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Inteligência Artificial

Universidade Presbiteriana Mackenzie

Deep Learning

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Tarefa da trilha 4: Modelos Sequenciais e Classificação com Keras TensorFlow
https://github.com/Fernandopessoa1959/MACKENZIE-IA

Introdução

Nesta tarefa devemos implementar um modelo de classificação binária ou multiclasse para um conjunto de dados `TensorFlow` e o `Keras`.

Dataset

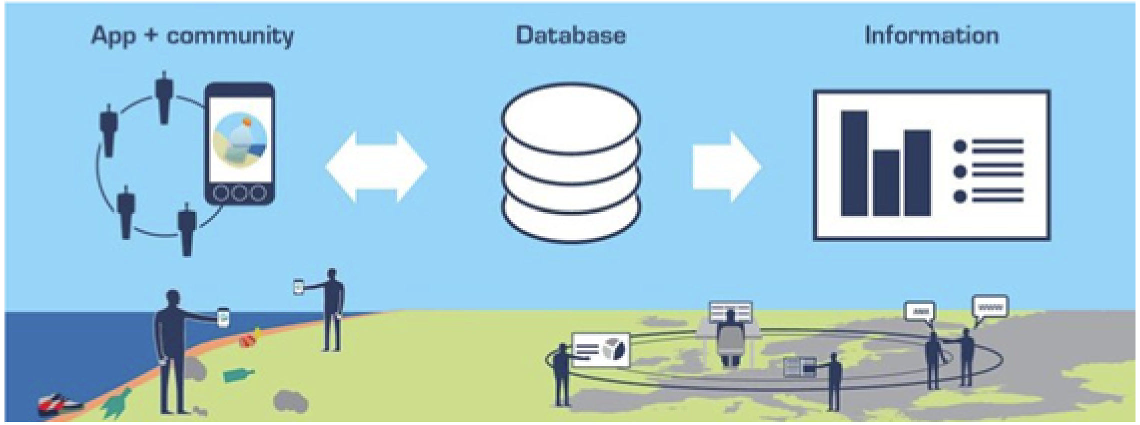
O dataset escolhido é o MLW_Data, este dataset fornecido pela Agência Europeia de Ambiente, é criado a partir de um aplicativo denominado LitterWatch, que é utilizados nas comunidades costeiras da Europa para identificar o lixo jogado ao oceano.

Fonte da base

https://www.eea.europa.eu/data-and-maps/data/marine-litter

Visualização por TABLEAU

https://www.eea.europa.eu/themes/water/europes-seas-and-coasts/assessments/marine-litterwatch/data-and-results/marine-litterwatch-data-viewer/marine-litterwatch-data-viewer



Objetivo do modelo

Tendo o levantamento do lixo, por tipo e quantidade, localizado em cada comunidade, nosso objetivo é treinar o modelo para identificar e categoraizar o local como POLUIDO ou LIMPO

Importando Bibliotecas

```
import pandas as pd
from IPython.display import display
import seaborn as sns
import numpy as np
from tensorflow import keras
```

```
from tensorflow.keras import layers
import tensorflow as tf
```

Importando datasets

Carregando os dados coletados no aplicativo e a tabela de categorias de lixo

Base de dados do agrupamento por tipo de lixo

```
# carregando dados de agrupamento para o Google Colab
from google.colab import files
uploaded = files.upload()
```

Escolher arquivos Nenhum arquivo selecionado Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving MLW_Meta.csv to MLW_Meta.csv
```

```
# Carregando o arquivo CSV em dataframe
Titulos = pd.read_csv('/content/MLW_Meta.csv', engine= 'python', sep = ';', encoding='utf-8')
```

```
#Analise da quantidade de colunas e linhas
Titulos.shape
```

```
(164, 3)
```

```
Titulos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 164 entries, 0 to 163
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype
```

```
---  ------       --------------  -----
 0   generalcode  164 non-null    object
 1   category     164 non-null    object
 2   generalname  164 non-null    object
dtypes: object(3)
memory usage: 4.0+ KB
```

```
Titulos.head(10)
```

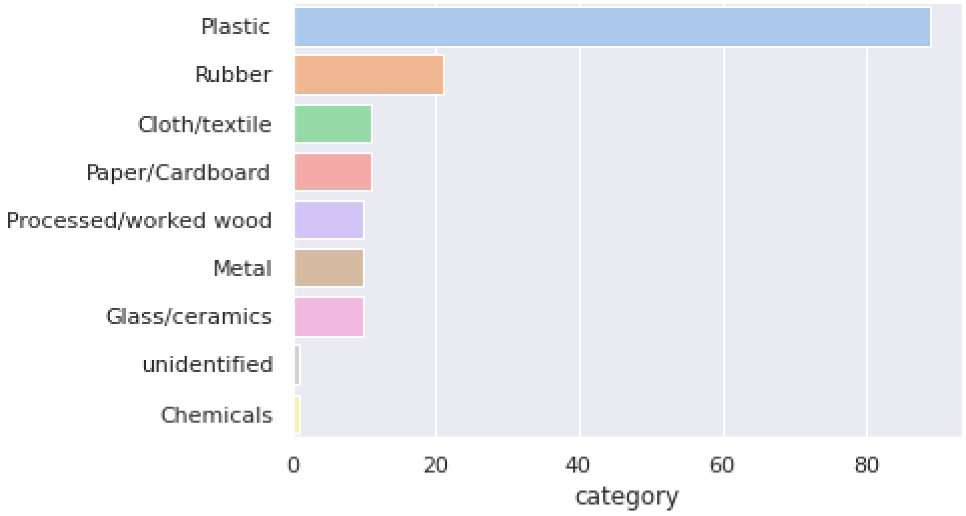
	generalcode	category	generalname
0	G1	Plastic	4/6-pack yokes, six-pack rings
1	G3	Plastic	Shopping Bags incl. pieces
2	G4	Plastic	Small plastic bags, e.g. freezer bags incl. pi...
3	G5	Plastic	Plastic bags collective role what remains from...
4	G7	Plastic	Drink bottles <=0.5l
5	G8	Plastic	Drink bottles >0.5l
6	G9	Plastic	Cleaner bottles & containers
7	G10	Plastic	Food containers incl. fast food containers
8	G11	Plastic	Beach use related cosmetic bottles and contain...
9	G12	Plastic	Other cosmetics bottles & containers

```
Titulos.groupby('category')['category'].count()
```

```
category
Chemicals                 1
Cloth/textile            11
Glass/ceramics           10
Metal                    21
Paper/Cardboard          10
Plastic                  89
Processed/worked wood    11
```

```
Rubber                 10
unidentified            1
Name: category, dtype: int64
```

```
sns.set(style="darkgrid")
categoria = Titulos['category'].unique()
cont = Titulos['category'].value_counts()
sns.barplot(x=cont,y=categoria, palette='pastel',orient='h');
```



Base de dados da pesquisa

```
# carregando o arquivo dados para o Google Colab
from google.colab import files
uploaded = files.upload()
```

Escolher arquivos Nenhum arquivo selecionado Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving MLW_Data.csv to MLW_Data.csv
```

```
data = pd.read_csv('/content/MLW_Data.csv', engine= 'python', sep = ';', encoding='latin-1')
```

```
data.shape
```

```
(254, 178)
```

```
data.head(5)
```

	CommunityName	BeachName	BeachCountrycode	BeachRegionalSea	BeachLength_m	BeachLocation	BeachType	EventDate	EventType
0	gBqsPxAZ	Neum	BA	Mediterranean Sea	1551.0	Urban	Other (mixed)	20160424.0	Cleanup
1	gBqsPxAZ	Ponton	BA	NaN	86.0	Urban	Other (mixed)	20160519.0	Cleanup
2	Surfrider Foundation Europe	Blakenberg beach	BE	North-east Atlantic Ocean	82.0	Urban	Sandy	20160812.0	Cleanup
3	Perseus	Alepu	BG	Black Sea	105.0	Rural	Sandy	20160317.0	Cleanup
4	gBqsPxAZ	alepu	BG	Black Sea	2779.0	Urban	Sandy	20160313.0	Cleanup

5 rows × 178 columns

Pré processamento da base

O objetivo desta etapa é tratar, preparar e montar os dados coletados em uma base para aplicação do algoritmo Keras - TensorFlow

```
#Verifica valores NAN
data.isnull().sum()
```

```
CommunityName         1
BeachName             1
BeachCountrycode      1
BeachRegionalSea      2
BeachLength_m         1
                   ...
G208                147
G210                216
G211                208
G213                235
CLASSE                0
Length: 178, dtype: int64
```

```
data.head()
```

	CommunityName	BeachName	BeachCountrycode	BeachRegionalSea	BeachLength_m	BeachLocation	BeachType	EventDate	EventType
0	gBqsPxAZ	Neum	BA	Mediterranean Sea	1551.0	Urban	Other (mixed)	20160424.0	Cleanup
1	gBqsPxAZ	Ponton	BA	NaN	86.0	Urban	Other (mixed)	20160519.0	Cleanup
2	Surfrider Foundation Europe	Blakenberg beach	BE	North-east Atlantic Ocean	82.0	Urban	Sandy	20160812.0	Cleanup
3	Perseus	Alepu	BG	Black Sea	105.0	Rural	Sandy	20160317.0	Cleanup
4	gBqsPxAZ	alepu	BG	Black Sea	2779.0	Urban	Sandy	20160313.0	Cleanup

5 rows × 178 columns

```
#Substitui os valores NAN por zero
dataT = data.fillna(0)
dataT.isnull().sum()
```

```
CommunityName       0
```

```
BeachName           0
BeachCountrycode    0
BeachRegionalSea    0
BeachLength_m       0
                   ..
G208                0
G210                0
G211                0
G213                0
CLASSE              0
Length: 178, dtype: int64
```

```
1   dataT.head()
```

	CommunityName	BeachName	BeachCountrycode	BeachRegionalSea	BeachLength_m	BeachLocation	BeachType	EventDate	EventType
0	gBqsPxAZ	Neum	BA	Mediterranean Sea	1551.0	Urban	Other (mixed)	20160424.0	Cleanup
1	gBqsPxAZ	Ponton	BA	0	86.0	Urban	Other (mixed)	20160519.0	Cleanup
2	Surfrider Foundation Europe	Blakenberg beach	BE	North-east Atlantic Ocean	82.0	Urban	Sandy	20160812.0	Cleanup
3	Perseus	Alepu	BG	Black Sea	105.0	Rural	Sandy	20160317.0	Cleanup
4	gBqsPxAZ	alepu	BG	Black Sea	2779.0	Urban	Sandy	20160313.0	Cleanup

5 rows × 178 columns

Preparando os Dados

As colunas que precisamos são os indicadores de poluição (coluna G1 a G213) e a coluna de atributo Poluido = 1 não poluido = 0

Também necessitamos susbtituir as quantidades das colunas G1 a g213 por atributo do tipo de poluente encontrado=1 ou não encontrado=0

Eliminando colunas

```
dataT1 =  dataT.drop(columns=['CommunityName','BeachName','BeachCountrycode','BeachRegionalSea','BeachLength_m','BeachLocation'
dataT1.head()
```

	G1	G3	G4	G5	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17	G18	G19	G21	G22	G23	G24	G25	G26	G2
0	0.0	37.0	15.0	0.0	56.0	17.0	0.0	14.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	90.0	0.0	0.0	0.0	0.0	0.0	895.
1	0.0	10.0	3.0	0.0	148.0	144.0	8.0	33.0	0.0	6.0	0.0	6.0	0.0	0.0	1.0	0.0	0.0	350.0	0.0	0.0	0.0	0.0	2.0	24.
2	0.0	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	6.0	0.0	0.0	0.0	0.0	6.0	0.0	0.0	0.0	0.0	0.0	0.
3	0.0	0.0	2.0	0.0	5.0	1.0	0.0	2.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	41.0	0.0	0.0	0.0	0.0	1.0	0.
4	0.0	26.0	0.0	0.0	14.0	16.0	4.0	0.0	2.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	36.0	4.0	32.0	36.0	2.0	1.0	20.

5 rows × 163 columns

Encode das quantidade do tipo de lixo para localizado=1 não localizado=0

```
dataT1.loc[dataT1.G1>1,'G1']=1
dataT1.loc[dataT1.G3>1,'G3']=1
dataT1.loc[dataT1.G4>1,'G4']=1
dataT1.loc[dataT1.G5>1,'G5']=1
dataT1.loc[dataT1.G7>1,'G7']=1
dataT1.loc[dataT1.G8>1,'G8']=1
dataT1.loc[dataT1.G9>1,'G9']=1
dataT1.loc[dataT1.G10>1,'G10']=1
dataT1.loc[dataT1.G11>1,'G11']=1
dataT1.loc[dataT1.G12>1,'G12']=1
dataT1.loc[dataT1.G13>1,'G13']=1
dataT1.loc[dataT1.G14>1,'G14']=1
```

```
dataT1.loc[dataT1.G15>1,'G15']=1
dataT1.loc[dataT1.G16>1,'G16']=1
dataT1.loc[dataT1.G17>1,'G17']=1
dataT1.loc[dataT1.G18>1,'G18']=1
dataT1.loc[dataT1.G19>1,'G19']=1
dataT1.loc[dataT1.G21>1,'G21']=1
dataT1.loc[dataT1.G22>1,'G22']=1
dataT1.loc[dataT1.G23>1,'G23']=1
dataT1.loc[dataT1.G24>1,'G24']=1
dataT1.loc[dataT1.G25>1,'G25']=1
dataT1.loc[dataT1.G26>1,'G26']=1
dataT1.loc[dataT1.G27>1,'G27']=1
dataT1.loc[dataT1.G28>1,'G28']=1
dataT1.loc[dataT1.G29>1,'G29']=1
dataT1.loc[dataT1.G30>1,'G30']=1
dataT1.loc[dataT1.G31>1,'G31']=1
dataT1.loc[dataT1.G32>1,'G32']=1
dataT1.loc[dataT1.G33>1,'G33']=1
dataT1.loc[dataT1.G34>1,'G34']=1
dataT1.loc[dataT1.G35>1,'G35']=1
dataT1.loc[dataT1.G36>1,'G36']=1
dataT1.loc[dataT1.G37>1,'G37']=1
dataT1.loc[dataT1.G40>1,'G40']=1
dataT1.loc[dataT1.G41>1,'G41']=1
dataT1.loc[dataT1.G42>1,'G42']=1
dataT1.loc[dataT1.G43>1,'G43']=1
dataT1.loc[dataT1.G44>1,'G44']=1
dataT1.loc[dataT1.G45>1,'G45']=1
dataT1.loc[dataT1.G46>1,'G46']=1
dataT1.loc[dataT1.G47>1,'G47']=1
dataT1.loc[dataT1.G49>1,'G49']=1
dataT1.loc[dataT1.G50>1,'G50']=1
dataT1.loc[dataT1.G52>1,'G52']=1
dataT1.loc[dataT1.G53>1,'G53']=1
dataT1.loc[dataT1.G54>1,'G54']=1
dataT1.loc[dataT1.G56>1,'G56']=1
dataT1.loc[dataT1.G57>1,'G57']=1
dataT1.loc[dataT1.G58>1,'G58']=1
```

```
dataT1.loc[dataT1.G59>1,'G59']=1
dataT1.loc[dataT1.G60>1,'G60']=1
dataT1.loc[dataT1.G62>1,'G62']=1
dataT1.loc[dataT1.G63>1,'G63']=1
dataT1.loc[dataT1.G64>1,'G64']=1
dataT1.loc[dataT1.G65>1,'G65']=1
dataT1.loc[dataT1.G66>1,'G66']=1
dataT1.loc[dataT1.G67>1,'G67']=1
dataT1.loc[dataT1.G68>1,'G68']=1
dataT1.loc[dataT1.G69>1,'G69']=1
dataT1.loc[dataT1.G70>1,'G70']=1
dataT1.loc[dataT1.G71>1,'G71']=1
dataT1.loc[dataT1.G72>1,'G72']=1
dataT1.loc[dataT1.G73>1,'G73']=1
dataT1.loc[dataT1.G76>1,'G76']=1
dataT1.loc[dataT1.G77>1,'G77']=1
dataT1.loc[dataT1.G79>1,'G79']=1
dataT1.loc[dataT1.G80>1,'G80']=1
dataT1.loc[dataT1.G82>1,'G82']=1
dataT1.loc[dataT1.G83>1,'G83']=1
dataT1.loc[dataT1.G84>1,'G84']=1
dataT1.loc[dataT1.G85>1,'G85']=1
dataT1.loc[dataT1.G86>1,'G86']=1
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dataT1.loc[dataT1.G89>1,'G89']=1
dataT1.loc[dataT1.G90>1,'G90']=1
dataT1.loc[dataT1.G91>1,'G91']=1
dataT1.loc[dataT1.G92>1,'G92']=1
dataT1.loc[dataT1.G93>1,'G93']=1
dataT1.loc[dataT1.G95>1,'G95']=1
dataT1.loc[dataT1.G96>1,'G96']=1
dataT1.loc[dataT1.G97>1,'G97']=1
dataT1.loc[dataT1.G98>1,'G98']=1
dataT1.loc[dataT1.G99>1,'G99']=1
dataT1.loc[dataT1.G100>1,'G100']=1
dataT1.loc[dataT1.G101>1,'G101']=1
dataT1.loc[dataT1.G102>1,'G102']=1
```

```
dataT1.loc[dataT1.G102>1,'G102']=1
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dataT1.loc[dataT1.G125>1,'G125']=1
dataT1.loc[dataT1.G126>1,'G126']=1
dataT1.loc[dataT1.G127>1,'G127']=1
dataT1.loc[dataT1.G128>1,'G128']=1
dataT1.loc[dataT1.G129>1,'G129']=1
dataT1.loc[dataT1.G130>1,'G130']=1
dataT1.loc[dataT1.G131>1,'G131']=1
dataT1.loc[dataT1.G132>1,'G132']=1
dataT1.loc[dataT1.G133>1,'G133']=1
dataT1.loc[dataT1.G134>1,'G134']=1
dataT1.loc[dataT1.G137>1,'G137']=1
dataT1.loc[dataT1.G138>1,'G138']=1
dataT1.loc[dataT1.G139>1,'G139']=1
dataT1.loc[dataT1.G140>1,'G140']=1
dataT1.loc[dataT1.G141>1,'G141']=1
dataT1.loc[dataT1.G142>1,'G142']=1
dataT1.loc[dataT1.G143>1,'G143']=1
dataT1.loc[dataT1.G144>1,'G144']=1
dataT1.loc[dataT1.G145>1,'G145']=1
dataT1.loc[dataT1.G147>1,'G147']=1
dataT1.loc[dataT1.G148>1,'G148']=1
dataT1.loc[dataT1.G150>1,'G150']=1
dataT1.loc[dataT1.G151>1,'G151']=1
dataT1.loc[dataT1.G152>1,'G152']=1
dataT1.loc[dataT1.G153>1,'G153']=1
dataT1.loc[dataT1.G154>1,'G154']=1
dataT1.loc[dataT1.G155>1,'G155']=1
dataT1.loc[dataT1.G156>1,'G156']=1
dataT1.loc[dataT1.G158>1,'G158']=1
dataT1.loc[dataT1.G159>1,'G159']=1
dataT1.loc[dataT1.G160>1,'G160']=1
dataT1.loc[dataT1.G161>1,'G161']=1
dataT1.loc[dataT1.G162>1,'G162']=1
dataT1.loc[dataT1.G163>1,'G163']=1
dataT1.loc[dataT1.G164>1,'G164']=1
dataT1.loc[dataT1.G165>1,'G165']=1
```

```
dataT1.loc[dataT1.G166>1,'G166']=1
dataT1.loc[dataT1.G167>1,'G167']=1
dataT1.loc[dataT1.G171>1,'G171']=1
dataT1.loc[dataT1.G172>1,'G172']=1
dataT1.loc[dataT1.G174>1,'G174']=1
dataT1.loc[dataT1.G175>1,'G175']=1
dataT1.loc[dataT1.G176>1,'G176']=1
dataT1.loc[dataT1.G177>1,'G177']=1
dataT1.loc[dataT1.G178>1,'G178']=1
dataT1.loc[dataT1.G179>1,'G179']=1
dataT1.loc[dataT1.G180>1,'G180']=1
dataT1.loc[dataT1.G181>1,'G181']=1
dataT1.loc[dataT1.G182>1,'G182']=1
dataT1.loc[dataT1.G184>1,'G184']=1
dataT1.loc[dataT1.G186>1,'G186']=1
dataT1.loc[dataT1.G187>1,'G187']=1
dataT1.loc[dataT1.G188>1,'G188']=1
dataT1.loc[dataT1.G189>1,'G189']=1
dataT1.loc[dataT1.G190>1,'G190']=1
dataT1.loc[dataT1.G191>1,'G191']=1
dataT1.loc[dataT1.G193>1,'G193']=1
dataT1.loc[dataT1.G194>1,'G194']=1
dataT1.loc[dataT1.G195>1,'G195']=1
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dataT1.loc[dataT1.G199>1,'G199']=1
dataT1.loc[dataT1.G200>1,'G200']=1
dataT1.loc[dataT1.G201>1,'G201']=1
dataT1.loc[dataT1.G202>1,'G202']=1
dataT1.loc[dataT1.G203>1,'G203']=1
dataT1.loc[dataT1.G204>1,'G204']=1
dataT1.loc[dataT1.G205>1,'G205']=1
dataT1.loc[dataT1.G206>1,'G206']=1
dataT1.loc[dataT1.G207>1,'G207']=1
dataT1.loc[dataT1.G208>1,'G208']=1
dataT1.loc[dataT1.G210>1,'G210']=1
dataT1.loc[dataT1.G211>1,'G211']=1
dataT1.loc[dataT1.G213>1,'G213']=1
```

```
dataT1.loc[dataT1.G1<0,'G1']=0
dataT1.loc[dataT1.G3<0,'G3']=0
dataT1.loc[dataT1.G4<0,'G4']=0
dataT1.loc[dataT1.G5<0,'G5']=0
dataT1.loc[dataT1.G7<0,'G7']=0
dataT1.loc[dataT1.G8<0,'G8']=0
dataT1.loc[dataT1.G9<0,'G9']=0
dataT1.loc[dataT1.G10<0,'G10']=0
dataT1.loc[dataT1.G11<0,'G11']=0
dataT1.loc[dataT1.G12<0,'G12']=0
dataT1.loc[dataT1.G13<0,'G13']=0
dataT1.loc[dataT1.G14<0,'G14']=0
dataT1.loc[dataT1.G15<0,'G15']=0
dataT1.loc[dataT1.G16<0,'G16']=0
dataT1.loc[dataT1.G17<0,'G17']=0
dataT1.loc[dataT1.G18<0,'G18']=0
dataT1.loc[dataT1.G19<0,'G19']=0
dataT1.loc[dataT1.G21<0,'G21']=0
dataT1.loc[dataT1.G22<0,'G22']=0
dataT1.loc[dataT1.G23<0,'G23']=0
dataT1.loc[dataT1.G24<0,'G24']=0
dataT1.loc[dataT1.G25<0,'G25']=0
dataT1.loc[dataT1.G26<0,'G26']=0
dataT1.loc[dataT1.G27<0,'G27']=0
dataT1.loc[dataT1.G28<0,'G28']=0
dataT1.loc[dataT1.G29<0,'G29']=0
dataT1.loc[dataT1.G30<0,'G30']=0
dataT1.loc[dataT1.G31<0,'G31']=0
dataT1.loc[dataT1.G32<0,'G32']=0
dataT1.loc[dataT1.G33<0,'G33']=0
dataT1.loc[dataT1.G34<0,'G34']=0
dataT1.loc[dataT1.G35<0,'G35']=0
dataT1.loc[dataT1.G36<0,'G36']=0
dataT1.loc[dataT1.G37<0,'G37']=0
dataT1.loc[dataT1.G40<0,'G40']=0
dataT1.loc[dataT1.G41<0,'G41']=0
dataT1.loc[dataT1.G42<0,'G42']=0
```

```
dataT1.loc[dataT1.G43<0,'G43']=0
dataT1.loc[dataT1.G44<0,'G44']=0
dataT1.loc[dataT1.G45<0,'G45']=0
dataT1.loc[dataT1.G46<0,'G46']=0
dataT1.loc[dataT1.G47<0,'G47']=0
dataT1.loc[dataT1.G49<0,'G49']=0
dataT1.loc[dataT1.G50<0,'G50']=0
dataT1.loc[dataT1.G52<0,'G52']=0
dataT1.loc[dataT1.G53<0,'G53']=0
dataT1.loc[dataT1.G54<0,'G54']=0
dataT1.loc[dataT1.G56<0,'G56']=0
dataT1.loc[dataT1.G57<0,'G57']=0
dataT1.loc[dataT1.G58<0,'G58']=0
dataT1.loc[dataT1.G59<0,'G59']=0
dataT1.loc[dataT1.G60<0,'G60']=0
dataT1.loc[dataT1.G62<0,'G62']=0
dataT1.loc[dataT1.G63<0,'G63']=0
dataT1.loc[dataT1.G64<0,'G64']=0
dataT1.loc[dataT1.G65<0,'G65']=0
dataT1.loc[dataT1.G66<0,'G66']=0
dataT1.loc[dataT1.G67<0,'G67']=0
dataT1.loc[dataT1.G68<0,'G68']=0
dataT1.loc[dataT1.G69<0,'G69']=0
dataT1.loc[dataT1.G70<0,'G70']=0
dataT1.loc[dataT1.G71<0,'G71']=0
dataT1.loc[dataT1.G72<0,'G72']=0
dataT1.loc[dataT1.G73<0,'G73']=0
dataT1.loc[dataT1.G76<0,'G76']=0
dataT1.loc[dataT1.G77<0,'G77']=0
dataT1.loc[dataT1.G79<0,'G79']=0
dataT1.loc[dataT1.G80<0,'G80']=0
dataT1.loc[dataT1.G82<0,'G82']=0
dataT1.loc[dataT1.G83<0,'G83']=0
dataT1.loc[dataT1.G84<0,'G84']=0
dataT1.loc[dataT1.G85<0,'G85']=0
dataT1.loc[dataT1.G86<0,'G86']=0
dataT1.loc[dataT1.G87<0,'G87']=0
dataT1.loc[dataT1.G88<0,'G88']=0
```

```
dataT1.loc[dataT1.G88<0,'G88']=0
dataT1.loc[dataT1.G89<0,'G89']=0
dataT1.loc[dataT1.G90<0,'G90']=0
dataT1.loc[dataT1.G91<0,'G91']=0
dataT1.loc[dataT1.G92<0,'G92']=0
dataT1.loc[dataT1.G93<0,'G93']=0
dataT1.loc[dataT1.G95<0,'G95']=0
dataT1.loc[dataT1.G96<0,'G96']=0
dataT1.loc[dataT1.G97<0,'G97']=0
dataT1.loc[dataT1.G98<0,'G98']=0
dataT1.loc[dataT1.G99<0,'G99']=0
dataT1.loc[dataT1.G100<0,'G100']=0
dataT1.loc[dataT1.G101<0,'G101']=0
dataT1.loc[dataT1.G102<0,'G102']=0
dataT1.loc[dataT1.G124<0,'G124']=0
dataT1.loc[dataT1.G125<0,'G125']=0
dataT1.loc[dataT1.G126<0,'G126']=0
dataT1.loc[dataT1.G127<0,'G127']=0
dataT1.loc[dataT1.G128<0,'G128']=0
dataT1.loc[dataT1.G129<0,'G129']=0
dataT1.loc[dataT1.G130<0,'G130']=0
dataT1.loc[dataT1.G131<0,'G131']=0
dataT1.loc[dataT1.G132<0,'G132']=0
dataT1.loc[dataT1.G133<0,'G133']=0
dataT1.loc[dataT1.G134<0,'G134']=0
dataT1.loc[dataT1.G137<0,'G137']=0
dataT1.loc[dataT1.G138<0,'G138']=0
dataT1.loc[dataT1.G139<0,'G139']=0
dataT1.loc[dataT1.G140<0,'G140']=0
dataT1.loc[dataT1.G141<0,'G141']=0
dataT1.loc[dataT1.G142<0,'G142']=0
dataT1.loc[dataT1.G143<0,'G143']=0
dataT1.loc[dataT1.G144<0,'G144']=0
dataT1.loc[dataT1.G145<0,'G145']=0
dataT1.loc[dataT1.G147<0,'G147']=0
dataT1.loc[dataT1.G148<0,'G148']=0
dataT1.loc[dataT1.G150<0,'G150']=0
dataT1.loc[dataT1.G151<0,'G151']=0
```

```
dataT1.loc[dataT1.G152<0,'G152']=0
dataT1.loc[dataT1.G153<0,'G153']=0
dataT1.loc[dataT1.G154<0,'G154']=0
dataT1.loc[dataT1.G155<0,'G155']=0
dataT1.loc[dataT1.G156<0,'G156']=0
dataT1.loc[dataT1.G158<0,'G158']=0
dataT1.loc[dataT1.G159<0,'G159']=0
dataT1.loc[dataT1.G160<0,'G160']=0
dataT1.loc[dataT1.G161<0,'G161']=0
dataT1.loc[dataT1.G162<0,'G162']=0
dataT1.loc[dataT1.G163<0,'G163']=0
dataT1.loc[dataT1.G164<0,'G164']=0
dataT1.loc[dataT1.G165<0,'G165']=0
dataT1.loc[dataT1.G166<0,'G166']=0
dataT1.loc[dataT1.G167<0,'G167']=0
dataT1.loc[dataT1.G171<0,'G171']=0
dataT1.loc[dataT1.G172<0,'G172']=0
dataT1.loc[dataT1.G174<0,'G174']=0
dataT1.loc[dataT1.G175<0,'G175']=0
dataT1.loc[dataT1.G176<0,'G176']=0
dataT1.loc[dataT1.G177<0,'G177']=0
dataT1.loc[dataT1.G178<0,'G178']=0
dataT1.loc[dataT1.G179<0,'G179']=0
dataT1.loc[dataT1.G180<0,'G180']=0
dataT1.loc[dataT1.G181<0,'G181']=0
dataT1.loc[dataT1.G182<0,'G182']=0
dataT1.loc[dataT1.G184<0,'G184']=0
dataT1.loc[dataT1.G186<0,'G186']=0
dataT1.loc[dataT1.G187<0,'G187']=0
dataT1.loc[dataT1.G188<0,'G188']=0
dataT1.loc[dataT1.G189<0,'G189']=0
dataT1.loc[dataT1.G190<0,'G190']=0
dataT1.loc[dataT1.G191<0,'G191']=0
dataT1.loc[dataT1.G193<0,'G193']=0
dataT1.loc[dataT1.G194<0,'G194']=0
dataT1.loc[dataT1.G195<0,'G195']=0
dataT1.loc[dataT1.G198<0,'G198']=0
dataT1.loc[dataT1.G199<0,'G199']=0
```

```
dataT1.loc[dataT1.G200<0,'G200']=0
dataT1.loc[dataT1.G201<0,'G201']=0
dataT1.loc[dataT1.G202<0,'G202']=0
dataT1.loc[dataT1.G203<0,'G203']=0
dataT1.loc[dataT1.G204<0,'G204']=0
dataT1.loc[dataT1.G205<0,'G205']=0
dataT1.loc[dataT1.G206<0,'G206']=0
dataT1.loc[dataT1.G207<0,'G207']=0
dataT1.loc[dataT1.G208<0,'G208']=0
dataT1.loc[dataT1.G210<0,'G210']=0
dataT1.loc[dataT1.G211<0,'G211']=0
dataT1.loc[dataT1.G213<0,'G213']=0
```

```
dataT1.head()
```

	G1	G3	G4	G5	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17	G18	G19	G21	G22	G23	G24	G25	G26	G27	G28	G29
0	0.0	1.0	1.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
1	0.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0
2	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	1.0	0.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
4	0.0	1.0	0.0	0.0	1.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	0.0

5 rows × 163 columns

Encode do atributo classe poluido=1 limpo=0

```
dataT1['CLASSE'].value_counts()
```

```
LIMPO      128
POLUIDO    125
```

```
                1
Name: CLASSE, dtype: int64
```

```
dataT1['CLASSE'] = dataT1['CLASSE'].map({'LIMPO': 0, 'POLUIDO': 1})
dataT1['CLASSE'].value_counts()
```

```
0.0    128
1.0    125
Name: CLASSE, dtype: int64
```

Separação do atributo classe

```
X = dataT1.drop('CLASSE', axis=1)
y = dataT1[['CLASSE']]
```

Definidos e tratados os dados de entrada `X` e `y` do nosso conjunto de exemplos, podemos então separar os conjuntos de treinamento e teste.

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=123)
```

```
display(X_train.head())
display(y_train.head())
```

	G1	G3	G4	G5	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17	G18	G19	G21	G22	G23	G24	G25	G26	G27	G28	G
221	0.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	'
50	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	'
197	0.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(
247	0.0	1.0	1.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	'
156	0.0	0.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	(

5 rows × 162 columns

	CLASSE
221	1.0
50	1.0
197	1.0

Modelo Sequencial

Declarando as Camadas

```
model = keras.Sequential(layers.Dense(161, activation='sigmoid', input_shape=[162]))
model.add(layers.Dense(1, activation='sigmoid'))
model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_6 (Dense)              (None, 161)               26243     
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 162       
```

```
=================================================================
Total params: 26,405
Trainable params: 26,405
Non-trainable params: 0
_________________________________________________________________
```

Compilando o Modelo

```
model.compile(loss='binary_crossentropy', metrics=['binary_accuracy'],)
```

Treinando o Modelo

```
history = model.fit(
    X_train, y_train,
    batch_size=32,
    validation_split=0.4,
    epochs=20,
    verbose=1,
)
```

```
Epoch 1/20
4/4 [==============================] - 1s 87ms/step - loss: 0.6415 - binary_accuracy: 0.6604 - val_loss: nan - val_binary_accur
Epoch 2/20
4/4 [==============================] - 0s 13ms/step - loss: 0.5391 - binary_accuracy: 0.7358 - val_loss: nan - val_binary_accur
Epoch 3/20
4/4 [==============================] - 0s 10ms/step - loss: 0.4870 - binary_accuracy: 0.8491 - val_loss: nan - val_binary_accur
Epoch 4/20
4/4 [==============================] - 0s 10ms/step - loss: 0.4458 - binary_accuracy: 0.9151 - val_loss: nan - val_binary_accur
Epoch 5/20
4/4 [==============================] - 0s 10ms/step - loss: 0.4163 - binary_accuracy: 0.9057 - val_loss: nan - val_binary_accur
Epoch 6/20
4/4 [==============================] - 0s 9ms/step - loss: 0.3915 - binary_accuracy: 0.9434 - val_loss: nan - val_binary_accura
Epoch 7/20
4/4 [==============================] - 0s 9ms/step - loss: 0.3665 - binary_accuracy: 0.9434 - val_loss: nan - val_binary_accura
```

```
Epoch 8/20
4/4 [==============================] - 0s 11ms/step - loss: 0.3480 - binary_accuracy: 0.9151 - val_loss: nan - val_binary_accur
Epoch 9/20
4/4 [==============================] - 0s 9ms/step - loss: 0.3285 - binary_accuracy: 0.9434 - val_loss: nan - val_binary_accura
Epoch 10/20
4/4 [==============================] - 0s 9ms/step - loss: 0.3135 - binary_accuracy: 0.9528 - val_loss: nan - val_binary_accura
Epoch 11/20
4/4 [==============================] - 0s 10ms/step - loss: 0.2991 - binary_accuracy: 0.9434 - val_loss: nan - val_binary_accur
Epoch 12/20
4/4 [==============================] - 0s 14ms/step - loss: 0.2839 - binary_accuracy: 0.9528 - val_loss: nan - val_binary_accur
Epoch 13/20
4/4 [==============================] - 0s 9ms/step - loss: 0.2714 - binary_accuracy: 0.9528 - val_loss: nan - val_binary_accura
Epoch 14/20
4/4 [==============================] - 0s 12ms/step - loss: 0.2608 - binary_accuracy: 0.9528 - val_loss: nan - val_binary_accur
Epoch 15/20
4/4 [==============================] - 0s 16ms/step - loss: 0.2487 - binary_accuracy: 0.9528 - val_loss: nan - val_binary_accur
Epoch 16/20
4/4 [==============================] - 0s 10ms/step - loss: 0.2381 - binary_accuracy: 0.9528 - val_loss: nan - val_binary_accur
Epoch 17/20
4/4 [==============================] - 0s 13ms/step - loss: 0.2281 - binary_accuracy: 0.9623 - val_loss: nan - val_binary_accur
Epoch 18/20
4/4 [==============================] - 0s 15ms/step - loss: 0.2199 - binary_accuracy: 0.9434 - val_loss: nan - val_binary_accur
Epoch 19/20
4/4 [==============================] - 0s 9ms/step - loss: 0.2105 - binary_accuracy: 0.9623 - val_loss: nan - val_binary_accura
Epoch 20/20
4/4 [==============================] - 0s 9ms/step - loss: 0.2030 - binary_accuracy: 0.9528 - val_loss: nan - val_binary_accura
```

Curva de Apredizado

```
def display_hist(history):
  history_df = pd.DataFrame(history.history)
  display(history_df.head())
  # Start the plot at epoch 0
  history_df.loc[0:, ['loss', 'val_loss']].plot()
  history_df.loc[0:, ['binary_accuracy', 'val_binary_accuracy']].plot()

  print(("Best Validation Loss: {:0.4f}" +\
```

```
      "\nBest Validation Accuracy: {:0.4f}")\
      .format(history_df['val_loss'].min(),
              history_df['val_binary_accuracy'].max()))
  return


```

```
display_hist(history)
```

	loss	binary_accuracy	val_loss	val_binary_accuracy
0	0.641506	0.660377	NaN	0.760563
1	0.539056	0.735849	NaN	0.830986
2	0.487034	0.849057	NaN	0.830986
3	0.445777	0.915094	NaN	0.845070
4	0.416320	0.905660	NaN	0.830986

```
Best Validation Loss: nan
```

Resultados

Podemos então avaliar os resultados do nosso modelo fazendo a predição do conjunto de teste selecionado anteriormente.

Aqui podemos empregar as métricas usuais do `Scikit-Learn`. A predição, tendo um único neurônio de saída com a função sigmóide (ou logística) devolve um único valor entre $[0, 1]$ e podemos entender esse valor como a chance de ser a classe `1`.

```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
def print_results(y_test, y_pred):
  print('Matriz de Confusão: \n' , confusion_matrix(y_test, y_pred))
  print(classification_report(y_test, y_pred))
  print('Acuracidade: ' , accuracy_score(y_test, y_pred))
  return
```

```
y_pred = model.predict(X_test) > 0.5

print_results(y_test, y_pred)

```

```
Matriz de Confusão:
 [[31 10]
 [ 1 35]]
              precision    recall  f1-score   support
```

```
         0.0       0.97      0.76      0.85        41
         1.0       0.78      0.97      0.86        36

    accuracy                           0.86        77
   macro avg       0.87      0.86      0.86        77
weighted avg       0.88      0.86      0.86        77

Acuracidade:  0.8571428571428571
```