

# COMP7035

## Python for Data Analytics and Artificial Intelligence

### Keras

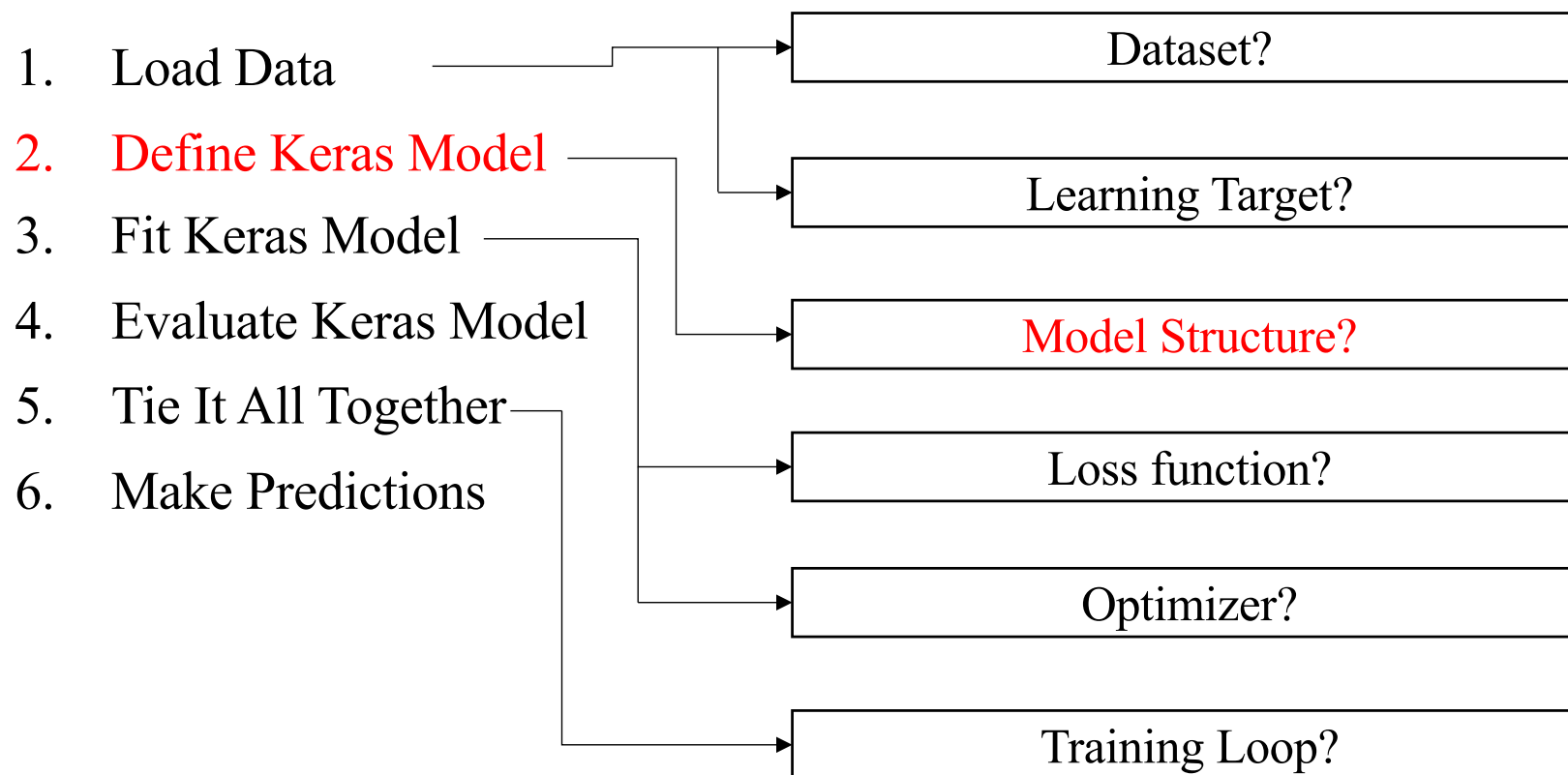
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12/03/2024

# What we will learn?

<u>Topic</u>	<u>Hours</u>
I. Python Fundamentals	12
A. Program control and logic	
B. Data types and structures	
C. Function	
D. File I/O	
II. Numerical Computing and Data Visualization	9
Tools and libraries such as	
A. NumPy	
B. Matplotlib	
C. Seaborn	
III. Exploratory Data Analysis (EDA) with Python	9
Tools and libraries such as	
A. Pandas	
B. Sweetviz	
IV. Artificial Intelligence and Machine Learning with Python	9
Tools and libraries such as	
A. Scikit-learn	
B. <b>Keras</b>	

# Key Components of Keras Pipeline



# Define Keras Model

## Keras Layers

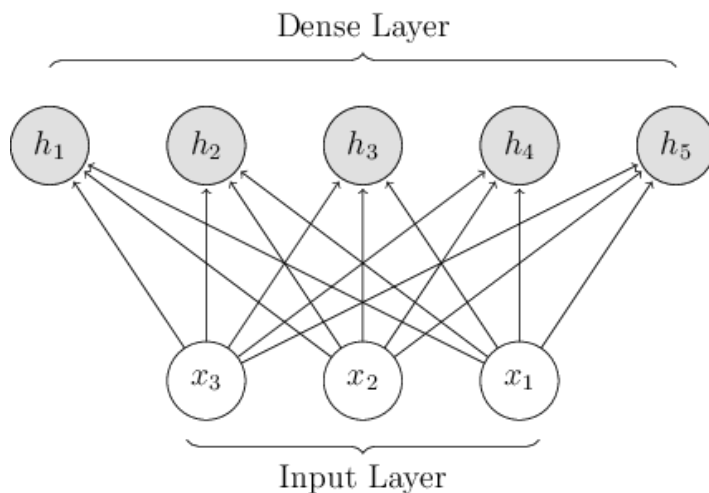
A DNN is built from many different types of layers, which mainly include

- **Linear layers (Dense)**
- RNN layers
- CNN layers

# Define Keras Model

Keras Layers

- Linear layers (Dense)
- RNN layers
- CNN layers



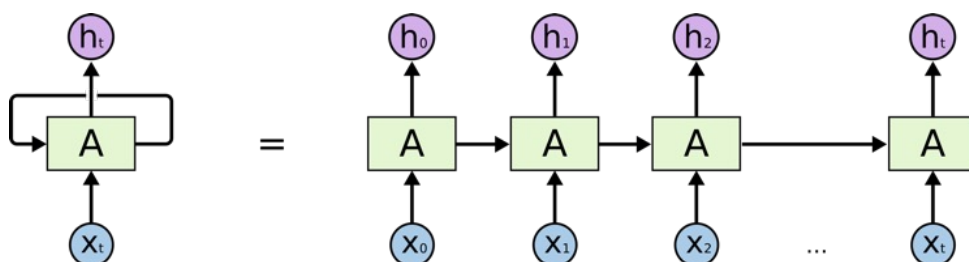
```
Dense( units, activation=None,  
       use_bias=True,  
       kernel_initializer="glorot_uniform",  
       bias_initializer="zeros",  
       kernel_regularizer=None,  
       bias_regularizer=None,  
       activity_regularizer=None,  
       kernel_constraint=None,  
       bias_constraint=None, **kwargs )
```

You can also specify the input dimension as introduced before

# Define Keras Model

## Keras Layers

- Linear layers (Dense)
- **RNN layers**
- CNN layers

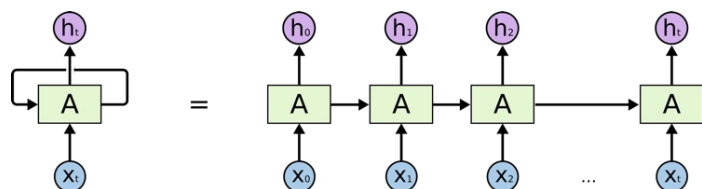


- RNN layers takes the sequence as input and output a new sequence.
- Mainly used to model sequential data (speech, stock price, etc)
- The most used RNN is LSTM (Long Short-Term Memory).

```
LSTM(units, activation="tanh",
      recurrent_activation="sigmoid",
      use_bias=True,
      kernel_initializer="glorot_uniform",
      recurrent_initializer="orthogonal",
      bias_initializer="zeros",
      unit_forget_bias=True,
      kernel_regularizer=None,
      recurrent_regularizer=None,
      bias_regularizer=None,
      activity_regularizer=None,
      kernel_constraint=None,
      recurrent_constraint=None,
      bias_constraint=None, dropout=0.0,
      recurrent_dropout=0.0,
      return_sequences=False, return_state=False,
      go_backwards=False, stateful=False,
      time_major=False, unroll=False, **kwargs )
```

# Define Keras Model

## Keras Layers



```
# Define the model using functional API:
from keras.layers import Dense, LSTM
import keras
import numpy as np
```

```
x = keras.backend.constant(np.random.randn(1, 100, 128))
lstm_layer1 = LSTM(512, return_sequences=True)
lstm_layer2 = LSTM(512, return_sequences=False)
y1 = lstm_layer1(x)
y2 = lstm_layer2(x)
```

```
for ii in [x, y1, y2]:
    print(ii.shape)
```

- Linear layers (Dense)
- **RNN layers**
- CNN layers

Run the codes, check, and understand the dimensions of different tensors.  
The first dimension of x is batch size, which will be studied later.

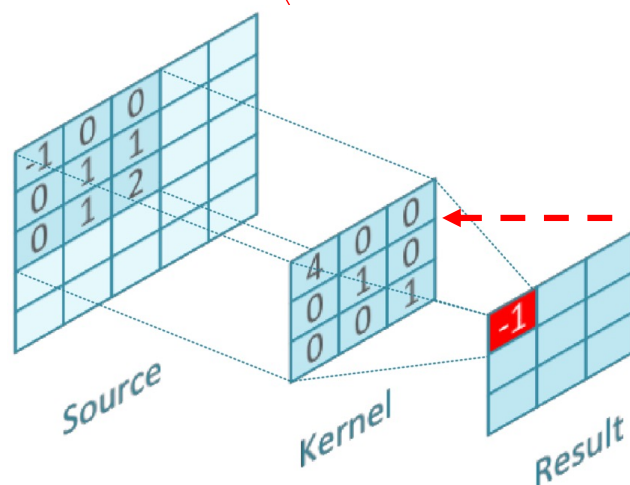
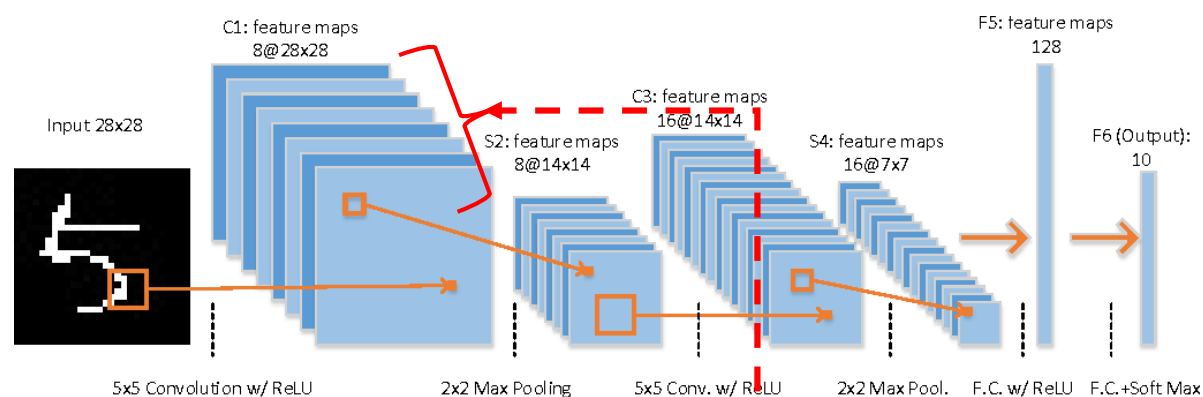
```
(1, 100, 128)
(1, 100, 512)
(1, 512)
```

# Define Keras Model

## Keras Layers

- Linear layers (Dense)
- RNN layers
- **CNN layers**

## 2D convolution



- Filters (how many do we generate)
- filter size (how large do we compute)
- Strides (how far do we move)

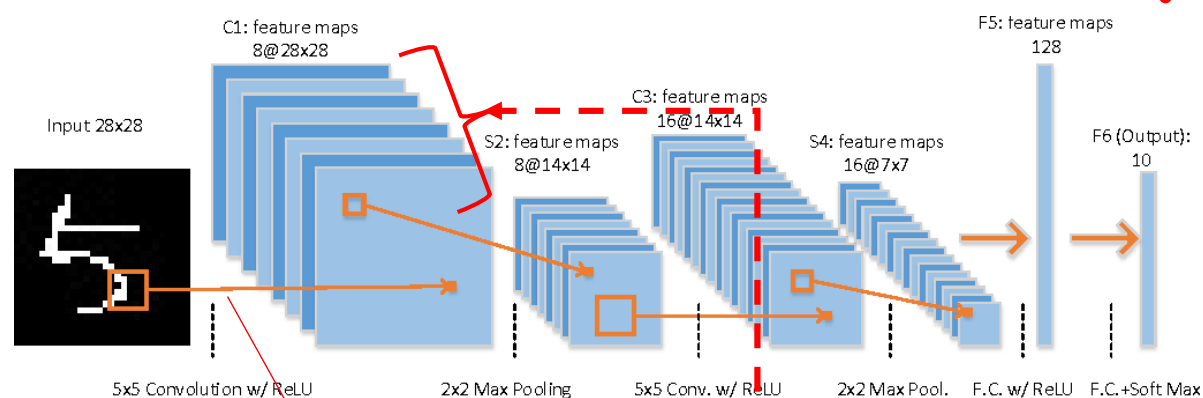


# Define Keras Model

## Keras Layers

- Linear layers (Dense)
- RNN layers
- **CNN layers**

## 2D convolution



## Strided convolution

$$\begin{bmatrix} 2 & 3 & 4 & 7 & 4 & 6 & 2 & 9 \\ 6 & 1 & 6 & 0 & 9 & 2 & 8 & 7 & 4 & 3 \\ 3 & 1 & 4 & 0 & 8 & 3 & 3 & 8 & 9 & 7 \\ 7 & 8 & 3 & 6 & 6 & 3 & 3 & 4 & & \\ 4 & 2 & 1 & 8 & 3 & 4 & 6 & & & \\ 3 & 2 & 4 & 1 & 9 & 8 & 3 & & & \\ 0 & 1 & 3 & 9 & 2 & 1 & 4 & & & \end{bmatrix} \begin{matrix} 7 \times 7 \\ \text{stride} = 2 \end{matrix} * \begin{bmatrix} 3 & 4 & 4 \\ 1 & 0 & 2 \\ -1 & 0 & 3 \end{bmatrix} \begin{matrix} 3 \times 3 \\ \text{filter size} \end{matrix} = \begin{bmatrix} 91 & & \\ & & \\ & & \end{bmatrix}$$

- Filters (how many do we generate)
- filter size (how large do we compute)
- Strides (how far do we move)

# Define Keras Model

## Keras Layers

```
# Define the model using functional API:
from keras.layers import Dense, Conv2D
import keras
import numpy as np

x = keras.backend.constant(np.random.randn(16, 28,
28, 1))
n_filter = 16
filter_size = 2
cnn_layer1 = Conv2D(n_filter, filter_size, input_shape=(28, 28, 1))
y1 = cnn_layer1(x)

n_filter = 32
filter_size = 4
cnn_layer2 = Conv2D(n_filter, filter_size, input_shape=(28, 28, 1))
y2 = cnn_layer2(x)

for ii in [x, y1, y2]:
    print(ii.shape)
```

- Linear layers (Dense)
- RNN layers
- CNN layers

## 2D convolution

```
tf.keras.layers.Conv2D(
    filters, kernel_size,
    strides=(1, 1),
    padding="valid",
    data_format=None,
    dilation_rate=(1, 1),
    groups=1, activation=None,
    use_bias=True,
    kernel_initializer="glorot_uniform",
    bias_initializer="zeros",
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None, **kwargs
```

# Define Keras Model

## Keras Layers

```
# Define the model using functional API:
from keras.layers import Dense, Conv2D
import keras
import numpy as np
```

```
x = keras.backend.constant(np.random.randn(16, 28,
28, 1))
n_filter = 16
filter_size = 2
cnn_layer1 = Conv2D(n_filter, filter_size, input_shape=(28, 28, 1))
y1 = cnn_layer1(x)
```

When using this layer as the first layer in a model, provide the keyword argument `input_shape`

```
n_filter = 32
filter_size = 4
cnn_layer2 = Conv2D(n_filter, filter_size, input_shape=(28, 28, 1))
y2 = cnn_layer2(x)
```

```
for ii in [x, y1, y2]:
    print(ii.shape)
```

- Linear layers (Dense)
- RNN layers
- CNN layers

## 2D convolution

```
tf.keras.layers.Conv2D(
    filters, kernel_size,
    strides=(1, 1),
    padding="valid",
    data_format=None,
    dilation_rate=(1, 1),
    groups=1, activation=None,
    use_bias=True,
    kernel_initializer="glorot_uniform",
    bias_initializer="zeros",
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None, **kwargs
```

# Define Keras Model

## Keras Layers

MaxPooling2D(pool\_size)

Max Pooling

29	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2  
pool size

100	184
12	45

Average Pooling

31	15	28	184
0	100	70	38
12	12	7	2
12	12	45	6

2 x 2  
pool size

36	80
12	15

- Linear layers (Dense)
- RNN layers
- **CNN layers**

## Pooling

```
# Define the model using functional API:
from keras.layers import Dense, Conv2D, MaxPool2D
import keras
import numpy as np

x = keras.backend.constant(np.random.randn(16, 28, 28, 1))

n_filter = 32
filter_size = 4
cnn_layer2 = Conv2D(n_filter, filter_size, input_shape=(
    28, 28, 1))
y1 = cnn_layer2(x)
pooling_layer = MaxPool2D(2)
y2 = pooling_layer(y1)

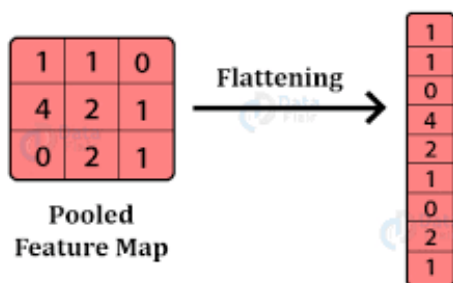
for ii in [x, y1, y2]:
    print(ii.shape)
```

```
(16, 28, 28, 1)
(16, 25, 25, 32)
(16, 12, 12, 32)
```

# Define Keras Model

## Other Common Keras Operations

### Flatten Layer in Keras



`Flatten()`

```
(16, 28, 28, 1)
(16, 784)
(16, 25, 25, 32)
(16, 20000)
```

# Define the model using functional API:

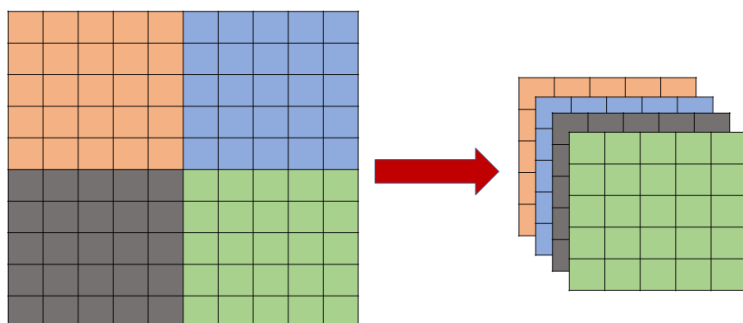
```
from keras.layers import Flatten, Reshape
from keras.models import Sequential
import keras
import numpy as np
```

```
x = keras.backend.constant(np.random.randn(16, 28, 28, 1))
y = Flatten()(x)
n_filter = 32
filter_size = 4
conv_layer = Conv2D(n_filter, filter_size, input_shape=(28, 28, 1))
z = conv_layer(x)
model = Sequential([conv_layer, Flatten()])
w = model(x)
```

```
for i in [x, y, z, w]:
    print(i.shape)
```

# Define Keras Model

## Other Common Keras Operations



`Reshape(target_shape)`

```
# Define the model using functional API:
from keras.layers import Flatten, Reshape
from keras.models import Sequential
import keras
import numpy as np
```

```
x = keras.backend.constant(np.random.randn(16, 28, 28, 1))
```

```
y = Reshape((14, 14, -1))(x)
```

```
print(y.shape)
```

```
y = Reshape((-1, 1))(x)
```

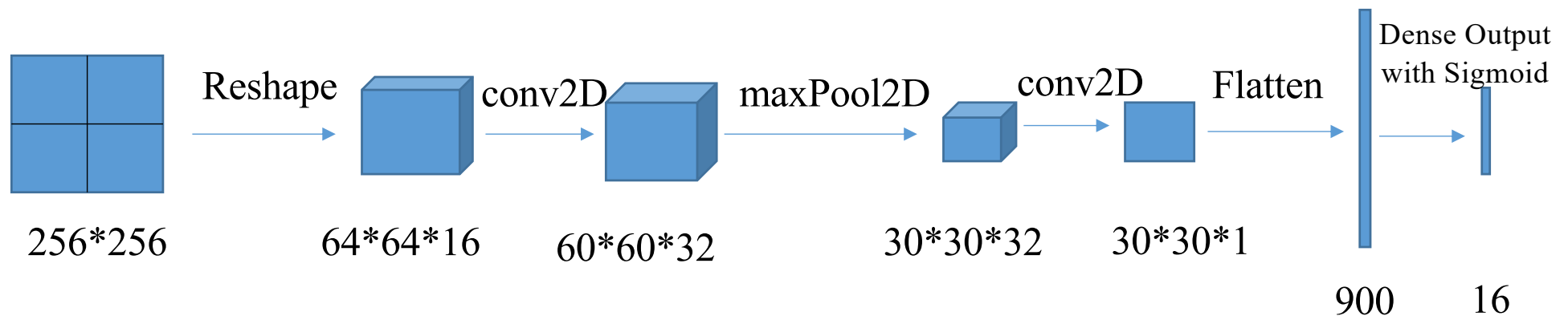
```
print(y.shape)
```

```
(16, 14, 14, 4)
```

```
(16, 784, 1)
```

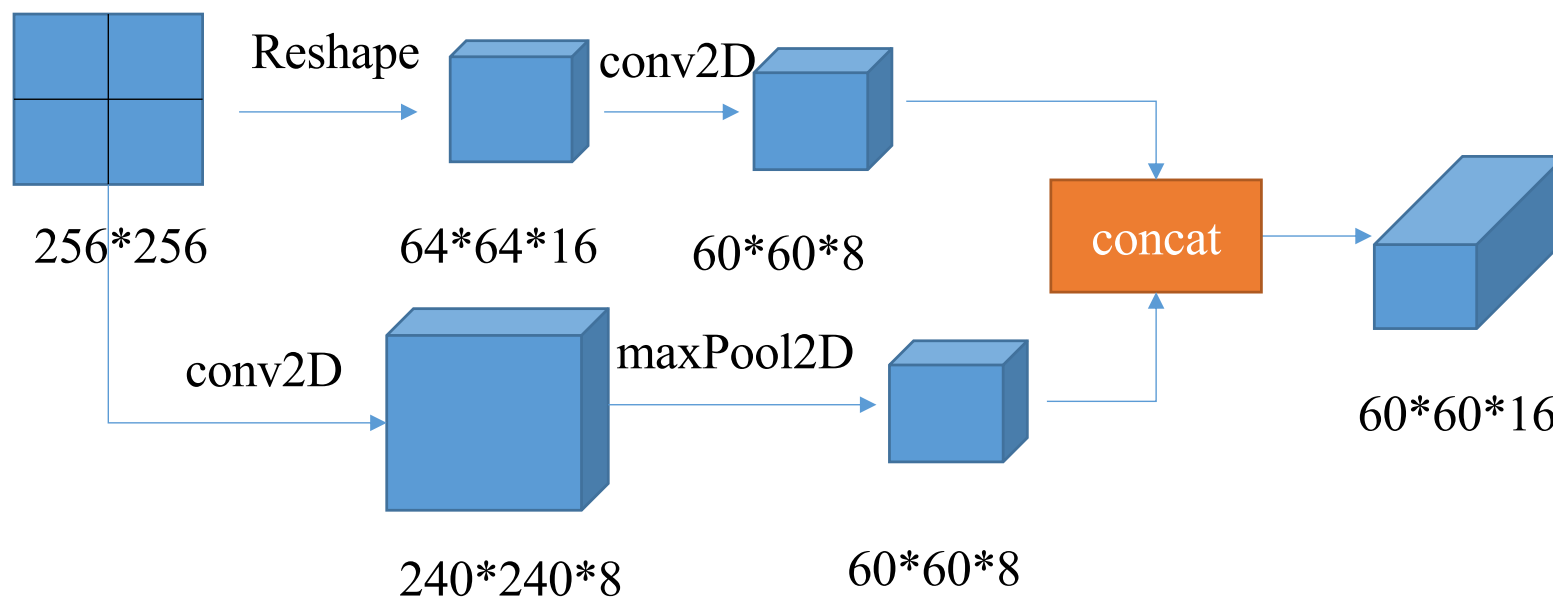
# Exercise

1. Define the following model using Sequential API. Assuming padding is not used.



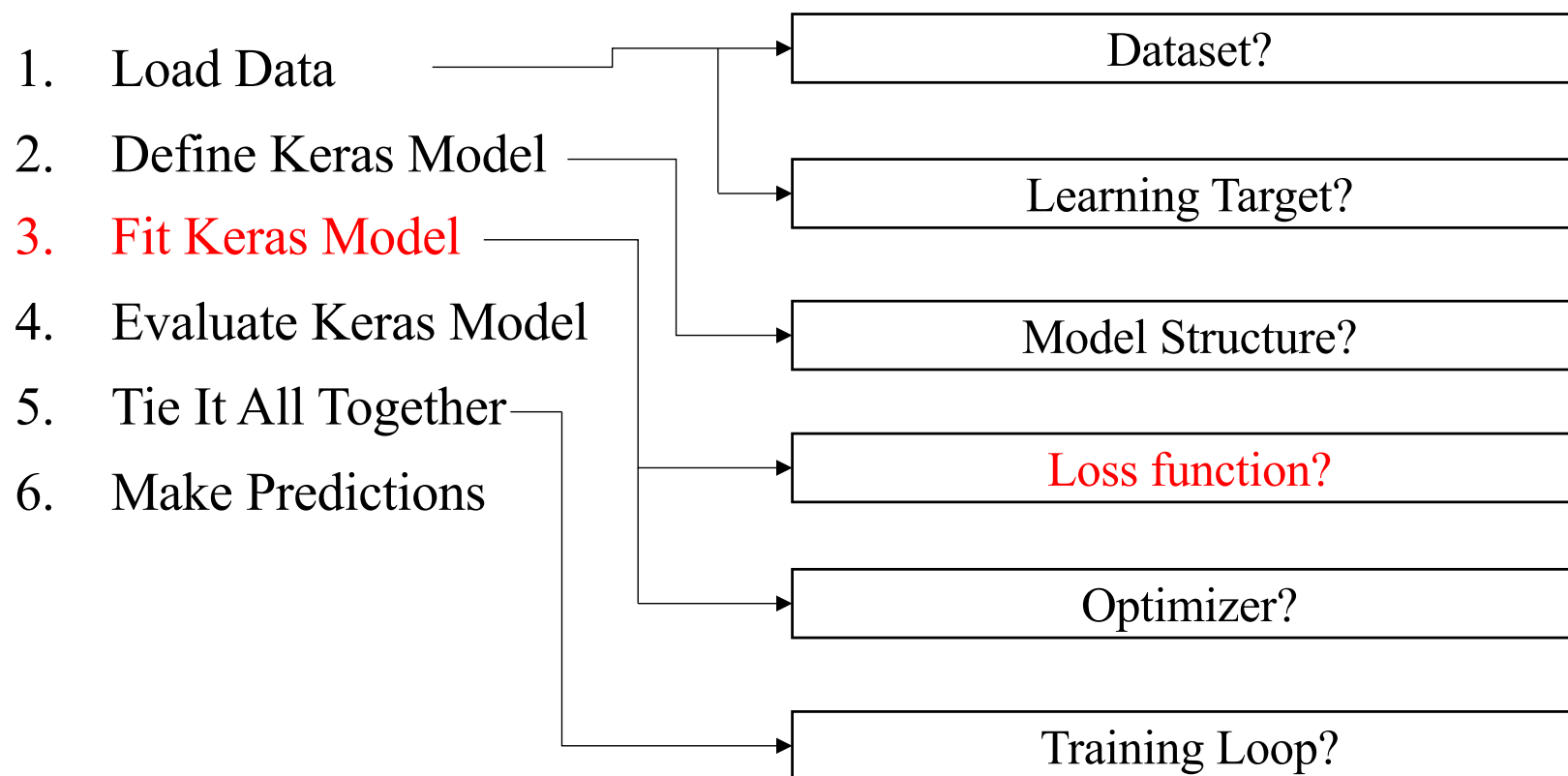
# Exercise

1. Define the following model using Sequential API. Assuming padding is not used.
2. Define the following model using Functional API.



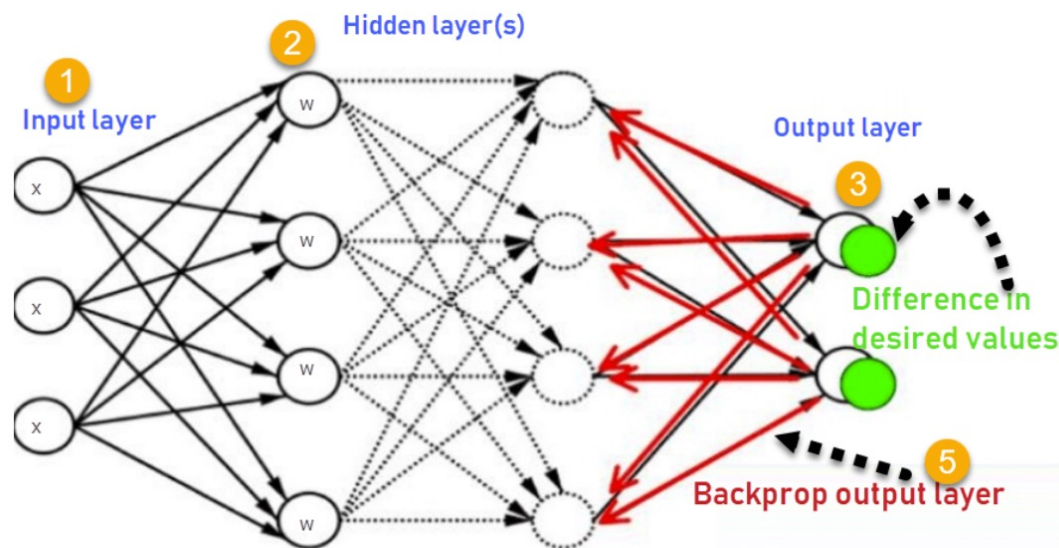


# Key Components of Keras Pipeline



# Loss Function

The DNN model is optimized through a feedback backpropagation (BP). The loss function is used to judge **how well the model can approximate the desired output**.



Types of loss functions

- Regression Loss Functions
- Classification Loss Functions
- Probabilistic Loss Functions
- Custom Loss Functions

# Loss Function

## Regression Loss Functions

- **Mean Squared Error (MSE)**

```
import keras
from keras.losses import MeanAbsoluteError, MeanSquaredError
mse = MeanSquaredError()
y_true = [[0., 0.3], [0., 1.]]
y_pred = [[1., 1.], [1., 0.]]
z = mse(y_true, y_pred)
print(z)
print(z.numpy())
```

# Loss Function

## Classification Loss Functions

- Categorical Cross-Entropy**

CROSS-ENTROPY

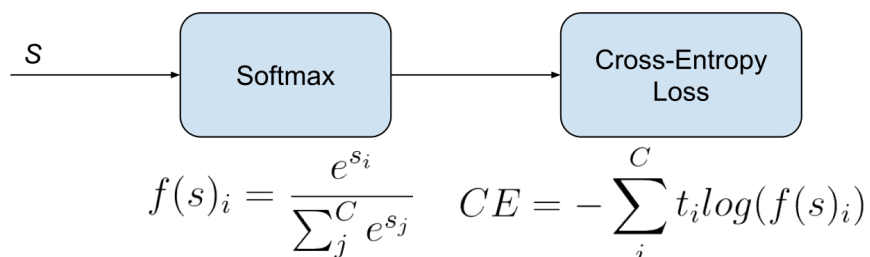
$S(Y)$

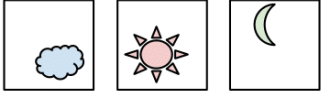

$L$

$D(S, L) = -\sum_i L_i \log(S_i)$

0.7  
0.2  
0.1

1.0  
0.0  
0.0



	Multi-Class	Multi-Label
C = 3	<p>Samples</p>  <p>Labels (t)</p> <p>[0 0 1] [1 0 0] [0 1 0]</p>	<p>Samples</p>  <p>Labels (t)</p> <p>[1 0 1] [0 1 0] [1 1 1]</p>

```
import keras
from keras.losses import CategoricalCrossentropy
loss = CategoricalCrossentropy()
y_true = [[0, 1, 0], [0, 0, 1]]
y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]]
z = loss(y_true, y_pred)
print(z.numpy())
```

- The prediction contains only one class
- The label is one-hot

# Loss Function

## Classification Loss Functions

- **Categorical Cross-Entropy**

CROSS-ENTROPY

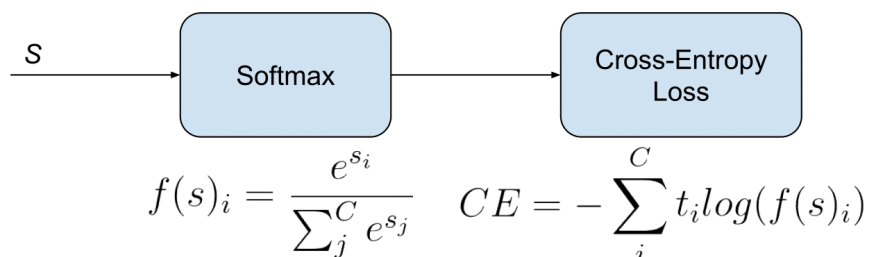
$S(Y)$

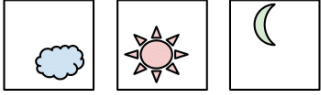

$L$

$D(S, L) = -\sum_i L_i \log(S_i)$

0.7  
0.2  
0.1

1.0  
0.0  
0.0



	Multi-Class	Multi-Label
C = 3	<p>Samples</p>  <p>Labels (t)</p> <p>[0 0 1] [1 0 0] [0 1 0]</p>	<p>Samples</p>  <p>Labels (t)</p> <p>[1 0 1] [0 1 0] [1 1 1]</p>

```
import keras
from keras.losses import SparseCategoricalC
rossentropy
loss = SparseCategoricalCrossentropy()
y_true = [1, 2]
y_pred = [[0.05, 0.95, 0], [0.1, 0.8, 0.1]]
z = loss(y_true, y_pred)
print(z.numpy())
```

- The prediction contains only one class
- The label is an integer.

# Loss Function

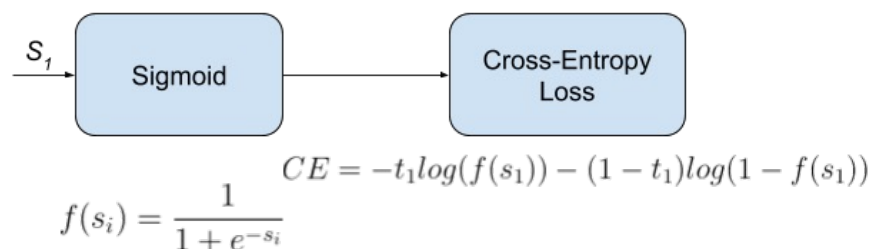
Probabilistic Loss Functions

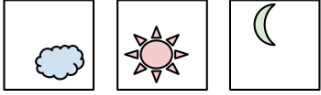



- **Binary Cross-Entropy**

CROSS-ENTROPY

$$D(S, L) = - \sum_i L_i \log(S_i)$$

Diagram illustrating the Cross-Entropy loss calculation. The predicted probabilities  $S$  are  $[0.7, 0.2, 0.1]$  and the target labels  $L$  are  $[1.0, 0.0, 0.0]$ . The loss is calculated as  $D(S, L) = - \sum_i L_i \log(S_i)$ .



	Multi-Class	Multi-Label
C = 3		
Samples		
Labels (t)	 [0 0 1] [1 0 0] [0 1 0]	 [1 0 1] [0 1 0] [1 1 1]

```
import keras
from keras.losses import BinaryCrossentropy
loss = BinaryCrossentropy()
y_true = [0, 1, 0, 0]
y_pred = [-18.6, 0.51, 2.94, -12.8]
z = loss(y_true, y_pred)
print(z.numpy())
```

- The prediction can contain multiple classes
- The label is multi-hot.

# Loss Function

## Custom Loss Functions

We can also define the loss as a function of prediction and target.

```
def custom_loss(y_true, y_pred):  
  
    # calculate loss, using y_pred  
  
    return loss
```

Supposing we want to define a loss function as  $MAE + 2 * MSE$

```
import keras  
from keras.losses import MeanAbsoluteError, MeanSquaredError  
def my_loss(y_true, y_pred):  
    loss = MeanAbsoluteError(y_true, y_pred) + 2 * MeanSquaredError(y_true, y_pred)  
    return loss
```

# Loss Function

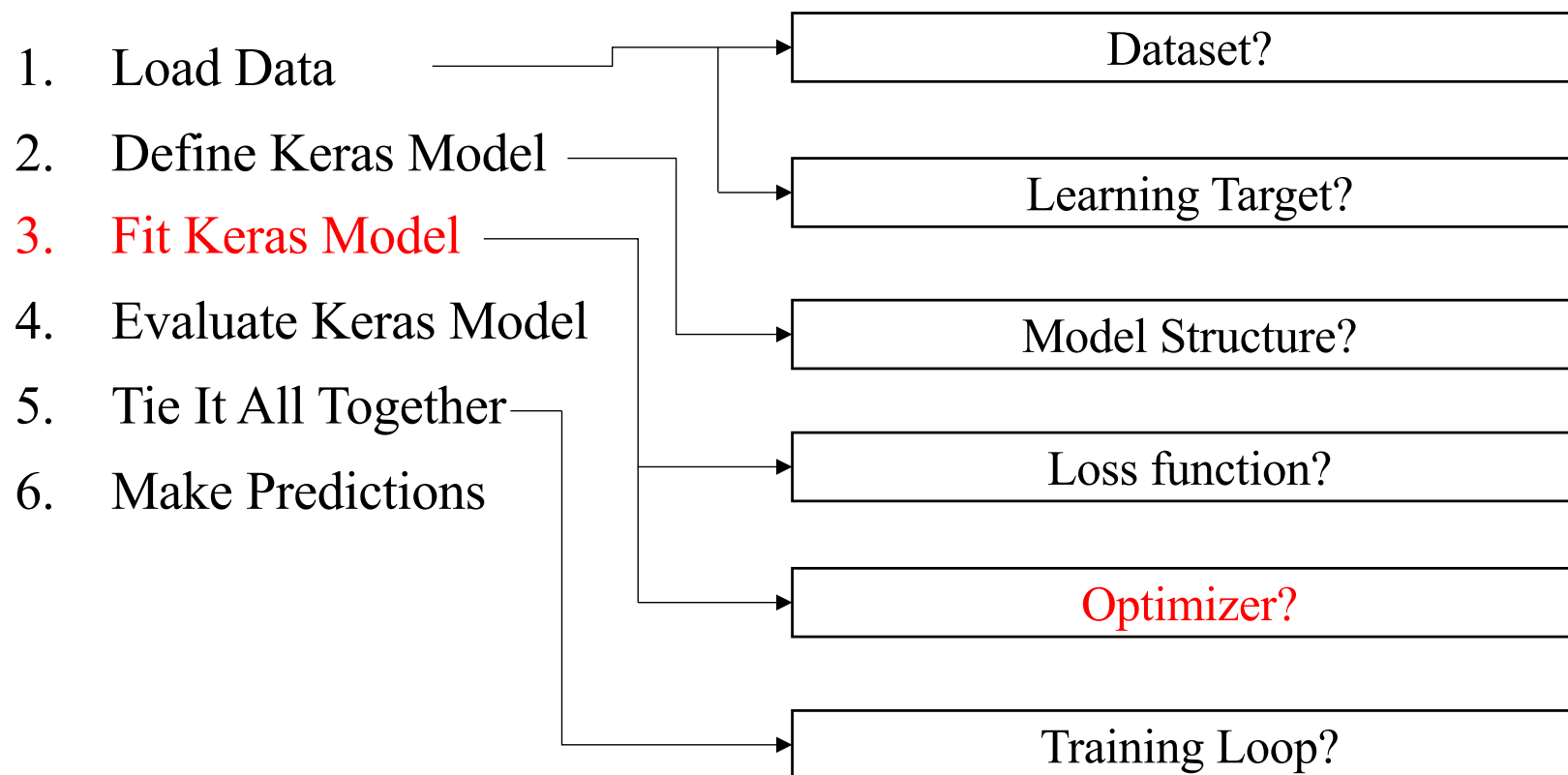
For the MNIST task, the loss function would be  
`loss = CategoricalCrossentropy()`  
for one-hot labels;

Or

`loss = SparseCategoricalCrossentropy()`  
for integer-valued labels.



# Key Components of Keras Pipeline



# Optimizer

The optimizer specifies how to update the DNN weights according to the loss function values.

- SGD
- RMSprop
- Adam
- Adadelta
- Adagrad
- e.g.,

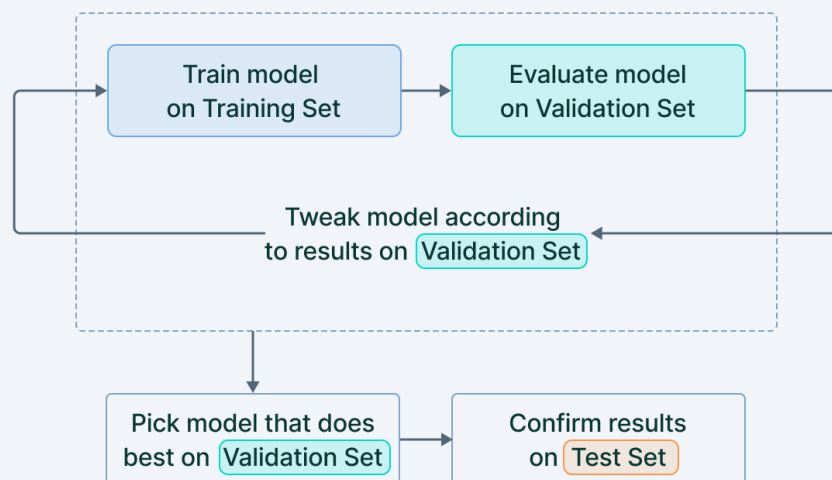
```
optimizer = keras.optimizers.Adam()  
optimizer = keras.optimizers.Adam(learning_rate=1e-3)
```

# Compile Model

- **There is one more thing before actually training the model:**
  - How to evaluate the generalization performance, in order to save the best model?

# Metrics

## Training data/validation/test



During training, we compute the metrics on the validation dataset and choose the model with the best evaluation metric.

Commonly used metric:

- Accuracy
- MSE
- ...

The loss function itself can also be taken as the metric.

# Compile Model

After we have figured out the loss function and optimizer, we can compile a defined model for training.

```
model.compile(optimizer=keras.optimizers.Adam(),  
              loss=keras.losses.SparseCategoricalCrossentropy(),  
              metrics=[tf.keras.metrics.Accuracy()])
```

or

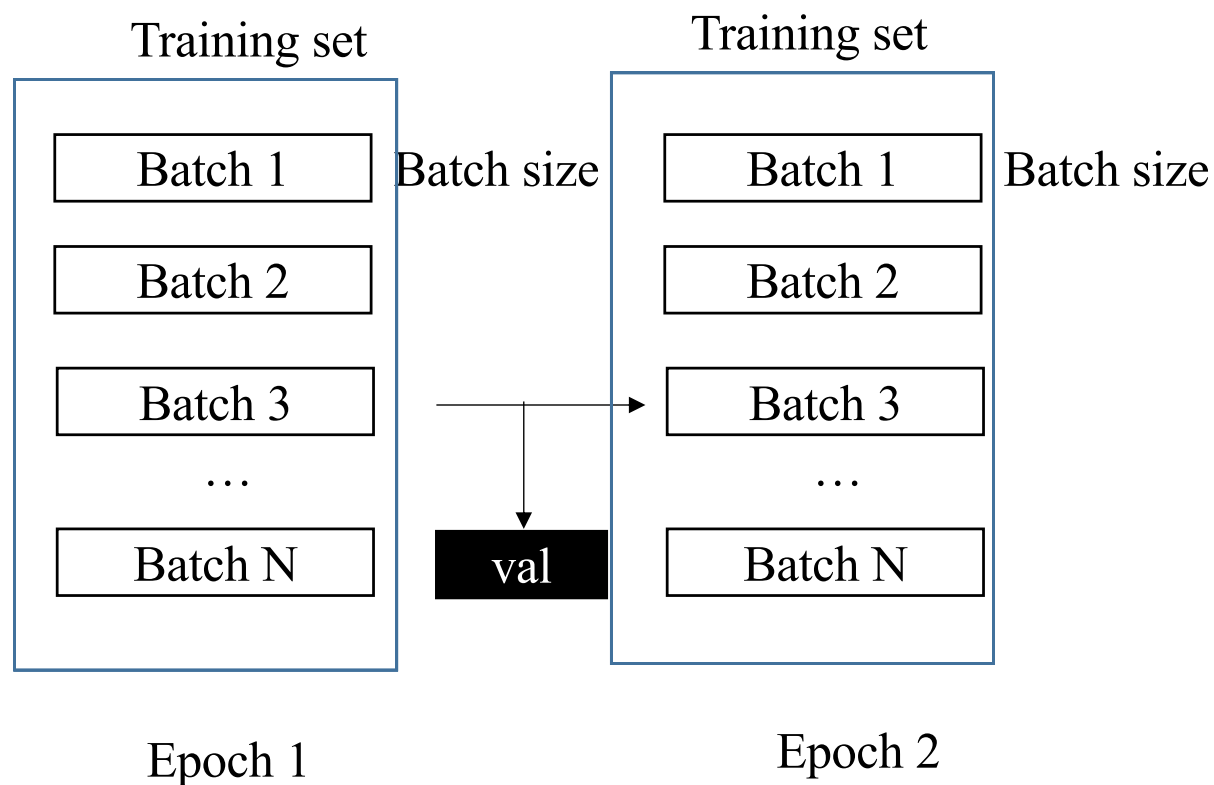
```
model.compile(optimizer='adam',  
              loss='sparse_categorical_crossentropy',  
              metrics=['accuracy'])
```

# Fit Model

The model can be optimized using the built-in API

**model.fit**

```
Model.fit(x=None, y=None,
batch_size=None, epochs=1,
verbose="auto",
callbacks=None,
validation_split=0.0,
validation_data=None,
shuffle=True,
class_weight=None,
sample_weight=None,
initial_epoch=0,
steps_per_epoch=None,
validation_steps=None,
validation_batch_size=None,
validation_freq=1,
max_queue_size=10, workers=1,
use_multiprocessing=False, )
```



# Fit Model

The model can be optimized using the built-in API

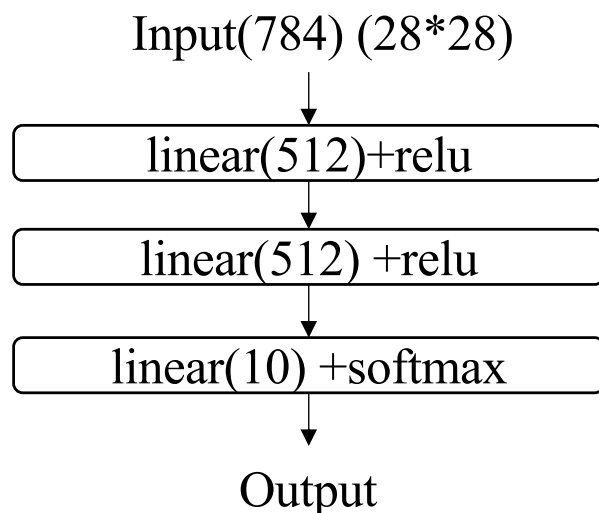
## model.fit

```
Model.fit(x=None, y=None,  
          batch_size=None, epochs=1,  
          verbose="auto",  
          callbacks=None,  
          validation_split=0.0,  
          validation_data=None,  
          shuffle=True,  
          class_weight=None,  
          sample_weight=None,  
          initial_epoch=0,  
          steps_per_epoch=None,  
          validation_steps=None,  
          validation_batch_size=None,  
          validation_freq=1,  
          max_queue_size=10, workers=1,  
          use_multiprocessing=False, )
```

```
batch_size = 128  
epochs = 15  
model.fit(x_train, y_train, batch_size=batch_size  
          , epochs=epochs, validation_split=0.1)
```

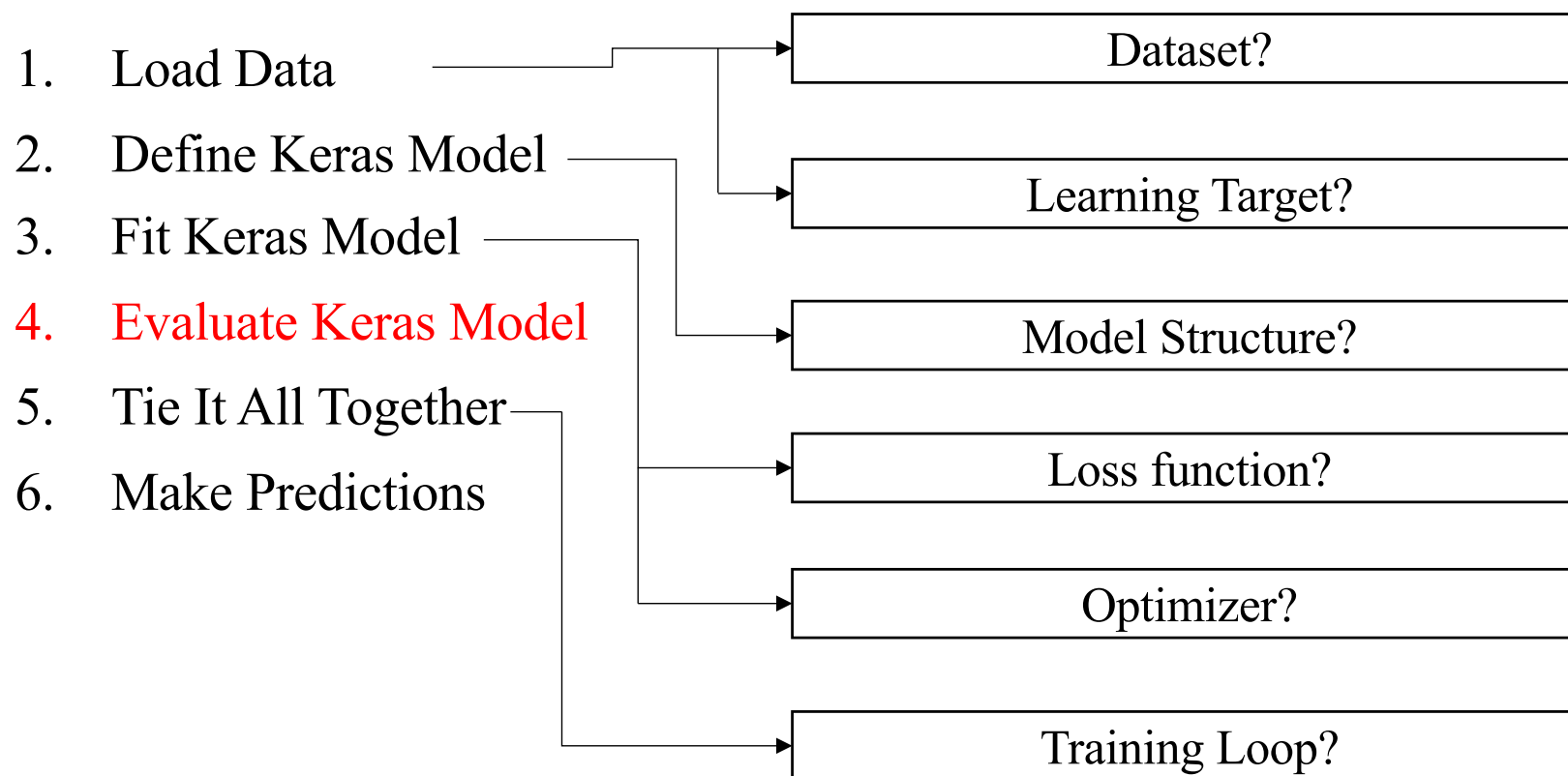
# Exercise

1. Define the following model using Sequential API. Assuming padding is not used.
2. Define the following model using Functional API.
3. Use the structure as below to train a model for the MNIST task. Try using the entire dataset and data generator to train the model.





# Key Components of Keras Pipeline



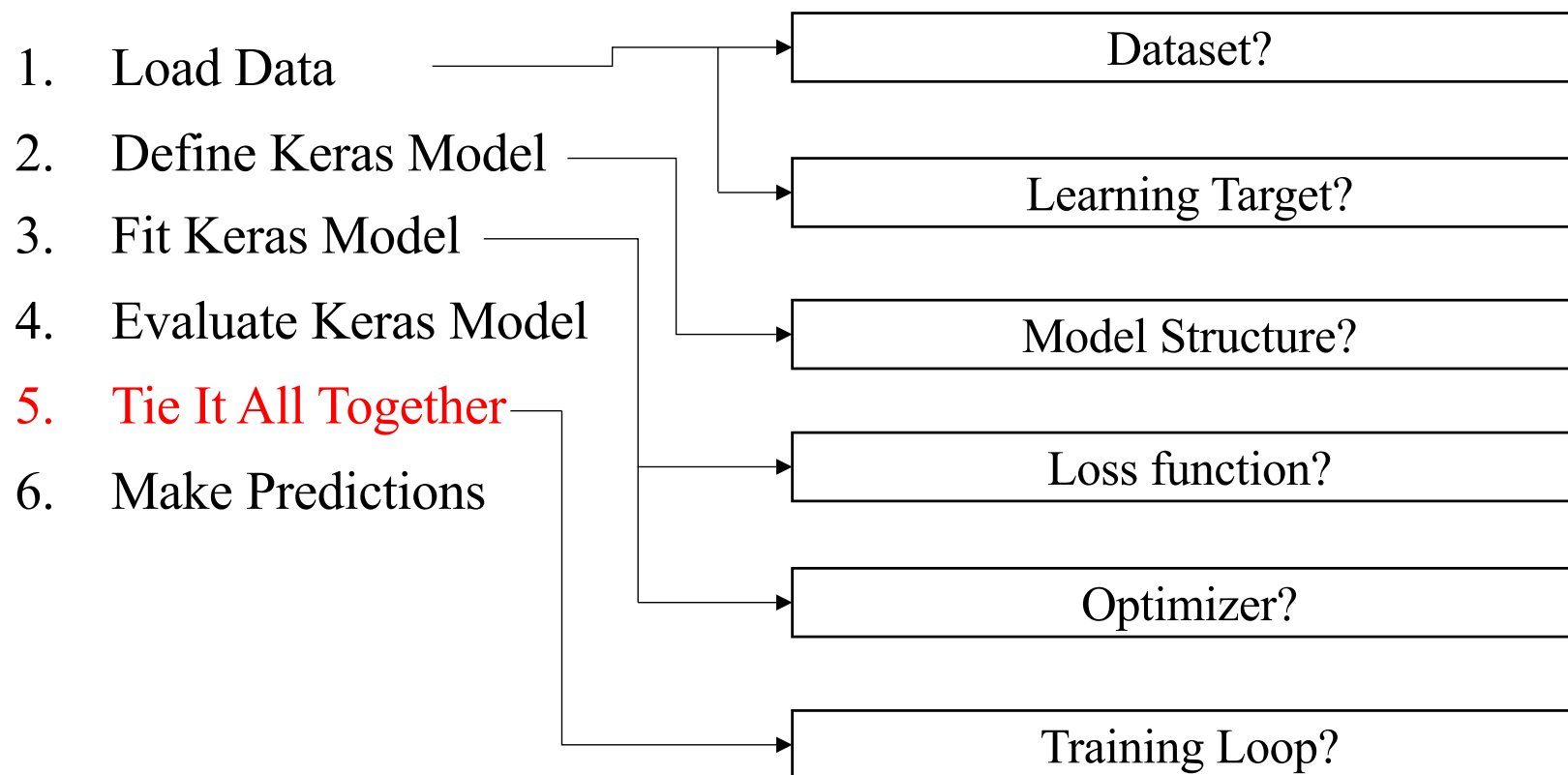
# Evaluate Model

using `model.evaluate` to evaluate the model, it will give us the loss and the metric values.

```
Model.evaluate( x=None, y=None,  
batch_size=None, verbose="auto",  
sample_weight=None, steps=None,  
callbacks=None,  
max_queue_size=10, workers=1,  
use_multiprocessing=False,  
return_dict=False, **kwargs )
```

```
score = model.evaluate(x_test, y_test)  
print('Test loss:', score[0])  
print('Test accuracy:', score[1])
```

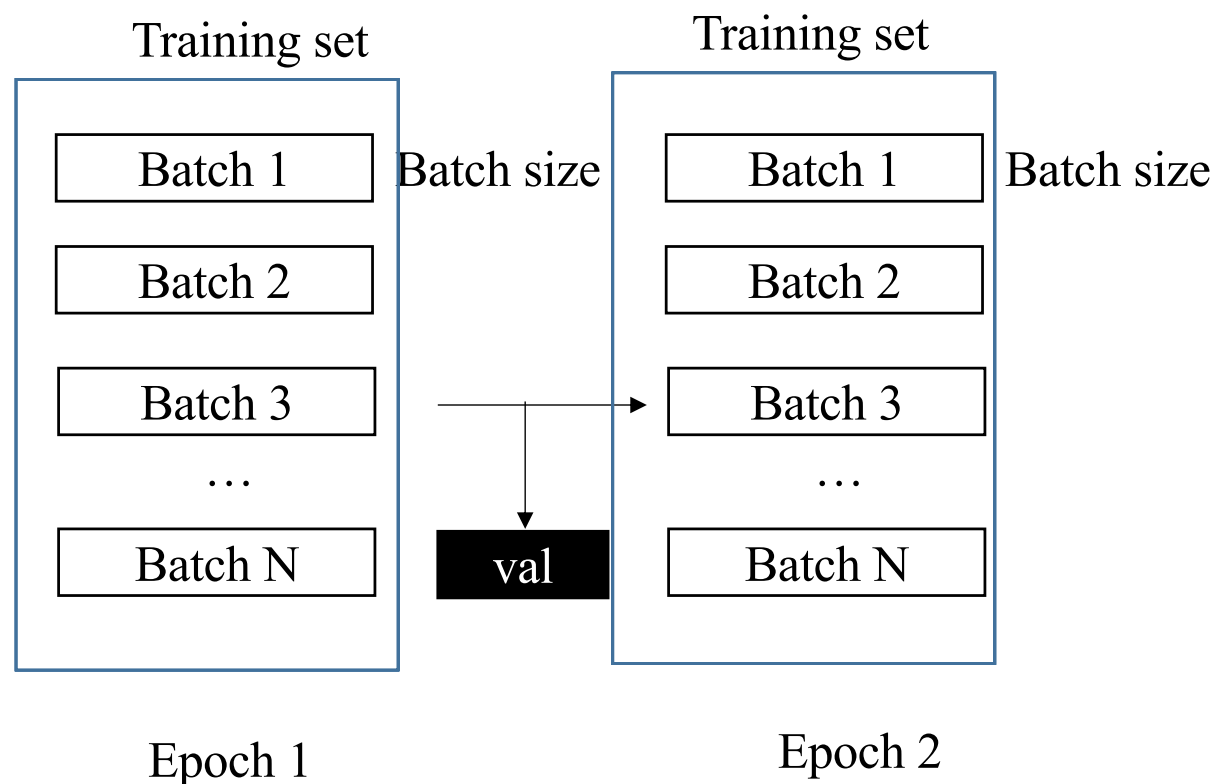
# Key Components of Keras Pipeline



# Customized Training Loop

Rather than using `model.fit`, the training loop can also be customized, in order to

- Save the model
- Adjust the learning rate
- etc



# Customized Training Loop

The training loop design:

```
for epoch in range(epochs):  
    for step, (x_batch_train, y_batch_train) in enumerate(train_dataset):  
        with tf.GradientTape() as tape:  
            logits = model(x_batch_train, training=True)  
            loss_value = loss_fn(y_batch_train, logits)  
            grads = tape.gradient(loss_value, model.trainable_weights)  
            optimizer.apply_gradients(zip(grads, model.trainable_weights))
```

- Open a **for** loop that iterates over epochs
- For each epoch, iterate over the dataset in batches
- For each batch, open a **GradientTape()** scope, forward pass and compute the loss
- Outside the scope, retrieve the gradients
- Use the optimizer to update the model

# Customized Training Loop

The training loop design:

```
val_acc_metric = keras.metrics.SparseCategoricalAccuracy()
best_metric = 10000
for epoch in range(epochs):
    for step, (x_batch_train, y_batch_train) in enumerate(train_dataset):
        with tf.GradientTape() as tape:
            logits = model(x_batch_train, training=True)
            loss_value = loss_fn(y_batch_train, logits)
            grads = tape.gradient(loss_value, model.trainable_weights)
            optimizer.apply_gradients(zip(grads, model.trainable_weights))
        for x_batch_val, y_batch_val in val_dataset:
            val_logits = model(x_batch_val, training=False)
            val_acc_metric.update_state(y_batch_val, val_logits)
        val_acc = val_acc_metric.result()
        if float(val_acc) < best_metric:
            best_metric = float(val_acc)
            model.save('path_to_location.h5')
        val_acc_metric.reset_states()
```

- Evaluate after each epoch, save the best model

# Customized Training Loop

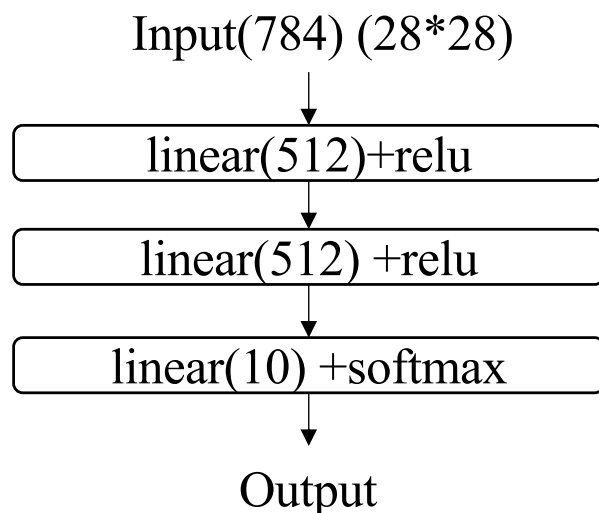
The training loop design:

```
import keras
from keras import backend as K
val_acc_metric = keras.metrics.SparseCategoricalAccuracy()
best_metric = 10000
for epoch in range(epochs):
    for step, (x_batch_train, y_batch_train) in enumerate(train_dataset):
        with tf.GradientTape() as tape:
            logits = model(x_batch_train, training=True)
            loss_value = loss_fn(y_batch_train, logits)
            grads = tape.gradient(loss_value, model.trainable_weights)
            optimizer.apply_gradients(zip(grads, model.trainable_weights))
        K.set_value(model.optimizer.learning_rate, 0.001)
```

- Change the learning rate

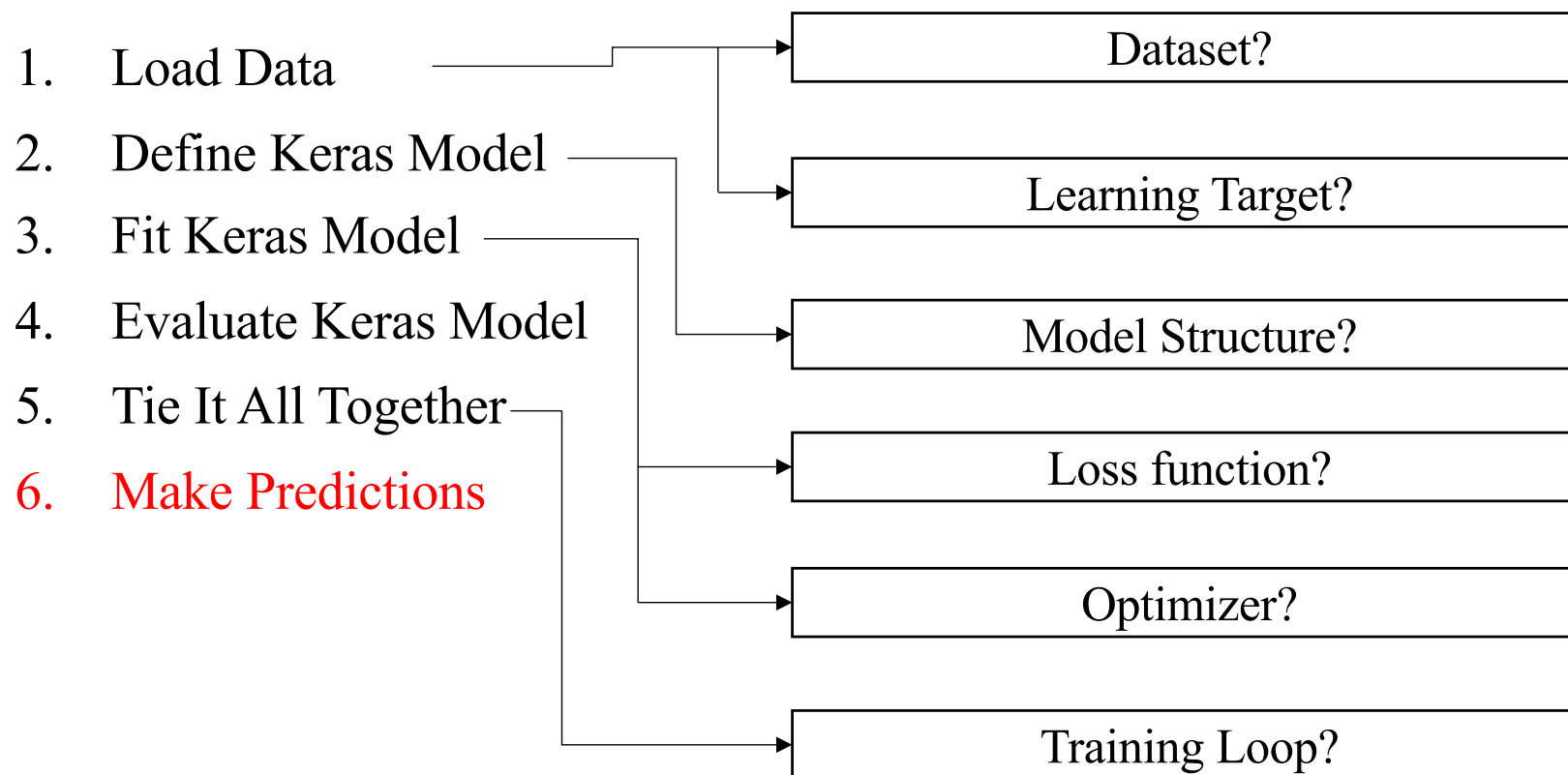
# Exercise

1. Define the following model using Sequential API. Assuming padding is not used.
2. Define the following model using Functional API.
3. Use the structure as below to train a model for the MNIST task. Try using the entire dataset and data generator to train the model.
4. Write customized training loop for the MNIST task.





# Key Components of Keras Pipeline



# Make Predictions

```
Model.predict( x,  
batch_size=None,  
verbose="auto",  
steps=None,  
callbacks=None,  
max_queue_size=10,  
workers=1,  
use_multiprocessing=False,  
)
```

```
prediction = model.predict(x_test)
```

# Exercise

1. Define the following model using Sequential API. Assuming padding is not used.

```
# Define the model using functional API:
from keras.models import Sequential
from keras.layers import Dense, Conv2D, MaxPool2D, Input, Reshape, Flatten
import keras
import numpy as np

layers = [Input(shape=(256, 256, 1)),
          Reshape((64, 64, -1)),
          Conv2D(filters=32, kernel_size=5),
          MaxPool2D(2),
          Conv2D(filters=1, kernel_size=1),
          Flatten(),
          Dense(16, activation='sigmoid')]
model = Sequential(layers)
model.summary()
```

# Exercise

1. Define the following model using Sequential API. Assuming padding is not used.
2. Define the following model using Functional API.

```
# Define the model using functional API:
from keras.models import Model
from keras.layers import Dense, Conv2D, MaxPool2D, Input, Reshape, Flatten, concatenate
import keras
import numpy as np
```

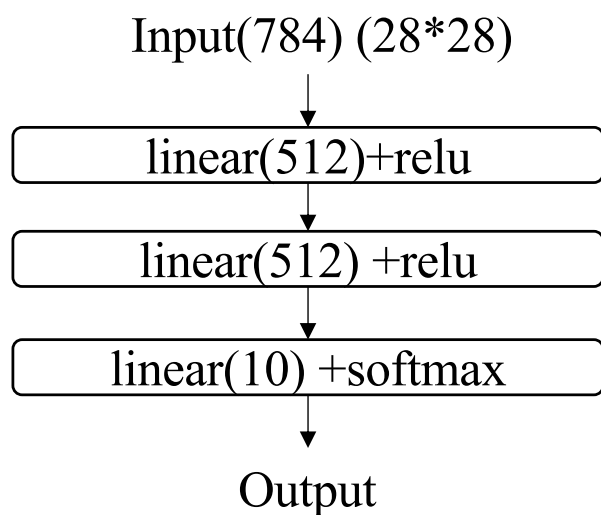
```
def my_model():
    # define layers
    input_tensor = Input(shape=(256, 256, 1))
    reshape_layer = Reshape((64, 64, -1))
    conv2d_1 = Conv2D(filters=8, kernel_size=5)
    conv2d_2 = Conv2D(filters=8, kernel_size=17)
    max_pool_layer = MaxPool2D(4)

    input_tensor_reshape = reshape_layer(input_tensor)
    conv1_out = conv2d_1(input_tensor_reshape)
    conv2_out = conv2d_2(input_tensor)
    max_pool_out = max_pool_layer(conv2_out)
    cat_out = concatenate([conv1_out, max_pool_out], axis=-1)
    model = Model(inputs=input_tensor, outputs=cat_out)
    return model
```

```
my_model = my_model()
my_model.summary()
```

# Exercise

Use the structure as below to train a model for the MNIST task. Try using **the entire dataset** and the data generator to train the model.



See next page

# Exercise

```
import pandas as pd
import keras
from keras.models import Sequential
from keras.layers import Dense, Input
from keras.losses import SparseCategoricalCrossentropy

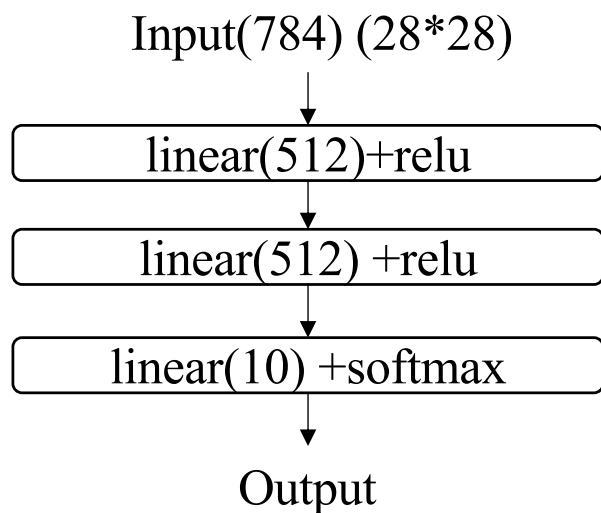
df_orig_train = pd.read_csv('/content/drive/MyDrive/keras/mnist_train.csv', header=None)
df_orig_test = pd.read_csv('/content/drive/MyDrive/keras/mnist_test.csv', header=None)
df_train_values = df_orig_train.values
df_test_values = df_orig_test.values
train_feat_ori, train_label_ori = df_train_values[:, 1:]/255.0, df_train_values[:, 0]
test_feat, test_label = df_test_values[:, 1:]/255.0, df_test_values[:, 0]
train_feat, val_feat = train_feat_ori[6000:], train_feat_ori[:6000]
train_label, val_label = train_label_ori[6000:], train_label_ori[:6000]

model = Sequential()
model.add(Input(shape=(784,)))
model.add(Dense(512, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dense(10, activation='softmax'))
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

batch_size = 128
epochs = 8
model.fit(train_feat, train_label, batch_size=batch_size, epochs=epochs, validation_data = (val_feat, val_label))
```

# Exercise

Use the structure as below to train a model for the MNIST task. Try using the entire dataset and the **data generator** to train the model.



See next page

# Exercise

```
import pandas as pd
import keras
from keras.models import Sequential
from keras.layers import Dense, Input
from keras.losses import SparseCategoricalCrossentropy

import numpy as np
import linecache
import random
```



# Exercise

```
class DataGenerator(keras.utils.Sequence):
    'Generates data for Keras'
    def __init__(self, csv_path, indexes, bs):
        # initializes some variables
        self.csv_path = csv_path
        self.norm_factor = 255.0
        self.indexes = indexes
        random.shuffle(self.indexes)
        self.bs = bs
    def __len__(self):
        # return the total number of samples in the dataset
        return len(self.indexes)//self.bs
    def __getitem__(self, index):
        # get one sample according to the index
        feat_all = []
        label_all = []
        for this_index in range(index*self.bs, (index+1)*self.bs):
            line_index = self.indexes[this_index]
            line_str = linecache.getline(self.csv_path, line_index)
            line_val = [int(i) for i in line_str.split(',')]
            label = line_val[0]
            feat = np.array(line_val[1:])/self.norm_factor
            feat_all.append(feat)
            label_all.append(label)

        return np.array(feat_all), np.array(label_all)
```

# Exercise

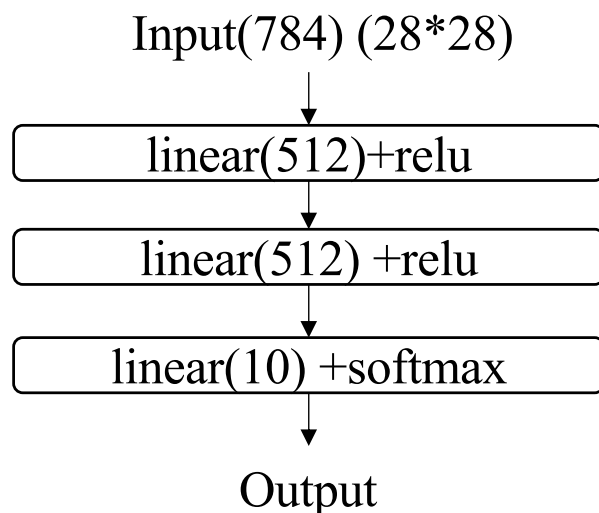
```
indexes = [i for i in range(60000)]
train_index = indexes[6000:]
val_index = indexes[:6000]
batch_size = 128
train_set = DataGenerator('/content/drive/MyDrive/keras/mnist_train.csv', train_index, batch_size)
val_set = DataGenerator('/content/drive/MyDrive/keras/mnist_train.csv', val_index, batch_size)

model = Sequential()
model.add(Input(shape=(784,)))
model.add(Dense(512, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dense(10, activation='softmax'))
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

epochs = 8
model.fit(train_set, steps_per_epoch = len(train_set), epochs=epochs, validation_data = val_set, validation_steps=len(val_set))
```

# Exercise

1. Define the following model using Sequential API. Assuming padding is not used.
2. Define the following model using Functional API.
3. Use the structure as below to train a model for the MNIST task. Try using the entire dataset and data generator to train the model.
4. Write customized training loop for the MNIST task.



# Exercise

```
import pandas as pd
import keras
from keras.models import Sequential
from keras.layers import Dense, Input
```

```
import numpy as np
import linecache
import random
import tensorflow as tf
```

# Exercise

```
class DataGenerator(keras.utils.Sequence):
    'Generates data for Keras'
    def __init__(self, csv_path, indexes, bs):
        # initilizes some variables
        self.csv_path = csv_path
        self.norm_facor = 255.0
        self.indexes = indexes
        self.bs = bs
        random.shuffle(self.indexes)
    def __len__(self):
        # return the total number of samples in the dataset
        return (len(self.indexes))//self.bs-1
    def __getitem__(self, index):
        # get one sample according to the index
        feat_all = []
        label_all = []
        for this_index in range(index*self.bs, (index+1)*self.bs):
            line_index = self.indexes[index]
            line_str = linecache.getline(self.csv_path, line_index)
            line_val = [int(i) for i in line_str.split(',') if len(i)]
            label = line_val[0]
            feat = np.array(line_val[1:])/self.norm_facor
            feat_all.append(feat)
            label_all.append(label)

        return np.array(feat_all), np.array(label_all)
    def shuffle(self):
        random.shuffle(self.indexes)
```

# Exercise

```
indexes = [i for i in range(60000)]
train_index = indexes[6000:]
val_index = indexes[:6000]
batch_size = 128
train_set = DataGenerator('/content/drive/MyDrive/keras/mnist_train.csv', train_index,
batch_size)
val_set = DataGenerator('/content/drive/MyDrive/keras/mnist_train.csv', val_index, batch_size)

model = Sequential()
model.add(Input(shape=(784,)))
model.add(Dense(512, activation='relu'))
model.add(Dense(512, activation='relu'))
model.add(Dense(10, activation='softmax'))
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

loss_fn = keras.losses.SparseCategoricalCrossentropy()
optimizer = keras.optimizers.Adam()
val_acc_metric = keras.metrics.SparseCategoricalAccuracy()
epochs = 15
best_metric = 100
```

# Exercise

```
for epoch in range(epochs):
    train_set.shuffle()
    for step, (x_batch_train, y_batch_train) in enumerate(train_set):
        with tf.GradientTape() as tape:
            logits = model(x_batch_train, training=True)
            loss_value = loss_fn(y_batch_train, logits)
            grads = tape.gradient(loss_value, model.trainable_weights)
            optimizer.apply_gradients(zip(grads, model.trainable_weights))
    for x_batch_val, y_batch_val in val_set:
        val_logits = model(x_batch_val, training=False)
        val_acc_metric.update_state(y_batch_val, val_logits)
    val_acc = val_acc_metric.result()
    print("[{}/{}] , val_acc: {}".format(epoch, epochs, float(val_acc)))
    if float(val_acc) < best_metric:
        best_metric = float(val_acc)
        model.save('path_to_location.h5')
    val_acc_metric.reset_states()
```