

# Exercício Titanic Kaggle

September 19, 2022

## 1 Exercício Titanic Kaggle

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### 1.1 Importações Gerais

```
[1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style('whitegrid')
```

### 1.2 Importações de Pré-Processamento

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

### 1.3 Importações Machine Learning

```
[3]: import catboost
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
from catboost import CatBoostClassifier, Pool, cv
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
```

## 1.4 Importando os arquivos necessarios

```
[4]: train = pd.read_csv('train.csv')
     test = pd.read_csv('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]: 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
```

```
[7]: train.isnull().sum()
```

```
[7]: 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
```

```
[8]: test
```

```
[8]:   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]

```
[9]: test.isnull().sum()
```

```
[9]: PassengerId      0
     Pclass          0
     Name            0
     Sex             0
     Age             86
     SibSp           0
     Parch           0
     Ticket          0
     Fare            1
     Cabin          327
     Embarked        0
     dtype: int64
```

```
[10]: #criando um DF que será enviado para o Kaggle
      passengerID = test['PassengerId']

      #criando um DF com o teste e o treino para tratar os dados mais rapidamente
      df_titanic = pd.concat([train, test], ignore_index=True)
```

```
[11]: df_titanic
```

```
[11]:   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	Cummings, 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]

```
[12]: #criando o índice para separar as df de treino e teste posteriormente
train_index = len(train)
test_index = len(df_titanic) - len(test)
```

```
[13]: df_titanic.isnull().sum()
```

```
[13]: 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
```

```
[14]: df_titanic.describe()
```

```
[14]:
```

	PassengerId	Survived	Pclass	Age	SibSp \
count	1309.000000	891.000000	1309.000000	1046.000000	1309.000000
mean	655.000000	0.383838	2.294882	29.881138	0.498854
std	378.020061	0.486592	0.837836	14.413493	1.041658
min	1.000000	0.000000	1.000000	0.170000	0.000000
25%	328.000000	0.000000	2.000000	21.000000	0.000000
50%	655.000000	0.000000	3.000000	28.000000	0.000000
75%	982.000000	1.000000	3.000000	39.000000	1.000000
max	1309.000000	1.000000	3.000000	80.000000	8.000000

	Parch	Fare
count	1309.000000	1308.000000
mean	0.385027	33.295479
std	0.865560	51.758668
min	0.000000	0.000000
25%	0.000000	7.895800
50%	0.000000	14.454200
75%	0.000000	31.275000
max	9.000000	512.329200

```
[15]: #criando um df que iremos tratar os campos relevantes a partir da base
      ↪titanic_df
      df = pd.DataFrame()
```

### 1.5 Tratando as coluna, usando a 'Survived' como exemplo

```
[16]: # encontrando a quantidade de valores únicos em "Survived"
      df_titanic['Survived'].nunique()
```

```
[16]: 2
```

```
[17]: # encontrando quais são os valores únicos em "Survived"
      df_titanic['Survived'].unique()
```

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

```
[18]: # encontrando a quantidade de valores nulos em "Survived"
df_titanic['Survived'].isnull().sum()
```

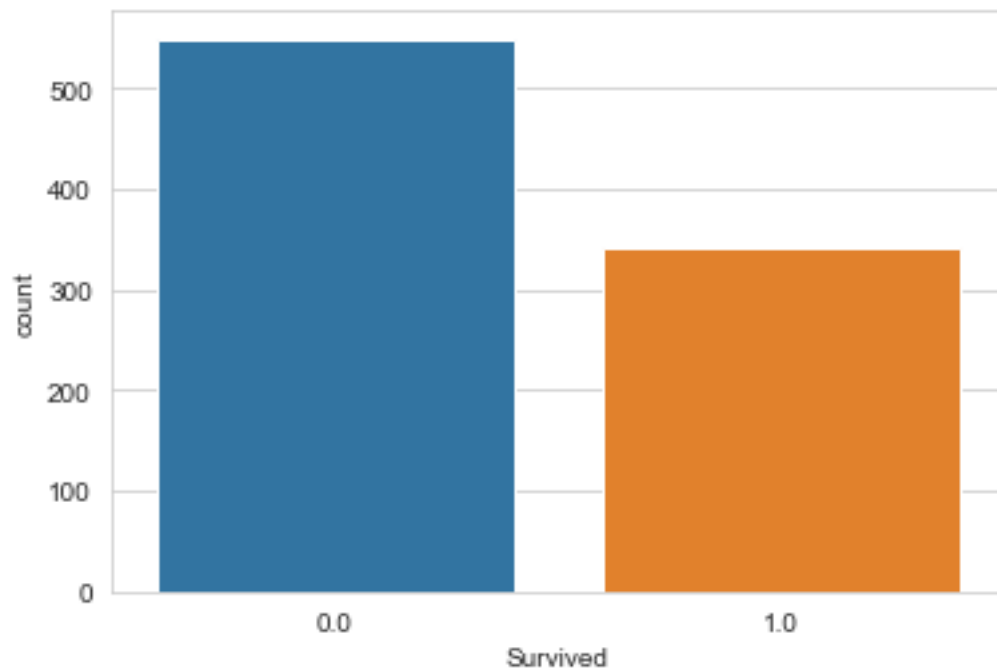
```
[18]: 418
```

```
[19]: # encontrando a quantidade de valores associados a cada variavel de "Survived"
df_titanic['Survived'].value_counts()
```

```
[19]: 0.0    549
      1.0    342
      Name: Survived, dtype: int64
```

```
[20]: # plotando os valores das colunas
sns.countplot(data = df_titanic, x = 'Survived')
```

```
[20]: <AxesSubplot:xlabel='Survived', ylabel='count'>
```



## 1.6 Função que traz informações sobre a coluna

```
[21]: #criando uma função que printa as informações sobre os valores das colunas
def df_info(data, column, count = True):
    print(f'Quantidade de valores únicos na {column}: \n{data[column].
    ↪unique()}')
    print(f'\nQuais são os valores únicos na {column}: \n{data[column].
    ↪unique()}')
```

```

    print(f'\nQuantidade de valores nulos na {column}: \n{data[column].isnull().
↪sum()}\n')
    print(f'\nQuantidade por opção na {column}: \n{data[column].
↪value_counts()}\n')

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

df_info(df_titanic, 'Survived')

```

Quantidade de valores únicos na Survived:

2

Quais são os valores únicos na Survived:

[ 0. 1. nan]

Quantidade de valores nulos na Survived:

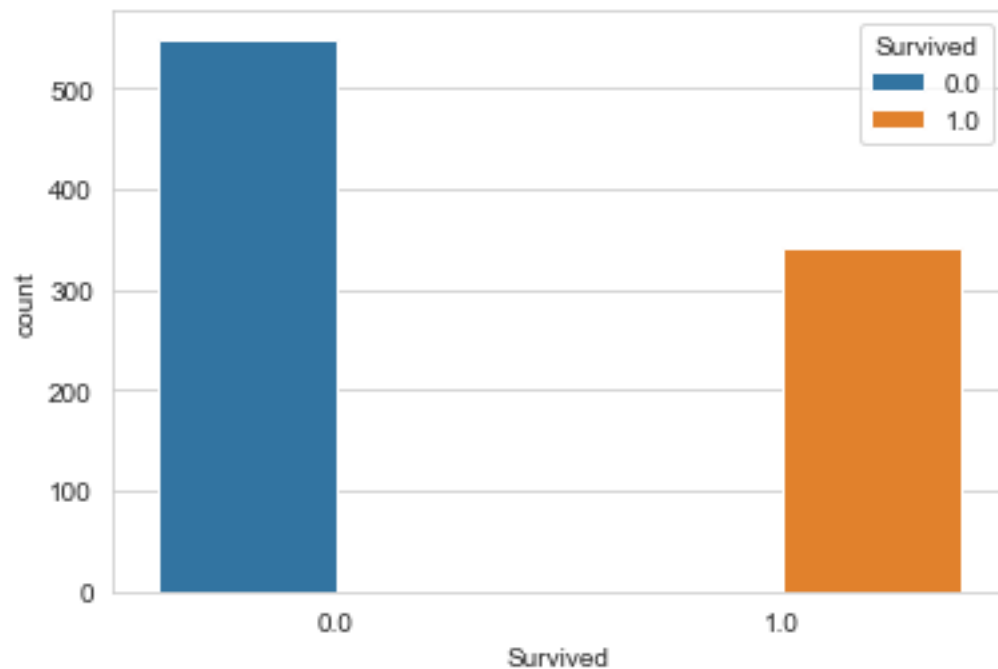
418

Quantidade por opção na Survived:

0.0 549

1.0 342

Name: Survived, dtype: int64





```
[22]: df['Survived'] = df_titanic['Survived']
```

```
[23]: df
```

```
[23]:      Survived
0         0.0
1         1.0
2         1.0
3         1.0
4         0.0
...      ...
1304      NaN
1305      NaN
1306      NaN
1307      NaN
1308      NaN
```

```
[1309 rows x 1 columns]
```

## 1.7 Tratando Pclass

```
[24]: df_info(df_titanic, 'Pclass')
```

Quantidade de valores únicos na Pclass:

3

Quais são os valores únicos na Pclass:

[3 1 2]

Quantidade de valores nulos na Pclass:

0

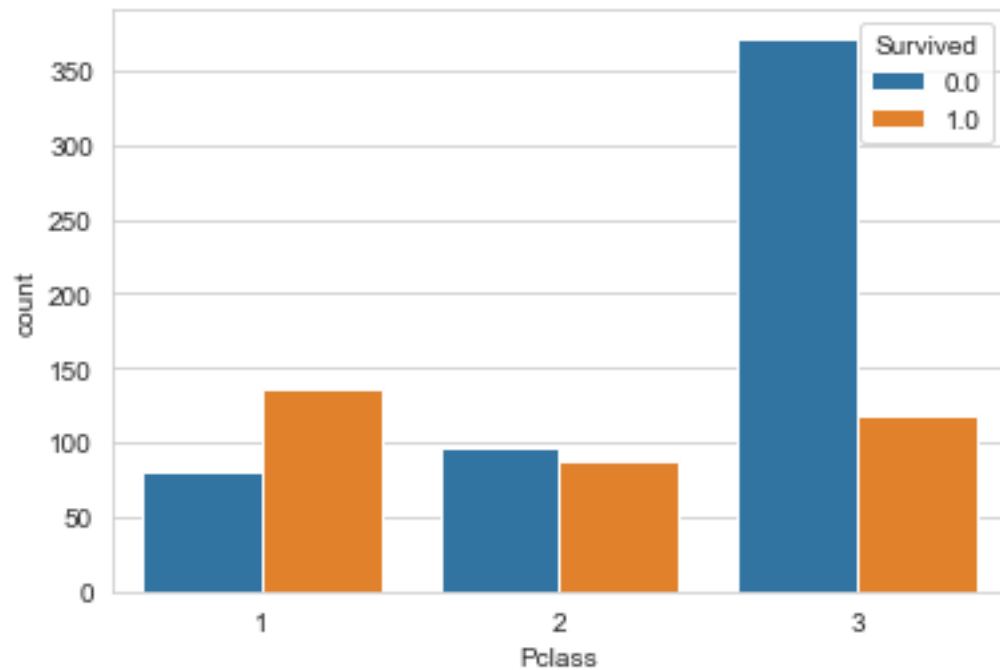
Quantidade por opção na Pclass:

3 709

1 323

2 277

Name: Pclass, dtype: int64



```
[25]: df['Pclass'] = df_titanic['Pclass']
df
```

```
[25]:
```

	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]

## 1.8 Tratando Sex

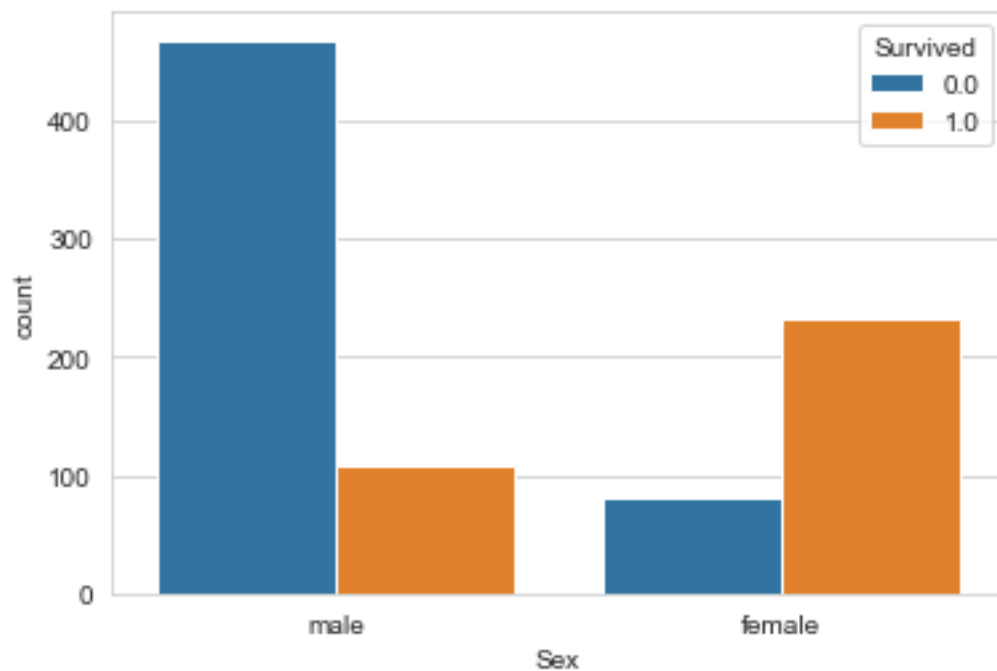
```
[26]: df_info(df_titanic, 'Sex')
```

Quantidade de valores únicos na Sex:  
2

Quais são os valores únicos na Sex:  
['male' 'female']

Quantidade de valores nulos na Sex:  
0

Quantidade por opção na Sex:  
male 843  
female 466  
Name: Sex, dtype: int64



```
[27]: df_titanic['Sex'] = df_titanic['Sex'].replace(['male', 'female'], [0, 1])
```

```
[28]: df['Sex'] = df_titanic['Sex']  
df
```

```
[28]:
```

	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]

## 1.9 Tratando o título

```
[29]: df_titanic['Title'] = df_titanic['Name'].apply(lambda name: name.split(',')[1].
    ↪split('.')[0].strip())
df_info(df_titanic, 'Title')
```

Quantidade de valores únicos na Title:

18

Quais são os valores únicos na Title:

```
['Mr' 'Mrs' 'Miss' 'Master' 'Don' 'Rev' 'Dr' 'Mme' 'Ms' 'Major' 'Lady'
 'Sir' 'Mlle' 'Col' 'Capt' 'the Countess' 'Jonkheer' 'Dona']
```

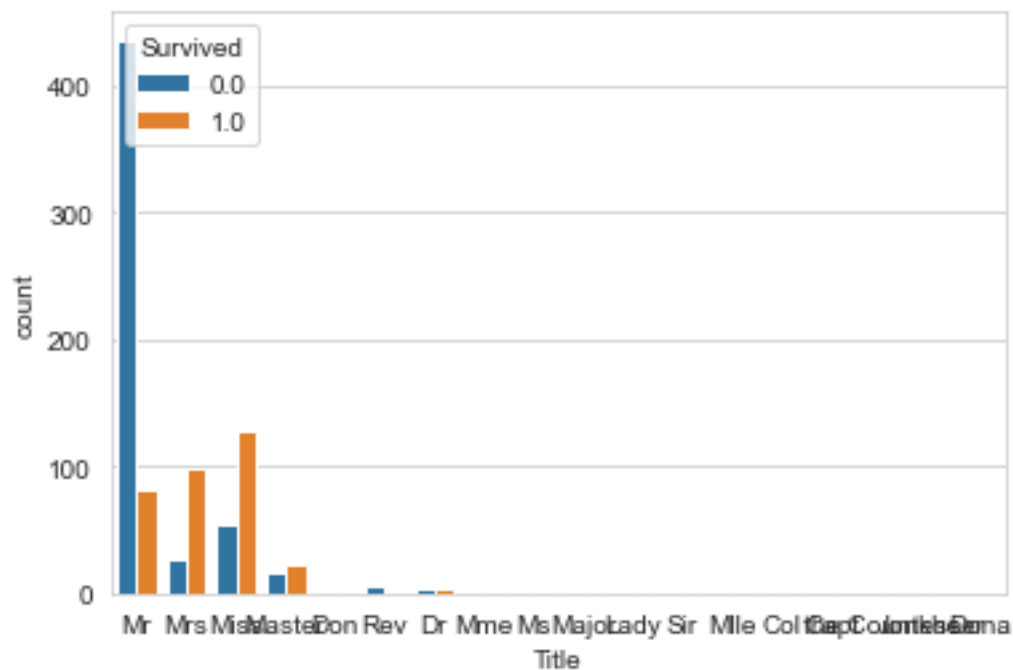
Quantidade de valores nulos na Title:

0

Quantidade por opção na 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: Title, dtype: int64



```
[30]: df_titanic
```

```
[30]:
```

	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	NaN	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	NaN	0
1308		Peter, Master. Michael J	0	NaN	1

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

[1309 rows x 13 columns]

```
[31]: number_title = dict(df_titanic['Title'].value_counts())
      keys_number_title = list(number_title)
      keys_number_title
```

```
[31]: ['Mr',
      'Miss',
      'Mrs',
      'Master',
      'Rev',
      'Dr',
      'Col',
      'Mlle',
      'Major',
      'Ms',
      'Lady',
      'Sir',
      'Mme',
      'Don',
      'Capt',
      'the Countess',
      'Jonkheer',
      'Dona']
```

```
[32]: df_titanic['Title'] = [n if n in keys_number_title[0:4] else 'Person' for n in
      ↪ df_titanic['Title']]
      df_titanic
```

```
[32]: 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	NaN	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	NaN	0	
1308	Peter, Master. Michael J	0	NaN	1	

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

[1309 rows x 13 columns]

```
[33]: number_title_actual = dict(df_titanic['Title'].value_counts())
keys_number_title_actual = list(number_title_actual)
keys_number_title_actual
```

```
[33]: ['Mr', 'Miss', 'Mrs', 'Master', 'Person']
```

```
[34]: df['Title'] = df_titanic['Title']
```

```
[35]: df.info(df, 'Title')
```

```
Quantidade de valores únicos na Title:  
5
```

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

```
Quantidade de valores nulos na Title:  
0
```

```
Quantidade por opção na Title:
```

```
Mr      757
```

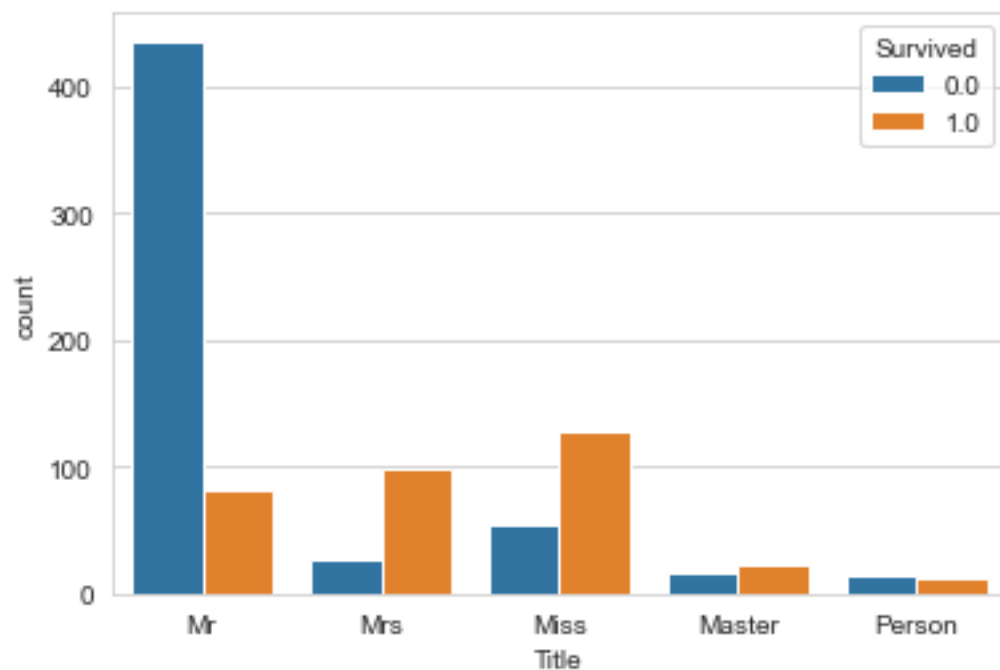
```
Miss    260
```

```
Mrs     197
```

```
Master   61
```

```
Person   34
```

```
Name: Title, dtype: int64
```



```
[36]: df
```

```
[36]:
```

	Survived	Pclass	Sex	Title
0	0.0	3	0	Mr
1	1.0	1	1	Mrs
2	1.0	3	1	Miss



3	1.0	1	1	Mrs
4	0.0	3	0	Mr
...	...	...	...	...
1304	NaN	3	0	Mr
1305	NaN	1	1	Person
1306	NaN	3	0	Mr
1307	NaN	3	0	Mr
1308	NaN	3	0	Master

[1309 rows x 4 columns]

## 1.10 Tratar Embarked

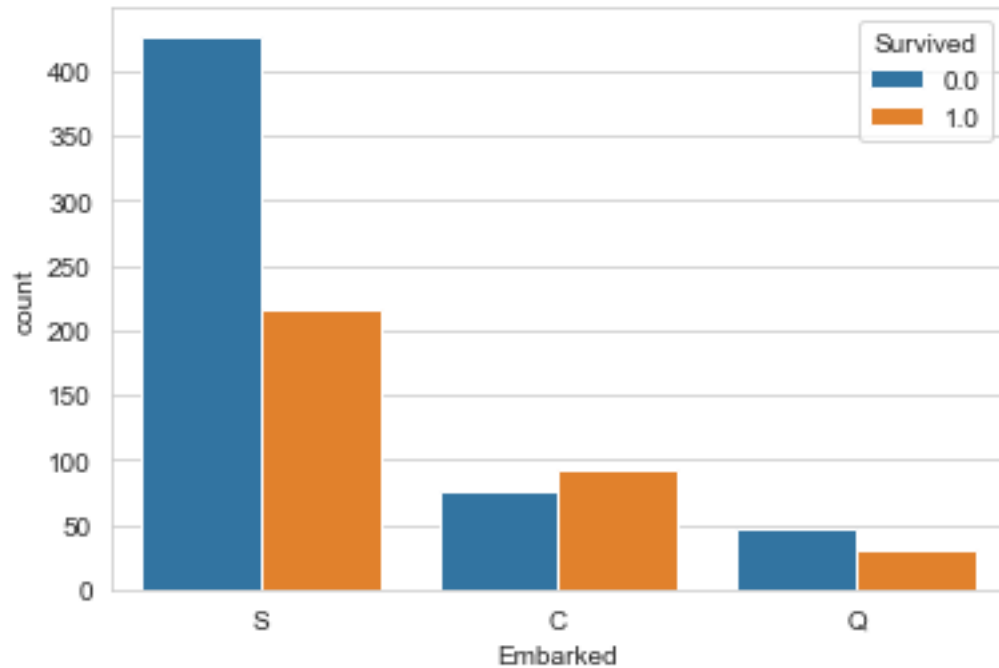
```
[37]: df_info(df_titanic, 'Embarked')
```

Quantidade de valores únicos na Embarked:  
3

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

Quantidade de valores nulos na Embarked:  
2

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



```
[38]: df_titanic.loc[df_titanic['Embarked'].isnull()]
```

```
[38]:
```

	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	Title
61	1	38.0	0	0	113572	80.0	B28	NaN	Miss
829	1	62.0	0	0	113572	80.0	B28	NaN	Mrs

```
[39]: df_titanic.loc[df_titanic['Embarked'] == "C"]['Pclass'].mean()
```

```
[39]: 1.8518518518518519
```

```
[40]: df_titanic['Embarked'].fillna('C', inplace = True)
```

```
[41]: df['Embarked'] = df_titanic['Embarked']
```

```
df
```

```
[41]:
```

	Survived	Pclass	Sex	Title	Embarked
0	0.0	3	0	Mr	S
1	1.0	1	1	Mrs	C
2	1.0	3	1	Miss	S
3	1.0	1	1	Mrs	S

4	0.0	3	0	Mr	S
...	...	...	...	...	...
1304	NaN	3	0	Mr	S
1305	NaN	1	1	Person	C
1306	NaN	3	0	Mr	S
1307	NaN	3	0	Mr	S
1308	NaN	3	0	Master	C

[1309 rows x 5 columns]

[ ]:

### 1.11 Tratar Title, Pclass, Embarked com Getdummies sem dropar first

```
[42]: pclass = pd.get_dummies(df['Pclass'], prefix = "Pclass")
title = pd.get_dummies(df['Title'], prefix = 'Title')
embarked = pd.get_dummies(df['Embarked'], prefix = 'Embarked')

df2 = pd.concat([df, pclass, title, embarked], axis = 1)
df2.drop(['Pclass', 'Title', 'Embarked'], axis=1, inplace=True)
```

### 1.12 Tratando idade (parte 1)

```
[43]: df_info(df_titanic, 'Age', False)
```

Quantidade de valores únicos na Age:  
98

Quais são os valores únicos na Age:

```
[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 na Age:  
263

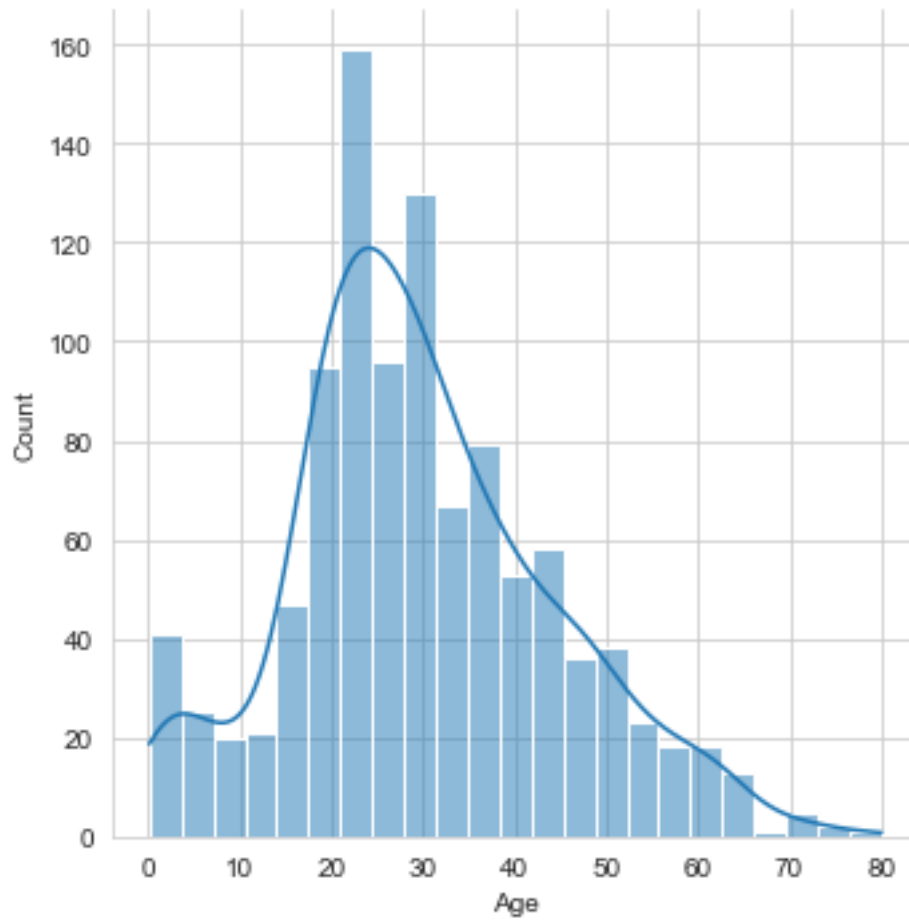
Quantidade por opção na Age:

```
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: Age, Length: 98, dtype: int64

```



```

[44]: df2['Age'] = df_titanic['Age']
df2

```

```

[44]:
   Survived  Sex  Pclass_1  Pclass_2  Pclass_3  Title_Master  Title_Miss  \
0         0.0   0         0         0         1             0           0
1         1.0   1         1         0         0             0           0
2         1.0   1         0         0         1             0           1
3         1.0   1         1         0         0             0           0
4         0.0   0         0         0         1             0           0

```

```

...      ...      ...      ...      ...      ...      ...
1304      NaN      0      0      0      1      0      0
1305      NaN      1      1      0      0      0      0
1306      NaN      0      0      0      1      0      0
1307      NaN      0      0      0      1      0      0
1308      NaN      0      0      0      1      1      0

      Title_Mr Title_Mrs Title_Person Embarked_C Embarked_Q Embarked_S \
0          1          0          0          0          0          1
1          0          1          0          1          0          0
2          0          0          0          0          0          1
3          0          1          0          0          0          1
4          1          0          0          0          0          1
...      ...      ...      ...      ...      ...      ...
1304      1          0          0          0          0          1
1305      0          0          1          1          0          0
1306      1          0          0          0          0          1
1307      1          0          0          0          0          1
1308      0          0          0          1          0          0

      Age
0      22.0
1      38.0
2      26.0
3      35.0
4      35.0
...      ...
1304      NaN
1305      39.0
1306      38.5
1307      NaN
1308      NaN

```

[1309 rows x 14 columns]

### 1.13 Encontrando melhor correlação para preencher valores vazios para idade

```
[45]: df_titanic.corr()
```

```

[45]:      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
```

```
[46]: #PCLASS POSSUI MAIOR MODULO DE CORRELAÇÃO PARA IDADE, IREMOS PREENCHER OS
      ↪VAZIOS BASEADOS
```

### 1.14 Encontrando media de idades baseados na classe e no titulo

```
[47]: df2.loc[(df2['Pclass_1'] == 1) & (df2['Title_Master'] == 1)]['Age']
```

```
[47]: 305      0.92
      445      4.00
      802     11.00
      955     13.00
     1087      6.00
      Name: Age, dtype: float64
```

```
[48]: pclass1_master_mean_age = df2.loc[(df2['Pclass_1'] == 1) & (df2['Title_Master']
      ↪== 1)]['Age'].mean()
```

```
[49]: pclass1_master_mean_age
```

```
[49]: 6.984
```

```
[50]: pclass_1_miss_mean_age = df2.loc[(df2['Pclass_1'] == 1) & (df2['Title_Miss'] ==
      ↪1)]['Age'].mean()
```

```
[51]: pclass_1_miss_mean_age
```

```
[51]: 30.338983050847457
```

```
[52]: pclass_1_mr_mean_age = df2.loc[(df2['Pclass_1'] == 1) & (df2['Title_Mr'] ==
      ↪1)]['Age'].mean()
```

```
[53]: pclass_1_mr_mean_age
```

```
[53]: 41.45075757575758
```

```
[54]: pclass_1_person_mean_age = df2.loc[(df2['Pclass_1'] == 1) &
      ↪(df2['Title_Person'] == 1)]['Age'].mean()

[55]: pclass_1_person_mean_age

[55]: 44.285714285714285

[56]: pclass2_master_mean_age = df2.loc[(df2['Pclass_2'] == 1) & (df2['Title_Master']
      ↪== 1)]['Age'].mean()

[57]: pclass2_master_mean_age

[57]: 2.7572727272727273

[58]: pclass2_miss_mean_age = df2.loc[(df2['Pclass_2'] == 1) & (df2['Title_Miss'] ==
      ↪1)]['Age'].mean()

[59]: pclass2_miss_mean_age

[59]: 20.717083333333333

[60]: pclass2_mr_mean_age = df2.loc[(df2['Pclass_2'] == 1) & (df2['Title_Mr'] ==
      ↪1)]['Age'].mean()

[61]: pclass2_mr_mean_age

[61]: 32.346715328467155

[62]: pclass2_mrs_mean_age = df2.loc[(df2['Pclass_2'] == 1) & (df2['Title_Mrs'] ==
      ↪1)]['Age'].mean()

[63]: pclass2_mrs_mean_age

[63]: 33.51851851851852

[64]: pclass2_person_mean_age = df2.loc[(df2['Pclass_2'] == 1) & (df2['Title_Person']
      ↪== 1)]['Age'].mean()

[65]: pclass2_person_mean_age

[65]: 39.54545454545455

[66]: pclass3_master_mean_age = df2.loc[(df2['Pclass_3'] == 1) & (df2['Title_Master']
      ↪== 1)]['Age'].mean()

[67]: pclass3_master_mean_age

[67]: 6.090000000000001
```

```
[68]: pclass3_mr_mean_age = df2.loc[(df2['Pclass_3'] == 1) & (df2['Title_Mr'] == 1)][
    'Age'].mean()

[69]: pclass3_mr_mean_age

[69]: 28.318910256410255

[70]: pclass3_mrs_mean_age = df2.loc[(df2['Pclass_3'] == 1) & (df2['Title_Mrs'] == 1)][
    'Age'].mean()

[71]: pclass3_mrs_mean_age

[71]: 32.326530612244895

[72]: df2.loc[(df2['Pclass_3'] == 1) & (df2['Title_Person'] == 1)]

[72]:
```

	Survived	Sex	Pclass_1	Pclass_2	Pclass_3	Title_Master	Title_Miss	\
979	NaN	1	0	0	1	0	0	

	Title_Mr	Title_Mrs	Title_Person	Embarked_C	Embarked_Q	Embarked_S	\
979	0	0	1	0	1	0	

	Age
979	NaN

```


[73]: pclass3_person_mean_age = df2.loc[(df2['Pclass_3'] == 1) & (df2['Title_Person'] == 1)][
    'Age'].mean()

[74]: pclass3_person_mean_age

[74]: nan

[75]: pclass3_mean = df2.loc[(df2['Pclass_3'] == 1)][
    'Age'].mean()

[75]: 24.81636726546906

[76]: df2.loc[(df2['Pclass_1'] == 1) & (df2['Title_Mr'] == 1)][
    'Age'].isnull().sum()

[76]: 27

[77]: pclasses = ['Pclass_1', 'Pclass_2', 'Pclass_3']
    titles = ['Title_Master', 'Title_Mr', 'Title_Mrs', 'Title_Miss', 'Title_Person']
    df2.loc[2, 'Age']

[77]: 26.0
```



```
[78]: for i in df2.index:

        if pd.isnull(df2['Age'][i]):
#             for classe, titulo in [(classe,titulo) for classe in pclasses and
↳ titulo in titles]:
                classe = df.loc[i, 'Pclass']
                titulo = df.loc[i, 'Title']
                mean_age = round(df2.loc[(df2[f'Pclass_{classe}'] == 1) &
↳ (df2[f'Titulo_{titulo}'] == 1)]['Age'].mean(), 0)
                mean_age_pclass = round(df2.loc[df2[f'Pclass_{classe}'] == 1]['Age'].
↳ mean(),0)
                if np.isnan(mean_age) == False:
                    df2.loc[i, 'Age'] = mean_age
                else:
                    df2.loc[i, 'Age'] = mean_age_pclass
df2['Age'].isnull().sum()
```

[78]: 0

### 1.15 Encontrando média de idade por Title

```
[79]: df_titanic
```

```
[79]:
```

	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	NaN	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	NaN	0	

```
1308                Peter, Master. Michael J    0   NaN    1
```

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

```
[1309 rows x 13 columns]
```

```
[80]: df2
```

```
[80]:
```

	Survived	Sex	Pclass_1	Pclass_2	Pclass_3	Title_Master	Title_Miss	\
0	0.0	0	0	0	1	0	0	
1	1.0	1	1	0	0	0	0	
2	1.0	1	0	0	1	0	1	
3	1.0	1	1	0	0	0	0	
4	0.0	0	0	0	1	0	0	
...	...	...	...	...	...	...	...	
1304	NaN	0	0	0	1	0	0	
1305	NaN	1	1	0	0	0	0	
1306	NaN	0	0	0	1	0	0	
1307	NaN	0	0	0	1	0	0	
1308	NaN	0	0	0	1	1	0	

	Title_Mr	Title_Mrs	Title_Person	Embarked_C	Embarked_Q	Embarked_S	\
0	1	0	0	0	0	1	
1	0	1	0	1	0	0	
2	0	0	0	0	0	1	
3	0	1	0	0	0	1	
4	1	0	0	0	0	1	
...	...	...	...	...	...	...	
1304	1	0	0	0	0	1	
1305	0	0	1	1	0	0	
1306	1	0	0	0	0	1	
1307	1	0	0	0	0	1	
1308	0	0	0	1	0	0	

	Age
0	22.0

```

1      38.0
2      26.0
3      35.0
4      35.0
...
1304   28.0
1305   39.0
1306   38.5
1307   28.0
1308    6.0

```

```
[1309 rows x 14 columns]
```

```
[81]: df2.drop(['Pclass_1', 'Title_Master', 'Embarked_C'], axis = 1, inplace = True)
df2
```

```
[81]:
```

	Survived	Sex	Pclass_2	Pclass_3	Title_Miss	Title_Mr	Title_Mrs	\
0	0.0	0	0	1	0	1	0	
1	1.0	1	0	0	0	0	1	
2	1.0	1	0	1	1	0	0	
3	1.0	1	0	0	0	0	1	
4	0.0	0	0	1	0	1	0	
...	...	...	...	...	...	...	...	
1304	NaN	0	0	1	0	1	0	
1305	NaN	1	0	0	0	0	0	
1306	NaN	0	0	1	0	1	0	
1307	NaN	0	0	1	0	1	0	
1308	NaN	0	0	1	0	0	0	

	Title_Person	Embarked_Q	Embarked_S	Age
0	0	0	1	22.0
1	0	0	0	38.0
2	0	0	1	26.0
3	0	0	1	35.0
4	0	0	1	35.0
...	...	...	...	...
1304	0	0	1	28.0
1305	1	0	0	39.0
1306	0	0	1	38.5
1307	0	0	1	28.0
1308	0	0	0	6.0

```
[1309 rows x 11 columns]
```

```
[82]: df_titanic.head(2)
```

```
[82]: 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 Title
0  A/5 21171   7.2500   NaN        S    Mr
1   PC 17599  71.2833   C85        C    Mrs
```

## 1.16 FamilySize

SibSp compreende a relação familiar como irmãos de sangue ou não + maridos/esposa Parch compreende a relação familiar como pai/padrastro, mae/madrasta, filhos de sangue ou nao

Poranto a o tamanho da familia é a pessoa + sibsp + parch

```
[83]: df2['FamilySize'] = df_titanic['SibSp'] + df_titanic['Parch'] + 1
df2
```

```
[83]: Survived  Sex  Pclass_2  Pclass_3  Title_Miss  Title_Mr  Title_Mrs  \
0          0.0    0          0          1          0          1          0
1          1.0    1          0          0          0          0          1
2          1.0    1          0          1          1          0          0
3          1.0    1          0          0          0          0          1
4          0.0    0          0          1          0          1          0
...      ...    ...      ...      ...      ...      ...      ...
1304       NaN    0          0          1          0          1          0
1305       NaN    1          0          0          0          0          0
1306       NaN    0          0          1          0          1          0
1307       NaN    0          0          1          0          1          0
1308       NaN    0          0          1          0          0          0

      Title_Person  Embarked_Q  Embarked_S  Age  FamilySize
0                0          0          1  22.0           2
1                0          0          0  38.0           2
2                0          0          1  26.0           1
3                0          0          1  35.0           2
4                0          0          1  35.0           1
...      ...      ...      ...      ...      ...
1304            0          0          1  28.0           1
1305            1          0          0  39.0           1
1306            0          0          1  38.5           1
1307            0          0          1  28.0           1
1308            0          0          0   6.0           3
```

[1309 rows x 12 columns]

## 1.17 Tratando Fare

```
[84]: df_titanic.head(5)
```

```
[84]: 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
```

```
                                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
2                Heikkinen, Miss. Laina      1  26.0      0      0
3  Futrelle, Mrs. Jacques Heath (Lily May Peel)    1  35.0      1      0
4                Allen, Mr. William Henry      0  35.0      0      0
```

```
          Ticket      Fare Cabin Embarked Title
0          A/5 21171   7.2500   NaN         S   Mr
1          PC 17599  71.2833   C85         C  Mrs
2  STON/O2. 3101282   7.9250   NaN         S  Miss
3          113803  53.1000  C123         S  Mrs
4          373450   8.0500   NaN         S   Mr
```

```
[85]: df_info(df_titanic, 'Fare', False)
```

Quantidade de valores únicos na Fare:  
281

Quais são os valores únicos na Fare:

```
[ 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]						

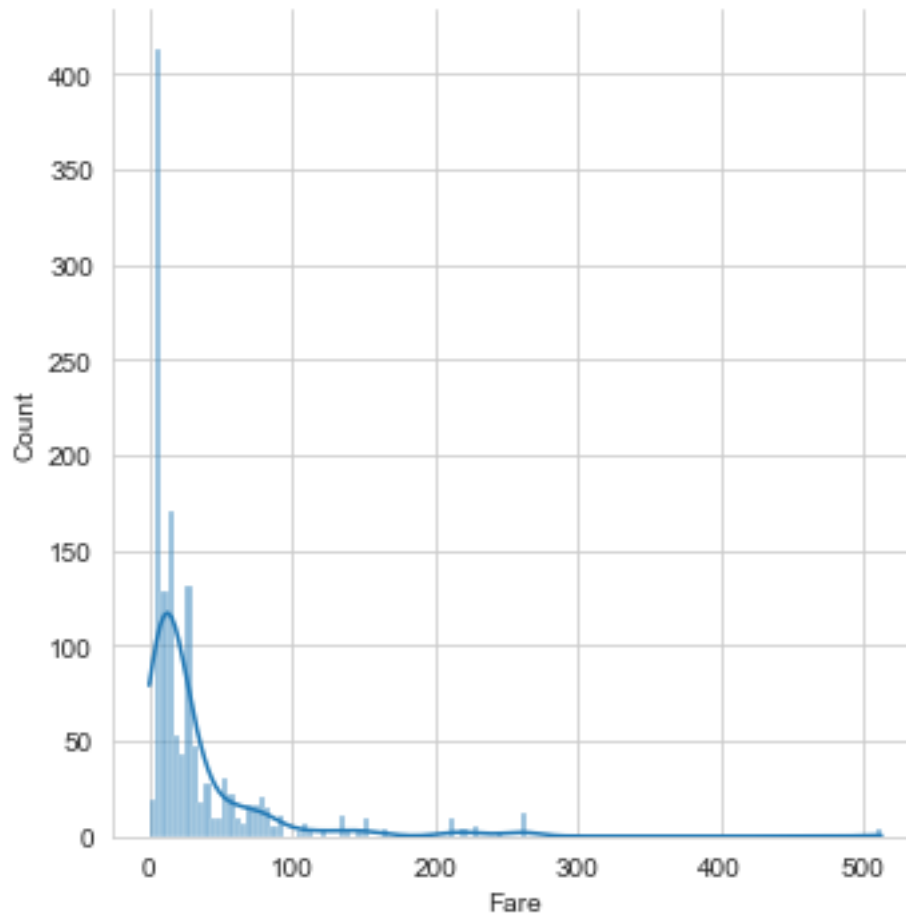
Quantidade de valores nulos na Fare:

1

Quantidade por opção na 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: Fare, Length: 281, dtype: int64



```
[86]: df_titanic.loc[df_titanic['Fare'].isnull()]
```

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

      Parch  Ticket  Fare  Cabin  Embarked  Title
1043      0   3701   NaN   NaN        S      Mr
```

```
[87]: fare_mean_class3 = df_titanic.loc[(df_titanic['Pclass'] == 3)]['Fare'].mean()
fare_mean_class3
```

```
[87]: 13.302888700564969
```

```
[88]: for i in df_titanic.index:
      if pd.isna(df_titanic.loc[i, 'Fare']):
          df_titanic.loc[i, 'Fare'] = fare_mean_class3

df_titanic['Fare'].isnull().sum()
```

```
[88]: 0
```

```
[89]: df2['Fare'] = df_titanic['Fare']
df2['Fare'].isnull().sum()
```

```
[89]: 0
```

## 1.18 Separando as bases

```
[90]: train = df2[:train_index].copy()
train
```

```
[90]:
```

	Survived	Sex	Pclass_2	Pclass_3	Title_Miss	Title_Mr	Title_Mrs	\
0	0.0	0	0	1	0	1	0	
1	1.0	1	0	0	0	0	1	
2	1.0	1	0	1	1	0	0	
3	1.0	1	0	0	0	0	1	
4	0.0	0	0	1	0	1	0	
..	...	...	...	...	...	...	...	
886	0.0	0	1	0	0	0	0	
887	1.0	1	0	0	1	0	0	
888	0.0	1	0	1	1	0	0	
889	1.0	0	0	0	0	1	0	
890	0.0	0	0	1	0	1	0	

	Title_Person	Embarked_Q	Embarked_S	Age	FamilySize	Fare
0	0	0	1	22.0	2	7.2500
1	0	0	0	38.0	2	71.2833
2	0	0	1	26.0	1	7.9250
3	0	0	1	35.0	2	53.1000
4	0	0	1	35.0	1	8.0500
..	...	...	...	...	...	...
886	1	0	1	27.0	1	13.0000
887	0	0	1	19.0	1	30.0000
888	0	0	1	17.0	4	23.4500
889	0	0	0	26.0	1	30.0000
890	0	1	0	32.0	1	7.7500

```
[891 rows x 13 columns]
```

```
[91]: test = df2[test_index:].copy()
test
```

```
[91]:
```

	Survived	Sex	Pclass_2	Pclass_3	Title_Miss	Title_Mr	Title_Mrs	\
891	NaN	0	0	1	0	1	0	
892	NaN	1	0	1	0	0	1	
893	NaN	0	1	0	0	1	0	



894	NaN	0	0	1	0	1	0
895	NaN	1	0	1	0	0	1
...	...	...	...	...	...	...	...
1304	NaN	0	0	1	0	1	0
1305	NaN	1	0	0	0	0	0
1306	NaN	0	0	1	0	1	0
1307	NaN	0	0	1	0	1	0
1308	NaN	0	0	1	0	0	0

	Title_Person	Embarked_Q	Embarked_S	Age	FamilySize	Fare
891	0	1	0	34.5	1	7.8292
892	0	0	1	47.0	2	7.0000
893	0	1	0	62.0	1	9.6875
894	0	0	1	27.0	1	8.6625
895	0	0	1	22.0	3	12.2875
...	...	...	...	...	...	...
1304	0	0	1	28.0	1	8.0500
1305	1	0	0	39.0	1	108.9000
1306	0	0	1	38.5	1	7.2500
1307	0	0	1	28.0	1	8.0500
1308	0	0	0	6.0	3	22.3583

[418 rows x 13 columns]

```
[92]: train['Survived'] = train['Survived'].astype(int)
train
```

```
[92]:
```

	Survived	Sex	Pclass_2	Pclass_3	Title_Miss	Title_Mr	Title_Mrs	\
0	0	0	0	1	0	1	0	
1	1	1	0	0	0	0	1	
2	1	1	0	1	1	0	0	
3	1	1	0	0	0	0	1	
4	0	0	0	1	0	1	0	
..	...	...	...	...	...	...	...	
886	0	0	1	0	0	0	0	
887	1	1	0	0	1	0	0	
888	0	1	0	1	1	0	0	
889	1	0	0	0	0	1	0	
890	0	0	0	1	0	1	0	

	Title_Person	Embarked_Q	Embarked_S	Age	FamilySize	Fare
0	0	0	1	22.0	2	7.2500
1	0	0	0	38.0	2	71.2833
2	0	0	1	26.0	1	7.9250
3	0	0	1	35.0	2	53.1000
4	0	0	1	35.0	1	8.0500
..	...	...	...	...	...	...

886	1	0	1	27.0	1	13.0000
887	0	0	1	19.0	1	30.0000
888	0	0	1	17.0	4	23.4500
889	0	0	0	26.0	1	30.0000
890	0	1	0	32.0	1	7.7500

[891 rows x 13 columns]

## 1.19 Definindo as variáveis X, y que irão no modelo

```
[93]: X = train.drop('Survived', axis = 1)
      y = train['Survived']
```

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

```
[108]: def acuracia_algoritmo(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)

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

```
[ ]:
```

## 1.20 Testando todos os Classificadores do SkLearn

### 1.21 Random Forest

```
[109]: acuracia_algoritmo(RandomForestClassifier(), X, y, 10)
```

Acurácia: 98.32

Acurácia Validação Cruzada: 81.37

### 1.22 Logistic Regression

```
[110]: acuracia_algoritmo(LogisticRegression(max_iter=1000), X, y, 10)
```

Acurácia: 82.94

Acurácia Validação Cruzada: 82.83

### 1.23 Gaussian Naives Bayes

```
[111]: acuracia_algoritmo(GaussianNB(), X, y, 10)
```

Acurácia: 78.0

Acurácia Validação Cruzada: 77.89

### 1.24 Linear Support Vector Machines (SVC)

```
[112]: acuracia_algoritmo(LinearSVC(dual = False), X, y, 10)
```

Acurácia: 83.28

Acurácia Validação Cruzada: 82.94

### 1.25 K-nearest Neighbours

```
[114]: acuracia_algoritmo(KNeighborsClassifier(), X, y, 10)
```

Acurácia: 81.59

Acurácia Validação Cruzada: 71.94

### 1.26 Stochastic Gradient Descent

```
[115]: acuracia_algoritmo(SGDClassifier(), X, y, 10)
```

Acurácia: 73.18

Acurácia Validação Cruzada: 73.4

### 1.27 Decision Tree Classifier

```
[116]: acuracia_algoritmo(DecisionTreeClassifier(), X, y, 10)
```

Acurácia: 98.32

Acurácia Validação Cruzada: 79.69

### 1.28 Gradient Boost Trees

```
[117]: acuracia_algoritmo(GradientBoostingClassifier(), X, y, 10)
```

Acurácia: 90.24

Acurácia Validação Cruzada: 83.28

### 1.29 Treinando automaticamente os melhores parametros do melhor classificador no GridSearch para encontrar a melhor performance

```
[131]: 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)],
```

```
)
```

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

### 1.30 Melhor classificador GRADIENT BOOSTING - Utilizando GridSearch para melhorar a performace

```
[133]: gbc_cv = GridSearchCV(estimator = gbc, param_grid = params, cv = 10)
```

```
[134]: gbc_cv.fit(X, y)
```

```
[134]: 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]})
```

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

Melhor pontuação: 0.8440324594257179

Melhores parâmetros: GradientBoostingClassifier(max\_depth=4, min\_samples\_leaf=2,  
min\_samples\_split=5,  
n\_estimators=30)

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

```
[138]: kaggle = pd.DataFrame({'PassengerId': passengerID, 'Survived':  
    ↳ gradientBoostingClassifier_pred})
```

```
[139]: kaggle
```

```
[139]:
```

	PassengerId	Survived
0	892	0
1	893	0
2	894	0
3	895	0
4	896	1
..	...	...
413	1305	0
414	1306	1
415	1307	0
416	1308	0
417	1309	1

[418 rows x 2 columns]

```
[140]: kaggle.to_csv('./titanic_gradient_boosting_pred.csv', index=False)
```

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