Neste exercício iremos criar um classificador sobre para classificar os indíviduos que sobreviveram ou não no titanic, logo nossa variável é a **Survived**

Import as bibliotecas

- Importe as bibliotecas necessárias (sklearn, pandas, ...)

In [1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
```

Acessando os dados

- Recupere o **titanic_ready_to_ml.csv**

In [2]:
```
df = pd.read_csv('titanic_ready_to_ml.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	Survived	Name	Age	SibSp	Parch	Ticket	Fare	Q	S	Pclass_2	Pclass_3	Sex_1	AgeGroup
0	0	Braund, Mr. Owen Harris	22.0	1	0	A/5 21171	0.014151	0	1	0	1	1	Adulto
1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	38.0	1	0	PC 17599	0.139136	0	0	0	0	0	Adulto
2	1	Heikkinen, Miss. Laina	26.0	0	0	STON/O2. 3101282	0.015469	0	1	0	1	0	Adulto
3	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	35.0	1	0	113803	0.103644	0	1	0	0	0	Adulto
4	0	Allen, Mr. William Henry	35.0	0	0	373450	0.015713	0	1	0	1	1	Adulto

Construindo do modelo

Importe a classe DecisionTreeClassifier e RandomForestClassifier do Sklearn

In [4]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import OneHotEncoder
```

Separe os dados em teste e treino

- Importe train_test_split, para facilitar a sepração do treino e do teste, utilize o test_size de 30% e random state igual a 16
- Crie as variáveis X_train, X_test, y_train, y_test a partir do retorno da função da função train_test_split

In [5]:
```
from sklearn.model_selection import train_test_split
```

In [6]:
```
# Separando as variáveis preditoras (X) e a variável alvo (y)
X = df.drop('Survived', axis=1)
y = df['Survived']

# One-hot encoding nas variáveis categóricas
ohe = OneHotEncoder()
X_encoded = ohe.fit_transform(X)

# Dividindo os dados em treino e teste
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.3, random_state=16)
```

Instacie um objeto da classe DecisionTreeClassifier()

In [7]:
```python
# Instanciando os dados
model_dt = DecisionTreeClassifier()
```

In [8]:
```python
# Treinando os dados
model_dt.fit(X_train, y_train)
```

Out[8]:
```
DecisionTreeClassifier()
```

Faça as predições, sobre os dados de teste criados anteriormente, invocando a função predict do modelo criado

- Chame a função *predict_proba* em outra célula. Qual a diferença desse método para o método predict?

In [9]:
```python
y_pred = model_dt.predict(X_test)
```

In [10]:
```python
# A função predict_proba retorna a probabilidade estimada de cada classe para cada amostra de teste.
proba = model_dt.predict_proba(X_test)
```

In [11]:
```python
# A diferença entre esses dois métodos é que predict retorna as classes previstas (por exemplo, 0 ou 1),
# enquanto predict_proba retorna a probabilidade de pertencer a cada classe
# (por exemplo, 0.7 para classe 0 e 0.3 para classe 1).
```

Avaliando o modelo

Importe e utilize a função confusion_matrix para construir a matriz de confusão, sobre os valores preditos e valores reais.

- *Dica:* Você pode querer visualizar a matriz, veja este exemplo
- **Para reflexão:** O que pode haver de comum entre os falsos positivos e os falsos negativos?

In [12]:
```python
from sklearn.metrics import confusion_matrix
```

In [13]:
```python
y_estimado = model_dt.predict(X_train)
cm = confusion_matrix(y_estimado, y_train, labels=[1, 0])
print(cm)
```

```
[[226   0]
 [  0 396]]
```

In [14]:
```python
probs = model_dt.predict_proba(X_train)
print(probs)
```

```
[[0. 1.]
 [1. 0.]
 [1. 0.]
 ...
 [1. 0.]
 [1. 0.]
 [1. 0.]]
```

In [15]:
```python
from sklearn.metrics import confusion_matrix

y_estimado = model_dt.predict(X_test)
cm = confusion_matrix(y_test, y_estimado, labels=[1, 0])

print(cm)
```

```
[[ 76  38]
 [ 10 143]]
```

In [16]:
```python
y_proba = model_dt.predict_proba(X_test)
print(y_proba)
```

```
[[0. 1.]
 [0. 1.]
 [1. 0.]
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[1. 0.]
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```

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 [1. 0.]
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 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [0. 1.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [1. 0.]
 [0. 1.]]
```

Importe e utilize a função classification_report para visualizar algumas métricas sobre o seu resultado

In [17]:

```
from sklearn.metrics import classification_report, precision_score

print(classification_report(y_estimado, y_test))
```

```
              precision    recall  f1-score   support

           0       0.93      0.79      0.86       181
           1       0.67      0.88      0.76        86

    accuracy                           0.82       267
   macro avg       0.80      0.84      0.81       267
weighted avg       0.85      0.82      0.83       267
```

In [18]:

```
precision = precision_score(y_estimado, y_test, average='weighted')
precision_percent = precision * 100
formatted_precision = "{:.2f}%".format(precision_percent)

print(formatted_precision)
```

```
84.83%
```

Interpretando os resultados do modelo

Quais as features mais importantes? Visualize o impacto das features na classificação

- *Dica:* Utilize a função feature*importances* do modelo construído

In [19]:

```
column_names = list(df.columns)
feature_importance = model_dt.feature_importances_

features = zip(column_names, feature_importance * 100)

for feature in features:
    print(f"Feature: {feature[0]}, Importância: {feature[1]:.2f}%")
```

```
Feature: Survived, Importância: 0.00%
Feature: Name, Importância: 0.00%
Feature: Age, Importância: 0.67%
Feature: SibSp, Importância: 0.00%
Feature: Parch, Importância: 0.00%
Feature: Ticket, Importância: 0.00%
Feature: Fare, Importância: 0.00%
Feature: Q, Importância: 0.00%
Feature: S, Importância: 0.00%
Feature: Pclass_2, Importância: 0.41%
Feature: Pclass_3, Importância: 0.00%
Feature: Sex_1, Importância: 0.00%
Feature: AgeGroup, Importância: 0.00%
```

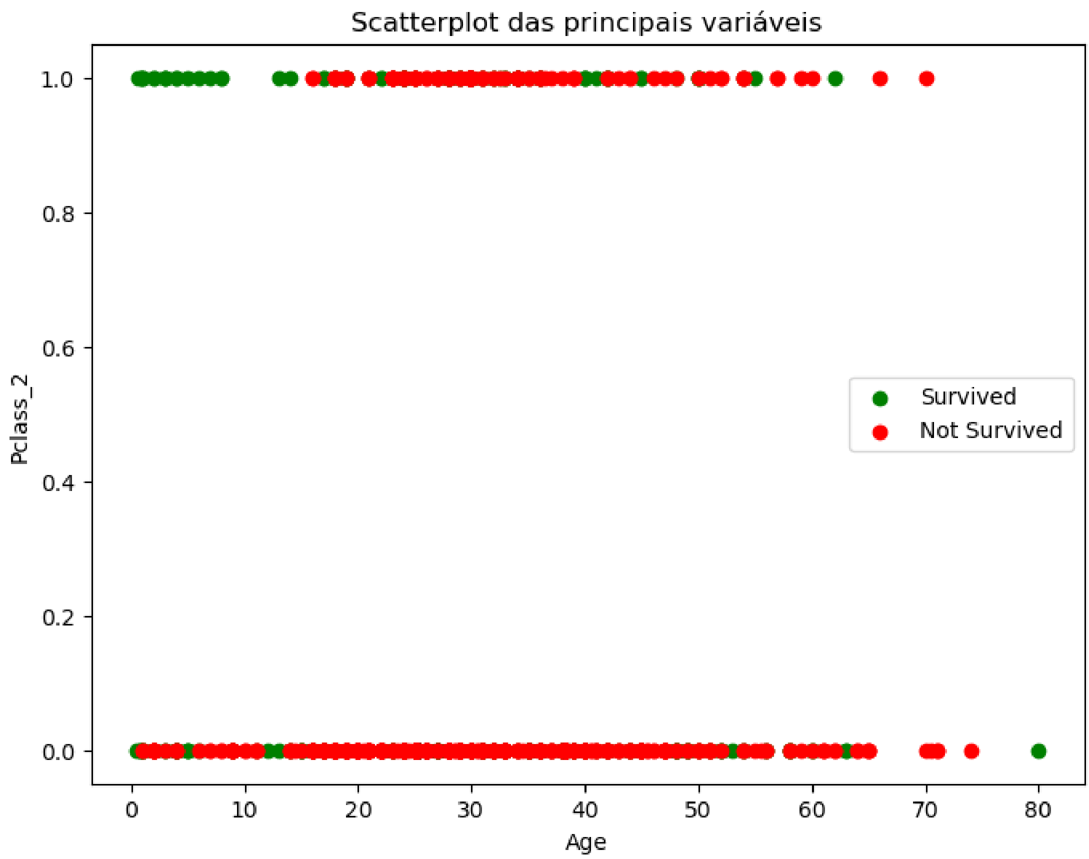
In [20]:

```python
features = dict(features)
features = pd.DataFrame.from_dict(features, orient='index', columns=['Importância'])
features = features.sort_values('Importância', ascending=False).head(5)
```

Plote em um scatterplot com duas das principais variáveis no eixo x e y e verifique a distinção das classes.

In [21]:

```python
import matplotlib.pyplot as plt

# DataFrame com as variáveis selecionadas e a classe
data_plot = df[['Age', 'Pclass_2', 'Survived']].copy()

# Converte os dados para tipos numéricos
data_plot['Age'] = pd.to_numeric(data_plot['Age'])
data_plot['Pclass_2'] = pd.to_numeric(data_plot['Pclass_2'])

# Plota o scatterplot
plt.figure(figsize=(8, 6))
plt.scatter(data_plot[data_plot['Survived'] == 1]['Age'], data_plot[data_plot['Survived'] == 1]['Pclass_2'],
plt.scatter(data_plot[data_plot['Survived'] == 0]['Age'], data_plot[data_plot['Survived'] == 0]['Pclass_2'],
plt.xlabel('Age')
plt.ylabel('Pclass_2')
plt.title('Scatterplot das principais variáveis')
plt.legend()
plt.show()
```



Tuning Model

Treine o modelo apenas com as 4 features mais importantes e veja a matriz de confusão

- Plus: Tente variar algum hiperparamêtro para tentar melhor as KPIs

In [22]:
```
# 4 features mais importantes
top_features = ['Age', 'Pclass_2', 'Fare', 'Sex_1']
```

In [23]:
```
# Separar as variáveis preditoras (X) e a variável alvo (y)
X = df[top_features]
y = df['Survived']
```

In [24]:
```
# Dividir os dados em treino e teste
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=16)
```

In [25]:
```
# Instanciar o modelo de árvore de decisão
model_dt = DecisionTreeClassifier()
```

In [26]:
```
# Treinar o modelo apenas com as 4 features selecionadas
model_dt.fit(X_train, y_train)
```

Out[26]:
```
DecisionTreeClassifier()
```

In [27]:
```
# Fazer as previsões no conjunto de teste
y_pred = model_dt.predict(X_test)
```

In [28]:
```
# Calcular a matriz de confusão
cm = confusion_matrix(y_test, y_pred)
```

In [29]:
```
print("Matriz de Confusão:")
print(cm)
```

```
Matriz de Confusão:
[[126  27]
 [ 34  80]]
```

In [30]:
```
# Ajuste de hiperparâmetros
#model_dt = DecisionTreeClassifier(max_depth=5, criterion='entropy', min_samples_split=10)
#model_dt.fit(X_train, y_train)
#y_pred = model_dt.predict(X_test)
#cm = confusion_matrix(y_test, y_pred)
#print("Matriz de Confusão:")
#print(cm)
```

Resolva as questoes anteriores, a partir da instanciação do objeto, para o algoritmo RandomForestClassifier

In [31]:
```
#RandomForestClassifier
# Instanciando os dados
model_rf = RandomForestClassifier()
```

In [32]:
```
# Treinando os dados
model_rf.fit(X_train, y_train)
```

Out[32]:
```
RandomForestClassifier()
```

In [33]:
```
# Previsões no conjunto de teste
y_pred = model_rf.predict(X_test)
```

In [34]:
```
print("Previsões:")
print(y_pred)
```

```
Previsões:
[0 1 0 1 1 0 1 0 0 1 1 0 0 0 0 1 1 0 0 1 1 1 0 0 0 0 0 1 0 0 1 0 1 0 0 0 0
 0 0 0 0 0 1 1 1 1 0 1 0 1 0 0 0 1 0 0 0 0 1 1 1 1 1 0 1 0 0 0 1 0 1 0 0 1
 0 0 0 0 1 1 0 0 0 0 1 1 1 0 0 1 0 0 1 0 0 0 0 0 0 0 1 1 0 1 1 0 1 0 0 0 1
 0 1 1 0 0 1 1 1 0 1 1 1 0 0 0 1 0 0 0 0 0 1 1 0 0 0 0 0 0 1 1 0 1 0 1 0 1
 1 0 0 0 1 0 1 1 1 0 0 1 1 0 0 0 1 0 0 1 0 1 1 1 0 0 0 0 0 1 1 0 0 0 0 0 0
 0 0 0 0 0 1 1 0 0 0 0 0 1 0 0 0 0 0 1 0 1 0 1 0 1 0 1 1 1 0 0 1 0 0 1 0 0
 0 1 0 1 1 1 0 0 0 1 1 0 0 1 0 1 1 1 0 0 0 0 0 1 0 0 1 0 1 0 0 0 0 1 0 0 0
 0 1 1 0 0 0 0 0]
```

In [35]:

```python
# Previsões de probabilidade usando o conjunto de teste
proba = model_rf.predict_proba(X_test)
```

In [36]:

```python
print("Previsões de probabilidade:")
print(proba)
```

```
Previsões de probabilidade:
[[0.74       0.26      ]
 [0.02       0.98      ]
 [0.92       0.08      ]
 [0.06       0.94      ]
 [0.10892136 0.89107864]
 [1.         0.        ]
 [0.26       0.74      ]
 [0.99177778 0.00822222]
 [0.99       0.01      ]
 [0.07       0.93      ]
 [0.13775755 0.86224245]
 [0.62       0.38      ]
 [0.88378387 0.11621613]
 [0.7        0.3       ]
 [0.82       0.18      ]
 [0.43       0.57      ]
 [0.35271429 0.64728571]
 [0.51       0.49      ]
 [0.813      0.187     ]
 [0.         1.        ]
 [0.3        0.7       ]
 [0.02       0.98      ]
 [0.98       0.02      ]
 [0.925      0.075     ]
 [0.99       0.01      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.06       0.94      ]
 [0.65       0.35      ]
 [0.97       0.03      ]
 [0.36       0.64      ]
 [0.93       0.07      ]
 [0.         1.        ]
 [0.97       0.03      ]
 [0.95       0.05      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.99444444 0.00555556]
 [1.         0.        ]
 [0.97       0.03      ]
 [0.7        0.3       ]
 [0.59       0.41      ]
 [0.32       0.68      ]
 [0.13       0.87      ]
 [0.06       0.94      ]
 [0.3225     0.6775    ]
 [0.97       0.03      ]
 [0.06       0.94      ]
 [0.97       0.03      ]
 [0.         1.        ]
 [0.85       0.15      ]
 [0.71       0.29      ]
 [0.77       0.23      ]
 [0.04       0.96      ]
 [0.89       0.11      ]
 [0.9025     0.0975    ]
 [0.81       0.19      ]
 [1.         0.        ]
 [0.05       0.95      ]
 [0.22       0.78      ]
 [0.05       0.95      ]
 [0.26       0.74      ]
 [0.32       0.68      ]
 [1.         0.        ]
 [0.07       0.93      ]
 [0.99       0.01      ]
 [1.         0.        ]
 [0.84       0.16      ]
 [0.22       0.78      ]
 [0.96       0.04      ]
 [0.12       0.88      ]
 [0.95       0.05      ]
 [0.90971429 0.09028571]
 [0.34083333 0.65916667]
 [0.99       0.01      ]
 [0.88378387 0.11621613]
 [0.93       0.07      ]
 [0.81083333 0.18916667]
 [0.18       0.82      ]
```

```
[0.01       0.99      ]
[0.97       0.03      ]
[0.66       0.34      ]
[0.80686508 0.19313492]
[1.         0.        ]
[0.04111111 0.95888889]
[0.         1.        ]
[0.13       0.87      ]
[0.78       0.22      ]
[0.73       0.27      ]
[0.26       0.74      ]
[0.94       0.06      ]
[0.97       0.03      ]
[0.15       0.85      ]
[1.         0.        ]
[1.         0.        ]
[0.94166667 0.05833333]
[0.99       0.01      ]
[0.61       0.39      ]
[0.92       0.08      ]
[0.99       0.01      ]
[0.17       0.83      ]
[0.03       0.97      ]
[1.         0.        ]
[0.         1.        ]
[0.05       0.95      ]
[0.98       0.02      ]
[0.35       0.65      ]
[0.88       0.12      ]
[0.99       0.01      ]
[1.         0.        ]
[0.01       0.99      ]
[0.74085209 0.25914791]
[0.39       0.61      ]
[0.15       0.85      ]
[1.         0.        ]
[1.         0.        ]
[0.04       0.96      ]
[0.02       0.98      ]
[0.24345747 0.75654253]
[0.98733333 0.01266667]
[0.37       0.63      ]
[0.         1.        ]
[0.07       0.93      ]
[1.         0.        ]
[1.         0.        ]
[0.98333333 0.01666667]
[0.11       0.89      ]
[0.97       0.03      ]
[0.83       0.17      ]
[1.         0.        ]
[1.         0.        ]
[0.8        0.2       ]
[0.18       0.82      ]
[0.06833333 0.93166667]
[0.9        0.1       ]
[0.9        0.1       ]
[0.78       0.22      ]
[0.72766667 0.27233333]
[0.84       0.16      ]
[0.99       0.01      ]
[0.08       0.92      ]
[0.24222222 0.75777778]
[1.         0.        ]
[0.06       0.94      ]
[0.9775     0.0225    ]
[0.03396825 0.96603175]
[0.88       0.12      ]
[0.04       0.96      ]
[0.42       0.58      ]
[1.         0.        ]
[0.63       0.37      ]
[1.         0.        ]
[0.05       0.95      ]
[0.98       0.02      ]
[0.         1.        ]
[0.02       0.98      ]
[0.02       0.98      ]
[0.87333333 0.12666667]
[0.74085209 0.25914791]
```

```
 [0.07       0.93      ]
 [0.02       0.98      ]
 [0.99       0.01      ]
 [0.87       0.13      ]
 [0.98       0.02      ]
 [0.05       0.95      ]
 [0.99       0.01      ]
 [1.         0.        ]
 [0.13775755 0.86224245]
 [0.99       0.01      ]
 [0.04139683 0.95860317]
 [0.         1.        ]
 [0.49       0.51      ]
 [0.63       0.37      ]
 [0.81       0.19      ]
 [0.94166667 0.05833333]
 [0.66       0.34      ]
 [1.         0.        ]
 [0.02       0.98      ]
 [0.07       0.93      ]
 [0.72766667 0.27233333]
 [0.99       0.01      ]
 [1.         0.        ]
 [0.91       0.09      ]
 [0.93       0.07      ]
 [0.975      0.025     ]
 [0.93       0.07      ]
 [1.         0.        ]
 [0.99       0.01      ]
 [0.94       0.06      ]
 [0.87       0.13      ]
 [0.24       0.76      ]
 [0.22       0.78      ]
 [0.71       0.29      ]
 [0.79454401 0.20545599]
 [1.         0.        ]
 [0.67       0.33      ]
 [0.99       0.01      ]
 [0.13       0.87      ]
 [0.88       0.12      ]
 [0.88       0.12      ]
 [0.98       0.02      ]
 [0.97       0.03      ]
 [0.98333333 0.01666667]
 [0.21       0.79      ]
 [0.97       0.03      ]
 [0.06       0.94      ]
 [0.95666667 0.04333333]
 [0.16       0.84      ]
 [0.80066667 0.19933333]
 [0.16       0.84      ]
 [1.         0.        ]
 [0.1        0.9       ]
 [0.24       0.76      ]
 [0.11       0.89      ]
 [0.89       0.11      ]
 [0.85       0.15      ]
 [0.14       0.86      ]
 [0.98       0.02      ]
 [0.99       0.01      ]
 [0.06       0.94      ]
 [1.         0.        ]
 [0.99       0.01      ]
 [1.         0.        ]
 [0.01       0.99      ]
 [1.         0.        ]
 [0.05       0.95      ]
 [0.28666667 0.71333333]
 [0.05       0.95      ]
 [0.98       0.02      ]
 [0.97       0.03      ]
 [1.         0.        ]
 [0.06       0.94      ]
 [0.36666667 0.63333333]
 [0.74       0.26      ]
 [0.98       0.02      ]
 [0.         1.        ]
 [0.5        0.5       ]
 [0.30790191 0.69209809]
 [0.04       0.96      ]
```

```
 [0.28       0.72      ]
 [0.51183333 0.48816667]
 [0.97       0.03      ]
 [0.86       0.14      ]
 [0.97       0.03      ]
 [0.95       0.05      ]
 [0.01       0.99      ]
 [1.         0.        ]
 [0.76       0.24      ]
 [0.47850794 0.52149206]
 [1.         0.        ]
 [0.06139683 0.93860317]
 [1.         0.        ]
 [0.87       0.13      ]
 [0.59       0.41      ]
 [0.99       0.01      ]
 [0.46       0.54      ]
 [1.         0.        ]
 [0.94666667 0.05333333]
 [0.8925     0.1075    ]
 [0.81       0.19      ]
 [0.37       0.63      ]
 [0.16       0.84      ]
 [0.96       0.04      ]
 [0.93       0.07      ]
 [0.81       0.19      ]
 [0.57083333 0.42916667]
 [0.71       0.29      ]]
```

In [37]:
```
from sklearn.metrics import confusion_matrix

# Construir a matriz de confusão
cm = confusion_matrix(y_test, y_pred)

# Exibir a matriz de confusão
print("Matriz de Confusão:")
print(cm)
```

```
Matriz de Confusão:
[[134  19]
 [ 32  82]]
```

In [38]:
```
probs = model_rf.predict_proba(X_train)
print(probs)
```

```
[[0.17 0.83]
 [1.   0.  ]
 [1.   0.  ]
 ...
 [0.96 0.04]
 [0.98 0.02]
 [1.   0.  ]]
```

In [39]:
```
from sklearn.metrics import confusion_matrix

y_estimado = model_rf.predict(X_test)
cm = confusion_matrix(y_test, y_estimado, labels=[1, 0])

print(cm)
```

```
[[ 82  32]
 [ 19 134]]
```

In [40]:
```
y_proba = model_rf.predict_proba(X_test)
print(y_proba)
```

```
[[0.74       0.26      ]
 [0.02       0.98      ]
 [0.92       0.08      ]
 [0.06       0.94      ]
 [0.10892136 0.89107864]
 [1.         0.        ]
 [0.26       0.74      ]
 [0.99177778 0.00822222]
 [0.99       0.01      ]
 [0.07       0.93      ]
 [0.13775755 0.86224245]
 [0.62       0.38      ]
 [0.88378387 0.11621613]
 [0.7        0.3       ]
 [0.82       0.18      ]
 [0.43       0.57      ]
 [0.35271429 0.64728571]
 [0.51       0.49      ]
 [0.813      0.187     ]
 [0.         1.        ]
 [0.3        0.7       ]
 [0.02       0.98      ]
 [0.98       0.02      ]
 [0.925      0.075     ]
 [0.99       0.01      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.06       0.94      ]
 [0.65       0.35      ]
 [0.97       0.03      ]
 [0.36       0.64      ]
 [0.93       0.07      ]
 [0.         1.        ]
 [0.97       0.03      ]
 [0.95       0.05      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.99444444 0.00555556]
 [1.         0.        ]
 [0.97       0.03      ]
 [0.7        0.3       ]
 [0.59       0.41      ]
 [0.32       0.68      ]
 [0.13       0.87      ]
 [0.06       0.94      ]
 [0.3225     0.6775    ]
 [0.97       0.03      ]
 [0.06       0.94      ]
 [0.97       0.03      ]
 [0.         1.        ]
 [0.85       0.15      ]
 [0.71       0.29      ]
 [0.77       0.23      ]
 [0.04       0.96      ]
 [0.89       0.11      ]
 [0.9025     0.0975    ]
 [0.81       0.19      ]
 [1.         0.        ]
 [0.05       0.95      ]
 [0.22       0.78      ]
 [0.05       0.95      ]
 [0.26       0.74      ]
 [0.32       0.68      ]
 [1.         0.        ]
 [0.07       0.93      ]
 [0.99       0.01      ]
 [1.         0.        ]
 [0.84       0.16      ]
 [0.22       0.78      ]
 [0.96       0.04      ]
 [0.12       0.88      ]
 [0.95       0.05      ]
 [0.90971429 0.09028571]
 [0.34083333 0.65916667]
 [0.99       0.01      ]
 [0.88378387 0.11621613]
 [0.93       0.07      ]
 [0.81083333 0.18916667]
 [0.18       0.82      ]
 [0.01       0.99      ]
```

```
 [0.97       0.03      ]
 [0.66       0.34      ]
 [0.80686508 0.19313492]
 [1.         0.        ]
 [0.04111111 0.95888889]
 [0.         1.        ]
 [0.13       0.87      ]
 [0.78       0.22      ]
 [0.73       0.27      ]
 [0.26       0.74      ]
 [0.94       0.06      ]
 [0.97       0.03      ]
 [0.15       0.85      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.94166667 0.05833333]
 [0.99       0.01      ]
 [0.61       0.39      ]
 [0.92       0.08      ]
 [0.99       0.01      ]
 [0.17       0.83      ]
 [0.03       0.97      ]
 [1.         0.        ]
 [0.         1.        ]
 [0.05       0.95      ]
 [0.98       0.02      ]
 [0.35       0.65      ]
 [0.88       0.12      ]
 [0.99       0.01      ]
 [1.         0.        ]
 [0.01       0.99      ]
 [0.74085209 0.25914791]
 [0.39       0.61      ]
 [0.15       0.85      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.04       0.96      ]
 [0.02       0.98      ]
 [0.24345747 0.75654253]
 [0.98733333 0.01266667]
 [0.37       0.63      ]
 [0.         1.        ]
 [0.07       0.93      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.98333333 0.01666667]
 [0.11       0.89      ]
 [0.97       0.03      ]
 [0.83       0.17      ]
 [1.         0.        ]
 [1.         0.        ]
 [0.8        0.2       ]
 [0.18       0.82      ]
 [0.06833333 0.93166667]
 [0.9        0.1       ]
 [0.9        0.1       ]
 [0.78       0.22      ]
 [0.72766667 0.27233333]
 [0.84       0.16      ]
 [0.99       0.01      ]
 [0.08       0.92      ]
 [0.24222222 0.75777778]
 [1.         0.        ]
 [0.06       0.94      ]
 [0.9775     0.0225    ]
 [0.03396825 0.96603175]
 [0.88       0.12      ]
 [0.04       0.96      ]
 [0.42       0.58      ]
 [1.         0.        ]
 [0.63       0.37      ]
 [1.         0.        ]
 [0.05       0.95      ]
 [0.98       0.02      ]
 [0.         1.        ]
 [0.02       0.98      ]
 [0.02       0.98      ]
 [0.87333333 0.12666667]
 [0.74085209 0.25914791]
 [0.07       0.93      ]
```

```
[0.02       0.98      ]
[0.99       0.01      ]
[0.87       0.13      ]
[0.98       0.02      ]
[0.05       0.95      ]
[0.99       0.01      ]
[1.         0.        ]
[0.13775755 0.86224245]
[0.99       0.01      ]
[0.04139683 0.95860317]
[0.         1.        ]
[0.49       0.51      ]
[0.63       0.37      ]
[0.81       0.19      ]
[0.94166667 0.05833333]
[0.66       0.34      ]
[1.         0.        ]
[0.02       0.98      ]
[0.07       0.93      ]
[0.72766667 0.27233333]
[0.99       0.01      ]
[1.         0.        ]
[0.91       0.09      ]
[0.93       0.07      ]
[0.975      0.025     ]
[0.93       0.07      ]
[1.         0.        ]
[0.99       0.01      ]
[0.94       0.06      ]
[0.87       0.13      ]
[0.24       0.76      ]
[0.22       0.78      ]
[0.71       0.29      ]
[0.79454401 0.20545599]
[1.         0.        ]
[0.67       0.33      ]
[0.99       0.01      ]
[0.13       0.87      ]
[0.88       0.12      ]
[0.88       0.12      ]
[0.98       0.02      ]
[0.97       0.03      ]
[0.98333333 0.01666667]
[0.21       0.79      ]
[0.97       0.03      ]
[0.06       0.94      ]
[0.95666667 0.04333333]
[0.16       0.84      ]
[0.80066667 0.19933333]
[0.16       0.84      ]
[1.         0.        ]
[0.1        0.9       ]
[0.24       0.76      ]
[0.11       0.89      ]
[0.89       0.11      ]
[0.85       0.15      ]
[0.14       0.86      ]
[0.98       0.02      ]
[0.99       0.01      ]
[0.06       0.94      ]
[1.         0.        ]
[0.99       0.01      ]
[1.         0.        ]
[0.01       0.99      ]
[1.         0.        ]
[0.05       0.95      ]
[0.28666667 0.71333333]
[0.05       0.95      ]
[0.98       0.02      ]
[0.97       0.03      ]
[1.         0.        ]
[0.06       0.94      ]
[0.36666667 0.63333333]
[0.74       0.26      ]
[0.98       0.02      ]
[0.         1.        ]
[0.5        0.5       ]
[0.30790191 0.69209809]
[0.04       0.96      ]
[0.28       0.72      ]
```

```
 [0.51183333 0.48816667]
 [0.97       0.03      ]
 [0.86       0.14      ]
 [0.97       0.03      ]
 [0.95       0.05      ]
 [0.01       0.99      ]
 [1.         0.        ]
 [0.76       0.24      ]
 [0.47850794 0.52149206]
 [1.         0.        ]
 [0.06139683 0.93860317]
 [1.         0.        ]
 [0.87       0.13      ]
 [0.59       0.41      ]
 [0.99       0.01      ]
 [0.46       0.54      ]
 [1.         0.        ]
 [0.94666667 0.05333333]
 [0.8925     0.1075    ]
 [0.81       0.19      ]
 [0.37       0.63      ]
 [0.16       0.84      ]
 [0.96       0.04      ]
 [0.93       0.07      ]
 [0.81       0.19      ]
 [0.57083333 0.42916667]
 [0.71       0.29      ]]
```

In [41]:
```
from sklearn.metrics import classification_report, precision_score

print(classification_report(y_estimado, y_test))
```

```
              precision    recall  f1-score   support

           0       0.88      0.81      0.84       166
           1       0.72      0.81      0.76       101

    accuracy                           0.81       267
   macro avg       0.80      0.81      0.80       267
weighted avg       0.82      0.81      0.81       267
```

In [42]:
```
precision = precision_score(y_estimado, y_test, average='weighted')
precision_percent = precision * 100
formatted_precision = "{:.2f}%".format(precision_percent)

print(formatted_precision)
```

```
81.66%
```

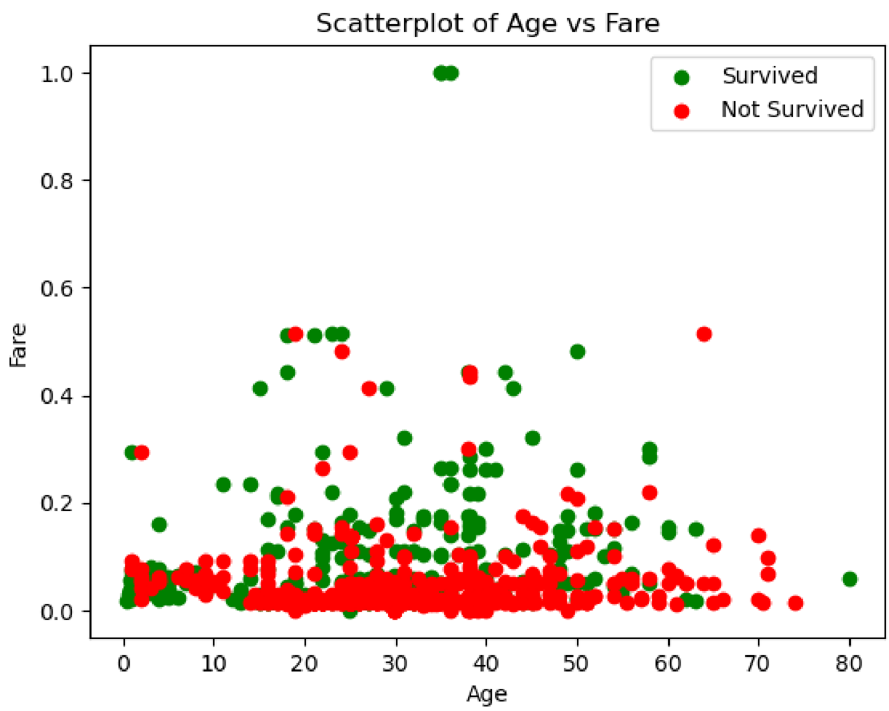
In [43]:
```
column_names = list(df.columns)
feature_importance = model_rf.feature_importances_

features = zip(column_names, feature_importance * 100)

for feature in features:
    print(f"Feature: {feature[0]}, Importância: {feature[1]:.2f}%")
```

```
Feature: Survived, Importância: 31.20%
Feature: Name, Importância: 3.70%
Feature: Age, Importância: 37.58%
Feature: SibSp, Importância: 27.51%
```

In [44]:
```
features = dict(features)
features = pd.DataFrame.from_dict(features, orient='index', columns=['Importância'])
features = features.sort_values('Importância', ascending=False).head(5)
```

In [45]:
```
import matplotlib.pyplot as plt

# Colunas desejadas
data_plot = df[['Age', 'Fare', 'Survived']]

# DataFrame divido em duas partes com base na classe (sobrevivente ou não)
survived = data_plot[data_plot['Survived'] == 1]
not_survived = data_plot[data_plot['Survived'] == 0]

# Plotar o scatterplot
plt.scatter(survived['Age'], survived['Fare'], color='green', label='Survived')
plt.scatter(not_survived['Age'], not_survived['Fare'], color='red', label='Not Survived')

# Rótulos e título do gráfico
```

```
plt.xlabel('Age')
plt.ylabel('Fare')
plt.title('Scatterplot of Age vs Fare')

# Adicionar legenda
plt.legend()

# Exibir o gráfico
plt.show()
```



In [46]:
```
# Separar as características e o alvo
X = df[['Age', 'Fare', 'SibSp', 'Pclass_2']]
y = df['Survived']
```

In [47]:
```
# Dividir os dados em conjunto de treinamento e teste
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

In [48]:
```
# Instancia do modelo com os hiperparâmetros desejados
model_rf = RandomForestClassifier(n_estimators=100, max_depth=5, random_state=42)
```

In [49]:
```
# Treino do modelo com as features selecionadas
model_rf.fit(X_train, y_train)
```

Out[49]:
```
RandomForestClassifier(max_depth=5, random_state=42)
```

In [50]:
```
# Predições no conjunto de teste
y_pred = model_rf.predict(X_test)
```

In [51]:
```
# Matriz de confusão
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[151  16]
 [ 64  36]]
```

In [52]:
```
# Ajuste de hiperparâmetros
#model_rf = RandomForestClassifier(n_estimators=100, max_depth=10, min_samples_split=2)
#model_rf.fit(X_train, y_train)
#y_pred = model_rf.predict(X_test)
#cm = confusion_matrix(y_test, y_pred)
#print(cm)
```

Calcule a área da curva ROC para os dois modelos

- Dica: Você querer [visualizar a área da curva ROC]
- Dica: Para o cálculo da área da curva roc é necessário passar como parâmetro as probabilidades, ou seja, utilize o método predict_proba() das predições

In [53]:
```
from sklearn.metrics import roc_auc_score

# DecisionTree
X_test_selected = X_test[['Age', 'Fare', 'SibSp']]
y_pred_dt = model_dt.predict_proba(X_test)[:, 1]
roc_auc_dt = roc_auc_score(y_test, y_pred_dt)
print("ROC DecisionTreeClassifier:", roc_auc_dt)

# RandomForest
y_pred_rf = model_rf.predict_proba(X_test)[:, 1]
roc_auc_rf = roc_auc_score(y_test, y_pred_rf)
print("ROC RandomForestClassifier:", roc_auc_rf)
```

```
ROC DecisionTreeClassifier: 0.5235029940119761
ROC RandomForestClassifier: 0.7447005988023953
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\base.py:493: FutureWarning: The feature names should mat
ch those that were passed during fit. Starting version 1.2, an error will be raised.
Feature names unseen at fit time:
- SibSp
Feature names seen at fit time, yet now missing:
- Sex_1

  warnings.warn(message, FutureWarning)
```

Challenge: Tente encontrar o melhor threshold que melhora a performance do modelos

In [ ]:
```
```

Challenge: Visualize a árvore de decisão

In [ ]:
```
```