Titanic Survival Data

Data dictionary

- survival - Survival (0 = No, 1 = Yes)
- pclass - Ticket class (1 = 1st, 2 = 2nd, 3 = 3rd)
- sex - Sex
- Age - Age in years
- sibsp - No of siblings / spouses aboard the Titanic
- parch - No of parents / children aboard the Titanic
- ticket - Ticket number
- fare - Passenger fare
- cabin - Cabin number
- embarked - Port of Embarkation (C = Cherbourg, Q = Queenstown, S = Southampton)

Importing Library

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

%matplotlib inline
```

Data Preprocessing

In [2]:
```python
ds = pd.read_csv('train.csv')
ds.head()
```

Out[2]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [3]:
```python
# Remove possible unrelated column and bad data column
ds = ds.drop(['PassengerId', 'Name', 'Ticket', 'Fare', 'Cabin', 'Embarked'], axis = 1)
```

In [4]:
```python
ds.head()
```

Out[4]:

	Survived	Pclass	Sex	Age	SibSp	Parch
0	0	3	male	22.0	1	0
1	1	1	female	38.0	1	0
2	1	3	female	26.0	0	0
3	1	1	female	35.0	1	0
4	0	3	male	35.0	0	0

In [5]:
```python
#Combine column that are related
ds['Family Onboard'] = ds.SibSp.astype(int) + ds.Parch.astype(int)
ds = ds.drop(['SibSp','Parch'],axis=1)
```

In [6]:
```
ds.head()
```

Out[6]:

	Survived	Pclass	Sex	Age	Family Onboard
0	0	3	male	22.0	1
1	1	1	female	38.0	1
2	1	3	female	26.0	0
3	1	1	female	35.0	1
4	0	3	male	35.0	0

In [7]:
```
#Find null column
ds.isnull().sum()
```

Out[7]:
```
Survived            0
Pclass              0
Sex                 0
Age               177
Family Onboard      0
dtype: int64
```

In [8]:
```
ds.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 5 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   Family Onboard  891 non-null    int32  
dtypes: float64(1), int32(1), int64(2), object(1)
memory usage: 31.4+ KB
```

In [9]:
```
#Replace missing value using simpler imputer with mean strategy
ds['Age'].fillna(ds['Age'].mean(),inplace=True)
```

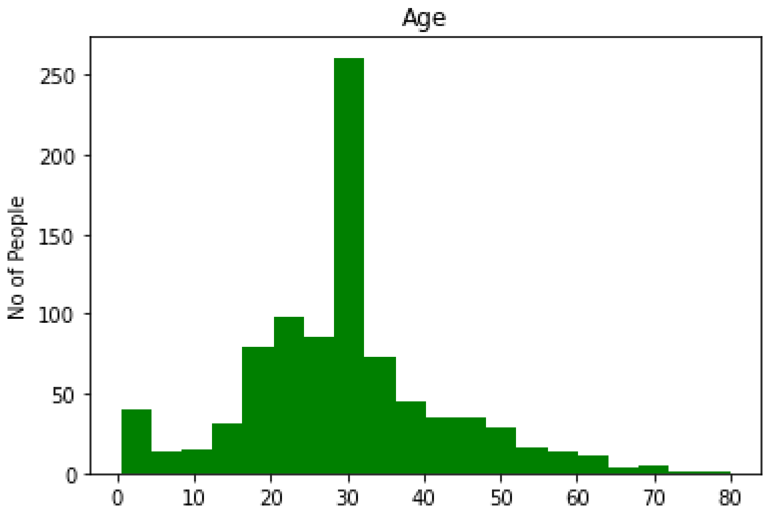
In [10]:
```
ds.isnull().sum()
```

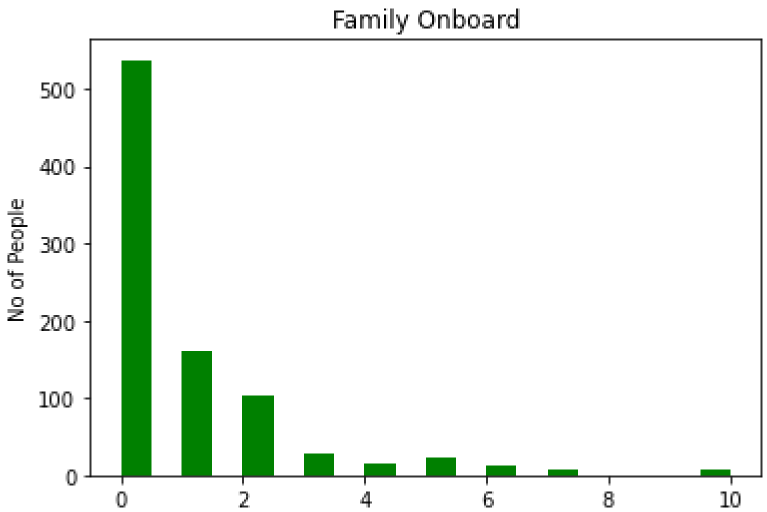
Out[10]:
```
Survived          0
Pclass            0
Sex               0
Age               0
Family Onboard    0
dtype: int64
```

EDA

In [11]:
```
#Seperate numerical and categorical values
ds_num = ds[['Age', 'Family Onboard']]
ds_cat = ds[['Survived','Pclass','Sex']]
```

In [12]:
```
for i in ds_num.columns:
    plt.hist(ds_num[i], color = 'green', bins = 20)
    plt.title(i)
    plt.ylabel('No of People')
    plt.show()
```



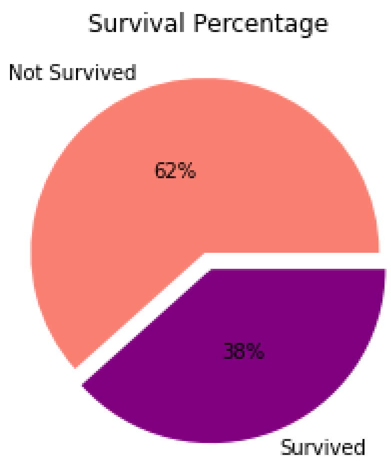


In [13]:
```
print('Oldest Passenger: ', ds.Age.max())
print(f'Youngest Passenger: {ds.Age.min() * 12} months')
print('Most Passenger Age: ', ds.Age.mode())
```

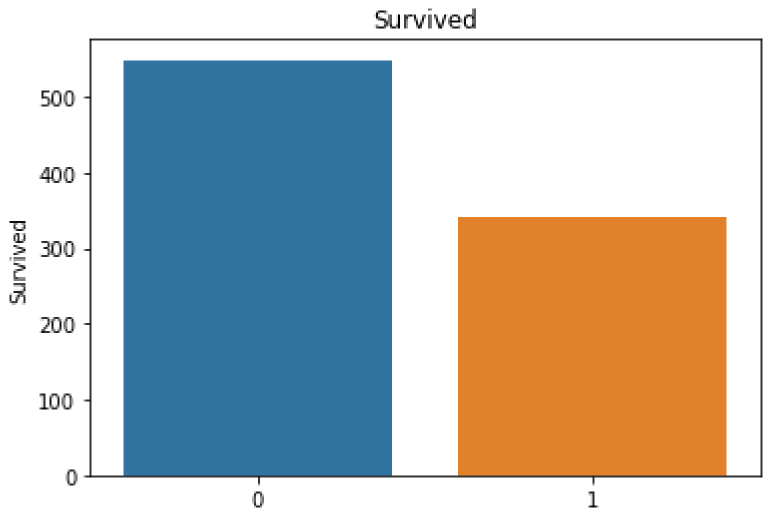
```
Oldest Passenger:  80.0
Youngest Passenger: 5.04 months
Most Passenger Age:  0    29.699118
dtype: float64
```

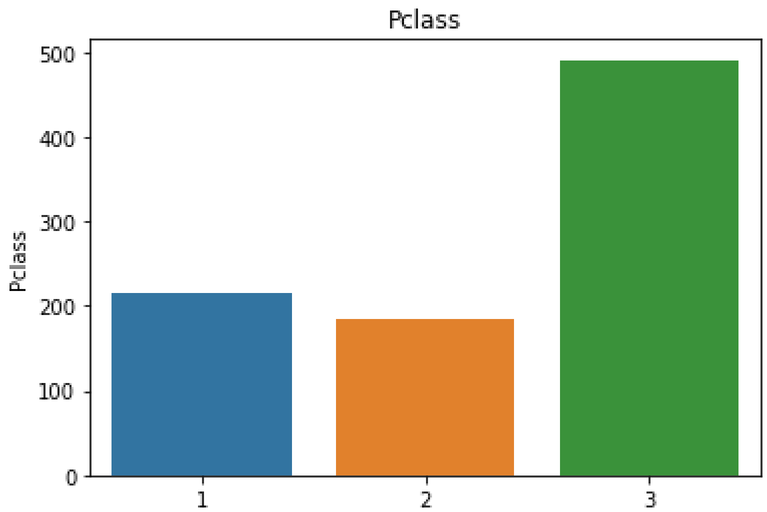
- Most of the passenger age is 29 years old. The most oldest passenger is 80 years old while the youngest passenger is 5 month old.
- Most of the passenger does not have and family member or spouse onboard. Maximum no of family member or spouse on bord is 9 people.

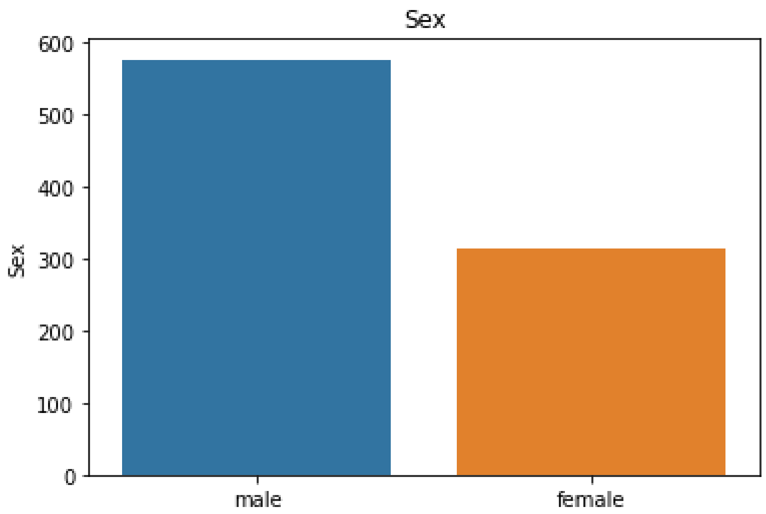
In [14]:
```
plt.pie(ds.Survived.value_counts(), autopct='%1.0f%%', explode=[0.05]*2, labels = ['Not Survived', 'Survived'], pctdista
plt.title('Survival Percentage')
plt.show()
```



In [15]:
```
for i in ds_cat.columns:
    sns.barplot(ds_cat[i].value_counts().index, ds_cat[i].value_counts()).set_title (i)
    plt.show()
```







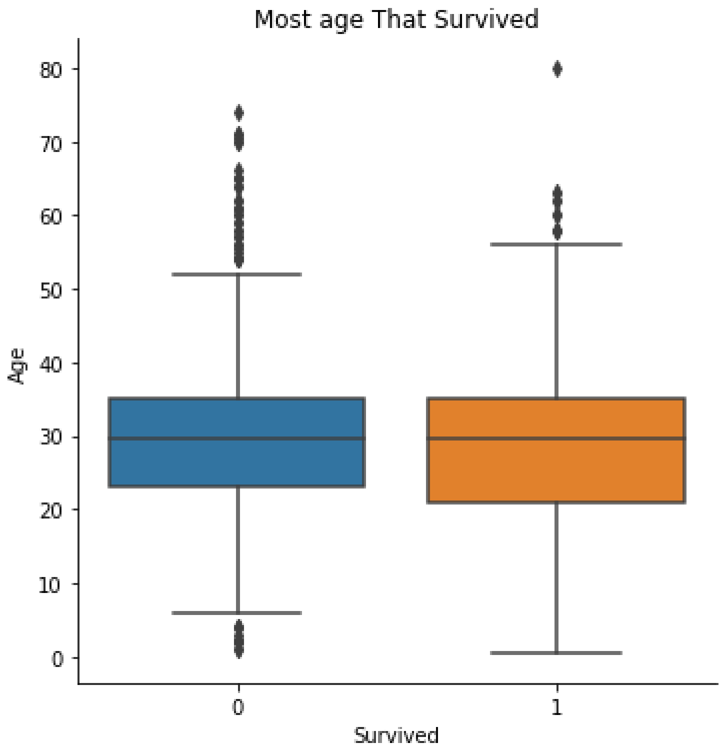
- From the pie chart, only 38% of the passenger survive the tragedy.
- Most of the passenger is 3rd Class passenger.
- Male passenger is the most passenger for Titanic.

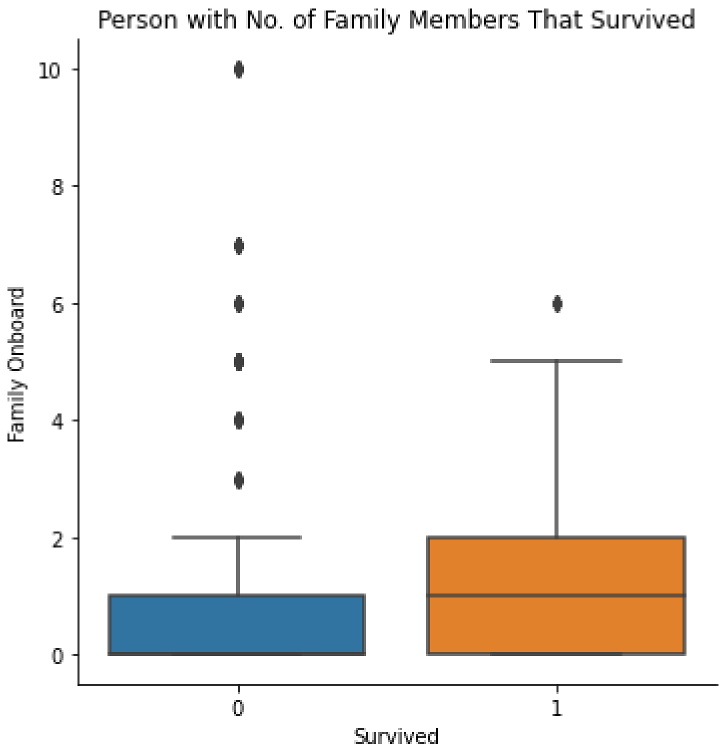
Visualizing numerical data with output

In [16]:
```
sns.catplot(x='Survived', y ='Age', data = ds, kind = 'box')
plt.title('Most age That Survived')

