Movielens Project

John Balzani

1/3/2020

Executive Summary:

How well can we predict how well someone will like a certain movie? The purpose of this project is to answer that by predicting the rating on a scale of 0.5 to 5 that users will give to movies. A model is tested which takes into account the impact of the individual movie, the impact of the individual user, and regularizes the ratings that are given to movies.

The dataset which this model is trained and tested on is the Movielens dataset, which is a dataset of 10 million ratings that users have given to movies. This dataset contains the following pieces of data: the userId of the user who rated the movie, the movieId of the move rated, the rating given to the movie, the title of the movie, and the genres that pertain to that movie. About 9 million observations were used to train the model (the "edx" dataset), with the remaining 1 million (the "validation" dataset) being used only for model validation.

This project undertook the following key steps. First, the data was cleaned and explored. Second, the model was created. Third, the model was tested with Root Mean Square Error (RMSE) being used as the metric to judge how much the rating predicted by the model deviated from the actual rating given. It was found that the final model had an RMSE of .86511, meaning that the predicted movie ratings were different from the actual ones by .86511 on average.

Methods and Analysis:

The edx dataset was briefly reviewed for NA values, outliers, and duplicates. It was found that there are no problematic outliers or NA data points, which can be seen below.

```
#check for NAs in data
edx %>% filter(is.na(userId))
```

```
## [1] userId    movieId   rating    timestamp title     genres
## <0 rows> (or 0-length row.names)
```

```
edx %>% filter(is.na(movieId))
```

```
## [1] userId    movieId   rating    timestamp title     genres
## <0 rows> (or 0-length row.names)
```

```
edx %>% filter(is.na(rating))
```

```
## [1] userId    movieId   rating    timestamp title     genres
## <0 rows> (or 0-length row.names)
```

```
edx %>% filter(is.na(timestamp))
```

```
## [1] userId    movieId   rating    timestamp title     genres
## <0 rows> (or 0-length row.names)
```

```
edx %>% filter(is.na(title))
```

```
## [1] userId    movieId   rating    timestamp title     genres
## <0 rows> (or 0-length row.names)
```

```
edx %>% filter(is.na(genres))
```

```
## [1] userId    movieId   rating    timestamp title     genres
## <0 rows> (or 0-length row.names)
```

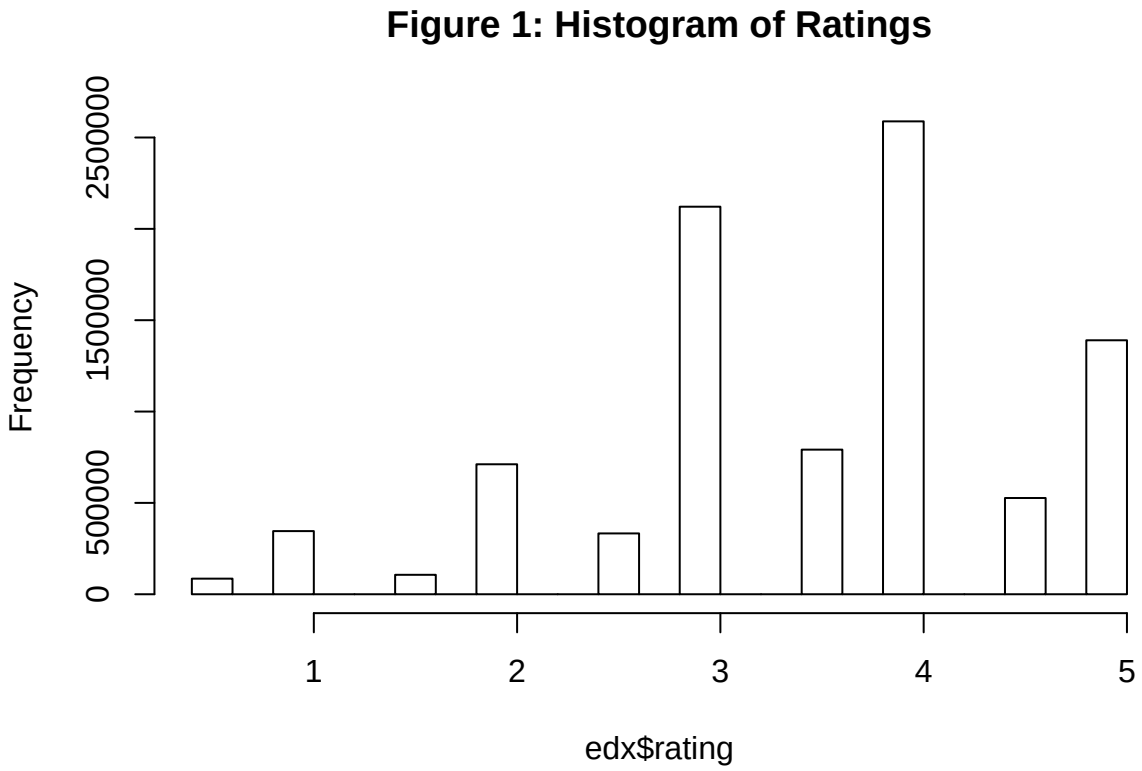
After checking for duplicates, it was found that there are no duplicate values, as can be seen below. After checking if data cleaning was needed, the data was next explored.

```
#check for duplicates
duplicates <- edx[duplicated(edx), ]
duplicates
```

```
## [1] userId    movieId   rating    timestamp title     genres
## <0 rows> (or 0-length row.names)
```

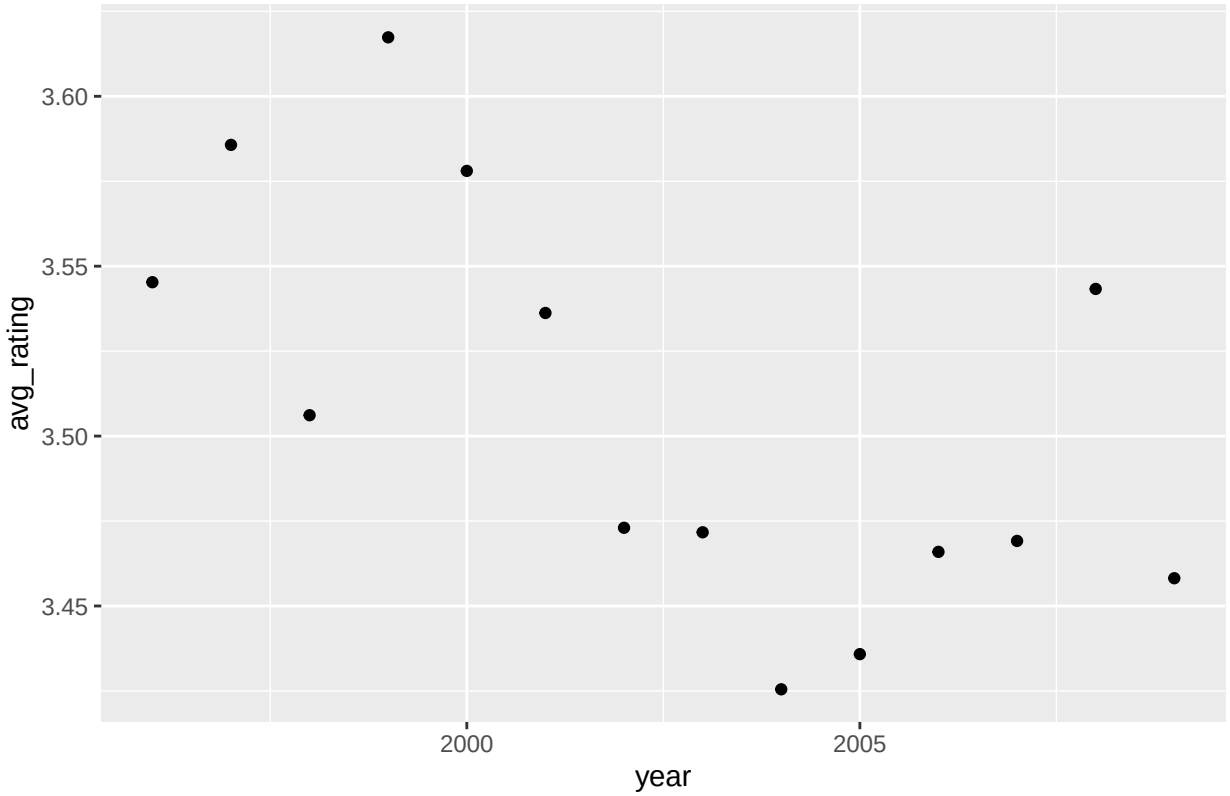
When exploring the data, it can be noticed that the ratings vary from 0.5 to 5, with a rating of 4 being most common, followed by a rating of a 3, and then a rating of a 5 (Figure 1). It seems that positive ratings (4 or 5) are more common than very negative ratings such as 2 or below. The average rating stands at 3.512, while the median rating is 4. The ratings have a standard deviation of 1.06.

A histogram of the ratings was generated, in order to better spot outliers and visualize the ratings distribution (Figure 1).



In order to explore the timestamp variable, the timestamp was converted into a date. We can see that the movie ratings were made between January of 1995 and January of 2005, which is a long period of time. In order to see whether there is any relationship between the rating and the time of the rating, as was seen in the Netflix dataset, the date of the movie review was plotted against the rating (Figure 2) (Koren, 2009). 1995 was removed since only 2 reviews were made during this year and the average rating of 4 was much different than the ratings for other years. From this, we can see that the average rating fluctuates by year, with a possible slight decline overall.

Figure 2: Rating vs. Time of Rating



In order to explore whether or not there is any relationship between the genre of the movie and its rating, the average rating for each genre was calculated. It appears that there is a genre impact, as some genres are rated higher than others. The 10 highest rated genres are shown below, with the highest rated genre being Crime|Mystery|Thriller having an average rating of 4.20.

Figure 3: Top 10 Highest Rated Genres

```
## # A tibble: 10 x 3
##    genres                                      n avg_rating
##    <chr>                                   <int>      <dbl>
##  1 Crime|Mystery|Thriller                  26892       4.20
##  2 Action|Adventure|Comedy|Fantasy|Romance 14809       4.20
##  3 Adventure|Drama|Film-Noir|Sci-Fi|Thriller 13957       4.15
##  4 Adventure|Drama|War                     14137       4.08
##  5 Crime|Horror|Thriller                   33757       4.08
##  6 Crime|Film-Noir|Mystery|Thriller        24961       4.06
##  7 Comedy|Crime|Drama|Thriller             24341       4.06
##  8 Adventure|Mystery|Thriller              14712       4.04
##  9 Comedy|Drama|Romance|War                41762       4.01
## 10 Crime|Drama|Sci-Fi|Thriller             10730       4.00
```

The 10 lowest rated genres are shown below, with the lowest genre being Adventure|Children|Drama with an average rating of 2.79.

Figure 4: Bottom 10 Lowest Rated Genres

```
## # A tibble: 10 x 3
##    genres                       n avg_rating
##    <chr>                    <int>      <dbl>
##  1 Adventure|Children|Drama 10144       2.79
##  2 Action|Crime|Sci-Fi      17331       2.82
##  3 Comedy|Horror            37394       2.84
##  4 Comedy|Thriller          13558       2.87
##  5 Children|Comedy|Fantasy  18784       2.88
##  6 Horror                   68738       2.88
##  7 Action|Horror|Sci-Fi     10364       2.91
##  8 Horror|Sci-Fi            31281       2.92
##  9 Children|Comedy          63483       2.92
## 10 Sci-Fi                   10125       2.93
```

If someone were to ask me to predict how much a movie rating would differ from the average rating, my first question would be "What is the movie?" For this reason, I thought it made sense to start with a model that looks at the impact that the specific movie has on the rating, since of course good movies will get better reviews than bad ones.

The algorithm is: subtract the rating for movies with that particular feature from the mean rating, and take the mean of that difference as the impact of the feature. Then use that feature impact as a predictor. Next, repeat the process with the residuals of the mean and all other feature impacts already calculated from the algorithm. In this case, the feature impact we are looking at is the indiviual movie impact, so we subtract the rating for the individual movie from the mean rating, and then we take the mean of that and use it as a predictor. The formula for this specific movie impact is spec_movie_dev = mean(rating - mean_edx), where mean_edx is the mean rating on the training set (Irizarry, 2019).

If I had to predict how a person would rate a movie knowing the movie title, I would then want to know more about the rater and how they rate other movies. For this reason, the expected deviation from the mean rating due to the user was included next in my model. The formula for this impact is user_dev = mean(rating - mean_edx - spec_movie_dev) (Irizarry, 2019).

Predicted ratings were generated for each entry. Predictions greater than a 5 were reduced to 5, and predictions lower than 0.5 were increased to 0.5. The RMSE thus far is 0.8565338. I believe a lower RMSE can be reached. I explore regularizing the specific movie and user deviations, using the formulas regul_spec_movie_dev = sum(rating = mean_edx)/(alpha + n) and regul_user_dev = sum(rating - mean_edx - regul_spec_movie_dev)/(a + n), where alpha is a sequence from 0 to 20 by 2 and n is the number of ratings (Irizarry, 2019). As Dr. Irizarry stated in his lectures, movies with few ratings are more likely to have large deviations from the mean (Irizarry, 2019). These extreme ratings given by only a few people are not representative of the rating that would be given by a larger number of people, and regularization can correct for this by penalizing ratings done by only a few people.

From observing the vector of the RMSE for each alpha, it can be seen that 0 is the lowest alpha.

```
##  [1] 0.8565338 0.8566076 0.8568072 0.8570850 0.8574159 0.8577836 0.8581767
##  [8] 0.8585878 0.8590113 0.8594429 0.8598796
```

I then look closer to see if there is an optimal alpha close to zero, with each alpha increasing by 0.1 from 0 to 1.

```
##  [1] 0.8565338 0.8565327 0.8565324 0.8565327 0.8565337 0.8565352 0.8565372
##  [8] 0.8565396 0.8565426 0.8565459 0.8565497
```

The optimal value for alpha is 0.2, which gives an RMSE of 0.8565324.

It appears that the RMSE is only slightly reduced by regularization on the training set. This model gives an RMSE on the **training** set of 0.8565324. This is a relatively low RMSE, so it's time to try my luck on the test set. For example, the winners of the Netflix competition, who were tasked with improving Netflix's recommendation algorithm, had an RMSE of .8713 on their winning algorithm (Koren, 2009). The final model is Predicted Rating = mean_edx + regul_spec_movie_dev + regul_user_dev + epsilon, where regul_spec_movie_dev is the regularized specific movie impact, regul_user_dev is the regularized user impact, and epsilon represents the residuals.

Results:

The RMSE of the final model on the test set was 0.8651118, meaning that the predicted rating deviated from the actual rating by 0.8651118 on average in the test set. Since the winners of the Netflix competition had an RMSE of .8713 on their winning algorithm, this is an acceptable RMSE for now (Koren, 2009).

Below is a histogram of the predicted ratings, with a histogram of the actual ratings below it (Figures 5, 6). It can be seen that the predicted ratings are generally close to the actual ratings.

Figure 5: Histogram of Predicted Ratings

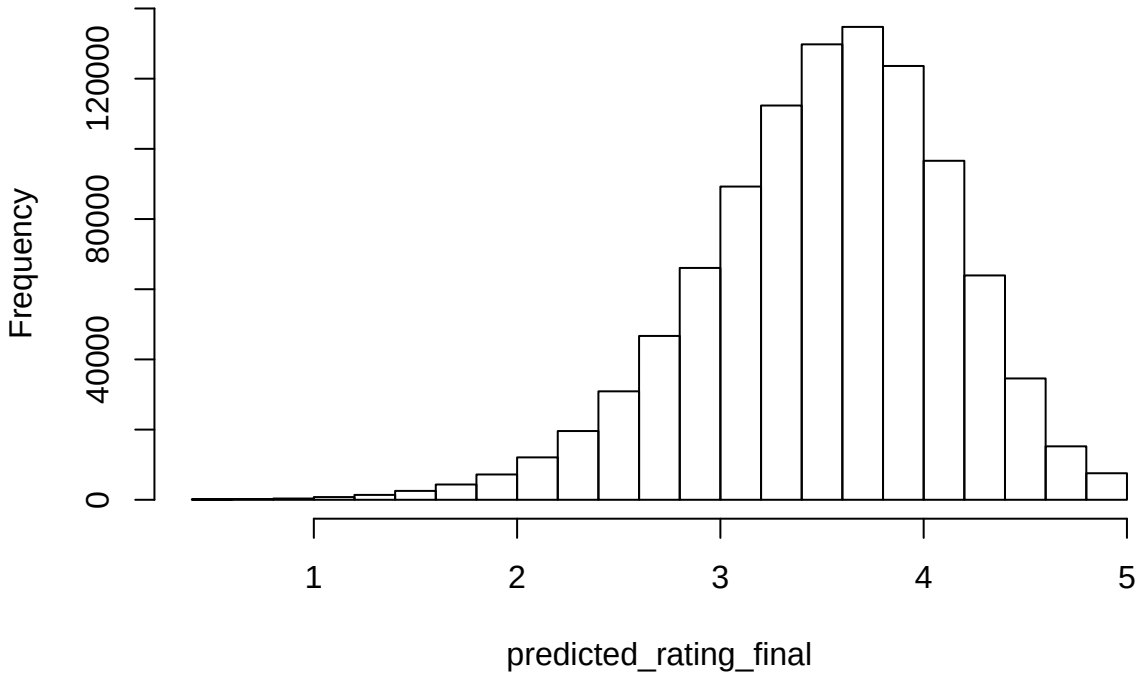
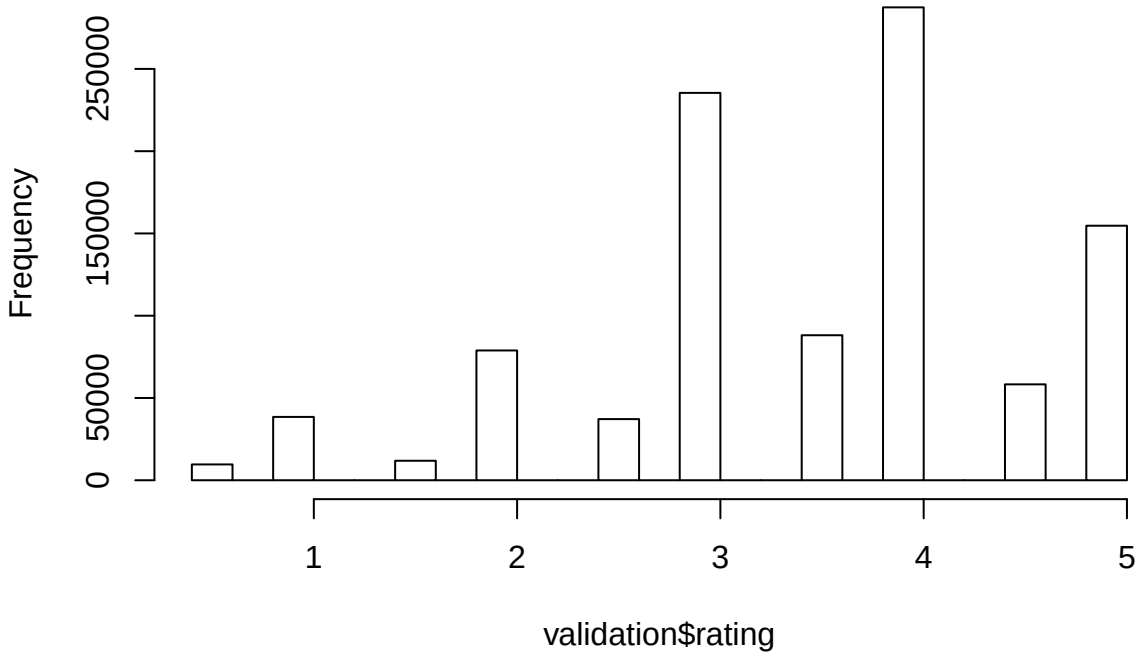


Figure 6: Histogram of Actual Ratings



Conclusion:

A model of rating prediction based on the regularized specific movie impact and the regularized user impact was developed using the edx portion of the Movielens dataset, and thie model was tested on the validation data set. This model was found to have an RMSE of 0.8651118.

While this RMSE is acceptable, there are limitations to this model. This model's predictions are not rounded to intervals of 0.5, such as the actual ratings are. As the project was only to provide predictions, and a prediction of 3.8, for example, is still very valuable, the predictions were not rounded. However, this would be an interesting area for future work. Another limitation of this model is that it does not take into account the genre of the movie or the time the rating was made. An area for future work involves incorporating these features into a model to further reduce RMSE.

References:

Irizarry, Rafael. Building the Recommendation System, n.d. ———. Regularization, n.d.

Koren, Yehuda. "The BellKor Solution to the Netflix Grand Prize," 2009.