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Inteligência Artificial

Universidade Presbiteriana Mackenzie

Deep Learning

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Tarefa da trilha 6: classificação binária ou multiclasse com o PyTorch
https://github.com/Fernandopessoa1959/MACKENZIE-IA
NOTEBOOK https://github.com/Fernandopessoa1959/MACKENZIE-IA/blob/main/TRILHA_6_TAREFA_FERNANDO_PESSOA.ipynb
DATASET https://github.com/Fernandopessoa1959/MACKENZIE-IA/blob/main/TRILHA_6_MLW_Data.csv

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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

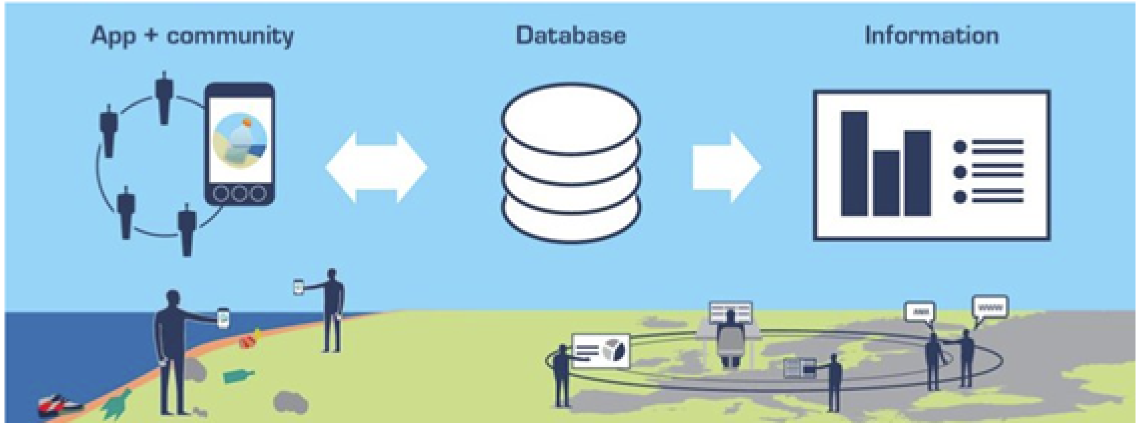
O dataset escolhido é o MLW_Data, este dataset fornecido pela Agência Europeia de Ambiente, é criado a partir de um aplicativo denominado LitterWatch, que é utilizados nas comunidades costeiras da Europa para identificar o lixo jogado ao oceano.

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
```

```
import pandas as pd
import torch
from torch import nn
import numpy as np
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Importando datasets

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

Base de dados da pesquisa

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

Escolher arquivos TRILHA_6_MLW_Data.csv

- **TRILHA_6_MLW_Data.csv**(application/vnd.ms-excel) - 100156 bytes, last modified: 06/09/2021 - 100% done

```
Saving TRILHA_6_MLW_Data.csv to TRILHA_6_MLW_Data (1).csv
```

```
data = pd.read_csv('/content/TRILHA_6_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
```

```
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.

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
```

```python
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.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 = dataT1.fillna(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
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

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
```

```
dataT1 = dataT1.fillna(0)
dataT1.isnull().sum().sum()
```

```
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

Preparação dos dados

```
from torch.utils.data import Dataset
from sklearn.preprocessing import LabelEncoder
```

```
class CSVDataset(Dataset):
  def __init__(self):
    self.X = dataT1.values[:, :-1]
    self.y = dataT1.values[:, -1]

    self.X = self.X.astype('float32')

    self.y = LabelEncoder().fit_transform(self.y)
    self.y = self.y.astype('float32')
    self.y = self.y.reshape((len(self.y), 1))

  def __len__(self):
    return len(self.X)

  def __getitem__(self, idx):
    return [self.X[idx], self.y[idx]]
```

```
dataset = CSVDataset()
```

```
print('Número de tuplas:' , dataset.__len__() )
print( dataset[0])
```

```
Número de tuplas: 254
[array([0., 1., 1., 0., 1., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       1., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 1., 1., 0., 0.,
       0., 0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0.,
       1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 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., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 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.], dtype=float32), array([0.], dtype=float32)]
```

```
for i in range(2):
  print(dataset.X[i], dataset.y[i])
```

```
[0. 1. 1. 0. 1. 1. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0. 1.
 0. 0. 1. 0. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 1. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 1. 0. 0. 0. 1. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 1. 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. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.
 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 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. 1. 1. 0. 1. 1. 1. 1. 0. 1. 0. 1. 0. 0. 1. 0. 0. 1. 0. 0. 0. 0. 1. 1.
 0. 0. 1. 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. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 1. 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. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 1.
 0. 0. 0. 0. 0. 0. 0. 1. 1. 1. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0.
 0. 0. 0. 0. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 1. 0. 0. 0.] [1.]
```

```
from torch.utils.data.dataset import random_split
import torch

train_len = int(0.7*len(dataset))
test_len = len(dataset) - train_len

train_dataset, test_dataset = random_split(dataset,[train_len,test_len], generator=torch.Generator().manual_seed(123),)
```

```
train_dataset[0:2]
```

```
[array([[0., 1., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 1., 0., 0., 0., 0., 1., 1., 0., 0., 1., 1., 1., 0., 0., 1.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 1.,
         0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 0.,
         0., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         1., 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., 1., 0., 0., 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., 0., 0., 0., 0.,
         0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 1., 0.,
         0., 0.],
        [0., 1., 0., 0., 1., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 1., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 1., 1., 1., 1.,
         0., 0., 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., 1., 0., 0.,
         0., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0.,
         0., 0., 0., 1., 0., 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., 0., 0.,
         0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 0., 1., 0.,
         0., 0.]], dtype=float32), array([[1.],
        [1.]], dtype=float32)]
```

```
from torch.utils.data import DataLoader

train = DataLoader(train_dataset, batch_size=2, shuffle=True)
test  = DataLoader(test_dataset, batch_size=2, shuffle=True)
```

```
X_test, y_test = next(iter(test))

print( X_test )
print( y_test )
```

```
tensor([[0., 0., 0., 0., 1., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1.,
         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., 1., 1., 0., 0., 0., 1., 0., 0., 0.,
         0., 0., 1., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0., 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., 0., 0., 1., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0.,
         0., 0., 1., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         1., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.],
        [0., 1., 1., 0., 1., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 1.,
         1., 1., 1., 0., 1., 0., 1., 1., 1., 1., 1., 1., 1., 1., 0., 1., 0., 0.,
         0., 0., 0., 0., 0., 0., 1., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 1., 1., 0., 1., 0., 0.,
         0., 0., 0., 1., 0., 0., 0., 1., 0., 1., 0., 0., 1., 1., 0., 1., 1., 1.,
         0., 0., 1., 1., 0., 1., 0., 0., 1., 1., 1., 0., 0., 1., 1., 0., 0., 1.,
         0., 0., 1., 0., 0., 1., 1., 0., 0., 0., 1., 0., 1., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 1., 1., 1., 0., 1., 0., 0., 0., 0., 0., 1., 0.]])
tensor([[1.],
        [1.]])
```

```
X_train, y_train = next(iter(train))

print( X_train )
print( y_train )
```

```
tensor([[0., 1., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.,
         0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 1., 0., 0., 0.,
         0., 0., 1., 1., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 1., 0., 0., 1., 0.,
         0., 0., 1., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 1.,
         0., 1., 1., 0., 1., 0., 0., 0., 0., 1., 1., 1., 0., 0., 0., 0., 0., 0.,
         0., 1., 0., 0., 1., 1., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0.],
        [0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
         0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
```

```
          0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
          0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.]])
tensor([[1.],
        [0.]])
```

Criação da Rede

```
import torch.nn as nn
```

```
class MLP(nn.Module):
  def __init__(self, n_inputs):
    super(MLP, self).__init__()

    self.hidden1 = nn.Linear(n_inputs, 200)
    self.act1 = nn.ReLU()
    self.hidden1_drop = nn.Dropout(p=0.2)

    self.hidden2 = nn.Linear(200,100)
    self.act2 = nn.ReLU()
    self.hidden2_drop = nn.Dropout(p=0.2)

    self.hidden3 = nn.Linear(100,30)
    self.act3 = nn.ReLU()
    self.hidden3_drop = nn.Dropout(p=0.2)

    self.hidden4 = nn.Linear(30, 1)
    self.act4 = nn.Sigmoid()

  #Forward
  def forward(self, X):
    X = self.hidden1(X)
    X = self.act1(X)
    X = self.hidden1_drop(X)
    X = self.hidden2(X)
```

```
        X = self.act2(X)
        X = self.hidden2_drop(X)
        X = self.hidden3(X)
        X = self.act3(X)
        X = self.hidden3_drop(X)
        X = self.hidden4(X)
        X = self.act4(X)
        return X
```

```
from torch.optim import SGD, Adam
```

```
model = MLP(162)
loss_fn = nn.BCELoss()
optimizer = Adam(model.parameters(), lr=0.001, weight_decay=1E-3)
print(model)
```

```
MLP(
  (hidden1): Linear(in_features=162, out_features=200, bias=True)
  (act1): ReLU()
  (hidden1_drop): Dropout(p=0.2, inplace=False)
  (hidden2): Linear(in_features=200, out_features=100, bias=True)
  (act2): ReLU()
  (hidden2_drop): Dropout(p=0.2, inplace=False)
  (hidden3): Linear(in_features=100, out_features=30, bias=True)
  (act3): ReLU()
  (hidden3_drop): Dropout(p=0.2, inplace=False)
  (hidden4): Linear(in_features=30, out_features=1, bias=True)
  (act4): Sigmoid()
)
```

```
model(X_train)[0:10]
```

```
tensor([[0.4782],
        [0.4747]], grad_fn=<SliceBackward>)
```

```
model(X_test)[0:10]
```

```
tensor([[0.4944],
        [0.4811]], grad_fn=<SliceBackward>)
```

Treinamento

```
import tqdm # somente para display da evolução do loop

EPOCHS  = 100

loss_list     = np.zeros((EPOCHS,))
accuracy_list = np.zeros((EPOCHS,))

for epoch in tqdm.trange(EPOCHS):
    y_pred = model(X_train)
    loss = loss_fn(y_pred, y_train)
    loss_list[epoch] = loss.item()

    # Zero gradients
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    with torch.no_grad():
        y_pred = model(X_test)
        correct = (torch.argmax(y_pred, dim=1) == y_test).type(torch.FloatTensor)
        accuracy_list[epoch] = correct.mean()
```

```
100%|██████████| 100/100 [00:00<00:00, 233.53it/s]
```

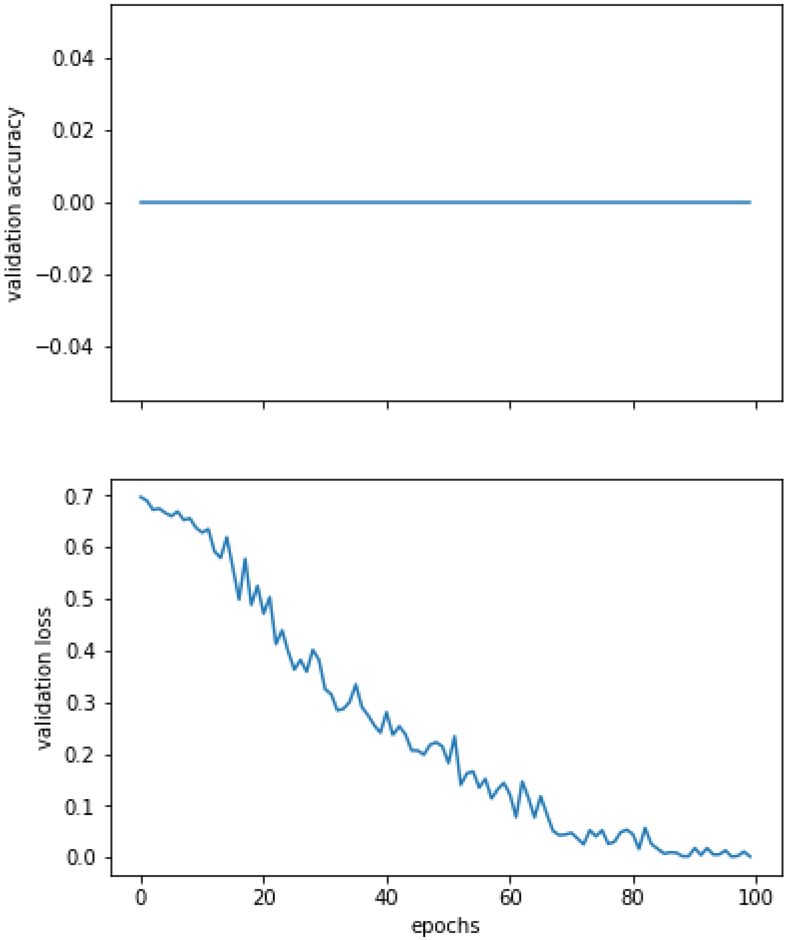
```
def plot_history(loss_list,  accuracy_list):
  fig, (ax1, ax2) = plt.subplots(2, figsize=(6, 8), sharex=True)

  ax1.plot(accuracy_list)
  ax1.set_ylabel("validation accuracy")
  ax2.plot(loss_list)
```

```
  ax2.set_ylabel("validation loss")
  ax2.set_xlabel("epochs")
  plt.show()

  return

plot_history(loss_list,  accuracy_list)
```



Identificação da Acurácia

```
test = DataLoader(test_dataset, batch_size=len(test_dataset),shuffle=True)
#test = DataLoader(test_dataset, batch_size=16,shuffle=True)
xx_test, yy_test = next(iter(test))
```

```
yy_pred = model(xx_test).round()
```

```
from sklearn.metrics import accuracy_score
print(accuracy_score(yy_test.detach().numpy(), yy_pred.detach().numpy()))
```

```
0.8441558441558441
```

Conclusão

Após o desenvolvimento o modelo apresenta acuracidade acima de .8 com 84,4%, para tanto foram utilizadas 2 tecnicas, sendo:

Dropout entre as camadas de entrada e saida de 0.2

L2 no otimizador ADAM com weight_decay=1E-3

Acuracidade antes da aplicação dos otimizadores éra de 68,75%

Identificação da Acurácia sem tecnicas de regularização

[105]
```
#test = DataLoader(test_dataset, batch_size=len(test_dataset),shuffle=True)
test = DataLoader(test_dataset, batch_size=16,shuffle=True)
xx_test, yy_test = next(iter(test))
```

[106]
```
yy_pred = model(xx_test).round()
```

```
from sklearn.metrics import accuracy_score
print(accuracy_score(yy_test.detach().numpy(), yy_pred.detach().numpy()))
```

```
0.6875
```

0s conclusão: 11:42