Titanic

October 19, 2019

ATRIBUTO CLASSIFICAÇÃO ESCALA PassegerId Qualitativo Nominal Survived Qualitativo Nominal Pclass Qualitativo Ordinal Name Qualitativo Nominal Sex Qualitativo Nominal Age Quantitativo discreto Racional SibSp Quantitativo discreto Racional Parch Quantitativo discreto Racional Ticket Qualitativo Nominal Fare Quantitativo contínuo Intervalar? Cabin Qualitativo Nominal Embarked Qualitativo Nominal

PassengerId: Unique ID of the passenger Survived: Survived (1) or died (0) Pclass: Passenger's class (1st, 2nd, or 3rd) Name: Passenger's name Sex: Passenger's sex Age: Passenger's age SibSp: Number of siblings/spouses aboard the Titanic Parch: Number of parents/children aboard the Titanic Ticket: Ticket number Fare: Fare paid for ticket Cabin: Cabin number Embarked: Where the passenger got on the ship (C - Cherbourg, S - Southampton, Q = Queenstown)

```
In [1]: import numpy as np
        import pandas as pd
        import seaborn as sns
        import matplotlib.pyplot as plt

        %matplotlib inline

        train = pd.read_csv("train.csv")
        test = pd.read_csv("test.csv")
```

0.1 Visualizando os dados

```
In [2]: train.describe()
```

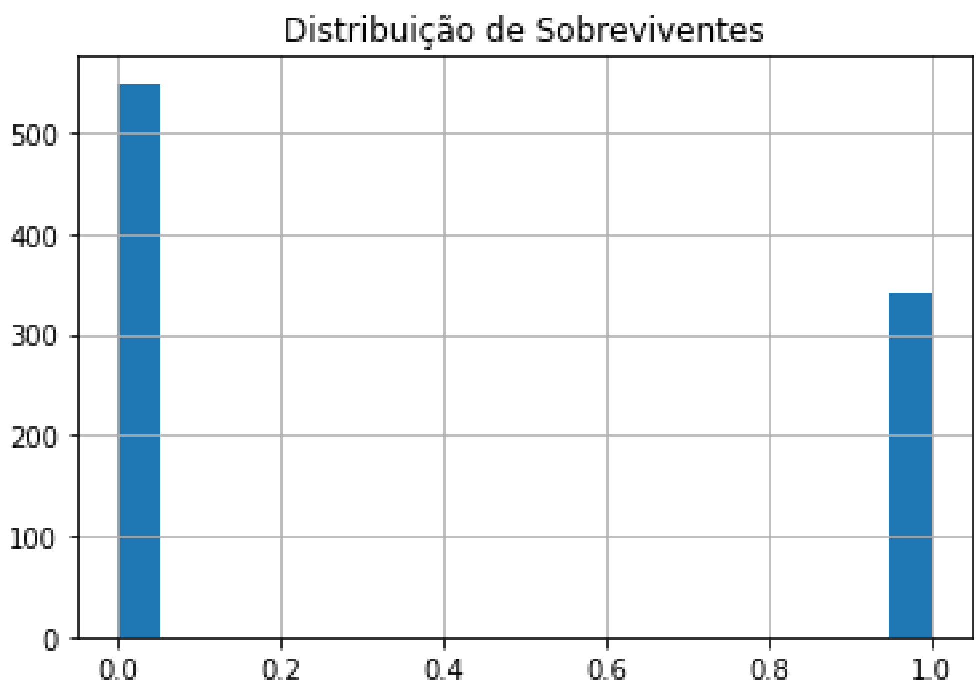
```
Out[2]:        PassengerId    Survived      Pclass         Age       SibSp  \
        count   891.000000  891.000000  891.000000  714.000000  891.000000
        mean    446.000000    0.383838    2.308642   29.699118    0.523008
        std     257.353842    0.486592    0.836071   14.526497    1.102743
        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
```

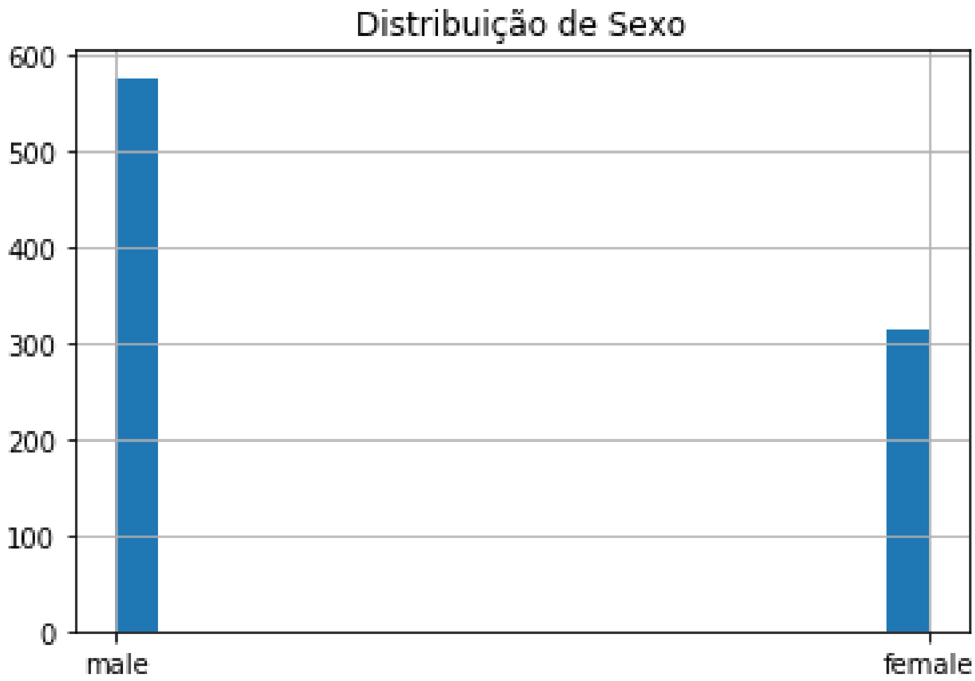
In [3]:
```
##Distribuição de sobreviventes
# Mais pessoas morreram do que sobreviveram(desbalanceado)
train.Survived.hist(bins=20)
plt.title("Distribuição de Sobreviventes")
```

Out[3]: `Text(0.5, 1.0, 'Distribuição de Sobreviventes')`



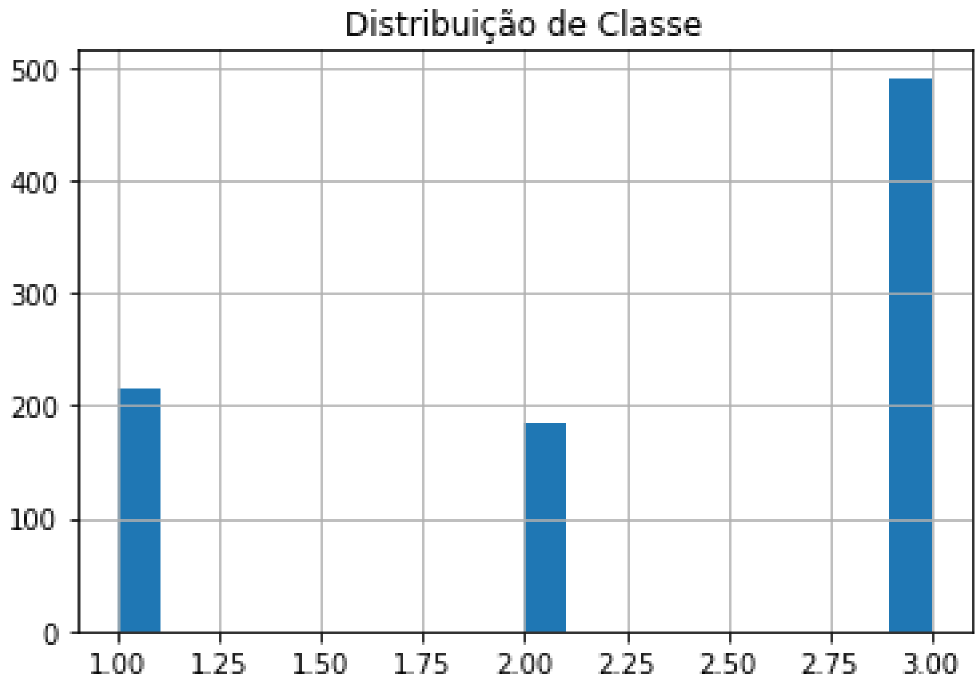
In [4]:
```
##Distribuição de sexo
# Mais homens que mulheres
# Como a maioria morreu e a maioria dos dados de treino são homens,
# pode haver uma relação entre ser homem e morrer.
train.Sex.hist(bins=20)
plt.title("Distribuição de Sexo")
```

Out[4]: `Text(0.5, 1.0, 'Distribuição de Sexo')`



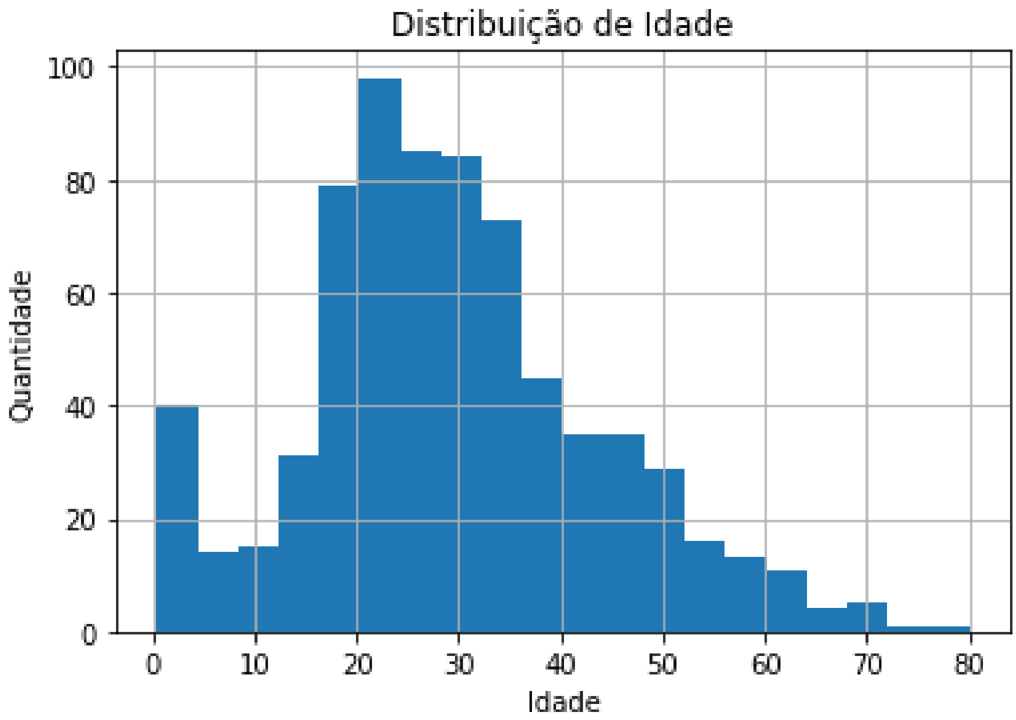

```
In [5]: ## Distribuição de Classe
        # Maioria é de terceira classe(Pode haver uma relação)
        train.Pclass.hist(bins=20)
        plt.title("Distribuição de Classe")

Out[5]: Text(0.5, 1.0, 'Distribuição de Classe')
```



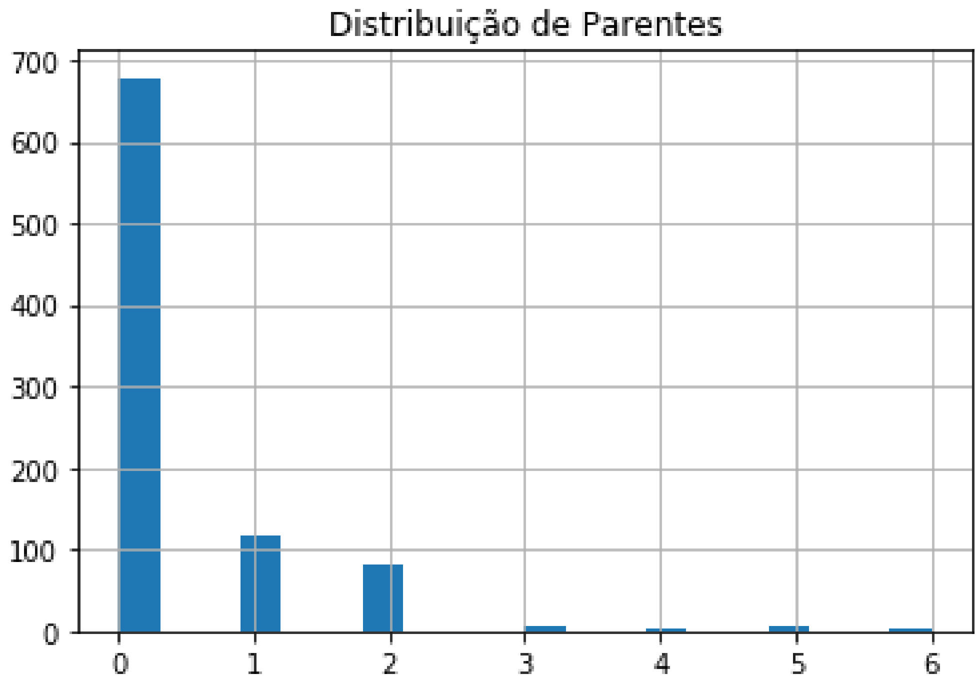
In [6]:
```
## Distribuição de Idade
# Maioria de meia idade
train.Age.hist(bins=20)
plt.xlabel("Idade")
plt.ylabel("Quantidade")
plt.title("Distribuição de Idade")
```

Out[6]:
```
Text(0.5, 1.0, 'Distribuição de Idade')
```




```
In [7]: ## Distribuição de Parentes
        train.Parch.hist(bins=20)
        plt.title("Distribuição de Parentes")

Out[7]: Text(0.5, 1.0, 'Distribuição de Parentes')
```




```
In [8]: ## Exploração de dados
        #  Prova que sobrevivem menos homens que mulheres
        train[["Survived", "Sex"]].groupby(['Sex'], as_index=False).mean().sort_values(by='Surv
```

```
Out[8]:       Sex  Survived
        0  female  0.742038
        1    male  0.188908
```

```
In [9]: ## Exploração de dados
        #  Prova que mesmo as pessoas sendo de maioria da terceira classe,
        #  elas foram a que menos sobreviveram
        train[["Pclass", "Survived"]].groupby(['Pclass'], as_index=False).mean().sort_values(by
```

```
Out[9]:    Pclass  Survived
        0       1  0.629630
        1       2  0.472826
        2       3  0.242363
```

```
In [10]: ## Exploração de dados
         #  Numero de parentes embarcados
         #  Intuitivamente parece relevante
         train[["Parch", "Survived"]].groupby(['Parch'], as_index=False).mean().sort_values(by=
```

```
Out[10]:    Parch  Survived
         3      3  0.600000
```

```
1      1  0.550847
2      2  0.500000
0      0  0.343658
5      5  0.200000
4      4  0.000000
6      6  0.000000
```

In [11]:
```
train[["SibSp", "Survived"]].groupby(['SibSp'], as_index=False).mean().sort_values(by=
```

Out[11]:
```
   SibSp  Survived
1      1  0.535885
2      2  0.464286
0      0  0.345395
3      3  0.250000
4      4  0.166667
5      5  0.000000
6      8  0.000000
```

In [12]:
```
## Dropando valores intuitivamente considerados desnecessários
train = train.drop(["Ticket"], axis=1)
test = test.drop(["Ticket"], axis=1)
```

0.2 Engenharia de dados

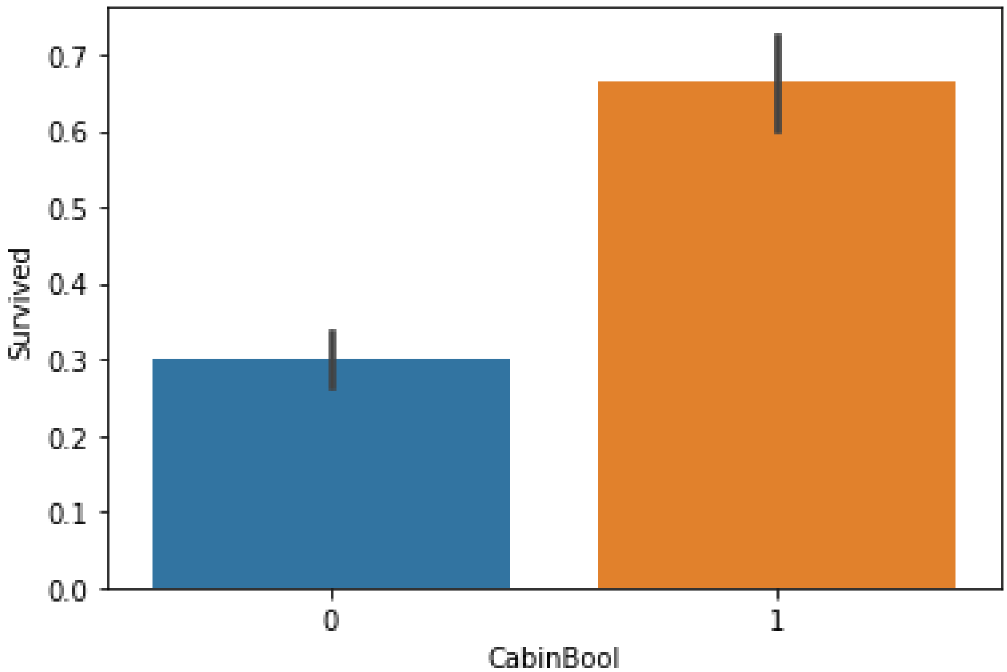
In [13]:
```
##Convertendo valores categóricos
##Convertendo  Cabin
train["CabinBool"] = (train["Cabin"].notnull().astype('int'))
test["CabinBool"] = (test["Cabin"].notnull().astype('int'))


print("Porcentagem de CabinBool = 1 sobreviventes:", train["Survived"][train["CabinBoo

print("Porcentagem de CabinBool = 0 sobreviventes:", train["Survived"][train["CabinBoo

sns.barplot(x="CabinBool", y="Survived", data=train)
plt.show()
#Pessoas com numero na cabine tem mais chances de sobreviver. (66.6% vs 29.9%)
train = train.drop(['Cabin'], axis = 1)
test = test.drop(['Cabin'], axis = 1)
```

```
Porcentagem de CabinBool = 1 sobreviventes: 66.66666666666666
Porcentagem de CabinBool = 0 sobreviventes: 29.985443959243085
```




```
In [14]: ##Tratando nomes usando o prefixo
         data_title = [i.split(",")[1].split(".")[0].strip() for i in train["Name"]]
         train["Title"] = pd.Series(data_title)
         tdata_title = [i.split(",")[1].split(".")[0].strip() for i in test["Name"]]
         test["Title"] = pd.Series(tdata_title)
         test["Title"].head()

Out[14]: 0      Mr
         1     Mrs
         2      Mr
         3      Mr
         4     Mrs
         Name: Title, dtype: object

In [15]: ##Tratando os nomes
         train["Title"] = train["Title"].replace(['Lady', 'the Countess','Countess','Capt', 'C
         train["Title"] = train["Title"].map({"Master":0, "Miss":1, "Ms" : 1 , "Mme":1, "Mlle"
         train["Title"] = train["Title"].astype(int)
         test["Title"] = test["Title"].replace(['Lady', 'the Countess','Countess','Capt', 'Col
         test["Title"] = test["Title"].map({"Master":0, "Miss":1, "Ms" : 1 , "Mme":1, "Mlle":1
         test["Title"] = test["Title"].astype(int)

         train.drop(labels = ["Name"], axis = 1, inplace = True)
         test.drop(labels = ["Name"], axis = 1, inplace = True)
```

In [16]:
```
##Convertendo valores categóricos
##Fazendo o one hot encoder
newdtrain = pd.get_dummies(train)
newdtest = pd.get_dummies(test)
newdtrain.head()
```

Out[16]:
```
   PassengerId  Survived  Pclass   Age  SibSp  Parch     Fare  CabinBool  \
0            1         0       3  22.0      1      0   7.2500          0
1            2         1       1  38.0      1      0  71.2833          1
2            3         1       3  26.0      0      0   7.9250          0
3            4         1       1  35.0      1      0  53.1000          1
4            5         0       3  35.0      0      0   8.0500          0

   Title  Sex_female  Sex_male  Embarked_C  Embarked_Q  Embarked_S
0      2           0         1           0           0           1
1      1           1         0           1           0           0
2      1           1         0           0           0           1
3      1           1         0           0           0           1
4      2           0         1           0           0           1
```

In [17]:
```
##Agrupando os dados
# Tamanho da familia
newdtrain["Fsize"] = newdtrain["SibSp"] + newdtrain["Parch"] + 1
newdtest["Fsize"] = newdtest["SibSp"] + newdtest["Parch"] + 1
```

In [18]:
```
newdtrain["Single"] = newdtrain["Fsize"].map(lambda x: 1 if x == 1 else 0)
newdtrain["Small"] = newdtrain["Fsize"].map(lambda x: 1 if x == 2 else 0)
newdtrain["Med"] = newdtrain["Fsize"].map(lambda x: 1 if 3 <= x <= 4 else 0)
newdtrain["Large"] = newdtrain["Fsize"].map(lambda x: 1 if x >= 5 else 0)

newdtest["Single"] = newdtest["Fsize"].map(lambda x: 1 if x == 1 else 0)
newdtest["Small"] = newdtest["Fsize"].map(lambda x: 1 if x == 2 else 0)
newdtest["Med"] = newdtest["Fsize"].map(lambda x: 1 if 3 <= x <= 4 else 0)
newdtest["Large"] = newdtest["Fsize"].map(lambda x: 1 if x >= 5 else 0)
```

In [19]:
```
newdtrain.isnull().sum().sort_values(ascending=False).head(10)
```

Out[19]:
```
Age           177
Large           0
Title           0
Survived        0
Pclass          0
SibSp           0
Parch           0
Fare            0
CabinBool       0
Sex_female      0
dtype: int64
```

1 Tratando os valores missing da idade usando média

In [20]:
```
newdtrain["Age"].fillna(newdtrain["Age"].mean(), inplace=True)
newdtest["Age"].fillna(newdtest["Age"].mean(), inplace=True)
```

In [21]:
```
## Convertendo idade para um intervalo
newdtrain['AgeBand'] = pd.cut(newdtrain['Age'], 5)
newdtest['AgeBand'] = pd.cut(newdtest['Age'], 5)
newdtrain[['AgeBand', 'Survived']].groupby(['AgeBand'], as_index=False).mean().sort_va
```

Out[21]:

	AgeBand	Survived
0	(0.34, 16.336]	0.550000
1	(16.336, 32.252]	0.344168
2	(32.252, 48.168]	0.404255
3	(48.168, 64.084]	0.434783
4	(64.084, 80.0]	0.090909

In [22]:
```
newdtrain.loc[newdtrain['Age'] <= 16, 'Age'] = 0
newdtrain.loc[(newdtrain['Age'] > 16) & (newdtrain['Age'] <= 32), 'Age'] = 1
newdtrain.loc[(newdtrain['Age'] > 32) & (newdtrain['Age'] <= 48), 'Age'] = 2
newdtrain.loc[(newdtrain['Age'] > 48) & (newdtrain['Age'] <= 64), 'Age'] = 3
newdtrain.loc[ newdtrain['Age'] > 64, 'Age'] = 4

newdtest.loc[newdtest['Age'] <= 16, 'Age'] = 0
newdtest.loc[(newdtest['Age'] > 16) & (newdtest['Age'] <= 32), 'Age'] = 1
newdtest.loc[(newdtest['Age'] > 32) & (newdtest['Age'] <= 48), 'Age'] = 2
newdtest.loc[(newdtest['Age'] > 48) & (newdtest['Age'] <= 64), 'Age'] = 3
newdtest.loc[ newdtest['Age'] > 64, 'Age'] = 4
```

In [23]:
```
newdtrain = newdtrain.drop(['AgeBand'], axis=1)
newdtest = newdtest.drop(['AgeBand'], axis=1)
```

In [24]:
```
## Convertendo valores FareBand
newdtrain['FareBand'] = pd.qcut(newdtrain['Fare'], 4)
newdtest['FareBand'] = pd.qcut(newdtest['Fare'], 4)
newdtrain[['FareBand', 'Survived']].groupby(['FareBand'], as_index=False).mean().sort_
```

Out[24]:

	FareBand	Survived
0	(-0.001, 7.91]	0.197309
1	(7.91, 14.454]	0.303571
2	(14.454, 31.0]	0.454955
3	(31.0, 512.329]	0.581081

In [25]:
```
newdtrain.loc[ newdtrain['Fare'] <= 7.91, 'Fare'] = 0
newdtrain.loc[(newdtrain['Fare'] > 7.91) & (newdtrain['Fare'] <= 14.454), 'Fare'] = 1
newdtrain.loc[(newdtrain['Fare'] > 14.454) & (newdtrain['Fare'] <= 31.0), 'Fare'] = 2
newdtrain.loc[newdtrain['Fare'] > 31.0, 'Fare'] = 3

newdtest.loc[ newdtest['Fare'] <= 7.91, 'Fare'] = 0
```

```
newdtest.loc[(newdtest['Fare'] > 7.91) & (newdtest['Fare'] <= 14.454), 'Fare'] = 1
newdtest.loc[(newdtest['Fare'] > 14.454) & (newdtest['Fare'] <= 31.0), 'Fare'] = 2
newdtest.loc[newdtest['Fare'] > 31.0, 'Fare'] = 3
```

In [26]:
```
newdtrain = newdtrain.drop(['FareBand'], axis=1)

newdtest = newdtest.drop(['FareBand'], axis=1)
```

In [27]:
```
newdtest.isnull().sum().sort_values(ascending=False).head(10)
```

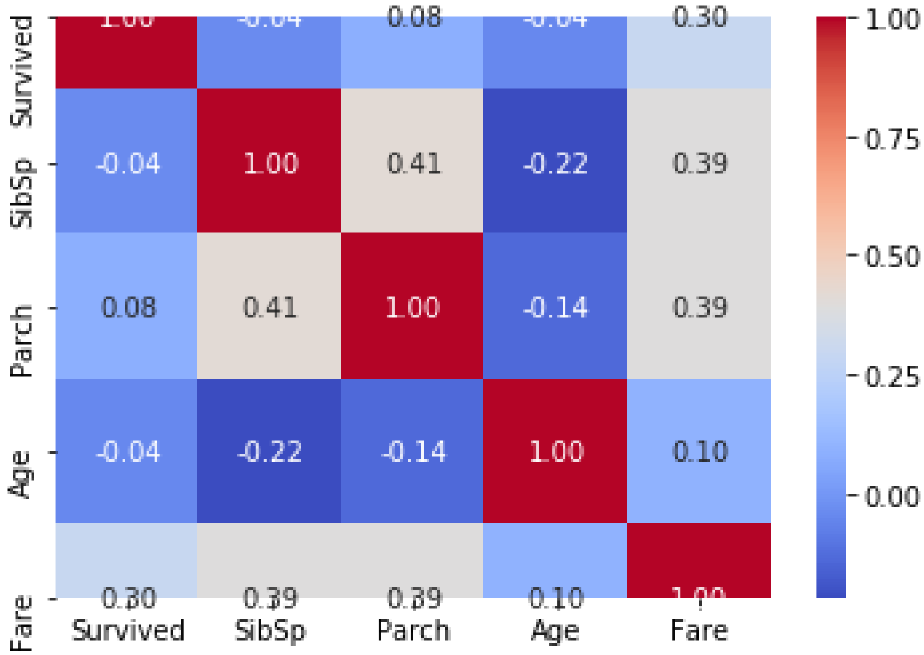
Out[27]:
```
Fare          1
Large         0
Med           0
Pclass        0
Age           0
SibSp         0
Parch         0
CabinBool     0
Title         0
Sex_female    0
dtype: int64
```

In [28]:
```
newdtest["Fare"].fillna(newdtest["Fare"].mean(), inplace=True)
```

In [29]:
```
X = newdtrain.drop("Survived", axis=1)
y = newdtrain["Survived"]
```

1.1 Visualizando as correlacões negativas e positivas

In [30]:
```
## Correlação de dados
g = sns.heatmap(newdtrain[["Survived", "SibSp", "Parch", "Age", "Fare"]].corr(), anno
```



1.2 Representação do modelo

```
In [31]: ## Modelo de predição
         # Árvore de decisão
         # Overfitting
         from sklearn.tree import DecisionTreeClassifier
         tree = DecisionTreeClassifier(max_depth = 10, random_state = 0)
         tree.fit(X, y)
         tree.score(X, y)
```

```
Out[31]: 0.9337822671156004
```

```
In [32]: ## Modelo de predição
         # Random Forest
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.model_selection import train_test_split
         Xtest = newdtest
```

```
In [33]: Xtrain, Xval, Ytrain, Yval = train_test_split(X, y, test_size=0.2, random_state=True)
```

```
In [34]: model = RandomForestClassifier(criterion='gini',
                                        n_estimators=1100,
                                        max_depth=5,
                                        min_samples_split=4,
                                        min_samples_leaf=5,
                                        max_features='auto',
                                        random_state=42)
         model.fit(Xtrain, Ytrain)
         tree.fit(Xtrain, Ytrain)
         print(model.score(Xtrain, Ytrain), model.score(Xval, Yval))
```

```
0.8441011235955056 0.8100558659217877
```

```
In [35]: from sklearn.metrics import accuracy_score
         Yprediction = model.predict(Xval)
         accuracy_score(Yval, Yprediction)
```

```
Out[35]: 0.8100558659217877
```

1.3 Exportando os resultados

```
In [36]: submission = pd.DataFrame()

         submission["PassengerId"] = Xtest["PassengerId"]
         submission["Survived"] = model.predict(Xtest)
         submission.to_csv("submission.csv", index=False)
         submission.head()
```

Out[36]:

	PassengerId	Survived
0	892	0
1	893	1
2	894	0
3	895	0
4	896	1