Homework 1

Start date: *18th Jan 2017*

Due date: *04 February 2017, 11:55 pm*

How to Submit

When you have completed the exercises and everything has finsihed running, click on 'File' in the menu-bar and tl 'Download .ipynb'. This file must be submitted to Moodle named as **studentnumber_DL_hw1.ipynb** before the de above.

Also send a **sharable link** to the notebook at the following email: ucl.coursework.submit@gmail.com. You can al: it sharable via link to everyone, up to you.

IMPORTANT

Please make sure you submission includes **all results/plots/tables** required for grading. We will not re-run your c

The Data

Handwritten Digit Recognition Dataset (MNIST)

In this assignment we will be using the [MNIST digit dataset].

The dataset contains images of hand-written digits $(0 - 9)$, and the corresponding labels.

The images have a resolution of 28×28 pixels.

The MNIST Dataset in TensorFlow

You can use the tensorflow build-in functionality to download and import the dataset into python (see *Setup* sect below).

The Assignment

Objectives

You will use TensorFlow to implement several neural network models (labelled Model 1-4, and described in the corresponding sections of the Colab).

You will then train these models to classify hand written digits from the Mnist dataset.

Variable Initialization

Initialize the variables containing the parameters using [Xavier initialization].

```
initializer = tf.contrib.layers.xavier_initializer()
my_variable = tf.Variable(initializer(shape))
```

Hyper-parameters

For each of these models you will be requested to run experiments with different hyper-parameters.

More specifically, you will be requested to try 3 sets of hyper-parameters per model, and report the resulting mod accuracy.

Each combination of hyper-parameter will specify how to set each of the following:

- **num_epochs**: Number of iterations through the training section of the dataset [*a positive integer*].
- **learning_rate**: Learning rate used by the gradient descent optimizer [*a scalar between 0 and 1*]

In all experiments use a *batch_size* of 100.

Loss function

All models, should be trained as to minimize the **cross-entropy loss** function:

$$\text{loss} \;=\; -\sum_{i=1}^{N} \log p(y_i|x_i, \theta) \;=\; -\sum_{i=1}^{N} \log \underbrace{\left(\frac{\exp(z_i[y_i])}{\sum_{c=1}^{10} \exp(z_i[c])} \right)}_{\text{softmax output}} \;=\; \sum_{i=1}^{N} \left(-z_i[y_i] + \log \left(\sum_{c=1}^{10} \exp(z$$

where $z \in \mathbb{R}^{10}$ is the input to the softmax layer and $z[c]$ denotes the c-th entry of vector z. And i is a index for th dataset $\{(x_i, y_i)\}_{i=1}^{N}$.

Note: Sum the loss across the elements of the batch with tf.reduce_sum().

Hint: read about TensorFlow's tf.nn.softmax_cross_entropy_with_logits function.

Optimization

Use **stochastic gradient descent (SGD)** for optimizing the loss function.

Hint: read about TensorFlow's tf.train.GradientDescentOptimizer().

Training and Evaluation

The tensorflow built-in functionality for downloading and importing the dataset into python returns a Datasets ob

This object will have three attributes:

- train
- validation
- test

Use only the **train** data in order to optimize the model.

Use *datasets.train.next_batch(100)* in order to sample mini-batches of data.

Every 20000 training samples (i.e. every 200 updates to the model), interrupt training and measure the accuracy model,

each time evaluate the accuracy of the model both on 20% of the **train** set and on the entire **test** set.

Reporting

For each model i, you will collect the learning curves associated to each combination of hyper-parameters.

Use the utility function `plot_learning_curves` to plot these learning curves,

and the and utility function `plot_summary_table` to generate a summary table of results.

For each run collect the train and test curves in a tuple, together with the hyper-parameters.

```
experiments_task_i = [

   (num_epochs_1, learning_rate_1), train_accuracy_1, test_accuracy_1),

   (num_epochs_2, learning_rate_2), train_accuracy_2, test_accuracy_2),


   (num_epochs_3, learning_rate_3), train_accuracy_3, test_accuracy_3)]
```

Hint

If you need some extra help, familiarizing yourselves with the dataset and the task of building models in TensorF can check the [TF tutorial for MNIST](#).

The tutorial will walk you through the MNIST classification task step-by-step, building and optimizing a model in TensorFlow.

(Please do not copy the provided code, though. Walk through the tutorial, but write your own implementation).

Imports and utility functions (do not modify!)

↳ *1 cells hidden*

Model 1 (20 pts)

Model

Train a neural network model consisting of 1 linear layer, followed by a softmax:

(input → linear layer → softmax → class probabilities)

Hyper-parameters

Train the model with three different hyper-parameter settings:

- *num_epochs*=5, *learning_rate*=0.0001
- *num_epochs*=5, *learning_rate*=0.005
- *num_epochs*=5, *learning_rate*=0.1

```
# CAREFUL: Running this CL resets the experiments_task1 dictionary where results sh
# Store results of runs with different configurations in a dictionary.
# Use a tuple (num_epochs, learning_rate) as keys, and a tuple (training_accuracy,
experiments_task1 = []
settings = [(5, 0.0001), (5, 0.005), (5, 0.1)]
```

```
print('Training Model 1')

# Train Model 1 with the different hyper-parameter settings.
for (num_epochs, learning_rate) in settings:

  # Reset graph, recreate placeholders and dataset.
  tf.reset_default_graph()
  x, y_ = get_placeholders()
  mnist = get_data()
  eval_mnist = get_data()

  # Define model, loss, update and evaluation metric.
  initializer = tf.contrib.layers.xavier_initializer()
  w = tf.Variable(initializer([784,10]))
  b = tf.Variable(initializer([10]))
  logits = tf.matmul(x,w)+b
  y = tf.nn.softmax(logits)
  loss = tf.reduce_sum(tf.nn.softmax_cross_entropy_with_logits(labels=y_,logits=log

  train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)
  correct_prediction = tf.equal(tf.argmax(y_,1),tf.argmax(y,1))
  accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
```

```
  accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

  # Train.
  i, train_accuracy, test_accuracy = 0, [], []
  log_period_updates = int(log_period_samples / batch_size)
  with tf.train.MonitoredSession() as sess:
    while mnist.train.epochs_completed < num_epochs:

      # Update.
      i += 1
      batch_xs, batch_ys = mnist.train.next_batch(batch_size)

      # Training step
      sess.run(train_step,feed_dict={x:batch_xs,y_:batch_ys})

      # Periodically evaluate.
      if i % log_period_updates == 0:

        # Compute and store train accuracy on 20% training data.
        a=0.2
        ex = eval_mnist.train.images
        ey = eval_mnist.train.labels
        size = int(ey.shape[0]*a)
        part_ex = ex[0:size,:]
        part_ey = ey[0:size,:]
        train = sess.run(accuracy,feed_dict={x:part_ex,y_:part_ey})
        print("%d th iter train accuracy %f" %(i,train))
        train_accuracy.append(train)

        # Compute and store test accuracy.
        test = sess.run(accuracy,feed_dict={x:eval_mnist.test.images,y_:eval_mnist.
        print("%d th iter test accuracy %f" %(i,test))
        test_accuracy.append(test)

  # save in a list
  experiments_task1.append(
      ((num_epochs, learning_rate), train_accuracy, test_accuracy))
```

SHOW HIDDEN OUTPUT

Model 2 (20 pts)

1 hidden layer (32 units) with a ReLU non-linearity, followed by a softmax.

(input → non-linear layer → linear layer → softmax → class probabilities)

Hyper-parameters

Train the model with three different hyper-parameter settings:

