EECE-4710 "IoT and TinyML"

Building Blocks of Deep Learning – Classification with (Dense) Neural Networks

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MARQUETTE UNIVERSITY

BE THE DIFFERENCE.

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From Regression to Classification

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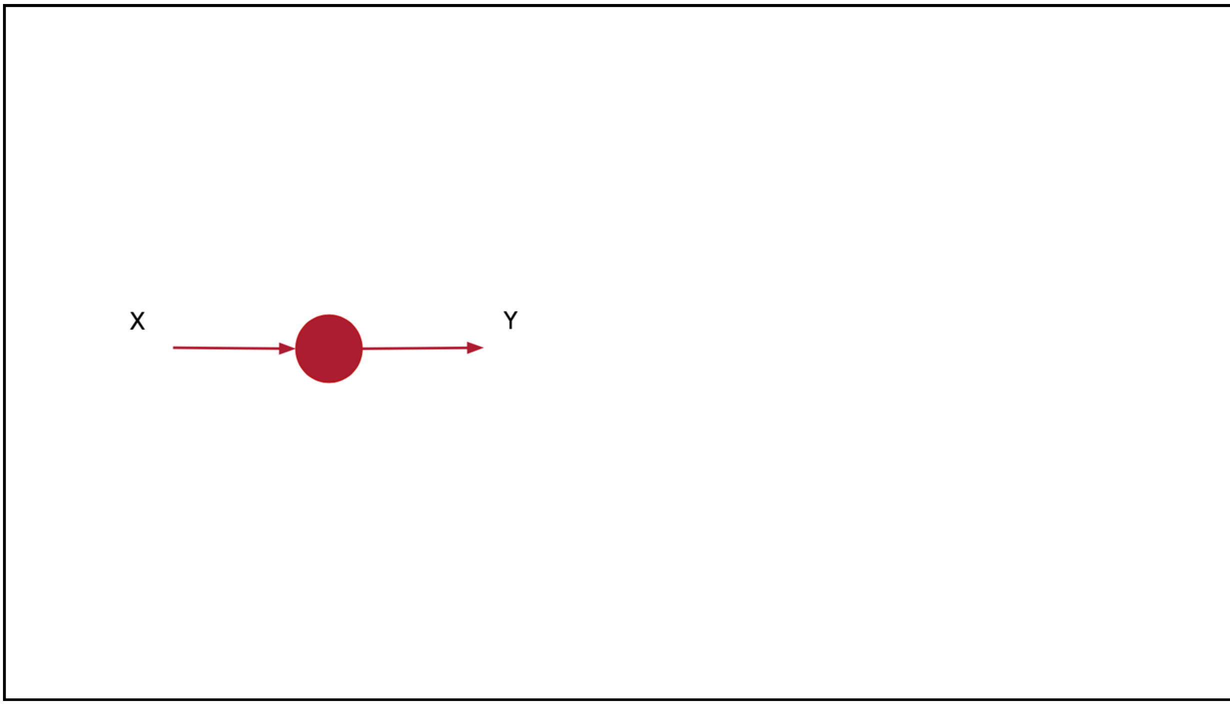

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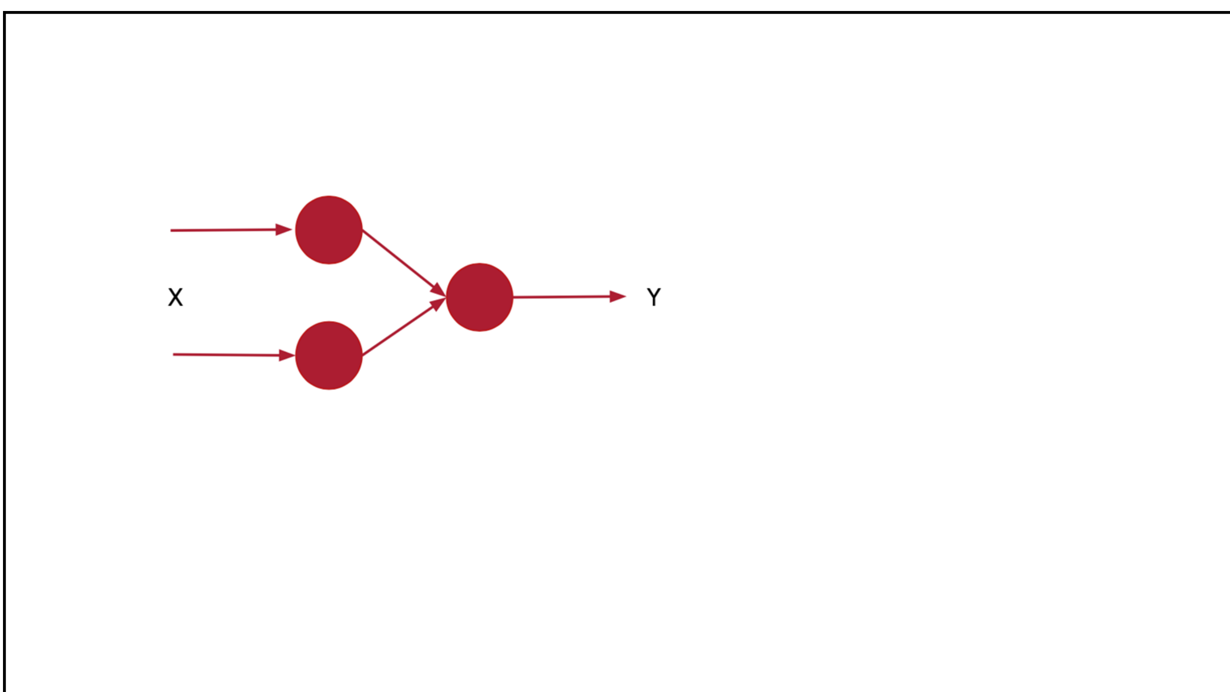

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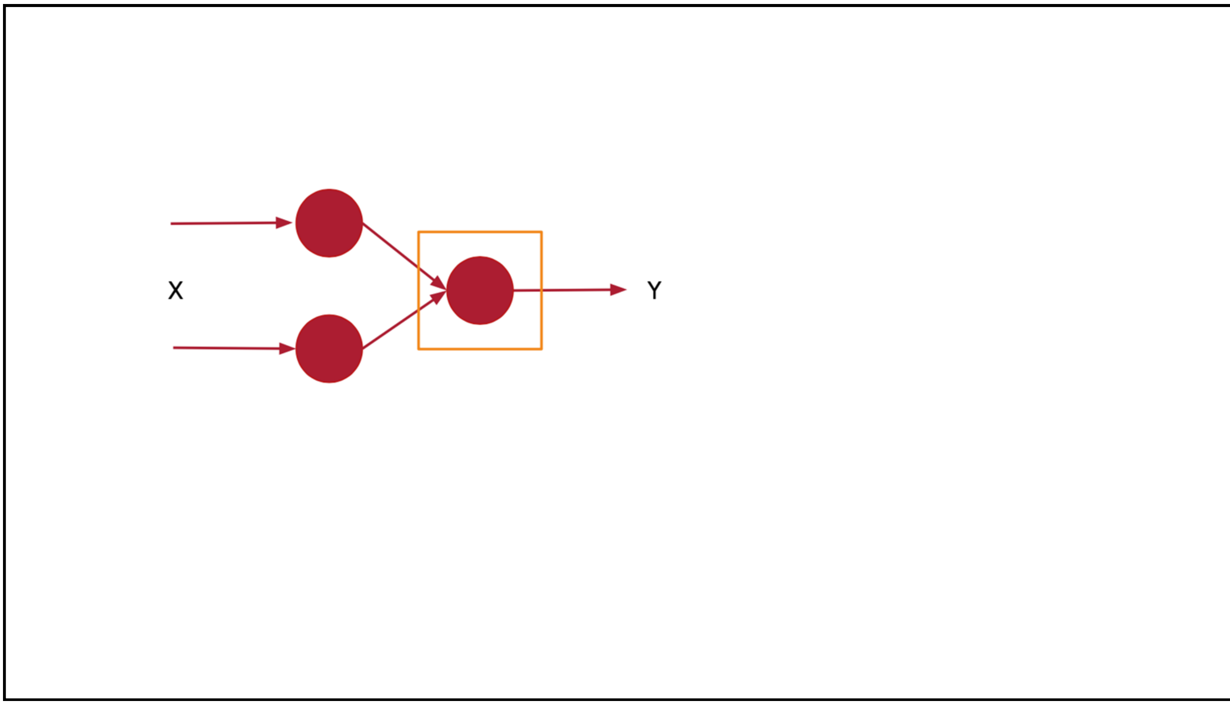

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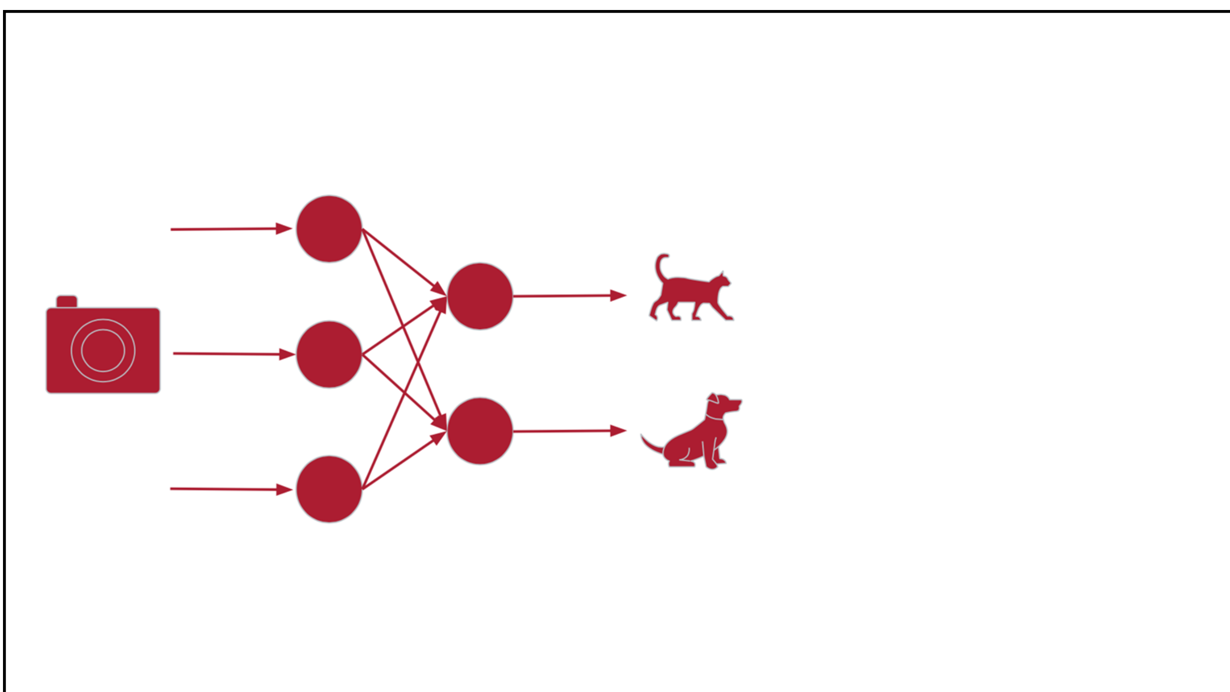

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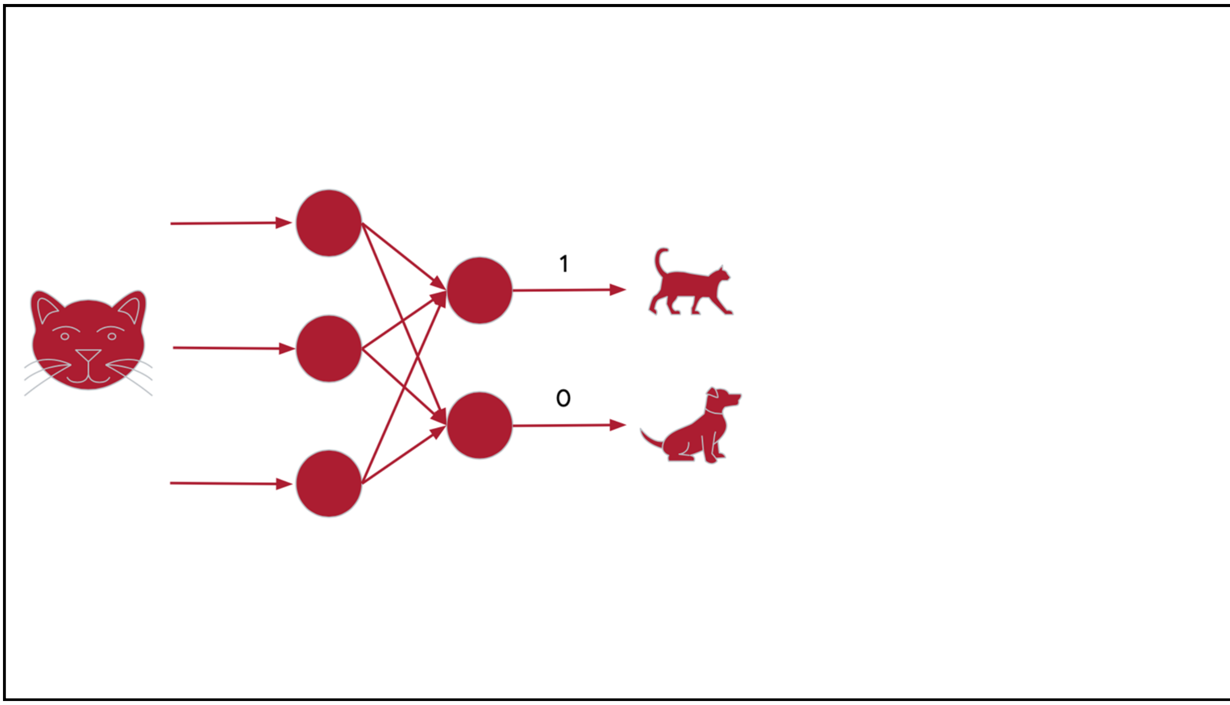

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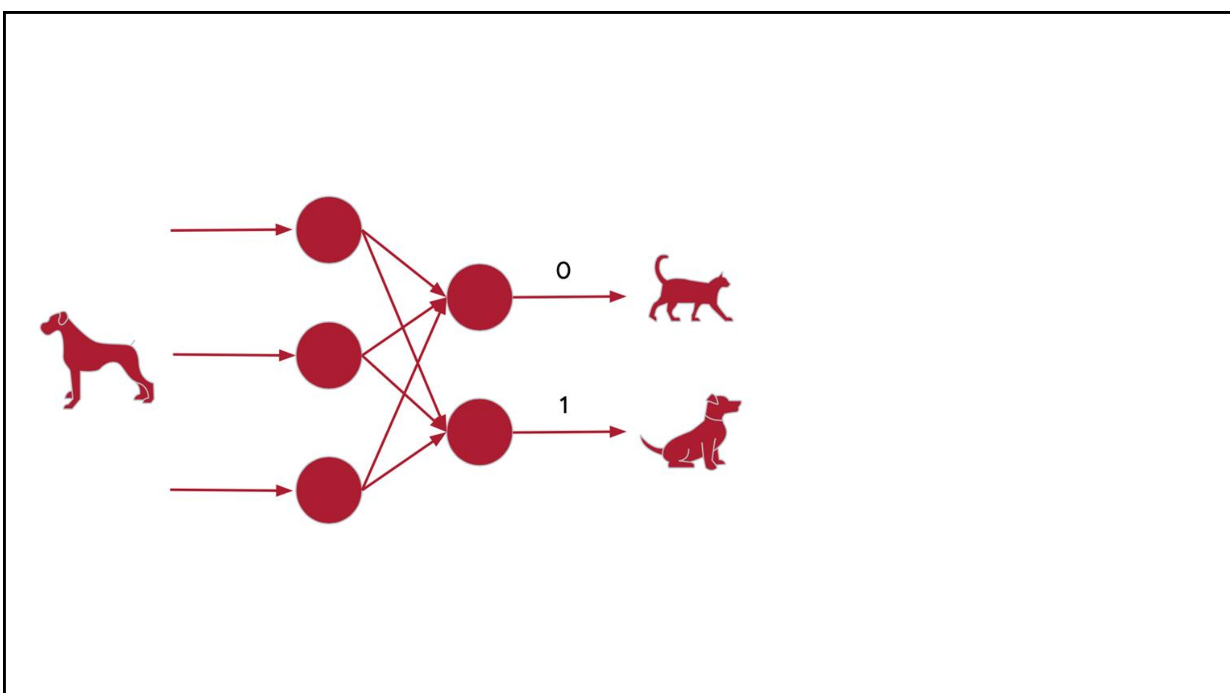

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Data Label

[1, 0]

[0, 1]

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Data	**Label**
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]

10

```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),
     tf.keras.layers.Dense(10, activation=tf.nn.softmax)])
```

Collect Data

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60,000 Labelled Training Examples
10.000 Labelled Validation Examples

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Preprocess Data

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Design a Model

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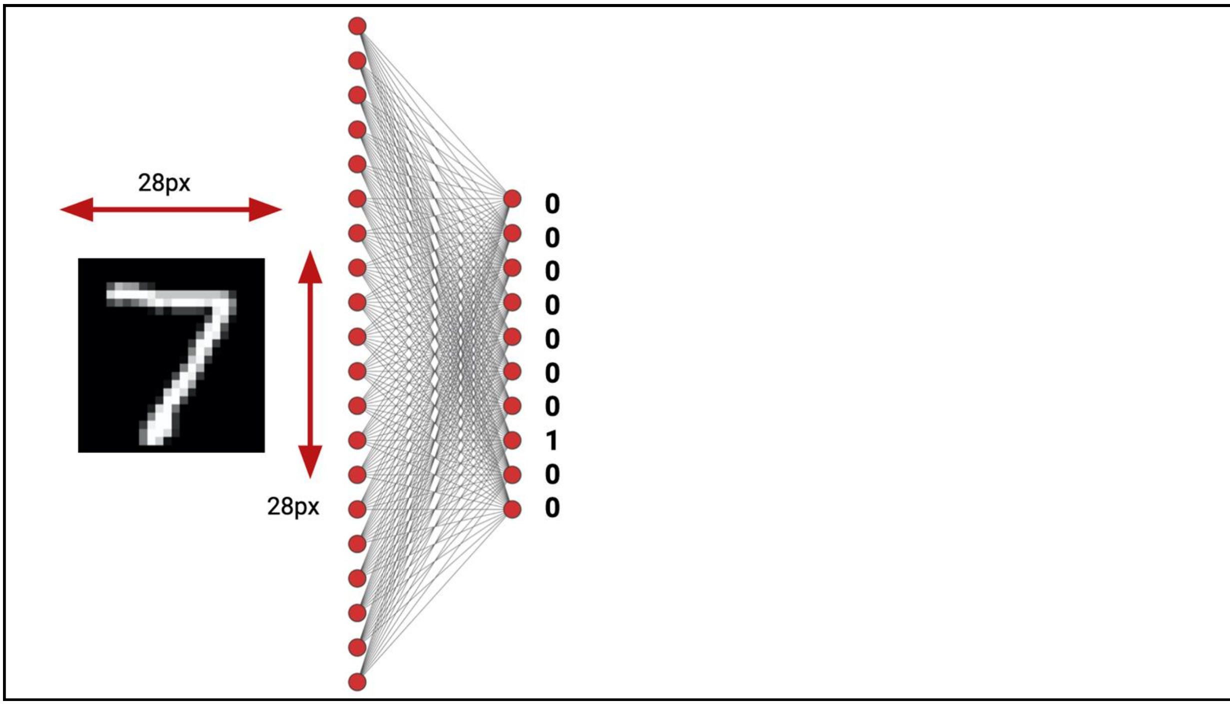

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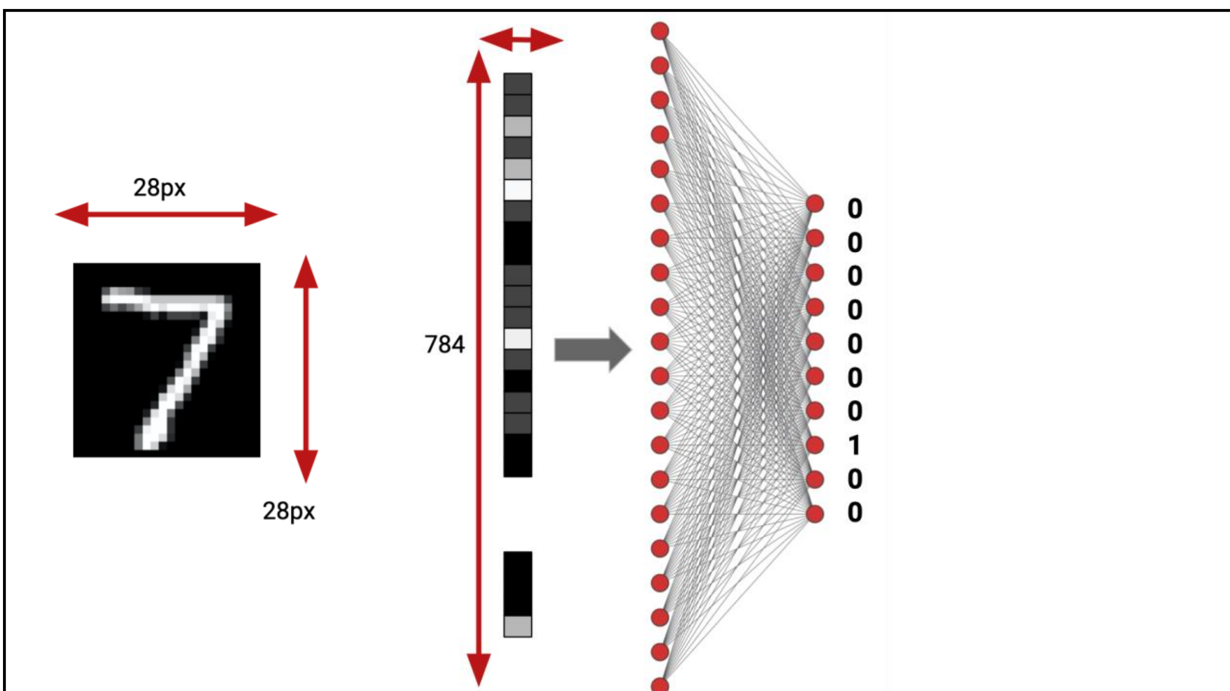

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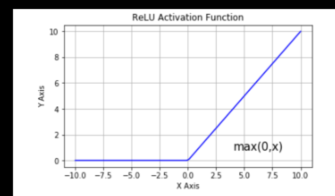

"ReLU applies much-needed non-linearity into the model. Non-linearity is necessary to produce non-linear decision boundaries, so that the output cannot be written as a linear combination of the inputs."

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

Design a Model

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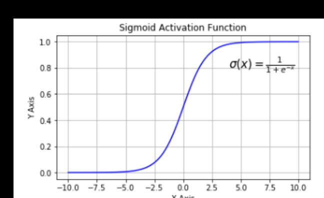

SOFTMAX: Generalization of the logistic function (or Sigmoid) to multiple dimensions. A softmax operation serves a key purpose: making sure the Neural Network (in this case, a Dense NN) outputs sum to 1. Because of this, softmax operations are useful to scale model outputs into probabilities.

Design a Model

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

Design a Model

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```

Mean Squared Error

Prediction

$$MSE = \frac{1}{N}\sum(t_i - s_i)^2$$

Ground Truth

Cross Entropy Loss

Classes   Prediction

$$CE = -\sum_{i}^{C} t_i log(s_i)$$

Ground Truth {0,1}

Design a Model

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model.compile(optimizer='adam',
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model.fit(training_images, training_labels, epochs=20)
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Train a Model

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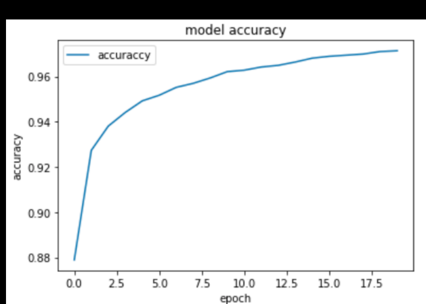

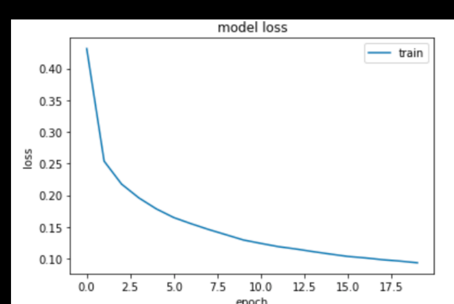

Evaluate
Optimize

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```
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]

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```

Make Inferences

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Digit Classification using Dense NN with TF2

Code Time!

TF_MNIST_Classification.ipynb

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Credits

- A previous edition of this course was developed in collaboration with Dr. Susan C. Schneider of Marquette University.
- We are very grateful and thank all the following professors, researchers, and practitioners for jump-starting courses on TinyML and for sharing their teaching materials:
- Prof. Marcelo Rovai - TinyML - Machine Learning for Embedding Devices, UNIFEI
  - https://github.com/Mjrovai/UNIFEI-IESTI01-TinyML-2022.1
- Prof. Vijay Janapa Reddi - CS249r: Tiny Machine Learning, Applied Machine Learning on Embedded IoT Devices, Harvard
  - https://sites.google.com/g.harvard.edu/tinyml/home
- Prof. Rahul Mangharam – ESE3600: Tiny Machine Learning, Univ. of Pennsylvania
  - https://tinyml.seas.upenn.edu/#
- Prof. Brian Plancher - Harvard CS249r: Tiny Machine Learning (TinyML), Barnard College, Columbia University
  - https://a2r-lab.org/courses/cs249r_tinyml/

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References

- Additional references from where information and other teaching materials were gathered include:
- Applications & Deploy textbook: “TinyML” by Pete Warden, Daniel Situnayake
  - https://www.oreilly.com/library/view/tinyml/9781492052036/
- Deploy textbook “TinyML Cookbook” by Gian Marco Iodice
  - https://github.com/PacktPublishing/TinyML-Cookbook
- Jason Brownlee
  - https://machinelearningmastery.com/
- TinyMLedu
  - https://tinyml.seas.harvard.edu/
- Professional Certificate in Tiny Machine Learning (TinyML) – edX/Harvard
  - https://www.edx.org/professional-certificate/harvardx-tiny-machine-learning
- Introduction to Embedded Machine Learning - Coursera/Edge Impulse
  - https://www.coursera.org/learn/introduction-to-embedded-machine-learning
- Computer Vision with Embedded Machine Learning - Coursera/Edge Impulse
  - https://www.coursera.org/learn/computer-vision-with-embedded-machine-learning

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