# Load the TensorBoard notebook extension
%load\_ext tensorboard



The tensorboard extension is already loaded. To reload it, use: %reload\_ext tensorboard

## Import libraries:

```
import tensorflow as tf
import datetime, os
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import sys
import keras
from keras.models import Sequential
from keras.layers import Dense
# !pip install tensorflow==2.0.0-alpha0
np.set_printoptions(threshold=sys.maxsize)
```

## Import Data

```
dataset = pd.read_csv('./bp1.csv')
X = dataset.iloc[:,3:13].values
y = dataset.iloc[:,13].values
```

## Preprocessing

```
from sklearn.preprocessing import LabelEncoder
label_encoder_X = LabelEncoder()
X[:, 1] = label_encoder_X.fit_transform(X[:, 1])
X[:, 2] = label_encoder_X.fit_transform(X[:, 2])

from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
columnTransformer = ColumnTransformer([("encoder", OneHotEncoder(), [1])], remainder='pass
X = np.array(columnTransformer.fit_transform(X), dtype=np.str)
X = X[:, 1:]

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)

from sklearn.preprocessing import StandardScaler
sc_x = StandardScaler()
```

```
X_train = sc_x.fit_transform(X_train)
X test = sc x.transform(X test)
```

#### Create Model

```
classifier = Sequential()
classifier.add(Dense(input_shape=(11,), units = 6, kernel_initializer = 'random_uniform',
classifier.add(Dense(units = 10, kernel_initializer = 'random_uniform', activation = 'reluclassifier.add(Dense(units = 1, kernel_initializer = 'random_uniform', activation = 'sigmc classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy' # classifier.fit(X_train, y_train, batch_size = 10, epochs = 100)
```

#### Train the model



```
Epoch 1/100
 2/800 [.....] - ETA: 29s - loss: 0.6932 - accuracy: 0.650
800/800 [================= ] - 1s 1ms/step - loss: 0.4721 - accuracy: 0.
Epoch 2/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4231 - accuracy: 0.
Epoch 3/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4163 - accuracy: 0.
Epoch 4/100
800/800 [============= ] - 1s 1ms/step - loss: 0.4126 - accuracy: 0.
Epoch 5/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4104 - accuracy: 0.
Epoch 6/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4085 - accuracy: 0.
Epoch 7/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4069 - accuracy: 0.
Epoch 8/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4050 - accuracy: 0.
Epoch 9/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.4048 - accuracy: 0.
Epoch 10/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4033 - accuracy: 0.
Epoch 11/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4028 - accuracy: 0.
Epoch 12/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.4024 - accuracy: 0.
Epoch 13/100
800/800 [============= ] - 1s 1ms/step - loss: 0.4017 - accuracy: 0.
Epoch 14/100
800/800 [============= ] - 1s 1ms/step - loss: 0.4012 - accuracy: 0.
Epoch 15/100
800/800 [============ ] - 1s 1ms/step - loss: 0.4006 - accuracy: 0.
Epoch 16/100
800/800 [============= ] - 1s 1ms/step - loss: 0.4002 - accuracy: 0.
Epoch 17/100
800/800 [============= ] - 1s 1ms/step - loss: 0.4003 - accuracy: 0.
Epoch 18/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3995 - accuracy: 0.
Epoch 19/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3992 - accuracy: 0.
Epoch 20/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3985 - accuracy: 0.
Epoch 21/100
800/800 [=============== ] - 1s 1ms/step - loss: 0.3978 - accuracy: 0.
Epoch 22/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3986 - accuracy: 0.
Epoch 23/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3978 - accuracy: 0.
Epoch 24/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3979 - accuracy: 0.
Epoch 25/100
800/800 [============== ] - 1s 1ms/step - loss: 0.3977 - accuracy: 0.
Epoch 26/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3978 - accuracy: 0.
Epoch 27/100
800/800 [================= ] - 1s 1ms/step - loss: 0.3979 - accuracy: 0.
Epoch 28/100
800/800 [================= ] - 1s 1ms/step - loss: 0.3973 - accuracy: 0.
Epoch 29/100
Epoch 30/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3971 - accuracy: 0.
```

```
Epoch 31/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3965 - accuracy: 0.
Epoch 32/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3964 - accuracy: 0.
Epoch 33/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3965 - accuracy: 0.
Epoch 34/100
Epoch 35/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3962 - accuracy: 0.
Epoch 36/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3962 - accuracy: 0.
Epoch 37/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3963 - accuracy: 0.
Epoch 38/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3960 - accuracy: 0.
Epoch 39/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3963 - accuracy: 0.
Epoch 40/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3959 - accuracy: 0.
Epoch 41/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3962 - accuracy: 0.
Epoch 42/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3957 - accuracy: 0.
Epoch 43/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3959 - accuracy: 0.
Epoch 44/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3957 - accuracy: 0.
Epoch 45/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3959 - accuracy: 0.
Epoch 46/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3958 - accuracy: 0.
Epoch 47/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3956 - accuracy: 0.
Epoch 48/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3955 - accuracy: 0.
Epoch 49/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3950 - accuracy: 0.
Epoch 50/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3949 - accuracy: 0.
Epoch 51/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3947 - accuracy: 0.
Epoch 52/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3956 - accuracy: 0.
Epoch 53/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3953 - accuracy: 0.
Epoch 54/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3957 - accuracy: 0.
Epoch 55/100
800/800 [============== ] - 1s 1ms/step - loss: 0.3955 - accuracy: 0.
Epoch 56/100
800/800 [================= ] - 1s 1ms/step - loss: 0.3956 - accuracy: 0.
Epoch 57/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3953 - accuracy: 0.
Epoch 58/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3952 - accuracy: 0.
Epoch 59/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3955 - accuracy: 0.
Epoch 60/100
Epoch 61/100
```

```
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                                             1000. 0.000 accaracy. 0.
Epoch 62/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3949 - accuracy: 0.
Epoch 63/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3952 - accuracy: 0.
Epoch 64/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3948 - accuracy: 0.
Epoch 65/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3951 - accuracy: 0.
Epoch 66/100
Epoch 67/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3952 - accuracy: 0.
Epoch 68/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3951 - accuracy: 0.
Epoch 69/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3943 - accuracy: 0.
Epoch 70/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3949 - accuracy: 0.
Epoch 71/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3953 - accuracy: 0.
Epoch 72/100
800/800 [============== ] - 1s 1ms/step - loss: 0.3948 - accuracy: 0.
Epoch 73/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3952 - accuracy: 0.
Epoch 74/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3951 - accuracy: 0.
Epoch 75/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3947 - accuracy: 0.
Epoch 76/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3946 - accuracy: 0.
Epoch 77/100
800/800 [=========== ] - 1s 1ms/step - loss: 0.3952 - accuracy: 0.
Epoch 78/100
Epoch 79/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3946 - accuracy: 0.
Epoch 80/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3942 - accuracy: 0.
Epoch 81/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3953 - accuracy: 0.
Epoch 82/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3944 - accuracy: 0.
Epoch 83/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3944 - accuracy: 0.
Epoch 84/100
800/800 [============== ] - 1s 1ms/step - loss: 0.3944 - accuracy: 0.
Epoch 85/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3946 - accuracy: 0.
Epoch 86/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3951 - accuracy: 0.
Epoch 87/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3945 - accuracy: 0.
Epoch 88/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3948 - accuracy: 0.
Epoch 89/100
800/800 [============ ] - 1s 1ms/step - loss: 0.3943 - accuracy: 0.
Epoch 90/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3942 - accuracy: 0.
Epoch 91/100
800/800 [============= ] - 1s 1ms/step - loss: 0.3942 - accuracy: 0.
Epoch 92/100
```

```
classifier.compile(optimizer = 'adam', loss = 'binary crossentropy', metrics = ['accurac
  logdir = os.path.join("logs", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
  tensorboard_callback = tf.keras.callbacks.TensorBoard(logdir, histogram_freq=1)
  classifier.fit(x=X_train,
           y=y_train,
           batch_size=8,
            epochs=200,
            validation_data=(X_test, y_test),
            callbacks=[tensorboard_callback])
train_model()
```



Reusing TensorBoard on port 6006 (pid 558), started 2:48:13 ago. (Use '!kill 558' to

TensorBoard SCALARS GRAPHS INACTIVE

As shown above, Tensorboard has visualized the accuracy of out model and the cost function (J(theta)). as the epoch increases, the value of the cost function decreases; which means our model predicts correctly than before. therefore, the accuracy of the model will increase as epoch increases. this increasement in accuracy was observed at both train and validation data.

with Smoothing option at the left section, we can zoom in or zoom out on the details of the changes in epoch\_accuracy and epoch\_loss curves. as Smoothing value increases, the curves will be smoother and as Smoothing value decreases, the curves will be sharper and display the details of the changes more accurate. what can be said about the oscillation of train and test data in epoch\_accuracy is that the oscillations in test data is more than the trains' one. this comparison can be different in other models and other data with respect to the nature of the data and also the behavior of the model. the remarkable point in epoch\_loss is that the loss error in test data is less than the loss error in train data which means that the model performs better on test data than the train data. this better performance is not general in machine learning projects.

# Second model(more epochs, more bath size, same NN)

```
70200802-222/10/train
classifier = Sequential()
classifier.add(Dense(input_shape=(11,), units = 6, kernel_initializer = 'random_uniform',
classifier.add(Dense(units = 10, kernel initializer = 'random uniform', activation = 'relu
classifier.add(Dense(units = 1, kernel_initializer = 'random_uniform', activation = 'sigmc
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'
         | U ZUZUU8U3-ZZ4Z18/1rain
                                             0.34
def train model():
 # model = create model()
  classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accurac
 logdir = os.path.join("logs", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
  tensorboard callback = tf.keras.callbacks.TensorBoard(logdir, histogram freq=1)
  classifier.fit(x=X_train,
           y=y_train,
           batch_size=64,
           epochs=200,
           validation data=(X test, y test),
           callbacks=[tensorboard callback])
train model()
```

#### Fourth model

```
classifier = Sequential()
classifier.add(Dense(input_shape=(11,), units = 16, kernel_initializer = 'random_uniform',
classifier.add(Dense(units = 8, kernel_initializer = 'random_uniform', activation = 'relu'
classifier.add(Dense(units = 8, kernel_initializer = 'random_uniform', activation = 'relu'
classifier.add(Dense(units = 1, kernel_initializer = 'random_uniform', activation = 'sigmc
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'
def train_model():
 # model = create_model()
  classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accurac
 logdir = os.path.join("logs", datetime.datetime.now().strftime("%Y%m%d-%H%M%S"))
 tensorboard callback = tf.keras.callbacks.TensorBoard(logdir, histogram freq=1)
 classifier.fit(x=X_train,
           y=y_train,
           batch_size=2,
           epochs=200,
           validation_data=(X_test, y_test),
            callbacks=[tensorboard_callback])
train_model()
```



```
Epoch 1/200
2/125 [.....] - ETA: 4s - loss: 0.6930 - accuracy: 0.5234
Epoch 2/200
Epoch 3/200
Epoch 4/200
Epoch 5/200
Epoch 6/200
Epoch 7/200
125/125 [============== ] - 0s 2ms/step - loss: 0.4204 - accuracy: 0.
Epoch 8/200
Epoch 9/200
Epoch 10/200
Epoch 11/200
Epoch 12/200
Epoch 13/200
Epoch 14/200
Epoch 15/200
Epoch 16/200
Epoch 17/200
Epoch 18/200
Epoch 19/200
Epoch 20/200
125/125 [============] - 0s 2ms/step - loss: 0.3964 - accuracy: 0.
Epoch 21/200
Epoch 22/200
Epoch 23/200
Epoch 24/200
Epoch 25/200
Epoch 26/200
Epoch 27/200
Epoch 28/200
Epoch 29/200
125/125 [============] - 0s 1ms/step - loss: 0.3921 - accuracy: 0.
Epoch 30/200
```

```
Epoch 31/200
Epoch 32/200
Epoch 33/200
Epoch 34/200
Epoch 35/200
Epoch 36/200
Epoch 37/200
Epoch 38/200
Epoch 39/200
125/125 [============== ] - 0s 1ms/step - loss: 0.3903 - accuracy: 0.
Epoch 40/200
Epoch 41/200
Epoch 42/200
Epoch 43/200
Epoch 44/200
Epoch 45/200
Epoch 46/200
Epoch 47/200
Epoch 48/200
Epoch 49/200
Epoch 50/200
Epoch 51/200
Epoch 52/200
Epoch 53/200
Epoch 54/200
Epoch 55/200
Epoch 56/200
Epoch 57/200
Epoch 58/200
Epoch 59/200
Epoch 60/200
Epoch 61/200
```

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Epoch 62/200
Epoch 63/200
Epoch 64/200
Epoch 65/200
Epoch 66/200
Epoch 67/200
Epoch 68/200
Epoch 69/200
Epoch 70/200
Epoch 71/200
Epoch 72/200
Epoch 73/200
Epoch 74/200
Epoch 75/200
Epoch 76/200
125/125 [============== ] - 0s 1ms/step - loss: 0.3879 - accuracy: 0.
Epoch 77/200
Epoch 78/200
Epoch 79/200
Epoch 80/200
Epoch 81/200
Epoch 82/200
Epoch 83/200
Epoch 84/200
Epoch 85/200
Epoch 86/200
Epoch 87/200
Epoch 88/200
Epoch 89/200
Epoch 90/200
Epoch 91/200
Epoch 92/200
```

```
Epoch 93/200
Epoch 94/200
Epoch 95/200
Epoch 96/200
Epoch 97/200
Epoch 98/200
Epoch 99/200
Epoch 100/200
Epoch 101/200
Epoch 102/200
Epoch 103/200
Epoch 104/200
Epoch 105/200
Epoch 106/200
Epoch 107/200
Epoch 108/200
Epoch 109/200
Epoch 110/200
Epoch 111/200
Epoch 112/200
Epoch 113/200
Epoch 114/200
Epoch 115/200
Epoch 116/200
Epoch 117/200
Epoch 118/200
Epoch 119/200
Epoch 120/200
Epoch 121/200
Epoch 122/200
Epoch 123/200
```

```
Epoch 124/200
Epoch 125/200
Epoch 126/200
Epoch 127/200
Epoch 128/200
Epoch 129/200
Epoch 130/200
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Epoch 144/200
Epoch 145/200
Epoch 146/200
Epoch 147/200
Epoch 148/200
Epoch 149/200
Epoch 150/200
Epoch 151/200
Epoch 152/200
Epoch 153/200
```

```
Epoch 154/200
Epoch 155/200
Epoch 156/200
125/125 [============== ] - 0s 1ms/step - loss: 0.3860 - accuracy: 0.
Epoch 157/200
Epoch 158/200
Epoch 159/200
Epoch 160/200
Epoch 161/200
125/125 [============== ] - 0s 2ms/step - loss: 0.3860 - accuracy: 0.
Epoch 162/200
Epoch 163/200
Epoch 164/200
Epoch 165/200
Epoch 166/200
Epoch 167/200
125/125 [============== ] - 0s 1ms/step - loss: 0.3860 - accuracy: 0.
Epoch 168/200
Epoch 169/200
Epoch 170/200
125/125 [============== ] - 0s 1ms/step - loss: 0.3860 - accuracy: 0.
Epoch 171/200
Epoch 172/200
125/125 [============== ] - 0s 1ms/step - loss: 0.3860 - accuracy: 0.
Epoch 173/200
Epoch 174/200
Epoch 175/200
Epoch 176/200
Epoch 177/200
Epoch 178/200
Epoch 179/200
Epoch 180/200
Epoch 181/200
Epoch 182/200
Epoch 183/200
Epoch 184/200
```

```
Epoch 185/200
Epoch 186/200
Epoch 187/200
Epoch 188/200
Epoch 189/200
Epoch 190/200
Epoch 191/200
Epoch 192/200
Epoch 193/200
Epoch 194/200
Epoch 195/200
Epoch 196/200
Epoch 197/200
Epoch 198/200
Epoch 199/200
Epoch 200/200
```

```
y_pred = classifier.predict(X_test)
y pred = (y pred > 0.5)
from sklearn.metrics import confusion matrix
cm = confusion_matrix(y_test, y_pred)
cm
print((cm[0][0] + cm[1][1])/2000)
    0.826
```

%tensorboard --logdir logs



one of the most important problem I deal with in this exercise, is overfitting, if the accuracy of he model on the training set is considerably more than the model accuracy on the test set, the it's said that the model overfits, it means that the model learns the training the training set very accurate but fails the learning of the test set in practice, this a common problem in machine learning. one important point I understand is it's better to use fewer mini-batch sizes. this tends to stochastic gradient descent(vs batch gradient descent) if we use mini-batch size = 1. but more sizes is sufficient in most cases.

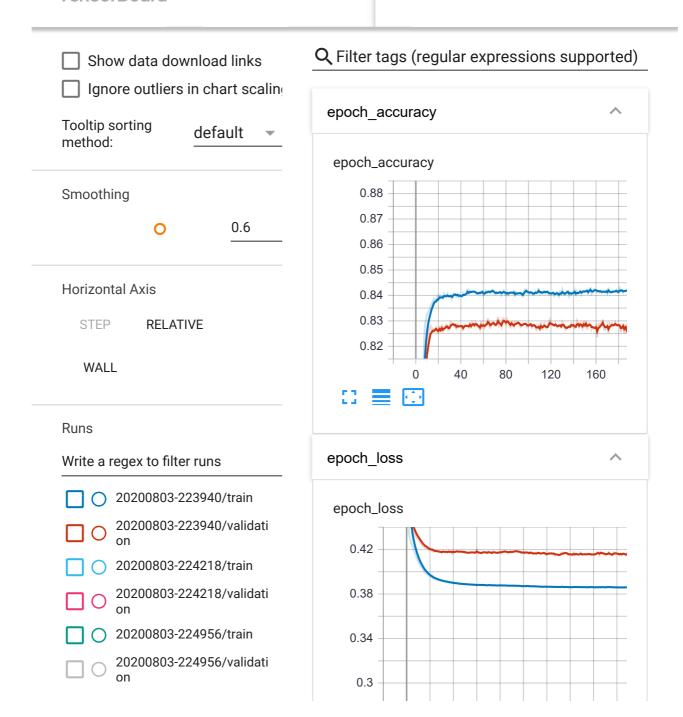
it's necessary to remember the improvement of the performance of a neural network depends on many hyperparameters such as learning rate, #iterations, regularization parameter,... and techniques such as dropout(to prevent overfitting), optimizer type(such as momentum, adam, RMSprop), regularization(to prevent overfitting), mini-batch gradient descent, #epochs, the complexity of the model, etc. if we select more suitable features and also get more data, it's very useful to improve the neural network performance.

according to said above, to improve the performance of the model considerably, we need to use mose these method in a good way.

Reusing TensorBoard on port 6006 (pid 558), started 2:46:45 ago. (Use '!kill 558' to

**TensorBoard** 

**SCALARS GRAPHS**  **INACTIVE** 



# Third model(more epoch, fewer bath size, more complex NN)

```
classifier = Sequential()
classifier.add(Dense(input_shape=(11,), units = 16, kernel_initializer = 'random_uniform',
classifier.add(Dense(units = 8, kernel_initializer = 'random_uniform', activation = 'relu'
classifier.add(Dense(units = 1, kernel_initializer = 'random_uniform', activation = 'sigmc
classifier.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'
def train_model():
```

```
Epoch 1/200
 Epoch 2/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3719 - accuracy:
Epoch 3/200
Epoch 4/200
Epoch 5/200
Epoch 6/200
Epoch 7/200
Epoch 8/200
Epoch 9/200
Epoch 10/200
Epoch 11/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3337 - accuracy:
Epoch 12/200
1000/1000 [============== ] - 1s 1ms/step - loss: 0.3337 - accuracy:
Epoch 13/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3333 - accuracy:
Epoch 14/200
Epoch 15/200
Epoch 16/200
Epoch 17/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3318 - accuracy:
Epoch 18/200
Epoch 19/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3308 - accuracy:
Epoch 20/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3298 - accuracy:
Epoch 21/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3307 - accuracy:
Epoch 22/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3302 - accuracy:
Epoch 23/200
Epoch 24/200
Epoch 25/200
Epoch 26/200
Epoch 27/200
Epoch 28/200
Epoch 29/200
1000/1000 [================= ] - 1s 1ms/step - loss: 0.3274 - accuracy:
Epoch 30/200
```

```
Epoch 31/200
Epoch 32/200
Epoch 33/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3274 - accuracy:
Epoch 34/200
1000/1000 [=================== ] - 1s 1ms/step - loss: 0.3275 - accuracy:
Epoch 35/200
Epoch 36/200
Epoch 37/200
Epoch 38/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3258 - accuracy:
Epoch 39/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3267 - accuracy:
Epoch 40/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3258 - accuracy:
Epoch 41/200
1000/1000 [============== ] - 1s 1ms/step - loss: 0.3256 - accuracy:
Epoch 42/200
Epoch 43/200
Epoch 44/200
Epoch 45/200
1000/1000 [================== ] - 1s 1ms/step - loss: 0.3244 - accuracy:
Epoch 46/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3249 - accuracy:
Epoch 47/200
Epoch 48/200
Epoch 49/200
Epoch 50/200
Epoch 51/200
Epoch 52/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3240 - accuracy:
Epoch 53/200
Epoch 54/200
Epoch 55/200
Epoch 56/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3232 - accuracy:
Epoch 57/200
Epoch 58/200
Epoch 59/200
1000/1000 [============== ] - 1s 1ms/step - loss: 0.3225 - accuracy:
Epoch 60/200
Epoch 61/200
```

```
-000/ -000 I
                      1000. 0.0222 accaracy.
Epoch 62/200
Epoch 63/200
Epoch 64/200
Epoch 65/200
Epoch 66/200
Epoch 67/200
Epoch 68/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3214 - accuracy:
Epoch 69/200
Epoch 70/200
Epoch 71/200
Epoch 72/200
Epoch 73/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3206 - accuracy:
Epoch 74/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3204 - accuracy:
Epoch 75/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3195 - accuracy:
Epoch 76/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3200 - accuracy:
Epoch 77/200
Epoch 78/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3200 - accuracy:
Epoch 79/200
Epoch 80/200
Epoch 81/200
Epoch 82/200
Epoch 83/200
Epoch 84/200
Epoch 85/200
Epoch 86/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3197 - accuracy:
Epoch 87/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3188 - accuracy:
Epoch 88/200
Epoch 89/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3188 - accuracy:
Epoch 90/200
Epoch 91/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3174 - accuracy:
Epoch 92/200
```

```
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3176 - accuracy:
Epoch 93/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3178 - accuracy:
Epoch 94/200
1000/1000 [============== ] - 1s 1ms/step - loss: 0.3176 - accuracy:
Epoch 95/200
Epoch 96/200
Epoch 97/200
Epoch 98/200
Epoch 99/200
Epoch 100/200
Epoch 101/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3166 - accuracy:
Epoch 102/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3159 - accuracy:
Epoch 103/200
Epoch 104/200
Epoch 105/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3163 - accuracy:
Epoch 106/200
Epoch 107/200
Epoch 108/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3159 - accuracy:
Epoch 109/200
Epoch 110/200
Epoch 111/200
Epoch 112/200
Epoch 113/200
Epoch 114/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3152 - accuracy:
Epoch 115/200
Epoch 116/200
Epoch 117/200
Epoch 118/200
Epoch 119/200
Epoch 120/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3146 - accuracy:
Epoch 121/200
1000/1000 [============== ] - 1s 1ms/step - loss: 0.3146 - accuracy:
Epoch 122/200
Epoch 123/200
```

```
Epoch 124/200
Epoch 125/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3143 - accuracy:
Epoch 126/200
Epoch 127/200
Epoch 128/200
1000/1000 [============== ] - 1s 1ms/step - loss: 0.3146 - accuracy:
Epoch 129/200
Epoch 130/200
Epoch 131/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3139 - accuracy:
Epoch 132/200
Epoch 133/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3136 - accuracy:
Epoch 134/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3140 - accuracy:
Epoch 135/200
Epoch 136/200
Epoch 137/200
Epoch 138/200
Epoch 139/200
Epoch 140/200
1000/1000 [================ ] - 1s 1ms/step - loss: 0.3131 - accuracy:
Epoch 141/200
Epoch 142/200
Epoch 143/200
1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3130 - accuracy:
Epoch 144/200
Epoch 145/200
Epoch 146/200
Epoch 147/200
Epoch 148/200
Epoch 149/200
Epoch 150/200
Epoch 151/200
Epoch 152/200
Epoch 153/200
```

```
Epoch 154/200
  1000/1000 [================ ] - 1s 1ms/step - loss: 0.3120 - accuracy:
  Epoch 155/200
  Epoch 156/200
  Epoch 157/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3119 - accuracy:
  Epoch 158/200
  Epoch 159/200
  Epoch 160/200
  1000/1000 [================ ] - 1s 1ms/step - loss: 0.3110 - accuracy:
  Epoch 161/200
  Epoch 162/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3110 - accuracy:
  Epoch 163/200
  1000/1000 [================ ] - 1s 1ms/step - loss: 0.3110 - accuracy:
  Epoch 164/200
  1000/1000 [============== ] - 1s 1ms/step - loss: 0.3110 - accuracy:
  Epoch 165/200
  Epoch 166/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3105 - accuracy:
  Epoch 167/200
  Epoch 168/200
  Epoch 169/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3104 - accuracy:
  Epoch 170/200
  Epoch 171/200
  Epoch 172/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3106 - accuracy:
  Epoch 173/200
  Epoch 174/200
  Epoch 175/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3100 - accuracy:
  Epoch 176/200
  Epoch 177/200
  Epoch 178/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3093 - accuracy:
  Epoch 179/200
  Epoch 180/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3101 - accuracy:
  Epoch 181/200
  1000/1000 [================ ] - 1s 1ms/step - loss: 0.3101 - accuracy:
  Epoch 182/200
  1000/1000 [=============== ] - 1s 1ms/step - loss: 0.3099 - accuracy:
y_pred = classifier.predict(X_test)
y_pred = (y_pred > 0.5)
```

https://colab.research.google.com/github/tensorflow/tensorboard/blob/master/docs/tensorboard\_in\_notebooks.ipynb#scrollTo=FIYq61Xzfvg-&pr... 22/33

from sklearn.metrics import confusion\_matrix cm = confusion\_matrix(y\_test, y\_pred)  $\mathsf{cm}$ print((cm[0][0] + cm[1][1])/2000)

0.851

Epoch 189/200

%tensorboard --logdir logs

Reusing TensorBoard on port 6006 (pid 558), started 2:45:18 ago. (Use '!kill 558' to

**TensorBoard** 

**SCALARS** 

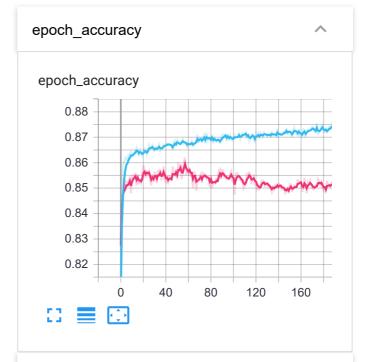
**GRAPHS** 

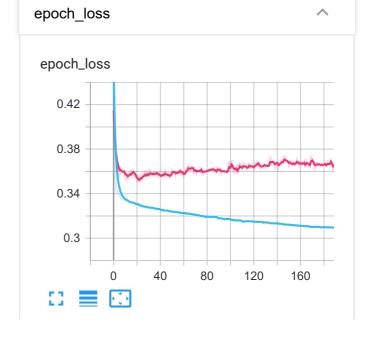
**INACTIVE** 

Sho	w data do	wnload link	S
☐ Igno	ore outlier	s in chart so	calin
Tooltip s method:		default	_
Smoothi	ing		
	0	0.6	
Horizont	tal Axis		
STEP	RELA	TIVE	
WALI	L		
Runs			
Write a r	egex to filt	er runs	
	20200803-	-223940/train	
	20200803- on	-223940/valid	ati
	20200803-	-224218/train	
	20200803- on	-224218/valid	ati
	20200803-	-224956/train	
	20200803- on	-224956/valid	ati
	TOGGLE AI	LL RUNS	

logs

# Q Filter tags (regular expressions supported)





```
Epoch 1/200
 2/4000 [.....] - ETA: 2:31 - loss: 0.6929 - accuracy: 0.
Epoch 2/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.4144 - accuracy:
Epoch 3/200
Epoch 4/200
Epoch 5/200
Epoch 6/200
Epoch 7/200
Epoch 8/200
Epoch 9/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.4020 - accuracy:
Epoch 10/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.4012 - accuracy:
Epoch 11/200
Epoch 12/200
Epoch 13/200
Epoch 14/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.4004 - accuracy:
Epoch 15/200
Epoch 16/200
4000/4000 [=============== ] - 6s 1ms/step - loss: 0.3990 - accuracy:
Epoch 17/200
Epoch 18/200
Epoch 19/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3979 - accuracy:
Epoch 20/200
Epoch 21/200
Epoch 22/200
Epoch 23/200
Epoch 24/200
Epoch 25/200
Epoch 26/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3942 - accuracy:
Epoch 27/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3936 - accuracy:
Epoch 28/200
Epoch 29/200
Epoch 30/200
```

```
Epoch 31/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3931 - accuracy:
Epoch 32/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3934 - accuracy:
Epoch 33/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3932 - accuracy:
Epoch 34/200
Epoch 35/200
Epoch 36/200
Epoch 37/200
Epoch 38/200
Epoch 39/200
Epoch 40/200
Epoch 41/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3914 - accuracy:
Epoch 42/200
Epoch 43/200
Epoch 44/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3905 - accuracy:
Epoch 45/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3919 - accuracy:
Epoch 46/200
Epoch 47/200
Epoch 48/200
Epoch 49/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3909 - accuracy:
Epoch 50/200
Epoch 51/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3905 - accuracy:
Epoch 52/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3907 - accuracy:
Epoch 53/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3900 - accuracy:
Epoch 54/200
Epoch 55/200
Epoch 56/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3901 - accuracy:
Epoch 57/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3906 - accuracy:
Epoch 58/200
Epoch 59/200
Epoch 60/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3902 - accuracy:
Epoch 61/200
```

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1000. 0.0000 acca.acy.
Epoch 62/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3901 - accuracy:
Epoch 63/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3896 - accuracy:
Epoch 64/200
Epoch 65/200
Epoch 66/200
Epoch 67/200
Epoch 68/200
Epoch 69/200
Epoch 70/200
Epoch 71/200
Epoch 72/200
Epoch 73/200
Epoch 74/200
Epoch 75/200
Epoch 76/200
Epoch 77/200
Epoch 78/200
Epoch 79/200
Epoch 80/200
Epoch 81/200
Epoch 82/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3404 - accuracy:
Epoch 83/200
Epoch 84/200
Epoch 85/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3330 - accuracy:
Epoch 86/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3317 - accuracy:
Epoch 87/200
Epoch 88/200
Epoch 89/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3301 - accuracy:
Epoch 90/200
Epoch 91/200
Epoch 92/200
```

```
Epoch 93/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3279 - accuracy:
Epoch 94/200
Epoch 95/200
Epoch 96/200
Epoch 97/200
Epoch 98/200
Epoch 99/200
Epoch 100/200
Epoch 101/200
Epoch 102/200
Epoch 103/200
Epoch 104/200
Epoch 105/200
Epoch 106/200
Epoch 107/200
Epoch 108/200
Epoch 109/200
Epoch 110/200
Epoch 111/200
Epoch 112/200
Epoch 113/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3231 - accuracy:
Epoch 114/200
Epoch 115/200
Epoch 116/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3255 - accuracy:
Epoch 117/200
Epoch 118/200
Epoch 119/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3248 - accuracy:
Epoch 120/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3244 - accuracy:
Epoch 121/200
Epoch 122/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3239 - accuracy:
Epoch 123/200
```

```
Epoch 124/200
Epoch 125/200
Epoch 126/200
Epoch 127/200
Epoch 128/200
Epoch 129/200
Epoch 130/200
Epoch 131/200
Epoch 132/200
Epoch 133/200
Epoch 134/200
Epoch 135/200
Epoch 136/200
Epoch 137/200
Epoch 138/200
Epoch 139/200
Epoch 140/200
Epoch 141/200
Epoch 142/200
Epoch 143/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3212 - accuracy:
Epoch 144/200
Epoch 145/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3212 - accuracy:
Epoch 146/200
Epoch 147/200
Epoch 148/200
Epoch 149/200
Epoch 150/200
Epoch 151/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3205 - accuracy:
Epoch 152/200
Epoch 153/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3209 - accuracy:
```

```
Epoch 154/200
Epoch 155/200
Epoch 156/200
Epoch 157/200
Epoch 158/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3196 - accuracy:
Epoch 159/200
Epoch 160/200
Epoch 161/200
Epoch 162/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3207 - accuracy:
Epoch 163/200
Epoch 164/200
Epoch 165/200
Epoch 166/200
Epoch 167/200
Epoch 168/200
Epoch 169/200
Epoch 170/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3208 - accuracy:
Epoch 171/200
Epoch 172/200
Epoch 173/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3189 - accuracy:
Epoch 174/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3189 - accuracy:
Epoch 175/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3182 - accuracy:
Epoch 176/200
Epoch 177/200
4000/4000 [=============== ] - 5s 1ms/step - loss: 0.3184 - accuracy:
Epoch 178/200
Epoch 179/200
Epoch 180/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3193 - accuracy:
Epoch 181/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3191 - accuracy:
Epoch 182/200
Epoch 183/200
4000/4000 [============== ] - 5s 1ms/step - loss: 0.3189 - accuracy:
Epoch 184/200
```

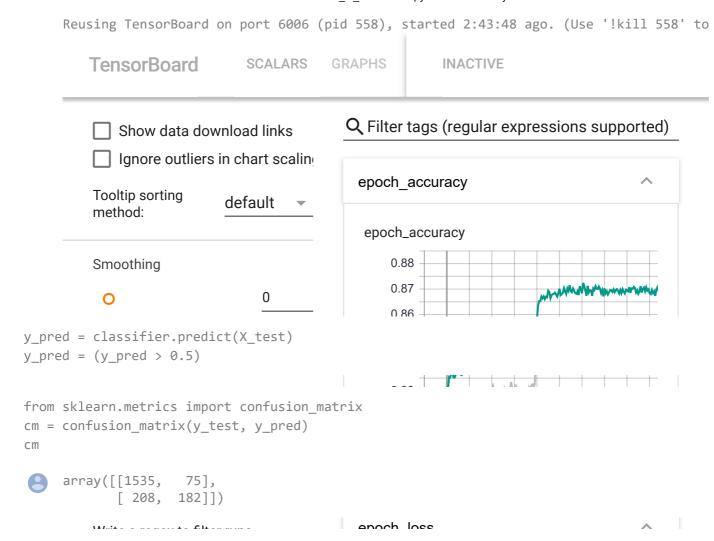
```
Epoch 185/200
 Epoch 186/200
 Epoch 187/200
 Epoch 188/200
 Epoch 189/200
 Epoch 190/200
 Epoch 191/200
 y_pred = classifier.predict(X_test)
y_pred = (y_pred > 0.5)
 Enach 101/200
from sklearn.metrics import confusion matrix
cm = confusion_matrix(y_test, y_pred)
print((cm[0][0] + cm[1][1])/2000)
 0.85
```



Lpoch 198/200

%tensorboard --logdir logs





In the first model, we have a neural network with 3 layers: layer 1 has 6 neuron units, layer 2 has 10 neuron units, and layer 3 or output layer has 1 neuron unit. the model is trained with minibatch size 10, and epochs = 100. our model is relatively simple. however, it work well in general.

In the second model, we have a neural network with 3 layers: layer 1 has 6 neuron units, layer 2 has 10 neuron units, and layer 3 or output layer has 1 neuron unit. the model is trained with minibatch size 64, and epochs = 200. in this model, we see a little bit increasement in training set accuracy but the test set accuracy got decreased a bit. this means that the increasement of the bacth size was not a good idea.

In the third model, we have a neural network with 3 layers: layer 1 has 16 neuron units, layer 2 has 8 neuron units, and layer 3 or output layer has 1 neuron unit. the model is trained with minibatch size 8, and epochs = 200. in this model, we have changed the num of hidden units in the hidden layers, and also decrease the batch size to 8. we see an increasement in both test set accuracy and training set accuracy.

In the fourth model, we have a neural network with 4 layers: layer 1 has 16 neuron units, layer 2 has 8 neuron units, and layer 3 has 8 neuron units, and layer 4 or output layer has 1 neuron unit. the model is trained with mini-batch size 2, and epochs = 200. in this model, we did our model more complex and add a hidden layer to it. and alse decrease the batch size, we see the training set accuracy increases but the test set accuracy is the same.