Importing all the necessary libraries for our analysis

In [1]:
```
import pandas as pd #Data Wrangling
import matplotlib.pyplot as plt #Visualisation
import numpy as np #Numpy
import seaborn as sns #Visualisaton
import pandas_profiling #Descriptive Analytics
%matplotlib inline

#Importing models for prediction and machine learning

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.preprocessing import OneHotEncoder
```

In [2]:
```
import warnings #To ignore the unnecessary warning notes.
warnings.filterwarnings('ignore')
```

Reading the datasets and their descriptive analysis

In [3]:
```
Movies = pd.read_csv('movies.dat', sep='::', names = ['MovieID', 'Title', 'Genres'])
```

In [4]:
```
Movies.head()
```

Out[4]:

	MovieID	Title	Genres
0	1	Toy Story (1995)	Animation|Children's|Comedy
1	2	Jumanji (1995)	Adventure|Children's|Fantasy
2	3	Grumpier Old Men (1995)	Comedy|Romance
3	4	Waiting to Exhale (1995)	Comedy|Drama
4	5	Father of the Bride Part II (1995)	Comedy

In [5]:
```
Movies.shape
```

Out[5]:
```
(3883, 3)
```

In [6]:
```
Movies.describe()
```

Out[6]:

	MovieID
count	3883.000000
mean	1986.049446
std	1146.778349
min	1.000000
25%	982.500000
50%	2010.000000
75%	2980.500000
max	3952.000000

In [7]:
```
Ratings = pd.read_csv('ratings.dat', sep='::', names = ['UserID', 'MovieID', 'Rating', 'Timestamp'])
```

In [8]:
```
Ratings.head()
```

Out[8]:

	UserID	MovieID	Rating	Timestamp
0	1	1193	5	978300760
1	1	661	3	978302109
2	1	914	3	978301968
3	1	3408	4	978300275
4	1	2355	5	978824291

In [9]:
```
Ratings.shape
```

Out[9]: (1000209, 4)

In [10]:
```
Ratings.describe()
```

Out[10]:

	UserID	MovieID	Rating	Timestamp
count	1.000209e+06	1.000209e+06	1.000209e+06	1.000209e+06
mean	3.024512e+03	1.865540e+03	3.581564e+00	9.722437e+08
std	1.728413e+03	1.096041e+03	1.117102e+00	1.215256e+07
min	1.000000e+00	1.000000e+00	1.000000e+00	9.567039e+08
25%	1.506000e+03	1.030000e+03	3.000000e+00	9.653026e+08
50%	3.070000e+03	1.835000e+03	4.000000e+00	9.730180e+08
75%	4.476000e+03	2.770000e+03	4.000000e+00	9.752209e+08
max	6.040000e+03	3.952000e+03	5.000000e+00	1.046455e+09

In [11]:
```
Users = pd.read_csv('users.dat', sep='::', names = ['UserID', 'Gender', 'Age', 'Occupation', 'Zip-code'])
Users.head()
```

Out[11]:

	UserID	Gender	Age	Occupation	Zip-code
0	1	F	1	10	48067
1	2	M	56	16	70072
2	3	M	25	15	55117
3	4	M	45	7	02460
4	5	M	25	20	55455

In [12]:
```
Users.shape
```

Out[12]: (6040, 5)

In [13]:
```
Users.describe()
```

Out[13]:

	UserID	Age	Occupation
count	6040.000000	6040.000000	6040.000000
mean	3020.500000	30.639238	8.146854
std	1743.742145	12.895962	6.329511
min	1.000000	1.000000	0.000000
25%	1510.750000	25.000000	3.000000
50%	3020.500000	25.000000	7.000000
75%	4530.250000	35.000000	14.000000
max	6040.000000	56.000000	20.000000

Creating Master_Data as per the first requirement of the analysis

In [14]:
```
RatingsUsers = Ratings.merge(Users, on = 'UserID')
RatingsUsers.head()
```

Out[14]:

	UserID	MovieID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
0	1	1193	5	978300760	F	1	10	48067
1	1	661	3	978302109	F	1	10	48067
2	1	914	3	978301968	F	1	10	48067
3	1	3408	4	978300275	F	1	10	48067
4	1	2355	5	978824291	F	1	10	48067

In [15]:
```
RatingsUsersMovies = RatingsUsers.merge(Movies, on = 'MovieID')
RatingsUsersMovies.head()
```

Out[15]:

	UserID	MovieID	Rating	Timestamp	Gender	Age	Occupation	Zip-code	Title	Genres
0	1	1193	5	978300760	F	1	10	48067	One Flew Over the Cuckoo's Nest (1975)	Drama
1	2	1193	5	978298413	M	56	16	70072	One Flew Over the Cuckoo's Nest (1975)	Drama
2	12	1193	4	978220179	M	25	12	32793	One Flew Over the Cuckoo's Nest (1975)	Drama
3	15	1193	4	978199279	M	25	7	22903	One Flew Over the Cuckoo's Nest (1975)	Drama
4	17	1193	5	978158471	M	50	1	95350	One Flew Over the Cuckoo's Nest (1975)	Drama

In [16]:
```
RatingsUsersMovies.to_csv('Master_Data.csv', index = False)
```

In [17]:
```
RatingsUsersMovies.drop(['Timestamp', 'Zip-code'], axis=1, inplace=True)
```

In [18]:
```
RatingsUsersMovies.columns
```

Out[18]:
```
Index(['UserID', 'MovieID', 'Rating', 'Gender', 'Age', 'Occupation', 'Title',
       'Genres'],
      dtype='object')
```

In [19]:
```
Master_Data = RatingsUsersMovies
Master_Data.head()
```

Out[19]:

	UserID	MovieID	Rating	Gender	Age	Occupation	Title	Genres
0	1	1193	5	F	1	10	One Flew Over the Cuckoo's Nest (1975)	Drama
1	2	1193	5	M	56	16	One Flew Over the Cuckoo's Nest (1975)	Drama
2	12	1193	4	M	25	12	One Flew Over the Cuckoo's Nest (1975)	Drama
3	15	1193	4	M	25	7	One Flew Over the Cuckoo's Nest (1975)	Drama
4	17	1193	5	M	50	1	One Flew Over the Cuckoo's Nest (1975)	Drama

In [20]:
```
Master_Data.isnull().sum()
```

Out[20]:
```
UserID        0
MovieID       0
Rating        0
Gender        0
Age           0
Occupation    0
Title         0
Genres        0
dtype: int64
```

In [21]:
```
Master_Data.shape, Ratings.shape, Users.shape, Movies.shape
```

Out[21]:
```
((1000209, 8), (1000209, 4), (6040, 5), (3883, 3))
```

Descriptive analysis of Master_Data using PandasProfiling

In [22]:
```
pandas_profiling.ProfileReport(Master_Data)
```

Out[22]:

Overview

Dataset info

Number of variables	8
Number of observations	1000209
Total Missing (%)	0.0%
Total size in memory	68.7 MiB
Average record size in memory	72.0 B

Variables types

Numeric	5
Categorical	3
Boolean	0
Date	0
Text (Unique)	0

In [23]:
```
pfr = pandas_profiling.ProfileReport(Master_Data)
pfr.to_file('Descriptive_Analysis_Master_Data.html')
```

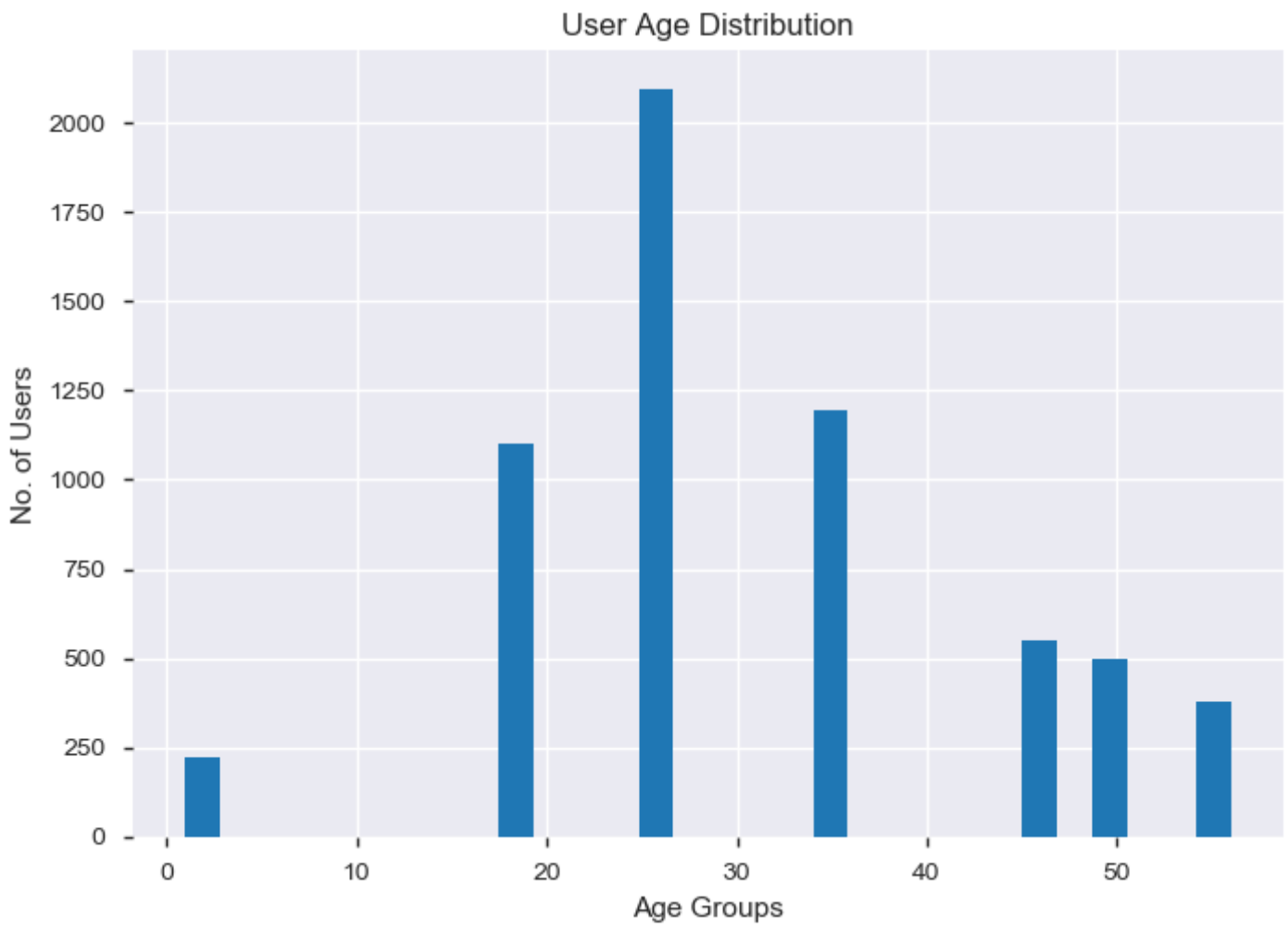
Exploratory Data Analysis

Exploring the datasets using visual representations (graphs or tables) and their findings

In [24]:
```
#User age distribution

Users['Age'].hist(bins=30)
plt.xlabel('Age Groups')
plt.ylabel('No. of Users')
plt.title('User Age Distribution')
plt.show
```

Out[24]: <function matplotlib.pyplot.show(*args, **kw)>



Findings 1: Above graph shows that the highest number of users belongs to 25 yrs. old group interval

In [25]:
```
#User rating of the movie “Toy Story”

Toy_Story_1995 = Master_Data[Master_Data.MovieID==1]
Toy_Story_1995.head(10)
```

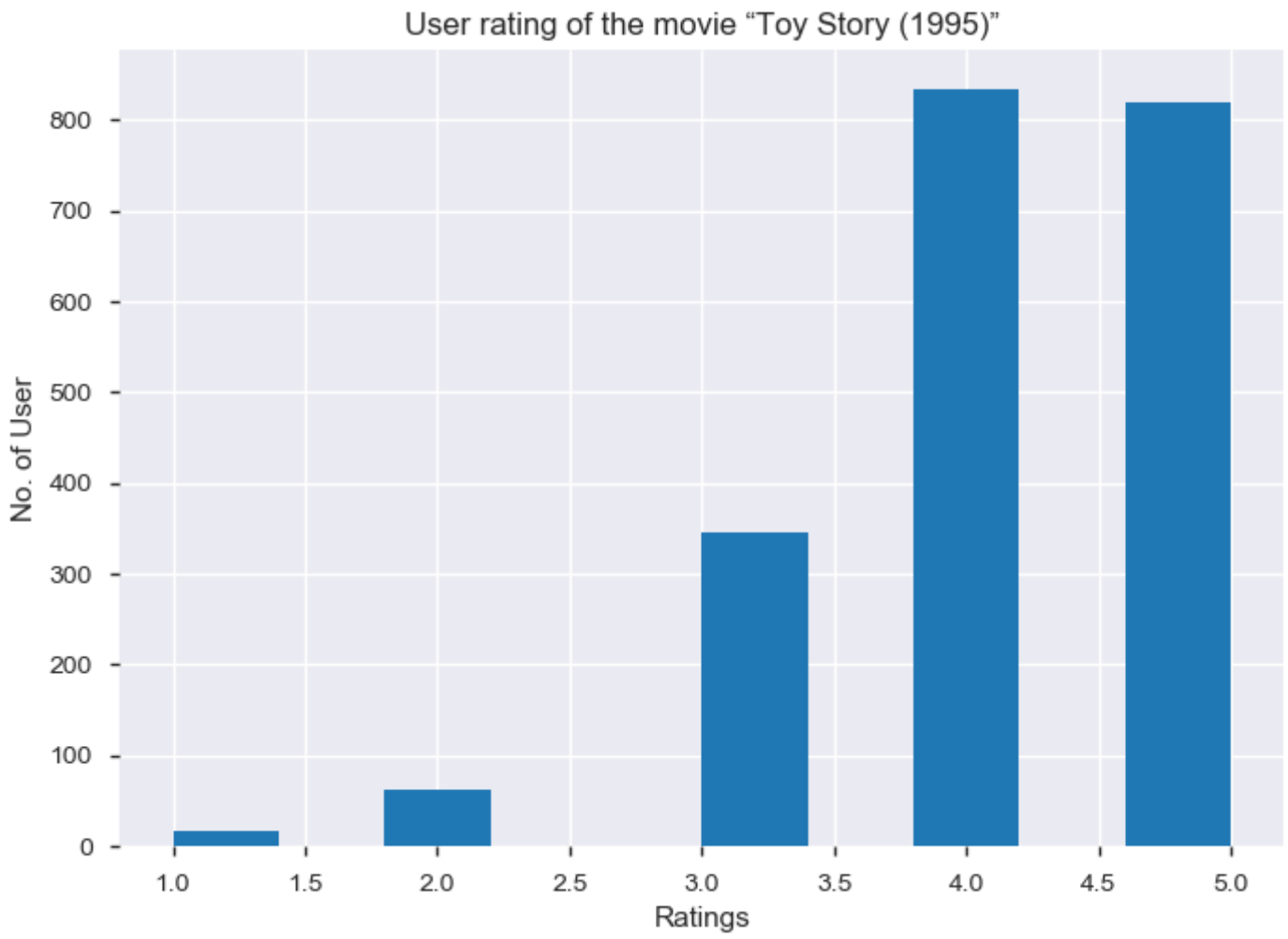
Out[25]:

	UserID	MovieID	Rating	Gender	Age	Occupation	Title	Genres
41626	1	1	5	F	1	10	Toy Story (1995)	Animation|Children's|Comedy
41627	6	1	4	F	50	9	Toy Story (1995)	Animation|Children's|Comedy
41628	8	1	4	M	25	12	Toy Story (1995)	Animation|Children's|Comedy
41629	9	1	5	M	25	17	Toy Story (1995)	Animation|Children's|Comedy
41630	10	1	5	F	35	1	Toy Story (1995)	Animation|Children's|Comedy
41631	18	1	4	F	18	3	Toy Story (1995)	Animation|Children's|Comedy
41632	19	1	5	M	1	10	Toy Story (1995)	Animation|Children's|Comedy
41633	21	1	3	M	18	16	Toy Story (1995)	Animation|Children's|Comedy
41634	23	1	4	M	35	0	Toy Story (1995)	Animation|Children's|Comedy
41635	26	1	3	M	25	7	Toy Story (1995)	Animation|Children's|Comedy

In [26]:
```
Toy_Story_1995.groupby('Rating').size()
```

Out[26]:
```
Rating
1     16
2     61
3    345
4    835
5    820
dtype: int64
```

In [27]:
```
plt.hist(x = Toy_Story_1995['Rating'])
plt.xlabel("Ratings")
plt.ylabel("No. of User")
plt.title("User rating of the movie “Toy Story (1995)”")
plt.show()
```



Findings 2: From above histogram, we found that "Toy Story (1995)" had been rated mostly with 4 out of 5 stars.

In [28]:
```
#Top 25 movies by viewership rating

Avg_Ratings = Master_Data.groupby(['Title'], as_index=False)
Avg_Movie_Ratings = Avg_Ratings.agg({'Rating':'mean'})
Top_25_Movies = Avg_Movie_Ratings.sort_values('Rating', ascending=False)
Top_25_Movies.head(26)
```

Out[28]:

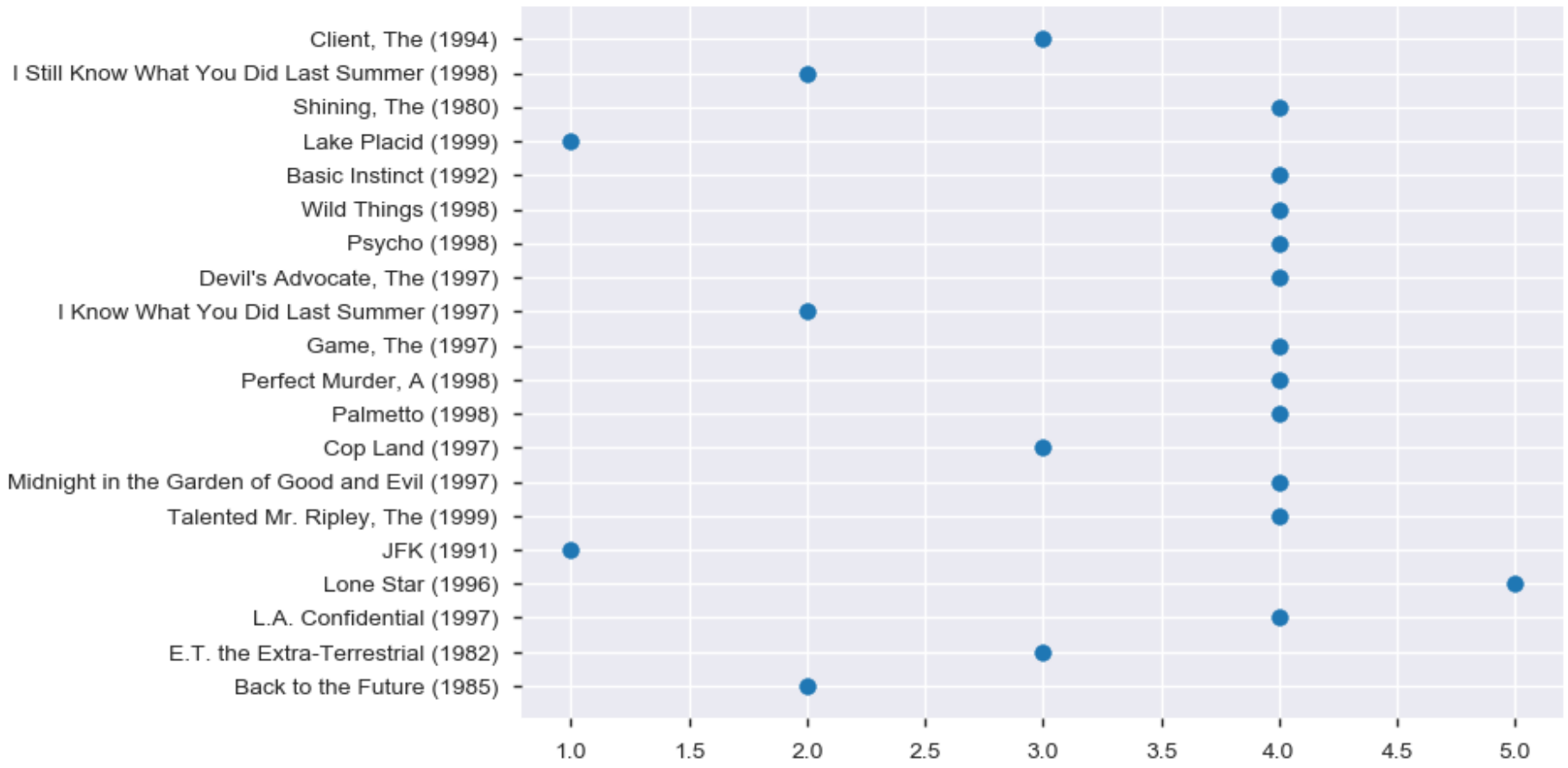
	Title	Rating
3477	Ulysses (Ulisse) (1954)	5.000000
2025	Lured (1947)	5.000000
1203	Follow the Bitch (1998)	5.000000
407	Bittersweet Motel (2000)	5.000000
3087	Song of Freedom (1936)	5.000000
2453	One Little Indian (1973)	5.000000
3044	Smashing Time (1967)	5.000000
2903	Schlafes Bruder (Brother of Sleep) (1995)	5.000000
1297	Gate of Heavenly Peace, The (1995)	5.000000
249	Baby, The (1973)	5.000000
1622	I Am Cuba (Soy Cuba/Ya Kuba) (1964)	4.800000
1870	Lamerica (1994)	4.750000
199	Apple, The (Sib) (1998)	4.666667
2883	Sanjuro (1962)	4.608696
2940	Seven Samurai (The Magnificent Seven) (Shichin...	4.560510
2970	Shawshank Redemption, The (1994)	4.554558
1354	Godfather, The (1972)	4.524966
713	Close Shave, A (1995)	4.520548
3504	Usual Suspects, The (1995)	4.517106
2901	Schindler's List (1993)	4.510417
3675	Wrong Trousers, The (1993)	4.507937
996	Dry Cleaning (Nettoyage à sec) (1997)	4.500000
1690	Inheritors, The (Die Siebtelbauern) (1998)	4.500000
2056	Mamma Roma (1962)	4.500000
342	Bells, The (1926)	4.500000
842	Dangerous Game (1993)	4.500000

Findings 3: From above list, we find that all the top 25 movies had recieved minimum average rating of 4.5 stars. In fact Top 10 movies were having exact 5 out of 5 ratings.

In [29]:
```
#Ratings for all the movies reviewed by for a particular user of user id = 2696

UserID_2696 = Master_Data[Master_Data['UserID']==2696]
UserID_2696
plt.scatter(y=UserID_2696.Title, x=UserID_2696.Rating)
```

Out[29]: <matplotlib.collections.PathCollection at 0x21113c22780>



Findings 4: UserID = 2696, has data for 20 movies which s/he has seen all before year 2000 and he has rated most of the movies with 4 stars as depicted from the above scatter plot.

Feature Engineering

In [30]:
```
Master_Data.dropna(inplace = True)
```

In [31]:
```
#All the unique genres

Master_Data["Genres"]= Master_Data["Genres"].str.split("|", n = -1, expand = True)
Master_Data.head()
```

Out[31]:

	UserID	MovieID	Rating	Gender	Age	Occupation	Title	Genres
0	1	1193	5	F	1	10	One Flew Over the Cuckoo's Nest (1975)	Drama
1	2	1193	5	M	56	16	One Flew Over the Cuckoo's Nest (1975)	Drama
2	12	1193	4	M	25	12	One Flew Over the Cuckoo's Nest (1975)	Drama
3	15	1193	4	M	25	7	One Flew Over the Cuckoo's Nest (1975)	Drama
4	17	1193	5	M	50	1	One Flew Over the Cuckoo's Nest (1975)	Drama

In [32]:
```
Master_Data.Genres.unique()
```

Out[32]:
```
array(['Drama', 'Animation', 'Musical', 'Action', 'Comedy', 'Adventure',
       'Romance', "Children's", 'Thriller', 'Crime', 'Western',
       'Documentary', 'Mystery', 'Horror', 'Sci-Fi', 'Film-Noir', 'War',
       'Fantasy'], dtype=object)
```

One-hot encoding for Genres

In [33]:
```
#One-hot encoding for genres

pd.get_dummies(Master_Data['Genres']).head()
```

Out[33]:

	Action	Adventure	Animation	Children's	Comedy	Crime	Documentary	Drama	Fantasy	Film-Noir	Horror	Musical	Mystery	Romance	Sci-Fi	Thril
0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	

In [34]:
```
SampleMasterData = Master_Data.head(200000)
SampleMasterData.shape
```

Out[34]: (200000, 8)

In [35]:
```
from sklearn.preprocessing import LabelEncoder
LE = LabelEncoder()

LE.fit(SampleMasterData['Age'])
x_Age = LE.transform(SampleMasterData['Age'])
x_Age
```

Out[35]: array([0, 6, 2, ..., 2, 2, 3], dtype=int64)

In [36]:
```
LE.fit(SampleMasterData['Occupation'])
x_Occ = LE.transform(SampleMasterData['Occupation'])
x_Occ
```

Out[36]: array([10, 16, 12, ..., 7, 4, 9], dtype=int64)

In [37]:
```
LE.fit(SampleMasterData['MovieID'])
x_MovieID = LE.transform(SampleMasterData['MovieID'])
x_MovieID
```

Out[37]: array([63, 63, 63, ..., 80, 80, 80], dtype=int64)

In [38]:
```
SampleMasterData['New_Age'] = x_Age
SampleMasterData['New_Occupation'] = x_Occ
SampleMasterData['New_MovieID'] = x_MovieID
```

In [39]:
```
# Feature Selection
x = SampleMasterData[['Age','Occupation','MovieID']]
y = SampleMasterData['Rating']
x.head()
```

Out[39]:

	Age	Occupation	MovieID
0	1	10	1193
1	56	16	1193
2	25	12	1193
3	25	7	1193
4	50	1	1193

In [40]:
```
# Split-out validation dataset

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state=40)
```

In [41]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[41]: ((160000, 3), (40000, 3), (160000,), (40000,))

In [42]:
```
# performing preprocessing part
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

In [43]:
```
# Applying PCA function on training
# and testing set of X component
from sklearn.decomposition import PCA

pca = PCA(n_components = 2)

x_train = pca.fit_transform(x_train)
x_test = pca.transform(x_test)

explained_variance = pca.explained_variance_ratio_
```

In [44]:
```
pca.explained_variance_ratio_
```

Out[44]:
```
array([0.36236092, 0.33290935])
```

Developing an appropriate model to predict the movie ratings

In [45]:
```
from sklearn.linear_model import LogisticRegression
logitReg = LogisticRegression()
lm = logitReg.fit(x_train, y_train)
```

In [46]:
```
Result = logitReg.predict(x_test)
```

In [47]:
```
Estimated = pd.Series(Result, name='Estimated Values')
```

In [48]:
```
Final_Result = pd.concat([y_test, Estimated], axis=1)
```

In [49]:
```
# Test options and evaluation metric
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

print (accuracy_score(y_test, Result))
print (confusion_matrix(y_test, Result))
print (classification_report(y_test, Result))
```

```
0.3729
[[    0     0     0   963    37]
 [    0     0     0  2476   107]
 [    0     0     0  8165   285]
 [    0     0     0 14534   460]
 [    0     0     0 12591   382]]
              precision    recall  f1-score   support

           1       0.00      0.00      0.00      1000
           2       0.00      0.00      0.00      2583
           3       0.00      0.00      0.00      8450
           4       0.38      0.97      0.54     14994
           5       0.30      0.03      0.05     12973

    accuracy                           0.37     40000
   macro avg       0.14      0.20      0.12     40000
weighted avg       0.24      0.37      0.22     40000
```

From above matrix we can see we have achieved 37% accuracy.

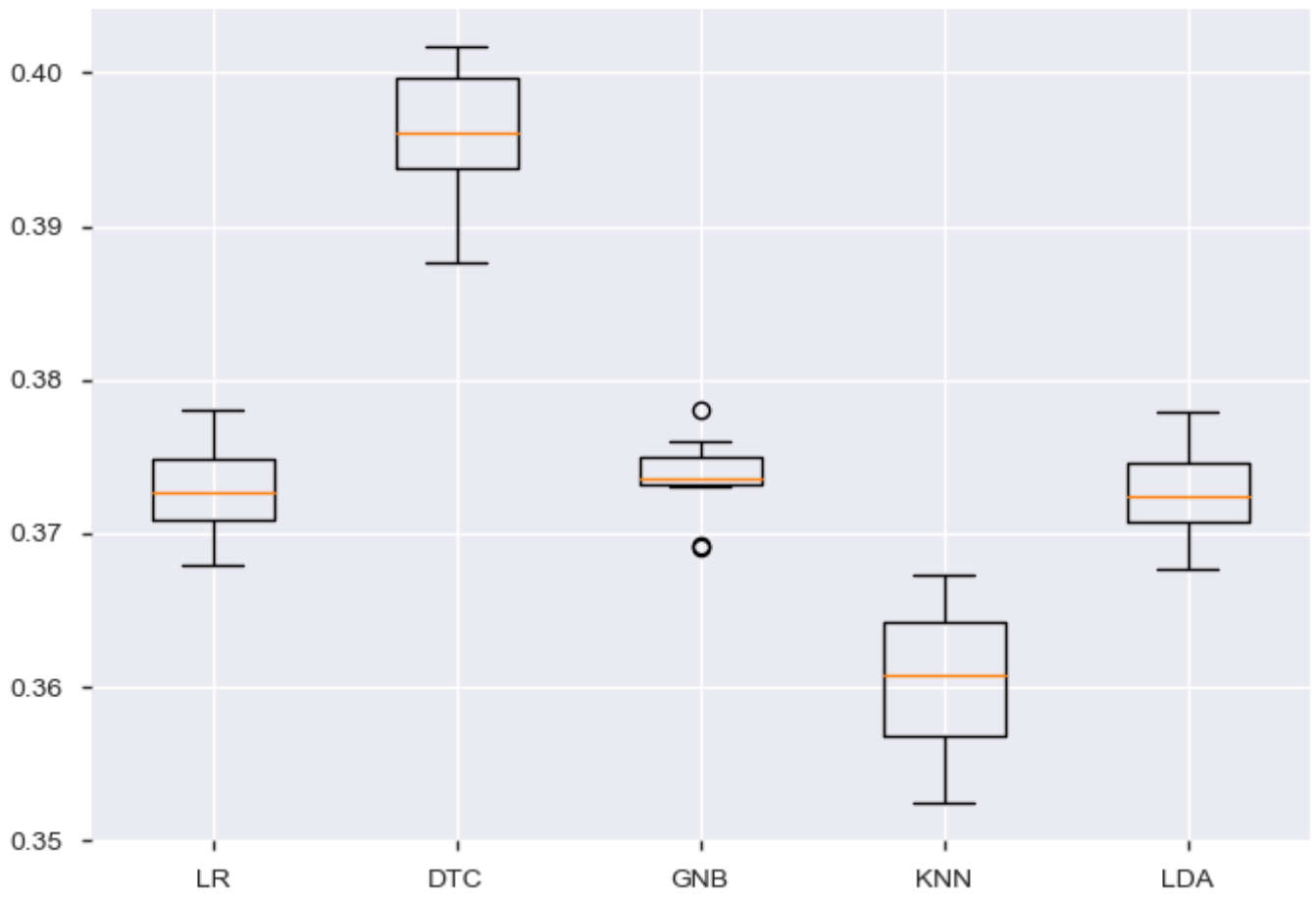
In [50]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
```

In [51]:
```
# Spot-Check Algorithms
seed = 6
models = []
models.append(('LR', LogisticRegression()))
models.append(('DTC', DecisionTreeClassifier()))
models.append(('GNB', GaussianNB()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('LDA', LinearDiscriminantAnalysis()))
```

In [52]:
```
# evaluate each model in turn
results = []
names = []
for name, model in models:
    kfold = KFold(n_splits=10, random_state=seed)
    cv_results = cross_val_score(model, x_train, y_train, cv=kfold, scoring='accuracy')
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.372694 (0.003088)
DTC: 0.396213 (0.003989)
GNB: 0.373562 (0.002602)
KNN: 0.360300 (0.004842)
LDA: 0.372519 (0.003015)
```

In [53]:
```
# Compare Algorithms
fig = plt.figure()
fig.suptitle('Comparison b/w all models')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



From above chart, we see Decision Tree Classifier gives more accurate results among others followed by Gaussian Naive Bayes.

In [ ]: