```
In [275... import numpy as np
          from scipy import stats
          import matplotlib.pyplot as plt
          import pandas as pd
          import scipy.stats as stats
          import statistics
          from tqdm import tqdm
          from sklearn.linear model import LinearRegression
          from sklearn.metrics import r2_score, roc_auc_score
          from sklearn.model selection import train test split, GridSearchCV
          from sklearn.linear_model import Ridge,Lasso,LogisticRegression
          import seaborn as sns
          data df=pd.read csv("movieReplicationSet.csv")
          movies=data df[data df.columns[:400]]
          movies2=movies.copy() #data after cleaning
          movie names=movies.columns
          s=movies.shape
In [276... for m in range(s[1]):
              for user in range(s[0]):
                  if np.isnan(movies.iloc[user,m]):
                      movies2.iloc[user,m]=(movies.iloc[:,m].mean()+movies.iloc[user,:
          movies2=movies2.drop(896,axis="index")
          s=movies2.shape
         movies2.to_csv("new.csv",index=False)
```

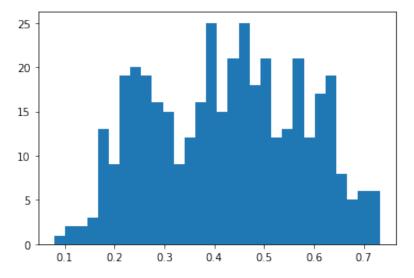
```
In [277... df=pd.read csv("new.csv")
In [278... | cod=[]
         for m in tqdm(range(s[1])):
             temp=[]
             for mm in range(s[1]):
                 if m!=mm:
                     x=df.iloc[:,mm].to_numpy()
                     y=df.iloc[:,m].to numpy()
                      reg = LinearRegression().fit(x.reshape(-1,1), y) #mm predict m
                      y_hat = reg.predict(x.reshape(-1,1))
                      r2 = r2 \ score(y,y \ hat)
                      temp.append(r2)
                 else:
                     temp.append(0)
             cod.append(temp)
         100% | 400/400 [00:53<00:00, 7.47it/s]
```

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```
In [279... best=[np.max(cod[i]) for i in range(s[1])]
    print(np.mean(best))
```

0.42378171067196035

```
In [280... plt.hist(best,bins=30)
   plt.show()
```



```
In [282... ans1
```

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Out[282]:	movi	es cod	

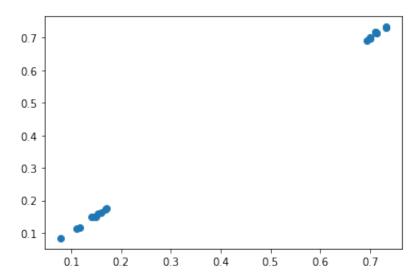
	movies	cod	best predictor
0	Heavy Traffic (1973)	0.692734	Ran (1985)
1	The Final Conflict (1981)	0.700188	The Lookout (2007)
2	The Straight Story (1999)	0.700569	Congo (1995)
3	Congo (1995)	0.700569	The Straight Story (1999)
4	The Bandit (1996)	0.711222	Best Laid Plans (1999)
5	Best Laid Plans (1999)	0.711222	The Bandit (1996)
6	Patton (1970)	0.713554	The Lookout (2007)
7	The Lookout (2007)	0.713554	Patton (1970)
8	I.Q. (1994)	0.731507	Erik the Viking (1989)
9	Erik the Viking (1989)	0.731507	I.Q. (1994)
10	Avatar (2009)	0.079485	Bad Boys (1995)
11	Interstellar (2014)	0.111343	Torque (2004)
12	Black Swan (2010)	0.117080	Sorority Boys (2002)
13	Clueless (1995)	0.141426	Escape from LA (1996)
14	The Cabin in the Woods (2012)	0.143887	The Evil Dead (1981)
15	La La Land (2016)	0.148514	The Lookout (2007)
16	Titanic (1997)	0.154136	Cocktail (1988)
17	13 Going on 30 (2004)	0.160164	Can't Hardly Wait (1998)
18	The Fast and the Furious (2001)	0.168991	Terminator 3: Rise of the Machines (2003)
19	Grown Ups 2 (2013)	0.171119	The Core (2003)

