Introduction to Deep Learning with TensorFlow

Jian Tao

jtao@tamu.edu

HPRC Short Course

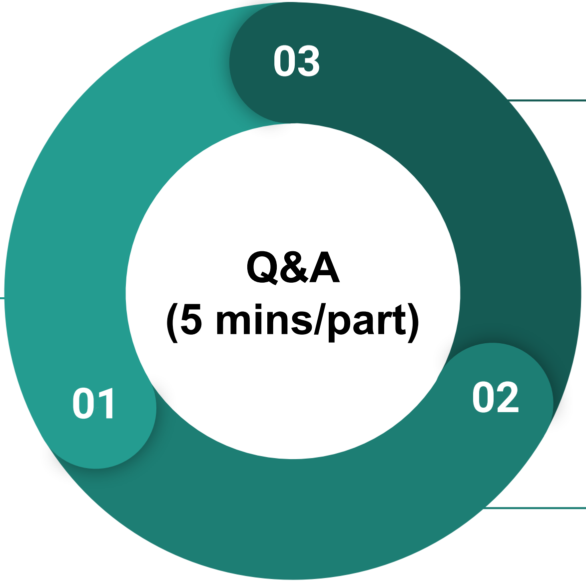
4/16/2021

Texas A&M Engineering Experiment Station

High Performance Research Computing
DIVISION OF RESEARCH

TEXAS A&M
Institute of Data Science

Introduction to Deep Learning with TensorFlow



Part I

Setting up a working environment (15 mins)

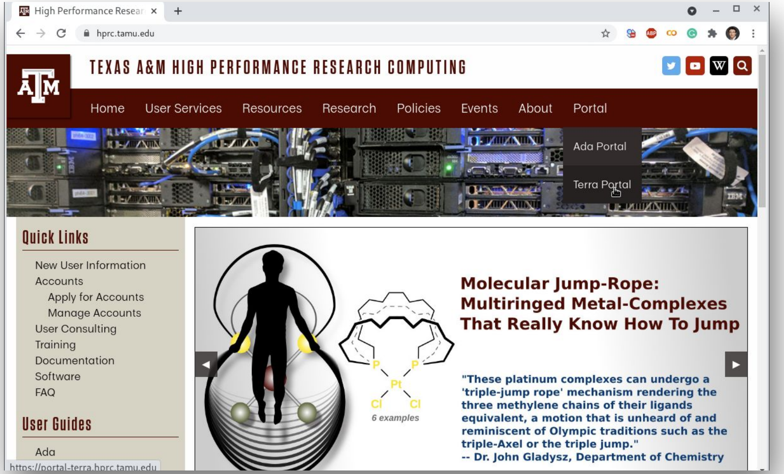
Part II

Introduction to Deep Learning (60 mins)

Part III

Introduction to TensorFlow (60 mins)

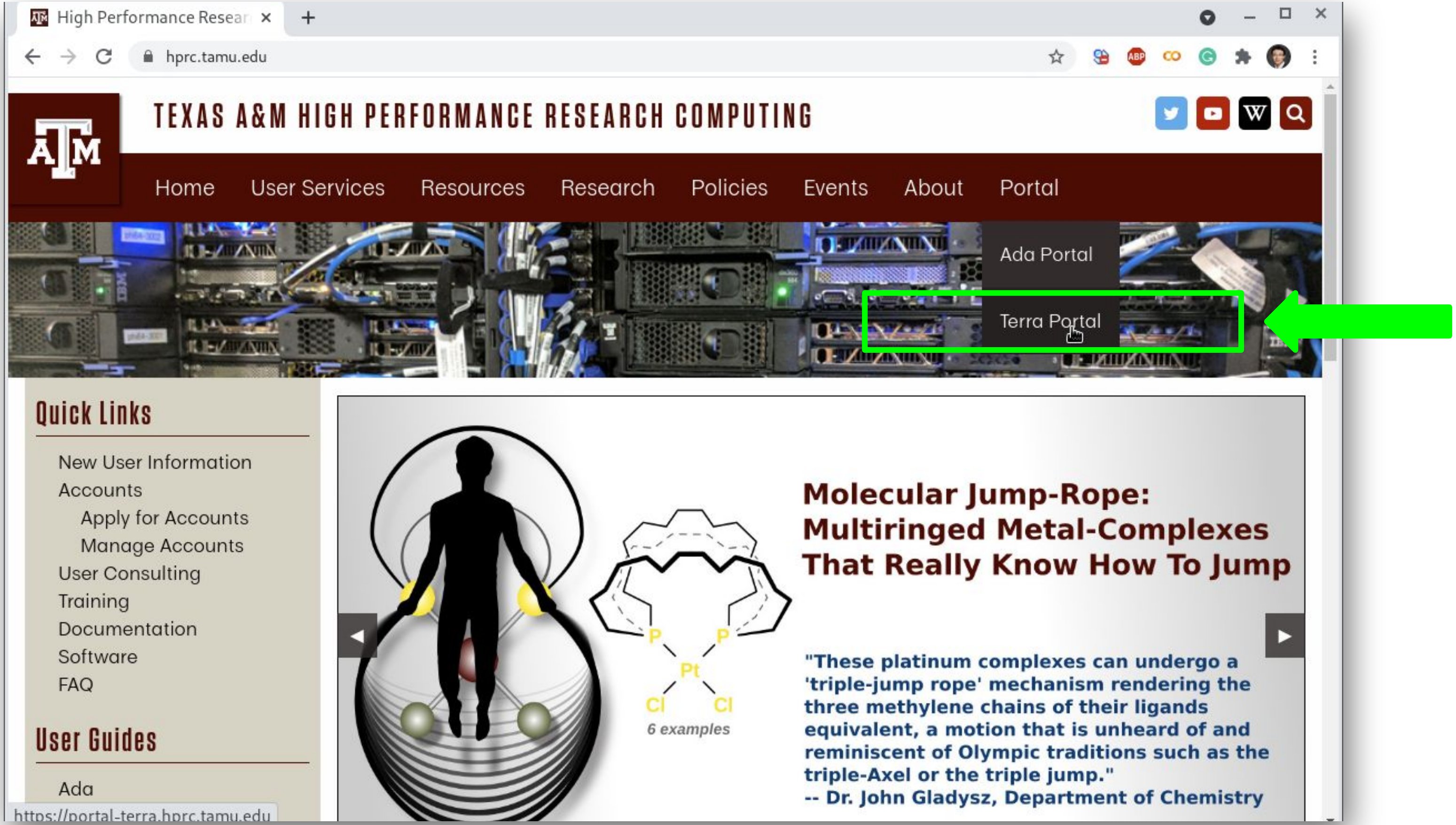
Part I. Working Environment



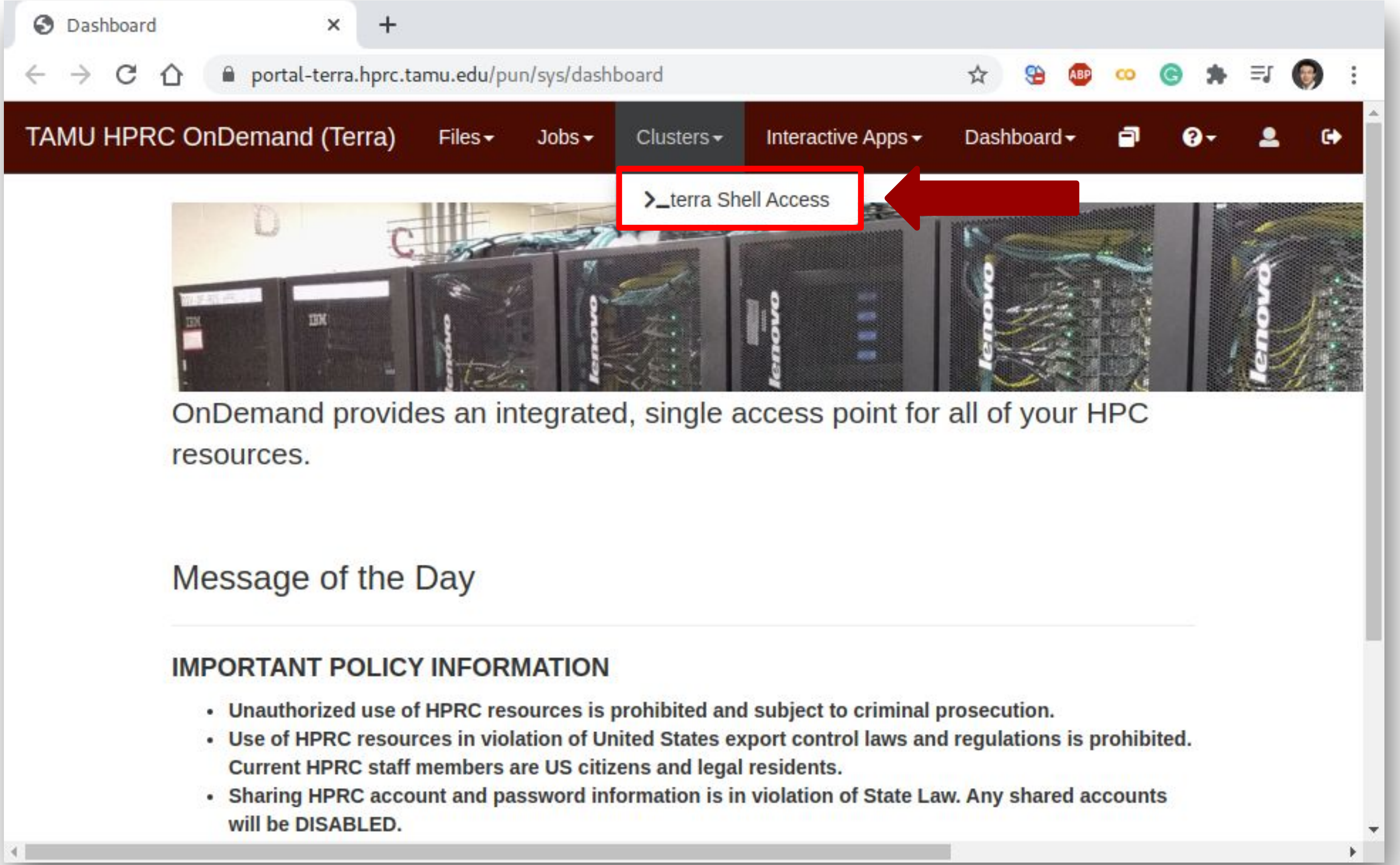
HPRC Portal

*** VPN is required for off-campus users.**

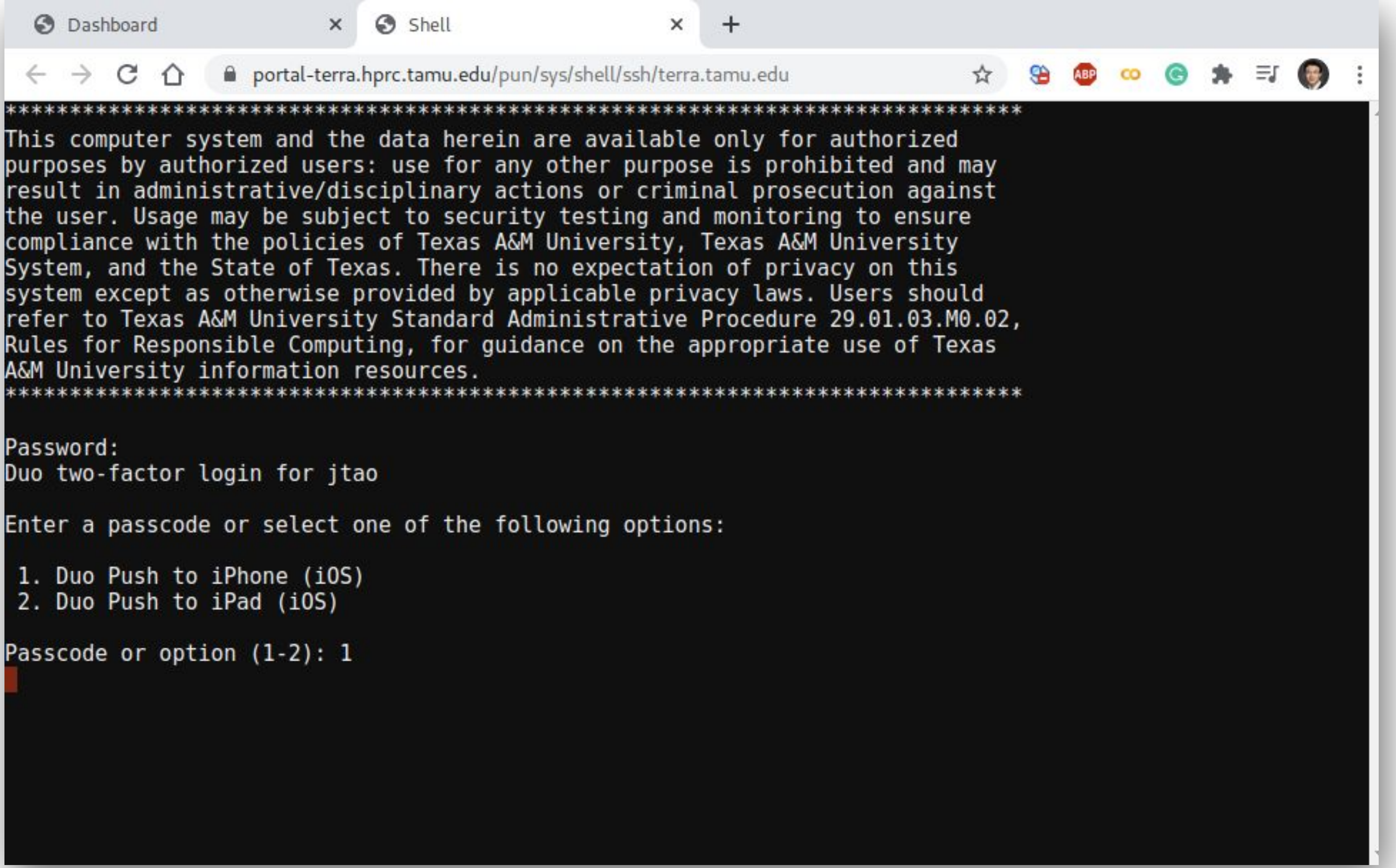
Login HPRC Portal (Terra)



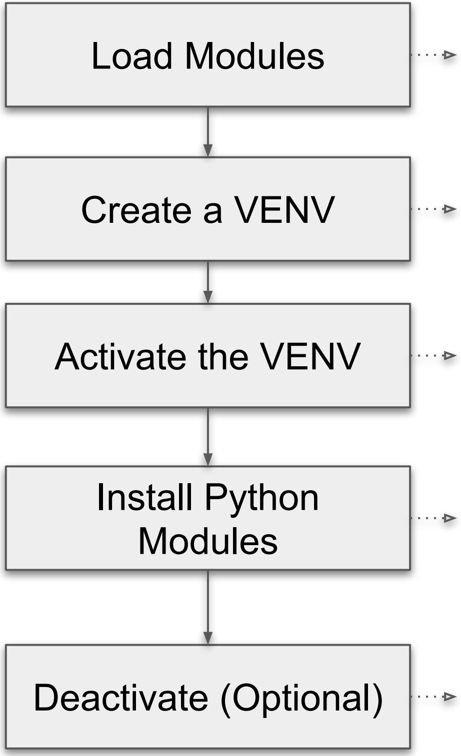
Terra Shell Access - I



Terra Shell Access - II

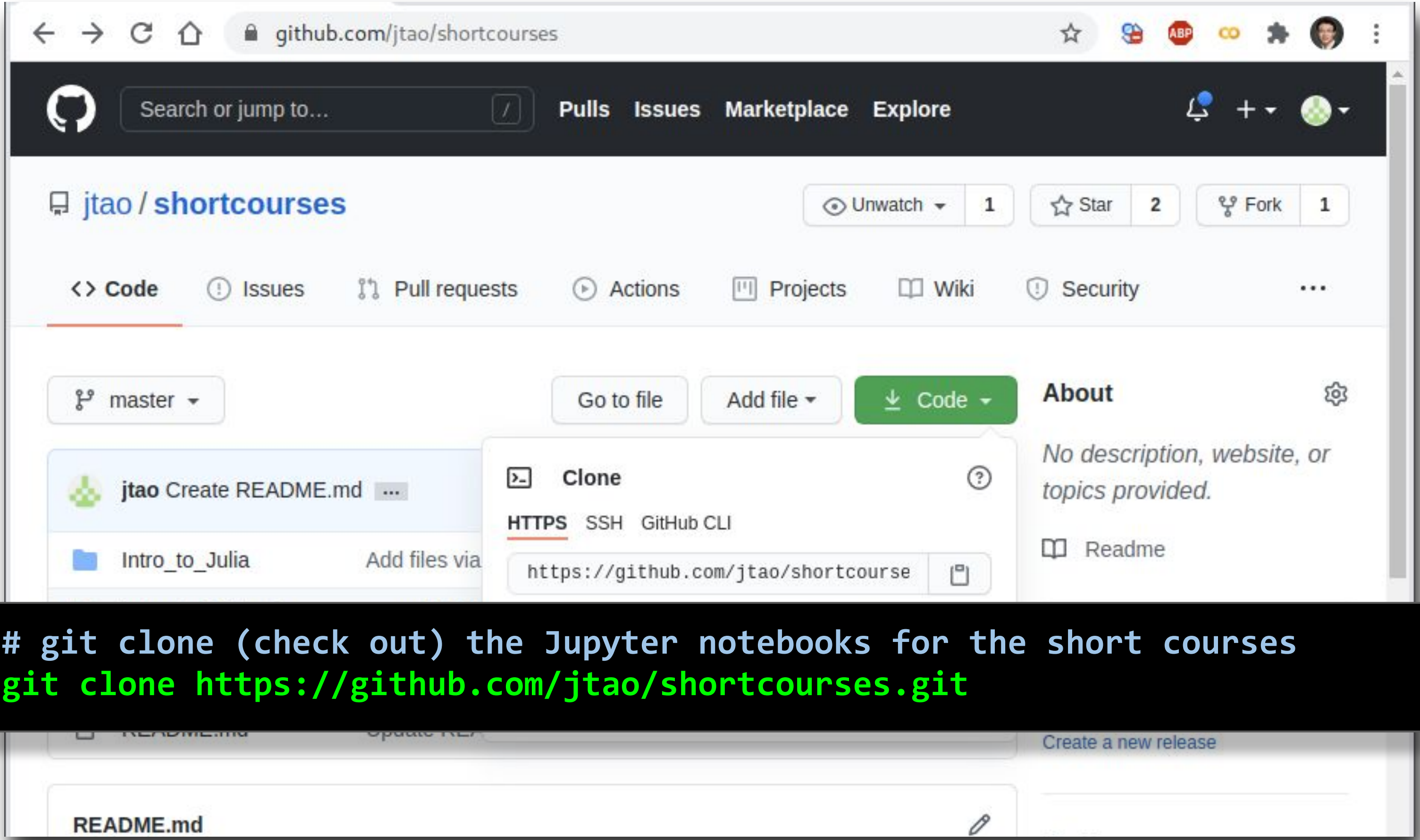


Python Virtual Environment (VENV)



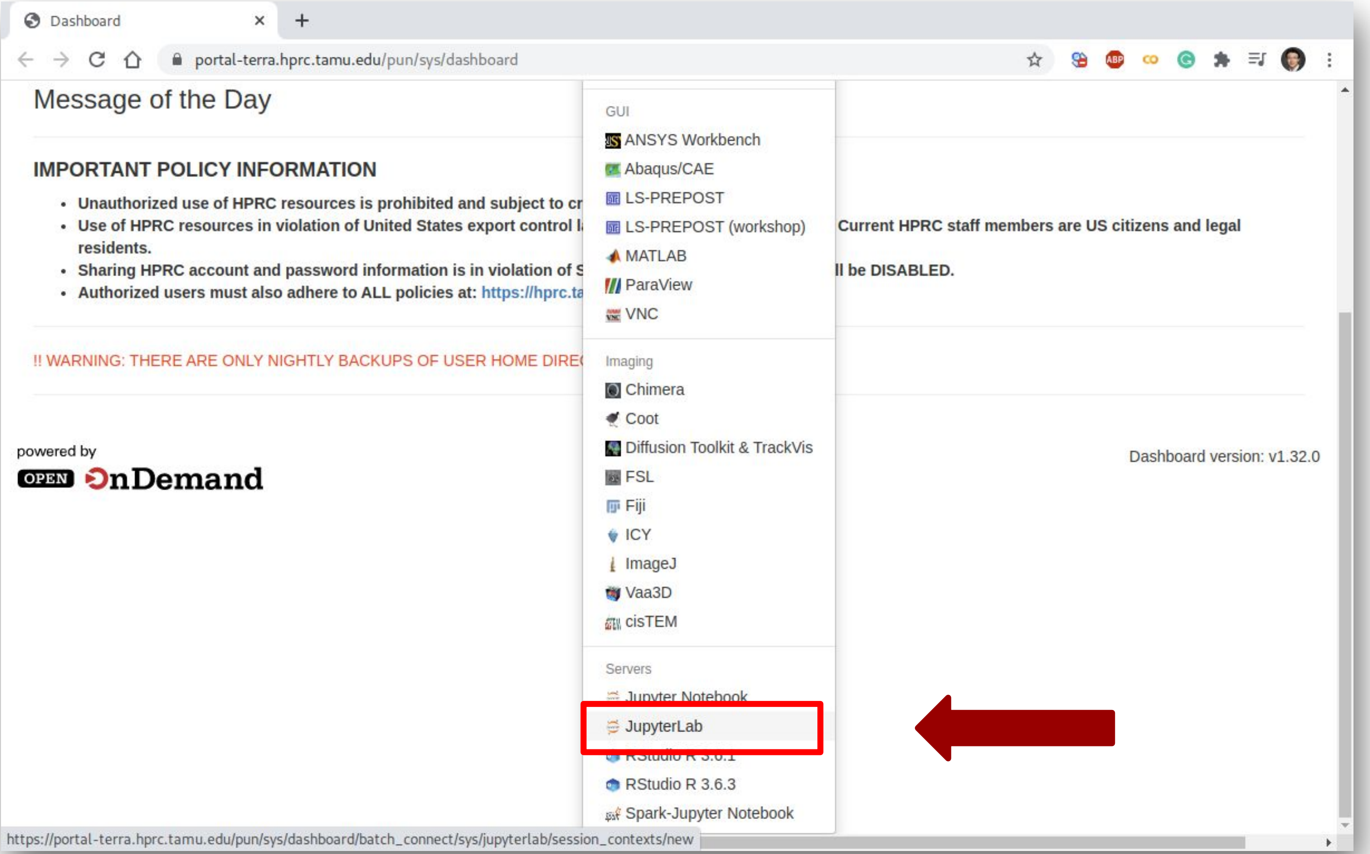

```
# clean up and load Anaconda
cd $SCRATCH
module purge
module load Python/3.7.4-GCCcore-8.3.0

# create a Python virtual environment
python -m venv mylab

# activate the virtual environment
source mylab/bin/activate


# install required package to be used in the portal
pip install --upgrade pip setuptools
pip install jupyterlab tensorflow sklearn matplotlib

# deactivate the virtual environment
# source deactivate
```

Check out Exercises

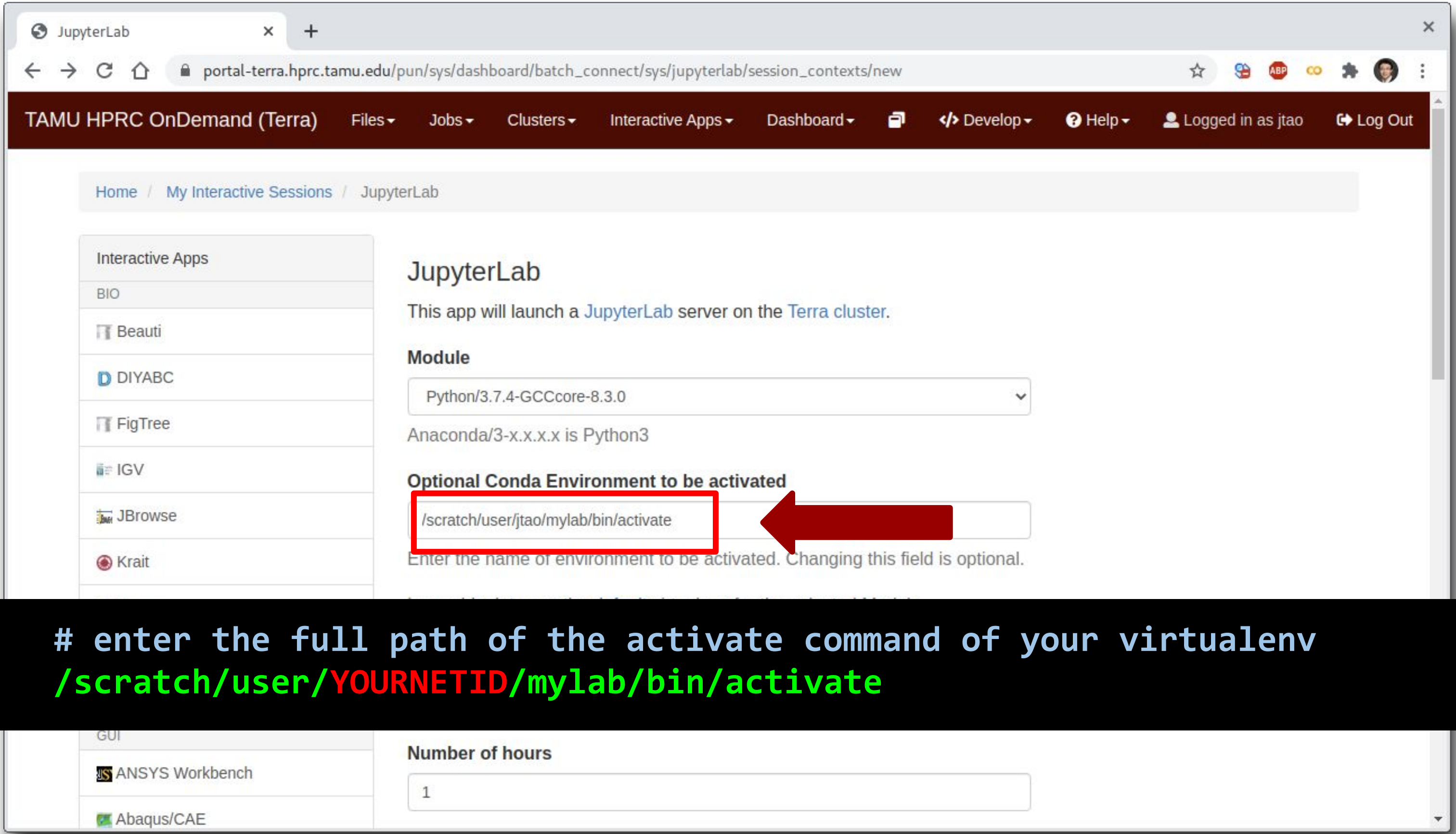



```
# git clone (check out) the Jupyter notebooks for the short courses
git clone https://github.com/jtao/shortcourses.git
```

Go to JupyterLab Page

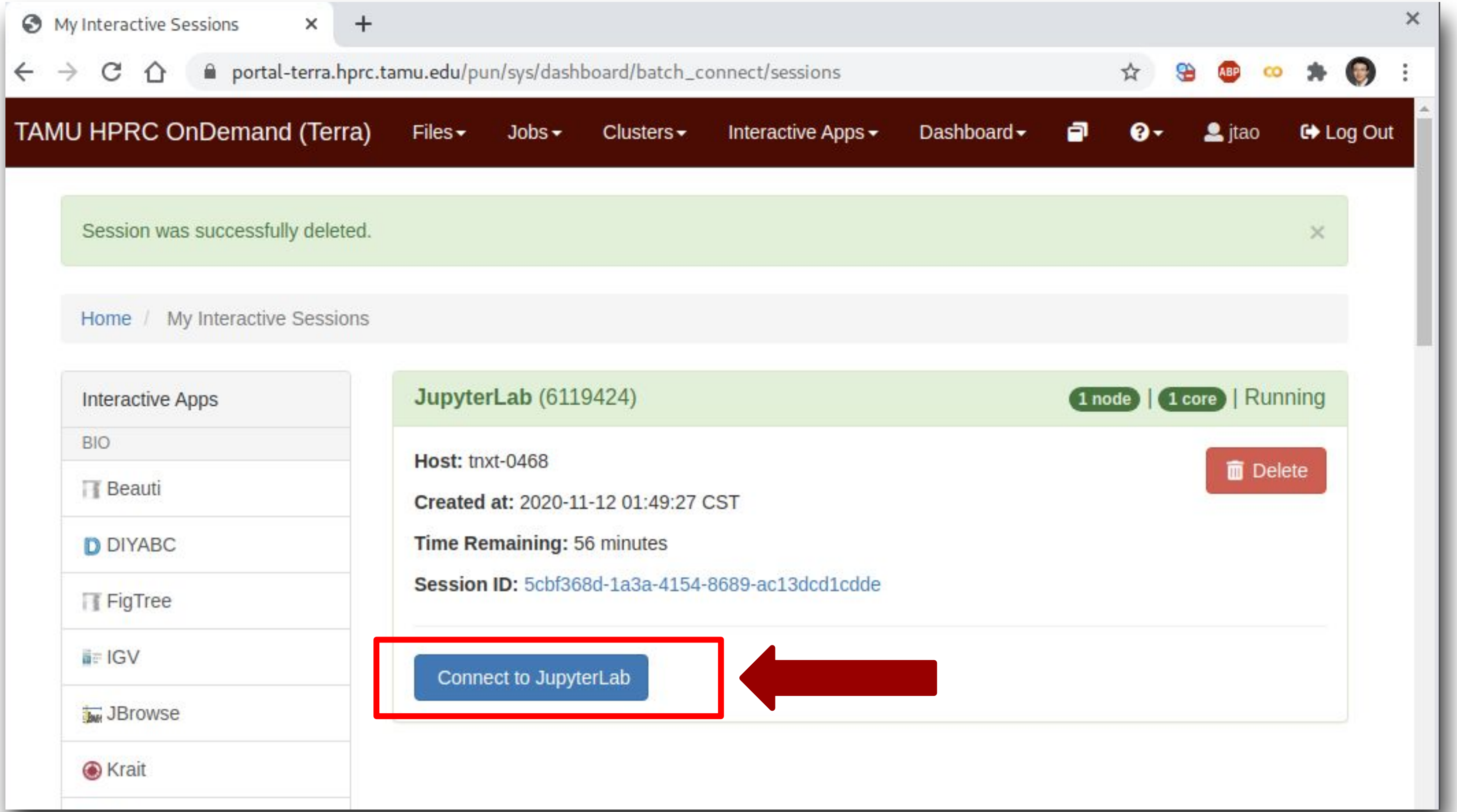


Set Virtual Environment

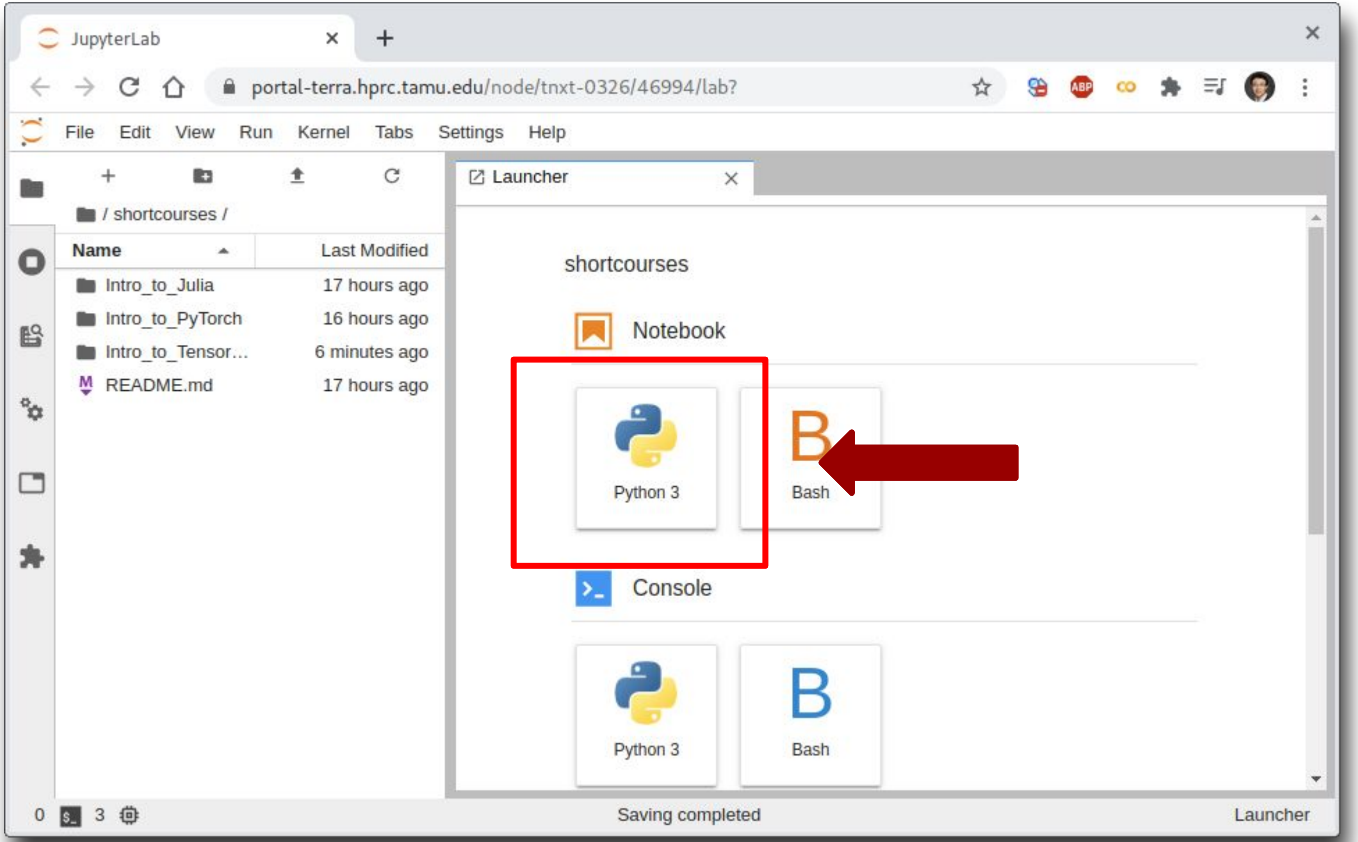



```
# enter the full path of the activate command of your virtualenv
/scratch/user/YOURNETID/mylab/bin/activate
```

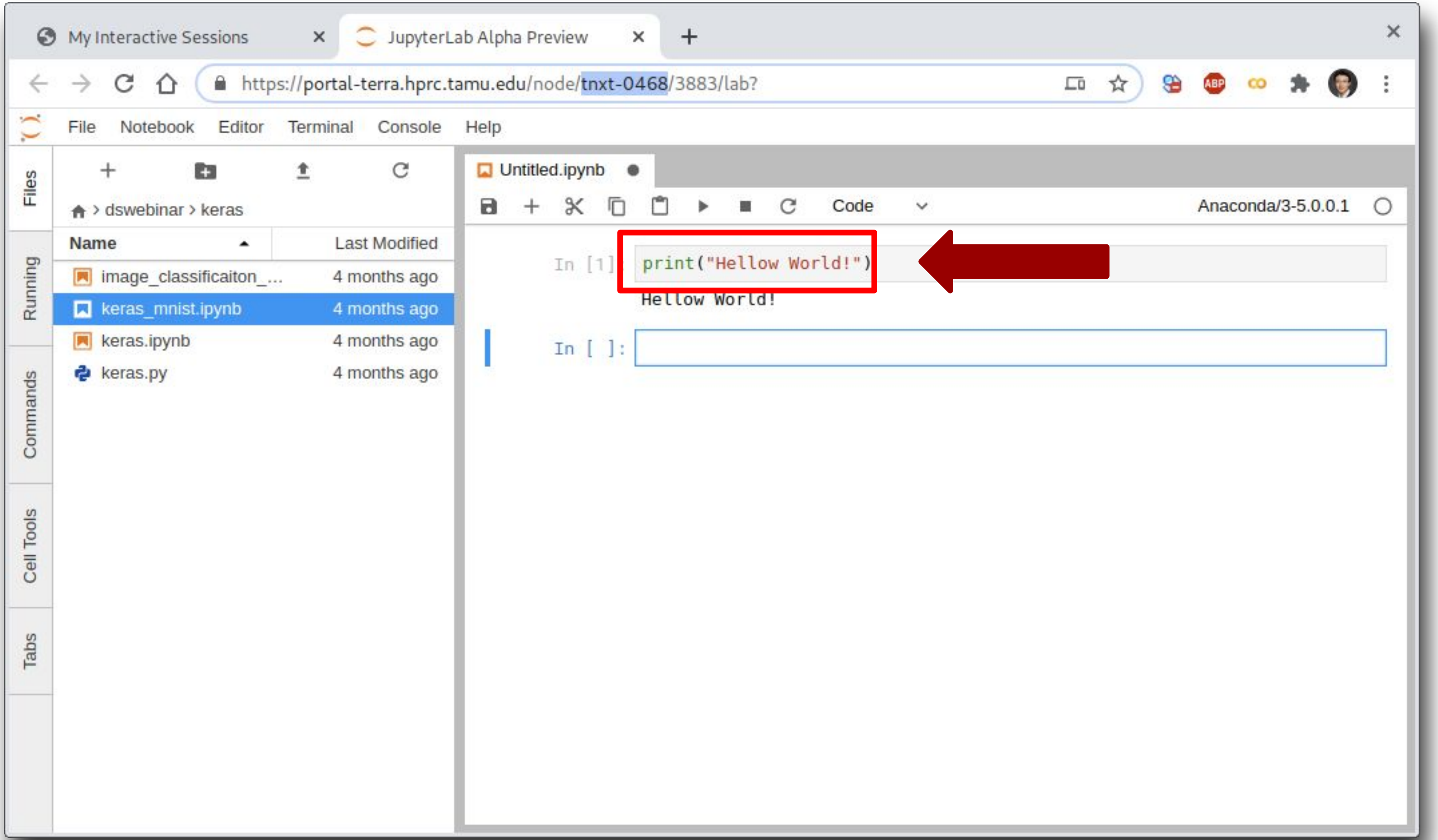
Connect to JupyterLab



Create a Jupyter Notebook



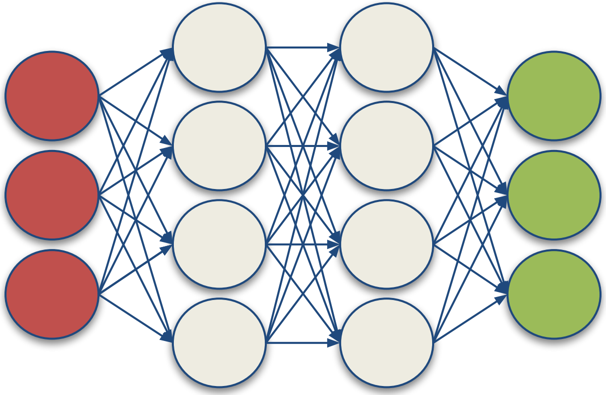
Test JupyterLab



Part II. Introduction to Deep Learning

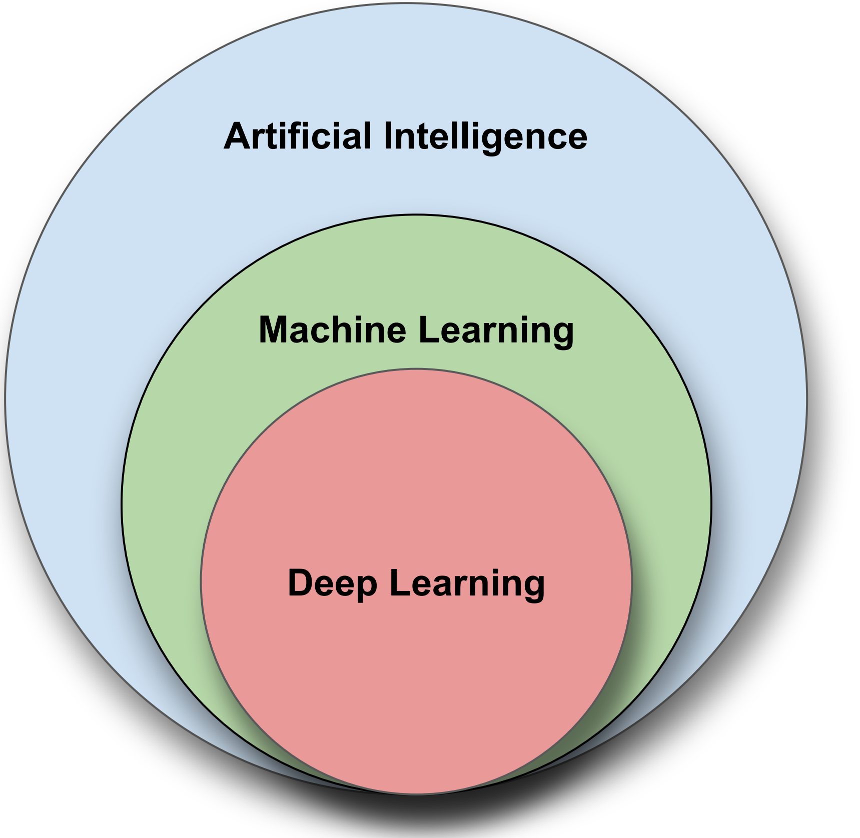
Deep Learning
by Ian Goodfellow, Yoshua Bengio, and Aaron Courville
http://www.deeplearningbook.org/

Animation of Neutron Networks
by Grant Sanderson
https://www.3blue1brown.com/

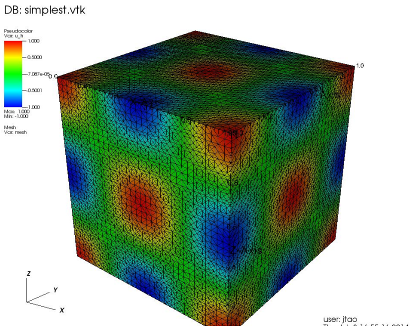


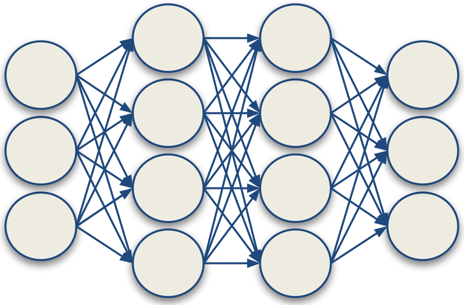
Relationship of AI, ML, and DL

- **Artificial Intelligence (AI)** is anything about man-made intelligence exhibited by machines.
- **Machine Learning (ML)** is an approach to achieve **AI**.
- **Deep Learning (DL)** is one technique to implement **ML**.

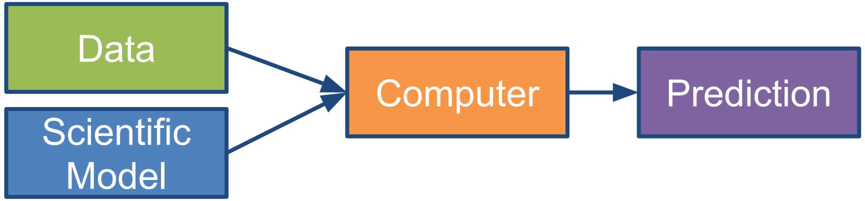


Machine Learning

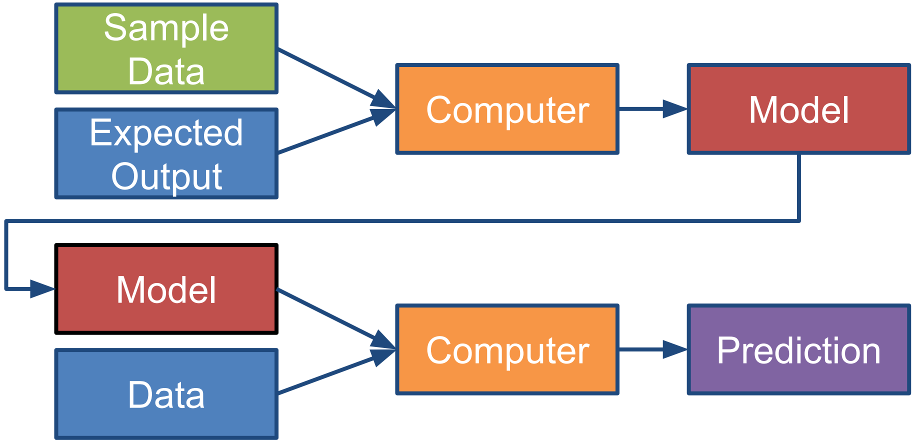




Traditional Modeling

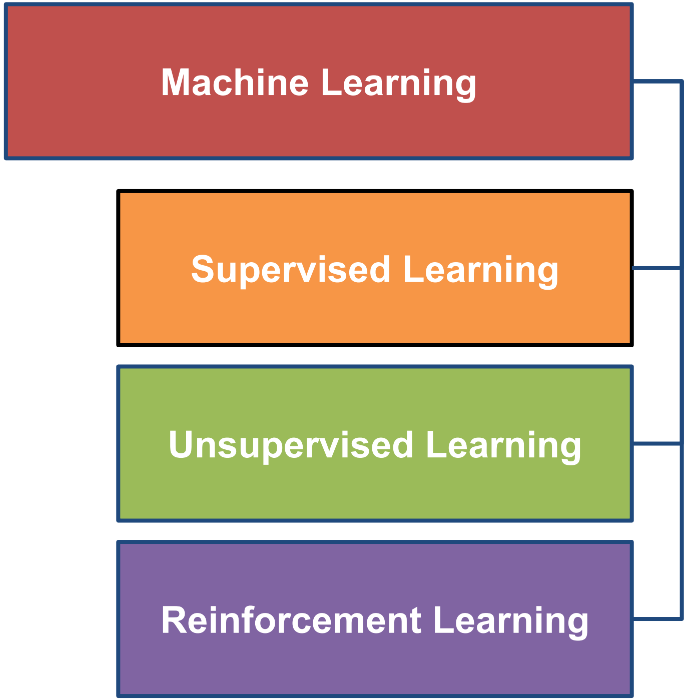


Machine Learning (Supervised Learning)



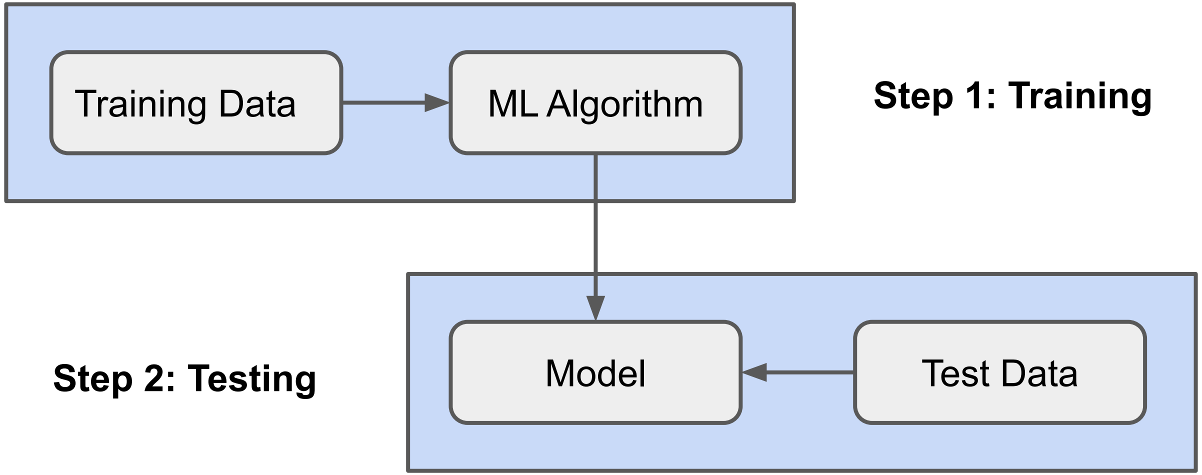
Types of ML Algorithms

- **Supervised Learning**
  - trained with labeled data; including regression and classification problems
- **Unsupervised Learning**
  - trained with unlabeled data; clustering and association rule learning problems.
- **Reinforcement Learning**
  - no training data; stochastic Markov decision process; robotics and self-driving cars.



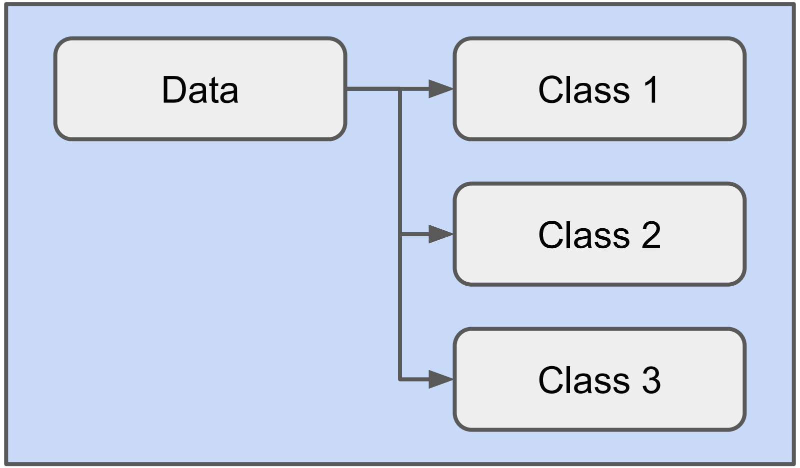
Supervised Learning

When both input variables - X and output variables - Y are known, one can approximate the mapping function from X to Y.



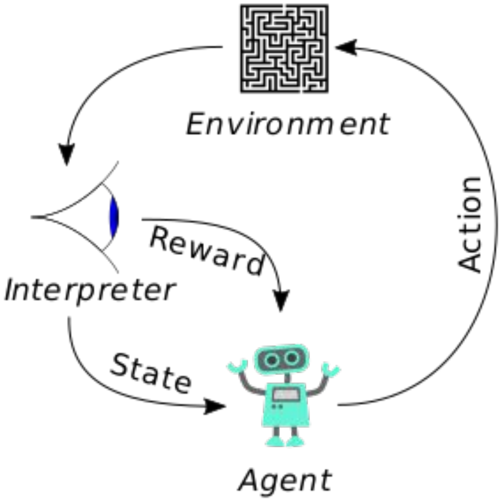
Unsupervised Learning

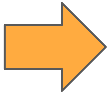
When only input variables - X are known and the training data is neither classified nor labeled. It is usually used for clustering problems.

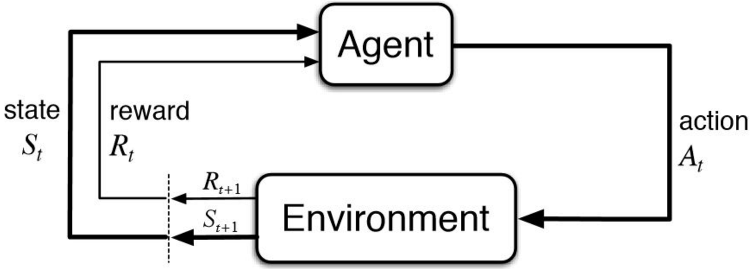


Reinforcement Learning

When the input variables are only available via interacting with the environment, reinforcement learning can be used to train an "**agent**".







(Image Credit: Wikipedia.org)

(Image Credit: deeplearning4j.org)

Why Deep Learning?

- Limitations of traditional machine learning algorithms
  - not good at handling high dimensional data.
  - difficult to do feature extraction and object recognition.

- Advantages of deep learning
  - DL is computationally expensive, but it is capable of handling high dimensional data.
  - feature extraction is done automatically.

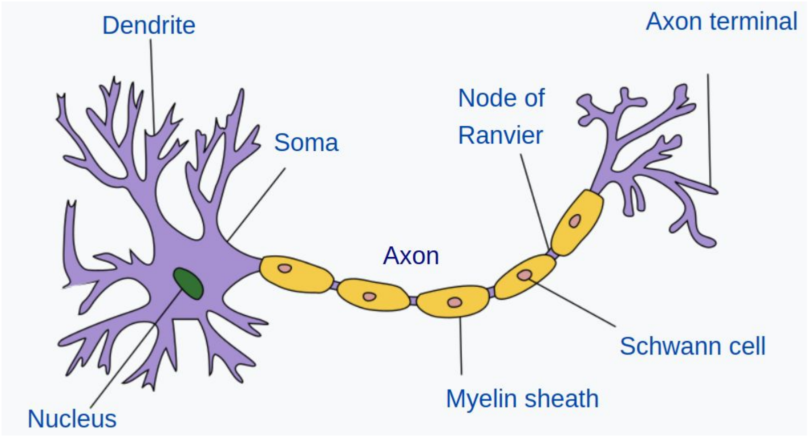
What is Deep Learning?

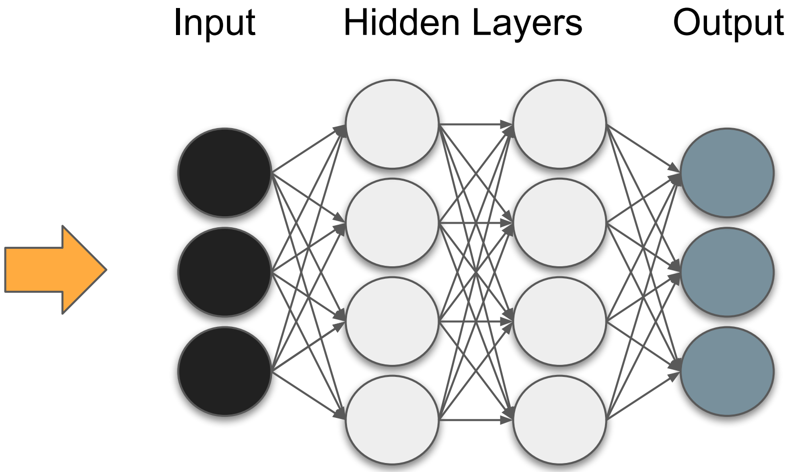
Deep learning is a class of machine learning algorithms that:

- use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation. Each successive layer uses the output from the previous layer as input.
- learn in supervised (e.g., classification) and/or unsupervised (e.g., pattern analysis) manners.
- learn multiple levels of representations that correspond to different levels of abstraction; the levels form a hierarchy of concepts.

(Source: Wikipedia)

Artificial Neural Network





(Image Credit: Wikipedia)

Inputs and Outputs

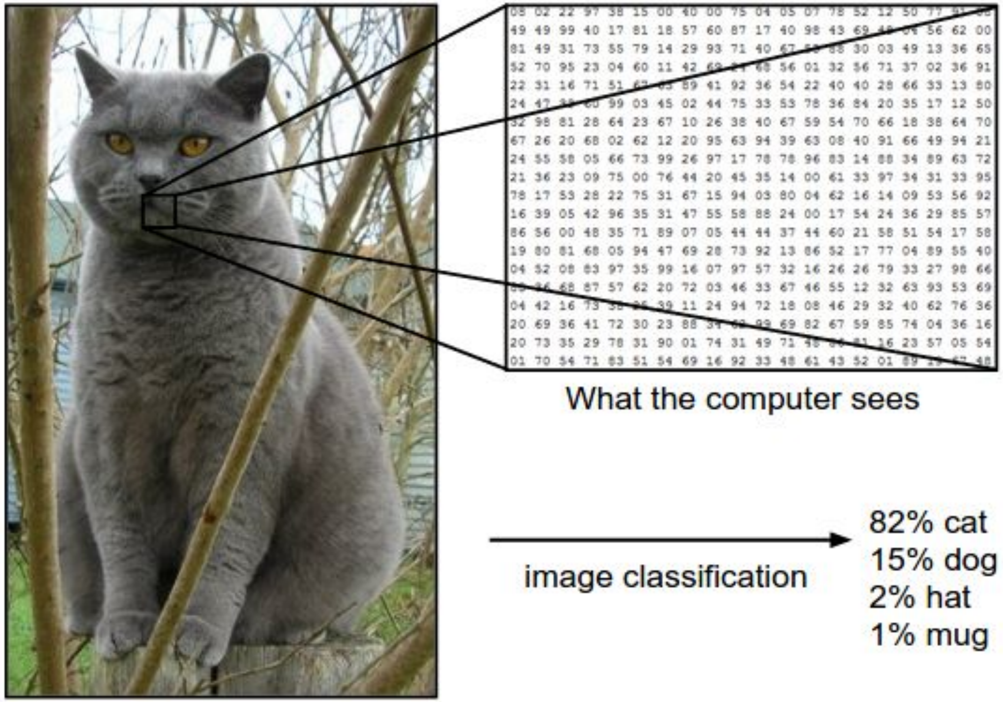
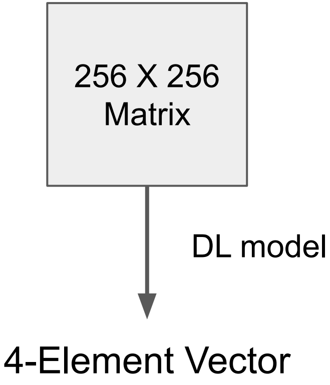
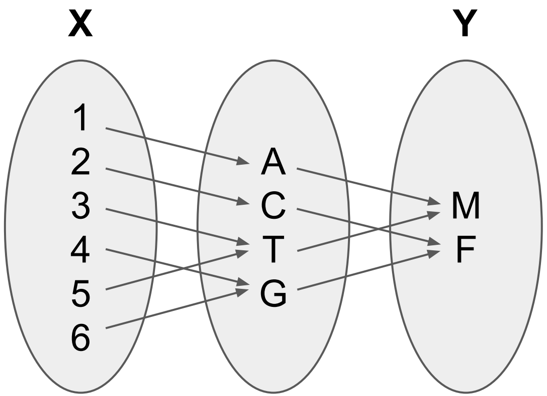


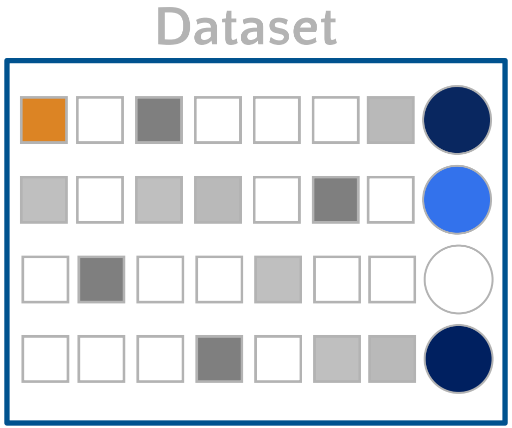
Image from the Stanford CS231 Course

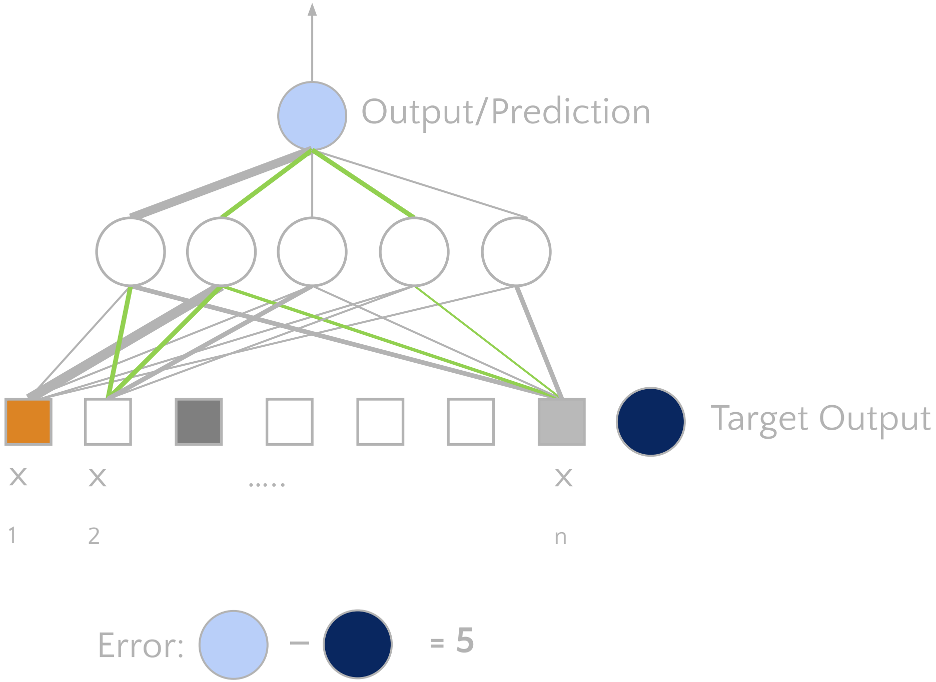




With deep learning, we are searching for a **surjective** (or **onto**) function **f** from a set **X** to a set **Y**.

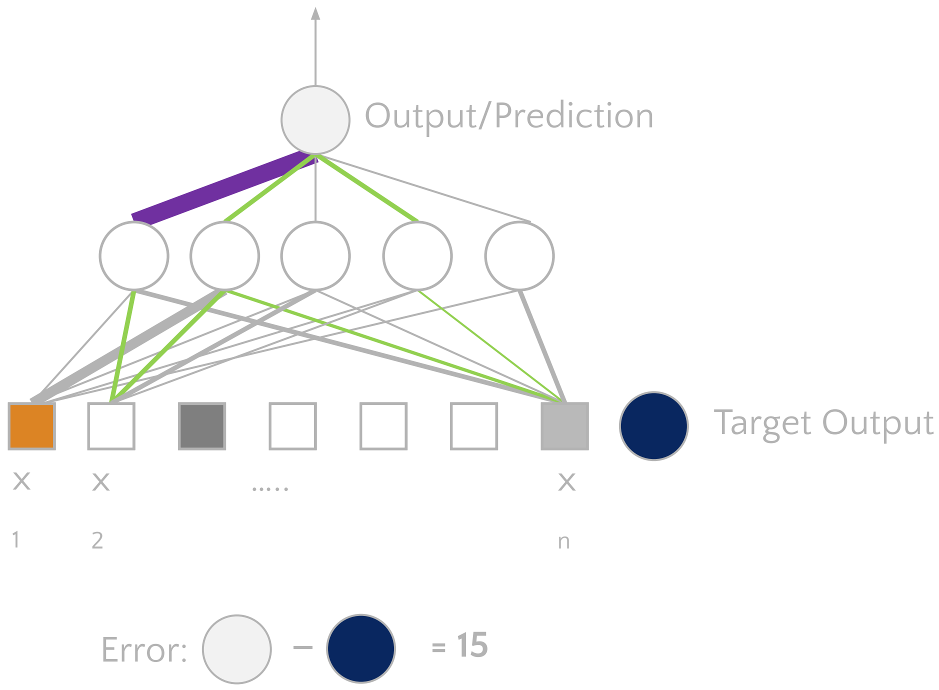
Learning Principle - I





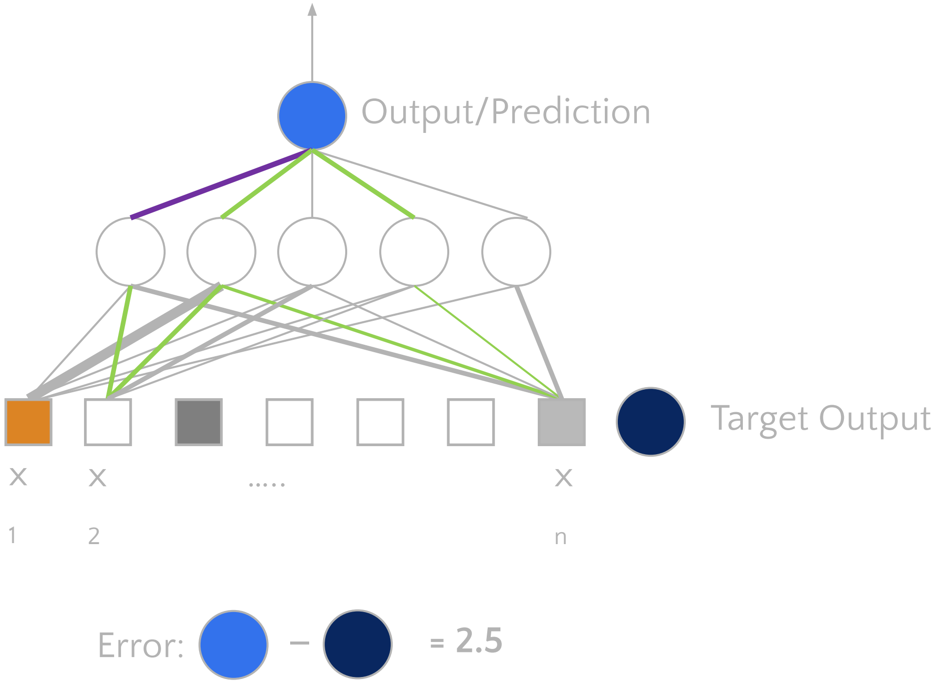
Credit: nvidia.com

Learning Principle - II



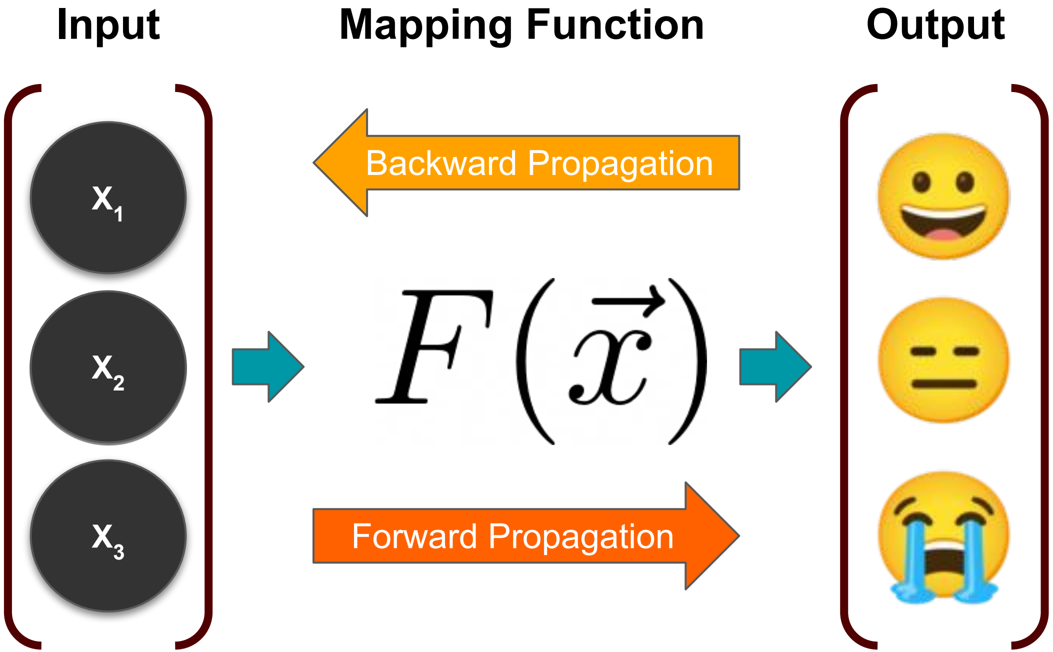
Credit: nvidia.com

Learning Principle - III



Credit: nvidia.com

Deep Neural Network as a Nonlinear Function



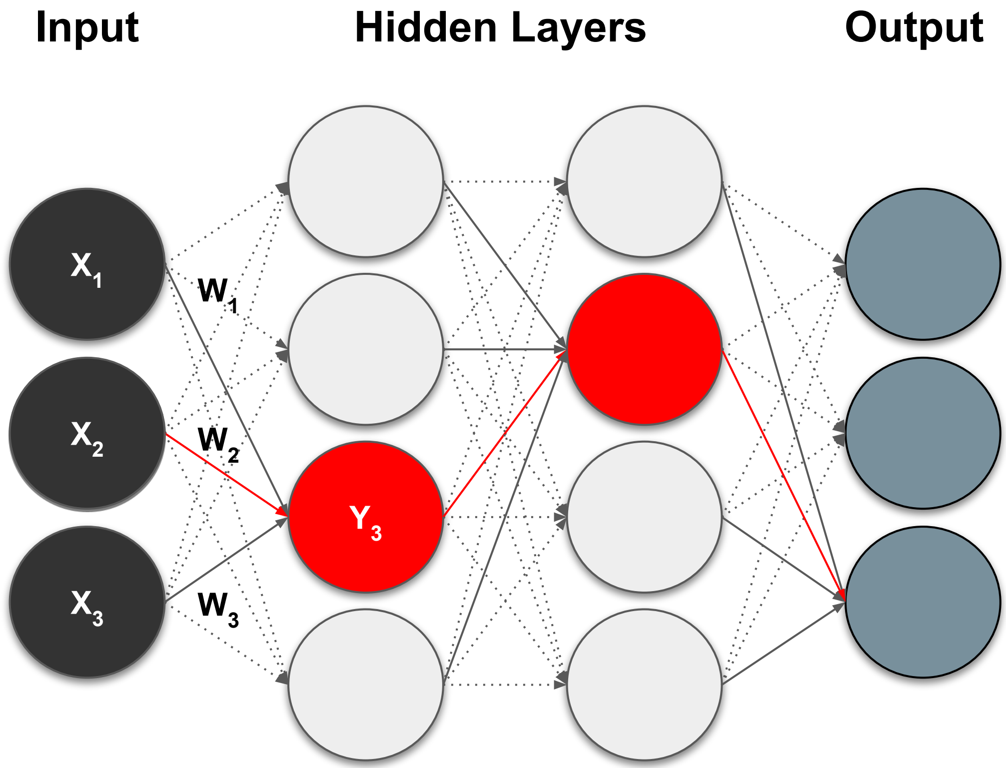
- **Training:** given **input** and **output**, find best-fit ***F***
- **Inference:** given **input** and ***F***, predict **output**

Supervised Deep Learning with Neural Networks

From one layer to the next

$$Y_j = f\left(\sum_i W_i X_i + b_i\right)$$

f is the activation function, W_i is the weight, and b_i is the bias.



Training - Minimizing the Loss

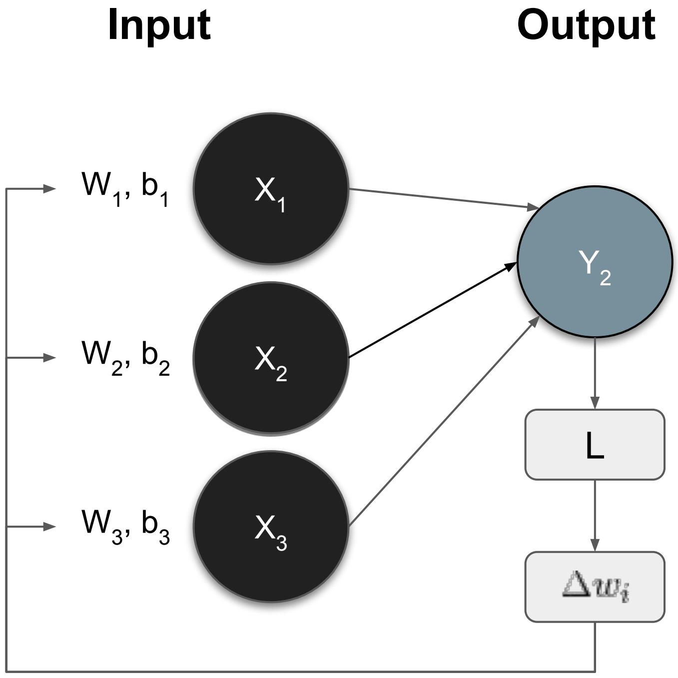
The loss function with regard to weights and biases can be defined as

$$L(\mathbf{w}, \mathbf{b}) = \frac{1}{2} \sum_i (\mathbf{Y}(\mathbf{X}, \mathbf{w}, \mathbf{b}) - \mathbf{Y}'(\mathbf{X}, \mathbf{w}, \mathbf{b}))^2$$

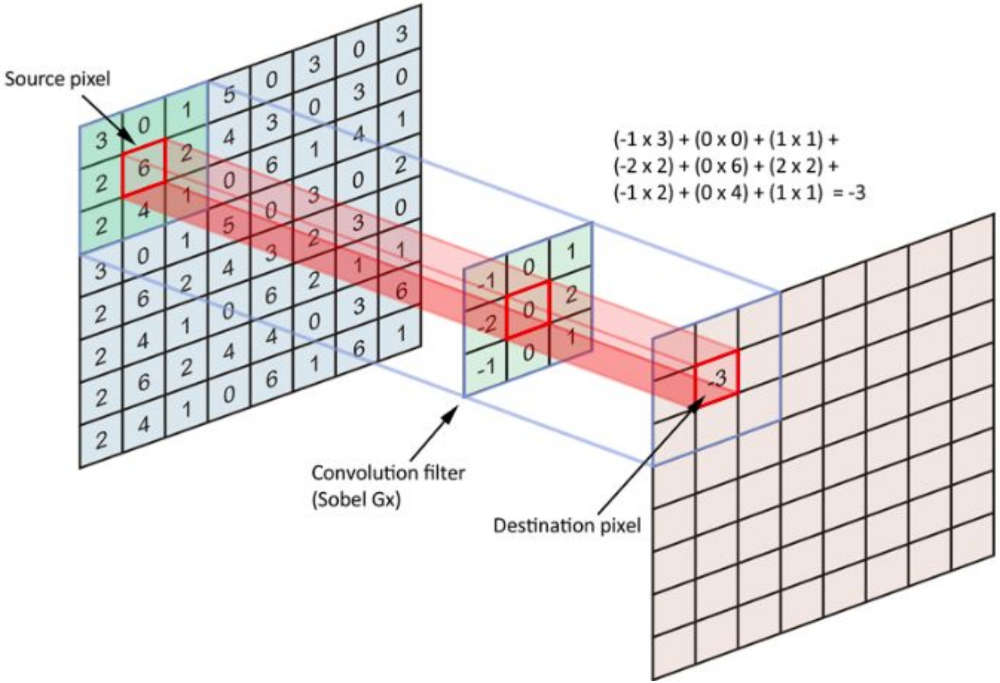
The weight update is computed by moving a step to the opposite direction of the cost gradient.

$$\Delta w_i = -\alpha \frac{\partial L}{\partial w_i}$$

Iterate until L stops decreasing.



Convolution in 2D



(Image Credit: [Applied Deep Learning | Arden Dertat])

Convolution Kernel

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

Input

1	0	1
0	1	0
1	0	1

Filter / Kernel

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

4		

(Image Credit: Applied Deep Learning | Arden Dertat)

Convolution on Image

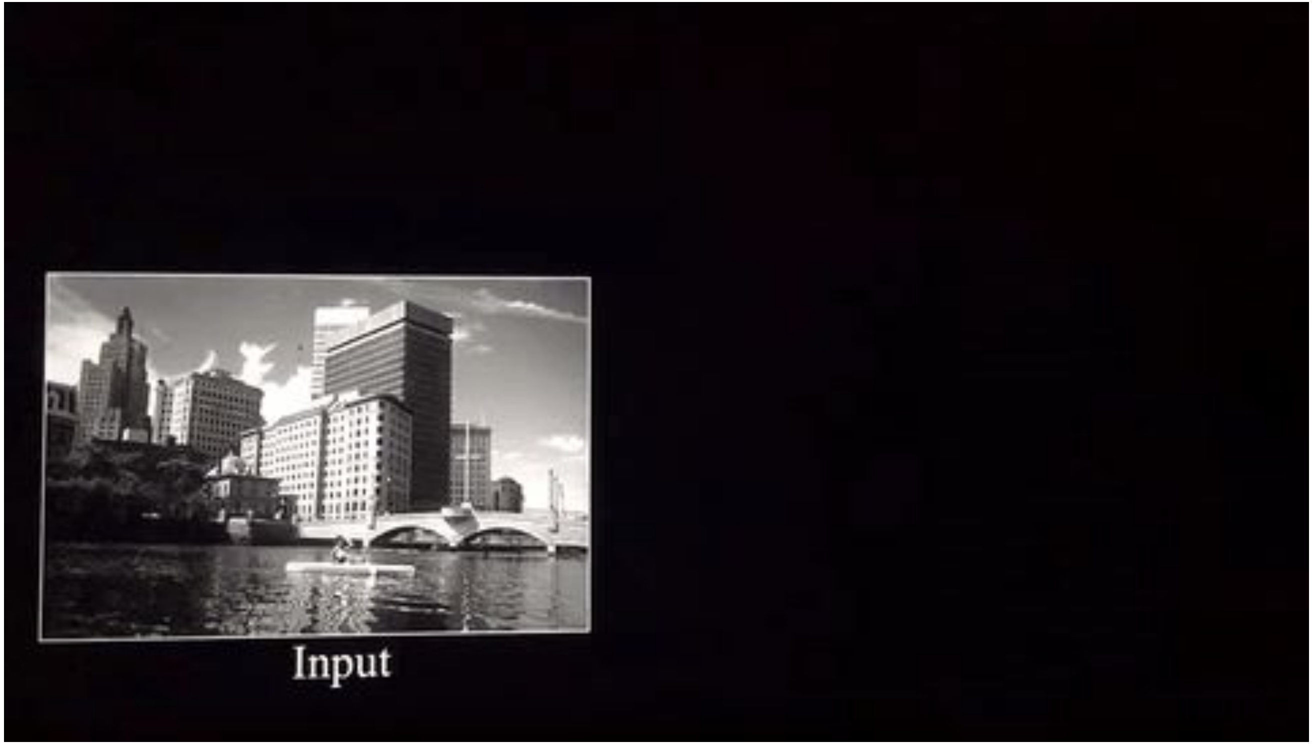
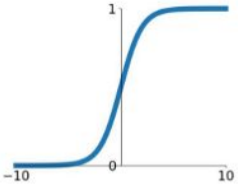


Image Credit: [Deep Learning Methods for Vision | CVPR 2012 Tutorial]

Activation Functions

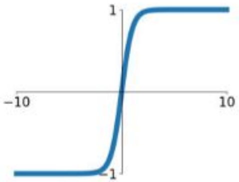
Sigmoid

$\sigma(x) = \frac{1}{1+e^{-x}}$



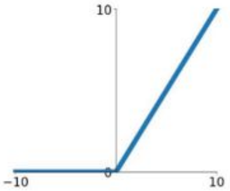
tanh

$\tanh(x)$



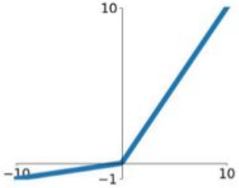
ReLU

$\max(0, x)$



Leaky ReLU

$\max(0.1x, x)$



Maxout

$\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

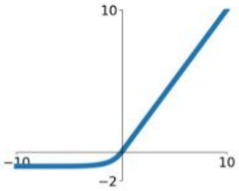


Image Credit: towardsdatascience.com

Introducing Non Linearity (ReLU)

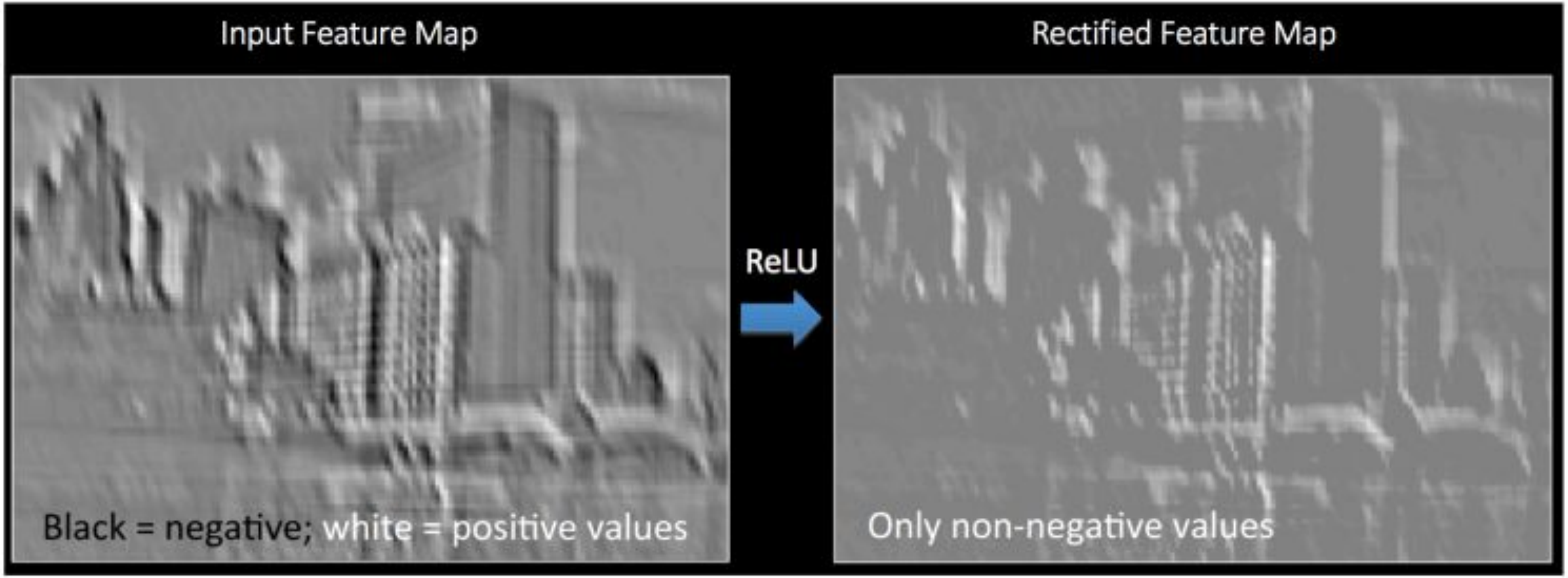
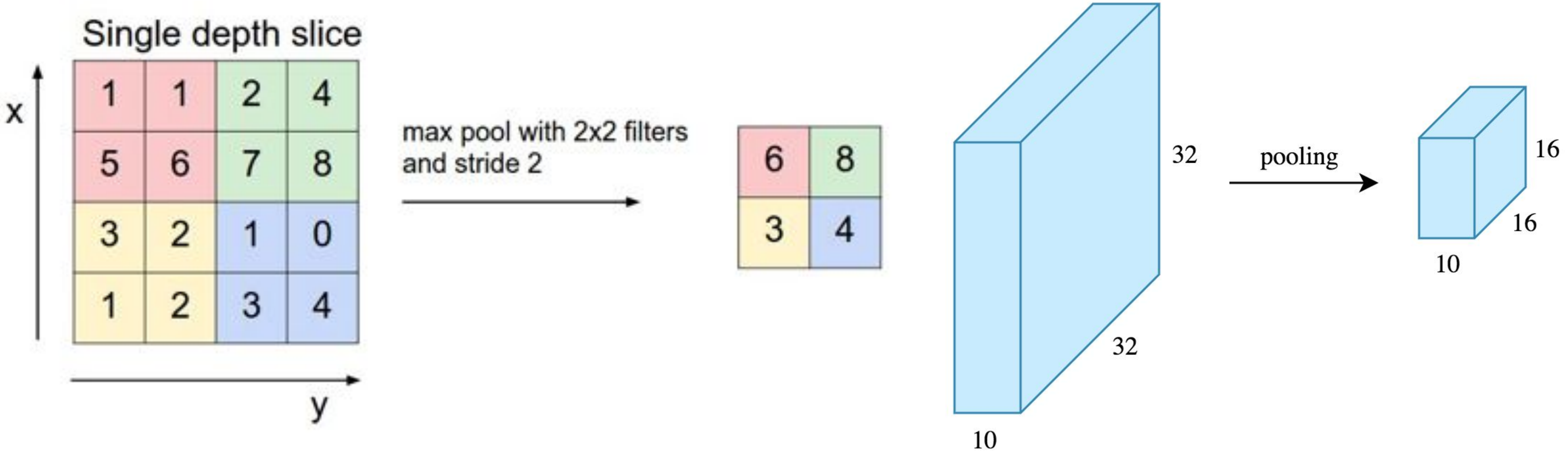


Image Credit: [Deep Learning Methods for Vision | CVPR 2012 Tutorial]

Max Pooling



(Image Credit: Applied Deep Learning | Arden Dertat)

Pooling - Max-Pooling and Sum-Pooling

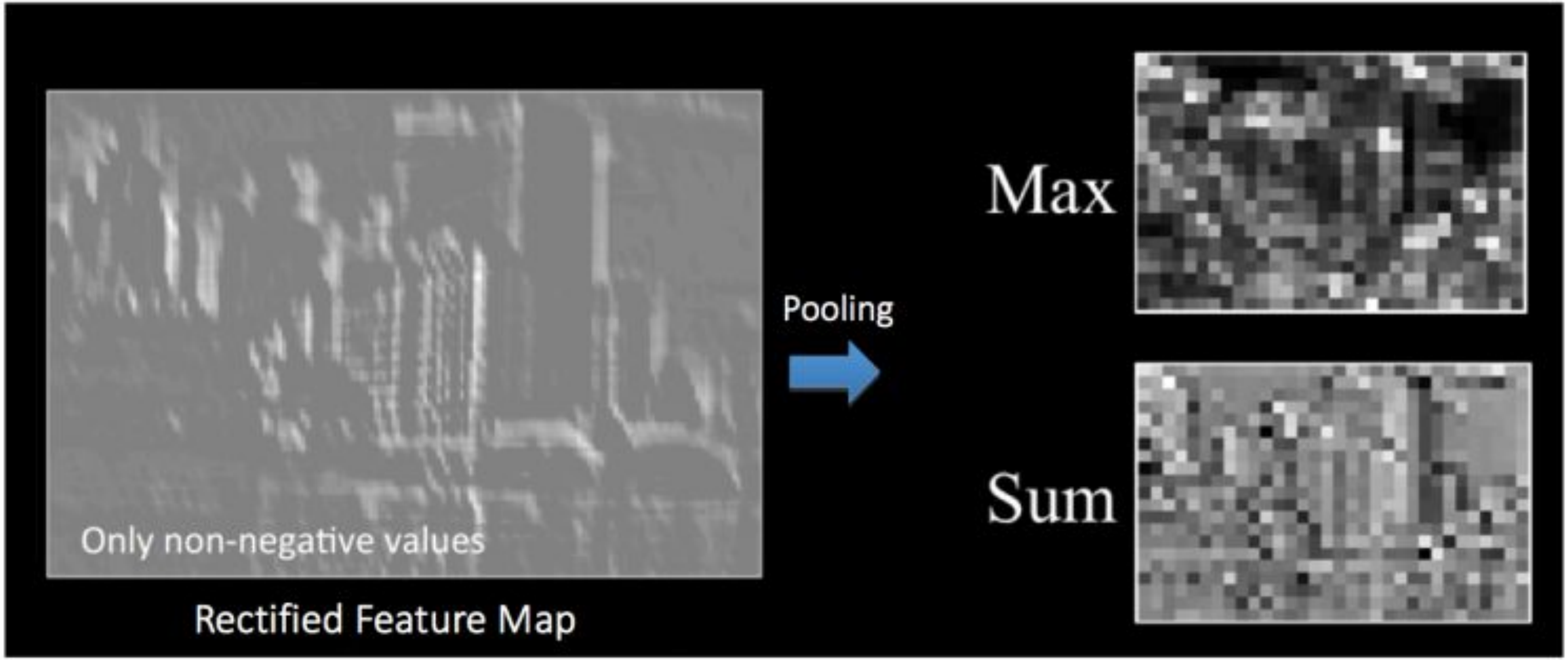
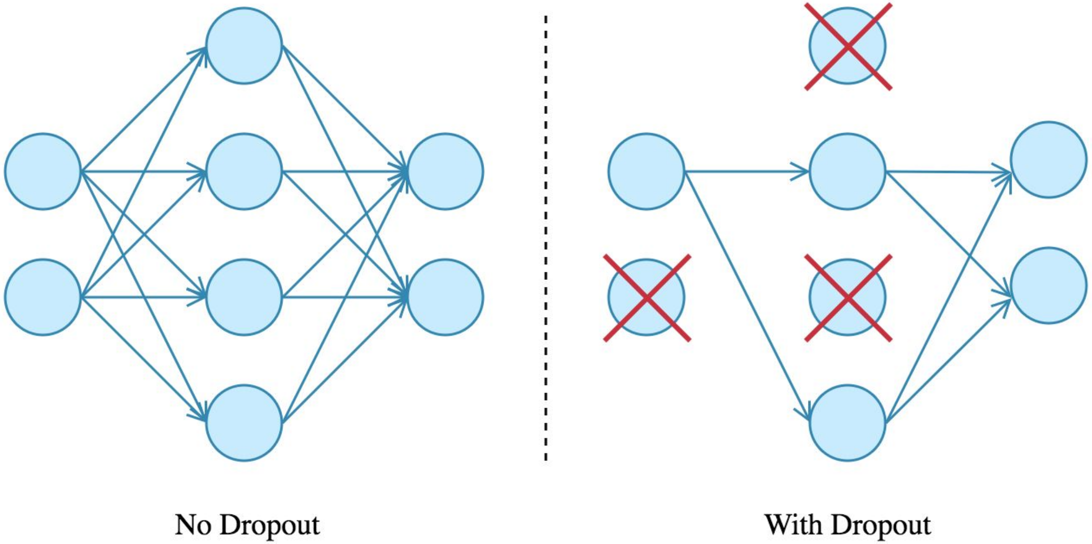


Image Credit: [Deep Learning Methods for Vision | CVPR 2012 Tutorial]

CNN Implementation - Drop Out

Dropout is used to prevent overfitting. A neuron is temporarily "dropped" or disabled with probability P during training.



(Image Credit: Applied Deep Learning | Arden Dertat)

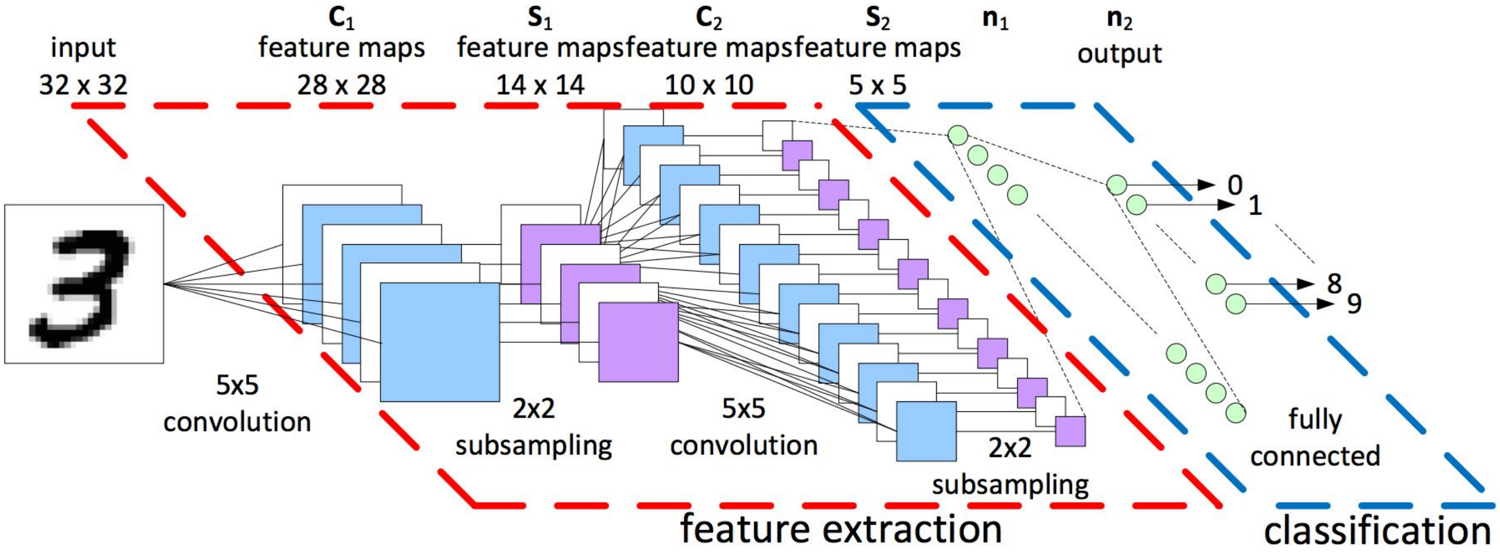
CNN Implementation - Data Augmentation (DA)

DA helps to popular artificial training instances from the existing train data sets.

(Image Credit: [Applied Deep Learning | Arden Dertat])

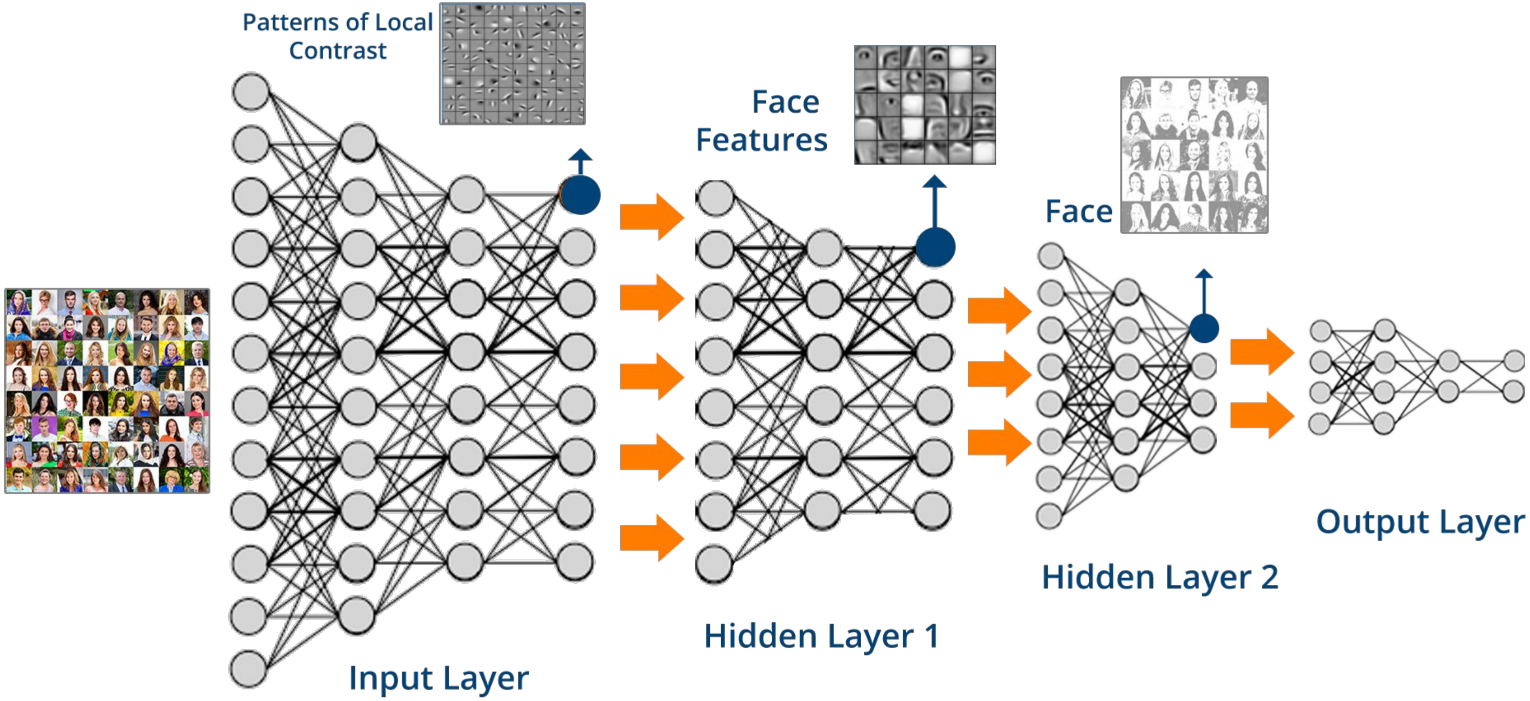
Convolutional Neural Networks

A convolutional neural network (**CNN**, or **ConvNet**) is a class of deep, feed-forward artificial neural networks that explicitly assumes that the inputs are images, which allows us to encode certain properties into the architecture.



LeNet-5 Architecture (image Credit: https://becominghuman.ai)

Deep Learning for Facial Recognition



(Image Credit: www.edureka.co)

Best Practice Guide for Training ML/DL Models

Model Capacity (*what can the model learn?*)

- Overtain on a small data set
- Synthetic data (with known features and properties)

Optimization Issues (*can we make the model learn?*)

- Look at the learning curves (testing vs training errors)
- Monitor gradient update ratios
- Hand-pick parameters for synthetic data

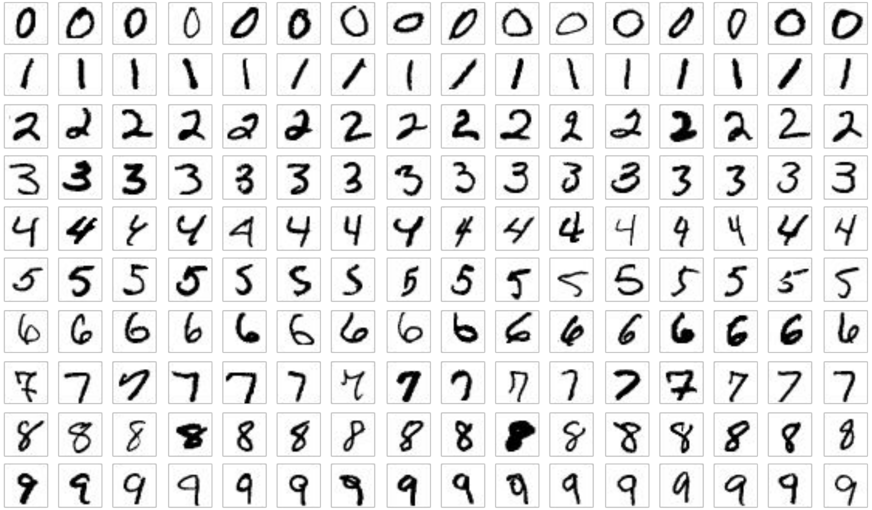
Other Model "Bugs" (*is the model doing what I want it to do?*)

- Generate samples from your model (if you can)
- Visualize learned representations (e.g., embeddings, nearest neighbors)
- Error analysis (examples where the model is failing, most "confident" errors)
- Simplify the problem/model
- Increase capacity, sweep hyperparameters

https://youtu.be/zCEYiCxrL_0

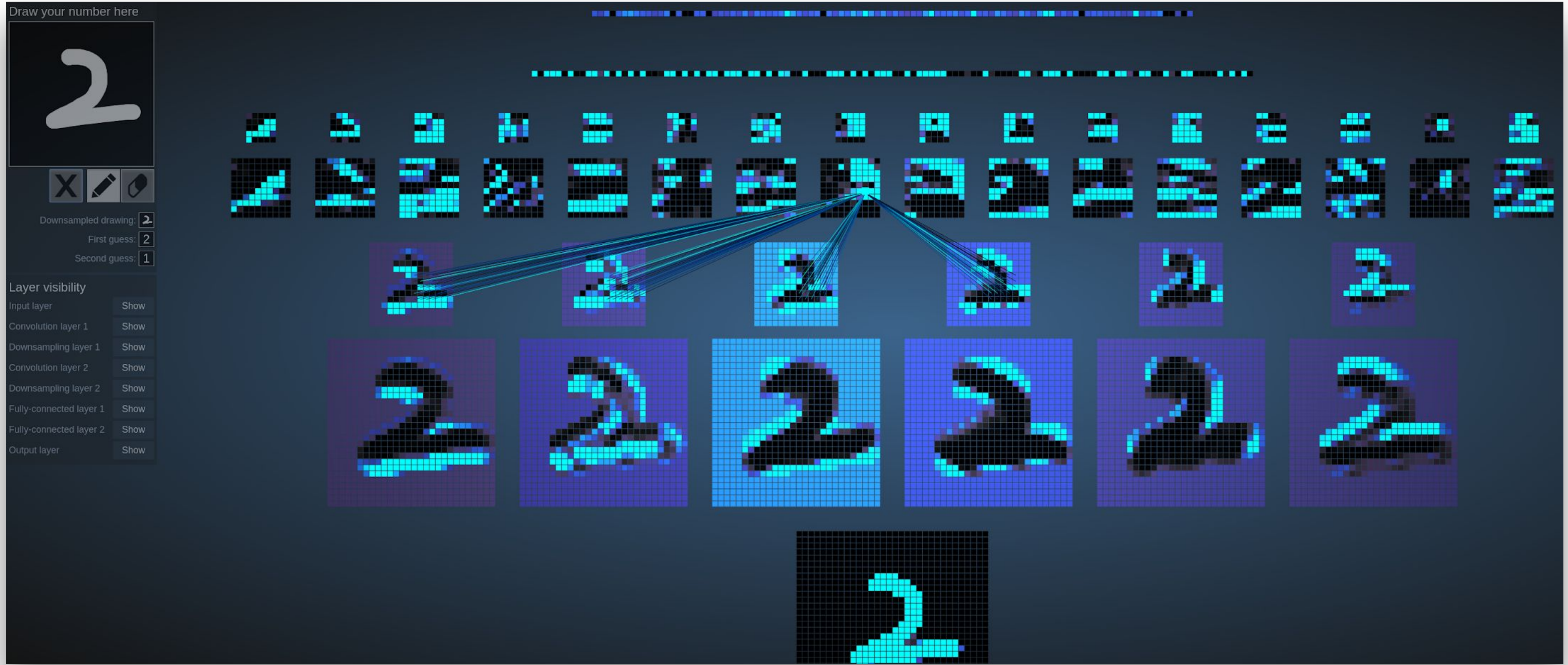
MNIST - Introduction

- **MNIST** (Mixed National Institute of Standards and Technology) is a database for handwritten digits, distributed by Yann Lecun.
- 60,000 examples, and a test set of 10,000 examples.
- 28x28 pixels each.
- Widely used for research and educational purposes.



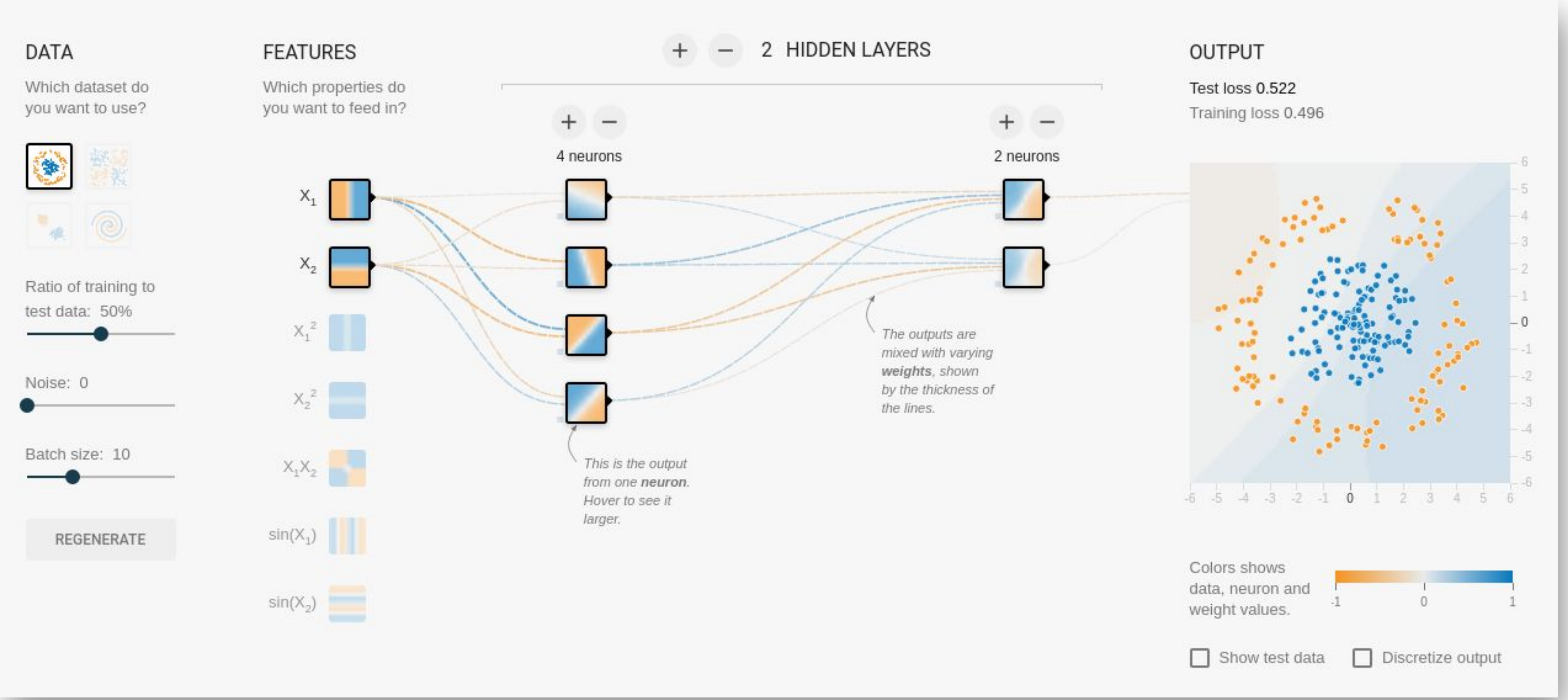
(Image Credit: Wikipedia)

MNIST - CNN Visualization



(Image Credit: http://scs.ryerson.ca/~aharley/vis/)

Neural Network Playground



(Image Credit: http://playground.tensorflow.org/)

Part III. Introduction to TensorFlow

TensorFlow Official Website
http://www.tensorflow.org

A Brief History of TensorFlow

TensorFlow is an end-to-end FOSS (free and open source software) library for dataflow, differentiable programming. TensorFlow is one of the most popular program frameworks for building machine learning applications.

- Google Brain built **DistBelief** in 2011 for internal usage.
- TensorFlow 1.0.0 was released on Feb 11, 2017
- TensorFlow 2.0 was released in Jan 2018.
- The latest stable version of TensorFlow is 2.3.0 as of Nov 2020.

TensorFlow, Keras, and PyTorch

TensorFlow

TensorFlow is an end-to-end open source **platform** for machine learning. It has a comprehensive, flexible ecosystem to build and deploy ML powered applications.

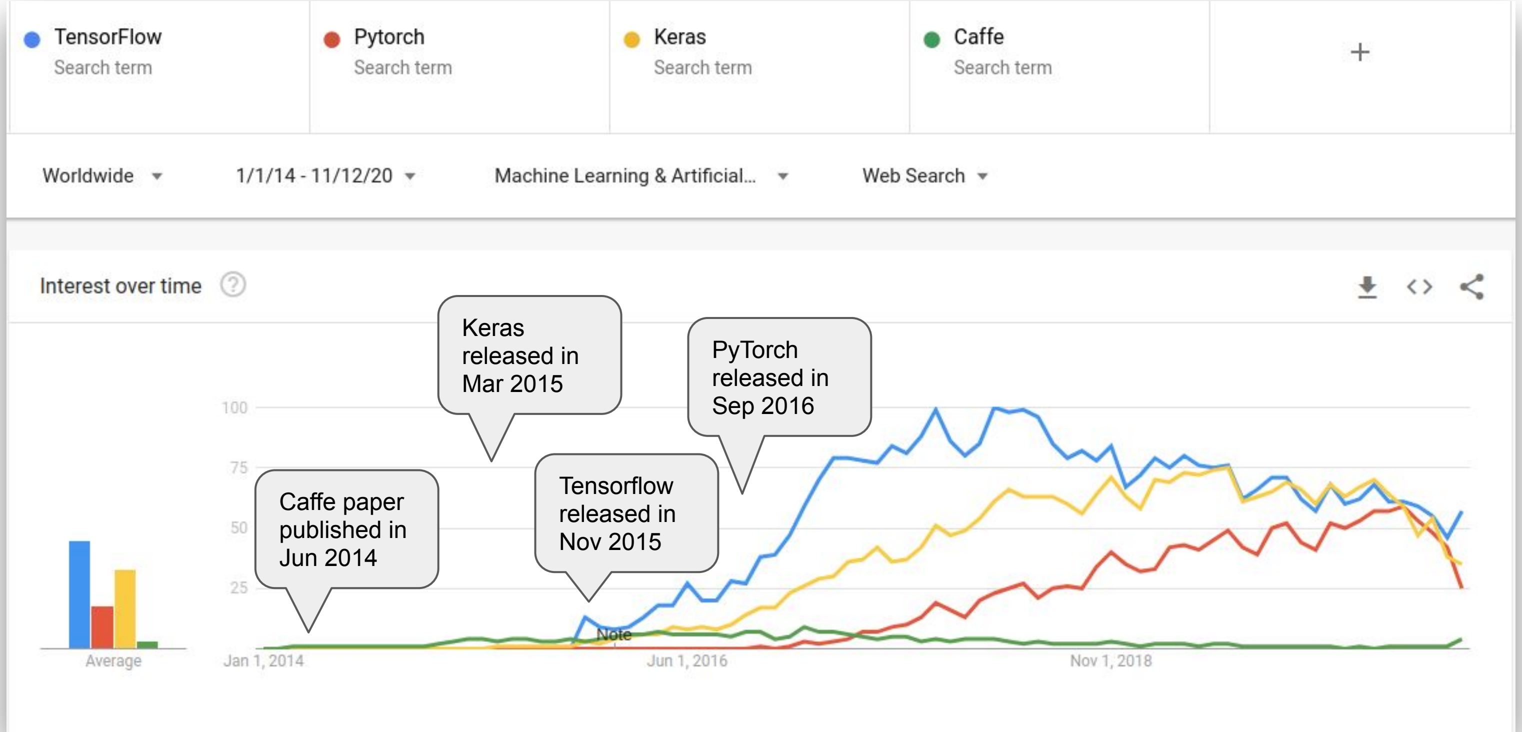
K Keras

Keras is a high-level neural networks **API**, written in Python and capable of running on top of *TensorFlow*, *CNTK*, or *Theano*. It was developed with a focus on enabling fast experimentation.

PyTorch

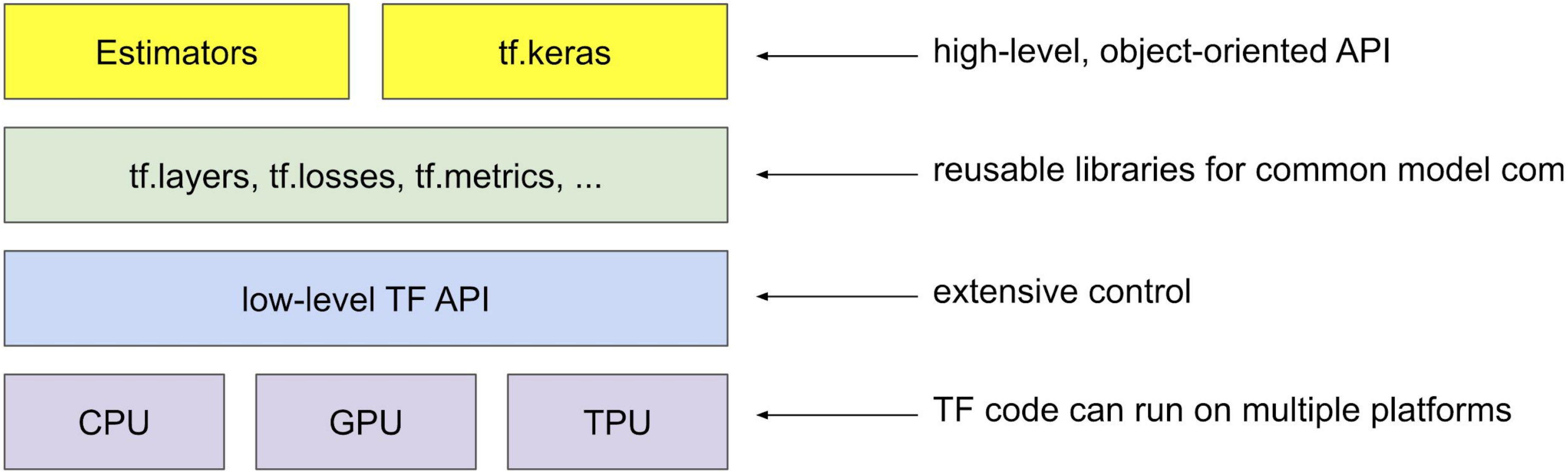
PyTorch is an open source machine learning **framework** that accelerates the path from research prototyping to production deployment.

Google Trends for Popular ML Frameworks



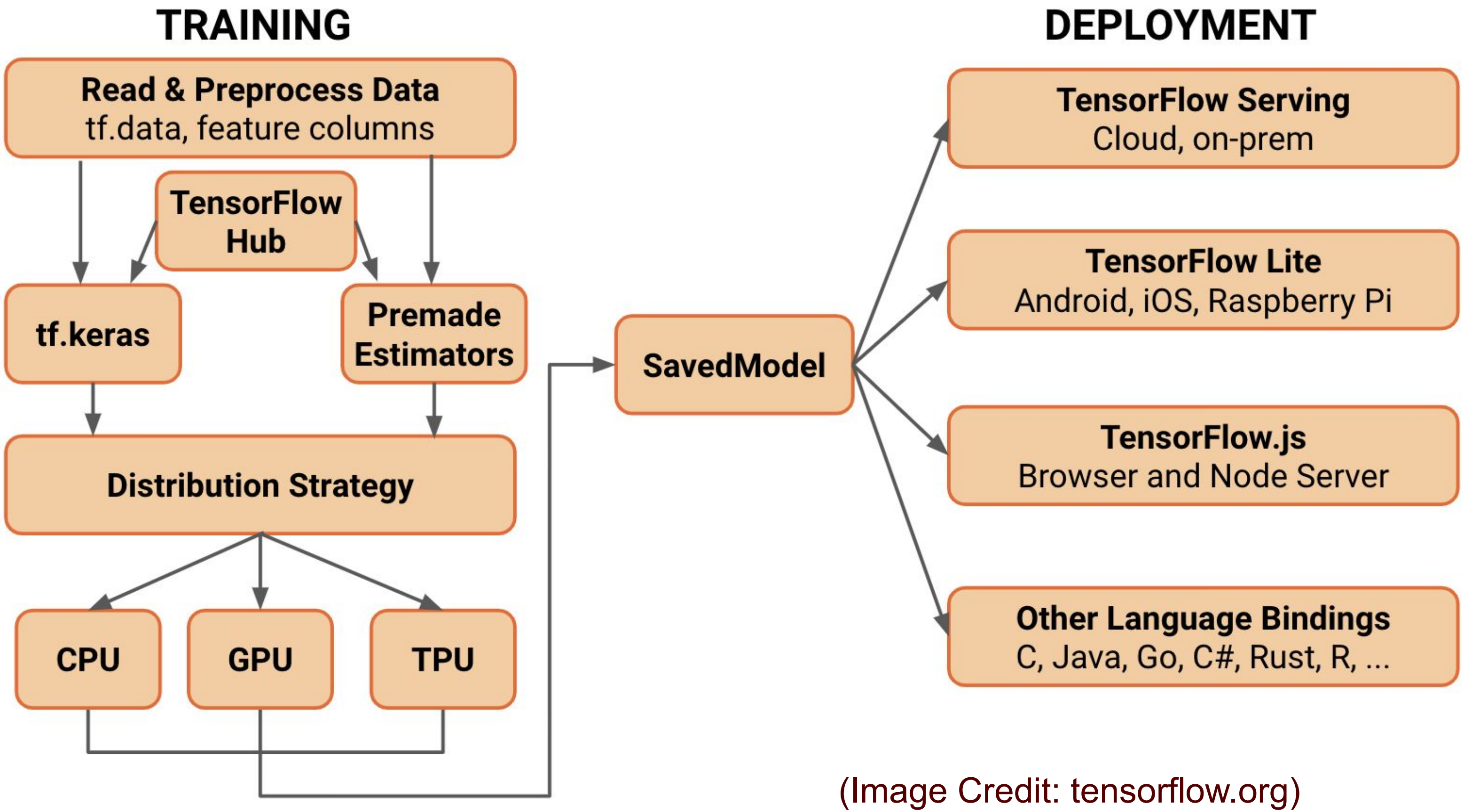
(Image Credit: https://trends.google.com/)

TensorFlow 2.0 Toolkits



(Image Credit: tensorflow.org)

Architecture of TF 2.0



(Image Credit: tensorflow.org)

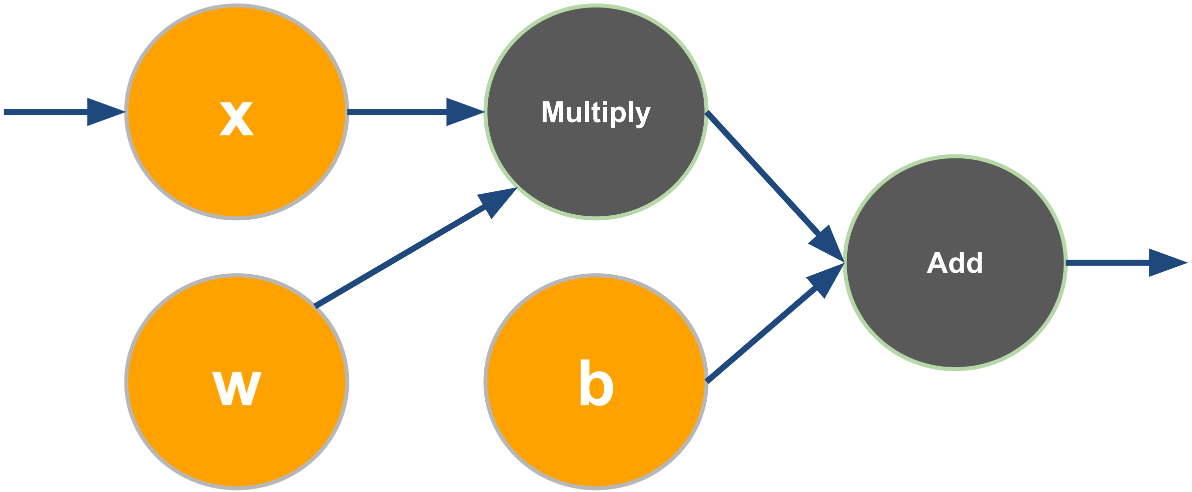
What is a Tensor in TensorFlow?

- **TensorFlow** uses a tensor data structure to represent all data. A TensorFlow tensor as an **n-dimensional array** or list. A tensor has a static type, a rank, and a shape.

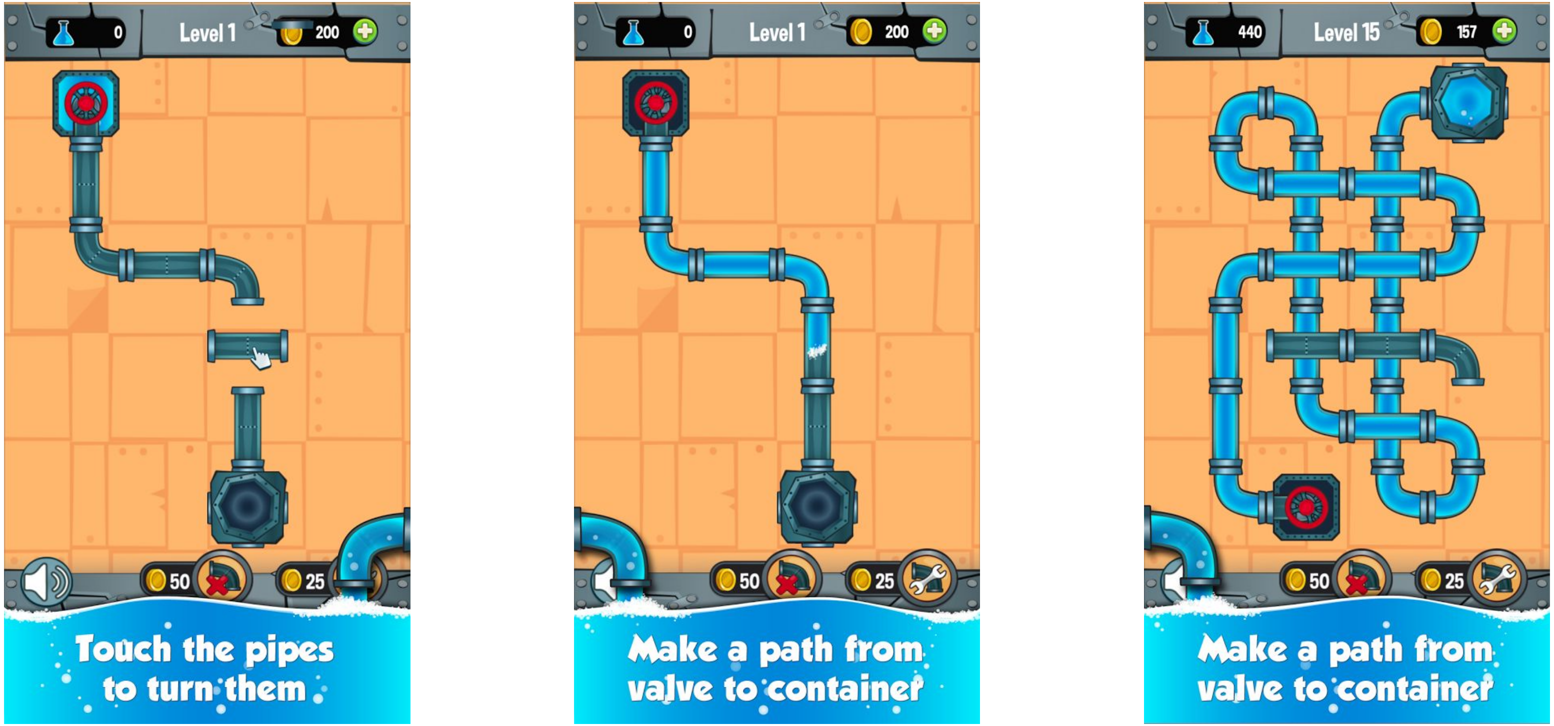
Name	Rank	Tensor
Scalar	0	[5]
Vector	1	[1 2 3]
Matrix	2	[[1 2 3 4], [5 6 7 8]]
Tensor	3	...

Computational Graph in TF 2.0

```
x = tf.random.normal(shape=(10,10))
w = tf.Variable(tf.random.normal(shape=(10,5)))
b = tf.Variable(tf.random.normal(shape=(5,)))
linear_model = w * x + b
```



A Connected Pipeline for the Flow of Tensors



(Image Credit: Plumber Game by Mobiloids)

TensorFlow Data Types

Basic TensorFlow data types include:

- **`int[8|16|32|64], float[16|32|64], double`**
- **`bool`**
- **`string`**

With **`tf.cast()`**, the data types of variables could be converted.

Hello World with TensorFlow

```
import tensorflow as tf

v = tf.constant("Hello World!")

tf.print(v)
```

TensorFlow Constants

TensorFlow provides several operations to generate constant tensors.

```
import tensorflow as tf

x = tf.constant(1, tf.int32)
zeros = tf.zeros([2, 3], tf.int32)
ones = tf.ones([2, 3], tf.int32)
y = x *(zeros + ones + ones)

tf.print(y)
```

TensorFlow Variables

TensorFlow variables can represent shared, persistent state manipulated by your program. **Weights** and **biases** are usually stored in variables.

```
import tensorflow as tf

W = tf.Variable(tf.random.normal([2,2], stddev=0.1),
name = "W")
b = tf.Variable(tf.zeros(shape=(2)), name="b")
```

GPU Acceleration

TensorFlow automatically decides if to use the CPU or GPU. One can explicitly pick a device to use. The string ends with **`CPU/GPU:<N>`** if the tensor is placed on the **`N-th CPU/GPU`** on the host.

```
# Force execution on CPU
with tf.device("CPU:0"):
    do_something()

# Force execution on GPU #0/1/2/... if available
if tf.config.experimental.list_physical_devices("GPU"):
    with tf.device("GPU:0"):
        do_something_else()
```

Machine Learning Workflow with tf.keras

Step 1

Prepare Train Data

The preprocessed data set needs to be shuffled and splitted into training and testing data.

Step 2

Define Model

A model could be defined with tf.keras Sequential model for a linear stack of layers or tf.keras functional API for complex network.

Step 3

Training Configuration

The configuration of the training process requires the specification of an optimizer, a loss function, and a list of metrics.

Step 4

Train Model

The training begins by calling the fit function. The number of epochs and batch size need to be set. The measurement metrics need to be evaluated.

tf.keras Built-in Datasets

- tf.keras provides many popular reference datasets that could be used for demonstrating and testing deep neural network models. To name a few,
  - Boston Housing (regression)
  - CIFAR100 (classification of 100 image labels)
  - MNIST (classification of 10 digits)
  - Fashion-MNIST (classification of 10 fashion categories)
  - Reuters News (multiclass text classification)

- The built-in datasets could be easily read in for training purpose. E.g.,

```
from tensorflow.keras.datasets import boston_housing
(x_train, y_train), (x_test, y_test) = boston_housing.load_data()
```

Prepare Datasets for tf.keras

In order to train a deep neural network model with Keras, the input data sets needs to be **cleaned**, **balanced**, **transformed**, **scaled**, and **splitted**.

- Balance the classes. Unbalanced classes will interfere with training.
- Transform the categorical variables into one-hot encoded variables.
- Extract the X (variables) and y (targets) values for the training and testing datasets.
- Scale/normalize the variables.
- Shuffle and split the dataset into training and testing datasets

One-hot encoding

Dog	Cat	Horse
1	0	0
0	1	0
0	0	1

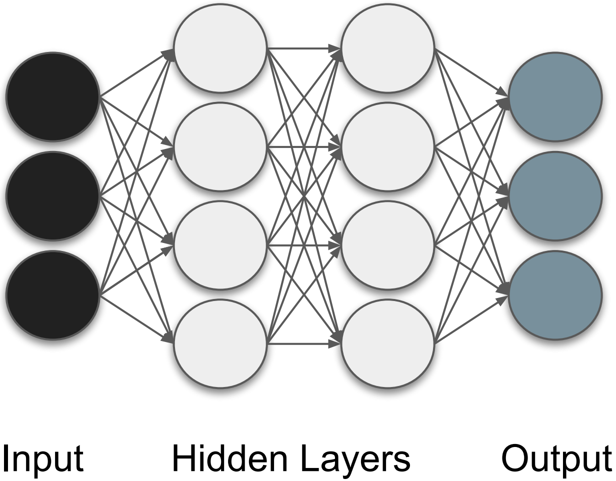
Numerical encoding

Dog	Cat	Horse
1	2	3

Create a tf.keras Model

- Layers are the fundamental building blocks of **tf.keras** models.
- The **Sequential** model is a linear stack of layers.
- A **Sequential** model can be created with a list of layer instances to the constructor or added with the **.add()** method.
- The input shape/dimension of the first layer need to be set.

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense,
Activation

model = Sequential([
    Dense(64, activation='relu', input_dim=20),
    Dense(10, activation='softmax')
])
```



Compile a tf.keras Model

The **compile** method of a Keras model configures the learning process before the model is trained. The following 3 arguments need to be set (the optimizer and loss function are required).

- An optimizer: **Adam**, **AdaGrad**, **SGD**, **RMSprop**, etc.
- A loss function: **mean_squared_error**, **mean_absolute_error**, **mean_squared_logarithmic_error**, **categorical_crossentropy**, **kullback_leibler_divergence**, etc.
- A list of measurement metrics: **accuracy**, **binary_accuracy**, **categorical_accuracy**, etc.

Train and Evaluate a tf.keras Model

tf.keras is trained on NumPy arrays of input data and labels. The training is done with the

- **fit()** function of the model class. In the fit function, the following two hyperparameters can be set:
  - **number of epochs**
  - **batch size**
- **evaluate()** function returns the loss value & metrics values for the model in test mode.
- **summary()** function prints out the network architecture.

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_11 (Dense)             (None, 64)                1344
_________________________________________________________________
dense_12 (Dense)             (None, 10)                650
=================================================================
Total params: 1,994
Trainable params: 1,994
Non-trainable params: 0
_________________________________________________________________
None
```

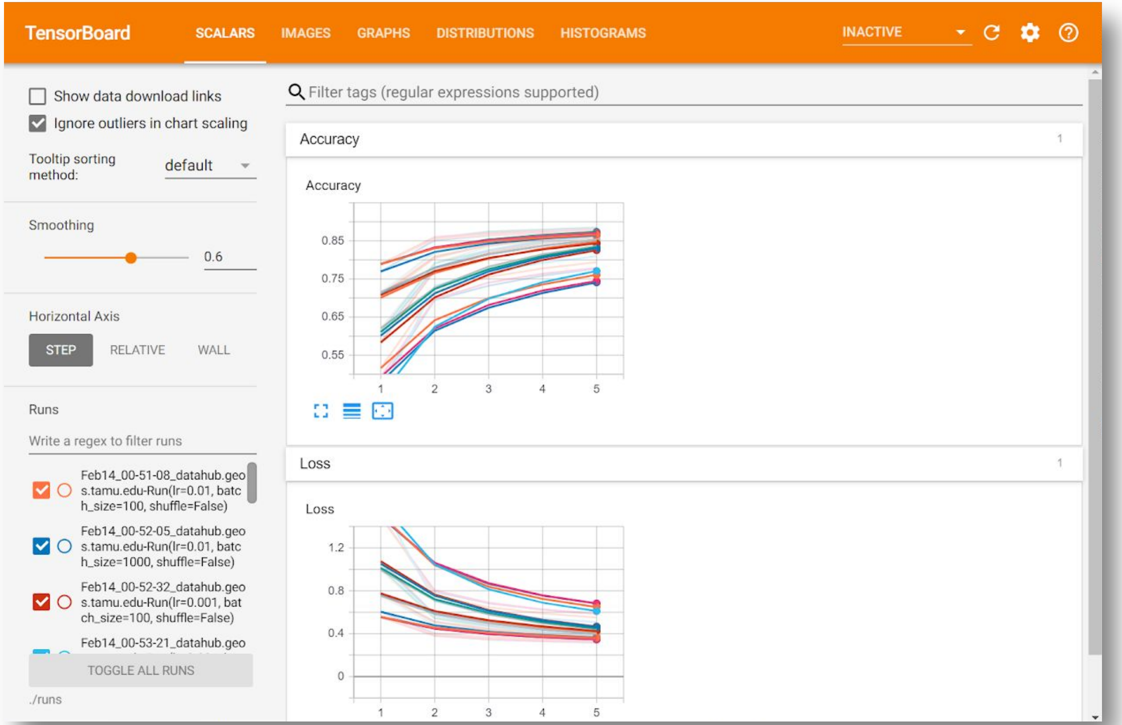
Make Predictions and More

After the model is trained,

- **predict()** function of the model class could be used to generate output predictions for the input samples.
- **get_weights()** function returns a list of all weight tensors in the model, as Numpy arrays.
- **to_json()** returns a representation of the model as a JSON string. Note that the representation does not include the weights, only the architecture.
- **save_weights(filepath)** saves the weights of the model as a HDF5 file.

Monitoring Training with Tensorboard

- TensorBoard is a User Interface (UI) tools designed for TensorFlow.
- More details on TensorBoard can be found at TensorBoard.
- Once you've installed TensorBoard, these utilities let you log TensorFlow models and metrics into a directory for visualization within the TensorBoard UI.



Hands-on Session #1

Getting Started with TensorFlow

TensorFlow

Hands-on Session #2
Classify Handwritten Digits with TensorFlow