exercise_3

November 14, 2017

1 DATA20001 Deep Learning - Exercise 3

Due Tuesday November 21, before 12:00 PM (noon)

In this second computer exercise we are going to work with images and convolutional neural networks, or CNNs. The entire exercise will be done using Keras.

1.1 Exercise 3.1. A simple CNN (2 points)

We'll start by showing you step by step how to create a simple CNN in Keras. At some points you'll have to fill some code yourself. You can refer to the Keras documentation to find the right commands.

First, let's load all the needed libraries.

```
In [1]: %matplotlib inline

        from keras.models import Sequential
        from keras.layers import *
        from keras.optimizers import *
        from keras.layers.convolutional import Conv2D

        import exer3_dataset
        from keras.utils import np_utils
        import matplotlib.pyplot as plt
        import numpy as np

        np.random.seed(123)
```

```
Using TensorFlow backend.
```

1.1.1 Dataset

A key part of machine learning is always handling and preprocessing the dataset. In this exercise we've made your life easier by having already prepared a dataset and split it into training and testing parts.

Run the following command to download the dataset. The first time you run this it will take while as it's pulling the data down over the network.

```
In [2]: (x_train, y_train), (x_test, y_test) = exer3_dataset.load_data()
```

Let's see how the data is formatted by printing the dimensionalities of the variables (tensors).

```
In [3]: print("x_train", x_train.shape)
        print("y_train", y_train.shape)
        print("x_test", x_test.shape)
        print("y_test", y_test.shape)
```

```
x_train (60000, 28, 28, 1)
y_train (60000,)
x_test (10000, 28, 28, 1)
y_test (10000,)
```

Above you can see we have 60000 samples of 28x28 images in `x_train`. The third dimension of the images is just 1 as there is just a single grayscale value. The test set is formatted in the same way, except we have just 10000 samples.

The class labels are stored in `y_train`. Let's print the first 10 values just to see what they are...

```
In [4]: print(y_train[:10])
```

```
[9 0 0 3 0 2 7 2 5 5]
```

These are the correct classes for each image. These actually refer to different types of clothing. Let's define the mapping from class indices to human-understandable labels as a Python dictionary. We have 10 classes, i.e., 10 categories of images to classify.

```
In [5]: num_classes = 10

        labels = {
          0: 'T-shirt/top',
          1: 'Trouser',
          2: 'Pullover',
          3: 'Dress',
          4: 'Coat',
          5: 'Sandal',
          6: 'Shirt',
          7: 'Sneaker',
          8: 'Bag',
          9: 'Ankle boot'
        }
```

So, according to this the first image is of class 9, which is an "Ankle boot". Let's look at the first image.

```
In [6]: img0=x_train[0,:,:].reshape(28,28)
        print(img0)
```

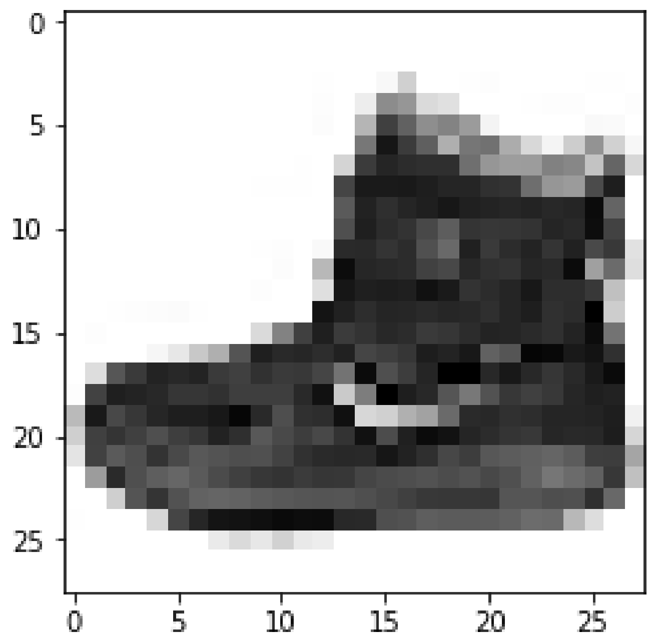
```
[[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   1   0   0  13  73   0
    0   1   4   0   0   0   0   1   1   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   3   0  36 136 127  62
   54   0   0   0   1   3   4   0   0   3]
 [  0   0   0   0   0   0   0   0   0   0   0   0   6   0 102 204 176 134
  144 123  23   0   0   0   0  12  10   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0 155 236 207 178
  107 156 161 109  64  23  77 130  72  15]
 [  0   0   0   0   0   0   0   0   0   0   0   1   0  69 207 223 218 216
  216 163 127 121 122 146 141  88 172  66]
 [  0   0   0   0   0   0   0   0   0   1   1   1   0 200 232 232 233 229
  223 223 215 213 164 127 123 196 229   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0 183 225 216 223 228
  235 227 224 222 224 221 223 245 173   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0 193 228 218 213 198
  180 212 210 211 213 223 220 243 202   0]
 [  0   0   0   0   0   0   0   0   0   1   3   0  12 219 220 212 218 192
  169 227 208 218 224 212 226 197 209  52]
 [  0   0   0   0   0   0   0   0   0   0   6   0  99 244 222 220 218 203
  198 221 215 213 222 220 245 119 167  56]
 [  0   0   0   0   0   0   0   0   0   4   0   0  55 236 228 230 228 240
  232 213 218 223 234 217 217 209  92   0]
 [  0   0   1   4   6   7   2   0   0   0   0   0 237 226 217 223 222 219
  222 221 216 223 229 215 218 255  77   0]
 [  0   3   0   0   0   0   0   0   0  62 145 204 228 207 213 221 218 208
  211 218 224 223 219 215 224 244 159   0]
 [  0   0   0   0  18  44  82 107 189 228 220 222 217 226 200 205 211 230
  224 234 176 188 250 248 233 238 215   0]
 [  0  57 187 208 224 221 224 208 204 214 208 209 200 159 245 193 206 223
  255 255 221 234 221 211 220 232 246   0]
 [  3 202 228 224 221 211 211 214 205 205 205 220 240  80 150 255 229 221
  188 154 191 210 204 209 222 228 225   0]
 [ 98 233 198 210 222 229 229 234 249 220 194 215 217 241  65  73 106 117
  168 219 221 215 217 223 223 224 229  29]
 [ 75 204 212 204 193 205 211 225 216 185 197 206 198 213 240 195 227 245
  239 223 218 212 209 222 220 221 230  67]
 [ 48 203 183 194 213 197 185 190 194 192 202 214 219 221 220 236 225 216
  199 206 186 181 177 172 181 205 206 115]
 [  0 122 219 193 179 171 183 196 204 210 213 207 211 210 200 196 194 191
  195 191 198 192 176 156 167 177 210  92]
 [  0   0  74 189 212 191 175 172 175 181 185 188 189 188 193 198 204 209
  210 210 211 188 188 194 192 216 170   0]
```

```
[  2   0   0   0  66 200 222 237 239 242 246 243 244 221 220 193 191 179
 182 182 181 176 166 168  99  58   0   0]
[  0   0   0   0   0   0   0  40  61  44  72  41  35   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0]
[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
   0   0   0   0   0   0   0   0   0   0]]
```

That's pretty hard to decipher. Let's instead draw it as an image, interpreting each number as a grayscale value.

```
In [7]: plt.imshow(img0, cmap='Greys', interpolation='none')
```

```
Out[7]: <matplotlib.image.AxesImage at 0x7efd88556518>
```



I suppose that's an ankle boot...

Typically we use so called one-hot encoding for the class labels in neural networks. That is instead of having a single value which can have one of 10 label values (e.g. 0, ..., 9), we have 10 values which can each be 1 or 0 depending on if that class is present.

Then for the output we typically expect something that looks like a probability distribution over these 10 classes, i.e., each neuron has a value between 0 and 1 indicating the probability of that class being present. For example if the tenth (last) neuron is 0.8, then we have 80% probability of the image containing an ankle boot. (The sum over all classes should also be 1.0 in order for it be a probability distribution.)

Here we'll call a utility function to transform the class labels into a one-hot encoding format.

```
In [8]: print("Old format", y_train[:5])
        y_train_cat = np_utils.to_categorical(y_train, num_classes)
        y_test_cat = np_utils.to_categorical(y_test, num_classes)
        print("One-hot encoding\n", y_train_cat[:5,])
```

```
Old format [9 0 0 3 0]
One-hot encoding
 [[ 0.  0.  0.  0.  0.  0.  0.  0.  0.  1.]
 [ 1.  0.  0.  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.  0.]
 [ 1.  0.  0.  0.  0.  0.  0.  0.  0.  0.]]
```

You can take a look at the output above. For example for the first image, which has label 9, the tenth value is 1, the rest are zero.

Let's display the first example image of each class just for fun.

```
In [9]: for l in range(10):
            idx = np.argwhere(y_train==l)[0]

            plt.subplot(2, 5, l+1)

            img = x_train[idx,:,:].reshape(28,28)

            plt.imshow(img, cmap='Greys', interpolation='none')
            plt.title(labels[l])
            plt.axis('off')
```

Finally, we normalize the images to be in the range 0.0 to 1.0 instead of 0 to 255.

```
In [10]: x_train = x_train/255
         x_test = x_test/255
```

1.1.2 Create the network

OK, let's create a simple CNN that learns to detect these classes.

Below you need to fill in the neural network layers, which are (in order):

- One 2D convolutional layer with kernel size 3x3 and 32 output filters/features
- ReLU activation
- Max pooling (2D) of size 2x2
- Fully-connected (dense) layer to 10 output units (for the 10 classes)
- Finally softmax activation to get a probability-like output.

Hint: For the first layer you'll need to specify the shape of the input tensor manually by giving this parameter: `input_shape=(28, 28, 1)`.

Before the dense layer we need a `Flatten()` layer. This is a special layer in Keras that transforms the 2D output into 1D. The 2D convolution works with neurons in 2D, but the dense layer works in 1D.

```
In [11]: # Initialize model
         model = Sequential()

         # Add layers here
         model.add(Conv2D(filters=32, kernel_size=(3, 3), input_shape=(28, 28, 1)))
         model.add(Activation("relu"))
         model.add(MaxPooling2D((2,2)))
         model.add(Flatten())
         model.add(Dense(units=10))
         model.add(Activation("softmax"))
         # Let's use categorical crossentry and sgd optmizer
         model.compile(loss='categorical_crossentropy',
                       optimizer='sgd',
                       metrics=['accuracy'])
         print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
activation_1 (Activation)    (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 5408)              0
```

```
_________________________________________________________________
dense_1 (Dense)              (None, 10)                54090
_________________________________________________________________
activation_2 (Activation)    (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

1.1.3 Training

Now let's train it for 10 epochs. This takes roughly 5 minutes on a CPU.

We use a batch size of 128, which means that the weight updates are calculated for 128 inputs at a time.

```
In [12]: %%time

         epochs = 10 # one epoch typically takes a minute or two

         history = model.fit(x_train,
                             y_train_cat,
                             epochs=epochs,
                             batch_size=128,
                             verbose=1)
```

```
Epoch 1/10
60000/60000 [==============================] - 12s - loss: 1.0384 - acc: 0.6646
Epoch 2/10
60000/60000 [==============================] - 12s - loss: 0.6088 - acc: 0.7872
Epoch 3/10
60000/60000 [==============================] - 12s - loss: 0.5487 - acc: 0.8053
Epoch 4/10
60000/60000 [==============================] - 12s - loss: 0.5243 - acc: 0.8132
Epoch 5/10
60000/60000 [==============================] - 12s - loss: 0.5017 - acc: 0.8233
Epoch 6/10
60000/60000 [==============================] - 12s - loss: 0.4884 - acc: 0.8277
Epoch 7/10
60000/60000 [==============================] - 13s - loss: 0.4762 - acc: 0.8321
Epoch 8/10
60000/60000 [==============================] - 12s - loss: 0.4634 - acc: 0.8374
Epoch 9/10
60000/60000 [==============================] - 12s - loss: 0.4556 - acc: 0.8389
Epoch 10/10
60000/60000 [==============================] - 13s - loss: 0.4486 - acc: 0.8438
```

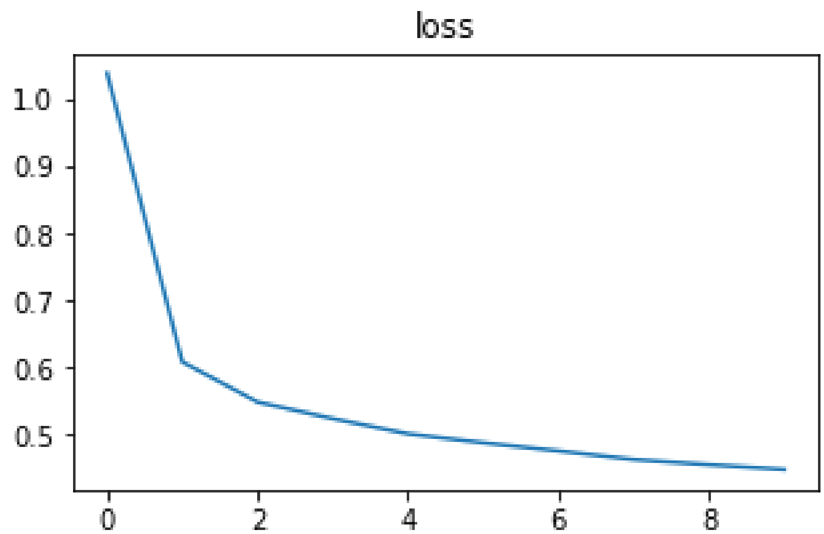
```
CPU times: user 5min 55s, sys: 1min 21s, total: 7min 16s
Wall time: 2min 6s
```

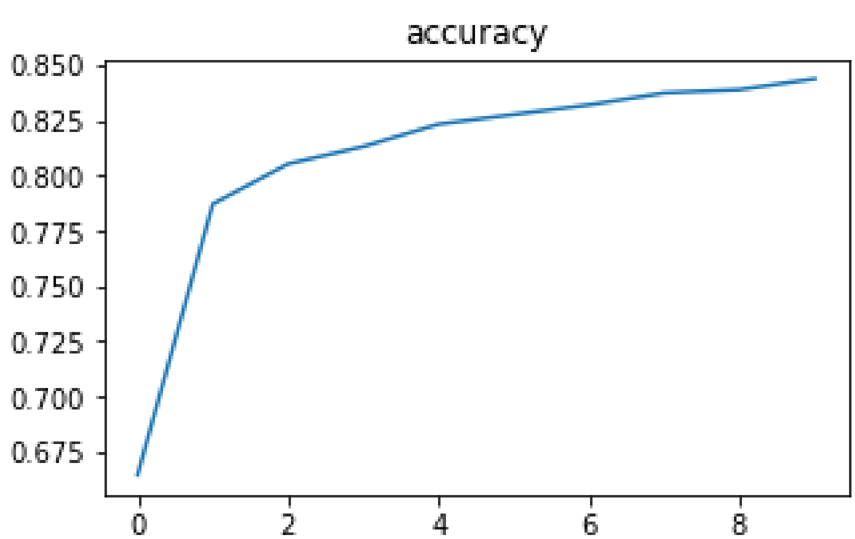
Let's plot how the loss and accuracy have changed over the training time.

```
In [13]: plt.figure(figsize=(5,3))
         plt.plot(history.epoch,history.history['loss'])
         plt.title('loss')

         plt.figure(figsize=(5,3))
         plt.plot(history.epoch,history.history['acc'])
         plt.title('accuracy')
```

```
Out[13]: <matplotlib.text.Text at 0x7efd884b5f98>
```





1.1.4 Inference

Next, let's how well the model can generalize to data it hasn't seen before, i.e., the test data. Recall from your basic machine learning that this is really the crucial part: it's trivial to learn to perfectly model the training set (you can just memorize each example), the hard part is to learn something general about the classes. So let's try to predict the labels of the test dataset, and compare to the correct labels.

```
In [14]: scores = model.evaluate(x_test, y_test_cat, verbose=2)
         print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
acc: 83.70%
```

You should get roughly 84% above if you have done exactly the same steps. The real result can vary a lot on the random initialisation as we run only 10 epochs here.

1.1.5 Visualise the weights

An interesting thing is to visualise the learned weights for the convolutional layer. We have 32 kernels of size 3x3, we can just plot them as images, mapping the weight values to grayscale.

```
In [15]: # Weights for the first convolutional layer
         w0=model.get_weights()[0][:,:,0,:]

         # Normalize to range 0.0 - 1.0
         w0-=np.min(w0)
         w0/=np.max(w0)

         for r in range(4):
             for c in range(8):
                 n=r*8+c
                 plt.subplot(4, 8, n+1)
                 plt.imshow(w0[:,:,n], interpolation='none')
                 plt.axis('off')
                 plt.gray()
         plt.show()
```

They might be a bit hard to interpret, but it seems they have learned to detect various corners and edges.

1.2 Exercise 3.2. Make a better CNN (4 points)

Make a network that performs better than the very simple one above. For your convenience we have copied the essential code from the previous exercise to the cells below. If you just did the previous exercise you don't need to rerun the first cell.

Your task is to do at least five (5) reparameterizations for the previous exercise's network and compare the results. At least one of them should have a 5% improvement in the test set result (generalization). Each reparameterization should change a different aspect in the network, while the rest of the parameters are the same as in 3.1. Print out all of the plots and results for each setup into the notebook you return, and analyze and discuss the results briefly in the last cell in the bottom.

You probably need to make a few more cells below, and copy-paste the model code (at least five times).

Example parameters to try to change:

- number of layers or neurons
- activation functions
- epochs
- batch sizes
- optimizer, see Keras' documentation on optimizers
- max-pooling on/off on certain layers

Notice that changing the final layer's softmax activation plus the categorical_crossentropy loss requires some consideration. Don't do it unless you have a good plan.

In [16]:
```
%matplotlib inline

from keras.models import Sequential
from keras.layers import *
from keras.optimizers import *
from keras.layers.convolutional import Conv2D

import exer3_dataset
from keras.utils import np_utils
import matplotlib.pyplot as plt

# Load the dataset
(x_train, y_train), (x_test, y_test) = exer3_dataset.load_data()

# Normalize
x_train = x_train/255
x_test = x_test/255

num_classes = 10

y_train_cat = np_utils.to_categorical(y_train, num_classes)
y_test_cat = np_utils.to_categorical(y_test, num_classes)
```

1.2.1 Variant 1

Change the number of layers and neurons

In [17]:
```
np.random.seed(123)
model = Sequential()

# Add model here
model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1)))
model.add(Activation("relu"))
model.add(MaxPooling2D((2,2)))
model.add(Conv2D(64, (3, 3)))
model.add(Flatten())
model.add(Dense(256)) #new layer
model.add(Dense(64)) #new layer
model.add(Dense(10))
model.add(Activation("softmax"))

# You can also try different optimizers below
model.compile(loss='categorical_crossentropy',
              optimizer='sgd',
              metrics=['accuracy'])
print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
conv2d_2 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
activation_3 (Activation)    (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
flatten_2 (Flatten)          (None, 7744)              0
_________________________________________________________________
dense_2 (Dense)              (None, 256)               1982720
_________________________________________________________________
dense_3 (Dense)              (None, 64)                16448
_________________________________________________________________
dense_4 (Dense)              (None, 10)                650
_________________________________________________________________
activation_4 (Activation)    (None, 10)                0
=================================================================
Total params: 2,018,634
Trainable params: 2,018,634
Non-trainable params: 0
_________________________________________________________________
None
```

In [18]:
```
%%time

# Training
epochs = 10

history = model.fit(x_train,
                    y_train_cat,
                    epochs=epochs,
                    batch_size=128,
                    verbose=1)
```

```
Epoch 1/10
60000/60000 [==============================] - 35s - loss: 0.8349 - acc: 0.7073
Epoch 2/10
60000/60000 [==============================] - 44s - loss: 0.5427 - acc: 0.8026
Epoch 3/10
60000/60000 [==============================] - 46s - loss: 0.4831 - acc: 0.8284
Epoch 4/10
60000/60000 [==============================] - 55s - loss: 0.4469 - acc: 0.8434
Epoch 5/10
60000/60000 [==============================] - 59s - loss: 0.4245 - acc: 0.8505
Epoch 6/10
```

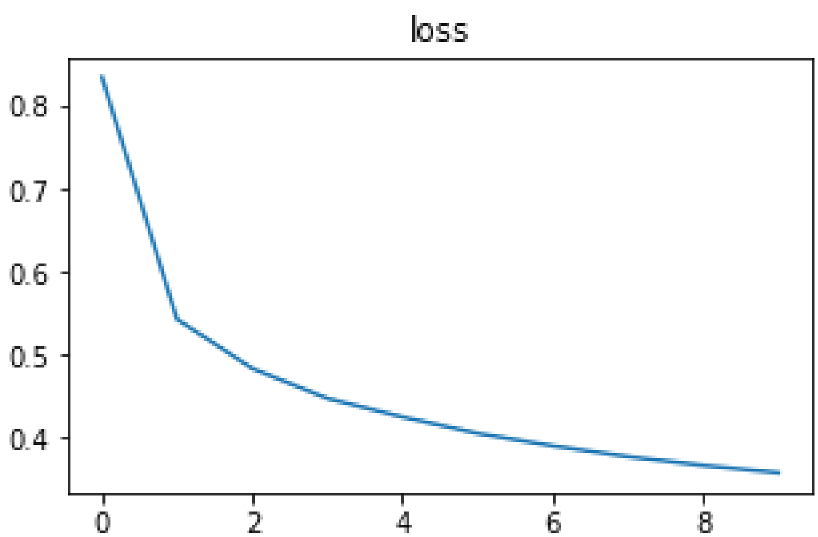
```
60000/60000 [==============================] - 62s - loss: 0.4047 - acc: 0.8578
Epoch 7/10
60000/60000 [==============================] - 60s - loss: 0.3897 - acc: 0.8636
Epoch 8/10
60000/60000 [==============================] - 49s - loss: 0.3767 - acc: 0.8689
Epoch 9/10
60000/60000 [==============================] - 46s - loss: 0.3662 - acc: 0.8728     - ETA:
Epoch 10/10
60000/60000 [==============================] - 53s - loss: 0.3575 - acc: 0.8756
CPU times: user 22min 45s, sys: 2min 50s, total: 25min 35s
Wall time: 8min 34s
```

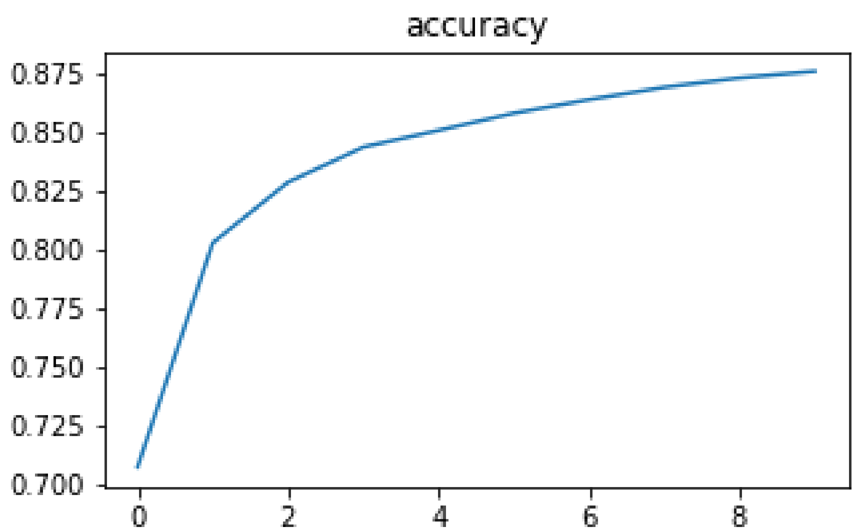
In [19]:
```
# Plot loss and accuracy in training

