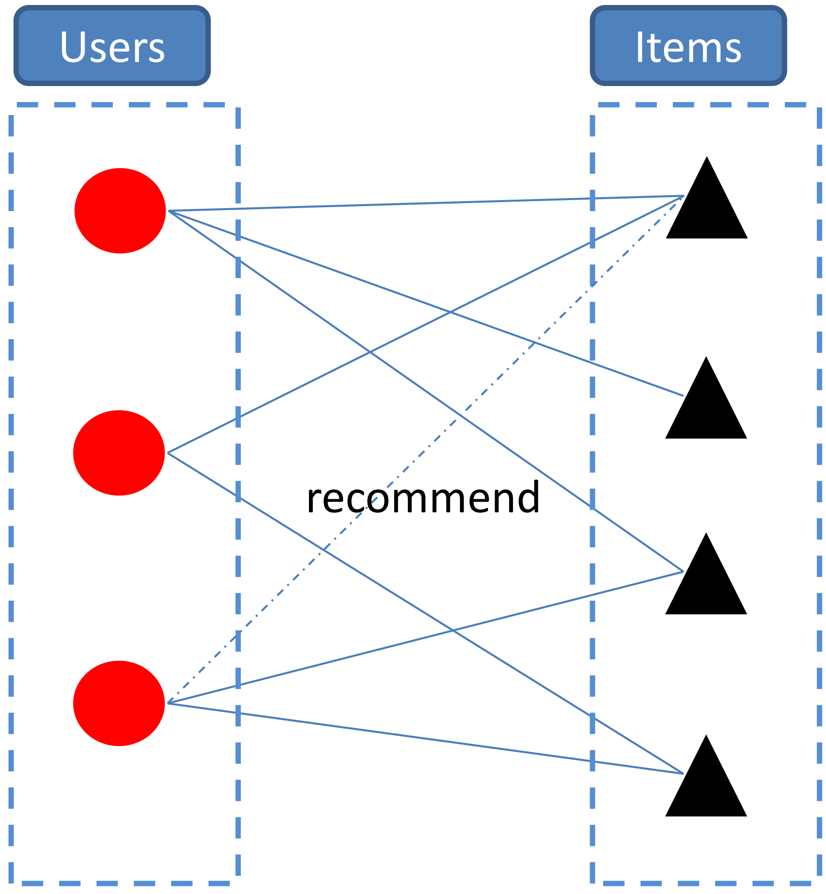
multiple relations(edge type)



Heterogeneous (information)network

数据挖掘实验室
Data Mining Lab

- The nature of recommendation can be considered as link prediction in (heterogeneous) network.

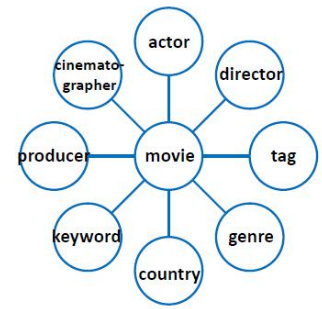


Recommendations with/in HIN

- Two categories:
  – Recommending items for users with heterogeneous information.

  Eg:

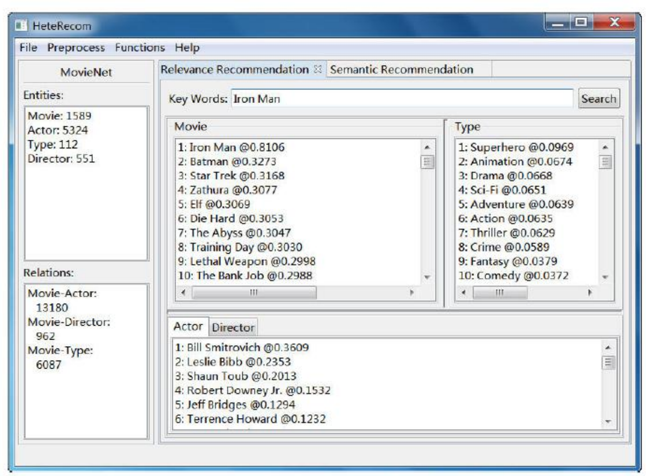
$$S^{l}_{MM} \begin{cases} \text{M-A-M} \\ \text{M-D-M} \\ \text{M-T-M} \\ \dots \end{cases}$$



(a) IMDb Network Schema

  – Recommending for entities in heterogeneous information network.

  Eg:



(b) Relevance recommendation

Outline

- Background
- Traditional Recommendation
- Heterogeneous Related Recommendation
  - With heterogeneous information(A)
  - In heterogenous network(B)
- Conclusion

Heterogeneous information

数据挖掘实验室

Data Mining Lab

- **Social relationship of users**
- **Social/Interest membership of users**
- **Profile network of items**

- How to fuse these heterogeneous information?

Fusing technology

数据挖掘实验室

Data Mining Lab

- **Regularization**

friends have similar preference.

$$\min_{u^*,i^*}\sum_{u,i}c_{ui}(p_{ui}-x_u^Ty_i)^2+\lambda\left(\sum_u\|x_u\|^2+\sum_i\|y_i\|^2\right)+\boxed{\lambda_f\left(\left\|x_u-\frac{1}{|F(u)|}\sum_{f\in F(u)}x_f\right\|\right)}$$

- **CMF(collective matrix factorization)**

Every entity has its latent factor.(take three entities as example)

$$\alpha\min_{u^*,i^*}\sum_{u,i}c_{ui}(p_{ui}-x_u^Ty_i)^2+\lambda\left(\sum_u\|x_u\|^2+\sum_i\|y_i\|^2\right)+$$

$$(1-\alpha)\min_{u^*,g^*}\sum_{u,i}c_{ug}{}^*(p_{ug}{}^*-x_u^Tz_g)^2+\lambda\left(\sum_u\|x_u\|^2+\sum_g\|z_g\|^2\right)$$

Combining above two factors also makes good recommendation

Fusing technology

- **Regularization**

  - local consistency(two similar items with high similar score are more likely to share similar low-rank representation)

$$min_{U,V,\theta} \|Y * (R - UV^T)\|_F^2 + \lambda_0(\|U\|_F^2 + \|V\|_F^2) + \frac{\lambda_1}{2} \cdot \sum_{i,j} \sum_{l=1} \theta_l S_{i,j}^{(l)} \|V_i - V_j\|_2^2 + \lambda_2 \|\theta\|_2^2$$

- **Seperate MF(seperate matrix factorization)**

  - Every similarity matrix can help constructing a new rating matrix. And has its latent factor.

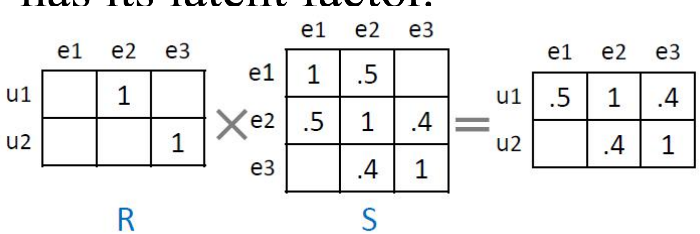


Figure 2: User preference diffusion with meta-path based item similarity matrix

$$\widetilde{R}^{(q)} = RS^{(q)},$$

$$(\hat{U}^{(q)}, \hat{V}^{(q)}) = \arg\min_{U,V} \left\| \widetilde{R}^{(q)} - UV^T \right\|_F^2,$$

$$\hat{r}(u_i, e_j) = \sum_{q=1}^{L} \theta_q \bullet \hat{U}_i^{(q)} \hat{V}_j^{(q)T}$$

Similar procedure for users.

What I can do

数据挖掘实验室
Data Mining Lab

- （社团检测）开始想到的是About community detection, we can use the idea of CMF(collective matrix factorization)。后面又发现这个与multi-view nmf那个本质是一样的。但是如果从latent factor的角度去解释感觉更强。
- （user-item推荐）推荐的两个主要对象User与item,当前的方法大都是从一个方面入手：要么借助user的网络信息来辅助推荐，要么借助item的网络信息来辅助。是否可以同时引入两者的信息来做呢？(又发现已经做过了=_=! $\hat{R}_{UI} = S_{UU} R_{UI} S_{II}$)
- eg:

$$\hat{R}_{UI} = \sum_{l=1}^{L_U} \theta_l S_{UU}^l R_{UI} + \sum_{l=1}^{L_I} \lambda_l R_{UI} S_{II}^l$$

$$\min_{X*,Y*} \left\| \hat{R}_{UI} - XY^T \right\|, \hat{r}(u_i, e_j) = X_i^* \cdot Y_j^{*T}$$

  - 关键问题：数据
  - 类似的，所有关于item方面信息的融合方法都应该可以扩展到同时融合两者信息。但是效果是否会更好有待论证。

Fusing technology(cont.)

- fusing user and item information simultaneously with preference diffusion.

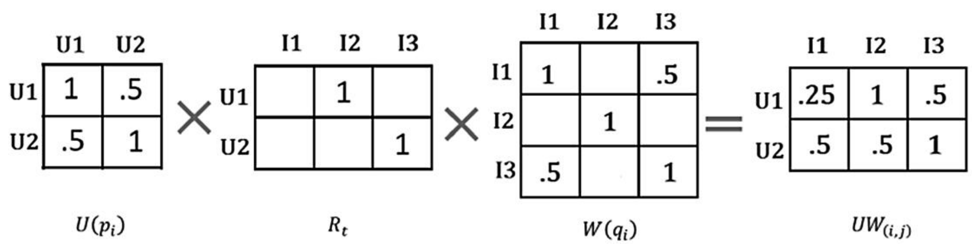


Fig. 1. preference diffusion process for method 3 with a toy example

- **Regularization:** fusing user and item information simultaneously via flexible regularization.

$$\min_{U,V} \mathcal{L}(R,U,V) = \frac{1}{2}\sum_{i=1}^{m}\sum_{j=1}^{n} I_{ij}(R_{ij} - U_i V_j^T)^2 + \frac{\alpha}{2} Reg_y^{\mathcal{U}} + \frac{\beta}{2} Reg_y^{\mathcal{I}} + \frac{\lambda_1}{2}\|U\|^2 + \frac{\lambda_2}{2}\|V\|^2,$$

$$Reg_{ave}^{\mathcal{U}} = \sum_{i=1}^{m}\left\| U_i - \frac{\sum_{f\in\mathcal{T}_u^+(i)} S_{if}^{\mathcal{U}} U_f}{\sum_{f\in\mathcal{T}_u^+(i)} S_{if}^{\mathcal{U}}}\right\|^2.$$

$$Reg_{ind}^{\mathcal{U}} = \sum_{i=1}^{m}\sum_{j=1}^{m} S_{ij}^{\mathcal{U}}\|U_i - U_j\|^2.$$

$$Reg_{ave}^{\mathcal{I}} = \sum_{j=1}^{n}\left\| V_j - \frac{\sum_{f\in\mathcal{T}_i^+(j)} S_{jf}^{\mathcal{I}} V_f}{\sum_{f\in\mathcal{T}_i^+(j)} S_{jf}^{\mathcal{I}}}\right\|^2,$$

$$Reg_{ind}^{\mathcal{I}} = \sum_{i=1}^{n}\sum_{j=1}^{n} S_{ij}^{\mathcal{I}}\|V_i - V_j\|^2.$$

What else can I do?

数据挖掘实验室

Data Mining Lab

- Factorization vs. Regularization: Fusing Heterogeneous Social Relationships in Top-N Recommendation
  - 根据这篇文的启发，在对friendship信息和membership信息进行融合时，CMF融合membership，Regularization融合friendship，那么对于user信息和item信息，这两者的地位肯定是不等价的。那么是否可以分别用不同的手段去同时融合这两个信息。（需要实验去验证）

    比如：用reg融合user信息，用矩阵分解融合item信息。

$$\widetilde{R}^{(q)} = RS^{(q)}, \hat{R} = \sum_{q=1}^{L} \theta_q \bullet \widetilde{R}^{(q)}$$

$$\arg\min_{U,V} \left\| \hat{R} - UV^T \right\|_F^2 + \mathrm{Re}\, g^U,$$

Outline

数据挖掘实验室

Data Mining Lab

- **Background**
- **Traditional Recommendation**
- **Heterogeneous Related Recommendation**
  - **With heterogeneous information(A)**
  - **In heterogenous network(B)**
- **Conclusion**

In Heterogeneous Network

- Formalize recommendation as a ranking problem in heterogeneous network.

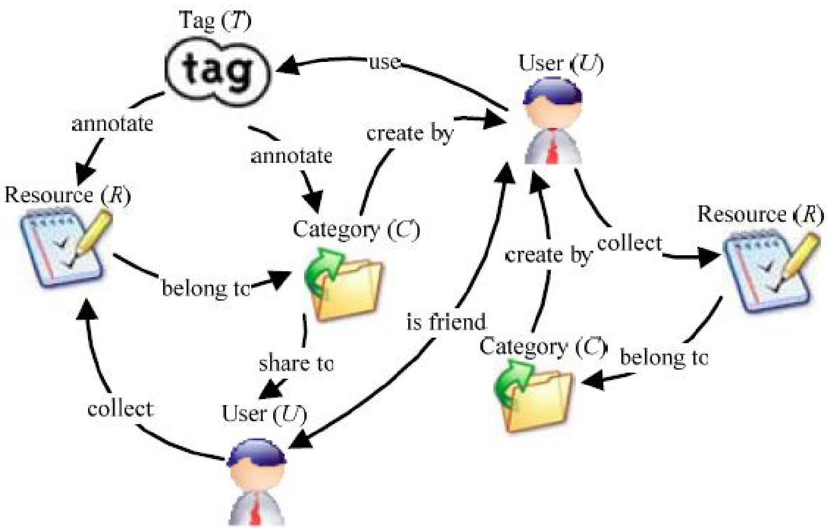


Figure 1. **A common social network**

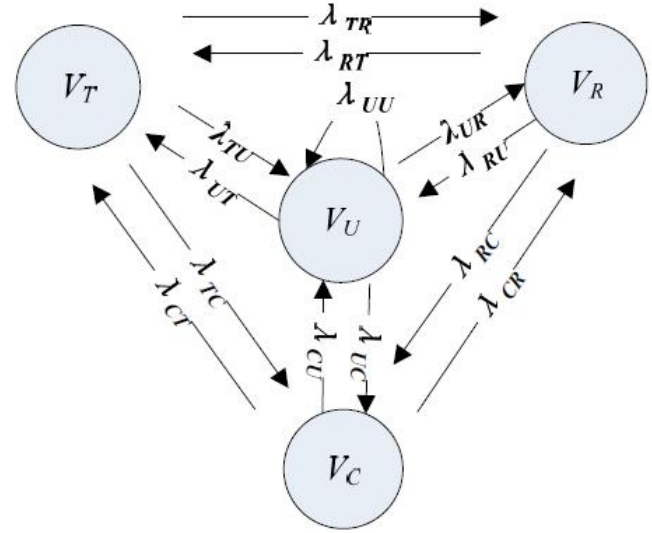


Figure 2. **A formalized heterogeneous graph**

- global importance score: $s_Y = \alpha \times E + (1-\alpha) \sum_{\lambda_{XY} \in \Lambda} \lambda_{XY} M_{XY}^T s_X$
- relevance score: language model $P(q \mid o) \prod_{t_i \in q} \left(\omega \cdot \frac{tf(t_i, o)}{|o|} + (1-\omega) \cdot \frac{tf(t_i, O)}{|O|} \right), \omega = \frac{|o|}{|o| + v}$
- Eg.:Recommendation of categories and users when browsing a category.

In Heterogeneous Network

数据挖掘实验室

Data Mining Lab

- Global Relevance Measure

$$HeteSim(s,t|R_1 \circ R_2 \circ \cdots \circ R_l) = \frac{1}{|O(s|R_1)||I(t|R_l)|} \sum_{i=1}^{|O(s|R_1)|} \sum_{j=1}^{|I(t|R_l)|} HeteSim(O_i(s|R_1), I_j(t|R_l)|R_2 \circ \cdots \circ R_{l-1}) \tag{1}$$

where $O(s|R_1)$ is the out-neighbors of s based on relation R_1, and $I(t|R_l)$ is the in-neighbors of t based on relation R_l.

$$Sim(A,B) = \sum_{i=1}^{N} \omega_i \cdot HeteSim(A,B\,|\,\mathrm{P}_i)$$

What else can I do?

数据挖掘实验室
Data Mining Lab

- 异构网络中的推荐：当前只能想到扩展CMF。即对于网络中的每个实体，它都有自己的一个latent factor。然后利用已知的网络中的连接矩阵进行相应分解，优化。（其实与multi-view nmf是一样的）。
  - 得到latent factor后，对感兴趣的两个实体进行链路预测即可。
  - 例如：DBLP数据中，有author, paper, term, venue四类实体。

$$\min \sum_{<X,Y>\in\Gamma} \sum_{i=1}^{n_X} \sum_{j=1}^{n_Y} I_{ij} (R_{ij}^{XY} - V_i^X \left(V_j^X\right)^T)^2 + \sum_{T\in\Lambda} \lambda_T \left\| V^T \right\|^2$$

$$\Gamma = \{< A, P >, < P, V >, < P, T >\}, \Lambda = \{A, P, V, T\}$$

Some common problems

- The position of weighted for different similarity matrices
- The selection of meta path still needs expert's experience.

Outline

- Background
- Traditional Recommendation
- Heterogeneous Related Recommendation
  - With heterogeneous information
  - In heterogenous network
- Conclusion

Conclusion

- USER information VS. ITEM information
  - transform into similarity matrix
  - original heterogeneous relation matrix
- Regularization , diffusion, CMF
  - Two regularization
    - average-based
    - individual-based
  - Three preference diffusion methods
    - single user diffusion
    - single item diffusion
    - both user and item diffusion

References

[1] Robin Burke, Fatemeh Vahedian, and Bamshad Mobasher. Hybrid recommendation in heterogeneous networks. In *International Conference on User Modeling, Adaptation, and Personalization*, pages 49–60. Springer, 2014.

[2] Mohsen Jamali and Laks Lakshmanan. Heteromf: recommendation in heterogeneous information networks using context dependent factor models. In *Proceedings of the 22nd international conference on World Wide Web*, pages 643–654. ACM, 2013.

[3] Yehuda Koren, Robert Bell, Chris Volinsky, et al. Matrix factorization techniques for recommender systems. *Computer*, 42(8):30–37, 2009.

[4] Hanbit Lee and Sang-goo Lee. Style recommendation for fashion items using heterogeneous information network. *Info Recommender Systems (RecSys), Volume, Page*, 2015.

[5] Chuan Shi, Xiangnan Kong, Philip S Yu, Sihong Xie, and Bin Wu. Relevance search in heterogeneous networks. In *Proceedings of the 15th International Conference on Extending Database Technology*, pages 180–191. ACM, 2012.

[6] Chuan Shi, Jian Liu, Fuzhen Zhuang, S Yu Philip, and Bin Wu. Integrating heterogeneous information via flexible regularization framework for recommendation. *Knowledge and Information Systems*, pages 1–25, 2016.

References

数据挖掘实验室

Data Mining Lab

[7] Chuan Shi, Zhiqiang Zhang, Ping Luo, Philip S Yu, Yading Yue, and Bin Wu. Semantic path based personalized recommendation on weighted heterogeneous information networks. In *Proceedings of the 24th ACM International on Conference on Information and Knowledge Management*, pages 453–462. ACM, 2015.

[8] Chuan Shi, Chong Zhou, Xiangnan Kong, Philip S Yu, Gang Liu, and Bai Wang. Heterecom: a semantic-based recommendation system in heterogeneous networks. In *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1552–1555. ACM, 2012.

[9] Xiao Yu, Xiang Ren, Quanquan Gu, Yizhou Sun, and Jiawei Han. Collaborative filtering with entity similarity regularization in heterogeneous information networks. *IJCAI HINA*, 2013.

[10] Xiao Yu, Xiang Ren, Yizhou Sun, Bradley Sturt, Urvashi Khandelwal, Quanquan Gu, Brandon Norick, and Jiawei Han. Recommendation in heterogeneous information networks with implicit user feedback. In *Proceedings of the 7th ACM conference on Recommender systems*, pages 347–350. ACM, 2013.

[11] Quan Yuan, Li Chen, and Shiwan Zhao. Factorization vs. regularization: fusing heterogeneous social relationships in top-n recommendation. In *Proceedings of the fifth ACM conference on Recommender systems*, pages 245–252. ACM, 2011.

References

数据挖掘实验室

Data Mining Lab

[12] Bangzuo Zhang, Shulin Tang, Zongming Ying, Yongjian Cai, Guiping Xu, and Kun Xu. A novel recommendation algorithm based on heterogeneous information network similarity and preference diffusion. In *International Conference on Web-Age Information Management*, pages 53–64. Springer, 2015.

[13] Jing Zhang, Jie Tang, Bangyong Liang, Zi Yang, Sijie Wang, Jingjing Zuo, and Juanzi Li. Recommendation over a heterogeneous social network. In *Web-Age Information Management, 2008. WAIM'08. The Ninth International Conference on*, pages 309–316. IEEE, 2008.