In [ ]:

```
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from tabulate import tabulate
from sklearn.linear_model import LinearRegression, Ridge, Lasso,
LogisticRegression
from sklearn.model_selection import train_test_split,
cross_val_score, GridSearchCV
from sklearn.metrics import r2_score, mean_squared_error, auc,
confusion_matrix, roc_curve
from itertools import product
seed_val = 201601058
np.random.seed(seed_val)
sns.set()
font_titlesize = 18
font_axeslabelsize = 14
font_legendsize = 10
```

In [ ]:

```
# Loading data
real_df = pd.read_csv('movieReplicationSet.csv')
mov_count = 400
real_df.head()
```

Out[ ]:

	The Life of David Gale (2003)	Wing Commander (1999)	Django Unchained (2012)	Alien (1979)	Indiana Jones and the Last Crusade (1989)	Snatch (2000)	Rambo: First Blood Part II (1985)	Fargo (1996)	Let the Right One In (2008)	B S (2(
0	NaN	NaN	4.0	NaN	3.0	NaN	NaN	NaN	NaN	
1	NaN	NaN	1.5	NaN	NaN	NaN	NaN	NaN	NaN	
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
3	NaN	NaN	2.0	NaN	3.0	NaN	NaN	NaN	NaN	
4	NaN	NaN	3.5	NaN	0.5	NaN	0.5	1.0	NaN	

5 rows × 477 columns

In [ ]:

```
# Eliminate rows that have all nans
rows_dropped = []
cols_dropped = []
for i in range(real_df.shape[0]):
    row_nan_count = real_df.iloc[i, 1:mov_count+1].isna().sum()
    if row_nan_count == mov_count:
        rows_dropped.append(i)

# Eliminate columns that have all nans
for j in range(1, real_df.shape[1]):
    col_nan_count = real_df.iloc[:, j].isna().sum()
    if col_nan_count == real_df.shape[0]:
        cols_dropped.append(j)

if len(rows_dropped) > 0:
    df = real_df.drop(rows_dropped).reset_index(drop=True)
    real_df = real_df.drop(rows_dropped).reset_index(drop=True)
if len(cols_dropped) > 0:
    df = real_df.drop(columns = df.columns[cols_dropped])
    real_df = real_df.drop(rows_dropped).reset_index(drop=True)
```

```
print(f'{len(rows_dropped)} rows and {len(cols_dropped)} were dropped.')
```

```
1 rows and 0 were dropped.
```

In [ ]:

```
ratings_df = df.iloc[:, :mov_count]

# Calculate column and row averages
col_avgs = ratings_df.mean(axis = 0)
row_avgs = ratings_df.mean(axis = 1)

# Replace missing values with the average of the column and row
for i in range(ratings_df.shape[0]):
    for j in range(ratings_df.shape[1]):
        if pd.isna(df.iloc[i, j]):
            # Compute the blend of the column and row means
            blend = round((col_avgs[j] + row_avgs[i]) / 2, 1)
            # Replace the missing value with the blend
            df.iloc[i, j] = blend
df.head()
```

Out[ ]:

	The Life of David Gale (2003)	Wing Commander (1999)	Django Unchained (2012)	Alien (1979)	Indiana Jones and the Last Crusade (1989)	Snatch (2000)	Rambo: First Blood Part II (1985)	Fargo (1996)	Let the Right One In (2008)	B S (2(
0	2.4	2.4	4.0	2.7	3.0	2.7	2.6	2.8	2.6	
1	2.4	2.4	1.5	2.7	2.8	2.7	2.5	2.8	2.6	
2	2.7	2.7	3.2	3.0	3.0	3.0	2.8	3.1	2.9	
3	2.3	2.2	2.0	2.6	3.0	2.5	2.4	2.7	2.5	
4	2.2	2.1	3.5	2.5	0.5	2.4	0.5	1.0	2.4	

5 rows × 477 columns

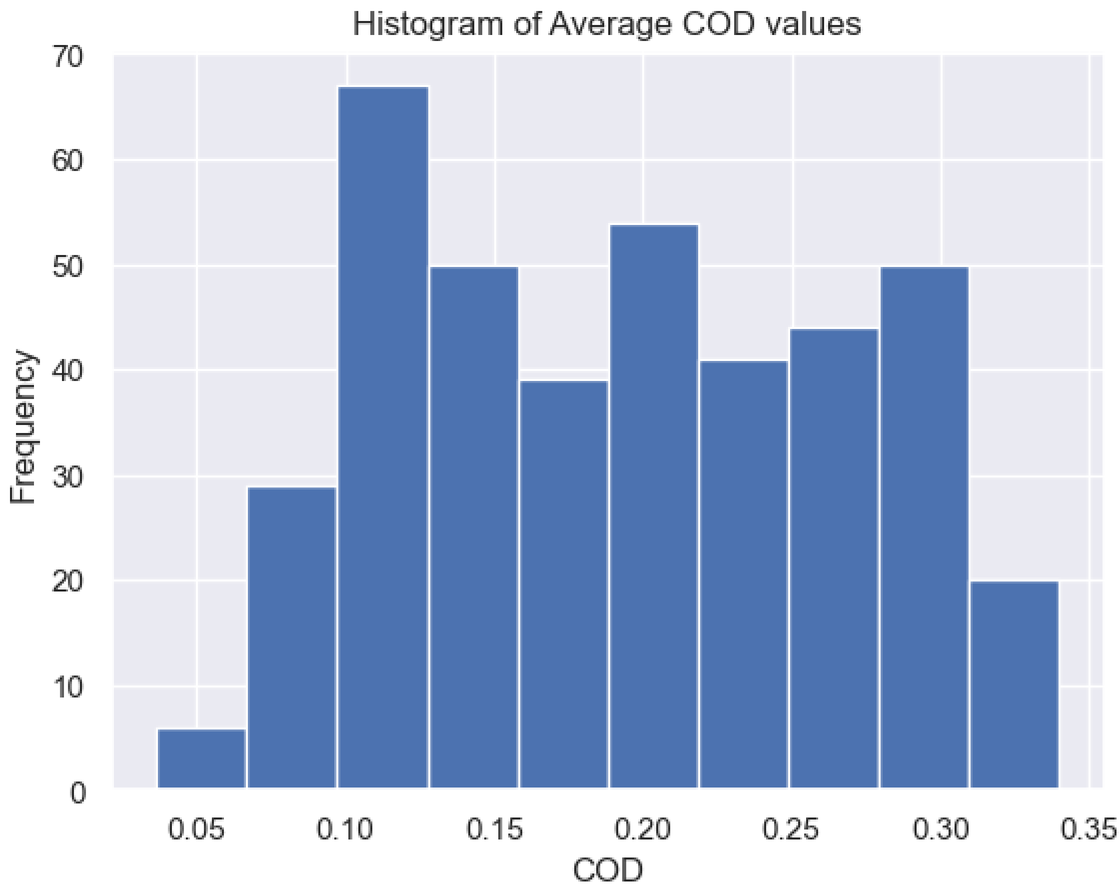
1) For each of the 400 movies, use a simple linear regression model to predict the ratings. Use the ratings of the other 399 movies in the dataset to predict the ratings of each movie (that means you'll have to build 399

models for each of the 400 movies). For each of the 400 movies, find the movie that predicts ratings the best. Then report the average COD of those 400 simple linear regression models. Please include a histogram of these 400 COD values and a table with the 10 movies that are most easily predicted from the ratings of a single other movie and the 10 movies that are hardest to predict from the ratings of a single other movie (and their associated COD values, as well as which movie ratings are the best predictor, so this table should have 3 columns).

