

# UBDA Workshop: State-of-the-art in Deep Learning Frameworks

University Research Facility in Big Data Analytics

2020 April

UBDA website:

<https://ubda.polyu.edu.hk/>



THE HONG KONG  
POLYTECHNIC UNIVERSITY  
香港理工大學

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# UBDA Workshop: State-of-the-art in Deep Learning Frameworks

## Ice-Breaker Activity

<http://etc.ch/WEwL>

Which Framework  
have you used in  
your research?



Which Framework do  
you plan to use in  
your research?

# Let's poll now!



# What is Deep Learning?

## ARTIFICIAL INTELLIGENCE

Any technique that enables computers to mimic human behavior



## MACHINE LEARNING

Ability to learn without explicitly being programmed



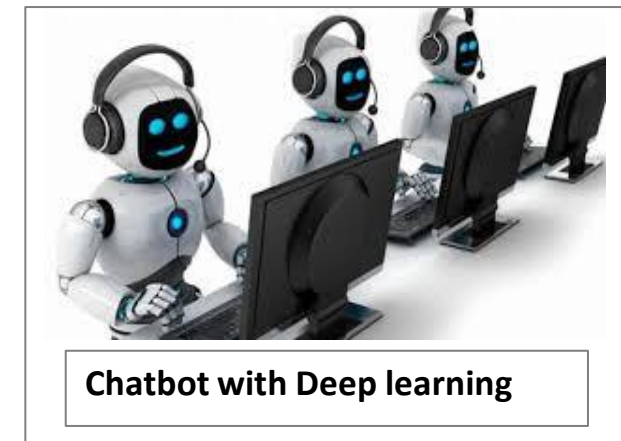
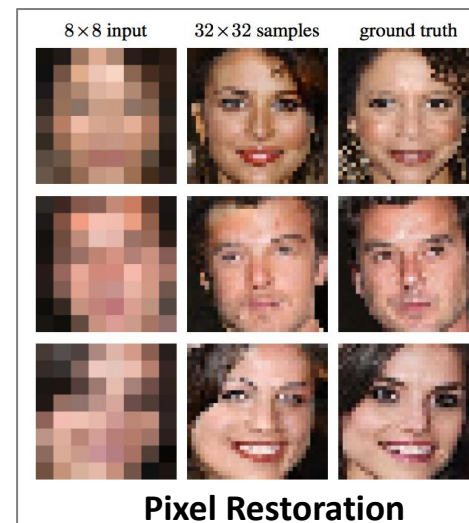
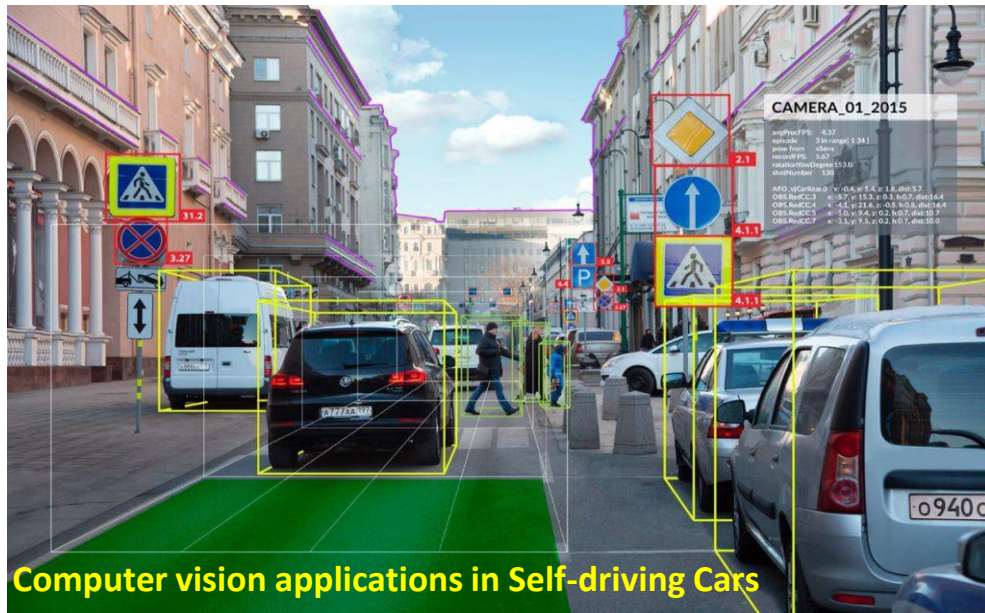
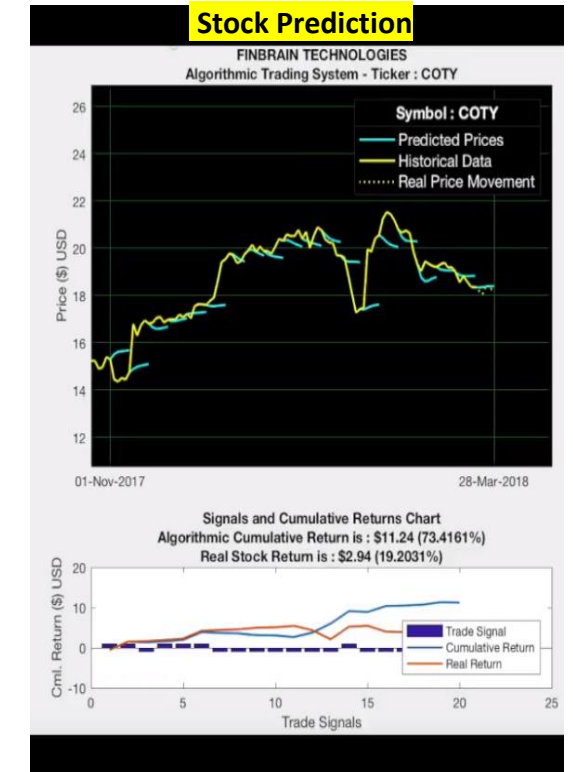
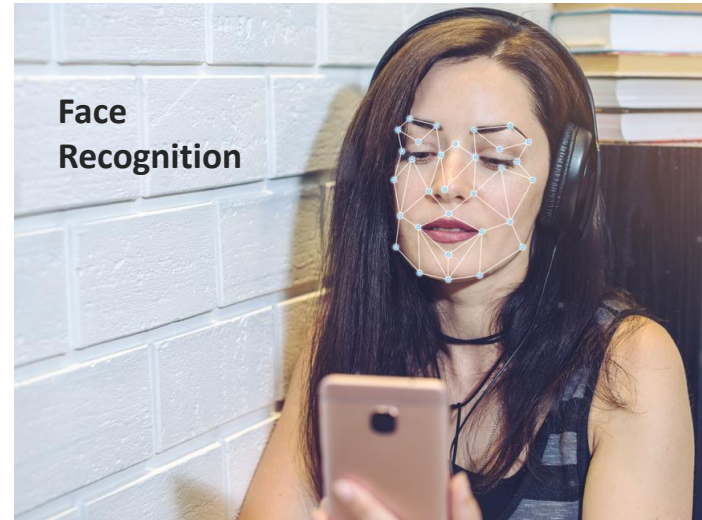
## DEEP LEARNING

Extract patterns from data using neural networks



Source: <http://www.introtodeeplearning.com>

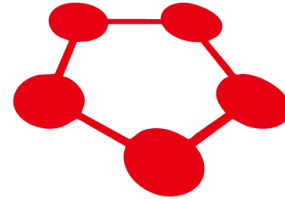
# Deep Learning Daily Life Examples



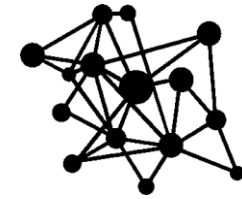
## Deep Learning Tools available in 2020



SWIFT



Chainer



DL4J



Keras



GLUON



Sonnet



ONNX



TensorFlow

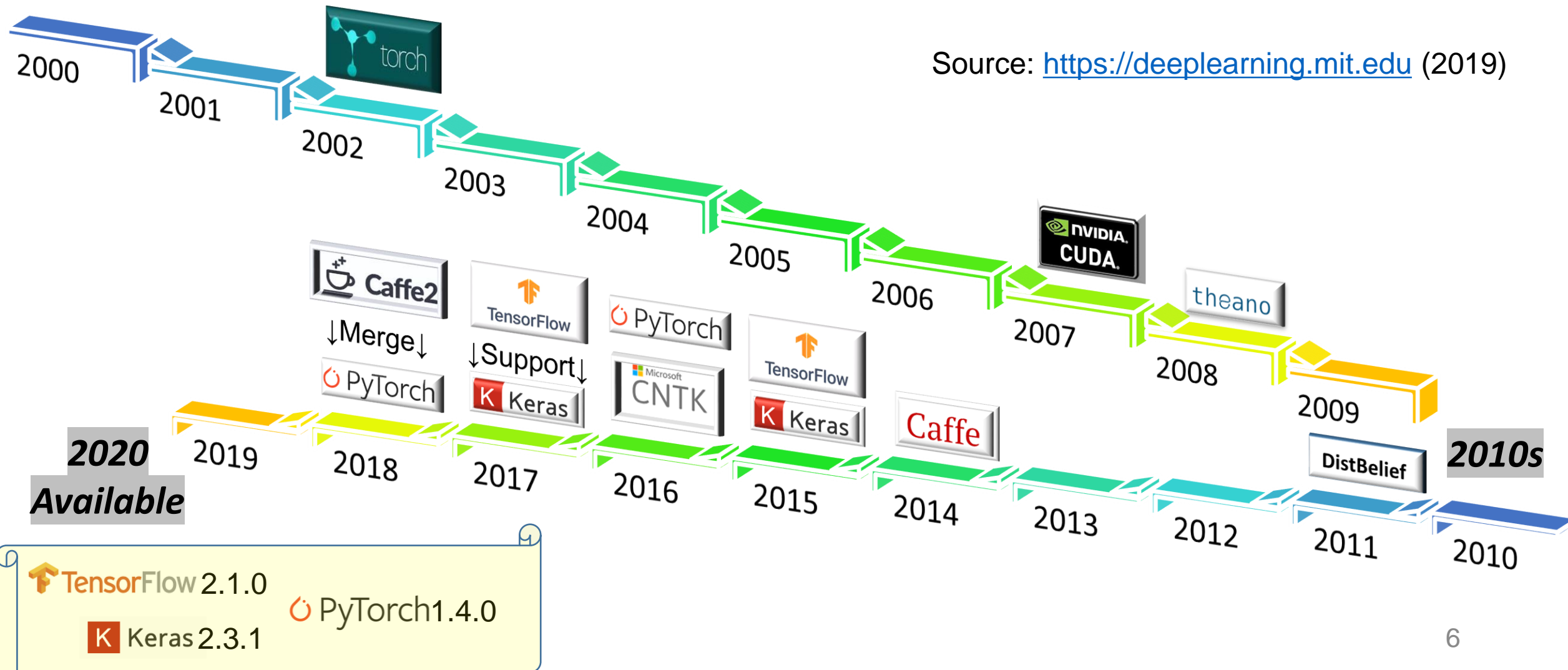
PYTORCH

mxnet



# History of Deep Learning Tools since 2000

Source: <https://deeplearning.mit.edu> (2019)



# Content of this workshop

## Most Popular Deep Learning Framework



## How UBDA supports your Deep Learning work?




Technical Support & Research Support

# Deep Learning Framework

## Keras **vs** TensorFlow **vs** PyTorch

Source:

<https://www.mygreatlearning.com/blog/computer-vision-using-pytorch/> (2020)

	Keras 	TensorFlow 	PyTorch 
Level of API	High-level API	Both high & low level APIs	Lower-level API
Speed	Slow	High	High
Architecture	Simple, more readable and concise	Not very easy to use	Complex
Debugging	No need to debug	Difficult to debugging	Good debugging capabilities
Dataset Compatibility	Slow & Small	Fast speed & large	Fast speed & large datasets
Popularity Rank	1	2	3
Uniqueness	Multiple back-end support	Object Detection Functionality	Flexibility & Short Training Duration
Created By	Not a library on its own	Created by Google	Created by Facebook
Ease of use	User-friendly	Incomprehensive API	Integrated with Python language
Computational graphs used	Static graphs	Static graphs	Dynamic computation graphs



# Deep Learning Framework

## Architecture of PyTorch

Package	Description
torch	The top-level PyTorch package and tensor library
torch.nn	A subpackage that contains modules and extensible classes for building neural networks.
torch.autograd	A subpackage that supports all the differentiable Tensor operations in PyTorch
torch.nn.functional	A functional interface that contains typical operations used for building neural networks like loss functions, activation functions, and convolution operations.
torch.optim	A subpackage that contains standard optimization operations like SGD and Adam
torch.utils	A subpackage that contains utility classes like data sets and data loaders that make data preprocessing easier
torchvision	A package that provides access to popular datasets, model architectures, and image transformations for computer vision.

- PyTorch is made of different modules which help in executing deep learning models for CV and Natural Language Processing (NLP)

# Deep Learning Framework

## Code Study 1: Train an image classifier in PyTorch

airplane



automobile



bird



cat



deer



dog



frog



horse



ship



truck



### ○ Setting up the Environment

```
import torch
import torchvision
import torchvision.transforms as transforms
```

# Deep Learning Framework

## Code Study 1: Train an image classifier in PyTorch

```
transform = transforms.Compose(
    [transforms.ToTensor(),
     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))])

trainset = torchvision.datasets.CIFAR10(root='./data', train=True,
                                         download=True, transform=transform)
trainloader = torch.utils.data.DataLoader(trainset, batch_size=4,
                                           shuffle=True, num_workers=2)

testset = torchvision.datasets.CIFAR10(root='./data', train=False,
                                         download=True, transform=transform)
testloader = torch.utils.data.DataLoader(testset, batch_size=4,
                                          shuffle=False, num_workers=2)

classes = ('plane', 'car', 'bird', 'cat',
           'deer', 'dog', 'frog', 'horse', 'ship', 'truck')
```

- Transform torchvision datasets to Tensors of normalized range

Out:

```
Downloading https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz to ./data/cifar-10-
python.tar.gz
Extracting ./data/cifar-10-python.tar.gz to ./data
Files already downloaded and verified
```



# Deep Learning Framework

## Code Study 1: Train an image classifier in PyTorch

```
import torch.nn as nn
import torch.nn.functional as F

class Net(nn.Module):
    def __init__(self):
        super(Net, self).__init__()
        self.conv1 = nn.Conv2d(3, 6, 5)
        self.pool = nn.MaxPool2d(2, 2)
        self.conv2 = nn.Conv2d(6, 16, 5)
        self.fc1 = nn.Linear(16 * 5 * 5, 120)
        self.fc2 = nn.Linear(120, 84)
        self.fc3 = nn.Linear(84, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 16 * 5 * 5)
        x = F.relu(self.fc1(x))
        x = F.relu(self.fc2(x))
        x = self.fc3(x)
        return x

net = Net()
```

- Define a Convolutional Neural Network

# Deep Learning Framework

## Code Study 1: Train an image classifier in PyTorch

- Define Loss function and optimizer

```
import torch.optim as optim

criterion = nn.CrossEntropyLoss()
optimizer = optim.SGD(net.parameters(), lr=0.001, momentum=0.9)
```

# Deep Learning Framework

## Code Study 1: Train an image classifier in PyTorch

### ○ Train the network

```
for epoch in range(2): # loop over the dataset multiple times

    running_loss = 0.0
    for i, data in enumerate(trainloader, 0):
        # get the inputs; data is a list of [inputs, labels]
        inputs, labels = data

        # zero the parameter gradients
        optimizer.zero_grad()

        # forward + backward + optimize
        outputs = net(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()

        # print statistics
        running_loss += loss.item()
        if i % 2000 == 1999: # print every 2000 mini-batches
            print('[%d, %5d] loss: %.3f' %
                  (epoch + 1, i + 1, running_loss / 2000))
            running_loss = 0.0

    print('Finished Training')
```

Out:

```
[1, 2000] loss: 2.197
[1, 4000] loss: 1.871
[1, 6000] loss: 1.670
[1, 8000] loss: 1.582
[1, 10000] loss: 1.508
[1, 12000] loss: 1.464
[2, 2000] loss: 1.390
[2, 4000] loss: 1.390
[2, 6000] loss: 1.327
[2, 8000] loss: 1.331
[2, 10000] loss: 1.293
[2, 12000] loss: 1.292
Finished Training
```



# Deep Learning Framework

## Code Study 1: Train an image classifier in PyTorch

```
correct = 0
total = 0
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs.data, 1)
        total += labels.size(0)
        correct += (predicted == labels).sum().item()

print('Accuracy of the network on the 10000 test images: %d %%' % (
    100 * correct / total))
```

- Test the network on the test data (overall)

Out:

```
Accuracy of the network on the 10000 test images: 55 %
```

# Deep Learning Framework

## Code Study 1: Train an image classifier in PyTorch

- Test the network on the test data (in class)

```
class_correct = list(0. for i in range(10))
class_total = list(0. for i in range(10))
with torch.no_grad():
    for data in testloader:
        images, labels = data
        outputs = net(images)
        _, predicted = torch.max(outputs, 1)
        c = (predicted == labels).squeeze()
        for i in range(4):
            label = labels[i]
            class_correct[label] += c[i].item()
            class_total[label] += 1

for i in range(10):
    print('Accuracy of %5s : %2d %%' % (
        classes[i], 100 * class_correct[i] / class_total[i]))
```

Out:

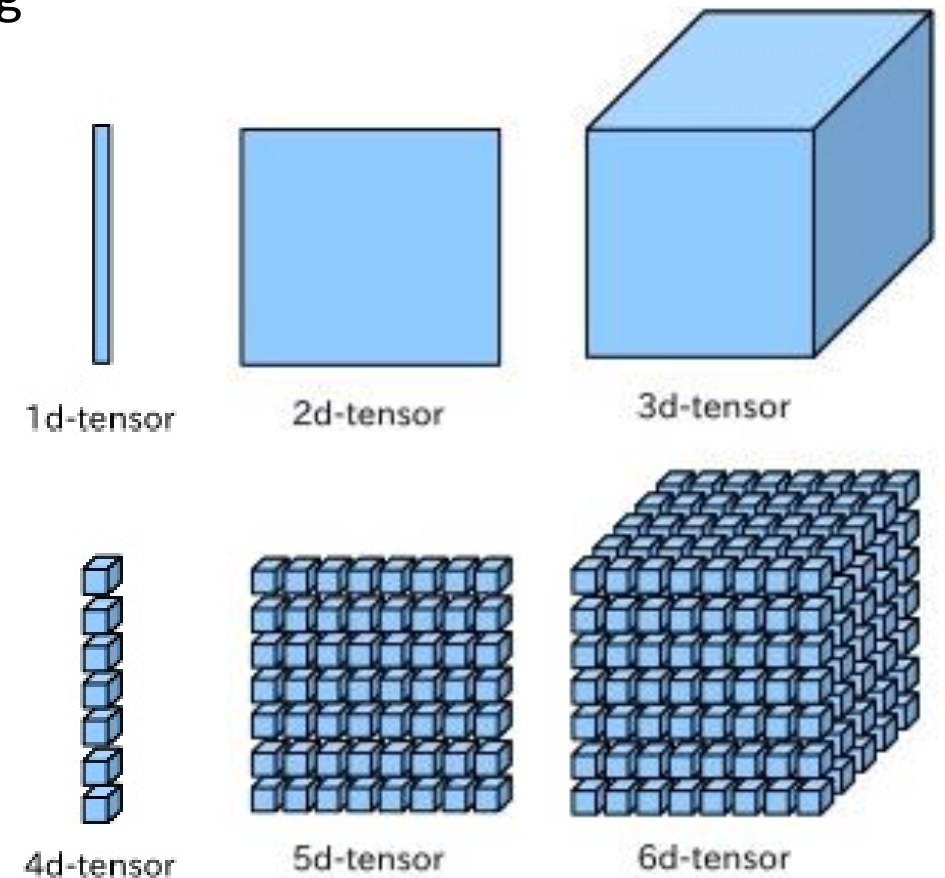
```
Accuracy of plane : 74 %
Accuracy of  car : 72 %
Accuracy of  bird : 23 %
Accuracy of  cat : 44 %
Accuracy of  deer : 55 %
Accuracy of  dog : 34 %
Accuracy of  frog : 56 %
Accuracy of horse : 66 %
Accuracy of  ship : 63 %
Accuracy of truck : 60 %
```

# PyTorch

## Tensors

- primary data structure used in deep learning
- multidimensional data arrays
- Sample is Scalar

Data	Tensor
Vector	1D tensors of shape (features)
Timeseries	2D tensors of shape (timesteps, features)
Images	3D tensors of shape (height, width, channels)
Video	4D tensors of shape (frames, height, width, channels)

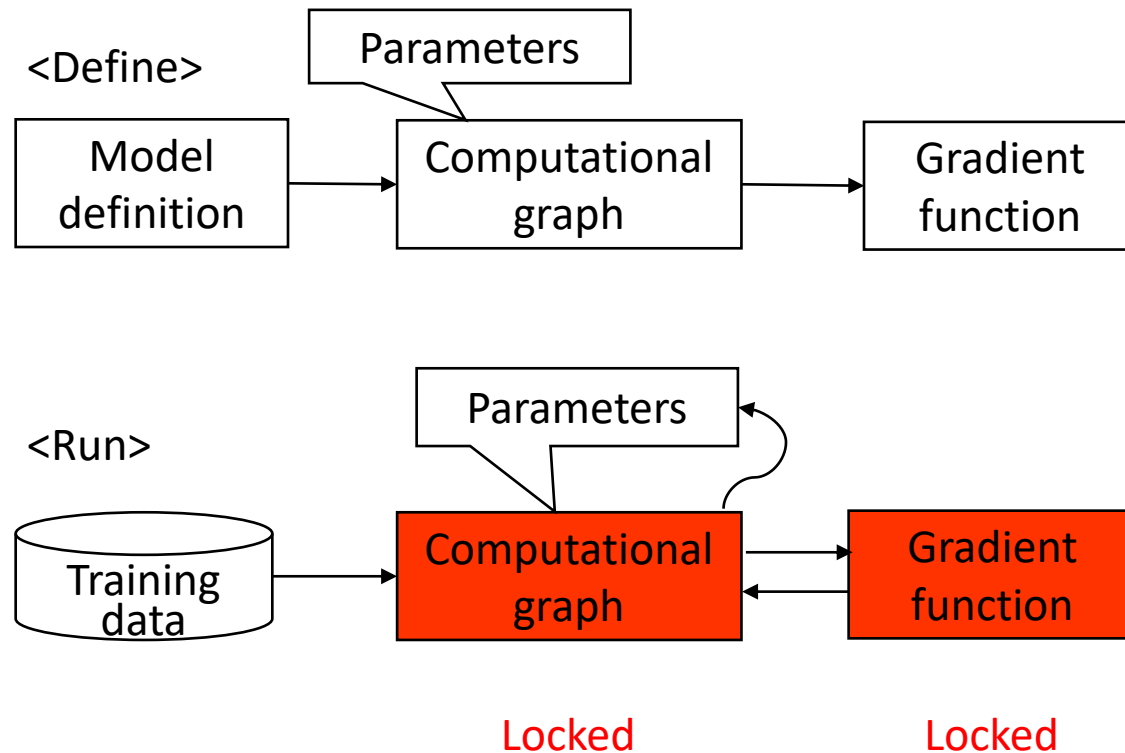




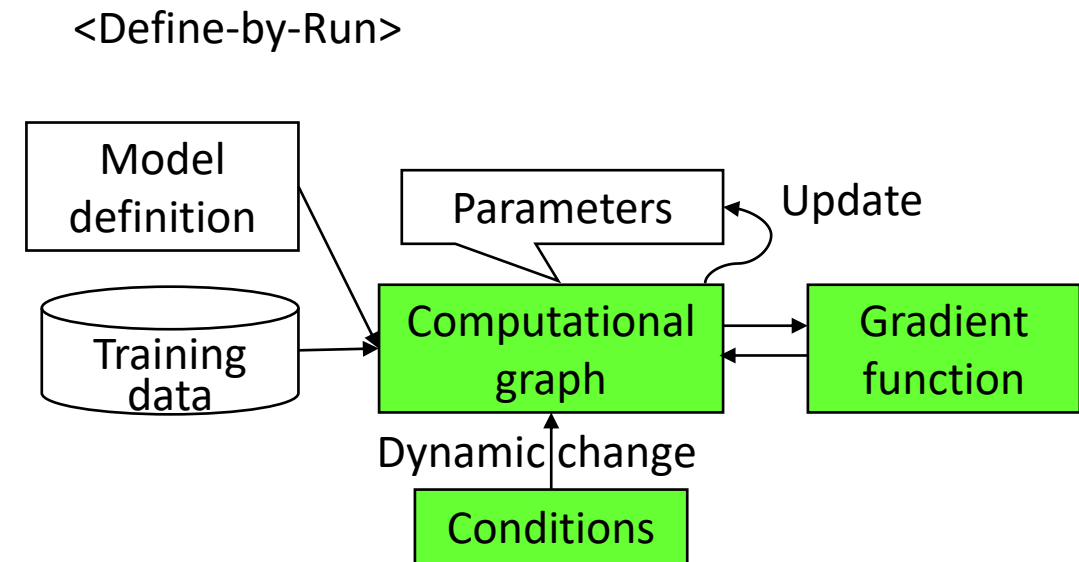


# Dynamic Computation Graph

## Static Computation Graph: Define-and-Run (Build graph once, then run many times)



## Dynamic Computation Graph: Define-by-Run (Each forward pass defines a new graph)



# Deep Learning Framework

## Keras Standout features

Focus on user  
experience

Large adoption in  
the industry

Multi-backend  
Multi-platform

Research  
community

Easy to grasp all  
concepts

# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

### # Import Libraries

#### *Written In R*

```
library(keras)
```

#### *Written in Python*

```
import numpy as np  
import pandas as pd  
import matplotlib.pyplot as plt  
import keras  
from keras.datasets import mnist  
from keras.models import Sequential  
from keras.layers import Dense, Dropout  
from keras.utils import to_categorical
```



# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

### # Import MNIST Dataset

#### *Written In R*

```
mnist <- dataset_mnist()  
x_train <- mnist$train$x  
y_train <- mnist$train$y  
x_test <- mnist$test$x  
y_test <- mnist$test$y
```

#### *Written in Python*

```
(x_train, y_train), (x_test, y_test) = mnist.load_data()
```

# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

### # Preprocess Train Set and Test Set and Scale the Input Features

#### *Written In R*

```
# Reshaping & Scaling the input and output dimensions
x_train <- array_reshape(x_train, c(nrow(x_train), 784))/255
x_test <- array_reshape(x_test, c(nrow(x_test), 784))/255

# Performing one-hot encoding on target variables
y_train <- to_categorical(y_train, 10)
y_test <- to_categorical(y_test, 10)
```

#### *Written in Python*

```
# Reshaping & Scaling the input and output dimensions
x_train=np.reshape(x_train,(x_train.shape[0],-1))/255
x_test =np.reshape(x_test,(x_test.shape[0],-1))/255

# Performing one-hot encoding on target variables
y_train = to_categorical(y_train, 10)
y_test = to_categorical(y_test, 10)
```

# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

### # Define Layers to this Model

# Sequential Model with One Input Layer[784 neurons], 1 Hidden Layer[256 neurons] with Dropout Rate 0.4, 1 Hidden Layer[128 neurons] with Dropout Rate 0.3, and 1 Output Layer [10 #neurons]

#### *Written In R*

```
# Defining the model and layers

model <- keras_model_sequential()

model %>%
  layer_dense(units = 256, activation = 'relu',
              input_shape = c(784)) %>%
  layer_dropout(rate = 0.4) %>%
  layer_dense(units = 128, activation = 'relu') %>%
  layer_dropout(rate = 0.3) %>%
  layer_dense(units = 10, activation = 'softmax')
```

#### *Written in Python*

```
# Defining the model and layers

model = Sequential()

model.add(Dense(256, activation='relu', input_shape=(784,)))

model.add(Dropout(0.4))

model.add(Dense(128, activation='relu'))

model.add(Dropout(0.3))

model.add(Dense(10, activation='softmax'))
```

# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

### # Display All Model Layers

#### *Written In R*

```
summary(model)
```

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 256)	200960
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32896
dropout_1 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 10)	1290
Total params: 235,146		
Trainable params: 235,146		
Non-trainable params: 0		

#### *Written in Python*

```
model.summary()
```

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 256)	200960
dropout_1 (Dropout)	(None, 256)	0
dense_2 (Dense)	(None, 128)	32896
dropout_2 (Dropout)	(None, 128)	0
dense_3 (Dense)	(None, 10)	1290
Total params: 235,146		
Trainable params: 235,146		
Non-trainable params: 0		



# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

# Specify the loss function and optimizer to use

# Using Adam optimizer and accuracy as metric

*Written In R*

```
model %>% compile(loss='categorical_crossentropy',  
                  optimizer = optimizer_adam(),  
                  metrics = c('accuracy'))
```

*Written in Python*

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

# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

### # Train the Model and Perform Validation

#### *Written In R*

```
history <- model %>% fit(x_train, y_train,  
  epochs = 30, batch_size = 512,  
  validation_split = 0.2)
```

#### *Written in Python*

```
history = model.fit(x_train, y_train,  
  epochs=30, batch_size=512,  
  validation_split=0.2)
```

# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

### Training Sequential Model Result (Output by R)

```
Epoch 21/30
48000/48000 [=====] - 3s 71us/sample - loss: 0.0468 - acc: 0.9848 - val_loss: 0.0763 - val_acc: 0.9797
Epoch 22/30
48000/48000 [=====] - 3s 63us/sample - loss: 0.0464 - acc: 0.9845 - val_loss: 0.0778 - val_acc: 0.9788
Epoch 23/30
48000/48000 [=====] - 3s 64us/sample - loss: 0.0440 - acc: 0.9852 - val_loss: 0.0759 - val_acc: 0.9788
Epoch 24/30
48000/48000 [=====] - 3s 61us/sample - loss: 0.0428 - acc: 0.9861 - val_loss: 0.0795 - val_acc: 0.9781
Epoch 25/30
48000/48000 [=====] - 3s 66us/sample - loss: 0.0402 - acc: 0.9865 - val_loss: 0.0804 - val_acc: 0.9785
Epoch 26/30
48000/48000 [=====] - 3s 63us/sample - loss: 0.0392 - acc: 0.9871 - val_loss: 0.0744 - val_acc: 0.9804
Epoch 27/30
48000/48000 [=====] - 3s 65us/sample - loss: 0.0371 - acc: 0.9875 - val_loss: 0.0764 - val_acc: 0.9799
Epoch 28/30
48000/48000 [=====] - 3s 60us/sample - loss: 0.0357 - acc: 0.9882 - val_loss: 0.0783 - val_acc: 0.9791
Epoch 29/30
48000/48000 [=====] - 3s 56us/sample - loss: 0.0343 - acc: 0.9885 - val_loss: 0.0800 - val_acc: 0.9794
Epoch 30/30
25600/48000 [=====>.....] - ETA: 1s - loss: 0.0338 - acc: 0.9887[I 15:06:21.615 NotebookApp] Saving file at /state-of-the-art/rkeras_minst.ipynb
48000/48000 [=====] - 3s 59us/sample - loss: 0.0338 - acc: 0.9886 - val_loss: 0.0778 - val_acc: 0.9796
[I 15:08:26.673 NotebookApp] Saving file at /state-of-the-art/rkeras_minst.ipynb
```

### Training Sequential Model Result (Output by Python)

```
Epoch 21/30
48000/48000 [=====] - 3s 56us/step - loss: 0.0461 - acc: 0.9859 - val_loss: 0.0752 - val_acc: 0.9795
Epoch 22/30
48000/48000 [=====] - 3s 58us/step - loss: 0.0469 - acc: 0.9854 - val_loss: 0.0781 - val_acc: 0.9788
Epoch 23/30
48000/48000 [=====] - 3s 61us/step - loss: 0.0439 - acc: 0.9857 - val_loss: 0.0792 - val_acc: 0.9785
Epoch 24/30
48000/48000 [=====] - 3s 59us/step - loss: 0.0428 - acc: 0.9865 - val_loss: 0.0746 - val_acc: 0.9787
Epoch 25/30
48000/48000 [=====] - 3s 64us/step - loss: 0.0400 - acc: 0.9869 - val_loss: 0.0786 - val_acc: 0.9793
Epoch 26/30
48000/48000 [=====] - 3s 60us/step - loss: 0.0384 - acc: 0.9867 - val_loss: 0.0789 - val_acc: 0.9799
Epoch 27/30
48000/48000 [=====] - 3s 61us/step - loss: 0.0368 - acc: 0.9884 - val_loss: 0.0780 - val_acc: 0.9800
Epoch 28/30
48000/48000 [=====] - 3s 64us/step - loss: 0.0361 - acc: 0.9883 - val_loss: 0.0772 - val_acc: 0.9802
Epoch 29/30
48000/48000 [=====] - 3s 61us/step - loss: 0.0345 - acc: 0.9885 - val_loss: 0.0777 - val_acc: 0.9803
Epoch 30/30
48000/48000 [=====] - 3s 64us/step - loss: 0.0327 - acc: 0.9891 - val_loss: 0.0770 - val_acc: 0.9804
```

# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

# Plot the Learning curves for this model

# Loss Plot and Accuracy Plot

*Written In R*

```
plot(history)
```

*Written in Python*

```
df_hist= pd.DataFrame(history.history)

plt.plot(df_hist['loss'],'--o')

plt.plot(df_hist['val_loss'], '--x')

plt.legend(['loss', 'val_loss']) ; plt.show()

plt.plot(df_hist['acc'],'--o')

plt.plot(df_hist['val_acc'],'--x')

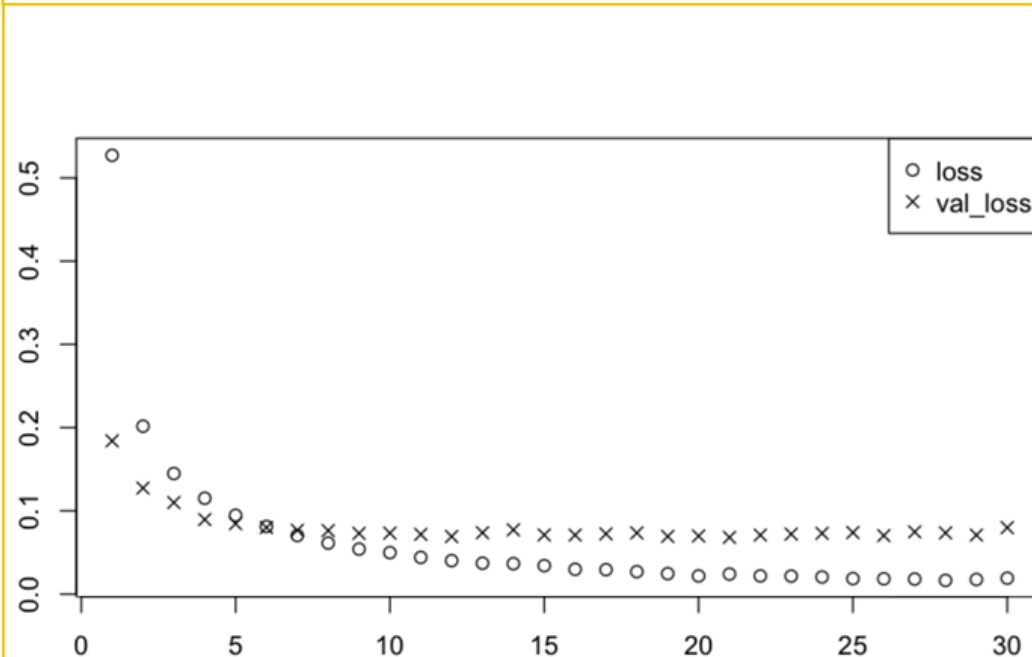
plt.legend(['acc', 'val_acc']) ; plt.show()
```



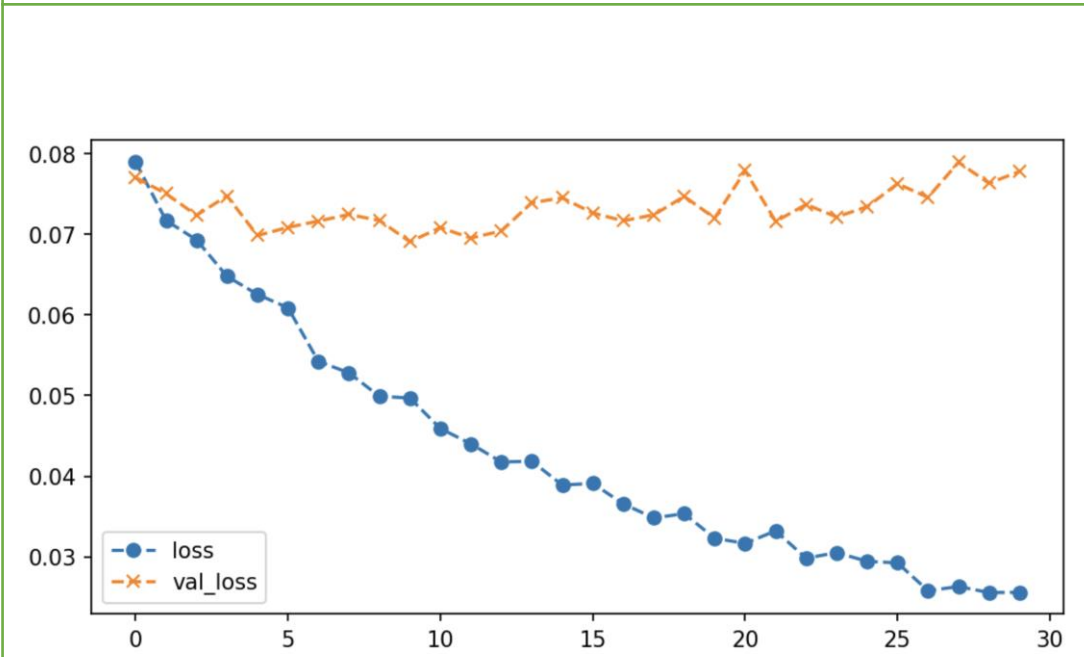
# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

*Learning Curves – Loss Plot  
(Output by R)*



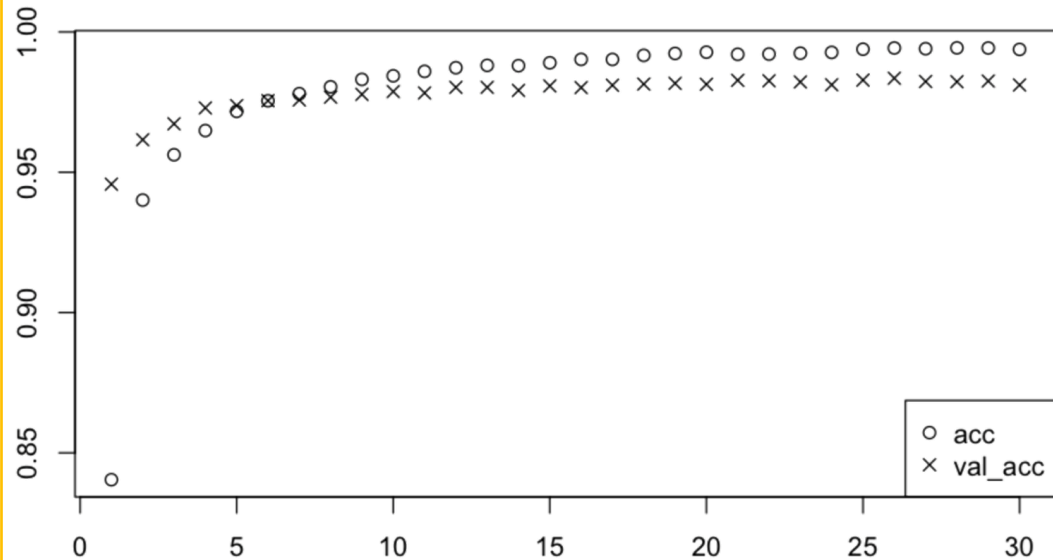
*Learning Curves – Loss Plot  
(Output by Python)*



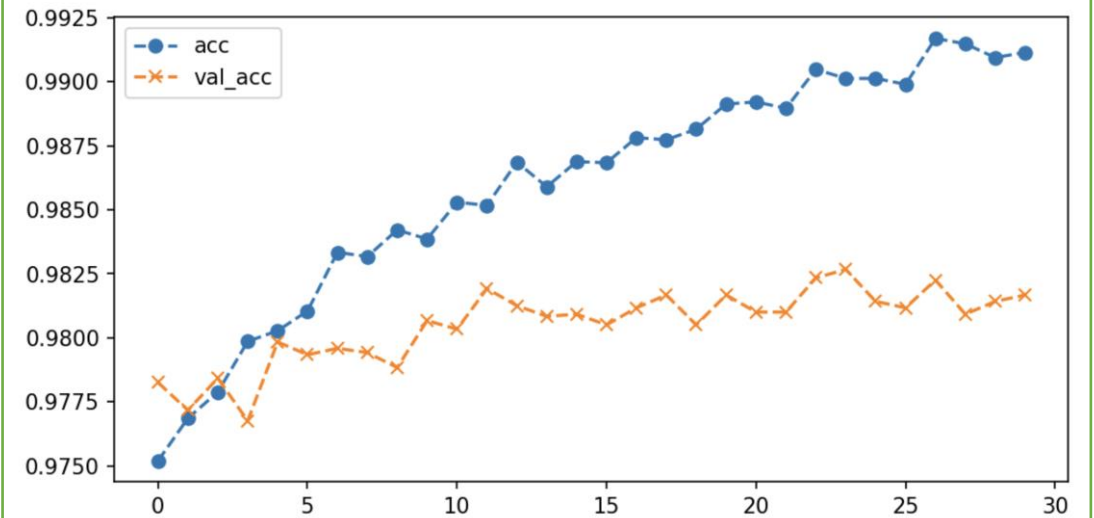
# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

*Learning Curves – Accuracy Plot  
(Output by R)*



*Learning Curves – Accuracy Plot  
(Output by Python)*



# Deep Learning Framework

## Code Study 2: Create Keras Model in TensorFlow 2.0

# Evaluate the model's performance on the test data

### *Written In R*

```
loss_acc_metrics <- model %>% evaluate(x_test,  
                                       y_test)
```

```
print(loss_acc_metrics)
```

Out:

\$loss

[1] 0.0683236

\$acc

[1] 0.9832

### *Written in Python*

```
loss_acc_metrics = model.evaluate(x_test, y_test)
```

```
print(loss_acc_metrics)
```

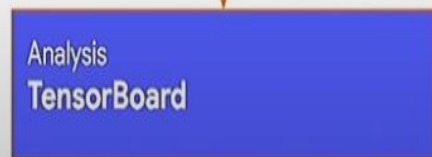
Out:

[0.07049376319068433, 0.9824]

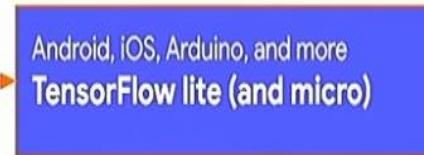
# Deep Learning Framework



## Training



## Deployment



## Major features and improvements

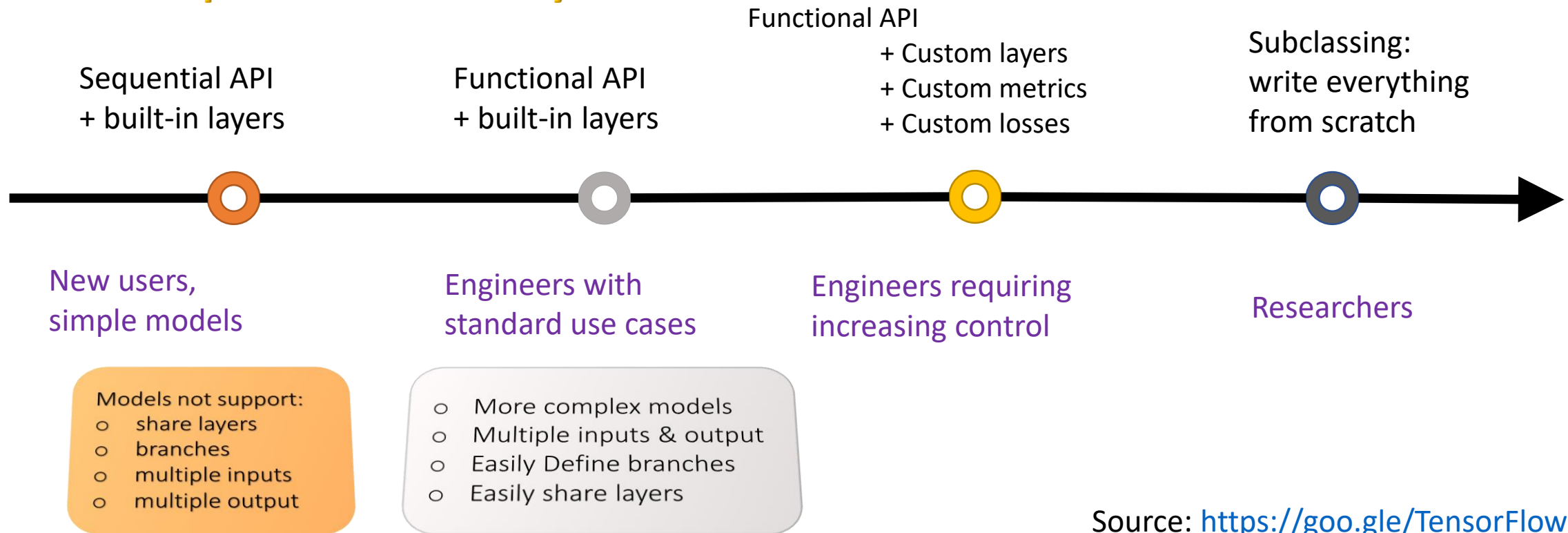
- [Keras](#) will be the high-level API for TensorFlow, and it's extended that all the advanced features of TensorFlow can be used directly from [tf.keras](#).
- Eager execution is now the default.
- TensorBoard integration with Keras
- Deep learning researchers will benefit from a low-level API which enables them to export internally used ops and continue to build models onto the internals of TensorFlow without having to rebuild TensorFlow.



# Deep Learning Framework

## TensorFlow Model Building Style

### From simple to arbitrarily flexible



# How UBDA support your Deep Learning work?

## ❖ Technical Support



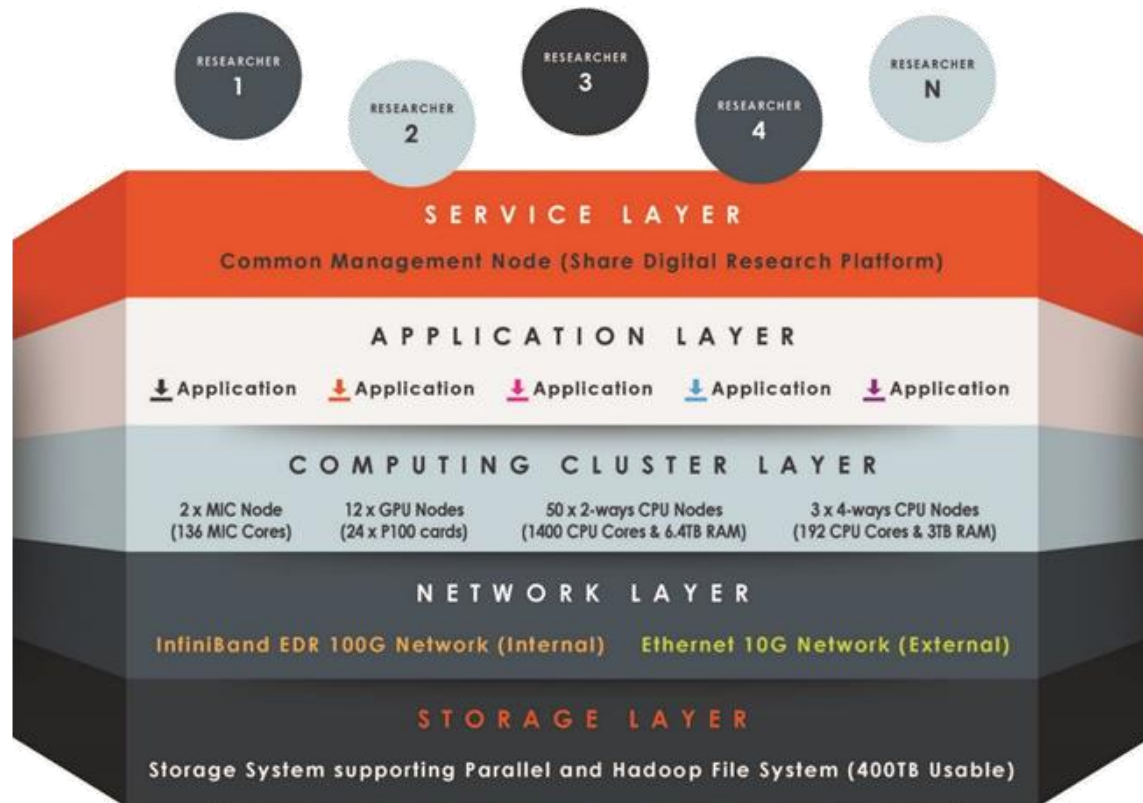
## ❖ Research Support



# UBDA Technical Support

## Secure and Scalable Infrastructure

- ✓ UBDA provides a dedicated, secure, and scalable 24/7 Linux platform for building deep learning model



- Storage layer consists of over 400 TB storage system with parallel file systems to allow users to store and process their research data in a reliable environment.
- External network connection is secured with SSH and PolyU Campus Network
- Support users execute their own developed application (C++, Python, R) with multiple (up to 104) CPU cores among multiple computing nodes via MPI
- Support Deep Learning with multiple (up to 4) nVidia P100 GPU Cards
- Allow users install/update libraries as well as software packages in their personal local accounts



# UBDA Technical Support

## Deep Learning related tool available in UBDA Platform

- Python (supported to 3.8.1)
- Anaconda (supported to 2019.10)
- CUDA Toolkit (supported to 10.0)
- Keras (supported to 2.3.1)
- PyTorch (supported to 1.4)
- TensorFlow (support to tensorflow 2.0, tensorflow-gpu 1.14.0)
- Intel MPI (support to 2018.0.3)
- OpenMPI (support to 4.0.1)
- MPICH (Support to 3.2.1)



# UBDA Technical Support

## Numerous job queues for different computing application

- Parallel Programming queue for huge dataset
- Large memory queue for Engineering and Mathematical Modelling
- GPU queue for Deep Learning
- MIC queue for High-Performance Computing (HPC)

# UBDA Technical Support

## List of Documents support users in platform application

- GUI Files Transfer (Window/Mac iOS)
- UBDA Platform Login (Window/ Mas iOS) and Interface
- UBDA Network Drive Mapping over SSH (Window/Mac iOS)
- **Deep Learning Framework installation with CUDA Support in user environment**
- Job Submission and Scheduling (PBS Scripts)
- Practice with Open-source Python Scripts (e.g. Keras, PyTorch, TensorFlow etc.)
- Job Creation on a Time-based schedule
- Status Information Check
- SSH Keys and Public Key Authentication

# UBDA Technical Support Consultation Service in UBDA Platform Application

Mr. Dillian Wong, Scientific Officer, [dillian.wong@polyu.edu.hk](mailto:dillian.wong@polyu.edu.hk)

Mr. Jack Wong, Scientific Officer, [jack.cw.wong@polyu.edu.hk](mailto:jack.cw.wong@polyu.edu.hk)

**Account Registration**

**Library Installation**

**Resource Request**

**Job Submission**

# UBDA Research Support Seminar, Talk, Lecture





# UBDA Research Support

## UBDA Deep Learning Workshop

### Topics:

- Deep Learning Algorithms and its Use Cases
- Deep Dive into Recurrent Neural Networks (RNN) model
- Deep Dive into Convolutional Neural Networks (CNN) model
- Deep Learning for Time Series Forecasting
- Unsupervised Deep Learning with Python



# UBDA Research Support UBDA Users Gathering

## Aims:

- Experience sharing for empowering users research idea
- enhance the collaborative use and transfer of acquired knowledge of the UBDA platform

# UBDA Research Support

## Consultation Service in Data-driven Research and Proposal Writing

- Help in analyzing data-driven research problem and formulating the data-driven problem-solving approach
- Support writing proposal related to data-driven research
- Help calculation on the budget involved with using UBDA facility
- Be the supporting party in fund application if necessary

# UBDA Research Support

## Consultation Service in Data-driven Research and Proposal Writing

Machine  
Learning

Dr. Divya SAXENA, [divya.saxena@polyu.edu.hk](mailto:divya.saxena@polyu.edu.hk)

Deep  
Learning

Statistical  
Analytics

Dr. Xiao WANG, [xiao-ubda.wang@polyu.edu.hk](mailto:xiao-ubda.wang@polyu.edu.hk)

Mathematical  
Optimization

AI

Dr. Jackei WONG, [jackei.wong@polyu.edu.hk](mailto:jackei.wong@polyu.edu.hk)

Big Data

Social  
Media  
Analysis

Dr. Vincent NG, [vincent.ng.comp@polyu.edu.hk](mailto:vincent.ng.comp@polyu.edu.hk)

Data  
Mining

Health Informatics



**Thank you !**

**Question and Answer Section**