Movielens - Feature Extraction Using Autoencoders

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1 MA691 Advanced Statistical Algorithms

2 Term Paper

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3.1 Introduction

We often use ICA or PCA to extract features from the high-dimensional data. The autoencoder is another interesting algorithm to achieve the same purpose in the context of Deep Learning.

With the purpose of learning a function to approximate the input data itself such that F(X) = X, an autoencoder consists of two parts, namely encoder and decoder. While the encoder aims to compress the original input data into a low-dimensional representation, the decoder tries to reconstruct the original input data based on the low-dimension representation generated by the encoder.

3.2 Implementation

We first use collaborative filtering - implicit characteristics based on similarity of users' preferences to those of other users to fill the ratings matrix (users x movies). Then this is inputed into the auto-encoder which encodes and decodes the ratings, the layers in middle reduce the features to lower dimension. To get missing rating of user a on movie p :

1) Consider all neighbours that have rated the movie.

2) Calculate the similarity between the users using Pearson's coefficient

$$PCC = corr(a,b) = \frac{cov(a,b)}{sqrt(var_a)sqrt(var_b)} \tag{1}$$

3) Missing rating (a,p) =

$$= r_{a,avg} + \frac{\sum_{neighbours(n)} sim(a,b) * (r_{b,p} - r_{b,avg})}{\sum_{neighbours(n)} sim(a,b)} \tag{2}$$

3.2.1 1. Collaborative Filtering

```
In [43]: import pandas as pd

         cols = ['user_id', 'movie_id', 'rating', 'unix_timestamp']
         df = pd.read_csv('ml-100k/u.data', sep='\t', names=cols)

In [44]: df.head()
```

Out[44]:

	user_id	movie_id	rating	unix_timestamp
0	196	242	3	881250949
1	186	302	3	891717742
2	22	377	1	878887116
3	244	51	2	880606923
4	166	346	1	886397596

```
In [45]: df = df.drop('unix_timestamp', 1)
         df.head()
```

Out[45]:

	user_id	movie_id	rating
0	196	242	3
1	186	302	3
2	22	377	1
3	244	51	2
4	166	346	1

```
In [46]: input_df = pd.DataFrame(index=range(1,max(df['user_id'])+1), columns=range(1,max(df['mo

In [47]: for index,row in df.iterrows():
             input_df[row['movie_id']][row['user_id']]=row['rating']

In [48]: input_df.shape

Out[48]: (943, 1682)
```

Truncate and use only first 64 features to reduce running time

```
In [49]: input_df=input_df.truncate(after=64,axis=1)
         for column in input_df:
             if input_df[column].count()<2:
                 print(column)

In [50]: input_df.shape

Out[50]: (943, 64)
```

```
In [51]: input_df=input_df.dropna(axis=0, how='all')

In [52]: for column in input_df:
             if input_df[column].count()<2:
                 print(column)

In [53]: input_df.shape

Out[53]: (797, 64)
```

Generate Similarity matrix

```
In [54]: import numpy as np
         import math

In [56]: mean_col = input_df.mean(axis=1)

In [57]: def user_similarity(a,b):
             if(not a in input_df.index or not b in input_df.index):
                 return np.nan
             cov=0.0
             var_a=0.0
             var_b=0.0
             for column in input_df:
                 avg_rating_a = mean_col[a]
                 avg_rating_b = mean_col[b]
                 j_rating_a = input_df[column][a]
                 j_rating_b = input_df[column][b]

                 if (not np.isnan(j_rating_a) and not np.isnan(j_rating_b)):
                     cov = cov + (j_rating_a-avg_rating_a)*(j_rating_b-avg_rating_b)
                     var_a = var_a + (j_rating_a-avg_rating_a)*(j_rating_a-avg_rating_a)
                     var_b = var_b + (j_rating_b-avg_rating_b)*(j_rating_b-avg_rating_b)
             if(var_a==0 or var_b==0):
                 return 0
             return (cov/(math.sqrt(var_a*var_b)))

In [13]: sim = np.zeros(shape=(max(df['user_id']),max(df['user_id'])))
         num_of_users = max(df['user_id'])
         it=0

         for i in range(num_of_users):
             for j in range(i+1):
                 sim[i][j] = user_similarity(i+1, j+1)
                 sim[j][i] = sim[i][j]

In [59]: sim
```