```
data_df=data_df.drop(896,axis="index")
```

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```
In [286...
        cod new=[]
        cod old=[]
        gender=data_df.iloc[:,-3].to_numpy()
        sib=data df.iloc[:,-2].to numpy()
        social=data_df.iloc[:,-1].to_numpy()
        for m in range(20):
            best_p=ans1.iloc[m,2]
            x_best_p=df[best_p].to_numpy()
            x=[]
            y_old=df[ans1["movies"][m]].to_numpy()
            y=[]
            for i in range(len(x_with0)):
               if np.isnan(x_with0[i][0])==False:
                   x.append(x_with0[i])
                   y.append(y old[i])
            reg = LinearRegression().fit(x,y)
            y hat = reg.predict(x)
            r2 = r2 \ score(y, y \ hat)
            cod_new.append(r2)
        for i in data:
            cod_old.append(i[1])
        plt.scatter(cod_old,cod_new)
```

## Out[286]: <matplotlib.collections.PathCollection at 0x7fd4e87e75b0>



3

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```
In [109...
         names=[]
          names2=[]
          for r in rank[185:215]:
              names.append(movie names[r]) #movies name in middle cod
          for r in rank[216:226]:
              names2.append(movie names[r])
          mov30=df.loc[:, names]
          mov10=df.loc[:, names2]
          a=[int(x) for x in np.linspace(start = 1, stop = 200, num = 200)]
          rmse m=[]
          r beta=[]
          r_alpha=[]
In [111...
         def rmse(predictions, targets):
              return np.sqrt(np.mean((predictions-targets)**2))
In [112...
          for i in tqdm(range(30)):
              X train, X test, Y train, Y test = train test split(mov10, mov30.iloc[:,
              param grid = {'alpha': a}
              model=Ridge()
              Ridge reg= GridSearchCV(model, param grid, scoring='neg mean squared err
              Ridge reg.fit(X train, Y train)
              pred=Ridge reg.predict(X test)
              rmse_m.append(rmse(pred,Y_test))
              r alpha.append(Ridge reg.best params ['alpha'])
         100%
                    30/30 [00:36<00:00, 1.20s/it]
In [113....
          for i in tqdm(range(30)):
              X train, X test, Y train, Y test = train test split(mov10, mov30.iloc[:,
              param grid = {'alpha': a}
              model=Ridge(r_alpha[i])
              model.fit(X_train, Y_train)
              r_beta.append(np.round(model.coef_, 3))
         100%
                         30/30 [00:00<00:00, 645.76it/s]
In [118....
          ans3_1=pd.DataFrame({'Movie': names, 'Best Alpha': r_alpha, 'RSME': np.round
          ans3 2 = pd.DataFrame(r beta, columns = names2)
          ans3 = pd.concat([ans3 1, ans3 2], axis = 1)
In [119...
          ans3
Out[119]:
                                         There's
                                                                                  Just
                                                                                        St
                                       Something
                                                            Toy
                                                                  Shrek
                                                 Predator
                           Best
                                                                         Shrek
                                                                                  Like
                                RSME
                   Movie
                                          About
                                                           Story
                                                                                       Bv
                          Alpha
                                                   (1987)
                                                                        (2001)
                                                                               Heaven
                                                          (1995) (2004)
                                           Marv
                                                                                       (19
                                                                                (2005)
                                          (1998)
                  Gone in
                    Sixty
                             24 0.338
                                           0.177
                                                   0.064
                                                           0.019 -0.000
                                                                         0.006
                                                                                 0.166
                                                                                        0.0
                  Seconds
```

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(2000)

	(2000)									
1	Crossroads (2002)	41	0.382	0.156	0.027	-0.002	0.024	0.024	0.164	0.
2	Austin Powers: The Spy Who Shagged Me (1999)	53	0.568	0.240	0.057	0.031	0.013	0.061	0.064	0.
3	Austin Powers in Goldmember (2002)	80	0.496	0.215	0.109	-0.005	0.017	0.071	0.075	0.0
4	Goodfellas (1990)	52	0.377	0.175	0.111	0.094	-0.028	0.006	0.038	0.
5	The Big Lebowski (1998)	73	0.367	0.085	0.088	0.034	0.020	0.052	0.083	0.
6	Twister (1996)	25	0.367	0.114	0.126	-0.003	-0.012	0.032	0.106	0.
7	Blues Brothers 2000 (1998)	83	0.393	0.104	0.073	0.035	0.028	-0.000	0.105	0.0
8	Dances with Wolves (1990)	71	0.319	0.056	0.156	0.046	0.023	0.012	0.059	0.
9	28 Days Later (2002)	56	0.370	0.114	0.159	0.050	0.005	0.010	0.030	0.
10	Knight and Day (2010)	42	0.450	0.059	0.100	-0.006	0.050	-0.030	0.126	0.0
11	The Evil Dead (1981)	52	0.378	0.076	0.169	0.085	-0.012	0.010	0.044	0.0
12	The Machinist (2004)	94	0.353	0.057	0.132	0.027	0.016	0.013	0.079	0.0
13	The Blue Lagoon (1980)	52	0.312	0.096	0.116	0.022	0.014	0.008	0.099	0.
14	Uptown Girls (2003)	29	0.419	0.262	0.040	0.048	0.017	0.018	0.139	0.
15	Men in Black (1997)	104	0.539	0.070	0.099	0.121	0.038	0.067	0.069	0.
16	Men in Black II (2002)	34	0.505	0.140	0.264	0.066	0.041	0.021	0.020	0.0

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17	The Green Mile (1999)	71	0.421	0.101	0.139	0.048	0.013	0.016	0.075	0.
18	The Rock (1996)	65	0.399	0.097	0.098	0.057	0.035	0.015	0.165	0.0
19	You're Next (2011)	61	0.337	0.097	0.147	0.027	-0.020	0.046	0.083	0.
20	The Poseidon Adventure (1972)	87	0.225	0.107	0.060	0.048	0.040	0.012	0.124	0.
21	The Good the Bad and the Ugly (1966)	63	0.354	0.157	0.039	0.027	-0.028	0.044	0.166	0.
22	Let the Right One In (2008)	20	0.319	0.145	0.113	0.009	0.003	0.013	0.195	0.
23	Equilibrium (2002)	42	0.310	0.066	0.019	0.016	0.032	-0.004	0.147	0.0
24	Just Married (2003)	52	0.371	0.118	0.112	0.044	0.028	-0.007	0.146	0.0
25	The Mummy Returns (2001)	97	0.487	0.066	0.127	0.040	0.010	0.044	0.018	0.
26	The Mummy (1999)	47	0.571	0.046	0.221	0.078	0.031	0.043	0.040	-0.
27	Reservoir Dogs (1992)	61	0.402	0.109	0.195	0.050	-0.026	0.014	0.030	0.0
28	Man on Fire (2004)	31	0.328	0.149	0.032	0.011	0.001	0.034	0.183	0.
29	The Prestige (2006)	60	0.344	0.134	0.158	0.065	0.003	0.024	0.084	0

4

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```
In [131...
         rmse m2=[]
          l beta=[]
          l alpha=[]
          a2=[round(x,5) \text{ for } x \text{ in } np.linspace(start = 0.0001, stop = 0.1, num = 1000)]
          for i in tqdm(range(30)):
               X train, X test, Y train, Y test = train test split(mov10, mov30.iloc[:,
               param_grid = {'alpha': a2}
               model=Lasso()
               Lasso reg= GridSearchCV(model, param grid, scoring='neg mean squared err
               Lasso_reg.fit(X_train, Y_train)
               pred=Lasso_reg.predict(X_test)
               rmse m2.append(rmse(pred,Y test))
               l_alpha.append(Lasso_reg.best_params_['alpha'])
          100%
                           30/30 [03:10<00:00, 6.33s/it]
In [132...
          for i in tqdm(range(30)):
               X train, X test, Y train, Y test = train test split(mov10, mov30.iloc[:,
               param grid = {'alpha': a}
               model=Lasso(l_alpha[i])
               model.fit(X_train, Y_train)
               l beta.append(np.round(model.coef , 3))
                           | 30/30 [00:00<00:00, 613.85it/s]
          100%
In [133...
          ans4_1=pd.DataFrame({'Movie': names, 'Best Alpha': l_alpha, 'RSME': np.round
          ans4 2 = pd.DataFrame(1 beta, columns = names2)
          ans4 = pd.concat([ans4_1, ans4_2], axis = 1)
          ans4
Out[133]:
                                            There's
                                                                                       Just
                                                                                             S
                                         Something
                                                                      Shrek
                                                                Toy
                                                    Predator
                                                                              Shrek
                             Best
                                                                                       Like
                     Movie
                                   RSME
                                                                                             B
                                              About
                                                               Story
                                                                          2
                            Alpha
                                                      (1987)
                                                                             (2001)
                                                                                    Heaven
                                              Mary
                                                              (1995)
                                                                     (2004)
                                                                                             (19
                                                                                     (2005)
                                             (1998)
                   Gone in
                      Sixty
            0
                            0.0061 0.341
                                              0.183
                                                       0.050
                                                               0.016
                                                                      0.000
                                                                              0.001
                                                                                      0.164
                                                                                              0
                   Seconds
                    (2000)
                 Crossroads
                           0.0032 0.384
                                              0.170
                                                                       0.021
                                                                              0.020
                                                                                      0.183
                                                       0.003 -0.000
                                                                                              (
                    (2002)
                     Austin
                Powers: The
            2
                  Spy Who
                           0.0046 0.572
                                              0.294
                                                       0.036
                                                               0.018
                                                                      0.005
                                                                              0.064
                                                                                      0.025
                                                                                              (
               Shagged Me
                    (1999)
                     Austin
                  Powers in
                            0.0106 0.499
                                              0.284
                                                        0.100 -0.000
                                                                      0.004
                                                                              0.070
                                                                                      0.051
                                                                                              C
               Goldmember
                    (2002)
```

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4	Goodfellas (1990)	0.0036	0.375	0.210	0.121	0.091	-0.024	0.000	0.005	(
5	The Big Lebowski (1998)	0.0016	0.365	0.088	0.095	0.021	0.016	0.052	0.088	(
6	Twister (1996)	0.0044	0.367	0.108	0.123	-0.000	-0.000	0.019	0.096	(
7	Blues Brothers 2000 (1998)	0.0010	0.395	0.121	0.070	0.025	0.025	-0.006	0.125	0
8	Dances with Wolves (1990)	0.0045	0.321	0.036	0.199	0.036	0.023	0.004	0.036	(
9	28 Days Later (2002)	0.0041	0.372	0.123	0.191	0.042	0.000	0.006	0.000	C
10	Knight and Day (2010)	0.0061	0.457	0.037	0.088	-0.000	0.034	-0.013	0.132	С
11	The Evil Dead (1981)	0.0072	0.382	0.069	0.203	0.083	-0.000	0.000	0.013	О
12	The Machinist (2004)	0.0037	0.368	0.035	0.170	0.013	0.009	0.008	0.061	0
13	The Blue Lagoon (1980)	0.0038	0.316	0.095	0.120	0.013	0.009	0.003	0.096	О
14	Uptown Girls (2003)	0.0021	0.419	0.297	0.024	0.043	0.016	0.014	0.148	0
15	Men in Black (1997)	0.0037	0.536	0.065	0.110	0.128	0.027	0.069	0.067	С
16	Men in Black II (2002)	0.0077	0.506	0.146	0.298	0.061	0.038	0.016	0.000	С
17	The Green Mile (1999)	0.0002	0.422	0.120	0.183	0.038	0.012	0.010	0.086	(
18	The Rock (1996)	0.0011	0.398	0.107	0.113	0.055	0.033	0.009	0.220	С
19	You're Next (2011)	0.0042	0.335	0.104	0.179	0.016	-0.013	0.038	0.082	0
20	The Poseidon Adventure (1972)	0.0016	0.225	0.126	0.049	0.043	0.040	0.002	0.160	(
21	The Good the Bad and	0.0050	0.364	0.188	0.010	0.018	-0.020	0.033	0.208	(

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	the Ugly (1966)									
22	Let the Right One In (2008)	0.0024	0.323	0.151	0.116	0.006	0.000	0.013	0.208	С
23	Equilibrium (2002)	0.0035	0.315	0.052	0.000	0.010	0.024	0.000	0.158	С
24	Just Married (2003)	0.0052	0.374	0.123	0.114	0.035	0.018	-0.000	0.172	(
25	The Mummy Returns (2001)	0.0102	0.481	0.052	0.149	0.027	0.000	0.042	0.000	(
26	The Mummy (1999)	0.0095	0.572	0.003	0.244	0.068	0.026	0.039	0.000	-0
27	Reservoir Dogs (1992)	0.0057	0.399	0.116	0.244	0.040	-0.015	0.000	0.000	С
28	Man on Fire (2004)	0.0051	0.330	0.152	0.010	0.006	0.000	0.031	0.192	(
29	The Prestige (2006)	0.0060	0.344	0.157	0.195	0.060	0.000	0.020	0.085	(

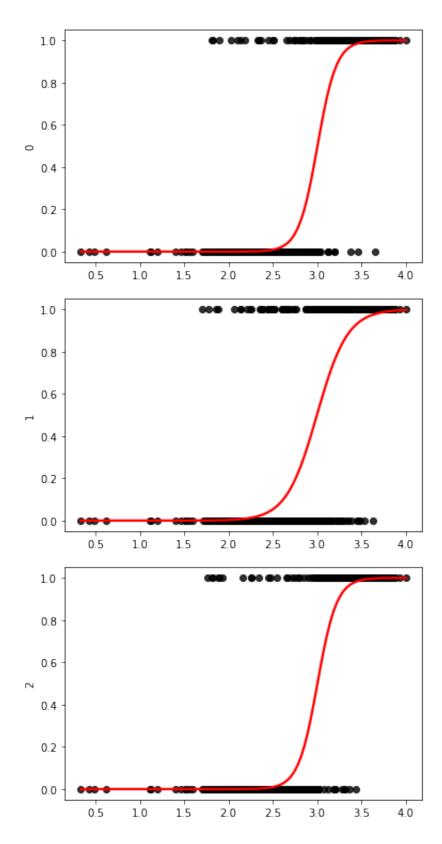
## 5

In [261... X = np.mean(movies, axis = 1).dropna().valuesmovie\_m=np.mean(movies, axis = 0).dropna().values

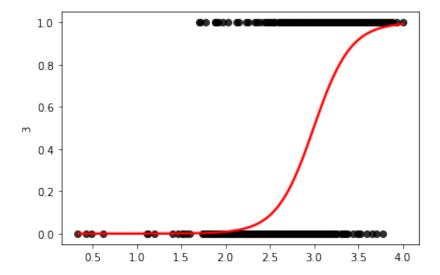
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```
In [272... s=df.shape[0]
          temp=np.argsort(movie m)
          mov4 names ind=temp[198:202]
          mov4 names=[]
          mov4 m=[]
          label=[]
          for i in mov4_names_ind:
              mov4_names.append(movie_names[i])
          for m in mov4 names ind:
              temp=[]
              median=df[movie_names[m]].median()
              for i in range(s):
                  if df.iloc[i,m]<median:</pre>
                      temp.append(0)
                  else:
                      temp.append(1)
              label.append(temp)
          auc=[]
          beta=[]
          df5=pd.DataFrame(np.array(label).T)
In [273... for i in range(4):
              X_train, X_test, Y_train, Y_test = train_test_split(X.reshape(-1,1), df5
              params = {'penalty': ['12', 'none']}
              model = LogisticRegression()
              1 = GridSearchCV(model, params)
              l=l.fit(X_train, Y_train)
              pred = 1.predict(X test)
              auc.append(roc_auc_score(Y_test, pred))
              beta.append(1.best_estimator_.fit(X_train, Y_train).coef_)
              plt.figure(i)
              print(mov4 names[i])
              sns.regplot(x = X.reshape(-1,1), y = df5.iloc[:,i], logistic = True, ci
          auc, beta
          Fahrenheit 9/11 (2004)
          Happy Gilmore (1996)
          Diamonds are Forever (1971)
          Scream (1996)
Out[273]: ([0.954545454545454546,
             0.8584078119827872,
             0.9540153833429824,
             0.8590909090909089],
            [array([[10.28532939]]),
             array([[5.96005022]]),
             array([[10.33151309]]),
             array([[4.97839277]])])
```

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## **Extra Credit**

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