1 Introduction [10 points]

Group Members: Luis Costa, Melba Nuzen, Serena Yan

Team Name: Learning Support

Division of Labor:

Luis: Implemented basic visualizations outlined in Part 4 of the spec.

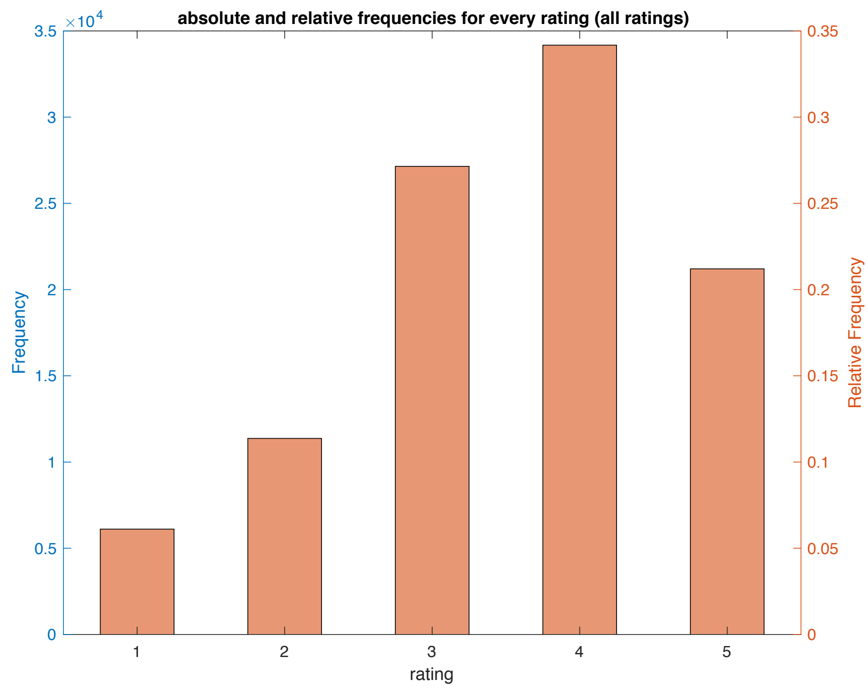
Melba: Implemented the original and off-the-shelf matrix factorization visualizations in Part 5 of the spec.

Serena: Implemented the original and bias term matrix factorization visualizations in Part 5 of the spec.

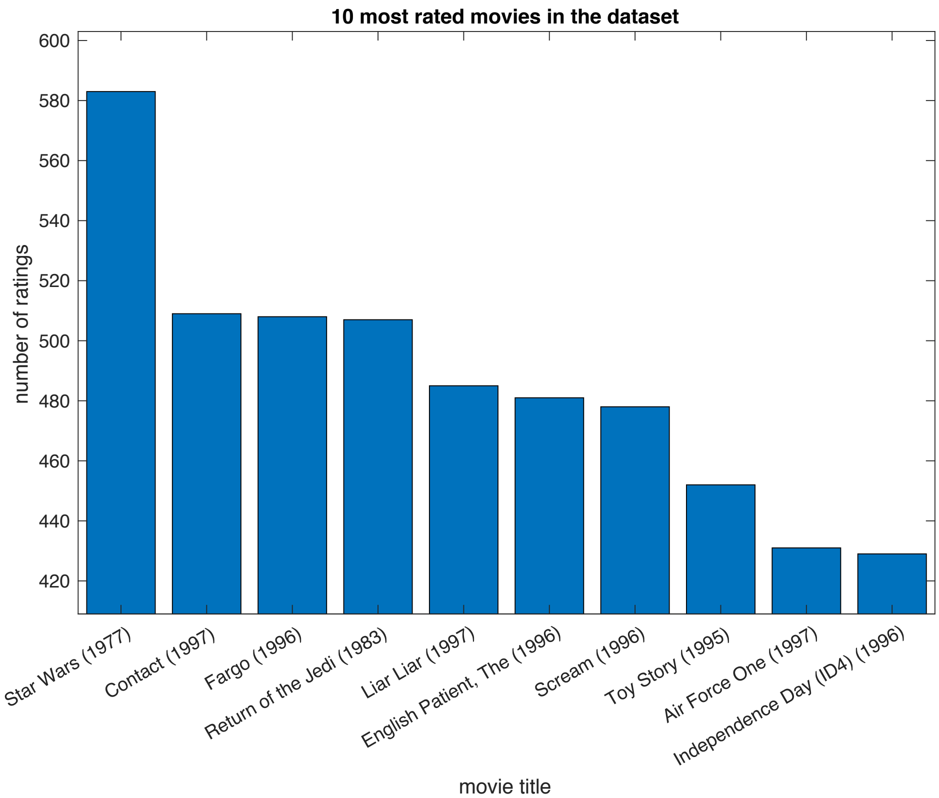
2 Basic Visualizations [20 points]

To first get an idea of what the MovieLens dataset contains, we create basic visualizations of the data in regards to ratings, genre, and popularity. Before visualizing, we pre-process our data by merging ratings for duplicate movies. Specifically, ratings for movies which had the same title but different IDs were changed to correspond to a single ID. We thought this better than removing duplicates, since this way we don't lose any ratings for movies which may be duplicated in the data.

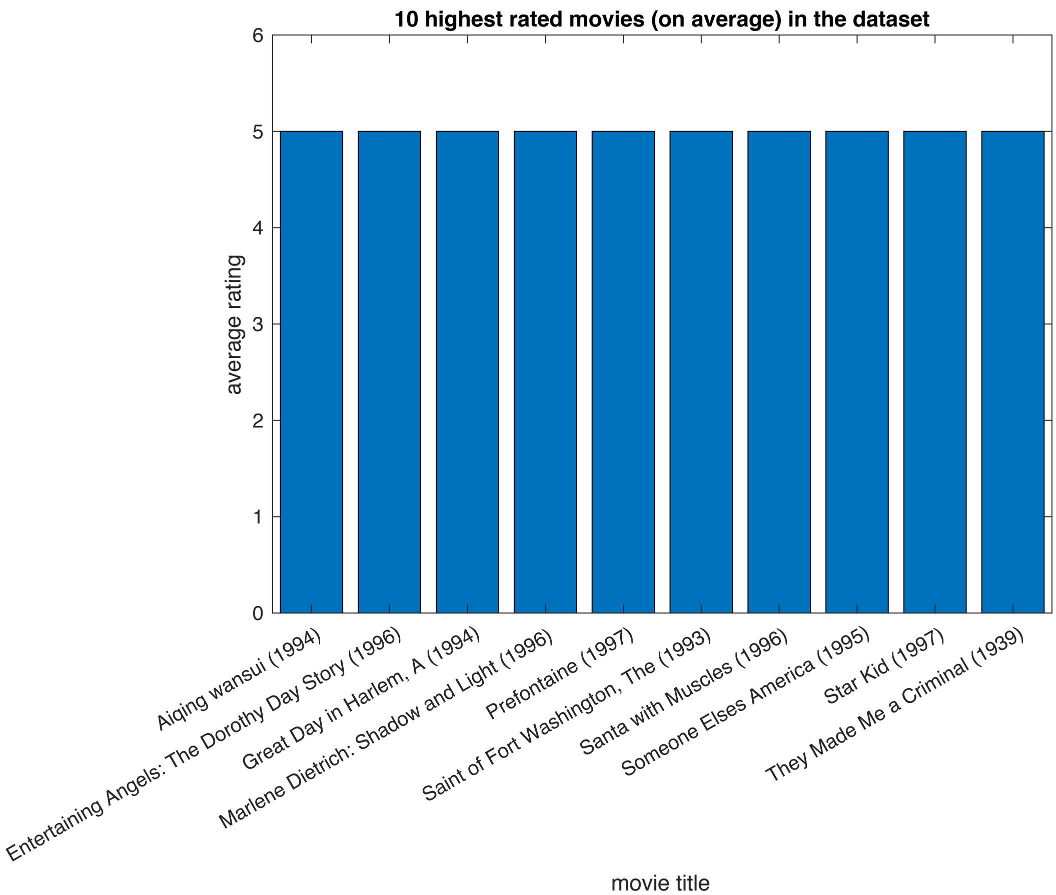
We first look at all the ratings in the MovieLens dataset. In our bar graph, we look at both actual frequency as well as relative frequency. We see that the mode of the ratings distribution is 4. Additionally, ratings are concentrated in the 3-5 range, with relatively few 1-2 ratings being given.



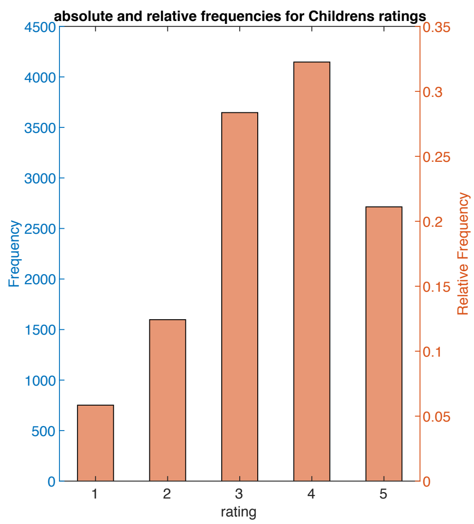
We examine the ratings of the ten most popular movies (movies which received the most ratings), which we notice were all released in the late 1990s, except for 'Return of the Jedi,' which was released in 1983 and 'Star Wars' which was released in 1977. (we put an axis break on the y-axis so that differences in number of ratings received can be seen more clearly).

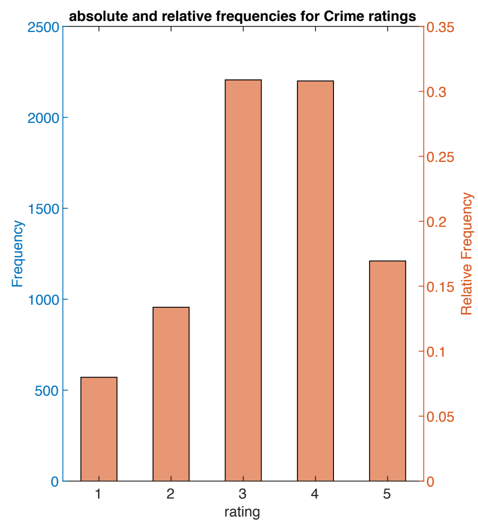


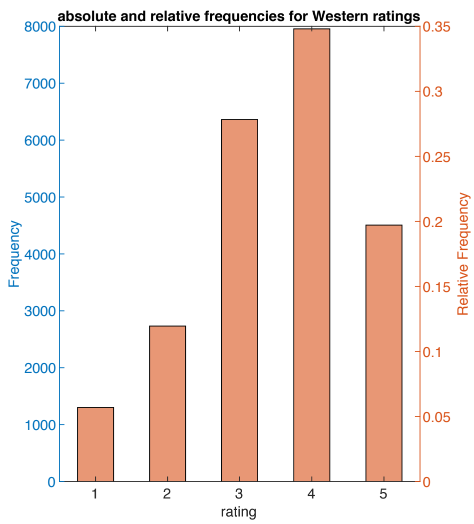
We also look at the ratings of the ten best movies (i.e. movies with the highest average ratings). We note that all of these movies have an average rating of 5, were only rated by 1-3 users in the dataset. Of course, this makes this measure of popularity seem somewhat naive, since a single person's rating of a movie is probably not sufficiently representative of how much others will like the movie.



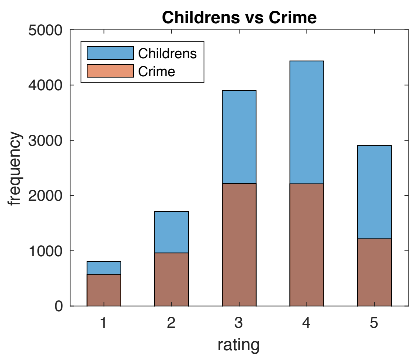
Finally, we examine the ratings of movies from three genres that we chose: Childrens, Crime, and Western. Let's first take a look at how ratings are distributed for these movies individually:

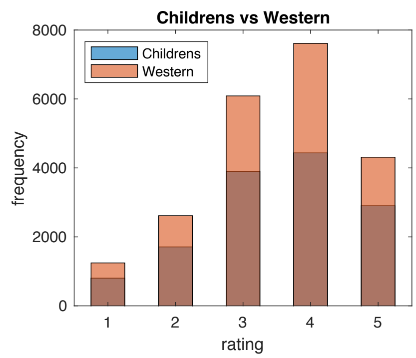

absolute and relative frequencies for Childrens ratings
Frequency
Relative Frequency
rating
0
500
1000
1500
2000
2500
3000
3500
4000
4500
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
1
2
3
4
5

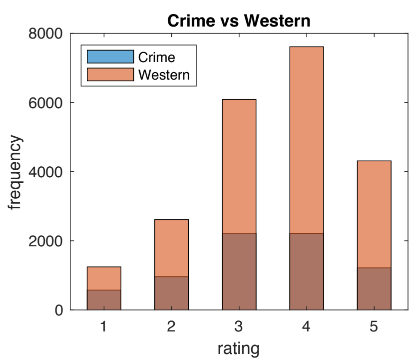

absolute and relative frequencies for Crime ratings
Frequency
Relative Frequency
rating
0
500
1000
1500
2000
2500
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
1
2
3
4
5


absolute and relative frequencies for Western ratings
Frequency
Relative Frequency
rating
0
1000
2000
3000
4000
5000
6000
7000
8000
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
1
2
3
4
5

Perhaps surprisingly, we see that these genres have a relatively similar ratings distribution and that their distributions are all,in turn, similar to what we observed for all movies. In particular, 3 and 4 are always the most common ratings (we observed the same thing when looking at the aggregation of all ratings) and 4 is also the mode of the distribution for Westerns and Childrens. For crime movies we see that both 3 and 4 seem to be the mode.
Now let's look at some head-to-head comparisons between the genres:

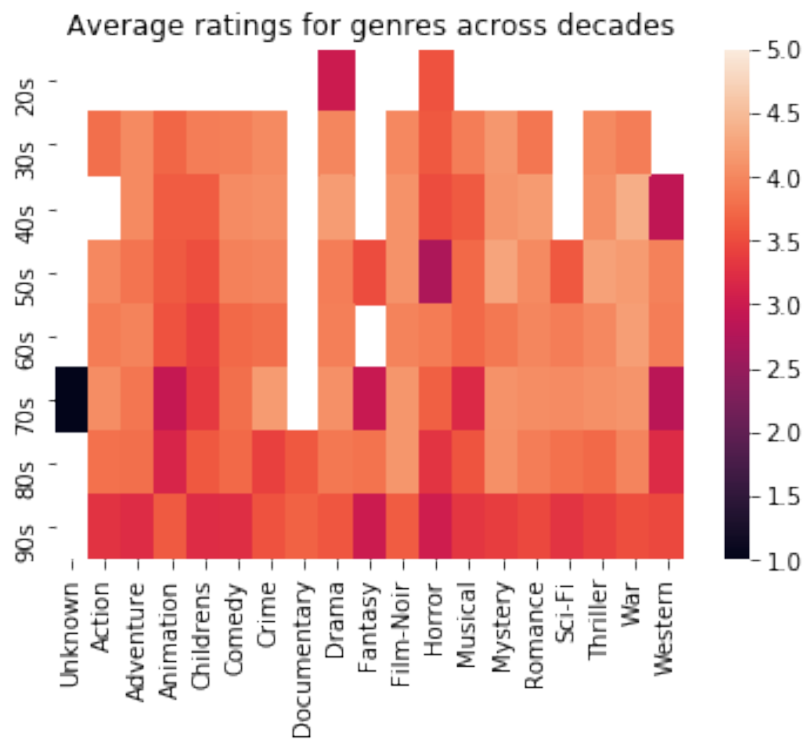






Since we are only plotting absolute frequency now, it becomes clear that Western movies have the most ratings out of the three genres, followed by Childrens and the Crime. While the distributions continue to look similar, we see some differences. Crime movies, for example, seem to have a much higher proportion of 1 ratings than either Western or Childrens. We can see this because for the 'Childrens vs Crime' and 'Crime vs Wastern' plots the bar corresponding to 1 ratings has a greater portion of its area covered by Crime movies than the 2-5 bars.

