Reto Kaggle Titanic

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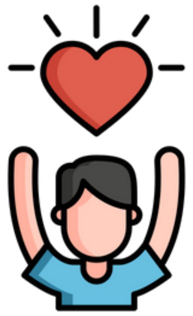
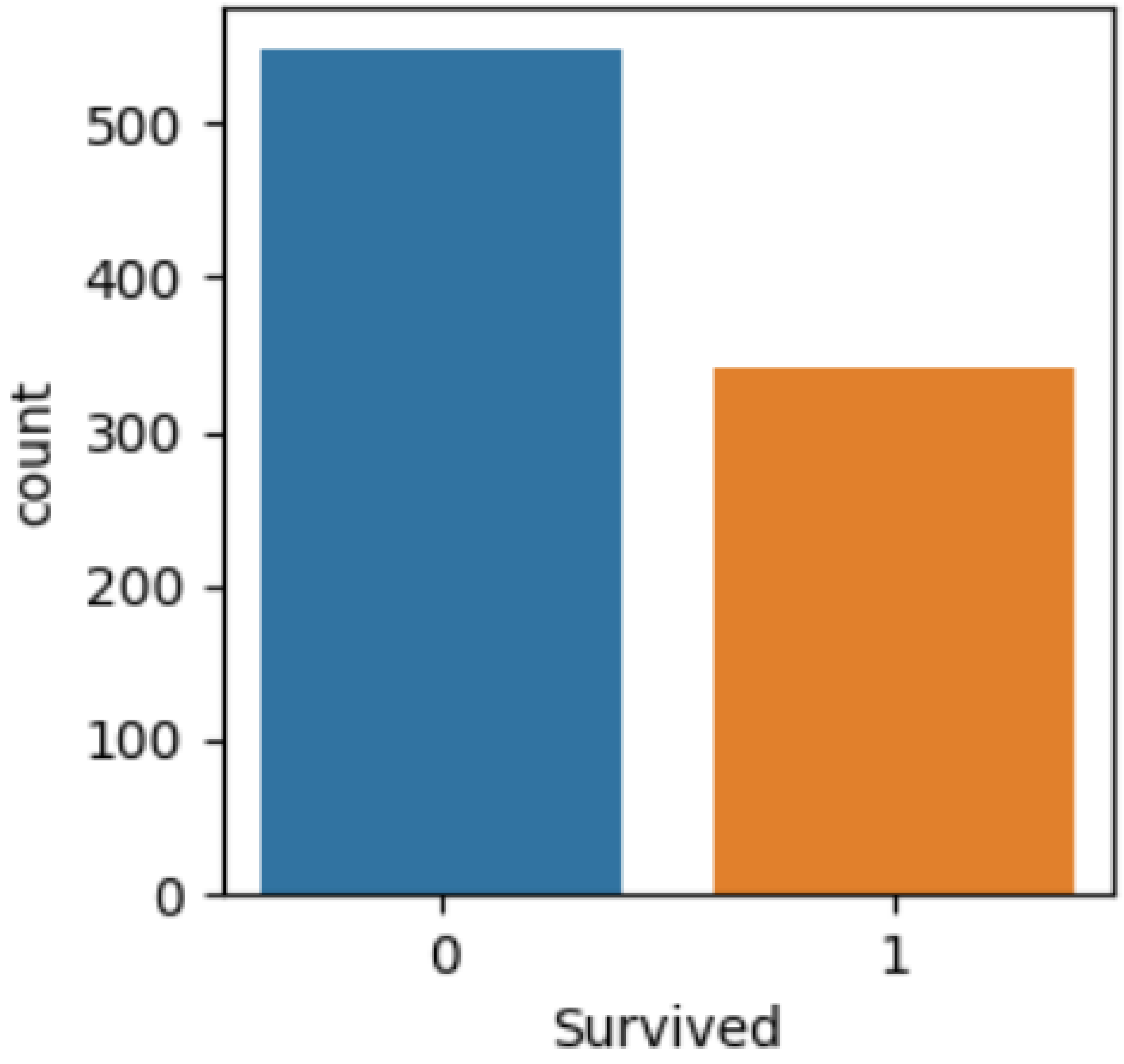
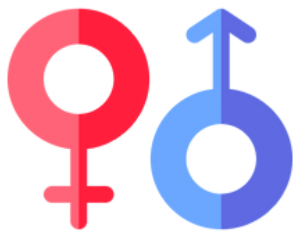
Distribuciones | Survived



```
Porcentage of survived:  61.62 %
Porcentage of no-survived:  38.38 %
[]
```



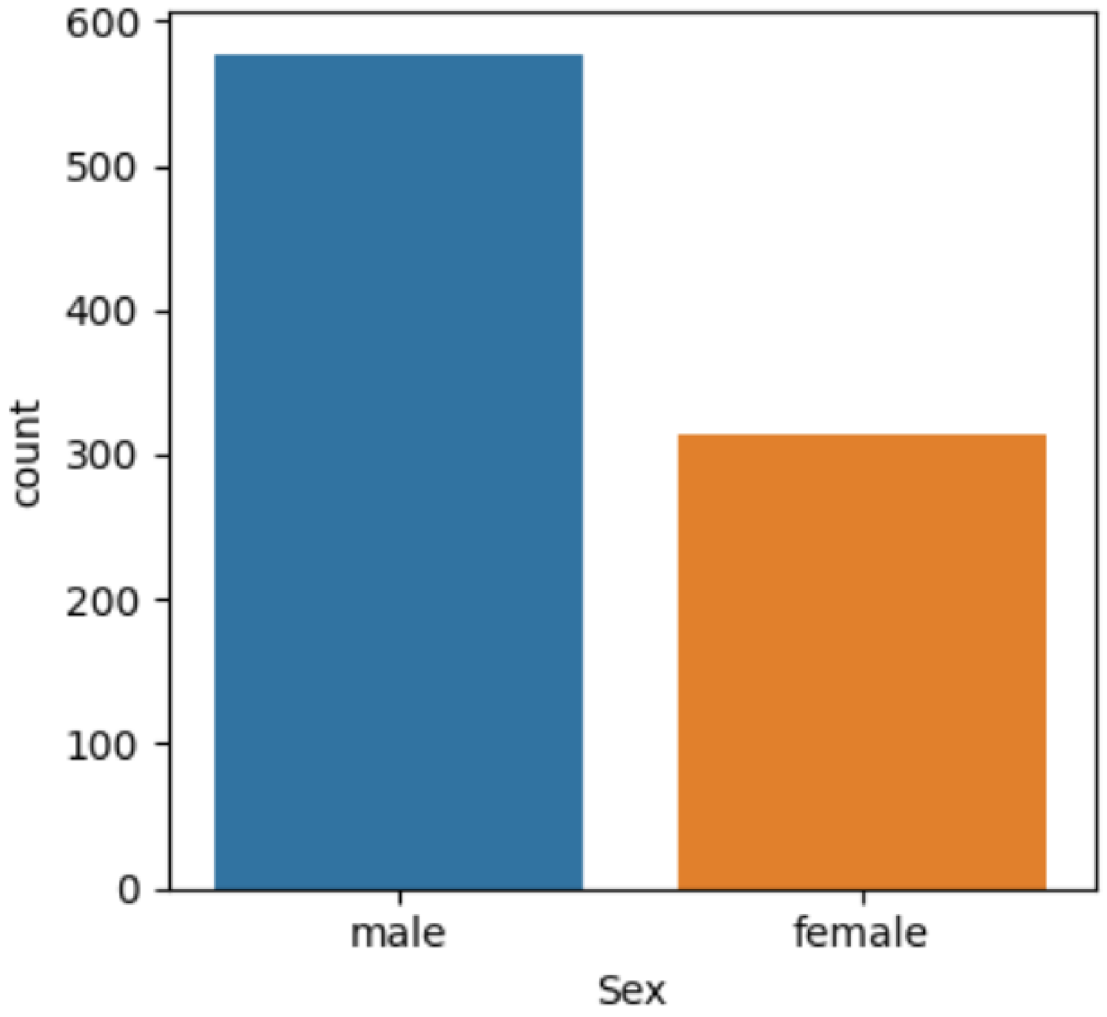
Distribuciones | Sex

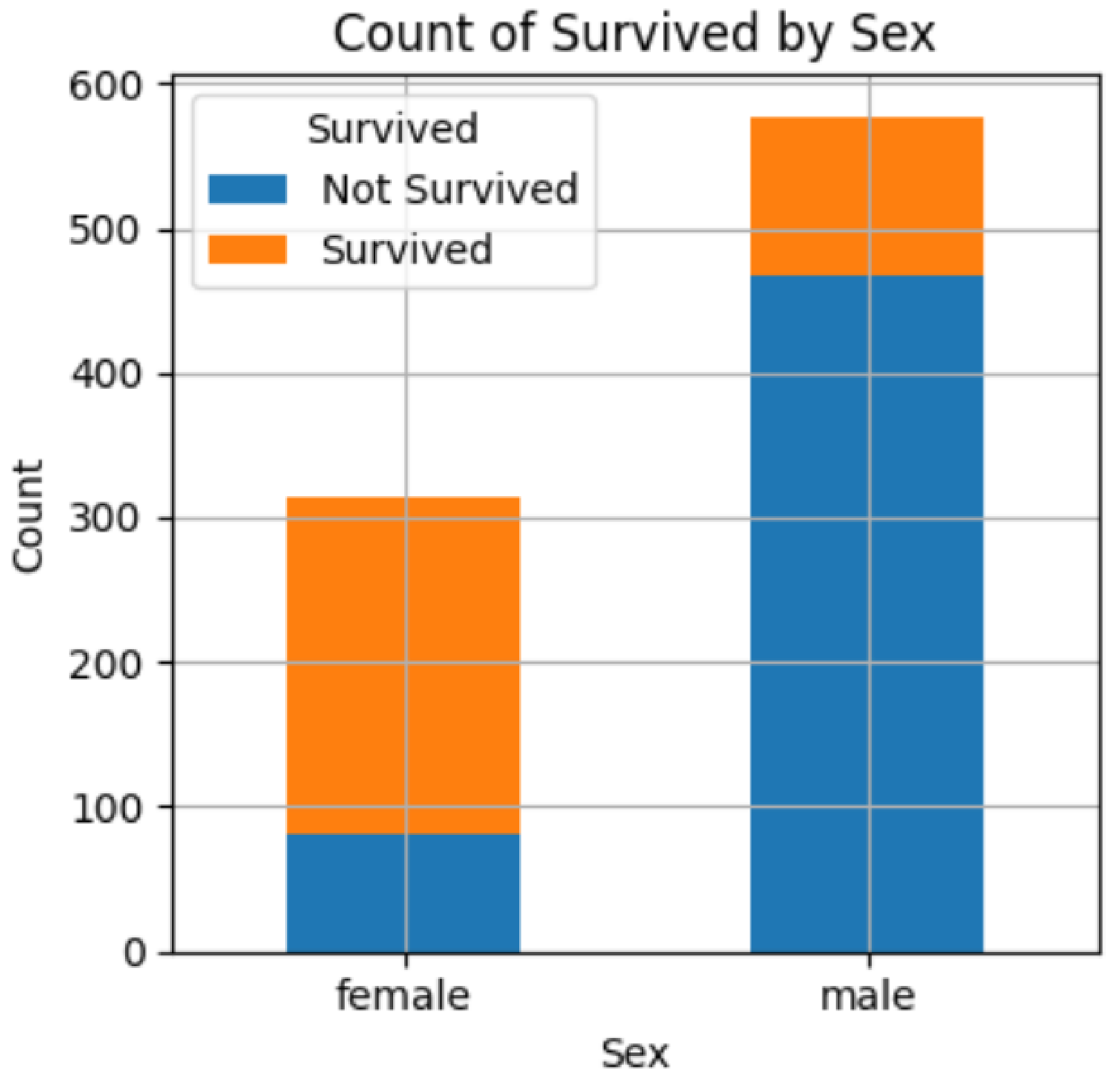


```
Porcentage of male ( 577 ):  64.76 %
Porcentage of female ( 314 ):  35.24 %


Porcentage of male surviving:  18.89 %
Porcentage of male not surviving:  81.11 %


Porcentage of female surviving:  74.2 %
Porcentage of female not surviving:  25.8 %
[]
```

