02_mnist_with_ffnn_and_lenet5

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1 Basic Image Classification with Feedforward NN and LetNet5

All libraries we introduced in the last chapter provide support for convolutional layers. We are going to illustrate the LeNet5 architecture using the most basic MNIST handwritten digit dataset, and then use AlexNet on CIFAR10, a simplified version of the original ImageNet to demonstrate the use of data augmentation. LeNet5 and MNIST using Keras.

1.1 Imports

[45]:
```
%matplotlib inline
from random import randint
import numpy as np
import pandas as pd

from keras.models import Sequential
from keras import models, layers
from keras.datasets import mnist
from keras.utils import np_utils
import keras.backend as K
from keras.callbacks import ModelCheckpoint
from keras.models import Sequential
from keras.layers import Conv2D, AveragePooling2D, Dense, Dropout, Flatten
from keras.losses import categorical_crossentropy
import matplotlib.pyplot as plt
import matplotlib.cm as cm
```

1.2 Load MNIST Database

The original MNIST dataset contains 60,000 images in 28x28 pixel resolution with a single grayscale containing handwritten digits from 0 to 9. A good alternative is the more challenging but structurally similar Fashion MNIST dataset that we encountered in Chapter 12 on Unsupervised Learning.

We can load it in keras out of the box:

[2]:
```
# use Keras to import pre-shuffled MNIST database
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
print("The MNIST database has a training set of %d examples." % len(X_train))
print("The MNIST database has a test set of %d examples." % len(X_test))
```

```
The MNIST database has a training set of 60000 examples.
The MNIST database has a test set of 10000 examples.
```

[3]:
```
X_train.shape, X_test.shape
```

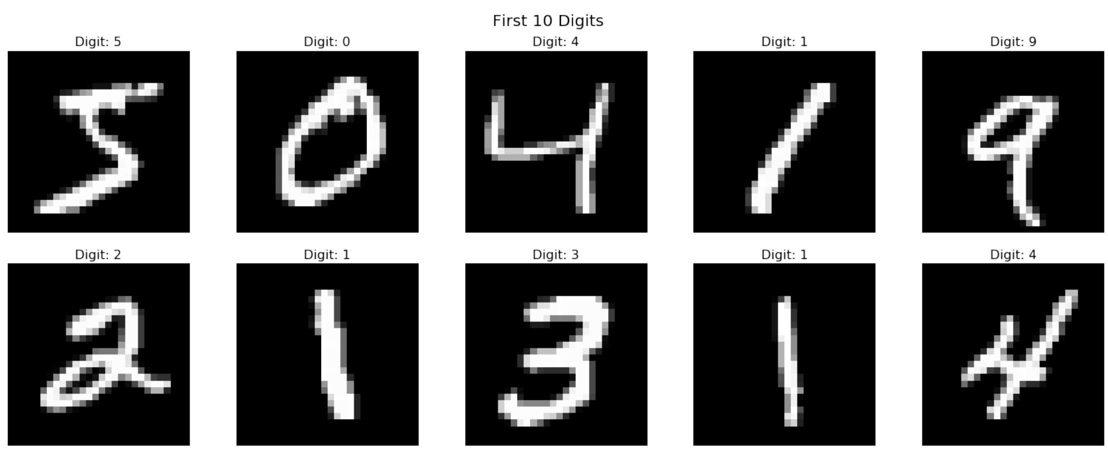
[3]:
```
((60000, 28, 28), (10000, 28, 28))
```

1.3 Visualize Data

1.3.1 Visualize First 10 Training Images

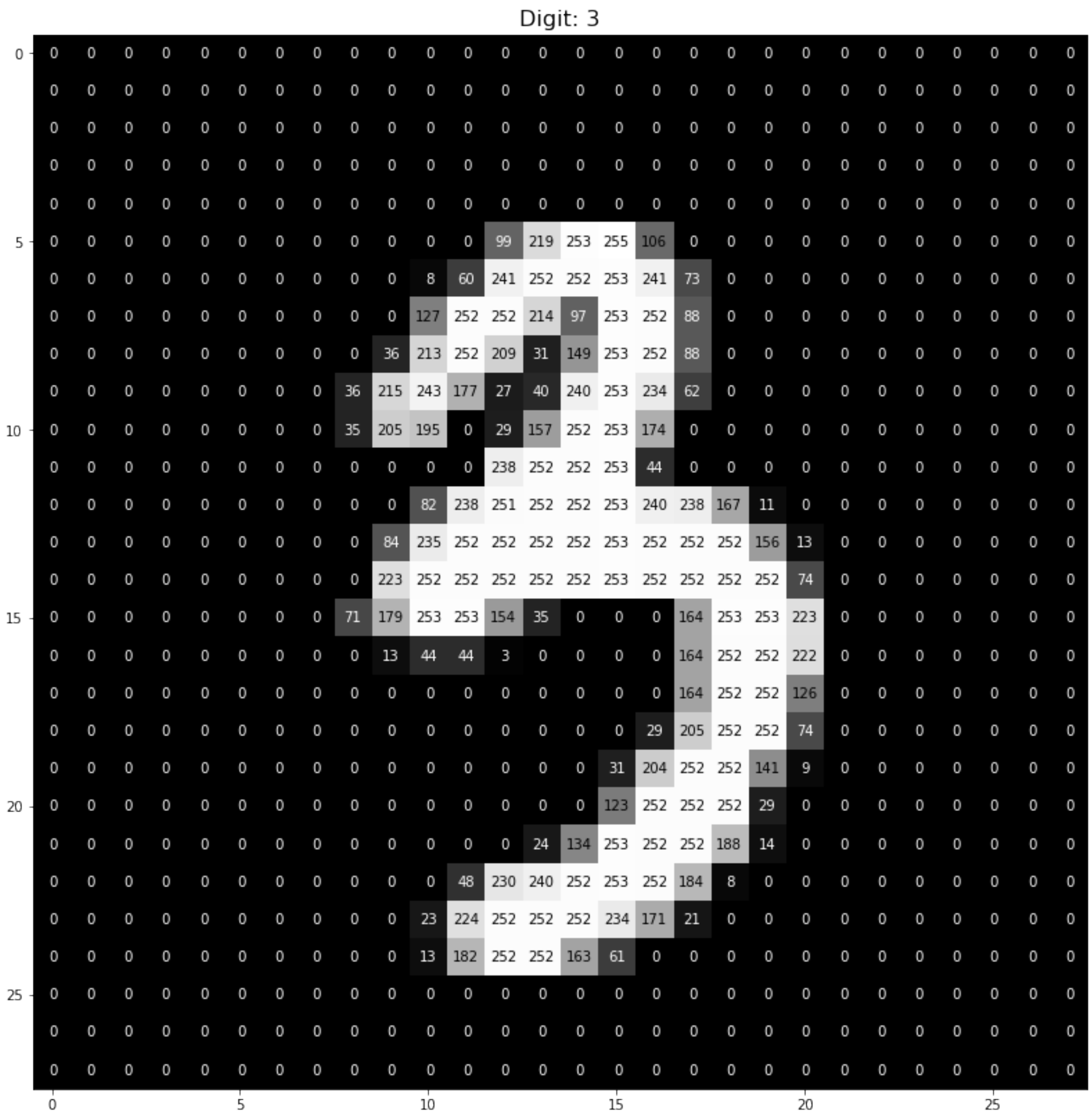
The below figure shows the first ten images in the dataset and highlights significant variation among instances of the same digit. On the right, it shows how the pixel values for an indivual image range from 0 to 255.

[4]:
```
fig, axes = plt.subplots(ncols=5, nrows=2, figsize=(20, 8))
axes = axes.flatten()
for i, ax in enumerate(axes):
    ax.imshow(X_train[i], cmap='gray')
    ax.axis('off')
    ax.set_title('Digit: {}'.format(y_train[i]), fontsize=16)
fig.suptitle('First 10 Digits', fontsize=20)
fig.tight_layout()
fig.subplots_adjust(top=.9)
```



1.3.2 Show random image in detail

[5]:
```
fig, ax = plt.subplots(figsize = (14, 14))

i = randint(0, len(X_train))
img = X_train[i]

ax.imshow(img, cmap='gray')
ax.set_title('Digit: {}'.format(y_train[i]), fontsize=16)

width, height = img.shape
thresh = img.max()/2.5
for x in range(width):
    for y in range(height):
        ax.annotate('{:2}'.format(img[x][y]),
                    xy=(y,x),
                    horizontalalignment='center',
                    verticalalignment='center',
                    color='white' if img[x][y]<thresh else 'black')
```



1.4 Prepare Data

1.4.1 Rescale pixel values

We rescale the pixel values to the range [0, 1] to normalize the training data and faciliate the backpropagation process and convert the data to 32 bit floats that reduce memory requirements and computational cost while providing sufficient precision for our use case:

[4]:
```
# rescale [0,255] --> [0,1]
X_train = X_train.astype('float32')/255
X_test = X_test.astype('float32')/255
```

1.4.2 One-Hot Label Encoding using Keras

Print first ten labels

[5]:
```
print('Integer-valued labels:')
print(y_train[:10])
```

```
Integer-valued labels:
[5 0 4 1 9 2 1 3 1 4]
```

We also need to convert the one-dimensional label to 10-dimensional one-hot encoding to make it compatible with the cross-entropy loss that receives a 10-class softmax output from the network:

[6]:
```
# one-hot encode the labels
y_train = np_utils.to_categorical(y_train, 10)
y_test = np_utils.to_categorical(y_test, 10)
```

[7]:
```
# print first ten (one-hot) training labels
y_train[:10]
```

[7]:
```
array([[0., 0., 0., 0., 0., 1., 0., 0., 0., 0.],
       [1., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 0., 0., 0., 0., 0., 1.],
       [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.]], dtype=float32)
```

1.5 Feed-Forward NN

1.5.1 Model Architecture

[35]:
```
model = Sequential()
model.add(Flatten(input_shape=X_train.shape[1:]))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(10, activation='softmax'))
```

[36]:
```
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
flatten_1 (Flatten)          (None, 784)               0
_________________________________________________________________
```

```
dense_1 (Dense)              (None, 512)               401920
_________________________________________________________________
dropout_1 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_2 (Dense)              (None, 512)               262656
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_3 (Dense)              (None, 10)                5130
=================================================================
Total params: 669,706
Trainable params: 669,706
Non-trainable params: 0

_________________________________________________________________
```

1.5.2 Compile the Model

[37]:
```python
model.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

1.5.3 Calculate Baseline Classification Accuracy

[8]:
```python
# evaluate test accuracy
score = model.evaluate(X_test, y_test, verbose=0)
accuracy = 100*score[1]

# print test accuracy
print('Test accuracy: %.4f%%' % accuracy)
```

```
Test accuracy: 10.4200%
```

1.5.4 Callback for model persistence

[ ]:
```python
mnist_path = 'models/mnist.ffn.best.hdf5'
```

[39]:
```python
checkpointer = ModelCheckpoint(filepath=mnist_path,
                               verbose=1,
                               save_best_only=True)
```

1.5.5 Train the Model

[40]:
```python
hist = model.fit(X_train,
                 y_train,
                 batch_size=128,
                 epochs=10,
                 validation_split=0.2,
```

```
                 callbacks=[checkpointer],
                 verbose=1,
                 shuffle=True)
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/10
48000/48000 [==============================] - 4s 76us/step - loss: 12.3566 -
acc: 0.2327 - val_loss: 11.6693 - val_acc: 0.2757

Epoch 00001: val_loss improved from inf to 11.66925, saving model to
mnist.model.best.hdf5
Epoch 2/10
48000/48000 [==============================] - 3s 69us/step - loss: 11.6842 -
acc: 0.2748 - val_loss: 11.6416 - val_acc: 0.2775

Epoch 00002: val_loss improved from 11.66925 to 11.64164, saving model to
mnist.model.best.hdf5
Epoch 3/10
48000/48000 [==============================] - 3s 67us/step - loss: 11.5629 -
acc: 0.2825 - val_loss: 11.6896 - val_acc: 0.2746

Epoch 00003: val_loss did not improve from 11.64164
Epoch 4/10
48000/48000 [==============================] - 3s 67us/step - loss: 11.5198 -
acc: 0.2851 - val_loss: 11.5825 - val_acc: 0.2812

Epoch 00004: val_loss improved from 11.64164 to 11.58248, saving model to
mnist.model.best.hdf5
Epoch 5/10
48000/48000 [==============================] - 3s 68us/step - loss: 11.2811 -
acc: 0.2997 - val_loss: 10.6698 - val_acc: 0.3377

Epoch 00005: val_loss improved from 11.58248 to 10.66979, saving model to
mnist.model.best.hdf5
Epoch 6/10
48000/48000 [==============================] - 3s 69us/step - loss: 10.7881 -
acc: 0.3304 - val_loss: 10.7308 - val_acc: 0.3339

Epoch 00006: val_loss did not improve from 10.66979
Epoch 7/10
48000/48000 [==============================] - 3s 68us/step - loss: 10.8279 -
acc: 0.3279 - val_loss: 10.7680 - val_acc: 0.3317

Epoch 00007: val_loss did not improve from 10.66979
Epoch 8/10
48000/48000 [==============================] - 3s 69us/step - loss: 10.5991 -
acc: 0.3421 - val_loss: 10.5127 - val_acc: 0.3476
```

```
Epoch 00008: val_loss improved from 10.66979 to 10.51270, saving model to
mnist.model.best.hdf5
Epoch 9/10
48000/48000 [==============================] - 3s 68us/step - loss: 10.3517 -
acc: 0.3575 - val_loss: 10.1866 - val_acc: 0.3680

Epoch 00009: val_loss improved from 10.51270 to 10.18657, saving model to
mnist.model.best.hdf5
Epoch 10/10
48000/48000 [==============================] - 3s 69us/step - loss: 10.4410 -
acc: 0.3520 - val_loss: 10.3458 - val_acc: 0.3581

Epoch 00010: val_loss did not improve from 10.18657
```

1.5.6 Load the Best Model

[41]:
```
# load the weights that yielded the best validation accuracy
model.load_weights(mnist_path)
```

1.5.7 Test Classification Accuracy

[44]:
```
# evaluate test accuracy
accuracy = model.evaluate(X_test, y_test, verbose=0)[1]

print(f'Test accuracy: {accuracy:.2%}')
```

```
Test accuracy: 37.36%
```

1.6 LeNet5

[33]:
```
K.clear_session()
```

We can define a simplified version of LeNet5 that omits the original final layer containing radial basis functions as follows, using the default 'valid' padding and single step strides unless defined otherwise:

[34]:
```
lenet5 = Sequential([
    Conv2D(filters=6, kernel_size=5, activation='relu', input_shape=(28, 28,␣
 ↪1), name='CONV1'),
    AveragePooling2D(pool_size=(2, 2), strides=(1, 1), padding='valid',␣
 ↪name='POOL1'),
    Conv2D(filters=16, kernel_size=(5, 5), activation='tanh', name='CONV2'),
    AveragePooling2D(pool_size=(2, 2), strides=(2, 2), name='POOL2'),
    Conv2D(filters=120, kernel_size=(5, 5), activation='tanh', name='CONV3'),
    Flatten(name='FLAT'),
    Dense(units=84, activation='tanh', name='FC6'),
    Dense(units=10, activation='softmax', name='FC7')
```

```
])
```

The summary indicates that the model thus defined has over 300,000 parameters:

[35]:
```
lenet5.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
CONV1 (Conv2D)               (None, 24, 24, 6)         156
_________________________________________________________________
POOL1 (AveragePooling2D)     (None, 23, 23, 6)         0
_________________________________________________________________
CONV2 (Conv2D)               (None, 19, 19, 16)        2416
_________________________________________________________________
POOL2 (AveragePooling2D)     (None, 9, 9, 16)          0
_________________________________________________________________
CONV3 (Conv2D)               (None, 5, 5, 120)         48120
_________________________________________________________________
FLAT (Flatten)               (None, 3000)              0
_________________________________________________________________
FC6 (Dense)                  (None, 84)                252084
_________________________________________________________________
FC7 (Dense)                  (None, 10)                850
=================================================================
Total params: 303,626
Trainable params: 303,626
Non-trainable params: 0
_________________________________________________________________
```

We compile using crossentropy loss and the original stochastic gradient optimizer:

[36]:
```
lenet5.compile(loss=categorical_crossentropy,
               optimizer='SGD',
               metrics=['accuracy'])
```

[37]:
```
lenet_path = 'models/mnist.lenet.best.hdf5'
```

[38]:
```
checkpointer = ModelCheckpoint(filepath=lenet_path,
                               verbose=1,
                               save_best_only=True)
```

Now we are ready to train the model. The model expects 4D input so we reshape accordingly. We use the standard batch size of 32, 80-20 train-validation split, use checkpointing to store the model weights if the validation error improves, and make sure the dataset is randomly shuffled:

[42]:
```
training = lenet5.fit(X_train.reshape(-1, 28, 28, 1),
                      y_train,
```

```
                       batch_size=32,
                        epochs=50,
                        validation_split=0.2, # use 0 to train on all data
                        callbacks=[checkpointer],
                        verbose=1,
                        shuffle=True)
```

```
Train on 48000 samples, validate on 12000 samples
Epoch 1/50
48000/48000 [==============================] - 3s 63us/step - loss: 0.0051 -
acc: 0.9995 - val_loss: 0.0058 - val_acc: 0.9994

Epoch 00001: val_loss improved from inf to 0.00576, saving model to
models/mnist.lenet.best.hdf5
Epoch 2/50
48000/48000 [==============================] - 3s 62us/step - loss: 0.0049 -
acc: 0.9995 - val_loss: 0.0058 - val_acc: 0.9993

Epoch 00002: val_loss did not improve from 0.00576
Epoch 3/50
48000/48000 [==============================] - 3s 66us/step - loss: 0.0046 -
acc: 0.9996 - val_loss: 0.0063 - val_acc: 0.9992

Epoch 00003: val_loss did not improve from 0.00576
Epoch 4/50
48000/48000 [==============================] - 3s 66us/step - loss: 0.0044 -
acc: 0.9996 - val_loss: 0.0063 - val_acc: 0.9989

Epoch 00004: val_loss did not improve from 0.00576
Epoch 5/50
48000/48000 [==============================] - 3s 69us/step - loss: 0.0043 -
acc: 0.9996 - val_loss: 0.0065 - val_acc: 0.9988

Epoch 00005: val_loss did not improve from 0.00576
Epoch 6/50
48000/48000 [==============================] - 3s 69us/step - loss: 0.0042 -
acc: 0.9996 - val_loss: 0.0064 - val_acc: 0.9991

Epoch 00006: val_loss did not improve from 0.00576
Epoch 7/50
48000/48000 [==============================] - 3s 69us/step - loss: 0.0041 -
acc: 0.9997 - val_loss: 0.0070 - val_acc: 0.9988

Epoch 00007: val_loss did not improve from 0.00576
Epoch 8/50
48000/48000 [==============================] - 3s 69us/step - loss: 0.0040 -
acc: 0.9997 - val_loss: 0.0067 - val_acc: 0.9989
```

```
Epoch 00008: val_loss did not improve from 0.00576
Epoch 9/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0039 -
acc: 0.9996 - val_loss: 0.0070 - val_acc: 0.9988

Epoch 00009: val_loss did not improve from 0.00576
Epoch 10/50
48000/48000 [==============================] - 3s 70us/step - loss: 0.0038 -
acc: 0.9997 - val_loss: 0.0067 - val_acc: 0.9990

Epoch 00010: val_loss did not improve from 0.00576
Epoch 11/50
48000/48000 [==============================] - 3s 67us/step - loss: 0.0036 -
acc: 0.9997 - val_loss: 0.0069 - val_acc: 0.9985

Epoch 00011: val_loss did not improve from 0.00576
Epoch 12/50
48000/48000 [==============================] - 3s 70us/step - loss: 0.0035 -
acc: 0.9997 - val_loss: 0.0070 - val_acc: 0.9986

Epoch 00012: val_loss did not improve from 0.00576
Epoch 13/50
48000/48000 [==============================] - 3s 70us/step - loss: 0.0034 -
acc: 0.9997 - val_loss: 0.0069 - val_acc: 0.9988

Epoch 00013: val_loss did not improve from 0.00576
Epoch 14/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0033 -
acc: 0.9998 - val_loss: 0.0069 - val_acc: 0.9987

Epoch 00014: val_loss did not improve from 0.00576
Epoch 15/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0032 -
acc: 0.9997 - val_loss: 0.0071 - val_acc: 0.9986

Epoch 00015: val_loss did not improve from 0.00576
Epoch 16/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0031 -
acc: 0.9998 - val_loss: 0.0072 - val_acc: 0.9985

Epoch 00016: val_loss did not improve from 0.00576
Epoch 17/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0031 -
acc: 0.9998 - val_loss: 0.0073 - val_acc: 0.9988

Epoch 00017: val_loss did not improve from 0.00576
Epoch 18/50
```

```
48000/48000 [==============================] - 3s 69us/step - loss: 0.0030 -
acc: 0.9998 - val_loss: 0.0075 - val_acc: 0.9983

Epoch 00018: val_loss did not improve from 0.00576
Epoch 19/50
48000/48000 [==============================] - 4s 73us/step - loss: 0.0029 -
acc: 0.9998 - val_loss: 0.0073 - val_acc: 0.9985

Epoch 00019: val_loss did not improve from 0.00576
Epoch 20/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0028 -
acc: 0.9998 - val_loss: 0.0075 - val_acc: 0.9982

Epoch 00020: val_loss did not improve from 0.00576
Epoch 21/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0028 -
acc: 0.9998 - val_loss: 0.0073 - val_acc: 0.9985

Epoch 00021: val_loss did not improve from 0.00576
Epoch 22/50
48000/48000 [==============================] - 3s 66us/step - loss: 0.0027 -
acc: 0.9999 - val_loss: 0.0074 - val_acc: 0.9983

Epoch 00022: val_loss did not improve from 0.00576
Epoch 23/50
48000/48000 [==============================] - 3s 64us/step - loss: 0.0027 -
acc: 0.9998 - val_loss: 0.0076 - val_acc: 0.9986

Epoch 00023: val_loss did not improve from 0.00576
Epoch 24/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0026 -
acc: 0.9999 - val_loss: 0.0076 - val_acc: 0.9982

Epoch 00024: val_loss did not improve from 0.00576
Epoch 25/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0026 -
acc: 0.9999 - val_loss: 0.0077 - val_acc: 0.9981

Epoch 00025: val_loss did not improve from 0.00576
Epoch 26/50
48000/48000 [==============================] - 3s 70us/step - loss: 0.0025 -
acc: 0.9999 - val_loss: 0.0076 - val_acc: 0.9982

Epoch 00026: val_loss did not improve from 0.00576
Epoch 27/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0024 -
acc: 0.9999 - val_loss: 0.0079 - val_acc: 0.9981
```

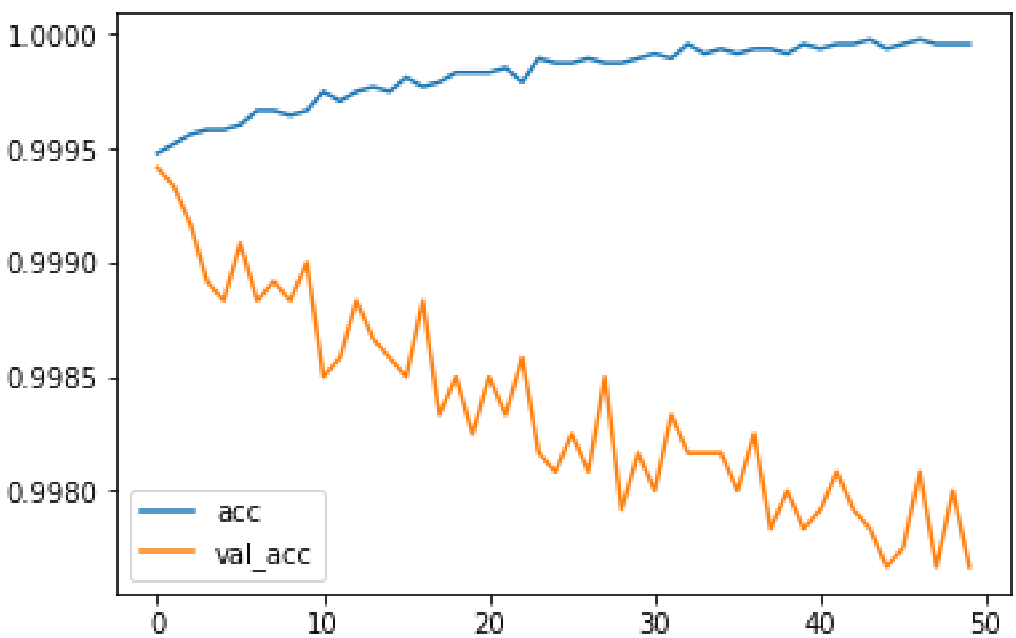
```
Epoch 00027: val_loss did not improve from 0.00576
Epoch 28/50
48000/48000 [==============================] - 3s 73us/step - loss: 0.0024 -
acc: 0.9999 - val_loss: 0.0079 - val_acc: 0.9985

Epoch 00028: val_loss did not improve from 0.00576
Epoch 29/50
48000/48000 [==============================] - 3s 68us/step - loss: 0.0023 -
acc: 0.9999 - val_loss: 0.0078 - val_acc: 0.9979

Epoch 00029: val_loss did not improve from 0.00576
Epoch 30/50
48000/48000 [==============================] - 3s 73us/step - loss: 0.0023 -
acc: 0.9999 - val_loss: 0.0076 - val_acc: 0.9982

Epoch 00030: val_loss did not improve from 0.00576
Epoch 31/50
48000/48000 [==============================] - 4s 73us/step - loss: 0.0022 -
acc: 0.9999 - val_loss: 0.0077 - val_acc: 0.9980

Epoch 00031: val_loss did not improve from 0.00576
Epoch 32/50
48000/48000 [==============================] - 3s 73us/step - loss: 0.0022 -
acc: 0.9999 - val_loss: 0.0078 - val_acc: 0.9983

Epoch 00032: val_loss did not improve from 0.00576
Epoch 33/50
48000/48000 [==============================] - 4s 73us/step - loss: 0.0021 -
acc: 1.0000 - val_loss: 0.0079 - val_acc: 0.9982

Epoch 00033: val_loss did not improve from 0.00576
Epoch 34/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0021 -
acc: 0.9999 - val_loss: 0.0077 - val_acc: 0.9982

Epoch 00034: val_loss did not improve from 0.00576
Epoch 35/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0021 -
acc: 0.9999 - val_loss: 0.0078 - val_acc: 0.9982

Epoch 00035: val_loss did not improve from 0.00576
Epoch 36/50
48000/48000 [==============================] - 3s 70us/step - loss: 0.0021 -
acc: 0.9999 - val_loss: 0.0079 - val_acc: 0.9980

Epoch 00036: val_loss did not improve from 0.00576
Epoch 37/50
48000/48000 [==============================] - 3s 65us/step - loss: 0.0020 -
```

```
acc: 0.9999 - val_loss: 0.0078 - val_acc: 0.9982

Epoch 00037: val_loss did not improve from 0.00576
Epoch 38/50
48000/48000 [==============================] - 4s 73us/step - loss: 0.0019 -
acc: 0.9999 - val_loss: 0.0081 - val_acc: 0.9978

Epoch 00038: val_loss did not improve from 0.00576
Epoch 39/50
48000/48000 [==============================] - 3s 73us/step - loss: 0.0019 -
acc: 0.9999 - val_loss: 0.0079 - val_acc: 0.9980

Epoch 00039: val_loss did not improve from 0.00576
Epoch 40/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0019 -
acc: 1.0000 - val_loss: 0.0081 - val_acc: 0.9978

Epoch 00040: val_loss did not improve from 0.00576
Epoch 41/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0018 -
acc: 0.9999 - val_loss: 0.0083 - val_acc: 0.9979

Epoch 00041: val_loss did not improve from 0.00576
Epoch 42/50
48000/48000 [==============================] - 4s 73us/step - loss: 0.0018 -
acc: 1.0000 - val_loss: 0.0081 - val_acc: 0.9981

Epoch 00042: val_loss did not improve from 0.00576
Epoch 43/50
48000/48000 [==============================] - 3s 72us/step - loss: 0.0018 -
acc: 1.0000 - val_loss: 0.0081 - val_acc: 0.9979

Epoch 00043: val_loss did not improve from 0.00576
Epoch 44/50
48000/48000 [==============================] - 3s 67us/step - loss: 0.0018 -
acc: 1.0000 - val_loss: 0.0083 - val_acc: 0.9978

Epoch 00044: val_loss did not improve from 0.00576
Epoch 45/50
48000/48000 [==============================] - 3s 65us/step - loss: 0.0017 -
acc: 0.9999 - val_loss: 0.0082 - val_acc: 0.9977

Epoch 00045: val_loss did not improve from 0.00576
Epoch 46/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0017 -
acc: 1.0000 - val_loss: 0.0081 - val_acc: 0.9978

Epoch 00046: val_loss did not improve from 0.00576
```

```
Epoch 47/50
48000/48000 [==============================] - 3s 69us/step - loss: 0.0017 -
acc: 1.0000 - val_loss: 0.0083 - val_acc: 0.9981

Epoch 00047: val_loss did not improve from 0.00576
Epoch 48/50
48000/48000 [==============================] - 3s 69us/step - loss: 0.0016 -
acc: 1.0000 - val_loss: 0.0084 - val_acc: 0.9977

Epoch 00048: val_loss did not improve from 0.00576
Epoch 49/50
48000/48000 [==============================] - 3s 68us/step - loss: 0.0016 -
acc: 1.0000 - val_loss: 0.0083 - val_acc: 0.9980

Epoch 00049: val_loss did not improve from 0.00576
Epoch 50/50
48000/48000 [==============================] - 3s 71us/step - loss: 0.0016 -
acc: 1.0000 - val_loss: 0.0083 - val_acc: 0.9977

Epoch 00050: val_loss did not improve from 0.00576
```

On a single GPU, 50 epochs take around 2.5 minutes, resulting in a test accuracy of 99.19%, almost exactly the same result as for the original LeNet5:

[48]:
```
pd.DataFrame(training.history)[['acc','val_acc']].plot();
```



[49]:
```
# evaluate test accuracy
accuracy = lenet5.evaluate(X_test.reshape(-1, 28, 28, 1), y_test, verbose=0)[1]
print('Test accuracy: {:.2%}'.format(accuracy))
```

```
Test accuracy: 99.19%
```

1.7 Summary

For comparison, a simple two-layer feedforward network achieves only 37.36% test accuracy.

The LeNet5 improvement on MNIST is, in fact, modest. Non-neural methods have also achieved classification accuracies greater than or equal to 99%, including K-Nearest Neighbours or Support Vector Machines. CNNs really shine with more challenging datasets as we will see next.

[ ]:
```

```