```python
import datetime
import os

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import utils_config
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import (RocCurveDisplay, accuracy_score,
f1_score,
                             precision_score, recall_score)
from sklearn.model_selection import StratifiedKFold, train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier

configs = utils_config.load_config("../config.json")

red = pd.read_csv(f'{configs.red}', sep=configs.sep)
white = pd.read_csv(f'{configs.white}', sep=configs.sep)

red
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar
chlorides
0               7.4             0.700         0.00             1.9
0.076  \
1               7.8             0.880         0.00             2.6
0.098
2               7.8             0.760         0.04             2.3
0.092
3              11.2             0.280         0.56             1.9
0.075
4               7.4             0.700         0.00             1.9
0.076
...             ...               ...          ...             ...
...
1594            6.2             0.600         0.08             2.0
0.090
1595            5.9             0.550         0.10             2.2
0.062
1596            6.3             0.510         0.13             2.3
0.076
1597            5.9             0.645         0.12             2.0
0.075
1598            6.0             0.310         0.47             3.6
0.067

      free sulfur dioxide  total sulfur dioxide  density    pH
```

```
sulphates
0                    11.0                  34.0  0.99780  3.51
0.56  \
1                    25.0                  67.0  0.99680  3.20
0.68
2                    15.0                  54.0  0.99700  3.26
0.65
3                    17.0                  60.0  0.99800  3.16
0.58
4                    11.0                  34.0  0.99780  3.51
0.56
...                   ...                   ...      ...   ...
...
1594                 32.0                  44.0  0.99490  3.45
0.58
1595                 39.0                  51.0  0.99512  3.52
0.76
1596                 29.0                  40.0  0.99574  3.42
0.75
1597                 32.0                  44.0  0.99547  3.57
0.71
1598                 18.0                  42.0  0.99549  3.39
0.66

      alcohol  quality
0         9.4        5
1         9.8        5
2         9.8        5
3         9.8        6
4         9.4        5
...       ...      ...
1594     10.5        5
1595     11.2        6
1596     11.0        6
1597     10.2        5
1598     11.0        6

[1599 rows x 12 columns]
```

white

```
      fixed acidity  volatile acidity  citric acid  residual sugar
chlorides
0               7.0              0.27         0.36            20.7
0.045  \
1               6.3              0.30         0.34             1.6
0.049
2               8.1              0.28         0.40             6.9
0.050
3               7.2              0.23         0.32             8.5
```

```
0.058
4               7.2               0.23         0.32              8.5
0.058
...             ...                ...          ...              ...
...
4893            6.2               0.21         0.29              1.6
0.039
4894            6.6               0.32         0.36              8.0
0.047
4895            6.5               0.24         0.19              1.2
0.041
4896            5.5               0.29         0.30              1.1
0.022
4897            6.0               0.21         0.38              0.8
0.020

      free sulfur dioxide  total sulfur dioxide  density    pH
sulphates
0                    45.0                 170.0  1.00100  3.00
0.45  \
1                    14.0                 132.0  0.99400  3.30
0.49
2                    30.0                  97.0  0.99510  3.26
0.44
3                    47.0                 186.0  0.99560  3.19
0.40
4                    47.0                 186.0  0.99560  3.19
0.40
...                   ...                   ...      ...   ...
...
4893                 24.0                  92.0  0.99114  3.27
0.50
4894                 57.0                 168.0  0.99490  3.15
0.46
4895                 30.0                 111.0  0.99254  2.99
0.46
4896                 20.0                 110.0  0.98869  3.34
0.38
4897                 22.0                  98.0  0.98941  3.26
0.32

      alcohol  quality
0         8.8        6
1         9.5        6
2        10.1        6
3         9.9        6
4         9.9        6
...       ...      ...
4893     11.2        6
4894      9.6        5
```

```
4895      9.4        6
4896     12.8        7
4897     11.8        6

[4898 rows x 12 columns]
```

---

3) Descreva as variáveis:

type = Tipo do vinho cadatrado na base. White (branco) ou Red (Tinto) **| Variável Contínua**
fixed acidity = Quantidade de Ácido Tartárico (g/dm^3) **| Variável Contínua**
volatile acidity = Quantidade de Ácido Acético (g/dm^3) **| Variável Contínua**
citric acid = Quantidade de Ácido Cítrico (g/dm^3) **| Variável Contínua**
residual sugar = Quantidade de Açucar Residual (g/dm^3) **| Variável Contínua**
chlorides = Quantidade de Cloreto de Sódio (g/dm^3) **| Variável Contínua**
free sulfur dioxide = Quantidade de Dióxido de Enxofre livre (mg/dm^3) **| Variável Contínua**
total sulfur dioxide = Quantidade total de Dióxido de Enxofre (md/dm^3) **| Variável Contínua**
density = Densidade (g/cm^3) **| Variável Contínua**
ph = Ph **| Variável Contínua**
sulphates = Quantidade de Sulfato de Potássio (g/dm^3) **| Variável Contínua**
alcohol = Alcool (% vol.) **| Variável Contínua**
quality = Qualidade do vinho de 0 a 10 **| Variável Categórica**

Média e Desvio Padrão - Vinhos Tinto

```
red.describe()

       fixed acidity  volatile acidity  citric acid  residual sugar
count    1599.000000       1599.000000  1599.000000     1599.000000  \
mean        8.319637          0.527821     0.270976        2.538806
std         1.741096          0.179060     0.194801        1.409928
min         4.600000          0.120000     0.000000        0.900000
25%         7.100000          0.390000     0.090000        1.900000
50%         7.900000          0.520000     0.260000        2.200000
75%         9.200000          0.640000     0.420000        2.600000
max        15.900000          1.580000     1.000000       15.500000

         chlorides  free sulfur dioxide  total sulfur dioxide
density
count  1599.000000          1599.000000           1599.000000
1599.000000  \
mean      0.087467            15.874922             46.467792
0.996747
std       0.047065            10.460157             32.895324
0.001887
```

```
min        0.012000             1.000000              6.000000
0.990070
25%        0.070000             7.000000             22.000000
0.995600
50%        0.079000            14.000000             38.000000
0.996750
75%        0.090000            21.000000             62.000000
0.997835
max        0.611000            72.000000            289.000000
1.003690

                pH    sulphates      alcohol      quality
count  1599.000000  1599.000000  1599.000000  1599.000000
mean      3.311113     0.658149    10.422983     5.636023
std       0.154386     0.169507     1.065668     0.807569
min       2.740000     0.330000     8.400000     3.000000
25%       3.210000     0.550000     9.500000     5.000000
50%       3.310000     0.620000    10.200000     6.000000
75%       3.400000     0.730000    11.100000     6.000000
max       4.010000     2.000000    14.900000     8.000000
```

Média e Desvio Padrão Vinhos Verde

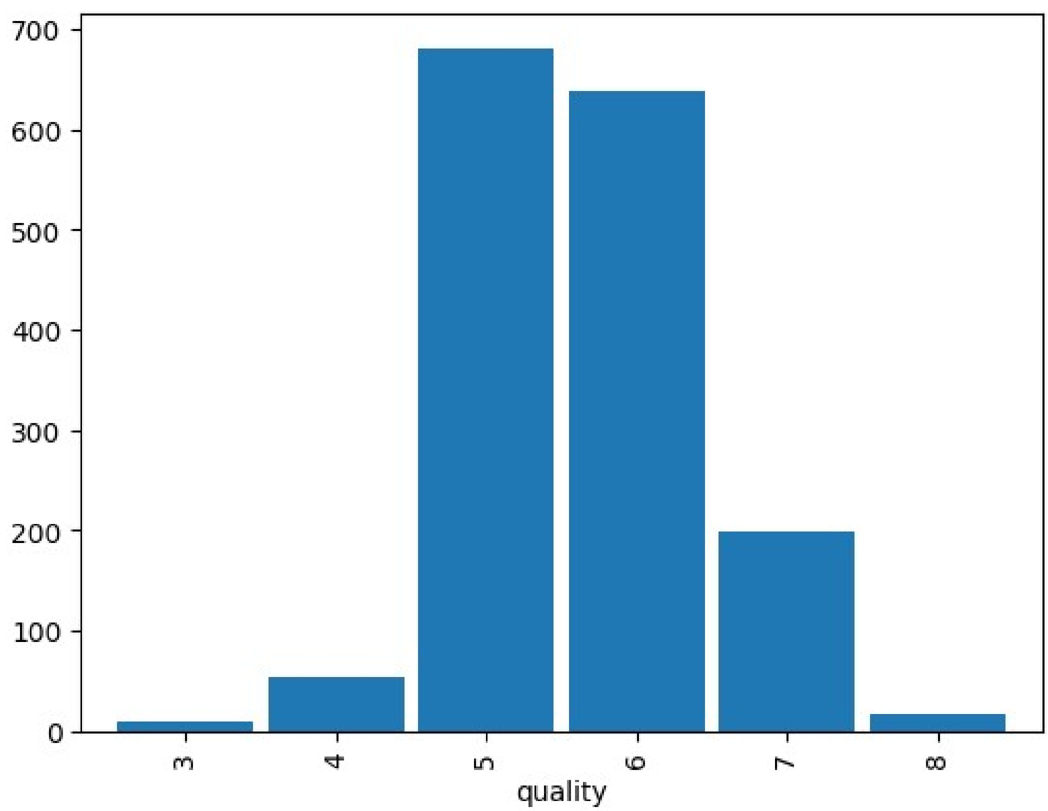
```
white.describe()
```

```
       fixed acidity  volatile acidity  citric acid  residual sugar  
count    4898.000000       4898.000000  4898.000000     4898.000000   \
mean        6.854788          0.278241     0.334192        6.391415
std         0.843868          0.100795     0.121020        5.072058
min         3.800000          0.080000     0.000000        0.600000
25%         6.300000          0.210000     0.270000        1.700000
50%         6.800000          0.260000     0.320000        5.200000
75%         7.300000          0.320000     0.390000        9.900000
max        14.200000          1.100000     1.660000       65.800000

         chlorides  free sulfur dioxide  total sulfur dioxide
density
count  4898.000000          4898.000000           4898.000000
4898.000000  \
mean      0.045772            35.308085            138.360657
0.994027
std       0.021848            17.007137             42.498065
0.002991
min       0.009000             2.000000              9.000000
0.987110
25%       0.036000            23.000000            108.000000
0.991723
50%       0.043000            34.000000            134.000000
0.993740
```

```
75%        0.050000            46.000000            167.000000
0.996100
max        0.346000           289.000000            440.000000
1.038980

                pH     sulphates       alcohol       quality
count  4898.000000   4898.000000   4898.000000   4898.000000
mean      3.188267      0.489847     10.514267      5.877909
std       0.151001      0.114126      1.230621      0.885639
min       2.720000      0.220000      8.000000      3.000000
25%       3.090000      0.410000      9.500000      5.000000
50%       3.180000      0.470000     10.400000      6.000000
75%       3.280000      0.550000     11.400000      6.000000
max       3.820000      1.080000     14.200000      9.000000
```

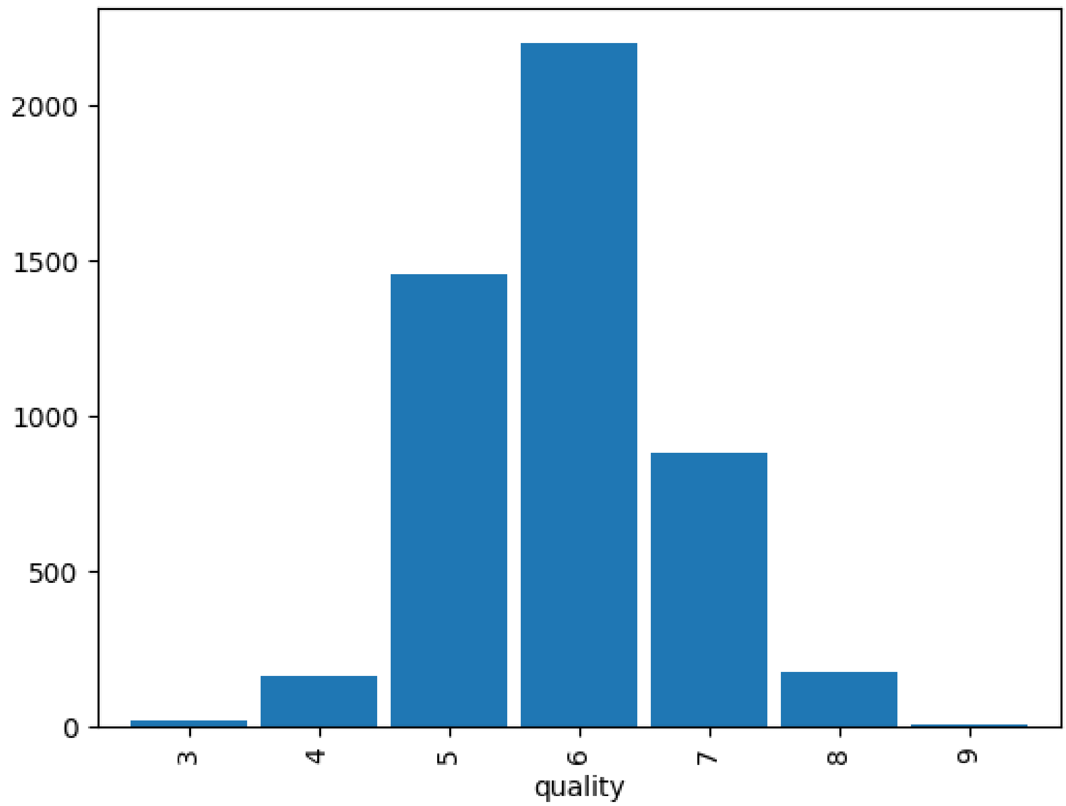
Distribuição da variável "Quality" - Vinhos Verde Tintos

```
_ = red.quality.value_counts().sort_index().plot.bar(width=0.9)
```



Distribuição da variável "Quality" - Vinhos Verde Brancos

```
_ = white.quality.value_counts().sort_index().plot.bar(width=0.9)
```



Correlação das variáves - Vinhos Verde Tintos

```
red.corr()

                      fixed acidity  volatile acidity  citric acid  \
fixed acidity              1.000000         -0.256131     0.671703
volatile acidity          -0.256131          1.000000    -0.552496
citric acid                0.671703         -0.552496     1.000000
residual sugar             0.114777          0.001918     0.143577
chlorides                  0.093705          0.061298     0.203823
free sulfur dioxide       -0.153794         -0.010504    -0.060978
total sulfur dioxide      -0.113181          0.076470     0.035533
density                    0.668047          0.022026     0.364947
pH                        -0.682978          0.234937    -0.541904
sulphates                  0.183006         -0.260987     0.312770
alcohol                   -0.061668         -0.202288     0.109903
quality                    0.124052         -0.390558     0.226373

                      residual sugar  chlorides  free sulfur dioxide

fixed acidity               0.114777   0.093705            -
0.153794  \
volatile acidity            0.001918   0.061298            -0.010504
```

```
citric acid                  0.143577   0.203823            -0.060978

residual sugar               1.000000   0.055610             0.187049

chlorides                    0.055610   1.000000             0.005562

free sulfur dioxide          0.187049   0.005562             1.000000

total sulfur dioxide         0.203028   0.047400             0.667666

density                      0.355283   0.200632            -0.021946

pH                          -0.085652  -0.265026             0.070377

sulphates                    0.005527   0.371260             0.051658

alcohol                      0.042075  -0.221141            -0.069408

quality                      0.013732  -0.128907            -0.050656


                      total sulfur dioxide   density        pH
sulphates
fixed acidity                    -0.113181  0.668047 -0.682978
0.183006  \
volatile acidity                  0.076470  0.022026  0.234937  -
0.260987
citric acid                       0.035533  0.364947 -0.541904
0.312770
residual sugar                    0.203028  0.355283 -0.085652
0.005527
chlorides                         0.047400  0.200632 -0.265026
0.371260
free sulfur dioxide               0.667666 -0.021946  0.070377
0.051658
total sulfur dioxide              1.000000  0.071269 -0.066495
0.042947
density                           0.071269  1.000000 -0.341699
0.148506
pH                               -0.066495 -0.341699  1.000000  -
0.196648
sulphates                         0.042947  0.148506 -0.196648
1.000000
alcohol                          -0.205654 -0.496180  0.205633
0.093595
quality                          -0.185100 -0.174919 -0.057731
0.251397

                       alcohol   quality
```

```
fixed acidity        -0.061668  0.124052
volatile acidity     -0.202288 -0.390558
citric acid           0.109903  0.226373
residual sugar        0.042075  0.013732
chlorides            -0.221141 -0.128907
free sulfur dioxide  -0.069408 -0.050656
total sulfur dioxide -0.205654 -0.185100
density              -0.496180 -0.174919
pH                    0.205633 -0.057731
sulphates             0.093595  0.251397
alcohol               1.000000  0.476166
quality               0.476166  1.000000
```

Correlação das variáves - Vinhos Verde Brancos

```
white.corr()
```

```
                      fixed acidity  volatile acidity  citric acid  
fixed acidity              1.000000         -0.022697     0.289181  \
volatile acidity          -0.022697          1.000000    -0.149472   
citric acid                0.289181         -0.149472     1.000000   
residual sugar             0.089021          0.064286     0.094212   
chlorides                  0.023086          0.070512     0.114364   
free sulfur dioxide       -0.049396         -0.097012     0.094077   
total sulfur dioxide       0.091070          0.089261     0.121131   
density                    0.265331          0.027114     0.149503   
pH                        -0.425858         -0.031915    -0.163748   
sulphates                 -0.017143         -0.035728     0.062331   
alcohol                   -0.120881          0.067718    -0.075729   
quality                   -0.113663         -0.194723    -0.009209   

                      residual sugar  chlorides  free sulfur dioxide

fixed acidity               0.089021   0.023086                -
0.049396  \
volatile acidity            0.064286   0.070512            -0.097012

citric acid                 0.094212   0.114364             0.094077

residual sugar              1.000000   0.088685             0.299098

chlorides                   0.088685   1.000000             0.101392

free sulfur dioxide         0.299098   0.101392             1.000000

total sulfur dioxide        0.401439   0.198910             0.615501

density                     0.838966   0.257211             0.294210
```

```
pH                          -0.194133  -0.090439           -0.000618

sulphates                   -0.026664   0.016763            0.059217

alcohol                     -0.450631  -0.360189           -0.250104

quality                     -0.097577  -0.209934            0.008158


                      total sulfur dioxide   density        pH
sulphates
fixed acidity                     0.091070  0.265331 -0.425858  -
0.017143  \
volatile acidity                  0.089261  0.027114 -0.031915  -
0.035728
citric acid                       0.121131  0.149503 -0.163748
0.062331
residual sugar                    0.401439  0.838966 -0.194133  -
0.026664
chlorides                         0.198910  0.257211 -0.090439
0.016763
free sulfur dioxide               0.615501  0.294210 -0.000618
0.059217
total sulfur dioxide              1.000000  0.529881  0.002321
0.134562
density                           0.529881  1.000000 -0.093591
0.074493
pH                                0.002321 -0.093591  1.000000
0.155951
sulphates                         0.134562  0.074493  0.155951
1.000000
alcohol                          -0.448892 -0.780138  0.121432  -
0.017433
quality                          -0.174737 -0.307123  0.099427
0.053678

                       alcohol   quality
fixed acidity        -0.120881 -0.113663
volatile acidity      0.067718 -0.194723
citric acid          -0.075729 -0.009209
residual sugar       -0.450631 -0.097577
chlorides            -0.360189 -0.209934
free sulfur dioxide  -0.250104  0.008158
total sulfur dioxide -0.448892 -0.174737
density              -0.780138 -0.307123
pH                    0.121432  0.099427
sulphates            -0.017433  0.053678
alcohol               1.000000  0.435575
quality               0.435575  1.000000
```

Etapas para criação de um modelo de classificação eficiente:

- Análise exploratória dos dados para saber como é o comportamento da base, escolher variáveis e ter uma ideia em que tipo de modelo ela melhor se encaixa;
- Escolha do modelo e treinamento com configurações diversas para testar as métricas de acurácia, recall, precisão e f1;
- Análise das métricas para saber eficiência do modelo.

Models

```
vars = [
        'fixed acidity',
        'volatile acidity',
        'citric acid',
        'residual sugar',
        'chlorides',
        'free sulfur dioxide',
        'total sulfur dioxide',
        'density',
        'pH',
        'sulphates',
        'alcohol',
            ]

def base(base, vars):
    list_arq = os.listdir(path='../data/')
    for name in list_arq:
        if base in name:
            wines = pd.read_csv(f'../data/{name}', sep=configs.sep)
            wines["category"] = (wines['quality'] >
configs.bad_wine_upper_bound).astype(float)
            X = wines[vars]
            y = wines['category']
            return X, y
        elif base in name:
            white = pd.read_csv(f'../data/{name}', sep=configs.sep)
            white["category"] = (white['quality'] >
configs.bad_wine_upper_bound).astype(float)
            X = white[vars]
            y = white['category']
            return X, y
        elif base in name:
            red = pd.read_csv(f'../data/{name}', sep=configs.sep)
            red["category"] = (red['quality'] >
configs.bad_wine_upper_bound).astype(float)
            X = red[vars]
            y = red['category']
            return X, y
```

```
config = [
    (SVC, {'kernel': 'rbf'}),
    (SVC, {'kernel': 'rbf', 'gamma': 2}),
    (SVC, {'degree': 3, 'kernel': 'poly'} ),
    (SVC, {'degree': 5, 'kernel': 'poly'} ),
    (SVC, {'degree': 10, 'kernel': 'poly'} ),
    (LogisticRegression, {}),
    (DecisionTreeClassifier, {'min_samples_leaf': 50})
    ]

var = 'white'
X, y = base(var, vars)

y.value_counts().sort_values()

category
0.0    1640
1.0    3258
Name: count, dtype: int64

test_size = 0.2
random_state = 42
stratify = y

X_train_cv, X_test, y_train_cv, y_test = train_test_split(X.values,
                                                          y.values,

test_size=test_size,

random_state=random_state,

stratify=stratify)

def interpolation(fpr, tpr):
    interp_fpr = np.linspace(0, 1, 100)
    interp_tpr = np.interp(interp_fpr, fpr, tpr)
    interp_tpr[0] = 0.
    return interp_fpr, interp_tpr

def train_cv(base, X, y, X_test, y_test, model_klass, model_kwargs =
{}):
    day_hour = datetime.datetime.now().strftime('%Y-%m-%d-%H-%M-%S')
    cv = StratifiedKFold(n_splits=configs.k_folds)
    fig, ax = plt.subplots(1, 1, figsize=(8, 8))
    fprs_list = []
    tprs_list = []
    auc_list  = []
    scaler_list = []
    model_list =[]
    f1_score_val_list = []
    f1_score_train_list = []
```

```
    acc_train = []
    acc_val = []
    recall_train = []
    recall_val = []
    prec_train = []
    prec_val = []

    # usar model_klass.__name__ para pegar o nome

    train_model = None
    if "SVC" in str(model_klass):
        train_model = "SVC"
    if "Tree" in str(model_klass):
        train_model = "DecisionTree"
    if "Logistic" in str(model_klass):
        train_model = "LogisticRegression"

    with
open(f"{configs.results}/{train_model}_{day_hour}_{base}.txt", "a") as
file:
            file.write(f"""Configs: {model_kwargs}\n""")

    for fold, (train_idx, val_idx) in enumerate(cv.split(X, y)):
        X_train = X[train_idx, :]
        y_train = y[train_idx]
        X_val = X[val_idx, :]
        y_val = y[val_idx]

        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_val_scaled = scaler.transform(X_val)
        scaler_list.append(scaler)

        model = model_klass(**model_kwargs)
        model.fit(X_train_scaled, y_train)
        y_pred = model.predict(X_train_scaled)
        y_pred_val = model.predict(X_val_scaled)

        with
open(f"{configs.results}/{train_model}_{day_hour}_{base}.txt", "a") as
file:
            file.write(f"""========================= FOLD {fold}
==========================
        O Resultado da ACURÁCIA em TREINO é: {100 *
accuracy_score(y_train, y_pred):.2f}%
        O Resultado da ACURÁCIA na VALIDAÇÃO é: {100 *
accuracy_score(y_val, y_pred_val):.2f}%
        O Resultado da SENSIBILIDADE em TREINO é: {100 *
recall_score(y_train, y_pred):.2f}%
        O Resultado da SENSIBILIDADE na VALIDAÇÃO é: {100 *
```

```
recall_score(y_val, y_pred_val):.2f}%
        O Resultado da PRECISÃO em TREINO é: {100*
precision_score(y_train, y_pred):.2f}%
        O Resultado da PRECISÃO na VALIDAÇÃO é: {100*
precision_score(y_val, y_pred_val):.2f}%
        O Resultado da de F1-Score em TREINO é: {f1_score(y_train,
y_pred):.2}
        O Resultado da de F1-Score na VALIDAÇÃO: {f1_score(y_val,
y_pred_val):.2}\n\n""")

        acc_train.append(accuracy_score(y_train, y_pred))
        acc_val.append(accuracy_score(y_val, y_pred_val))
        recall_train.append(recall_score(y_train, y_pred))
        recall_val.append(recall_score(y_val, y_pred_val))
        prec_train.append(precision_score(y_train, y_pred))
        prec_val.append(precision_score(y_val, y_pred_val))
        f1_score_train_list.append(f1_score(y_train, y_pred))
        f1_score_val_list.append(f1_score(y_val, y_pred_val))
        model_list.append(model)

        viz = RocCurveDisplay.from_estimator(
            model,
            X_val_scaled,
            y_val,
            ax = ax,
            alpha=0.3,
            lw=1
        )
        interp_fpr, interp_tpr = interpolation(viz.fpr, viz.tpr)
        fprs_list.append(interp_fpr)
        tprs_list.append(interp_tpr)
        auc_list.append(viz.roc_auc)

    with
open(f"{configs.results}/{train_model}_{day_hour}_{base}.txt", "a") as
file:
            file.write(f"""======================== Resultado Médio
========================
        O resultado Médio da ACURÁCIA em TREINO é:
{np.mean(acc_train): .2} +- {np.std(acc_train): .2}
        O resultado Médio da ACURÁCIA em VALIDAÇÃO é:
{np.mean(acc_val): .2} +- {np.std(acc_val): .2}
        O resultado Médio da SENSIBILIDADE em TREINO é:
{np.mean(recall_train): .2} +- {np.std(recall_train): .2}
        O resultado Médio da SENSIBILIDADE em VALIDAÇÃO é:
{np.mean(recall_val): .2} +- {np.std(recall_val): .2}
        O resultado Médio da PRECISÃO em TREINO é:
{np.mean(prec_train): .2} +- {np.std(prec_train): .2}
        O resultado Médio da PRECISÃO em VALIDAÇÃO é:
{np.mean(prec_val): .2} +- {np.std(prec_val): .2}
```

```
        O resultado Médio da F1-Score em TREINO é
{np.mean(f1_score_train_list): .2} +-
{np.std(f1_score_train_list): .2}
        O resultado Médio da F1-Score em VALIDAÇÃO é:
{np.mean(f1_score_val_list): .2} +- {np.std(f1_score_val_list): .2}\n
    ===================================================\n""")

    best_model_idx = np.argmax(f1_score_val_list)
    with
open(f"{configs.results}/{train_model}_{day_hour}_{base}.txt", "a") as
file:
            file.write(f"""Meu melhor fold é: {best_model_idx}\n""")

    best_model = model_list[best_model_idx]
    best_scaler = scaler_list[best_model_idx]
    X_test_scaled = best_scaler.transform(X_test)
    y_pred_test = model.predict(X_test_scaled)

    with
open(f"{configs.results}/{train_model}_{day_hour}_{base}.txt", "a") as
file:
            file.write(f"""Meu resultado de F1-Score para o conjunto
de TESTE é: {f1_score(y_test, y_pred_test):.2}
O resultado Médio da ACURÁCIA em TESTE é: {100 *
accuracy_score(y_test, y_pred_test):.2f}%
O resultado Médio da SENSIBILIDADE em TESTE é: {100 *
recall_score(y_test, y_pred_test):.2f}%
O resultado Médio da PRECISÃO em TESTE é: {100 *
precision_score(y_test, y_pred_test):.2f}%
=====================================================\n
=====================================================\n""")

    mean_fpr = np.mean(fprs_list, axis=0)
    mean_tpr = np.mean(tprs_list, axis=0)
    mean_auc = np.mean(auc_list)
    std_auc = np.std(auc_list)

    ax.plot(
        mean_fpr,
        mean_tpr,
        color='blue',
        lw=2,
        label=r"Mean ROC (AUC = %.2f $\pm$ %.2f)" %(mean_auc, std_auc)
    )
    ax.plot(np.linspace(0, 1, 100),
            np.linspace(0, 1, 100),
            color='g',
            ls=":",
            lw=0.5)
    ax.legend()
```

```python
    return best_model, best_scaler
```

Training Models

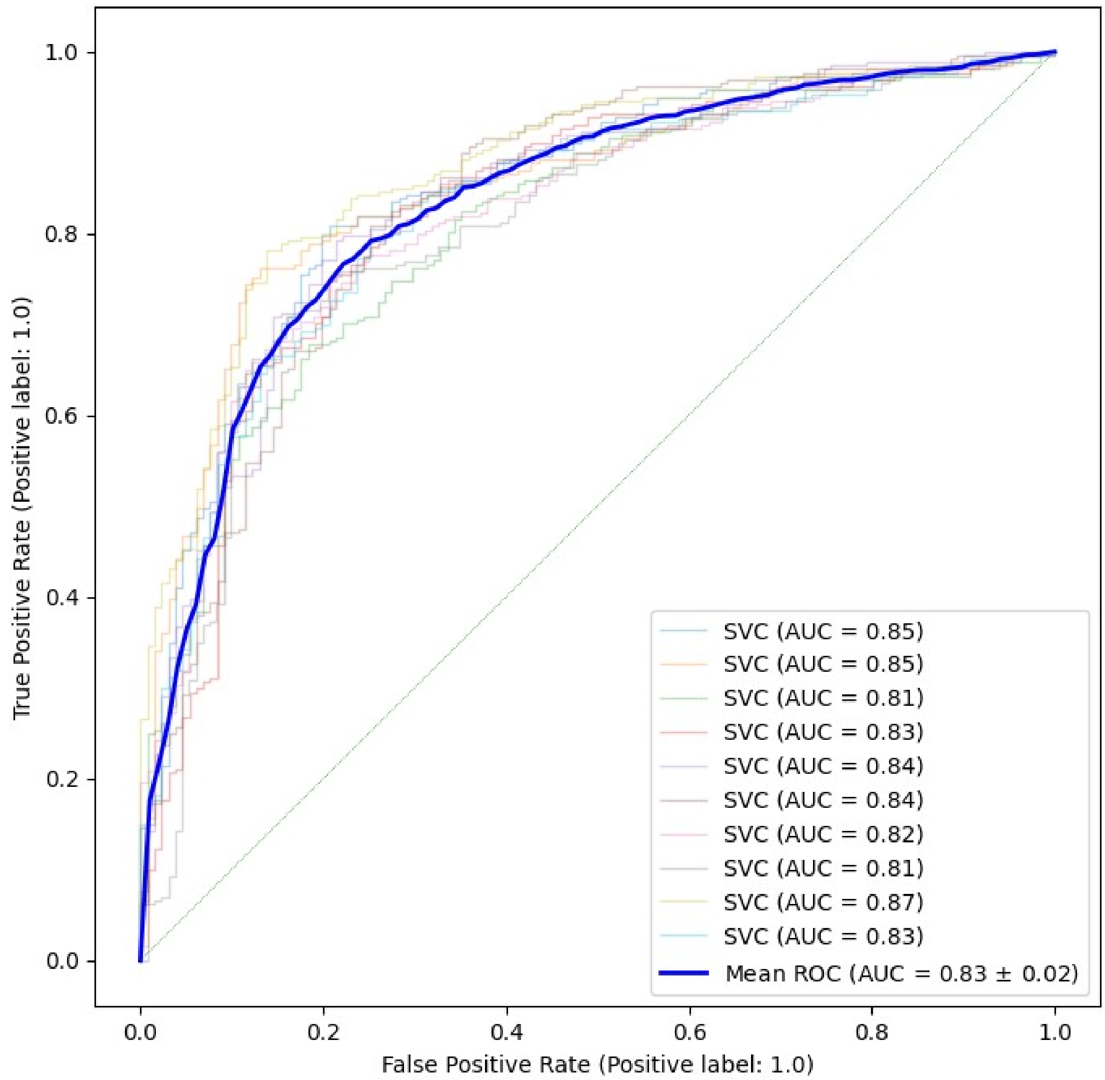
Dentre os modelos testados a seguir:

```
(SVC, {'kernel': 'rbf'}),
(SVC, {'kernel': 'rbf', 'gamma': 2}),
(SVC, {'degree': 3, 'kernel': 'poly'} ),
(SVC, {'degree': 5, 'kernel': 'poly'} ),
(SVC, {'degree': 10, 'kernel': 'poly'} ),
(LogisticRegression, {}),
(DecisionTreeClassifier, {'min_samples_leaf': 50})
```

O melhor resultado foi obtido com o modelo SVC, com kernel = rbf e gamma = 2, com uma AUC = 0.84 +- 0.02 de desvio padrão. As médias de Curva Roc podem ser vistas abaixo, e os arquivos de log podem ser conferidos na pasta "Results"

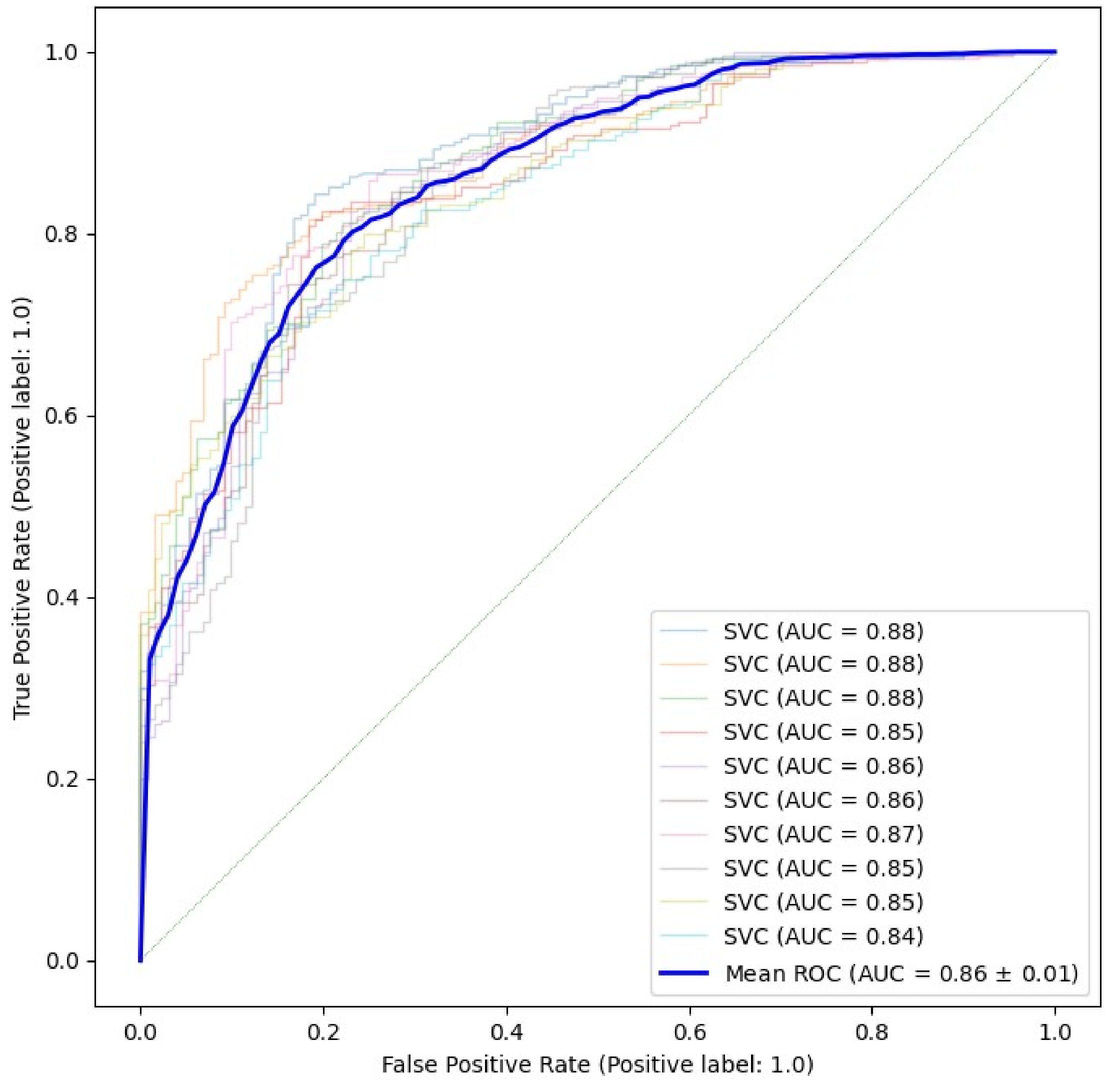
```python
train_cv(var, X_train_cv, y_train_cv, X_test, y_test, config[0][0],
config[0][1])
```

```
(SVC(), StandardScaler())
```



Melhor modelo

```
best_model, best_scaler = train_cv(var, X_train_cv, y_train_cv,
X_test, y_test, config[1][0], config[1][1])
```



Predição e distribuição das categorias encontradas pelo modelo

```
X_scaled = best_scaler.transform(X)
```

```
c:\Users\claud\OneDrive\Documentos\Python\Coded\wine-predict\.venv\
lib\site-packages\sklearn\base.py:432: UserWarning: X has feature
names, but StandardScaler was fitted without feature names
  warnings.warn(
```

```
y_pred = best_model.predict(X_scaled)
```

```
white["pred"] = y_pred
```

```
white
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar
chlorides
```

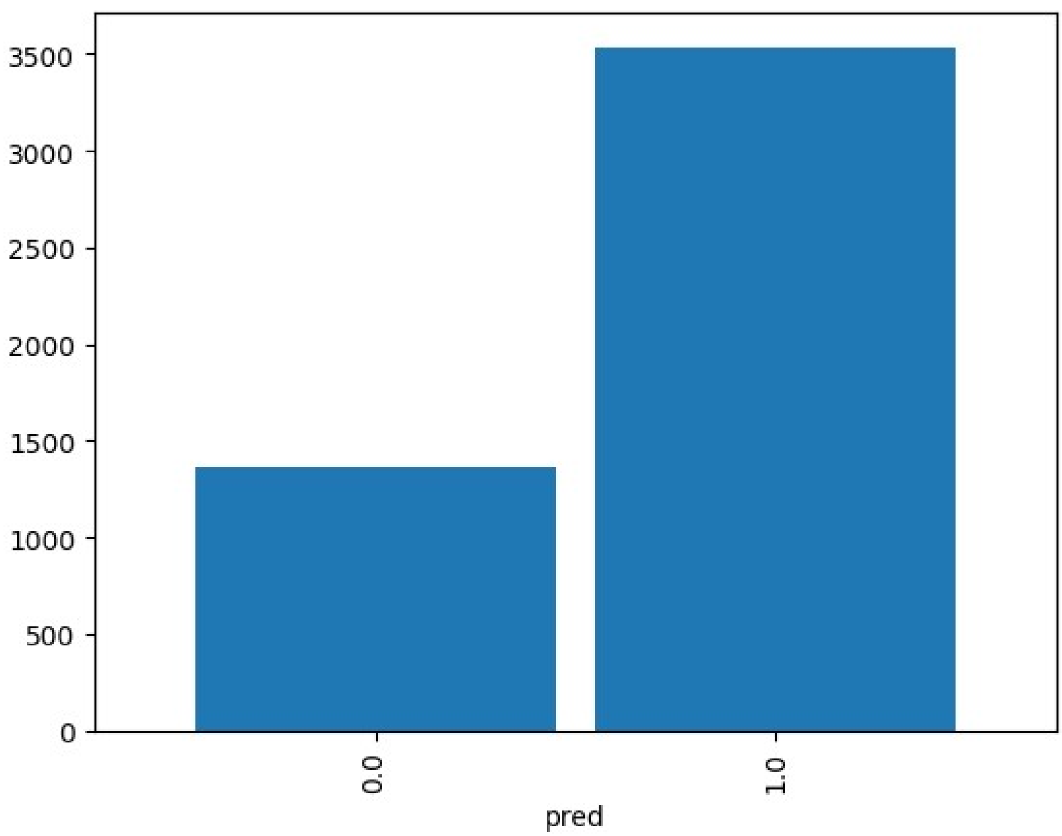
```
0               7.0              0.27         0.36            20.7
0.045  \
1               6.3              0.30         0.34             1.6
0.049
2               8.1              0.28         0.40             6.9
0.050
3               7.2              0.23         0.32             8.5
0.058
4               7.2              0.23         0.32             8.5
0.058
...             ...               ...          ...             ...
...
4893            6.2              0.21         0.29             1.6
0.039
4894            6.6              0.32         0.36             8.0
0.047
4895            6.5              0.24         0.19             1.2
0.041
4896            5.5              0.29         0.30             1.1
0.022
4897            6.0              0.21         0.38             0.8
0.020

      free sulfur dioxide  total sulfur dioxide  density    pH
sulphates
0                    45.0                 170.0  1.00100  3.00
0.45  \
1                    14.0                 132.0  0.99400  3.30
0.49
2                    30.0                  97.0  0.99510  3.26
0.44
3                    47.0                 186.0  0.99560  3.19
0.40
4                    47.0                 186.0  0.99560  3.19
0.40
...                   ...                   ...      ...   ...
...
4893                 24.0                  92.0  0.99114  3.27
0.50
4894                 57.0                 168.0  0.99490  3.15
0.46
4895                 30.0                 111.0  0.99254  2.99
0.46
4896                 20.0                 110.0  0.98869  3.34
0.38
4897                 22.0                  98.0  0.98941  3.26
0.32

      alcohol  quality  pred
0         8.8        6   1.0
```

```
1          9.5        6   1.0
2         10.1        6   1.0
3          9.9        6   1.0
4          9.9        6   1.0
...        ...      ...   ...
4893      11.2        6   1.0
4894       9.6        5   0.0
4895       9.4        6   1.0
4896      12.8        7   1.0
4897      11.8        6   1.0

[4898 rows x 13 columns]
```

```python
white['pred'].value_counts().sort_values()
```

```
pred
0.0    1361
1.0    3537
Name: count, dtype: int64
```

```python
_ = white.pred.value_counts().sort_index().plot.bar(width=0.9)
```



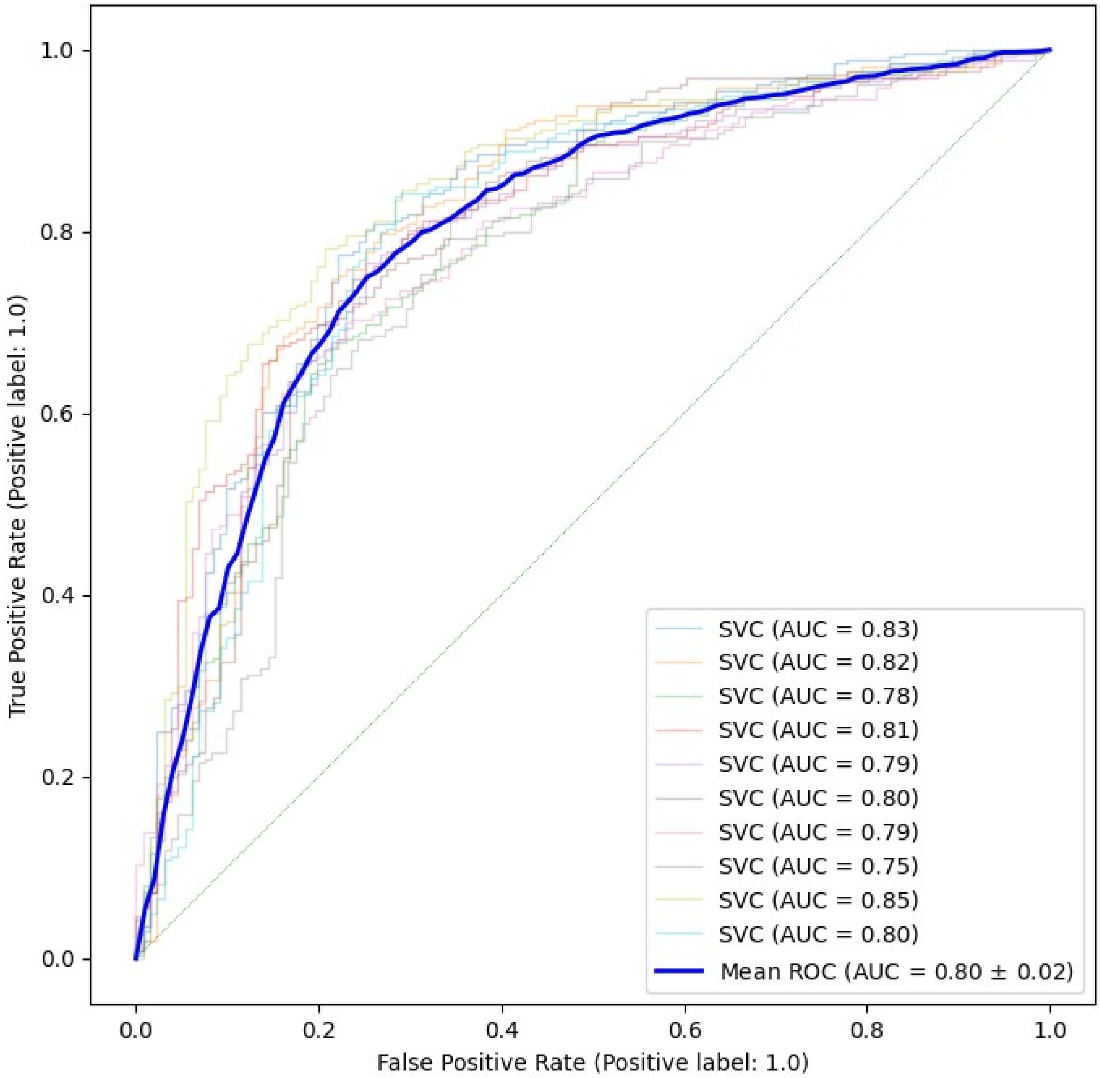

```python
# fazer função
```

```
print(f"""O resultado Médio da ACURÁCIA na Predição é: {100 *
accuracy_score(y, y_pred):.2f}%
O resultado Médio da SENSIBILIDADE na Predição é: {100 *
recall_score(y, y_pred):.2f}%
O resultado Médio da PRECISÃO na Predição é: {100 * precision_score(y,
y_pred):.2f}%
O Resultado da de F1-Score na Predição: {f1_score(y, y_pred):.2}""")
```

```
O resultado Médio da ACURÁCIA na Predição é: 93.24%
O resultado Médio da SENSIBILIDADE na Predição é: 99.20%
O resultado Médio da PRECISÃO na Predição é: 91.38%
O Resultado da de F1-Score na Predição: 0.95
```

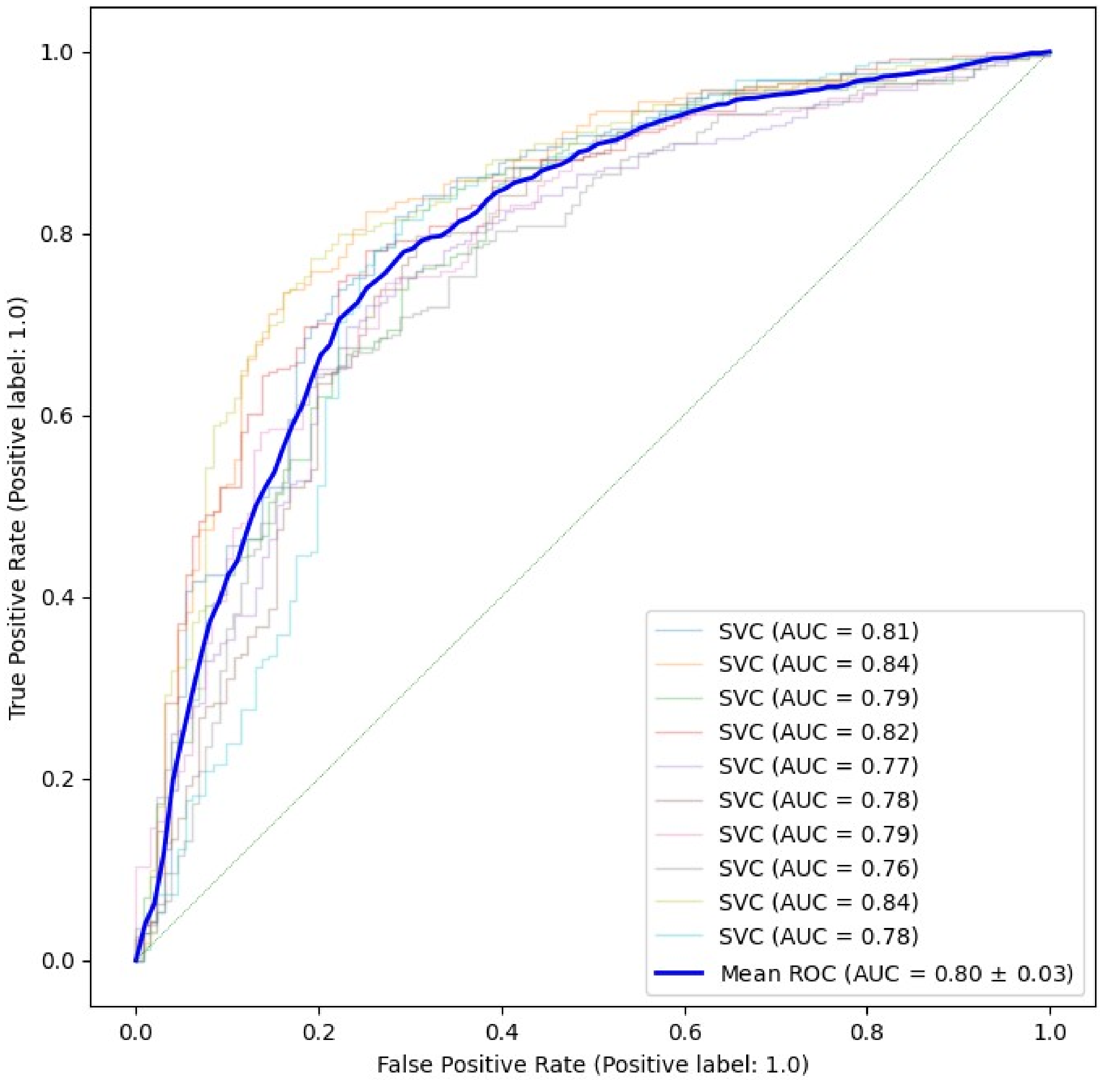
```
train_cv(var, X_train_cv, y_train_cv, X_test, y_test, config[2][0],
config[2][1])
```

```
(SVC(kernel='poly'), StandardScaler())
```



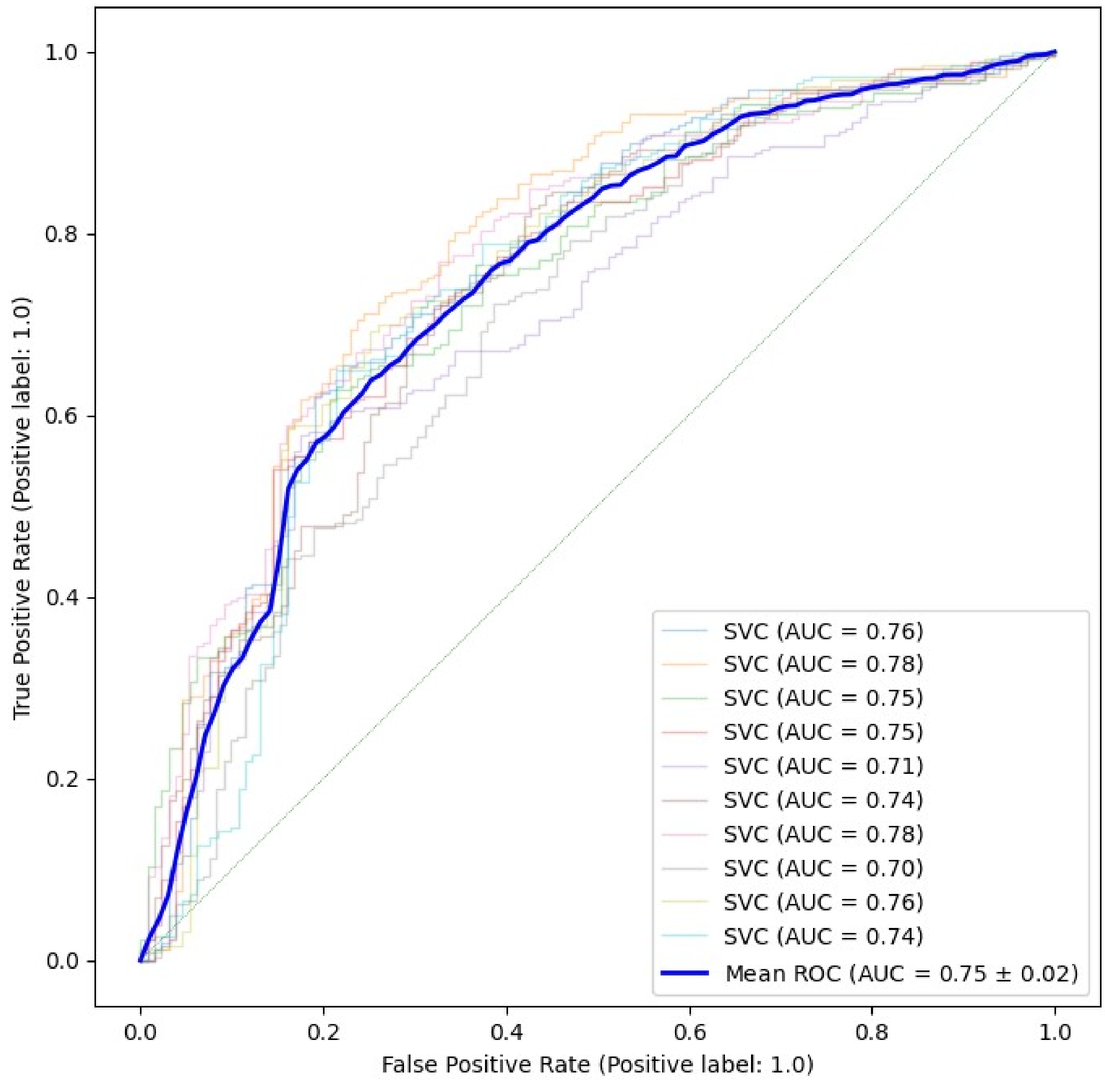

```
train_cv(var, X_train_cv, y_train_cv, X_test, y_test, config[3][0],
config[3][1])
```

```
(SVC(degree=5, kernel='poly'), StandardScaler())
```



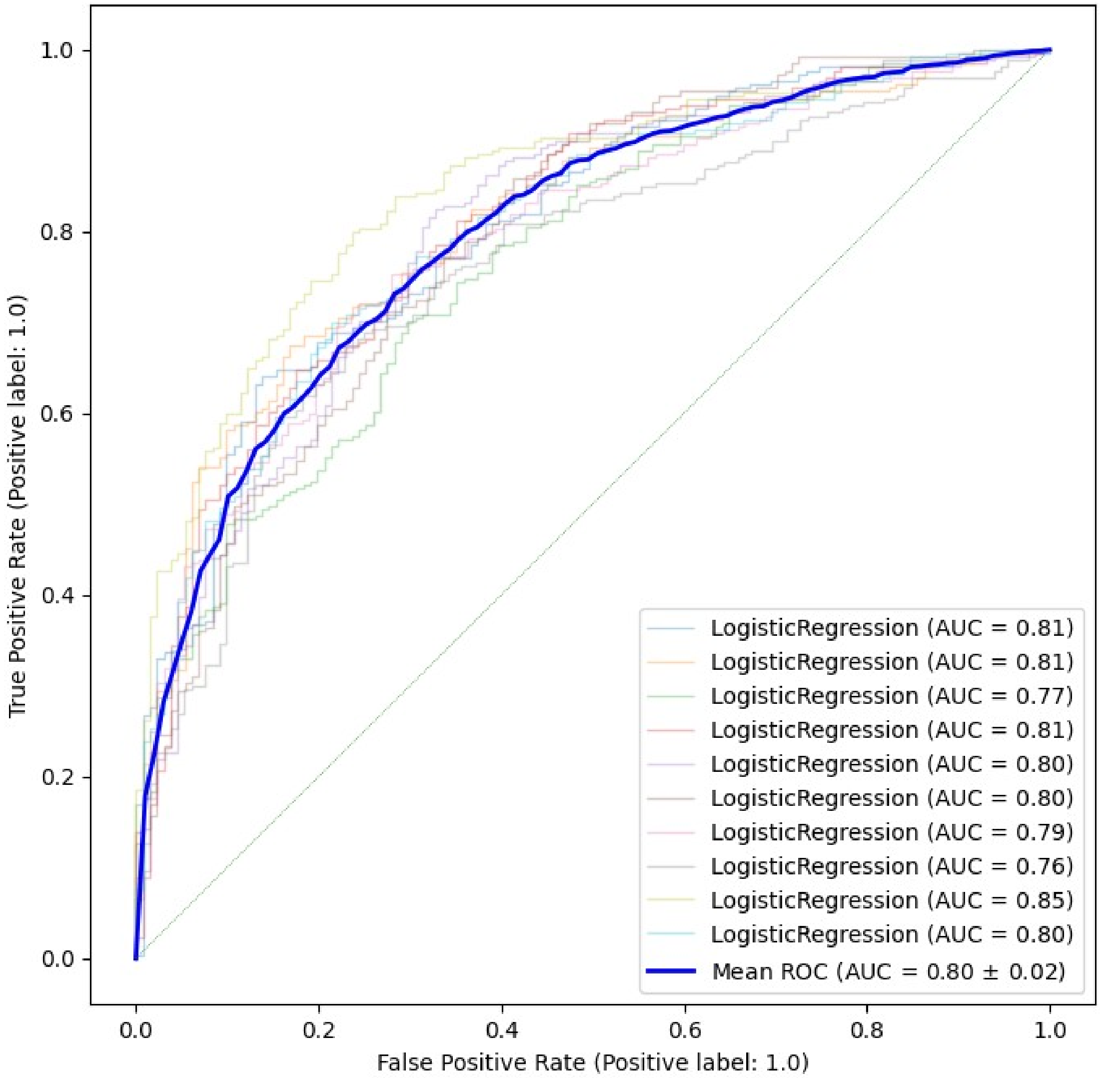

```
train_cv(var, X_train_cv, y_train_cv, X_test, y_test, config[4][0],
config[4][1])
```

```
(SVC(degree=10, kernel='poly'), StandardScaler())
```



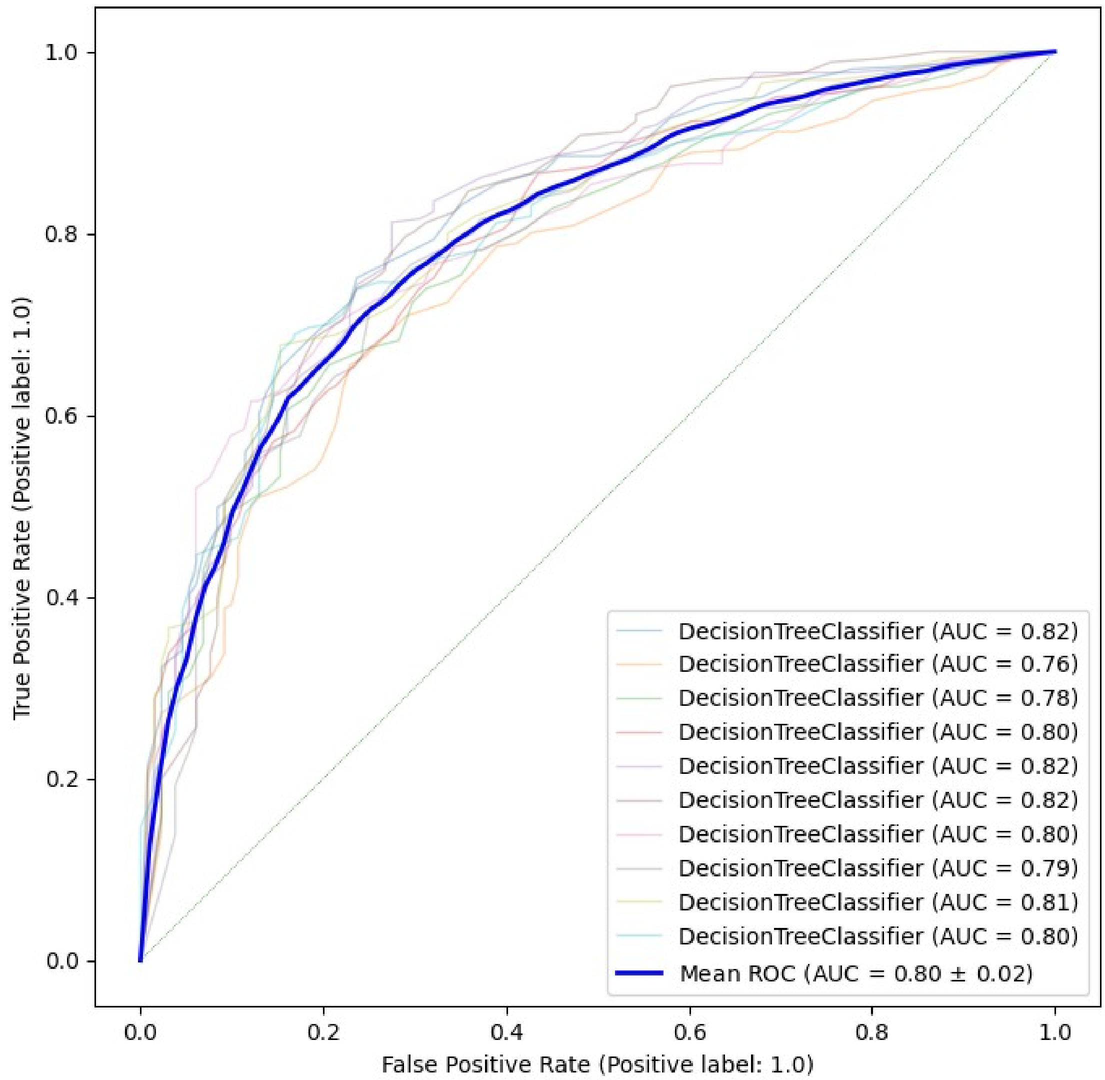

```
train_cv(var, X_train_cv, y_train_cv, X_test, y_test, config[5][0],
config[5][1])
```

```
(LogisticRegression(), StandardScaler())
```




```
train_cv(var, X_train_cv, y_train_cv, X_test, y_test, config[6][0],
config[6][1])
```

```
(DecisionTreeClassifier(min_samples_leaf=50), StandardScaler())
```



Usar o modelo e scaler do base RED para a base WHITE

```
var2 = 'red'
X_red, y_red = base(var2, vars)
```

```
X_red
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar  
chlorides
0               7.4              0.700         0.00             1.9   
0.076  \
1               7.8              0.880         0.00             2.6   
0.098
2               7.8              0.760         0.04             2.3   
0.092
3              11.2              0.280         0.56             1.9   
```

```
0.075
4               7.4              0.700         0.00             1.9
0.076
...             ...                ...          ...             ...
...
1594            6.2              0.600         0.08             2.0
0.090
1595            5.9              0.550         0.10             2.2
0.062
1596            6.3              0.510         0.13             2.3
0.076
1597            5.9              0.645         0.12             2.0
0.075
1598            6.0              0.310         0.47             3.6
0.067

      free sulfur dioxide  total sulfur dioxide  density    pH
sulphates
0                    11.0                  34.0  0.99780  3.51
0.56  \
1                    25.0                  67.0  0.99680  3.20
0.68
2                    15.0                  54.0  0.99700  3.26
0.65
3                    17.0                  60.0  0.99800  3.16
0.58
4                    11.0                  34.0  0.99780  3.51
0.56
...                   ...                   ...      ...   ...
...
1594                 32.0                  44.0  0.99490  3.45
0.58
1595                 39.0                  51.0  0.99512  3.52
0.76
1596                 29.0                  40.0  0.99574  3.42
0.75
1597                 32.0                  44.0  0.99547  3.57
0.71
1598                 18.0                  42.0  0.99549  3.39
0.66

      alcohol
0         9.4
1         9.8
2         9.8
3         9.8
4         9.4
...       ...
1594     10.5
1595     11.2
```

```
1596     11.0
1597     10.2
1598     11.0

[1599 rows x 11 columns]
```

```
X_scaled_red = best_scaler.transform(X_red)
```

```
c:\Users\claud\OneDrive\Documentos\Python\Coded\wine-predict\.venv\
lib\site-packages\sklearn\base.py:432: UserWarning: X has feature
names, but StandardScaler was fitted without feature names
  warnings.warn(
```

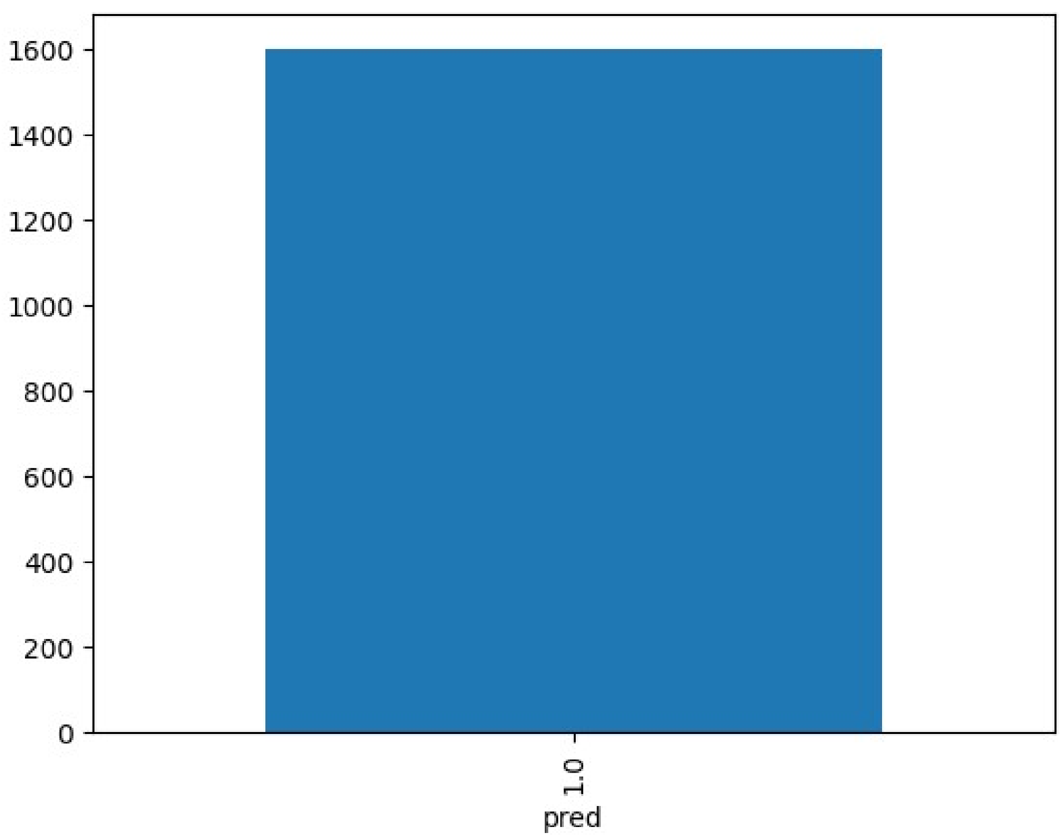
```
y_pred_red = best_model.predict(X_scaled_red)
```

```
red["pred"] = y_pred_red
```

```
red['pred'].value_counts().sort_values()
```

```
pred
1.0    1599
Name: count, dtype: int64
```

```
_ = red.pred.value_counts().sort_index().plot.bar(width=0.9)
```



Não é possível usar o mesmo modelo para diferentes tipos de vinhos pois os dois tem caracteristicas diferentes. Justamente pq um é branco, e outro tinto, se não, seriam todos a mesma coisa.