Since none of the visualizations outlined in the project guide considered release date, we incorporated a temporal aspect into the visualization of all of our ratings in the following heat map (which was used for the blog post):



Each box in the heatmap corresponds to a time-frame (1920-1929,1930-1939,. . . , 1990-1999) and a genre. The colour of the box indicates the average rating of all movies released in that particular time-frame that were marked as belonging to that particular genre. We decided to group movies by decade because we thought that considering simply the year vs the genre would probably lead to the data being too sparse. We see that some genres, such as War movies and Mystery receive fairly high ratings for all time-frames. By contrast, for some movies release date seems to play a greater role. Westerns released during the 50s and 60s, for example, seem to be fairly well rated, but Westerns released during the 40s and 70s have a poor average rating. Another interesting feature of this figure is that for most genres it seems to be the case that average rating drops for movies released in the 90s (these movies make up the bulk of the data).

3 Matrix Factorization Methods [40 points]

We used three different implementations of matrix factorization: basic factorization (as used in Homework 5), factorization with bias terms, and an off the shelf method with SciPy's SVD. For consistency, for every model, we used a k value of 20, a regularization value of 0.1, an eta learning rate of 0.03, a maximum epoch of 300, and a stopping condition as specified in hw 5. We chose these parameters because they gave us the best performances across the models.

Basic

The basic matrix factorization implementation was heavily based off of the code we used in Homework Set 5. During the training, the model try to minimize MSE through SGD at each point. Our initially randomized V and U matrices then became factors of the target matrix M, which contains the rating for all the movies across all the users. We primarily adjusted the hyperparameters to see if we could reduce error. Similar to what we found in hw 5, we noticed that $k = 20, \lambda = 0.1, \eta = 0.03$ gave the best performance. So we decided to use these parameters to test across the three models. We also settled on 300 epochs and the stopping condition as described in hw 5.

Bias Term

The bias matrix factorization works almost identical to the hw5 basic method, with two additional bias terms–a, a vector containing the bias adjustment for each user, and b, a vector containing the bias adjustment for each movie. We took the gradients of the error function with respect to V_i, U_j, a_i, b_j and used those gradients in our implementation of SGD just like hw 5 (see derivation below).

$$\text{Error} = \frac{\lambda}{2}\left(\|U\|^2 + \|V\|^2 + \|a\|^2 + \|b\|^2\right) + \frac{1}{2}\sum_{i,j}\left(Y_{i,j} - \mu - u_i^T v_j - a_i - b_j\right)^2$$

$$\partial u_i = \lambda u_i - v_j\left(y_{ij} - \mu - u_i^T v_j - a_i - b_j\right)$$

$$\partial v_j = \lambda v_j - u_i\left(y_{ij} - \mu - u_i^T v_j - a_i - b_j\right)$$

$$\partial a_i = \lambda a_i - \left(y_{ij} - \mu - u_i^T v_j - a_i - b_j\right)$$

$$\partial b_j = \lambda b_j - \left(y_{ij} - \mu - u_i^T v_j - a_i - b_j\right)$$

Off-the-Shelf Finally, our off the shelf implementation used SciPy's SVDS package, which was a simpler implementation of SVD that didn't offer parameters for us to input any regularization or any bias terms. For all other parameters, we used the standard values from SciPy, without modification. Thus when comparing the graphs, visualizations, and error values of the three factorization methods, we should remember that the results for our off the shelf implementation remains contingent on the fact that this model uses the preset parameters from SciPy—in comparison to basic matrix factorization and bias matrix factorization, which, since we wrote most of the code for, we could input our specified parameters.

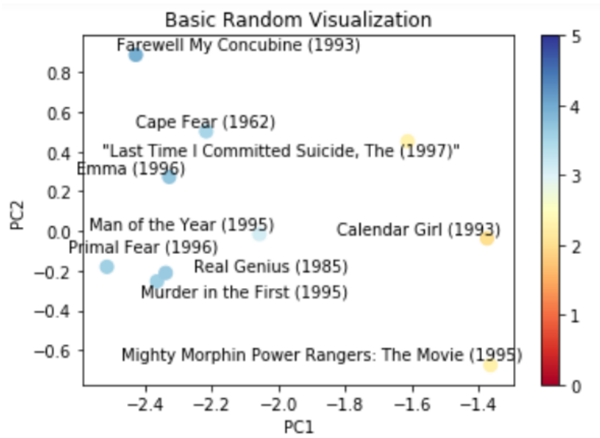
If we compare the error rates of the three models, we see that—

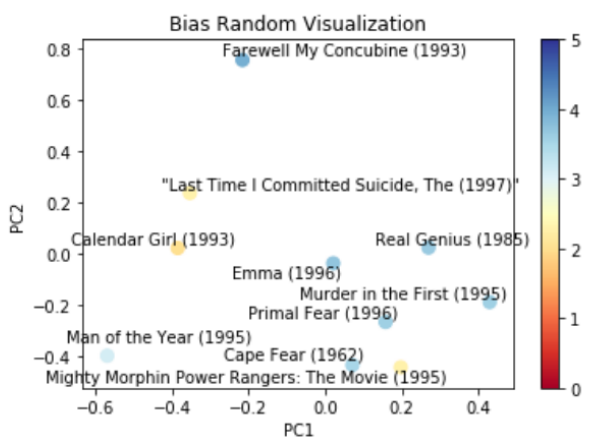
- Basic factorization had the following errors—in sample: 0.331730; out of sample: 0.455144
- Bias factorization had the following errors—in sample: 0.258507; out of sample: 0.440941
- Off the shelf factorization had the following errors—in sample: 2.39485; out of sample: 3.134535

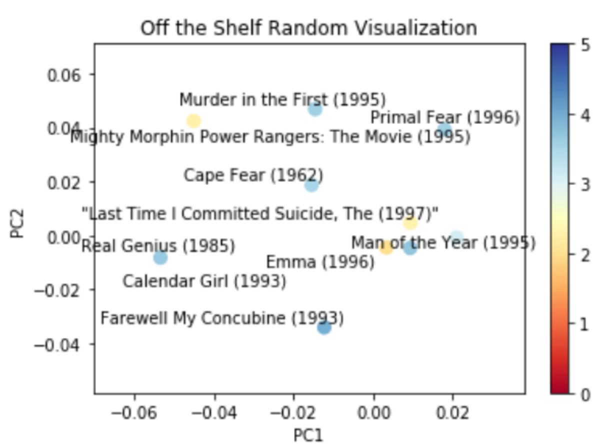
The differences in performance can be explained by the differences in models. We see that basic factorization and bias factorization have similar errors, though basic factorization has a slightly higher out of sample error. This makes sense since with the bias terms taken into account, our model have more parameters to train for and should be more robust and accurate in matrix factorization. In contrast, our off the shelf factorization had a much higher error rate than the other two methods, which is due to the limited number of parameters that we can control for the method. This correlates slightly with the plots generated from these three visualizations: bias visualization and basic visualization have more distinguishable and interpretable plots, whereas our off the shelf visualization seems more scattered and the movie points seem more randomly placed.

Below are the 18 graphs required:

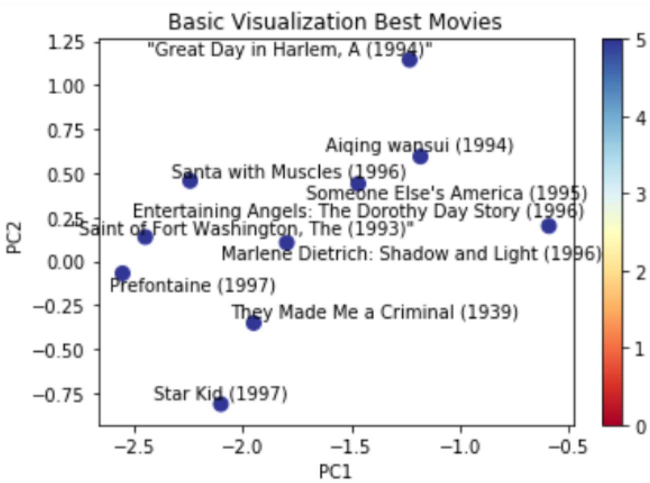
10 randomly selected movies

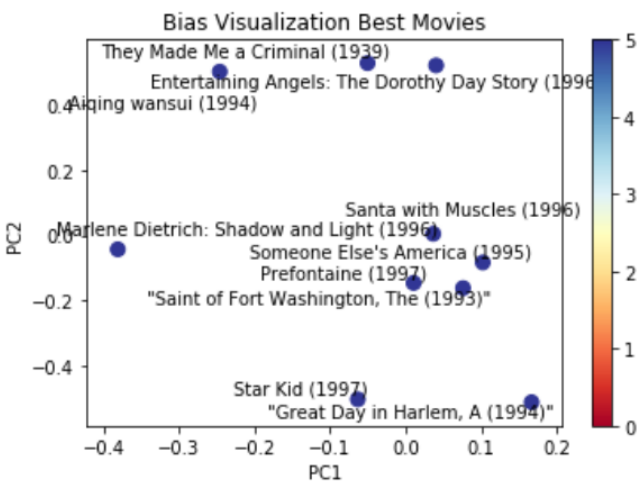


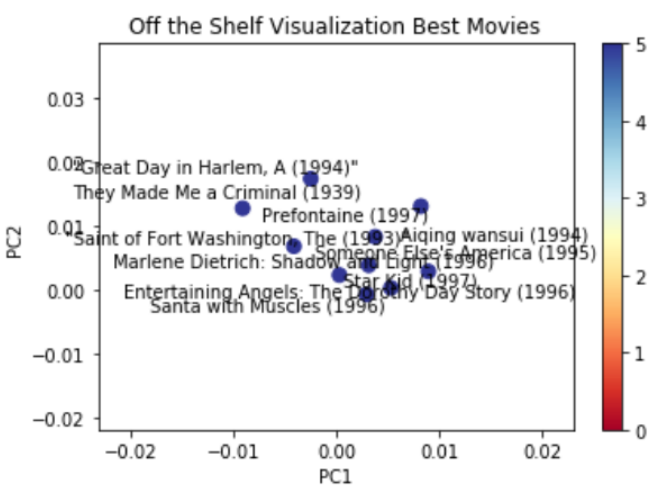




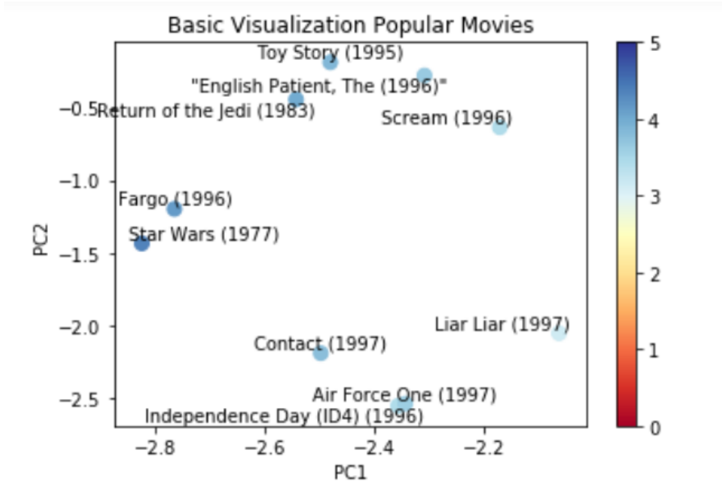
10 highest rating movies

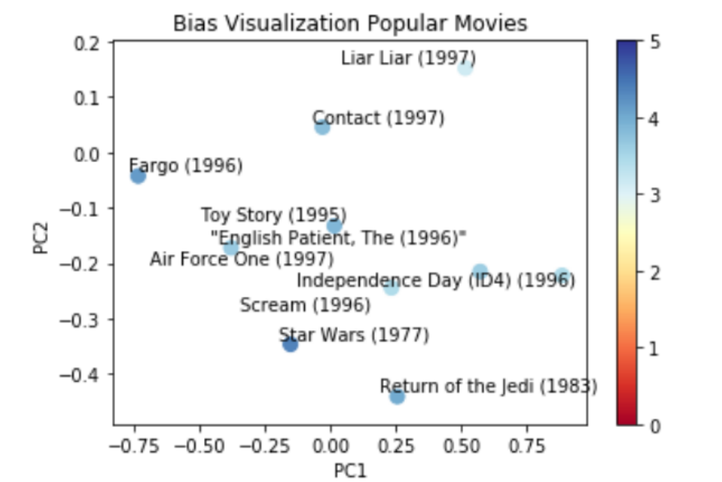


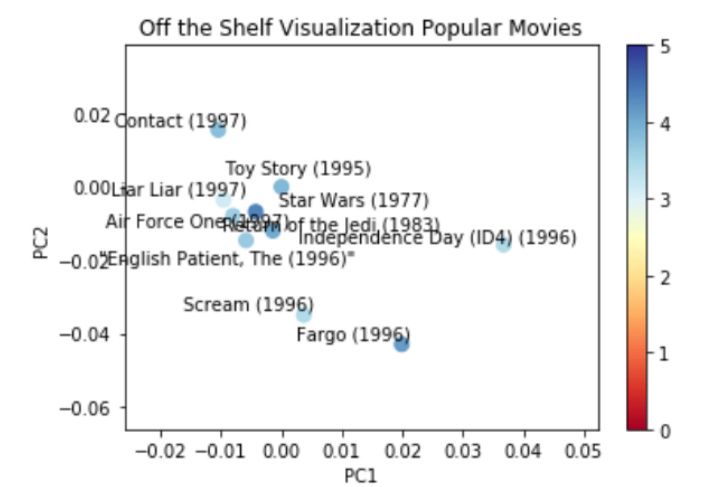




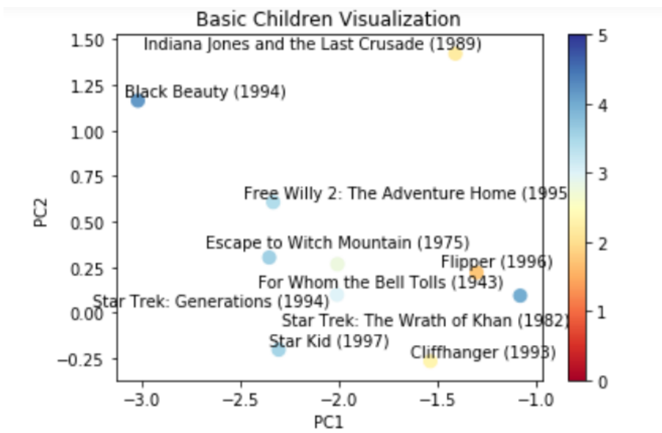
10 most popular movies

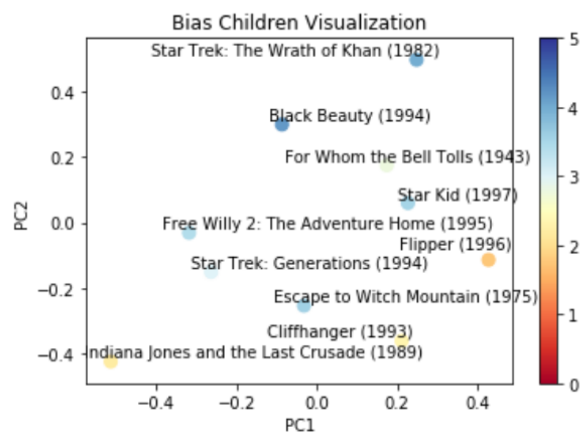


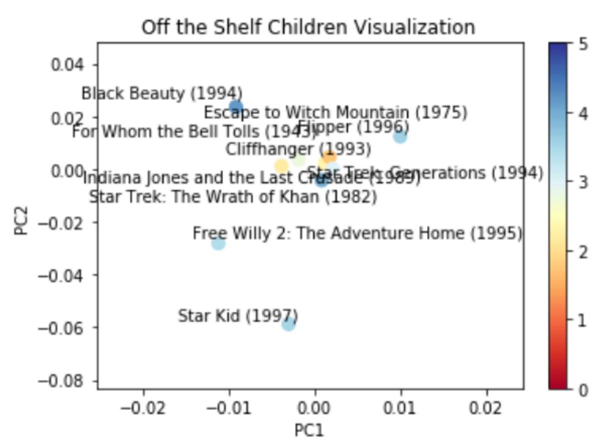


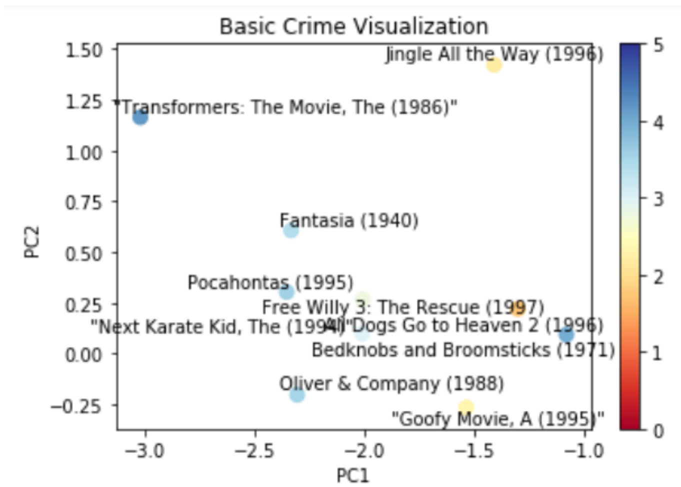


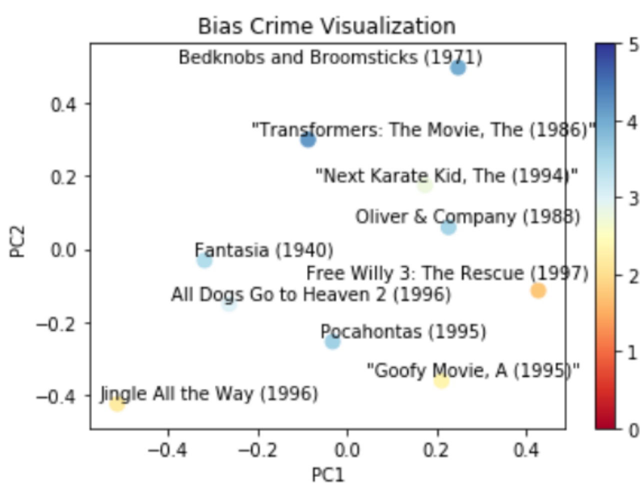
Finally, we examine the three genres we chose previously.

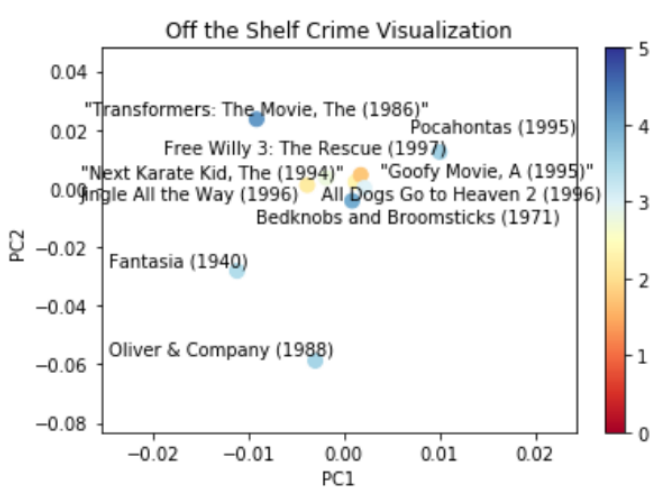


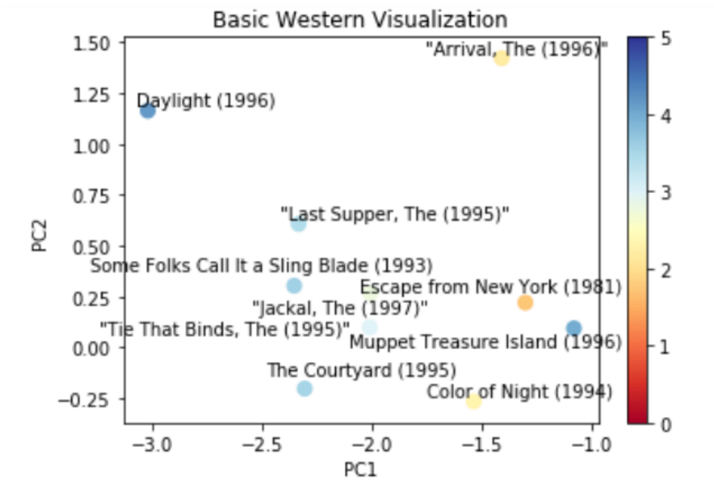


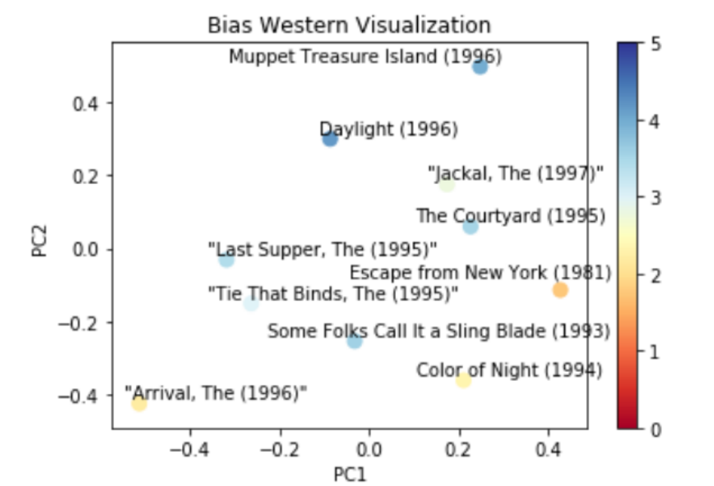


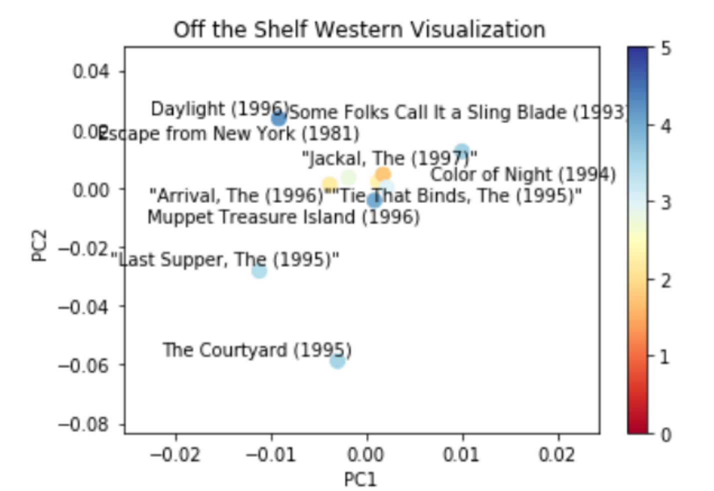

Basic Crime Visualization
Jingle All the Way (1996)
"Transformers: The Movie, The (1986)"
Fantasia (1940)
Pocahontas (1995)
Free Willy 3: The Rescue (1997)
"Next Karate Kid, The (1994)"
All Dogs Go to Heaven 2 (1996)
Bedknobs and Broomsticks (1971)
Oliver & Company (1988)
"Goofy Movie, A (1995)"
PC1
PC2


Bias Crime Visualization
Bedknobs and Broomsticks (1971)
"Transformers: The Movie, The (1986)"
"Next Karate Kid, The (1994)"
Oliver & Company (1988)
Fantasia (1940)
Free Willy 3: The Rescue (1997)
All Dogs Go to Heaven 2 (1996)
Pocahontas (1995)
"Goofy Movie, A (1995)"
Jingle All the Way (1996)
PC1
PC2


Off the Shelf Crime Visualization
"Transformers: The Movie, The (1986)"
Pocahontas (1995)
Free Willy 3: The Rescue (1997)
"Next Karate Kid, The (1994)"
"Goofy Movie, A (1995)"
Jingle All the Way (1996)
All Dogs Go to Heaven 2 (1996)
Bedknobs and Broomsticks (1971)
Fantasia (1940)
Oliver & Company (1988)
PC1
PC2


Basic Western Visualization
"Arrival, The (1996)"
Daylight (1996)
"Last Supper, The (1995)"
Some Folks Call It a Sling Blade (1993)
Escape from New York (1981)
"Jackal, The (1997)"
"Tie That Binds, The (1995)"
Muppet Treasure Island (1996)
The Courtyard (1995)
Color of Night (1994)
PC1
PC2


Bias Western Visualization
Muppet Treasure Island (1996)
Daylight (1996)
"Jackal, The (1997)"
The Courtyard (1995)
"Last Supper, The (1995)"
Escape from New York (1981)
"Tie That Binds, The (1995)"
Some Folks Call It a Sling Blade (1993)
Color of Night (1994)
"Arrival, The (1996)"
PC1
PC2

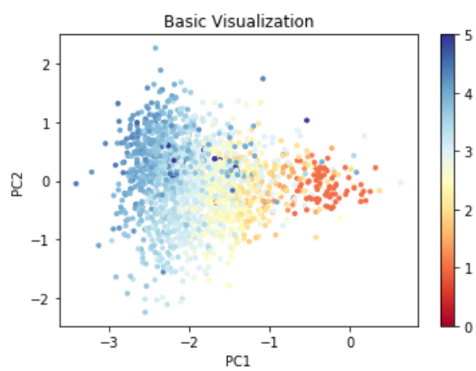

Off the Shelf Western Visualization
Daylight (1996)
Some Folks Call It a Sling Blade (1993)
Escape from New York (1981)
"Jackal, The (1997)"
Color of Night (1994)
"Arrival, The (1996)"
"Tie That Binds, The (1995)"
Muppet Treasure Island (1996)
"Last Supper, The (1995)"
The Courtyard (1995)
PC1
PC2

4 Matrix Factorization Visualizations [30 points]

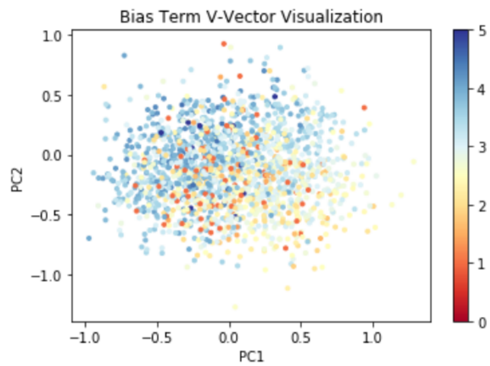
For all three models, we used the same 2D visualization code that projects a matrix into 2 dimensions, and produces a scatterplot of that projection. We used a color spectrum from `cmap` with a rainbow gradient, where warm colors (red, orange) represent lower ratings and cool colors (blue, green) represent higher ratings on a scale from 0 to 5, with 0 being red and 5 being blue.

The largest visualizations that we produced were the ones with every single movie given to us in our data set, seen in the graphs below. In these graphs, each dot in the visualization represents a movie found in our dataset; the color of the dot represents the rating of that particular movie. On the x and y axes, we have our principal components 1 and 2 respectively.

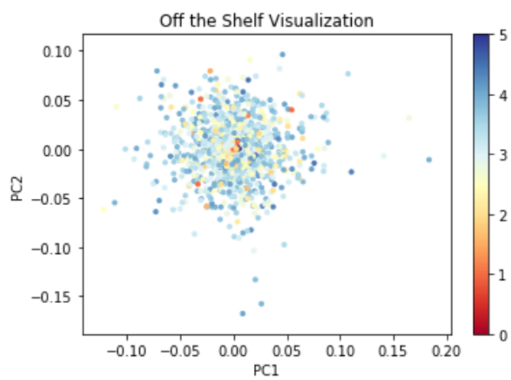
Out of all of the model implementations, we found that our basic factorization, which used the code used from Homework 5, produced the most interpretable and contiguous plots. We see that movies of similar ratings tend to group together, forming an almost linear relationship along the first principal component axis.



For our bias term visualization, we see that the movies with higher average ratings tend to cluster towards the upper left corner while those with lower average ratings tend to cluster towards the lower right corner. Although this trend is not very obvious and might be the result of noise.



In comparison, our off the shelf visualization seems much more scattered than our first two visualizations, with a few outliers with high ratings.