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['loss'])
plt.title('loss')

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['acc'])
plt.title('accuracy')
```

Out[19]: <matplotlib.text.Text at 0x7efd848fce10>






```
In [20]: # Evaluate on test set
         scores = model.evaluate(x_test, y_test_cat, verbose=2)
         print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
acc: 86.96%
```

1.2.2 Variant 2

Change the activation function

```
In [21]: np.random.seed(123)
         model = Sequential()

         # Add model here
         model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1)))
         model.add(Activation("tanh")) #replace relu with sigmoid
         model.add(MaxPooling2D((2,2)))
         model.add(Flatten())
         model.add(Dense(10))
         model.add(Activation("softmax"))

         # You can also try different optimizers below
         model.compile(loss='categorical_crossentropy',
                       optimizer='sgd',
                       metrics=['accuracy'])
         print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
conv2d_4 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
activation_5 (Activation)    (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
flatten_3 (Flatten)          (None, 5408)              0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                54090
_________________________________________________________________
activation_6 (Activation)    (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [22]: %%time

         # Training
         epochs = 10

         history = model.fit(x_train,
                             y_train_cat,
                             epochs=epochs,
                             batch_size=128,
                             verbose=1)
```

```
Epoch 1/10
60000/60000 [==============================] - 14s - loss: 1.0092 - acc: 0.6904
Epoch 2/10
60000/60000 [==============================] - 20s - loss: 0.5962 - acc: 0.7933
Epoch 3/10
60000/60000 [==============================] - 19s - loss: 0.5327 - acc: 0.8129
Epoch 4/10
60000/60000 [==============================] - 15s - loss: 0.4995 - acc: 0.8246
Epoch 5/10
60000/60000 [==============================] - 17s - loss: 0.4762 - acc: 0.8334
Epoch 6/10
60000/60000 [==============================] - 14s - loss: 0.4597 - acc: 0.8397
Epoch 7/10
60000/60000 [==============================] - 18s - loss: 0.4468 - acc: 0.8444
Epoch 8/10
60000/60000 [==============================] - 15s - loss: 0.4352 - acc: 0.8477     -
Epoch 9/10
```

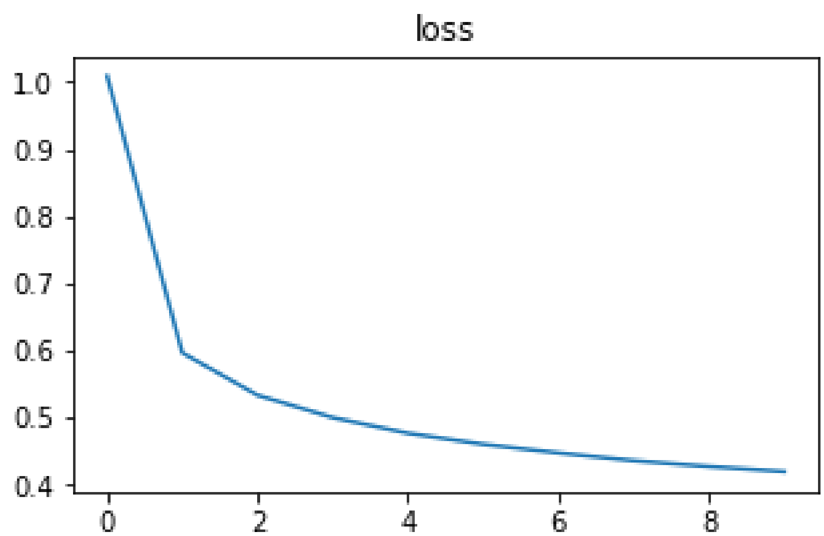
```
60000/60000 [==============================] - 17s - loss: 0.4264 - acc: 0.8507
Epoch 10/10
60000/60000 [==============================] - 18s - loss: 0.4189 - acc: 0.8536
CPU times: user 5min 46s, sys: 1min 7s, total: 6min 53s
Wall time: 2min 52s
```

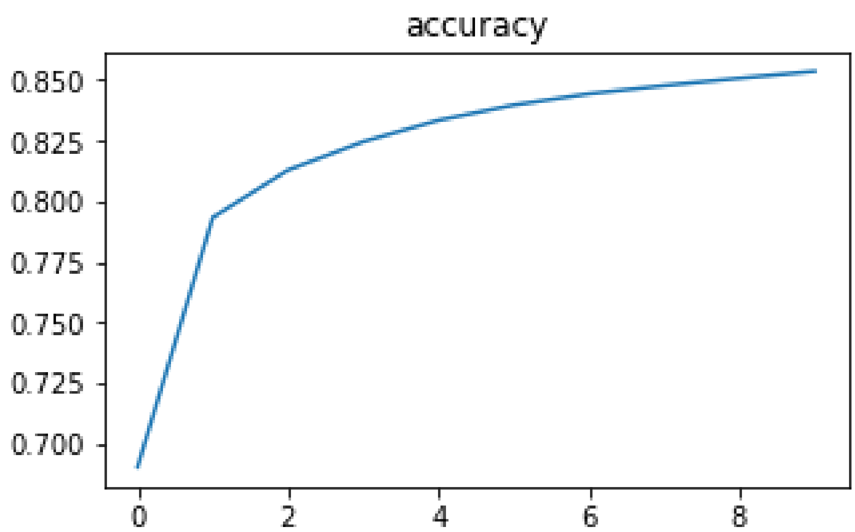
In [23]:
```python
# Plot loss and accuracy in training

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['loss'])
plt.title('loss')

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['acc'])
plt.title('accuracy')
```

Out[23]: <matplotlib.text.Text at 0x7efd02487080>






```
In [24]: # Evaluate on test set
         scores = model.evaluate(x_test, y_test_cat, verbose=2)
         print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
acc: 84.52%
```

1.2.3 Variant 3

Change the number of epoch

```
In [25]: np.random.seed(123)
         model = Sequential()

         # Add model here
         model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1)))
         model.add(Activation("relu"))
         model.add(MaxPooling2D((2,2)))
         model.add(Flatten())
         model.add(Dense(10))
         model.add(Activation("softmax"))

         # You can also try different optimizers below
         model.compile(loss='categorical_crossentropy',
                       optimizer='sgd',
                       metrics=['accuracy'])
         print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
conv2d_5 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
activation_7 (Activation)    (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
flatten_4 (Flatten)          (None, 5408)              0
_________________________________________________________________
dense_6 (Dense)              (None, 10)                54090
_________________________________________________________________
activation_8 (Activation)    (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

In [26]:
```
%%time

# Training
epochs = 40 #run with 40 epochs instead of 10

history = model.fit(x_train,
                    y_train_cat,
                    epochs=epochs,
                    batch_size=128,
                    verbose=1)
```

```
Epoch 1/40
60000/60000 [==============================] - 17s - loss: 1.0394 - acc: 0.6643
Epoch 2/40
60000/60000 [==============================] - 14s - loss: 0.6091 - acc: 0.7872
Epoch 3/40
60000/60000 [==============================] - 19s - loss: 0.5488 - acc: 0.8054
Epoch 4/40
60000/60000 [==============================] - 16s - loss: 0.5241 - acc: 0.8133
Epoch 5/40
60000/60000 [==============================] - 16s - loss: 0.5014 - acc: 0.8234
Epoch 6/40
60000/60000 [==============================] - 18s - loss: 0.4879 - acc: 0.8278
Epoch 7/40
60000/60000 [==============================] - 20s - loss: 0.4755 - acc: 0.8326
Epoch 8/40
60000/60000 [==============================] - 19s - loss: 0.4625 - acc: 0.8381
Epoch 9/40
```

```
60000/60000 [==============================] - 18s - loss: 0.4545 - acc: 0.8397
Epoch 10/40
60000/60000 [==============================] - 16s - loss: 0.4471 - acc: 0.8441
Epoch 11/40
60000/60000 [==============================] - 15s - loss: 0.4388 - acc: 0.8475
Epoch 12/40
60000/60000 [==============================] - 16s - loss: 0.4323 - acc: 0.8486
Epoch 13/40
60000/60000 [==============================] - 16s - loss: 0.4264 - acc: 0.8512
Epoch 14/40
60000/60000 [==============================] - 15s - loss: 0.4218 - acc: 0.8530
Epoch 15/40
60000/60000 [==============================] - 16s - loss: 0.4131 - acc: 0.8556
Epoch 16/40
60000/60000 [==============================] - 15s - loss: 0.4088 - acc: 0.8579
Epoch 17/40
60000/60000 [==============================] - 12s - loss: 0.4036 - acc: 0.8586
Epoch 18/40
60000/60000 [==============================] - 12s - loss: 0.3986 - acc: 0.8616
Epoch 19/40
60000/60000 [==============================] - 13s - loss: 0.3942 - acc: 0.8628
Epoch 20/40
60000/60000 [==============================] - 16s - loss: 0.3898 - acc: 0.8645
Epoch 21/40
60000/60000 [==============================] - 16s - loss: 0.3847 - acc: 0.8663
Epoch 22/40
60000/60000 [==============================] - 16s - loss: 0.3798 - acc: 0.8683
Epoch 23/40
60000/60000 [==============================] - 16s - loss: 0.3758 - acc: 0.8707
Epoch 24/40
60000/60000 [==============================] - 15s - loss: 0.3734 - acc: 0.8703
Epoch 25/40
60000/60000 [==============================] - 13s - loss: 0.3690 - acc: 0.8727
Epoch 26/40
60000/60000 [==============================] - 12s - loss: 0.3666 - acc: 0.8729
Epoch 27/40
60000/60000 [==============================] - 12s - loss: 0.3622 - acc: 0.8742
Epoch 28/40
60000/60000 [==============================] - 12s - loss: 0.3604 - acc: 0.8752
Epoch 29/40
60000/60000 [==============================] - 11s - loss: 0.3570 - acc: 0.8765
Epoch 30/40
60000/60000 [==============================] - 13s - loss: 0.3547 - acc: 0.8776
Epoch 31/40
60000/60000 [==============================] - 13s - loss: 0.3528 - acc: 0.8776
Epoch 32/40
60000/60000 [==============================] - 13s - loss: 0.3501 - acc: 0.8790
Epoch 33/40
```

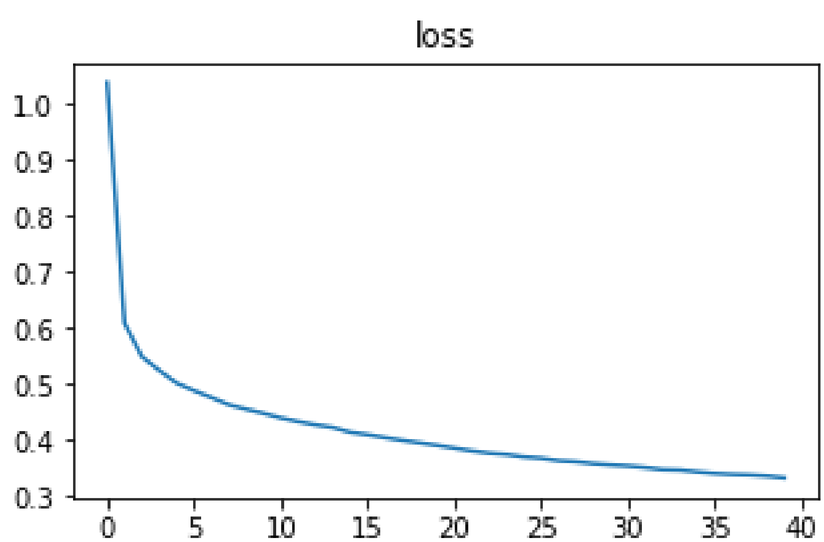
```
60000/60000 [==============================] - 13s - loss: 0.3465 - acc: 0.8808
Epoch 34/40
60000/60000 [==============================] - 11s - loss: 0.3457 - acc: 0.8796
Epoch 35/40
60000/60000 [==============================] - 11s - loss: 0.3424 - acc: 0.8813
Epoch 36/40
60000/60000 [==============================] - 11s - loss: 0.3396 - acc: 0.8827
Epoch 37/40
60000/60000 [==============================] - 12s - loss: 0.3380 - acc: 0.8826
Epoch 38/40
60000/60000 [==============================] - 12s - loss: 0.3370 - acc: 0.8828
Epoch 39/40
60000/60000 [==============================] - 13s - loss: 0.3351 - acc: 0.8848
Epoch 40/40
60000/60000 [==============================] - 12s - loss: 0.3319 - acc: 0.8853
CPU times: user 23min 50s, sys: 5min 3s, total: 28min 53s
Wall time: 9min 56s
```

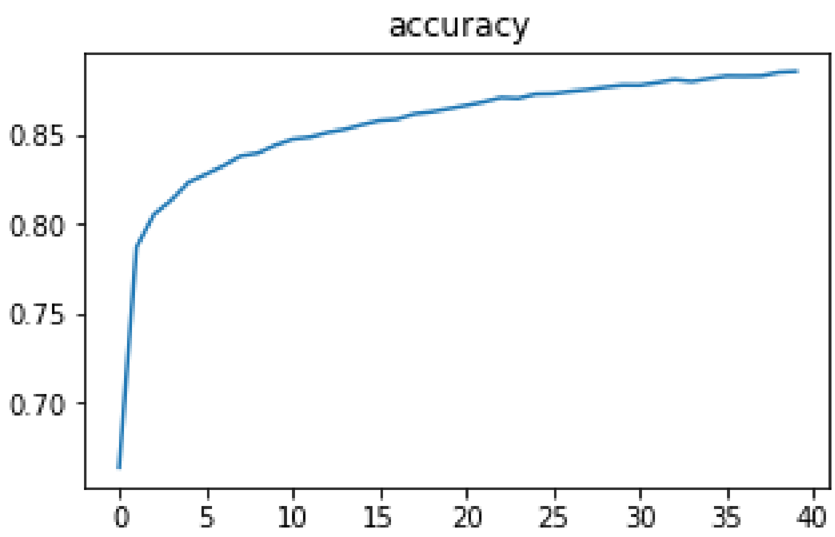
In [27]:
```
# Plot loss and accuracy in training

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['loss'])
plt.title('loss')

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['acc'])
plt.title('accuracy')
```

Out[27]: <matplotlib.text.Text at 0x7efd843a4710>






```
In [28]: # Evaluate on test set
         scores = model.evaluate(x_test, y_test_cat, verbose=2)
         print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
acc: 87.21%
```

1.2.4 Variant 4

Change the batch size

```
In [29]: np.random.seed(123)
         model = Sequential()

         # Add model here
         model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1)))
         model.add(Activation("relu"))
         model.add(MaxPooling2D((2,2)))
         model.add(Flatten())
         model.add(Dense(10))
         model.add(Activation("softmax"))

         # You can also try different optimizers below
         model.compile(loss='categorical_crossentropy',
                       optimizer='sgd',
                       metrics=['accuracy'])
         print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
conv2d_6 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
activation_9 (Activation)    (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
flatten_5 (Flatten)          (None, 5408)              0
_________________________________________________________________
dense_7 (Dense)              (None, 10)                54090
_________________________________________________________________
activation_10 (Activation)   (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

In [30]:
```
%%time

# Training
epochs = 10

history = model.fit(x_train,
                    y_train_cat,
                    epochs=epochs,
                    batch_size=256, #use 256 as batch size instead of 128
                    verbose=1)
```

```
Epoch 1/10
60000/60000 [==============================] - 12s - loss: 1.3449 - acc: 0.5825
Epoch 2/10
60000/60000 [==============================] - 11s - loss: 0.7259 - acc: 0.7533
Epoch 3/10
60000/60000 [==============================] - 11s - loss: 0.6245 - acc: 0.7859
Epoch 4/10
60000/60000 [==============================] - 11s - loss: 0.5778 - acc: 0.7984
Epoch 5/10
60000/60000 [==============================] - 11s - loss: 0.5491 - acc: 0.8083
Epoch 6/10
60000/60000 [==============================] - 11s - loss: 0.5306 - acc: 0.8143
Epoch 7/10
60000/60000 [==============================] - 11s - loss: 0.5175 - acc: 0.8166
Epoch 8/10
60000/60000 [==============================] - 11s - loss: 0.5042 - acc: 0.8222
Epoch 9/10
```

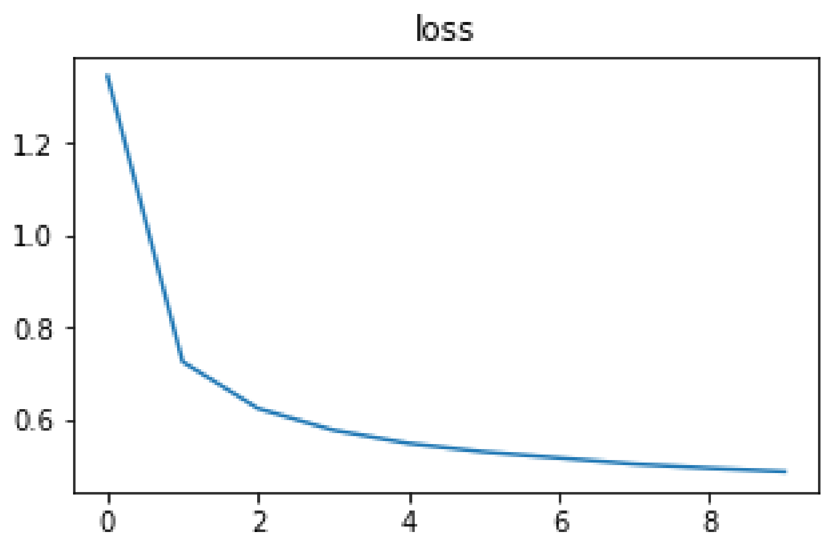
```
60000/60000 [==============================] - 11s - loss: 0.4951 - acc: 0.8254
Epoch 10/10
60000/60000 [==============================] - 10s - loss: 0.4878 - acc: 0.8279
CPU times: user 5min 56s, sys: 1min, total: 6min 57s
Wall time: 1min 54s
```

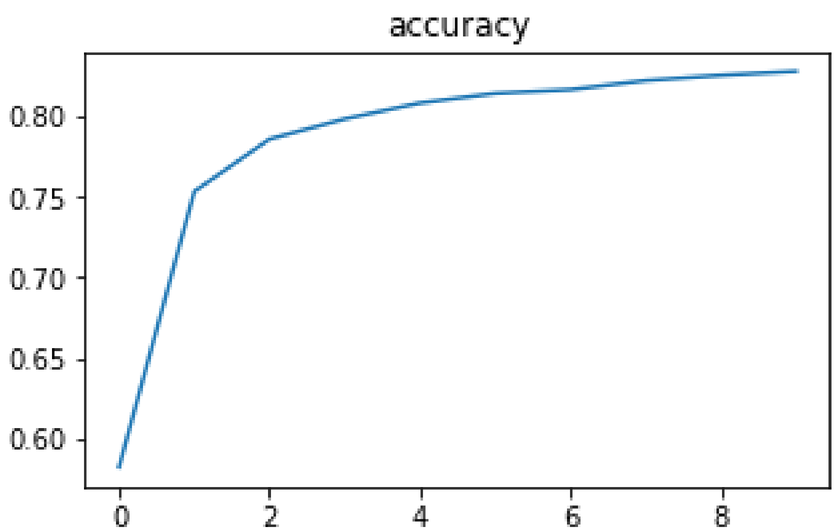
In [31]:
```
# Plot loss and accuracy in training

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['loss'])
plt.title('loss')

plt.figure(figsize=(5,3))
plt.plot(history.epoch,history.history['acc'])
plt.title('accuracy')
```

Out[31]: <matplotlib.text.Text at 0x7efd3d67c080>






```
In [32]: # Evaluate on test set
         scores = model.evaluate(x_test, y_test_cat, verbose=2)
         print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
acc: 82.10%
```

1.2.5 Variant 5

Change the type of optimizer

```
In [33]: np.random.seed(123)
         model = Sequential()

         # Add model here
         model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1)))
         model.add(Activation("relu"))
         model.add(MaxPooling2D((2,2)))
         model.add(Flatten())
         model.add(Dense(10))
         model.add(Activation("softmax"))

         # You can also try different optimizers below
         model.compile(loss='categorical_crossentropy',
                       optimizer="adam", #use adam instead of sgd
                       metrics=['accuracy'])
         print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
```

```
=================================================================
conv2d_7 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
activation_11 (Activation)   (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
flatten_6 (Flatten)          (None, 5408)              0
_________________________________________________________________
dense_8 (Dense)              (None, 10)                54090
_________________________________________________________________
activation_12 (Activation)   (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [34]: %%time
         # Training
         epochs = 10

         history = model.fit(x_train,
                             y_train_cat,
                             epochs=epochs,
                             batch_size=128,
                             verbose=1)
```

```
Epoch 1/10
60000/60000 [==============================] - 12s - loss: 0.5324 - acc: 0.8169
Epoch 2/10
60000/60000 [==============================] - 11s - loss: 0.3539 - acc: 0.8779
Epoch 3/10
60000/60000 [==============================] - 13s - loss: 0.3162 - acc: 0.8894
Epoch 4/10
60000/60000 [==============================] - 13s - loss: 0.2943 - acc: 0.8971
Epoch 5/10
60000/60000 [==============================] - 12s - loss: 0.2760 - acc: 0.9030
Epoch 6/10
60000/60000 [==============================] - 13s - loss: 0.2646 - acc: 0.9060
Epoch 7/10
60000/60000 [==============================] - 12s - loss: 0.2537 - acc: 0.9099
Epoch 8/10
60000/60000 [==============================] - 12s - loss: 0.2436 - acc: 0.9136
Epoch 9/10
60000/60000 [==============================] - 13s - loss: 0.2370 - acc: 0.9155
```

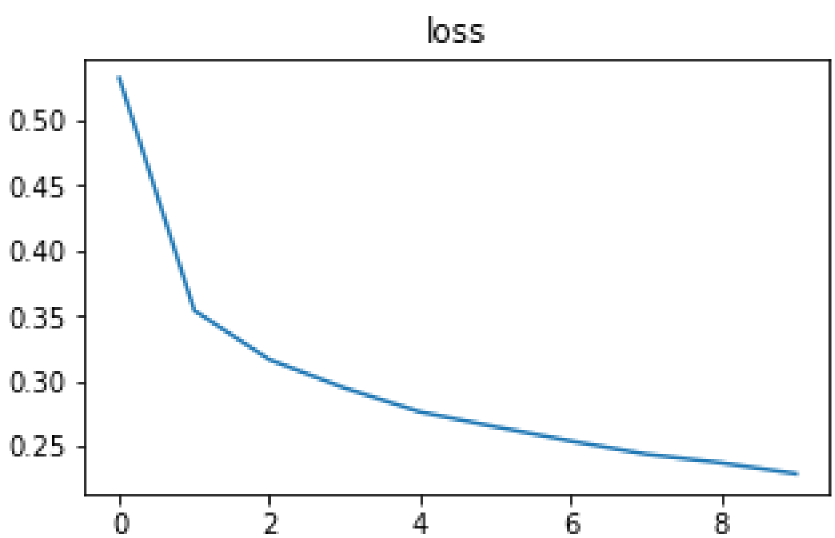
```
Epoch 10/10
60000/60000 [==============================] - 14s - loss: 0.2287 - acc: 0.9187
CPU times: user 6min 5s, sys: 1min 21s, total: 7min 27s
Wall time: 2min 9s
```

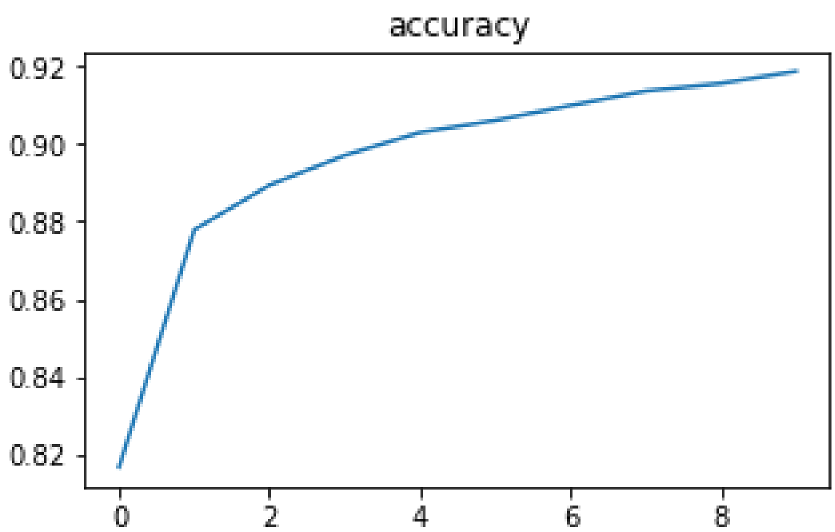
```
In [35]: # Plot loss and accuracy in training

         plt.figure(figsize=(5,3))
         plt.plot(history.epoch,history.history['loss'])
         plt.title('loss')

         plt.figure(figsize=(5,3))
         plt.plot(history.epoch,history.history['acc'])
         plt.title('accuracy')
```

```
Out[35]: <matplotlib.text.Text at 0x7efd3c08f470>
```






```
In [36]: # Evaluate on test set
         scores = model.evaluate(x_test, y_test_cat, verbose=2)
         print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
acc: 89.80%
```

1.2.6 Fully-changed Variant

I changed only one aspect of the network in the previous 5 variants. And the variant with "adam" has already met what is requested. In this variant, I would like to change more than one aspect.

```
In [37]: np.random.seed(123)
         model = Sequential()

         # Add model here
         model.add(Conv2D(32,(3, 3), input_shape=(28,28,1),activation="relu"))
         model.add(Conv2D(64, (3, 3), activation='relu'))
         model.add(MaxPooling2D((2, 2)))
         model.add(Dropout(0.25))
         model.add(BatchNormalization())
         model.add(Flatten())
         model.add(Dense(256, activation="relu"))
         model.add(Dropout(0.4))
         model.add(BatchNormalization())
         model.add(Dense(10,activation="softmax"))

         # You can also try different optimizers below
         model.compile(loss='categorical_crossentropy',
```

```
                    optimizer="adam",
                    metrics=['accuracy'])
         print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_8 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 24, 24, 64)        18496
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 12, 12, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 12, 12, 64)        0
_________________________________________________________________
batch_normalization_1 (Batch (None, 12, 12, 64)        256
_________________________________________________________________
flatten_7 (Flatten)          (None, 9216)              0
_________________________________________________________________
dense_9 (Dense)              (None, 256)               2359552
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
batch_normalization_2 (Batch (None, 256)               1024
_________________________________________________________________
dense_10 (Dense)             (None, 10)                2570
=================================================================
Total params: 2,382,218
Trainable params: 2,381,578
Non-trainable params: 640
_________________________________________________________________
None
```

In [38]:
```
%%time

         # Training
         epochs = 25

         history = model.fit(x_train,
                             y_train_cat,
                             epochs=epochs,
                             batch_size=128,
                             verbose=1)
```

```
Epoch 1/25
60000/60000 [==============================] - 125s - loss: 0.4068 - acc: 0.8556
Epoch 2/25
```

```
60000/60000 [==============================] - 131s - loss: 0.2551 - acc: 0.9080
Epoch 3/25
60000/60000 [==============================] - 144s - loss: 0.2074 - acc: 0.9242
Epoch 4/25
60000/60000 [==============================] - 127s - loss: 0.1775 - acc: 0.9341
Epoch 5/25
60000/60000 [==============================] - 136s - loss: 0.1528 - acc: 0.9446
Epoch 6/25
60000/60000 [==============================] - 123s - loss: 0.1342 - acc: 0.9510
Epoch 7/25
60000/60000 [==============================] - 131s - loss: 0.1159 - acc: 0.9566
Epoch 8/25
60000/60000 [==============================] - 131s - loss: 0.1003 - acc: 0.9624
Epoch 9/25
60000/60000 [==============================] - 175s - loss: 0.0941 - acc: 0.9653
Epoch 10/25
60000/60000 [==============================] - 169s - loss: 0.0815 - acc: 0.9699
Epoch 11/25
60000/60000 [==============================] - 190s - loss: 0.0745 - acc: 0.9727
Epoch 12/25
60000/60000 [==============================] - 226s - loss: 0.0688 - acc: 0.9753
Epoch 13/25
60000/60000 [==============================] - 239s - loss: 0.0682 - acc: 0.9750
Epoch 14/25
60000/60000 [==============================] - 203s - loss: 0.0565 - acc: 0.9789
Epoch 15/25
60000/60000 [==============================] - 101s - loss: 0.0570 - acc: 0.9793
Epoch 16/25
60000/60000 [==============================] - 151s - loss: 0.0499 - acc: 0.9814
Epoch 17/25
60000/60000 [==============================] - 125s - loss: 0.0480 - acc: 0.9826
Epoch 18/25
60000/60000 [==============================] - 147s - loss: 0.0470 - acc: 0.9829
Epoch 19/25
60000/60000 [==============================] - 143s - loss: 0.0411 - acc: 0.9848
Epoch 20/25
60000/60000 [==============================] - 154s - loss: 0.0412 - acc: 0.9854
Epoch 21/25
60000/60000 [==============================] - 170s - loss: 0.0384 - acc: 0.9862
Epoch 22/25
60000/60000 [==============================] - 106s - loss: 0.0358 - acc: 0.9872
Epoch 23/25
60000/60000 [==============================] - 143s - loss: 0.0368 - acc: 0.9867
Epoch 24/25
60000/60000 [==============================] - 183s - loss: 0.0331 - acc: 0.9886
Epoch 25/25
60000/60000 [==============================] - 142s - loss: 0.0344 - acc: 0.9878
CPU times: user 3h 10min 36s, sys: 19min 54s, total: 3h 30min 31s
```

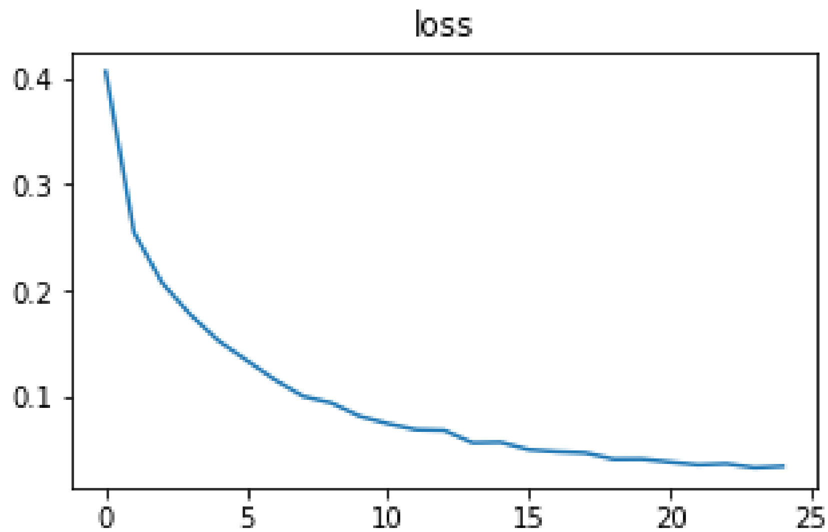
```
Wall time: 1h 3min 47s
```

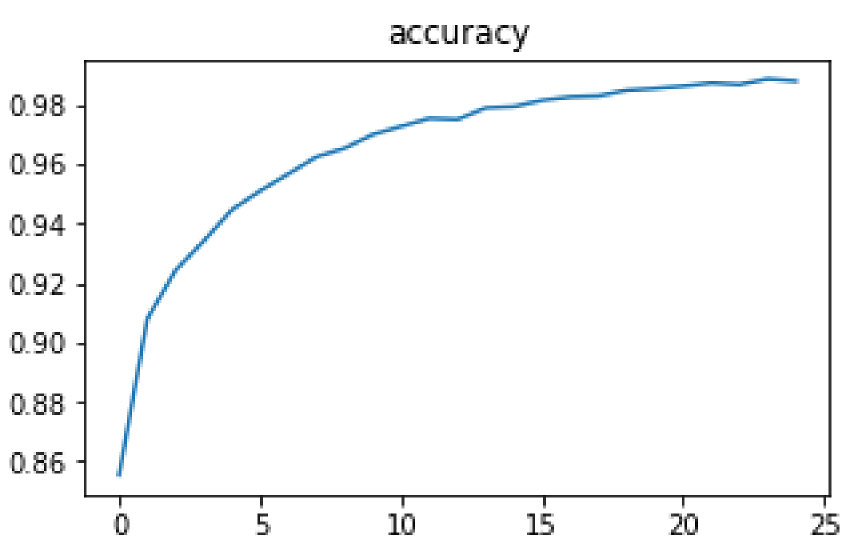
```
In [39]: # Plot loss and accuracy in training

         plt.figure(figsize=(5,3))
         plt.plot(history.epoch,history.history['loss'])
         plt.title('loss')

         plt.figure(figsize=(5,3))
         plt.plot(history.epoch,history.history['acc'])
         plt.title('accuracy')

Out[39]: <matplotlib.text.Text at 0x7efce9b2bfd0>
```





```
In [40]: # Evaluate on test set
         scores = model.evaluate(x_test, y_test_cat, verbose=2)
         print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
acc: 93.15%
```

1.2.7 Discussion

I have only changed one aspect of the network in the first five variants, while almost everything has been changed in the last one. One of the first 5 variants, the one with optimizer changed, has met the requirement, which is to have a 5% improvement. All the accuracy is listed below:

Variant	Accuracy
Original	83.7%
Number of Layers and Neurons	86.9%
Activation	84.5%
Number of Epochs	87.2%
Batch Size	82.1%
Optimizer	89.8%
Fully-changed	93.2%

If we refer to that only one aspect of the original network is changed, most of the accuracy of the first 5 variants are better than the accuracy of the original one. As what is illustrated in the 1st variant, a network with more complicated structure may be better than a simpler one, but it is also rather noticeable that the complicated one will surely take more time to train. For the 2nd variant, it has a small improvement. But it is not as good as others. So, in practice, it is quite reasonable that we need to adjust almost every aspect of the network to achieve a better result. For the 3rd variant, the fact that the variant with more epochs will have a higher accuracy is quite obvious since weights are more close to optima if compared to the original one. For the 4th variant, the result actually is worse than the original one. I have tried with different values, such as 64, 256,512 and 1024. None of them can lead to a better result. I suppose more trials are needed. For the 5th variant, it seems that "adam" optimizer outperform the "sgd" optimizer. Overall, we can see that the accuracy can be improved by adjusting the parameter of different aspects. However, it seems to be difficult to achieve over 90% accuracy with only one aspect changeable.

To achieve a better accuracy, I have changed the almost everything of the network in the last variant. Additionally, I use Dropout layer and BatchNormalization layer to improve the overall accuracy and speed up the computation. As what has shown in the first 5 variants, I increase the number of epochs and change the optimizer to "adam" as well. However, because of the complicated topological structures and the number of epochs, this variant took significantly longer time than others.