MOVIE RECOMMENDATION SYSTEM.

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INTRODUCTION

Movies are a great way to pass time especially after a long day of work and all you can think about is something to help you relax. What if there was a recommender system that recommends movies based on ratings and how users. The recommender system makes recommendations based on previous movies you have watched and how you rated them so that you can be able to continue enjoying movies of your choice without much effort of looking.

PROBLEM STATEMENT.

In today's digital age, the entertainment industry is experiencing rapid growth, with an ever-expanding library of movies and TV shows available to audiences. However, this abundance of content often leads to decision fatigue among viewers who are overwhelmed by the choices. To address this issue and enhance the user experience, our objective is to make a movie recommendation system that will address this issue and reduce dissatisfaction when looking for a movie.

MAIN OBJECTIVE

The primary goal of this project is to develop a movie recommendation system that can provide personalized movie suggestions to users based on their preferences, viewing history, and behavior.

SPECIFIC OBJECTIVES.

. To build a recommender system using user-user similarity.

. To find the optimal parameters to use for singular value decomposition.

.To use evaluation metrics such as the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) to check the performance of the model.

BUILDING THE RECOMMENDATION SYSTEM.

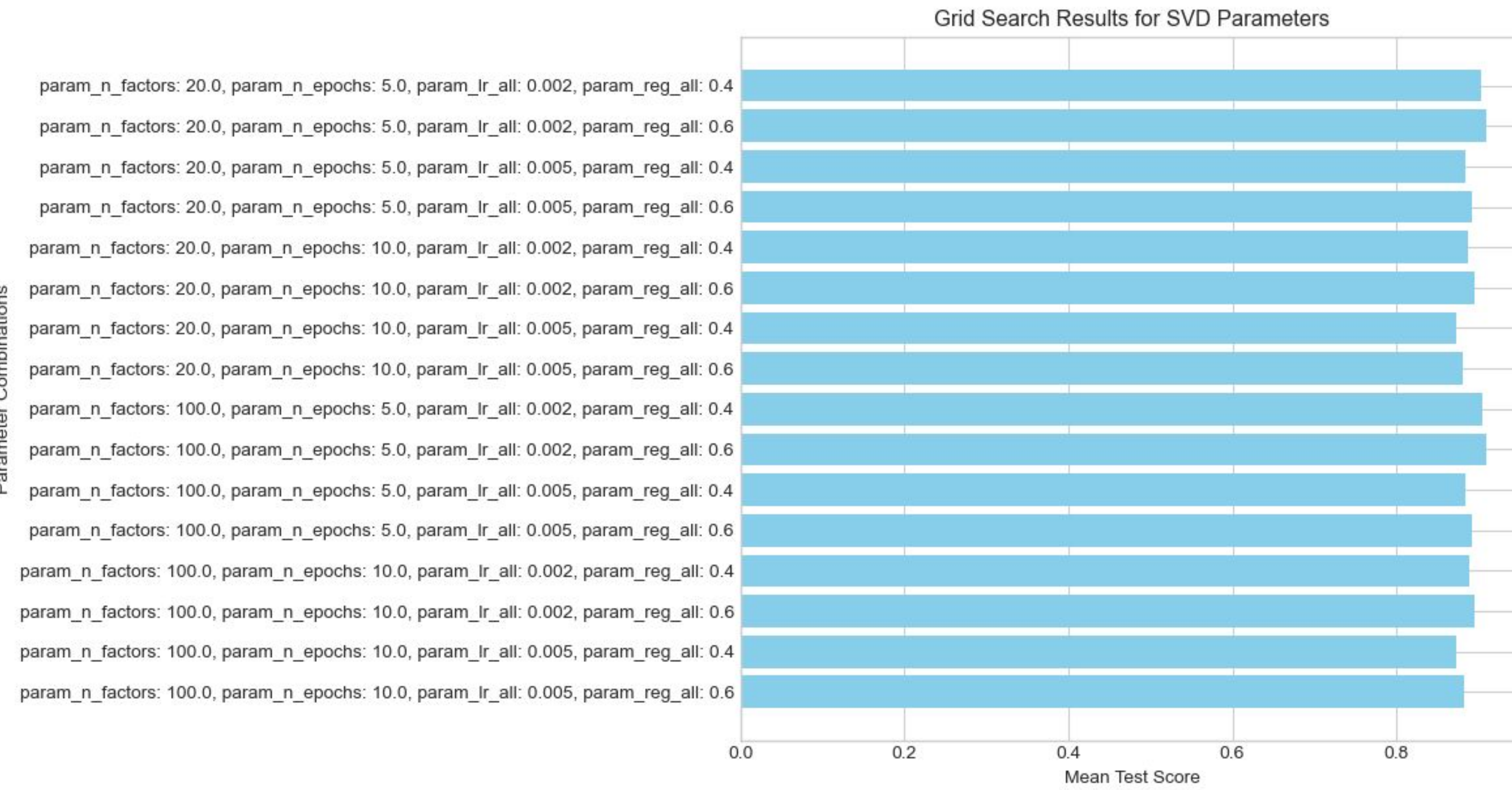
The recommendation system was built based on singular value decomposition(SVD) having hypertuned the parameters to find the optimal parameters. Thereafter, it was fit to the training data and finally made predictions is movie recommendations to a new user. This was done through building a function that prompts the user to make ratings for a movie. Through these ratings, the system is able to make recommendations to a user based on user- similarity.

BUILDING THE RECOMMENDATION SYSTEM.

The evaluation metrics used to check the performance of the system was Root Mean Squared Error(RMSE) and Mean Absolute Error(MAE). The system performed well and was able to provide recommendations for the new user.

HYPERPARAMETER TUNING GRAPH.

The graph below shows the results of the grid search in order to provide the optimal parameters to use for the Singular Value Decomposition used to fit the data and later make predictions for recommendations of movies.


Grid Search Results for SVD Parameters
Parameter Combinations
param_n_factors: 20.0, param_n_epochs: 5.0, param_lr_all: 0.002, param_reg_all: 0.4
param_n_factors: 20.0, param_n_epochs: 5.0, param_lr_all: 0.002, param_reg_all: 0.6
param_n_factors: 20.0, param_n_epochs: 5.0, param_lr_all: 0.005, param_reg_all: 0.4
param_n_factors: 20.0, param_n_epochs: 5.0, param_lr_all: 0.005, param_reg_all: 0.6
param_n_factors: 20.0, param_n_epochs: 10.0, param_lr_all: 0.002, param_reg_all: 0.4
param_n_factors: 20.0, param_n_epochs: 10.0, param_lr_all: 0.002, param_reg_all: 0.6
param_n_factors: 20.0, param_n_epochs: 10.0, param_lr_all: 0.005, param_reg_all: 0.4
param_n_factors: 20.0, param_n_epochs: 10.0, param_lr_all: 0.005, param_reg_all: 0.6
param_n_factors: 100.0, param_n_epochs: 5.0, param_lr_all: 0.002, param_reg_all: 0.4
param_n_factors: 100.0, param_n_epochs: 5.0, param_lr_all: 0.002, param_reg_all: 0.6
param_n_factors: 100.0, param_n_epochs: 5.0, param_lr_all: 0.005, param_reg_all: 0.4
param_n_factors: 100.0, param_n_epochs: 5.0, param_lr_all: 0.005, param_reg_all: 0.6
param_n_factors: 100.0, param_n_epochs: 10.0, param_lr_all: 0.002, param_reg_all: 0.4
param_n_factors: 100.0, param_n_epochs: 10.0, param_lr_all: 0.002, param_reg_all: 0.6
param_n_factors: 100.0, param_n_epochs: 10.0, param_lr_all: 0.005, param_reg_all: 0.4
param_n_factors: 100.0, param_n_epochs: 10.0, param_lr_all: 0.005, param_reg_all: 0.6
0.0
0.2
0.4
0.6
0.8
Mean Test Score

SUMMARY.

. Effectiveness of collaborative filtering method, In this project I used user-user similarity which proved to be the right approach to take since there were fewer users than items. However there consists other methods like content based filtering are good approaches which can be customized to suit user preferences.

SUMMARY.

. When working with a large dataset it is important to have adequate memory or use a sample of the data that is representative of the whole to make predictions, however using the entire dataset would yield better results since it is training and learning from a huge dataset which makes it easier to make accurate predictions, consequently it is important to be cautious not to overfit.

SUMMARY.

I used the singular value decompositions and generated a grid search in pursuit of the best parameters in order to make right predictions and cross validated using the KNNBasic and the KNNBaseline, the latter yielded better results in reducing the test rmse after making predictions. The optimum parameters were, n_factors = 20, n_epochs = 20, lr_all = 0.05, reg_all = 0.4 respectively.

SUMMARY.

. Implementing user friendly interfaces increases the chance of users rating a movie thus makes collection of metadata easier in order to provide insightful recommendations suited to the liking of the user.

RECOMMENDATIONS.

. To address the cold start problem, that is, the system finds it difficult to make recommendations for users or items that have fewer interactions with it. Content-based methods and hybrid recommendation systems can address this issue by incorporating item features and metadata.

RECOMMENDATIONS.

. The performance of recommendation system depends on hyperparameter settings. Careful tuning of hyperparameters, such as the number of neighbors (k) in KNN or the regularization term in matrix factorization, is essential for optimal results. This can be done by using a grid search that takes in a range of values for different parameters and find the best parameters based on the problem at hand.

RECOMMENDATIONS.

. The user experience should be a priority. Implement user-friendly interfaces that allow users to provide feedback, rate items, and refine their preferences. User feedback can be used to continuously improve recommendations.

CONTACT INFORMATION.

Thank you for giving me the opportunity to present my findings. In case of any questions you can contact me through:

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