- *num_epochs*=15, *learning_rate*=0.0001
- *num_epochs*=15, *learning_rate*=0.005
- *num_epochs*=15, *learning_rate*=0.1

```
# CAREFUL: Running this CL resets the experiments_task1 dictionary where results sh
# Store results of runs with different configurations in a dictionary.
# Use a tuple (num_epochs, learning_rate) as keys, and a tuple (training_accuracy,
experiments_task2 = []
settings = [(15, 0.0001), (15, 0.005), (15, 0.1)]
```

```
print('Training Model 2')

# Train Model 2 with the different hyper-parameter settings.
for (num_epochs, learning_rate) in settings:

  # Reset graph, recreate placeholders and dataset.
```

```
# Reset graph, recreate placeholders and dataset.
tf.reset_default_graph()  # reset the tensorflow graph
x, y_ = get_placeholders()
mnist = get_data()  # use for training.
eval_mnist = get_data()  # use for evaluation.

# Define model, loss, update and evaluation metric.
initializer = tf.contrib.layers.xavier_initializer()

# non-linear layer
w_1 = tf.Variable(initializer([784,32]))
b_1 = tf.Variable(initializer([32]))
h_1 = tf.nn.relu(tf.matmul(x,w_1)+b_1)

# linear layer
w_2 = tf.Variable(initializer([32,10]))
b_2 = tf.Variable(initializer([10]))
logits = tf.matmul(h_1,w_2)+b_2
y = tf.nn.softmax(logits)
loss = tf.reduce_sum(tf.nn.softmax_cross_entropy_with_logits(labels=y_,logits=log
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

# evalutaion
correct_prediction = tf.equal(tf.argmax(y_,1),tf.argmax(y,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

# Train.
i, train_accuracy, test_accuracy = 0, [], []
log_period_updates = int(log_period_samples / batch_size)
with tf.train.MonitoredSession() as sess:
  while mnist.train.epochs_completed < num_epochs:

    # Update.
    i += 1
    batch_xs, batch_ys = mnist.train.next_batch(batch_size)

    # Training step
    sess.run(train_step,feed_dict={x:batch_xs,y_:batch_ys})

    # Periodically evaluate.
    if i % log_period_updates == 0:

      # Compute and store train accuracy on 20% training data.
      a=0.2
      ex = eval_mnist.train.images
      ey = eval_mnist.train.labels
      size = int(ey.shape[0]*a)
      part_ex = ex[0:size,:]
      part_ey = ey[0:size,:]
      train = sess.run(accuracy,feed_dict={x:part_ex,y_:part_ey})
      print("%d th iter train accuracy %f" %(i,train))
      train_accuracy.append(train)

      # Compute and store test accuracy.
      test = sess.run(accuracy,feed_dict={x:eval_mnist.test.images,y_:eval_mnist.
      print("%d th iter test accuracy %f" %(i,test))
      test_accuracy.append(test)

  experiments_task2.append(
      ((num_epochs, learning_rate), train_accuracy, test_accuracy))
```

SHOW HIDDEN OUTPUT

Model 3 (20 pts)

2 hidden layers (32 units) each, with ReLU non-linearity, followed by a softmax.

(input → non-linear layer → non-linear layer → linear layer → softmax → class probabilities)

Hyper-parameters

Train the model with three different hyper-parameter settings:

- *num_epochs*=5, *learning_rate*=0.003
- *num_epochs*=40, *learning_rate*=0.003
- *num_epochs*=40, *learning_rate*=0.05

```
# CAREFUL: Running this CL resets the experiments_task1 dictionary where results sh
# Store results of runs with different configurations in a dictionary.
# Use a tuple (num_epochs, learning_rate) as keys, and a tuple (training_accuracy,
experiments_task3 = []
settings = [(5, 0.003), (40, 0.003), (40, 0.05)]
```

```
print('Training Model 3')

# Train Model 3 with the different hyper-parameter settings.
for (num_epochs, learning_rate) in settings:

  # Reset graph, recreate placeholders and dataset.
  tf.reset_default_graph()  # reset the tensorflow graph
  x, y_ = get_placeholders()
  mnist = get_data()  # use for training.
  eval_mnist = get_data()  # use for evaluation.

  # Define model, loss, update and evaluation metric.
  initializer = tf.contrib.layers.xavier_initializer()

  # non-linear layer 1
  w_1 = tf.Variable(initializer([784,32]))
  b_1 = tf.Variable(initializer([32]))
  h_1 = tf.nn.relu(tf.matmul(x,w_1)+b_1)

  # non-linear layer 2
  w_2 = tf.Variable(initializer([32,32]))
  b_2 = tf.Variable(initializer([32]))
  h_2 = tf.nn.relu(tf.matmul(h_1,w_2)+b_2)

  # linear layer
  w_3 = tf.Variable(initializer([32,10]))
  b_3 = tf.Variable(initializer([10]))
  logits = tf.matmul(h_2,w_3)+b_3
  y = tf.nn.softmax(logits)
  loss = tf.reduce_sum(tf.nn.softmax_cross_entropy_with_logits(labels=y_,logits=log
  train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

  # evalutaion
  correct_prediction = tf.equal(tf.argmax(y_,1),tf.argmax(y,1))
  accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

  # Train.
  i, train_accuracy, test_accuracy = 0, [], []
  log_period_updates = int(log_period_samples / batch_size)
  with tf.train.MonitoredSession() as sess:
    while mnist.train.epochs_completed < num_epochs:

      # Update.
      i += 1
      batch_xs, batch_ys = mnist.train.next_batch(batch_size)

      # Training step
      sess.run(train_step,feed_dict={x:batch_xs,y_:batch_ys})

      # Periodically evaluate.
      if i % log_period_updates == 0:

        # Compute and store train accuracy on 20% training data.
        a=0.2
        ex = eval_mnist.train.images
        ey = eval_mnist.train.labels
```

```
        ey = eval_mnist.train.labels
        size = int(ey.shape[0]*a)
        part_ex = ex[0:size,:]
        part_ey = ey[0:size,:]
        train = sess.run(accuracy,feed_dict={x:part_ex,y_:part_ey})
        print("%d th iter train accuracy %f" %(i,train))
        train_accuracy.append(train)

        # Compute and store test accuracy.
        test = sess.run(accuracy,feed_dict={x:eval_mnist.test.images,y_:eval_mnist.
        print("%d th iter test accuracy %f" %(i,test))
        test_accuracy.append(test)

    experiments_task3.append(
        ((num_epochs, learning_rate), train_accuracy, test_accuracy))
```

SHOW HIDDEN OUTPUT

Model 4 (20 pts)

Model

3 layer convolutional model (2 convolutional layers followed by max pooling) + 1 non-linear layer (32 units), followed by softmax.

(input(28x28) → conv(3x3x8) + maxpool(2x2) → conv(3x3x8) + maxpool(2x2) → flatten → non-linear → linear layer → softmax → class probabilities)

- Use *padding = 'SAME'* for both the convolution and the max pooling layers.
- Employ plain convolution (no stride) and for max pooling operations use 2x2 sliding windows, with no overlapping pixels (note: this operation will down-sample the input image by 2x2).

Hyper-parameters

Train the model with three different hyper-parameter settings:

- num_epochs=5, learning_rate=0.01
- num_epochs=10, learning_rate=0.001
- num_epochs=20, learning_rate=0.001

```
# CAREFUL: Running this CL resets the experiments_task1 dictionary where results sh
# Store results of runs with different configurations in a dictionary.
# Use a tuple (num_epochs, learning_rate) as keys, and a tuple (training_accuracy,
experiments_task4 = []
settings = [(5, 0.01), (10, 0.001), (20, 0.001)]
```

```
print('Training Model 4')

# Train Model 4 with the different hyper-parameter settings.
for (num_epochs, learning_rate) in settings:

  # Reset graph, recreate placeholders and dataset.
  tf.reset_default_graph()  # reset the tensorflow graph
  x, y_ = get_placeholders()
  x_image = tf.reshape(x, [-1, 28, 28, 1])
  mnist = get_data()  # use for training.
  eval_mnist = get_data()  # use for evaluation.

  # Define model, loss, update and evaluation metric.

  initializer = tf.contrib.layers.xavier_initializer()

  # conv layer 1
```

```
# conv layer 1
w_conv1 = tf.Variable(initializer([3,3,1,8]))
b_conv1 = tf.Variable(initializer([8]))
h_conv1 = tf.nn.relu(tf.nn.conv2d(x_image, w_conv1, strides=[1, 1, 1, 1], padding
h_pool1 = tf.nn.max_pool(h_conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], paddi

# conv layer 2
w_conv2 = tf.Variable(initializer([3,3,8,8]))
b_conv2 = tf.Variable(initializer([8]))
h_conv2 = tf.nn.relu(tf.nn.conv2d(h_pool1, w_conv2, strides=[1, 1, 1, 1], padding
h_pool2 = tf.nn.max_pool(h_conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], paddi

# flatten
h_flat = tf.reshape(h_pool2, [-1, 7*7*8])

# non-linear layer
w_n = tf.Variable(initializer([7*7*8,32]))
b_n = tf.Variable(initializer([32]))
h_n = tf.nn.relu(tf.matmul(h_flat,w_n)+b_n)

# linear layer + softmax & loss
w_linear = tf.Variable(initializer([32,10]))
b_linear = tf.Variable(initializer([10]))
logits = tf.matmul(h_n,w_linear)+b_linear
y = tf.nn.softmax(logits)
loss = tf.reduce_sum(tf.nn.softmax_cross_entropy_with_logits(labels=y_,logits=log
train_step = tf.train.GradientDescentOptimizer(learning_rate).minimize(loss)

# evalutaion
correct_prediction = tf.equal(tf.argmax(y_,1),tf.argmax(y,1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

# Train.
i, train_accuracy, test_accuracy = 0, [], []
log_period_updates = int(log_period_samples / batch_size)
with tf.train.MonitoredSession() as sess:
  while mnist.train.epochs_completed < num_epochs:

    # Update.
    i += 1
    batch_xs, batch_ys = mnist.train.next_batch(batch_size)

    # Training step
    sess.run(train_step,feed_dict={x:batch_xs,y_:batch_ys})

    # Periodically evaluate.
    if i % log_period_updates == 0:

      # Compute and store train accuracy on 20% training data.
      a=0.2
      ex = eval_mnist.train.images
      ey = eval_mnist.train.labels
      size = int(ey.shape[0]*a)
      part_ex = ex[0:size,:]
      part_ey = ey[0:size,:]
      train = sess.run(accuracy,feed_dict={x:part_ex,y_:part_ey})
      print("%d th iter train accuracy %f" %(i,train))
      train_accuracy.append(train)

      # Compute and store test accuracy.
      test = sess.run(accuracy,feed_dict={x:eval_mnist.test.images,y_:eval_mnist.
      print("%d th iter test accuracy %f" %(i,test))
      test_accuracy.append(test)

  experiments_task4.append(
      ((num_epochs, learning_rate), train_accuracy, test_accuracy))
```

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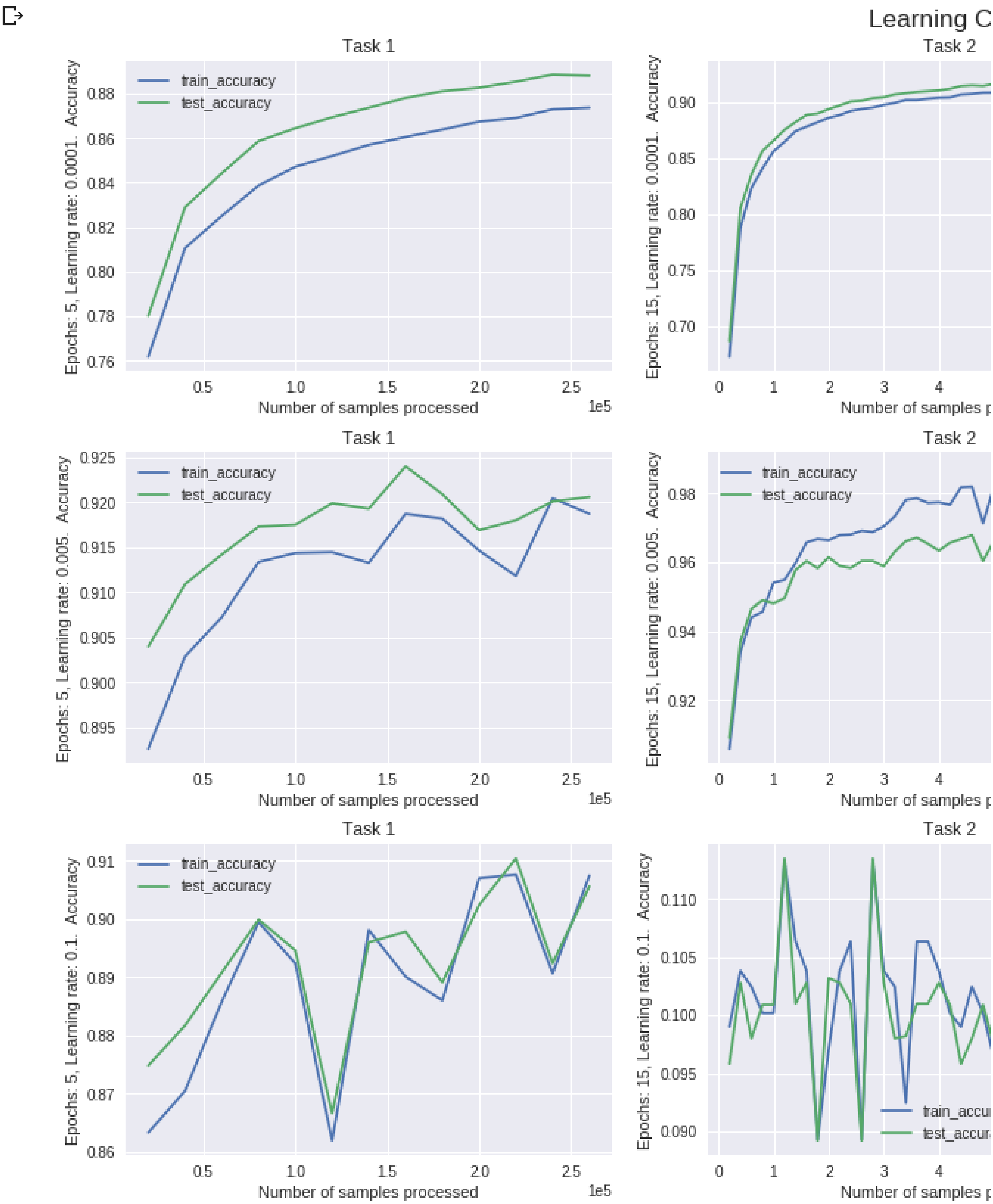
Evaluation

```
plot_learning_curves([experiments_task1, experiments_task2, experiments_task3, expe
```




```
plot_summary_table([experiments_task1, experiments_task2, experiments_task3, experi
```

	Setting 1	Setting 2	Setting 3
Model 1	0.8881	0.9206	0.9056
Model 2	0.9251	0.9687	0.0959
Model 3	0.9679	0.9686	0.101
Model 4	0.1135	0.9825	0.9842

Questions

Q1 (5 pts): Indicate which of the previous experiments constitute an example of over-fitting. Why is this happening?

Task 2 Setting 2: training for so long & learning rate is high

Task 3 Setting 2: training for so long

Task 4 Setting 3: training for so long & model is complex

Q2 (5 pts): Indicate which of the previous experiments constitute an example of under-fitting. Why is this happening?

Task 2 Setting 3 & Task 3 Setting 3 & Task 4 Setting 1: learning rate is too high

Task 1 Setting 1-3: the model is too simple(linear)

Task 2 Setting 1: not enough training

Q3 (10 pts): How would you prevent over-/under-fitting from happening?

To prevent overfitting, we can

- Stop training early
- Use simpler model
- Use fewer features
- Increase regularisation
- Use batch normalisation

To prevernt underfitting

- Train for longer
- Use more complex model
- Use more features

- Reduce regularisation
- Feed more training data

- Feed more training data

Extension (Ungraded)

In the previous tasks you have used plain Stohastic Gradient Descent to train the models.

There is a large literatures on variants of Stochastic Gradient Descent, that improve learning speed and robustness to hyper-parameters.

[Here](#) you can find the documentation for several optimizers already implemented in TensorFlow, as well as the original papers proposing these methods.*italicized text*.

AdamOptimizer and RMSProp are among the most commonly employed in Deep Learning.

How does replacing SGD with these optimizers affect the previous results?

```
from tensorflow.python.client import device_lib
device_lib.list_local_devices()
```

SHOW HIDDEN OUTPUT

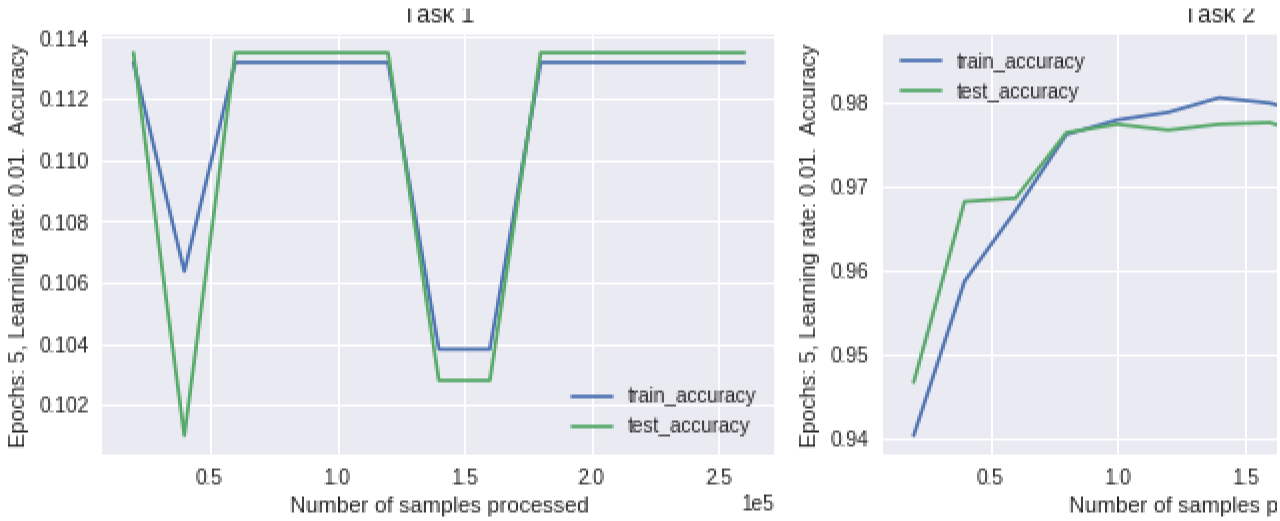
```
# CAREFUL: Running this CL resets the experiments_task5 using RMSPropOptimizer dict
# Store results of runs with different configurations in a dictionary.
# Use a tuple (num_epochs, learning_rate) as keys, and a tuple (training_accuracy,
experiments_task5 = []
settings = [(5, 0.01), (10, 0.001), (20, 0.001)]
```

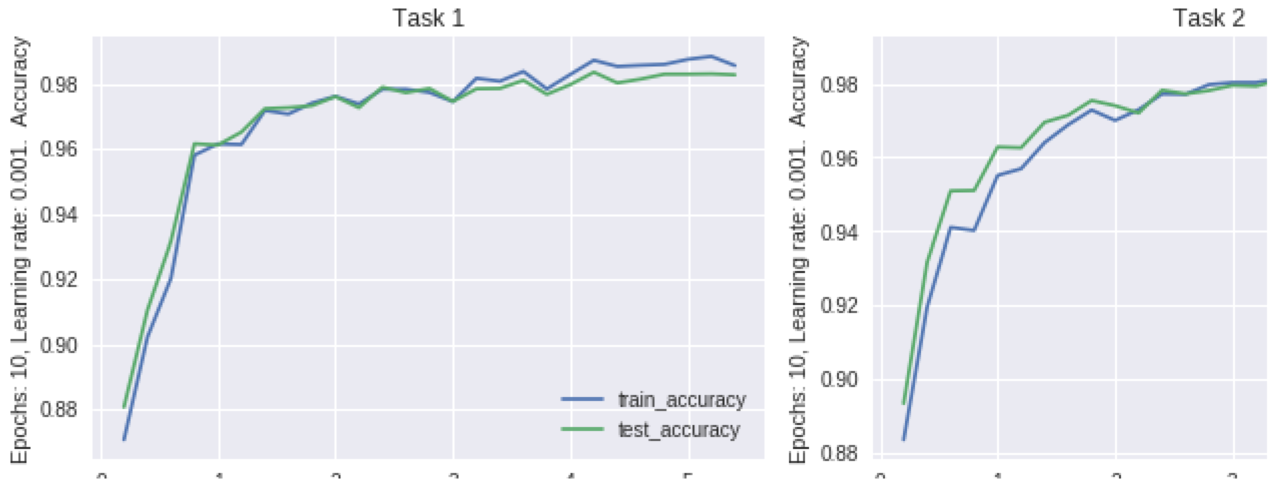
```
print('Training Model 4.2')

# Train Model 4.2 with the different hyper-parameter settings.
for (num_epochs, learning_rate) in settings:

  # Reset graph, recreate placeholders and dataset.
  tf.reset_default_graph()  # reset the tensorflow graph
  x, y_ = get_placeholders()
  x_image = tf.reshape(x, [-1, 28, 28, 1])
  mnist = get_data()  # use for training.
  eval_mnist = get_data()  # use for evaluation.

  # Define model, loss, update and evaluation metric.
  initializer = tf.contrib.layers.xavier_initializer()

  # conv layer 1
  w_conv1 = tf.Variable(initializer([3,3,1,8]))
  b_conv1 = tf.Variable(initializer([8]))
  h_conv1 = tf.nn.relu(tf.nn.conv2d(x_image, w_conv1, strides=[1, 1, 1, 1], padding
  h_pool1 = tf.nn.max_pool(h_conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], paddi

  # conv layer 2
  w_conv2 = tf.Variable(initializer([3,3,8,8]))
  b_conv2 = tf.Variable(initializer([8]))
  h_conv2 = tf.nn.relu(tf.nn.conv2d(h_pool1, w_conv2, strides=[1, 1, 1, 1], padding
  h_pool2 = tf.nn.max_pool(h_conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], paddi

  # flatten
  h_flat = tf.reshape(h_pool2, [-1, 7*7*8])

  # non-linear layer
  w_n = tf.Variable(initializer([7*7*8,32]))
  b_n = tf.Variable(initializer([32]))
  h_n = tf.nn.relu(tf.matmul(h_flat,w_n)+b_n)

  # linear layer + softmax & loss
  w_linear = tf.Variable(initializer([32,10]))
  b_linear = tf.Variable(initializer([10]))
  logits = tf.matmul(h_n,w_linear)+b_linear
  y = tf.nn.softmax(logits)
```

```
  y = tf.nn.softmax(logits)
  loss = tf.reduce_sum(tf.nn.softmax_cross_entropy_with_logits(labels=y_,logits=lo
  train_step = tf.train.RMSPropOptimizer(learning_rate).minimize(loss)

  # evalutaion
  correct_prediction = tf.equal(tf.argmax(y_,1),tf.argmax(y,1))
  accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

  # Train.
  i, train_accuracy, test_accuracy = 0, [], []
  log_period_updates = int(log_period_samples / batch_size)
  with tf.train.MonitoredSession() as sess:
    while mnist.train.epochs_completed < num_epochs:

      # Update.
      i += 1
      batch_xs, batch_ys = mnist.train.next_batch(batch_size)

      # Training step
      sess.run(train_step,feed_dict={x:batch_xs,y_:batch_ys})

      # Periodically evaluate.
      if i % log_period_updates == 0:

        # Compute and store train accuracy on 20% training data.
        a=0.2
        ex = eval_mnist.train.images
        ey = eval_mnist.train.labels
        size = int(ey.shape[0]*a)
        part_ex = ex[0:size,:]
        part_ey = ey[0:size,:]
        train = sess.run(accuracy,feed_dict={x:part_ex,y_:part_ey})
        print("%d th iter train accuracy %f" %(i,train))
        train_accuracy.append(train)

        # Compute and store test accuracy.
        test = sess.run(accuracy,feed_dict={x:eval_mnist.test.images,y_:eval_mnist.
        print("%d th iter test accuracy %f" %(i,test))
        test_accuracy.append(test)

    experiments_task5.append(
        ((num_epochs, learning_rate), train_accuracy, test_accuracy))
```

SHOW HIDDEN OUTPUT

```
plot_learning_curves([experiments_task4, experiments_task5])
```





From the curves we can see that, RMSProp is much steadier than SGD. Even for a larger learning rate, this method is still able to find better parameters without suffering from gradient problems. Also, it finds optimal values more quickly. This is the advantage of mini-batch with a flexible learning rate.