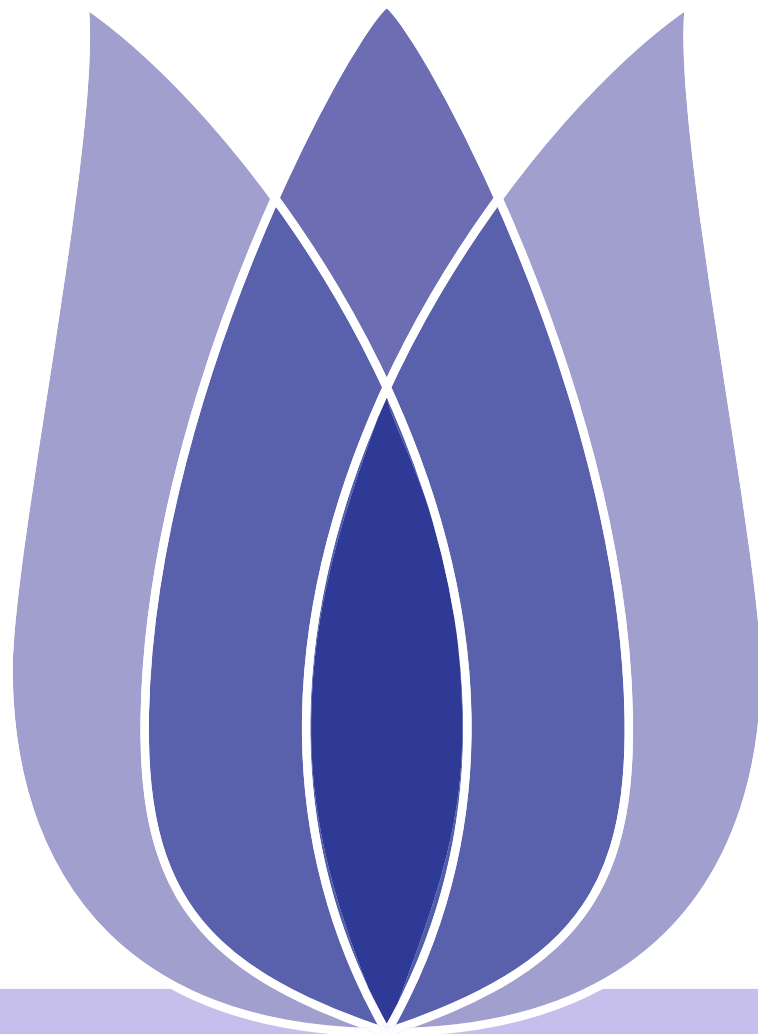


Titanic Survial Prediction

Pratikshya Parajuli

Ministry of Finance
Governmnet of Nepal

August 13, 2022





Overview

Overview
Introduction
Exploratory Data Analysis(EDA)
Feature Engineering and Data Cleaning
Predictive Modeling
Conclusion

Introduction

Exploratory Data Analysis(EDA)

Feature Engineering and Data Cleaning

Predictive Modeling

Conclusion



Overview

Introduction

Overview

Exploratory Data Analysis(EDA)

Feature Engineering and Data
Cleaning

Predictive Modeling

Conclusion

Introduction



Overview

- Overview
- Introduction
- Overview
- Exploratory Data Analysis(EDA)
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

The sinking of the Titanic is one of the most infamous shipwrecks in history. This project aims to create a model that predicts which passengers survived the disaster.

- Useful features are Pclass, Name, Sex, Age, SibSp, Parch, Ticket, Fare, Cabin, Embarked
- Target feature is Survived



- Overview
- Introduction
- Exploratory Data Analysis(EDA)**
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

Exploratory Data Analysis(EDA)



Dataset

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset**
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

