```
import pandas as pd
import numpy as np
import warnings as wg
wg.filterwarnings('ignore')

df = pd.read_csv('/content/drive/My Drive/Colab Notebooks/titanic_data.csv')
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	F
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.:
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs	female	38.0	1	0	PC 17599	71.:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.00000C
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.20420ε
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.69342ς
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.00000C
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.91040C
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.45420C
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.00000C
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.32920C

```
df.describe(include='O')
```

	Name	Sex	Ticket	Cabin	Embarked
count	891	891	891	204	889
unique	891	2	681	147	3
top	McMahon, Mr. Martin	male	CA. 2343	C23 C25 C27	S
freq	1	577	7	4	644

All of the data is self explonatory except SibSp, Parch, Embarked

Sib/Sp: It is the number of sibings or spouses

Parch : It is the number of Parents or childrens

Embarked: Port of Embarkation C= Cherboug, S= Southamptom, Q = Queenstown

```
print(df.columns)
```

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

```
#Dropping the PassengerId
df = df.drop(labels= 'PassengerId' , axis = 1, inplace = False)
df.head(3)
```

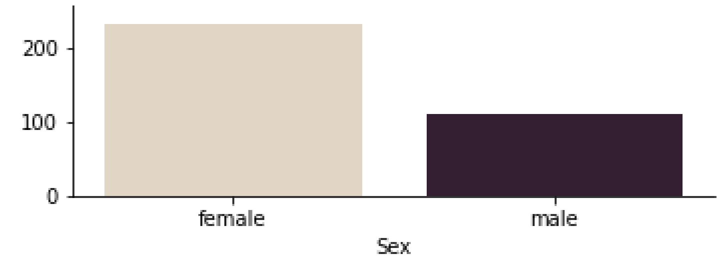
	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	E
0	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
			Cumings, Mrs. John								

```
# converting the Survived to Categorical column.

df['Survived'] = df['Survived'].astype('object')
```

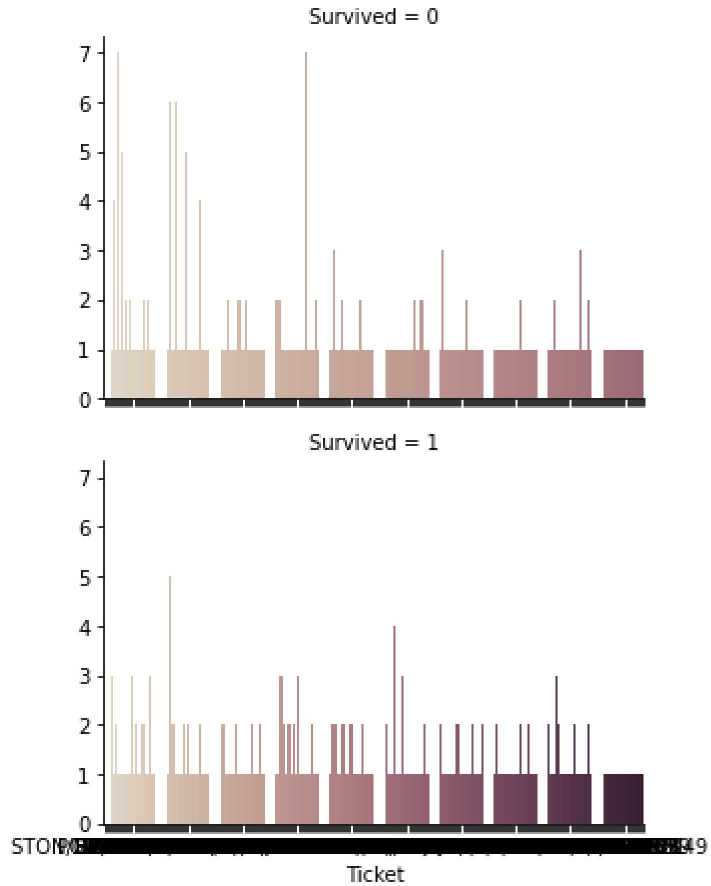
```
#printing the categorical columns and numerical columns

cat = [x for x in df.columns if(df[x].dtype)=='object']
print("Categorical Columns: ", cat)

num = [x for x in df.columns if (df[x]. dtype =='int64') | (df[x]. dtype =='float64')
print("Numerical Columns: ", num)
```

```
Categorical Columns:  ['Survived', 'Name', 'Sex', 'Ticket', 'Cabin', 'Embarked']
Numerical Columns:  ['Pclass', 'Age', 'SibSp', 'Parch', 'Fare']
```

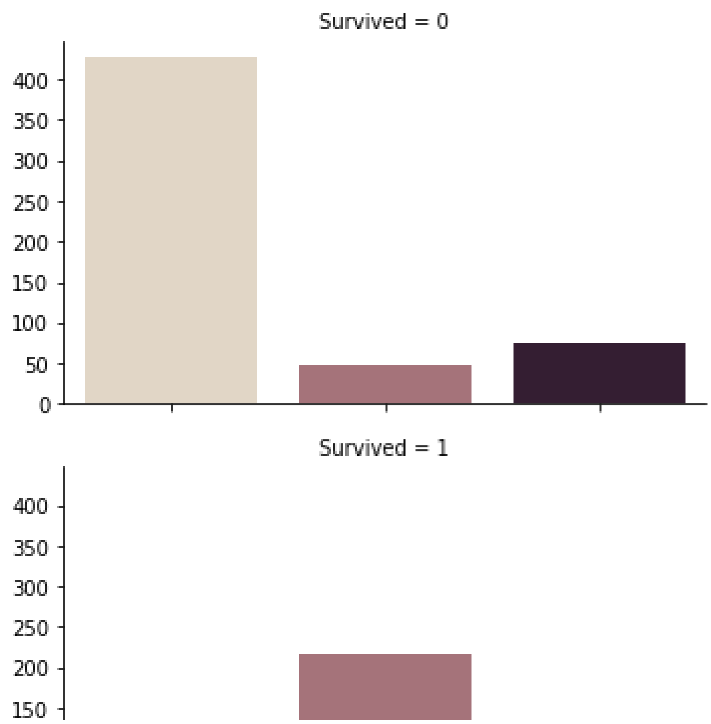
```
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns

cols = ['Sex', 'Ticket', 'Embarked']

for cn in cols:
  grid = sns.FacetGrid(df, 'Survived', palette='ch:.26', size = 3.2, aspect= 1.6)
  grid.map(sns.countplot, cn, palette='ch:.26')

  plt.show()
  print(20*'===')
```

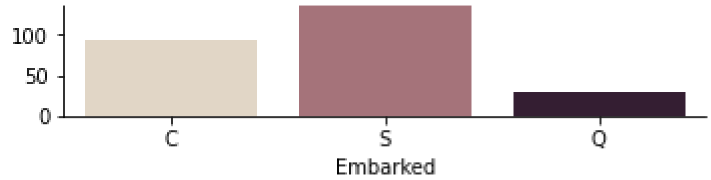

200
100
0
female
male
Sex

==


Survived = 0
7
6
5
4
3
2
1
0
Survived = 1
Ticket

==


Survived = 0
400
350
300
250
200
150
100
50
0
Survived = 1




```
============================================================
```

Observations:

1. When comes to sex There more Females who got surived but aslo there are more females who
2. Coming to Embarked Category of S Survivied more rathar than other two categories and catego

```
#segregating the Categorical and numerical columns
categorical = df.loc[:, cat]
numerical = df.loc[:, num]
print(categorical.head())
print(numerical.head())
```

```
      Survived                                              Name  ... Cabin Embarke
```

Handling the missing values in the Categorical Variables

```
# checking the Missing values in Categorical columns
categorical.isnull().sum()
```

```
Survived      0
Name          0
Sex           0
Ticket        0
Cabin       687
Embarked      2
dtype: int64
```

Observations:

we drop the **Cabin** column in the Data Because there are lot of missing values in i
the unique cabin number that generates too much bias in the model which we do

```
#dropping the Cabin column.
categorical = categorical.drop(labels='Cabin', axis = 1, inplace= False)
categorical.head(3)
```

	Survived	Name	Sex	Ticket	Embarke
0	0	Braund, Mr. Owen Harris	male	A/5 21171	
1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	PC 17599	
				STON/O2.	

```
#now we handle the missing values in the Embarked
categorical = categorical.apply(lambda x: x.fillna(x.value_counts().index[0]))
print(categorical.isnull().sum())
categorical.head()
```

```
Survived    0
Name        0
Sex         0
Ticket      0
Embarked    0
dtype: int64
```

	Survived	Name	Sex	Ticket	Embarke
0	0	Braund, Mr. Owen Harris	male	A/5 21171	

```
#Encoding the categorical into numerical values
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in categorical:
  categorical[i] = le.fit_transform(categorical[i])
categorical.head()
```

	Survived	Name	Sex	Ticket	Embarked
0	0	108	1	523	2
1	1	190	0	596	0
2	1	353	0	669	2
3	1	272	0	49	2
4	0	15	1	472	2

```
y = categorical.Survived
categorical = categorical.drop('Survived', axis =1 , inplace=False)
```

```
categorical.head(3)
```

	Name	Sex	Ticket	Embarked
0	108	1	523	2
1	190	0	596	0
2	353	0	669	2

Handling the missing values in numercal Columns

```
numerical.isnull().sum()
```

```
numerical.isnull().sum()
```

```
Pclass      0
Age       177
SibSp       0
Parch       0
Fare        0
dtype: int64
```

```
#Replacing the missing value with the mean values
for i in numerical.columns:
  numerical[i] = numerical.apply(lambda x: x.fillna(numerical[i].median()))
```

```
print(numerical.isnull().sum())
numerical.describe()
```

```
Pclass    0
Age       0
SibSp     0
Parch     0
Fare      0
dtype: int64
```

	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	891.000000	891.000000
mean	2.308642	2.308642	2.308642	2.308642	2.308642
std	0.836071	0.836071	0.836071	0.836071	0.836071
min	1.000000	1.000000	1.000000	1.000000	1.000000
25%	2.000000	2.000000	2.000000	2.000000	2.000000
50%	3.000000	3.000000	3.000000	3.000000	3.000000
75%	3.000000	3.000000	3.000000	3.000000	3.000000
max	3.000000	3.000000	3.000000	3.000000	3.000000

```
df.groupby('Survived').median()
```

Pclass Age SibSp Parch Fare

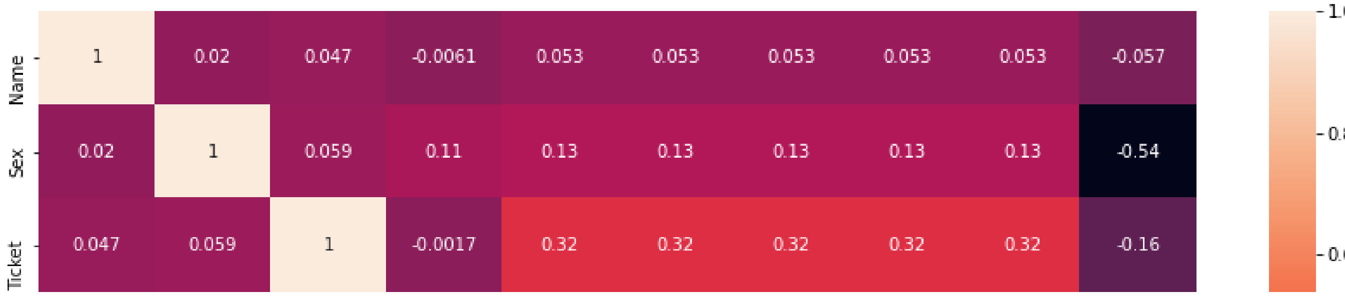
Observation :

- The people with the highest **Fare** value and persons of **Pclass** 2 are the Survived ones.

```
df_final = pd.concat([categorical, numerical, y], axis =1)
df_final.head()
```

	Name	Sex	Ticket	Embarked	Pclass	Age	SibSp	Parch	Fare	Survived
0	108	1	523	2	3.0	3.0	3.0	3.0	3.0	0
1	190	0	596	0	1.0	1.0	1.0	1.0	1.0	1
2	353	0	669	2	3.0	3.0	3.0	3.0	3.0	1
3	272	0	49	2	1.0	1.0	1.0	1.0	1.0	1
4	15	1	472	2	3.0	3.0	3.0	3.0	3.0	0

```
#Plotting the Heatmap to find the Correlation among the Columns
fig, ax = plt.subplots(figsize= (15, 10))
corr = df_final.corr()
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns, annot=True)
plt.show()
```



Observations:

1. Sex is the Highly Negatively correlated with the Survivied Column.
2. Age, Sibblings/ Spouses, Parents/Childern, Fare and Pclass are next Negatively correlated Varia
3. Ticket is the column which is Highly Positively Corralted with Age, Sibblings/ Spouses, Parents/ lead multicollinearity.

```
X = df_final.loc[:,df_final.columns[:-1]]

print(X.shape, y.shape)
```

```
(891, 9) (891,)
```

```
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_sta

print("Train: ", X_train.shape, "Test :", X_test.shape, y_train.shape, y_test.shape,
```

```
Train:  (712, 9)        Test :  (179, 9)        (712,)  (179,)
```

```
print(X_train.dtypes)
```

```
Name          int64
Sex           int64
Ticket        int64
Embarked      int64
Pclass      float64
Age         float64
SibSp       float64
Parch       float64
Fare        float64
dtype: object
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import f1_score, accuracy_score, classification_report
```

```
dc = DecisionTreeClassifier( splitter='random')

model = dc.fit(X_train, y_train)
y_train_pred  = model.predict(X_train)
y_pred_dc= model.predict(X_test)


print("\n\n")
#checking the Accuracy During the validation phase
print("Test accuracy Score: ", accuracy_score(y_test, y_pred_dc))
print("Test F1 score: ", f1_score(y_test, y_pred_dc))

print("CONFUSION_MATRIX: ")
pd.crosstab(y_test, y_pred_dc, rownames=['True'], colnames=['Predicted'], margins=Tru
```

```
Test accuracy Score:  0.8268156424581006
Test F1 score:  0.7973856209150328
CONFUSION_MATRIX:
```

Predicted	0	1	All
True			
0	87	18	105
1	13	61	74
All	100	79	179

Observations

1. There are 36 mis classified labels with accuracy score of 80% and F1 score as 76%.
2. majority of miss classifications are observed in which 16 survivors are classifed as Non Survivo Survivors.
3. we use more classfication algorithms to see if we can improve the accuracy of the model.

```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
```

```
model = lr.fit(X_train, y_train)
y_pred = model.predict(X_test)

print("Test Accuracy: ", accuracy_score(y_test, y_pred))
print("F1 score: ", f1_score(y_test, y_pred))

print("CONFUSION MATRIX: ")
pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted'], margins=True
```

```
Test Accuracy:  0.776536312849162
F1 score:  0.736842105263158
CONFUSION MATRIX:
```

Predicted	0	1	All
Actual			
0	83	22	105
1	18	56	74
All	101	78	179

observations

1. Here Total 40 labels are miss classified out of which 18 are classified as Non-Survivors but are a Survivors but are classfied as Non-survivors.
2. Comparing to regression model DecisionTree classifier worked better.

```
from sklearn.neighbors import KNeighborsClassifier

kc = KNeighborsClassifier()
model = kc.fit(X_train, y_train)
y_pred = model.predict(X_test)

print("Accuracy Score: ", accuracy_score(y_test, y_pred))
print("F1 Score: ", f1_score(y_test, y_pred))

print("Confusion Matrix: ")
pd.crosstab(y_test, y_pred, rownames=["Actual"], colnames=["Predicted"], margins=True
```

```
Accuracy Score:  0.659217877094972
F1 Score:  0.5481481481481482
Confusion Matrix:
 Predicted  0  1  All
```

Observations:

1. 61 points are missclassified out of which are 37 are classified as Non-survivors but are Survivor classified as survivors.
2. Comparing Knearest neighbour classfier with the Decision tree and logistic Regression Decision

```
from sklearn.svm import SVC

sc = SVC()
model = sc.fit(X_train, y_train)
y_pred = model.predict(X_test)

print("Accuracy Score: ", accuracy_score(y_test, y_pred))
print("F1 Score: ", f1_score(y_test, y_pred))

print("Confusion Matrix")
pd.crosstab(y_test, y_pred, rownames=["Actual"], colnames=['Predicted'], margins=True
```

```
Accuracy Score:  0.664804469273743
F1 Score:  0.3877551020408163
Confusion Matrix
```

Predicted	0	1	All
Actual			
0	100	5	105
1	55	19	74
All	155	24	179

Observations

1. 55 number of Survivors are misclassified as non-survivors.
2. 5 number of non-survivors are misclassified as survivors.
3. But if we consider the situation of survivors this model performed good because we want more less accuracy the model is not preffered.
4. After comparing with all the algorithsm Decison Tree classifier has performed better than all the

```
from sklearn.ensemble import BaggingClassifier
```

```
from sklearn.ensemble import BaggingClassifier
from sklearn.metrics import confusion_matrix as cm
from sklearn.ensemble import AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier

dt = DecisionTreeClassifier()
dt.fit(X_train,y_train)
pred_dt = dt.predict(X_test)



# Bagging
bag_clf = BaggingClassifier(
    DecisionTreeClassifier(random_state=29), n_estimators=500,
    max_samples=100, bootstrap=True, n_jobs=-1, random_state=29
)

bag_clf.fit(X_train, y_train)
pred_bagging = bag_clf.predict(X_test)


#Boosting
# Boosting
ada_clf = AdaBoostClassifier(
    DecisionTreeClassifier(max_depth=1), n_estimators=200,
    learning_rate=0.5, random_state=50
)

ada_clf.fit(X_train, y_train)
pred_boosting = ada_clf.predict(X_test)


print("Bagging accuracy:",accuracy_score(y_test, pred_bagging))
print("Bagging f1 score:",f1_score(y_test, pred_bagging))
print("\n")
print("Boosting accuracy:",accuracy_score(y_test, pred_boosting))
print("Boosting f1 score:",f1_score(y_test, pred_boosting))
print("\n")

print("Confusion Matrix for Decision_Tree Classifier: ")
pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Decision Tree'], margins=
```

```
Bagging accuracy: 0.7877094972067039
Bagging f1 score: 0.7076923076923075


Boosting accuracy: 0.7877094972067039
Boosting f1 score: 0.7397260273972601


Confusion Matrix for Decision_Tree Classifier:
```

Decision Tree 0 1 All

```
print("Confusion Matrix for  afte Bagging: ")
pd.crosstab(y_test, pred_bagging, rownames=['Actual'], colnames=['Bagging'], margins=
```

```
Confusion Matrix for  afte Bagging:
```

Bagging	0	1	All
Actual			
0	95	10	105
1	28	46	74
All	123	56	179

```
print("Confusion Matrix for Boosting: ")
pd.crosstab(y_test, pred_boosting, rownames=['Actual'], colnames=['Boosting'], margin
```

```
Confusion Matrix for Boosting:
```

Boosting	0	1	All
Actual			
0	87	18	105
1	20	54	74
All	107	72	179

Observations

1. Even after Applying bagging and boosting there was no such imporovement in the.
2. Decision tree classfier is the highest accuracte model within this context

```
val_acc= []
val_f1_c = []
min_samples_leaf = []
import numpy as np
for samples_leaf in range(1,30): ### Sweeping from 1% samples to 10% samples per leaf
    tree_clf = DecisionTreeClassifier(max_depth=3,min_samples_leaf = samples_leaf)
    tree_clf.fit(X_train,y_train)
    y_pred = tree_clf.predict(X_test)

    val_accuracy = accuracy_score(y_test,y_pred)
    val_f1 = f1_score(y_test,y_pred)



    val_acc.append(val_accuracy)
    val_f1_c.append(val_f1)
    min_samples_leaf.append(samples_leaf)


Tuning_min_samples_leaf = {"Validation Accuracy": val_acc, "Validation F1":val_f1_c,
Tuning_min_samples_leaf_df = pd.DataFrame.from_dict(Tuning_min_samples_leaf)

plot_df = Tuning_min_samples_leaf_df.melt('Min_Samples_leaf',var_name='Metrics',value
fig,ax = plt.subplots(figsize=(15,5))
sns.pointplot(x="Min_Samples_leaf", y="Values",hue="Metrics", data=plot_df,ax=ax)
plt.show()
```