MovieLens

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Project 2 - MovieLens

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Generates predicted movie ratings and calculates RMSE.

```
## Joining, by = c("userId", "movieId", "rating", "timestamp", "title", "genres")
```

Quiz

Q1) How many rows and columns are there in the edx dataset?

```
## [1] "The edx dataset has 8333401 rows and 6 columns."
```

Q2) How many zeros and threes were given in the edx dataset?

```
## [1] "0 ratings with 0 were given and 1964616 ratings with 3"
```

Q3) How many different movies are in the edx dataset?

```
##   n_movies
## 1    10677
```

Q4) How many different users are in the edx dataset?

```
##   n_users
## 1   69878
```

Q5) How many movie ratings are in each of the following genres in the edx dataset?

```
## [1] "Drama has 3620412 movies"

## [1] "Comedy has 3279256 movies"

## [1] "Thriller has 2153457 movies"

## [1] "Romance has 1586080 movies"
```

Q6) Which movie has the greatest number of ratings?

```
## # A tibble: 10,676 x 2
##    title                                                     number
##    <fct>                                                      <int>
##  1 Pulp Fiction (1994)                                        28892
##  2 Forrest Gump (1994)                                        28801
##  3 Silence of the Lambs, The (1991)                           28085
##  4 Jurassic Park (1993)                                       27177
##  5 Shawshank Redemption, The (1994)                           26006
##  6 Braveheart (1995)                                          24366
##  7 Terminator 2: Judgment Day (1991)                          24077
##  8 Fugitive, The (1993)                                       23985
##  9 Star Wars: Episode IV - A New Hope (a.k.a. Star Wars) (1977)  23743
## 10 Apollo 13 (1995)                                           22498
## # ... with 10,666 more rows
```

Q7) What are the five most given ratings in order from most to least?

```
##
##       4       3       5     3.5       2
## -2396162 -1964616 -1287473  -733522  -658534
```

Q8) True or False:

In general, half star ratings are less common than whole star ratings (e.g., there are fewer ratings of 3.5 than there are ratings of 3 or 4, etc.).

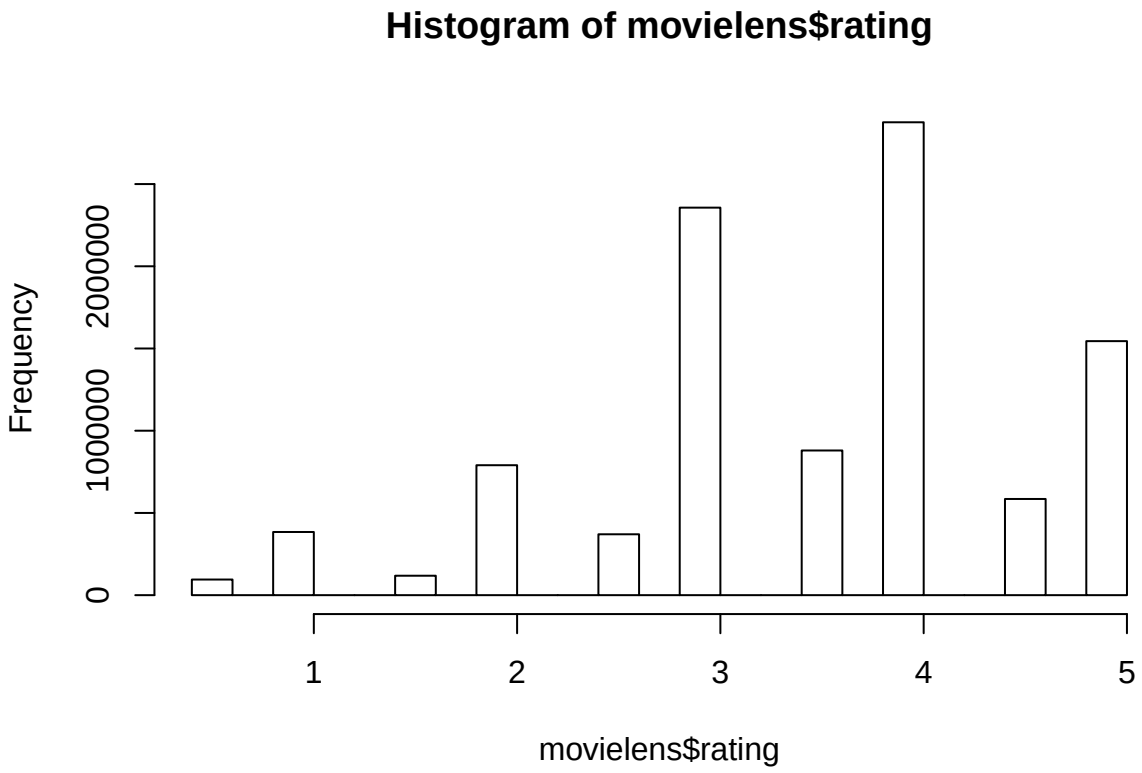
```
## [1] TRUE
```

Data Analysis

More than 10 million ratings.

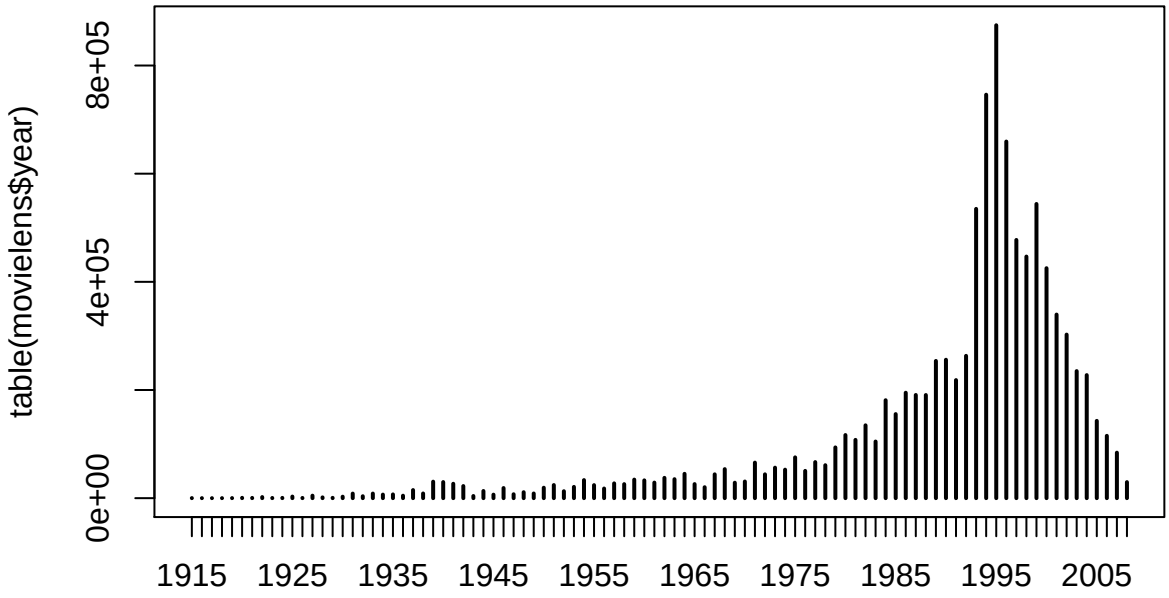
```
## 'data.frame':    10000054 obs. of  6 variables:
##  $ userId   : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ movieId  : int  122 185 231 292 316 329 355 356 362 364 ...
##  $ rating   : num  5 5 5 5 5 5 5 5 5 5 ...
##  $ timestamp: int  838985046 838983525 838983392 838983421 838983392 838983392 838984474 838983653 83
##  $ title    : Factor w/ 10676 levels "...All the Marbles (a.k.a. The California Dolls) (1981)",..: 13
##  $ genres   : Factor w/ 797 levels "(no genres listed)",..: 577 187 489 210 98 71 460 542 309 274 ..
```

The plot shows that 5 ratings are more common that 0.5.

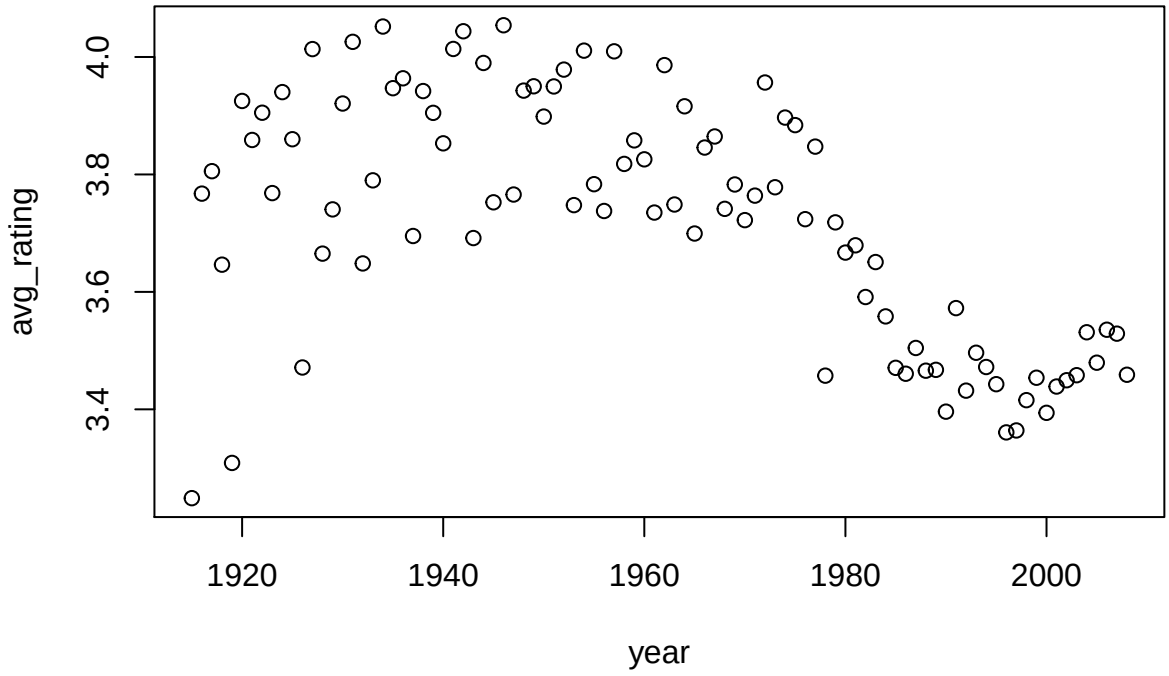



```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.500   3.000   4.000   3.512   4.000   5.000
```

