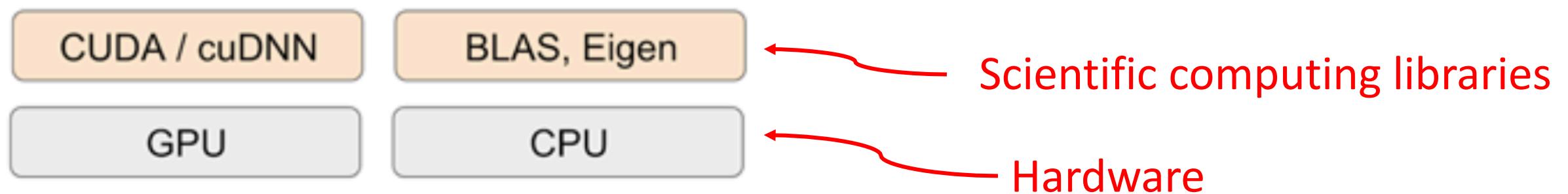


# **Train a Neural Networks using Keras**

**Shusen Wang**

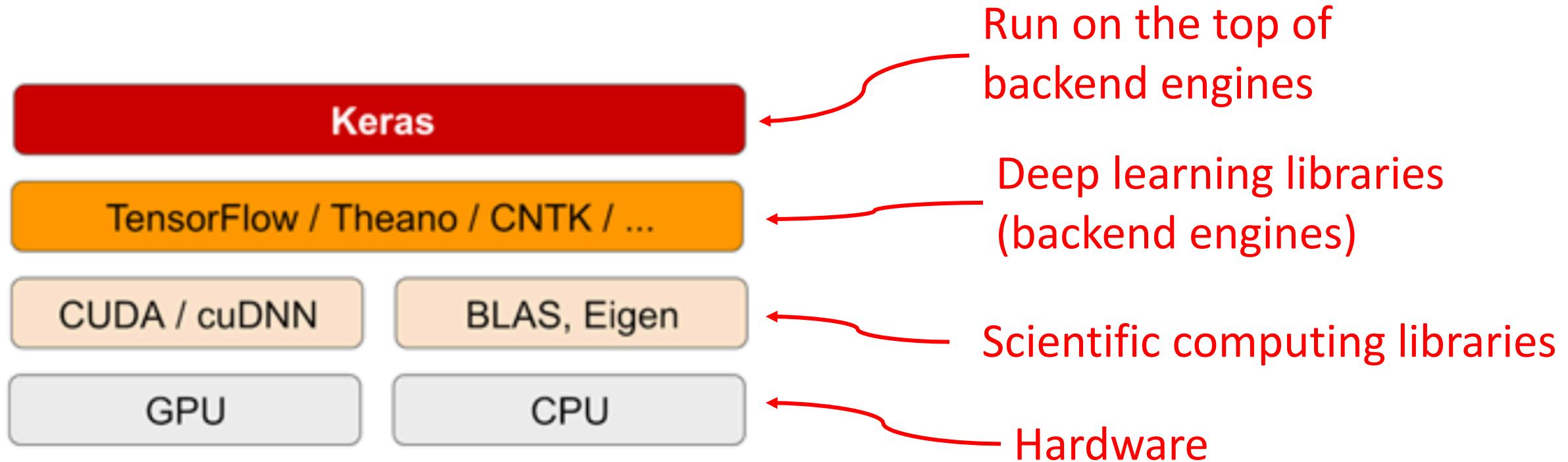
# Deep Learning Systems



# Deep Learning Systems



# Deep Learning Systems



# Implement a Softmax Classifier Using Keras

# Softmax Classifier

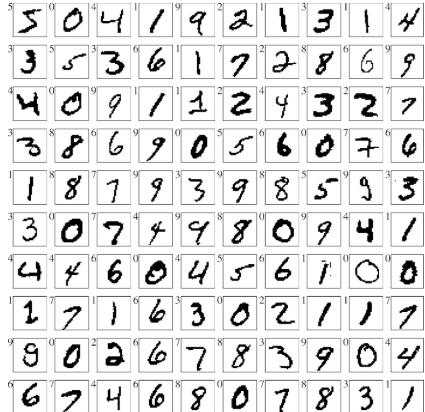
## The MNIST Dataset

5	0	4	1	9	2	1	3	1	4
3	5	3	6	1	7	2	8	6	9
4	0	9	1	1	2	4	3	2	7
3	8	6	9	0	5	6	0	7	6
1	8	1	9	3	9	8	5	9	3
3	0	7	4	9	8	0	9	4	1
4	4	6	0	4	5	6	1	0	0
1	7	1	6	3	0	2	1	1	7
9	0	2	6	7	8	3	9	0	4
6	7	4	6	8	0	7	8	3	1

- $n = 60,000$  training samples  $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)$ .
- Each  $\mathbf{x}_j$  is a  $28 \times 28$  image.
- Each  $y_j$  is an integer in  $\{0, 1, 2, \dots, 9\}$ .

# Softmax Classifier

## The MNIST Dataset



- $n = 60,000$  training samples  $(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)$ .
- Each  $\mathbf{x}_j$  is a  $28 \times 28$  image.
- Each  $y_j$  is an integer in  $\{0, 1, 2, \dots, 9\}$ .

## Softmax classifier ( $f: \mathbb{R}^{784} \mapsto \mathbb{R}^{10}$ ) for MNIST:

- **Input:** vector  $\mathbf{x} \in \mathbb{R}^{784}$ .
- $\mathbf{z} = \mathbf{W}\mathbf{x} + \mathbf{b} \in \mathbb{R}^{10}$ .
- **Output:**  $f(\mathbf{x}) = \text{SoftMax}(\mathbf{z})$ .

Trainable parameters:

- $\mathbf{W} \in \mathbb{R}^{10 \times 784}$
- $\mathbf{b} \in \mathbb{R}^{10}$

# 1. Load and Process the MNIST Dataset

## Load data

```
from keras.datasets import mnist

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

print('Shape of x_train: ' + str(x_train.shape))
print('Shape of x_test: ' + str(x_test.shape))
print('Shape of y_train: ' + str(y_train.shape))
print('Shape of y_test: ' + str(y_test.shape))
```

Shape of x\_train: (60000, 28, 28)

Shape of x\_test: (10000, 28, 28)

Shape of y\_train: (60000,)

Shape of y\_test: (10000,)

# 1. Load and Process the MNIST Dataset

**Vectorization:** convert the  $28 \times 28$  **images** to 784-dim vectors.

```
x_train_vec = x_train.reshape(60000, 784)
x_test_vec = x_test.reshape(10000, 784)

print('Shape of x_train_vec is ' + str(x_train_vec.shape))

Shape of x_train_vec is (60000, 784)
```

# 1. Load and Process the MNIST Dataset

**One-hot encode:** convert the **labels** (an integer in  $\{0, 1, \dots, 9\}$ ) to 10-dim vectors.

```
def to_one_hot(labels, dimension=10):
    results = np.zeros((len(labels), dimension))
    for i, label in enumerate(labels):
        results[i, label] = 1.
    return results

y_train_vec = to_one_hot(y_train)
y_test_vec = to_one_hot(y_test)
print('Shape of y_train_vec is ' + str(y_train_vec.shape))
```

Shape of y\_train\_vec is (60000, 10)

# 1. Load and Process the MNIST Dataset

Partition the **training** set to **training** and **validation** sets.

labels



features



$n$  training samples



$m$  test samples

# 1. Load and Process the MNIST Dataset

Partition the **training** set to **training** and **validation** sets.

labels



features



$n$  training samples

$n_{\text{val}}$  validation  
samples

$m$  test samples



# 1. Load and Process the MNIST Dataset

```
rand_indices = np.random.permutation(60000)
train_indices = rand_indices[0:50000]
valid_indices = rand_indices[50000:60000]

x_valid_vec = x_train_vec[valid_indices, :]
y_valid_vec = y_train_vec[valid_indices, :]

x_train_vec = x_train_vec[train_indices, :]
y_train_vec = y_train_vec[train_indices, :]

print('Shape of x_valid_vec: ' + str(x_valid_vec.shape))
print('Shape of y_valid_vec: ' + str(y_valid_vec.shape))
print('Shape of x_train_vec: ' + str(x_train_vec.shape))
print('Shape of y_train_vec: ' + str(y_train_vec.shape))
```

Shape of x\_valid\_vec: (10000, 784)

Shape of y\_valid\_vec: (10000, 10)

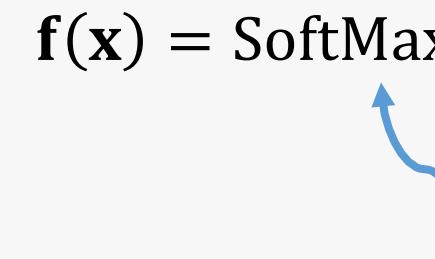
Shape of x\_train\_vec: (50000, 784)

Shape of y\_train\_vec: (50000, 10)

## 2. Build the Softmax Classifier

```
from keras import models      f(x) = SoftMax(W x + b)
from keras import layers

model = models.Sequential()
model.add(layers.Dense(10, activation='softmax', input_shape=(784,)))
```



## 2. Build the Softmax Classifier

```
from keras import models      f(x) = SoftMax(W x + b)
from keras import layers

model = models.Sequential()
model.add(layers.Dense(10, activation='softmax', input_shape=(784,)))

# print the summary of the model.
model.summary()
```

Layer (type)	Output Shape	Param #
=====		
dense_1 (Dense)	(None, 10)	7850
=====		
Total params:	7,850	
Trainable params:	7,850	
Non-trainable params:	0	

### 3. Train the Softmax Classifier

Specify: optimization algorithm, learning rate (LR), loss function, and metric.

```
from keras import optimizers  
model.compile(optimizers.RMSprop(lr=0.0001),  
              loss='categorical_crossentropy',  
              metrics=['accuracy'])
```

# 3. Train the Softmax Classifier

**Specify:** batch size and number of epochs.

```
history = model.fit(x_train_vec, y_train_vec,  
                     batch_size=128, epochs=50,  
                     validation_data=(x_valid_vec, y_valid_vec))
```

```
Train on 50000 samples, validate on 10000 samples  
Epoch 1/50  
50000/50000 [=====] - 1s 19us/step - loss: 11.2824 - acc: 0.2816 - val_loss: 8.7464 - val_acc: 0.4398  
Epoch 2/50  
50000/50000 [=====] - 1s 13us/step - loss: 7.1525 - acc: 0.5384 - val_loss: 5.7830 - val_acc: 0.6221  
Epoch 3/50  
50000/50000 [=====] - 1s 13us/step - loss: 5.1013 - acc: 0.6661 - val_loss: 4.5210 - val_acc: 0.7036  
Epoch 4/50  
50000/50000 [=====] - 1s 13us/step - loss: 4.0385 - acc: 0.7339 - val_loss: 3.7206 - val_acc: 0.7533  
●  
●  
●  
Epoch 49/50  
50000/50000 [=====] - 1s 13us/step - loss: 1.1430 - acc: 0.9228 - val_loss: 1.3567 - val_acc: 0.9088  
Epoch 50/50  
50000/50000 [=====] - 1s 14us/step - loss: 1.1407 - acc: 0.9230 - val_loss: 1.3526 - val_acc: 0.9077
```

### 3. Train the Softmax Classifier

**Epoch:** One pass over the  $n$  training samples.

- Suppose we use mini-batch SGD and set the batch size to  $b$ .
- In the  $t$ -th iteration,
  - use a mini-batch of  $b$  samples to evaluate the gradient,  $\bar{\mathbf{g}}_t$ ;
  - update the model parameters using  $\bar{\mathbf{g}}_t$ .
- $\frac{n}{b}$  iterations is equivalent to one epoch.

n: 样本容量

b: batch size

每次 迭代 用的是 一个 batch size  
一个epoch 是 n 个样本 全部迭代完

# 4. Examine the Results

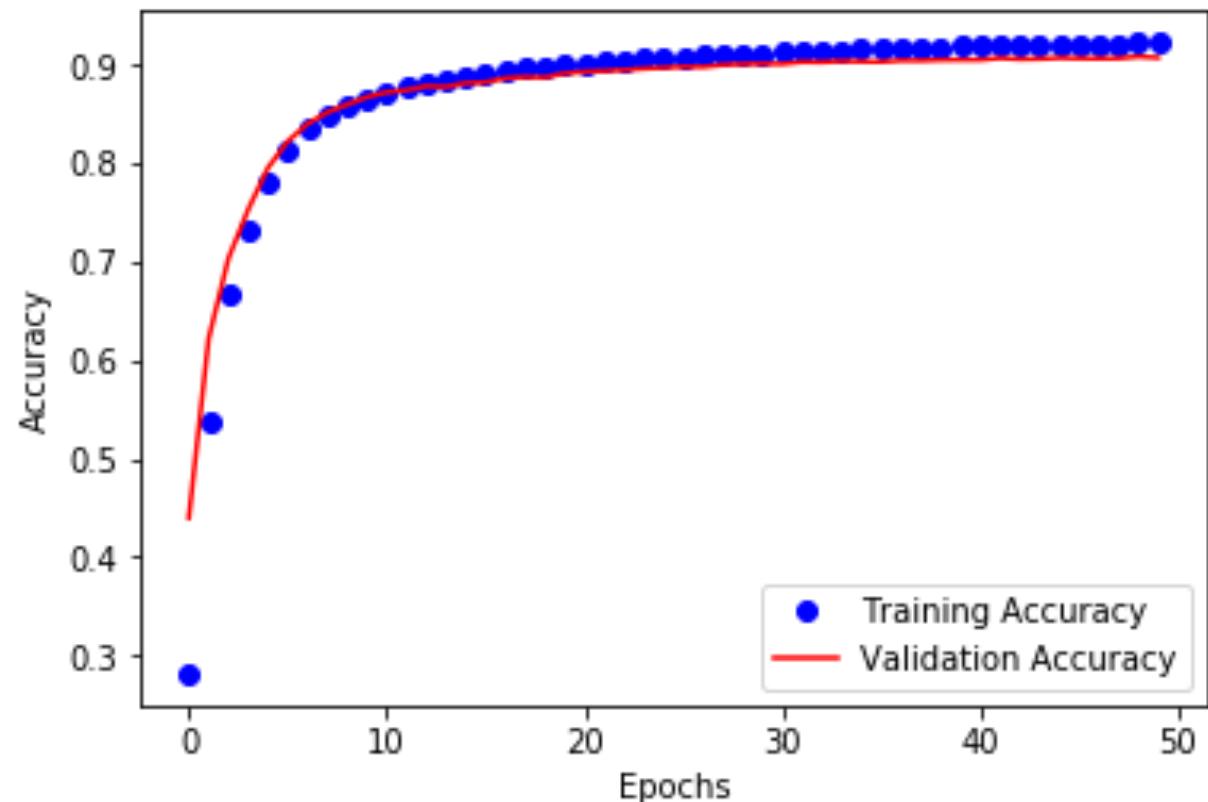
Plot the *accuracy* against *epochs* (1 epoch = 1 pass over the data).

```
import matplotlib.pyplot as plt
%matplotlib inline

epochs = range(50) # 50 is the number of epochs
train_acc = history.history['acc']
valid_acc = history.history['val_acc']
plt.plot(epochs, train_acc, 'bo', label='Training Accuracy')
plt.plot(epochs, valid_acc, 'r', label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

# 4. Examine the Results

Plot the *accuracy* against *epochs* (1 epoch = 1 pass over the data).



Why using the validation set?

- Tune the hyper-parameters, e.g., learning rate, regularization.
- Check whether overfit or underfit.

## 4. Examine the Results

Evaluate the model on the *test* set. (So far, the model has not seen the *test* set.)

```
loss_and_acc = model.evaluate(x_test_vec, y_test_vec)
print('loss = ' + str(loss_and_acc[0]))
print('accuracy = ' + str(loss_and_acc[1]))
```

```
10000/10000 [=====] - 0s 20us/step
loss = 1.2781493856459185
accuracy = 0.9131
```

## 4. Examine the Results

- Training accuracy: 92.3%
- Validation accuracy: 90.8%
- Test accuracy: 91.3%

Not bad! A random guess has only 10% accuracy.

# Implement a Neural Network Using Keras

# Full-Connected Neural Network

- **Input:** vector  $\mathbf{x}^{(0)} \in \mathbb{R}^{784}$ .

- $\mathbf{z}^{(1)} = \mathbf{W}^{(0)} \mathbf{x}^{(0)} + \mathbf{b}^{(0)} \in \mathbb{R}^{d_1}$ .
- $\mathbf{x}^{(1)} = \max\{\mathbf{0}, \mathbf{z}^{(1)}\} \in \mathbb{R}^{d_1}$ .

Hidden Layer 1

- $\mathbf{z}^{(2)} = \mathbf{W}^{(1)} \mathbf{x}^{(1)} + \mathbf{b}^{(1)} \in \mathbb{R}^{d_2}$ .
- $\mathbf{x}^{(2)} = \max\{\mathbf{0}, \mathbf{z}^{(2)}\} \in \mathbb{R}^{d_2}$ .

Hidden Layer 2

- $\mathbf{z}^{(3)} = \mathbf{W}^{(2)} \mathbf{x}^{(2)} + \mathbf{b}^{(2)} \in \mathbb{R}^{10}$ .

Output Layer

- **Output:** SoftMax( $\mathbf{z}^{(3)}$ ).

## Trainable parameters:

- $\mathbf{W}^{(0)} \in \mathbb{R}^{d_1 \times 784}$ ,
- $\mathbf{W}^{(1)} \in \mathbb{R}^{d_2 \times d_1}$ ,
- $\mathbf{W}^{(2)} \in \mathbb{R}^{10 \times d_2}$ ,
- $\mathbf{b}^{(0)} \in \mathbb{R}^{d_1}$ ,
- $\mathbf{b}^{(1)} \in \mathbb{R}^{d_1}$ ,
- $\mathbf{b}^{(2)} \in \mathbb{R}^{10}$ .

## 2. Build the Softmax Classifier

```
from keras import models
from keras import layers

d1 = 500 # width of the 1st hidden layer
d2 = 500 # width of the 2nd hidden layer

model = models.Sequential()
model.add(layers.Dense(d1, activation='relu', input_shape=(784, )))
model.add(layers.Dense(d2, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
```

## 2. Build the Softmax Classifier

```
# print the summary of the model.  
model.summary()
```

Layer (type)	Output Shape	Param #
=====		
dense_4 (Dense)	(None, 500)	392500
dense_5 (Dense)	(None, 500)	250500
dense_6 (Dense)	(None, 10)	5010
=====		
Total params:	648,010	
Trainable params:	648,010	
Non-trainable params:	0	

### 3. Train the Softmax Classifier

Specify: optimization algorithm, learning rate (LR), loss function, and metric.

```
from keras import optimizers  
model.compile(optimizers.RMSprop(lr=0.0001),  
              loss='categorical_crossentropy',  
              metrics=['accuracy'])
```

# 3. Train the Softmax Classifier

**Specify:** batch size and number of epochs.

```
history = model.fit(x_train_vec, y_train_vec,  
                     batch_size=128, epochs=50,  
                     validation_data=(x_valid_vec, y_valid_vec))
```

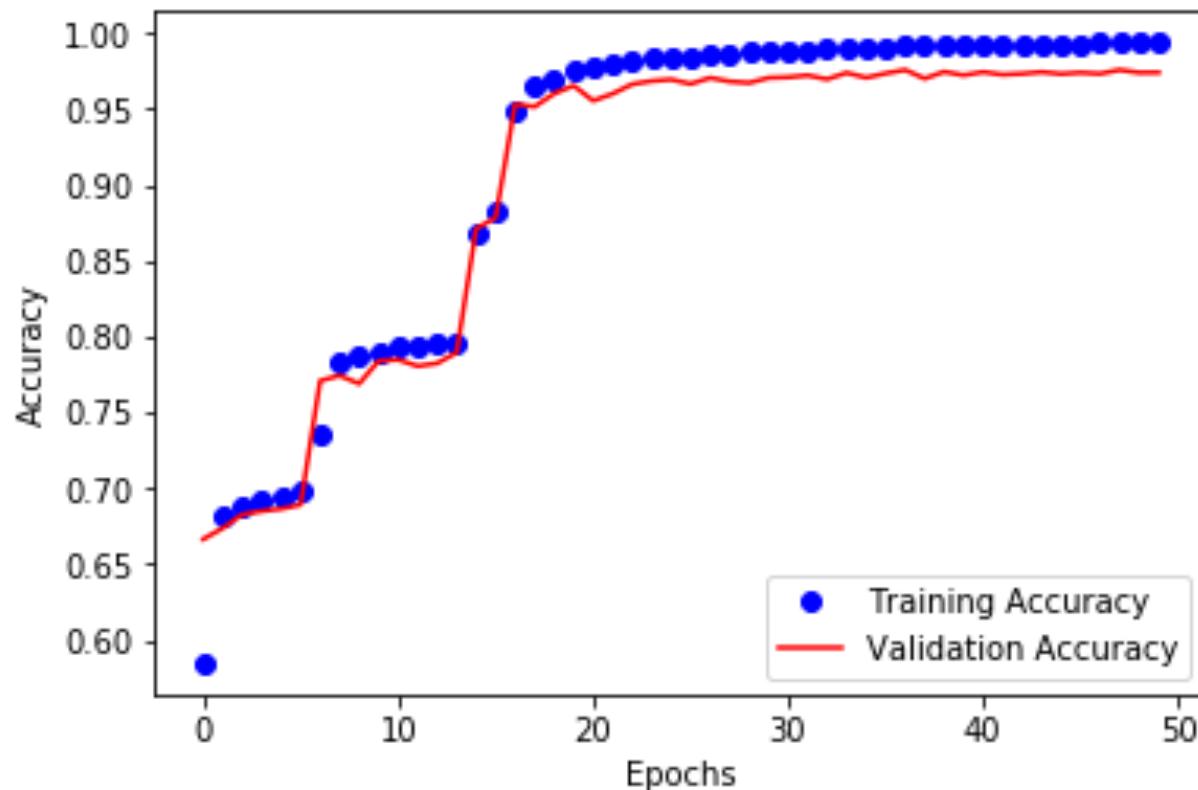
```
Train on 50000 samples, validate on 10000 samples  
Epoch 1/50  
50000/50000 [=====] - 5s 92us/step - loss: 6.5323 - acc: 0.5850 - val_loss: 5.2988 - val_acc: 0.6666  
Epoch 2/50  
50000/50000 [=====] - 4s 84us/step - loss: 5.0559 - acc: 0.6817 - val_loss: 5.1904 - val_acc: 0.6738  
Epoch 3/50  
50000/50000 [=====] - 3s 64us/step - loss: 4.9762 - acc: 0.6881 - val_loss: 5.0556 - val_acc: 0.6828
```

●  
●  
●

```
Epoch 49/50  
50000/50000 [=====] - 5s 93us/step - loss: 0.0912 - acc: 0.9934 - val_loss: 0.3404 - val_acc: 0.9738  
Epoch 50/50  
50000/50000 [=====] - 4s 79us/step - loss: 0.0920 - acc: 0.9934 - val_loss: 0.3327 - val_acc: 0.9739
```

## 4. Examine the Results

Plot the *accuracy* against *epochs* (1 epoch = 1 pass over the data).



## 4. Examine the Results

Evaluate the model on the ***test*** set. (So far, the model has not seen the ***test*** set.)

```
loss_and_acc = model.evaluate(x_test_vec, y_test_vec)
print('loss = ' + str(loss_and_acc[0]))
print('accuracy = ' + str(loss_and_acc[1]))
```

```
10000/10000 [=====] - 0s 43us/step
loss = 0.3648844491034643
accuracy = 0.9724
```

## 4. Examine the Results

- Training accuracy: 99.3%
- Validation accuracy: 97.4%
- Test accuracy: 97.2%

Much better than the linear softmax classifier (91.3% accuracy).

# Summary

# Train a Neural Network for Digit Recognition

## 1. Examine and process the data.

- Reshape images to vectors. (Matrix to vector.)
- One-hot encode the labels. (Integer to vector.)
- Partition to training and validation sets.

# Train a Neural Network for Digit Recognition

1. Examine and process the data.
2. Build the network (just like Lego.)



# Train a Neural Network for Digit Recognition

1. Examine and process the data.
2. Build the network (just like Lego.)
3. Compile the model (specify loss function, optimization algorithm, and evaluation metrics.)

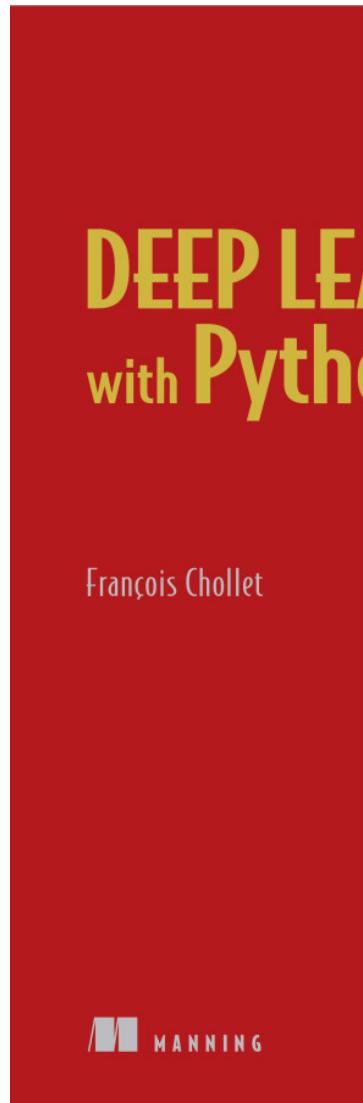
# Train a Neural Network for Digit Recognition

1. Examine and process the data.
2. Build the network (just like Lego.)
3. Compile the model (specify loss function, optimization algorithm, and evaluation metrics.)
4. Fit the model on training data.
  - Record training and validation accuracies.
  - Use the validation accuracies to tune the hyper-parameter.

# Train a Neural Network for Digit Recognition

1. Examine and process the data.
2. Build the network (just like Lego.)
3. Compile the model (specify loss function, optimization algorithm, and evaluation metrics.)
4. Fit the model on training data.
5. Make predictions for test data.

# Practice! Practice! Practice!



- Read the textbook.
- Run his sample code.
- If you do not practice, you will forget everything learned from this course.