shaikat_303527_exercise_10

January 25, 2020

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        from collections import Counter
        import seaborn as sns
        from sklearn.decomposition import NMF
        import math as Math
```

1 Exercise 1: Recommender Dataset

```
In [2]: data=pd.read_csv(r"E:\Documents\University of Hildesheim\Machine learning lab\lab10\ml-
                          names=["userId","itemId","rating","timestamp"])
        data.head()
```

Out[2]:

	userId	itemId	rating	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

1.0.1 Encoding female as 1 and male as 0

```
In [3]: userdata=pd.read_csv(r"E:\Documents\University of Hildesheim\Machine learning lab\lab1
                             names=["userId","age","gender","occupation","zipcode"],sep="|")
        userdata=userdata.replace(['F','M'],[1,0])
        userdata.head()
```

Out[3]:

	userId	age	gender	occupation	zipcode
0	1	24	0	technician	85711
1	2	53	1	other	94043
2	3	23	0	writer	32067
3	4	24	0	technician	43537
4	5	33	1	other	15213

```
In [4]: itemdata=pd.read_csv(r"E:\Documents\University of Hildesheim\Machine learning lab\lab1
                           "IMDbURL","unknown","Action","Adventure", "Animation",
                           "Children's","Comedy", "Crime", "Documentary","Drama","Fantasy",
```

```
                  "Film-Noir","Horror","Musical", "Mystery","Romance","Sci-Fi",
                  "Thriller", "War", "Western"],sep="|",encoding="ISO-8859-1")
itemdata.head()
```

Out[4]:

	movieid	movietitle	releasedate	videoreleasedate	\
0	1	Toy Story (1995)	01-Jan-1995	NaN	
1	2	GoldenEye (1995)	01-Jan-1995	NaN	
2	3	Four Rooms (1995)	01-Jan-1995	NaN	
3	4	Get Shorty (1995)	01-Jan-1995	NaN	
4	5	Copycat (1995)	01-Jan-1995	NaN	

	IMDbURL	unknown	Action	\
0	http://us.imdb.com/M/title-exact?Toy%20Story%2...	0	0	
1	http://us.imdb.com/M/title-exact?GoldenEye%20(...	0	1	
2	http://us.imdb.com/M/title-exact?Four%20Rooms%...	0	0	
3	http://us.imdb.com/M/title-exact?Get%20Shorty%...	0	1	
4	http://us.imdb.com/M/title-exact?Copycat%20(1995)	0	0	

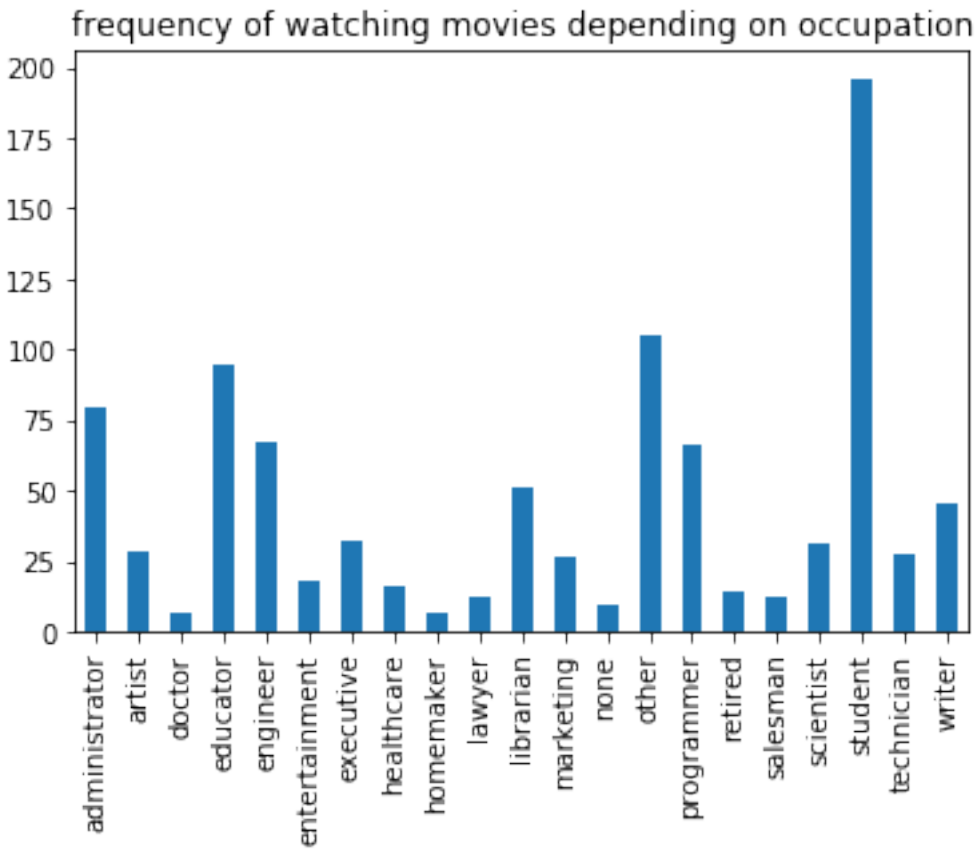
	Adventure	Animation	Children's	...	Fantasy	Film-Noir	Horror	Musical	\
0	0	1	1	...	0	0	0	0	
1	1	0	0	...	0	0	0	0	
2	0	0	0	...	0	0	0	0	
3	0	0	0	...	0	0	0	0	
4	0	0	0	...	0	0	0	0	

	Mystery	Romance	Sci-Fi	Thriller	War	Western
0	0	0	0	0	0	0
1	0	0	0	1	0	0
2	0	0	0	1	0	0
3	0	0	0	0	0	0
4	0	0	0	1	0	0

[5 rows x 24 columns]

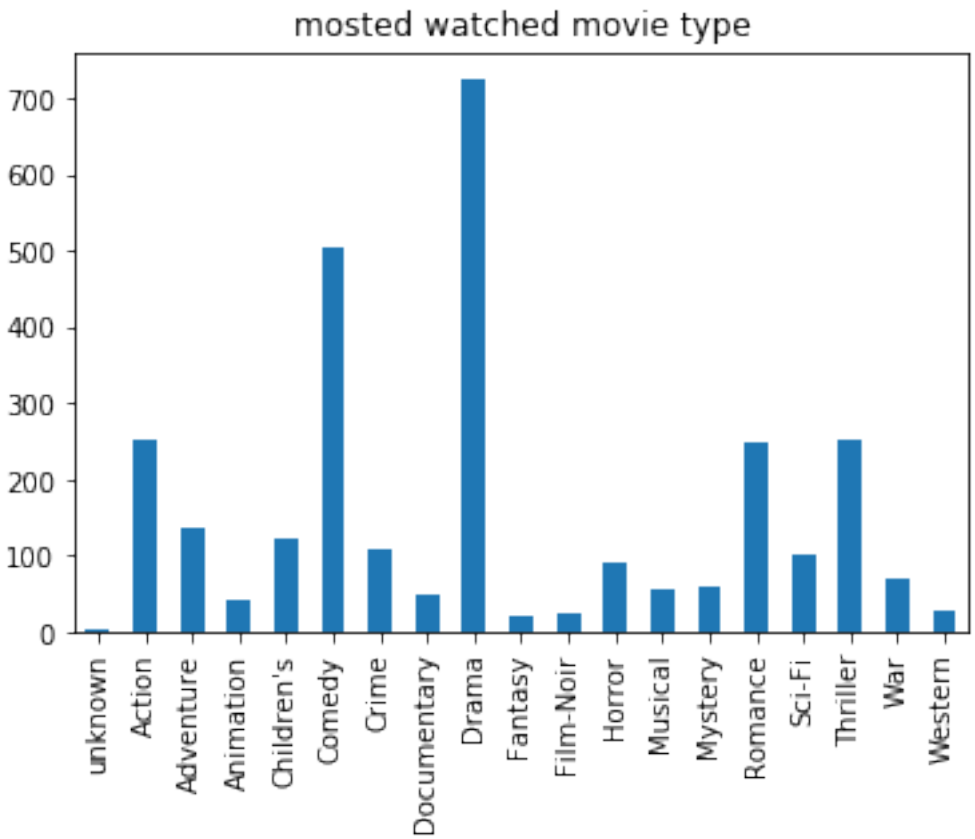
1.1 Finding 1: After analyzing the bar plot we found out that students watch more movies than any other occupants.

In [5]:
```
bplot=userdata["occupation"].value_counts()
bplot=bplot.sort_index()
bplot.plot(kind='bar')
plt.title("frequency of watching movies depending on occupation")
plt.show()
```



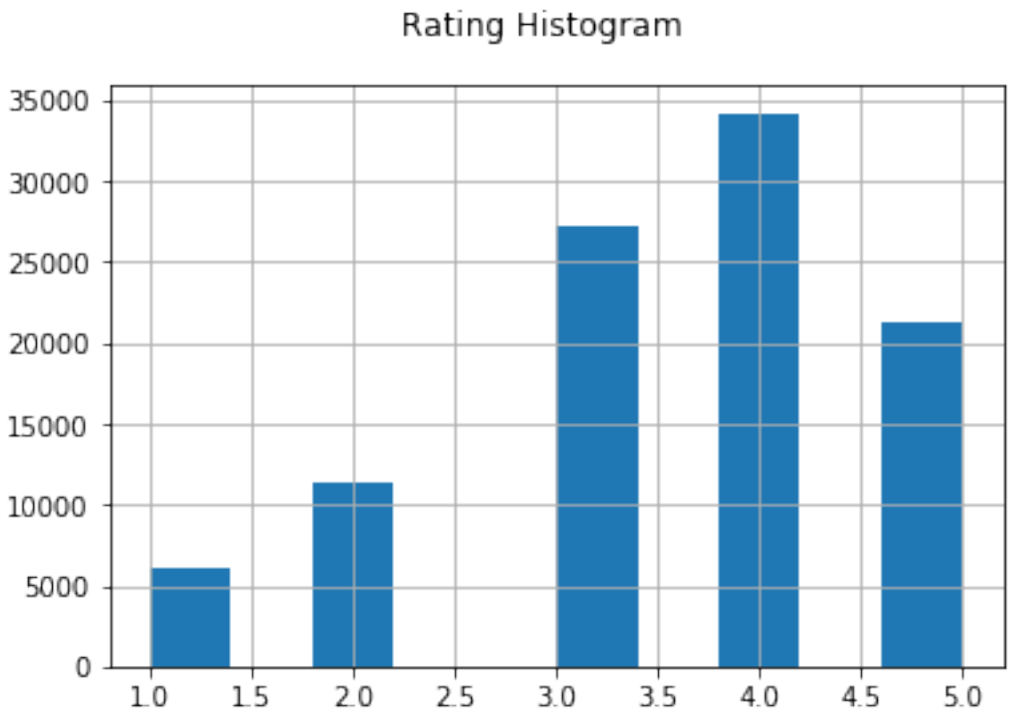
1.2 Finding 2: After analyzing the barplot we can observe that the most watched movie is type drama

```
In [6]: freq_array=pd.Series()
        for column in itemdata.columns[5:]:
            freq_array[column]=sum(itemdata[column].values)
        bplot=freq_array
        bplot.plot(kind='bar')
        plt.title("mosted watched movie type")
        plt.show()
```



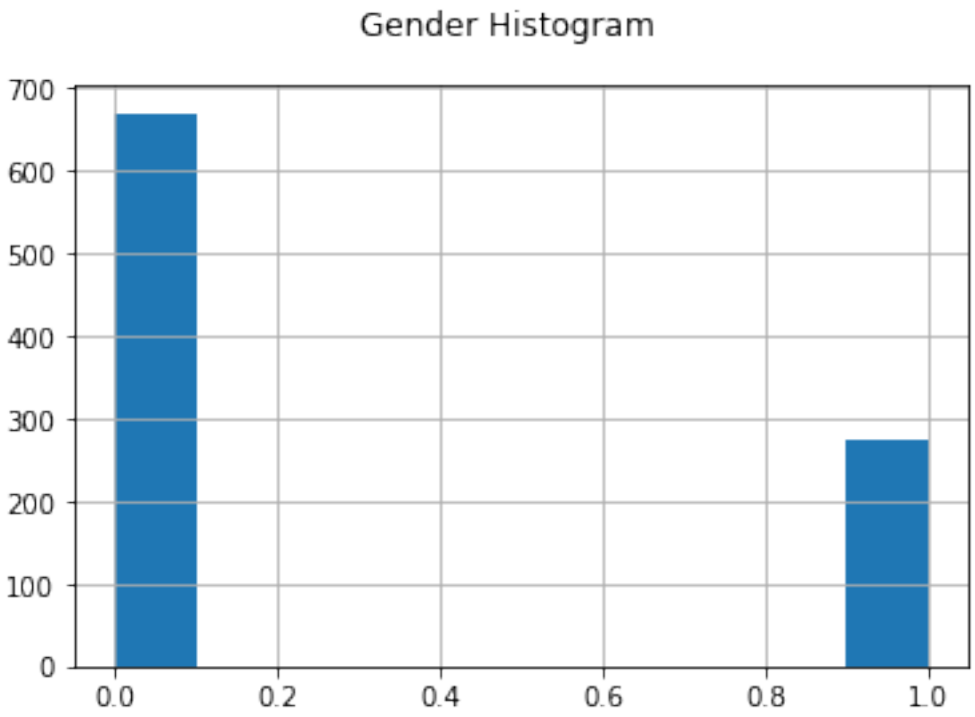
1.3 Finding 3: After Analyzing the histogram we can see that the highest rating is 4 for the movies

```
In [7]: data["rating"].hist()
        plt.suptitle("Rating Histogram")
        plt.show()
```



1.4 Finding 4: After Analyzing the histogram we can see that males watch more movies than females

```
In [8]: userdata["gender"].hist()
        plt.suptitle("Gender Histogram")
        plt.show()
```



2 Exercise 2 : Implement basic matrix factorization (MF) technique for recommender systems

```
In [9]: def Matrixfact(matrix,k,alpha,beta,epoch,sample,testsample):
            n_users,n_items=matrix.shape

            P=pd.DataFrame(np.random.normal(scale=1./k, size=( n_users,k)),columns=[0,1],
                           index=sample['userId'].unique())
            Q=pd.DataFrame(np.random.normal(scale=1./k,size=( n_items,k)),columns=[0,1],
                           index=sample['itemId'].unique())
            user_bais=pd.DataFrame(0,columns=[0],
                           index=sample['userId'].unique())
            item_bais=pd.DataFrame(0,columns=[0],
                           index=sample['itemId'].unique())
            sample=sample.values
            matrix=matrix.values
            bais=np.mean(matrix[np.where(matrix!=0)])

            rmse=[]
            for i in range(epoch):
                np.random.shuffle(sample)
                P,Q,user_bais,item_bais=sgd(sample,P,Q,user_bais,item_bais,bais,alpha,beta)
                error=errorRMSE(matrix,bais,user_bais,item_bais,P,Q,testsample)
```

```
            rmse.append(error)
            if (i+1)%10 == 0:
                print("iteration:",i,"error",error)
        return rmse,P,Q,user_bais,item_bais,bais
```

In [10]:
```
def errorRMSE (matrix,bais,user_bais,item_bais,P,Q,testsample):
    pred=full_matrix(bais,user_bais,item_bais,P,Q)
    yhat,y=predict(matrix,pred,testsample)
    return RMSE(y['rating'],yhat)
```

In [11]:
```
def full_matrix(bais,user_bais,item_bais,P,Q):
    user_item_bais=np.zeros((len(user_bais),len(item_bais)))
    for i in range (0,len(user_bais)):
        for j in range (0,len(item_bais)):
            user_item_bais[i][j]=user_bais.iloc[i][0]+item_bais.iloc[j][0]
    return bais + user_item_bais + P.dot(Q.T)
```

In [12]:
```
def sgd(sample,P,Q,user_bais,item_bais,bais,alpha,beta):
    for i,j,r in sample:
        pred=get_rating(P,Q,i,j,user_bais,item_bais,bais)
        e=(r-pred)

        user_bais.loc[i] += alpha * (e[0]- beta * user_bais.loc[i])
        item_bais.loc[j] += alpha * (e[0]- beta * item_bais.loc[j])

        P.loc[i] += alpha * (e[0] * Q.loc[j]-beta * P.loc[i])
        Q.loc[j] += alpha * (e[0] * P.loc[i]-beta * Q.loc[j])

    return P,Q,user_bais,item_bais
```

In [13]:
```
def get_rating (P,Q,user,item,user_bais,item_bais,bais):
    pred=bais+user_bais.loc[user] + item_bais.loc[item]+P.loc[user].dot(Q.loc[item].T)
    return pred
```

In [14]:
```
def predict(matrix_,matrix,test):
    yhat=[]
    dval=[]
    for i in range (0,len(test)):
        flag=1
        if(test.iloc[i]['userId'] in matrix.index):
            if(test.iloc[i]['itemId'] in matrix.columns):
                flag=0
        if (flag):
            dval.append(i)
        else:
            yhat.append(matrix[test.iloc[i]['itemId']][test.iloc[i]['userId']])
    return yhat,test.drop(test.index[dval])
```

```
In [15]: def RMSE(y,yhat):
             rmse =Math.sqrt(np.sum(pow((y-yhat),2))/len(y))
             return rmse

In [16]: def data_k_divide(data,k):
             k_size=Math.floor(len(data)/k)
             k_data=[]
             c=0
             for i in range (0,k):
                 data_set=pd.DataFrame(data.head(0))
                 for j in range(i*k_size,(i*k_size)+k_size):
                     data_set=data_set.append(data.iloc[j])
                     c=c+1
                 k_data.append(data_set)

             #adding datas which are remaining at the end of k division
             for j in range(c,len(data)):
                 k_data[k-1]=k_data[k-1].append(data.iloc[j])
             return k_data

         def k_data_train_test(x,k):
             k_folded_data=[]
             for i in range(0,k):
                 x_test=x[i]

                 x_train=pd.DataFrame()

                 for j in range(0,k):
                     if i!=j:
                         x_train=x_train.append(x[j])

                 final_data=dict([('x_train',x_train),('x_test',x_test)])
                 k_folded_data.append(final_data)
             return k_folded_data

         def kfold(x_train,k,alpha,lamda):
             rmse=[]
             x_train_k=data_k_divide(x_train,k)
             kdata=k_data_train_test(x_train_k,k)
             for i in range(0,k):
                 rMatrix=kdata[i]['x_train'].pivot(index='userId',columns='itemId',values='rati
                 rMatrix=rMatrix.replace(np.nan,0)
                 rmsearr,P,Q,user_bais,item_bais,bais=Matrixfact(rMatrix,2,alpha,lamda,1,kdata
                                                                 kdata[i]['x_test'][["userId",'
                 rmse.append(sum(rmsearr)/len(rmsearr))
             return sum(rmse)/k

In [17]: def gridsearch(alpha,lamda):
             comb=[]
```

```
            for i in range(0,len(alpha)):
                for k in range(0,len(lamda)):
                    comb.append(dict([('alpha',alpha[i]),('lamda',lamda[k])]))
            return comb
```

In [18]:
```
alpha=[0.1,0.0000001]
lamda=[0.1,0.0001]
grid=gridsearch(alpha,lamda)

for i in range (0,len(grid)):
    rmse=kfold(data,3,grid[i]["alpha"],grid[i]["lamda"])
    print("testrmse:" ,rmse,"for k values of :",grid[i])
```

```
testrmse: 0.9866806359944896 for k values of : {'alpha': 0.1, 'lamda': 0.1}
testrmse: 4.294415493862302e+51 for k values of : {'alpha': 0.1, 'lamda': 0.0001}
testrmse: 1.1810406190458984 for k values of : {'alpha': 1e-07, 'lamda': 0.1}
testrmse: 1.1812300027031035 for k values of : {'alpha': 1e-07, 'lamda': 0.0001}
```

2.0.1 The best RMSE score is 0.986 for K values of : {'alpha': 0.1, 'lamda': 0.1}

In [ ]: