

Perceptron Model

```
In [ ]: import numpy as np
import pandas as pd
import sklearn
from sklearn.datasets import load_digits
```

```
In [ ]: digits = load_digits()
digits
```

```
Out[2]: {'data': array([[ 0.,  0.,  5., ...,  0.,  0.,  0.],
                        [ 0.,  0.,  0., ..., 10.,  0.,  0.],
                        [ 0.,  0.,  0., ..., 16.,  9.,  0.],
                        ...,
                        [ 0.,  0.,  1., ...,  6.,  0.,  0.],
                        [ 0.,  0.,  2., ..., 12.,  0.,  0.],
                        [ 0.,  0., 10., ..., 12.,  1.,  0.])),
         'target': array([0, 1, 2, ..., 8, 9, 8]),
         'frame': None,
         'feature_names': ['pixel_0_0',
                           'pixel_0_1',
                           'pixel_0_2',
                           'pixel_0_3',
                           'pixel_0_4',
                           'pixel_0_5',
                           'pixel_0_6',
                           'pixel_0_7',
                           'pixel_1_0',
                           'pixel_1_1',
                           ...],
         ...}
```

```
In [ ]: digits['data']
```

```
Out[3]: array([[ 0.,  0.,  5., ...,  0.,  0.,  0.],
                [ 0.,  0.,  0., ..., 10.,  0.,  0.],
                [ 0.,  0.,  0., ..., 16.,  9.,  0.],
                ...,
                [ 0.,  0.,  1., ...,  6.,  0.,  0.],
                [ 0.,  0.,  2., ..., 12.,  0.,  0.],
                [ 0.,  0., 10., ..., 12.,  1.,  0.]])
```

```
In [ ]: digits['target']
```

```
Out[4]: array([0, 1, 2, ..., 8, 9, 8])
```

```
In [ ]: x = digits.data
y = digits.target
```

```
In [ ]: #x = x/255.0
```

```
In [ ]: # split the data into training and test
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.25, r
```

```
In [ ]: # Building perceptron model
from sklearn.linear_model import Perceptron
```

```
In [ ]: perceptron_model = Perceptron()
perceptron_model.fit(x_train, y_train)
```

Out[9]: Perceptron()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```

In [ ]: print("What is the Traingin Accuracy of Perceptron Model :")
print(perceptron_model.score(x_train, y_train))

print("What is the Test Accuracy of Perceptron Model :")
print(perceptron_model.score(x_test, y_test))

predicted_train = perceptron_model.predict(x_train)
predicted_test = perceptron_model.predict(x_test)

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
print("Training Accuracy", accuracy_score(y_train, predicted_train))
print("Test Accuracy", accuracy_score(y_test, predicted_test))

print("classification_report Training")
print(classification_report(y_train, predicted_train))
print("classification_report Test")
print(classification_report(y_test, predicted_test))

```

What is the Traingin Accuracy of Perceptron Model :
0.9762435040831478

What is the Test Accuracy of Perceptron Model :
0.9688888888888889

Training Accuracy 0.9762435040831478

Test Accuracy 0.9688888888888889

classification_report Training

	precision	recall	f1-score	support
0	0.99	1.00	1.00	125
1	0.95	0.99	0.97	140
2	0.98	1.00	0.99	136
3	0.98	0.98	0.98	131
4	1.00	0.99	1.00	134
5	0.93	1.00	0.97	143
6	0.98	0.99	0.98	138
7	0.98	1.00	0.99	131
8	1.00	0.85	0.92	137
9	0.99	0.97	0.98	132
accuracy			0.98	1347
macro avg	0.98	0.98	0.98	1347
weighted avg	0.98	0.98	0.98	1347

classification_report Test

	precision	recall	f1-score	support
0	1.00	1.00	1.00	53
1	0.98	0.98	0.98	42
2	0.91	0.98	0.94	41
3	0.98	0.96	0.97	52
4	0.98	1.00	0.99	47
5	0.91	1.00	0.95	39
6	1.00	1.00	1.00	43
7	1.00	0.98	0.99	48
8	1.00	0.81	0.90	37
9	0.94	0.96	0.95	48
accuracy			0.97	450
macro avg	0.97	0.97	0.97	450
weighted avg	0.97	0.97	0.97	450

In []:

In []:

Regression Problem

```
In [ ]: import tensorflow as tf
from tensorflow import keras
from keras import Sequential
from keras.layers import Dense, Dropout, BatchNormalization
```

```
In [ ]: data = pd.read_csv("/content/boston.csv")
data.head()
```

Out[23]:

	CRIM	ZN	INDUS	CHAS	NX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	

```
In [ ]: data.isnull().sum()
```

Out[24]:

CRIM	0
ZN	0
INDUS	0
CHAS	0
NX	0
RM	0
AGE	0
DIS	0
RAD	0
TAX	0
PTRATIO	0
B	0
LSTAT	0
MEDV	0

dtype: int64

```
In [ ]: x = data.iloc[:, :-1]
y = data.iloc[:, -1]
```

```
In [ ]: x.head()
```

```
Out[26]:
```

	CRIM	ZN	INDUS	CHAS	NX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	L
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	

```
In [ ]: from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x = sc.fit_transform(x)
pd.DataFrame(x).head()
```

```
Out[27]:
```

	0	1	2	3	4	5	6	7	
0	-0.419782	0.284830	-1.287909	-0.272599	-0.144217	0.413672	-0.120013	0.140214	-0.982
1	-0.417339	-0.487722	-0.593381	-0.272599	-0.740262	0.194274	0.367166	0.557160	-0.867
2	-0.417342	-0.487722	-0.593381	-0.272599	-0.740262	1.282714	-0.265812	0.557160	-0.867
3	-0.416750	-0.487722	-1.306878	-0.272599	-0.835284	1.016303	-0.809889	1.077737	-0.752
4	-0.412482	-0.487722	-1.306878	-0.272599	-0.835284	1.228577	-0.511180	1.077737	-0.752

```
In [ ]: y.head()
```

```
Out[28]:
```

0	24.0
1	21.6
2	34.7
3	33.4
4	36.2

Name: MEDV, dtype: float64

```
In [ ]: from sklearn.model_selection import train_test_split
x_train,x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, ran
```

```
In [ ]: print(x_train.shape, y_train.shape, x_test.shape, y_test.shape )

(404, 13) (404,) (102, 13) (102,)
```

MultiLayer Perceptron Model - DNN

```
In [ ]: dnn = Sequential()
# add hidden layer 1
dnn.add(Dense(16, activation='relu', input_dim = 13))
# batch normalization
#dnn.add(BatchNormalization())
# dropout
#dnn.add(Dropout(0.25))
# add one more hidden layer
#dnn.add(Dense(8, activation='relu'))
# batch normalization
#dnn.add(BatchNormalization())
# dropout
#dnn.add(Dropout(0.5))
# output
dnn.add(Dense(1, activation='linear'))
# summary
dnn.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
dense_15 (Dense)	(None, 8)	112
batch_normalization_8 (Batch Normalization)	(None, 8)	32
dropout_6 (Dropout)	(None, 8)	0
dense_16 (Dense)	(None, 8)	72
batch_normalization_9 (Batch Normalization)	(None, 8)	32
dropout_7 (Dropout)	(None, 8)	0
dense_17 (Dense)	(None, 1)	9
Total params: 257 (1.00 KB)		
Trainable params: 225 (900.00 Byte)		
Non-trainable params: 32 (128.00 Byte)		

```
In [ ]: # compile the model while using optimization and loss function
dnn.compile(optimizer='sgd', loss='mean_squared_error')

# Fit the model
history = dnn.fit(x_train, y_train, epochs=500)
```

```
Epoch 1/500
13/13 [=====] - 6s 6ms/step - loss: 263.7253
Epoch 2/500
13/13 [=====] - 0s 4ms/step - loss: 109.8043
Epoch 3/500
13/13 [=====] - 0s 4ms/step - loss: 83.4480
Epoch 4/500
13/13 [=====] - 0s 4ms/step - loss: 77.0359
Epoch 5/500
13/13 [=====] - 0s 4ms/step - loss: 67.9864
Epoch 6/500
13/13 [=====] - 0s 4ms/step - loss: 62.2285
Epoch 7/500
13/13 [=====] - 0s 4ms/step - loss: 67.8151
Epoch 8/500
13/13 [=====] - 0s 5ms/step - loss: 69.2439
Epoch 9/500
13/13 [=====] - 0s 4ms/step - loss: 70.1299
Epoch 10/500
13/13 [=====] - 0s 4ms/step - loss: 70.3315
```

```
In [ ]: # Predict the test dataset  
y_pred = dnn.predict(x_test)  
y_pred
```

4/4 [=====] - 0s 3ms/step


```
Out[38]: array([[42.066048 ],
                [28.673164 ],
                [16.047989 ],
                [16.490643 ],
                [28.134983 ],
                [36.2645   ],
                [42.893303 ],
                [11.216604 ],
                [31.150734 ],
                [ 9.252087 ],
                [24.992077 ],
                [15.366667 ],
                [20.12103  ],
                [20.722178 ],
                [22.332483 ],
                [21.97967  ],
                [11.298435 ],
                [33.14695  ],
                [25.301653 ],
                [23.739754 ],
                [13.843197 ],
                [20.791662 ],
                [21.458355 ],
                [29.901642 ],
                [36.99926  ],
                [17.445225 ],
                [27.09676  ],
                [17.777788 ],
                [25.060944 ],
                [34.022118 ],
                [21.52371  ],
                [19.667759 ],
                [39.86638  ],
                [42.36988  ],
                [30.88499  ],
                [22.008015 ],
                [15.616453 ],
                [17.78113  ],
                [ 7.3795614],
                [26.07758  ],
                [22.365658 ],
                [20.86047  ],
                [41.318607 ],
                [15.815165 ],
                [21.978218 ],
                [22.592115 ],
                [30.622635 ],
                [16.55214  ],
                [24.264685 ],
                [23.215982 ],
                [37.48295  ],
                [43.706207 ],
                [21.787628 ],
                [17.050863 ],
                [32.200417 ],
                [ 8.377619 ],
                [20.678692 ],
                [17.705532 ],
                [21.615456 ],
                [20.649569 ],
                [33.85414  ],
```

```
[ 9.616957 ],  
[48.48142  ],  
[20.65918  ],  
[12.436285 ],  
[22.0219   ],  
[23.070957 ],  
[20.644348 ],  
[14.936278 ],  
[20.5262    ],  
[21.847637 ],  
[21.954939 ],  
[20.8123    ],  
[19.319645 ],  
[24.192919 ],  
[20.01855   ],  
[40.93      ],  
[12.7487755],  
[25.183353  ],  
[15.0503845],  
[16.093025  ],  
[18.678638  ],  
[28.624542  ],  
[14.727659  ],  
[13.854645  ],  
[20.466852  ],  
[21.5724    ],  
[29.666527  ],  
[22.34641   ],  
[21.232998  ],  
[14.41136   ],  
[13.176874  ],  
[25.100262  ],  
[34.81701   ],  
[ 7.779066  ],  
[41.445396  ],  
[12.45356   ],  
[33.16234   ],  
[ 7.682678  ],  
[21.435665  ],  
[37.624245  ],  
[20.483479  ]], dtype=float32)
```

```
In [ ]: print(y_pred[0:10])
print("*****"*5)
print(y_test[0:10])
```

```
[[42.066048]
 [28.673164]
 [16.047989]
 [16.490643]
 [28.134983]
 [36.2645  ]
 [42.893303]
 [11.216604]
 [31.150734]
 [ 9.252087]]
*****
195    50.0
4      36.2
434    11.7
458    14.9
39     30.8
304    36.1
225    50.0
32     13.2
157    41.3
404     8.5
Name: MEDV, dtype: float64
```

```
In [ ]: from sklearn.metrics import r2_score
```

```
In [ ]: print(r2_score(y_test, y_pred))
```

```
0.742262016726801
```

```
In [ ]:
```

```
In [ ]:
```

Classification Problem

```
In [ ]: import pandas as pd
dataset = pd.read_csv("/content/Churn_Modelling.csv")
dataset.head()
```

```
Out[2]:
```

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Bal
0	1	15634602	Hargrave	619	France	Female	42	2	
1	2	15647311	Hill	608	Spain	Female	41	1	8380
2	3	15619304	Onio	502	France	Female	42	8	15966
3	4	15701354	Boni	699	France	Female	39	1	
4	5	15737888	Mitchell	850	Spain	Female	43	2	12551

```
In [ ]: dataset['Exited'].value_counts()
```

```
Out[3]: 0    7963
        1    2037
        Name: Exited, dtype: int64
```

```
In [ ]: dataset = dataset.iloc[:,3:]
        dataset.head()
```

```
Out[4]:
```

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	Is
0	619	France	Female	42	2	0.00	1	1	
1	608	Spain	Female	41	1	83807.86	1	0	
2	502	France	Female	42	8	159660.80	3	1	
3	699	France	Female	39	1	0.00	2	0	
4	850	Spain	Female	43	2	125510.82	1	1	

```
In [ ]: dataset.isnull().sum()
```

```
Out[61]: CreditScore      0
         Geography      0
         Gender         0
         Age           0
         Tenure        0
         Balance       0
         NumOfProducts 0
         HasCrCard     0
         IsActiveMember 0
         EstimatedSalary 0
         Exited        0
         dtype: int64
```

```
In [ ]: dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column                Non-Null Count  Dtype  
---  -
 0   CreditScore           10000 non-null  int64  
 1   Geography              10000 non-null  object  
 2   Gender                10000 non-null  object  
 3   Age                   10000 non-null  int64  
 4   Tenure                 10000 non-null  int64  
 5   Balance                10000 non-null  float64 
 6   NumOfProducts          10000 non-null  int64  
 7   HasCrCard              10000 non-null  int64  
 8   IsActiveMember         10000 non-null  int64  
 9   EstimatedSalary        10000 non-null  float64 
10   Exited                 10000 non-null  int64  
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

```
In [ ]: dataset = pd.get_dummies(dataset, columns=['Geography', 'Gender'], drop_fir
```

```
In [ ]: dataset.head()
```

```
Out[64]:
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estima
0	619	42	2	0.00	1	1	1	
1	608	41	1	83807.86	1	0	1	
2	502	42	8	159660.80	3	1	0	
3	699	39	1	0.00	2	0	0	
4	850	43	2	125510.82	1	1	1	

```
In [ ]: # split the data into ind and dep variable  
x = dataset.drop(['Exited'], axis=1)  
y = dataset[['Exited']]
```

```
In [ ]: x.shape
```

```
Out[71]: (10000, 11)
```

```
In [ ]: x.head()
```

```
Out[66]:
```

	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estima
0	619	42	2	0.00	1	1	1	
1	608	41	1	83807.86	1	0	1	
2	502	42	8	159660.80	3	1	0	
3	699	39	1	0.00	2	0	0	
4	850	43	2	125510.82	1	1	1	

```
In [ ]: y.head()
```

```
Out[67]:
```

	Exited
0	1
1	0
2	1
3	0
4	0

```
In [ ]: # Balance the data
from imblearn.over_sampling import SMOTE
smote = SMOTE()
x_smote, y_smote = smote.fit_resample(x, y)
print(y.value_counts())
print(y_smote.value_counts())
```

Exited

0 7963

1 2037

dtype: int64

Exited

0 7963

1 7963

dtype: int64

```
In [ ]: # split the data into train and test
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x_smote, y_smote, test_
```

```
In [ ]: # feature scaling
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
x_train = sc.fit_transform(x_train)
x_test = sc.transform(x_test)
```

MLP

```
In [ ]: model = Sequential()
model.add(Dense(32, activation='relu', kernel_regularizer = keras.regulariz
          kernel_initializer='he_normal', input_dim=11))
model.add(Dropout(0.5))
model.add(BatchNormalization())

model.add(Dense(32, activation='relu', kernel_regularizer = keras.regulari
model.add(Dropout(0.5))
model.add(BatchNormalization())

model.add(Dense(1, activation='sigmoid'))

model.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
=====		
dense_18 (Dense)	(None, 32)	384
dropout_8 (Dropout)	(None, 32)	0
batch_normalization_10 (Batch Normalization)	(None, 32)	128
dense_19 (Dense)	(None, 32)	1056
dropout_9 (Dropout)	(None, 32)	0
batch_normalization_11 (Batch Normalization)	(None, 32)	128
dense_20 (Dense)	(None, 1)	33
=====		
Total params: 1729 (6.75 KB)		
Trainable params: 1601 (6.25 KB)		
Non-trainable params: 128 (512.00 Byte)		
=====		

In []:

In []: initial_weights = model.get_weights()

```
In [ ]: initial_weights[0]
```



```

Out[79]: array([[ -0.54668975, -0.65129626, -0.34773925, -0.43765387, -0.13219708,
    0.40628335, 0.5963399 , -0.13944611, -0.67357314, 0.46777704,
    0.08202546, 0.09328174, -0.4894623 , -0.46160665, -0.2967626 ,
    0.43073124, -0.0424548 , 0.3775512 , -0.16614582, -0.88848394,
    0.25903097, -0.3694219 , 0.11888529, -0.3252677 , -0.90093344,
    0.258748 , -0.19535325, 0.03168226, -0.43863618, -0.22901714,
    -0.37371907, -0.00289603],
 [-0.33343717, 0.34203184, -0.1816835 , -0.5410051 , 0.42010593,
    0.03782547, -0.9005688 , 0.42557123, 0.33136138, -0.14479339,
    0.17061973, 0.572867 , 0.53384614, -0.16065665, 0.09030482,
    -0.43708202, -0.05674174, -0.9229993 , 0.01270335, -0.13720037,
    -0.21643294, -0.0176984 , -0.3769747 , 0.0724934 , 0.52268326,
    0.11909305, 0.3787435 , -0.11065734, 0.11946512, 0.35163096,
    -0.3049398 , -0.17288749],
 [-0.6707052 , 0.19441552, 0.85444504, 0.09757277, -0.24736226,
    0.30902478, -0.9635952 , 0.5798555 , 0.07710464, 0.3685232 ,
    0.30412 , 0.30889067, -0.37271994, 0.0338873 , -0.03606715,
    -0.5522396 , 0.20524049, -0.12220731, 0.15795179, -0.11916168,
    0.81712294, -0.15985255, 0.43719903, -0.0882709 , 0.16368422,
    -0.4094959 , 0.46604523, 0.87715536, -0.9229087 , 0.05420799,
    0.20145623, 0.06400491],
 [-0.59011155, -0.1706088 , -0.15418188, -0.46109855, 0.376051 ,
    -0.53830504, -0.4536028 , 0.49561328, 0.87093824, 0.15209937,
    0.8967263 , -0.10867216, 0.236418 , 0.20448625, -0.3178406 ,
    0.62380826, 0.40930378, -0.3401883 , -0.440784 , -0.2554839 ,
    -0.24463907, -0.38798544, -0.25914854, -0.03174952, 0.56282204,
    -0.7897501 , -0.10709798, -0.07273412, -0.0012857 , 0.28835443,
    0.76596403, -0.35351098],
 [ 0.16178158, 0.5164875 , 0.5986191 , 0.7643257 , -0.02356788,
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```

```

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-0.36096147, 0.11240108]], dtype=float32)

```

```
In [ ]: model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

```
In [ ]: history = model.fit(x_train, y_train, batch_size=32, epochs=100, validation_data=(x_val, y_val))
```

```

Epoch 1/100
374/374 [=====] - 5s 6ms/step - loss: 2.8482 - accuracy: 0.5841 - val_loss: 1.5506 - val_accuracy: 0.7572
Epoch 2/100
374/374 [=====] - 2s 5ms/step - loss: 1.1256 - accuracy: 0.7222 - val_loss: 0.7566 - val_accuracy: 0.7953
Epoch 3/100
374/374 [=====] - 3s 8ms/step - loss: 0.6724 - accuracy: 0.7687 - val_loss: 0.5505 - val_accuracy: 0.7961
Epoch 4/100
374/374 [=====] - 2s 5ms/step - loss: 0.5483 - accuracy: 0.7863 - val_loss: 0.4821 - val_accuracy: 0.8046
Epoch 5/100
374/374 [=====] - 2s 5ms/step - loss: 0.5106 - accuracy: 0.7854 - val_loss: 0.4532 - val_accuracy: 0.8134
Epoch 6/100
374/374 [=====] - 2s 6ms/step - loss: 0.4943 - accuracy: 0.7935 - val_loss: 0.4462 - val_accuracy: 0.8144
Epoch 7/100
374/374 [=====] - 2s 5ms/step - loss: 0.4800 - accuracy: 0.7980 - val_loss: 0.4400 - val_accuracy: 0.8150

```

```
In [ ]:
```

```
In [ ]:
```

Optimization Method

```
In [ ]: model = Sequential()
model.add(Dense(32, activation='relu', input_dim=11))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 32)	384
dense_1 (Dense)	(None, 32)	1056
dense_2 (Dense)	(None, 1)	33
Total params: 1473 (5.75 KB)		
Trainable params: 1473 (5.75 KB)		
Non-trainable params: 0 (0.00 Byte)		

BGD -

```
In [ ]: model.compile(loss='binary_crossentropy', metrics=['accuracy'])
import time
```

```
In [ ]: print(x_train.shape, x_test.shape)
```

(11944, 11) (3982, 11)

```
In [ ]: start = time.time()
history = model.fit(x_train, y_train, batch_size=11944, epochs=5, validation_data=(x_test, y_test))
print(time.time()-start)
```

Epoch 1/5

1/1 [=====] - 5s 5s/step - loss: 0.7188 - accuracy: 0.5041 - val_loss: 0.6945 - val_accuracy: 0.5402

Epoch 2/5

1/1 [=====] - 0s 34ms/step - loss: 0.6991 - accuracy: 0.5321 - val_loss: 0.6818 - val_accuracy: 0.5600

Epoch 3/5

1/1 [=====] - 0s 32ms/step - loss: 0.6862 - accuracy: 0.5504 - val_loss: 0.6716 - val_accuracy: 0.5801

Epoch 4/5

1/1 [=====] - 0s 33ms/step - loss: 0.6759 - accuracy: 0.5661 - val_loss: 0.6629 - val_accuracy: 0.5974

Epoch 5/5

1/1 [=====] - 0s 34ms/step - loss: 0.6672 - accuracy: 0.5826 - val_loss: 0.6551 - val_accuracy: 0.6123

5.600061655044556

BGD :

Time : 5.600061655044556

loss: 0.6672 - accuracy: 0.5826 - val_loss: 0.6551 - val_accuracy: 0.6123

SGD

```
In [ ]: model = Sequential()
model.add(Dense(32, activation='relu', input_dim=11))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', metrics=['accuracy'])
```

```
In [ ]: start = time.time()
history1 = model.fit(x_train, y_train, batch_size=1, epochs=5, validation_data=(x_val, y_val))
print(time.time()-start)
```

```
Epoch 1/5
11944/11944 [=====] - 47s 4ms/step - loss: 0.4665
- accuracy: 0.7970 - val_loss: 0.4622 - val_accuracy: 0.8122
Epoch 2/5
11944/11944 [=====] - 40s 3ms/step - loss: 0.4460
- accuracy: 0.8178 - val_loss: 0.4346 - val_accuracy: 0.8109
Epoch 3/5
11944/11944 [=====] - 41s 3ms/step - loss: 0.4390
- accuracy: 0.8207 - val_loss: 0.4356 - val_accuracy: 0.8227
Epoch 4/5
11944/11944 [=====] - 41s 3ms/step - loss: 0.4383
- accuracy: 0.8192 - val_loss: 0.4469 - val_accuracy: 0.8240
Epoch 5/5
11944/11944 [=====] - 45s 4ms/step - loss: 0.4372
- accuracy: 0.8245 - val_loss: 0.4524 - val_accuracy: 0.8187
213.92868089675903
```

```
In [ ]: 11944/64
```

Out[22]: 186.625

```
In [ ]: # BGD :
## Time : 5.600061655044556
## Loss: 0.6672 - accuracy: 0.5826 - val_loss: 0.6551 - val_accuracy: 0.6123

# SGD
## Time : 213.92868089675903
## Loss: 0.4372 - accuracy: 0.8245 - val_loss: 0.4524 - val_accuracy: 0.8187

# MBGD
```

```
In [ ]: model = Sequential()
model.add(Dense(32, activation='relu', input_dim=11))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', metrics=['accuracy'])

start = time.time()
history2 = model.fit(x_train, y_train, batch_size=64, epochs=5, validation_
print(time.time()-start)
```

Epoch 1/5

187/187 [=====] - 3s 7ms/step - loss: 0.5168 - accuracy: 0.7608 - val_loss: 0.4604 - val_accuracy: 0.7850

Epoch 2/5

187/187 [=====] - 1s 4ms/step - loss: 0.4469 - accuracy: 0.7954 - val_loss: 0.4343 - val_accuracy: 0.7973

Epoch 3/5

187/187 [=====] - 1s 4ms/step - loss: 0.4218 - accuracy: 0.8086 - val_loss: 0.4175 - val_accuracy: 0.8106

Epoch 4/5

187/187 [=====] - 1s 4ms/step - loss: 0.4044 - accuracy: 0.8186 - val_loss: 0.4035 - val_accuracy: 0.8189

Epoch 5/5

187/187 [=====] - 1s 4ms/step - loss: 0.3926 - accuracy: 0.8255 - val_loss: 0.3983 - val_accuracy: 0.8214

10.908029556274414

BGD :

Time : 5.600061655044556

**loss: 0.6672 - accuracy: 0.5826 - val_loss: 0.6551 -
val_accuracy: 0.6123**

SGD

Time : 213.92868089675903

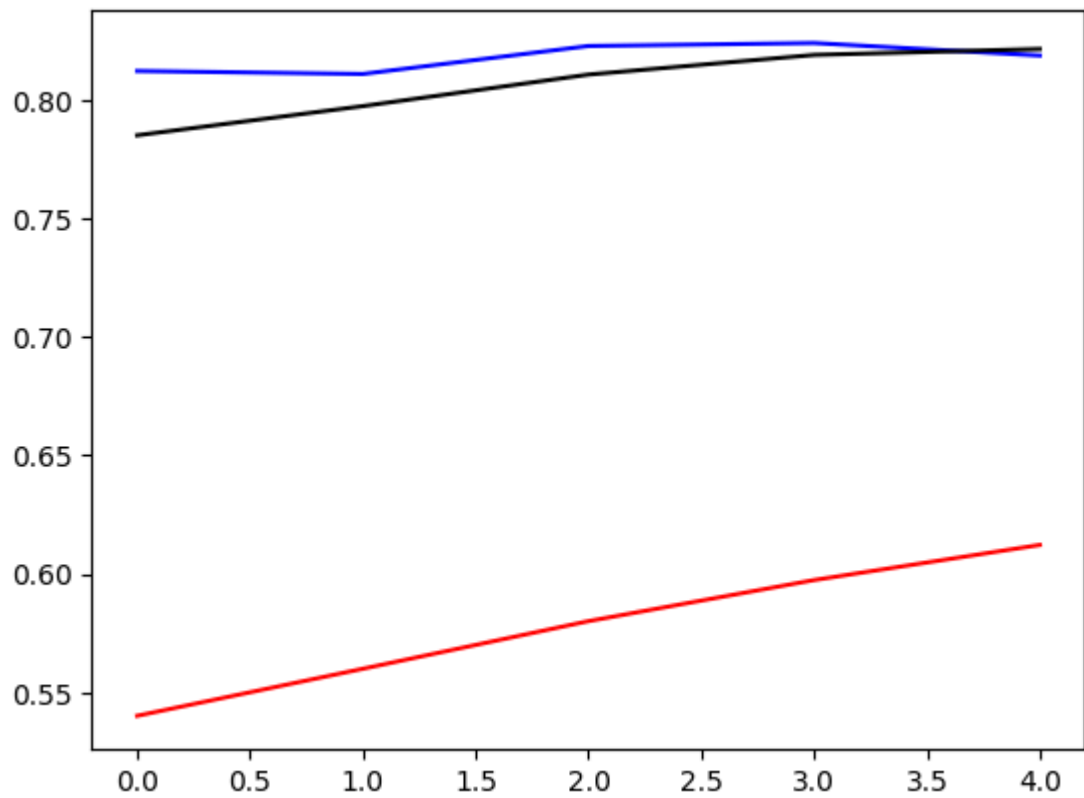
**loss: 0.4372 - accuracy: 0.8245 - val_loss: 0.4524 -
val_accuracy: 0.8187**

MBGD

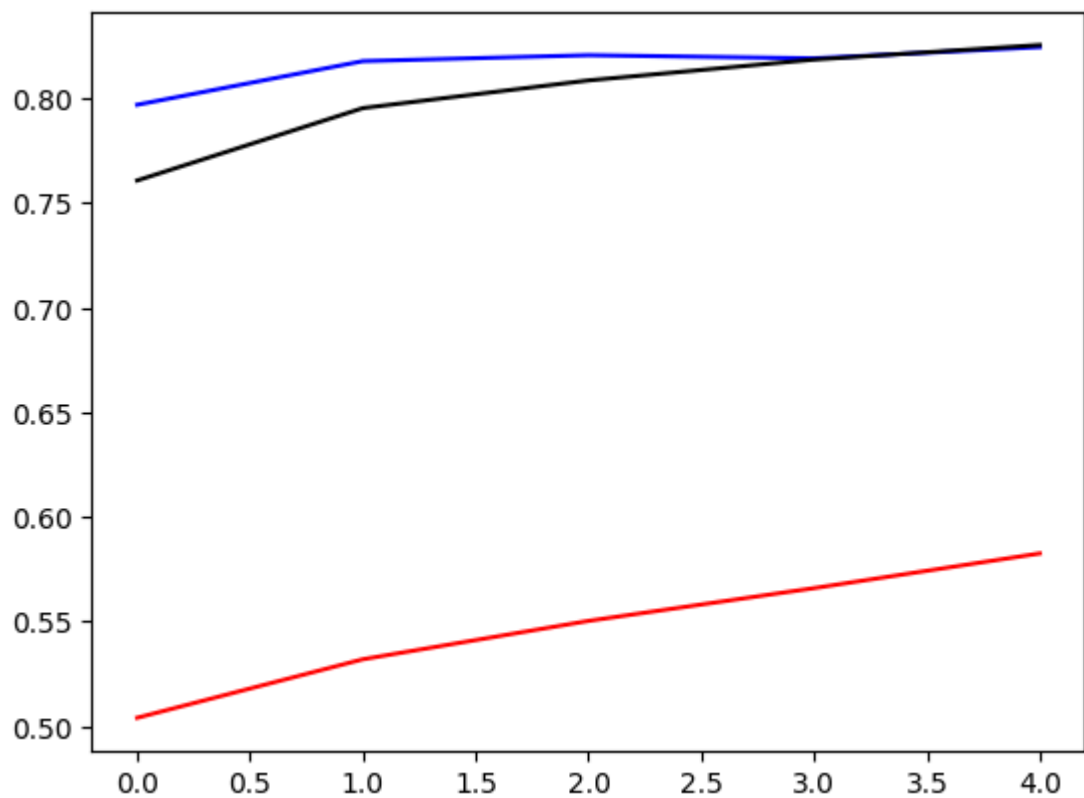
Time : 10.908029556274414

**loss: 0.3926 - accuracy: 0.8255 - val_loss: 0.3983 -
val_accuracy: 0.8214**

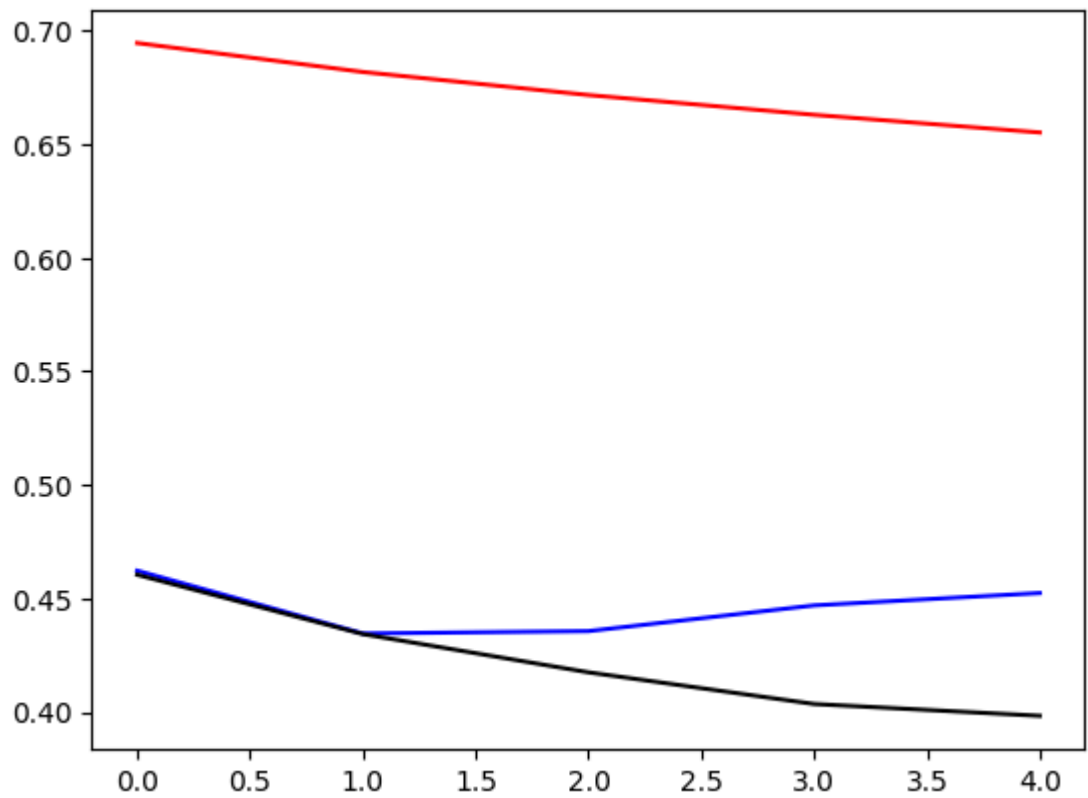
```
In [ ]: import matplotlib.pyplot as plt
plt.plot(history.history['val_accuracy'], color='red')
plt.plot(history1.history['val_accuracy'], color='blue')
plt.plot(history2.history['val_accuracy'], color='black')
plt.show()
```



```
In [ ]: plt.plot(history.history['accuracy'], color='red')
plt.plot(history1.history['accuracy'], color='blue')
plt.plot(history2.history['accuracy'], color='black')
plt.show()
```



```
In [ ]: plt.plot(history.history['val_loss'], color='red')
plt.plot(history1.history['val_loss'], color='blue')
plt.plot(history2.history['val_loss'], color='black')
plt.show()
```



In []:

In []: