

Capstone project report:

IMPROVING NETFLIX MOVIE RECOMMENDATIONS

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NETFLIX

The Client ?:

NETFLIX, an online entertainment platform that offers streaming of movies and TV series

The Problem ?:

NETFLIX relies on an accurate recommender system to provide users with a selection of digital content that is most likely to be enjoyed by the users

**Can the accuracy of predicted ratings
be improved ?**

Obtaining the Data: The Netflix Prize Dataset

- Originally released as part of an online competition to improve Netflix recommendation engine
- Downloaded from :
<https://www.kaggle.com/netflix-inc/netflix-prize-data>
- The entire data set contains 4 .txt files, comprising 100480507 ratings, by 480189 users, for a collection of 17770 movies
- The data set also contains a .csv file with a list of movie IDs and titles

Data Wrangling

The format of the data in the .txt files is as follows:

MovieX:

Customer ID_A, rating, date of rating

Customer ID_B, rating, date of rating

Movie Y:

Customer ID_C, rating, date of rating

CustomerID_D, rating, date of rating

The 4 .txt files were compiled and formatted into a single data frame, as shown here:

	User ID	Rating	Date	Movie ID
1	1488844	3	2005-09-06	1
2	822109	5	2005-05-13	1
3	885013	4	2005-10-19	1
4	30878	4	2005-12-26	1
5	823519	3	2004-05-03	1

Data Wrangling:

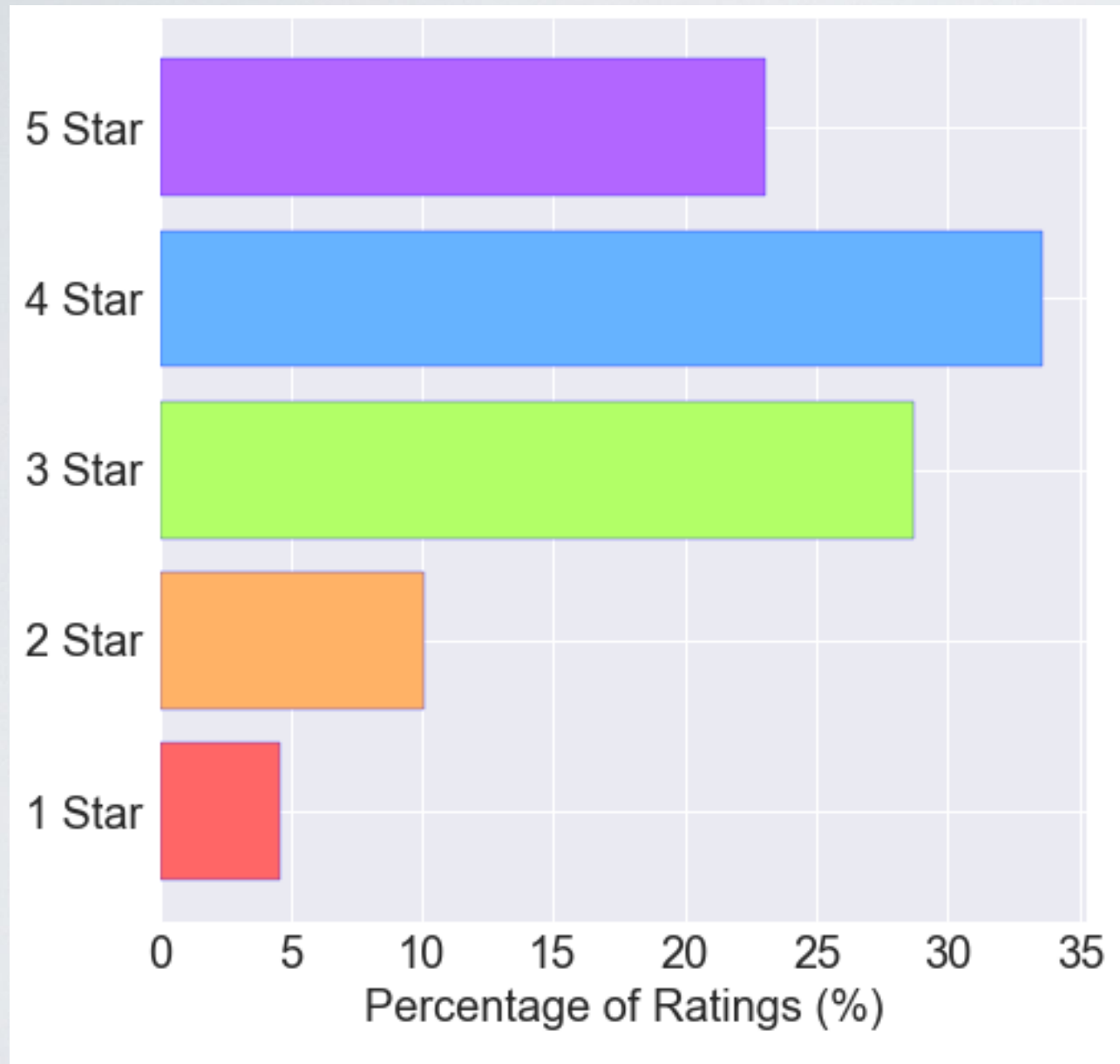
Querying the Open Movie Database (OMDb)

- The OMDb was queried to retrieve the genre of each movie on the dataset. This information was included in the original .csv file containing movie names, as shown here:

	Name	Year	Genres
1	Dinosaur Planet	2003	Documentary, Animation, Family
2	Isle of Man TT 2004 Review	2004	None
3	Character	1997	Crime, Drama, Mystery
4	Paula Abdul's Get Up & Dance	1994	None
5	The Rise and Fall of ECW	2004	None
6	Sick	1997	Short, Drama
7	8 Man	1992	Action, Sci-Fi
8	What the #\$! Do We Know!?	2004	None
9	Class of Nuke 'Em High 2	1991	None
10	Fighter	2001	Action, Drama

Exploratory Data Analysis:

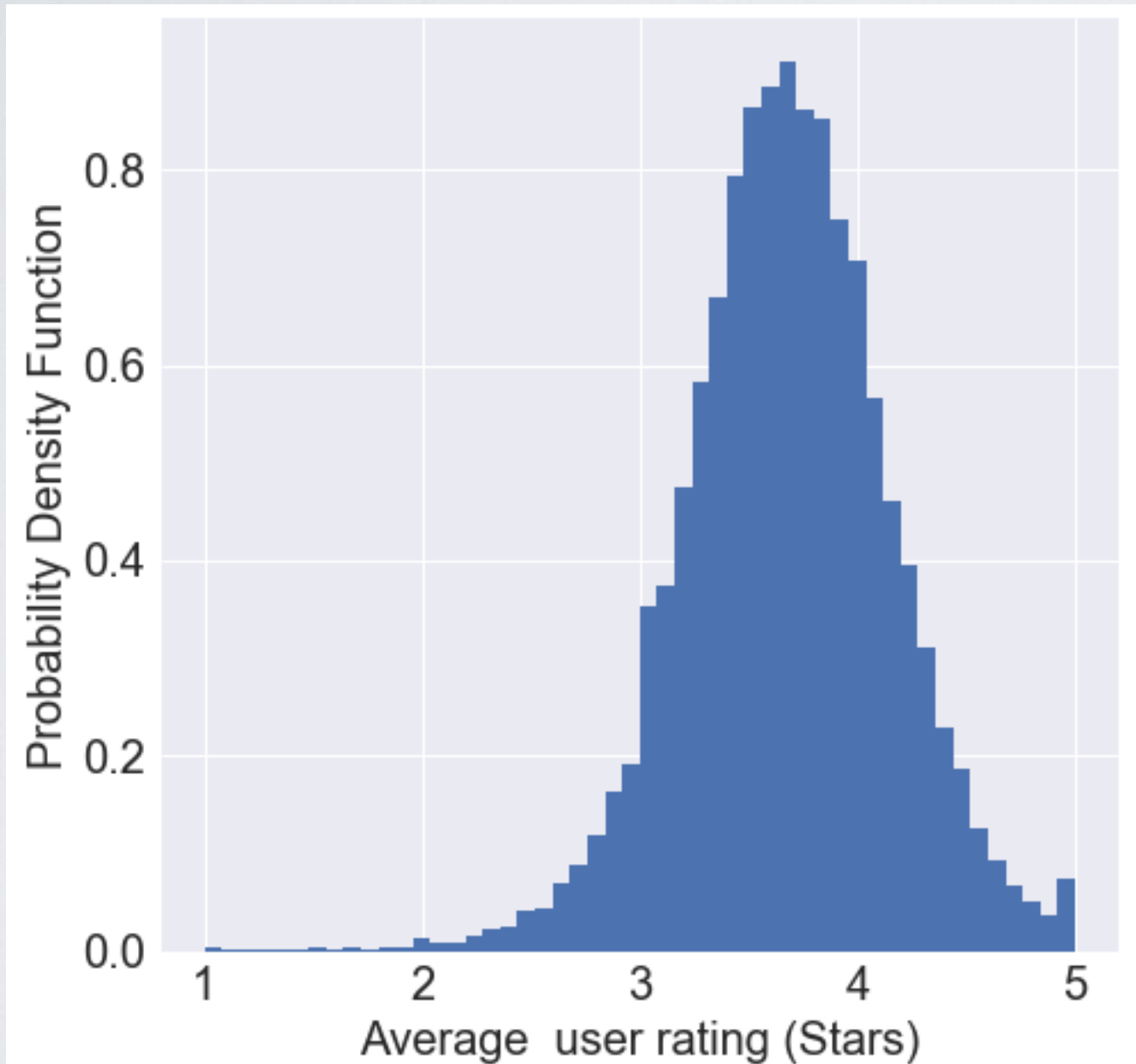
Ratings Frequency Distribution



- Most frequent rating: 4 Stars
- 56% are “good ratings”
(4 or 5 Stars)
- Average rating : ~3.6 Stars
- Standar deviation: 1.09 Stars

Exploratory Data Analysis:

