MOVIE RECOMMENDATION SYSTEM USING ML

In [1]:

```
#IMPORTING THE REQUIRED LIBRARIES -
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O
import warnings
warnings.filterwarnings("ignore")

#VISUALISATION
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

#MACHINE LEARNING MODEL
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
```

In [2]:

```
#LOADING THE REQUIRED DATASETS
df_movies= pd.read_csv('movies.csv') #contains data about movies
df_rating=pd.read_csv('ratings.csv') #contains data about ratings

#Since user data doesn't have any column name we are alloting column name.
column_names_users = ['user_id', 'gender', 'age', 'occupation', 'zipcode']
df_user= pd.read_csv('users.csv', delimiter = ';', names= column_names_users,header = 0)
df_user.dropna(inplace=True) #dropping na values
```

In [3]:

```
#dropping unwanted columns from movies dataset
df_movie=df_movies.drop('genres',axis=1)
```

In [4]:

```
#merging movies and ratings dataset on column movie id
movie_rating_df=pd.merge(df_movie,df_rating,on="movieId")
movie_rating_df.head()
```

Out[4]:

	movieId	title	userId	rating	timestamp
0	1	Toy Story (1995)	1	4.0	964982703
1	1	Toy Story (1995)	5	4.0	847434962
2	1	Toy Story (1995)	7	4.5	1106635946
3	1	Toy Story (1995)	15	2.5	1510577970
4	1	Toy Story (1995)	17	4.5	1305696483

In [5]:

```
#creating a table with all needed columns
df = pd.concat([movie_rating_df,df_user], axis=1)
df.head()
```

Out[5]:

	movieId	title	userId	rating	timestamp	user_id	gender	age	occupation	zipcode
0	1	Toy Story (1995)	1	4.0	964982703	1.0	F	1.0	10.0	48067
1	1	Toy Story (1995)	5	4.0	847434962	2.0	M	56.0	16.0	70072
2	1	Toy Story (1995)	7	4.5	1106635946	3.0	M	25.0	15.0	55117
3	1	Toy Story (1995)	15	2.5	1510577970	4.0	M	45.0	7.0	2460
4	1	Toy Story (1995)	17	4.5	1305696483	5.0	M	25.0	20.0	55455

In [6]:

```
df.isna().any() #checking for null values
```

Out[6]:

```
movieId       False
title         False
userId        False
rating        False
timestamp     False
user_id        True
gender         True
age            True
occupation     True
zipcode        True
dtype: bool
```

In [7]:

```
df=df.dropna() #dropping the null values
```

In [8]:

```
#ADDING NEW COLUMN
#to create seperate column for age group data

labels = ['0-9', '10-19', '20-29', '30-39', '40-49', '50-59', '60-69', '70-79']
df['age_group'] = pd.cut(df.age, range(0, 81, 10), right=False, labels=labels)
df[['age', 'age_group']].drop_duplicates()[:10]
```

Out[8]:

	age	age_group
0	1.0	0-9
1	56.0	50-59
2	25.0	20-29
3	45.0	40-49
5	50.0	50-59
6	35.0	30-39
17	18.0	10-19

In [9]:

```
# We need to categorize the imdb values in the range of 1,2,3,4 and 5 to mark them as the bad,average,good and excellent movies r
df["rating"]=pd.cut(df['rating'], bins=[1,2,3,4,5], right=True, labels=False)+1
```

In [10]:

```
#First 500 extracted records
df.dropna(inplace=True)
```

In [11]:

```
df['gender']=df['gender'].replace('M',1)  #CONVERTING CATEGORICAL VALUE TO BINARY VALUE
df['gender']=df['gender'].replace('F',0)
```

EDA

In [12]:

```
df.describe()
```

Out[12]:

	movieId	userId	rating	timestamp	user_id	gender	age	occupation
count	5748.000000	5748.000000	5748.000000	5.748000e+03	5748.000000	5748.000000	5748.000000	5748.000000
mean	92.287752	310.526444	2.692241	1.052242e+09	2997.955115	0.716249	30.740953	8.164057
std	69.166061	185.329731	0.918705	2.200185e+08	1740.336688	0.450857	12.860763	6.332890
min	1.000000	1.000000	1.000000	8.281246e+08	1.000000	0.000000	1.000000	0.000000
25%	31.000000	142.000000	2.000000	8.474352e+08	1494.750000	0.000000	25.000000	3.000000
50%	81.000000	313.000000	3.000000	9.731055e+08	2996.500000	1.000000	25.000000	7.000000
75%	158.000000	469.000000	3.000000	1.189457e+09	4491.250000	1.000000	35.000000	14.000000
max	223.000000	610.000000	4.000000	1.537799e+09	6040.000000	1.000000	56.000000	20.000000

In [13]:

```
df.shape
```

Out[13]:

```
(5748, 11)
```

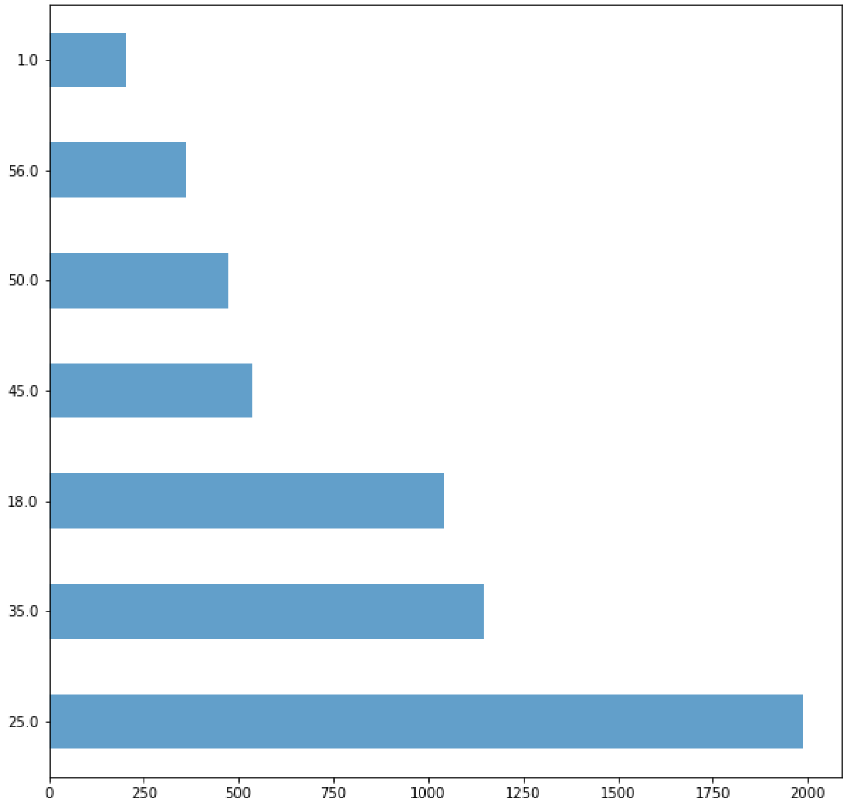
In [14]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5748 entries, 0 to 6039
Data columns (total 11 columns):
 #   Column      Non-Null Count  Dtype   
---  ------      --------------  -----   
 0   movieId     5748 non-null   int64   
 1   title       5748 non-null   object  
 2   userId      5748 non-null   int64   
 3   rating      5748 non-null   float64 
 4   timestamp   5748 non-null   int64   
 5   user_id     5748 non-null   float64 
 6   gender      5748 non-null   int64   
 7   age         5748 non-null   float64 
 8   occupation  5748 non-null   float64 
 9   zipcode     5748 non-null   object  
 10  age_group   5748 non-null   category
dtypes: category(1), float64(4), int64(4), object(2)
memory usage: 499.9+ KB
```

In [15]:

```
#Visualize user age distribution
df['age'].value_counts().plot(kind='barh',alpha=0.7,figsize=(10,10))
plt.show()
```



In [16]:

```
df
```

Out[16]:

	movieId	title	userId	rating	timestamp	user_id	gender	age	occupation	zipcode	age_group
0	1	Toy Story (1995)	1	3.0	964982703	1.0	0	1.0	10.0	48067	0-9
1	1	Toy Story (1995)	5	3.0	847434962	2.0	1	56.0	16.0	70072	50-59
2	1	Toy Story (1995)	7	4.0	1106635946	3.0	1	25.0	15.0	55117	20-29
3	1	Toy Story (1995)	15	2.0	1510577970	4.0	1	45.0	7.0	2460	40-49
4	1	Toy Story (1995)	17	4.0	1305696483	5.0	1	25.0	20.0	55455	20-29
...	...	...	...	...	...	...	...	...	...	...	...
6035	223	Clerks (1994)	591	3.0	970524802	6036.0	0	25.0	15.0	32603	20-29
6036	223	Clerks (1994)	594	3.0	1109037031	6037.0	0	45.0	1.0	76006	40-49
6037	223	Clerks (1994)	597	2.0	941558145	6038.0	0	56.0	1.0	14706	50-59
6038	223	Clerks (1994)	599	3.0	1498500829	6039.0	0	45.0	0.0	1060	40-49
6039	223	Clerks (1994)	600	2.0	1237715120	6040.0	1	25.0	6.0	11106	20-29

5748 rows × 11 columns

SPLITTING THE DATASET FOR MACHINE LEARNING MODEL

#Use the following features:movie id,age,occupation x = df.drop('rating',axis=1) #x=independent x.drop(['title','userId','occupation','zipcode','age_group'],axis=1,inplace=True)

In [72]:

```
#features:gender,age,occupation
x = df.drop('rating',axis=1) #x=independent
x.drop(['user_id','zipcode','age_group','timestamp','movieId','userId','title'],axis=1,inplace=True)
```

In [73]:

```
x
```

Out[73]:

	gender	age	occupation
0	0	1.0	10.0
1	1	56.0	16.0
2	1	25.0	15.0
3	1	45.0	7.0
4	1	25.0	20.0
...	...	...	...
6035	0	25.0	15.0
6036	0	45.0	1.0
6037	0	56.0	1.0
6038	0	45.0	0.0
6039	1	25.0	6.0

5748 rows × 3 columns

In [78]:

```
#Used rating as label
y =df['rating'].values #dependent= rating
df['rating']
```

Out[78]:

```
0       3.0
1       3.0
2       4.0
3       2.0
4       4.0
       ...
6035    3.0
6036    3.0
6037    2.0
6038    3.0
6039    2.0
Name: rating, Length: 5748, dtype: float64
```

In [77]:

```
y
```

Out[77]:

```
array([3., 3., 4., ..., 2., 3., 2.])
```

In [75]:

```
#Create train and test data set
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.25,random_state=42)
```

In [76]:

```
# Decision Tree

decision_tree = DecisionTreeClassifier()
decision_tree.fit(x_train,y_train)
Y_pred = decision_tree.predict(x_test)
Y_pred
```

Out[76]:

```
array([3., 3., 3., ..., 3., 3., 3.])
```

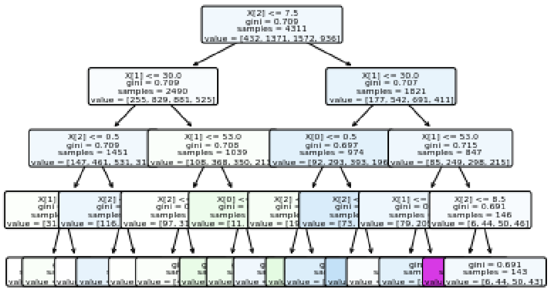
In [61]:

```
import sklearn.datasets as datasets
from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import plot_tree
import matplotlib.pyplot as plt

import sklearn
print(sklearn.__version__)

from sklearn import tree
clf=DecisionTreeClassifier(max_depth=4,random_state=0)
clf.fit(x_train,y_train)
tree.plot_tree(clf,fontsize=6,filled=True,
              rounded=True)
plt.figure(figsize=(10,10))
plt.savefig('mov.png')
from matplotlib import pyplot as plt
```

```
1.0.2
```




```
<Figure size 720x720 with 0 Axes>
```

In [62]:

```
acc_dec= round(decision_tree.score(x_train,y_train) * 100, 2)
acc_dec
```

Out[62]:

```
41.68
```

GAUSSIAN NAIVE BAYES

In [63]:

```
# Gaussian Naive Bayes

gaussian = GaussianNB()
gauss=gaussian.fit(x_train,y_train)
Y_pred = gaussian.predict(x_test)
Y_pred
```

Out[63]:

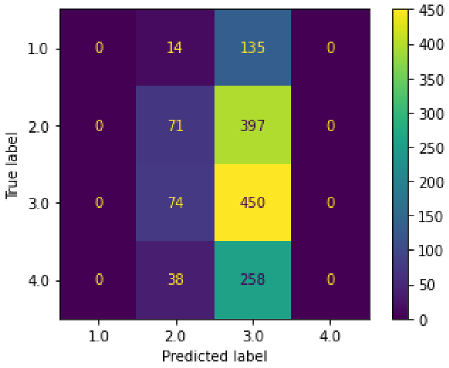
```
array([2., 3., 3., ..., 3., 3., 3.])
```

In [64]:

```
from sklearn.metrics import plot_confusion_matrix
plot_confusion_matrix(gauss,x_test,y_test)
```

Out[64]:

```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x2a4c93fcd30>
```



In [65]:

```
acc_gaussian = round(gaussian.score(x_train,y_train) * 100, 2)
acc_gaussian
```

Out[65]:

```
36.63
```

KNN

In [69]:

```
# K Nearest Neighbors Classifier
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(x_train, y_train)
Y_predic = knn.predict(x_test)
Y_predic
```

Out[69]:

```
array([1., 3., 4., ..., 2., 3., 2.])
```

In [33]:

```
#KNN PLOTTING
```

In [70]:

```
acc_knn = round(knn.score(x_train,y_train) * 100, 2)
acc_knn
```

Out[70]:

```
33.66
```

In [71]:

```
models = pd.DataFrame({
    'Model': [ 'KNN','Random Forest', 'Naive Bayes','Decision Tree'],
    'Score': [ acc_knn, acc_random_forest, acc_gaussian,acc_dec]})
models.sort_values(by='Score', ascending=False)
```

Out[71]:

	Model	Score
1	Random Forest	41.68
3	Decision Tree	41.68
2	Naive Bayes	36.63
0	KNN	33.66

In [79]:

```
df.groupby('title')['rating'].count().sort_values(ascending=False).head()
```

Out[79]:

```
title
Braveheart (1995)              232
Toy Story (1995)               214
Usual Suspects, The (1995)     202
Apollo 13 (1995)               200
Seven (a.k.a. Se7en) (1995)    199
Name: rating, dtype: int64
```

In [39]:

```
ratings = pd.DataFrame(df.groupby('title')['rating'].mean())
ratings.head()
```

Out[39]:

title	rating
Ace Ventura: When Nature Calls (1995)	2.076923
Addiction, The (1995)	1.000000
Amateur (1994)	1.000000
Amazing Panda Adventure, The (1995)	2.333333
American President, The (1995)	2.782609

In [40]:

```
ratings['num of ratings'] = pd.DataFrame(df.groupby('title')['rating'].count())
ratings.head()
```

Out[40]:

title	rating	num of ratings
Ace Ventura: When Nature Calls (1995)	2.076923	78
Addiction, The (1995)	1.000000	1
Amateur (1994)	1.000000	1
Amazing Panda Adventure, The (1995)	2.333333	3
American President, The (1995)	2.782609	69

In [41]:

```
movie_Recommendation = movie_rating_df.pivot_table(index='userId',columns='title',values='rating')
movie_Recommendation
```

Out[41]:

title	'71 (2014)	'Hellboy': The Seeds of Creation (2004)	'Round Midnight (1986)	'Salem's Lot (2004)	'Til There Was You (1997)	'Tis the Season for Love (2015)	'burbs, The (1989)	'night Mother (1986)	(500) Days of Summer (2009)	*batteries not included (1987)	...	Zulu (2013)	[REC] (2007)	[REC]^2 (2009)	[REC]^3 3 Génesis (2012)	anohana The Flowe We Sav That Day - The Movi (2013
userId																
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
2	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	..
606	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
607	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
608	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
609	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
610	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.5	NaN	...	NaN	4.0	3.5	3.0	NaN

610 rows × 9719 columns

In [42]:

```
a=input("Enter the movie name ")
n=int(input("Enter the number of recommendations needed "))
movie_name = movie_Recommendation[a]
movie_name.head()
```

```
Enter the movie name Apollo 13 (1995)
Enter the number of recommendations needed 5
```

Out[42]:

```
userId
1    NaN
2    NaN
3    NaN
4    NaN
5    3.0
Name: Apollo 13 (1995), dtype: float64
```

In [43]:

```
ss = movie_Recommendation.corrwith(movie_name)
```

In [40]:

```
corr_ = pd.DataFrame(ss,columns=['Correlation'])
corr_.dropna(inplace=True)
corr_.head()
```

Out[40]:

	Correlation
title	
'burbs, The (1989)	0.034329
(500) Days of Summer (2009)	0.352152
***batteries not included (1987)**	0.419314
...And Justice for All (1979)	-1.000000
10 Cloverfield Lane (2016)	0.188982

In [41]:

```
corr_.sort_values('Correlation',ascending=False).head(n)
```

Out[41]:

title	Correlation
Rare Exports: A Christmas Tale (Rare Exports) (2010)	1.0
Angel-A (2005)	1.0
Poison Ivy (1992)	1.0
Dr. Jekyll and Mr. Hyde (1931)	1.0
Police Academy 6: City Under Siege (1989)	1.0

In [42]:

```
corr_ = corr_.join(ratings['num of ratings'])
corr_.head()
```

Out[42]:

title	Correlation	num of ratings
'burbs, The (1989)	0.034329	NaN
(500) Days of Summer (2009)	0.352152	NaN
*batteries not included (1987)	0.419314	NaN
...And Justice for All (1979)	-1.000000	NaN
10 Cloverfield Lane (2016)	0.188982	NaN

In [45]:

```
rec=corr_[corr_['num of ratings']>100].sort_values('Correlation',ascending=False).head()
```

In [47]:

```
rec['num of ratings']
```

Out[47]:

```
title
Apollo 13 (1995)          200.0
Net, The (1995)           102.0
Batman Forever (1995)     128.0
Crimson Tide (1995)       101.0
Babe (1995)               124.0
Name: num of ratings, dtype: float64
```