UNIVERSIDADE ESTADUAL PAULISTA

"JÚLIO DE MESQUITA FILHO"

Instituto de Geociências e Ciências Exatas - IGCE

Curso de Bacharelado em Ciências da Computação

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TRABALHO DE REGRESSÃO

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Rio Claro - SP

2020

1 Introdução

Este trabalho consiste em aplicar o conhecimento de clustering adquirido na disciplina Tópicos: Aprendizado de Máquina, tendo assim como objetivo:

- Escolha dois conjuntos de dados para trabalhar o problema de regressão. Separe cada dataset em conjunto de treinamento e conjunto de teste. Explique o seu critério de separação e o método utilizado.
- Você deverá implementar soluções para cada dataset usando:

  regressão linear (ou regressão múltipla)

  regressão polinomial

  SVR (use os kernels linear, sigmoide, RBF e polinomial)

  rede neural (MLP ou RBF).
- Descreva os parâmetros/arquiteturas de cada modelo.
- Compare os resultados (para treinamento e teste) com as medidas de desempenho SEQ, EQM, REQM, EAM e r2 , e verifique qual a melhor opção dentre os métodos implementados que melhor se ajusta a seus dados.
- Você deverá fazer a visualização dos dados originais com os dados ajustados em cada experimento, tanto para o conjunto de treinamento quanto para o de teste. Os gráficos devem conter títulos nos eixos e legenda. Comente os resultados encontrados na visualização.

regression-framingham

August 19, 2020

[0]:

```

```

1 0. Introdução

Trabalho:

Aluno: Gabriel Luiz

Disciplina: Tópico em Aprendizado de Máquina

Objetivos :

- Escolha dois conjuntos de dados para trabalhar o problema de regressão. Separe cada dataset em conjunto de treinamento e conjunto de teste. Explique o seu critério de separação e o método utilizado.
- Você deverá implementar soluções para cada dataset usando:
-   – regressão linear (ou regressão múltipla)
-   – regressão polinomial
-   – SVR (use os kernels linear, sigmoide, RBF e polinomial)
-   – rede neural (MLP ou RBF).
- Descreva os parâmetros/arquiteturas de cada modelo.
- Compare os resultados (para treinamento e teste) com as medidas de desempenho SEQ, EQM, REQM, EAM e r^2 , e verifique qual a melhor opção dentre os métodos implementados que melhor se ajusta a seus dados.
- Você deverá fazer a visualização dos dados originais com os dados ajustados em cada experimento, tanto para o conjunto de treinamento quanto para o de teste. Os gráficos devem conter títulos nos eixos e legenda. Comente os resultados encontrados na visualização.

1.1 0.1 Dependências

Para realização da tarefa foram utilizados as seguintes bibliotecas:

[1]:
```python
#Utils
import pandas as pd
import numpy as np
import pandas_profiling
import math

#Preprocess
from sklearn.preprocessing import StandardScaler

# Split
from sklearn.model_selection import train_test_split

# Regressores
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor

#Metricas
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

#Visualização
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

2 1. Dados

O conjunto de dados possui informações sobre pacientes que podem ter risco de doenças do coração em 10 anos. Possui mais de 4 mil registros e 15 atributos

Fonte: https://www.kaggle.com/dileep070/heart-disease-prediction-using-logistic-regression

2.1 1.1 Informações sobre os dados:

Atributos:

- Sex: male or female(Nominal)
- Age: Age of the patient;(Continuous - Although the recorded ages have been truncated to whole numbers, the concept of age is continuous) Behavioral
- Current Smoker: whether or not the patient is a current smoker (Nominal)
- Cigs Per Day: the number of cigarettes that the person smoked on average in one day.(can be considered continuous as one can have any number of cigarettes, even half a cigarette.)

Medical(history)

- BP Meds: whether or not the patient was on blood pressure medication (Nominal)
- Prevalent Stroke: whether or not the patient had previously had a stroke (Nominal)
- Prevalent Hyp: whether or not the patient was hypertensive (Nominal)
- Diabetes: whether or not the patient had diabetes (Nominal) Medical(current)
- Tot Chol: total cholesterol level (Continuous)
- Sys BP: systolic blood pressure (Continuous)
- Dia BP: diastolic blood pressure (Continuous)
- BMI: Body Mass Index (Continuous)
- Heart Rate: heart rate (Continuous - In medical research, variables such as heart rate though in fact discrete, yet are considered continuous because of large number of possible values.)
- Glucose: glucose level (Continuous) Predict variable (desired target)
- 10 year risk of coronary heart disease CHD (binary: “1”, means “Yes”, “0” means “No”)

2.2 Importando Dataset

[2]:
```
dataset = './dataset/datasets_222487_478477_framingham.csv'

data_raw = pd.read_csv(dataset)
```

[3]:
```
data_raw.head()
```

[3]:
```
   male  age  education  currentSmoker  cigsPerDay  BPMeds  prevalentStroke  \
0     1   39        4.0              0         0.0     0.0                0
1     0   46        2.0              0         0.0     0.0                0
2     1   48        1.0              1        20.0     0.0                0
3     0   61        3.0              1        30.0     0.0                0
4     0   46        3.0              1        23.0     0.0                0

   prevalentHyp  diabetes  totChol  sysBP  diaBP    BMI  heartRate  glucose  \
0             0         0    195.0  106.0   70.0  26.97       80.0     77.0
1             0         0    250.0  121.0   81.0  28.73       95.0     76.0
2             0         0    245.0  127.5   80.0  25.34       75.0     70.0
3             1         0    225.0  150.0   95.0  28.58       65.0    103.0
4             0         0    285.0  130.0   84.0  23.10       85.0     85.0

   TenYearCHD
0           0
1           0
2           0
3           1
4           0
```

[4]:
```
data_raw.education = data_raw.education.fillna(0)
data_raw.cigsPerDay = data_raw.cigsPerDay.fillna(data_raw.cigsPerDay.mean())
data_raw.BPMeds = data_raw.BPMeds.fillna(0)
```

```
data_raw.totChol = data_raw.totChol.fillna(data_raw.totChol.mean())
data_raw.BMI = data_raw.BMI.fillna(data_raw.BMI.mean())
data_raw.heartRate = data_raw.heartRate.fillna(data_raw.heartRate.mean())
data_raw.glucose = data_raw.glucose.fillna(data_raw.glucose.mean())
```

[4]: array([4., 2., 1., 3., 0.])

2.3 Pré-processamento

[11]:
```
# pandas_profiling.ProfileReport(data_raw)
```

2.4 Visualização

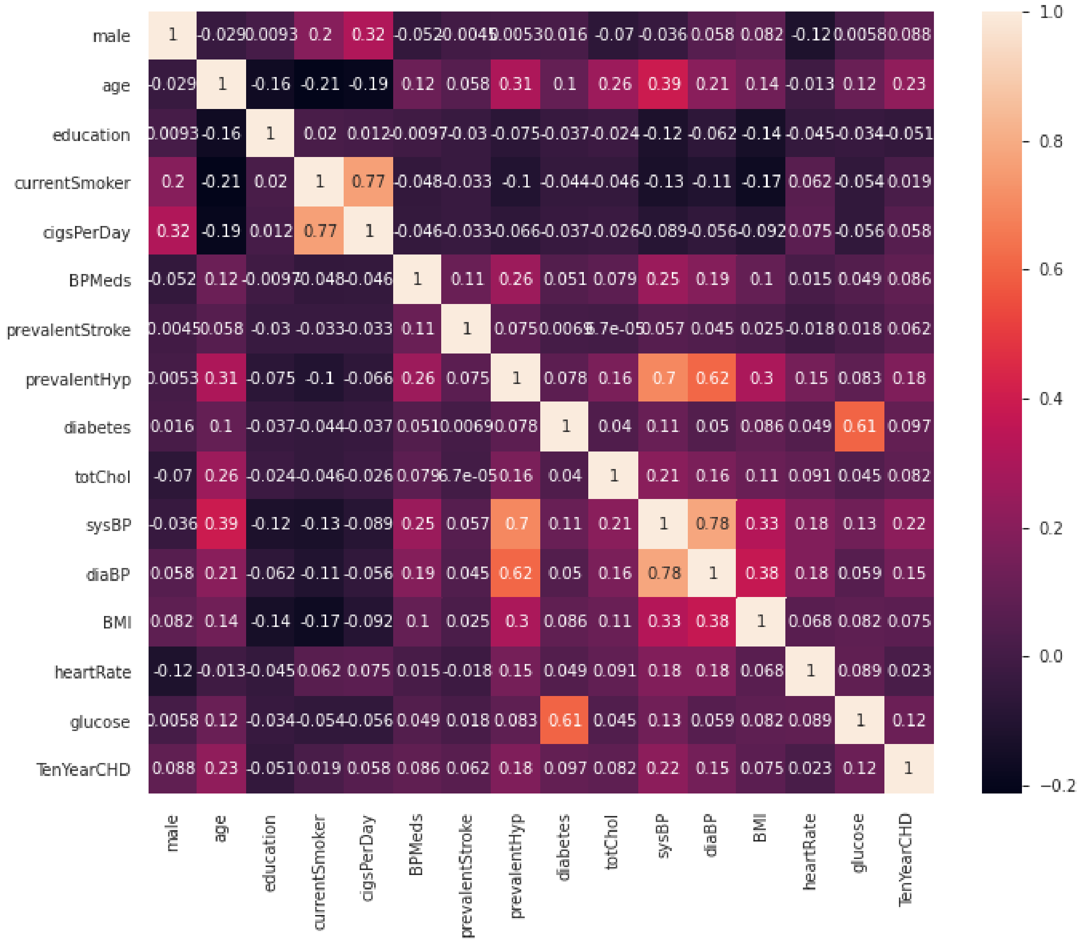
[12]:
```
# sns.pairplot(data_raw)
```

[13]:
```
plt.clf()
```

<Figure size 432x288 with 0 Axes>

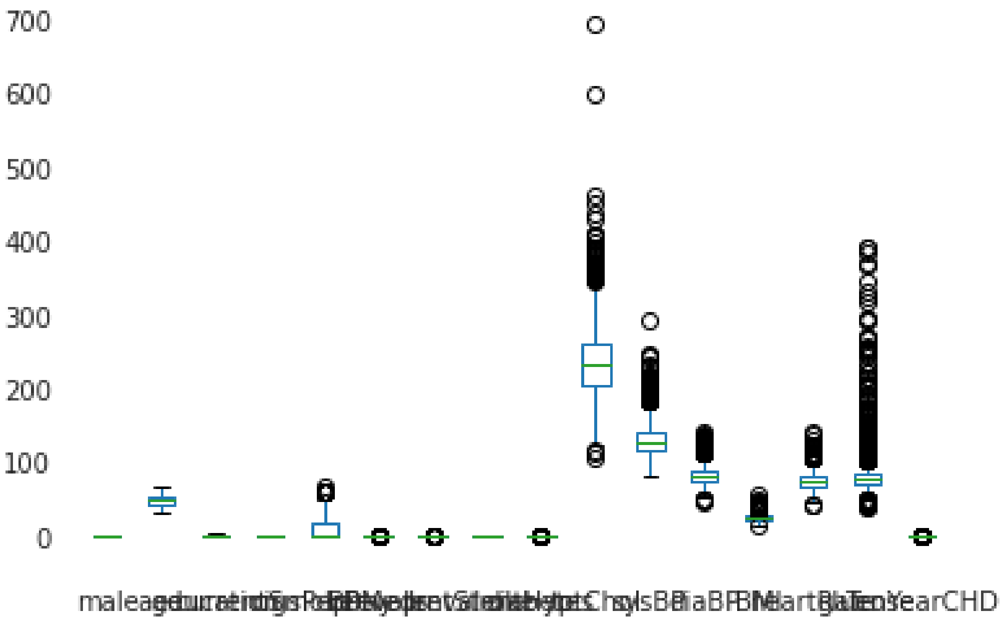
[14]:
```
plt.subplots(figsize=(11, 9))
sns.heatmap(data_raw.corr(), annot=True)
```

[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1a306d3898>



[15]:
```
data_raw.plot.box()
```

[15]: <matplotlib.axes._subplots.AxesSubplot at 0x7f1a2dd18160>



2.5 Escalonando

[16]:
```
scaler = StandardScaler().fit(data_raw)
data_scaled = scaler.transform(data_raw)
```

[17]:
```
data_scaled_df = pd.DataFrame(data_scaled, columns=data_raw.columns)
```

[18]:
```
data_scaled_df.head()
```

[18]:

	male	age	education	currentSmoker	cigsPerDay	BPMeds	\
0	1.153192	-1.234951	1.966086	-0.988271	-0.757974	-0.173612	
1	-0.867158	-0.418257	0.066560	-0.988271	-0.757974	-0.173612	
2	1.153192	-0.184916	-0.883204	1.011868	0.925835	-0.173612	
3	-0.867158	1.331800	1.016323	1.011868	1.767740	-0.173612	
4	-0.867158	-0.418257	1.016323	1.011868	1.178407	-0.173612	

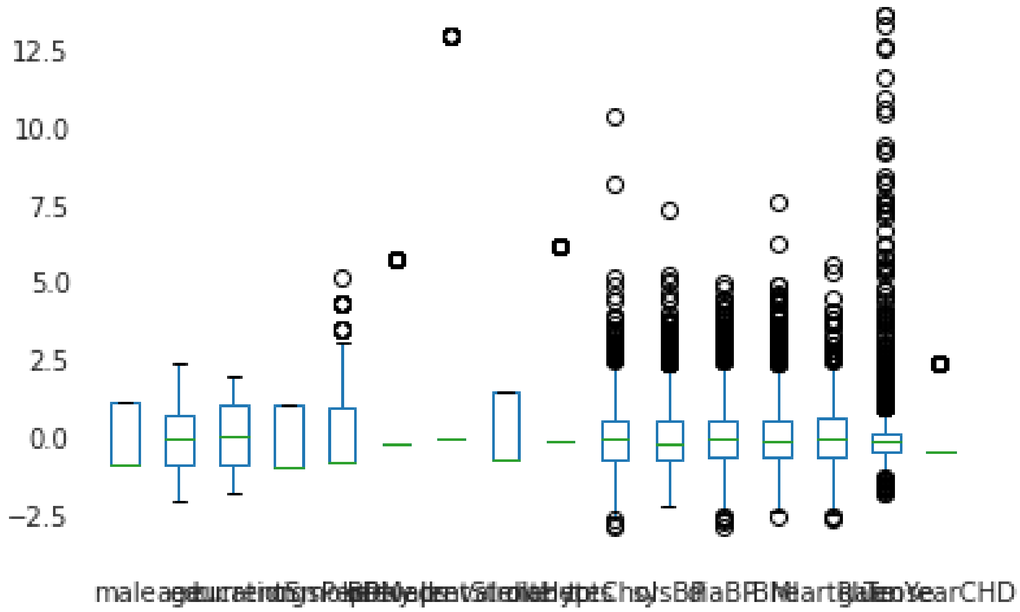
	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	\
0	-0.077033	-0.671101	-0.162477	-0.941346	-1.195907	-1.082625	
1	-0.077033	-0.671101	-0.162477	0.299595	-0.515187	-0.158988	
2	-0.077033	-0.671101	-0.162477	0.186782	-0.220209	-0.242955	
3	-0.077033	1.490089	-0.162477	-0.264469	0.800871	1.016549	
4	-0.077033	-0.671101	-0.162477	1.089284	-0.106755	0.092912	

	BMI	heartRate	glucose	TenYearCHD

```
0  0.286943   0.342744 -0.217517   -0.423305
1  0.719325   1.590275 -0.261311   -0.423305
2 -0.113502  -0.073099 -0.524078   -0.423305
3  0.682474  -0.904786  0.921141    2.362360
4 -0.663807   0.758588  0.132840   -0.423305
```

[19]:
```
data_scaled_df.plot.box()
```

[19]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1a2dd164a8>
```



2.6 Utilidades

[20]:
```
lista_metricas_treino = []
lista_metricas_teste = []
```

[21]:
```
def metricas(y_true, y_pred, alg):
    r2 = r2_score(y_true, y_pred)
    eqm = mean_squared_error(y_true, y_pred)
    seq = len(y_true)*eqm
    reqm = math.sqrt(eqm)

    return {'Algoritmo':alg, 'R2':r2, 'EQM':eqm, 'REQM':reqm, 'SEQ':seq}
```

2.7 Separando conjuntos de Treino e Teste

Para a separação utilizou-se do train_test_split que divide o conjunto em treino e teste aleatóriamente

[22]:
```
test_attr = 'male';
output_attr = 'TenYearCHD';
train, test = train_test_split(data_scaled_df, test_size = 0.2, shuffle=True)

x_train = train.drop(columns=[output_attr])
y_train = train[output_attr]

x_test = test.drop(columns=[output_attr])
y_test = test[output_attr]
```

2.8 Aplicando a Regressão

2.8.1 Regressão Linear

[23]:
```
lire = LinearRegression()
```

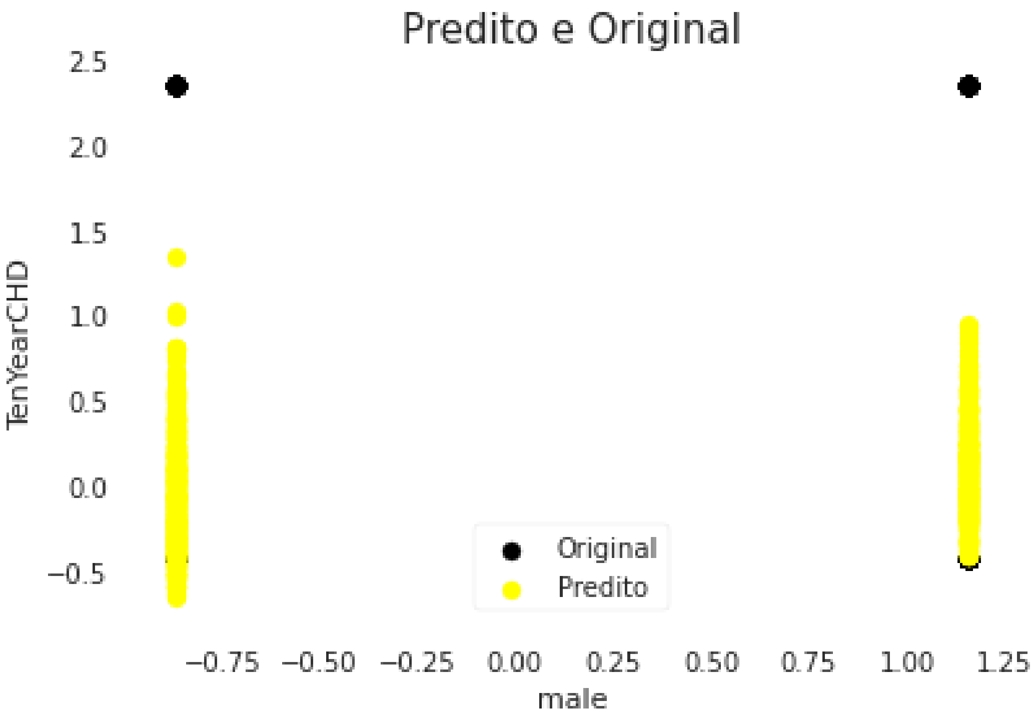
[24]:
```
lire.fit(x_train, y_train)
```

[24]:
```
LinearRegression()
```

2.9 Avaliação para Teste

[25]:
```
y_pred = lire.predict(x_test)
linear_metricas = metricas(y_test, y_pred, 'Regressão Linear - Teste')
lista_metricas_teste.append(linear_metricas)
```

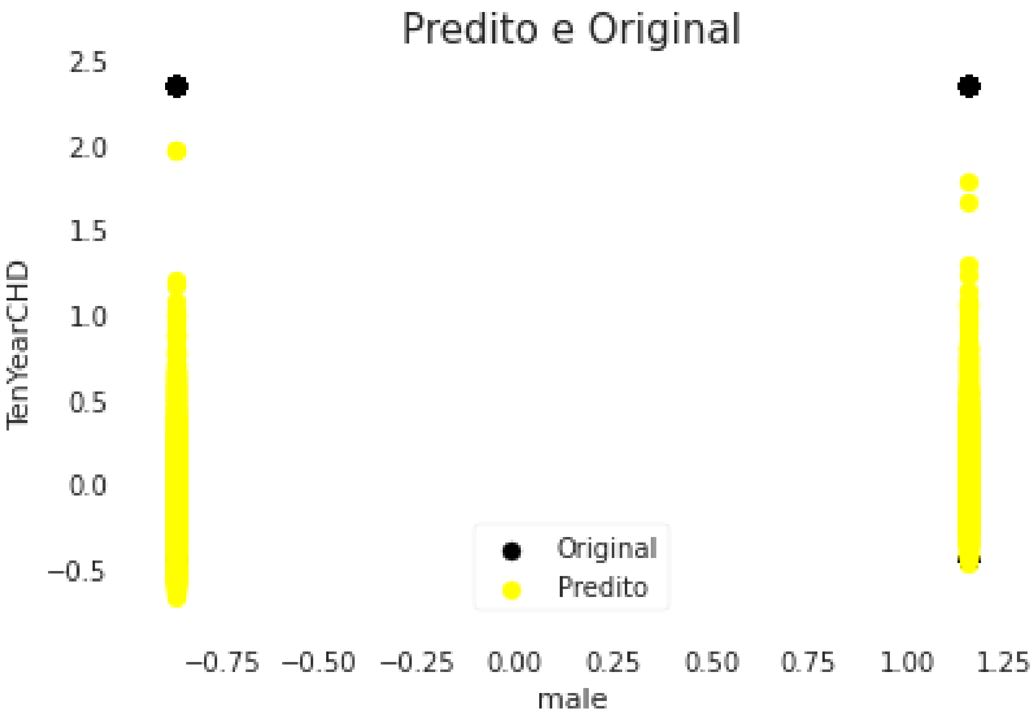
[26]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.10 Avaliação para Treino

[27]:
```
y_pred = lire.predict(x_train)
linear_metricas = metricas(y_train, y_pred, 'Regressão Linear - Treino')
lista_metricas_treino.append(linear_metricas)
```

[28]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.11 SVR

2.11.1 Kernel RBF

[29]:
```
svr_reg = SVR(kernel='rbf')
```

[30]:
```
svr_reg.fit(x_train, y_train)
```

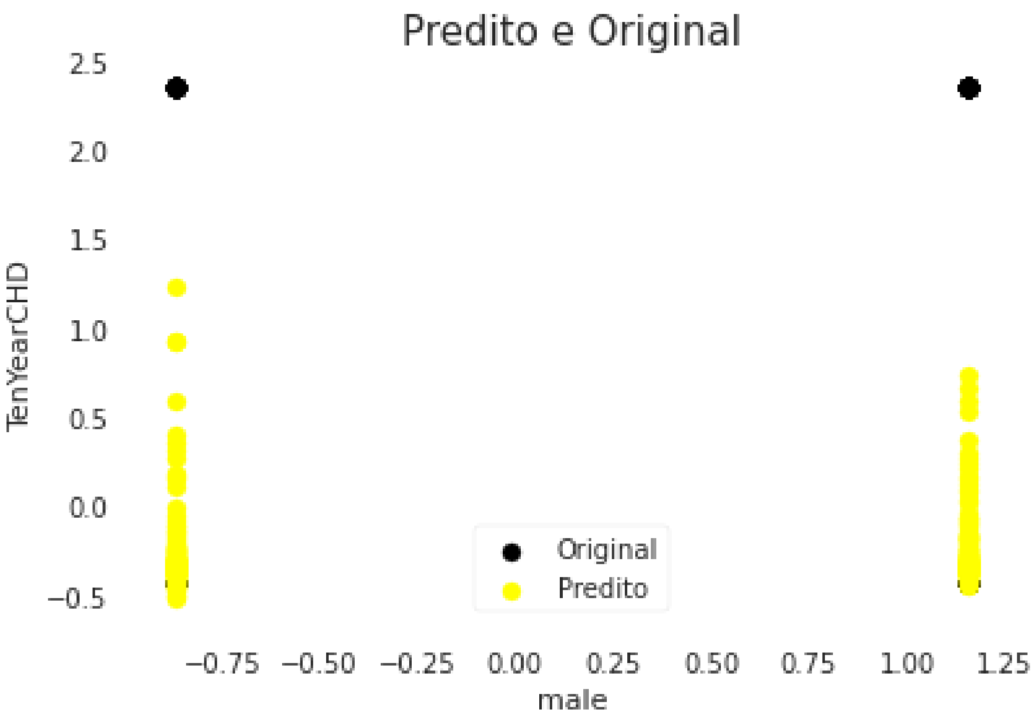
[30]: SVR()

2.12 Avaliação para Teste

[31]:
```
y_pred = svr_reg.predict(x_test)
svr_metricas = metricas(y_test, y_pred, 'SVR - RBF - Teste')
lista_metricas_teste.append(svr_metricas)
```

[32]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
```

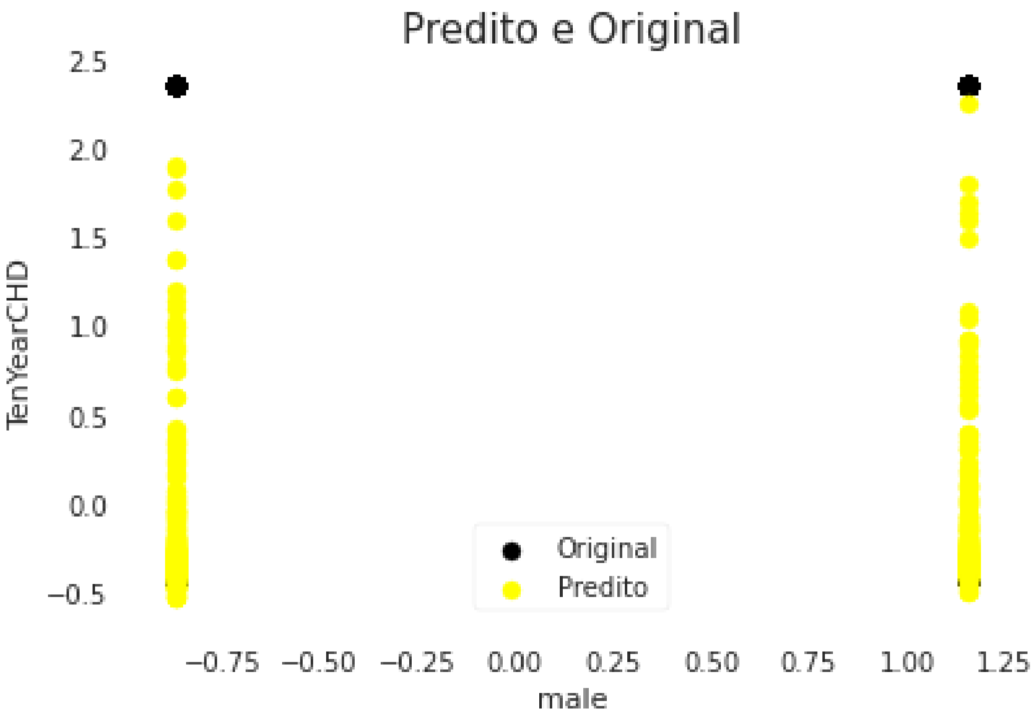
```
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.13 Avaliação para Treino

[33]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - RBF - Treino')
lista_metricas_treino.append(svr_metricas)
```

[34]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.13.1 Kernel Linear

[35]:
```
svr_reg = SVR(kernel='linear')
```

[36]:
```
svr_reg.fit(x_train, y_train)
```

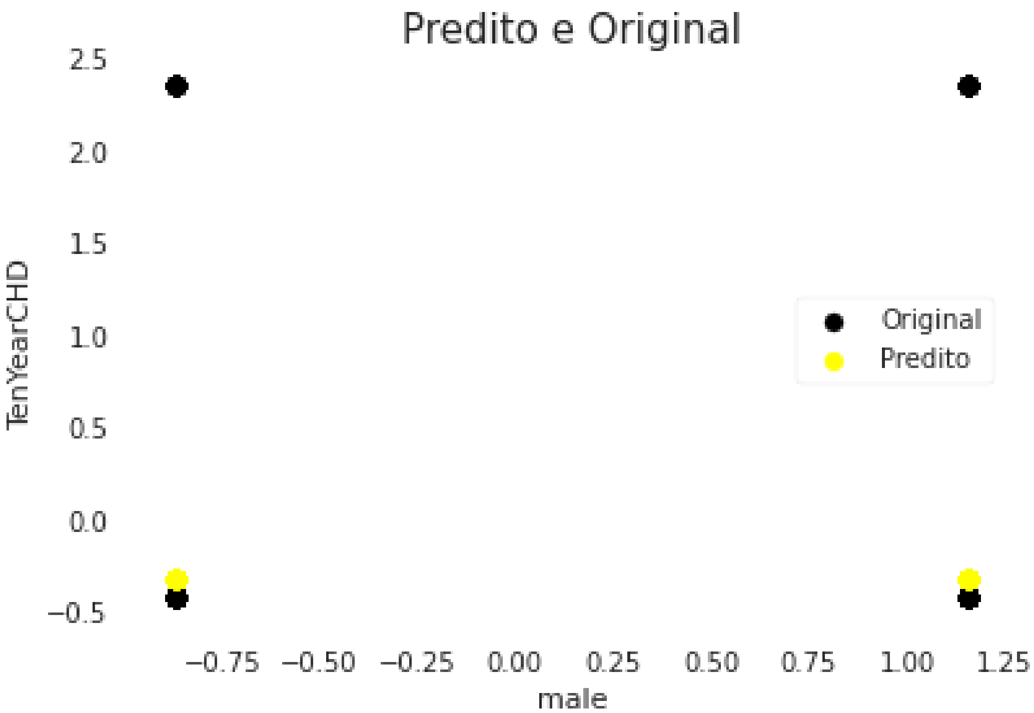
[36]: SVR(kernel='linear')

2.14 Avaliação para Teste

[37]:
```
y_pred = svr_reg.predict(x_test)
metricas_svr = metricas(y_test, y_pred, 'SVR - Linear - Teste')
lista_metricas_teste.append(metricas_svr)
```

[38]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
```

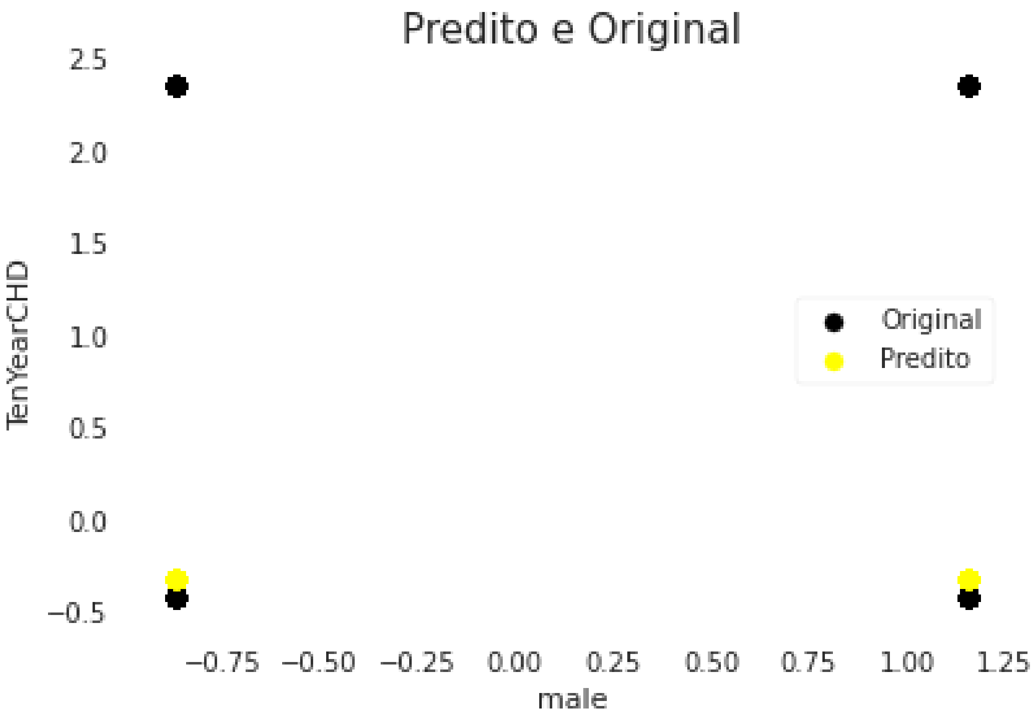
```
plt.show()
```



2.15 Avaliação para Treino

[39]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - Linear - Treino')
lista_metricas_treino.append(svr_metricas)
```

[40]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.15.1 Kernel Sigmoide

[41]:
```
train, test = train_test_split(data_raw, test_size = 0.2, shuffle=True)

x_train_sig = train.drop(columns=[output_attr])
y_train_sig  = train[output_attr]

x_test_sig  = test.drop(columns=[output_attr])
y_test_sig  = test[output_attr]
```

[42]:
```
svr_reg = SVR(kernel='sigmoid')
```

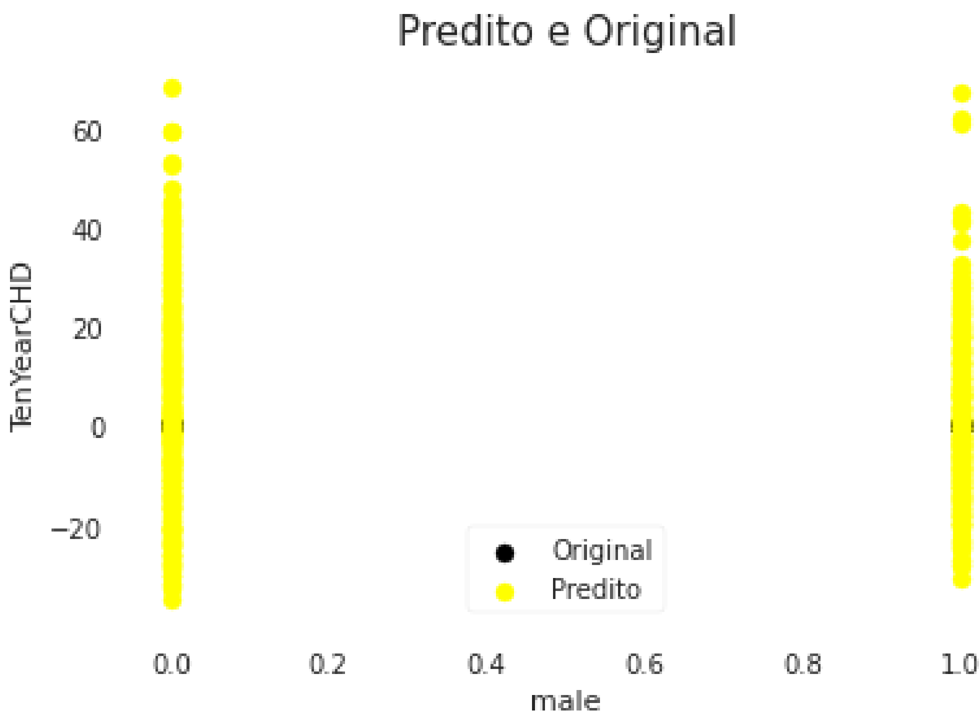
[43]:
```
svr_reg.fit(x_train_sig , y_train_sig )
```

[43]:
```
SVR(kernel='sigmoid')
```

2.16 Avaliação para Teste

[44]:
```
y_pred_sig  = svr_reg.predict(x_test_sig)
metricas_svr = metricas(y_test_sig , y_pred_sig , 'SVR - Sigmoide - Teste')
lista_metricas_teste.append(metricas_svr)
```

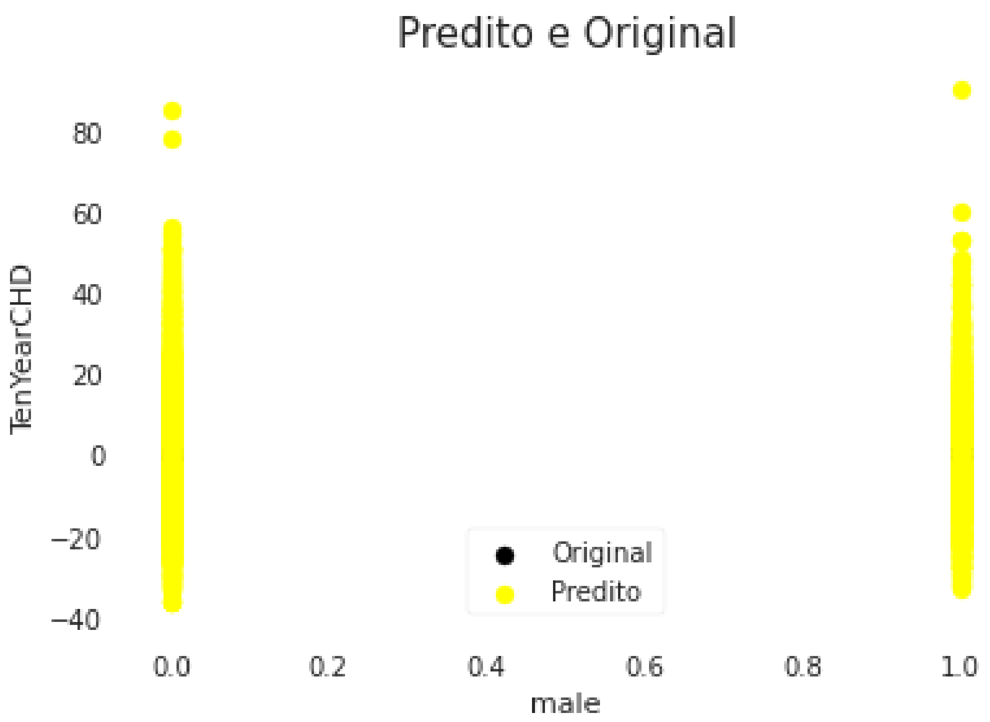
[45]:
```
plt.scatter(x_test_sig [test_attr], y_test_sig ,  color='black')
plt.scatter(x_test_sig [test_attr], y_pred_sig , color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.17 Avaliação para Treino

[46]:
```
y_pred_sig  = svr_reg.predict(x_train_sig)
svr_metricas = metricas(y_train_sig , y_pred_sig , 'SVR - Sigmoide - Treino')
lista_metricas_treino.append(svr_metricas)
```

[47]:
```
plt.scatter(x_train_sig [test_attr], y_train_sig ,  color='black')
plt.scatter(x_train_sig [test_attr], y_pred_sig , color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.17.1 Kernel Polinomial

[48]:
```
svr_reg = SVR(kernel='poly', degree=3)
```

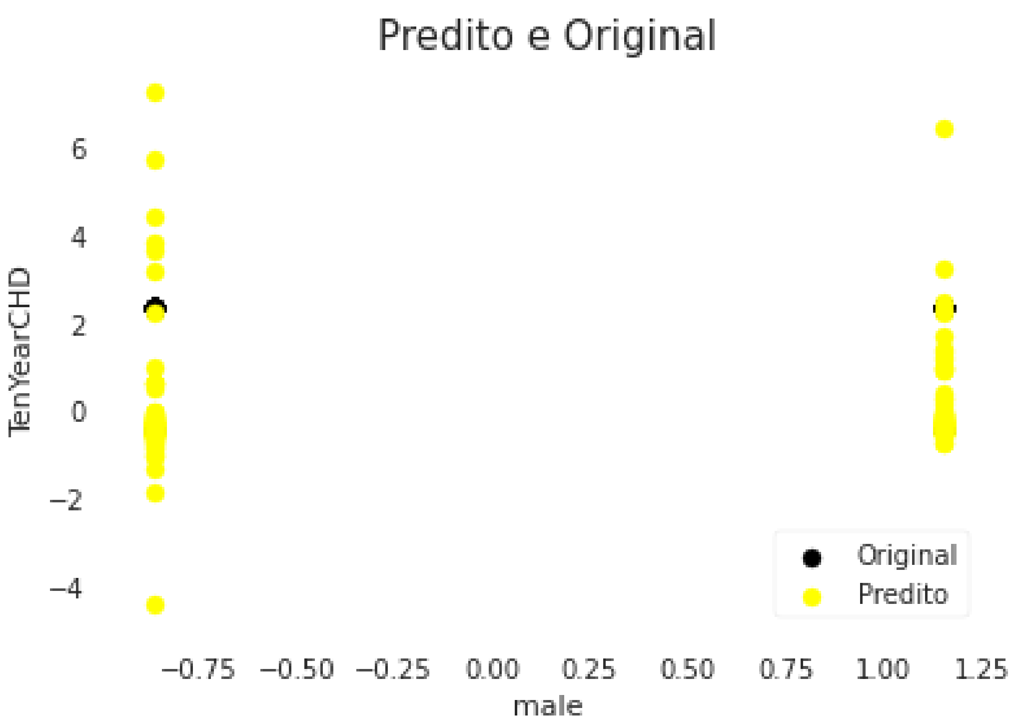
[49]:
```
svr_reg.fit(x_train, y_train)
```

[49]: SVR(kernel='poly')

2.18 Avaliação para Teste

[50]:
```
y_pred = svr_reg.predict(x_test)
svr_metricas = metricas(y_test, y_pred, 'SVR - Polinomial - Teste')
lista_metricas_teste.append(svr_metricas)
```

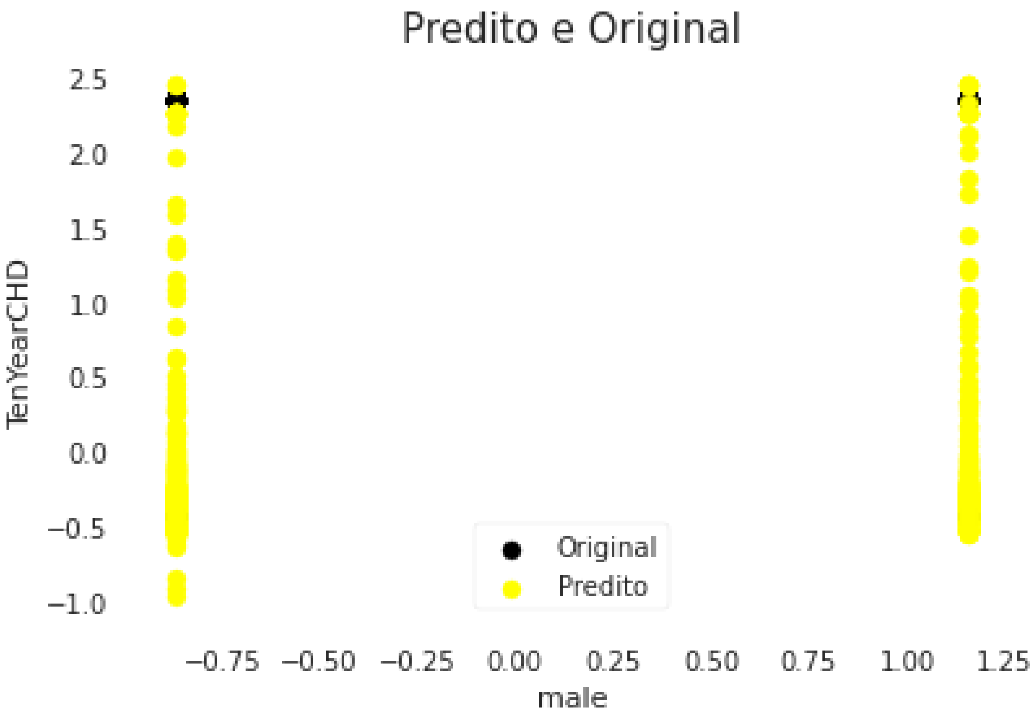
[51]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.19 Avaliação para Treino

[52]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - Polinomial - Treino')
lista_metricas_treino.append(svr_metricas)
```

[53]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.20 Redes Neurais

2.20.1 Kernel Linear

[54]:
```
mlp_reg = MLPRegressor()
```

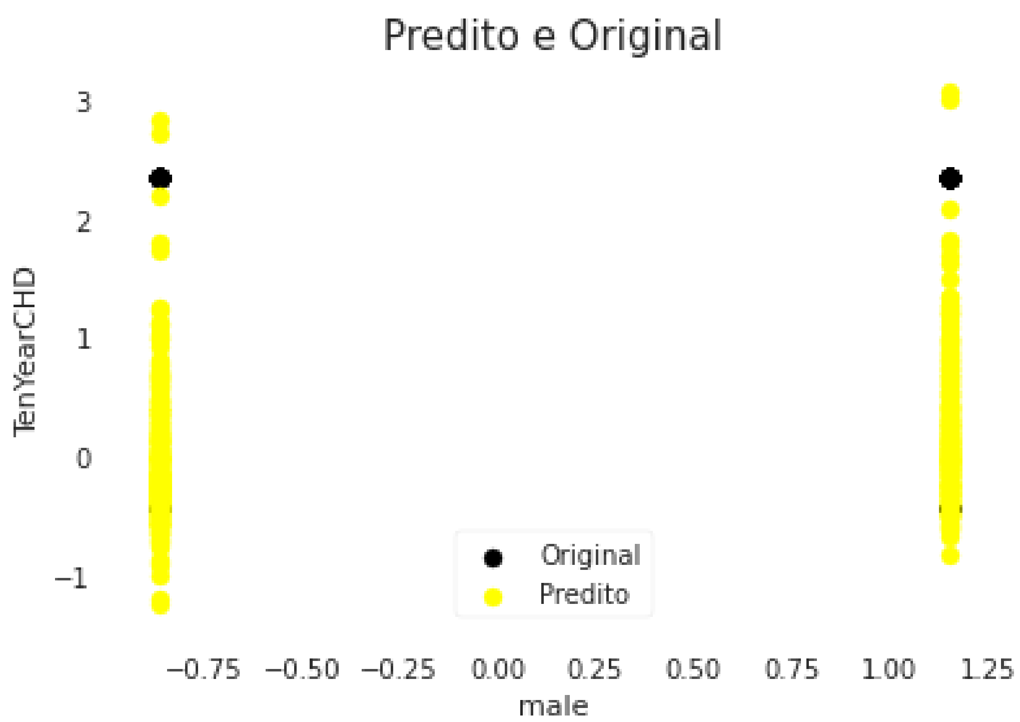
[55]:
```
mlp_reg.fit(x_train, y_train)
```

[55]:
```
MLPRegressor()
```

2.21 Avaliação para Teste

[56]:
```
y_pred = mlp_reg.predict(x_test)
mlp_metricas = metricas(y_test, y_pred, 'MLP - Teste')
lista_metricas_teste.append(mlp_metricas)
```

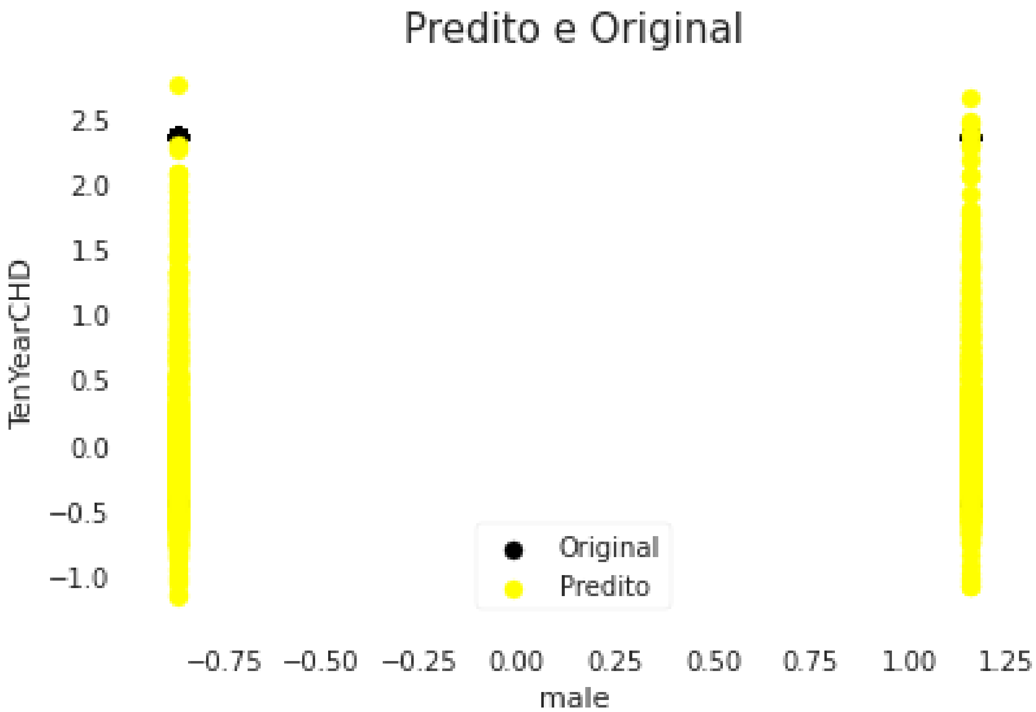
[57]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.22 Avaliação para Treino

[58]:
```
y_pred = mlp_reg.predict(x_train)
mlp_metricas = metricas(y_train, y_pred, 'MLP - Treino')
lista_metricas_treino.append(mlp_metricas)
```

[59]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



3 Resultados

[60]:
```
metricas_teste = pd.DataFrame(lista_metricas_teste)
metricas_teste
```

[60]:

	Algoritmo	R2	EQM	REQM	SEQ
0	Regressão Linear - Teste	0.087893	0.907098	0.952417	769.219422
1	SVR - RBF - Teste	-0.049167	1.043406	1.021473	884.808664
2	SVR - Linear - Teste	-0.103276	1.097218	1.047482	930.441172
3	SVR - Sigmoide - Teste	-2198.824687	281.928404	16.790724	239075.286764
4	SVR - Polinomial - Teste	-0.275246	1.268243	1.126163	1075.470262
5	MLP - Teste	-0.012818	1.007257	1.003622	854.153811

[61]:
```
metricas_teste = round(metricas_teste, 3)
```

[62]:
```
metricas_teste
```

[62]:
```
                    Algoritmo        R2      EQM    REQM        SEQ
0  Regressão Linear - Teste     0.088    0.907   0.952    769.219
1         SVR - RBF - Teste    -0.049    1.043   1.021    884.809
2      SVR - Linear - Teste    -0.103    1.097   1.047    930.441
3    SVR - Sigmoide - Teste -2198.825  281.928  16.791 239075.287
4  SVR - Polinomial - Teste    -0.275    1.268   1.126   1075.470
5               MLP - Teste    -0.013    1.007   1.004    854.154
```

[63]:
```
metricas_teste.to_excel('framingham_metricas_teste.xlsx')
```

[64]:
```
metricas_treino = pd.DataFrame(lista_metricas_treino)
metricas_treino
```

[64]:
```
                    Algoritmo           R2         EQM       REQM  \
0  Regressão Linear - Treino     0.098059    0.903177   0.950356
1         SVR - RBF - Treino     0.028599    0.972733   0.986272
2      SVR - Linear - Treino    -0.104831    1.106346   1.051830
3    SVR - Sigmoide - Treino -2119.951812  273.695635  16.543749
4  SVR - Polinomial - Treino     0.060553    0.940735   0.969915
5               MLP - Treino     0.341441    0.659462   0.812073

             SEQ
0    3061.771151
1    3297.563799
2    3750.512228
3  927828.201264
4    3189.090403
5    2235.577091
```

[65]:
```
metricas_treino = round(metricas_treino, 3)
```

[66]:
```
metricas_treino.to_excel('framingham.xlsx')
```

regression-wine

August 19, 2020

[61]:

```

```

1 0. Introdução

Trabalho:

Aluno: Gabriel Luiz

Disciplina: Tópico em Aprendizado de Máquina

Objetivos :

- Escolha dois conjuntos de dados para trabalhar o problema de regressão. Separe cada dataset em conjunto de treinamento e conjunto de teste. Explique o seu critério de separação e o método utilizado.
- Você deverá implementar soluções para cada dataset usando:
- – regressão linear (ou regressão múltipla)
- – regressão polinomial
- – SVR (use os kernels linear, sigmoide, RBF e polinomial)
- – rede neural (MLP ou RBF).
- Descreva os parâmetros/arquiteturas de cada modelo.
- Compare os resultados (para treinamento e teste) com as medidas de desempenho SEQ, EQM, REQM, EAM e r^2 , e verifique qual a melhor opção dentre os métodos implementados que melhor se ajusta a seus dados.
- Você deverá fazer a visualização dos dados originais com os dados ajustados em cada experimento, tanto para o conjunto de treinamento quanto para o de teste. Os gráficos devem conter títulos nos eixos e legenda. Comente os resultados encontrados na visualização.

1.1 0.1 Dependências

Para realização da tarefa foram utilizados as seguintes bibliotecas:

[62]:
```
#Utils
import pandas as pd
import numpy as np
import pandas_profiling
import math

#Preprocess
from sklearn.preprocessing import StandardScaler

# Split
from sklearn.model_selection import train_test_split

# Regressores
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor

#Metricas
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

#Visualização
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

2 1. Dados

O conjunto de dados possui informações quimicas de vinhos Possui mais de 1500 registros e 12 atributos

Fonte: https://www.kaggle.com/uciml/red-wine-quality-cortez-et-al-2009

2.1 1.1 Informações sobre os dados:

Atributos: Input variables (based on physicochemical tests):

- fixed acidity
- volatile acidity
- citric acid
- residual sugar
- chlorides
- free sulfur dioxide

- total sulfur dioxide
- density
- pH
- sulphates
- alcohol

Output variable (based on sensory data): - quality (score between 0 and 10)

2.2 Importando Dataset

[63]:
```
dataset = './dataset/datasets_4458_8204_winequality-red.csv'

data_raw = pd.read_csv(dataset)
```

[64]:
```
data_raw.head()
```

[64]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
3      9.8        6
4      9.4        5
```

[65]:
```
wine_quality = []
for quality in data_raw.quality:
    if quality >= 6:
        wine_quality.append(1)
    else:
        wine_quality.append(0)

data_raw.quality = wine_quality
```

[66]:
```
for col in data_raw:
    print(col, data_raw[col].unique())
```

```
fixed acidity [ 7.4  7.8 11.2  7.9  7.3  7.5  6.7  5.6  8.9  8.5  8.1  7.6  6.9
6.3
  7.1  8.3  5.2  5.7  8.8  6.8  4.6  7.7  8.7  6.4  6.6  8.6 10.2  7.
  7.2  9.3  8.   9.7  6.2  5.   4.7  8.4 10.1  9.4  9.   8.2  6.1  5.8
  9.2 11.5  5.4  9.6 12.8 11.  11.6 12.  15.  10.8 11.1 10.  12.5 11.8
 10.9 10.3 11.4  9.9 10.4 13.3 10.6  9.8 13.4 10.7 11.9 12.4 12.2 13.8
  9.1 13.5 10.5 12.6 14.  13.7  9.5 12.7 12.3 15.6  5.3 11.3 13.   6.5
 12.9 14.3 15.5 11.7 13.2 15.9 12.1  5.1  4.9  5.9  6.   5.5]
volatile acidity [0.7   0.88  0.76  0.28  0.66  0.6   0.65  0.58  0.5   0.615
0.61  0.62
 0.56  0.59  0.32  0.22  0.39  0.43  0.49  0.4   0.41  0.71  0.645 0.675
 0.685 0.655 0.605 0.38  1.13  0.45  0.67  0.52  0.935 0.29  0.31  0.51
 0.42  0.63  0.69  0.735 0.725 0.705 0.785 0.75  0.625 0.3   0.55  1.02
 0.775 0.9   0.545 0.575 0.33  0.54  1.07  0.695 1.33  0.745 1.04  0.715
 0.415 0.34  0.68  0.95  0.53  0.64  0.885 0.805 0.73  0.37  0.835 1.09
 0.57  0.44  0.635 0.82  0.48  1.    0.21  0.35  0.975 0.26  0.87  0.18
 0.27  0.2   0.36  0.83  0.46  0.47  0.77  0.815 0.795 0.665 0.765 0.24
 0.85  0.84  0.96  0.78  0.23  0.315 0.365 0.25  0.825 0.72  0.595 0.585
 0.915 0.755 0.845 1.24  0.8   0.98  1.185 0.92  1.035 1.025 0.565 0.74
 1.115 0.865 0.875 0.965 0.91  0.89  1.01  0.305 0.395 0.12  0.86  0.295
 1.005 0.19  0.955 0.16  1.58  0.79  1.18  0.475 0.81  0.895 0.855]
citric acid [0.   0.04 0.56 0.06 0.02 0.36 0.08 0.29 0.18 0.19 0.28 0.51 0.48
0.31
 0.21 0.11 0.14 0.16 0.24 0.07 0.12 0.25 0.09 0.3  0.2  0.22 0.15 0.43
 0.52 0.23 0.37 0.26 0.57 0.4  0.49 0.05 0.54 0.64 0.7  0.47 0.44 0.17
 0.68 0.53 0.1  0.01 0.55 1.   0.03 0.42 0.33 0.32 0.35 0.6  0.74 0.58
 0.5  0.76 0.46 0.45 0.38 0.39 0.66 0.62 0.67 0.79 0.63 0.61 0.71 0.65
 0.59 0.34 0.69 0.73 0.72 0.41 0.27 0.75 0.13 0.78]
residual sugar [ 1.9   2.6   2.3   1.8   1.6   1.2   2.    6.1   3.8   3.9   1.7
4.4
  2.4   1.4   2.5  10.7   5.5   2.1   1.5   5.9   2.8   2.2   3.    3.4
  5.1   4.65  1.3   7.3   7.2   2.9   2.7   5.6   3.1   3.2   3.3   3.6
  4.    7.    6.4   3.5  11.    3.65  4.5   4.8   2.95  5.8   6.2   4.2
  7.9   3.7   6.7   6.6   2.15  5.2   2.55 15.5   4.1   8.3   6.55  4.6
  4.3   5.15  6.3   6.    8.6   7.5   2.25  4.25  2.85  3.45  2.35  2.65
  9.    8.8   5.    1.65  2.05  0.9   8.9   8.1   4.7   1.75  7.8  12.9
 13.4   5.4  15.4   3.75 13.8   5.7  13.9 ]
chlorides [0.076 0.098 0.092 0.075 0.069 0.065 0.073 0.071 0.097 0.089 0.114
0.176
 0.17  0.368 0.086 0.341 0.077 0.082 0.106 0.084 0.085 0.08  0.105 0.083
 0.103 0.066 0.172 0.074 0.088 0.332 0.05  0.054 0.113 0.068 0.081 0.11
 0.07  0.111 0.079 0.115 0.094 0.093 0.104 0.464 0.401 0.062 0.107 0.045
 0.058 0.102 0.467 0.091 0.122 0.09  0.119 0.178 0.146 0.072 0.118 0.049
 0.06  0.117 0.087 0.236 0.61  0.095 0.1   0.36  0.067 0.27  0.099 0.046
```

```
 0.061 0.056 0.039 0.059 0.101 0.057 0.337 0.078 0.263 0.063 0.611 0.064
 0.096 0.358 0.343 0.186 0.112 0.213 0.214 0.121 0.128 0.052 0.12  0.116
 0.109 0.159 0.124 0.174 0.047 0.127 0.413 0.152 0.053 0.055 0.051 0.125
 0.2   0.171 0.226 0.25  0.108 0.148 0.143 0.222 0.157 0.422 0.034 0.387
 0.415 0.243 0.241 0.19  0.132 0.126 0.038 0.044 0.041 0.165 0.048 0.145
 0.147 0.012 0.194 0.161 0.123 0.414 0.216 0.043 0.042 0.369 0.166 0.136
 0.403 0.137 0.168 0.153 0.267 0.169 0.205 0.235 0.23 ]
free sulfur dioxide [11.  25.  15.  17.  13.   9.  16.  52.  51.  35.   6.  29.
23.  10.
 21.   4.  14.   8.  22.  40.   5.   3.   7.  12.  30.  33.  50.  19.
 20.  27.  18.  28.  34.  42.  41.  37.  32.  36.  24.  26.  39.  40.5
 68.  31.  38.  43.  47.   1.  54.  46.  45.   2.   5.5 53.  37.5 57.
 48.  72.  55.  66. ]
total sulfur dioxide [ 34.   67.   54.   60.   40.   59.   21.   18.  102.   65.
29.  145.
 148.  103.   56.   71.   37.   23.   11.   35.   16.   82.  113.   83.
  50.   15.   30.   19.   87.   46.   14.  114.   12.   96.  119.   73.
  45.   10.  110.   52.  112.   39.   27.   94.   43.   42.   80.   51.
  61.  136.   31.  125.   24.  140.  133.   85.  106.   22.   36.   69.
  64.  153.   47.  108.  111.   62.   28.   89.   13.   90.  134.   99.
  26.   63.  105.   20.  141.   88.  129.  128.   86.  121.  101.   44.
   8.   49.   38.  143.  144.  127.  126.  120.   55.   93.   95.   41.
  58.   72.   81.  109.   33.   53.   98.   48.   70.   25.  135.   92.
  74.   32.   77.  165.   75.  124.   78.  122.   66.   68.   17.   91.
  76.  151.  142.  116.  149.   57.  104.   84.  147.  155.  152.    9.
 139.  130.    7.  100.  115.    6.   79.  278.  289.  160.   77.5 131. ]
density [0.9978  0.9968  0.997   0.998   0.9964  0.9946  0.9959  0.9943  0.9974
 0.9986  0.9969  0.9982  0.9966  0.9955  0.9962  0.9972  0.9958  0.9993
 0.9957  0.9975  0.994   0.9976  0.9934  0.9954  0.9971  0.9956  0.9983
 0.9967  0.9961  0.9984  0.9938  0.9932  0.9965  0.9963  0.996   0.9973
 0.9988  0.9937  0.9952  0.9916  0.9944  0.9996  0.995   0.9981  0.9953
 0.9924  0.9948  0.99695 0.99545 0.99615 0.9994  0.99625 0.99585 0.99685
 0.99655 0.99525 0.99815 0.99745 0.9927  0.99675 0.99925 0.99565 1.00005
 0.9985  0.99965 0.99575 0.9999  1.00025 0.9987  0.99935 0.99735 0.99915
 0.9991  1.00015 0.9997  1.001   0.9979  1.0014  1.0001  0.99855 0.99845
 0.9998  0.99645 0.99865 0.9989  0.99975 0.999   1.0015  1.0002  0.9992
 1.0008  1.      1.0006  1.0004  1.0018  0.9912  1.0022  1.0003  0.9949
 0.9951  1.0032  0.9947  0.9995  0.9977  1.0026  1.00315 1.0021  0.9917
 0.9922  0.9921  0.99788 1.00024 0.99768 0.99782 0.99761 0.99803 0.99785
 0.99656 0.99488 0.99823 0.99779 0.99738 0.99701 0.99888 0.99938 0.99744
 0.99668 0.99727 0.99586 0.99612 0.99676 0.99732 0.99814 0.99746 0.99708
 0.99818 0.99639 0.99531 0.99786 0.99526 0.99641 0.99264 0.99682 0.99356
 0.99386 0.99702 0.99693 0.99562 1.00012 0.99462 0.99939 0.99632 0.99976
 0.99606 0.99154 0.99624 0.99417 0.99376 0.99832 0.99836 0.99694 0.99064
 0.99672 0.99647 0.99736 0.99629 0.99689 0.99801 0.99652 0.99538 0.99594
 0.99686 0.99438 0.99357 0.99628 0.99748 0.99578 0.99371 0.99522 0.99576
 0.99552 0.99664 0.99614 0.99517 0.99787 0.99533 0.99536 0.99824 0.99577
 0.99491 1.00289 0.99743 0.99774 0.99444 0.99892 0.99528 0.99331 0.99901
```

```
 0.99674 0.99512 0.99395 0.99504 0.99516 0.99604 0.99468 0.99543 0.99791
 0.99425 0.99509 0.99484 0.99834 0.99864 0.99498 0.99566 0.99408 0.99458
 0.99648 0.99568 0.99613 0.99519 0.99518 0.99592 0.99654 0.99546 0.99554
 0.99733 0.99669 0.99724 0.99643 0.99605 0.99658 0.99416 0.99712 0.99418
 0.99596 0.99556 0.99918 0.99697 0.99378 0.99162 0.99495 0.9928  0.99603
 0.99549 0.99722 0.99354 0.99635 0.99454 0.99598 0.99486 0.99007 0.99636
 0.99642 0.99584 0.99506 0.99822 0.99364 0.99514 0.99854 0.99739 0.99683
 0.99692 0.99756 0.99547 0.99859 0.99294 0.99634 0.99704 0.99258 0.99426
 0.99747 0.99784 0.99358 0.99572 0.99769 0.99534 0.99817 0.99316 0.99471
 0.99617 0.99529 0.99451 0.99479 0.99772 0.99666 0.99392 0.99388 0.99402
 0.9936  0.99374 0.99523 0.99593 0.99396 0.99698 0.9902  0.99252 0.99256
 0.99235 0.99352 0.99557 0.99394 0.9915  0.99379 0.99798 0.99341 0.9933
 0.99684 0.99524 0.99764 0.99588 0.99473 0.99616 0.99622 0.99544 0.99728
 0.99551 0.99434 0.99709 0.99384 0.99502 0.99667 0.99649 0.99716 0.99541
 0.99318 0.99346 0.99599 0.99478 0.99754 0.99439 0.99633 0.99419 0.99878
 0.99752 0.99428 0.99659 0.99677 0.99734 0.99678 0.99638 0.99922 0.99157
 0.99718 0.99621 0.99242 0.99494 0.99729 0.99414 0.99721 0.99627 0.99569
 0.99499 0.99437 0.99726 0.99456 0.99564 0.9908  0.99084 0.9935  0.99385
 0.99688 0.99619 0.99476 0.99328 0.99286 0.99914 0.99521 0.99362 0.99558
 0.99323 0.99191 0.99501 0.9929  0.99532 0.99796 0.99581 0.99608 0.99387
 0.99448 0.99589 0.99852 0.99472 0.99587 0.99332 0.99464 0.99699 0.99725
 0.99623 0.99609 0.99292 0.9942  1.00369 0.99713 0.99322 0.99706 0.99974
 0.99467 0.99236 0.99705 0.99334 0.99336 1.00242 0.99182 0.99808 0.99828
 0.99719 0.99542 0.99496 0.99344 0.99348 0.99459 0.99492 0.99508 0.99582
 0.99555 0.9941  0.99661 0.99842 0.99489 0.99665 0.99553 0.99714 0.99631
 0.99573 0.99717 0.99397 0.99646 0.99758 0.99306 0.99783 0.99765 0.99474
 0.99483 0.99314 0.99574 0.99651]
pH [3.51 3.2  3.26 3.16 3.3  3.39 3.36 3.35 3.28 3.58 3.17 3.11 3.38 3.04
 3.52 3.43 3.34 3.47 3.46 3.45 3.4  3.42 3.23 3.5  3.33 3.21 3.48 3.9
 3.25 3.32 3.15 3.41 3.44 3.31 3.54 3.13 2.93 3.14 3.75 3.85 3.29 3.08
 3.37 3.19 3.07 3.49 3.53 3.24 3.63 3.22 3.68 2.74 3.59 3.   3.12 3.57
 3.61 3.06 3.6  3.69 3.1  3.05 3.67 3.27 3.18 3.02 3.55 2.99 3.01 3.56
 3.03 3.62 2.88 2.95 2.98 3.09 2.86 3.74 2.92 3.72 2.87 2.89 2.94 3.66
 3.71 3.78 3.7  4.01 2.9 ]
sulphates [0.56 0.68 0.65 0.58 0.46 0.47 0.57 0.8  0.54 0.52 1.56 0.88 0.93 0.75
 1.28 0.5  1.08 0.53 0.91 0.63 0.59 0.55 0.66 0.6  0.73 0.48 0.83 0.51
 0.9  1.2  0.74 0.64 0.77 0.71 0.62 0.39 0.79 0.95 0.82 1.12 1.14 0.78
 1.95 1.22 1.98 0.61 1.31 0.69 0.67 0.7  0.49 0.92 2.   0.72 1.59 0.33
 1.02 0.97 0.85 0.43 1.03 0.86 0.76 1.61 1.09 0.84 0.96 0.45 1.26 0.87
 0.81 1.   1.36 1.18 0.89 0.98 1.13 1.04 1.11 0.99 1.07 0.44 1.06 1.05
 0.42 1.17 1.62 0.94 1.34 1.16 1.1  0.4  1.15 0.37 1.33 1.01]
alcohol [ 9.4        9.8        10.         9.5        10.5        9.2
  9.9        9.1         9.3        9.         9.7        10.1
 10.6        9.6        10.8       10.3       13.1       10.2
 10.9       10.7       12.9       10.4       13.        14.
 11.5       11.4       12.4       11.        12.2       12.8
 12.6       12.5       11.7       11.3       12.3       12.
 11.9       11.8        8.7       13.3       11.2       11.6
```

```
 11.1        13.4        12.1         8.4        12.7        14.9
 13.2        13.6        13.5        10.03333333  9.55        8.5
 11.06666667  9.56666667 10.55        8.8        13.56666667 11.95
  9.95        9.23333333  9.25        9.05       10.75      ]
quality [0 1]
```

2.3 Pré-processamento

[67]:
```
# pandas_profiling.ProfileReport(data_raw)
```

2.4 Visualização

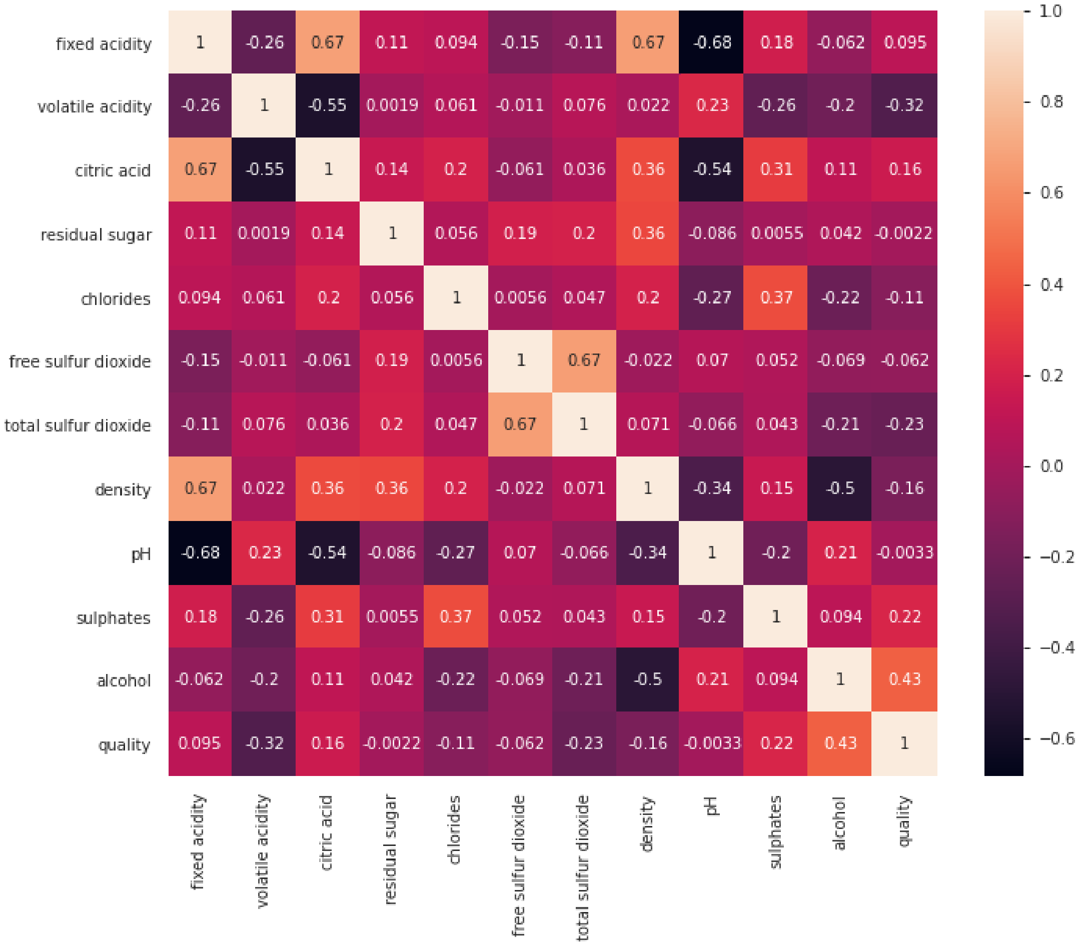
[68]:
```
# sns.pairplot(data_raw)
```

[69]:
```
plt.clf()
```

```
<Figure size 432x288 with 0 Axes>
```

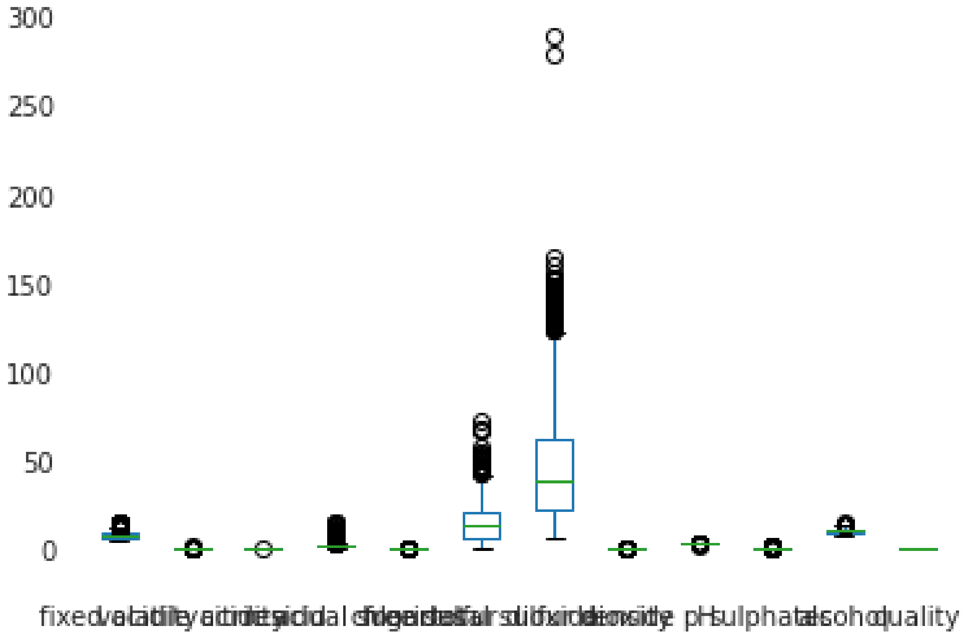
[70]:
```
plt.subplots(figsize=(11, 9))
sns.heatmap(data_raw.corr(), annot=True)
```

[70]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73f56554e0>
```



[71]:
```
data_raw.plot.box()
```

[71]: <matplotlib.axes._subplots.AxesSubplot at 0x7f73d6781c50>



2.5 Escalonando

[72]:
```
scaler = StandardScaler().fit(data_raw)
data_scaled = scaler.transform(data_raw)
```

[73]:
```
data_scaled_df = pd.DataFrame(data_scaled, columns=data_raw.columns)
```

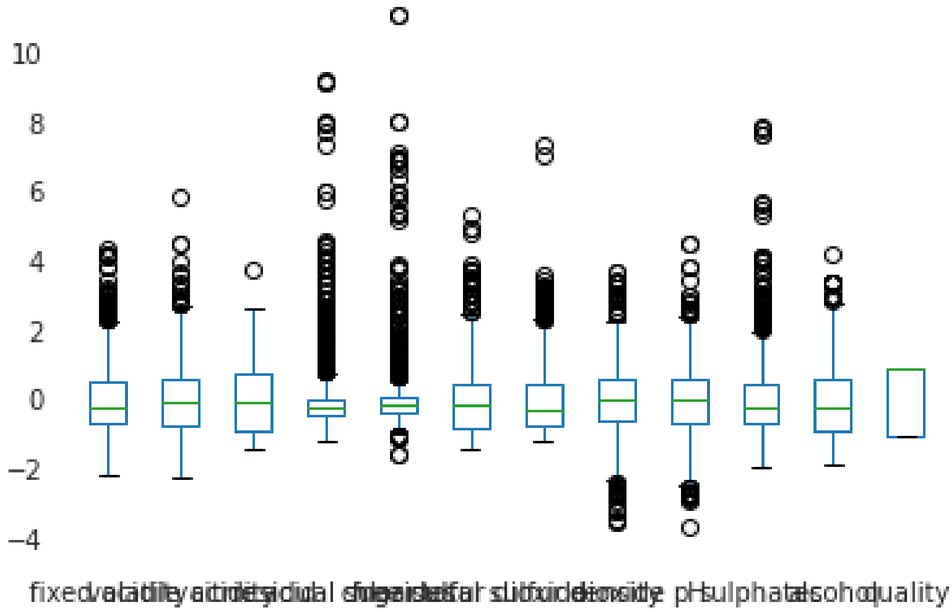
[74]:
```
data_scaled_df.head()
```

[74]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0      -0.528360          0.961877    -1.391472       -0.453218  -0.243707
1      -0.298547          1.967442    -1.391472        0.043416   0.223875
2      -0.298547          1.297065    -1.186070       -0.169427   0.096353
3       1.654856         -1.384443     1.484154       -0.453218  -0.264960
4      -0.528360          0.961877    -1.391472       -0.453218  -0.243707

   free sulfur dioxide  total sulfur dioxide   density        pH  sulphates  \
0            -0.466193             -0.379133  0.558274  1.288643  -0.579207
1             0.872638              0.624363  0.028261 -0.719933   0.128950
2            -0.083669              0.229047  0.134264 -0.331177  -0.048089
3             0.107592              0.411500  0.664277 -0.979104  -0.461180
4            -0.466193             -0.379133  0.558274  1.288643  -0.579207

    alcohol   quality
```

```
0 -0.960246 -1.072004
1 -0.584777 -1.072004
2 -0.584777 -1.072004
3 -0.584777  0.932832
4 -0.960246 -1.072004
```

[75]:
```
data_scaled_df.plot.box()
```

[75]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73d6671eb8>
```



2.6 Utilidades

[76]:
```
lista_metricas_treino = []
lista_metricas_teste = []
```

[77]:
```
def metricas(y_true, y_pred, alg):
    r2 = r2_score(y_true, y_pred)
    eqm = mean_squared_error(y_true, y_pred)
    seq = len(y_true)*eqm
    reqm = math.sqrt(eqm)

    return {'Algoritmo':alg, 'R2':r2, 'EQM':eqm, 'REQM':reqm, 'SEQ':seq}
```

2.7 Separando conjuntos de Treino e Teste

Para a separação utilizou-se do train_test_split que divide o conjunto em treino e teste aleatóriamente

[78]:
```
test_attr = 'fixed acidity';
output_attr = 'quality';
train, test = train_test_split(data_scaled_df, test_size = 0.2, shuffle=True)

x_train = train.drop(columns=[output_attr])
y_train = train[output_attr]

x_test = test.drop(columns=[output_attr])
y_test = test[output_attr]
```

2.8 Aplicando a Regressão

2.8.1 Regressão Linear

[79]:
```
lire = LinearRegression()
```

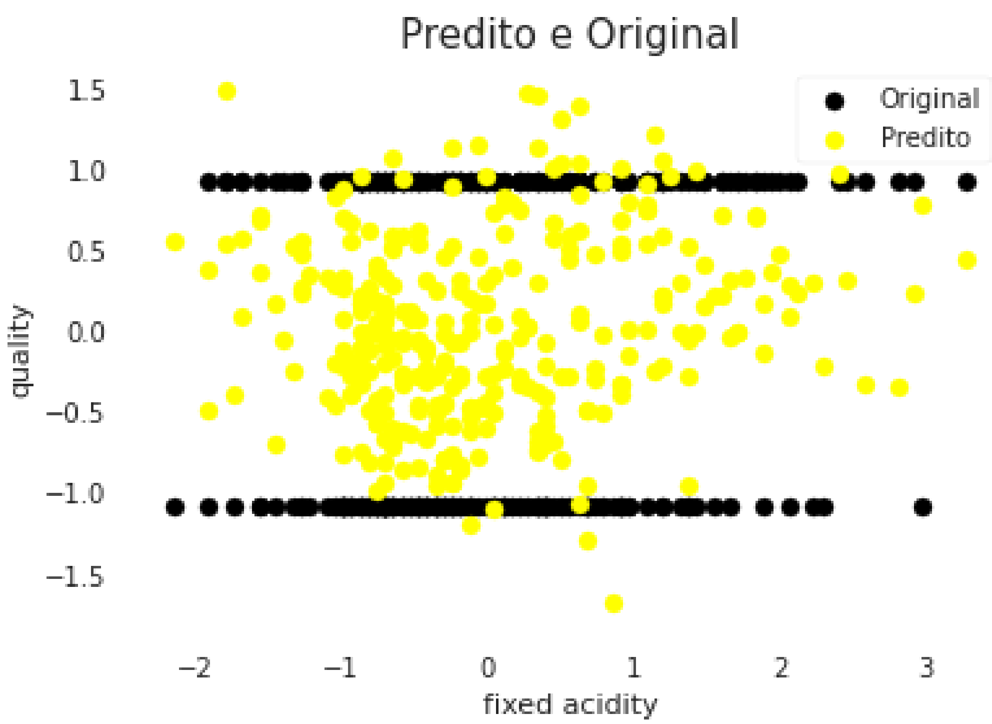
[80]:
```
lire.fit(x_train, y_train)
```

[80]:
```
LinearRegression()
```

2.9 Avaliação para Teste

[81]:
```
y_pred = lire.predict(x_test)
linear_metricas = metricas(y_test, y_pred, 'Regressão Linear - Teste')
lista_metricas_teste.append(linear_metricas)
```

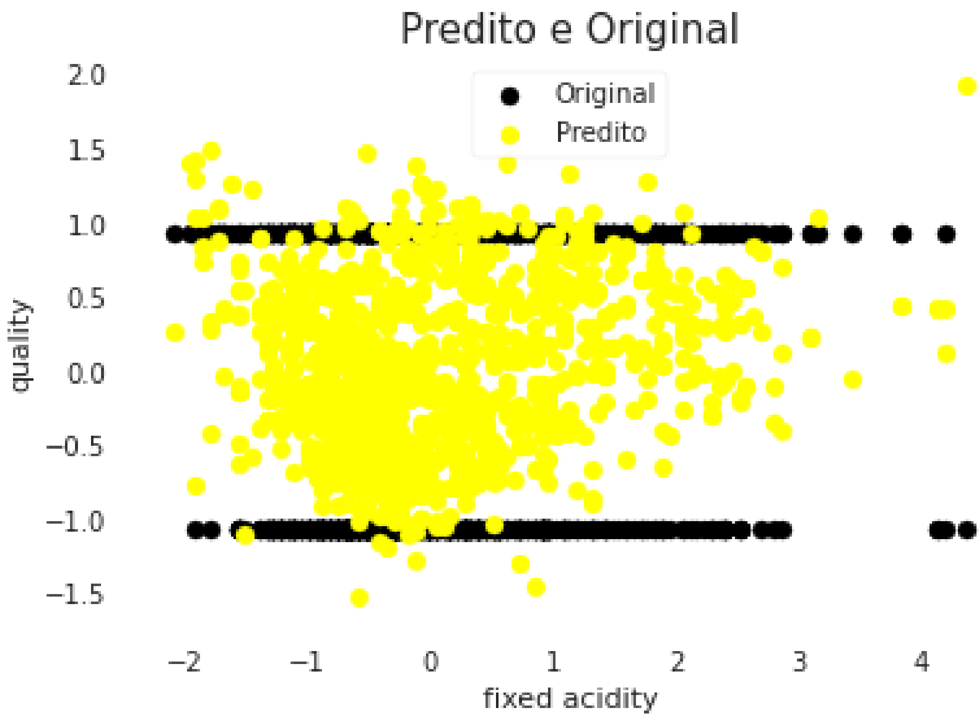
[82]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.10 Avaliação para Treino

[83]:
```
y_pred = lire.predict(x_train)
linear_metricas = metricas(y_train, y_pred, 'Regressão Linear - Treino')
lista_metricas_treino.append(linear_metricas)
```

[84]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.11 SVR

2.11.1 Kernel RBF

[85]:
```
svr_reg = SVR(kernel='rbf')
```

[86]:
```
svr_reg.fit(x_train, y_train)
```

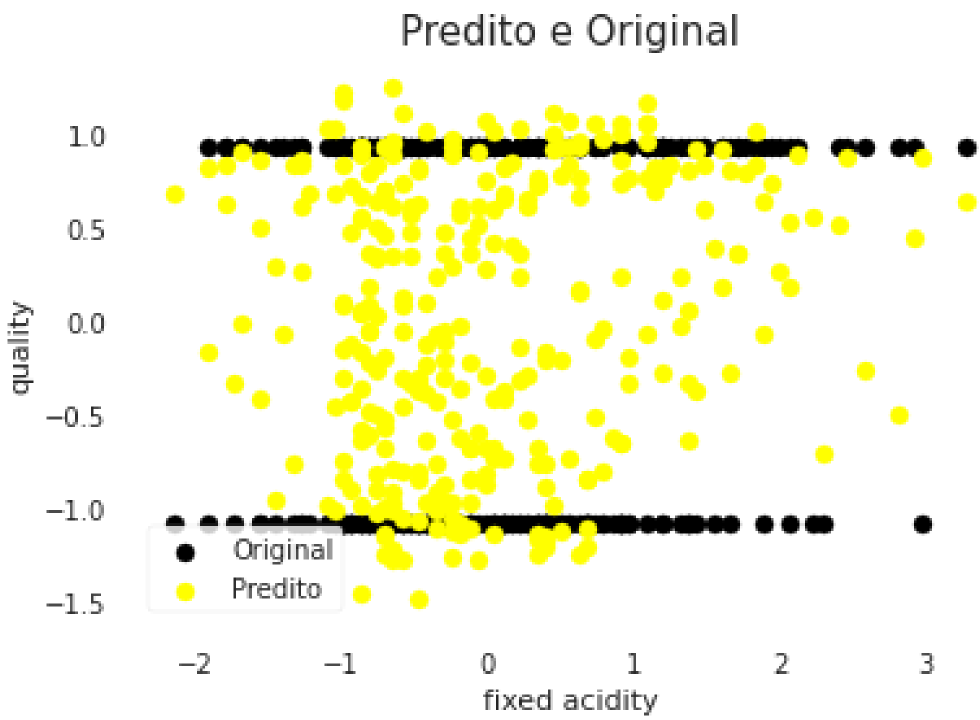
[86]: SVR()

2.12 Avaliação para Teste

[87]:
```
y_pred = svr_reg.predict(x_test)
svr_metricas = metricas(y_test, y_pred, 'SVR - RBF - Teste')
lista_metricas_teste.append(svr_metricas)
```

[88]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
```

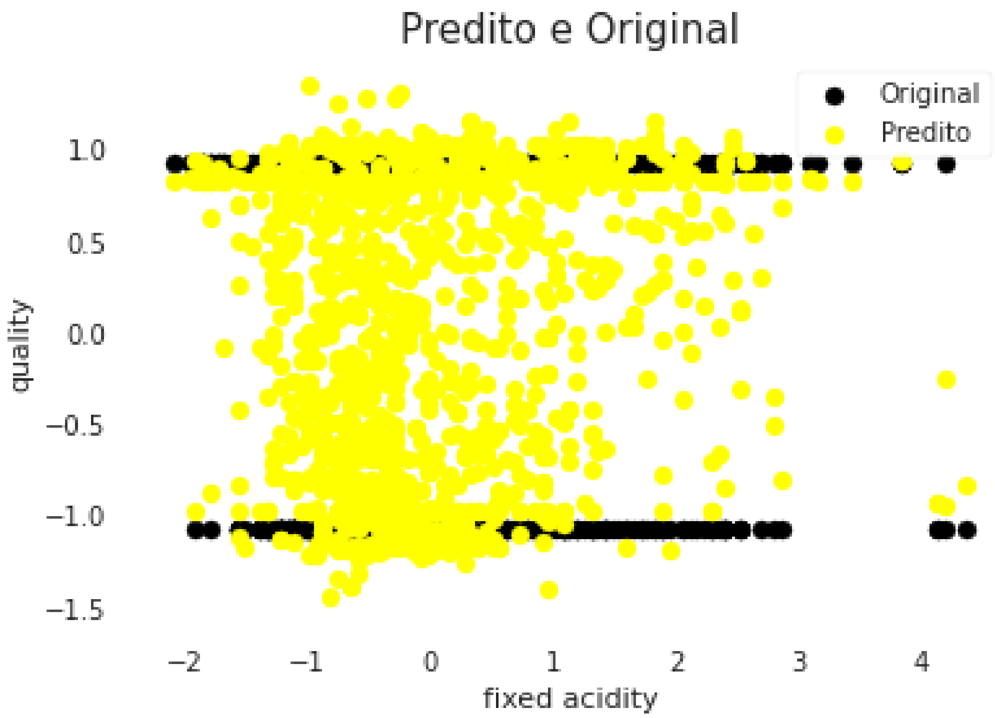
```
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.13 Avaliação para Treino

[89]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - RBF - Treino')
lista_metricas_treino.append(svr_metricas)
```

[90]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.13.1 Kernel Linear

[91]:
```
svr_reg = SVR(kernel='linear')
```

[92]:
```
svr_reg.fit(x_train, y_train)
```

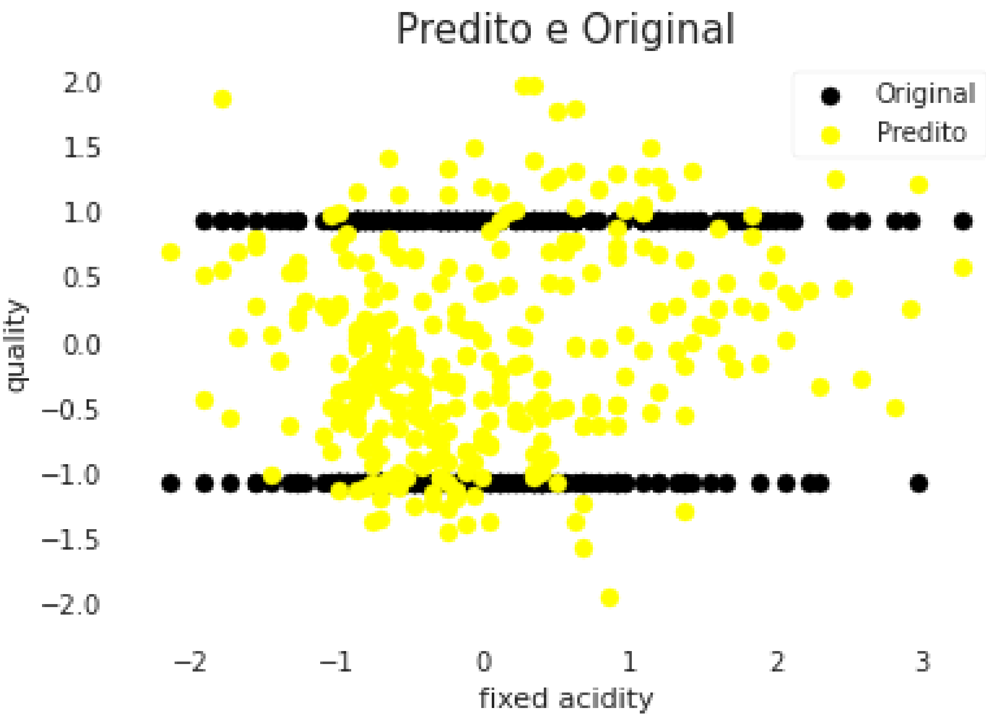
[92]:
```
SVR(kernel='linear')
```

2.14 Avaliação para Teste

[93]:
```
y_pred = svr_reg.predict(x_test)
metricas_svr = metricas(y_test, y_pred, 'SVR - Linear - Teste')
lista_metricas_teste.append(metricas_svr)
```

[94]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
```

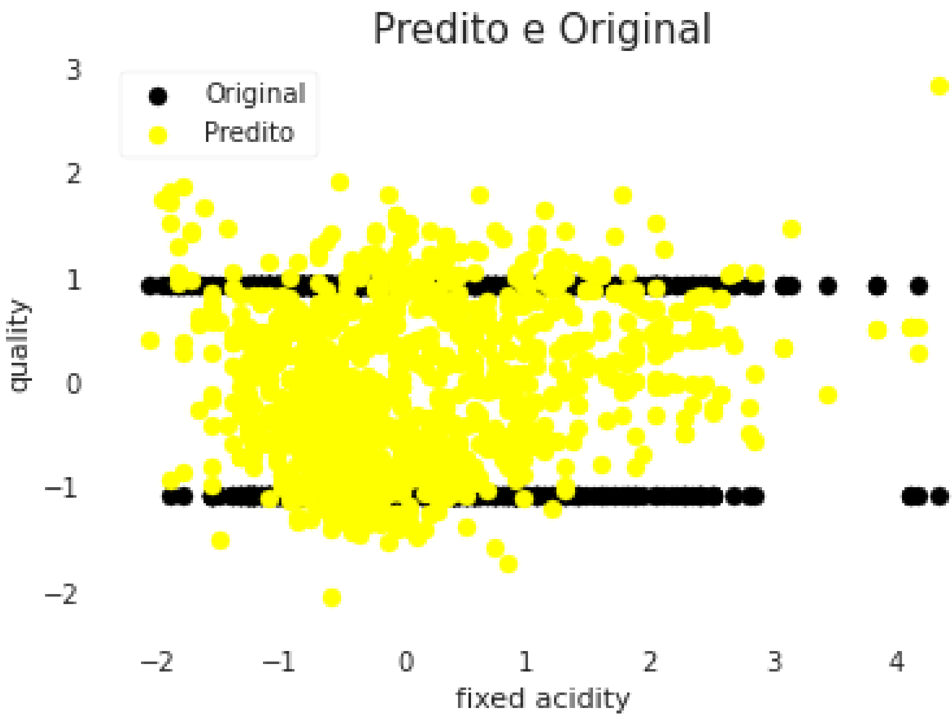
```
plt.show()
```



2.15 Avaliação para Treino

[95]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - Linear - Treino')
lista_metricas_treino.append(svr_metricas)
```

[96]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.15.1 Kernel Sigmoide

[97]:
```
train, test = train_test_split(data_raw, test_size = 0.2, shuffle=True)

x_train_sig = train.drop(columns=[output_attr])
y_train_sig  = train[output_attr]

x_test_sig  = test.drop(columns=[output_attr])
y_test_sig  = test[output_attr]
```

[98]:
```
svr_reg = SVR(kernel='sigmoid')
```

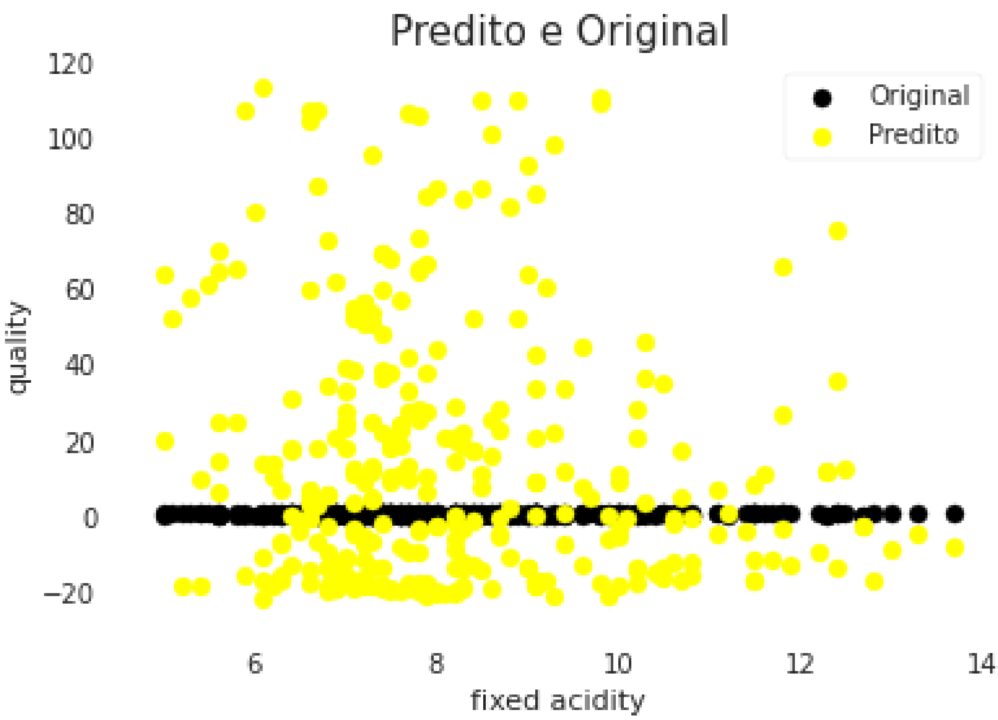
[99]:
```
svr_reg.fit(x_train_sig , y_train_sig )
```

[99]:
```
SVR(kernel='sigmoid')
```

2.16 Avaliação para Teste

[100]:
```
y_pred_sig  = svr_reg.predict(x_test_sig)
metricas_svr = metricas(y_test_sig , y_pred_sig , 'SVR - Sigmoide - Teste')
lista_metricas_teste.append(metricas_svr)
```

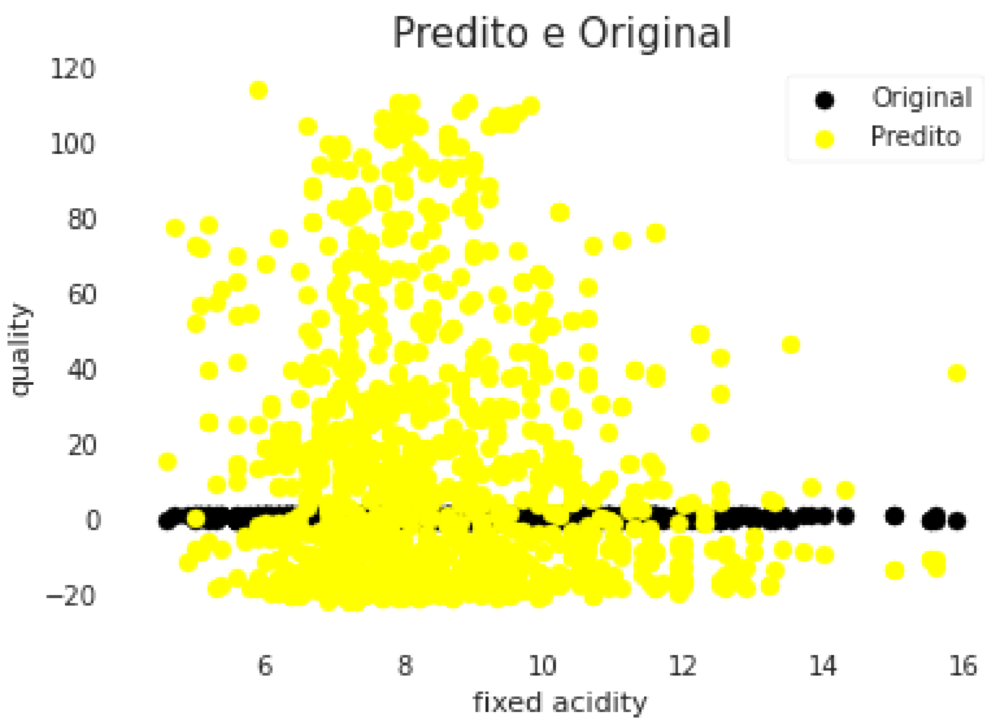
[101]:
```
plt.scatter(x_test_sig [test_attr], y_test_sig ,  color='black')
plt.scatter(x_test_sig [test_attr], y_pred_sig , color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.17 Avaliação para Treino

[102]:
```
y_pred_sig  = svr_reg.predict(x_train_sig)
svr_metricas = metricas(y_train_sig , y_pred_sig , 'SVR - Sigmoide - Treino')
lista_metricas_treino.append(svr_metricas)
```

[103]:
```
plt.scatter(x_train_sig [test_attr], y_train_sig ,  color='black')
plt.scatter(x_train_sig [test_attr], y_pred_sig , color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.17.1 Kernel Polinomial

[104]:
```
svr_reg = SVR(kernel='poly', degree=3)
```

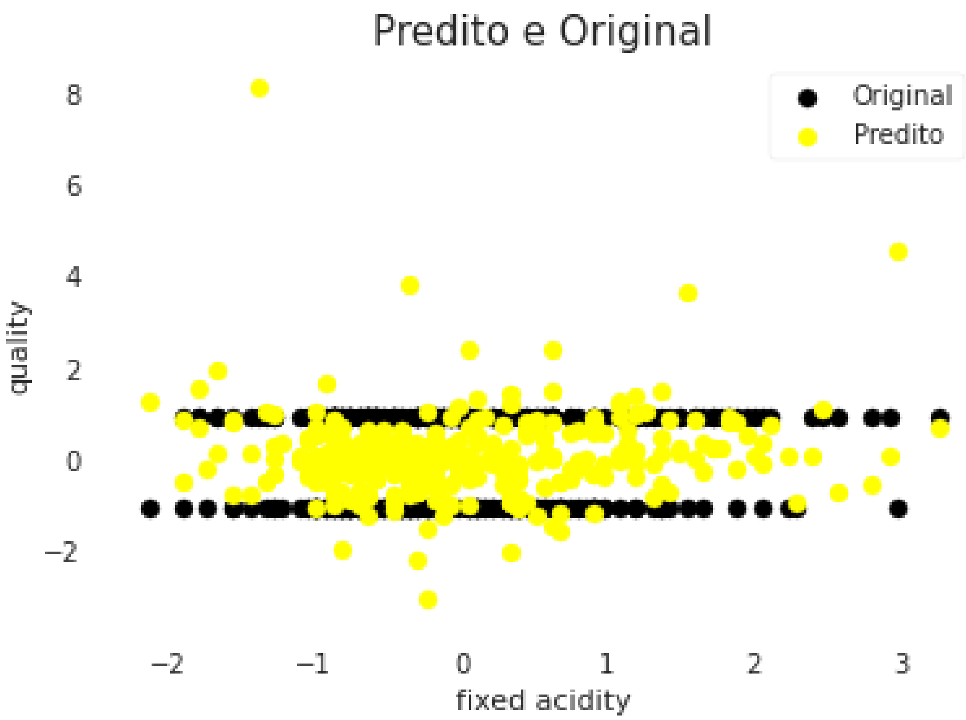
[105]:
```
svr_reg.fit(x_train, y_train)
```

[105]: SVR(kernel='poly')

2.18 Avaliação para Teste

[106]:
```
y_pred = svr_reg.predict(x_test)
svr_metricas = metricas(y_test, y_pred, 'SVR - Polinomial - Teste')
lista_metricas_teste.append(svr_metricas)
```

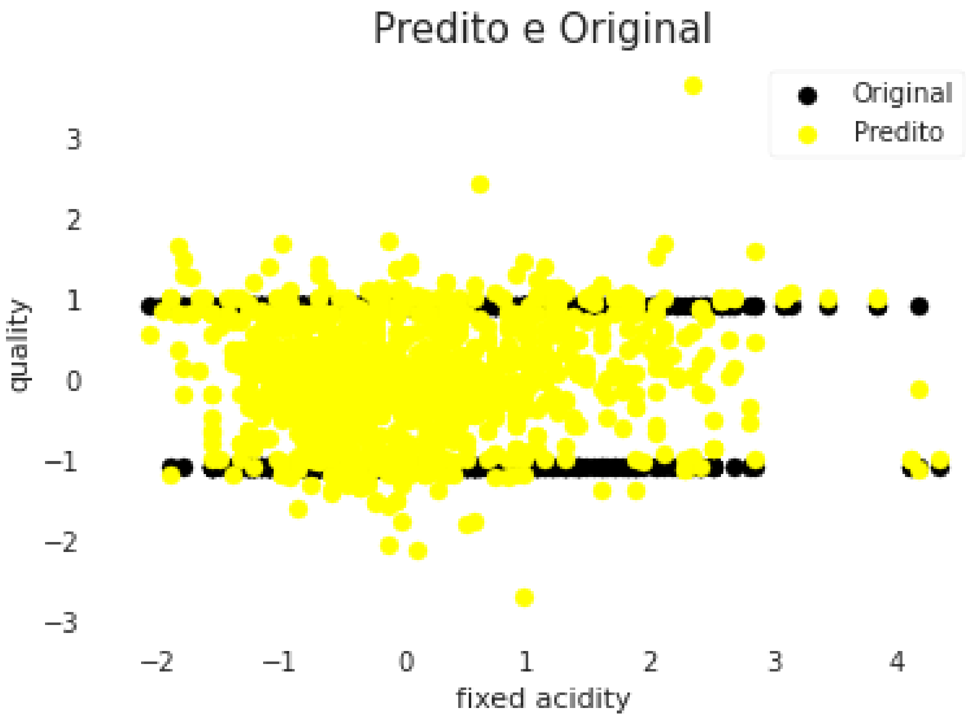
[107]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.19 Avaliação para Treino

[108]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - Polinomial - Treino')
lista_metricas_treino.append(svr_metricas)
```

[109]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.20 Redes Neurais

2.20.1 Kernel Linear

[110]:
```
mlp_reg = MLPRegressor()
```

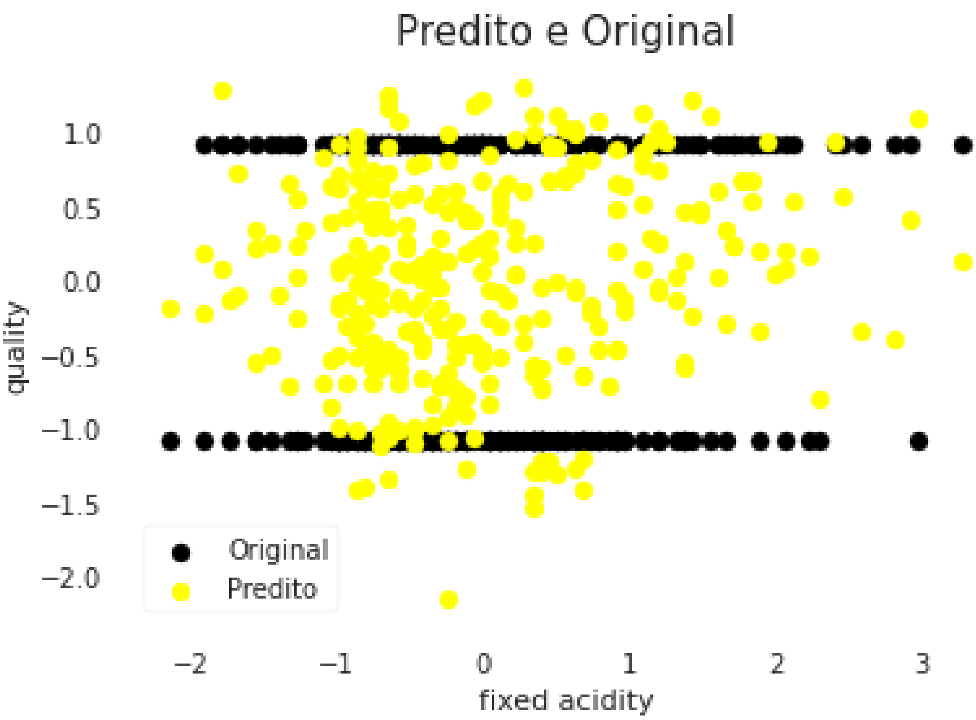
[111]:
```
mlp_reg.fit(x_train, y_train)
```

[111]: MLPRegressor()

2.21 Avaliação para Teste

[112]:
```
y_pred = mlp_reg.predict(x_test)
mlp_metricas = metricas(y_test, y_pred, 'MLP - Teste')
lista_metricas_teste.append(mlp_metricas)
```

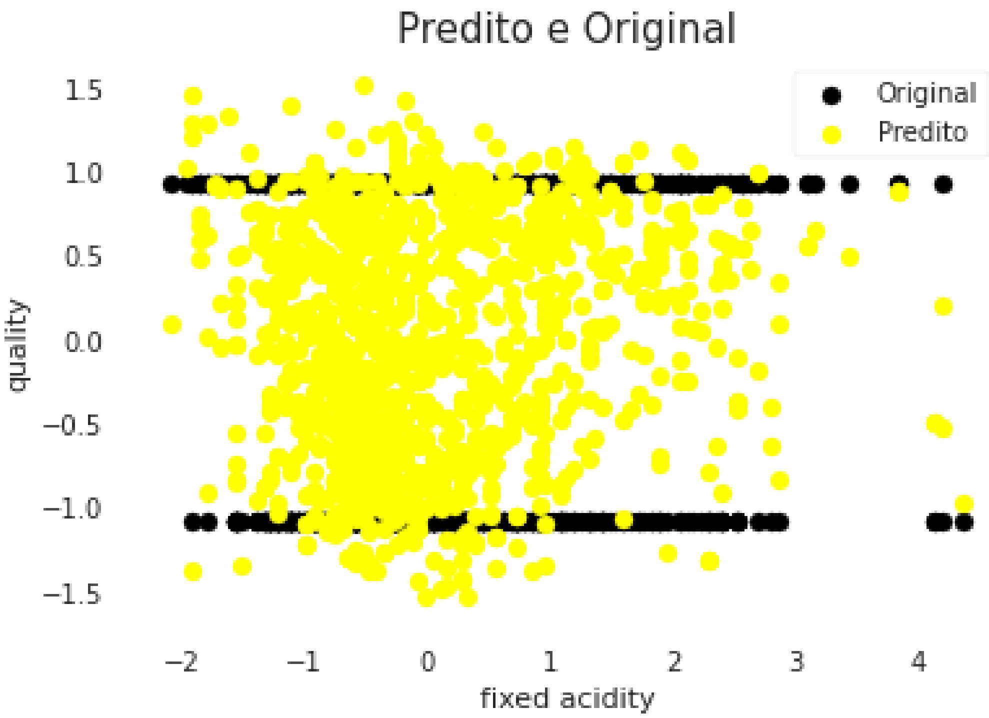
[113]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.22 Avaliação para Treino

[114]:
```
y_pred = mlp_reg.predict(x_train)
mlp_metricas = metricas(y_train, y_pred, 'MLP - Treino')
lista_metricas_treino.append(mlp_metricas)
```

[115]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



3 Resultados

[116]:
```
metricas_teste = pd.DataFrame(lista_metricas_teste)
metricas_teste
```

[116]:

	Algoritmo	R2	EQM	REQM	\
0	Regressão Linear - Teste	0.300920	0.701121	0.837330	
1	SVR - RBF - Teste	0.348163	0.653740	0.808542	
2	SVR - Linear - Teste	0.244870	0.757334	0.870249	
3	SVR - Sigmoide - Teste	-5542.359159	1359.638756	36.873280	
4	SVR - Polinomial - Teste	-0.104436	1.107660	1.052454	
5	MLP - Teste	0.357232	0.644644	0.802898	

```
            SEQ
0      224.358630
1      209.196795
2      242.346802
3  435084.401967
4      354.451058
5      206.286211
```

[117]:
```python
metricas_teste = round(metricas_teste, 3)
```

[118]:
```python
metricas_teste
```

[118]:
```
                    Algoritmo        R2       EQM    REQM         SEQ
0   Regressão Linear - Teste     0.301     0.701   0.837     224.359
1            SVR - RBF - Teste     0.348     0.654   0.809     209.197
2         SVR - Linear - Teste     0.245     0.757   0.870     242.347
3       SVR - Sigmoide - Teste -5542.359  1359.639  36.873  435084.402
4   SVR - Polinomial - Teste    -0.104     1.108   1.052     354.451
5                  MLP - Teste     0.357     0.645   0.803     206.286
```

[119]:
```python
metricas_teste.to_excel('wine_metricas_teste.xlsx')
```

[120]:
```python
metricas_treino = pd.DataFrame(lista_metricas_treino)
metricas_treino
```

[120]:
```
                     Algoritmo           R2          EQM       REQM  \
0   Regressão Linear - Treino     0.293268     0.706070   0.840280
1            SVR - RBF - Treino     0.428526     0.570938   0.755604
2         SVR - Linear - Treino     0.235066     0.764217   0.874195
3       SVR - Sigmoide - Treino -5079.800090  1266.714398  35.590931
4   SVR - Polinomial - Treino     0.376087     0.623328   0.789512
5                  MLP - Treino     0.543536     0.456036   0.675304

           SEQ
0  9.030631e+02
1  7.302295e+02
2  9.774335e+02
3  1.620128e+06
4  7.972371e+02
5  5.832697e+02
```

[121]:
```python
metricas_treino = round(metricas_treino, 3)
```

[122]:
```python
metricas_treino.to_excel('wine.xlsx')
```

regression-wine-2

August 19, 2020

[0]:

```

```

1 0. Introdução

Trabalho:

Aluno: Gabriel Luiz

Disciplina: Tópico em Aprendizado de Máquina

Objetivos :

- Escolha dois conjuntos de dados para trabalhar o problema de regressão. Separe cada dataset em conjunto de treinamento e conjunto de teste. Explique o seu critério de separação e o método utilizado.
- Você deverá implementar soluções para cada dataset usando:
- – regressão linear (ou regressão múltipla)
- – regressão polinomial
- – SVR (use os kernels linear, sigmoide, RBF e polinomial)
- – rede neural (MLP ou RBF).
- Descreva os parâmetros/arquiteturas de cada modelo.
- Compare os resultados (para treinamento e teste) com as medidas de desempenho SEQ, EQM, REQM, EAM e r^2 , e verifique qual a melhor opção dentre os métodos implementados que melhor se ajusta a seus dados.
- Você deverá fazer a visualização dos dados originais com os dados ajustados em cada experimento, tanto para o conjunto de treinamento quanto para o de teste. Os gráficos devem conter títulos nos eixos e legenda. Comente os resultados encontrados na visualização.

1.1 0.1 Dependências

Para realização da tarefa foram utilizados as seguintes bibliotecas:

[1]:
```python
#Utils
import pandas as pd
import numpy as np
import pandas_profiling
import math

#Preprocess
from sklearn.preprocessing import StandardScaler

# Split
from sklearn.model_selection import train_test_split

# Regressores
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.neural_network import MLPRegressor

#Metricas
from sklearn.metrics import r2_score
from sklearn.metrics import mean_squared_error

#Visualização
import seaborn as sns
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

2 1. Dados

O conjunto de dados possui informações quimicas de vinhos Possui mais de 1500 registros e 12 atributos

Fonte: https://www.kaggle.com/uciml/red-wine-quality-cortez-et-al-2009

2.1 1.1 Informações sobre os dados:

Atributos: Input variables (based on physicochemical tests):

- fixed acidity
- volatile acidity
- citric acid
- residual sugar
- chlorides
- free sulfur dioxide

- total sulfur dioxide
- density
- pH
- sulphates
- alcohol

Output variable (based on sensory data): - quality (score between 0 and 10)

2.2 Importando Dataset

[2]:
```
dataset = './dataset/datasets_4458_8204_winequality-red.csv'

data_raw = pd.read_csv(dataset)
```

[3]:
```
data_raw.head()
```

[3]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076
1            7.8              0.88         0.00             2.6      0.098
2            7.8              0.76         0.04             2.3      0.092
3           11.2              0.28         0.56             1.9      0.075
4            7.4              0.70         0.00             1.9      0.076

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56
1                 25.0                  67.0   0.9968  3.20       0.68
2                 15.0                  54.0   0.9970  3.26       0.65
3                 17.0                  60.0   0.9980  3.16       0.58
4                 11.0                  34.0   0.9978  3.51       0.56

   alcohol  quality
0      9.4        5
1      9.8        5
2      9.8        5
3      9.8        6
4      9.4        5
```

[4]:
```
# wine_quality = []
# for quality in data_raw.quality:
#     if quality >= 6:
#         wine_quality.append(1)
#     else:
#         wine_quality.append(0)
#
# data_raw.quality = wine_quality
```

[5]:
```python
for col in data_raw:
    print(col, data_raw[col].unique())
```

```
fixed acidity [ 7.4  7.8 11.2  7.9  7.3  7.5  6.7  5.6  8.9  8.5  8.1  7.6  6.9
6.3
  7.1  8.3  5.2  5.7  8.8  6.8  4.6  7.7  8.7  6.4  6.6  8.6 10.2  7.
  7.2  9.3  8.   9.7  6.2  5.   4.7  8.4 10.1  9.4  9.   8.2  6.1  5.8
  9.2 11.5  5.4  9.6 12.8 11.  11.6 12.  15.  10.8 11.1 10.  12.5 11.8
 10.9 10.3 11.4  9.9 10.4 13.3 10.6  9.8 13.4 10.7 11.9 12.4 12.2 13.8
  9.1 13.5 10.5 12.6 14.  13.7  9.5 12.7 12.3 15.6  5.3 11.3 13.   6.5
 12.9 14.3 15.5 11.7 13.2 15.9 12.1  5.1  4.9  5.9  6.   5.5]
volatile acidity [0.7   0.88  0.76  0.28  0.66  0.6   0.65  0.58  0.5   0.615
0.61  0.62
 0.56  0.59  0.32  0.22  0.39  0.43  0.49  0.4   0.41  0.71  0.645 0.675
 0.685 0.655 0.605 0.38  1.13  0.45  0.67  0.52  0.935 0.29  0.31  0.51
 0.42  0.63  0.69  0.735 0.725 0.705 0.785 0.75  0.625 0.3   0.55  1.02
 0.775 0.9   0.545 0.575 0.33  0.54  1.07  0.695 1.33  0.745 1.04  0.715
 0.415 0.34  0.68  0.95  0.53  0.64  0.885 0.805 0.73  0.37  0.835 1.09
 0.57  0.44  0.635 0.82  0.48  1.    0.21  0.35  0.975 0.26  0.87  0.18
 0.27  0.2   0.36  0.83  0.46  0.47  0.77  0.815 0.795 0.665 0.765 0.24
 0.85  0.84  0.96  0.78  0.23  0.315 0.365 0.25  0.825 0.72  0.595 0.585
 0.915 0.755 0.845 1.24  0.8   0.98  1.185 0.92  1.035 1.025 0.565 0.74
 1.115 0.865 0.875 0.965 0.91  0.89  1.01  0.305 0.395 0.12  0.86  0.295
 1.005 0.19  0.955 0.16  1.58  0.79  1.18  0.475 0.81  0.895 0.855]
citric acid [0.   0.04 0.56 0.06 0.02 0.36 0.08 0.29 0.18 0.19 0.28 0.51 0.48
0.31
 0.21 0.11 0.14 0.16 0.24 0.07 0.12 0.25 0.09 0.3  0.2  0.22 0.15 0.43
 0.52 0.23 0.37 0.26 0.57 0.4  0.49 0.05 0.54 0.64 0.7  0.47 0.44 0.17
 0.68 0.53 0.1  0.01 0.55 1.   0.03 0.42 0.33 0.32 0.35 0.6  0.74 0.58
 0.5  0.76 0.46 0.45 0.38 0.39 0.66 0.62 0.67 0.79 0.63 0.61 0.71 0.65
 0.59 0.34 0.69 0.73 0.72 0.41 0.27 0.75 0.13 0.78]
residual sugar [ 1.9   2.6   2.3   1.8   1.6   1.2   2.    6.1   3.8   3.9   1.7
4.4
  2.4   1.4   2.5  10.7   5.5   2.1   1.5   5.9   2.8   2.2   3.    3.4
  5.1   4.65  1.3   7.3   7.2   2.9   2.7   5.6   3.1   3.2   3.3   3.6
  4.    7.    6.4   3.5  11.    3.65  4.5   4.8   2.95  5.8   6.2   4.2
  7.9   3.7   6.7   6.6   2.15  5.2   2.55 15.5   4.1   8.3   6.55  4.6
  4.3   5.15  6.3   6.    8.6   7.5   2.25  4.25  2.85  3.45  2.35  2.65
  9.    8.8   5.    1.65  2.05  0.9   8.9   8.1   4.7   1.75  7.8  12.9
 13.4   5.4  15.4   3.75 13.8   5.7  13.9 ]
chlorides [0.076 0.098 0.092 0.075 0.069 0.065 0.073 0.071 0.097 0.089 0.114
0.176
 0.17  0.368 0.086 0.341 0.077 0.082 0.106 0.084 0.085 0.08  0.105 0.083
 0.103 0.066 0.172 0.074 0.088 0.332 0.05  0.054 0.113 0.068 0.081 0.11
 0.07  0.111 0.079 0.115 0.094 0.093 0.104 0.464 0.401 0.062 0.107 0.045
 0.058 0.102 0.467 0.091 0.122 0.09  0.119 0.178 0.146 0.072 0.118 0.049
 0.06  0.117 0.087 0.236 0.61  0.095 0.1   0.36  0.067 0.27  0.099 0.046
```

```
 0.061 0.056 0.039 0.059 0.101 0.057 0.337 0.078 0.263 0.063 0.611 0.064
 0.096 0.358 0.343 0.186 0.112 0.213 0.214 0.121 0.128 0.052 0.12  0.116
 0.109 0.159 0.124 0.174 0.047 0.127 0.413 0.152 0.053 0.055 0.051 0.125
 0.2   0.171 0.226 0.25  0.108 0.148 0.143 0.222 0.157 0.422 0.034 0.387
 0.415 0.243 0.241 0.19  0.132 0.126 0.038 0.044 0.041 0.165 0.048 0.145
 0.147 0.012 0.194 0.161 0.123 0.414 0.216 0.043 0.042 0.369 0.166 0.136
 0.403 0.137 0.168 0.153 0.267 0.169 0.205 0.235 0.23 ]
free sulfur dioxide [11.  25.  15.  17.  13.   9.  16.  52.  51.  35.   6.  29.
23.  10.
 21.   4.  14.   8.  22.  40.   5.   3.   7.  12.  30.  33.  50.  19.
 20.  27.  18.  28.  34.  42.  41.  37.  32.  36.  24.  26.  39.  40.5
 68.  31.  38.  43.  47.   1.  54.  46.  45.   2.   5.5 53.  37.5 57.
 48.  72.  55.  66. ]
total sulfur dioxide [ 34.   67.   54.   60.   40.   59.   21.   18.  102.   65.
29.  145.
 148.  103.   56.   71.   37.   23.   11.   35.   16.   82.  113.   83.
  50.   15.   30.   19.   87.   46.   14.  114.   12.   96.  119.   73.
  45.   10.  110.   52.  112.   39.   27.   94.   43.   42.   80.   51.
  61.  136.   31.  125.   24.  140.  133.   85.  106.   22.   36.   69.
  64.  153.   47.  108.  111.   62.   28.   89.   13.   90.  134.   99.
  26.   63.  105.   20.  141.   88.  129.  128.   86.  121.  101.   44.
   8.   49.   38.  143.  144.  127.  126.  120.   55.   93.   95.   41.
  58.   72.   81.  109.   33.   53.   98.   48.   70.   25.  135.   92.
  74.   32.   77.  165.   75.  124.   78.  122.   66.   68.   17.   91.
  76.  151.  142.  116.  149.   57.  104.   84.  147.  155.  152.    9.
 139.  130.    7.  100.  115.    6.   79.  278.  289.  160.   77.5 131. ]
density [0.9978  0.9968  0.997   0.998   0.9964  0.9946  0.9959  0.9943  0.9974
 0.9986  0.9969  0.9982  0.9966  0.9955  0.9962  0.9972  0.9958  0.9993
 0.9957  0.9975  0.994   0.9976  0.9934  0.9954  0.9971  0.9956  0.9983
 0.9967  0.9961  0.9984  0.9938  0.9932  0.9965  0.9963  0.996   0.9973
 0.9988  0.9937  0.9952  0.9916  0.9944  0.9996  0.995   0.9981  0.9953
 0.9924  0.9948  0.99695 0.99545 0.99615 0.9994  0.99625 0.99585 0.99685
 0.99655 0.99525 0.99815 0.99745 0.9927  0.99675 0.99925 0.99565 1.00005
 0.9985  0.99965 0.99575 0.9999  1.00025 0.9987  0.99935 0.99735 0.99915
 0.9991  1.00015 0.9997  1.001   0.9979  1.0014  1.0001  0.99855 0.99845
 0.9998  0.99645 0.99865 0.9989  0.99975 0.999   1.0015  1.0002  0.9992
 1.0008  1.      1.0006  1.0004  1.0018  0.9912  1.0022  1.0003  0.9949
 0.9951  1.0032  0.9947  0.9995  0.9977  1.0026  1.00315 1.0021  0.9917
 0.9922  0.9921  0.99788 1.00024 0.99768 0.99782 0.99761 0.99803 0.99785
 0.99656 0.99488 0.99823 0.99779 0.99738 0.99701 0.99888 0.99938 0.99744
 0.99668 0.99727 0.99586 0.99612 0.99676 0.99732 0.99814 0.99746 0.99708
 0.99818 0.99639 0.99531 0.99786 0.99526 0.99641 0.99264 0.99682 0.99356
 0.99386 0.99702 0.99693 0.99562 1.00012 0.99462 0.99939 0.99632 0.99976
 0.99606 0.99154 0.99624 0.99417 0.99376 0.99832 0.99836 0.99694 0.99064
 0.99672 0.99647 0.99736 0.99629 0.99689 0.99801 0.99652 0.99538 0.99594
 0.99686 0.99438 0.99357 0.99628 0.99748 0.99578 0.99371 0.99522 0.99576
 0.99552 0.99664 0.99614 0.99517 0.99787 0.99533 0.99536 0.99824 0.99577
 0.99491 1.00289 0.99743 0.99774 0.99444 0.99892 0.99528 0.99331 0.99901
```

```
 0.99674 0.99512 0.99395 0.99504 0.99516 0.99604 0.99468 0.99543 0.99791
 0.99425 0.99509 0.99484 0.99834 0.99864 0.99498 0.99566 0.99408 0.99458
 0.99648 0.99568 0.99613 0.99519 0.99518 0.99592 0.99654 0.99546 0.99554
 0.99733 0.99669 0.99724 0.99643 0.99605 0.99658 0.99416 0.99712 0.99418
 0.99596 0.99556 0.99918 0.99697 0.99378 0.99162 0.99495 0.9928  0.99603
 0.99549 0.99722 0.99354 0.99635 0.99454 0.99598 0.99486 0.99007 0.99636
 0.99642 0.99584 0.99506 0.99822 0.99364 0.99514 0.99854 0.99739 0.99683
 0.99692 0.99756 0.99547 0.99859 0.99294 0.99634 0.99704 0.99258 0.99426
 0.99747 0.99784 0.99358 0.99572 0.99769 0.99534 0.99817 0.99316 0.99471
 0.99617 0.99529 0.99451 0.99479 0.99772 0.99666 0.99392 0.99388 0.99402
 0.9936  0.99374 0.99523 0.99593 0.99396 0.99698 0.9902  0.99252 0.99256
 0.99235 0.99352 0.99557 0.99394 0.9915  0.99379 0.99798 0.99341 0.9933
 0.99684 0.99524 0.99764 0.99588 0.99473 0.99616 0.99622 0.99544 0.99728
 0.99551 0.99434 0.99709 0.99384 0.99502 0.99667 0.99649 0.99716 0.99541
 0.99318 0.99346 0.99599 0.99478 0.99754 0.99439 0.99633 0.99419 0.99878
 0.99752 0.99428 0.99659 0.99677 0.99734 0.99678 0.99638 0.99922 0.99157
 0.99718 0.99621 0.99242 0.99494 0.99729 0.99414 0.99721 0.99627 0.99569
 0.99499 0.99437 0.99726 0.99456 0.99564 0.9908  0.99084 0.9935  0.99385
 0.99688 0.99619 0.99476 0.99328 0.99286 0.99914 0.99521 0.99362 0.99558
 0.99323 0.99191 0.99501 0.9929  0.99532 0.99796 0.99581 0.99608 0.99387
 0.99448 0.99589 0.99852 0.99472 0.99587 0.99332 0.99464 0.99699 0.99725
 0.99623 0.99609 0.99292 0.9942  1.00369 0.99713 0.99322 0.99706 0.99974
 0.99467 0.99236 0.99705 0.99334 0.99336 1.00242 0.99182 0.99808 0.99828
 0.99719 0.99542 0.99496 0.99344 0.99348 0.99459 0.99492 0.99508 0.99582
 0.99555 0.9941  0.99661 0.99842 0.99489 0.99665 0.99553 0.99714 0.99631
 0.99573 0.99717 0.99397 0.99646 0.99758 0.99306 0.99783 0.99765 0.99474
 0.99483 0.99314 0.99574 0.99651]
pH [3.51 3.2  3.26 3.16 3.3  3.39 3.36 3.35 3.28 3.58 3.17 3.11 3.38 3.04
 3.52 3.43 3.34 3.47 3.46 3.45 3.4  3.42 3.23 3.5  3.33 3.21 3.48 3.9
 3.25 3.32 3.15 3.41 3.44 3.31 3.54 3.13 2.93 3.14 3.75 3.85 3.29 3.08
 3.37 3.19 3.07 3.49 3.53 3.24 3.63 3.22 3.68 2.74 3.59 3.   3.12 3.57
 3.61 3.06 3.6  3.69 3.1  3.05 3.67 3.27 3.18 3.02 3.55 2.99 3.01 3.56
 3.03 3.62 2.88 2.95 2.98 3.09 2.86 3.74 2.92 3.72 2.87 2.89 2.94 3.66
 3.71 3.78 3.7  4.01 2.9 ]
sulphates [0.56 0.68 0.65 0.58 0.46 0.47 0.57 0.8  0.54 0.52 1.56 0.88 0.93 0.75
 1.28 0.5  1.08 0.53 0.91 0.63 0.59 0.55 0.66 0.6  0.73 0.48 0.83 0.51
 0.9  1.2  0.74 0.64 0.77 0.71 0.62 0.39 0.79 0.95 0.82 1.12 1.14 0.78
 1.95 1.22 1.98 0.61 1.31 0.69 0.67 0.7  0.49 0.92 2.   0.72 1.59 0.33
 1.02 0.97 0.85 0.43 1.03 0.86 0.76 1.61 1.09 0.84 0.96 0.45 1.26 0.87
 0.81 1.   1.36 1.18 0.89 0.98 1.13 1.04 1.11 0.99 1.07 0.44 1.06 1.05
 0.42 1.17 1.62 0.94 1.34 1.16 1.1  0.4  1.15 0.37 1.33 1.01]
alcohol [ 9.4         9.8        10.         9.5        10.5         9.2
  9.9         9.1         9.3         9.          9.7        10.1
 10.6         9.6        10.8        10.3        13.1        10.2
 10.9        10.7        12.9        10.4        13.         14.
 11.5        11.4        12.4        11.         12.2        12.8
 12.6        12.5        11.7        11.3        12.3        12.
 11.9        11.8         8.7        13.3        11.2        11.6
```

```
 11.1        13.4        12.1         8.4        12.7        14.9
 13.2        13.6        13.5        10.03333333  9.55        8.5
 11.06666667  9.56666667 10.55        8.8        13.56666667 11.95
  9.95        9.23333333  9.25        9.05       10.75       ]
quality [5 6 7 4 8 3]
```

2.3 Pré-processamento

[6]:
```python
# pandas_profiling.ProfileReport(data_raw)
```

2.4 Visualização

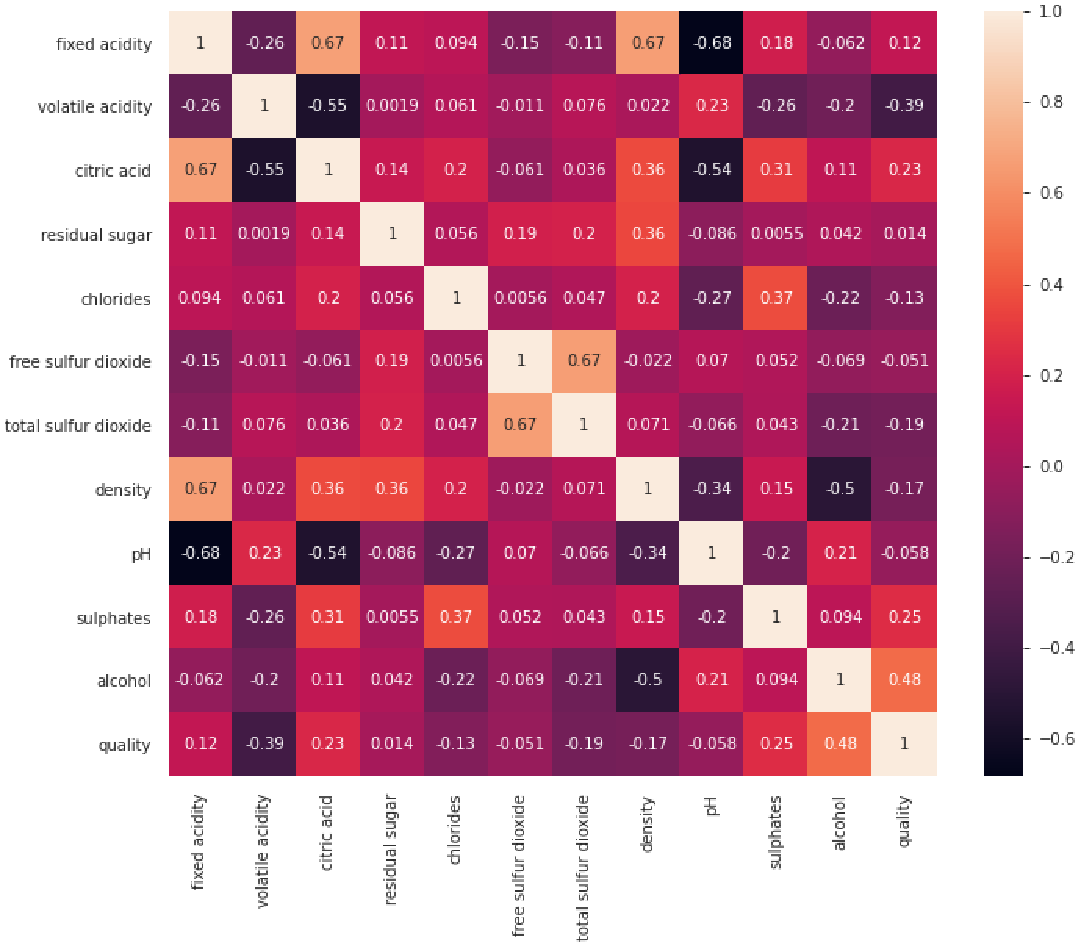
[7]:
```python
# sns.pairplot(data_raw)
```

[8]:
```python
plt.clf()
```

```
<Figure size 432x288 with 0 Axes>
```

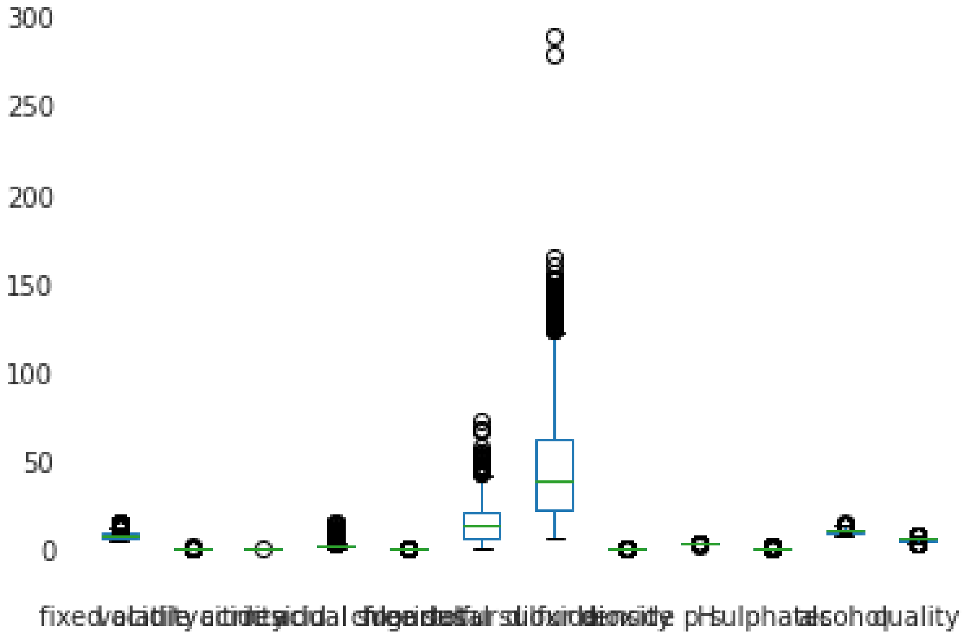
[9]:
```python
plt.subplots(figsize=(11, 9))
sns.heatmap(data_raw.corr(), annot=True)
```

[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73df4fbb38>
```



[10]:
```
data_raw.plot.box()
```

[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f73dcbd6898>



2.5 Escalonando

[11]:
```
scaler = StandardScaler().fit(data_raw)
data_scaled = scaler.transform(data_raw)
```

[12]:
```
data_scaled_df = pd.DataFrame(data_scaled, columns=data_raw.columns)
```

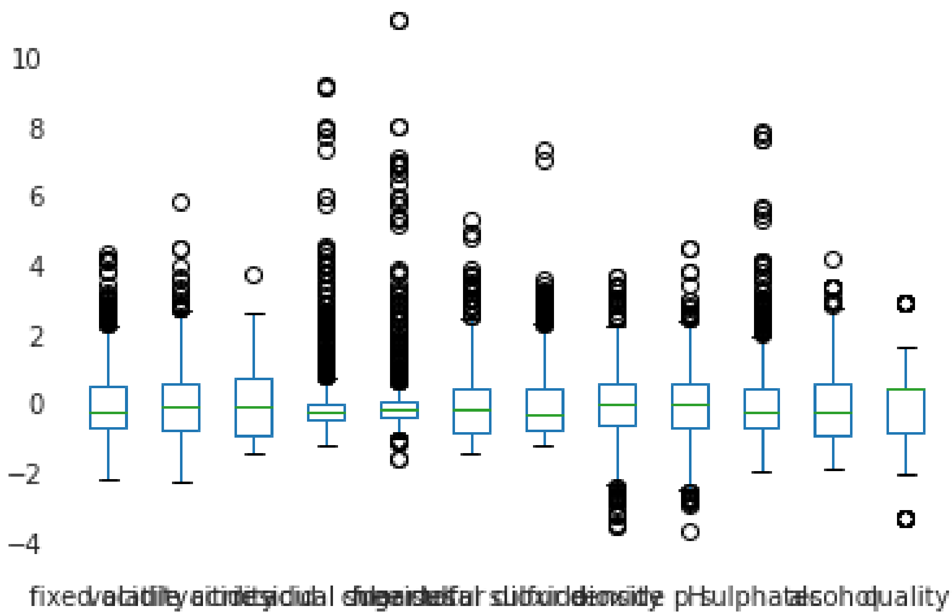
[13]:
```
data_scaled_df.head()
```

[13]:
```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0      -0.528360          0.961877    -1.391472       -0.453218  -0.243707
1      -0.298547          1.967442    -1.391472        0.043416   0.223875
2      -0.298547          1.297065    -1.186070       -0.169427   0.096353
3       1.654856         -1.384443     1.484154       -0.453218  -0.264960
4      -0.528360          0.961877    -1.391472       -0.453218  -0.243707

   free sulfur dioxide  total sulfur dioxide   density        pH  sulphates  \
0            -0.466193             -0.379133  0.558274  1.288643  -0.579207
1             0.872638              0.624363  0.028261 -0.719933   0.128950
2            -0.083669              0.229047  0.134264 -0.331177  -0.048089
3             0.107592              0.411500  0.664277 -0.979104  -0.461180
4            -0.466193             -0.379133  0.558274  1.288643  -0.579207

    alcohol   quality
```

```
0 -0.960246 -0.787823
1 -0.584777 -0.787823
2 -0.584777 -0.787823
3 -0.584777  0.450848
4 -0.960246 -0.787823
```

[14]:
```
data_scaled_df.plot.box()
```

[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f73dc2a1518>
```



2.6 Utilidades

[15]:
```
lista_metricas_treino = []
lista_metricas_teste = []
```

[16]:
```
def metricas(y_true, y_pred, alg):
    r2 = r2_score(y_true, y_pred)
    eqm = mean_squared_error(y_true, y_pred)
    seq = len(y_true)*eqm
    reqm = math.sqrt(eqm)

    return {'Algoritmo':alg, 'R2':r2, 'EQM':eqm, 'REQM':reqm, 'SEQ':seq}
```

2.7 Separando conjuntos de Treino e Teste

Para a separação utilizou-se do train_test_split que divide o conjunto em treino e teste aleatóriamente

[17]:
```
test_attr = 'fixed acidity';
output_attr = 'quality';
train, test = train_test_split(data_scaled_df, test_size = 0.2, shuffle=True)

x_train = train.drop(columns=[output_attr])
y_train = train[output_attr]

x_test = test.drop(columns=[output_attr])
y_test = test[output_attr]
```

2.8 Aplicando a Regressão

2.8.1 Regressão Linear

[18]:
```
lire = LinearRegression()
```

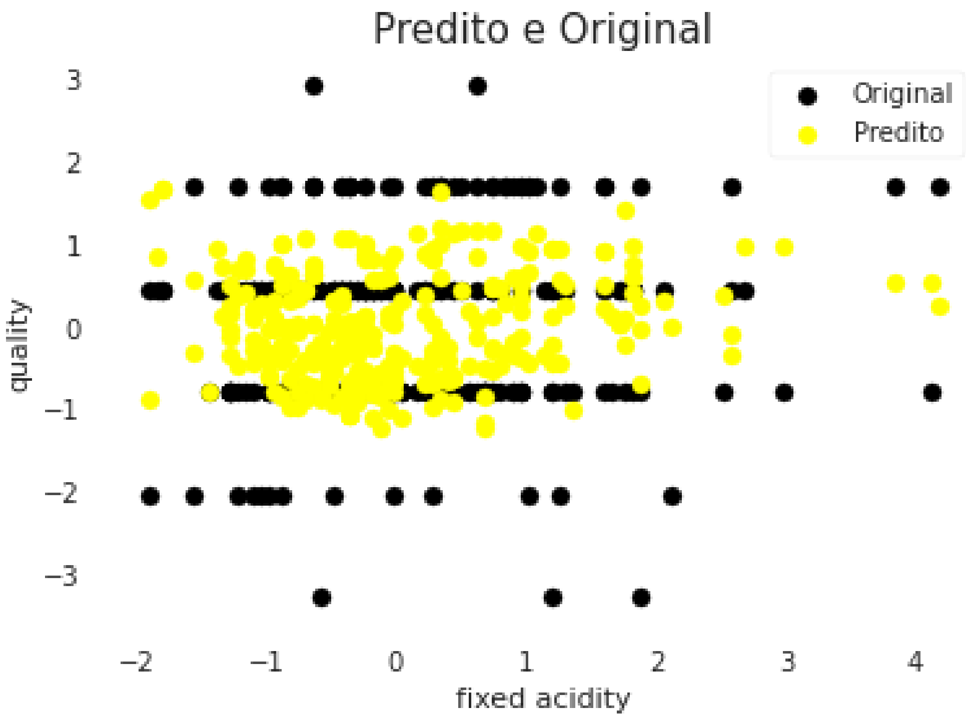
[19]:
```
lire.fit(x_train, y_train)
```

[19]:
```
LinearRegression()
```

2.9 Avaliação para Teste

[20]:
```
y_pred = lire.predict(x_test)
linear_metricas = metricas(y_test, y_pred, 'Regressão Linear - Teste')
lista_metricas_teste.append(linear_metricas)
```

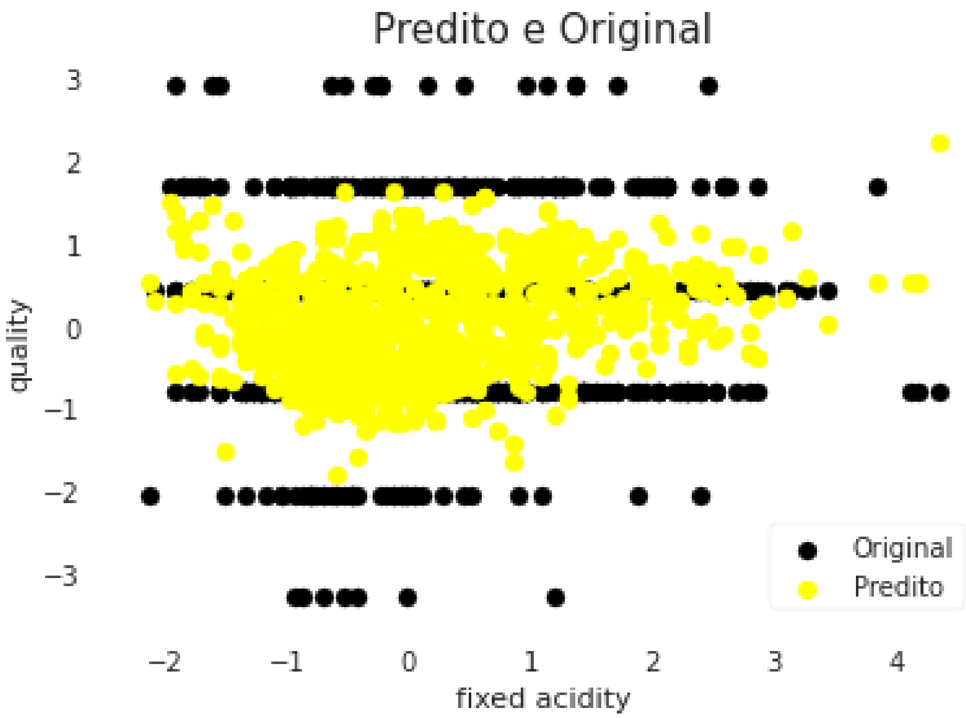
[21]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.10 Avaliação para Treino

[22]:
```
y_pred = lire.predict(x_train)
linear_metricas = metricas(y_train, y_pred, 'Regressão Linear - Treino')
lista_metricas_treino.append(linear_metricas)
```

[23]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.11 SVR

2.11.1 Kernel RBF

[24]:
```
svr_reg = SVR(kernel='rbf')
```

[25]:
```
svr_reg.fit(x_train, y_train)
```

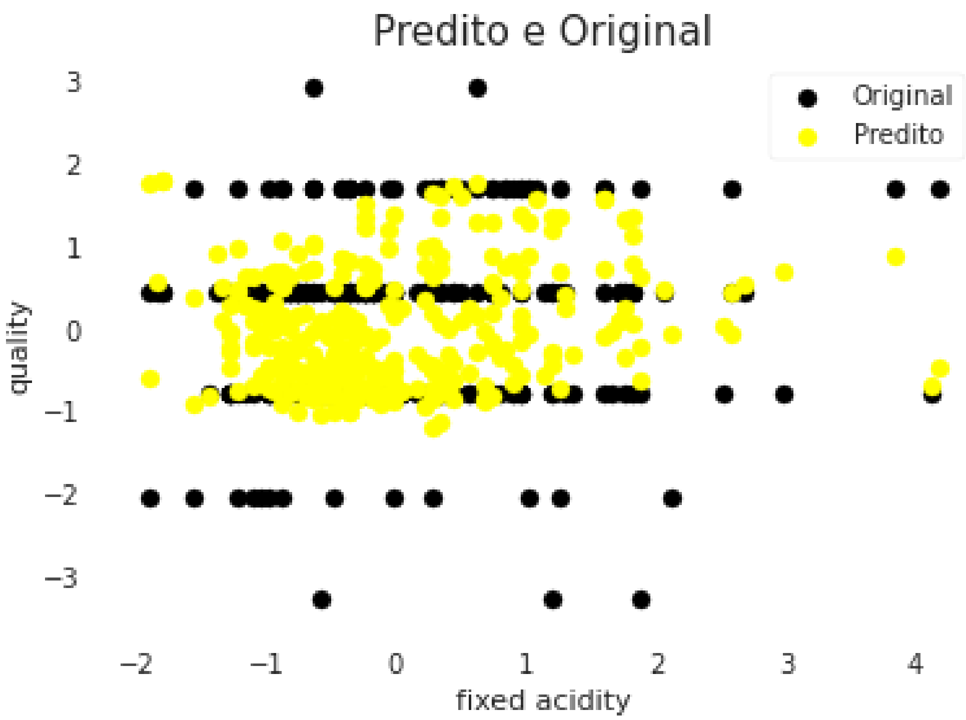
[25]: SVR()

2.12 Avaliação para Teste

[26]:
```
y_pred = svr_reg.predict(x_test)
svr_metricas = metricas(y_test, y_pred, 'SVR - RBF - Teste')
lista_metricas_teste.append(svr_metricas)
```

[27]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
```

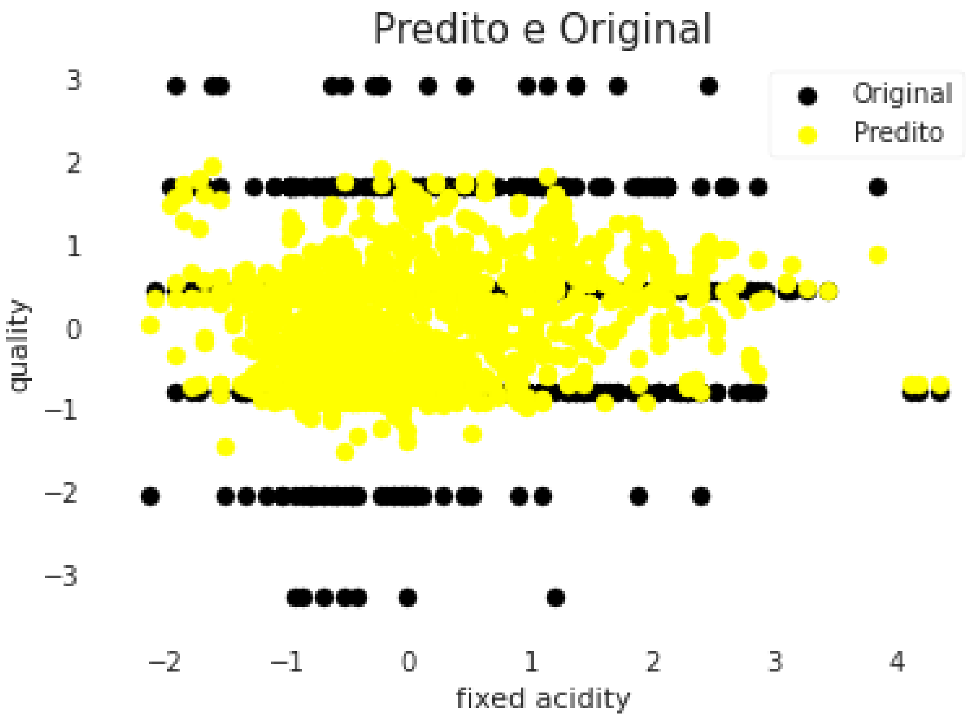
```
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.13 Avaliação para Treino

[28]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - RBF - Treino')
lista_metricas_treino.append(svr_metricas)
```

[29]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.13.1 Kernel Linear

[30]:
```
svr_reg = SVR(kernel='linear')
```

[31]:
```
svr_reg.fit(x_train, y_train)
```

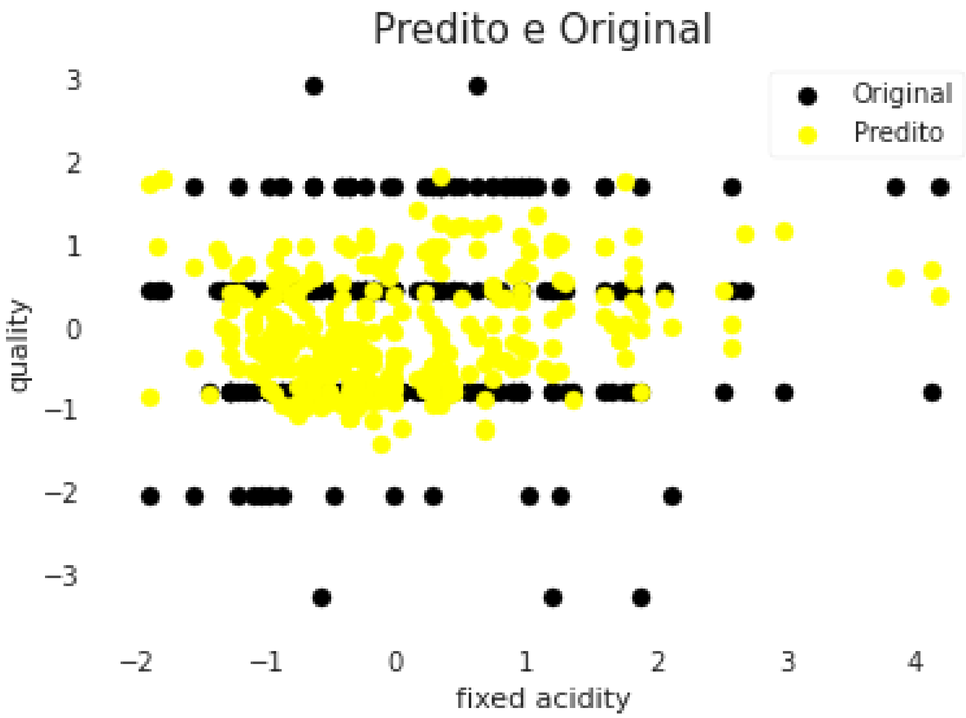
[31]:
```
SVR(kernel='linear')
```

2.14 Avaliação para Teste

[32]:
```
y_pred = svr_reg.predict(x_test)
metricas_svr = metricas(y_test, y_pred, 'SVR - Linear - Teste')
lista_metricas_teste.append(metricas_svr)
```

[33]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
```

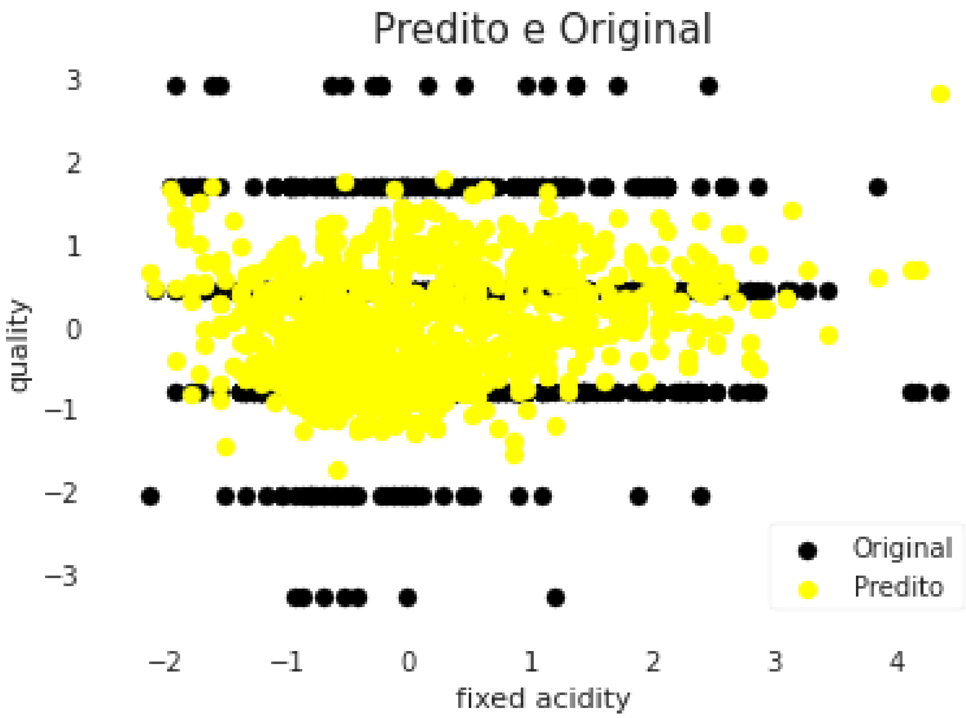
```
plt.show()
```



2.15 Avaliação para Treino

[34]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - Linear - Treino')
lista_metricas_treino.append(svr_metricas)
```

[35]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.15.1 Kernel Sigmoide

[36]:
```
train, test = train_test_split(data_raw, test_size = 0.2, shuffle=True)

x_train_sig = train.drop(columns=[output_attr])
y_train_sig  = train[output_attr]

x_test_sig  = test.drop(columns=[output_attr])
y_test_sig  = test[output_attr]
```

[37]:
```
svr_reg = SVR(kernel='sigmoid')
```

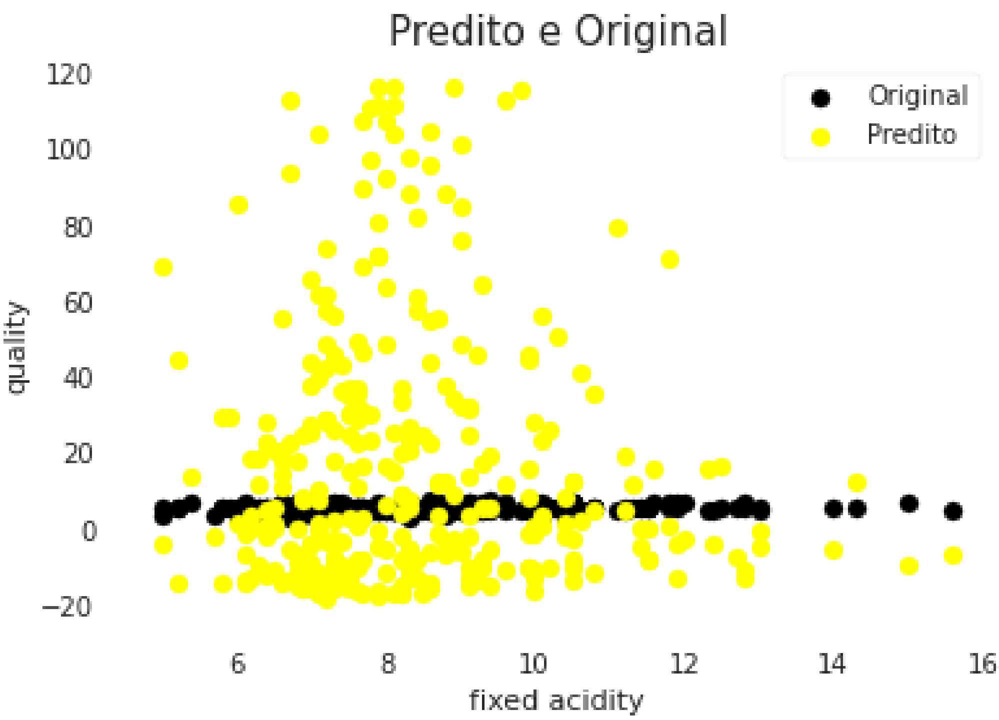
[38]:
```
svr_reg.fit(x_train_sig , y_train_sig )
```

[38]:
```
SVR(kernel='sigmoid')
```

2.16 Avaliação para Teste

[39]:
```
y_pred_sig  = svr_reg.predict(x_test_sig)
metricas_svr = metricas(y_test_sig , y_pred_sig , 'SVR - Sigmoide - Teste')
lista_metricas_teste.append(metricas_svr)
```

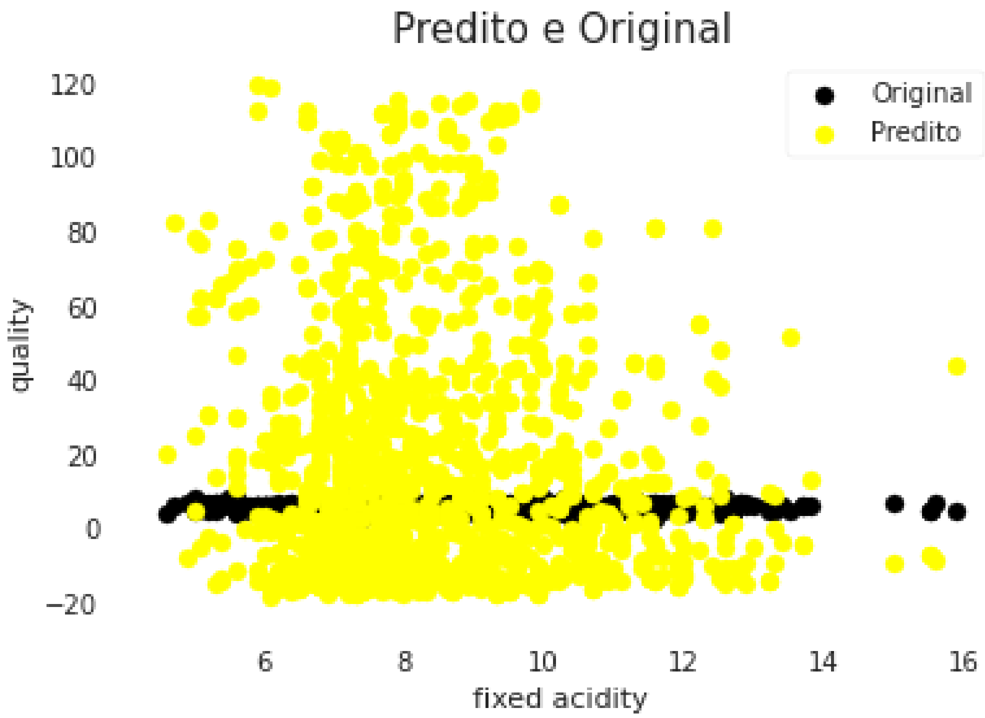
[40]:
```
plt.scatter(x_test_sig [test_attr], y_test_sig ,  color='black')
plt.scatter(x_test_sig [test_attr], y_pred_sig , color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.17 Avaliação para Treino

[41]:
```
y_pred_sig  = svr_reg.predict(x_train_sig)
svr_metricas = metricas(y_train_sig , y_pred_sig , 'SVR - Sigmoide - Treino')
lista_metricas_treino.append(svr_metricas)
```

[42]:
```
plt.scatter(x_train_sig [test_attr], y_train_sig ,  color='black')
plt.scatter(x_train_sig [test_attr], y_pred_sig , color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.17.1 Kernel Polinomial

[43]:
```
svr_reg = SVR(kernel='poly', degree=3)
```

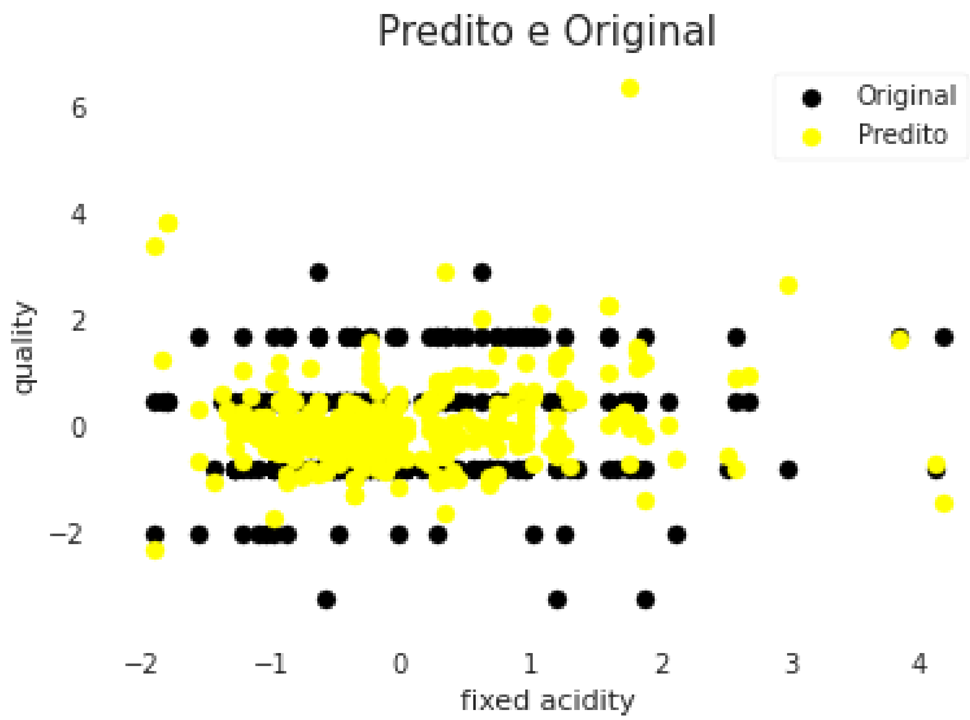
[44]:
```
svr_reg.fit(x_train, y_train)
```

[44]: SVR(kernel='poly')

2.18 Avaliação para Teste

[45]:
```
y_pred = svr_reg.predict(x_test)
svr_metricas = metricas(y_test, y_pred, 'SVR - Polinomial - Teste')
lista_metricas_teste.append(svr_metricas)
```

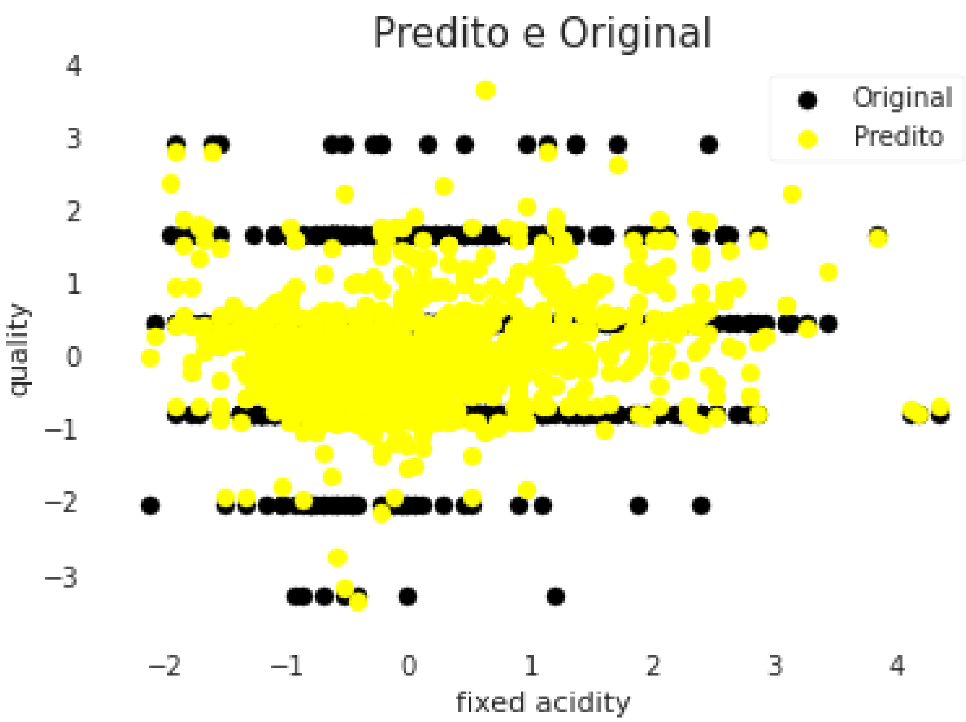
[46]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.19 Avaliação para Treino

[47]:
```
y_pred = svr_reg.predict(x_train)
svr_metricas = metricas(y_train, y_pred, 'SVR - Polinomial - Treino')
lista_metricas_treino.append(svr_metricas)
```

[48]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.20 Redes Neurais

2.20.1 Kernel Linear

[49]:
```
mlp_reg = MLPRegressor()
```

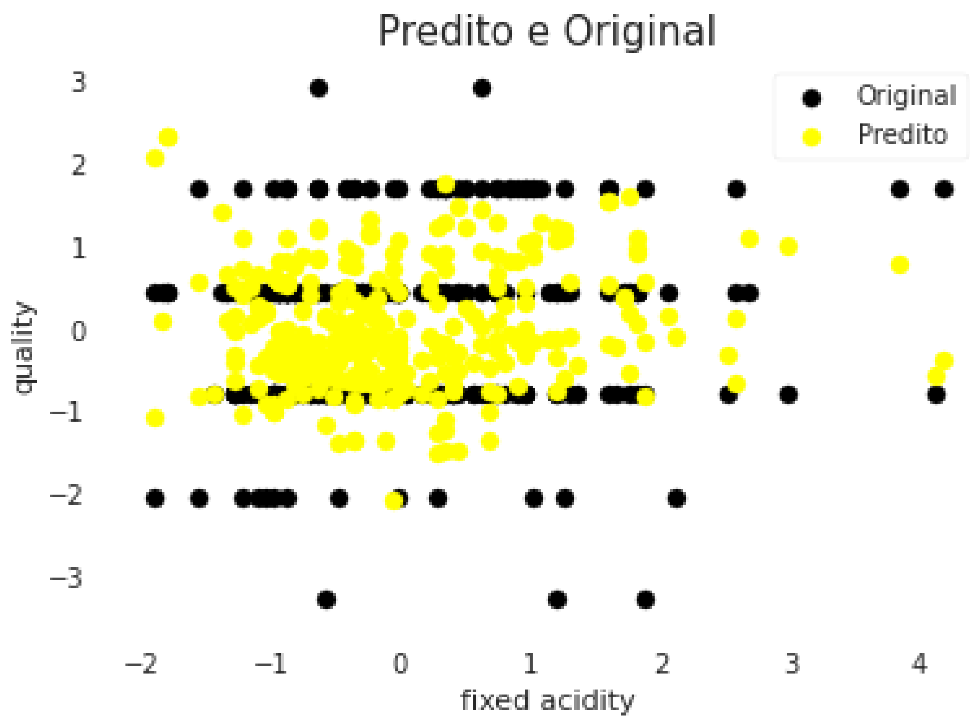
[50]:
```
mlp_reg.fit(x_train, y_train)
```

[50]:
```
MLPRegressor()
```

2.21 Avaliação para Teste

[51]:
```
y_pred = mlp_reg.predict(x_test)
mlp_metricas = metricas(y_test, y_pred, 'MLP - Teste')
lista_metricas_teste.append(mlp_metricas)
```

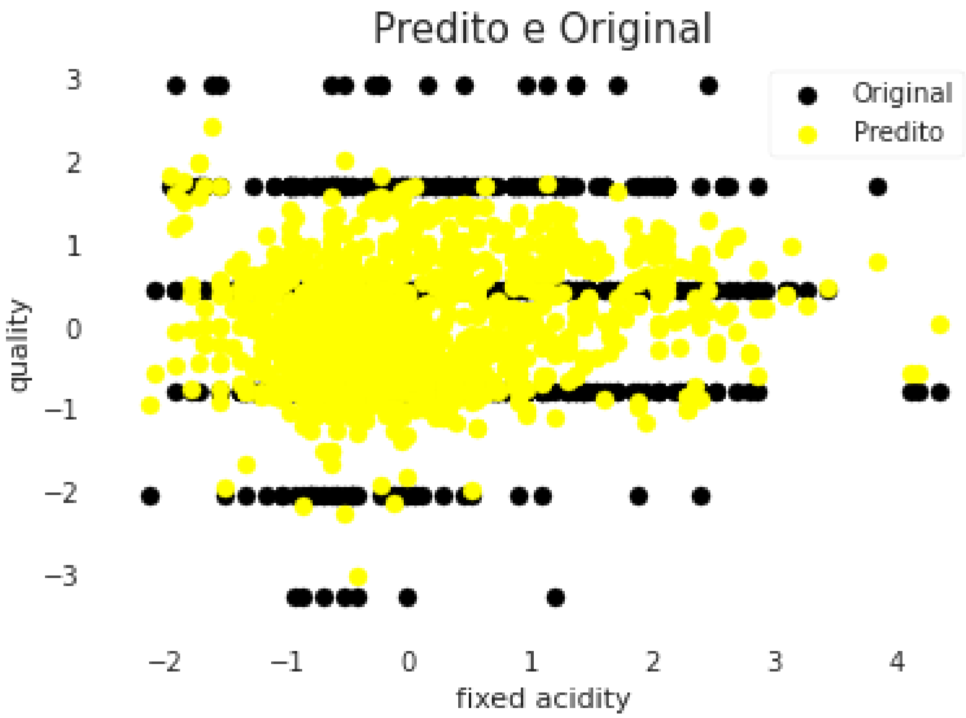
[52]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



2.22 Avaliação para Treino

[53]:
```
y_pred = mlp_reg.predict(x_train)
mlp_metricas = metricas(y_train, y_pred, 'MLP - Treino')
lista_metricas_treino.append(mlp_metricas)
```

[54]:
```
plt.scatter(x_train[test_attr], y_train,  color='black')
plt.scatter(x_train[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



3 Resultados

[55]:
```
metricas_teste = pd.DataFrame(lista_metricas_teste)
metricas_teste
```

[55]:

	Algoritmo	R2	EQM	REQM	\
0	Regressão Linear - Teste	0.322617	0.708590	0.841778	
1	SVR - RBF - Teste	0.385657	0.642646	0.801652	
2	SVR - Linear - Teste	0.303653	0.728427	0.853480	
3	SVR - Sigmoide - Teste	-1955.626553	1316.117972	36.278340	
4	SVR - Polinomial - Teste	0.099509	0.941977	0.970555	
5	MLP - Teste	0.375016	0.653777	0.808565	

```
          SEQ
0      226.748957
1      205.646758
2      233.096752
3   421157.751023
4      301.432642
5      209.208543
```

[56]:
```
metricas_teste = round(metricas_teste, 3)
```

[57]:
```
metricas_teste
```

[57]:
```
                  Algoritmo        R2       EQM    REQM         SEQ
0   Regressão Linear - Teste     0.323     0.709   0.842     226.749
1          SVR - RBF - Teste     0.386     0.643   0.802     205.647
2       SVR - Linear - Teste     0.304     0.728   0.853     233.097
3     SVR - Sigmoide - Teste -1955.627  1316.118  36.278  421157.751
4   SVR - Polinomial - Teste     0.100     0.942   0.971     301.433
5                MLP - Teste     0.375     0.654   0.809     209.209
```

[58]:
```
metricas_teste.to_excel('wine_metricas_teste.xlsx')
```

[59]:
```
metricas_treino = pd.DataFrame(lista_metricas_treino)
metricas_treino
```

[59]:
```
                   Algoritmo           R2          EQM       REQM  \
0   Regressão Linear - Treino     0.366947     0.625541   0.790911
1          SVR - RBF - Treino     0.535704     0.458786   0.677337
2       SVR - Linear - Treino     0.354539     0.637801   0.798625
3     SVR - Sigmoide - Treino -2007.247559  1298.276549  36.031605
4   SVR - Polinomial - Treino     0.472925     0.520820   0.721679
5                MLP - Treino     0.592636     0.402530   0.634453

            SEQ
0  8.000668e+02
1  5.867869e+02
2  8.157479e+02
3  1.660496e+06
4  6.661287e+02
5  5.148359e+02
```

[60]:
```
metricas_treino = round(metricas_treino, 3)
```

[61]:
```
metricas_treino.to_excel('wine.xlsx')
```