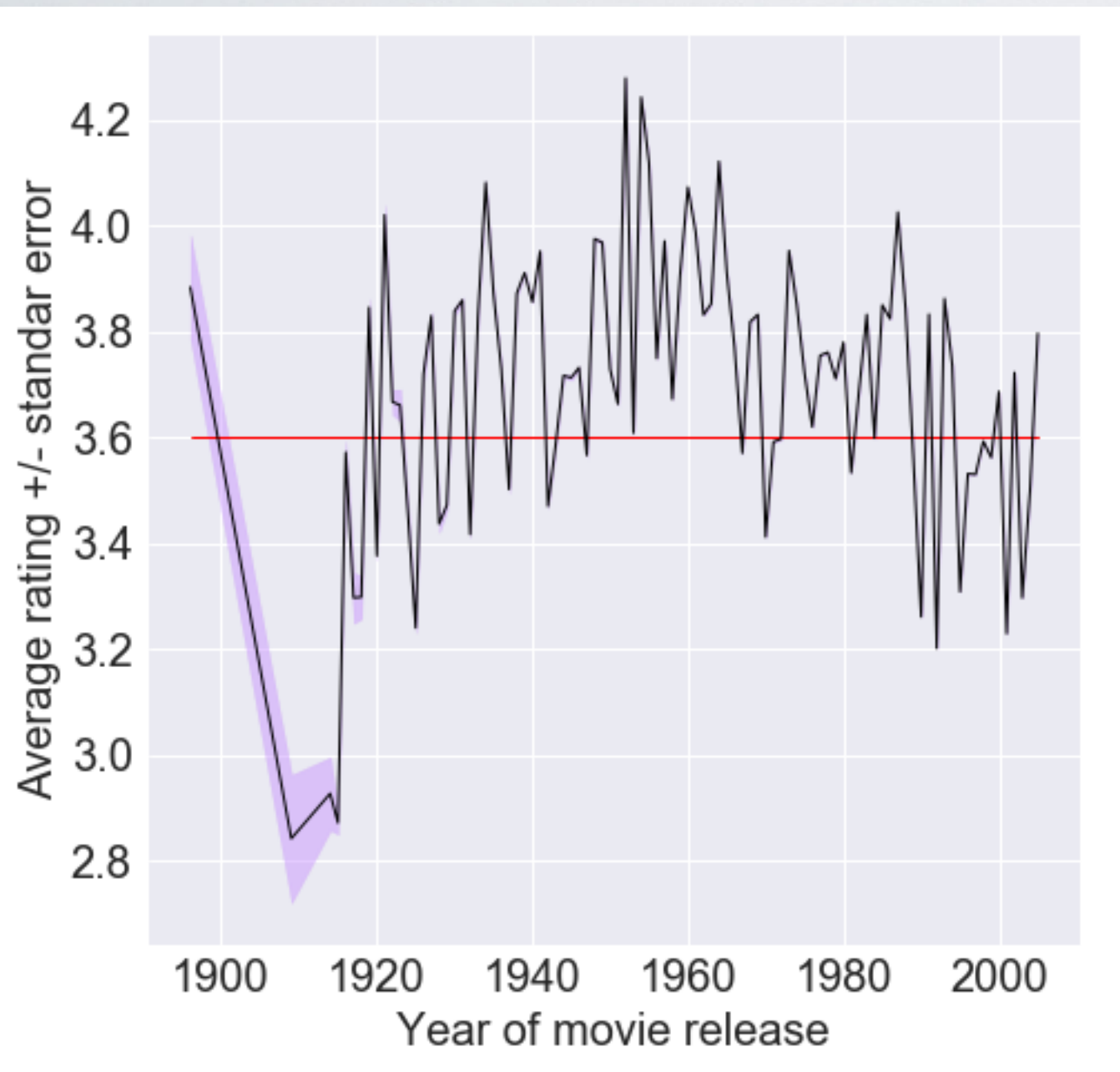
Distribution of users average ratings



- Normally distributed
- ~30% of users have average ratings lower than 3 or higher than 4 Stars.
- Suggests that some users might have a positive or negative rating bias

Exploratory Data Analysis:

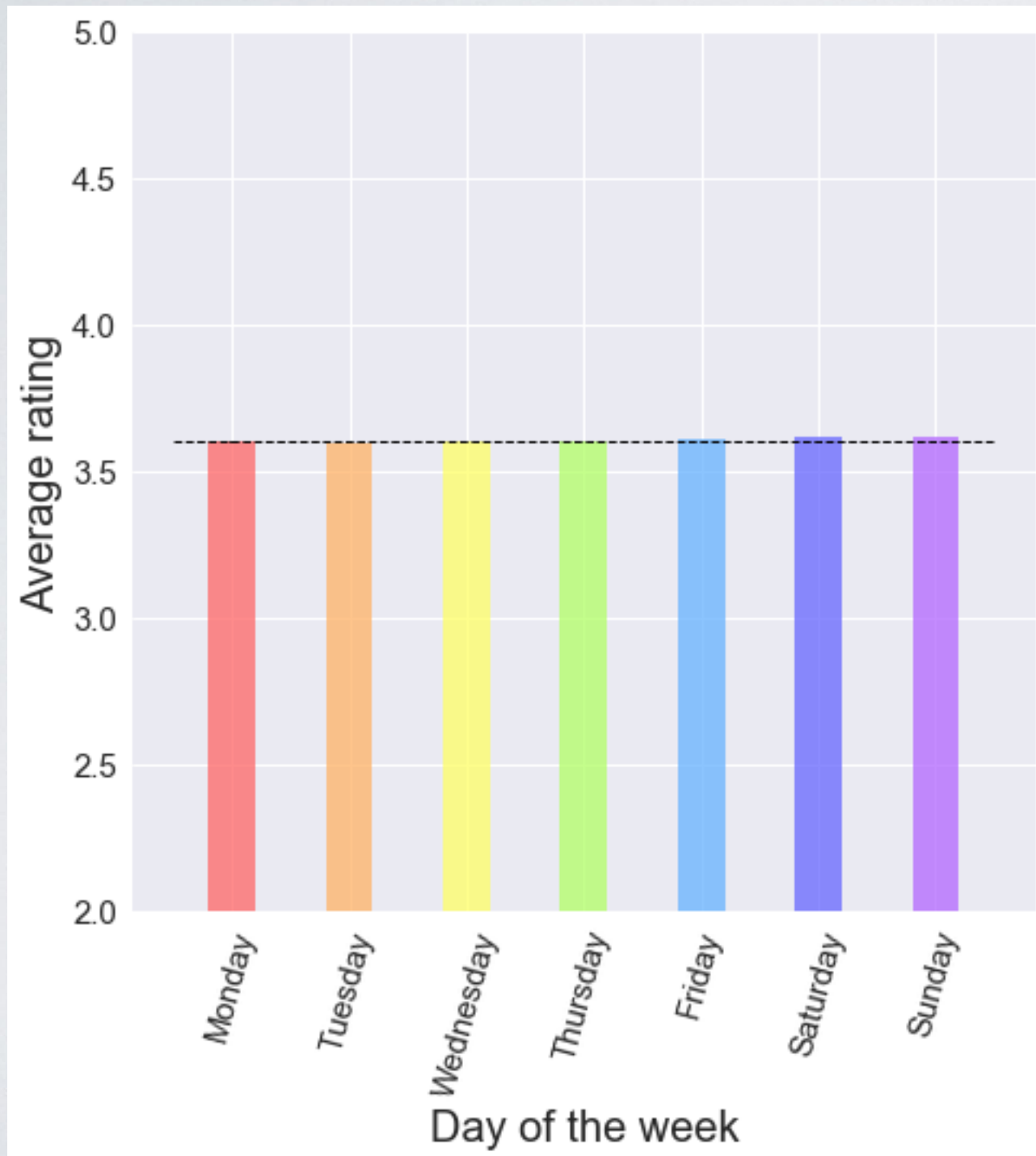
Does the movie release year have an effect on ratings?



- 89 out of 94 years, show significant differences from the overall average (red line)
- Suggest that a movie's release year might significantly affect its rating

Exploratory Data Analysis:

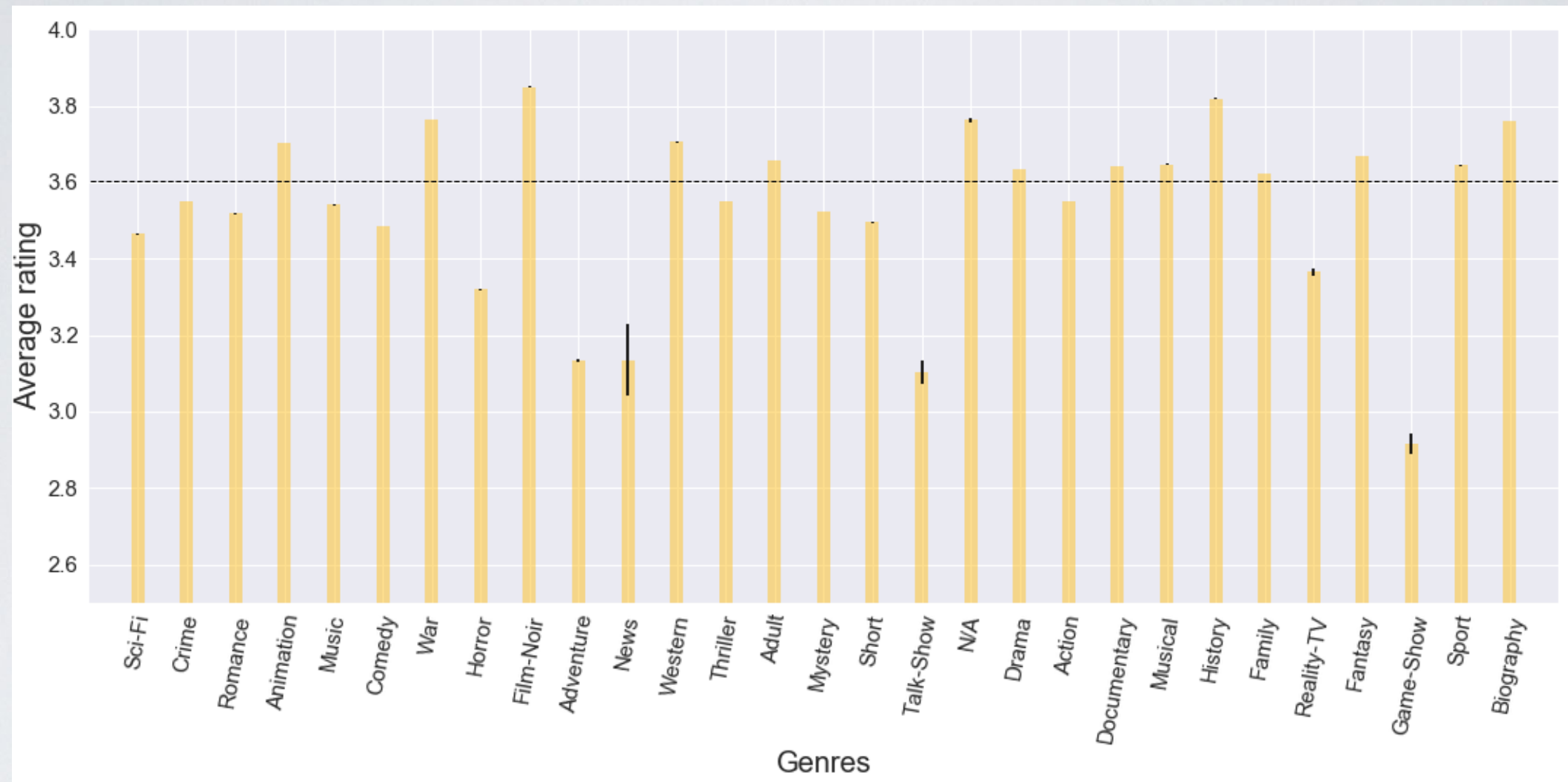
Does the day of the week have an effect of the ratings ?



- Date of rating was converted to day of the week, and the data was grouped accordingly
- No day of the week shows significant differences from the average (dashed line)
- Suggests that the day of the week, does not have an effect on the ratings

Exploratory Data Analysis:

Is the rating of a movie affected by its genre ?



- One-sample t-test showed that all genres differ significantly from the average (dashed line).

Exploratory Data Analysis:

Conclusions

'User specific bias', 'Year of movie release' and 'Movie's Genre' are factors that significantly affect the rating of movies, thus, they can potentially be incorporated into a predictive model for movie preferences and ratings

Predicting movie ratings:

Raw Average

- Rating is predicted as the average of the entire dataset
- In addition, user-, movie-, year-of-release- and genre-specific biases were used to adjusted the predicted ratings
- The root mean squared error (RMSE) was used as a measure of prediction error

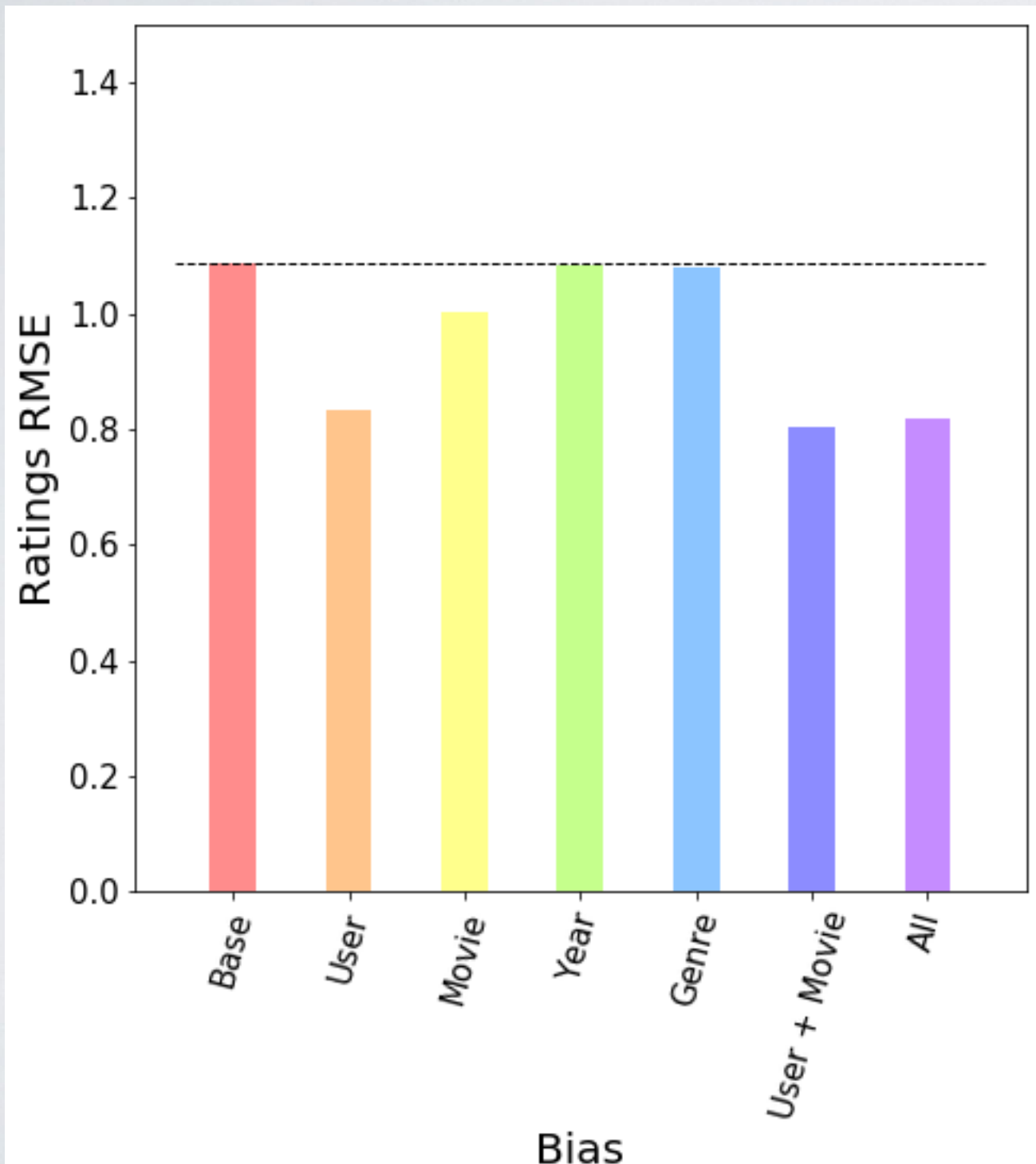
Predicting movie ratings:

Raw Average

******Trying to work with the entire NetFlix prize data set on a single machine proved to be too computationally intensive. Instead, I opted to take a random sample of 1 million rating to work with. The following analysis were performed using this sample******


























Predicting movie ratings:

Raw Average Prediction errors



- Incorporating individual biases (user & movie) gives a modest reduction to errors of the predicted ratings
- Combining multiple biases does not provide further improvement

Predicting movie ratings: Colaborative Filtering (CF).

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- CF methods predict ratings based on the similarity of the items rated by multiple users
- Alternate Least Squares (ALS), is one of such methods, and can be implemented from the pyspark's MLlib

Image: <http://kurapa.com/wp-content/uploads/2014/08/image54.png>

Predicting movie ratings:

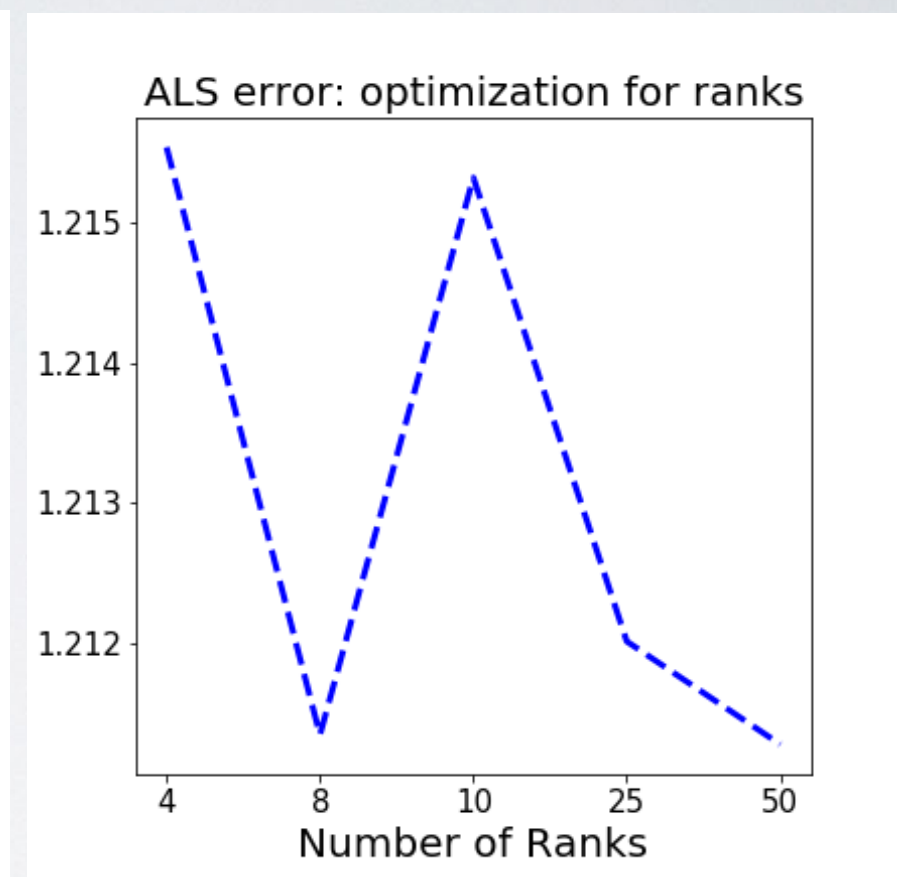
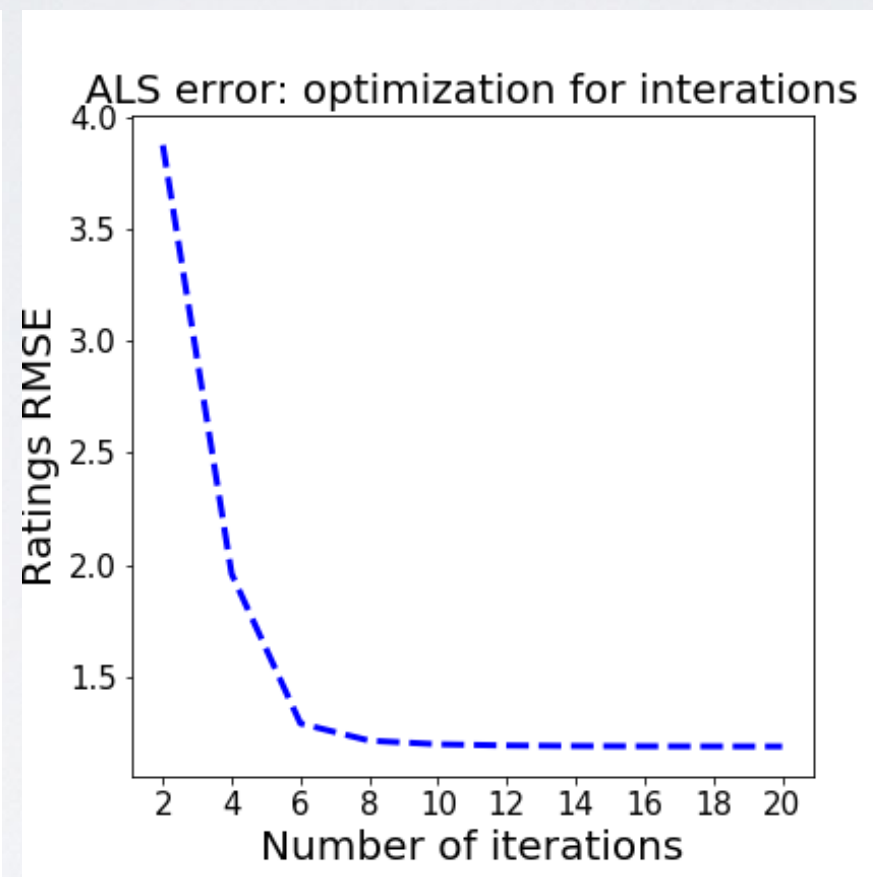
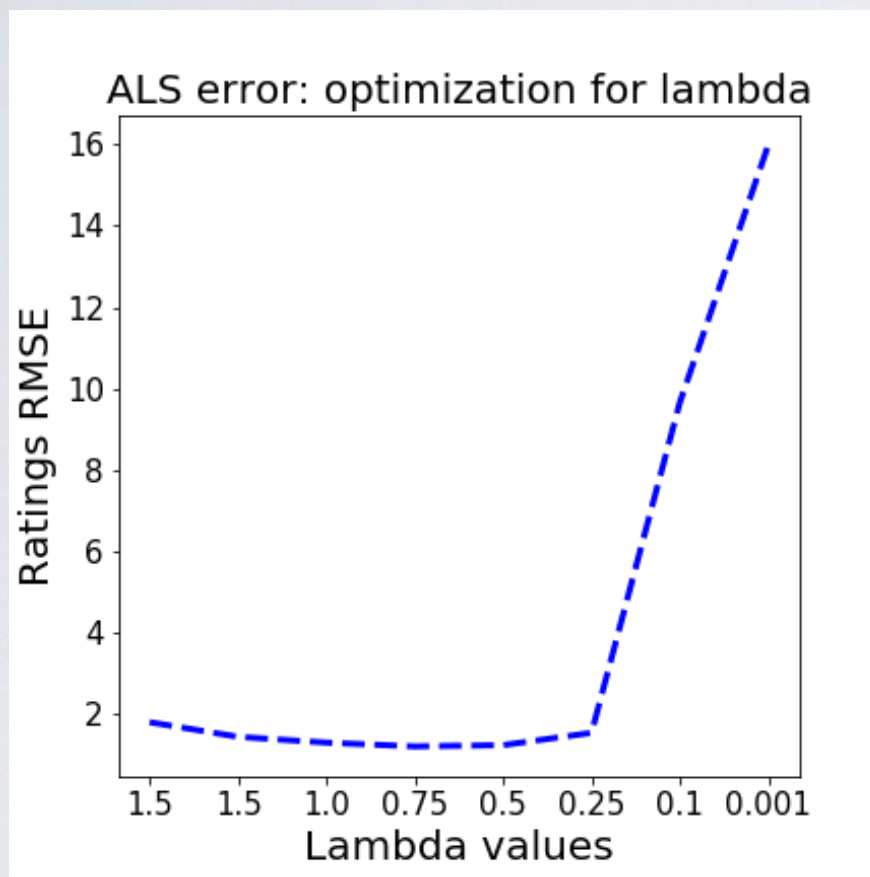
ALS hyperparameters

-) **numBlocks**: is the number of blocks the users and items will be partitioned into in order to parallelize computation (defaults to 10).
-) **rank**: is the number of latent factors in the model (defaults to 10).
-) **maxIter**: is the maximum number of iterations to run (defaults to 10).
-) **regParam**: specifies the regularization parameter in ALS (defaults to 1.0).
-) **implicitPrefs**: specifies whether to use the explicit feedback ALS variant or one adapted for implicit feedback data (defaults to false which means using explicit feedback).
-) **alpha**: is a parameter applicable to the implicit feedback variant of ALS that governs the baseline confidence in preference observations (defaults to 1.0).
-) **nonnegative**: specifies whether or not to use nonnegative constraints for least squares (defaults to false).

Predicting movie ratings:

ALS hyperparameters optimization

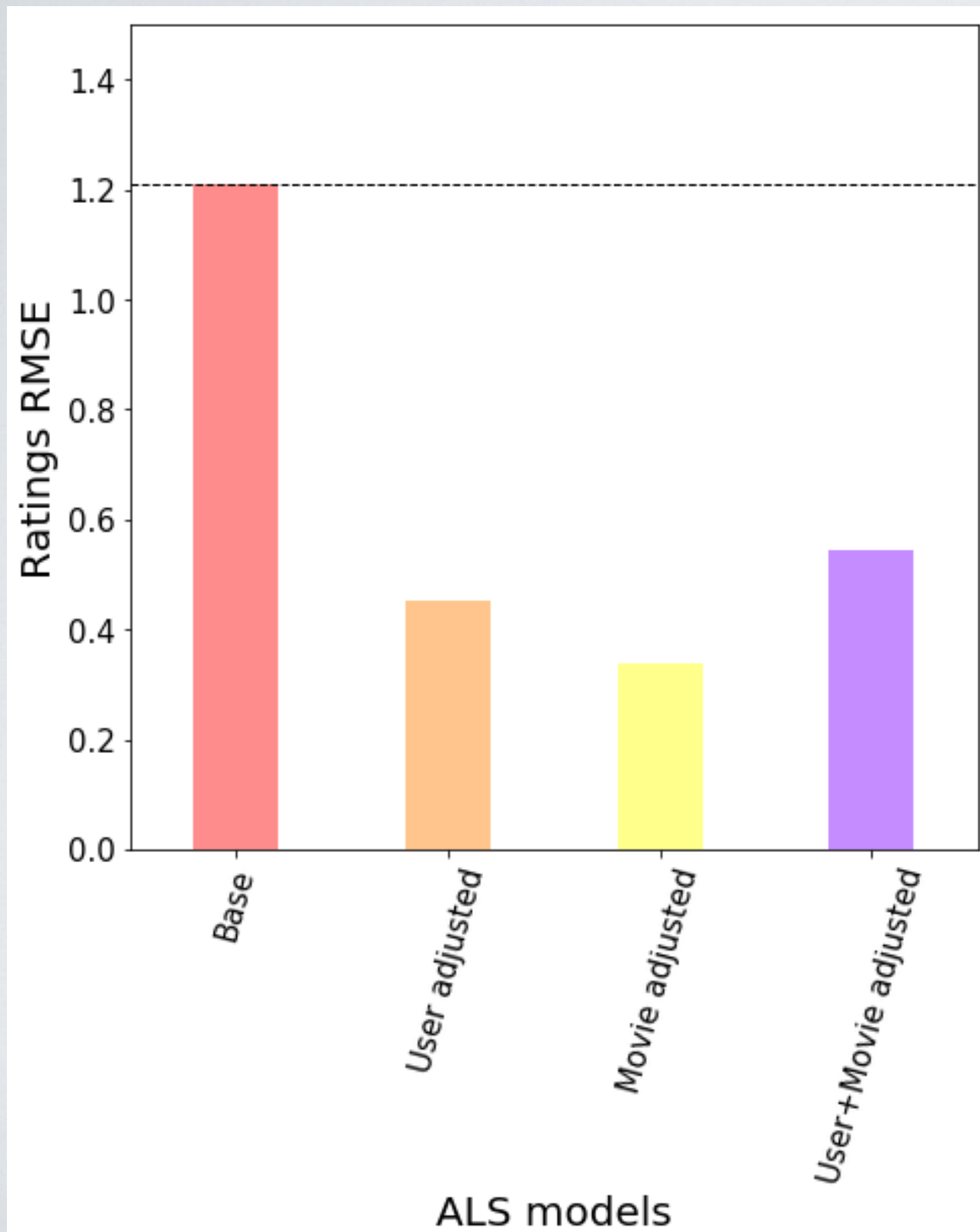
-) Two of the parameters (rank, maxIter, regParam or lambda) were kept constant, while changing the third one. As before, to measure the errors I used RMSE.



