

# IESTI01 – TinyML

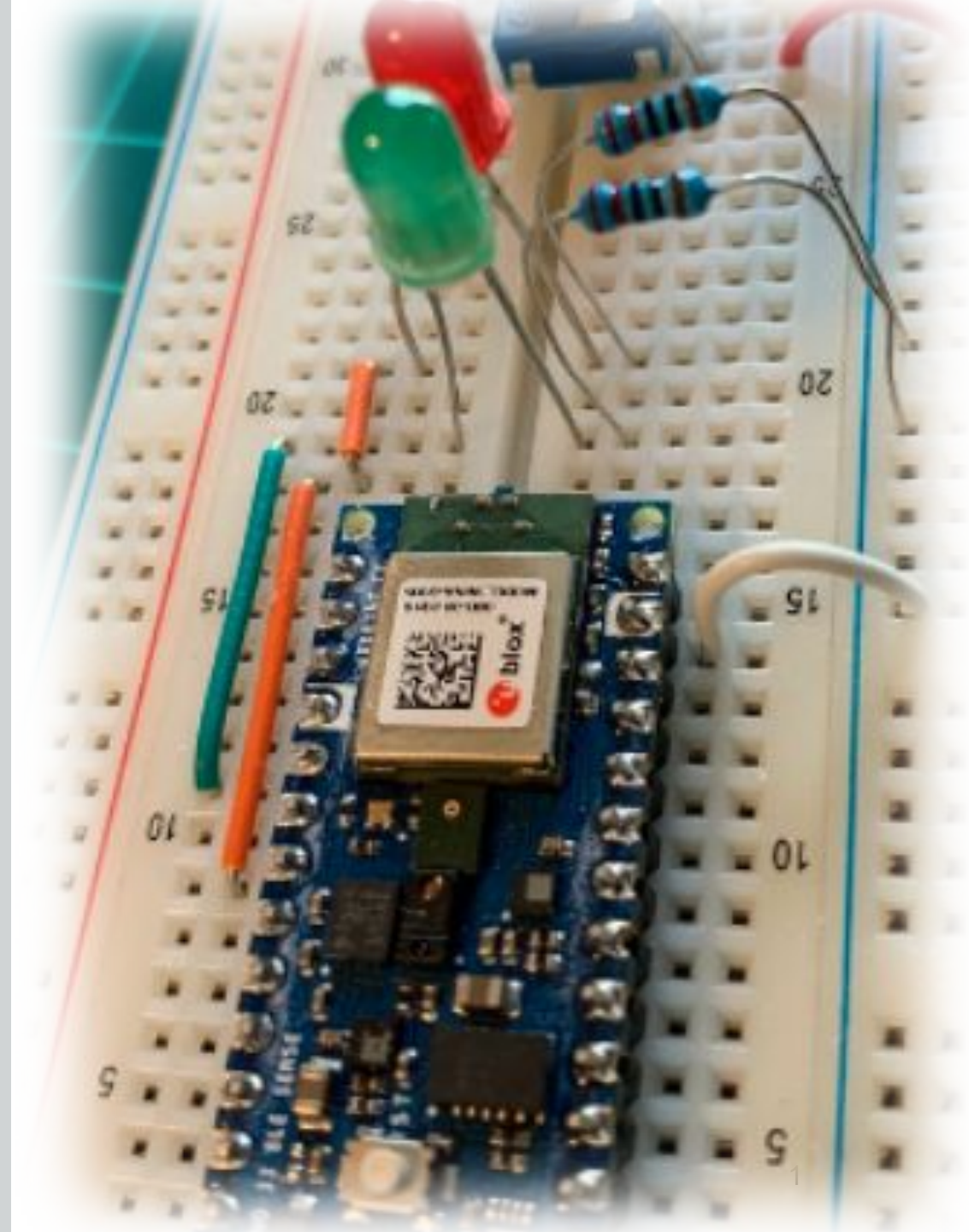
## Embedded Machine Learning

9. The Building Blocks of Deep Learning – Part C
- DNN Recap & ML Metrics



Prof. Marcelo Rovai

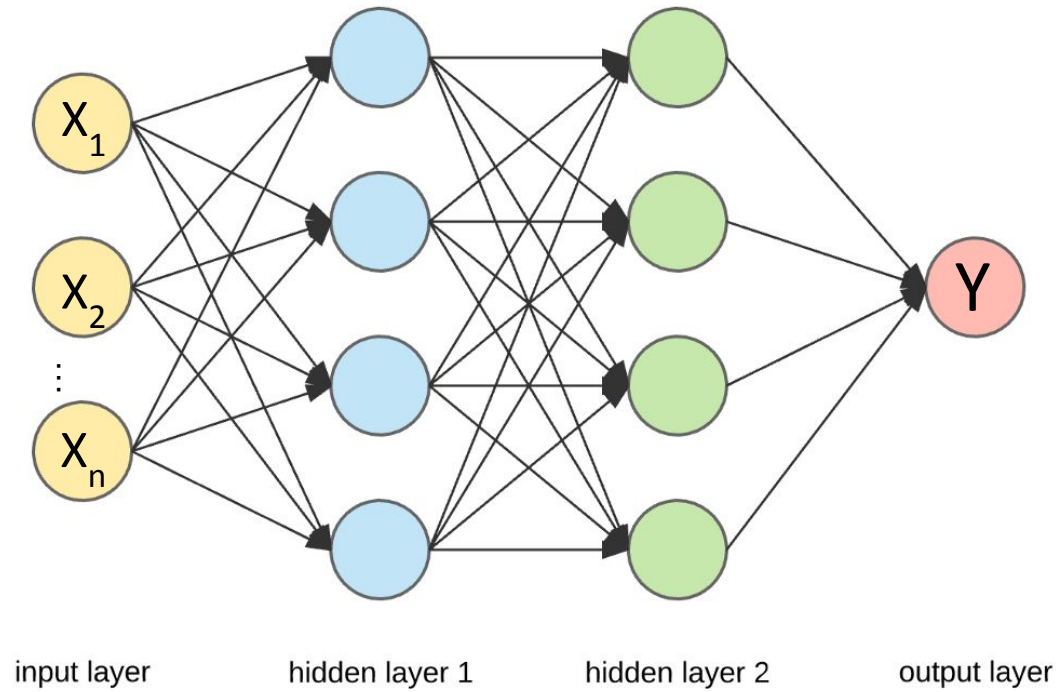
UNIFEI

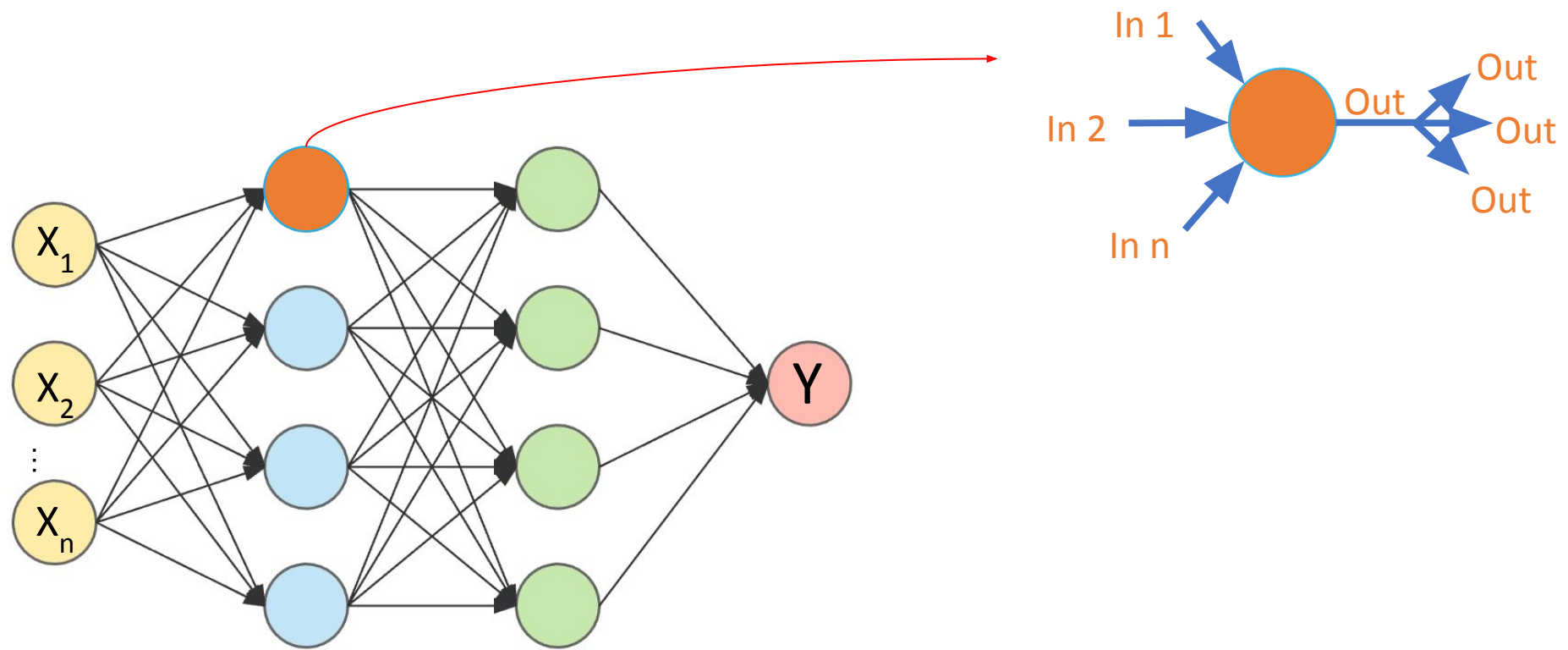


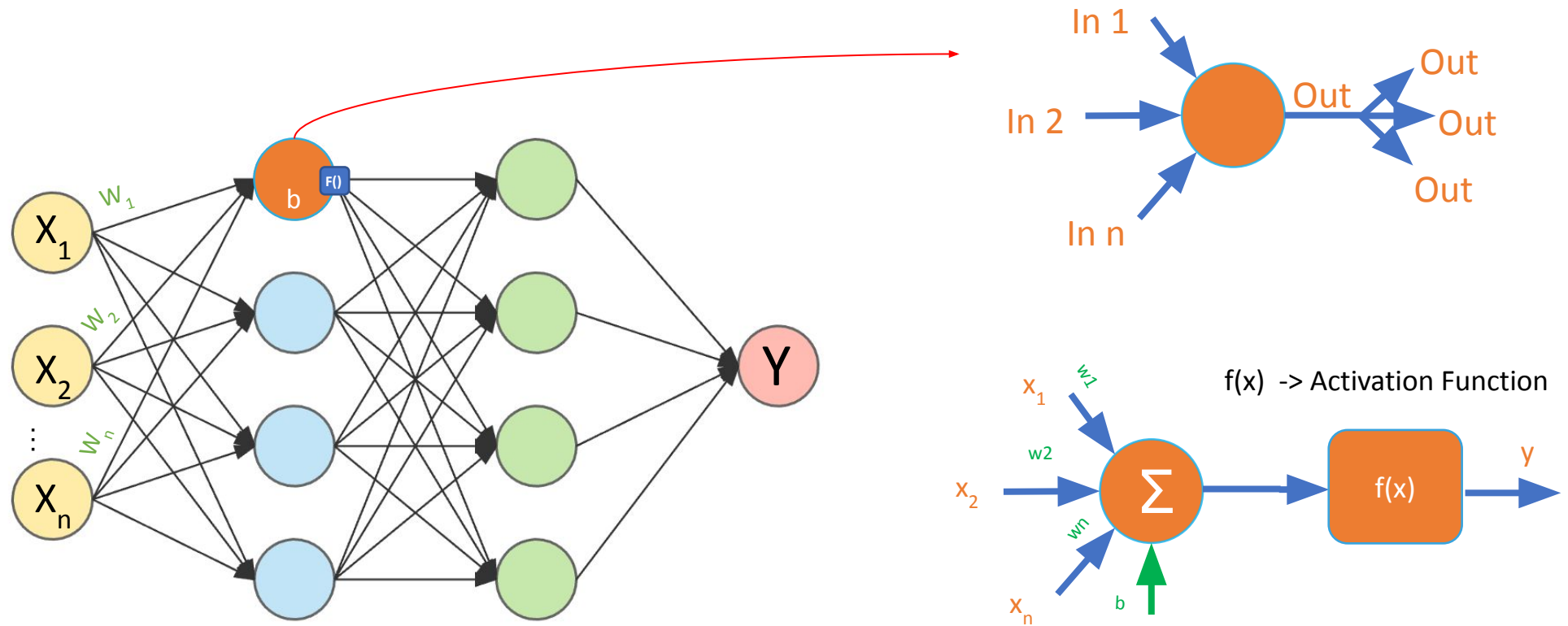
# DNN Dense Neural Network

Recap

# Supervised Machine Learning with DNN

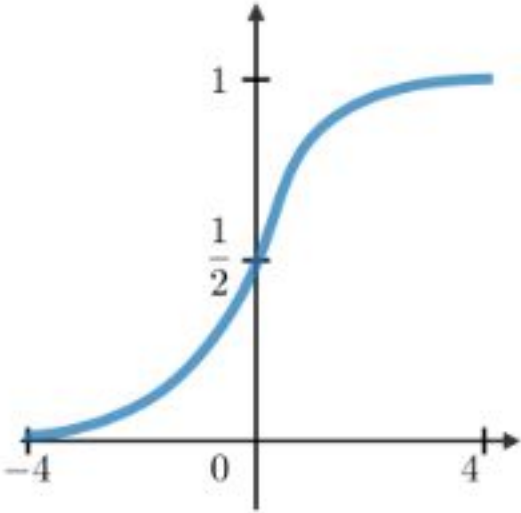
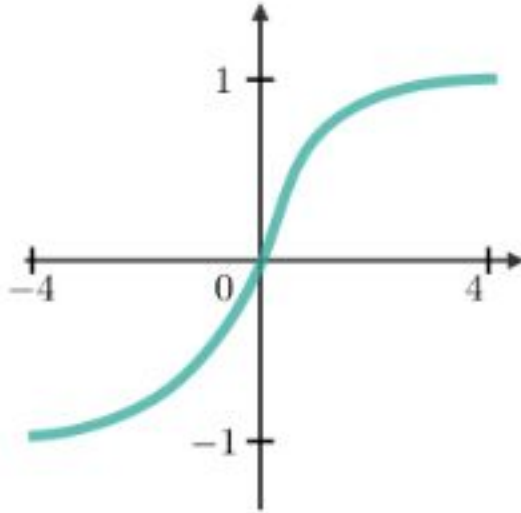
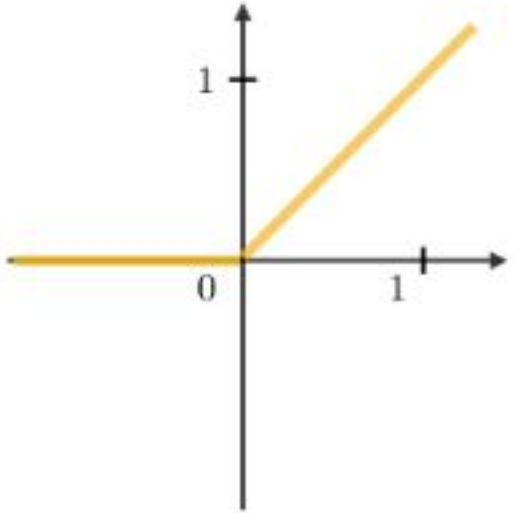


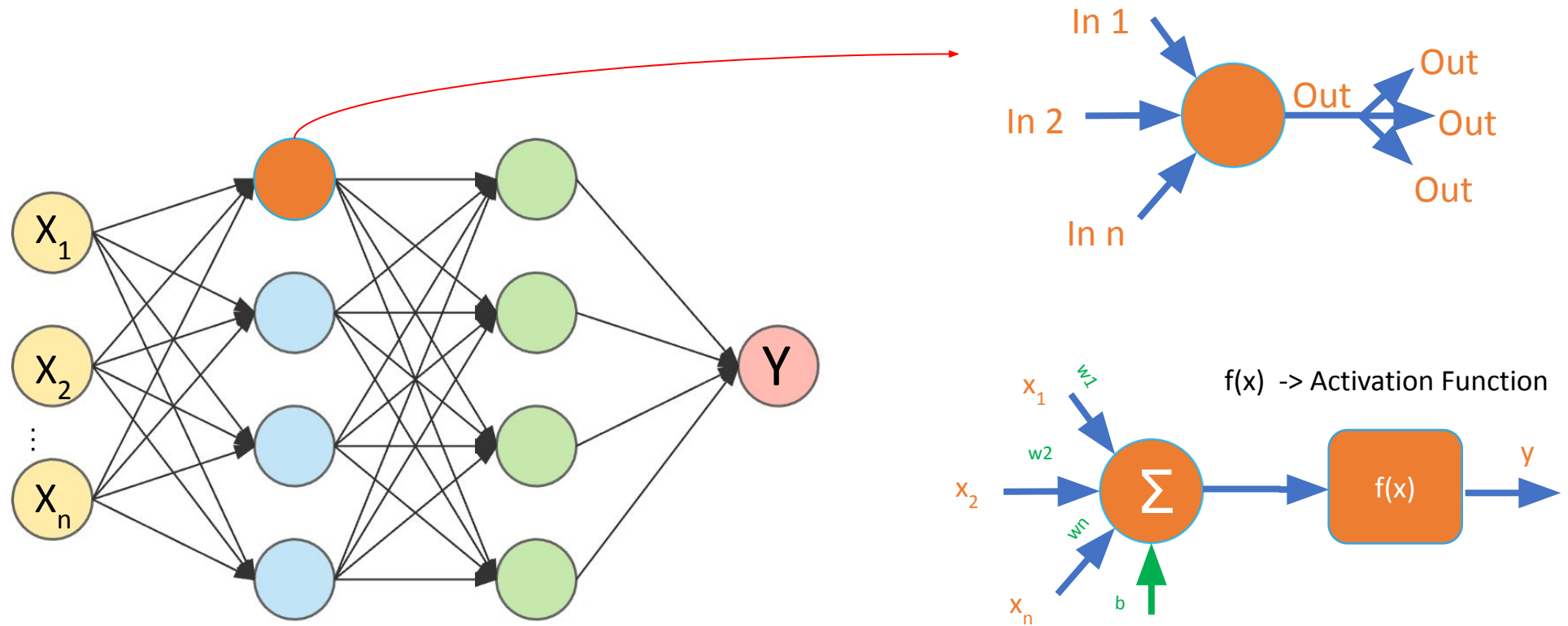




$$y = f\left(\sum_{i=1}^n x_i w_i + b\right)$$

# Activation Functions

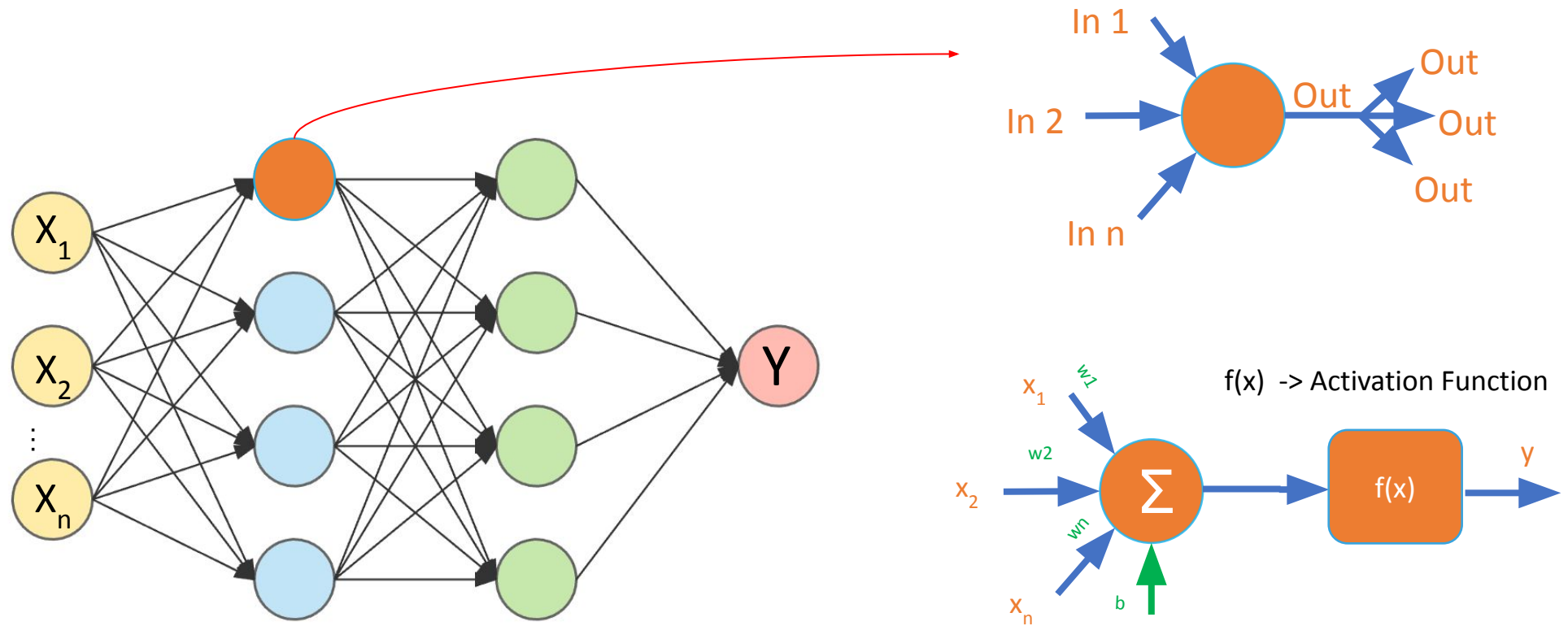
Sigmoid	Tanh	RELU
$g(z) = \frac{1}{1 + e^{-z}}$	$g(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$	$g(z) = \max(0, z)$
		



Parameters to be found during training, to reach minimum error

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



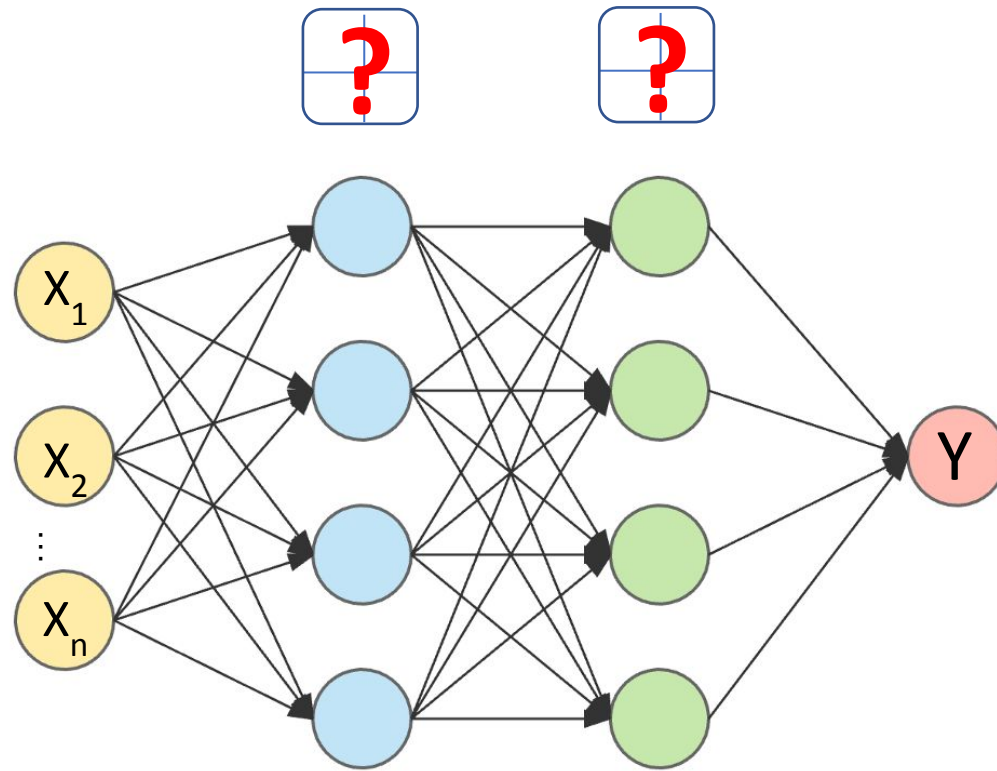


- Error Measurement (Loss)
- Optimization

Parameters to be found during training, to reach minimum error

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





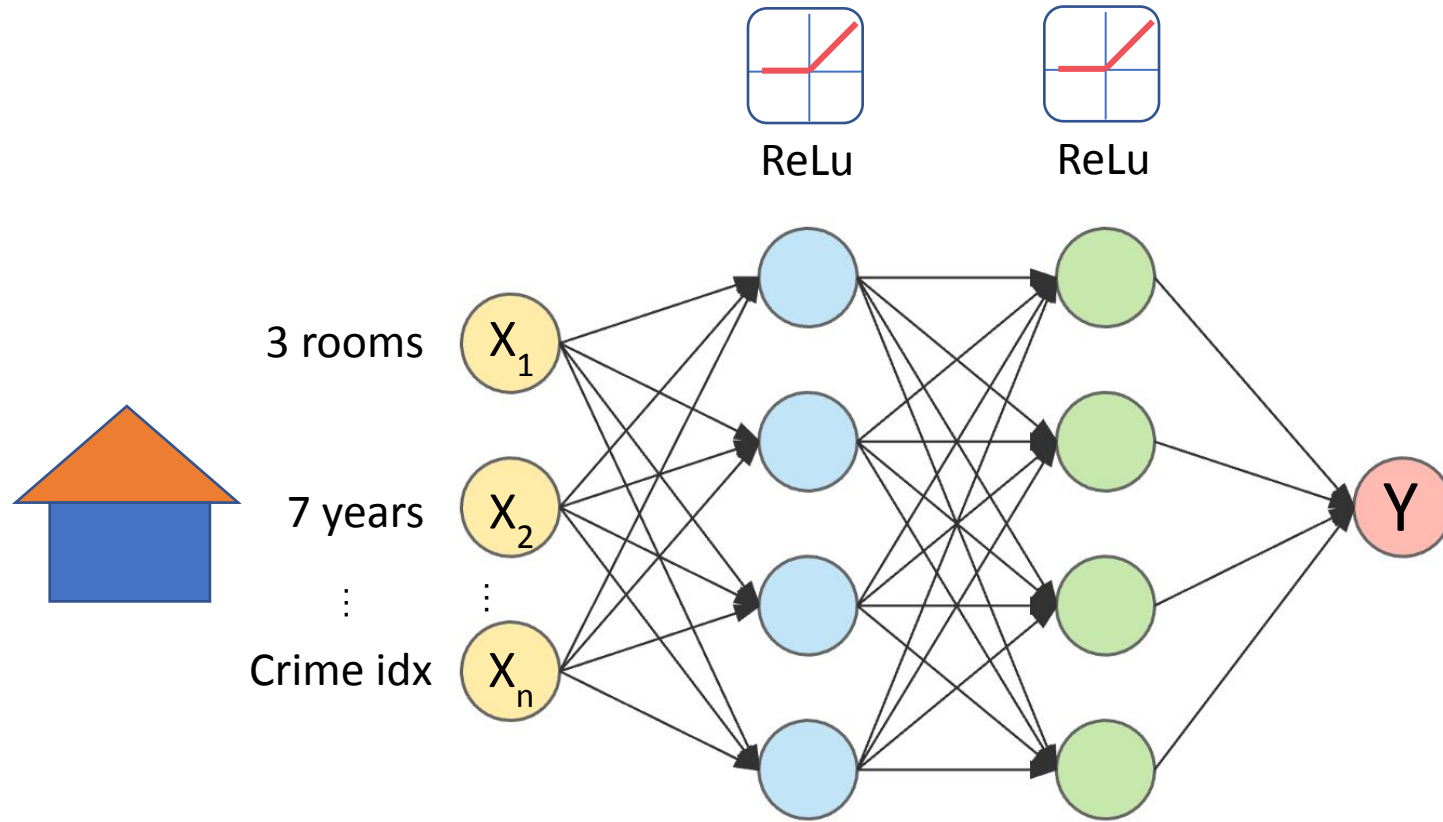
Loss -> ?  
Optimizer -> ?

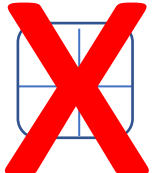
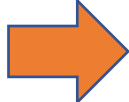


# Regression

Loss -> MSE or MAE

Optimizer -> SGD or Adam



  \$34.8

# Binary Classification

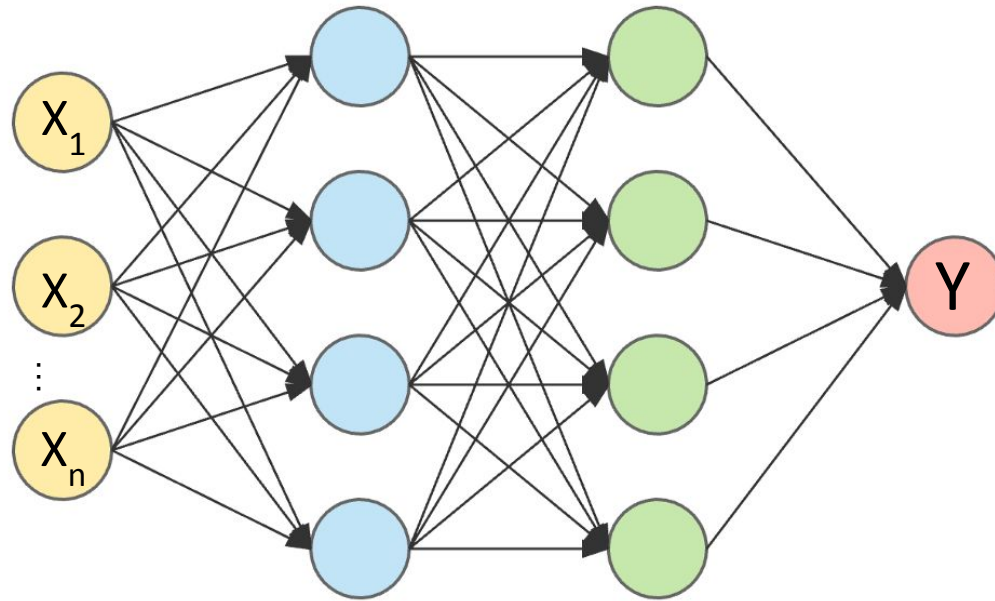
Loss -> Binary Crossentropy  
Optimizer -> SGD or Adam



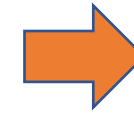
(28,28)

Flatten

(784)

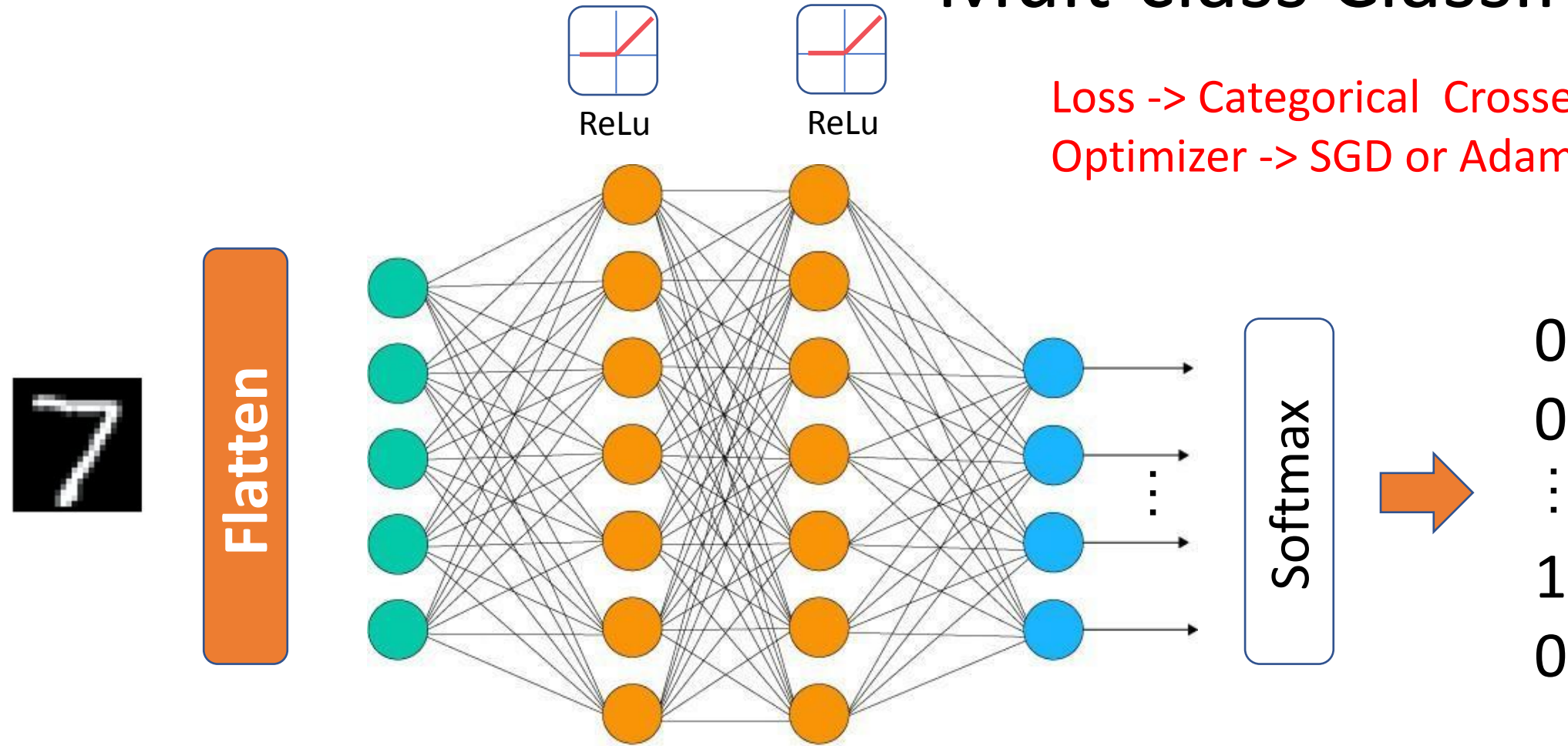


Sigmoid



0: Cat  
1: Dog

# Mult-class Classification



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

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

# Going Further

The Datasets to training and test





# Classifying Shoes

# Steps to take

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





na  
visjem



# 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
```

# Steps to take

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



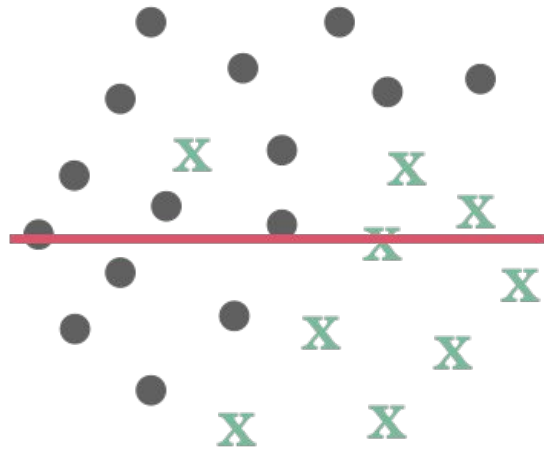
# Data

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

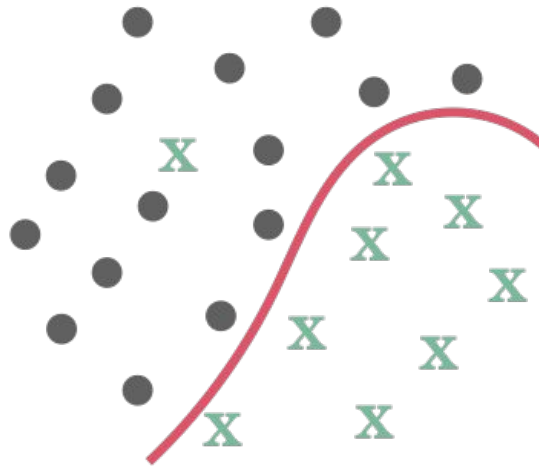
# Data

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

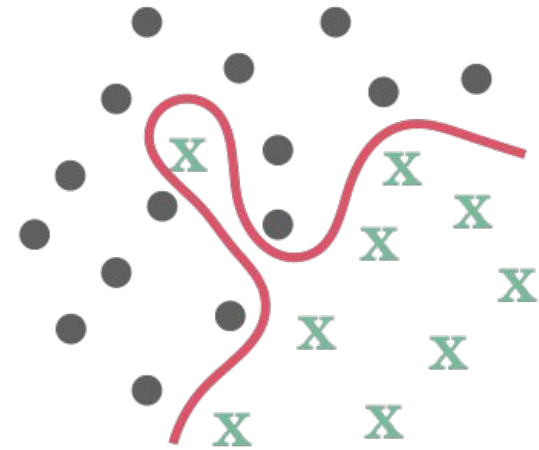
Underfitting



Desired



Overfitting







## Data

## Validation Data

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



**Data**

**Validation Data**

**Test Data**

The network 'sees' a subset of your data. You can use an unseen subset to measure its accuracy while training (validation), and then another subset to measure its accuracy after it's finished training (test).



Is used to evaluate the current training epoch



Is used to evaluate the final model after training

**Data**

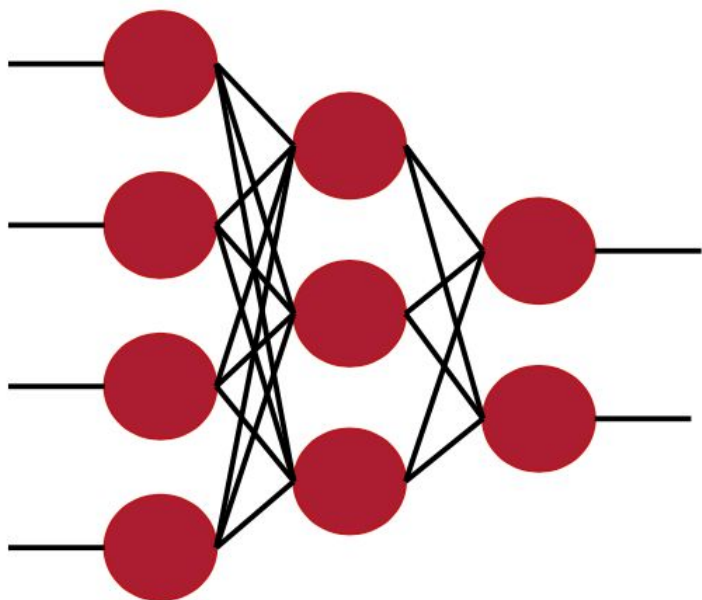
**Validation Data**

**Test Data**

**Accuracy: 0.999**

**Accuracy: 0.920**

**Accuracy: 0.800**



**Data**

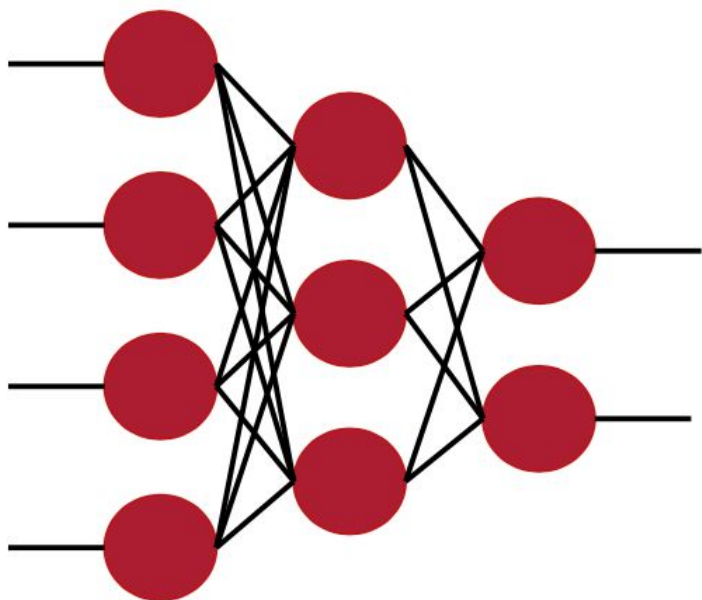
**Validation Data**

**Test Data**

**Accuracy: 0.999**

**Accuracy: 0.920**

**Accuracy: 0.800**



**Data**

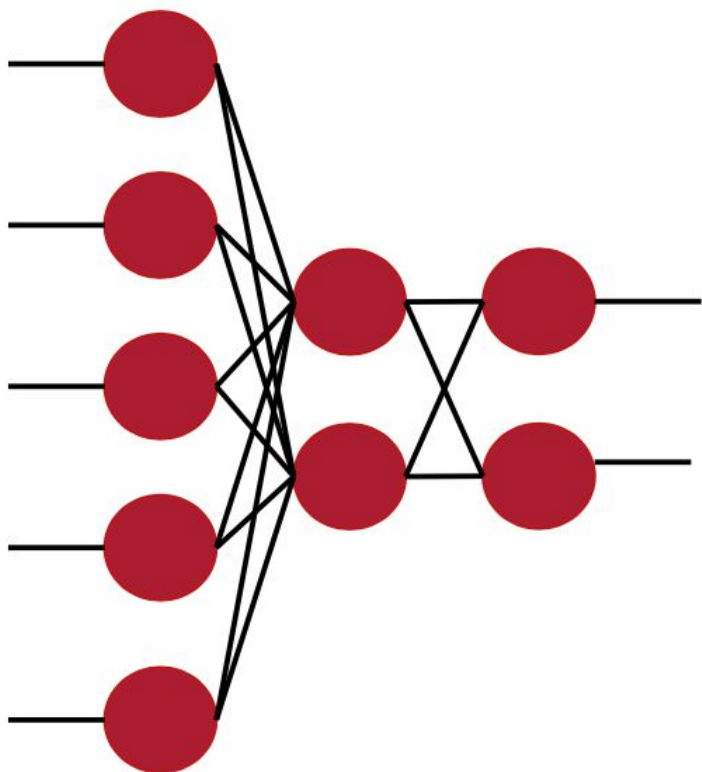
**Validation Data**

**Test Data**

**Accuracy: 0.942**

**Accuracy: 0.930**

**Accuracy: 0.925**



# Digits Classification: validation and test dataset

## Code Time!

TF\_MNIST\_Classification\_v2.ipynb



```
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)
```

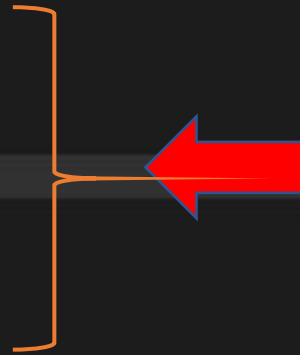
```
(60000, 28, 28)
(60000,)
```

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

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

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

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



Split tt data in:

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

```
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,)
```



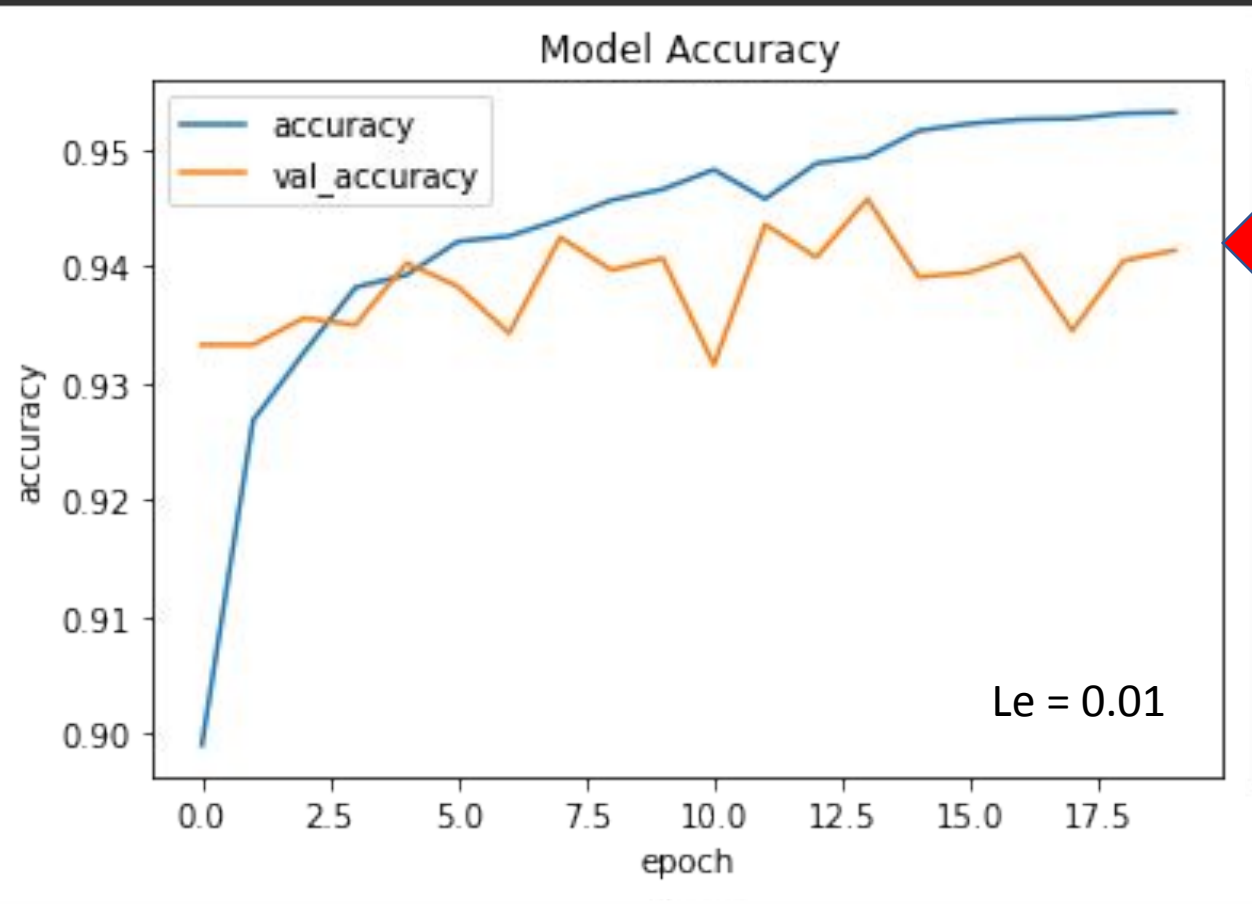
```
1 history = model.fit(  
2     train_images,  
3     train_labels,  
4     epochs=20,  
5     validation_data=(val_images, val_labels)  
6 )
```

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

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

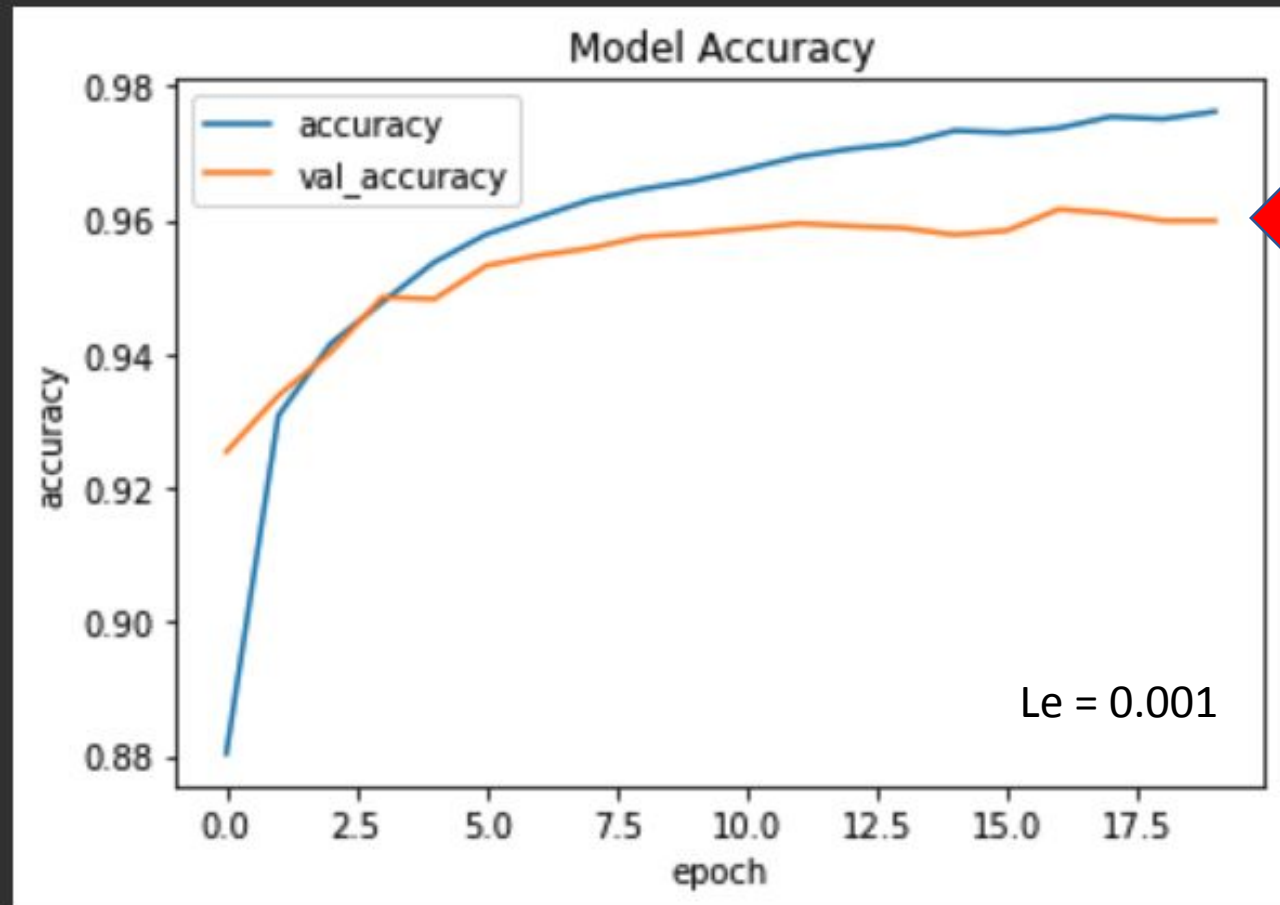
In this case, TF will split the validation data by itself.

```
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 “unstable”, could be that Learning Rate is high (try to reduce it).

```
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.

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

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

Data

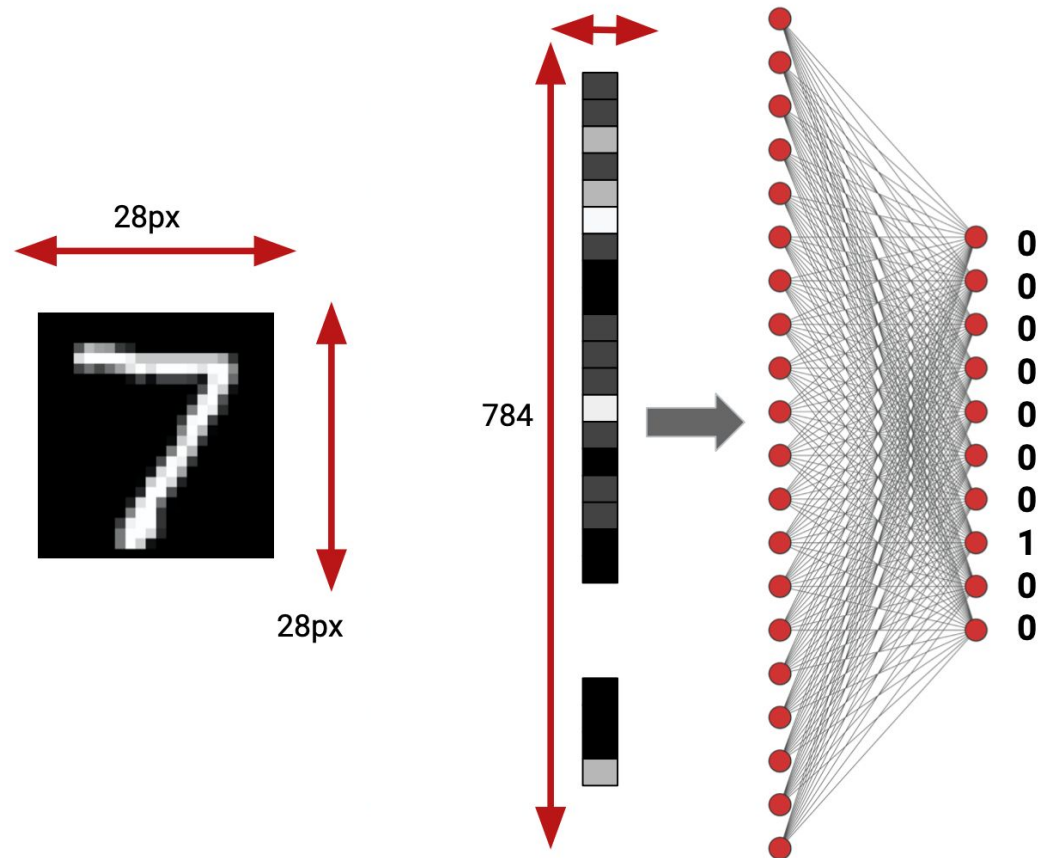
Validation Data

Test Data

Accuracy: 0.976

Accuracy: 0.963

Accuracy: 0.957



# In summary

**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**

# Going Further

Classification Model Performance Metrics





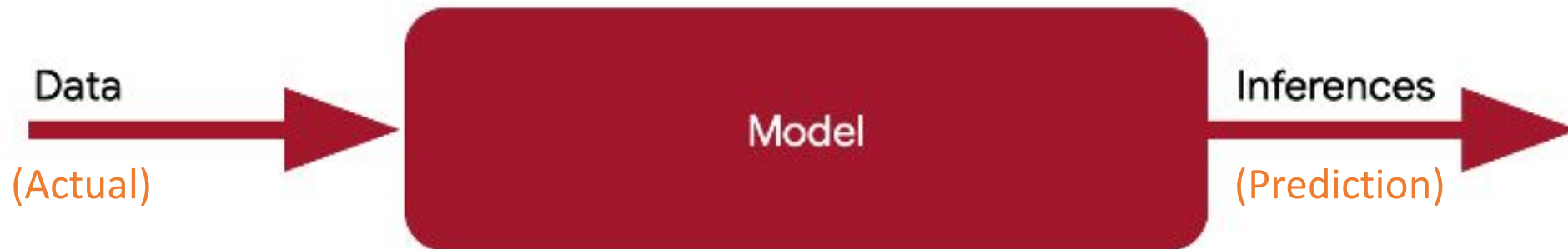
Class = [1]

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

12 pictures, 8 of cats and 4 of dogs

# 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 (Confusion Matrix)

		predicted condition	
		prediction positive (PP)	prediction negative (PN)
true condition	total population (P + N)		
	condition positive (P)	<b>True Positive (TP)</b>	<b>False Negative (FN)</b> (type II error)
	condition negative (N)	<b>False Positive (FP)</b> (Type I error)	<b>True Negative (TN)</b>

## Type I error (false positive)



## Type II error (false negative)



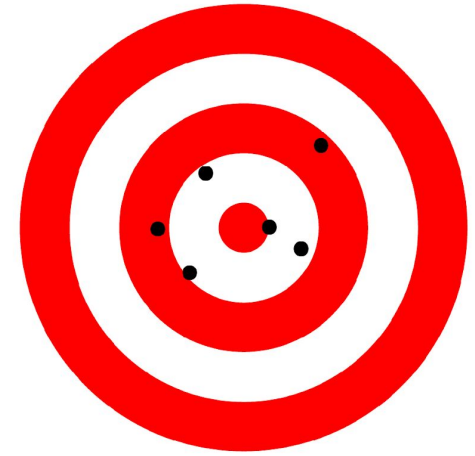
# Precision vs. Accuracy

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



# 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)

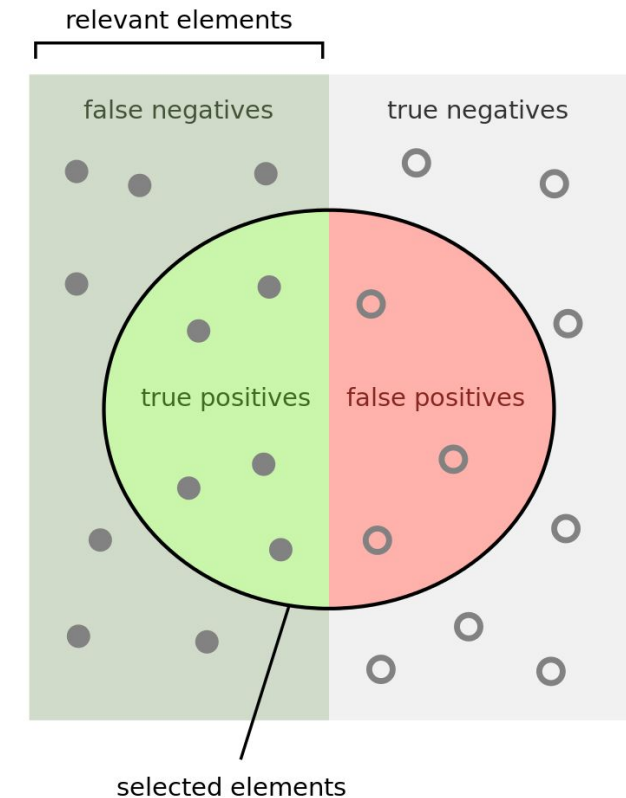
$$\frac{\text{Total Positive}}{\text{Total Actual Positive}}$$

# 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?

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

How many relevant items are selected?

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

# Classification Report

## Code Time!

Classification\_Report.ipynb



```
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, 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

# Reading Material



# Main references

- [Harvard School of Engineering and Applied Sciences - CS249r: Tiny Machine Learning](#)
- [Professional Certificate in Tiny Machine Learning \(TinyML\) – edX/Harvard](#)
- [Introduction to Embedded Machine Learning - Coursera/Edge Impulse](#)
- [Computer Vision with Embedded Machine Learning - Coursera/Edge Impulse](#)
- Fundamentals textbook: [“Deep Learning with Python” by François Chollet](#)
- Applications & Deploy textbook: [“TinyML” by Pete Warden, Daniel Situnayake](#)
- Deploy textbook [“TinyML Cookbook” by Gian Marco Iodice](#)

I want to thank **Shawn Hymel** and Edge Impulse, **Pete Warden** and **Laurence Moroney** from Google, Professor **Vijay Janapa Reddi** and **Brian Plancher** from Harvard, and the rest of the **TinyMLedu** team for preparing the excellent material on TinyML that is the basis of this course at UNIFEI.

The IESTI01 course is part of the **TinyML4D**, an initiative to make TinyML education available to everyone globally.

Thanks



**UNIFEI**