Zee Recommender System

In [90]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
from sklearn.metrics.pairwise import cosine_similarity
from scipy.sparse import csr_matrix
```

In [91]:
```
m = pd.read_fwf('data/zee-movies.dat')
r = pd.read_fwf('data/zee-ratings.dat')
u = pd.read_fwf('data/zee-users.dat')
```

In [92]:
```
m.head()
```

Out[92]:

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

In [93]:
```
movies=m.drop(columns=['Unnamed: 1','Unnamed: 2'])
```

In [94]:
```
movies.head()
```

Out[94]:

	Movie ID::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 [95]:
```
movies=movies['Movie ID::Title::Genres'].str.split('::',expand=True)
movies.columns=['MovieID','Title','Genres']
```

In [96]:
```
movies.head()
```

Out[96]:

	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 [97]:
```
def findYear(x):
    if('19' in x):
        a=x.index('19')
        return int(x[a:a+4])
    elif('20' in x):
        a=x.index('20')
        return int(x[a:a+4])
    else:
        return 0
```

In [98]:
```
def Title(x):
    if('19' in x or '20' in x):
        return x[:-7]
    else:
        return x
```

In [99]:
```
movies['Year'] = movies['Title'].apply(lambda x:findYear(x))
movies['Title'] = movies['Title'].apply(lambda x:Title(x))
```

In [100]:
```
movies.head(5)
```

Out[100]:

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

In [101]:
```python
movies['Title']
```

Out[101]:
```
0                         Toy Story
1                           Jumanji
2                  Grumpier Old Men
3                 Waiting to Exhale
4       Father of the Bride Part II
                   ...
3878               Meet the Parents
3879            Requiem for a Dream
3880                      Tigerland
3881               Two Family House
3882                 Contender, The
Name: Title, Length: 3883, dtype: object
```

In [102]:
```python
movies.loc[movies['Title'].str.contains('Outlaw, The')]
```

Out[102]:

	MovieID	Title	Genres	Year
955	967	Outlaw, The	Western	1943

In [103]:
```python
movies.shape
```

Out[103]:
```
(3883, 4)
```

There are 3883 movies in the dataset

In [104]:
```python
movies['Year'].unique()
```

Out[104]:
```
array([1995, 1994, 1996,    0, 1976, 1993, 1992, 1988, 1967, 1964, 1977,
       1965, 1982, 1962, 1990, 1991, 1989, 1937, 1940, 1969, 1981, 1973,
       1970, 1960, 1955, 1956, 1959, 1968, 1980, 1975, 1986, 1948, 1943,
       1950, 1946, 1987, 1997, 1974, 1958, 1949, 1972, 1998, 1933, 1952,
       1951, 1957, 1961, 1954, 1934, 1944, 1963, 1942, 1941, 1953, 1939,
       1947, 1945, 1938, 1935, 1936, 1926, 1932, 1930, 1971, 1979, 1966,
       1978, 1985, 1983, 1984, 1931, 1922,   19, 1927, 1929,  195, 1928,
       1925, 1923, 1999, 1900, 1919, 2000, 1920, 1921], dtype=int64)
```

In [105]:
```python
mode_year=movies['Year'].mode()
movies.replace({'Year':{
    0 : mode_year,
    19: mode_year,
    195 : mode_year
}},
    inplace=True          )
```

In [106]:
```
movies['Year'].unique()
```

Out[106]:
```
array([1995, 1994, 1996, 1976, 1993, 1992, 1988, 1967, 1964, 1977, 1965,
       1982, 1962, 1990, 1991, 1989, 1937, 1940, 1969, 1981, 1973, 1970,
       1960, 1955, 1956, 1959, 1968, 1980, 1975, 1986, 1948, 1943, 1950,
       1946, 1987, 1997, 1974, 1958, 1949, 1972, 1998, 1933, 1952, 1951,
       1957, 1961, 1954, 1934, 1944, 1963, 1942, 1941, 1953, 1939, 1947,
       1945, 1938, 1935, 1936, 1926, 1932, 1930, 1971, 1979, 1966, 1978,
       1985, 1983, 1984, 1931, 1922, 1927, 1929, 1928, 1925, 1923, 1999,
       1900, 1919, 2000, 1920, 1921], dtype=int64)
```

In [107]:
```
max(movies['Year']) - min(movies['Year'])
```

Out[107]:
```
100
```

These movies belongs to 19th Century

In [108]:
```
r.head()
```

Out[108]:

	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 [109]:
```
ratings=r
ratings.head()
```

Out[109]:

	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 [110]:
```
ratings=ratings['UserID::MovieID::Rating::Timestamp'].str.split('::',expand=True)
ratings.columns=['UserID','MovieID','Rating','Timestamp']
ratings.sample(5)
```

Out[110]:

	UserID	MovieID	Rating	Timestamp
518422	3200	1653	4	968629872
494263	3032	2355	5	970345633
34568	235	1500	5	976770421
324177	1921	455	3	974693607
435841	2664	2145	3	973455388

In [111]:
```
ratings.shape
```

Out[111]:
```
(1000209, 4)
```

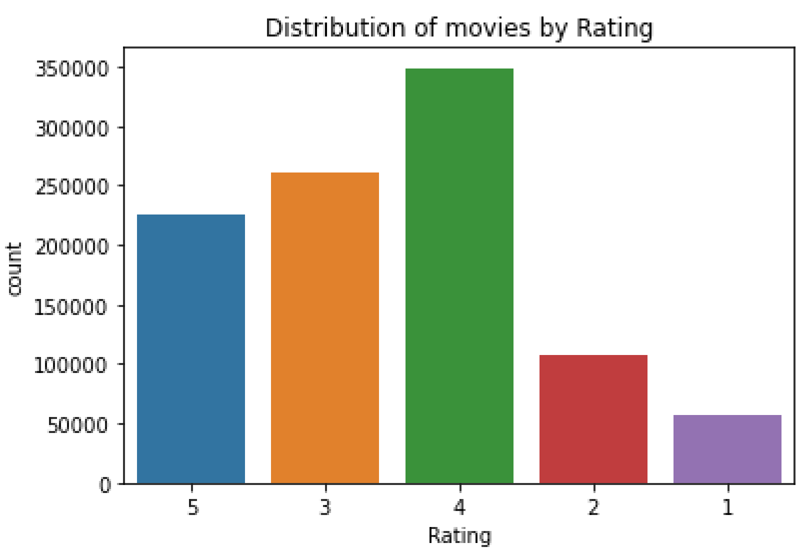
The data has total 1000209 reatings

Basic EDA on data

In [112]:
```
sns.countplot('Rating',data=ratings)
plt.title('Distribution of movies by Rating')
```

```
C:\Users\user\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarn
ing: Pass the following variable as a keyword arg: x. From version 0.12, the on
ly valid positional argument will be `data`, and passing other arguments withou
t an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[112]:
```
Text(0.5, 1.0, 'Distribution of movies by Rating')
```



Most of the times users has rated the movies as '4'

In [113]:
```python
def decade(x):
    if(x<2000):
        return str((((x)%1900)//10)*10)+'s'
    else:
        return "2000s"
movies['Decade'] = movies['Year'].apply(lambda x:decade(x))
```

In [114]:
```python
movies.head()
```

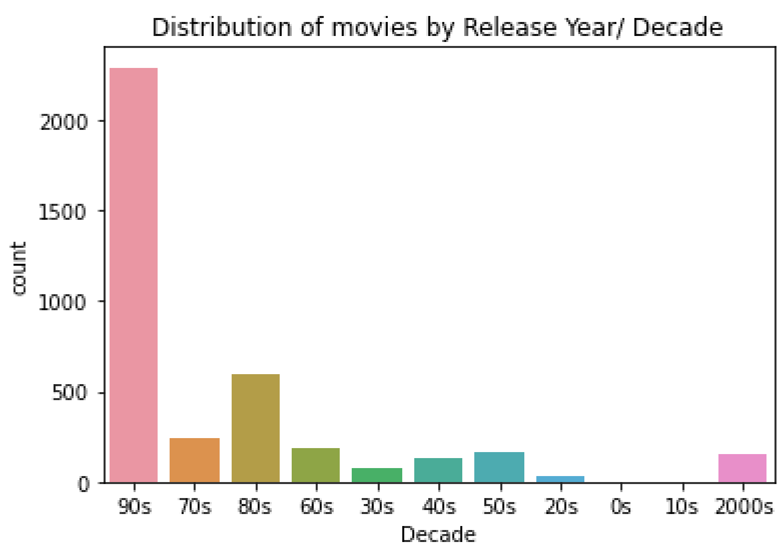
Out[114]:

	MovieID	Title	Genres	Year	Decade
0	1	Toy Story	Animation|Children's|Comedy	1995	90s
1	2	Jumanji	Adventure|Children's|Fantasy	1995	90s
2	3	Grumpier Old Men	Comedy|Romance	1995	90s
3	4	Waiting to Exhale	Comedy|Drama	1995	90s
4	5	Father of the Bride Part II	Comedy	1995	90s

In [115]:
```python
sns.countplot('Decade',data=movies)
plt.title('Distribution of movies by Release Year/ Decade')
```

```
C:\Users\user\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarn
ing: Pass the following variable as a keyword arg: x. From version 0.12, the on
ly valid positional argument will be `data`, and passing other arguments withou
t an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[115]: `Text(0.5, 1.0, 'Distribution of movies by Release Year/ Decade')`



Most of the movies are from 90's

In [116]:
```
users=u
u.sample(5)
```

Out[116]:

	UserID::Gender::Age::Occupation::Zip-code
1014	1015::M::35::3::11220
5682	5683::F::18::9::94538
2926	2927::M::25::12::24060
5144	5145::M::35::7::77565-2332
1270	1271::F::45::6::54401

In [117]:
```
users=users['UserID::Gender::Age::Occupation::Zip-code'].str.split('::',expand=Tr
users.columns=['UserID','Gender','Age','Occupation','ZipCode']
users.sample(5)
```

Out[117]:

	UserID	Gender	Age	Occupation	ZipCode
1950	1951	F	18	4	90630
3445	3446	M	25	7	30620
423	424	M	25	17	55112
623	624	M	25	1	75207
4219	4220	M	35	0	97225

In [118]:
```
users['Age'].unique()
```

Out[118]:
```
array(['1', '56', '25', '45', '50', '35', '18'], dtype=object)
```

In [119]:
```
users.replace({'Age':{ '1' : 'Under 18','18': "18-24",

'25': "25-34",

'35': "35-44",

'45': "45-49",

'50': "50-55",

'56': "56+"}},inplace=True)
```

In [120]:

```
users.replace({'Occupation' : {'0': "other",

'1': "academic/educator",

'2': "artist",

'3': "clerical/admin",

'4': "college/grad student",

'5': "customer service",

'6': "doctor/health care",

'7': "executive/managerial",

'8': "farmer",

'9': "homemaker",

'10': "K-12 student",

'11': "lawyer",

'12': "programmer",

'13': "retired",

'14': "sales/marketing",

'15': "scientist",

'16': "self-employed",

'17': "technician/engineer",

'18': "tradesman/craftsman",

'19': "unemployed",

'20': "writer"}},inplace=True)
```

In [121]:
```
users.sample(10)
```

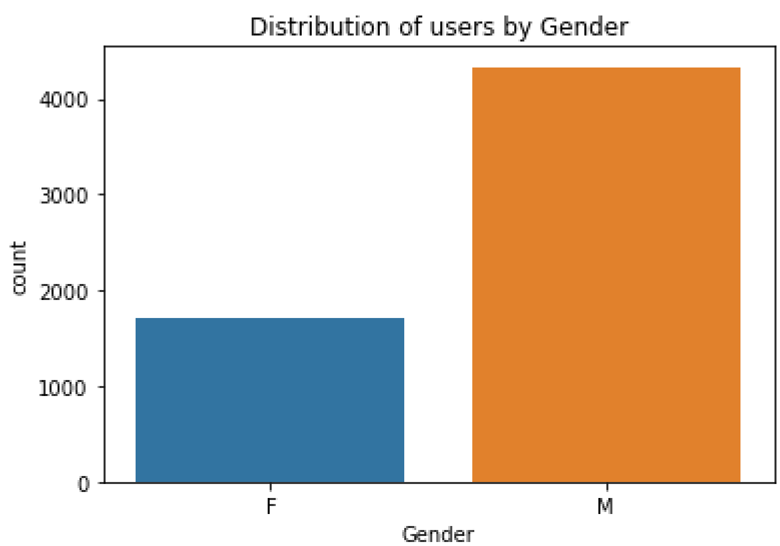
Out[121]:

	UserID	Gender	Age	Occupation	ZipCode
3068	3069	M	18-24	college/grad student	97470
3616	3617	M	35-44	executive/managerial	49034
5442	5443	M	25-34	programmer	01915
3263	3264	F	25-34	academic/educator	94536
1148	1149	M	25-34	programmer	98103
5877	5878	F	25-34	other	60640
90	91	M	35-44	executive/managerial	07650
1747	1748	M	50-55	academic/educator	04240
5346	5347	M	25-34	doctor/health care	53705
839	840	F	25-34	clerical/admin	02828

In [122]:
```
sns.countplot('Gender',data=users)
plt.title('Distribution of users by Gender')
```

```
C:\Users\user\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarn
ing: Pass the following variable as a keyword arg: x. From version 0.12, the on
ly valid positional argument will be `data`, and passing other arguments withou
t an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[122]: Text(0.5, 1.0, 'Distribution of users by Gender')

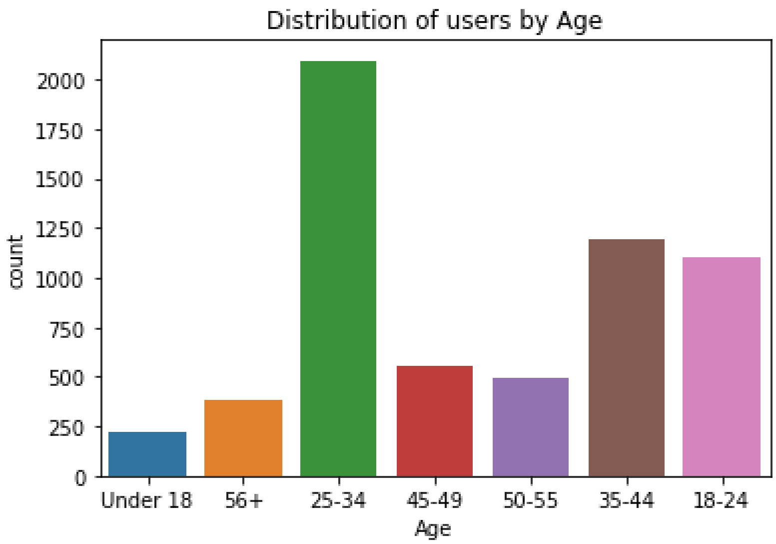


most users are male

In [123]:
```
sns.countplot('Age',data=users)
plt.title('Distribution of users by Age')
```

```
C:\Users\user\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarn
ing: Pass the following variable as a keyword arg: x. From version 0.12, the on
ly valid positional argument will be `data`, and passing other arguments withou
t an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

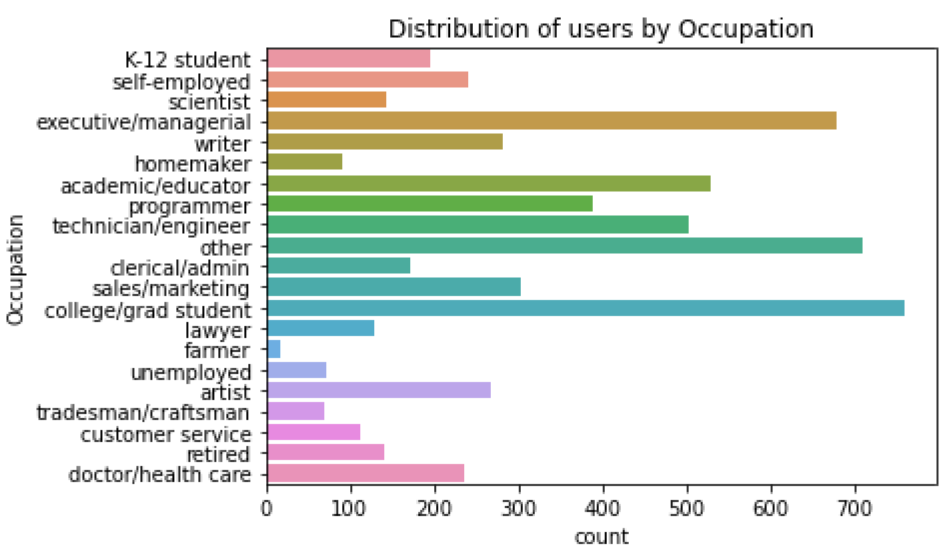
Out[123]: Text(0.5, 1.0, 'Distribution of users by Age')



Most users belongs to age group of 25-34

In [124]:
```
sns.countplot(y='Occupation',data=users,orient="h")
plt.title('Distribution of users by Occupation')
```

Out[124]: Text(0.5, 1.0, 'Distribution of users by Occupation')



Most number of users are college/ grad student

Merging the datasets

In [125]:
```
df1= pd.merge(movies,ratings,how='inner',on='MovieID')
df1.head(10)
```

Out[125]:

	MovieID	Title	Genres	Year	Decade	UserID	Rating	Timestamp
0	1	Toy Story	Animation|Children's|Comedy	1995	90s	1	5	978824268
1	1	Toy Story	Animation|Children's|Comedy	1995	90s	6	4	978237008
2	1	Toy Story	Animation|Children's|Comedy	1995	90s	8	4	978233496
3	1	Toy Story	Animation|Children's|Comedy	1995	90s	9	5	978225952
4	1	Toy Story	Animation|Children's|Comedy	1995	90s	10	5	978226474
5	1	Toy Story	Animation|Children's|Comedy	1995	90s	18	4	978154768
6	1	Toy Story	Animation|Children's|Comedy	1995	90s	19	5	978555994
7	1	Toy Story	Animation|Children's|Comedy	1995	90s	21	3	978139347
8	1	Toy Story	Animation|Children's|Comedy	1995	90s	23	4	978463614
9	1	Toy Story	Animation|Children's|Comedy	1995	90s	26	3	978130703

In [126]:
```python
dff = pd.merge(df1,users,how='inner',on='UserID')
dff.sample(20)
```

Out[126]:

	MovieID	Title	Genres	Year	Decade	UserID	Rating	Timesta
792179	2243	Broadcast News	Comedy|Drama|Romance	1987	80s	3981	3	965628
625768	1676	Starship Troopers	Action|Adventure|Sci-Fi|War	1997	90s	5443	3	959980
71197	2283	Sheltering Sky, The	Drama	1990	90s	795	2	1038693
192639	2901	Phantasm	Horror|Sci-Fi	1979	70s	1922	2	974694
183114	491	Man Without a Face, The	Drama	1993	90s	1861	3	974705
704093	2757	Frances	Drama	1982	80s	2129	5	983416
337541	1597	Conspiracy Theory	Action|Mystery|Romance|Thriller	1997	90s	3562	3	966792
162918	2407	Cocoon	Comedy|Sci-Fi	1985	80s	1671	4	1018225
939842	2133	Adventures in Babysitting	Adventure|Comedy	1987	80s	4688	4	963619
345264	555	True Romance	Action|Crime|Romance	1993	90s	3626	3	966608
86527	2872	Excalibur	Action|Drama|Fantasy|Romance	1981	80s	963	4	975120
550776	3219	Pacific Heights	Thriller	1990	90s	5749	2	962844
610525	590	Dances with Wolves	Adventure|Drama|Western	1990	90s	4131	3	965350
218538	1257	Better Off Dead...	Comedy	1985	80s	2109	3	974656
981853	1230	Annie Hall	Comedy|Romance	1977	70s	3241	4	968346
27166	2136	Nutty Professor, The	Comedy	1963	60s	333	2	996357
103366	159	Clockers	Drama	1995	90s	1124	3	974910
851717	527	Schindler's List	Drama|War	1993	90s	3069	5	970358
189800	2193	Willow	Action|Adventure|Fantasy	1988	80s	1904	3	974759
772408	1625	Game, The	Mystery|Thriller	1997	90s	4783	3	963005

In [127]:
```
dff.tail(50)
```

Out[127]:

	MovieID	Title	Genres	Year	Decade	UserID	Rating
1000159	2028	Saving Private Ryan	Action|Drama|War	1998	90s	5727	4
1000160	2306	Holy Man	Comedy	1998	90s	5727	2
1000161	2335	Waterboy, The	Comedy	1998	90s	5727	1
1000162	2355	Bug's Life, A	Animation|Children's|Comedy	1998	90s	5727	4
1000163	2394	Prince of Egypt, The	Animation|Musical	1998	90s	5727	3
1000164	2605	Entrapment	Crime|Thriller	1999	90s	5727	4
1000165	2634	Mummy, The	Horror	1959	50s	5727	2

In [128]:
```
dff.dtypes
```

Out[128]:
```
MovieID       object
Title         object
Genres        object
Year           int64
Decade        object
UserID        object
Rating        object
Timestamp     object
Gender        object
Age           object
Occupation    object
ZipCode       object
dtype: object
```

In [129]:
```
dff["Rating"] = dff["Rating"].astype(str).astype(int)
```

In [130]:
```
dff['Timestamp'] = pd.to_datetime(dff['Timestamp'],unit='s')
```

In [131]:
```
dff.dtypes
```

Out[131]:
```
MovieID                object
Title                  object
Genres                 object
Year                    int64
Decade                 object
UserID                 object
Rating                  int32
Timestamp      datetime64[ns]
Gender                 object
Age                    object
Occupation             object
ZipCode                object
dtype: object
```

In [132]:
```
dff['Rating'].unique()
```

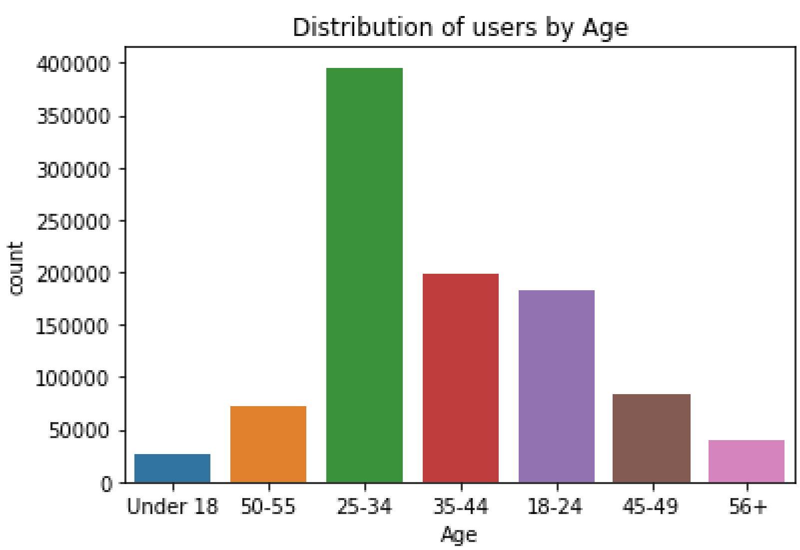
Out[132]:
```
array([5, 4, 3, 2, 1])
```

Even though we have found what is the age group of most number of users, but we are not sure whether the same age group has rated more number of movies. Hence doing this plot on merged Dataset

In [192]:
```
sns.countplot('Age',data=dff)
plt.title('Distribution of users by Age')
```

