✨ Apresentação

Curso : Machine Learning

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Atividade de implementação de modelos e verificação de eficiência da estratégia adotada em problemas de regressão e classificação - 23/05/2023.

Este conjunto de dados contém classificações de consumo de combustível específicas do modelo e emissões estimadas de dióxido de carbono para novos veículos leves para venda no varejo no Canadá.

- MODELYEAR e.g. 2014
- MAKE e.g. Acura
- MODEL e.g. ILX
- VEHICLE CLASS e.g. SUV
- ENGINE SIZE e.g. 4.7
- CYLINDERS e.g 6
- TRANSMISSION e.g. A6
- FUEL CONSUMPTION in CITY(L/100 km) e.g. 9.9
- FUEL CONSUMPTION in HWY (L/100 km) e.g. 8.9
- FUEL CONSUMPTION COMB (L/100 km) e.g. 9.2
- CO2 EMISSIONS (g/km) e.g. 182 --> low --> 0

🎲 Coleta e Preparação

```
#Preparando o Ambiente
import pandas as pd

#Importando o arquivo de dados
df = pd.read_csv('/content/FuelConsumptionCo2.csv')

# Identifica os tipos de dados
df.dtypes
```

```
MODELYEAR                     int64
MAKE                         object
MODEL                        object
VEHICLECLASS                 object
ENGINESIZE                  float64
CYLINDERS                     int64
TRANSMISSION                 object
FUELTYPE                     object
FUELCONSUMPTION_CITY        float64
FUELCONSUMPTION_HWY         float64
FUELCONSUMPTION_COMB        float64
FUELCONSUMPTION_COMB_MPG      int64
CO2EMISSIONS                  int64
dtype: object
```

```
#Verificando o formato do conjunto de dados
print("Shape do conjunto de dados: ",df.shape)
```

```
Shape do conjunto de dados:  (1067, 13)
```

```
#Visualizando amostra do conjunto de dados
df.head(10)
```

	MODELYEAR	MAKE	MODEL	VEHICLECLASS	ENGINESIZE	CYLINDERS	TRANSMISSION
0	2014	ACURA	ILX	COMPACT	2.0	4	AS5
1	2014	ACURA	ILX	COMPACT	2.4	4	M6
2	2014	ACURA	ILX HYBRID	COMPACT	1.5	4	AV7
3	2014	ACURA	MDX 4WD	SUV - SMALL	3.5	6	AS6
4	2014	ACURA	RDX AWD	SUV - SMALL	3.5	6	AS6
5	2014	ACURA	RLX	MID-SIZE	3.5	6	AS6

Exiba a Matriz de Correlação entre as Variáveis

8	2014	ACURA	TL AWD	MID-SIZE	3.7	6	M6

```
df.columns
```

```
Index(['MODELYEAR', 'MAKE', 'MODEL', 'VEHICLECLASS', 'ENGINESIZE', 'CYLINDERS',
       'TRANSMISSION', 'FUELTYPE', 'FUELCONSUMPTION_CITY',
       'FUELCONSUMPTION_HWY', 'FUELCONSUMPTION_COMB',
       'FUELCONSUMPTION_COMB_MPG', 'CO2EMISSIONS'],
      dtype='object')
```

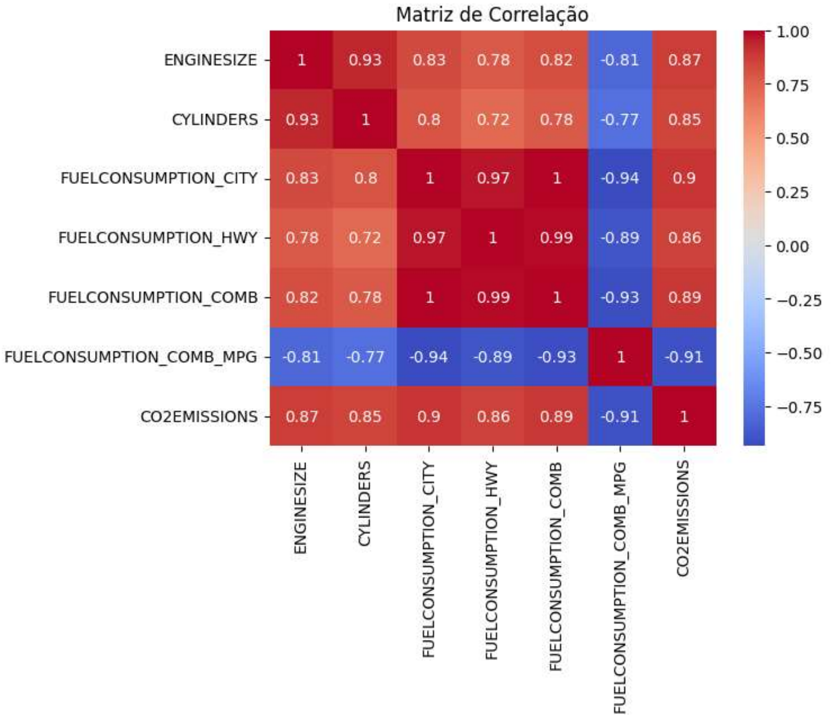
```
import seaborn as sns
import matplotlib.pyplot as plt

# Selecionar apenas as colunas relevantes (excluindo a primeira coluna)
df_subset = df.iloc[:, 1:]

# Calcular a matriz de correlação
correlation_matrix = df_subset.corr()

# Exibir matriz de correlação com heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Matriz de Correlação')
plt.show()
```

```
<ipython-input-571-1a5a6818485c>:8: FutureWarning: The default value of numeric_on
  correlation_matrix = df_subset.corr()
```



```
# Matrix de Correlação (Pearson)
corr = df.iloc[:, 1:].corr()
display(corr.style.background_gradient(cmap='BuGn').set_precision(2))
```

```
<ipython-input-572-06651845d749>:2: FutureWarning: The default value of numeric_on
  corr = df.iloc[:, 1:].corr()
<ipython-input-572-06651845d749>:3: FutureWarning: this method is deprecated in fa
  display(corr.style.background_gradient(cmap='BuGn').set_precision(2))
```

	ENGINESIZE	CYLINDERS	FUELCONSUMPTION_CITY	FUEL(
ENGINESIZE	1.00	0.93	0.83	
CYLINDERS	0.93	1.00	0.80	
FUELCONSUMPTION_CITY	0.83	0.80	1.00	
FUELCONSUMPTION_HWY	0.78	0.72	0.97	
FUELCONSUMPTION_COMB	0.82	0.78	1.00	
FUELCONSUMPTION_COMB_MPG	-0.81	-0.77	-0.94	
CO2EMISSIONS	0.87	0.85	0.90	

🎲 Atualize os nomes das colunas

```
df.rename(columns={'FUELCONSUMPTION_CITY': 'FUELCONSCITY'}, inplace=True)

df.rename(columns={'FUELCONSUMPTION_HWY': 'FUELCONSHWY'}, inplace=True)

df.rename(columns={'FUELCONSUMPTION_COMB': 'FUELCONSCOMB'}, inplace=True)

df.rename(columns={'FUELCONSUMPTION_COMB_MPG': 'FUELCONSCOMBMPG'}, inplace=True)
```

```
# Matrix de Correlação (Pearson)
corr = df.iloc[:, 1:].corr()
display(corr.style.background_gradient(cmap='BuGn').set_precision(2))
```

```
<ipython-input-574-06651845d749>:2: FutureWarning: The default value of numeric_on
  corr = df.iloc[:, 1:].corr()
<ipython-input-574-06651845d749>:3: FutureWarning: this method is deprecated in fa
  display(corr.style.background_gradient(cmap='BuGn').set_precision(2))
```

	ENGINESIZE	CYLINDERS	FUELCONSCITY	FUELCONSHWY	FUELCONSCO
ENGINESIZE	1.00	0.93	0.83	0.78	0.
CYLINDERS	0.93	1.00	0.80	0.72	0.
FUELCONSCITY	0.83	0.80	1.00	0.97	1.
FUELCONSHWY	0.78	0.72	0.97	1.00	0.
FUELCONSCOMB	0.82	0.78	1.00	0.99	1.
FUELCONSCOMBMPG	-0.81	-0.77	-0.94	-0.89	-0.
CO2EMISSIONS	0.87	0.85	0.90	0.86	0.

🎲 Crie um novo dataframe

```
# Criar novo DataFrame com as colunas desejadas
cdf = df.loc[:, ['ENGINESIZE', 'CYLINDERS', 'FUELCONSCOMB', 'CO2EMISSIONS']].copy()
cdf.head(10)
```

	ENGINESIZE	CYLINDERS	FUELCONSCOMB	CO2EMISSIONS
0	2.0	4	8.5	196
1	2.4	4	9.6	221
2	1.5	4	5.9	136
3	3.5	6	11.1	255

```
cdf.shape
```

```
(1067, 4)
```

```
6          3.5          6          10.1          232
```

Faça as seguintes análises

4.1. Separe os dados de treino e teste

```
# bibliotecas utilizadas
import numpy as np
import warnings
import os

# O Scikit-learn é uma biblioteca popular em Python para aprendizado de máquina e inclui o conjunto de dados Iris
from sklearn.linear_model import LogisticRegression
```

```
# Separando os dados de treino e teste
msk = np.random.rand(len(df)) < 0.80
dfTrain = cdf[msk]
dfTest = cdf[~msk]
```

```
print('Dataset de Treino = ', dfTrain.shape)
print('Dataset de Test   = ', dfTest.shape)
```

```
Dataset de Treino =  (878, 4)
Dataset de Test   =  (189, 4)
```

4.2. Import sklearn library

```
# Import sklearn library
from sklearn import linear_model
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
import numpy as np
```

4.3. Crie a variável com o modelo de Regressão Linear

```
# Linear Regression Model
regr = linear_model.LinearRegression()
```

4.4. Separe os dados de treino e teste

```
test_x_e = np.asanyarray(dfTest[['ENGINESIZE']])
test_x_c = np.asanyarray(dfTest[['CYLINDERS']])
test_x_f = np.asanyarray(dfTest[['FUELCONSCOMB']])

test_y = np.asanyarray(dfTest[['CO2EMISSIONS']])
```

4.5. Separe as Features de Treino e Teste

```
# Training X values (Variáveis independentes - Explanatory) e Y (Variável dependente - Target)
train_x_e = np.asanyarray(dfTrain[['ENGINESIZE']])
train_x_c = np.asanyarray(dfTrain[['CYLINDERS']])
train_x_f = np.asanyarray(dfTrain[['FUELCONSCOMB']])

train_y = np.asanyarray(dfTrain[['CO2EMISSIONS']])
```

4.6. Defina os valores para os coeficientes Theta 0: Intercepto e Theta 1: Coeficiente

```
# Ajuste da reta
regr.fit(train_x_e, train_y)
# Defining the values for coefficients - Theta 0: Intercepto e Theta 1: Coeficiente
print ('Coefficients: ', regr.coef_)
print ('Intercept: ', regr.intercept_)
```

```
Coefficients:  [[39.2397057]]
Intercept:  [124.9043427]
```

```
# Ajuste da reta
regr.fit(train_x_c, train_y)
# Defining the values for coefficients - Theta 0: Intercepto e Theta 1: Coeficiente
print ('Coefficients: ', regr.coef_)
print ('Intercept: ', regr.intercept_)
```

```
Coefficients:  [[30.10877116]]
Intercept:  [81.60362912]
```

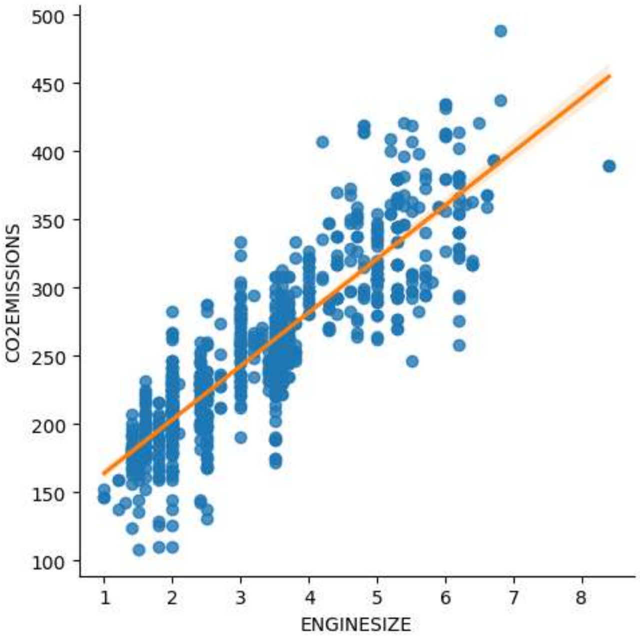
```
# Ajuste da reta
regr.fit(train_x_f, train_y)
# Defining the values for coefficients - Theta 0: Intercepto e Theta 1: Coeficiente
print ('Coefficients: ', regr.coef_)
print ('Intercept: ', regr.intercept_)
```

```
Coefficients:  [[15.89356536]]
Intercept:  [71.23987146]
```

4.7. Plot o Gráfico de Regressão Linear com a Reta Ajustada

```
sns.lmplot(x='ENGINESIZE', y='CO2EMISSIONS', line_kws={"color": "C1"}, data=dfTrain)
```

```
<seaborn.axisgrid.FacetGrid at 0x7ffa58b0e500>
```



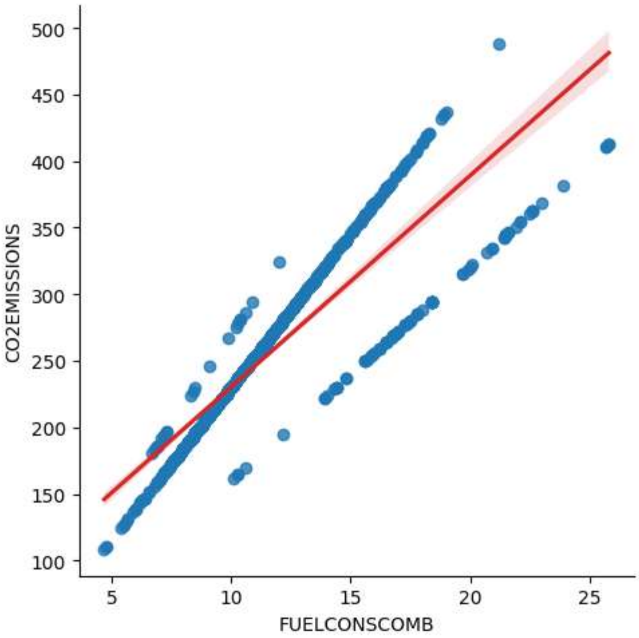
```
sns.lmplot(x='CYLINDERS', y='CO2EMISSIONS', line_kws={"color": "C2"}, data=dfTrain)
```

```
<seaborn.axisgrid.FacetGrid at 0x7ffa5e7e89d0>
```

500
450
400
350

```
sns.lmplot(x='FUELCONSCOMB', y='CO2EMISSIONS', line_kws={"color": "C3"}, data=dfTrain)
```

```
<seaborn.axisgrid.FacetGrid at 0x7ffa5e773be0>
```

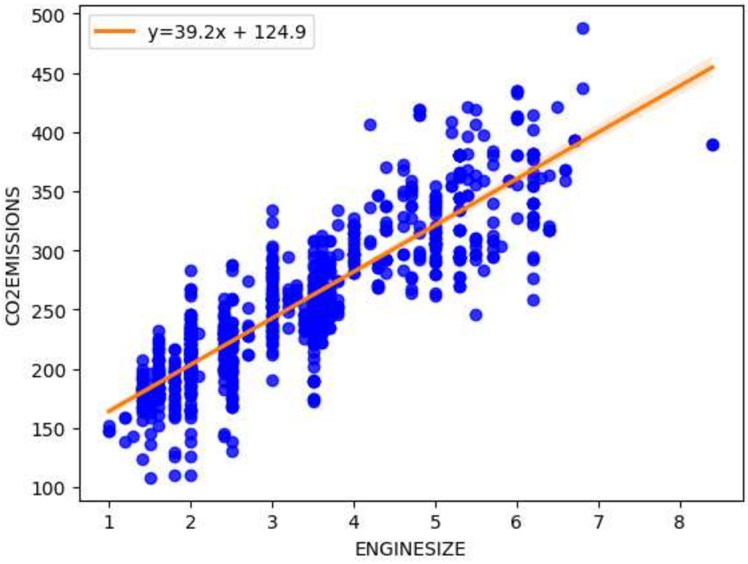


```
slope, intercept, r_value, p_value, std_err = stats.linregress(dfTrain['ENGINESIZE'],dfTrain['CO2EMISSIONS'])

ax = sns.regplot(x="ENGINESIZE",
                 y="CO2EMISSIONS",
                 data=dfTrain, color='b',
                 line_kws={'label':"y={0:.1f}x + {1:.1f}".format(slope,intercept),"color": "C1"})

ax.legend()

plt.show()
```

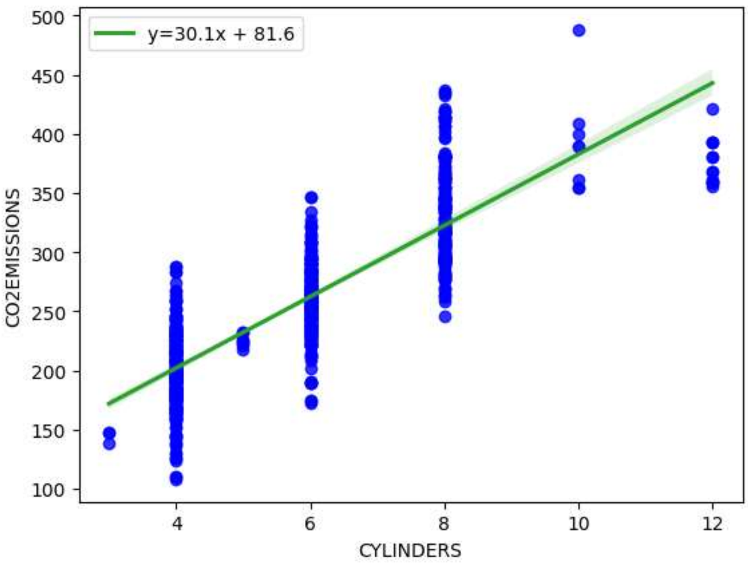


```
slope, intercept, r_value, p_value, std_err = stats.linregress(dfTrain['CYLINDERS'],dfTrain['CO2EMISSIONS'])

ax = sns.regplot(x="CYLINDERS",
                 y="CO2EMISSIONS",
                 data=dfTrain, color='b',
                 line_kws={'label':"y={0:.1f}x + {1:.1f}".format(slope,intercept),"color": "C2"})
```

```
ax.legend()

plt.show()
```

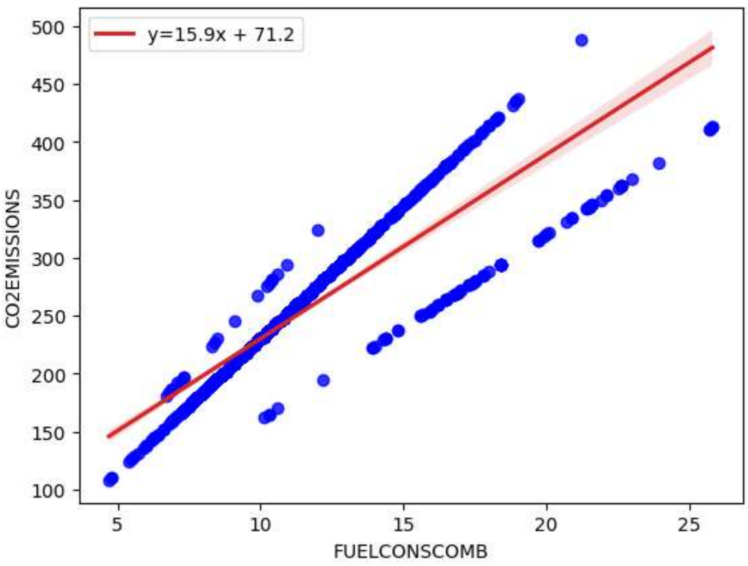


```
slope, intercept, r_value, p_value, std_err = stats.linregress(dfTrain['FUELCONSCOMB'],dfTrain['CO2EMISSIONS'])

ax = sns.regplot(x="FUELCONSCOMB",
                 y="CO2EMISSIONS",
                 data=dfTrain, color='b',
                 line_kws={'label':"y={0:.1f}x + {1:.1f}".format(slope,intercept),"color": "C3"})

ax.legend()

plt.show()
```



4.8. Encontre o R2-Score

```
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression

# Combinações de variáveis
combinations = [('FUELCONSCOMB',), ('CYLINDERS',), ('ENGINESIZE',)]

best_r2_score = 0
best_variable_combination = None

for combination in combinations:
    # Separar as variáveis independentes (X) e a variável dependente (y)
    X = df[list(combination)]
    y = df['CO2EMISSIONS']
    # Separar os dados em conjunto de treinamento e teste
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Criar o modelo de Regressão Linear
    regression_model = LinearRegression()

    # Treinar o modelo usando o conjunto de treinamento
    regression_model.fit(X_train, y_train)

    # Calcular o R2-Score
    r2_score = regression_model.score(X_test, y_test)

    print("Variáveis:", combination)
    print("R2-Score:", r2_score)
```

```
Variáveis: ('FUELCONSCOMB',)
R2-Score: 0.8071474868274242
Variáveis: ('CYLINDERS',)
R2-Score: 0.7317140029783895
Variáveis: ('ENGINESIZE',)
R2-Score: 0.7615595731934373
```

🎲 Encontre o Melhor ajuste (R2-Score)

Entre as seguintes combinações de variáveis:

- FUELCONSCOMB & CO2EMISSIONS
- CYLINDERS & CO2EMISSIONS
- ENGINESIZE & CO2EMISSIONS

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score

# Lista das combinações de variáveis
combinations_pair = [('FUELCONSCOMB', 'CO2EMISSIONS'),
               ('CYLINDERS', 'CO2EMISSIONS'),
               ('ENGINESIZE', 'CO2EMISSIONS')]

best_r2_score = -1  # Inicialização do melhor R2-Score

for feature, target in combinations_pair:
    # Separe os dados de treino e teste
    train_cdf, test_cdf = train_test_split(cdf, test_size=0.2, random_state=42)

    # Crie a variável com o modelo de Regressão Linear
    model = LinearRegression()

    # Separe as Features de Treino e Teste
    train_x = train_cdf[[feature]]
    train_y = train_cdf[target]
    test_x = test_cdf[[feature]]
    test_y = test_cdf[target]

    # Rode o Modelo
    model.fit(train_x, train_y)

    # Encontre o R2-Score
    y_pred = model.predict(test_x)
    r2 = r2_score(test_y, y_pred)

    if r2 > best_r2_score:
        best_r2_score = r2
        best_feature = feature
        best_target = target

print("Melhor ajuste:")
print("Variável de Feature:", best_feature)
print("Variável de Target:", best_target)
print("Melhor R2-Score:", best_r2_score)
```

```
Melhor ajuste:
Variável de Feature: FUELCONSCOMB
Variável de Target: CO2EMISSIONS
Melhor R2-Score: 0.8071474868274242
```

🎲 Regressão Linear Múltipla

Usando as variáveis:

- ENGINESIZE
- CYLINDERS
- FUELCONSCOMB

```
# Import sklearn library
from sklearn import linear_model
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats

# Linear Regression Model
regr = linear_model.LinearRegression()

# Training X values (Var Independent - Explanatory)  e Y (Var Dependent - Target)
train_x = np.asanyarray(dfTrain[['ENGINESIZE', 'CYLINDERS', 'FUELCONSCOMB']])
train_y = np.asanyarray(dfTrain[['CO2EMISSIONS']])

# Performing Line Adjustment
regr.fit(train_x, train_y)

# Defining the values for coefficients - Theta 0: Intercepto e Theta 1: Coeficiente
print ('Coefficients: ', regr.coef_)
print ('Intercept: ', regr.intercept_)
```

```
Coefficients:  [[11.43455109  7.3905759   9.28830002]]
Intercept:  [67.05954605]
```

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