In [232…

```
import pandas as pd
import numpy as np
import matplotlib as mat
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.feature_selection import f_regression
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
import re
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE
from sklearn.preprocessing import MinMaxScaler
```

In [233…

```
data_url = 'https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.
```

In [234…

```
df = pd.read_csv(data_url)
```

In [235…

```
df.head()
```

Out[235]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	E
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	

In [236…

```
df.tail()
```

Out[236]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Emb
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	

In [237…

```
df.describe()
```

Out[237]:

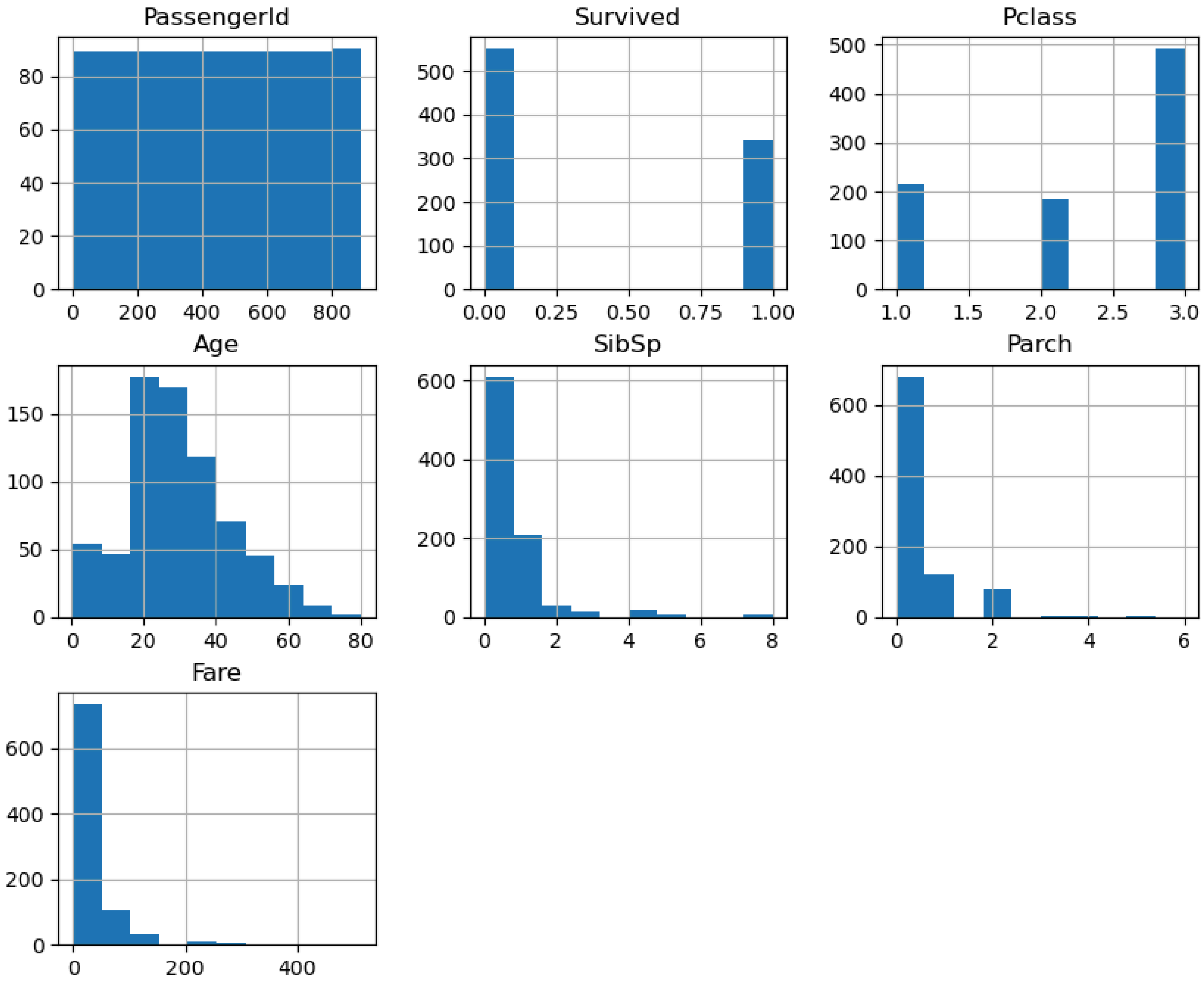
	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	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 [238…

```
df.hist(figsize=(10, 8))
```

Out[238]:

```
array([[<Axes: title={'center': 'PassengerId'}>,
        <Axes: title={'center': 'Survived'}>,
        <Axes: title={'center': 'Pclass'}>],
       [<Axes: title={'center': 'Age'}>,
        <Axes: title={'center': 'SibSp'}>,
        <Axes: title={'center': 'Parch'}>],
       [<Axes: title={'center': 'Fare'}>, <Axes: >, <Axes: >]],
      dtype=object)
```

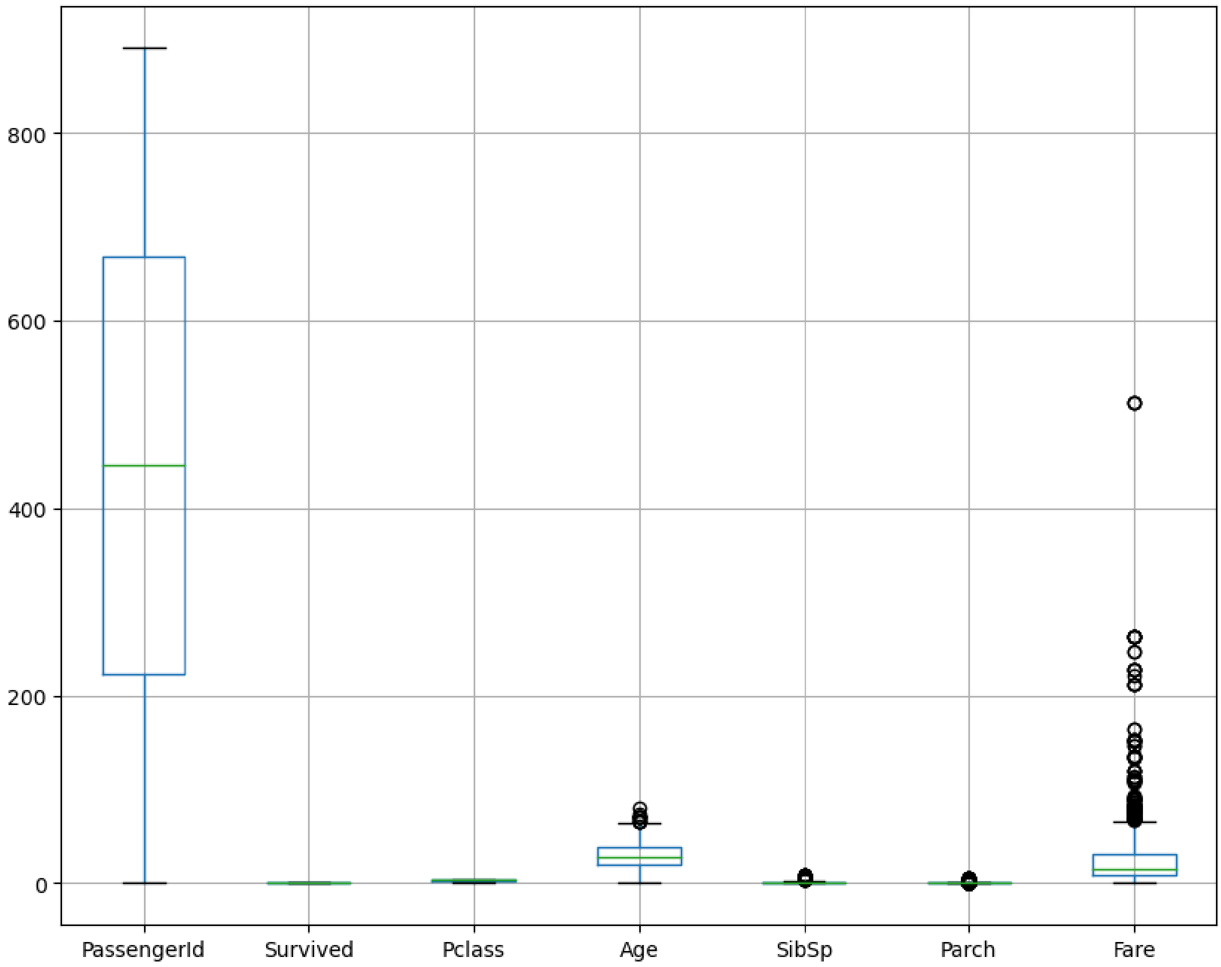


In [239…

```
df.boxplot(figsize=(10,8))
```

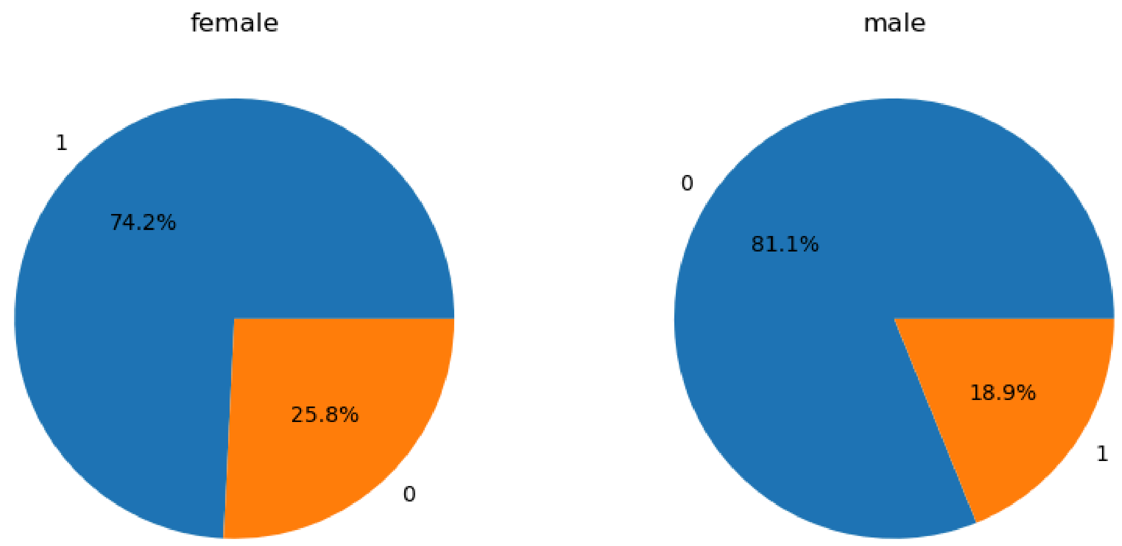
Out[239]:

```
<Axes: >
```



In [240…

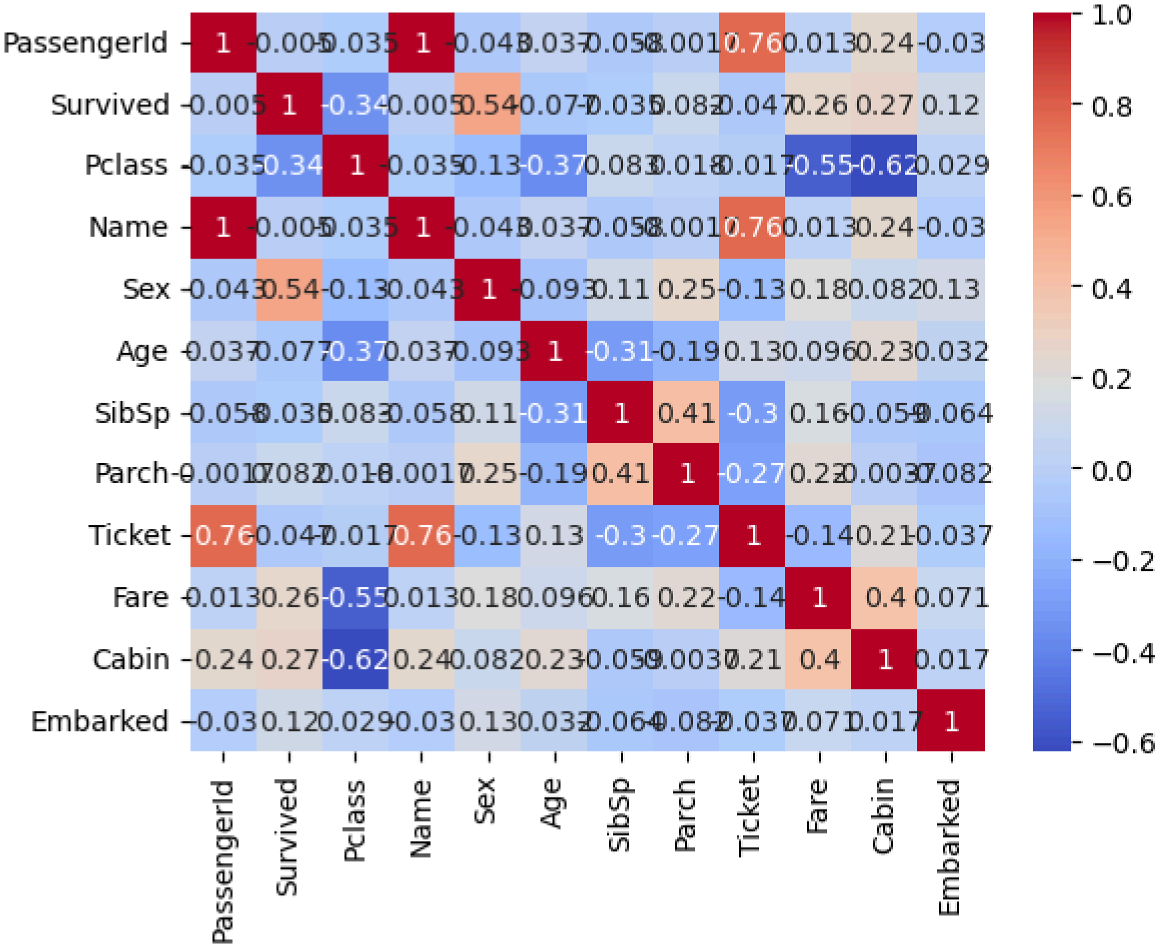
```
# Group the data by sex

if 'Embarked' in df.columns:
    grouped_data = df.groupby('Sex')

# Create a pie chart for each sex
fig, axes = mat.pyplot.subplots(nrows=1, ncols=2, figsize=(10, 5))

for i, (sex, group) in enumerate(grouped_data):
    group['Survived'].value_counts().plot(kind='pie', ax=axes[i], autopct='%1.1f%%')
    axes[i].set_title(sex)
    axes[i].set_ylabel('')
```



In [241…

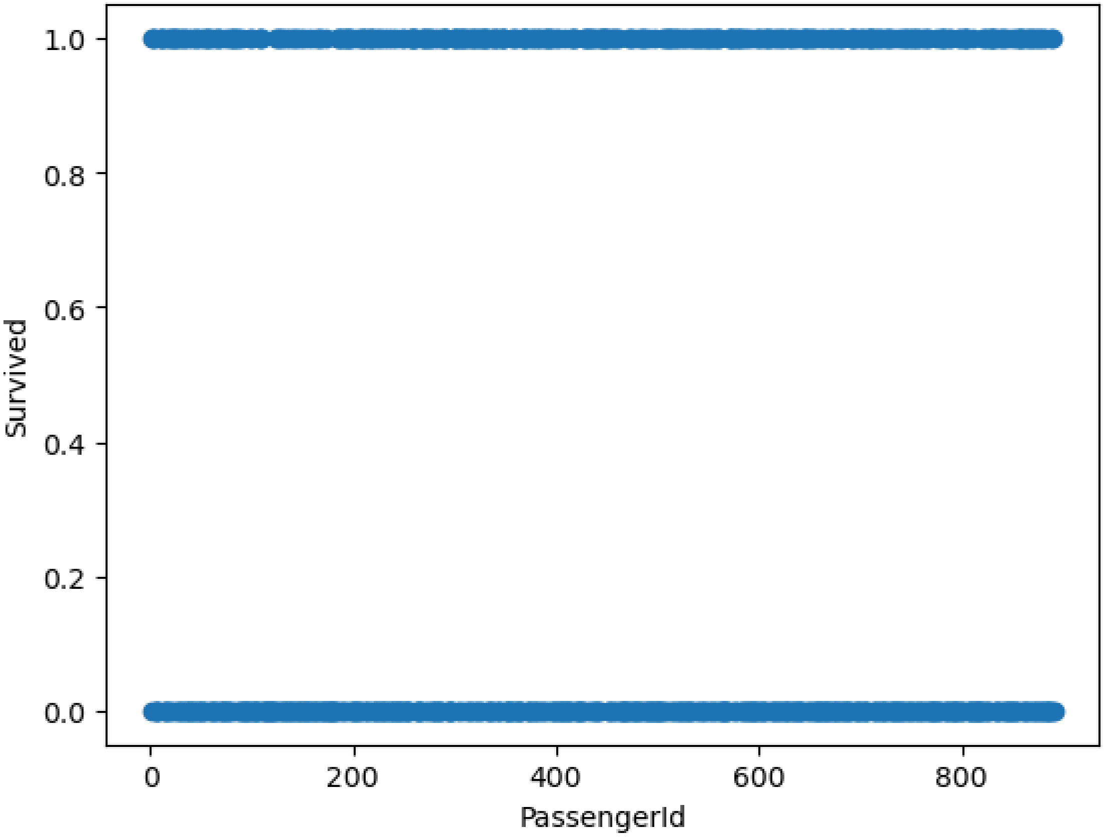
```
# Select the columns with string values
string_columns = df.select_dtypes(include=['object']).columns

# Define a mapping dictionary for each string column
mapping_dict = {}
for col in string_columns:
  mapping_dict[col] = {value: i for i, value in enumerate(df[col].unique())}

# Encode the string values
for col, mapping in mapping_dict.items():
  df[col] = df[col].map(mapping)

# Print the encoded data frame
print(df.head())





corr_matrix = df.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
mat.pyplot.show()
```

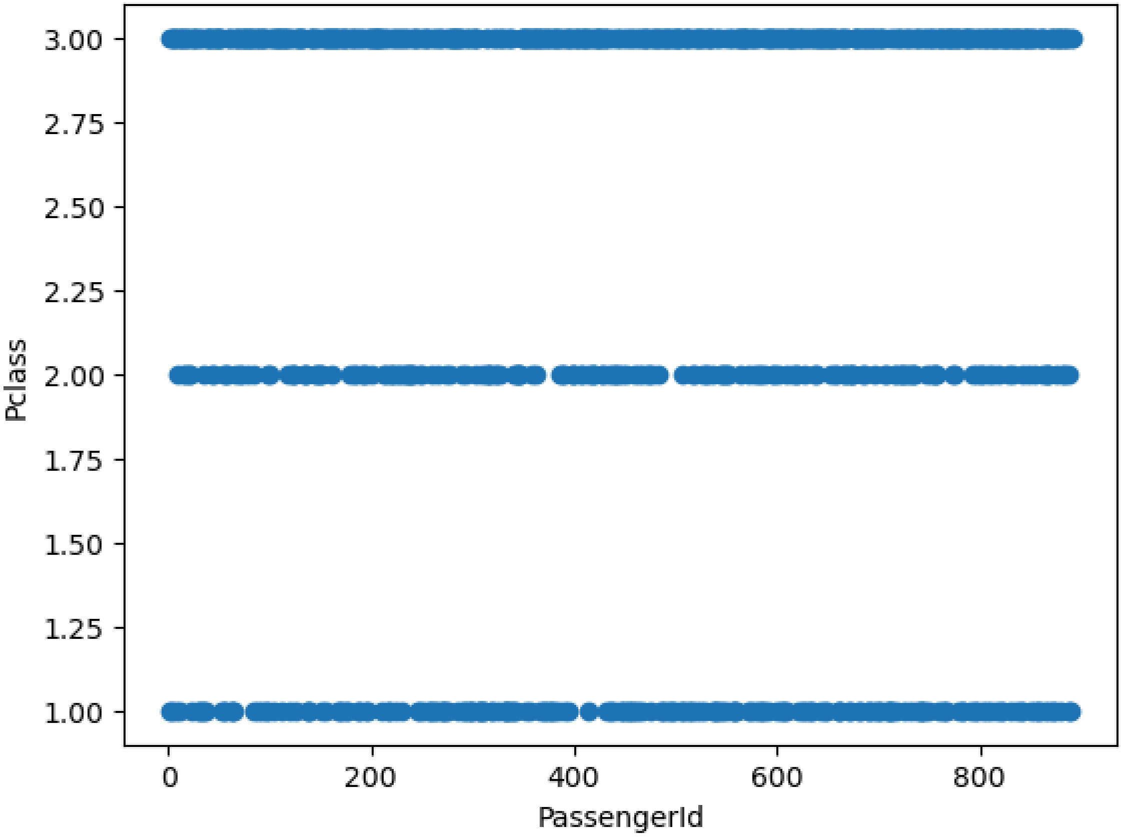
```
   PassengerId  Survived  Pclass  Name  Sex   Age  SibSp  Parch  Ticket  \
0            1         0       3     0    0  22.0      1      0       0   
1            2         1       1     1    1  38.0      1      0       1   
2            3         1       3     2    1  26.0      0      0       2   
3            4         1       1     3    1  35.0      1      0       3   
4            5         0       3     4    0  35.0      0      0       4   

      Fare  Cabin  Embarked  
0   7.2500      0         0  
1  71.2833      1         1  
2   7.9250      0         0  
3  53.1000      2         0  
4   8.0500      0         0  
```

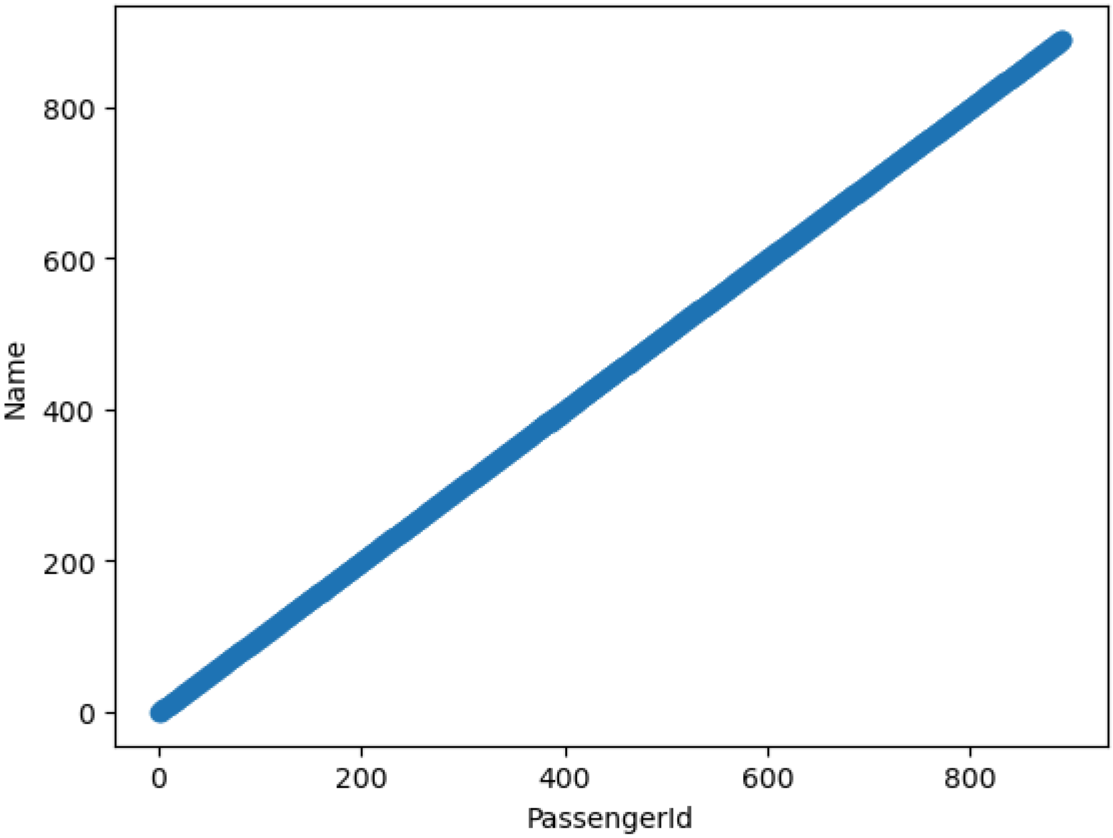


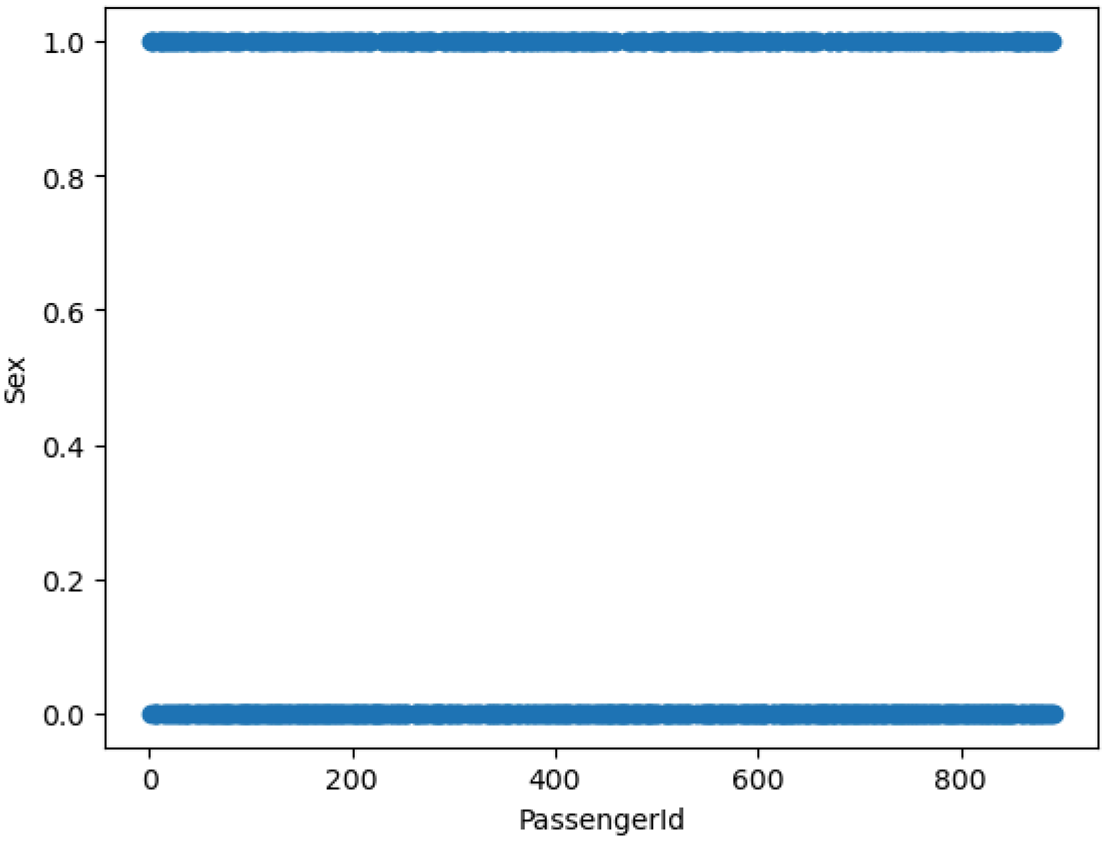
In [242…

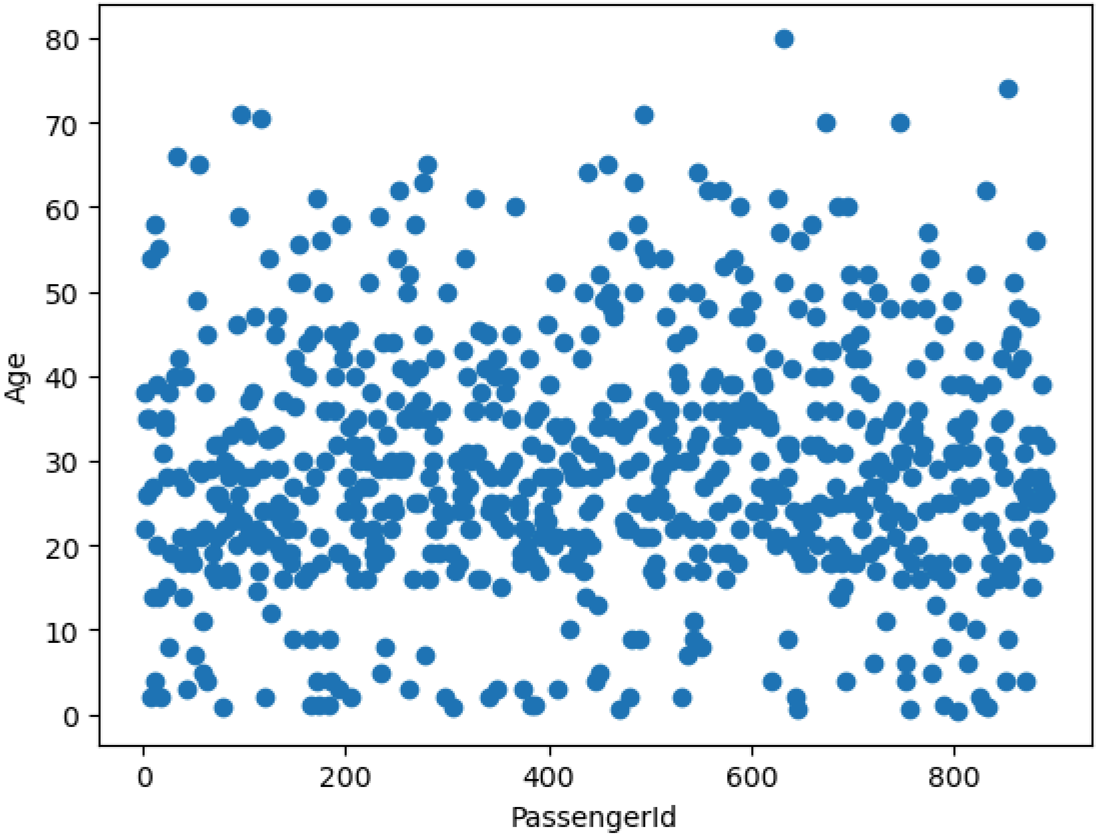
```
# Create a list of all columns
columns = df.columns.tolist()

# Create scatterplots for each pair of columns
for i in range(len(columns)):
    for j in range(i + 1, len(columns)):
        mat.pyplot.scatter(df[columns[i]], df[columns[j]])
        mat.pyplot.xlabel(columns[i])
        mat.pyplot.ylabel(columns[j])
        mat.pyplot.show()
```

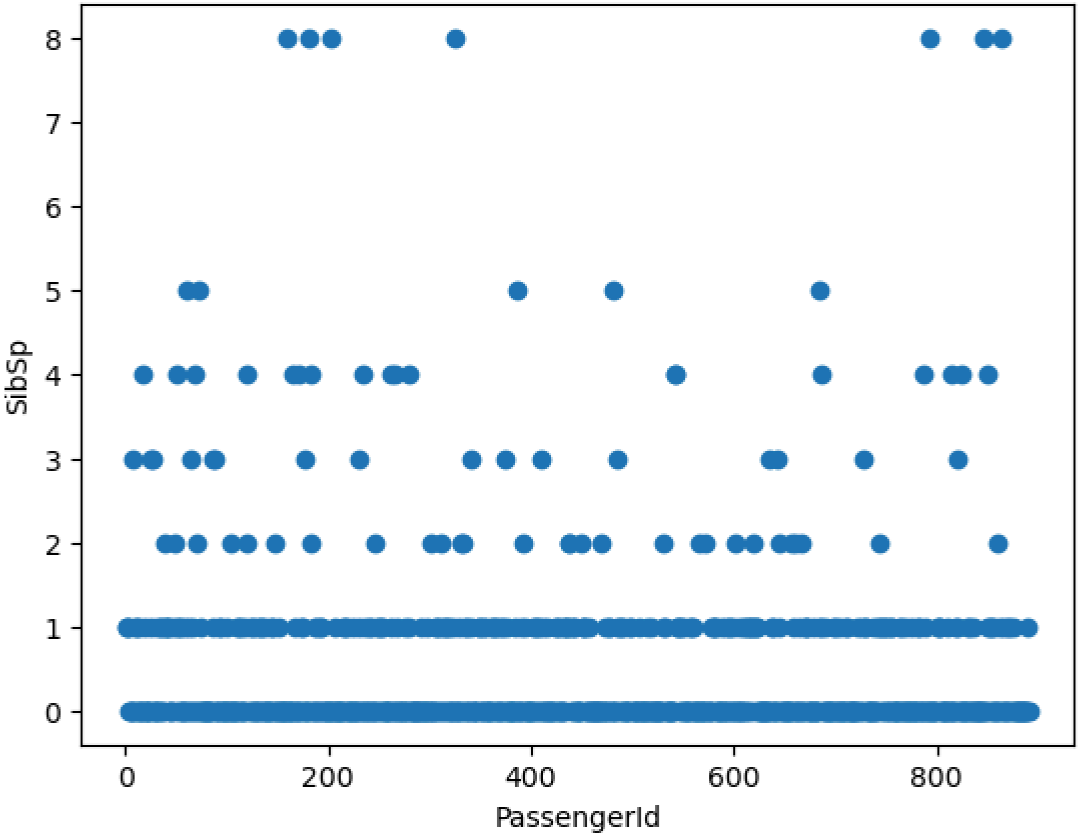

1.0
0.8
0.6
0.4
0.2
0.0
Survived
0
200
400
600
800
PassengerId

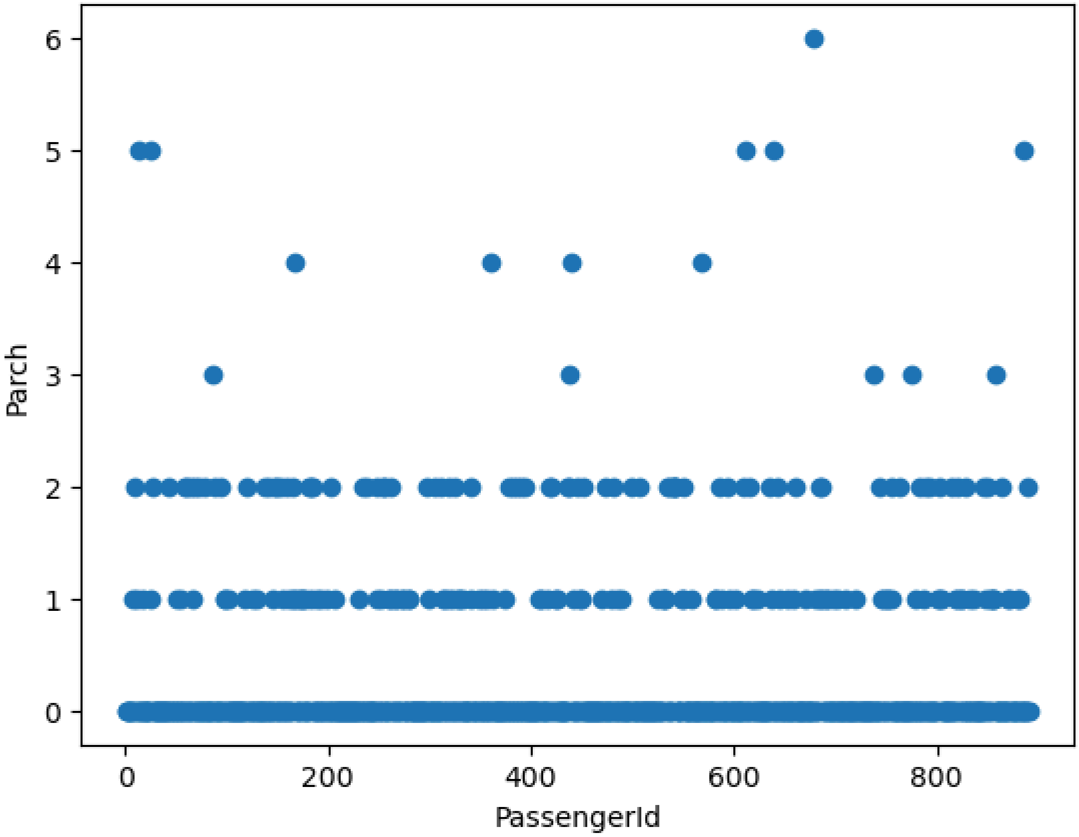

3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
Pclass
0
200
400
600
800
PassengerId

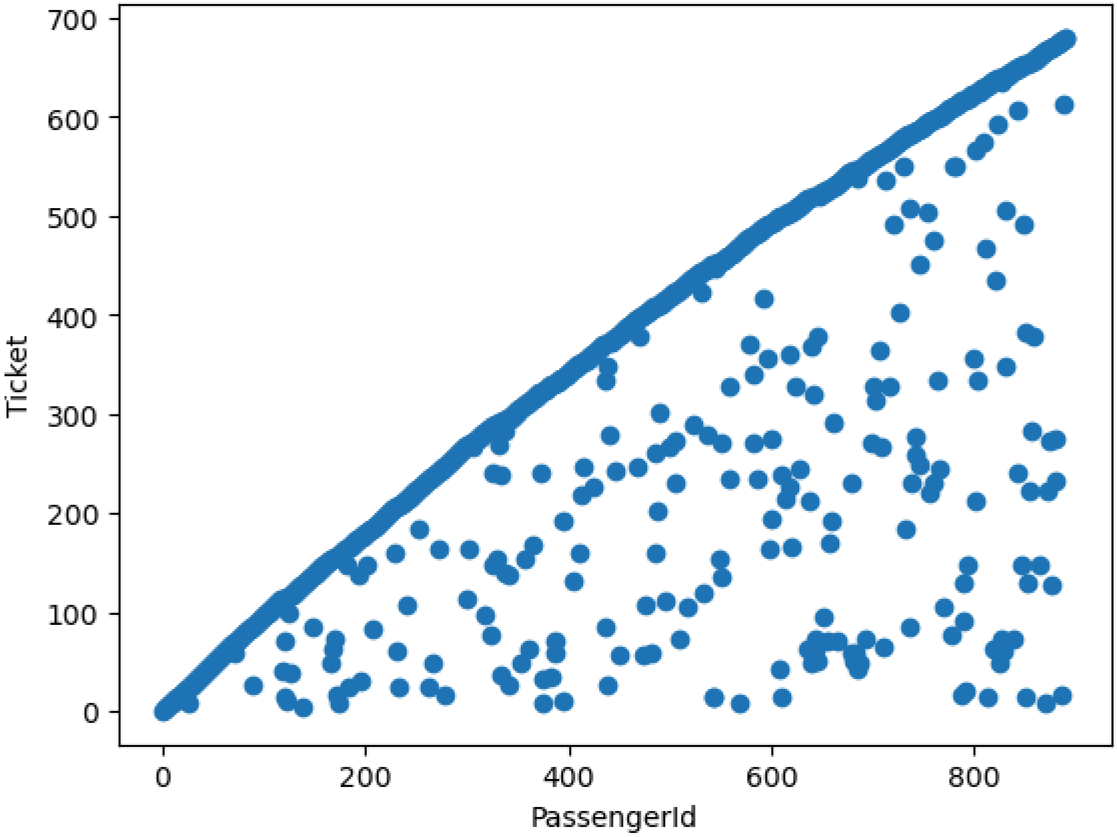

Name
0
200
400
600
800
0
200
400
600
800
PassengerId

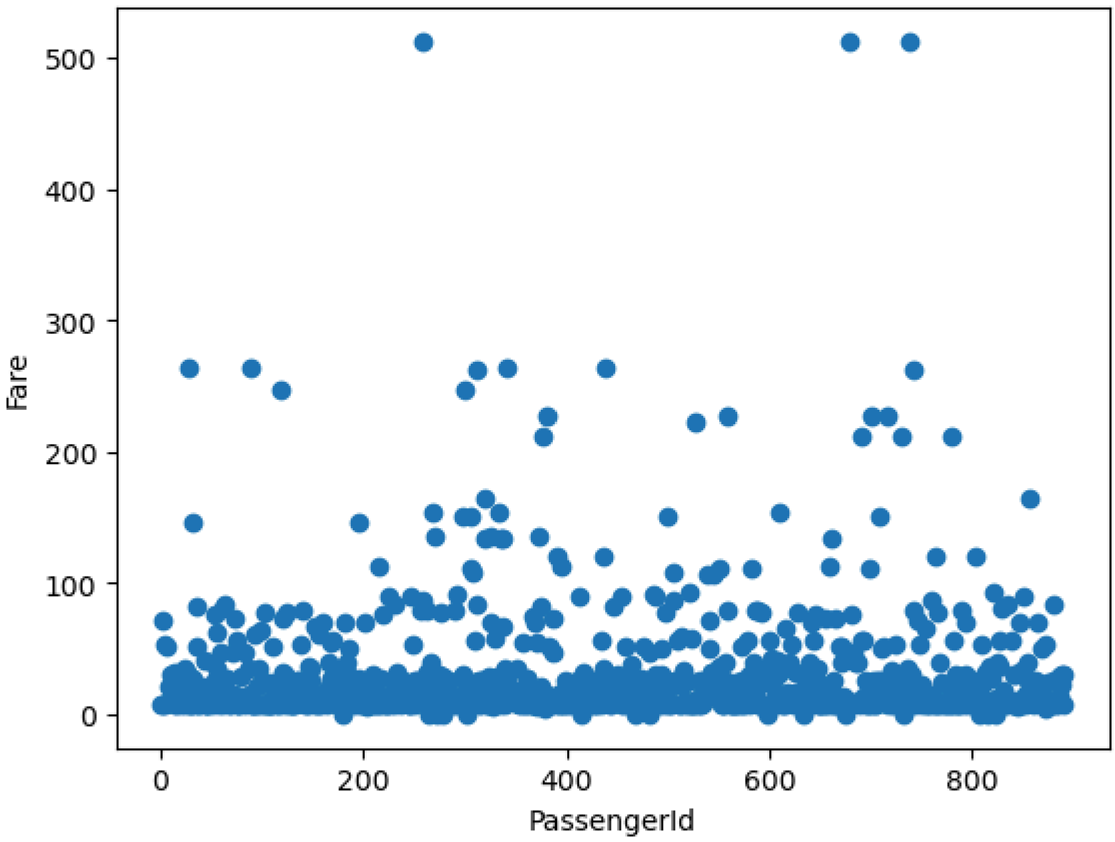

Sex
0.0
0.2
0.4
0.6
0.8
1.0
0
200
400
600
800
PassengerId

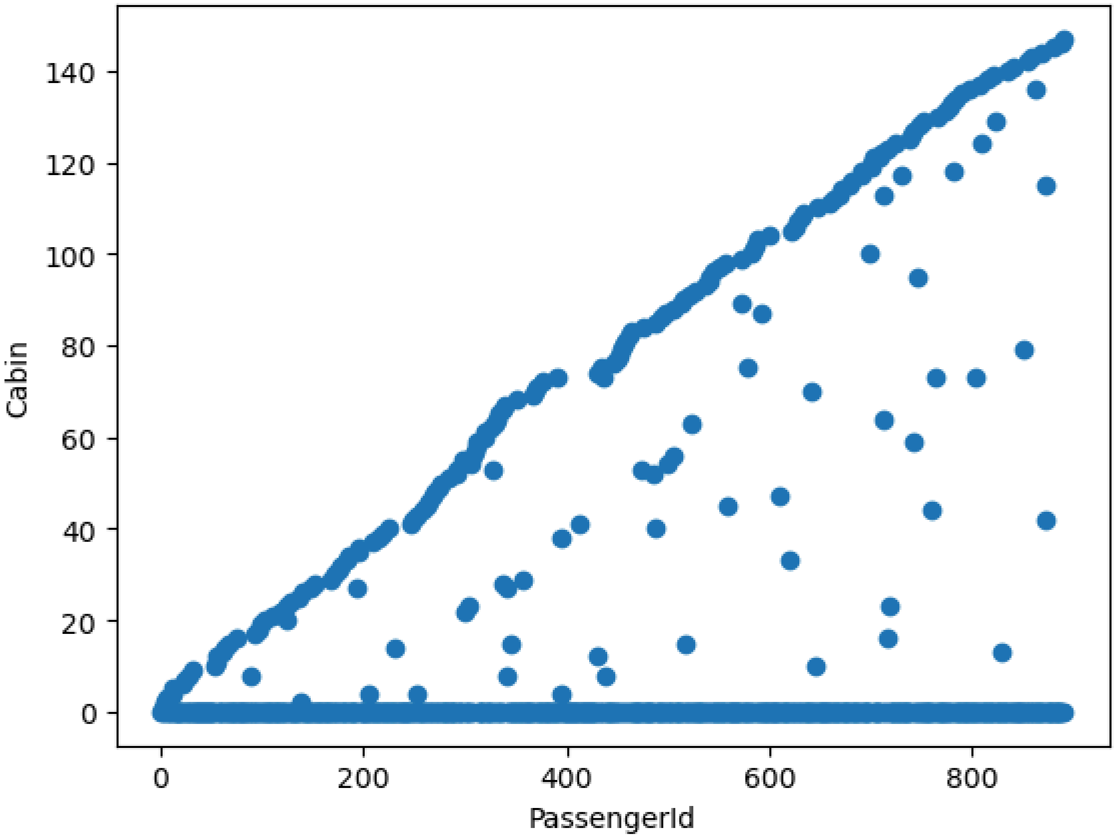

Age
80
70
60
50
40
30
20
10
0
0
200
400
600
800
PassengerId

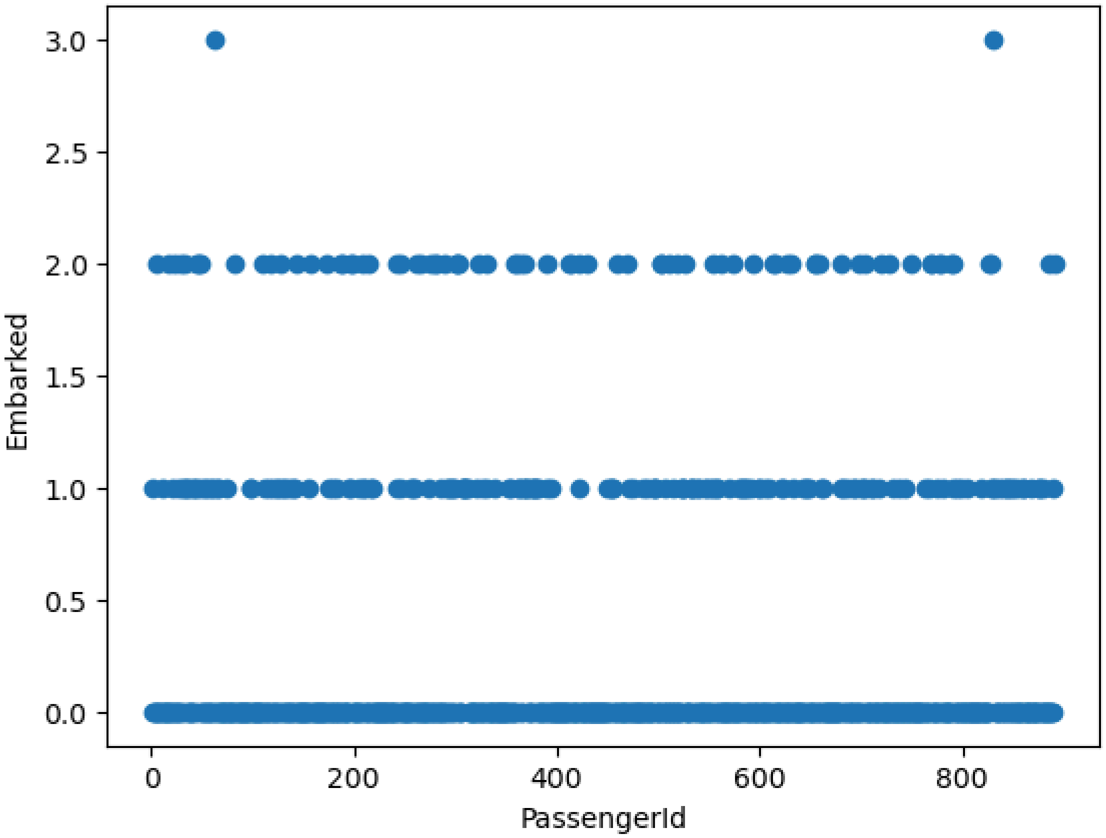

SibSp
8
7
6
5
4
3
2
1
0
0
200
400
600
800
PassengerId

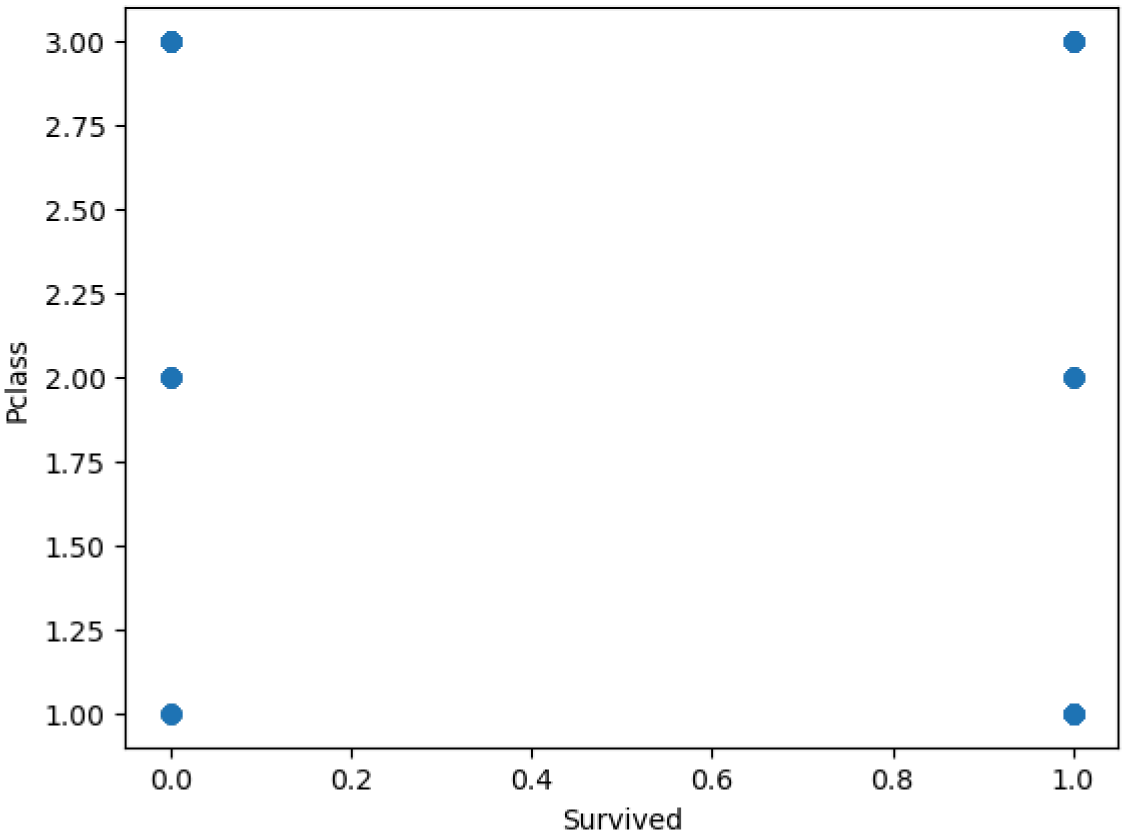

Parch
0
1
2
3
4
5
6
0
200
400
600
800
PassengerId

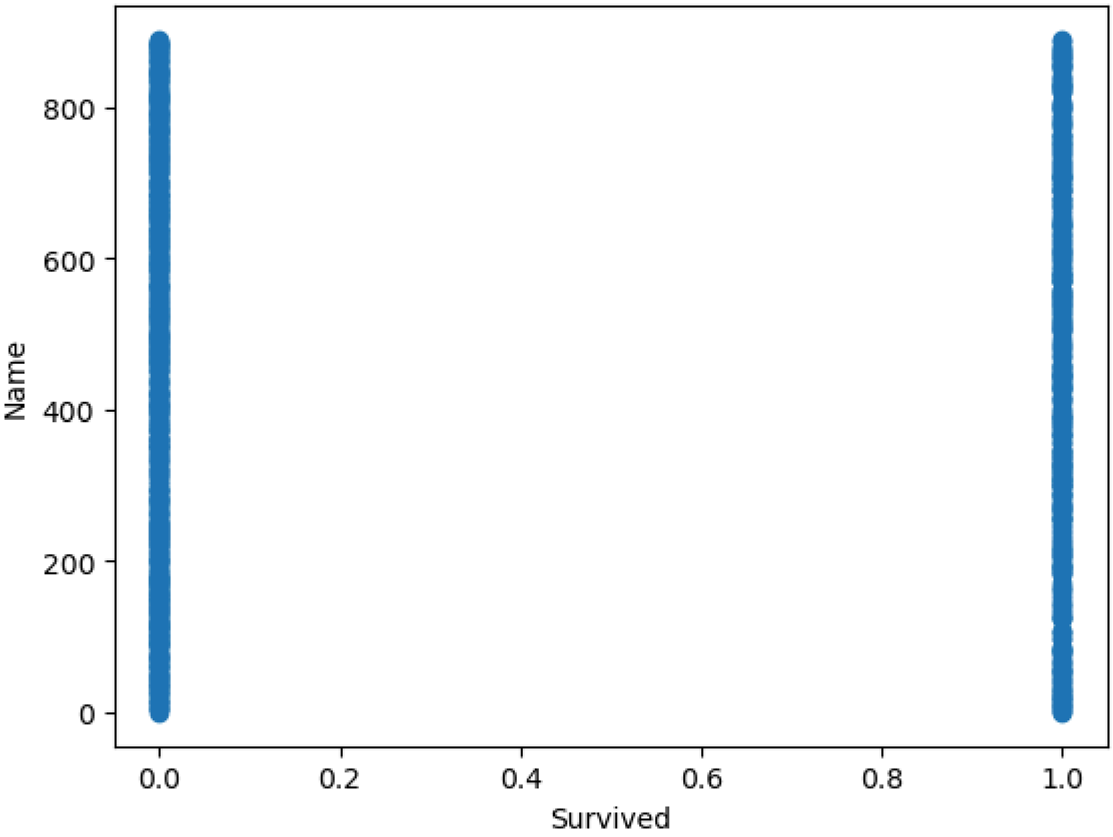

Ticket
0
100
200
300
400
500
600
700
0
200
400
600
800
PassengerId

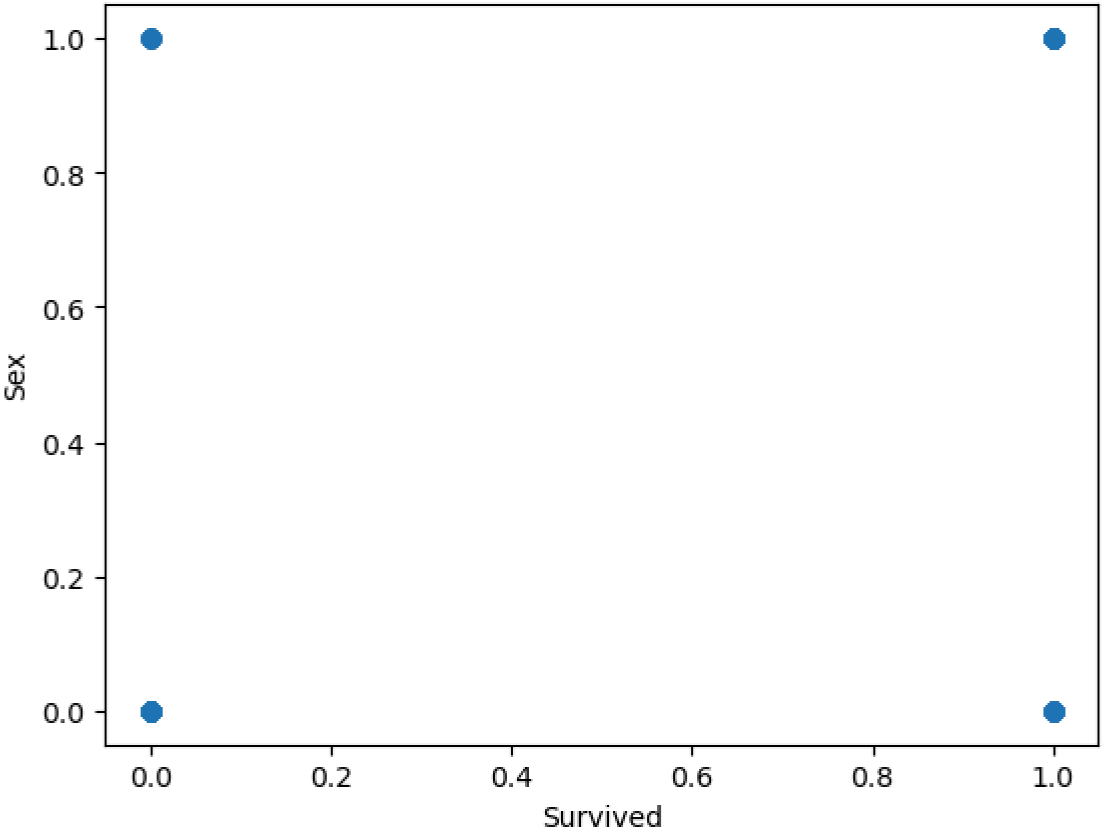

Fare
500
400
300
200
100
0
0
200
400
600
800
PassengerId

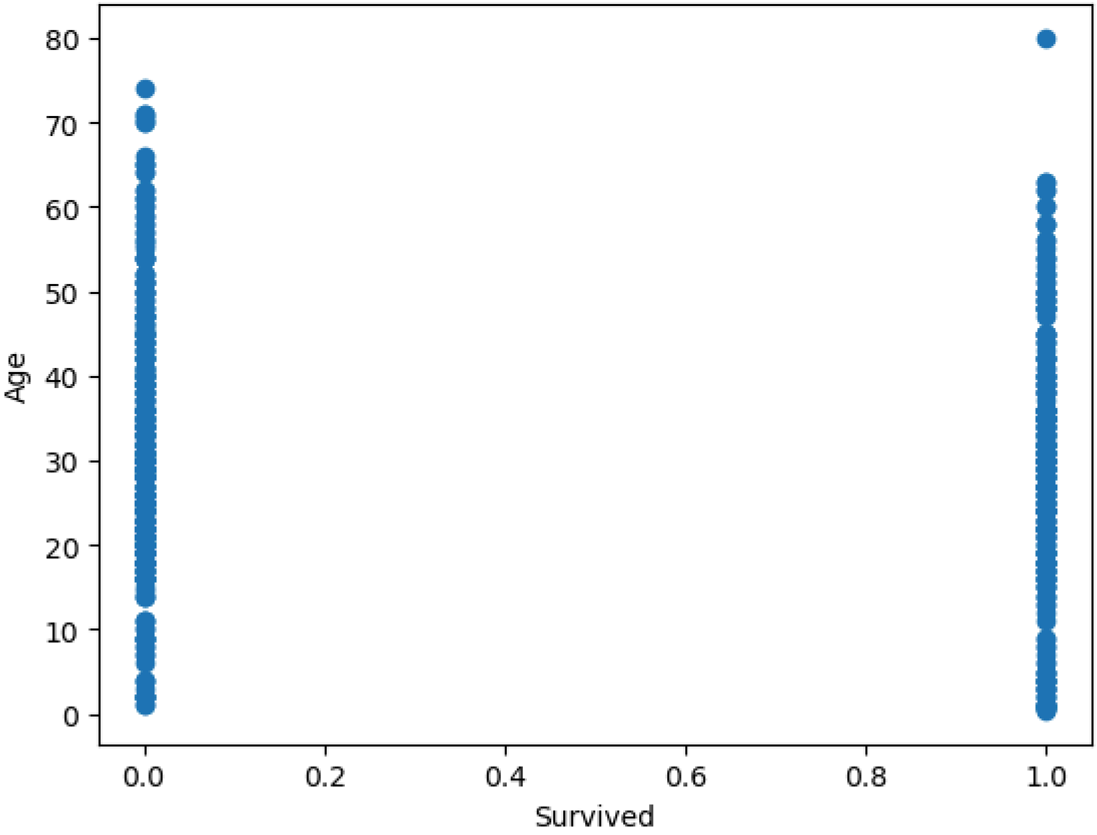

Cabin
140
120
100
80
60
40
20
0
0
200
400
600
800
PassengerId


Embarked
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
200
400
600
800
PassengerId

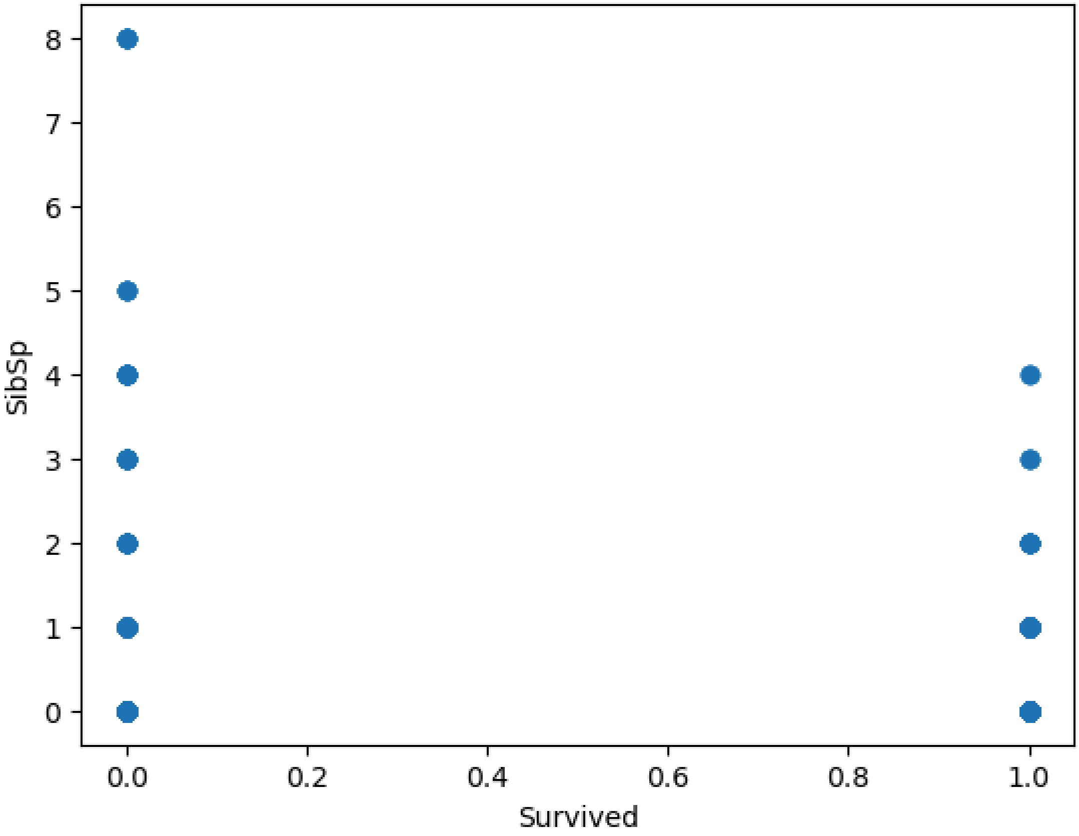

Pclass
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0.0
0.2
0.4
0.6
0.8
1.0
Survived


800
600
400
200
0
Name
0.0
0.2
0.4
0.6
0.8
1.0
Survived

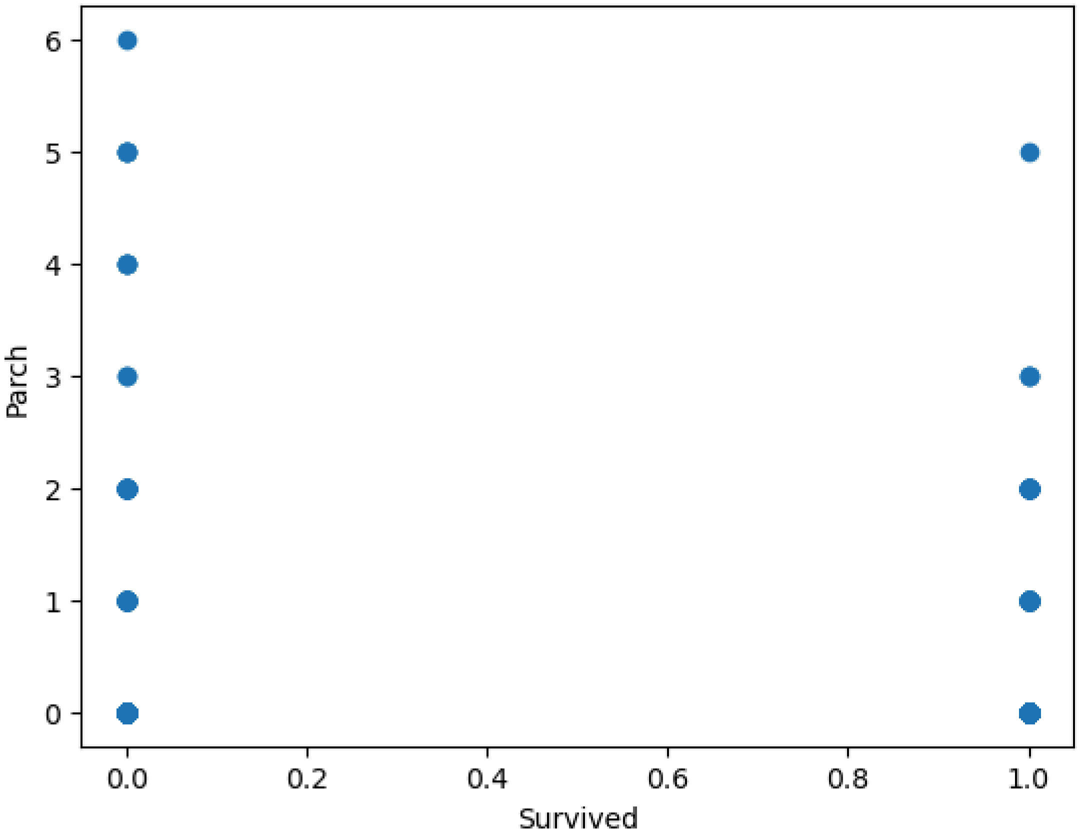

1.0
0.8
0.6
0.4
0.2
0.0
Sex
0.0
0.2
0.4
0.6
0.8
1.0
Survived

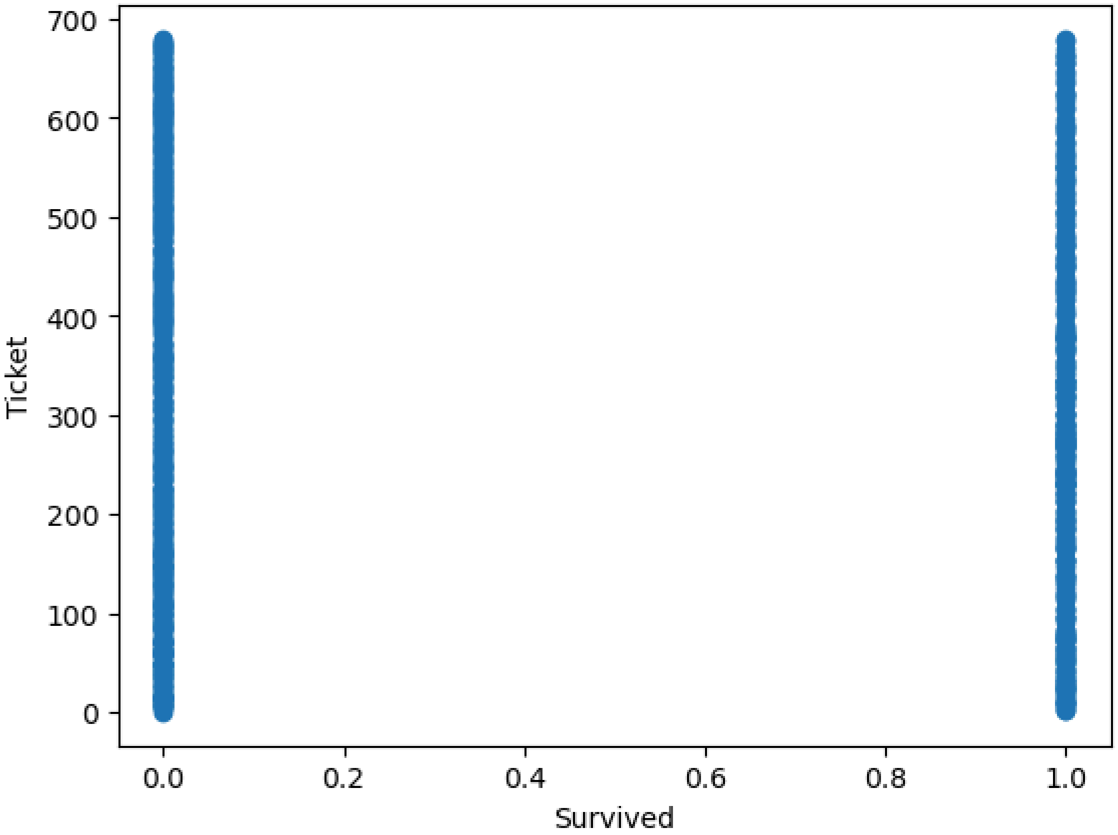


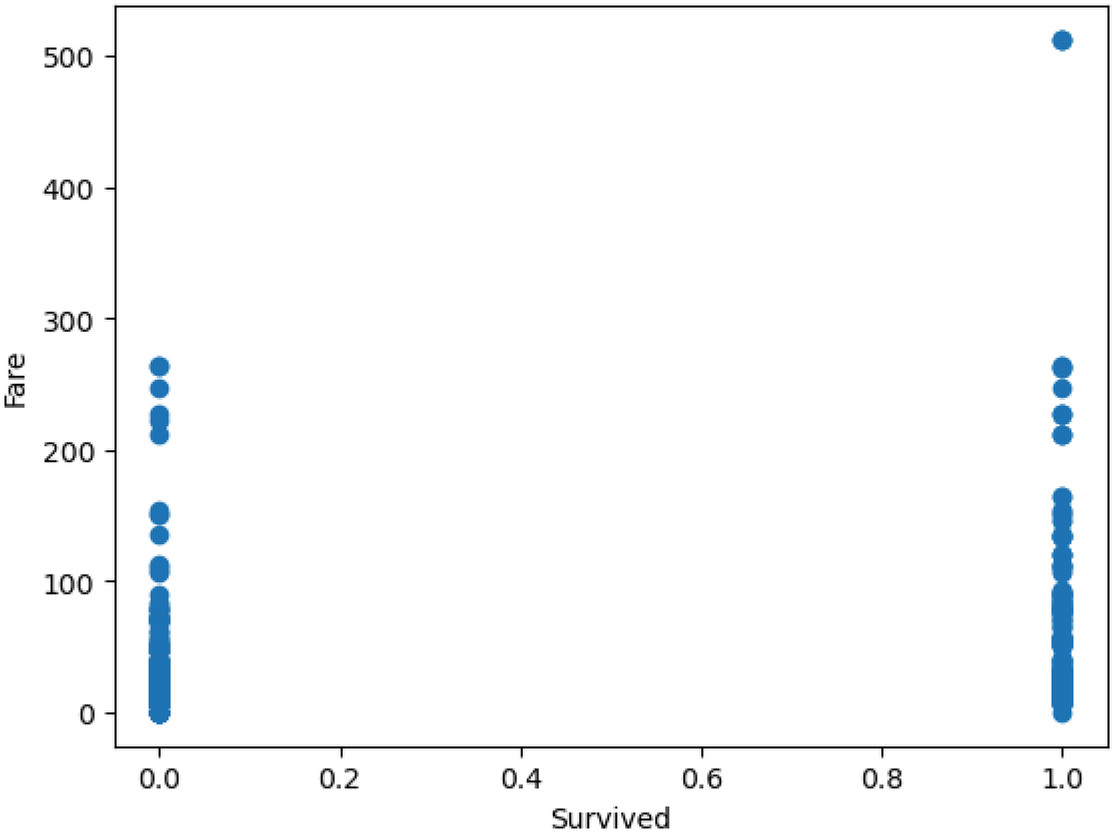
Age
80
70
60
50
40
30
20
10
0
0.0
0.2
0.4
0.6
0.8
1.0
Survived

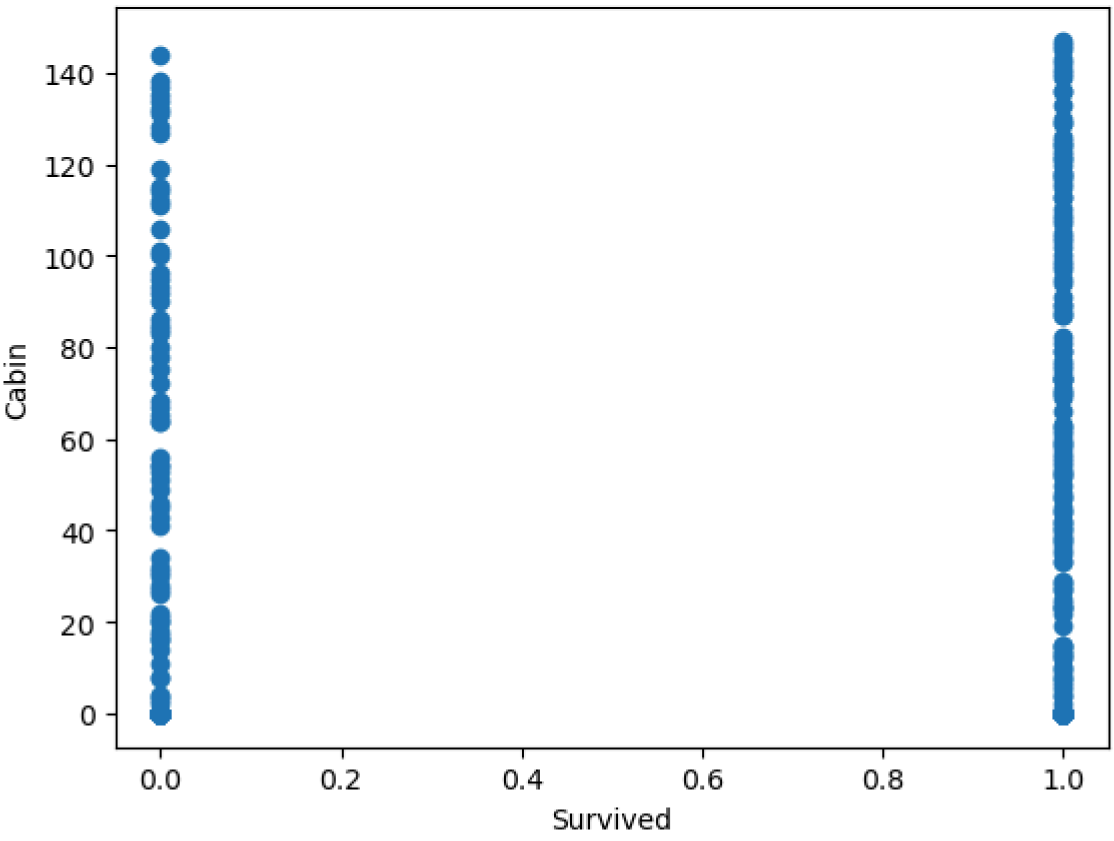


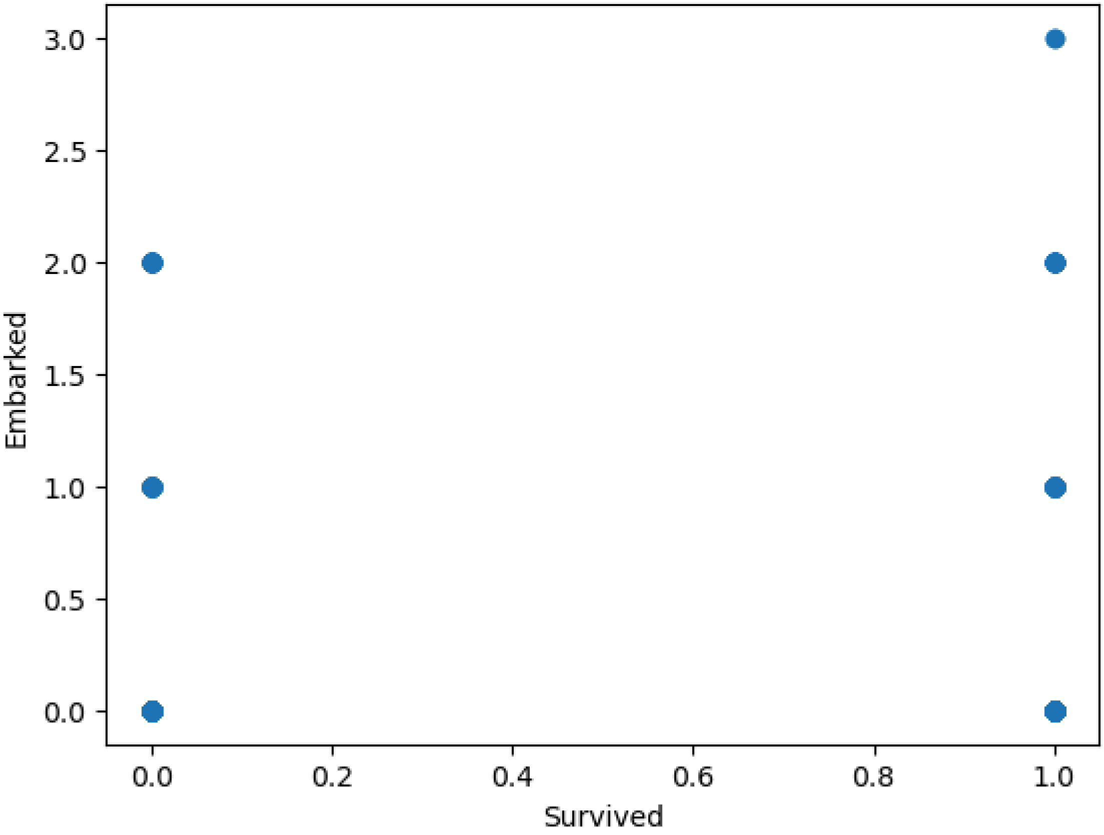
SibSp
8
7
6
5
4
3
2
1
0
0.0
0.2
0.4
0.6
0.8
1.0
Survived

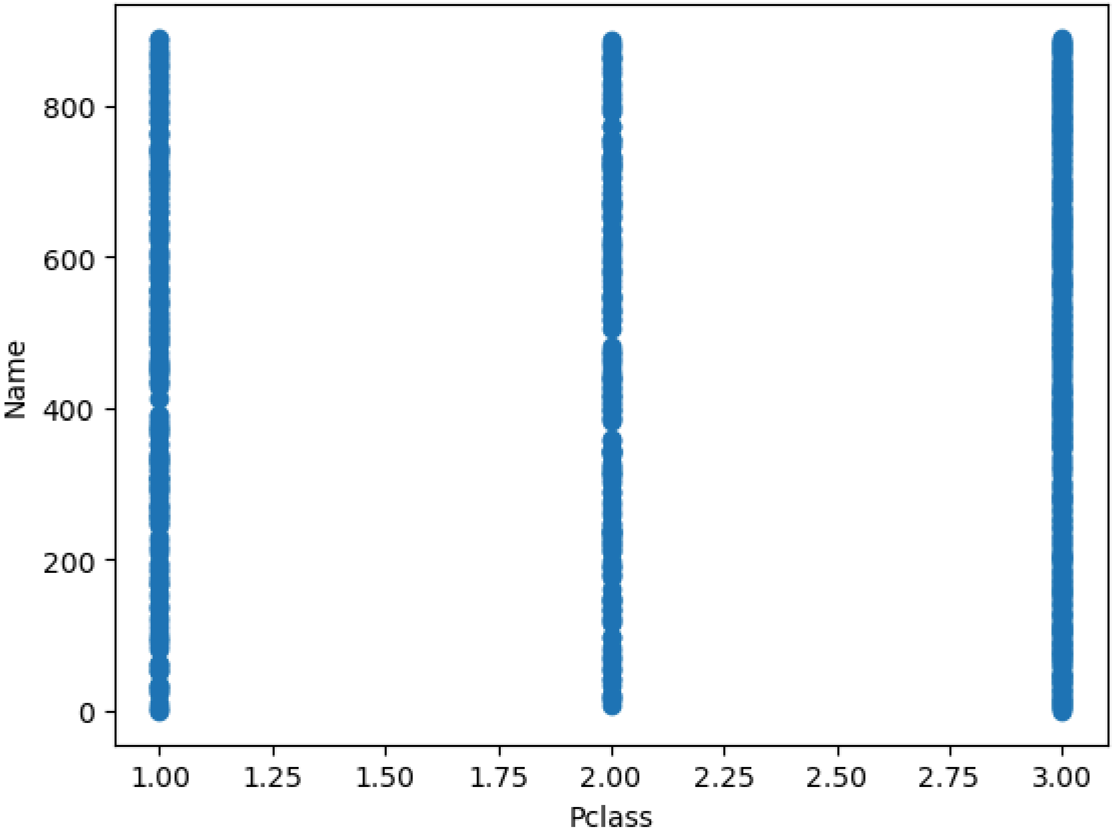

Parch
6
5
4
3
2
1
0
0.0
0.2
0.4
0.6
0.8
1.0
Survived

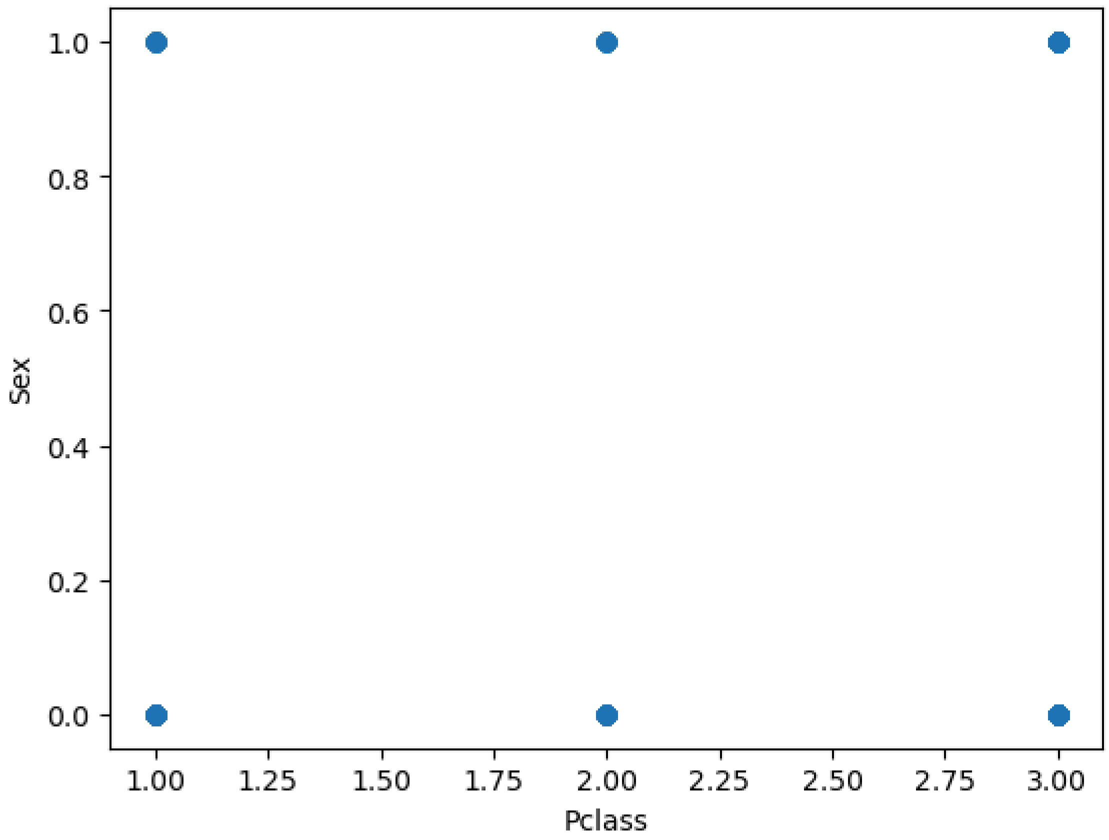

Ticket
700
600
500
400
300
200
100
0
0.0
0.2
0.4
0.6
0.8
1.0
Survived

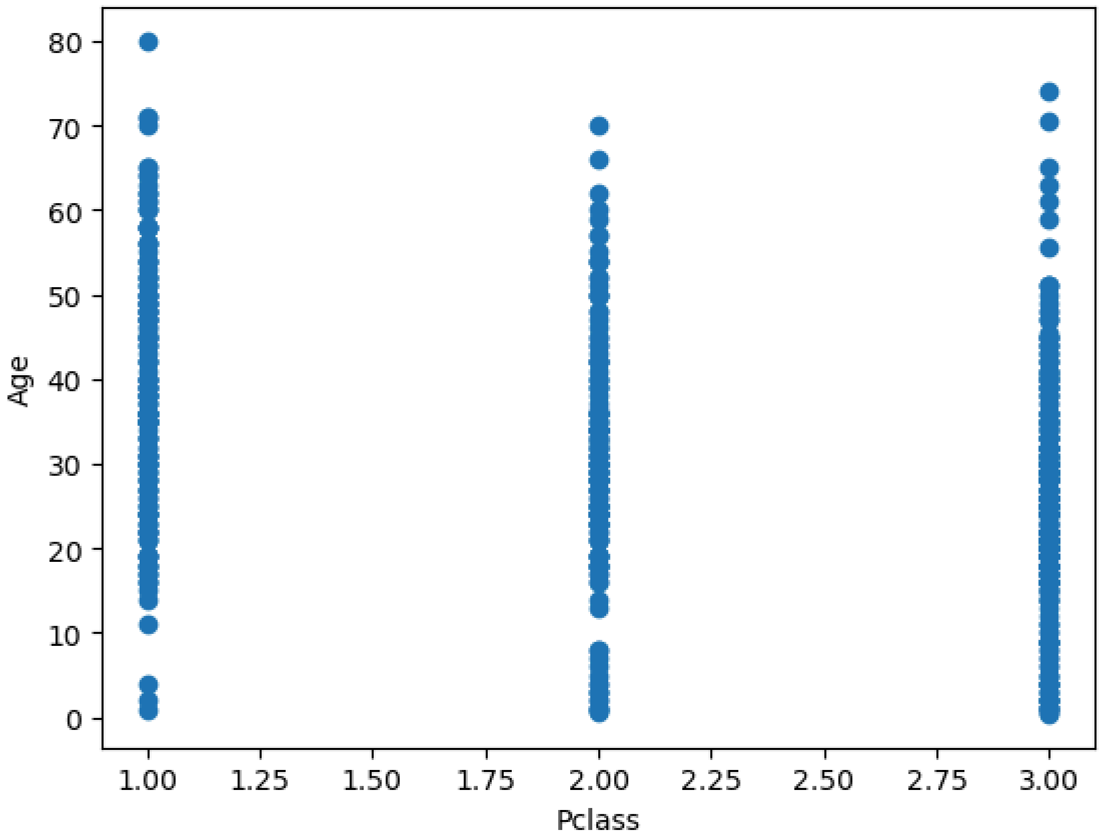

Fare
500
400
300
200
100
0
0.0
0.2
0.4
0.6
0.8
1.0
Survived

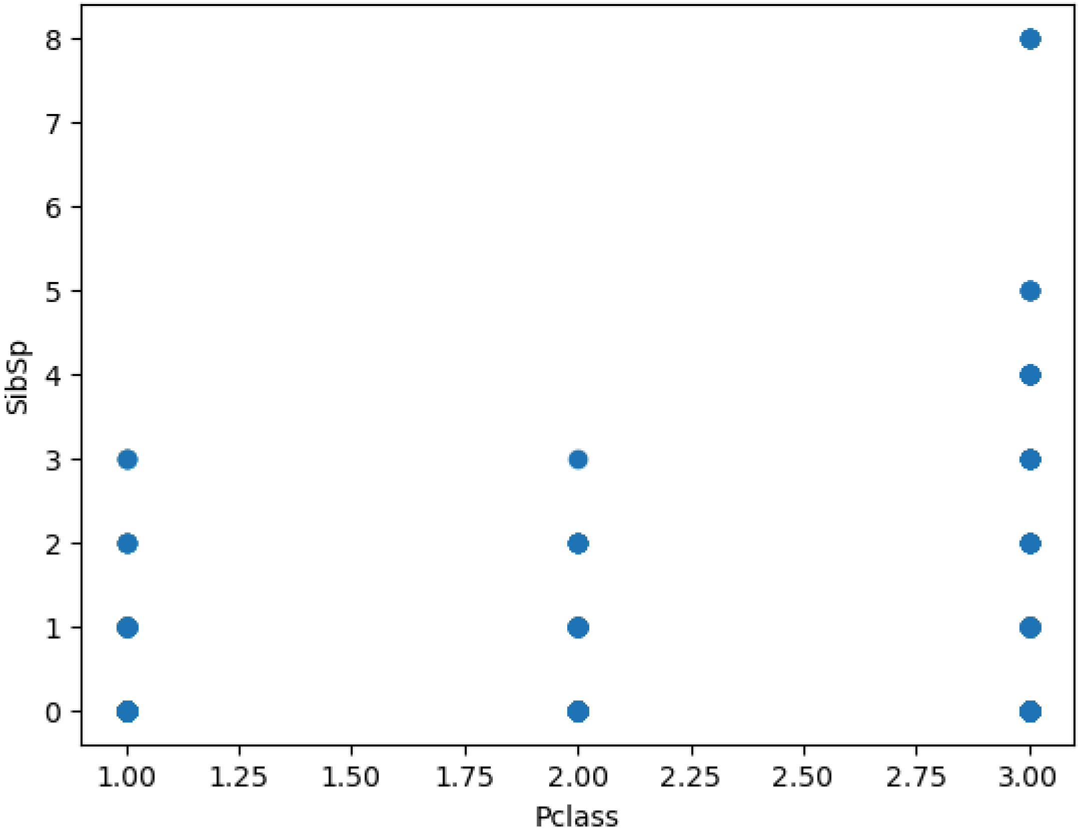

Cabin
140
120
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0
Survived

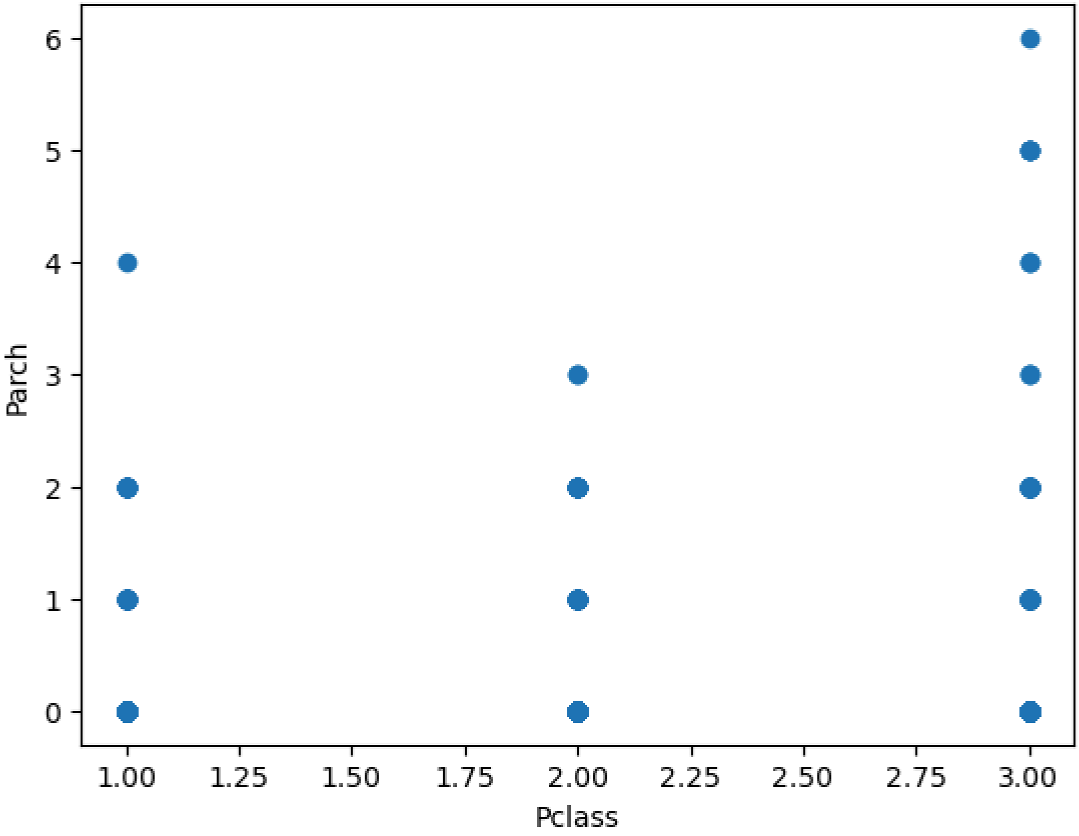

3.0
2.5
2.0
1.5
1.0
0.5
0.0
Embarked
0.0
0.2
0.4
0.6
0.8
1.0
Survived

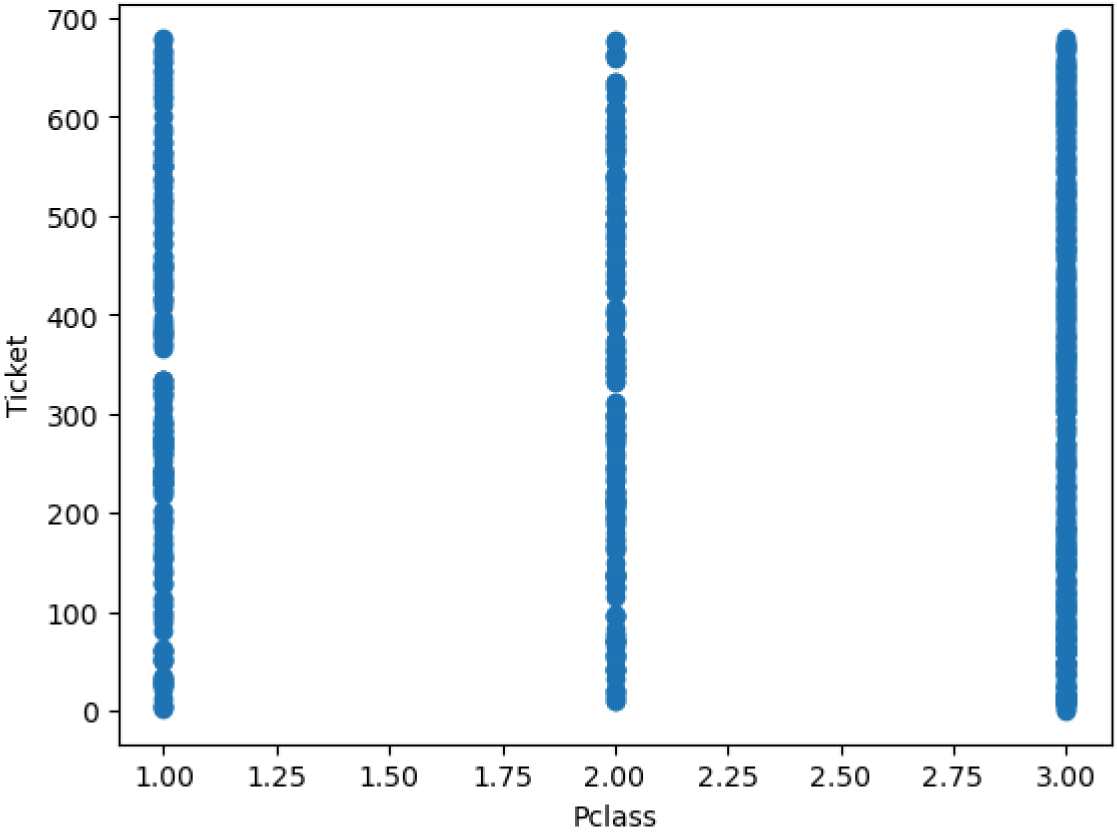

800
600
400
200
0
Name
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass

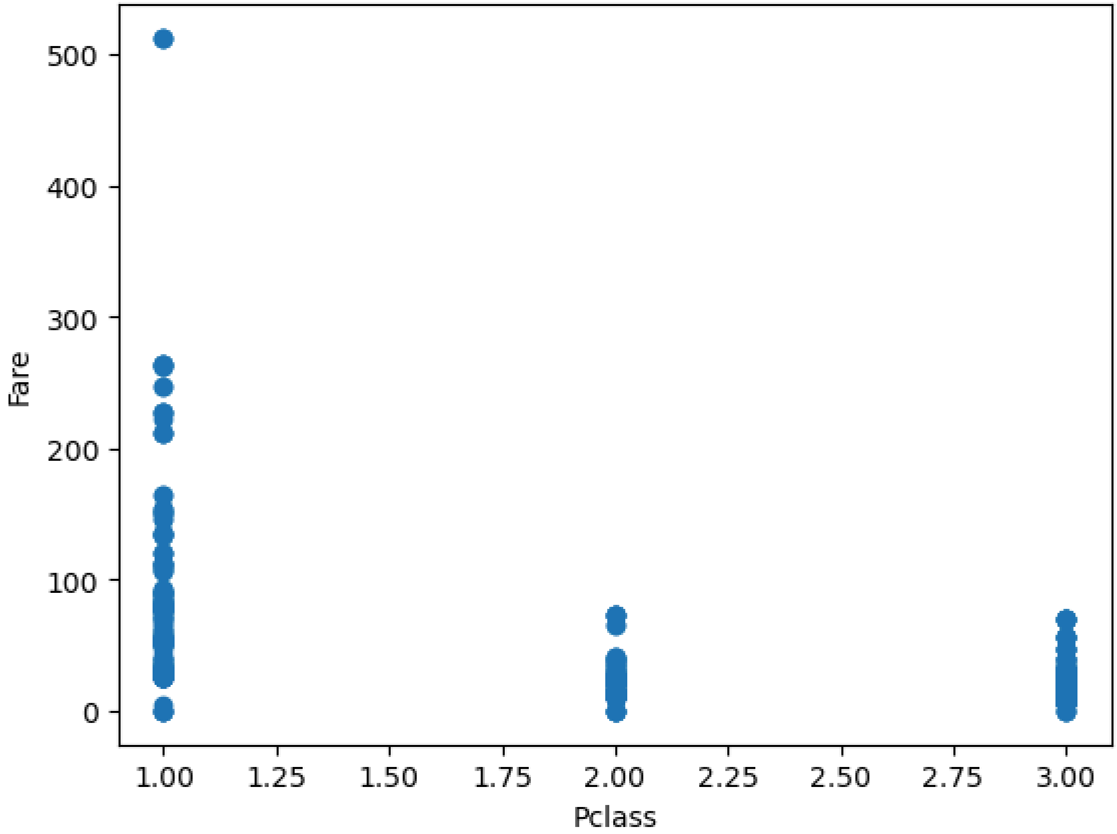

1.0
0.8
0.6
0.4
0.2
0.0
Sex
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass

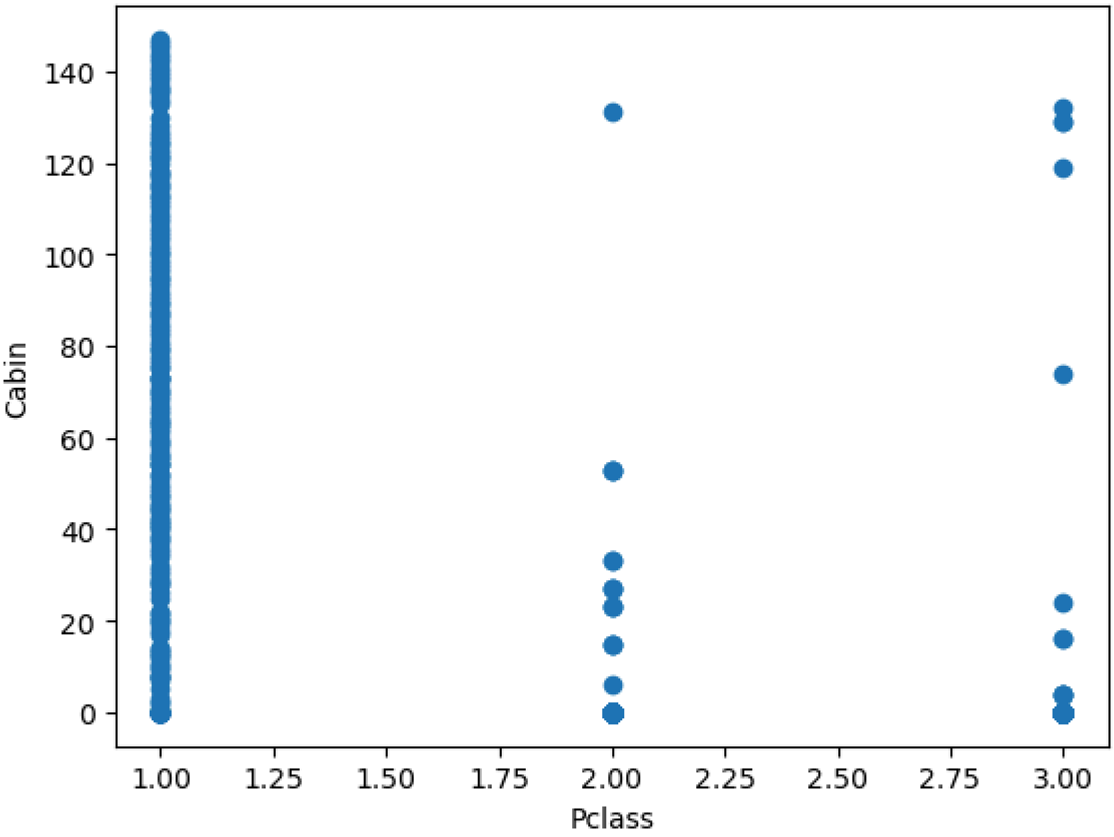

80
70
60
50
40
30
20
10
0
Age
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass

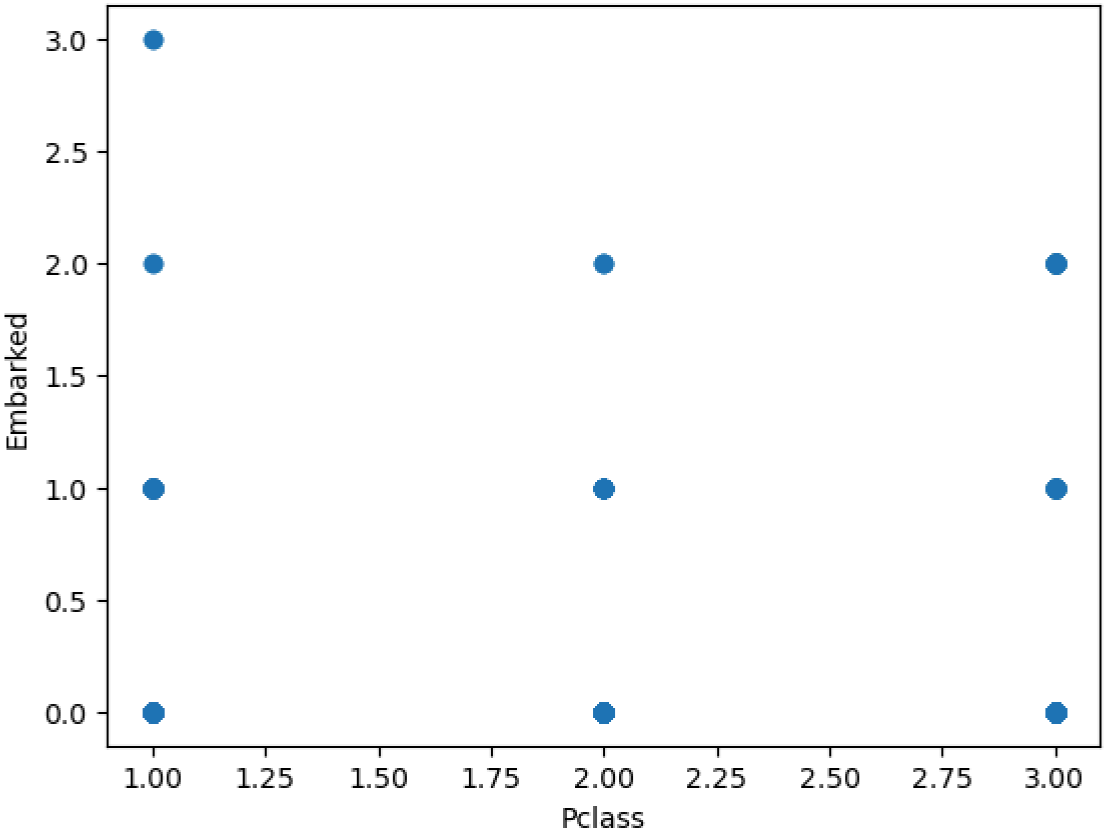

SibSp
0
1
2
3
4
5
6
7
8
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass

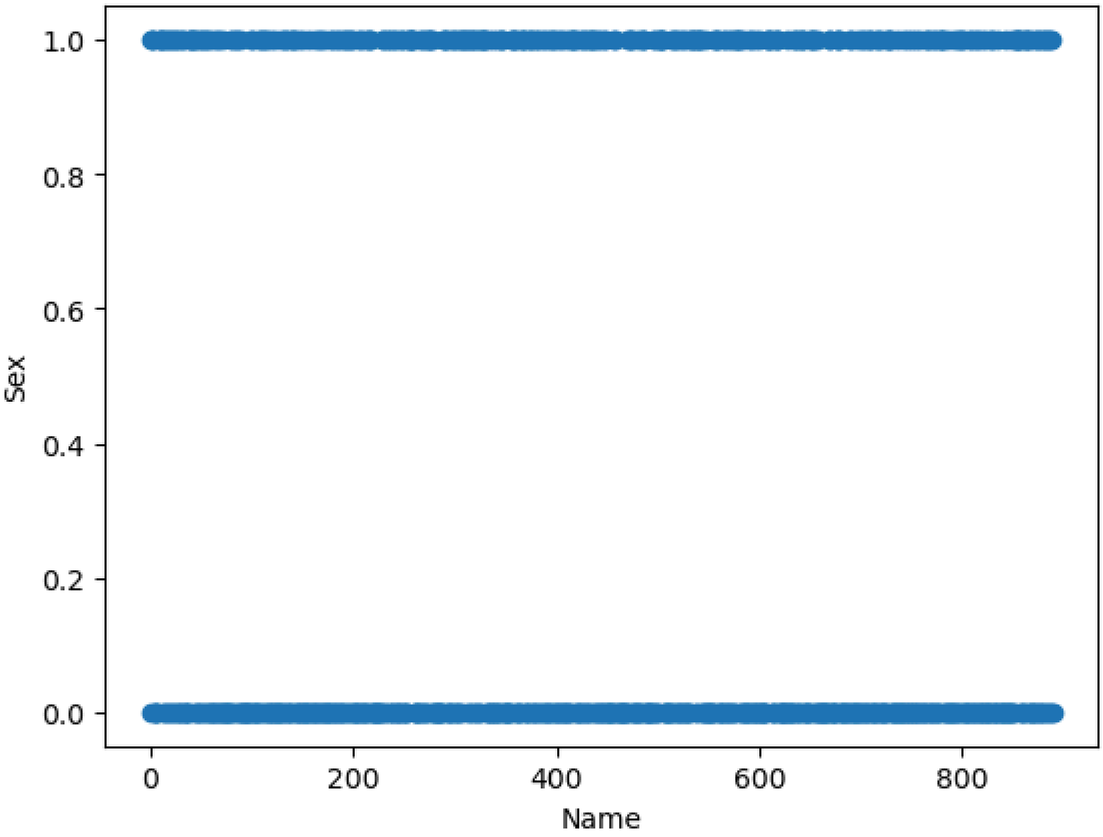

Parch
0
1
2
3
4
5
6
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass

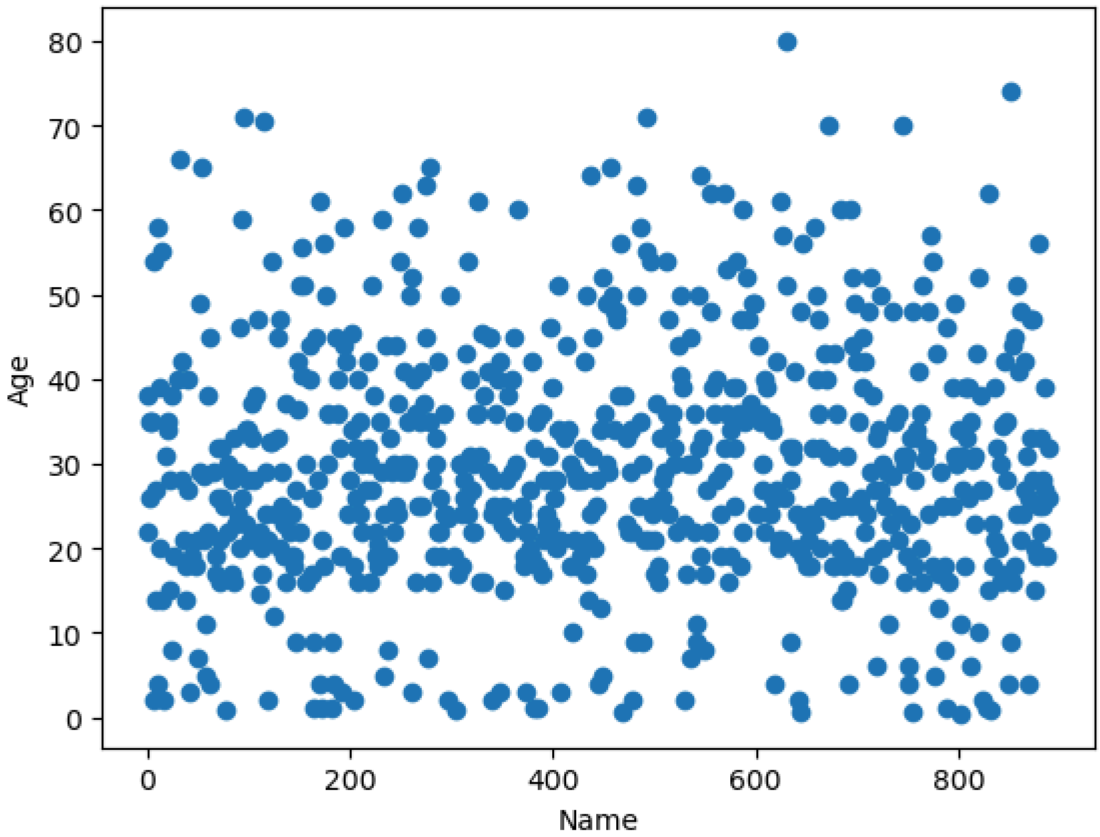

Ticket
700
600
500
400
300
200
100
0
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass

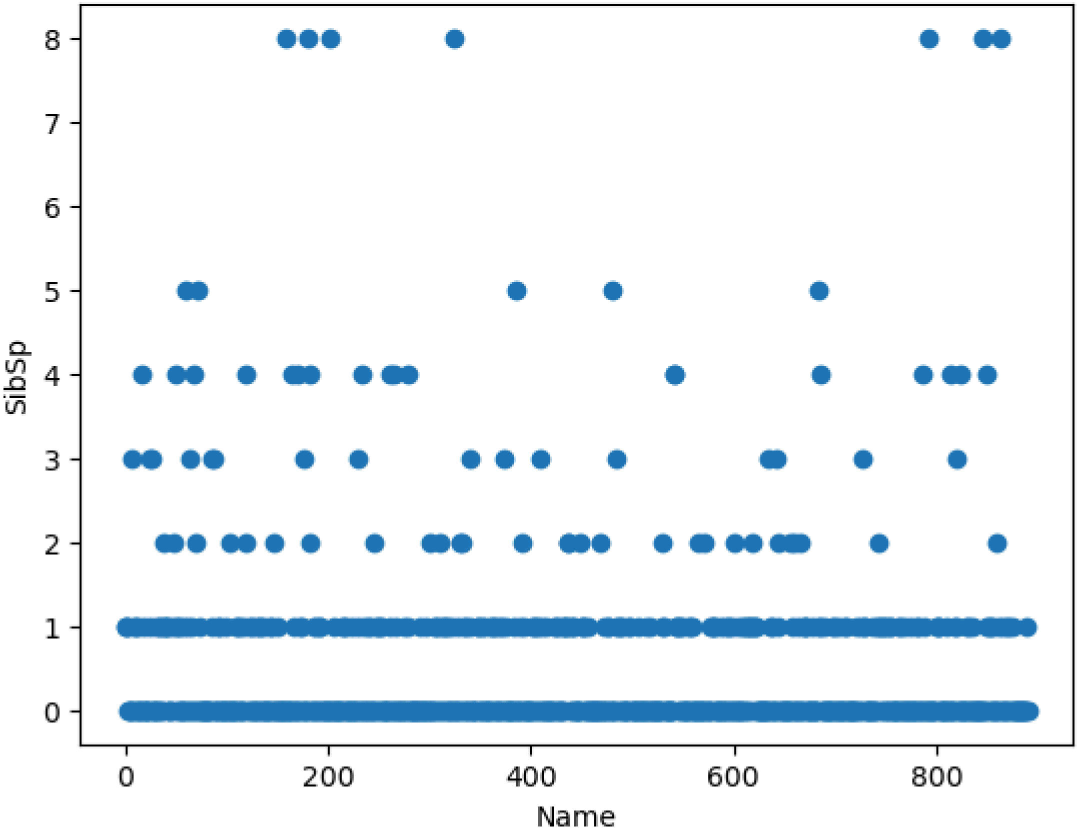

Fare
500
400
300
200
100
0
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Pclass

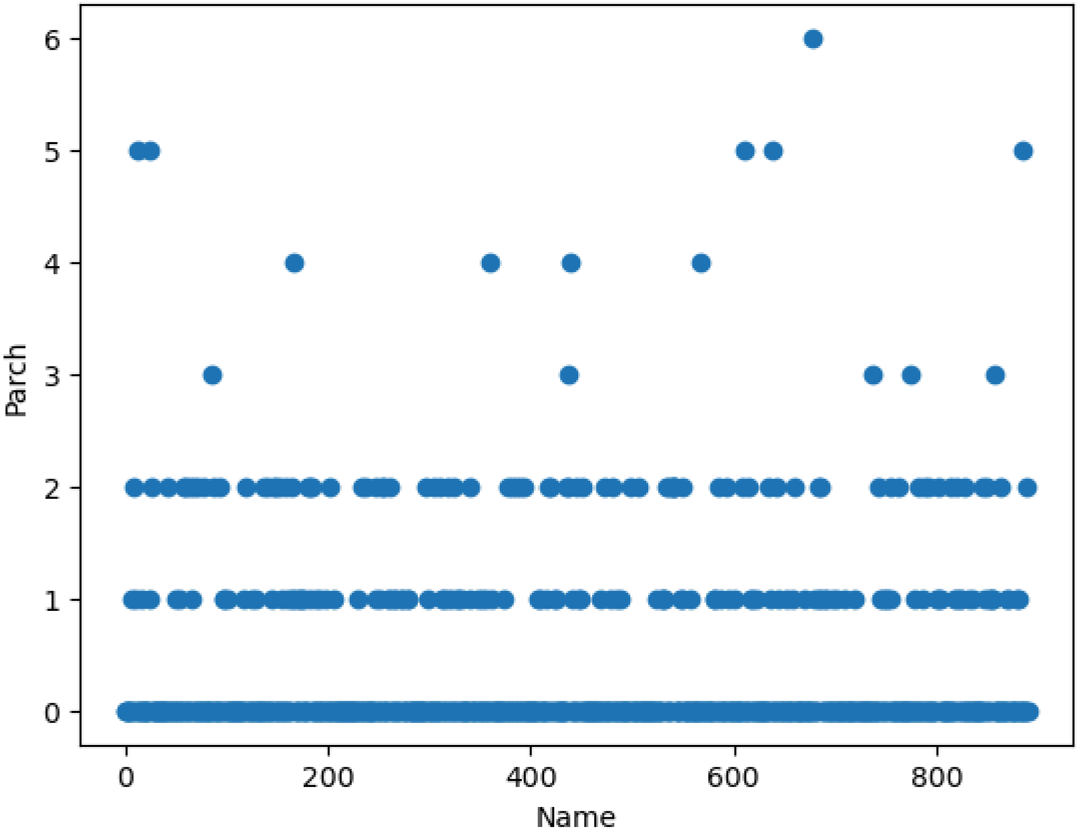

Cabin
0
20
40
60
80
100
120
140
Pclass
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00

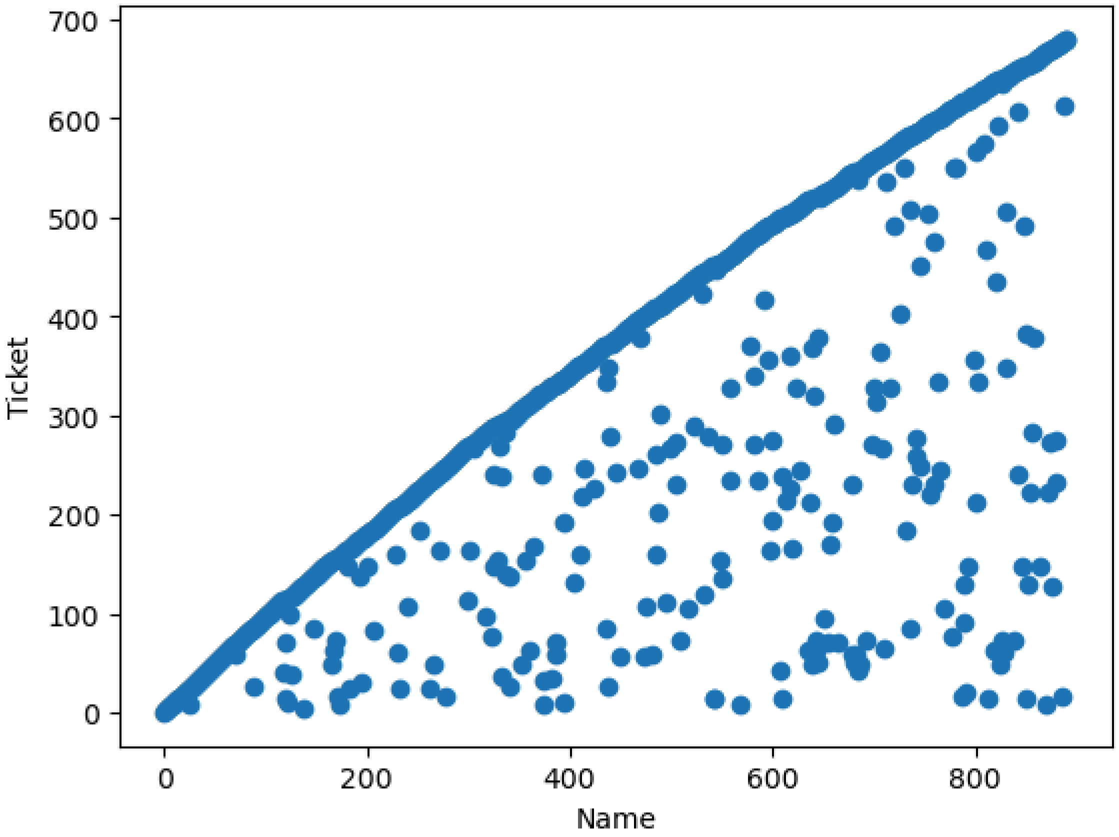

Embarked
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Pclass
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00

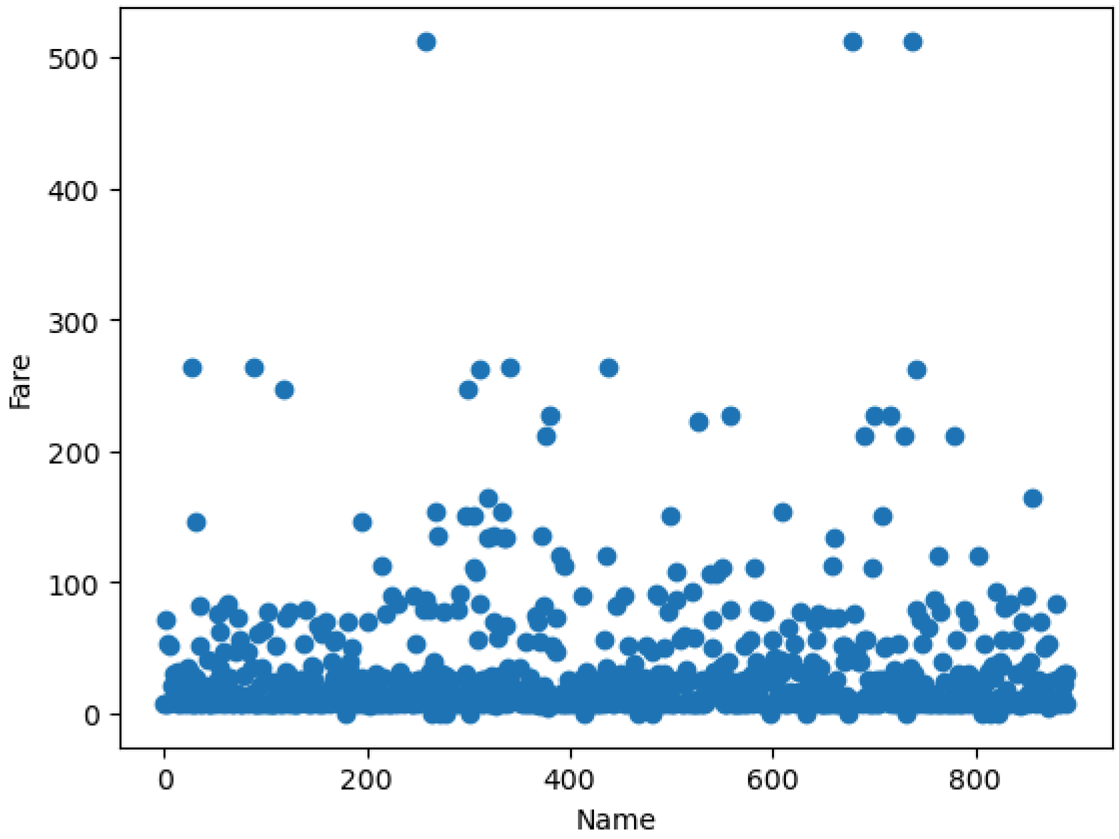

Sex
1.0
0.8
0.6
0.4
0.2
0.0
0
200
400
600
800
Name

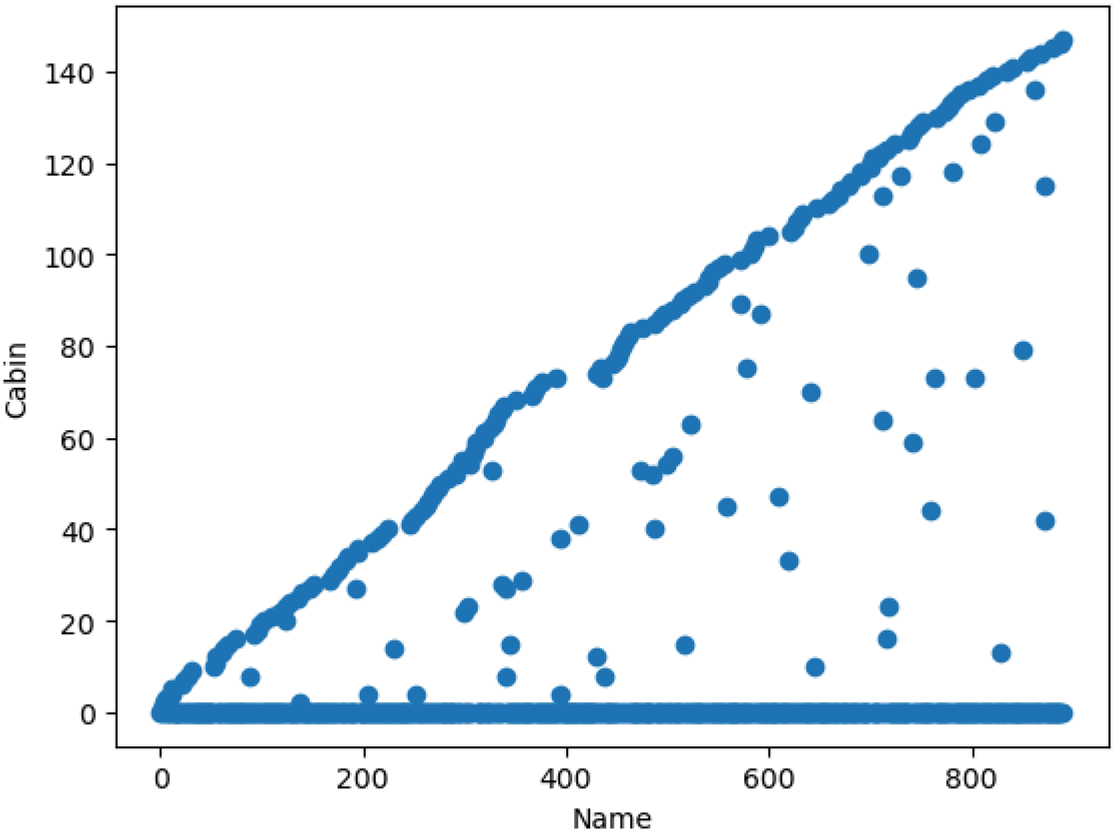

Age
80
70
60
50
40
30
20
10
0
0
200
400
600
800
Name

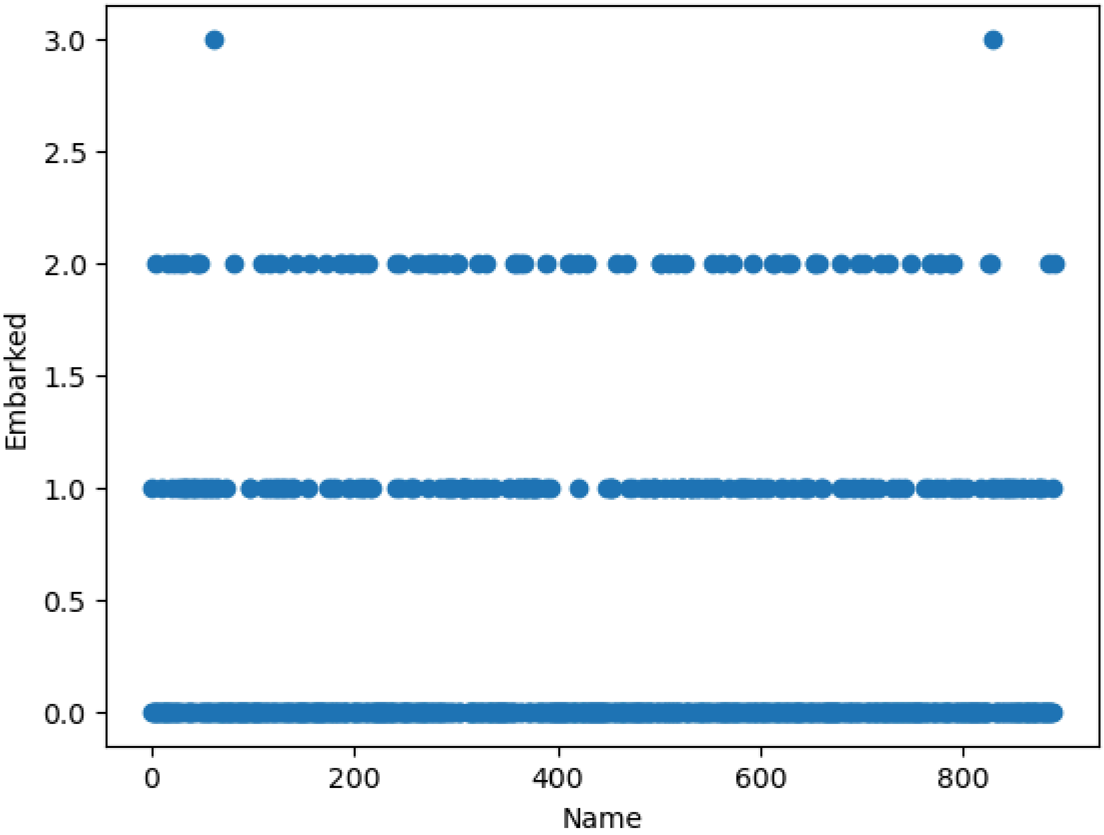

SibSp
0
1
2
3
4
5
6
7
8
Name
0
200
400
600
800

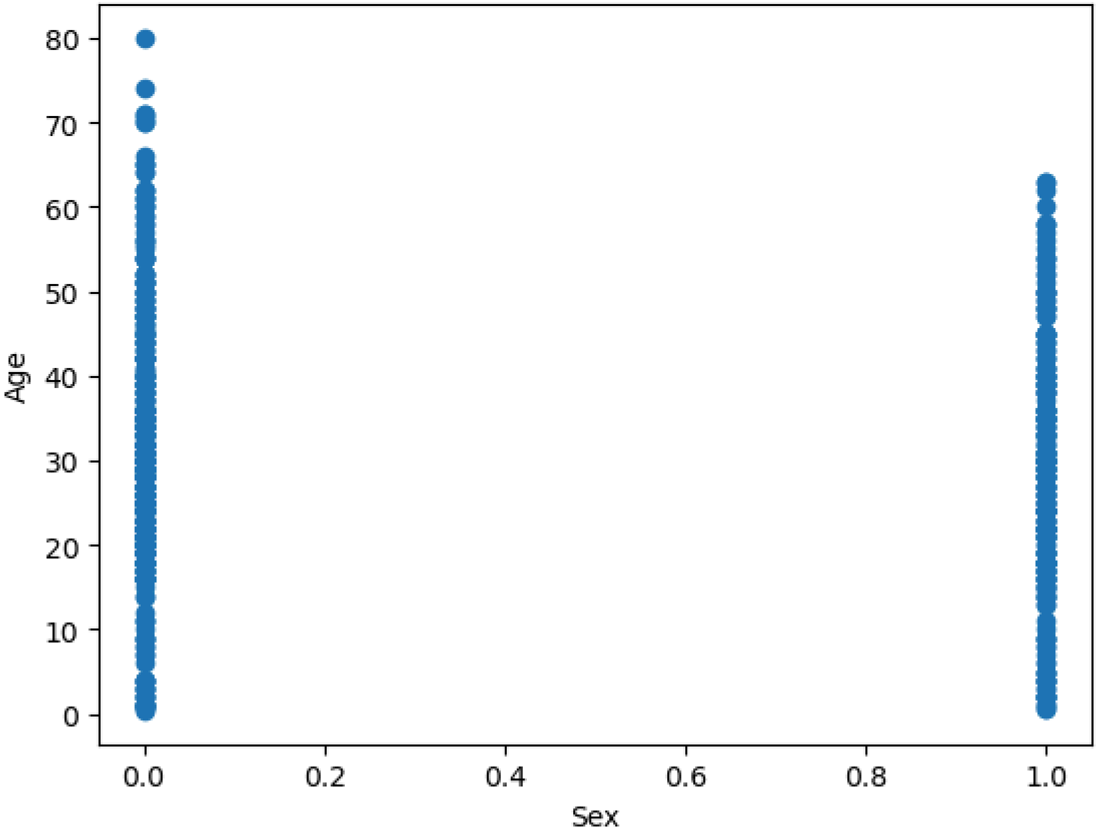

Parch
0
1
2
3
4
5
6
Name
0
200
400
600
800


Ticket
700
600
500
400
300
200
100
0
0
200
400
600
800
Name

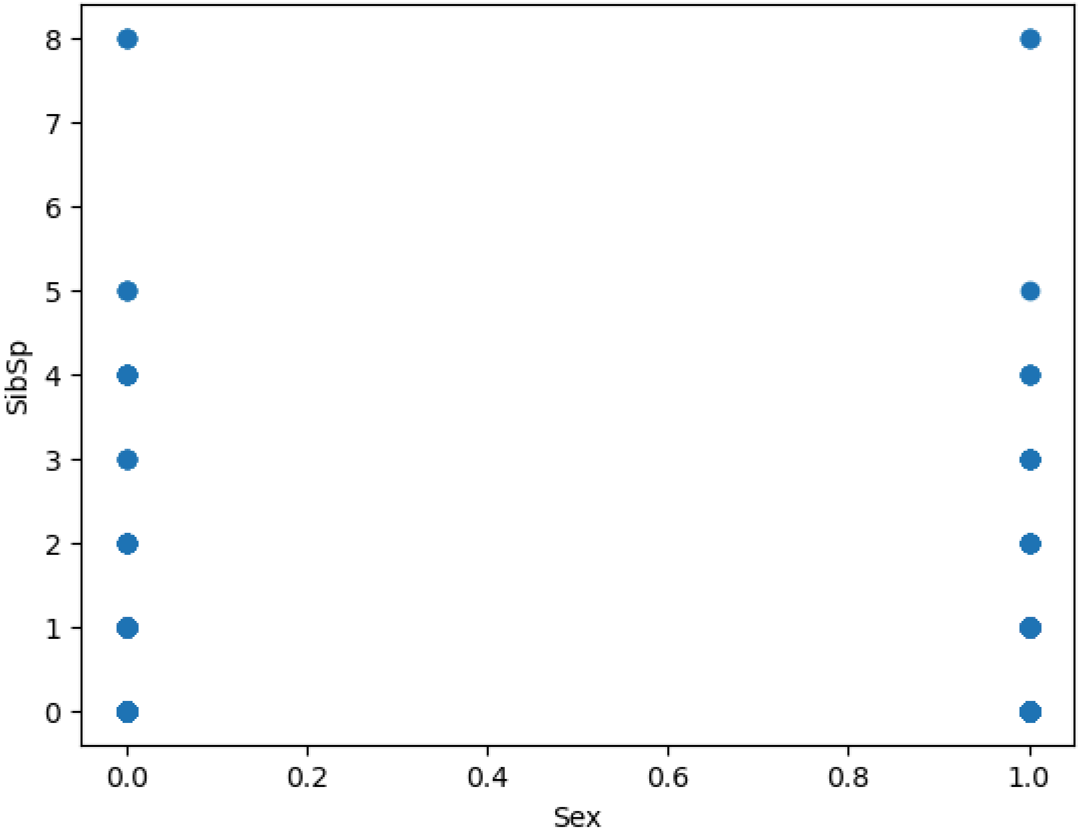

Fare
500
400
300
200
100
0
0
200
400
600
800
Name


Cabin
0
20
40
60
80
100
120
140
0
200
400
600
800
Name

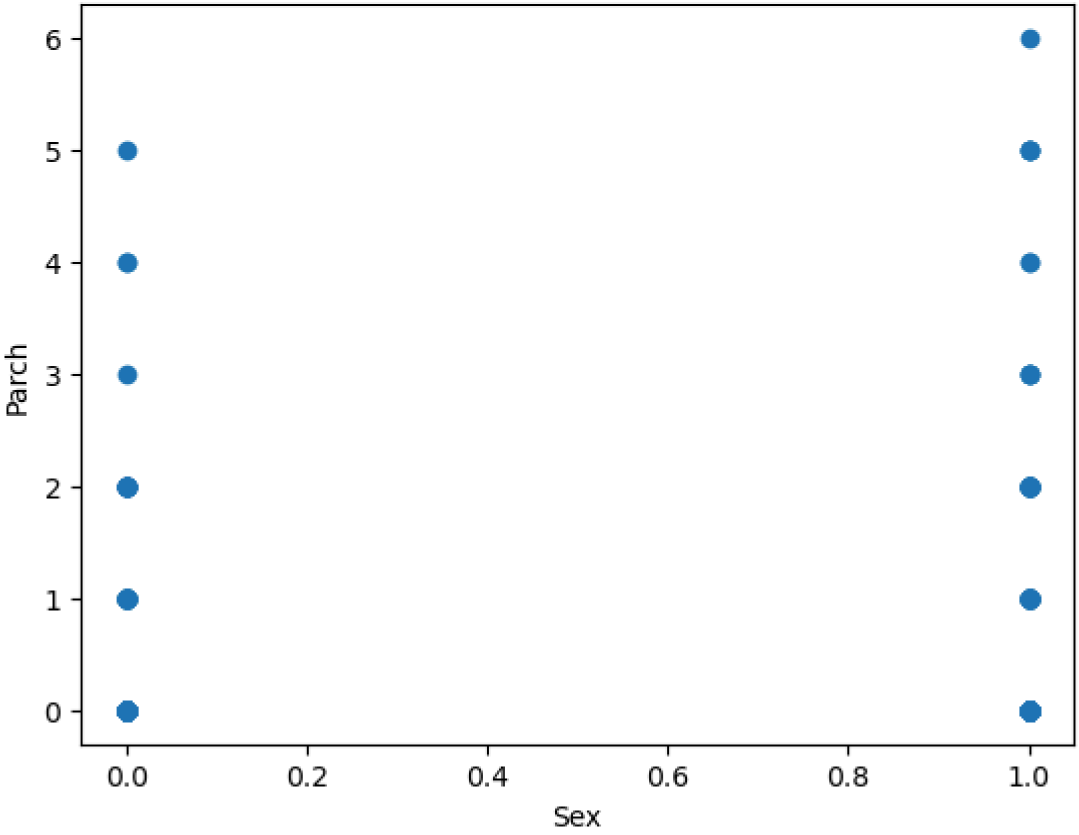

Embarked
0.0
0.5
1.0
1.5
2.0
2.5
3.0
0
200
400
600
800
Name

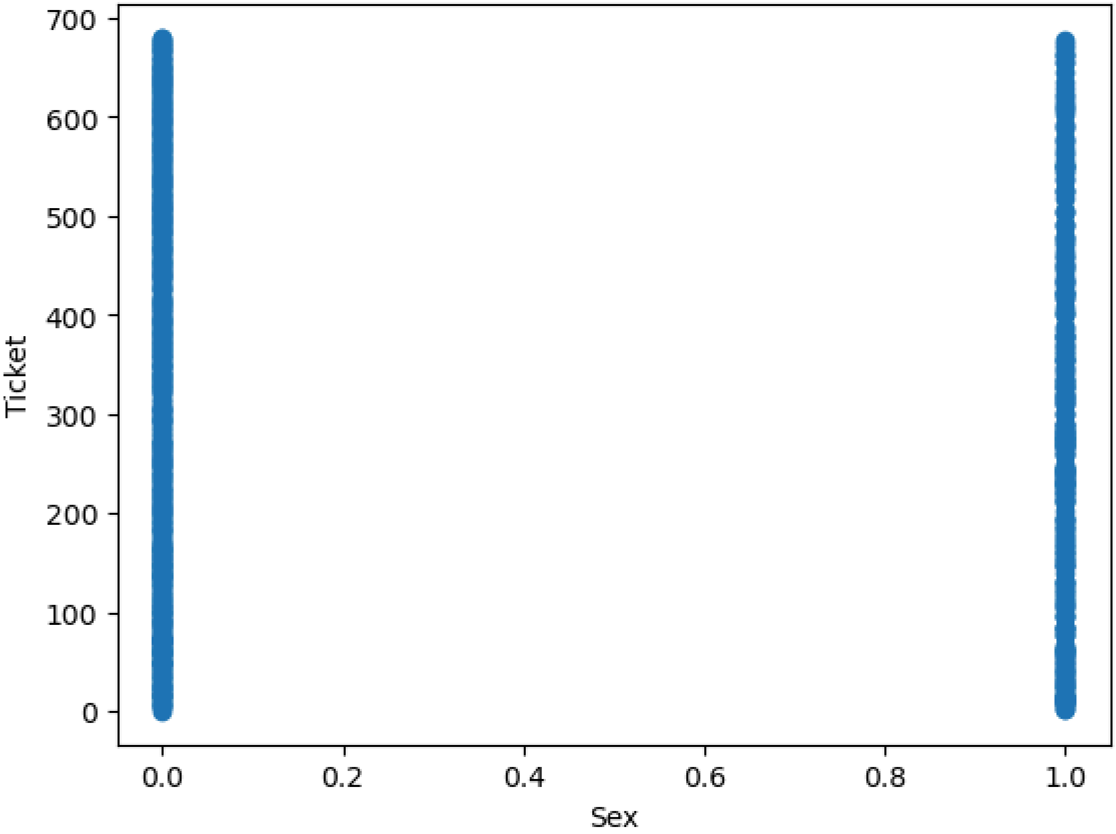


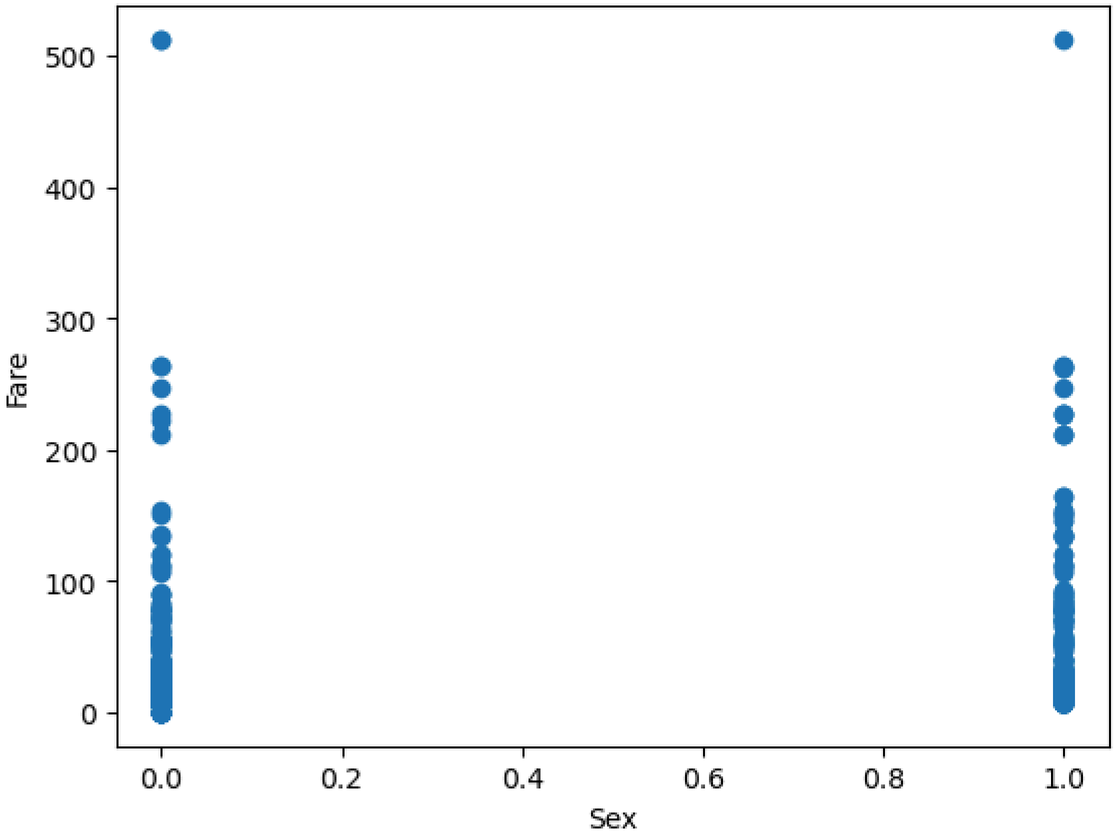
80
70
60
50
40
30
20
10
0
Age
0.0
0.2
0.4
0.6
0.8
1.0
Sex

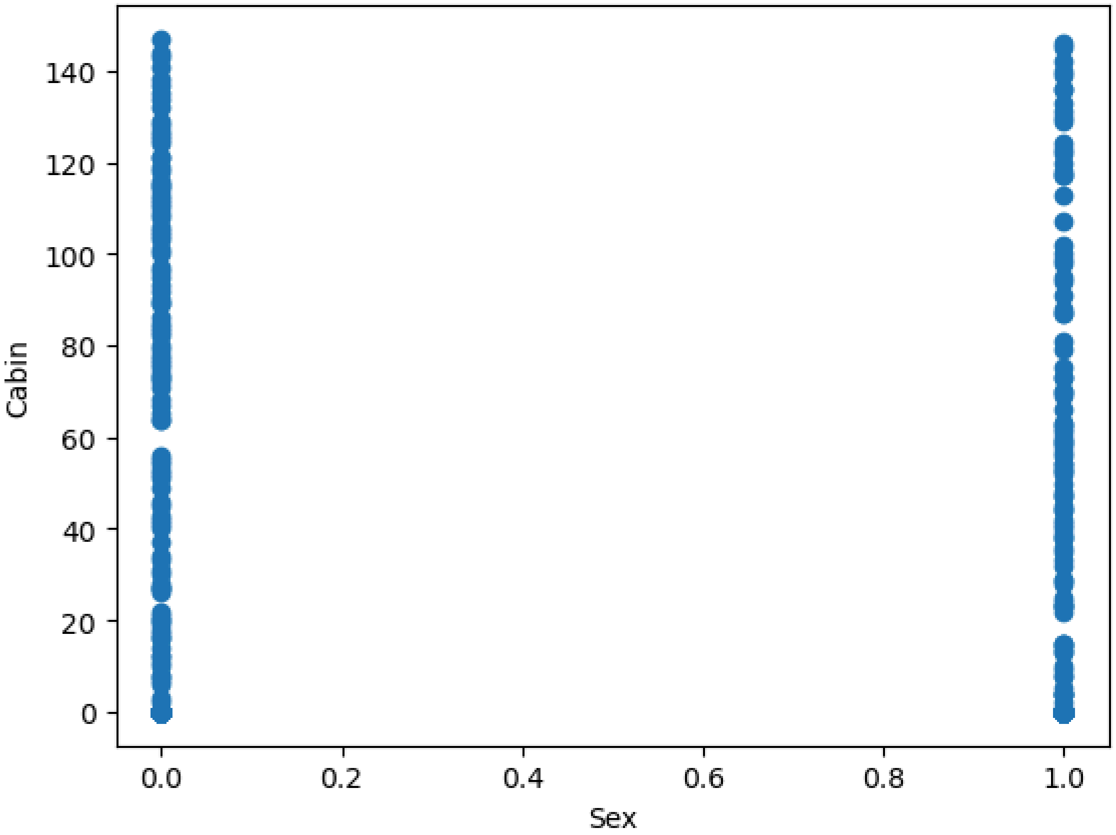


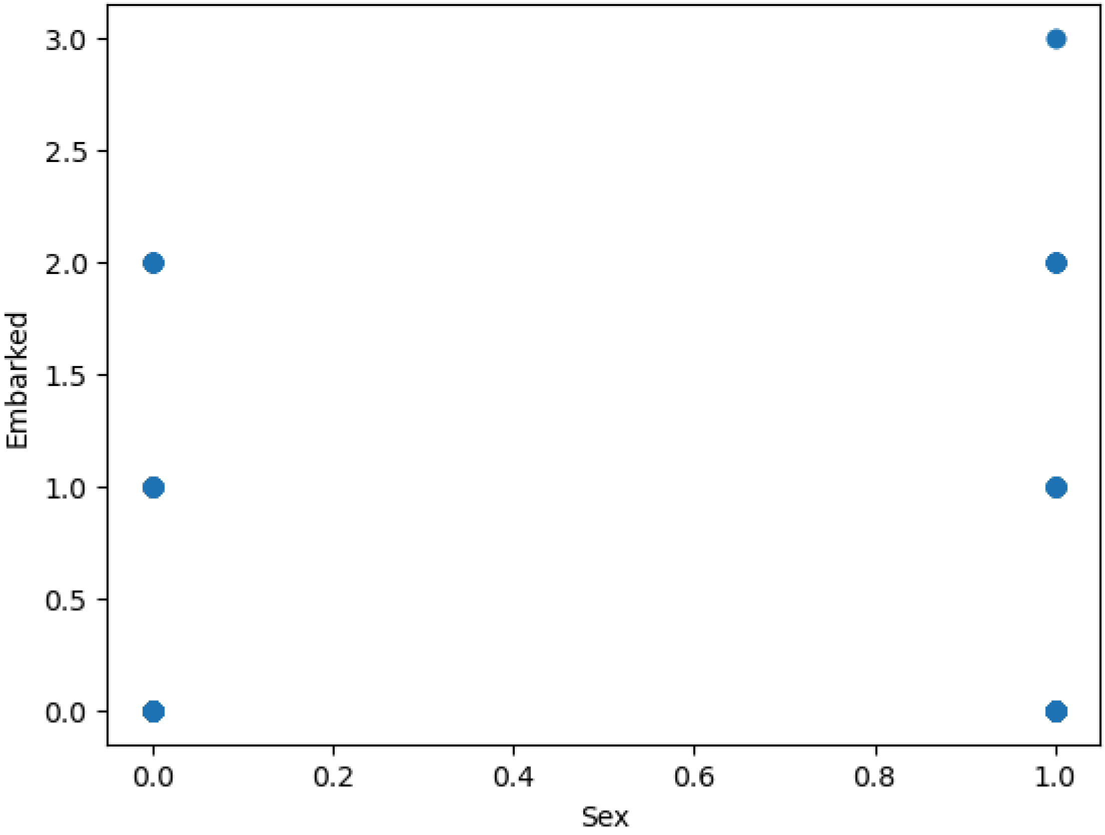
8
7
6
5
4
3
2
1
0
SibSp
0.0
0.2
0.4
0.6
0.8
1.0
Sex

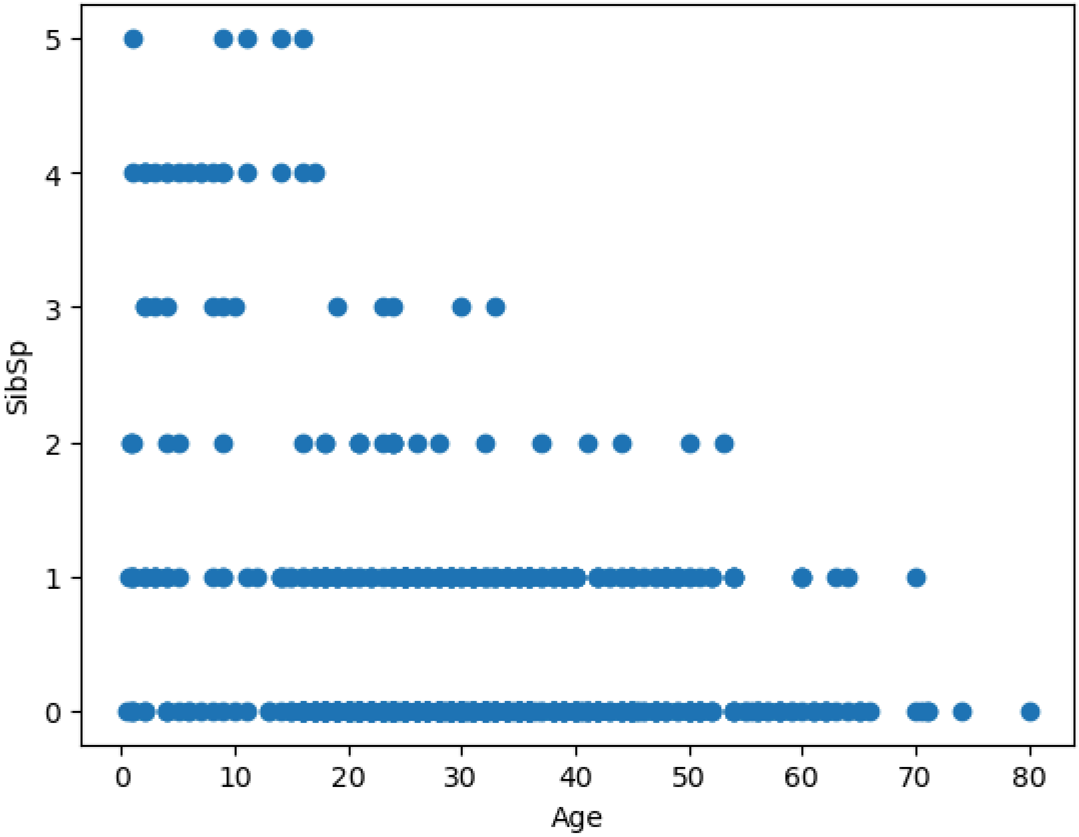

6
5
4
3
2
1
0
Parch
0.0
0.2
0.4
0.6
0.8
1.0
Sex

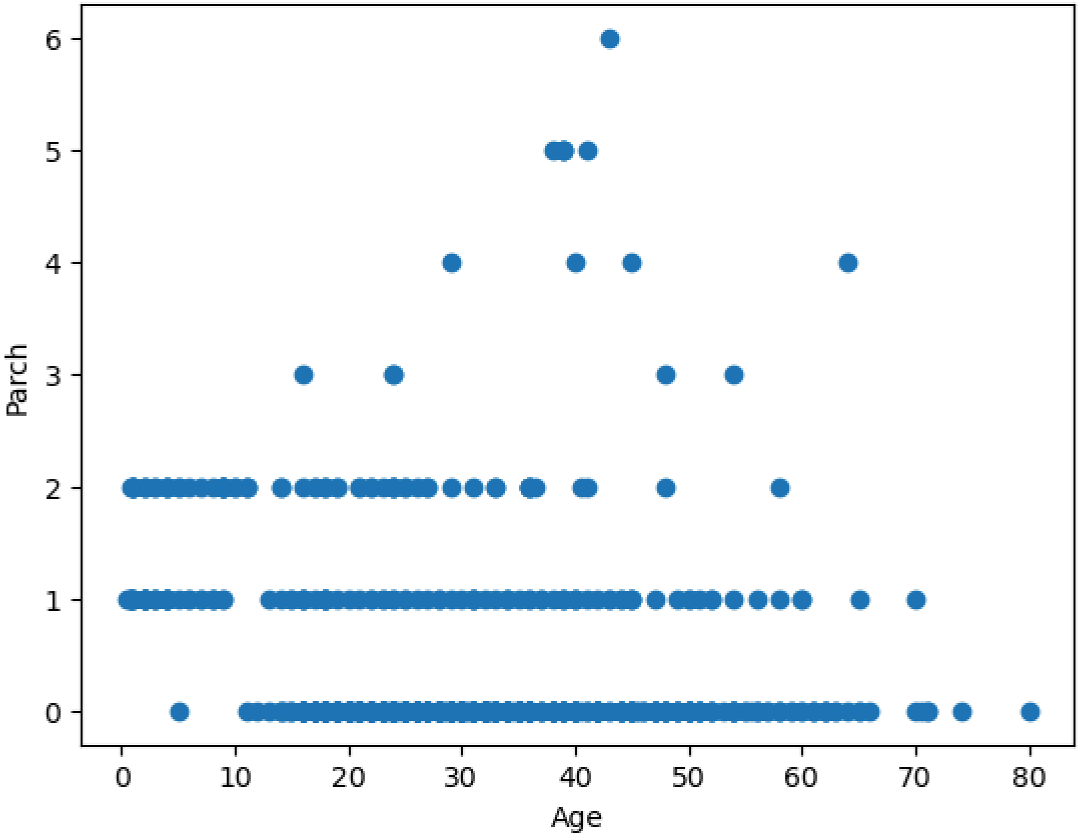

700
600
500
400
300
200
100
0
Ticket
0.0
0.2
0.4
0.6
0.8
1.0
Sex

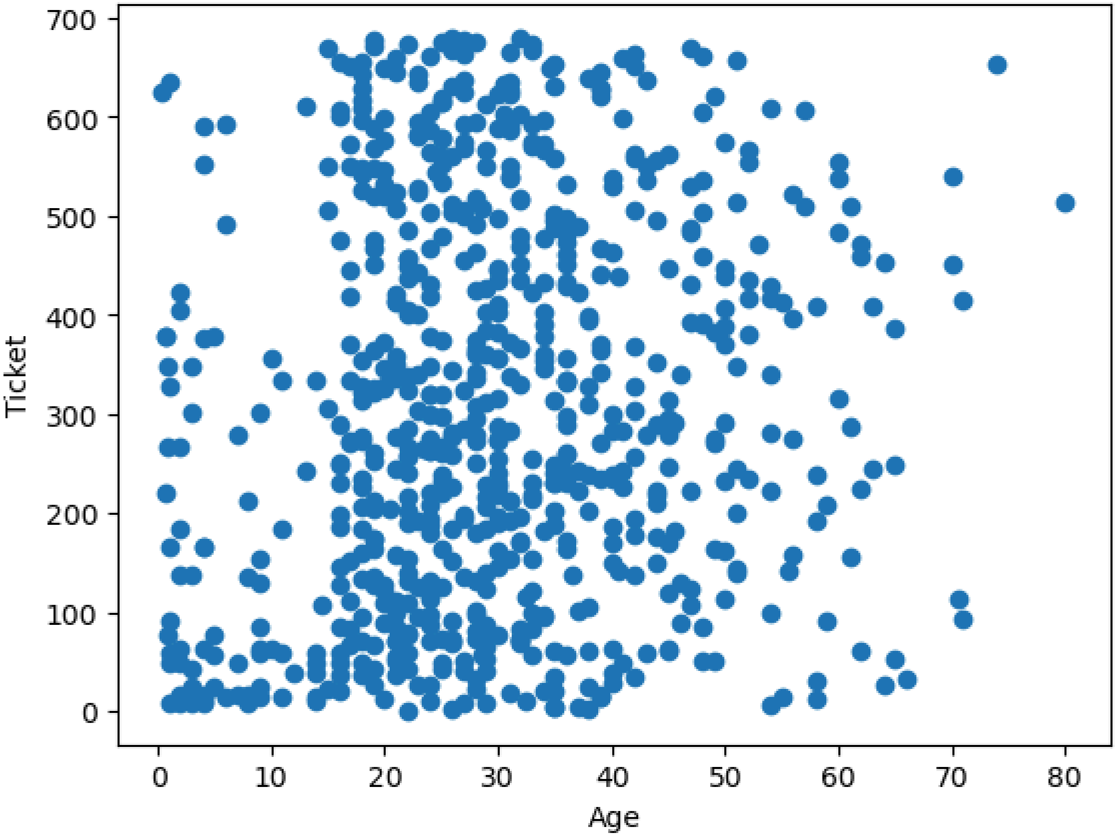

500
400
300
200
100
0
Fare
0.0
0.2
0.4
0.6
0.8
1.0
Sex

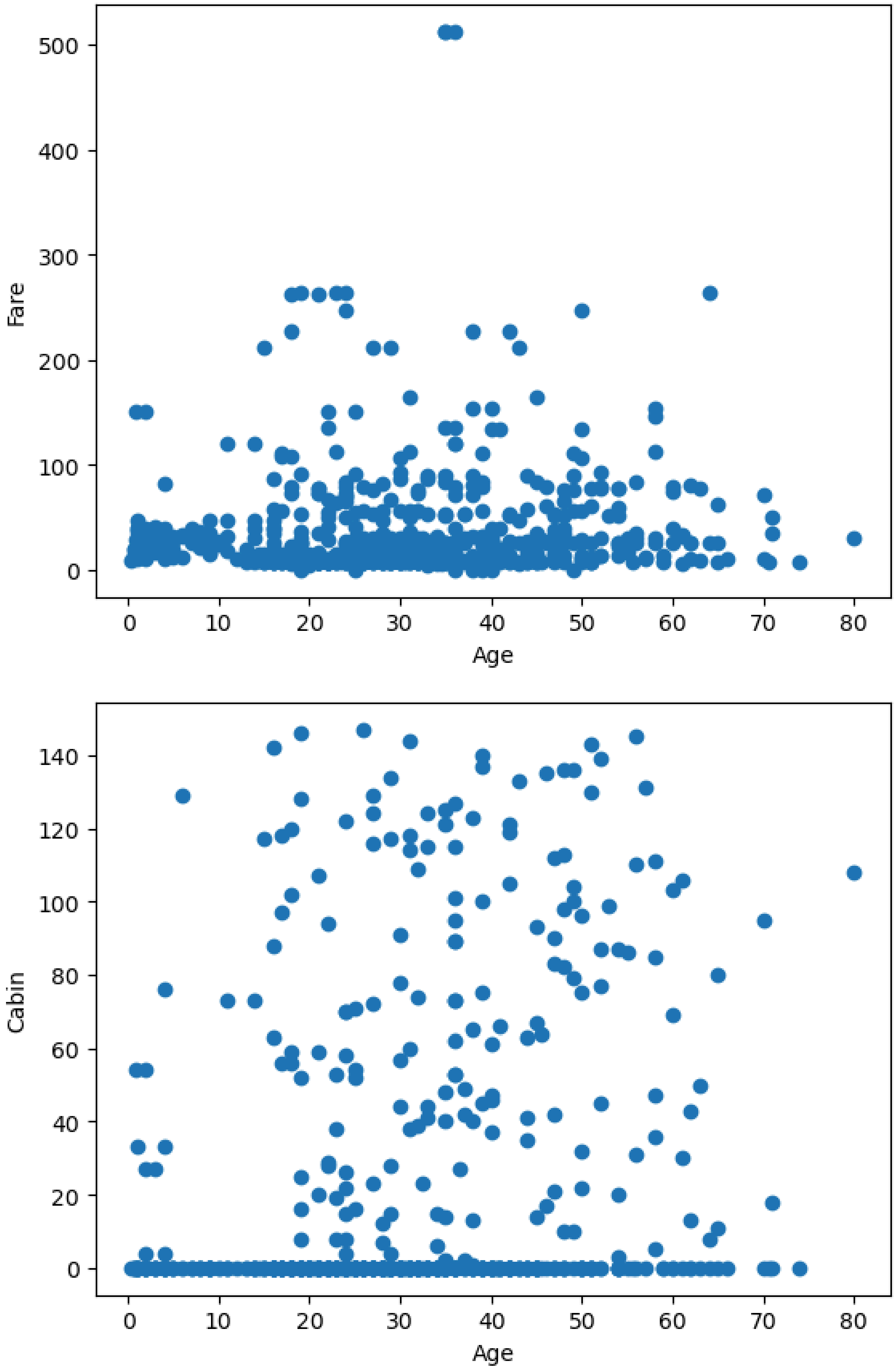

140
120
100
80
60
40
20
0
Cabin
0.0
0.2
0.4
0.6
0.8
1.0
Sex

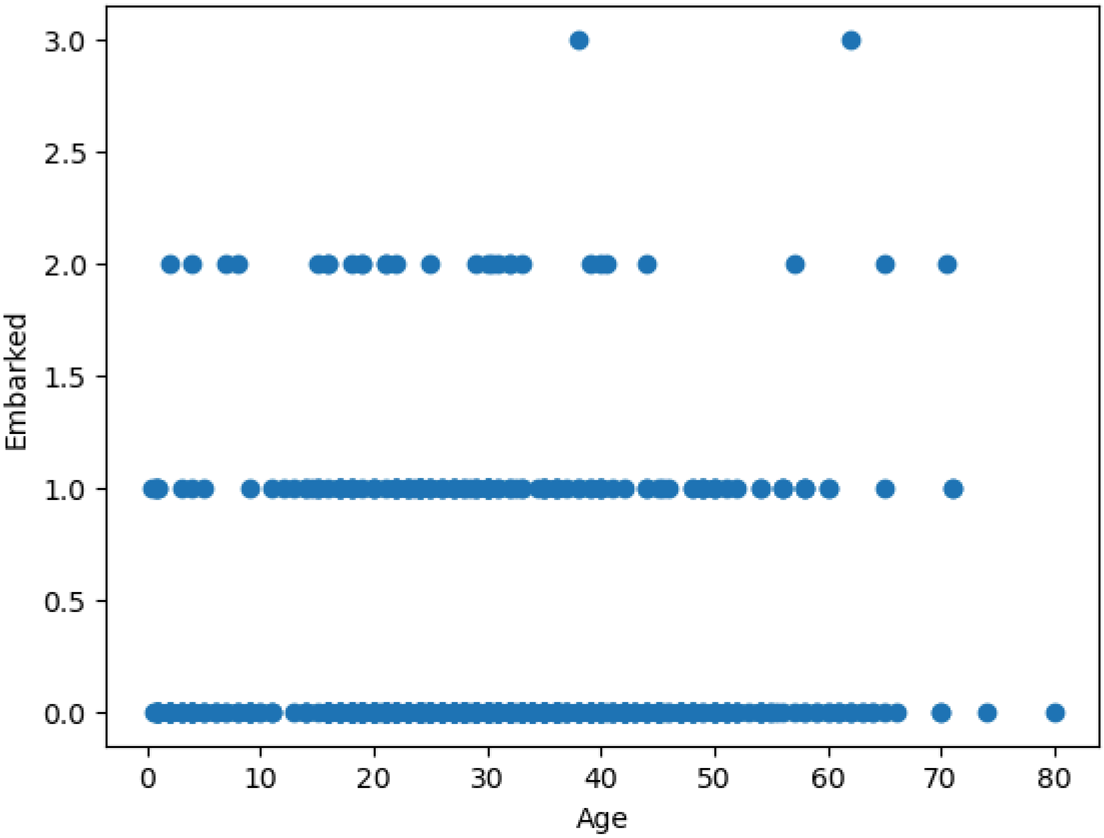

Embarked
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Sex

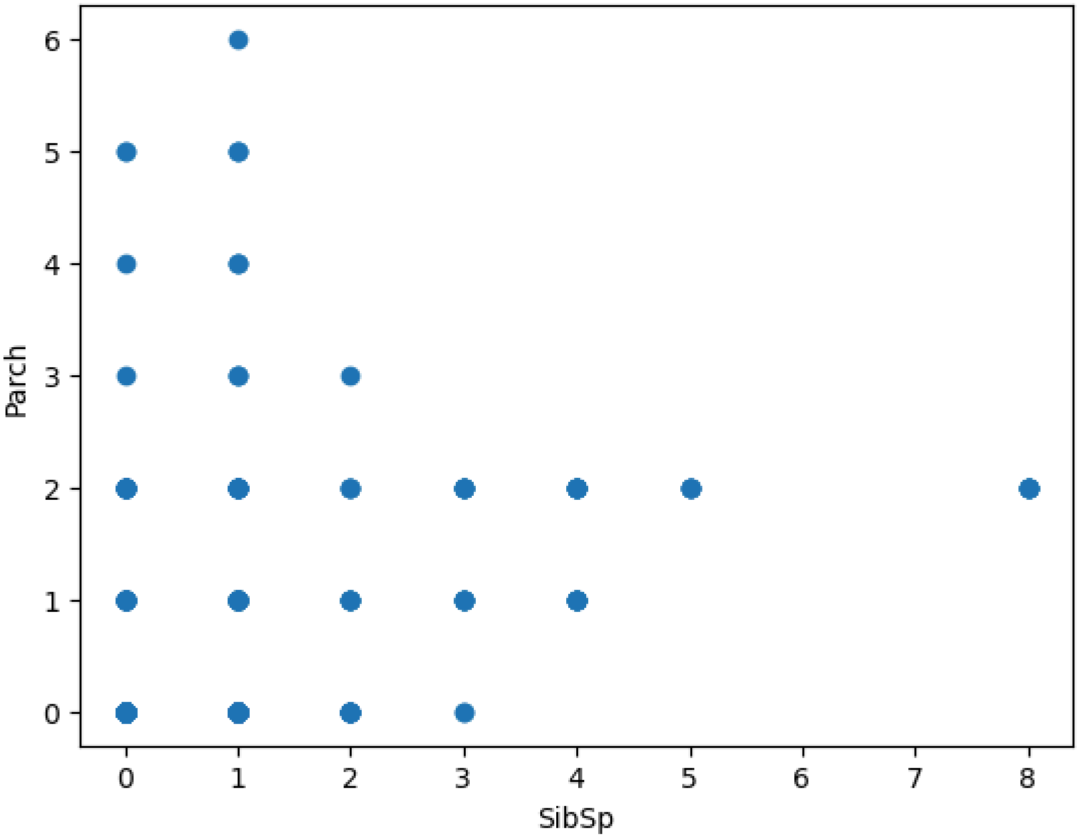

SibSp
5
4
3
2
1
0
0
10
20
30
40
50
60
70
80
Age

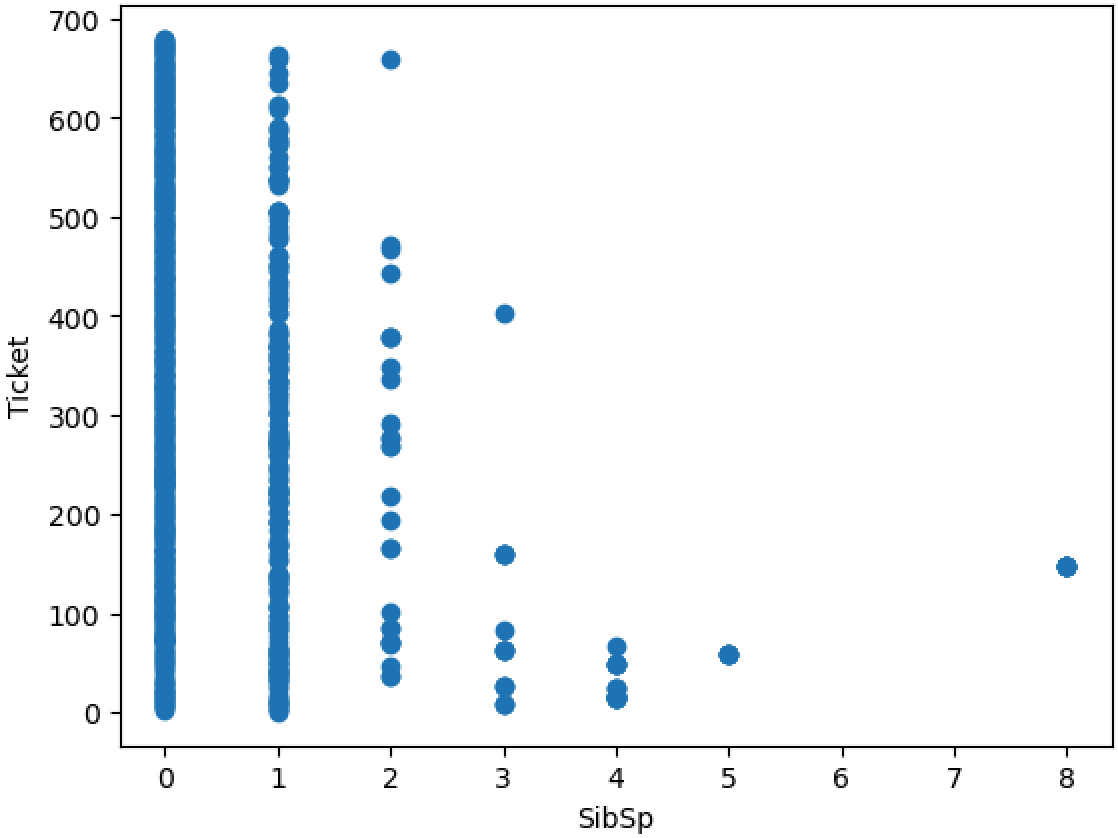

Parch
6
5
4
3
2
1
0
0
10
20
30
40
50
60
70
80
Age

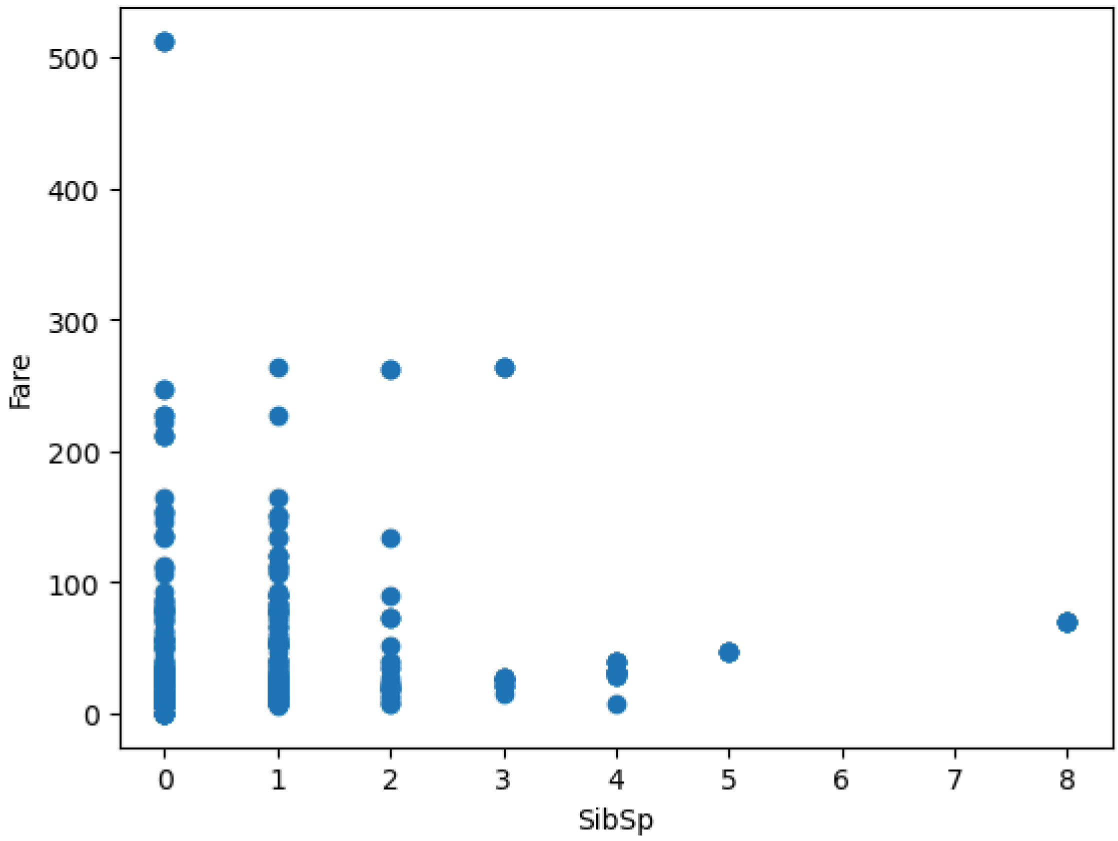

Ticket
700
600
500
400
300
200
100
0
0
10
20
30
40
50
60
70
80
Age

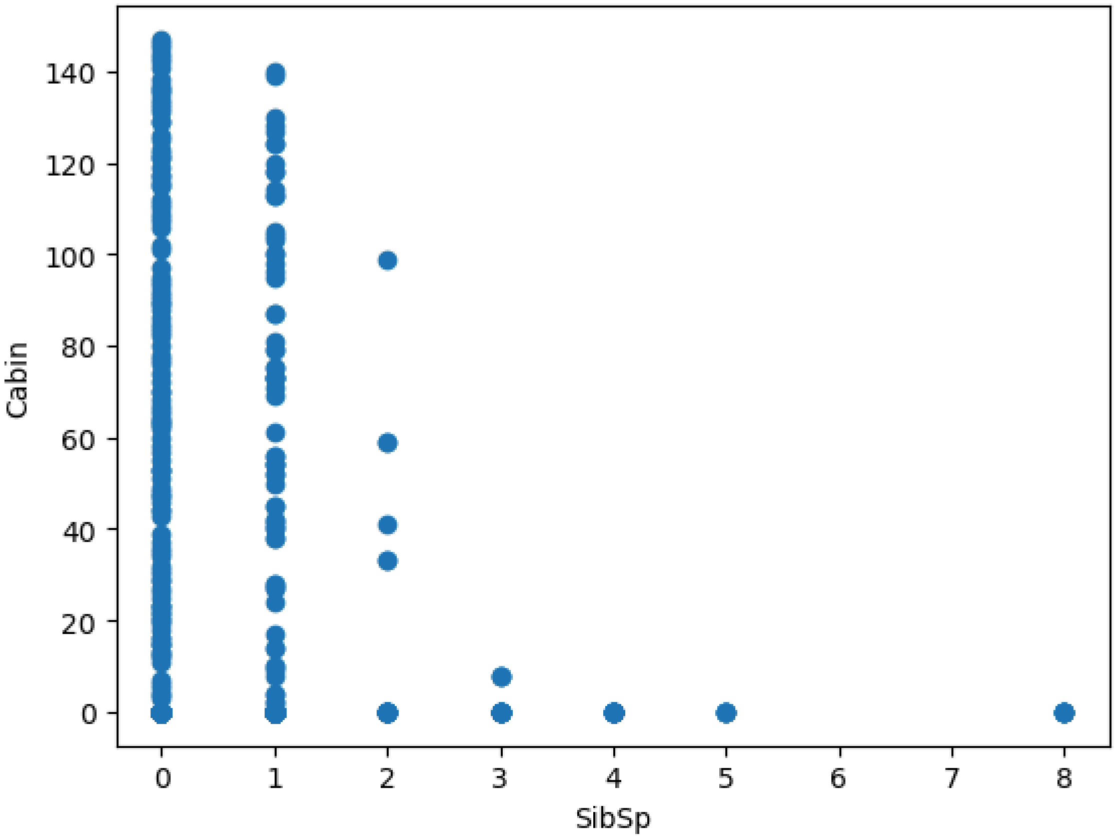

Fare
500
400
300
200
100
0
0
10
20
30
40
50
60
70
80
Age
Cabin
140
120
100
80
60
40
20
0
0
10
20
30
40
50
60
70
80
Age

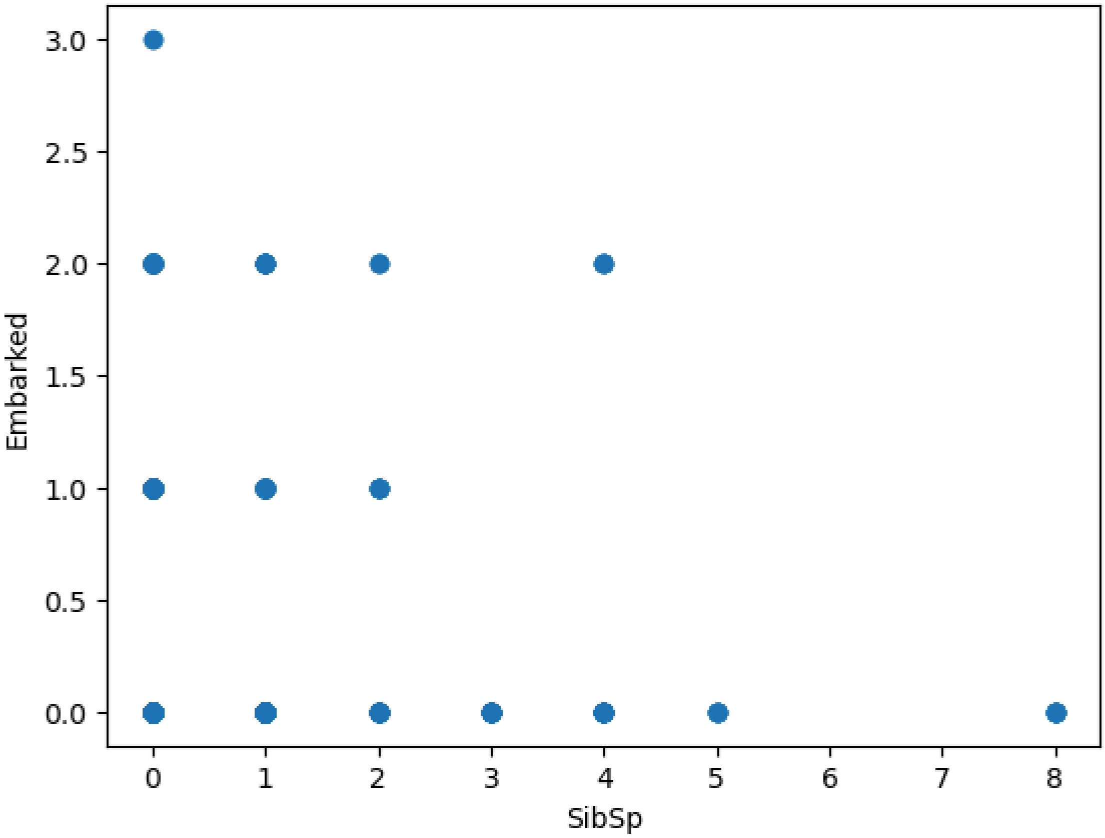

3.0
2.5
2.0
1.5
1.0
0.5
0.0
Embarked
0
10
20
30
40
50
60
70
80
Age

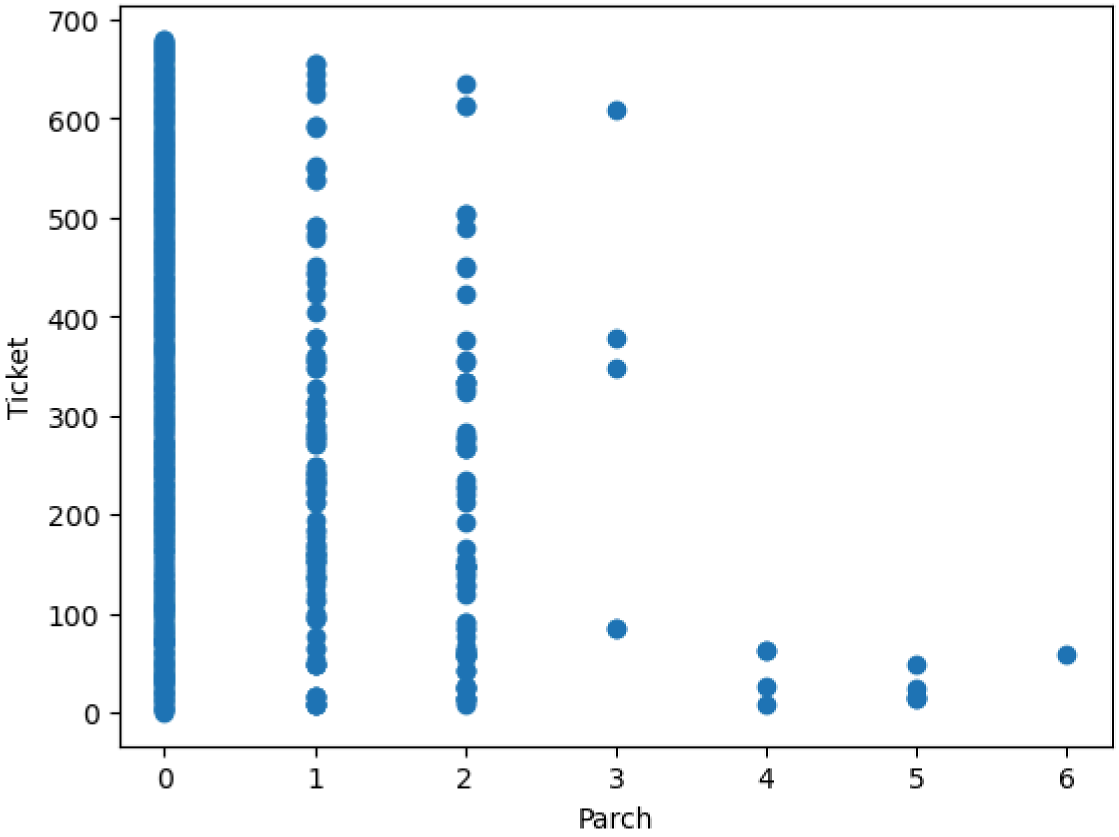

6
5
4
3
2
1
0
Parch
0
1
2
3
4
5
6
7
8
SibSp

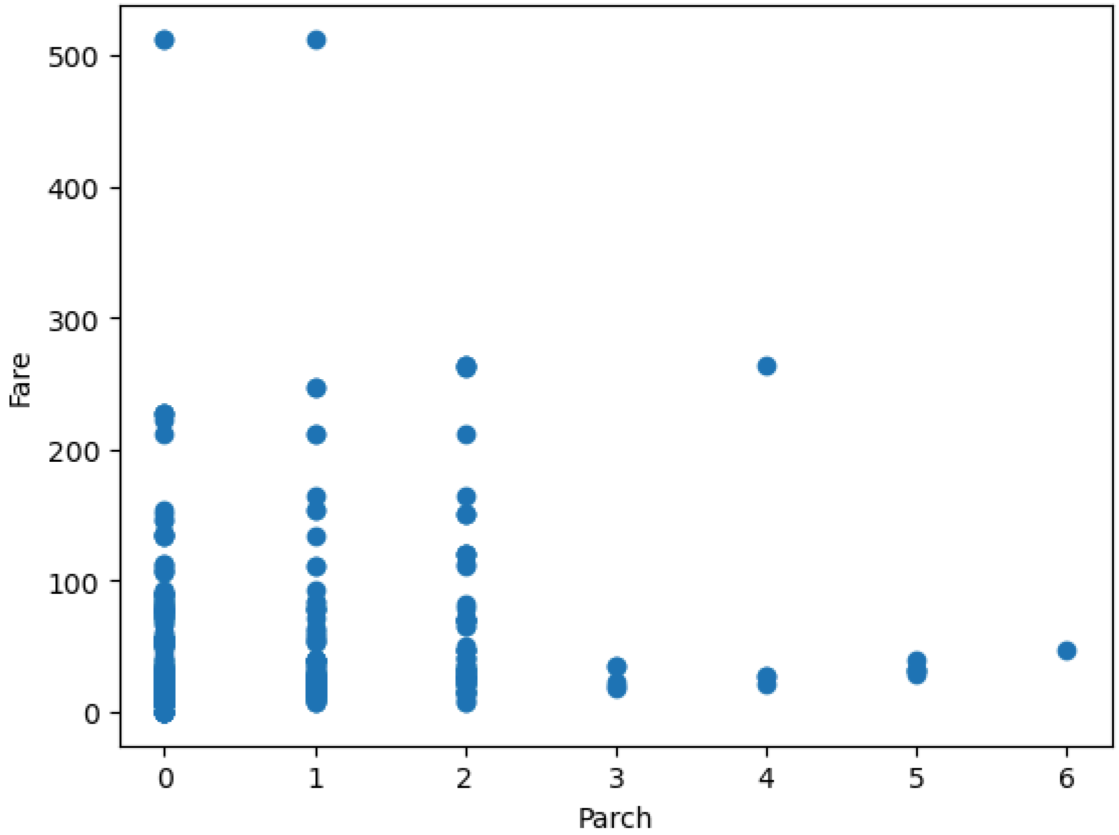

Ticket
700
600
500
400
300
200
100
0
0
1
2
3
4
5
6
7
8
SibSp

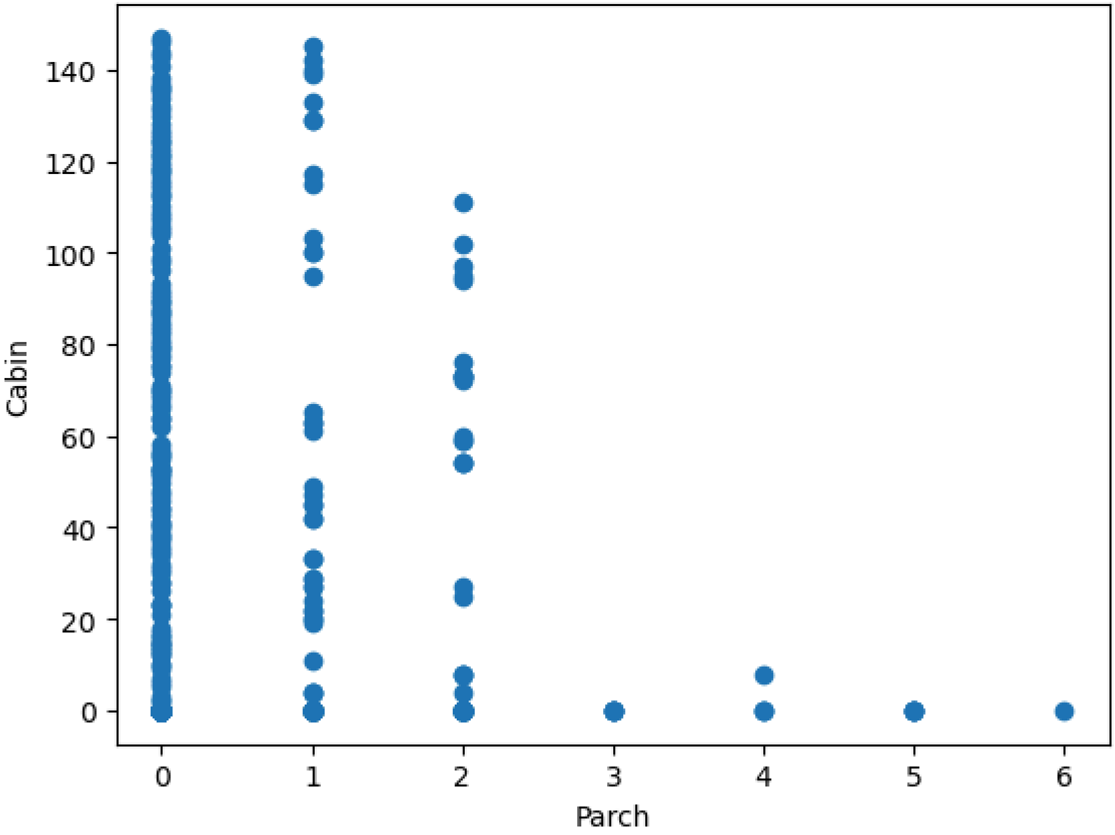

Fare
500
400
300
200
100
0
0
1
2
3
4
5
6
7
8
SibSp

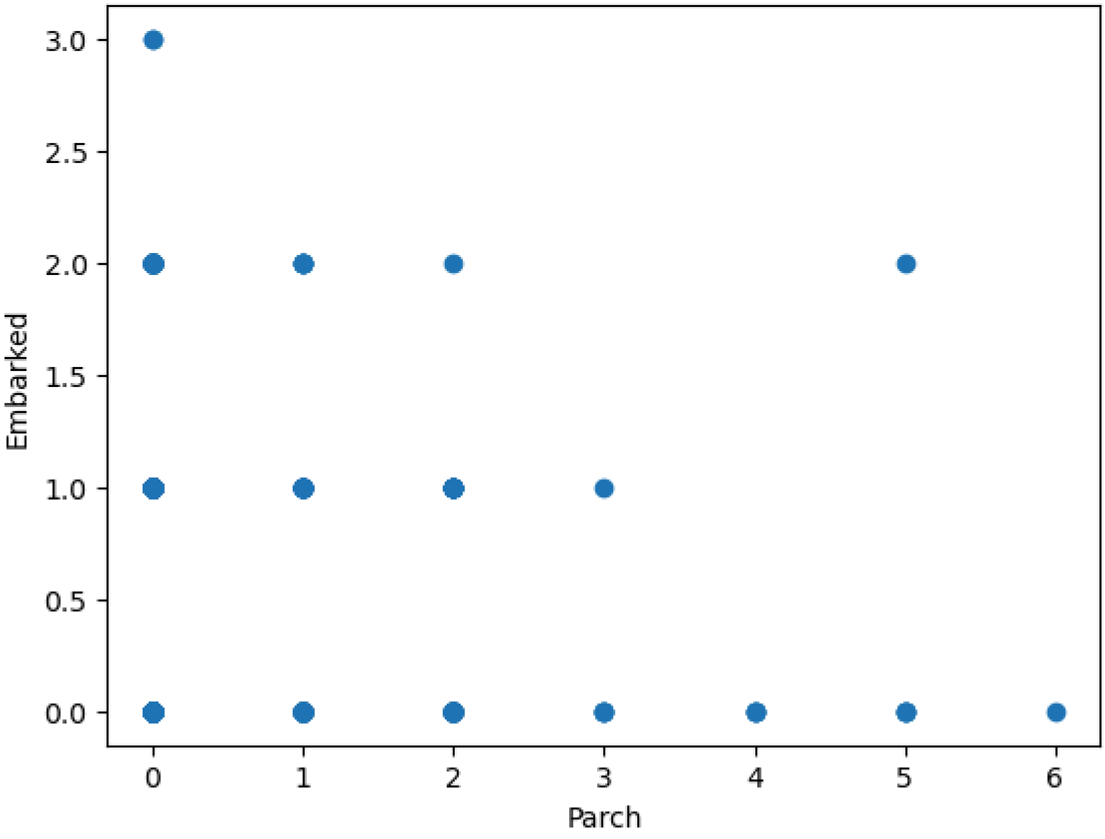

Cabin
0
20
40
60
80
100
120
140
SibSp
0
1
2
3
4
5
6
7
8

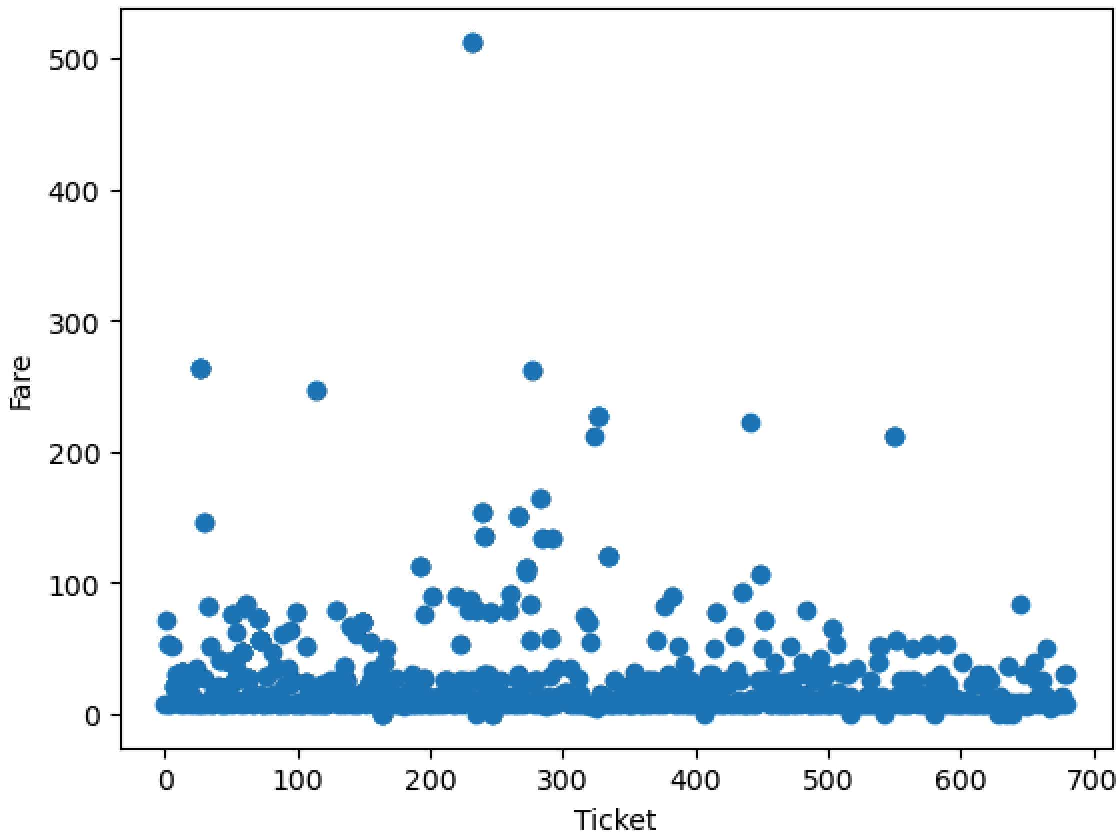

Embarked
0.0
0.5
1.0
1.5
2.0
2.5
3.0
SibSp
0
1
2
3
4
5
6
7
8

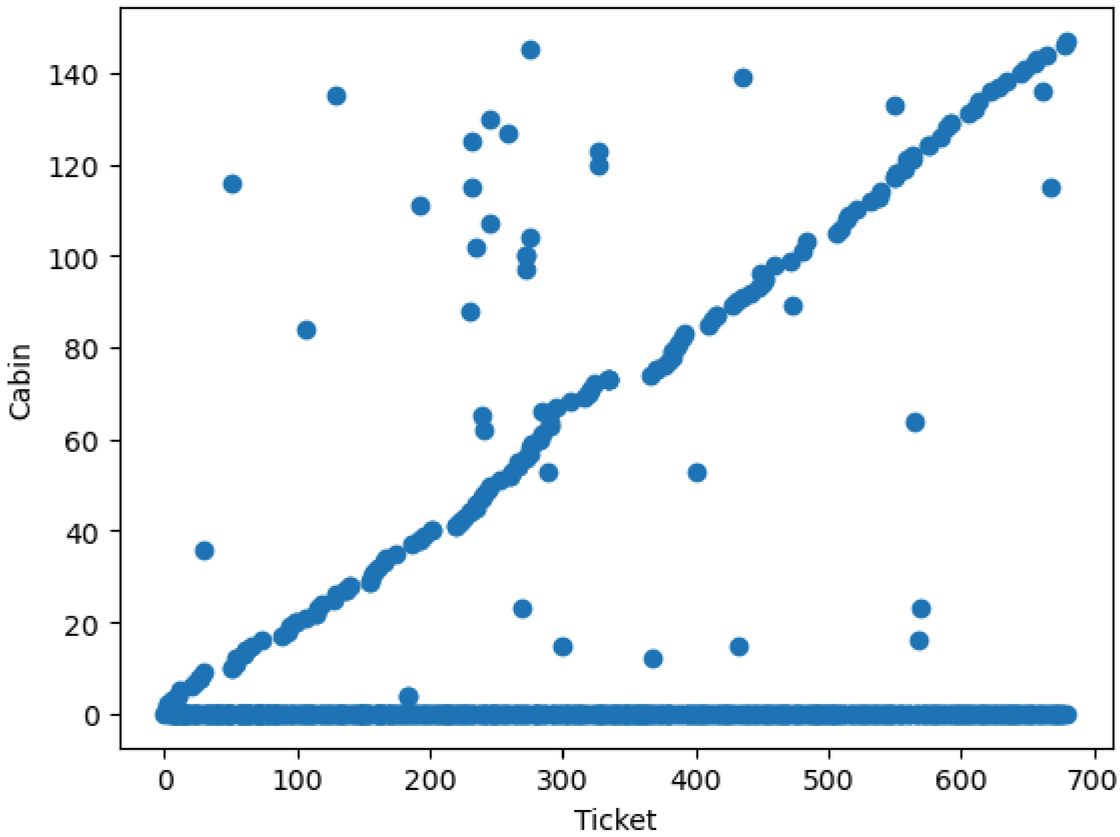

Ticket
0
100
200
300
400
500
600
700
0
1
2
3
4
5
6
Parch

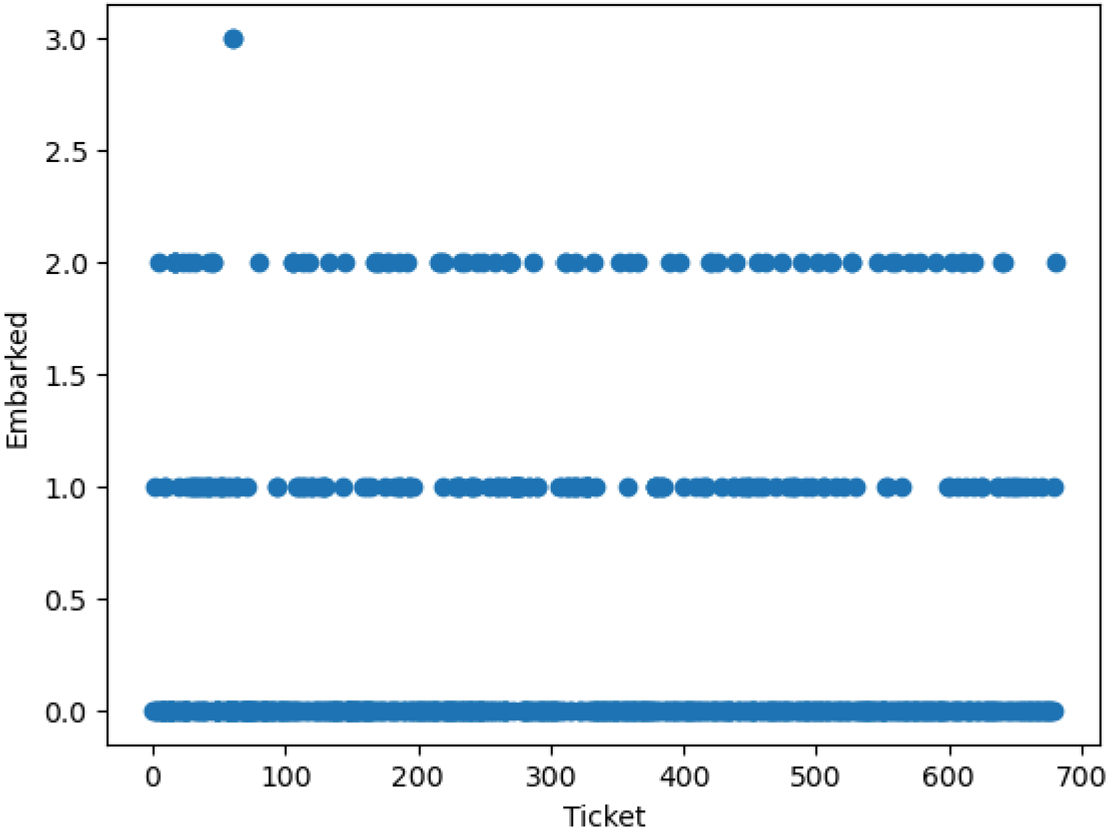

Fare
0
100
200
300
400
500
0
1
2
3
4
5
6
Parch


Cabin
0
20
40
60
80
100
120
140
Parch
0
1
2
3
4
5
6

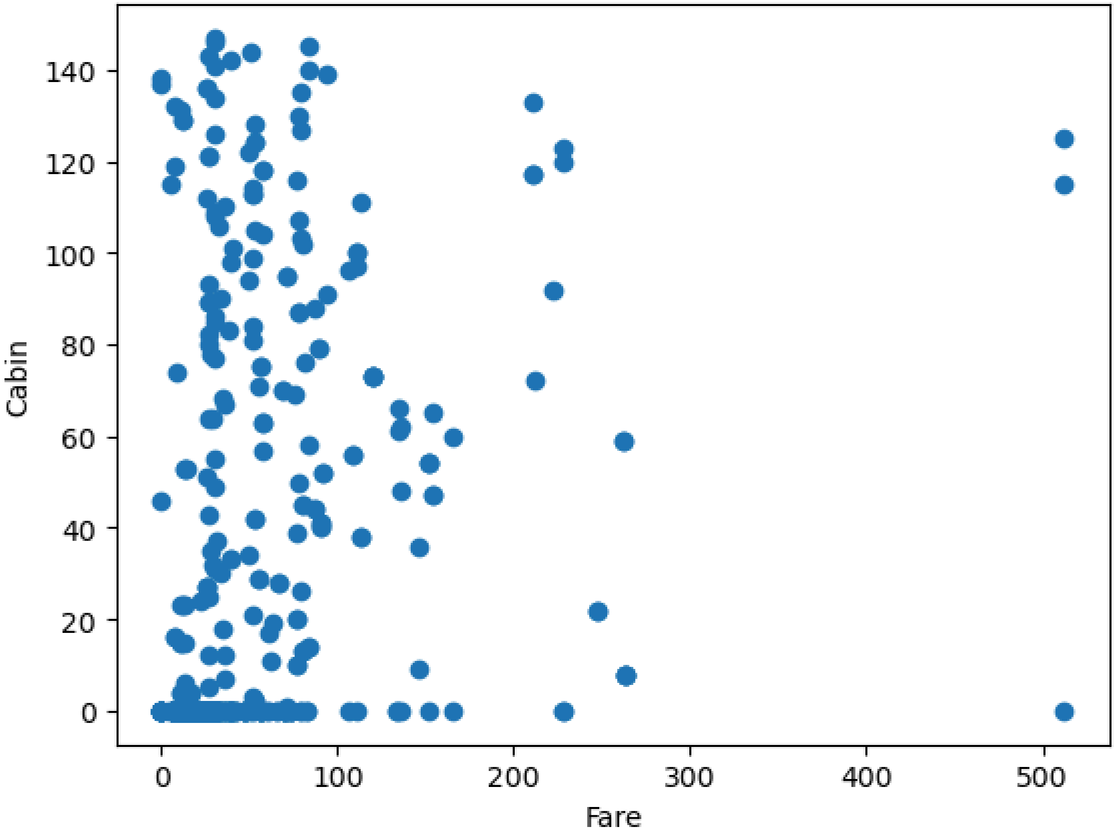

Embarked
0.0
0.5
1.0
1.5
2.0
2.5
3.0
Parch
0
1
2
3
4
5
6


Fare
500
400
300
200
100
0
0
100
200
300
400
500
600
700
Ticket

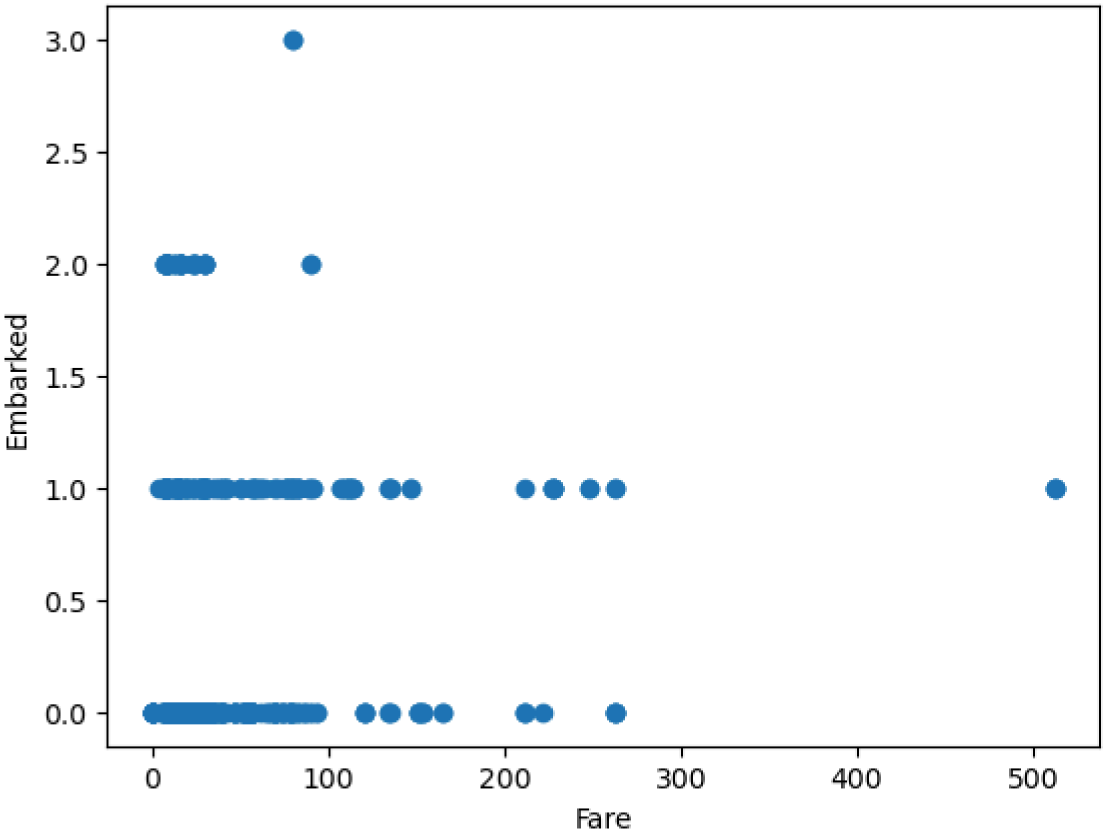

Cabin
140
120
100
80
60
40
20
0
0
100
200
300
400
500
600
700
Ticket

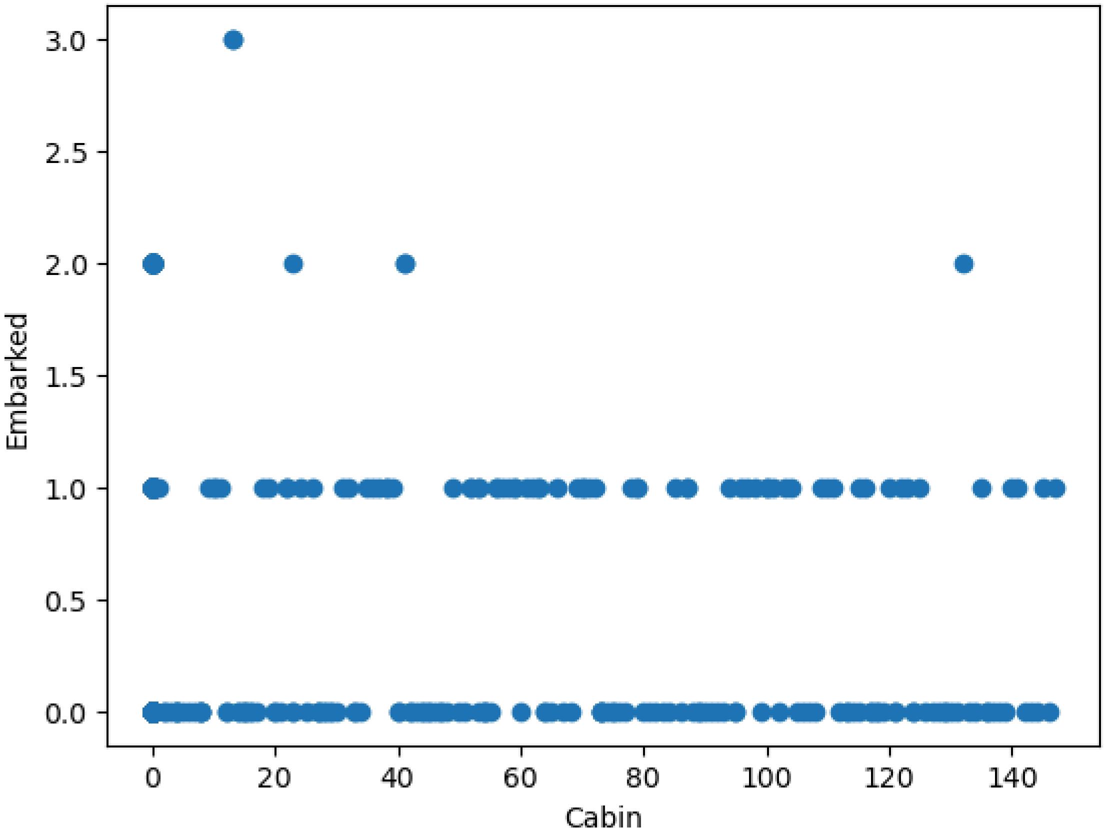


Embarked
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
100
200
300
400
500
600
700
Ticket



Cabin
140
120
100
80
60
40
20
0
0
100
200
300
400
500
Fare





In [243…

```
missing_data = df.isnull().sum()

for column, missing_count in missing_data.items():
  if missing_count > 0:
    print(f"Column '{column}' has {missing_count} missing values.")
    missing_rows = df[df[column].isnull()].index
    print(f"Missing data locations: {missing_rows}")
```

```
Column 'Age' has 177 missing values.
Missing data locations: Index([  5,  17,  19,  26,  28,  29,  31,  32,  36,  42,
       ...
       832, 837, 839, 846, 849, 859, 863, 868, 878, 888],
      dtype='int64', length=177)
```

In [244…

```
# Identify categorical columns with missing values
cat_cols = df.select_dtypes(include='object').columns[df.select_dtypes(include='object

# Perform one-hot encoding on categorical columns with missing values
df = pd.get_dummies(df, columns=cat_cols, dummy_na=True)

# Print the updated DataFrame
print(df)
```

```
     PassengerId  Survived  Pclass  Name  Sex   Age  SibSp  Parch  Ticket  \
0              1         0       3     0    0  22.0      1      0       0   
1              2         1       1     1    1  38.0      1      0       1   
2              3         1       3     2    1  26.0      0      0       2   
3              4         1       1     3    1  35.0      1      0       3   
4              5         0       3     4    0  35.0      0      0       4   
..           ...       ...     ...   ...  ...   ...    ...    ...     ...   
886          887         0       2   886    0  27.0      0      0     677   
887          888         1       1   887    1  19.0      0      0     678   
888          889         0       3   888    1   NaN      1      2     614   
889          890         1       1   889    0  26.0      0      0     679   
890          891         0       3   890    0  32.0      0      0     680   

        Fare  Cabin  Embarked  
0     7.2500      0         0  
1    71.2833      1         1  
2     7.9250      0         0  
3    53.1000      2         0  
4     8.0500      0         0  
..       ...    ...       ...  
886  13.0000      0         0  
887  30.0000    146         0  
888  23.4500      0         0  
889  30.0000    147         1  
890   7.7500      0         2  

[891 rows x 12 columns]
```

In [245…

```
# Identify numerical columns
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns

# Define outlier thresholds
lower_boundary = df[numerical_columns].mean() - 3 * df[numerical_columns].std()
upper_boundary = df[numerical_columns].mean() + 3 * df[numerical_columns].std()

# Remove outliers
df = df[(df[numerical_columns] >= lower_boundary) & (df[numerical_columns] <= upper_bo

# Print the cleaned DataFrame
print(df)
```

```
     PassengerId  Survived  Pclass  Name  Sex   Age  SibSp  Parch  Ticket  \
0              1         0       3     0    0  22.0    1.0    0.0       0   
1              2         1       1     1    1  38.0    1.0    0.0       1   
2              3         1       3     2    1  26.0    0.0    0.0       2   
3              4         1       1     3    1  35.0    1.0    0.0       3   
4              5         0       3     4    0  35.0    0.0    0.0       4   
..           ...       ...     ...   ...  ...   ...    ...    ...     ...   
886          887         0       2   886    0  27.0    0.0    0.0     677   
887          888         1       1   887    1  19.0    0.0    0.0     678   
888          889         0       3   888    1   NaN    1.0    2.0     614   
889          890         1       1   889    0  26.0    0.0    0.0     679   
890          891         0       3   890    0  32.0    0.0    0.0     680   

        Fare  Cabin  Embarked  
0     7.2500    0.0       0.0  
1    71.2833    1.0       1.0  
2     7.9250    0.0       0.0  
3    53.1000    2.0       0.0  
4     8.0500    0.0       0.0  
..       ...    ...       ...  
886  13.0000    0.0       0.0  
887  30.0000    NaN       0.0  
888  23.4500    0.0       0.0  
889  30.0000    NaN       1.0  
890   7.7500    0.0       2.0  

[891 rows x 12 columns]
```

In [246…

```python
# Define a function to clean the data
def clean_data(df):
  # Replace typos and inconsistencies
  df['Sex'] = df['Sex'].replace({'Malee': 'Male', 'Femal': 'Female'})
  df['Embarked'] = df['Embarked'].replace({'Qeenstown': 'Queenstown', 'N/A': np.nan})

  # Convert invalid int values to NaN
  df['Age'] = df['Age'].replace(r'\D+', np.nan, regex=True)

  return df

# Clean the data
df = clean_data(df)

# Impute missing values with the median
df = df.apply(lambda x: x.fillna(x.median()))

# Print the new data frame
print(df.head())
```

```
   PassengerId  Survived  Pclass  Name  Sex   Age  SibSp  Parch  Ticket  \
0            1         0       3     0    0  22.0    1.0    0.0       0
1            2         1       1     1    1  38.0    1.0    0.0       1
2            3         1       3     2    1  26.0    0.0    0.0       2
3            4         1       1     3    1  35.0    1.0    0.0       3
4            5         0       3     4    0  35.0    0.0    0.0       4

      Fare  Cabin  Embarked
0   7.2500    0.0       0.0
1  71.2833    1.0       1.0
2   7.9250    0.0       0.0
3  53.1000    2.0       0.0
4   8.0500    0.0       0.0
```

In [247…

```
# Calculate the correlation matrix
corr = df.corr()

# Select the upper triangle of the correlation matrix
upper = corr.where(~np.tril(np.ones(corr.shape)).astype(bool))

# Find the features with high correlation
to_drop = [column for column in upper.columns if any(upper[column] > 0.9)]

# Drop the highly correlated features
df.drop(to_drop, axis=1, inplace=True)

# Print the new data frame
print(df.head())
```

```
   PassengerId  Survived  Pclass  Sex   Age  SibSp  Parch  Ticket     Fare  \
0            1         0       3    0  22.0    1.0    0.0       0   7.2500
1            2         1       1    1  38.0    1.0    0.0       1  71.2833
2            3         1       3    1  26.0    0.0    0.0       2   7.9250
3            4         1       1    1  35.0    1.0    0.0       3  53.1000
4            5         0       3    0  35.0    0.0    0.0       4   8.0500

   Cabin  Embarked
0    0.0       0.0
1    1.0       1.0
2    0.0       0.0
3    2.0       0.0
4    0.0       0.0
```

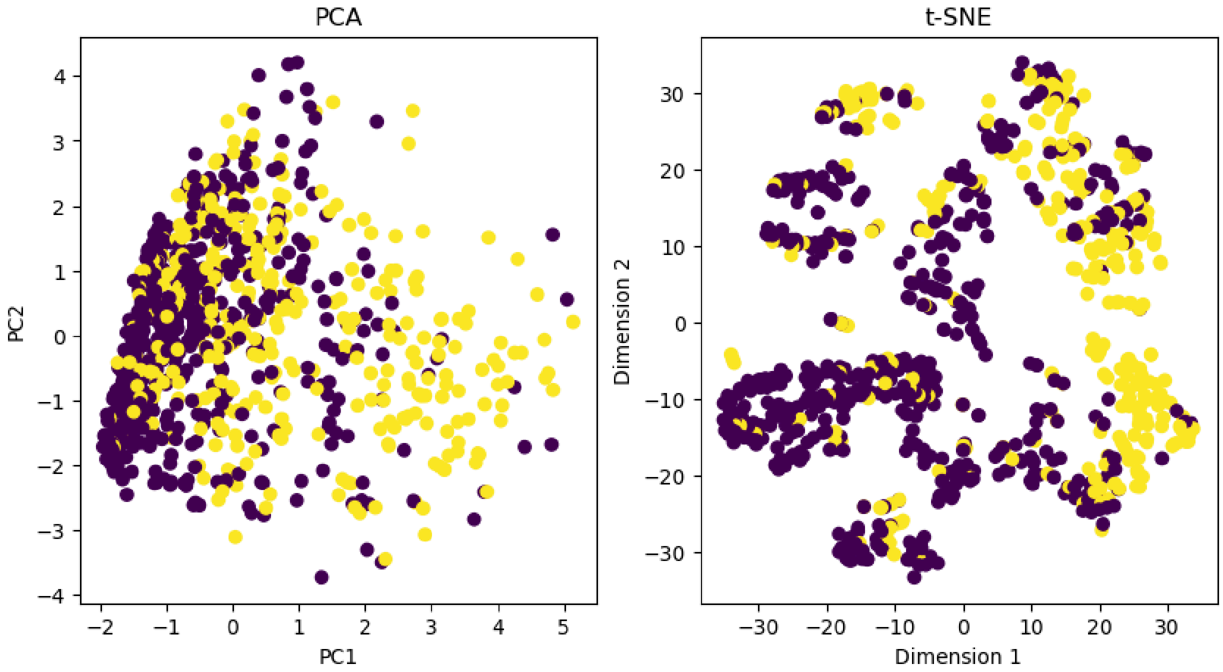
In [248…

```
X = df.drop('Survived', axis=1)
y = df['Survived']

# Select the top 5 features with the highest chi-squared scores
selector = SelectKBest(chi2, k=5)
X_new = selector.fit_transform(X, y)

# Get the names of the selected features
selected_features = X.columns[selector.get_support()]

# Create a new DataFrame with the selected features
df_new = df[selected_features]

# Print the new DataFrame
print(df_new.head())
```

```
   Pclass  Sex  Ticket     Fare  Cabin
0       3    0       0   7.2500    0.0
1       1    1       1  71.2833    1.0
2       3    1       2   7.9250    0.0
3       1    1       3  53.1000    2.0
4       3    0       4   8.0500    0.0
```

In [249…

```
# Separate features and target
X = df.drop('Survived', axis=1)
y = df['Survived']

# Standardize the features
X = (X - X.mean()) / X.std()

# Perform PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

# Perform t-SNE
tsne = TSNE(n_components=2)
X_tsne = tsne.fit_transform(X)

# Plot the results
plt.figure(figsize=(10, 5))
plt.subplot(1, 2, 1)
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='viridis')
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.title('PCA')

plt.subplot(1, 2, 2)
plt.scatter(X_tsne[:, 0], X_tsne[:, 1], c=y, cmap='viridis')
plt.xlabel('Dimension 1')
plt.ylabel('Dimension 2')
plt.title('t-SNE')

plt.show()
```



In [250…

```
# Check for date-time format mismatches
for col in df.select_dtypes(include=['datetime64']):
  unique_formats = df[col].dt.strftime('%Y-%m-%d').unique()
  if len(unique_formats) > 1:
    print(f"Inconsistent date-time format in column '{col}'")

# Check for units of measurement variations
for col in df.select_dtypes(include=['float64', 'int64']):
  unique_units = df[col].unique()
  if any(not isinstance(x, (int, float)) for x in unique_units):
    print(f"Inconsistent units of measurement in column '{col}'")

# Check for capitalization differences
for col in df.select_dtypes(include=['object']):
  unique_values = df[col].unique()
  if any(x.lower() != x for x in unique_values):
    print(f"Inconsistent capitalization in column '{col}'")
```

```
Inconsistent units of measurement in column 'PassengerId'
Inconsistent units of measurement in column 'Survived'
Inconsistent units of measurement in column 'Pclass'
Inconsistent units of measurement in column 'Sex'
Inconsistent units of measurement in column 'Ticket'
```

In [251…

```
# Standardize the column names
df.columns = df.columns.str.lower().str.replace(' ', '_')

# Standardize the data types
for column in df:
    if df[column].dtype == 'object':
        df[column] = df[column].astype('category')
    elif df[column].dtype in ['int64', 'float64']:
        df[column] = df[column].astype('float32')

# Print the standardized data frame
print(df.head())
```

```
   passengerid  survived  pclass  sex   age  sibsp  parch  ticket       fare  \
0          1.0       0.0     3.0  0.0  22.0    1.0    0.0     0.0   7.250000
1          2.0       1.0     1.0  1.0  38.0    1.0    0.0     1.0  71.283302
2          3.0       1.0     3.0  1.0  26.0    0.0    0.0     2.0   7.925000
3          4.0       1.0     1.0  1.0  35.0    1.0    0.0     3.0  53.099998
4          5.0       0.0     3.0  0.0  35.0    0.0    0.0     4.0   8.050000

   cabin  embarked
0    0.0       0.0
1    1.0       1.0
2    0.0       0.0
3    2.0       0.0
4    0.0       0.0
```

In [252…

```
# Find categorical columns
cat_cols = df.select_dtypes(include='object').columns.tolist()

# Define a dictionary to map old labels to new labels
mapping = {
    "male": "Male",
    "female": "Female",
    "S": "Southampton",
    "C": "Cherbourg",
    "Q": "Queenstown",
}

# Replace old labels with new labels
for col in cat_cols:
    df[col] = df[col].map(mapping)

# Print the updated data frame
print(df.head())
```

```
   passengerid  survived  pclass  sex   age  sibsp  parch  ticket       fare  \
0          1.0       0.0     3.0  0.0  22.0    1.0    0.0     0.0   7.250000
1          2.0       1.0     1.0  1.0  38.0    1.0    0.0     1.0  71.283302
2          3.0       1.0     3.0  1.0  26.0    0.0    0.0     2.0   7.925000
3          4.0       1.0     1.0  1.0  35.0    1.0    0.0     3.0  53.099998
4          5.0       0.0     3.0  0.0  35.0    0.0    0.0     4.0   8.050000

   cabin  embarked
0    0.0       0.0
1    1.0       1.0
2    0.0       0.0
3    2.0       0.0
4    0.0       0.0
```

In [253…

```
numerical_features = df.select_dtypes(include=['int64', 'float64']).columns

# Normalize the numerical features
for feature in numerical_features:
    df[feature] = (df[feature] - df[feature].min()) / (df[feature].max() - df[feature]

# Print the new data frame
print(df.head())
```

```
   passengerid  survived  pclass  sex   age  sibsp  parch  ticket       fare  \
0          1.0       0.0     3.0  0.0  22.0    1.0    0.0     0.0   7.250000
1          2.0       1.0     1.0  1.0  38.0    1.0    0.0     1.0  71.283302
2          3.0       1.0     3.0  1.0  26.0    0.0    0.0     2.0   7.925000
3          4.0       1.0     1.0  1.0  35.0    1.0    0.0     3.0  53.099998
4          5.0       0.0     3.0  0.0  35.0    0.0    0.0     4.0   8.050000

   cabin  embarked
0    0.0       0.0
1    1.0       1.0
2    0.0       0.0
3    2.0       0.0
4    0.0       0.0
```

In [254…

```
# Load the data
url = 'https://raw.githubusercontent.com/datasciencedojo/datasets/master/titanic.csv'
df = pd.read_csv(url)

# Identify categorical features
categorical_features = df.select_dtypes(include=['object']).columns

# One-hot encode categorical features
df = pd.get_dummies(df, columns=categorical_features)

# Save the processed CSV to a new file
df.to_csv('processed_titanic.csv', index=False)
```

In [ ]:

```
```