DATA SCIENCE AND VISUALIZATION LABORATORY

Lab Journal

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In [ ]:

```
# Practical No. 1
# Data Science and Visualization

'''Access an open source dataset "Titanic".
Apply pre-processing techniques on the raw dataset.'''
```

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [3]:

```
pd.__version__
```

Out[3]:

```
'1.2.4'
```

In [4]:

```
np.__version__
```

Out[4]:

```
'1.20.1'
```

In [5]:

```
sns.__version__
```

Out[5]:

```
'0.11.1'
```

In [6]:

```
sns.get_dataset_names()
```

Out[6]:

```
['anagrams',
 'anscombe',
 'attention',
 'brain_networks',
 'car_crashes',
 'diamonds',
 'dots',
 'exercise',
 'flights',
 'fmri',
 'gammas',
 'geyser',
 'iris',
 'mpg',
 'penguins',
 'planets',
 'taxis',
 'tips',
 'titanic']
```

In [7]:

```
dataset = sns.load_dataset('titanic')
```

In [8]:

In [8]:

```
dataset
```

Out[8]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
886	0	2	male	27.0	0	0	13.0000	S	Second	man	True	NaN	Southampton	no
887	1	1	female	19.0	0	0	30.0000	S	First	woman	False	B	Southampton	yes
888	0	3	female	NaN	1	2	23.4500	S	Third	woman	False	NaN	Southampton	no
889	1	1	male	26.0	0	0	30.0000	C	First	man	True	C	Cherbourg	yes
890	0	3	male	32.0	0	0	7.7500	Q	Third	man	True	NaN	Queenstown	no

891 rows × 15 columns

In [9]:

```
df = pd.read_csv('https://web.stanford.edu/class/archive/cs/cs109/cs109.1166/stuff/titanic.csv')
```

In [10]:

```
df
```

Out[10]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
0	0	3	Mr. Owen Harris Braund	male	22.0	1	0	7.2500
1	1	1	Mrs. John Bradley (Florence Briggs Thayer) Cum...	female	38.0	1	0	71.2833
2	1	3	Miss. Laina Heikkinen	female	26.0	0	0	7.9250
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1	0	53.1000
4	0	3	Mr. William Henry Allen	male	35.0	0	0	8.0500
...	...	...	...	...	...	...	...	...
882	0	2	Rev. Juozas Montvila	male	27.0	0	0	13.0000
883	1	1	Miss. Margaret Edith Graham	female	19.0	0	0	30.0000
884	0	3	Miss. Catherine Helen Johnston	female	7.0	1	2	23.4500
885	1	1	Mr. Karl Howell Behr	male	26.0	0	0	30.0000
886	0	3	Mr. Patrick Dooley	male	32.0	0	0	7.7500

887 rows × 8 columns

In [11]:

```
import os
os.getcwd()
os.chdir('C:\\Users\\OJUS\\OneDrive\\Desktop\\ \\DS\\Data Set')
os.getcwd()
```

Out[11]:

```
'C:\\Users\\OJUS\\OneDrive\\Desktop\\ \\DS\\Data Set'
```

In [12]:

```
df = pd.read_csv('titanic.csv')
```

In [13]:

```
df
```

Out[13]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
0	0	3	Mr. Owen Harris Braund	male	22.0	1	0	7.2500
1	1	1	Mrs. John Bradley (Florence Briggs Thayer) Cum...	female	38.0	1	0	71.2833
2	1	3	Miss. Laina Heikkinen	female	26.0	0	0	7.9250
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1	0	53.1000
4	0	3	Mr. William Henry Allen	male	35.0	0	0	8.0500
...	...	...	...	...	...	...	...	...
882	0	2	Rev. Juozas Montvila	male	27.0	0	0	13.0000
883	1	1	Miss. Margaret Edith Graham	female	19.0	0	0	30.0000
884	0	3	Miss. Catherine Helen Johnston	female	7.0	1	2	23.4500
885	1	1	Mr. Karl Howell Behr	male	26.0	0	0	30.0000
886	0	3	Mr. Patrick Dooley	male	32.0	0	0	7.7500

887 rows × 8 columns

In [14]:

```
df.columns
```

Out[14]:

```
Index(['Survived', 'Pclass', 'Name', 'Sex', 'Age', 'Siblings/Spouses Aboard',
       'Parents/Children Aboard', 'Fare'],
      dtype='object')
```

In [15]:

```
df.shape
```

Out[15]:

```
(887, 8)
```

In [16]:

```
dataset.shape
```

Out[16]:

```
(891, 15)
```

In [17]:

```
dataset.columns
```

Out[17]:

```
Index(['survived', 'pclass', 'sex', 'age', 'sibsp', 'parch', 'fare',
       'embarked', 'class', 'who', 'adult_male', 'deck', 'embark_town',
```

```
       'alive', 'alone'],
      dtype='object')
```

In [18]:

```
df.head()
```

Out[18]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
0	0	3	Mr. Owen Harris Braund	male	22.0	1	0	7.2500
1	1	1	Mrs. John Bradley (Florence Briggs Thayer) Cum...	female	38.0	1	0	71.2833
2	1	3	Miss. Laina Heikkinen	female	26.0	0	0	7.9250
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1	0	53.1000
4	0	3	Mr. William Henry Allen	male	35.0	0	0	8.0500

In [19]:

```
dataset.head()
```

Out[19]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	Fa
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	Fa
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	Tı
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	Fa
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	Tı

