CS145 Midterm Report

February 18th, 2019

1 Team Information

- Group Number: 4
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2 Problem Definition and Formalization

Companies like IMDb, Netflix, and MovieLens all include a recommendation system where users can find potential movies given their previous browsing history and ratings. They are able to construct user profiles with this information, and further improve the films that they would recommend.

In this project, we are given a dataset consisting of several CSV files that include movie metadata, user ratings, and movie genome tags. Using all of this information, we want to evaluate several different models so that we can answer the following question: given an unseen {user, movie} pair, what would the user rate that movie?

3 Proposed Methods

3.1 Subtasks and Problem Formalization

We will break this project into the subtasks of data processing, learning method implementation, and model tuning. In the data processing stage we will try to gather our data into a format that we can easily work with. Currently our data exists in multiple CSV files that need to be transformed into a feature vector. Then we can use this feature vector to learn and predict ratings. We will try different learning algorithms and test and tune the hyperparameters for these algorithms.

3.2 Data Preparation

Our rating data exists in tuples that contain a user ID, a movie ID, and a rating. The ID numbers do not tell us anything about the properties of a user or movie, so we need some way to convert these into meaningful features. We have a file that links the movie ID to a genome tag vector, which is a feature vector with the length of 1128. Each attribute in the vector has a value from 0 to 1. One idea we have is to use this genome information as the feature vector for the movie ID. For the user ID, we can calculate another feature vector with the same dimensionality as the movie feature vector. We will do this by using the user's rating for a movie to weight the movie's genome tag vector and summing across all the movies that a user has rated. This generates a user genome tag vector that indicates which types of movies appeal to that user. Then for each movie and user pair, we can generate a similarity value by calculating the distance between the user feature vector and the movie feature vector. We can try this using an euclidean distance function or by taking the dot product of the two feature vectors. Then we can then train our models from this similarity value.

Another idea that we have is to use the movie's genre information and manually generate attributes to learn from. We can encode the genres with 1 or 0 to indicate whether a movie is categorized as a given genre or not. We could also use other information such as the movie's release year and average movie rating. This would result in a smaller feature vector which we would be able to more easily work with. We could also capture details that would be left out with the genome tag approach. We would generate a user feature vector in the same fashion. This could include attributes such as a user's average rating for movies of each genre and the total number of a user's reviews. We will try to normalize this data and test if this produces better results.

3.3 Learning Algorithms

We plan to use linear regression and deep neural networks in order to learn from the data. For linear regression, we would use gradient descent to minimize our error. We would also try to see if regularization improves our regression. Testing must be done in order to find which regularization constant fits the best. In our deep neural network we will use backpropagation to decrease our training error. We could tune the number of hidden layers, the size of our hidden layers, the connectedness of our network, and the activation functions that each neuron uses. We will submit our best model out of both of these two methods.

4 Experiment Design and Evaluation

4.1 Evaluation Metric

To assess our model's accuracy, we will use the root mean square error (RMSE) shown below.

$$\text{Error} = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{N}\left(y_{i_{\text{predicted}}} - y_{i_{\text{actual}}}\right)^2\right)}$$

This is an appropriate cost metric, because we want to minimize the difference between our predicted ratings and the actual values. Furthermore, we want to more severely punish larger errors as opposed to smaller errors, and thus squaring makes sense.

4.2 Model Selection

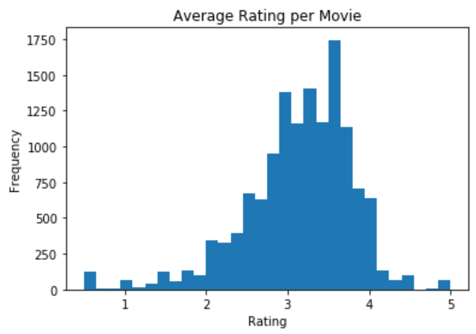
In order to perform model selection for different methods, we evaluate our models based upon our validation set. We first partition our given data into mutually exclusive sets: (1) training data, and (2) validation data. We will try to train models using linear regression and deep neural networks on the training data. In the process we will fine-tune the hyperparameters of each method by selecting different activation functions, changing the size of our neural networks, modifying the regularization constant, etc. Then we can select the best model by selecting the one that achieves the lowest RMSE.

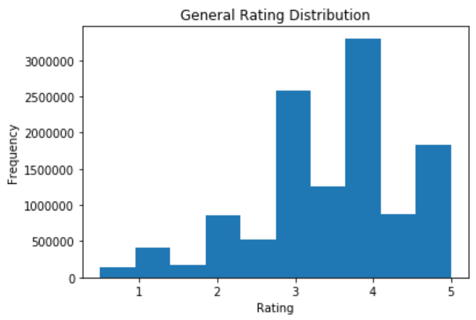
4.3 Current Kaggle Submission

Our current Kaggle score is 1.03952. This score was achieved simply by finding the average rating for all the user-movie pairs in the training data and predicting that average rating for all the points in the test data. The main purpose of trying this method was to get more familiar with the data formatting for the Kaggle submission. It gave a surprisingly good score, beating many other teams despite the model's simplicity.

5 Discussion

From the data preprocessing stage, we gained insights about the general distribution of the data. The data is right skewed which led us to consider whether we should normalize data and which normalization methods we should choose.





As shown in plots above, the average rating per movie is between three and four. Also, users tend to give full rather than half scores, and there are fewer low ratings when compared to medium and high ratings.

Following those observations, we have decided to normalize the ratings so that the low scores can reflect the correct amount of negativity. Furthermore, we have discussed whether we should round our predictions to the nearest half or whole number. Since RMSE is used for evaluating our Kaggle submission, we have decided to keep the real values from the predicted output. This way the performance of our models more accurately corresponds to our submission score.

Lastly, we found that there are some potential performance issue when training our models. Due to the sheer size of the data, when we attempted to use `genome_tags.csv` to convert the movie and user ids into feature vectors, the amount of data caused us to run out of memory. We had to use lazy loading and other workarounds to fix the problem. We resolved the issue by exporting our intermediate processed data as a CSV file.

6 Schedule

- February 24th: Finish data preprocessing
- March 3rd: Train 2 different models: Linear Regression and Deep Neural Network
- March 6th: Tune hyperparameters and finalize features used
- March 10th: Begin final report
- March 16th: Double check our current Kaggle ranking
- March 17th: Finalize report and Kaggle submission

7 References

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3. Spark, C. (2018, October). Tutorial: Practical Introduction to Recommender Systems.
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