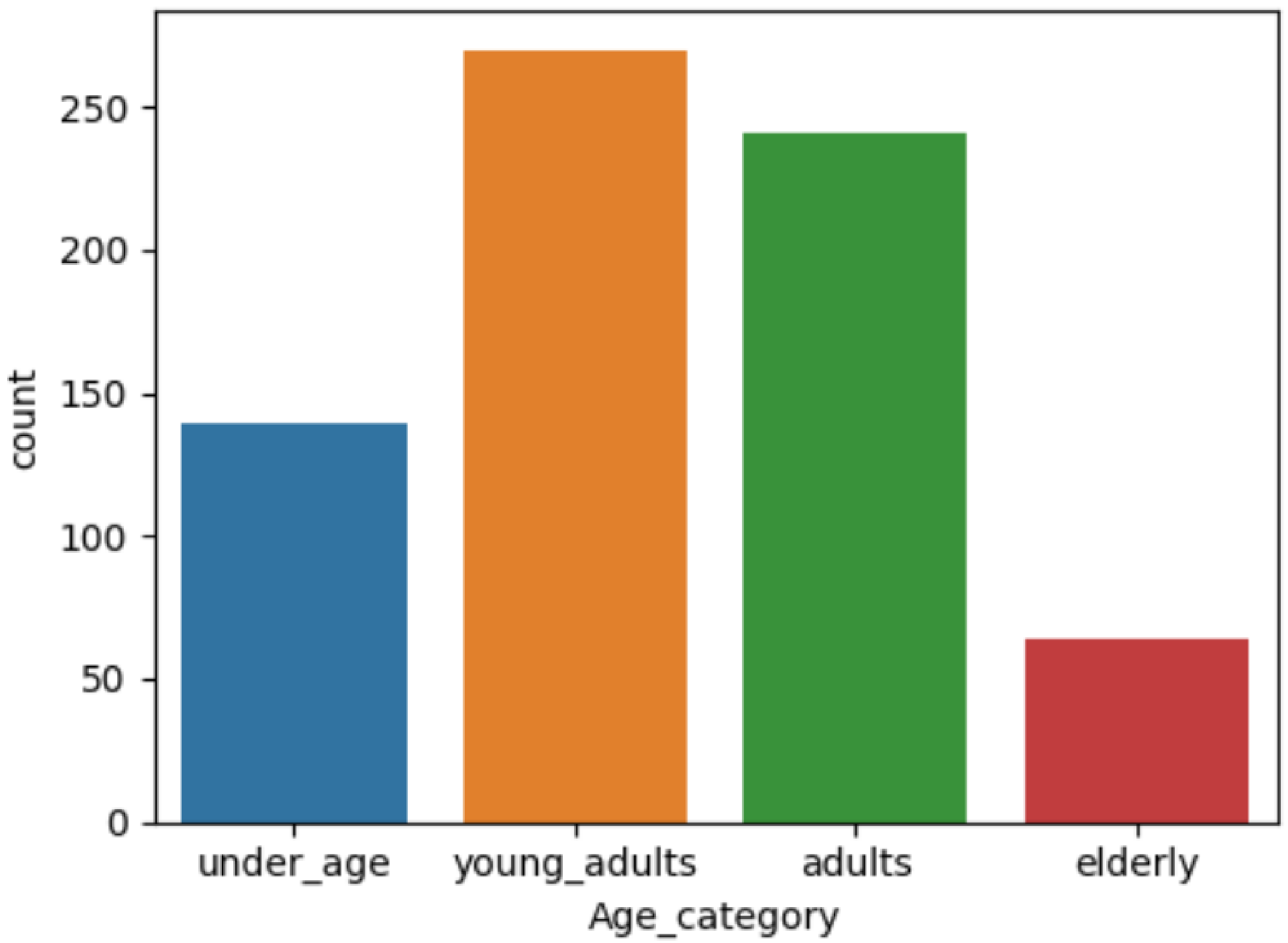


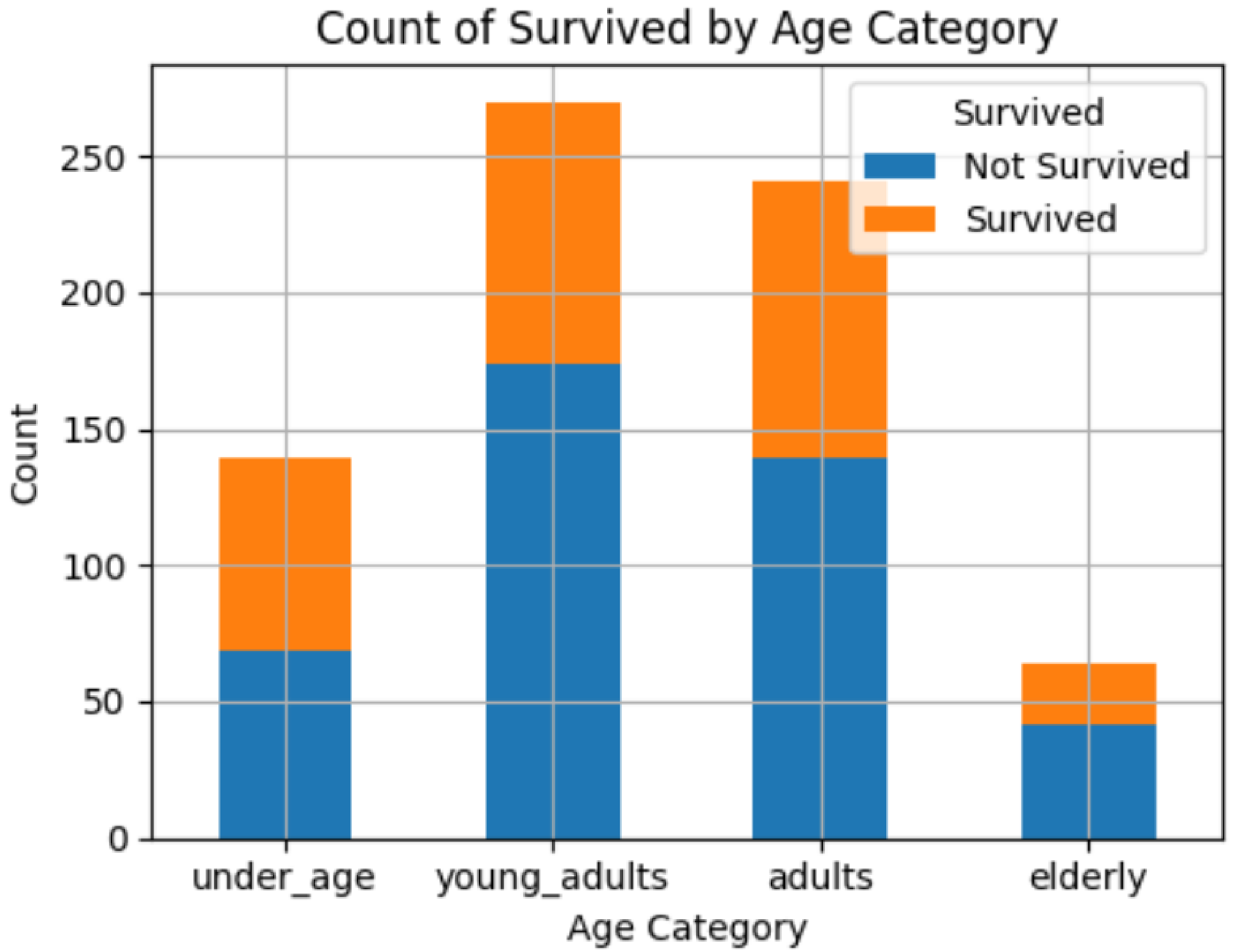


1. Exploración y preprocesamiento de los datos

Distribuciones | Age

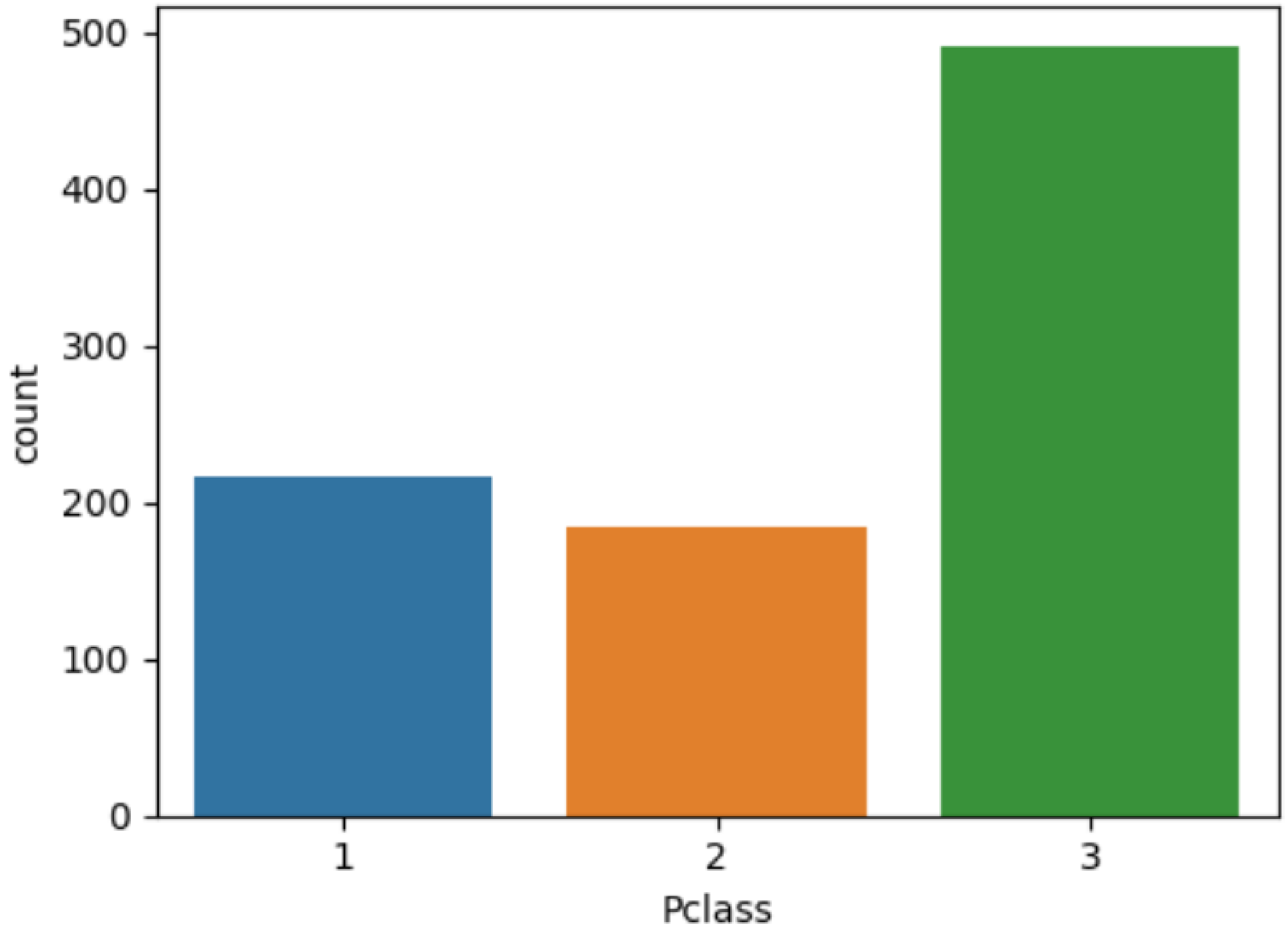
```
Under age:      0 – 18 years old        Not–Survived:  49.64 %        Survived: 50.36 %
Young adults:   19 – 30 years old       Not–Survived:  64.44 %        Survived: 35.56 %
Adults:         30 – 50 years old       Not–Survived:  57.68 %        Survived: 42.32 %
Elderly:        50+ years old           Not–Survived:  65.62 %        Survived: 34.38 %
```

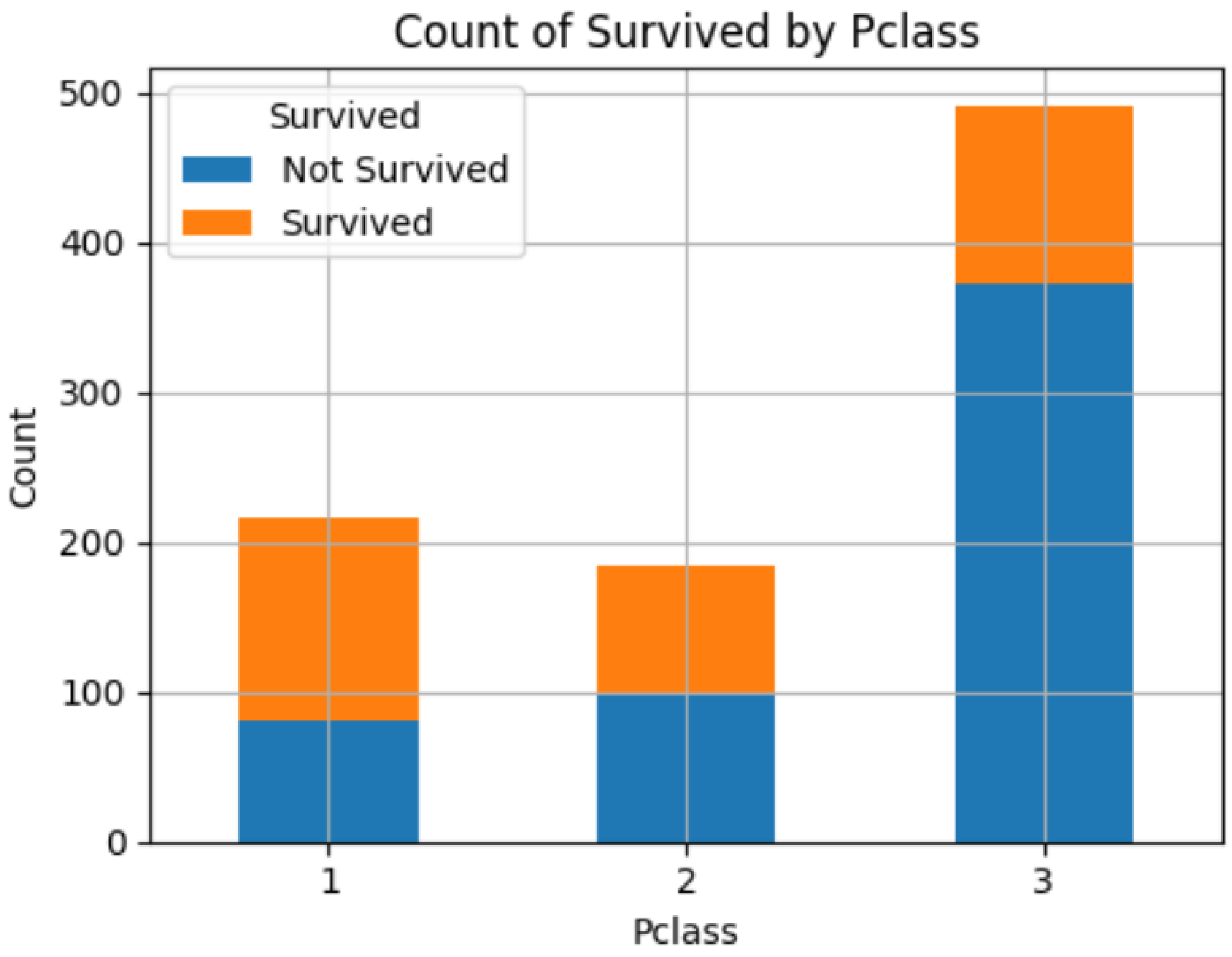




Distribuciones | Pclass

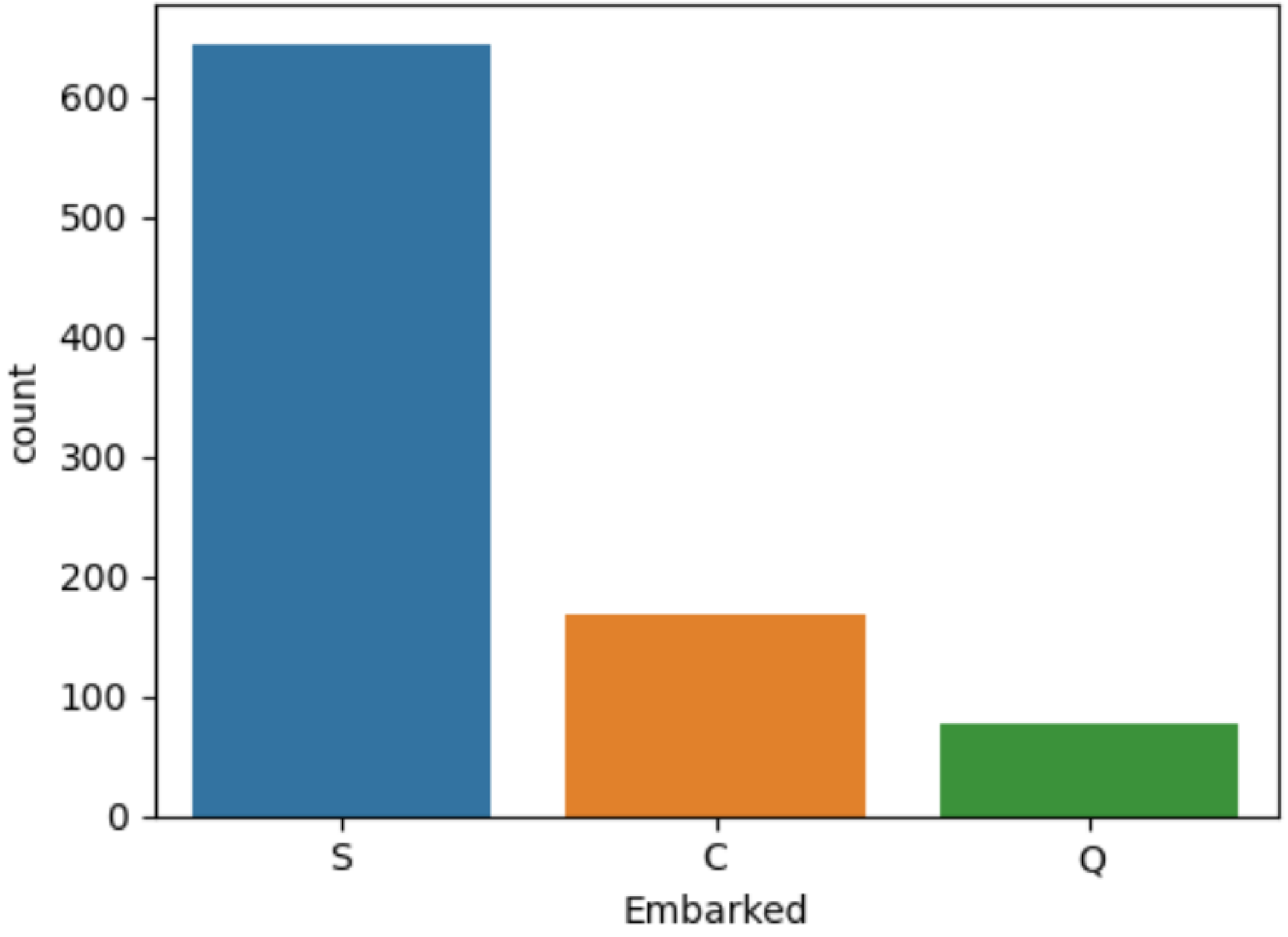
```
Porcentage of people in 1st class ( 184 ):  20.65 %      Not-Survived:  37.04 %        Survived: 62.96 %
Porcentage of people 2nd class ( 216 ):  24.24 %         Not-Survived:  52.72 %        Survived: 47.28 %
Porcentage of people 3rd class ( 491 ):  55.11 %         Not-Survived:  75.76 %        Survived: 24.24 %
```

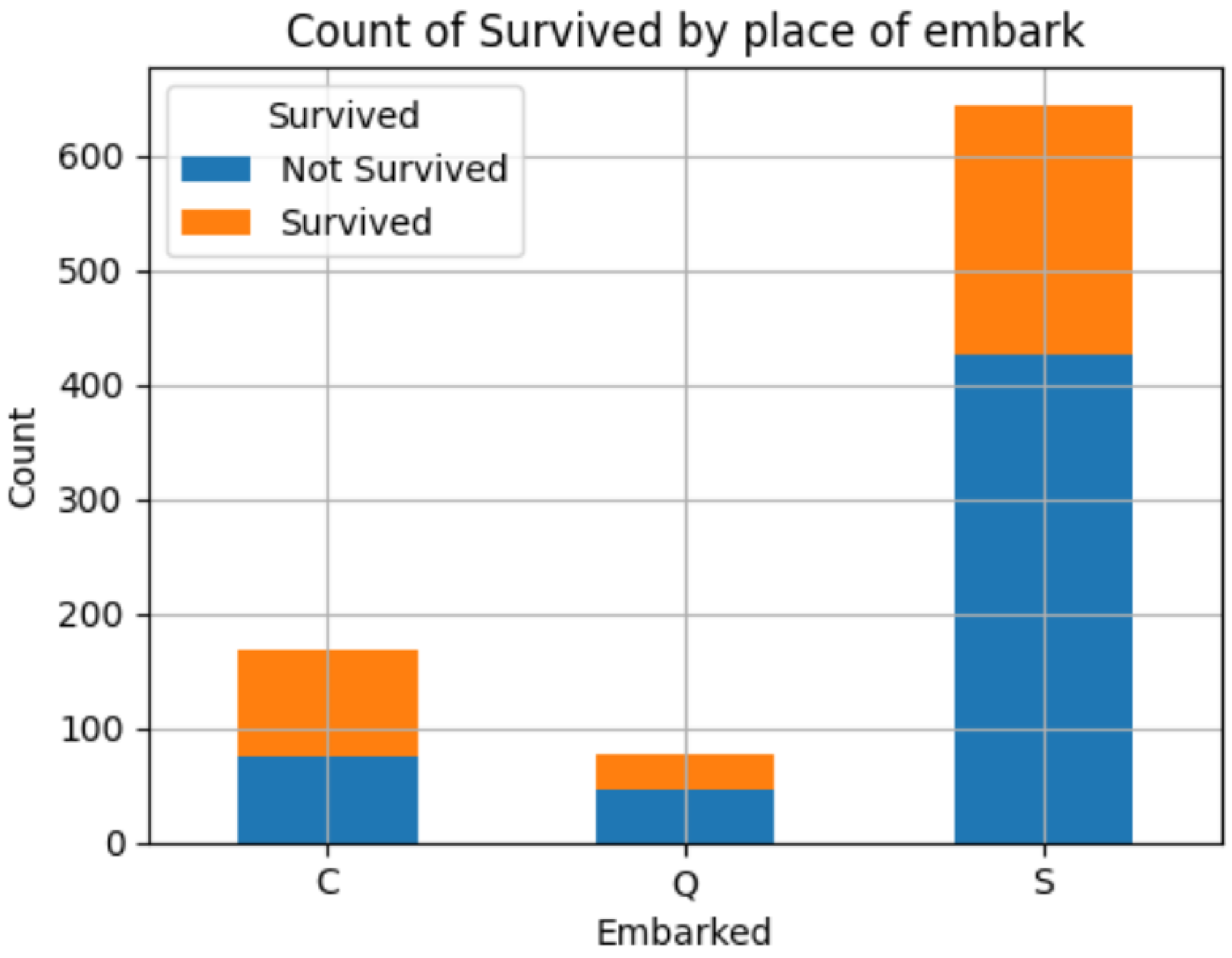




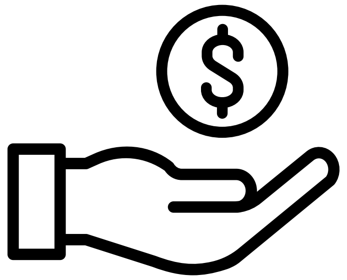
Distribuciones | Embarked

```
Porcentage of embark in C = Cherbourg ( 168 ):  18.86 %        Not-Survived:  44.64 %        Survived: 55.36 %
Porcentage of embark in Q = Queenstown ( 77 ):  8.64 %         Not-Survived:  61.04 %        Survived: 38.96 %
Porcentage of embark in S = Southampton ( 644 ):  72.28 %      Not-Survived:  66.3 %         Survived: 33.7 %
```

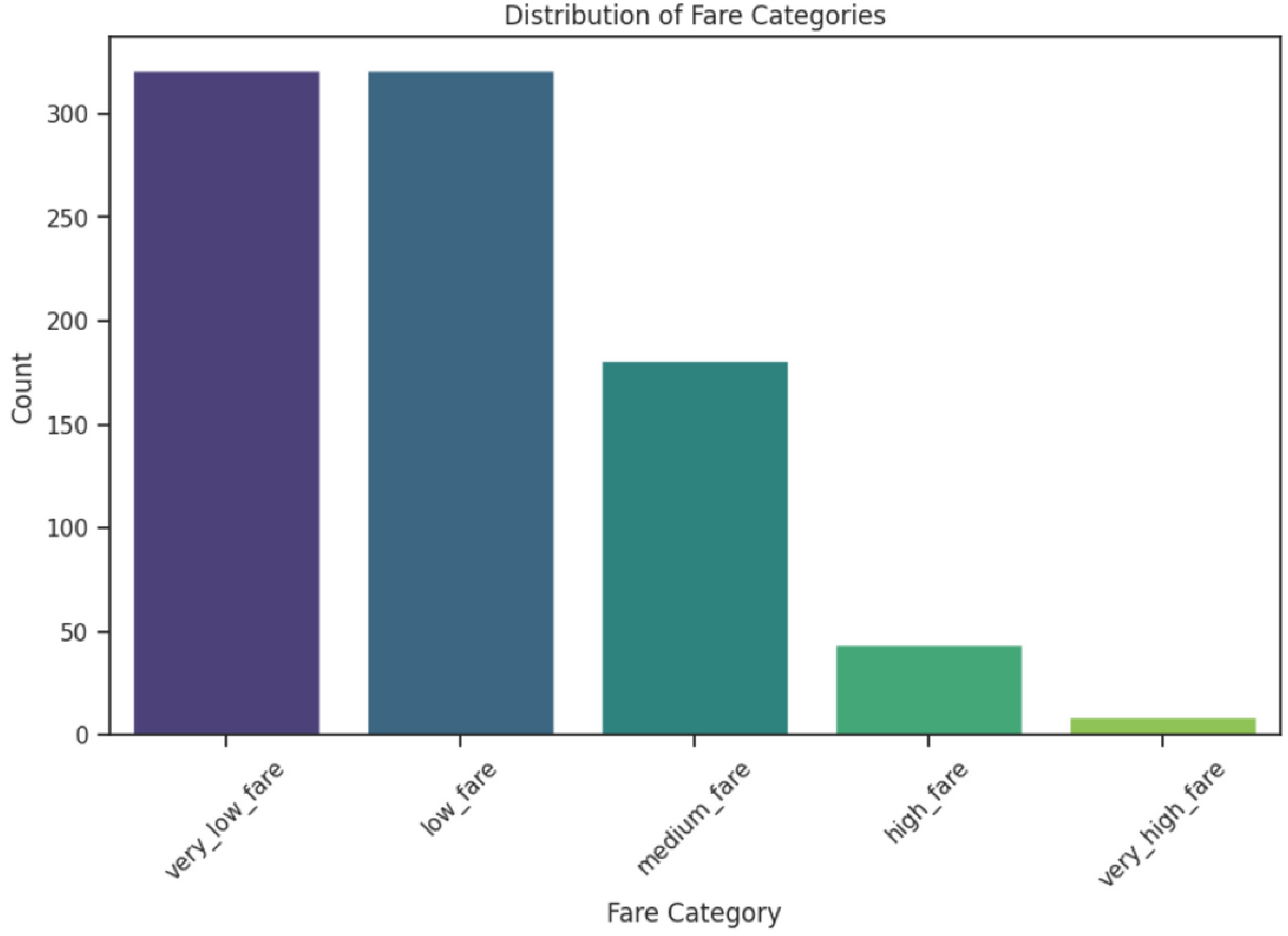




Distribuciones | Fare



```
Very Low Fare paid ($0 - $10 dlls):       321 people.
Low Fare paid ($11 - $30 dlls):           321 people.
Medium Fare paid ($31 - $100 dlls):       181 people.
High Fare paid ($101 - $250 dlls):        44 people.
Very High Fare paid ($251 - $550 dlls):   9 people.
```



Distribuciones | Feature Engineering

Total Family

$$TotalFamily = \frac{Siblings}{Spouse} + \frac{Parents}{Children} = \frac{Siblings + Parents}{Spouse + Children}$$

if Total_Family == 0

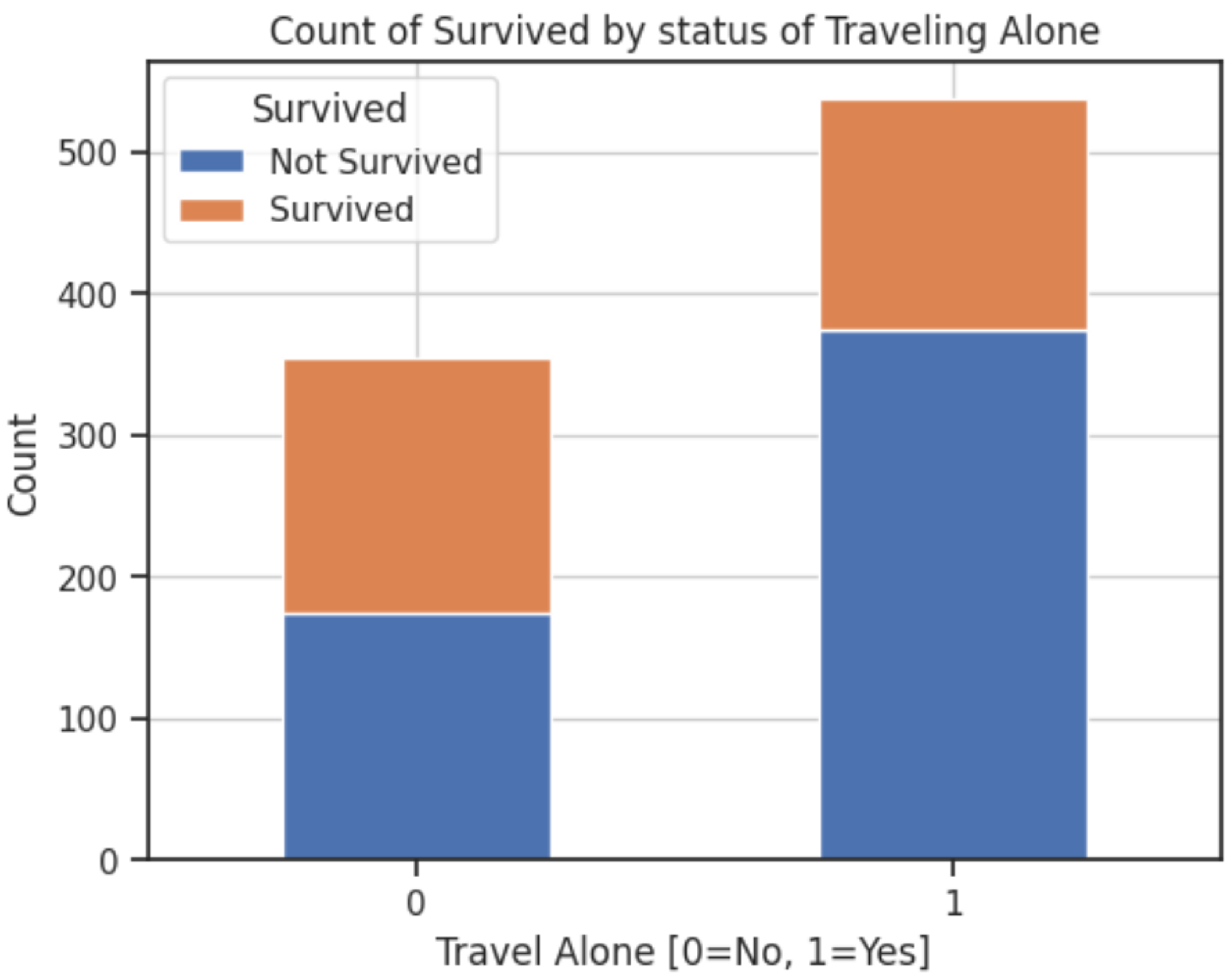
then travels alone

else if Total_Family > 0

then travels with company

```
Count of people Traveling Alone:  354
Count of people Not-Traveling Alone:  537
```

Travel Alone?



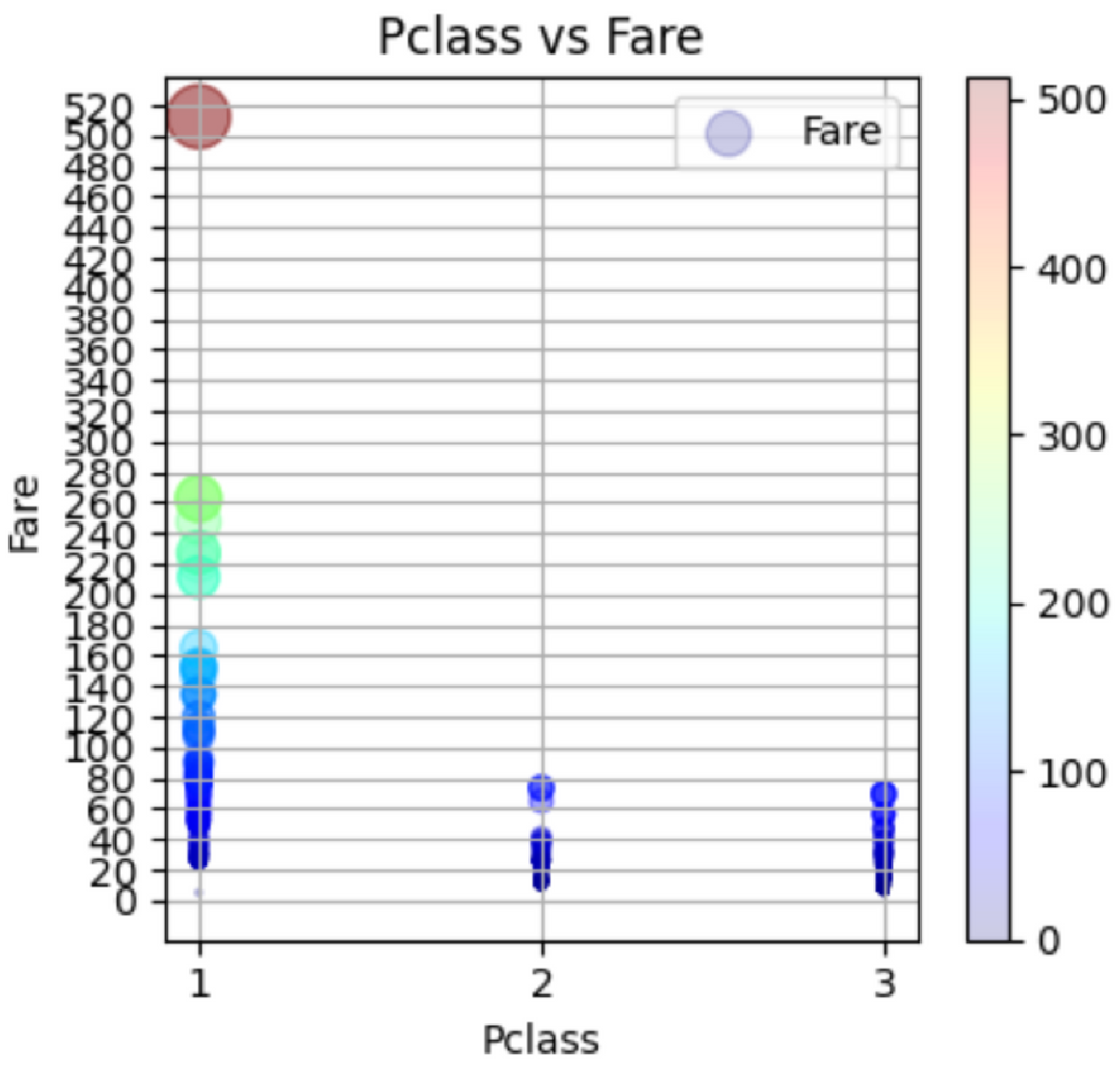
Distribuciones

Analyzing Pclass vs Fare

This graph reveals some interesting insights. It's noticeable that the fare prices for 2nd and 3rd class tickets are similar.

However, when it comes to 1st class tickets, we observe a wider range of fare prices. Some 1st class tickets were sold at prices comparable to those of 2nd and 3rd classes.

On the other hand, certain 1st class tickets were sold at significantly higher prices. This suggests the presence of outliers in the Fare attribute.



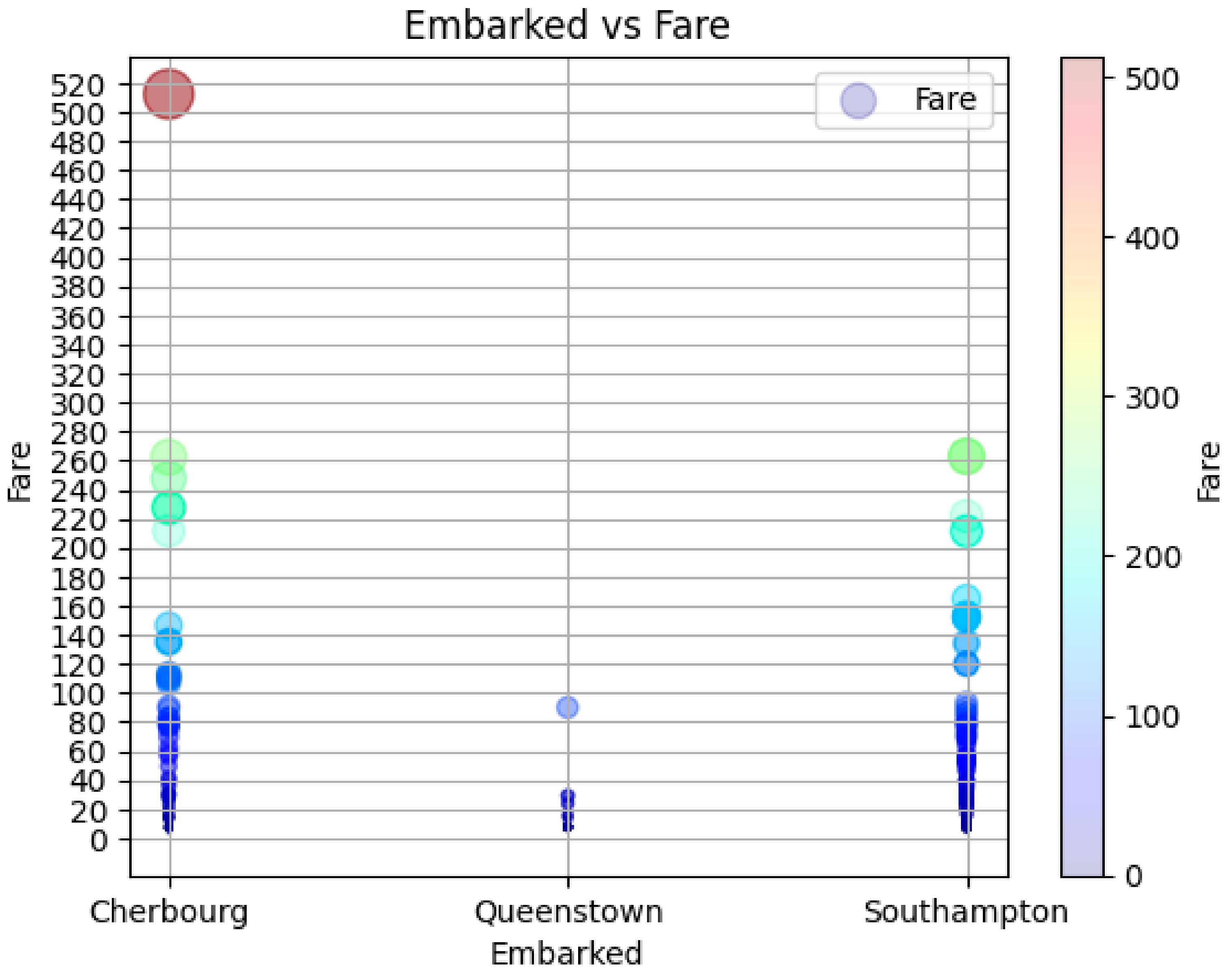
Distribuciones

Analyzing Port of embarkation vs Fare

This graph illustrates fare prices based on the port of embarkation.

The data shows that fares from Cherbourg were notably higher, followed by Southampton, while Queenstown had the lowest fares.

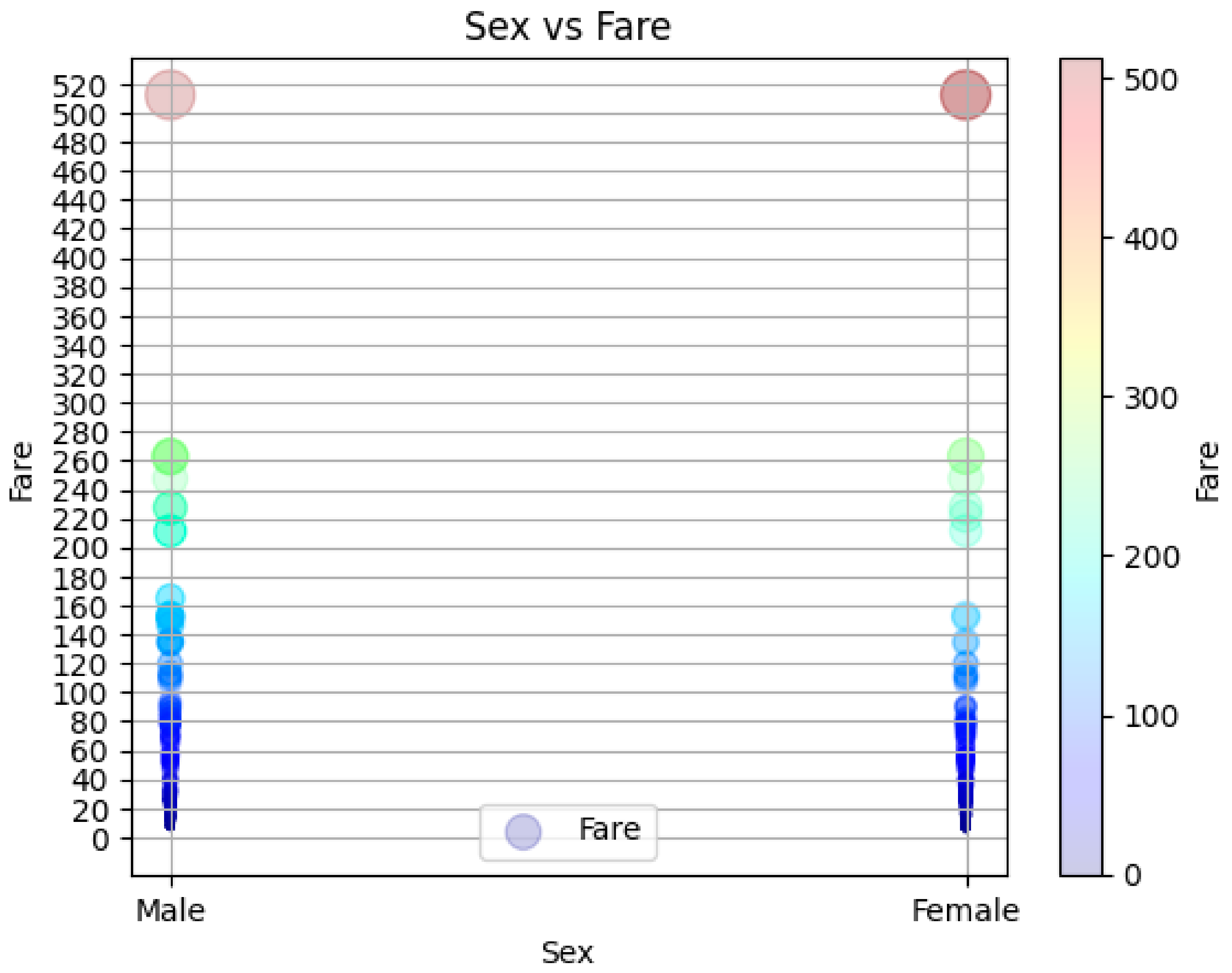
This suggests a trend where 1st class tickets originated from Cherbourg, 2nd class from Southampton, and 3rd class from Queenstown."



Distribuciones

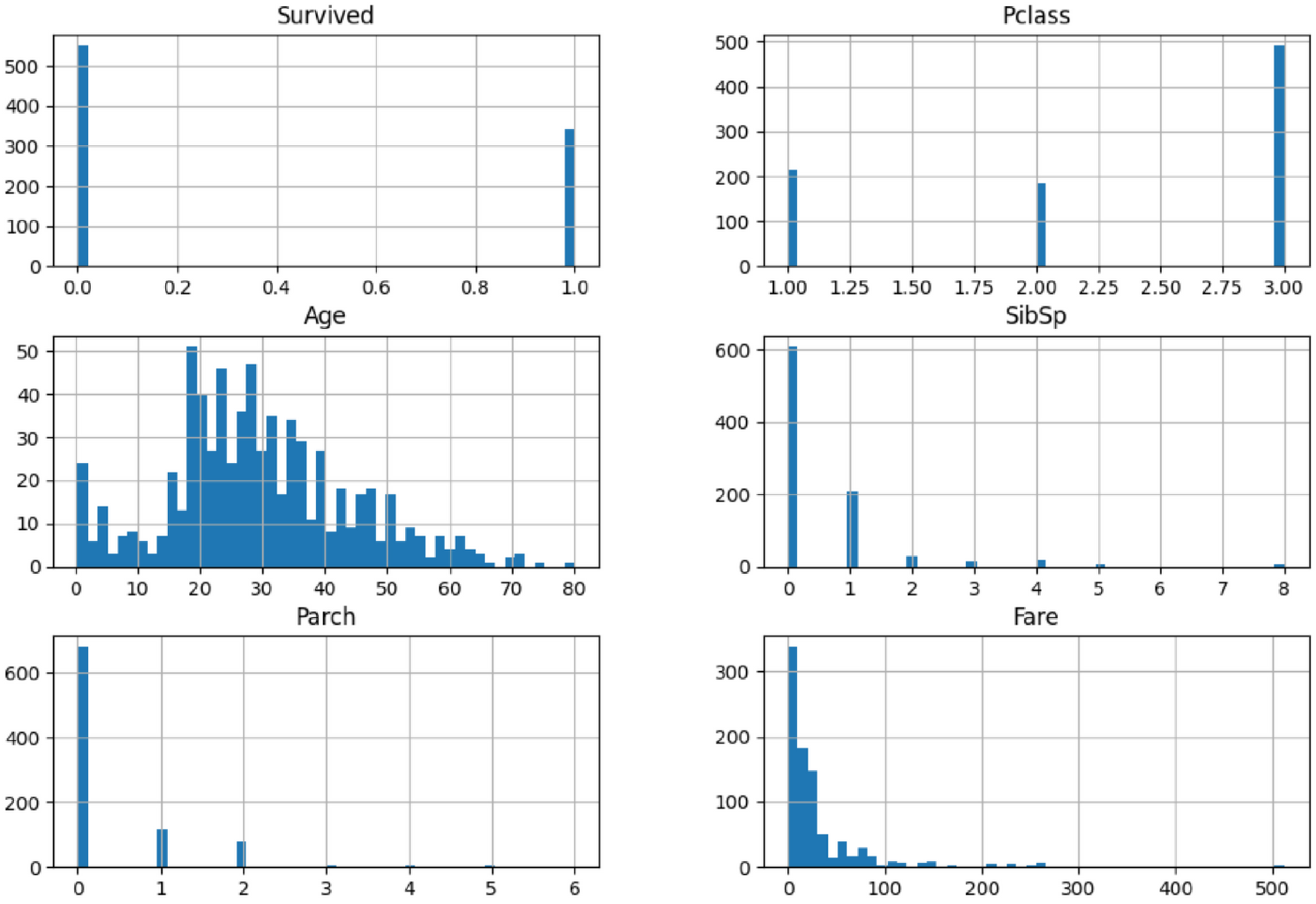
Analyzing Sex vs Fare

This graph illustrates fare prices based on the sex. We found no outliers or any insights worth nothing except that prices were sold evenly for men and women.



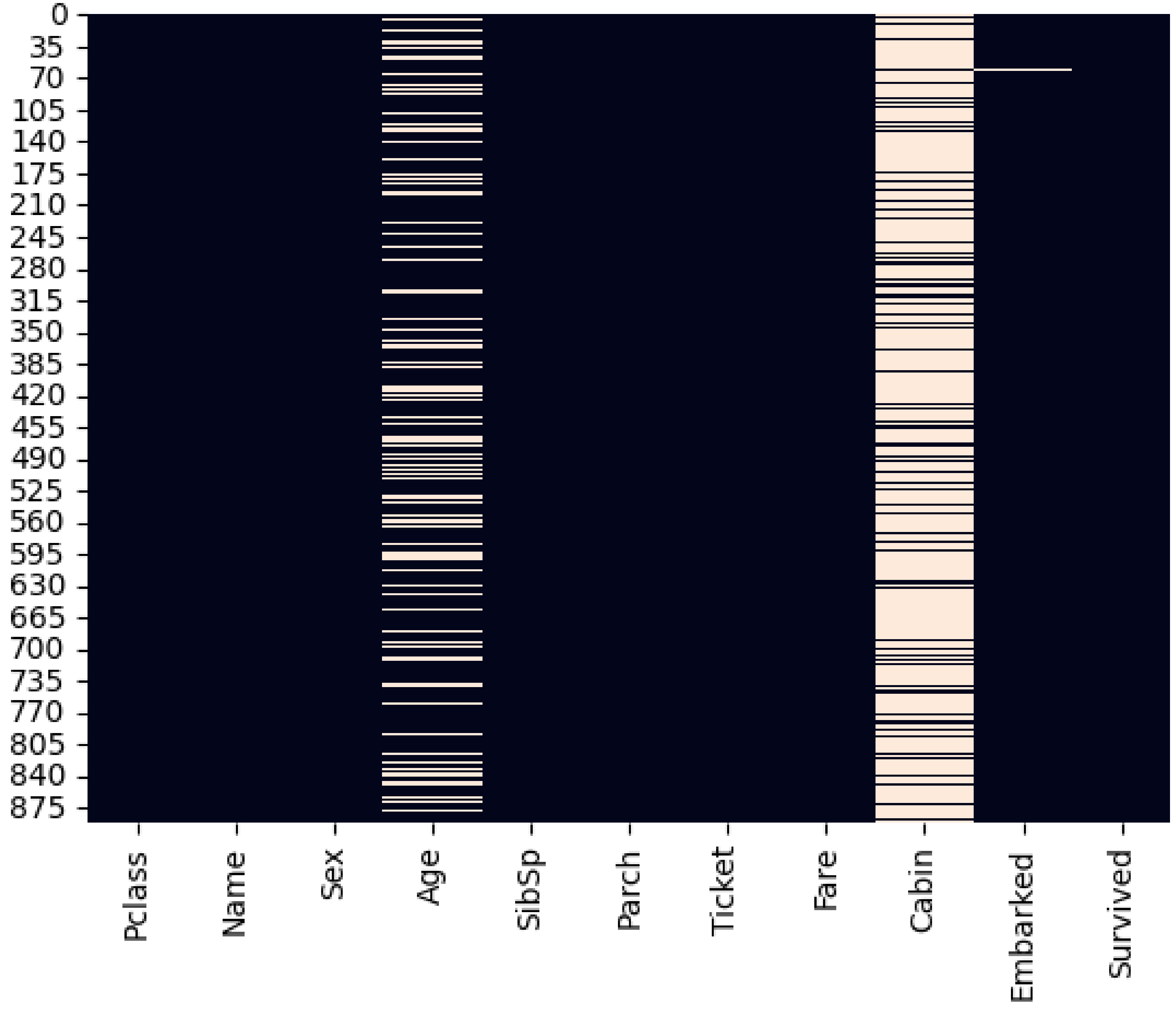
Distribuciones

Atributos numéricos (6 / 11)

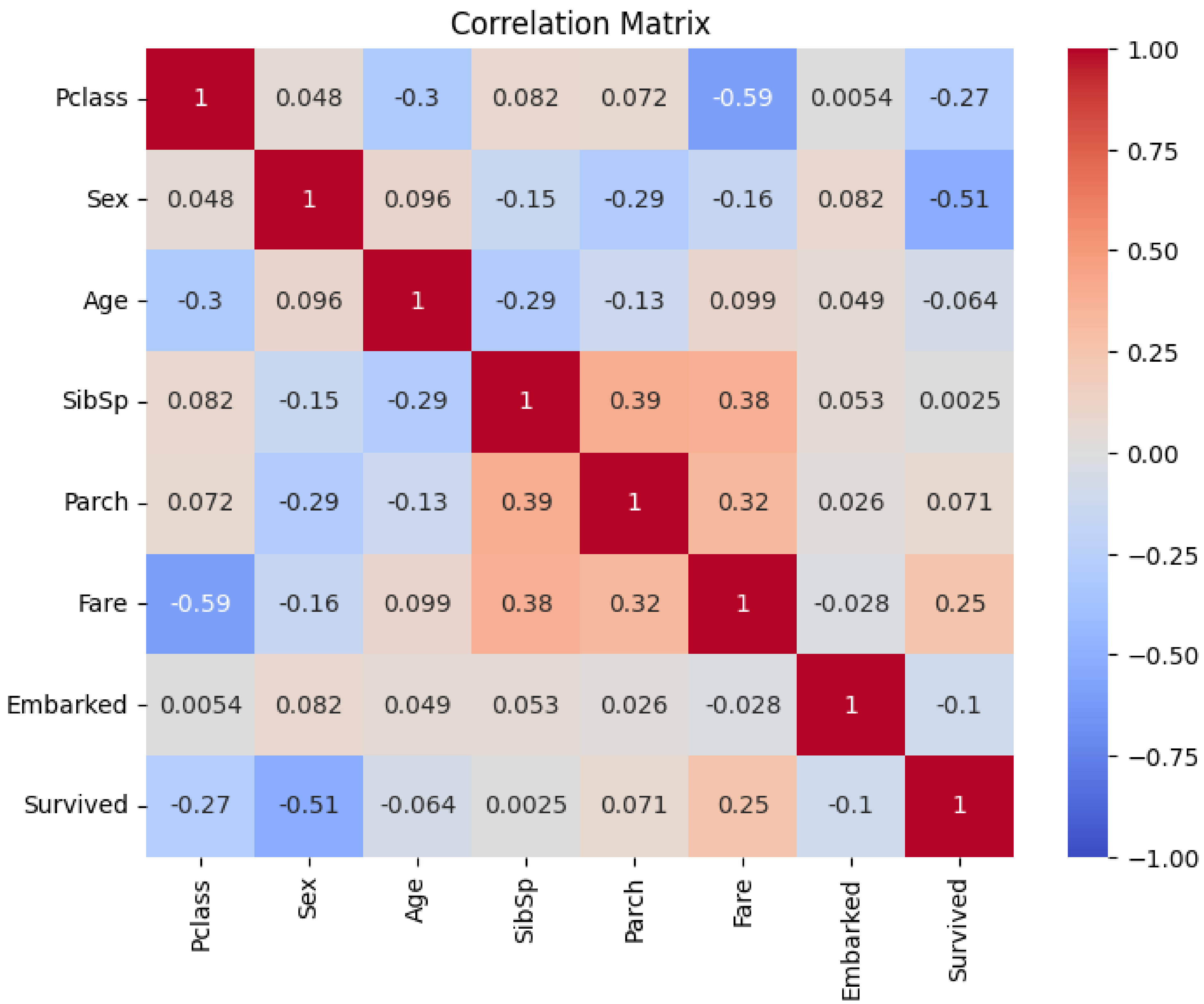


Datos Faltantes

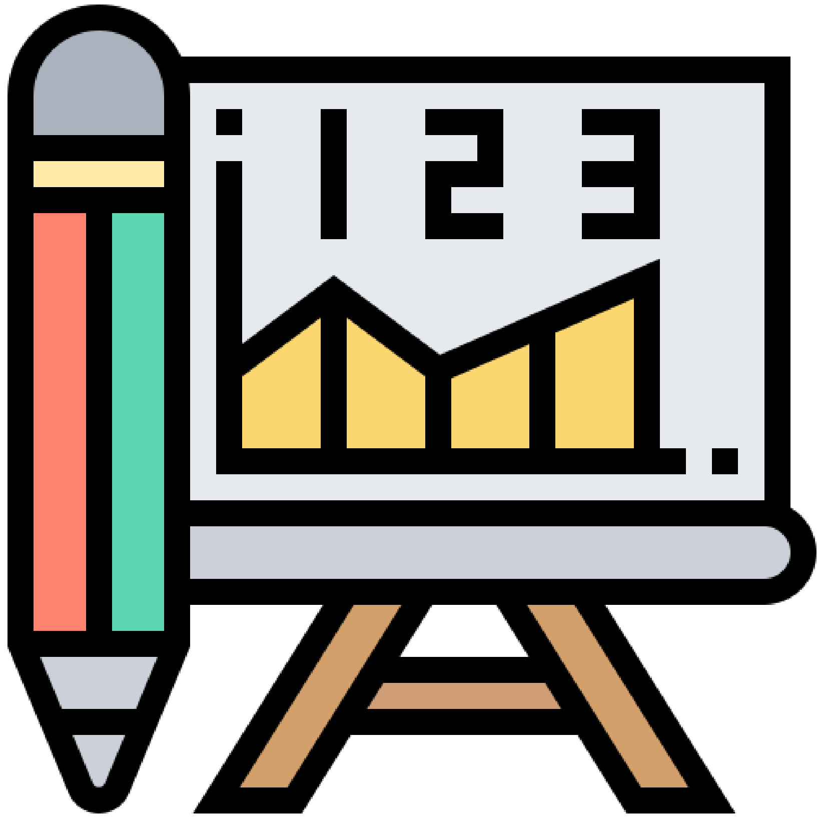
Pclass has 0 missing values
Name has 0 missing values
Sex has 0 missing values
Age has 177 missing values
SibSp has 0 missing values
Parch has 0 missing values
Ticket has 0 missing values
Fare has 0 missing values
Cabin has 687 missing values
Embarked has 2 missing values
Survived has 0 missing values



Análisis de Correlación



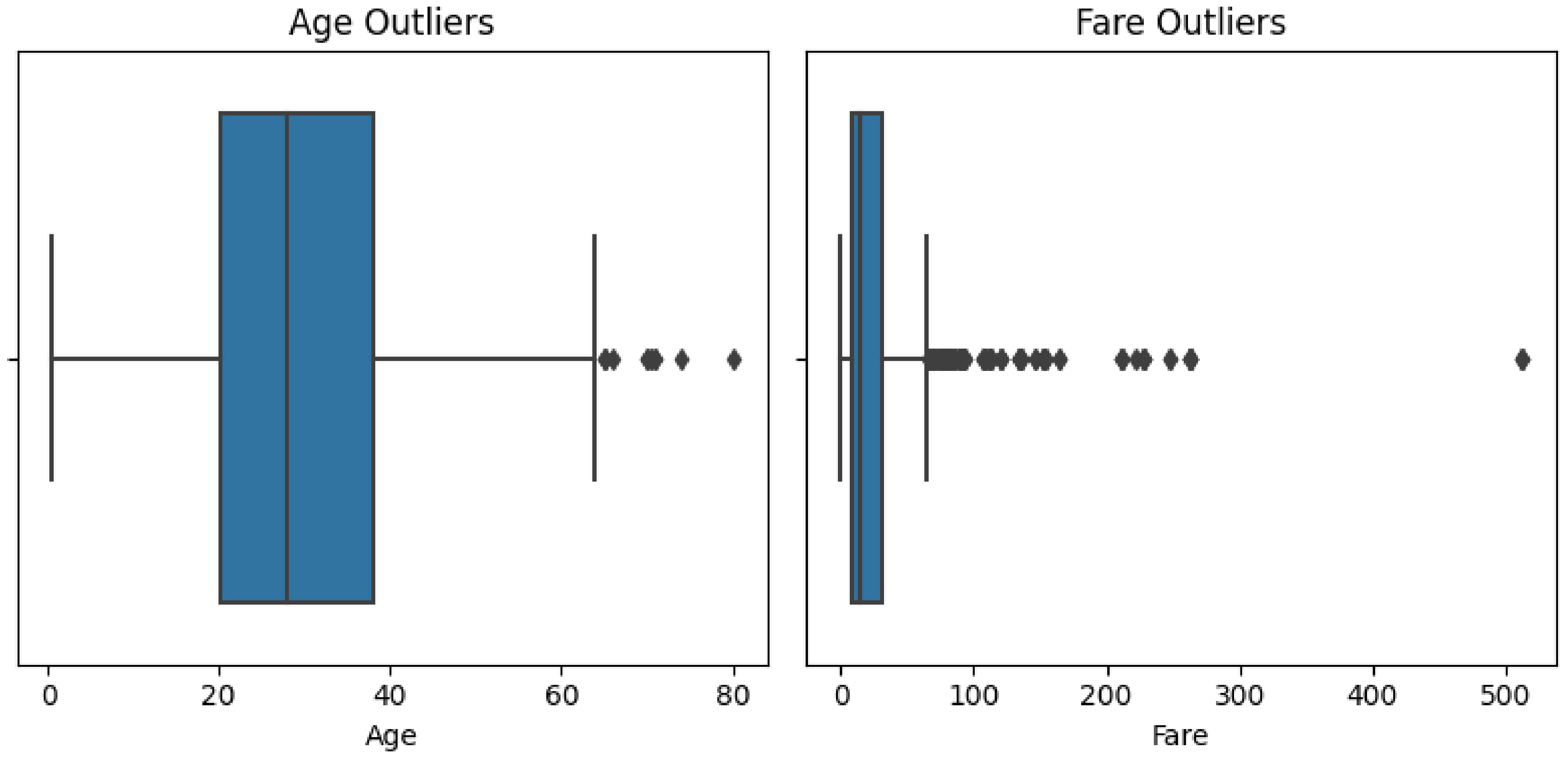
The values that are most related to the target variable are Fare, Parch and SibSp.



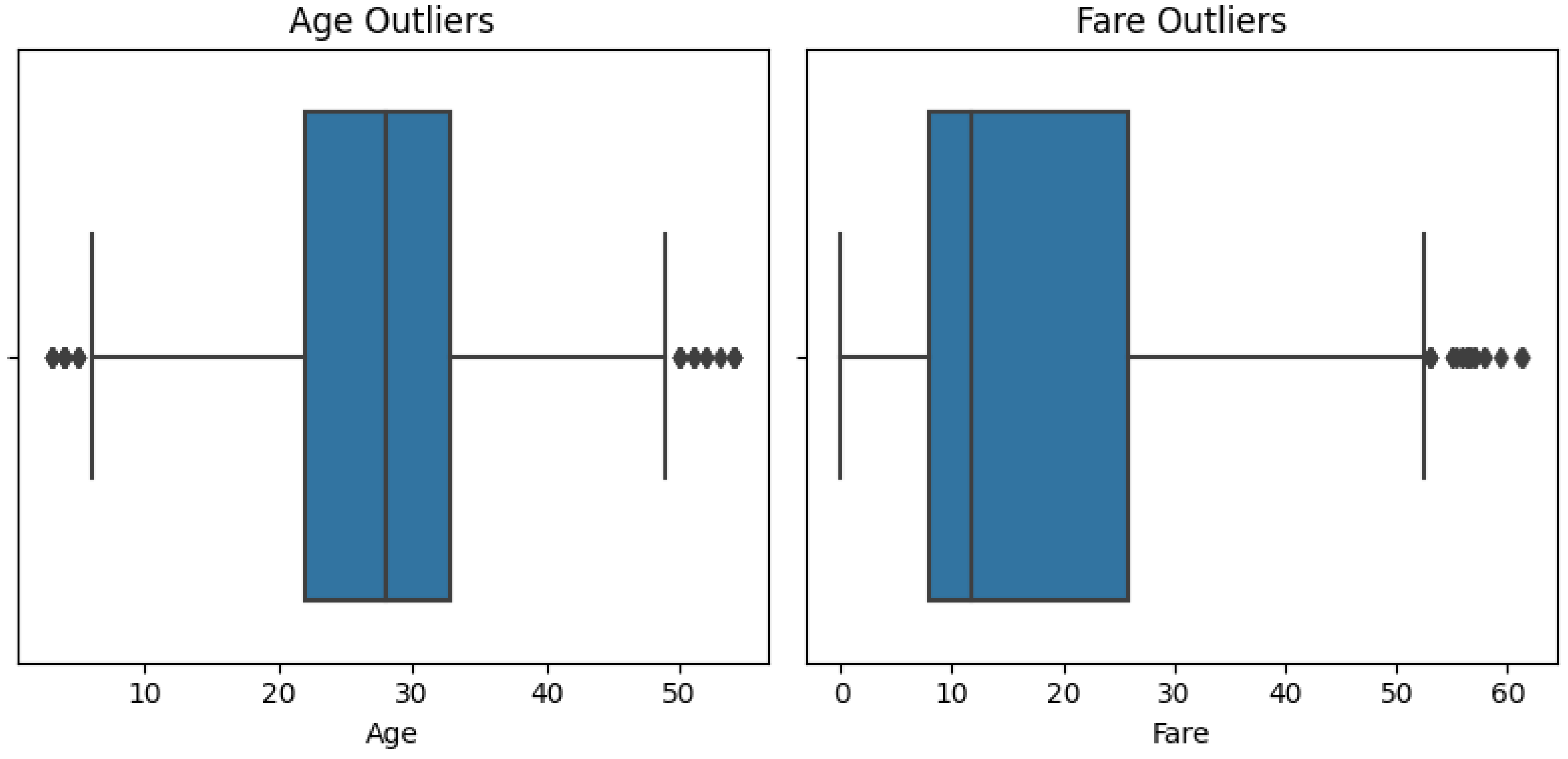
Transformación de datos

The obtained results by using the IQR Method to reduce outliers indicate that there was some data that was not useful for training the ML models, therefore it was removed using an interquartil range of 90% to 10% for high limit and low limit respectively.

Before

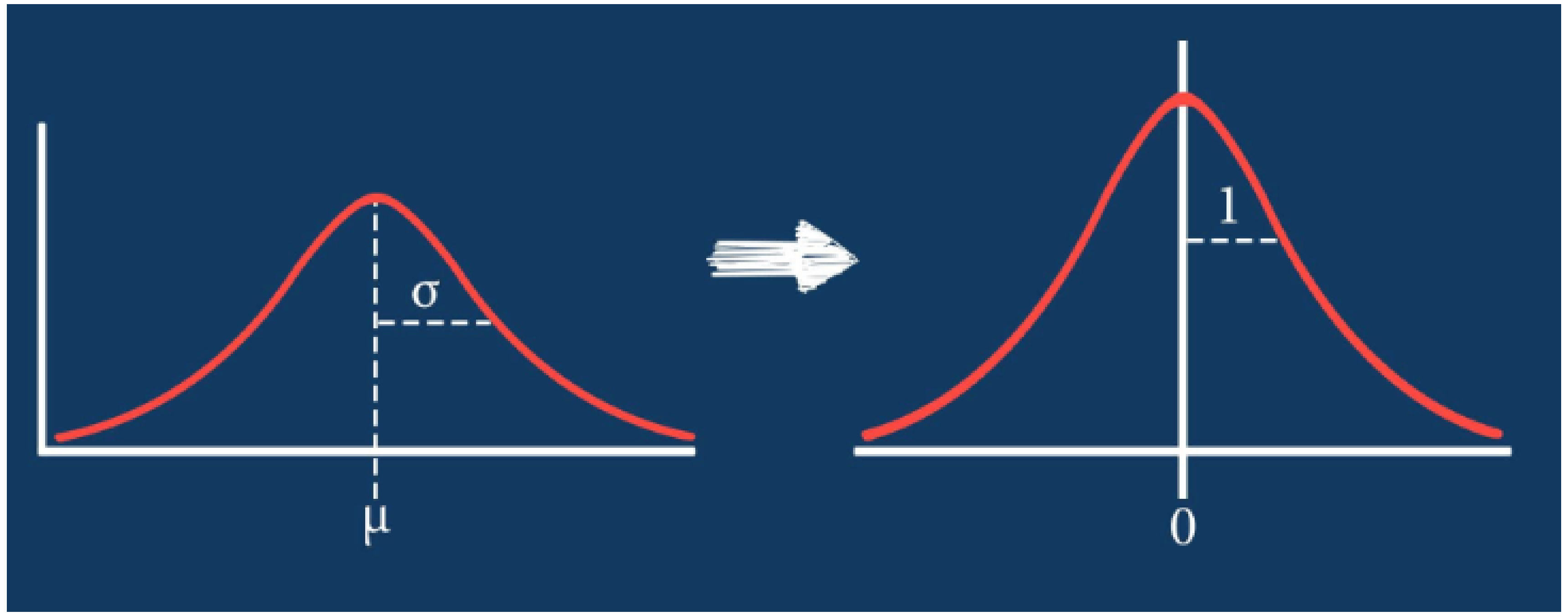


After



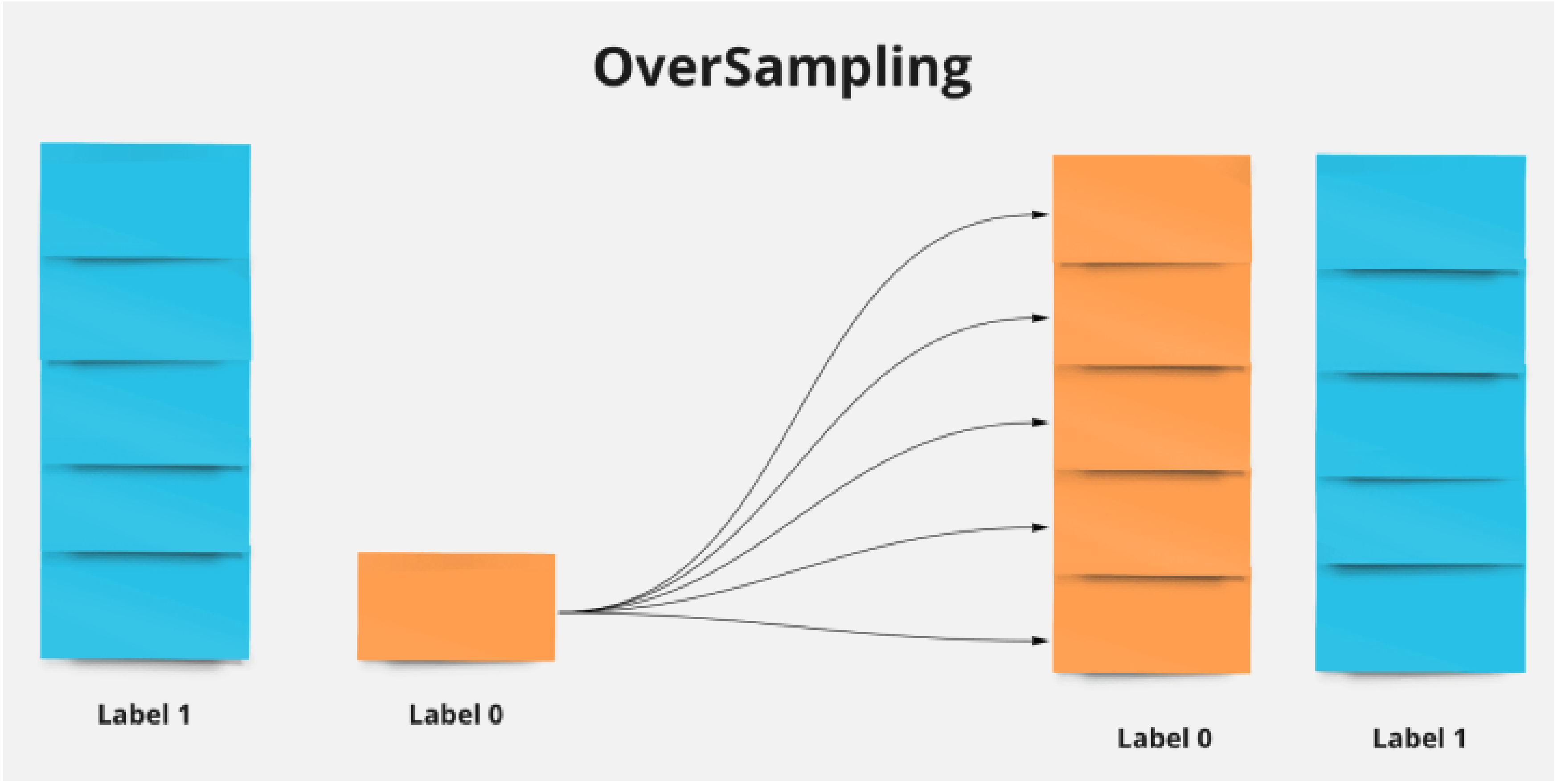
Data Scaling

To ensure optimal performance of our machine learning algorithms, especially those that are distance-based such as k-nearest neighbors and support vector machines, we apply a scaling technique.



Handling imbalanced datasets

Our dataset is imbalanced. Techniques that solve this exist, but sometimes they can be detrimental and it's worth exploring both to determine the most effective approach.



Selección de clasificadores

1. Logistic Regression
2. Random Forest Classifier
3. Support Vector Machine
4. K Nearest Neighbors

Métricas de evaluación

Desbalanceado | Preprocesado

Métrica / Clasificador	Clase	Random Forest (Desbalanceado)	Random Forest (Preprocesado)	Logistic Regression (Desbalanceado)	Logistic Regression (Preprocesado)	Support Vector Machine (Desbalanceado)	Support Vector Machine (Preprocesado)	KNN (Desbalanceado)	KNN (Preprocesado)
Accuracy		0.98	0.94	0.80	0.81	0.84	0.84	0.83	0.83
Precision	0	0.98	0.94	0.82	0.83	0.84	0.84	0.82	0.83
	1	0.98	0.95	0.76	0.77	0.83	0.82	0.84	0.84
Recall	0	0.99	0.97	0.86	0.87	0.91	0.90	0.92	0.92
	1	0.96	0.90	0.70	0.71	0.72	0.73	0.68	0.69
F1 Score	0	0.98	0.94	0.84	0.85	0.87	0.87	0.87	0.87
	1	0.97	0.95	0.73	0.74	0.77	0.77	0.75	0.76
Kaggle		0.75598	0.7344	0.7655	0.77511	0.77511	0.7829	0.75837	0.72248

Métricas de evaluación | Dataset desbalanceado

Colab / Kaggle

```
▼ LogisticRegression
LogisticRegression()
```

	precision	recall	f1-score	support
0	0.82	0.86	0.84	549
1	0.76	0.70	0.73	342
accuracy			0.80	891

Submission and Description — Public Score

LogisticRegressionDesbalanceado.csv — Complete · now — **0.76555**

```
▼ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

	precision	recall	f1-score	support
0	0.82	0.92	0.87	549
1	0.84	0.68	0.75	342
accuracy			0.83	891

Submission and Description — Public Score

KNNDesbalanceado.csv — Complete · now — **0.75837**

```
▼ SVC
SVC(random_state=42)
```

	precision	recall	f1-score	support
0	0.84	0.91	0.87	549
1	0.83	0.72	0.77	342
accuracy			0.84	891

Submission and Description — Public Score

SVMDesbalanceado.csv — Complete · now — **0.77511**

```
▼ RandomForestClassifier
RandomForestClassifier(random_state=15)
```

	precision	recall	f1-score	support
0	0.98	0.99	0.98	549
1	0.98	0.96	0.97	342
accuracy			0.98	891

Submission and Description — Public Score

RandomForestDesbalanceado.csv — Complete · now — **0.75598**

Métricas de evaluación | Dataset balanceado y preprocesado

	Colab	Kaggle

LogisticRegression

LogisticRegression()

	precision	recall	f1-score	support
0	0.83	0.87	0.85	549
1	0.77	0.71	0.74	342
accuracy			0.81	891

Submission and Description	Public Score
LogisticRegressionBalanceado.csv Complete · now	0.77511

RandomForestClassifier

RandomForestClassifier(random_state=15)

	precision	recall	f1-score	support
0	0.94	0.97	0.95	549
1	0.95	0.90	0.92	342
accuracy			0.94	891

Submission and Description	Public Score
RandomForestBalanceado.csv Complete · now	0.73444

KNeighborsClassifier

KNeighborsClassifier(n_neighbors=3)

	precision	recall	f1-score	support
0	0.83	0.92	0.87	549
1	0.84	0.69	0.76	342
accuracy			0.83	891

Submission and Description	Public Score
KNNBalanceado.csv Complete · now	0.72248

SVC

SVC(random_state=42)

	precision	recall	f1-score	support
0	0.84	0.90	0.87	549
1	0.82	0.73	0.77	342
accuracy			0.84	891

Submission and Description	Public Score
SVMBalanceado.csv Complete · now	0.78229