In [ ]:

```
best_predictors = []
avg_cod = []
best_cod = []
for movie_idx in range(mov_count):
    # Target movie column
    y = df.iloc[:, movie_idx].values.reshape(-1, 1)
    # Create an array to store r2 for model fits for this model
    r2_vals =[]
    not_this_movie = [i for i in range(mov_count) if i !=
movie_idx]
    for predictor_idx in not_this_movie:
        # Predictor movie columns
        x = df.iloc[:, predictor_idx].values.reshape(-1, 1)

        # Model fitting
        model = LinearRegression()
        model.fit(x, y)

        # Model predictions
        yp = model.predict(x)
        r2_vals.append(r2_score(y, yp))

    max_r2_idx = np.argmax(r2_vals)
    if max_r2_idx >= movie_idx:
        max_r2_idx += 1
    best_predictors.append(df.columns[max_r2_idx])
    best_cod.append(np.max(r2_vals))
    avg_cod.append(np.mean(r2_vals))

# Plot the COD values
plt.hist(avg_cod)
plt.xlabel('COD')
plt.ylabel('Frequency')
plt.title('Histogram of Average COD values')
plt.show()
```

```
# Create a summary dataframe by combining target movies,
cod_values, best_predictors and their beta values
summary_df = pd.DataFrame({'Target movie': df.columns[:mov_count],
'avg COD': avg_cod, 'best COD': best_cod, 'Best Predictor':
best_predictors})
summary_df.head(10)
```



Out[ ]:

	Target movie	avg COD	best COD	Best Predictor
0	The Life of David Gale (2003)	0.275091	0.556450	The King of Marvin Gardens (1972)
1	Wing Commander (1999)	0.265670	0.559571	Sexy Beast (2000)
2	Django Unchained (2012)	0.112930	0.234026	The Life of David Gale (2003)
3	Alien (1979)	0.138351	0.327509	Aliens (1986)
4	Indiana Jones and the Last Crusade (1989)	0.115277	0.372925	Indiana Jones and the Temple of Doom (1984)
5	Snatch (2000)	0.215485	0.454504	Slackers (2002)
6	Rambo: First Blood Part II (1985)	0.142467	0.289481	Pieces of April (2003)
7	Fargo (1996)	0.141444	0.285784	The King of Marvin Gardens (1972)
8	Let the Right One In (2008)	0.226720	0.436487	The King of Marvin Gardens (1972)
9	Black Swan (2010)	0.058105	0.116818	Once Upon a Time in America (1984)

In [ ]:

```
# 10 movies that are easily predicted from the ratings of single
```

```
other movie
top10_df = summary_df.sort_values(by='best COD', ascending =
False).set_index('Target movie').iloc[:10, :]
print(tabulate(top10_df, headers = 'keys', tablefmt = 'psql'))
```

```
+----------------------------+-----------+------------+----------------------
-----+
| Target movie               |   avg COD |   best COD | Best Predictor
|
|----------------------------+-----------+------------+----------------------
-----|
| Erik the Viking (1989)     |  0.331554 |   0.723343 | I.Q. (1994)
|
| I.Q. (1994)                |  0.318552 |   0.723343 | Erik the Viking (198
9)     |
| The Lookout (2007)         |  0.33555  |   0.704884 | Patton (1970)
|
| Patton (1970)              |  0.32425  |   0.704884 | The Lookout (2007)
|
| Best Laid Plans (1999)     |  0.314417 |   0.703987 | The Bandit (1996)
|
| The Bandit (1996)          |  0.323771 |   0.703987 | Best Laid Plans (199
9)     |
| Congo (1995)               |  0.30289  |   0.701036 | The Straight Story (1
999) |
| The Straight Story (1999) |  0.323542 |   0.701036 | Congo (1995)
|
| Heavy Traffic (1973)       |  0.322479 |   0.687072 | Ran (1985)
|
| Ran (1985)                 |  0.281607 |   0.687072 | Heavy Traffic (1973)
|
+----------------------------+-----------+------------+----------------------
-----+
```

In [ ]:

```
# 10 movies that are difficult to predict from the ratings of
single other movie
bottom10_df = summary_df.sort_values(by='best COD', ascending =
True).set_index('Target movie').iloc[:10, :]
print(tabulate(bottom10_df, headers = 'keys', tablefmt = 'psql'))
```

Target movie	avg COD	best COD	Best Predictor
Avatar (2009)	0.0366044	0.0791126	Indiana Jones and the Kingdom of the Crystal Skull (2008)
Interstellar (2014)	0.052851	0.108968	Torque (2004)
Black Swan (2010)	0.0581053	0.116818	Once Upon a Time in America (1984)
Clueless (1995)	0.0707808	0.138304	Love Story (1970)
The Cabin in the Woods (2012)	0.0645385	0.142478	The Evil Dead (1981)
La La Land (2016)	0.0757999	0.146454	The Lookout (2007)
Titanic (1997)	0.0798079	0.155495	Cocktail (1988)
13 Going on 30 (2004)	0.0843149	0.15811	Can't Hardly Wait (1998)
The Fast and the Furious (2001)	0.0788591	0.168981	Terminator 3: Rise of the Machines (2003)
Grown Ups 2 (2013)	0.0814149	0.170761	The Core (2003)

2) For the 10 movies that are best and least well predicted from the ratings of a single other movie (so 20 in total), build multiple regression models that include gender identity (column 475), sibship status (column 476) and social viewing preferences (column 477) as additional predictors (in addition to the best predicting movie from question 1). Comment on how R^2 has changed relative to the answers in question 1. Please include a figure with a scatterplot where the old COD (for the simple linear regression models from the previous question) is on the x-axis and the new R^2 (for the new multiple regression models) is on the y-axis.

In [ ]:

```
additional_cols = np.asarray(['Gender identity (1 = female; 2 = male; 3 = self-described)',
         'Are you an only child? (1: Yes; 0: No; -1: Did not respond)',
         'Movies are best enjoyed alone (1: Yes; 0: No; -1: Did not respond)'])

q2_df = df.copy(deep=True)
q2_df.rename(columns = {'Gender identity (1 = female; 2 = male; 3 = self-described)': 'Gender',
              'Are you an only child? (1: Yes; 0: No; -1: Did not respond)': 'sibship',
              'Movies are best enjoyed alone (1: Yes; 0: No; -1: Did
```

```
not respond)': 'socialviewing'}, inplace = True)

# Eliminate rows where Gender is not Self-described, or sibship
and social viewing is not reported or if any of these entries are
q2_df = q2_df.drop(q2_df[(q2_df['Gender'] == 3) |
(q2_df['sibship'] == -1) | (q2_df['socialviewing'] ==
-1)].index).dropna(subset = ['Gender'], axis=0)
q2_df.head()
```

Out[ ]:

	The Life of David Gale (2003)	Wing Commander (1999)	Django Unchained (2012)	Alien (1979)	Indiana Jones and the Last Crusade (1989)	Snatch (2000)	Rambo: First Blood Part II (1985)	Fargo (1996)	Let the Right One In (2008)	B S (2(
0	2.4	2.4	4.0	2.7	3.0	2.7	2.6	2.8	2.6	
1	2.4	2.4	1.5	2.7	2.8	2.7	2.5	2.8	2.6	
2	2.7	2.7	3.2	3.0	3.0	3.0	2.8	3.1	2.9	
3	2.3	2.2	2.0	2.6	3.0	2.5	2.4	2.7	2.5	
4	2.2	2.1	3.5	2.5	0.5	2.4	0.5	1.0	2.4	

5 rows × 477 columns

In [ ]:

```
# One hot encode gender for regression
gender_dummy = pd.get_dummies(q2_df['Gender'], prefix = 'gender',
drop_first = True)
q2_df = q2_df.drop('Gender', axis = 1)

q2_df = q2_df.join(gender_dummy)
q2_df.head()
```

Out[ ]:

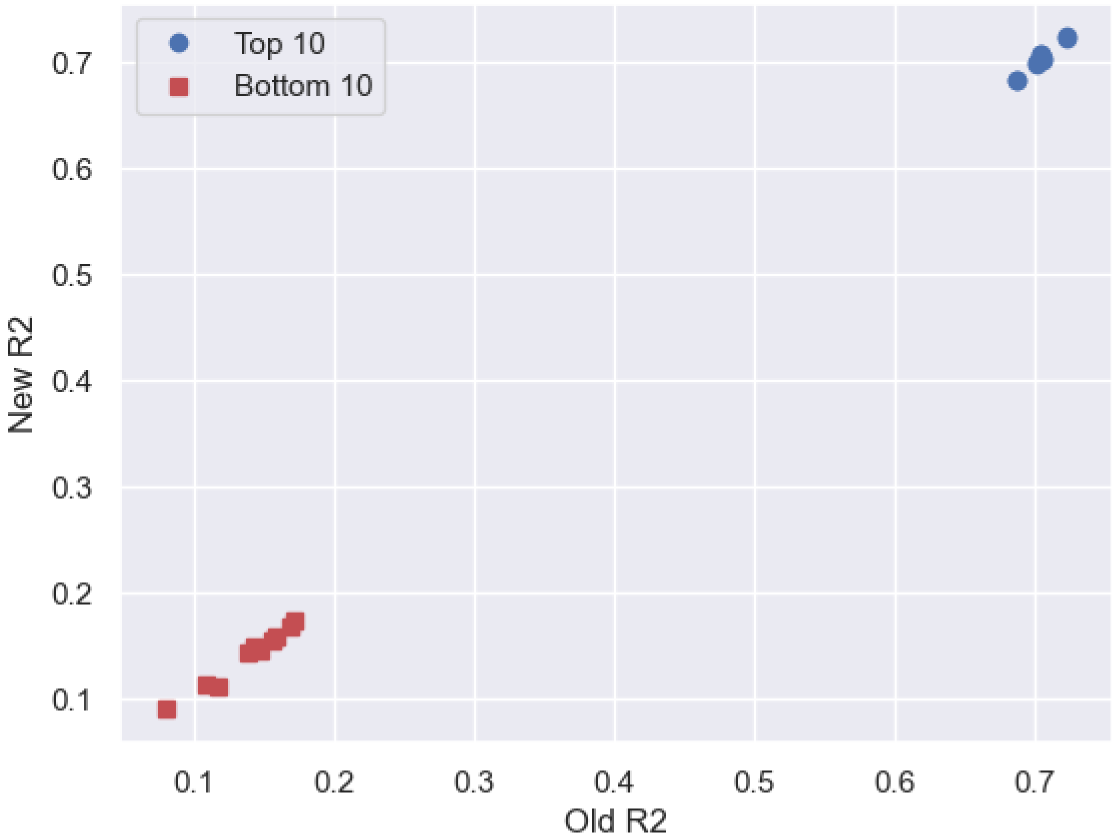
	The Life of David Gale (2003)	Wing Commander (1999)	Django Unchained (2012)	Alien (1979)	Indiana Jones and the Last Crusade (1989)	Snatch (2000)	Rambo: First Blood Part II (1985)	Fargo (1996)	Let the Right One In (2008)	B S (2(
0	2.4	2.4	4.0	2.7	3.0	2.7	2.6	2.8	2.6	
1	2.4	2.4	1.5	2.7	2.8	2.7	2.5	2.8	2.6	
2	2.7	2.7	3.2	3.0	3.0	3.0	2.8	3.1	2.9	
3	2.3	2.2	2.0	2.6	3.0	2.5	2.4	2.7	2.5	
4	2.2	2.1	3.5	2.5	0.5	2.4	0.5	1.0	2.4	

5 rows × 477 columns

In [ ]:

```
top10_r2 = top10_df['best COD'][0:10].to_numpy()
bottom10_r2 = bottom10_df['best COD'][0:10].to_numpy()
top10_predictor = top10_df['Best Predictor'][0:10].to_numpy()
bottom10_predictor = bottom10_df['Best Predictor']
[0:10].to_numpy()
top10_movies = top10_df.index[0:10].to_numpy()
bottom10_movies = bottom10_df.index[0:10].to_numpy()

concat_r2 = np.concatenate((top10_r2, bottom10_r2))
concat_predictor = np.concatenate((top10_predictor,
bottom10_predictor))
concat_movies = np.concatenate((top10_movies, bottom10_movies))

mlg_cod = []
for movie_idx in range(20):
    target_name = concat_movies[movie_idx]
    # Target movie column
    y = q2_df[target_name].values.reshape(-1, 1)
    predictors = [concat_predictor[movie_idx], 'sibship',
'socialviewing', 'gender_2.0']
    X = q2_df[predictors]
    model = LinearRegression()
```

```
    model.fit(X, y)

    # Model predictions
    yp = model.predict(X)
    mlg_cod.append(r2_score(y, yp))

# Plot the COD values
plt.plot(top10_r2, mlg_cod[0:10], 'bo', label = 'Top 10')
plt.plot(bottom10_r2, mlg_cod[10:20], 'rs', label = 'Bottom 10')
plt.xlabel('Old R2')
plt.ylabel('New R2')
plt.legend()
plt.show()
```



In [ ]:

```
q2_result_df = pd.DataFrame(index = concat_movies)
q2_result_df['Old CODs'] = concat_r2
q2_result_df['New CODs'] = mlg_cod
q2_result_df.head(20)
```

Out[ ]:

	Old CODs	New CODs
Erik the Viking (1989)	0.723343	0.723456
I.Q. (1994)	0.723343	0.722357
The Lookout (2007)	0.704884	0.703801
Patton (1970)	0.704884	0.702488
Best Laid Plans (1999)	0.703987	0.707138
The Bandit (1996)	0.703987	0.707293
Congo (1995)	0.701036	0.698630
The Straight Story (1999)	0.701036	0.699555
Heavy Traffic (1973)	0.687072	0.683754
Ran (1985)	0.687072	0.683491
Avatar (2009)	0.079113	0.090646
Interstellar (2014)	0.108968	0.114530
Black Swan (2010)	0.116818	0.112969
Clueless (1995)	0.138304	0.143289
The Cabin in the Woods (2012)	0.142478	0.150682
La La Land (2016)	0.146454	0.146517
Titanic (1997)	0.155495	0.155839
13 Going on 30 (2004)	0.158110	0.158590
The Fast and the Furious (2001)	0.168981	0.168441
Grown Ups 2 (2013)	0.170761	0.174203

3) Pick 30 movies in the middle of the COD range, as identified by question 1 (that were not used in question 2). Now build a regularized regression model with the ratings from 10 other movies (picked randomly, or deliberately by you) as an input. Please use ridge regression, and make sure to do suitable hyperparameter tuning. Also make sure to report the RMSE for each of these 30 movies in a table, after doing an 80/20 train/test split. Comment on the hyperparameters you use and betas you find by doing so.

In [ ]:

```
# Look at the middle 30 movies based on the COD range
middle_df = summary_df.sort_values(by='best COD', ascending =
True).set_index('Target movie').iloc[mov_count//2 -
15:mov_count//2 + 15, :]
middle_df.head(10)
```

Out[ ]:

Target movie	avg COD	best COD	Best Predictor
Twister (1996)	0.224547	0.411274	Sexy Beast (2000)
Aliens (1986)	0.196537	0.412504	Miller's Crossing (1990)
Austin Powers in Goldmember (2002)	0.153687	0.412922	Austin Powers: The Spy Who Shagged Me (1999)
Austin Powers: The Spy Who Shagged Me (1999)	0.162034	0.412922	Austin Powers in Goldmember (2002)
Gone in Sixty Seconds (2000)	0.199683	0.413679	Change of Habit (1969)
28 Days Later (2002)	0.206534	0.414014	Miller's Crossing (1990)
The Big Lebowski (1998)	0.209929	0.414669	Escape from LA (1996)
Blues Brothers 2000 (1998)	0.201530	0.416080	The 51st State (2001)
Goodfellas (1990)	0.214517	0.416278	The Sting (1973)
Dances with Wolves (1990)	0.206653	0.422910	The Deer Hunter (1978)

In [ ]:

```
q3_df = df[middle_df.index]
X = df[top10_df.index]
idxs = np.arange(X.shape[0])
train_idx, test_idx = train_test_split(idxs, test_size = 0.2,
random_state = seed_val)
X_train = X.iloc[train_idx, :]
X_test = X.iloc[test_idx, :]
```

In [ ]:

```
alphas_to_try_first_pass = np.linspace(0, 1000, 100)
params = {'alpha': alphas_to_try_first_pass}
best_alpha = []
for movie_idx in range(30):
    # Target movie column
    y = q3_df.iloc[:, movie_idx].values.reshape(-1, 1)
    y_train = y[train_idx, :]
    clf = GridSearchCV(Ridge(), params, scoring = 'r2', n_jobs=-1,
cv = 10).fit(X_train, y_train)
    best_alpha.append(clf.best_params_['alpha'])
print(np.round(np.asarray(best_alpha), 3))
```

```
[ 80.808   80.808   30.303   50.505 141.414   70.707   30.303 151.515   50.505
 101.01    50.505   30.303   40.404   60.606   40.404   10.101   50.505   90.909
  80.808 121.212   50.505   80.808   50.505   30.303 232.323   50.505   60.606
 181.818   80.808   30.303]
```

In [ ]:

```
alphas_to_try_second_pass = np.linspace(25, 250, 200)
params = {'alpha': alphas_to_try_second_pass}
```

```
best_alpha = []
for movie_idx in range(30):
    # Target movie column
    y = q3_df.iloc[:, movie_idx].values.reshape(-1, 1)
    y_train = y[train_idx, :]
    clf = GridSearchCV(Ridge(), params, scoring = 'r2', n_jobs =
-1, cv = 10).fit(X_train, y_train)
    best_alpha.append(clf.best_params_['alpha'])
print(np.round(np.asarray(best_alpha), 3))
```

```
[ 81.533  77.01   27.261  45.352 141.457  65.704  29.523 150.503  51.005
 103.015  54.397  30.653  41.96   65.704  37.437  25.     55.528  95.101
  83.794 121.106  51.005  84.925  47.613  35.176 233.04   54.397  61.181
 179.899  83.794  28.392]
```

In [ ]:

```
RMSE_train = np.zeros((30,))
RMSE_test = np.zeros((30,))
betas = np.zeros((30, 10))
intercepts = np.zeros((30,))

for movie_idx in range(30):
    # Target movie column
    y = q3_df.iloc[:, movie_idx].values.reshape(-1, 1)
    y_train = y[train_idx, :]
    y_test = y[test_idx, :]

    # Initialize and fit model to train data
    model = Ridge(alpha = best_alpha[movie_idx], random_state =
seed_val)
    model.fit(X_train, y_train)

    # Compute betas
    betas[movie_idx, :] = np.round(model.coef_[0], 2)
    intercepts[movie_idx] = np.round(model.intercept_, 2)

    # Generate train and test predictions
    yp_train = model.predict(X_train)
    yp_test = model.predict(X_test)

    # Compute RMSE for train and test
    RMSE_train[movie_idx] = mean_squared_error(y_train, yp_train,
squared = False)
```

```
    RMSE_test[movie_idx] = mean_squared_error(y_test, yp_test,
squared = False)
```

In [ ]:

```
q3_summary_df = pd.DataFrame(index = q3_df.columns, columns =
range(0, 10))
for ii in range(q3_summary_df.shape[0]):
    q3_summary_df.iloc[ii, :] = betas[ii, :]
q3_summary_df['Intercept'] = intercepts
q3_summary_df['alpha'] = np.round(best_alpha, 2)
q3_summary_df['RMSE train'] = np.round(RMSE_train, 2)
q3_summary_df['RMSE test'] = np.round(RMSE_test, 2)

q3_summary_df.head(30)
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	Intercept	alph
Twister (1996)	0.06	0.08	0.13	0.1	0.13	0.09	0.08	0.05	0.09	0.1	0.32	81.5
Aliens (1986)	0.1	0.11	0.13	0.18	0.07	0.09	0.06	0.11	0.08	0.1	0.20	77.0
Austin Powers in Goldmember (2002)	0.1	0.05	0.19	0.26	0.06	0.1	-0.01	0.04	0.19	0.16	-0.28	27.2
Austin Powers: The Spy Who Shagged Me (1999)	0.12	0.23	0.1	0.2	0.17	0.11	0.07	0.12	0.11	-0.03	-0.35	45.3
Gone in Sixty Seconds (2000)	0.04	0.02	0.12	0.1	0.1	0.13	0.06	0.05	0.06	0.05	0.69	141.4
28 Days Later (2002)	0.09	0.0	0.09	0.18	0.07	0.14	0.05	0.08	0.12	0.1	0.41	65.7
The Big Lebowski (1998)	0.07	0.02	0.17	0.2	0.2	0.01	-0.05	0.04	0.15	0.2	0.37	29.5
Blues Brothers 2000 (1998)	0.08	0.06	0.09	0.05	0.06	0.12	0.07	0.09	0.07	0.09	0.67	150.5
Goodfellas (1990)	0.12	0.17	0.04	0.18	0.04	0.08	0.1	0.04	0.15	0.09	0.44	51.0
Dances with Wolves (1990)	0.08	0.1	0.07	0.08	0.09	0.1	0.04	0.07	0.12	0.08	0.59	103.0
The Green Mile (1999)	0.09	0.01	0.11	0.15	0.04	0.09	0.03	0.13	0.13	0.12	0.68	54.4
The Blue Lagoon (1980)	0.1	0.07	0.27	0.12	0.01	0.11	0.05	0.17	0.02	0.03	0.28	30.6
Uptown Girls (2003)	0.16	0.15	0.07	0.15	0.14	0.12	0.04	0.17	0.05	0.06	0.03	41.9
The Machinist (2004)	0.07	0.09	0.06	0.1	0.12	0.01	0.02	0.13	0.13	0.15	0.45	65.7
Knight and Day (2010)	0.14	0.14	0.07	0.07	0.19	0.23	-0.06	0.14	-0.01	0.03	0.30	37.4
The Evil Dead (1981)	0.16	0.22	0.1	0.14	0.15	0.03	0.04	0.03	-0.05	0.15	0.23	25.0
Men in Black (1997)	0.17	0.07	0.19	0.16	0.1	0.1	0.03	0.11	0.1	0.03	0.28	55.5
Men in Black II (2002)	0.13	0.06	0.12	0.13	0.12	0.07	0.1	0.12	0.12	0.14	0.05	95.1
Equilibrium (2002)	0.08	0.09	0.03	0.02	0.08	0.03	0.07	0.09	0.11	0.1	0.86	83.7

	0	1	2	3	4	5	6	7	8	9	Intercept	alph
The Good the Bad and the Ugly (1966)	0.07	0.11	0.09	0.07	0.11	0.12	0.04	0.11	0.07	0.09	0.67	121.1
The Rock (1996)	0.15	0.06	0.14	0.07	0.18	0.12	-0.01	0.01	0.09	0.02	0.66	51.0
Let the Right One In (2008)	0.04	0.05	0.08	0.12	0.06	0.09	0.1	0.06	0.11	0.1	0.60	84.9
You're Next (2011)	0.07	0.07	0.16	0.16	0.09	0.16	0.0	0.11	0.04	0.09	0.13	47.6
Reservoir Dogs (1992)	0.07	0.01	0.05	0.22	0.08	0.06	0.07	0.21	0.09	0.18	0.27	35.1
The Poseidon Adventure (1972)	0.06	0.07	0.04	0.05	0.07	0.07	0.08	0.06	0.07	0.06	0.90	233.0
The Prestige (2006)	0.16	0.16	0.04	-0.01	0.12	0.08	0.11	0.14	0.12	-0.01	0.73	54.4
There's Something About Mary (1998)	0.08	0.16	0.06	0.19	0.09	0.07	0.16	0.11	0.07	0.05	0.07	61.1
The Mummy Returns (2001)	0.06	0.08	0.09	0.1	0.08	0.09	0.09	0.07	0.1	0.08	0.56	179.9
The Mummy (1999)	0.13	0.1	0.12	0.05	0.08	0.03	0.1	0.11	0.13	0.11	0.37	83.7
Just Married (2003)	0.17	0.03	0.08	0.03	0.08	0.1	-0.06	0.27	0.14	0.15	0.10	28.3

4) Repeat question 3) with LASSO regression. Again, make sure to comment on the hyperparameters you use and betas you find by doing so.

In [ ]:

```
q4_df = df[middle_df.index]
X = df[top10_df.index]
idxs = np.arange(X.shape[0])
train_idx, test_idx = train_test_split(idxs, test_size = 0.2,
random_state = seed_val)
X_train = X.iloc[train_idx, :]
X_test = X.iloc[test_idx, :]
```

In [ ]:

```
alphas_to_try_first_pass = np.linspace(1e-14, 1, 100)
params = {'alpha': alphas_to_try_first_pass}
best_alpha = []
for movie_idx in range(30):
```

```python
    # Target movie column
    y = q4_df.iloc[:, movie_idx].values.reshape(-1, 1)
    y_train = y[train_idx, :]
    clf = GridSearchCV(Lasso(), params, scoring = 'r2', n_jobs=-1,
cv = 10).fit(X_train, y_train)
    best_alpha.append(clf.best_params_['alpha'])
low_idx = np.where(np.asarray(best_alpha) < 1e-13)[0]
print(np.asarray(best_alpha))
```

```
[1.01010101e-02 1.01010101e-02 1.01010101e-02 1.01010101e-02
 2.02020202e-02 1.00000000e-14 1.01010101e-02 1.01010101e-02
 1.01010101e-02 1.01010101e-02 1.01010101e-02 1.01010101e-02
 1.01010101e-02 1.01010101e-02 1.01010101e-02 1.00000000e-14
 1.01010101e-02 1.01010101e-02 1.01010101e-02 1.01010101e-02
 1.01010101e-02 1.01010101e-02 1.01010101e-02 1.01010101e-02
 2.02020202e-02 1.01010101e-02 1.01010101e-02 2.02020202e-02
 1.01010101e-02 1.01010101e-02]
```

In [ ]:

```python
alphas_to_try_second_pass = np.linspace(1e-3, 1e-1, 200)
params = {'alpha': alphas_to_try_second_pass}
best_alpha = []
for movie_idx in range(30):
    # Target movie column
    y = q4_df.iloc[:, movie_idx].values.reshape(-1, 1)
    y_train = y[train_idx, :]
    clf = GridSearchCV(Lasso(), params, scoring = 'r2', n_jobs=-1,
cv = 10).fit(X_train, y_train)
    best_alpha.append(clf.best_params_['alpha'])
best_alpha = np.asarray(best_alpha)
best_alpha[low_idx] = 1e-14
print(best_alpha)
```

```
[5.47738693e-03 6.96984925e-03 6.96984925e-03 9.45728643e-03
 1.54271357e-02 1.00000000e-14 5.47738693e-03 9.95477387e-03
 5.47738693e-03 9.45728643e-03 5.47738693e-03 4.48241206e-03
 2.49246231e-03 6.47236181e-03 1.49748744e-03 1.00000000e-14
 1.34371859e-02 1.34371859e-02 4.48241206e-03 8.46231156e-03
 5.97487437e-03 6.96984925e-03 1.49748744e-03 4.97989950e-03
 2.13969849e-02 5.47738693e-03 4.97989950e-03 1.59246231e-02
 4.97989950e-03 1.99497487e-03]
```

In [ ]:

```python
RMSE_train = np.zeros((30,))
RMSE_test = np.zeros((30,))
betas = np.zeros((30, 10))
intercepts = np.zeros((30,))

for movie_idx in range(30):
```

```python
    # Target movie column
    y = q4_df.iloc[:, movie_idx].values.reshape(-1, 1)
    y_train = y[train_idx, :]
    y_test = y[test_idx, :]

    # Initialize and fit model to train data
    model = Lasso(alpha = best_alpha[movie_idx], random_state =
seed_val)
    model.fit(X_train, y_train)
    # Compute betas
    betas[movie_idx, :] = np.round(model.coef_, 2)
    intercepts[movie_idx] = np.round(model.intercept_, 2)

    # Generate train and test predictions
    yp_train = model.predict(X_train)
    yp_test = model.predict(X_test)

    # Compute RMSE for train and test
    RMSE_train[movie_idx] = mean_squared_error(y_train, yp_train,
squared = False)
    RMSE_test[movie_idx] = mean_squared_error(y_test, yp_test,
squared = False)
```

In [ ]:

```python
q4_summary_df = pd.DataFrame(index = q4_df.columns, columns =
range(0, 10))
for ii in range(q4_summary_df.shape[0]):
    q4_summary_df.iloc[ii, :] = betas[ii, :]
q4_summary_df['Intercept'] = intercepts
q4_summary_df['alpha'] = best_alpha
q4_summary_df['RMSE train'] = np.round(RMSE_train, 2)
q4_summary_df['RMSE test'] = np.round(RMSE_test, 2)

q4_summary_df.head(30)
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	Intercept	
Twister (1996)	0.0	0.09	0.28	0.06	0.26	0.02	0.09	0.0	0.06	0.1	0.22	5.4
Aliens (1986)	0.09	0.13	0.12	0.4	0.02	0.04	0.0	0.16	0.01	0.06	0.12	6.96
Austin Powers in Goldmember (2002)	0.1	0.0	0.18	0.37	0.0	0.09	0.0	0.0	0.29	0.12	-0.23	6.96
Austin Powers: The Spy Who Shagged Me (1999)	0.0	0.42	0.0	0.35	0.27	0.03	0.0	0.12	0.0	0.0	-0.29	9.4
Gone in Sixty Seconds (2000)	0.0	0.0	0.17	0.14	0.04	0.39	0.0	0.0	0.0	0.0	0.66	1.5
28 Days Later (2002)	0.15	-0.29	-0.19	0.52	0.02	0.36	-0.09	0.11	0.38	0.0	0.20	1.00
The Big Lebowski (1998)	0.0	0.0	0.12	0.27	0.27	0.0	-0.0	0.0	0.1	0.24	0.39	5.4
Blues Brothers 2000 (1998)	0.11	0.0	0.08	0.0	0.0	0.38	0.0	0.08	0.0	0.18	0.52	9.9
Goodfellas (1990)	0.09	0.26	0.0	0.32	0.0	0.03	0.05	0.0	0.27	0.01	0.40	5.4
Dances with Wolves (1990)	0.02	0.11	0.0	0.07	0.05	0.21	0.0	0.0	0.34	0.03	0.57	9.4
The Green Mile (1999)	0.03	-0.0	0.06	0.25	0.0	0.06	0.0	0.2	0.22	0.1	0.63	5.4
The Blue Lagoon (1980)	0.1	0.05	0.53	0.0	0.0	0.03	0.0	0.26	0.0	0.0	0.23	4.4
Uptown Girls (2003)	0.18	0.14	0.0	0.27	0.19	0.08	-0.0	0.29	0.0	0.0	-0.05	2.4
The Machinist (2004)	0.0	0.05	0.0	0.1	0.17	-0.0	-0.0	0.21	0.2	0.18	0.39	6.4
Knight and Day (2010)	0.13	0.18	0.0	0.06	0.23	0.44	-0.25	0.21	-0.06	0.03	0.20	1.4
The Evil Dead (1981)	0.17	0.4	0.14	0.17	0.26	-0.06	0.02	-0.04	-0.38	0.3	0.18	1.00
Men in Black (1997)	0.34	0.0	0.37	0.15	0.04	0.0	0.0	0.09	0.01	0.0	0.39	1.3
Men in Black II (2002)	0.17	0.0	0.05	0.22	0.16	0.0	0.01	0.19	0.1	0.19	0.05	1.3
Equilibrium (2002)	0.06	0.1	0.0	-0.0	0.09	0.0	0.0	0.14	0.25	0.1	0.76	4.4

	0	1	2	3	4	5	6	7	8	9	Intercept	
The Good the Bad and the Ugly (1966)	0.0	0.18	0.08	0.0	0.16	0.23	0.0	0.15	0.0	0.12	0.54	8.4
The Rock (1996)	0.25	0.0	0.24	0.0	0.27	0.06	-0.0	0.0	0.0	0.0	0.65	5.9
Let the Right One In (2008)	0.0	0.0	0.0	0.22	0.0	0.17	0.14	0.0	0.25	0.05	0.56	6.96
You're Next (2011)	0.03	0.06	0.21	0.25	0.05	0.27	-0.08	0.16	-0.0	0.07	-0.03	1.4
Reservoir Dogs (1992)	0.0	0.0	0.0	0.37	0.09	0.0	0.0	0.37	0.0	0.23	0.23	4.9
The Poseidon Adventure (1972)	0.0	0.1	0.0	0.0	0.13	0.03	0.16	0.02	0.12	0.02	1.03	2.1
The Prestige (2006)	0.22	0.2	0.0	-0.0	0.15	0.0	0.06	0.2	0.1	-0.0	0.70	5.4
There's Something About Mary (1998)	0.0	0.27	0.0	0.39	0.08	0.0	0.24	0.09	0.0	0.0	0.00	4.9
The Mummy Returns (2001)	0.0	0.05	0.07	0.19	0.03	0.16	0.09	0.0	0.27	0.01	0.49	1.5
The Mummy (1999)	0.24	0.04	0.21	-0.0	0.0	-0.0	0.06	0.13	0.28	0.05	0.22	4.9
Just Married (2003)	0.2	-0.0	0.05	0.0	0.05	0.07	-0.19	0.48	0.19	0.15	0.02	1.9

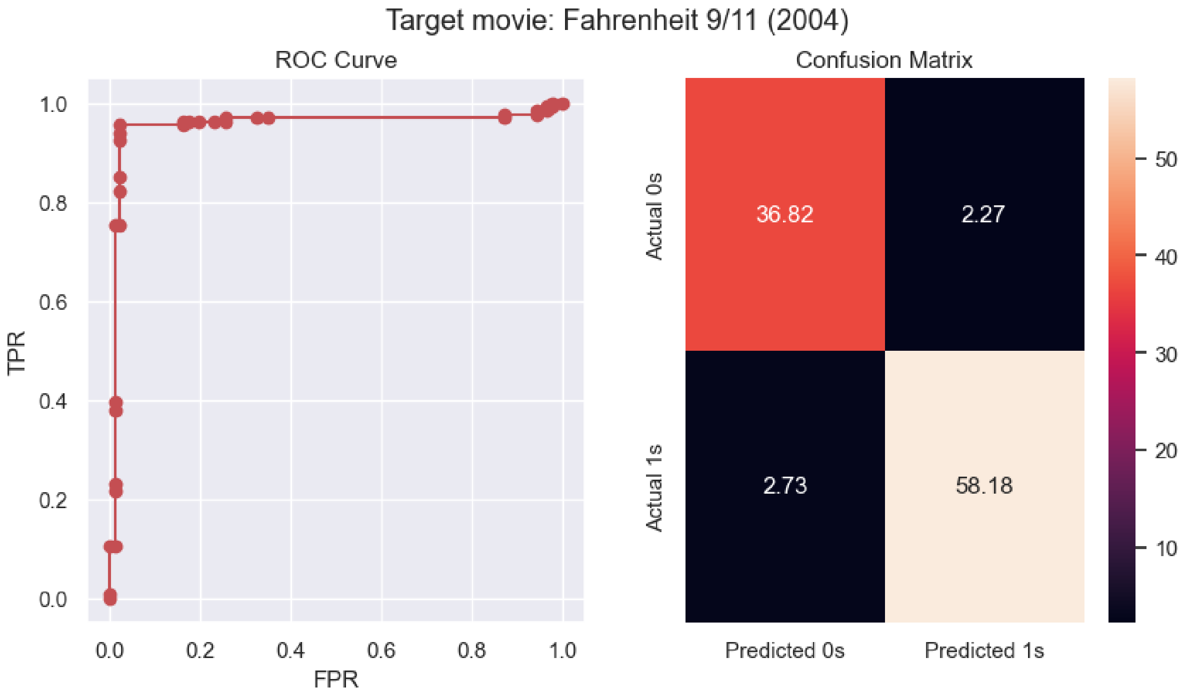
5) Compute the average movie enjoyment for each user (using only real, non-imputed data). Use these averages as the predictor variable X in a logistic regression model. Sort the movies order of increasing rating (also using only real, non-imputed data). Now pick the 4 movies in the middle of the score range as your target movie. For each of them, do a median split (now using the imputed data) of ratings to code movies above the median rating with the Y label 1 (= enjoyed) and movies below the median with the label 0 (= not enjoyed). For each of these movies, build a logistic regression model (using X to predict Y), show figures with the outcomes and report the betas as well as the AUC values. Comment on the quality of your models. Make sure to use cross-validation methods to avoid overfitting.

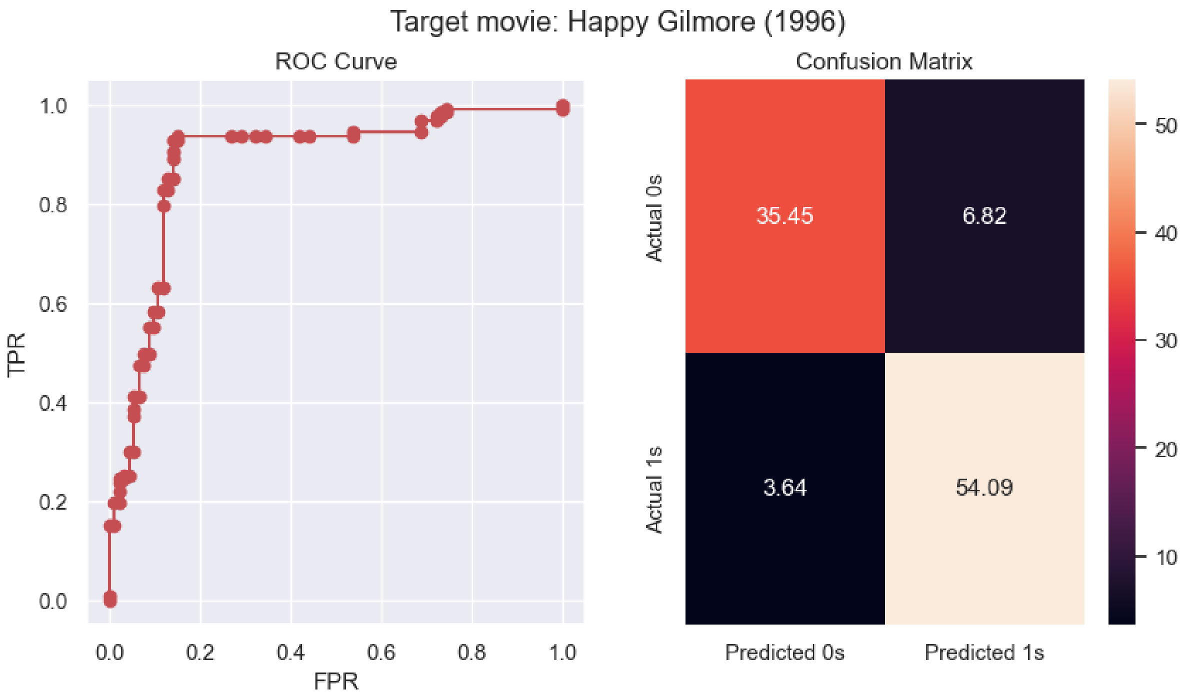
In [ ]:

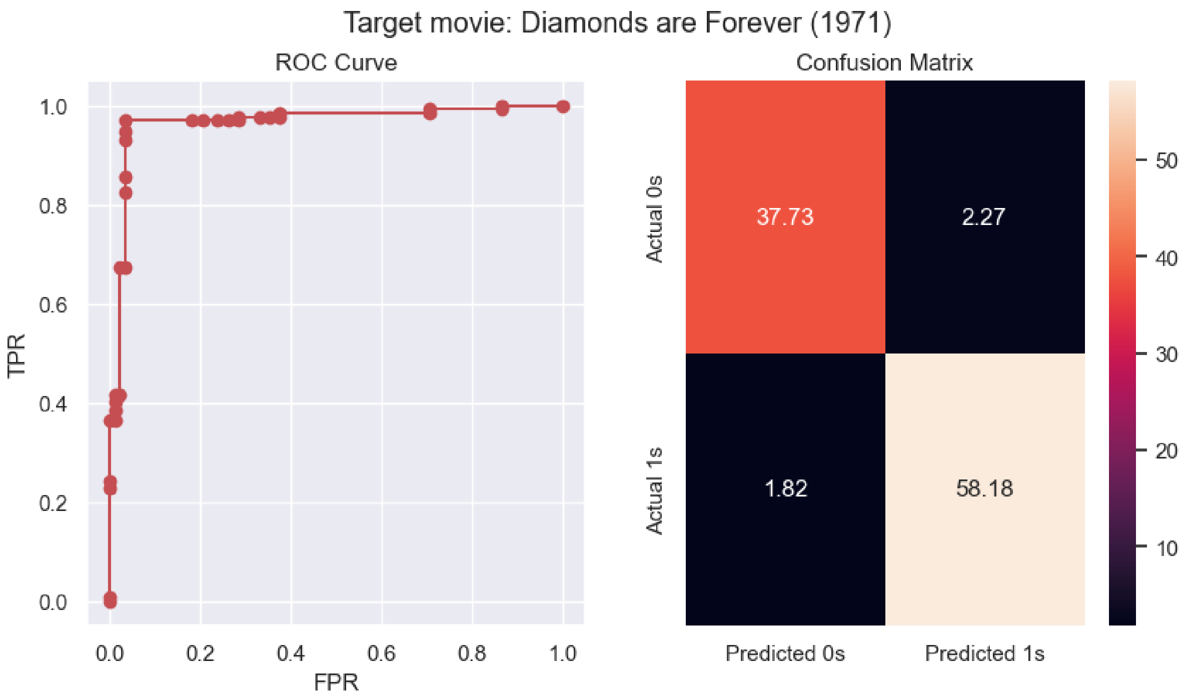
```
# Predictors
X = real_df.iloc[:, :mov_count].mean(axis = 1).values.reshape(-1,
1) # average movie enjoyment for each user

# Target
avg_movie_rating = real_df.iloc[:, :mov_count].mean(axis =
```

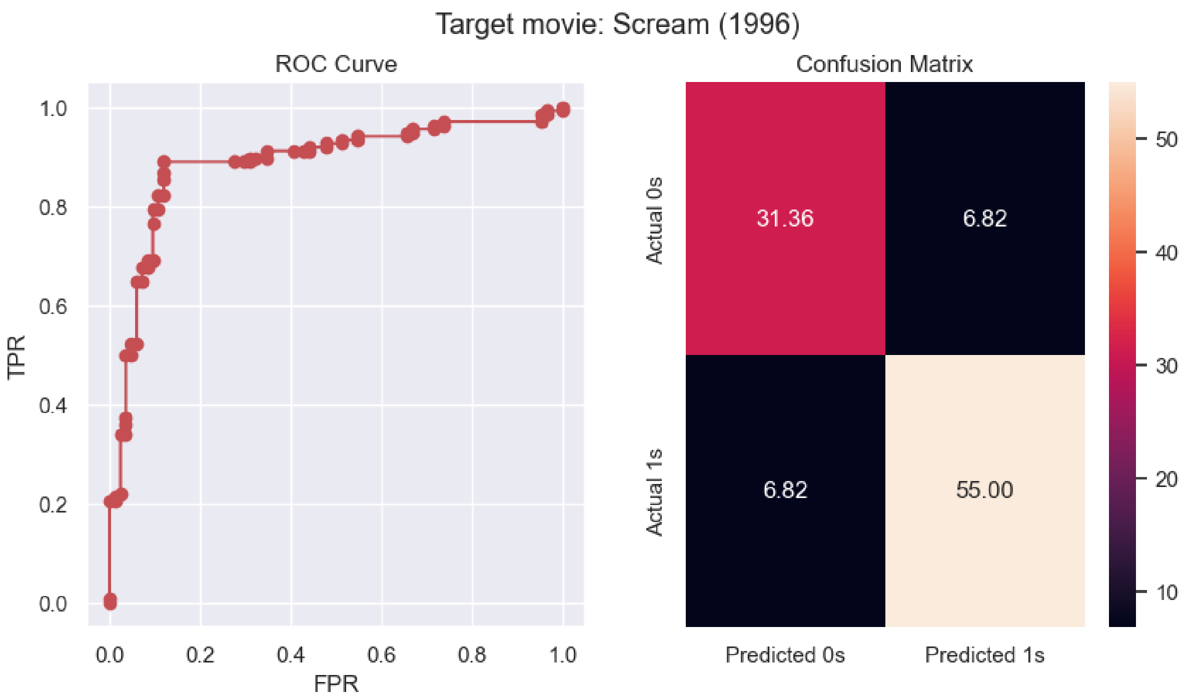
```
0).sort_values(ascending = True)
predictor_movies = avg_movie_rating[len(avg_movie_rating)//2 -
2:len(avg_movie_rating)//2 + 2].index
y_rating = df[predictor_movies]

cv_score = []
auc_score = []
betas = []
intercepts = []

for mov in predictor_movies:
    # Median-split target variable
    y = (y_rating[mov]>=y_rating[mov].median()).replace({True:1,
False:0})
    # Split data into train and test
    X_train, X_test, y_train, y_test = train_test_split(
        X, y, test_size = 0.2, random_state=seed_val)

    # Logistic Regression Model
    model = LogisticRegression(penalty = 'none', random_state =
seed_val)
    cv_score.append(cross_val_score(model, X_train, y_train, cv =
10, scoring = 'roc_auc').mean())
    model.fit(X_train, y_train)
    betas.append(model.coef_[0][0])
    intercepts.append(model.intercept_[0])

    # Evaluate the model
    p_pred = model.predict_proba(X_test)
    y_pred = model.predict(X_test)

    # score_ = model.score(X_test, y_test)
    conf_m = confusion_matrix(y_test, y_pred, normalize = 'all')
    # report = classification_report(y, y_pred)
    fpr, tpr, _ = roc_curve(y_test, p_pred[:, 1])
    auc_score.append(auc(fpr, tpr))
    fig, ax = plt.subplots(1, 2, figsize = (10, 5))
    plt.suptitle(f'Target movie: {mov}')
    ax[0].plot(fpr, tpr, 'ro-')
    ax[0].set_xlabel('FPR')
    ax[0].set_ylabel('TPR')
    ax[0].set_title('ROC Curve')
```

```
ax[1] = sns.heatmap(conf_m*100, annot = True, fmt = '.2f')
ax[1].xaxis.set(ticklabels=('Predicted 0s', 'Predicted 1s'))
ax[1].yaxis.set(ticklabels=('Actual 0s', 'Actual 1s'))
ax[1].set_title('Confusion Matrix')
plt.show()
```









In [ ]:

```
q5_df = pd.DataFrame(index = predictor_movies)
q5_df['cv score'] = cv_score
q5_df['auc'] = auc_score
q5_df['beta'] = betas
q5_df['intercept'] = intercepts
q5_df
```

Out[ ]:

	cv score	auc	beta	intercept
Fahrenheit 9/11 (2004)	0.971195	0.956612	10.825480	-31.365859
Happy Gilmore (1996)	0.928488	0.887393	6.227364	-17.959968
Diamonds are Forever (1971)	0.966630	0.966598	9.155192	-26.492592
Scream (1996)	0.901363	0.887824	5.076217	-14.564222