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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

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Introdução

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

Dataset

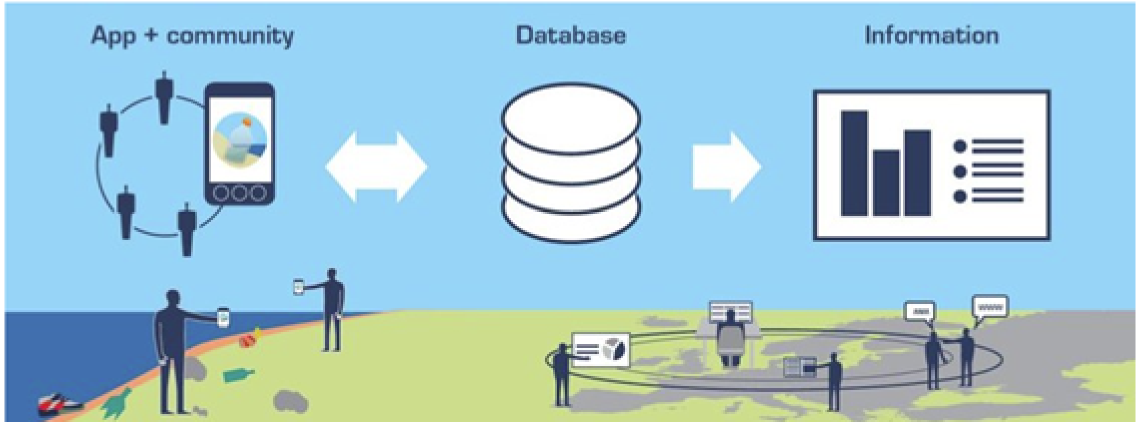
O dataset escolhido é o MLW_Data, este dataset fornecido pela Agência Europeia de Ambiente, é criado a partir de um aplicativo denominado LitterWatch, que é utilizado nas comunidades costeiras da Europa para identificar o lixo jogado ao oceano.

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 categorizar 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 MLW_Meta.csv

- **MLW_Meta.csv**(application/vnd.ms-excel) - 6826 bytes, last modified: 06/09/2021 - 100% done

```
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)
```

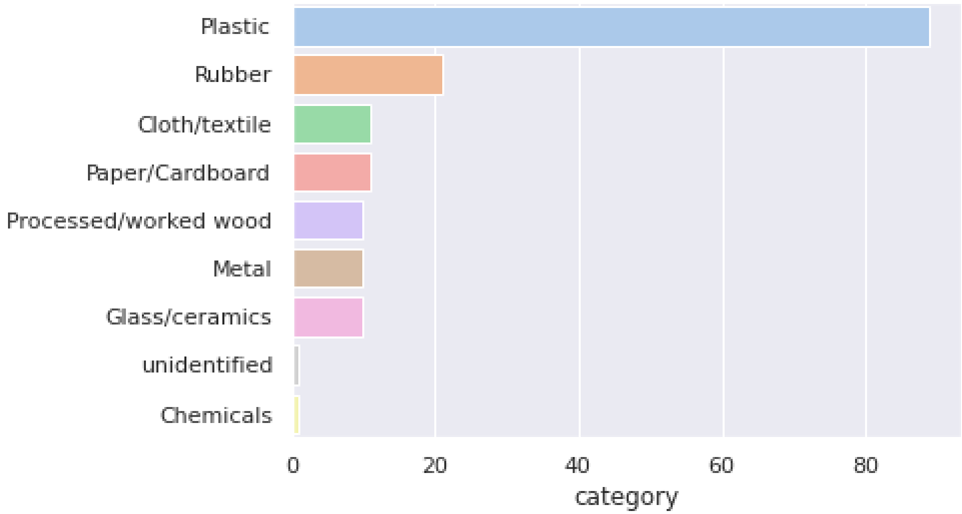
	generalcode	category	generalname
0	G1	Plastic	4/6-pack yokes, six-pack rings
1	G3	Plastic	Shopping Bags incl. pieces
2	G4	Plastic	Small plastic bags, e.g. freezer bags incl. pi...
3	G5	Plastic	Plastic bags collective role what remains from...
4	G7	Plastic	Drink bottles <=0.5l
5	G8	Plastic	Drink bottles >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 MLW_Data.csv

- **MLW_Data.csv**(application/vnd.ms-excel) - 100156 bytes, last modified: 06/09/2021 - 100% done

```
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()
```

G1	G3	G4	G5	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17	G18	G19	G21	G22	G23	G24	G25
NaN	37.0	15.0	NaN	56.0	17.0	NaN	14.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	90.0	NaN	NaN	NaN	NaN
NaN	10.0	3.0	NaN	148.0	144.0	8.0	33.0	NaN	6.0	NaN	6.0	NaN	NaN	1.0	NaN	NaN	350.0	NaN	NaN	NaN	NaN
NaN	4.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6.0	NaN	NaN	NaN	NaN	6.0	NaN	NaN	NaN	NaN
NaN	NaN	2.0	NaN	5.0	1.0	NaN	2.0	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN	NaN	41.0	NaN	NaN	NaN	NaN
NaN	26.0	NaN	NaN	14.0	16.0	4.0	NaN	2.0	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	36.0	4.0	32.0	36.0	2.0

```
#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
```

```
dataT.head()
```

l: .4	G1	G3	G4	G5	G7	G8	G9	G10	G11	G12	G13	G14	G15	G16	G17	G18	G19	G21	G22	G23	G24	G25	G26	G27
.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	895.0
.0	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	24.0
.0	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	0.0
.0	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	0.0
.0	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	20.0

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

Substituição das quantidades 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
dataT1.loc[dataT1.G87>1,'G87']=1
dataT1.loc[dataT1.G88>1,'G88']=1
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.G124>1,'G124']=1
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
dataT1.loc[dataT1.G198>1,'G198']=1
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.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	

Modelo Sequencial

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	

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
```

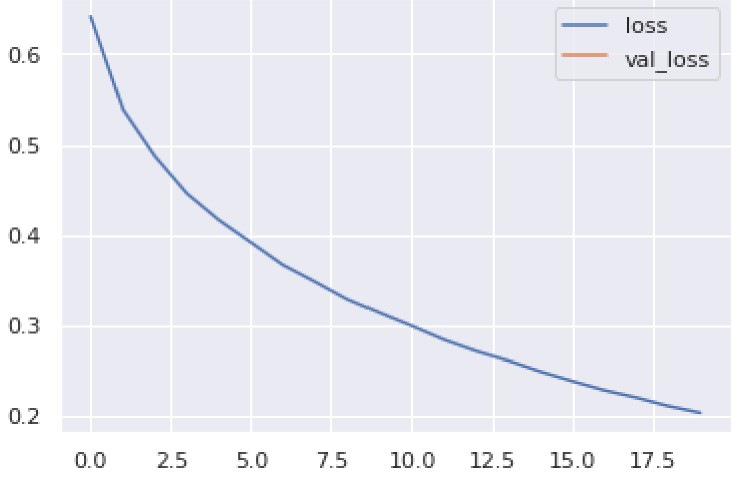
Curva de Apredizado

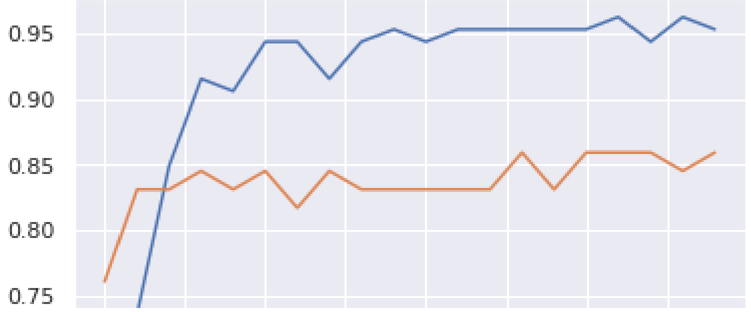
```
def display_hist(history):
  history_df = pd.DataFrame(history.history)
  display(history_df.head())
  # Start the plot at epoch 0
  history_df.loc[0:, ['loss', 'val_loss']].plot()
  history_df.loc[0:, ['binary_accuracy', 'val_binary_accuracy']].plot()

  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
Best Validation Accuracy: 0.8592
```





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
```

Conclusão

O objetivo de acuracidade de 0.8 foi atingido com o valor de 0.857, no entanto o dataset exigiu um validation_split=0.4 ao invés de 0.3 do modelo original, por retornar NAN no Loss para valores abaixo de 0.4.

0s conclusão: 13:32