Predict what sorts of people were more likely to survive in the infamous Titanic shipwreck using Logistic Regression, Decision Trees, RandomForest Artificial Neural Network and comparing the model predictions

Kaggle Dataset: https://www.kaggle.com/c/titanic

Import required libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Load Training Dataset

In [3]:
```
training_data = pd.read_csv('titanic_train.csv')
```

Do Exploratory Data Analysis

In [4]:
```
training_data.shape
```

Out[4]:
```
(891, 12)
```

In [5]:
```
training_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [6]:
```
training_data.columns
```

Out[6]:
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [7]:
```
training_data.head()
```

Out[7]:

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

In [8]:

```
training_data.describe()
```

Out[8]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [9]:

```
training_data.corr()
```

Out[9]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000

In [11]:

```
training_data.isnull()
```

Out[11]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	False	False	False	False	False	False	False	False	False	False	True	False
1	False	False	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	True	False
3	False	False	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False	True	False
...	...	...	...	...	...	...	...	...	...	...	...	...
886	False	False	False	False	False	False	False	False	False	False	True	False
887	False	False	False	False	False	False	False	False	False	False	False	False
888	False	False	False	False	False	True	False	False	False	False	True	False
889	False	False	False	False	False	False	False	False	False	False	False	False
890	False	False	False	False	False	False	False	False	False	False	True	False

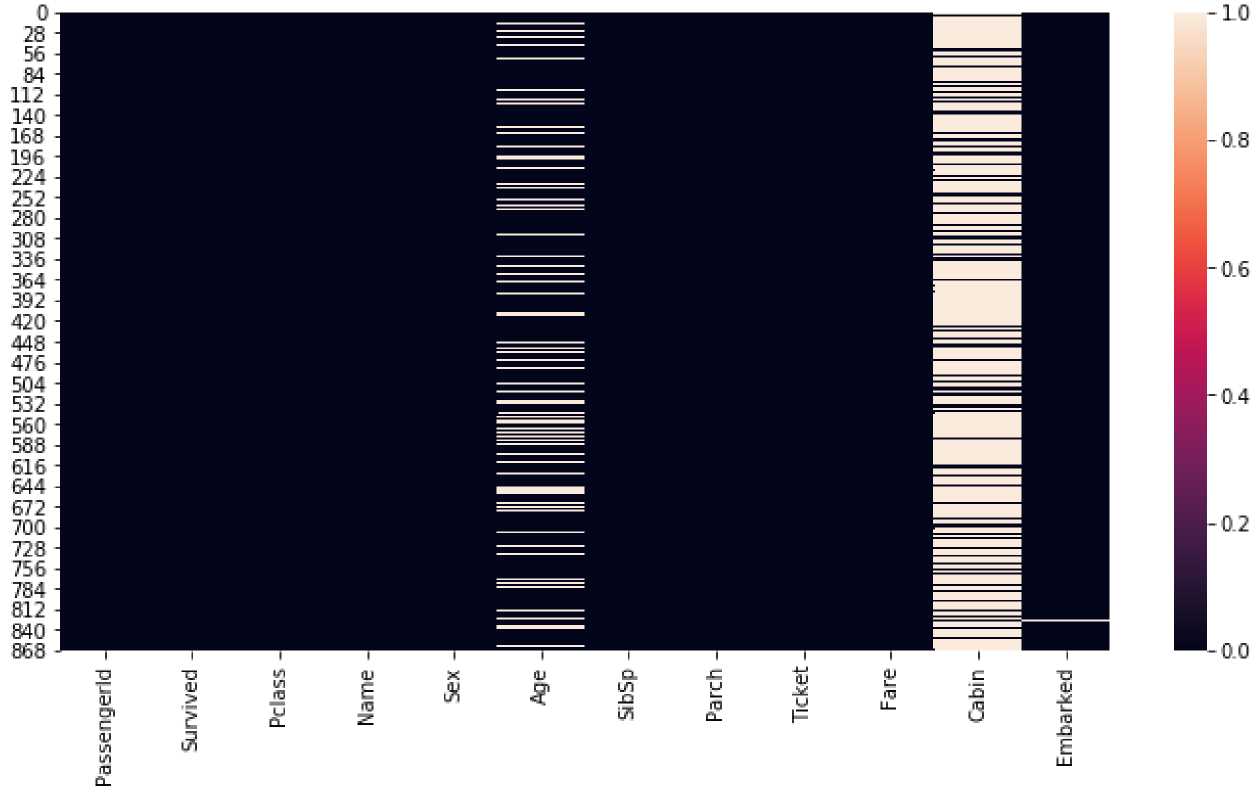
891 rows × 12 columns

Data Visualization

In [23]:

```
plt.figure(figsize=(12,6))
sns.heatmap(data=training_data.isnull())
```

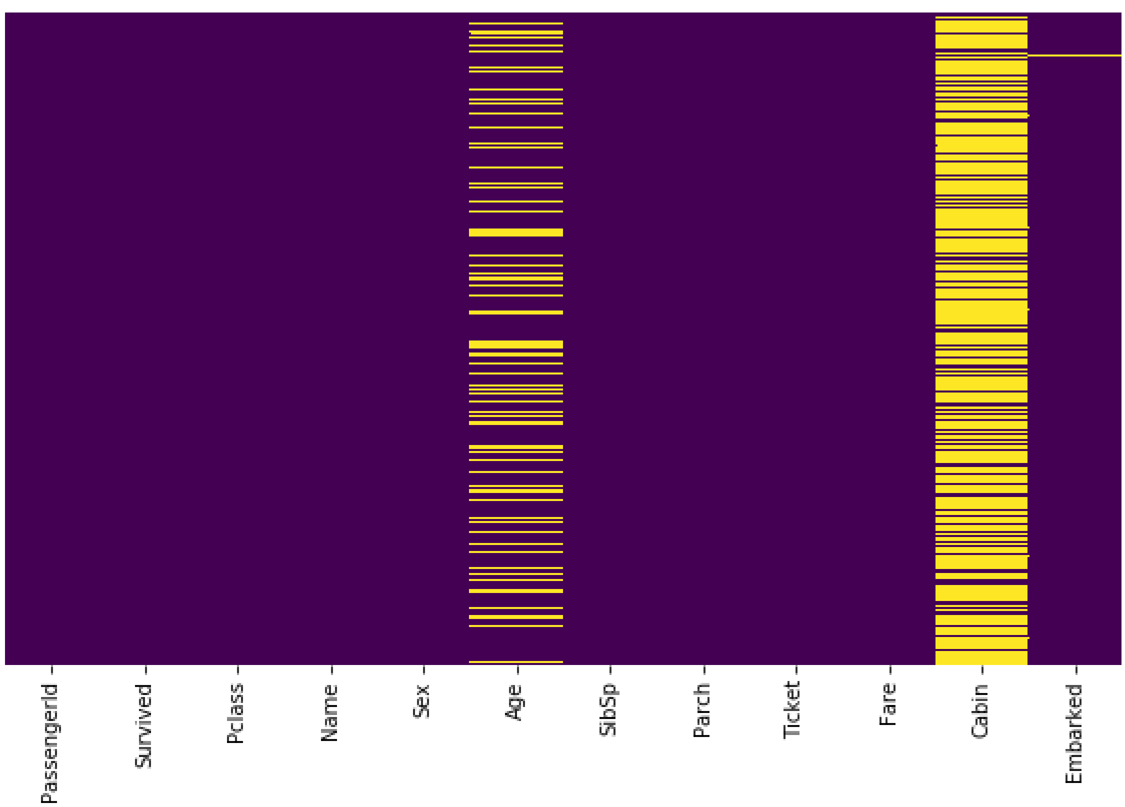
Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x25ad02375c8>



In [25]:

```
plt.figure(figsize=(10,6))
sns.heatmap(data=training_data.isnull(),cmap='viridis',yticklabels=False,cbar=False)
```

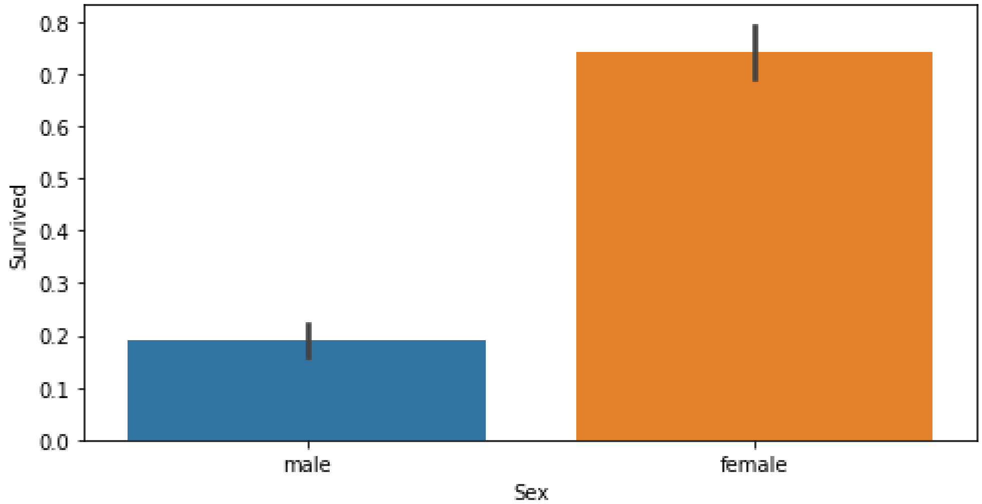
Out[25]: <matplotlib.axes._subplots.AxesSubplot at 0x25ad0032fc8>



In [33]:

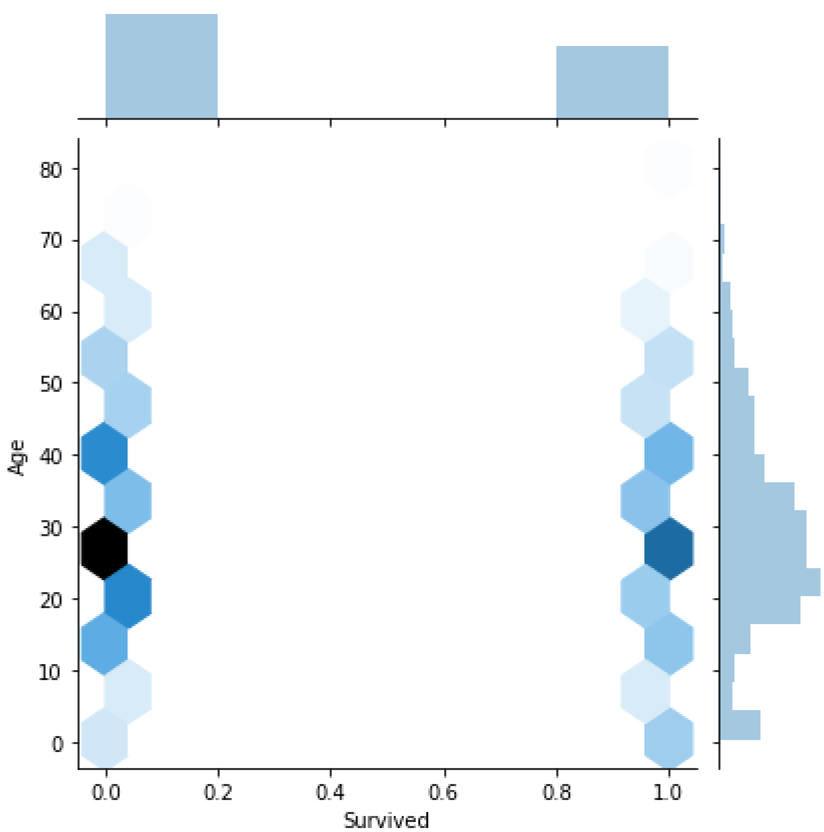
```
plt.figure(figsize=(8,4))
sns.barplot(x='Sex',y='Survived',data=training_data)
```

Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x25ad0618448>



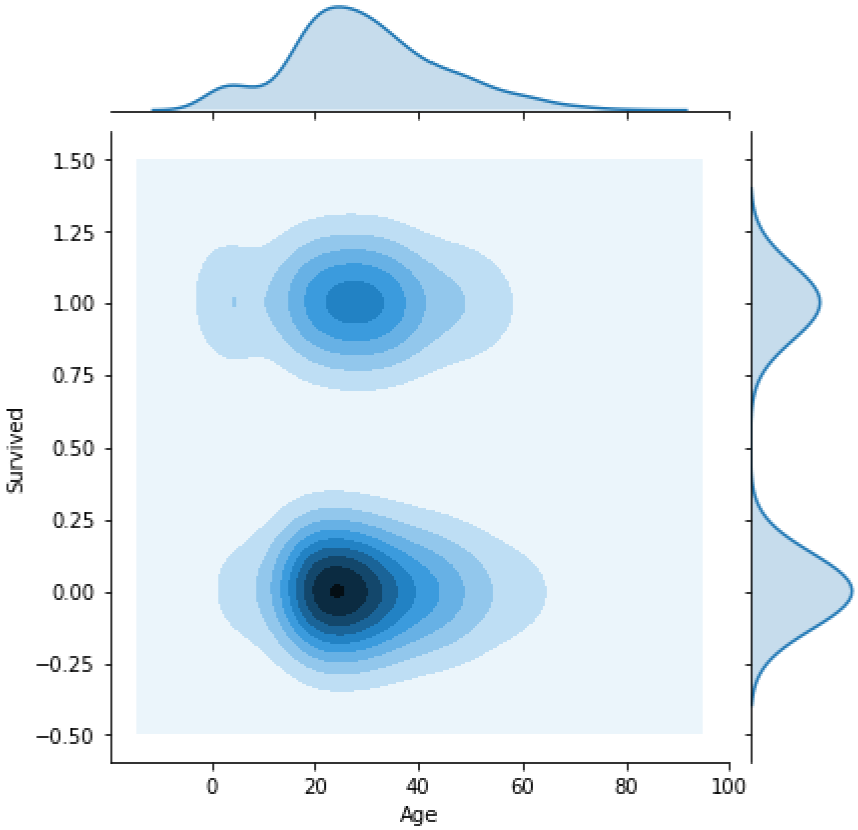
In [39]:
```
sns.jointplot(x='Survived',y='Age',data=training_data, kind='hex')
```

Out[39]: <seaborn.axisgrid.JointGrid at 0x25ad0dc7288>



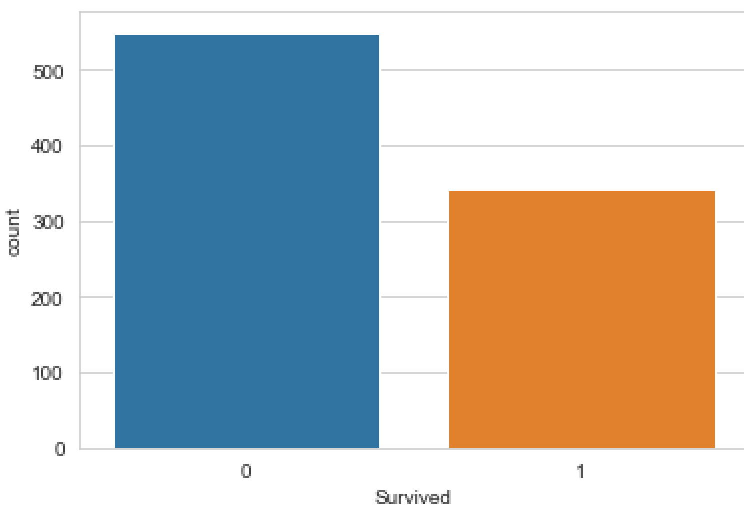
In [42]:
```
sns.jointplot(x='Age',y='Survived',data=training_data, kind='kde')
```

Out[42]: <seaborn.axisgrid.JointGrid at 0x25ad51d14c8>



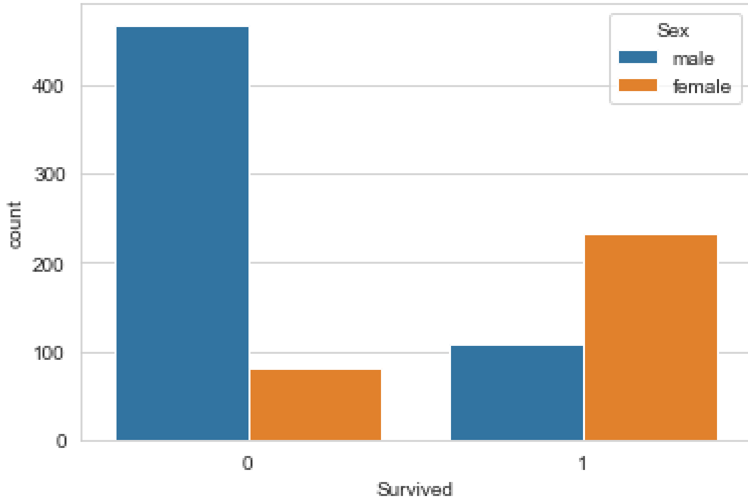
In [47]:
```
sns.set_style('whitegrid')
