Titanic Survial Prediction

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Overview

Introduction

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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

Exploratory Data Analysis(EDA)

Dataset

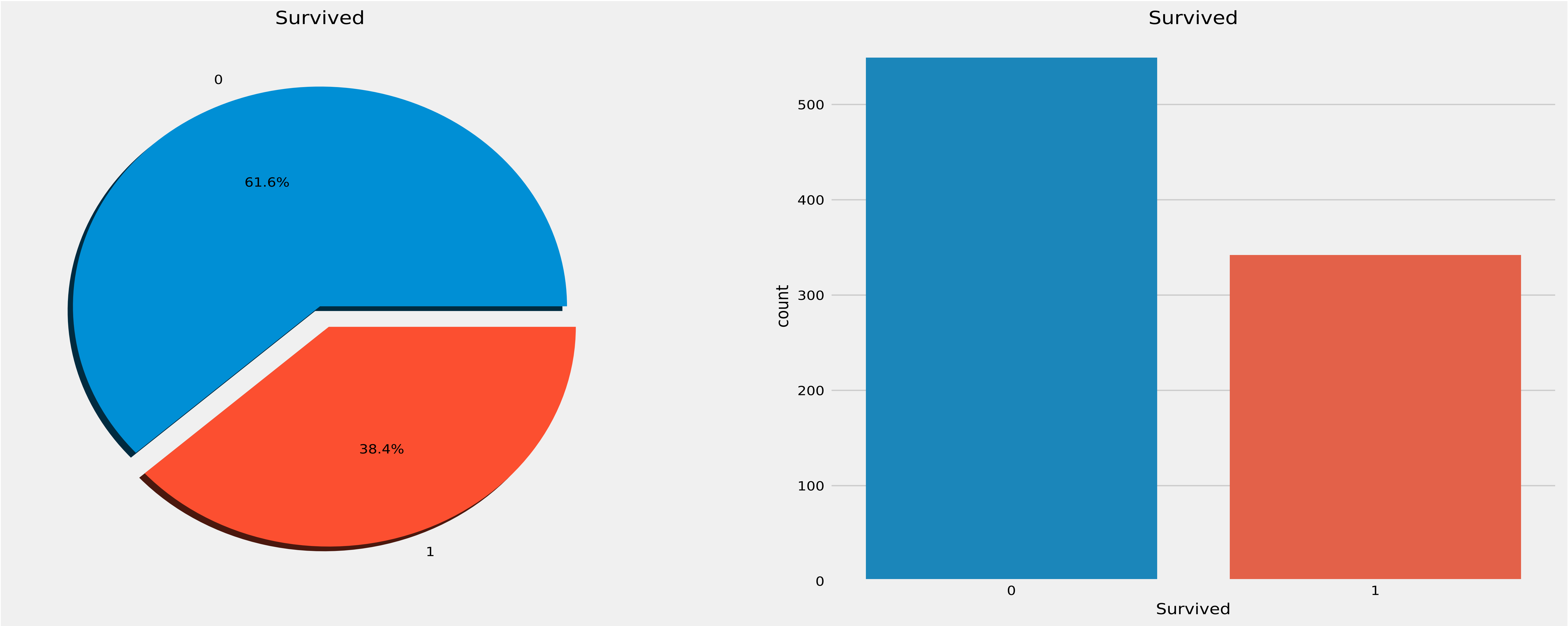
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 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.

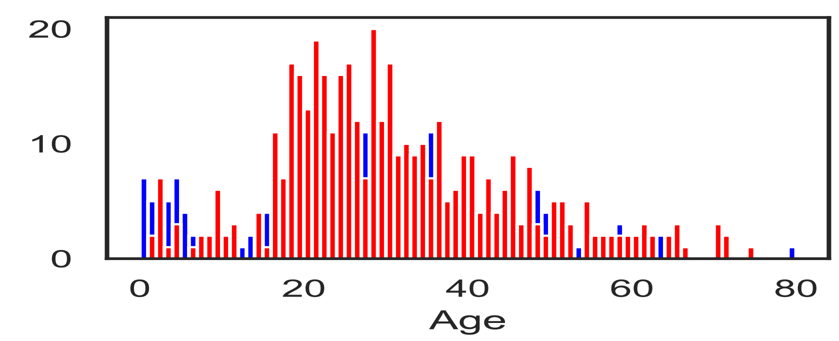
How many Survived?

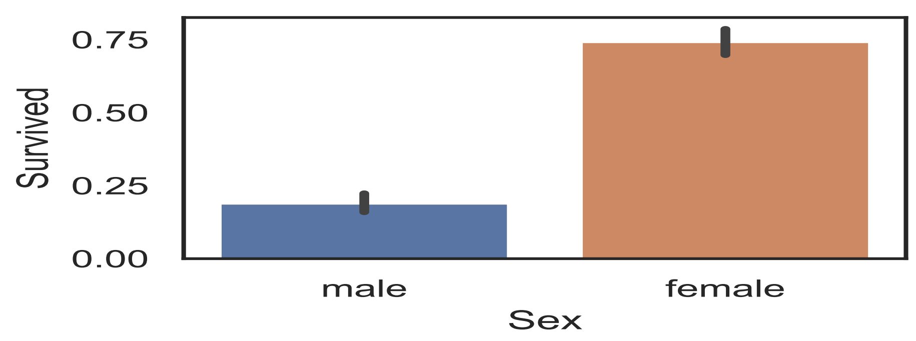


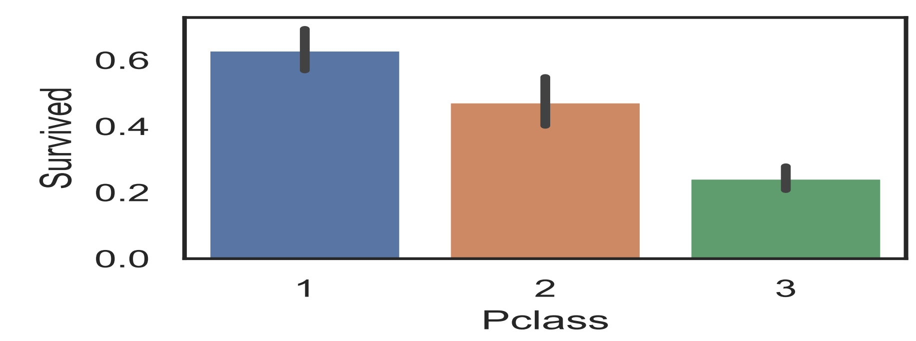
- We will try to check the survival rate by using the different features of the dataset. Some of the features being Sex, Port Of Embarcation, Age,etc.

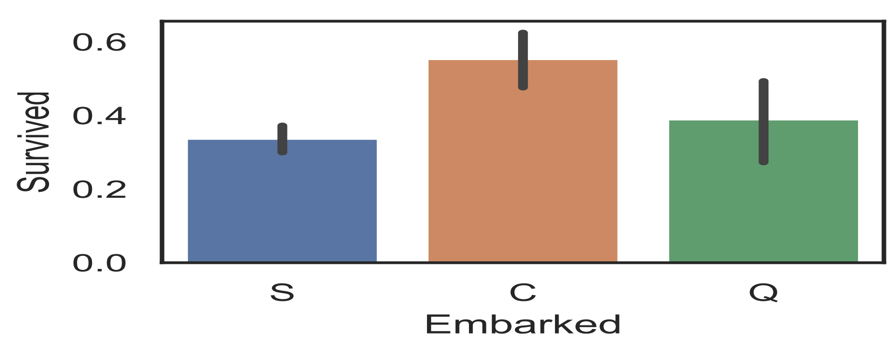
Analysis of the Features

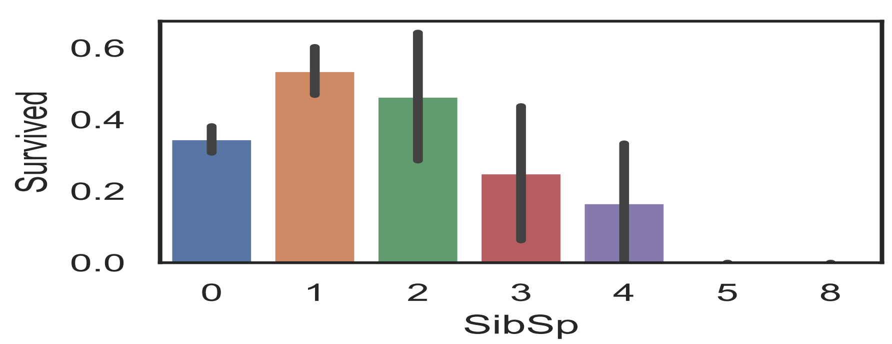
- Categorical Features in the dataset - Sex, Embarked
- Ordinal Features in the dataset - Pclass
- Continuous Features in the dataset - Age

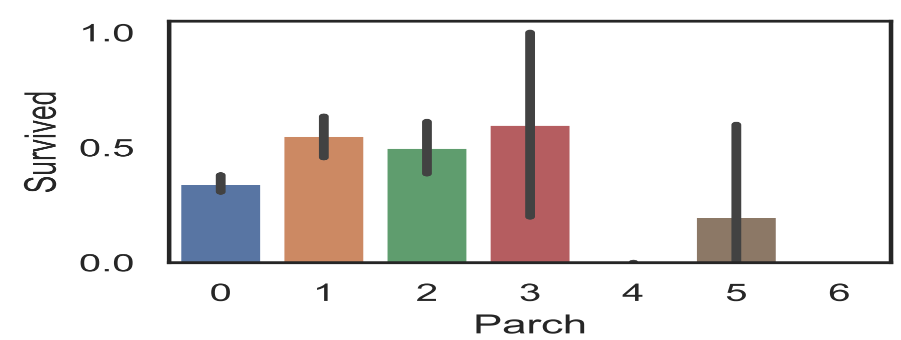


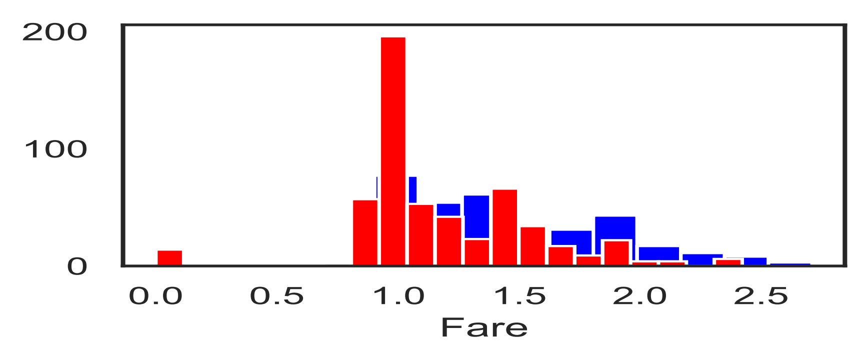








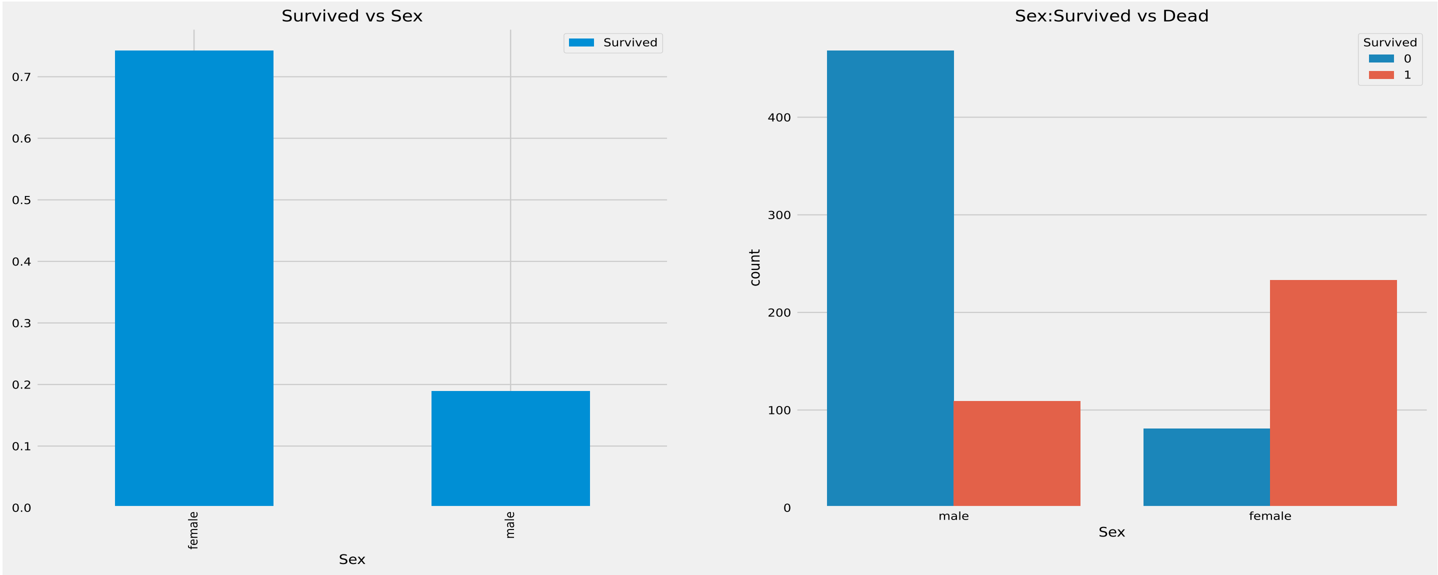




Sex - Categorical Feature

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

Table 2: Numbers of Passengers by Pclass

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

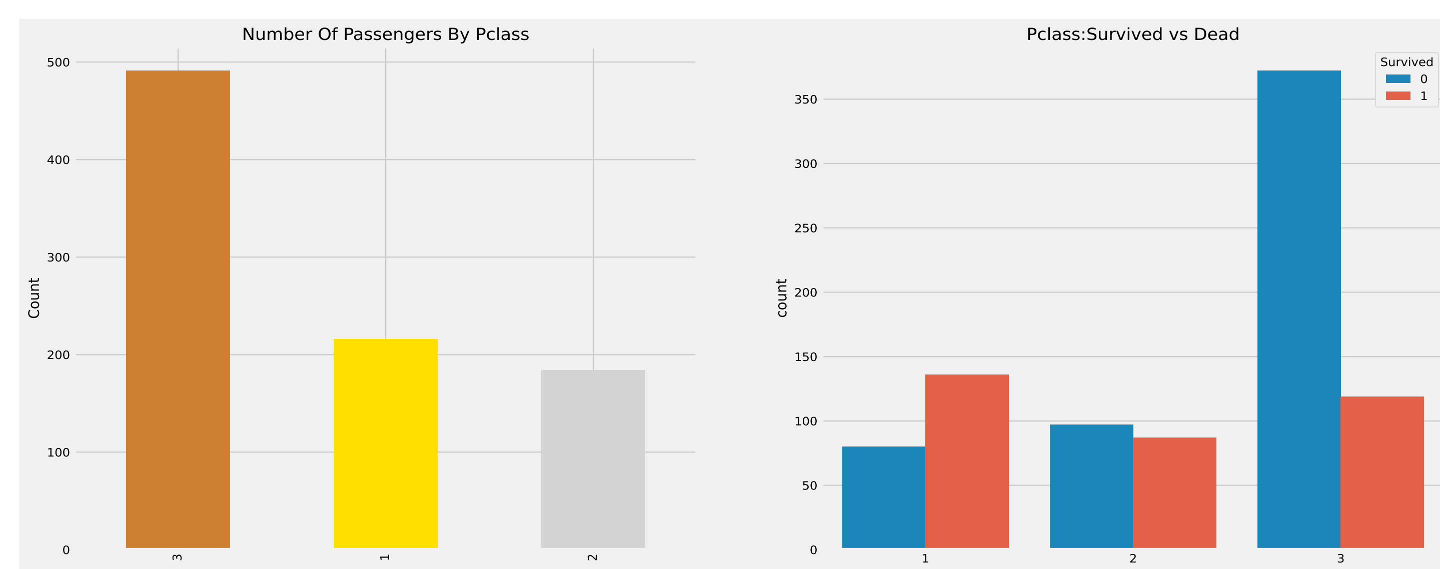


Figure 1: Pclass:Survived vs Dead

Survival rate with Sex and Pclass Together

Table 3: Survival rate with Sex and Pclass Together

Sex	PclassSurvived	1	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

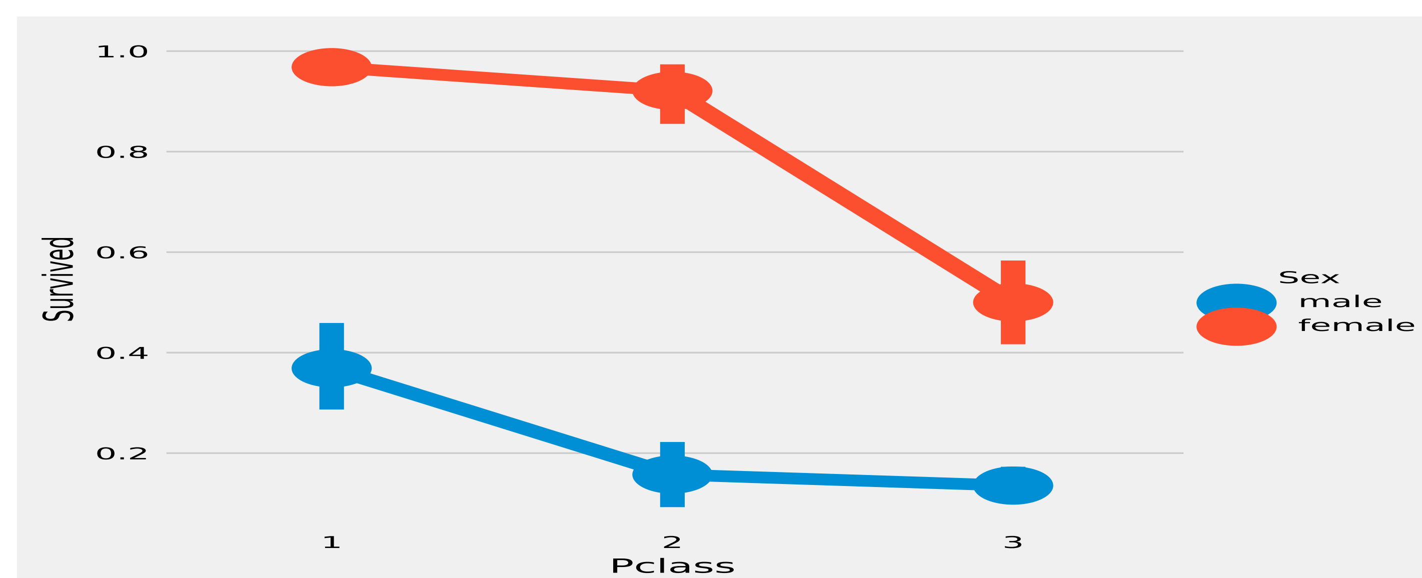


Figure 2: Survival rate with Sex and Pclass Together

Age - Continuous Feature

Oldest Passenger was of: 80.0 Years

Youngest Passenger was of: 0.42 Years

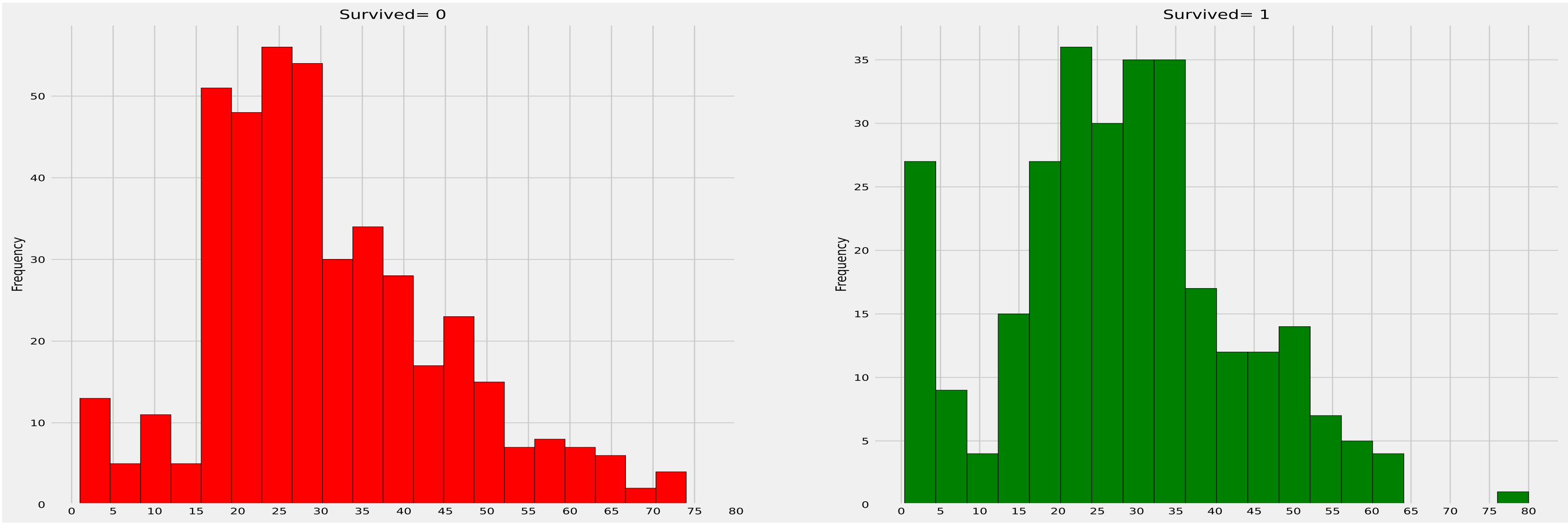


Figure 3: Survival rate with Age

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

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.

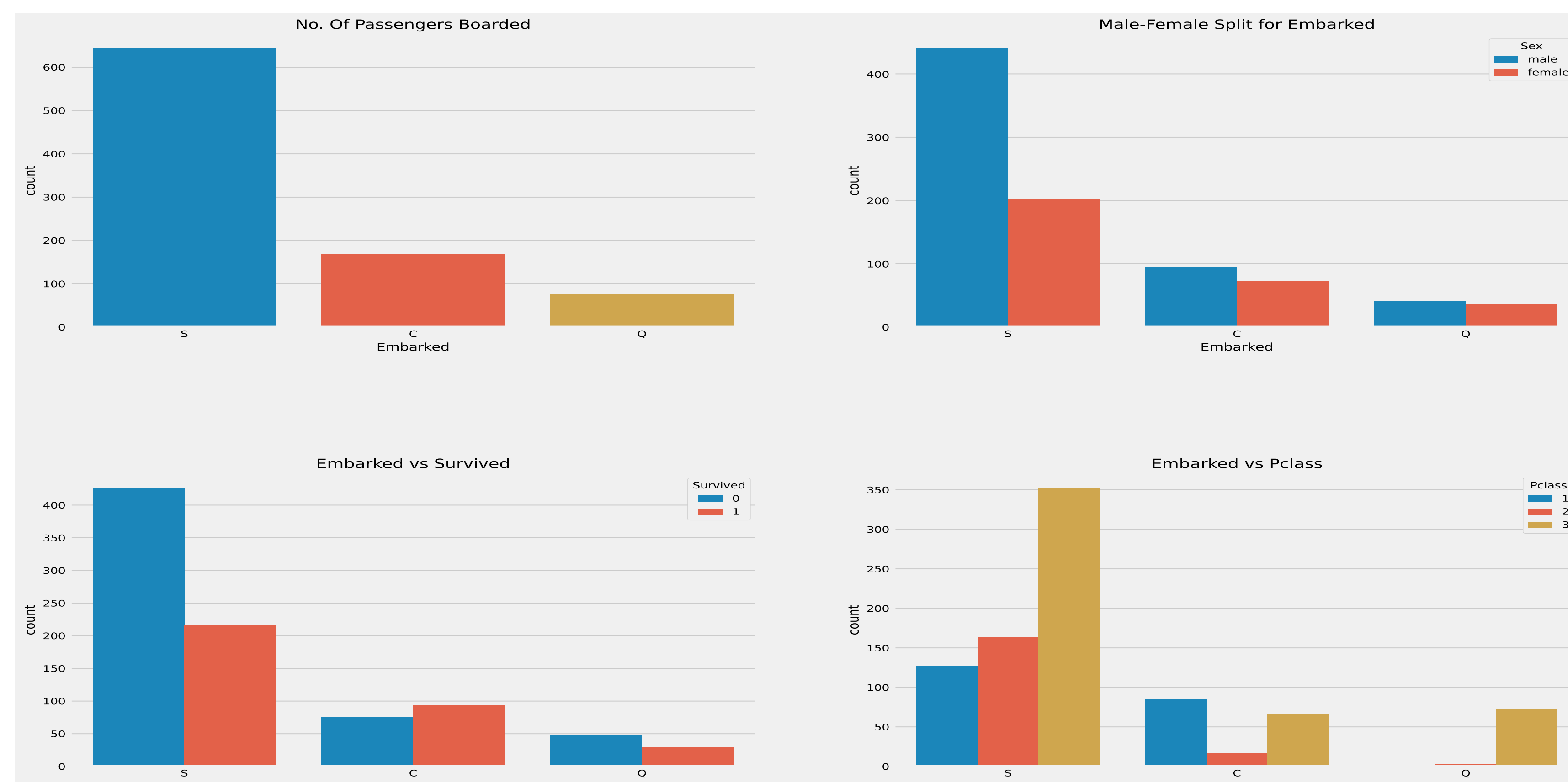


Figure 4: Survival rate with Port of Embarkation

Correlatoin Matrix

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

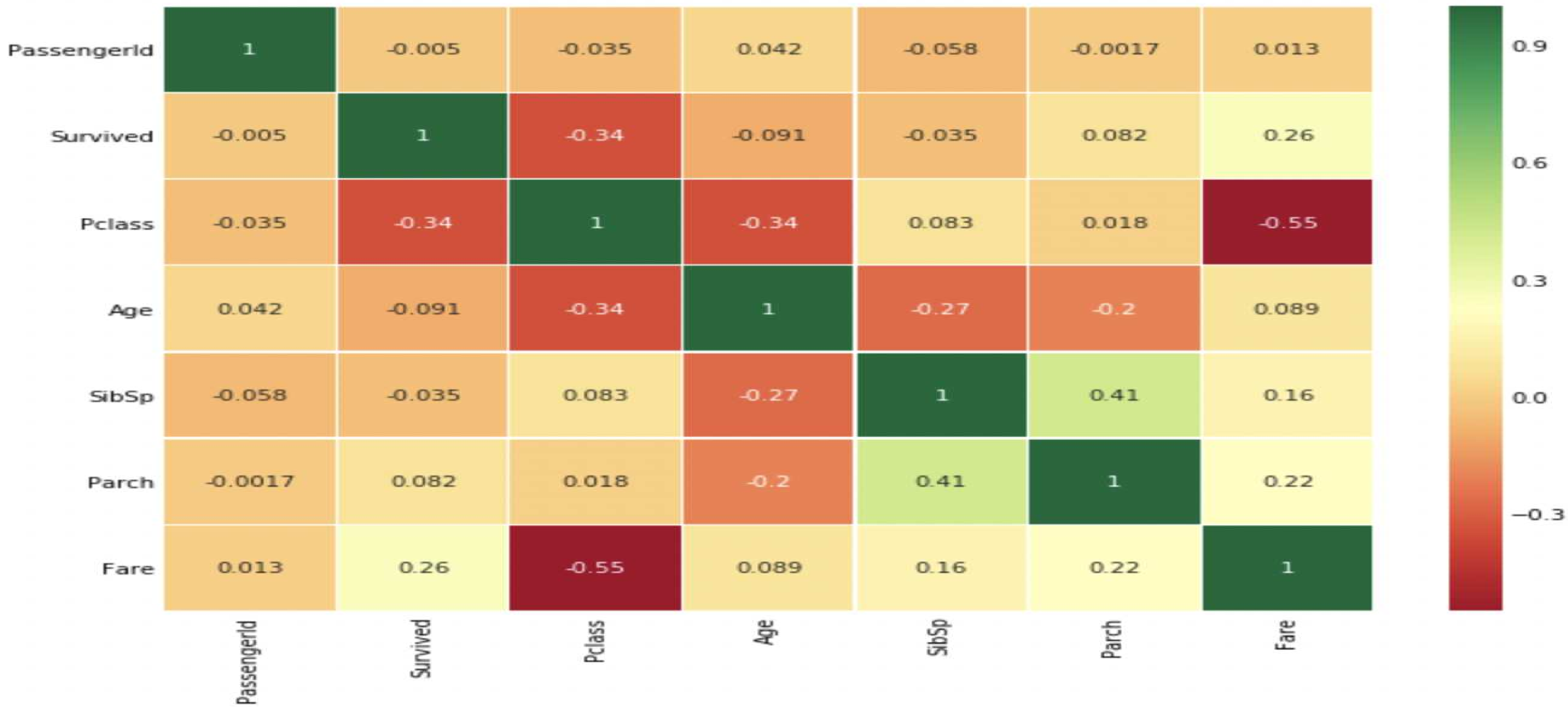


Figure 5: Interpreting the heatmap

Feature Engineering and Data Cleaning

Converting features into suitable form for modeling

- 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

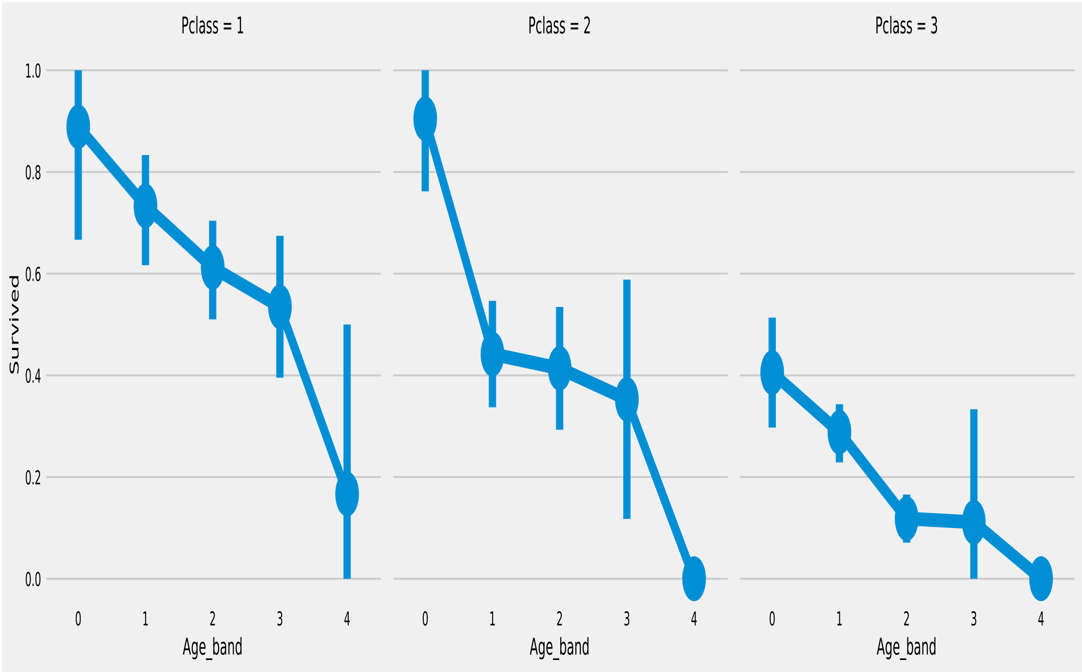


Figure 6: Age_Band

Removing Redundant features

- 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

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

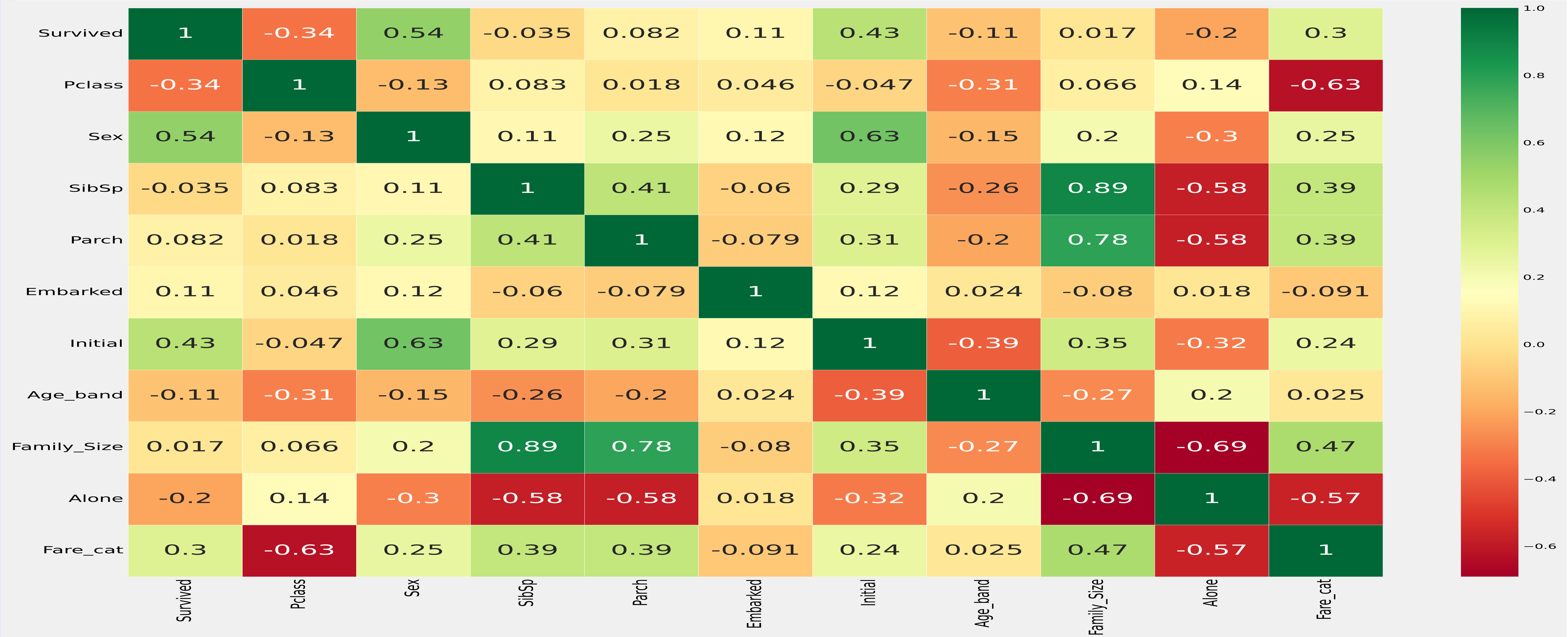


Figure 7: Correlation Matrix after Data Cleaning

Predictive Modeling

Evaluation Classification Algorithms

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

Prediction Accuracy

- 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

Conclusion

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- 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

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