In [20]:

```
df.tail()
```

Out[20]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
882	0	2	Rev. Juozas Montvila	male	27.0	0	0	13.00
883	1	1	Miss. Margaret Edith Graham	female	19.0	0	0	30.00
884	0	3	Miss. Catherine Helen Johnston	female	7.0	1	2	23.45
885	1	1	Mr. Karl Howell Behr	male	26.0	0	0	30.00
886	0	3	Mr. Patrick Dooley	male	32.0	0	0	7.75

In [21]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 887 entries, 0 to 886
Data columns (total 8 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Survived                 887 non-null    int64  
 1   Pclass                   887 non-null    int64  
 2   Name                     887 non-null    object 
 3   Sex                      887 non-null    object 
```

```
 4   Age                        887 non-null    float64
 5   Siblings/Spouses Aboard    887 non-null    int64
 6   Parents/Children Aboard    887 non-null    int64
 7   Fare                       887 non-null    float64
dtypes: float64(2), int64(4), object(2)
memory usage: 55.6+ KB
```

In [22]:

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    object
 3   age          714 non-null    float64
 4   sibsp        891 non-null    int64
 5   parch        891 non-null    int64
 6   fare         891 non-null    float64
 7   embarked     889 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  deck         203 non-null    category
 12  embark_town  889 non-null    object
 13  alive        891 non-null    object
 14  alone        891 non-null    bool
dtypes: bool(2), category(2), float64(2), int64(4), object(5)
memory usage: 80.7+ KB
```

In [23]:

```
dataset.describe()
```

Out[23]:

	survived	pclass	age	sibsp	parch	fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [24]:

```
df.describe()
```

Out[24]:

	Survived	Pclass	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
count	887.000000	887.000000	887.000000	887.000000	887.000000	887.00000
mean	0.385569	2.305524	29.471443	0.525366	0.383315	32.30542
std	0.487004	0.836662	14.121908	1.104669	0.807466	49.78204
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.00000
25%	0.000000	2.000000	20.250000	0.000000	0.000000	7.92500

	Survived	Pclass	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.45420
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.13750
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.32920

In [25]:

```
df.count()
```

Out[25]:

```
Survived                   887
Pclass                     887
Name                       887
Sex                        887
Age                        887
Siblings/Spouses Aboard    887
Parents/Children Aboard    887
Fare                       887
dtype: int64
```

In [26]:

```
dataset.count()
```

Out[26]:

```
survived       891
pclass         891
sex            891
age            714
sibsp          891
parch          891
fare           891
embarked       889
class          891
who            891
adult_male     891
deck           203
embark_town    889
alive          891
alone          891
dtype: int64
```

In [27]:

```
dataset.isnull().sum()
```

Out[27]:

```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
deck           688
embark_town      2
alive            0
alone            0
dtype: int64
```

In [28]:

```
dataset = dataset.drop('deck', axis = 1)
```

In [29]:

```
dataset.isnull().sum()
```

Out[29]:

```
survived         0
pclass           0
sex              0
age            177
sibsp            0
parch            0
fare             0
embarked         2
class            0
who              0
adult_male       0
embark_town      2
alive            0
alone            0
dtype: int64
```

In [30]:

```
dataset['age'] = dataset['age'].fillna(dataset['age'].median())
```

In [31]:

```
dataset.isnull().sum()
```

Out[31]:

```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       2
class          0
who            0
adult_male     0
embark_town    2
alive          0
alone          0
dtype: int64
```

In [32]:

```
dataset['embarked'].mode()[0]
```

Out[32]:

```
'S'
```

In [33]:

```
dataset['embark_town'].mode()[0]
```

Out[33]:

```
'Southampton'
```

In [34]:

```
dataset['embarked'] = dataset['embarked'].fillna(
    dataset['embarked'].mode()[0])
```

In [35]:

```
dataset['embark_town'] = dataset['embark_town'].fillna(
    dataset['embark_town'].mode()[0])
```

In [36]:

```
dataset.isnull().sum()
```

Out[36]:

```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
embark_town    0
alive          0
alone          0
dtype: int64
```

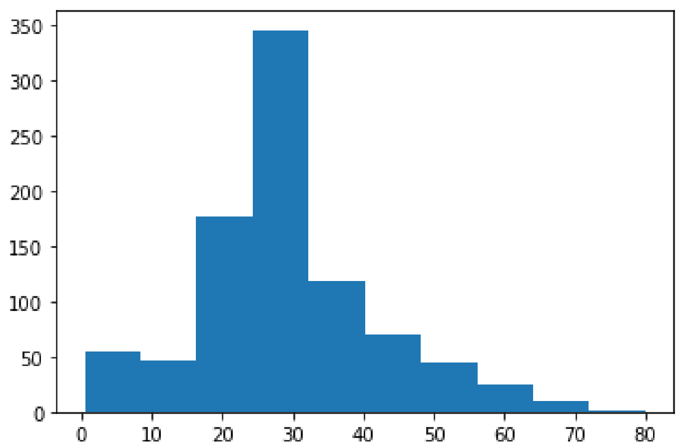
In [37]:

```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype   
---  ------       --------------  -----   
 0   survived     891 non-null    int64   
 1   pclass       891 non-null    int64   
 2   sex          891 non-null    object  
 3   age          891 non-null    float64 
 4   sibsp        891 non-null    int64   
 5   parch        891 non-null    int64   
 6   fare         891 non-null    float64 
 7   embarked     891 non-null    object  
 8   class        891 non-null    category
 9   who          891 non-null    object  
 10  adult_male   891 non-null    bool    
 11  embark_town  891 non-null    object  
 12  alive        891 non-null    object  
 13  alone        891 non-null    bool    
dtypes: bool(2), category(1), float64(2), int64(4), object(5)
memory usage: 79.4+ KB
```

In [38]:

```
plt.hist(dataset['age']);
```

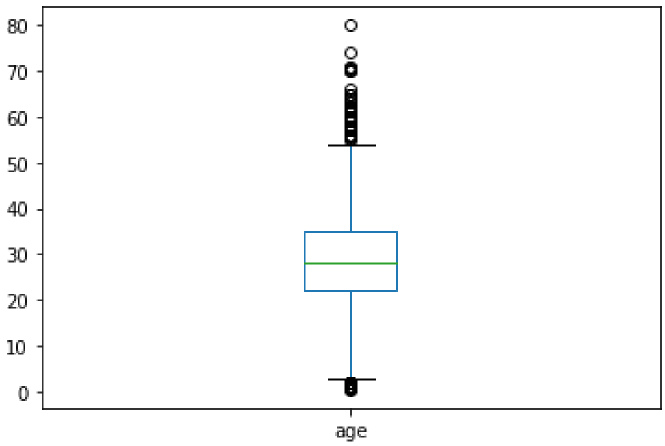


In [39]:

```
dataset['age'].plot(kind='box')
```

Out[39]:

```
<AxesSubplot:>
```

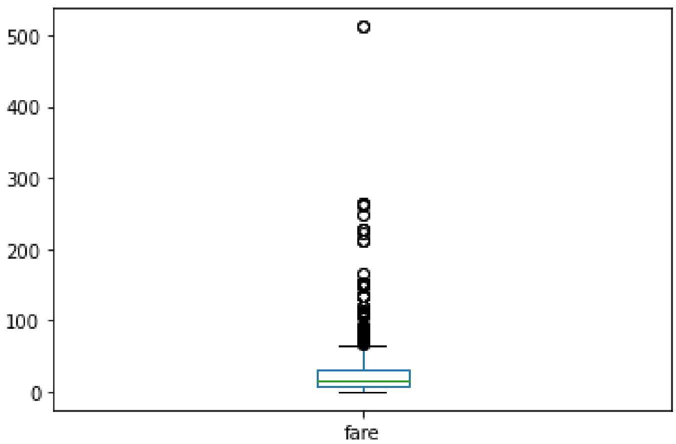


In [40]:

```python
dataset['fare'].plot(kind='box')
```

Out[40]:

```
<AxesSubplot:>
```



In [41]:

```python
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype   
---  ------       --------------  -----   
 0   survived     891 non-null    int64   
 1   pclass       891 non-null    int64   
 2   sex          891 non-null    object  
 3   age          891 non-null    float64 
 4   sibsp        891 non-null    int64   
 5   parch        891 non-null    int64   
 6   fare         891 non-null    float64 
 7   embarked     891 non-null    object  
 8   class        891 non-null    category
 9   who          891 non-null    object  
 10  adult_male   891 non-null    bool    
 11  embark_town  891 non-null    object  
 12  alive        891 non-null    object  
 13  alone        891 non-null    bool    
dtypes: bool(2), category(1), float64(2), int64(4), object(5)
memory usage: 79.4+ KB
```

In [42]:

```python
pd.get_dummies(dataset).head()
```

Out[42]:

	survived	pclass	age	sibsp	parch	fare	adult_male	alone	sex_female	sex_male	...	class_Second	class_Third	whc
0	0	3	22.0	1	0	7.2500	True	False	0	1	...	0	1	
1	1	1	38.0	1	0	71.2833	False	False	1	0	...	0	0	
2	1	3	26.0	0	0	7.9250	False	True	1	0	...	0	1	
3	1	1	35.0	1	0	53.1000	False	False	1	0	...	0	0	
4	0	3	35.0	0	0	8.0500	True	True	0	1	...	0	1	

5 rows × 24 columns

In [43]:

```
from sklearn.model_selection import train_test_split
```

In [44]:

```
train, test = train_test_split(dataset,test_size=0.20)
```

In [45]:

```
len(dataset)
```

Out[45]:

891

In [46]:

```
len(train)
```

Out[46]:

712

In [47]:

```
len(test)
```

Out[47]:

179

In [ ]:

```
```

In [ ]:

```
# Practical No. 2
# Data Science and Visualization

'''Build training and testing dataset of assignment 1 to predict the probability of a sur
vival
of a person based on gender, age and passenger-class.'''
```

In [2]:

```
import numpy as np
import seaborn as sns
import pandas as pd
```

In [3]:

```
ds = sns.load_dataset('titanic')
```

In [4]:

```
ds.head()
```

Out[4]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult_male	deck	embark_town	alive	alo
0	0	3	male	22.0	1	0	7.2500	S	Third	man	True	NaN	Southampton	no	Fa
1	1	1	female	38.0	1	0	71.2833	C	First	woman	False	C	Cherbourg	yes	Fa
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	False	NaN	Southampton	yes	Tı
3	1	1	female	35.0	1	0	53.1000	S	First	woman	False	C	Southampton	yes	Fa
4	0	3	male	35.0	0	0	8.0500	S	Third	man	True	NaN	Southampton	no	Tı

In [5]:

```
len(ds)
```

Out[5]:

891

In [6]:

```
ds['age'] = ds['age'].fillna(ds['age'].median())
# Data Cleaning

x = ds['age'].values  #input
y = ds['survived'] #output
```

In [7]:

```
x = x.reshape(-1,1)
x.shape
```

Out[7]:

(891, 1)

In [8]:

```
from sklearn.model_selection import train_test_split
```

In [9]:

```
x_train,x_test,y_train,y_test=train_test_split(
```

```
    x, y, random_state = 0, test_size = 0.25)
# build train and test
```

In [10]:

```
len(x_train)
```

Out[10]:

```
668
```

In [11]:

```
len(x_test)
```

Out[11]:

```
223
```

In [12]:

```
from collections import Counter
```

In [13]:

```
Counter(y)
```

Out[13]:

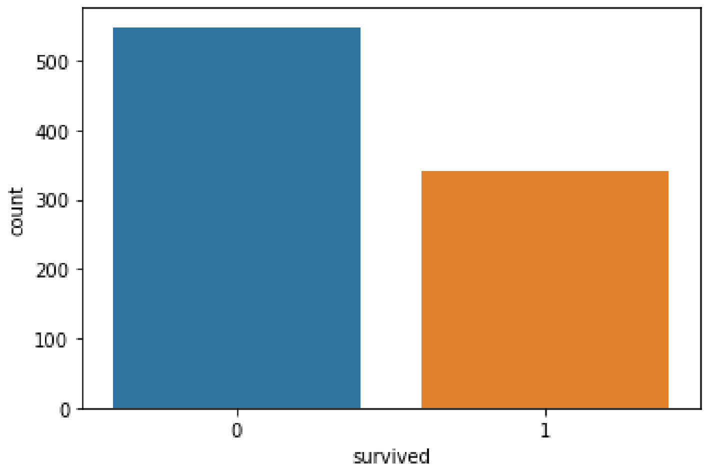
```
Counter({0: 549, 1: 342})
```

In [14]:

```
sns.countplot(x=y)
```

Out[14]:

```
<AxesSubplot:xlabel='survived', ylabel='count'>
```



In [15]:

```
from sklearn.naive_bayes import GaussianNB
```

In [16]:

```
model = GaussianNB()
```

In [17]:

```
# train the algorithm with given training data
model.fit(x_train, y_train)
```

Out[17]:

```
GaussianNB()
```

In [18]:

```
y_pred = model.predict_proba(x_test)
```

In [19]:

```
y_pred
```

Out[19]:

```
array([[0.62876821, 0.37123179],
       [0.62876821, 0.37123179],
       [0.51657653, 0.48342347],
       [0.62876821, 0.37123179],
       [0.63148867, 0.36851133],
       [0.62876821, 0.37123179],
       [0.64689984, 0.35310016],
       [0.63625703, 0.36374297],
       [0.6192395 , 0.3807605 ],
       [0.62876821, 0.37123179],
       [0.62264556, 0.37735444],
       [0.64689984, 0.35310016],
       [0.62876821, 0.37123179],
       [0.51657653, 0.48342347],
       [0.61560095, 0.38439905],
       [0.56600603, 0.43399397],
       [0.61172787, 0.38827213],
       [0.59385049, 0.40614951],
       [0.64314813, 0.35685187],
       [0.45943048, 0.54056952],
       [0.58877545, 0.41122455],
       [0.60761825, 0.39238175],
       [0.62876821, 0.37123179],
       [0.62876821, 0.37123179],
       [0.60761825, 0.39238175],
       [0.64689984, 0.35310016],
       [0.63830829, 0.36169171],
       [0.60761825, 0.39238175],
       [0.6192395 , 0.3807605 ],
       [0.47403058, 0.52596942],
       [0.64013966, 0.35986034],
       [0.63835894, 0.36164106],
       [0.62876821, 0.37123179],
       [0.62876821, 0.37123179],
       [0.63148867, 0.36851133],
       [0.63830829, 0.36169171],
       [0.64658851, 0.35341149],
       [0.62876821, 0.37123179],
       [0.6192395 , 0.3807605 ],
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       [0.59385049, 0.40614951],
       [0.6032701 , 0.3967299 ],
       [0.49173773, 0.50826227]])
```

In [20]:

```
y_pred = model.predict(x_test)
from sklearn.metrics import accuracy_score
```

In [21]:

```
accuracy_score(y_test, y_pred) * 100
```

Out[21]:

```
65.47085201793722
```

In [22]:

```
x = ds['pclass'].values
y = ds['survived']
x = x.reshape(-1,1)
```

In [23]:

```
x_train,x_test,y_train,y_test=train_test_split(
    x, y, random_state = 0, test_size = 0.25)
# build train and test
```

In [24]:

```
model = GaussianNB()
model.fit(x_train, y_train)
```

Out[24]:

```
GaussianNB()
```

In [25]:

```
model.predict_proba(x_test);
```

In [26]:

```
y_pred = model.predict(x_test)
```

In [27]:

```
accuracy_score(y_test, y_pred) * 100
```

Out[27]:

```
70.85201793721974
```

In [28]:

```
x = ds[['sex','pclass']]
y = ds['survived']
```

In [29]:

```
from sklearn.preprocessing import LabelEncoder
enc = LabelEncoder()
x['sex'] = enc.fit_transform(x['sex'])
```

```
<ipython-input-29-61f95b308646>:3: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_g
uide/indexing.html#returning-a-view-versus-a-copy
  x['sex'] = enc.fit_transform(x['sex'])
```