sns.countplot(x='Survived',data=training_data)
```

Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x25add577788>



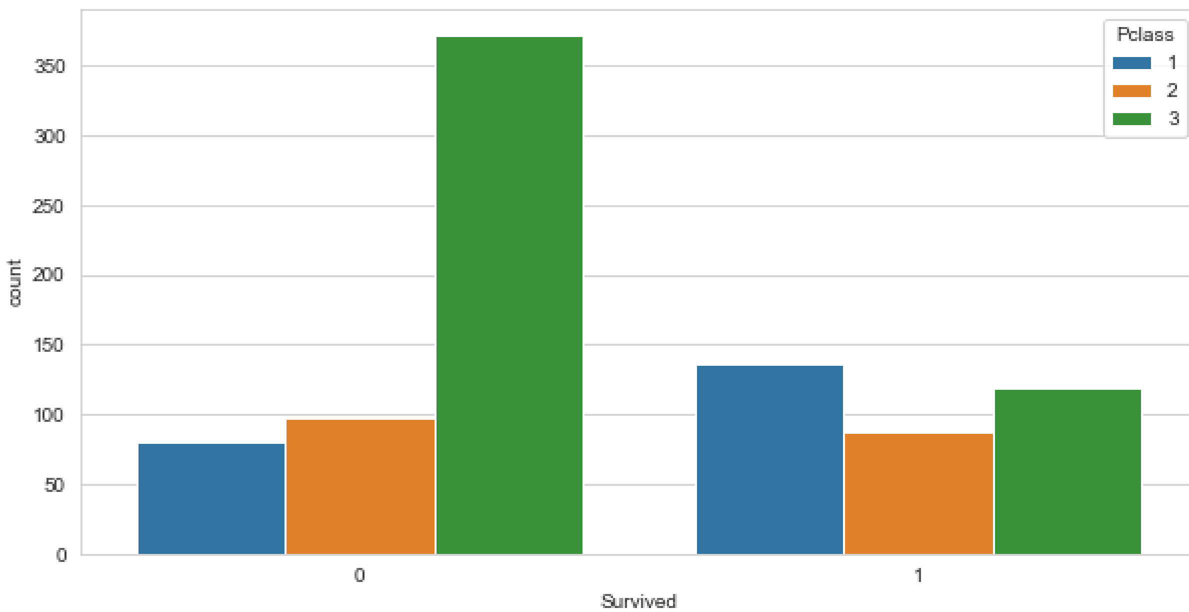
In [48]:
```
sns.countplot(x='Survived',data=training_data,hue='Sex')
```

Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x25ada10ce88>



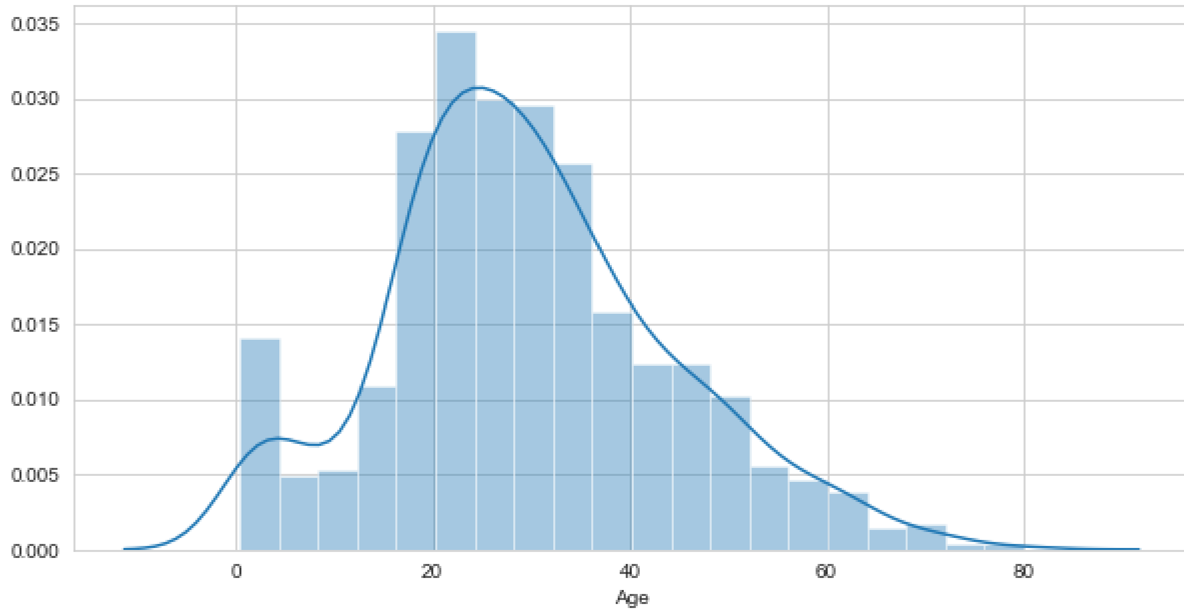
In [51]:
```
plt.figure(figsize=(10,5))
sns.countplot(x='Survived',data=training_data,hue='Pclass')
```

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x25adb1d5908>



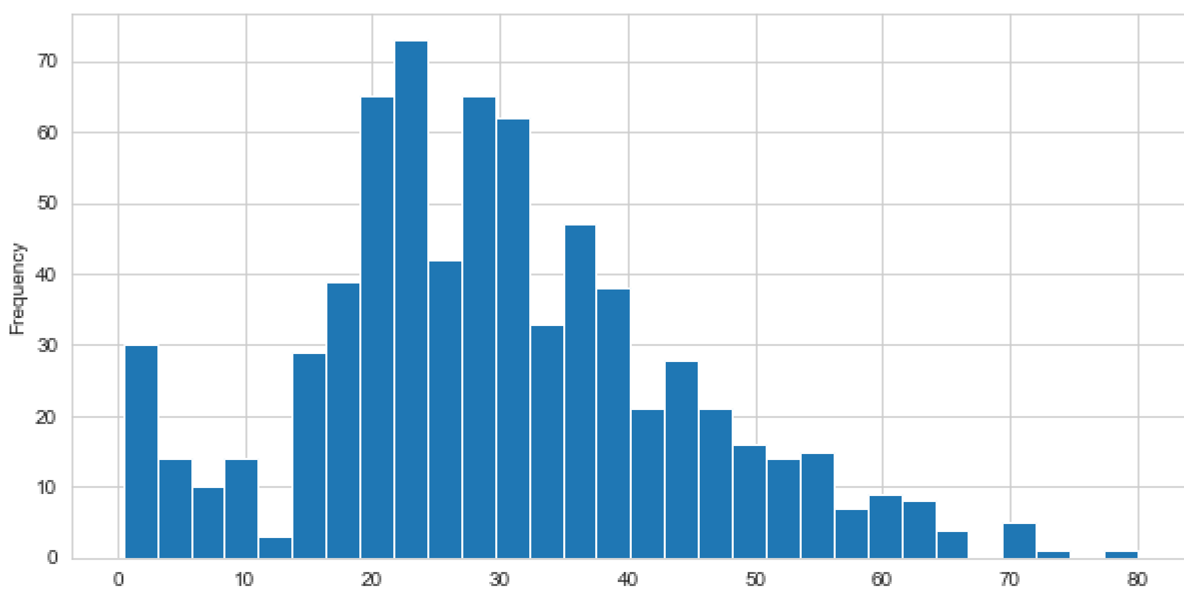
In [55]:
```
plt.figure(figsize=(10,5))
sns.distplot(training_data['Age'].dropna())
```

Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x25ade7ca8c8>



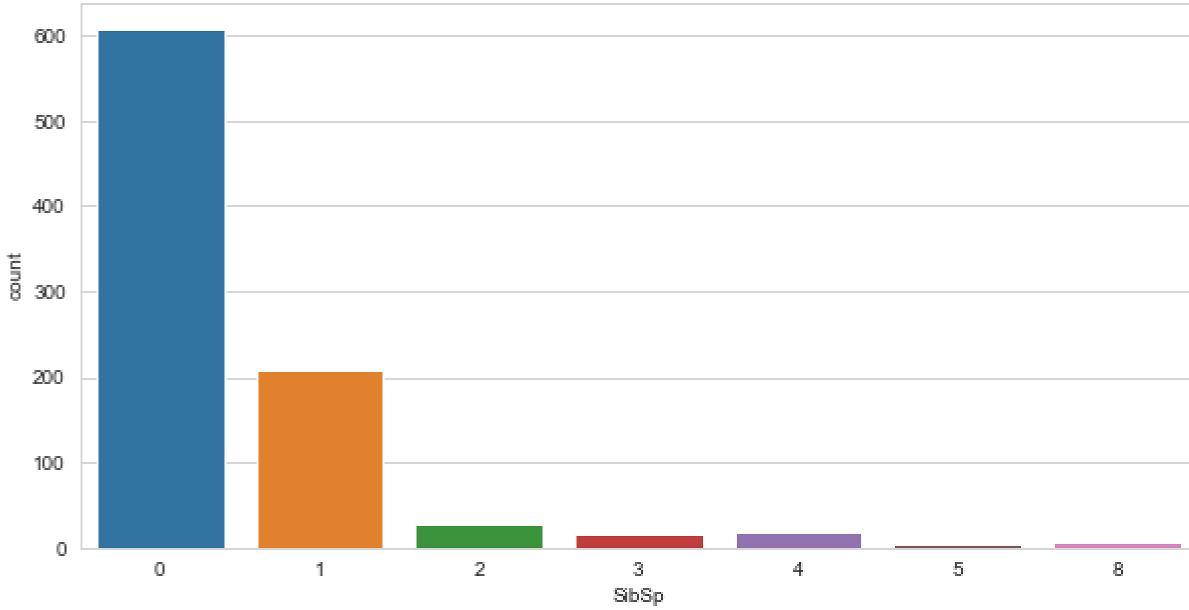
In [58]:
```
plt.figure(figsize=(10,5))
training_data['Age'].plot.hist(bins=30)
```

Out[58]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x25adeafba48>
```



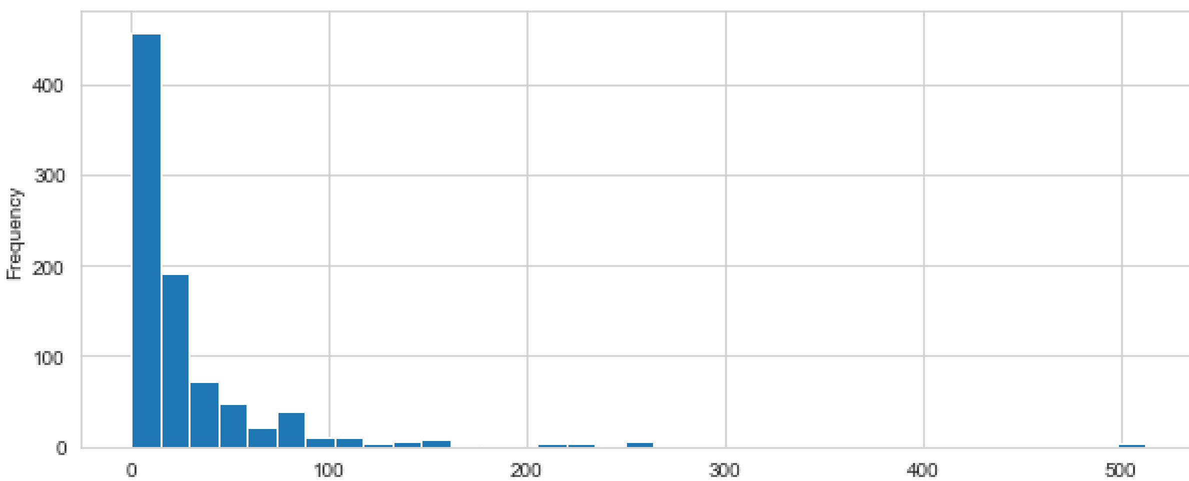
In [59]:
```
plt.figure(figsize=(10,5))
sns.countplot(x='SibSp',data=training_data)
```

Out[59]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x25ade787688>
```



In [61]:
```
training_data['Fare'].plot.hist(bins=35,figsize=(10,4))
```

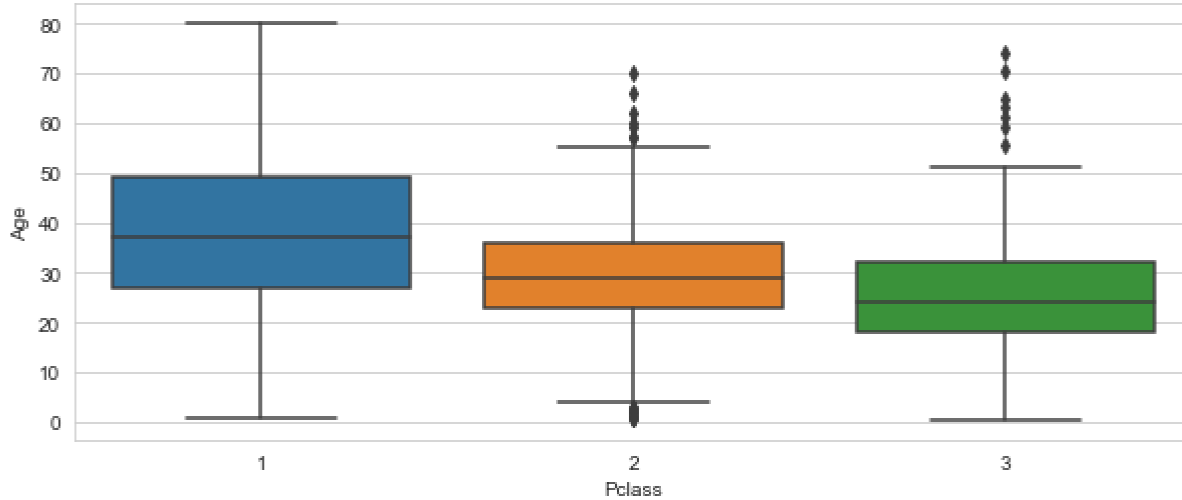
Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0x25adec65448>



Cleaning data for further processing and visualization

In [64]:
```
plt.figure(figsize=(10,4))
sns.boxplot(x='Pclass',y='Age',data=training_data)
```

Out[64]: <matplotlib.axes._subplots.AxesSubplot at 0x25aded45848>



Implementing mean imputation for replacing missing age data

In [66]:
```
def age_imputation(cols):
    age = cols[0]
    p_class = cols[1]

    if pd.isnull(age):

        if p_class==1:
            return 37
        elif p_class==2:
            return 29
        else:
            return 24
    else:
        return age
```

Note: In the above method, we are directly getting the age based on the above boxplot. Else we can compute mean for each Pclass ourselves

Replacing missing data

In [67]:
```
training_data['Age'] = training_data[['Age','Pclass']].apply(age_imputation, axis=1)
```

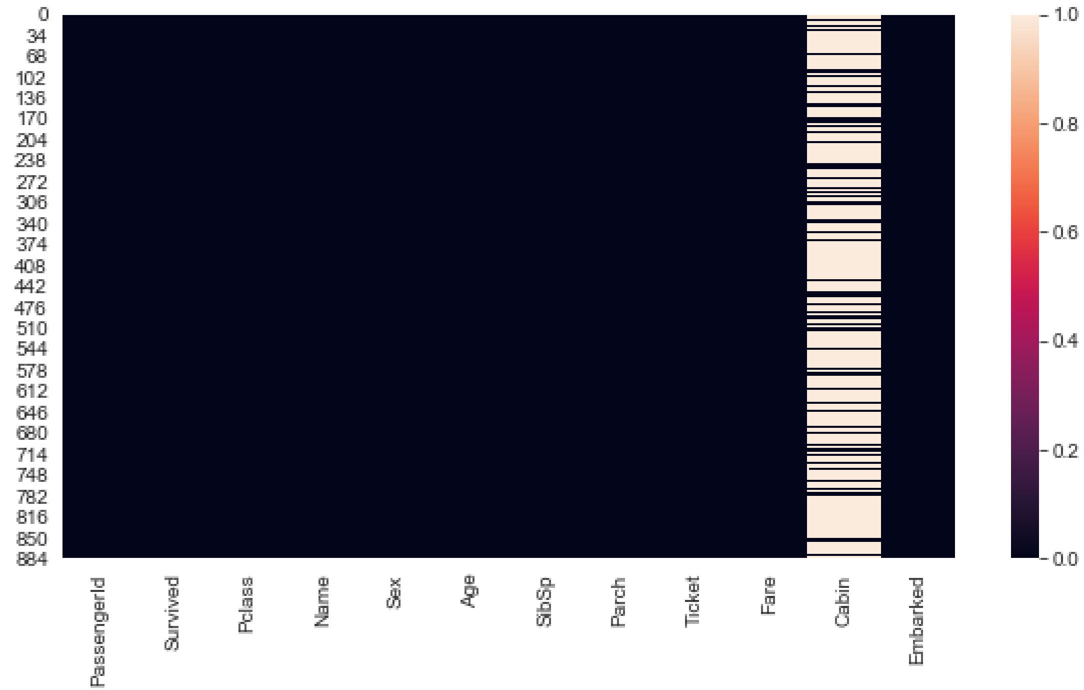
In [68]:
```
training_data.shape
```

Out[68]:
```
(891, 12)
```

In [72]:
```
#training_data['Age'].isnull()
```

In [74]:
```
plt.figure(figsize=(10,5))
sns.heatmap(training_data.isnull())
```

Out[74]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x25ade9026c8>
```



Missing values for Age has been successfully computed. But Cabin is having almost 95% missing values, hence we drop it from the dataset

In [75]:
```
training_data.drop('Cabin',axis=1,inplace=True)
```

Revisualizing the dataset

In [80]:
```
plt.figure(figsize=(10,5))
sns.heatmap(data=training_data.isnull(),cbar=False) #set cbar to false to view other mi
```

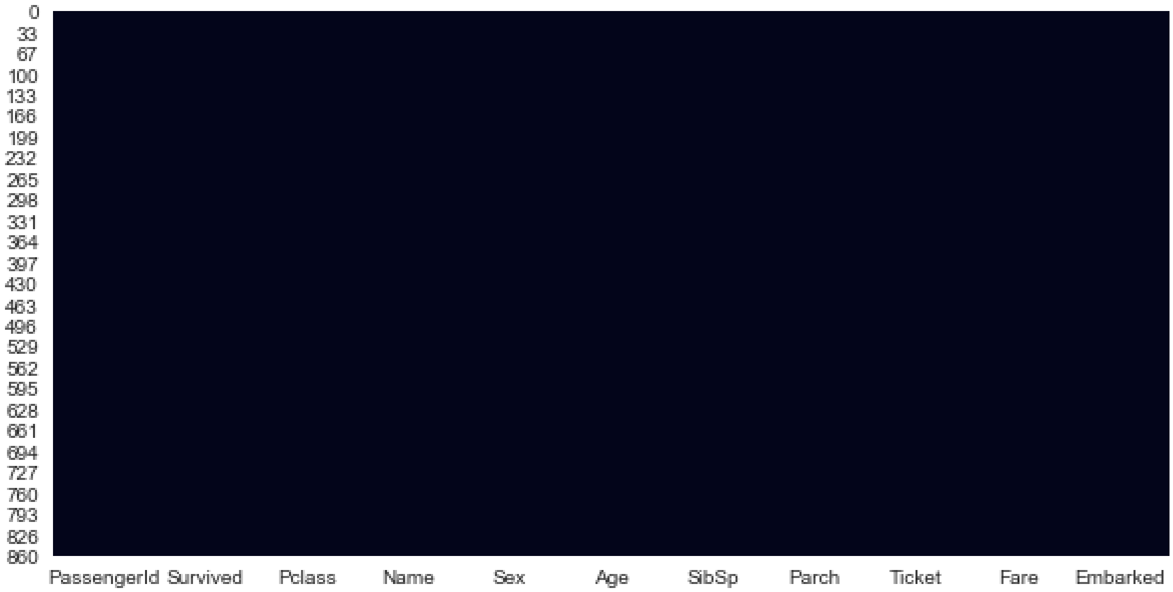
Out[80]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x25adc962488>
```

Dropping missing values for Embarked field

In [81]:
```
training_data.dropna(inplace=True)
```

In [82]:
```
plt.figure(figsize=(10,5))
sns.heatmap(data=training_data.isnull(),cbar=False)
```

Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x25add364508>



Convert categorical varibales into dummy/indicator varibales

In [87]:
```
#Remove columns which are perfect predictors of each other to avoid multicolinearity
```

In [88]:
```
sex = pd.get_dummies(training_data['Sex'],drop_first=True)
embarked = pd.get_dummies(training_data['Embarked'],drop_first=True)
```

In [89]:
```
sex.head()
```

Out[89]:

	male
0	1
1	0
2	0
3	0
4	1

In [90]:
```
embarked.head()
```

Out[90]:

	Q	S
0	0	1
1	0	0
2	0	1
3	0	1
4	0	1

In [91]:
```
training_data = pd.concat([training_data,sex,embarked],axis=1)
```

In [92]:
```
training_data.head(2)
```

Out[92]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	m
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C	

Based on Feature engineering, we are doing Feature Selection and dropping unneccessary data which are not fruitful for model prediction

In [93]:
```
training_data.drop(['Sex','Embarked','Name','Ticket'],axis=1,inplace=True)
```

In [94]:
```
training_data.head(3)
```

Out[94]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
0	1	0	3	22.0	1	0	7.2500	1	0	1
1	2	1	1	38.0	1	0	71.2833	0	0	0
2	3	1	3	26.0	0	0	7.9250	0	0	1

In [95]:
```
training_data.tail()
```

Out[95]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
886	887	0	2	27.0	0	0	13.00	1	0	1
887	888	1	1	19.0	0	0	30.00	0	0	1
888	889	0	3	24.0	1	2	23.45	0	0	1
889	890	1	1	26.0	0	0	30.00	1	0	0
890	891	0	3	32.0	0	0	7.75	1	1	0

In [96]:
```
training_data.drop('PassengerId',axis=1,inplace=True)
```

In [97]:
```
training_data.head()
```

Out[97]:

	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
0	0	3	22.0	1	0	7.2500	1	0	1

	Survived	Pclass	Age	SibSp	Parch	Fare	male	Q	S
1	1	1	38.0	1	0	71.2833	0	0	0
2	1	3	26.0	0	0	7.9250	0	0	1
3	1	1	35.0	1	0	53.1000	0	0	1
4	0	3	35.0	0	0	8.0500	1	0	1

Parch column above is also a categorical data. We will create 2 separate models, one with the Parch column as it is and another by converting Parch to dummy varibales

In [98]:
```
X = training_data.drop('Survived',axis=1)
y = training_data['Survived']
```

Creating test train split from training data

In [100…
```
from sklearn.model_selection import train_test_split
```

In [105…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=
```

In [106…
```
X_train.shape
```

Out[106…
```
(666, 8)
```

In [107…
```
y_test.shape
```

Out[107…
```
(223,)
```

In [108…
```
X_test.shape
```

Out[108…
```
(223, 8)
```

Do Model Training using Logistic Regression

In [109…
```
from sklearn.linear_model import LogisticRegression
```

In [112…
```
logremodel = LogisticRegression()
```

In [117…
```
logremodel.fit(X_train,y_train)
```

```
e:\users\user.desktop-3hhgvth\anaconda3\envs\mytfenv\lib\site-packages\sklearn\linear_mo
del\logistic.py:432: FutureWarning: Default solver will be changed to 'lbfgs' in 0.22. S
pecify a solver to silence this warning.
  FutureWarning)
```

Out[117…
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbose=0,
                   warm_start=False)
```

In [118…
```
predictions = logremodel.predict(X_test)
```

Evaluation Metrics

In [119…
```
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

In [120…
```
print(confusion_matrix(y_test,predictions))
```

```
[[118  20]
 [ 25  60]]
```

In [121…
```
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.83      0.86      0.84       138
           1       0.75      0.71      0.73        85

    accuracy                           0.80       223
   macro avg       0.79      0.78      0.78       223
weighted avg       0.80      0.80      0.80       223
```

In [122…
```
training_data['Survived'].value_counts()
```

Out[122…
```
0    549
1    340
Name: Survived, dtype: int64
```

Do Model Training & Prediction using Decision Trees

In [123…
```
from sklearn.tree import DecisionTreeClassifier
```

In [124…
```
tree = DecisionTreeClassifier()
```

In [125…
```
tree.fit(X_train,y_train)
```

Out[125…
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                       max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort=False,
                       random_state=None, splitter='best')
```

In [126…
```
dt_preds = tree.predict(X_test)
```

Evaluation Metrics

In [127…
```
print(classification_report(y_test,dt_preds))
print('\n')
print(confusion_matrix(y_test,dt_preds))
```

```
              precision    recall  f1-score   support

           0       0.85      0.84      0.85       138
           1       0.75      0.76      0.76        85

    accuracy                           0.81       223
   macro avg       0.80      0.80      0.80       223
weighted avg       0.81      0.81      0.81       223
```

```
[[116  22]
 [ 20  65]]
```

Do Model Training & Prediction using Random Forest Algorithm

In [129…

```
from sklearn.ensemble import RandomForestClassifier
```

In [133…

```
rfc = RandomForestClassifier(n_estimators=200)
```

In [134…

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

Out[134…

```
RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                       max_depth=None, max_features='auto', max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=200,
                       n_jobs=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)
```

In [136…

```
rfc_preds = rfc.predict(X_test)
```

Evaluation Metrics

In [138…

```
print(classification_report(y_test,rfc_preds))
print('\n')
print(confusion_matrix(y_test,rfc_preds))
```

```
              precision    recall  f1-score   support

           0       0.82      0.86      0.84       138
           1       0.75      0.69      0.72        85

    accuracy                           0.79       223
   macro avg       0.78      0.77      0.78       223
weighted avg       0.79      0.79      0.79       223



[[118  20]
 [ 26  59]]
```

Do Model Training & Prediction using Deep Learning ANNs

In [142…

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
```

In [144…

```
dl_model = Sequential()

dl_model.add(Dense(50,activation='relu'))
dl_model.add(Dense(30,activation='relu'))

dl_model.add(Dense(1,activation='sigmoid'))

dl_model.compile(optimizer='adam',loss='binary_crossentropy')
```

Scale the data

In [182…

```
from sklearn.preprocessing import MinMaxScaler
```

In [183…
```
scaler = MinMaxScaler()
```

In [184…
```
X = training_data.drop('Survived',axis=1).values
y = training_data['Survived'].values
y=np.array(y)
```

In [185…
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=
```

In [186…
```
print(X_train.shape,X_test.shape,y_train.shape,y_test.shape)
```

```
(666, 8) (223, 8) (666,) (223,)
```

In [187…
```
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [188…
```
print(type(X_train),type(y_train),type(X_test),type(y_test))
```

```
<class 'numpy.ndarray'> <class 'numpy.ndarray'> <class 'numpy.ndarray'> <class 'numpy.nd
array'>
```

In [189…
```
dl_model.fit(X_train,y_train,epochs=100)
```

```
Train on 666 samples
Epoch 1/100
666/666 [==============================] - 0s 100us/sample - loss: 0.3738
Epoch 2/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3749
Epoch 3/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3729
Epoch 4/100
666/666 [==============================] - 0s 69us/sample - loss: 0.3730
Epoch 5/100
666/666 [==============================] - 0s 77us/sample - loss: 0.3715
Epoch 6/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3735
Epoch 7/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3798
Epoch 8/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3730
Epoch 9/100
666/666 [==============================] - 0s 87us/sample - loss: 0.3711
Epoch 10/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3702
Epoch 11/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3702
Epoch 12/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3703
Epoch 13/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3748
Epoch 14/100
666/666 [==============================] - 0s 77us/sample - loss: 0.3704
Epoch 15/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3715
Epoch 16/100
666/666 [==============================] - 0s 72us/sample - loss: 0.3705
Epoch 17/100
666/666 [==============================] - 0s 77us/sample - loss: 0.3684
Epoch 18/100
666/666 [==============================] - 0s 75us/sample - loss: 0.3693
Epoch 19/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3683
Epoch 20/100
```

```
666/666 [==============================] - 0s 74us/sample - loss: 0.3677
Epoch 21/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3703
Epoch 22/100
666/666 [==============================] - 0s 75us/sample - loss: 0.3735
Epoch 23/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3686
Epoch 24/100
666/666 [==============================] - 0s 87us/sample - loss: 0.3666
Epoch 25/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3667
Epoch 26/100
666/666 [==============================] - 0s 69us/sample - loss: 0.3665
Epoch 27/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3678
Epoch 28/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3666
Epoch 29/100
666/666 [==============================] - 0s 75us/sample - loss: 0.3653
Epoch 30/100
666/666 [==============================] - 0s 75us/sample - loss: 0.3676
Epoch 31/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3670
Epoch 32/100
666/666 [==============================] - 0s 72us/sample - loss: 0.3668
Epoch 33/100
666/666 [==============================] - 0s 77us/sample - loss: 0.3668
Epoch 34/100
666/666 [==============================] - 0s 83us/sample - loss: 0.3671
Epoch 35/100
666/666 [==============================] - 0s 72us/sample - loss: 0.3647
Epoch 36/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3655
Epoch 37/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3661
Epoch 38/100
666/666 [==============================] - 0s 68us/sample - loss: 0.3650
Epoch 39/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3649
Epoch 40/100
666/666 [==============================] - 0s 98us/sample - loss: 0.3641
Epoch 41/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3655
Epoch 42/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3638
Epoch 43/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3626
Epoch 44/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3637
Epoch 45/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3624
Epoch 46/100
666/666 [==============================] - 0s 75us/sample - loss: 0.3635
Epoch 47/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3622
Epoch 48/100
666/666 [==============================] - 0s 77us/sample - loss: 0.3624
Epoch 49/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3655
Epoch 50/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3620
Epoch 51/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3656
Epoch 52/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3689
```

```
Epoch 53/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3653
Epoch 54/100
666/666 [==============================] - 0s 92us/sample - loss: 0.3657
Epoch 55/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3620
Epoch 56/100
666/666 [==============================] - 0s 87us/sample - loss: 0.3621
Epoch 57/100
666/666 [==============================] - 0s 86us/sample - loss: 0.3631
Epoch 58/100
666/666 [==============================] - 0s 99us/sample - loss: 0.3600
Epoch 59/100
666/666 [==============================] - 0s 84us/sample - loss: 0.3647
Epoch 60/100
666/666 [==============================] - 0s 96us/sample - loss: 0.3627
Epoch 61/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3617
Epoch 62/100
666/666 [==============================] - 0s 98us/sample - loss: 0.3599
Epoch 63/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3634
Epoch 64/100
666/666 [==============================] - 0s 83us/sample - loss: 0.3593
Epoch 65/100
666/666 [==============================] - 0s 68us/sample - loss: 0.3597
Epoch 66/100
666/666 [==============================] - 0s 71us/sample - loss: 0.3588
Epoch 67/100
666/666 [==============================] - 0s 71us/sample - loss: 0.3602
Epoch 68/100
666/666 [==============================] - 0s 69us/sample - loss: 0.3601
Epoch 69/100
666/666 [==============================] - 0s 72us/sample - loss: 0.3649
Epoch 70/100
666/666 [==============================] - 0s 68us/sample - loss: 0.3616
Epoch 71/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3589
Epoch 72/100
666/666 [==============================] - 0s 66us/sample - loss: 0.3594
Epoch 73/100
666/666 [==============================] - 0s 69us/sample - loss: 0.3581
Epoch 74/100
666/666 [==============================] - 0s 72us/sample - loss: 0.3600
Epoch 75/100
666/666 [==============================] - 0s 77us/sample - loss: 0.3640
Epoch 76/100
666/666 [==============================] - 0s 66us/sample - loss: 0.3597
Epoch 77/100
666/666 [==============================] - 0s 71us/sample - loss: 0.3592
Epoch 78/100
666/666 [==============================] - 0s 68us/sample - loss: 0.3590
Epoch 79/100
666/666 [==============================] - 0s 66us/sample - loss: 0.3573
Epoch 80/100
666/666 [==============================] - 0s 71us/sample - loss: 0.3563
Epoch 81/100
666/666 [==============================] - 0s 68us/sample - loss: 0.3567
Epoch 82/100
666/666 [==============================] - 0s 68us/sample - loss: 0.3569
Epoch 83/100
666/666 [==============================] - 0s 72us/sample - loss: 0.3581
Epoch 84/100
666/666 [==============================] - 0s 71us/sample - loss: 0.3553
Epoch 85/100
```

```
666/666 [==============================] - 0s 72us/sample - loss: 0.3564
Epoch 86/100
666/666 [==============================] - 0s 71us/sample - loss: 0.3567
Epoch 87/100
666/666 [==============================] - 0s 93us/sample - loss: 0.3558
Epoch 88/100
666/666 [==============================] - ETA: 0s - loss: 0.322 - 0s 80us/sample - los
s: 0.3557
Epoch 89/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3550
Epoch 90/100
666/666 [==============================] - 0s 87us/sample - loss: 0.3559
Epoch 91/100
666/666 [==============================] - 0s 75us/sample - loss: 0.3550
Epoch 92/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3548
Epoch 93/100
666/666 [==============================] - 0s 80us/sample - loss: 0.3560
Epoch 94/100
666/666 [==============================] - 0s 83us/sample - loss: 0.3528
Epoch 95/100
666/666 [==============================] - 0s 93us/sample - loss: 0.3568
Epoch 96/100
666/666 [==============================] - 0s 78us/sample - loss: 0.3570
Epoch 97/100
666/666 [==============================] - 0s 81us/sample - loss: 0.3572
Epoch 98/100
666/666 [==============================] - 0s 74us/sample - loss: 0.3562
Epoch 99/100
666/666 [==============================] - 0s 66us/sample - loss: 0.3566
Epoch 100/100
666/666 [==============================] - 0s 63us/sample - loss: 0.3544
```

Out[189…

```
<tensorflow.python.keras.callbacks.History at 0x25ad9d01808>
```

In [191…

```python
dl_preds = dl_model.predict_classes(X_test)
```

Evaluation Metrics

In [192…

```python
print(classification_report(y_test,dl_preds))
print('\n')
print(confusion_matrix(y_test,dl_preds))
```

```
              precision    recall  f1-score   support

           0       0.83      0.90      0.86       138
           1       0.81      0.71      0.75        85

    accuracy                           0.83       223
   macro avg       0.82      0.80      0.81       223
weighted avg       0.82      0.83      0.82       223



[[124  14]
 [ 25  60]]
```

We have used 4 different algorithms for predicting the survival of Titanic passengers. Out of those, the ANN model has the highest evaluation metrics followed by Decision Tree, Logistic Regression & Random Forest

In [ ]: