Titanic

February 8, 2025

1 Titanic - Machine Learning from Disaster

1.0.1 A competição é simples: usar aprendizado de máquina para criar um modelo que preveja quais passageiros sobreviveram ao naufrágio do Titanic.

[1]:
```
#Importando as bibliotecas
import pandas as pd
import numpy as np
!pip install scikit-learn
!pip install matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
```

```
Requirement already satisfied: scikit-learn in c:\users\acer\anaconda3\lib\site-
packages (1.5.1)
Requirement already satisfied: numpy>=1.19.5 in
c:\users\acer\anaconda3\lib\site-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in c:\users\acer\anaconda3\lib\site-
packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in
c:\users\acer\anaconda3\lib\site-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
c:\users\acer\anaconda3\lib\site-packages (from scikit-learn) (3.5.0)
Requirement already satisfied: matplotlib in c:\users\acer\anaconda3\lib\site-
packages (3.9.2)
Requirement already satisfied: contourpy>=1.0.1 in
c:\users\acer\anaconda3\lib\site-packages (from matplotlib) (1.2.0)
Requirement already satisfied: cycler>=0.10 in c:\users\acer\anaconda3\lib\site-
packages (from matplotlib) (0.11.0)
```

```
Requirement already satisfied: fonttools>=4.22.0 in
c:\users\acer\anaconda3\lib\site-packages (from matplotlib) (4.51.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
c:\users\acer\anaconda3\lib\site-packages (from matplotlib) (1.4.4)
Requirement already satisfied: numpy>=1.23 in c:\users\acer\anaconda3\lib\site-
packages (from matplotlib) (1.26.4)
Requirement already satisfied: packaging>=20.0 in
c:\users\acer\anaconda3\lib\site-packages (from matplotlib) (24.1)
Requirement already satisfied: pillow>=8 in c:\users\acer\anaconda3\lib\site-
packages (from matplotlib) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
c:\users\acer\anaconda3\lib\site-packages (from matplotlib) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in
c:\users\acer\anaconda3\lib\site-packages (from matplotlib) (2.9.0.post0)
Requirement already satisfied: six>=1.5 in c:\users\acer\anaconda3\lib\site-
packages (from python-dateutil>=2.7->matplotlib) (1.16.0)
```

[2]:
```
#Preprocessing
from sklearn.preprocessing import OneHotEncoder, LabelEncoder, label_binarize

# Machine learning
from sklearn.model_selection import train_test_split
from sklearn import model_selection, tree, preprocessing, metrics, linear_model
from sklearn.svm import LinearSVC
from sklearn.ensemble import GradientBoostingClassifier, RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LinearRegression, LogisticRegression,␣
 ↪SGDClassifier
from sklearn.tree import DecisionTreeClassifier
```

[3]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

[4]:
```
#Lendo os arquivo de treino
train = pd.read_csv("C:/Users/Acer/Documents/Kaggle/Titanic/train.csv")
test = pd.read_csv("C:/Users/Acer/Documents/Kaggle/Titanic/test.csv")
```

[5]:
```
train
```

[5]:

	PassengerId	Survived	Pclass	\
0	1	0	3	
1	2	1	1	
2	3	1	3	
3	4	1	1	
4	5	0	3	
..	…	…	…	

```
886          887         0       2
887          888         1       1
888          889         0       3
889          890         1       1
890          891         0       3

                                                 Name     Sex   Age  SibSp  \
0                             Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                              Heikkinen, Miss. Laina  female  26.0      0
3        Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                            Allen, Mr. William Henry    male  35.0      0
..                                                ...     …   …    …
886                            Montvila, Rev. Juozas    male  27.0      0
887                     Graham, Miss. Margaret Edith  female  19.0      0
888         Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                            Behr, Mr. Karl Howell    male  26.0      0
890                              Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …      …   …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[6]:
```
#Saber quantas colunas e linhas tem na tabela treino
train.shape
```

[6]:
```
(891, 12)
```

[7]:
```
# Ver as informações
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
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
```

[8]:
```
#Somando os valores nulos do dataframe
train.isnull().sum()
```

[8]:
```
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
```

[9]:
```
train.describe()
```

[9]:

	PassengerId	Survived	Pclass	Age	SibSp	\
count	891.000000	891.000000	891.000000	714.000000	891.000000	
mean	446.000000	0.383838	2.308642	29.699118	0.523008	
std	257.353842	0.486592	0.836071	14.526497	1.102743	
min	1.000000	0.000000	1.000000	0.420000	0.000000	
25%	223.500000	0.000000	2.000000	20.125000	0.000000	
50%	446.000000	0.000000	3.000000	28.000000	0.000000	
75%	668.500000	1.000000	3.000000	38.000000	1.000000	
max	891.000000	1.000000	3.000000	80.000000	8.000000	

	Parch	Fare
count	891.000000	891.000000
mean	0.381594	32.204208
std	0.806057	49.693429
min	0.000000	0.000000

```
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

[10]:
```
test.describe()
```

[10]:
```
       PassengerId      Pclass         Age       SibSp       Parch        Fare
count   418.000000  418.000000  332.000000  418.000000  418.000000  417.000000
mean   1100.500000    2.265550   30.272590    0.447368    0.392344   35.627188
std     120.810458    0.841838   14.181209    0.896760    0.981429   55.907576
min     892.000000    1.000000    0.170000    0.000000    0.000000    0.000000
25%     996.250000    1.000000   21.000000    0.000000    0.000000    7.895800
50%    1100.500000    3.000000   27.000000    0.000000    0.000000   14.454200
75%    1204.750000    3.000000   39.000000    1.000000    0.000000   31.500000
max    1309.000000    3.000000   76.000000    8.000000    9.000000  512.329200
```

[11]:
```
# Vendo a tabela de teste, ela possui somente 11 colunas, do contrário da␣
↪tabela de treino que possui 12 colunas
test
```

[11]:
```
     PassengerId  Pclass                                          Name  \
0            892       3                              Kelly, Mr. James
1            893       3              Wilkes, Mrs. James (Ellen Needs)
2            894       2                     Myles, Mr. Thomas Francis
3            895       3                              Wirz, Mr. Albert
4            896       3  Hirvonen, Mrs. Alexander (Helga E Lindqvist)
..           …     …                                               …
413         1305       3                           Spector, Mr. Woolf
414         1306       1                 Oliva y Ocana, Dona. Fermina
415         1307       3                 Saether, Mr. Simon Sivertsen
416         1308       3                          Ware, Mr. Frederick
417         1309       3                     Peter, Master. Michael J

        Sex   Age  SibSp  Parch              Ticket      Fare Cabin Embarked
0      male  34.5      0      0              330911    7.8292   NaN        Q
1    female  47.0      1      0              363272    7.0000   NaN        S
2      male  62.0      0      0              240276    9.6875   NaN        Q
3      male  27.0      0      0              315154    8.6625   NaN        S
4    female  22.0      1      1             3101298   12.2875   NaN        S
..      …   …    …    …                 …        …   …      …
413    male   NaN      0      0           A.5. 3236    8.0500   NaN        S
414  female  39.0      0      0            PC 17758  108.9000  C105        C
415    male  38.5      0      0  SOTON/O.Q. 3101262    7.2500   NaN        S
416    male   NaN      0      0              359309    8.0500   NaN        S
417    male   NaN      1      1                2668   22.3583   NaN        C
```

```
[418 rows x 11 columns]
```

[12]:
```
#Separando a coluna de passageiro ID da tabela teste e fazendo uma união entre␣
 ↪as tabelas treino e teste.
passengerID = test["PassengerId"]
titanic_df = pd.concat([train, test],ignore_index=True)
```

[13]:
```
titanic_df
```

[13]:
```
      PassengerId  Survived  Pclass  \
0               1       0.0       3
1               2       1.0       1
2               3       1.0       3
3               4       1.0       1
4               5       0.0       3
…             …       …       …
1304         1305       NaN       3
1305         1306       NaN       1
1306         1307       NaN       3
1307         1308       NaN       3
1308         1309       NaN       3

                                                 Name     Sex   Age  SibSp  \
0                             Braund, Mr. Owen Harris    male  22.0      1
1     Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                              Heikkinen, Miss. Laina  female  26.0      0
3        Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                            Allen, Mr. William Henry    male  35.0      0
…                                                 …     …   …    …
1304                               Spector, Mr. Woolf    male   NaN      0
1305                     Oliva y Ocana, Dona. Fermina  female  39.0      0
1306                     Saether, Mr. Simon Sivertsen    male  38.5      0
1307                              Ware, Mr. Frederick    male   NaN      0
1308                         Peter, Master. Michael J    male   NaN      1

      Parch              Ticket      Fare Cabin Embarked
0         0           A/5 21171    7.2500   NaN        S
1         0            PC 17599   71.2833   C85        C
2         0    STON/O2. 3101282    7.9250   NaN        S
3         0              113803   53.1000  C123        S
4         0              373450    8.0500   NaN        S
…     …                  …       …   …      …
1304      0           A.5. 3236    8.0500   NaN        S
1305      0            PC 17758  108.9000  C105        C
1306      0  SOTON/O.Q. 3101262    7.2500   NaN        S
1307      0              359309    8.0500   NaN        S
1308      1                2668   22.3583   NaN        C
```

```
[1309 rows x 12 columns]
```

[14]:
```
titanic_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1309 entries, 0 to 1308
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  1309 non-null   int64
 1   Survived     891 non-null    float64
 2   Pclass       1309 non-null   int64
 3   Name         1309 non-null   object
 4   Sex          1309 non-null   object
 5   Age          1046 non-null   float64
 6   SibSp        1309 non-null   int64
 7   Parch        1309 non-null   int64
 8   Ticket       1309 non-null   object
 9   Fare         1308 non-null   float64
 10  Cabin        295 non-null    object
 11  Embarked     1307 non-null   object
dtypes: float64(3), int64(4), object(5)
memory usage: 122.8+ KB
```

[15]:
```
titanic_df.isnull().sum()
```

[15]:
```
PassengerId       0
Survived        418
Pclass            0
Name              0
Sex               0
Age             263
SibSp             0
Parch             0
Ticket            0
Fare              1
Cabin          1014
Embarked          2
dtype: int64
```

[16]:
```
#Tamanho do data frame de treino e onde começa o data frame teste
train_index = len(train)
test_index = len(titanic_df) - len(test)
```

[17]:
```
df = pd.DataFrame()
```

1.0.2 Survived

[18]:
```
#Para saber a quantidade de opções
titanic_df["Survived"].nunique()
```

[18]:
```
2
```

[19]:
```
#Para saber a quantidade de opções
titanic_df["Survived"].unique()
```

[19]:
```
array([ 0.,  1., nan])
```

[20]:
```
#Quantidade de valores nulos
titanic_df["Survived"].isnull().sum()
```

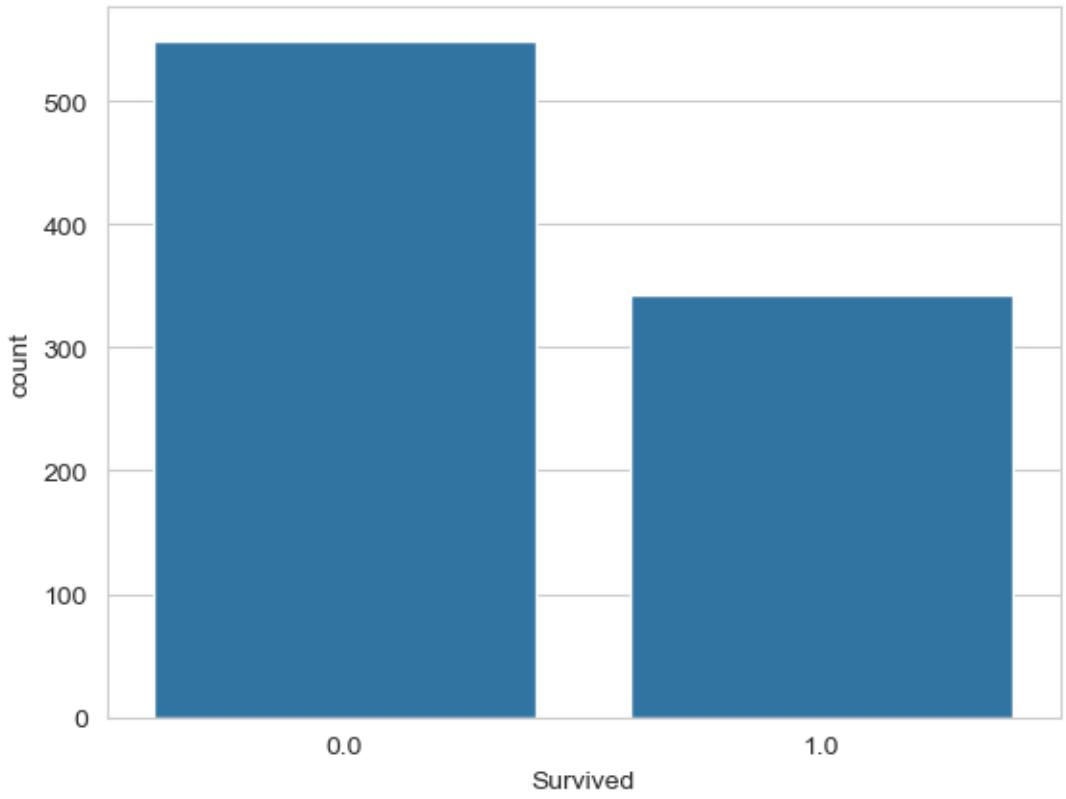
[20]:
```
418
```

[21]:
```
#Para saber quantos sobreviveram no desastre
titanic_df["Survived"].value_counts()
```

[21]:
```
Survived
0.0    549
1.0    342
Name: count, dtype: int64
```

[22]:
```
sns.countplot(data=titanic_df,x="Survived")
```

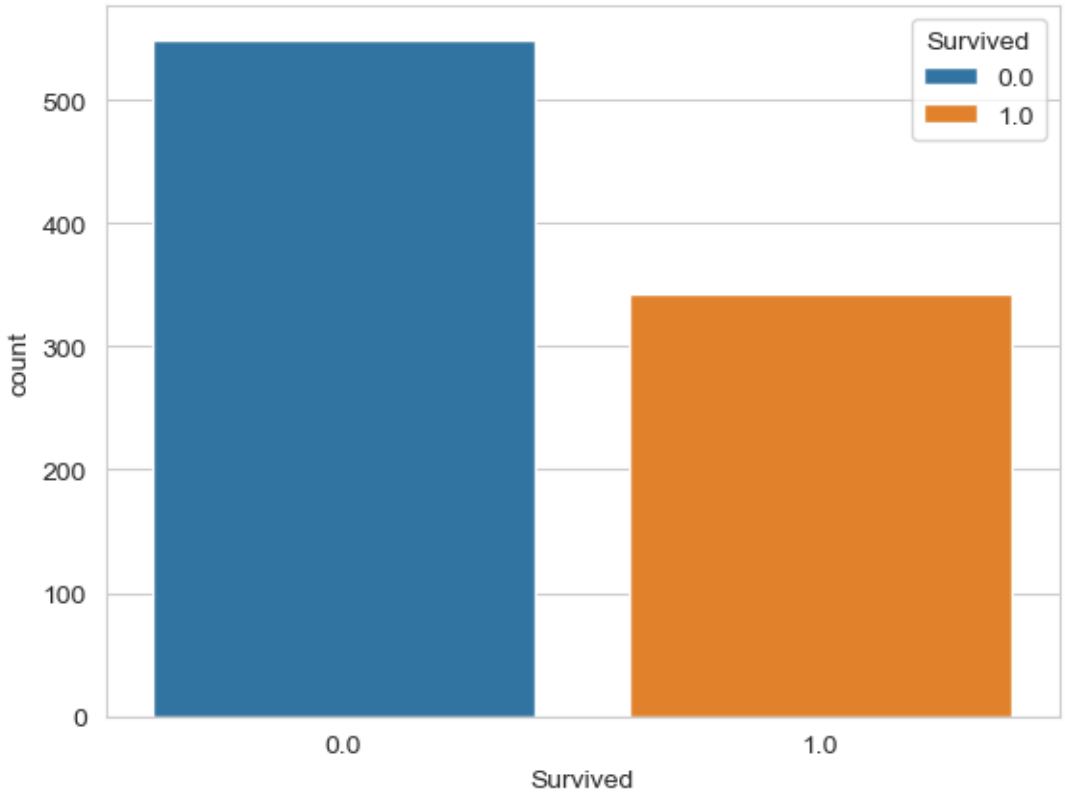
[22]:
```
<Axes: xlabel='Survived', ylabel='count'>
```



[23]:
```
# Criando uma função para ajudar no momento de visualizar as informações de␣
 ↪cada coluna

def titanic_func(data, column, count = True):
    print(f'Quantidade de valores únicos: {data[column].nunique()}')
    print(f'\nQuais são os valores únicos: {data[column].unique()}')
    print(f'\nQuantidade de valores nulos: {data[column].isnull().sum()}')
    print(f'\nQuantidade por opção: \n{data[column].value_counts()}')

    if count == True:
        sns.countplot(data = data, x = column, hue = 'Survived')
    else:
        sns.displot(data[column], kde = True)


titanic_func(titanic_df, 'Survived')
```

```
Quantidade de valores únicos: 2

Quais são os valores únicos: [ 0.  1. nan]

Quantidade de valores nulos: 418
```

```
Quantidade por opção:
Survived
0.0    549
1.0    342
Name: count, dtype: int64
```



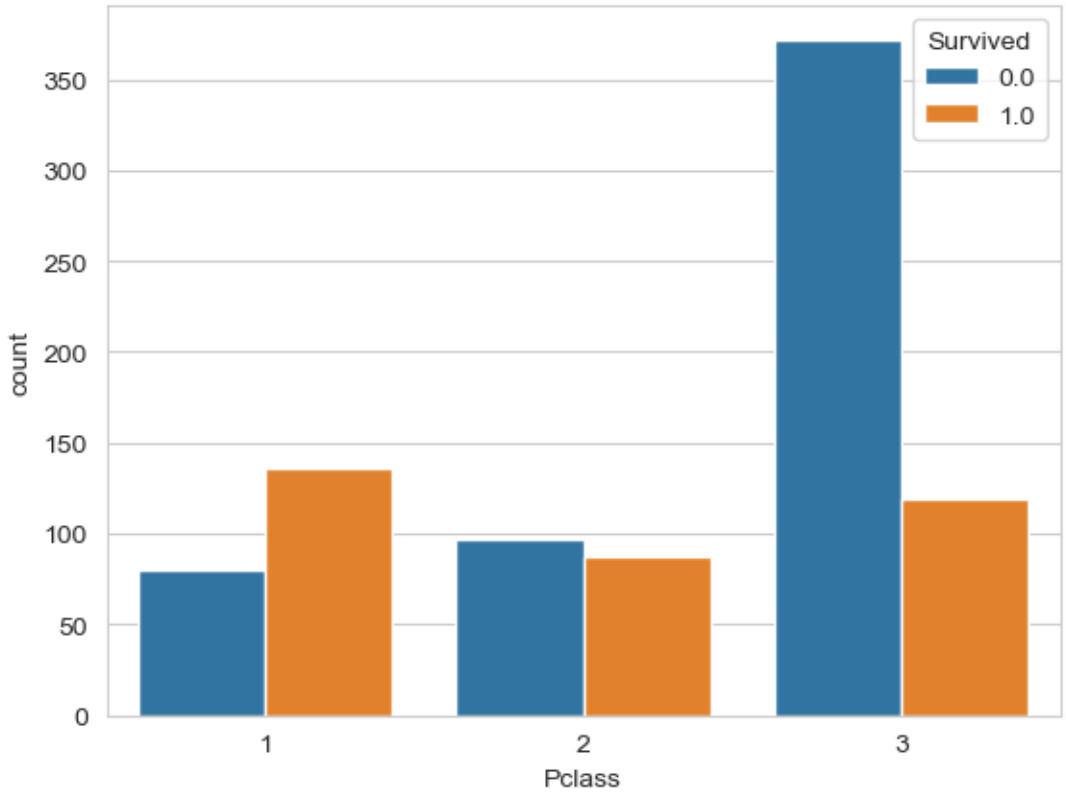
[24]:
```
df["Survived"] = titanic_df["Survived"]
```

1.0.3 Pclass

[25]:
```
titanic_func(titanic_df,'Pclass')
```

```
Quantidade de valores únicos: 3

Quais são os valores únicos: [3 1 2]

Quantidade de valores nulos: 0

Quantidade por opção:
Pclass
3    709
```

```
1    323
2    277
Name: count, dtype: int64
```



[26]:
```
df['Pclass'] = titanic_df['Pclass']
df
```

[26]:

	Survived	Pclass
0	0.0	3
1	1.0	1
2	1.0	3
3	1.0	1
4	0.0	3
…	…	…
1304	NaN	3
1305	NaN	1
1306	NaN	3
1307	NaN	3
1308	NaN	3

[1309 rows x 2 columns]

[27]:
```
titanic_df.head(2)
```

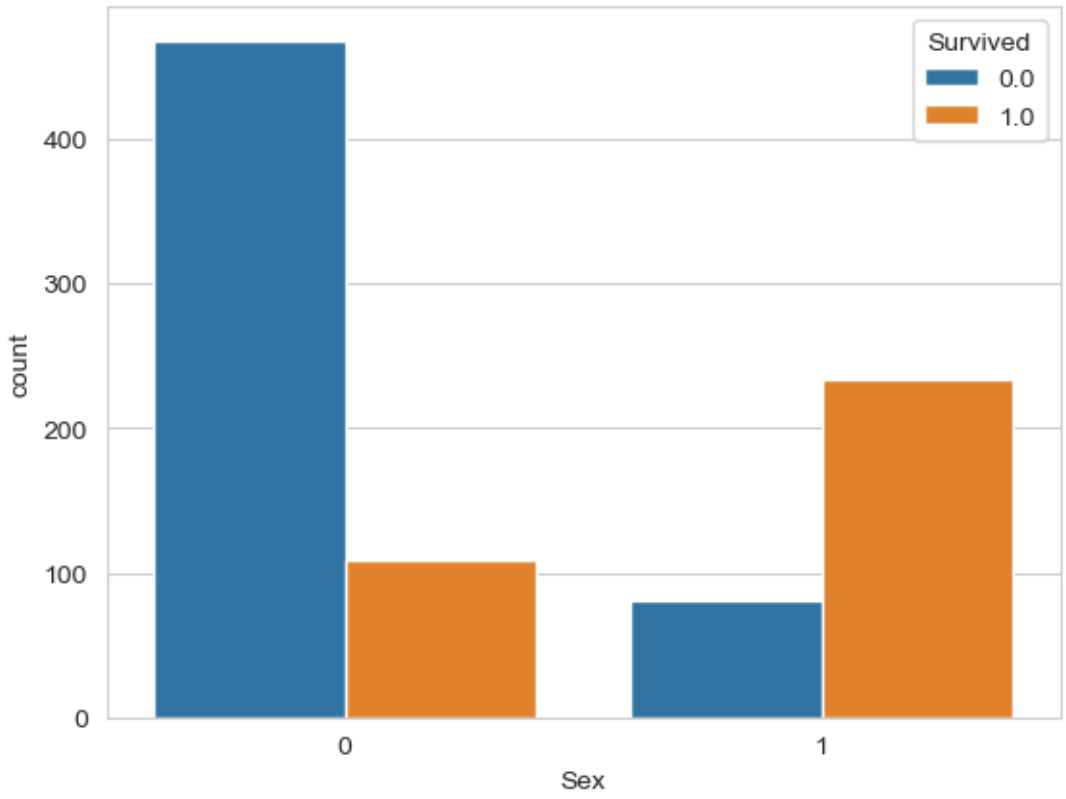
[27]:
```
   PassengerId  Survived  Pclass  \
0            1       0.0       3
1            2       1.0       1

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1

   Parch     Ticket     Fare Cabin Embarked
0      0  A/5 21171   7.2500   NaN        S
1      0   PC 17599  71.2833   C85        C
```

1.0.4 Analisando o Sexo

[ ]:
```
#Convertendo os valores male e female por 0 e 1, respectivamente
#titanic_df['Sex'].map({'female':1, 'male':0})
titanic_df['Sex'] = titanic_df['Sex'].replace(['male','female'],[0,1])
```

[29]:
```
titanic_func(titanic_df,'Sex')
```

```
Quantidade de valores únicos: 2

Quais são os valores únicos: [0 1]

Quantidade de valores nulos: 0

Quantidade por opção:
Sex
0    843
1    466
Name: count, dtype: int64
```



[30]:
```
#Colocando em df a coluna Sex que está no dataframe titanic_df
df['Sex'] = titanic_df['Sex']
df
```

[30]:

	Survived	Pclass	Sex
0	0.0	3	0
1	1.0	1	1
2	1.0	3	1
3	1.0	1	1
4	0.0	3	0
…	…	…	…
1304	NaN	3	0
1305	NaN	1	1
1306	NaN	3	0
1307	NaN	3	0
1308	NaN	3	0

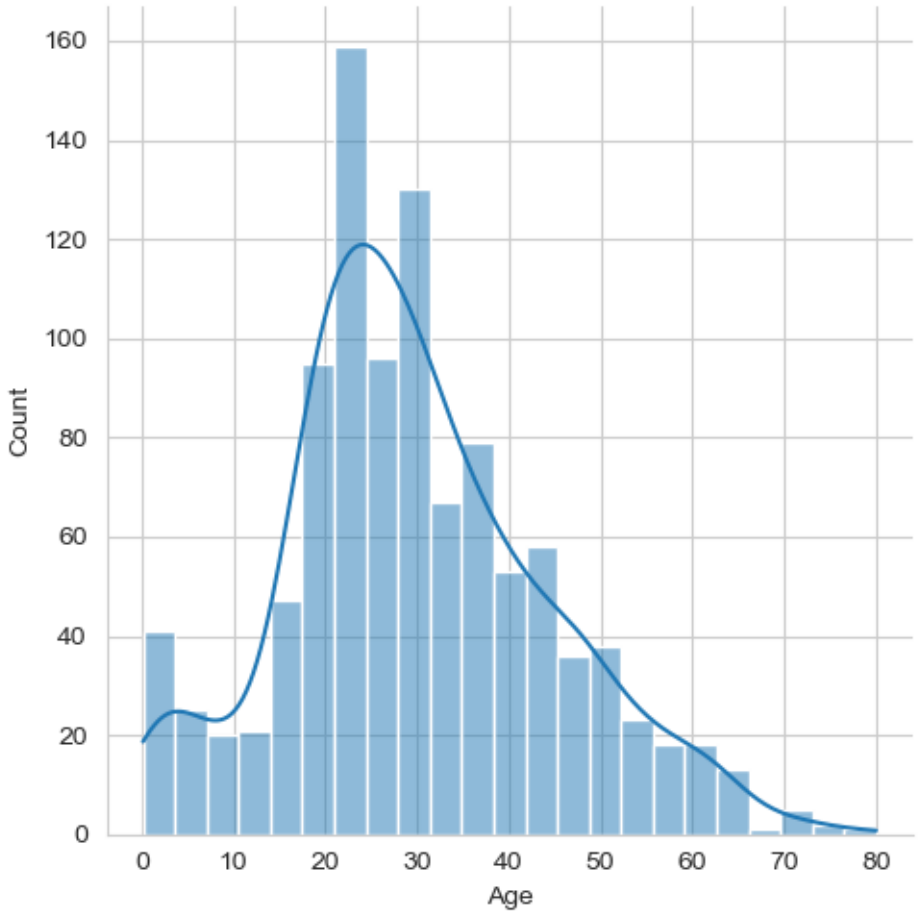
[1309 rows x 3 columns]

[31]:
```
titanic_df.head(2)
```

[31]:
```
   PassengerId  Survived  Pclass  \
0            1       0.0       3
1            2       1.0       1

                                                Name  Sex   Age  SibSp  Parch  \
0                            Braund, Mr. Owen Harris    0  22.0      1      0
1  Cumings, Mrs. John Bradley (Florence Briggs Th…    1  38.0      1      0

      Ticket     Fare Cabin Embarked
0  A/5 21171   7.2500   NaN        S
1   PC 17599  71.2833   C85        C
```

[32]:
```
titanic_func(titanic_df,'Age', False)
```

```
Quantidade de valores únicos: 98

Quais são os valores únicos: [22.   38.   26.   35.     nan 54.    2.   27.
14.    4.   58.   20.
 39.   55.   31.   34.   15.   28.    8.   19.   40.   66.   42.   21.
 18.    3.    7.   49.   29.   65.   28.5   5.   11.   45.   17.   32.
 16.   25.    0.83 30.   33.   23.   24.   46.   59.   71.   37.   47.
 14.5  70.5  32.5  12.    9.   36.5  51.   55.5  40.5  44.    1.   61.
 56.   50.   36.   45.5  20.5  62.   41.   52.   63.   23.5   0.92 43.
 60.   10.   64.   13.   48.    0.75 53.   57.   80.   70.   24.5   6.
  0.67 30.5   0.42 34.5  74.   22.5  18.5  67.   76.   26.5  60.5  11.5
  0.33  0.17 38.5 ]

Quantidade de valores nulos: 263

Quantidade por opção:
Age
24.0    47
22.0    43
21.0    41
30.0    40
18.0    39
        ..
23.5     1
70.5     1
55.5     1
20.5     1
38.5     1
Name: count, Length: 98, dtype: int64
```



[33]:
```
titanic_df['Age'].mean()
```

[33]:
```
29.881137667304014
```

[34]:
```
titanic_df.corr(numeric_only=True)
```

[34]:
```
             PassengerId  Survived    Pclass       Sex       Age     SibSp  \
PassengerId     1.000000 -0.005007 -0.038354 -0.013406  0.028814 -0.055224
Survived       -0.005007  1.000000 -0.338481  0.543351 -0.077221 -0.035322
Pclass         -0.038354 -0.338481  1.000000 -0.124617 -0.408106  0.060832
Sex            -0.013406  0.543351 -0.124617  1.000000 -0.063645  0.109609
Age             0.028814 -0.077221 -0.408106 -0.063645  1.000000 -0.243699
SibSp          -0.055224 -0.035322  0.060832  0.109609 -0.243699  1.000000
Parch           0.008942  0.081629  0.018322  0.213125 -0.150917  0.373587
Fare            0.031428  0.257307 -0.558629  0.185523  0.178740  0.160238

                Parch      Fare
PassengerId  0.008942  0.031428
```

```
Survived     0.081629  0.257307
Pclass       0.018322 -0.558629
Sex          0.213125  0.185523
Age         -0.150917  0.178740
SibSp        0.373587  0.160238
Parch        1.000000  0.221539
Fare         0.221539  1.000000
```

[35]:
```
#Média de idade dos passageiros 1º classe
titanic_df[titanic_df['Pclass'] ==1]['Age'].mean()
```

[35]: 39.15992957746479

[36]:
```
#Média de idade dos passageiros 2º classe
titanic_df[titanic_df['Pclass'] ==2]['Age'].mean()
```

[36]: 29.506704980842912

[37]:
```
#Média de idade dos passageiros 3º classe
titanic_df[titanic_df['Pclass'] ==3]['Age'].mean()
```

[37]: 24.81636726546906

[38]:
```
for i in titanic_df['Pclass'].unique():
    print(f'Pessoas da {i}º classe tem a média de idade de:␣
 ↪{titanic_df[titanic_df["Pclass"] ==i]["Age"].mean():.2f}')
```

```
Pessoas da 3º classe tem a média de idade de: 24.82
Pessoas da 1º classe tem a média de idade de: 39.16
Pessoas da 2º classe tem a média de idade de: 29.51
```

[39]:
```
titanic_df["Age"].isnull().sum()
```

[39]: 263

[40]:
```
pd.isnull(titanic_df['Age'][4])
```

[40]: False

[41]:
```
# Calculando as médias das idades por Pclass uma vez antes do loop
mean_age_pclass_1 = round(titanic_df[titanic_df['Pclass'] == 1]['Age'].mean())
mean_age_pclass_2 = round(titanic_df[titanic_df['Pclass'] == 2]['Age'].mean())
mean_age_pclass_3 = round(titanic_df[titanic_df['Pclass'] == 3]['Age'].mean())

for i in titanic_df.index:
    if pd.isnull(titanic_df['Age'][i]):
        if titanic_df['Pclass'][i] == 1:
```

```
            titanic_df.loc[i, 'Age'] = mean_age_pclass_1  # Usando .loc para␣
↪atribuição
        elif titanic_df['Pclass'][i] == 2:
            titanic_df.loc[i, 'Age'] = mean_age_pclass_2
        elif titanic_df['Pclass'][i] == 3:
            titanic_df.loc[i, 'Age'] = mean_age_pclass_3
```

[42]:
```
#Agora sem valores nulos na idade
titanic_df.isnull().sum()
```

[42]:
```
PassengerId       0
Survived        418
Pclass            0
Name              0
Sex               0
Age               0
SibSp             0
Parch             0
Ticket            0
Fare              1
Cabin          1014
Embarked          2
dtype: int64
```

[43]:
```
df['Age'] = titanic_df['Age']
df
```

[43]:

	Survived	Pclass	Sex	Age
0	0.0	3	0	22.0
1	1.0	1	1	38.0
2	1.0	3	1	26.0
3	1.0	1	1	35.0
4	0.0	3	0	35.0
…	…	…	…	…
1304	NaN	3	0	25.0
1305	NaN	1	1	39.0
1306	NaN	3	0	38.5
1307	NaN	3	0	25.0
1308	NaN	3	0	25.0

[1309 rows x 4 columns]

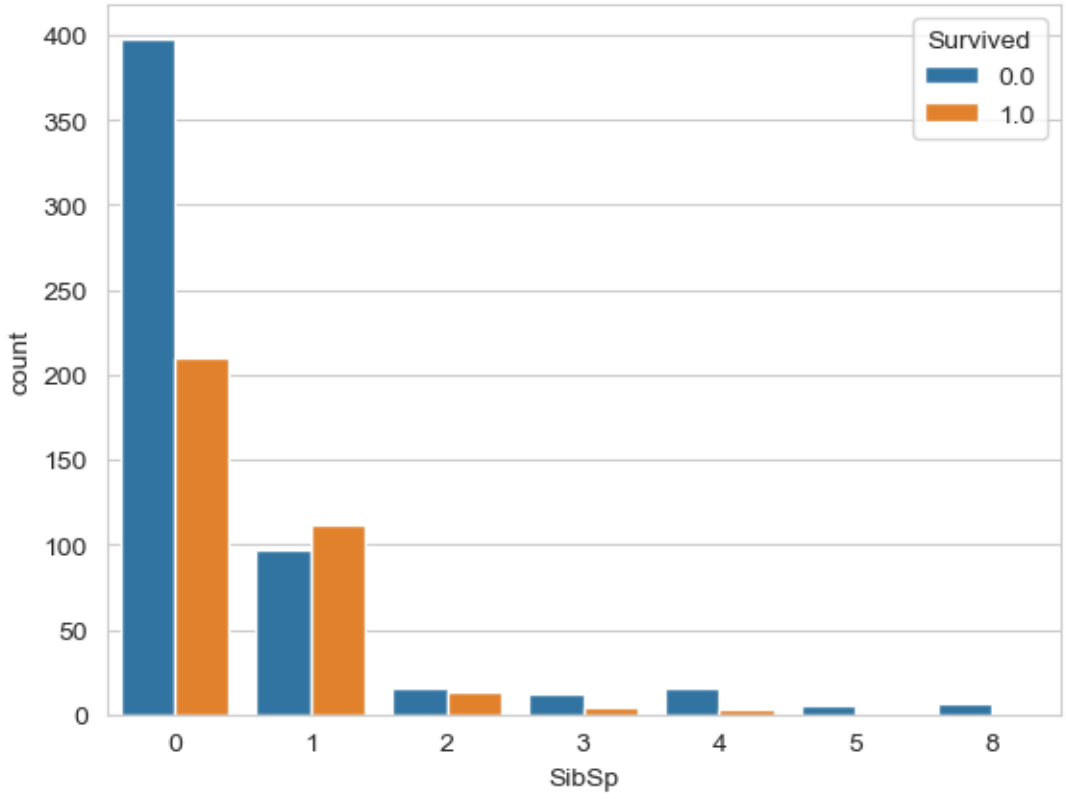
1.0.5 SibSp: O conjunto de dados define as relações familiares desta forma...

Irmão = irmão, irmã, meio-irmão, meia-irmã

Cônjuge = marido, esposa (amantes e noivos foram ignorados)

[44]:
```
titanic_func(titanic_df, 'SibSp')
```

```
Quantidade de valores únicos: 7

Quais são os valores únicos: [1 0 3 4 2 5 8]

Quantidade de valores nulos: 0

Quantidade por opção:
SibSp
0    891
1    319
2     42
4     22
3     20
8      9
5      6
Name: count, dtype: int64
```



[45]:
```
df['SibSp'] = titanic_df['SibSp']
df
```

[45]:

	Survived	Pclass	Sex	Age	SibSp
0	0.0	3	0	22.0	1
1	1.0	1	1	38.0	1
2	1.0	3	1	26.0	0
3	1.0	1	1	35.0	1
4	0.0	3	0	35.0	0
…	…	…	…	…	…
1304	NaN	3	0	25.0	0
1305	NaN	1	1	39.0	0
1306	NaN	3	0	38.5	0
1307	NaN	3	0	25.0	0
1308	NaN	3	0	25.0	1

[1309 rows x 5 columns]

1.0.6 Parch: O conjunto de dados define as relações familiares desta forma...

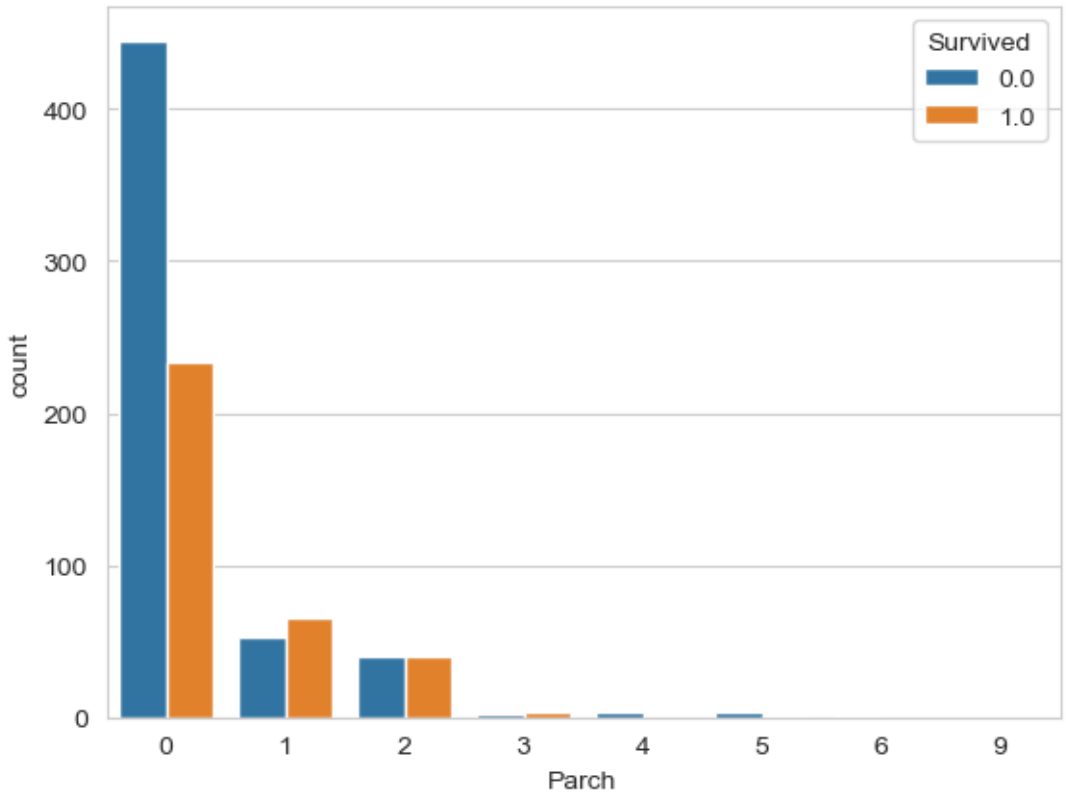
Pai = mãe, pai

Filho = filha, filho, enteada, enteado

Algumas crianças viajaram apenas com uma babá, portanto parch=0 para elas.

[46]:
```
titanic_func(titanic_df, 'Parch')
```

```
Quantidade de valores únicos: 8

Quais são os valores únicos: [0 1 2 5 3 4 6 9]

Quantidade de valores nulos: 0

Quantidade por opção:
Parch
0    1002
1     170
2     113
3       8
5       6
4       6
6       2
9       2
Name: count, dtype: int64
```



1.0.7 FAMILY SIZE

[47]:
```
# Fazendo o tamanho total da família
titanic_df['FamilySize'] = titanic_df['SibSp'] + titanic_df['Parch'] + 1
titanic_df
```

[47]:
```
      PassengerId  Survived  Pclass  \
0               1       0.0       3
1               2       1.0       1
2               3       1.0       3
3               4       1.0       1
4               5       0.0       3
…             …         …       …
1304         1305       NaN       3
1305         1306       NaN       1
1306         1307       NaN       3
1307         1308       NaN       3
1308         1309       NaN       3

                                                 Name  Sex   Age  SibSp  \
0                             Braund, Mr. Owen Harris    0  22.0      1
```

```
1     Cumings, Mrs. John Bradley (Florence Briggs Th…    1  38.0      1
2                                Heikkinen, Miss. Laina    1  26.0      0
3          Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  35.0      1
4                              Allen, Mr. William Henry    0  35.0      0
…                                                    …  …    …    …
1304                                 Spector, Mr. Woolf    0  25.0      0
1305                       Oliva y Ocana, Dona. Fermina    1  39.0      0
1306                       Saether, Mr. Simon Sivertsen    0  38.5      0
1307                                Ware, Mr. Frederick    0  25.0      0
1308                            Peter, Master. Michael J    0  25.0      1

      Parch              Ticket      Fare Cabin Embarked  FamilySize
0         0           A/5 21171    7.2500   NaN        S           2
1         0            PC 17599   71.2833   C85        C           2
2         0    STON/O2. 3101282    7.9250   NaN        S           1
3         0              113803   53.1000  C123        S           2
4         0              373450    8.0500   NaN        S           1
…     …                   …       …   …      …          …
1304      0           A.5. 3236    8.0500   NaN        S           1
1305      0            PC 17758  108.9000  C105        C           1
1306      0  SOTON/O.Q. 3101262    7.2500   NaN        S           1
1307      0              359309    8.0500   NaN        S           1
1308      1                2668   22.3583   NaN        C           3

[1309 rows x 13 columns]
```

[48]:
```
# Colocando no novo dataframe df a coluna tamanho da família
df['FamilySize'] = titanic_df['FamilySize']
df
```

[48]:
```
      Survived  Pclass  Sex   Age  SibSp  FamilySize
0          0.0       3    0  22.0      1           2
1          1.0       1    1  38.0      1           2
2          1.0       3    1  26.0      0           1
3          1.0       1    1  35.0      1           2
4          0.0       3    0  35.0      0           1
…          …     …  …   …    …          …
1304       NaN       3    0  25.0      0           1
1305       NaN       1    1  39.0      0           1
1306       NaN       3    0  38.5      0           1
1307       NaN       3    0  25.0      0           1
1308       NaN       3    0  25.0      1           3

[1309 rows x 6 columns]
```

[49]:
```
titanic_df.head(10)
```

[49]:

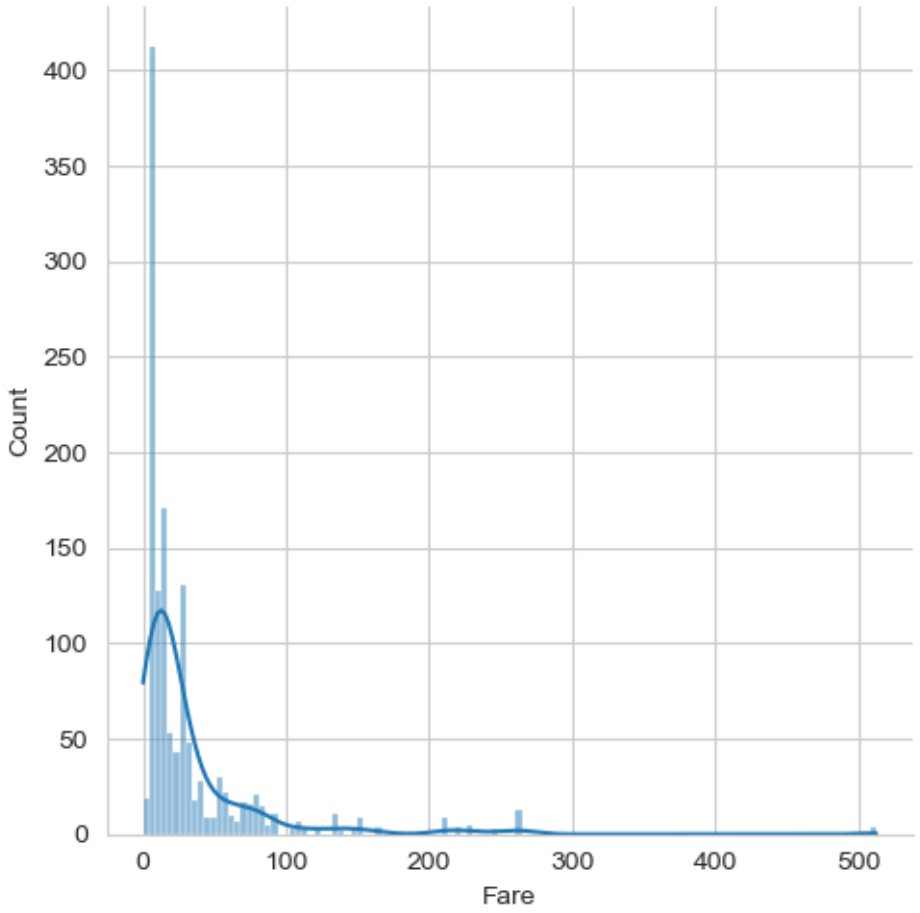
	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	FamilySize
0	1	0.0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	NaN	S	2
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th…	1	38.0	1	0	PC 17599	71.2833	C85	C	2
2	3	1.0	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S	1
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	C123	S	2
4	5	0.0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	NaN	S	1
5	6	0.0	3	Moran, Mr. James	0	25.0	0	0	330877	8.4583	NaN	Q	1
6	7	0.0	1	McCarthy, Mr. Timothy J	0	54.0	0	0	17463	51.8625	E46	S	1
7	8	0.0	3	Palsson, Master. Gosta Leonard	0	2.0	3	1	349909	21.0750	NaN	S	5
8	9	1.0	3	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	1	27.0	0	2	347742	11.1333	NaN	S	3
9	10	1.0	2	Nasser, Mrs. Nicholas (Adele Achem)	1	14.0	1	0	237736	30.0708	NaN	C	2

1.0.8 Fare: Tarifas dos passageiros

[50]:
```
titanic_func(titanic_df, 'Fare', False)
```

```
Quantidade de valores únicos: 281

Quais são os valores únicos: [  7.25    71.2833   7.925   53.1      8.05
8.4583  51.8625  21.075
  11.1333  30.0708  16.7     26.55    31.275    7.8542  16.      29.125
  13.      18.       7.225   26.       8.0292  35.5     31.3875 263.
   7.8792   7.8958  27.7208 146.5208   7.75    10.5     82.1708  52.
   7.2292  11.2417   9.475   21.      41.5792  15.5     21.6792  17.8
```

```
  39.6875   7.8     76.7292  61.9792  27.75    46.9     80.      83.475
  27.9     15.2458   8.1583   8.6625  73.5     14.4542  56.4958   7.65
  29.      12.475    9.       9.5      7.7875  47.1     15.85    34.375
  61.175   20.575   34.6542  63.3583  23.      77.2875   8.6542   7.775
  24.15     9.825   14.4583 247.5208   7.1417  22.3583   6.975    7.05
  14.5     15.0458  26.2833   9.2167  79.2      6.75    11.5     36.75
   7.7958  12.525   66.6      7.3125  61.3792   7.7333  69.55    16.1
  15.75    20.525   55.      25.925   33.5     30.6958  25.4667  28.7125
   0.      15.05    39.      22.025   50.       8.4042   6.4958  10.4625
  18.7875  31.     113.275   27.      76.2917  90.       9.35    13.5
   7.55    26.25    12.275    7.125   52.5542  20.2125  86.5    512.3292
  79.65   153.4625 135.6333  19.5     29.7     77.9583  20.25    78.85
  91.0792  12.875    8.85   151.55    30.5     23.25    12.35   110.8833
 108.9     24.      56.9292  83.1583 262.375   14.     164.8667 134.5
   6.2375  57.9792  28.5    133.65    15.9      9.225   35.      75.25
  69.3     55.4417 211.5      4.0125 227.525   15.7417   7.7292  12.
 120.      12.65    18.75     6.8583  32.5      7.875   14.4     55.9
   8.1125  81.8583  19.2583  19.9667  89.1042  38.5      7.725   13.7917
   9.8375   7.0458   7.5208  12.2875   9.5875  49.5042  78.2667  15.1
   7.6292  22.525   26.2875  59.4      7.4958  34.0208  93.5    221.7792
 106.425   49.5     71.      13.8625   7.8292  39.6     17.4     51.4792
  26.3875  30.      40.125    8.7125  15.      33.      42.4     15.55
  65.      32.3208   7.0542   8.4333  25.5875   9.8417   8.1375  10.1708
 211.3375  57.      13.4167   7.7417   9.4833   7.7375   8.3625  23.45
  25.9292   8.6833   8.5167   7.8875  37.0042   6.45     6.95     8.3
   6.4375  39.4     14.1083  13.8583  50.4958   5.       9.8458  10.5167
   7.       9.6875  82.2667   3.1708  31.6833  31.5     57.75     7.85
  60.      15.0333  15.5792  28.5375  25.7     10.7083  13.9      7.8208
   7.7792  31.6792   7.2833  75.2417      nan  12.1833  13.775    8.9625
  25.7417  42.5     27.4458 136.7792   9.325   12.7375  45.5      7.575
   7.5792   7.7208]

Quantidade de valores nulos: 1

Quantidade por opção:
Fare
8.0500     60
13.0000    59
7.7500     55
26.0000    50
7.8958     49
           ..
7.7417      1
8.1583      1
8.4583      1
7.8000      1
7.7208      1
Name: count, Length: 281, dtype: int64
```



