Titanic Passanger Survival Analysis

In [128…
```python
from IPython.display import Image
Image(url= "https://static1.squarespace.com/static/5006453fe4b09ef2252ba068/5095eabce4b06cb305058603/5095eabce4b02d37bef4c24c/1352
```

Out[128…

Data Import and Loading

In [129…
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [130…
```python
df = pd.read_csv("train.csv")

df.head()
```

Out[130…

	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

Data Study

In [131…
```python
print("shape of the data is :", df.shape)
```

```
shape of the data is : (891, 12)
```

Checking data types and missing values to guide cleaning.

In [132…
```python
df.info()
```

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
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 [133…

```python
df.describe()
```

Out[133…

	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 [134…

```python
print("null values in the data :")
df.isnull().sum()
```

```
null values in the data :
```

Out[134…

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

Data Visualization

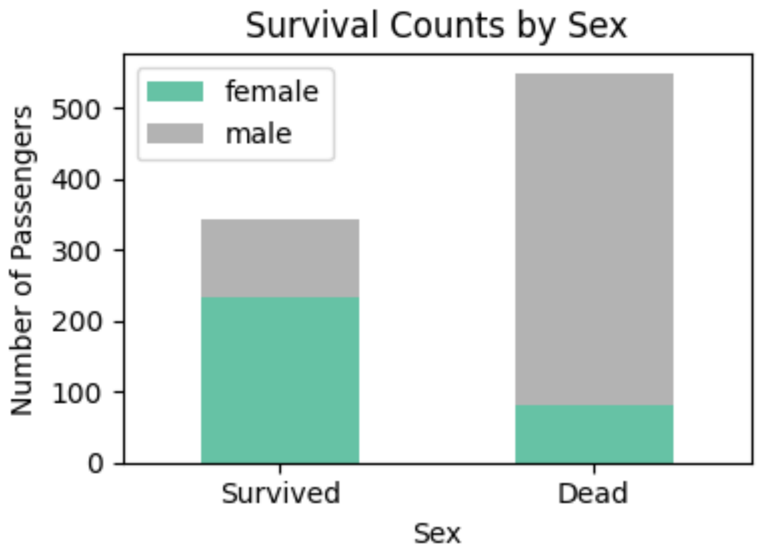
In [135…

```python
def bar_plot(data, feature) :
    survived = data[data["Survived"] == 1][feature].value_counts()
    dead = data[data["Survived"] == 0][feature].value_counts()
    df = pd.DataFrame([survived, dead])
    df.index = ['Survived', 'Dead']
    print("Survived :\n", survived)
    print("Dead:\n", dead)
    df.plot(kind="bar", stacked = True, figsize=(4, 3), colormap='Set2')
    plt.title(f"Survival Counts by {feature}")
    plt.xlabel(feature)
    plt.ylabel("Number of Passengers")
    plt.xticks(rotation=0)
    plt.legend()
    plt.tight_layout()
    plt.show()
```

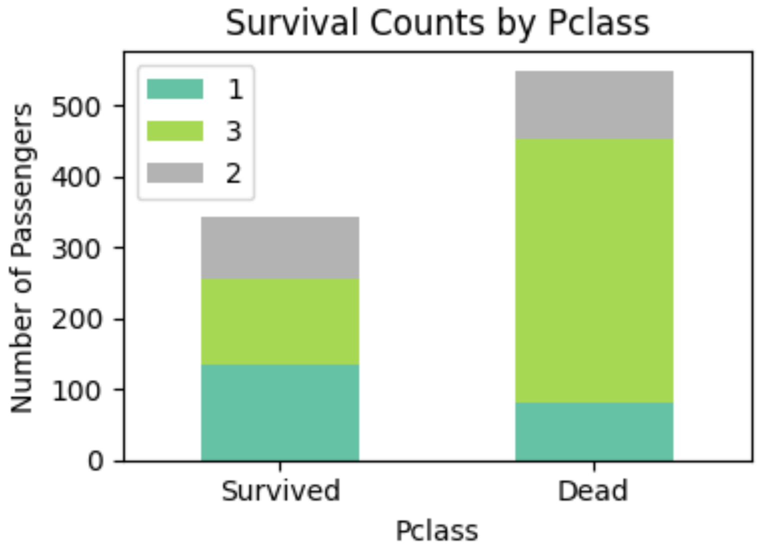
In [136…

```python
features = ["Sex", "Pclass", "SibSp", "Parch", "Embarked"]
for col in features:
    bar_plot(df, col)
```

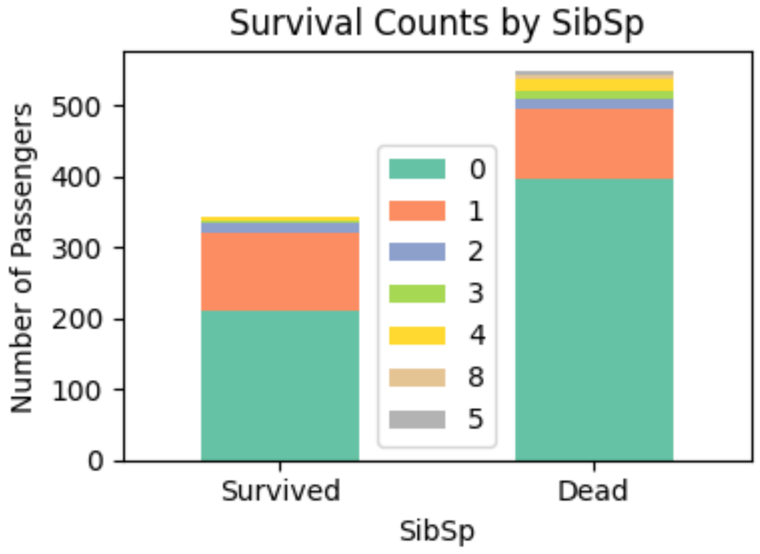
```
Survived :
 Sex
female    233
male      109
Name: count, dtype: int64
Dead:
 Sex
male      468
female     81
Name: count, dtype: int64
```



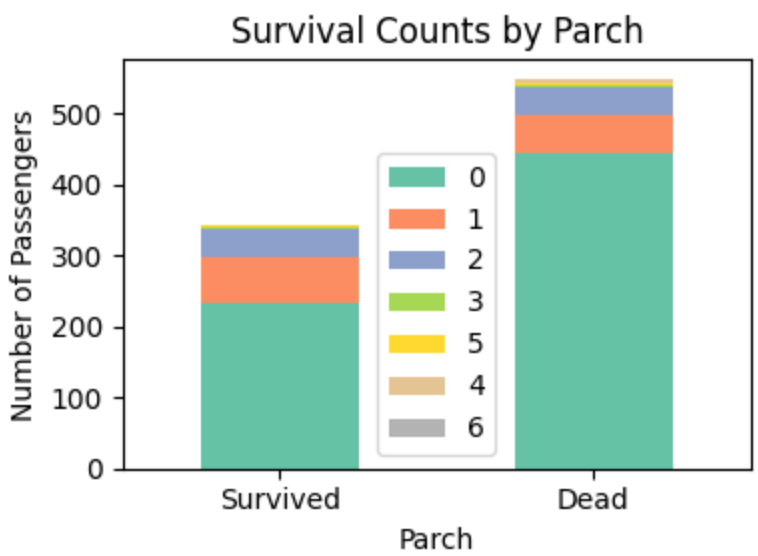

```
Survived :
 Pclass
1    136
3    119
2     87
Name: count, dtype: int64
Dead:
 Pclass
3    372
2     97
1     80
Name: count, dtype: int64
```



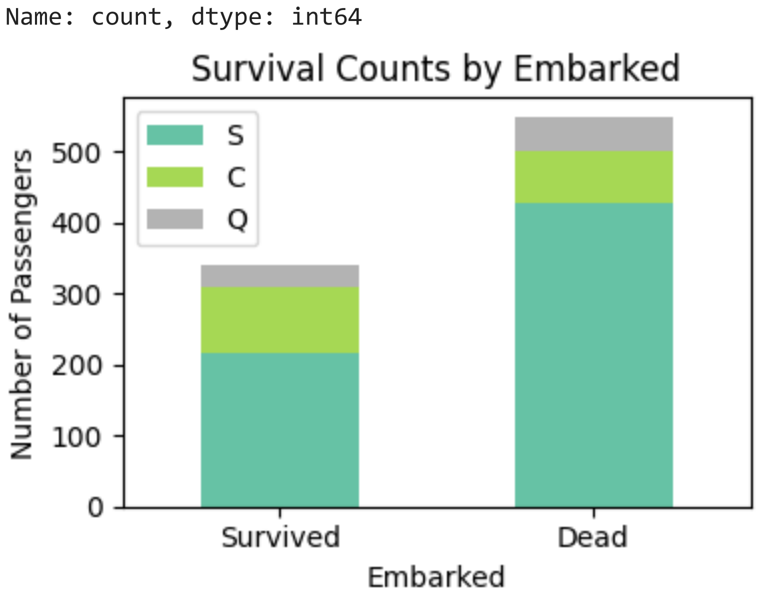

```
Survived :
 SibSp
0    210
1    112
2     13
3      4
4      3
Name: count, dtype: int64
Dead:
 SibSp
0    398
1     97
4     15
2     15
3     12
8      7
5      5
Name: count, dtype: int64
```



```
Survived :
 Parch
0    233
1     65
2     40
3      3
5      1
Name: count, dtype: int64
Dead:
 Parch
0    445
1     53
2     40
5      4
4      4
3      2
6      1
Name: count, dtype: int64
```




```
Survived :
 Embarked
S    217
C     93
Q     30
Name: count, dtype: int64
Dead:
 Embarked
S    427
C     75
Q     47
Name: count, dtype: int64
```



Summary of the Data

Females are more likely survivied than Males.

Class 1 survived the more than other classes Class 3 are more likely to be dead

People aboarded with more than 2 siblings or spouse more likely survived. People aboarded without siblings or spouse are more likely to be dead

Passengers with no family (SibSp = 0) were most common and had high mortality (398 died, 210 survived). Passengers with 1 sibling/spouse had a relatively better chance of survival (112 survived vs. 97 died).

Having a large number of siblings/spouses (≥3) strongly correlates with lower survival.

The Chart confirms a person aboarded from C slightly more likely survived. The Chart confirms a person aboarded from Q more likely dead. The Chart confirms a person aboarded from S more likely dead.

In Short

Women, the wealthy, and those with close family had the best chance of survival.

Men, 3rd Class travelers, and those alone or in big families were at higher risk.

Feature Engineering

Creating new input features or modifying existing ones to improve the performance of the machine learning model.

Extracting Titles from Name to get their social status.

In [137…
```
df["Title"] = df["Name"].str.extract('([A-Za-z]+)\.', expand = False)
```

In [138…
```
print("Data: \n",
    df["Title"].value_counts())
```

```
Data:
 Title
Mr          517
Miss        182
Mrs         125
Master       40
Dr            7
Rev           6
Mlle          2
Major         2
Col           2
Countess      1
Capt          1
Ms            1
Sir           1
Lady          1
Mme           1
Don           1
Jonkheer      1
Name: count, dtype: int64
```

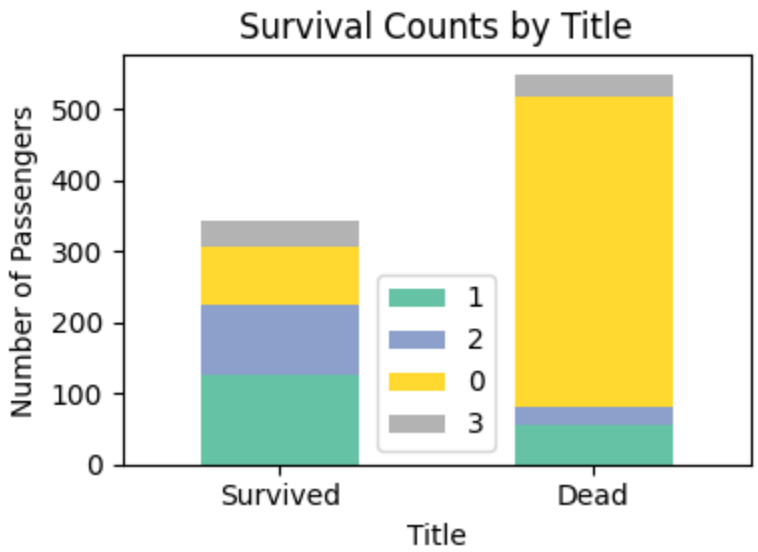
In [139…
```
title_mapping = {"Mr": 0, "Miss": 1, "Mrs": 2, 'Master': 3,
                 "Dr": 3, "Rev": 3, "Col": 3, "Major": 3, "Mlle": 3,"Countess": 3,
                 "Ms": 3, "Lady": 3, "Jonkheer": 3, "Don": 3, "Dona" : 3, "Mme": 3,"Capt": 3,"Sir": 3 }

df['Title'] = df["Title"].map(title_mapping)
```

In [140…
```
df.drop(columns="Name", inplace = True)
```

In [141…
```
bar_plot(df, "Title")
```

```
Survived :
 Title
1    127
2     99
0     81
3     35
Name: count, dtype: int64
Dead:
 Title
0    436
1     55
3     32
2     26
Name: count, dtype: int64
```



Interpretation

Women (Miss, Mrs) had the highest survival rates.

Men (Mr) had the lowest survival rate.

Rare titles and children (Master) had mixed outcomes — some survived, but also dead.

Sex Mapping

In [142…
```
sex_mapping = {"female" : 0, 'male': 1}

df["Sex"] = df["Sex"].map(sex_mapping)
```

In [143…

```python
df.head(3)
```

Out[143…

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title
0	1	0	3	1	22.0	1	0	A/5 21171	7.2500	NaN	S	0
1	2	1	1	0	38.0	1	0	PC 17599	71.2833	C85	C	2
2	3	1	3	0	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1

Filling up NaN values in Age column and Binning age in groups

In [144…

```python
df["Age"] = df["Age"].fillna(df.groupby("Title")["Age"].transform("median"))

df["Age"].isnull().sum()
```

Out[144… 0

In [145…

```python
facet = sns.FacetGrid(df, hue="Survived",aspect=4)
facet.map(sns.kdeplot,'Age',shade= True)
facet.set(xlim=(0, df['Age'].max()))
facet.add_legend()
plt.show()
```

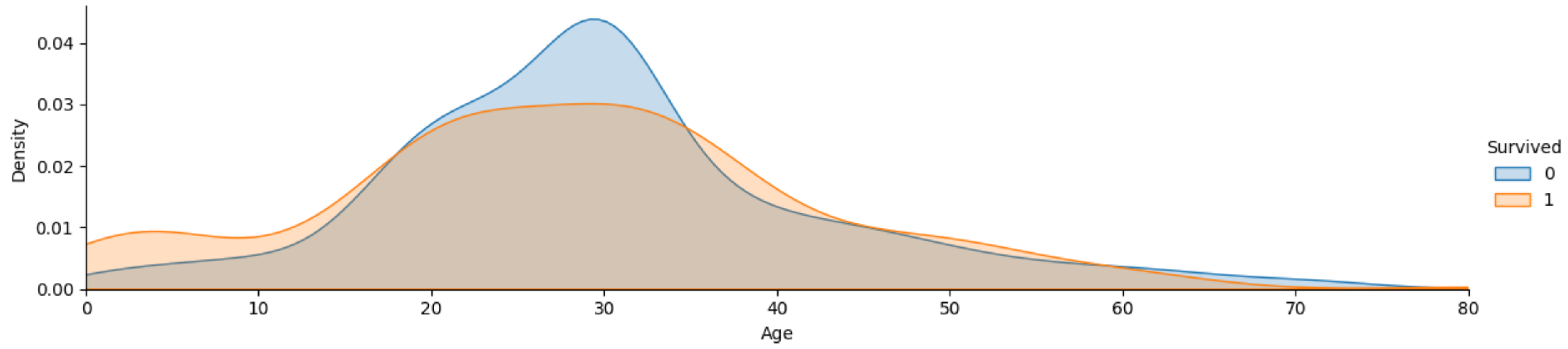
```
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: FutureWarning: is_categorical_dtype is deprecated and will be removed in a future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: FutureWarning: is_categorical_dtype is deprecated and will be removed in a future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  func(*plot_args, **plot_kwargs)
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: FutureWarning: is_categorical_dtype is deprecated and will be removed in a future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\axisgrid.py:848: FutureWarning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  func(*plot_args, **plot_kwargs)
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: FutureWarning: is_categorical_dtype is deprecated and will be removed in a future version. Use isinstance(dtype, CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\Users\91982\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Those who were 25-35 years old were more dead and more survived.

In [146…

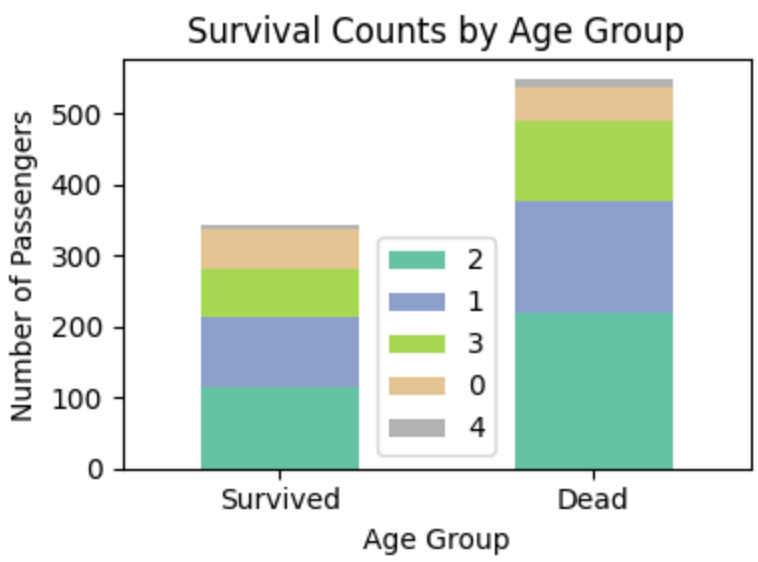
```python
def age_groups(age):
    if age <= 16:
        return 0  # Child
    elif age <= 26:
        return 1  # Young Adult
    elif age <= 36:
        return 2  # Adult
    elif age <= 62:
        return 3  # Middle Aged
    else:
        return 4  # Senior


df["Age Group"] = df["Age"].apply(age_groups)
```

In [147…

```python
bar_plot(df, "Age Group")
```

```
Survived :
 Age Group
2    116
1     97
3     69
0     57
4      3
Name: count, dtype: int64
Dead:
 Age Group
2    220
1    158
3    111
0     48
4     12
Name: count, dtype: int64
```



Interpretation

Younger passengers (age ≤ 16) had a higher survival rate, while survival decreased with age. Middle-aged and older passengers were less likely to survive.

This matches the historical "women and children first" pattern.

Mapping & Filling Null values in Embarked Feature

In [148…
```
emb_mapping = {'S': 0, 'C': 1, 'Q': 2}

df["Embarked"] = df["Embarked"].fillna(df["Embarked"].mode()[0]).map(emb_mapping)
```

In [149…
```
df.isnull().sum()
```

Out[149…
```
PassengerId      0
Survived         0
Pclass           0
Sex              0
Age              0
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         0
Title            0
Age Group        0
dtype: int64
```

Mapping & Filling Null values in Cabin Feature

In [150…
```
df["Cabin"] = df["Cabin"].fillna("Missing").str[0]
```

Since there are Categorical values, we use Encoding for transforming them into numerical

In [151…
```
from sklearn.preprocessing import LabelEncoder

encoder = LabelEncoder()

df["Cabin"] = encoder.fit_transform(df["Cabin"])
```

In [152…
```
df.isnull().sum()
```

Out[152...

```
PassengerId    0
Survived       0
Pclass         0
Sex            0
Age            0
SibSp          0
Parch          0
Ticket         0
Fare           0
Cabin          0
Embarked       0
Title          0
Age Group      0
dtype: int64
```

Family mapping

Since, "SibSp" and "Parch" represents related information: your family on board.

If it is used as-is then the model will treats them as independent features, even though they both desctibes the same thing(family). This could reduce the Performance.

In [153...

```
def family_size_group(n):
    if n == 1:
        return 0
    elif n <= 3:
        return 1
    elif n <= 6:
        return 2
    else:
        return 3
```

In [154...

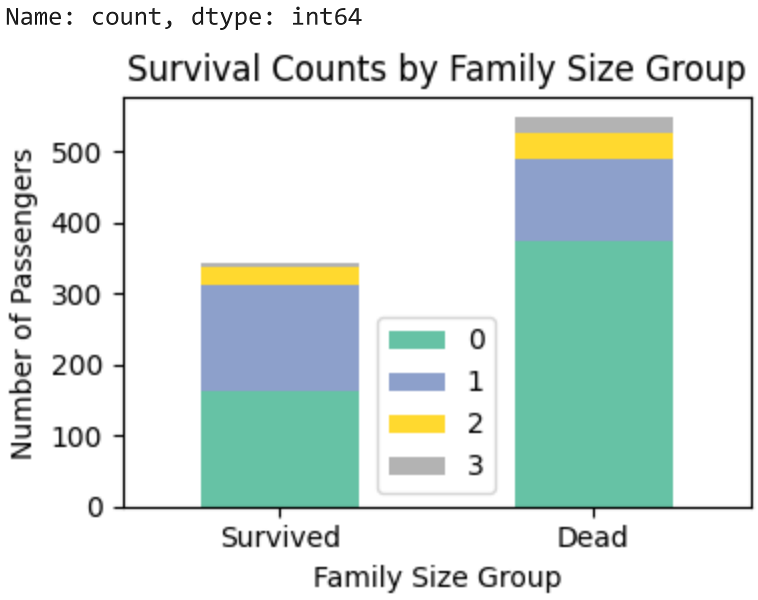
```
df["Family Size"] = df["SibSp"] + df["Parch"] + 1  # we add 1 for the passenger

df["Family Size Group"] = df["Family Size"].apply(family_size_group)
```

In [155...

```
bar_plot(df, "Family Size Group")
```

```
Survived :
 Family Size Group
0    163
1    148
2     27
3      4
Name: count, dtype: int64
Dead:
 Family Size Group
0    374
1    115
2     39
3     21
Name: count, dtype: int64
```



Passengers traveling alone (Group 0) had the lowest survival rate (30%), while those with small families (2–4 members, Group 1) had the highest (56%).

Larger families (Groups 2 & 3) showed decreasing survival rates, likely due to challenges in staying together during evacuation.

Creating fare per person

In [156...

```
df["Fare per Person"] = df["Fare"] / df["Family Size"]
```

Create is alone feature

In [157...

```
df['IsAlone'] = (df['Family Size'] == 1).astype(int)
```

Removing Unneccessary Columns

In [158...

```
df.drop(columns=['PassengerId', 'Ticket', 'SibSp', 'Parch', 'Age', 'Fare', 'Family Size'], inplace=True)
```

In [159...

```
df.head(3)
```

Out[159...

	Survived	Pclass	Sex	Cabin	Embarked	Title	Age Group	Family Size Group	Fare per Person	IsAlone
0	0	3	1	7	0	0	1	1	3.62500	0
1	1	1	0	2	1	2	3	1	35.64165	0
2	1	3	0	7	0	1	1	0	7.92500	1

Spliting the Data

In [160...

```
X = df.drop(columns="Survived")
y = df["Survived"]
```

We use scaling to standardize feature values so models can learn more effectively and converge faster.

In [161...

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

In [162...

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=485, stratify = y)
```

Modeling

We are selecting the best model

Comparing models using 10-fold cross-validation for robustness.

In [163...

```
# Importing Classifier Modules
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
```

Cross Validation(k-fold)

In [164...

```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
k_fold = KFold(n_splits=10, shuffle=True, random_state=0)
```

In [165...

```
models = [
    ("Random Forest", RandomForestClassifier(n_estimators=200, max_depth=5, min_samples_split=4, class_weight='balanced', random_s
    ("KNN", KNeighborsClassifier()),
    ("Decision Tree", DecisionTreeClassifier(class_weight='balanced', random_state=10)),
    ("Naive Bayes", GaussianNB()),
    ("SVM", SVC(probability=True, class_weight='balanced', random_state=10)),
    ("GBG", GradientBoostingClassifier(n_estimators=100, random_state=10))
]

for name, model in models:
    score = cross_val_score(model, X_train, y_train, cv=k_fold, scoring='accuracy')
    print(f"Average Accuracy of {name} model is :, {score.mean():.4f}")
```

```
Average Accuracy of Random Forest model is :, 0.8272
Average Accuracy of KNN model is :, 0.7992
Average Accuracy of Decision Tree model is :, 0.7794
Average Accuracy of Naive Bayes model is :, 0.7754
Average Accuracy of SVM model is :, 0.8244
Average Accuracy of GBG model is :, 0.8216
```

Random Forest Classifier is Working better

In [166...

```
RFC = RandomForestClassifier(n_estimators=200, max_depth=5, min_samples_split=4, class_weight='balanced', random_state=10)

RFC.fit(X_train, y_train)

y_pred = RFC.predict(X_test)
```

Evalution of the Model

In [167...

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

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

```
              precision    recall  f1-score   support

           0       0.85      0.85      0.85       110
           1       0.76      0.75      0.76        69

    accuracy                           0.82       179
   macro avg       0.81      0.80      0.80       179
weighted avg       0.82      0.82      0.82       179
```

In [168…

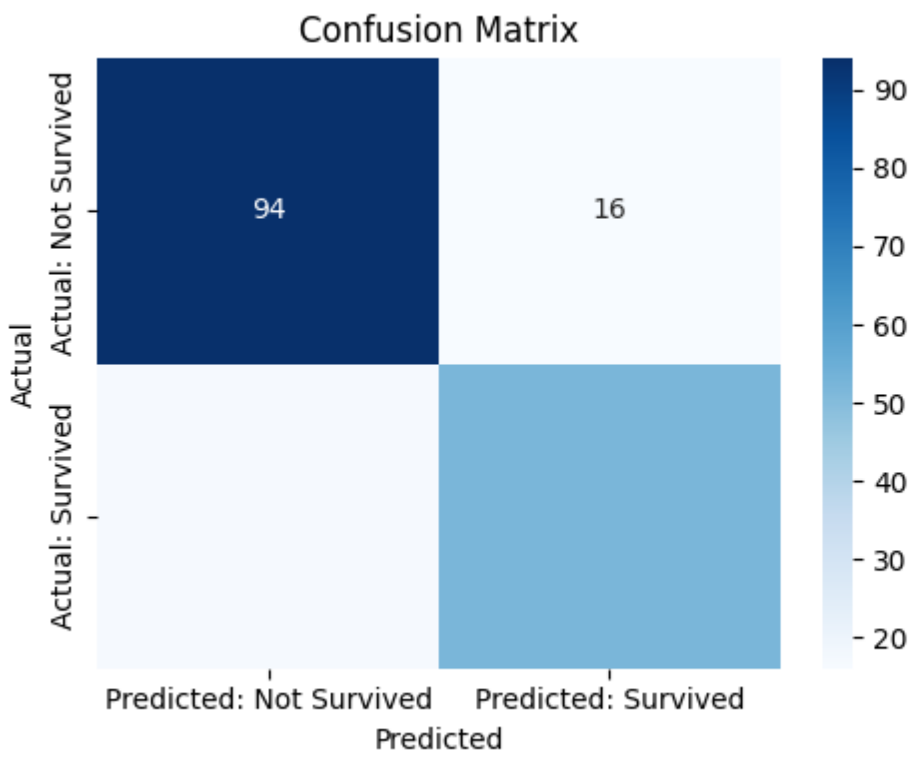
```python
conf_mat = confusion_matrix(y_test, y_pred)

print("The Confusion Matrix is as :\n\n",conf_mat, "\n\n")
plt.figure(figsize=(5, 4))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted: Not Survived', 'Predicted: Survived'],
            yticklabels=['Actual: Not Survived', 'Actual: Survived'])

plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.tight_layout()
plt.show()
```

```
The Confusion Matrix is as :

 [[94 16]
 [17 52]]
```



Conclusion

Model Performance Summary

The machine learning model built to predict Titanic passenger survival performs reasonably well, achieving an overall accuracy of 82%. It shows particularly strong results in identifying passengers who did not survive (class 0), with both precision and recall scores of 85%. This means when the model predicts someone didn't survive, it's correct 85% of the time, and it successfully identifies 85% of all actual non-survivors.

However, the model is slightly less effective at predicting survivors (class 1). While it still maintains decent performance with 76% precision and 75% recall, this indicates room for improvement. The model misses about 25% of actual survivors, incorrectly labeling them as non-survivors.

The confusion matrix shows:

True Negatives (94): Correctly predicted non-survivors (model said "died" and they actually died). False Positives (16): Incorrectly predicted as survivors (model said "survived" but they actually died). False Negatives (17): Incorrectly predicted as non-survivors (model said "died" but they actually survived). True Positives (52): Correctly predicted survivors (model said "survived" and they did).

Overall, the model demonstrates that machine learning can effectively uncover patterns in historical survival data, with women, children, and higher-class passengers being more likely to survive - findings that align with known historical accounts of the disaster. The current implementation provides a solid foundation that could be enhanced with more sophisticated techniques.