

Mini Projeto MLP

Grupo

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Objetivo

Verificar como a alteração de parâmtros (número de camadas, número de unidades, taxa de aprendizagem, funções de ativação, dropout, regularização, etc) interfere no resultado do experimento (os testes serão realizados com o Conjunto de Dados de Sintomas de Lombalgia disponível no Kaggle), utilizando sklearn.neural\_network.MLPClassifier. Importante avaliar os dados, ver normalização e eliminar atributos identificadores. Medir acurácia, matriz de confusão, precision, recall.

Importações e Downloads

```
1 !pip install scikit-optimize

1 import pandas as pd
2 import numpy as np
3 from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler
4 from sklearn.model_selection import train_test_split, ShuffleSplit
5 from sklearn.neural_network import MLPClassifier
6 from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
7 import matplotlib.pyplot as plt
8 import seaborn as sns
9 from skopt.optimizer import gbrt_minimize
10 from skopt.space.space import Categorical, Integer, Real
11 from skopt.utils import use_named_args
12 from imblearn.over_sampling import SMOTE
```

Preparando os dados

```
1 from google.colab import drive
2 drive.mount('/content/drive')

Mounted at /content/drive

1 df = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/backpain/Dataset_spine.csv")
2 df.drop([df.columns[-1]],axis=1,inplace=True)
3 df.head()
```

	Col1	Col2	Col3	Col4	Col5	Col6	Col7	Col
0	63.027817	22.552586	39.609117	40.475232	98.672917	-0.254400	0.744503	12.566
1	39.056951	10.060991	25.015378	28.995960	114.405425	4.564259	0.415186	12.887
2	68.832021	22.218482	50.092194	46.613539	105.985135	-3.530317	0.474889	26.834
3	69.297008	24.652878	44.311238	44.644130	101.868495	11.211523	0.369345	23.560
4	49.712859	9.652075	28.317406	40.060784	108.168725	7.918501	0.543360	35.494

Pelo dicionário de dados, sabemos que:

- Col1 - pelvic\_incidence
- Col2 - pelvic tilt
- Col3 - lumbar\_lordosis\_angle
- Col4 - sacral\_slope
- Col5 - pelvic\_radius
- Col6 - degree\_spondylolisthesis
- Col7 - pelvic\_slope
- Col8 - direct\_tilt
- Col9 - thoracic\_slope

- Col10 - cervical\_tilt
- Col11 - sacrum\_angle
- Col12 - scoliosis\_slope
- Class\_att - Abnormal, Normal (Normality)

Por meio dos doze primeiros atributos, iremos prever o último.

```
1 #Renomeando colunas
2 new_columns = ['pelvic_incidence','pelvic_tilt','lumbar_lordosis_angle',
3               'sacral_slope','pelvic_radius','degree_spondylolisthesis',
4               'pelvic_slope','direct_tilt','thoracic_slope','cervical_tilt',
5               'sacrum_angle','scoliosis_slope','normality']
6
7 df.columns = new_columns
8 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 310 entries, 0 to 309
Data columns (total 13 columns):
#   Column                Non-Null Count  Dtype
---  -
0   pelvic_incidence       310 non-null   float64
1   pelvic_tilt            310 non-null   float64
2   lumbar_lordosis_angle  310 non-null   float64
3   sacral_slope           310 non-null   float64
4   pelvic_radius          310 non-null   float64
5   degree_spondylolisthesis 310 non-null   float64
6   pelvic_slope           310 non-null   float64
7   direct_tilt            310 non-null   float64
8   thoracic_slope         310 non-null   float64
9   cervical_tilt          310 non-null   float64
10  sacrum_angle           310 non-null   float64
11  scoliosis_slope        310 non-null   float64
12  normality              310 non-null   object
dtypes: float64(12), object(1)
memory usage: 31.6+ KB
```

Os dados estão completos, sem campos NaN. Os atributos são todos do tipo numérico, no entanto o target é do tipo object.

```
1 df["normality"].value_counts()
```

```
Abnormal    210
Normal      100
Name: normality, dtype: int64
```

```
1 #Transformar o último campo com encoder para 0 (Abnormal) e 1 (Normal)
2 label_encoder = LabelEncoder()
3 df["normality"] = label_encoder.fit_transform(df["normality"])
4 df["normality"].value_counts()
```

```
0    210
1    100
Name: normality, dtype: int64
```

```
1 #Separar atributos e label
2 x = df.iloc[:, :-1]
3 y = df["normality"]
```

## ▼ Análise Exploratória dos Dados e Pré-Processamento

### ▼ Verificar eficácia sem pré-processamento

```
1 def estimar_loss(x, y):
2     x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.15, random_state=42, shuffle=True)
3     #Modelo com valores usuais
4     mlp_classifier = MLPClassifier(hidden_layer_sizes=(100,), activation='relu', solver='adam', alpha=0.0001,
5                                   batch_size='auto', learning_rate='constant', learning_rate_init=0.001, power_t=0.5,
6                                   max_iter=200, shuffle=True, random_state=42, tol=0.0001, verbose=False,
7                                   warm_start=False, momentum=0.9, nesterovs_momentum=True, early_stopping=False,
8                                   validation_fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e-08, n_iter_no_change=10,
9                                   max_fun=15000)
10    #Treinando
11    mlp_classifier.fit(x_train, y_train)
12    print("Loss do MLP Classifier:", np.mean(mlp_classifier.loss_))
13
```

14 #Avaliação Iterativa: A loss será avaliada em cada estágio do pré-processamento, para entender como cada etapa afeta o desempenho do  
 15 #loss não será usada para melhorar o pré-processamento, apenas ilustrar o desempenho

```
1 estimar_loss(x,y)
```

```
Loss do MLP Classifier: 0.27808027948957015
```

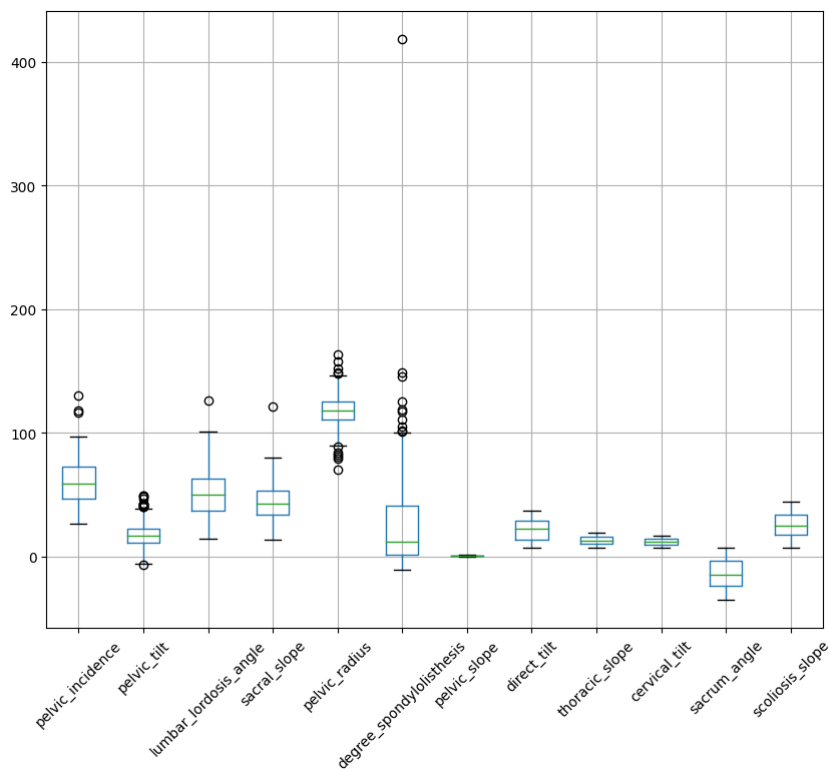
```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizers: warn(
```

## ▼ Retirando Outliers

### Box Plot

Os box plots são úteis para visualizar a distribuição de valores em cada característica, mostrando a mediana, quartis e outliers. Isso ajuda a identificar discrepâncias nos dados que podem afetar a modelagem.

```
1 #Box plot
2 plt.figure(figsize=(10, 8))
3 x.boxplot()
4 plt.xticks(rotation=45)
5 plt.show()
```

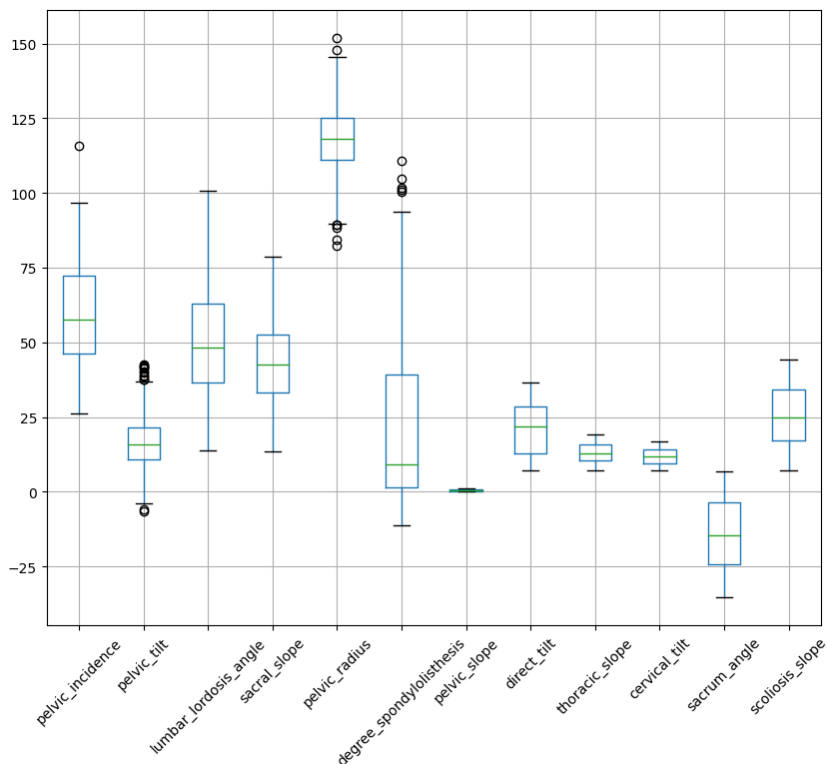


Em um conjunto de dados relativamente pequeno, observamos pelo box plot que a maioria dos outliers está localizada nas proximidades das margens do Intervalo Interquartil (IQR). A abordagem padrão para identificar outliers é a regra dos 1,5 vezes o IQR, mas optamos por aumentar o fator multiplicador para 2, devido ao seu tamanho limitado e à distribuição observada dos outliers.

```
1 #Retirada de outliers
2 df_clean = df.copy()
3 for col in x:
4     lower_bound = df_clean[col].quantile(0.25) - 2 * (df_clean[col].quantile(0.75) - df_clean[col].quantile(0.25))
5     upper_bound = df_clean[col].quantile(0.75) + 2 * (df_clean[col].quantile(0.75) - df_clean[col].quantile(0.25))
6     df_clean = df_clean[(df_clean[col] >= lower_bound) & (df_clean[col] <= upper_bound)]
7 x_clean = df_clean.iloc[:, :-1]
```

```
8 v_clean = df_clean["normality"]
Loss do MLP Classifier: 0.30581135424572015
```

```
1 #Box plot
2 plt.figure(figsize=(10, 8))
3 x_clean.boxplot()
4 plt.xticks(rotation=45)
5 plt.show()
```



## ▼ Balanceamento de classes

### Análise dos Atributos Binários

Gráfico de contagem adequado para atributos binários, mostra a distribuição da variável. Relevante para entender o equilíbrio da classe.

```
1 #Análise dos atributos binários
2 plt.figure(figsize=(6, 4))
3 sns.countplot(x="normality", data=df_clean)
4 plt.xlabel("Atributo Binário")
5 plt.ylabel("Contagem")
6 plt.show()
```



```
1 print(df_clean["normality"].value_counts())
```

```
0    196
1    100
Name: normality, dtype: int64
```

```
1 #Balanceando dados
```

```
2 smote = SMOTE(random_state=42)
```

```
3 x_resampled, y_resampled = smote.fit_resample(x_clean, y_clean)
```

```
4 balanced_df = pd.concat([pd.DataFrame(x_resampled, columns=x_clean.columns), pd.Series(y_resampled, name="normality")], axis=1)
```

```
5 balanced_x = balanced_df.iloc[:, :-1]
```

```
6 balanced_y = balanced_df["normality"]
```

```
7 estimar_loss(balanced_x, balanced_y)
```

```
8 print(balanced_df["normality"].value_counts())
```

```
Loss do MLP Classifier: 0.23469823051296654
```

```
0    196
```

```
1    196
```

```
Name: normality, dtype: int64
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimizers: warn(
```

```
1 #Análise dos atributos binários
```

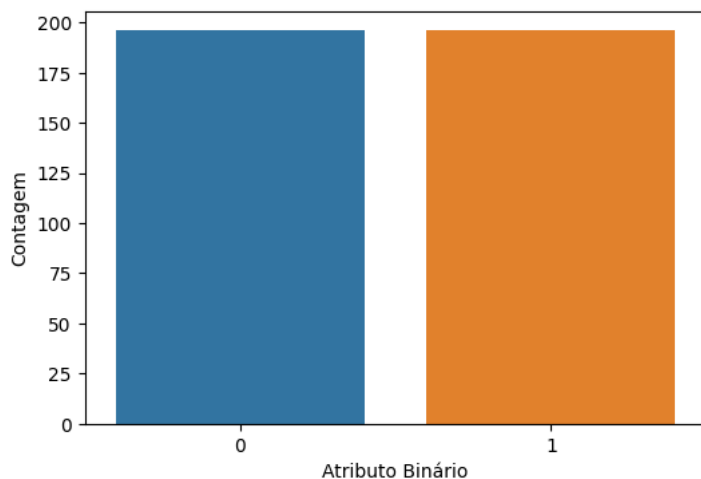
```
2 plt.figure(figsize=(6, 4))
```

```
3 sns.countplot(x="normality", data=balanced_df)
```

```
4 plt.xlabel("Atributo Binário")
```

```
5 plt.ylabel("Contagem")
```

```
6 plt.show()
```



## ▼ Normalização e Padronização

### Sumário Estatístico

O resumo estatístico fornece estatísticas descritivas básicas para cada característica no df. Isso inclui a contagem de exemplos, média, desvio padrão, valor mínimo, quartis e valor máximo. Isso ajuda a ter uma visão geral das características e de suas escalas. Pode ser útil para identificar características com escalas muito diferentes e visualizar a necessidade de normalização.

```
1 #Sumário Estatístico
```

```
2 balanced_df.describe()
```

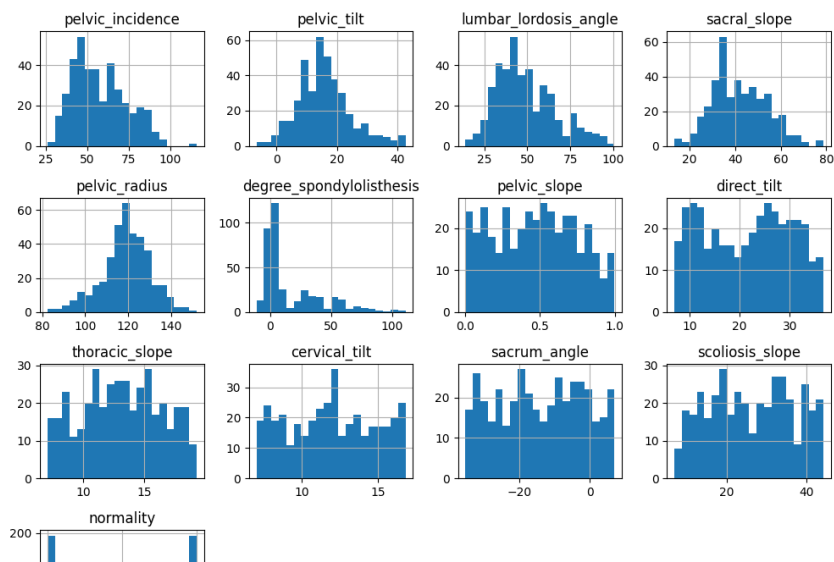
	pelvic_incidence	pelvic_tilt	lumbar_lordosis_angle	sacral_slope	pelvic_
count	392.000000	392.000000	392.000000	392.000000	392.
mean	57.810532	15.906806	49.330108	41.903726	119.
std	15.078780	8.756700	17.283002	11.835850	11

Distribuição de valores

Os histogramas e os gráficos KDE mostram a distribuição dos valores em cada característica. Isso ajuda a entender a forma da distribuição, verificar se as características seguem uma distribuição normal e observar como os valores estão distribuídos. Isso pode influenciar a decisão de normalizar ou padronizar as características.

```

1 #Distribuição de valores
2 balanced_df.hist(bins=20, figsize=(10, 8))
3 plt.tight_layout()
4 plt.show()
5
6 sns.set(style="whitegrid")
7 plt.figure(figsize=(10, 8))
8 for col in x:
9     sns.kdeplot(balanced_df[col], label=col)
10 plt.legend()
11 plt.show()
```



```

1 #Normalização
2 columns_to_normalize = ['pelvic_incidence','pelvic_tilt','lumbar_lordosis_angle','pelvic_radius'] #Distribuição semelhante a normal
3 scaler = MinMaxScaler()
4 normalized_df = balanced_df.copy()
5 normalized_df[columns_to_normalize] = scaler.fit_transform(balanced_df[columns_to_normalize])
6 normalized_x = normalized_df.iloc[:, :-1]
7 normalized_y = normalized_df["normality"]
8 estimar_loss(normalized_x, normalized_y)

```

Loss do MLP Classifier: 0.20813731852034187

/usr/local/lib/python3.10/dist-packages/sklearn/neural\_network/\_multilayer\_perceptron.py:686: ConvergenceWarning: Stochastic Optimizers: SGD does not have a 'loss' attribute. Please use 'loss\_' instead.



```

1 #Padronização
2 columns_to_standardize = ['pelvic_tilt','sacral_slope','pelvic_radius','pelvic_slope','direct_tilt','thoracic_slope',
3                           'cervical_tilt','sacrum_angle','scoliosis_slope'] #Desvio padrão pequeno
4 scaler = StandardScaler()
5 standardize_df = normalized_df.copy()
6 standardize_df[columns_to_standardize] = scaler.fit_transform(normalized_df[columns_to_standardize])
7 standardize_x = standardize_df.iloc[:, :-1]
8 standardize_y = standardize_df["normality"]
9 estimar_loss(standardize_x, standardize_y)

```

Loss do MLP Classifier: 0.15922471077707612

/usr/local/lib/python3.10/dist-packages/sklearn/neural\_network/\_multilayer\_perceptron.py:686: ConvergenceWarning: Stochastic Optimizers: SGD does not have a 'loss' attribute. Please use 'loss\_' instead.



## ▼ Análise de Atributos

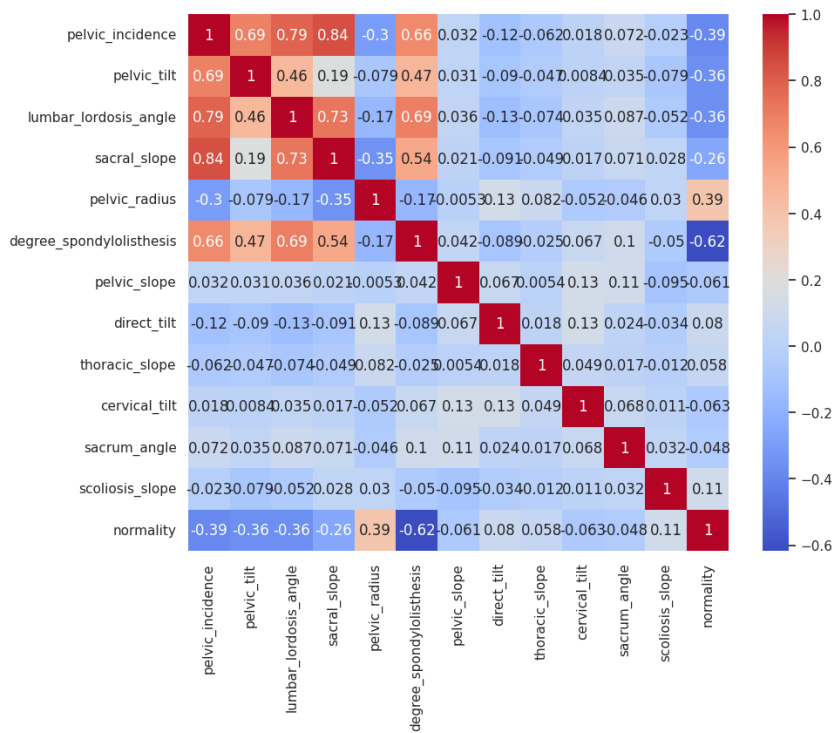
### Análise de Correlações

A matriz de correlação e o mapa de calor ajudam a entender as relações lineares entre as características. Isso pode ser útil para identificar pares que estão altamente correlacionados, o que pode indicar redundância. Em alguns casos, pode ser útil para a seleção de atributos, removendo características altamente correlacionadas.

```

1 #Análise de Correlações
2 correlation_matrix = standardize_df.corr()
3 plt.figure(figsize=(10, 8))
4 sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm")
5 plt.show()

```



```

1 correlation_matrix = standardize_df.corr()
2 df_filtered = standardize_df.copy()
3 corr_threshold = 0.8
4 #Caso nenhuma coluna tenha correlação de 80% ou mais, ficará o mesmo df
5 highly_correlated = (correlation_matrix.abs() > corr_threshold) & (correlation_matrix != 1)
6 features_to_remove = set()
7 for col in highly_correlated.columns:
8     correlated_cols = highly_correlated.index[highly_correlated[col]].tolist()
9     if len(correlated_cols) > 1:
10         features_to_remove.add(correlated_cols[1])
11 df_filtered = df_filtered.drop(columns=features_to_remove)
12 x_filtered = df_filtered.iloc[:, :-1]
13 y_filtered = df_filtered["normality"]
14 estimar_loss(x_filtered,y_filtered)

```

Loss do MLP Classifier: 0.15922471077707612

/usr/local/lib/python3.10/dist-packages/sklearn/neural\_network/\_multilayer\_perceptron.py:686: ConvergenceWarning: Stochastic Optimizer: WARNING: warnings.warn()

## ▼ Treinamento e Teste (Valores Usuais)

```

1 #Divisão conjunto treino e test
2 x_train, x_test, y_train, y_test = train_test_split(x_filtered, y_filtered, test_size=0.15, random_state=42, shuffle=True)
3 print(f'x_train: {x_train.shape}')
4 print(f'x_test: {x_test.shape}')

x_train: (333, 12)
x_test: (59, 12)

1 # Criando MLP
2 losses = []
3 for i in range(10):
4     mlp_classifier = MLPClassifier(hidden_layer_sizes=(100,), activation='relu', solver='adam', alpha=0.0001,
5                                     batch_size='auto', learning_rate='constant', learning_rate_init=0.001, power_t=0.5,
6                                     max_iter=200, shuffle=True, random_state=None, tol=0.0001, verbose=False,
7                                     warm_start=False, momentum=0.9, nesterovs_momentum=True, early_stopping=False,
8                                     validation_fraction=0.1, beta_1=0.9, beta_2=0.999, epsilon=1e-08, n_iter_no_change=10,
9                                     max_fun=15000)
10
11 # Treinando com os parâmetros usuais
12 mlp_classifier.fit(x_train, y_train)
13 losses.append(mlp_classifier.loss_)
14 print("Loss do MLP Classifier:", np.mean(losses))

```



```

/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
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/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(
Loss do MLP Classifier: 0.15478382217131986
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:686: ConvergenceWarning: Stochastic Optimiz
warnings.warn(

```

```

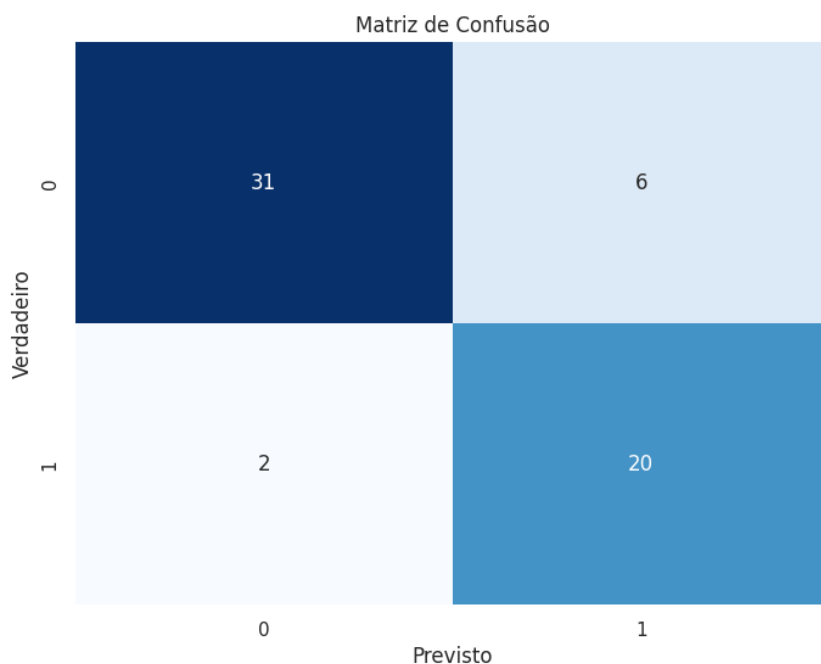
1 y_pred = mlp_classifier.predict(x_test)
2
3 accuracy = accuracy_score(y_test, y_pred)
4 print(f"Acurácia do modelo: {accuracy:.2f}")
5 print("Classification Report")
6 print(classification_report(y_test, y_pred))
7
8 confusion = confusion_matrix(y_test, y_pred)
9 plt.figure(figsize=(8, 6))
10 sns.heatmap(confusion, annot=True, fmt="d", cmap="Blues", cbar=False)
11 plt.xlabel('Previsto')
12 plt.ylabel('Verdadeiro')
13 plt.title('Matriz de Confusão')
14 plt.show()

```

Acurácia do modelo: 0.86

Classification Report

	precision	recall	f1-score	support
0	0.94	0.84	0.89	37
1	0.77	0.91	0.83	22
accuracy			0.86	59
macro avg	0.85	0.87	0.86	59
weighted avg	0.88	0.86	0.87	59



## ▼ Otimização de Hiperparâmetros

```

1 parameters = [Integer(1, 2, name='num_layers'),
2               Integer(1, 128, name='nn_fst_layer'),
3               Integer(1, 128, name='nn_snd_layer'),
4               Categorical(['identity', 'logistic', 'tanh', 'relu'], name='activation'),
5               Categorical(['adam', 'sgd', 'lbfgs'], name='solver'),
6               Real(1e-6, 1e-2, prior='log-uniform', name='alpha'),
7               Integer(1, 100, name='batch_size'),
8               Categorical(['constant', 'invscaling', 'adaptive'], name='learning_rate'),
9               Real(1e-6, 1e-3, prior='log-uniform', name='learning_rate_init'),
10              Real(1e-6, 1e-1, prior='log-uniform', name='power_t'),
11              Integer(500, 1000, name='max_iter'),
12              Real(1e-6, 1e-2, prior='log-uniform', name='tol'),
13              Real(0.1, 0.9, name='momentum'),
14              Categorical([True, False], name='nesterovs_momentum'),
15              Real(0.01, 0.5, name='validation_fraction'),
16              Real(0.1, 0.9, name='beta_1'),
17              Real(0.001, 0.999, name='beta_2'),
18              Real(1e-10, 1e-6, prior='log-uniform', name='epsilon'),
19              Integer(1, 100, name='n_iter_no_change'),
20              Integer(1, 30000, name='max_fun')]
21
22 @use_named_args(parameters)
23 def objective(**params):
24     print(params)
25     split = ShuffleSplit(n_splits=2, test_size=0.15)
26     indices = [train for (train, test) in split.split(x_train.to_numpy())]
27     data_x, data_y = (x_train.to_numpy())[indices[0]], (y_train.to_numpy())[indices[0]]
28     split = ShuffleSplit(n_splits=5, test_size=0.2)
29     accuracy = []
30     for train, test in split.split(data_x):
31         if(params["num_layers"] == 1):
32             hidden_layer=(params["nn_fst_layer"],)
33         if(params["num_layers"] == 2):
34             hidden_layer=(params["nn_fst_layer"],params["nn_snd_layer"])
35
36     mlp_classifier = MLPClassifier(hidden_layer_sizes=hidden_layer, activation=params['activation'], solver=params['solver'],
37                                   alpha=params['alpha'],batch_size=params['batch_size'], learning_rate=params['learning_rate'],
38                                   learning_rate_init=params['learning_rate_init'], power_t=params['power_t'],
39                                   max_iter=params['max_iter'], shuffle=True, random_state=42,
40                                   tol=params['tol'], verbose=False, warm_start=False, momentum=params['momentum'],
41                                   nesterovs_momentum=params['nesterovs_momentum'], early_stopping=False,
42                                   validation_fraction=params['validation_fraction'], beta_1=params['beta_1'],
43                                   beta_2=params['beta_2'], epsilon=params['epsilon'], n_iter_no_change=params['n_iter_no_change'],
44                                   max_fun=params['max_fun'])
45     mlp_classifier.fit(data_x[train], data_y[train])
46     y_pred = mlp_classifier.predict(x_test)
47     accuracy.append(accuracy_score(y_test, y_pred))
48     return -np.array(accuracy).mean()
49
50 result = gbrt_minimize(func=objective, dimensions=parameters, n_calls=50, acq_func='EI', n_jobs=-1)

```

```
{ 'num_layers': 2, 'mlp_test_layer': 00, 'mlp_hidden_layer': 1, 'activation': 'logistic', 'solver': 'lbfgs', 'alpha': 0.004523100020/400
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:541: ConvergenceWarning: lbfgs failed to
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

```
self.n_iter_ = _check_optimize_result("lbfgs", opt_res, self.max_iter)
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but MLPClassifier was fitted witho
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:541: ConvergenceWarning: lbfgs failed to
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

```
self.n_iter_ = _check_optimize_result("lbfgs", opt_res, self.max_iter)
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:432: UserWarning: X has feature names, but MLPClassifier was fitted witho
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:541: ConvergenceWarning: lbfgs failed to
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

```
self.n_iter_ = _check_optimize_result("lbfgs", opt_res, self.max_iter)
```

1 result.x

```
[2,
 42,
 71,
 'logistic',
 'lbfgs',
 0.0016797304312511862,
 52,
 'invscaling',
 0.0005208012653703742,
 1.3499894600491117e-06,
 801,
 2.437733590381186e-06,
 0.805771513687481,
 False,
 0.4688985210894677,
 0.2334915810999844,
 0.9522742442962157,
 3.351998611086149e-07,
 53,
 23205]
```

```
1 if(result.x[0] == 1):
2     hidden_layer=(result.x[1],)
3 if(result.x[0] == 2):
4     hidden_layer=(result.x[1],result.x[2])
5
6 losses = []
7 for i in range(10):
8     mlp_classifier = MLPClassifier(hidden_layer_sizes=hidden_layer, activation=result.x[3], solver=result.x[4], alpha=result.x[5],
9                                     batch_size=result.x[6], learning_rate=result.x[7], learning_rate_init=result.x[8], power_t=result.x[9]
10                                     max_iter=result.x[10], shuffle=True, random_state=None, tol=result.x[11], verbose=False,
11                                     warm_start=False, momentum=result.x[12], nesterovs_momentum=result.x[13], early_stopping=False,
12                                     validation_fraction=result.x[14], beta_1=result.x[15], beta_2=result.x[16], epsilon=result.x[17],
13                                     n_iter_no_change=result.x[18], max_fun=result.x[19])
14
15 mlp_classifier.fit(x_train, y_train)
16 losses.append(mlp_classifier.loss_)
17 print("Loss do MLP Classifier:", np.mean(losses))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:541: ConvergenceWarning: lbfgs failed to c
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

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self.n_iter_ = _check_optimize_result("lbfgs", opt_res, self.max_iter)
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STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
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STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
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STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
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<https://scikit-learn.org/stable/modules/preprocessing.html>

```
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/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:541: ConvergenceWarning: lbfgs failed to c
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

```
self.n_iter_ = _check_optimize_result("lbfgs", opt_res, self.max_iter)
Loss do MLP Classifier: 0.0013173242808889325
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.py:541: ConvergenceWarning: lbfgs failed to c
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
```

Increase the number of iterations (max\_iter) or scale the data as shown in:

<https://scikit-learn.org/stable/modules/preprocessing.html>

```
self.n_iter_ = _check_optimize_result("lbfgs", opt_res, self.max_iter)
```

```
1 y_pred = mlp_classifier.predict(x_test)
2
3 accuracy = accuracy_score(y_test, y_pred)
4 print(f"Acurácia do modelo: {accuracy:.2f}")
5 print("Classification Report")
6 print(classification_report(y_test, y_pred))
7
8 confusion = confusion_matrix(y_test, y_pred)
9 plt.figure(figsize=(8, 6))
10 sns.heatmap(confusion, annot=True, fmt="d", cmap="Blues", cbar=False)
11 plt.xlabel('Previsto')
12 plt.ylabel('Verdadeiro')
13 plt.title('Matriz de Confusão')
14 plt.show()
```

Acurácia do modelo: 0.90

## ▼ Salvar como PDF

```
1 !apt-get install texlive texlive-xetex texlive-latex-extra pandoc
2 !pip install py pandoc
```

```
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
pandoc is already the newest version (2.9.2.1-3ubuntu2).
pandoc set to manually installed.
The following additional packages will be installed:
  dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono
  fonts-texgyre fonts-urw-base35 libapache-pom-java libcommons-logging-java
  libcommons-parent-java libfontbox-java libfontenc1 libgs9 libgs9-common
  libidn12 libijs-0.35 libjbig2dec0 libkpathsea6 libpdfbox-java libptexenc1
  libruby3.0 libsynctex2 libteckit0 libtexlua53 libtexlua53 libwoff1
  libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby
  ruby-net-telnet ruby-rubygems ruby-webrick ruby-xmlrpc ruby3.0
  rubygems-integration t1utils teckit tex-common tex-gyre texlive-base
  texlive-binaries texlive-fonts-recommended texlive-latex-base
  texlive-latex-recommended texlive-pictures texlive-plain-generic tipa
  xfonts-encodings xfonts-utils
```

Suggested packages:

```
fonts-noto fonts-freefont-otf | fonts-freefont-ttf libavalon-framework-java
libcommons-logging-java-doc libexcalibur-logkit-java liblog4j1.2-java
poppler-utils ghostscript fonts-japanese-mincho | fonts-ipafont-mincho
fonts-japanese-gothic | fonts-ipafont-gothic fonts-arphic-ukai
fonts-arphic-uming fonts-nanum ri ruby-dev bundler debhelper gv
| postscript-viewer perl-tk xpdf | pdf-viewer xzdec
texlive-fonts-recommended-doc texlive-latex-base-doc python3-pygments
icc-profiles libfile-which-perl libspreadsheet-parseexcel-perl
texlive-latex-extra-doc texlive-latex-recommended-doc texlive-luatex
texlive-pstricks dot2tex prerex texlive-pictures-doc vprerex
default-jre-headless tipa-doc
```

The following NEW packages will be installed:

```
dvisvgm fonts-droid-fallback fonts-lato fonts-lmodern fonts-noto-mono
fonts-texgyre fonts-urw-base35 libapache-pom-java libcommons-logging-java
libcommons-parent-java libfontbox-java libfontenc1 libgs9 libgs9-common
libidn12 libijs-0.35 libjbig2dec0 libkpathsea6 libpdfbox-java libptexenc1
libruby3.0 libsynctex2 libteckit0 libtexlua53 libtexlua53 libwoff1
libzzip-0-13 lmodern poppler-data preview-latex-style rake ruby
ruby-net-telnet ruby-rubygems ruby-webrick ruby-xmlrpc ruby3.0
rubygems-integration t1utils teckit tex-common tex-gyre texlive texlive-base
texlive-binaries texlive-fonts-recommended texlive-latex-base
texlive-latex-extra texlive-latex-recommended texlive-pictures
texlive-plain-generic texlive-xetex tipa xfonts-encodings xfonts-utils
```

0 upgraded, 55 newly installed, 0 to remove and 16 not upgraded.

Need to get 182 MB of archives.

After this operation, 572 MB of additional disk space will be used.

```
Get:1 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-droid-fallback all 1:6.0.1r16-1.1build1 [1,805 kB]
Get:2 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-lato all 2.0-2.1 [2,696 kB]
Get:3 http://archive.ubuntu.com/ubuntu jammy/main amd64 poppler-data all 0.4.11-1 [2,171 kB]
Get:4 http://archive.ubuntu.com/ubuntu jammy/universe amd64 tex-common all 6.17 [33.7 kB]
Get:5 http://archive.ubuntu.com/ubuntu jammy/main amd64 fonts-urw-base35 all 20200910-1 [6,367 kB]
Get:6 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libgs9-common all 9.55.0~dfsg1-0ubuntu5.4 [752 kB]
Get:7 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libidn12 amd64 1.38-4ubuntu1 [60.0 kB]
Get:8 http://archive.ubuntu.com/ubuntu jammy/main amd64 libijs-0.35 amd64 0.35-15build2 [16.5 kB]
Get:9 http://archive.ubuntu.com/ubuntu jammy/main amd64 libjbig2dec0 amd64 0.19-3build2 [64.7 kB]
Get:10 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libgs9 amd64 9.55.0~dfsg1-0ubuntu5.4 [5,032 kB]
Get:11 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 libkpathsea6 amd64 2021.20210626.59705-1ubuntu0.1 [60.3 kB]
Get:12 http://archive.ubuntu.com/ubuntu jammy/main amd64 libwoff1 amd64 1.0.2-1build4 [45.2 kB]
Get:13 http://archive.ubuntu.com/ubuntu jammy/universe amd64 dvisvgm amd64 2.13.1-1 [1,221 kB]
```

```
1 !jupyter nbconvert --to PDF "/content/drive/MyDrive/Colab Notebooks/Mini-projeto-MLP.ipynb"
```

```
[NbConvertApp] Converting notebook /content/drive/MyDrive/Colab Notebooks/Mini-projeto-MLP.ipynb to PDF
[NbConvertApp] Support files will be in Mini-projeto-MLP_files/
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Making directory ./Mini-projeto-MLP_files
[NbConvertApp] Writing 214309 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 583171 bytes to /content/drive/MyDrive/Colab Notebooks/Mini-projeto-MLP.pdf
```

✓ 19s completed at 8:36 AM

● ✕