Recent movies get more ratings.



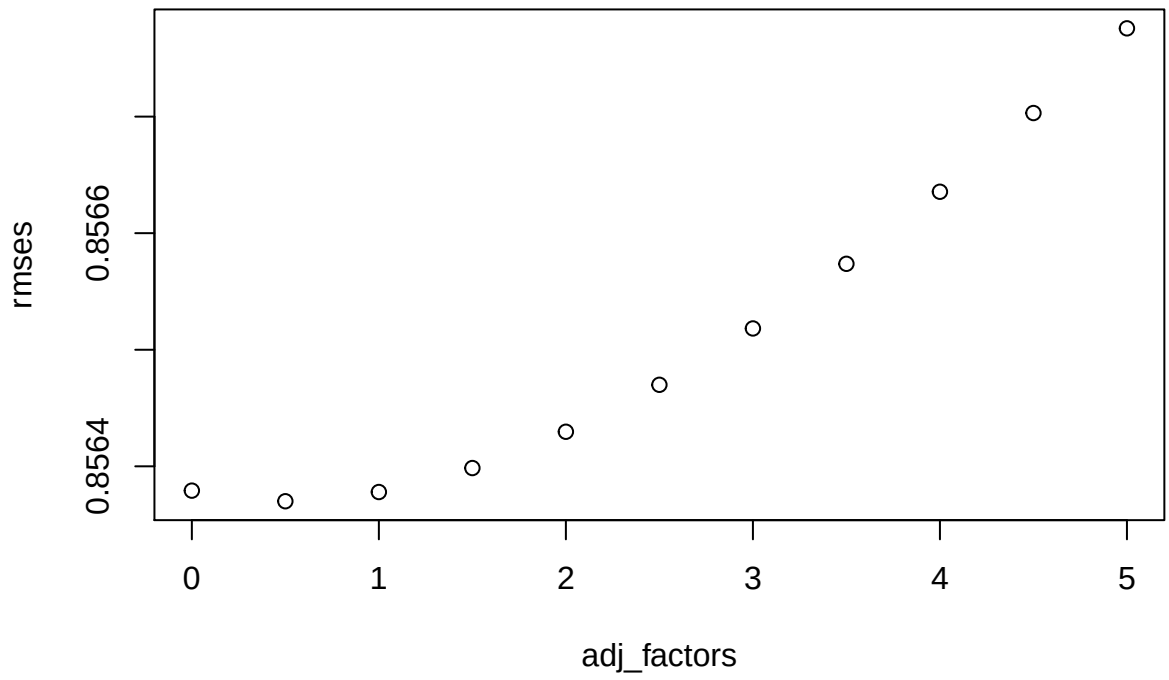
Last decades, ratings average get lower.



Results

RMSE

$\sqrt{\overline{(TrueRatings - PredictedRatings)^2}}$




```
## [1] "Best RMSE: 0.856370050305869 is achieved with Adjustment Factor: 0.5"
```

Predictions

CSV file <predictions.csv>

```
predictions <- sapply(adj_factor,function(l){

  # The mean of training set
  mts <- mean(edx$rating)

  # Get movie effect with best adjustment factor
  me <- edx %>%
    group_by(movieId) %>%
    summarize(me = sum(rating - mts)/(n()+l))

  # Best adjust
  am <- edx %>%
    left_join(me, by="movieId") %>%
    group_by(userId) %>%
    summarize(am = sum(rating - me - mts)/(n()+l))

  # Predict on validation set
```

```
  predicted_ratings <-
    validation %>%
    left_join(me, by = "movieId") %>%
    left_join(am, by = "userId") %>%
    mutate(pred = mts + me + am) %>%
    .$pred

  return(predicted_ratings)

})

write.csv(validation %>% select(userId, movieId) %>% mutate(rating = predictions),
          "predictions.csv", na = "", row.names=FALSE)
```

Conclusion

Using 1/6 as part of the data for the MovieLens validation set and removing the low rating

records in the training model, it was possible to obtain an RMSE index of 0.8563 and,

verifying it with actual data, the model was reasonably efficient.

References

http://www.montana.edu/rotella/documents/ https://www.calvin.edu/~rpruim/courses/ http://www.datainsight.at/report/ https://r4ds.had.co.nz http://stackoverflow/