ann-classification

July 20, 2023

Welcome to Colab!

If you're already familiar with Colab, check out this video to learn about interactive tables, the executed code history view, and the command palette.

What is Colab?

Colab, or "Colaboratory", allows you to write and execute Python in your browser, with - Zero configuration required - Access to GPUs free of charge - Easy sharing

Whether you're a **student**, a **data scientist** or an **AI researcher**, Colab can make your work easier. Watch Introduction to Colab to learn more, or just get started below!

0.1 Getting started

The document you are reading is not a static web page, but an interactive environment called a **Colab notebook** that lets you write and execute code.

For example, here is a **code cell** with a short Python script that computes a value, stores it in a variable, and prints the result:

```
[]: seconds_in_a_day = 24 * 60 * 60 seconds_in_a_day
```

[]: 86400

To execute the code in the above cell, select it with a click and then either press the play button to the left of the code, or use the keyboard shortcut "Command/Ctrl+Enter". To edit the code, just click the cell and start editing.

Variables that you define in one cell can later be used in other cells:

```
[]: seconds_in_a_week = 7 * seconds_in_a_day seconds_in_a_week
```

[]: 604800

Colab notebooks allow you to combine **executable code** and **rich text** in a single document, along with **images**, **HTML**, **LaTeX** and more. When you create your own Colab notebooks, they are stored in your Google Drive account. You can easily share your Colab notebooks with co-workers or friends, allowing them to comment on your notebooks or even edit them. To learn

more, see Overview of Colab. To create a new Colab notebook you can use the File menu above, or use the following link: create a new Colab notebook.

Colab notebooks are Jupyter notebooks that are hosted by Colab. To learn more about the Jupyter project, see jupyter.org.

0.2 Data science

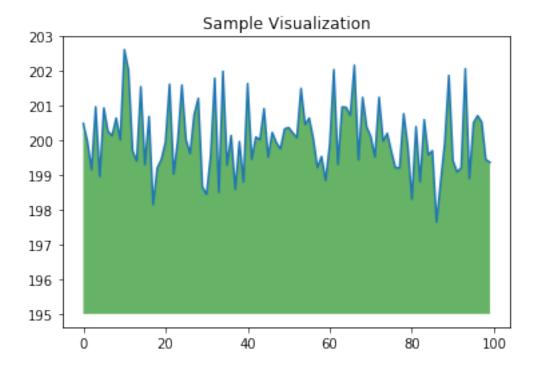
With Colab you can harness the full power of popular Python libraries to analyze and visualize data. The code cell below uses **numpy** to generate some random data, and uses **matplotlib** to visualize it. To edit the code, just click the cell and start editing.

```
[]: import numpy as np
from matplotlib import pyplot as plt

ys = 200 + np.random.randn(100)
x = [x for x in range(len(ys))]

plt.plot(x, ys, '-')
plt.fill_between(x, ys, 195, where=(ys > 195), facecolor='g', alpha=0.6)

plt.title("Sample Visualization")
plt.show()
```



You can import your own data into Colab notebooks from your Google Drive account, including from spreadsheets, as well as from Github and many other sources. To learn more about importing

data, and how Colab can be used for data science, see the links below under Working with Data.

0.3 Machine learning

With Colab you can import an image dataset, train an image classifier on it, and evaluate the model, all in just a few lines of code. Colab notebooks execute code on Google's cloud servers, meaning you can leverage the power of Google hardware, including GPUs and TPUs, regardless of the power of your machine. All you need is a browser.

Colab is used extensively in the machine learning community with applications including: - Getting started with TensorFlow - Developing and training neural networks - Experimenting with TPUs - Disseminating AI research - Creating tutorials

To see sample Colab notebooks that demonstrate machine learning applications, see the machine learning examples below.

0.4 More Resources

0.4.1 Working with Notebooks in Colab

- Overview of Colaboratory
- Guide to Markdown
- Importing libraries and installing dependencies
- Saving and loading notebooks in GitHub
- Interactive forms
- Interactive widgets

•

Working with Data

- Loading data: Drive, Sheets, and Google Cloud Storage
- Charts: visualizing data
- Getting started with BigQuery

0.4.2 Machine Learning Crash Course

These are a few of the notebooks from Google's online Machine Learning course. See the full course website for more. - Intro to Pandas DataFrame - Linear regression with tf.keras using synthetic data

Using Accelerated Hardware

- TensorFlow with GPUs
- TensorFlow with TPUs

0.4.3 Featured examples

- NeMo Voice Swap: Use Nvidia's NeMo conversational AI Toolkit to swap a voice in an audio fragment with a computer generated one.
- Retraining an Image Classifier: Build a Keras model on top of a pre-trained image classifier to distinguish flowers.

- Text Classification: Classify IMDB movie reviews as either positive or negative.
- Style Transfer: Use deep learning to transfer style between images.
- Multilingual Universal Sentence Encoder Q&A: Use a machine learning model to answer questions from the SQuAD dataset.
- Video Interpolation: Predict what happened in a video between the first and the last frame.

```
[3]: import tensorflow as tf
      import pandas as pd
      import numpy as np
      df=pd.read_csv('/content/Churn_Modelling.csv')
      df.head()
 [3]:
         RowNumber
                    CustomerId
                                   Surname
                                            CreditScore Geography
                                                                     Gender
                                                                              Age
                                                                     Female
                  1
                       15634602
                                 Hargrave
                                                            France
                                                                               42
      0
                                                     619
                                                                     Female
      1
                  2
                       15647311
                                      Hill
                                                     608
                                                              Spain
                                                                               41
      2
                  3
                       15619304
                                      Onio
                                                     502
                                                            France
                                                                     Female
                                                                               42
      3
                  4
                       15701354
                                      Boni
                                                                     Female
                                                     699
                                                            France
                                                                               39
                  5
                       15737888
                                 Mitchell
                                                     850
                                                              Spain Female
                                                                               43
                                                         IsActiveMember
         Tenure
                    Balance
                             NumOfProducts
                                             HasCrCard
      0
              2
                       0.00
                                                      1
                                                                       1
                                                      0
      1
               1
                   83807.86
                                          1
                                                                       1
      2
                                          3
                                                                       0
              8
                  159660.80
                                                      1
      3
                                          2
              1
                       0.00
                                                      0
                                                                       0
      4
                  125510.82
                                          1
                                                      1
                                                                       1
         EstimatedSalary Exited
      0
               101348.88
                                 1
                                 0
      1
               112542.58
      2
                113931.57
                                 1
      3
                 93826.63
                                 0
                 79084.10
                                 0
[31]: df['Geography'].value_counts()
[31]: France
                  5014
      Germany
                  2509
                  2477
      Spain
      Name: Geography, dtype: int64
```

4

[4]: tf.__version__

[4]: '2.12.0'

```
[9]: X=df.iloc[:,3:-1].values
      Y=df.iloc[:,-1].values
[10]: print(X)
     [[619 'France' 'Female' ... 1 1 101348.88]
      [608 'Spain' 'Female' ... 0 1 112542.58]
      [502 'France' 'Female' ... 1 0 113931.57]
      [709 'France' 'Female' ... 0 1 42085.58]
      [772 'Germany' 'Male' ... 1 0 92888.52]
      [792 'France' 'Female' ... 1 0 38190.78]]
[11]: print(Y)
     [1 0 1 ... 1 1 0]
[12]: from sklearn.preprocessing import LabelEncoder
      le=LabelEncoder()
      X[:,2]=le.fit_transform(X[:,2])
[13]: print(X)
      [[619 'France' 0 ... 1 1 101348.88]
      [608 'Spain' 0 ... 0 1 112542.58]
      [502 'France' 0 ... 1 0 113931.57]
      [709 'France' 0 ... 0 1 42085.58]
      [772 'Germany' 1 ... 1 0 92888.52]
      [792 'France' 0 ... 1 0 38190.78]]
[14]: from sklearn.compose import ColumnTransformer
      from sklearn.preprocessing import OneHotEncoder
      ct=ColumnTransformer(transformers=[('encoder',OneHotEncoder(),[1])],remainder='passthrough')
      X=np.array(ct.fit_transform(X))
      print(X)
     [[1.0 0.0 0.0 ... 1 1 101348.88]
      [0.0 0.0 1.0 ... 0 1 112542.58]
      [1.0 0.0 0.0 ... 1 0 113931.57]
      [1.0 0.0 0.0 ... 0 1 42085.58]
      [0.0 1.0 0.0 ... 1 0 92888.52]
      [1.0 0.0 0.0 ... 1 0 38190.78]]
```

```
[16]: from sklearn.model_selection import train_test_split
      X_train, X_test, Y_train, Y_test=train_test_split(X, Y, test_size=0.20)
[17]: print(X_train)
     [[0.0 0.0 1.0 ... 0 0 197602.29]
      [0.0 0.0 1.0 ... 1 0 109659.12]
      [1.0 0.0 0.0 ... 0 0 30781.77]
      [1.0 0.0 0.0 ... 0 1 88815.25]
      [1.0 0.0 0.0 ... 1 1 65998.26]
      [1.0 0.0 0.0 ... 0 1 91981.85]]
[18]: print(X_test)
     [[0.0 1.0 0.0 ... 0 0 127095.14]
      [1.0 0.0 0.0 ... 1 0 158049.9]
      [0.0 0.0 1.0 ... 1 1 186841.71]
      [1.0 0.0 0.0 ... 1 1 159044.1]
      [0.0 1.0 0.0 ... 0 0 27345.18]
      [1.0 0.0 0.0 ... 1 1 169915.02]]
[19]: print(Y_train)
     [0 0 0 ... 0 0 1]
[20]: print(Y_test)
     [0 0 0 ... 0 1 0]
[21]: from sklearn.preprocessing import StandardScaler
      sc=StandardScaler()
      X_train=sc.fit_transform(X_train)
      X_test=sc.transform(X_test)
[22]: X_train
[22]: array([[-0.99700449, -0.57965968, 1.73205081, ..., -1.5547807,
              -1.02148066, 1.68810678],
             [-0.99700449, -0.57965968, 1.73205081, ..., 0.64317752,
              -1.02148066, 0.16015636],
             [1.00300451, -0.57965968, -0.57735027, ..., -1.5547807,
              -1.02148066, -1.21028185],
             [1.00300451, -0.57965968, -0.57735027, ..., -1.5547807]
```

```
0.97897106, -0.20199115,
             [ 1.00300451, -0.57965968, -0.57735027, ..., 0.64317752,
              0.97897106, -0.59842022,
             [1.00300451, -0.57965968, -0.57735027, ..., -1.5547807]
              0.97897106, -0.14697371]])
[23]: X_test
[23]: array([[-0.99700449, 1.72515018, -0.57735027, ..., -1.5547807,
             -1.02148066, 0.46309488],
             [1.00300451, -0.57965968, -0.57735027, ..., 0.64317752,
             -1.02148066, 1.00091196],
             [-0.99700449, -0.57965968, 1.73205081, ..., 0.64317752,
              0.97897106, 1.50114931],
             [1.00300451, -0.57965968, -0.57735027, ..., 0.64317752,
              0.97897106, 1.01818548],
             [-0.99700449, 1.72515018, -0.57735027, ..., -1.5547807,
             -1.02148066, -1.26999017],
             [ 1.00300451, -0.57965968, -0.57735027, ..., 0.64317752,
              0.97897106, 1.20706003]])
[24]: #Building the ANN
      ann=tf.keras.models.Sequential()
[25]: #Adding the input layer and the first hidden layer
      ann.add(tf.keras.layers.Dense(units=6,activation='relu'))
[27]: #Adding the second hidden layer
      ann.add(tf.keras.layers.Dense(units=6,activation='relu'))
[28]: #Adding the output layer
      ann.add(tf.keras.layers.Dense(units=1,activation='sigmoid'))
[29]: #Trainig the ann
      ann.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
[40]: #Compliling the ann
      ann.fit(X_train,Y_train,batch_size=32,epochs=500)
     Epoch 1/500
     250/250 [============= ] - 1s 3ms/step - loss: 0.3307 -
     accuracy: 0.8644
```

```
Epoch 2/500
accuracy: 0.8625
Epoch 3/500
accuracy: 0.8610
Epoch 4/500
accuracy: 0.8641
Epoch 5/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3295 -
accuracy: 0.8641
Epoch 6/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3312 -
accuracy: 0.8635
Epoch 7/500
accuracy: 0.8641
Epoch 8/500
accuracy: 0.8636
Epoch 9/500
accuracy: 0.8646
Epoch 10/500
accuracy: 0.8648
Epoch 11/500
accuracy: 0.8635
Epoch 12/500
accuracy: 0.8644
Epoch 13/500
accuracy: 0.8626
Epoch 14/500
accuracy: 0.8644
Epoch 15/500
accuracy: 0.8635
Epoch 16/500
accuracy: 0.8627
Epoch 17/500
accuracy: 0.8626
```

```
Epoch 18/500
accuracy: 0.8643
Epoch 19/500
accuracy: 0.8640
Epoch 20/500
accuracy: 0.8634
Epoch 21/500
accuracy: 0.8639
Epoch 22/500
accuracy: 0.8637
Epoch 23/500
accuracy: 0.8656
Epoch 24/500
accuracy: 0.8625
Epoch 25/500
accuracy: 0.8631
Epoch 26/500
accuracy: 0.8636
Epoch 27/500
accuracy: 0.8640
Epoch 28/500
accuracy: 0.8619
Epoch 29/500
accuracy: 0.8651
Epoch 30/500
accuracy: 0.8645
Epoch 31/500
accuracy: 0.8635
Epoch 32/500
accuracy: 0.8639
Epoch 33/500
accuracy: 0.8627
```

```
Epoch 34/500
accuracy: 0.8633
Epoch 35/500
accuracy: 0.8648
Epoch 36/500
accuracy: 0.8624
Epoch 37/500
accuracy: 0.8656
Epoch 38/500
accuracy: 0.8640
Epoch 39/500
accuracy: 0.8645
Epoch 40/500
accuracy: 0.8645
Epoch 41/500
accuracy: 0.8627
Epoch 42/500
accuracy: 0.8615
Epoch 43/500
accuracy: 0.8641
Epoch 44/500
accuracy: 0.8629
Epoch 45/500
accuracy: 0.8650
Epoch 46/500
accuracy: 0.8654
Epoch 47/500
accuracy: 0.8650
Epoch 48/500
accuracy: 0.8645
Epoch 49/500
accuracy: 0.8650
```

```
Epoch 50/500
accuracy: 0.8626
Epoch 51/500
accuracy: 0.8627
Epoch 52/500
accuracy: 0.8654
Epoch 53/500
accuracy: 0.8652
Epoch 54/500
accuracy: 0.8635
Epoch 55/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3276 -
accuracy: 0.8646
Epoch 56/500
accuracy: 0.8649
Epoch 57/500
accuracy: 0.8654
Epoch 58/500
accuracy: 0.8629
Epoch 59/500
accuracy: 0.8645
Epoch 60/500
accuracy: 0.8630
Epoch 61/500
accuracy: 0.8641
Epoch 62/500
accuracy: 0.8646
Epoch 63/500
accuracy: 0.8639
Epoch 64/500
accuracy: 0.8648
Epoch 65/500
accuracy: 0.8656
```

```
Epoch 66/500
accuracy: 0.8670
Epoch 67/500
accuracy: 0.8640
Epoch 68/500
accuracy: 0.8668
Epoch 69/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3270 -
accuracy: 0.8646
Epoch 70/500
accuracy: 0.8654
Epoch 71/500
accuracy: 0.8648
Epoch 72/500
accuracy: 0.8651
Epoch 73/500
accuracy: 0.8648
Epoch 74/500
accuracy: 0.8673
Epoch 75/500
accuracy: 0.8660
Epoch 76/500
accuracy: 0.8641
Epoch 77/500
accuracy: 0.8634
Epoch 78/500
accuracy: 0.8625
Epoch 79/500
accuracy: 0.8626
Epoch 80/500
accuracy: 0.8641
Epoch 81/500
accuracy: 0.8652
```

```
Epoch 82/500
accuracy: 0.8645
Epoch 83/500
accuracy: 0.8664
Epoch 84/500
accuracy: 0.8630
Epoch 85/500
accuracy: 0.8661
Epoch 86/500
accuracy: 0.8646
Epoch 87/500
250/250 [============ ] - 1s 2ms/step - loss: 0.3273 -
accuracy: 0.8633
Epoch 88/500
accuracy: 0.8662
Epoch 89/500
accuracy: 0.8620
Epoch 90/500
accuracy: 0.8677
Epoch 91/500
accuracy: 0.8652
Epoch 92/500
accuracy: 0.8660
Epoch 93/500
accuracy: 0.8650
Epoch 94/500
accuracy: 0.8654
Epoch 95/500
accuracy: 0.8641
Epoch 96/500
accuracy: 0.8656
Epoch 97/500
accuracy: 0.8681
```

```
Epoch 98/500
accuracy: 0.8644
Epoch 99/500
accuracy: 0.8658
Epoch 100/500
accuracy: 0.8658
Epoch 101/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3262 -
accuracy: 0.8671
Epoch 102/500
accuracy: 0.8666
Epoch 103/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3261 -
accuracy: 0.8660
Epoch 104/500
accuracy: 0.8659
Epoch 105/500
accuracy: 0.8664
Epoch 106/500
accuracy: 0.8654
Epoch 107/500
accuracy: 0.8645
Epoch 108/500
accuracy: 0.8643
Epoch 109/500
accuracy: 0.8665
Epoch 110/500
accuracy: 0.8670
Epoch 111/500
accuracy: 0.8652
Epoch 112/500
accuracy: 0.8648
Epoch 113/500
accuracy: 0.8669
```

```
Epoch 114/500
accuracy: 0.8649
Epoch 115/500
accuracy: 0.8666
Epoch 116/500
accuracy: 0.8677
Epoch 117/500
accuracy: 0.8644
Epoch 118/500
accuracy: 0.8690
Epoch 119/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3267 -
accuracy: 0.8665
Epoch 120/500
accuracy: 0.8655
Epoch 121/500
accuracy: 0.8669
Epoch 122/500
accuracy: 0.8662
Epoch 123/500
accuracy: 0.8648
Epoch 124/500
accuracy: 0.8651
Epoch 125/500
accuracy: 0.8660
Epoch 126/500
accuracy: 0.8659
Epoch 127/500
accuracy: 0.8640
Epoch 128/500
accuracy: 0.8685
Epoch 129/500
accuracy: 0.8655
```

```
Epoch 130/500
accuracy: 0.8661
Epoch 131/500
accuracy: 0.8652
Epoch 132/500
accuracy: 0.8668
Epoch 133/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3256 -
accuracy: 0.8662
Epoch 134/500
accuracy: 0.8669
Epoch 135/500
250/250 [=========== ] - 1s 3ms/step - loss: 0.3249 -
accuracy: 0.8654
Epoch 136/500
accuracy: 0.8661
Epoch 137/500
accuracy: 0.8650
Epoch 138/500
accuracy: 0.8666
Epoch 139/500
accuracy: 0.8665
Epoch 140/500
accuracy: 0.8659
Epoch 141/500
accuracy: 0.8652
Epoch 142/500
accuracy: 0.8669
Epoch 143/500
accuracy: 0.8660
Epoch 144/500
accuracy: 0.8677
Epoch 145/500
accuracy: 0.8670
```

```
Epoch 146/500
accuracy: 0.8673
Epoch 147/500
accuracy: 0.8676
Epoch 148/500
accuracy: 0.8670
Epoch 149/500
accuracy: 0.8684
Epoch 150/500
accuracy: 0.8677
Epoch 151/500
accuracy: 0.8686
Epoch 152/500
accuracy: 0.8675
Epoch 153/500
accuracy: 0.8652
Epoch 154/500
accuracy: 0.8669
Epoch 155/500
accuracy: 0.8666
Epoch 156/500
accuracy: 0.8662
Epoch 157/500
accuracy: 0.8670
Epoch 158/500
accuracy: 0.8681
Epoch 159/500
accuracy: 0.8656
Epoch 160/500
accuracy: 0.8668
Epoch 161/500
accuracy: 0.8684
```

```
Epoch 162/500
accuracy: 0.8675
Epoch 163/500
accuracy: 0.8662
Epoch 164/500
accuracy: 0.8650
Epoch 165/500
250/250 [============ ] - 1s 2ms/step - loss: 0.3251 -
accuracy: 0.8671
Epoch 166/500
accuracy: 0.8661
Epoch 167/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3251 -
accuracy: 0.8670
Epoch 168/500
accuracy: 0.8669
Epoch 169/500
accuracy: 0.8671
Epoch 170/500
accuracy: 0.8685
Epoch 171/500
accuracy: 0.8668
Epoch 172/500
accuracy: 0.8673
Epoch 173/500
accuracy: 0.8669
Epoch 174/500
accuracy: 0.8691
Epoch 175/500
accuracy: 0.8659
Epoch 176/500
accuracy: 0.8662
Epoch 177/500
accuracy: 0.8675
```

```
Epoch 178/500
accuracy: 0.8684
Epoch 179/500
accuracy: 0.8655
Epoch 180/500
accuracy: 0.8684
Epoch 181/500
accuracy: 0.8668
Epoch 182/500
accuracy: 0.8666
Epoch 183/500
250/250 [=========== ] - 1s 3ms/step - loss: 0.3244 -
accuracy: 0.8654
Epoch 184/500
accuracy: 0.8664
Epoch 185/500
accuracy: 0.8679
Epoch 186/500
accuracy: 0.8662
Epoch 187/500
accuracy: 0.8670
Epoch 188/500
accuracy: 0.8686
Epoch 189/500
accuracy: 0.8686
Epoch 190/500
accuracy: 0.8686
Epoch 191/500
accuracy: 0.8666
Epoch 192/500
accuracy: 0.8686
Epoch 193/500
accuracy: 0.8671
```

```
Epoch 194/500
accuracy: 0.8676
Epoch 195/500
accuracy: 0.8687
Epoch 196/500
accuracy: 0.8673
Epoch 197/500
accuracy: 0.8664
Epoch 198/500
accuracy: 0.8670
Epoch 199/500
accuracy: 0.8665
Epoch 200/500
accuracy: 0.8662
Epoch 201/500
accuracy: 0.8664
Epoch 202/500
accuracy: 0.8665
Epoch 203/500
accuracy: 0.8676
Epoch 204/500
accuracy: 0.8676
Epoch 205/500
accuracy: 0.8680
Epoch 206/500
accuracy: 0.8662
Epoch 207/500
accuracy: 0.8692
Epoch 208/500
accuracy: 0.8685
Epoch 209/500
accuracy: 0.8702
```

```
Epoch 210/500
accuracy: 0.8675
Epoch 211/500
accuracy: 0.8690
Epoch 212/500
accuracy: 0.8675
Epoch 213/500
250/250 [============ ] - 1s 2ms/step - loss: 0.3246 -
accuracy: 0.8686
Epoch 214/500
accuracy: 0.8679
Epoch 215/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3231 -
accuracy: 0.8675
Epoch 216/500
accuracy: 0.8676
Epoch 217/500
accuracy: 0.8664
Epoch 218/500
accuracy: 0.8681
Epoch 219/500
accuracy: 0.8676
Epoch 220/500
accuracy: 0.8668
Epoch 221/500
accuracy: 0.8676
Epoch 222/500
accuracy: 0.8666
Epoch 223/500
accuracy: 0.8671
Epoch 224/500
accuracy: 0.8692
Epoch 225/500
accuracy: 0.8671
```

```
Epoch 226/500
accuracy: 0.8664
Epoch 227/500
accuracy: 0.8669
Epoch 228/500
accuracy: 0.8674
Epoch 229/500
250/250 [=========== ] - 1s 3ms/step - loss: 0.3237 -
accuracy: 0.8679
Epoch 230/500
accuracy: 0.8690
Epoch 231/500
250/250 [============ ] - 1s 3ms/step - loss: 0.3237 -
accuracy: 0.8665
Epoch 232/500
accuracy: 0.8673
Epoch 233/500
accuracy: 0.8679
Epoch 234/500
accuracy: 0.8662
Epoch 235/500
accuracy: 0.8677
Epoch 236/500
accuracy: 0.8665
Epoch 237/500
accuracy: 0.8690
Epoch 238/500
accuracy: 0.8691
Epoch 239/500
accuracy: 0.8674
Epoch 240/500
accuracy: 0.8665
Epoch 241/500
accuracy: 0.8680
```

```
Epoch 242/500
accuracy: 0.8689
Epoch 243/500
accuracy: 0.8683
Epoch 244/500
accuracy: 0.8664
Epoch 245/500
accuracy: 0.8691
Epoch 246/500
accuracy: 0.8674
Epoch 247/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3235 -
accuracy: 0.8689
Epoch 248/500
accuracy: 0.8668
Epoch 249/500
accuracy: 0.8691
Epoch 250/500
accuracy: 0.8674
Epoch 251/500
accuracy: 0.8677
Epoch 252/500
accuracy: 0.8677
Epoch 253/500
accuracy: 0.8665
Epoch 254/500
accuracy: 0.8669
Epoch 255/500
accuracy: 0.8671
Epoch 256/500
accuracy: 0.8671
Epoch 257/500
accuracy: 0.8695
```

```
Epoch 258/500
accuracy: 0.8669
Epoch 259/500
accuracy: 0.8679
Epoch 260/500
accuracy: 0.8686
Epoch 261/500
accuracy: 0.8683
Epoch 262/500
accuracy: 0.8673
Epoch 263/500
accuracy: 0.8668
Epoch 264/500
accuracy: 0.8676
Epoch 265/500
accuracy: 0.8668
Epoch 266/500
accuracy: 0.8671
Epoch 267/500
accuracy: 0.8668
Epoch 268/500
accuracy: 0.8661
Epoch 269/500
accuracy: 0.8665
Epoch 270/500
accuracy: 0.8680
Epoch 271/500
accuracy: 0.8679
Epoch 272/500
accuracy: 0.8684
Epoch 273/500
accuracy: 0.8652
```

```
Epoch 274/500
accuracy: 0.8694
Epoch 275/500
accuracy: 0.8666
Epoch 276/500
accuracy: 0.8679
Epoch 277/500
accuracy: 0.8692
Epoch 278/500
accuracy: 0.8683
Epoch 279/500
250/250 [============ ] - Os 2ms/step - loss: 0.3235 -
accuracy: 0.8673
Epoch 280/500
accuracy: 0.8675
Epoch 281/500
accuracy: 0.8685
Epoch 282/500
accuracy: 0.8669
Epoch 283/500
accuracy: 0.8671
Epoch 284/500
accuracy: 0.8679
Epoch 285/500
accuracy: 0.8679
Epoch 286/500
accuracy: 0.8671
Epoch 287/500
accuracy: 0.8683
Epoch 288/500
accuracy: 0.8671
Epoch 289/500
accuracy: 0.8674
```

```
Epoch 290/500
accuracy: 0.8675
Epoch 291/500
accuracy: 0.8674
Epoch 292/500
accuracy: 0.8665
Epoch 293/500
accuracy: 0.8680
Epoch 294/500
accuracy: 0.8665
Epoch 295/500
250/250 [============ ] - Os 2ms/step - loss: 0.3239 -
accuracy: 0.8690
Epoch 296/500
accuracy: 0.8675
Epoch 297/500
accuracy: 0.8683
Epoch 298/500
accuracy: 0.8686
Epoch 299/500
accuracy: 0.8658
Epoch 300/500
accuracy: 0.8674
Epoch 301/500
accuracy: 0.8676
Epoch 302/500
accuracy: 0.8675
Epoch 303/500
accuracy: 0.8685
Epoch 304/500
accuracy: 0.8668
Epoch 305/500
accuracy: 0.8671
```

```
Epoch 306/500
accuracy: 0.8689
Epoch 307/500
accuracy: 0.8677
Epoch 308/500
accuracy: 0.8676
Epoch 309/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3237 -
accuracy: 0.8679
Epoch 310/500
accuracy: 0.8679
Epoch 311/500
250/250 [============ ] - 1s 2ms/step - loss: 0.3235 -
accuracy: 0.8680
Epoch 312/500
accuracy: 0.8676
Epoch 313/500
accuracy: 0.8671
Epoch 314/500
accuracy: 0.8687
Epoch 315/500
accuracy: 0.8689
Epoch 316/500
accuracy: 0.8686
Epoch 317/500
accuracy: 0.8677
Epoch 318/500
accuracy: 0.8673
Epoch 319/500
accuracy: 0.8680
Epoch 320/500
accuracy: 0.8679
Epoch 321/500
accuracy: 0.8676
```

```
Epoch 322/500
accuracy: 0.8690
Epoch 323/500
accuracy: 0.8705
Epoch 324/500
accuracy: 0.8681
Epoch 325/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3234 -
accuracy: 0.8677
Epoch 326/500
accuracy: 0.8673
Epoch 327/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3233 -
accuracy: 0.8692
Epoch 328/500
accuracy: 0.8702
Epoch 329/500
accuracy: 0.8687
Epoch 330/500
accuracy: 0.8681
Epoch 331/500
accuracy: 0.8689
Epoch 332/500
accuracy: 0.8670
Epoch 333/500
accuracy: 0.8661
Epoch 334/500
accuracy: 0.8665
Epoch 335/500
accuracy: 0.8676
Epoch 336/500
accuracy: 0.8675
Epoch 337/500
accuracy: 0.8696
```

```
Epoch 338/500
accuracy: 0.8674
Epoch 339/500
accuracy: 0.8673
Epoch 340/500
accuracy: 0.8677
Epoch 341/500
250/250 [=========== ] - 1s 3ms/step - loss: 0.3228 -
accuracy: 0.8670
Epoch 342/500
accuracy: 0.8687
Epoch 343/500
250/250 [=========== ] - 1s 3ms/step - loss: 0.3236 -
accuracy: 0.8666
Epoch 344/500
accuracy: 0.8674
Epoch 345/500
accuracy: 0.8679
Epoch 346/500
accuracy: 0.8666
Epoch 347/500
accuracy: 0.8656
Epoch 348/500
accuracy: 0.8691
Epoch 349/500
accuracy: 0.8677
Epoch 350/500
accuracy: 0.8684
Epoch 351/500
accuracy: 0.8685
Epoch 352/500
accuracy: 0.8684
Epoch 353/500
accuracy: 0.8679
```

```
Epoch 354/500
accuracy: 0.8674
Epoch 355/500
accuracy: 0.8671
Epoch 356/500
accuracy: 0.8671
Epoch 357/500
accuracy: 0.8660
Epoch 358/500
accuracy: 0.8656
Epoch 359/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3238 -
accuracy: 0.8665
Epoch 360/500
accuracy: 0.8677
Epoch 361/500
accuracy: 0.8687
Epoch 362/500
accuracy: 0.8669
Epoch 363/500
accuracy: 0.8686
Epoch 364/500
accuracy: 0.8676
Epoch 365/500
accuracy: 0.8674
Epoch 366/500
accuracy: 0.8664
Epoch 367/500
accuracy: 0.8669
Epoch 368/500
accuracy: 0.8684
Epoch 369/500
accuracy: 0.8690
```

```
Epoch 370/500
accuracy: 0.8652
Epoch 371/500
accuracy: 0.8676
Epoch 372/500
accuracy: 0.8698
Epoch 373/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3233 -
accuracy: 0.8684
Epoch 374/500
accuracy: 0.8669
Epoch 375/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3229 -
accuracy: 0.8649
Epoch 376/500
accuracy: 0.8686
Epoch 377/500
accuracy: 0.8680
Epoch 378/500
accuracy: 0.8686
Epoch 379/500
accuracy: 0.8692
Epoch 380/500
accuracy: 0.8675
Epoch 381/500
accuracy: 0.8690
Epoch 382/500
accuracy: 0.8676
Epoch 383/500
accuracy: 0.8674
Epoch 384/500
accuracy: 0.8666
Epoch 385/500
accuracy: 0.8673
```

```
Epoch 386/500
accuracy: 0.8695
Epoch 387/500
accuracy: 0.8699
Epoch 388/500
accuracy: 0.8687
Epoch 389/500
250/250 [=========== ] - 1s 3ms/step - loss: 0.3233 -
accuracy: 0.8677
Epoch 390/500
accuracy: 0.8686
Epoch 391/500
250/250 [============ ] - 1s 4ms/step - loss: 0.3225 -
accuracy: 0.8687
Epoch 392/500
accuracy: 0.8675
Epoch 393/500
accuracy: 0.8689
Epoch 394/500
accuracy: 0.8687
Epoch 395/500
accuracy: 0.8681
Epoch 396/500
accuracy: 0.8700
Epoch 397/500
accuracy: 0.8692
Epoch 398/500
accuracy: 0.8661
Epoch 399/500
accuracy: 0.8690
Epoch 400/500
accuracy: 0.8684
Epoch 401/500
accuracy: 0.8685
```

```
Epoch 402/500
accuracy: 0.8676
Epoch 403/500
accuracy: 0.8680
Epoch 404/500
accuracy: 0.8685
Epoch 405/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3228 -
accuracy: 0.8661
Epoch 406/500
accuracy: 0.8675
Epoch 407/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3235 -
accuracy: 0.8671
Epoch 408/500
accuracy: 0.8686
Epoch 409/500
accuracy: 0.8681
Epoch 410/500
accuracy: 0.8668
Epoch 411/500
accuracy: 0.8660
Epoch 412/500
accuracy: 0.8686
Epoch 413/500
accuracy: 0.8698
Epoch 414/500
accuracy: 0.8677
Epoch 415/500
accuracy: 0.8680
Epoch 416/500
accuracy: 0.8679
Epoch 417/500
accuracy: 0.8676
```

```
Epoch 418/500
accuracy: 0.8668
Epoch 419/500
accuracy: 0.8700
Epoch 420/500
accuracy: 0.8692
Epoch 421/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3233 -
accuracy: 0.8681
Epoch 422/500
accuracy: 0.8673
Epoch 423/500
250/250 [============= ] - 1s 2ms/step - loss: 0.3233 -
accuracy: 0.8681
Epoch 424/500
accuracy: 0.8679
Epoch 425/500
accuracy: 0.8669
Epoch 426/500
accuracy: 0.8696
Epoch 427/500
accuracy: 0.8669
Epoch 428/500
accuracy: 0.8679
Epoch 429/500
accuracy: 0.8673
Epoch 430/500
accuracy: 0.8695
Epoch 431/500
accuracy: 0.8673
Epoch 432/500
accuracy: 0.8681
Epoch 433/500
accuracy: 0.8680
```

```
Epoch 434/500
accuracy: 0.8666
Epoch 435/500
accuracy: 0.8685
Epoch 436/500
accuracy: 0.8687
Epoch 437/500
250/250 [=========== ] - 1s 3ms/step - loss: 0.3232 -
accuracy: 0.8679
Epoch 438/500
accuracy: 0.8686
Epoch 439/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3229 -
accuracy: 0.8700
Epoch 440/500
accuracy: 0.8676
Epoch 441/500
accuracy: 0.8662
Epoch 442/500
accuracy: 0.8674
Epoch 443/500
accuracy: 0.8686
Epoch 444/500
accuracy: 0.8696
Epoch 445/500
accuracy: 0.8674
Epoch 446/500
accuracy: 0.8666
Epoch 447/500
accuracy: 0.8666
Epoch 448/500
accuracy: 0.8671
Epoch 449/500
accuracy: 0.8683
```

```
Epoch 450/500
accuracy: 0.8692
Epoch 451/500
accuracy: 0.8680
Epoch 452/500
accuracy: 0.8681
Epoch 453/500
250/250 [=========== ] - 1s 2ms/step - loss: 0.3228 -
accuracy: 0.8675
Epoch 454/500
accuracy: 0.8683
Epoch 455/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3227 -
accuracy: 0.8676
Epoch 456/500
accuracy: 0.8677
Epoch 457/500
accuracy: 0.8679
Epoch 458/500
accuracy: 0.8658
Epoch 459/500
accuracy: 0.8687
Epoch 460/500
accuracy: 0.8691
Epoch 461/500
accuracy: 0.8680
Epoch 462/500
accuracy: 0.8689
Epoch 463/500
accuracy: 0.8683
Epoch 464/500
accuracy: 0.8664
Epoch 465/500
accuracy: 0.8685
```

```
Epoch 466/500
accuracy: 0.8679
Epoch 467/500
accuracy: 0.8670
Epoch 468/500
accuracy: 0.8680
Epoch 469/500
accuracy: 0.8675
Epoch 470/500
accuracy: 0.8669
Epoch 471/500
250/250 [============ ] - 1s 2ms/step - loss: 0.3225 -
accuracy: 0.8684
Epoch 472/500
accuracy: 0.8687
Epoch 473/500
accuracy: 0.8684
Epoch 474/500
accuracy: 0.8676
Epoch 475/500
accuracy: 0.8669
Epoch 476/500
accuracy: 0.8675
Epoch 477/500
accuracy: 0.8668
Epoch 478/500
accuracy: 0.8694
Epoch 479/500
accuracy: 0.8687
Epoch 480/500
accuracy: 0.8681
Epoch 481/500
accuracy: 0.8676
```

```
Epoch 482/500
accuracy: 0.8686
Epoch 483/500
accuracy: 0.8683
Epoch 484/500
accuracy: 0.8687
Epoch 485/500
accuracy: 0.8679
Epoch 486/500
accuracy: 0.8686
Epoch 487/500
250/250 [=========== ] - Os 2ms/step - loss: 0.3229 -
accuracy: 0.8664
Epoch 488/500
accuracy: 0.8685
Epoch 489/500
accuracy: 0.8686
Epoch 490/500
accuracy: 0.8685
Epoch 491/500
accuracy: 0.8674
Epoch 492/500
accuracy: 0.8671
Epoch 493/500
accuracy: 0.8665
Epoch 494/500
accuracy: 0.8679
Epoch 495/500
accuracy: 0.8690
Epoch 496/500
accuracy: 0.8675
Epoch 497/500
accuracy: 0.8671
```

```
Epoch 498/500
    accuracy: 0.8679
    Epoch 499/500
    250/250 [============ ] - 1s 2ms/step - loss: 0.3222 -
    accuracy: 0.8690
    Epoch 500/500
    accuracy: 0.8681
[40]: <keras.callbacks.History at 0x7e24ec2819c0>
[41]: print(ann.predict(sc.transform([[1,0,0,600,1,40,3,60000,2,1,1,50000]]))>0.5)
    1/1 [======] - Os 23ms/step
    [[False]]
[44]: y_pred=ann.predict(X_test)
    y_pred=(y_pred>0.5)
    print(np.concatenate((y_pred.reshape(len(y_pred),1), Y_test.
     →reshape(len(Y_test),1)),1))
    63/63 [======== ] - Os 1ms/step
    [[0 0]]
     [0 0]
     [0 0]
     [0 0]
     [0 1]
     [0 0]]
[45]: from sklearn.metrics import confusion_matrix,accuracy_score
    cm=confusion_matrix(Y_test,y_pred)
    print(cm)
    accuracy_score(Y_test,y_pred)
    [[1540
           49]
     [ 230 181]]
[45]: 0.8605
[]:
```