Out[59]:
```
array([[1.        , 0.44046501, 0.        , ..., 0.21411269, 0.        ,
        0.22533549],
       [0.44046501, 1.        , 0.        , ..., 1.        , 0.        ,
        1.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       ...,
       [0.21411269, 1.        , 0.        , ..., 1.        , 0.        ,
        0.        ],
       [0.        , 0.        , 0.        , ..., 0.        , 0.        ,
        0.        ],
       [0.22533549, 1.        , 0.        , ..., 0.        , 0.        ,
        1.        ]])
```

In [60]:
```
def round_off_rating(val):
    new_val=int(val)
    frac=val-int(val)
    if(frac>=0.75):
        new_val=new_val+1
    elif(frac>=0.25):
        new_val=new_val+0.5
    return max(min(new_val,5.0),1)

def predict_column_rating(column_no):
    temp=input_df[input_df[column_no].notnull()][column_no]
    for index, null_rating in input_df[column_no].iteritems():
        num_sum=0
        den_sum=0
        if(np.isnan(null_rating)):
            for i, rating in temp.iteritems():
                num_sum=num_sum+sim[index-1][i-1]*(rating-mean_col[i])
                den_sum=den_sum+sim[index-1][i-1]
            if(den_sum==0):
                input_df[column_no][index] = round_off_rating(mean_col[index])
            else:
                input_df[column_no][index] = round_off_rating(mean_col[index]+num_sum/d
```

In [61]:
```
for column_no in input_df:
    predict_column_rating(column_no)
```

In [62]:
```
input_df.head()
```

Out[62]:

	1	2	3	4	5	6	7	8	9	10	...	55	56	57	58	\
1	5	3	4	3	3	5	4	1	5	3	...	5	4	5	4	
2	4	3.5	3	3.5	3.5	3.5	3.5	4	3.5	2	...	3.5	4	4	3.5	
4	4.5	4	3.5	4.5	4	4	4.5	5	4	4	...	4.5	4.5	5	4.5	
5	4	3	3	3	3.5	5	3.5	3.5	3	2.5	...	3.5	3.5	3	3.5	
6	4	2.5	3	3.5	3	3.5	2	4	4	4	...	3.5	4	4	3.5	

```
    59   60   61 62 63   64
1    5    5    4  3  2    5
2    3  3.5    3  3  3  4.5
4    5  4.5  4.5  4  4    5
5  3.5  2.5    4  4  1    4
6    5    4    4  3  2    4

[5 rows x 64 columns]
```

```
In [63]: input_df.to_csv("filtered_input.csv", index_label=False)
```

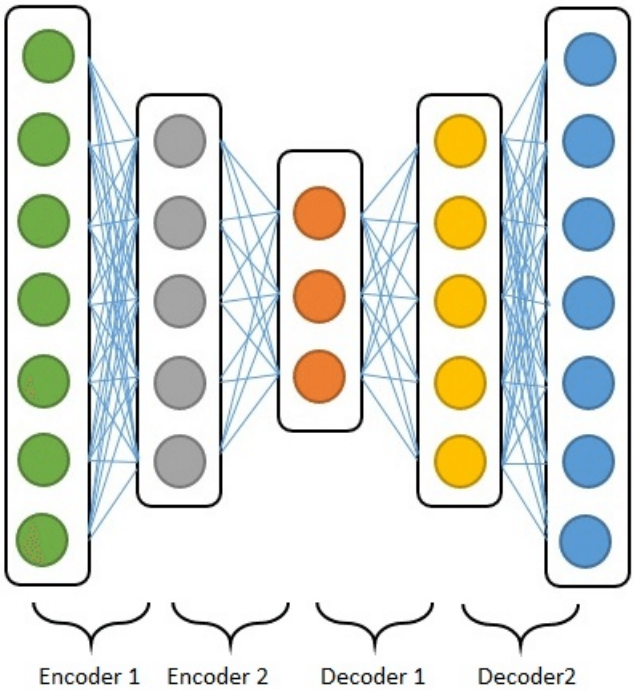
3.2.2 Now the input is finally ready, all the missing values have been filled as shown above.

3.2.3 2. Dimensionality Reduction using Autoencoders

```
In [64]: from keras.layers import Input, Dense
         from keras.models import Model
```

```
Using TensorFlow backend.
```

The following architecture is used for the autoencoder, the input ratings are of dimension 64 and then the next layer reduces it to 16 and the bottleneck layer reduce it further down to 5. Then we decode back to 16 and then the output layer gives dimesion 64 output.




```
In [65]: encoding_dim1 = 16
         encoding_dim2 = 5
         input_rating = Input(shape=(64,))
```

```
        encoded = Dense(16, activation='relu')(input_rating) #64->16
        encoded = Dense(5, activation='relu')(encoded)       #16->05
        decoded = Dense(16, activation='relu')(encoded)      #05->16
        decoded = Dense(64, activation='sigmoid')(decoded)   #16->64
        autoencoder = Model(input_rating, decoded)
```

```
In [66]: encoder1 = Model(input_rating, autoencoder.layers[1](input_rating))
         input_encoding = Input(shape=(encoding_dim1,))
         encoder2 = Model(input_encoding, autoencoder.layers[2](input_encoding))
         encoded_input1 = Input(shape=(encoding_dim2,))
         encoded_input2 = Input(shape=(encoding_dim1,))
         decoder_layer1 = autoencoder.layers[-2]
         decoder_layer2 = autoencoder.layers[-1]
         decoder1 = Model(encoded_input1, decoder_layer1(encoded_input1))
         decoder2 = Model(encoded_input2, decoder_layer2(encoded_input2))
```

```
In [67]: autoencoder.compile(optimizer='adam', loss='mse')
```

```
In [68]: input_df=input_df/5
         input_df.head()
```

```
Out[68]:     1    2    3    4    5    6    7    8    9    10 ...    55   56   57   58  \
         1    1  0.6  0.8  0.6  0.6    1  0.8  0.2    1  0.6 ...     1  0.8    1  0.8
         2  0.8  0.7  0.6  0.7  0.7  0.7  0.7  0.8  0.7  0.4 ...   0.7  0.8  0.8  0.7
         4  0.9  0.8  0.7  0.9  0.8  0.8  0.9    1  0.8  0.8 ...   0.9  0.9    1  0.9
         5  0.8  0.6  0.6  0.6  0.7    1  0.7  0.7  0.6  0.5 ...   0.7  0.7  0.6  0.7
         6  0.8  0.5  0.6  0.7  0.6  0.7  0.4  0.8  0.8  0.8 ...   0.7  0.8  0.8  0.7

             59   60   61   62   63   64
         1    1    1  0.8  0.6  0.4    1
         2  0.6  0.7  0.6  0.6  0.6  0.9
         4    1  0.9  0.9  0.8  0.8    1
         5  0.7  0.5  0.8  0.8  0.2  0.8
         6    1  0.8  0.8  0.6  0.4  0.8

         [5 rows x 64 columns]
```

```
In [69]: x_train=input_df.sample(frac=0.8,random_state=200)
         x_test=input_df.drop(x_train.index)
```

```
In [70]: x_train.shape
```

```
Out[70]: (638, 64)
```

```
In [71]: autoencoder.fit(x_train,x_train,epochs=100, batch_size=100, shuffle=True, validation_da

Train on 638 samples, validate on 159 samples
Epoch 1/100
638/638 [==============================] - 0s 354us/step - loss: 0.0907 - val_loss: 0.0971
```

```
Epoch 2/100
638/638 [==============================] - 0s 53us/step - loss: 0.0836 - val_loss: 0.0933
Epoch 3/100
638/638 [==============================] - 0s 42us/step - loss: 0.0812 - val_loss: 0.0918
Epoch 4/100
638/638 [==============================] - 0s 48us/step - loss: 0.0797 - val_loss: 0.0894
Epoch 5/100
638/638 [==============================] - 0s 47us/step - loss: 0.0770 - val_loss: 0.0855
Epoch 6/100
638/638 [==============================] - 0s 50us/step - loss: 0.0734 - val_loss: 0.0805
Epoch 7/100
638/638 [==============================] - 0s 54us/step - loss: 0.0691 - val_loss: 0.0746
Epoch 8/100
638/638 [==============================] - 0s 50us/step - loss: 0.0642 - val_loss: 0.0679
Epoch 9/100
638/638 [==============================] - 0s 53us/step - loss: 0.0588 - val_loss: 0.0611
Epoch 10/100
638/638 [==============================] - 0s 51us/step - loss: 0.0534 - val_loss: 0.0545
Epoch 11/100
