Machine Discovery HW3 Report

0. Team Members

Validation, Testing and Debugging

- ▲ B03902010 耿宗揚

Task2/3 Model Design and Implementation

- ▲ B03902015 簡瑋德

Task1 Model Design and Implementation

- ▲ B03902086 李鈺昇

1. Description of Tasks

Discovering connections in/across domains to boost the quality of recommendation.

- Given
 - Sparse source/target rating matrix with many unknown entries.
- Output
 - Some predicted values in target rating matrix.

| Task | Domain | User | Item | Mapping | Sets of records |
|------|-----------|-----------|-----------|---------|-----------------|
| 1 | same | same | same | unknown | disjoint |
| 2 | same | different | different | unknown | mostly disjoint |
| 3 | different | different | different | unknown | disjoint |

2. Implementations

Task 1

Let the target, source matrices be R_1 , R_2 , respectively.

For $i \in \{1,2\}$, we first use matrix factorization (MF) to obtain $P_iQ_i^T \approx R_i$. The first dimensions of P and Q are clearly the dimensions of R, and the second dimensions of P and Q are some chosen integer, K. For the sake of memory usage and running time, we only test $K \leq 10$. Larger value of K may help increase the rating performance, but it's a trade-off between resources and results.

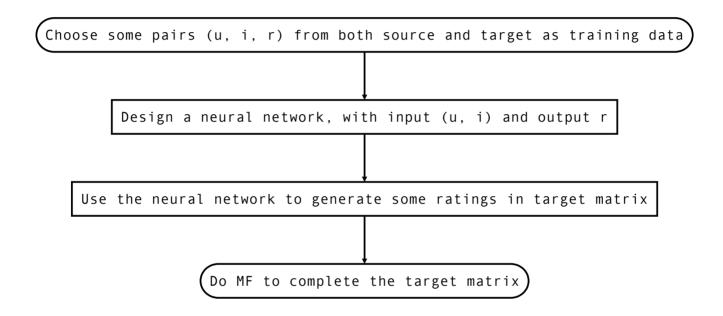
Next, by singular value decomposition (SVD), we obtain orthogonal U_i, V_i and diagonal D_i such that $\hat{R}_i \equiv U_i D_i V_i^T \approx P_i Q_i^T$.

Since the mapping is unknown, one simple way is to find out two auxiliary permutation-like matrices G_L , G_R such that $\hat{R_1} \approx G_L \hat{R_2} G_R$. Then we let $R \equiv \lambda \hat{R_1} + (1 - \lambda) G_L \hat{R_2} G_R$ to be the resulting rating matrix with the help of R_2 , where $\lambda \in [0, 1]$ is determined by cross validation. Finally, we choose λ to be 0.38. More details are given later.

Now we can make predictions with R. Given user-item pair (u, i), our predicted rating that user u gives item i is simply R_{ii} .

Task 2

Flow



Input of the Neural Network

For each (user, item) pair,
$$D = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_{|U|} \\ i_1 \\ i_2 \\ \vdots \\ i_{|I|} \end{bmatrix}$$
, where

- |U| is the number of users and |I| is the number of items
- $u_k = 1$ [user is the k^{th} one]
- $i_k = 1$ [item is the k^{th} one]

Variables of the Neural Network

$$\text{Embedding Matrix } E = \begin{bmatrix} e_{11} & \dots & e_{1|U|} & e_{1(|U|+1)} & \dots & e_{1(|U|+|I|)} \\ e_{21} & \dots & e_{2|U|} & e_{2(|U|+1)} & \dots & e_{2(|U|+|I|)} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ e_{r1} & \dots & e_{r|U|} & e_{r(|U|+1)} & \dots & e_{r(|U|+|I|)} \end{bmatrix}$$

Weight Vector
$$W = \begin{bmatrix} w_1 & w_2 & \dots & w_r \end{bmatrix}$$

- r is the dimension of the latent vector (embedding), in this task, we set r=10
- $[e_{1k}, e_{2k}, \ldots, e_{rk}]$ is the latent vector of the k^{th} user
- $[e_{1(|U|+k)},e_{2(|U|+k)},\ldots,e_{r(|U|+k)}]$ is the latent vector of the k^{th} item

Output and Training of the Neural Network

- Potential Value $P = W \cdot E \cdot D$
- Output Rating $R = \frac{1}{1+e^{-P}}$, where $0 \le R \le 1$
- Lost Function = $\sum_{(u,i) \in \text{Training Pairs}} (R_{u,i} r)^2$
- Parameters are initialized using random uniform distribution and updated using gradient decent

Adding New Ratings to Target Matrix

- · After training the neural network, we are able to add some new ratings
- If we have the latent vector of a user u and item i, we can calculate the rating r using the network

Performing Matrix Factorization

- When the target matrix becomes denser, perform MF to complete the matrix
- Parameters are randomly initialized

Task 3

The only differences between the models of Task 2 and Task 3 are the weight matrix and the output layer.

Weight Matrix
$$W = \begin{bmatrix} w_{11} & w_{12} & \dots & w_{1r} \\ \vdots & \vdots & \ddots & \vdots \\ w_{51} & w_{52} & \dots & w_{5r} \end{bmatrix}$$

For Output Layer, Potential
$$P = \begin{bmatrix} p_1 \\ \vdots \\ p_5 \end{bmatrix} = W \cdot E \cdot D$$

$$\mathbb{P}(R = r) = \frac{e^{p_r}}{\sum_{i=1}^{5} e^{p_i}}, r \in \{1, 2, 3, 4, 5\}, \text{ which is the softmax function.}$$

3. More Details on Validation

We only do validation for task 1, partly because we need to find out the best value of λ . We randomly take 10% of the data from train.txt for validation. The results for different values of λ follows.

| λ | RMSE |
|-----|---------------------|
| 0.0 | 0.19121172836885114 |
| 0.1 | 0.18981906234427 |
| 0.2 | 0.18888050921949595 |
| 0.3 | 0.1884028557827018 |
| 0.4 | 0.1883896078382336 |
| 0.5 | 0.18884086312584142 |
| 0.6 | 0.18975330774741603 |
| 0.7 | 0.1911203364018659 |
| 0.8 | 0.1929322864166143 |
| 0.9 | 0.19517676672141657 |
| 1.0 | 0.19783905672039154 |

And, as mentioned above, 0.38 is the value we choose.

4. References

- [1] https://www.tensorflow.org/tutorials/ (https://www.tensorflow.org/tutorials/)
- [2] C.-Y. Li and S.-D. Lin. Matching Users and Items Across Domains to Improve the Recommendation Quality