In [1]:

```
from keras.datasets import mnist
from keras.utils import np_utils
from keras.models import Sequential
from keras import models, layers
import keras
import matplotlib.pyplot as plt


#Load dataset as train and test sets
(x_train, y_train), (x_test, y_test) = mnist.load_data()

#Set numeric type to float32 from uint8
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')

#Normalize value to [0, 1]
x_train /= 255
x_test /= 255

#Transform lables to one-hot encoding
y_train = np_utils.to_categorical(y_train, 10)
y_test = np_utils.to_categorical(y_test, 10)

#Reshape the dataset into 4D array
x_train = x_train.reshape(x_train.shape[0], 28,28,1)
x_test = x_test.reshape(x_test.shape[0], 28,28,1)

print('trainImages size:' + str(x_train.shape))
print('trainLabels size:' + str(y_train.shape))
print('testImages size:' + str(x_test.shape))
print('testLabels size:' + str(y_test.shape))
```

```
Using TensorFlow backend.

trainImages size:(60000, 28, 28, 1)
trainLabels size:(60000, 10)
testImages size:(10000, 28, 28, 1)
testLabels size:(10000, 10)
```

In [2]:

```
#Instantiate an empty model
model = Sequential()

#C1 Convolutional Layer
model.add(layers.Conv2D(6, kernel_size=(5, 5), strides=(1, 1),
                        activation='tanh', input_shape=(28,28,1), padding="same"))

#S2 Pooling Layer
model.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding="valid")

#C3 Convolutional Layer
model.add(layers.Conv2D(16, kernel_size=(5, 5), strides=(1, 1), activation='tanh', p

#S4 Pooling Layer
model.add(layers.AveragePooling2D(pool_size=(2, 2), strides=(2, 2), padding="valid")

#Flatten the CNN output so that we can connect it with fully connected layers
model.add(layers.Flatten())

#FC5 Fully Connected Layer
model.add(layers.Dense(120, activation='tanh'))

#FC6 Fully Connected Layer
model.add(layers.Dense(84, activation='tanh'))

#Output Layer with softmax activation
model.add(layers.Dense(10, activation='softmax'))

#Compile the model
model.compile(loss=keras.losses.categorical_crossentropy, optimizer='SGD', metrics=[

hist = model.fit(x=x_train,y=y_train, epochs=20, batch_size=64, validation_data=(x_t
```

```
WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:74: The nam
e tf.get_default_graph is deprecated. Please use tf.compat.v1.get_defa
ult_graph instead.

WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:517: The na
me tf.placeholder is deprecated. Please use tf.compat.v1.placeholder i
nstead.

WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:4138: The n
ame tf.random_uniform is deprecated. Please use tf.random.uniform inst
ead.

WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:3980: The n
ame tf.nn.avg_pool is deprecated. Please use tf.nn.avg_pool2d instead.

WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/keras/optimizers.py:790: The name tf.train.Opti
mizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:3295: The n
ame tf.log is deprecated. Please use tf.math.log instead.
```

```
WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/tensorflow/python/ops/math_grad.py:1250: add_di
spatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops)
is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /home/jdsantos/anaconda3/envs/tensorflow/lib/p
ython3.7/site-packages/keras/backend/tensorflow_backend.py:986: The na
me tf.assign_add is deprecated. Please use tf.compat.v1.assign_add ins
tead.

Train on 60000 samples, validate on 10000 samples
Epoch 1/20
60000/60000 [==============================] - 20s 326us/step - loss:
0.8020 - acc: 0.7967 - val_loss: 0.3878 - val_acc: 0.8955
Epoch 2/20
60000/60000 [==============================] - 19s 322us/step - loss:
0.3417 - acc: 0.9038 - val_loss: 0.2840 - val_acc: 0.9188
Epoch 3/20
60000/60000 [==============================] - 24s 393us/step - loss:
0.2730 - acc: 0.9206 - val_loss: 0.2372 - val_acc: 0.9303
Epoch 4/20
60000/60000 [==============================] - 19s 320us/step - loss:
0.2314 - acc: 0.9324 - val_loss: 0.2036 - val_acc: 0.9403
Epoch 5/20
60000/60000 [==============================] - 20s 335us/step - loss:
0.2004 - acc: 0.9415 - val_loss: 0.1758 - val_acc: 0.9476
Epoch 6/20
60000/60000 [==============================] - 20s 339us/step - loss:
0.1763 - acc: 0.9487 - val_loss: 0.1552 - val_acc: 0.9560
Epoch 7/20
60000/60000 [==============================] - 21s 346us/step - loss:
0.1568 - acc: 0.9539 - val_loss: 0.1395 - val_acc: 0.9612
Epoch 8/20
60000/60000 [==============================] - 20s 330us/step - loss:
0.1409 - acc: 0.9585 - val_loss: 0.1252 - val_acc: 0.9650
Epoch 9/20
60000/60000 [==============================] - 20s 338us/step - loss:
0.1278 - acc: 0.9625 - val_loss: 0.1157 - val_acc: 0.9684
Epoch 10/20
60000/60000 [==============================] - 20s 340us/step - loss:
0.1170 - acc: 0.9659 - val_loss: 0.1062 - val_acc: 0.9693
Epoch 11/20
60000/60000 [==============================] - 21s 348us/step - loss:
0.1074 - acc: 0.9688 - val_loss: 0.0969 - val_acc: 0.9710
Epoch 12/20
60000/60000 [==============================] - 19s 315us/step - loss:
0.0996 - acc: 0.9712 - val_loss: 0.0910 - val_acc: 0.9744
Epoch 13/20
60000/60000 [==============================] - 21s 342us/step - loss:
0.0929 - acc: 0.9726 - val_loss: 0.0847 - val_acc: 0.9757
Epoch 14/20
60000/60000 [==============================] - 21s 351us/step - loss:
0.0868 - acc: 0.9749 - val_loss: 0.0800 - val_acc: 0.9760
Epoch 15/20
60000/60000 [==============================] - 20s 330us/step - loss:
0.0817 - acc: 0.9766 - val_loss: 0.0775 - val_acc: 0.9771
Epoch 16/20
60000/60000 [==============================] - 21s 350us/step - loss:
0.0773 - acc: 0.9779 - val_loss: 0.0727 - val_acc: 0.9775
```

```
Epoch 17/20
60000/60000 [==============================] - 20s 340us/step - loss:
0.0731 - acc: 0.9796 - val_loss: 0.0701 - val_acc: 0.9788
Epoch 18/20
60000/60000 [==============================] - 20s 331us/step - loss:
0.0697 - acc: 0.9801 - val_loss: 0.0657 - val_acc: 0.9797
Epoch 19/20
60000/60000 [==============================] - 20s 333us/step - loss:
0.0664 - acc: 0.9814 - val_loss: 0.0647 - val_acc: 0.9804
Epoch 20/20
60000/60000 [==============================] - 20s 340us/step - loss:
0.0635 - acc: 0.9821 - val_loss: 0.0624 - val_acc: 0.9809
```

In [3]:

```
test_score = model.evaluate(x_test, y_test)
print("Test loss {:.4f}, accuracy {:.2f}%".format(test_score[0], test_score[1] * 10(
```

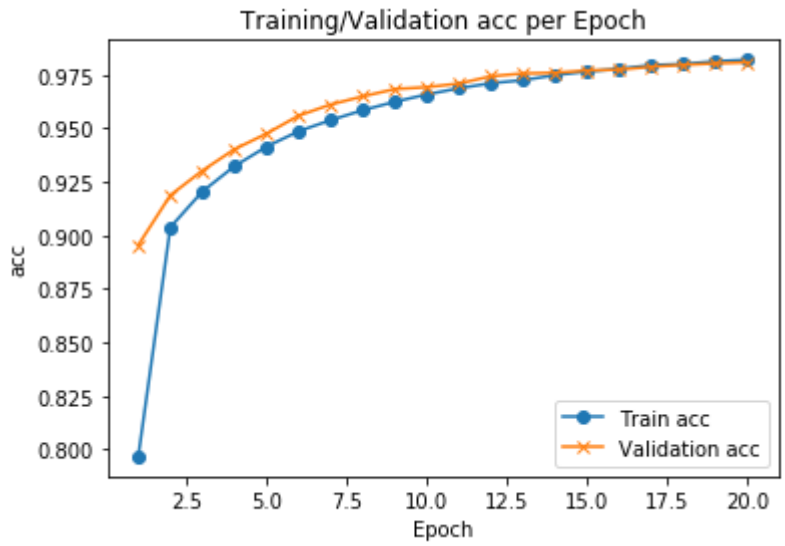
```
10000/10000 [==============================] - 2s 166us/step
Test loss 0.0624, accuracy 98.09%
```

In [5]:

```
f,ax = plt.subplots()
ax.plot([None] + hist.history['acc'], 'o-')
ax.plot([None] + hist.history['val_acc'], 'x-')
# Plot legend and use the best location automatically: loc = 0.
ax.legend(['Train acc', 'Validation acc'], loc = 0)
ax.set_title('Training/Validation acc per Epoch')
ax.set_xlabel('Epoch')
ax.set_ylabel('acc')
```

Out[5]:

```
Text(0, 0.5, 'acc')
```

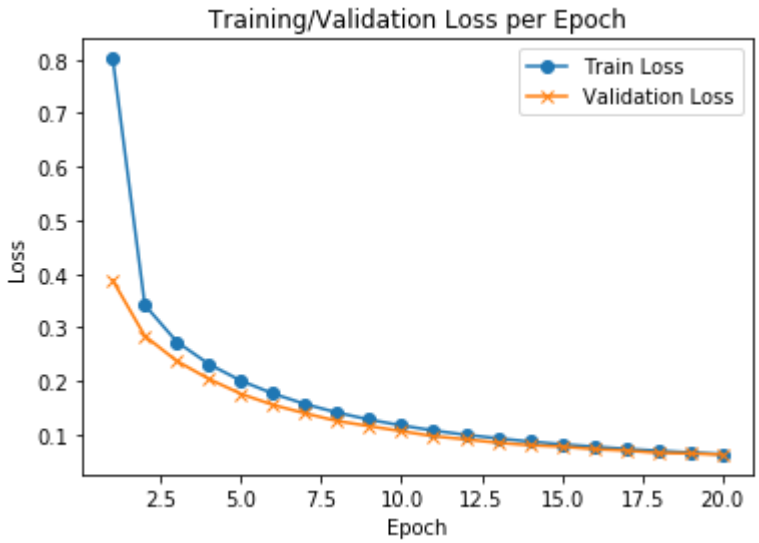


In [11]:

```
f, ax = plt.subplots()
ax.plot([None] + hist.history['loss'], 'o-')
ax.plot([None] + hist.history['val_loss'], 'x-')
# Plot legend and use the best location automatically: loc = 0.
ax.legend(['Train Loss', 'Validation Loss'], loc = 0)
ax.set_title('Training/Validation Loss per Epoch')
ax.set_xlabel('Epoch')
ax.set_ylabel('Loss')
```

Out[11]:

```
Text(0, 0.5, 'Loss')
```



In [ ]: