# RLT: Residual-Loop Training in Collaborative Filtering for Combining Factorization and Global-Local Neighborhood

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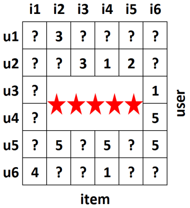
# Problem Definition




## Rating Prediction

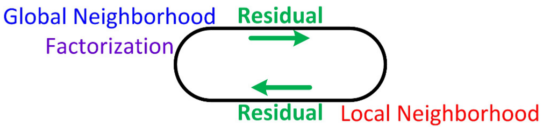
- Input: A set of (user, item, rating) triples as training data denoted by $\mathcal{R} = \{(u, i, r_{ui})\}$, where $r_{ui}$ is the numerical rating assigned by user $u$ to item $i$.
- Goal: Estimate the preference of user $u$ to item $j$, i.e., $\hat{r}_{uj}$, for each record in the test data $\mathcal{R}^{te} = \{(u, j, r_{uj})\}$.

# Limitations of Related Work

Traditional pipelined residual training paradigm may not be able to fully exploit the merits of factorization- and neighborhood-based methods.

1. There are two different types of neighborhood, i.e., global neighborhood in FISM and SVD++, and local neighborhood in ICF, but most residual training approaches ignore the global neighborhood.
2. Combining the factorization-based method and neighborhood-based method in a pipelined residual chain may not be the best because the one-time interaction between the two methods may not be sufficient.

# Overall of Our Solution




**Residual-Loop Training (RLT)**: a new residual training paradigm, which aims to fully exploit the complementarity of factorization, global neighborhood and local neighborhood in one single algorithm.

# Advantages of Our Solution

1. We recognize the difference between global neighborhood and local neighborhood in the context of residual training.
2. We propose to combine factorization-, global neighborhood-, and local neighborhood-based methods by residual training.
3. We propose a new residual training paradigm called residual-loop training (RLT).

# Notations

Table: Some notations and explanations.

| | |
|---|---|
| $u$ | user ID |
| $i, i', j$ | item ID |
| $r_{ui}$ | rating of user $u$ to item $i$ |
| $\mathcal{R} = \{(u, i, r_{ui})\}$ | rating records of training data |
| $\mathcal{U}_i$ | users who rate item $i$ |
| $\mathcal{I}_u$ | items rated by user $u$ |
| $\mathcal{N}_i$ | nearest neighbors of item $i$ |
| $\mu \in \mathbb{R}$ | global average rating value |
| $b_u \in \mathbb{R}$ | user bias |
| $b_i \in \mathbb{R}$ | item bias |
| $d \in \mathbb{R}$ | number of latent dimensions |
| $U_{u\cdot} \in \mathbb{R}^{1\times d}$ | user-specific latent feature vector |
| $V_{i\cdot}, W_{i\cdot} \in \mathbb{R}^{1\times d}$ | item-specific latent feature vector |
| $\mathcal{R}^{te} = \{(u, j, r_{uj})\}$ | rating records of test data |
| $\hat{r}_{ui}$ | predicted rating of user $u$ to item $i$ |
| $\lambda$ | tradeoff parameter |
| $T$ | iteration number in the algorithm |

# Factorization-based Method

Probabilistic matrix factorization (PMF) is a factorization-based method for rating prediction in collaborative filtering. Specifically, the prediction rule of the rating assigned by user $u$ to item $i$ is as follows,

$$\hat{r}_{ui}^{\mathrm{F}} = \mu + b_u + b_i + U_{u\cdot} V_{i\cdot}^T, \tag{1}$$

where $\mu$, $b_u$ and $b_i$ are the global average, the user bias, and the item bias, respectively, and $U_{u\cdot} \in \mathbb{R}^{1\times d}$ and $V_{i\cdot} \in \mathbb{R}^{1\times d}$ are the user-specific latent feature vector and the item-specific latent feature vector, respectively.

# Local Neighborhood-based Method

Item-oriented collaborative filtering (ICF) is a neighborhood-based method for preference estimation in recommendation. The estimated preference of user $u$ to item $i$ can be written as follows,

$$\hat{r}_{ui}^{\mathrm{N}_\ell} = \sum_{i' \in \mathcal{I}_u \cap \mathcal{N}_i} \bar{s}_{i'i} r_{ui'}, \tag{2}$$

where $\bar{s}_{i'i} = s_{i'i} / \sum_{i' \in \mathcal{I}_u \cap \mathcal{N}_i} s_{i'i}$ is the normalized similarity with $s_{i'i} = |\mathcal{U}_{i'} \cap \mathcal{U}_i| / |\mathcal{U}_{i'} \cup \mathcal{U}_i|$ as the Jaccard index between item $i'$ and item $i$.

- $\mathcal{N}_i$ is a set of locally nearest neighboring items of item $i$, i.e., their similarities are predefined without global propagation among the users, thus we call it a local neighborhood-based method.

# Global Neighborhood-based Method

The similarity in Eq.(2) may also be learned from the data instead of being calculated, e.g., in asymmetric factor model (AFM), the prediction rule of user $u$ to item $i$ is as follows,

$$\hat{r}_{ui}^{N_g} = \sum_{i' \in \mathcal{I}_u \backslash \{i\}} \bar{p}_{i'i}, \tag{3}$$

where $\bar{p}_{i'i} = W_{i'\cdot} V_{i\cdot} / \sqrt{|\mathcal{I}_u \backslash \{i\}|}$.

1. Two items without common users may still be well connected via the learned latent factors.
2. The prediction rule in Eq.(3) does not restrict to a local neighborhood set $\mathcal{N}_i$ as that in Eq.(2).

We thus call AMF with the prediction rule in Eq.(3) a global neighborhood-based method.

# Factorization- and Global Neighborhood-based Method

Matrix factorization with implicit feedback (SVD++) integrates the prediction rules of a factorization-based method and a global neighborhood-based method,

$$\begin{aligned}\hat{r}_{ui}^{\text{F-N}g} &= \mu + b_u + b_i + U_{u\cdot} V_{i\cdot}^T + \sum_{i' \in \mathcal{I}_u \backslash \{i\}} \bar{p}_{i'i}, \\ &= \hat{r}_{ui}^{\text{F}} + \hat{r}_{ui}^{\text{N}g}, \end{aligned} \tag{4}$$

from which we can see that SVD++ is a generalized factorization model that inherits the merits of both factorization- and global neighborhood-based methods.

# Residual Training

Residual training (RT) is an alternative approach to combining a factorization-based method and a neighborhood-based method. Specifically, a factorization-based model is built using the training data, and a predicted rating $\hat{r}^{\mathrm{F}}_{ui}$ for each $(u, i, r_{ui}) \in \mathcal{R}$ can then be obtained, based on which a neighborhood-based method is developed using $\sum_{i' \in \mathcal{I}_u \cap \mathcal{N}_i} \bar{s}_{i'i} r^{res}_{ui'}$, where $r^{res}_{ui'} = r_{ui'} - \hat{r}^{\mathrm{F}}_{ui'}$ is the residual. The learning procedure can be represented as follows,

$$\hat{r}^{\mathrm{F}}_{ui} \rightarrow \hat{r}^{\mathrm{N}_\ell}_{ui}. \tag{5}$$

The final prediction rule is then the summation of $\hat{r}^{\mathrm{F}}_{ui}$ and $\hat{r}^{\mathrm{N}_\ell}_{ui}$, i.e., $\hat{r}^{\mathrm{F}}_{ui} + \hat{r}^{\mathrm{N}_\ell}_{ui}$.

# Differences between SVD++ and RT

The main differences between SVD++ and RT are:

1. SVD++ is an integrative method with one single prediction rule, while RT is a two-step approach with two separate prediction rules.
2. SVD++ exploits factorization and global neighborhood, while RT makes use of factorization and local neighborhood.

# Residual-Loop Training (1/3)

In order to fully exploit the complementarity of factorization, global neighborhood and local neighborhood, we propose a new residual training paradigm called residual-loop training (RLT), which is depicted as follows,

$$\hat{r}_{ui}^{\text{F-N}g} \rightarrow \hat{r}_{ui}^{\text{N}\ell} \rightarrow \hat{r}_{ui}^{\text{F-N}g} \tag{6}$$

where $\hat{r}_{ui}^{\text{F-N}g}$ is from Eq.(4) and $\hat{r}_{ui}^{\text{N}\ell}$ is from Eq.(2).

# Residual-Loop Training (2/3)

1. For the first $\hat{r}_{ui}^{\text{F-N}_g}$ in Eq.(6), we aim to exploit both factorization and global neighborhood. The interaction between the factorization-based method and the global neighborhood-based method is richer in such an integrative method than that in two separate steps of RT.
2. For $\hat{r}_{ui}^{\text{N}_\ell}$, we aim to boost the performance via local neighborhood, i.e., explicitly combining factorization, global neighborhood and local neighborhood for rating prediction in a residual-training manner.
3. For the second $\hat{r}_{ui}^{\text{F-N}_g}$, we aim to further capture the remaining effects related to users' preferences that have not been modeled by the previous two methods yet.

# Residual-Loop Training (3/3)

**Input**: Users' rating records $\mathcal{R} = \{(u, i, r_{ui})\}$.

**Output**: Predicted preference of each record in the test data, i.e., $\hat{r}_{uj}$, $(u, j) \in \mathcal{R}^{te}$.

Task 1. Conduct factorization- and global neighborhood-based preference learning (i.e., SVD++), and estimate the preference of each record in the training data $\hat{r}_{ui}^{\text{F-N}_g}$ and the preference of each record in the test data $\hat{r}_{uj}^{\text{F-N}_g}$.

Task 2. Conduct local neighborhood-based preference learning (i.e., ICF) on the residual $r_{ui} - \hat{r}_{ui}^{\text{F-N}_g}$, and estimate the preference of each record in the training data $\hat{r}_{ui}^{\text{N}_\ell}$ and the preference of each record in test data $\hat{r}_{uj}^{\text{N}_\ell}$.

Task 3. Conduct factorization- and global neighborhood-based preference learning again (i.e., SVD++) on the residual $r_{ui} - \hat{r}_{ui}^{\text{F-N}_g} - \hat{r}_{ui}^{\text{N}_\ell}$, and estimate the preference of each record in the test data $\hat{r}_{uj}^{\text{F-N}_g\prime}$. Finally, the prediction of each record in the test data is obtained $\hat{r}_{uj} = \hat{r}_{uj}^{\text{F-N}_g} + \hat{r}_{uj}^{\text{N}_\ell} + \hat{r}_{uj}^{\text{F-N}_g\prime}$.

Figure: The algorithm of residual-loop training (RLT).

# Datasets and Evaluation Metric

- We conduct extensive experiments on three public datasets, including MovieLens 100K (ML100K), MovieLens 1M (ML1M) and MovieLens 10M (ML10M)[1].
- Each dataset is divided into training and test sets with the proportion of 80% and 20% respectively, and the splitting procedure is repeated for five times for five-fold cross validation.
- We adopt the commonly used root mean square error (RMSE) in our performance evaluation, and report the average result from five-time evaluation.

[1] http://grouplens.org/datasets/movielens/

# Baselines

- Item-oriented collaborative filtering (ICF) with Jaccard index as the similarity measurement.
- Probabilistic matrix factorization (PMF).
- Hybrid collaborative filtering (HCF) that averages the predictions of ICF and PMF, i.e., $\hat{r}_{ui} = (\hat{r}_{ui}^{ICF} + \hat{r}_{ui}^{PMF})/2$.
- Singular value decomposition with implicit feedback (SVD++).
- Residual training (RT) with PMF and ICF as two dependent components in a sequential manner.

# Parameter Configurations

- For all factorization-based methods, we fix the number of latent dimensions as $d = 20$, the learning rate $\gamma = 0.01$, the iteration number as $T = 50$, and search the value of tradeoff parameters from $\{0.001, 0.01, 0.1\}$.
- For neighborhood-based methods, we take top-20 items from $\mathcal{I}_u \cap \mathcal{N}_i$ with highest Jaccard index as the neighbors. Notice that when $|\mathcal{I}_u \cap \mathcal{N}_i| < 20$, we use all items from $\mathcal{I}_u \cap \mathcal{N}_i$.

# Main Results (1/4)

Table: Recommendation performance of item-oriented collaborative filtering (ICF), probabilistic matrix factorization (PMF), hybrid recommendation combining ICF and PMF (HCF), SVD++, residual training (RT) and our residual-loop training (RLT). The significantly best results are marked in bold ($p < 0.01$). The values of the tradeoff parameter $\lambda$ are also included for reproducibility.

| | ML100K | ML1M | ML10M |
|---|---|---|---|
| ICF | 0.9537±0.0038 | 0.9093±0.0021 | 0.8683±0.0012 |
| PMF | 0.9441±0.0038<br>($\lambda = 0.01$) | 0.8838±0.0023<br>($\lambda = 0.001$) | 0.7911±0.0005<br>($\lambda = 0.01$) |
| HCF | 0.9242±0.0032<br>($\lambda = 0.01$) | 0.8739±0.0023<br>($\lambda = 0.001$) | 0.8052±0.0007<br>($\lambda = 0.01$) |
| SVD++ | 0.9246±0.0031<br>($\lambda = 0.001$) | 0.8515±0.0018<br>($\lambda = 0.001$) | 0.7873±0.0007<br>($\lambda = 0.01$) |
| RT | 0.9145±0.0041<br>($\lambda = 0.001$) | 0.8567±0.0021<br>($\lambda = 0.001$) | 0.7847±0.0008<br>($\lambda = 0.01$) |
| RLT | **0.8968**±0.0040<br>($\lambda = 0.001$)<br>($\lambda = 0.001$) | **0.8385**±0.0016<br>($\lambda = 0.001$)<br>($\lambda = 0.001$) | **0.7812**±0.0007<br>($\lambda = 0.01$)<br>($\lambda = 0.01$) |

# Main Results (2/4)

**Observations**

- Our RLT predicts the users' preferences significantly more accurately than all other baseline methods, which clearly shows the advantage of our residual-loop training paradigm.
- For the performance of SVD++ and RT, we can see that their performance results are very close though the former exploits factorization and global neighborhood in an integrative way, and the latter exploits the factorization and local neighborhood in a pipelined manner, which also motivates us to further exploit the complementarity of factorization, global neighborhood, and local neighborhood.

# Main Results (3/4)

We further study the performance of each task in our RLT.

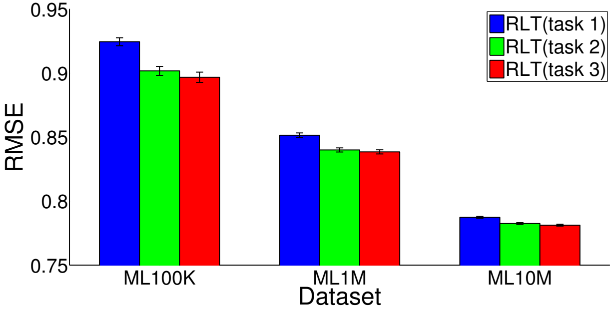



Figure: Recommendation performance of three tasks in RLT, i.e., task 1 is SVD++, task 2 is ICF, and task 3 is SVD++ again.

# Main Results (4/4)

### Observations

- The performance improves in each subsequent task, e.g., "from SVD++ to ICF" and "from ICF to SVD++", which shows the effectiveness of our residual-training mechanism that links factorization- and global-local neighborhood-based methods.
- The improvement "from SVD++ to ICF" is much larger than that "from ICF to SVD++", which implies that the second task is very useful while the third task is only marginally useful. This can be interpreted by the fact that the factorization and global-local neighborhood are somehow already well exploited in "SVD++ to ICF". Notice that although the further improvement in the third task of "from ICF to SVD++" is small, the improvement is still statistically significant.

# Conclusions

- We design a new residual training paradigm called residual-loop training (RLT), which aims to combine factorization, global neighborhood and local neighborhood in one single algorithm so as to fully exploit their complementarity.
- Experimental results on three public datasets show the significantly better performance of our RLT than several state-of-the-art factorization- and neighborhood-based methods.

# Thank you!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