## DL 03 EX-2

March 17, 2021

Deep Learning		
Rogério de Oliveira		

MLP com TensorFlow

### 1 Case: Steel Plates Fault

Aqui você vai trabalhar com um conjunto de dados sobre características de produção de chapas de aço, classificadas em 7 tipos diferentes de falhas ou defeitos. O objetivo é **treinar um modelo deep learning** (MLP TensorFlow/Keras) para o reconhecimento automático dos padrões de falha e sua classificação nos **7 tipos**.

Dataset

Info

Type of dependent variables (7 Types of Steel Plates Faults):

```
1.Pastry
```

- $2.Z\_Scratch$
- 3.K Scatch
- 4.Stains
- 5.Dirtiness
- 6.Bumps
- $7.Other\_Faults$

## 2 imports

```
[1]: # imports
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
```

```
import os
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report

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

## 3 Exercício. Acesse e Explore os Dados

Que transformações são necessárias para o treinamento dos dados?

```
[2]: df = pd.read_csv("http://meusite.mackenzie.br/rogerio/STEEL_faults.csv")
[3]: df.head()
[3]:
        X Minimum
                    X Maximum
                               Y Minimum
                                           Y Maximum
                                                       Pixels Areas
                                                                       X Perimeter
                42
                            50
                                   270900
                                               270944
                                                                  267
     1
               645
                           651
                                  2538079
                                              2538108
                                                                  108
                                                                                 10
     2
               829
                          835
                                  1553913
                                              1553931
                                                                  71
                                                                                 8
     3
               853
                          860
                                                                  176
                                                                                 13
                                   369370
                                               369415
     4
              1289
                         1306
                                   498078
                                               498335
                                                                2409
                                                                                 60
                      Sum_of_Luminosity Minimum_of_Luminosity
        Y_Perimeter
     0
                  44
                                   24220
                                                               76
                  30
                                   11397
                                                               84
     1
     2
                  19
                                    7972
                                                               99
     3
                  45
                                   18996
                                                               99
     4
                 260
                                  246930
                                                               37
        Maximum_of_Luminosity
                                    Orientation_Index Luminosity_Index
     0
                            108
                                                0.8182
                                                                   -0.2913
     1
                            123
                                                0.7931
                                                                   -0.1756
     2
                            125 ...
                                                                  -0.1228
                                                0.6667
     3
                            126
                                                0.8444
                                                                   -0.1568
     4
                            126
                                                0.9338
                                                                   -0.1992
        SigmoidOfAreas Pastry
                                  Z_Scratch K_Scatch
                                                         Stains
                                                                             Bumps
                                                                 Dirtiness
                 0.5822
                                           0
                                                      0
                                                              0
     0
                               1
                                                                          0
                                                                                  0
                                           0
                                                      0
                                                              0
                                                                          0
     1
                 0.2984
                               1
                                                                                  0
     2
                 0.2150
                               1
                                           0
                                                      0
                                                              0
                                                                          0
                                                                                  0
     3
                 0.5212
                               1
                                           0
                                                              0
                                                                          0
                                                                                  0
```

```
0
                                                                            0
4
            1.0000
                            1
                                         0
                                                              0
                                                                                    0
   Other_Faults
0
                0
1
2
                0
                0
3
                0
4
```

[5 rows x 34 columns]

```
[4]: df.shape
```

[4]: (1941, 34)

### 4 Exercício. Prepare os Dados de Entrada X

Lembre-se a normalização das entradas é necessária. Empregue o scale.

```
[6]: from sklearn.preprocessing import scale X_norm = scale(X)
```

# 5 Exercício. Prepare a saída y

Lembre-se no Keras/TensorFlow há uma saída binária para cada classe.

```
[8]: y = df.iloc[:, -7:]
```

## 6 Exercício. Separe os dados de Treinamento e Teste

Empregue o scikit-learn para separar os dados de treinamento e teste. Empregue 0.3 de dados de teste e o seed=1234 para geração dos dados.

```
[9]: seed = 1234
X_train, X_test, y_train, y_test = train_test_split(X_norm, y, test_size=0.3, 
→stratify=y, random_state=seed)
```

```
[10]: y_train.shape
```

[10]: (1358, 7)

### 7 Exercício. Faça o Treinamento do Modelo Deep Learning

Empregue o modelo de código da aula para completar o código abaixo e treine o Modelo Neural. Você vai configurar camadas oculta de 16, 32, 16 neurônios e função de ativação relu. Empregue 0.2 para dados de validação e a função sigmoid nas camadas de entrada e saída.

```
[11]: from numpy.random import seed # para garantir a reprodutibilidade dos_
      \rightarrow resultados
      seed(1234)
      tf.random.set_seed(1234)
      # modelo
      model = Sequential([layers.Dense(X.shape[1], activation='sigmoid', __
       →input_shape=[X.shape[1],])])
      # camada de entrada
      model.add(layers.Dense(7, activation='sigmoid'))
      # camada ocultas
      model.add(layers.Dense(16, activation='relu'))
      model.add(layers.Dense(32, activation='relu'))
      model.add(layers.Dense(16, activation='relu'))
      # camada de saída
      model.add(layers.Dense(7, activation='sigmoid'))
      # compilação do modelo
      model.compile(loss='categorical_crossentropy', optimizer='adam', u
       →metrics=['accuracy'])
      # treinamento do modelo com 0.2 dos dados para validação e 200 iterações de L
       \rightarrow treinamento
      history = model.fit(X_train, y_train, validation_split=0.2, epochs=200)
```

```
0.4866 - val_loss: 1.3329 - val_accuracy: 0.4743
Epoch 6/200
0.4949 - val_loss: 1.2974 - val_accuracy: 0.4706
Epoch 7/200
0.4970 - val_loss: 1.2782 - val_accuracy: 0.4816
Epoch 8/200
0.5404 - val_loss: 1.2555 - val_accuracy: 0.5147
Epoch 9/200
0.5291 - val_loss: 1.2443 - val_accuracy: 0.4816
Epoch 10/200
0.5269 - val_loss: 1.2269 - val_accuracy: 0.5037
Epoch 11/200
0.5267 - val_loss: 1.2223 - val_accuracy: 0.4706
Epoch 12/200
0.5416 - val_loss: 1.2112 - val_accuracy: 0.4853
Epoch 13/200
0.5488 - val_loss: 1.1906 - val_accuracy: 0.5294
Epoch 14/200
0.4997 - val_loss: 1.1988 - val_accuracy: 0.4890
Epoch 15/200
0.5102 - val_loss: 1.1810 - val_accuracy: 0.4743
Epoch 16/200
0.5240 - val_loss: 1.1606 - val_accuracy: 0.5184
Epoch 17/200
0.5163 - val_loss: 1.1505 - val_accuracy: 0.4890
Epoch 18/200
0.5071 - val_loss: 1.1302 - val_accuracy: 0.4926
Epoch 19/200
0.5554 - val_loss: 1.0941 - val_accuracy: 0.5515
Epoch 20/200
0.5339 - val_loss: 1.0914 - val_accuracy: 0.5000
Epoch 21/200
```

```
0.5619 - val_loss: 1.0688 - val_accuracy: 0.4853
Epoch 22/200
0.5622 - val_loss: 1.0497 - val_accuracy: 0.5404
Epoch 23/200
0.6232 - val_loss: 1.0273 - val_accuracy: 0.5441
Epoch 24/200
0.6168 - val_loss: 1.0214 - val_accuracy: 0.5294
Epoch 25/200
0.6152 - val_loss: 0.9928 - val_accuracy: 0.5441
Epoch 26/200
0.6249 - val_loss: 0.9805 - val_accuracy: 0.5478
Epoch 27/200
0.6432 - val_loss: 0.9750 - val_accuracy: 0.5478
Epoch 28/200
0.6267 - val_loss: 0.9604 - val_accuracy: 0.6066
Epoch 29/200
0.6263 - val_loss: 0.9579 - val_accuracy: 0.5699
Epoch 30/200
0.6468 - val_loss: 0.9478 - val_accuracy: 0.5662
0.6402 - val_loss: 0.9315 - val_accuracy: 0.6029
Epoch 32/200
0.6261 - val_loss: 0.9222 - val_accuracy: 0.5919
Epoch 33/200
0.6566 - val_loss: 0.9291 - val_accuracy: 0.5735
Epoch 34/200
0.6443 - val_loss: 0.9242 - val_accuracy: 0.6213
Epoch 35/200
0.6533 - val_loss: 0.9041 - val_accuracy: 0.6066
Epoch 36/200
0.6711 - val_loss: 0.9073 - val_accuracy: 0.5809
Epoch 37/200
```

```
0.6276 - val_loss: 0.9174 - val_accuracy: 0.6066
Epoch 38/200
0.6648 - val_loss: 0.8843 - val_accuracy: 0.6581
Epoch 39/200
0.6850 - val_loss: 0.8816 - val_accuracy: 0.6103
Epoch 40/200
0.6552 - val_loss: 0.8626 - val_accuracy: 0.7022
Epoch 41/200
0.6745 - val_loss: 0.8546 - val_accuracy: 0.6838
Epoch 42/200
0.6685 - val_loss: 0.8597 - val_accuracy: 0.6434
Epoch 43/200
0.6721 - val_loss: 0.8575 - val_accuracy: 0.6434
Epoch 44/200
0.6946 - val_loss: 0.8418 - val_accuracy: 0.7059
Epoch 45/200
0.6770 - val_loss: 0.8578 - val_accuracy: 0.6029
Epoch 46/200
0.6812 - val_loss: 0.8624 - val_accuracy: 0.6250
0.6900 - val_loss: 0.8393 - val_accuracy: 0.6912
Epoch 48/200
0.6937 - val_loss: 0.8350 - val_accuracy: 0.6912
Epoch 49/200
0.6929 - val_loss: 0.8280 - val_accuracy: 0.6728
Epoch 50/200
0.7189 - val_loss: 0.8228 - val_accuracy: 0.6949
Epoch 51/200
0.6855 - val_loss: 0.8181 - val_accuracy: 0.6728
Epoch 52/200
0.7014 - val_loss: 0.8105 - val_accuracy: 0.7022
Epoch 53/200
```

```
0.7079 - val_loss: 0.8042 - val_accuracy: 0.7022
Epoch 54/200
0.6866 - val_loss: 0.8078 - val_accuracy: 0.6765
Epoch 55/200
0.7065 - val_loss: 0.8018 - val_accuracy: 0.7059
Epoch 56/200
0.7165 - val_loss: 0.8010 - val_accuracy: 0.6728
Epoch 57/200
0.6915 - val_loss: 0.7877 - val_accuracy: 0.7316
Epoch 58/200
0.7173 - val_loss: 0.7875 - val_accuracy: 0.6985
Epoch 59/200
0.6955 - val_loss: 0.7970 - val_accuracy: 0.6838
Epoch 60/200
0.7053 - val_loss: 0.7779 - val_accuracy: 0.7059
Epoch 61/200
0.7069 - val_loss: 0.7959 - val_accuracy: 0.6691
Epoch 62/200
0.7262 - val_loss: 0.8045 - val_accuracy: 0.6912
0.7129 - val_loss: 0.8232 - val_accuracy: 0.6875
Epoch 64/200
0.7326 - val_loss: 0.7938 - val_accuracy: 0.6618
Epoch 65/200
0.7113 - val_loss: 0.7667 - val_accuracy: 0.7279
Epoch 66/200
0.7174 - val_loss: 0.7655 - val_accuracy: 0.7243
Epoch 67/200
0.7631 - val_loss: 0.7632 - val_accuracy: 0.7022
Epoch 68/200
0.7268 - val_loss: 0.7800 - val_accuracy: 0.6801
Epoch 69/200
```

```
0.6982 - val_loss: 0.7827 - val_accuracy: 0.7206
Epoch 70/200
0.7470 - val_loss: 0.7635 - val_accuracy: 0.7243
Epoch 71/200
0.7267 - val_loss: 0.7786 - val_accuracy: 0.7169
Epoch 72/200
0.7537 - val_loss: 0.7566 - val_accuracy: 0.7316
Epoch 73/200
0.7237 - val_loss: 0.7857 - val_accuracy: 0.7022
Epoch 74/200
0.7186 - val_loss: 0.7612 - val_accuracy: 0.7243
Epoch 75/200
0.7153 - val_loss: 0.7920 - val_accuracy: 0.6875
Epoch 76/200
0.7459 - val_loss: 0.7625 - val_accuracy: 0.7096
Epoch 77/200
0.7198 - val_loss: 0.7685 - val_accuracy: 0.6949
Epoch 78/200
0.7242 - val_loss: 0.7610 - val_accuracy: 0.7169
Epoch 79/200
0.7333 - val_loss: 0.7480 - val_accuracy: 0.7206
Epoch 80/200
0.7462 - val_loss: 0.7545 - val_accuracy: 0.7169
Epoch 81/200
0.7273 - val_loss: 0.7478 - val_accuracy: 0.7243
Epoch 82/200
0.7516 - val_loss: 0.7504 - val_accuracy: 0.7316
Epoch 83/200
0.7129 - val_loss: 0.7721 - val_accuracy: 0.7096
Epoch 84/200
0.7336 - val_loss: 0.7748 - val_accuracy: 0.6912
Epoch 85/200
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0.7418 - val_loss: 0.7499 - val_accuracy: 0.6912
Epoch 86/200
0.7333 - val_loss: 0.7769 - val_accuracy: 0.6875
Epoch 87/200
0.7612 - val_loss: 0.7513 - val_accuracy: 0.7022
Epoch 88/200
0.7331 - val_loss: 0.7547 - val_accuracy: 0.7206
Epoch 89/200
0.7484 - val_loss: 0.7478 - val_accuracy: 0.7353
Epoch 90/200
0.7612 - val_loss: 0.7561 - val_accuracy: 0.7316
Epoch 91/200
0.7445 - val_loss: 0.7445 - val_accuracy: 0.7243
Epoch 92/200
0.7678 - val_loss: 0.7475 - val_accuracy: 0.7206
Epoch 93/200
0.7629 - val_loss: 0.7537 - val_accuracy: 0.7059
Epoch 94/200
0.7479 - val_loss: 0.7653 - val_accuracy: 0.6949
0.7436 - val_loss: 0.7415 - val_accuracy: 0.7243
Epoch 96/200
0.7551 - val_loss: 0.7477 - val_accuracy: 0.7243
Epoch 97/200
0.7513 - val_loss: 0.7429 - val_accuracy: 0.7316
Epoch 98/200
0.7565 - val_loss: 0.7488 - val_accuracy: 0.7316
Epoch 99/200
0.7279 - val_loss: 0.7491 - val_accuracy: 0.7353
Epoch 100/200
0.7636 - val_loss: 0.7478 - val_accuracy: 0.7353
Epoch 101/200
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0.7701 - val_loss: 0.7876 - val_accuracy: 0.6985
Epoch 102/200
0.7224 - val_loss: 0.7850 - val_accuracy: 0.7243
Epoch 103/200
0.7743 - val_loss: 0.7755 - val_accuracy: 0.6949
Epoch 104/200
0.7470 - val_loss: 0.7569 - val_accuracy: 0.7279
Epoch 105/200
0.7603 - val_loss: 0.7427 - val_accuracy: 0.7243
Epoch 106/200
0.7501 - val_loss: 0.7570 - val_accuracy: 0.7279
Epoch 107/200
0.7752 - val_loss: 0.7638 - val_accuracy: 0.7096
Epoch 108/200
0.7415 - val_loss: 0.7560 - val_accuracy: 0.7022
Epoch 109/200
0.7666 - val_loss: 0.7566 - val_accuracy: 0.7132
Epoch 110/200
0.7690 - val_loss: 0.7747 - val_accuracy: 0.7096
Epoch 111/200
0.7630 - val_loss: 0.7587 - val_accuracy: 0.7169
Epoch 112/200
0.7575 - val_loss: 0.7597 - val_accuracy: 0.7243
Epoch 113/200
0.7706 - val_loss: 0.7670 - val_accuracy: 0.7022
Epoch 114/200
0.7735 - val_loss: 0.7944 - val_accuracy: 0.7132
Epoch 115/200
0.7383 - val_loss: 0.7771 - val_accuracy: 0.6985
Epoch 116/200
0.7570 - val_loss: 0.7598 - val_accuracy: 0.7169
Epoch 117/200
```

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0.7591 - val_loss: 0.7580 - val_accuracy: 0.7206
Epoch 118/200
0.7745 - val_loss: 0.7540 - val_accuracy: 0.7353
Epoch 119/200
0.7823 - val_loss: 0.7864 - val_accuracy: 0.7316
Epoch 120/200
0.7661 - val_loss: 0.7574 - val_accuracy: 0.6985
Epoch 121/200
0.7345 - val_loss: 0.7797 - val_accuracy: 0.7279
Epoch 122/200
0.7980 - val_loss: 0.7546 - val_accuracy: 0.7463
Epoch 123/200
0.7593 - val_loss: 0.7567 - val_accuracy: 0.7243
Epoch 124/200
0.7475 - val_loss: 0.7733 - val_accuracy: 0.7316
Epoch 125/200
0.7848 - val_loss: 0.7720 - val_accuracy: 0.7353
Epoch 126/200
0.7709 - val_loss: 0.7902 - val_accuracy: 0.7022
Epoch 127/200
0.7604 - val_loss: 0.7727 - val_accuracy: 0.7096
Epoch 128/200
0.7580 - val_loss: 0.7738 - val_accuracy: 0.7132
Epoch 129/200
0.7941 - val_loss: 0.7732 - val_accuracy: 0.7279
Epoch 130/200
0.7836 - val_loss: 0.7802 - val_accuracy: 0.7096
Epoch 131/200
0.7565 - val_loss: 0.7960 - val_accuracy: 0.7022
Epoch 132/200
0.7943 - val_loss: 0.7675 - val_accuracy: 0.7537
Epoch 133/200
```

```
0.7900 - val_loss: 0.7692 - val_accuracy: 0.7279
Epoch 134/200
0.7517 - val_loss: 0.7980 - val_accuracy: 0.7243
Epoch 135/200
0.7769 - val_loss: 0.7692 - val_accuracy: 0.7426
Epoch 136/200
0.7895 - val_loss: 0.7712 - val_accuracy: 0.7353
Epoch 137/200
0.7702 - val_loss: 0.7744 - val_accuracy: 0.7500
Epoch 138/200
0.7682 - val_loss: 0.7840 - val_accuracy: 0.7206
Epoch 139/200
0.7929 - val_loss: 0.7772 - val_accuracy: 0.7353
Epoch 140/200
0.7770 - val_loss: 0.7623 - val_accuracy: 0.7243
Epoch 141/200
0.7920 - val_loss: 0.8008 - val_accuracy: 0.7096
Epoch 142/200
0.7932 - val_loss: 0.7824 - val_accuracy: 0.7206
Epoch 143/200
0.7683 - val_loss: 0.7716 - val_accuracy: 0.7206
Epoch 144/200
0.7773 - val_loss: 0.7976 - val_accuracy: 0.7353
Epoch 145/200
0.7988 - val_loss: 0.7837 - val_accuracy: 0.7316
Epoch 146/200
0.7848 - val_loss: 0.7744 - val_accuracy: 0.7132
Epoch 147/200
0.7572 - val_loss: 0.8142 - val_accuracy: 0.7132
Epoch 148/200
0.7833 - val_loss: 0.7741 - val_accuracy: 0.7096
Epoch 149/200
```

```
0.7817 - val_loss: 0.7986 - val_accuracy: 0.7059
Epoch 150/200
0.7886 - val_loss: 0.7735 - val_accuracy: 0.7316
Epoch 151/200
0.7882 - val_loss: 0.7690 - val_accuracy: 0.7537
Epoch 152/200
0.7971 - val_loss: 0.7708 - val_accuracy: 0.7243
Epoch 153/200
0.7757 - val_loss: 0.7724 - val_accuracy: 0.7279
Epoch 154/200
0.7881 - val_loss: 0.8203 - val_accuracy: 0.7353
Epoch 155/200
0.7918 - val_loss: 0.7789 - val_accuracy: 0.7353
Epoch 156/200
0.7713 - val_loss: 0.7713 - val_accuracy: 0.7243
Epoch 157/200
0.7969 - val_loss: 0.7967 - val_accuracy: 0.7243
Epoch 158/200
0.8006 - val_loss: 0.8040 - val_accuracy: 0.7169
Epoch 159/200
0.7951 - val_loss: 0.7968 - val_accuracy: 0.7206
Epoch 160/200
0.7879 - val_loss: 0.7937 - val_accuracy: 0.7279
Epoch 161/200
0.7945 - val loss: 0.7996 - val accuracy: 0.7206
Epoch 162/200
0.8087 - val_loss: 0.8094 - val_accuracy: 0.6985
Epoch 163/200
0.7907 - val_loss: 0.8113 - val_accuracy: 0.7243
Epoch 164/200
0.8084 - val_loss: 0.7974 - val_accuracy: 0.7353
Epoch 165/200
```

```
0.7823 - val_loss: 0.7920 - val_accuracy: 0.7206
Epoch 166/200
0.7960 - val_loss: 0.7912 - val_accuracy: 0.7316
Epoch 167/200
0.8052 - val_loss: 0.8342 - val_accuracy: 0.7279
Epoch 168/200
0.7966 - val_loss: 0.8192 - val_accuracy: 0.7243
Epoch 169/200
0.7980 - val_loss: 0.8163 - val_accuracy: 0.7169
Epoch 170/200
0.8079 - val_loss: 0.7897 - val_accuracy: 0.7316
Epoch 171/200
0.7851 - val_loss: 0.7905 - val_accuracy: 0.7243
Epoch 172/200
0.7952 - val_loss: 0.7986 - val_accuracy: 0.7316
Epoch 173/200
0.7899 - val_loss: 0.7890 - val_accuracy: 0.7279
Epoch 174/200
0.8030 - val_loss: 0.8194 - val_accuracy: 0.7279
Epoch 175/200
0.7944 - val_loss: 0.7933 - val_accuracy: 0.7353
Epoch 176/200
0.8055 - val_loss: 0.8167 - val_accuracy: 0.7132
Epoch 177/200
0.8033 - val_loss: 0.8116 - val_accuracy: 0.7316
Epoch 178/200
0.7925 - val_loss: 0.7954 - val_accuracy: 0.7279
Epoch 179/200
0.7982 - val_loss: 0.8323 - val_accuracy: 0.7096
Epoch 180/200
0.7875 - val_loss: 0.8008 - val_accuracy: 0.7279
Epoch 181/200
```

```
0.7932 - val_loss: 0.8453 - val_accuracy: 0.7096
Epoch 182/200
0.8282 - val_loss: 0.8157 - val_accuracy: 0.7132
Epoch 183/200
0.7982 - val_loss: 0.7845 - val_accuracy: 0.7390
Epoch 184/200
0.8319 - val_loss: 0.8145 - val_accuracy: 0.7206
Epoch 185/200
0.8014 - val_loss: 0.8269 - val_accuracy: 0.7169
Epoch 186/200
0.8036 - val_loss: 0.8767 - val_accuracy: 0.7206
Epoch 187/200
0.7886 - val_loss: 0.8106 - val_accuracy: 0.7316
Epoch 188/200
0.8150 - val_loss: 0.8163 - val_accuracy: 0.7132
Epoch 189/200
0.8214 - val_loss: 0.8379 - val_accuracy: 0.7169
Epoch 190/200
0.8441 - val_loss: 0.8060 - val_accuracy: 0.7243
Epoch 191/200
0.8071 - val_loss: 0.8070 - val_accuracy: 0.7243
Epoch 192/200
0.7971 - val_loss: 0.8442 - val_accuracy: 0.7206
Epoch 193/200
0.8297 - val_loss: 0.8370 - val_accuracy: 0.7132
Epoch 194/200
0.7982 - val_loss: 0.8242 - val_accuracy: 0.7279
Epoch 195/200
0.8021 - val_loss: 0.8526 - val_accuracy: 0.7206
Epoch 196/200
0.8232 - val_loss: 0.8217 - val_accuracy: 0.7169
Epoch 197/200
```

#### 8 Exercício. Visualize o modelo

Empregue o comando model.summary() para exibir o modelo. O código a seguir exibe graficamente a rede criada.

### [13]: print(model.summary())

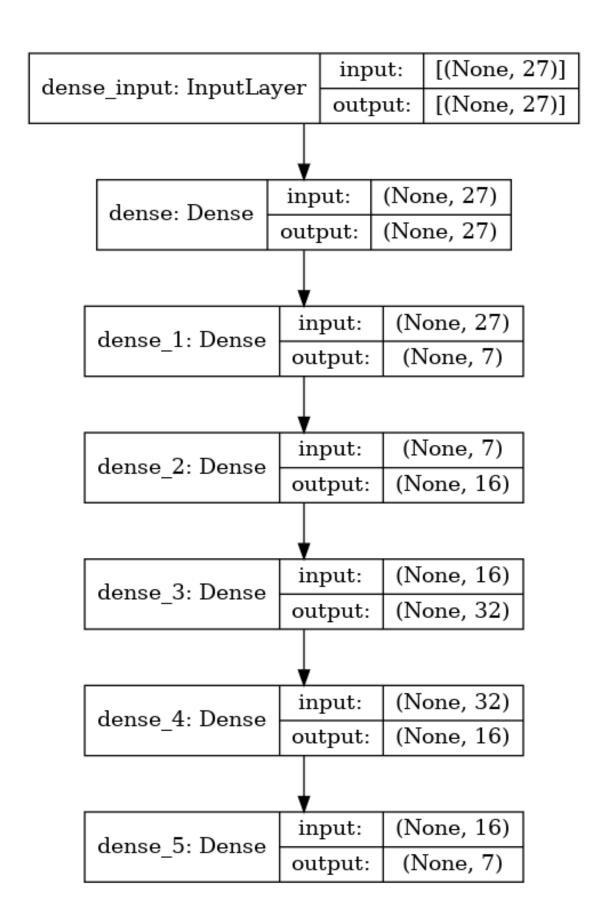
```
Model: "sequential"
```

Non-trainable params: 0

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 27)	756
dense_1 (Dense)	(None, 7)	196
dense_2 (Dense)	(None, 16)	128
dense_3 (Dense)	(None, 32)	544
dense_4 (Dense)	(None, 16)	528
dense_5 (Dense)	(None, 7)	119
Total params: 2,271 Trainable params: 2,271		

None

[14]:

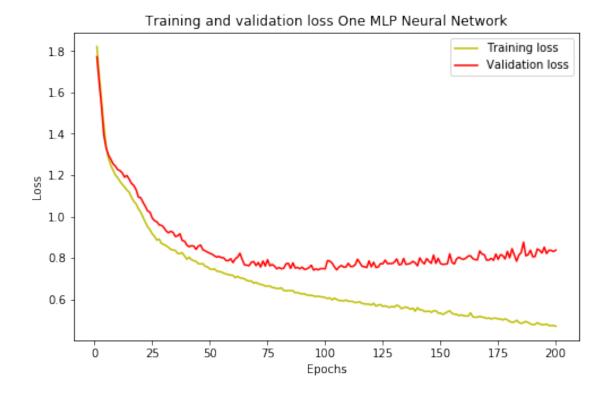


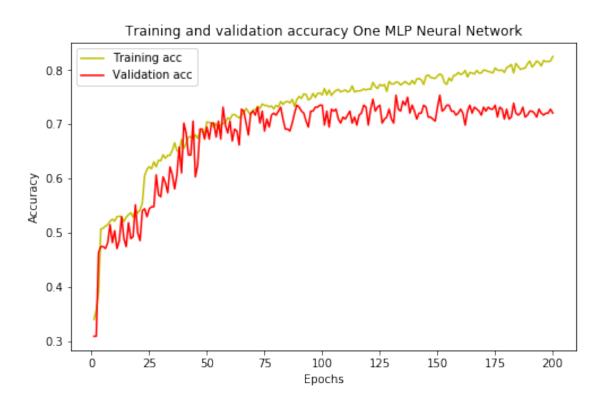
### 9 Exercício. Análise o Treinamento da Rede

Empregue a função plot\_loss\_acc abaixo (veja a sintaxe da chamada na teoria) para analisar o treinamento da rede.

```
[15]: def plot loss acc(history, more title=''):
          loss = history.history['loss']
          val_loss = history.history['val_loss']
          epochs = range(1, len(loss) + 1)
          plt.figure(figsize=(8,5))
          plt.plot(epochs, loss, 'y', label='Training loss')
          plt.plot(epochs, val_loss, 'r', label='Validation loss')
          plt.title('Training and validation loss' + ' ' + more_title)
          plt.xlabel('Epochs')
          plt.ylabel('Loss')
          plt.legend()
          plt.show()
          acc = history.history['accuracy']
          val_acc = history.history['val_accuracy']
          plt.figure(figsize=(8,5))
          plt.plot(epochs, acc, 'y', label='Training acc')
          plt.plot(epochs, val_acc, 'r', label='Validation acc')
          plt.title('Training and validation accuracy' + ' ' + more_title)
          plt.xlabel('Epochs')
          plt.ylabel('Accuracy')
          plt.legend()
          plt.show()
          print(more title + 'Accuracy Train: {:.2f} %, Accuracy Test: {:.2f} %'.
       \rightarrowformat(acc[len(acc)-1] *100, val_acc[len(val_acc)-1]*100))
          return loss, val_loss, acc, val_acc
```

```
[16]: loss, val_loss, acc, val_acc = plot_loss_acc(history,'One MLP Neural Network')
```





## 10 Overfitting

O overfitting se caracteriza por um sobreajuste do conjunto de treinamento durante o aprendizado. Esse sobreaprendizado produz uma acuracidade excessiva do modelo no conjunto de treinamento e leva a modelos pouco generalizados. Em outras palavras, o modelo prevê corretamente a grande maioria dos casos conhecidos, mas tende a falhar na predição de novos casos.

É um problema bastante comum para Árvores de Decisão de Modelos Neurais. Para modelos Neurais o **Drop Out** e a redução de épocas de treinamento são as técnicas mais empregadas. (para Árvores de Decisão, o uso de Random Forest é em geral a melhor solução).

Você pode identificar o overfitting buscando o ponto em que as curvas de aprendizado do conjunto de treinamento e de validação passam a divergir, isto é, erro no conjunto de treinamento se reduz mas sem uma correspondente redução no conjunto de teste.

### 11 Exercício. Reduzindo o Overfitting

Aqui empregaremos uma técnica chamada drop out. Basta reproduzir o resto da solução aqui. Você ainda pode reduzir o númere de épocas verificando o número adequado no gráfico de evolução do treinamento da rede.

```
[17]: all_results = []
      from keras.layers import Dropout
      from numpy.random import seed
      seed(1234)
      tf.random.set_seed(1234)
      # Modelo
      # ...
      # modelo
      model = Sequential([layers.Dense(X.shape[1], activation='sigmoid',__
       →input_shape=[X.shape[1],])])
      # Drop Out
      model.add(Dropout(0.20))
      # camada de entrada
      model.add(layers.Dense(7, activation='sigmoid'))
      # camada ocultas
      model.add(layers.Dense(16, activation='relu'))
      model.add(layers.Dense(32, activation='relu'))
      model.add(layers.Dense(16, activation='relu'))
      # Resto do modelo e treinamento...
```

```
# ...
# camada de saída
model.add(layers.Dense(7, activation='sigmoid'))
# compilação do modelo
model.compile(loss='categorical_crossentropy', optimizer='adam',__
→metrics=['accuracy'])
# treinamento do modelo com 0.2 dos dados para validação e 200 iterações de L
\hookrightarrow treinamento
history = model.fit(X_train, y_train, validation_split=0.2, epochs=200)
Epoch 1/200
0.3052 - val_loss: 1.7700 - val_accuracy: 0.3088
Epoch 2/200
0.3613 - val_loss: 1.6422 - val_accuracy: 0.3088
Epoch 3/200
0.3881 - val_loss: 1.5196 - val_accuracy: 0.4816
Epoch 4/200
0.5252 - val_loss: 1.3898 - val_accuracy: 0.4779
Epoch 5/200
0.4690 - val_loss: 1.3374 - val_accuracy: 0.4779
Epoch 6/200
0.4915 - val_loss: 1.2995 - val_accuracy: 0.4743
Epoch 7/200
0.4925 - val_loss: 1.2827 - val_accuracy: 0.4706
Epoch 8/200
0.5340 - val_loss: 1.2652 - val_accuracy: 0.4743
Epoch 9/200
0.5134 - val_loss: 1.2514 - val_accuracy: 0.4853
Epoch 10/200
0.5198 - val_loss: 1.2384 - val_accuracy: 0.4816
Epoch 11/200
0.5138 - val_loss: 1.2342 - val_accuracy: 0.4816
Epoch 12/200
```

```
0.5300 - val_loss: 1.2282 - val_accuracy: 0.4853
Epoch 13/200
0.5339 - val_loss: 1.2137 - val_accuracy: 0.5184
Epoch 14/200
0.4967 - val_loss: 1.2109 - val_accuracy: 0.4816
Epoch 15/200
0.5092 - val_loss: 1.1976 - val_accuracy: 0.4779
Epoch 16/200
0.5147 - val_loss: 1.1822 - val_accuracy: 0.5074
Epoch 17/200
0.5016 - val_loss: 1.1895 - val_accuracy: 0.4743
Epoch 18/200
0.5033 - val_loss: 1.1621 - val_accuracy: 0.4779
Epoch 19/200
0.5503 - val_loss: 1.1399 - val_accuracy: 0.4779
Epoch 20/200
0.5276 - val_loss: 1.1417 - val_accuracy: 0.4816
Epoch 21/200
0.5388 - val_loss: 1.1201 - val_accuracy: 0.4890
Epoch 22/200
0.5620 - val_loss: 1.1128 - val_accuracy: 0.5000
Epoch 23/200
0.5441 - val_loss: 1.1014 - val_accuracy: 0.4926
Epoch 24/200
0.5273 - val_loss: 1.0971 - val_accuracy: 0.4853
Epoch 25/200
0.5103 - val_loss: 1.0803 - val_accuracy: 0.4853
Epoch 26/200
0.5441 - val_loss: 1.0713 - val_accuracy: 0.4926
Epoch 27/200
0.5289 - val_loss: 1.0638 - val_accuracy: 0.5294
Epoch 28/200
```

```
0.5668 - val_loss: 1.0594 - val_accuracy: 0.5919
Epoch 29/200
0.5397 - val_loss: 1.0588 - val_accuracy: 0.5441
Epoch 30/200
0.5845 - val_loss: 1.0370 - val_accuracy: 0.5551
Epoch 31/200
0.5715 - val_loss: 1.0162 - val_accuracy: 0.5441
Epoch 32/200
0.5454 - val_loss: 1.0085 - val_accuracy: 0.5441
Epoch 33/200
0.5897 - val_loss: 1.0064 - val_accuracy: 0.5515
Epoch 34/200
0.5938 - val_loss: 0.9890 - val_accuracy: 0.5588
Epoch 35/200
0.5753 - val_loss: 0.9863 - val_accuracy: 0.5551
Epoch 36/200
0.6044 - val_loss: 0.9889 - val_accuracy: 0.5551
Epoch 37/200
0.5869 - val_loss: 0.9930 - val_accuracy: 0.5515
0.6107 - val_loss: 0.9753 - val_accuracy: 0.5515
Epoch 39/200
0.5867 - val_loss: 0.9690 - val_accuracy: 0.5551
Epoch 40/200
0.6126 - val_loss: 0.9475 - val_accuracy: 0.5625
Epoch 41/200
0.6020 - val_loss: 0.9332 - val_accuracy: 0.6250
Epoch 42/200
0.5853 - val_loss: 0.9339 - val_accuracy: 0.5699
Epoch 43/200
0.6042 - val_loss: 0.9522 - val_accuracy: 0.5551
Epoch 44/200
```

```
0.6257 - val_loss: 0.9228 - val_accuracy: 0.5919
Epoch 45/200
0.5848 - val_loss: 0.9536 - val_accuracy: 0.5662
Epoch 46/200
0.6143 - val_loss: 0.9330 - val_accuracy: 0.5625
Epoch 47/200
0.6014 - val_loss: 0.9304 - val_accuracy: 0.5956
Epoch 48/200
0.6143 - val_loss: 0.9167 - val_accuracy: 0.5735
Epoch 49/200
0.6328 - val_loss: 0.9031 - val_accuracy: 0.6066
Epoch 50/200
0.5961 - val_loss: 0.9054 - val_accuracy: 0.6103
Epoch 51/200
0.6228 - val_loss: 0.8998 - val_accuracy: 0.6140
Epoch 52/200
0.6027 - val_loss: 0.9002 - val_accuracy: 0.5919
Epoch 53/200
0.6420 - val_loss: 0.8934 - val_accuracy: 0.6287
0.6049 - val_loss: 0.9002 - val_accuracy: 0.6066
Epoch 55/200
0.6287 - val_loss: 0.8928 - val_accuracy: 0.6176
Epoch 56/200
0.6130 - val_loss: 0.8933 - val_accuracy: 0.6213
Epoch 57/200
0.6558 - val_loss: 0.8841 - val_accuracy: 0.5993
Epoch 58/200
0.6441 - val_loss: 0.8773 - val_accuracy: 0.6213
Epoch 59/200
0.6537 - val_loss: 0.8839 - val_accuracy: 0.6176
Epoch 60/200
```

```
0.6408 - val_loss: 0.8758 - val_accuracy: 0.6250
Epoch 61/200
0.6454 - val_loss: 0.8973 - val_accuracy: 0.5846
Epoch 62/200
0.6134 - val_loss: 0.8841 - val_accuracy: 0.5956
Epoch 63/200
0.6016 - val_loss: 0.9035 - val_accuracy: 0.5919
Epoch 64/200
0.6350 - val_loss: 0.8839 - val_accuracy: 0.6176
Epoch 65/200
0.6223 - val_loss: 0.8609 - val_accuracy: 0.6581
Epoch 66/200
0.6375 - val_loss: 0.8573 - val_accuracy: 0.6360
Epoch 67/200
0.6407 - val_loss: 0.8574 - val_accuracy: 0.6397
Epoch 68/200
0.6565 - val_loss: 0.8624 - val_accuracy: 0.6250
Epoch 69/200
0.6315 - val_loss: 0.8776 - val_accuracy: 0.6324
0.6702 - val_loss: 0.8566 - val_accuracy: 0.6544
Epoch 71/200
0.6309 - val_loss: 0.8749 - val_accuracy: 0.5993
Epoch 72/200
0.6632 - val_loss: 0.8446 - val_accuracy: 0.6544
Epoch 73/200
0.6457 - val_loss: 0.8697 - val_accuracy: 0.6250
Epoch 74/200
0.6454 - val_loss: 0.8492 - val_accuracy: 0.6434
Epoch 75/200
0.6675 - val_loss: 0.8722 - val_accuracy: 0.6176
Epoch 76/200
```

```
0.6586 - val_loss: 0.8472 - val_accuracy: 0.6654
Epoch 77/200
0.6210 - val_loss: 0.8448 - val_accuracy: 0.6471
Epoch 78/200
0.6774 - val_loss: 0.8416 - val_accuracy: 0.6581
Epoch 79/200
0.6674 - val_loss: 0.8372 - val_accuracy: 0.6581
Epoch 80/200
0.6897 - val_loss: 0.8301 - val_accuracy: 0.6618
Epoch 81/200
0.6526 - val_loss: 0.8309 - val_accuracy: 0.6654
Epoch 82/200
0.6676 - val_loss: 0.8421 - val_accuracy: 0.6507
Epoch 83/200
0.6494 - val_loss: 0.8518 - val_accuracy: 0.6544
Epoch 84/200
0.6639 - val_loss: 0.8506 - val_accuracy: 0.6397
Epoch 85/200
0.6646 - val_loss: 0.8148 - val_accuracy: 0.6765
0.6547 - val_loss: 0.8306 - val_accuracy: 0.6691
Epoch 87/200
0.6817 - val_loss: 0.8126 - val_accuracy: 0.6691
Epoch 88/200
0.6433 - val_loss: 0.8245 - val_accuracy: 0.6544
Epoch 89/200
0.6773 - val_loss: 0.8102 - val_accuracy: 0.6654
Epoch 90/200
0.6703 - val_loss: 0.8100 - val_accuracy: 0.6691
Epoch 91/200
0.6836 - val_loss: 0.8027 - val_accuracy: 0.6691
Epoch 92/200
```

```
0.6837 - val_loss: 0.8024 - val_accuracy: 0.6691
Epoch 93/200
0.6947 - val_loss: 0.8060 - val_accuracy: 0.6801
Epoch 94/200
0.6703 - val_loss: 0.8022 - val_accuracy: 0.6654
Epoch 95/200
0.6634 - val_loss: 0.7938 - val_accuracy: 0.6765
Epoch 96/200
0.6651 - val_loss: 0.7904 - val_accuracy: 0.6875
Epoch 97/200
0.6799 - val_loss: 0.7933 - val_accuracy: 0.6765
Epoch 98/200
0.7111 - val_loss: 0.8180 - val_accuracy: 0.6728
Epoch 99/200
0.6704 - val_loss: 0.7975 - val_accuracy: 0.6801
Epoch 100/200
0.6826 - val_loss: 0.7915 - val_accuracy: 0.6985
Epoch 101/200
0.6661 - val_loss: 0.8162 - val_accuracy: 0.6471
Epoch 102/200
0.6636 - val_loss: 0.8004 - val_accuracy: 0.6838
Epoch 103/200
0.6878 - val_loss: 0.7988 - val_accuracy: 0.6801
Epoch 104/200
0.6911 - val_loss: 0.7829 - val_accuracy: 0.6949
Epoch 105/200
0.6880 - val_loss: 0.7761 - val_accuracy: 0.7022
Epoch 106/200
0.6833 - val_loss: 0.7851 - val_accuracy: 0.7022
Epoch 107/200
0.7039 - val_loss: 0.8012 - val_accuracy: 0.6985
Epoch 108/200
```

```
0.6246 - val_loss: 0.7850 - val_accuracy: 0.6949
Epoch 109/200
0.6948 - val_loss: 0.7725 - val_accuracy: 0.6875
Epoch 110/200
0.6726 - val_loss: 0.7965 - val_accuracy: 0.6875
Epoch 111/200
0.6848 - val_loss: 0.7719 - val_accuracy: 0.7059
Epoch 112/200
0.6711 - val_loss: 0.7875 - val_accuracy: 0.6801
Epoch 113/200
0.6945 - val_loss: 0.7619 - val_accuracy: 0.6985
Epoch 114/200
0.6975 - val_loss: 0.8043 - val_accuracy: 0.6728
Epoch 115/200
0.6854 - val_loss: 0.7759 - val_accuracy: 0.6985
Epoch 116/200
0.6892 - val_loss: 0.7668 - val_accuracy: 0.7022
Epoch 117/200
0.7010 - val_loss: 0.7587 - val_accuracy: 0.6949
Epoch 118/200
0.7079 - val_loss: 0.7596 - val_accuracy: 0.7022
Epoch 119/200
0.7060 - val_loss: 0.7786 - val_accuracy: 0.6985
Epoch 120/200
0.6672 - val_loss: 0.7614 - val_accuracy: 0.7022
Epoch 121/200
0.6603 - val_loss: 0.7597 - val_accuracy: 0.7132
Epoch 122/200
0.7041 - val_loss: 0.7474 - val_accuracy: 0.7059
Epoch 123/200
0.7042 - val_loss: 0.7565 - val_accuracy: 0.7022
Epoch 124/200
```

```
0.6941 - val_loss: 0.7880 - val_accuracy: 0.7059
Epoch 125/200
0.7135 - val_loss: 0.7895 - val_accuracy: 0.6985
Epoch 126/200
0.7144 - val_loss: 0.7633 - val_accuracy: 0.7096
Epoch 127/200
0.6693 - val_loss: 0.7763 - val_accuracy: 0.6912
Epoch 128/200
0.6909 - val_loss: 0.7515 - val_accuracy: 0.7132
Epoch 129/200
0.7085 - val_loss: 0.7536 - val_accuracy: 0.6912
Epoch 130/200
0.7147 - val_loss: 0.7567 - val_accuracy: 0.6912
Epoch 131/200
0.6890 - val_loss: 0.7669 - val_accuracy: 0.6949
Epoch 132/200
0.7282 - val_loss: 0.7585 - val_accuracy: 0.7169
Epoch 133/200
0.7240 - val_loss: 0.7649 - val_accuracy: 0.7022
Epoch 134/200
0.6907 - val_loss: 0.7623 - val_accuracy: 0.7132
Epoch 135/200
0.7072 - val_loss: 0.7453 - val_accuracy: 0.7206
Epoch 136/200
0.7240 - val_loss: 0.7685 - val_accuracy: 0.7022
Epoch 137/200
0.7064 - val_loss: 0.7519 - val_accuracy: 0.7059
Epoch 138/200
0.7162 - val_loss: 0.7606 - val_accuracy: 0.6985
Epoch 139/200
0.7153 - val_loss: 0.7518 - val_accuracy: 0.7059
Epoch 140/200
```

```
0.7051 - val_loss: 0.7498 - val_accuracy: 0.7132
Epoch 141/200
0.7146 - val_loss: 0.7488 - val_accuracy: 0.6985
Epoch 142/200
0.7132 - val_loss: 0.7538 - val_accuracy: 0.7059
Epoch 143/200
0.6788 - val_loss: 0.7444 - val_accuracy: 0.7022
Epoch 144/200
0.7131 - val_loss: 0.7569 - val_accuracy: 0.6985
Epoch 145/200
0.6818 - val_loss: 0.7627 - val_accuracy: 0.6985
Epoch 146/200
0.7046 - val_loss: 0.7371 - val_accuracy: 0.7096
Epoch 147/200
0.6879 - val_loss: 0.7667 - val_accuracy: 0.6875
Epoch 148/200
0.7040 - val_loss: 0.7516 - val_accuracy: 0.6875
Epoch 149/200
0.6924 - val_loss: 0.7667 - val_accuracy: 0.6838
Epoch 150/200
0.7080 - val_loss: 0.7536 - val_accuracy: 0.6912
Epoch 151/200
0.6878 - val_loss: 0.7321 - val_accuracy: 0.7059
Epoch 152/200
0.7185 - val_loss: 0.7351 - val_accuracy: 0.6949
Epoch 153/200
0.6990 - val_loss: 0.7415 - val_accuracy: 0.7132
Epoch 154/200
0.7116 - val_loss: 0.7470 - val_accuracy: 0.7096
Epoch 155/200
0.7209 - val_loss: 0.7461 - val_accuracy: 0.7206
Epoch 156/200
```

```
0.7361 - val_loss: 0.7483 - val_accuracy: 0.6875
Epoch 157/200
0.7236 - val_loss: 0.7395 - val_accuracy: 0.7096
Epoch 158/200
0.7225 - val_loss: 0.7451 - val_accuracy: 0.7132
Epoch 159/200
0.7128 - val_loss: 0.7485 - val_accuracy: 0.7096
Epoch 160/200
0.7098 - val_loss: 0.7423 - val_accuracy: 0.7243
Epoch 161/200
0.7217 - val_loss: 0.7699 - val_accuracy: 0.6949
Epoch 162/200
0.7008 - val_loss: 0.7500 - val_accuracy: 0.6949
Epoch 163/200
0.7078 - val_loss: 0.7418 - val_accuracy: 0.7022
Epoch 164/200
0.7351 - val_loss: 0.7334 - val_accuracy: 0.7132
Epoch 165/200
0.7157 - val_loss: 0.7404 - val_accuracy: 0.7059
Epoch 166/200
0.7229 - val_loss: 0.7353 - val_accuracy: 0.7096
Epoch 167/200
0.7254 - val_loss: 0.7486 - val_accuracy: 0.7022
Epoch 168/200
0.7200 - val loss: 0.7496 - val accuracy: 0.7059
Epoch 169/200
0.7137 - val_loss: 0.7466 - val_accuracy: 0.7022
Epoch 170/200
0.7382 - val_loss: 0.7276 - val_accuracy: 0.7096
Epoch 171/200
0.6859 - val_loss: 0.7312 - val_accuracy: 0.7132
Epoch 172/200
```

```
0.7087 - val_loss: 0.7378 - val_accuracy: 0.7206
Epoch 173/200
0.7256 - val_loss: 0.7434 - val_accuracy: 0.7096
Epoch 174/200
0.7358 - val_loss: 0.7421 - val_accuracy: 0.7353
Epoch 175/200
0.7303 - val_loss: 0.7385 - val_accuracy: 0.7243
Epoch 176/200
0.6927 - val_loss: 0.7422 - val_accuracy: 0.7059
Epoch 177/200
0.7325 - val_loss: 0.7287 - val_accuracy: 0.7243
Epoch 178/200
0.7350 - val_loss: 0.7196 - val_accuracy: 0.7206
Epoch 179/200
0.7285 - val_loss: 0.7478 - val_accuracy: 0.6949
Epoch 180/200
0.7169 - val_loss: 0.7194 - val_accuracy: 0.7169
Epoch 181/200
0.7171 - val_loss: 0.7609 - val_accuracy: 0.6912
Epoch 182/200
0.7375 - val_loss: 0.7351 - val_accuracy: 0.7169
Epoch 183/200
0.7325 - val_loss: 0.7303 - val_accuracy: 0.7132
Epoch 184/200
0.7344 - val_loss: 0.7352 - val_accuracy: 0.7243
Epoch 185/200
0.7293 - val_loss: 0.7245 - val_accuracy: 0.7243
Epoch 186/200
0.7063 - val_loss: 0.7919 - val_accuracy: 0.7059
Epoch 187/200
0.7059 - val_loss: 0.7173 - val_accuracy: 0.7169
Epoch 188/200
```

```
0.7403 - val_loss: 0.7246 - val_accuracy: 0.7096
Epoch 189/200
0.7159 - val_loss: 0.7432 - val_accuracy: 0.7022
Epoch 190/200
0.7421 - val_loss: 0.7150 - val_accuracy: 0.7169
Epoch 191/200
0.7179 - val_loss: 0.7215 - val_accuracy: 0.7206
Epoch 192/200
0.6876 - val_loss: 0.7217 - val_accuracy: 0.7279
Epoch 193/200
0.7455 - val_loss: 0.7289 - val_accuracy: 0.7132
Epoch 194/200
0.7305 - val_loss: 0.7200 - val_accuracy: 0.7206
Epoch 195/200
0.7436 - val_loss: 0.7257 - val_accuracy: 0.7096
Epoch 196/200
0.7146 - val_loss: 0.7289 - val_accuracy: 0.7169
Epoch 197/200
0.7282 - val_loss: 0.7311 - val_accuracy: 0.7206
Epoch 198/200
0.7474 - val_loss: 0.7152 - val_accuracy: 0.7279
Epoch 199/200
0.7298 - val_loss: 0.7156 - val_accuracy: 0.7390
Epoch 200/200
0.7046 - val loss: 0.7259 - val accuracy: 0.7132
```

# 12 Exercício. Fazendo a Predição dos dados de Teste

Faça a predição dos casos de teste e analise os resultados empregando o classification\_report do scikit-learn.

Lembre-se, cada neurônio de saída da rede retorna a probabilidade de uma das 7 classes, e a seleção do neurônio com maior probabilidade retorna a classe mais provável (empregue o comando np.argmax()).

```
[62]: from sklearn.metrics import classification_report
      y_pred = np.argmax(model.predict(X_test), axis=-1)
[63]: y_test = np.array(y_test)
[64]: y_test_1 = []
      count = 0
      for i in y_test:
          for j in i:
              if (j):
                   y_test_l.append(count)
                   count=0
                   break
               count+=1
[65]: y_pred = y_pred.tolist()
[66]: print(classification_report(y_pred,y_test_1))
                    precision
                                                      support
                                  recall
                                          f1-score
                 0
                          0.49
                                    0.66
                                               0.56
                                                            35
                 1
                          0.88
                                    0.85
                                               0.86
                                                            59
                 2
                          0.94
                                    0.95
                                               0.94
                                                           116
                 3
                          0.95
                                    0.88
                                               0.91
                                                            24
                 4
                         0.24
                                    1.00
                                               0.38
                                                             4
                 5
                          0.50
                                    0.70
                                               0.58
                                                            86
                          0.80
                                    0.63
                                               0.70
                 6
                                                           259
                                               0.74
         accuracy
                                                           583
                          0.68
                                    0.81
                                               0.71
                                                           583
        macro avg
     weighted avg
                          0.78
                                    0.74
                                               0.75
                                                           583
```

# 13 Exercício. Faça o Treinamento de outros Modelos

Faça o treinamento de outras configurações e procude obter um acuracidade do conjunto de teste superior aos resultados obtidos até aqui. Discuta os seus resultados.

```
[70]: all_results = []
from keras.layers import Dropout

from numpy.random import seed
seed(1234)
tf.random.set_seed(1234)

# Modelo
```

```
# ...
# modelo
model = Sequential([layers.Dense(X.shape[1], activation='sigmoid', __
 →input_shape=[X.shape[1],])])
# Drop Out
model.add(Dropout(0.20))
# camada de entrada
model.add(layers.Dense(7, activation='sigmoid'))
# camada ocultas
model.add(layers.Dense(16, activation='relu'))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(16, activation='relu'))
# Resto do modelo e treinamento...
# ...
# camada de saída
model.add(layers.Dense(7, activation='sigmoid'))
# compilação do modelo
model.compile(loss='categorical_crossentropy', optimizer='adam', u
 →metrics=['accuracy'])
# treinamento do modelo com 0.2 dos dados para validação e 200 iterações de L
 \rightarrow treinamento
history = model.fit(X_train, y_train, validation_split=0.2, epochs=200)
Epoch 1/200
0.1987 - val_loss: 1.7703 - val_accuracy: 0.3088
Epoch 2/200
0.3613 - val_loss: 1.6928 - val_accuracy: 0.3088
Epoch 3/200
0.3754 - val_loss: 1.6288 - val_accuracy: 0.4559
Epoch 4/200
0.5091 - val_loss: 1.4778 - val_accuracy: 0.4669
0.4720 - val_loss: 1.4103 - val_accuracy: 0.4779
Epoch 6/200
```

```
0.4859 - val_loss: 1.3559 - val_accuracy: 0.4779
Epoch 7/200
0.5032 - val_loss: 1.3289 - val_accuracy: 0.4743
Epoch 8/200
0.5332 - val_loss: 1.3144 - val_accuracy: 0.4779
Epoch 9/200
0.5234 - val_loss: 1.2936 - val_accuracy: 0.4779
Epoch 10/200
0.5195 - val_loss: 1.2820 - val_accuracy: 0.4743
Epoch 11/200
0.5129 - val_loss: 1.2809 - val_accuracy: 0.4706
Epoch 12/200
0.5346 - val_loss: 1.2570 - val_accuracy: 0.4669
Epoch 13/200
0.5375 - val_loss: 1.2539 - val_accuracy: 0.4743
Epoch 14/200
0.4921 - val_loss: 1.2373 - val_accuracy: 0.4669
Epoch 15/200
0.5013 - val_loss: 1.2259 - val_accuracy: 0.4669
Epoch 16/200
0.5220 - val_loss: 1.2180 - val_accuracy: 0.4669
Epoch 17/200
0.5045 - val_loss: 1.2194 - val_accuracy: 0.4669
Epoch 18/200
0.4990 - val_loss: 1.2064 - val_accuracy: 0.4779
Epoch 19/200
0.5324 - val_loss: 1.1692 - val_accuracy: 0.4743
Epoch 20/200
0.5545 - val_loss: 1.1701 - val_accuracy: 0.4669
Epoch 21/200
0.5278 - val_loss: 1.1517 - val_accuracy: 0.4669
Epoch 22/200
```

```
0.5480 - val_loss: 1.1279 - val_accuracy: 0.4779
Epoch 23/200
0.5422 - val_loss: 1.1235 - val_accuracy: 0.4963
Epoch 24/200
0.5532 - val_loss: 1.1186 - val_accuracy: 0.5110
Epoch 25/200
0.5378 - val_loss: 1.0927 - val_accuracy: 0.5147
Epoch 26/200
0.5666 - val_loss: 1.0852 - val_accuracy: 0.5037
Epoch 27/200
0.5623 - val_loss: 1.0492 - val_accuracy: 0.5515
Epoch 28/200
0.5996 - val_loss: 1.0210 - val_accuracy: 0.5772
Epoch 29/200
0.5980 - val_loss: 1.0161 - val_accuracy: 0.5625
Epoch 30/200
0.5873 - val_loss: 1.0080 - val_accuracy: 0.5956
Epoch 31/200
0.5964 - val_loss: 0.9841 - val_accuracy: 0.5956
Epoch 32/200
0.5911 - val_loss: 0.9670 - val_accuracy: 0.6103
Epoch 33/200
0.6014 - val_loss: 0.9719 - val_accuracy: 0.6250
Epoch 34/200
0.6279 - val_loss: 0.9715 - val_accuracy: 0.5625
Epoch 35/200
0.6091 - val_loss: 0.9527 - val_accuracy: 0.6029
Epoch 36/200
0.6064 - val_loss: 0.9341 - val_accuracy: 0.5956
Epoch 37/200
0.6130 - val_loss: 0.9324 - val_accuracy: 0.5882
Epoch 38/200
```

```
0.6399 - val_loss: 0.9298 - val_accuracy: 0.6140
Epoch 39/200
0.6158 - val_loss: 0.9350 - val_accuracy: 0.5919
Epoch 40/200
0.6439 - val_loss: 0.9187 - val_accuracy: 0.6213
Epoch 41/200
0.5924 - val_loss: 0.9006 - val_accuracy: 0.6250
Epoch 42/200
0.6399 - val_loss: 0.9207 - val_accuracy: 0.5956
Epoch 43/200
0.6227 - val_loss: 0.9241 - val_accuracy: 0.5735
Epoch 44/200
0.6516 - val_loss: 0.8901 - val_accuracy: 0.6434
Epoch 45/200
0.6181 - val_loss: 0.9085 - val_accuracy: 0.5662
Epoch 46/200
0.6455 - val_loss: 0.8965 - val_accuracy: 0.5809
Epoch 47/200
0.6390 - val_loss: 0.8804 - val_accuracy: 0.6176
Epoch 48/200
0.6252 - val_loss: 0.8802 - val_accuracy: 0.6287
Epoch 49/200
0.6507 - val loss: 0.8788 - val accuracy: 0.6360
Epoch 50/200
0.6275 - val_loss: 0.8945 - val_accuracy: 0.6434
Epoch 51/200
0.6572 - val_loss: 0.8850 - val_accuracy: 0.6140
Epoch 52/200
0.6205 - val_loss: 0.9104 - val_accuracy: 0.5699
Epoch 53/200
0.6321 - val_loss: 0.8613 - val_accuracy: 0.6618
Epoch 54/200
```

```
0.6346 - val_loss: 0.8668 - val_accuracy: 0.6434
Epoch 55/200
0.6442 - val_loss: 0.8686 - val_accuracy: 0.6287
Epoch 56/200
0.6611 - val_loss: 0.8710 - val_accuracy: 0.6324
Epoch 57/200
0.6426 - val_loss: 0.8623 - val_accuracy: 0.6471
Epoch 58/200
0.6802 - val_loss: 0.8641 - val_accuracy: 0.6397
Epoch 59/200
0.6497 - val_loss: 0.8584 - val_accuracy: 0.6507
Epoch 60/200
0.6412 - val_loss: 0.8456 - val_accuracy: 0.6801
Epoch 61/200
0.6441 - val_loss: 0.8646 - val_accuracy: 0.6213
Epoch 62/200
0.6309 - val_loss: 0.8580 - val_accuracy: 0.6287
Epoch 63/200
0.6319 - val_loss: 0.8673 - val_accuracy: 0.6287
Epoch 64/200
0.6448 - val_loss: 0.8757 - val_accuracy: 0.5919
Epoch 65/200
0.6346 - val_loss: 0.8562 - val_accuracy: 0.6397
Epoch 66/200
0.6633 - val_loss: 0.8630 - val_accuracy: 0.6176
Epoch 67/200
0.6879 - val_loss: 0.8678 - val_accuracy: 0.6140
Epoch 68/200
0.6568 - val_loss: 0.8536 - val_accuracy: 0.6471
Epoch 69/200
0.6513 - val_loss: 0.8464 - val_accuracy: 0.6654
Epoch 70/200
```

```
0.6634 - val_loss: 0.8458 - val_accuracy: 0.6471
Epoch 71/200
0.6520 - val_loss: 0.8483 - val_accuracy: 0.6507
Epoch 72/200
0.6588 - val_loss: 0.8333 - val_accuracy: 0.6985
Epoch 73/200
0.6448 - val_loss: 0.8428 - val_accuracy: 0.6654
Epoch 74/200
0.6415 - val_loss: 0.8518 - val_accuracy: 0.6544
Epoch 75/200
0.6530 - val_loss: 0.8542 - val_accuracy: 0.6213
Epoch 76/200
0.6566 - val_loss: 0.8299 - val_accuracy: 0.6949
Epoch 77/200
0.6230 - val_loss: 0.8399 - val_accuracy: 0.6544
Epoch 78/200
0.6793 - val_loss: 0.8396 - val_accuracy: 0.6471
Epoch 79/200
0.6505 - val_loss: 0.8395 - val_accuracy: 0.6471
Epoch 80/200
0.6696 - val_loss: 0.8419 - val_accuracy: 0.6581
Epoch 81/200
0.6619 - val_loss: 0.8520 - val_accuracy: 0.6324
Epoch 82/200
0.6670 - val_loss: 0.8517 - val_accuracy: 0.6507
Epoch 83/200
0.6769 - val_loss: 0.8376 - val_accuracy: 0.6581
Epoch 84/200
0.6681 - val_loss: 0.8235 - val_accuracy: 0.6765
Epoch 85/200
0.6642 - val_loss: 0.8271 - val_accuracy: 0.6654
Epoch 86/200
```

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0.6433 - val_loss: 0.8351 - val_accuracy: 0.6581
Epoch 87/200
0.6754 - val_loss: 0.8311 - val_accuracy: 0.6507
Epoch 88/200
0.6578 - val_loss: 0.8307 - val_accuracy: 0.6728
Epoch 89/200
0.6671 - val_loss: 0.8134 - val_accuracy: 0.7059
Epoch 90/200
0.6834 - val_loss: 0.8276 - val_accuracy: 0.6507
Epoch 91/200
0.6463 - val_loss: 0.8308 - val_accuracy: 0.6618
Epoch 92/200
0.6792 - val_loss: 0.8207 - val_accuracy: 0.6838
Epoch 93/200
0.6871 - val_loss: 0.8197 - val_accuracy: 0.6912
Epoch 94/200
0.6670 - val_loss: 0.8237 - val_accuracy: 0.6801
Epoch 95/200
0.6600 - val_loss: 0.8308 - val_accuracy: 0.6691
Epoch 96/200
0.6660 - val_loss: 0.8164 - val_accuracy: 0.6801
Epoch 97/200
0.6730 - val_loss: 0.8138 - val_accuracy: 0.6765
Epoch 98/200
0.6458 - val_loss: 0.8100 - val_accuracy: 0.6949
Epoch 99/200
0.6627 - val_loss: 0.8133 - val_accuracy: 0.6765
Epoch 100/200
0.6849 - val_loss: 0.8243 - val_accuracy: 0.6728
Epoch 101/200
0.6792 - val_loss: 0.8167 - val_accuracy: 0.6691
Epoch 102/200
```

```
0.6477 - val_loss: 0.7998 - val_accuracy: 0.6949
Epoch 103/200
0.6843 - val_loss: 0.8354 - val_accuracy: 0.6103
Epoch 104/200
0.6448 - val_loss: 0.7988 - val_accuracy: 0.7059
Epoch 105/200
0.6838 - val_loss: 0.7999 - val_accuracy: 0.6949
Epoch 106/200
0.6641 - val_loss: 0.7972 - val_accuracy: 0.7096
Epoch 107/200
0.6877 - val_loss: 0.8189 - val_accuracy: 0.6875
Epoch 108/200
0.6474 - val_loss: 0.7977 - val_accuracy: 0.6949
Epoch 109/200
0.6566 - val_loss: 0.7995 - val_accuracy: 0.7169
Epoch 110/200
0.6688 - val_loss: 0.7916 - val_accuracy: 0.7096
Epoch 111/200
0.6862 - val_loss: 0.7933 - val_accuracy: 0.6985
Epoch 112/200
0.6765 - val_loss: 0.7944 - val_accuracy: 0.6985
Epoch 113/200
0.6823 - val_loss: 0.7979 - val_accuracy: 0.6949
Epoch 114/200
0.6752 - val_loss: 0.8046 - val_accuracy: 0.6949
Epoch 115/200
0.6511 - val_loss: 0.8058 - val_accuracy: 0.6985
Epoch 116/200
0.6917 - val_loss: 0.8158 - val_accuracy: 0.6471
Epoch 117/200
0.6794 - val_loss: 0.7993 - val_accuracy: 0.6985
Epoch 118/200
```

```
0.6865 - val_loss: 0.8054 - val_accuracy: 0.6801
Epoch 119/200
0.6903 - val_loss: 0.7937 - val_accuracy: 0.6875
Epoch 120/200
0.7097 - val_loss: 0.8165 - val_accuracy: 0.6838
Epoch 121/200
0.6706 - val_loss: 0.7975 - val_accuracy: 0.7169
Epoch 122/200
0.6778 - val_loss: 0.7948 - val_accuracy: 0.7132
Epoch 123/200
0.6812 - val_loss: 0.8001 - val_accuracy: 0.6912
Epoch 124/200
0.6781 - val_loss: 0.7903 - val_accuracy: 0.7096
Epoch 125/200
0.6947 - val_loss: 0.8123 - val_accuracy: 0.6654
Epoch 126/200
0.7035 - val_loss: 0.8047 - val_accuracy: 0.6765
Epoch 127/200
0.6600 - val_loss: 0.8138 - val_accuracy: 0.6581
Epoch 128/200
0.6778 - val_loss: 0.8265 - val_accuracy: 0.6176
Epoch 129/200
0.6779 - val_loss: 0.7944 - val_accuracy: 0.6875
Epoch 130/200
0.7149 - val_loss: 0.8137 - val_accuracy: 0.6618
Epoch 131/200
0.6634 - val_loss: 0.8075 - val_accuracy: 0.6949
Epoch 132/200
0.7204 - val_loss: 0.7977 - val_accuracy: 0.6949
Epoch 133/200
0.7109 - val_loss: 0.8028 - val_accuracy: 0.6801
Epoch 134/200
```

```
0.6664 - val_loss: 0.8143 - val_accuracy: 0.6691
Epoch 135/200
0.6816 - val_loss: 0.7916 - val_accuracy: 0.6691
Epoch 136/200
0.6993 - val_loss: 0.7872 - val_accuracy: 0.6949
Epoch 137/200
0.6802 - val_loss: 0.7983 - val_accuracy: 0.6949
Epoch 138/200
0.6629 - val_loss: 0.7954 - val_accuracy: 0.6691
Epoch 139/200
0.6974 - val_loss: 0.8114 - val_accuracy: 0.6765
Epoch 140/200
0.6872 - val_loss: 0.7827 - val_accuracy: 0.7059
Epoch 141/200
0.6752 - val_loss: 0.7844 - val_accuracy: 0.6949
Epoch 142/200
0.6857 - val_loss: 0.7832 - val_accuracy: 0.6765
Epoch 143/200
0.7024 - val_loss: 0.7966 - val_accuracy: 0.6875
Epoch 144/200
0.6626 - val_loss: 0.8005 - val_accuracy: 0.7059
Epoch 145/200
0.6876 - val_loss: 0.7849 - val_accuracy: 0.7022
Epoch 146/200
0.6866 - val_loss: 0.7887 - val_accuracy: 0.6728
Epoch 147/200
0.6694 - val_loss: 0.7841 - val_accuracy: 0.6838
Epoch 148/200
0.7105 - val_loss: 0.7949 - val_accuracy: 0.6507
Epoch 149/200
0.6820 - val_loss: 0.7849 - val_accuracy: 0.6949
Epoch 150/200
```

```
0.7042 - val_loss: 0.7708 - val_accuracy: 0.6985
Epoch 151/200
0.6682 - val_loss: 0.7795 - val_accuracy: 0.7132
Epoch 152/200
0.7116 - val_loss: 0.7783 - val_accuracy: 0.6949
Epoch 153/200
0.6888 - val_loss: 0.7830 - val_accuracy: 0.6765
Epoch 154/200
0.6879 - val_loss: 0.7697 - val_accuracy: 0.7169
Epoch 155/200
0.7026 - val_loss: 0.7829 - val_accuracy: 0.7059
Epoch 156/200
0.7116 - val_loss: 0.7868 - val_accuracy: 0.6765
Epoch 157/200
0.7087 - val_loss: 0.7712 - val_accuracy: 0.6875
Epoch 158/200
0.7027 - val_loss: 0.7712 - val_accuracy: 0.6912
Epoch 159/200
0.7105 - val_loss: 0.7704 - val_accuracy: 0.7132
Epoch 160/200
0.6857 - val_loss: 0.7816 - val_accuracy: 0.6838
Epoch 161/200
0.7159 - val_loss: 0.7746 - val_accuracy: 0.7022
Epoch 162/200
0.6998 - val_loss: 0.7797 - val_accuracy: 0.6875
Epoch 163/200
0.6821 - val_loss: 0.7656 - val_accuracy: 0.6875
Epoch 164/200
0.6993 - val_loss: 0.7675 - val_accuracy: 0.6949
Epoch 165/200
0.6762 - val_loss: 0.7693 - val_accuracy: 0.6765
Epoch 166/200
```

```
0.7091 - val_loss: 0.7663 - val_accuracy: 0.6875
Epoch 167/200
0.7222 - val_loss: 0.7601 - val_accuracy: 0.6985
Epoch 168/200
0.6860 - val_loss: 0.7866 - val_accuracy: 0.6691
Epoch 169/200
0.7021 - val_loss: 0.7653 - val_accuracy: 0.7059
Epoch 170/200
0.7311 - val_loss: 0.7797 - val_accuracy: 0.6838
Epoch 171/200
0.7208 - val_loss: 0.7613 - val_accuracy: 0.6949
Epoch 172/200
0.6994 - val_loss: 0.7706 - val_accuracy: 0.6838
Epoch 173/200
0.7082 - val_loss: 0.7727 - val_accuracy: 0.6801
Epoch 174/200
0.7363 - val_loss: 0.7632 - val_accuracy: 0.6985
Epoch 175/200
0.6929 - val_loss: 0.7592 - val_accuracy: 0.6949
Epoch 176/200
0.6791 - val_loss: 0.7567 - val_accuracy: 0.7132
Epoch 177/200
0.6970 - val_loss: 0.7606 - val_accuracy: 0.6985
Epoch 178/200
0.6954 - val_loss: 0.7574 - val_accuracy: 0.6875
Epoch 179/200
0.7130 - val_loss: 0.7643 - val_accuracy: 0.6949
Epoch 180/200
0.7101 - val_loss: 0.7577 - val_accuracy: 0.6875
Epoch 181/200
0.7011 - val_loss: 0.7601 - val_accuracy: 0.6875
Epoch 182/200
```

```
0.7095 - val_loss: 0.7745 - val_accuracy: 0.6912
Epoch 183/200
0.6844 - val_loss: 0.7672 - val_accuracy: 0.6875
Epoch 184/200
0.7196 - val_loss: 0.7661 - val_accuracy: 0.6912
Epoch 185/200
0.6921 - val_loss: 0.7714 - val_accuracy: 0.6985
Epoch 186/200
0.6988 - val_loss: 0.7600 - val_accuracy: 0.6912
Epoch 187/200
0.6904 - val_loss: 0.7760 - val_accuracy: 0.6801
Epoch 188/200
0.7039 - val_loss: 0.7659 - val_accuracy: 0.6875
Epoch 189/200
0.7065 - val_loss: 0.7539 - val_accuracy: 0.6985
Epoch 190/200
0.7170 - val_loss: 0.7764 - val_accuracy: 0.7022
Epoch 191/200
0.7037 - val_loss: 0.7572 - val_accuracy: 0.6985
Epoch 192/200
0.6927 - val_loss: 0.7870 - val_accuracy: 0.6949
Epoch 193/200
0.7222 - val_loss: 0.7538 - val_accuracy: 0.6985
Epoch 194/200
0.7187 - val_loss: 0.7641 - val_accuracy: 0.6985
Epoch 195/200
0.7187 - val_loss: 0.7585 - val_accuracy: 0.6949
Epoch 196/200
0.7171 - val_loss: 0.7509 - val_accuracy: 0.6949
Epoch 197/200
0.7147 - val_loss: 0.7566 - val_accuracy: 0.6985
Epoch 198/200
```