mnist_mlp

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Note: Comments and additional useful info have been added to the original notebook **mnist-mlp/mnist_mlp.ipynb** from `https://github.com/udacity/aind2-cnn.git`

1 Artificial Intelligence Nanodegree

1.1 Convolutional Neural Networks

In this notebook, we train an MLP (Multi-Layer Perceptron) to classify images from the MNIST database.

1.1.1 1. Load MNIST Database

MNIST database of handwritten digits consists of

- Train dataset of 60,000 28x28 grayscale images of the 10 digits *0 to 9*
- Test dataset of 10,000 28x28 grayscale images

Usage:

```
from keras.datasets import mnist

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

The function returns 2 tuples:

- x_train, x_test: unit8 array of grayscale image data with shape (num_samples, 28, 28)
- y_train, y_test: uint8 array of digit labels (integers in range 0-9) with shape (num_samples)

Reference: https://keras.io/datasets/

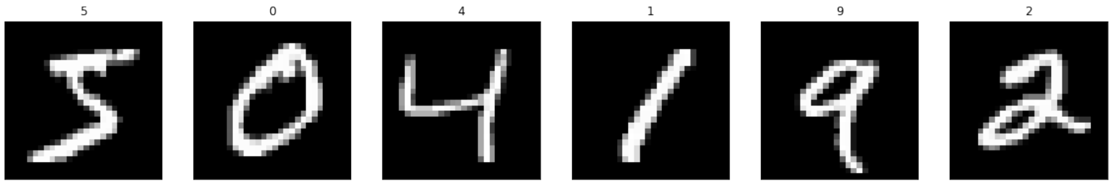
```
In [1]: from keras.datasets import mnist

        # 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))
print('X_train shape:', X_train.shape)
print('y_train shape:', y_train.shape)
print('X_test shape:', X_test.shape)
print('y_test shape:', y_test.shape)
```

```
/home/supannee/tensorflow/lib/python3.5/site-packages/h5py/__init__.py:36: FutureWarning: Conver
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.


The MNIST database has a training set of 60000 examples.
The MNIST database has a test set of 10000 examples.
X_train shape: (60000, 28, 28)
y_train shape: (60000,)
X_test shape: (10000, 28, 28)
y_test shape: (10000,)
```

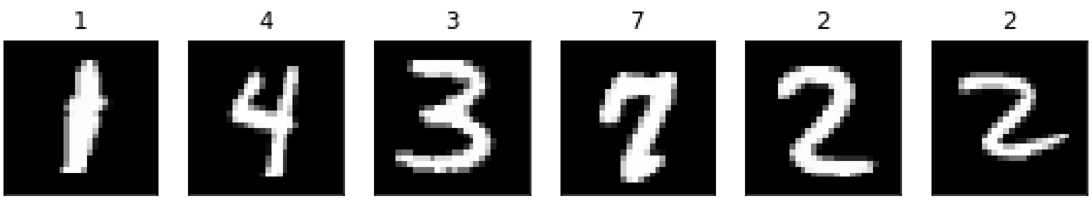
1.1.2 2. Visualize the First Six Training Images

In [2]:
```
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.cm as cm
import numpy as np

# plot first six training images
fig = plt.figure(figsize=(20,20)) # Create a figure object of size 20x20 inches
for i in range(6):
    # subplot: 1 row x 6 cols
    ax = fig.add_subplot(1, 6, i+1, xticks=[], yticks=[]) # the subplot takes position (
    ax.imshow(X_train[i], cmap='gray')
    ax.set_title(str(y_train[i]))
```



In [3]:
```
# Display image as random
import matplotlib.pyplot as plt
%matplotlib inline
import matplotlib.cm as cm
import numpy as np
```

```
import random # to random number

# plot six random training images
fig = plt.figure(figsize=(10,10)) # Create a figure object of size 10x10 inches
for i in range(6):
    # subplot: 1 row x 6 cols
    ax = fig.add_subplot(1, 6, i+1, xticks=[], yticks=[]) # the subplot takes position (
    # display a random sample
    n = random.randint(0, len(X_train))
    ax.imshow(X_train[n], cmap='gray')
    ax.set_title(str(y_train[n]))
```

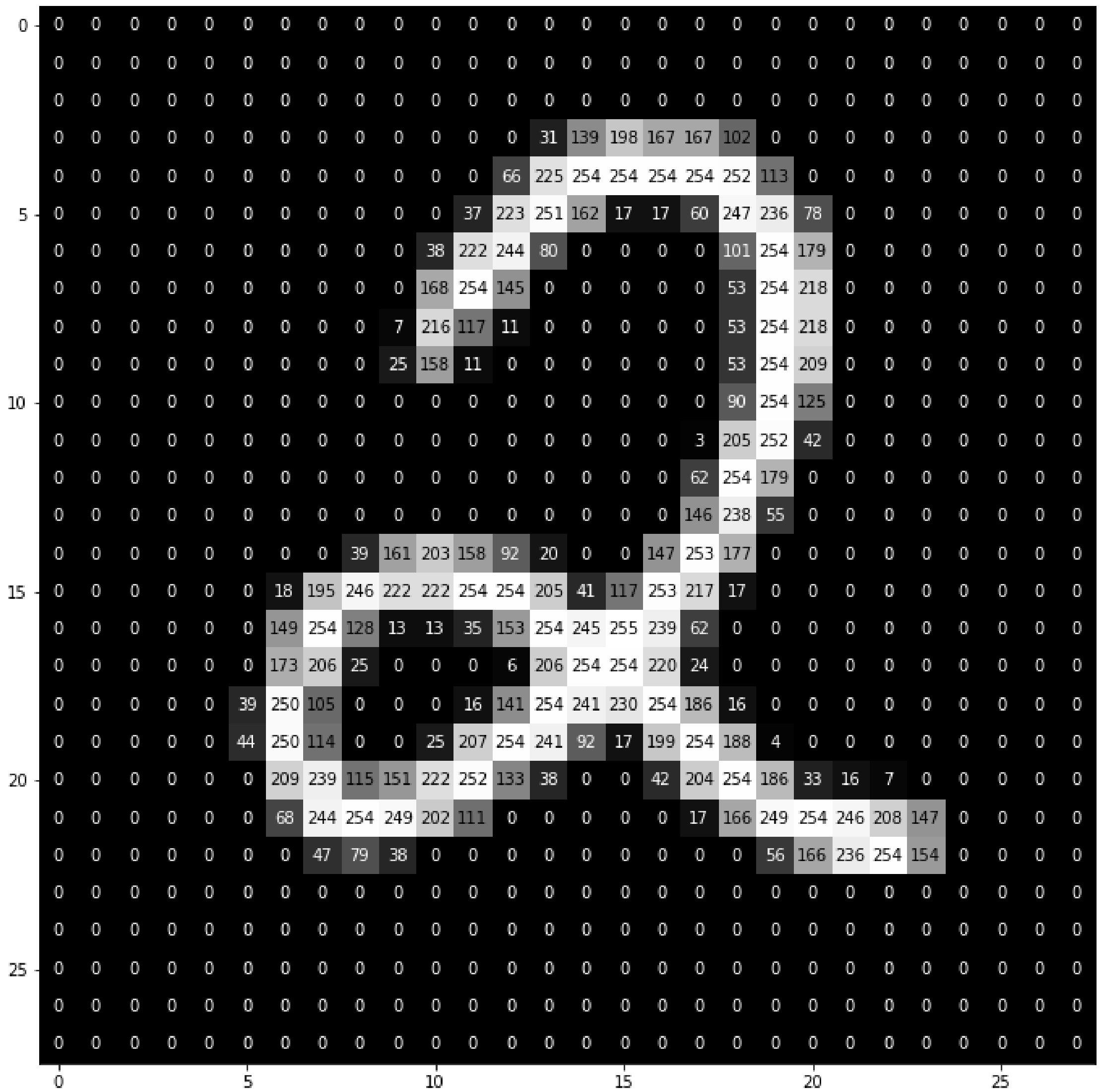


1.1.3 3. View an Image in More Detail

In [4]:
```
def visualize_input(img, ax): # pass subplot object
    ax.imshow(img, cmap='gray')
    width, height = img.shape
    thresh = img.max()/2.5
    print('width: {}, height: {}'.format(width, height))
    print('thresh = {}/2.5 = {}'.format(img.max(), thresh))
    for x in range(width):
        for y in range(height):
            ax.annotate(str(round(img[x][y],2)), # text = round img[x][y] to 2 digits af
                        xy=(y,x), # coordinate as a tuple (row, col)
                        horizontalalignment='center',
                        verticalalignment='center',
                        color='white' if img[x][y]<thresh else 'black') # text color
                        #color='green' if img[x][y]<40.0 else 'red')

fig = plt.figure(figsize = (12,12))
ax = fig.add_subplot(111) # gride of 1 row x 1 col and display at 1th
#visualize_input(X_train[0], ax)
#visualise a random image
n = random.randint(0, len(X_train))
visualize_input(X_train[n], ax)
#ax.set_title(str(y_train[n]))
```

```
width: 28, height: 28
```

```
thresh = 255/2.5 = 102.0
```



1.1.4 4. Rescale the Images by Dividing Every Pixel in Every Image by 255

```
In [5]: # rescale [0,255] --> [0,1]
        X_train = X_train.astype('float32')/255
        X_test = X_test.astype('float32')/255
```

1.1.5 5. Encode Categorical Integer Labels Using a One-Hot Scheme

Usage:

```
keras.utils.to_categorical(y, num_classes = None)
```

Converts a class vector (integers) to binary class matrix > **y:** class vector to be converted (must be integers from 0 to num_classes)
> **num_class:** total number of classes

Example: a one-hot encoder for 1, 3, 9 with 10 classes is

```
0123456789 # position
0100000000 # one-hot for 1
0001000000 # one-hot for 3
0000000001 # one-hot for 9
```

Reference: https://keras.io/utils/

```
In [6]: from keras.utils import np_utils

        # print first ten (integer-valued) training labels
        print('Integer-valued labels:')
        print(y_train[:10])

        # one-hot encode the labels
        y_train = np_utils.to_categorical(y_train, 10)
        y_test = np_utils.to_categorical(y_test, 10)

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

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

1.1.6 6. Define the Model Architecture

We first start by creating a `Sequential` model.

```
# define the model
model = Sequential()
```

We can then add layers via the `.add()` method or passing a list of layer intances to the constructor above.
Since the model needs to know what input shape to be expected, we need to pass the shape of the input in the first layer.

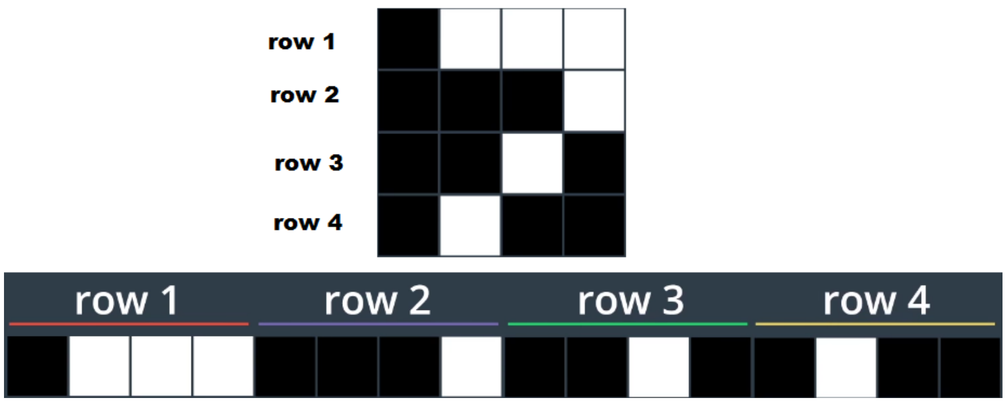
The input shape is defined by `input_shape=X_train.shape[1:]` in which `X_train.shape[1:]` is `(28, 28)`.

`print(X_train.shape[1:]) # (28,28)`

The first thing we have to do is to convert the input matrix into a row vector using `Flatten`.

```
model.add(Flatten(input_shape=X_train.shape[1:]))
```

`Flatten()` converts the input matrix X into a row vector as illustrated in the figure below:



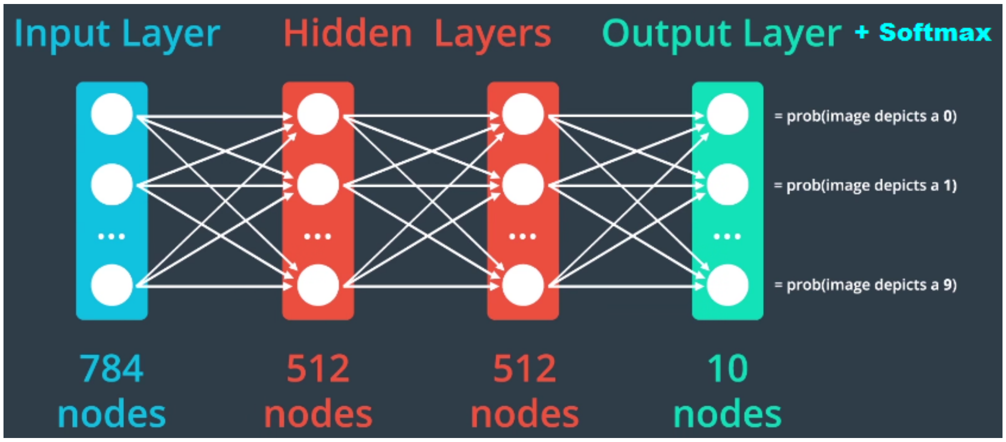
"Illustration of Flatten"

For the input shape (28,28) it is convert to a row vector of size (1,784) from $28x28 = 784$.
Then add the remaining layers in the sequence.

```
# Add a fully connected layer with 512 hidden units
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
# Add a fully connected layers with 10 hidden units ~ number of classes
model.add(Dense(10, activation='softmax'))
```

The MLP architecture for our MNIST digit classifer is depicted below
Reference: https://keras.io/getting-started/sequential-model-guide/

```
In [7]: from keras.models import Sequential
        from keras.layers import Dense, Dropout, Flatten

        # define the model
        model = Sequential()
        # Flatten X from a matrix into a row vector
        model.add(Flatten(input_shape=X_train.shape[1:]))
        model.add(Dense(512, activation='relu'))
```



"MLP architecture"

```
model.add(Dropout(0.2))
model.add(Dense(512, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(10, activation='softmax'))

# summarize the model
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
_________________________________________________________________
```

1.1.7 7. Compile the Model

We use `compile()` to configure the model for training.
Usage:

compile(self, optimizer, loss=None, metrics=None, loss_weights=None, sample_weight_mode=None, weighted_metrics=None, target_tensors=None)

Details for optimiser can be found on this link: https://keras.io/optimizers/

```
In [8]: # compile the model
        model.compile(loss='categorical_crossentropy', optimizer='rmsprop',
                      metrics=['accuracy'])
```

1.1.8 8. Calculate the Classification Accuracy on the Test Set (Before Training)

```
In [9]: # 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: 13.4100%
```

1.1.9 9. Train the Model

```
In [10]: from keras.callbacks import ModelCheckpoint

         # train the model
         checkpointer = ModelCheckpoint(filepath='mnist.model.best.hdf5',
                                        verbose=1, save_best_only=True)
         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 [==============================] - 2s 37us/step - loss: 0.2757 - acc: 0.9137 - val_l

Epoch 00001: val_loss improved from inf to 0.13493, saving model to mnist.model.best.hdf5
Epoch 2/10
48000/48000 [==============================] - 2s 34us/step - loss: 0.1125 - acc: 0.9654 - val_l

Epoch 00002: val_loss improved from 0.13493 to 0.09148, saving model to mnist.model.best.hdf5
Epoch 3/10
48000/48000 [==============================] - 2s 33us/step - loss: 0.0795 - acc: 0.9748 - val_l

Epoch 00003: val_loss improved from 0.09148 to 0.08339, saving model to mnist.model.best.hdf5
Epoch 4/10
48000/48000 [==============================] - 2s 35us/step - loss: 0.0624 - acc: 0.9807 - val_l

Epoch 00004: val_loss did not improve
Epoch 5/10
```

```
48000/48000 [==============================] - 2s 35us/step - loss: 0.0531 - acc: 0.9836 - val_l

Epoch 00005: val_loss did not improve
Epoch 6/10
48000/48000 [==============================] - 2s 34us/step - loss: 0.0445 - acc: 0.9859 - val_l

Epoch 00006: val_loss did not improve
Epoch 7/10
48000/48000 [==============================] - 2s 35us/step - loss: 0.0387 - acc: 0.9885 - val_l

Epoch 00007: val_loss did not improve
Epoch 8/10
48000/48000 [==============================] - 2s 34us/step - loss: 0.0326 - acc: 0.9904 - val_l

Epoch 00008: val_loss did not improve
Epoch 9/10
48000/48000 [==============================] - 2s 33us/step - loss: 0.0308 - acc: 0.9907 - val_l

Epoch 00009: val_loss did not improve
Epoch 10/10
48000/48000 [==============================] - 2s 34us/step - loss: 0.0274 - acc: 0.9917 - val_l

Epoch 00010: val_loss did not improve
```

1.1.10 10. Load the Model with the Best Classification Accuracy on the Validation Set

In [11]:
```
# load the weights that yielded the best validation accuracy
model.load_weights('mnist.model.best.hdf5')
```

1.1.11 11. Calculate the Classification Accuracy on the Test Set

In [12]:
```
# 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: 97.8400%
```