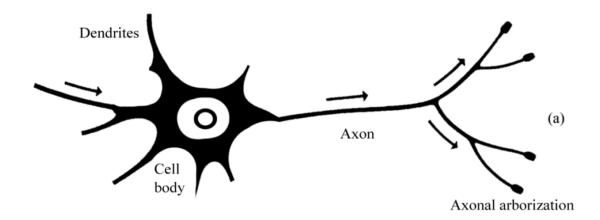
# Session 8 notebook

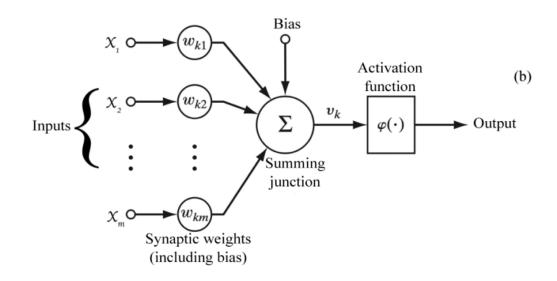
The notebook has been written during the session please watch the video on "Course Materials" section of iLearn for the full description

## May 22, 2020

### 0.1 Artificial Neural Network

The idea of perceptron developed by Frank Rosenblatt in 1958. Biologically neurons accept some sort of input signal and then nucleus does some sort of calculations (something happens in the nucleus of this neuron) and then it outputs as a signal in Axon. How can we express this simplified biological model in a mathematical way?

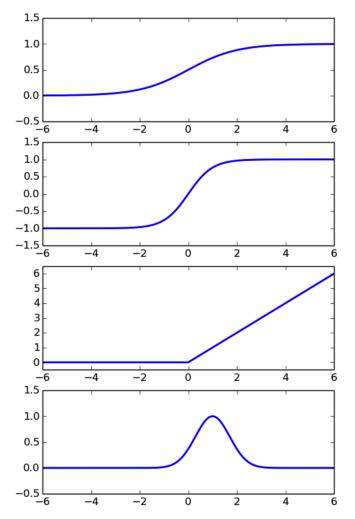




Source of the figure: Akgün+18

Input layer —-> Hidden layers —-> Output layer

Activation is a function that acts on the weighted combination of the inputs plus bias. There is a wide variety of activation functions.



## Sigmoid

$$\phi(z) = \frac{1}{1 + e^{-z}}$$

## Hyperbolic Tangent

$$\phi(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

### Rectified Linear

$$\phi(z) = \begin{cases} 0 & \text{if } z < 0 \\ z & \text{if } z \ge 0 \end{cases}$$

### **Radial Basis Function**

$$\phi(z,c) = e^{-(\epsilon ||z-c||)^2}$$

Source of the figure: Hughes+16

Multi-Class problems: 1) Non-Exclusive Classes 2) Mutually Exclusive Classes

For Non-Exclusive classes, we can use Sigmoid activation function.

$$\phi(z) = \frac{1}{1 + e^{-z}}$$

2

For Mutually Exclusive Classes, we can use softmax activation function.

$$\phi(z) = \frac{e^{z_i}}{\sum e^{z_i}}$$

To train the neural net, we need to define a cost function and optimize it. There are different optimizing algorithms. For more info about gradient descent algorithms see this paper. In most of the cases, Adaptive Moment Estimation (Adam) optimizer is a good choice.

For regression problems, we usually use mean squared error (MSE) loss (cost) function. For classification problems, we usually use cross entropy loss function.

In the lecture you learned about backpropagation algorithm which is used to train a neural network. So, let's jump into the implementation of a feedforward neural network using Keras. Keras is a high level API built on TensorFlow.

We are given a pseudo dataset which has 7 inputs and 3 outputs. We will build a simple NN model to solve this regression problem. First let's get the data:

```
[3]: import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pylab as plt
```

[5]: Data=pd.read\_csv('Data.csv')
Data.head()

```
[5]:
              I1
                        12
                                  13
                                            14
                                                      15
                                                                16
                                                                          17
        2.402260
                 2.631375
                           2.620065
                                      2.741343
                                                2.855368
                                                          3.369216
                                                                    3.565848
       2.262583
                 2.384253
                           2.413262
                                      2.704121
                                                2.807388
                                                          3.053078
                                                                    3.041393
     1
                                      2.336109
                                                2.601325
     2 2.295275
                 2.413758 2.355623
                                                          2.748188
                                                                   2.653213
     3 2.352647
                 2.419292 2.590186
                                      2.835756
                                                2.943433
                                                          2.770852
                                                                   2.556303
       3.006206 3.247684
                           3.253961
                                     3.220793 3.286278 3.133539 2.875061
```

```
02
         01
                             03
  2.763428
            3.214844
                      3.262451
1
  2.812913
             2.602060
                       2.698970
2 2.477121
             2.690196
                      2.806180
3 2.518514
            2.716003
                      2.934498
 3.230449
            3.173186 3.225309
```

Do we have any missing data?

```
[8]: Data.isnull().sum()
```

```
[8]: I1 0 I2 0 I3 0 I4 0 I5 0 I6 0
```

```
17     0
01     0
02     0
03     0
dtype: int64
```

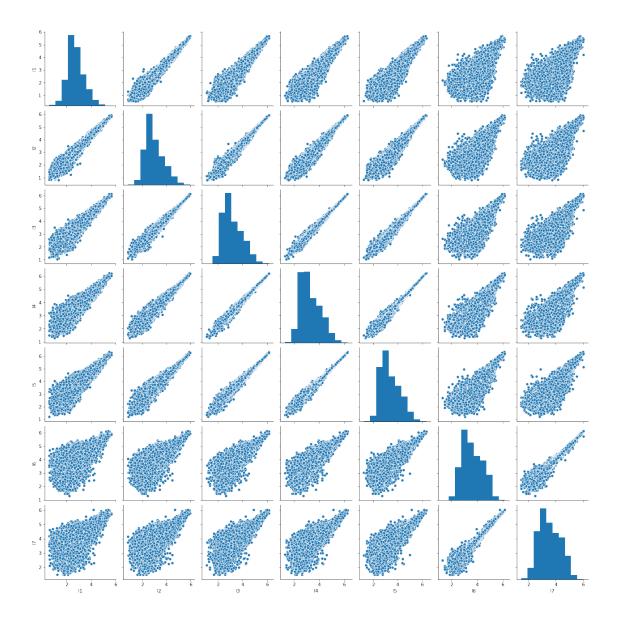
[9]: X=Data[['I1','I2','I3','I4','I5','I6','I7']] y=Data[['01','02','03']]

[12]: plt.figure(figsize=(10,7))
sns.heatmap(X.corr(),annot=True)
plt.show()



[13]: sns.pairplot(X)

[13]: <seaborn.axisgrid.PairGrid at 0x1095f2a90>



```
[14]: from sklearn.model_selection import train_test_split
```

```
[15]: X_train,X_test,y_train,y_test=train_test_split(X.values,y.values,test_size=0.

→3,random_state=100)
```

We should scale our data considering the distribution of each input

```
[16]: from sklearn.preprocessing import MinMaxScaler
```

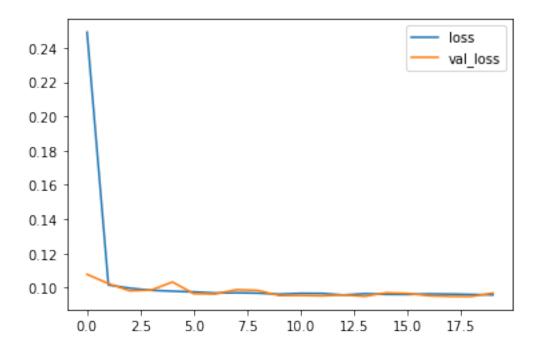
```
[19]: scaler=MinMaxScaler()
```

```
[20]: X_train=scaler.fit_transform(X_train)
X_test=scaler.transform(X_test)
```

```
[22]: from tensorflow.keras.models import Sequential
    from tensorflow.keras.layers import Dense, Activation
    from tensorflow.keras.optimizers import Adam
[24]: model=Sequential()
    model.add(Dense(7,activation='linear'))
    model.add(Dense(10,activation='linear'))
    model.add(Dense(10,activation='linear'))
    model.add(Dense(3))
    model.compile(optimizer='adam',loss='mean_absolute_error')
[26]: model.

→fit(x=X_train,y=y_train,validation_data=(X_test,y_test),batch_size=32,epochs=20)
   Epoch 1/20
   950/950 [=========== ] - 1s 1ms/step - loss: 0.2491 -
   val_loss: 0.1078
   Epoch 2/20
   val_loss: 0.1024
   Epoch 3/20
   950/950 [=========== ] - 1s 1ms/step - loss: 0.0997 -
   val_loss: 0.0981
   Epoch 4/20
   val_loss: 0.0986
   Epoch 5/20
   val_loss: 0.1033
   Epoch 6/20
   950/950 [============ ] - 1s 1ms/step - loss: 0.0975 -
   val_loss: 0.0965
   Epoch 7/20
   val_loss: 0.0963
   Epoch 8/20
   950/950 [===========] - 1s 1ms/step - loss: 0.0970 -
   val_loss: 0.0988
   Epoch 9/20
   val_loss: 0.0984
   Epoch 10/20
```

```
val_loss: 0.0954
  Epoch 11/20
  val_loss: 0.0954
  Epoch 12/20
  val_loss: 0.0952
  Epoch 13/20
  val_loss: 0.0958
  Epoch 14/20
  val_loss: 0.0949
  Epoch 15/20
  val_loss: 0.0970
  Epoch 16/20
  val_loss: 0.0967
  Epoch 17/20
  val_loss: 0.0953
  Epoch 18/20
  val_loss: 0.0949
  Epoch 19/20
  val_loss: 0.0949
  Epoch 20/20
  val_loss: 0.0969
[26]: <tensorflow.python.keras.callbacks.History at 0x140d69c40>
[29]: loss=pd.DataFrame(model.history.history)
[30]: loss.plot()
[30]: <matplotlib.axes._subplots.AxesSubplot at 0x14155cc10>
```



```
[31]: predictions=model.predict(X_test)

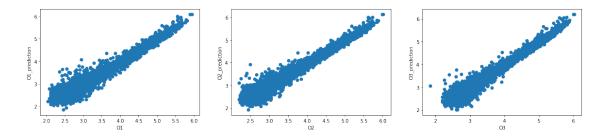
[34]: fig,ax=plt.subplots(1,3,figsize=(20,4))

ax[0].scatter(y_test.T[0],predictions.T[0])
ax[0].set_xlabel('01')
ax[0].set_ylabel('01_prediction')

ax[1].scatter(y_test.T[1],predictions.T[1])
ax[1].set_xlabel('02')
ax[1].set_ylabel('02_prediction')

ax[2].scatter(y_test.T[2],predictions.T[2])
ax[2].set_xlabel('03')
ax[2].set_ylabel('03_prediction')
```

[34]: Text(0, 0.5, '03\_prediction')



[]: