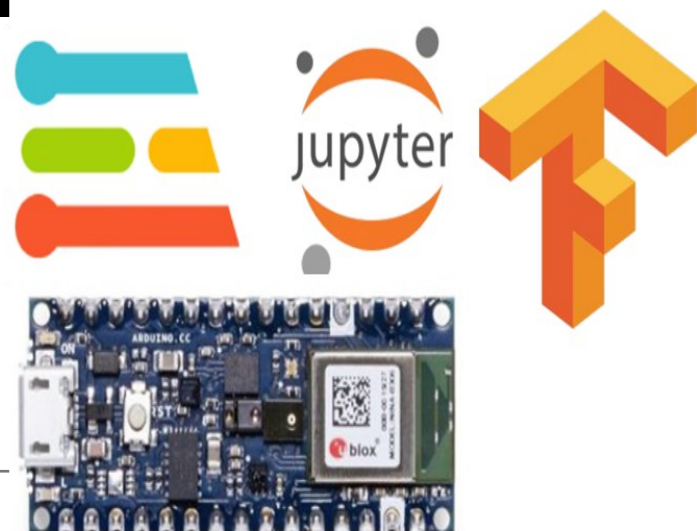


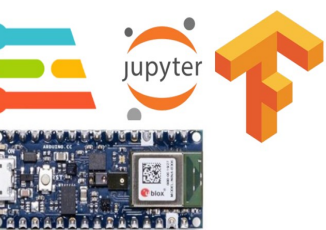


AI

# DNN AND ML METRICS

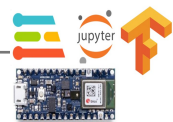
Dennis A. N. Gookyi





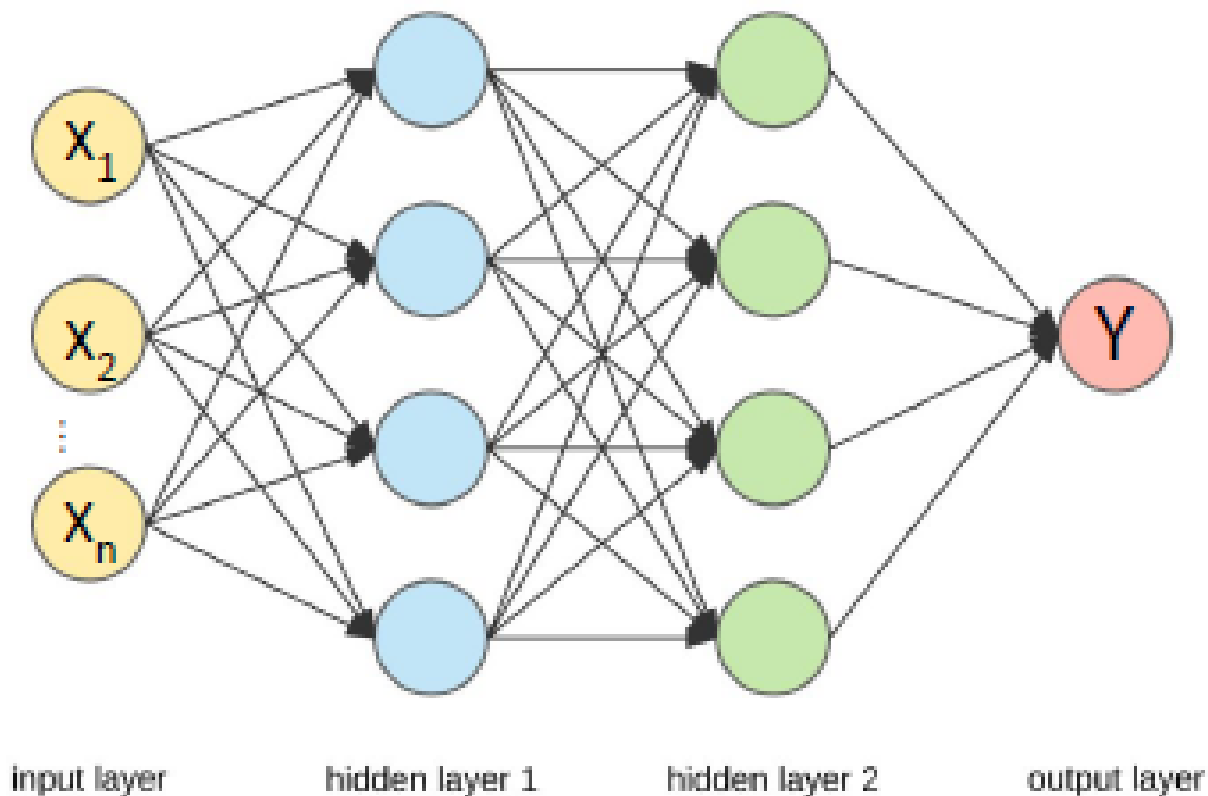
# CONTENTS

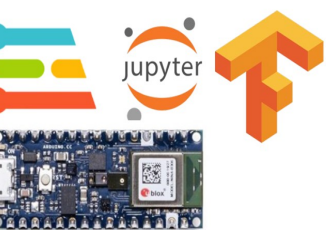
## ❖ DNN and ML Metrics



# DNN

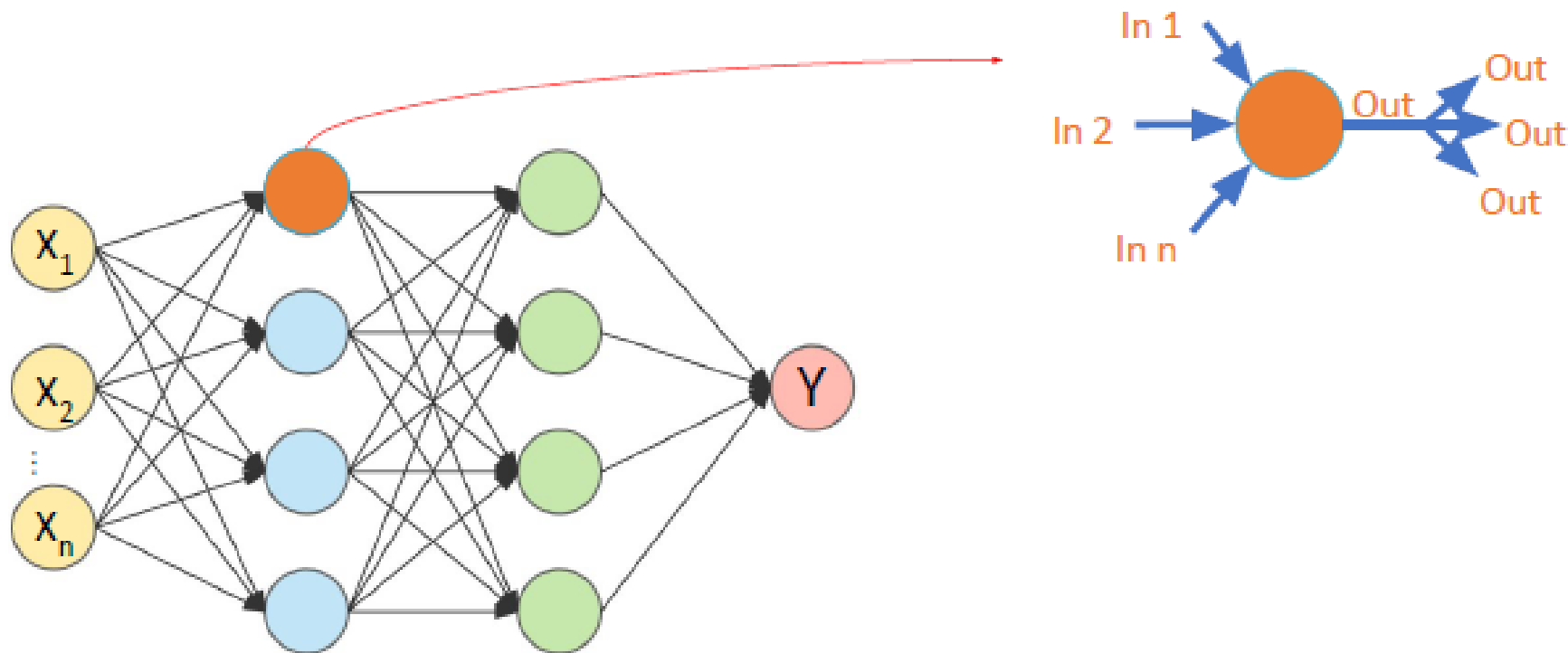
## ❖ Supervised machine learning with DNN

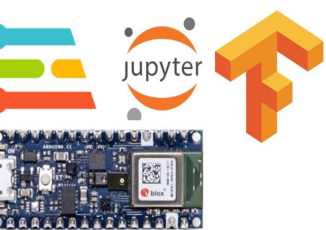




# DNN

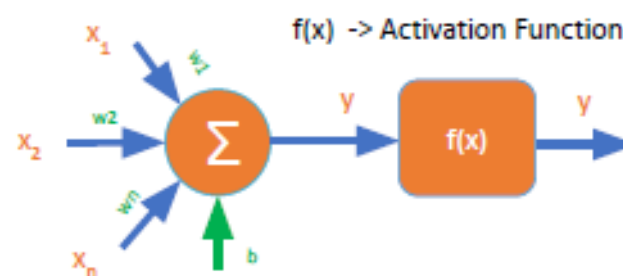
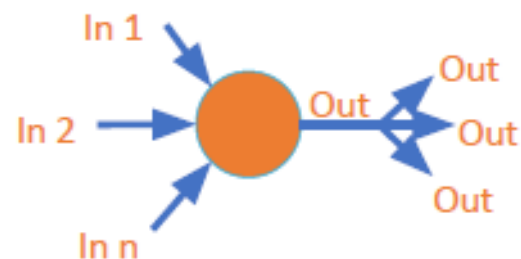
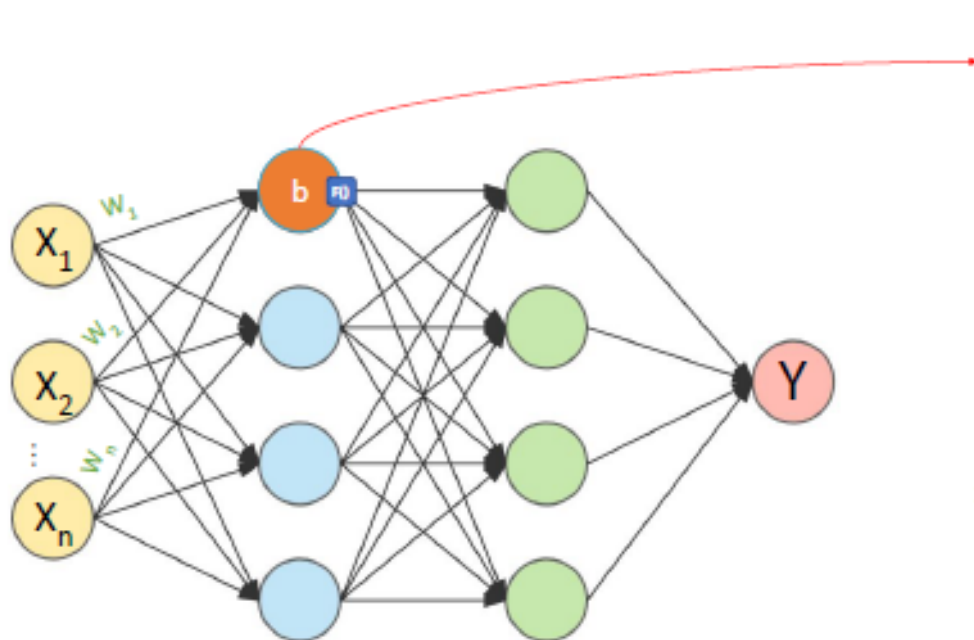
## ❖ Supervised machine learning with DNN



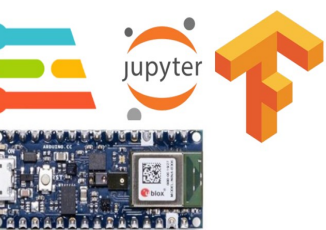


# DNN

## ❖ Supervised machine learning with DNN



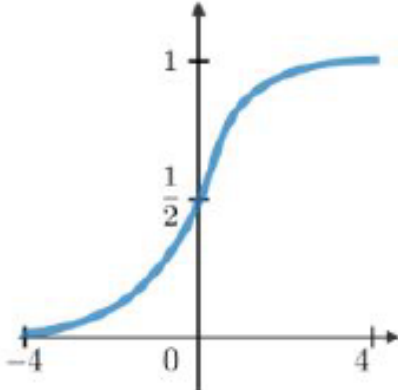
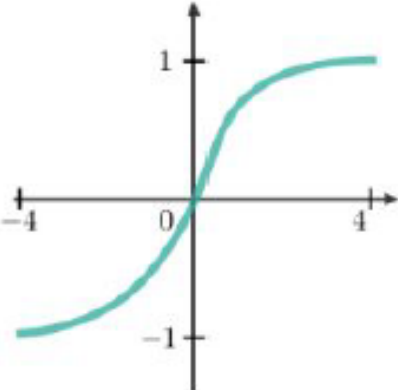
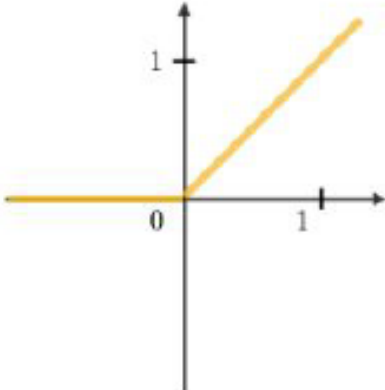
$$y = f\left(\sum_{i=1}^n x_i w_i + b\right)$$

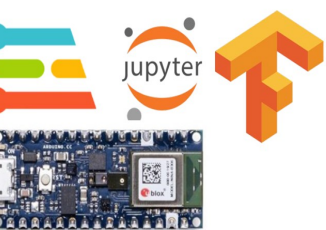


# DNN

## ❖ Supervised machine learning with DNN

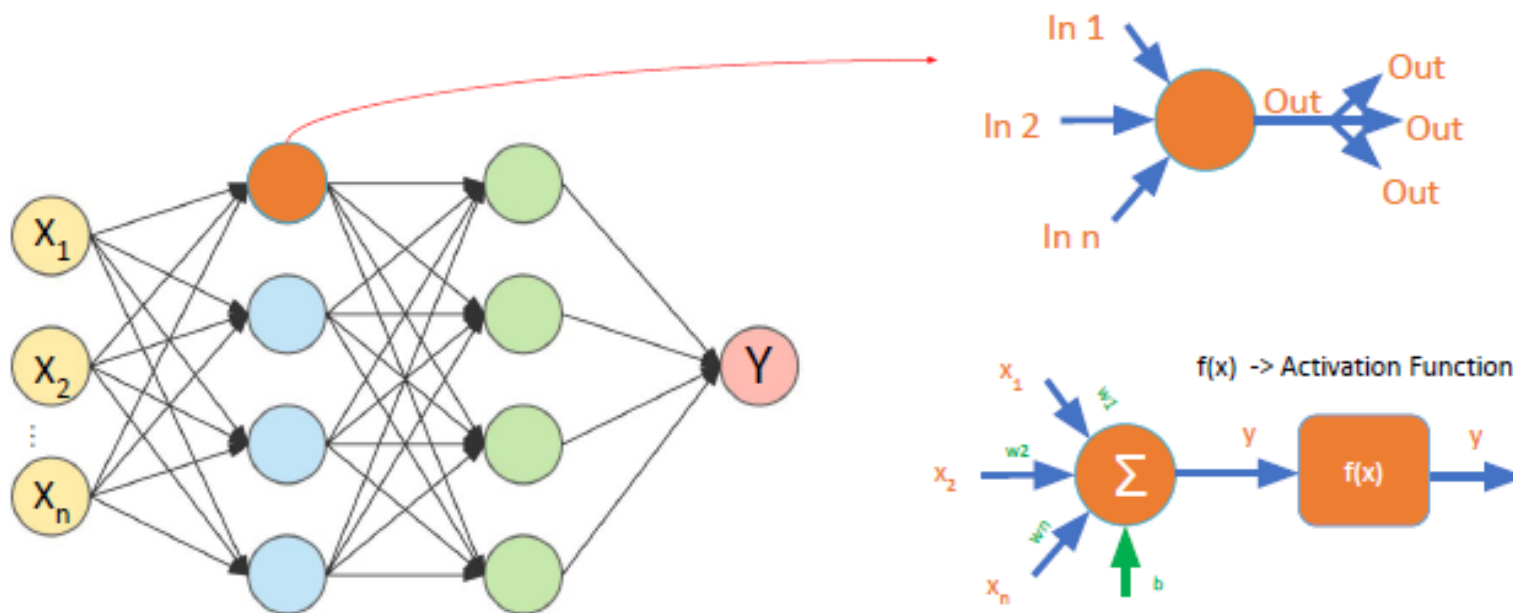
### □ Activation Functions

Sigmoid	Tanh	RELU
$g(z) = \frac{1}{1 + e^{-z}}$	$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	$g(z) = \max(0, z)$
		



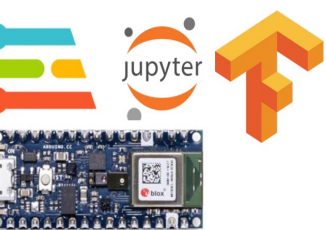
# DNN

## ❖ Supervised machine learning with DNN



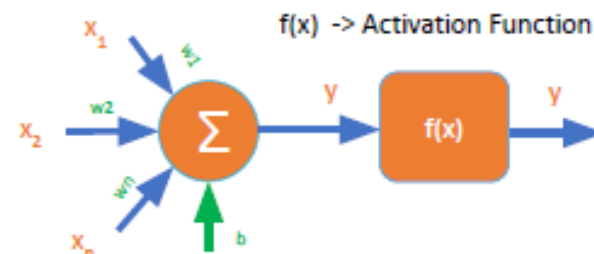
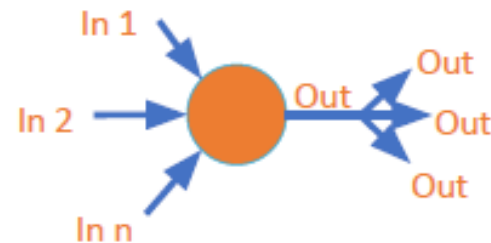
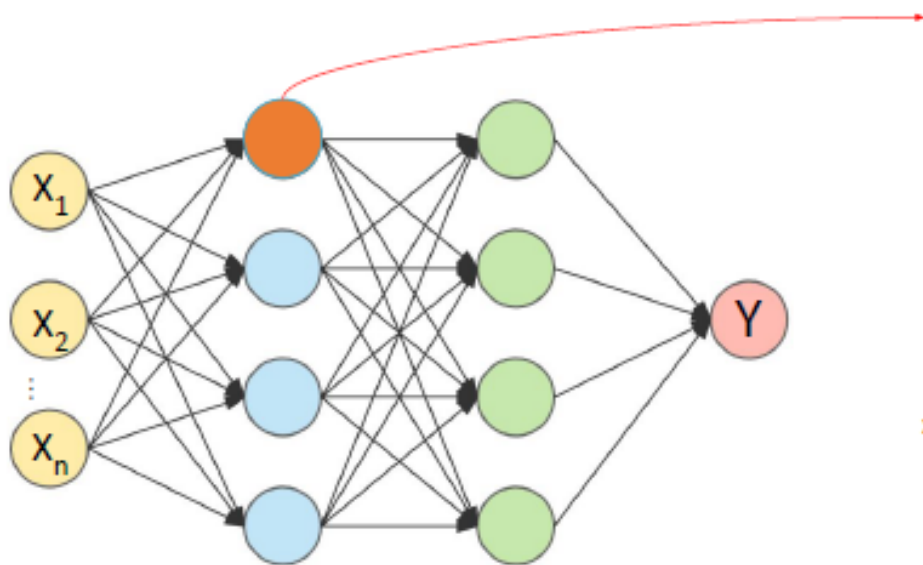
Parameters to be found during training, to reach minimum error

$$y = f\left(\sum_{i=1}^n x_i w_i + b\right)$$



# DNN

## ❖ Supervised machine learning with DNN



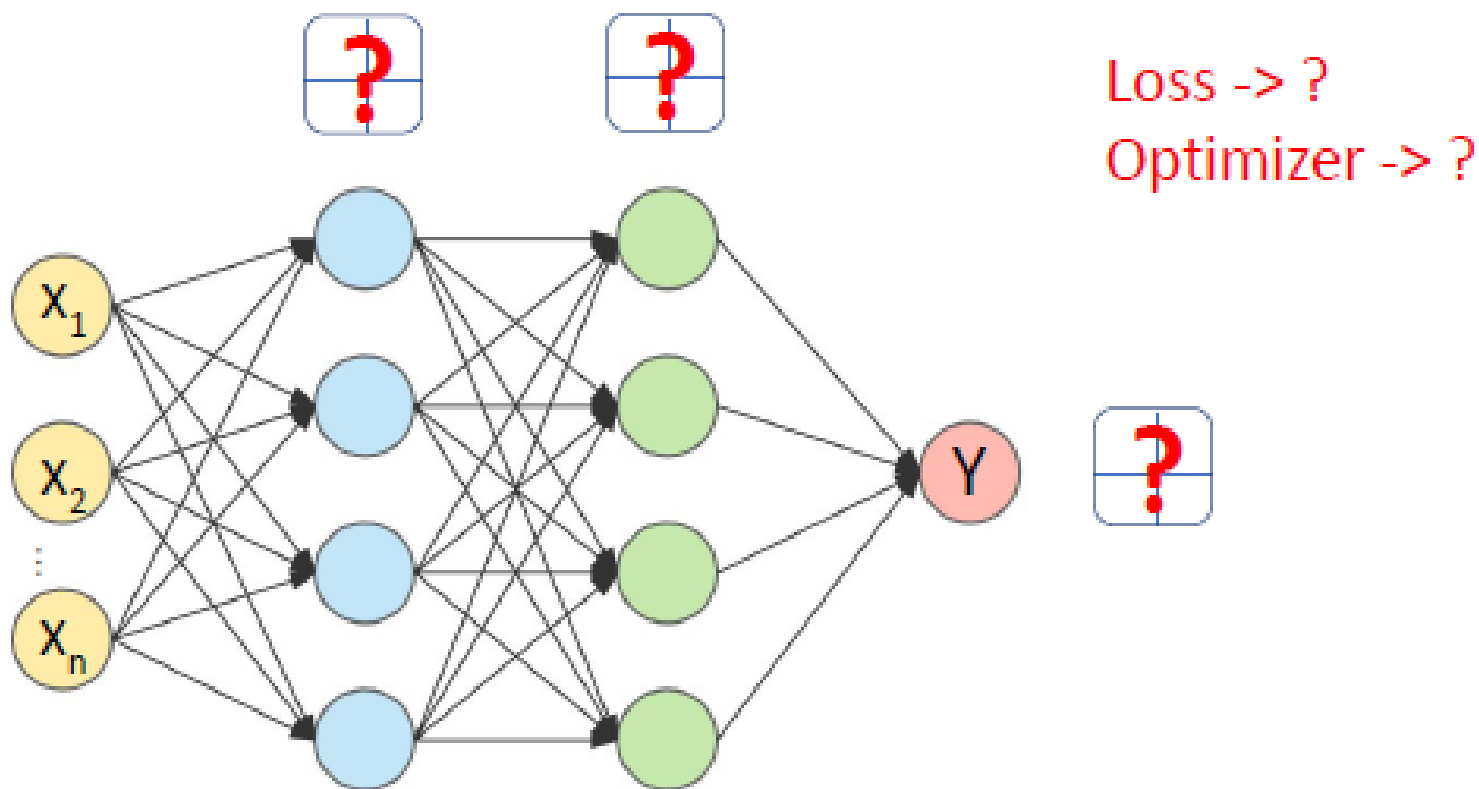
- Error Measurement (Loss)
- Optimization

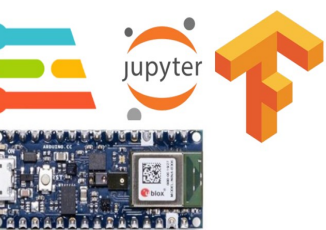
Parameters to be found during training, to reach minimum error

$$y = f\left(\sum_{i=1}^n x_i w_i + b\right)$$



## ❖ Supervised machine learning with DNN



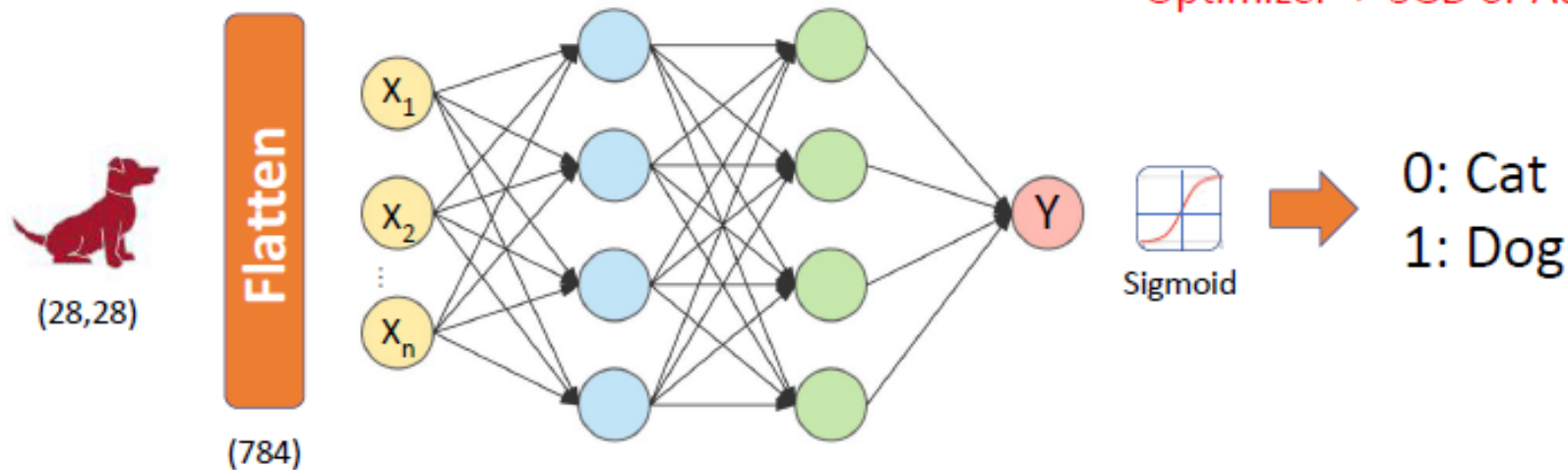


# DNN

## ❖ Supervised machine learning with DNN

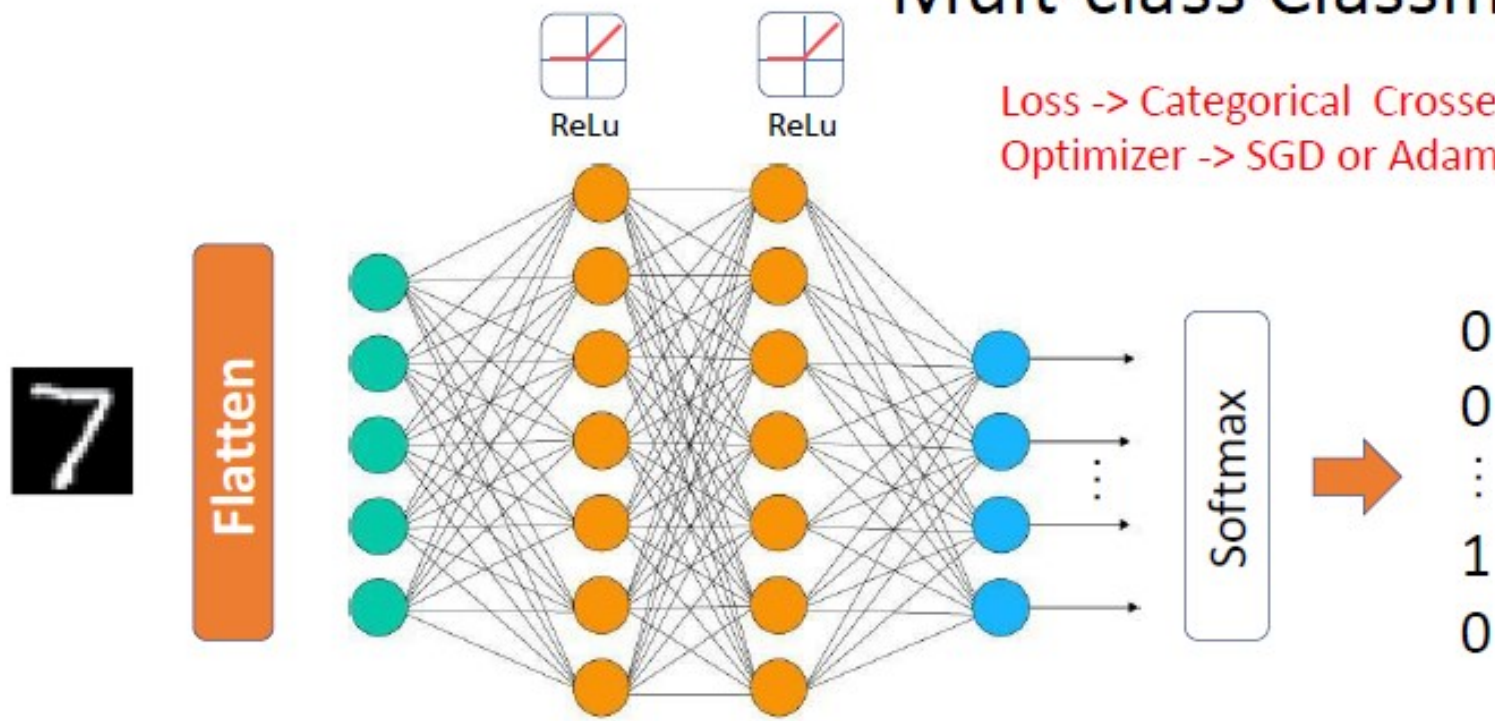
### Binary Classification

Loss -> Binary Crossentropy  
Optimizer -> SGD or Adam



## ❖ Supervised machine learning with DNN

### Mult-class Classification



Loss -> Categorical Crossentropy \*  
Optimizer -> SGD or Adam

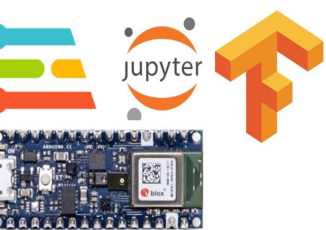
\* or "Sparse Categorical Crossentropy" if label is 1, 2, 3, ...

## ❖ Supervised machine learning with DNN

- Dataset for training and testing



Classifying Shoes



# DNN

- ❖ Supervised machine learning with DNN
  - Dataset for training and testing

## Steps to take

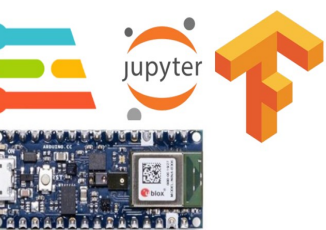
1. Get as many examples of shoes as possible
2. Train using these examples
3. Profit!



## ❖ Supervised machine learning with DNN

- Dataset for training and testing





# DNN

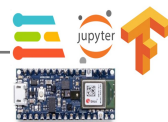
## ❖ Supervised machine learning with DNN

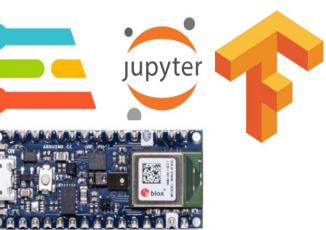
- Dataset for training and testing

## Steps to take

1. Get as many examples of shoes as possible
2. Train using these examples
3. Profit!

```
Training accuracy: .920
Training accuracy: .935
Training accuracy: .947
Training accuracy: .961
Training accuracy: .977
Training accuracy: .995
Training accuracy: 1.00
```





# DNN

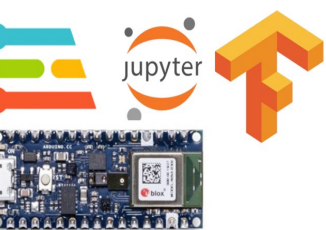
- ❖ Supervised machine learning with DNN
  - Dataset for training and testing

## Steps to take

- ~~1. Get as many examples of shoes as possible~~
- ~~2. Train using these examples~~
3. Profit?







# DNN

- ❖ Supervised machine learning with DNN
  - Dataset for training and testing

## Data

The network 'sees' everything. Has no context for measuring how well it does with data it has never previously been exposed to.

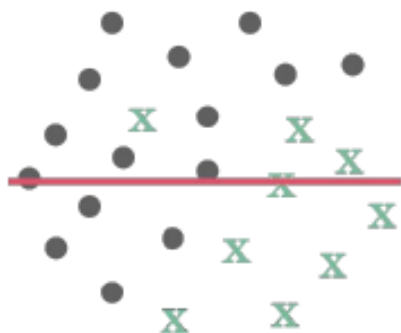
## ❖ Supervised machine learning with DNN

- Dataset for training and testing

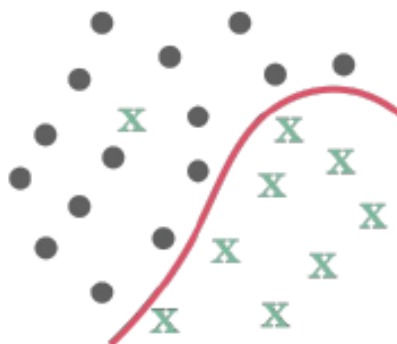
### Data

The network 'sees' everything. Has no context for measuring how well it does with data it has never previously been exposed to.

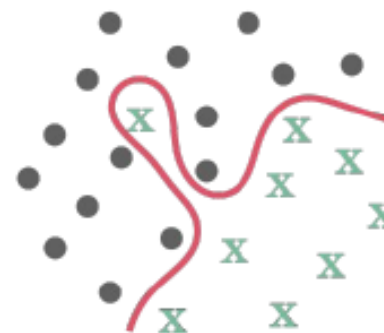
Underfitting

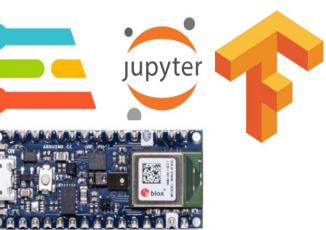


Desired



**Overfitting**





# DNN

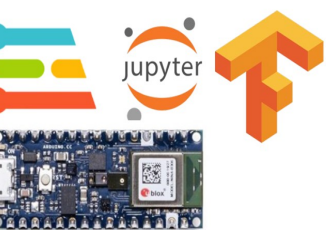
## ❖ Supervised machine learning with DNN

- Dataset for training and testing

**Data**

**Validation Data**

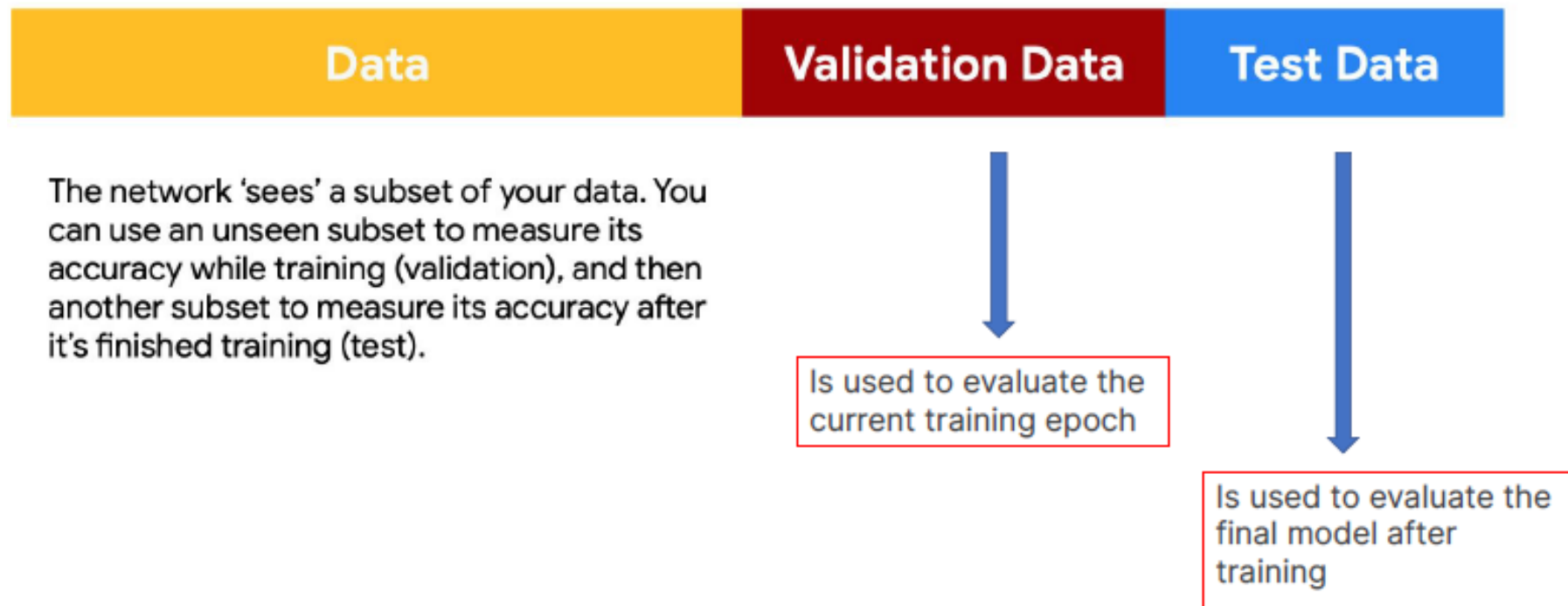
The network 'sees' a subset of your data. You can use the rest to measure its performance against previously unseen data.

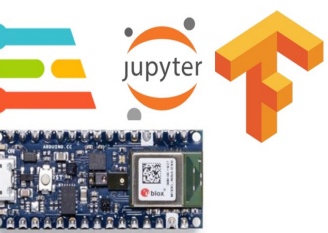


# DNN

## ❖ Supervised machine learning with DNN

- Dataset for training and testing



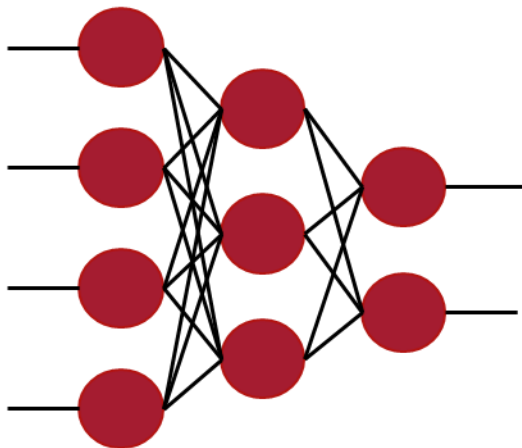


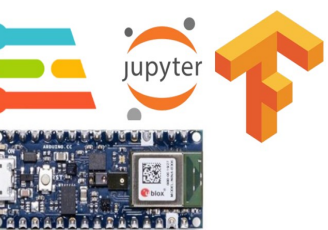
# DNN

## ❖ Supervised machine learning with DNN

- Dataset for training and testing

Data	Validation Data	Test Data
Accuracy: 0.999	Accuracy: 0.920	Accuracy: 0.800



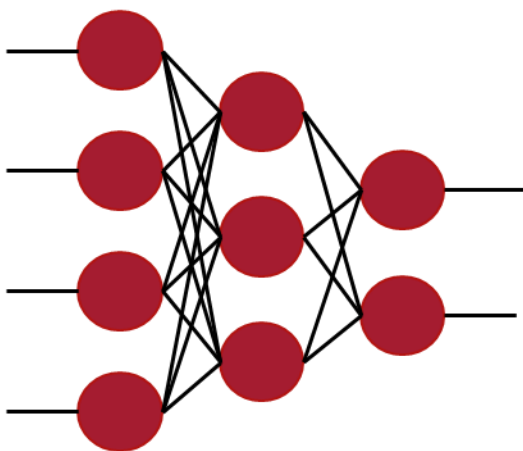


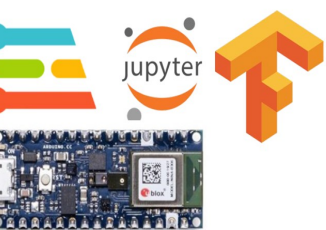
# DNN

## ❖ Supervised machine learning with DNN

- Dataset for training and testing

Data	Validation Data	Test Data
Accuracy: 0.999	Accuracy: 0.920	Accuracy: 0.800



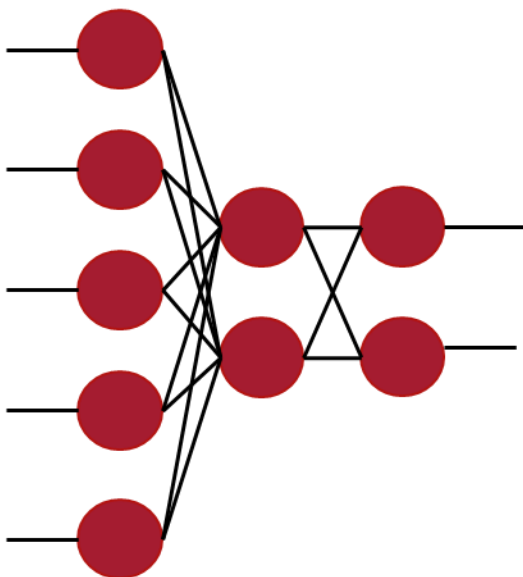


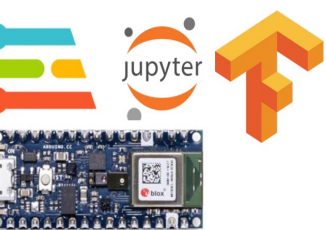
# DNN

## ❖ Supervised machine learning with DNN

- Dataset for training and testing

Data	Validation Data	Test Data
Accuracy: 0.942	Accuracy: 0.930	Accuracy: 0.925





# DNN

- ❖ Supervised machine learning with DNN
  - Dataset for training and testing

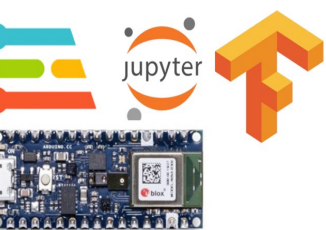
## Digits Classification: validation and test dataset

Code Time!

TF\_MNIST\_Classification\_v2.ipynb







# DNN

## ❖ Supervised machine learning with DNN

- Dataset for training and testing

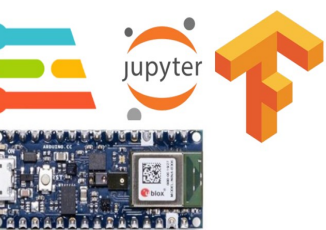
```
1 data = tf.keras.datasets.mnist
2
3 (tt_images, tt_labels), (test_images, test_labels) = data.load_data()
```

```
1 print(tt_images.shape)
2 print(tt_labels.shape)
```

```
(60000, 28, 28)
(60000,)
```

```
1 print(test_images.shape)
2 print(test_labels.shape)
```

```
(10000, 28, 28)
(10000,)
```



# DNN

## ❖ Supervised machine learning with DNN

### □ Dataset for training and testing

```
1 val_images = tt_images[:10000]
2 val_labels = tt_labels[:10000]
```

```
1 train_images = tt_images[10000:]
2 train_labels = tt_labels[10000:]
```

```
1 print(train_images.shape)
2 print(train_labels.shape)
```

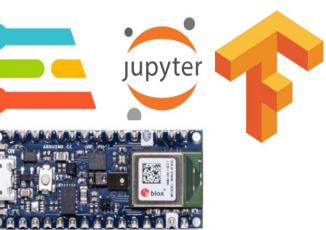
```
(50000, 28, 28)
(50000,)
```

```
1 print(val_images.shape)
2 print(val_labels.shape)
```

```
(10000, 28, 28)
(10000,)
```

Split tt data in:

- train (50,000) and,
- validation (10,000)



# DNN

## ❖ Supervised machine learning with DNN

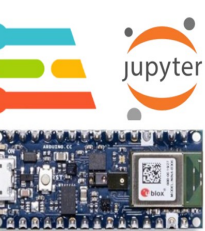
- Dataset for training and testing

```
1 history = model.fit(  
2     train_images,  
3     train_labels,  
4     epochs=20,  
5     validation_data=(val_images, val_labels)  
6 )
```

You could leave the training data with all samples, and alternatively use:

- *validation\_split=0.1* instead of *validation\_data=(val\_images, val\_labels)*.

In this case, TF will split the validation data by itself.

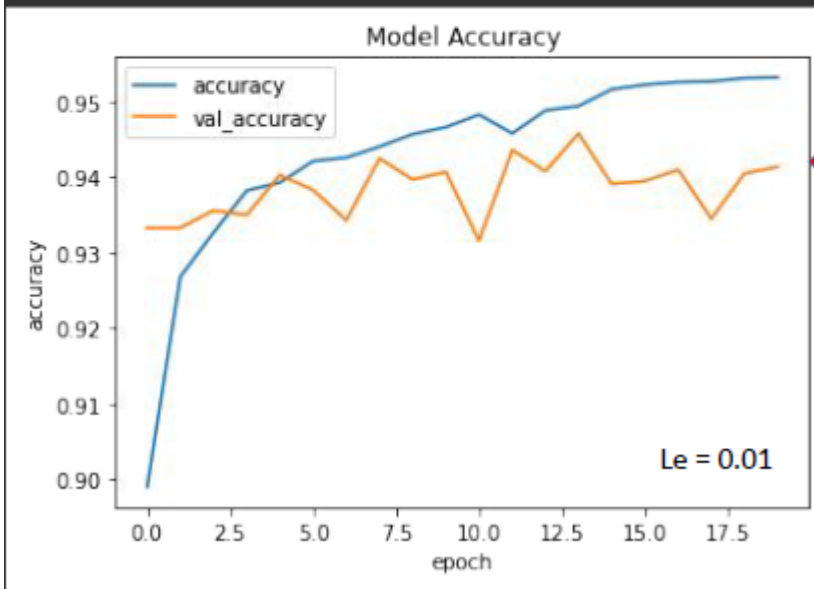


# DNN

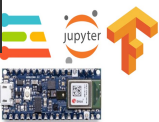
## ❖ Supervised machine learning with DNN

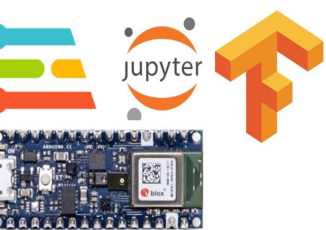
### □ Dataset for training and testing

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.title('Model Accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(loc='upper left')
plt.show()
```



If validation accuracy seems “instable”, could be that Learning Rate is high (try to reduce it).



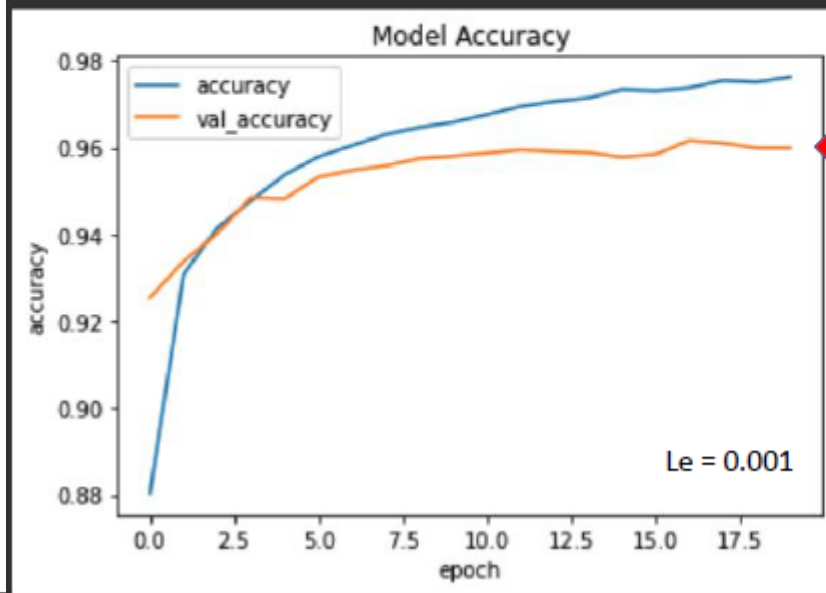


# DNN

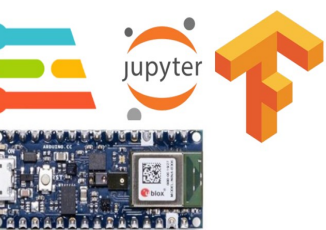
## ❖ Supervised machine learning with DNN

### □ Dataset for training and testing

```
plt.plot(history.history['accuracy'], label='accuracy')
plt.plot(history.history['val_accuracy'], label='val_accuracy')
plt.title('Model Accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(loc='upper left')
plt.show()
```



If validation accuracy goes down (or became stable), even if train accuracy goes up, means that probably the model is overfitting. In this case the training (epochs) should terminate.

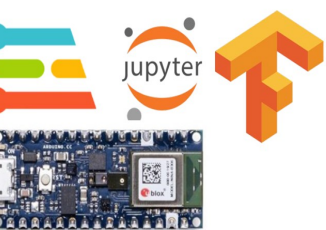


# DNN

- ❖ Supervised machine learning with DNN
  - Dataset for training and testing

```
model.evaluate(test_images, test_labels)
```

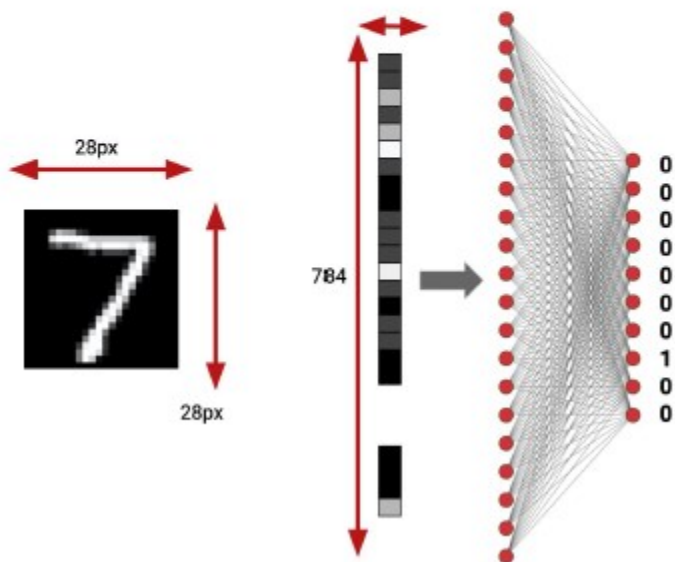
```
313/313 [=====] - 1s 2ms/step - loss: 0.1495 - accuracy: 0.9569
```

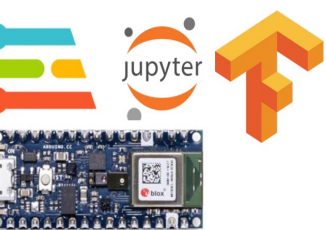


# DNN

## ❖ Supervised machine learning with DNN

- Dataset for training and testing





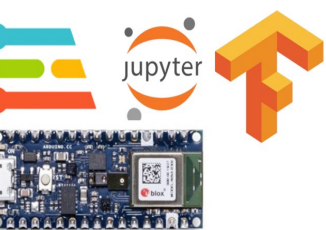
# DNN

## ❖ Supervised machine learning with DNN

### □ Dataset for training and testing

- Training Data
  - ◇ Used to train model parameters
- Validation Data
  - ◇ Used to determine what model hyperparameters to adjust (and re-training)
- Test Data
  - ◇ Used to get model final performance metric





# MODEL PERFORMANCE METRICS

## ❖ Classification model performance metrics



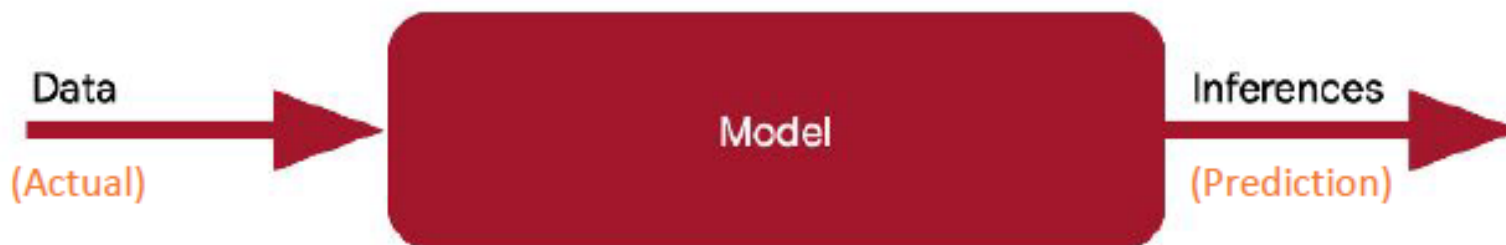
Class = [1]

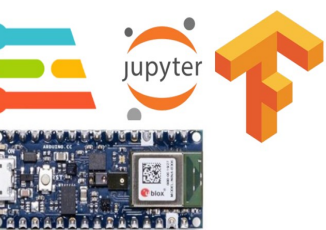
actual = [1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0]

prediction = [0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1]



Class = [0]





# MODEL PERFORMANCE METRICS

## ❖ Classification model performance metrics



Class = [1]

actual = [1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0]



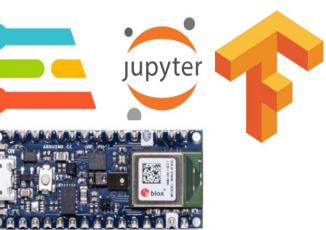
Class = [0]

prediction = [0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1]

## Model Performance (Confusion Matrix)

		predicted condition	
		Cat [1]	Dog [0]
true condition	Cat [1]	6	2
	Dog [0]	1	3





# MODEL PERFORMANCE METRICS

## ❖ Classification model performance metrics



Class = [1]

actual = [1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0]

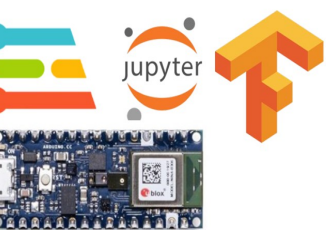


Class = [0]

prediction = [0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1]

## Model Performance (Confusion Matrix)

		predicted condition	
		Cat [1]	Dog [0]
true condition	Cat [1]	True Positive (TP) 6	False Negative (FN) (type II error) 2
	Dog [0]	False Positive (FP) (Type I error) 1	True Negative (TN) 3

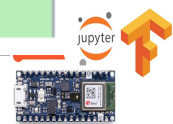


# MODEL PERFORMANCE METRICS

- ❖ Classification model performance metrics

## Model Performance (Confusion Matrix)

		predicted condition	
		prediction positive (PP)	prediction negative (PN)
true condition	condition positive (P)	True Positive (TP)	False Negative (FN) (type II error)
	condition negative (N)	False Positive (FP) (Type I error)	True Negative (TN)



# MODEL PERFORMANCE METRICS

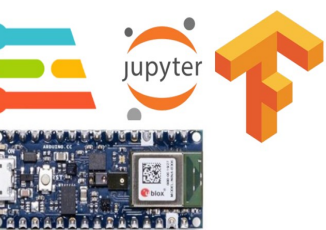
## ❖ Classification model performance metrics

**Type I error (false positive)**



**Type II error (false negative)**





# MODEL PERFORMANCE METRICS

## ❖ Classification model performance metrics

Precision

VS.

Accuracy

In a set of measurements:

- **Accuracy** is closeness of the measurements to a specific value
- **Precision** is the closeness of the measurements to each other.



High Precision, High Accuracy



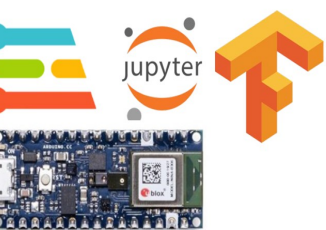
Low Precision, High Accuracy



High Precision, Low Accuracy



Low Precision, Low Accuracy



# MODEL PERFORMANCE METRICS

## ❖ Classification model performance metrics

### Accuracy , Precision and Recall

$$\text{Accuracy} = \frac{TP + TN}{(P + N)} = \frac{TP + TN}{(TP + TN + FP + FN)} = \frac{6 + 3}{(6 + 3 + 1 + 2)} = \frac{9}{12} = 0.75$$

$$\text{Precision} = \frac{TP}{(TP + FP)} = \frac{6}{(6 + 1)} = \frac{6}{7} = 0.86$$

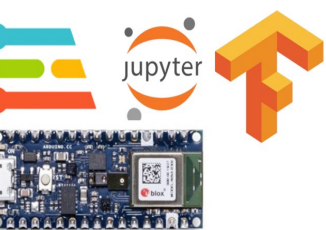
$$\frac{\text{Total Positive}}{\text{Total Predict Positive}}$$

$$\text{Recall} = \frac{TP}{(TP + FN)} = \frac{6}{(6 + 2)} = \frac{6}{8} = 0.75$$

(or Sensitivity)

$$\frac{\text{Total Positive}}{\text{Total Actual Positive}}$$





# MODEL PERFORMANCE METRICS

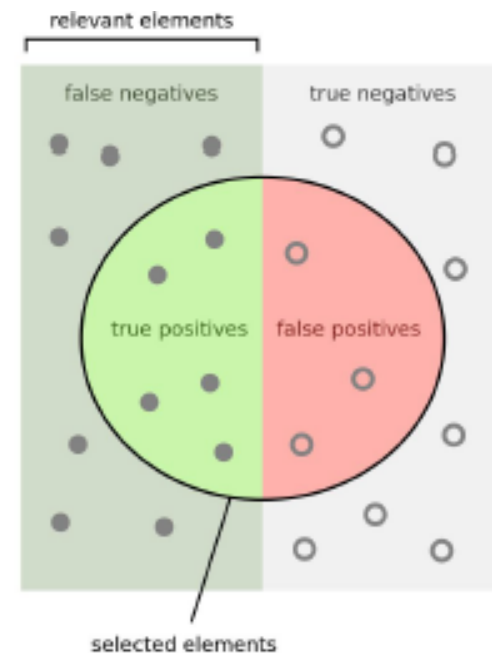
## ❖ Classification model performance metrics

### F1-Score

$$F1 = 2 \times \frac{(\text{Precision} * \text{Recall})}{(\text{Precision} + \text{Recall})}$$

$$F1 = 2 \times \frac{(0.86 * 0.75)}{(0.86 + 0.75)} = 2 \times \frac{0.65}{1.61} = 0.80$$

The F1-score is a way of combining the **precision** and **recall** of the model

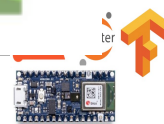


How many selected items are relevant?

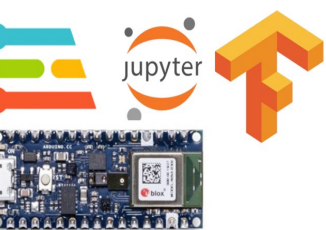
Precision =  $\frac{\text{true positives}}{\text{true positives} + \text{false positives}}$

How many relevant items are selected?

Recall =  $\frac{\text{true positives}}{\text{true positives} + \text{false negatives}}$







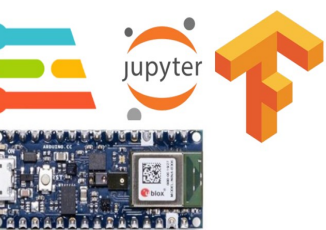
# MODEL PERFORMANCE METRICS

- ❖ Classification model performance metrics

Classification Report  
Code Time!

Classification\_Report.ipynb





# MODEL PERFORMANCE METRICS

## ❖ Classification model performance metrics

```
1 from sklearn.metrics import classification_report
```

```
1 actual = [1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0]
2 prediction = [0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1]
```

```
1 target_names = ['Dogs', 'Cats']
```

```
1 print(classification_report(actual, prediction, target_names=target_names))
```

	precision	recall	f1-score	support
Dogs	0.60	0.75	0.67	4
Cats	0.86	0.75	0.80	8
accuracy			0.75	12
macro avg	0.73	0.75	0.73	12
weighted avg	0.77	0.75	0.76	12

