A Study of Static and Dynamic Significance Weighting Multipliers on the Pearson Correlation for Collaborative Filtering

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Abstract

Recommender systems as a field of data mining and knowledge discovery have a tremendous impact on movie recommendation platforms. Proper recommendation for the audience, considering profiles, is a measurable argument. By inferring the linear combinations between some numerical data such as user rating actions, statistical analyses can be done. Thus, any item such as a movie can be recommended or not. The numerical calculation of correlations, namely the similarity weight, should be recomputed before prediction to increase the effect of user similarities for further constant multiplications. This method is named as the significance weighting that processes one more step to stress the impact of similarities. The affinity between users can simply be the total number of co-rated items, or any further inference using more complex computations. In this work, the significance weighting method related to Pearson Correlation is inspected using comparative approaches. The MovieLens dataset, both including ML100K and ML1M releases, are used in the experiments. k-fold cross-validation method is applied in a shifting fashion to increase the number of tests. After having Pearson Correlation Coefficients for user-user similarities, weights are signified using three different approaches. Then, neighbors are sorted to choose the top-N closest users for the user in the test. Concerning experimental results, over two other techniques, an explicit method that utilizes only the co-rated item count is preferred taking its simplicity and performance into account. In the plots of experimental results section, accuracy and error metrics are presented for three different significance weighting approaches. Especially for the ML100K dataset, the simple weighting method outperforms in terms of the error metrics.

Keywords: Collaborative filtering, MovieLens, Pearson similarity, recommender systems, significance weighting.

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Analternative method is proposed by Breese et al. (1998), and its main advantage is that it is simple to implement and understand. However, it is not as effective as some other methods, such as the K-Nearest Neighbors (KNN) method, which uses the average rating of similar users to predict a user's rating for an item. The KNN method is able to achieve better accuracy than the alternative method, especially in large datasets.

The overall methodology will be presented in this section. First, the similarity and prediction equations will be given. After that, the weight significance will follow, presenting three approaches.
2.1. Equations

The primary step is about how to compute linear similarities between two arguments. As user-user similarities are in our focus, the similarity coefficient between two users is calculated using the following formula in Equation 1.

\[
    w_{a,u}^{PCC} = \frac{\sum_{i \in \{i \mid u \in I_i \}} (r_{a,i} - \bar{r}_a) \times (r_{u,i} - \bar{r}_u)}{\sqrt{\sum_{i \in \{i \mid u \in I_i \}} (r_{a,i} - \bar{r}_a)^2 \times \sum_{i \in \{i \mid u \in I_i \}} (r_{u,i} - \bar{r}_u)^2}}
\]  

(1)

The PCC weight value, \(w_{a,u}^{PCC}\), is calculated using the ratings of active (a) user \(r_{a,i}\) and the ratings of prospective neighbor (u), \(r_{u,i}\), who has commonly rated the item of interest, \(i\). The overall rated items of the active user, \(I_a\) and the other user items \(I_u\) are also utilized for the intersection subset in the denominator, where each rating deviation from the overall rating mean \((\bar{r})\) is employed.

The calculated weight is then utilized in Equation 2, as it stands for the numerical prediction calculation. This will give to obtain rating value, which is to be then checked in terms of the performance comparison considering the actual rating value. Therefore, the weight parameter in the equation is quite crucial to decide the prediction; even more, there can be an enhancement over \(w\). Thus, a significance weighting (SW) is a method to highlight the correlation between two users if there is any other inference between the two of them.

\[
p_{a,i} = \frac{\sum_a ((r_{a,i} - \bar{r}_a) \times w_{a,u}^{PCC})}{\sum_u (w_{a,u}^{PCC})} + \bar{r}_a
\]

(2)

In the next subsection, three perspectives are given on the utilization of the commonly rated item counts. During the prediction, the number of neighbors to be included in the calculation is a well-known phenomenon. In this work, the best neighbor count (BNC) is decided by being set parametrically starting from 5 to 100 with a 5-neighbor increment at every attempt.

2.2. Significance Weighting

Significance weighting can be thought of as a constant multiplication for the calculated weight as the user-user correlation. This constant is denoted as \(\mu\) and given in Equation 3. The multiplication constant, \(\mu\), can be based on a static or dynamic approach. In this work, we group these two perspectives, where the first is a static multiplication based on a predefined value, \(\alpha\). Then, the dynamic approach is proposed to see the effect of multiple commonly rated user relations.

\[
w_{a,u}^{SW} = \mu \times w_{a,u}
\]  

(3)

All figures in the following subsections are based on the real data (rounded to a 3-digit fraction) obtained from the 15th active user and the 18th item test pair \((a=15, i=18)\), for all \(u\) values in the randomly folded train-test sets).

2.2.1. Static Multiplier

In the static multiplication, each co-rated item count of the neighbors is processed with an only constant, \(\alpha\). As shown in Equation 4, \(\alpha\) is applied to CIC with a condition (Herlocker et al., 2017). In this work, we set \(\alpha = \{10, 25, 50, 75, 100\}\) for our parametric tests. All the weights in progress free from their values are processed with stable \(\alpha\).

\[
\mu = \begin{cases} 
\frac{|I_a \cap I_u|}{\alpha} & \text{if } |I_a \cap I_u| < \alpha \\
1 & \text{otherwise}
\end{cases}
\]  

(4)

In Figure 1, the real example of the static multiplier is shown. Each CIC between \(a\) and \(u\) is considered together with the static \(\alpha\), which is then processed for signed weight, \(w_{a,u}^{SW}\).

![Figure 1](image_url)  

Figure 1. Example of applying multiplier \(\alpha = 50\), (a) Sorted original PCC weights, (b) Significance weighted (\(\alpha\) applied) PCC weights, (c) Sorted significance weighted (\(\alpha\) applied) PCC weights.
2.2.2. Dynamic Multiplier

In the dynamic approach, instead of a constant predefined $\alpha$, an inference-based technique is performed during the prediction calculation. By considering all neighbors in the co-rating list, the mean value is obtained as $\frac{\sum \text{CIC}_s}{\left| \text{CIC}_s \right|}$. Instead of taking the exact maximum depending on a single value, the adaptive solution is preferred. Thus, the mean is doubled by treating all elements in a vector. Then, it is normalized with a fraction that is an intentional parameter, namely $\beta$, to show the effect of different mappings by setting $\beta = 1/4$, $1/3$, $1/2$, $2/3$, $3/4$ during our experiment. With this approach, a generalized $\alpha$ is obtained fitting into the current values of $a_i$ pair. Then, the same procedure in Equation 4 is applied to all weights from neighbors. In Equation 5, the calculation of the aforementioned general solution is shown as it is rounded to the nearest integer as either $\lceil \beta \times 2 \times \frac{\sum \text{CIC}_s}{\left| \text{CIC}_s \right|} \rceil$ or $\lfloor \beta \times 2 \times \frac{\sum \text{CIC}_s}{\left| \text{CIC}_s \right|} \rfloor$.

$$\alpha \approx \left( \beta \times 2 \times \frac{\sum \text{CIC}_s}{\left| \text{CIC}_s \right|} \right)$$  \hspace{1cm} (5)

In Figure 2, the example from the real dataset is shown.

![Figure 2](image)

(b) Significance weighted (β applied) PCC weights, (c) Sorted significance weighted (β applied) PCC weights.

2.2.3. Direct CIC Multiplier

Last but not least, a pure CIC-based approach without an additional operation is applied apart from the above. The multiplier constant is directly taken as $\mu = |I_u|/|I_a|$ (Bellogín et al., 2014; Raeesi and Shajari, 2012). The bright side of the CIC usage is more than the calculation simplicity of it. In the first and the second approaches, the CIC as a threshold is considered with a further normalization, wherein the second, one more adaptive solution is designed with the overall CICs. However, it is experimentally proved in the next section that CIC between users, neither with a further normalization nor with the mean of all intersections, gives the top solution. Especially with the performance in real-time systems, this approach as a single expander of weights works well. In Figure 3, an example of the direct CIC multiplication is shown.

![Figure 3](image)

(a) Sorted original PCC weights, (b) Significance weighted (β applied) PCC weights, (c) Sorted significance weighted (β applied) PCC weights.

3. Tests and Results

In this section, test results of significance weighting methods are given comparatively. For each user, five rated items are randomly chosen to be tested. At each test, the dataset is divided into ten folds stochastically, and tests are repeated 100 times. On each test, prediction values are computed distinctively for the same train-test set couples used in the compared methods for a fair analogy. Predicted values are labeled as liked or disliked depending on whether being greater or less than 3.5 of 5-scale ratings. Then, actual ratings and calculated results are processed for binary analyses on behalf of four renowned performance metrics given in Figure 4.
Figure 4. Comparative test results of SW methods over PCC taking all μ-based approaches. The results are given as the average of all individual tests.

The plots in Figure 4 show that the standard approach without SW (line in black color) falls behind the ones with SW. Focusing on α (lines in red color) and β (lines in blue color) parameters, the enhanced performance results are recorded for their increased values within the approach that brings less erroneous results. Besides, the pure CIC-based method (line in green color) outperforms dominantly in error metrics for the ML100K. The pure CIC-based method is recommended to be applied with a decreased number of neighbors when there is a large-sized dataset in use. Even though the results related to methods concerning α and β vary in different metrics, the pure CIC-based approach outperforms in the F1-measure that supplies compound information holding both precision and recall metrics together inside.
4. Conclusion

In RS science, there are loads of efforts to increase recommendation efficiency using different methods. In this work, we have shared the observations related to the three approaches for correlation weight significance. Especially for the real-time systems, the less complicated but higher performable approaches are required during the correlation calculation and prediction measurement. Therefore, we perform three different approaches of SW. Detailed experiments in the previous section have shown that the pure CIC method gives indicative results, especially for the ML100K dataset. In addition to the simple computation facility of pure CIC SW multiplier, satisfactory results are obtained. In a small set of the neighborhood, the acceptable results are gathered. For future work, the extensive performance metrics of CIC-based SW methods can be performed.

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