IESTI01 – TinyML

Embedded Machine Learning

8. The Building Blocks of Deep Learning – Part B
    - Classification

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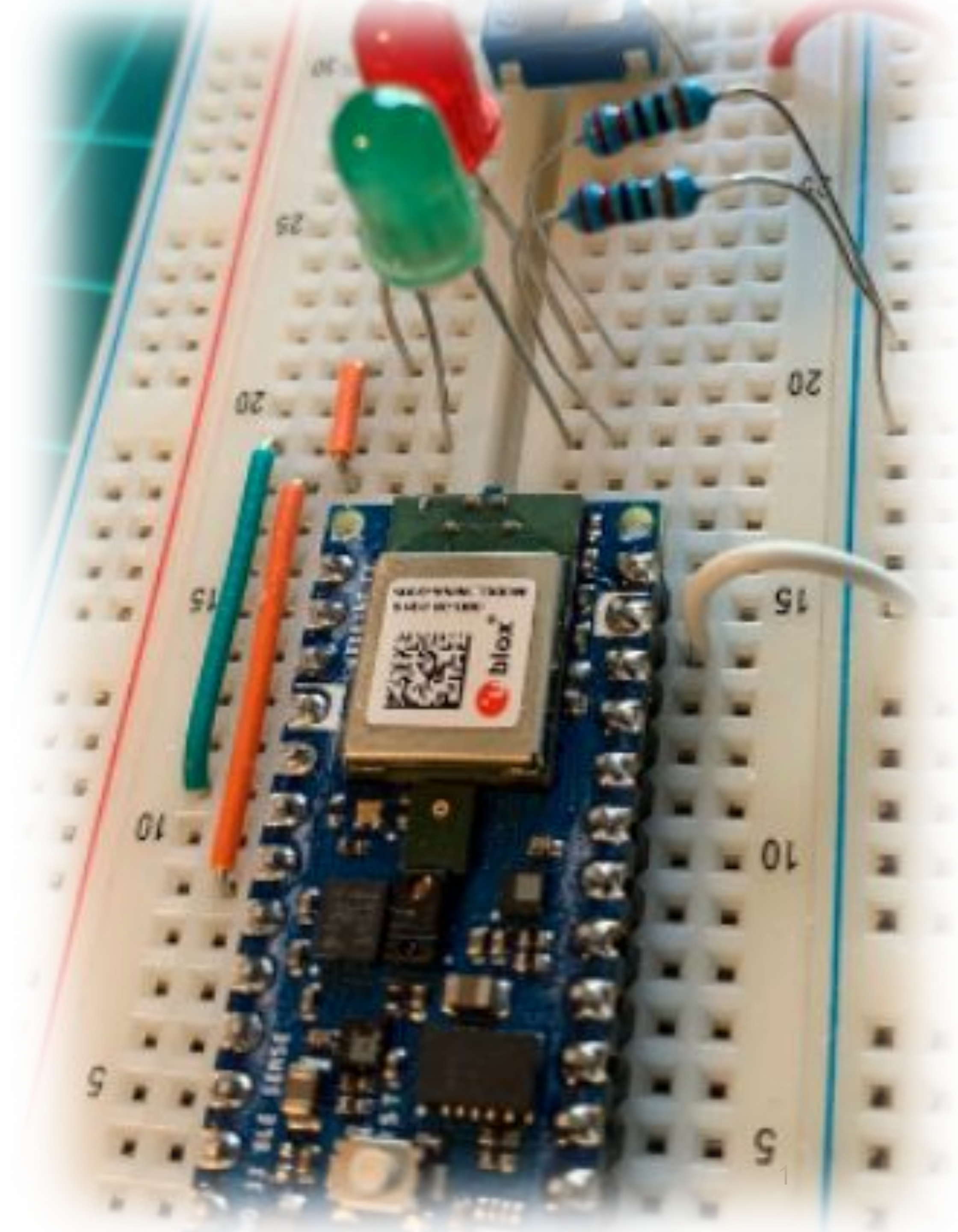
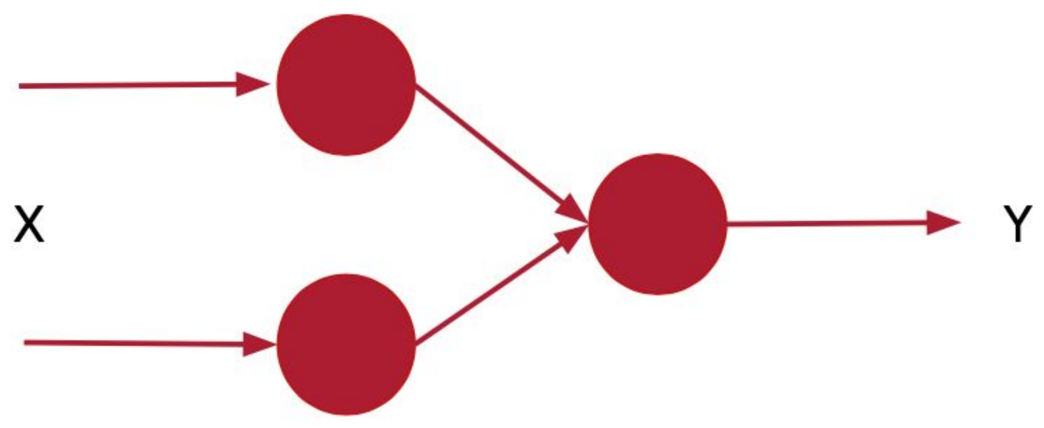
UNIFEI

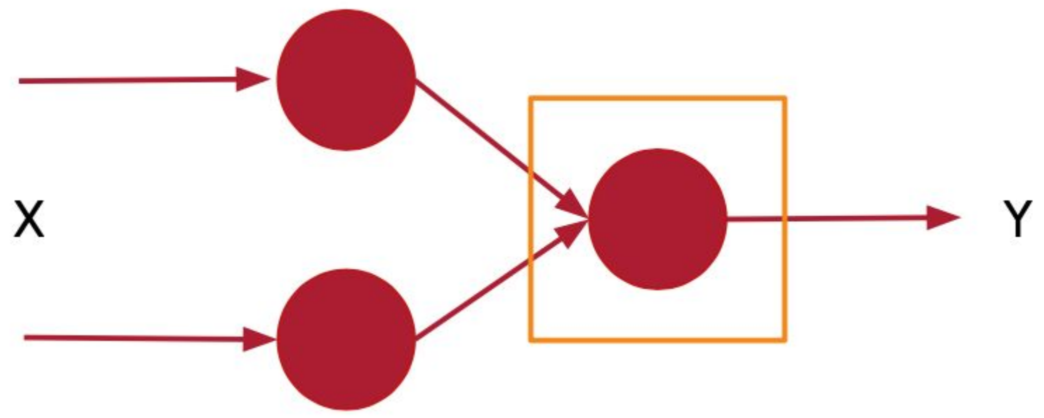


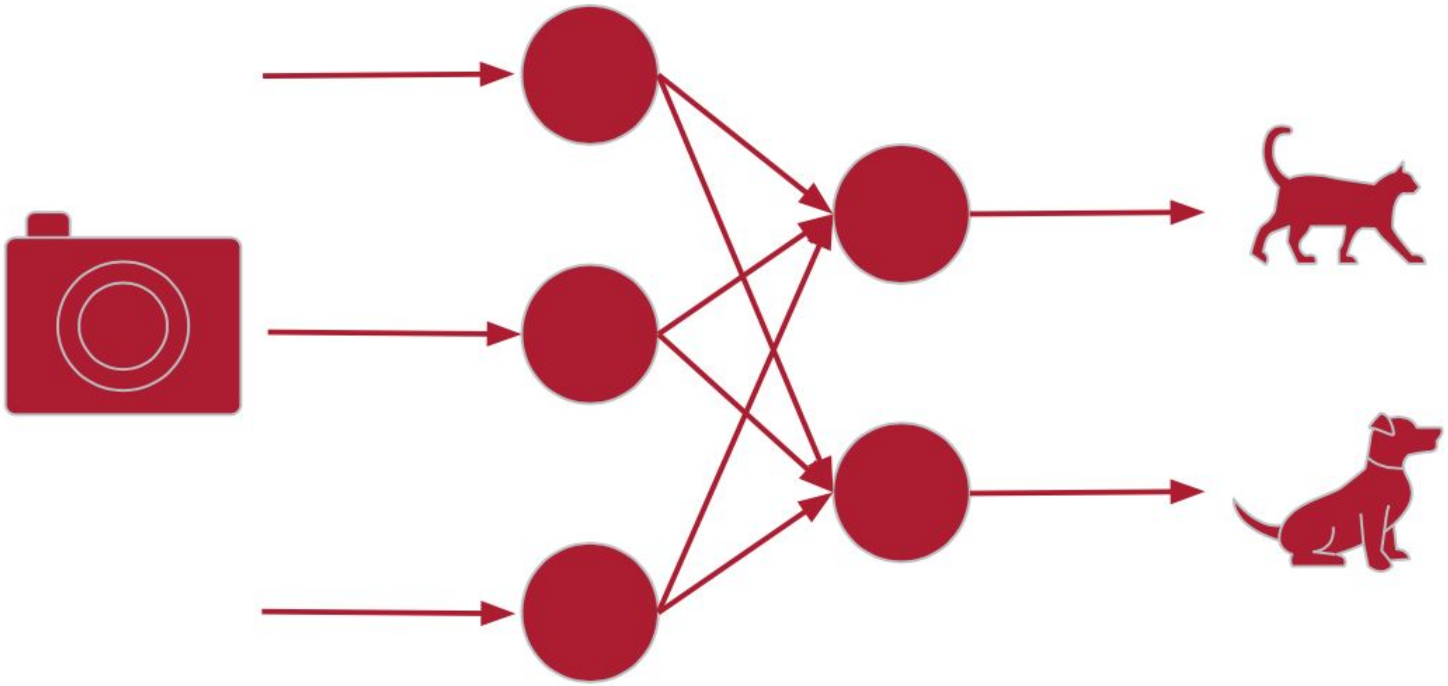
Going Further

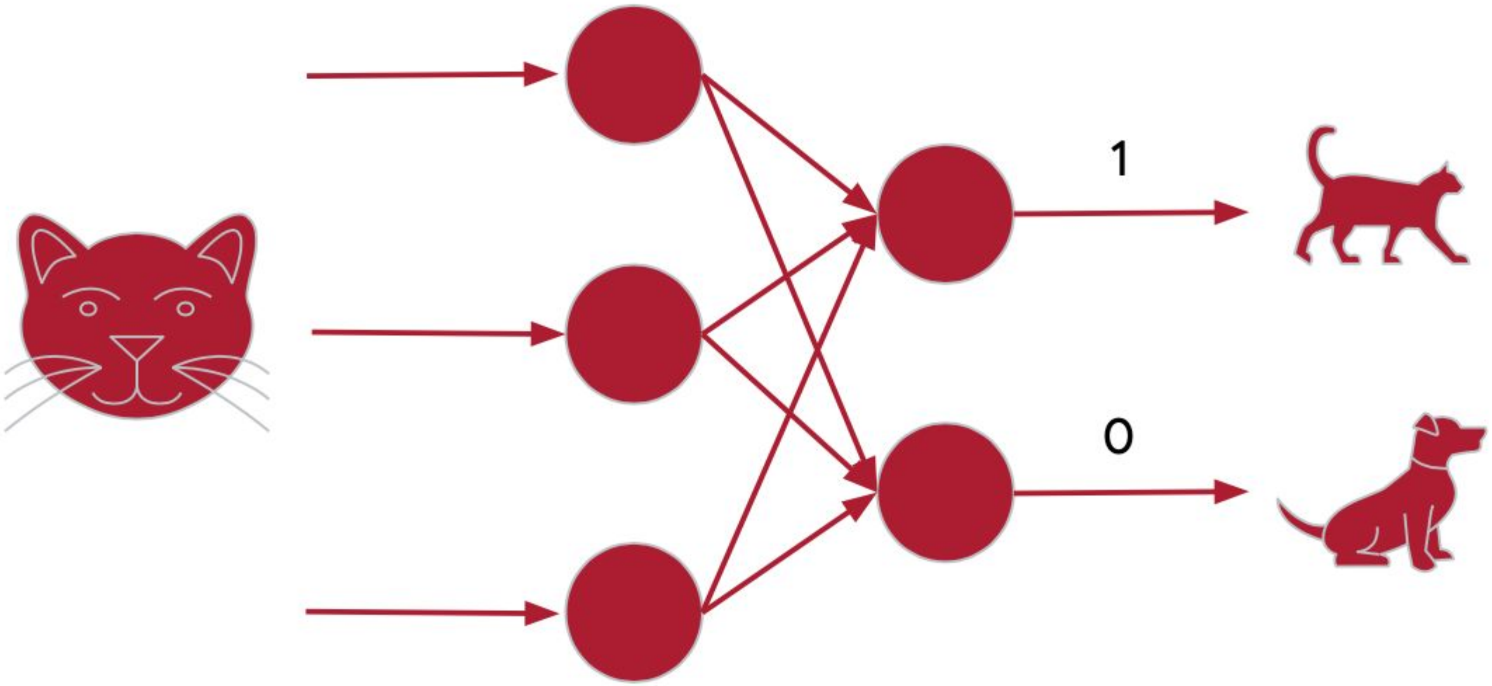
From regression to classification

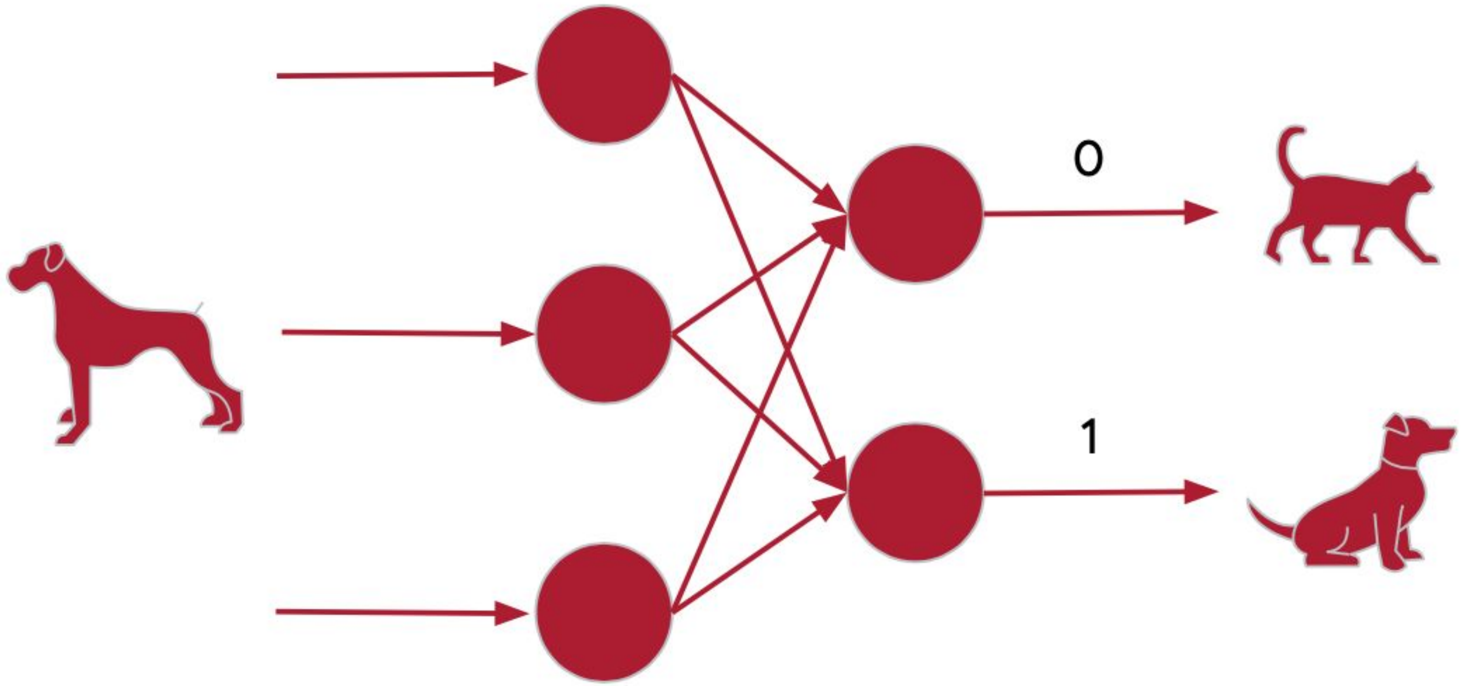

X
Y

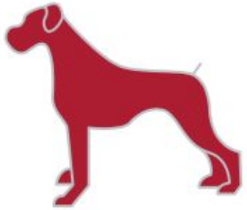

X
Y


X
Y




1
0


0
1

Data	Label
	[1, 0]
	[0, 1]

0 [1, 0, 0, 0, 0, 0, 0, 0, 0, 0]

1 [0, 1, 0, 0, 0, 0, 0, 0, 0, 0]

2 [0, 0, 1, 0, 0, 0, 0, 0, 0, 0]

3 [0, 0, 0, 1, 0, 0, 0, 0, 0, 0]

4 [0, 0, 0, 0, 1, 0, 0, 0, 0, 0]

5 [0, 0, 0, 0, 0, 1, 0, 0, 0, 0]

6 [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]

7 [0, 0, 0, 0, 0, 0, 0, 1, 0, 0]

8 [0, 0, 0, 0, 0, 0, 0, 0, 1, 0]

9 [0, 0, 0, 0, 0, 0, 0, 0, 0, 1]

```python
import tensorflow as tf

data = tf.keras.datasets.mnist
(training_images, training_labels), (val_images, val_labels) = data.load_data()

training_images  = training_images / 255.0
val_images = val_images / 255.0

model = tf.keras.models.Sequential(
    [tf.keras.layers.Flatten(input_shape=(28,28)),
     tf.keras.layers.Dense(20, activation=tf.nn.relu),
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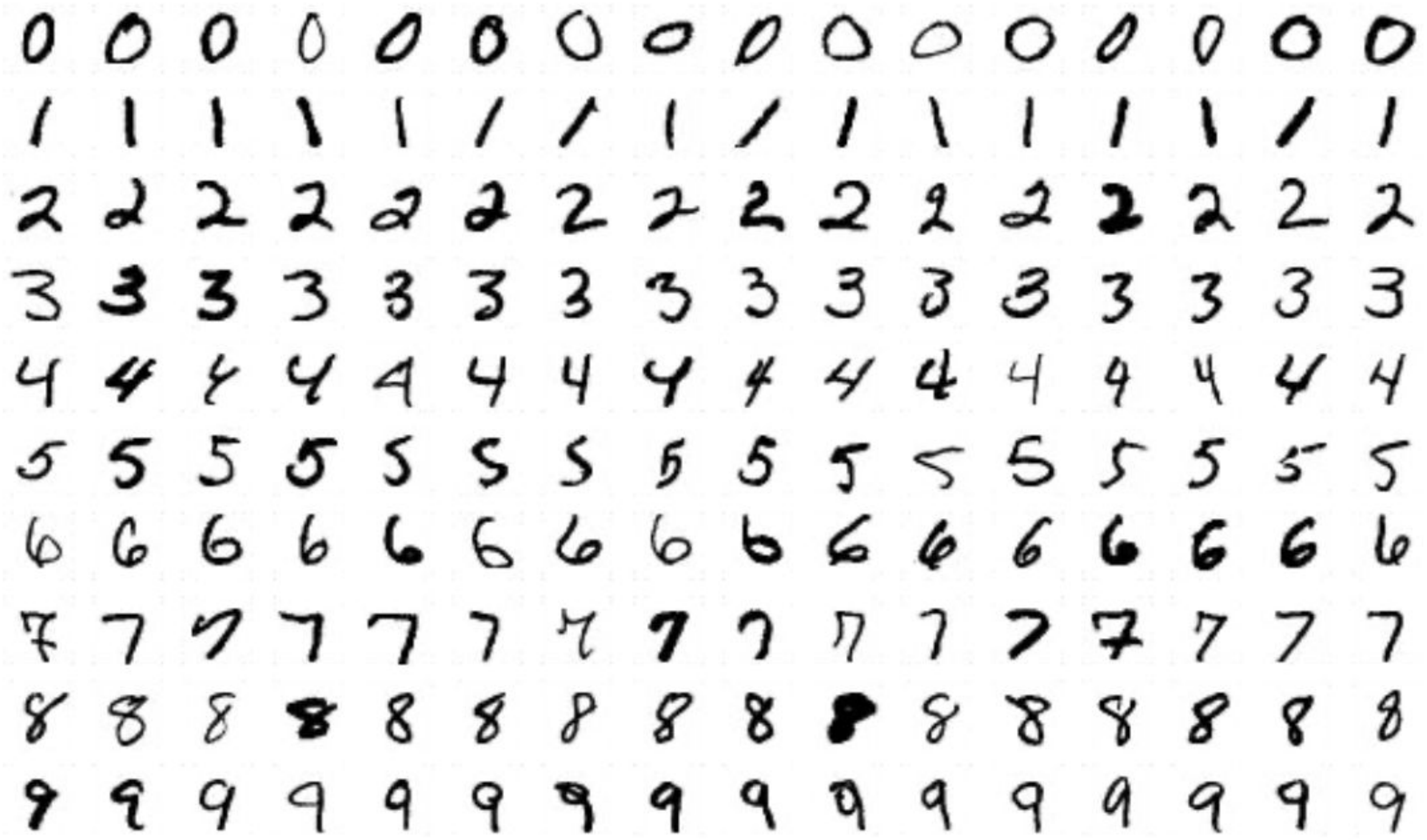
```

Collect Data



60,000 Labelled Training Examples
10.000 Labelled Validation Examples

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Preprocess Data

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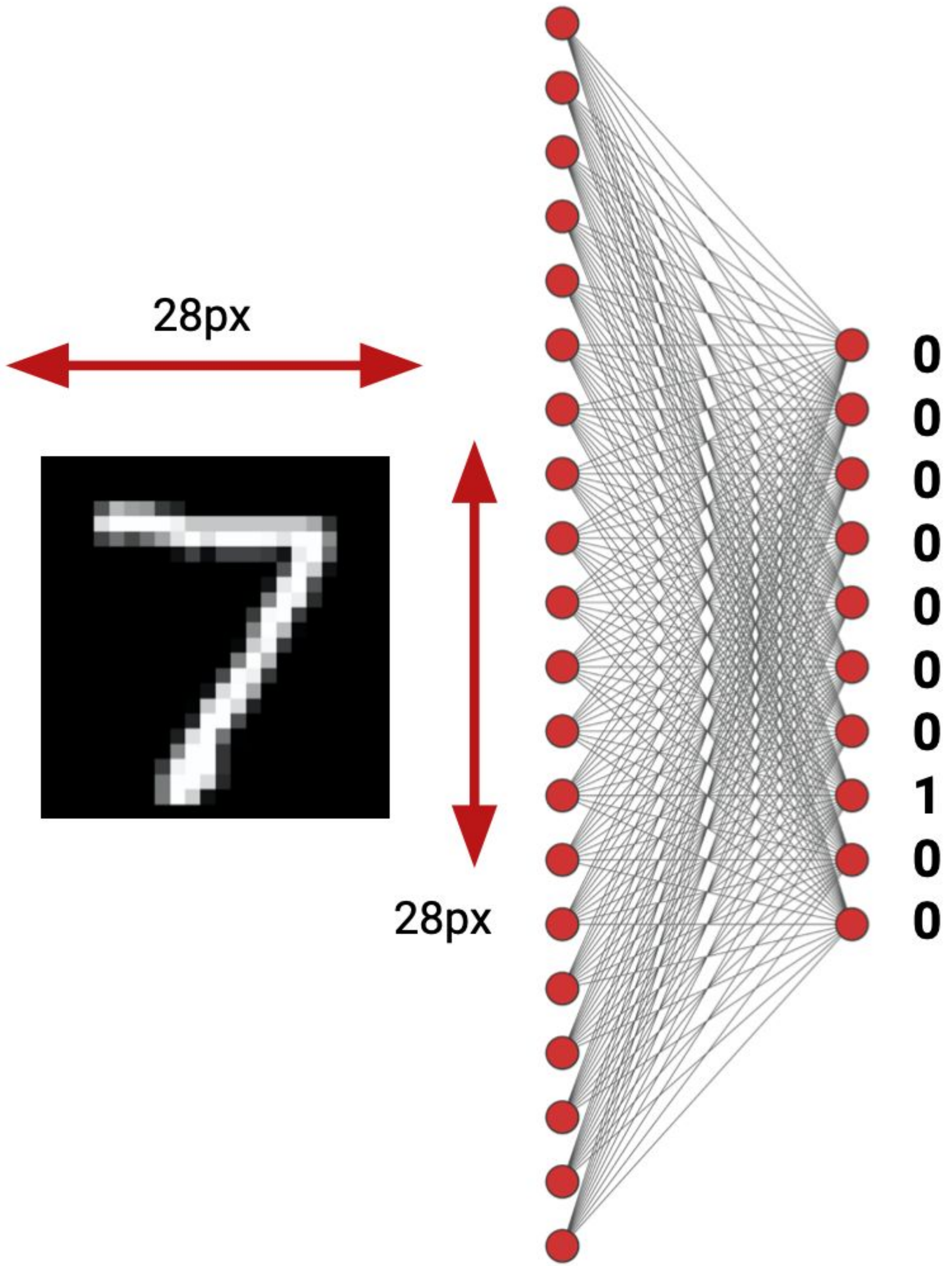
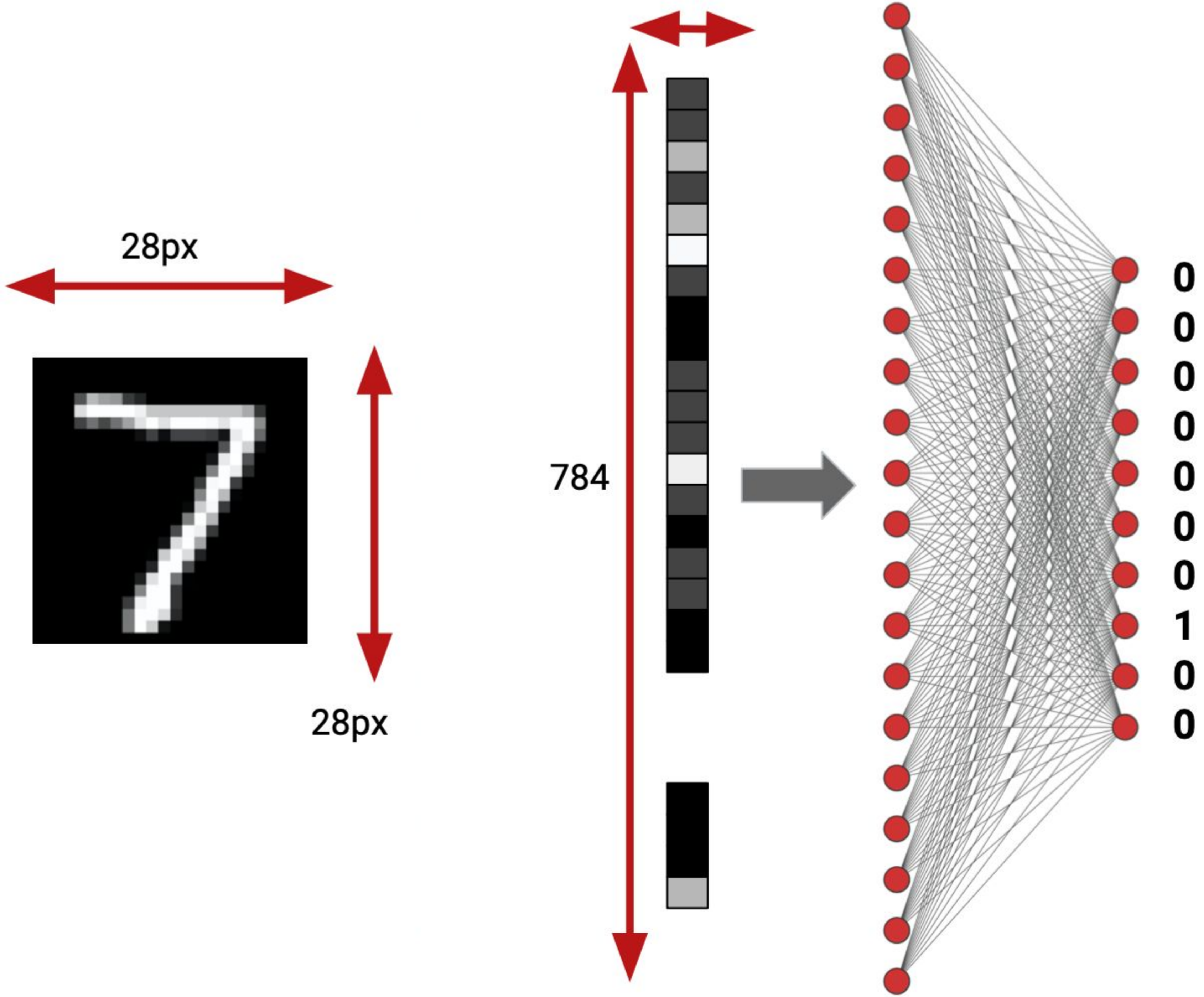
Design a Model



28px
28px
0
0
0
0
0
0
0
1
0
0


28px
28px
784
0
0
0
0
0
0
0
1
0
0

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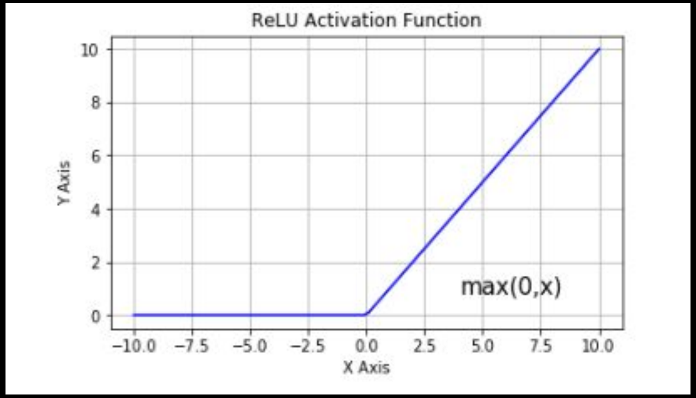

ReLU applies much-needed non-linearity into the model. Non-linearity is necessary to produce non-linear decision boundaries, so that the output cannot be written as a linear combination of the inputs.

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

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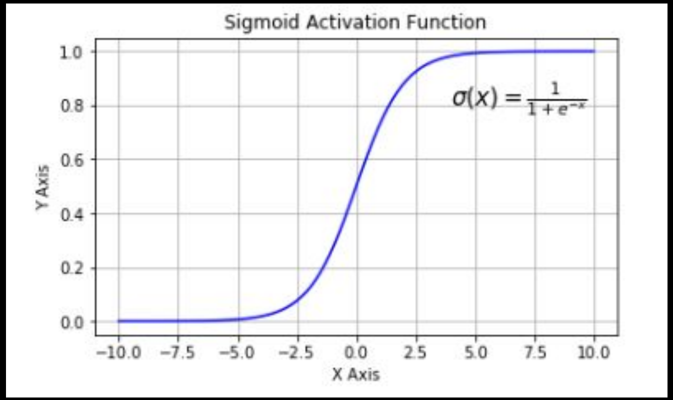

SOFTMAX: Generalization of the logistic function (or Sigmoid) to multiple dimensions. A softmax operation serves a key purpose: making sure the Neural Network (in this case, a DNN) outputs sum to 1. Because of this, softmax operations are useful to scale model outputs into probabilities.

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])
```

Design a Model

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```

Mean Squared Error

$$MSE = \frac{1}{N}\sum(\underbrace{t_i}_{\text{Ground Truth}} - \overbrace{s_i}^{\text{Prediction}})^2$$

Cross Entropy Loss

$$CE = -\sum_{i}^{\overset{\text{Classes}}{C}} \underbrace{t_i}_{\text{Ground Truth \{0,1\}}} log(\overbrace{s_i}^{\text{Prediction}})$$

Design a Model

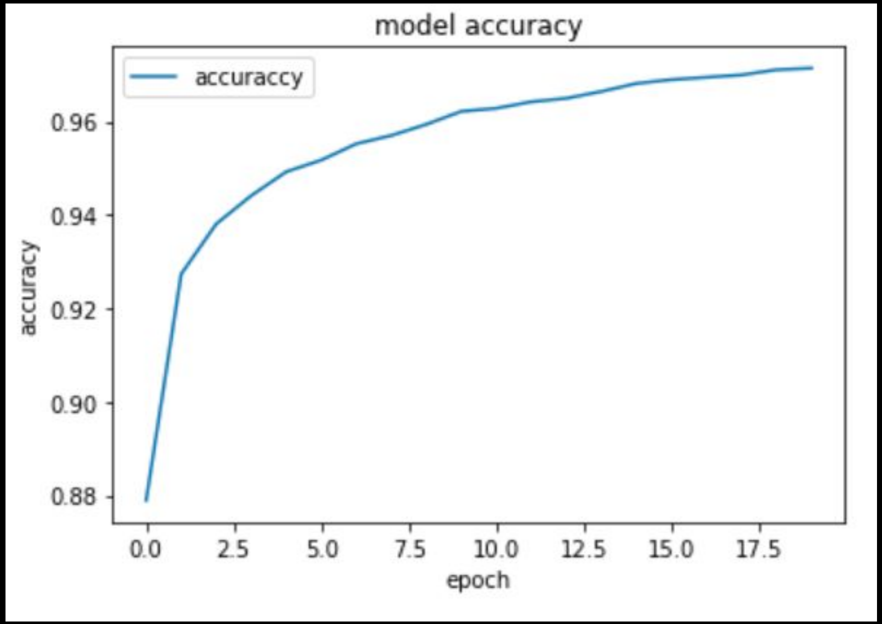
```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

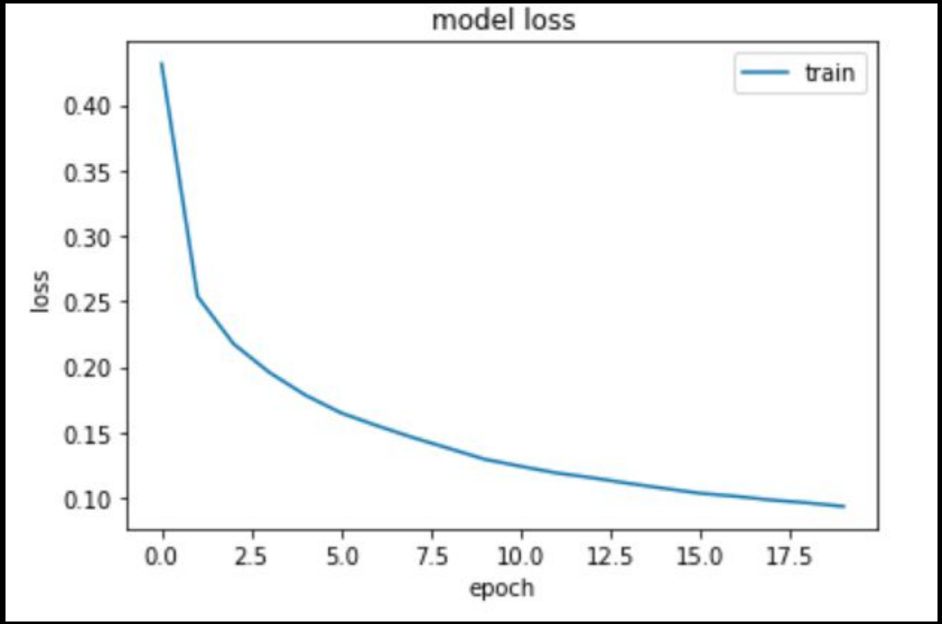
model.fit(training_images, training_labels, epochs=20)
```

Train a Model

```
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(training_images, training_labels, epochs=20)
```





Evaluate
Optimize

```
classifications = model.predict(val_images)

print(classifications[0])

print(test_labels[0])
```

```
[2.4921512e-09 1.3765138e-10 8.8281205e-08
1.0477231e-03 2.8455029e-12 4.0820678e-06
2.0070659e-16 9.9894780e-01 1.0296049e-07
2.9972372e-07]

7
```

Make Inferences

Digits Classification using DNN with TF2

Code Time!

TF_MNIST_Classification.ipynb

Going deeper with Deep Learning

Initializing neural networks

https://www.deeplearning.ai/ai-notes/initialization/

Neural networks – PlayList - 3Blue1Brown

https://www.youtube.com/playlist?list=PLZHQObOWTQDNU6R1_67000Dx_ZCJB-3pi

An introductory lecture for MIT course 6.S094 by Prof. Lex Fridman

https://youtu.be/O5xeyoRL95U

A Complete Machine Learning Package by Jean de Dieu Nyandwi

https://github.com/Nyandwi/machine_learning_complete

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

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