MOVIE LENS PROJECT ANALYSIS

1. Prepare Problem

In [1]:
```
# a) Load libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

In [2]:
```
# b) Load dataset
movie_data = pd.read_csv("C:\\Umaima\\Data Science\\Python\\Projects\\Projects
for Submission\\Project4_Movielens\\movies.dat",
                       sep="::", header=None, names=['MovieID','Title','Genre
s'],
                       dtype={'MovieID': np.int32, 'Title': np.str, 'Genres':
np.str}, engine='python')
users_data = pd.read_csv("C:\\Umaima\\Data Science\\Python\\Projects\\Projects
for Submission\\Project4_Movielens\\users.dat",
                       sep="::", header=None, names=['UserID','Gender','Age',
'Occupation','Zip-code'],
    dtype={'UserID': np.int32, 'Gender': np.str, 'Age': np.int32, 'Occupation'
: np.int32, 'Zip-code' : np.str}, engine='python')
ratings_data = pd.read_csv("C:\\Umaima\\Data Science\\Python\\Projects\\Projec
ts for Submission\\Project4_Movielens\\ratings.dat",
                       sep="::", header=None, names=['UserID','MovieID','Ratin
g','Timestamp'],
                dtype={'UserID': np.int32, 'MovieID': np.int32, 'Rating': np.i
nt32, 'Timestamp' : np.str}, engine='python')
```

2. Summarize Data

In [3]:
```
# a) Descriptive statistics
# On movie_data
movie_data.head()
```

Out[3]:

	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 [4]:
```
movie_data.shape
```

Out[4]:
```
(3883, 3)
```

In [5]:
```
movie_data.isnull().sum()
# Results show that no columns are empty or null
```

Out[5]:
```
MovieID     0
Title       0
Genres      0
dtype: int64
```

In [6]:
```
movie_data.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]:
```
movie_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3883 entries, 0 to 3882
Data columns (total 3 columns):
MovieID     3883 non-null int32
Title       3883 non-null object
Genres      3883 non-null object
dtypes: int32(1), object(2)
memory usage: 75.9+ KB
```

In [8]:
```
# On users data
users_data.shape
```

Out[8]:
```
(6040, 5)
```

In [9]:
```
users_data.head()
```

Out[9]:

	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 [10]:
```
users_data.describe()
```

Out[10]:

	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

In [11]:
```
users_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6040 entries, 0 to 6039
Data columns (total 5 columns):
UserID        6040 non-null int32
Gender        6040 non-null object
Age           6040 non-null int32
Occupation    6040 non-null int32
Zip-code      6040 non-null object
dtypes: int32(3), object(2)
memory usage: 165.2+ KB
```

In [12]:
```
users_data.isnull().sum()
# Results show that no columns are empty or null
```

Out[12]:
```
UserID        0
Gender        0
Age           0
Occupation    0
Zip-code      0
dtype: int64
```

In [13]:
```
# On Ratings data
ratings_data.head()
```

Out[13]:

	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 [14]:
```
ratings_data.shape
```

Out[14]:
```
(1000209, 4)
```

In [15]:
```
ratings_data.describe()
```

Out[15]:

	UserID	MovieID	Rating
count	1.000209e+06	1.000209e+06	1.000209e+06
mean	3.024512e+03	1.865540e+03	3.581564e+00
std	1.728413e+03	1.096041e+03	1.117102e+00
min	1.000000e+00	1.000000e+00	1.000000e+00
25%	1.506000e+03	1.030000e+03	3.000000e+00
50%	3.070000e+03	1.835000e+03	4.000000e+00
75%	4.476000e+03	2.770000e+03	4.000000e+00
max	6.040000e+03	3.952000e+03	5.000000e+00

In [16]:
```
ratings_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000209 entries, 0 to 1000208
Data columns (total 4 columns):
UserID       1000209 non-null int32
MovieID      1000209 non-null int32
Rating       1000209 non-null int32
Timestamp    1000209 non-null object
dtypes: int32(3), object(1)
memory usage: 19.1+ MB
```

In [17]:
```
ratings_data.isnull().sum()
# Results show that no columns are empty or null
```

Out[17]:
```
UserID       0
MovieID      0
Rating       0
Timestamp    0
dtype: int64
```

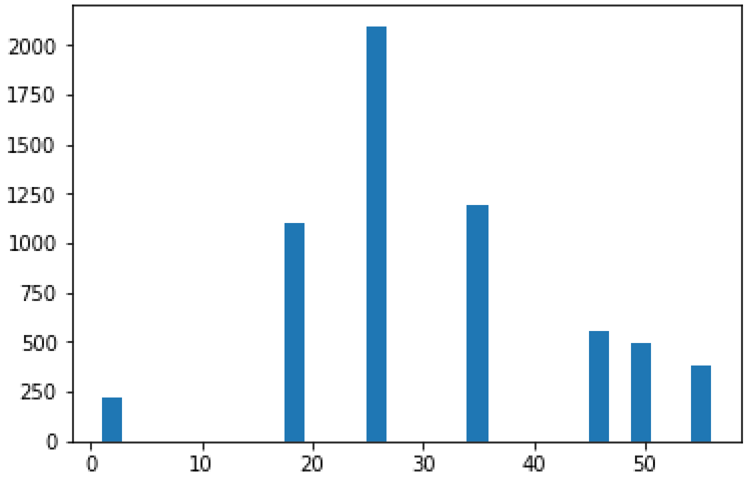
3. Data Visualizations

User Age Distribution

In [18]:
```
age_group = users_data.groupby('Age').size()
age_group
```

Out[18]:
```
Age
1      222
18    1103
25    2096
35    1193
45     550
50     496
56     380
dtype: int64
```

In [19]:
```
plt.hist(data=age_group,x=users_data.Age, bins=30)
plt.show()
```



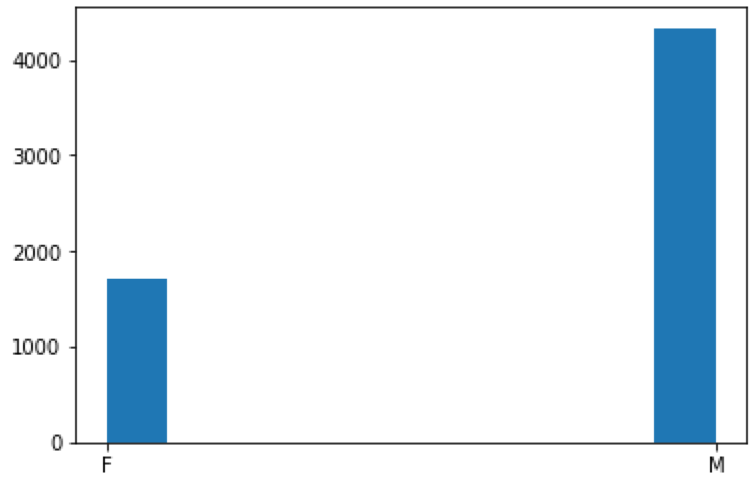
The above age distribution shows that most of the users are 25 years old

GenderDistribution

In [20]:
```
gender_group = users_data.groupby('Gender').size()
gender_group
```

Out[20]:
```
Gender
F    1709
M    4331
dtype: int64
```

In [21]:
```
plt.hist(data=gender_group,x=users_data.Gender)
plt.show()
```



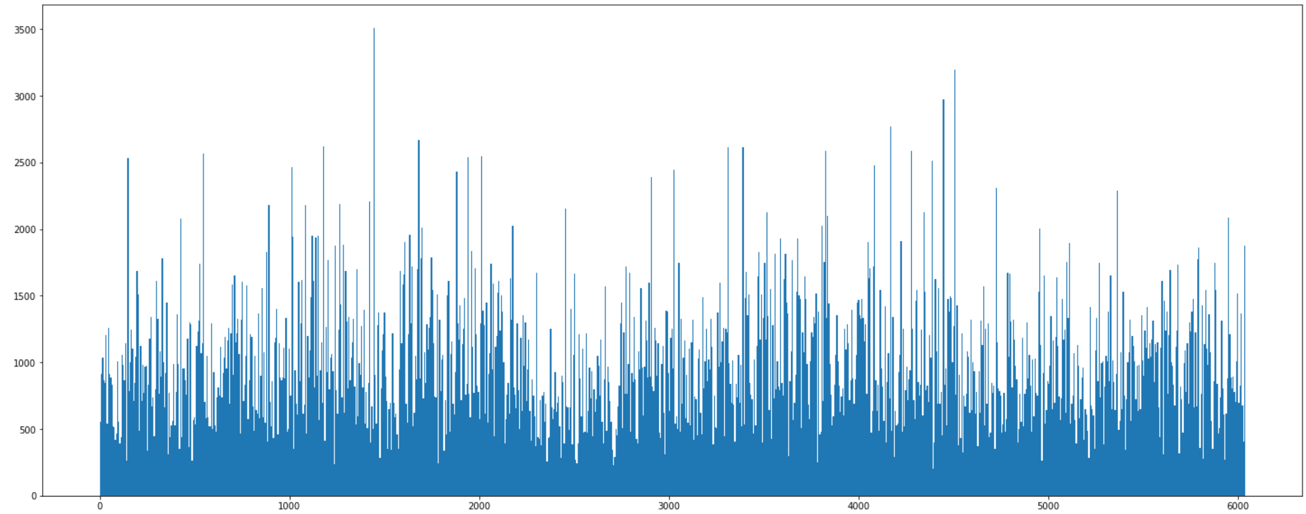
The above distribution shows that most of the users are Males

User Ratings

In [22]:
```
user_group = ratings_data.groupby(['UserID']).size()
user_group.head(10)
```

Out[22]:
```
UserID
1      53
2     129
3      51
4      21
5     198
6      71
7      31
8     139
9     106
10    401
dtype: int64
```

In [23]:
```
plt.figure(figsize=(25,10))
plt.hist(x=[ratings_data.UserID], bins=1000)
plt.show()
```



Toystory data

In [24]:
```
toystory_data = ratings_data[ratings_data.MovieID==1]
toystory_data.head(10)
```

Out[24]:

	UserID	MovieID	Rating	Timestamp
40	1	1	5	978824268
469	6	1	4	978237008
581	8	1	4	978233496
711	9	1	5	978225952
837	10	1	5	978226474
1966	18	1	4	978154768
2276	19	1	5	978555994
2530	21	1	3	978139347
2870	23	1	4	978463614
3405	26	1	3	978130703

In [25]:
```
toystory_data.groupby('Rating').size()
```

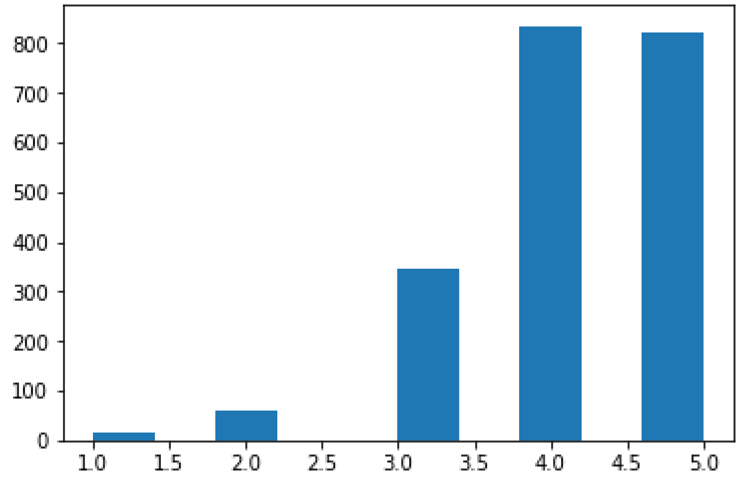
Out[25]:
```
Rating
1     16
2     61
3    345
4    835
5    820
dtype: int64
```

In [26]:
```
toystory_data_group = toystory_data.groupby('Rating')
toystory_data_group.agg({'Rating':'mean'})
```

Out[26]:

	Rating
Rating	
1	1
2	2
3	3
4	4
5	5

```
In [27]: plt.hist(x=toystory_data['Rating'])
         plt.show()
```



The above plot shows that the movie 'Toystory' has got 4 ** (stars) maximum

The average rating of this movie is

Viewership by Age for Toystory

```
In [28]: viewership = pd.merge(ratings_data, users_data, how='left', left_on=['UserID'
         ], right_on=['UserID'])
```

```
In [29]: viewership.shape
```

```
Out[29]: (1000209, 8)
```

```
In [30]: ratings_data.shape
```

```
Out[30]: (1000209, 4)
```

```
In [31]: viewership.head()
```

Out[31]:

	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 [32]: #select only 'Toystory' data
         viewership_of_toystory = viewership[viewership['MovieID'] == 1]
         viewership_of_toystory.shape
```

```
Out[32]: (2077, 8)
```

In [33]:
```
viewership_of_toystory.head()
```

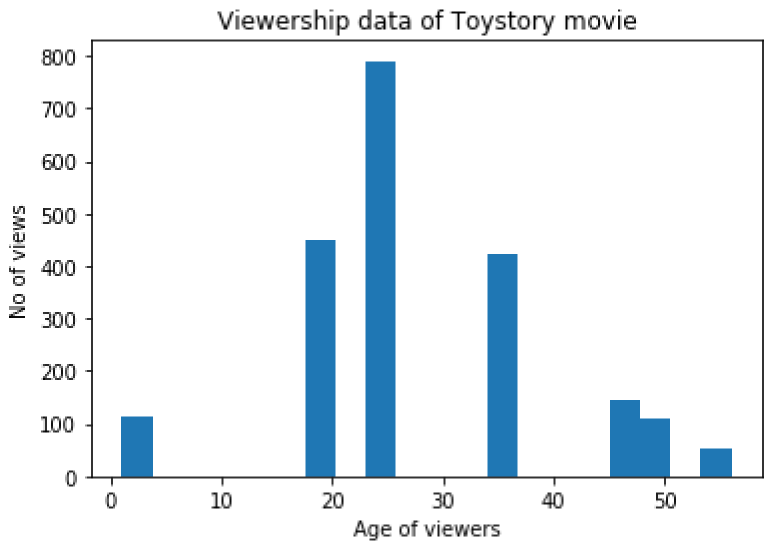
Out[33]:

	UserID	MovieID	Rating	Timestamp	Gender	Age	Occupation	Zip-code
40	1	1	5	978824268	F	1	10	48067
469	6	1	4	978237008	F	50	9	55117
581	8	1	4	978233496	M	25	12	11413
711	9	1	5	978225952	M	25	17	61614
837	10	1	5	978226474	F	35	1	95370

In [34]:
```
viewership_of_toystory.groupby('Age').size()
```

Out[34]:
```
Age
1      112
18     448
25     790
35     423
45     143
50     108
56      53
dtype: int64
```

In [35]:
```
plt.hist(x=viewership_of_toystory['Age'], data=viewership_of_toystory, bins=20
)
plt.xlabel("Age of viewers")
plt.ylabel("No of views")
plt.title("Viewership data of Toystory movie")
plt.show()
```



The above plot shows that the Toystory movie is more popular for viewers between Age group 20-25 years

Top 25 movies by viewership rating

In [36]:
```
movie_rating = ratings_data.groupby(['MovieID'], as_index=False)
average_movie_ratings = movie_rating.agg({'Rating':'mean'})
top_25_movies = average_movie_ratings.sort_values('Rating', ascending=False).h
ead(25)
top_25_movies
```

Out[36]:

	MovieID	Rating
926	989	5.000000
3635	3881	5.000000
1652	1830	5.000000
3152	3382	5.000000
744	787	5.000000
3054	3280	5.000000
3367	3607	5.000000
3010	3233	5.000000
2955	3172	5.000000
3414	3656	5.000000
3021	3245	4.800000
51	53	4.750000
2309	2503	4.666667
2698	2905	4.608696
1839	2019	4.560510
309	318	4.554558
802	858	4.524966
708	745	4.520548
49	50	4.517106
513	527	4.510417
1066	1148	4.507937
2117	2309	4.500000
1626	1795	4.500000
2287	2480	4.500000
425	439	4.500000

In [37]:
```
#The below list shows top 25 movies by viewership data
pd.merge(top_25_movies, movie_data, how='left', left_on=['MovieID'], right_on=
['MovieID'])
```

Out[37]:

	MovieID	Rating	Title	Genres
0	989	5.000000	Schlafes Bruder (Brother of Sleep) (1995)	Drama
1	3881	5.000000	Bittersweet Motel (2000)	Documentary
2	1830	5.000000	Follow the Bitch (1998)	Comedy
3	3382	5.000000	Song of Freedom (1936)	Drama
4	787	5.000000	Gate of Heavenly Peace, The (1995)	Documentary
5	3280	5.000000	Baby, The (1973)	Horror
6	3607	5.000000	One Little Indian (1973)	Comedy|Drama|Western
7	3233	5.000000	Smashing Time (1967)	Comedy
8	3172	5.000000	Ulysses (Ulisse) (1954)	Adventure
9	3656	5.000000	Lured (1947)	Crime
10	3245	4.800000	I Am Cuba (Soy Cuba/Ya Kuba) (1964)	Drama
11	53	4.750000	Lamerica (1994)	Drama
12	2503	4.666667	Apple, The (Sib) (1998)	Drama
13	2905	4.608696	Sanjuro (1962)	Action|Adventure
14	2019	4.560510	Seven Samurai (The Magnificent Seven) (Shichin...	Action|Drama
15	318	4.554558	Shawshank Redemption, The (1994)	Drama
16	858	4.524966	Godfather, The (1972)	Action|Crime|Drama
17	745	4.520548	Close Shave, A (1995)	Animation|Comedy|Thriller
18	50	4.517106	Usual Suspects, The (1995)	Crime|Thriller
19	527	4.510417	Schindler's List (1993)	Drama|War
20	1148	4.507937	Wrong Trousers, The (1993)	Animation|Comedy
21	2309	4.500000	Inheritors, The (Die Siebtelbauern) (1998)	Drama
22	1795	4.500000	Callejón de los milagros, El (1995)	Drama
23	2480	4.500000	Dry Cleaning (Nettoyage à sec) (1997)	Drama
24	439	4.500000	Dangerous Game (1993)	Drama

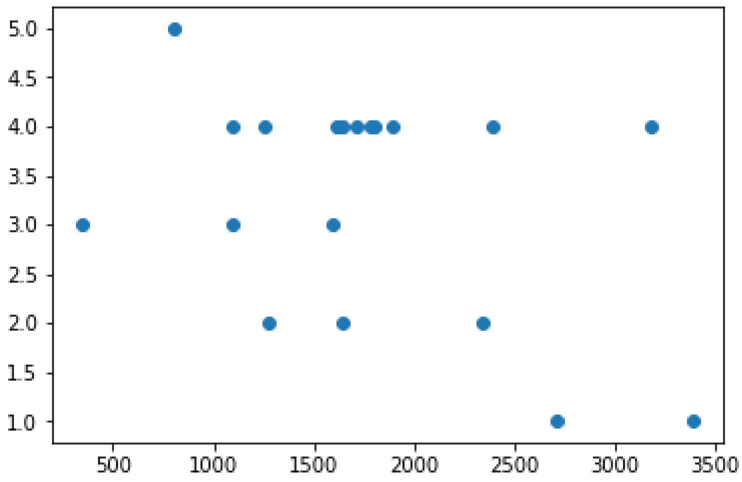
Rating of userid = 2696

In [38]:
```
user_rating_data = ratings_data[ratings_data['UserID']==2696]
user_rating_data.head()
```

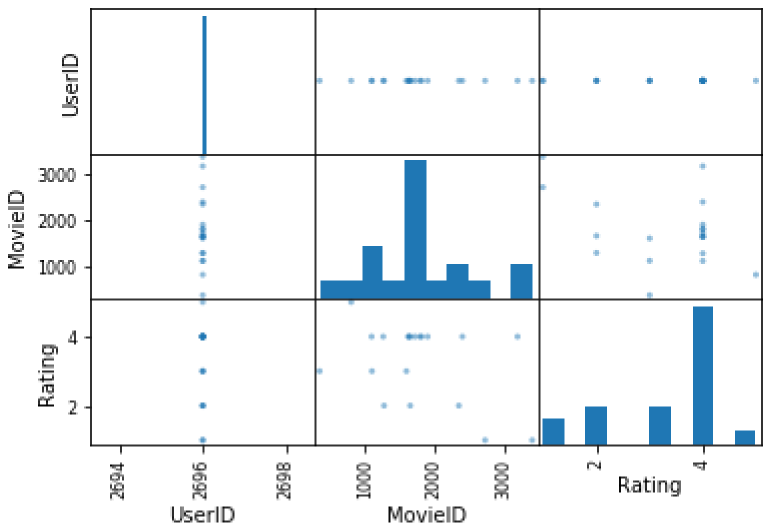
Out[38]:

	UserID	MovieID	Rating	Timestamp
440667	2696	1258	4	973308710
440668	2696	1270	2	973308676
440669	2696	1617	4	973308842
440670	2696	1625	4	973308842
440671	2696	1644	2	973308920

In [39]:
```
# plotting the above data
plt.scatter(x=user_rating_data['MovieID'], y=user_rating_data['Rating'])
plt.show()
```



In [40]:
```
from pandas.plotting import scatter_matrix
scatter_matrix(user_rating_data)
plt.show()
```



3. Prepare Data

In [43]:
```
few_viewership = viewership.head(500)
few_viewership.shape
```

Out[43]: (500, 8)

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

Out[44]:

	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 [45]:
```python
# preprocess data
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

le.fit(few_viewership['Age'])
x_age = le.transform(few_viewership['Age'])
x_age
```

Out[45]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3], dtype=int64)
```

In [46]:
```python
le.fit(few_viewership['Occupation'])
x_occ = le.transform(few_viewership['Occupation'])
x_occ
```

Out[46]:
```
array([2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1], dtype=int64)
```

In [47]:

```
le.fit(few_viewership['MovieID'])
x_movieid = le.transform(few_viewership['MovieID'])
x_movieid
```

Out[47]:

```
array([130,  78,  95, 374, 280, 132, 156, 321,  71,  96,  72,  98, 287,
       330, 107, 318, 304, 251, 355, 319, 274,  80, 154,  61, 278,  12,
       119, 211, 186,  84, 271, 364, 189,  67, 231,  86, 226, 103, 316,
        18,   0, 243, 244, 305,  29, 104, 105, 135, 252,  62, 359,  74,
       145, 161, 346, 184,  75, 264,  76, 266, 302, 121, 329, 379, 136,
       222, 205, 137, 392, 326, 342, 139, 355,  49, 260, 356, 357, 343,
       148, 194,  33, 265, 347,  92,  44, 149, 360, 185, 158, 127, 366,
       367, 368,  17, 267, 293, 225, 380,  68, 207, 398, 323, 237, 100,
       227, 324, 140, 252,  60,  50, 272,  30, 170, 113, 403,  54, 173,
       255, 151, 162, 130, 224, 163, 279, 372, 289,  69, 131, 187,  83,
       133,  70, 281,  15, 308, 297, 234, 286, 407, 239, 193, 413, 240,
       241,  28, 122, 242,  20,   3,  21, 274, 115,  46, 294,  39,  51,
       118,  97,  52, 181, 376, 166, 378, 353,  85,  56, 312, 247, 244,
       220, 331, 248,  36, 135, 246, 400, 143,  41, 144, 145, 415, 146,
       377, 198,  76, 169, 389,  16, 314, 136, 172, 414, 112, 338, 195,
       157, 149,  77, 262, 191, 396,  29, 324, 359, 111, 150,  64,  54,
       151, 152,  82, 131,  69, 280, 132, 133, 164,  70, 165, 391, 160,
       154, 292, 362, 301, 243, 399, 248, 325, 259, 246, 124, 257, 379,
       136, 333, 138, 108,  29, 252,  54, 131, 133, 240, 119, 376, 404,
       282, 167, 388, 134, 305, 332, 141, 337, 276, 126,   9,  32, 277,
       183, 168, 266, 175,  89, 203,  90, 204, 329, 317,  25, 219,  57,
       392,  58, 147, 411,  59,  10, 194, 254, 412, 338,  11, 306,  34,
        66, 196,  81,  35, 350, 296, 232,  18,  26, 406,  27,   1, 339,
       324, 110,  60,  87,  13,  14, 128, 129,  82, 351,  45, 279, 153,
       352, 289, 385, 290, 280, 268, 386, 188, 233,  70, 281, 307, 176,
       308, 297, 269,  19, 123, 340, 256, 208, 361, 291, 270, 197, 155,
       309, 310, 235, 311, 236, 298, 373, 408,  99,  91, 341, 221,  36,
        22,  53,  74, 171, 261, 209, 199, 365, 363, 210, 322, 313, 200,
        37, 249, 354, 334, 137, 223, 299, 177, 355, 335, 178, 211, 212,
       201,  93, 191, 202, 283, 213, 381, 327, 358, 252,   2,  30, 253,
        23,  63, 179, 344, 273, 180, 114, 369,  94, 214, 374, 375, 300,
       174, 215, 216, 284, 217, 370, 371,  96, 397, 285, 192, 303,  48,
       315, 101, 228, 229,  31,   4, 345,  38, 275, 116,   5,  65, 117,
       181, 182, 376, 263,  55,  24, 218, 328, 316, 305, 245, 382,  40,
         6, 142, 230, 125, 410,   7,  41,  42,   8,  79, 288, 120, 405,
       106, 206, 107, 392,  43, 383, 348,  44,  34,  12, 349, 127, 384,
        67,   0, 109, 324,  45,  69,  72,  73,  47, 295, 387, 189, 190,
       248, 257, 258, 393, 394, 320, 389, 390, 136, 409, 401, 250, 402,
       395, 159,  88, 102, 238, 336], dtype=int64)
```

In [48]:

```
few_viewership['New Age'] = x_age
few_viewership['New Occupation'] = x_occ
few_viewership['New MovieID'] = x_movieid
```

In [49]:

```
# Feature Selection
x_input = few_viewership[['New Age','New Occupation','New MovieID']]
y_target = few_viewership['Rating']
```

In [50]:
```
x_input.head()
```

Out[50]:

	New Age	New Occupation	New MovieID
0	0	2	130
1	0	2	78
2	0	2	95
3	0	2	374
4	0	2	280

4. Evaluate Algorithms

In [51]:
```
# Split-out validation dataset
x_train, x_test, y_train, y_test = train_test_split(x_input, y_target, test_si
ze=0.25)
```

In [52]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[52]:
```
((375, 3), (125, 3), (375,), (125,))
```

In [53]:
```
from sklearn.linear_model import LogisticRegression
logitReg = LogisticRegression()
lm = logitReg.fit(x_train, y_train)
```

In [54]:
```
result = logitReg.predict(x_test)
```

In [55]:
```
estimated = pd.Series(result, name='Estimated Values')
```

In [56]:
```
final_result = pd.concat([y_test, estimated], axis=1)
```

In [57]:
```
# Test options and evaluation metric
print (accuracy_score(y_test, result))
print (confusion_matrix(y_test, result))
print (classification_report(y_test, result))
```

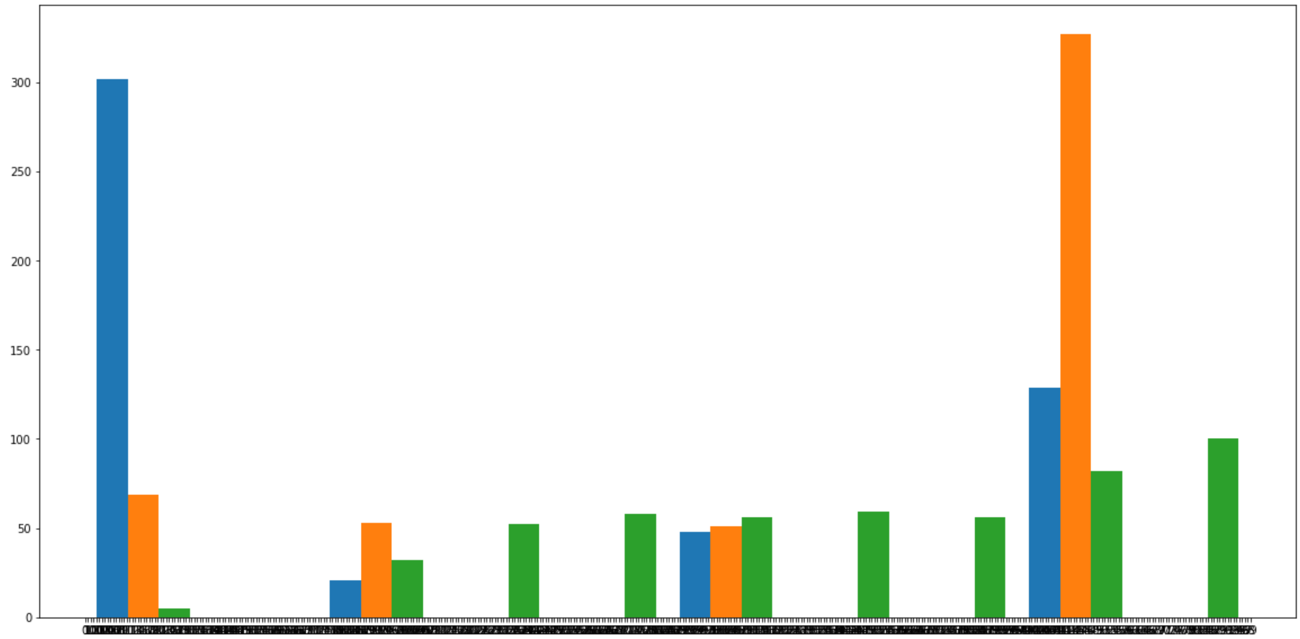
```
0.304
[[ 0  0  0  4  1]
 [ 0  0  1 13  0]
 [ 0  0 10 28  0]
 [ 0  0  9 28  2]
 [ 0  0  7 22  0]]
             precision    recall  f1-score   support

          1       0.00      0.00      0.00         5
          2       0.00      0.00      0.00        14
          3       0.37      0.26      0.31        38
          4       0.29      0.72      0.42        39
          5       0.00      0.00      0.00        29

avg / total       0.20      0.30      0.22       125
```

Accuracy of the above matrix is 30.4 %

In [58]:
```
# Plot the histogram
plt.figure(figsize=(20,10))
plt.hist(x=x_input)
plt.legend()
plt.show()
```



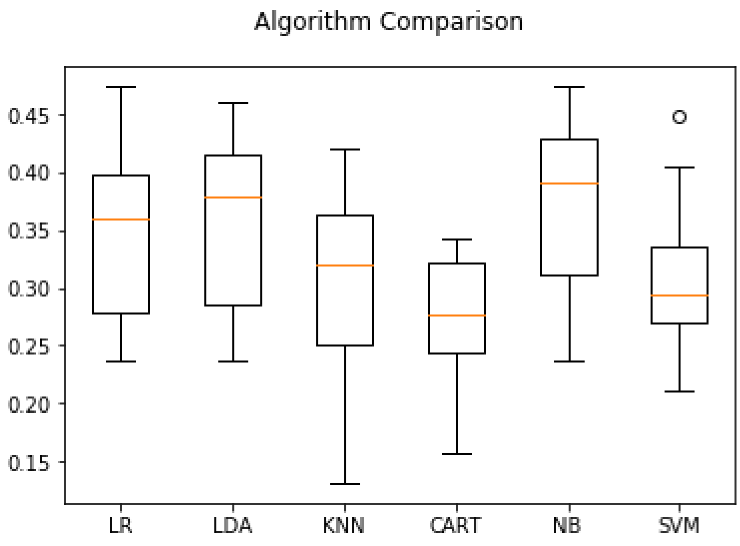
In [60]:
```
# Spot-Check Algorithms
seed = 7
models = []
models.append(('LR', LogisticRegression()))
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('NB', GaussianNB()))
models.append(('SVM', SVC()))
# 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='a
ccuracy')
    results.append(cv_results)
    names.append(name)
    msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
    print(msg)
```

```
LR: 0.349716 (0.074064)
LDA: 0.357895 (0.073962)
KNN: 0.295590 (0.089280)

CART: 0.274680 (0.053029)
NB: 0.371124 (0.076266)
SVM: 0.309175 (0.068645)
```

In [62]:

```
# Compare Algorithms
fig = plt.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
plt.boxplot(results)
ax.set_xticklabels(names)
plt.show()
```



From the above plot we see that Naive Bayes gives the most accurate results

In [ ]: