Supplementary material
Well-argued recommendation: adaptive models based on words in recommender systems

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1 Manhattan Weighted Corrected (MWC)

Manhattan Weighted Corrected similarity (MWC) is derived from the distance of Manhattan, also known as the taxicab distance. This method is used for both users and items. k is either an item or user, (x, y) is a pair of items or users depending on the case.

The difference of the means $\overline{r_x} - \overline{r_y}$, is taken into account with a coefficient F.
$MWC(x, y)$ is defined as follows:

$$1 - \frac{\sum_{k \in T_x \cap T_y} |r_{k,x} - r_{k,y}| + F|\overline{r_x} - \overline{r_y}|}{(|T_x \cap T_y| + F)MaxD} \quad (1)$$

2 Metrics

2.1 Root Mean Squared Error

The *Root Mean Square Error* is a popular measure used to assess the quality of recommender systems. It is generally admitted that minimizing the RMSE is equivalent to improve the pertinence and accuracy of the recommendations. Let R be the set of the predicted ratings, the RMSE is defined as follows :

$$RMSE = \sqrt{\frac{1}{|R|} \sum_{(u,i,r) \in R} (\hat{r}_{u,i} - r_{u,i})^2} \quad (2)$$

2.2 Mean Absolute Error

The Mean Absolute Error (MAE) is also useful to evaluate how precise predictions are as compared to the actual real ratings.

$$MAE = \frac{1}{|R|} \sum_{(u,i,r) \in R} |\hat{r}_{u,i} - r_{u,i}| \quad (3)$$

3 Evaluation details

If the estimated rating $\hat{r}_{u,i}$ is less than some threshold r_{min}, we consider item i as not recommendable for user u. In this way, any prediction under this threshold is dismissed in the evaluation. As a matter of fact, in the case where $\hat{r}_{u,i} > r_{min}$ and $r_{u,i} > r_{min}$, we assume our recommendation is successful.

There are two features recommender systems should include. On one hand, the system must promote items liked by few people to every potential user likely to appreciate it.
On the other hand, the system has to recommend the maximum number of items an user can potentially like. In the best case, we should be able to evaluate both features.

In this work, we do a mixed or hybrid evaluation. Each pair (u, i) is evaluated. Therefore, we can consider our system as being in between the promotions of users for items and the promotion of items for users.

4 Iterative relations used in Adaptation

We have used an iterative relation to update both IDF(w) and σ_w^2.

$$X_{t+1} = X_t + K \quad (4)$$

With a simple addition, we update every parameter in a very efficient way. Thus we keep the adaptation algorithm complexity very low.