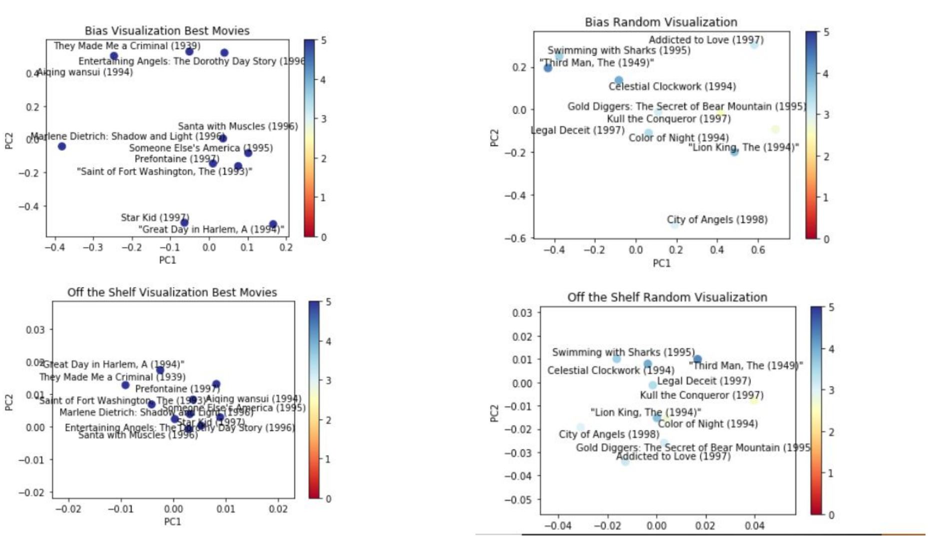
We see that the cleanest graph, as mentioned before, was the graph produced by our basic implementation; in contrast, the off the shelf method produced the most scattered-looking graph, most likely again because of the built-in parameters of the SVD model we implemented. The bias term visualization falls somewhere in between—somewhat organized based on rating in our visualization of all of the movies, but still more scattered than the basic visualization.
In addition to the graphs where we plotted the entirety of V from our matrix factorization, we also plotted smaller groups of 10 movies. We can compare all three methods with the following categories: 10 randomly selected movies, 10 best movies (highest average ratings), 10 most popular movies (most ratings), and the movies in the genres we selected.

We see that across the graphs, although the spatial locations of movies might be different, in the same types of visualizations we see certain outliers across factorization methods. For example, in our visualizations of the best rated movies, across all three methods we see 'Great Day in Harlem, A' and 'They Made Me a Criminal' as a spatial outlier in the three visualizations.

Results vs Expectation
Overall, we were actually not expecting the bias term and SVD method to produce graphs with no apparent trends (or at least no trend that we can see by our eyes). At first glance, we thought that more complex models would produce more interpretable graphs but the simplest, basic model—–the same implementation we used in Homework 5—-turned out to be the most visually attractive graph. This could be due to a number of reasons: the nuances of the data given, the fact that the particular off the shelf implementation we chose was not flexible in terms of inputted parameters.

Most popular movies vs best movies
For the basic method and bias term method, there is no apparent difference between the most popular movies and best movies (other than the obvious observation that popular movies tend to be rated very high and best movies tend to have higher ratings than popular movies). However for the off-the-shelf SVD, the 10 best (highest rating) movies tend to cluster way more than the 10 most popular movies. This implies that best movies tend to have similar traits, which could be genre, decade (almost all 1990s), and the number of ratings. In fact, a big possibility that these movies are rated high is because they are not as popular and thus have less bad ratings.

Different matrix factorization methods comparison
The off-the-shelf implementation tend to produce more clustered graph when we only visualize the top 10 movies in ratings or popularity. This trend can be confirmed by the fact that the 10 randomly selected movie graphs look equally random for all three method.



For the 10 most popular movies, SVD (off-the-shelf) is clearly more clustered than the bias term method. However, they are equally random in the 10 randomly selected movie.

5 Conclusion

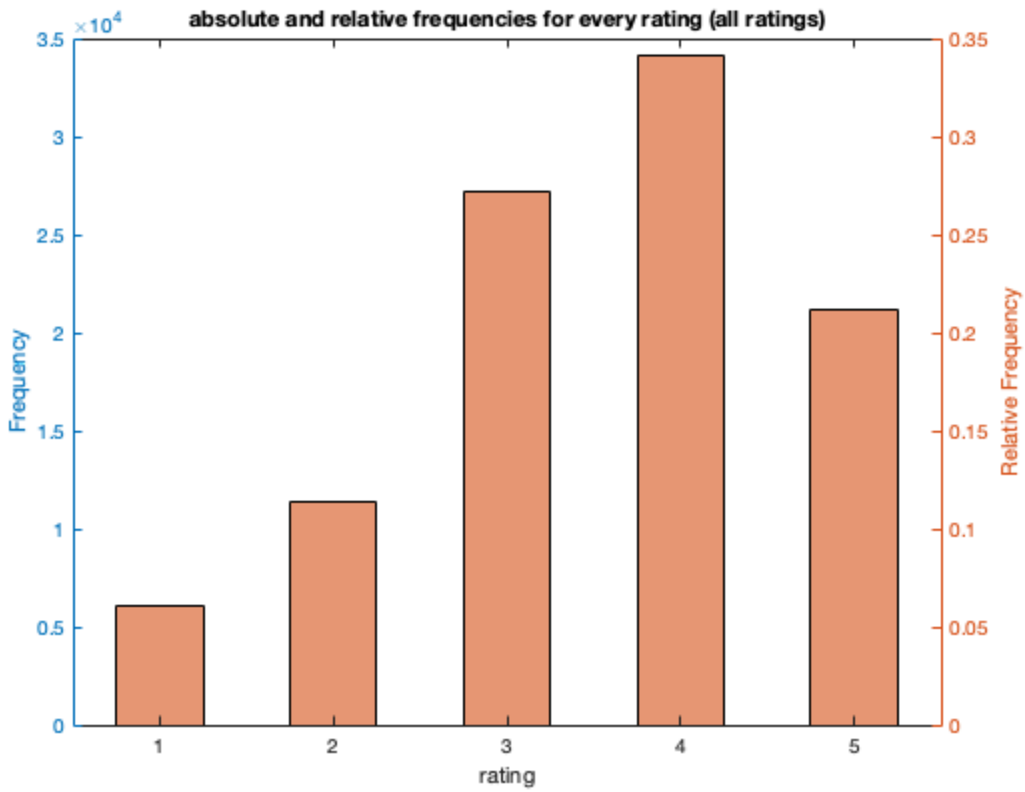
Overall, implementing the SVD with various models gave us insight into the various options available for matrix factorization. Though we predicted that more complicated models (e.g. adding bias terms, using off the shelf models) would give us visualizations with high correlations, we found that our basic visualization implementation (from Homework 5) produced a very readable plot for all of the movie data.

For all of these graphs, the amount of movies made all visualizations difficult to read and distinguish trends because of the sheer number of movies. We spent a non-insignificant amount of time ensuring that the movie dots would be visible and that the rating color spectrum would be easy to understand. In retrospect, although it is clear that matrix factorization is a powerful tool in reducing a dataset's dimensions, effectively implementing it and ensuring that the correct model or design is not trivial. Off by one errors and forgetting transpositions can completely skew data. However, once correctly implemented, the visualizations help unearth trends within data that would otherwise be difficult to pick out.

```
% CODE USED FOR 4.1

load('data.txt')
ratings = data(:,3); %column corresponding to tratings

%%histogram for all ratings
yyaxis left %want frequency on left y-axis
C = categorical(ratings,[1 2 3 4 5],{'1','2','3','4','5'}); %ratings
 are discrete so plot as categorical data
histogram(C,'BarWidth',0.5)
xlabel('rating')
ylabel('frequency')
yyaxis right %want relative frequency on right y-axis
histogram(C,'BarWidth',0.5,'Normalization','probability')
yyaxis left
title('absolute and relative frequencies for every rating (all
 ratings)')
ylabel('Frequency')
yyaxis right
ylabel('Relative Frequency')
```



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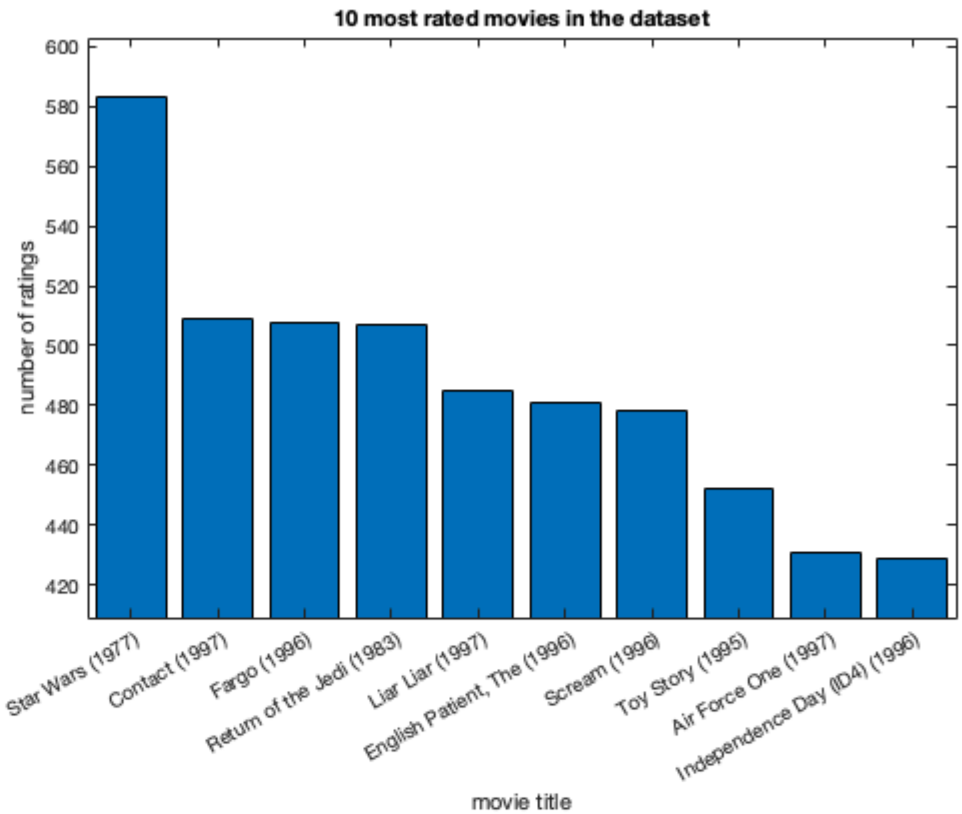
```
%CODE USED FOR 4.2

load('clean_ratings.txt');
movie_ids = clean_ratings(:,2);
unique_ids = unique(movie_ids);

freq_counts = [unique_ids,histc(movie_ids(:),unique_ids)]; %left
 column movie ids, right column number of ratings
disp(size(freq_counts))
[~,idx] = sort(freq_counts(:,2),'descend'); % sort by the 2nd column
sortedmat = freq_counts(idx,:);
top10 = sortedmat(1:10,:); %has top 10 in format (id,#ratings)
disp(top10)
X = categorical({'Star Wars (1977)','Contact (1997)','Fargo
 (1996)','Return of the Jedi (1983)','Liar Liar (1997)','English
 Patient, The (1996)','Scream (1996)','Toy Story (1995)','Air Force
 One (1997)','Independence Day (ID4) (1996)'});
X = reordercats(X,{'Star Wars (1977)','Contact (1997)','Fargo
 (1996)','Return of the Jedi (1983)','Liar Liar (1997)','English
 Patient, The (1996)','Scream (1996)','Toy Story (1995)','Air Force
 One (1997)','Independence Day (ID4) (1996)'});
%second one is to preserve order

bar(X,top10(:,2))
ylim([min(top10(:,2))-20,max(top10(:,2))+20])
title('10 most rated movies in the dataset')
ylabel('number of ratings')
xlabel('movie title')
```

```
        1664           2

    50   583
   258   509
   100   508
   181   507
   294   485
   286   481
   288   478
     1   452
   300   431
   121   429
```



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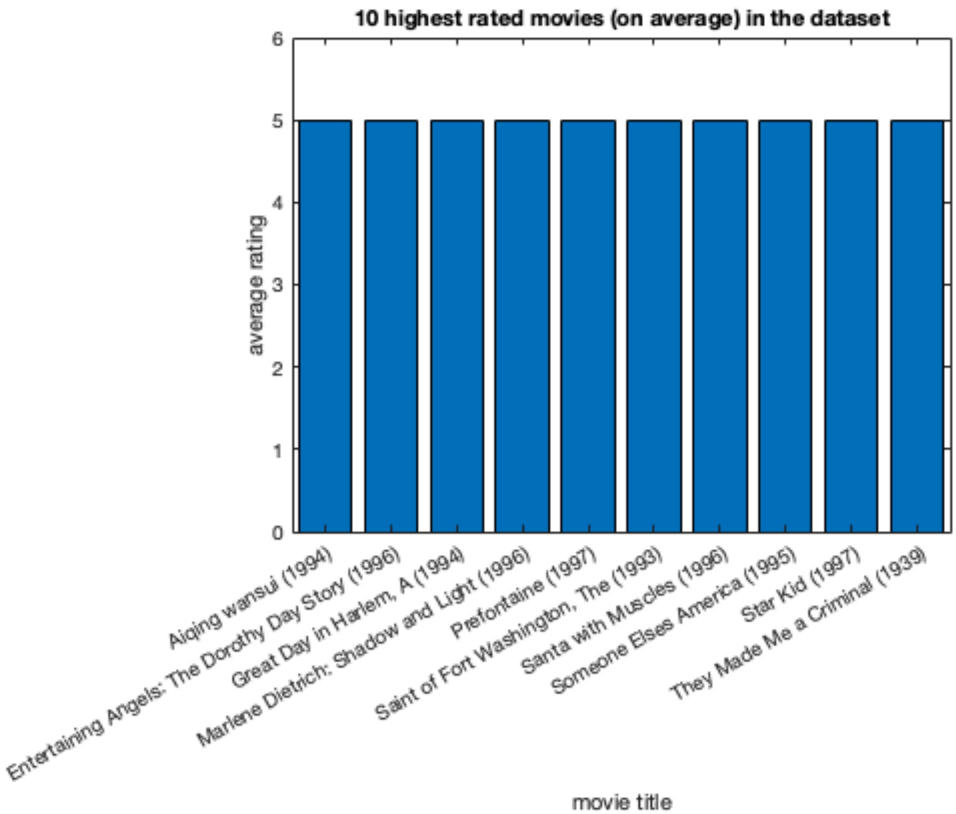
```
%CODE USED FOR 4.3

load('clean_ratings.txt');
movie_ids = clean_ratings(:,2);
ratings = clean_ratings(:,3);
unique_ids = unique(movie_ids);
avg_ratings = zeros(length(unique_ids),1);
for i=1:length(unique_ids) %for each movie_id in the dataset,
 calculate the average rating
    movie_ratings =
 clean_ratings(clean_ratings(:,2)==unique_ids(i),3);
    number_ratings = length(movie_ratings);
    sum_ratings = sum(movie_ratings);
    avg_rating = sum_ratings/number_ratings;
    avg_ratings(i) = avg_rating;
end

[~,idx] = sort(avg_ratings,'descend');
top10_ratings = avg_ratings(idx);
top10_ratings = top10_ratings(1:10);
top10_ids = unique_ids(idx);
top10_ids = top10_ids(1:10);

X = categorical({'Great Day in Harlem, A (1994)','They Made Me a
 Criminal (1939)','Prefontaine (1997)','Marlene Dietrich: Shadow
 and Light (1996)','Star Kid (1997)','Saint of Fort Washington, The
 (1993)','Someone Elses America (1995)','Entertaining Angels: The
 Dorothy Day Story (1996)','Santa with Muscles (1996)','Aiqing wansui
 (1994)'});

bar(X,top10_ratings)
title('10 highest rated movies (on average) in the dataset')
ylabel('average rating')
xlabel('movie title')
ylim([0,6])
```



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In [241]:
```
#FOR TASK 4.4
#this is to get lists of ratings for genres specified by their indices in 'genres'.
#Selected genres randomly but we ended up plotting for (crime,western,children)
# which have genre indices 4,6,18. This constructs the arrays which were used for
#plotting in MATLAB.
genres = list(np.random.randint(0,19,size=(3,1)))
genre_scores = [[],[],[]]
clean_ratings = np.loadtxt('clean_ratings.txt',dtype=int)
movies = pd.read_csv('movies.txt', sep="\t",header=None)

for row in clean_ratings:
    user_id,movie_id,rating = row[0],row[1],row[2]
    genre_row = movies.loc[movie_id-1][2:]
    for i,genre in enumerate(genres):
        if int(genre_row[genre]) == 1: #if movie is of a particular genre,append the rating
            genre_scores[i].append(rating)
```

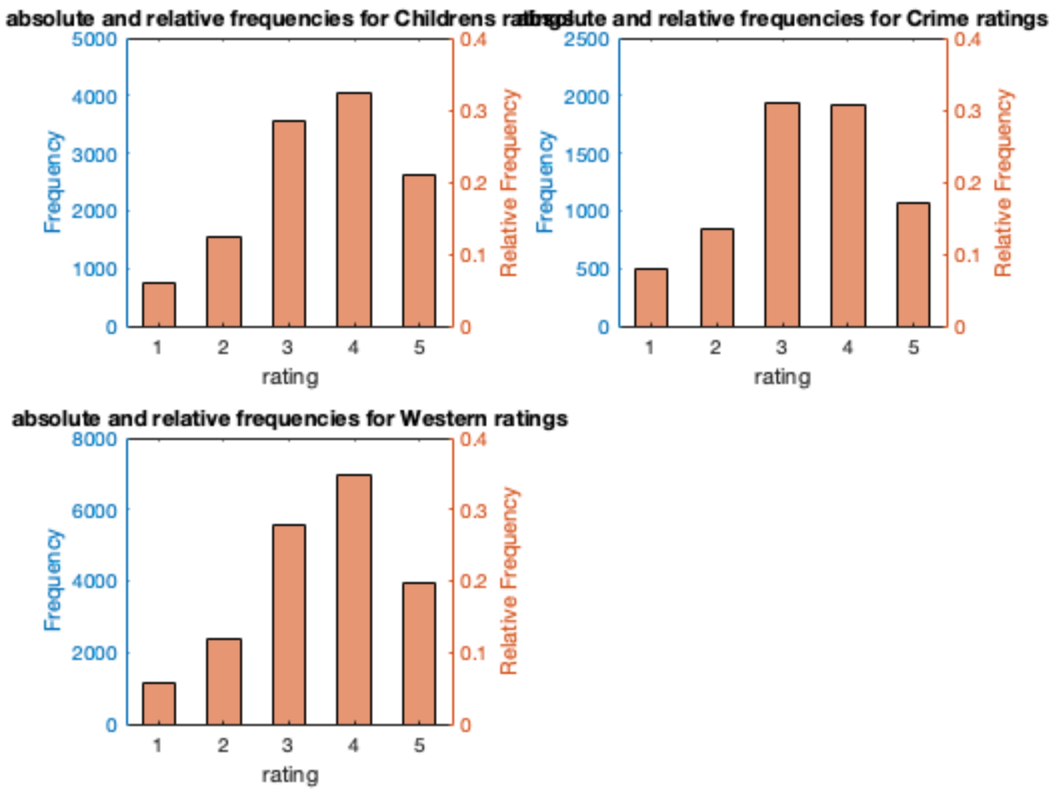
In [243]:
```
np.savetxt('genre_array1.txt',np.array(genre_scores[0]),fmt='%d')
np.savetxt('genre_array2.txt',np.array(genre_scores[1]),fmt='%d')
np.savetxt('genre_array3.txt',np.array(genre_scores[2]),fmt='%d')
```

```
%CODE USED FOR 4.4

%each genre array simply contains all ratings for movies of that genre
load('genre_array1.txt')
load('genre_array2.txt')
load('genre_array3.txt')
```

FOR INDIVIDUAL PLOTS

```
%%histogram for genre1
subplot(2,2,1)
yyaxis left
C = categorical(genre_array1,[1 2 3 4 5],{'1','2','3','4','5'});
histogram(C,'BarWidth',0.5)
xlabel('rating')
ylabel('frequency')
yyaxis right
histogram(C,'BarWidth',0.5,'Normalization','probability')
yyaxis left
title('absolute and relative frequencies for Childrens ratings')
ylabel('Frequency')
yyaxis right
ylabel('Relative Frequency')
%%histogram for genre2
subplot(2,2,2)
yyaxis left
C = categorical(genre_array2,[1 2 3 4 5],{'1','2','3','4','5'});
histogram(C,'BarWidth',0.5)
xlabel('rating')
ylabel('frequency')
yyaxis right
histogram(C,'BarWidth',0.5,'Normalization','probability')
yyaxis left
title('absolute and relative frequencies for Crime ratings')
ylabel('Frequency')
yyaxis right
ylabel('Relative Frequency')
%%histogram for genre3
subplot(2,2,3)
yyaxis left
C = categorical(genre_array3,[1 2 3 4 5],{'1','2','3','4','5'});
histogram(C,'BarWidth',0.5)
xlabel('rating')
ylabel('frequency')
yyaxis right
histogram(C,'BarWidth',0.5,'Normalization','probability')
yyaxis left
title('absolute and relative frequencies for Western ratings')
ylabel('Frequency')
yyaxis right
ylabel('Relative Frequency')
```



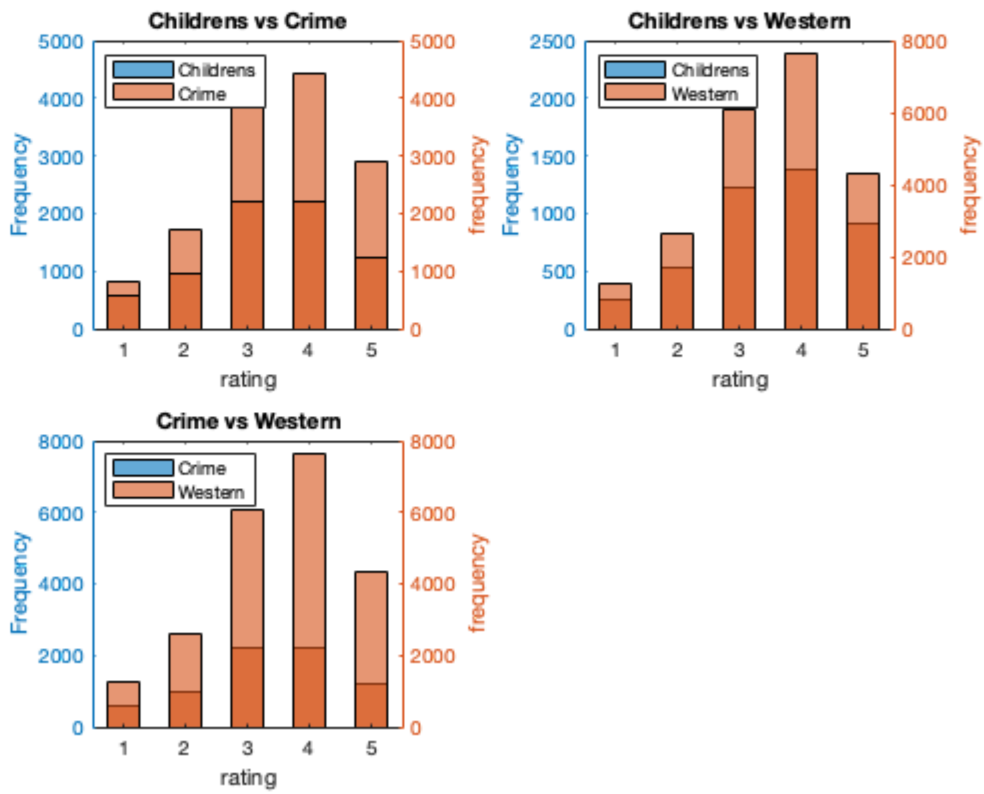
FOR PAIRWISE COMPARISON PLOTS

```
subplot(2,2,1)
C = categorical(genre_array1,[1 2 3 4 5],{'1','2','3','4','5'});
C2 = categorical(genre_array2,[1 2 3 4 5],{'1','2','3','4','5'});
h1 = histogram(C,'BarWidth',0.5); lbl = 'Childrens';
hold on;
h2 = histogram(C2,'BarWidth',0.5); lbl2 = 'Crime';
legend(lbl,lbl2,'Location','northwest')
title('Childrens vs Crime')
ylabel('frequency')
xlabel('rating')

subplot(2,2,2)
C = categorical(genre_array1,[1 2 3 4 5],{'1','2','3','4','5'});
C2 = categorical(genre_array3,[1 2 3 4 5],{'1','2','3','4','5'});
h1 = histogram(C,'BarWidth',0.5); lbl = 'Childrens';
hold on;
h2 = histogram(C2,'BarWidth',0.5); lbl2 = 'Western';
legend(lbl,lbl2,'Location','northwest')
title('Childrens vs Western')
ylabel('frequency')
xlabel('rating')

subplot(2,2,3)
```

```
C = categorical(genre_array2,[1 2 3 4 5],{'1','2','3','4','5'});
C2 = categorical(genre_array3,[1 2 3 4 5],{'1','2','3','4','5'});
h1 = histogram(C,'BarWidth',0.5); lbl = 'Crime';
hold on;
h2 = histogram(C2,'BarWidth',0.5); lbl2 = 'Western';
legend(lbl,lbl2,'Location','northwest')
title('Crime vs Western')
ylabel('frequency')
xlabel('rating')
```



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In [262]:
```
#CODE FOR THE HEATMAP
movies = pd.read_csv('movies.txt', sep="\t",header=None)
#arrays to store sum of ratings for each decade,genre pair, as well as count for averaging later
years_genres = np.zeros((8,19)) #20s up to 90s are dim1. genres are dim2
years_genres_counts = np.zeros((8,19))
```

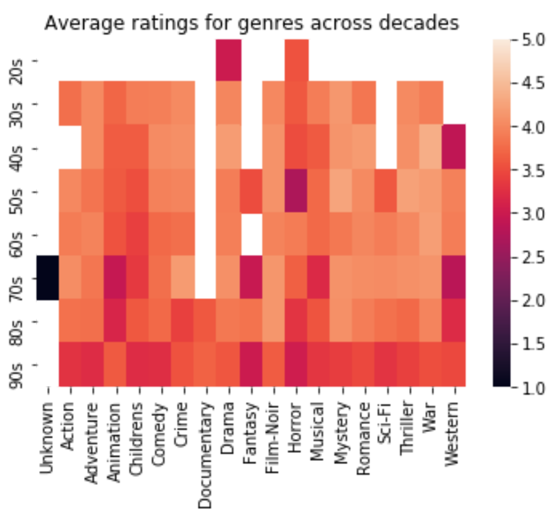
In [314]:
```
for row in clean_ratings:
    user_id,movie_id,rating = row[0],row[1],row[2]
    movie_info = movies.loc[movie_id-1]
    movie_title = movie_info[1]
    if movie_title == 'unknown': #ignore this movie
        continue
    year = re.findall('(\d{4})', movie_title)[-1] #regex to match 4digit sequencees.year always last.
    decade = int(year[2]) #3rd int in year indicates which decade
    genres = np.array(movie_info[2:])
    for i in range(19): #for each genre the movie is a member of, we add its rating and +1 to counts
        if int(genres[i]) == 1:
            years_genres[decade-2,i] += rating
            years_genres_counts[decade-2,i] += 1
```

In [272]:
```
avg_years_genres = np.divide(years_genres,years_genres_counts) #array holding average ratings
```

```
/Users/luiscosta/miniconda3/envs/myenv/lib/python3.7/site-packages/ipykernel_launcher.py:1: RuntimeWa
rning: invalid value encountered in true_divide
  """Entry point for launching an IPython kernel.
```

In [306]:
```
sns.heatmap(avg_years_genres,yticklabels = ylabels,xticklabels = xlabels,vmin=1,vmax=5)
plt.title('Average ratings for genres across decades')
```

Out[306]:
```
Text(0.5, 1, 'Average ratings for genres across decades')
```



In [3]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import random
```

HELPER FUNCTIONS

In [4]:
```
def clean_data(movies_file, data_file):
    unique_title_id_map = {}  # to keep track of titles that already have an id
    needed_updates = {}  # this array will map ids that need to be changed to the
id
    # they should be changed to
    with open(movies_file, 'r') as f:
        for line in f:
            line_data = line.strip('\n').split('\t')
            movie_id, title = line_data[0], line_data[1]
            if str(title) in unique_title_id_map:
                needed_updates[movie_id] = unique_title_id_map[str(title)]
            else:
                unique_title_id_map[str(title)] = str(movie_id)
    # print(needed_updates)

    data_arr = np.loadtxt(data_file, dtype=np.int)
    for i, row in enumerate(data_arr):
        if str(row[1]) in needed_updates:
            data_arr[i, 1] = needed_updates[str(row[1])]
    return (data_arr)
```

In [5]:
```
Y_train = np.loadtxt('data/train.txt').astype(int)
Y_test = np.loadtxt('data/test.txt').astype(int)

#movie_cols = ['Movie ID','Movie Title', 'Unknown', 'Action', 'Adventure', 'Animat
ion', 'Childrens', 'Comedy', 'Crime', 'Documentary',
#'Drama', 'Fantasy', 'Film-Noir', 'Horror', 'Musical', 'Mystery', 'Romance', 'Sci-
Fi', 'Thriller', 'War', 'Western']

data_arr = clean_data('data/movies.txt','data/data.txt')
```

Basic Method

In [6]:
```python
def grad_U(Ui, Yij, Vj, reg, eta):
    """
    Takes as input Ui (the ith row of U), a training point Yij, the column
    vector Vj (jth column of V^T), reg (the regularization parameter lambda),
    and eta (the learning rate).

    Returns the gradient of the regularized loss function with
    respect to Ui multiplied by eta.
    """
    return eta * np.subtract(reg * Ui, (Yij - np.dot(Ui, Vj))* Vj)

def grad_V(Vj, Yij, Ui, reg, eta):
    """
    Takes as input the column vector Vj (jth column of V^T), a training point Yij,
    Ui (the ith row of U), reg (the regularization parameter lambda),
    and eta (the learning rate).

    Returns the gradient of the regularized loss function with
    respect to Vj multiplied by eta.
    """
    return eta * np.subtract(reg * Vj, (Yij - np.dot(Ui, Vj))* Ui)

def get_err(U, V, Y, reg=0.0):
    """
    Takes as input a matrix Y of triples (i, j, Y_ij) where i is the index of a us
er,
    j is the index of a movie, and Y_ij is user i's rating of movie j and
    user/movie matrices U and V.

    Returns the mean regularized squared-error of predictions made by
    estimating Y_{ij} as the dot product of the ith row of U and the jth column of
V^T

    sum = 0.0
    for x in range(len(Y)):
        i = Y[x, 0] - 1
        j = Y[x, 1] - 1
        Yij = Y[x, 2]
        sum += (Yij - np.dot(U[i], V[j]))**2
    return reg / 2 * (np.linalg.norm(U)**2 + np.linalg.norm(V)**2) + 0.5 * sum"""
    N,D = Y.shape
    err = 0

    for n in range(N):
        i = Y[n,0] - 1
        j = Y[n,1] - 1
        yij = Y[n,2]
        err += (yij - np.dot(U[i], V[j]))**2

    U_norm = np.linalg.norm(U)
    V_norm = np.linalg.norm(V)

    return (reg/2 *(U_norm**2 + V_norm**2) + err/2) / N
```

In [ ]:
```python
def train_model(M, N, K, eta, reg, Y, eps=0.0001, max_epochs=300):
    """
    Given a training data matrix Y containing rows (i, j, Y_ij)
    where Y_ij is user i's rating on movie j, learns an
    M x K matrix U and N x K matrix V such that rating Y_ij is approximated
    by (UV^T)_ij.

    Uses a learning rate of <eta> and regularization of <reg>. Stops after
    <max_epochs> epochs, or once the magnitude of the decrease in regularized
    MSE between epochs is smaller than a fraction <eps> of the decrease in
    MSE after the first epoch.

    Returns a tuple (U, V, err) consisting of U, V, and the unregularized MSE
    of the model.
    """
    a, b = -0.5, 0.5
    U = (b - a) * np.random.random_sample((M, K)) + a
    V = (b - a) * np.random.random_sample((N, K)) + a

    # first iteration, get loss reduction for initial epoch
    err0 = get_err(U, V, Y)
    arr = np.arange(len(Y))
    np.random.shuffle(arr)
    for index in arr:
        i = Y[index, 0] - 1
        j = Y[index, 1] - 1
        Yij = Y[index, 2]
        U[i] -= grad_U(U[i], Yij, V[j], reg, eta)
        V[j] -= grad_V(V[j], Yij, U[i], reg, eta)
    err01 = err0 - get_err(U, V, Y)

    # second through last iterations
    for epoch in range(max_epochs - 1):
        last_err = get_err(U, V, Y)
        arr = np.arange(len(Y))
        np.random.shuffle(arr)
        for index in arr:
            i = Y[index, 0] - 1
            j = Y[index, 1] - 1
            Yij = Y[index, 2]
            U[i] -= grad_U(U[i], Yij, V[j], reg, eta)
            V[j] -= grad_V(V[j], Yij, U[i], reg, eta)
        curr_err = get_err(U, V, Y)
        if (last_err - curr_err) / err01 < eps:
            last_err = curr_err
            break
        last_err = curr_err
    return (U, V, last_err)
```

Bias Term Method

In [7]:
```
def bgrad_U(Yij, Ui, Vj, reg, eta, ai, bj, mu):
    """
    Takes as input Ui (the ith row of U), a training point Yij, the column
    vector Vj (jth column of V^T), reg (the regularization parameter lambda),
    and eta (the learning rate), ai (the bias term for user), bj (bias
    term for movie), mu (the average of Y)

    Returns the gradient of the regularized loss function with
    respect to Ui multiplied by eta.
    """
    return eta * np.subtract(reg * Ui, (Yij - mu - np.dot(Ui, Vj) - ai - bj)* Vj)

def bgrad_V(Yij, Ui, Vj, reg, eta, ai, bj, mu):
    """
    Takes as input Ui (the ith row of U), a training point Yij, the column
    vector Vj (jth column of V^T), reg (the regularization parameter lambda),
    and eta (the learning rate), ai (the bias term for user), bj (bias
    term for movie), mu (the average of Y)

    Returns the gradient of the regularized loss function with
    respect to Vj multiplied by eta.
    """
    return eta * np.subtract(reg * Vj, (Yij - mu - np.dot(Ui, Vj) - ai - bj)* Ui)

def bgrad_a(Yij, Ui, Vj, reg, eta, ai, bj, mu):
    """
    Takes as input Ui (the ith row of U), a training point Yij, the column
    vector Vj (jth column of V^T), reg (the regularization parameter lambda),
    and eta (the learning rate), ai (the bias term for user), bj (bias
    term for movie), mu (the average of Y)

    Returns the gradient of the regularized loss function with
    respect to ai multiplied by eta.
    """
    return eta * (reg * ai - Yij + mu + np.dot(Ui, Vj) + ai + bj)

def bgrad_b(Yij, Ui, Vj, reg, eta, ai, bj, mu):
    """
    Takes as input Ui (the ith row of U), a training point Yij, the column
    vector Vj (jth column of V^T), reg (the regularization parameter lambda),
    and eta (the learning rate), ai (the bias term for user), bj (bias
    term for movie), mu (the average of Y)

    Returns the gradient of the regularized loss function with
    respect to bj multiplied by eta.
    """
    return eta * (reg * bj - Yij + mu + np.dot(Ui, Vj) + ai + bj)
```

In [ ]:
```
def bget_err(Y, U, V, reg, a, b, mu):
    """
    Takes as input a matrix Y of triples (i, j, Y_ij) where i is the index of a us
er,
    j is the index of a movie, and Y_ij is user i's rating of movie j, the
    user/movie matrices U and V, the bias vectors a and b, and the average observe
d rating mu

    Returns the mean regularized squared-error of predictions made by
    estimating Y_{ij} as the dot product of the ith row of U and the jth column of
V^T
    """
    sum = 0.0
    for x in range(len(Y)):
        i = Y[x, 0] - 1
        j = Y[x, 1] - 1
        Yij = Y[x, 2]
        sum += (Yij - mu - np.dot(U[i], V[j]) - a[i] - b[j])**2
    return reg / 2 * (np.linalg.norm(U)**2 + np.linalg.norm(V)**2 + np.linalg.norm
(a)**2 + np.linalg.norm(b)**2) + 0.5 * sum
```

In [ ]:
```
def btrain_model(M, N, K, eta, reg, Y, eps=0.0001, max_epochs=300):
    """
    Given a training data matrix Y containing rows (i, j, Y_ij)
    where Y_ij is user i's rating on movie j, learns an
    M x K matrix U and N x K matrix V such that rating Y_ij is approximated
    by (UV^T)_ij.

    Uses a learning rate of <eta> and regularization of <reg>. Stops after
    <max_epochs> epochs, or once the magnitude of the decrease in regularized
    MSE between epochs is smaller than a fraction <eps> of the decrease in
    MSE after the first epoch.

    Returns a tuple (U, V, a, b, err) consisting of U, V, the bias vectors, and th
e MSE
    of the model.
    """
    a, b = -0.5, 0.5
    U = (b - a) * np.random.random_sample((M, K)) + a
    V = (b - a) * np.random.random_sample((N, K)) + a
    A = (b - a) * np.random.random_sample((M, 1)) + a # bias for user
    B = (b - a) * np.random.random_sample((N, 1)) + a # bias for movie
    mu = np.mean(Y[:, 2]) # average of all observed rating

    # first iteration, get loss reduction for initial epoch
    err0 = bget_err(Y, U, V, reg, A, B, mu)
    arr = np.arange(len(Y))
    np.random.shuffle(arr)
    for index in arr:
        i = Y[index, 0] - 1
        j = Y[index, 1] - 1
        Yij = Y[index, 2]
        Ui, Vj, Ai, Bj = U[i], V[j], A[i], B[j]
        U[i] -= bgrad_U(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
        V[j] -= bgrad_V(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
        A[i] -= bgrad_a(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
        B[j] -= bgrad_b(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
    err01 = err0 - bget_err(Y, U, V, reg, A, B, mu)
    print(err01)

    # second through last iterations
    for epoch in range(max_epochs - 1):
        last_err = bget_err(Y, U, V, reg, A, B, mu)
        arr = np.arange(len(Y))
        np.random.shuffle(arr)
        for index in arr:
            i = Y[index, 0] - 1
            j = Y[index, 1] - 1
            Yij = Y[index, 2]
            Ui, Vj, Ai, Bj = U[i], V[j], A[i], B[j]
            U[i] -= bgrad_U(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
            V[j] -= bgrad_V(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
            A[i] -= bgrad_a(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
            B[j] -= bgrad_b(Yij, Ui, Vj, reg, eta, Ai, Bj, mu)
        curr_err = bget_err(Y, U, V, reg, A, B, mu)
        print('change in err / initial = ' + str((last_err - curr_err) / err01))
        if (last_err - curr_err) / err01 < eps:
            last_err = curr_err
            break
        last_err = curr_err
    return (U, V, A, B, last_err)
```

In [ ]:
```
def clean_data(movies_file, data_file):
    unique_title_id_map = {}  # to keep track of titles that already have an id
    needed_updates = {}  # this array will map ids that need to be changed to the
id
    # they should be changed to
    with open(movies_file, 'r', encoding='utf-8') as f:
        for line in f:
            line_data = line.strip('\n').split('\t')
            movie_id, title = line_data[0], line_data[1]
            if str(title) in unique_title_id_map:
                needed_updates[movie_id] = unique_title_id_map[str(title)]
            else:
                unique_title_id_map[str(title)] = str(movie_id)
    # print(needed_updates)

    data_arr = np.loadtxt(data_file, dtype=np.int)
    for i, row in enumerate(data_arr):
        if str(row[1]) in needed_updates:
            data_arr[i, 1] = needed_updates[str(row[1])]
    return (data_arr)
```

Basic Method Training

In [8]:
```
M = max(max(Y_train[:,0]), max(Y_test[:,0])).astype(int) # users
N = max(max(Y_train[:,1]), max(Y_test[:,1])).astype(int) # movies

K = 20

reg = 0 #10**-3
eta = 0.03 # learning rate
E_in = 0
E_out = 0

# Use to compute Ein and Eout
U,V, err = train_model(M, N, K, eta, reg, Y_train)
E_in = err
E_out = get_err(U, V, Y_test)
```

Bias Term Method Training

In [9]:
```
M = max(max(Y_train[:,0]), max(Y_test[:,0])).astype(int) # users
N = max(max(Y_train[:,1]), max(Y_test[:,1])).astype(int) # movies
k = 20

reg = 0.1
eta = 0.03 # learning rate

print("Training model with M = %s, N = %s, k = %s, eta = %s, reg = %s"%(M, N, k, e
ta, reg))
bU, bV, A, B, e_in = btrain_model(M, N, k, eta, reg, Y_train)
```

```
Training model with M = 943, N = 1682, k = 20, eta = 0.03, reg = 0.1
[32786.5871227]
change in err / initial = [0.06823691]
change in err / initial = [0.04008331]
change in err / initial = [0.037765]
change in err / initial = [0.03760799]
change in err / initial = [0.0327737]
change in err / initial = [0.03067323]
change in err / initial = [0.02888244]
change in err / initial = [0.02354312]
change in err / initial = [0.02084751]
change in err / initial = [0.01869495]
change in err / initial = [0.01650587]
change in err / initial = [0.01298676]
change in err / initial = [0.01122367]
change in err / initial = [0.01479754]
change in err / initial = [0.00723683]
change in err / initial = [0.00894381]
change in err / initial = [0.0057497]
change in err / initial = [0.00738018]
change in err / initial = [0.00532938]
change in err / initial = [0.00775237]
change in err / initial = [0.00287223]
change in err / initial = [0.00553559]
change in err / initial = [0.00418568]
change in err / initial = [0.00322388]
change in err / initial = [0.00142367]
change in err / initial = [0.00394849]
change in err / initial = [0.00176765]
change in err / initial = [0.00527642]
change in err / initial = [-0.00027041]
```

In [ ]:
```
e_in /= len(Y_train)
e_out = get_err(Y_test, U, V, reg, A, B, np.mean(Y_test[:, 2]))/ len(Y_test)
```

In [ ]:
```
print('E_in is ' + str(e_in))
print('E_out is ' + str(e_out))
```

Off the Shelf

In [10]:
```
import numpy as np
from scipy.sparse.linalg import svds

def off_train(M, N, Y):
    train_m = np.zeros((M,N))
    arr = np.arange(len(Y))

    for index in arr:
        i = Y[index, 0] - 1
        j = Y[index, 1] - 1
        Yij = Y[index,2]
        train_m[i][j] = Yij

    #U, s, V = svds(train_m, k = 20)
    U, s, V = np.linalg.svd(train_m)

    return U, s, V

M = max(max(Y_train[:,0]), max(Y_test[:,0])).astype(int) # users
N = max(max(Y_train[:,1]), max(Y_test[:,1])).astype(int) # movies

K = 20

reg = 0 #10**-3
eta = 0.03 # learning rate
E_in = 0
E_out = 0

# Use to compute Ein and Eout
U_off, Sigma, V_off = off_train(M, N, Y_train)
```

Find the average rating for each movie

In [19]:
```
movie_rating = np.zeros((1682,))
movie_num_user_rating = np.zeros((1682,))
for row in Y_train:
    # 0 is user id, 1 is movie id, 2 is rating
    movie_rating[row[1]-1] += row[2]
    movie_num_user_rating[row[1]-1] += 1
for row in Y_test:
    # 0 is user id, 1 is movie id, 2 is rating
    movie_rating[row[1]-1] += row[2]
    movie_num_user_rating[row[1]-1] += 1
movie_avg_rating = np.divide(np.array(movie_rating), np.array(movie_num_user_ratin
g))
print(movie_avg_rating)
```

```
[3.87831858 3.20610687 3.03333333 ... 2.         3.         3.        ]
```

Importing outside library AdjustText to make movie names not overlap

In [116]:
```
!pip install adjustText
```

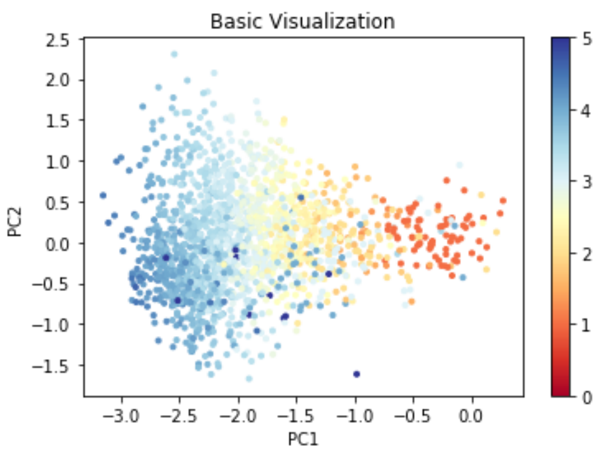
```
Collecting adjustText
  Downloading https://files.pythonhosted.org/packages/9e/15/4157718bf323fd5f5b81
c891c660d0f388e042d2689a558bf1389632dc44/adjustText-0.7.3.tar.gz
Requirement already satisfied: numpy in c:\users\serena\anaconda3\lib\site-packa
ges (from adjustText) (1.16.5)
Requirement already satisfied: matplotlib in c:\users\serena\anaconda3\lib\site-
packages (from adjustText) (3.1.1)
Requirement already satisfied: cycler>=0.10 in c:\users\serena\anaconda3\lib\sit
e-packages (from matplotlib->adjustText) (0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\serena\anaconda3\li
b\site-packages (from matplotlib->adjustText) (1.1.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\us
ers\serena\anaconda3\lib\site-packages (from matplotlib->adjustText) (2.4.2)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\serena\anaconda
3\lib\site-packages (from matplotlib->adjustText) (2.8.0)
Requirement already satisfied: six in c:\users\serena\anaconda3\lib\site-package
s (from cycler>=0.10->matplotlib->adjustText) (1.12.0)
Requirement already satisfied: setuptools in c:\users\serena\anaconda3\lib\site-
packages (from kiwisolver>=1.0.1->matplotlib->adjustText) (41.4.0)
Building wheels for collected packages: adjustText
  Building wheel for adjustText (setup.py): started
  Building wheel for adjustText (setup.py): finished with status 'done'
  Created wheel for adjustText: filename=adjustText-0.7.3-cp37-none-any.whl size
=7104 sha256=c4263acf1a0d03153ae0fe6a71ff16a917ac07de66488c34eadd3235078fb502
  Stored in directory: C:\Users\serena\AppData\Local\pip\Cache\wheels\41\95\74\7
d347e136d672f8bc28e937032bc92baf4f80856763a7e7b72
Successfully built adjustText
Installing collected packages: adjustText
Successfully installed adjustText-0.7.3
```

Matrix Visualization with PC1 and PC2

In [20]:
```
from adjustText import adjust_text

def visualize_2d(M, title, index, marker_sz, **kwargs):
    """Project a matrix into 2 dimensions and visualize it.
    args:
    M - matrix to project (V matrix)
    index - indices of the movies to project
    names - names of the movies for labeling

    """
    names = kwargs.get('names', None)

    A, sigma, B = np.linalg.svd(M)
    M_proj = np.matmul(A[:,:2].transpose(), M)

    cm = plt.cm.get_cmap('RdYlBu')

    sc = plt.scatter(M_proj[0,index], M_proj[1,index], s=marker_sz**2, vmin=0,vmax
=5, c=movie_avg_rating[index], cmap=cm)
    if names != None:
        texts = []
        for i, name in zip(index, names):
            texts.append(plt.annotate(name, (M_proj[0, i], M_proj[1, i])))
        adjust_text(texts, autoalign='y')
    plt.colorbar(sc)
    plt.title(title)
    plt.xlabel('PC1')
    plt.ylabel('PC2')
    plt.show()

    return M_proj
```

Basic All Movies

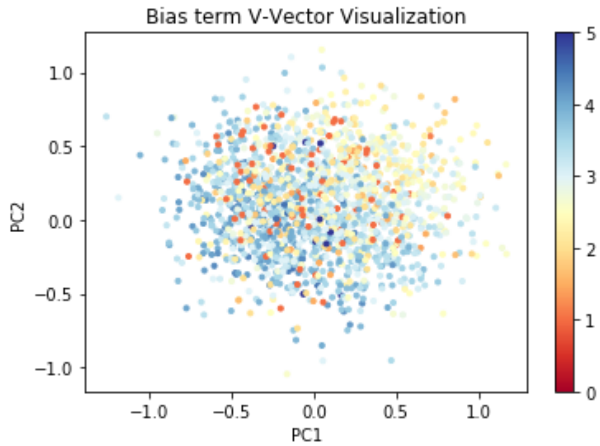
In [26]:
```
index = range((V.T).shape[1])
title = 'Basic Visualization'
visualize_2d(V.T,title, index, 3)
```



Out[26]:
```
array([[-2.77240821, -2.1366022 , -2.03999763, ..., -0.44030291,
        -0.91240738, -0.96931671],
       [ 1.14030668,  0.57141901,  0.87178507, ...,  0.07297196,
         0.30603668, -0.47763089]])
```

Bias Term All Movies

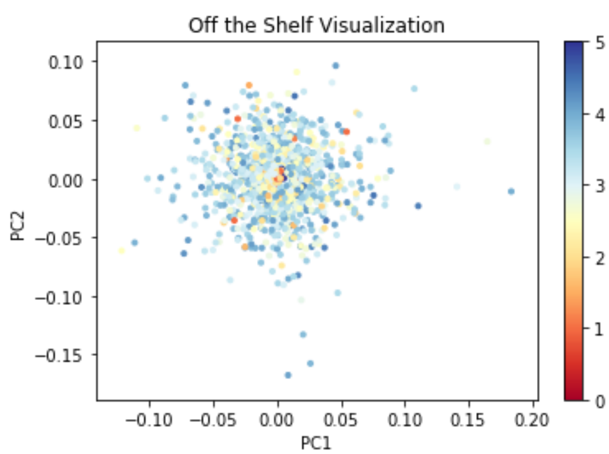
In [42]:
```
index = range((bV.T).shape[1])
visualize_2d(bV.T, 'Bias term V-Vector Visualization',index, 3)
```



Out[42]:
```
array([[ 0.01393449,  0.45263381,  0.21225774, ..., -0.13400777,
        -0.37313518,  0.16808487],
       [-0.13288461,  0.05326039,  0.36411833, ...,  0.0366133 ,
        -0.18325579, -0.0774266 ]])
```

Off the Shelf of All Movies

In [50]:
```
index = range((V_off.T).shape[1])
visualize_2d(V_off.T, 'Off the Shelf Visualization',index, 3)
```



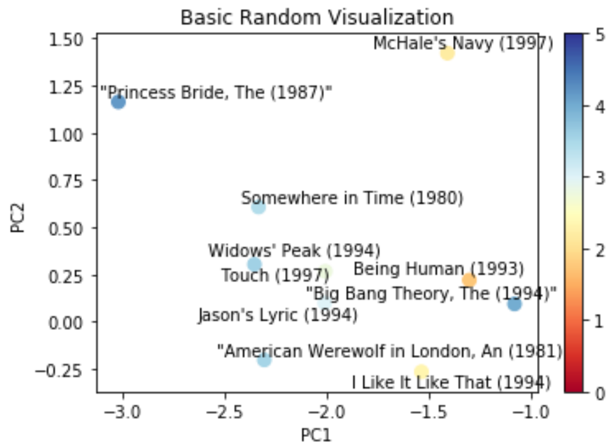
Out[50]:
```
array([[ 3.19975166e-17, -6.81846868e-02,  7.63564244e-02, ...,
         2.49092379e-03, -4.92054703e-03, -1.94694697e-03],
       [ 1.02762037e-17,  1.69763209e-02,  3.23234102e-02, ...,
         3.67341793e-04,  6.49603545e-03,  3.95882009e-03]])
```

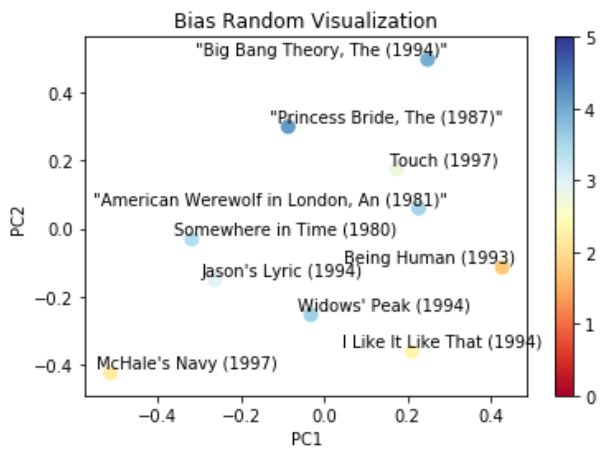
Get Movie Names

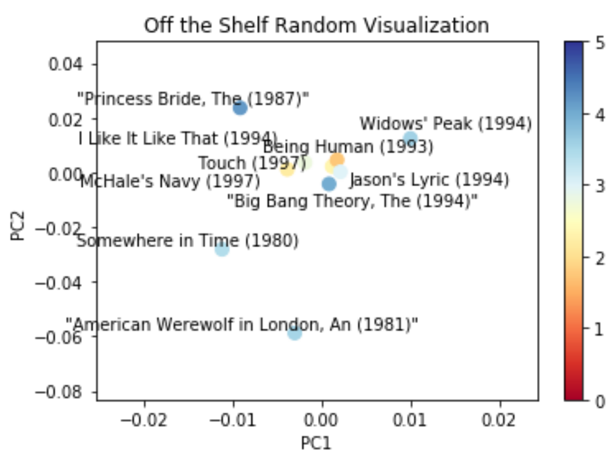
In [14]:
```
all_movies_names = []
with open('data/movies.txt', 'r', encoding='utf-8') as f:
    for line in f:
        line_data = line.strip('\n').split('\t')
        all_movies_names.append(line_data[1])

def get_movie_names(index):
    chosen = []
    for i in index:
        chosen.append(all_movies_names[i])
    return chosen
```

10 randomly selected movies

In [21]:
```
import random

num_movies = 1682
rand_index = np.random.choice(num_movies, 10, replace=False)
chosen_movie_names = get_movie_names(rand_index)
visualize_2d(V.T, 'Basic Random Visualization',rand_index, 8, names=chosen_movie_n
ames)
visualize_2d(bV.T, 'Bias Random Visualization',rand_index, 8, names=chosen_movie_n
ames)
visualize_2d(V_off.T, 'Off the Shelf Random Visualization',rand_index, 8, names=ch
osen_movie_names)
```





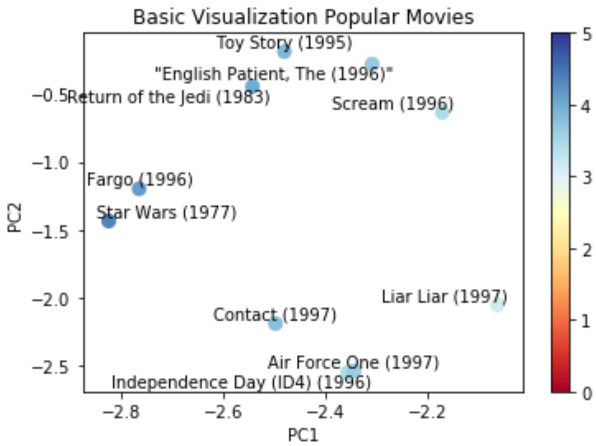


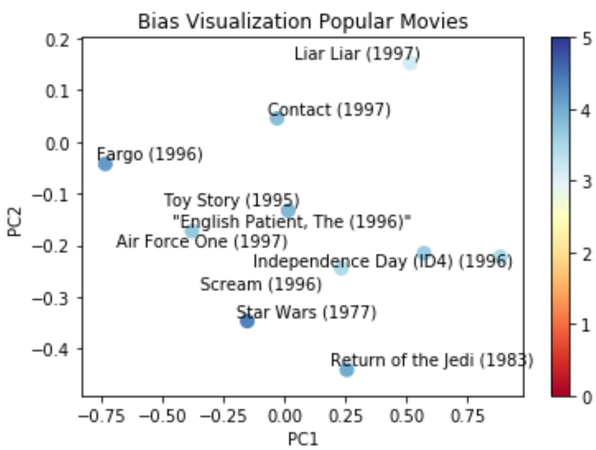

```
Out[21]: array([[ 3.19975166e-17, -6.81846868e-02,  7.63564244e-02, ...,
                  2.49092379e-03, -4.92054703e-03, -1.94694697e-03],
                [ 1.02762037e-17,  1.69763209e-02,  3.23234102e-02, ...,
                  3.67341793e-04,  6.49603545e-03,  3.95882009e-03]])
```

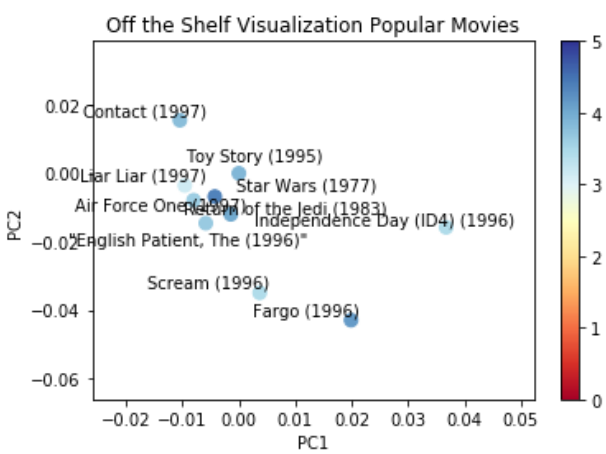
Top 10 Most Popular Movies

In [52]:
```
# index of top 10 by number of ratings
copy_num_rating = movie_num_user_rating.copy()
index_top10_popular = copy_num_rating.argsort()[-10:]
chosen_movie_names = get_movie_names(index_top10_popular)
for name in chosen_movie_names:
    print(name)
visualize_2d(V.T, 'Basic Visualization Popular Movies',index_top10_popular, 8, nam
es=chosen_movie_names)
visualize_2d(bV.T, 'Bias Visualization Popular Movies',index_top10_popular, 8, nam
es=chosen_movie_names)
visualize_2d(V_off.T, 'Off the Shelf Visualization Popular Movies',index_top10_pop
ular, 8, names=chosen_movie_names)

# maybe need to include genre??
```

```
Independence Day (ID4) (1996)
Air Force One (1997)
Toy Story (1995)
Scream (1996)
"English Patient, The (1996)"
Liar Liar (1997)
Return of the Jedi (1983)
Fargo (1996)
Contact (1997)
Star Wars (1977)
```





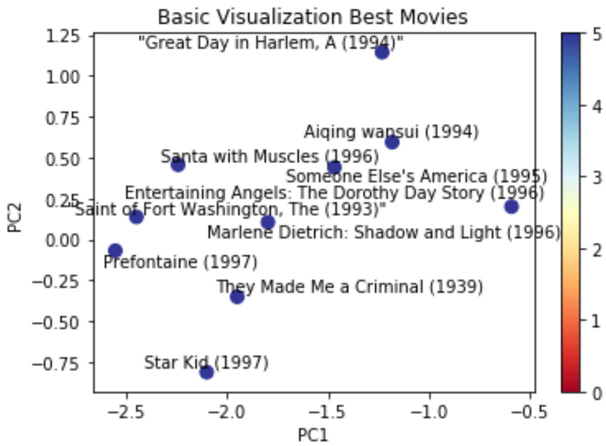


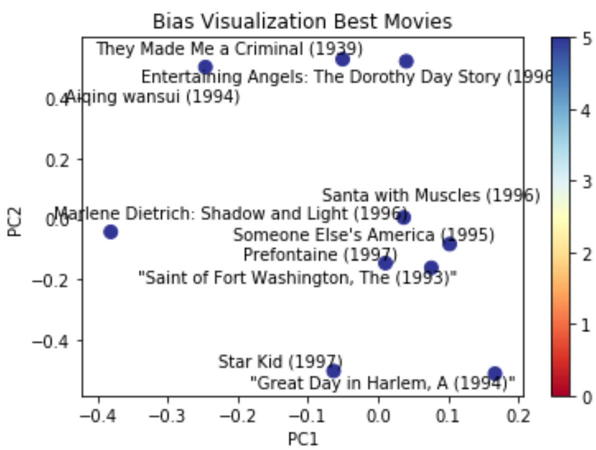
Out[52]:
```
array([[ 3.19975166e-17, -6.81846868e-02,  7.63564244e-02, ...,
         2.49092379e-03, -4.92054703e-03, -1.94694697e-03],
       [ 1.02762037e-17,  1.69763209e-02,  3.23234102e-02, ...,
         3.67341793e-04,  6.49603545e-03,  3.95882009e-03]])
```

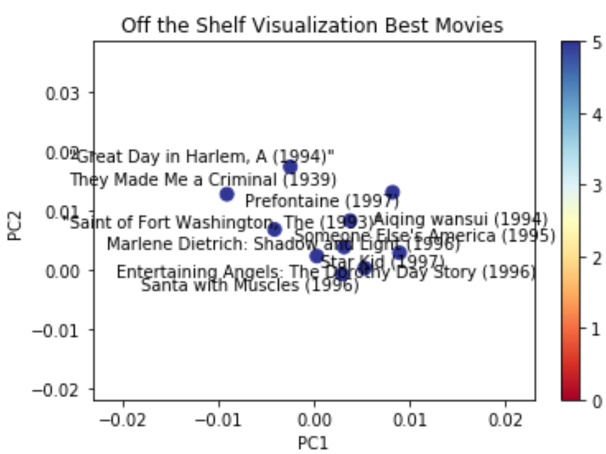
Top 10 Best Movies by Ratings

In [53]:
```
# index of top 10 by number of ratings
copy_avg_rating = movie_avg_rating.copy()
index_top10_rating = copy_avg_rating.argsort()[-10:]
chosen_movie_names = get_movie_names(index_top10_rating)
for name in chosen_movie_names:
    print(name)
visualize_2d(V.T,'Basic Visualization Best Movies', index_top10_rating, 8, names=c
hosen_movie_names)
visualize_2d(bV.T,'Bias Visualization Best Movies', index_top10_rating, 8, names=c
hosen_movie_names)
visualize_2d(V_off.T,'Off the Shelf Visualization Best Movies', index_top10_ratin
g, 8, names=chosen_movie_names)

# maybe need to include genre??
```

```
Aiqing wansui (1994)
Santa with Muscles (1996)
Prefontaine (1997)
Marlene Dietrich: Shadow and Light (1996)
Someone Else's America (1995)
They Made Me a Criminal (1939)
"Great Day in Harlem, A (1994)"
Entertaining Angels: The Dorothy Day Story (1996)
"Saint of Fort Washington, The (1993)"
Star Kid (1997)
```







Out[53]:
```
array([[ 3.19975166e-17, -6.81846868e-02,  7.63564244e-02, ...,
         2.49092379e-03, -4.92054703e-03, -1.94694697e-03],
       [ 1.02762037e-17,  1.69763209e-02,  3.23234102e-02, ...,
         3.67341793e-04,  6.49603545e-03,  3.95882009e-03]])
```

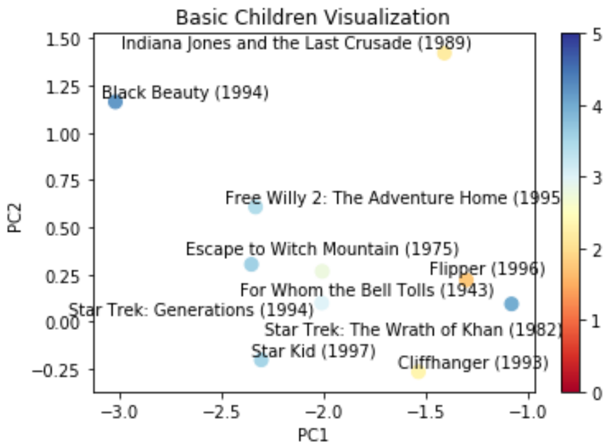
Selected Genre: Children, Crime, Western

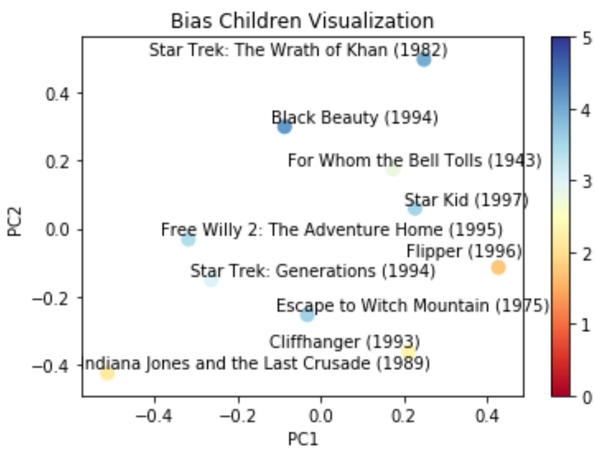
Getting the movie names and id from the 3 genres

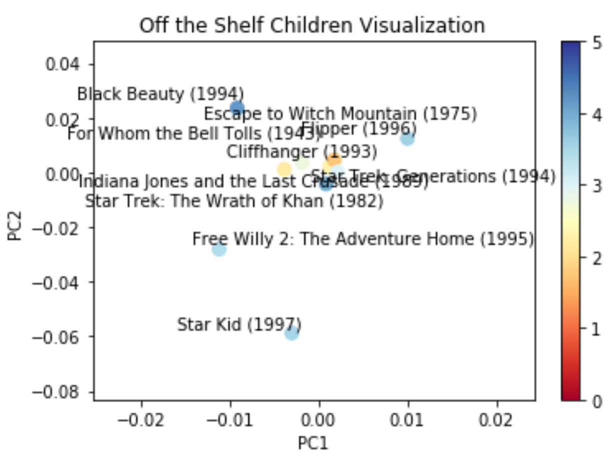
In [22]:
```
# (children, crime, western,) have indices 4,6,18
genres = [4, 6, 18]
movies_by_genre = [[], [], []] # children, crime, western
movies = pd.read_csv('data/movies.txt', sep="\t",header=None)
for row in range(len(movies)):
    genre_row = movies.loc[row][2:]
    movie_name = movies.loc[row][1]
    movie_id = movies.loc[row][0]
    for i,genre in enumerate(genres):
        if int(genre_row[genre]) == 1:
            movies_by_genre[i].append([movie_id, movie_name])

children, crime, western = np.array(movies_by_genre[0]).T, np.array(movies_by_genr
e[1]).T, np.array(movies_by_genre[2]).T
```

Children Visualization

In [23]:
```
# Children visualization
children_chosen = np.random.choice(children[0].astype(int), 10, replace=False) - 1
chosen_movie_names = get_movie_names(children_chosen)
visualize_2d(V.T, 'Basic Children Visualization',rand_index, 8, names=chosen_movie
_names)
visualize_2d(bV.T, 'Bias Children Visualization',rand_index, 8, names=chosen_movie
_names)
visualize_2d(V_off.T, 'Off the Shelf Children Visualization',rand_index, 8, names=
chosen_movie_names)
```





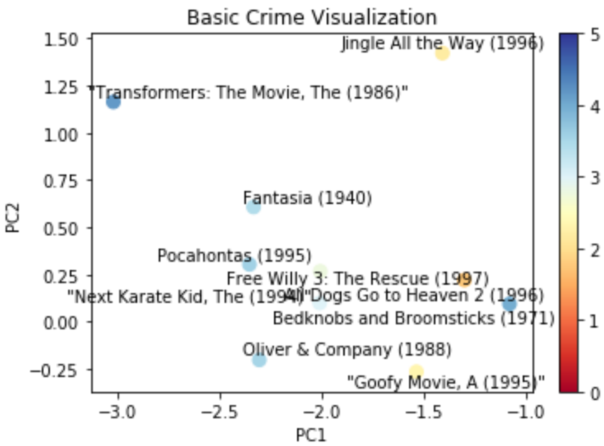


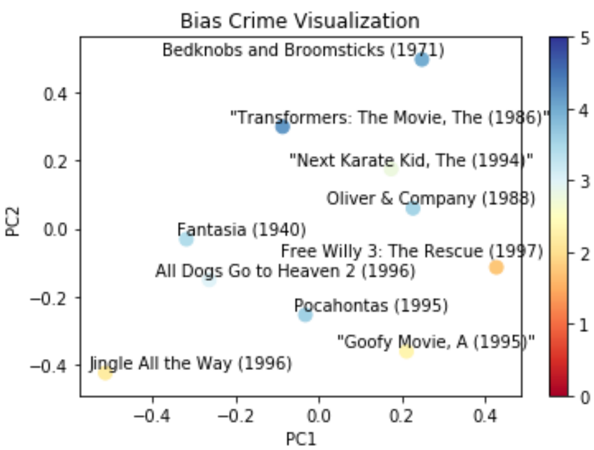

```
Out[23]: array([[ 3.19975166e-17, -6.81846868e-02,  7.63564244e-02, ...,
                  2.49092379e-03, -4.92054703e-03, -1.94694697e-03],
                [ 1.02762037e-17,  1.69763209e-02,  3.23234102e-02, ...,
                  3.67341793e-04,  6.49603545e-03,  3.95882009e-03]])
```

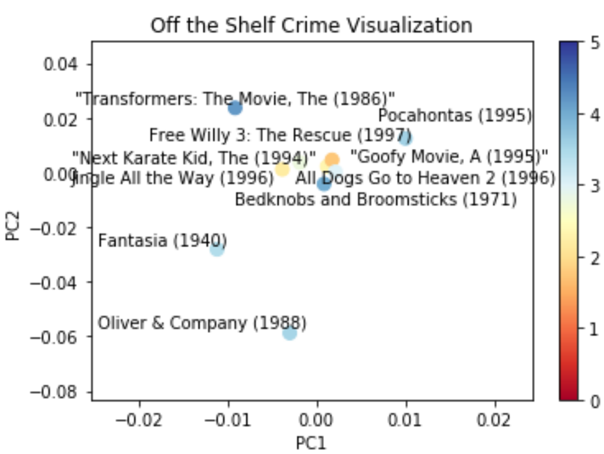
Crime Visualization

In [24]:

```
# Crime visualization
crime_chosen = np.random.choice(crime[0].astype(int), 10, replace=False) - 1
chosen_movie_names = get_movie_names(crime_chosen)
visualize_2d(V.T, 'Basic Crime Visualization',rand_index, 8, names=chosen_movie_na
mes)
visualize_2d(bV.T, 'Bias Crime Visualization',rand_index, 8, names=chosen_movie_na
mes)
visualize_2d(V_off.T, 'Off the Shelf Crime Visualization',rand_index, 8, names=cho
sen_movie_names)
```



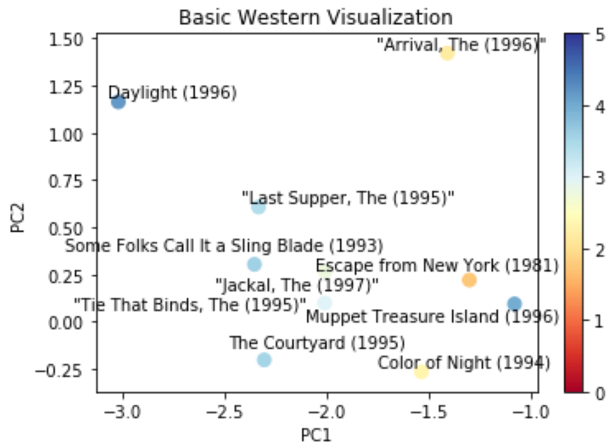


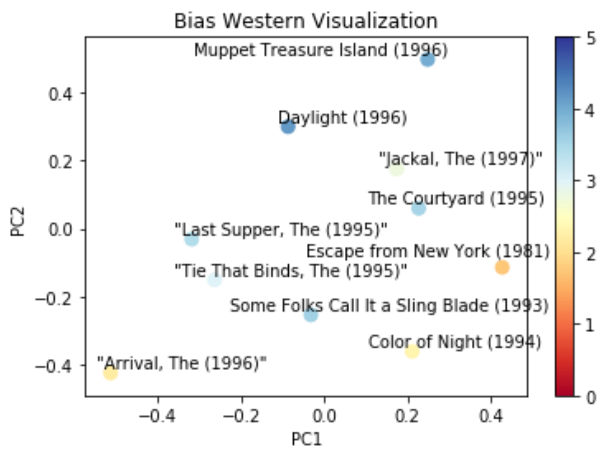


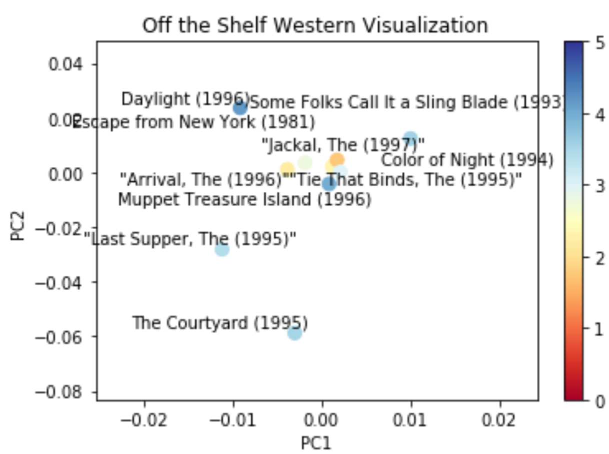

```
Out[24]: array([[ 3.19975166e-17, -6.81846868e-02,  7.63564244e-02, ...,
                  2.49092379e-03, -4.92054703e-03, -1.94694697e-03],
                [ 1.02762037e-17,  1.69763209e-02,  3.23234102e-02, ...,
                  3.67341793e-04,  6.49603545e-03,  3.95882009e-03]])
```

Western Visualization

In [25]:
```
# Western visualization
western_chosen = np.random.choice(western[0].astype(int), 10, replace=False) - 1
chosen_movie_names = get_movie_names(western_chosen)
visualize_2d(V.T, 'Basic Western Visualization',rand_index, 8, names=chosen_movie_
names)
visualize_2d(bV.T, 'Bias Western Visualization',rand_index, 8, names=chosen_movie_
names)
visualize_2d(V_off.T, 'Off the Shelf Western Visualization',rand_index, 8, names=c
hosen_movie_names)
```







Out[25]:
```
array([[ 3.19975166e-17, -6.81846868e-02,  7.63564244e-02, ...,
         2.49092379e-03, -4.92054703e-03, -1.94694697e-03],
       [ 1.02762037e-17,  1.69763209e-02,  3.23234102e-02, ...,
         3.67341793e-04,  6.49603545e-03,  3.95882009e-03]])
```

In [ ]:

In [ ]: