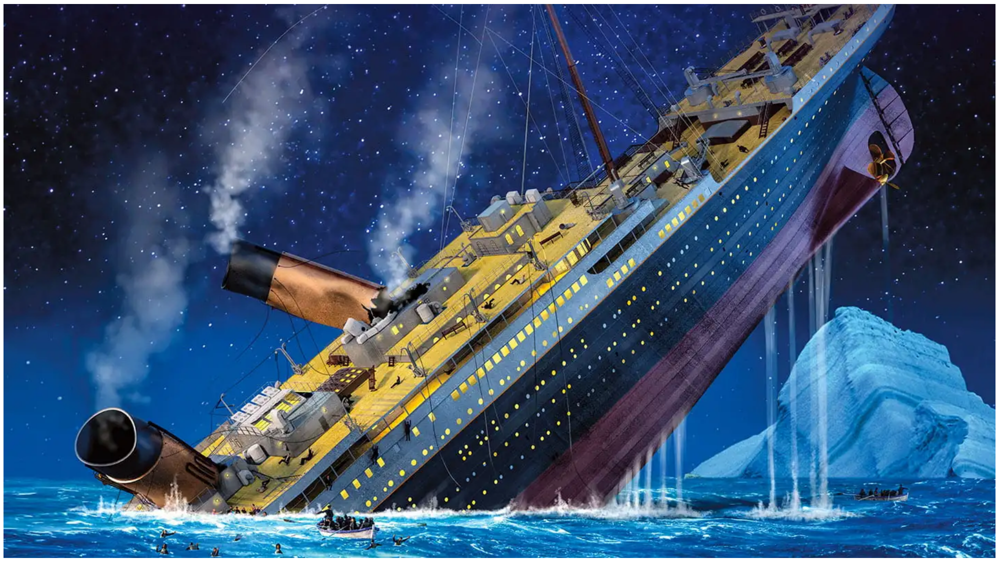


Introduction

The sinking of the RMS Titanic in 1912 is a tragic tale of opulence and disaster. On its maiden voyage, the "unsinkable" ship struck an iceberg, leading to the loss of over 1,500 lives. Despite advanced safety features, including watertight compartments, the combination of excessive speed, insufficient lifeboats, and class-based evacuation policies proved fatal. The diverse passenger and crew makeup, ranging from wealthy elites to hopeful immigrants, adds to the poignancy. This maritime catastrophe prompted significant changes in safety regulations and remains a somber reminder of human vulnerability in the face of nature's forces, echoing through history and popular culture.

In [1]:
```
# Titanic Survival
```

1 import Necessary Library

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
```

2 import Dataset

In [3]:
```
df = pd.read_csv("/kaggle/input/titanic-dataset/Titanic-Dataset.csv")
```

3 Data Analysis

In [4]:
```
df.head()
```

```
df.head()
```

Out[4]:

	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	7.2
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0

In [5]:
```
df.tail()
```

Out[5]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Far
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.7

In [6]:
```
df.shape
```

Out[6]: (891, 12)

In [7]:
```
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
```

In [8]:
```
df.dtypes
```

Out[8]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

In [9]:
```
df.describe()
```

Out[9]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	I
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.00(
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.69:
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.00(
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.91(
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.00(
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.32!

In [10]:
```
df.ndim
```

Out[10]: 2

4 Data cleaning and Preprocessing:

In [11]:
```
# Data preprocessing
df.drop(['Name', 'Ticket', 'Fare', 'Cabin', 'PassengerId'], axis=1, inplace=Tru
df['Family'] = df['SibSp'] + df['Parch'] + 1
df.drop(['SibSp', 'Parch'], axis=1, inplace=True)
df['Sex'].replace(['male', 'female'], [0, 1], inplace=True)
df.Embarked.replace(['S', 'C', 'Q'], [1, 2, 3], inplace=True)
```

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
Survived      0
Pclass        0
Sex           0
Age         177
Embarked      2
Family        0
dtype: int64
```

In [13]:
```
df['Age'].fillna(df['Age'].median(), inplace=True)
df['Embarked'].fillna(1, inplace=True)
```

In [14]:
```
df.columns
```

Out[14]:
```
Index(['Survived', 'Pclass', 'Sex', 'Age', 'Embarked', 'Family'], dtype='objec
t')
```

In [15]:
```
df.head()
```

Out[15]:

	Survived	Pclass	Sex	Age	Embarked	Family
0	0	3	0	22.0	1.0	2
1	1	1	1	38.0	2.0	2
2	1	3	1	26.0	1.0	1
3	1	1	1	35.0	1.0	2
4	0	3	0	35.0	1.0	1

In [16]:
```
# Define features and target variable
x = df[['Pclass', 'Sex', 'Age', 'Embarked', 'Family']]
y = df['Survived']
```

In [17]:
```
df.isnull().any()
```

Out[17]:
```
Survived    False
Pclass      False
Sex         False
Age         False
Embarked    False
Family      False
dtype: bool
```

In [18]:

```
df.dtypes
```

Out[18]:
```
Survived      int64
Pclass        int64
Sex           int64
Age         float64
Embarked    float64
Family        int64
dtype: object
```

In [19]:
```
df['Survived'].value_counts()
```

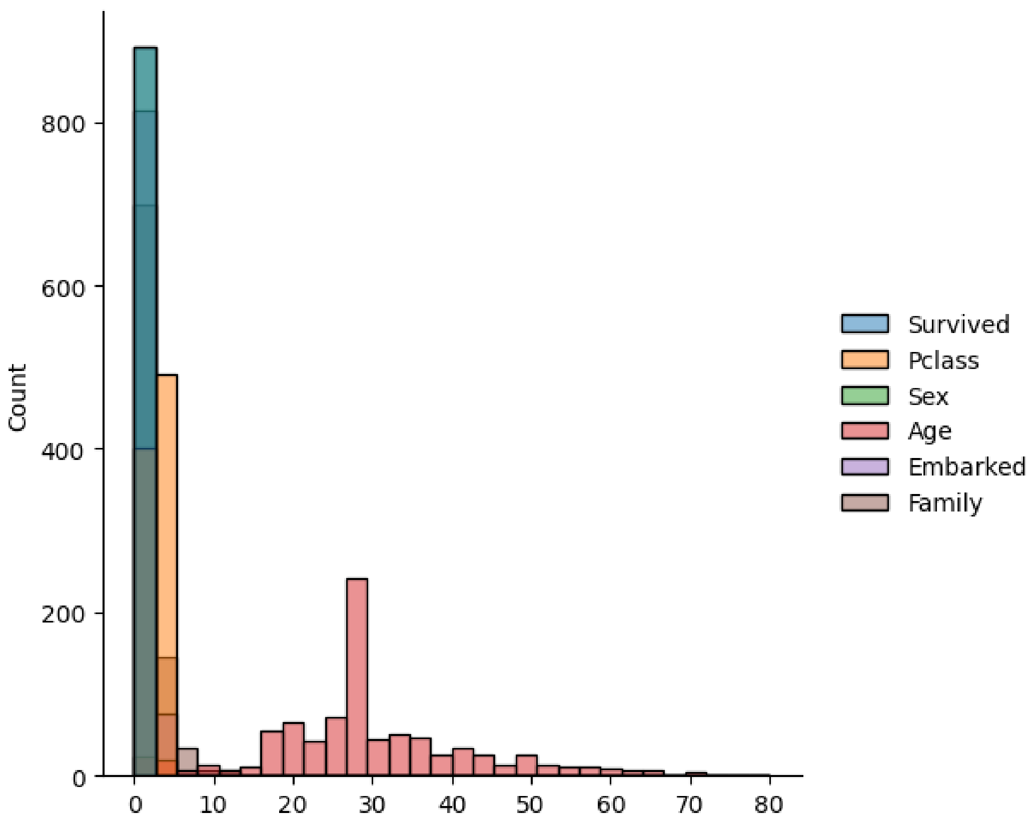
Out[19]:
```
Survived
0    549
1    342
Name: count, dtype: int64
```

5| Data visualisation 📊 📉

EDA (Exploratory Data Analysis)

5.1 displot

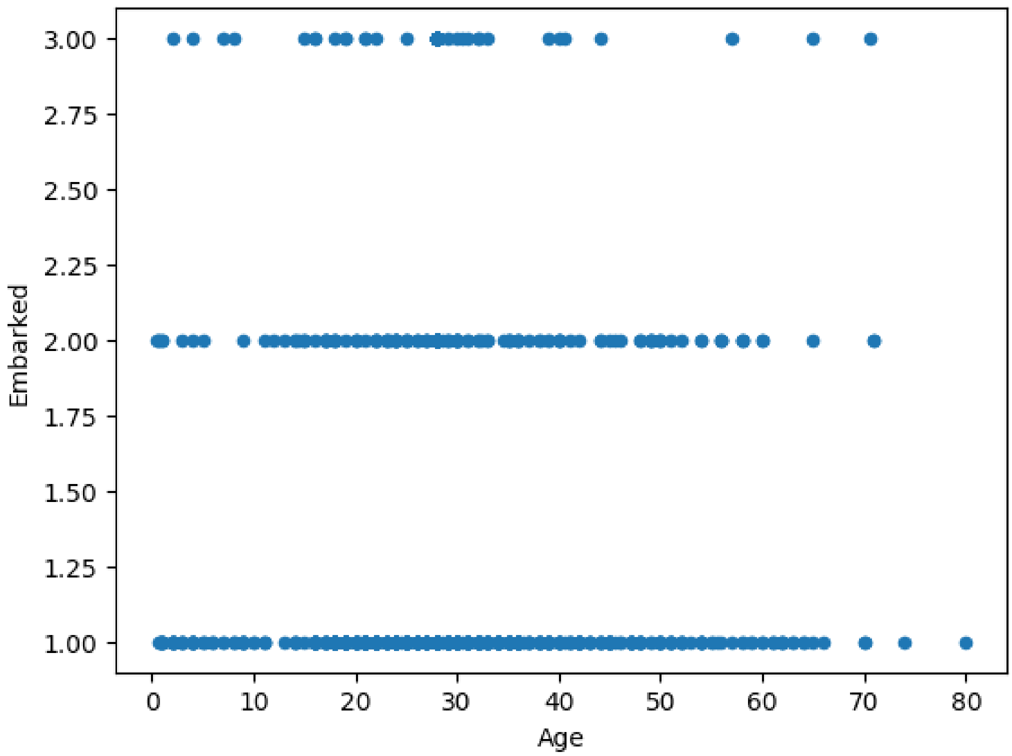
In [20]:
```
sns.displot(df, kde=False, bins=30)
plt.show()
```



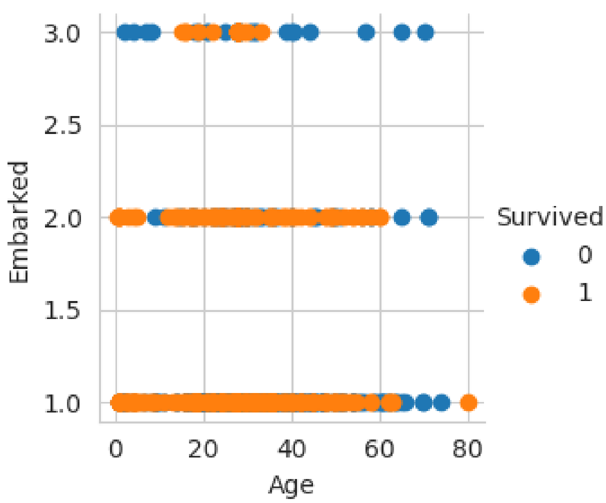
5.2 Scatter Plot

5.2 Scatter Plot

In [21]:
```
df.plot(kind='scatter', x='Age', y='Embarked')
plt.show()
```



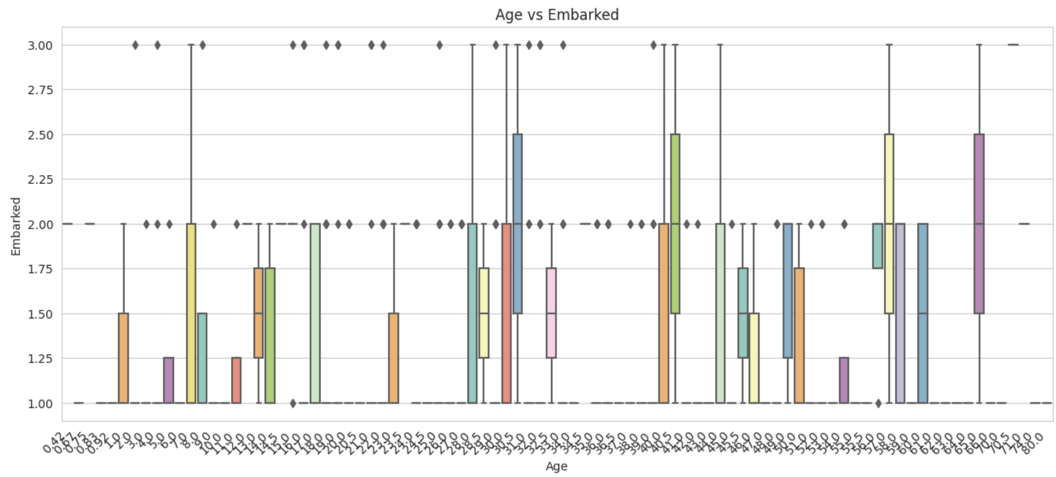
In [22]:
```
sns.set_style("whitegrid");
sns.FacetGrid(df, hue="Survived").map(plt.scatter, "Age", "Embarked").add_legen
plt.show();
```



5.3 boxplot

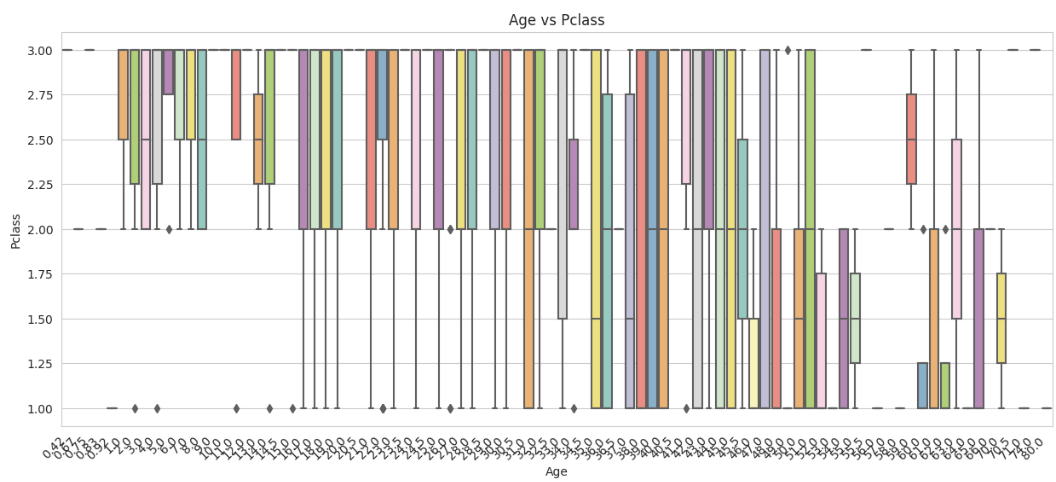
In [23]:
```
# sepal_length vs sepal_width boxplot

plt.figure(figsize=(15, 6))
sns.boxplot(x='Age', y='Embarked', data=df, palette='Set3')
plt.title('Age vs Embarked')
plt.xlabel('Age')
```

```
plt.ylabel('Embarked')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [24]:

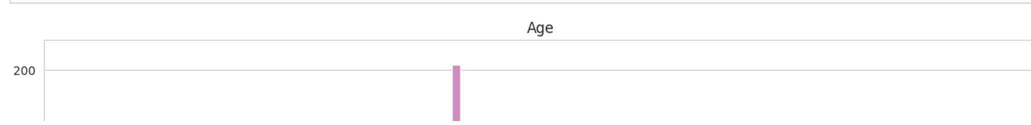
```
# petal_length vs petal_width boxplot

plt.figure(figsize=(15, 6))
sns.boxplot(x='Age', y='Pclass', data=df, palette='Set3')
plt.title('Age vs Pclass')
plt.xlabel('Age')
plt.ylabel('Pclass')
plt.xticks(rotation=45, ha='right')
plt.show()
```

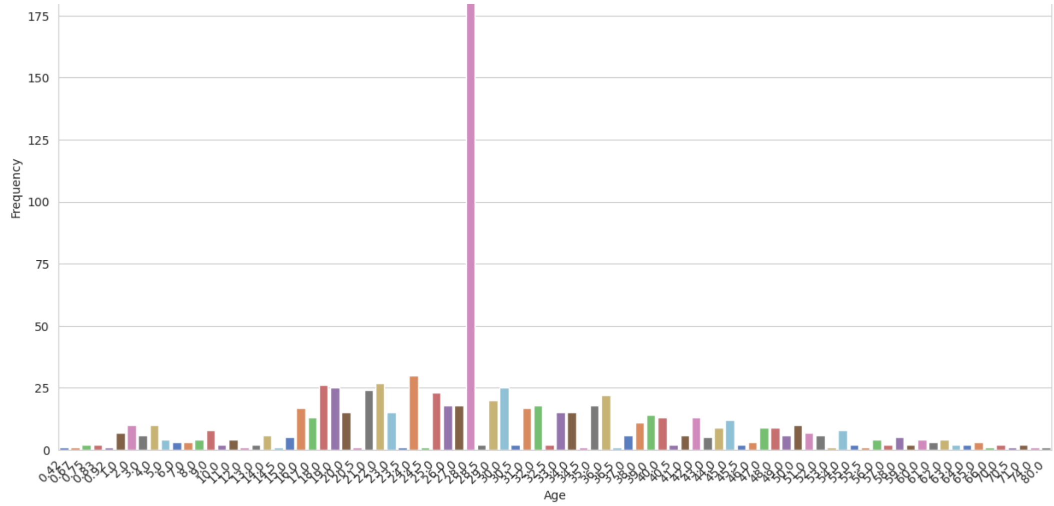


5.4 countplot

In [25]:

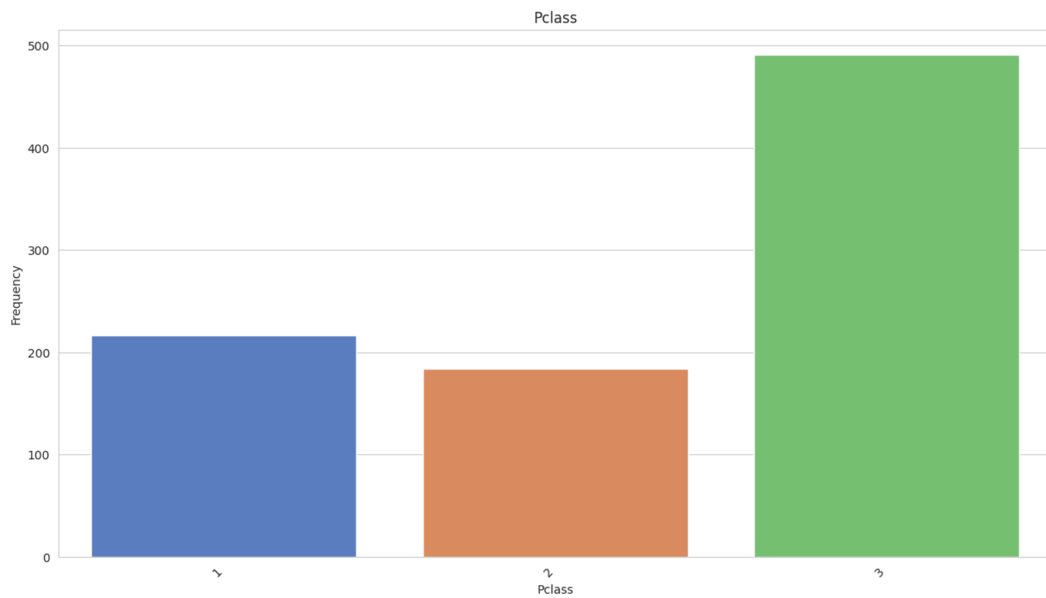
```
# sepal_length
plt.figure(figsize=(15, 8))
sns.countplot(x='Age', data=df, palette='muted')
plt.title('Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```





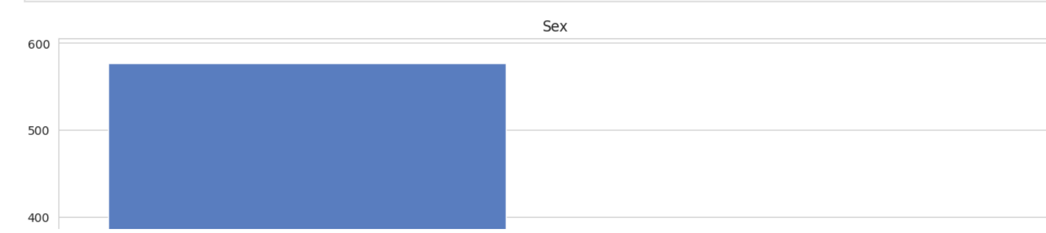
In [26]:

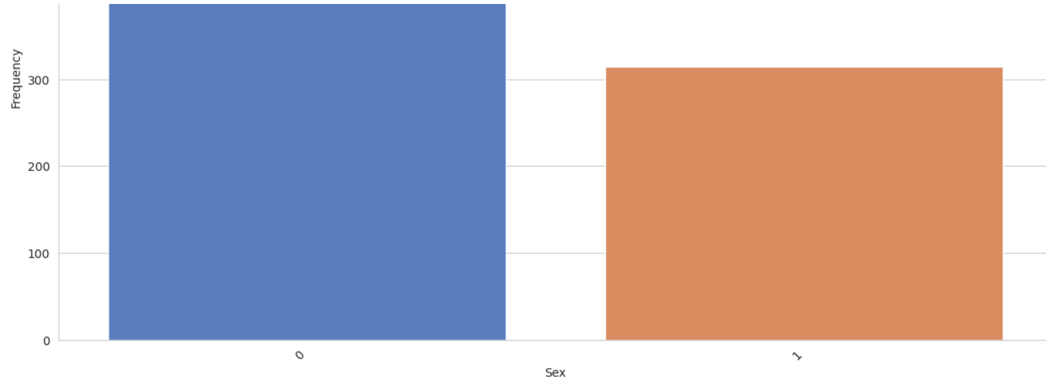
```
# sepal_width
plt.figure(figsize=(15, 8))
sns.countplot(x='Pclass', data=df, palette='muted')
plt.title('Pclass')
plt.xlabel('Pclass')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```



In [27]:

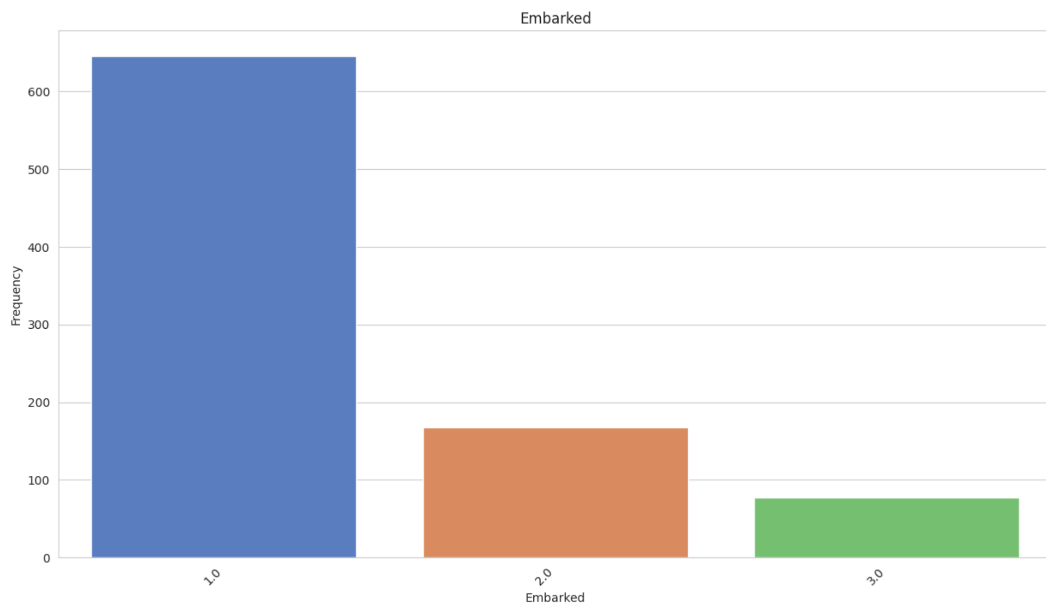
```
# petal_length
plt.figure(figsize=(15, 8))
sns.countplot(x='Sex', data=df, palette='muted')
plt.title('Sex')
plt.xlabel('Sex')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```





In [28]:

```
# sepal_width
plt.figure(figsize=(15, 8))
sns.countplot(x='Embarked', data=df, palette='muted')
plt.title('Embarked')
plt.xlabel('Embarked')
plt.ylabel('Frequency')
plt.xticks(rotation=45, ha='right')
plt.show()
```

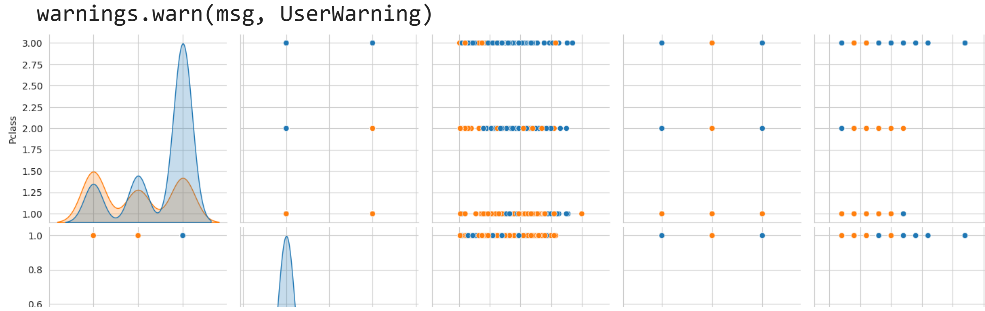


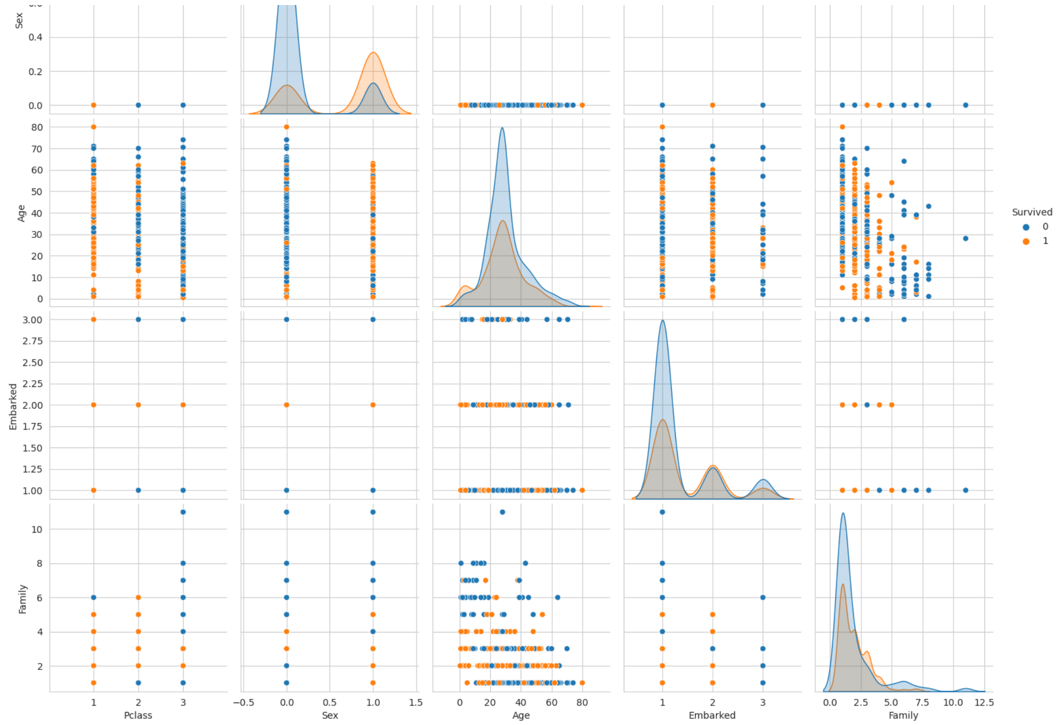
5.5 pairplot

In [29]:

```
sns.set_style("whitegrid")
sns.pairplot(df, hue="Survived", size=3)
plt.show()
```

```
/opt/conda/lib/python3.10/site-packages/seaborn/axisgrid.py:2095: UserWarning: Th
e `size` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

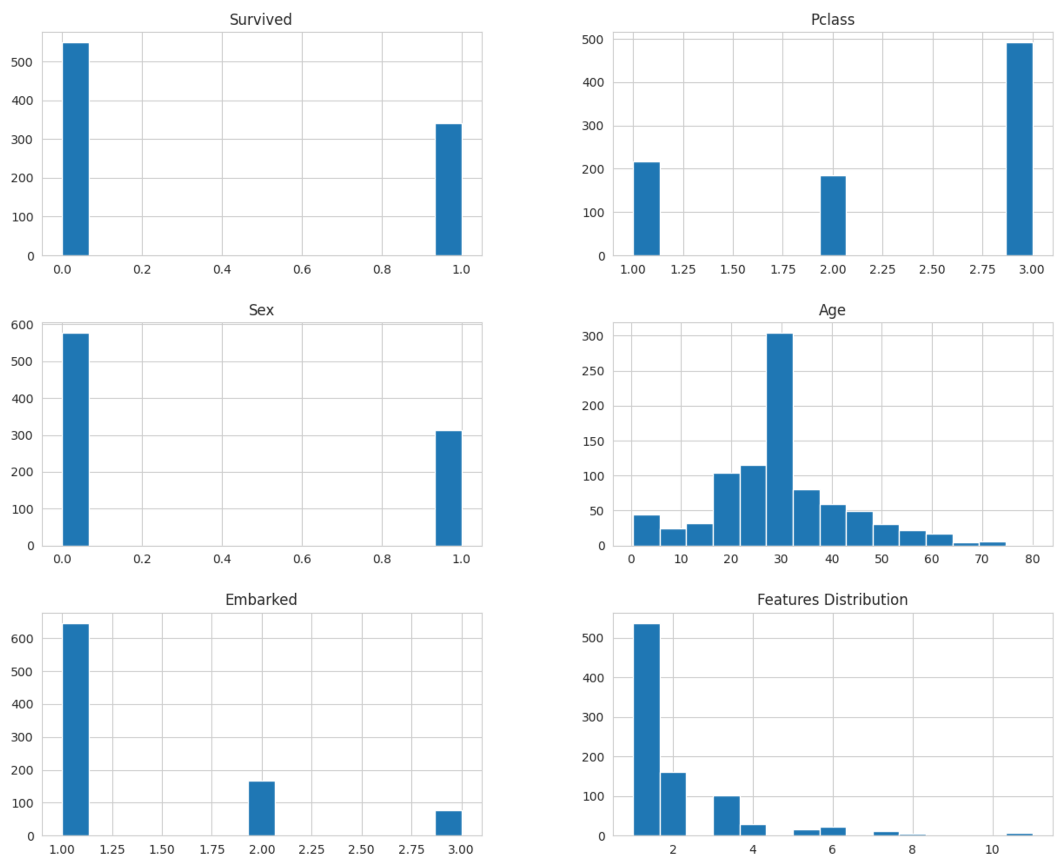




5.6 Hist Plot

In [30]:

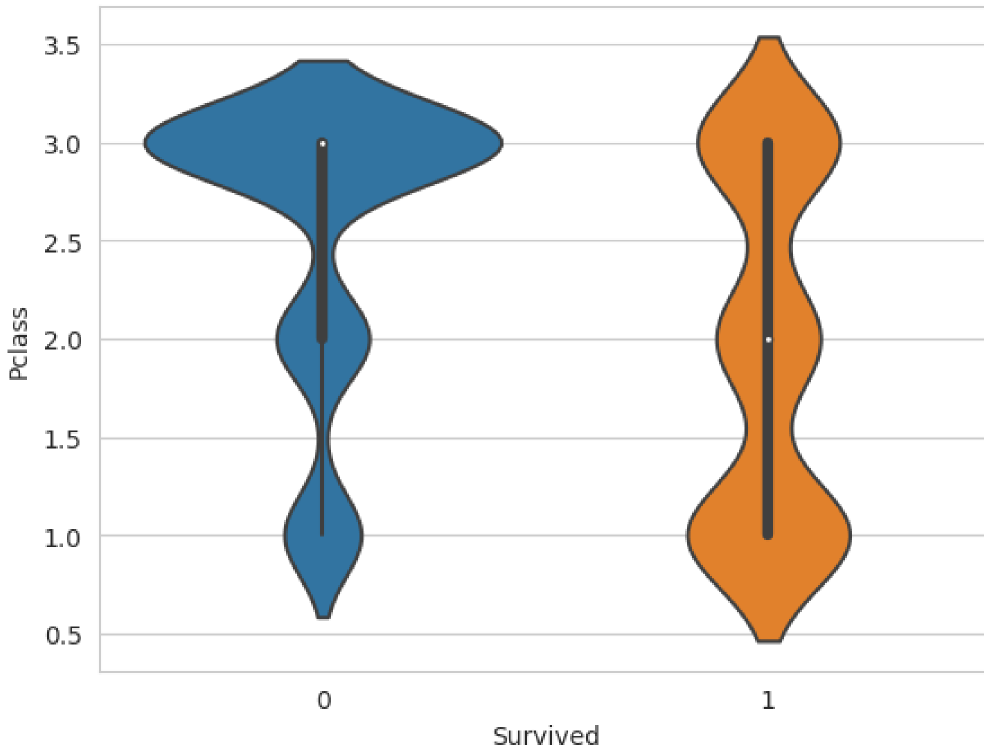
```
df.hist(figsize=(15,12),bins = 15)
plt.title("Features Distribution")
plt.show()
```



5.7 violinplot

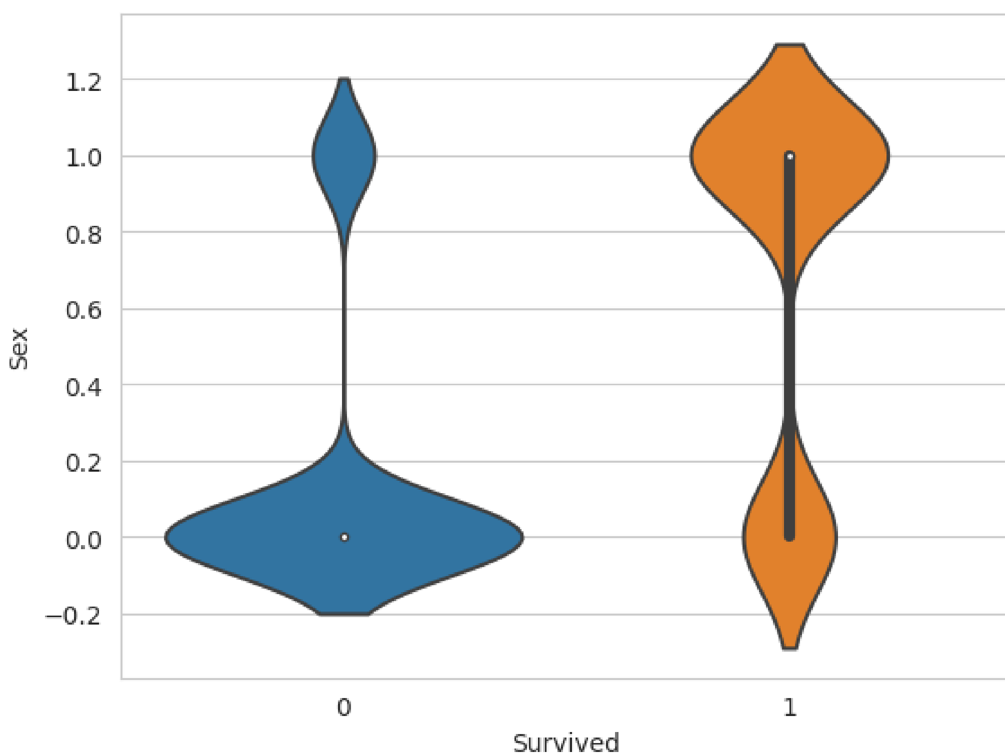
In [31]:
```
sns.violinplot(x="Survived",y="Pclass", data=df, size = 8)
```

Out[31]: <Axes: xlabel='Survived', ylabel='Pclass'>



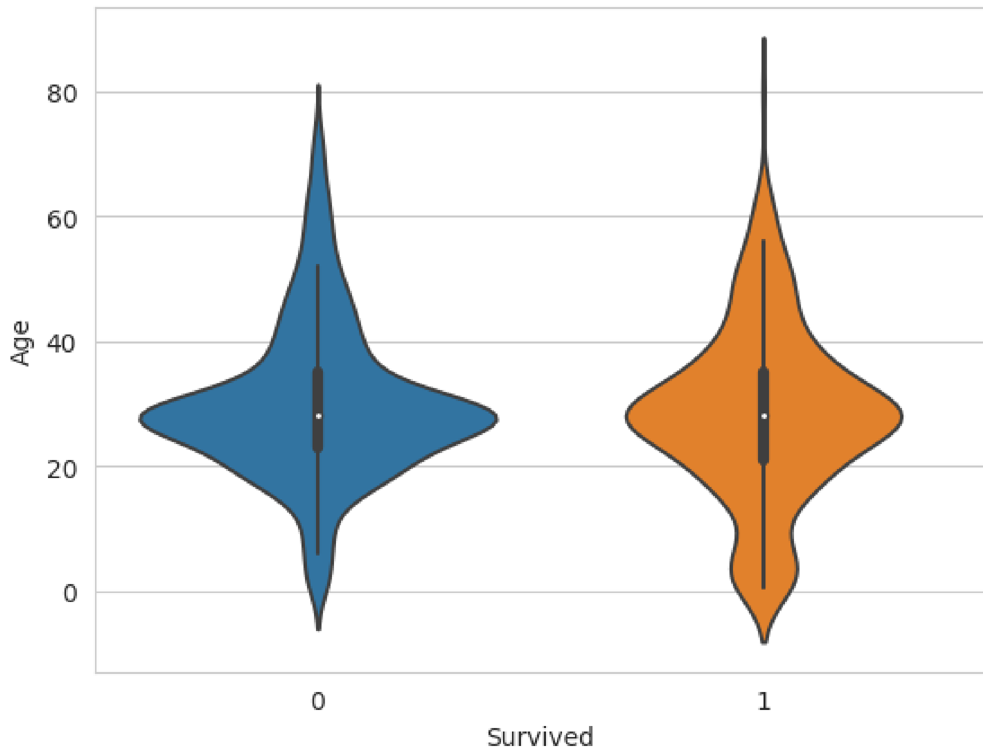
In [32]:
```
sns.violinplot(x="Survived",y="Sex", data=df, size = 8)
```

Out[32]: <Axes: xlabel='Survived', ylabel='Sex'>



In [33]:
```
sns.violinplot(x="Survived",y="Age", data=df, size = 8)
```

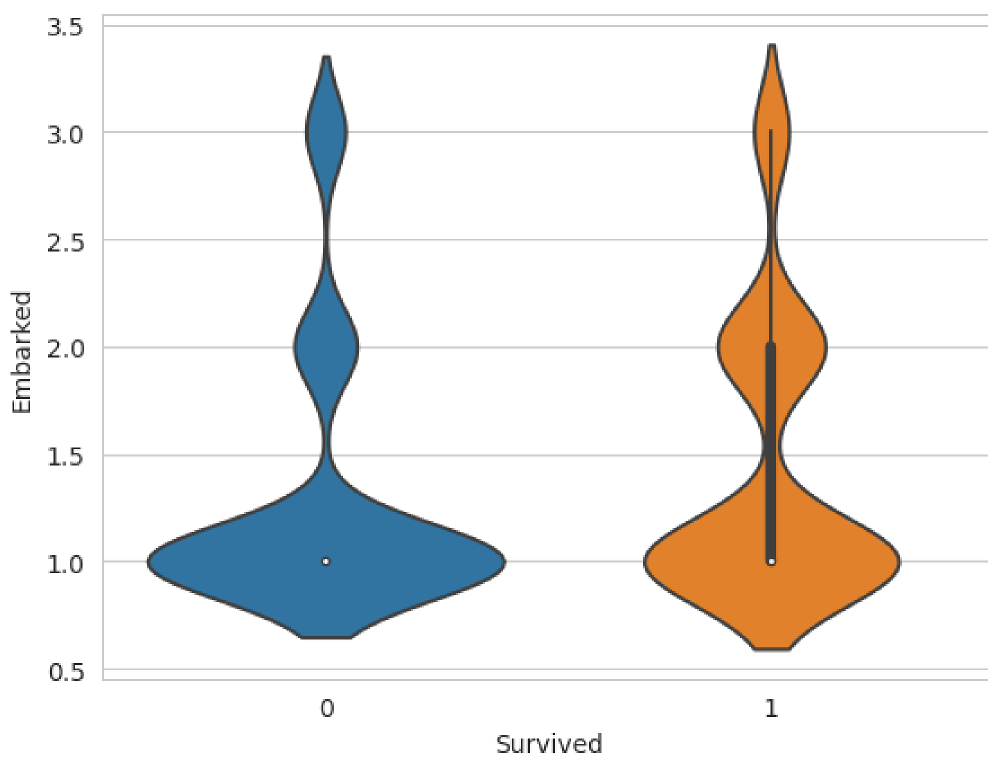
Out[33]: <Axes: xlabel='Survived', ylabel='Age'>



In [34]:

```
sns.violinplot(x="Survived",y="Embarked", data=df, size = 8)
```

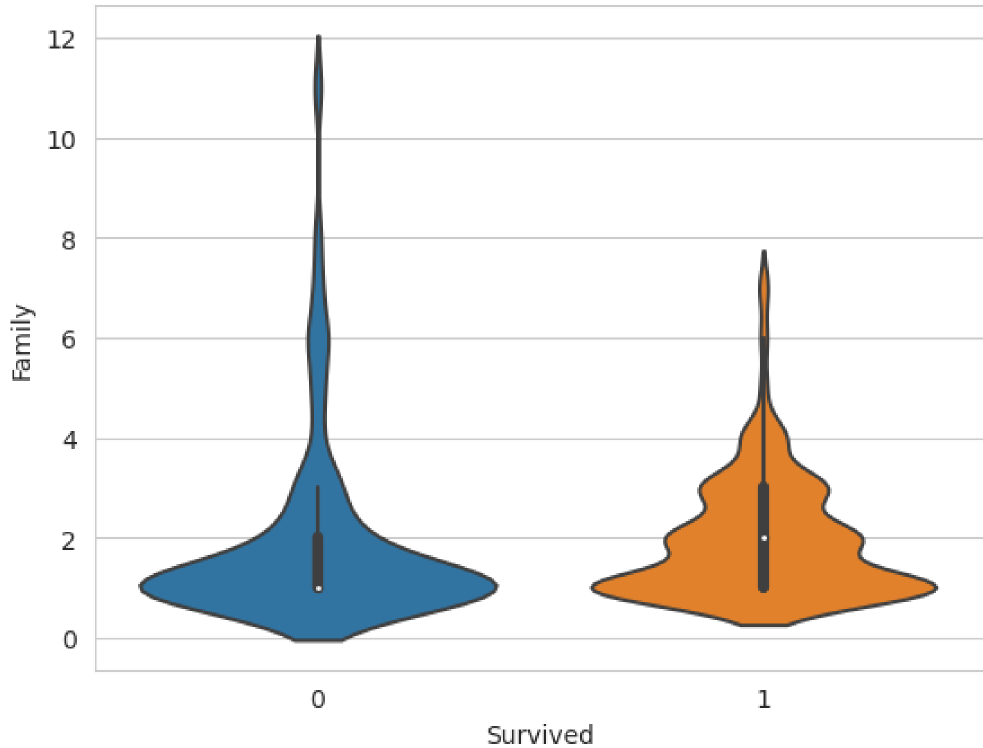
Out[34]: <Axes: xlabel='Survived', ylabel='Embarked'>



In [35]:

```
sns.violinplot(x="Survived",y="Family", data=df, size = 8)
```

Out[35]: <Axes: xlabel='Survived', ylabel='Family'>



5.8 Pie Plot

In [36]:

```
# ax=plt.subplots(1,1,figsize=(10,8))
# df['species'].value_counts().plot.pie(explode=[0.1,0.1,0.1],autopct='%1.1f%%'
# plt.title("Iris Species %")
# plt.show()
```

6 | Split the Dataset

In [37]:

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

In [38]:

```
df.head()
```

Out[38]:

	Survived	Pclass	Sex	Age	Embarked	Family
0	0	3	0	22.0	1.0	2
1	1	1	1	38.0	2.0	2
2	1	3	1	26.0	1.0	1
3	1	1	1	35.0	1.0	2
4	0	3	0	35.0	1.0	1

In [39]:

```
X = df[["Pclass", "Sex", "Age", "Embarked","Family"]]
```

In [40]:

```
y = df['Survived']
```

In [41]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random
```

In [42]:
```
X_train.shape,X_test.shape,y_train.shape,y_test.shape
```

Out[42]:
```
((712, 5), (179, 5), (712,), (179,))
```

7 | PCA (Principal Component Analysis)

In [43]:
```
from sklearn.decomposition import PCA
```

In [44]:
```
pca = PCA(n_components=2)
```

In [45]:
```
pca
```

Out[45]:
```
PCA(n_components=2)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [46]:
```
X_pca = pca.fit_transform(X)
```

In [47]:
```
X_pca[0]
```

Out[47]:
```
array([-7.37313857, -0.14876855])
```

In [48]:
```
print("Explained Variance Ratio:")
print(pca.explained_variance_ratio_)
```

```
Explained Variance Ratio:
[0.97870884 0.01416231]
```

In [49]:
```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X = scaler.fit_transform(X)
```

In [50]:
```
X[0]
```

Out[50]:
```
array([1.        , 0.        , 0.27117366, 0.        , 0.1       ])
```

In [51]:
```
X[1]
```

Out[51]:
```
array([0.       , 1.       , 0.4722292, 0.5      , 0.1      ])
```

Algorithm 🔄

(1) KNN

In [52]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
```

In [53]:
```
knn_classifier = KNeighborsClassifier(n_neighbors=3)
```

In [54]:
```
knn_classifier.fit(X_train, y_train)
```

Out[54]:
```
KNeighborsClassifier(n_neighbors=3)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [55]:
```
train_predictions = knn_classifier.predict(X_train)

train_accuracy1 = accuracy_score(y_train, train_predictions)
```

In [56]:
```
test_predictions = knn_classifier.predict(X_test)

test_accuracy1 = accuracy_score(y_test, test_predictions)
```

In [57]:
```
print(f"Training Accuracy: {train_accuracy1}")
print(f"Testing Accuracy: {test_accuracy1}")
```

```
Training Accuracy: 0.8553370786516854
Testing Accuracy: 0.770949720670391
```

(2) Naive Bayes classifier 🔄

In [58]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB

from sklearn import metrics
```

In [59]:
```
# GaussianNB
```

In [60]:
```
G_classifier = GaussianNB()
```

In [61]:
```
G_classifier.fit(X_train, y_train)
```

Out[61]:
```
GaussianNB()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [62]:
```
train_predictions = G_classifier.predict(X_train)

train_accuracy21 = accuracy_score(y_train, train_predictions)
```

In [63]:
```
test_predictions = G_classifier.predict(X_test)

test_accuracy21 = accuracy_score(y_test, test_predictions)
```

In [64]:
```
print(f"Training Accuracy: {train_accuracy21}")
print(f"Testing Accuracy: {test_accuracy21}")
```

```
Training Accuracy: 0.7935393258426966
Testing Accuracy: 0.7653631284916201
```

In [65]:
```
# BernoulliNB
```

In [66]:
```
B_classifier = BernoulliNB()
```

In [67]:
```
B_classifier.fit(X_train, y_train)
```

Out[67]: BernoulliNB()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [68]:
```
train_predictions = B_classifier.predict(X_train)

train_accuracy22 = accuracy_score(y_train, train_predictions)
```

In [69]:
```
test_predictions = G_classifier.predict(X_test)

test_accuracy22 = accuracy_score(y_test, test_predictions)
```

In [70]:
```
print(f"Training Accuracy: {train_accuracy22}")
print(f"Testing Accuracy: {test_accuracy22}")
```

```
Training Accuracy: 0.7879213483146067
Testing Accuracy: 0.7653631284916201
```

In [71]:
```
# MultinomialNB
```

In [72]:
```
M_classifier = MultinomialNB()
```

In [73]:
```
M_classifier.fit(X_train, y_train)
```

Out[73]: MultinomialNB()

In a Jupyter environment, please rerun this cell to show the HTML representation

or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [74]:
```
train_predictions = M_classifier.predict(X_train)

train_accuracy23 = accuracy_score(y_train, train_predictions)
```

In [75]:
```
test_predictions = M_classifier.predict(X_test)

test_accuracy23 = accuracy_score(y_test, test_predictions)
```

In [76]:
```
print(f"Training Accuracy: {train_accuracy23}")
print(f"Testing Accuracy: {test_accuracy23}")
```

```
Training Accuracy: 0.7865168539325843
Testing Accuracy: 0.7821229050279329
```

In [77]:
```
# GaussianNB
# BernoulliNB
# MultinomialNB

# Being the best of them | GaussianNB |
```

(3) Decision Tree 🔄

In [78]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [79]:
```
clf = DecisionTreeClassifier()
```

In [80]:
```
clf.fit(X_train, y_train)
```

Out[80]:
```
DecisionTreeClassifier()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [81]:
```
train_predictions = clf.predict(X_train)

train_accuracy3 = accuracy_score(y_train, train_predictions)
```

In [82]:
```
test_predictions = clf.predict(X_test)

test_accuracy3 = accuracy_score(y_test, test_predictions)
```

In [83]:
```
print(f"Training Accuracy: {train_accuracy3}")
print(f"Testing Accuracy: {test_accuracy3}")
```

```
Training Accuracy: 0.9339887640449438
```

```
Testing Accuracy: 0.7932960893854749
```

(4) Random Forest 🔄

In [84]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [85]:
```
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)
```

In [86]:
```
rf_classifier.fit(X_train, y_train)
```

Out[86]:
```
RandomForestClassifier(random_state=42)
```

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In [87]:
```
train_predictions = rf_classifier.predict(X_train)

train_accuracy4 = accuracy_score(y_train, train_predictions)
```

In [88]:
```
test_predictions = rf_classifier.predict(X_test)

test_accuracy4 = accuracy_score(y_test, test_predictions)
```

In [89]:
```
print(f"Training Accuracy: {train_accuracy4}")
print(f"Testing Accuracy: {test_accuracy4}")
```

```
Training Accuracy: 0.9339887640449438
Testing Accuracy: 0.8212290502793296
```

(5) Boosting Algorithm 🔄

In [90]:
```
from sklearn.ensemble import AdaBoostClassifier
```

In [91]:
```
base_classifier = DecisionTreeClassifier(max_depth=3)
```

In [92]:
```
adaboost_classifier = AdaBoostClassifier(base_classifier, n_estimators=50, rar
```

In [93]:
```
adaboost_classifier.fit(X_train, y_train)
```

Out[93]:
```
AdaBoostClassifier(estimator=DecisionTreeClassifier(max_depth=3),
                   random_state=42)
```

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In [94]:
```
train_predictions = adaboost_classifier.predict(X_train)

train_accuracy5 = accuracy_score(y_train, train_predictions)
```

In [95]:
```
test_predictions = adaboost_classifier.predict(X_test)

test_accuracy5 = accuracy_score(y_test, test_predictions)
```

In [96]:
```
print(f"Training Accuracy: {train_accuracy5}")
print(f"Testing Accuracy: {test_accuracy5}")
```

```
Training Accuracy: 0.925561797752809
Testing Accuracy: 0.7877094972067039
```

(6).SVM

In [97]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
```

In [98]:
```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [99]:
```
svm_classifier = SVC(kernel='linear', C=1.0)
```

In [100…
```
svm_classifier.fit(X_train, y_train)
```

Out[100…
```
SVC(kernel='linear')
```

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In [101…
```
train_predictions = svm_classifier.predict(X_train)

train_accuracy6 = accuracy_score(y_train, train_predictions)
```

In [102…
```
test_predictions = svm_classifier.predict(X_test)

test_accuracy6 = accuracy_score(y_test, test_predictions)
```

In [103…
```
print(f"Training Accuracy: {train_accuracy6}")
print(f"Testing Accuracy: {test_accuracy6}")
```

```
Training Accuracy: 0.7879213483146067
Testing Accuracy: 0.7821229050279329
```

(7). Logistic Regression

In [104…

```
from sklearn import linear_model
```

In [105…

```
lrg = linear_model.LogisticRegression()
```

In [106…

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

Out[106…

```
LogisticRegression()
```

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In [107…

```
train_predictions = lrg.predict(X_train)

train_accuracy7 = accuracy_score(y_train, train_predictions)
```

In [108…

```
test_predictions = lrg.predict(X_test)

test_accuracy7 = accuracy_score(y_test, test_predictions)
```

In [109…

```
print(f"Training Accuracy: {train_accuracy7}")
print(f"Testing Accuracy: {test_accuracy7}")
```

```
Training Accuracy: 0.8033707865168539
Testing Accuracy: 0.8044692737430168
```

(8).Linear Regression

In [110…

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
```

In [111…

```
model = LinearRegression()
```

In [112…

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

Out[112…

```
LinearRegression()
```

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In [113…

```
train_predictions = clf.predict(X_train)

train_accuracy8 = accuracy_score(y_train, train_predictions)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but DecisionTreeClassifier was fitted with feature
names
  warnings.warn(
```

In [114

```
test_predictions = clf.predict(X_test)

test_accuracy8 = accuracy_score(y_test, test_predictions)
```

```
/opt/conda/lib/python3.10/site-packages/sklearn/base.py:439: UserWarning: X does
not have valid feature names, but DecisionTreeClassifier was fitted with feature
names
  warnings.warn(
```

In [115…

```
print(f"Training Accuracy: {train_accuracy8}")
print(f"Testing Accuracy: {test_accuracy8}")
```

```
Training Accuracy: 0.3890449438202247
Testing Accuracy: 0.4134078212290503
```

(9).Gradient Boosting Machines (GBM)

In [116…

```
from sklearn.ensemble import GradientBoostingClassifier
```

In [117…

```
model = GradientBoostingClassifier(n_estimators=100, learning_rate=0.1, max_de
```

In [118…

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

Out[118…

```
GradientBoostingClassifier(random_state=42)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [119…

```
train_predictions = model.predict(X_train)

train_accuracy9 = accuracy_score(y_train, train_predictions)
```

In [120…

```
test_predictions = model.predict(X_test)

test_accuracy9 = accuracy_score(y_test, test_predictions)
```

In [121…

```
print(f"Training Accuracy: {train_accuracy9}")
print(f"Testing Accuracy: {test_accuracy9}")
```

```
Training Accuracy: 0.8707865168539326
Testing Accuracy: 0.8156424581005587
```

Random Forest, Decision Tree, Gradient Boosting Machines (GBM), Algorithm is the best accuracy

(GradientBoostingClassifier)

accuracy mean = 0.90

accuracy mean = 0.90

10 | Hierarchical Clustering

In [122…

```
from scipy.cluster.hierarchy import linkage, dendrogram, fcluster
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
```

In [123…

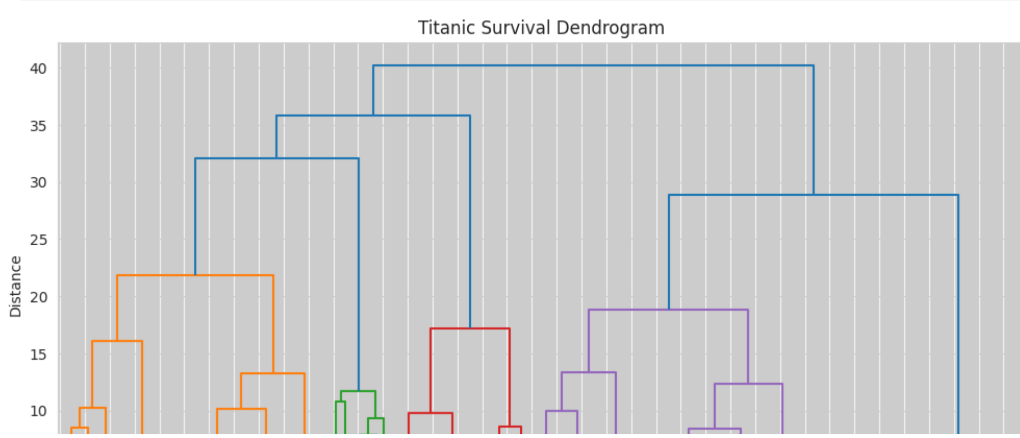
```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

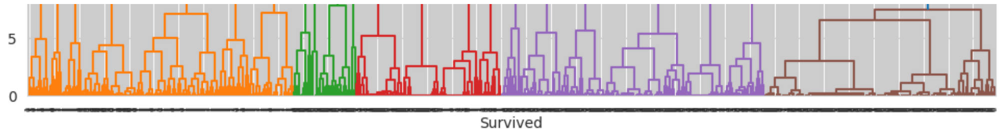
In [124…

```
linkage_matrix = linkage(X_scaled, method='ward')
```

In [125…

```
plt.figure(figsize=(12, 6))
dendrogram(linkage_matrix, labels=df['Survived'].values, orientation='top', di
plt.title('Titanic Survival Dendrogram')
plt.xlabel('Survived')
plt.ylabel('Distance')
plt.show()
```





In [ ]: