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Artificial Intelligence Course

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Module 9 – Deep Learning Methods with TensorFlow and Keras

Artificial Intelligence Course

Chapter Description

Chapter objectives

- ✓ Build and train the deep neural networks.
- ✓ Optimize the deep learning neural networks preventing the overfitting and vanishing gradient problems.
- ✓ Gain proficiency with the deep learning libraries such as TensorFlow and Keras.

Chapter contents

- ✓ Unit 1. TensorFlow Basics
- ✓ Unit 2. Deep Learning Methods with TensorFlow and Keras

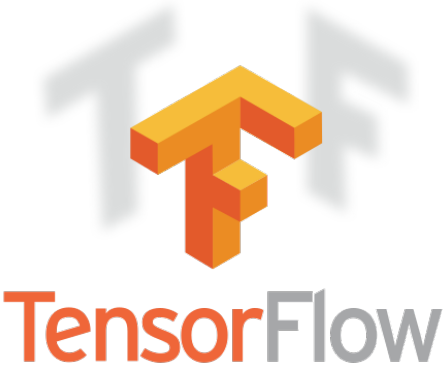
Unit 1.

TensorFlow Basics

Introduction to TensorFlow

About the TensorFlow

- Tensorflow can utilize both CPU and GPU to improve the training performance of a machine learning model.
- It can produce maximum performance only with GPU
- Tensorflow officially supports CUDA-capable GPU.
- Support for OpenCL GPU is still on progress.
- It’s likely that OpenCL will be officially supported soon.
- Tensoflow is a front-end interface that supports various programming languages.



About the TensorFlow

- Since Tensorflow's Python API is fully mature, it is popular to deep learning and machine learning technologists.
- Tensorflow has its official C ++ API as well.
- In addition, two new TensorFlow-based libraries, Tensorflow.js and Tensorflow Lite were introduced.
- APIs for Java, Haskell, Node.js or Go are not yet stable.
- Tensorflow developers and open source community are constantly working to resolve such issues.

What is TensorFlow?

- Tensorflow generates a computational graph composed of a serios of nodes.
- Each node expresses an operation that can denote more than 0 input or output.
- Tensor was created as a symbolic handle to refer to inputs and outputs of such operation.

Why TensorFlow?

- Tensorflow immensely expedites the machine learning process.
  - Performance issue

    →Since the performance of computer processors consistently improved in the past years, it can train more complex and powerful machine learning systems.

    →It can enhance machine learning model's prediction accuracy.
  - Even the cheapest computer hardwares carry processors with a number of cores.
  - Numerous functions from Scikit-learn can disperse an operation into numbers of processes.
  - Generally, Python can only run one core due to GIL (Global Interpreter Lock).
  - Multiproceessing libraries can disperse an operation into multiple cores, but even the most advanced desktop PCs do not carry more than 8 or 16 cores.

Why TensorFlow?

- Even the simplest multilayer perceptron has a hundred units in a single hidden layer.
- You need about 80,000 weight parameters ([784×100 + 100] + [100×10 + 10] = 79,510) to train a model to classify even the simplest images.
  - MNIST is a relatively small image (28×28 pixel)
- The number of weight parameters will radically increase when processing high-pixel images or adding hidden layers.
- Such tasks are difficult to operate on a single process.
- How can you effectively resolve such an issue?

Why TensorFlow?

- A foolproof solution to this issue is a GPU of exceptional performance level.
- A graphic card could be considered as a small computer cluster within a computer.
- You can buy a GPU that carries 290 times more core and executes 10 times more floating point operations per second, with 70% price of the latest CPU.
- Writing a code for a certain CPU is not as easy as running a code on a Python interpreter.
- There are packages such as CUDA or OpenCL that enable usage of designated GPUs.
- However, CUDA or OpenCL does not offer the best environment to write code for machine learning algorithms.
- TensorFlow was developed from such background.

What is TensorFlow?

- Refer to the figure below to precisely understand the notion of a tensor.
- First row shows rank 0 and rank 1 tensors. Second row shows rank 2 and rank 3 tensors.

Ex Tensors

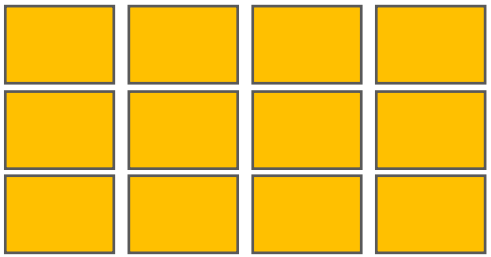
Rank 0:

(scalar)

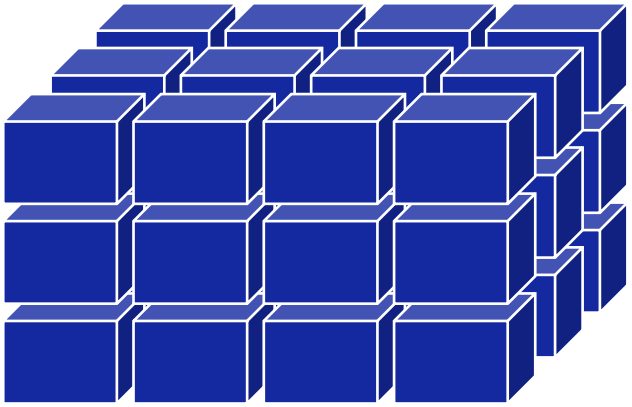
Rank 1:

(vector)

Rank 2: (matrix)



Rank 3:



What is TensorFlow?

- Tensorflow creates a computational graph composed of a serios of nodes.
- Each node expresses an operation that can denote more than 0 input or output.
- Tensor was created as a symbolic handle to refer to inputs and outputs of such operation.
- A tensor can be understood in mathematical forms of scalar, vector, matrix etc.
- To be more precise, a scalar can be defined as a rank 0 tensor, vector as rank 1 tensor, matrix as rank 2 tensor, and a matrix with three dimensions a rank 3 tensor.
- The actual values are stored as NumPy arrays, and the tensor provides a reference for this array.

What is TensorFlow?

- Let’s discuss programming mechanisms of TensorFlow.
- Learn how to create and modify tensors.
- Learn how to load data and use TensorFlow Dataset objects which efficiently circulate datasets.
- Study the datasets in the tensorflow datasets module.
- Let’s get acquainted with tf.keras API and build a machine learning model.
- Learn how to compile and train this model and store the trained model in a drive.

What is TensorFlow?

- In TensorFlow version 1.x, it supported static computational graph tat expressed flow of data.
- Many users had a difficult time utilizing the static computational graph. In the recent 1.0 version, this issue has been resolved, and the user can create and train neural network model more easily.
- TensorFlow 1.0 still supports static computational graphs, but dynamic computational graphs are the default.

Installing TensorFlow

- Use Python's pip installer to install TensorFlow from PyPI.
- Run following command on the terminal.

```
> pip install tensorflow
```

- This command installs the most recent, stable version
- Version 1.5.0 at the time of writing.
- Recommend using TensorFlow 1.5.0 for codes (in this chapter) to show expected results.
- The command below installs a designated version.

```
> pip install tensorflow==[desired-version]
```

Checking TensorFlow version

- Run code as below to check the version

```
In [1]: import tensorflow as tf

In [2]: tf.__version__
Out[2]: '2.5.0'
```

Installing TensorFlow

- For GPU, you need an NVIDIA compatible graphic card, and installation of CUDA Toolkit and cuDNN library. (GPU is recommended for neural network training)
- If above conditions are fulfilled, you can install TensorFlow GPU version.

```
> pip install tensorflow-gpu
```

- Refer to the official website for more information on installation. (https://www.tensorflow.org/install/gpu)

TensorFlow learning procedure

- New version is released every few months, due to TensorFlow's fast developing rate.
- Let's study several ways to create a tensor.
- Then, study the features of TensorFlow, and methods for modification.
- First, use **tf.convert to tensor** to create a tensor in list or NumPy array.

```
In [3]: import numpy as np

In [4]: np.set_printoptions(precision=3)
```

TensorFlow learning procedure

- New version is released every few months, due to TensorFlow's fast developing rate.
- Let's study several ways to create a tensor.
- Then, study the features of TensorFlow, and methods for modification.
- First, use **tf.convert to tensor** to create a tensor in list or NumPy array.

```
In [5]: a = np.array([1, 2, 3], dtype=np.int32)
        b = [4, 5, 6]

        t_a = tf.convert_to_tensor(a)
        t_b = tf.convert_to_tensor(b)

        print(t_a)
        print(t_b)

        tf.Tensor([1 2 3], shape=(3,), dtype=int32)
        tf.Tensor([4 5 6], shape=(3,), dtype=int32)

In [6]: tf.is_tensor(a), tf.is_tensor(t_a)

Out[6]: (False, True)
```

Creating a tensor in TensorFlow

```
In [7]: t_ones = tf.ones((2, 3))

        t_ones.shape

Out[7]: TensorShape([2, 3])

In [8]: t_ones.numpy()

Out[8]: array([[1., 1., 1.],
               [1., 1., 1.]], dtype=float32)

In [9]: const_tensor = tf.constant([1.2, 5, np.pi], dtype=tf.float32)

        print(const_tensor)

        tf.Tensor([1.2   5.    3.142], shape=(3,), dtype=float32)
```

- tf.convert to tensor function supports tf.Variable objects, unlike the tf.constant function (which will be dicussed soon)
- tf.fill function and tf.one hot function creates a tensor as well.

Creating a tensor in TensorFlow

- tf.fill function generates a tensor composed of scalar inputs.
- First parameter delivers the shape of the tensor like the tf.ones function.
- Second parameter delivers the desired scalar input. The code below returns the following result identical to that of tf.ones ((2,3)).

```
In [10]: tf.fill((2, 3), 1)

Out[10]: <tf.Tensor: shape=(2, 3), dtype=int32, numpy=
         array([[1, 1, 1],
                [1, 1, 1]])>
```

- tf.fill function is more efficient than the tf.ones to generate tensors of larger size.

Creating a tensor in TensorFlow

- tf.one_hot is a useful function to generate a one-hot encoding matrix.
- First parameter : index that displays the location for one-hot encoding.
- Second parameter : the length of the one-hot encoding vector.
- The size of the generated matrix is (length of the first parameter x second parameter)

Ex The code below generates a one-hot encoding matrix of (3 x 4) size.

```
In [11]: tf.one_hot([0, 1, 2], 4)

Out[11]: <tf.Tensor: shape=(3, 4), dtype=float32, numpy=
         array([[1., 0., 0., 0.],
                [0., 1., 0., 0.],
                [0., 0., 1., 0.]], dtype=float32)>
```

Modifying shape and data type of a tensor

In [12]:
```
t_a_new = tf.cast(t_a, tf.int64)

print(t_a_new.dtype)
```

```
<dtype: 'int64'>
```

In [13]:
```
t = tf.random.uniform(shape=(3, 5))

t_tr = tf.transpose(t)
print(t.shape, ' --> ', t_tr.shape)
```

```
(3, 5)  -->  (5, 3)
```

Modifying shape and data type of a tensor

In [14]:
```
t = tf.zeros((30,))

t_reshape = tf.reshape(t, shape=(5, 6))

print(t_reshape.shape)
```

```
(5, 6)
```

In [15]:
```
t = tf.zeros((1, 2, 1, 4, 1))

t_sqz = tf.squeeze(t, axis=(2, 4))

print(t.shape, ' --> ', t_sqz.shape)
```

```
(1, 2, 1, 4, 1)  -->  (1, 2, 4)
```

Applying math operation on a tensor

In [16]:
```
tf.random.set_seed(1)

t1 = tf.random.uniform(shape=(5, 2),
                       minval=-1.0,
                       maxval=1.0)

t2 = tf.random.normal(shape=(5, 2),
                      mean=0.0,
                      stddev=1.0)
```

In [17]:
```
t3 = tf.multiply(t1, t2).numpy()
print(t3)
```

```
[[-0.27  -0.874]
 [-0.017 -0.175]
 [-0.296 -0.139]
 [-0.727  0.135]
 [-0.401  0.004]]
```

Applying math operation on a tensor

In [18]:
```
t4 = tf.math.reduce_mean(t1, axis=0)

print(t4)
```

```
tf.Tensor([0.09  0.207], shape=(2,), dtype=float32)
```

In [19]:
```
t5 = tf.linalg.matmul(t1, t2, transpose_b=True)

print(t5.numpy())
```

```
[[-1.144  1.115 -0.87  -0.321  0.856]
 [ 0.248 -0.191  0.25  -0.064 -0.331]
 [-0.478  0.407 -0.436  0.022  0.527]
 [ 0.525 -0.234  0.741 -0.593 -1.194]
 [-0.099  0.26   0.125 -0.462 -0.396]]
```

In [20]:
```
t6 = tf.linalg.matmul(t1, t2, transpose_a=True)

print(t6.numpy())
```

```
[[-1.711  0.302]
 [ 0.371 -1.049]]
```

Applying math operation on a tensor

```
In [21]: norm_t1 = tf.norm(t1, ord=2, axis=1).numpy()
         print(norm_t1)
         [1.046 0.293 0.504 0.96  0.383]

In [22]: np.sqrt(np.sum(np.square(t1), axis=1))
Out[22]: array([1.046, 0.293, 0.504, 0.96 , 0.383], dtype=float32)
```

Applying math operation on a tensor

- NumPy function loads __array__() method of the pertaining object before processing the input parameter. This part of the process makes the object compatible with NumPy.
- For example, you can use Series object from pandas in NumPy API. Since this method is embodied in the tensor as well, you can put a tensor as an input in a NumPy function.
- Many mathematical functions are referrable in the most advanced level. For example, they can be referred as tf.multiply (), tf.reduce_mean(), tf.reduce_sum(), tf.matmul(). For Python 2.5 version or above, it can perform matrix operations using @ operator. For example, The computation below return the results identical to that of the previous slide.

```
In [23]: t1 @ tf.transpose(t2)

Out[23]: <tf.Tensor: shape=(5, 5), dtype=float32, numpy=
         array([[-1.144,  1.115, -0.87 , -0.321,  0.856],
                [ 0.248, -0.191,  0.25 , -0.064, -0.331],
                [-0.478,  0.407, -0.436,  0.022,  0.527],
                [ 0.525, -0.234,  0.741, -0.593, -1.194],
                [-0.099,  0.26 ,  0.125, -0.462, -0.396]], dtype=float32)>
```

split(), stack(), concatenate() function

In [24]:
```
tf.random.set_seed(1)

t = tf.random.uniform((6,))

print(t.numpy())

t_splits = tf.split(t, 3)

[item.numpy() for item in t_splits]
```

```
[0.165 0.901 0.631 0.435 0.292 0.643]
```

Out[24]:
```
[array([0.165, 0.901], dtype=float32),
 array([0.631, 0.435], dtype=float32),
 array([0.292, 0.643], dtype=float32)]
```

split(), stack(), concatenate() function

In [26]:
```
A = tf.ones((3,))
B = tf.zeros((2,))

C = tf.concat([A, B], axis=0)
print(C.numpy())
```

```
[1. 1. 1. 0. 0.]
```

In [27]:
```
A = tf.ones((3,))
B = tf.zeros((3,))

S = tf.stack([A, B], axis=1)
print(S.numpy())
```

```
[[1. 0.]
 [1. 0.]
 [1. 0.]]
```

Coding Exercise #0601

Follow practice steps on ‘ex_0601_a.ipynb' file

Unit 1.

TensorFlow Basics

Building TensorFlow dataset in a tensor

In [28]:
```
a = [1.2, 3.4, 7.5, 4.1, 5.0, 1.0]

ds = tf.data.Dataset.from_tensor_slices(a)

print(ds)
```

```
<TensorSliceDataset shapes: (), types: tf.float32>
```

In [29]:
```
for item in ds:
    print(item)
```

```
tf.Tensor(1.2, shape=(), dtype=float32)
tf.Tensor(3.4, shape=(), dtype=float32)
tf.Tensor(7.5, shape=(), dtype=float32)
tf.Tensor(4.1, shape=(), dtype=float32)
tf.Tensor(5.0, shape=(), dtype=float32)
tf.Tensor(1.0, shape=(), dtype=float32)
```

In [30]:
```
ds_batch = ds.batch(3)

for i, elem in enumerate(ds_batch, 100):
    print('batch {}:'.format(i), elem.numpy())
```

```
batch 100: [1.2 3.4 7.5]
batch 101: [4.1 5.  1. ]
```

Connecting two tensors in one dataset (1/2)

Approach 1

In [31]:
```
tf.random.set_seed(1)

t_x = tf.random.uniform([4, 3], dtype=tf.float32)
t_y = tf.range(4)
```

In [32]:
```
ds_x = tf.data.Dataset.from_tensor_slices(t_x)
ds_y = tf.data.Dataset.from_tensor_slices(t_y)

ds_joint = tf.data.Dataset.zip((ds_x, ds_y))

for example in ds_joint:
    print('  x: ', example[0].numpy(),
          '  y: ', example[1].numpy())
```

```
  x:  [0.165 0.901 0.631]   y:  0
  x:  [0.435 0.292 0.643]   y:  1
  x:  [0.976 0.435 0.66 ]   y:  2
  x:  [0.605 0.637 0.614]   y:  3
```

Connecting two tensors in one dataset (2/2)

Approach 2

In [33]:
```
ds_joint = tf.data.Dataset.from_tensor_slices((t_x, t_y))

for example in ds_joint:
    print('  x: ', example[0].numpy(),
          '  y: ', example[1].numpy())
```

```
  x:  [0.165 0.901 0.631]   y:  0
  x:  [0.435 0.292 0.643]   y:  1
  x:  [0.976 0.435 0.66 ]   y:  2
  x:  [0.605 0.637 0.614]   y:  3
```

In [34]:
```
ds_trans = ds_joint.map(lambda x, y: (x*2-1.0, y))

for example in ds_trans:
    print('  x: ', example[0].numpy(),
          '  y: ', example[1].numpy())
```

```
  x:  [-0.67   0.803  0.262]   y:  0
  x:  [-0.131 -0.416  0.285]   y:  1
  x:  [ 0.952 -0.13   0.32 ]   y:  2
  x:  [0.21  0.273 0.229]   y:  3
```

shuffle(), batch(), repeat() method (1/6)

In [35]:
```
tf.random.set_seed(1)
ds = ds_joint.shuffle(buffer_size=len(t_x))

for example in ds:
    print('  x: ', example[0].numpy(),
          '  y: ', example[1].numpy())
```

```
  x:  [0.976 0.435 0.66 ]   y:  2
  x:  [0.435 0.292 0.643]   y:  1
  x:  [0.165 0.901 0.631]   y:  0
  x:  [0.605 0.637 0.614]   y:  3
```

In [36]:
```
ds = ds_joint.batch(batch_size=3,
                    drop_remainder=False)

batch_x, batch_y = next(iter(ds))

print('batch x: \n', batch_x.numpy())

print('batch y:   ', batch_y.numpy())
```

```
batch x:
 [[0.165 0.901 0.631]
 [0.435 0.292 0.643]
 [0.976 0.435 0.66 ]]
batch y:    [0 1 2]
```

shuffle(), batch(), repeat() method (2/6)

In [37]:
```
ds = ds_joint.batch(3).repeat(count=2)

for i,(batch_x, batch_y) in enumerate(ds):
    print(i, batch_x.shape, batch_y.numpy())
```

```
0 (3, 3) [0 1 2]
1 (1, 3) [3]
2 (3, 3) [0 1 2]
3 (1, 3) [3]
```

In [38]:
```
ds = ds_joint.repeat(count=2).batch(3)

for i,(batch_x, batch_y) in enumerate(ds):
    print(i, batch_x.shape, batch_y.numpy())
```

```
0 (3, 3) [0 1 2]
1 (3, 3) [3 0 1]
2 (2, 3) [2 3]
```

shuffle(), batch(), repeat() method (3/6)

In [39]:
```
tf.random.set_seed(1)

## Step 1 : shuffle -> batch -> repeat
ds = ds_joint.shuffle(4).batch(2).repeat(3)

for i,(batch_x, batch_y) in enumerate(ds):
    print(i, batch_x.shape, batch_y.numpy())
```

```
0 (2, 3) [2 1]
1 (2, 3) [0 3]
2 (2, 3) [0 3]
3 (2, 3) [1 2]
4 (2, 3) [3 0]
5 (2, 3) [1 2]
```

shuffle(), batch(), repeat() method (4/6)

In [40]:
```
tf.random.set_seed(1)

## Step 1: shuffle -> batch -> repeat
ds = ds_joint.shuffle(4).batch(2).repeat(20)

for i,(batch_x, batch_y) in enumerate(ds):
    print(i, batch_x.shape, batch_y.numpy())
```

```
0 (2, 3) [2 1]
1 (2, 3) [0 3]
2 (2, 3) [0 3]
3 (2, 3) [1 2]
4 (2, 3) [3 0]
5 (2, 3) [1 2]
6 (2, 3) [1 3]
7 (2, 3) [2 0]
8 (2, 3) [1 2]
9 (2, 3) [3 0]
10 (2, 3) [3 0]
11 (2, 3) [2 1]
12 (2, 3) [3 0]
13 (2, 3) [1 2]
14 (2, 3) [3 0]
15 (2, 3) [2 1]
16 (2, 3) [2 3]
```

shuffle(), batch(), repeat() method (4/6)

In [41]:
```
tf.random.set_seed(1)

## Step 2: batch -> shuffle -> repeat
ds = ds_joint.batch(2).shuffle(4).repeat(3)

for i,(batch_x, batch_y) in enumerate(ds):
    print(i, batch_x.shape, batch_y.numpy())
```

```
0 (2, 3) [0 1]
1 (2, 3) [2 3]
2 (2, 3) [0 1]
3 (2, 3) [2 3]
4 (2, 3) [2 3]
5 (2, 3) [0 1]
```

shuffle(), batch(), repeat() method (5/6)

In [42]:
```
tf.random.set_seed(1)

## Step 2: batch -> shuffle -> repeat
ds = ds_joint.batch(2).shuffle(4).repeat(20)

for i,(batch_x, batch_y) in enumerate(ds):
    print(i, batch_x.shape, batch_y.numpy())
```

```
0 (2, 3) [0 1]
1 (2, 3) [2 3]
2 (2, 3) [0 1]
3 (2, 3) [2 3]
4 (2, 3) [2 3]
5 (2, 3) [0 1]
6 (2, 3) [2 3]
7 (2, 3) [0 1]
8 (2, 3) [2 3]
9 (2, 3) [0 1]
10 (2, 3) [2 3]
11 (2, 3) [0 1]
12 (2, 3) [2 3]
13 (2, 3) [0 1]
14 (2, 3) [2 3]
15 (2, 3) [0 1]
16 (2, 3) [0 1]
```

shuffle(), batch(), repeat() method (6/6)

In [43]:
```
tf.random.set_seed(1)

## Step 3: batch -> repeat -> shuffle
ds = ds_joint.batch(2).repeat(3).shuffle(4)

for i,(batch_x, batch_y) in enumerate(ds):
    print(i, batch_x.shape, batch_y.numpy())
```

```
0 (2, 3) [0 1]
1 (2, 3) [0 1]
2 (2, 3) [2 3]
3 (2, 3) [2 3]
4 (2, 3) [0 1]
5 (2, 3) [2 3]
```

Building dataset from a file stored in a local drive (1/6)

In [44]:
```
import pathlib

imgdir_path = pathlib.Path('cat_dog_images')

file_list = sorted([str(path) for path in imgdir_path.glob('*.jpg')])

print(file_list)
```

```
['cat_dog_images\\cat-01.jpg', 'cat_dog_images\\cat-02.jpg', 'cat_dog_images\\cat-03.jpg', 'cat_dog_images\\dog-01.jpg',
'cat_dog_images\\dog-02.jpg', 'cat_dog_images\\dog-03.jpg']
```

Building dataset from a file stored in a local drive (2/6)

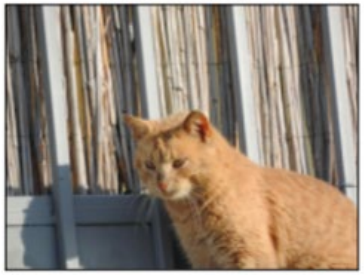
In [45]:
```
import matplotlib.pyplot as plt
import os


fig = plt.figure(figsize=(10, 5))
for i,file in enumerate(file_list):
    img_raw = tf.io.read_file(file)
    img = tf.image.decode_image(img_raw)
    print( 'Image Size:  ', img.shape)
    ax = fig.add_subplot(2, 3, i+1)
    ax.set_xticks([]); ax.set_yticks([])
    ax.imshow(img)
    ax.set_title(os.path.basename(file), size=15)

# plt.savefig('images/13_1.png', dpi=300)
plt.tight_layout()
plt.show()
```

Building dataset from a file stored in a local drive (3/6)

```
Image size:  (900, 1200, 3)
Image size:  (900, 1200, 3)
Image size:  (900, 742, 3)
Image size:  (800, 1200, 3)
Image size:  (800, 1200, 3)
Image size:  (900, 1200, 3)
```

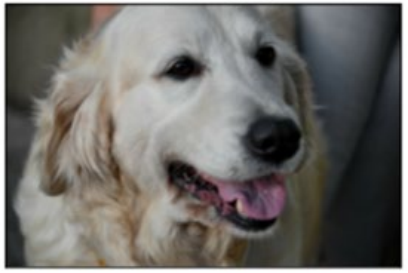
cat-01.jpg

cat-02.jpg



cat-03.jpg

dog-01.jpg



dog-02.jpg

dog-03.jpg

Building dataset from a file stored in a local drive (4/6)

In [46]:
```
labels = [1 if 'dog' in os.path.basename(file) else 0
          for file in file_list]
print(labels)
```

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

In [47]:
```
ds_files_labels = tf.data.Dataset.from_tensor_slices(
    (file_list, labels))

for item in ds_files_labels:
    print(item[0].numpy(), item[1].numpy())
```

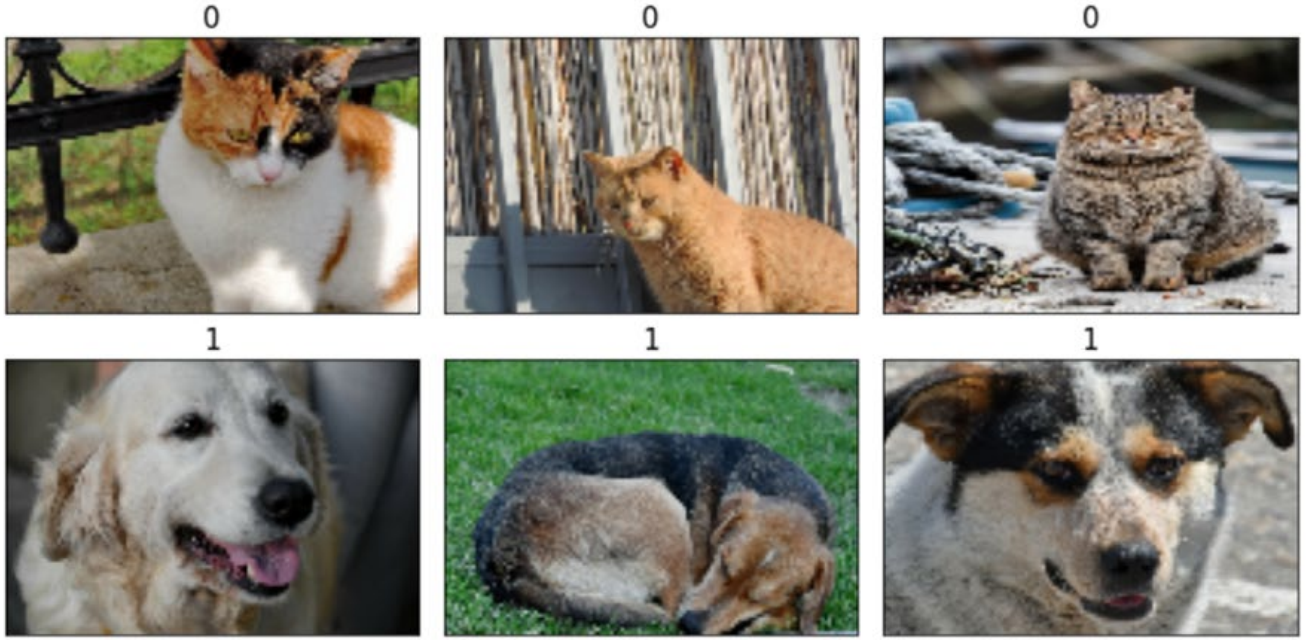
```
b'cat_dog_images\\cat-01.jpg' 0
b'cat_dog_images\\cat-02.jpg' 0
b'cat_dog_images\\cat-03.jpg' 0
b'cat_dog_images\\dog-01.jpg' 1
b'cat_dog_images\\dog-02.jpg' 1
b'cat_dog_images\\dog-03.jpg' 1
```

Building dataset from a file stored in a local drive (5/6)

In [48]:
```
def load_and_preprocess(path, label):
    image = tf.io.read_file(path)
    image = tf.image.decode_jpeg(image, channels=3)
    image = tf.image.resize(image, [img_height, img_width])
    image /= 255.0

    return image, label

img_width, img_height = 120, 80

ds_images_labels = ds_files_labels.map(load_and_preprocess)

fig = plt.figure(figsize=(10, 5))
for i,example in enumerate(ds_images_labels):
    print(example[0].shape, example[1].numpy())
    ax = fig.add_subplot(2, 3, i+1)
    ax.set_xticks([]); ax.set_yticks([])
    ax.imshow(example[0])
    ax.set_title('{}'.format(example[1].numpy()),
                 size=15)

plt.tight_layout()

plt.show()
```

Building dataset from a file stored in a local drive (6/6)

```
(80, 120, 3) 0
(80, 120, 3) 0
(80, 120, 3) 0
(80, 120, 3) 1
(80, 120, 3) 1
(80, 120, 3) 1
```



Loading datasets from tensorflow.datasets library (1/10)

```
In [49]: !pip install --upgrade tensorflow-datasets
```

```
Collecting tensorflow-datasets
  Downloading tensorflow_datasets-4.4.0-py3-none-any.whl (4.0 MB)
Requirement already satisfied: tqdm in c:\users\emcast\anaconda3\lib\site-packages (from tensorflow-datasets) (4.59.0)
Collecting dill
  Downloading dill-0.3.4-py2.py3-none-any.whl (86 kB)
Requirement already satisfied: six in c:\users\emcast\anaconda3\lib\site-packages (from tensorflow-datasets) (1.15.0)
Requirement already satisfied: absl-py in c:\users\emcast\anaconda3\lib\site-packages (from tensorflow-datasets) (0.13.0)
Collecting promise
  Downloading promise-2.3.tar.gz (19 kB)
```

Loading datasets from tensorflow.datasets library (2/10)

In [50]:
```
import tensorflow_datasets as tfds

print(len(tfds.list_builders()))
print(tfds.list_builders()[:5])
```

```
278
['abstract_reasoning', 'accentdb', 'aeslc', 'aflw2k3d', 'ag_news_subset']
```

Loading datasets from tensorflow.datasets library (3/10)

The following command generates the entire list.

```
In [51]: tfds.list_builders()

Out[51]: ['abstract_reasoning',
          'accentdb',
          'aeslc',
          'aflw2k3d',
          'ag_news_subset',
          'ai2_arc',
          'ai2_arc_with_ir',
          'amazon_us_reviews',
          'anli',
          'arc',
          'bair_robot_pushing_small',
          'bccd',
          'beans',
          'big_patent',
          'bigearthnet',
          'billsum',
          'binarized_mnist',
          'binary_alpha_digits',
          'blimp',
          'bool_q',
          'c4',
          'caltech101',
          'caltech_birds2010',
          'caltech_birds2011',
          'cars196',
          'cassava',
```

Loading datasets from tensorflow.datasets library (4/10)

Downloading CelebA dataset.

```
In [52]: celeba_bldr = tfds.builder('celeb_a')

         print(celeba_bldr.info.features)
         print('\n', 30*"=", '\n')
         print(celeba_bldr.info.features.keys())
         print('\n', 30*"=", '\n')
         print(celeba_bldr.info.features['image'])
         print('\n', 30*"=", '\n')
         print(celeba_bldr.info.features['attributes'].keys())
         print('\n', 30*"=", '\n')
         print(celeba_bldr.info.citation)
```

```
FeaturesDict({
    'attributes': FeaturesDict({
        '5_o_Clock_Shadow': tf.bool,
        'Arched_Eyebrows': tf.bool,
        'Attractive': tf.bool,
        'Bags_Under_Eyes': tf.bool,
        'Bald': tf.bool,
        'Bangs': tf.bool,
        'Big_Lips': tf.bool,
        'Big_Nose': tf.bool,
        'Black_Hair': tf.bool,
        'Blond_Hair': tf.bool,
```

Loading datasets from tensorflow.datasets library (5/10)

Download and save data in the local drive.

```
In [53]: celeba_bldr.download_and_prepare()
```

```
Downloading and preparing dataset Unknown size (download: Unknown size, generated: Unknown size, total: Unknown size) to
C:\Users\emcast\tensorflow_datasets\celeb_a\2.0.1...

Dl Completed...: 100% 4/4 [08:34<00:00, 197.62s/ url]

Dl Size...: 1414/0 [08:34<00:00, 2.65 MiB/s]

Dataset celeb_a downloaded and prepared to C:\Users\emcast\tensorflow_datasets\celeb_a\2.0.1. Subsequent calls will reuse
this data.
```

Loading datasets from tensorflow.datasets library (6/10)

Load data from the drive by tf.data.Datasets

```
In [54]: datasets = celeba_bldr.as_dataset(shuffle_files=False)

         datasets.keys()

Out[54]: dict_keys([Split('train'), Split('validation'), Split('test')])
```

Loading datasets from tensorflow.datasets library (7/10)

In [55]:
```
ds_train = datasets['train']
assert isinstance(ds_train, tf.data.Dataset)

example = next(iter(ds_train))
print(type(example))
print(example.keys())
```

```
<class 'dict'>
dict_keys(['attributes', 'image', 'landmarks'])
```

Loading datasets from tensorflow.datasets library (8/10)

In [56]:
```
ds_train = ds_train.map(lambda item:
     (item['image'], tf.cast(item['attributes']['Male'], tf.int32)))
```

In [57]:
```
ds_train = ds_train.batch(18)
images, labels = next(iter(ds_train))

print(images.shape, labels)
```

```
(18, 218, 178, 3) tf.Tensor([0 1 0 0 1 1 1 1 1 0 0 0 1 0 0 1 1 1], shape=(18,), dtype=int32)
```

Loading datasets from tensorflow.datasets library (9/10)

In [58]:
```
fig = plt.figure(figsize=(12, 8))
for i,(image,label) in enumerate(zip(images, labels)):
    ax = fig.add_subplot(3, 6, i+1)
    ax.set_xticks([]); ax.set_yticks([])
    ax.imshow(image)
    ax.set_title('{}'.format(label), size=15)

# plt.savefig('images/13_3.png', dpi=300)
plt.show()
```

Loading datasets from tensorflow.datasets library (10/10)

Another approach to loading datasets (1/3)

In [59]:
```
mnist, mnist_info = tfds.load('mnist', with_info=True,
                              shuffle_files=False)

print(mnist_info)

print(mnist.keys())
```

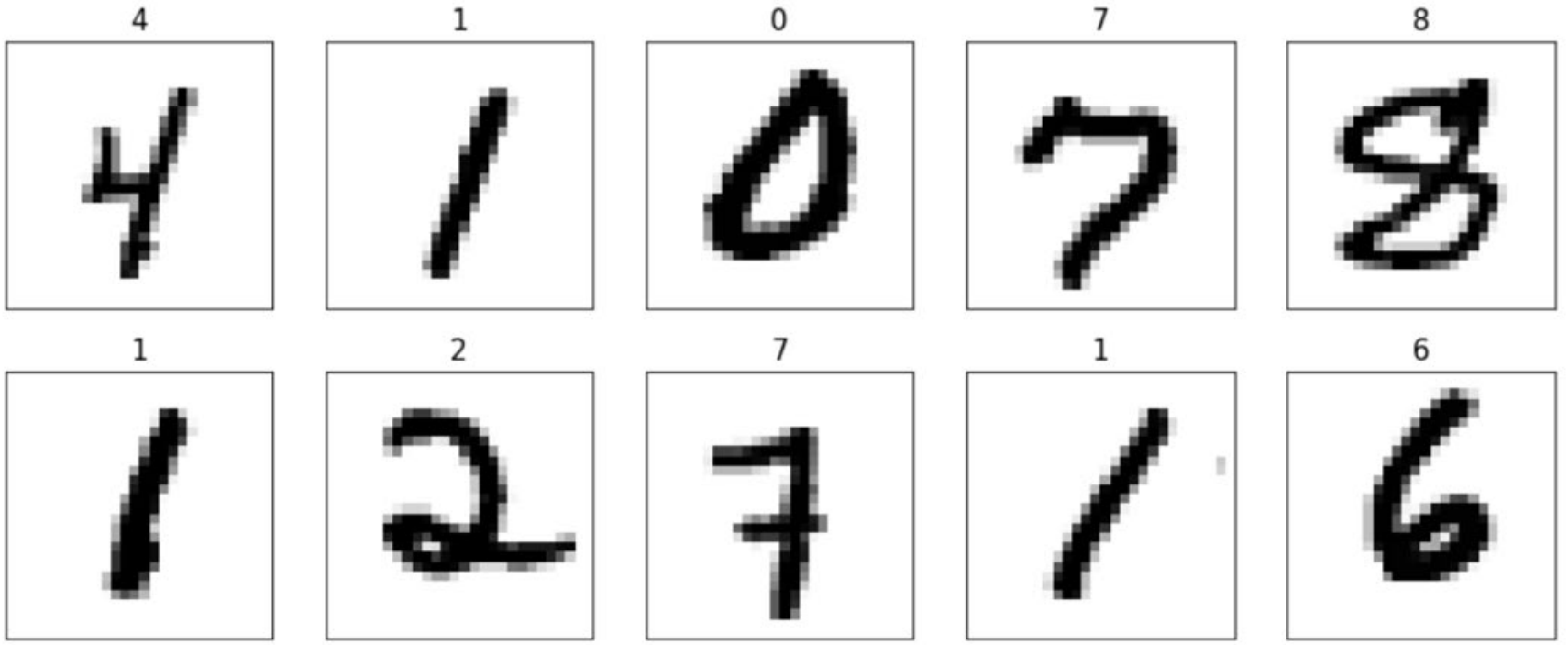
```
Downloading and preparing dataset Unknown size (download: Unknown size, generated: Unknown size, total: Unknown size) to
C:\Users\emcast\tensorflow_datasets\mnist\3.0.1...

Dl Completed...: 100% 4/4 [00:09<00:00, 2.57s/ url]

Dl Size...: 100% 10/10 [00:09<00:00, 1.47 MiB/s]

Extraction completed...: 100% 4/4 [00:09<00:00, 2.77s/ file]
```

Another approach to loading datasets (2/3)

In [60]:
```
ds_train = mnist['train']

assert isinstance(ds_train, tf.data.Dataset)

ds_train = ds_train.map(lambda item:
     (item['image'], item['label']))

ds_train = ds_train.batch(10)
batch = next(iter(ds_train))
print(batch[0].shape, batch[1])

fig = plt.figure(figsize=(15, 6))
for i,(image,label) in enumerate(zip(batch[0], batch[1])):
    ax = fig.add_subplot(2, 5, i+1)
    ax.set_xticks([]); ax.set_yticks([])
    ax.imshow(image[:, :, 0], cmap='gray_r')
    ax.set_title('{}'.format(label), size=15)


plt.show()
```

Another approach to loading datasets (3/3)

```
(10, 28, 28, 1) tf.Tensor([4 1 0 7 8 1 2 7 1 6], shape=(10,), dtype=int64)
```

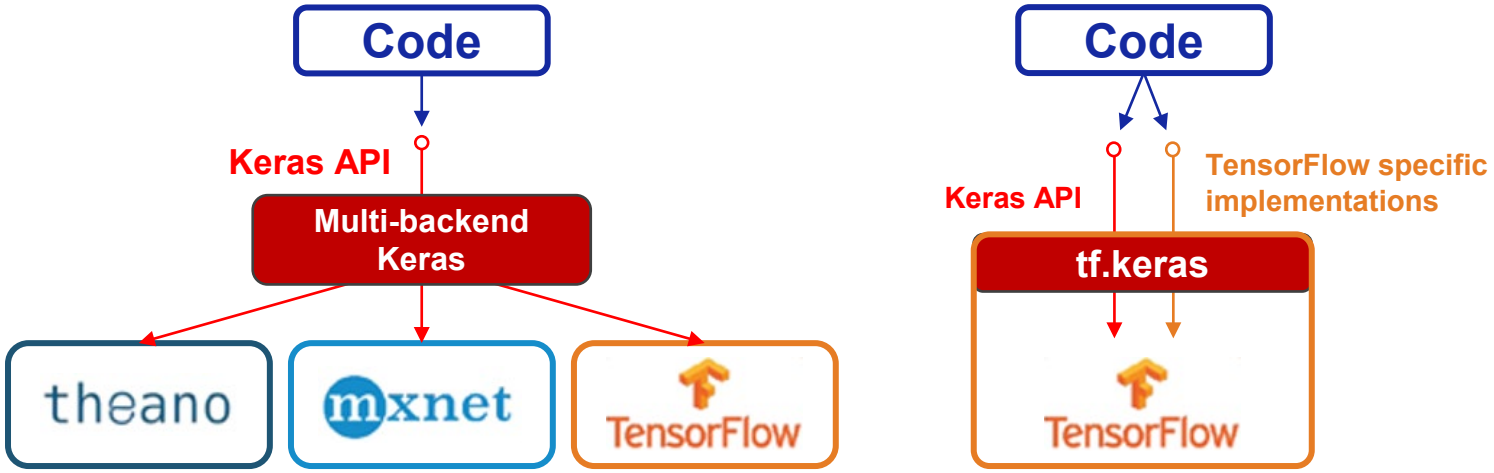


Unit 1.

TensorFlow Basics

Keras

high-level API that allows users to build, train, evaluate and execute all kinds of neural networks.



Building a neural network with TensorFlow

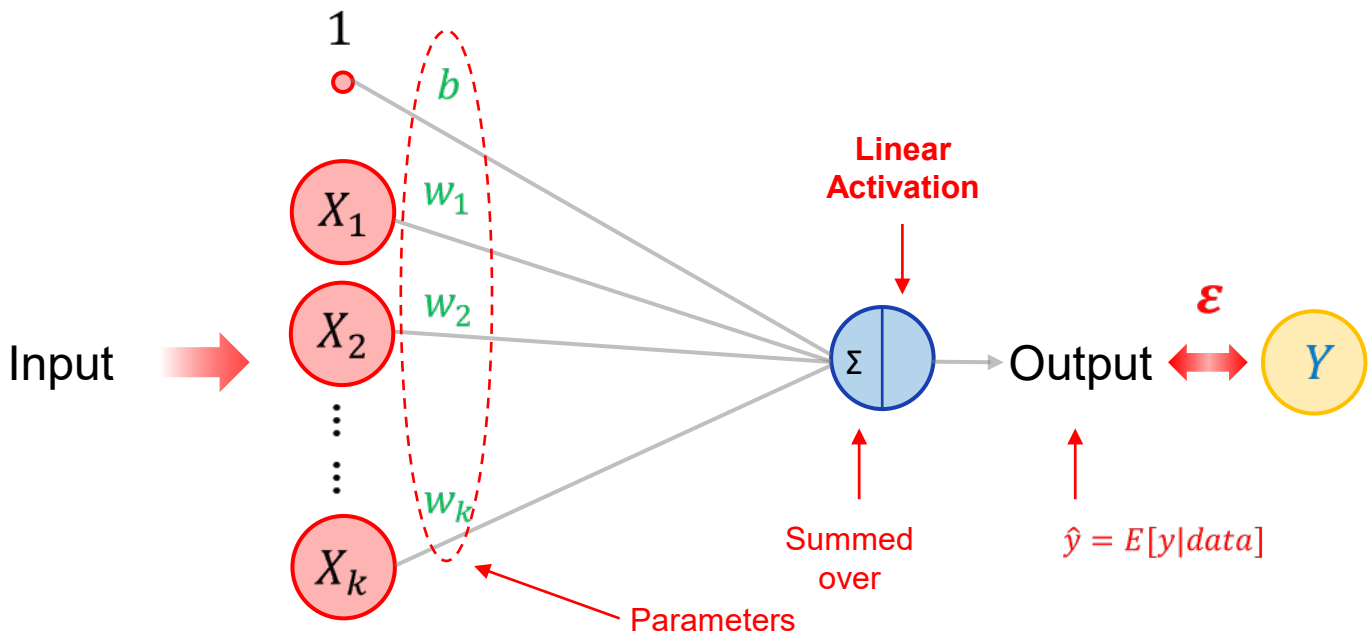
Linear regression with TensorFlow:

- There is one or more explanatory variables: $X_1, X_2, \ldots, X_k$
- There is one response variable: Y
- The variables X_i and Y are connected by a linear relation:

$$Y = b + w_1 X_1 + w_2 X_2 + \cdots + w_k X_k + \varepsilon$$

  - The coefficients previously denoted as β_i, from now and on will be called "weights" w_i.
  - The intercept previously denoted as β_0, from now and on will be called "bias" b.
- We will use the "linear" activation function.

Linear regression with TensorFlow:



- The disagreement between the predicted $\hat{y}$ and the true y has to be minimized by training.

Linear regression with TensorFlow:

- As we have an over determined system of linear equations, the exact solution does not exist.
- We can minimize the loss (cost) defined as $\left|\boldsymbol{Y}-\widehat{\boldsymbol{Y}}\right|^2$ or $\left|\boldsymbol{Y}-\widehat{\boldsymbol{Y}}\right|$ and get the "best" solution $(b,\boldsymbol{W})$.
- If we define the loss as $L=\left|\boldsymbol{Y}-\widehat{\boldsymbol{Y}}\right|^2$, the solution $(b,\boldsymbol{W})$ can be calculated using matrices.
  - However, with TensorFlow we will take a different approach: **Gradient descent algorithm.**

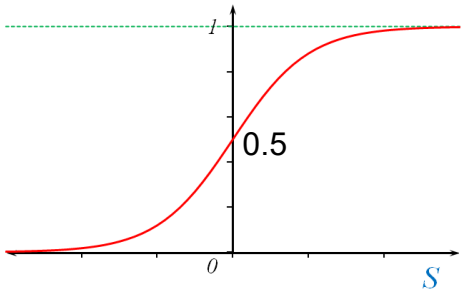
Logistic regression with TensorFlow:

- The linear combinations of variables X_i is the so-called "Logit" denoted here as S :

$$S = b + w_1 X_1 + w_2 X_2 + \cdots + w_k X_k$$

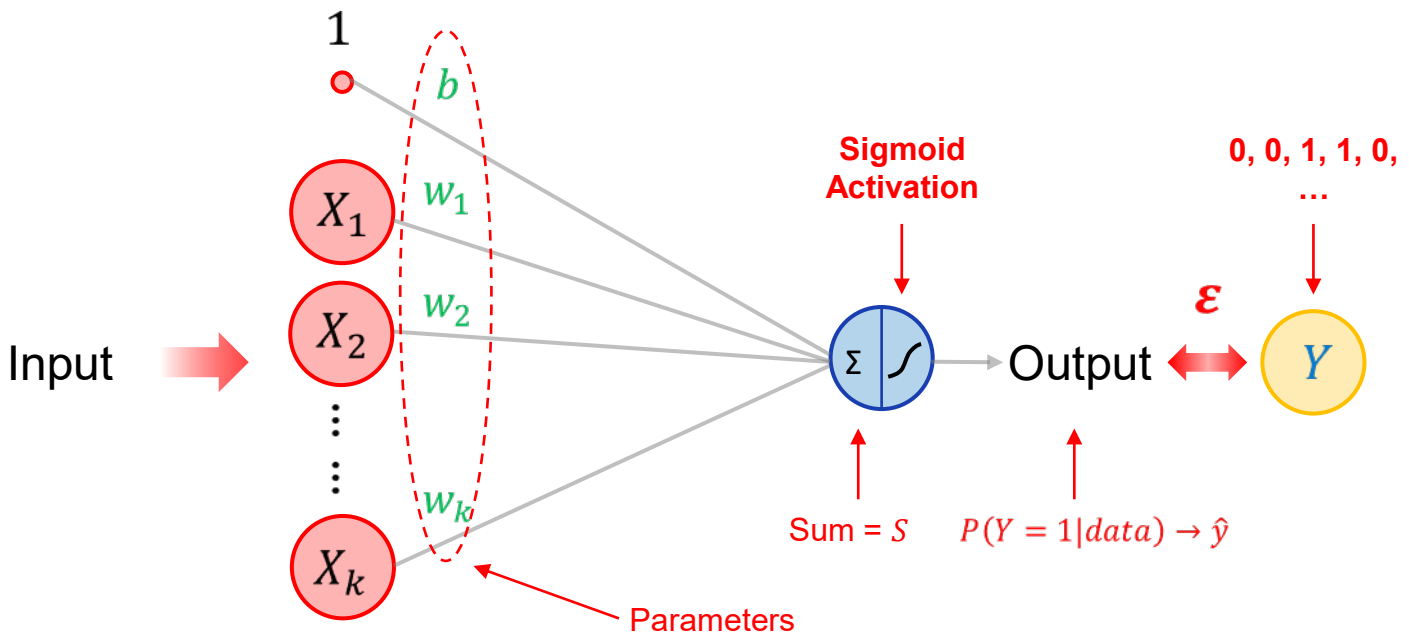
- The conditional probability of Y being equal to 1 is denoted as $P(Y=1|\{x_i\})$.
- A "Sigmoid" function connects the probability with the logit:

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



- This Sigmoid is the "activation function" ⇐ the biggest difference with the linear regression.

Logistic regression with TensorFlow:



- The mismatch between the predicted $\hat{y}$ and the true y has to be minimized by training.

Logistic regression with TensorFlow:

- We can recall the negative of logarithmic likelihood with the redefined $y_i = -1 \text{ or } +1$. (*)

$$-\sum_{i=1}^{n} Log(1 + e^{-y_i S})$$

- We now rename this as the "entropy" and express it in terms of the predicted probability $\hat{p}_i$.

$$L = -\frac{1}{n}\sum_{i=1}^{n} (y_i log(\hat{p}_i) + (1 - y_i)\ log(1 - \hat{p}_i))$$

  - We went back to the definition $y_i = 0 \text{ or } 1$.
  - This is the loss function we'd like to minimize by the gradient descent algorithm.

- Binary logistic regression can be generalized to the **multi-class version** using the Softmax activation and multi-class cross entropy as the loss function.

Loss (cost) functions in TensorFlow:

Name	Formula	TensorFlow Expression
Squared Error (L2 Error)		tf.reduce_sum(tf.square(y_true – y_model))
Absolute Error (L1 Error)		tf.reduce_sum(tf.abs(y_true – y_model))
Binary Cross Entropy		tf.reduce_mean(tf.nn.sigmoid_cross_entropy_with_logits(labels=y_true, logits=y_model))
Multi-Class Cross Entropy		tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits_v2(labels=y_true, logits=y_model))

- Cross entropy is the appropriate loss function for the classification.

Gradient descent algorithm:

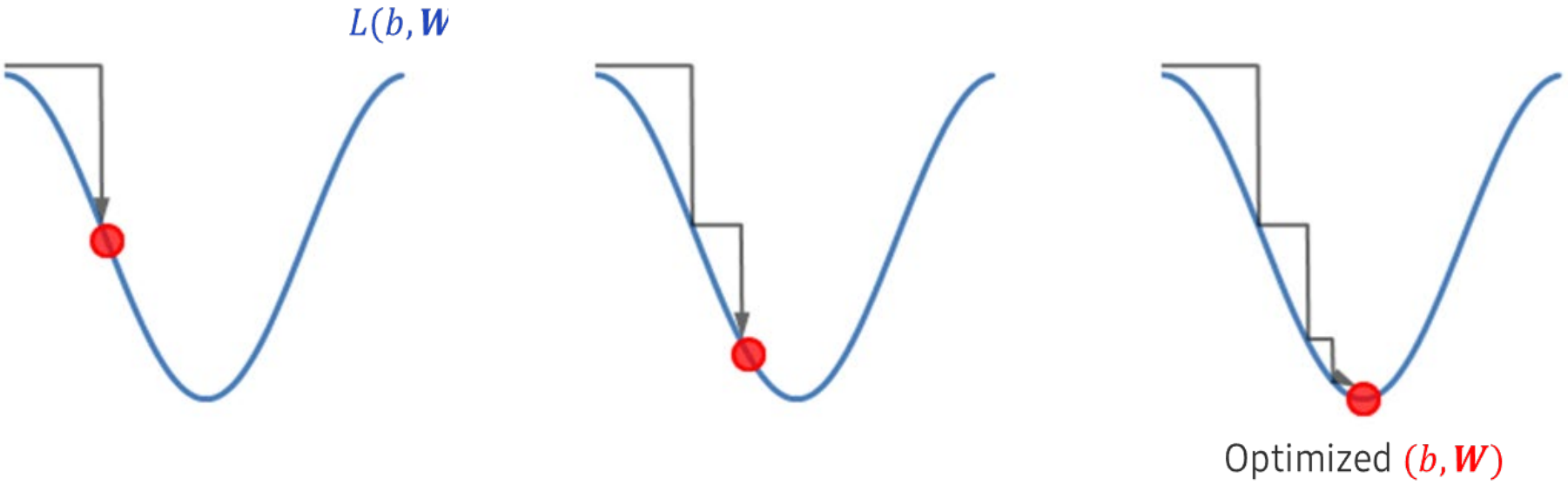
- $L(b,\boldsymbol{W})$ is minimized iteratively in small "steps" pushing $(b,\boldsymbol{W})$ along the direction $-\nabla L(b,\boldsymbol{W})$:

1) $(b,\boldsymbol{W})$ is randomly initialized.
2) Calculate the gradient $\nabla L(b,\boldsymbol{W})$.
3) Update $(b,\boldsymbol{W})$ by one step: $(b,\boldsymbol{W}) \leftarrow (b,\boldsymbol{W}) - \eta\, \nabla L(b,\boldsymbol{W})$.

   Convergence speed is controlled by the "Learning rate" η.
4) Repeat from the step 2) for a fix number of times (epochs).

Gradient descent algorithm:

- $L(b,\boldsymbol{W})$ is minimized iteratively in small “steps” pushing $(b,\boldsymbol{W})$ along the direction $-\nabla L(b,\boldsymbol{W})$:



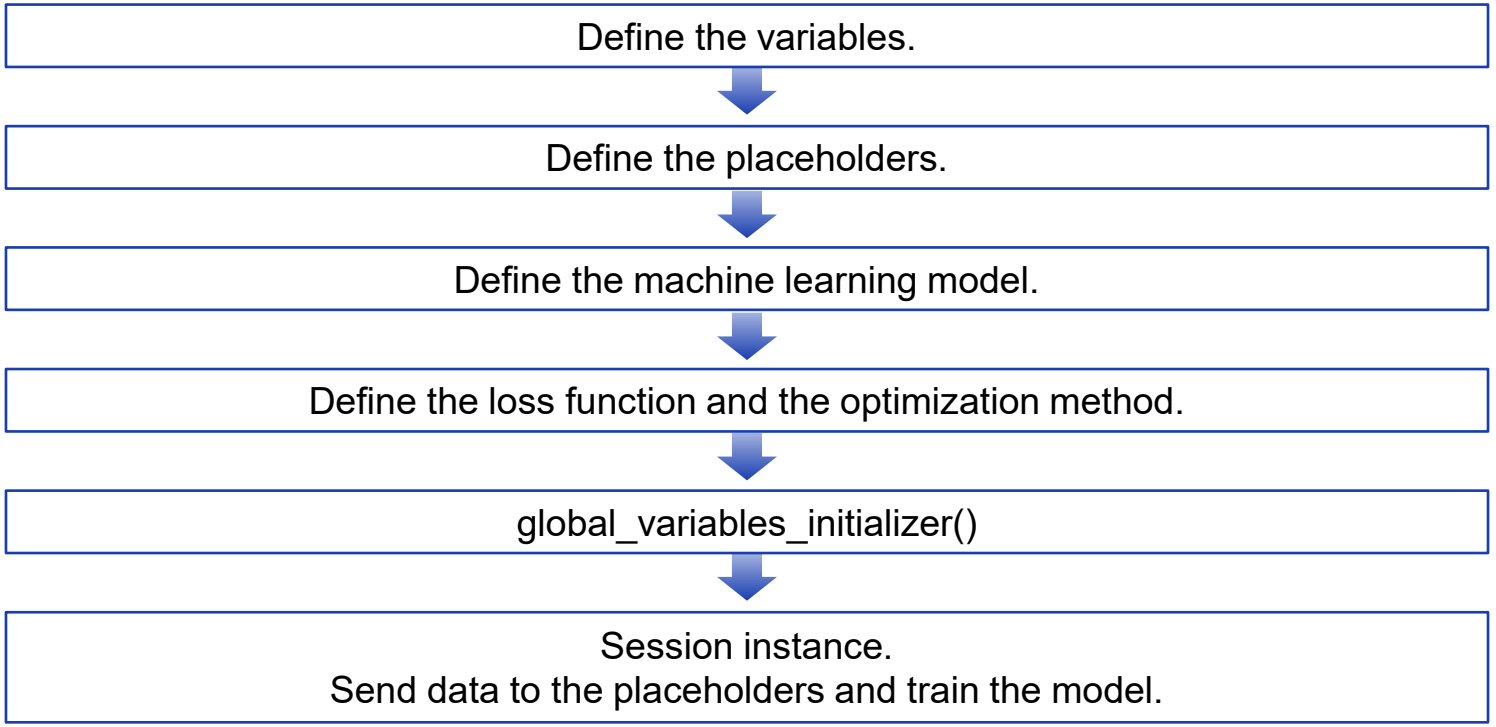
Batch learning (or mini-batch gradient descent):

- Instead of using the whole training dataset for calculating the gradient, only a subset (batch) is used.
- Batch is randomly sampled at every gradient descent step.
- Batch size is small independent of the whole training data size.
- It is advantageous for the generalization (testing).
- It requires less computing power.

Gradient descent algorithms:

Algorithm	Explanation	TensorFlow
Gradient Descent	Gradient descent algorithm with batch learning.	tf.train.GradientDescentOptimizer()
Momentum	Takes into account the gradient from the previous step.	tf.train.MomentumOptimizer(nesterov=False)
Nesterov Momentum	Minimizes unnecessary movements.	tf.train.MomentumOptimizer(nesterov=True)
Adagrad	Adaptative step size.	tf.train.AdagradOptimizer()
RMSProp	Improves upon the Adagrad.	tf.train.RMSPropOptimizer()
Adam	Combines the best properties of Adagrad and RMSProp.	tf.train.AdamOptimizer()

Training work flow:



MNIST data of handwritten digits:

- Handwritten images of digits (0~9). Image size is 28×28 (748 pixels).
- There are 55,000 training and 10,000 testing cases.
- The digit label is one-hot-encoded.

X0	X1	X2	X3	X4	X5	X6	X7	X8	X9
0	0	0	0	0	1	0	0	0	0

Coding Exercise #0602

Follow practice steps on ‘ex_0601.ipynb' file

Coding Exercise #0603

Follow practice steps on ‘ex_0602.ipynb' file

Coding Exercise #0604a

Follow practice steps on ‘ex_0604a.ipynb' file

Coding Exercise #0604b

Follow practice steps on ‘ex_0604b.ipynb' file

Unit 2.

Deep Learning Methods with TensorFlow and Keras

- 2.1. Main Features of TensorFlow
- 2.1. Keras Basics
- 2.2. AI with Keras

Main features of TensorFlow (1/3)

- TensorFlow is a programming interface used to build and execute machine learning algorithms. It supports many platforms, and it is flexible for expansion.
- TensorFlow API has become more stable and mature after the initial release of 1.0 in 2017.
- It was renewed after the release of 1.0 in 2019.

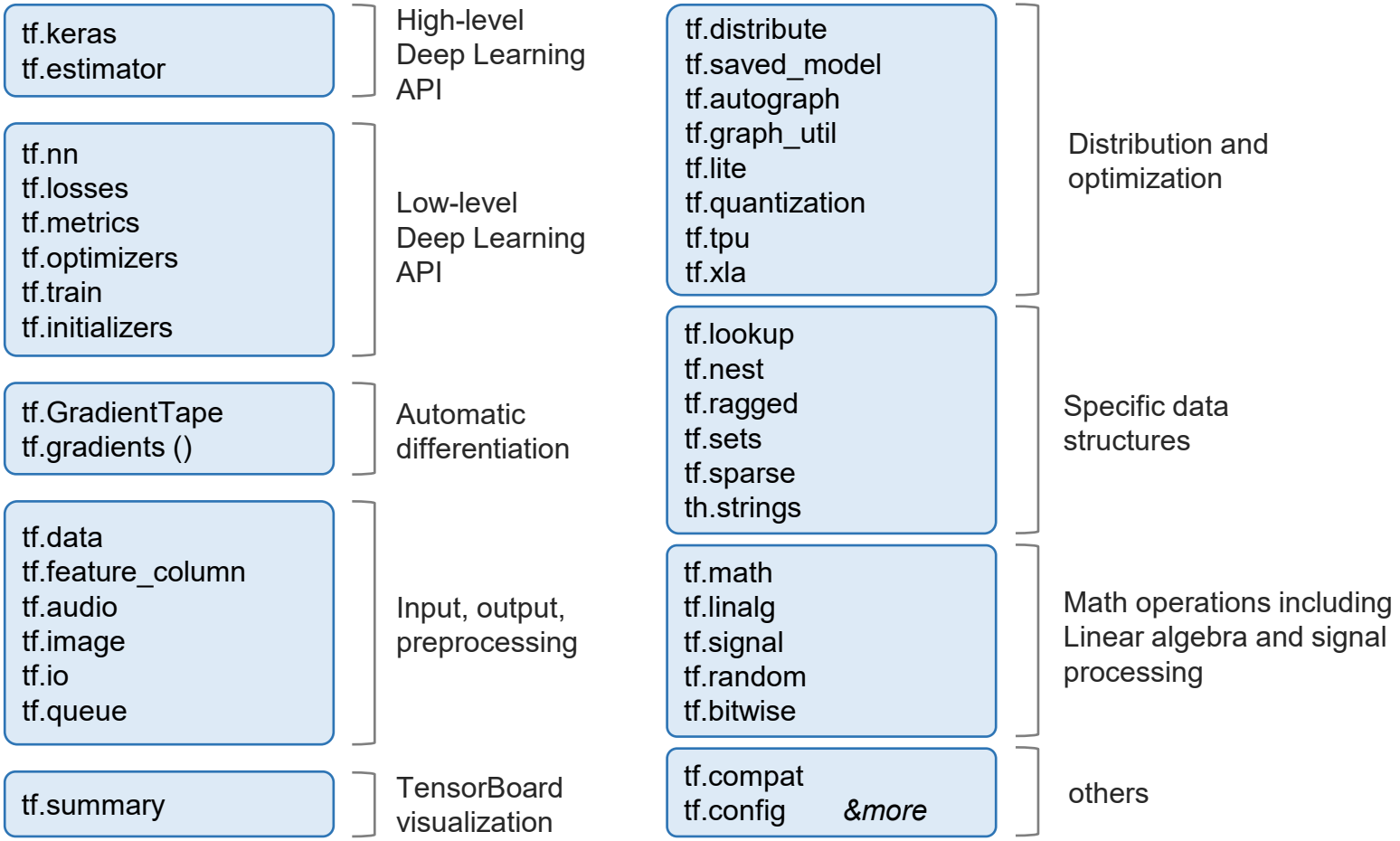
Main features of TensorFlow (2/3)

- Based on user feedbacks, the TensorFlow team decided to support dynamic computational graph for TensorFlow 1.0.
- Thus, Building and training neural networks became much easier.
- Since dynamic computational graphs iterate graph execution and graph declaration, TensorFlow 1.0 will be much more natural and comfortable for Python and NumPy users.
- TensorFlow 1.0 offers TensorFlow 1.x API in tf.compat module.
- Using the above model, users will be able to gradually migrate their codes to TensorFlow v.2 API.

Main features of TensorFlow (3/3)

- Another central feature of TensorFlow is capability to use one or multiple GPUs.
- You can efficiently train deep learning models in large-scale datasets and systems.
- TensorFlow is an open-source library for the public, but it is sponsored and supported by Google.
- A large team of software engineers is consistently expanding and improving the library.
- Since it is an open-source library, many developers are supporting TensorFlow.

Summary of the entire Python API in TensorFlow



Unit 1.

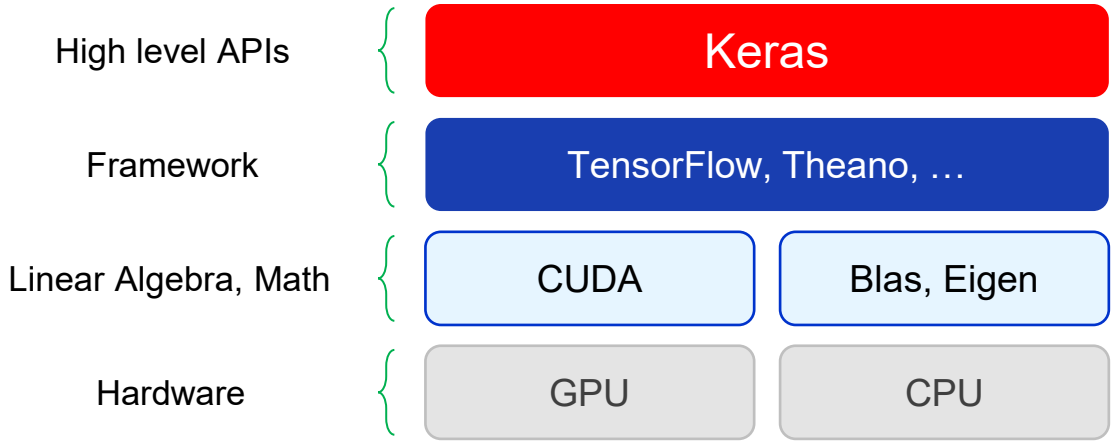
Deep Learning Methods with TensorFlow and Keras

Keras basics

- The most popular backend up to this day was TensorFlow which was the default backend for Keras.
- Since more and more TensorFlow users worked with Keras for high-level APIs, TensorFlow developers had to consider containing Keras project in a separate module (tf.keras).
- In TensorFlow 1.0, Keras and tf.keras are synchnoized.

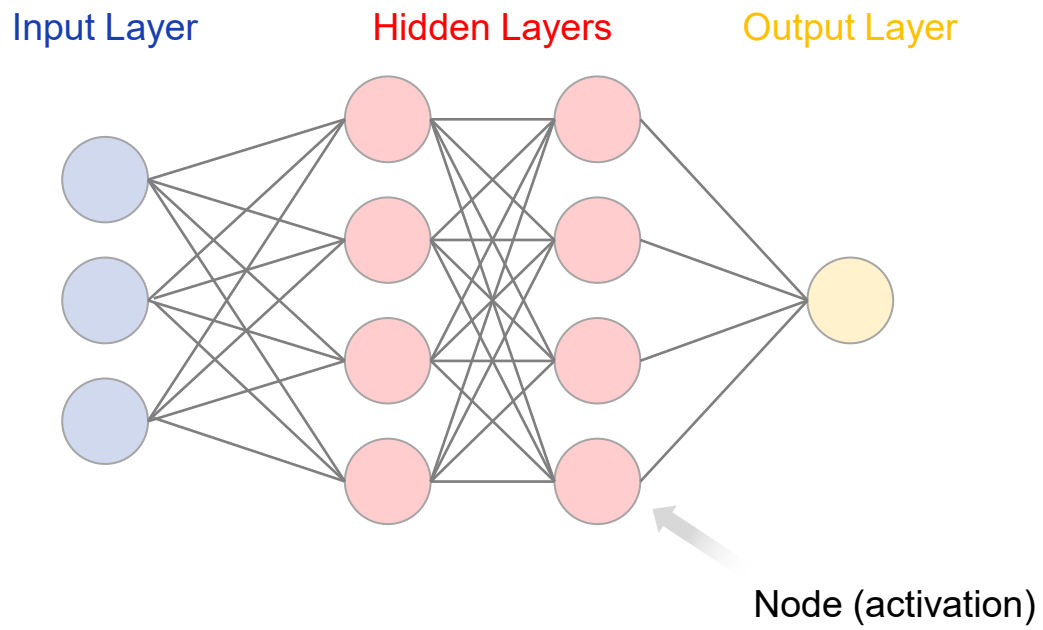
About the Keras library

- A high-end deep learning library.
- Does not support the low-end tensor operations.
- Runs on top of TensorFlow.



About the Keras library

- It is easy to model deep neural networks with Keras.



Training work flow:

- It is easy to model deep neural networks with Keras.

Define a model's layer structure (specify the activation functions).

↓

Define the loss function and the optimization method.

↓

Compile the model.

↓

Specify the batch learning method and start the training (gradient descent).

Loss (cost) functions in Keras:

- It is easy to model deep neural networks with Keras.

Name	Formula	Keras Expression
Squared Error (L2 Error)		loss = "mse"
Absolute Error (L1 Error)		loss = "mae"
Binary Cross Entropy		loss = "binary_crossentropy"
Multi-Class Cross Entropy		loss = "categorical_crossentropy"

Gradient descent algorithms:

Algorithm	Explanation	Keras
Stochastic Gradient Descent	Gradient descent algorithm with batch learning.	SGD(lr=0.1)
Momentum	Takes into account the gradient from the previous step.	SGD(momentum=0.9)
Nesterov Momentum	Minimizes unnecessary movements.	SGD(lr=0.01, momentum=0.9, nesterov=True)
Adagrad	Adaptative step size.	Adagrad(lr=0.01)
RMSProp	Improves upon the Adagrad.	RMSProp(lr=0.01)
Adam	Combines the best properties of Adagrad and RMSProp.	Adam(lr=0.01)

Activation functions:

Name	Formula	Keras
Linear		activation="linear"
Sigmoid		activation="sigmoid"
Tanh		activation="tanh"
ReLu		activation="relu"
Softmax		activation="softmax"

Layers:

Keras	Explanation
Dense()	Dense layer.
Conv1D()	1D convolution layer.
Conv2D()	2D convolution layer.
MaxPooling1D()	1D max pooling layer.
MaxPooling2D()	2D max pooling layer.
Dropout()	Applies dropout to the input.
Flatten()	Flattens the input.
Embedding()	Turns positive integers (label encoding) into dense vectors.
SimpleRNN()	RNN where the output is fed back to input.
LSTM()	LSTM layer.
TimeDistributed()	A wrapper that applies a layer to every time slice.
Input()	The first layer for a functional API model.

Two ways of building models with Keras:

1). Sequential API:

- Layers are added to a “Sequential” object.
- Easy but less flexible.

2). Functional API:

- The first layer must be defined as “Input” where the data shape is specified.
- Each layer defined as a function that takes in as argument the previous layer.
- A “Model” object takes in as arguments the first and the last layers.
- More flexible.

Datasets provided by Keras:

- Useful for learning/practicing purpose.
- Provided by the “keras.datasets” module.

Name	Description
cifar10	
cifar100	
imdb	25000 movie reviews from IMDB with binary labeling (positive or negative).
reuters	11228 newswires from Reuters, labeled over 46 topics.
mnist	
fashion_mnist	
boston_housing	13 attributes of houses at different locations around Boston suburbs in the late 1970s.

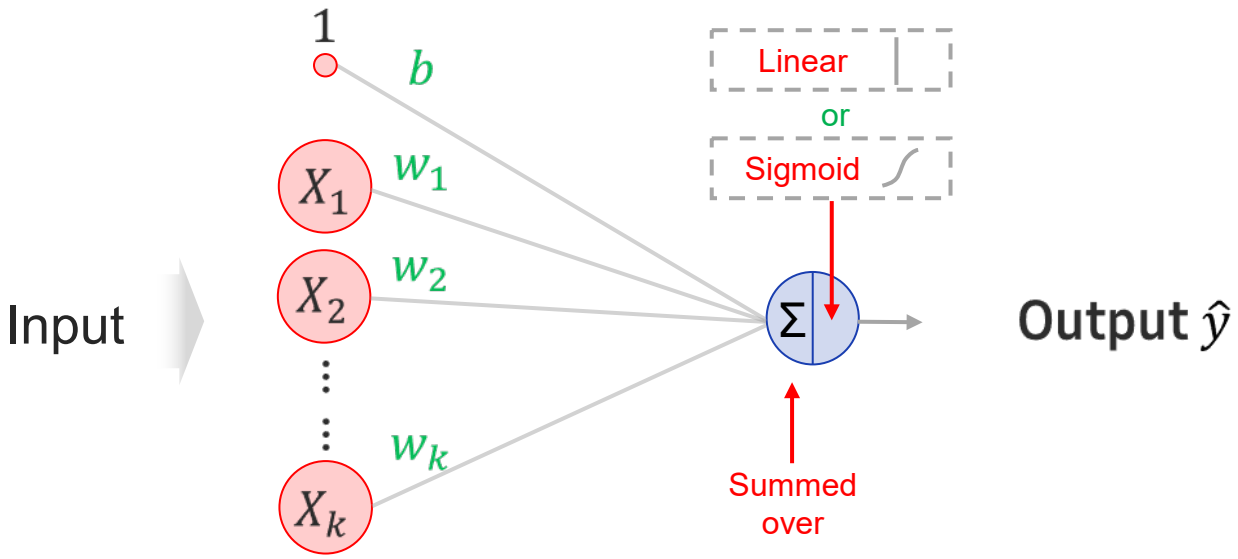
Unit 1.

Deep Learning Methods with TensorFlow and Keras

- 2.1. Main Features of TensorFlow
- 2.1. Keras Basics
- 2.2. AI with Keras

AI with Keras

Linear/Logistic regression with Keras:



- The major difference between linear and logistic regression lies in the choice of activation function.

Keras Sequential API model:

In [83]:
```
# Import the necessary classes.
from keras.models import Sequential
from keras.layers import Dense
```

In [84]:
```
keras.__version__
```

Out[84]:
```
'2.5.0'
```

In [86]:
```
import pandas as pd
import numpy as np
import os
import warnings
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam, RMSprop, SGD
warnings.filterwarnings('ignore')                    # Turn the warnings off.
%matplotlib inline
```

[3]:
```
# Import the necessary classes.
import keras
from keras.models import Sequential
from keras.layers import Dense

keras.__version__
```

Read in the data and explore:

- read

```
In [87]: df = pd.read_csv('data_boston.csv', header='infer',encoding = 'latin1')
         X = df.drop(columns=['PRICE'])
         y = df['PRICE']
```

- view

```
In [88]: df.head(5)
```

Out[88]:

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	PRICE
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	5.33	36.2

Read in the data and explore:

- Scale the X data.

```
In [89]: scaler = MinMaxScaler()
         X = scaler.fit_transform(X)
```

- Spit the data into training and testing.

```
In [90]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=123)
         n_vars = X_train.shape[1]
```

```
[17]: from sklearn.preprocessing import MinMaxScaler
      from sklearn.model_selection import train_test_split
      scaler = MinMaxScaler()
      X = scaler.fit_transform(X)
      X_train, X_test, y_train, y_test =  train_test_split(X, y, test_size=0.3, random_state=123)
      n_vars = X_train.shape[1]
```

Define a Sequential API model:

- Add layers on a sequential objects.

```
In [91]: my_model1 = Sequential()
         my_model1.add(Dense(input_dim = n_vars, units = 1, activation="linear"))

In [92]: my_model1.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 1)                 14
=================================================================
Total params: 14
Trainable params: 14
Non-trainable params: 0
_________________________________________________________________
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 1)                 15

=================================================================
Total params: 15
Trainable params: 15
Non-trainable params: 0
```

Line 91

- Add an output layer for linear regression.

Line 92

- Summary of the model.

Define the hyperparameters and optimizer:

In [93]:
```
n_epochs = 2000
batch_size = 10
learn_rate = 0.002
```

In [94]:
```
my_optimizer=Adam(lr=learn_rate)
my_model1.compile(loss = "mae", optimizer = my_optimizer, metrics=["mse"])
```

Line 93

- Hyperparameters.

Line 94

- Define the optimizer and then compile.

Train the model and visualize the history:

- Train the model.

```
In [95]: my_summary = my_model1.fit(X_train, y_train, epochs=n_epochs, batch_size = batch_size,
                                    validation_split = 0.2, verbose = 0)

In [96]: my_summary.history.keys()

Out[96]: dict_keys(['loss', 'mse', 'val_loss', 'val_mse'])
```

Line 95

- verbose = 0 means no output. verbose = 1 to view the epochs.

Line 96

- View the keys.

Train the model and visualize the history:

- Visualize the training history.

In [97]:

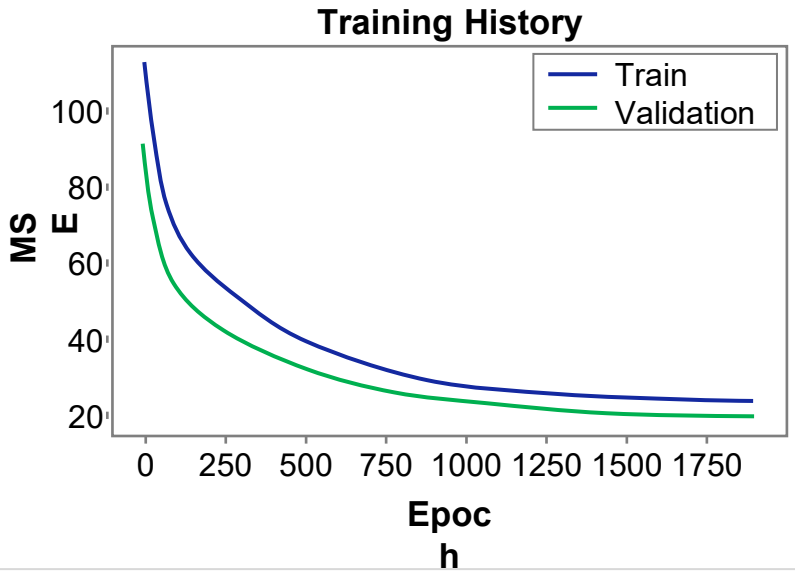
```
1 n_skip = 100
2 plt.plot(my_summary.history['mse'][n_skip:], c="b")
3 plt.plot(my_summary.history['val_mse'][n_skip:], c="g")
4 plt.title('Training History')
5 plt.ylabel('MSE')
6 plt.xlabel('Epoch')
7 plt.legend(['Train', 'Validation'], loc='upper right')
8 plt.show()
```

Line 97-1

- Skip the first few steps.

Train the model and visualize the history:

- Visualize the training history.



Testing:

- Predict and test using a formula.

```
In [99]: y_pred = my_model1.predict(X_test)[:,0]
         RMSE = np.sqrt(np.mean((y_test-y_pred)**2))
         np.round(RMSE,3)

Out[99]: 5.647
```

- Use the evaluate() method.

```
In [100]: MSE = my_model1.evaluate(X_test, y_test, verbose=0)[1]
          RMSE = np.sqrt(MSE)
          print("Test RMSE : {}".format(np.round(RMSE,3)))

          Test RMSE : 5.647
```

Line 100

- Returns the 0 = loss value and 1 = metrics value.

Keras Functional API model:

```
In [101]: from keras.models import Model
          from keras.layers import Input, Dense
```

Define a Functional API model:

In [102]:
```
1 my_input = Input(shape=(n_vars,))
2 my_output = Dense(units=1,activation='linear')(my_input)
```

Line 102-1

- Input layer

Line 102-2

- Output layer

Define a Functional API model:

- The model & The summary of the model.

```
In [103]: my_model2 = Model(inputs=my_input,outputs=my_output)

In [104]: my_model2.summary()
          Model: "model"
          _________________________________________________________________
          Layer (type)                 Output Shape              Param #
          =================================================================
          input_1 (InputLayer)         [(None, 13)]              0
          _________________________________________________________________
          dense_1 (Dense)              (None, 1)                 14
          =================================================================
          Total params: 14
          Trainable params: 14
          Non-trainable params: 0
          _________________________________________________________________
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_3 (InputLayer)        [(None, 14)]              0

 dense_7 (Dense)             (None, 1)                 15

=================================================================
Total params: 15
Trainable params: 15
Non-trainable params: 0
```

Define a Functional API model:

- Define the optimizer and then compile.

```
In [105]: my_optimizer=Adam(lr=learn_rate)
          my_model2.compile(loss = "mae", optimizer = my_optimizer, metrics=["mse"])
```

Line 105

- Loss = MAE (L1) and Metrics = MSE (L2).

Train the model and visualize the history:

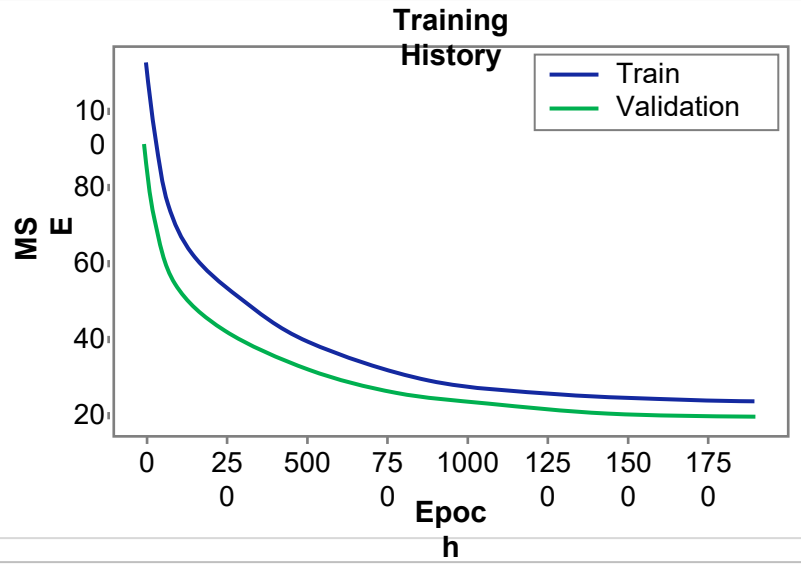
- Train the model

```
In [107]: my_summary = my_model2.fit(X_train, y_train, epochs=n_epochs, batch_size = batch_size,
                                     validation_split = 0.2, verbose = 0)
```

Train the model and visualize the history:

- Visualize the training history.

```
In [108]: n_skip = 100
          plt.plot(my_summary.history['mse'][n_skip:], c="b")
          plt.plot(my_summary.history['val_mse'][n_skip:], c="g")
          plt.title('Training History')
          plt.ylabel('MSE')
          plt.xlabel('Epoch')
          plt.legend(['Train', 'Validation'], loc='upper right')
          plt.show()
```



Train the model and visualize the history:

- Use the evaluate() method.

```
In [109]: MSE = my_model2.evaluate(X_test, y_test, verbose=0)[1]
          RMSE = np.sqrt(MSE)
          print("Test RMSE : {}".format(np.round(RMSE,3)))

          Test RMSE : 5.641
```

Line 109

- Returns the 0 = loss value and 1 = metrics value.

Softmax regression with Keras:

In [113]:
```
import os
import pandas as pd
import numpy as np
import warnings
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.datasets import load_iris
from keras.models import Sequential
from keras.layers import Dense
from keras.optimizers import Adam, RMSprop, SGD
import matplotlib.pyplot as plt
warnings.filterwarnings('ignore')                    # Turn the warnings off.
%matplotlib inline
```

Softmax regression with Keras:

- Read in the data and prepare:

In [114]:
```
data_raw = load_iris()
X = data_raw['data']
y0 = data_raw['target'].reshape(-1,1)
```

In [117]:
```
import tensorflow as tf
```

Softmax regression with Keras:

- One-hot-encoding for y

```
In [119]: y = tf.keras.utils.to_categorical(y0, num_classes=3)
```

- View as DataFrame

```
In [120]: header = ['SepalLength','SepalWidth','PetalLength','PetalWidth','Species_0', 'Species_1', 'Species_2']
          df = pd.DataFrame(np.concatenate([X,y],axis=1),columns=header)
          df.head(5)
```

Out[120]:

	SepalLength	SepalWidth	PetalLength	PetalWidth	Species_0	Species_1	Species_2
0	5.1	3.5	1.4	0.2	1.0	0.0	0.0
1	4.9	3.0	1.4	0.2	1.0	0.0	0.0
2	4.7	3.2	1.3	0.2	1.0	0.0	0.0
3	4.6	3.1	1.5	0.2	1.0	0.0	0.0
4	5.0	3.6	1.4	0.2	1.0	0.0	0.0

Softmax regression with Keras:

- Scale the X data.

```
In [121]: scaler = MinMaxScaler()
          X = scaler.fit_transform(X)
```

- Split the data into training and testing.

```
In [122]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=123)
          n_vars = X_train.shape[1]
```

Softmax regression with Keras:

- Define a Sequential API model

```
In [123]: my_model = Sequential()
          my_model.add(Dense(input_dim=n_vars, units = 3, activation="softmax"))

In [124]: my_model.summary()

          Model: "sequential_2"
          _________________________________________________________________
          Layer (type)                 Output Shape              Param #
          =================================================================
          dense_2 (Dense)              (None, 3)                 15
          =================================================================
          Total params: 15
          Trainable params: 15
          Non-trainable params: 0
```

Line 123

- Add layers on a Sequential object.
- units = N# of output variables.

Line 124

- Summary of the model.

```
[66]:  1 my_model = Sequential()
       2 my_model.add(Dense(input_dim=n_vars, units=3, activation="sof
       3 my_model.summary()

Model: "sequential_3"
_________________________________________________________________
 Layer (type)                 Output Shape              Param #
=================================================================
 dense_10 (Dense)             (None, 3)                 15

=================================================================
Total params: 15
Trainable params: 15
Non-trainable params: 0
_________________________________________________________________
```

Softmax regression with Keras:

- Define the hyperparameters and optimizer:

In [125]:
```
n_epochs = 500
batch_size = 10
learn_rate = 0.005
```

In [126]:
```
my_optimizer=Adam(lr=learn_rate)
my_model.compile(loss = "categorical_crossentropy", optimizer = my_optimizer, metrics=["accuracy"])
```

Softmax regression with Keras:

- Train the model and visualize the history

```
In [128]: my_summary = my_model.fit(X_train, y_train, epochs=n_epochs, batch_size = batch_size,
                                    validation_split = 0.2, verbose = 0)

In [129]: my_summary.history.keys()

Out[129]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

Line 128

- Verbose = 0 means no output. Verbose = 1 to view the epochs.

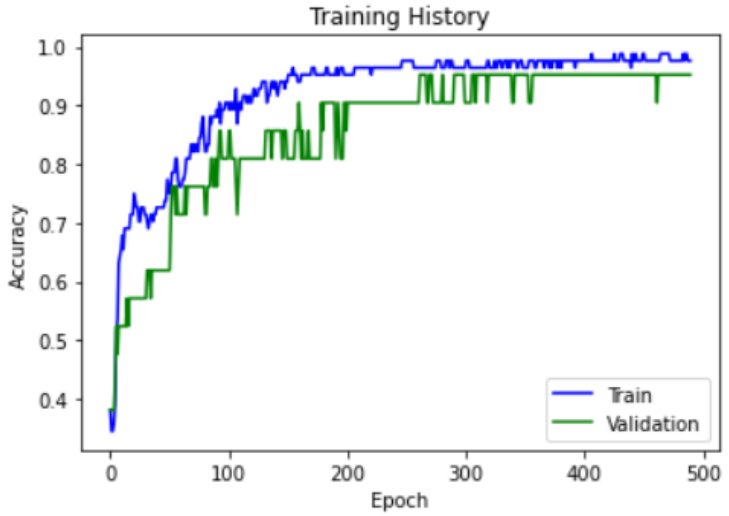
Line 129

- View the keys

Softmax regression with Keras:

- Visualize the training history

In [130]:
```
n_skip = 10
plt.plot(my_summary.history['accuracy'][n_skip:], c="b")
plt.plot(my_summary.history['val_accuracy'][n_skip:], c="g")
plt.title('Training History')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='lower right')
plt.show()
```



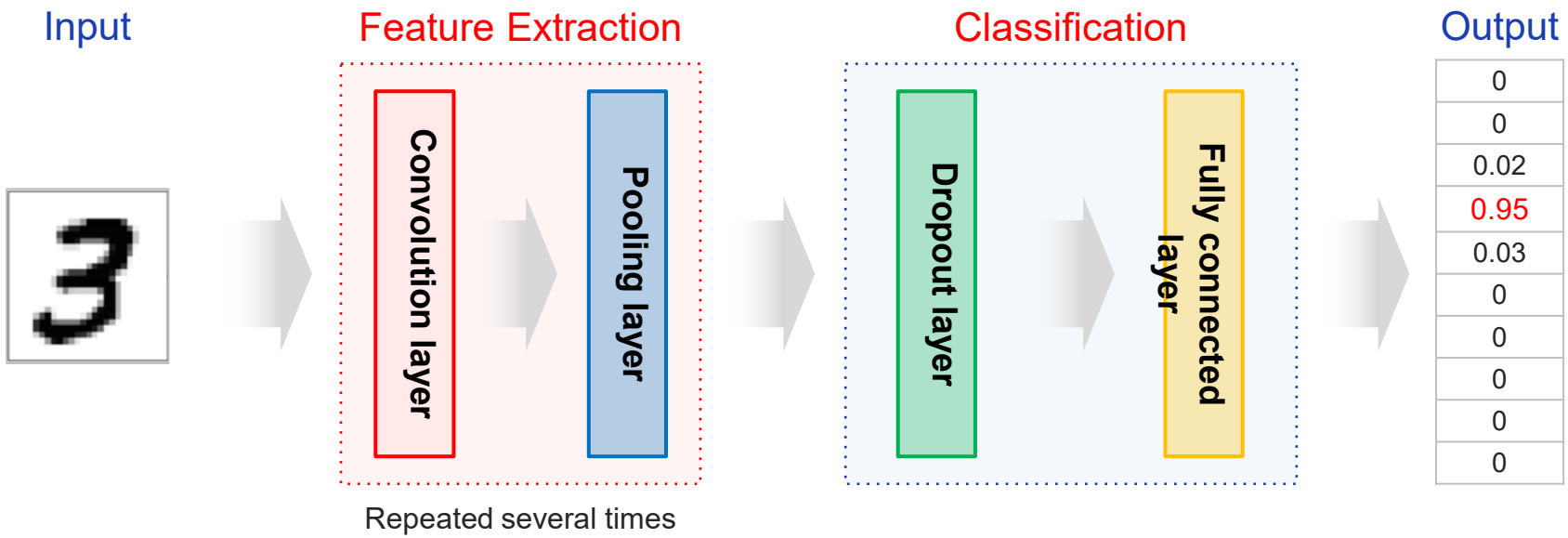
Softmax regression with Keras:

- Testing

```
In [131]: ACC = my_model.evaluate(X_test, y_test, verbose=0)[1]
          print("Test Accuracy : {}".format(np.round(ACC,3)))

          Test Accuracy : 0.956
```

Diagram of a Convolutional Neural Network (CNN):

- The convolution and pooling layers are repeated several times.
- There is a fully connected layer just before the output.



Read in the data

In [132]:
```
import numpy as np
import matplotlib.pyplot as plt
import warnings
from sklearn.model_selection import train_test_split
from keras.datasets.mnist import load_data
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Dropout, Flatten, MaxPooling2D

from keras.optimizers import Adam, RMSprop, SGD
warnings.filterwarnings('ignore')                    # Turn the warnings off.
%matplotlib inline
```

Read in the data

- Bring in the data

```
In [133]: (X_train, y_train), (X_test, y_test) = load_data()
          n_train_size = X_train.shape[0]
```

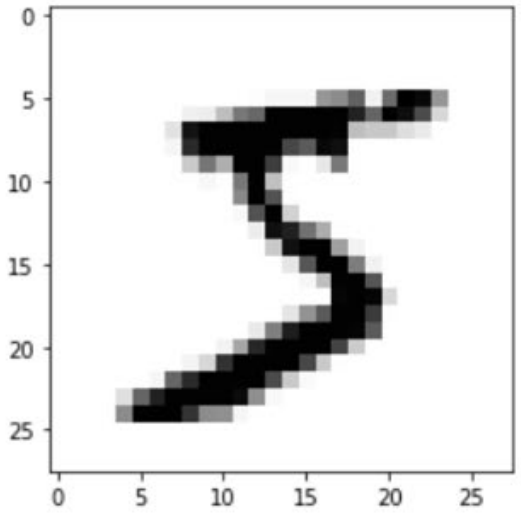
- View the shapes.

```
In [134]: print("-"*50)
          print("Training data X shape: {}".format(X_train.shape))
          print("Training data y shape: {}".format(y_train.shape))
          print("-"*50)
          print("Test data X shape: {}".format(X_test.shape))
          print("Test data y shape: {}".format(y_test.shape))
          print("-"*50)

          --------------------------------------------------
          Training data X shape: (60000, 28, 28)
          Training data y shape: (60000,)
          --------------------------------------------------
          Test data X shape: (10000, 28, 28)
          Test data y shape: (10000,)
          --------------------------------------------------
```

Visualize the data:

In [135]:

```
1 i_image = 0
2 plt.imshow(X_train[i_image,:,:],cmap="Greys")
3 plt.show()
```



Line 135-1

- You may change this at will.

Prepare the data:

- Scaling

```
In [136]: X_train = X_train/255
          X_test = X_test/255
```

- Reshaping

```
In [137]: X_train = X_train.reshape(-1,28,28,1)
          X_test = X_test.reshape(-1,28,28,1)
```

Prepare the data:

- One-hot-encoding.

```
In [139]: y = np.concatenate([y_train,y_test],axis=0)
          y = tf.keras.utils.to_categorical(y,10)
          y_train = y[:n_train_size,:]
          y_test = y[n_train_size:,:]
```

Define a CNN model

In [140]:

```
1  drop_prob = 0.5
2  my_model = Sequential()
3  # 1st convolution + pooling.
4  my_model.add(Conv2D(input_shape=(28,28,1),filters=32,kernel_size=(5,5),padding='same',activation="relu"))
5  my_model.add(MaxPooling2D(pool_size=2))
6  # 2nd convolution + pooling.
7  my_model.add(Conv2D(filters=64,kernel_size=(5,5), padding='same',activation="relu"))
8  my_model.add(MaxPooling2D(pool_size=2))
9  # Flattened fully connected layer.
10 my_model.add(Flatten())
11 my_model.add(Dense(units = 1024, activation="relu"))
12 # Apply dropout.
13 my_model.add(Dropout(rate=drop_prob))
14 # Output layer.
15 my_model.add(Dense(units = 10, activation="softmax"))
```

Line 140-1

- 1 channel of grayscale.

Define a CNN model

- View the summary

```
In [141]: my_model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 28, 28, 32)        832
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 14, 14, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 14, 14, 64)        51264
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 7, 7, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 3136)              0
_________________________________________________________________
dense_3 (Dense)              (None, 1024)              3212288
_________________________________________________________________
dropout (Dropout)            (None, 1024)              0
_________________________________________________________________
dense_4 (Dense)              (None, 10)                10250
=================================================================
Total params: 3,274,634
Trainable params: 3,274,634
Non-trainable params: 0
```

Define the hyperparameters and optimizer

In [142]:
```
n_epochs = 10
batch_size = 200
learn_rate = 0.001
```

In [143]:
```
my_optimizer=Adam(lr=learn_rate)
my_model.compile(loss = "categorical_crossentropy", optimizer = my_optimizer, metrics=["accuracy"])
```

Train the model and visualize the history:

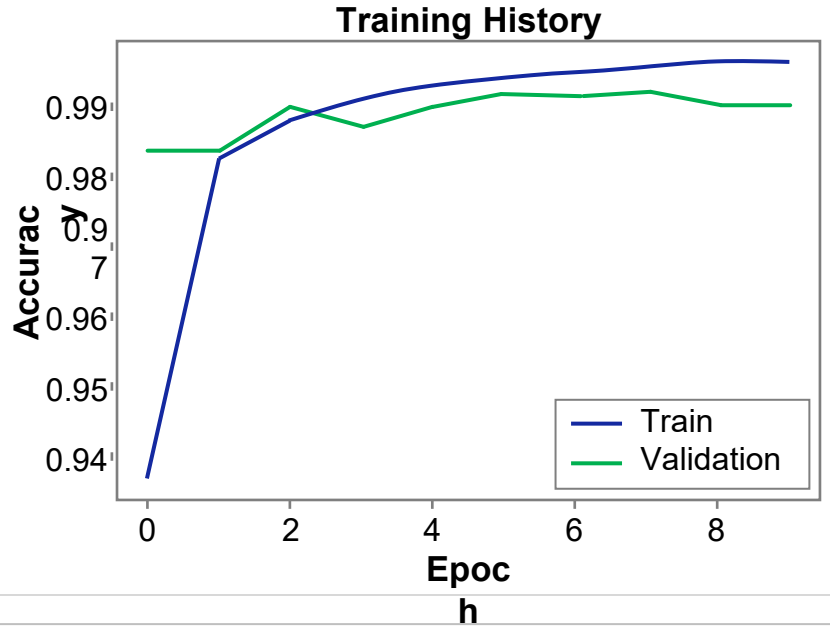
```
In [144]: my_summary = my_model.fit(X_train, y_train, epochs=n_epochs, batch_size = batch_size, validation_split = 0.2, verbose = 1)

          Epoch 1/10
          240/240 [==============================] - 42s 162ms/step - loss: 0.4622 - accuracy: 0.8538 - val_loss: 0.0525 - val_accur
          acy: 0.9837
          Epoch 2/10
          240/240 [==============================] - 39s 162ms/step - loss: 0.0607 - accuracy: 0.9819 - val_loss: 0.0533 - val_accur
          acy: 0.9835
          Epoch 3/10
          240/240 [==============================] - 39s 164ms/step - loss: 0.0419 - accuracy: 0.9873 - val_loss: 0.0360 - val_accur
          acy: 0.9893
          Epoch 4/10
          240/240 [==============================] - 39s 161ms/step - loss: 0.0296 - accuracy: 0.9908 - val_loss: 0.0441 - val_accur
          acy: 0.9872
          Epoch 5/10
          240/240 [==============================] - 39s 160ms/step - loss: 0.0233 - accuracy: 0.9923 - val_loss: 0.0349 - val_accur
```

Line 144

- verbose = 0 means no output. verbose = 1 to view the epochs.

Train the model and visualize the history:

In [145]:
```
n_skip = 0
plt.plot(my_summary.history['accuracy'][n_skip:], c="b")
plt.plot(my_summary.history['val_accuracy'][n_skip:], c="g")
plt.title('Training History')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='lower right')
plt.show()
```



Testing:

In [146]:
```
ACC = my_model.evaluate(X_test, y_test, verbose=0)[1]
print("Test Accuracy : {}".format(np.round(ACC,3)))
```

```
Test Accuracy : 0.992
```

Convolutional Neural Network with Keras (color images):

In [147]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import warnings
from sklearn.model_selection import train_test_split
from keras.datasets.cifar10 import load_data
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Dropout, Flatten, MaxPooling2D

from keras.optimizers import Adam, RMSprop, SGD
warnings.filterwarnings('ignore')                    # Turn the warnings off.
%matplotlib inline
```

Read in the data:

In [148]:
```
(X_train, y_train), (X_test, y_test) = load_data()
n_train_size = X_train.shape[0]
```

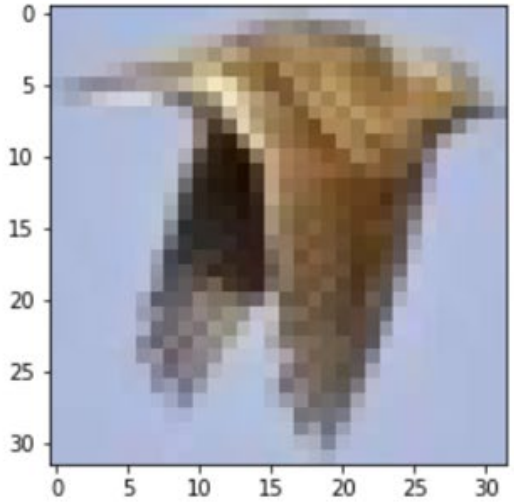
```
Downloading data from https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
170500096/170498071 [==============================] - 11s 0us/step
170508288/170498071 [==============================] - 11s 0us/step
```

In [149]:
```
print("-"*50)
print("Training data X shape: {}".format(X_train.shape))
print("Training data y shape: {}".format(y_train.shape))
print("-"*50)
print("Test data X shape: {}".format(X_test.shape))
print("Test data y shape: {}".format(y_test.shape))
print("-"*50)
```

```
--------------------------------------------------
Training data X shape: (50000, 32, 32, 3)
Training data y shape: (50000, 1)
--------------------------------------------------
Test data X shape: (10000, 32, 32, 3)
Test data y shape: (10000, 1)
```

Visualize the data:

In [150]:
```
i_image = 123                                    # You may change this at will.
plt.imshow(X_train[i_image,:,:])
plt.show()
```



Prepare the data

- Scaling

```
In [151]: X_train = X_train/255
          X_test = X_test/255
```

- Reshaping

```
In [152]: X_train = X_train.reshape(-1,32,32,3)
          X_test = X_test.reshape(-1,32,32,3)
```

- One-hot-encoding

```
In [154]: y = np.concatenate([y_train,y_test],axis=0)
          y = tf.keras.utils.to_categorical(y,10)
          y_train = y[:n_train_size,:]
          y_test = y[n_train_size:,:]
```

Define a CNN model

In [155]:
```
drop_prob = 0.7
my_model = Sequential()
# 1st convolution + pooling.
my_model.add(Conv2D(input_shape=(32,32,3),filters=32,kernel_size=(5,5),padding='same',activation="relu"))
my_model.add(MaxPooling2D(pool_size=2))
# 2nd convolution + pooling.
my_model.add(Conv2D(filters=64,kernel_size=(5,5), padding='same',activation="relu"))
my_model.add(MaxPooling2D(pool_size=2))
# Flattened fully connected layer.
my_model.add(Flatten())
my_model.add(Dense(units = 1024, activation="relu"))
# Apply dropout.
my_model.add(Dropout(rate=drop_prob))
# Output layer.
my_model.add(Dense(units = 10, activation="softmax"))
```

Line 155

- 3 channels of color

Define a CNN model

```
In [156]: my_model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 32, 32, 32)        2432
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 64)        51264
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 8, 8, 64)          0
_________________________________________________________________
flatten_1 (Flatten)          (None, 4096)              0
_________________________________________________________________
dense_5 (Dense)              (None, 1024)              4195328
_________________________________________________________________
dropout_1 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_6 (Dense)              (None, 10)                10250
=================================================================
Total params: 4,259,274
Trainable params: 4,259,274
Non-trainable params: 0
```

Define the hyperparameters and optimizer:

In [157]:
```
n_epochs = 20
batch_size = 20
learn_rate = 0.0001
```

In [158]:
```
my_optimizer=Adam(lr=learn_rate)
my_model.compile(loss = "categorical_crossentropy", optimizer = my_optimizer, metrics=["accuracy"])
```

Train the model and visualize the history:

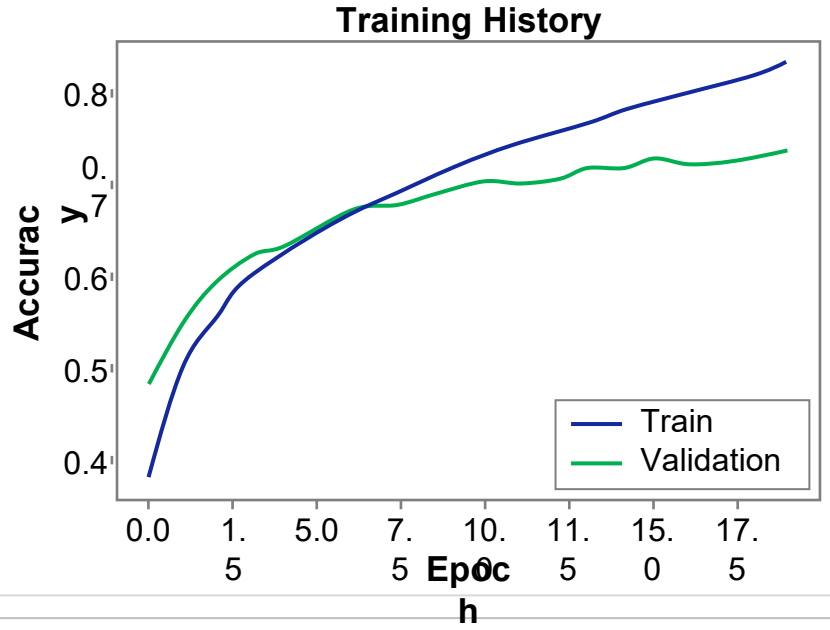
```
In [159]: my_summary = my_model.fit(X_train, y_train, epochs=n_epochs, batch_size = batch_size, validation_split = 0.3, verbose = 1)

          Epoch 1/20
          1750/1750 [==============================] - 78s 44ms/step - loss: 1.8939 - accuracy: 0.3080 - val_loss: 1.4602 - val_accu
          racy: 0.4831
          Epoch 2/20
          1750/1750 [==============================] - 75s 43ms/step - loss: 1.4393 - accuracy: 0.4840 - val_loss: 1.2612 - val_accu
          racy: 0.5509
          Epoch 3/20
          1750/1750 [==============================] - 75s 43ms/step - loss: 1.2723 - accuracy: 0.5427 - val_loss: 1.1496 - val_accu
          racy: 0.5935
          Epoch 4/20
          1750/1750 [==============================] - 76s 43ms/step - loss: 1.1506 - accuracy: 0.5904 - val_loss: 1.0775 - val_accu
          racy: 0.6227
          Epoch 5/20
          1750/1750 [==============================] - 75s 43ms/step - loss: 1.0781 - accuracy: 0.6181 - val_loss: 1.0373 - val_accu
          racy: 0.6330
```

Line 159

- verbose = 0 means no output. verbose = 1 to view the epochs.

Train the model and visualize the history:

In [160]:
```
n_skip = 0
plt.plot(my_summary.history['accuracy'][n_skip:], c="b")
plt.plot(my_summary.history['val_accuracy'][n_skip:], c="g")
plt.title('Training History')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Validation'], loc='lower right')
plt.show()
```

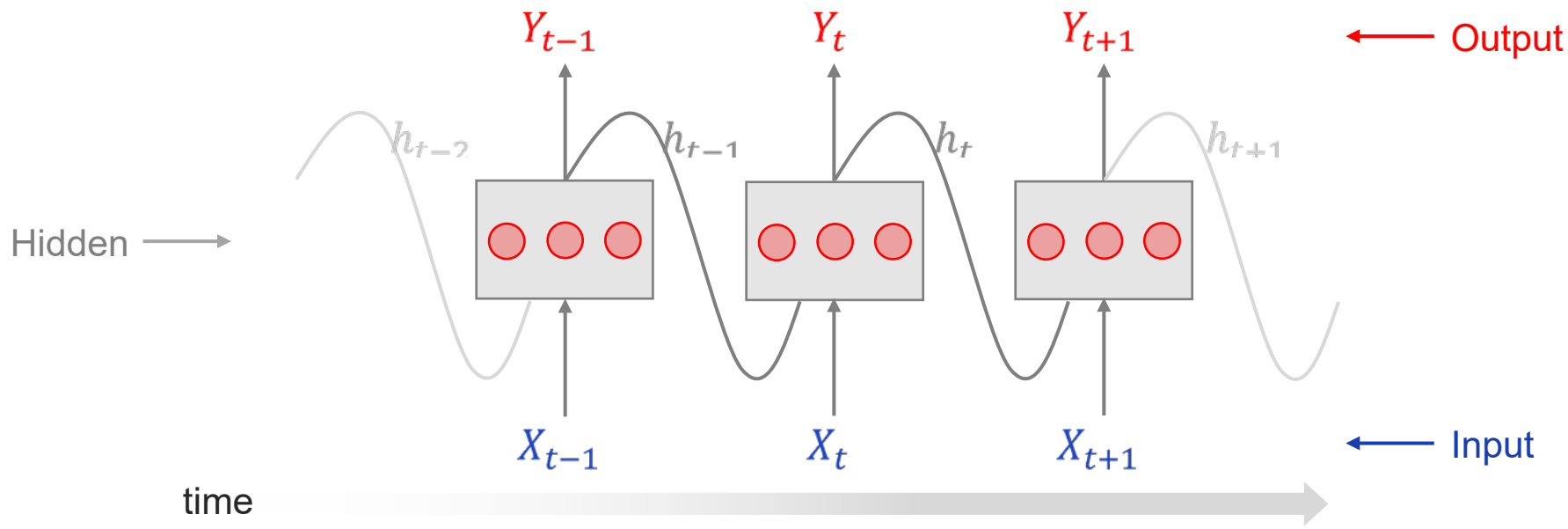


Testing:

In [161]:
```
ACC = my_model.evaluate(X_test, y_test, verbose=0)[1]
print("Test Accuracy : {}".format(np.round(ACC,3)))
```

```
Test Accuracy : 0.732
```

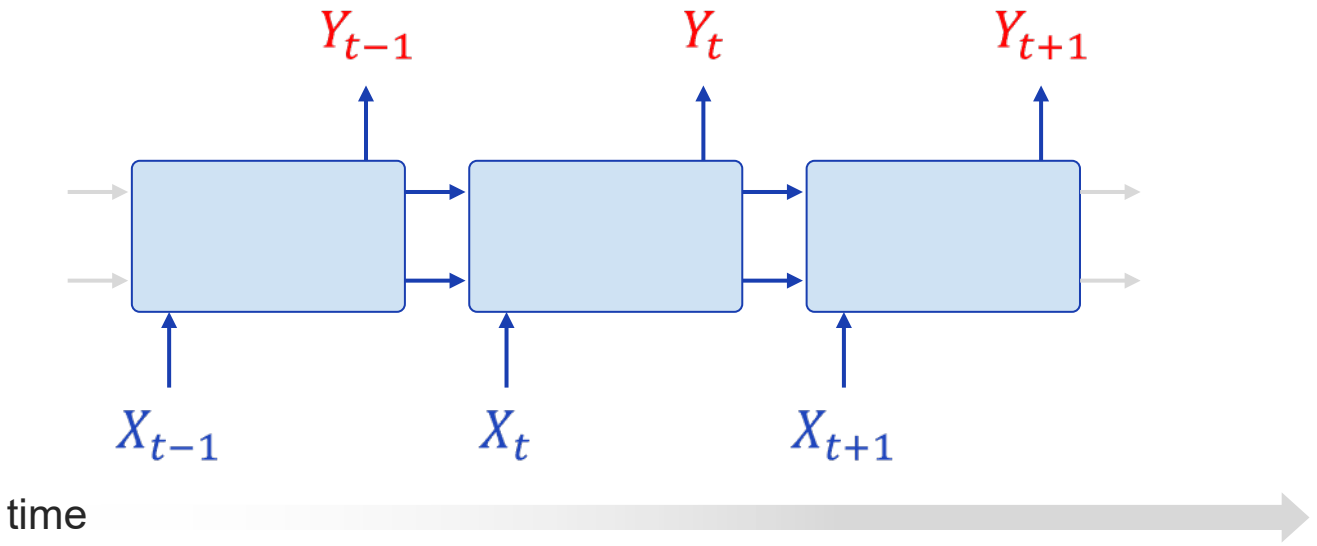
Recurrent Neural Network (RNN)



- This is a “Sequence in and Sequence out” model.

Long Short Term Memory (LSTM) network:

- LSTM cells can form a sequence just like the regular RNN cells.
- The following is a “Sequence in and Sequence out” model.



Read in the data and explore:

In [164]:
```
df = pd.read_csv('data_time_series.csv', header='infer',encoding = 'latin1')
n_time_steps = df.shape[0]
print(df.shape)
```

```
(41, 1)
```

- Display the dataframe

In [165]:
```
df.head()
```

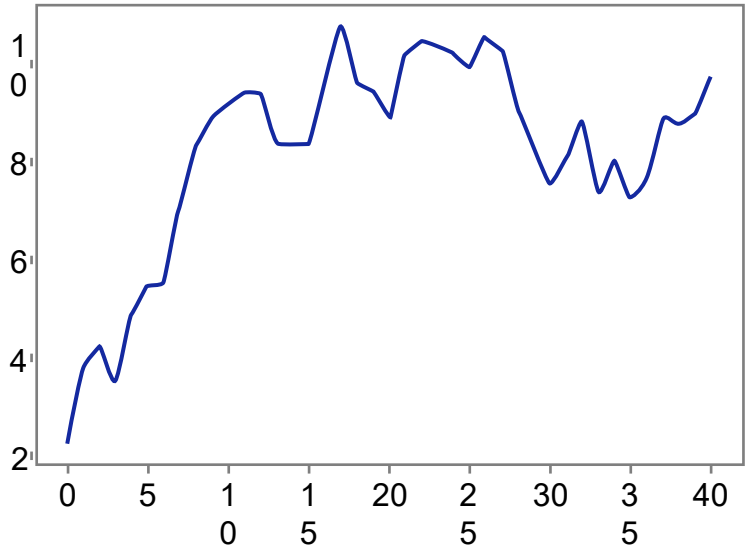
Out[165]:

	Value
0	2.26483
1	3.80588
2	4.21088
3	3.48790
4	4.86365

Read in the data and explore:

- Visualize the time series.

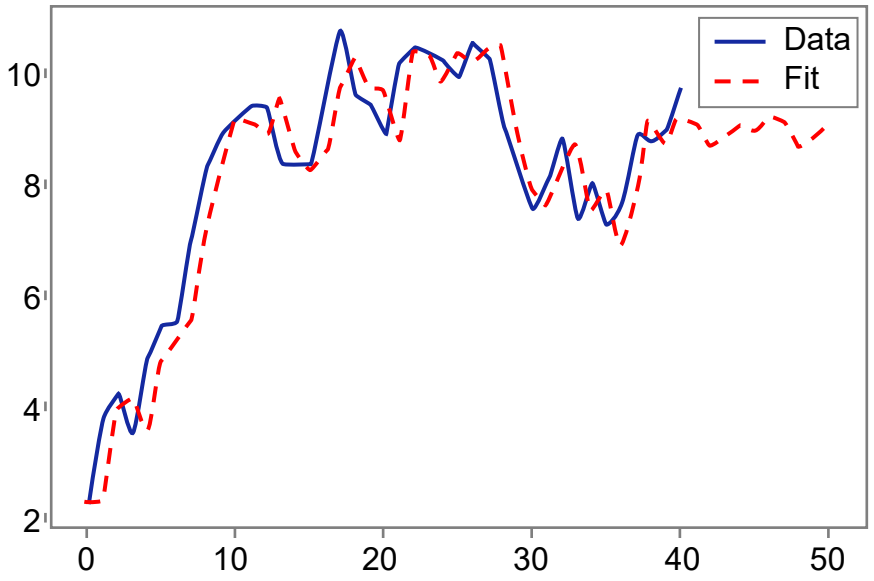
```
In [166]: plt.plot(df.Value, c="b", linewidth=2, linestyle="-")
          plt.show()
```



Read in the data and explore:

- Multiplicative exponential smoothing model.

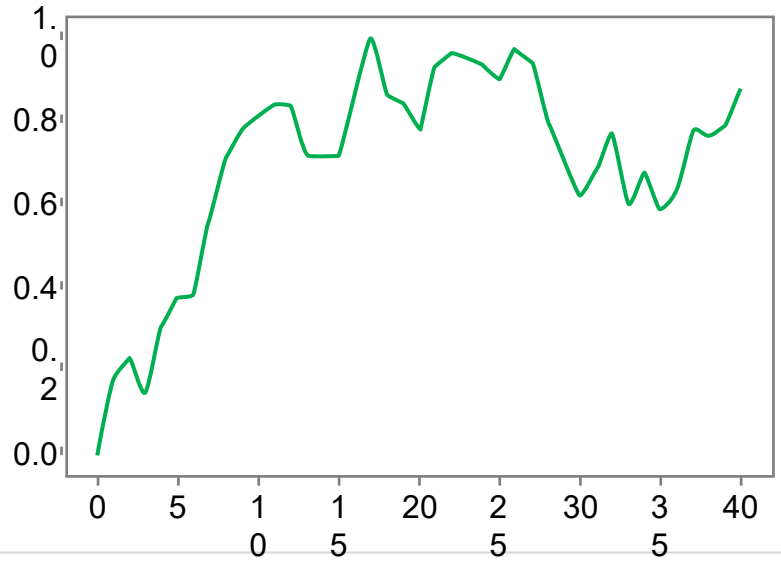
```
In [167]: model = ExponentialSmoothing(df['Value'][0:40], seasonal='mul',seasonal_periods=6).fit()
          pred = model.predict(start= 0, end=50)
          plt.plot(df,c='b',linewidth=2, linestyle="-", label="Data")
          plt.plot(pred,c='r',linewidth=2, linestyle="--", label="Fit")
          plt.legend()
          plt.tight_layout()
          plt.show()
```



Recurrent neural network (RNN):

- Pre-processing:
- Scaling (please pay attention to the vertical scale of the plot)

```
In [168]: scaler = MinMaxScaler()
          ts_scaled = scaler.fit_transform(df)
          plt.plot(ts_scaled,c = "g", linewidth=2, linestyle="-")
          plt.show()
```



Recurrent neural network (RNN):

- Reshaping (batch_size, time series length, n_input)

```
In [169]: ts_scaled_2 = ts_scaled.reshape(1,-1,1)
```

Do the necessary definitions:

- Hyperparameters

In [170]:
```
1 n_epochs = 1001
2 batch_size = 1
3 learn_rate = 0.0002
```

Line 170-2

- There is only 1 time series data. No other choice but 1

Do the necessary definitions:

- Hyperparameters

In [171]:
```
1 n_input = 1
2 n_neurons = 100
3 n_output = 1
```

Line 171-1

- Scalar input

Line 171-2

- N# of neurons per layer

Line 171-3

- Scalar output

Recurrent neural network (RNN):

- RNN or LSTM network

```
In [172]: my_model = Sequential()
          my_model.add(SimpleRNN(units=n_neurons,return_sequences=True, input_shape=(None, n_input)))      # RNN.
                                                                                                          # LSTM.
          my_model.add(TimeDistributed(Dense(units=n_output, activation="linear")))     # I
```

Line 172

- Return sequences = True: means “Sequence to Sequence”.
- Input shape = (None, n inputs) : variable length of the time series.

Recurrent neural network (RNN):

- View the summary.

```
In [173]: my_model.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn (SimpleRNN)       (None, None, 100)         10200
_________________________________________________________________
time_distributed (TimeDistri (None, None, 1)           101
=================================================================
Total params: 10,301
Trainable params: 10,301
Non-trainable params: 0
```

Recurrent neural network (RNN):

- Define the optimizer and compile

```
In [174]: my_optimizer=Adam(lr=learn_rate)
          my_model.compile(loss = "mse", optimizer = my_optimizer, metrics=["mse"])
```

Recurrent neural network (RNN):

- Train the model:

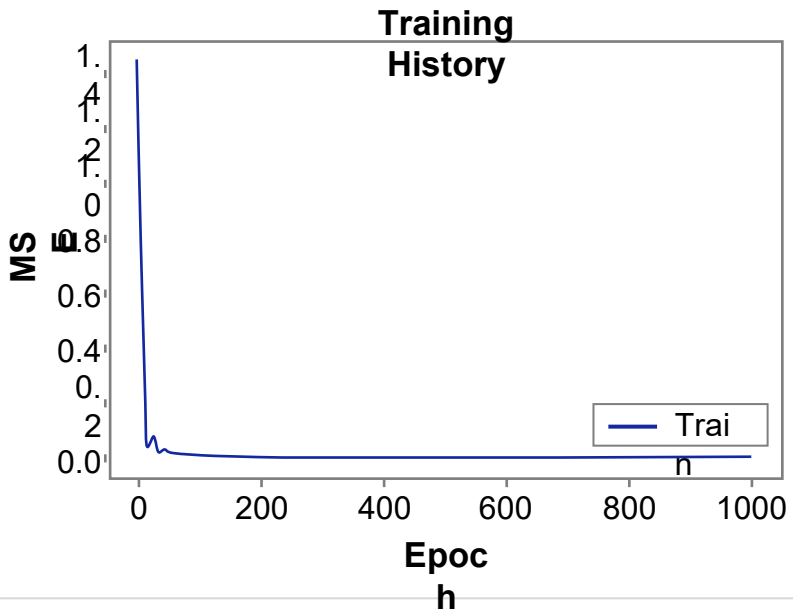
```
In [176]: my_summary = my_model.fit(ts_scaled_2[:,:-1,:], ts_scaled_2[:,1:,:], epochs=n_epochs,
                                    batch_size = batch_size, verbose = 0)

In [177]: my_summary.history.keys()

Out[177]: dict_keys(['loss', 'mse'])
```

Line 176

- No validation.
- CAUTION: y is X shifted by +1

Recurrent neural network (RNN):

```
In [178]: plt.plot(my_summary.history['mse'], c="b")
          plt.title('Training History')
          plt.ylabel('MSE')
          plt.xlabel('Epoch')
          plt.legend(['Train'], loc='lower right')
          plt.show()
```



Recurrent neural network (RNN):

- Predict the future

```
In [180]:
1 n_ts_seed = 5
2 n_predict_time_steps = 55
```

Line 180-1

- Seed length

Line 180-2

- Prediction length

Recurrent neural network (RNN):

- Prediction loop

In [181]:

```
1 ts_seed = ts_scaled[0:n_ts_seed]
2 for i in range(n_predict_time_steps):
3     X = ts_seed.reshape(1,-1,1)
4     y_pred = my_model.predict(X)
5     y_last= y_pred[0,-1,0]
6     ts_seed = np.concatenate((ts_seed, np.array([y_last]).reshape(1,1)), axis=0)
```

Line 181-3

- Reshape

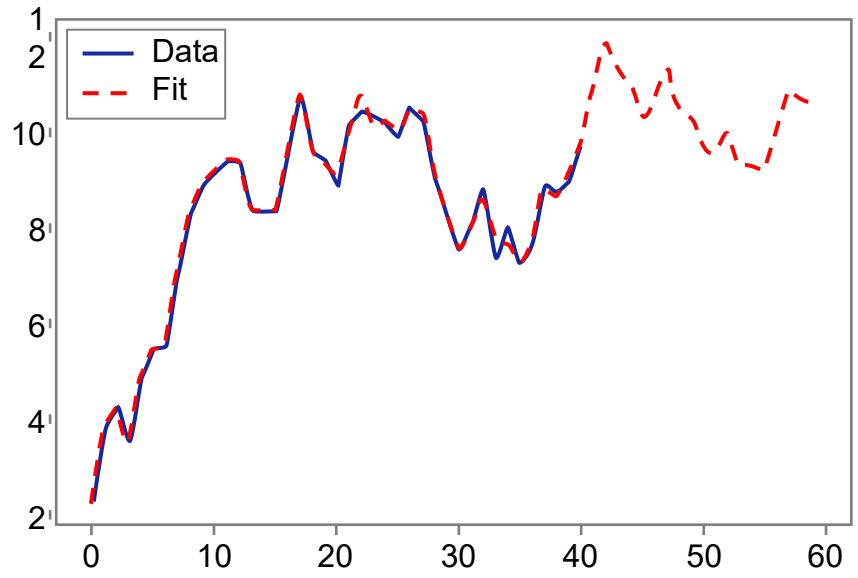
Line 181-5

- The last output is the predicted y

Recurrent neural network (RNN):

- Do the inverse transform and show the times series.

```
In [182]: ts = scaler.inverse_transform(ts_seed)
          plt.plot(df.Value,c='b',linewidth=2, linestyle="-",label="Data")
          plt.plot(ts,c='r',linewidth=2, linestyle="--",label="Fit")
          plt.legend()
          plt.tight_layout()
          plt.savefig("out.png")
          plt.show()
```



Coding Exercise #0601

Follow practice steps on ‘ex_0601.ipynb' file

Coding Exercise #0602

Follow practice steps on ‘ex_0602.ipynb' file

Coding Exercise #0603

Follow practice steps on ‘ex_0603.ipynb' file

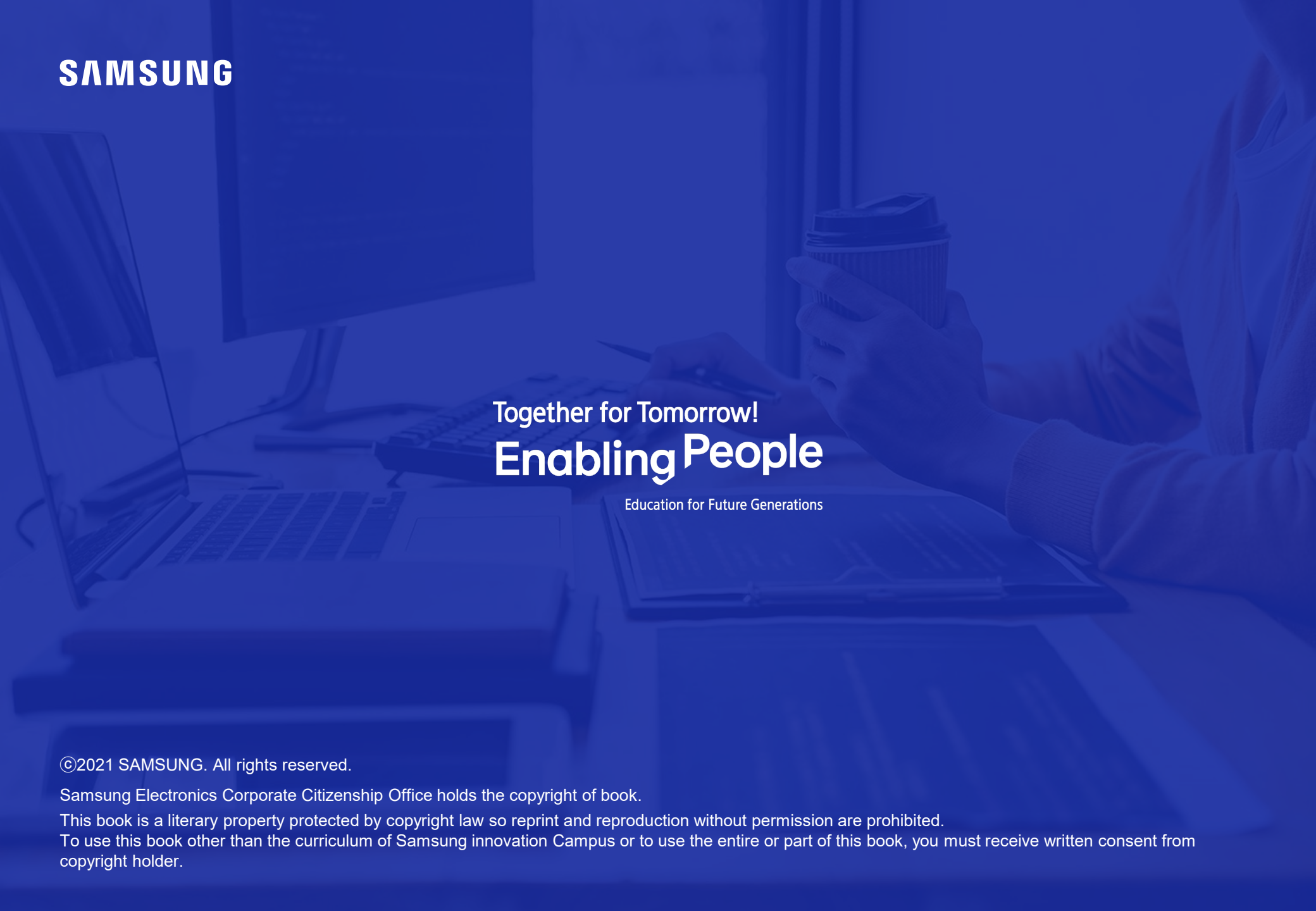
Coding Exercise #0604

Follow practice steps on ‘ex_0604.ipynb' file

Coding Exercise #0605

Follow practice steps on ‘ex_0605.ipynb' file


End of
Document



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