638/638 [==============================] - 0s 49us/step - loss: 0.0482 - val_loss: 0.0485
Epoch 12/100
638/638 [==============================] - 0s 49us/step - loss: 0.0438 - val_loss: 0.0433
Epoch 13/100
638/638 [==============================] - 0s 43us/step - loss: 0.0401 - val_loss: 0.0394
Epoch 14/100
638/638 [==============================] - 0s 49us/step - loss: 0.0371 - val_loss: 0.0365
Epoch 15/100
638/638 [==============================] - 0s 39us/step - loss: 0.0349 - val_loss: 0.0341
Epoch 16/100
638/638 [==============================] - 0s 47us/step - loss: 0.0334 - val_loss: 0.0326
Epoch 17/100
638/638 [==============================] - 0s 50us/step - loss: 0.0322 - val_loss: 0.0316
Epoch 18/100
638/638 [==============================] - 0s 42us/step - loss: 0.0314 - val_loss: 0.0310
Epoch 19/100
638/638 [==============================] - 0s 47us/step - loss: 0.0308 - val_loss: 0.0305
Epoch 20/100
638/638 [==============================] - 0s 41us/step - loss: 0.0304 - val_loss: 0.0301
Epoch 21/100
638/638 [==============================] - 0s 37us/step - loss: 0.0301 - val_loss: 0.0297
Epoch 22/100
638/638 [==============================] - 0s 42us/step - loss: 0.0299 - val_loss: 0.0296
Epoch 23/100
638/638 [==============================] - 0s 38us/step - loss: 0.0297 - val_loss: 0.0294
Epoch 24/100
638/638 [==============================] - 0s 48us/step - loss: 0.0296 - val_loss: 0.0293
Epoch 25/100
638/638 [==============================] - 0s 44us/step - loss: 0.0295 - val_loss: 0.0292
```

```
Epoch 26/100
638/638 [==============================] - 0s 43us/step - loss: 0.0294 - val_loss: 0.0290
Epoch 27/100
638/638 [==============================] - 0s 56us/step - loss: 0.0293 - val_loss: 0.0291
Epoch 28/100
638/638 [==============================] - 0s 46us/step - loss: 0.0292 - val_loss: 0.0289
Epoch 29/100
638/638 [==============================] - 0s 40us/step - loss: 0.0292 - val_loss: 0.0289
Epoch 30/100
638/638 [==============================] - 0s 53us/step - loss: 0.0291 - val_loss: 0.0289
Epoch 31/100
638/638 [==============================] - 0s 66us/step - loss: 0.0291 - val_loss: 0.0288
Epoch 32/100
638/638 [==============================] - 0s 44us/step - loss: 0.0290 - val_loss: 0.0288
Epoch 33/100
638/638 [==============================] - 0s 49us/step - loss: 0.0290 - val_loss: 0.0287
Epoch 34/100
638/638 [==============================] - 0s 39us/step - loss: 0.0289 - val_loss: 0.0286
Epoch 35/100
638/638 [==============================] - 0s 51us/step - loss: 0.0288 - val_loss: 0.0285
Epoch 36/100
638/638 [==============================] - 0s 59us/step - loss: 0.0288 - val_loss: 0.0286
Epoch 37/100
638/638 [==============================] - 0s 56us/step - loss: 0.0287 - val_loss: 0.0285
Epoch 38/100
638/638 [==============================] - 0s 53us/step - loss: 0.0287 - val_loss: 0.0285
Epoch 39/100
638/638 [==============================] - 0s 66us/step - loss: 0.0286 - val_loss: 0.0284
Epoch 40/100
638/638 [==============================] - 0s 67us/step - loss: 0.0286 - val_loss: 0.0283
Epoch 41/100
638/638 [==============================] - 0s 51us/step - loss: 0.0285 - val_loss: 0.0282
Epoch 42/100
638/638 [==============================] - 0s 63us/step - loss: 0.0284 - val_loss: 0.0283
Epoch 43/100
638/638 [==============================] - 0s 56us/step - loss: 0.0284 - val_loss: 0.0282
Epoch 44/100
638/638 [==============================] - 0s 44us/step - loss: 0.0283 - val_loss: 0.0280
Epoch 45/100
638/638 [==============================] - 0s 60us/step - loss: 0.0282 - val_loss: 0.0281
Epoch 46/100
638/638 [==============================] - 0s 51us/step - loss: 0.0282 - val_loss: 0.0279
Epoch 47/100
638/638 [==============================] - 0s 58us/step - loss: 0.0281 - val_loss: 0.0280
Epoch 48/100
638/638 [==============================] - 0s 50us/step - loss: 0.0281 - val_loss: 0.0277
Epoch 49/100
638/638 [==============================] - 0s 56us/step - loss: 0.0280 - val_loss: 0.0279
```

```
Epoch 50/100
638/638 [==============================] - 0s 41us/step - loss: 0.0279 - val_loss: 0.0276
Epoch 51/100
638/638 [==============================] - 0s 65us/step - loss: 0.0278 - val_loss: 0.0276
Epoch 52/100
638/638 [==============================] - 0s 48us/step - loss: 0.0277 - val_loss: 0.0276
Epoch 53/100
638/638 [==============================] - 0s 42us/step - loss: 0.0276 - val_loss: 0.0275
Epoch 54/100
638/638 [==============================] - 0s 46us/step - loss: 0.0276 - val_loss: 0.0274
Epoch 55/100
638/638 [==============================] - 0s 45us/step - loss: 0.0275 - val_loss: 0.0273
Epoch 56/100
638/638 [==============================] - 0s 51us/step - loss: 0.0274 - val_loss: 0.0271
Epoch 57/100
638/638 [==============================] - 0s 41us/step - loss: 0.0273 - val_loss: 0.0273
Epoch 58/100
638/638 [==============================] - 0s 52us/step - loss: 0.0272 - val_loss: 0.0270
Epoch 59/100
638/638 [==============================] - 0s 48us/step - loss: 0.0271 - val_loss: 0.0270
Epoch 60/100
638/638 [==============================] - 0s 47us/step - loss: 0.0270 - val_loss: 0.0270
Epoch 61/100
638/638 [==============================] - 0s 45us/step - loss: 0.0269 - val_loss: 0.0269
Epoch 62/100
638/638 [==============================] - 0s 37us/step - loss: 0.0268 - val_loss: 0.0267
Epoch 63/100
638/638 [==============================] - 0s 38us/step - loss: 0.0267 - val_loss: 0.0266
Epoch 64/100
638/638 [==============================] - 0s 40us/step - loss: 0.0266 - val_loss: 0.0265
Epoch 65/100
638/638 [==============================] - 0s 32us/step - loss: 0.0265 - val_loss: 0.0264
Epoch 66/100
638/638 [==============================] - 0s 46us/step - loss: 0.0264 - val_loss: 0.0264
Epoch 67/100
638/638 [==============================] - 0s 38us/step - loss: 0.0264 - val_loss: 0.0262
Epoch 68/100
638/638 [==============================] - 0s 34us/step - loss: 0.0263 - val_loss: 0.0263
Epoch 69/100
638/638 [==============================] - 0s 38us/step - loss: 0.0262 - val_loss: 0.0261
Epoch 70/100
638/638 [==============================] - 0s 35us/step - loss: 0.0261 - val_loss: 0.0260
Epoch 71/100
638/638 [==============================] - 0s 36us/step - loss: 0.0260 - val_loss: 0.0259
Epoch 72/100
638/638 [==============================] - 0s 34us/step - loss: 0.0259 - val_loss: 0.0260
Epoch 73/100
638/638 [==============================] - 0s 46us/step - loss: 0.0258 - val_loss: 0.0258
```

```
Epoch 74/100
638/638 [==============================] - 0s 33us/step - loss: 0.0257 - val_loss: 0.0259
Epoch 75/100
638/638 [==============================] - 0s 50us/step - loss: 0.0256 - val_loss: 0.0256
Epoch 76/100
638/638 [==============================] - 0s 41us/step - loss: 0.0255 - val_loss: 0.0256
Epoch 77/100
638/638 [==============================] - 0s 39us/step - loss: 0.0255 - val_loss: 0.0255
Epoch 78/100
638/638 [==============================] - 0s 33us/step - loss: 0.0254 - val_loss: 0.0254
Epoch 79/100
638/638 [==============================] - 0s 38us/step - loss: 0.0253 - val_loss: 0.0254
Epoch 80/100
638/638 [==============================] - 0s 39us/step - loss: 0.0252 - val_loss: 0.0253
Epoch 81/100
638/638 [==============================] - 0s 45us/step - loss: 0.0252 - val_loss: 0.0252
Epoch 82/100
638/638 [==============================] - 0s 35us/step - loss: 0.0251 - val_loss: 0.0251
Epoch 83/100
638/638 [==============================] - 0s 38us/step - loss: 0.0250 - val_loss: 0.0252
Epoch 84/100
638/638 [==============================] - 0s 37us/step - loss: 0.0249 - val_loss: 0.0249
Epoch 85/100
638/638 [==============================] - 0s 45us/step - loss: 0.0249 - val_loss: 0.0250
Epoch 86/100
638/638 [==============================] - 0s 48us/step - loss: 0.0248 - val_loss: 0.0249
Epoch 87/100
638/638 [==============================] - 0s 41us/step - loss: 0.0247 - val_loss: 0.0248
Epoch 88/100
638/638 [==============================] - 0s 41us/step - loss: 0.0247 - val_loss: 0.0248
Epoch 89/100
638/638 [==============================] - 0s 39us/step - loss: 0.0246 - val_loss: 0.0247
Epoch 90/100
638/638 [==============================] - 0s 43us/step - loss: 0.0245 - val_loss: 0.0246
Epoch 91/100
638/638 [==============================] - 0s 40us/step - loss: 0.0245 - val_loss: 0.0247
Epoch 92/100
638/638 [==============================] - 0s 35us/step - loss: 0.0244 - val_loss: 0.0245
Epoch 93/100
638/638 [==============================] - 0s 42us/step - loss: 0.0244 - val_loss: 0.0245
Epoch 94/100
638/638 [==============================] - 0s 49us/step - loss: 0.0243 - val_loss: 0.0244
Epoch 95/100
638/638 [==============================] - 0s 53us/step - loss: 0.0242 - val_loss: 0.0245
Epoch 96/100
638/638 [==============================] - 0s 54us/step - loss: 0.0242 - val_loss: 0.0243
Epoch 97/100
638/638 [==============================] - 0s 54us/step - loss: 0.0241 - val_loss: 0.0243
```

```
Epoch 98/100
638/638 [==============================] - 0s 52us/step - loss: 0.0241 - val_loss: 0.0244
Epoch 99/100
638/638 [==============================] - 0s 45us/step - loss: 0.0241 - val_loss: 0.0241
Epoch 100/100
638/638 [==============================] - 0s 49us/step - loss: 0.0240 - val_loss: 0.0245
```

```
Out[71]: <keras.callbacks.History at 0x7faa7318f2d0>
```

```
In [72]: encoded_output1 = encoder1.predict(input_df)
         encoded_output2 = encoder2.predict(encoded_output1)
         decoded_output1 = decoder1.predict(encoded_output2)
         decoded_output2 = decoder2.predict(decoded_output1)
```

```
In [73]: encoded_output2
```

```
Out[73]: array([[0.       , 0.       , 0.       , 0.       , 2.5467837],
                [0.       , 0.       , 0.       , 0.       , 3.0671315],
                [0.       , 0.       , 0.       , 0.       , 4.9697094],
                ...,
                [0.       , 0.       , 0.       , 0.       , 5.081753 ],
                [0.       , 0.       , 0.       , 0.       , 8.523407 ],
                [0.       , 0.       , 0.       , 0.       , 4.541972 ]],
               dtype=float32)
```

```
In [74]: decoded_output2
```

```
Out[74]: array([[0.6766077 , 0.585756  , 0.54231805, ..., 0.58392555, 0.5763431 ,
                 0.76945156],
                [0.7094686 , 0.62192684, 0.5763254 , ..., 0.6131011 , 0.60951674,
                 0.80978876],
                [0.81122655, 0.7409461 , 0.69261825, ..., 0.71186453, 0.7207205 ,
                 0.9120297 ],
                ...,
                [0.816271  , 0.7471496 , 0.6989093 , ..., 0.7171989 , 0.7266409 ,
                 0.916145  ],
                [0.92509604, 0.88934785, 0.85258865, ..., 0.84991616, 0.868425  ,
                 0.9820333 ],
                [0.7909949 , 0.71637094, 0.6679497 , ..., 0.6909611 , 0.6974129 ,
                 0.8945963 ]], dtype=float32)
```

```
In [75]: ans=decoded_output2*5
         for (x,y), value in np.ndenumerate(ans):
             ans[x][y] = round_off_rating(ans[x][y])
```

```
In [76]: ans
```

```
Out[76]: array([[3.5, 3. , 2.5, ..., 3. , 3. , 4. ],
                [3.5, 3. , 3. , ..., 3. , 3. , 4. ],
```

```
       [4. , 3.5, 3.5, ..., 3.5, 3.5, 4.5],
       ...,
       [4. , 3.5, 3.5, ..., 3.5, 3.5, 4.5],
       [4.5, 4.5, 4.5, ..., 4. , 4.5, 5. ],
       [4. , 3.5, 3.5, ..., 3.5, 3.5, 4.5]], dtype=float32)
```

```
In [77]: ans_df=pd.DataFrame(ans)
```

```
In [78]: df=input_df.copy()
         df=df*5
```

```
In [79]: ans_df.head()
```

Out[79]:

	0	1	2	3	4	5	6	7	8	9	...	54	55	56	57	\
0	3.5	3.0	2.5	3.0	3.0	3.0	3.0	3.5	3.5	3.0	...	3.0	3.5	3.5	3.5	
1	3.5	3.0	3.0	3.5	3.0	3.0	3.5	3.5	3.5	3.5	...	3.5	3.5	3.5	3.5	
2	4.0	3.5	3.5	4.0	3.5	3.5	4.0	4.5	4.0	4.0	...	4.0	4.0	4.0	4.0	
3	4.0	3.5	3.5	4.0	3.5	3.5	4.0	4.0	4.0	4.0	...	4.0	4.0	4.0	4.0	
4	3.5	3.0	3.0	3.5	3.0	3.5	3.5	4.0	3.5	3.5	...	3.5	3.5	3.5	3.5	

	58	59	60	61	62	63
0	3.5	3.0	3.0	3.0	3.0	4.0
1	3.5	3.5	3.5	3.0	3.0	4.0
2	4.0	4.0	4.0	3.5	3.5	4.5
3	4.0	4.0	4.0	3.5	3.5	4.5
4	3.5	3.5	3.5	3.0	3.0	4.0

[5 rows x 64 columns]

```
In [80]: df.head()
```

Out[80]:

	1	2	3	4	5	6	7	8	9	10	...	55	56	57	58	\
1	5	3	4	3	3	5	4	1	5	3	...	5	4	5	4	
2	4	3.5	3	3.5	3.5	3.5	3.5	4	3.5	2	...	3.5	4	4	3.5	
4	4.5	4	3.5	4.5	4	4	4.5	5	4	4	...	4.5	4.5	5	4.5	
5	4	3	3	3	3.5	5	3.5	3.5	3	2.5	...	3.5	3.5	3	3.5	
6	4	2.5	3	3.5	3	3.5	2	4	4	4	...	3.5	4	4	3.5	

	59	60	61	62	63	64
1	5	5	4	3	2	5
2	3	3.5	3	3	3	4.5
4	5	4.5	4.5	4	4	5
5	3.5	2.5	4	4	1	4
6	5	4	4	3	2	4

[5 rows x 64 columns]

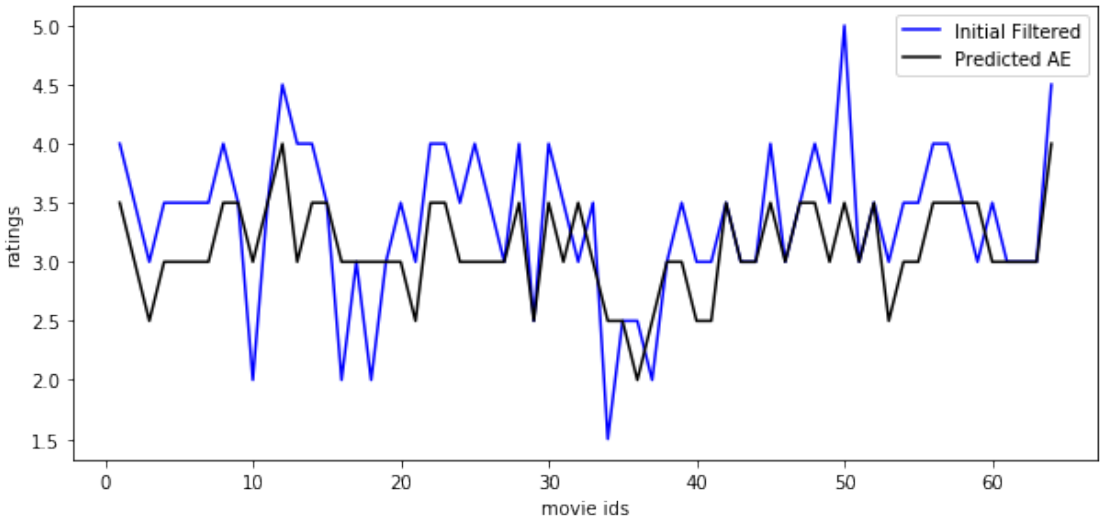
3.3 Results

```
In [84]: import matplotlib.pyplot as plt
```

3.3.1 Plot of initial filtered and the autoencoder(AE) predictions for user-1 ratings

```
In [99]: plt.figure(figsize=(10,10))
         plt.subplot(211)
         line1,=plt.plot(range(1,65), df.iloc[1], 'b')
         line2,=plt.plot(range(1,65), ans_df.iloc[0], 'k')
         plt.ylabel('ratings')
         plt.xlabel('movie ids')
         plt.legend([line1, line2], ['Initial Filtered', 'Predicted AE'])

Out[99]: <matplotlib.legend.Legend at 0x7faa6c2dad90>
```

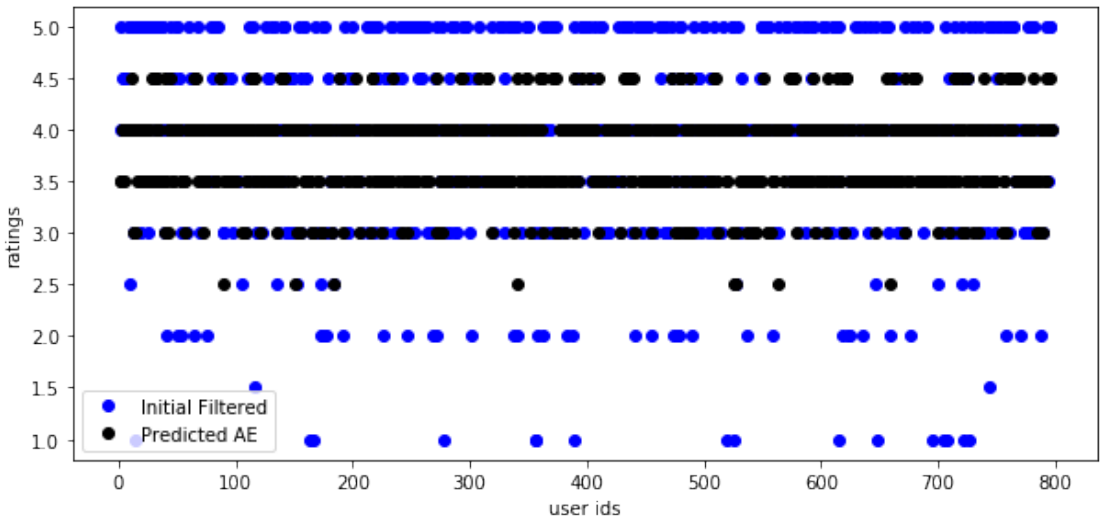


We see here that the autoencoder captures the ratings fairely neatly and captures the nature of the ratings.

3.3.2 Plot of movie-1 ratings

```
In [101]: plt.figure(figsize=(10,10))
          plt.subplot(212)
          line1,=plt.plot(range(1,798), df[1].tolist(), 'bo')
          line2,=plt.plot(range(1,798), ans_df[0].tolist(), 'ko')
          plt.ylabel('ratings')
          plt.xlabel('user ids')
          plt.legend([line1, line2], ['Initial Filtered', 'Predicted AE'])

Out[101]: <matplotlib.legend.Legend at 0x7faa6c1bee10>
```



Again, this observations all indicates that the autoencoder captures the ratings for movie1 upto a good accuracy.

Therefore, we were able to reduce the dimension of the features from 64 to 5 and still recover the ratings of the users using autoencoders.