[51]:
```
titanic_df[titanic_df['Fare'].isnull()]
```

[51]:
```
      PassengerId  Survived  Pclass                Name  Sex   Age  SibSp  \
1043         1044       NaN       3  Storey, Mr. Thomas    0  60.5      0

      Parch Ticket  Fare Cabin Embarked  FamilySize
1043      0   3701   NaN   NaN        S           1
```

[52]:
```
titanic_df[titanic_df['Pclass']==3]['Fare'].mean()
```

[52]:
```
13.302888700564973
```

[ ]:
```
#Substituindo os valores nulos pela média da classe 3
titanic_df['Fare'].fillna(titanic_df[titanic_df['Pclass']==3]['Fare'].
 ↪mean(),inplace = True)
```

[54]:
```
# Conferindo os valores nulos
titanic_df.isnull().sum()
```

[54]:
```
PassengerId       0
Survived        418
Pclass            0
Name              0
Sex               0
Age               0
SibSp             0
Parch             0
Ticket            0
Fare              0
Cabin          1014
Embarked          2
FamilySize        0
dtype: int64
```

1.0.9 Cabin : Número de cabines

[55]:
```
titanic_df['Cabin'].isnull().sum()
```

[55]:
```
1014
```

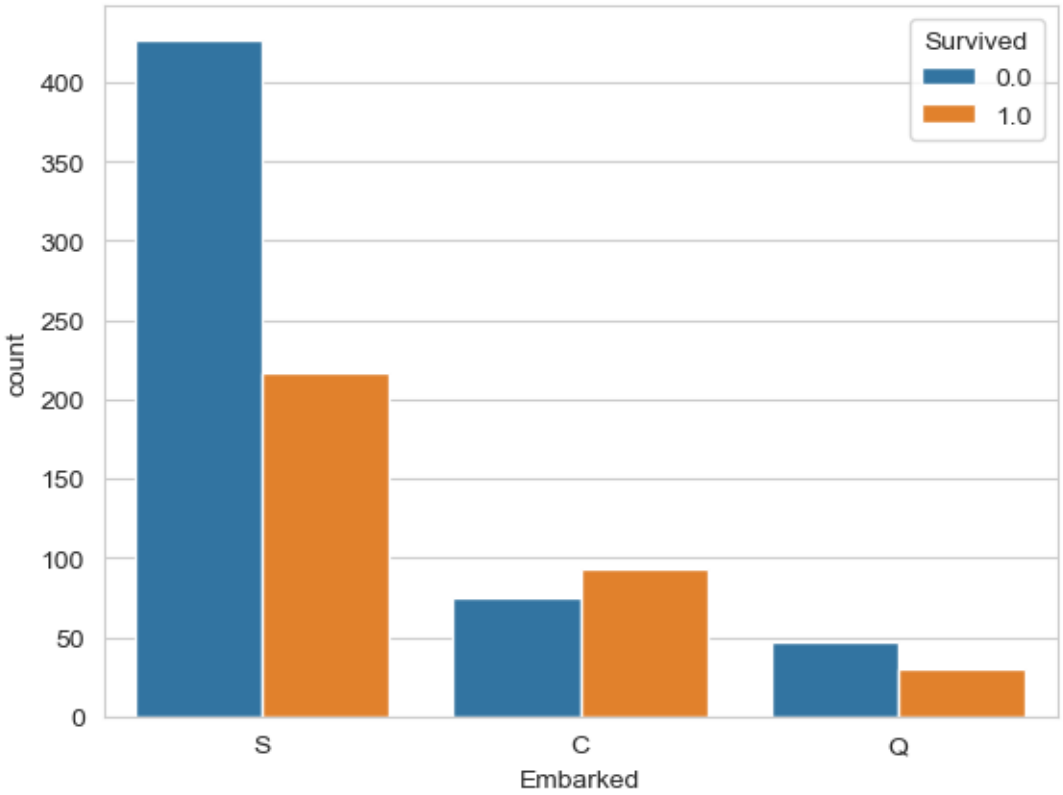
[56]:
```
titanic_df['Cabin'].unique()
```

[56]:
```
array([nan, 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'B28', 'C83', 'F33',
       'F G73', 'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101',
       'F E69', 'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4',
       'A32', 'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35',
       'C87', 'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19',
       'B49', 'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54',
       'B57 B59 B63 B66', 'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40',
       'T', 'C128', 'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44',
       'A34', 'C104', 'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14',
       'B37', 'C30', 'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38',
       'B39', 'B22', 'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68',
       'B41', 'A20', 'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48',
       'E58', 'C126', 'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63',
       'C62 C64', 'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30',
       'E121', 'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36',
       'B102', 'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42',
       'C148', 'B45', 'B36', 'A21', 'D34', 'A9', 'C31', 'B61', 'C53',
       'D43', 'C130', 'C132', 'C55 C57', 'C116', 'F', 'A29', 'C6', 'C28',
       'C51', 'C97', 'D22', 'B10', 'E45', 'E52', 'A11', 'B11', 'C80',
       'C89', 'F E46', 'B26', 'F E57', 'A18', 'E60', 'E39 E41',
       'B52 B54 B56', 'C39', 'B24', 'D40', 'D38', 'C105'], dtype=object)
```

1.0.10 Embaked: Ponto de embarque

[57]:
```
titanic_func(titanic_df, "Embarked")
```

```
Quantidade de valores únicos: 3

Quais são os valores únicos: ['S' 'C' 'Q' nan]

Quantidade de valores nulos: 2

Quantidade por opção:
Embarked
S    914
C    270
Q    123
Name: count, dtype: int64
```



[58]:
```
#33% das pessoas que passaram no portão S sobreviveram
titanic_df[titanic_df['Embarked'] == 'S']['Survived'].mean()
```

[58]: 0.33695652173913043

[59]:
```
#55% das pessoas que passaram no portão C sobreviveram
titanic_df[titanic_df['Embarked'] == 'C']['Survived'].mean()
```

[59]:
```
0.5535714285714286
```

[60]:
```
#38% das pessoas que passaram no portão Q sobreviveram
titanic_df[titanic_df['Embarked'] == 'Q']['Survived'].mean()
```

[60]:
```
0.38961038961038963
```

[61]:
```
#classe das pessoas que passaram no portão S sobreviveram
titanic_df[titanic_df['Embarked'] == 'S']['Pclass'].mean()
```

[61]:
```
2.3479212253829322
```

[62]:
```
#classe das pessoas que passaram no portão C sobreviveram
titanic_df[titanic_df['Embarked'] == 'C']['Pclass'].mean()
```

[62]:
```
1.8518518518518519
```

[63]:
```
#classe das pessoas que passaram no portão Q sobreviveram
titanic_df[titanic_df['Embarked'] == 'Q']['Pclass'].mean()
```

[63]:
```
2.894308943089431
```

[64]:
```
titanic_df[titanic_df['Embarked'].isnull()]
```

[64]:
```
     PassengerId  Survived  Pclass                                      Name  \
61            62       1.0       1                       Icard, Miss. Amelie
829          830       1.0       1  Stone, Mrs. George Nelson (Martha Evelyn)

     Sex   Age  SibSp  Parch  Ticket  Fare Cabin Embarked  FamilySize
61     1  38.0      0      0  113572  80.0   B28      NaN           1
829    1  62.0      0      0  113572  80.0   B28      NaN           1
```

[ ]:
```
# Preenchendo os valores nulos como se tivessem passado pelo portão C.
titanic_df['Embarked'].fillna("C", inplace=True)
```

[66]:
```
#Conferindo que completou-se os valores nulos
titanic_df.isnull().sum()
```

[66]:
```
PassengerId       0
Survived        418
Pclass            0
Name              0
Sex               0
Age               0
SibSp             0
```

```
Parch             0
Ticket            0
Fare              0
Cabin          1014
Embarked          0
FamilySize        0
dtype: int64
```

[67]:
```
df['Embarked'] = titanic_df['Embarked']
df
```

[67]:

	Survived	Pclass	Sex	Age	SibSp	FamilySize	Embarked
0	0.0	3	0	22.0	1	2	S
1	1.0	1	1	38.0	1	2	C
2	1.0	3	1	26.0	0	1	S
3	1.0	1	1	35.0	1	2	S
4	0.0	3	0	35.0	0	1	S
…	…	…	…	…	…	…	…
1304	NaN	3	0	25.0	0	1	S
1305	NaN	1	1	39.0	0	1	C
1306	NaN	3	0	38.5	0	1	S
1307	NaN	3	0	25.0	0	1	S
1308	NaN	3	0	25.0	1	3	C

[1309 rows x 7 columns]

[68]:
```
titanic_df.head(50)
```

[68]:

	PassengerId	Survived	Pclass	\
0	1	0.0	3	
1	2	1.0	1	
2	3	1.0	3	
3	4	1.0	1	
4	5	0.0	3	
5	6	0.0	3	
6	7	0.0	1	
7	8	0.0	3	
8	9	1.0	3	
9	10	1.0	2	
10	11	1.0	3	
11	12	1.0	1	
12	13	0.0	3	
13	14	0.0	3	
14	15	0.0	3	
15	16	1.0	2	
16	17	0.0	3	
17	18	1.0	2	

18	19	0.0	3
19	20	1.0	3
20	21	0.0	2
21	22	1.0	2
22	23	1.0	3
23	24	1.0	1
24	25	0.0	3
25	26	1.0	3
26	27	0.0	3
27	28	0.0	1
28	29	1.0	3
29	30	0.0	3
30	31	0.0	1
31	32	1.0	1
32	33	1.0	3
33	34	0.0	2
34	35	0.0	1
35	36	0.0	1
36	37	1.0	3
37	38	0.0	3
38	39	0.0	3
39	40	1.0	3
40	41	0.0	3
41	42	0.0	2
42	43	0.0	3
43	44	1.0	2
44	45	1.0	3
45	46	0.0	3
46	47	0.0	3
47	48	1.0	3
48	49	0.0	3
49	50	0.0	3

	Name	Sex	Age	SibSp	\
0	Braund, Mr. Owen Harris	0	22.0	1	
1	Cumings, Mrs. John Bradley (Florence Briggs Th…	1	38.0	1	
2	Heikkinen, Miss. Laina	1	26.0	0	
3	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	
4	Allen, Mr. William Henry	0	35.0	0	
5	Moran, Mr. James	0	25.0	0	
6	McCarthy, Mr. Timothy J	0	54.0	0	
7	Palsson, Master. Gosta Leonard	0	2.0	3	
8	Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)	1	27.0	0	
9	Nasser, Mrs. Nicholas (Adele Achem)	1	14.0	1	
10	Sandstrom, Miss. Marguerite Rut	1	4.0	1	
11	Bonnell, Miss. Elizabeth	1	58.0	0	
12	Saundercock, Mr. William Henry	0	20.0	0	

13	Andersson, Mr. Anders Johan	0	39.0	1			
14	Vestrom, Miss. Hulda Amanda Adolfina	1	14.0	0			
15	Hewlett, Mrs. (Mary D Kingcome)	1	55.0	0			
16	Rice, Master. Eugene	0	2.0	4			
17	Williams, Mr. Charles Eugene	0	30.0	0			
18	Vander Planke, Mrs. Julius (Emelia Maria Vande…	1	31.0	1			
19	Masselmani, Mrs. Fatima	1	25.0	0			
20	Fynney, Mr. Joseph J	0	35.0	0			
21	Beesley, Mr. Lawrence	0	34.0	0			
22	McGowan, Miss. Anna "Annie"	1	15.0	0			
23	Sloper, Mr. William Thompson	0	28.0	0			
24	Palsson, Miss. Torborg Danira	1	8.0	3			
25	Asplund, Mrs. Carl Oscar (Selma Augusta Emilia…	1	38.0	1			
26	Emir, Mr. Farred Chehab	0	25.0	0			
27	Fortune, Mr. Charles Alexander	0	19.0	3			
28	O'Dwyer, Miss. Ellen "Nellie"	1	25.0	0			
29	Todoroff, Mr. Lalio	0	25.0	0			
30	Uruchurtu, Don. Manuel E	0	40.0	0			
31	Spencer, Mrs. William Augustus (Marie Eugenie)	1	39.0	1			
32	Glynn, Miss. Mary Agatha	1	25.0	0			
33	Wheadon, Mr. Edward H	0	66.0	0			
34	Meyer, Mr. Edgar Joseph	0	28.0	1			
35	Holverson, Mr. Alexander Oskar	0	42.0	1			
36	Mamee, Mr. Hanna	0	25.0	0			
37	Cann, Mr. Ernest Charles	0	21.0	0			
38	Vander Planke, Miss. Augusta Maria	1	18.0	2			
39	Nicola-Yarred, Miss. Jamila	1	14.0	1			
40	Ahlin, Mrs. Johan (Johanna Persdotter Larsson)	1	40.0	1			
41	Turpin, Mrs. William John Robert (Dorothy Ann …	1	27.0	1			
42	Kraeff, Mr. Theodor	0	25.0	0			
43	Laroche, Miss. Simonne Marie Anne Andree	1	3.0	1			
44	Devaney, Miss. Margaret Delia	1	19.0	0			
45	Rogers, Mr. William John	0	25.0	0			
46	Lennon, Mr. Denis	0	25.0	1			
47	O'Driscoll, Miss. Bridget	1	25.0	0			
48	Samaan, Mr. Youssef	0	25.0	2			
49	Arnold-Franchi, Mrs. Josef (Josefine Franchi)	1	18.0	1			

	Parch	Ticket	Fare	Cabin	Embarked	FamilySize
0	0	A/5 21171	7.2500	NaN	S	2
1	0	PC 17599	71.2833	C85	C	2
2	0	STON/O2. 3101282	7.9250	NaN	S	1
3	0	113803	53.1000	C123	S	2
4	0	373450	8.0500	NaN	S	1
5	0	330877	8.4583	NaN	Q	1
6	0	17463	51.8625	E46	S	1
7	1	349909	21.0750	NaN	S	5

8	2	347742	11.1333	NaN	S	3
9	0	237736	30.0708	NaN	C	2
10	1	PP 9549	16.7000	G6	S	3
11	0	113783	26.5500	C103	S	1
12	0	A/5. 2151	8.0500	NaN	S	1
13	5	347082	31.2750	NaN	S	7
14	0	350406	7.8542	NaN	S	1
15	0	248706	16.0000	NaN	S	1
16	1	382652	29.1250	NaN	Q	6
17	0	244373	13.0000	NaN	S	1
18	0	345763	18.0000	NaN	S	2
19	0	2649	7.2250	NaN	C	1
20	0	239865	26.0000	NaN	S	1
21	0	248698	13.0000	D56	S	1
22	0	330923	8.0292	NaN	Q	1
23	0	113788	35.5000	A6	S	1
24	1	349909	21.0750	NaN	S	5
25	5	347077	31.3875	NaN	S	7
26	0	2631	7.2250	NaN	C	1
27	2	19950	263.0000	C23 C25 C27	S	6
28	0	330959	7.8792	NaN	Q	1
29	0	349216	7.8958	NaN	S	1
30	0	PC 17601	27.7208	NaN	C	1
31	0	PC 17569	146.5208	B78	C	2
32	0	335677	7.7500	NaN	Q	1
33	0	C.A. 24579	10.5000	NaN	S	1
34	0	PC 17604	82.1708	NaN	C	2
35	0	113789	52.0000	NaN	S	2
36	0	2677	7.2292	NaN	C	1
37	0	A./5. 2152	8.0500	NaN	S	1
38	0	345764	18.0000	NaN	S	3
39	0	2651	11.2417	NaN	C	2
40	0	7546	9.4750	NaN	S	2
41	0	11668	21.0000	NaN	S	2
42	0	349253	7.8958	NaN	C	1
43	2	SC/Paris 2123	41.5792	NaN	C	4
44	0	330958	7.8792	NaN	Q	1
45	0	S.C./A.4. 23567	8.0500	NaN	S	1
46	0	370371	15.5000	NaN	Q	2
47	0	14311	7.7500	NaN	Q	1
48	0	2662	21.6792	NaN	C	3
49	0	349237	17.8000	NaN	S	2

1.0.11 Name

[69]:
```
titanic_df['Name']
```

[69]:
```
0                                  Braund, Mr. Owen Harris
1        Cumings, Mrs. John Bradley (Florence Briggs Th…
2                                   Heikkinen, Miss. Laina
3             Futrelle, Mrs. Jacques Heath (Lily May Peel)
4                                 Allen, Mr. William Henry
                                 …
1304                                    Spector, Mr. Woolf
1305                          Oliva y Ocana, Dona. Fermina
1306                          Saether, Mr. Simon Sivertsen
1307                                   Ware, Mr. Frederick
1308                              Peter, Master. Michael J
Name: Name, Length: 1309, dtype: object
```

[70]:
```
#Captando as siglas dos nomes (Mr, Mrs, Miss, etc...)
#[titanic_df['Name'][n].split(',')[1].split('.')[0].strip() for n in titanic_df.
 ↪index]
titanic_df['Title'] = titanic_df["Name"].apply(lambda name: name.split(',')[1].
 ↪split('.')[0].strip())
```

[148]:
```
titanic_df
```

[148]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp
0	1	0.0	3	Braund, Mr. Owen Harris	0	22.0	1
1	2	1.0	1	Cumings, Mrs. John Bradley (Florence Briggs Th…	1	38.0	1
2	3	1.0	3	Heikkinen, Miss. Laina	1	26.0	0
3	4	1.0	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1
4	5	0.0	3	Allen, Mr. William Henry	0	35.0	0
…	…	…	…	…	…	…	…
1304	1305	NaN	3	Spector, Mr. Woolf	0	25.0	0
1305	1306	NaN	1	Oliva y Ocana, Dona. Fermina	1	39.0	0
1306	1307	NaN	3	Saether, Mr. Simon Sivertsen	0	38.5	0
1307	1308	NaN	3	Ware, Mr. Frederick	0	25.0	0
1308	1309	NaN	3	Peter, Master. Michael J	0	25.0	1

```
      Parch             Ticket      Fare Cabin Embarked  FamilySize   Title
0         0          A/5 21171    7.2500   NaN        S           2      Mr
1         0           PC 17599   71.2833   C85        C           2     Mrs
2         0  STON/O2. 3101282    7.9250   NaN        S           1    Miss
3         0             113803   53.1000  C123        S           2     Mrs
4         0             373450    8.0500   NaN        S           1      Mr
…     …                 …       …   …      …          …     …
1304      0          A.5. 3236    8.0500   NaN        S           1      Mr
1305      0           PC 17758  108.9000  C105        C           1  Person
1306      0  SOTON/O.Q. 3101262    7.2500   NaN        S           1      Mr
1307      0             359309    8.0500   NaN        S           1      Mr
1308      1               2668   22.3583   NaN        C           3  Master

[1309 rows x 14 columns]
```

[149]:
```
titanic_df['Title'].nunique()
```

[149]:
```
5
```

[150]:
```
titanic_df['Title'].unique()
```

[150]:
```
array(['Mr', 'Mrs', 'Miss', 'Master', 'Person'], dtype=object)
```

[74]:
```
titanic_df['Title'].value_counts()
```

[74]:
```
Title
Mr              757
Miss            260
Mrs             197
Master           61
Rev               8
Dr                8
Col               4
Mlle              2
Major             2
Ms                2
Lady              1
Sir               1
Mme               1
Don               1
Capt              1
the Countess      1
Jonkheer          1
Dona              1
Name: count, dtype: int64
```

[81]:
```
# Fazendo um List comprehension - Substituindo os Titulos a partir de Rev. para␣
↪baixo em 'Person' para simplificação.
titanic_df['Title'] = [n if n in ['Mr','Miss', 'Mrs', 'Master'] else 'Person'␣
↪for n in titanic_df['Title']]
```

[82]:
```
titanic_df.head(50)
```

[82]:

	PassengerId	Survived	Pclass	\
0	1	0.0	3	
1	2	1.0	1	
2	3	1.0	3	
3	4	1.0	1	
4	5	0.0	3	
5	6	0.0	3	
6	7	0.0	1	
7	8	0.0	3	
8	9	1.0	3	
9	10	1.0	2	
10	11	1.0	3	
11	12	1.0	1	
12	13	0.0	3	
13	14	0.0	3	
14	15	0.0	3	
15	16	1.0	2	
16	17	0.0	3	
17	18	1.0	2	
18	19	0.0	3	
19	20	1.0	3	
20	21	0.0	2	
21	22	1.0	2	
22	23	1.0	3	
23	24	1.0	1	
24	25	0.0	3	
25	26	1.0	3	
26	27	0.0	3	
27	28	0.0	1	
28	29	1.0	3	
29	30	0.0	3	
30	31	0.0	1	
31	32	1.0	1	
32	33	1.0	3	
33	34	0.0	2	
34	35	0.0	1	
35	36	0.0	1	
36	37	1.0	3	
37	38	0.0	3	
38	39	0.0	3	

```
39           40       1.0       3
40           41       0.0       3
41           42       0.0       2
42           43       0.0       3
43           44       1.0       2
44           45       1.0       3
45           46       0.0       3
46           47       0.0       3
47           48       1.0       3
48           49       0.0       3
49           50       0.0       3

                                                 Name  Sex   Age  SibSp  \
0                             Braund, Mr. Owen Harris    0  22.0      1
1   Cumings, Mrs. John Bradley (Florence Briggs Th…    1  38.0      1
2                              Heikkinen, Miss. Laina    1  26.0      0
3        Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  35.0      1
4                            Allen, Mr. William Henry    0  35.0      0
5                                    Moran, Mr. James    0  25.0      0
6                             McCarthy, Mr. Timothy J    0  54.0      0
7                      Palsson, Master. Gosta Leonard    0   2.0      3
8   Johnson, Mrs. Oscar W (Elisabeth Vilhelmina Berg)    1  27.0      0
9                 Nasser, Mrs. Nicholas (Adele Achem)    1  14.0      1
10                    Sandstrom, Miss. Marguerite Rut    1   4.0      1
11                           Bonnell, Miss. Elizabeth    1  58.0      0
12                     Saundercock, Mr. William Henry    0  20.0      0
13                        Andersson, Mr. Anders Johan    0  39.0      1
14               Vestrom, Miss. Hulda Amanda Adolfina    1  14.0      0
15                   Hewlett, Mrs. (Mary D Kingcome)     1  55.0      0
16                               Rice, Master. Eugene    0   2.0      4
17                       Williams, Mr. Charles Eugene    0  30.0      0
18  Vander Planke, Mrs. Julius (Emelia Maria Vande…    1  31.0      1
19                            Masselmani, Mrs. Fatima    1  25.0      0
20                               Fynney, Mr. Joseph J    0  35.0      0
21                              Beesley, Mr. Lawrence    0  34.0      0
22                        McGowan, Miss. Anna "Annie"    1  15.0      0
23                       Sloper, Mr. William Thompson    0  28.0      0
24                      Palsson, Miss. Torborg Danira    1   8.0      3
25  Asplund, Mrs. Carl Oscar (Selma Augusta Emilia…    1  38.0      1
26                              Emir, Mr. Farred Chehab    0  25.0      0
27                      Fortune, Mr. Charles Alexander    0  19.0      3
28                       O'Dwyer, Miss. Ellen "Nellie"    1  25.0      0
29                                Todoroff, Mr. Lalio    0  25.0      0
30                             Uruchurtu, Don. Manuel E    0  40.0      0
31     Spencer, Mrs. William Augustus (Marie Eugenie)    1  39.0      1
32                             Glynn, Miss. Mary Agatha    1  25.0      0
33                                Wheadon, Mr. Edward H    0  66.0      0
```

34		Meyer, Mr. Edgar Joseph	0	28.0	1			
35		Holverson, Mr. Alexander Oskar	0	42.0	1			
36		Mamee, Mr. Hanna	0	25.0	0			
37		Cann, Mr. Ernest Charles	0	21.0	0			
38		Vander Planke, Miss. Augusta Maria	1	18.0	2			
39		Nicola-Yarred, Miss. Jamila	1	14.0	1			
40		Ahlin, Mrs. Johan (Johanna Persdotter Larsson)	1	40.0	1			
41		Turpin, Mrs. William John Robert (Dorothy Ann …	1	27.0	1			
42		Kraeff, Mr. Theodor	0	25.0	0			
43		Laroche, Miss. Simonne Marie Anne Andree	1	3.0	1			
44		Devaney, Miss. Margaret Delia	1	19.0	0			
45		Rogers, Mr. William John	0	25.0	0			
46		Lennon, Mr. Denis	0	25.0	1			
47		O'Driscoll, Miss. Bridget	1	25.0	0			
48		Samaan, Mr. Youssef	0	25.0	2			
49		Arnold-Franchi, Mrs. Josef (Josefine Franchi)	1	18.0	1			

	Parch	Ticket	Fare	Cabin	Embarked	FamilySize	\
0	0	A/5 21171	7.2500	NaN	S	2	
1	0	PC 17599	71.2833	C85	C	2	
2	0	STON/O2. 3101282	7.9250	NaN	S	1	
3	0	113803	53.1000	C123	S	2	
4	0	373450	8.0500	NaN	S	1	
5	0	330877	8.4583	NaN	Q	1	
6	0	17463	51.8625	E46	S	1	
7	1	349909	21.0750	NaN	S	5	
8	2	347742	11.1333	NaN	S	3	
9	0	237736	30.0708	NaN	C	2	
10	1	PP 9549	16.7000	G6	S	3	
11	0	113783	26.5500	C103	S	1	
12	0	A/5. 2151	8.0500	NaN	S	1	
13	5	347082	31.2750	NaN	S	7	
14	0	350406	7.8542	NaN	S	1	
15	0	248706	16.0000	NaN	S	1	
16	1	382652	29.1250	NaN	Q	6	
17	0	244373	13.0000	NaN	S	1	
18	0	345763	18.0000	NaN	S	2	
19	0	2649	7.2250	NaN	C	1	
20	0	239865	26.0000	NaN	S	1	
21	0	248698	13.0000	D56	S	1	
22	0	330923	8.0292	NaN	Q	1	
23	0	113788	35.5000	A6	S	1	
24	1	349909	21.0750	NaN	S	5	
25	5	347077	31.3875	NaN	S	7	
26	0	2631	7.2250	NaN	C	1	
27	2	19950	263.0000	C23 C25 C27	S	6	
28	0	330959	7.8792	NaN	Q	1	

29	0	349216	7.8958	NaN	S	1
30	0	PC 17601	27.7208	NaN	C	1
31	0	PC 17569	146.5208	B78	C	2
32	0	335677	7.7500	NaN	Q	1
33	0	C.A. 24579	10.5000	NaN	S	1
34	0	PC 17604	82.1708	NaN	C	2
35	0	113789	52.0000	NaN	S	2
36	0	2677	7.2292	NaN	C	1
37	0	A./5. 2152	8.0500	NaN	S	1
38	0	345764	18.0000	NaN	S	3
39	0	2651	11.2417	NaN	C	2
40	0	7546	9.4750	NaN	S	2
41	0	11668	21.0000	NaN	S	2
42	0	349253	7.8958	NaN	C	1
43	2	SC/Paris 2123	41.5792	NaN	C	4
44	0	330958	7.8792	NaN	Q	1
45	0	S.C./A.4. 23567	8.0500	NaN	S	1
46	0	370371	15.5000	NaN	Q	2
47	0	14311	7.7500	NaN	Q	1
48	0	2662	21.6792	NaN	C	3
49	0	349237	17.8000	NaN	S	2

	Title
0	Mr
1	Mrs
2	Miss
3	Mrs
4	Mr
5	Mr
6	Mr
7	Master
8	Mrs
9	Mrs
10	Miss
11	Miss
12	Mr
13	Mr
14	Miss
15	Mrs
16	Master
17	Mr
18	Mrs
19	Mrs
20	Mr
21	Mr
22	Miss
23	Mr

```
24    Miss
25     Mrs
26      Mr
27      Mr
28    Miss
29      Mr
30  Person
31     Mrs
32    Miss
33      Mr
34      Mr
35      Mr
36      Mr
37      Mr
38    Miss
39    Miss
40     Mrs
41     Mrs
42      Mr
43    Miss
44    Miss
45      Mr
46      Mr
47    Miss
48      Mr
49     Mrs
```

[83]:
```
df['Title'] = titanic_df['Title']
df
```

[83]:

	Survived	Pclass	Sex	Age	SibSp	FamilySize	Embarked	Title
0	0.0	3	0	22.0	1	2	S	Mr
1	1.0	1	1	38.0	1	2	C	Mrs
2	1.0	3	1	26.0	0	1	S	Miss
3	1.0	1	1	35.0	1	2	S	Mrs
4	0.0	3	0	35.0	0	1	S	Mr
…	…	…	…	…	…	…	…	…
1304	NaN	3	0	25.0	0	1	S	Mr
1305	NaN	1	1	39.0	0	1	C	Person
1306	NaN	3	0	38.5	0	1	S	Mr
1307	NaN	3	0	25.0	0	1	S	Mr
1308	NaN	3	0	25.0	1	3	C	Master

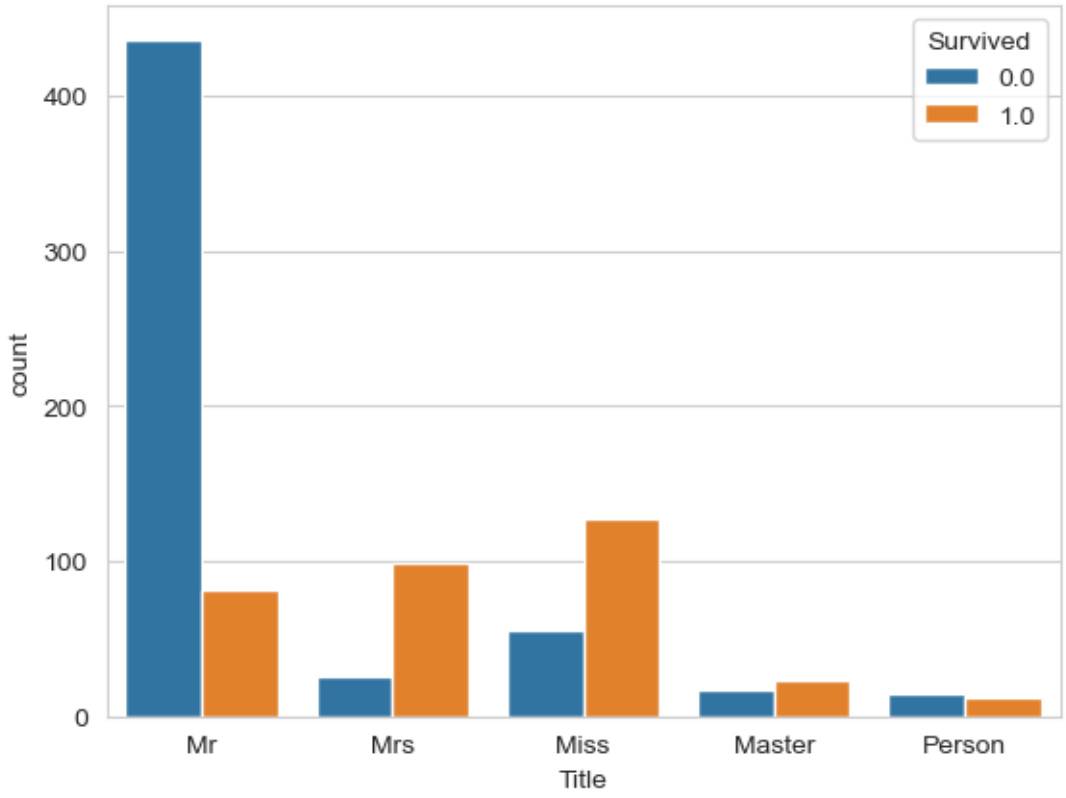
[1309 rows x 8 columns]

[84]:
```
# O data frame do modelo somente com 5 tipos de pessoas
df['Title'].unique()
```

[84]:
```
array(['Mr', 'Mrs', 'Miss', 'Master', 'Person'], dtype=object)
```

[151]:
```
titanic_func(titanic_df, 'Title')
```

```
Quantidade de valores únicos: 5

Quais são os valores únicos: ['Mr' 'Mrs' 'Miss' 'Master' 'Person']

Quantidade de valores nulos: 0

Quantidade por opção:
Title
Mr        757
Miss      260
Mrs       197
Master     61
Person     34
Name: count, dtype: int64
```



[87]:
```
# Colocando a coluna Fare que antes não tinha colocado.
df['Fare'] = titanic_df['Fare']
```

[91]:
```
df
```

[91]:
```
      Survived  Pclass  Sex   Age  SibSp  FamilySize Embarked   Title  \
0          0.0       3    0  22.0      1           2        S      Mr
1          1.0       1    1  38.0      1           2        C     Mrs
2          1.0       3    1  26.0      0           1        S    Miss
3          1.0       1    1  35.0      1           2        S     Mrs
4          0.0       3    0  35.0      0           1        S      Mr
…          …     …   …   …    …          …       …      …
1304       NaN       3    0  25.0      0           1        S      Mr
1305       NaN       1    1  39.0      0           1        C  Person
1306       NaN       3    0  38.5      0           1        S      Mr
1307       NaN       3    0  25.0      0           1        S      Mr
1308       NaN       3    0  25.0      1           3        C  Master

          Fare
0       7.2500
1      71.2833
2       7.9250
3      53.1000
4       8.0500
…          …
1304    8.0500
1305  108.9000
1306    7.2500
1307    8.0500
1308   22.3583

[1309 rows x 9 columns]
```

[108]:
```
#Conferindo os valores unicos
df['Pclass'] = df['Pclass'].astype(int)
print(df['Pclass'].unique())
```

```
[3 1 2]
```

[130]:
```
#Fazendo primeiro da classe - It is used to convert categorical variable(s)␣
 ↪into dummy/indicator variable
pclass = pd.get_dummies(df['Pclass'], prefix='Pclass', drop_first=True)
print(pclass)
int_list = [int(value) for value in pclass.iloc[:,0]]
duo_list = [int(value) for value in pclass.iloc[:,1]]
pclass = pd.DataFrame({
    'Pclass_2': int_list,
    'Pclass_3': duo_list
})

# Exibindo o DataFrame
```

```
print(pclass)
```

```
      Pclass_2  Pclass_3
0        False      True
1        False     False
2        False      True
3        False     False
4        False      True
…          …         …
1304     False      True
1305     False     False
1306     False      True
1307     False      True
1308     False      True

[1309 rows x 2 columns]
      Pclass_2  Pclass_3
0            0         1
1            0         0
2            0         1
3            0         0
4            0         1
…          …         …
1304         0         1
1305         0         0
1306         0         1
1307         0         1
1308         0         1

[1309 rows x 2 columns]
```

[152]:
```
print(df['Title'].unique())
df['Title'] = df['Title'].astype(object)
df['Title'].dtype
```

```
['Mr' 'Mrs' 'Miss' 'Master' 'Person']
```

[152]:
```
dtype('O')
```

[153]:
```
#df['Title'] = df['Title'].astype(int)
print(df['Title'].unique())
title = pd.get_dummies(df['Title'], prefix='Title', drop_first=True)
print(title)
```

```
['Mr' 'Mrs' 'Miss' 'Master' 'Person']
      Title_Miss  Title_Mr  Title_Mrs  Title_Person
0          False      True      False         False
1          False     False       True         False
2           True     False      False         False
```

```
3          False     False       True         False
4          False      True      False         False
…              …        …          …             …
1304       False      True      False         False
1305       False     False      False          True
1306       False      True      False         False
1307       False      True      False         False
1308       False     False      False         False

[1309 rows x 4 columns]
```

[158]:
```
#Passando os valores para booleanos
primeira_list = [int(value) for value in title.iloc[:,0]]
segunda_list = [int(value) for value in title.iloc[:,1]]
terceira_list = [int(value) for value in title.iloc[:,2]]
quarta_list = [int(value) for value in title.iloc[:,3]]

title = pd.DataFrame({
    'Title_Miss': primeira_list,
    'Title_Mr': segunda_list,
    'Title_Mrs': terceira_list,
    'Title_Person': quarta_list
    })

# Exibindo o DataFrame
print(title)
```

```
      Title_Miss  Title_Mr  Title_Mrs  Title_Person
0              0         1          0             0
1              0         0          1             0
2              1         0          0             0
3              0         0          1             0
4              0         1          0             0
…            …       …          …             …
1304           0         1          0             0
1305           0         0          0             1
1306           0         1          0             0
1307           0         1          0             0
1308           0         0          0             0

[1309 rows x 4 columns]
```

[160]:
```
embarked = pd.get_dummies(df['Embarked'], prefix='Embarked', drop_first=True)
print(embarked)
```

```
      Embarked_Q  Embarked_S
0          False        True
1          False       False
2          False        True
```

```
3          False        True
4          False        True
…          …         …
1304       False        True
1305       False       False
1306       False        True
1307       False        True
1308       False       False

[1309 rows x 2 columns]
```

[161]:
```
int_list = [int(value) for value in embarked.iloc[:,0]]
duo_list = [int(value) for value in embarked.iloc[:,1]]
embarked = pd.DataFrame({
    'Embarked_Q': int_list,
    'Embarked_S': duo_list
})

# Exibindo o DataFrame
print(embarked)
```

```
      Embarked_Q  Embarked_S
0              0           1
1              0           0
2              0           1
3              0           1
4              0           1
…          …         …
1304           0           1
1305           0           0
1306           0           1
1307           0           1
1308           0           0

[1309 rows x 2 columns]
```

[164]:
```
# Agora temos 3 tabelas com variáveis Dummies
print(pclass)
print(title)
print(embarked)
```

```
      Pclass_2  Pclass_3
0            0         1
1            0         0
2            0         1
3            0         0
4            0         1
…        …       …
1304         0         1
```

```
1305          0          0
1306          0          1
1307          0          1
1308          0          1

[1309 rows x 2 columns]
      Title_Miss  Title_Mr  Title_Mrs  Title_Person
0              0         1          0             0
1              0         0          1             0
2              1         0          0             0
3              0         0          1             0
4              0         1          0             0
…            …         …          …             …
1304           0         1          0             0
1305           0         0          0             1
1306           0         1          0             0
1307           0         1          0             0
1308           0         0          0             0

[1309 rows x 4 columns]
      Embarked_Q  Embarked_S
0              0           1
1              0           0
2              0           1
3              0           1
4              0           1
…            …           …
1304           0           1
1305           0           0
1306           0           1
1307           0           1
1308           0           0

[1309 rows x 2 columns]
```

[165]:
```
# Tabela Final que vai nos modelos
tabela_final = pd.concat([df,pclass,title, embarked],axis=1)
tabela_final
```

[165]:
```
      Survived  Pclass  Sex   Age  SibSp  FamilySize Embarked   Title  \
0          0.0       3    0  22.0      1           2        S      Mr
1          1.0       1    1  38.0      1           2        C     Mrs
2          1.0       3    1  26.0      0           1        S    Miss
3          1.0       1    1  35.0      1           2        S     Mrs
4          0.0       3    0  35.0      0           1        S      Mr
…        …     …  …   …    …          …       …      …
1304       NaN       3    0  25.0      0           1        S      Mr
```

```
1305       NaN       1    1  39.0      0           1        C  Person
1306       NaN       3    0  38.5      0           1        S      Mr
1307       NaN       3    0  25.0      0           1        S      Mr
1308       NaN       3    0  25.0      1           3        C  Master

          Fare  Pclass_2  Pclass_3  Title_Miss  Title_Mr  Title_Mrs  \
0       7.2500         0         1           0         1          0
1      71.2833         0         0           0         0          1
2       7.9250         0         1           1         0          0
3      53.1000         0         0           0         0          1
4       8.0500         0         1           0         1          0
…          …       …         …           …         …          …
1304    8.0500         0         1           0         1          0
1305  108.9000         0         0           0         0          0
1306    7.2500         0         1           0         1          0
1307    8.0500         0         1           0         1          0
1308   22.3583         0         1           0         0          0

      Title_Person  Embarked_Q  Embarked_S
0                0           0           1
1                0           0           0
2                0           0           1
3                0           0           1
4                0           0           1
…              …           …           …
1304             0           0           1
1305             1           0           0
1306             0           0           1
1307             0           0           1
1308             0           0           0

[1309 rows x 17 columns]
```

[167]:
```
# Excluindo as colunas originais de Classe, Titulo e Embarque.
tabela_final.drop(['Pclass','Title','Embarked'],axis=1,inplace=True)
```

[167]:
```
      Survived  Sex   Age  SibSp  FamilySize      Fare  Pclass_2  Pclass_3  \
0          0.0    0  22.0      1           2    7.2500         0         1
1          1.0    1  38.0      1           2   71.2833         0         0
2          1.0    1  26.0      0           1    7.9250         0         1
3          1.0    1  35.0      1           2   53.1000         0         0
4          0.0    0  35.0      0           1    8.0500         0         1
…          …  …    …    …           …       …       …         …         …
1304       NaN    0  25.0      0           1    8.0500         0         1
1305       NaN    1  39.0      0           1  108.9000         0         0
1306       NaN    0  38.5      0           1    7.2500         0         1
1307       NaN    0  25.0      0           1    8.0500         0         1
```

```
1308       NaN    0  25.0      1           3   22.3583         0         1

      Title_Miss  Title_Mr  Title_Mrs  Title_Person  Embarked_Q  Embarked_S
0              0         1          0             0           0           1
1              0         0          1             0           0           0
2              1         0          0             0           0           1
3              0         0          1             0           0           1
4              0         1          0             0           0           1
…            …       …        …          …           …         …
1304           0         1          0             0           0           1
1305           0         0          0             1           0           0
1306           0         1          0             0           0           1
1307           0         1          0             0           0           1
1308           0         0          0             0           0           0

[1309 rows x 14 columns]
```

[170]:
```
#Adicionando a coluna de Parch que faltou
tabela_final['Parch'] = titanic_df['Parch']
tabela_final
```

[170]:
```
      Survived  Sex   Age  SibSp  FamilySize      Fare  Pclass_2  Pclass_3  \
0          0.0    0  22.0      1           2    7.2500         0         1
1          1.0    1  38.0      1           2   71.2833         0         0
2          1.0    1  26.0      0           1    7.9250         0         1
3          1.0    1  35.0      1           2   53.1000         0         0
4          0.0    0  35.0      0           1    8.0500         0         1
…        …  …    …    …           …       …        …       …
1304       NaN    0  25.0      0           1    8.0500         0         1
1305       NaN    1  39.0      0           1  108.9000         0         0
1306       NaN    0  38.5      0           1    7.2500         0         1
1307       NaN    0  25.0      0           1    8.0500         0         1
1308       NaN    0  25.0      1           3   22.3583         0         1

      Title_Miss  Title_Mr  Title_Mrs  Title_Person  Embarked_Q  Embarked_S  \
0              0         1          0             0           0           1
1              0         0          1             0           0           0
2              1         0          0             0           0           1
3              0         0          1             0           0           1
4              0         1          0             0           0           1
…            …       …        …          …           …         …
1304           0         1          0             0           0           1
1305           0         0          0             1           0           0
1306           0         1          0             0           0           1
1307           0         1          0             0           0           1
1308           0         0          0             0           0           0
```

```
      Parch
0         0
1         0
2         0
3         0
4         0
…       …
1304      0
1305      0
1306      0
1307      0
1308      1

[1309 rows x 15 columns]
```

[173]:
```
#Dividindo a tabela final com os dados de treino e dados de teste
train = tabela_final[:train_index].copy()
test = tabela_final[test_index:].copy()
```

[174]:
```
train
```

[174]:
```
      Survived  Sex   Age  SibSp  FamilySize     Fare  Pclass_2  Pclass_3  \
0          0.0    0  22.0      1           2   7.2500         0         1
1          1.0    1  38.0      1           2  71.2833         0         0
2          1.0    1  26.0      0           1   7.9250         0         1
3          1.0    1  35.0      1           2  53.1000         0         0
4          0.0    0  35.0      0           1   8.0500         0         1
..         …  …    …    …          …       …       …       …
886        0.0    0  27.0      0           1  13.0000         1         0
887        1.0    1  19.0      0           1  30.0000         0         0
888        0.0    1  25.0      1           4  23.4500         0         1
889        1.0    0  26.0      0           1  30.0000         0         0
890        0.0    0  32.0      0           1   7.7500         0         1

     Title_Miss  Title_Mr  Title_Mrs  Title_Person  Embarked_Q  Embarked_S  \
0             0         1          0             0           0           1
1             0         0          1             0           0           0
2             1         0          0             0           0           1
3             0         0          1             0           0           1
4             0         1          0             0           0           1
..          …       …        …           …         …         …
886           0         0          0             1           0           1
887           1         0          0             0           0           1
888           1         0          0             0           0           1
889           0         1          0             0           0           0
890           0         1          0             0           1           0
```

```
     Parch
0        0
1        0
2        0
3        0
4        0
..     …
886      0
887      0
888      2
889      0
890      0

[891 rows x 15 columns]
```

[175]:
```
#Transformando os dados do Survived em inteiro
train['Survived'] = train['Survived'].astype(int)
```

[177]:
```
# separando a coluna Survived da tabela e colocada no y
X = train.drop('Survived',axis=1)
y = train['Survived']
```

[178]:
```
X_test = test.drop('Survived',axis=1)
```

1.0.12 Criando os modelos

[180]:
```
def func_acuracia(algoritmo, X_train, y_train, vc):
    modelo = algoritmo.fit(X_train,y_train)
    acuracia = round(modelo.score(X_train, y_train)*100,2)

    train_pred = model_selection.cross_val_predict(algoritmo,X_train,y_train,␣
 ↪cv=vc, n_jobs= -1)
    acuracia_vc = round(metrics.accuracy_score(y_train,train_pred)*100,2)

    return acuracia, acuracia_vc
```

[181]:
```
#Random Forest
acc_rf, acc_vc_rf = func_acuracia(RandomForestClassifier(), X, y,10)
print(f"Acuracia: {acc_rf}")
print(f"Acurácia Validação Cruzada: {acc_vc_rf}")
```

```
Acuracia: 98.32
Acurácia Validação Cruzada: 80.36
```

[182]:
```
#Logistic Regression
acc_log, acc_vc_log = func_acuracia(LogisticRegression(max_iter=1000), X, y, 10)

print(f"Acurácia: {acc_log}")
print(f"Acurácia Validação Cruzada: {acc_vc_log}")
```

```
Acurácia: 82.94
Acurácia Validação Cruzada: 82.38
```

[183]:
```
# K-Nearest Neighbours
acc_knn, acc_vc_knn = func_acuracia(KNeighborsClassifier(), X, y, 10)

print(f"Acurácia: {acc_knn}")
print(f"Acurácia Validação Cruzada: {acc_vc_knn}")
```

```
Acurácia: 80.81
Acurácia Validação Cruzada: 72.39
```

[184]:
```
# Gaussian Naive Bayes
acc_gaussian, acc_vc_gaussian = func_acuracia(GaussianNB(), X, y, 10)

print(f"Acurácia: {acc_gaussian}")
print(f"Acurácia Validação Cruzada: {acc_vc_gaussian}")
```

```
Acurácia: 78.79
Acurácia Validação Cruzada: 78.56
```

[185]:
```
# Linear Support Vector Machines (SVC)
acc_linear_svc, acc_vc_linear_svc = func_acuracia(LinearSVC(dual=False), X, y,␣
↪10)

print(f"Acurácia: {acc_linear_svc}")
print(f"Acurácia Validação Cruzada: {acc_vc_linear_svc}")
```

```
Acurácia: 83.28
Acurácia Validação Cruzada: 82.72
```

[186]:
```
#Stochastic Gradient Descent
acc_sgd, acc_vc_sgd = func_acuracia(SGDClassifier(), X, y, 10)

print(f"Acurácia: {acc_sgd}")
print(f"Acurácia Validação Cruzada: {acc_vc_sgd}")
```

```
Acurácia: 72.84
Acurácia Validação Cruzada: 71.38
```

[187]:
```
#Decision Tree Classifier
acc_dt, acc_vc_dt = func_acuracia(DecisionTreeClassifier(), X, y, 10)

print(f"Acurácia: {acc_dt}")
```

```
print(f"Acurácia Validação Cruzada: {acc_vc_dt}")
```

```
Acurácia: 98.32
Acurácia Validação Cruzada: 79.24
```

[188]:
```
#Gradient Boost Classifier
acc_gbt, acc_vc_gbt = func_acuracia(GradientBoostingClassifier(), X, y, 10)

print(f"Acurácia: {acc_gbt}")
print(f"Acurácia Validação Cruzada: {acc_vc_gbt}")
```

```
Acurácia: 89.67
Acurácia Validação Cruzada: 83.16
```

1.1 Os modelos que apresentaram melhores acurácias foram Random Forest e Decision Tree, mas na validação cruzada foi Gradient Boost Classifier, este é o que vou usar abaixo

[189]:
```
params = dict(
    max_depth = [n for n in range(1, 5)],
    min_samples_split = [n for n in range(2, 6)],
    min_samples_leaf = [n for n in range(2, 6)],
    n_estimators = [n for n in range(10, 50, 10)],
)
```

[190]:
```
gbc = GradientBoostingClassifier()
```

[191]:
```
gbc_cv = GridSearchCV(estimator = gbc, param_grid = params, cv = 10)
gbc_cv.fit(X, y)
```

[191]:
```
GridSearchCV(cv=10, estimator=GradientBoostingClassifier(),
             param_grid={'max_depth': [1, 2, 3, 4],
                         'min_samples_leaf': [2, 3, 4, 5],
                         'min_samples_split': [2, 3, 4, 5],
                         'n_estimators': [10, 20, 30, 40]})
```

[192]:
```
print(f"Melhor pontuação: {gbc_cv.best_score_}")
print(f"Melhores parâmetros: {gbc_cv.best_estimator_}")
```

```
Melhor pontuação: 0.8485143570536829
Melhores parâmetros: GradientBoostingClassifier(max_depth=4, min_samples_leaf=2,
n_estimators=30)
```

[193]:
```
gradientBoostingClassifier_pred = gbc_cv.predict(X_test)
```

[195]:
```
kaggle = pd.DataFrame({'PassengerId': passengerID, 'Survived':␣
↪gradientBoostingClassifier_pred})
# save to csv
kaggle.to_csv('./titanic_gradient_boosting_pred.csv', index=False)
```