sns.catplot(x='Survived', y ='Family Onboard', data = ds, kind = 'box')
plt.title('Person with No. of Family Members That Survived')
```

Out[16]:
```
Text(0.5, 1.0, 'Person with No. of Family Members That Survived')
```





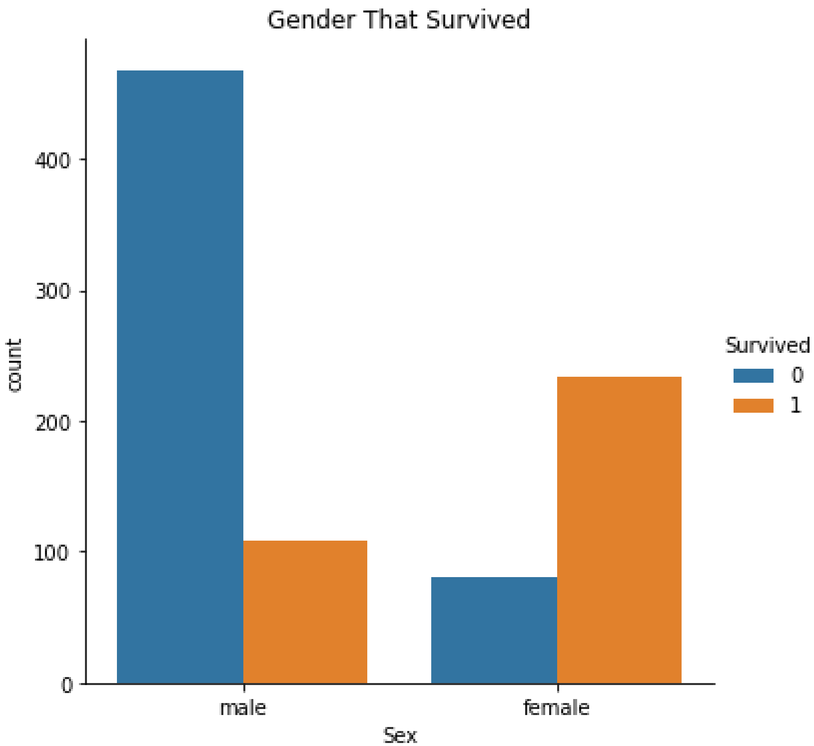
- Most passenger that survived the tragedy has age range from 20 years old until 35 years old.
- Most passenger that have 0 until 2 family member onboard survived the tragedy while most passenger that have more than 2 family member onboard did not survived the tragedy

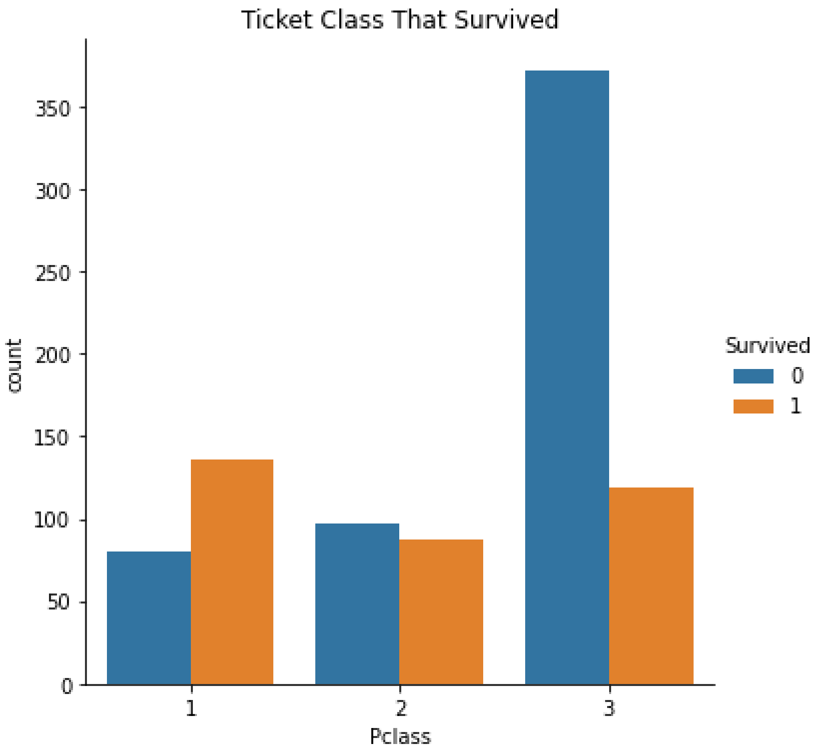
Visualizing categorical data with output

In [17]:
```
sns.catplot(x = 'Sex', data = ds, kind = 'count', hue = 'Survived')
plt.title('Gender That Survived')

sns.catplot(x = 'Pclass', data = ds, kind = 'count', hue = 'Survived')
plt.title('Ticket Class That Survived')
```

Out[17]:
```
Text(0.5, 1.0, 'Ticket Class That Survived')
```





- Most female passenger survived the tragedy
- First class passenger have the highest percentage of survival rather than second and third class passenger.

Machine Learning

Seperate input and ouput variable

In [113]:
```
X = ds.iloc[:,1:].values
y = ds.iloc[:,0].values
X
```

Out[113]:
```
array([[3, 'male', 22.0, 1],
       [1, 'female', 38.0, 1],
       [3, 'female', 26.0, 0],
       ...,
       [3, 'female', 29.69911764705882, 3],
       [1, 'male', 26.0, 0],
       [3, 'male', 32.0, 0]], dtype=object)
```

Change gender into numeric value using Label Encoder

In [114]:
```
from sklearn.preprocessing import LabelEncoder

labelencoder_X = LabelEncoder()
X[:, 1] = labelencoder_X.fit_transform(X[:, 1])

X
```

Out[114]:
```
array([[3, 1, 22.0, 1],
       [1, 0, 38.0, 1],
       [3, 0, 26.0, 0],
       ...,
       [3, 0, 29.69911764705882, 3],
       [1, 1, 26.0, 0],
       [3, 1, 32.0, 0]], dtype=object)
```

Seperate data into train and test

In [115]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
```

Feature scaling

In [128]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.fit_transform(X_test)
```

Naive Bayes

In [22]:
```
from sklearn.naive_bayes import GaussianNB
classifierNB = GaussianNB()
classifierNB = classifierNB.fit(X_train,y_train)
```

In [23]:
```
y_pred = classifierNB.predict(X_test)
```

In [24]:
```
from sklearn.metrics import confusion_matrix

cmNB = confusion_matrix(y_test, y_pred)
print(cmNB)
```

```
[[96 14]
 [20 49]]
```

In [25]:
```
from sklearn.metrics import accuracy_score
ACC_NB = accuracy_score(y_test, y_pred)*100
print('The accurancy score is ', ACC_NB)
model_acc={}
model_acc['Naive Bayes'] = ACC_NB
```

```
The accurancy score is  81.00558659217877
```

Logistic regression

In [26]:
```
from sklearn.linear_model import LogisticRegression
classifierLR = LogisticRegression(random_state=0)
classifierLR.fit(X_train,y_train)
```

Out[26]:
```
LogisticRegression(random_state=0)
```

In [27]:
```
y_pred = classifierLR.predict(X_test)
```

In [28]:
```
cmLR = confusion_matrix(y_test, y_pred)
print(cmLR)
```

```
[[97 13]
 [23 46]]
```

In [29]:
```
from sklearn.metrics import accuracy_score
ACC_LR = accuracy_score(y_test, y_pred)*100
print('The accurancy score is ', ACC_LR)
model_acc['Logistic Regression'] = ACC_LR
```

```
The accurancy score is  79.88826815642457
```

K Nearest Neighbours

In [30]:
```
from sklearn.neighbors import KNeighborsClassifier

classifierKNN = KNeighborsClassifier(n_neighbors=9, metric='minkowski',p=2)
classifierKNN.fit(X_train,y_train)
y_pred=classifierKNN.predict(X_test)
cmKNN = confusion_matrix(y_test,y_pred)
print(cmKNN)
```

```
[[100  10]
 [ 21  48]]
```

In [31]:
```
from sklearn.metrics import accuracy_score
ACC_KNN = accuracy_score(y_test, y_pred)*100
print('The accurancy score is ', ACC_KNN)
model_acc['K Nearest Neighbour'] = ACC_KNN
```

```
The accurancy score is  82.68156424581005
```

Support Vector Machine

In [32]:
```
from sklearn.svm import SVC
classifierSVC = SVC(kernel='rbf', random_state=0) #kernel can be changed to increase accurancy
classifierSVC.fit(X_train,y_train)
y_pred = classifierSVC.predict(X_test)
cmSVC = confusion_matrix(y_test,y_pred)
print(cmSVC)
```

```
[[99 11]
 [23 46]]
```

In [33]:
```
from sklearn.metrics import accuracy_score
ACC_SVC = accuracy_score(y_test, y_pred)*100
print('The accuracy score is ', ACC_SVC)
model_acc['Support Vector Machine'] = ACC_SVC
```

```
The accuracy score is  81.00558659217877
```

Random Forest

In [34]:
```
from sklearn.ensemble import RandomForestClassifier

classifierRFC = RandomForestClassifier(n_estimators = 20, criterion = 'entropy', random_state=0)
classifierRFC.fit(X_train, y_train)
y_pred = classifierRFC.predict(X_test)
cmRFC = confusion_matrix(y_test,y_pred)
print(cmRFC)
```

```
[[99 11]
 [21 48]]
```

In [35]:
```
from sklearn.metrics import accuracy_score
ACC_RFC = accuracy_score(y_test, y_pred)*100
print('The accurancy score is ', ACC_RFC)
model_acc['Random Forest Classification'] = ACC_RFC
```

```
The accurancy score is  82.12290502793296
```

Desicion Tree

In [36]:
```
from sklearn.tree import DecisionTreeClassifier
classifierDT = DecisionTreeClassifier(criterion='entropy', random_state=0)
classifierDT.fit(X_train, y_train)
y_pred = classifierDT.predict(X_test)
cmDT = confusion_matrix(y_test, y_pred)
print(cmDT)
ACC_DT = accuracy_score(y_test, y_pred)*100
print('The accurancy score is ', ACC_DT)
model_acc['Decision Tree'] = ACC_DT
```

```
[[99 11]
 [22 47]]
The accurancy score is  81.56424581005587
```

XGBOOST

In [129]:
```
import xgboost as xgb

clf= xgb.XGBClassifier(max_depth=3, n_estimators=100, colsample_bytree=1.0, subsample=1.0, learning_rate=0.12)
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
```

```
[13:32:47] WARNING: ..\src\learner.cc:1095: Starting in XGBoost 1.3.0, the default evaluation metric used with the obje
ctive 'binary:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
```

In [130]:
```
cmXG = confusion_matrix(y_test,y_pred)
print(cmXG)
```

```
[[102   8]
 [ 22  47]]
```

In [131]:
```
ACC_XG = accuracy_score(y_test, y_pred)*100
print('The accurancy score is ', ACC_XG)
model_acc['XGBoost'] = ACC_XG
```

```
The accurancy score is  83.24022346368714
```

Artificial Neural Network

In [67]:
```
import tensorflow as tf

ann = tf.keras.models.Sequential()
ann.add(tf.keras.layers.Dense(units=10, activation='relu')) #input layer and first hidden layer
ann.add(tf.keras.layers.Dense(units=10, activation='relu')) #second hidden layer
ann.add(tf.keras.layers.Dense(units=1, activation='sigmoid')) #output layer
```

In [68]:
```python
ann.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
ann.fit(X_train, y_train, batch_size = 32, epochs = 100)
```

```
Epoch 9/100
23/23 [==============================] - 0s 6ms/step - loss: 0.4999 - accuracy: 0.7907
Epoch 10/100
23/23 [==============================] - 0s 4ms/step - loss: 0.4893 - accuracy: 0.7963
Epoch 11/100
23/23 [==============================] - 0s 4ms/step - loss: 0.4811 - accuracy: 0.8006
Epoch 12/100
23/23 [==============================] - 0s 6ms/step - loss: 0.4742 - accuracy: 0.8048
Epoch 13/100
23/23 [==============================] - 0s 6ms/step - loss: 0.4686 - accuracy: 0.8090
Epoch 14/100
23/23 [==============================] - 0s 4ms/step - loss: 0.4635 - accuracy: 0.8132
Epoch 15/100
23/23 [==============================] - 0s 4ms/step - loss: 0.4592 - accuracy: 0.8132
Epoch 16/100
23/23 [==============================] - 0s 4ms/step - loss: 0.4559 - accuracy: 0.8118
Epoch 17/100
23/23 [==============================] - 0s 5ms/step - loss: 0.4520 - accuracy: 0.8132
Epoch 18/100
23/23 [==============================] - 0s 4ms/step - loss: 0.4495 - accuracy: 0.8118
```

In [69]:
```
y_pred = ann.predict(X_test)
y_pred = (y_pred > 0.5)
np.concatenate((y_pred.reshape(len(y_pred),1), y_test.reshape(len(y_test),1)),1)
```

```
       [0, 0],
       [0, 1],
       [0, 0],
       [0, 0],
       [1, 1],
       [0, 0],
       [0, 1],
       [0, 0],
       [1, 1],
       [0, 0],
       [1, 1],
       [1, 1],
       [1, 1],
       [0, 1],
       [0, 0],
       [0, 0],
       [0, 0],
       [1, 1],
       [0, 0],
       [0, 0],
```

In [70]:
```
cmAnn = confusion_matrix(y_test, y_pred)
print(cmAnn)
```

```
[[100  10]
 [ 23  46]]
```

In [71]:
```
ACC_Ann = accuracy_score(y_test, y_pred)*100
print('The accurancy score is ', ACC_Ann)
model_acc['Artificial Neural Network'] = ACC_Ann
```

```
The accurancy score is  81.56424581005587
```

Accuracy score of all model

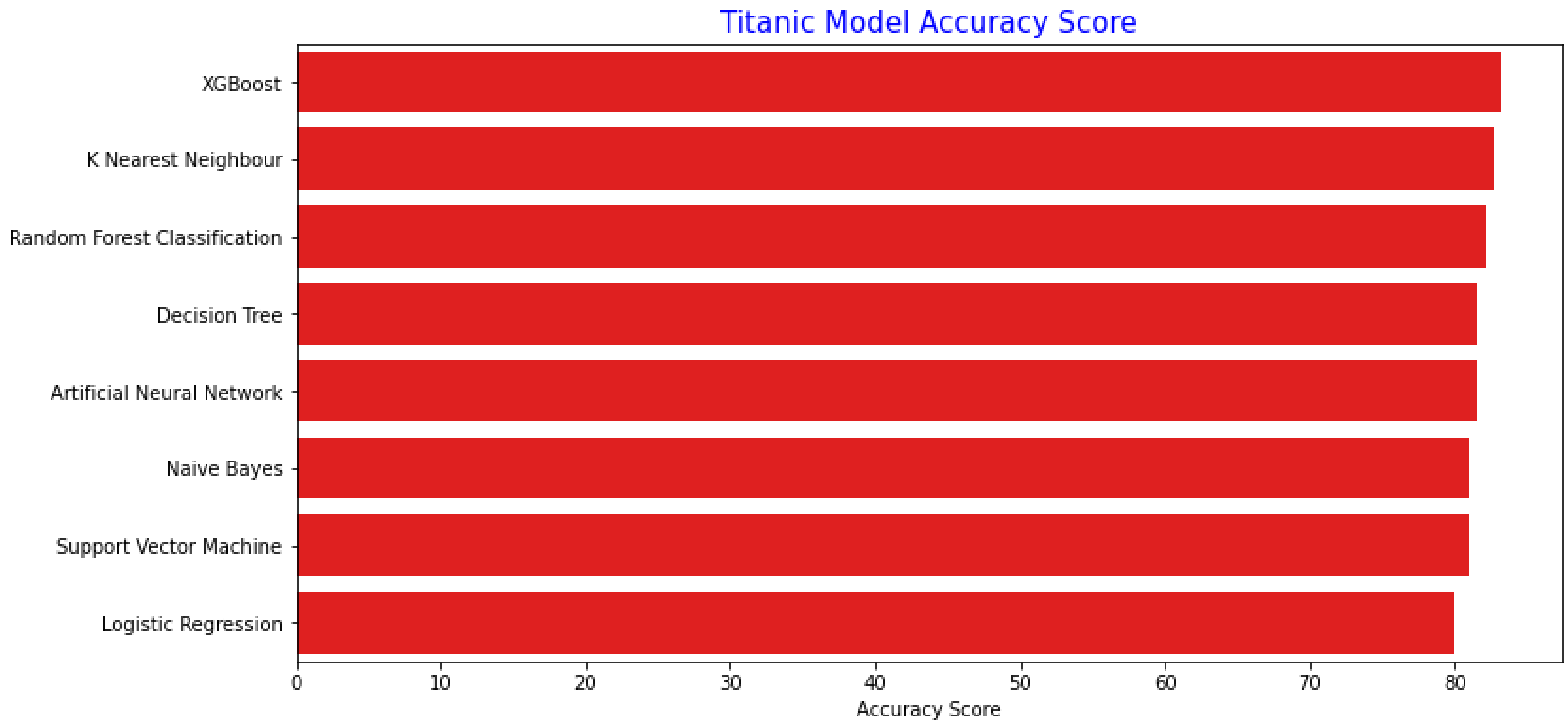
In [109]:
```
model_ds = pd.DataFrame.from_dict(model_acc,orient = 'index',columns = ['Accuracy Score'])
model_ds = model_ds.sort_values(by ='Accuracy Score',ascending = False)
model_ds
```

Out[109]:

	Accuracy Score
XGBoost	83.240223
K Nearest Neighbour	82.681564
Random Forest Classification	82.122905
Decision Tree	81.564246
Artificial Neural Network	81.564246
Naive Bayes	81.005587
Support Vector Machine	81.005587
Logistic Regression	79.888268

In [110]:
```
gig,ax = plt.subplots(figsize = (12,6))
sns.barplot(x="Accuracy Score", y=model_ds.index, data=model_ds,color = 'red')
plt.title('Titanic Model Accuracy Score', fontsize=15, color="blue")
```

Out[110]:
```
Text(0.5, 1.0, 'Titanic Model Accuracy Score')
```



In [ ]: