

# Item-based Recommendation via Matrix Factorization and Green's Function

(Some ideas during my ongoing study)

**Wang Dingyan**  
CSE, CUHK



# [ Outline ]

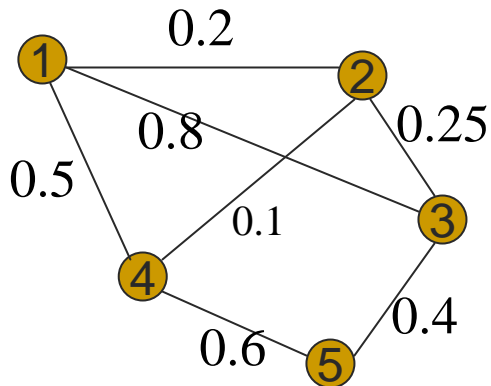
---

- Previous Work
- Similarity Computation
- Matrix Factorization
- Motivations
- Recommendation using Green's Function & Matrix Factorization
- Discussion

# Previous Work

## ■ Green's Function

❖ Given a weighted graph  $G=(V,E)$ ,



$$W = \begin{pmatrix} 1 & 0.2 & 0.8 & 0.5 & 0 \\ 0.2 & 1 & 0.25 & 0.1 & 0 \\ 0.8 & 0.25 & 1 & 0 & 0.4 \\ 0.5 & 0.1 & 0 & 1 & 0.6 \\ 0 & 0 & 0.4 & 0.6 & 1 \end{pmatrix}$$

$$D = \begin{pmatrix} 2.5 & 0 & 0 & 0 & 0 \\ 0 & 1.55 & 0 & 0 & 0 \\ 0 & 0 & 2.45 & 0 & 0 \\ 0 & 0 & 0 & 2.2 & 0 \\ 0 & 0 & 0 & 0 & 2 \end{pmatrix}$$

❖ The Graph Laplacian matrix  $L = D - W$ .

# Previous Work

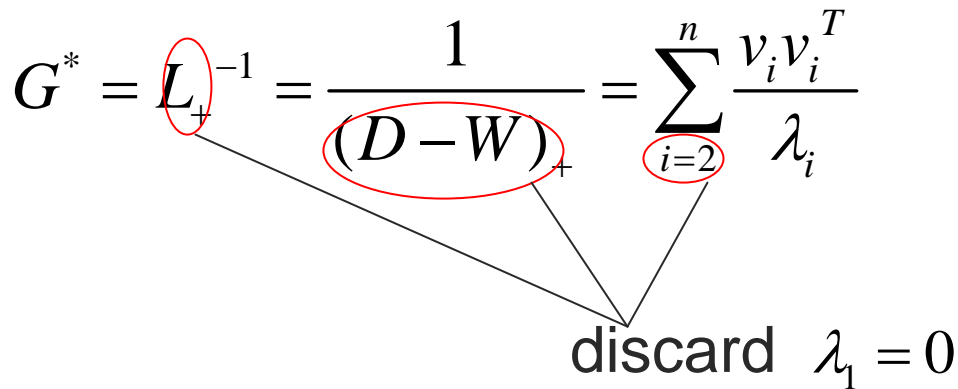
## ■ Green's Function

- ❖ Defined as the inverse of  $L = D - W$  with zero-mode discarded.

$$L v_k = \lambda_k v_k, \quad 0 = \lambda_1 \leq \lambda_2 \leq \dots \leq \lambda_n$$

$$G^* = L_+^{-1} = \frac{1}{(D - W)_+} = \sum_{i=2}^n \frac{v_i v_i^T}{\lambda_i}$$

discard  $\lambda_1 = 0$



# Previous Work

## ■ Item-based Recommendation

- ❖ To calculate unknown rating by averaging rating of similar items by test users

- ❖ User-item  $M \times N$  matrix  $R$ ,

$R_{pq}$  :  $u_p$  rates  $i_q$

- ❖ Item Graph  $G=(V,E)$

typical similarity: *cosine similarity, PCC...*

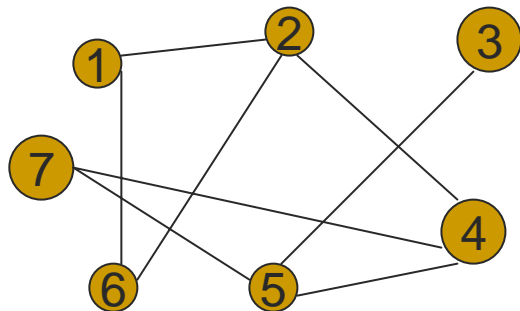
# Previous Work

## ■ Recommendation with Green's Function

$$R_0 = \begin{pmatrix} 2 & 3 & 8 & 5 & 0 & 1 & 0 \\ 1 & 0 & 0 & 5 & 0 & 0 & 2 \\ 0 & 2 & 7 & 4 & 7 & 3 & 0 \\ 2 & 4 & 6 & 6 & 8 & 0 & 0 \\ 0 & 1 & 5 & 0 & 5 & 0 & 8 \\ 3 & 2 & 7 & 9 & 0 & 0 & 0 \\ 3 & 6 & 0 & 0 & 0 & 4 & 0 \\ 4 & 5 & 6 & 0 & 0 & 5 & 8 \end{pmatrix}$$



$$R^T = GR_0^T$$



$$G = \frac{1}{(D - W)_+}$$

# Similarity Computation

- Similarity Computation :

- *Cosine similarity*

$$Sim(i, j) = \frac{\|r_i\| \cdot \|r_j\|}{r_i \cdot r_j}$$

- *Pearson Correlation Coefficient (PCC)*

$$Sim(i, j) = \frac{\sum_{u \in U(i) \cap U(j)} (r_{u,i} - \bar{r}_i) \cdot (r_{u,j} - \bar{r}_j)}{\sqrt{\sum_{u \in U(i) \cap U(j)} (r_{u,i} - \bar{r}_i)^2} \cdot \sqrt{\sum_{u \in U(i) \cap U(j)} (r_{u,j} - \bar{r}_j)^2}}$$

# [ Similarity Computation ]

- Disadvantages:
  - Data Sparsity
  - One-sided: only rating-related



# Matrix Factorization

- Matrix Factorization:
  - User-item matrix decomposition
  - Dimensionality reduction

$$A = UV \quad \hat{r}_{ij} = \sum_{l=1}^k u_{il} v_{jl}$$

user-item matrix  $A$ :  $m \times n$

user factor matrix  $U$ :  $m \times k$

item factor matrix  $V$ :  $k \times n$

# Matrix Factorization

- Matrix Factorization Methods:

- RMF
- MMMF
- Non-negative MF
- Probabilistic MF...

$$\min L(U, V)$$

Loss function :  $L(U, V)$

Gradient descent algorithm

# [ Matrix Factorization ]

- Matrix Factorization:
  - Solve the data sparsity problem
- Disadvantages:
  - Information Loss
    - Discard some matrix information

# [ Motivation ]

- To construct a more accurate item graph
- To solve data sparsity problem
- To balance robustness and accuracy



Recommendation with Green's Function  
& Matrix Factorization.

# Recommendation with Green's Function & Matrix Factorization

- Given a user-item matrix , then use Non-negative MF

$$R_0 = \begin{pmatrix} 2 & 3 & 8 & 5 & 0 & 1 & 0 \\ 1 & 0 & 0 & 5 & 0 & 0 & 2 \\ 0 & 2 & 7 & 4 & 7 & 3 & 0 \\ 2 & 4 & 6 & 6 & 8 & 0 & 0 \\ 0 & 1 & 5 & 0 & 5 & 0 & 8 \\ 3 & 2 & 7 & 9 & 0 & 0 & 0 \\ 3 & 6 & 0 & 0 & 0 & 4 & 0 \\ 4 & 5 & 6 & 0 & 0 & 5 & 8 \end{pmatrix}$$

$$\longrightarrow R_0 \approx U_{8 \times k} V_{k \times 7} \quad (1 \leq k < 8)$$

# Recommendation with Green's Function & Matrix Factorization

- Similarity computation:

$$V = \begin{pmatrix} \mathbf{v}_{11} & \cdots & \mathbf{v}_{1n} \\ \vdots & \mathbf{v}_{ij} & \vdots \\ \mathbf{v}_{k1} & \cdots & \mathbf{v}_{kn} \end{pmatrix} \longrightarrow \text{Sim}_1(i, j) = \frac{\|\mathbf{v}_i\| \cdot \|\mathbf{v}_j\|}{\mathbf{v}_i \cdot \mathbf{v}_j}$$

A feature vector for item 1

# Recommendation with Green's Function & Matrix Factorization

- Similarity computation:

$$Sim_2(i, j) = \frac{\sum_{u \in U(i) \cap U(j)} (r_{u,i} - \bar{r}_i) \cdot (r_{u,j} - \bar{r}_j)}{\sqrt{\sum_{u \in U(i) \cap U(j)} (r_{u,i} - \bar{r}_i)^2} \cdot \sqrt{\sum_{u \in U(i) \cap U(j)} (r_{u,j} - \bar{r}_j)^2}}$$

$$Sim(i, j) = \lambda Sim_1(i, j) + (1 - \lambda) Sim_2(i, j)$$

$$\lambda \in [0, 1]$$

# Recommendation with Green's Function & Matrix Factorization

## ■ Construct Graph:

- According to  $\text{Sim}(i,j)$ , construct a weighted item graph  $G = (v, e)$
- Given a threshold  $\varepsilon (0 < \varepsilon < 1)$ , if  $\text{sim}(i,j) < \varepsilon$  the two items are not connected.
- $W(i,j) = \text{Sim}(i,j)$



# [ Recommendation with Green's Function & Matrix Factorization ]

- Recommendation with Green's Function

$$G = \frac{1}{(D - W)_+}$$



$$R^T = GR_0^T$$

# Recommendation with Green's Function & Matrix Factorization

- Sorry, the experiment is on-going.
- Disadvantages:
  - Time consuming
  - Accumulated loss
- Extension:
  - Iterative training
  - Incorporate with additional information: social network, confidence level, implicit feedback.....

# Discussion and Suggestion

---

***Any Suggestion?***

***Any Inspiration?***



---

Thank You!