	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.isnull().sum() #checking for total null values
```

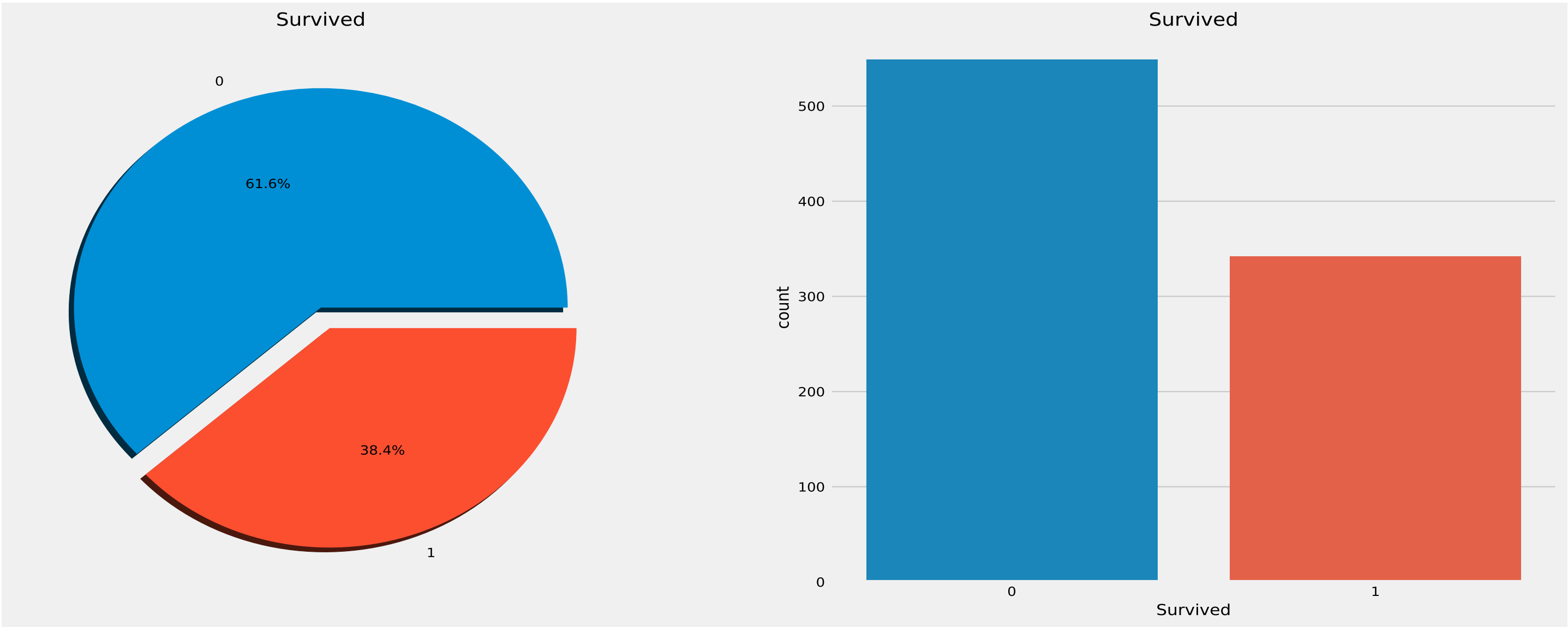
```
PassengerId    0
Survived        0
Pclass          0
Name            0
Sex             0
Age            177
SibSp           0
Parch           0
Ticket          0
Fare            0
Cabin          687
Embarked        2
dtype: int64
```

■ Age, Sex, Embarked have null values.



How many Survived?

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?**
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion



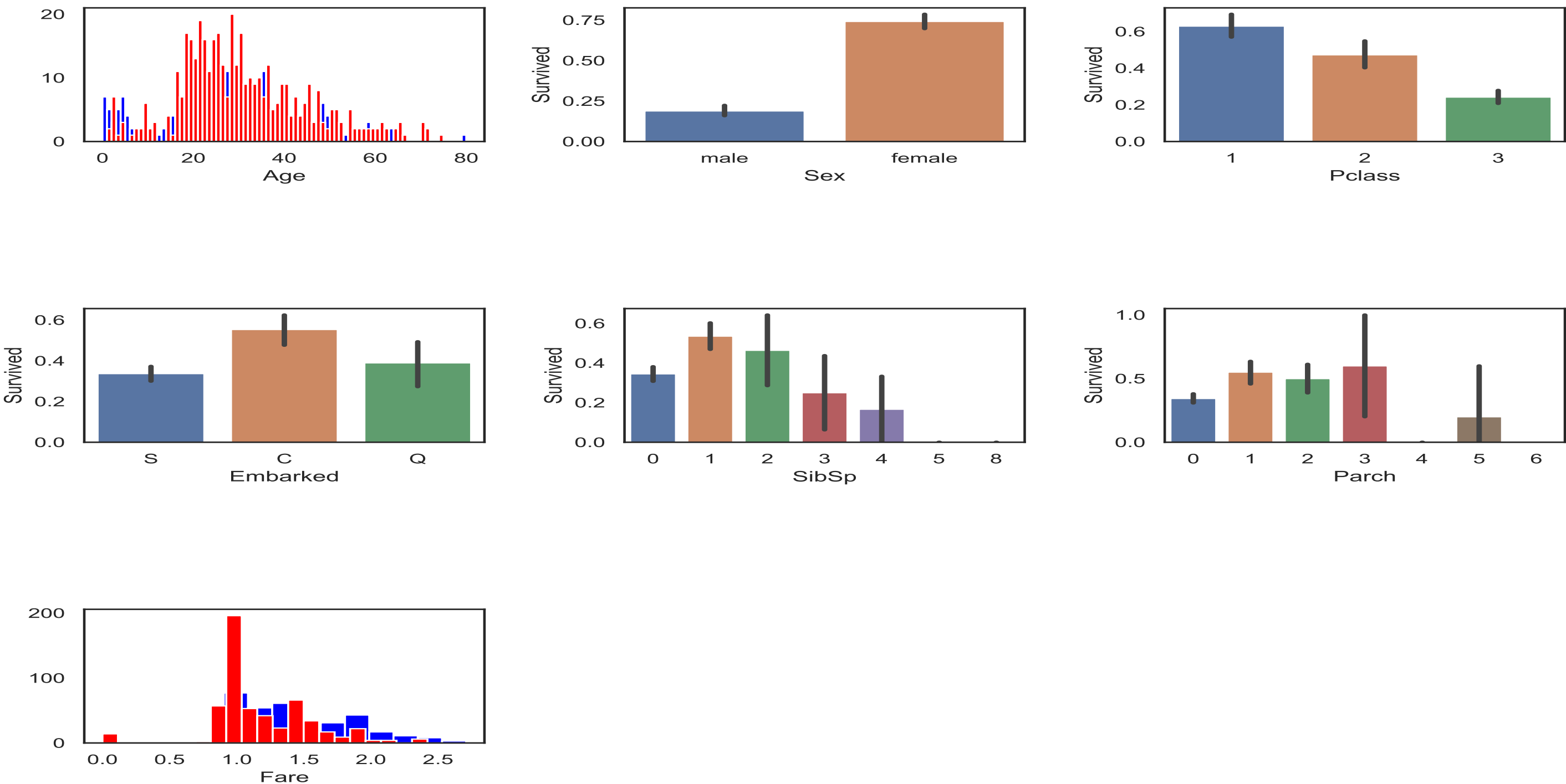
- We will try to check the survival rate by using the different features of the dataset. Some of the features being Sex, Port Of Embarcation, Age,etc.



Analysis of the Features

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

- Categorical Features in the dataset - Sex, Embarked
- Ordinal Features in the dataset - Pclass
- Continuous Features in the dataset - Age



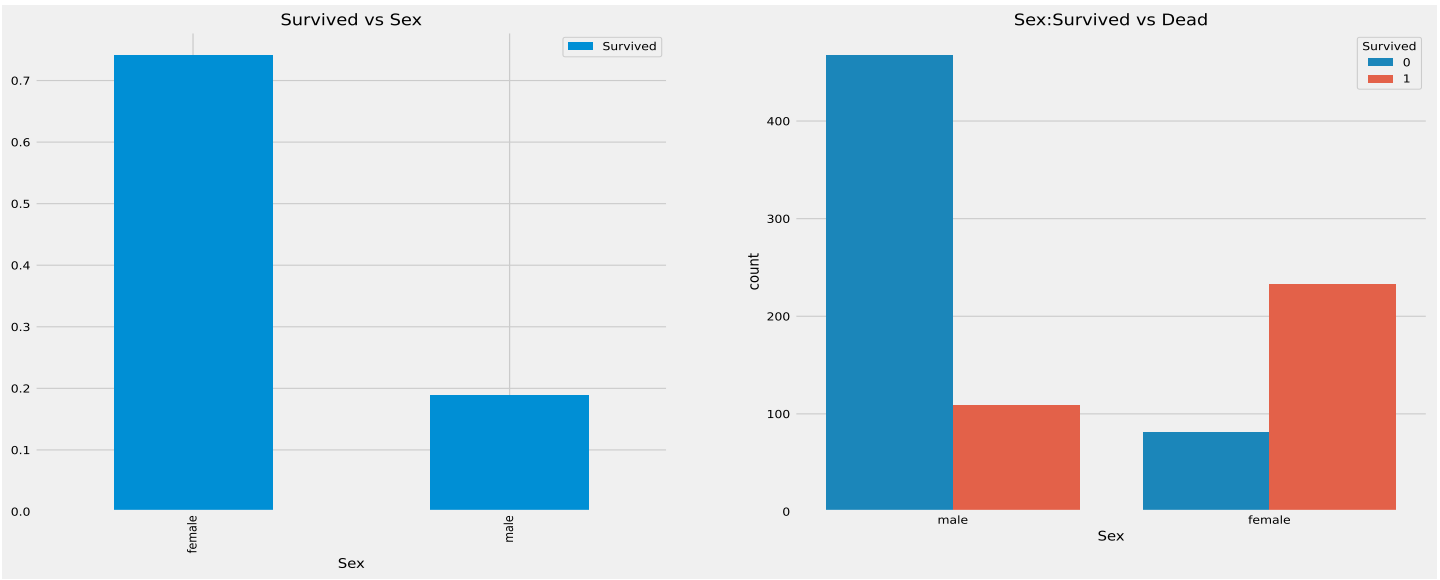


Sex - Categorical Feature

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

Table 1: Survived vs. Sex

Sex	Survived	Numbers
Female	0	81
	1	233
Male	0	468
	1	109



- Survival rates for a women: 75 percent and men: 18-19 percent.



Pclass - Ordianal Feature

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

Table 2: Numbers of Passengers by Pclass

Survived	0	1	All
Pclass			
1	80	136	216
2	97	87	184
3	372	119	491
All	549	342	891

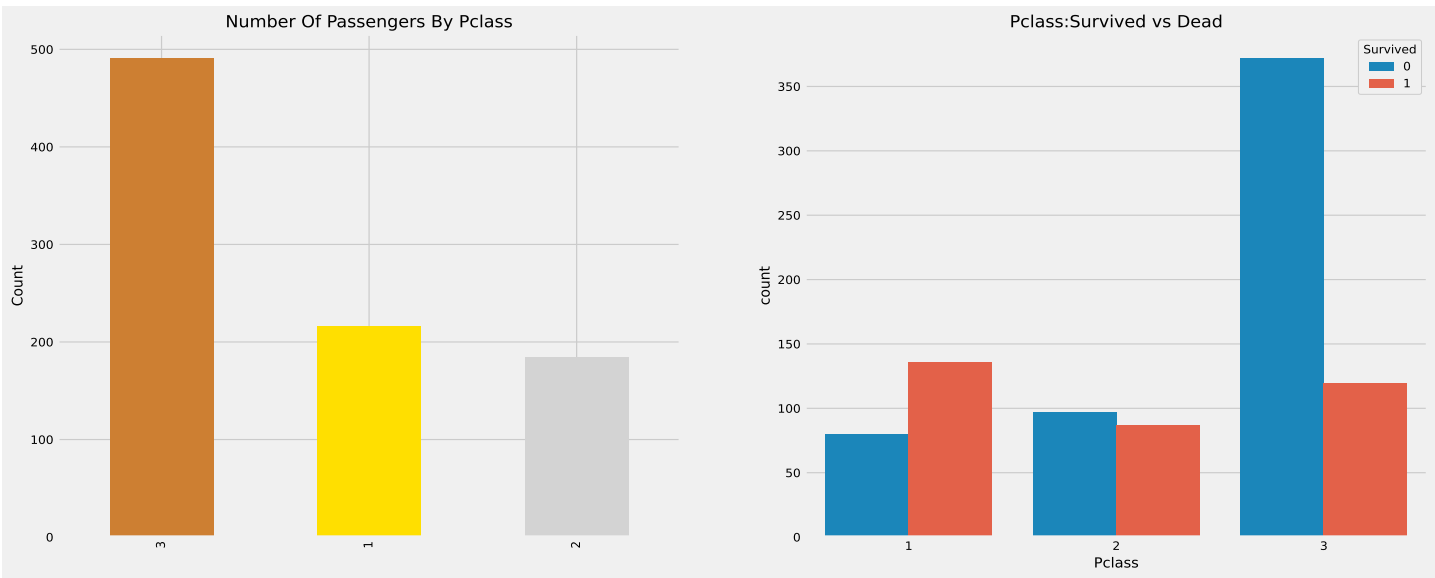


Figure 1: Pclass:Survived vs Dead



Survival rate with Sex and Pclass Together

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

Table 3: Survival rate with Sex and Pclass Together

Sex	Pclass	Survived	2	3	All
Female	0	3	6	72	81
	1	91	70	72	233
Male	0	77	91	300	468
	1	45	17	47	109
All		216	184	491	891

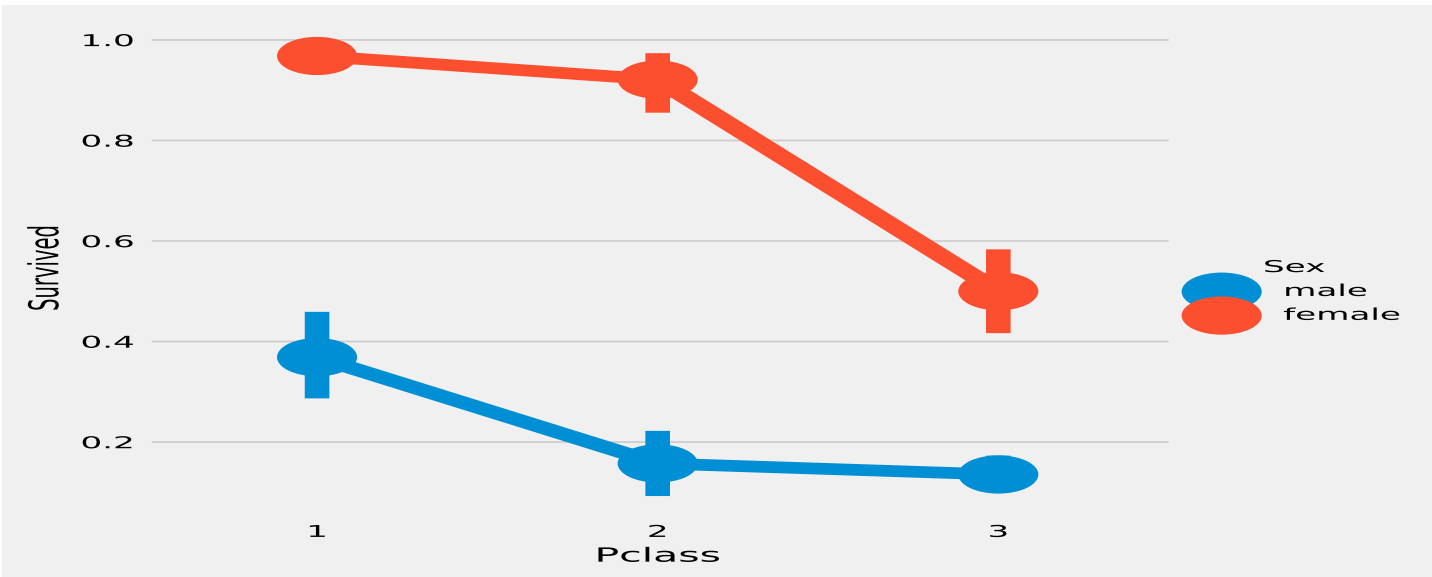


Figure 2: Survival rate with Sex and Pclass Together



Age - Continuous Feature

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

Oldest Passenger was of: 80.0 Years
Youngest Passenger was of: 0.42 Years

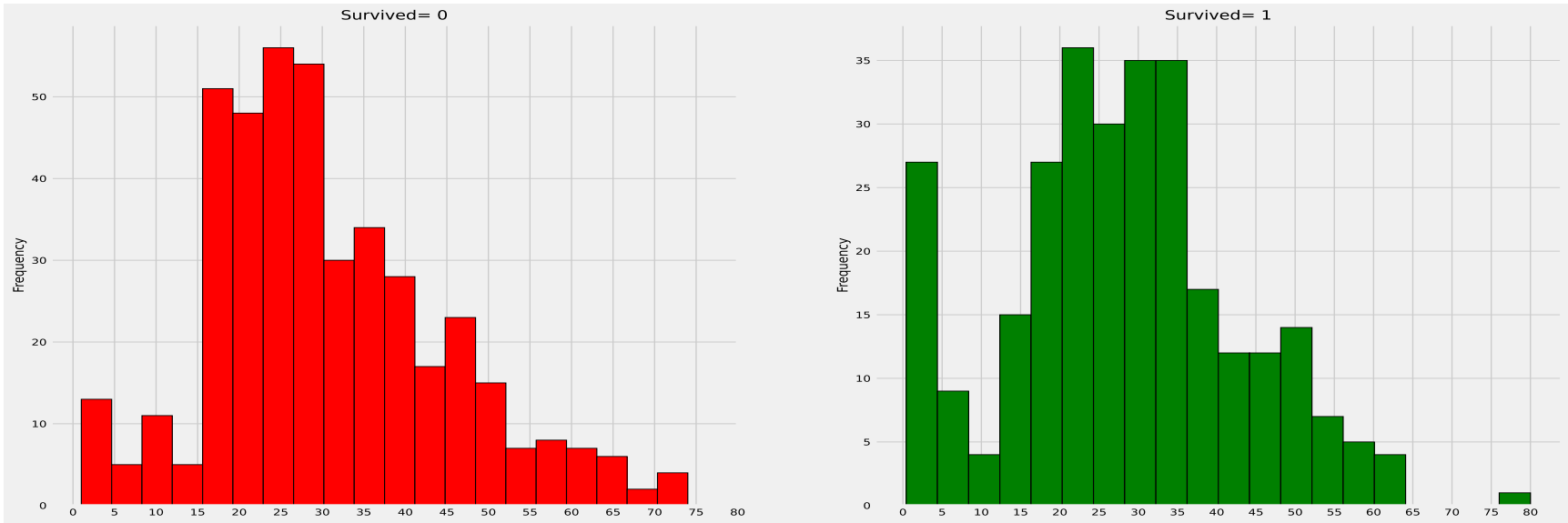


Figure 3: Survival rate with Age

Observations:

- 1)The Toddlers(age<5) were saved in large numbers.
- 2)The oldest Passenger was saved(80 years).
- 3)Maximum number of deaths were in the age group of 30-40.



Embarked - Categorical Value

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

- 1)Maximum passenegers boarded from S. Majority of them being from Pclass3.
- 2)The Passengers from C survived.
- 3)The Embark S looks to the port from where majority of the rich people boarded. Still the chances for survival is low here.
- 4)Port Q had almost 95 percent of the passengers were from Pclass3.

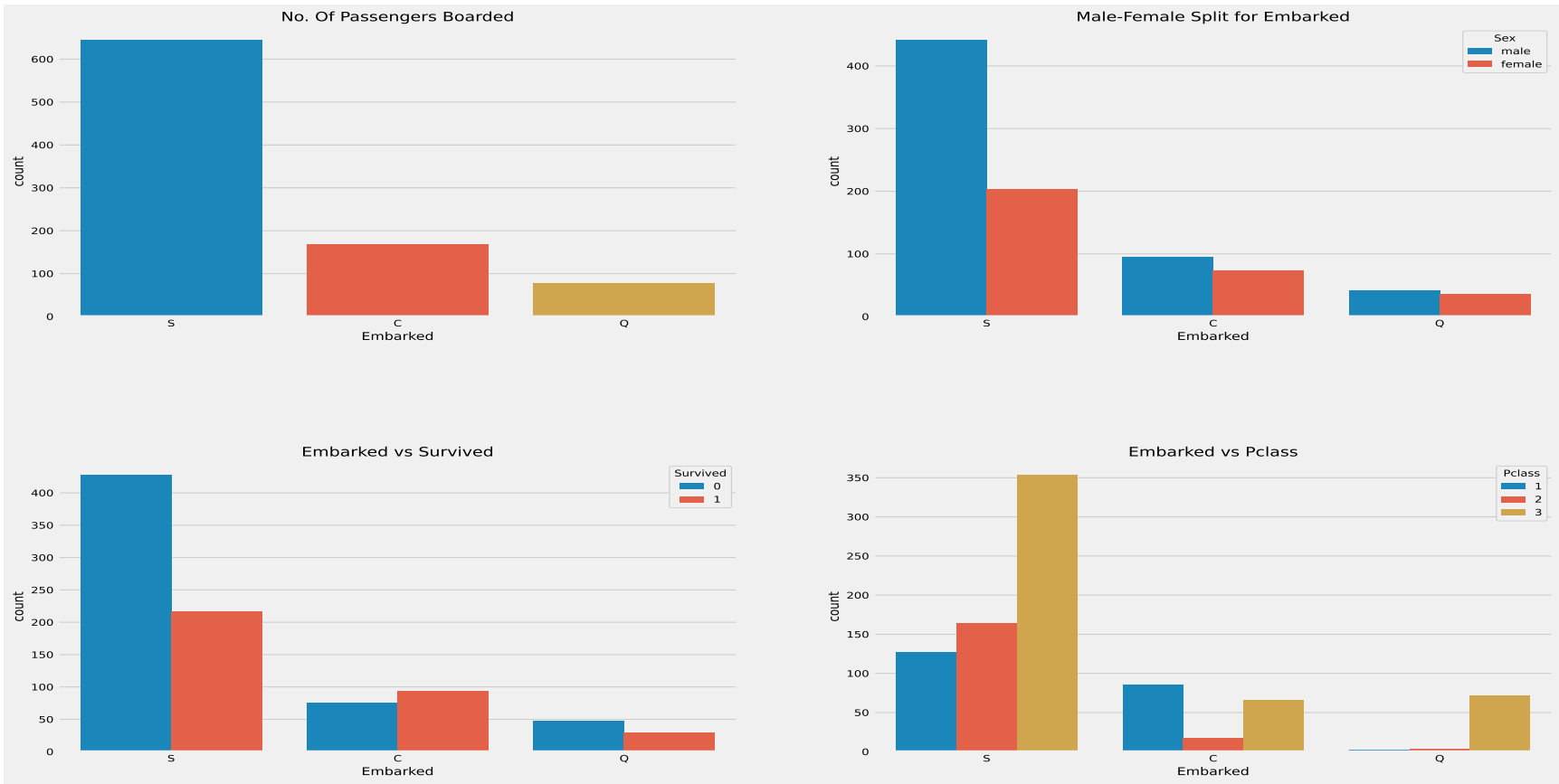


Figure 4: Survival rate with Port of Embarkation



Correlatoin Matrix

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Dataset
- How many Survived?
- Analysis of the Features
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

The highest correlation is between SibSp and Parch i.e 0.41.

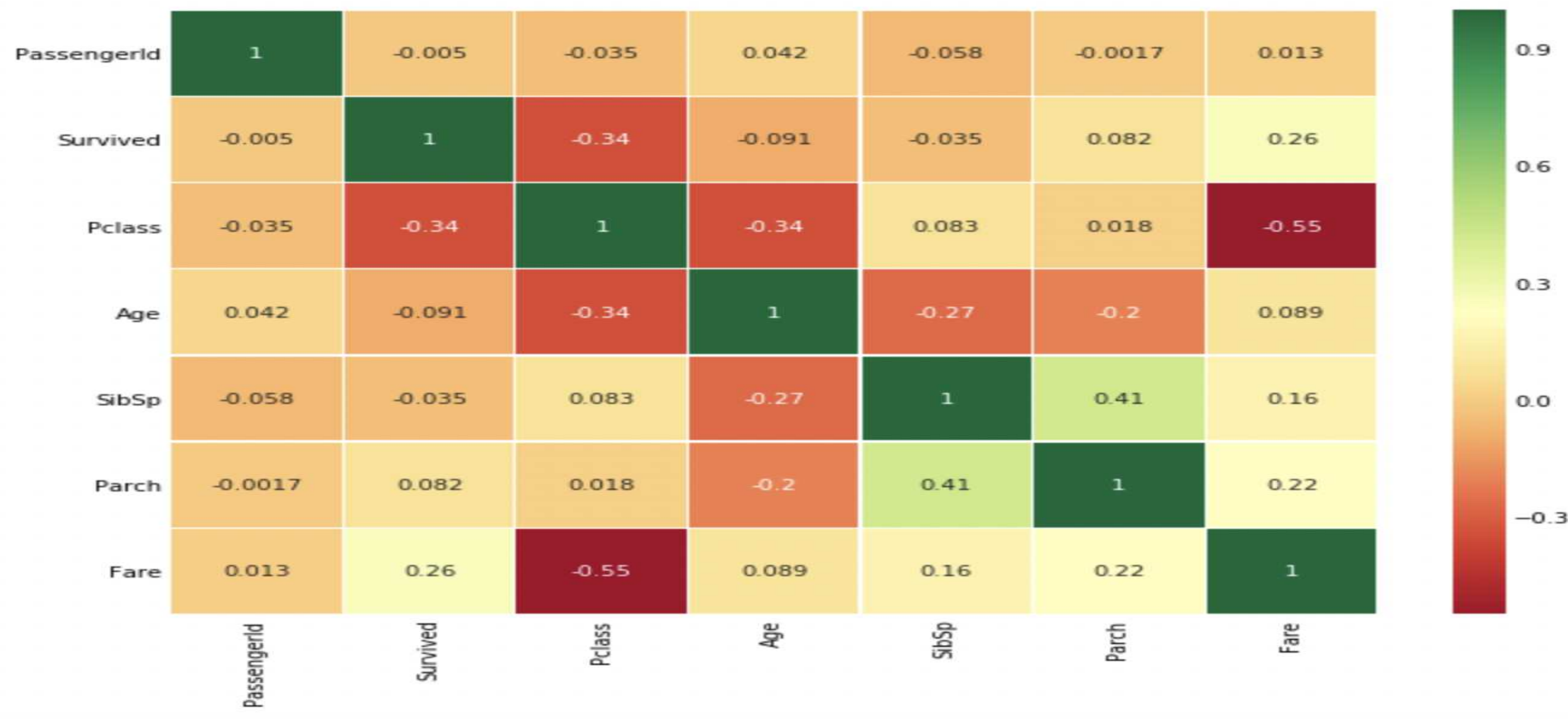


Figure 5: Interpreting the heatmap



Overview

Introduction

Exploratory Data Analysis(EDA)

Feature Engineering and Data
Cleaning

Removing Redundant features
Correlation Matrix after Data
Cleaning

Predictive Modeling

Conclusion

Feature Engineering and Data Cleaning



Converting features into suitable form for modeling

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Feature Engineering and Data Cleaning
- Removing Redundant features
- Correlation Matrix after Data Cleaning
- Predictive Modeling
- Conclusion

- Age: Age_band
- Family_size and Alone: Summation of Parch and SibSp
- Fare: Fare_cat

Table 4: Age_Band

Age_band	Numbers
1	382
2	325
0	104
3	69
4	11

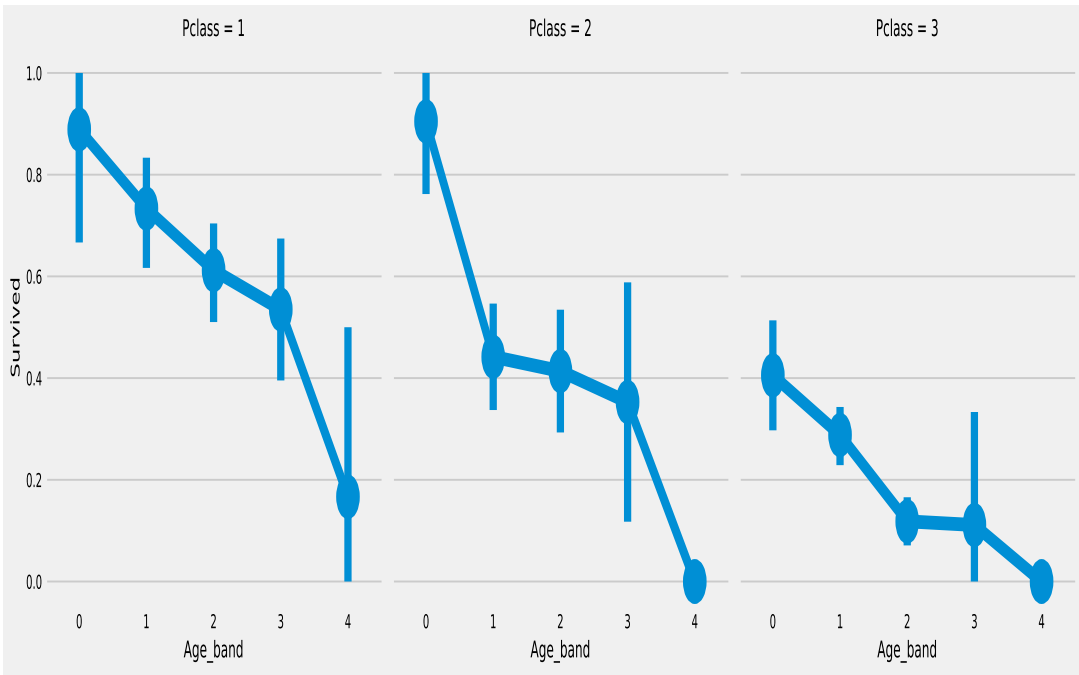


Figure 6: Age_Band



Removing Redundant features

Overview
Introduction
Exploratory Data Analysis(EDA)
Feature Engineering and Data Cleaning
Removing Redundant features
Correlation Matrix after Data Cleaning
Predictive Modeling
Conclusion

- Name→ We don't need name feature as it cannot be converted into any categorical value.
- Ticket→ It is any random string that cannot be categorised.
- Fare→ We have the Fare_cat feature, so unneeded
- Cabin→ A lot of NaN values and also many passengers have multiple cabins. So this is a useless feature.
- Fare_Range→ We have the fare_cat feature.
- PassengerId→ Cannot be categorised.



Correlation Matrix after Data Cleaning

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Feature Engineering and Data Cleaning
- Removing Redundant features
- Correlation Matrix after Data Cleaning
- Predictive Modeling
- Conclusion

Positive correlation: SibSp and Family_Size and Parch and Family_Size and Negative correlation: Alone and Family_Size

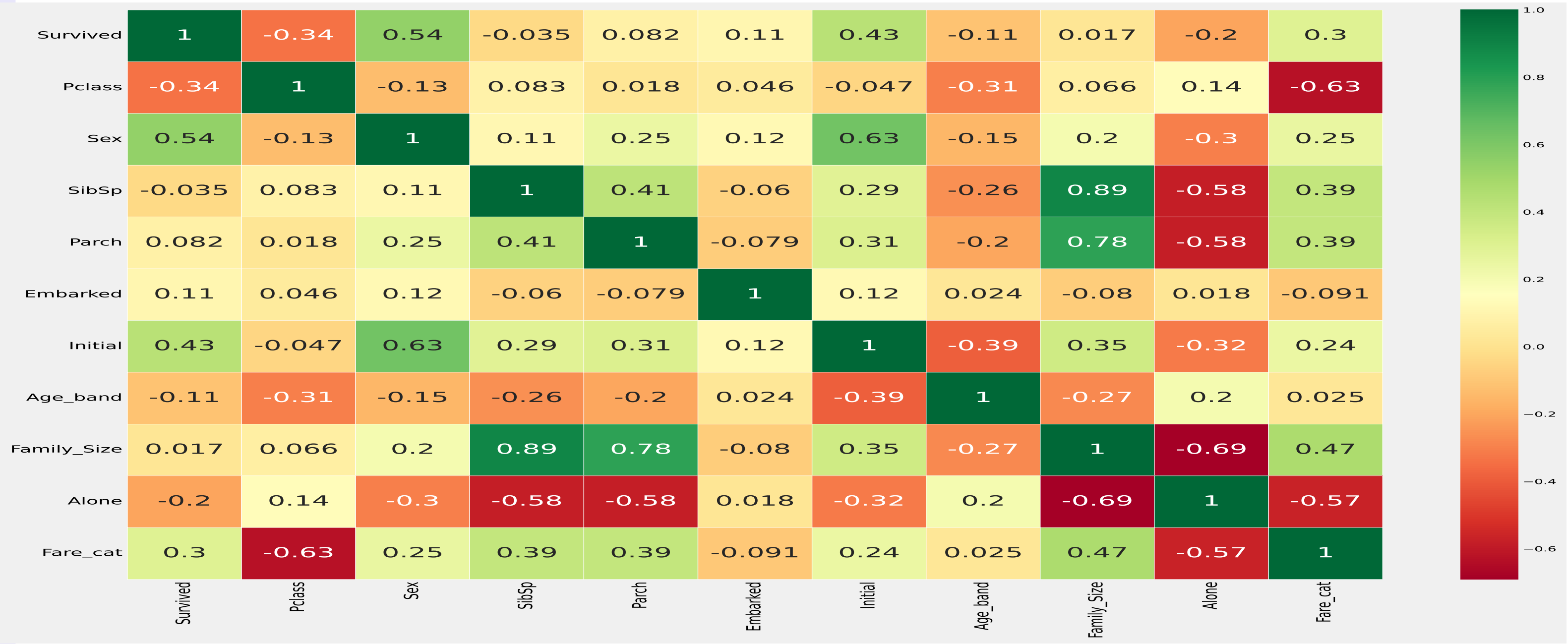


Figure 7: Correlation Matrix after Data Cleaning



- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Feature Engineering and Data Cleaning
- Predictive Modeling**
- Prediction Accuracy
- Conclusion

Predictive Modeling



Evaluation Classification Algorithms

Overview

Introduction

Exploratory Data Analysis(EDA)

Feature Engineering and Data
Cleaning

Predictive Modeling

Prediction Accuracy

Conclusion

- Logistic Regression
- Support Vector Machines (Linear and radial)
- Random Forest
- K-Nearest Neighbours
- Naive Bayes
- Decision Tree



TULIP

Team for Universal Learning and Intelligent Processing



Prediction Accuracy

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Prediction Accuracy**
- Conclusion

- Split the train sample into train and test dataset
- Train Data_size : 0.7 and Test Data_size : 0.3
- Total sample size = 891; training sample size = 623, testing sample size = 268

Table 5: Accuracy Comparison of different Classifier Algorithms

	Acuracy
Radial Support Vector Machines(rbf-SVM)	0.835820895522388
Linear Support Vector Machine(linear-SVM)	0.8171641791044776
Logistic Regression	0.8134328358208955
Decision Tree	0.8059701492537313
K-Nearest Neighbours(KNN)	0.832089552238806
Gaussian Naive Bayes	0.8134328358208955
Random Forests	0.8208955223880597



- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion**

Conclusion



Conclusion

- Overview
- Introduction
- Exploratory Data Analysis(EDA)
- Feature Engineering and Data Cleaning
- Predictive Modeling
- Conclusion

- Basic modeling of the data
- To overcome the model variance, and get a generalized model,we can use Cross Validation
- Results can be further enhanced



Contact Information

Pratikshya Parajuli
Ministry of Finance
Government of Nepal



PPARAJULI@MOF.GOV.NP

