

# DL\_03\_EX-1

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Deep Learning

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MLP com TensorFlow

## 1 IMPORTANTE: Antes de começar

Execute a célula final desse Lab. Ela irá **inicializar** o seu ambiente com rotinas que são empregadas aqui.

## 2 Código completo

Aqui o código completo em uma única célula.

```
[1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import os
warnings.filterwarnings("ignore")

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

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

[2]: def mlp_plot(hot=1, norm=1, layers_qty=3, n=10, act='sigmoid', get_date=0):
    fraud = pd.read_csv("http://meusite.mackenzie.br/rogerio/ML/
↳qconlondon2016_sample_data.csv")
    if (get_date):
        fraud['day'] = fraud['charge_time'].str.slice(8,10).astype(int)
```

```

    fraud['month'] = fraud['charge_time'].str.slice(5,7).astype(int)

fraud.drop(columns=['charge_time'],inplace=True)

X = fraud.drop(columns=['fraudulent'])

if (hot):
    ## Hot Encode
    X_number = X.select_dtypes(include='number')
    X_categorical = X.select_dtypes(exclude='number')

    dummies = [pd.get_dummies(X[c],prefix=c, prefix_sep='_') for c in
↪X_categorical.columns]
    X_dummies = pd.concat(dummies, axis=1)

    X = pd.concat([X_number,X_dummies], axis=1)
    X.head()
else:
    ## Label Encode
    from sklearn.preprocessing import LabelEncoder
    labelencoder = LabelEncoder()
    X['card_country_label'] = labelencoder.fit_transform(X['card_country'])
    X = X.drop(columns=['card_country'])
if (norm):
    ## Normalize
    from sklearn.preprocessing import scale
    X_norm = scale(X)
    X_norm
else:
    ## Without normalization
    X_norm = X
    X_norm

## Preparando a saída `y`

fraud.fraudulent = fraud.fraudulent.replace(True,1)
fraud.fraudulent = fraud.fraudulent.replace(False,0)

y_num = fraud.fraudulent
y_num

## Separando os dados de Treinamento e Teste

seed = 1234
X_train, X_test, y_train, y_test = train_test_split(X_norm, y_num,
↪test_size=0.3, stratify=y_num, random_state=seed)

```

```

## Adequando categorical(y_train) para o `Keras`

from keras.utils import to_categorical

y_train = to_categorical(y_train)
y_train

## Configuração da Rede DeepLearning

model = Sequential([layers.Dense(X.shape[1], activation='sigmoid',
↪input_shape=[X.shape[1],])])
    for i in range(layers_qty):
        model.add(layers.Dense(n, activation=act))
#    model.add(layers.Dense(8, activation='sigmoid'))

    model.add(layers.Dense(2, activation='sigmoid'))
    model.compile(loss='categorical_crossentropy', optimizer='adam',
↪metrics=['accuracy'])

## Treinamento da Rede DeepLearning

history = model.fit(X_train, y_train, validation_split=0.2, epochs=20)

## Avaliação do Treinamento

loss, val_loss, acc, val_acc = plot_loss_acc(history, 'Two Hidden Layer
↪Neural Network 5,8,8,2 (sigmoid)')

## Predição, aplicando e avaliando o modelo

y_pred = np.argmax(model.predict(X_test), axis=-1)

print(y_pred)
print(confusion_matrix(y_pred,y_test))

print(classification_report(y_pred,y_test))

print(y_test)

```

### 3 Exercício.

Execute o modelo acima sem normalização dos dados. O modelo é sensível a normalização?

```
[5]: mlp_plot()
```

```

Epoch 1/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6929 -

```

accuracy: 0.5098 - val\_loss: 0.6721 - val\_accuracy: 0.6503  
Epoch 2/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6489 -  
accuracy: 0.6456 - val\_loss: 0.6160 - val\_accuracy: 0.6719  
Epoch 3/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6165 -  
accuracy: 0.6715 - val\_loss: 0.6159 - val\_accuracy: 0.6735  
Epoch 4/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6179 -  
accuracy: 0.6691 - val\_loss: 0.6094 - val\_accuracy: 0.6766  
Epoch 5/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6143 -  
accuracy: 0.6701 - val\_loss: 0.6092 - val\_accuracy: 0.6744  
Epoch 6/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6143 -  
accuracy: 0.6711 - val\_loss: 0.6093 - val\_accuracy: 0.6732  
Epoch 7/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6110 -  
accuracy: 0.6724 - val\_loss: 0.6092 - val\_accuracy: 0.6748  
Epoch 8/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6153 -  
accuracy: 0.6696 - val\_loss: 0.6091 - val\_accuracy: 0.6726  
Epoch 9/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6144 -  
accuracy: 0.6702 - val\_loss: 0.6091 - val\_accuracy: 0.6740  
Epoch 10/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6120 -  
accuracy: 0.6735 - val\_loss: 0.6088 - val\_accuracy: 0.6750  
Epoch 11/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6117 -  
accuracy: 0.6721 - val\_loss: 0.6100 - val\_accuracy: 0.6720  
Epoch 12/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6121 -  
accuracy: 0.6709 - val\_loss: 0.6086 - val\_accuracy: 0.6761  
Epoch 13/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6086 -  
accuracy: 0.6749 - val\_loss: 0.6102 - val\_accuracy: 0.6732  
Epoch 14/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6144 -  
accuracy: 0.6672 - val\_loss: 0.6082 - val\_accuracy: 0.6753  
Epoch 15/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6113 -  
accuracy: 0.6702 - val\_loss: 0.6081 - val\_accuracy: 0.6738  
Epoch 16/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6090 -  
accuracy: 0.6729 - val\_loss: 0.6080 - val\_accuracy: 0.6732  
Epoch 17/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6080 -

accuracy: 0.6747 - val\_loss: 0.6083 - val\_accuracy: 0.6733

Epoch 18/20

1565/1565 [=====] - 2s 2ms/step - loss: 0.6113 -

accuracy: 0.6679 - val\_loss: 0.6077 - val\_accuracy: 0.6732

Epoch 19/20

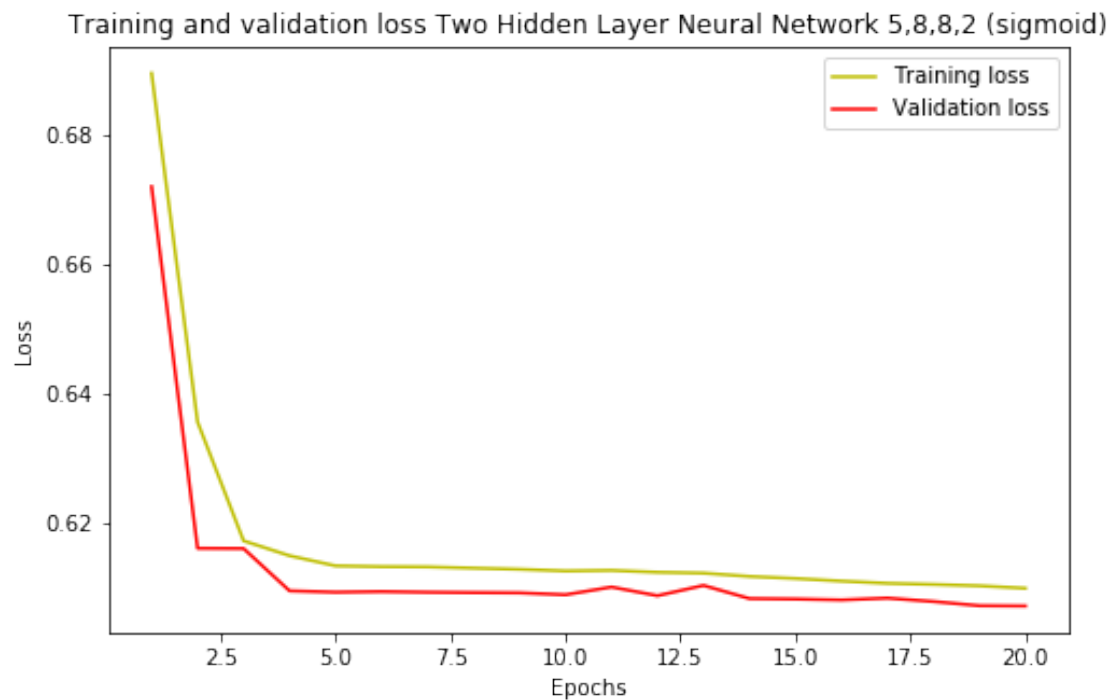
1565/1565 [=====] - 2s 2ms/step - loss: 0.6103 -

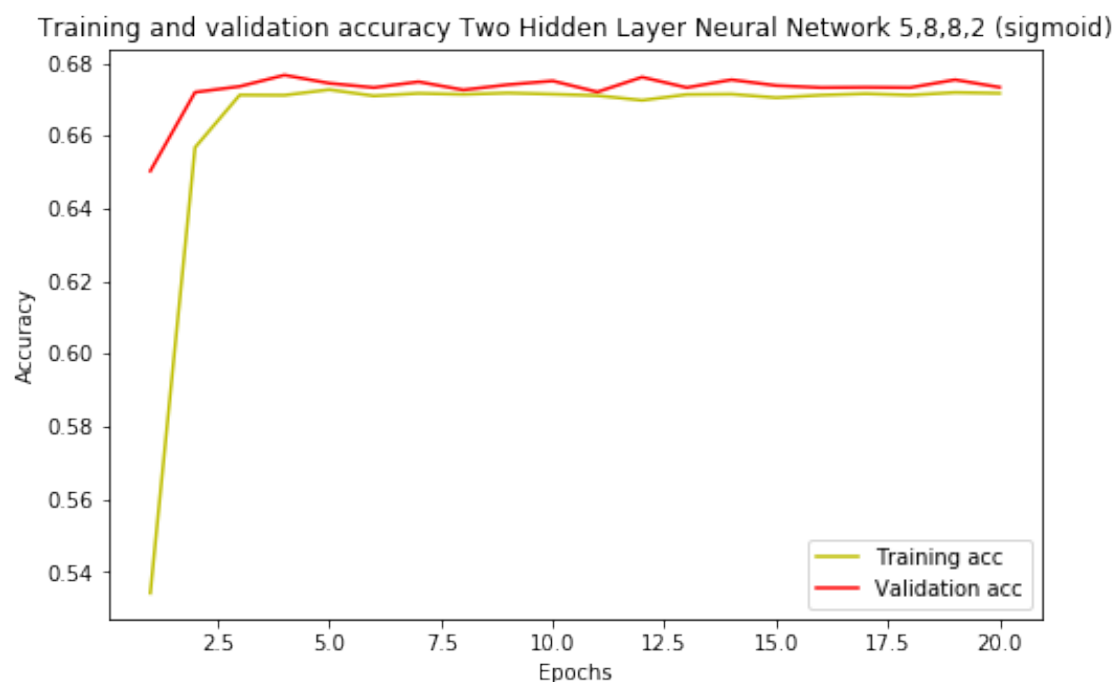
accuracy: 0.6723 - val\_loss: 0.6071 - val\_accuracy: 0.6753

Epoch 20/20

1565/1565 [=====] - 2s 2ms/step - loss: 0.6078 -

accuracy: 0.6737 - val\_loss: 0.6070 - val\_accuracy: 0.6733





Two Hidden Layer Neural Network 5,8,8,2 (sigmoid)Accuracy Train: 67.16 %,

Accuracy Test: 67.33 %

[0 0 0 ... 0 0 0]

[[10544 5823]

[ 3008 7443]]

	precision	recall	f1-score	support
0	0.78	0.64	0.70	16367
1	0.56	0.71	0.63	10451
accuracy			0.67	26818
macro avg	0.67	0.68	0.67	26818
weighted avg	0.69	0.67	0.67	26818

9484 0.0

74480 1.0

9602 0.0

956 0.0

52324 1.0

...

47854 1.0

30665 0.0

24197 0.0

5977 0.0

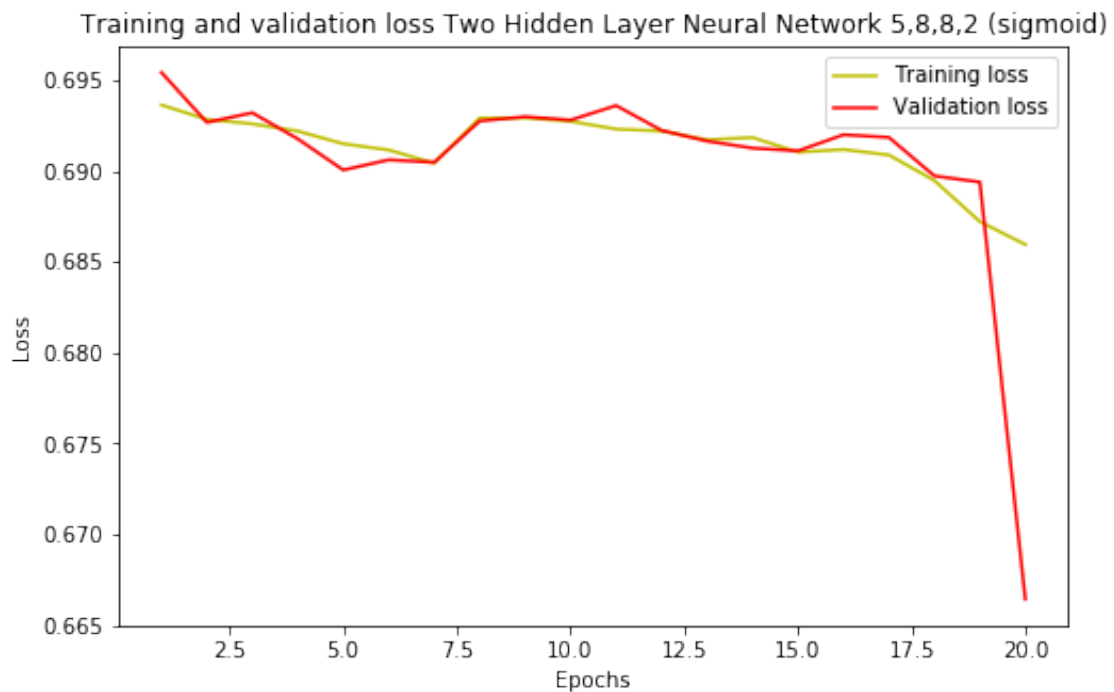
3248 0.0

Name: fraudulent, Length: 26818, dtype: float64

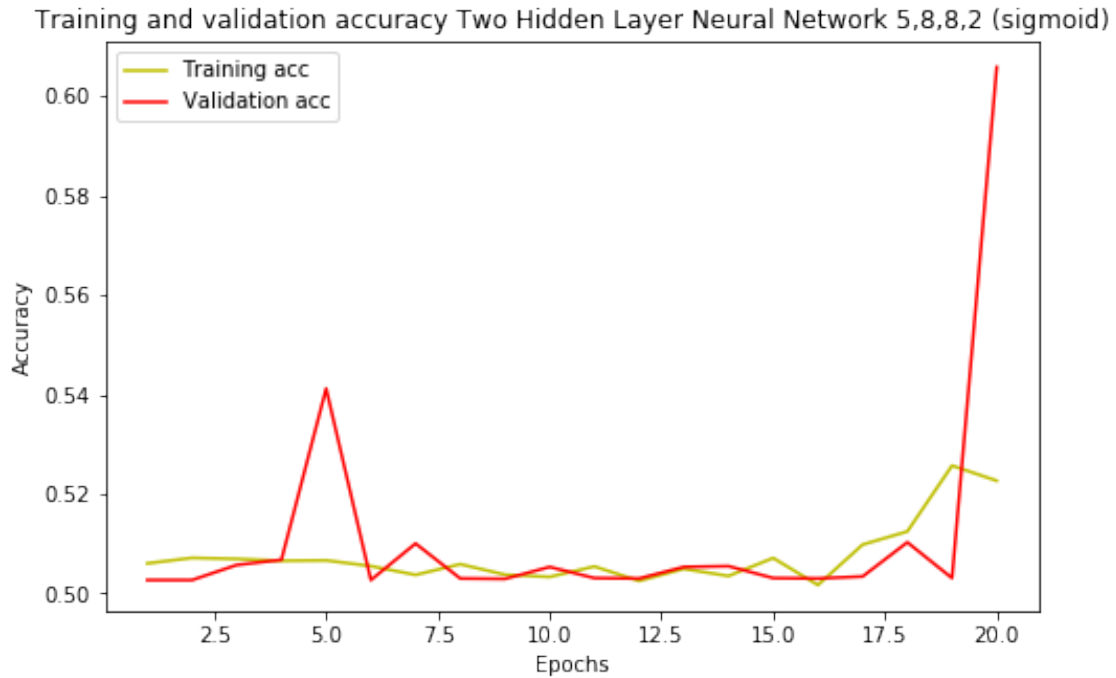
```
[65]: mlp_plot(norm=0)
```

```
Epoch 1/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6960 -
accuracy: 0.5010 - val_loss: 0.6954 - val_accuracy: 0.5027
Epoch 2/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6931 -
accuracy: 0.5041 - val_loss: 0.6927 - val_accuracy: 0.5027
Epoch 3/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6927 -
accuracy: 0.5063 - val_loss: 0.6932 - val_accuracy: 0.5057
Epoch 4/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6925 -
accuracy: 0.5059 - val_loss: 0.6918 - val_accuracy: 0.5068
Epoch 5/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6918 -
accuracy: 0.5060 - val_loss: 0.6901 - val_accuracy: 0.5412
Epoch 6/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6913 -
accuracy: 0.5082 - val_loss: 0.6906 - val_accuracy: 0.5027
Epoch 7/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6899 -
accuracy: 0.5015 - val_loss: 0.6905 - val_accuracy: 0.5100
Epoch 8/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6920 -
accuracy: 0.5135 - val_loss: 0.6927 - val_accuracy: 0.5030
Epoch 9/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6930 -
accuracy: 0.5021 - val_loss: 0.6930 - val_accuracy: 0.5029
Epoch 10/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6925 -
accuracy: 0.5091 - val_loss: 0.6928 - val_accuracy: 0.5053
Epoch 11/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6924 -
accuracy: 0.5075 - val_loss: 0.6936 - val_accuracy: 0.5031
Epoch 12/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6930 -
accuracy: 0.5013 - val_loss: 0.6922 - val_accuracy: 0.5030
Epoch 13/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6916 -
accuracy: 0.5082 - val_loss: 0.6916 - val_accuracy: 0.5053
Epoch 14/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6921 -
accuracy: 0.5027 - val_loss: 0.6913 - val_accuracy: 0.5055
Epoch 15/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6912 -
```

accuracy: 0.5088 - val\_loss: 0.6911 - val\_accuracy: 0.5031  
Epoch 16/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6914 -  
accuracy: 0.5003 - val\_loss: 0.6920 - val\_accuracy: 0.5030  
Epoch 17/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6912 -  
accuracy: 0.5077 - val\_loss: 0.6918 - val\_accuracy: 0.5034  
Epoch 18/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6899 -  
accuracy: 0.5074 - val\_loss: 0.6897 - val\_accuracy: 0.5103  
Epoch 19/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6885 -  
accuracy: 0.5164 - val\_loss: 0.6894 - val\_accuracy: 0.5031  
Epoch 20/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6885 -  
accuracy: 0.5121 - val\_loss: 0.6664 - val\_accuracy: 0.6058







Two Hidden Layer Neural Network 5,8,8,2 (sigmoid)Accuracy Train: 52.27 %,  
 Accuracy Test: 60.58 %  
 [0 0 0 ... 0 0 0]  
 [[12168 9030]  
 [ 1384 4236]]

	precision	recall	f1-score	support
0	0.90	0.57	0.70	21198
1	0.32	0.75	0.45	5620
accuracy			0.61	26818
macro avg	0.61	0.66	0.57	26818
weighted avg	0.78	0.61	0.65	26818

O modelo fica pior:

C/ Normalização: Accuracy = +- 67%

S/ Normalização: Accuracy +- 51%

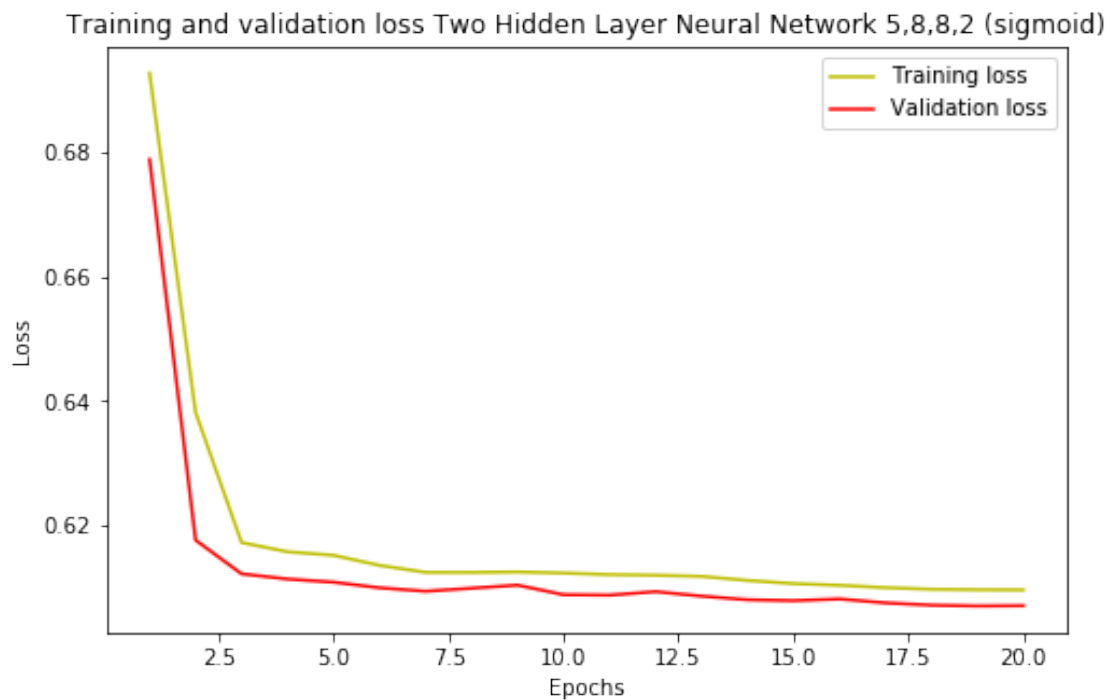
## 4 Exercício.

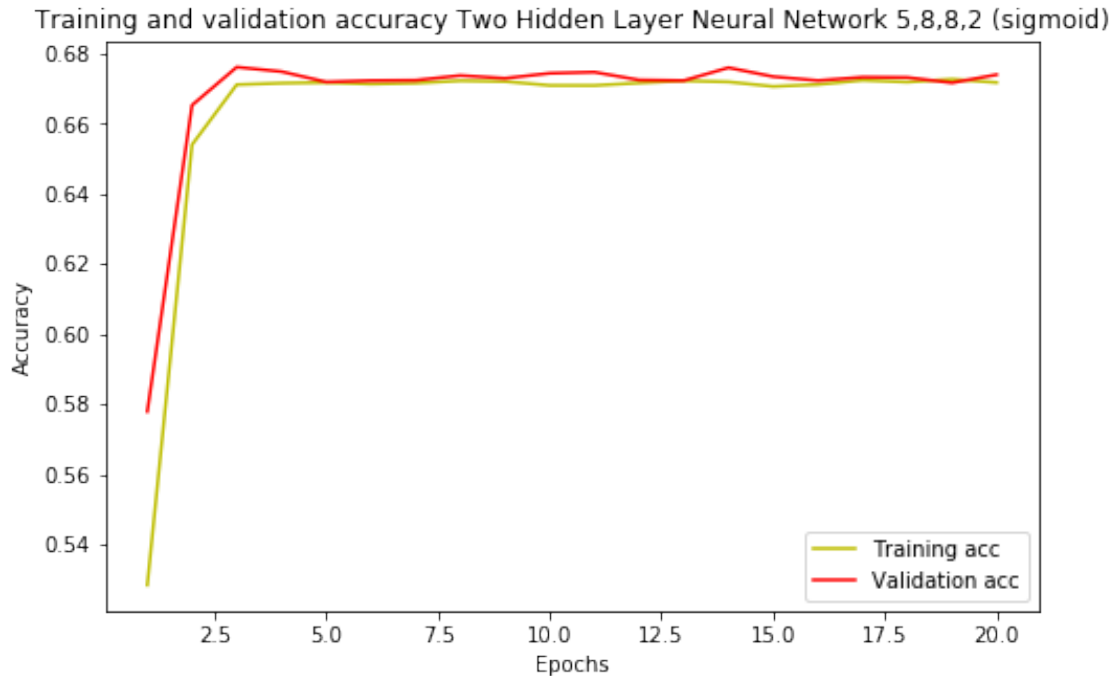
Execute o modelo agora empregando *label encode* do atributo `card_country`.

```
[68]: # Com o hot encoding desativado (hot=0), a função faz o label encoding
mlp_plot(hot=0)
```

```
Epoch 1/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.7022 -
accuracy: 0.5087 - val_loss: 0.6789 - val_accuracy: 0.5779
Epoch 2/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6546 -
accuracy: 0.6375 - val_loss: 0.6177 - val_accuracy: 0.6653
Epoch 3/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6203 -
accuracy: 0.6674 - val_loss: 0.6122 - val_accuracy: 0.6761
Epoch 4/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6151 -
accuracy: 0.6720 - val_loss: 0.6114 - val_accuracy: 0.6749
Epoch 5/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6147 -
accuracy: 0.6719 - val_loss: 0.6109 - val_accuracy: 0.6719
Epoch 6/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6140 -
accuracy: 0.6726 - val_loss: 0.6100 - val_accuracy: 0.6723
Epoch 7/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6154 -
accuracy: 0.6700 - val_loss: 0.6094 - val_accuracy: 0.6724
Epoch 8/20
1565/1565 [=====] - 2s 1ms/step - loss: 0.6116 -
accuracy: 0.6736 - val_loss: 0.6099 - val_accuracy: 0.6738
Epoch 9/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6144 -
accuracy: 0.6692 - val_loss: 0.6104 - val_accuracy: 0.6730
Epoch 10/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6120 -
accuracy: 0.6710 - val_loss: 0.6089 - val_accuracy: 0.6744
Epoch 11/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6121 -
accuracy: 0.6733 - val_loss: 0.6088 - val_accuracy: 0.6747
Epoch 12/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6144 -
accuracy: 0.6697 - val_loss: 0.6094 - val_accuracy: 0.6725
Epoch 13/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6146 -
accuracy: 0.6688 - val_loss: 0.6087 - val_accuracy: 0.6723
Epoch 14/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.6141 -
accuracy: 0.6692 - val_loss: 0.6081 - val_accuracy: 0.6760
Epoch 15/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.6108 -
```

accuracy: 0.6703 - val\_loss: 0.6079 - val\_accuracy: 0.6734  
Epoch 16/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6100 -  
accuracy: 0.6720 - val\_loss: 0.6082 - val\_accuracy: 0.6723  
Epoch 17/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6077 -  
accuracy: 0.6740 - val\_loss: 0.6076 - val\_accuracy: 0.6733  
Epoch 18/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.6089 -  
accuracy: 0.6748 - val\_loss: 0.6072 - val\_accuracy: 0.6732  
Epoch 19/20  
1565/1565 [=====] - 2s 1ms/step - loss: 0.6092 -  
accuracy: 0.6739 - val\_loss: 0.6071 - val\_accuracy: 0.6717  
Epoch 20/20  
1565/1565 [=====] - 2s 1ms/step - loss: 0.6116 -  
accuracy: 0.6713 - val\_loss: 0.6071 - val\_accuracy: 0.6740





Two Hidden Layer Neural Network 5,8,8,2 (sigmoid)Accuracy Train: 67.18 %,  
 Accuracy Test: 67.40 %  
 [0 0 0 ... 0 0 0]  
 [[10714 5973]  
 [ 2838 7293]]

	precision	recall	f1-score	support
0	0.79	0.64	0.71	16687
1	0.55	0.72	0.62	10131
accuracy			0.67	26818
macro avg	0.67	0.68	0.67	26818
weighted avg	0.70	0.67	0.68	26818

## 5 Exercício.

Agora varie parâmetros da rede neural, como número de camadas, número de neurônios e função de ativação. Veja se consegue obter um resultado significativamente melhor que os anteriores.

```
[70]: mlp_plot(layers_qty=5, n=20, act='relu')
```

Epoch 1/20

1565/1565 [=====] - 3s 2ms/step - loss: 0.6465 -  
 accuracy: 0.6171 - val\_loss: 0.6087 - val\_accuracy: 0.6717

Epoch 2/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6110 -  
accuracy: 0.6729 - val\_loss: 0.6101 - val\_accuracy: 0.6726  
Epoch 3/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6110 -  
accuracy: 0.6684 - val\_loss: 0.6069 - val\_accuracy: 0.6760  
Epoch 4/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6109 -  
accuracy: 0.6720 - val\_loss: 0.6099 - val\_accuracy: 0.6717  
Epoch 5/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6105 -  
accuracy: 0.6711 - val\_loss: 0.6143 - val\_accuracy: 0.6686  
Epoch 6/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6088 -  
accuracy: 0.6744 - val\_loss: 0.6081 - val\_accuracy: 0.6724  
Epoch 7/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6117 -  
accuracy: 0.6660 - val\_loss: 0.6104 - val\_accuracy: 0.6728  
Epoch 8/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6113 -  
accuracy: 0.6684 - val\_loss: 0.6075 - val\_accuracy: 0.6720  
Epoch 9/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6088 -  
accuracy: 0.6710 - val\_loss: 0.6059 - val\_accuracy: 0.6722  
Epoch 10/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6098 -  
accuracy: 0.6703 - val\_loss: 0.6065 - val\_accuracy: 0.6738  
Epoch 11/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6077 -  
accuracy: 0.6741 - val\_loss: 0.6071 - val\_accuracy: 0.6738  
Epoch 12/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6095 -  
accuracy: 0.6718 - val\_loss: 0.6068 - val\_accuracy: 0.6746  
Epoch 13/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6093 -  
accuracy: 0.6702 - val\_loss: 0.6063 - val\_accuracy: 0.6769  
Epoch 14/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6056 -  
accuracy: 0.6742 - val\_loss: 0.6074 - val\_accuracy: 0.6707  
Epoch 15/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6062 -  
accuracy: 0.6739 - val\_loss: 0.6075 - val\_accuracy: 0.6743  
Epoch 16/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6040 -  
accuracy: 0.6796 - val\_loss: 0.6046 - val\_accuracy: 0.6726  
Epoch 17/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.6052 -  
accuracy: 0.6767 - val\_loss: 0.6044 - val\_accuracy: 0.6799

Epoch 18/20

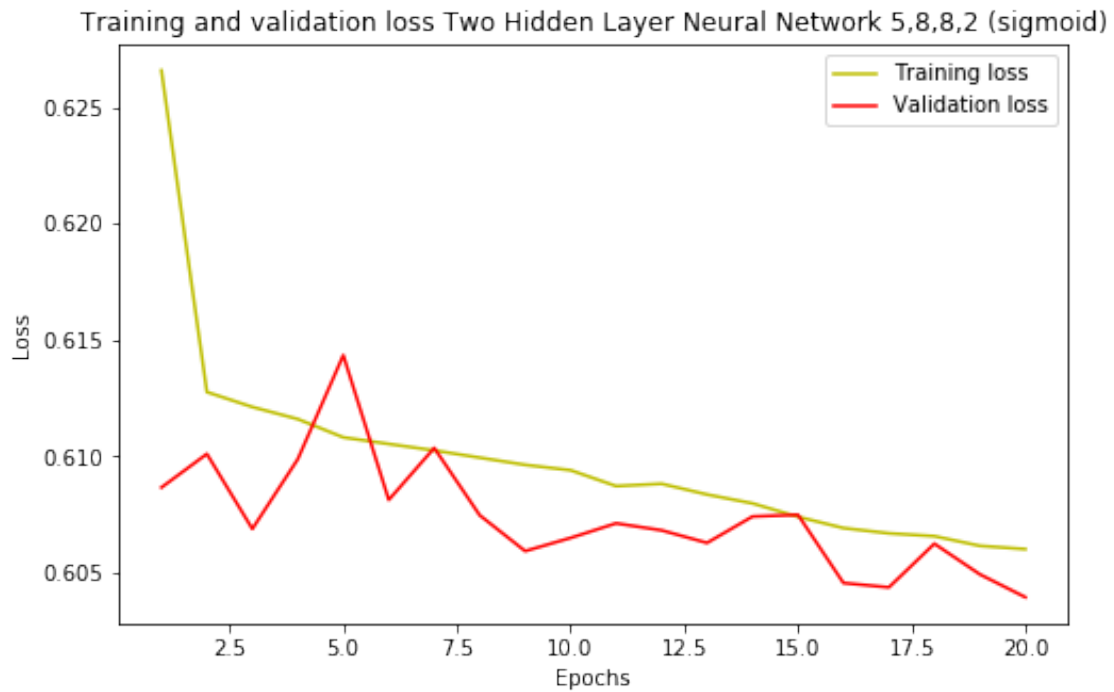
1565/1565 [=====] - 3s 2ms/step - loss: 0.6054 - accuracy: 0.6762 - val\_loss: 0.6063 - val\_accuracy: 0.6750

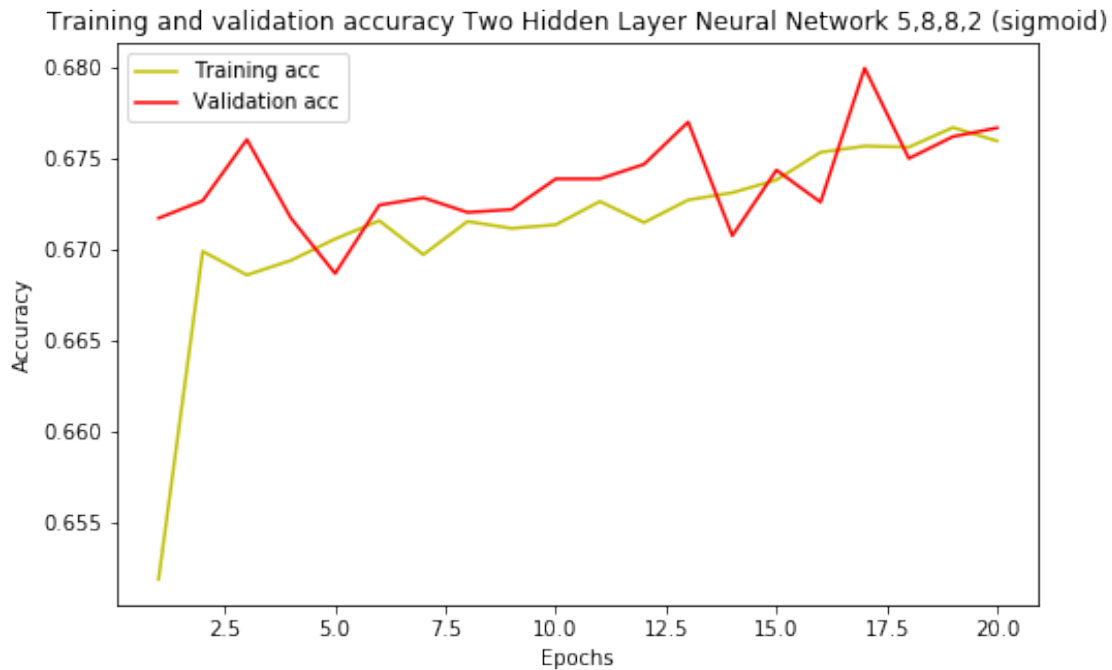
Epoch 19/20

1565/1565 [=====] - 3s 2ms/step - loss: 0.6090 - accuracy: 0.6737 - val\_loss: 0.6049 - val\_accuracy: 0.6761

Epoch 20/20

1565/1565 [=====] - 3s 2ms/step - loss: 0.6048 - accuracy: 0.6787 - val\_loss: 0.6040 - val\_accuracy: 0.6766





Two Hidden Layer Neural Network 5,8,8,2 (sigmoid)Accuracy Train: 67.59 %,  
 Accuracy Test: 67.66 %  
 [0 0 0 ... 0 0 0]  
 [[10578 5694]  
 [ 2974 7572]]

	precision	recall	f1-score	support
0	0.78	0.65	0.71	16272
1	0.57	0.72	0.64	10546
accuracy			0.68	26818
macro avg	0.68	0.68	0.67	26818
weighted avg	0.70	0.68	0.68	26818

## 6 Exercício.

Empregue os modelos acima e refaça o treinamento dos dados de fraude incluindo agora o dia e o mês das operações.

```
[3]: fraud = pd.read_csv("http://meusite.mackenzie.br/rogerio/ML/
    ↳ qconlondon2016_sample_data.csv")
```

```
[46]: fraud.shape
    print(fraud.charge_time[80000][8:10])
```

```
[58]: fraud['day'] = fraud['charge_time'].str.slice(8,10).astype(int)
      fraud['month'] = fraud['charge_time'].str.slice(5,7).astype(int)
```

```
[59]: fraud.dtypes
```

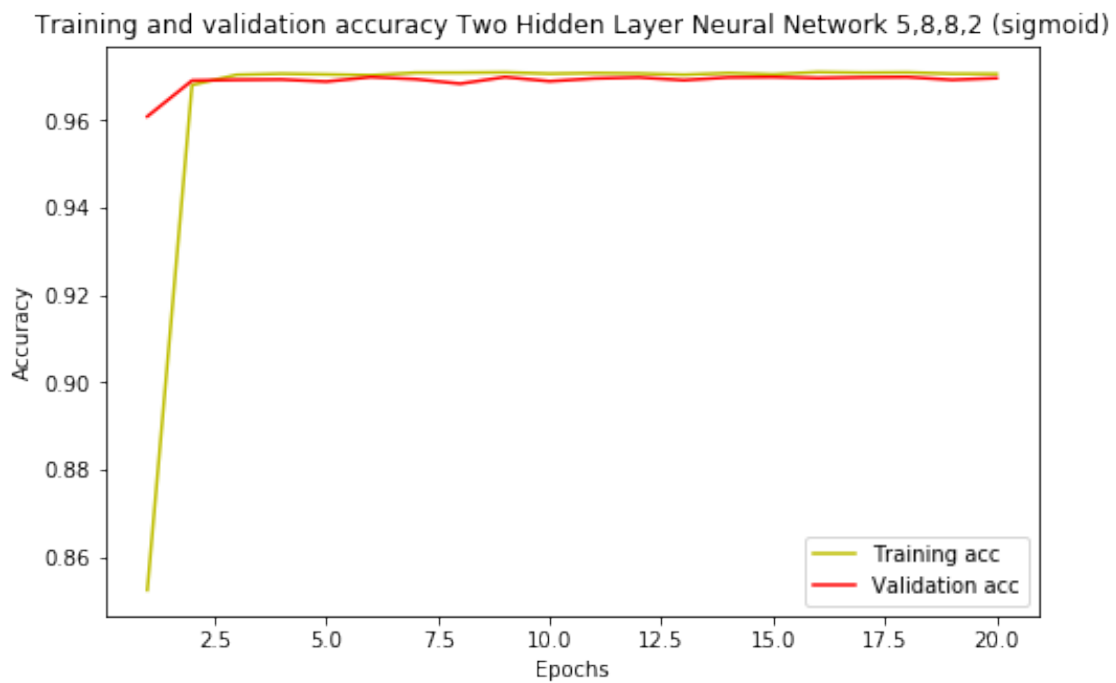
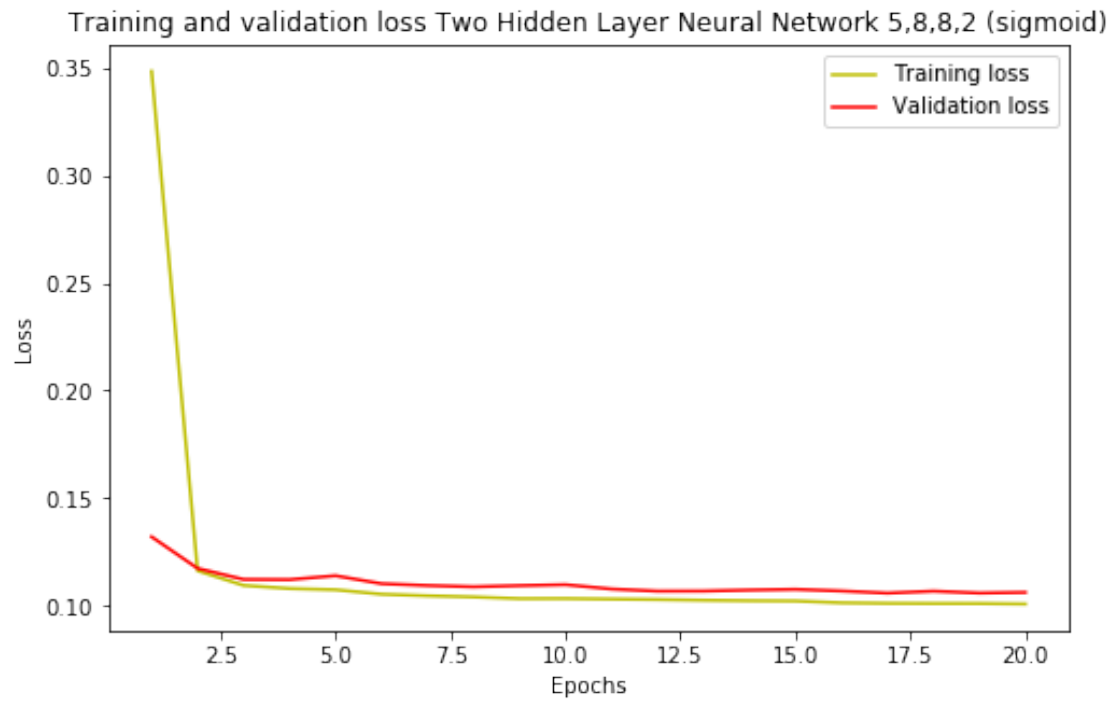
```
[59]: fraudulent      bool
      charge_time     object
      amount          int64
      card_country     object
      card_use_24h     int64
      day             int64
      month           int64
      dtype: object
```

```
[7]: mlp_plot(get_date=1)
```

```
Epoch 1/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.5428 -
accuracy: 0.7113 - val_loss: 0.1321 - val_accuracy: 0.9609
Epoch 2/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.1230 -
accuracy: 0.9642 - val_loss: 0.1174 - val_accuracy: 0.9692
Epoch 3/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.1082 -
accuracy: 0.9714 - val_loss: 0.1123 - val_accuracy: 0.9693
Epoch 4/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.1094 -
accuracy: 0.9700 - val_loss: 0.1122 - val_accuracy: 0.9694
Epoch 5/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.1106 -
accuracy: 0.9695 - val_loss: 0.1140 - val_accuracy: 0.9689
Epoch 6/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.1055 -
accuracy: 0.9704 - val_loss: 0.1103 - val_accuracy: 0.9700
Epoch 7/20
1565/1565 [=====] - 3s 2ms/step - loss: 0.1046 -
accuracy: 0.9712 - val_loss: 0.1095 - val_accuracy: 0.9695
Epoch 8/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.1058 -
accuracy: 0.9705 - val_loss: 0.1089 - val_accuracy: 0.9684
Epoch 9/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.1017 -
accuracy: 0.9713 - val_loss: 0.1094 - val_accuracy: 0.9700
Epoch 10/20
1565/1565 [=====] - 2s 2ms/step - loss: 0.1043 -
accuracy: 0.9701 - val_loss: 0.1099 - val_accuracy: 0.9690
```



Epoch 11/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.1041 -  
accuracy: 0.9712 - val\_loss: 0.1079 - val\_accuracy: 0.9696  
Epoch 12/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.1081 -  
accuracy: 0.9686 - val\_loss: 0.1069 - val\_accuracy: 0.9699  
Epoch 13/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.0992 -  
accuracy: 0.9713 - val\_loss: 0.1069 - val\_accuracy: 0.9692  
Epoch 14/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.1044 -  
accuracy: 0.9702 - val\_loss: 0.1074 - val\_accuracy: 0.9699  
Epoch 15/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.1038 -  
accuracy: 0.9702 - val\_loss: 0.1077 - val\_accuracy: 0.9700  
Epoch 16/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.0992 -  
accuracy: 0.9722 - val\_loss: 0.1069 - val\_accuracy: 0.9697  
Epoch 17/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.1049 -  
accuracy: 0.9697 - val\_loss: 0.1060 - val\_accuracy: 0.9699  
Epoch 18/20  
1565/1565 [=====] - 3s 2ms/step - loss: 0.1020 -  
accuracy: 0.9707 - val\_loss: 0.1069 - val\_accuracy: 0.9700  
Epoch 19/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.1027 -  
accuracy: 0.9706 - val\_loss: 0.1060 - val\_accuracy: 0.9693  
Epoch 20/20  
1565/1565 [=====] - 2s 2ms/step - loss: 0.0996 -  
accuracy: 0.9709 - val\_loss: 0.1063 - val\_accuracy: 0.9697



Two Hidden Layer Neural Network 5,8,8,2 (sigmoid) Accuracy Train: 97.07 %, Accuracy Test: 96.97 %

```
[0 1 0 ... 0 0 0]
[[13432  596]
 [ 120 12670]]
```

	precision	recall	f1-score	support
0	0.99	0.96	0.97	14028
1	0.96	0.99	0.97	12790
accuracy			0.97	26818
macro avg	0.97	0.97	0.97	26818
weighted avg	0.97	0.97	0.97	26818

## 6.1 LAB SET UP

Execute antes de iniciar o Lab.

```
[4]: import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import os
warnings.filterwarnings("ignore")

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

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

def plot_loss_acc(history,more_title=''):

    loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs = range(1, len(loss) + 1)
    plt.figure(figsize=(8,5))
    plt.plot(epochs, loss, 'y', label='Training loss')
    plt.plot(epochs, val_loss, 'r', label='Validation loss')
    plt.title('Training and validation loss' + ' ' + more_title)
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()
```

```

acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
plt.figure(figsize=(8,5))
plt.plot(epochs, acc, 'y', label='Training acc')
plt.plot(epochs, val_acc, 'r', label='Validation acc')
plt.title('Training and validation accuracy' + ' ' + more_title)
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

print(more_title + 'Accuracy Train: {:.2f} %, Accuracy Test: {:.2f} %'.
→format(acc[len(acc)-1] *100, val_acc[len(val_acc)-1]*100))

return loss, val_loss, acc, val_acc

print('Set Up completed!')

```

Set Up completed!

[ ]: