Aula 18

Métodos de ajuste de hiperparâmetros e regularização

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1. Objetivo

Apresentar como realizar o ajuste de hiper parâmetros e a regularização de uma RNA.

Importar bibliotecas

```
import numpy as np
import matplotlib.pyplot as plt
import tensorflow as tf
tf.__version__
```

{"type":"string"}

2. Conjunto de dados

Vamos utlizar o conjunto de dados CIFAR10, que consiste em classificação multiclasse de imagens

```
# Carregar Dados CIFAR
from tensorflow.keras.datasets import cifar10

# load dataset
(Xtrain, Ytrain), (Xtest, Ytest) = cifar10.load_data()
```

```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170498071/170498071 ━━━━━━━━━━━━━━━━━━━━ 6s 0us/step
```

```
# Normalização das imagens
x_train = (Xtrain - 127.5)/127.5
x_test = (Xtest - 127.5)/127.5

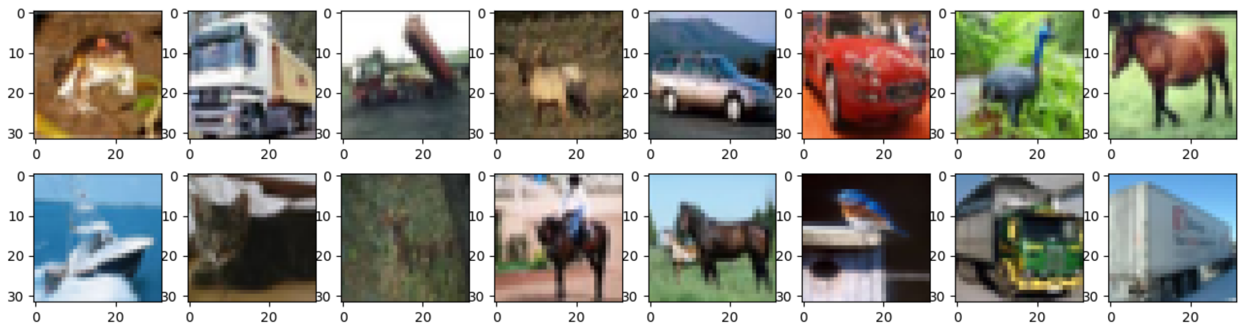
# Codificação one-hot das saídas
y_train_hot = tf.keras.utils.to_categorical(Ytrain, 10)
y_test_hot = tf.keras.utils.to_categorical(Ytest, 10)

print('Dimensão dos dados de entrada:', x_train.shape, x_test.shape)
```

```
print('Maximos e mínimos treinamento:', np.min(x_train),
np.mean(x_train), np.max(x_train))
print('Maximos e mínimos teste:', np.min(x_test), np.mean(x_test),
np.max(x_test))
print('exemplos de entradas:', x_train[0,16])
print('Exemplos de saídas:', y_train_hot.shape, y_test_hot.shape, '\
n', Ytrain[:5].T, '\n', y_train_hot[:5])
```

```
Dimensão dos dados de entrada: (50000, 32, 32, 3) (10000, 32, 32, 3)
Maximos e mínimos treinamento: -1.0 -0.05327399902982031 1.0
Maximos e mínimos teste: -1.0 -0.046830158803104496 1.0
exemplos de entradas: [[ 0.16862745 -0.09803922 -0.38039216]
 [ 0.12156863 -0.25490196 -0.61568627]
 [ 0.12941176 -0.23921569 -0.6       ]
 [ 0.18431373 -0.22352941 -0.6       ]
 [ 0.03529412 -0.31764706 -0.61568627]
 [-0.49803922 -0.68627451 -0.83529412]
 [-0.34117647 -0.5372549  -0.67843137]
 [-0.12156863 -0.45882353 -0.70980392]
 [ 0.27843137 -0.05098039 -0.41176471]
 [ 0.74901961  0.6         0.30196078]
 [ 0.61568627  0.42745098  0.23137255]
 [ 0.1372549  -0.29411765 -0.56078431]
 [ 0.5372549   0.04313725 -0.34117647]
 [ 0.6         0.23137255 -0.1372549 ]
 [ 0.7254902   0.4745098   0.22352941]
 [ 0.90588235  0.77254902  0.63137255]
 [ 0.92156863  0.85882353  0.77254902]
 [ 0.8745098   0.82745098  0.68627451]
 [ 0.83529412  0.75686275  0.57647059]
 [ 0.81176471  0.70196078  0.50588235]
 [ 0.52941176  0.41960784  0.19215686]
 [ 0.17647059  0.0745098  -0.21568627]
 [ 0.63137255  0.51372549  0.20784314]
 [ 0.96078431  0.89019608  0.69411765]
 [ 0.78039216  0.69411765  0.35686275]
 [ 0.27843137  0.11372549 -0.38823529]
 [ 0.1372549  -0.00392157 -0.52941176]
 [ 0.12156863  0.01176471 -0.51372549]
 [ 0.09803922 -0.03529412 -0.56862745]
 [ 0.06666667 -0.09019608 -0.63921569]
 [-0.05098039 -0.25490196 -0.76470588]
 [-0.10588235 -0.35686275 -0.68627451]]
Exemplos de saídas: (50000, 10) (10000, 10)
 [[6 9 9 4 1]]
 [[0. 0. 0. 0. 0. 0. 1. 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. 1. 0. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]]
```

```
fig, axs = plt.subplots(2, 8, figsize=(16, 4))
index = 0
for i in range(2):
    for j in range(8):
        axs[i,j].imshow(Xtrain[index], cmap='gray')
        index += 1
plt.show()
```



3. Rede sem regularização

3.1 Modelo simples inicial

```
from tensorflow.keras import models
from tensorflow.keras import layers
from tensorflow.keras import optimizers

rna = models.Sequential()
rna.add(layers.Flatten(input_shape=(32,32,3)))
rna.add(layers.Dense(64, activation='relu'))
rna.add(layers.Dense(10, activation='softmax'))

rna.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/reshaping/
flatten.py:37: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

Model: "sequential"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                           ┃ Output Shape                 ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┩
━━━━━━━━━━━━━━━━━┩
│ flatten (Flatten)                      │ (None, 3072)                 │
0 │
```

```
├──────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dense (Dense)                        │ (None, 64)                   │
196,672 │
├──────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dense_1 (Dense)                      │ (None, 10)                   │
650 │
└──────────────────────────────────────┴──────────────────────────────┴
─────────────────┘

 Total params: 197,322 (770.79 KB)

 Trainable params: 197,322 (770.79 KB)

 Non-trainable params: 0 (0.00 B)
```

```
Nepocas = 100
Nlote = 256

opt = optimizers.SGD(learning_rate=0.01, momentum=0.92, nesterov=True)
rna.compile(optimizer=opt, loss='categorical_crossentropy',
metrics=['accuracy'])
historia = rna.fit(x_train, y_train_hot, epochs=Nepocas,
batch_size=Nlote, validation_data=(x_test, y_test_hot))
```

```
Epoch 1/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 5s 14ms/step - accuracy: 0.3337 - loss:
1.8829 - val_accuracy: 0.4407 - val_loss: 1.5951
Epoch 2/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4606 - loss:
1.5489 - val_accuracy: 0.4662 - val_loss: 1.5175
Epoch 3/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4942 - loss:
1.4510 - val_accuracy: 0.4805 - val_loss: 1.4756
Epoch 4/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.5120 - loss:
1.3990 - val_accuracy: 0.4839 - val_loss: 1.4655
Epoch 5/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5283 - loss:
1.3538 - val_accuracy: 0.5006 - val_loss: 1.4361
Epoch 6/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5382 - loss:
1.3224 - val_accuracy: 0.5032 - val_loss: 1.4222
Epoch 7/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5586 - loss:
1.2720 - val_accuracy: 0.5028 - val_loss: 1.4225
Epoch 8/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5644 - loss:
1.2487 - val_accuracy: 0.4977 - val_loss: 1.4292
Epoch 9/100
```

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5736 - loss:
1.2293 - val_accuracy: 0.5017 - val_loss: 1.4332
Epoch 10/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5793 - loss:
1.2042 - val_accuracy: 0.5068 - val_loss: 1.4242
Epoch 11/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5881 - loss:
1.1818 - val_accuracy: 0.5071 - val_loss: 1.4296
Epoch 12/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5933 - loss:
1.1708 - val_accuracy: 0.5043 - val_loss: 1.4387
Epoch 13/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5981 - loss:
1.1551 - val_accuracy: 0.5046 - val_loss: 1.4394
Epoch 14/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6030 - loss:
1.1321 - val_accuracy: 0.5112 - val_loss: 1.4351
Epoch 15/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6098 - loss:
1.1248 - val_accuracy: 0.5020 - val_loss: 1.4541
Epoch 16/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6148 - loss:
1.1045 - val_accuracy: 0.5047 - val_loss: 1.4522
Epoch 17/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6156 - loss:
1.0938 - val_accuracy: 0.4963 - val_loss: 1.4732
Epoch 18/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6266 - loss:
1.0732 - val_accuracy: 0.5057 - val_loss: 1.4525
Epoch 19/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6325 - loss:
1.0595 - val_accuracy: 0.5040 - val_loss: 1.4681
Epoch 20/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6274 - loss:
1.0580 - val_accuracy: 0.4981 - val_loss: 1.4985
Epoch 21/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6373 - loss:
1.0407 - val_accuracy: 0.4976 - val_loss: 1.4825
Epoch 22/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6417 - loss:
1.0306 - val_accuracy: 0.4974 - val_loss: 1.5118
Epoch 23/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6379 - loss:
1.0279 - val_accuracy: 0.4973 - val_loss: 1.5071
Epoch 24/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6465 - loss:
1.0136 - val_accuracy: 0.4932 - val_loss: 1.5072
Epoch 25/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6507 - loss:
```

```
0.9988 - val_accuracy: 0.4983 - val_loss: 1.5126
Epoch 26/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6533 - loss:
0.9890 - val_accuracy: 0.4951 - val_loss: 1.5309
Epoch 27/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6572 - loss:
0.9781 - val_accuracy: 0.4969 - val_loss: 1.5494
Epoch 28/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6625 - loss:
0.9689 - val_accuracy: 0.4915 - val_loss: 1.5479
Epoch 29/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6668 - loss:
0.9511 - val_accuracy: 0.4897 - val_loss: 1.5540
Epoch 30/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6675 - loss:
0.9467 - val_accuracy: 0.4987 - val_loss: 1.5590
Epoch 31/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6720 - loss:
0.9332 - val_accuracy: 0.4909 - val_loss: 1.5728
Epoch 32/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6741 - loss:
0.9299 - val_accuracy: 0.4928 - val_loss: 1.5765
Epoch 33/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6755 - loss:
0.9212 - val_accuracy: 0.4893 - val_loss: 1.5860
Epoch 34/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6800 - loss:
0.9096 - val_accuracy: 0.4915 - val_loss: 1.6017
Epoch 35/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6793 - loss:
0.9124 - val_accuracy: 0.4836 - val_loss: 1.6168
Epoch 36/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6842 - loss:
0.9076 - val_accuracy: 0.4789 - val_loss: 1.6666
Epoch 37/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6827 - loss:
0.8953 - val_accuracy: 0.4796 - val_loss: 1.6605
Epoch 38/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6869 - loss:
0.8933 - val_accuracy: 0.4891 - val_loss: 1.6616
Epoch 39/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6938 - loss:
0.8829 - val_accuracy: 0.4900 - val_loss: 1.6513
Epoch 40/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6933 - loss:
0.8718 - val_accuracy: 0.4919 - val_loss: 1.6519
Epoch 41/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.6982 - loss:
0.8613 - val_accuracy: 0.4851 - val_loss: 1.6689
```

```
Epoch 42/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6998 - loss: 0.8628 - val_accuracy: 0.4810 - val_loss: 1.6829
Epoch 43/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.7036 - loss: 0.8437 - val_accuracy: 0.4831 - val_loss: 1.7026
Epoch 44/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 3ms/step - accuracy: 0.7044 - loss: 0.8330 - val_accuracy: 0.4854 - val_loss: 1.6995
Epoch 45/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7067 - loss: 0.8336 - val_accuracy: 0.4842 - val_loss: 1.7155
Epoch 46/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7102 - loss: 0.8241 - val_accuracy: 0.4786 - val_loss: 1.7185
Epoch 47/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7131 - loss: 0.8189 - val_accuracy: 0.4785 - val_loss: 1.7288
Epoch 48/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7167 - loss: 0.8062 - val_accuracy: 0.4800 - val_loss: 1.7644
Epoch 49/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7157 - loss: 0.8126 - val_accuracy: 0.4798 - val_loss: 1.7453
Epoch 50/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7249 - loss: 0.7930 - val_accuracy: 0.4747 - val_loss: 1.7768
Epoch 51/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7228 - loss: 0.7922 - val_accuracy: 0.4718 - val_loss: 1.7843
Epoch 52/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7189 - loss: 0.7967 - val_accuracy: 0.4763 - val_loss: 1.7906
Epoch 53/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7316 - loss: 0.7670 - val_accuracy: 0.4816 - val_loss: 1.7892
Epoch 54/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7277 - loss: 0.7799 - val_accuracy: 0.4750 - val_loss: 1.8167
Epoch 55/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7323 - loss: 0.7682 - val_accuracy: 0.4756 - val_loss: 1.8265
Epoch 56/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7342 - loss: 0.7568 - val_accuracy: 0.4748 - val_loss: 1.8347
Epoch 57/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7350 - loss: 0.7549 - val_accuracy: 0.4765 - val_loss: 1.8374
Epoch 58/100
```

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7379 - loss:
0.7476 - val_accuracy: 0.4778 - val_loss: 1.8465
Epoch 59/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7426 - loss:
0.7345 - val_accuracy: 0.4728 - val_loss: 1.8619
Epoch 60/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7375 - loss:
0.7467 - val_accuracy: 0.4755 - val_loss: 1.8754
Epoch 61/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7457 - loss:
0.7298 - val_accuracy: 0.4754 - val_loss: 1.9085
Epoch 62/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7491 - loss:
0.7264 - val_accuracy: 0.4702 - val_loss: 1.9050
Epoch 63/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7449 - loss:
0.7293 - val_accuracy: 0.4725 - val_loss: 1.9333
Epoch 64/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7462 - loss:
0.7225 - val_accuracy: 0.4650 - val_loss: 1.9473
Epoch 65/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7514 - loss:
0.7042 - val_accuracy: 0.4731 - val_loss: 1.9292
Epoch 66/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7468 - loss:
0.7163 - val_accuracy: 0.4687 - val_loss: 1.9615
Epoch 67/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7515 - loss:
0.7112 - val_accuracy: 0.4625 - val_loss: 1.9725
Epoch 68/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7541 - loss:
0.7004 - val_accuracy: 0.4694 - val_loss: 1.9810
Epoch 69/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.7565 - loss:
0.6984 - val_accuracy: 0.4739 - val_loss: 1.9662
Epoch 70/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7605 - loss:
0.6876 - val_accuracy: 0.4705 - val_loss: 1.9956
Epoch 71/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7664 - loss:
0.6706 - val_accuracy: 0.4684 - val_loss: 2.0209
Epoch 72/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7616 - loss:
0.6817 - val_accuracy: 0.4690 - val_loss: 2.0141
Epoch 73/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7639 - loss:
0.6749 - val_accuracy: 0.4522 - val_loss: 2.0487
Epoch 74/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7644 - loss:
```

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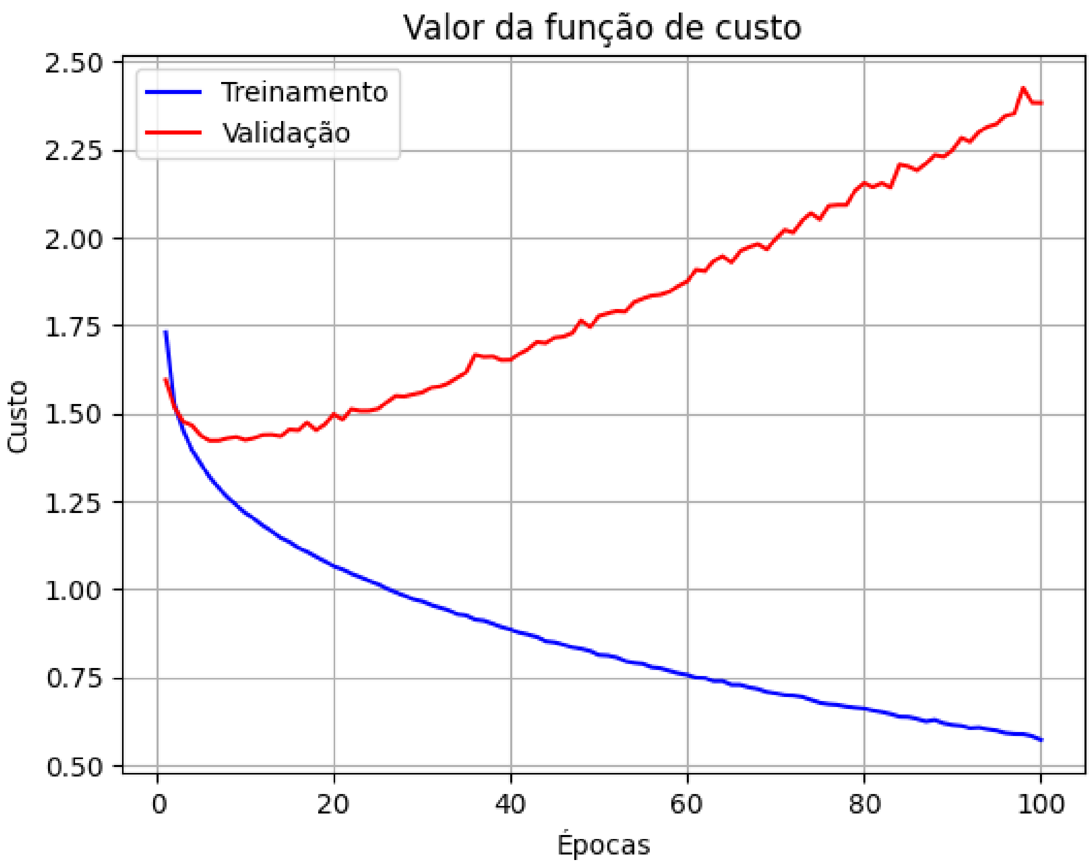
0.6702 - val_accuracy: 0.4648 - val_loss: 2.0688
Epoch 75/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7660 - loss:
0.6639 - val_accuracy: 0.4747 - val_loss: 2.0512
Epoch 76/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7720 - loss:
0.6546 - val_accuracy: 0.4666 - val_loss: 2.0904
Epoch 77/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7703 - loss:
0.6549 - val_accuracy: 0.4677 - val_loss: 2.0929
Epoch 78/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7755 - loss:
0.6447 - val_accuracy: 0.4646 - val_loss: 2.0928
Epoch 79/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7749 - loss:
0.6441 - val_accuracy: 0.4652 - val_loss: 2.1336
Epoch 80/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7715 - loss:
0.6515 - val_accuracy: 0.4581 - val_loss: 2.1546
Epoch 81/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7771 - loss:
0.6382 - val_accuracy: 0.4572 - val_loss: 2.1434
Epoch 82/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7788 - loss:
0.6351 - val_accuracy: 0.4663 - val_loss: 2.1543
Epoch 83/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7830 - loss:
0.6234 - val_accuracy: 0.4642 - val_loss: 2.1425
Epoch 84/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 4ms/step - accuracy: 0.7825 - loss:
0.6242 - val_accuracy: 0.4624 - val_loss: 2.2078
Epoch 85/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7844 - loss:
0.6211 - val_accuracy: 0.4604 - val_loss: 2.2020
Epoch 86/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7835 - loss:
0.6179 - val_accuracy: 0.4617 - val_loss: 2.1908
Epoch 87/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7863 - loss:
0.6117 - val_accuracy: 0.4570 - val_loss: 2.2103
Epoch 88/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7887 - loss:
0.6109 - val_accuracy: 0.4614 - val_loss: 2.2346
Epoch 89/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7883 - loss:
0.6035 - val_accuracy: 0.4606 - val_loss: 2.2300
Epoch 90/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7899 - loss:
0.6028 - val_accuracy: 0.4671 - val_loss: 2.2478
```

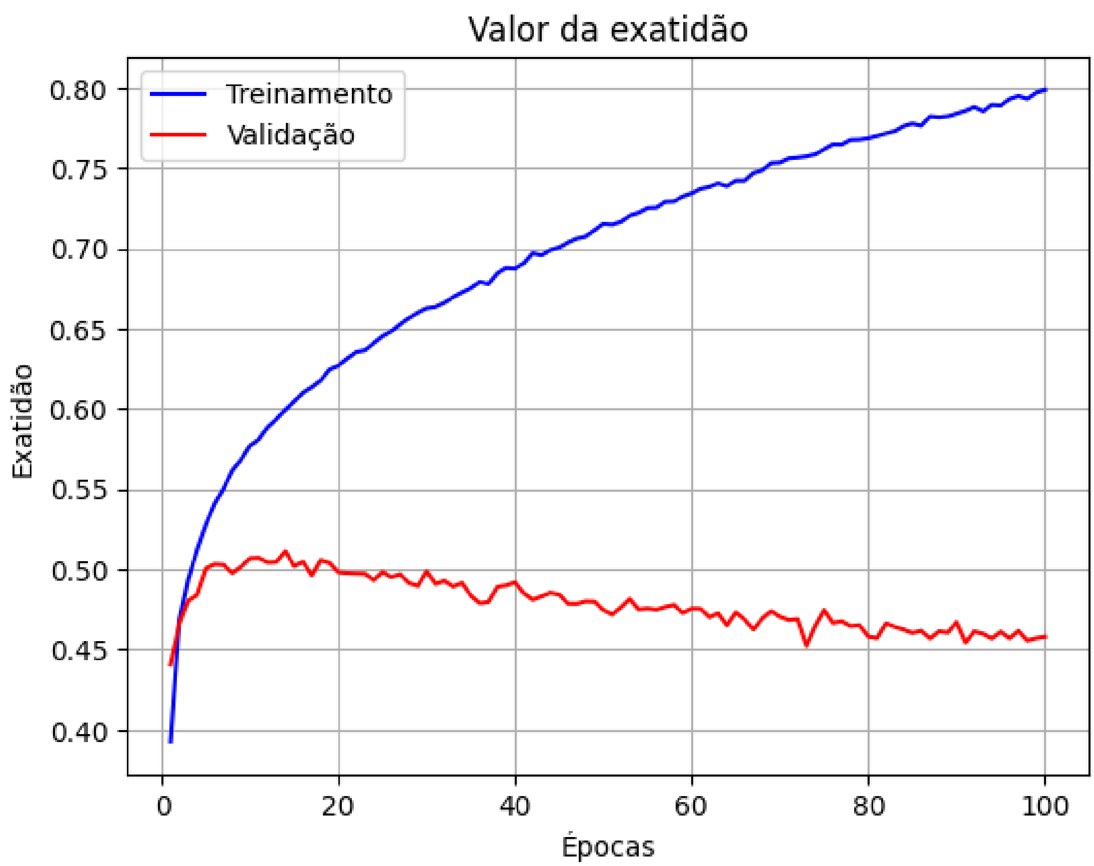
```
Epoch 91/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7944 - loss:
0.5904 - val_accuracy: 0.4544 - val_loss: 2.2832
Epoch 92/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7922 - loss:
0.5928 - val_accuracy: 0.4613 - val_loss: 2.2725
Epoch 93/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7911 - loss:
0.5964 - val_accuracy: 0.4598 - val_loss: 2.3008
Epoch 94/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7975 - loss:
0.5809 - val_accuracy: 0.4570 - val_loss: 2.3149
Epoch 95/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7951 - loss:
0.5787 - val_accuracy: 0.4611 - val_loss: 2.3232
Epoch 96/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.7987 - loss:
0.5753 - val_accuracy: 0.4571 - val_loss: 2.3459
Epoch 97/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.8003 - loss:
0.5765 - val_accuracy: 0.4617 - val_loss: 2.3526
Epoch 98/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8019 - loss:
0.5655 - val_accuracy: 0.4557 - val_loss: 2.4254
Epoch 99/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8015 - loss:
0.5710 - val_accuracy: 0.4571 - val_loss: 2.3833
Epoch 100/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8032 - loss:
0.5633 - val_accuracy: 0.4580 - val_loss: 2.3825

# Salva custo,métrica e épocas em vetores
historia_dict = historia.history
custo = historia_dict['loss']
exatidao = historia_dict['accuracy']
custo_val = historia_dict['val_loss']
exatidao_val = historia_dict['val_accuracy']

# Cria vetor de épocas
epocas = range(1, len(custo) + 1)
# Gráfico do custo
plt.plot(epocas, custo, 'b')
plt.plot(epocas, custo_val, 'r')
plt.title('Valor da função de custo')
plt.xlabel('Épocas')
plt.ylabel('Custo')
plt.legend(['Treinamento', 'Validação'])
plt.grid()
plt.show()
```

```python
# Gráfico da exatidão
plt.plot(epocas, exatidao, 'b')
plt.plot(epocas, exatidao_val, 'r')
plt.title('Valor da exatidão')
plt.xlabel('Épocas')
plt.ylabel('Exatidão')
plt.legend(['Treinamento', 'Validação'])
plt.grid()
plt.show()
```





3.2 Modelo com mais parâmetros

```
from tensorflow.keras import models
from tensorflow.keras import layers

rna = models.Sequential()
rna.add(layers.Flatten(input_shape=(32,32,3)))
rna.add(layers.Dense(1024, activation='relu'))
rna.add(layers.Dense(512, activation='relu'))
rna.add(layers.Dense(256, activation='relu'))
rna.add(layers.Dense(128, activation='relu'))
rna.add(layers.Dense(10, activation='softmax'))

rna.summary()

Model: "sequential_3"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇
━━━━━━━━━┩
│ flatten_3 (Flatten)                  │ (None, 3072)                │
```

```
0 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_12 (Dense)                     │ (None, 1024)                │
3,146,752 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_13 (Dense)                     │ (None, 512)                 │
524,800 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_14 (Dense)                     │ (None, 256)                 │
131,328 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_15 (Dense)                     │ (None, 128)                 │
32,896 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_16 (Dense)                     │ (None, 10)                  │
1,290 │
└──────────────────────────────────────┴─────────────────────────────┴
─────────────────┘

 Total params: 3,837,066 (14.64 MB)

 Trainable params: 3,837,066 (14.64 MB)

 Non-trainable params: 0 (0.00 B)

opt = optimizers.SGD(learning_rate=0.001, momentum=0.92,
nesterov=True)
rna.compile(optimizer=opt, loss='categorical_crossentropy',
metrics=['accuracy'])
historia = rna.fit(x_train, y_train_hot, epochs=Nepocas,
batch_size=Nlote, validation_data=(x_test, y_test_hot))

Epoch 1/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 4s 12ms/step - accuracy: 0.2007 - loss:
2.1898 - val_accuracy: 0.3548 - val_loss: 1.8522
Epoch 2/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - accuracy: 0.3667 - loss:
1.7992 - val_accuracy: 0.4031 - val_loss: 1.6951
Epoch 3/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4127 - loss:
1.6632 - val_accuracy: 0.4337 - val_loss: 1.6130
Epoch 4/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4466 - loss:
1.5829 - val_accuracy: 0.4524 - val_loss: 1.5561
Epoch 5/100
```

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4756 - loss:
1.5107 - val_accuracy: 0.4629 - val_loss: 1.5157
Epoch 6/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4906 - loss:
1.4576 - val_accuracy: 0.4731 - val_loss: 1.4832
Epoch 7/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5112 - loss:
1.4065 - val_accuracy: 0.4826 - val_loss: 1.4526
Epoch 8/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5274 - loss:
1.3632 - val_accuracy: 0.4957 - val_loss: 1.4269
Epoch 9/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5457 - loss:
1.3108 - val_accuracy: 0.5014 - val_loss: 1.4068
Epoch 10/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5617 - loss:
1.2656 - val_accuracy: 0.5056 - val_loss: 1.3991
Epoch 11/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5741 - loss:
1.2312 - val_accuracy: 0.5104 - val_loss: 1.3791
Epoch 12/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5931 - loss:
1.1912 - val_accuracy: 0.5145 - val_loss: 1.3653
Epoch 13/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6068 - loss:
1.1525 - val_accuracy: 0.5200 - val_loss: 1.3553
Epoch 14/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6188 - loss:
1.1096 - val_accuracy: 0.5255 - val_loss: 1.3512
Epoch 15/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6370 - loss:
1.0683 - val_accuracy: 0.5232 - val_loss: 1.3446
Epoch 16/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6453 - loss:
1.0409 - val_accuracy: 0.5252 - val_loss: 1.3460
Epoch 17/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6603 - loss:
0.9974 - val_accuracy: 0.5284 - val_loss: 1.3458
Epoch 18/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6729 - loss:
0.9617 - val_accuracy: 0.5303 - val_loss: 1.3414
Epoch 19/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6882 - loss:
0.9263 - val_accuracy: 0.5351 - val_loss: 1.3439
Epoch 20/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7039 - loss:
0.8859 - val_accuracy: 0.5323 - val_loss: 1.3658
Epoch 21/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7167 - loss:
```

```
0.8452 - val_accuracy: 0.5306 - val_loss: 1.3886
Epoch 22/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7278 - loss:
0.8114 - val_accuracy: 0.5320 - val_loss: 1.3791
Epoch 23/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.7465 - loss:
0.7654 - val_accuracy: 0.5329 - val_loss: 1.4060
Epoch 24/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.7605 - loss:
0.7286 - val_accuracy: 0.5312 - val_loss: 1.4139
Epoch 25/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.7757 - loss:
0.6857 - val_accuracy: 0.5368 - val_loss: 1.4162
Epoch 26/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 8ms/step - accuracy: 0.7902 - loss:
0.6466 - val_accuracy: 0.5394 - val_loss: 1.4446
Epoch 27/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.8039 - loss:
0.6155 - val_accuracy: 0.5336 - val_loss: 1.4637
Epoch 28/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8155 - loss:
0.5769 - val_accuracy: 0.5300 - val_loss: 1.5178
Epoch 29/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8315 - loss:
0.5382 - val_accuracy: 0.5225 - val_loss: 1.5573
Epoch 30/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8434 - loss:
0.5007 - val_accuracy: 0.5240 - val_loss: 1.5966
Epoch 31/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8600 - loss:
0.4625 - val_accuracy: 0.5263 - val_loss: 1.5909
Epoch 32/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8697 - loss:
0.4309 - val_accuracy: 0.5197 - val_loss: 1.6641
Epoch 33/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8818 - loss:
0.4015 - val_accuracy: 0.5226 - val_loss: 1.6755
Epoch 34/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8973 - loss:
0.3609 - val_accuracy: 0.5227 - val_loss: 1.7280
Epoch 35/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9064 - loss:
0.3339 - val_accuracy: 0.5202 - val_loss: 1.7770
Epoch 36/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.9196 - loss:
0.2994 - val_accuracy: 0.5147 - val_loss: 1.8325
Epoch 37/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9267 - loss:
0.2788 - val_accuracy: 0.5184 - val_loss: 1.9070
```

```
Epoch 38/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9353 - loss:
0.2537 - val_accuracy: 0.5212 - val_loss: 1.9165
Epoch 39/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9462 - loss:
0.2257 - val_accuracy: 0.5212 - val_loss: 1.9456
Epoch 40/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9543 - loss:
0.2006 - val_accuracy: 0.5198 - val_loss: 2.0128
Epoch 41/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9591 - loss:
0.1825 - val_accuracy: 0.5257 - val_loss: 2.0427
Epoch 42/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9691 - loss:
0.1584 - val_accuracy: 0.5169 - val_loss: 2.1139
Epoch 43/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9686 - loss:
0.1513 - val_accuracy: 0.5093 - val_loss: 2.2421
Epoch 44/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9747 - loss:
0.1323 - val_accuracy: 0.5161 - val_loss: 2.2388
Epoch 45/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9781 - loss:
0.1193 - val_accuracy: 0.5219 - val_loss: 2.2528
Epoch 46/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9851 - loss:
0.1002 - val_accuracy: 0.5244 - val_loss: 2.3070
Epoch 47/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.9867 - loss:
0.0901 - val_accuracy: 0.5175 - val_loss: 2.3909
Epoch 48/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9885 - loss:
0.0809 - val_accuracy: 0.5202 - val_loss: 2.3911
Epoch 49/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9930 - loss:
0.0665 - val_accuracy: 0.5215 - val_loss: 2.4528
Epoch 50/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9926 - loss:
0.0634 - val_accuracy: 0.5200 - val_loss: 2.4994
Epoch 51/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9953 - loss:
0.0515 - val_accuracy: 0.5233 - val_loss: 2.5420
Epoch 52/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9957 - loss:
0.0483 - val_accuracy: 0.5078 - val_loss: 2.7080
Epoch 53/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9942 - loss:
0.0510 - val_accuracy: 0.5170 - val_loss: 2.6641
Epoch 54/100
```

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9975 - loss:
0.0384 - val_accuracy: 0.5195 - val_loss: 2.6844
Epoch 55/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9980 - loss:
0.0335 - val_accuracy: 0.5215 - val_loss: 2.7044
Epoch 56/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9989 - loss:
0.0275 - val_accuracy: 0.5212 - val_loss: 2.7572
Epoch 57/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9989 - loss:
0.0267 - val_accuracy: 0.5202 - val_loss: 2.7730
Epoch 58/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9994 - loss:
0.0228 - val_accuracy: 0.5198 - val_loss: 2.8060
Epoch 59/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9995 - loss:
0.0202 - val_accuracy: 0.5248 - val_loss: 2.8762
Epoch 60/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9985 - loss:
0.0232 - val_accuracy: 0.5208 - val_loss: 2.8703
Epoch 61/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9997 - loss:
0.0179 - val_accuracy: 0.5237 - val_loss: 2.8985
Epoch 62/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9996 - loss:
0.0167 - val_accuracy: 0.5205 - val_loss: 2.9287
Epoch 63/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9998 - loss:
0.0150 - val_accuracy: 0.5226 - val_loss: 2.9484
Epoch 64/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9999 - loss:
0.0134 - val_accuracy: 0.5219 - val_loss: 2.9777
Epoch 65/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9999 - loss:
0.0120 - val_accuracy: 0.5223 - val_loss: 3.0047
Epoch 66/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9999 - loss:
0.0115 - val_accuracy: 0.5214 - val_loss: 3.0205
Epoch 67/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9999 - loss:
0.0107 - val_accuracy: 0.5258 - val_loss: 3.0473
Epoch 68/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 1.0000 - loss:
0.0101 - val_accuracy: 0.5219 - val_loss: 3.0656
Epoch 69/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss:
0.0095 - val_accuracy: 0.5227 - val_loss: 3.0935
Epoch 70/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss:
```

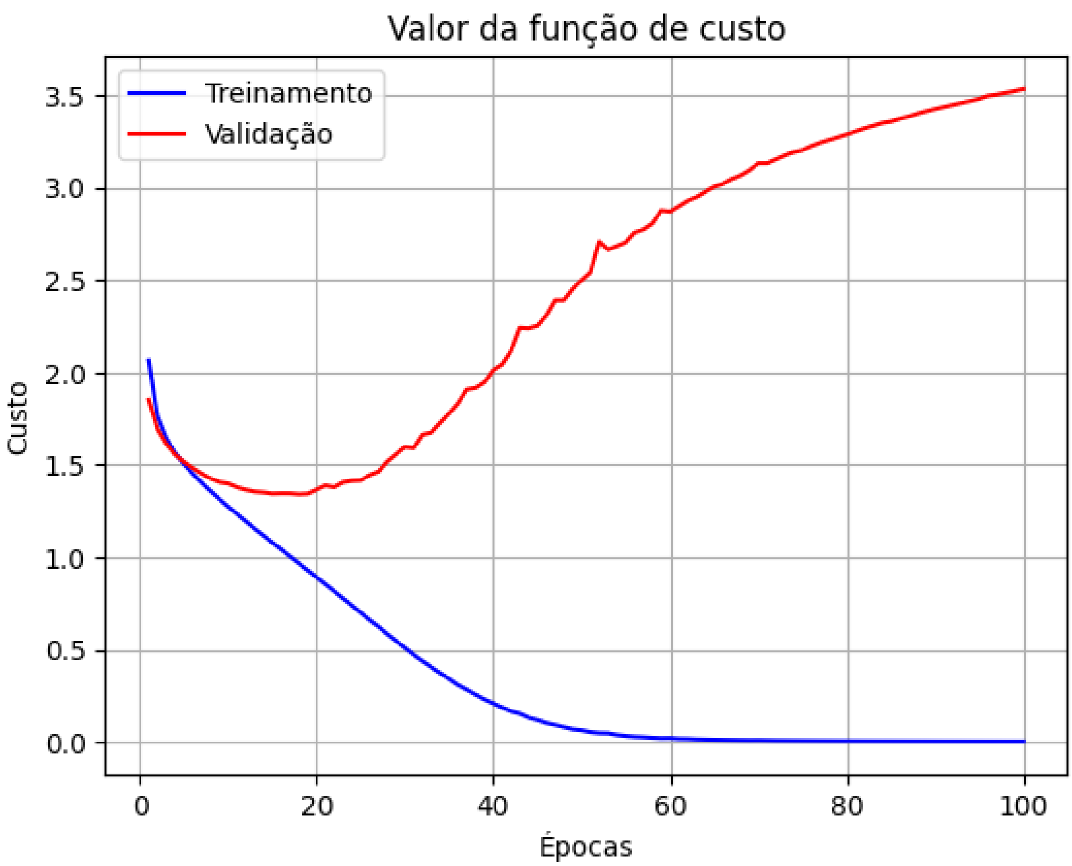
```
0.0092 - val_accuracy: 0.5195 - val_loss: 3.1324
Epoch 71/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0091 - val_accuracy: 0.5230 - val_loss: 3.1327
Epoch 72/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0081 - val_accuracy: 0.5199 - val_loss: 3.1535
Epoch 73/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0077 - val_accuracy: 0.5217 - val_loss: 3.1745
Epoch 74/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss:
0.0073 - val_accuracy: 0.5247 - val_loss: 3.1919
Epoch 75/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss:
0.0071 - val_accuracy: 0.5229 - val_loss: 3.2030
Epoch 76/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0067 - val_accuracy: 0.5224 - val_loss: 3.2251
Epoch 77/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0064 - val_accuracy: 0.5217 - val_loss: 3.2428
Epoch 78/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss:
0.0062 - val_accuracy: 0.5241 - val_loss: 3.2577
Epoch 79/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 1.0000 - loss:
0.0060 - val_accuracy: 0.5215 - val_loss: 3.2717
Epoch 80/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss:
0.0057 - val_accuracy: 0.5212 - val_loss: 3.2875
Epoch 81/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0055 - val_accuracy: 0.5228 - val_loss: 3.3040
Epoch 82/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0054 - val_accuracy: 0.5218 - val_loss: 3.3211
Epoch 83/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0052 - val_accuracy: 0.5230 - val_loss: 3.3345
Epoch 84/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0050 - val_accuracy: 0.5219 - val_loss: 3.3497
Epoch 85/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0048 - val_accuracy: 0.5225 - val_loss: 3.3575
Epoch 86/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss:
0.0047 - val_accuracy: 0.5228 - val_loss: 3.3726
```

```
Epoch 87/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss: 0.0046 - val_accuracy: 0.5223 - val_loss: 3.3846
Epoch 88/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss: 0.0044 - val_accuracy: 0.5213 - val_loss: 3.3997
Epoch 89/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss: 0.0042 - val_accuracy: 0.5231 - val_loss: 3.4132
Epoch 90/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 1.0000 - loss: 0.0042 - val_accuracy: 0.5210 - val_loss: 3.4249
Epoch 91/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss: 0.0040 - val_accuracy: 0.5216 - val_loss: 3.4362
Epoch 92/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss: 0.0039 - val_accuracy: 0.5229 - val_loss: 3.4465
Epoch 93/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss: 0.0038 - val_accuracy: 0.5201 - val_loss: 3.4580
Epoch 94/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss: 0.0037 - val_accuracy: 0.5226 - val_loss: 3.4683
Epoch 95/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss: 0.0036 - val_accuracy: 0.5239 - val_loss: 3.4806
Epoch 96/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss: 0.0035 - val_accuracy: 0.5210 - val_loss: 3.4968
Epoch 97/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss: 0.0034 - val_accuracy: 0.5221 - val_loss: 3.5036
Epoch 98/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 1.0000 - loss: 0.0034 - val_accuracy: 0.5231 - val_loss: 3.5132
Epoch 99/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 1.0000 - loss: 0.0032 - val_accuracy: 0.5230 - val_loss: 3.5223
Epoch 100/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 1.0000 - loss: 0.0032 - val_accuracy: 0.5235 - val_loss: 3.5338

# Salva custo,métrica e épocas em vetores
historia_dict = historia.history
custo = historia_dict['loss']
exatidao = historia_dict['accuracy']
custo_val = historia_dict['val_loss']
exatidao_val = historia_dict['val_accuracy']
```

```python
# Cria vetor de épocas
epocas = range(1, len(custo) + 1)
# Gráfico do custo
plt.plot(epocas, custo, 'b')
plt.plot(epocas, custo_val, 'r')
plt.title('Valor da função de custo')
plt.xlabel('Épocas')
plt.ylabel('Custo')
plt.legend(['Treinamento', 'Validação'])
plt.grid()
plt.show()

# Gráfico da exatidão
plt.plot(epocas, exatidao, 'b')
plt.plot(epocas, exatidao_val, 'r')
plt.title('Valor da exatidão')
plt.xlabel('Épocas')
plt.ylabel('Exatidão')
plt.legend(['Treinamento', 'Validação'])
plt.grid()
plt.show()
```




```
cm_train = rna.evaluate(x_train, y_train_hot)
cm_test = rna.evaluate(x_test, y_test_hot)

1563/1563 ━━━━━━━━━━━━━━━━━━━━ 4s 2ms/step - accuracy: 1.0000 - loss:
0.0031
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5266 - loss:
3.5363
```

4. Rede com regularização L2

```
from tensorflow.keras import models
from tensorflow.keras import layers

rna = models.Sequential()
rna.add(layers.Flatten(input_shape=(32,32,3)))
rna.add(layers.Dense(1024, activation='relu',
kernel_regularizer=tf.keras.regularizers.L2(0.003)))
rna.add(layers.Dense(512, activation='relu',
kernel_regularizer=tf.keras.regularizers.L2(0.003)))
rna.add(layers.Dense(256, activation='relu',
kernel_regularizer=tf.keras.regularizers.L2(0.003)))
rna.add(layers.Dense(128, activation='relu'))
rna.add(layers.Dense(10, activation='softmax'))
```

```
rna.summary()
```

```
Model: "sequential_4"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇
━━━━━━━━━━━━━━━━━┩
│ flatten_4 (Flatten)                  │ (None, 3072)                │
0 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_17 (Dense)                     │ (None, 1024)                │
3,146,752 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_18 (Dense)                     │ (None, 512)                 │
524,800 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_19 (Dense)                     │ (None, 256)                 │
131,328 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_20 (Dense)                     │ (None, 128)                 │
32,896 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_21 (Dense)                     │ (None, 10)                  │
1,290 │
└──────────────────────────────────────┴─────────────────────────────┴
─────────────────┘

 Total params: 3,837,066 (14.64 MB)

 Trainable params: 3,837,066 (14.64 MB)

 Non-trainable params: 0 (0.00 B)
```

```
opt = optimizers.SGD(learning_rate=0.001, momentum=0.92,
nesterov=True)
rna.compile(optimizer=opt, loss='categorical_crossentropy',
metrics=['accuracy'])
historia = rna.fit(x_train, y_train_hot, epochs=Nepocas,
batch_size=Nlote, validation_data=(x_test, y_test_hot))
```

```
Epoch 1/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 7s 25ms/step - accuracy: 0.2071 - loss:
```

```
9.8238 - val_accuracy: 0.3525 - val_loss: 9.3488
Epoch 2/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.3712 - loss:
9.2452 - val_accuracy: 0.4031 - val_loss: 8.9681
Epoch 3/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4165 - loss:
8.8895 - val_accuracy: 0.4349 - val_loss: 8.6796
Epoch 4/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4505 - loss:
8.5956 - val_accuracy: 0.4540 - val_loss: 8.4230
Epoch 5/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4721 - loss:
8.3295 - val_accuracy: 0.4627 - val_loss: 8.1905
Epoch 6/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4861 - loss:
8.0891 - val_accuracy: 0.4744 - val_loss: 7.9659
Epoch 7/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5001 - loss:
7.8643 - val_accuracy: 0.4859 - val_loss: 7.7589
Epoch 8/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5241 - loss:
7.6286 - val_accuracy: 0.4972 - val_loss: 7.5576
Epoch 9/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5351 - loss:
7.4217 - val_accuracy: 0.5034 - val_loss: 7.3611
Epoch 10/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.5453 - loss:
7.2166 - val_accuracy: 0.5074 - val_loss: 7.1741
Epoch 11/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.5603 - loss:
7.0122 - val_accuracy: 0.5140 - val_loss: 7.0023
Epoch 12/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.5709 - loss:
6.8190 - val_accuracy: 0.5182 - val_loss: 6.8282
Epoch 13/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5830 - loss:
6.6330 - val_accuracy: 0.5222 - val_loss: 6.6652
Epoch 14/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5925 - loss:
6.4574 - val_accuracy: 0.5204 - val_loss: 6.5180
Epoch 15/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6049 - loss:
6.2704 - val_accuracy: 0.5253 - val_loss: 6.3551
Epoch 16/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6162 - loss:
6.1018 - val_accuracy: 0.5304 - val_loss: 6.2078
Epoch 17/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.6288 - loss:
5.9317 - val_accuracy: 0.5314 - val_loss: 6.0736
```

```
Epoch 18/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 7ms/step - accuracy: 0.6360 - loss:
5.7725 - val_accuracy: 0.5372 - val_loss: 5.9322
Epoch 19/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6487 - loss:
5.6185 - val_accuracy: 0.5369 - val_loss: 5.8083
Epoch 20/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6656 - loss:
5.4473 - val_accuracy: 0.5294 - val_loss: 5.6911
Epoch 21/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6683 - loss:
5.3149 - val_accuracy: 0.5403 - val_loss: 5.5760
Epoch 22/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6831 - loss:
5.1647 - val_accuracy: 0.5375 - val_loss: 5.4542
Epoch 23/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6908 - loss:
5.0240 - val_accuracy: 0.5401 - val_loss: 5.3450
Epoch 24/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7071 - loss:
4.8867 - val_accuracy: 0.5371 - val_loss: 5.2494
Epoch 25/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7155 - loss:
4.7439 - val_accuracy: 0.5401 - val_loss: 5.1434
Epoch 26/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7270 - loss:
4.6140 - val_accuracy: 0.5383 - val_loss: 5.0552
Epoch 27/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7402 - loss:
4.4848 - val_accuracy: 0.5386 - val_loss: 4.9676
Epoch 28/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7469 - loss:
4.3666 - val_accuracy: 0.5405 - val_loss: 4.8974
Epoch 29/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7616 - loss:
4.2412 - val_accuracy: 0.5298 - val_loss: 4.8319
Epoch 30/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7726 - loss:
4.1171 - val_accuracy: 0.5365 - val_loss: 4.7235
Epoch 31/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7801 - loss:
4.0072 - val_accuracy: 0.5363 - val_loss: 4.6679
Epoch 32/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7919 - loss:
3.8894 - val_accuracy: 0.5399 - val_loss: 4.5812
Epoch 33/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8035 - loss:
3.7765 - val_accuracy: 0.5381 - val_loss: 4.5086
Epoch 34/100
```

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196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8175 - loss: 
3.6681 - val_accuracy: 0.5376 - val_loss: 4.4633
Epoch 35/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8246 - loss: 
3.5691 - val_accuracy: 0.5290 - val_loss: 4.4323
Epoch 36/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8324 - loss: 
3.4701 - val_accuracy: 0.5203 - val_loss: 4.3670
Epoch 37/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8397 - loss: 
3.3730 - val_accuracy: 0.5238 - val_loss: 4.3305
Epoch 38/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8508 - loss: 
3.2766 - val_accuracy: 0.5166 - val_loss: 4.3169
Epoch 39/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8654 - loss: 
3.1765 - val_accuracy: 0.5201 - val_loss: 4.2884
Epoch 40/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8701 - loss: 
3.0938 - val_accuracy: 0.5263 - val_loss: 4.1783
Epoch 41/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8804 - loss: 
3.0042 - val_accuracy: 0.5169 - val_loss: 4.2179
Epoch 42/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8871 - loss: 
2.9237 - val_accuracy: 0.5302 - val_loss: 4.0862
Epoch 43/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8949 - loss: 
2.8428 - val_accuracy: 0.5210 - val_loss: 4.0643
Epoch 44/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9020 - loss: 
2.7625 - val_accuracy: 0.5260 - val_loss: 4.0591
Epoch 45/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9041 - loss: 
2.6948 - val_accuracy: 0.5188 - val_loss: 4.0988
Epoch 46/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9100 - loss: 
2.6258 - val_accuracy: 0.5278 - val_loss: 3.9486
Epoch 47/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9150 - loss: 
2.5544 - val_accuracy: 0.5189 - val_loss: 3.9228
Epoch 48/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9234 - loss: 
2.4804 - val_accuracy: 0.5231 - val_loss: 3.9368
Epoch 49/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9268 - loss: 
2.4207 - val_accuracy: 0.5216 - val_loss: 3.8818
Epoch 50/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9328 - loss: 
```

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2.3535 - val_accuracy: 0.4873 - val_loss: 4.2395
Epoch 51/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9217 - loss:
2.3366 - val_accuracy: 0.5007 - val_loss: 4.0484
Epoch 52/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9417 - loss:
2.2329 - val_accuracy: 0.5032 - val_loss: 4.0177
Epoch 53/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9185 - loss:
2.2530 - val_accuracy: 0.5186 - val_loss: 3.8099
Epoch 54/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9504 - loss:
2.1172 - val_accuracy: 0.5199 - val_loss: 3.8044
Epoch 55/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9513 - loss:
2.0709 - val_accuracy: 0.5206 - val_loss: 3.7727
Epoch 56/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9562 - loss:
2.0120 - val_accuracy: 0.5255 - val_loss: 3.7288
Epoch 57/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9474 - loss:
1.9893 - val_accuracy: 0.5249 - val_loss: 3.6641
Epoch 58/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9587 - loss:
1.9232 - val_accuracy: 0.5295 - val_loss: 3.6499
Epoch 59/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9672 - loss:
1.8597 - val_accuracy: 0.5291 - val_loss: 3.5820
Epoch 60/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9695 - loss:
1.8146 - val_accuracy: 0.5256 - val_loss: 3.6099
Epoch 61/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9371 - loss:
1.8677 - val_accuracy: 0.5259 - val_loss: 3.5842
Epoch 62/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9669 - loss:
1.7485 - val_accuracy: 0.5282 - val_loss: 3.5716
Epoch 63/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9411 - loss:
1.7846 - val_accuracy: 0.5275 - val_loss: 3.4700
Epoch 64/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9780 - loss:
1.6473 - val_accuracy: 0.5299 - val_loss: 3.4440
Epoch 65/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9805 - loss:
1.6057 - val_accuracy: 0.5033 - val_loss: 3.7216
Epoch 66/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9467 - loss:
1.6651 - val_accuracy: 0.5299 - val_loss: 3.4198
```
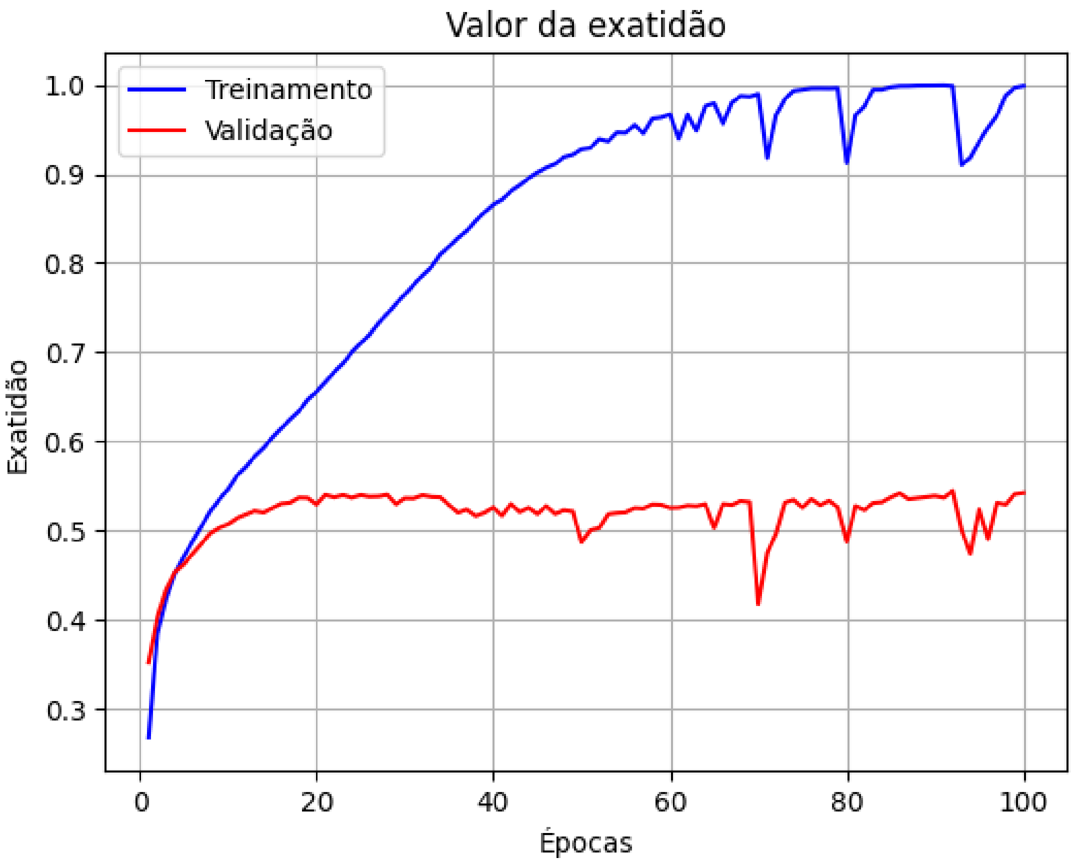

```
Epoch 67/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9771 - loss:
1.5442 - val_accuracy: 0.5289 - val_loss: 3.3733
Epoch 68/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9888 - loss:
1.4840 - val_accuracy: 0.5334 - val_loss: 3.3726
Epoch 69/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9882 - loss:
1.4519 - val_accuracy: 0.5323 - val_loss: 3.3180
Epoch 70/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9897 - loss:
1.4138 - val_accuracy: 0.4180 - val_loss: 5.4471
Epoch 71/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9008 - loss:
1.6536 - val_accuracy: 0.4752 - val_loss: 3.9187
Epoch 72/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9537 - loss:
1.4556 - val_accuracy: 0.4963 - val_loss: 3.5425
Epoch 73/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9764 - loss:
1.3689 - val_accuracy: 0.5315 - val_loss: 3.2360
Epoch 74/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9922 - loss:
1.2984 - val_accuracy: 0.5346 - val_loss: 3.2103
Epoch 75/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9938 - loss:
1.2617 - val_accuracy: 0.5258 - val_loss: 3.2736
Epoch 76/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9954 - loss:
1.2283 - val_accuracy: 0.5355 - val_loss: 3.1418
Epoch 77/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9954 - loss:
1.2025 - val_accuracy: 0.5286 - val_loss: 3.1994
Epoch 78/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9955 - loss:
1.1752 - val_accuracy: 0.5336 - val_loss: 3.0984
Epoch 79/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9969 - loss:
1.1442 - val_accuracy: 0.5264 - val_loss: 3.1541
Epoch 80/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9316 - loss:
1.3286 - val_accuracy: 0.4878 - val_loss: 3.4713
Epoch 81/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9534 - loss:
1.2232 - val_accuracy: 0.5278 - val_loss: 3.1460
Epoch 82/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9638 - loss:
1.1805 - val_accuracy: 0.5232 - val_loss: 3.1092
Epoch 83/100
```

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9927 - loss:
1.0797 - val_accuracy: 0.5311 - val_loss: 3.0584
Epoch 84/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9954 - loss:
1.0437 - val_accuracy: 0.5321 - val_loss: 3.0143
Epoch 85/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9965 - loss:
1.0214 - val_accuracy: 0.5375 - val_loss: 2.9378
Epoch 86/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9989 - loss:
0.9869 - val_accuracy: 0.5422 - val_loss: 2.9118
Epoch 87/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9987 - loss:
0.9648 - val_accuracy: 0.5355 - val_loss: 2.8953
Epoch 88/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9986 - loss:
0.9426 - val_accuracy: 0.5367 - val_loss: 2.8976
Epoch 89/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9993 - loss:
0.9215 - val_accuracy: 0.5379 - val_loss: 2.8848
Epoch 90/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9992 - loss:
0.9024 - val_accuracy: 0.5391 - val_loss: 2.8243
Epoch 91/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9994 - loss:
0.8811 - val_accuracy: 0.5371 - val_loss: 2.8526
Epoch 92/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9988 - loss:
0.8655 - val_accuracy: 0.5449 - val_loss: 2.8222
Epoch 93/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9708 - loss:
0.9679 - val_accuracy: 0.5007 - val_loss: 2.8544
Epoch 94/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9132 - loss:
1.0686 - val_accuracy: 0.4744 - val_loss: 3.4744
Epoch 95/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.9298 - loss:
1.0317 - val_accuracy: 0.5242 - val_loss: 2.8165
Epoch 96/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.9598 - loss:
0.9290 - val_accuracy: 0.4909 - val_loss: 3.1015
Epoch 97/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9512 - loss:
0.9416 - val_accuracy: 0.5314 - val_loss: 2.7735
Epoch 98/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9832 - loss:
0.8462 - val_accuracy: 0.5294 - val_loss: 2.7436
Epoch 99/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.9950 - loss:
0.7955 - val_accuracy: 0.5411 - val_loss: 2.6933
```

```
Epoch 100/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.9986 - loss:
0.7656 - val_accuracy: 0.5426 - val_loss: 2.6794
```

```python
# Salva custo,métrica e épocas em vetores
historia_dict = historia.history
custo = historia_dict['loss']
exatidao = historia_dict['accuracy']
custo_val = historia_dict['val_loss']
exatidao_val = historia_dict['val_accuracy']

# Cria vetor de épocas
epocas = range(1, len(custo) + 1)
# Gráfico do custo
plt.plot(epocas, custo, 'b')
plt.plot(epocas, custo_val, 'r')
plt.title('Valor da função de custo')
plt.xlabel('Épocas')
plt.ylabel('Custo')
plt.legend(['Treinamento', 'Validação'])
plt.grid()
plt.show()

# Gráfico da exatidão
plt.plot(epocas, exatidao, 'b')
plt.plot(epocas, exatidao_val, 'r')
plt.title('Valor da exatidão')
plt.xlabel('Épocas')
plt.ylabel('Exatidão')
plt.legend(['Treinamento', 'Validação'])
plt.grid()
plt.show()
```


Valor da função de custo
Treinamento
Validação
Custo
Épocas
10
8
6
4
2
0
20
40
60
80
100




```
cm_train = rna.evaluate(x_train, y_train_hot)
cm_test = rna.evaluate(x_test, y_test_hot)

1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.9993 - loss:
0.7485
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5448 - loss:
2.6759
```

5. Rede com dropout

```
from tensorflow.keras import models
from tensorflow.keras import layers

rna = models.Sequential()
rna.add(layers.Flatten(input_shape=(32,32,3)))
rna.add(layers.Dense(1024, activation='relu',
kernel_constraint=tf.keras.constraints.MaxNorm(3.0)))
rna.add(layers.Dropout(0.4))
rna.add(layers.Dense(512, activation='relu',
kernel_constraint=tf.keras.constraints.MaxNorm(3.0)))
rna.add(layers.Dropout(0.3))
rna.add(layers.Dense(256, activation='relu',
kernel_constraint=tf.keras.constraints.MaxNorm(3.0)))
```

```
rna.add(layers.Dropout(0.2))
rna.add(layers.Dense(128, activation='relu',
kernel_constraint=tf.keras.constraints.MaxNorm(3.0)))
rna.add(layers.Dropout(0.1))
rna.add(layers.Dense(10, activation='softmax'))

rna.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/reshaping/
flatten.py:37: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)

Model: "sequential_5"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape               ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇
━━━━━━━━━━━━━━━━━┩
│ flatten_5 (Flatten)                  │ (None, 3072)               │
0 │
├──────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dense_22 (Dense)                     │ (None, 1024)               │
3,146,752 │
├──────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dropout (Dropout)                    │ (None, 1024)               │
0 │
├──────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dense_23 (Dense)                     │ (None, 512)                │
524,800 │
├──────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dropout_1 (Dropout)                  │ (None, 512)                │
0 │
├──────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dense_24 (Dense)                     │ (None, 256)                │
131,328 │
├──────────────────────────────────────┼────────────────────────────┼
─────────────────┤
│ dropout_2 (Dropout)                  │ (None, 256)                │
0 │
├──────────────────────────────────────┼────────────────────────────┼
─────────────────┤
```

```
│ dense_25 (Dense)                     │ (None, 128)                  │
32,896 │
├──────────────────────────────────────┼──────────────────────────────┤
─────────────────┤
│ dropout_3 (Dropout)                  │ (None, 128)                  │
0 │
├──────────────────────────────────────┼──────────────────────────────┤
─────────────────┤
│ dense_26 (Dense)                     │ (None, 10)                   │
1,290 │
└──────────────────────────────────────┴──────────────────────────────┴
─────────────────┘

 Total params: 3,837,066 (14.64 MB)

 Trainable params: 3,837,066 (14.64 MB)

 Non-trainable params: 0 (0.00 B)
```

```
opt = optimizers.SGD(learning_rate=0.01, momentum=0.92, nesterov=True)
rna.compile(optimizer=opt, loss='categorical_crossentropy',
metrics=['accuracy'])
historia = rna.fit(x_train, y_train_hot, batch_size=Nlote,
epochs=Nepocas, validation_data=(x_test, y_test_hot))
```

```
Epoch 1/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 9s 21ms/step - accuracy: 0.2461 - loss:
2.0674 - val_accuracy: 0.4288 - val_loss: 1.6326
Epoch 2/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 4s 5ms/step - accuracy: 0.3843 - loss:
1.7168 - val_accuracy: 0.4605 - val_loss: 1.5571
Epoch 3/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4249 - loss:
1.6189 - val_accuracy: 0.4751 - val_loss: 1.4913
Epoch 4/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.4473 - loss:
1.5565 - val_accuracy: 0.4929 - val_loss: 1.4438
Epoch 5/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.4701 - loss:
1.4951 - val_accuracy: 0.4988 - val_loss: 1.4154
Epoch 6/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.4856 - loss:
1.4490 - val_accuracy: 0.5105 - val_loss: 1.3777
Epoch 7/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4947 - loss:
1.4201 - val_accuracy: 0.5171 - val_loss: 1.3628
Epoch 8/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5115 - loss:
1.3779 - val_accuracy: 0.5265 - val_loss: 1.3453
Epoch 9/100
```

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5199 - loss:
1.3525 - val_accuracy: 0.5275 - val_loss: 1.3341
Epoch 10/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5306 - loss:
1.3194 - val_accuracy: 0.5279 - val_loss: 1.3271
Epoch 11/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5392 - loss:
1.2879 - val_accuracy: 0.5361 - val_loss: 1.3158
Epoch 12/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5448 - loss:
1.2731 - val_accuracy: 0.5397 - val_loss: 1.3015
Epoch 13/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5567 - loss:
1.2476 - val_accuracy: 0.5391 - val_loss: 1.2938
Epoch 14/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5628 - loss:
1.2294 - val_accuracy: 0.5443 - val_loss: 1.2912
Epoch 15/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5732 - loss:
1.2028 - val_accuracy: 0.5446 - val_loss: 1.2925
Epoch 16/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5795 - loss:
1.1790 - val_accuracy: 0.5518 - val_loss: 1.2688
Epoch 17/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5815 - loss:
1.1699 - val_accuracy: 0.5530 - val_loss: 1.2659
Epoch 18/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5975 - loss:
1.1370 - val_accuracy: 0.5540 - val_loss: 1.2598
Epoch 19/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5980 - loss:
1.1244 - val_accuracy: 0.5505 - val_loss: 1.2755
Epoch 20/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6058 - loss:
1.1104 - val_accuracy: 0.5591 - val_loss: 1.2523
Epoch 21/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6091 - loss:
1.0866 - val_accuracy: 0.5502 - val_loss: 1.2641
Epoch 22/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6155 - loss:
1.0733 - val_accuracy: 0.5565 - val_loss: 1.2616
Epoch 23/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6262 - loss:
1.0479 - val_accuracy: 0.5586 - val_loss: 1.2625
Epoch 24/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.6263 - loss:
1.0460 - val_accuracy: 0.5667 - val_loss: 1.2419
Epoch 25/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6401 - loss:
```

```
1.0142 - val_accuracy: 0.5706 - val_loss: 1.2386
Epoch 26/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6401 - loss:
1.0057 - val_accuracy: 0.5635 - val_loss: 1.2424
Epoch 27/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6475 - loss:
0.9823 - val_accuracy: 0.5678 - val_loss: 1.2401
Epoch 28/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6503 - loss:
0.9751 - val_accuracy: 0.5697 - val_loss: 1.2474
Epoch 29/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6594 - loss:
0.9623 - val_accuracy: 0.5732 - val_loss: 1.2339
Epoch 30/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6603 - loss:
0.9483 - val_accuracy: 0.5692 - val_loss: 1.2577
Epoch 31/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6666 - loss:
0.9276 - val_accuracy: 0.5702 - val_loss: 1.2570
Epoch 32/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6692 - loss:
0.9263 - val_accuracy: 0.5675 - val_loss: 1.2665
Epoch 33/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6764 - loss:
0.9009 - val_accuracy: 0.5699 - val_loss: 1.2640
Epoch 34/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6819 - loss:
0.8887 - val_accuracy: 0.5739 - val_loss: 1.2522
Epoch 35/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6855 - loss:
0.8770 - val_accuracy: 0.5719 - val_loss: 1.2653
Epoch 36/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6877 - loss:
0.8742 - val_accuracy: 0.5743 - val_loss: 1.2637
Epoch 37/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6940 - loss:
0.8517 - val_accuracy: 0.5706 - val_loss: 1.2687
Epoch 38/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.6967 - loss:
0.8467 - val_accuracy: 0.5699 - val_loss: 1.2586
Epoch 39/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7039 - loss:
0.8355 - val_accuracy: 0.5706 - val_loss: 1.2822
Epoch 40/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.7079 - loss:
0.8177 - val_accuracy: 0.5712 - val_loss: 1.2725
Epoch 41/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.7094 - loss:
0.8113 - val_accuracy: 0.5717 - val_loss: 1.2825
```

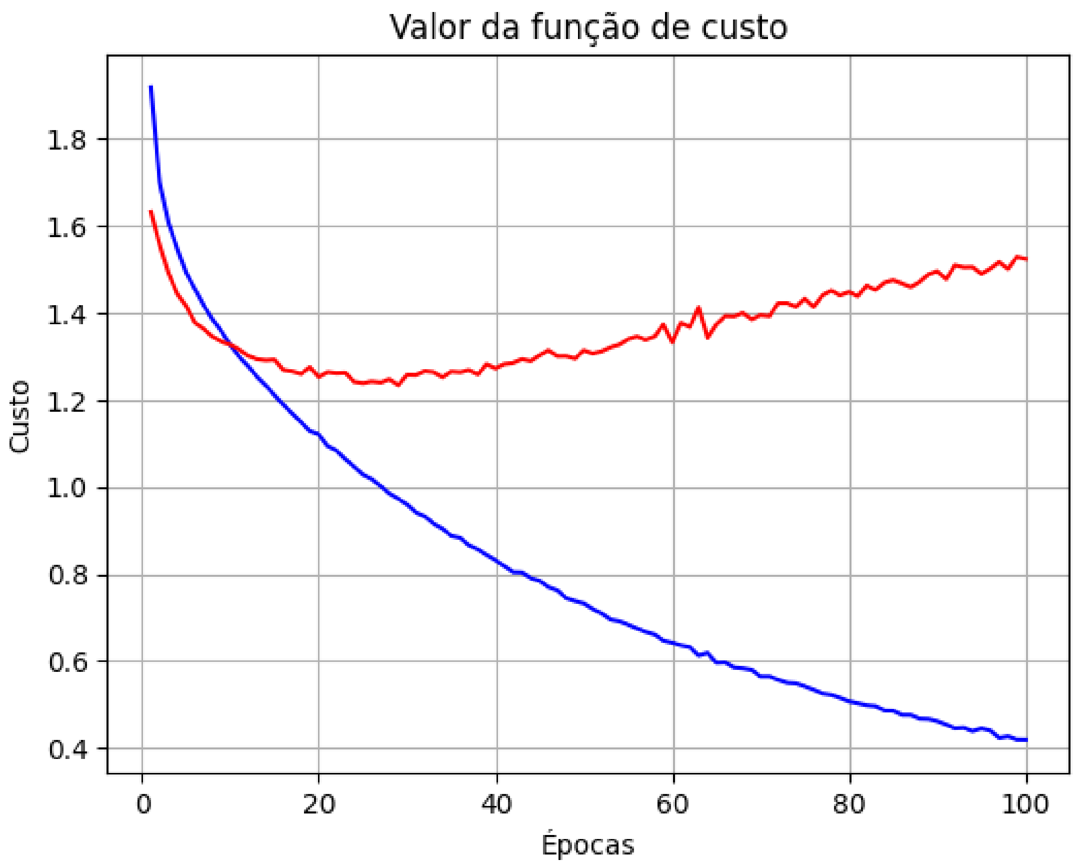
```
Epoch 42/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7191 - loss:
0.7926 - val_accuracy: 0.5722 - val_loss: 1.2849
Epoch 43/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7116 - loss:
0.8016 - val_accuracy: 0.5724 - val_loss: 1.2939
Epoch 44/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7196 - loss:
0.7860 - val_accuracy: 0.5716 - val_loss: 1.2893
Epoch 45/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7221 - loss:
0.7787 - val_accuracy: 0.5715 - val_loss: 1.3028
Epoch 46/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7295 - loss:
0.7566 - val_accuracy: 0.5719 - val_loss: 1.3141
Epoch 47/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7342 - loss:
0.7515 - val_accuracy: 0.5746 - val_loss: 1.3007
Epoch 48/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7397 - loss:
0.7351 - val_accuracy: 0.5739 - val_loss: 1.3009
Epoch 49/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7418 - loss:
0.7249 - val_accuracy: 0.5786 - val_loss: 1.2950
Epoch 50/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7398 - loss:
0.7284 - val_accuracy: 0.5735 - val_loss: 1.3139
Epoch 51/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7439 - loss:
0.7169 - val_accuracy: 0.5788 - val_loss: 1.3065
Epoch 52/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7523 - loss:
0.6974 - val_accuracy: 0.5778 - val_loss: 1.3115
Epoch 53/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.7559 - loss:
0.6854 - val_accuracy: 0.5793 - val_loss: 1.3210
Epoch 54/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7613 - loss:
0.6711 - val_accuracy: 0.5772 - val_loss: 1.3271
Epoch 55/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7622 - loss:
0.6749 - val_accuracy: 0.5713 - val_loss: 1.3395
Epoch 56/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.7667 - loss:
0.6551 - val_accuracy: 0.5800 - val_loss: 1.3458
Epoch 57/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7649 - loss:
0.6547 - val_accuracy: 0.5797 - val_loss: 1.3381
Epoch 58/100
```

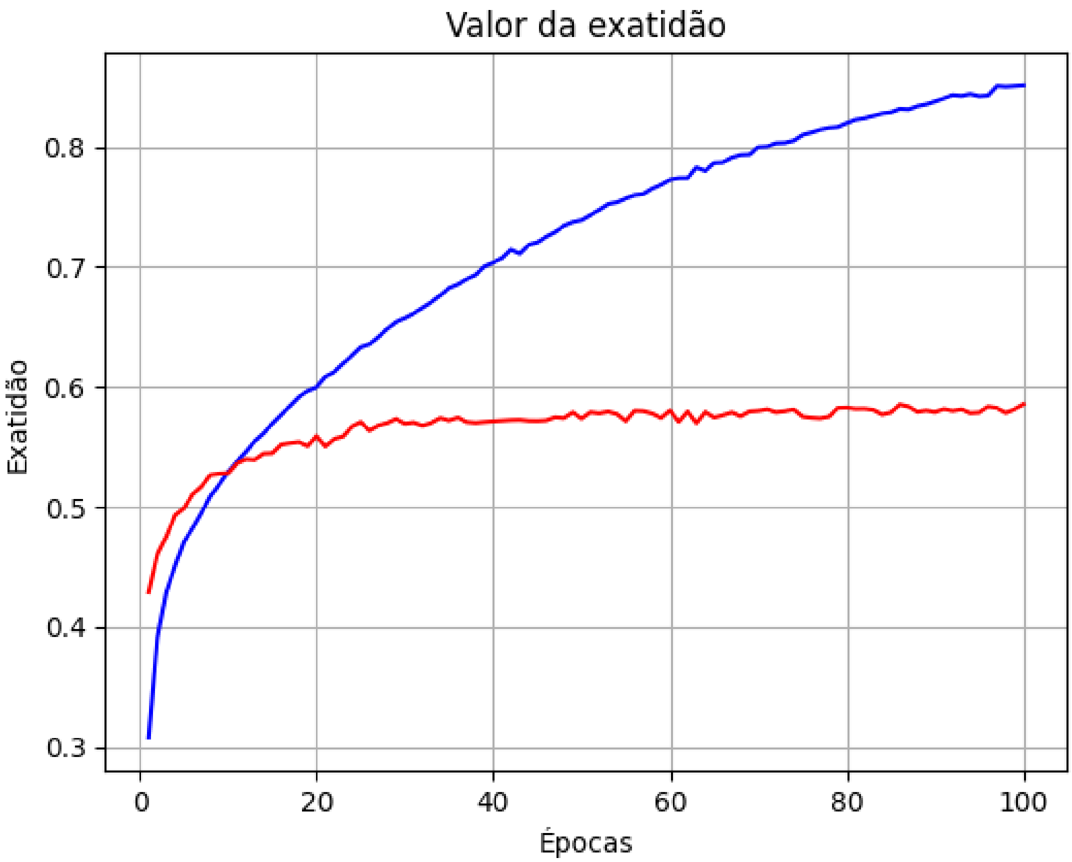
```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7676 - loss:
0.6566 - val_accuracy: 0.5776 - val_loss: 1.3458
Epoch 59/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7724 - loss:
0.6355 - val_accuracy: 0.5740 - val_loss: 1.3737
Epoch 60/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.7749 - loss:
0.6370 - val_accuracy: 0.5802 - val_loss: 1.3324
Epoch 61/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.7764 - loss:
0.6319 - val_accuracy: 0.5708 - val_loss: 1.3772
Epoch 62/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7750 - loss:
0.6269 - val_accuracy: 0.5794 - val_loss: 1.3675
Epoch 63/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7849 - loss:
0.6074 - val_accuracy: 0.5698 - val_loss: 1.4130
Epoch 64/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7811 - loss:
0.6192 - val_accuracy: 0.5790 - val_loss: 1.3423
Epoch 65/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7900 - loss:
0.5888 - val_accuracy: 0.5744 - val_loss: 1.3737
Epoch 66/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.7908 - loss:
0.5907 - val_accuracy: 0.5763 - val_loss: 1.3930
Epoch 67/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7935 - loss:
0.5785 - val_accuracy: 0.5786 - val_loss: 1.3923
Epoch 68/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7968 - loss:
0.5726 - val_accuracy: 0.5754 - val_loss: 1.4000
Epoch 69/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7980 - loss:
0.5688 - val_accuracy: 0.5794 - val_loss: 1.3853
Epoch 70/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8012 - loss:
0.5559 - val_accuracy: 0.5799 - val_loss: 1.3952
Epoch 71/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 4ms/step - accuracy: 0.8033 - loss:
0.5535 - val_accuracy: 0.5813 - val_loss: 1.3928
Epoch 72/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8073 - loss:
0.5462 - val_accuracy: 0.5787 - val_loss: 1.4224
Epoch 73/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8070 - loss:
0.5389 - val_accuracy: 0.5796 - val_loss: 1.4226
Epoch 74/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8062 - loss:
```

```
0.5433 - val_accuracy: 0.5811 - val_loss: 1.4143
Epoch 75/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8128 - loss:
0.5387 - val_accuracy: 0.5751 - val_loss: 1.4330
Epoch 76/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8165 - loss:
0.5227 - val_accuracy: 0.5742 - val_loss: 1.4141
Epoch 77/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.8159 - loss:
0.5216 - val_accuracy: 0.5737 - val_loss: 1.4402
Epoch 78/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8176 - loss:
0.5203 - val_accuracy: 0.5751 - val_loss: 1.4515
Epoch 79/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8194 - loss:
0.5129 - val_accuracy: 0.5823 - val_loss: 1.4404
Epoch 80/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8213 - loss:
0.4998 - val_accuracy: 0.5826 - val_loss: 1.4483
Epoch 81/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8253 - loss:
0.4965 - val_accuracy: 0.5816 - val_loss: 1.4384
Epoch 82/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8242 - loss:
0.4920 - val_accuracy: 0.5817 - val_loss: 1.4629
Epoch 83/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8276 - loss:
0.4907 - val_accuracy: 0.5808 - val_loss: 1.4530
Epoch 84/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8325 - loss:
0.4754 - val_accuracy: 0.5768 - val_loss: 1.4696
Epoch 85/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8314 - loss:
0.4773 - val_accuracy: 0.5785 - val_loss: 1.4753
Epoch 86/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8332 - loss:
0.4696 - val_accuracy: 0.5853 - val_loss: 1.4677
Epoch 87/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8342 - loss:
0.4685 - val_accuracy: 0.5835 - val_loss: 1.4599
Epoch 88/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8355 - loss:
0.4615 - val_accuracy: 0.5790 - val_loss: 1.4712
Epoch 89/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8354 - loss:
0.4653 - val_accuracy: 0.5802 - val_loss: 1.4886
Epoch 90/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8397 - loss:
0.4579 - val_accuracy: 0.5788 - val_loss: 1.4958
```

```
Epoch 91/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8417 - loss:
0.4483 - val_accuracy: 0.5815 - val_loss: 1.4777
Epoch 92/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8458 - loss:
0.4395 - val_accuracy: 0.5799 - val_loss: 1.5096
Epoch 93/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8483 - loss:
0.4351 - val_accuracy: 0.5812 - val_loss: 1.5049
Epoch 94/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8460 - loss:
0.4325 - val_accuracy: 0.5780 - val_loss: 1.5055
Epoch 95/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8456 - loss:
0.4370 - val_accuracy: 0.5785 - val_loss: 1.4895
Epoch 96/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8439 - loss:
0.4389 - val_accuracy: 0.5835 - val_loss: 1.5018
Epoch 97/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8528 - loss:
0.4187 - val_accuracy: 0.5823 - val_loss: 1.5173
Epoch 98/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8513 - loss:
0.4210 - val_accuracy: 0.5782 - val_loss: 1.5013
Epoch 99/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8529 - loss:
0.4126 - val_accuracy: 0.5812 - val_loss: 1.5291
Epoch 100/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8523 - loss:
0.4139 - val_accuracy: 0.5855 - val_loss: 1.5242

# Salva custo,métrica e épocas em vetores
historia_dict = historia.history
custo = historia_dict['loss']
exatidao = historia_dict['accuracy']
custo_val = historia_dict['val_loss']
exatidao_val = historia_dict['val_accuracy']

# Cria vetor de épocas
epocas = range(1, len(custo) + 1)

# Gráfico do custo
plt.plot(epocas, custo, 'b')
plt.plot(epocas, custo_val, 'r')
plt.title('Valor da função de custo')
plt.xlabel('Épocas')
plt.ylabel('Custo')
plt.grid()
plt.show()
```

```
# Gráfico da exatidão
plt.plot(epocas, exatidao, 'b')
plt.plot(epocas, exatidao_val, 'r')
plt.title('Valor da exatidão')
plt.xlabel('Épocas')
plt.ylabel('Exatidão')
plt.grid()
plt.show()
```






```
cm_train = rna.evaluate(x_train, y_train_hot)
cm_test = rna.evaluate(x_test, y_test_hot)

1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.9658 - loss:
0.1385
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5855 - loss:
1.5166
```

6. Rede com normalização de batelada

```
from tensorflow.keras import models
from tensorflow.keras import layers

rna = models.Sequential()
rna.add(layers.Flatten(input_shape=(32,32,3)))
rna.add(layers.Dense(1024,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.4))
rna.add(layers.Dense(512,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
```

```
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.3))
rna.add(layers.Dense(256,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.2))
rna.add(layers.Dense(128,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.1))
rna.add(layers.Dense(10, activation='softmax'))

rna.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/reshaping/
flatten.py:37: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

```
Model: "sequential_6"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                        ┃ Output Shape                ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┩
━━━━━━━━━━━━━━━━━┩
│ flatten_6 (Flatten)                 │ (None, 3072)                │
0 │
├─────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ dense_27 (Dense)                    │ (None, 1024)                │
3,145,728 │
├─────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ batch_normalization                 │ (None, 1024)                │
4,096 │
│ (BatchNormalization)                │                             │
│
├─────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ activation (Activation)             │ (None, 1024)                │
0 │
├─────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ dropout_4 (Dropout)                 │ (None, 1024)                │
0 │
```

```
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_28 (Dense)                     │ (None, 512)                 │
524,288 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ batch_normalization_1                │ (None, 512)                 │
2,048 │
│ (BatchNormalization)                 │                             │
│
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ activation_1 (Activation)            │ (None, 512)                 │
0 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dropout_5 (Dropout)                  │ (None, 512)                 │
0 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_29 (Dense)                     │ (None, 256)                 │
131,072 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ batch_normalization_2                │ (None, 256)                 │
1,024 │
│ (BatchNormalization)                 │                             │
│
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ activation_2 (Activation)            │ (None, 256)                 │
0 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dropout_6 (Dropout)                  │ (None, 256)                 │
0 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ dense_30 (Dense)                     │ (None, 128)                 │
32,768 │
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ batch_normalization_3                │ (None, 128)                 │
512 │
│ (BatchNormalization)                 │                             │
│
├──────────────────────────────────────┼─────────────────────────────┼
─────────────────┤
│ activation_3 (Activation)            │ (None, 128)                 │
```

```
0 │
├──────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dropout_7 (Dropout)                  │ (None, 128)                  │
0 │
├──────────────────────────────────────┼──────────────────────────────┼
─────────────────┤
│ dense_31 (Dense)                     │ (None, 10)                   │
1,290 │
└──────────────────────────────────────┴──────────────────────────────┴
─────────────────┘

 Total params: 3,842,826 (14.66 MB)

 Trainable params: 3,838,986 (14.64 MB)

 Non-trainable params: 3,840 (15.00 KB)
```

```
opt = optimizers.SGD(learning_rate=0.01, momentum=0.92, nesterov=True)
rna.compile(optimizer=opt, loss='categorical_crossentropy',
metrics=['accuracy'])
historia = rna.fit(x_train, y_train_hot, batch_size=Nlote,
epochs=Nepocas, validation_data=(x_test, y_test_hot))
```

```
Epoch 1/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 10s 30ms/step - accuracy: 0.2572 - loss:
2.1043 - val_accuracy: 0.4207 - val_loss: 1.6203
Epoch 2/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 3s 5ms/step - accuracy: 0.3953 - loss:
1.6848 - val_accuracy: 0.4659 - val_loss: 1.4969
Epoch 3/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4369 - loss:
1.5749 - val_accuracy: 0.4821 - val_loss: 1.4382
Epoch 4/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4572 - loss:
1.5134 - val_accuracy: 0.4975 - val_loss: 1.4070
Epoch 5/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4748 - loss:
1.4681 - val_accuracy: 0.5114 - val_loss: 1.3725
Epoch 6/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.4837 - loss:
1.4344 - val_accuracy: 0.5193 - val_loss: 1.3416
Epoch 7/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5000 - loss:
1.3945 - val_accuracy: 0.5261 - val_loss: 1.3384
Epoch 8/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 6ms/step - accuracy: 0.5150 - loss:
1.3618 - val_accuracy: 0.5316 - val_loss: 1.3116
Epoch 9/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5224 - loss:
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1.3382 - val_accuracy: 0.5340 - val_loss: 1.3094
Epoch 10/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5318 - loss:
1.3137 - val_accuracy: 0.5423 - val_loss: 1.2797
Epoch 11/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5341 - loss:
1.3005 - val_accuracy: 0.5445 - val_loss: 1.2780
Epoch 12/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5442 - loss:
1.2777 - val_accuracy: 0.5428 - val_loss: 1.2790
Epoch 13/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5508 - loss:
1.2561 - val_accuracy: 0.5520 - val_loss: 1.2600
Epoch 14/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5602 - loss:
1.2309 - val_accuracy: 0.5522 - val_loss: 1.2572
Epoch 15/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5645 - loss:
1.2122 - val_accuracy: 0.5568 - val_loss: 1.2501
Epoch 16/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5733 - loss:
1.1945 - val_accuracy: 0.5613 - val_loss: 1.2412
Epoch 17/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5764 - loss:
1.1853 - val_accuracy: 0.5589 - val_loss: 1.2474
Epoch 18/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5801 - loss:
1.1706 - val_accuracy: 0.5618 - val_loss: 1.2357
Epoch 19/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5903 - loss:
1.1523 - val_accuracy: 0.5684 - val_loss: 1.2308
Epoch 20/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.5966 - loss:
1.1314 - val_accuracy: 0.5630 - val_loss: 1.2314
Epoch 21/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.5978 - loss:
1.1268 - val_accuracy: 0.5633 - val_loss: 1.2235
Epoch 22/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6015 - loss:
1.1139 - val_accuracy: 0.5650 - val_loss: 1.2328
Epoch 23/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6065 - loss:
1.0928 - val_accuracy: 0.5649 - val_loss: 1.2244
Epoch 24/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6123 - loss:
1.0844 - val_accuracy: 0.5730 - val_loss: 1.2170
Epoch 25/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6191 - loss:
1.0679 - val_accuracy: 0.5683 - val_loss: 1.2284
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Epoch 26/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6117 - loss:
1.0742 - val_accuracy: 0.5717 - val_loss: 1.2180
Epoch 27/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6277 - loss:
1.0386 - val_accuracy: 0.5721 - val_loss: 1.2177
Epoch 28/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6337 - loss:
1.0229 - val_accuracy: 0.5735 - val_loss: 1.2232
Epoch 29/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6336 - loss:
1.0190 - val_accuracy: 0.5751 - val_loss: 1.2218
Epoch 30/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.6339 - loss:
1.0214 - val_accuracy: 0.5774 - val_loss: 1.2160
Epoch 31/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.6448 - loss:
0.9915 - val_accuracy: 0.5773 - val_loss: 1.2110
Epoch 32/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6470 - loss:
0.9865 - val_accuracy: 0.5791 - val_loss: 1.2120
Epoch 33/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6501 - loss:
0.9755 - val_accuracy: 0.5815 - val_loss: 1.2110
Epoch 34/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6525 - loss:
0.9668 - val_accuracy: 0.5818 - val_loss: 1.2169
Epoch 35/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6587 - loss:
0.9576 - val_accuracy: 0.5772 - val_loss: 1.2268
Epoch 36/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6614 - loss:
0.9411 - val_accuracy: 0.5782 - val_loss: 1.2281
Epoch 37/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6667 - loss:
0.9281 - val_accuracy: 0.5751 - val_loss: 1.2306
Epoch 38/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6696 - loss:
0.9259 - val_accuracy: 0.5828 - val_loss: 1.2245
Epoch 39/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.6768 - loss:
0.9098 - val_accuracy: 0.5797 - val_loss: 1.2347
Epoch 40/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 7ms/step - accuracy: 0.6792 - loss:
0.9067 - val_accuracy: 0.5848 - val_loss: 1.2181
Epoch 41/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 2s 5ms/step - accuracy: 0.6844 - loss:
0.8833 - val_accuracy: 0.5875 - val_loss: 1.2196
Epoch 42/100
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196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6879 - loss:
0.8780 - val_accuracy: 0.5875 - val_loss: 1.2228
Epoch 43/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6873 - loss:
0.8637 - val_accuracy: 0.5889 - val_loss: 1.2257
Epoch 44/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6965 - loss:
0.8531 - val_accuracy: 0.5874 - val_loss: 1.2274
Epoch 45/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6993 - loss:
0.8440 - val_accuracy: 0.5902 - val_loss: 1.2381
Epoch 46/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.6968 - loss:
0.8440 - val_accuracy: 0.5872 - val_loss: 1.2400
Epoch 47/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7077 - loss:
0.8212 - val_accuracy: 0.5913 - val_loss: 1.2365
Epoch 48/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7091 - loss:
0.8160 - val_accuracy: 0.5892 - val_loss: 1.2465
Epoch 49/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7084 - loss:
0.8148 - val_accuracy: 0.5911 - val_loss: 1.2429
Epoch 50/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7125 - loss:
0.8003 - val_accuracy: 0.5896 - val_loss: 1.2549
Epoch 51/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7163 - loss:
0.7946 - val_accuracy: 0.5888 - val_loss: 1.2424
Epoch 52/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7210 - loss:
0.7819 - val_accuracy: 0.5899 - val_loss: 1.2607
Epoch 53/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7244 - loss:
0.7746 - val_accuracy: 0.5906 - val_loss: 1.2676
Epoch 54/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7272 - loss:
0.7707 - val_accuracy: 0.5880 - val_loss: 1.2700
Epoch 55/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7288 - loss:
0.7567 - val_accuracy: 0.5937 - val_loss: 1.2553
Epoch 56/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7376 - loss:
0.7422 - val_accuracy: 0.5970 - val_loss: 1.2463
Epoch 57/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7323 - loss:
0.7432 - val_accuracy: 0.5862 - val_loss: 1.2776
Epoch 58/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7385 - loss:
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0.7330 - val_accuracy: 0.5919 - val_loss: 1.2689
Epoch 59/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7394 - loss:
0.7231 - val_accuracy: 0.5910 - val_loss: 1.2796
Epoch 60/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7403 - loss:
0.7334 - val_accuracy: 0.5914 - val_loss: 1.2862
Epoch 61/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7474 - loss:
0.7064 - val_accuracy: 0.5950 - val_loss: 1.2814
Epoch 62/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7517 - loss:
0.6985 - val_accuracy: 0.5965 - val_loss: 1.2730
Epoch 63/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7571 - loss:
0.6859 - val_accuracy: 0.5901 - val_loss: 1.2989
Epoch 64/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7531 - loss:
0.6938 - val_accuracy: 0.5938 - val_loss: 1.2979
Epoch 65/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7579 - loss:
0.6810 - val_accuracy: 0.5915 - val_loss: 1.3144
Epoch 66/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7644 - loss:
0.6659 - val_accuracy: 0.5944 - val_loss: 1.3021
Epoch 67/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7687 - loss:
0.6506 - val_accuracy: 0.5920 - val_loss: 1.3062
Epoch 68/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7651 - loss:
0.6566 - val_accuracy: 0.5906 - val_loss: 1.2968
Epoch 69/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7679 - loss:
0.6498 - val_accuracy: 0.5901 - val_loss: 1.3151
Epoch 70/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7729 - loss:
0.6406 - val_accuracy: 0.5931 - val_loss: 1.3318
Epoch 71/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7730 - loss:
0.6348 - val_accuracy: 0.5939 - val_loss: 1.3229
Epoch 72/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7803 - loss:
0.6203 - val_accuracy: 0.5906 - val_loss: 1.3327
Epoch 73/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7805 - loss:
0.6238 - val_accuracy: 0.5947 - val_loss: 1.3276
Epoch 74/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7773 - loss:
0.6133 - val_accuracy: 0.5863 - val_loss: 1.3419
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Epoch 75/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7831 - loss:
0.6078 - val_accuracy: 0.5904 - val_loss: 1.3535
Epoch 76/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7874 - loss:
0.5998 - val_accuracy: 0.5926 - val_loss: 1.3465
Epoch 77/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7879 - loss:
0.5964 - val_accuracy: 0.5956 - val_loss: 1.3428
Epoch 78/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7954 - loss:
0.5774 - val_accuracy: 0.5941 - val_loss: 1.3668
Epoch 79/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7965 - loss:
0.5708 - val_accuracy: 0.5971 - val_loss: 1.3566
Epoch 80/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.7983 - loss:
0.5671 - val_accuracy: 0.5992 - val_loss: 1.3714
Epoch 81/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.7996 - loss:
0.5635 - val_accuracy: 0.5960 - val_loss: 1.3530
Epoch 82/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.8026 - loss:
0.5589 - val_accuracy: 0.5929 - val_loss: 1.3714
Epoch 83/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8030 - loss:
0.5586 - val_accuracy: 0.5906 - val_loss: 1.3860
Epoch 84/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8069 - loss:
0.5409 - val_accuracy: 0.5928 - val_loss: 1.3840
Epoch 85/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8128 - loss:
0.5242 - val_accuracy: 0.5924 - val_loss: 1.3831
Epoch 86/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8085 - loss:
0.5387 - val_accuracy: 0.5906 - val_loss: 1.3916
Epoch 87/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8070 - loss:
0.5356 - val_accuracy: 0.5893 - val_loss: 1.4026
Epoch 88/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8144 - loss:
0.5241 - val_accuracy: 0.5932 - val_loss: 1.4000
Epoch 89/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8146 - loss:
0.5222 - val_accuracy: 0.5930 - val_loss: 1.4272
Epoch 90/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8112 - loss:
0.5236 - val_accuracy: 0.5891 - val_loss: 1.4230
Epoch 91/100
```
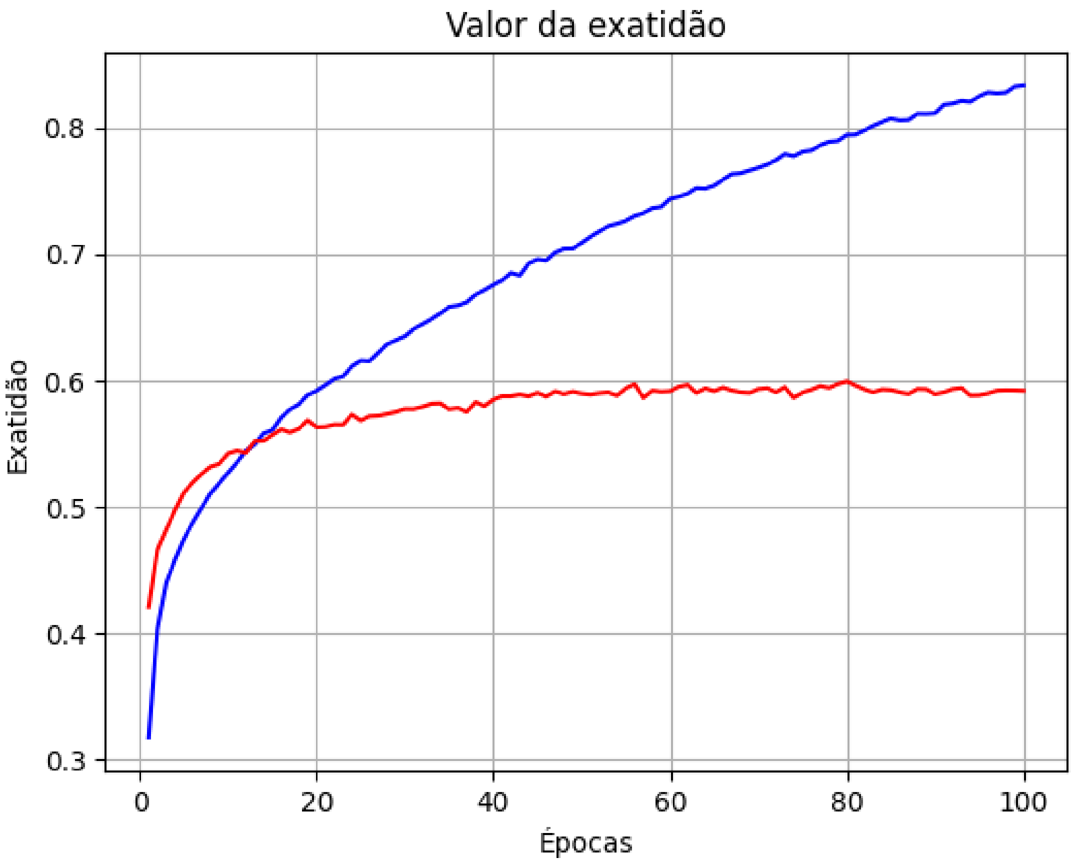

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8149 - loss: 0.5195 - val_accuracy: 0.5906 - val_loss: 1.4360
Epoch 92/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8248 - loss: 0.4987 - val_accuracy: 0.5931 - val_loss: 1.4154
Epoch 93/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 6ms/step - accuracy: 0.8219 - loss: 0.5016 - val_accuracy: 0.5940 - val_loss: 1.4375
Epoch 94/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8256 - loss: 0.4863 - val_accuracy: 0.5881 - val_loss: 1.4241
Epoch 95/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8287 - loss: 0.4866 - val_accuracy: 0.5883 - val_loss: 1.4413
Epoch 96/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8287 - loss: 0.4788 - val_accuracy: 0.5897 - val_loss: 1.4486
Epoch 97/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8326 - loss: 0.4704 - val_accuracy: 0.5919 - val_loss: 1.4402
Epoch 98/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8330 - loss: 0.4772 - val_accuracy: 0.5922 - val_loss: 1.4392
Epoch 99/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8365 - loss: 0.4654 - val_accuracy: 0.5921 - val_loss: 1.4491
Epoch 100/100
196/196 ━━━━━━━━━━━━━━━━━━━━ 1s 5ms/step - accuracy: 0.8383 - loss: 0.4602 - val_accuracy: 0.5918 - val_loss: 1.4490
```

```python
# Salva custo,métrica e épocas em vetores
historia_dict = historia.history
custo = historia_dict['loss']
exatidao = historia_dict['accuracy']
custo_val = historia_dict['val_loss']
exatidao_val = historia_dict['val_accuracy']

# Cria vetor de épocas
epocas = range(1, len(custo) + 1)

# Gráfico do custo
plt.plot(epocas, custo, 'b')
plt.plot(epocas, custo_val, 'r')
plt.title('Valor da função de custo')
plt.xlabel('Épocas')
plt.ylabel('Custo')
plt.grid()
plt.show()

# Gráfico da exatidão
```

```
plt.plot(epocas, exatidao, 'b')
plt.plot(epocas, exatidao_val, 'r')
plt.title('Valor da exatidão')
plt.xlabel('Épocas')
plt.ylabel('Exatidão')
plt.grid()
plt.show()
```




```
cm_train = rna.evaluate(x_train, y_train_hot)
cm_test = rna.evaluate(x_test, y_test_hot)

1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.9539 - loss:
0.1593
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 2ms/step - accuracy: 0.5908 - loss:
1.4266
```

7. Treinamento com data augmentation

```
# Cria gerador de dados
datagen =
tf.keras.preprocessing.image.ImageDataGenerator(width_shift_range=0.1,
height_shift_range=0.1, horizontal_flip=True, zoom_range=0.2,
rotation_range=3.0)

# Instancia gerador de lotes
batches = datagen.flow(x_train, y_train_hot, batch_size=Nlote)

from tensorflow.keras import models
from tensorflow.keras import layers

rna = models.Sequential()
```

```
rna = models.Sequential()
rna.add(layers.Flatten(input_shape=(32,32,3)))
rna.add(layers.Dense(1024,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.4))
rna.add(layers.Dense(512,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.3))
rna.add(layers.Dense(256,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.2))
rna.add(layers.Dense(128,
kernel_constraint=tf.keras.constraints.MaxNorm(3.0), use_bias=False))
rna.add(layers.BatchNormalization())
rna.add(layers.Activation('relu'))
rna.add(layers.Dropout(0.1))
rna.add(layers.Dense(10, activation='softmax'))

rna.summary()
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/reshaping/
flatten.py:37: UserWarning: Do not pass an `input_shape`/`input_dim`
argument to a layer. When using Sequential models, prefer using an
`Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

```
Model: "sequential_10"

┏━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┳━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┓
━━━━━━━━━━━━━━━━━┓
┃ Layer (type)                         ┃ Output Shape                ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━━━━━━┩
━━━━━━━━━━━━━━━━━┩
│ flatten_8 (Flatten)                  │ (None, 3072)                │
0 │
├──────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ dense_37 (Dense)                     │ (None, 1024)                │
3,145,728 │
├──────────────────────────────────────┼─────────────────────────────┤
─────────────────┤
│ batch_normalization_8                │ (None, 1024)                │
4,096 │
```

```
│ (BatchNormalization)                      │                               │
│
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ activation_8 (Activation)                 │ (None, 1024)                  │
0 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ dropout_12 (Dropout)                      │ (None, 1024)                  │
0 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ dense_38 (Dense)                          │ (None, 512)                   │
524,288 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ batch_normalization_9                     │ (None, 512)                   │
2,048 │
│ (BatchNormalization)                      │                               │
│
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ activation_9 (Activation)                 │ (None, 512)                   │
0 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ dropout_13 (Dropout)                      │ (None, 512)                   │
0 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ dense_39 (Dense)                          │ (None, 256)                   │
131,072 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ batch_normalization_10                    │ (None, 256)                   │
1,024 │
│ (BatchNormalization)                      │                               │
│
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ activation_10 (Activation)                │ (None, 256)                   │
0 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ dropout_14 (Dropout)                      │ (None, 256)                   │
0 │
├───────────────────────────────────────────┼───────────────────────────────┼
─────────────────┤
│ dense_40 (Dense)                          │ (None, 128)                   │
```

```
32,768 │
├─────────────────────────────────────┼─────────────────────────────┼
────────────────┤
│ batch_normalization_11              │ (None, 128)                 │
512 │
│ (BatchNormalization)                │                             │
│
├─────────────────────────────────────┼─────────────────────────────┼
────────────────┤
│ activation_11 (Activation)          │ (None, 128)                 │
0 │
├─────────────────────────────────────┼─────────────────────────────┼
────────────────┤
│ dropout_15 (Dropout)                │ (None, 128)                 │
0 │
├─────────────────────────────────────┼─────────────────────────────┼
────────────────┤
│ dense_41 (Dense)                    │ (None, 10)                  │
1,290 │
└─────────────────────────────────────┴─────────────────────────────┴
────────────────┘

 Total params: 3,842,826 (14.66 MB)

 Trainable params: 3,838,986 (14.64 MB)

 Non-trainable params: 3,840 (15.00 KB)
```

```
from tensorflow.keras import optimizers
opt = optimizers.SGD(learning_rate=0.01, momentum=0.92, nesterov=True)
rna.compile(optimizer=opt, loss='categorical_crossentropy',
metrics=['accuracy'])
historia = rna.fit(batches, epochs=60, validation_data=(x_test,
y_test_hot))
```

```
Epoch 1/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 42s 182ms/step - accuracy: 0.2367 - loss:
2.1670 - val_accuracy: 0.4116 - val_loss: 1.6541
Epoch 2/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 163ms/step - accuracy: 0.3521 - loss:
1.7937 - val_accuracy: 0.4532 - val_loss: 1.5384
Epoch 3/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 166ms/step - accuracy: 0.3866 - loss:
1.7033 - val_accuracy: 0.4638 - val_loss: 1.4915
Epoch 4/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 164ms/step - accuracy: 0.4026 - loss:
1.6622 - val_accuracy: 0.4897 - val_loss: 1.4396
Epoch 5/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 32s 160ms/step - accuracy: 0.4138 - loss:
1.6272 - val_accuracy: 0.4970 - val_loss: 1.4146
```

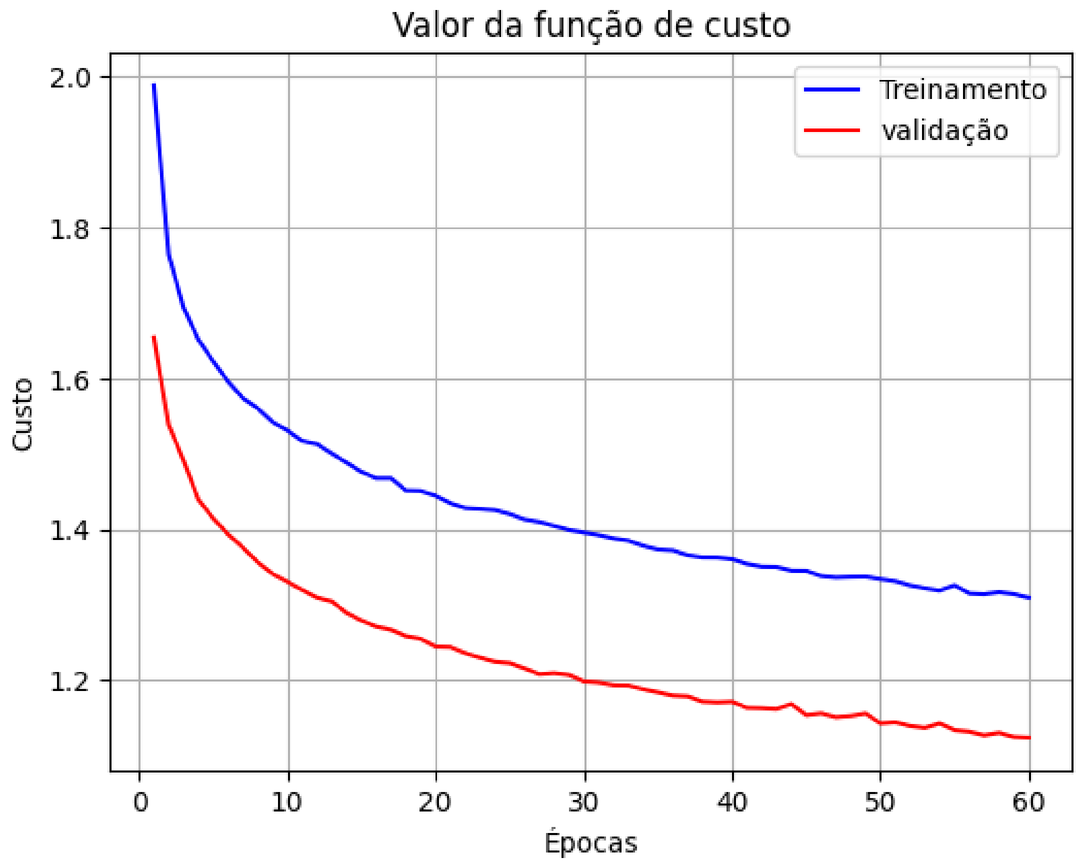
```
Epoch 6/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 43s 169ms/step - accuracy: 0.4236 - loss:
1.5974 - val_accuracy: 0.5001 - val_loss: 1.3937
Epoch 7/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 32s 160ms/step - accuracy: 0.4317 - loss:
1.5731 - val_accuracy: 0.5115 - val_loss: 1.3760
Epoch 8/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 171ms/step - accuracy: 0.4353 - loss:
1.5667 - val_accuracy: 0.5153 - val_loss: 1.3565
Epoch 9/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 40s 164ms/step - accuracy: 0.4453 - loss:
1.5400 - val_accuracy: 0.5217 - val_loss: 1.3412
Epoch 10/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 169ms/step - accuracy: 0.4455 - loss:
1.5440 - val_accuracy: 0.5238 - val_loss: 1.3306
Epoch 11/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 32s 161ms/step - accuracy: 0.4528 - loss:
1.5257 - val_accuracy: 0.5319 - val_loss: 1.3197
Epoch 12/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 43s 168ms/step - accuracy: 0.4586 - loss:
1.5134 - val_accuracy: 0.5334 - val_loss: 1.3096
Epoch 13/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 163ms/step - accuracy: 0.4604 - loss:
1.4998 - val_accuracy: 0.5356 - val_loss: 1.3047
Epoch 14/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 169ms/step - accuracy: 0.4671 - loss:
1.4844 - val_accuracy: 0.5397 - val_loss: 1.2892
Epoch 15/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 40s 164ms/step - accuracy: 0.4674 - loss:
1.4816 - val_accuracy: 0.5421 - val_loss: 1.2792
Epoch 16/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 167ms/step - accuracy: 0.4722 - loss:
1.4638 - val_accuracy: 0.5486 - val_loss: 1.2711
Epoch 17/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 164ms/step - accuracy: 0.4733 - loss:
1.4672 - val_accuracy: 0.5502 - val_loss: 1.2669
Epoch 18/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 35s 175ms/step - accuracy: 0.4799 - loss:
1.4516 - val_accuracy: 0.5518 - val_loss: 1.2586
Epoch 19/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 166ms/step - accuracy: 0.4797 - loss:
1.4534 - val_accuracy: 0.5511 - val_loss: 1.2550
Epoch 20/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 165ms/step - accuracy: 0.4786 - loss:
1.4478 - val_accuracy: 0.5549 - val_loss: 1.2447
Epoch 21/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 32s 157ms/step - accuracy: 0.4825 - loss:
1.4316 - val_accuracy: 0.5530 - val_loss: 1.2441
Epoch 22/60
```

```
196/196 ━━━━━━━━━━━━━━━━━━━━ 42s 164ms/step - accuracy: 0.4870 - loss:
1.4307 - val_accuracy: 0.5553 - val_loss: 1.2359
Epoch 23/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 166ms/step - accuracy: 0.4923 - loss:
1.4279 - val_accuracy: 0.5598 - val_loss: 1.2299
Epoch 24/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 42s 171ms/step - accuracy: 0.4858 - loss:
1.4306 - val_accuracy: 0.5629 - val_loss: 1.2246
Epoch 25/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 39s 164ms/step - accuracy: 0.4900 - loss:
1.4174 - val_accuracy: 0.5649 - val_loss: 1.2228
Epoch 26/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 165ms/step - accuracy: 0.4903 - loss:
1.4133 - val_accuracy: 0.5660 - val_loss: 1.2159
Epoch 27/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 166ms/step - accuracy: 0.5008 - loss:
1.3963 - val_accuracy: 0.5683 - val_loss: 1.2082
Epoch 28/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 168ms/step - accuracy: 0.4945 - loss:
1.4059 - val_accuracy: 0.5664 - val_loss: 1.2096
Epoch 29/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 168ms/step - accuracy: 0.4970 - loss:
1.3989 - val_accuracy: 0.5679 - val_loss: 1.2072
Epoch 30/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 42s 172ms/step - accuracy: 0.5007 - loss:
1.3965 - val_accuracy: 0.5688 - val_loss: 1.1986
Epoch 31/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 39s 164ms/step - accuracy: 0.5008 - loss:
1.3899 - val_accuracy: 0.5717 - val_loss: 1.1972
Epoch 32/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 167ms/step - accuracy: 0.5022 - loss:
1.3832 - val_accuracy: 0.5711 - val_loss: 1.1936
Epoch 33/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 36s 177ms/step - accuracy: 0.5019 - loss:
1.3835 - val_accuracy: 0.5746 - val_loss: 1.1931
Epoch 34/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 39s 167ms/step - accuracy: 0.5070 - loss:
1.3745 - val_accuracy: 0.5715 - val_loss: 1.1882
Epoch 35/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 167ms/step - accuracy: 0.5054 - loss:
1.3756 - val_accuracy: 0.5751 - val_loss: 1.1840
Epoch 36/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 35s 173ms/step - accuracy: 0.5056 - loss:
1.3698 - val_accuracy: 0.5760 - val_loss: 1.1797
Epoch 37/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 39s 166ms/step - accuracy: 0.5127 - loss:
1.3576 - val_accuracy: 0.5785 - val_loss: 1.1787
Epoch 38/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 42s 170ms/step - accuracy: 0.5111 - loss:
```

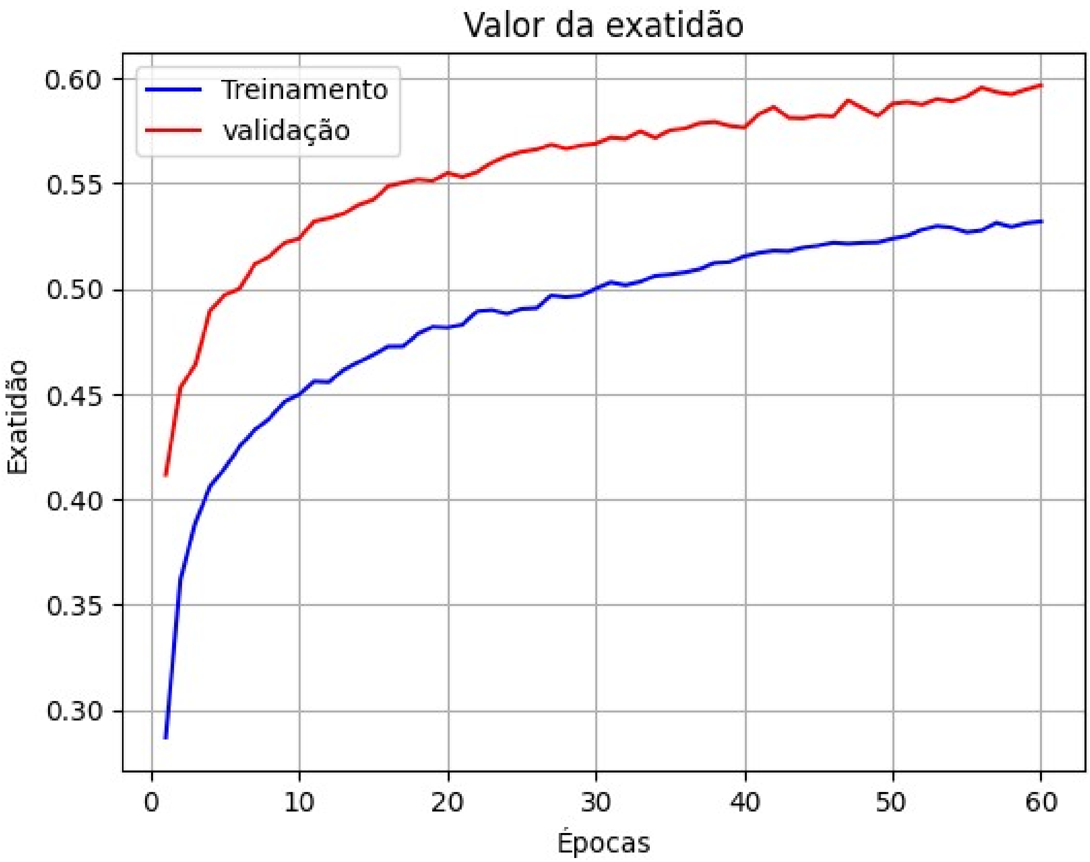
```
1.3657 - val_accuracy: 0.5791 - val_loss: 1.1718
Epoch 39/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 165ms/step - accuracy: 0.5106 - loss:
1.3567 - val_accuracy: 0.5773 - val_loss: 1.1709
Epoch 40/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 32s 161ms/step - accuracy: 0.5178 - loss:
1.3538 - val_accuracy: 0.5764 - val_loss: 1.1716
Epoch 41/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 43s 170ms/step - accuracy: 0.5177 - loss:
1.3506 - val_accuracy: 0.5828 - val_loss: 1.1636
Epoch 42/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 168ms/step - accuracy: 0.5164 - loss:
1.3490 - val_accuracy: 0.5862 - val_loss: 1.1632
Epoch 43/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 168ms/step - accuracy: 0.5186 - loss:
1.3482 - val_accuracy: 0.5810 - val_loss: 1.1619
Epoch 44/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 161ms/step - accuracy: 0.5185 - loss:
1.3431 - val_accuracy: 0.5808 - val_loss: 1.1687
Epoch 45/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 163ms/step - accuracy: 0.5182 - loss:
1.3472 - val_accuracy: 0.5821 - val_loss: 1.1539
Epoch 46/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 42s 165ms/step - accuracy: 0.5225 - loss:
1.3394 - val_accuracy: 0.5817 - val_loss: 1.1562
Epoch 47/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 163ms/step - accuracy: 0.5256 - loss:
1.3303 - val_accuracy: 0.5893 - val_loss: 1.1512
Epoch 48/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 35s 168ms/step - accuracy: 0.5219 - loss:
1.3320 - val_accuracy: 0.5856 - val_loss: 1.1528
Epoch 49/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 36s 174ms/step - accuracy: 0.5226 - loss:
1.3374 - val_accuracy: 0.5820 - val_loss: 1.1561
Epoch 50/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 39s 167ms/step - accuracy: 0.5253 - loss:
1.3329 - val_accuracy: 0.5877 - val_loss: 1.1430
Epoch 51/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 163ms/step - accuracy: 0.5249 - loss:
1.3320 - val_accuracy: 0.5885 - val_loss: 1.1444
Epoch 52/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 32s 160ms/step - accuracy: 0.5264 - loss:
1.3291 - val_accuracy: 0.5873 - val_loss: 1.1396
Epoch 53/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 167ms/step - accuracy: 0.5312 - loss:
1.3247 - val_accuracy: 0.5900 - val_loss: 1.1370
Epoch 54/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 34s 170ms/step - accuracy: 0.5319 - loss:
1.3208 - val_accuracy: 0.5888 - val_loss: 1.1429
```

```
Epoch 55/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 41s 172ms/step - accuracy: 0.5266 - loss: 1.3258 - val_accuracy: 0.5912 - val_loss: 1.1340
Epoch 56/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 161ms/step - accuracy: 0.5266 - loss: 1.3142 - val_accuracy: 0.5954 - val_loss: 1.1320
Epoch 57/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 35s 171ms/step - accuracy: 0.5324 - loss: 1.3126 - val_accuracy: 0.5933 - val_loss: 1.1273
Epoch 58/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 39s 161ms/step - accuracy: 0.5314 - loss: 1.3097 - val_accuracy: 0.5922 - val_loss: 1.1305
Epoch 59/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 35s 172ms/step - accuracy: 0.5332 - loss: 1.3122 - val_accuracy: 0.5945 - val_loss: 1.1250
Epoch 60/60
196/196 ━━━━━━━━━━━━━━━━━━━━ 33s 164ms/step - accuracy: 0.5325 - loss: 1.3042 - val_accuracy: 0.5964 - val_loss: 1.1241
```

```
# Salva custo,métrica e épocas em vetores
historia_dict = historia.history
custo = historia_dict['loss']
exatidao = historia_dict['accuracy']
custo_val = historia_dict['val_loss']
exatidao_val = historia_dict['val_accuracy']

# Cria vetor de épocas
epocas = range(1, len(custo) + 1)

# Gráfico do custo
plt.plot(epocas, custo, 'b', label='Treinamento')
plt.plot(epocas, custo_val, 'r', label='validação')
plt.title('Valor da função de custo')
plt.xlabel('Épocas')
plt.ylabel('Custo')
plt.legend()
plt.grid()
plt.show()

# Gráfico da exatidão
plt.plot(epocas, exatidao, 'b', label='Treinamento')
plt.plot(epocas, exatidao_val, 'r', label='validação')
plt.title('Valor da exatidão')
plt.xlabel('Épocas')
plt.ylabel('Exatidão')
plt.legend()
plt.grid()
plt.show()
```



Valor da função de custo
Treinamento
validação
Custo
Épocas
2.0
1.8
1.6
1.4
1.2
0
10
20
30
40
50
60




```
cm_train = rna.evaluate(x_train, y_train_hot)
cm_test = rna.evaluate(x_test, y_test_hot)
```

```
1563/1563 ━━━━━━━━━━━━━━━━━━━━ 3s 2ms/step - accuracy: 0.6273 - loss:
1.0493
313/313 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step - accuracy: 0.5992 - loss:
1.1212
```