- **ALS optimal hyperparameters:**
 - regParam: 0.5
 - iterations: 8
 - ranks: 8

Predicting movie ratings:

optimal ALS model + user & movie biases



- Optimal hyperparameters were used to train an ALS model.
- Predicted ratings are adjusted with user and movie rating biases
- Predicted ratings were also adjusted to the 1 to 5 Stars Netflix Scale
- Incorporating individual biases (user & movie) reduces the errors of the predicted ratings
- Combining multiple biases does not provide further improvement

Using the optimal ALS model to make movie recommendations

We use the optimal ALS model to make movie recommendations for a new user (not in the original dataset):

- We start with a list of movies (shown below) the the user has rated

```
new_ratings = [  
    (0,14941,4),# The Matrix  
    (0,14928,4),# Dead Poets Society  
    (0,5344,5),# Fullmetal Alchemist  
    (0,10463,4),# Pokemon: The First Movie  
    (0,10453,4),# Pokemon Advanced  
    (0,5732,4),# Good Will Hunting  
    (0,15096,5),# The Notebook  
    (0,17132,5),# Waking Life  
    (0,11763,3),# Serendipity  
    (0,178,5) #A Beautiful Mind  
]
```

- We add this ratings to the dataset, and retrain the model
- We recommend movie only if they have a high recommended rating

Using the optimal ALS model to make movie recommendations

For a movie to be recommended, I considered it should have:

- A predicted rating of 4.5 Stars or more
- At least 20 reviews in the dataset used to train the ALS model

A sample recommended movies is shown below

Sample list of recommended movies:

```
Angel: Season 5. Predicted rating: 5 Stars
Spirited Away. Predicted rating: 4.67015305531 Stars
Batman Begins. Predicted rating: 4.80449606347 Stars
I. Predicted rating: 4.69739734497 Stars
Buffy the Vampire Slayer: Season 4. Predicted rating: 5 Stars
The Shield: Season 3. Predicted rating: 5 Stars
Home Improvement: Season 1. Predicted rating: 4.69458404747 Stars
Dark Angel: Season 1. Predicted rating: 4.79938823529 Stars
Stargate SG-1: Season 4. Predicted rating: 4.76801740771 Stars
Million Dollar Baby. Predicted rating: 4.64580944925 Stars
Freaks & Geeks: The Complete Series. Predicted rating: 5 Stars
Sex and the City: Season 1. Predicted rating: 4.74706793216 Stars
Absolutely Fabulous: Series 1. Predicted rating: 4.64477690002 Stars
Star Trek: The Next Generation: Season 6. Predicted rating: 4.94167663198 Stars
Curb Your Enthusiasm: Season 4. Predicted rating: 5 Stars
CSI: Season 3. Predicted rating: 5 Stars
Braveheart. Predicted rating: 4.77114929443 Stars
Finding Nemo (Widescreen). Predicted rating: 5 Stars
Six Feet Under: Season 1. Predicted rating: 4.91393002626 Stars
Life Is Beautiful. Predicted rating: 4.65389538027 Stars
```

Total number of recommended movies: 419

Using the optimal ALS model to make movie recommendations

The sample of recommended movie has some consistency with the initial set of new ratings:

- If you liked "*The Matrix*" you might also like "Batman Begins" or "Star Gate SG-1"
- If you liked "Full Metal Alchemist" or "Pokemon", you might also like "Spirited Away"
- The only recommended movie/series in the sample list that seems a bit out of place, might be "Sex and the City".

Conclusion and Future Directions

- Ratings prediction errors greatly diminished if a user-specific or movie-specific bias is considered. Therefore, it is suggested that future recommender systems would benefit from incorporating this type of biases in ratings.
- Better, more accurate, recommendations might be achieved when training the model with the complete dataset, or when more ratings are available for the new user
- Better predictions can also be achieve by combining multiple predictive algorithms.

Conclusion and Future Directions

"Collaborative Filtering - RDD-based API",

Link: <https://spark.apache.org/docs/2.2.0/mllib-collaborative-filtering.html>

"An on-line movie recommending service using Spark",

Link: <https://github.com/jadianes/spark-movie-lens/blob/master/notebooks/building-recommender.ipynb>

"Netflix Prize Methods",

Link:

https://www.youtube.com/watch?v=q97VFt56vRs&list=PL4tNSz2ghvn_cv9rjiS5AQDTkWB1sh9YM&index=2

"Winning the Netflix Prize: A Summary",

Link: <http://blog.echen.me/2011/10/24/winning-the-netflix-prize-a-summary/>

"Netflix Never Used Its \$1 Million Algorithm Due To Engineering Costs",

Link: <https://www.wired.com/2012/04/netflix-prize-costs/>

