Classificação - Segundo Trabalho IA - 2023.2

Para a classificação com algoritmo de regressão logística, foi utilizada a seguinte base de dados: Heart Attack Analysis

Segue o código com os comentários nas células anteriores:

Importando as bibliotecas e funções.

In [ ]:
```
import piplite
await piplite.install('seaborn')
```

In [ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
from sklearn.neural_network import MLPClassifier
from sklearn import metrics
```

Base de dados de análise de ataques cardíacos

Esse dataset tem informações sobre pacientes, com o objetivo de prever se terão ataques cardíacos ou não.

In [ ]:
```
heart = pd.read_csv('data/heart.csv')
heart.head()
```

Out[ ]:

	age	sex	cp	trtbps	chol	fbs	restecg	thalachh	exng	oldpeak	slp	caa	thall
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2

O conjunto de dados é baseado em aspectos como idade, sexo, pressão arterial, índice de colesterol no sangue, entre outros.

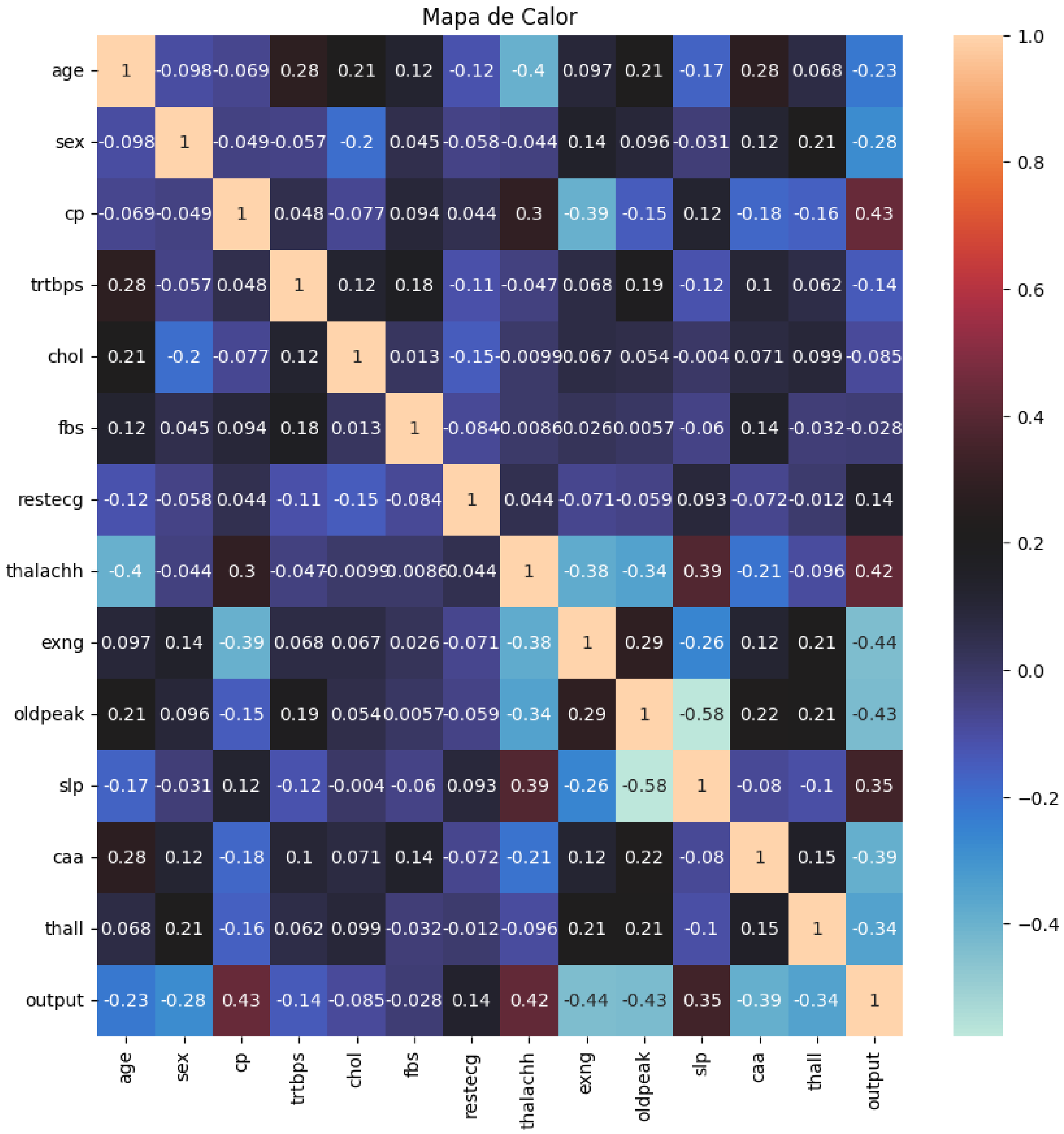
In [ ]:
```
heart.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       303 non-null    int64  
 1   sex       303 non-null    int64  
 2   cp        303 non-null    int64  
 3   trtbps    303 non-null    int64  
 4   chol      303 non-null    int64  
 5   fbs       303 non-null    int64  
 6   restecg   303 non-null    int64  
 7   thalachh  303 non-null    int64  
 8   exng      303 non-null    int64  
 9   oldpeak   303 non-null    float64
 10  slp       303 non-null    int64  
 11  caa       303 non-null    int64  
 12  thall     303 non-null    int64  
 13  output    303 non-null    int64  
dtypes: float64(1), int64(13)
memory usage: 33.2 KB
```

Heatmap

O mapa térmico (heatmap) de correlação é utilizado para verificar a força das relações entre as variáveis no conjunto de dados.

In [ ]:
```
plt.figure(figsize=(10, 10))
sns.heatmap(heart.corr(), annot=True, cmap='icefire').set_title('Mapa de Calor')
plt.show()
```



Para obter-se uma melhor observação dos valores em relação ao resultado (coluna 'output'), os resultados da correlação são elencados abaixo.

```
In [ ]: correlacoes = heart.corr().loc[:, 'output'].drop('output')
        maiores_correlacoes = correlacoes.nlargest(10)
        print(f"Os maiores valores de correlação com o resultado:")
        print(maiores_correlacoes)
```

```
Os maiores valores de correlação com o resultado:
cp          0.433798
thalachh    0.421741
slp         0.345877
restecg     0.137230
fbs        -0.028046
chol       -0.085239
trtbps     -0.144931
age        -0.225439
sex        -0.280937
thall      -0.344029
Name: output, dtype: float64
```

Os dados são dividos entre treino e teste.

```
In [ ]: X = heart.drop('output', axis = 1)
        y = heart['output']

        X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, randc
```

Em seguida, os dados são normalizados.

```
In [ ]: scaler = StandardScaler()
        X_train = scaler.fit_transform(X_train)
        X_test = scaler.transform(X_test)
```

Regressão Logística

É realizada a chamada da função de Regressão Logística. O modelo é treinado e testado.

```
In [ ]: lr = LogisticRegression(max_iter = 1000)
        lr.fit(X_train, y_train)
        y_pred = lr.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)
        print(f"Acurácia da Regressão Logística: {accuracy:.4f}")
        print("Classification Report:")
        print(classification_report(y_test, y_pred))
```

```
Acurácia da Regressão Logística: 0.8132
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.78      0.79        41
           1       0.82      0.84      0.83        50

    accuracy                           0.81        91
   macro avg       0.81      0.81      0.81        91
weighted avg       0.81      0.81      0.81        91
```

SVM

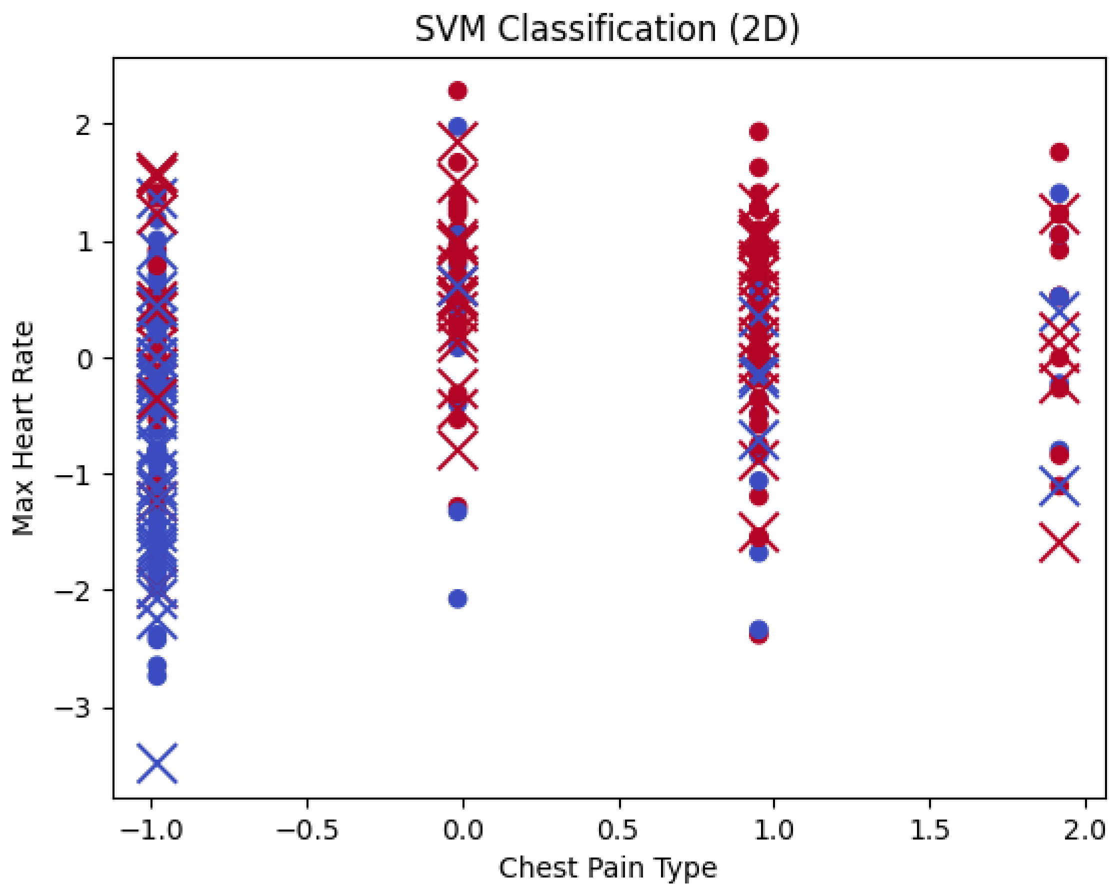
É realizada a chamada da função de Máquina de Vetor de Suporte. O modelo é treinado e testado.

```
In [ ]: svm_classifier = SVC(kernel = 'rbf', C = 1, gamma = 'scale', random_state = 42)
        svm_classifier.fit(X_train, y_train)
        y_pred = svm_classifier.predict(X_test)
        accuracy = accuracy_score(y_test, y_pred)
        print(f"Acurácia do método SVM: {accuracy:.4f}")
        print("Classification Report:")
        print(classification_report(y_test, y_pred))
```

```
Acurácia do método SVM: 0.8242
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.80      0.80        41
           1       0.84      0.84      0.84        50

    accuracy                           0.82        91
   macro avg       0.82      0.82      0.82        91
weighted avg       0.82      0.82      0.82        91
```

Para observação no gráfico, foram escolhidas as colunas referentes ao tipo de dor no peito ('cp') e à frequência cardíaca máxima alcançada.

In [ ]:
```
plt.scatter(X_train[:, 2], X_train[:, 7], c = y_train, cmap = plt.cm.coolwarm)
plt.scatter(X_test[:, 2], X_test[:, 7], c=y_test, cmap=plt.cm.coolwarm, marker='
plt.title('SVM Classification (2D)')
plt.xlabel('Chest Pain Type')
plt.ylabel('Max Heart Rate')
plt.show()
```



MLP

É realizada a chamada da função de Percetron de Múltiplas Camadas. O modelo é treinado e testado, suas iterações são apresentadas.

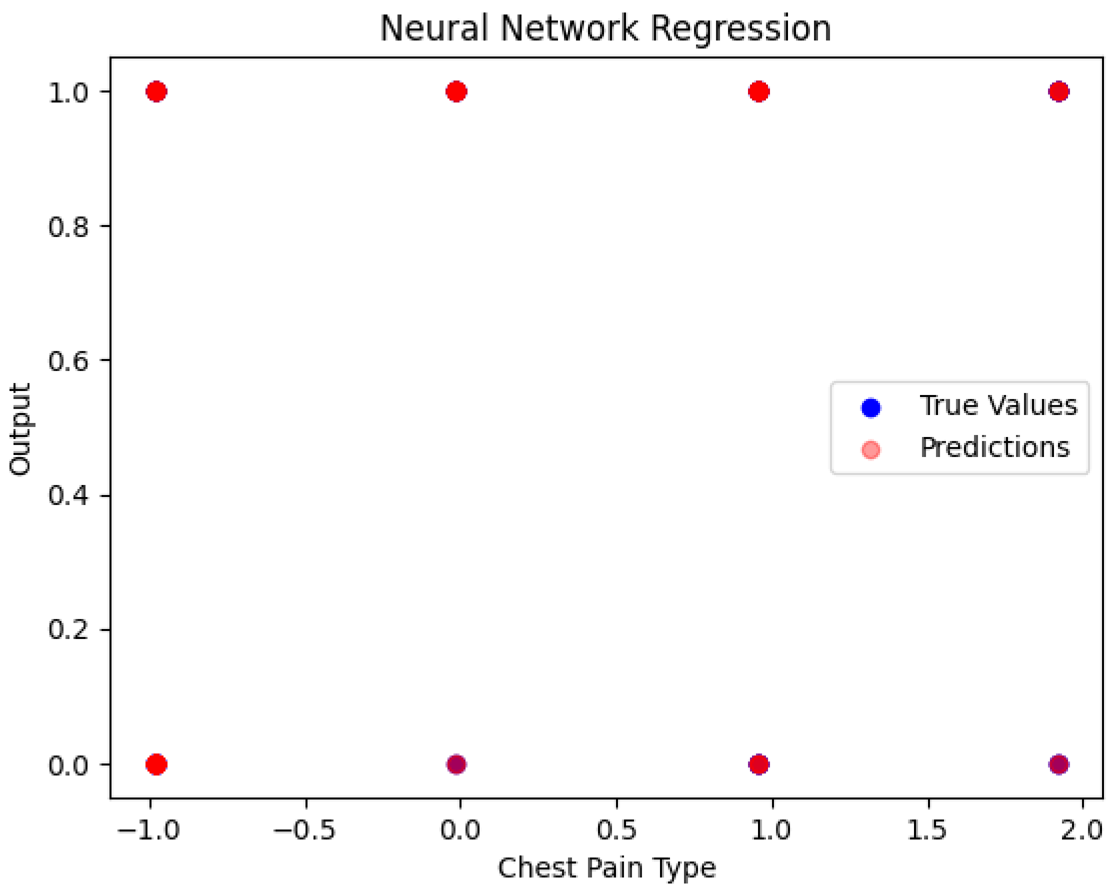
In [ ]:
```
mlp_classifier = MLPClassifier(hidden_layer_sizes=(50, 50), activation = 'relu',
mlp_classifier.fit(X_train, y_train)
y_pred = mlp_classifier.predict(X_test)
```

```python
accuracy = accuracy_score(y_test, y_pred)
print(f"Acurácia do método MLP: {accuracy:.4f}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Training loss did not improve more than tol=0.000100 for 10 consecutive epochs. S
topping.
Acurácia do método MLP: 0.8242
Classification Report:
              precision    recall  f1-score   support

           0       0.79      0.83      0.81        41
           1       0.85      0.82      0.84        50

    accuracy                           0.82        91
   macro avg       0.82      0.82      0.82        91
weighted avg       0.83      0.82      0.82        91
```

Novamente, observa-se o resultado de acordo com as varíaveis mais influentes no resultado.

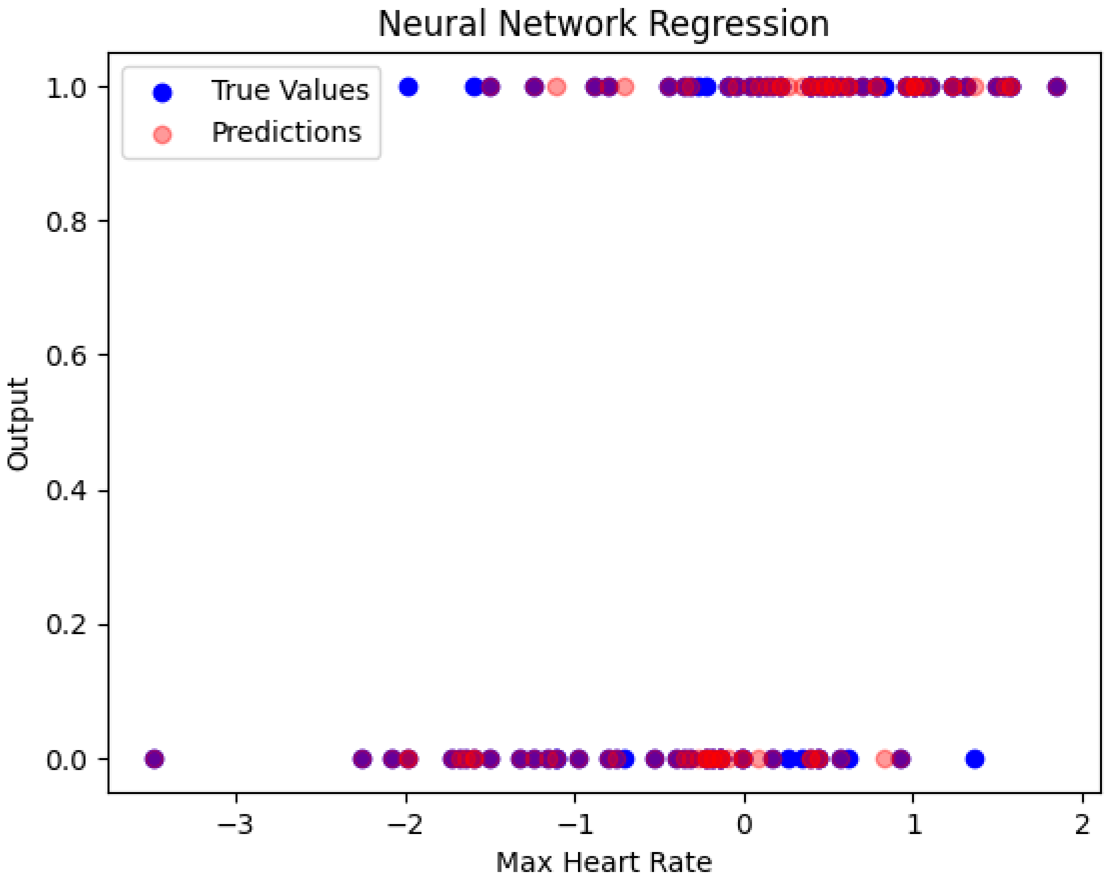
In [ ]:
```
plt.scatter(X_test[:, 2], y_test, color='blue')
plt.scatter(X_test[:, 2], y_pred, color = 'red', alpha =.4)

plt.xlabel('Chest Pain Type')
plt.ylabel('Output')
plt.title('Neural Network Regression')

plt.legend(['True Values', 'Predictions'])
plt.show()
```



In [ ]:
```
plt.scatter(X_test[:, 7], y_test, color='blue')
plt.scatter(X_test[:, 7], y_pred, color = 'red', alpha =.4)

plt.xlabel('Max Heart Rate')
plt.ylabel('Output')
```

```python
plt.title('Neural Network Regression')

plt.legend(['True Values', 'Predictions'])
plt.show()
```



Resultados

Observando a acurácia, destaca-se o desempenho muito semelhante entre os três métodos. Um possível motivo para isso é a base de dados não possuir uma complexidade alta a ponto de precisar de abordagens diferentes para interpretar correta e satisfatoriamente os dados, de acordo com o requisito do trabalho (80% de acurácia). Assim, os métodos SVM e MLP, mais complexos, obtiveram um resultado ligeiramente superior à Regressão Logística.

Regressão - Trabaho IA - 2023.2

Para a classificação com algoritmo de regressão linear, SVM e MLP foi utilizada a seguinte base de dados: neural net regression data. Segue o código com os comentários nas células anteriores: Importando as bibliotecas e funções.

```
import pandas as pd
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
```

Base de dados

Lendo dados do arquivo CSV

```
profit = pd.read_csv('fake_reg.csv')
profit.head()
```

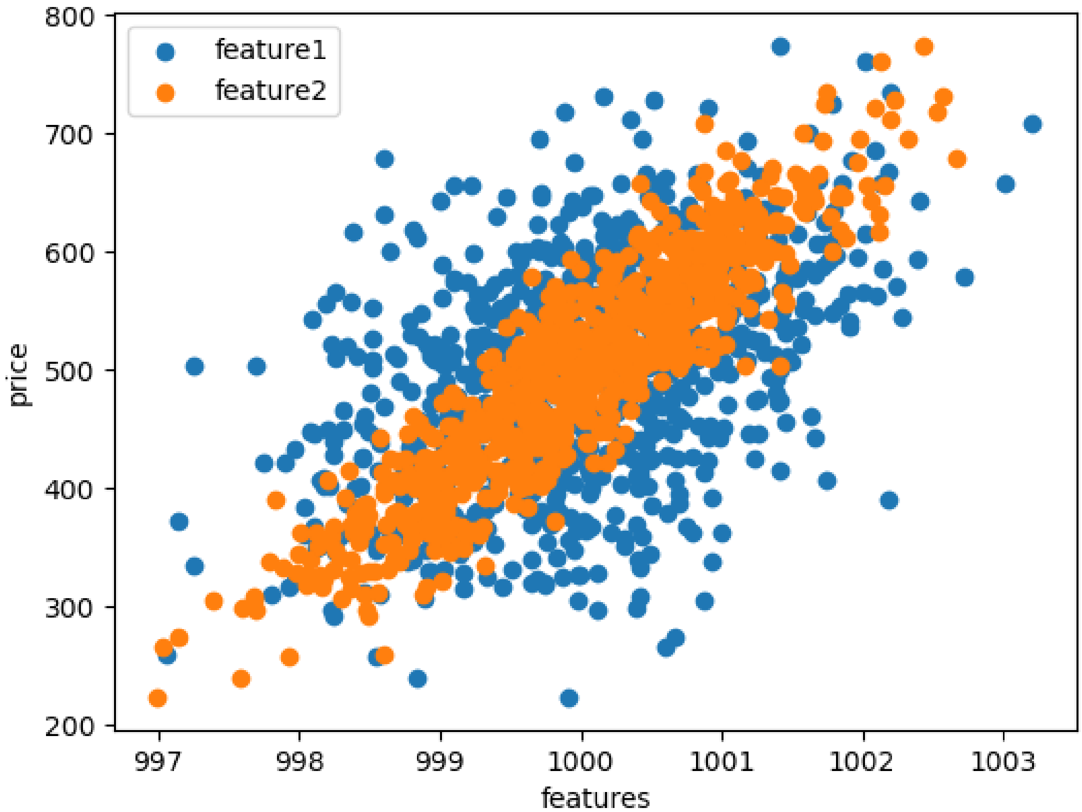
	price	feature1	feature2
0	461.527929	999.787558	999.766096
1	548.130011	998.861615	1001.042403
2	410.297162	1000.070267	998.844015
3	540.382220	999.952251	1000.440940
4	546.024553	1000.446011	1000.338531

dividindo em treinamento(80%) e teste(20%):

```
x_val = profit.drop(['price'], axis=1)
y_val = profit['price']
X_train, X_test, y_train, y_test = train_test_split(x_val, y_val,
test_size=0.2, random_state=42)
```

Plotando os dados

```
plt.scatter(X_train['feature1'], y_train, label='feature1')
plt.scatter(X_train['feature2'], y_train, label='feature2')
#plt.scatter(X_train['Marketing Spend'], y_train, label='Marketing
Spend Budget')
plt.xlabel('features')
plt.ylabel('price')
plt.legend()
plt.show()
```



Normalizando os dados

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_train) # Don't cheat - fit only on training data
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test) # apply same transformation to test
data
```

Criando e utilizando MLP para regreção

```
from sklearn.neural_network import MLPRegressor
from sklearn.datasets import make_regression
from sklearn.model_selection import train_test_split
model = MLPRegressor(
    hidden_layer_sizes=[62,62],
    activation='relu',
    solver='adam',
    verbose=True,
    random_state=1,
    max_iter=1400)
model = model.fit(X_train, y_train)
```

```
Iteration 1, loss = 127663.64691961
Iteration 2, loss = 127554.74469284
Iteration 3, loss = 127444.92467452
Iteration 4, loss = 127332.32677298
Iteration 5, loss = 127217.03250398
Iteration 6, loss = 127095.17022512
Iteration 7, loss = 126966.26891460
Iteration 8, loss = 126827.70731930
Iteration 9, loss = 126675.78869056
Iteration 10, loss = 126509.50896640
Iteration 11, loss = 126327.40313574
Iteration 12, loss = 126127.01491168
Iteration 13, loss = 125902.34616198
Iteration 14, loss = 125659.52946040
Iteration 15, loss = 125386.01183819
Iteration 16, loss = 125082.56318260
Iteration 17, loss = 124754.38114170
Iteration 18, loss = 124387.71711036
Iteration 19, loss = 123988.48180558
Iteration 20, loss = 123547.98989864
Iteration 21, loss = 123065.03557686
Iteration 22, loss = 122539.39076850
Iteration 23, loss = 121964.16799312
Iteration 24, loss = 121343.16477053
Iteration 25, loss = 120662.51391963
Iteration 26, loss = 119944.68825320
Iteration 27, loss = 119147.83614609
Iteration 28, loss = 118303.33343480
Iteration 29, loss = 117386.81436537
Iteration 30, loss = 116413.51552792
Iteration 31, loss = 115367.59573187
Iteration 32, loss = 114235.39319650
Iteration 33, loss = 113037.22379949
Iteration 34, loss = 111761.97066179
Iteration 35, loss = 110405.32063594
Iteration 36, loss = 108967.23207268
Iteration 37, loss = 107443.22153157
Iteration 38, loss = 105860.70513740
Iteration 39, loss = 104172.99766098
Iteration 40, loss = 102408.32216260
Iteration 41, loss = 100572.88876531
Iteration 42, loss = 98632.73550495
Iteration 43, loss = 96661.54484015
Iteration 44, loss = 94555.92355812
Iteration 45, loss = 92407.56821236
Iteration 46, loss = 90169.57229675
Iteration 47, loss = 87893.95129082
Iteration 48, loss = 85509.18482856
Iteration 49, loss = 83105.59818814
Iteration 50, loss = 80610.28064933
```

```
Iteration 51, loss = 78073.27136360
Iteration 52, loss = 75490.97925757
Iteration 53, loss = 72865.45255015
Iteration 54, loss = 70194.11850501
Iteration 55, loss = 67519.88644987
Iteration 56, loss = 64835.49462285
Iteration 57, loss = 62120.44078938
Iteration 58, loss = 59370.01268115
Iteration 59, loss = 56641.61836670
Iteration 60, loss = 53937.20567435
Iteration 61, loss = 51247.08642080
Iteration 62, loss = 48583.52888027
Iteration 63, loss = 45950.17160806
Iteration 64, loss = 43354.50343651
Iteration 65, loss = 40836.22305860
Iteration 66, loss = 38345.06448705
Iteration 67, loss = 35942.08279910
Iteration 68, loss = 33599.40539349
Iteration 69, loss = 31361.42548150
Iteration 70, loss = 29185.48392180
Iteration 71, loss = 27112.63489903
Iteration 72, loss = 25137.61853971
Iteration 73, loss = 23288.76353799
Iteration 74, loss = 21510.10598070
Iteration 75, loss = 19851.52637978
Iteration 76, loss = 18297.93737848
Iteration 77, loss = 16847.93153257
Iteration 78, loss = 15526.00393182
Iteration 79, loss = 14313.38077571
Iteration 80, loss = 13184.22480798
Iteration 81, loss = 12172.96462457
Iteration 82, loss = 11251.05955193
Iteration 83, loss = 10420.02935285
Iteration 84, loss = 9685.60320504
Iteration 85, loss = 9003.92873212
Iteration 86, loss = 8444.22402966
Iteration 87, loss = 7926.85703235
Iteration 88, loss = 7473.90797617
Iteration 89, loss = 7087.57367107
Iteration 90, loss = 6742.06750706
Iteration 91, loss = 6442.88115625
Iteration 92, loss = 6176.53348477
Iteration 93, loss = 5956.37798362
Iteration 94, loss = 5755.89831947
Iteration 95, loss = 5589.97420835
Iteration 96, loss = 5435.56876658
Iteration 97, loss = 5298.53711057
Iteration 98, loss = 5182.19466812
Iteration 99, loss = 5076.83212509
Iteration 100, loss = 4983.16712118
```

```
Iteration 101, loss = 4892.49480302
Iteration 102, loss = 4812.44782891
Iteration 103, loss = 4732.88593559
Iteration 104, loss = 4659.57640874
Iteration 105, loss = 4590.55027968
Iteration 106, loss = 4523.20506433
Iteration 107, loss = 4460.34629229
Iteration 108, loss = 4393.77679044
Iteration 109, loss = 4331.59895662
Iteration 110, loss = 4271.44450967
Iteration 111, loss = 4211.35980571
Iteration 112, loss = 4152.13077762
Iteration 113, loss = 4094.27210203
Iteration 114, loss = 4035.83282913
Iteration 115, loss = 3979.08485024
Iteration 116, loss = 3924.15720994
Iteration 117, loss = 3867.65232543
Iteration 118, loss = 3811.39627582
Iteration 119, loss = 3756.79483508
Iteration 120, loss = 3702.03388946
Iteration 121, loss = 3648.80678280
Iteration 122, loss = 3594.70078230
Iteration 123, loss = 3542.19999375
Iteration 124, loss = 3489.54430948
Iteration 125, loss = 3437.13166311
Iteration 126, loss = 3385.37684836
Iteration 127, loss = 3334.15985739
Iteration 128, loss = 3283.02659085
Iteration 129, loss = 3232.55302920
Iteration 130, loss = 3181.36603405
Iteration 131, loss = 3132.00861331
Iteration 132, loss = 3080.31565055
Iteration 133, loss = 3029.49632603
Iteration 134, loss = 2980.09430726
Iteration 135, loss = 2933.29450235
Iteration 136, loss = 2884.32406953
Iteration 137, loss = 2836.11938117
Iteration 138, loss = 2788.60356460
Iteration 139, loss = 2742.63207013
Iteration 140, loss = 2694.17346421
Iteration 141, loss = 2649.81015191
Iteration 142, loss = 2604.82109605
Iteration 143, loss = 2559.98848871
Iteration 144, loss = 2516.26657290
Iteration 145, loss = 2471.34184722
Iteration 146, loss = 2429.83339692
Iteration 147, loss = 2387.36454305
Iteration 148, loss = 2345.40025884
Iteration 149, loss = 2303.95367044
Iteration 150, loss = 2263.13794944
```

```
Iteration 151, loss = 2223.47711894
Iteration 152, loss = 2185.06940314
Iteration 153, loss = 2145.25832236
Iteration 154, loss = 2107.64291900
Iteration 155, loss = 2067.88326966
Iteration 156, loss = 2031.88049662
Iteration 157, loss = 1995.49589249
Iteration 158, loss = 1958.92117581
Iteration 159, loss = 1922.90169040
Iteration 160, loss = 1887.91916134
Iteration 161, loss = 1854.21424517
Iteration 162, loss = 1819.06378722
Iteration 163, loss = 1786.65761024
Iteration 164, loss = 1753.56308313
Iteration 165, loss = 1722.05404158
Iteration 166, loss = 1689.56674188
Iteration 167, loss = 1659.58367230
Iteration 168, loss = 1628.02629439
Iteration 169, loss = 1597.99882118
Iteration 170, loss = 1568.32138430
Iteration 171, loss = 1539.78959085
Iteration 172, loss = 1510.13782283
Iteration 173, loss = 1482.14961753
Iteration 174, loss = 1454.51745057
Iteration 175, loss = 1427.22664809
Iteration 176, loss = 1400.22925796
Iteration 177, loss = 1374.02449431
Iteration 178, loss = 1347.81495275
Iteration 179, loss = 1322.18414405
Iteration 180, loss = 1296.73658159
Iteration 181, loss = 1272.14703481
Iteration 182, loss = 1248.37442157
Iteration 183, loss = 1224.28039354
Iteration 184, loss = 1201.21260794
Iteration 185, loss = 1178.06959954
Iteration 186, loss = 1155.46550875
Iteration 187, loss = 1133.41979096
Iteration 188, loss = 1112.25178157
Iteration 189, loss = 1090.14565069
Iteration 190, loss = 1069.66698692
Iteration 191, loss = 1049.70430929
Iteration 192, loss = 1028.31499794
Iteration 193, loss = 1009.12008224
Iteration 194, loss = 989.30017988
Iteration 195, loss = 971.09335936
Iteration 196, loss = 951.47540420
Iteration 197, loss = 933.05174947
Iteration 198, loss = 915.16210875
Iteration 199, loss = 898.00284780
Iteration 200, loss = 880.16188163
```

```
Iteration 201, loss = 862.59464675
Iteration 202, loss = 846.54078974
Iteration 203, loss = 829.72354718
Iteration 204, loss = 814.07330294
Iteration 205, loss = 797.52210110
Iteration 206, loss = 781.67070515
Iteration 207, loss = 767.50263440
Iteration 208, loss = 751.87402317
Iteration 209, loss = 737.11686319
Iteration 210, loss = 723.04664269
Iteration 211, loss = 709.31826895
Iteration 212, loss = 694.67660239
Iteration 213, loss = 681.27440032
Iteration 214, loss = 668.48861642
Iteration 215, loss = 655.38272255
Iteration 216, loss = 642.25857721
Iteration 217, loss = 629.84662690
Iteration 218, loss = 617.76999760
Iteration 219, loss = 606.24835121
Iteration 220, loss = 594.17503485
Iteration 221, loss = 582.33729462
Iteration 222, loss = 571.49064809
Iteration 223, loss = 560.09236950
Iteration 224, loss = 549.52754396
Iteration 225, loss = 538.96962250
Iteration 226, loss = 528.63831017
Iteration 227, loss = 517.96119680
Iteration 228, loss = 508.45444836
Iteration 229, loss = 498.59772498
Iteration 230, loss = 488.76443339
Iteration 231, loss = 479.78106545
Iteration 232, loss = 470.66512891
Iteration 233, loss = 461.20389545
Iteration 234, loss = 452.63622276
Iteration 235, loss = 443.74873398
Iteration 236, loss = 435.48724982
Iteration 237, loss = 426.75313803
Iteration 238, loss = 418.75030898
Iteration 239, loss = 410.46779070
Iteration 240, loss = 402.53975226
Iteration 241, loss = 394.73773001
Iteration 242, loss = 387.45932964
Iteration 243, loss = 379.60431482
Iteration 244, loss = 372.40634609
Iteration 245, loss = 365.14057439
Iteration 246, loss = 358.02281052
Iteration 247, loss = 351.15029458
Iteration 248, loss = 344.49682908
Iteration 249, loss = 337.69509515
Iteration 250, loss = 331.03296424
```

```
Iteration 251, loss = 324.88614864
Iteration 252, loss = 318.74498912
Iteration 253, loss = 312.38736349
Iteration 254, loss = 306.44557463
Iteration 255, loss = 300.41531293
Iteration 256, loss = 294.35163681
Iteration 257, loss = 288.79469953
Iteration 258, loss = 283.17081549
Iteration 259, loss = 277.81681716
Iteration 260, loss = 272.27605779
Iteration 261, loss = 267.04219486
Iteration 262, loss = 262.08381451
Iteration 263, loss = 256.91140223
Iteration 264, loss = 251.94705217
Iteration 265, loss = 247.15309464
Iteration 266, loss = 242.52092082
Iteration 267, loss = 237.76783725
Iteration 268, loss = 233.24160431
Iteration 269, loss = 228.68790523
Iteration 270, loss = 224.35231502
Iteration 271, loss = 220.37274080
Iteration 272, loss = 215.91368731
Iteration 273, loss = 211.90044656
Iteration 274, loss = 207.93000668
Iteration 275, loss = 204.00499960
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Iteration 860, loss = 12.27468124
Iteration 861, loss = 12.27203684
Iteration 862, loss = 12.26995911
Iteration 863, loss = 12.26397821
Iteration 864, loss = 12.27115901
Iteration 865, loss = 12.27358604
Iteration 866, loss = 12.25440806
Iteration 867, loss = 12.26924328
Iteration 868, loss = 12.26633705
Iteration 869, loss = 12.25222271
Iteration 870, loss = 12.25788281
Iteration 871, loss = 12.24605415
Iteration 872, loss = 12.24697651
Iteration 873, loss = 12.25387667
Iteration 874, loss = 12.23491770
Iteration 875, loss = 12.23617717
Iteration 876, loss = 12.24661398
Iteration 877, loss = 12.22618634
Iteration 878, loss = 12.24327635
Iteration 879, loss = 12.22824757
Iteration 880, loss = 12.21378895
Iteration 881, loss = 12.21004824
Iteration 882, loss = 12.22394622
Iteration 883, loss = 12.22252781
Iteration 884, loss = 12.22003893
Iteration 885, loss = 12.22053286
Iteration 886, loss = 12.21404003
Iteration 887, loss = 12.21579023
Iteration 888, loss = 12.20261724
Iteration 889, loss = 12.21477867
Iteration 890, loss = 12.21196331
Iteration 891, loss = 12.18965935
Iteration 892, loss = 12.22040145
Iteration 893, loss = 12.18730327
```

```
Iteration 894, loss = 12.18733008
Iteration 895, loss = 12.21534242
Iteration 896, loss = 12.17703651
Iteration 897, loss = 12.18539147
Iteration 898, loss = 12.17182883
Iteration 899, loss = 12.17165868
Iteration 900, loss = 12.16177216
Iteration 901, loss = 12.17394806
Iteration 902, loss = 12.17221693
Iteration 903, loss = 12.16772313
Iteration 904, loss = 12.16825965
Iteration 905, loss = 12.14527510
Iteration 906, loss = 12.15566161
Iteration 907, loss = 12.15366184
Iteration 908, loss = 12.14853896
Iteration 909, loss = 12.14337072
Iteration 910, loss = 12.14511402
Iteration 911, loss = 12.15512499
Iteration 912, loss = 12.13612177
Iteration 913, loss = 12.13434514
Iteration 914, loss = 12.13376529
Iteration 915, loss = 12.13093740
Iteration 916, loss = 12.12445169
Iteration 917, loss = 12.12136886
Iteration 918, loss = 12.13690841
Iteration 919, loss = 12.10605462
Iteration 920, loss = 12.11614664
Iteration 921, loss = 12.12214794
Iteration 922, loss = 12.10983164
Iteration 923, loss = 12.10709778
Iteration 924, loss = 12.11566436
Iteration 925, loss = 12.10060265
Iteration 926, loss = 12.11107637
Iteration 927, loss = 12.08433447
Iteration 928, loss = 12.08297917
Iteration 929, loss = 12.09753573
Iteration 930, loss = 12.08577139
Iteration 931, loss = 12.08531963
Iteration 932, loss = 12.08921580
Iteration 933, loss = 12.07857273
Iteration 934, loss = 12.07827668
Iteration 935, loss = 12.07448953
Iteration 936, loss = 12.07284879
Iteration 937, loss = 12.07350690
Iteration 938, loss = 12.07547404
Iteration 939, loss = 12.06436984
Iteration 940, loss = 12.06706033
Iteration 941, loss = 12.06293206
Iteration 942, loss = 12.07743856
```

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Iteration 943, loss = 12.04845523
Iteration 944, loss = 12.06593075
Iteration 945, loss = 12.06509896
Iteration 946, loss = 12.04223003
Iteration 947, loss = 12.04685290
Iteration 948, loss = 12.04076626
Iteration 949, loss = 12.04093753
Iteration 950, loss = 12.02961785
Iteration 951, loss = 12.03546856
Iteration 952, loss = 12.03359577
Iteration 953, loss = 12.03557247
Iteration 954, loss = 12.03681044
Iteration 955, loss = 12.02672107
Iteration 956, loss = 12.02500488
Iteration 957, loss = 12.02744439
Iteration 958, loss = 12.02856905
Iteration 959, loss = 12.03617253
Iteration 960, loss = 12.02087239
Iteration 961, loss = 12.02652999
Iteration 962, loss = 12.00909034
Iteration 963, loss = 12.00082703
Iteration 964, loss = 12.01238000
Iteration 965, loss = 12.00045847
Iteration 966, loss = 12.01610998
Iteration 967, loss = 12.00313883
Iteration 968, loss = 11.99265574
Iteration 969, loss = 12.01532735
Iteration 970, loss = 12.00805097
Iteration 971, loss = 12.01914730
Iteration 972, loss = 11.99467873
Iteration 973, loss = 11.98712103
Iteration 974, loss = 11.99077557
Iteration 975, loss = 11.99620781
Iteration 976, loss = 11.99023597
Iteration 977, loss = 12.02290562
Iteration 978, loss = 11.99750169
Iteration 979, loss = 11.99207492
Iteration 980, loss = 12.00676676
Iteration 981, loss = 12.02228869
Iteration 982, loss = 12.00075333
Iteration 983, loss = 11.98754963
Iteration 984, loss = 11.97595760
Iteration 985, loss = 11.97757728
Iteration 986, loss = 11.97924427
Iteration 987, loss = 11.98274545
Iteration 988, loss = 11.96365330
Iteration 989, loss = 11.96276812
Iteration 990, loss = 11.96157196
Iteration 991, loss = 11.97714887
```

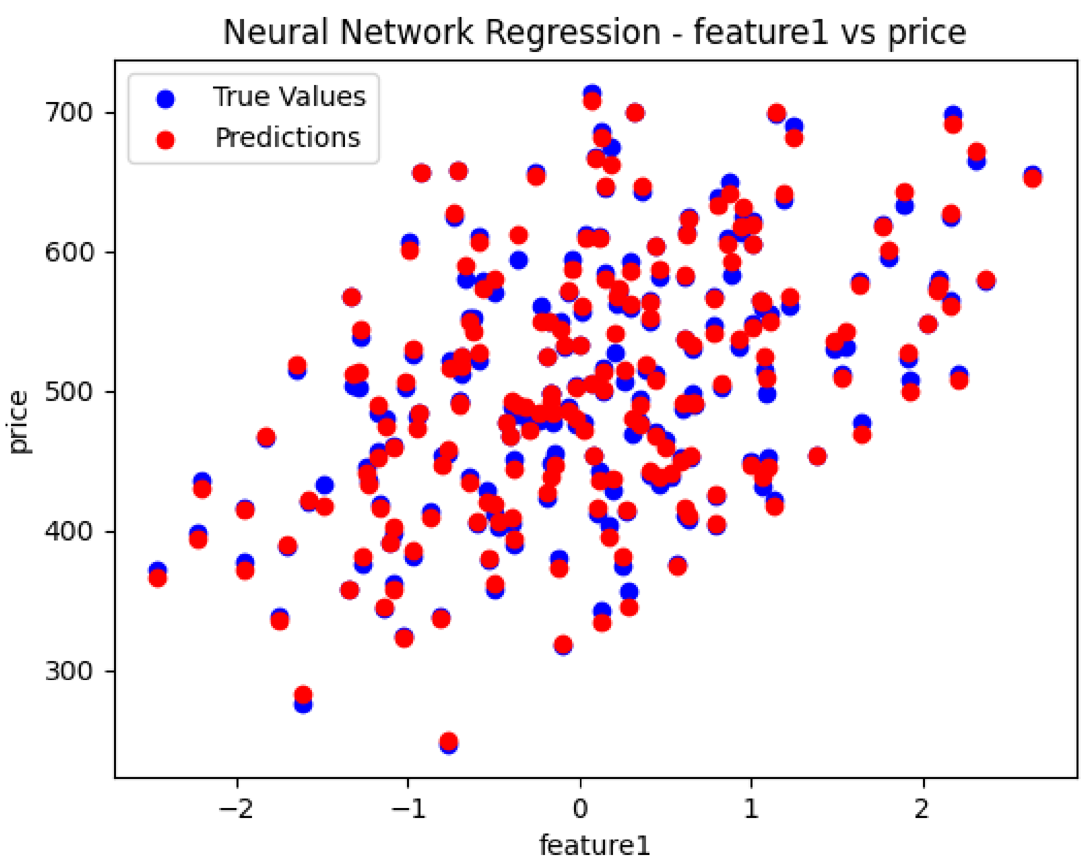
```
Iteration 992, loss = 11.95161107
Iteration 993, loss = 11.97820865
Iteration 994, loss = 11.96349974
Iteration 995, loss = 11.96695710
Iteration 996, loss = 11.96198223
Iteration 997, loss = 11.95493759
Iteration 998, loss = 11.97699391
Iteration 999, loss = 11.95045140
Iteration 1000, loss = 11.95603471
Iteration 1001, loss = 11.95767189
Iteration 1002, loss = 11.93837739
Iteration 1003, loss = 11.94490632
Iteration 1004, loss = 11.94855388
Iteration 1005, loss = 11.93889354
Iteration 1006, loss = 11.94654739
Iteration 1007, loss = 11.93192139
Iteration 1008, loss = 11.93499755
Iteration 1009, loss = 11.93905208
Iteration 1010, loss = 11.93142842
Iteration 1011, loss = 11.93864682
Iteration 1012, loss = 11.93373677
Iteration 1013, loss = 11.92623433
Iteration 1014, loss = 11.91887489
Iteration 1015, loss = 11.92331539
Iteration 1016, loss = 11.92312636
Iteration 1017, loss = 11.91940804
Iteration 1018, loss = 11.92761101
Iteration 1019, loss = 11.92297517
Iteration 1020, loss = 11.91695818
Iteration 1021, loss = 11.91914838
Iteration 1022, loss = 11.94465575
Iteration 1023, loss = 11.95719062
Iteration 1024, loss = 11.91415362
Iteration 1025, loss = 11.93670609
Iteration 1026, loss = 11.91569604
Iteration 1027, loss = 11.90033059
Iteration 1028, loss = 11.90558868
Iteration 1029, loss = 11.91319874
Iteration 1030, loss = 11.91955327
Iteration 1031, loss = 11.90389053
Iteration 1032, loss = 11.90427080
Iteration 1033, loss = 11.89657151
Iteration 1034, loss = 11.90163773
Iteration 1035, loss = 11.89160908
Iteration 1036, loss = 11.92294742
Iteration 1037, loss = 11.89333508
Iteration 1038, loss = 11.90627367
Iteration 1039, loss = 11.90932942
Iteration 1040, loss = 11.89284074
Iteration 1041, loss = 11.89408846
```

```
Iteration 1042, loss = 11.91264320
Iteration 1043, loss = 11.90913432
Iteration 1044, loss = 11.91191373
Iteration 1045, loss = 11.90074428
Iteration 1046, loss = 11.90242843
Training loss did not improve more than tol=0.000100 for 10
consecutive epochs. Stopping.

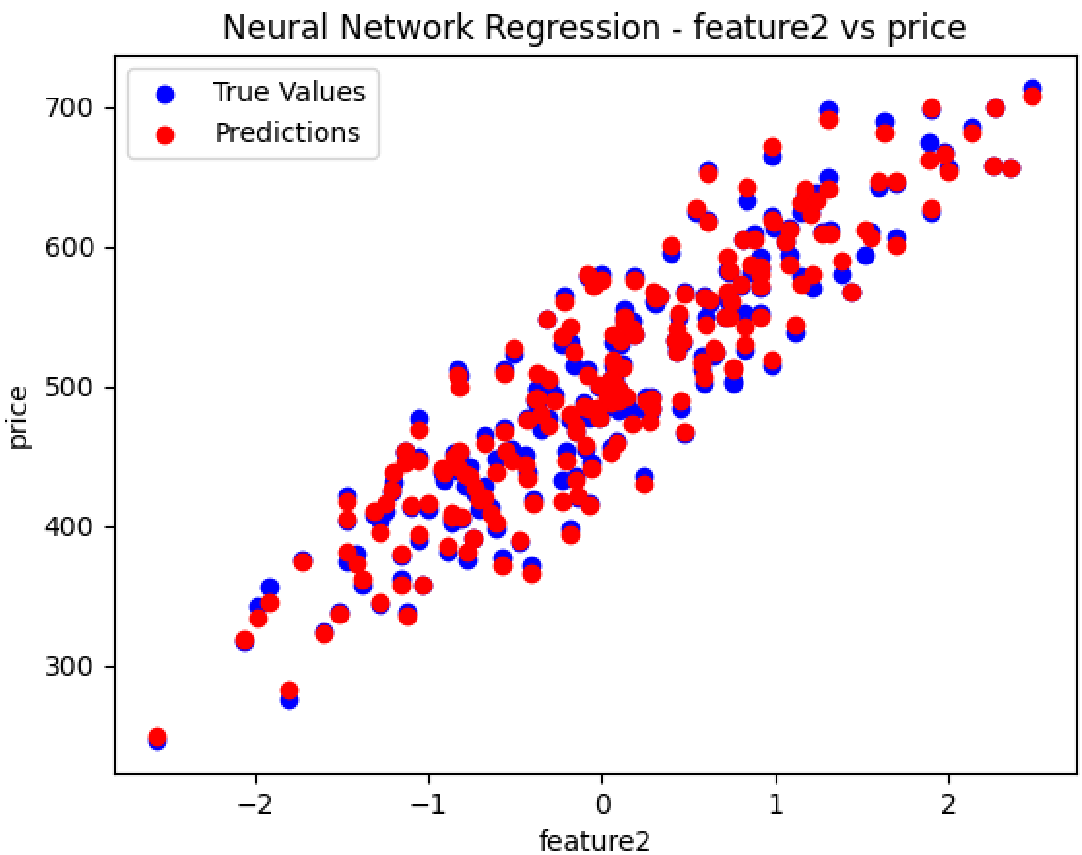
y_pred = model.predict(X_test)
model.score(X_test, y_test) # R Squared

0.9966286345849324

plt.scatter(X_test[:,0], y_test, color='blue')
plt.scatter(X_test[:,0], y_pred, color='red')
# Set the axis labels and title
plt.xlabel('feature1')
plt.ylabel('price')
plt.title('Neural Network Regression - feature1 vs price')
# Add a legend to the plot
plt.legend(['True Values', 'Predictions'])
plt.show()
```



```
plt.scatter(X_test[:,1], y_test, color='blue')
plt.scatter(X_test[:,1], y_pred, color='red')
# Set the axis labels and title
plt.xlabel('feature2')
plt.ylabel('price')
plt.title('Neural Network Regression - feature2 vs price')
# Add a legend to the plot
plt.legend(['True Values', 'Predictions'])
plt.show()
```



Imprimindo métricas do modelo

```
from sklearn import metrics
import numpy as np
def print_evaluate(real, predicted):
    mae = metrics.mean_absolute_error(real, predicted)
    mape = metrics.mean_absolute_percentage_error(real, predicted)
    mse = metrics.mean_squared_error(real, predicted)
    rmse = np.sqrt(mse)
    r2_square = metrics.r2_score(real, predicted)
    print("MAE:", mae)
    print("MAPE:", mape)
```

```
    print("MSE:", mse)
    print("RMSE:", rmse)
    print("R2 Square:", r2_square)

print("Métricas de Desempenho (RNA):")
print("\nDados de teste:")
print_evaluate(y_test, y_pred)
```

```
Métricas de Desempenho (RNA):

Dados de teste:
MAE: 4.27513938553281
MAPE: 0.008729802073419278
MSE: 28.427624825648152
RMSE: 5.331756260900169
R2 Square: 0.9966286345849324
```

Comparando com Regressor Linear

```
from sklearn.linear_model import LinearRegression
# regressão (treinamento)
my_model = LinearRegression()
my_model.fit(X_train, y_train)
print("R2 (test) =", my_model.score(X_test, y_test)) # r2 squared
```

```
R2 (test) = 0.9969271004939649
```

```
#regressão (teste)
y_pred = my_model.predict(X_test)
print("Métricas de Desempenho (Linear):")
print("\nDados de teste:")
print_evaluate(y_test, y_pred)
```

```
Métricas de Desempenho (Linear):

Dados de teste:
MAE: 4.059737026111618
MAPE: 0.008309205902040373
MSE: 25.910936231970744
RMSE: 5.0902786006240115
R2 Square: 0.9969271004939649
```

Comparando com SVM

```
from sklearn.svm import SVR
svr = SVR(C=30.0, epsilon=0.5)
svr.fit(X_train, y_train)
svr.score(X_test, y_test)
#regressão (teste)
y_pred = svr.predict(X_test)
```

```python
print("Métricas de Desempenho (Linear):")
print("\nDados de teste:")
print_evaluate(y_test, y_pred)
```

```
Métricas de Desempenho (Linear):

Dados de teste:
MAE: 4.802595762419471
MAPE: 0.010398254884641956
MSE: 56.17818954367445
RMSE: 7.4952111073454395
R2 Square: 0.9933375649049029
```

Ressultados

Observando os resultados, vê-se que eles são muito parecidos nos três métodos. Uma possiblidade pode ser que a base de dados não é tão complexa de uma maneiera de necessitar de diferentes abordagens.