In [29]:
```python
# Importando bibliotecas
import pandas as pd
import numpy as np
from imblearn.over_sampling import SMOTE
import seaborn as sb
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, class
ification_report
import warnings
warnings.filterwarnings('ignore', category=DeprecationWarning)
import joblib
```

In [2]:
```python
# Carregando o arquivo para um Dataset
dataset = pd.read_csv('wine.csv')
```

In [3]:
```python
# Análise Exploratória

# Verificando a estrutura do Dataset
dataset.head()
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	al
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	

In [4]:
```python
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6497 entries, 0 to 6496
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         6497 non-null   float64
 1   volatile acidity      6497 non-null   float64
 2   citric acid           6497 non-null   float64
 3   residual sugar        6497 non-null   float64
 4   chlorides             6497 non-null   float64
 5   free sulfur dioxide   6497 non-null   float64
 6   total sulfur dioxide  6497 non-null   float64
 7   density               6497 non-null   float64
 8   pH                    6497 non-null   float64
 9   sulphates             6497 non-null   float64
 10  alcohol               6497 non-null   float64
 11  quality               6497 non-null   int64  
 12  type                  6497 non-null   object 
dtypes: float64(11), int64(1), object(1)
memory usage: 660.0+ KB
```

In [5]:
```python
# Verificando os valores possíveis da variável TARGET (type)
dataset.type.unique()
```

Out[5]:
```
array(['red', 'white'], dtype=object)
```

In [6]:
```python
# Verificando se existe algum valor nulo dentro do Dataset
dataset.isnull().sum()
```

Out[6]:
```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
type                    0
dtype: int64
```

In [7]:
```python
# Alterando o tipo da coluna 'type' de object para category
dataset.type = dataset.type.astype('category')
```

In [8]:
```
dataset.info()
```

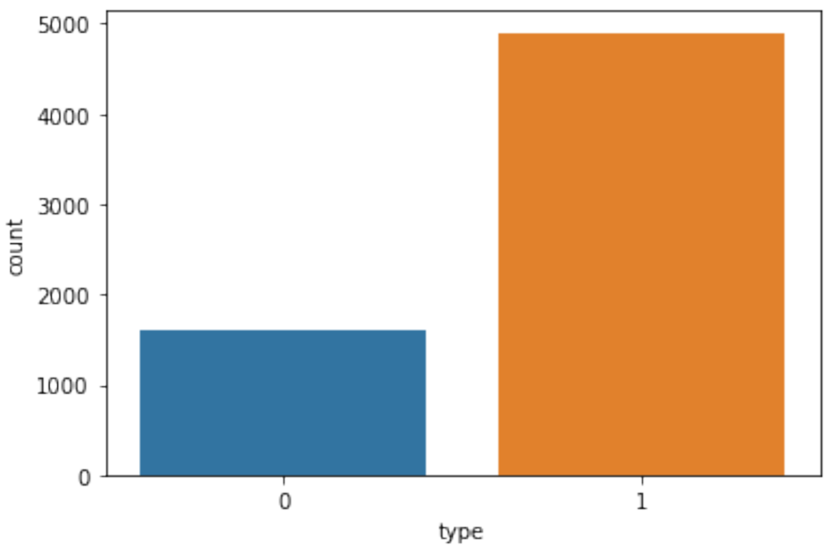
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6497 entries, 0 to 6496
Data columns (total 13 columns):
 #   Column                Non-Null Count  Dtype   
---  ------                --------------  -----   
 0   fixed acidity         6497 non-null   float64 
 1   volatile acidity      6497 non-null   float64 
 2   citric acid           6497 non-null   float64 
 3   residual sugar        6497 non-null   float64 
 4   chlorides             6497 non-null   float64 
 5   free sulfur dioxide   6497 non-null   float64 
 6   total sulfur dioxide  6497 non-null   float64 
 7   density               6497 non-null   float64 
 8   pH                    6497 non-null   float64 
 9   sulphates             6497 non-null   float64 
 10  alcohol               6497 non-null   float64 
 11  quality               6497 non-null   int64   
 12  type                  6497 non-null   category
dtypes: category(1), float64(11), int64(1)
memory usage: 615.7 KB
```

In [9]:
```
# Transformando a coluna 'type' em categórica numérica
dataset.type = dataset.type.map({'red': 0, 'white': 1})
```

In [10]:
```
# Verificando o balanceamento das classes da variável Target (colun
a 'type'
dataset.type.value_counts()
```

Out[10]:
```
1    4898
0    1599
Name: type, dtype: int64
```

In [11]:
```
# Visualizando graficamente a distribuição das classes
class_distribution = sb.countplot(x=dataset.type, data=dataset)
```



In [12]:
```
# Observe acima que existem mais vinhos do tipo branco do que tinto
. Esse desbalancealemto pode afetar
# o modelo de Machine Learning no que diz respeito a sua acurácia.
# Para corrigir esse problema de balanceamento de classes podemos a
plicar a técnica de Undersampling ou Oversampling
# Neste caso, como os dados históricos não são tão numerosos, optei
em realizar o Oversampling, igualando a
# quantidade da classe minoritária com a majoritária de forma aleat
ória.

# Antes de aplicar o algoritmo SMOTE é necessário separar as variáv
eis preditoras da variável target.
# Vou chamar de x as variáveis preditoras (as características que d
efinem o tipo de vinho) e y a variável target
x = dataset.drop('type', axis=1)
y = dataset.type
```

In [13]:
```
# Visualziando a separação dos dados
x.head(1)
```

Out[13]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	al
0	7.4	0.7	0.0	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	

In [14]:
```
y.head(1)
```

Out[14]:
```
0    0
Name: type, dtype: category
Categories (2, int64): [0, 1]
```

In [15]:
```
x.shape , y.shape
```

Out[15]:
```
((6497, 12), (6497,))
```

In [16]:
```
# Utilizando o algoritmo SMOTE para gerar dados sintéticos e assim
igualar as classes

# Instânciando o algoritmo SMOTE
smt = SMOTE()
```

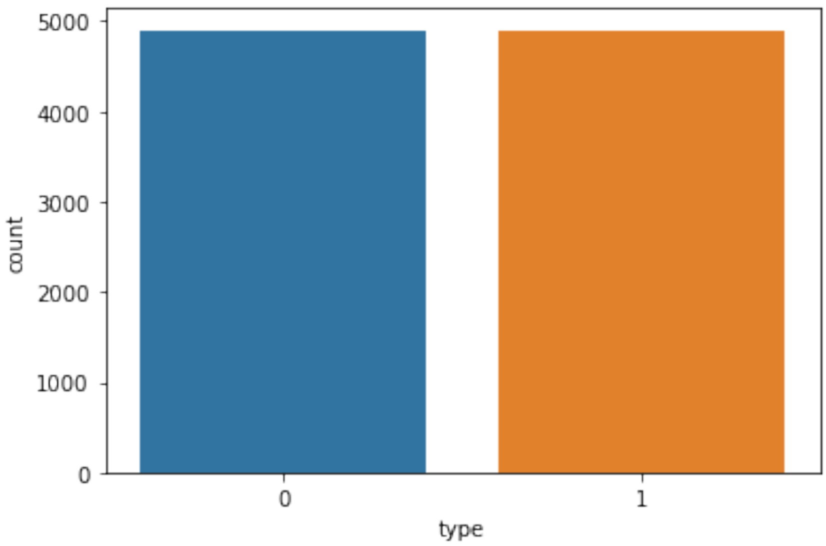
In [17]:
```
# Aplicando o SMOTE nos dados
x,y = smt.fit_sample(x,y)
```

In [18]:
```
# Visualizando novamente a dstribuição das classes após a aplicação
do algoritmo
y.value_counts()
```

Out[18]:
```
1    4898
0    4898
Name: type, dtype: int64
```

In [19]:
```python
sb.countplot(x=y)
```

Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f808af69780>



In [20]:
```python
# Separando os dados de Treino e os dados de Teste
xTrain, xTest, yTrain, yTest = train_test_split(x,y)
```

In [21]:
```python
# Para este projeto utilizei o algoritmo Logistic Regression. Poder
ia utilizar qualquer outro. Numa outra
# análise utilizarei o PIPELINE para treinar os dados com vários al
goritmos.

# Instânciando o Classificador
model = LogisticRegression(max_iter=200)
```

In [22]:
```python
# Treinando o modelo
model.fit(xTrain, yTrain)
```

```
/Users/rp/Anaconda3/anaconda3/lib/python3.7/site-packages/sklearn/
linear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver opti
ons:
    https://scikit-learn.org/stable/modules/linear_model.html#logi
stic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

Out[22]: LogisticRegression(max_iter=200)

In [23]:
```python
# Fazendo as pedições
prediction = model.predict(xTest)
```

In [24]:
```
# Checando a acurácia do modelo
accuracy_score(yTest, prediction)
```

Out[24]:
```
0.9755002041649653
```

In [25]:
```
# Checando Precisão, Recall, f1-score
print(classification_report(yTest, prediction))
```

```
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      1257
           1       0.97      0.98      0.97      1192

    accuracy                           0.98      2449
   macro avg       0.98      0.98      0.98      2449
weighted avg       0.98      0.98      0.98      2449
```

In [26]:
```
# Gerando a Confusion Matrix
print(pd.crosstab(yTest, prediction, rownames=['Real'], colnames=['
Predito'], margins=True))
```

```
Predito     0     1   All
Real
0        1225    32  1257
1          28  1164  1192
All      1253  1196  2449
```

In [27]:
```
# Observe acima na Confusion Matrix que o modelo errou apenas 32 ve
zes as predições para vinho Tinto e 28 vezes
# para vinho branco.
```

In [30]:
```
# Realizando o Deploy do modelo em disco utilizando o Joblib
joblib.dump(model, 'Model_Classification_Wine.joblib')
```

Out[30]:
```
['Model_Classification_Wine.joblib']
```

In [31]:
```
!ls
```

```
Model_Classification_Wine.joblib wine.csv
TiposDeVinhos.ipynb
```