```
C:\Users\user\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarn
ing: Pass the following variable as a keyword arg: x. From version 0.12, the on
ly valid positional argument will be `data`, and passing other arguments withou
t an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[192]:
```
Text(0.5, 1.0, 'Distribution of users by Age')
```

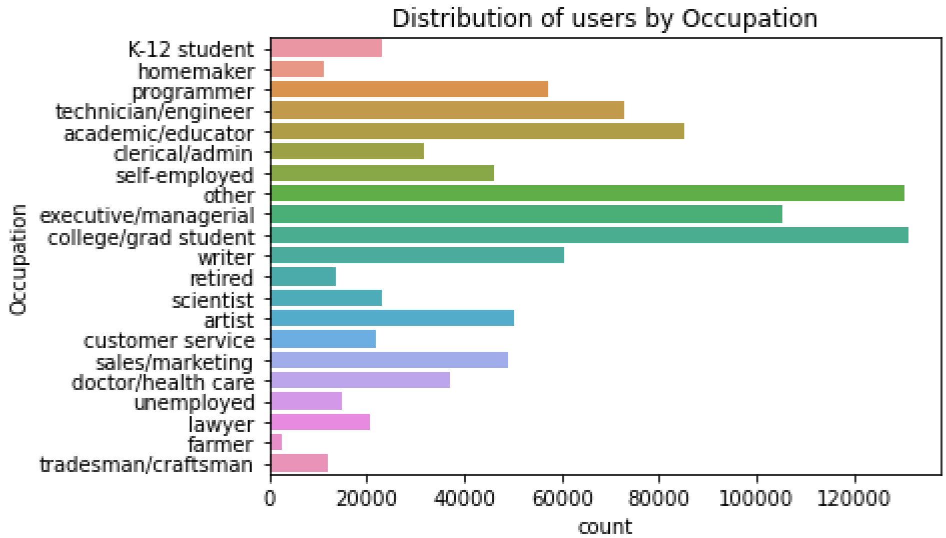


Even though we have found what is the age occupation of most number of users from

users dataset, but we are not sure whether the people of same occupation has rated more number of movies. Hence doing this plot on merged Dataset

In [193]:
```
sns.countplot(y='Occupation',data=dff,orient="h")
plt.title('Distribution of users by Occupation')
```

Out[193]: `Text(0.5, 1.0, 'Distribution of users by Occupation')`



Grouping the data with respect to Movies to find high rated movies

In [133]:
```
temp1=dff.groupby(['MovieID','Title'])\
                            .agg(no_of_ratings=('Rating','size'),Avg_Rating=('Rat
                            .sort_values(by=['Avg_Rating'],ascending=False)\
                            .reset_index()
```

In [134]:
```
temp1.loc[temp1['no_of_ratings']>100]
```

Out[134]:

	MovieID	Title	no_of_ratings	Avg_Rating
14	2019	Seven Samurai (The Magnificent Seven) (Shichin...	628	4.560510
15	318	Shawshank Redemption, The	2227	4.554558
16	858	Godfather, The	2223	4.524966
17	745	Close Shave, A	657	4.520548
18	50	Usual Suspects, The	1783	4.517106
...	...	...	...	...
3623	2555	Baby Geniuses	164	1.701220
3641	2383	Police Academy 6: City Under Siege	149	1.657718
3645	2817	Aces: Iron Eagle III	125	1.640000
3648	3593	Battlefield Earth	342	1.611111
3664	810	Kazaam	120	1.466667

2006 rows × 4 columns

Just considering the cutoff that a movie should be rated by atleaset 100 users to be rated as a genuine rated film. Hence **Seven Samurai** is the high rated film in the data

In [135]:
```
temp1.loc[temp1['no_of_ratings'] == max(temp1['no_of_ratings'])]
```

Out[135]:

	MovieID	Title	no_of_ratings	Avg_Rating
75	2858	American Beauty	3428	4.317386

More number of users have given their rating for **American Beauty**

In [136]:
```
temp1.loc[(temp1['no_of_ratings']>100) & (temp1['Avg_Rating']>=4)]
```

Out[136]:

	MovieID	Title	no_of_ratings	Avg_Rating
14	2019	Seven Samurai (The Magnificent Seven) (Shichin...	628	4.560510
15	318	Shawshank Redemption, The	2227	4.554558
16	858	Godfather, The	2223	4.524966
17	745	Close Shave, A	657	4.520548
18	50	Usual Suspects, The	1783	4.517106
...	...	...	...	...
373	497	Much Ado About Nothing	667	4.000000
374	1827	Big One, The	102	4.000000
382	2670	Run Silent, Run Deep	220	4.000000
415	1238	Local Hero	351	4.000000
419	2575	Dreamlife of Angels, The (La Vie rêvée des anges)	141	4.000000

302 rows × 4 columns

There are around 302 movies where the movies are considered good with rating above 4

In [137]:
```
temp2=dff.groupby(['UserID'])\
                            .agg(no_of_ratings=('Rating','size'),Avg_Rating=('Rat
                            .sort_values(by=['Avg_Rating'],ascending=False)\
                            .reset_index()
```

In [138]:
```
temp2
```

Out[138]:

	UserID	no_of_ratings	Avg_Rating
0	283	27	4.962963
1	2339	23	4.956522
2	3324	21	4.904762
3	3902	165	4.890909
4	446	51	4.843137
...	...	...	...
6035	5850	58	1.844828
6036	4539	119	1.815126
6037	2744	138	1.304348
6038	4486	51	1.058824
6039	3598	65	1.015385

6040 rows × 3 columns

In [139]:
```
temp2.loc[temp2['no_of_ratings']>10]
```

Out[139]:

	UserID	no_of_ratings	Avg_Rating
0	283	27	4.962963
1	2339	23	4.956522
2	3324	21	4.904762
3	3902	165	4.890909
4	446	51	4.843137
...	...	...	...
6035	5850	58	1.844828
6036	4539	119	1.815126
6037	2744	138	1.304348
6038	4486	51	1.058824
6039	3598	65	1.015385

6040 rows × 3 columns

The user with ID **283** has given rated movies higher and the user with ID **3598** has rated most of the movies as low

In [140]:
```
temp2.loc[temp2['no_of_ratings'] == max(temp2['no_of_ratings'])]
```

Out[140]:

	UserID	no_of_ratings	Avg_Rating
4056	4169	2314	3.551858

The User with UserID **4169** has given ratings for more number of movies

Creating a Pivot Table

In [141]:
```
matrix = pd.pivot_table(dff,index="UserID",columns='Title',values='Rating')
matrix.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 6040 entries, 1 to 999
Columns: 3664 entries, $1,000,000 Duck to eXistenZ
dtypes: float64(3664)
memory usage: 168.9+ MB
```

In [142]:
```python
matrix.head(20)
```

Out[142]:

Title	$1,000,000 Duck	'Night Mother	'Til There Was You	'burbs, The	...And Justice for All	1-900	10 Things I Hate About You	101 Dalmatians	12 Angry Men	13th Warrior, The	...
UserID											
1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
10	NaN	NaN	NaN	4.0	NaN	NaN	NaN	NaN	3.0	4.0	...
100	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4.0	NaN	NaN	...
1001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	3.0	NaN	NaN	...
1002	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1003	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1004	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4.0	NaN	NaN	...
1005	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1006	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1007	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1008	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1009	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
101	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	4.0	...
1010	NaN	NaN	NaN	1.0	NaN	NaN	3.0	1.0	4.0	NaN	...
1011	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1012	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1013	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1014	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...
1015	NaN	3.0	2.0	NaN	3.0	NaN	3.0	4.0	NaN	NaN	...

20 rows × 3664 columns

In [143]:
```
matrix.fillna(0,inplace=True)
matrix.head(10)
```

Out[143]:

Title	$1,000,000 Duck	'Night Mother	'Til There Was You	'burbs, The	...And Justice for All	1-900	10 Things I Hate About You	101 Dalmatians	12 Angry Men	13th Warrior, The	...
UserID											
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
10	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	3.0	4.0	...
100	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	...
1001	0.0	0.0	0.0	0.0	0.0	0.0	0.0	3.0	0.0	0.0	...
1002	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	0.0	0.0	...
1005	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...
1006	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...

10 rows × 3664 columns

In [144]:
```
matrix.columns
```

Out[144]:
```
Index(['$1,000,000 Duck', ''Night Mother', ''Til There Was You', ''burbs, The',
       '...And Justice for All', '1-900', '10 Things I Hate About You',
       '101 Dalmatians', '12 Angry Men', '13th Warrior, The',
       ...
       'Young Poisoner's Handbook, The', 'Young Sherlock Holmes',
       'Young and Innocent', 'Your Friends and Neighbors', 'Zachariah',
       'Zed & Two Noughts, A', 'Zero Effect',
       'Zero Kelvin (Kjærlighetens kjøtere)', 'Zeus and Roxanne', 'eXistenZ'],
      dtype='object', name='Title', length=3664)
```

Item Based Approach : Pearson Correlation

In [194]:
```
input_movie = input('Enter a Movie name:')
rating_movie = matrix[input_movie]
similar_rated_movies = matrix.corrwith(rating_movie)
```

```
Enter a Movie name:Liar Liar
```

In [195]:
```
similar_rated_movies
```

Out[195]:
```
Title
$1,000,000 Duck                          0.063723
'Night Mother                            0.048226
'Til There Was You                       0.073924
'burbs, The                              0.225559
...And Justice for All                   0.074494
                                           ...
Zed & Two Noughts, A                     0.014045
Zero Effect                              0.174860
Zero Kelvin (Kjærlighetens kjøtere)     -0.006114
Zeus and Roxanne                         0.067541
eXistenZ                                 0.085360
Length: 3664, dtype: float64
```

In [196]:
```
df_similar = pd.DataFrame(similar_rated_movies,columns=['Correlation Value'])
df_similar.sort_values('Correlation Value',ascending=False,inplace=True)
df_similar.iloc[1:].head()
```

Out[196]:

Title	Correlation Value
Mrs. Doubtfire	0.499927
Dumb & Dumber	0.459601
Ace Ventura: Pet Detective	0.458654
Home Alone	0.455967
Wedding Singer, The	0.429222

Item Based Approach : Cosine Similarity

Item Similarity Matrix

In [197]:

```
item_sim_matrix = cosine_similarity(matrix.T)
item_sim_matrix = pd.DataFrame(item_sim_matrix,index=matrix.columns,columns=matri
item_sim_matrix.head()
```

Out[197]:

Title	$1,000,000 Duck	'Night Mother	'Til There Was You	'burbs, The	...And Justice for All	1-900	10 Things I Hate About You	101 Dalmatians	A
Title									
$1,000,000 Duck	1.000000	0.072357	0.037011	0.079291	0.060838	0.00000	0.058619	0.189843	0.0
'Night Mother	0.072357	1.000000	0.115290	0.115545	0.159526	0.00000	0.076798	0.137135	0.1
'Til There Was You	0.037011	0.115290	1.000000	0.098756	0.066301	0.08025	0.127895	0.128523	0.0
'burbs, The	0.079291	0.115545	0.098756	1.000000	0.143620	0.00000	0.192191	0.250140	0.1
...And Justice for All	0.060838	0.159526	0.066301	0.143620	1.000000	0.00000	0.075093	0.178928	0.2

5 rows × 3664 columns

User Similarity Matrix

```
In [198]: user_sim_matrix = cosine_similarity(matrix)
          user_sim_matrix = pd.DataFrame(user_sim_matrix,index=matrix.index,columns= matri
          user_sim_matrix.head()
```

Out[198]:

UserID	1	10	100	1000	1001	1002	1003	1004	1005
UserID									
1	1.000000	0.254736	0.123967	0.207800	0.139112	0.110320	0.121384	0.180073	0.103137
10	0.254736	1.000000	0.259052	0.279838	0.158108	0.112659	0.141661	0.431184	0.193049
100	0.123967	0.259052	1.000000	0.306067	0.075625	0.110450	0.358686	0.237292	0.171609
1000	0.207800	0.279838	0.306067	1.000000	0.098971	0.047677	0.201722	0.355619	0.323584
1001	0.139112	0.158108	0.075625	0.098971	1.000000	0.164611	0.053807	0.149848	0.137387

5 rows × 6040 columns

CSR matrix and Printing recommendations based on KNN

```
In [199]: csrmatrix = csr_matrix(matrix.T.values)
          csrmatrix
```

```
Out[199]: <3664x6040 sparse matrix of type '<class 'numpy.float64'>'
                  with 997085 stored elements in Compressed Sparse Row format>
```

```
In [200]: from sklearn.neighbors import NearestNeighbors
```

```
In [201]: knn = NearestNeighbors(n_neighbors=5,metric='cosine',n_jobs=-1)
          knn.fit(csrmatrix)
```

```
Out[201]: NearestNeighbors(metric='cosine', n_jobs=-1)
```

```
In [202]: query_movie = input('Enter a movie name:')
          distances,indices = knn.kneighbors(matrix[query_movie].values.reshape(1,-1),n_nei

          for i in range(0,len(distances.flatten())):
              if(i==0):
                  print('Recommendations for {0}: \n'.format(query_movie))
              else:
                  print('{0}. {1}'.format(i,matrix.columns[indices.flatten()[i]]))
```

```
Enter a movie name:Liar Liar
Recommendations for Liar Liar:

1. Mrs. Doubtfire
2. Ace Ventura: Pet Detective
3. Dumb & Dumber
4. Home Alone
5. Wayne's World
```

Matrix Factorization

In [154]:
```
#pip install keras
```

In [155]:
```
#pip install tensorflow
```

In [156]:
```
from keras.models import load_model
from sklearn.model_selection import train_test_split
from keras.layers import Input, Embedding, Flatten, Dot, Dense, Concatenate
from keras.models import Model
```

In [174]:
```
u = dff.UserID.unique()
m = dff.MovieID.unique()

userid_to_idx = {o:i for i,o in enumerate(u)}
movieid_to_idx = {o:i for i,o in enumerate(m)}
```

In [175]:
```
dff['UserID'] = dff['UserID'].apply(lambda x: userid_to_idx[x])
dff['MovieID'] = dff['MovieID'].apply(lambda x: movieid_to_idx[x])
split = np.random.rand(len(dff)) < 0.8
train_val = dff[split]
test = dff[~split]
split1 = np.random.rand(len(train_val)) < 0.75
train = train_val[split1]
validation = train_val[~split1]
```

In [176]:
```
train.shape, validation.shape, test.shape
```

Out[176]:
```
((599763, 12), (200276, 12), (200170, 12))
```

In [177]:
```
no_of_unique_movies = len(dff['MovieID'].unique())
no_of_unique_users = len(dff['UserID'].unique())

print(no_of_unique_movies,no_of_unique_users)
```

```
3706 6040
```

In [178]:
```
latent_factors = 64
user_input = Input(shape=(1,),name='User-input',dtype='int64')
```

In [179]:
```
user_embedding = Embedding(no_of_unique_users,latent_factors,name='user_embedding
```

In [180]:
```
user_vec=Flatten(name="Flatten-Users")(user_embedding)
```

In [181]:
```
movie_input = Input(shape=(1,), name="Movie-Input")
movie_embedding = Embedding(no_of_unique_movies, latent_factors, name="Movie-Embe
movie_vec = Flatten(name="Flatten-Movies")(movie_embedding)
```

In [182]:
```
import tensorflow as tf
import keras
sim =tf.keras.layers.dot([user_vec,movie_vec],name='Similarity-Dot-Product',axes=
model = keras.models.Model([user_input,movie_input],sim)
model.compile(optimizer=tf.keras.optimizers.Adam(lr=1e-4),loss='mse')
```

In [183]:
```
model.summary()
```

```
Model: "model_2"
____________________________________________________________________________
_____________________
 Layer (type)                Output Shape         Param #     Connected to
============================================================================
=====================
 User-input (InputLayer)     [(None, 1)]          0           []

 Movie-Input (InputLayer)    [(None, 1)]          0           []

 user_embedding (Embedding)  (None, 1, 64)        386560      ['User-input
[0][0]']

 Movie-Embedding (Embedding)  (None, 1, 64)       237184      ['Movie-Inpu
t[0][0]']

 Flatten-Users (Flatten)     (None, 64)           0           ['user_embed
ding[0][0]']

 Flatten-Movies (Flatten)    (None, 64)           0           ['Movie-Embe
dding[0][0]']

 Similarity-Dot-Product (Dot)  (None, 1)          0           ['Flatten-Us
ers[0][0]',
                                                               'Flatten-Mo
vies[0][0]']

============================================================================
=====================
Total params: 623,744
Trainable params: 623,744
Non-trainable params: 0
____________________________________________________________________________
_____________________
```

In [184]:
```
model_hist = model.fit([train.UserID,train.MovieID],train.Rating,
                       batch_size=128,epochs=20,
                        validation_data = ([validation.UserID,validation.MovieID],
                        verbose=1)
```

```
Epoch 1/20
4686/4686 [==============================] - 59s 12ms/step - loss: 14.0455 -
val_loss: 13.9637
Epoch 2/20
4686/4686 [==============================] - 61s 13ms/step - loss: 12.4078 -
val_loss: 9.7863
Epoch 3/20
4686/4686 [==============================] - 58s 12ms/step - loss: 6.4557 - v
al_loss: 3.9350
Epoch 4/20
4686/4686 [==============================] - 58s 12ms/step - loss: 2.7675 - v
al_loss: 2.0785
Epoch 5/20
4686/4686 [==============================] - 61s 13ms/step - loss: 1.6608 - v
al_loss: 1.4246
Epoch 6/20
4686/4686 [==============================] - 69s 15ms/step - loss: 1.2311 - v
al_loss: 1.1426
Epoch 7/20
4686/4686 [==============================] - 65s 14ms/step - loss: 1.0378 - v
al_loss: 1.0070
Epoch 8/20
4686/4686 [==============================] - 65s 14ms/step - loss: 0.9410 - v
al_loss: 0.9358
Epoch 9/20
4686/4686 [==============================] - 77s 16ms/step - loss: 0.8887 - v
al_loss: 0.8958
Epoch 10/20
4686/4686 [==============================] - 74s 16ms/step - loss: 0.8584 - v
al_loss: 0.8721
Epoch 11/20
4686/4686 [==============================] - 73s 15ms/step - loss: 0.8394 - v
al_loss: 0.8575
Epoch 12/20
4686/4686 [==============================] - 71s 15ms/step - loss: 0.8264 - v
al_loss: 0.8475
Epoch 13/20
4686/4686 [==============================] - 73s 16ms/step - loss: 0.8168 - v
al_loss: 0.8397
Epoch 14/20
4686/4686 [==============================] - 81s 17ms/step - loss: 0.8088 - v
al_loss: 0.8337
Epoch 15/20
4686/4686 [==============================] - 83s 18ms/step - loss: 0.8020 - v
al_loss: 0.8287
Epoch 16/20
4686/4686 [==============================] - 70s 15ms/step - loss: 0.7954 - v
al_loss: 0.8241
Epoch 17/20
4686/4686 [==============================] - 72s 15ms/step - loss: 0.7894 - v
al_loss: 0.8197
```

```
Epoch 18/20
4686/4686 [==============================] - 68s 15ms/step - loss: 0.7834 - v
al_loss: 0.8158
Epoch 19/20
4686/4686 [==============================] - 53s 11ms/step - loss: 0.7775 - v
al_loss: 0.8120
Epoch 20/20
4686/4686 [==============================] - 53s 11ms/step - loss: 0.7717 - v
al_loss: 0.8079
```

In [185]:
```
y_pred = model.predict([test.UserID,test.MovieID],verbose=0)
```

Calulating RMSE

In [189]:
```
from sklearn.metrics import mean_squared_error
rmse = mean_squared_error(test.Rating,y_pred,squared=False)
print('Root mean squared error :{:.3f}'.format(rmse))
```

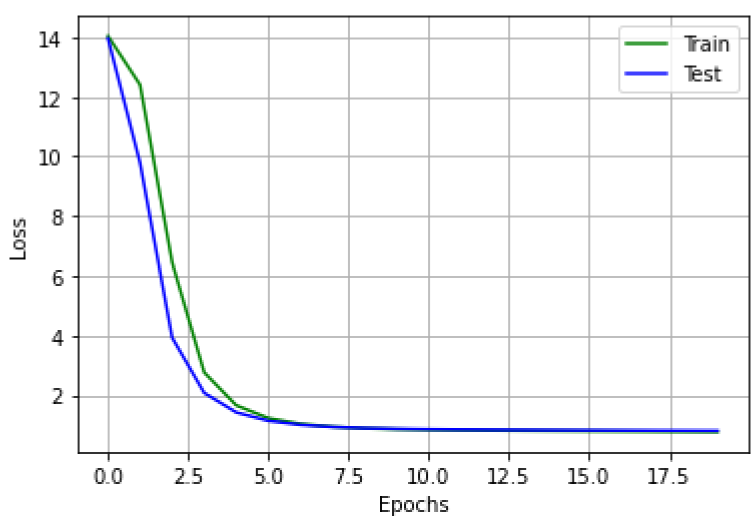
```
Root mean squared error :0.898
```

Calculating MAPE

In [190]:
```
from sklearn.metrics import mean_absolute_percentage_error
mape = mean_absolute_percentage_error(test.Rating,y_pred)
print('Mean absolute Percentage error :{:.3f}'.format(mape))
```

```
Mean absolute Percentage error :0.275
```

In [191]:
```
plt.plot(model_hist.history['loss'],'g')
plt.plot(model_hist.history['val_loss'],'b')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend(['Train','Test'],loc='upper right')
plt.grid(True)
plt.show()
```



In [ ]: