

Multi-layer Perceptron (MLP)

Feedforward Artificial Neural Network (ANN)



Summary

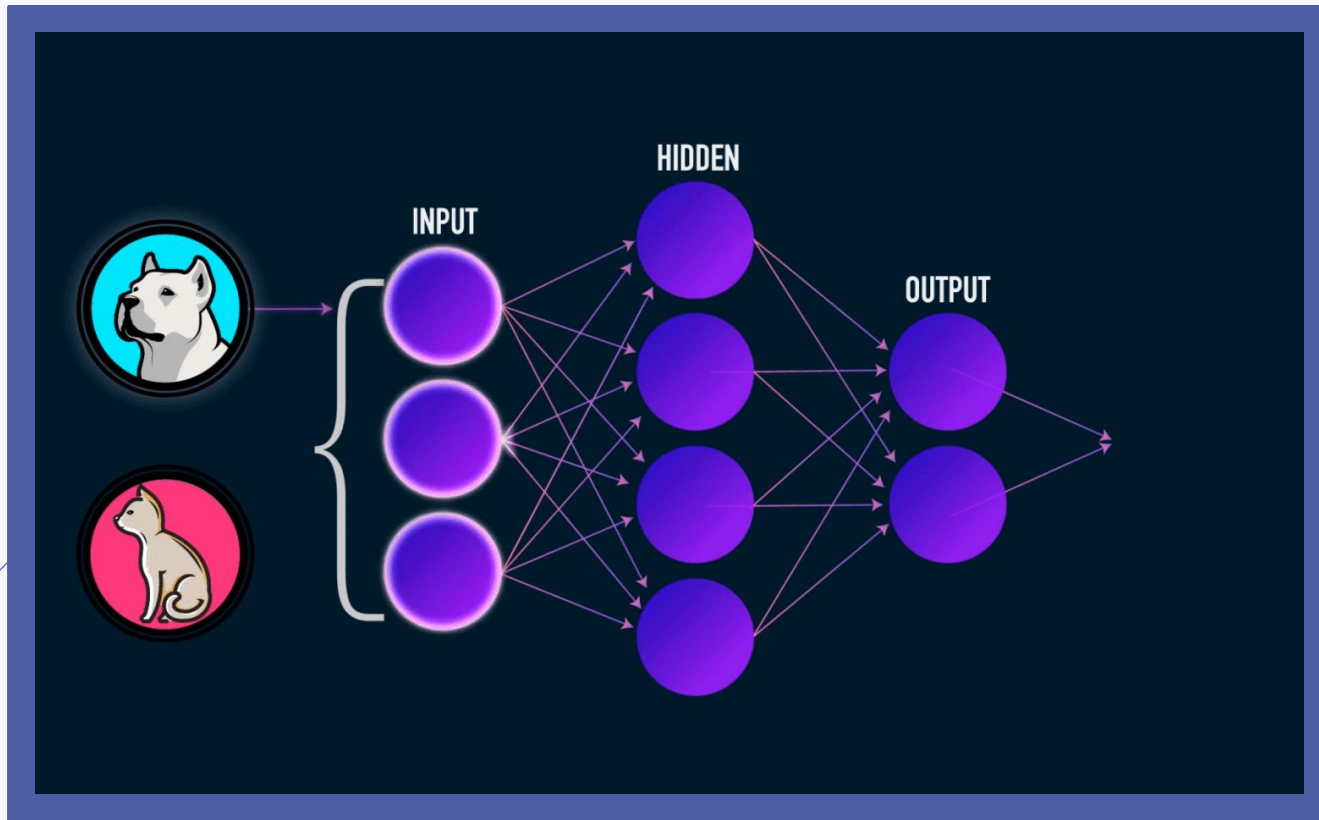
1. Introduction

**2. MLP
implementation**

3. Results

4. Conclusion





Example of an artificial neural network

1. Introduction

Multi-layer Perceptron

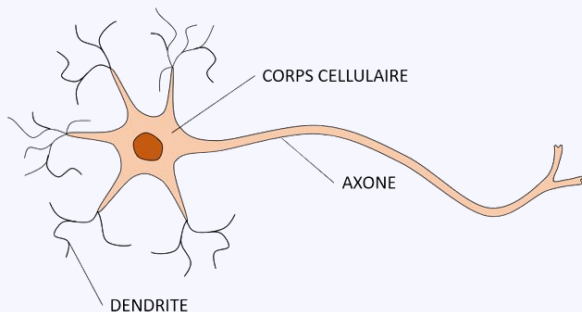


Image 1: Representation of a biological neurone

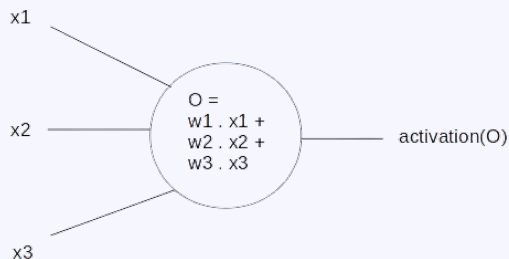


Image 2: Representation of an artificial neurone

An MLP is an **Artificial Neural Networks (ANN)**

Inspired by **biological neural networks**

Applications:

Speech and image recognition, text processing...

At least **3 layers** of nodes: an **input** layer, a **hidden** layer and a **output** layer.

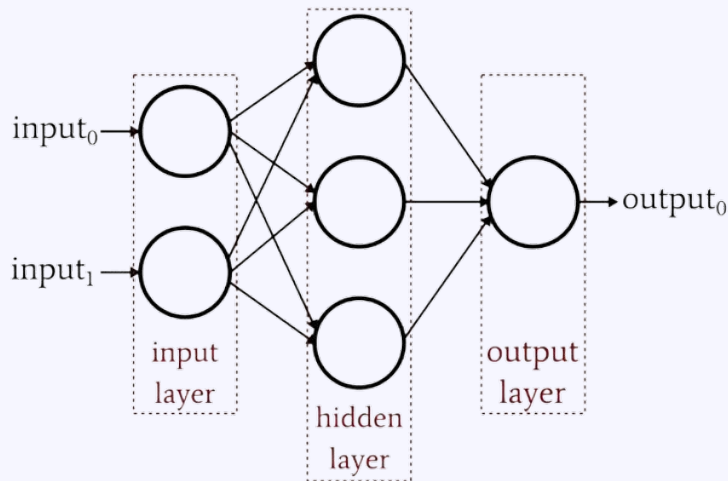
Learns by **training** on a dataset

Image 1: <https://svtdiderot.fr/cordewener/4eme-cordewener/le-systeme-nerveux/>

Image 2: <https://cdancette.fr/assets/neuron.png>

1. Introduction

Multi-layer Perceptron



An MLP is an **Artificial Neural Networks (ANN)**

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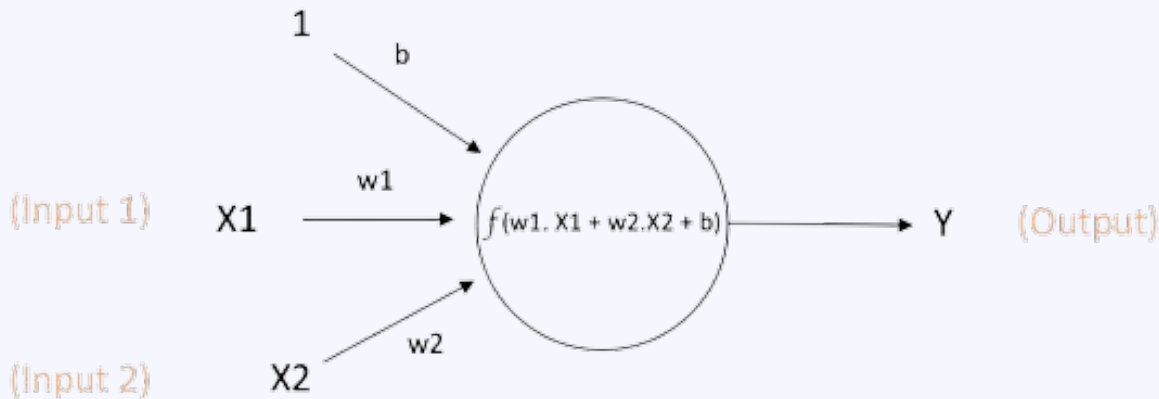
Learns by **training** on a dataset

1. Introduction

A single neurone

Also called **node** or **unit**

- **Inputs:** X_1 , X_2 , Bias 1
- **Weights:** w_1 , w_2 , b
- **Output:** Y
- **Activation function:** non-linear function



$$\text{Output of neuron} = Y = f(w_1 \cdot X_1 + w_2 \cdot X_2 + b)$$

1. Introduction

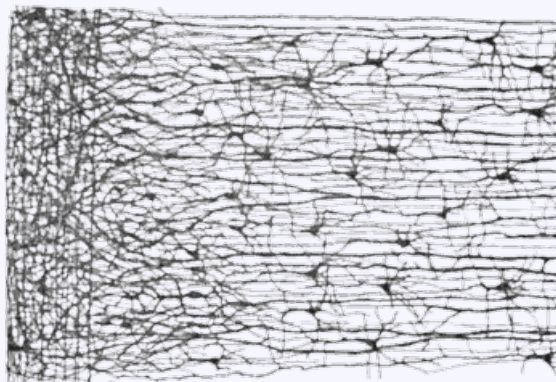


Image 4: Multiple layers in a biological neural network

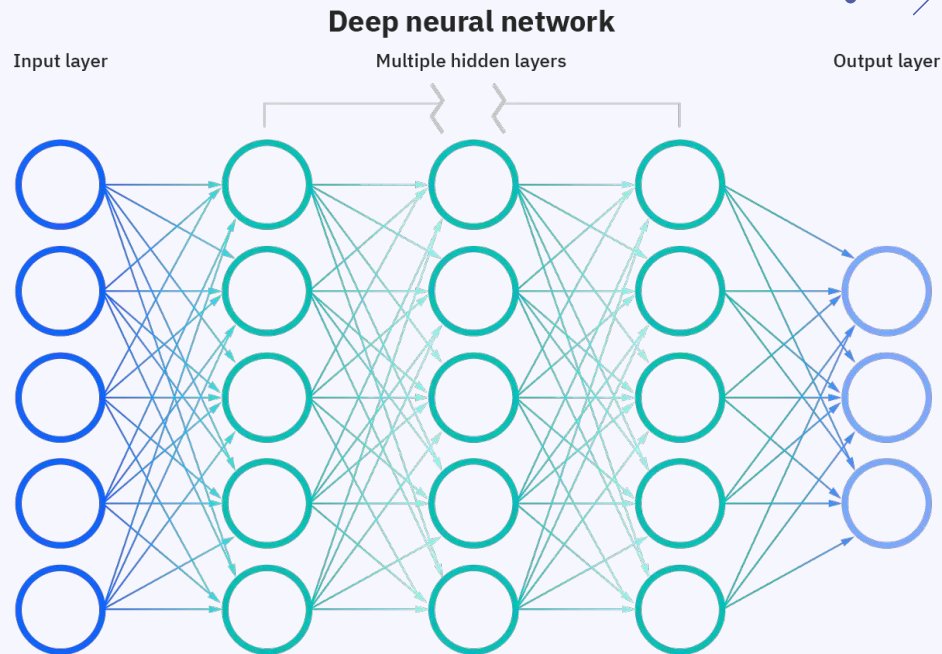
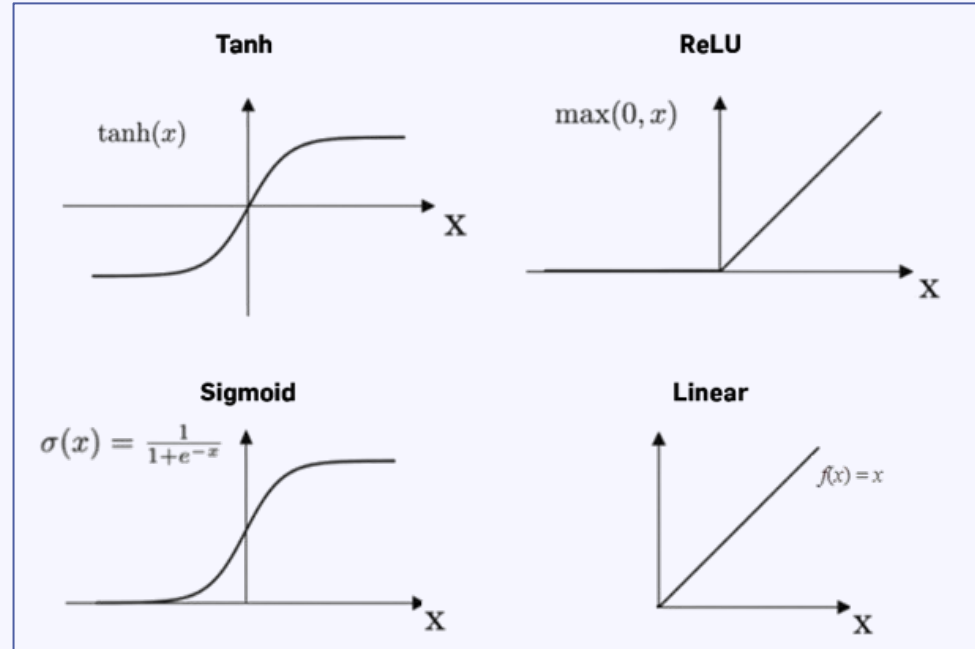
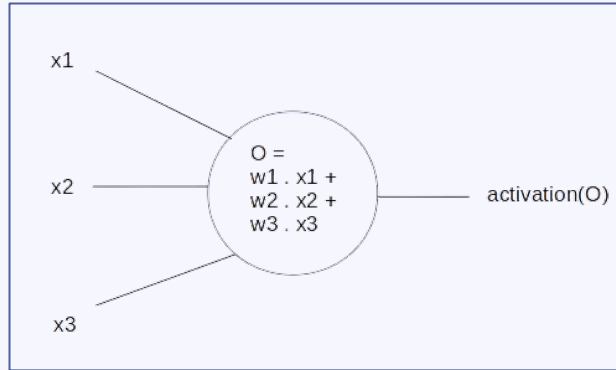


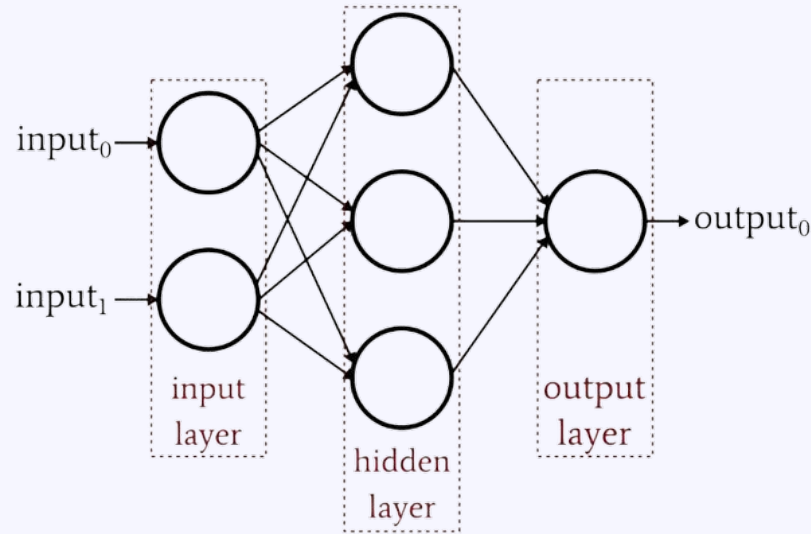
Image 5: Multiple layers in an artificial neural network

1. Introduction

Activation function



Feedforward and Backpropagation



1. Feedforward propagation

2. Backpropagation

Epoch

Requirements



Pandas

Open csv
file



Numpy

Operation
and matrix



Scikitlearn

Model
implementation
Cross-validation



Matplotlib

Data
visualization



Seaborn

Heat Map

Pam50 dataset: It contains the expression of 50 known human genes with patterns according to a subtype of breast cancer.

2. MLP implementation

Data importation

```
Data_Pam = pd.read_csv("data/Data_Pam50.csv")
```

```
label_raw = Data_Pam.iloc[:,1]  
data_raw = Data_Pam.iloc[:,2:]
```

	Unnamed: 0	subtype	ACTR3B	ANLN	BAG1	BCL2	BIRC5	BLVRA
0	Normal.Breast.10	Normal	-1.151	-3.736	0.260	1.300	-2.860	-0.569
1	Normal.Breast.2	Normal	-0.485	-3.739	0.591	1.580	-3.250	-0.533
2	Normal.Breast.3	Normal	0.298	-2.848	0.359	1.292	-2.493	-0.687
3	Normal.Breast.4.Custom	Normal	1.153	-4.717	0.098	1.954	-3.237	-0.535
4	Normal.Breast.7	Normal	-0.287	-3.681	0.441	1.911	-2.156	-0.965
...
67	H1AUNC.1319.C	LumB	-0.267	-0.803	-0.409	0.329	0.179	1.542
68	H1AUNC.1323.C	LumB	-0.938	-1.999	-0.910	0.472	-1.564	0.352
69	H1AUNC.1462.C	LumB	-0.950	-1.757	0.250	0.099	-1.289	1.219
70	H1AUNC.1471.C	LumB	0.039	-1.937	0.095	0.137	-0.948	2.833
71	H1AUNC.1474.C	LumB	-1.441	-2.706	-1.142	0.393	-1.330	0.333

72 rows × 52 columns

Portion of the data frame

Slicing

0	Normal
1	Normal
2	Normal
3	Normal
4	Normal
...	...
67	LumB
68	LumB
69	LumB
70	LumB
71	LumB

Raw Labels

+

	ACTR3B	ANLN	BAG1	BCL2	BIRC5	BLVRA	CCNB1	CCNB2
0	-1.151	-3.736	0.260	1.300	-2.860	-0.569	-2.981	-1.981
1	-0.485	-3.739	0.591	1.580	-3.250	-0.533	-2.935	-1.035
2	0.298	-2.848	0.359	1.292	-2.493	-0.687	-2.810	-1.710
3	1.153	-4.717	0.098	1.954	-3.237	-0.535	-3.558	-2.708
4	-0.287	-3.681	0.441	1.911	-2.156	-0.965	-2.869	-1.769
...
67	-0.267	-0.803	-0.409	0.329	0.179	1.542	-0.854	-1.754
68	-0.938	-1.999	-0.910	0.472	-1.564	0.352	-1.842	-1.542
69	-0.950	-1.757	0.250	0.099	-1.289	1.219	-1.135	-1.219
70	0.039	-1.937	0.095	0.137	-0.948	2.833	-1.669	-0.948
71	-1.441	-2.706	-1.142	0.393	-1.330	0.333	-1.415	-1.330

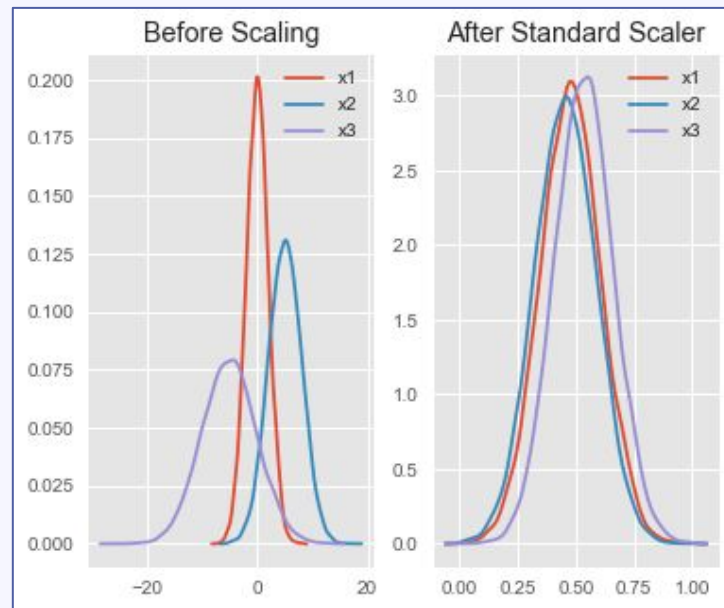
72 rows × 50 columns

Raw Data

2. MLP implementation

Data Scaling

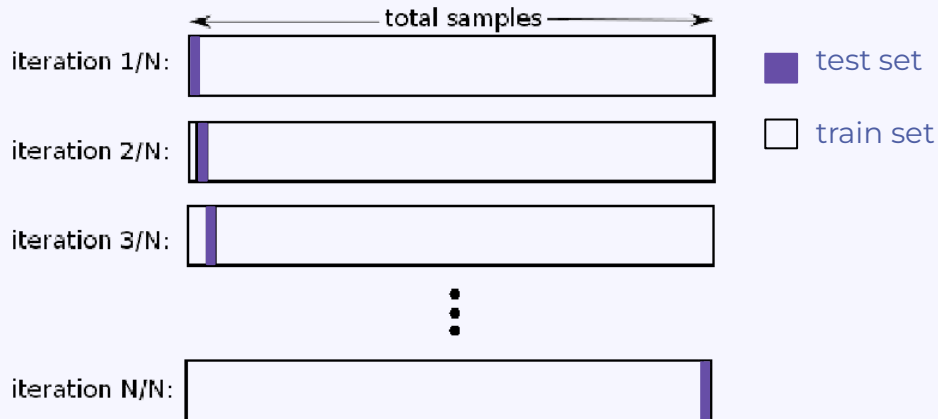
```
from sklearn.preprocessing import StandardScaler  
sc_X = StandardScaler()  
X_train_scaled=sc_X.fit_transform(X_train)  
X_test_scaled=sc_X.transform(X_test)
```



Example of scaling with StandardScaler

Cross-validation

```
loo = LeaveOneOut()
for train, test in loo.split(data_scaled):
    clf = MLPClassifier(hidden_layer_sizes=layer,
                        random_state=1, max_iter=epochs, tol = tols).fit(data_scaled[train],
                                                                           label_target[train])
```



Parameters and GridSearchCV

```
layer = [(100,1),(200,1),(100,10),(200,10),(100,20),(200,20),(50,10)]  
tols = [10e-4, 10e-5, 10e-3, 10e-2, 10e-6, 10e-7]  
epochs = [100,50,20,200,300]
```

```
clf = GridSearchCV(  
    MLPClassifier(),  
    param_grid= {  
        'hidden_layer_sizes': layer,  
        'tol' : tols,  
        'max_iter' : epochs  
    },  
    refit='True',  
    cv=2,  
    n_jobs=-1,  
)
```

MLPClassifier parameters:

- *hidden_layer_sizes*
- *max_iter*
- *tol* (tolerance)

2. MLP implementation

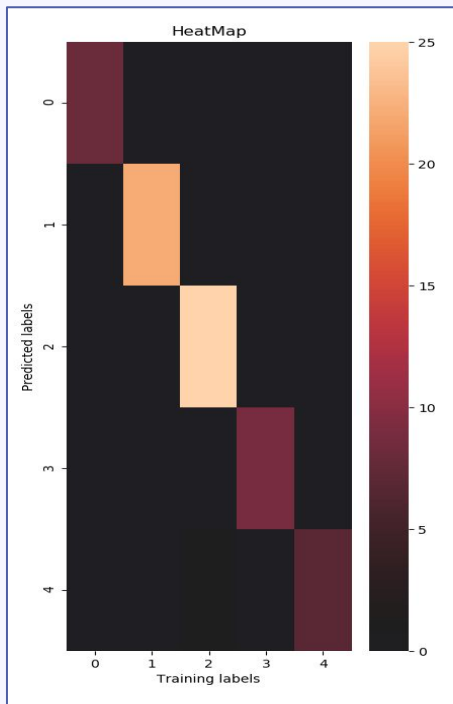
Heat Map

Repartitionition of the labels

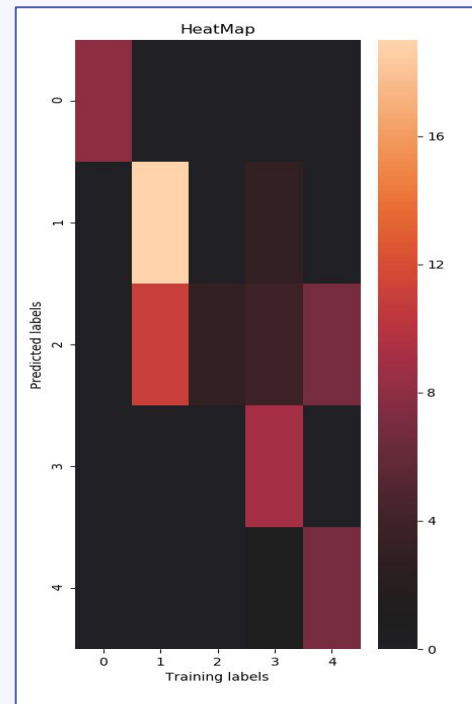
→ Each number is a category for a label

A Heat Map with high accuracy:

- First predicted labels should match with first true labels, etc.



Heat map with high accuracy

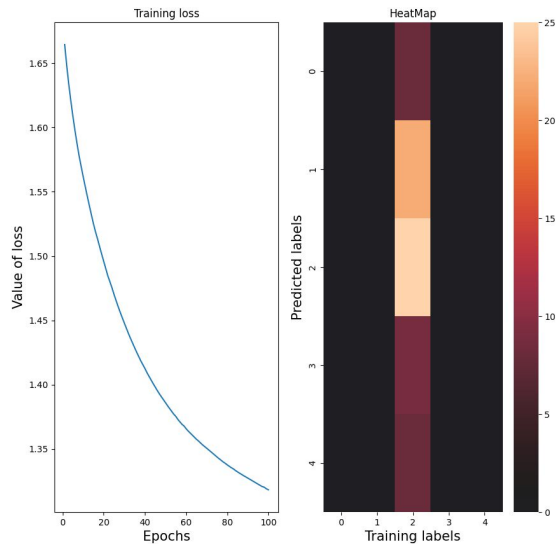


Heat map with low accuracy

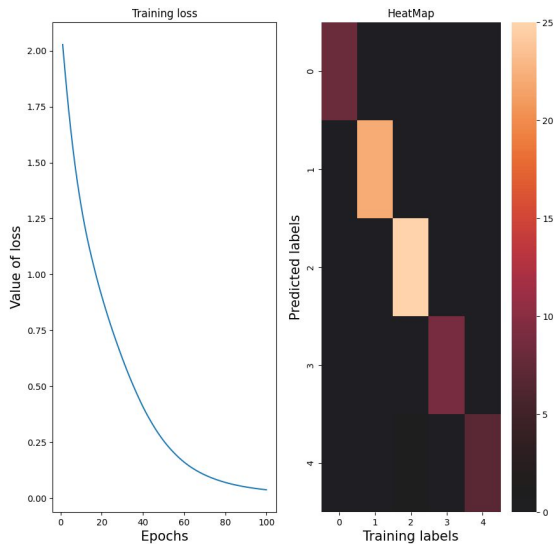
3. Results

1st parameter : size of network

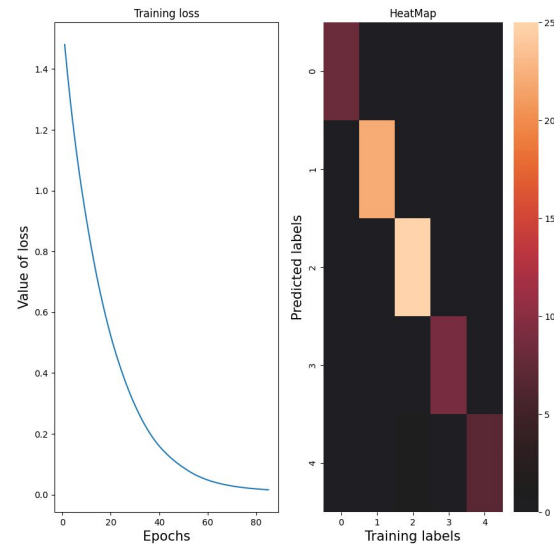
Results for 1 layers of 100 nodes, 100 epochs and a tol of 0.001
Accuracy = 34.72222222222222 %



Results for 10 layers of 100 nodes, 100 epochs and a tol of 0.001
Accuracy = 94.44444444444444 %



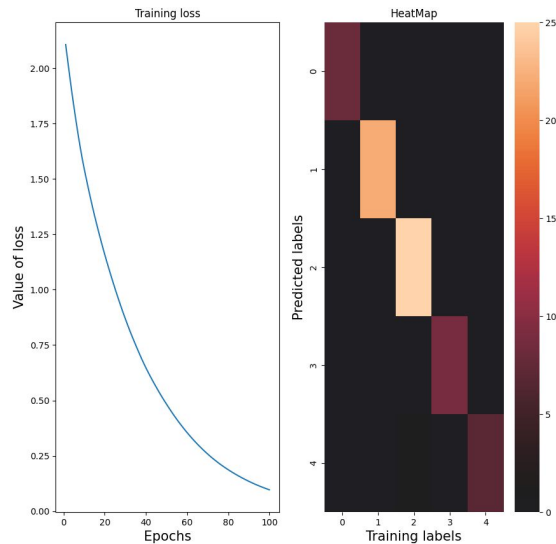
Results for 20 layers of 100 nodes, 100 epochs and a tol of 0.001
Accuracy = 93.05555555555556 %



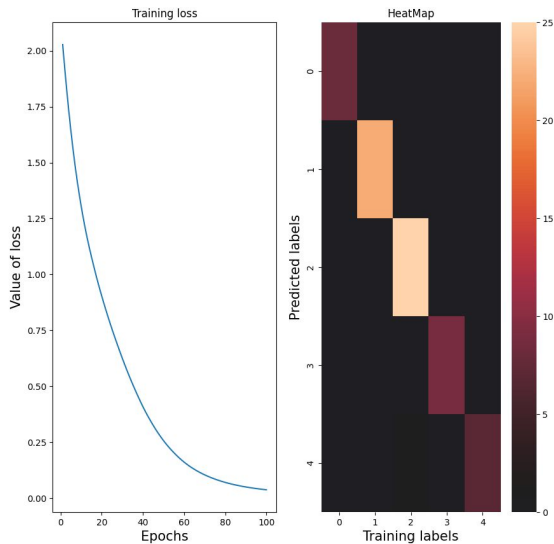
3. Results

1st parameter : size of network

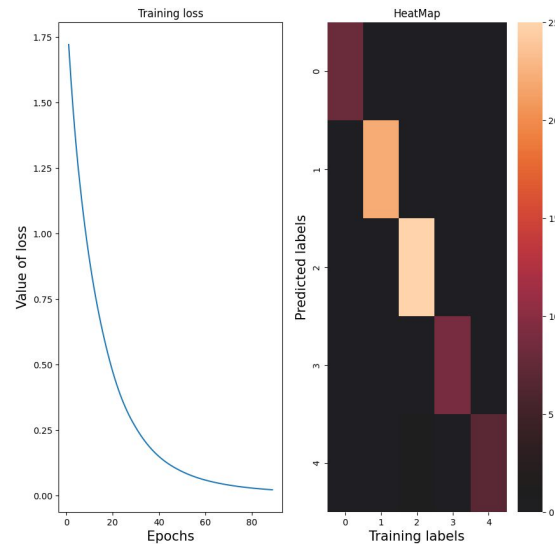
Results for 10 layers of 50 nodes, 100 epochs and a tol of 0.001
Accuracy = 88.888888888889 %



Results for 10 layers of 100 nodes, 100 epochs and a tol of 0.001
Accuracy = 94.444444444444 %



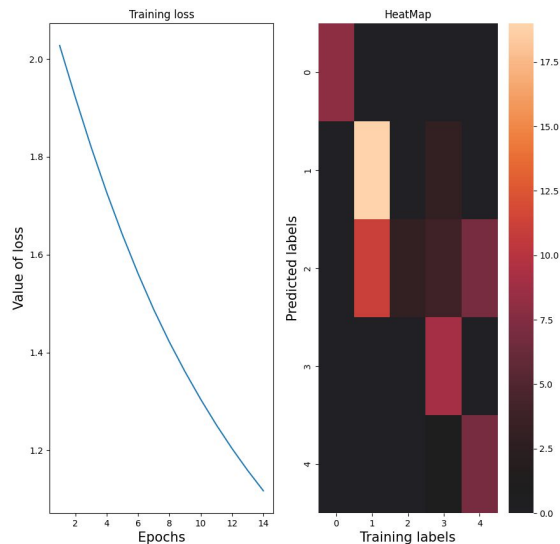
Results for 10 layers of 200 nodes, 100 epochs and a tol of 0.001
Accuracy = 90.277777777778 %



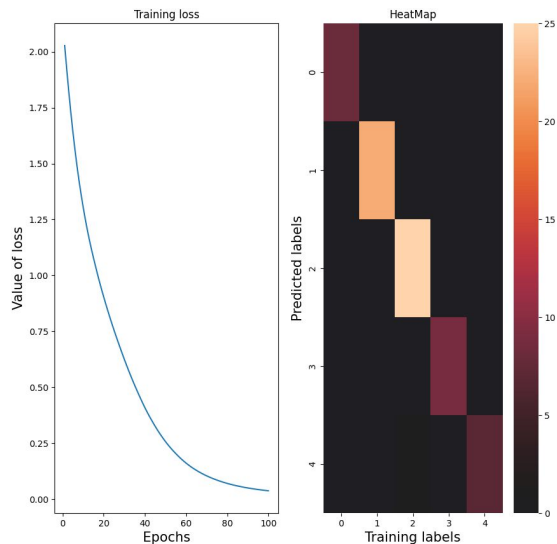
3. Results

2nd parameter : tolerance

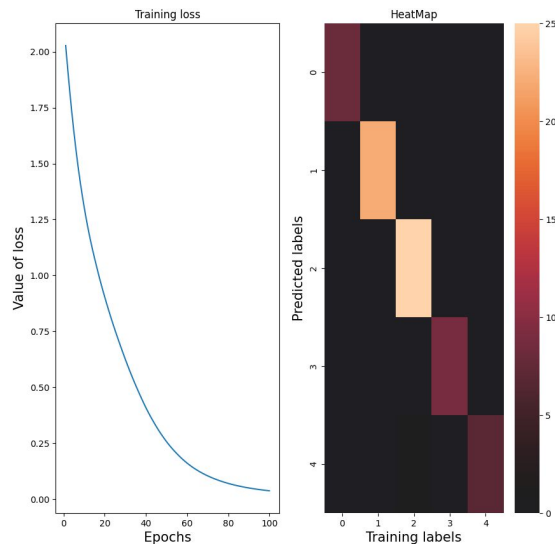
Results for 10 layers of 100 nodes, 100 epochs and a tol of 0.1
Accuracy = 51.38888888888886 %



Results for 10 layers of 100 nodes, 100 epochs and a tol of 0.001
Accuracy = 94.44444444444444 %



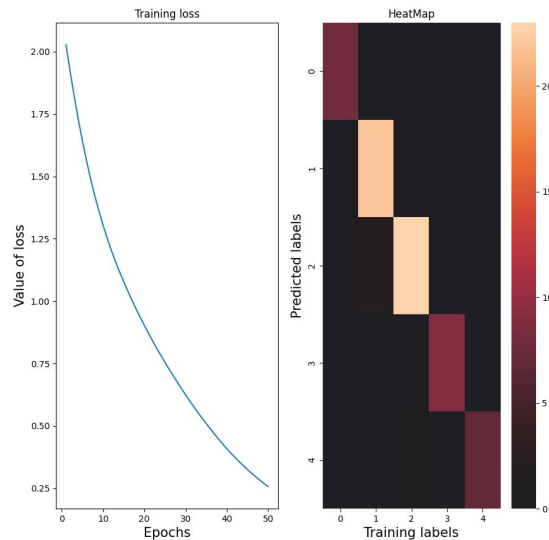
Results for 10 layers of 100 nodes, 100 epochs and a tol of 1e-06
Accuracy = 94.44444444444444 %



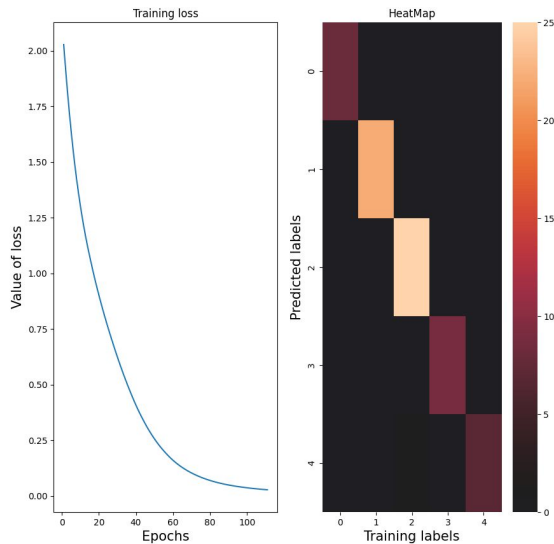
3. Results

3rd parameter : number of epochs

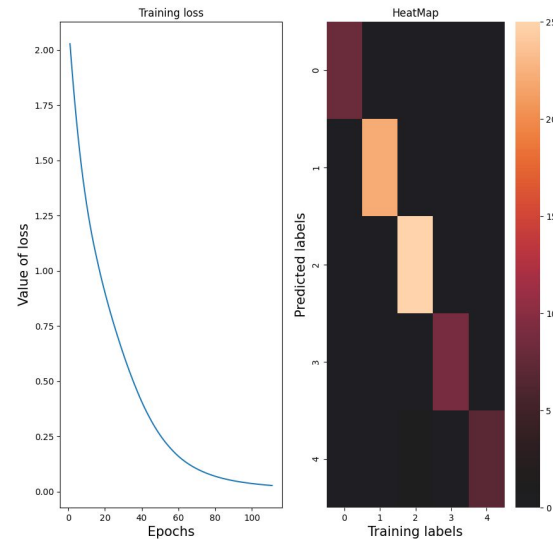
Results for 10 layers of 100 nodes, 50 epochs and a tol of 0.001
Accuracy = 91.666666666666 %



Results for 10 layers of 100 nodes, 200 epochs and a tol of 0.001
Accuracy = 94.444444444444 %



Results for 10 layers of 100 nodes, 300 epochs and a tol of 0.001
Accuracy = 94.444444444444 %

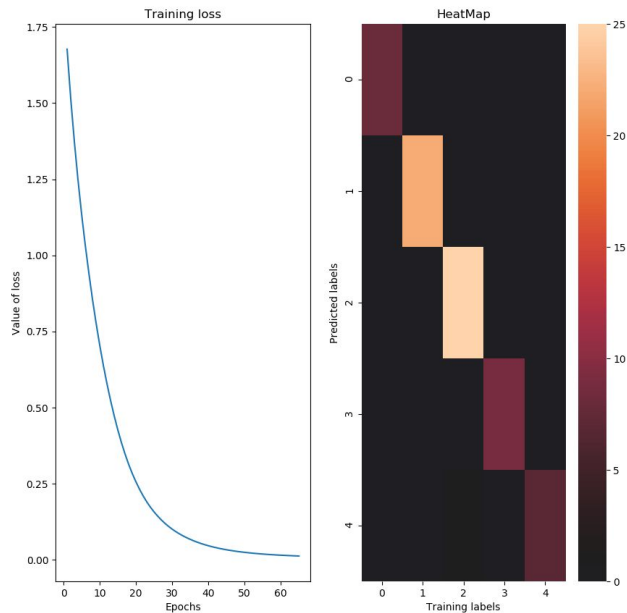


3. Results

GridSearchCV

```
{'hidden_layer_sizes': (200, 20), 'max_iter': 200, 'tol': 1e-05}
```

Results for 20 layers of 200 nodes, 200 epochs and a tol of 0.001
Accuracy = 91.66666666666666 %



4. Conclusion

Multi-layer Perceptron : at least 3 layers (input, hidden, output)

Epoch : feedforward propagation and backpropagation

Scaling is important

Cross-validation used for small datasets

Multiple **parameters** for estimator

Avoid overfitting (100% accuracy)

Bibliography

Scikit-learn documentation :

https://scikit-learn.org/stable/modules/neural_networks_supervised.html

https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

Other :

<https://ujjwalkarn.me/2016/08/09/quick-intro-neural-networks/>

<https://www.ibm.com/cloud/learn/neural-networks>

https://en.wikipedia.org/wiki/Multilayer_perceptron

Git :

<https://github.com/TexierLouis/Multilayer-perceptron>