regression-framingham

August 19, 2020

[0]:

1 0. Introdução

Trabalho:

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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]:
```
#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	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose	TenYearCHD
0	1	39	4.0	0	0.0	0.0	0	0	0	195.0	106.0	70.0	26.97	80.0	77.0	0
1	0	46	2.0	0	0.0	0.0	0	0	0	250.0	121.0	81.0	28.73	95.0	76.0	0
2	1	48	1.0	1	20.0	0.0	0	0	0	245.0	127.5	80.0	25.34	75.0	70.0	0
3	0	61	3.0	1	30.0	0.0	0	1	0	225.0	150.0	95.0	28.58	65.0	103.0	1
4	0	46	3.0	1	23.0	0.0	0	0	0	285.0	130.0	84.0	23.10	85.0	85.0	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

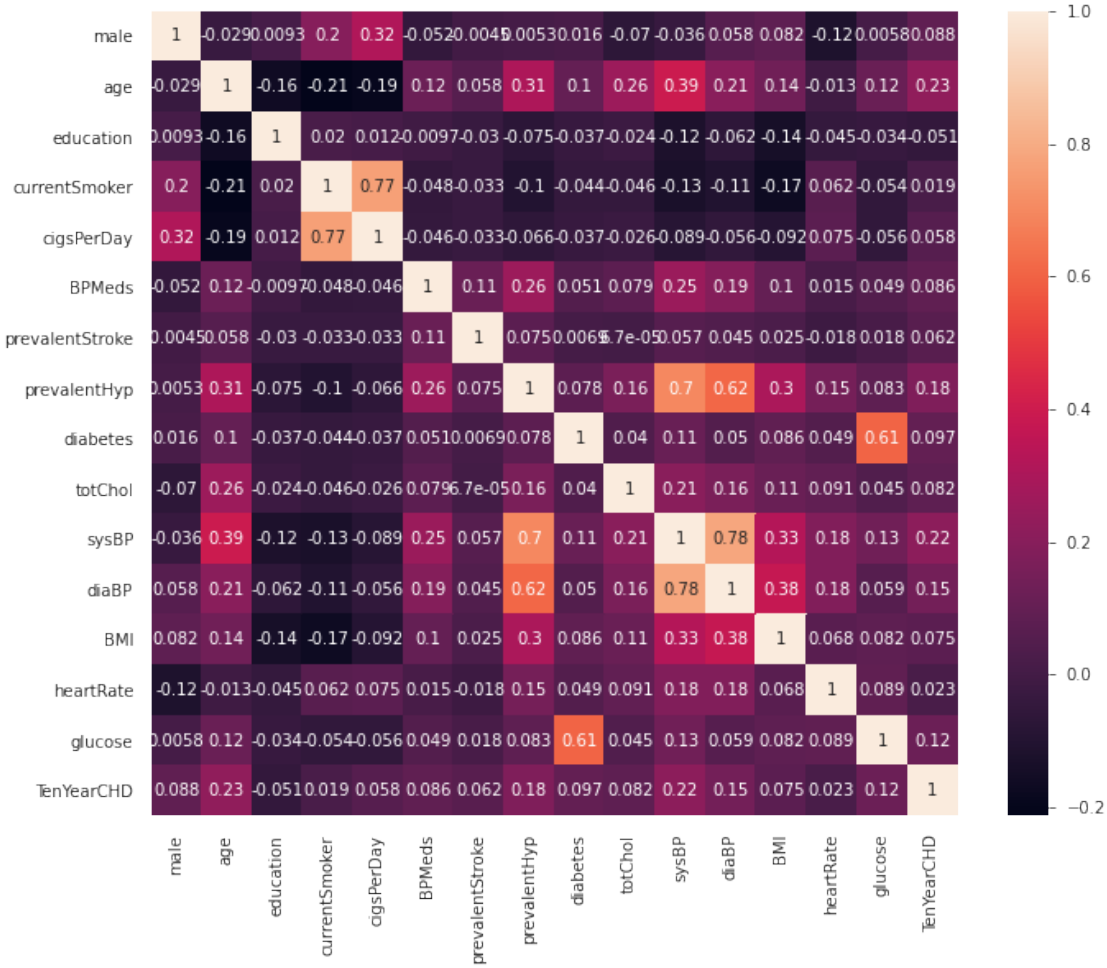
[12]:
```
# sns.pairplot(data_raw)
```

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

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

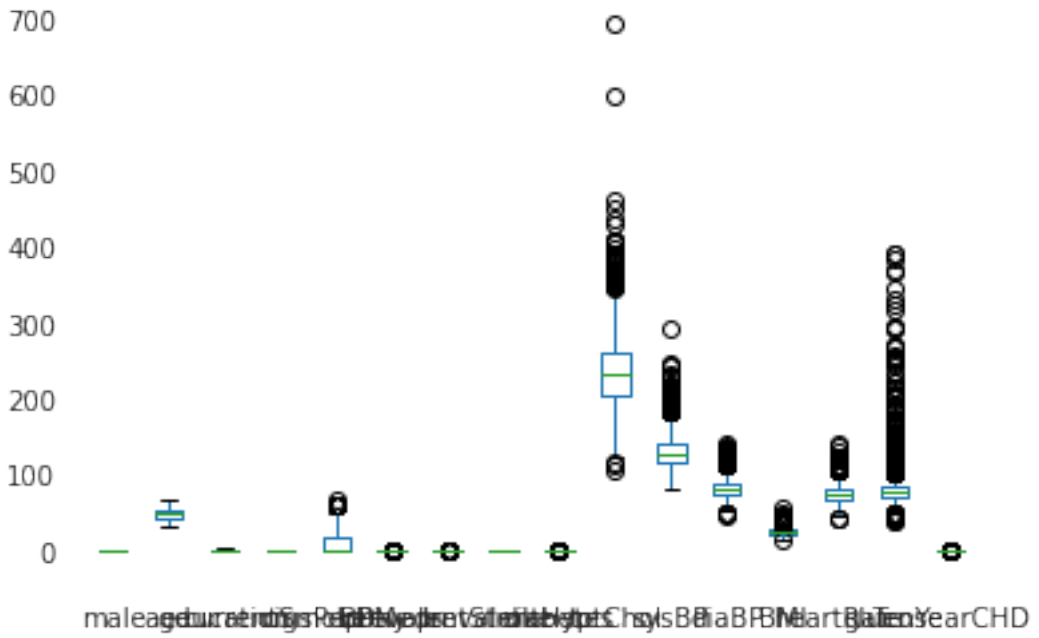
[14]:
```
plt.subplots(figsize=(11, 9))
sns.heatmap(data_raw.corr(), annot=True)
```

[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()
```

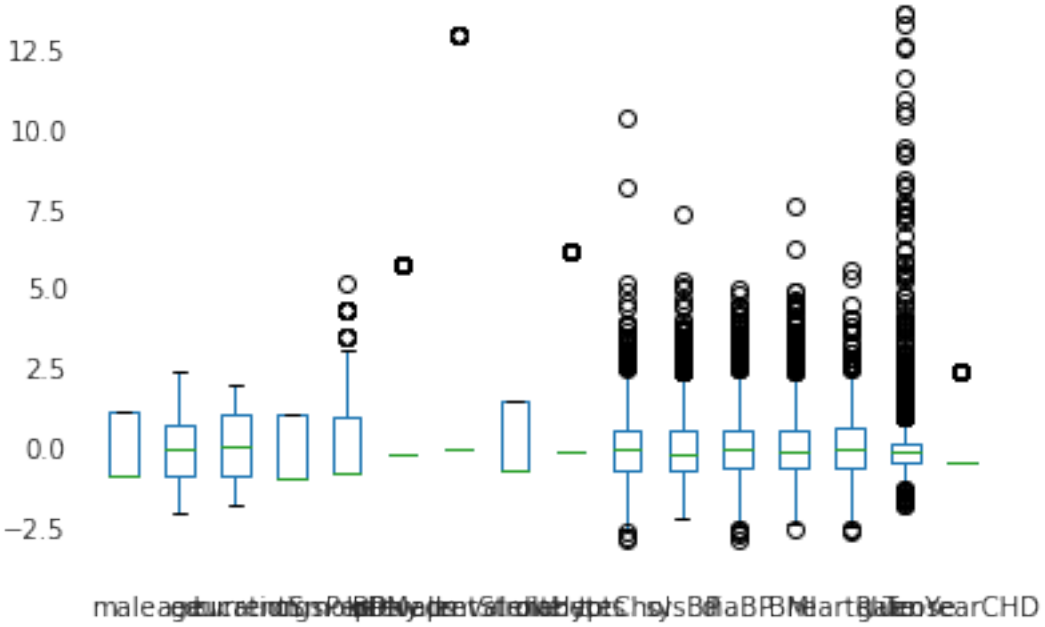
[18]:

	male	age	education	currentSmoker	cigsPerDay	BPMeds	prevalentStroke	prevalentHyp	diabetes	totChol	sysBP	diaBP	BMI	heartRate	glucose	TenYearCHD
0	1.153192	-1.234951	1.966086	-0.988271	-0.757974	-0.173612	-0.077033	-0.671101	-0.162477	-0.941346	-1.195907	-1.082625				
1	-0.867158	-0.418257	0.066560	-0.988271	-0.757974	-0.173612	-0.077033	-0.671101	-0.162477	0.299595	-0.515187	-0.158988				
2	1.153192	-0.184916	-0.883204	1.011868	0.925835	-0.173612	-0.077033	-0.671101	-0.162477	0.186782	-0.220209	-0.242955				
3	-0.867158	1.331800	1.016323	1.011868	1.767740	-0.173612	-0.077033	1.490089	-0.162477	-0.264469	0.800871	1.016549				
4	-0.867158	-0.418257	1.016323	1.011868	1.178407	-0.173612	-0.077033	-0.671101	-0.162477	1.089284	-0.106755	0.092912				

```
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()
```

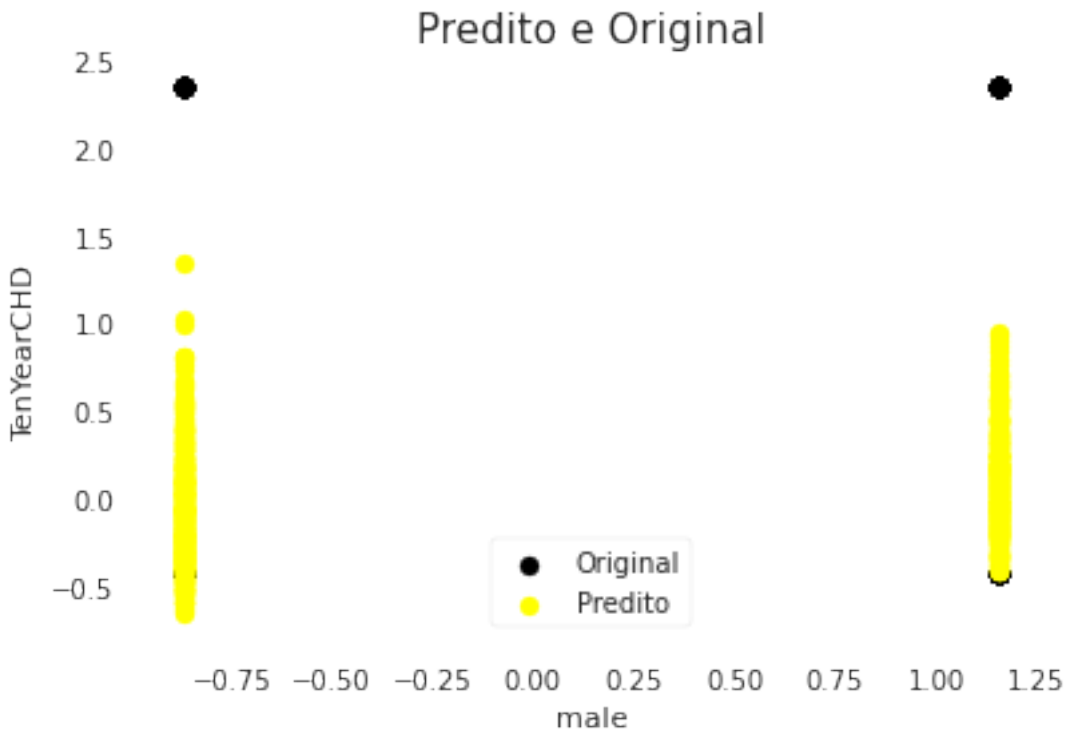
[24]:
```
lire.fit(x_train, y_train)
```

[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)
```

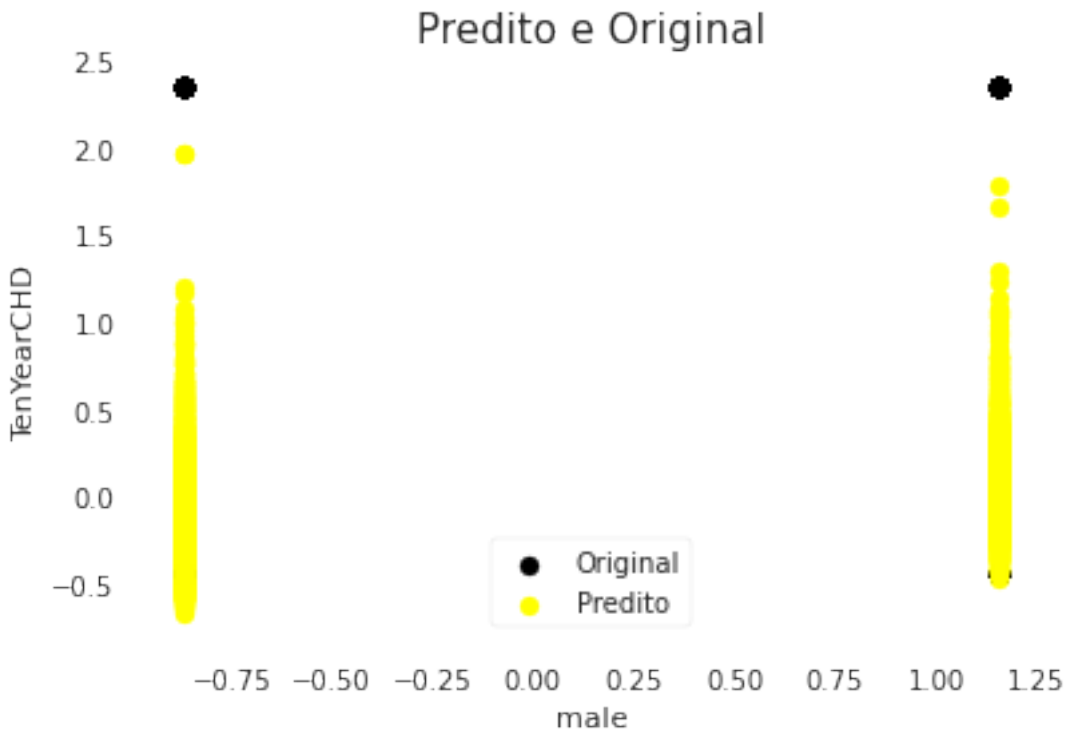
[26]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



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)
```

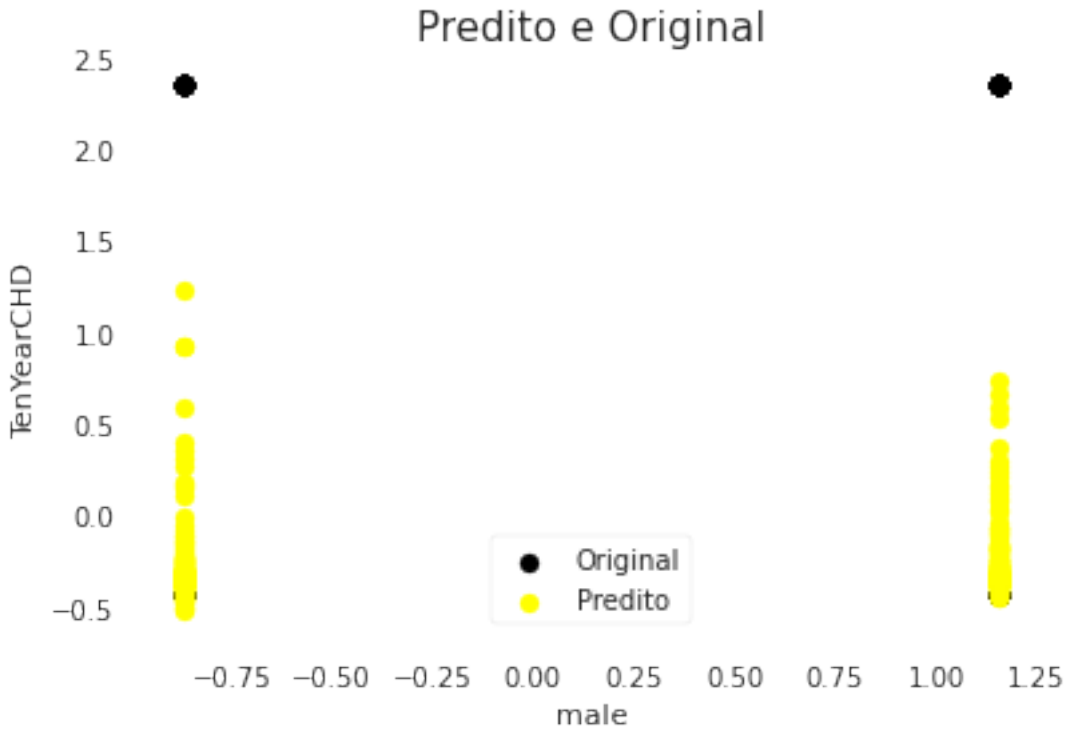
[30]:
```
SVR()
```

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)
```

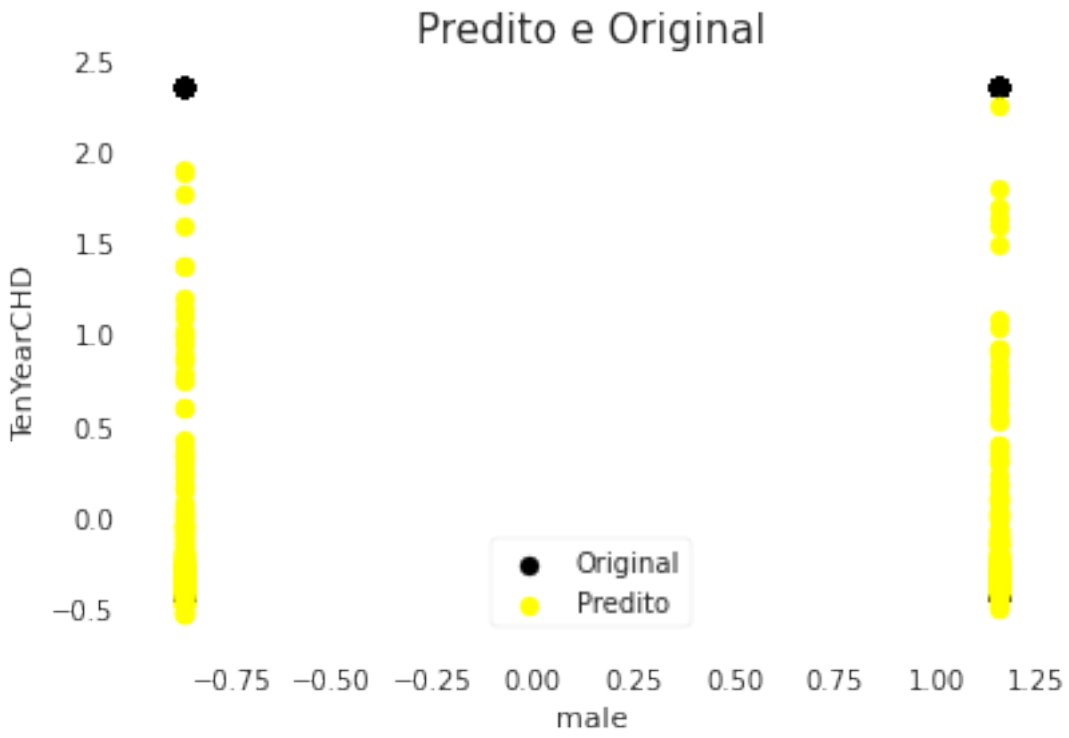
```
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



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)
```

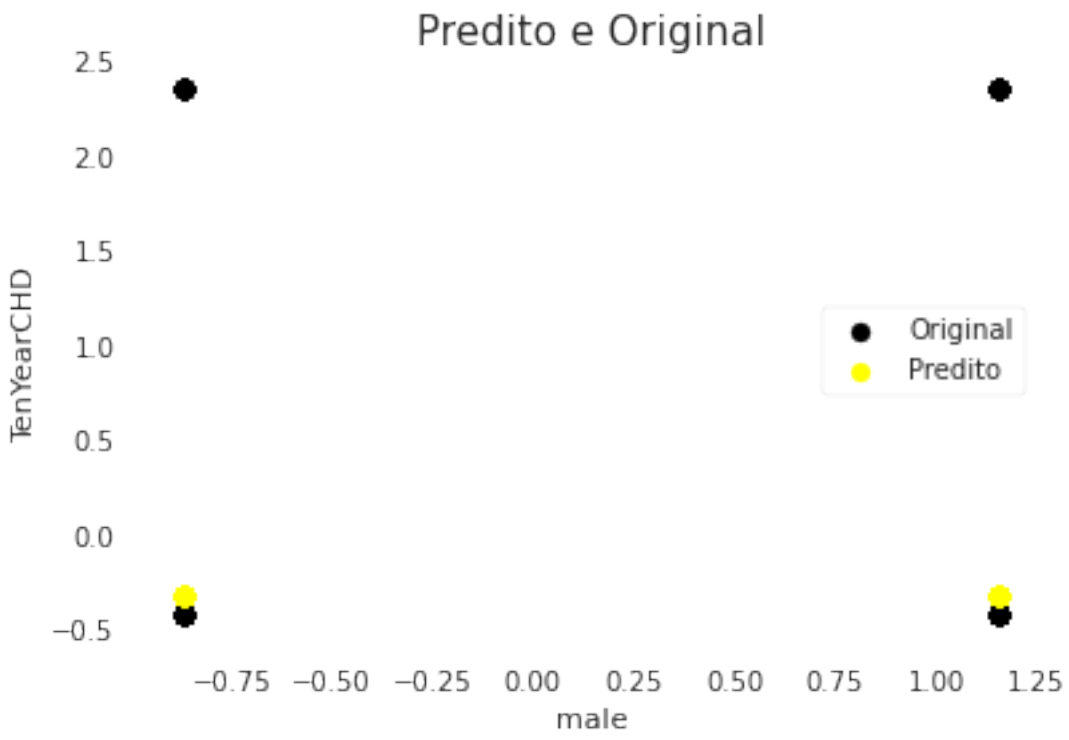
[36]:
```
SVR(kernel='linear')
```

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'])
```

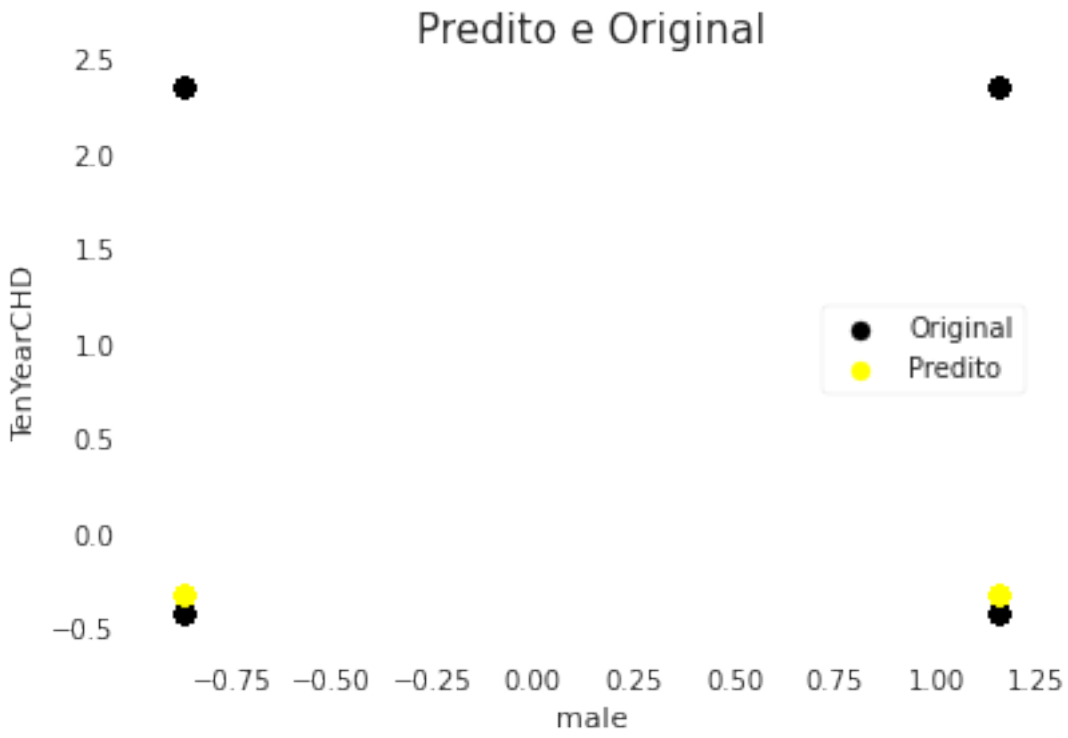
```
plt.show()
```



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')
```

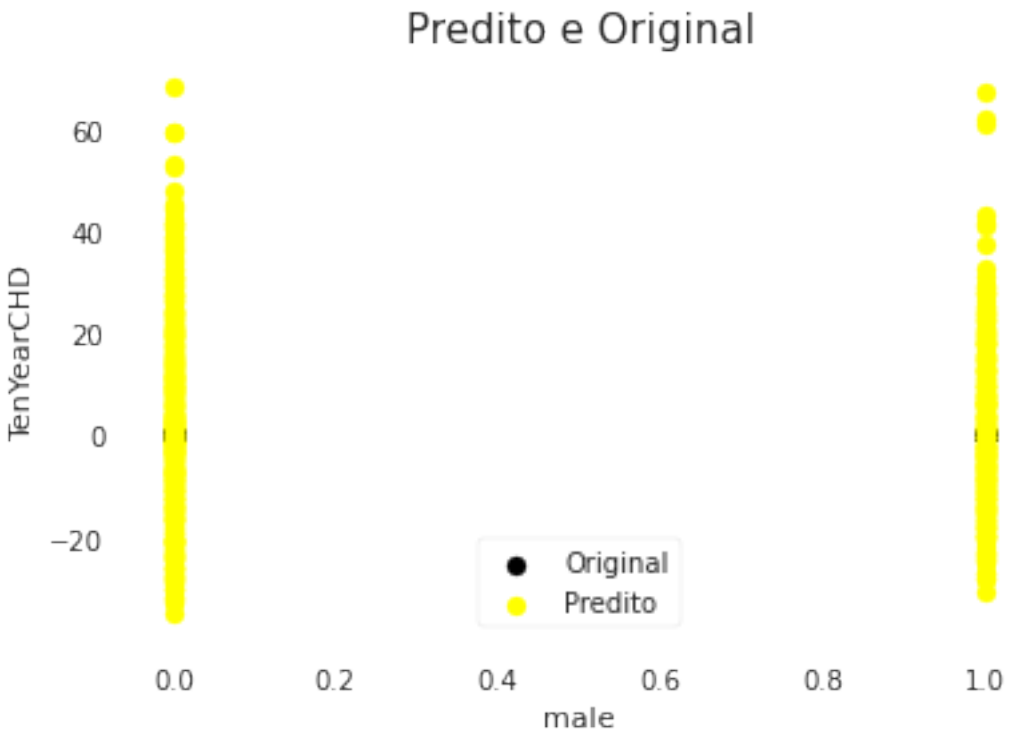
[43]:
```
svr_reg.fit(x_train_sig , y_train_sig )
```

[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)
```

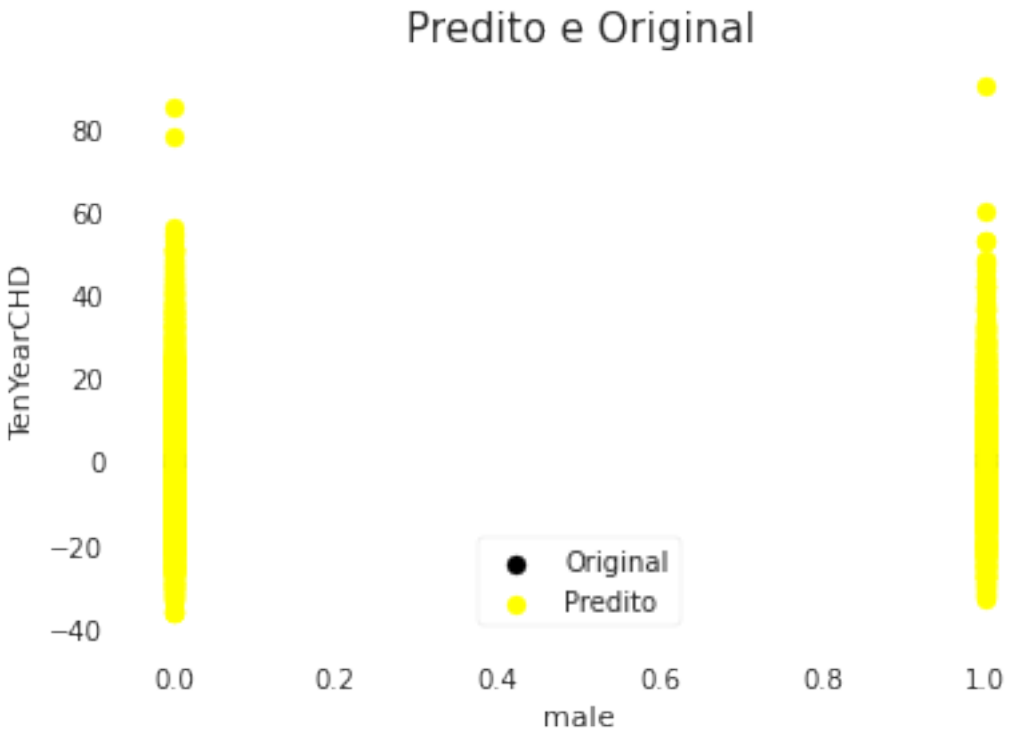
[45]:
```
plt.scatter(x_test_sig [test_attr], y_test_sig ,  color='black')
plt.scatter(x_test_sig [test_attr], y_pred_sig , color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



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)
```

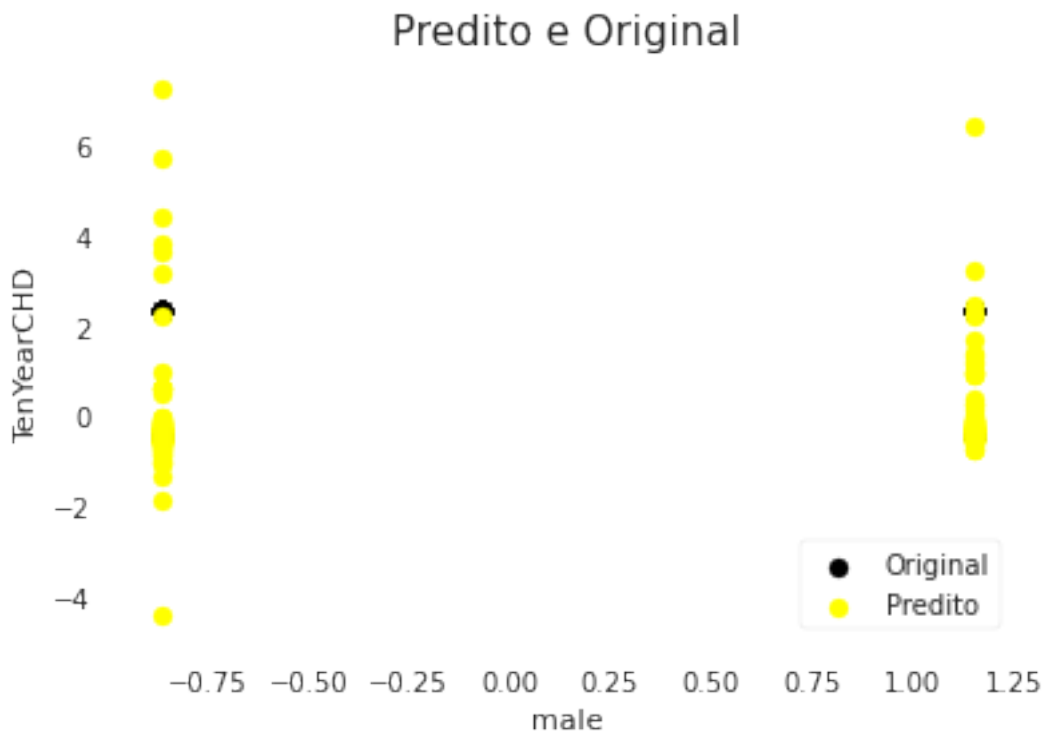
[49]:
```
svr_reg.fit(x_train, y_train)
```

[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)
```

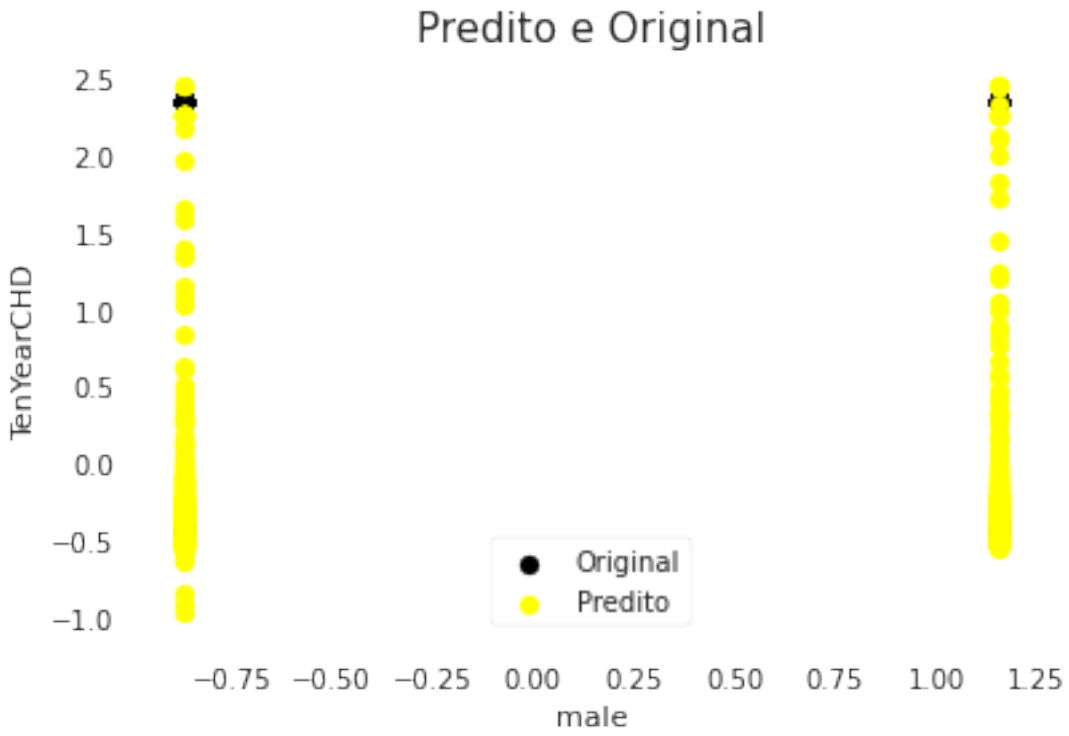
[51]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



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()
```

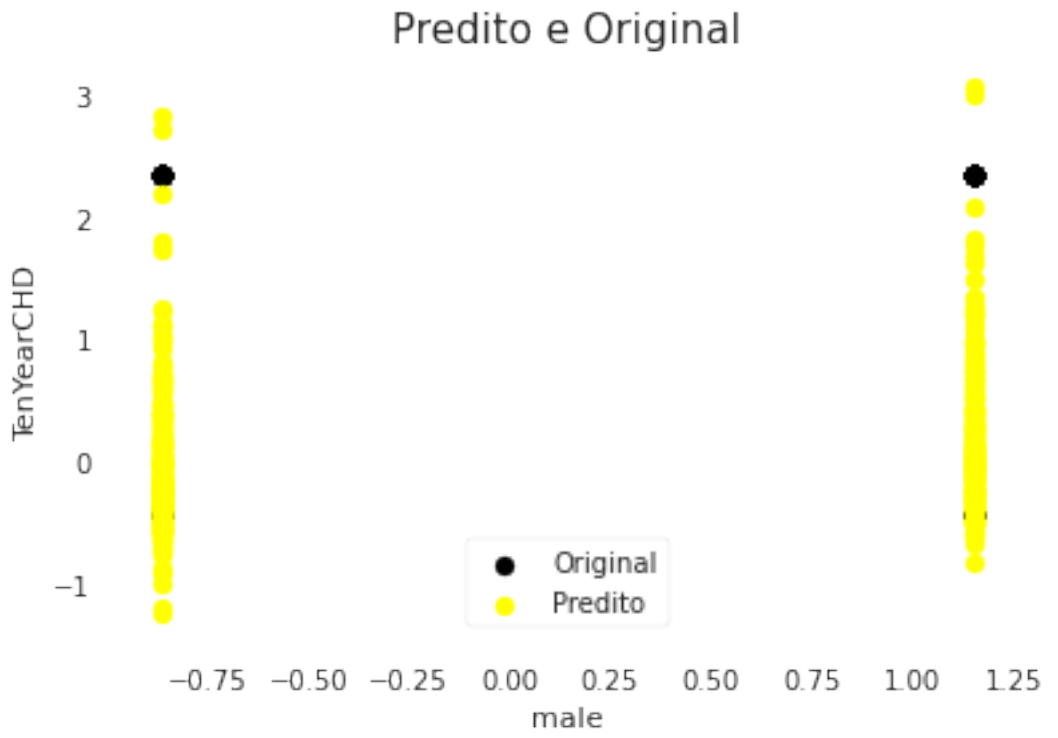
[55]:
```
mlp_reg.fit(x_train, y_train)
```

[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)
```

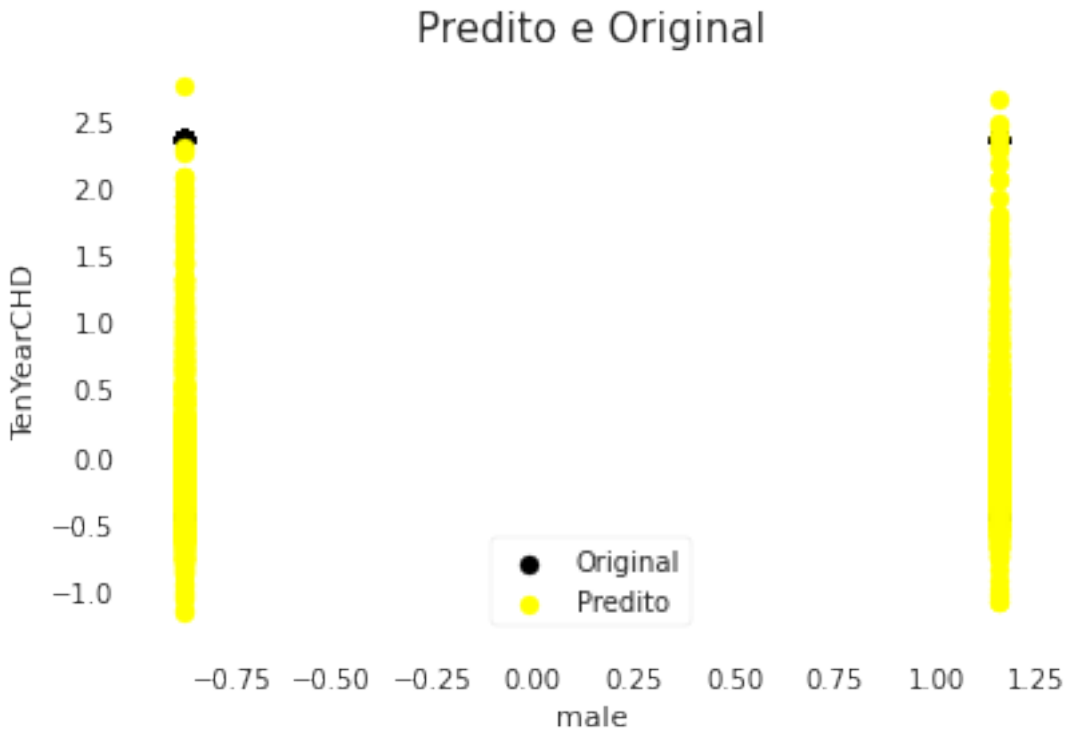
[57]:
```
plt.scatter(x_test[test_attr], y_test,  color='black')
plt.scatter(x_test[test_attr], y_pred, color='yellow')
plt.xlabel(test_attr)
plt.ylabel(output_attr)
plt.title('Predito e Original',fontsize=15)
plt.legend(['Original', 'Predito'])
plt.show()
```



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	SEQ
0	Regressão Linear - Treino	0.098059	0.903177	0.950356	3061.771151
1	SVR - RBF - Treino	0.028599	0.972733	0.986272	3297.563799
2	SVR - Linear - Treino	-0.104831	1.106346	1.051830	3750.512228
3	SVR - Sigmoide - Treino	-2119.951812	273.695635	16.543749	927828.201264
4	SVR - Polinomial - Treino	0.060553	0.940735	0.969915	3189.090403
5	MLP - Treino	0.341441	0.659462	0.812073	2235.577091

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

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