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()
```

```
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-id
 8192/29515 [=======>...] - ETA: 0sDownloading data from http://fashion-mnist.s3-website.eu-cent
26402816/26421880 [============================>.] - ETA: 0sDownloading data from http://fashion
8192/5148 [===============================================] - 0s
Downloading data from http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx
4349952/4422102 [============================>.] - ETA: 0s
```

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)
```

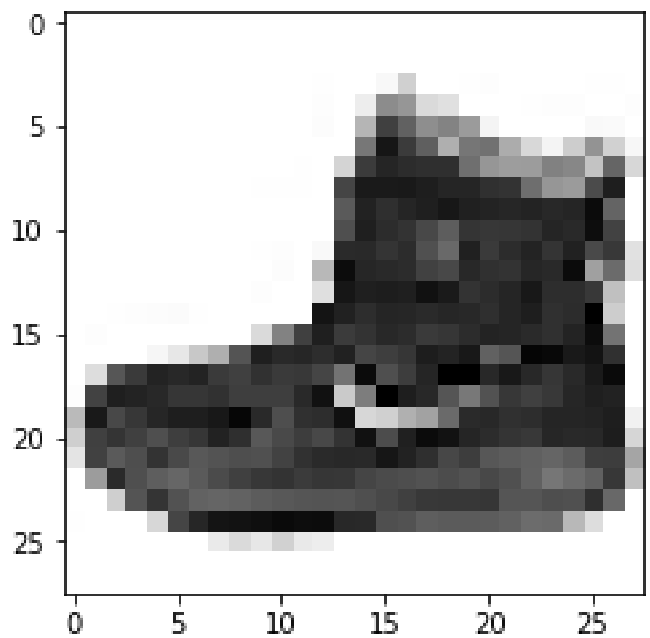
```
[[  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   0
    0   0   0   0   0   0   0   0   0   0]
 [  0   0   0   0   0   0   0   0   0   0   0   0   0   0   0   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 0x7f22f9e40390>
```



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(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'))
# 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)
```

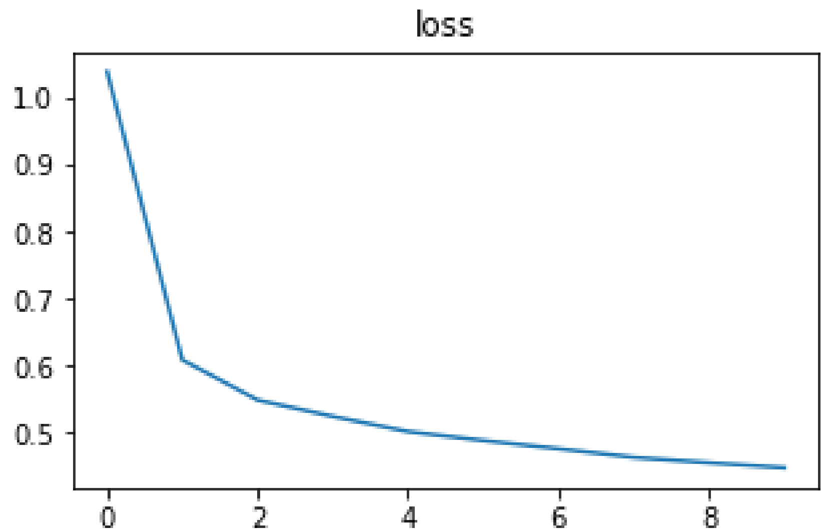
```
Epoch 1/10
60000/60000 [==============================] - 13s - loss: 1.0389 - acc: 0.6645     - ETA: 0s - l
Epoch 2/10
60000/60000 [==============================] - 12s - loss: 0.6088 - acc: 0.7871
Epoch 3/10
60000/60000 [==============================] - 12s - loss: 0.5488 - acc: 0.8053
Epoch 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: 0.4883 - acc: 0.8278
Epoch 7/10
60000/60000 [==============================] - 12s - loss: 0.4761 - acc: 0.8322
Epoch 8/10
60000/60000 [==============================] - 10s - loss: 0.4634 - acc: 0.8375
Epoch 9/10
60000/60000 [==============================] - 10s - loss: 0.4554 - acc: 0.8390
Epoch 10/10
60000/60000 [==============================] - 10s - loss: 0.4481 - acc: 0.8440
CPU times: user 6min 14s, sys: 1min 33s, total: 7min 48s
Wall time: 2min 1s
```

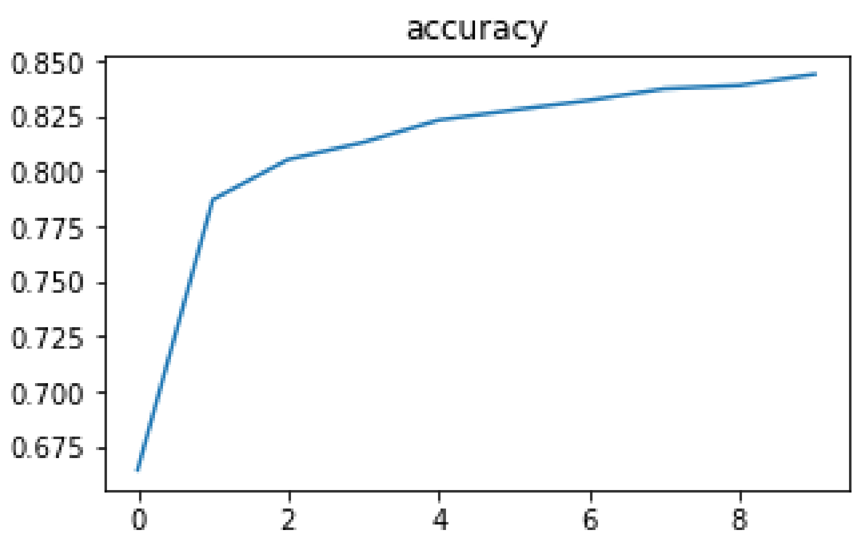
Let's plot how the loss and accuracy have changed over the training time.

```
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 0x7f22f5fb3630>
```





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: 83.73%
```

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.

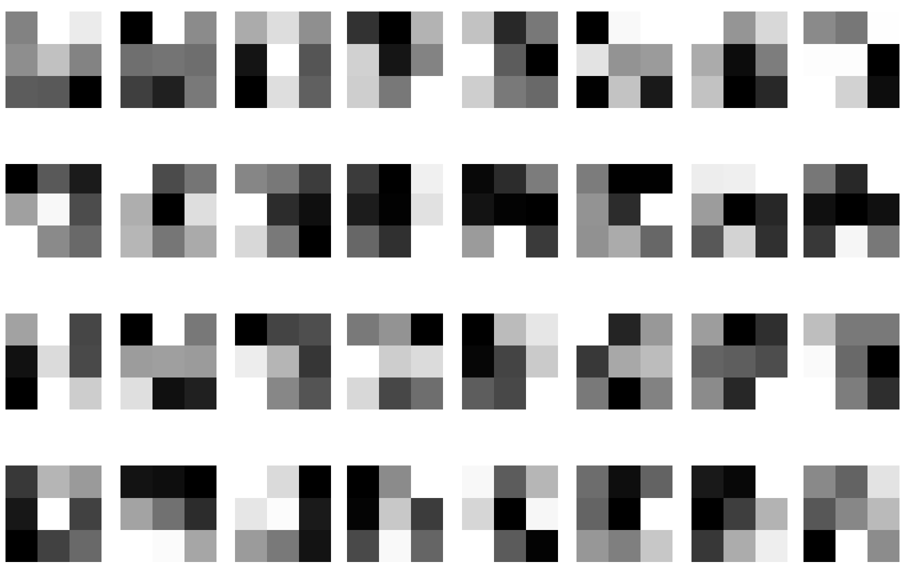
1.1.5 Visualise the weights

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 [ ]: %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)
```

```
In [20]: 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='rmsprop',
                  metrics=['accuracy'])
    print(model.summary())
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_4 (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_4 (Dense)              (None, 10)                54090
_________________________________________________________________
activation_8 (Activation)    (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [21]: %%time

    # Training
    epochs = 10

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

```
Epoch 1/10
```

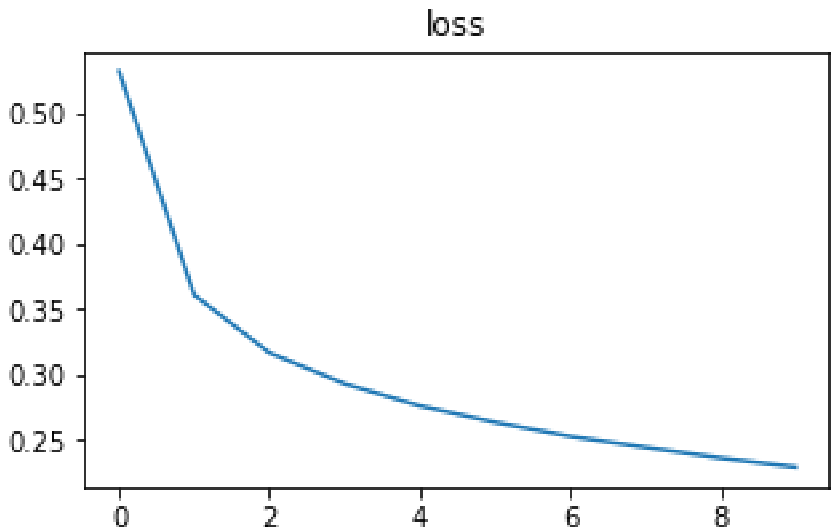
```
60000/60000 [==============================] - 11s - loss: 0.5314 - acc: 0.8142
Epoch 2/10
60000/60000 [==============================] - 10s - loss: 0.3608 - acc: 0.8733
Epoch 3/10
60000/60000 [==============================] - 10s - loss: 0.3166 - acc: 0.8896
Epoch 4/10
60000/60000 [==============================] - 10s - loss: 0.2930 - acc: 0.8970
Epoch 5/10
60000/60000 [==============================] - 10s - loss: 0.2761 - acc: 0.9036
Epoch 6/10
60000/60000 [==============================] - 11s - loss: 0.2636 - acc: 0.9082
Epoch 7/10
60000/60000 [==============================] - 11s - loss: 0.2528 - acc: 0.9112
Epoch 8/10
60000/60000 [==============================] - 11s - loss: 0.2444 - acc: 0.9144
Epoch 9/10
60000/60000 [==============================] - 11s - loss: 0.2365 - acc: 0.9172
Epoch 10/10
60000/60000 [==============================] - 11s - loss: 0.2296 - acc: 0.9202
CPU times: user 6min 24s, sys: 1min 44s, total: 8min 9s
Wall time: 1min 50s
```

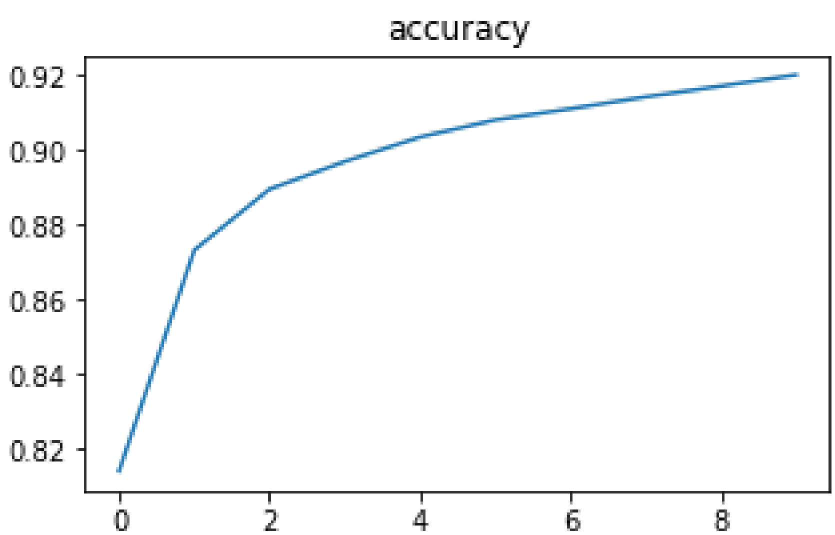
In [22]:
```
# Plot loss and accuracy in training

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[22]:
```
<matplotlib.text.Text at 0x7f22b0464c88>
```






```
In [23]: # 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: 89.55%
```

```
In [ ]: %matplotlib inline

        from keras.models import Sequential
```

```python
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)
```

In [24]:
```python
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(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_9 (Activation)    (None, 26, 26, 32)        0
_________________________________________________________________
flatten_5 (Flatten)          (None, 21632)             0
_________________________________________________________________
dense_5 (Dense)              (None, 10)                216330
_________________________________________________________________
activation_10 (Activation)   (None, 10)                0
```

```
=================================================================
Total params: 216,650
Trainable params: 216,650
Non-trainable params: 0
_________________________________________________________________
None
```

In [25]:
```
%%time

# Training
epochs = 10

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

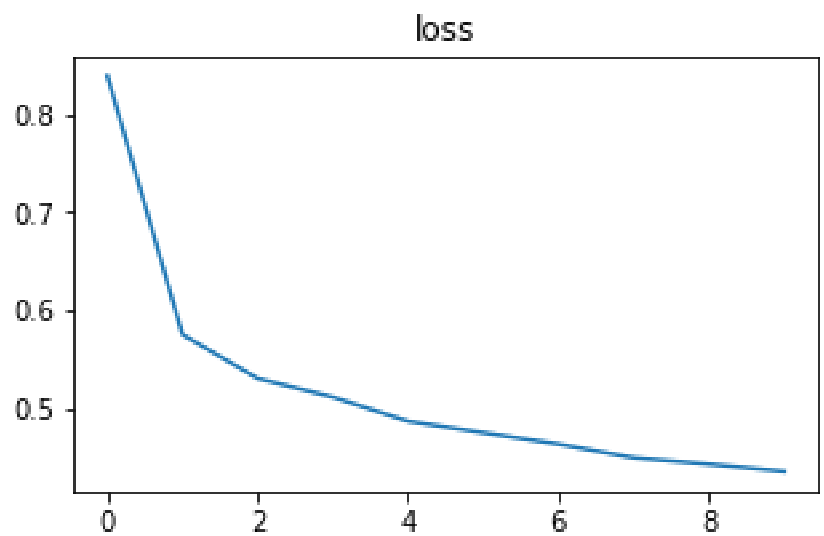
```
Epoch 1/10
60000/60000 [==============================] - 14s - loss: 0.8398 - acc: 0.7223
Epoch 2/10
60000/60000 [==============================] - 12s - loss: 0.5752 - acc: 0.7970
Epoch 3/10
60000/60000 [==============================] - 12s - loss: 0.5304 - acc: 0.8139
Epoch 4/10
60000/60000 [==============================] - 12s - loss: 0.5112 - acc: 0.8207
Epoch 5/10
60000/60000 [==============================] - 12s - loss: 0.4865 - acc: 0.8315
Epoch 6/10
60000/60000 [==============================] - 12s - loss: 0.4748 - acc: 0.8357
Epoch 7/10
60000/60000 [==============================] - 12s - loss: 0.4631 - acc: 0.8385
Epoch 8/10
60000/60000 [==============================] - 12s - loss: 0.4492 - acc: 0.8438
Epoch 9/10
60000/60000 [==============================] - 13s - loss: 0.4425 - acc: 0.8459
Epoch 10/10
60000/60000 [==============================] - 13s - loss: 0.4352 - acc: 0.8492
CPU times: user 6min 46s, sys: 50.5 s, total: 7min 36s
Wall time: 2min 8s
```

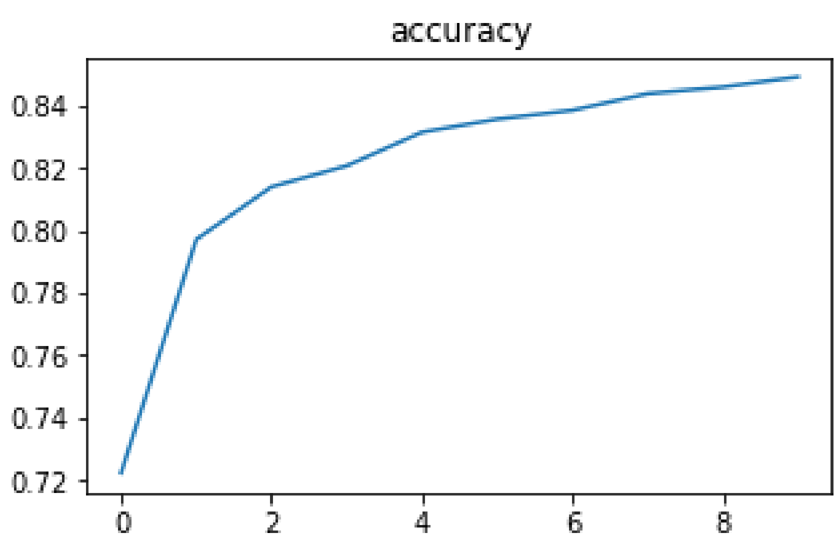
In [26]:
```
# Plot loss and accuracy in training

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[26]: <matplotlib.text.Text at 0x7f22cad3c710>





In [27]:
```
# 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: 84.21%
```

```
In [ ]: %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)
```

```
In [40]: 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(32, (3, 3), activation='relu'))
         model.add(AveragePooling2D((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_11 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
activation_17 (Activation)   (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_8 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_12 (Conv2D)           (None, 11, 11, 32)        9248
_________________________________________________________________
average_pooling2d_1 (Average (None, 5, 5, 32)          0
_________________________________________________________________
flatten_9 (Flatten)          (None, 800)               0
_________________________________________________________________
dense_9 (Dense)              (None, 10)                8010
_________________________________________________________________
activation_18 (Activation)   (None, 10)                0
=================================================================
Total params: 17,578
Trainable params: 17,578
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [41]: %%time

         # Training
         epochs = 10

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

```
Epoch 1/10
60000/60000 [==============================] - 17s - loss: 1.3875 - acc: 0.5536
Epoch 2/10
60000/60000 [==============================] - 16s - loss: 0.8088 - acc: 0.7113
Epoch 3/10
60000/60000 [==============================] - 17s - loss: 0.7309 - acc: 0.7334
Epoch 4/10
60000/60000 [==============================] - 17s - loss: 0.6878 - acc: 0.7468
Epoch 5/10
60000/60000 [==============================] - 16s - loss: 0.6584 - acc: 0.7584
Epoch 6/10
60000/60000 [==============================] - 16s - loss: 0.6376 - acc: 0.7650
Epoch 7/10
60000/60000 [==============================] - 17s - loss: 0.6157 - acc: 0.7723
```

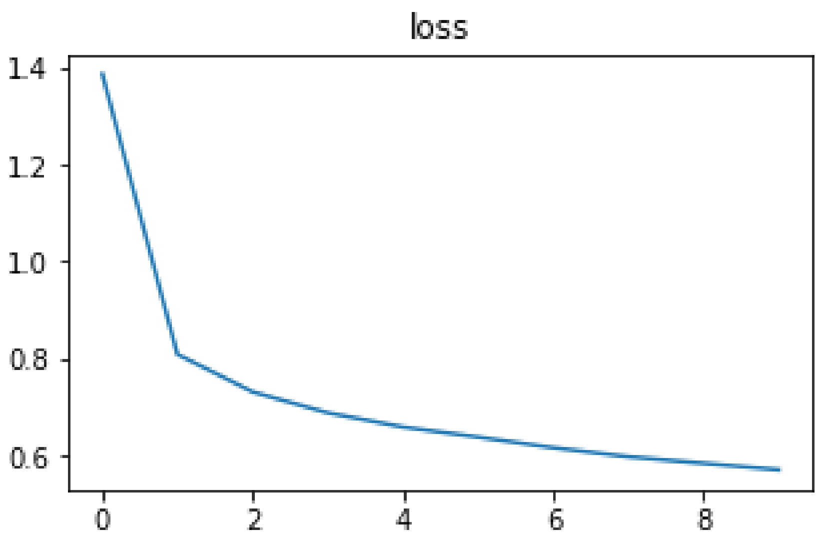
```
Epoch 8/10
60000/60000 [==============================] - 17s - loss: 0.5971 - acc: 0.7801
Epoch 9/10
60000/60000 [==============================] - 16s - loss: 0.5837 - acc: 0.7864
Epoch 10/10
60000/60000 [==============================] - 16s - loss: 0.5706 - acc: 0.7927
CPU times: user 12min 59s, sys: 3min 25s, total: 16min 25s
Wall time: 2min 52s
```

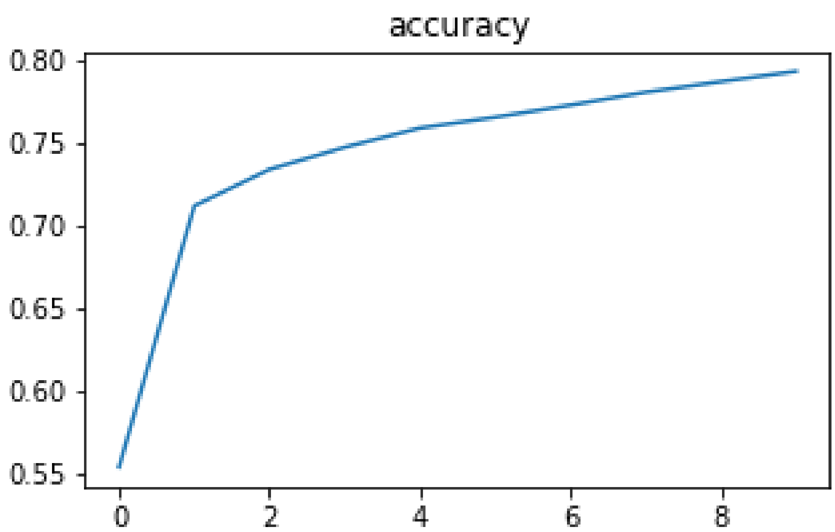
In [42]:
```python
# Plot loss and accuracy in training

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[42]: <matplotlib.text.Text at 0x7f2268cbb438>






```
In [43]: # 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: 76.90%
```

```
In [48]: %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)
```

```
In [64]: # Initialize model
         model = Sequential()

         # Add layers here
         model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1)))
         model.add(Activation('selu'))
         model.add(MaxPooling2D((2, 2)))
         model.add(Flatten())
         model.add(Dense(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_17 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
activation_27 (Activation)   (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_13 (MaxPooling (None, 13, 13, 32)        0
_________________________________________________________________
flatten_14 (Flatten)         (None, 5408)              0
_________________________________________________________________
dense_14 (Dense)             (None, 10)                54090
_________________________________________________________________
activation_28 (Activation)   (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

```
In [65]: %%time

         # Training
         epochs = 10

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

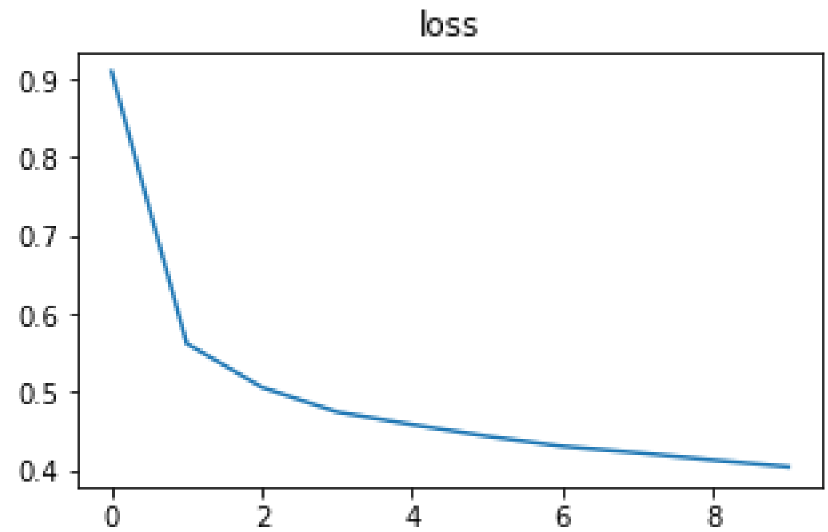
```
Epoch 1/10
60000/60000 [==============================] - 17s - loss: 0.9101 - acc: 0.7172
Epoch 2/10
60000/60000 [==============================] - 15s - loss: 0.5622 - acc: 0.8047
Epoch 3/10
60000/60000 [==============================] - 15s - loss: 0.5059 - acc: 0.8235
Epoch 4/10
60000/60000 [==============================] - 15s - loss: 0.4744 - acc: 0.8356
Epoch 5/10
60000/60000 [==============================] - 15s - loss: 0.4582 - acc: 0.8394     - ETA: 0s - l
Epoch 6/10
60000/60000 [==============================] - 16s - loss: 0.4433 - acc: 0.8450
Epoch 7/10
60000/60000 [==============================] - 15s - loss: 0.4304 - acc: 0.8492
Epoch 8/10
60000/60000 [==============================] - 15s - loss: 0.4222 - acc: 0.8533
Epoch 9/10
60000/60000 [==============================] - 15s - loss: 0.4131 - acc: 0.8556
Epoch 10/10
60000/60000 [==============================] - 16s - loss: 0.4046 - acc: 0.8591
CPU times: user 9min 43s, sys: 3min 29s, total: 13min 13s
Wall time: 2min 41s
```

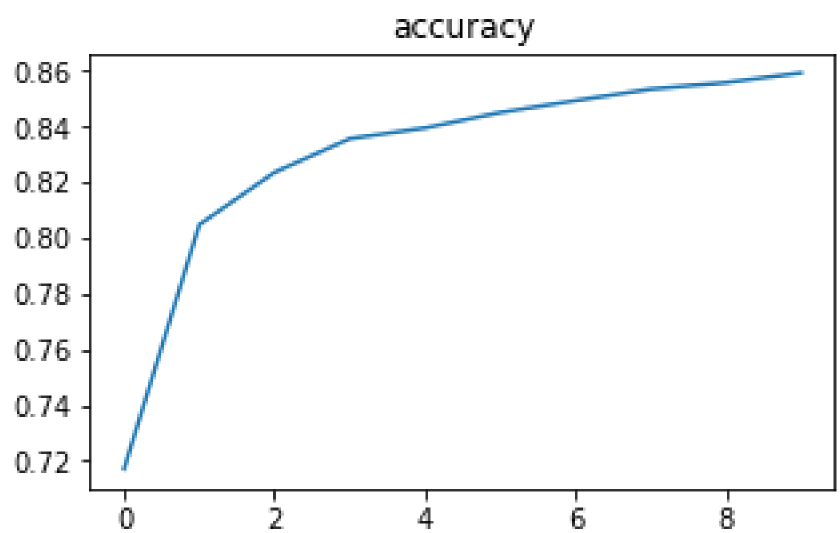
In [66]:
```
# Plot loss and accuracy in training

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[66]:
```
<matplotlib.text.Text at 0x7f22605294a8>
```






```
In [67]: # 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: 84.20%
```

```
In [ ]: %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)
```

```
In [91]: # Initialize model
         model = Sequential()

         # Add layers 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'))
         # 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_22 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
activation_37 (Activation)   (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_18 (MaxPooling (None, 13, 13, 32)        0
_________________________________________________________________
flatten_19 (Flatten)         (None, 5408)              0
_________________________________________________________________
dense_19 (Dense)             (None, 10)                54090
```

```
-----------------------------------------------------------------
activation_38 (Activation)   (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
-----------------------------------------------------------------
None
```

In [92]:
```
%%time

# Training
epochs = 30

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

```
Epoch 1/30
60000/60000 [==============================] - 16s - loss: 1.0128 - acc: 0.6768
Epoch 2/30
60000/60000 [==============================] - 16s - loss: 0.6097 - acc: 0.7887
Epoch 3/30
60000/60000 [==============================] - 17s - loss: 0.5511 - acc: 0.8051
Epoch 4/30
60000/60000 [==============================] - 16s - loss: 0.5219 - acc: 0.8162
Epoch 5/30
60000/60000 [==============================] - 15s - loss: 0.5080 - acc: 0.8204
Epoch 6/30
60000/60000 [==============================] - 11s - loss: 0.4933 - acc: 0.8252
Epoch 7/30
60000/60000 [==============================] - 11s - loss: 0.4862 - acc: 0.8285
Epoch 8/30
60000/60000 [==============================] - 10s - loss: 0.4768 - acc: 0.8333
Epoch 9/30
60000/60000 [==============================] - 10s - loss: 0.4700 - acc: 0.8347
Epoch 10/30
60000/60000 [==============================] - 12s - loss: 0.4659 - acc: 0.8365
Epoch 11/30
60000/60000 [==============================] - 15s - loss: 0.4631 - acc: 0.8394
Epoch 12/30
60000/60000 [==============================] - 15s - loss: 0.4484 - acc: 0.8431
Epoch 13/30
60000/60000 [==============================] - 15s - loss: 0.4432 - acc: 0.8443
Epoch 14/30
```

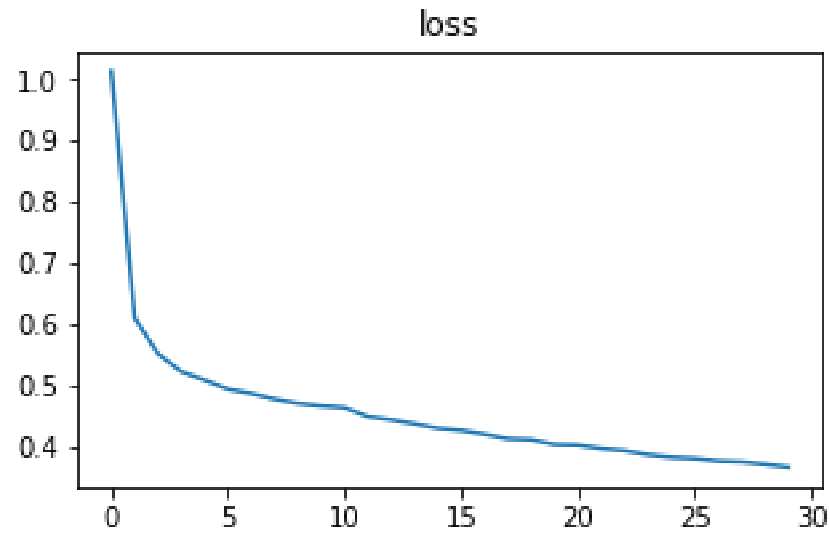
```
60000/60000 [==============================] - 15s - loss: 0.4367 - acc: 0.8471
Epoch 15/30
60000/60000 [==============================] - 16s - loss: 0.4293 - acc: 0.8490
Epoch 16/30
60000/60000 [==============================] - 16s - loss: 0.4258 - acc: 0.8511
Epoch 17/30
60000/60000 [==============================] - 16s - loss: 0.4196 - acc: 0.8530
Epoch 18/30
60000/60000 [==============================] - 16s - loss: 0.4120 - acc: 0.8556
Epoch 19/30
60000/60000 [==============================] - 17s - loss: 0.4106 - acc: 0.8572
Epoch 20/30
60000/60000 [==============================] - 17s - loss: 0.4028 - acc: 0.8589
Epoch 21/30
60000/60000 [==============================] - 16s - loss: 0.4019 - acc: 0.8591
Epoch 22/30
60000/60000 [==============================] - 16s - loss: 0.3963 - acc: 0.8622
Epoch 23/30
60000/60000 [==============================] - 17s - loss: 0.3928 - acc: 0.8633
Epoch 24/30
60000/60000 [==============================] - 12s - loss: 0.3862 - acc: 0.8660
Epoch 25/30
60000/60000 [==============================] - 11s - loss: 0.3821 - acc: 0.8665
Epoch 26/30
60000/60000 [==============================] - 11s - loss: 0.3804 - acc: 0.8672
Epoch 27/30
60000/60000 [==============================] - 11s - loss: 0.3762 - acc: 0.8694
Epoch 28/30
60000/60000 [==============================] - 10s - loss: 0.3749 - acc: 0.8689
Epoch 29/30
60000/60000 [==============================] - 10s - loss: 0.3711 - acc: 0.8706
Epoch 30/30
60000/60000 [==============================] - 10s - loss: 0.3665 - acc: 0.8723
CPU times: user 19min 3s, sys: 4min 33s, total: 23min 37s
Wall time: 7min 8s
```

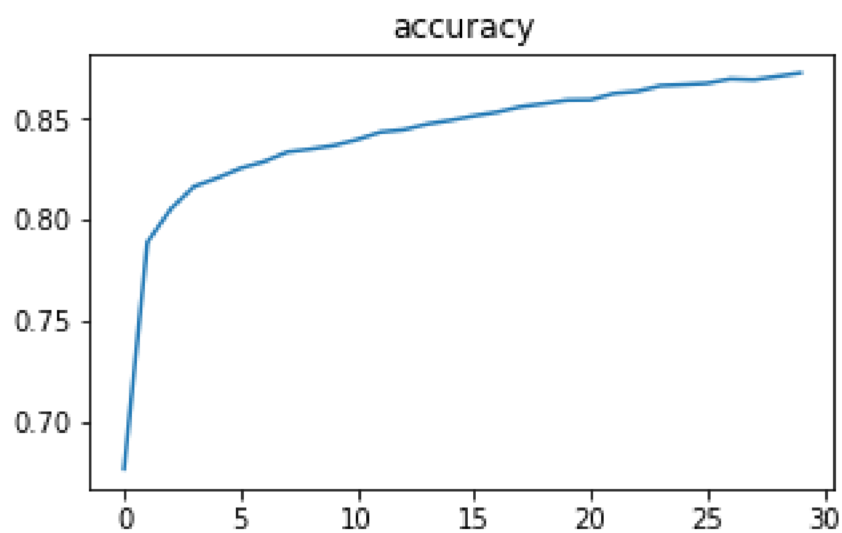
In [93]:
```
# Plot loss and accuracy in training

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[93]: <matplotlib.text.Text at 0x7f2222dd7940>






```
In [94]: # 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: 86.08%
```

```
In [ ]: %matplotlib inline

        from keras.models import Sequential
```

```python
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)
```

In [76]:
```python
# Initialize model
model = Sequential()

# Add layers here
model.add(Conv2D(32, (3, 3), input_shape=(28, 28, 1)))
model.add(Activation('relu'))
model.add(MaxPooling2D((2, 2)))
model.add(UpSampling2D(size=(2, 2)))
model.add(Flatten())
model.add(Dense(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_19 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
activation_31 (Activation)   (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_15 (MaxPooling (None, 13, 13, 32)        0
_________________________________________________________________
up_sampling2d_1 (UpSampling2 (None, 26, 26, 32)        0
_________________________________________________________________
```

```
flatten_16 (Flatten)         (None, 21632)             0
_________________________________________________________________
dense_16 (Dense)             (None, 10)                216330
_________________________________________________________________
activation_32 (Activation)   (None, 10)                0
=================================================================
Total params: 216,650
Trainable params: 216,650
Non-trainable params: 0
_________________________________________________________________
None
```

In [77]:
```
%%time

# Training
epochs = 10

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

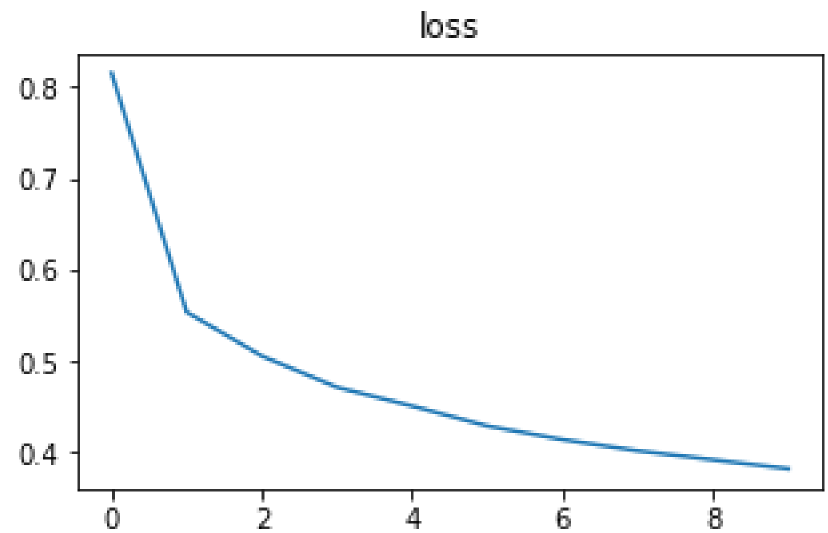
```
Epoch 1/10
60000/60000 [==============================] - 39s - loss: 0.8156 - acc: 0.7293
Epoch 2/10
60000/60000 [==============================] - 40s - loss: 0.5536 - acc: 0.8036
Epoch 3/10
60000/60000 [==============================] - 41s - loss: 0.5053 - acc: 0.8211
Epoch 4/10
60000/60000 [==============================] - 40s - loss: 0.4711 - acc: 0.8345
Epoch 5/10
60000/60000 [==============================] - 37s - loss: 0.4505 - acc: 0.8423
Epoch 6/10
60000/60000 [==============================] - 37s - loss: 0.4287 - acc: 0.8500
Epoch 7/10
60000/60000 [==============================] - 40s - loss: 0.4137 - acc: 0.8571
Epoch 8/10
60000/60000 [==============================] - 41s - loss: 0.4014 - acc: 0.8604
Epoch 9/10
60000/60000 [==============================] - 38s - loss: 0.3917 - acc: 0.8643
Epoch 10/10
60000/60000 [==============================] - 32s - loss: 0.3820 - acc: 0.8684
CPU times: user 15min 35s, sys: 3min, total: 18min 35s
Wall time: 6min 31s
```

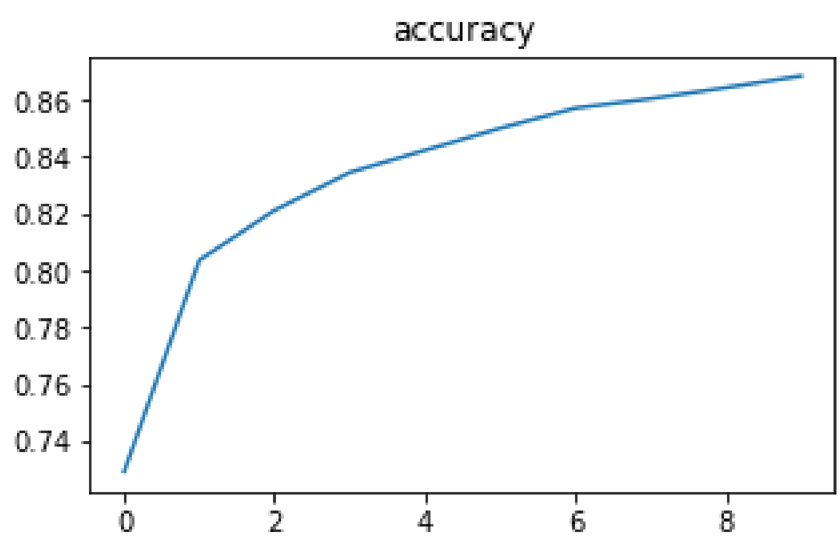
In [78]:
```
# Plot loss and accuracy in training
```

```python
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[78]: <matplotlib.text.Text at 0x7f22605adba8>





```
In [79]: # 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: 86.43%
```

```
In [ ]: %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)
```

```
In [87]: # Initialize model
         model = Sequential()

         # Add layers 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'))
         # Let's use categorical crossentry and sgd optmizer
         model.compile(loss='categorical_crossentropy',
                       optimizer='adam',
                       metrics=['accuracy'])
         print(model.summary())
```

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

```
conv2d_21 (Conv2D)           (None, 26, 26, 32)        320
_________________________________________________________________
activation_35 (Activation)   (None, 26, 26, 32)        0
_________________________________________________________________
max_pooling2d_17 (MaxPooling (None, 13, 13, 32)        0
_________________________________________________________________
flatten_18 (Flatten)         (None, 5408)              0
_________________________________________________________________
dense_18 (Dense)             (None, 10)                54090
_________________________________________________________________
activation_36 (Activation)   (None, 10)                0
=================================================================
Total params: 54,410
Trainable params: 54,410
Non-trainable params: 0
_________________________________________________________________
None
```

In [88]:
```
%%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: 0.5357 - acc: 0.8160
Epoch 2/10
60000/60000 [==============================] - 12s - loss: 0.3543 - acc: 0.8778
Epoch 3/10
60000/60000 [==============================] - 12s - loss: 0.3151 - acc: 0.8909
Epoch 4/10
60000/60000 [==============================] - 12s - loss: 0.2933 - acc: 0.8972
Epoch 5/10
60000/60000 [==============================] - 12s - loss: 0.2748 - acc: 0.9033
Epoch 6/10
60000/60000 [==============================] - 12s - loss: 0.2607 - acc: 0.9089
Epoch 7/10
60000/60000 [==============================] - 12s - loss: 0.2505 - acc: 0.9124
Epoch 8/10
60000/60000 [==============================] - 12s - loss: 0.2401 - acc: 0.9156
Epoch 9/10
60000/60000 [==============================] - 12s - loss: 0.2333 - acc: 0.9176
```

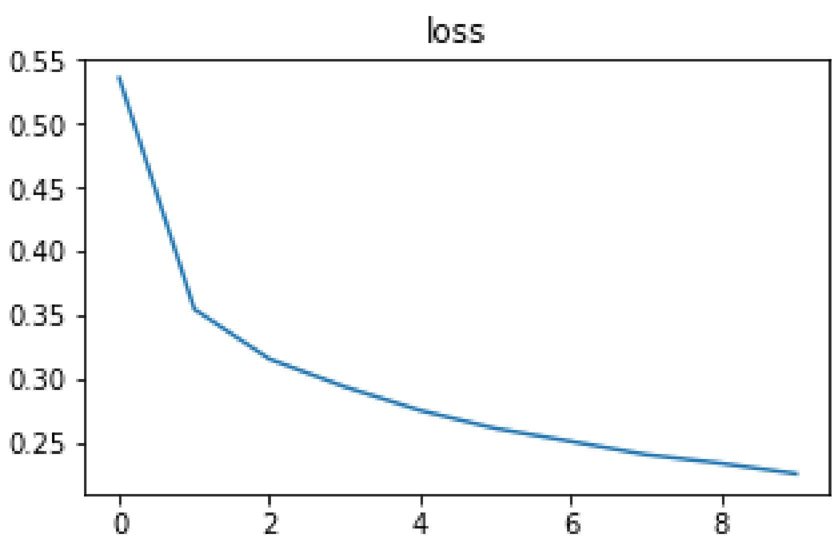
```
Epoch 10/10
60000/60000 [==============================] - 12s - loss: 0.2252 - acc: 0.9207
CPU times: user 6min 36s, sys: 1min 37s, total: 8min 14s
Wall time: 2min 6s
```

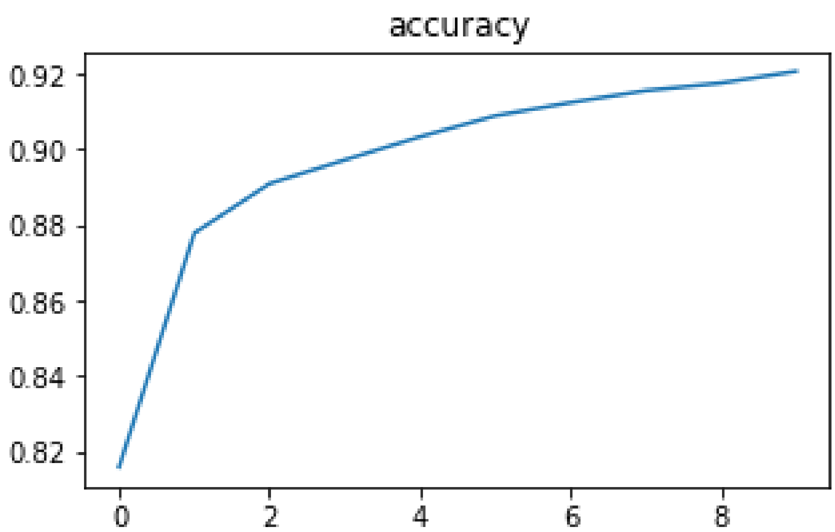
In [89]:
```
# Plot loss and accuracy in training

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[89]: <matplotlib.text.Text at 0x7f2223237b38>





In [90]:
```
# 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: 89.64%
```

Discussion: I have tried 7 times: 1st time: I only change the optimizer to be RMSprop, the accuracy of test data is 89.55%. 2nd time: I only remove the maxpooling, accuracy of test data is 84.21%. 3rd time: I only add another convolutional layer, accuracy of test data is 76.9%. 4th time: I only change the activation function of convolutional layer to be selu, accuracy of test data is 84.2%. 5th time: I only change the epochs to be 30, the accuracy of test data is 86.08%. 6th time: I only add an upsampling layer, accuracy of test data is 86.43%. 7th time: I only change the optimizer to be Adam, the accuracy of test data is 89.64%. The original accuracy of test data is 83.73%. Thus changing optimizer can improve performance of models the best and in my case, Adam can give better result and it has 5.91% improvement in the test set result. In addition, RMSprop has 5.82% improvement in the test set result. Adding upsampling layer before the dense layer is the third best method to improve performance of the model in my case. Changing activation function does not improve performance of the model that much. Adding another convolutional layer after the first convolutional layer makes performance of the model worse in my case.