A Preliminary Study on a Recommender System for the Million Songs Dataset Challenge

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Abstract. In this paper, the preliminary study we have conducted on the Million Songs Dataset (MSD) challenge is described. The task of the competition was to suggest a set of songs to a user given half of its listening history and complete listening history of other 1 million people. We focus on memory-based collaborative filtering approaches since they are able to deal with large datasets in an efficient and effective way. In particular, we investigated on *i)* defining suitable similarity functions, *ii)* studying the effect of the "locality" of the collaborative scoring function, that is, how many of the neirest neighboors (and how much) they influence the score computation, and *iii)* aggregating multiple ranking strategies to define the overall recommendation. Using this technique we won the MSD challenge which counted about 150 registered teams.

1 Introduction

The Million Song Dataset Challenge [9] was a large scale, music recommendation challenge, where the task was the one to predict which songs a user will listen to, provided the listening history of the user. The challenge was based on the Million Song Dataset (MSD), a freely-available collection of meta data for one million of contemporary songs (e.g. song titles, artists, year of publication, audio features, and much more) [4]. About one hundred and fifty teams participated to the challenge. The subset of data actually used in the challenge was the so called Taste Profile Subset that consists of more than 48 million triplets *(user,song,count)* gathered from user listening histories. Data consists of about 1.2 million users and covers more than 380,000 songs in MSD. The user-item matrix is very sparse as the fraction of non-zero entries (the density) is only 0.01%.

The task of the challenge was to recommend the most appropriate songs for a user given half of her listening history and the complete history of another 1 million users. Thus, the challenge focused on the ordering of the songs on the basis of the relevance for a given user, and this makes the particular problem different from the more classical problem of predicting rates a user will give to unseen items [6, 11]. For example, popular tasks like the Netflix [3] and Movielens fall in this last case. A second important characteristic of the MSD problem is that we do not have explicit or direct feedback about what users like and how much they like it. In fact, we only have information of the form "user u listened to song i" without any knowledge about wether user u actually liked song i or not. A third important aspect of the MSD data is the presence of meta data concerning songs including title, artist, year of publication, etc. An interesting question then was wether this additional information could help or not. Finally, given the huge size of the datasets involved, time and memory efficiency of the method used turned out to be another very important issue in the challenge.

Collaborative Filtering (CF) is a technology that uses the item by user matrix to discover other users with similar tastes as the active user for which we want to make the prediction. The intuition is that if other users, similar to the active user, already purchased a certain item, then it is likely that the active user will like that item as well. A similar (dual) consideration can be made by changing the point of view. If we know that a set of items are often purchased together (they are similar in some sense), then, if the active user has bought one of them, probably he/she will be interested to the other as well. In this paper, we show that, even if this second view has been far more useful to win the MSD competition, the first view also brings useful and diverse information that can be aggregated in order to boost the performance of the recommendation.

In Section 2, collaborative filtering is described and proposed as a first approach to solve the problem of MSD. In particular, we briefly discuss the most popular state-of-the-art techniques: model based and memory based CF methods. In the same section, we propose a variant of memory based CF particularly suitable to tasks with implicit feedback and binary ratings, and we propose a new parameterized similarity function that can be adapted to different applicative domains. Finally, in Section 3, empirical results of the proposed techniques are presented and discussed.

2 A Collaborative Filtering approach to the MSD task

Collaborative Filtering techniques use a database in the form of a user-item matrix R of preferences. In a typical Collaborative Filtering scenario, a set $\mathcal{U}$ of n users and a set $\mathcal{I}$ of m items exist and the entries of $R = \{r_{ui}\} \in \mathbb{R}^{n \times m}$ represent how much user u likes item i. In this paper, we assume $r_{ui} \in \{0, 1\}$ as this was the setting of the MSD challenge[1]. Entries r_{ui} represent the fact that user u have listened to (or would like to listen to) the song i. In the following we refer to items or songs interchangeably. The MSD challenge task has been more properly described as a *top-τ recommendation* task. Specifically, for any *active user* u, we want to identify a list of τ ($\tau = 500$ in the challenge) items $I_u \subseteq \mathcal{I}$ that he/she will like the most. Clearly, this set must be disjoint with the set of items already rated (purchased, or listened to) by the active user.

2.1 Model-based Collaborative Filtering

Model-based CF techniques construct a model of the information contained in the matrix R. There are many proposed techniques of this type, including Bayesian models, Clustering models, Latent Factor models, and Classification/Regression models.

In recent literature about CF, matrix factorization techniques [8] have become a very popular and effective choice to implement the CF idea. In this kind of models one tries to learn a linear embedding of both users and items into a smaller dimensional

[1] Note that in this definition we neglet the information given by the *count* attribute of the triplets indicating how many times the song has been listened to by a user. In fact, at the start of the competition, the organizers warned us on the fact that this attribute could be unreliable and absolutely not correlated with likings.

space. More formally, in its basic form, one needs to find two matrices $P \in \mathbb{R}^{n \times k}$ and $Q \in \mathbb{R}^{k \times m}$, such that $R = PQ$, in such a way to minimize a loss over training data. A common choice for this loss is the root mean square error (RMSE).

Despite the fact that matrix factorization is recognized as a state-of-the-art technique in CF, we note that it has some drawbacks that make it unsuitable for the MSD task. First of all, learning the model is generally computationally very expansive and this is a problem when the size of the matrix R is very large as it was in our case. Second, since it is tipically modelled as a regression problem, it does not seem very good for implicit feedback tasks. In this cases we only have binary values of relevance and the value 0 cannot properly be considered the same as unrelevant since the no-action on an item can be due to many other reasons beyond not liking it (the user can be unaware of the existence of the item, for example). Finally, baseline provided by the organizers of the challenge and other teams entries, both based on matrix factorization techniques, have shown quite poor results for this particular task, thus confirming our previous claims.

2.2 Memory-based Collaborative Filtering

In memory-based Collaborative Filtering algorithms, also known as Neighborhood Models, the entire user-item matrix is used to generate a prediction. Generally, given a new user for which we want to obtain the prediction, the set of items to suggest are computed looking at similar users. This strategy is typically referred to as *user-based recommendation*. Alternatively, in the *item-based recommendation* strategy, one computes the most similar items for the items that have been already purchased by the active user, and then aggregates those items to form the final recommendation. There are many different proposal on how to aggregate the information provided by similar users/items (see [11] for a good survey). However, most of them are tailored to classical recommendation systems and they are not promptly compliant with the implicit feedback setting where only binary relevance values are available. More importantly, computing the neirest neighbors requires the computation of similarities for every pair of users or songs. This is simply infeasible in our domain given the huge size of the datasets involved. So, we propose to use a simple weighted sum strategy the considers positive information only. A deeper analysis of this simple strategy will allows us to highlight an interesting duality which exists between user-based and item-based recommendation algorithms.

In the *user-based* type of recommendation, the scoring function, on the basis of which the recommendation is made, is computed by

$$h_{ui}^{U} = \sum_{v \in \mathcal{U}} f(w_{uv}) r_{vi} = \sum_{v \in \mathcal{U}(i)} f(w_{uv}),$$

that is, the score obtained on an item for a target user is proportional to the similarities between the target user u and other users v that have purchased the item i ($v \in \mathcal{U}(i)$). This score will be higher for items which are often rated by similar users.

On the other hand, within a *item-based* type of recommendation [5, 10], the target item i is associated with a score

$$h_{ui}^{S} = \sum_{j \in \mathcal{I}} f(w_{ij}) r_{uj} = \sum_{j \in \mathcal{I}(u)} f(w_{ij}),$$

and hence, the score is proportional to the similarities between item i and other items already purchased by the user u ($j \in \mathcal{I}(u)$).

Note that, the two formulations above do not have a normalization factor. A normalization with the sum of the similarities with the neighbors is tipically performed in neighboorhood models for tasks with explicit rates. In our case, we wanted to consider positive information only in the model. As we see in the following, an effect similar to the normalization is given by the function $f(w)$. The proposed strategy seems appropriate in our setting and makes the prediction much faster as we only need to compute pair similarities with only a few other (in the order of tens in our task) users/items.

The function $f(w)$ can be assumed monotonic not decreasing and its role is to emphasize/deemphasize similarity contributions in such a way to adjust the *locality* of the scoring function, that is how many of the nearest users/items really matter in the computation. As we will see, a correct setting of this function turned out to be very useful with the challenge data.

Interestingly, in both cases, we can decompose the user and item contributions in a linear way, that is, we can write $h^U_{ui} = \mathbf{w}_u^\top \mathbf{r}_i$, $\mathbf{w}_u \in \mathbb{R}^n$, and $h^S_{ui} = \mathbf{w}_i^\top \mathbf{r}_u$, $\mathbf{w}_i \in \mathbb{R}^m$. In other words, we are defining an embedding for items (in user based recommendation systems) and for users (in item based recommendation systems). In the specific case above, this corresponds to choose the particular vector $\mathbf{r}_i$ as the vector with n entries in $\{0, 1\}$, where $\mathbf{r}_i^{(u)} = r_{ui}$. Similarly, for the representation of users in item-based scoring, we choose $\mathbf{r}_u$ as the vector with m entries in $\{0, 1\}$, such that $\mathbf{r}_u^{(i)} = r_{ui}$. In the present paper we mainly focus on exploring how we can learn the vectors $\mathbf{w}_i$ and $\mathbf{w}_u$ in a principled way by using the entire user-item preference matrix on-the-fly when a new recommendation has to be done. Alternatively, we could also try to learn the weight vectors from data by noticing that a recommendation task can be seen as a multilabel classification problem where songs represent the labels and users represent the examples. We have performed preliminary experiments in this sense using the preference learning approach described in [1]. The results were promising but the problem in this case was the computational requirements of a *model-based* paradigm like this. For this reason we decided to postpone a further analysis of this setting to future works.

2.3 User-based and Song-based similarity

In large part of CF literature the cosine similarity is the standard measure of correlation and not much work has been done until now to adapt the similarity to a given problem. Our opinion is that it cannot exist a single similarity measure that can fit all possible domains where collaborative filtering is used. With the aim to bridge this gap, in this section, we try to define a parametric family of user-based and item-based similarities that can fit different problems.

In the challenge, we have not relevance grades since the ratings are binary values. This is a first simplification we can exploit in the definition of the similarity functions. The similarity function that is commonly used in this case, both for the user-based case and the item-based case, is the cosine similarity. In the case of binary grades the cosine similarity can be simplified as in the following. Let $\mathcal{I}(u)$ be the set of items rated by a generic user u, then the cosine similarity between two users u, v is defined by

$$w_{uv} = \frac{|\mathcal{I}(u) \cap \mathcal{I}(v)|}{|\mathcal{I}(u)|^{\frac{1}{2}} |\mathcal{I}(v)|^{\frac{1}{2}}}$$

and, similarly for items, by setting $\mathcal{U}(i)$ the set of users which have rated item i, we obtain:

$$w_{ij} = \frac{|\mathcal{U}(i) \cap \mathcal{U}(j)|}{|\mathcal{U}(i)|^{\frac{1}{2}} |\mathcal{U}(j)|^{\frac{1}{2}}}.$$

The cosine similarity has the nice property to be symmetric but, as we show in the experimental section, it might not be the better choice. In fact, especially for the item case, we are more interested in computing how likely it is that an item will be appreciated by a user when we *already* know that the same user likes another item. It is clear that this definition is not symmetric. As an alternative to the cosine similarity, we can resort to the conditional probability measure which can be estimated with the following formulas:

$$w_{uv} = P(u|v) = \frac{|\mathcal{I}(u) \cap \mathcal{I}(v)|}{|\mathcal{I}(v)|}$$

and

$$w_{ij} = P(i|j) = \frac{|\mathcal{U}(i) \cap \mathcal{U}(j)|}{|\mathcal{U}(j)|}$$

Previous works (see [7] for example) pointed out that the conditional probability measure of similarity, $P(i|j)$, has the limitation that items which are purchased frequently tend to have higher values not because of their co-occurrence frequency but instead because of their popularity. In our opinion, this might not be a limitation in a recommendation setting like ours. Perhaps, this could be an undesired feature when we want to cluster items. In fact, this correlation measure has not to be thought of as a real similarity measure. As we will see, experimental results seem to confirm this hypothesis, at least in the item-based similarity case.

Now, we are able to propose a parametric generalization of the above similarity measures. This parametrization permits ad-hoc optimizations of the similarity function for the domain of interest. For example, this can be done by validating on available data. Specifically, we propose to use the following combination of conditional probabilities:

$$w_{uv} = P(v|u)^{\alpha} P(u|v)^{1-\alpha} \quad w_{ij} = P(j|i)^{\alpha} P(i|j)^{1-\alpha} \tag{1}$$

where $\alpha \in [0, 1]$ is a parameter to tune. As above, we estimate the probabilities by resorting to the frequencies in the data and derive the following:

$$w_{uv} = \frac{|\mathcal{I}(u) \cap \mathcal{I}(v)|}{|\mathcal{I}(u)|^{\alpha} |\mathcal{I}(v)|^{1-\alpha}} \quad w_{ij} = \frac{|\mathcal{U}(i) \cap \mathcal{U}(j)|}{|\mathcal{U}(i)|^{\alpha} |\mathcal{U}(j)|^{1-\alpha}}. \tag{2}$$

It is easy to note that the standard similarity based on the conditional probability $P(u|v)$ (resp. $P(i|j)$) is obtained setting $\alpha = 0$, the other inverted conditional $P(v|u)$ (resp. $P(j|i)$) is obtained setting $\alpha = 1$, and, finally, the cosine similarity case is obtained when $\alpha = \frac{1}{2}$. This analysis also suggests an interesting interpretation of the cosine similarity on the basis of conditionals.

2.4 Locality of the Scoring Function

In Section 2 we have seen how the final recommendation is computed by a scoring function that aggregates the scores obtained using individual users or items. So, it is important to determine how much each individual scoring component influences the overall scoring. This is the role of the function $f(w)$. In the following experiments we use the exponential family of functions, that is $f(w) = w^q$ where $q \in \mathbb{N}$. The effect of this exponentiation is the following. When q is high, smaller weights drop to zero while higher ones are (relatively) emphasized. At the other extreme, when $q = 0$, the aggregation is performed by simply adding up the ratings. We can note that, in the user-based type of scoring function, this corresponds to take the popularity of an item as its score, while, in the case of item-based type of scoring function, this would turn out in a constant for all items (the number of ratings made by the active user).

2.5 Ranking Aggregation

There are many sources of information available regarding songs. For example, it could be useful to consider the additional meta-data which are also available and to construct alternative rankings based on that. It is always difficult to determine a single strategy which is able to correctly rank the songs. An alternative is to use multiple strategies, generate multiple rankings, and finally combine those rankings. Typically, these different strategies are individually *precision oriented*, meaning that each strategy is able to correctly recommend a few of the correct songs with high confidence but, it may be that, other songs which the user likes, cannot be suggested by that particular ranker. Hopefully, if the rankers are different, then the rankers can recommend different songs. If this is the case, a possible solution is to predict a final recommendation that contains all the songs for which the single strategies are more confident. The stochastic aggregation strategy that we used in the challenge can be described in the following way. We assume we are provided with the list of songs, not yet rated by the active user, given in order of confidence, for all the basic strategies. On each step, the recommender randomly choose one of the lists according to a probability distribution p_i over the predictors and recommends the best scored item of the list which has not yet been inserted in the current recommendation. In our approach the best p_i values are simply determined by validation on training data.

3 Experiments and Results

In the MSD challenge we have: *i)* the full listening history for about 1M users, *ii)* half of the listening history for 110K users (10K validation set, 100K test set), and we have to predict the missing half. Further, we also prepared a "home-made" validation subset (*HV*) of the original training data of about 900K users of training (*HVtr*, with full listening history). The remaining 100K user's histories has been split in two halves (*HVvi* the visible one, *HVhi* the hidden one).

The experiments presented in this section are based on this *HV* data and compare different similarities and different approaches. The baseline is represented by the simple popularity based method which recommends the most popular songs not yet listened to by the user. Besides the baseline, we report experiments on both the user-based and song-based scoring functions, and an example of the application of ranking aggregation. Given the size of the datasets involved we do not stress on the significance of the presented results. This is confirmed by the fact that the presented results do not differ significantly from the results obtained over the indipendent set of users used as the test set in the challenge.

3.1 Taste Profile Subset Stats

For completeness, in this section, we report some statistics about the original training data. In particular, the following table shows the minimum, maximum, and average, number of users per song and songs per user. The median value is also reported.

Data Statistics	min	max	ave	median
users per song	1	110479	125.794	13
songs per user	10	4400	47.45681	27

We can see that the large majority of songs have only few users which listened to it (less than 13 users for half of the songs) and the large majority of users have listened to few songs (less than 27 for half of the users). These characteristics of the dataset make the top-τ recommendation task quite challenging.

3.2 Truncated Mean Average Precision

Conformingly to the challenge, we used the truncated mAP (mean average precision) as the evaluation metric [9]. Let y denote a ranking over items, where $y(p) = i$ means that item i is ranked at position p. The mAP metric emphasizes the top recommendations. For any $k \leq \tau$, the *precision at k* (π_k) is defined as the proportion of correct recommendations within the top-k of the predicted ranking (assuming the ranking y does not contain the visible songs),

$$\pi_k(u, y) = \frac{1}{k} \sum_{p=1}^{k} r_{uy(p)}$$

For each user the (truncated) average precision is the average precision at each recall point:

$$AP(u, y) = \frac{1}{\tau_u} \sum_{p=1}^{\tau} \pi_k(u, y) r_{uy(p)}$$

where τ_u is the smaller between τ and the number of user u's positively associated songs. Finally, the average of $AP(u, y_u)$'s over all users gives the mean average precision (mAP).

3.3 Results

The result obtained on the HV data with the baseline (recommendation by popularity) is presented in Table 1(a). With this strategy, each song i simply gets a score proportional to the number of users $|\mathcal{U}(i)|$ which listened to the song.

In Table 1, we also report on experiments that show the effect of the locality parameter q for different strategies: item based and user based (both conditional probability and cosine versions). As we can see, beside the case IS with cosine similarity (Table 1c), a correct setting of the parameter q drammatically improves the effectiveness on HV data. We can clearly see that the best performance is reached with the conditional probability on an item based strategy (Table 1b).

Method	mAP@500
Baseline (Recommendation by Popularity)	0.02262

(a)

IS ($\alpha = 0$)	mAP@500
q=1	0.12224
q=2	0.16581
q=3	**0.17144**
q=4	0.17004
q=5	0.16830

(b)

IS ($\alpha = \frac{1}{2}$)	mAP@500
q=1	**0.16439**
q=2	0.16214
q=3	0.15587
q=4	0.15021
q=5	0.14621

(c)

US ($\alpha = 0$)	mAP@500
q=1	0.08030
q=2	0.10747
q=3	0.12479
q=4	0.13298
q=5	**0.13400**
q=6	0.13187
q=7	0.12878

(d)

US ($\alpha = \frac{1}{2}$)	mAP@500
q=1	0.07679
q=2	0.10436
q=3	0.12532
q=4	0.13779
q=5	0.14355
q=6	**0.14487**
q=7	0.14352

(e)

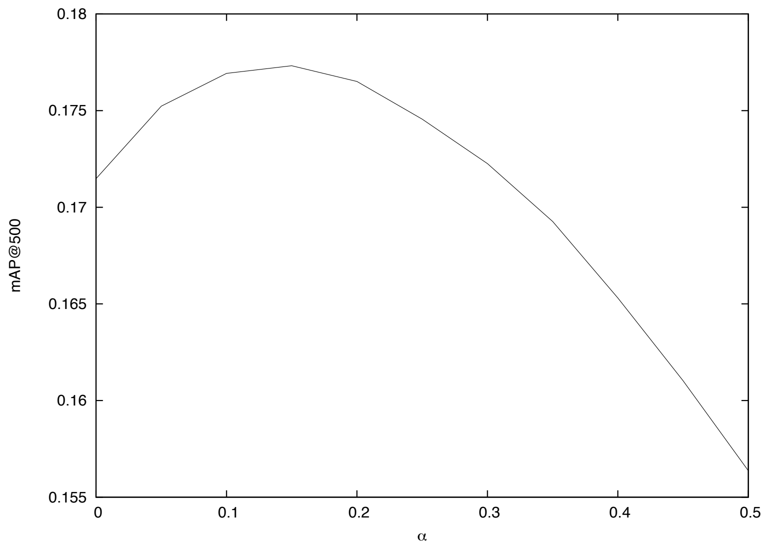
Table 1: Results obtained by the baseline, item-based (IS) and user-based (US) CF methods varying the locality parameter (exponent q) of the similarity function.

In Figure 1, results obtained fixing the parameter q and varying the parameter α for both user-based and item-based recommendation strategies are given. We see that, in the item-based case, the results improve when setting a non-trivial α. In fact, the best result has been obtained for $\alpha = 0.15$.

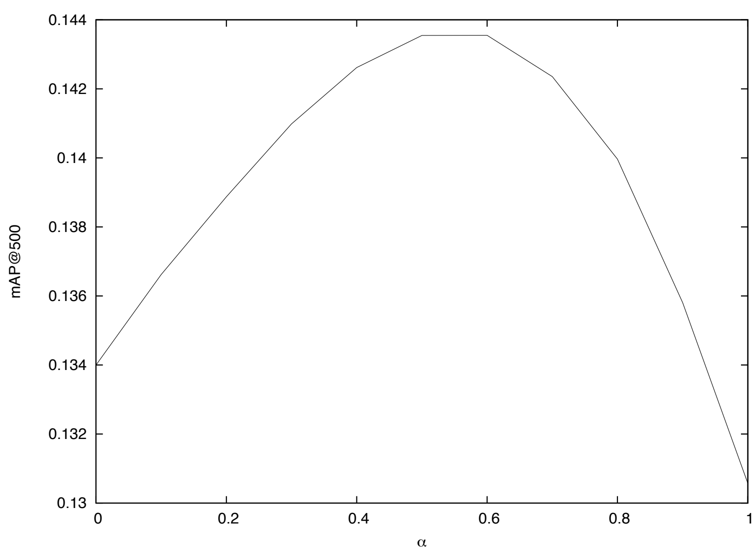
Finally, in Table 2, two of the best performing rankers are combined, and their recommendation aggregated, by using the stochastic algorithm described in Section 2.5. In particular, in order to maximize the diversity of the two rankers, we aggregated an item-based ranker with a user-based ranker. We can see that the combined performance improves further on validation data. Building alternative and effective rankers based on available meta-data is not a trivial task and it was not the focus of our current study. For this we decided to postpone this additional analysis to a near future.

3.4 Comparison with other approaches

We end this section by comparing our with other approaches that have been used in the challenge. Best ranked teams all used variants of memory based CF, besides the



(a) IS with $0 \leq \alpha \leq 0.5$, $q = 3$, best-mAP@500: $0.177322(\alpha = 0.15)$



(b) US with $0 \leq \alpha \leq 1$, $q = 5$, best-mAP@500: $0.143551(\alpha = 0.6)$

Fig. 1: Results obtained by item-based (IS) and user-based (US) CF methods varying the α parameter.

(IS, $\alpha = 0.15$, $q = 3$)	(US, $\alpha = 0.3$, $q = 5$)	mAP@500
0.0	1.0	0.14098
0.1	0.9	0.14813
0.2	0.8	0.15559
0.3	0.7	0.16248
0.4	0.6	0.16859
0.5	0.5	0.17362
0.6	0.4	0.17684
0.7	0.3	0.17870
0.8	0.2	**0.17896**
0.9	0.1	0.17813
1.0	0.0	0.17732

(a)

Table 2: Results obtained aggregating the rankings of two different strategies, item-based (IS, $\alpha = 0.15$, $q = 3$) and user-based (US, $\alpha = 0.3$, $q = 5$), with different combinations.

5-th ranked team that used the Absorption algorithm by YouTube [2] which is a graph based method that performs a random walk on the rating graph to propagate preferences information over the graph. On the other side, matrix factorization based techniques showed a very poor performance on this task and people working on that faced serious memory and time efficiency problems. Finally, some teams tried to inject meta data information in the prediction process with scarse results. In our opinion, this can be due to the fact that there is a lot of implicit information contained in the user's history and this is much more than explicit information one can get from metadata. We conclude that meta data information can be more effectively used in a *cold start* setting.

4 Conclusion

In this paper we have presented the technique we used to win the MSD challenge. The main contributions of the paper are: a novel scoring function for memory based CF that results particularly effective (and efficient) on implicit rating settings and a new similarity measure that can be adapted to the problem at hand. In the near future we want to investigate on the possibility of using metadata information to boost the performance and in a more solid way to aggregate multiple predictions.

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