In [30]:

```
#x =  x.reshape(-1,1)
```

In [31]:

```
x_train,x_test,y_train,y_test=train_test_split(
    x, y, random_state = 0, test_size = 0.25)
# build train and test
model = GaussianNB()
model.fit(x_train, y_train)
```

Out[31]:

```
GaussianNB()
```

In [32]:

```
model.predict_proba(x_test);
```

In [33]:

```
y_pred = model.predict(x_test)
accuracy_score(y_test, y_pred) * 100
```

Out[33]:

```
78.02690582959642
```

In [ ]:

```

```

In [ ]:

```
# Practical No. 3
# Data Science and Visualization

'''Download Abalone dataset. (URL: http://archive.ics.uci.edu/ml/datasets/Abalone)
   Data set has total 8 Number of Attributes.
   Load the data from data file and split it into training and test datasets. Summarize t
he properties in the training dataset.
   The number of rings is the value to predict: either as a continuous value or as a clas
sification problem.
   Predict the age of abalone from physical measurements using linear regression or predi
ct ring class as classification
   problem.'''
```

In [2]:

```
import pandas as pd
```

In [3]:

```
col = ['sex','length','diameter','height','weight','sweight',
       'vweight','shweight','rings']
df = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/abalone/abalon
e.data', names=col)
```

In [4]:

```
df.head()
```

Out[4]:

	sex	length	diameter	height	weight	sweight	vweight	shweight	rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

In [5]:

```
df.describe()
```

Out[5]:

	length	diameter	height	weight	sweight	vweight	shweight	rings
count	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
mean	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	9.933684
std	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
min	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	1.000000
25%	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	8.000000
50%	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	9.000000
75%	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	11.000000
max	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	29.000000

In [6]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4177 entries, 0 to 4176
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   sex       4177 non-null   object 
 1   length    4177 non-null   float64
 2   diameter  4177 non-null   float64
 3   height    4177 non-null   float64
 4   weight    4177 non-null   float64
 5   sweight   4177 non-null   float64
 6   vweight   4177 non-null   float64
 7   shweight  4177 non-null   float64
 8   rings     4177 non-null   int64  
dtypes: float64(7), int64(1), object(1)
memory usage: 293.8+ KB
```

In [7]:

```
X = df.drop('rings', axis=1) #input
y = df['rings']    #output
```

In [8]:

```
X.head()
```

Out[8]:

	sex	length	diameter	height	weight	sweight	vweight	shweight
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055

In [9]:

```
from collections import Counter
Counter(y)
```

Out[9]:

```
Counter({15: 103,
         7: 391,
         9: 689,
         10: 634,
         8: 568,
         20: 26,
         16: 67,
         19: 32,
         14: 126,
         11: 487,
         12: 267,
         18: 42,
         13: 203,
         5: 115,
         4: 57,
         6: 259,
         21: 14,
         17: 58,
         22: 6,
         1: 1,
         3: 15,
         26: 1,
         23: 9,
         29: 1,
         2: 1,
         27: 2,
```

```
25: 1,
24: 2})
```

In [10]:

```
set(X['sex'])
```

Out[10]:

```
{'F', 'I', 'M'}
```

In [11]:

```
from sklearn.preprocessing import LabelEncoder
enc = LabelEncoder()
X['sex'] = enc.fit_transform(X['sex'])
```

In [12]:

```
set(X['sex'])
```

Out[12]:

```
{0, 1, 2}
```

In [13]:

```
df.head()
```

Out[13]:

	sex	length	diameter	height	weight	sweight	vweight	shweight	rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

In [14]:

```
from sklearn.model_selection import train_test_split
```

In [15]:

```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, random_state = 0, test_size = 0.25)
```

In [16]:

```
len(X_train)
```

Out[16]:

```
3132
```

In [17]:

```
len(X_test)
```

Out[17]:

```
1045
```

In [18]:

```
X_train.head()
```

Out[18]:

	sex	length	diameter	height	weight	sweight	vweight	shweight
940	1	0.460	0.345	0.105	0.4490	0.1960	0.0945	0.1265
2688	2	0.630	0.465	0.150	1.0270	0.5370	0.1880	0.1760
1948	2	0.635	0.515	0.165	1.2290	0.5055	0.2975	0.3535
713	2	0.355	0.265	0.085	0.2010	0.0690	0.0530	0.0695
3743	0	0.705	0.555	0.195	1.7525	0.7105	0.4215	0.5160

In [19]:

```
from sklearn.naive_bayes import GaussianNB
```

In [20]:

```
clf = GaussianNB()
```

In [21]:

```
# train
clf.fit(X_train, y_train)
```

Out[21]:

```
GaussianNB()
```

In [22]:

```
y_pred = clf.predict(X_test)
```

In [23]:

```
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
```

In [24]:

```
accuracy_score(y_test, y_pred) * 100
```

Out[24]:

```
26.02870813397129
```

In [25]:

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           3       0.50      1.00      0.67         7
           4       0.30      0.62      0.40        13
           5       0.27      0.42      0.33        40
           6       0.32      0.43      0.36        63
           7       0.26      0.36      0.30       114
           8       0.27      0.29      0.28       139
           9       0.25      0.30      0.27       152
          10       0.21      0.24      0.23       139
          11       0.26      0.42      0.32       121
          12       0.50      0.01      0.02        93
          13       0.00      0.00      0.00        51
          14       0.00      0.00      0.00        32
          15       0.00      0.00      0.00        22
          16       0.00      0.00      0.00        16
          17       0.00      0.00      0.00        12
          18       0.00      0.00      0.00         6
          19       0.00      0.00      0.00        10
          20       0.00      0.00      0.00         8
          21       0.00      0.00      0.00         2
          22       0.00      0.00      0.00         1
          23       0.00      0.00      0.00         2
```

```
          24       0.00      0.00      0.00         1
          27       0.00      0.00      0.00         0
          29       0.00      0.00      0.00         1

    accuracy                           0.26      1045
   macro avg       0.13      0.17      0.13      1045
weighted avg       0.24      0.26      0.22      1045
```

```
D:\Program Files\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Und
efinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Program Files\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Und
efinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels wi
th no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Program Files\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Und
efinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Program Files\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Und
efinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels wi
th no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Program Files\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Und
efinedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
D:\Program Files\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Und
efinedMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels wi
th no true samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [26]:

```
from sklearn.linear_model import LinearRegression
```

In [27]:

```
reg = LinearRegression()
```

In [28]:

```
reg.fit(X_train, y_train)
```

Out[28]:

```
LinearRegression()
```

In [29]:

```
y_pred = reg.predict(X_test)
```

In [30]:

```
y_pred
```

Out[30]:

```
array([13.10451425,  9.66747548, 10.35605247, ...,  9.95962005,
       12.59111443, 12.18516586])
```

In [31]:

```
from sklearn.metrics import mean_absolute_error
```

In [32]:

```
mean_absolute_error(y_test, y_pred)
```

Out[32]:

```
1.5955158378194023
```

In [33]:

```
from sklearn.metrics import r2_score
```

In [34]:

```
r2_score(y_test, y_pred)
```

Out[34]:

```
0.5354158501894077
```

In [ ]:

```

```

In [ ]:

```
# Practical No. 4
# Data Science and Visualization

'''Use Netflix Movies and TV Shows dataset from Kaggle and perform following operation :
   1. Make a visualization showing the total number of movies watched by children
   2. Make a visualization showing the total number of standup comedies
   3. Make a visualization showing most watched shows.
   4. Make a visualization showing highest rated show.
   Make a dashboard (DASHBOARD A) containing all of these above visualizations.'''
```

In [2]:

```
import pandas as pd
```

In [3]:

```
df = pd.read_csv('C:\\Users\\OJUS\\OneDrive\\Desktop\\ \\DS\\Data Set\\netflix_titles.cs
v')
```

In [4]:

```
df.shape
```

Out[4]:

```
(7787, 13)
```

In [5]:

```
categories = df['listed_in']
```

In [6]:

```
total_child = sum(df['listed_in'].str.contains('Child'))
```

In [7]:

```
total_child
```

Out[7]:

```
532
```

In [8]:

```
standup_comedies = sum(df['listed_in'].str.contains('Stand'))
```

In [9]:

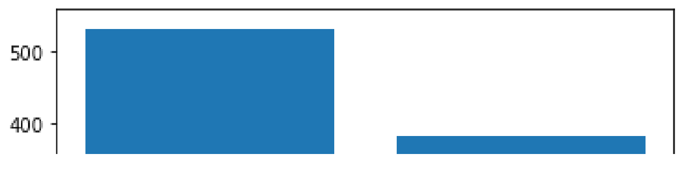
```
standup_comedies
```

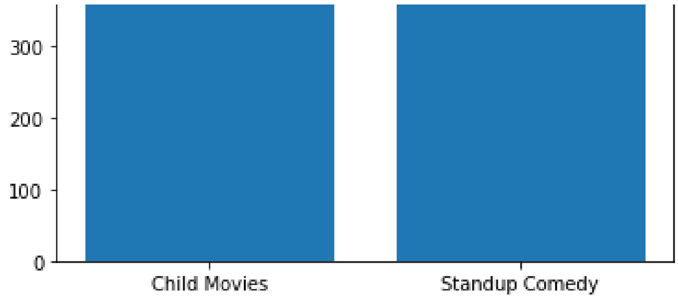
Out[9]:

```
381
```

In [10]:

```
import matplotlib.pyplot as plt
plt.bar(['Child Movies','Standup Comedy'],
        [total_child, standup_comedies])
plt.show()
```





In [11]:

```
set(df['type'])
```

Out[11]:

```
{'Movie', 'TV Show'}
```

In [12]:

```
tv_shows = df[df['type'] == 'TV Show']   # Boolean filtering
```

In [13]:

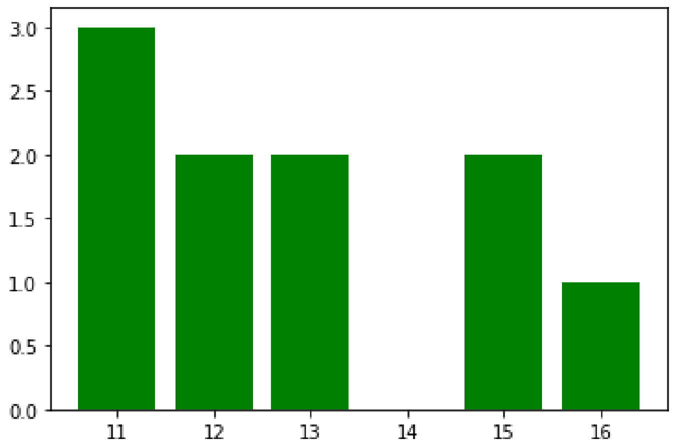
```
seasons13 = tv_shows[tv_shows['duration'] == '13 Seasons']
seasons15 = tv_shows[tv_shows['duration'] == '15 Seasons']
seasons16 = tv_shows[tv_shows['duration'] == '16 Seasons']
seasons12 = tv_shows[tv_shows['duration'] == '12 Seasons']
seasons11 = tv_shows[tv_shows['duration'] == '11 Seasons']
```

In [14]:

```
plt.bar([11,12,13,15,16],
         [len(seasons11),len(seasons12),len(seasons13),
          len(seasons15),len(seasons16)],
        color='green')
```

Out[14]:

```
<BarContainer object of 5 artists>
```



In [15]:

```
from collections import Counter
ratings = Counter(df['rating'])
```

In [16]:

```
ratings = dict(ratings)
```

In [17]:

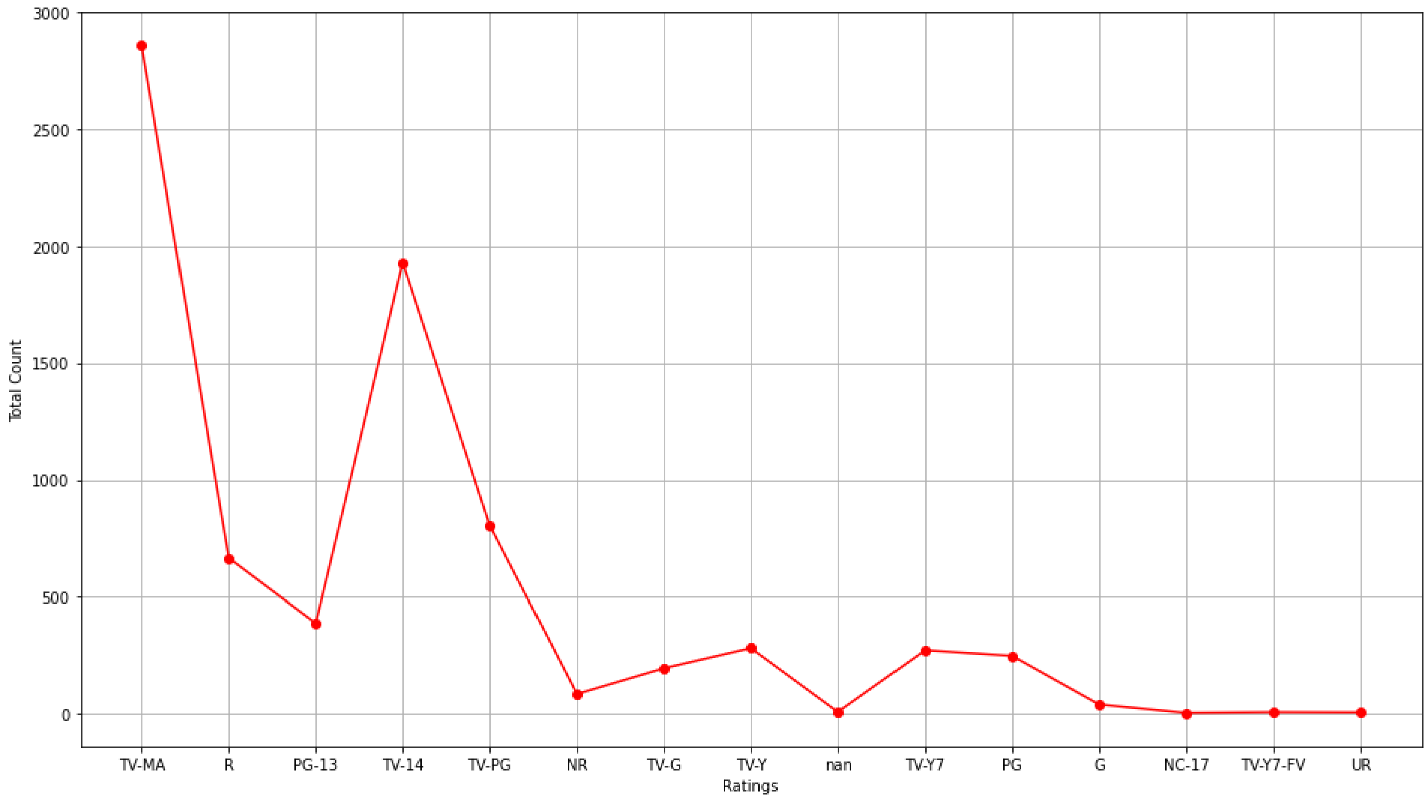
```
ratings
```

Out[17]:

```
{'TV-MA': 2863,
 'R': 665,
 'PG-13': 386,
 'TV-14': 1931,
 'TV-PG': 806,
 'NR': 84,
 'TV-G': 194,
 'TV-Y': 280,
 nan: 7,
 'TV-Y7': 271,
 'PG': 247,
 'G': 39,
 'NC-17': 3,
 'TV-Y7-FV': 6,
 'UR': 5}
```

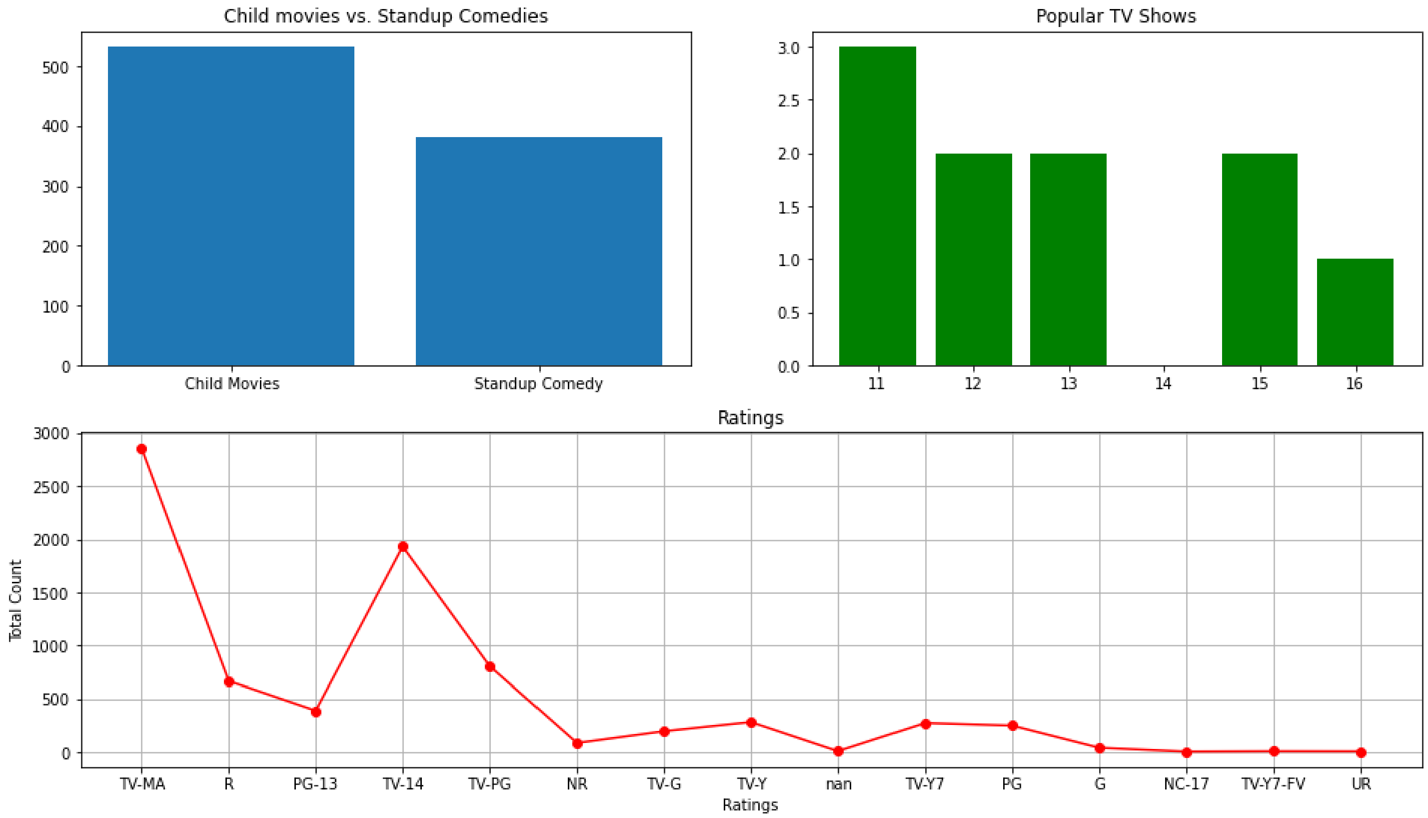
In [18]:

```
plt.figure(figsize=(16,9))
plt.plot(ratings.keys(), ratings.values(), color = 'red', marker='o')
plt.xlabel('Ratings');     plt.ylabel('Total Count')
plt.grid()
```



In [19]:

```
plt.figure(figsize=(16,9))
#plot1
plt.subplot(2,2,1)
plt.title('Child movies vs. Standup Comedies')
plt.bar(['Child Movies','Standup Comedy'],
        [total_child, standup_comedies])
#plot2
plt.subplot(2,2,2)
plt.title('Popular TV Shows')
plt.bar([11,12,13,15,16],
        [len(seasons11),len(seasons12),len(seasons13),
         len(seasons15),len(seasons16)],
       color='green')
#plot3
plt.subplot(2,1,2)
plt.title('Ratings')
plt.plot(ratings.keys(), ratings.values(), color = 'red', marker='o')
plt.xlabel('Ratings');     plt.ylabel('Total Count')
plt.grid()
```


Child movies vs. Standup Comedies
0
100
200
300
400
500
Child Movies
Standup Comedy
Popular TV Shows
0.0
0.5
1.0
1.5
2.0
2.5
3.0
11
12
13
14
15
16
Ratings
Total Count
0
500
1000
1500
2000
2500
3000
TV-MA
R
PG-13
TV-14
TV-PG
NR
TV-G
TV-Y
nan
TV-Y7
PG
G
NC-17
TV-Y7-FV
UR
Ratings

In [ ]: