PCML CS-433: Recommender System

Team: *Just keep swimming !*

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***Abstract*—Active Collaborative Filtering Recommender Systems for movie collection using blending of 30 different methods (8 direct scoring methods[1] and 9 iterative ones, plus 13 variations of them) in order to achieve around 0.97452 RMSE on Kaggle's EPFL ML Recommender System challenge.**

I. Introduction

Collaborative filtering is a set of techniques aiming at the creation of recommender systems. Usually, we define three types of collaborative filter: **active**, **passive** and **content-based** (the best one being obviously a mix of the three). In industry, recommenders are mainly used to suggest new item to users based on their taste: movies, music tracks, items to purchase, ...

The objective of the project is to develop a recommender system using **active collaborative filtering** (i.e. pseudonymised items[2] rated by pseudonymised users).

We first go through a general **data analysis** in order to evaluate the quality of the data (spammers and participation of the users). Then we test different models, starting from a basic mean given a prediction baseline and improving the score with more advanced algorithms.

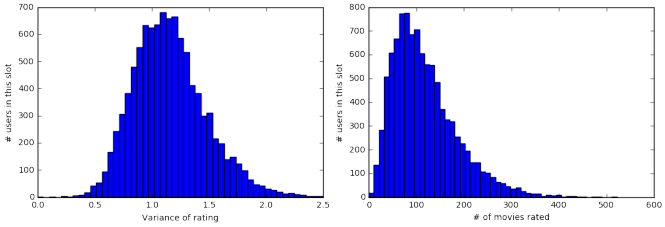
According to *BellKor's Pragmatic Chaos*[3] scientific paper [1] the best recommender is obtained through a clever blend of several models. Exploiting this approach, **we ultimately blended 30 different methods (8 direct scoring methods and 9 iterative ones, plus 13 variations of them)** eventually achieving around 0.95962 RMSE on local Cross-Validation (0.97452 on Kaggle test set).

The implemented model will be part of the **Kaggle's EPFL ML Recommender System** challenge in which predictions are rated by their RMSE compared with ground truth values. All external libraries are allowed as long as they are properly documented.

[1] means, medians, ...

[2] Items anonymized by an ID, i.e. we have access neither to the name nor any content of it.

[3] Winner team of 2009 Netflix Prize



(a) Distribution of variances of ratings per user. No spammers.

(b) Number of movies rated per user. Good user participation.

Figure 1: Statistical description of the data

II. Data Description

The data represent ratings from $10'000$ users on $1'000$ movies in an integer scale from 1 to 5. Both of them are pseudonymized by an ID. This scale represents the number of *stars* given by the users, 1 being the lowest grade and 5 the best.

The training set used to train our algorithm contains $1'176'952$ ratings which represent around 12% of filled ratings. Another $1'176'952$ ratings are hidden from us and must be predicted by our recommender algorithm in order to be scored on Kaggle platform.

III. Data Exploration

A. Search for Spammers

One of the first step before starting learning from data is to ensure that they are real ones, and not produced by bots (spammers). As we know, spammers can act in different ways: **uniform spammers** constantly rate movies in the same way, while **random spammers** randomly rate movies. In order to check their existence, we analyzed the variances of user ratings: uniform spammers would be put in evidence by null variance, while random spammers present abnormally high variance. Figure (1a) shows the Gaussian

distribution of the rating variances and ensure the data are free of spammers.

B. Participation of Users

Even free of spammers, data can still contain **inactive users**, i.e. users who subscribed to a platform but never use it or never rate movies. If they are in too big number compared with active users, they can disturb learning algorithms. Figure (1b) shows histograms of number of movies rated by users and confirm us the good participation of the users.

C. User "Moods" (Deviation)

Because of mood/education//habits users having the same appreciation of a movie can rate it differently. Indeed, we show in the figure (2) that some users systematically rate lower/higher than others. It's important to take this effect into account in both evaluation of a movie and recommendation for the user and proceed to a normalization of the ratings. As shown later, we will keep some algorithms in both their normalized and unnormalized forms (see section **??**).

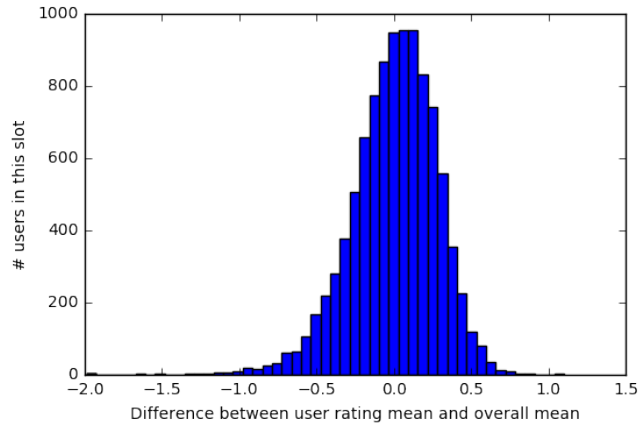


Figure 2: Difference of rating mean of each user compared with overall mean. Illustrates the differences of judgement that users give in average or what we call in this paper the "moods".

IV. Models

A. Global mean/median (2 models)

The simplest model is to take all the ratings in the train set and apply the mean or the median value. We return this value as the prediction. This give a baseline score from which we can compare further models.

B. User/Movie mean/median (4 models)

Another simple model is to compute the mean or median value for the users or the movies.

C. Movie mean/median with normalized user moods (2 models)

The third set of model uses the mean or median value for each movie. We also compute the "mood" of the users this way:

$$d_u = \overline{U} - \overline{u} \quad \forall u \in U \tag{1}$$

where $\overline{U} = \frac{1}{\#U} \sum_{u \in U} \overline{u}$ and $\overline{u}$ being the average rating of the user u.

Then, we return the prediction of a user u on a movie m:

$$p_{m,u} = \overline{m} + d_u \tag{2}$$

where $\overline{m}$ is either the mean or the median of the ratings on the movie m.

D. Matrix Factorization using Stochastic Gradient Descent (MF-SGD)

Matrix factorization techniques proved to be one of the most effective strategies to implement recommender systems. Given D items, N users and the corresponding rating matrix $X \in \mathbb{R}^{D \times N}$, we aim to find two matrices $W \in \mathbb{R}^{D \times K}$ and $Z \in \mathbb{R}^{N \times K}$ such that the quantity

$$E = \frac{1}{2} \sum_{\substack{d=1,\dots,D \\ n=1,\dots,N}} \left(x_{dn} - \left(W Z^T \right)_{dn} \right)^2 + \frac{\lambda}{2} \|W\|^2 + \frac{\lambda}{2} \|Z\|^2 \tag{3}$$

is minimized. K is a parameter, corresponding to the number of the *latent factors*; λ is a scalar that weight the regularization terms.

Different techniques have been deployed to solve this minimization problem. In this Subsection we will present the Stochastic Gradient Descent method, while in the next one we explain the Alternating Least Square optimization. The Stochastic Gradient Descent method is a faster variant of the standard gradient descent optimization. The gradient of the functional 3 is computed only on a single element of the summation, randomly chosen. The update process then follows the same rules of the batch gradient descent. An almost certain convergence to a local minimum is guaranteed under not restrictive hypothesis.

Using the `scipy.sparse` matrix library, we implemented the SGD method from scratch. Through a cross validation process we chose the best values for the parameters K, λ and the number of iterations. The results that we obtained will be presented in Section VI-A.

E. Matrix Factorization using Alternating Least Square (ALS)

ALS is one of the main alternatives to the SGD to solve the problem 3. It is an iterative algorithm consisting in alternately fixing one of the two matrices W or Z, while optimizing the problem 3 with respect to the other matrix. The optimization problem at each iteration is much easier to solve compared to the one solved by the SGD. A simple least squares technique can be exploited.

One of the most advanced open source frameworks available to solve this problem is Apache Spark. It is a cluster computing framework that provides to the programmers an application programming interface to efficiently execute streaming, machine learning or SQL workloads that require fast iterative access to datasets. The Spark package `mllib` contains several implementations of different machine learning algorithms, including the ALS for collaborative filtering. Therefore we decided to exploit this library for the implementation. Spark also allows to specify the parameters K, the number of iterations and λ. We perform a cross validation to choose the best parameters, whose results will be discussed in Section VI-A.

F. PyFM

PyFM is a python implementation of Factorization Machines. This library is a wrapper of the C++ library libFM [2], one of the most advanced matrix factorization libraries. It can be found on Github [3]. The idea behind the algorithm is similar to the MF-SGD IV-D.

The usage of this library is really simple. It uses a few parameters:

- Number of factors corresponding to the scalar K in the MF-SGD.
- Number of iterations
- Initial learning rate

The number of iterations was fixed. The two other parameters were chosen with the use of a simple cross validation process.

G. Matrix Factorization using Ridge Regression (MF-RR)

Small description

V. Blending

The *Bellkor's Pragmatic Chaos* team, winner of 2009 *Netflix Prize*, explain in its paper that its solution was obtained by blending a hundred different models. [1] Without having the same number of models, we proceed the same to obtain our final solution. We perform a weighted sum that we optimize using **Sequential Least Squares Programming** (SLSQP) method provided by `scipy.optimize.minimize` library. Initial weights are set to $1/n$ for each model (n being the number of models). Instead of constraining the weights to be between 0 and 1, and to have a sum equal to 1, we choose to let the optimizer have more flexibility.

A. SLSQP method

Sequential Least Squares Programming method is a **Quasi-Newton method**. Unlike Newton method, it does not compute the Hessian matrix but estimates it by successive gradient vector analyze [4] using **Broyden-Fletcher-Goldfarb-Shanno** algorithm (BFGS). This method allows optimization for function without knowing Hessian matrix, in a short computation time.

Model	RMSE
global_mean	1.11905
global_median	1.12811
user_mean	1.09516
user_median	1.15146
movie_mean	1.03043
movie_mean_rescaled	1.00562
movie_median	1.09968
movie_median_rescaled	1.02267
movie_median_deviation_user	1.07220
movie_median_deviation_user_rescaled	1.06465
movie_mean_deviation_user	0.99661
movie_mean_deviation_user_rescaled	1.04494
mf_rr	1.02774
mf_rr_rescaled	1.02746
mf_sgd	1.00080
mf_sgd_rescaled	0.99993
als	0.98874
als_rescaled	0.98903
pyfm	0.98802
pyfm_rescaled	0.98863
baseline	0.99925
baseline_rescaled	1.00039
slope_one	1.00010
slope_one_rescaled	1.00032
svd	0.99835
svd_rescaled	0.99840
knn_ib	0.99031
knn_ib_rescaled	0.99043
knn_ub	0.99244
knn_ub_rescaled	0.99351
blending	0.95962

Table I: Benchmark of models.

VI. Result

In order to create our recommender algorithm, we followed the steps:

1) Tuning the parameters for each model one-by-one following a grid-search method scored by a 5-fold Cross-Validation.
2) Computing the predictions for each model for 5 folded set of data. This result to a set of $5n$ prediction tables (n being the number of models).
3) Optimizing the weights for each model prediction produced by the previous step, by running a SLSQP optimization method (as explained in section V-A) on the 5 folded prediction tables. This allows to optimize the 5-fold Cross-Validation score.

A. Benchmark

Table I presents the average RMSE of each model applied on the validation sets for the blending cross validation process. Last line is the result of the blending on the same validation sets.

The blending gives a 0.97452 RMSE on Kaggle's test set.

B. Blending

Table II provides the weights after minimizing on the average RMSE. It also provides the parameters used for each model.

Model	weight	parameters
Global mean	2.87634	-
Global median	0.88256	-
User mean	-3.81181	-
User median	0.00362	-
Movie mean	-1.57271	-
Movie mean (mood norm.)	1.65276	-
Movie median	-2.27553	-
Movie median (mood norm.)	2.27933	-
MF-SGD (mood normalization)	-0.16857	$\lambda = 0.004$ features = 20 iterations = 20
ALS	0.75256	$\lambda = 0.081$ rank = 8 iterations = 24
Collab. Filtering	0.04356	$\alpha = 19$ features = 20
PyFM	0.30050	factors = 20 iterations = 100 learning rate = 0.001

Table II: Blending of models.

VII. Discussion of the results

Excluding the trivial models based on the user/movie mean/median, we mainly focused on **Matrix Factorization algorithms**, exploiting different techniques to achieve the best factorization possible. Content-based filtering algorithms are not suited for this problem since the users and the movies are fully anonymized and without additional information.

Blending plays an important role in our project. As we can see in table I, no models are scored under 0.99 while blending achieve around 0.96 RMSE. This can be explained by the fact that certain model compensate themselves well.

1) Choice of the models: It should be legitimate to ask **why we are keeping both normalized and unnormalized model for some models**. Looking at the coefficients gives a partial answer. As we see in table II, normalized and unnormalized models oppose themselves almost exactly, with a little advantage for normalized models. The effect is that the method is more taken into account for users in the tail of the Gaussian deviation curve (figure 2) than for the central ones. Then, it allows the optimizer to have finer control on the blending.

2) Blending Choices: REVIEW The role of the blending part is extremely important in obtaining the best score possible. The large number of models available would be pointless without a good blend. Moreover, we mainly consider simple models, leaving to the blender the task of building a more complex one.

As mentioned in Section V we used the Sequential Least Square Programming method to optimize the weighted sum of models. Simpler methods, like a grid search, are computationally too expensive and less accurate than the algorithm used. We spent some time in finding the best optimization method for our purposes. review

The optimization choice also allows negative weights. We decided not to put any constraint about that for two reasons:

- We obtained better results.
- Negative weights may help in better fitting the distribution of the training dataset. This can lead to overfitting, as we discuss in the next subsection, but, at the same time, it also produces better results.

We also did not put any constraint on the sum of the weight (i.e. the sum is not fixed to 1) for the same reasons.

3) Overfitting: We apply several techniques to reduce as much as possible the overfitting of the models we used. In particular we used a 5-fold cross-validation both to determine the best parameters for each model and to choose the best weights in the blending. Despite this, the model slightly overfits the data. With a 0.95962 RMSE on our local Cross-Validation and 0.97452 on Kaggle's test set, we notice a small difference that indicates overfitting.

There are many possible reasons underlying this behaviour. Probably the blending process that we used, although the proven accuracy, introduces too much complexity in the model, thus overfitting the training database.

References

[1] Y. Koren, "The BellKor Solution to the Netflix Grand Prize," 2009.

[2] S. Rendle, "Factorization machines with libFM," *ACM Trans. Intell. Syst. Technol.*, vol. 3, no. 3, pp. 57:1–57:22, 2012.

[3] CoreyLynch, "pyfm: Factorization machines in python," https://github.com/coreylynch/pyFM, 2016.

[4] Wikipedia, "Quasi-Newton Method — Wikipedia, The Free Encyclopedia," 2016, [Online; accessed 20-December-2016]. [Online]. Available: https://en.wikipedia.org/wiki/Quasi-Newton_method