

IESTI01 – TinyML

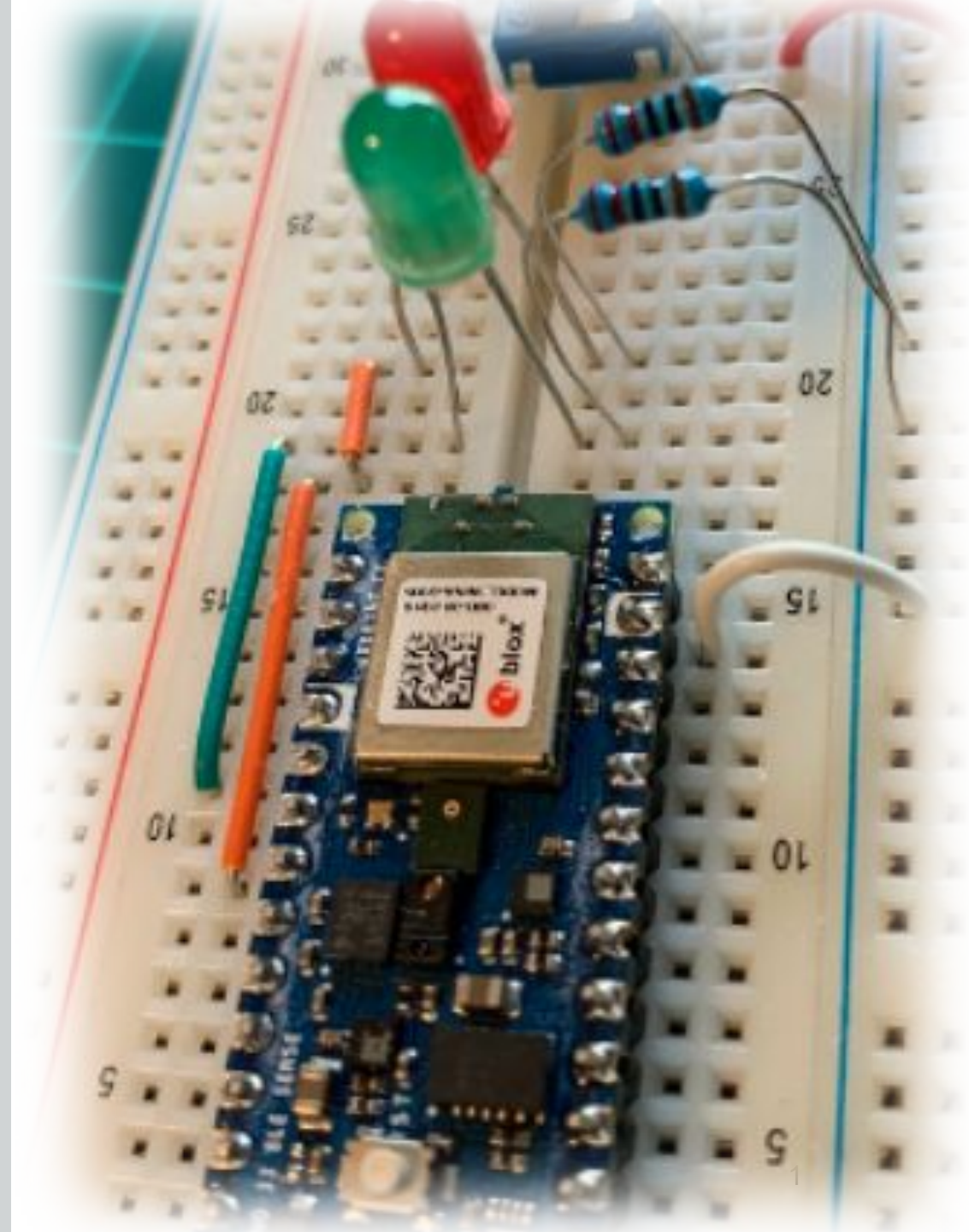
Embedded Machine Learning

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



Prof. Marcelo Rovai

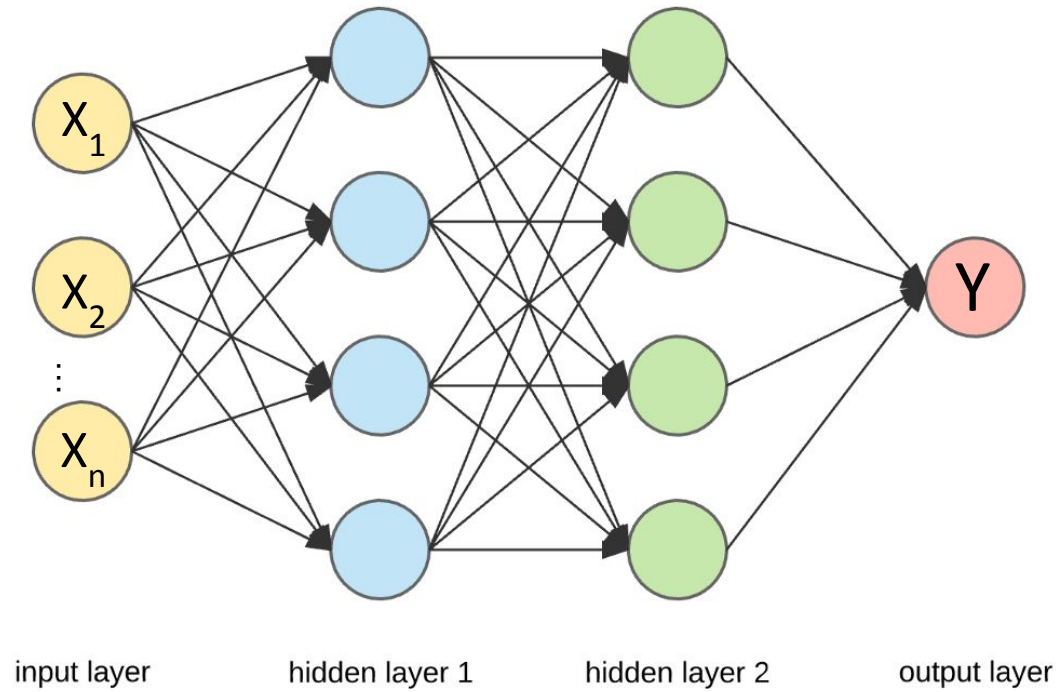
UNIFEI

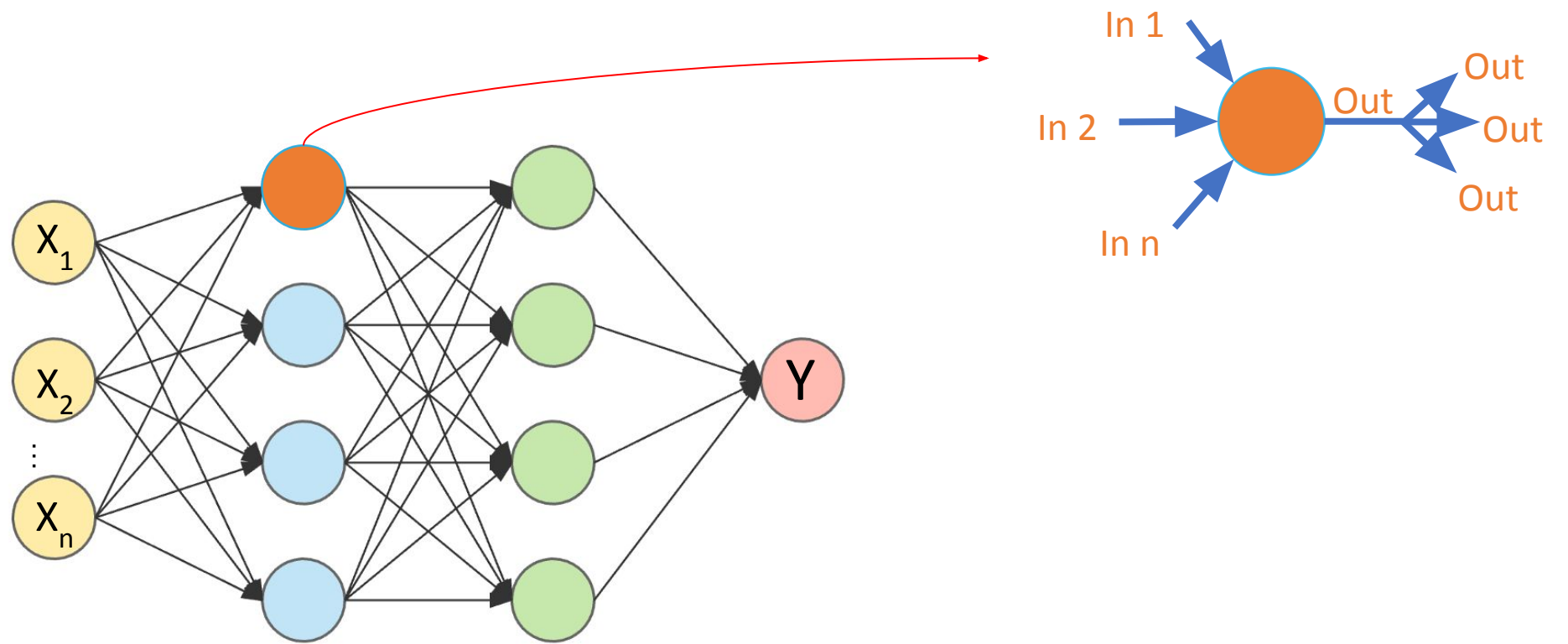


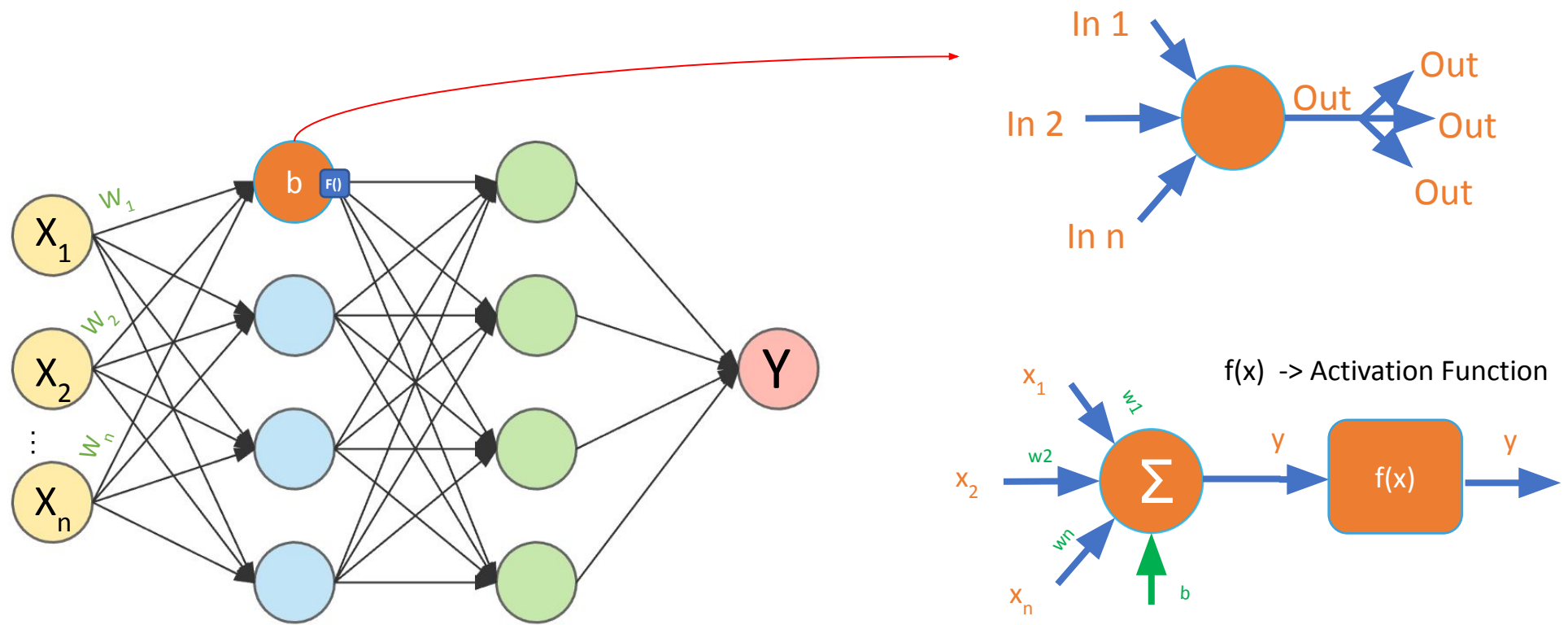
DNN Dense Neural Network

Recap

Supervised Machine Learning with DNN

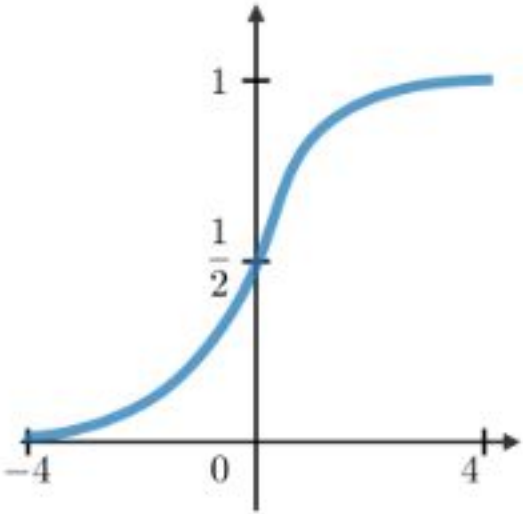
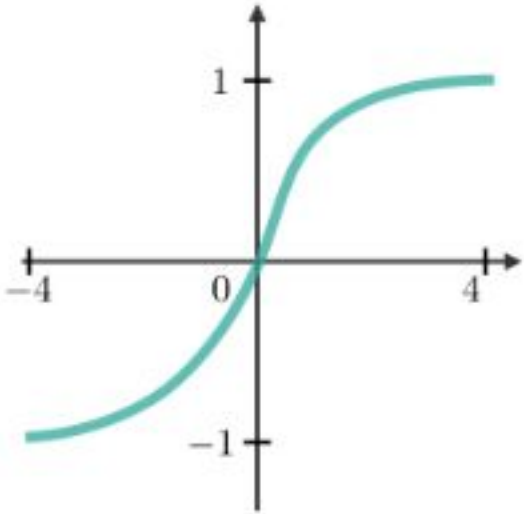
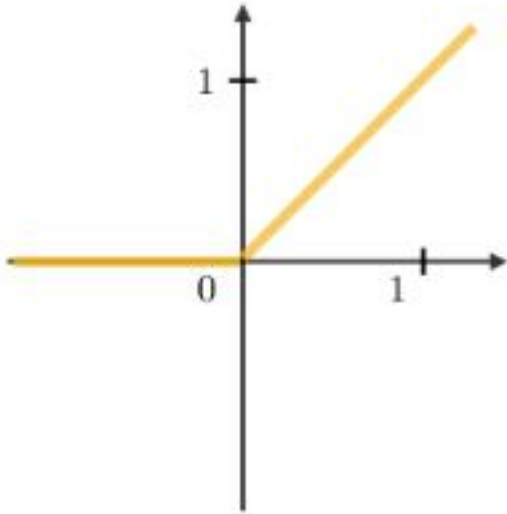


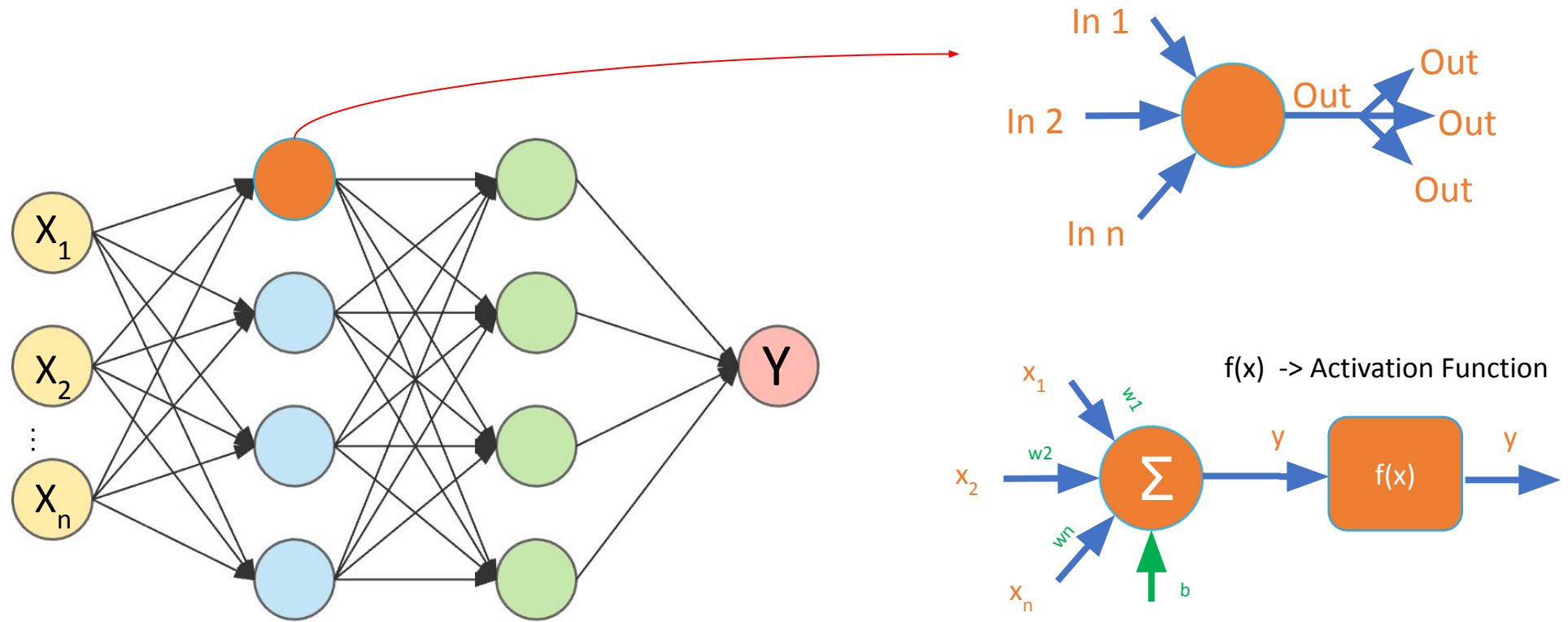




$$y = f\left(\sum_{i=1}^n x_i w_i + b\right)$$

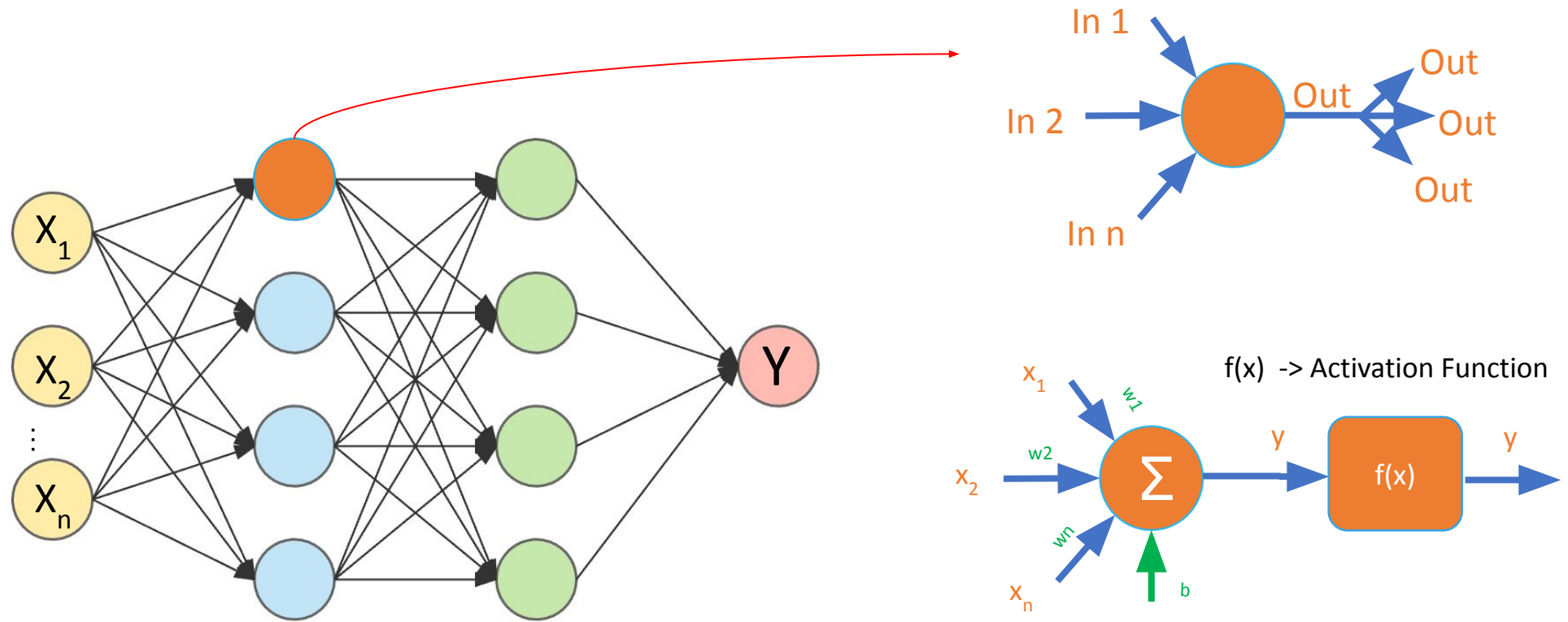
Activation Functions

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

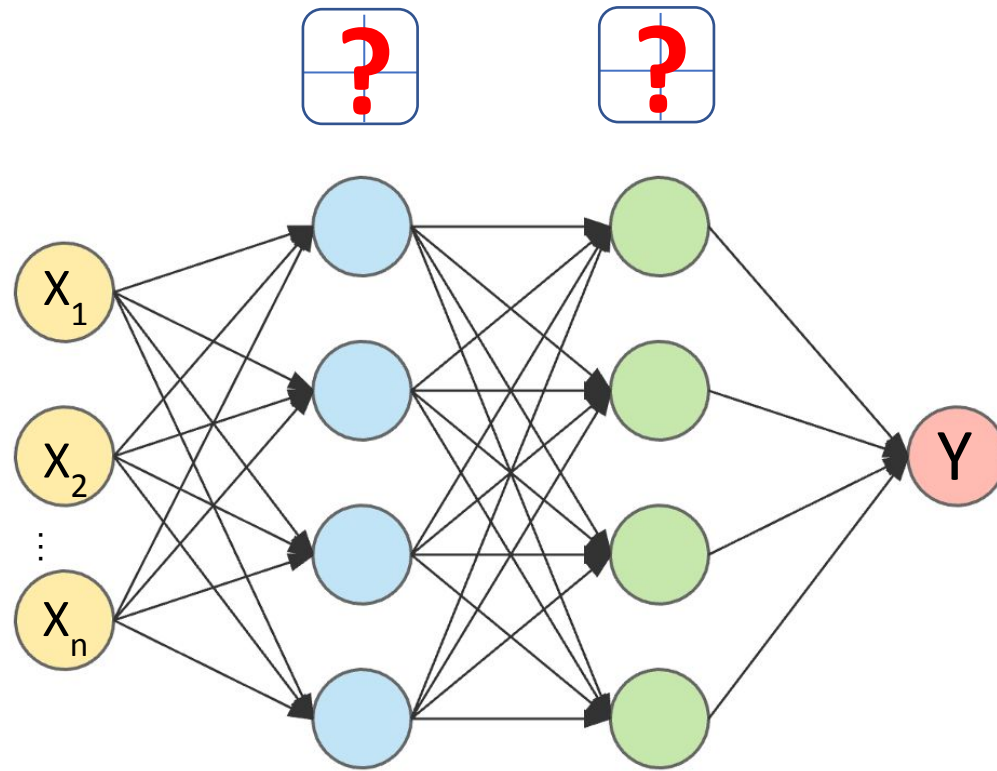
$$y = f\left(\sum_{i=1}^n x_i w_i + b\right)$$



- Error Measurement (Loss)
- Optimization

Parameters to be found during training, to reach minimum error

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



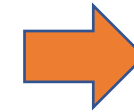
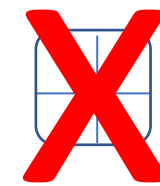
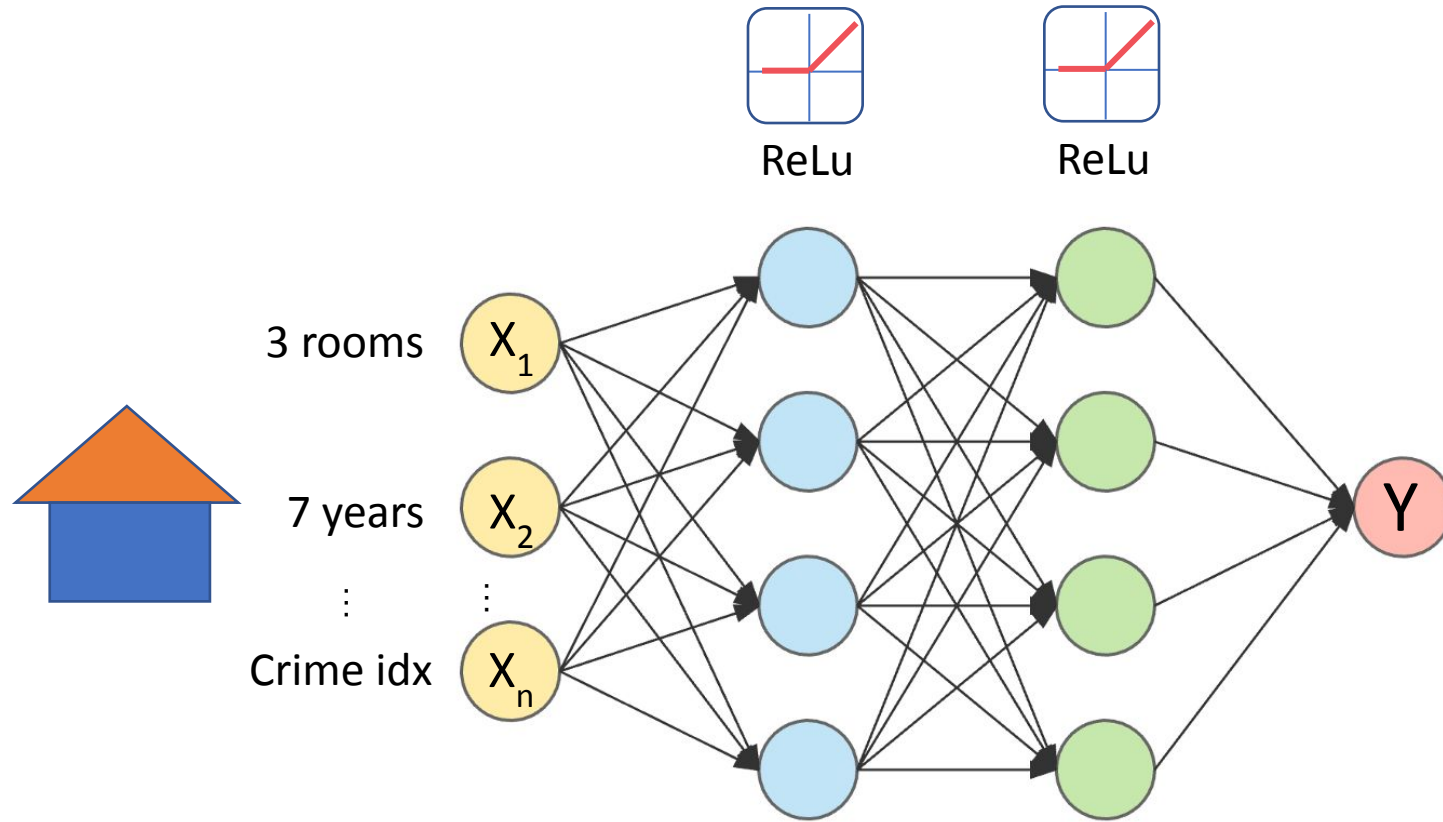
Loss -> ?
Optimizer -> ?



Regression

Loss -> MSE or MAE

Optimizer -> SGD or Adam



\$34.8

Binary Classification

Loss -> Binary Crossentropy

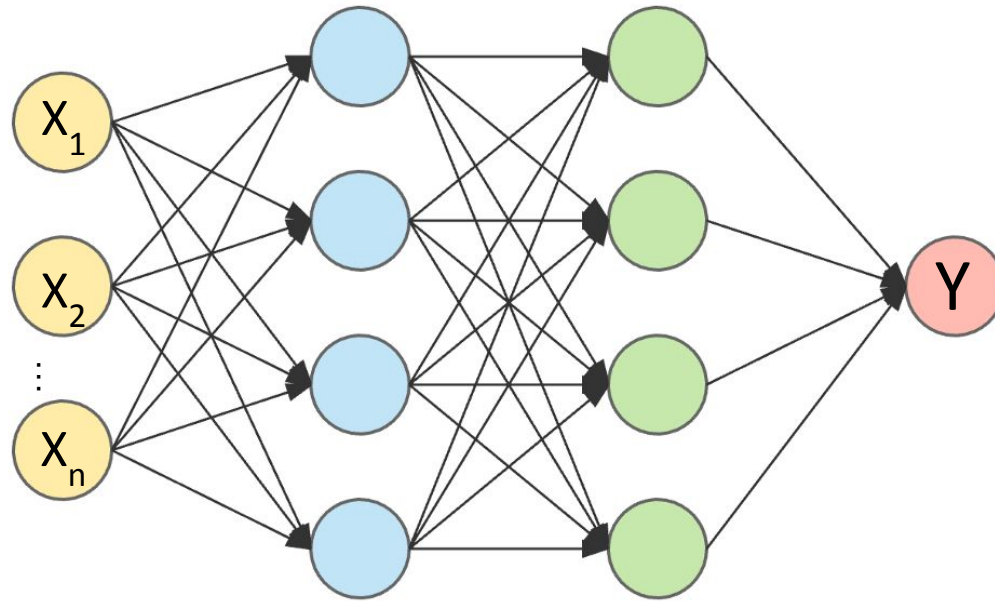
Optimizer -> SGD or Adam



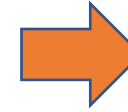
(28,28)

Flatten

(784)

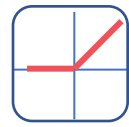


Sigmoid

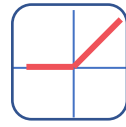


0: Cat
1: Dog

Mult-class Classification



ReLu

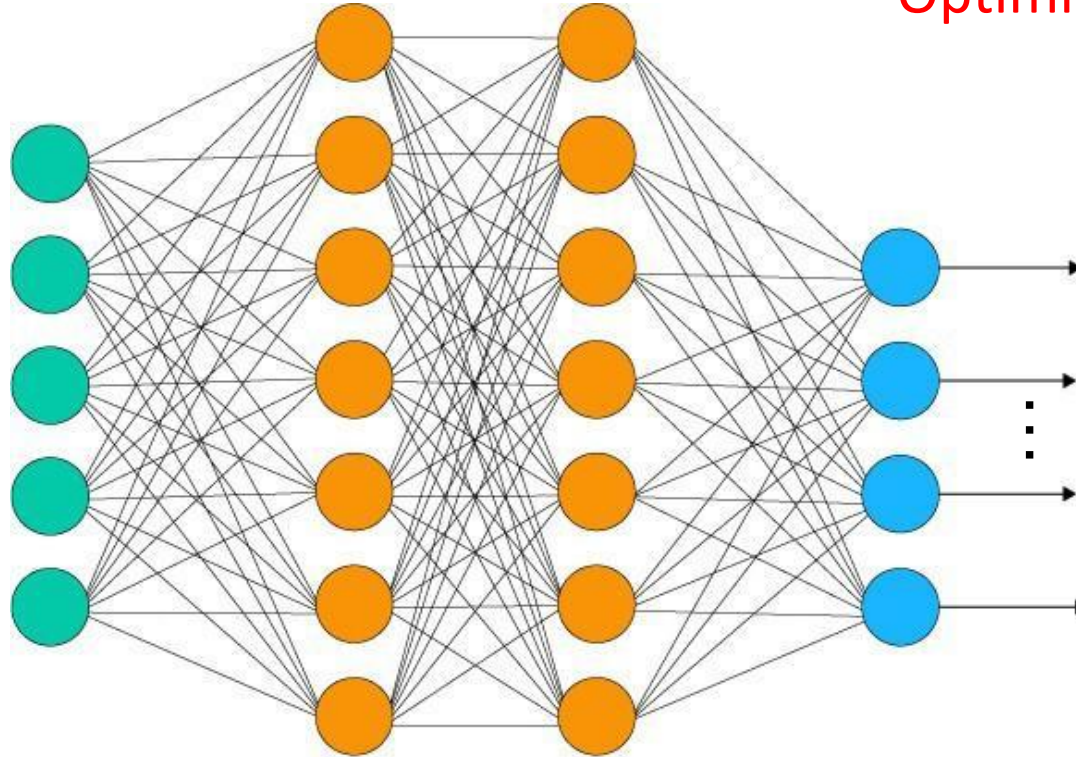


ReLu

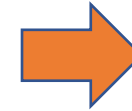
Loss -> Categorical Crossentropy *
Optimizer -> SGD or Adam



Flatten



Softmax



0
0
:
1
0

* 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?



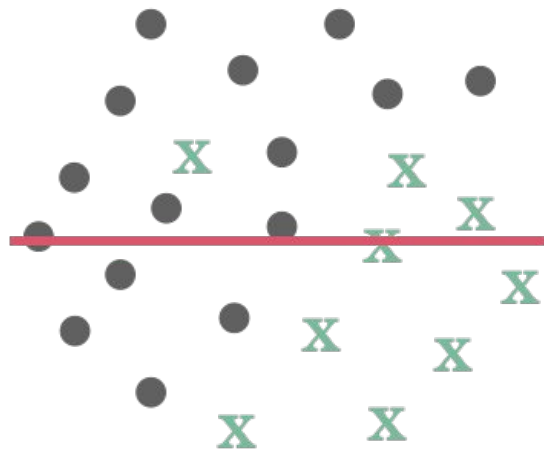
Data

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

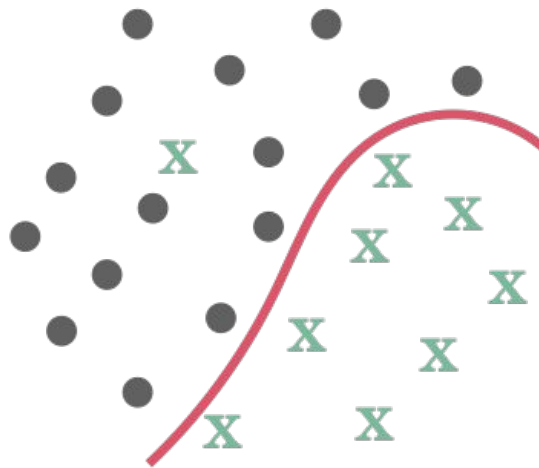
Data

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

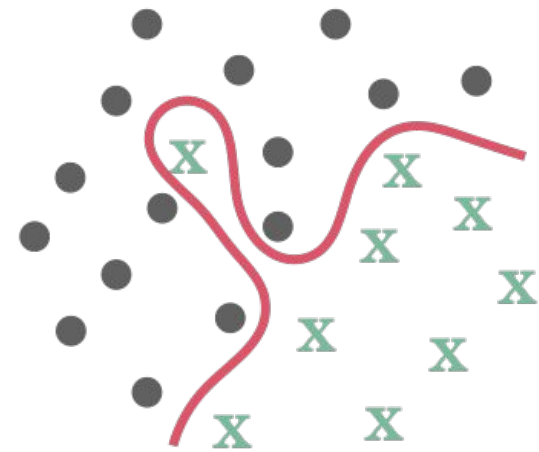
Underfitting



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

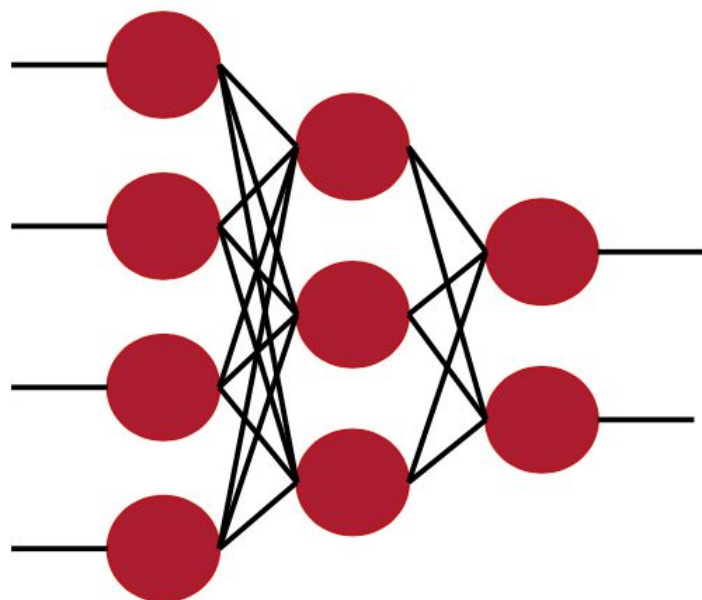
Validation Data

Test Data

Accuracy: 0.999

Accuracy: 0.920

Accuracy: 0.800



Data

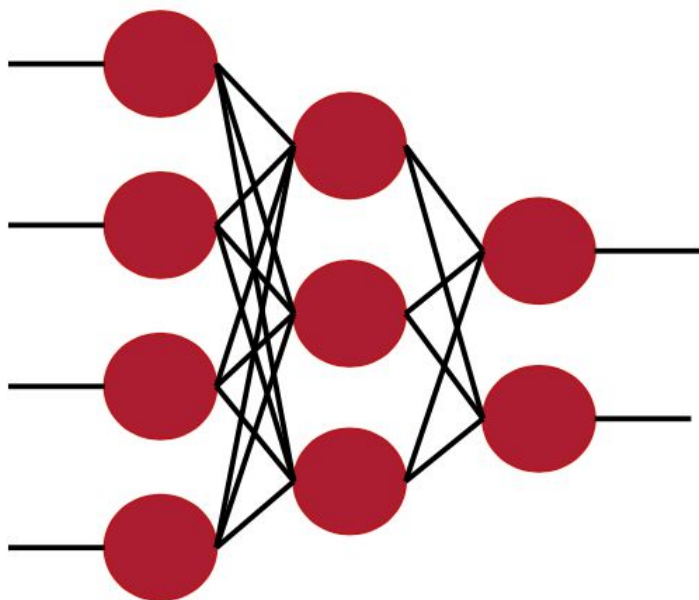
Validation Data

Test Data

Accuracy: 0.999

Accuracy: 0.920

Accuracy: 0.800



Data

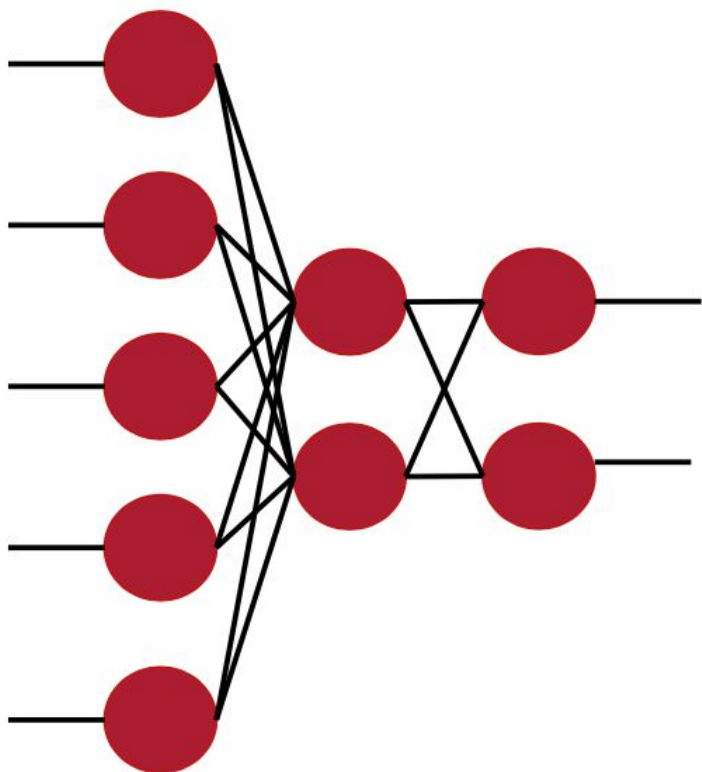
Validation Data

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)
```

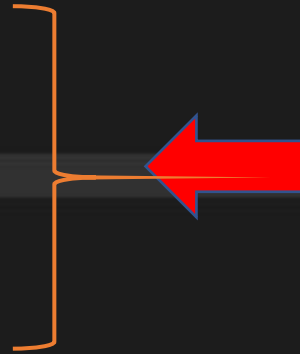
```
(60000, 28, 28)
(60000,)
```

```
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,)
```



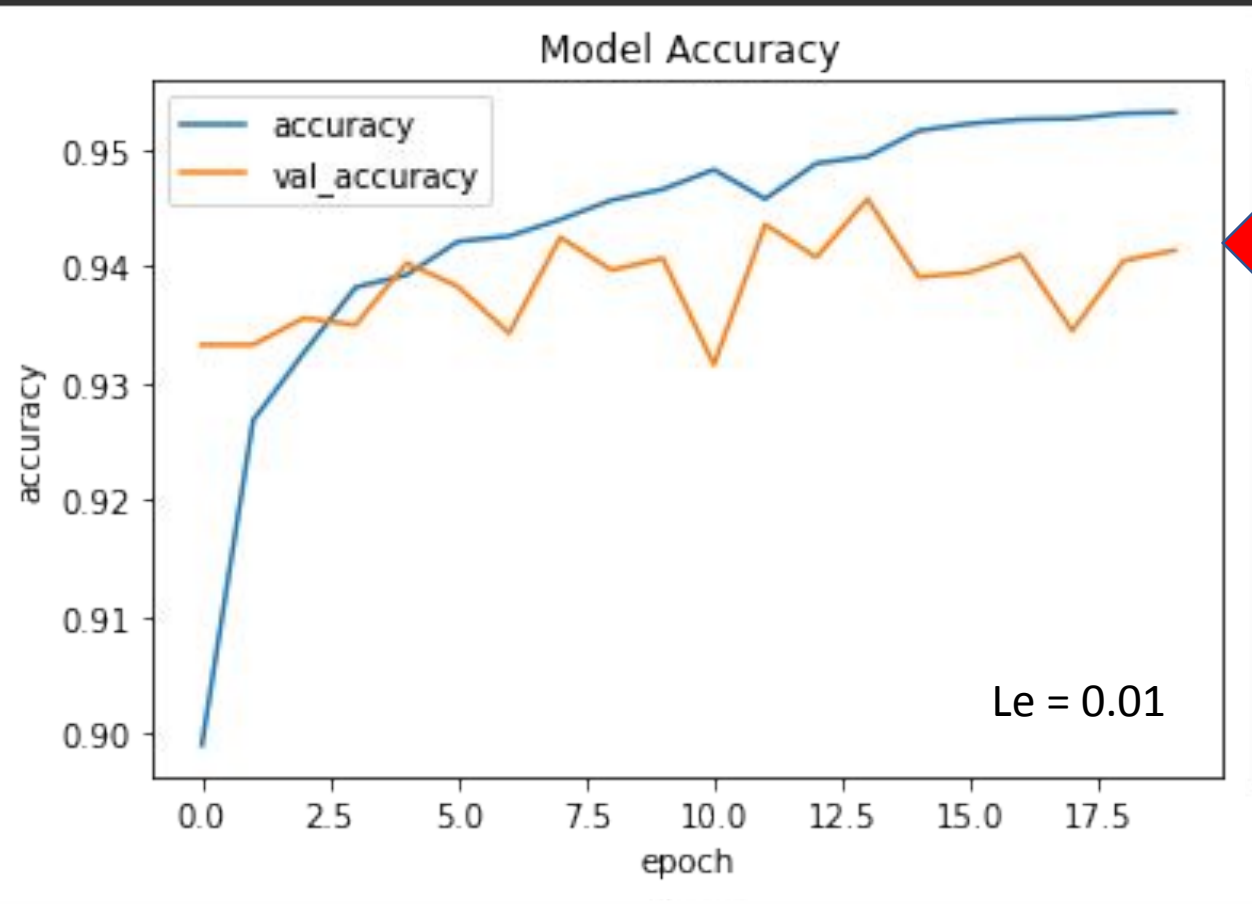
```
1 history = model.fit(  
2     train_images,  
3     train_labels,  
4     epochs=20,  
5     validation_data=(val_images, val_labels)  
6 )
```

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

- *validation_split=0.1* instead of *validation_data=(val_images, val_labels)*.

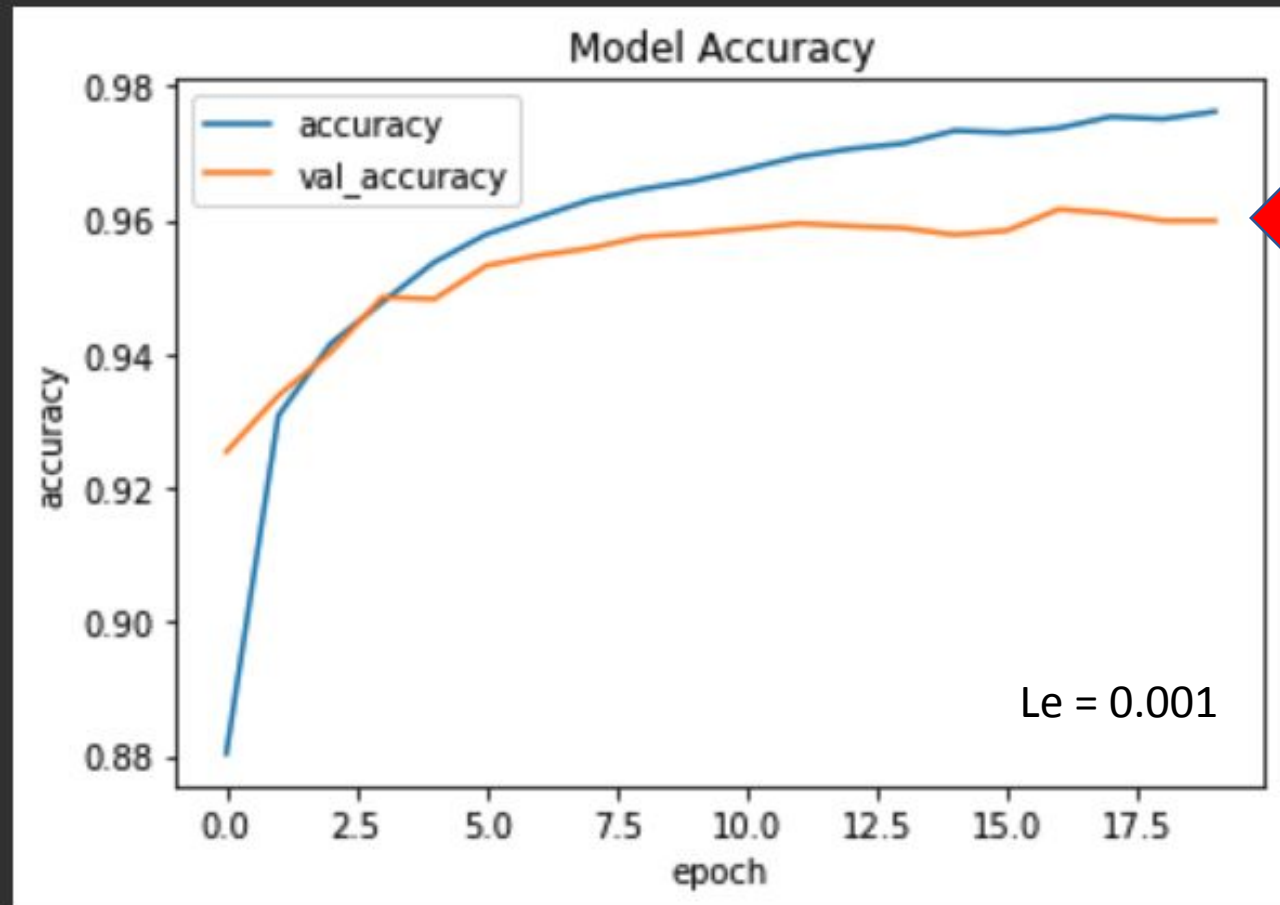
In this case, TF will split the validation data by itself.

```
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 “instable”, 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

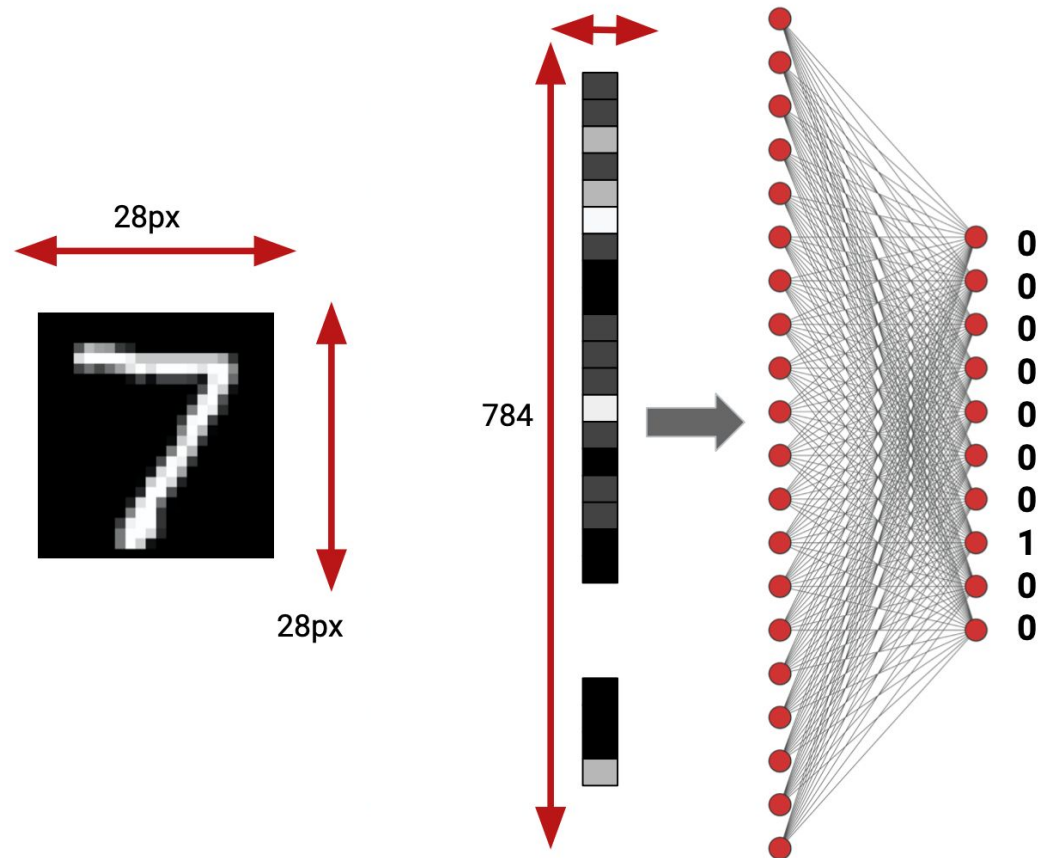
Validation Data

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)	True Positive (TP)	False Negative (FN) (type II error)
	condition negative (N)	False Positive (FP) (Type I error)	True Negative (TN)

Type I error (false positive)



Type II error (false negative)



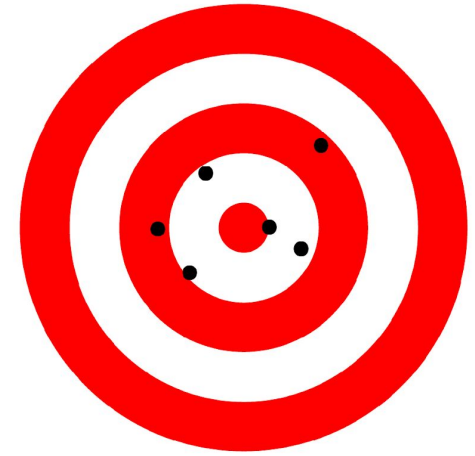
Precision vs. Accuracy

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)

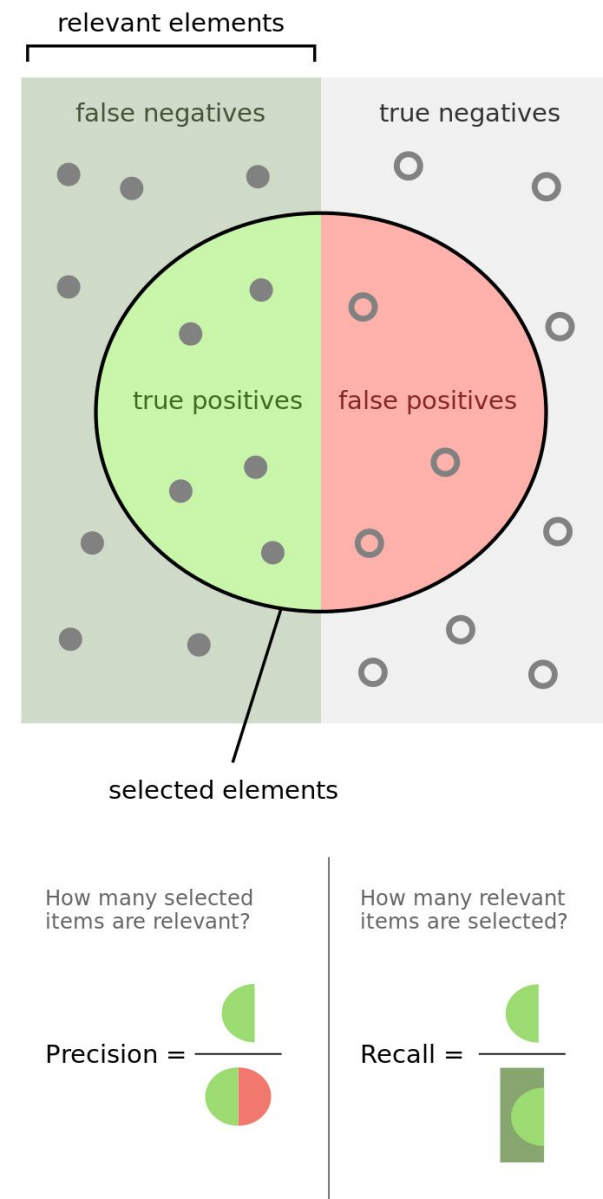
$$\frac{\text{Total Positive}}{\text{Total Actual Positive}}$$

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



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 \(Coursera\)](#)
- [Text Book: "TinyML" by Pete Warden, Daniel Situnayake](#)

I want to thank Shawn Hymel and Edge Impulse, Pete Warden and Laurence Moroney from Google, and especially Harvard professor Vijay Janapa Reddi, Ph.D. student Brian Plancher and their staff 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
And stay safe!



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