12_MLP_Architectures_MNIST

April 11, 2019

```
In [1]: # import all required packages
        import pandas as pd
        import numpy as np
        from datetime import datetime

        # package for MLP
        import tensorflow as tf

        # Plot related packages
        import matplotlib.pyplot as plt
        import seaborn as sns
        sns.set()

        # math package
        import math

        # dataset related packages
        from tensorflow.examples.tutorials.mnist import input_data
```

```
/home/amd_3/anaconda3/lib/python3.6/site-packages/h5py/__init__.py:36: FutureWarning: Conversion
  from ._conv import register_converters as _register_converters
```

0.1 Load the data

```
In [2]: mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
```

```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
```

The data is already standardized to fall in the range 0.0 to 1.0

1 UTIL functions

```
In [3]: def plot_loss_curve(train_metric_list, val_metric_list):
            """
```

```
        This function plots the loss curve for train and validation
        """

        # get x-label list
        epcoh_list = range(1, len(train_metric_list) + 1 )

        # get train_accuracy data
        train_acc_list = [ item[1] for item in train_metric_list]

        # get validation accuracy data
        val_acc_list = [ item[1] for item in val_metric_list]

        # plot both train, validation curve
        plt.plot(epcoh_list, train_acc_list, label='Train Loss', color='r')
        plt.plot(epcoh_list, val_acc_list, label='Validation Loss', color='b')
        plt.xlabel('Training Epoch')
        plt.ylabel('Cross Entropy Error')
        plt.title('Training Loss Vs Validation Loss')
        plt.legend()
        plt.show()
```

```
In [4]: def plot_accuracy_curve(train_metric_list, val_metric_list):
            """
            This function plots the accuracy curve for train and validation
            """

            # get x-label list
            epcoh_list = range(1, len(train_metric_list) + 1 )

            # get train_accuracy data
            train_acc_list = [ item[2] for item in train_metric_list]

            # get validation accuracy data
            val_acc_list = [ item[2] for item in val_metric_list]

            # plot both train, validation curve
            plt.plot(epcoh_list, train_acc_list, label='Train Accuracy', color='r')
            plt.plot(epcoh_list, val_acc_list, label='Validation Accuracy', color='b')
            plt.xlabel('Training Epoch')
            plt.ylabel('Accuracy')
            plt.title('Training Accuracy Vs Validation Accuracy')
            plt.legend()
            plt.show()
```

2 MODEL

```
In [5]: # declare placeholders for input and output
        X = tf.placeholder(tf.float32, [None, 784])
```

```
    y = tf.placeholder(tf.float32, [None, 10])
    keep_probability = tf.placeholder(tf.float32) # This is for dropout in a layer
```

In [6]:
```
def train_and_evaluate_model(custom_model, keep_prob_val, num_epochs = 2):
    """
    This function train and evaluate the model
    """

    batch_size = 100
    total_batchs = int(mnist.train.num_examples / batch_size)

    # define the loss function
    cee = tf.reduce_mean(-tf.reduce_sum(y * tf.log(custom_model), reduction_indices=[1])
    # defien the train step
    train_step = tf.train.AdamOptimizer(1e-03).minimize(cee)
    # define the accuracy
    accuracy = tf.reduce_mean(tf.cast(tf.equal(tf.argmax(y,1), tf.argmax(custom_model,1)


    # declare two list for holding loss, accuracy for both train, validation
    train_metric_list = list()
    val_metric_list = list()

    # create a session and execute the code
    with tf.Session() as sess:

        # initialize variables
        tf.global_variables_initializer().run()

        # run multiple epochs
        for epoch in range(1, num_epochs + 1):

            # run batch by batch
            for batch_id in range(total_batchs):

                # get the train data into features and labels
                X_train, y_train = mnist.train.next_batch(batch_size)

                # run the training
                _ = sess.run([train_step], feed_dict={X:X_train, y:y_train, keep_probabi


            # find predicted value, loss and accuracy for both train &test data sets
            tr_pred, tr_cee, tr_acc = sess.run([custom_model, cee, accuracy], feed_dict=
                                                                              y:mnist.t
                                                                              keep_prob
            train_metric_list.append((tr_pred, tr_cee, tr_acc,))
```

```
                val_pred, val_cee, val_acc = sess.run([custom_model, cee, accuracy], feed_di
                                                                                          y:mnis
                                                                                          keep_p
                val_metric_list.append((val_pred, val_cee, val_acc,))

            # Test the model
            ts_pred, ts_cee, ts_acc = sess.run([custom_model, cee, accuracy], feed_dict={X :
                                                                                  y : mnist.test
                                                                                  keep_probabili

            test_loss = ts_cee.mean()

            print('Test accuracy of model :%f, Test loss:%f'%(ts_acc, test_loss,))

        return (test_loss, ts_acc, train_metric_list, val_metric_list,)
```

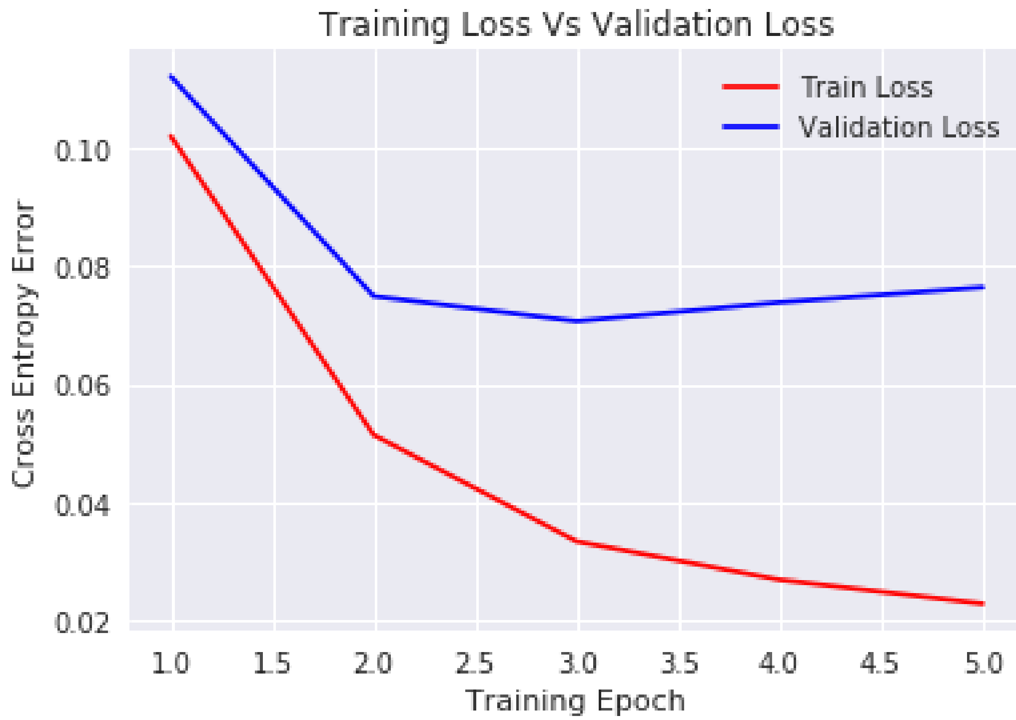
2.1 a) MLP with 2 hidden layer, relu

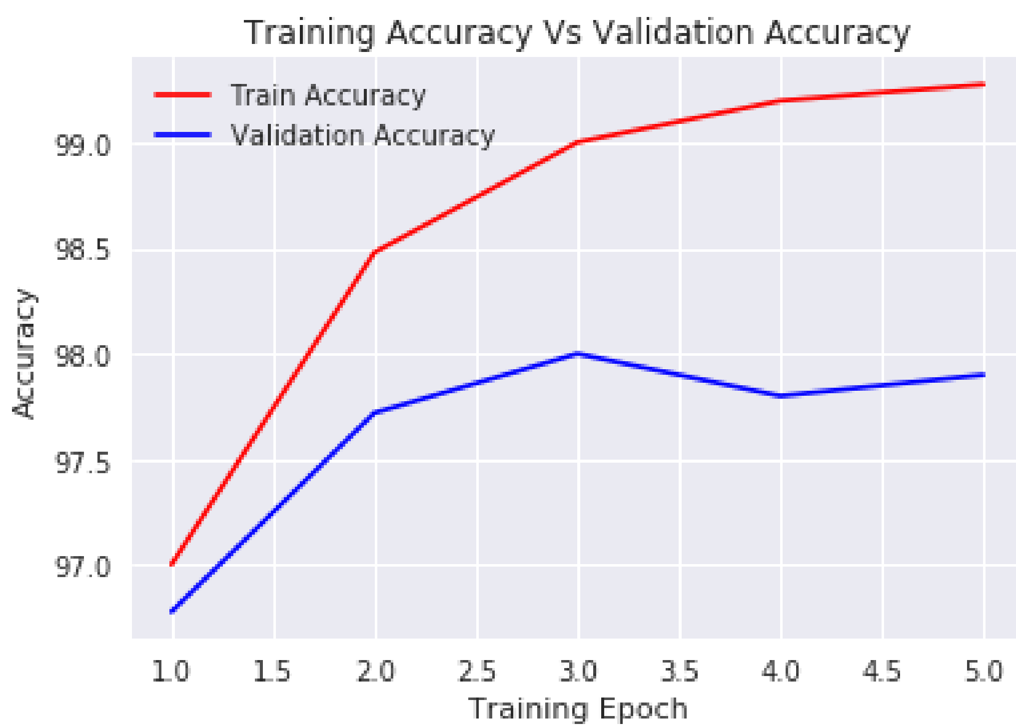
```
In [7]: def build_model_a(X):
            """
            This functions builds the architecture for the MLP.
            """

            # model architecture
            num_input_neurons = 784
            num_hidden_neurons_1 =  512
            num_hidden_neurons_2 = 128
            num_output_neurons = 10

            # for relu activation function we need to use He normal initialization of weights as
            # If we sample weights from a normal distribution N(0,) we satisfy this condition wi
            # weights =>  =(2/(fan_in+1) => N(0,)

            # relu activation specific standard deviations
            l1_stddev = math.sqrt(2 / (num_input_neurons + 1))
            l2_stddev = math.sqrt(2 / (num_hidden_neurons_1 + 1))
            out_stddev = math.sqrt(2 / (num_hidden_neurons_2 + 1))


            # ===================================== hidden layer 1 ============================
            l1_weights = tf.Variable(tf.random_normal(shape=[num_input_neurons, num_hidden_neuro
                                                      mean=0.0, stddev=l1_stddev))
            l1_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_1], mean=0.0, st

            l1_net_input = tf.matmul(X, l1_weights) + l1_biases
            l1_output = tf.nn.relu(l1_net_input) # activation function
            #=================================================================================
```

```
        # ======================================== hidden layer 2 ============================
        l2_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_1, num_hidden_ne
                                                  mean=0.0, stddev=l2_stddev))
        l2_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_2], mean=0.0, st

        l2_net_input = tf.matmul(l1_output, l2_weights) + l2_biases
        l2_output = tf.nn.relu(l2_net_input) # activation function
        #====================================================================================



        # ==================================  output layer ===================================
        l3_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_2, num_output_ne
                                                  mean=0.0, stddev=out_stddev))
        l3_biases  = tf.Variable(tf.random_normal(shape=[num_output_neurons], mean=0.0, stdd

        l3_net_input = tf.matmul(l2_output, l3_weights) + l3_biases

        # ===================================================================================

        # return output using the softmax layer
        output = tf.nn.softmax(l3_net_input)

        return output
```

In [8]:
```
# buid the model a
mlp_a = build_model_a(X)

# train and evaluate the model
keep_prob_val = 1.0
num_epochs = 5

ts_loss_mlp_a, ts_acc_mlp_a, train_metric_list, val_metric_list = train_and_evaluate_mod


# plot the loss curve
plot_loss_curve(train_metric_list, val_metric_list)
# plot the accuracy curve
plot_accuracy_curve(train_metric_list, val_metric_list)
```

```
Test accuracy of model :98.000000, Test loss:0.074359
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.10
0.08
0.06
0.04
0.02
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch


Training Accuracy Vs Validation Accuracy
Train Accuracy
Validation Accuracy
Accuracy
99.0
98.5
98.0
97.5
97.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch

2.1.1 Observation

As the number of epochs pass 3, validation loss starts increasing slightly

2.2 b) MLP with 3 Hidden layers, dropout, batch normalization

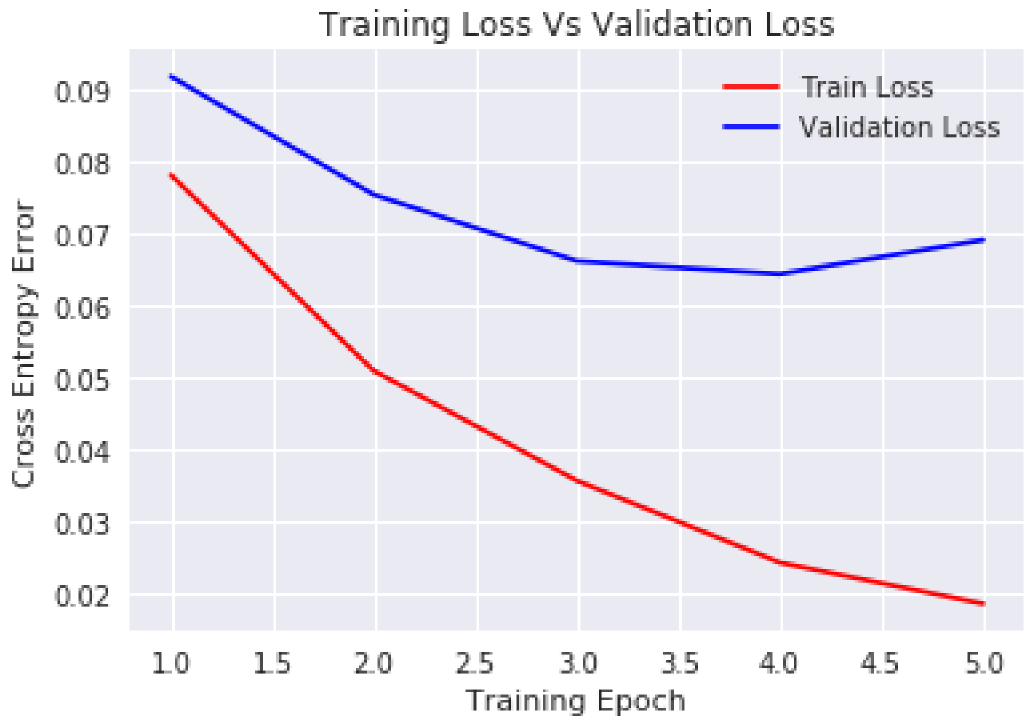
```
In [9]: def build_model_b(X):
            """
            This functions builds the architecture for the MLP.
            """

            # model architecture
            num_input_neurons = 784
            num_hidden_neurons_1 =  432
            num_hidden_neurons_2 = 234
            num_hidden_neurons_3 = 110
            num_output_neurons = 10

            # for relu activation function we need to use He normal initialization of weights as
            # If we sample weights from a normal distribution N(0,) we satisfy this condition wi
            # weights =>  =(2/(fan_in+1) => N(0,)

            # relu activation specific standard deviations
            l1_stddev = math.sqrt(2 / (num_input_neurons + 1))
            l2_stddev = math.sqrt(2 / (num_hidden_neurons_1 + 1))
            l3_stddev = math.sqrt(2 / (num_hidden_neurons_2 + 1))
            out_stddev = math.sqrt(2 / (num_hidden_neurons_3 + 1))


            # ====================================== hidden layer 1 ============================
            l1_weights = tf.Variable(tf.random_normal(shape=[num_input_neurons, num_hidden_neuro
                                                         mean=0.0, stddev=l1_stddev))
            l1_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_1], mean=0.0, st

            l1_net_input = tf.matmul(X, l1_weights) + l1_biases
            l1_output = tf.nn.relu(l1_net_input) # activation function
            #=====================================================================================

             # ====================================== hidden layer 2 ===========================
            l2_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_1, num_hidden_ne
                                                         mean=0.0, stddev=l2_stddev))
            l2_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_2], mean=0.0, st

            l2_net_input = tf.matmul(l1_output, l2_weights) + l2_biases

            # apply batch normalization
            # Calculate the mean and variance of x.
            batch_mean_l2, batch_var_l2 = tf.nn.moments(l2_net_input, [0])
```

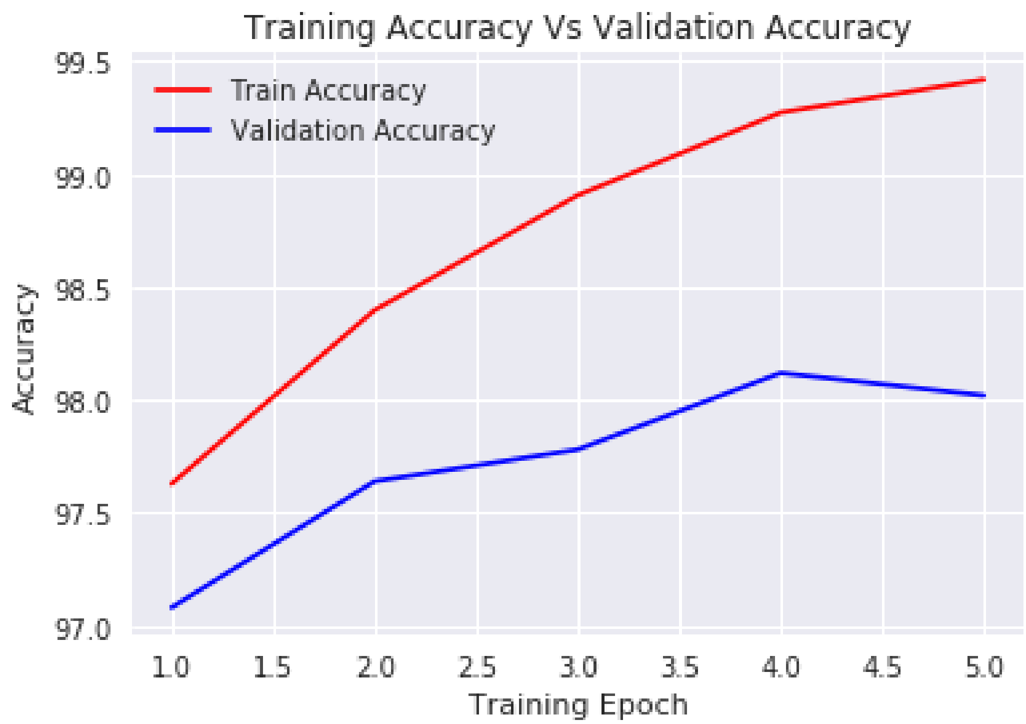
```
alpha_l2 = tf.Variable(tf.ones([num_hidden_neurons_2]))
beta_l2 = tf.Variable(tf.zeros([num_hidden_neurons_2]))

# do batch normalization on net input
epsilon = 1e-03
l2_net_input = tf.nn.batch_normalization(l2_net_input, batch_mean_l2, batch_var_l2,
                                          beta_l2, alpha_l2, epsilon)



l2_output = tf.nn.relu(l2_net_input) # activation function
l2_output = tf.nn.dropout(l2_output, keep_prob=keep_probability)
#==================================================================================

# ====================================== hidden layer 3 ===========================
l3_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_2, num_hidden_ne
                                         mean=0.0, stddev=l3_stddev))
l3_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_3], mean=0.0, st

l3_net_input = tf.matmul(l2_output, l3_weights) + l3_biases

# apply batch normalization
# Calculate the mean and variance of x.
batch_mean_l3, batch_var_l3 = tf.nn.moments(l3_net_input, [0])

alpha_l3 = tf.Variable(tf.ones([num_hidden_neurons_3]))
beta_l3 = tf.Variable(tf.zeros([num_hidden_neurons_3]))

# do batch normalization on net input
epsilon = 1e-03
l3_net_input = tf.nn.batch_normalization(l3_net_input, batch_mean_l3, batch_var_l3,
                                          beta_l3, alpha_l3, epsilon)



l3_output = tf.nn.relu(l3_net_input) # activation function
l3_output = tf.nn.dropout(l3_output, keep_prob=keep_probability)
#==================================================================================



# ================================  output layer ==================================
l4_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_3, num_output_ne
                                         mean=0.0, stddev=out_stddev))
l4_biases  = tf.Variable(tf.random_normal(shape=[num_output_neurons], mean=0.0, stdd

l4_net_input = tf.matmul(l3_output, l4_weights) + l4_biases
```

```
        # ==========================================================================

        # return output using the softmax layer
        output = tf.nn.softmax(l4_net_input)

        return output
```

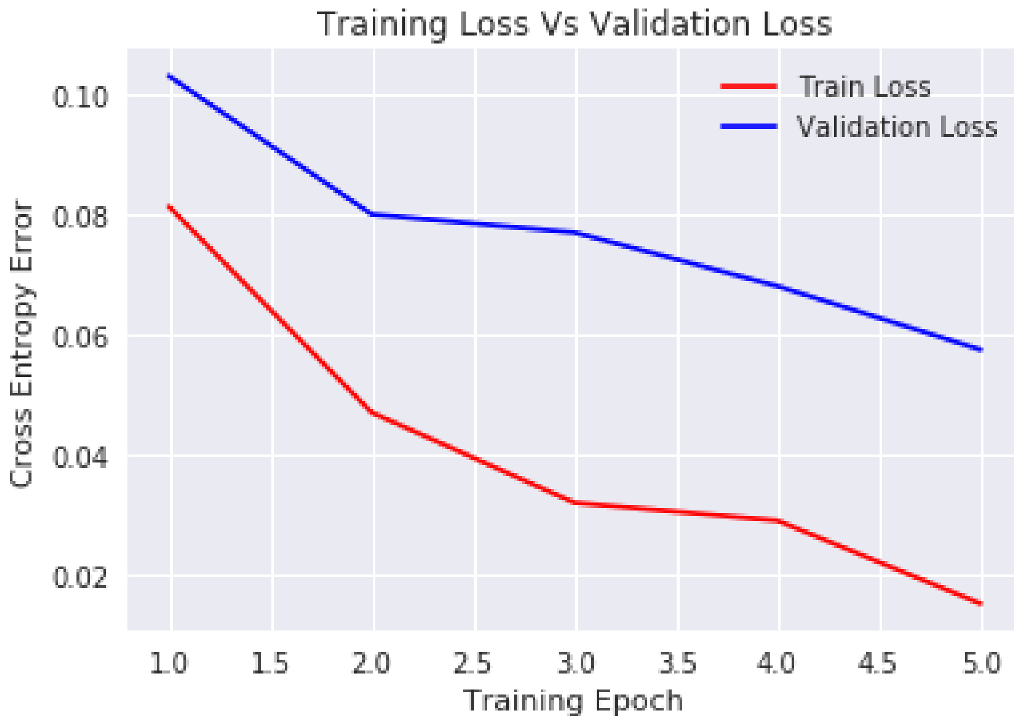
```
In [10]: # buid the model a
         mlp_b = build_model_b(X)

         #keep_prob_val = 0.92
         keep_prob_val_list_b = [0.80, 0.84, 0.88, 0.92]
         num_epochs = 5

         # decalre a list for all the dropout value metrics
         metric_list_b = list()

         # try with different dropout rate
         for keep_prob_val in keep_prob_val_list_b:

             print('='*100)

             print('With keep probability: %f'%keep_prob_val)

             # train and evaluate the model
             ts_loss_mlp_b, ts_acc_mlp_b, train_metric_list, val_metric_list = train_and_evaluat
                                                                                  keep_prob_val,
             # append to list
             metric_list_b.append(( ts_loss_mlp_b, ts_acc_mlp_b,))

             # plot the loss curve
             plot_loss_curve(train_metric_list, val_metric_list)
             # plot the accuracy curve
             plot_accuracy_curve(train_metric_list, val_metric_list)

             print('='*100)
```

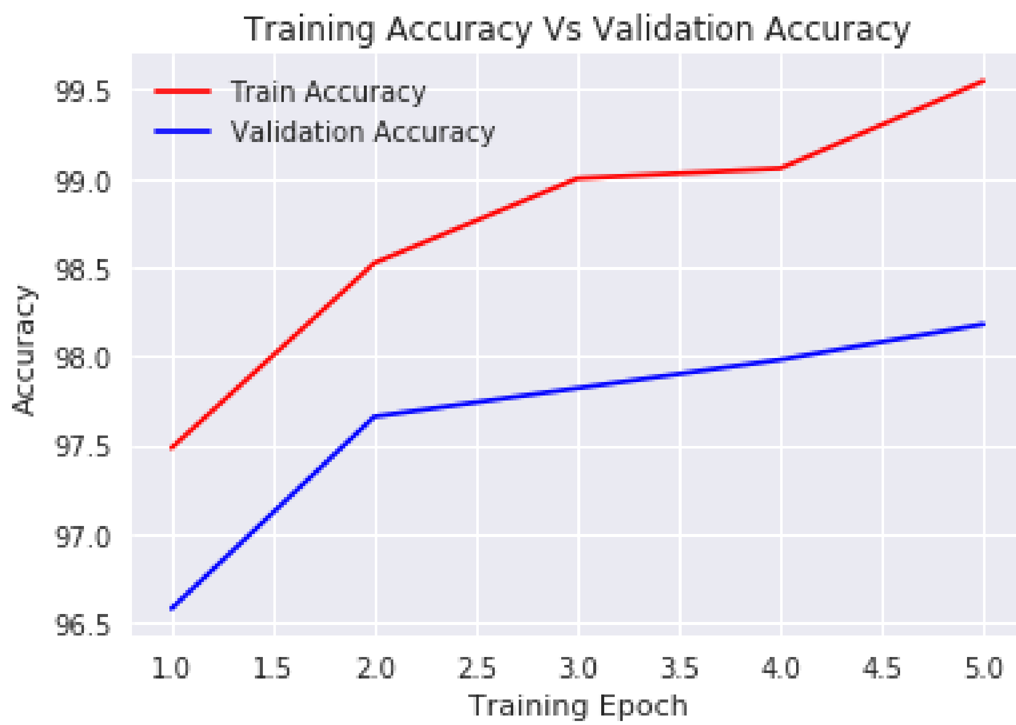
```
==========================================================================================
With keep probability: 0.800000
Test accuracy of model :98.009995, Test loss:0.069162
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch

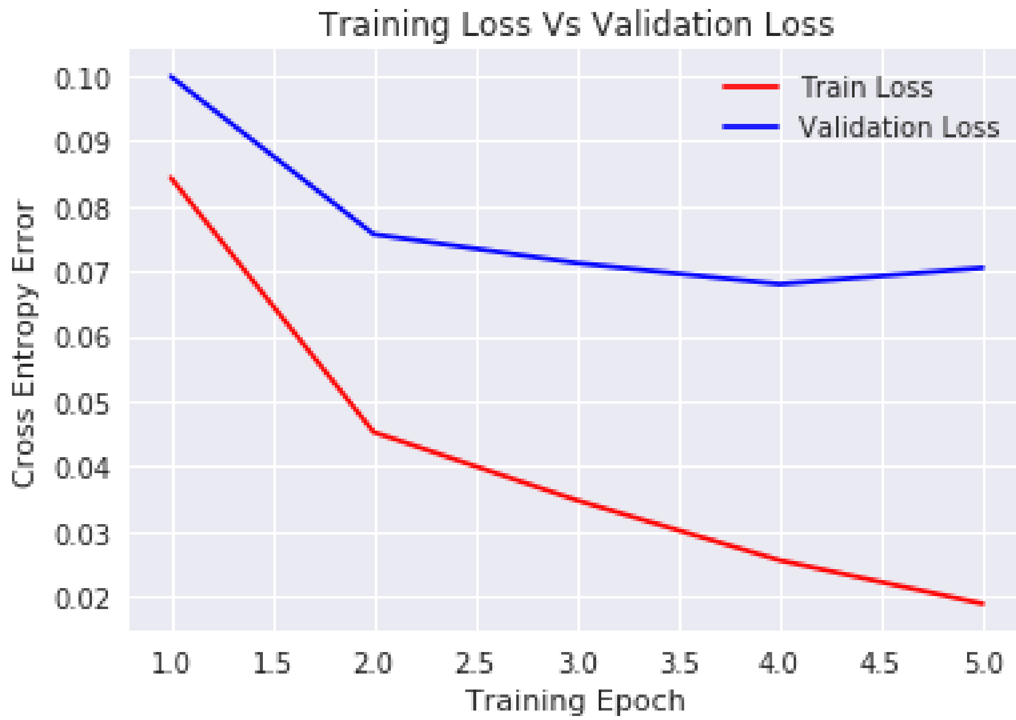

Training Accuracy Vs Validation Accuracy
Train Accuracy
Validation Accuracy
Accuracy
99.5
99.0
98.5
98.0
97.5
97.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch

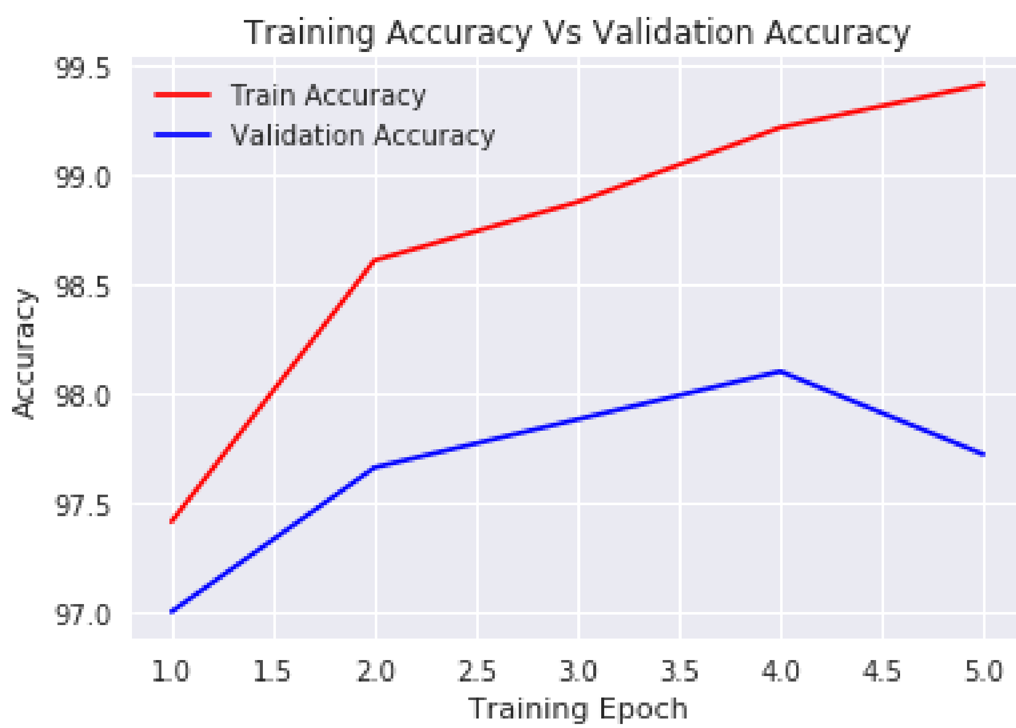
```
==============================================================================
==============================================================================
With keep probability: 0.840000
Test accuracy of model :98.199997, Test loss:0.061258
```



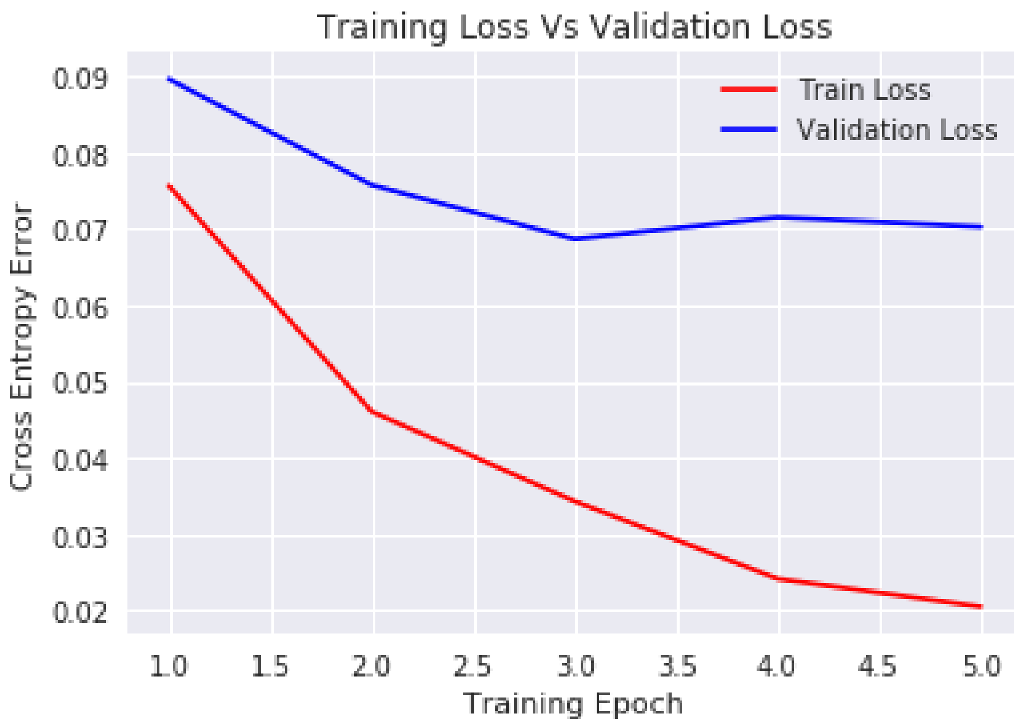


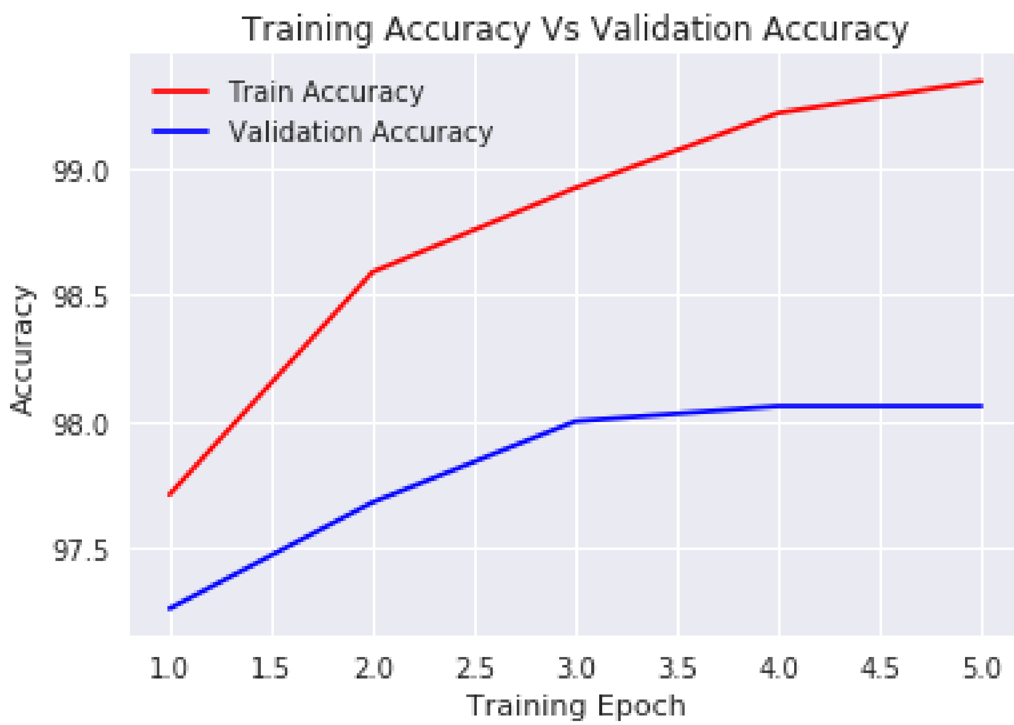

```
==================================================================================================
==================================================================================================
With keep probability: 0.880000
Test accuracy of model :97.939995, Test loss:0.067430
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch


Training Accuracy Vs Validation Accuracy
Train Accuracy
Validation Accuracy
Accuracy
99.5
99.0
98.5
98.0
97.5
97.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch

```
==================================================================================================
==================================================================================================
With keep probability: 0.920000
Test accuracy of model :97.899994, Test loss:0.067173
```





==

2.3 Observation

0.84 is the best keep_prob for which the model showed best performance

2.4 c) MLP with 5 Hidden layers, dropout, batch normalization

```
In [11]: def build_model_c(X):
             """
             This functions builds the architecture for the MLP.
             """

             # model architecture
             num_input_neurons = 784
             num_hidden_neurons_1 =  489
             num_hidden_neurons_2 = 265
             num_hidden_neurons_3 = 112
             num_hidden_neurons_4 = 40
             num_hidden_neurons_5 = 22
             num_output_neurons = 10

             # for relu activation function we need to use He normal initialization of weights a
```

```
# If we sample weights from a normal distribution N(0,) we satisfy this condition u
# weights =>  =(2/(fan_in+1) => N(0,)

# relu activation specific standard deviations
l1_stddev = math.sqrt(2 / (num_input_neurons + 1))
l2_stddev = math.sqrt(2 / (num_hidden_neurons_1 + 1))
l3_stddev = math.sqrt(2 / (num_hidden_neurons_2 + 1))
l4_stddev = math.sqrt(2 / (num_hidden_neurons_3 + 1))
l5_stddev = math.sqrt(2 / (num_hidden_neurons_4 + 1))
out_stddev = math.sqrt(2 / (num_hidden_neurons_5 + 1))


# ======================================= hidden layer 1 ===========================
l1_weights = tf.Variable(tf.random_normal(shape=[num_input_neurons, num_hidden_neur
                                          mean=0.0, stddev=l1_stddev))
l1_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_1], mean=0.0, s

l1_net_input = tf.matmul(X, l1_weights) + l1_biases
l1_output = tf.nn.relu(l1_net_input) # activation function
#=================================================================================

 # ======================================= hidden layer 2 ==========================
l2_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_1, num_hidden_n
                                          mean=0.0, stddev=l2_stddev))
l2_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_2], mean=0.0, s

l2_net_input = tf.matmul(l1_output, l2_weights) + l2_biases

# apply batch normalization
# Calculate the mean and variance of x.
batch_mean_l2, batch_var_l2 = tf.nn.moments(l2_net_input, [0])

alpha_l2 = tf.Variable(tf.ones([num_hidden_neurons_2]))
beta_l2 = tf.Variable(tf.zeros([num_hidden_neurons_2]))

# do batch normalization on net input
epsilon = 1e-03
l2_net_input = tf.nn.batch_normalization(l2_net_input, batch_mean_l2, batch_var_l2,
                                           beta_l2, alpha_l2, epsilon)



l2_output = tf.nn.relu(l2_net_input) # activation function
#=================================================================================

# ======================================= hidden layer 3 ===========================
l3_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_2, num_hidden_n
                                          mean=0.0, stddev=l3_stddev))
```

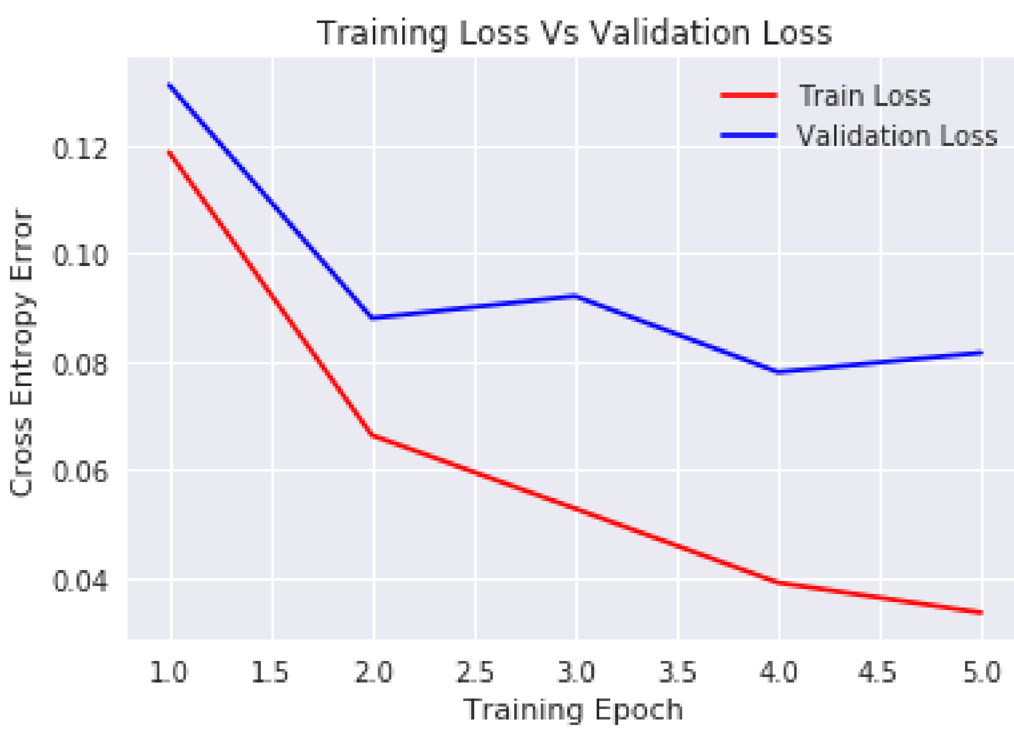
```
l3_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_3], mean=0.0, s

l3_net_input = tf.matmul(l2_output, l3_weights) + l3_biases

# apply batch normalization
# Calculate the mean and variance of x.
batch_mean_l3, batch_var_l3 = tf.nn.moments(l3_net_input, [0])

alpha_l3 = tf.Variable(tf.ones([num_hidden_neurons_3]))
beta_l3 = tf.Variable(tf.zeros([num_hidden_neurons_3]))

# do batch normalization on net input
epsilon = 1e-03
l3_net_input = tf.nn.batch_normalization(l3_net_input, batch_mean_l3, batch_var_l3,
                                          beta_l3, alpha_l3, epsilon)



l3_output = tf.nn.relu(l3_net_input) # activation function
l3_output = tf.nn.dropout(l3_output, keep_prob=keep_probability)
#==============================================================================

# ====================================== hidden layer 4 ========================
l4_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_3, num_hidden_n
                                         mean=0.0, stddev=l4_stddev))
l4_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_4], mean=0.0, s

l4_net_input = tf.matmul(l3_output, l4_weights) + l4_biases

# apply batch normalization
# Calculate the mean and variance of x.
batch_mean_l4, batch_var_l4 = tf.nn.moments(l4_net_input, [0])

alpha_l4 = tf.Variable(tf.ones([num_hidden_neurons_4]))
beta_l4 = tf.Variable(tf.zeros([num_hidden_neurons_4]))

# do batch normalization on net input
epsilon = 1e-03
l4_net_input = tf.nn.batch_normalization(l4_net_input, batch_mean_l4, batch_var_l4,
                                          beta_l4, alpha_l4, epsilon)

l4_output = tf.nn.relu(l4_net_input) # activation function
l4_output = tf.nn.dropout(l4_output, keep_prob=keep_probability)
#==============================================================================


# ====================================== hidden layer 5 ========================
l5_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_4, num_hidden_n
```

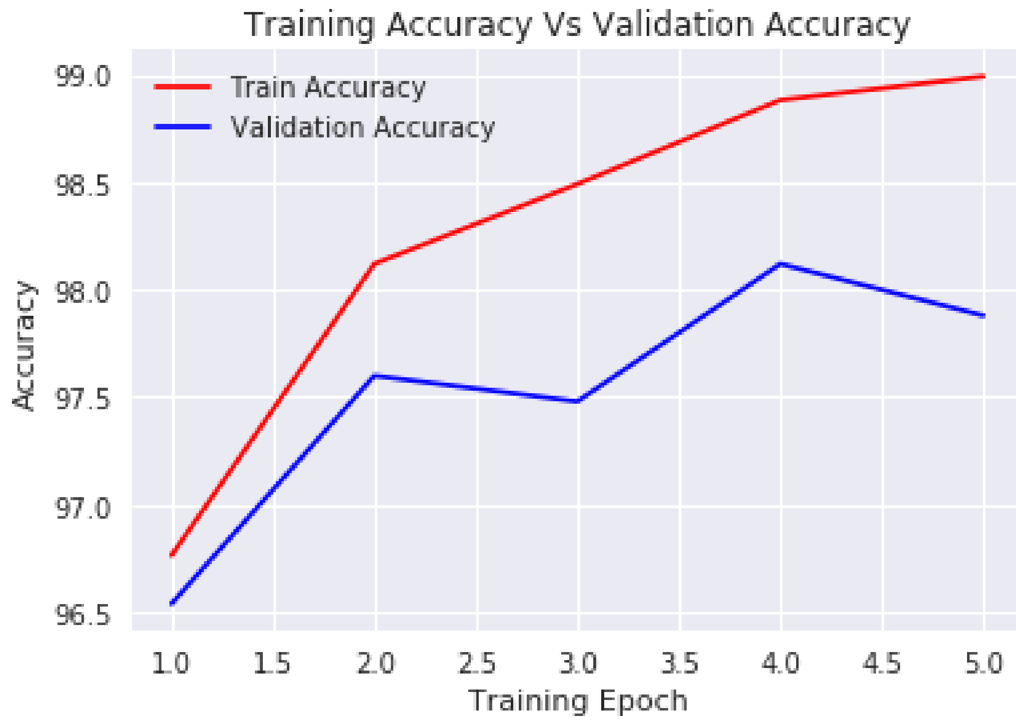
```
                                                  mean=0.0, stddev=l5_stddev))
    l5_biases  = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_5], mean=0.0, s

    l5_net_input = tf.matmul(l4_output, l5_weights) + l5_biases

    # apply batch normalization
    # Calculate the mean and variance of x.
    batch_mean_l5, batch_var_l5 = tf.nn.moments(l5_net_input, [0])

    alpha_l5 = tf.Variable(tf.ones([num_hidden_neurons_5]))
    beta_l5 = tf.Variable(tf.zeros([num_hidden_neurons_5]))

    # do batch normalization on net input
    epsilon = 1e-03
    l5_net_input = tf.nn.batch_normalization(l5_net_input, batch_mean_l5, batch_var_l5,
                                                   beta_l5, alpha_l5, epsilon)

    l5_output = tf.nn.relu(l5_net_input) # activation function
    l5_output = tf.nn.dropout(l5_output, keep_prob=keep_probability)
    #==========================================================================


    # ================================  output layer ==============================
    l6_weights = tf.Variable(tf.random_normal(shape=[num_hidden_neurons_5, num_output_n
                                                  mean=0.0, stddev=out_stddev))
    l6_biases  = tf.Variable(tf.random_normal(shape=[num_output_neurons], mean=0.0, std

    l6_net_input = tf.matmul(l5_output, l6_weights) + l6_biases

    # ==========================================================================

    # return output using the softmax layer
    output = tf.nn.softmax(l6_net_input)

    return output
```

In [12]:
```
# buid the model a
mlp_c = build_model_c(X)

# train and evaluate the model
#keep_prob_val = 0.92
keep_prob_val_list_c = [0.82, 0.86, 0.90, 0.94]
num_epochs = 5

# decalre a list for all the dropout value metrics
metric_list_c = list()

# try with different dropout rate
```

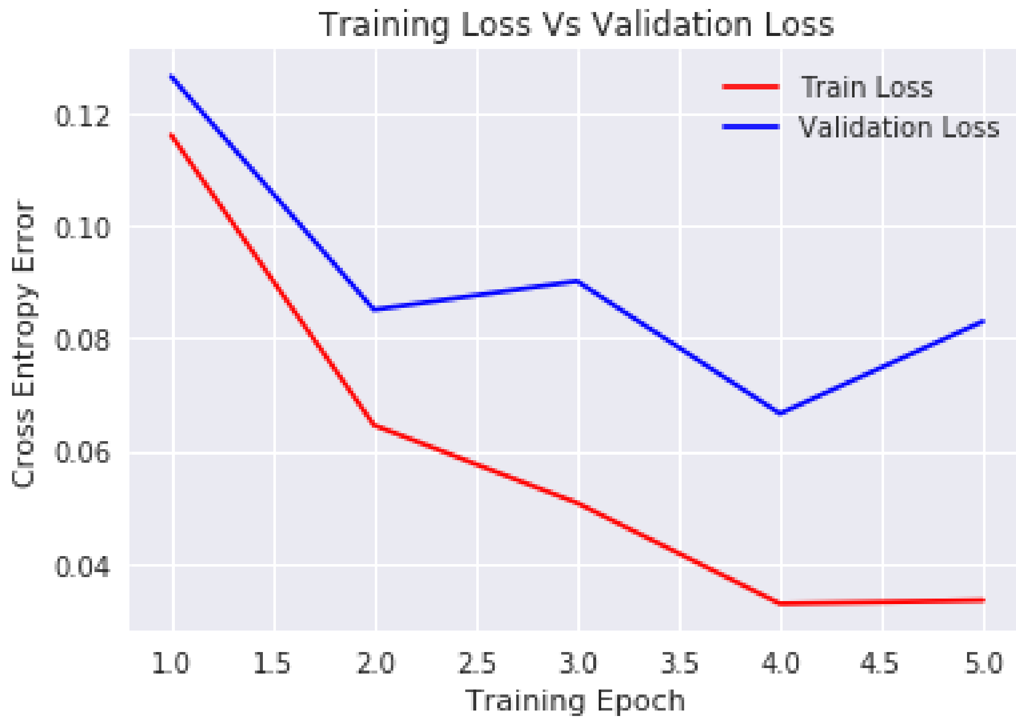
```
for keep_prob_val in keep_prob_val_list_c:

    print('='*100)

    print('With keep probability: %f'%keep_prob_val)

    ts_loss_mlp_c, ts_acc_mlp_c, train_metric_list, val_metric_list = train_and_evaluat
                                                                                  keep_pr
    # append results to list
    metric_list_c.append(( ts_loss_mlp_c, ts_acc_mlp_c,))

    # plot the loss curve
    plot_loss_curve(train_metric_list, val_metric_list)
    # plot the accuracy curve
    plot_accuracy_curve(train_metric_list, val_metric_list)

    print('='*100)
```

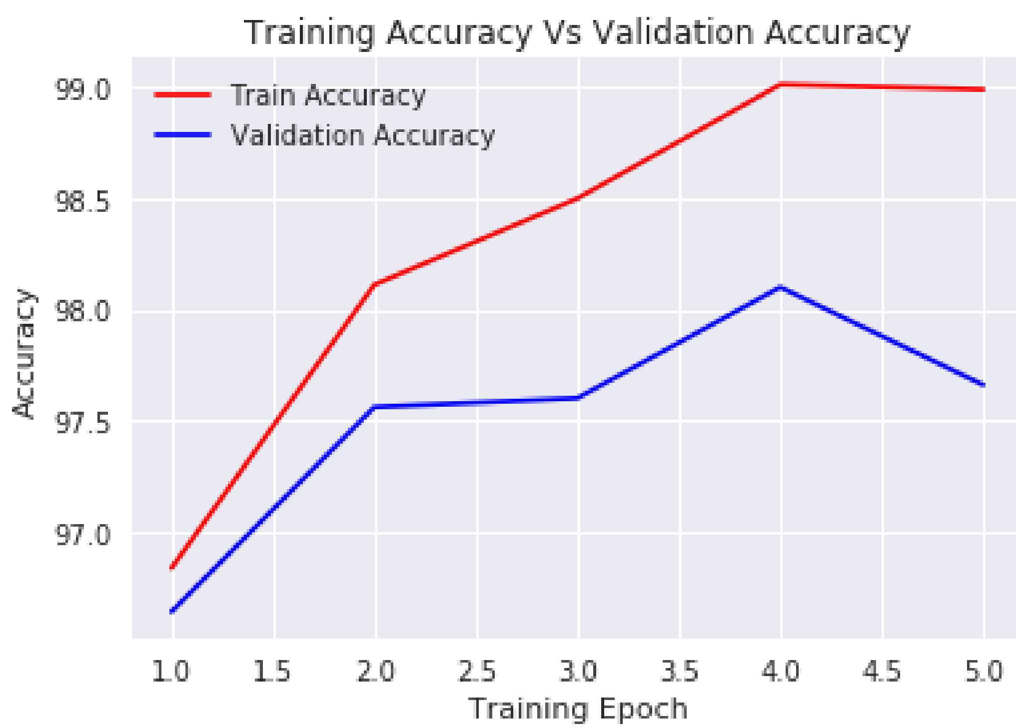
```
================================================================================================
With keep probability: 0.820000
Test accuracy of model :97.809998, Test loss:0.082611
```



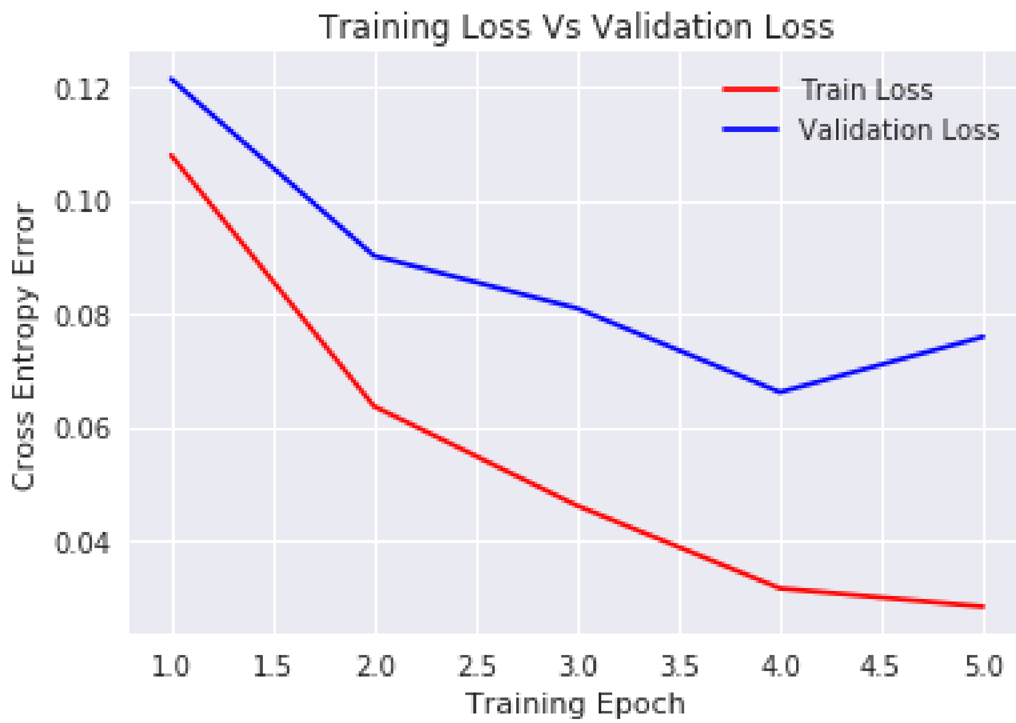


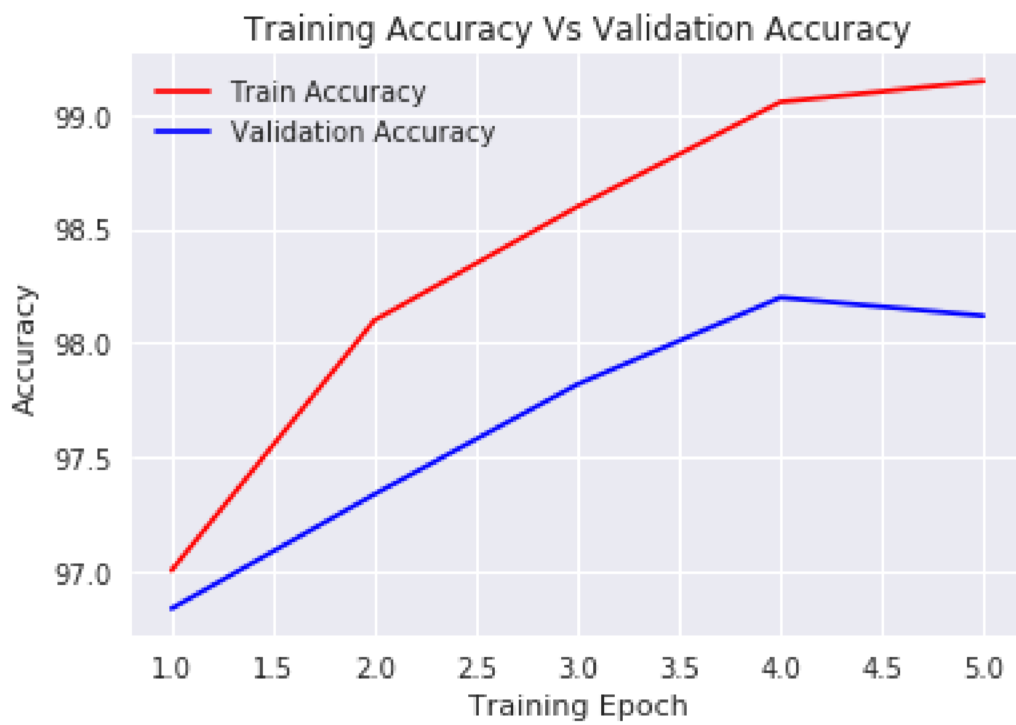

```
==============================================================================================
==============================================================================================
With keep probability: 0.860000
Test accuracy of model :98.029999, Test loss:0.076954
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.12
0.10
0.08
0.06
0.04
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch

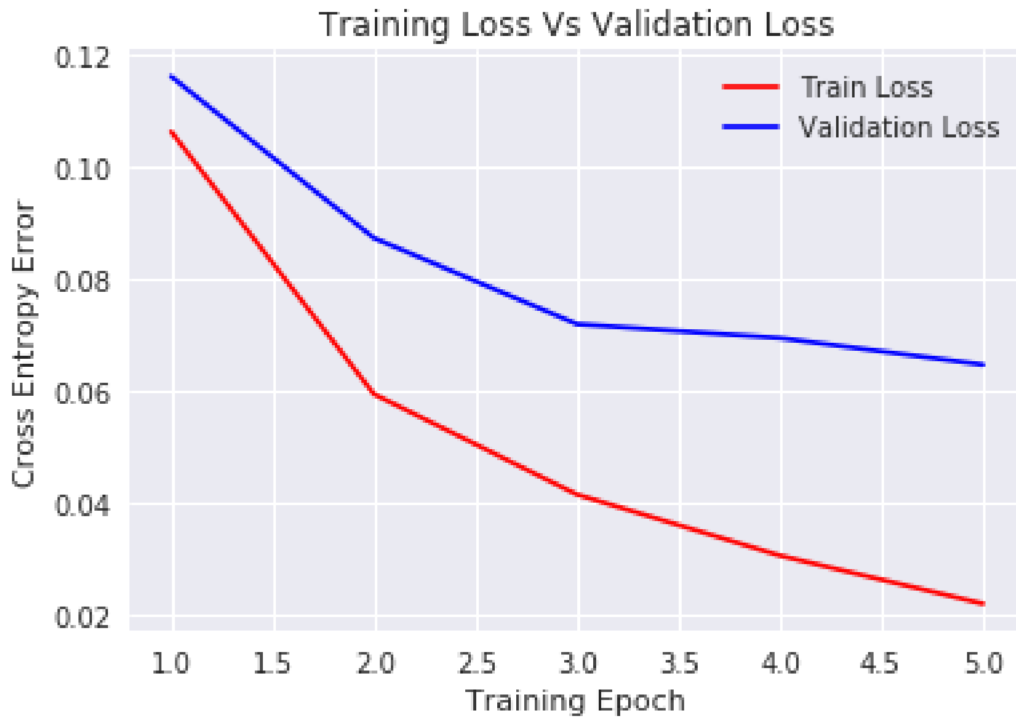

Training Accuracy Vs Validation Accuracy
Train Accuracy
Validation Accuracy
Accuracy
99.0
98.5
98.0
97.5
97.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch

```
==========================================================================================
==========================================================================================
With keep probability: 0.900000
Test accuracy of model :97.860001, Test loss:0.080251
```

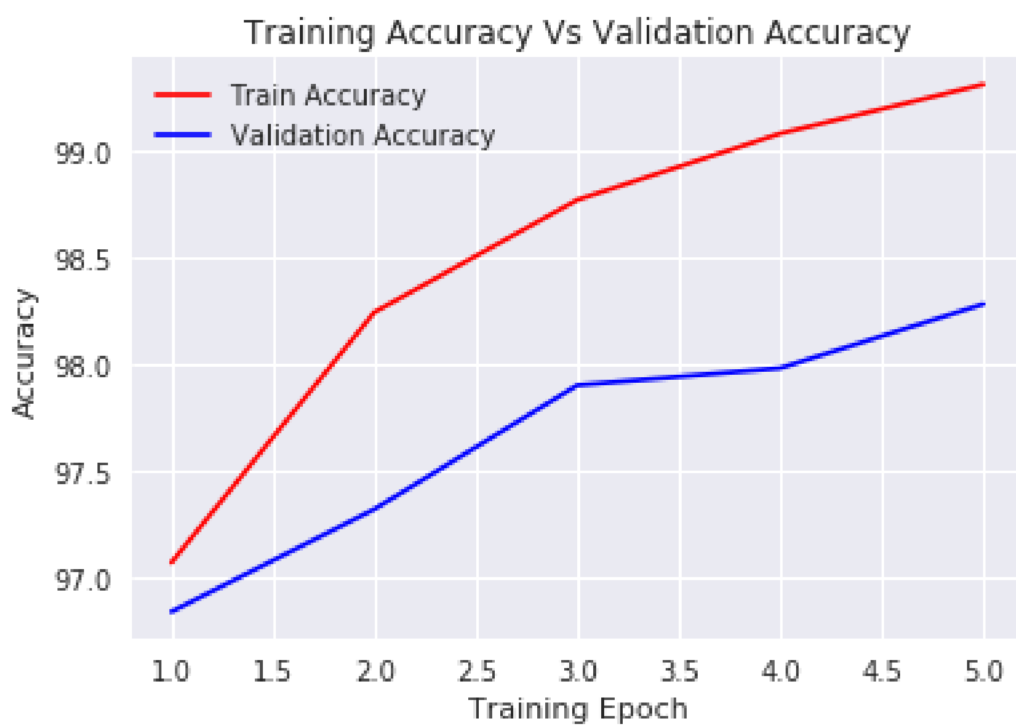





```
================================================================================================
================================================================================================
With keep probability: 0.940000
Test accuracy of model :98.009995, Test loss:0.070729
```



Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.12
0.10
0.08
0.06
0.04
0.02
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch



Training Accuracy Vs Validation Accuracy
Train Accuracy
Validation Accuracy
Accuracy
99.0
98.5
98.0
97.5
97.0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Training Epoch

==

2.5 Observation

Model showed best performace on test data set with 0.86 keep_prob value

3 Procedure Summary

Design various MLP networks with different number of layers, neuros , batch normalization, dropout rate

Train and evaluate all the models to see its performance

Select the best model based on the loss value as well as accuracy on unseen data

4 Results Summary

```
In [13]: from prettytable import PrettyTable
```

```
In [14]: ptable = PrettyTable()
         ptable.title = 'Comparison of MLP Models'
         ptable.field_names = ['Model', 'Architecure', 'Keep_Prob', 'Loss', 'Accuracy']
```

```
In [15]: # append result of model a with no dropout
         ptable.add_row(['MLP-a', '2-HL', 1.0, ts_loss_mlp_a, ts_acc_mlp_a, ])

         # append results of model b
         for index, keep_prob_val in enumerate(keep_prob_val_list_b):
             ts_loss_mlp_b = metric_list_c[index][0]
             ts_acc_mlp_b = metric_list_c[index][1]
             ptable.add_row(['MLP-b', '3-HL, 2-Dropout, 2-BN', keep_prob_val, ts_loss_mlp_b, ts_

         # append results of model c
         for index, keep_prob_val in enumerate(keep_prob_val_list_c):
             ts_loss_mlp_c = metric_list_c[index][0]
             ts_acc_mlp_c = metric_list_c[index][1]
             ptable.add_row(['MLP-c', '5-HL, 3-Dropout, 4-BN', keep_prob_val,ts_loss_mlp_c, ts_a
```

```
In [16]: print(ptable)
```

```
+-----------------------------------------------------------------------+
|                       Comparison of MLP Models                        |
+-------+-----------------------+-----------+-------------+-----------+
| Model |      Architecure      | Keep_Prob |     Loss    |  Accuracy |
+-------+-----------------------+-----------+-------------+-----------+
| MLP-a |          2-HL         |    1.0    | 0.074358895 |    98.0   |
| MLP-b | 3-HL, 2-Dropout, 2-BN |    0.8    |  0.08261111 |   97.81   |
| MLP-b | 3-HL, 2-Dropout, 2-BN |    0.84   |  0.07695403 |   98.03   |
| MLP-b | 3-HL, 2-Dropout, 2-BN |    0.88   |  0.08025092 |   97.86   |
```

MLP-b	3-HL, 2-Dropout, 2-BN	0.92	0.070729315	98.009995
MLP-c	5-HL, 3-Dropout, 4-BN	0.82	0.08261111	97.81
MLP-c	5-HL, 3-Dropout, 4-BN	0.86	0.07695403	98.03
MLP-c	5-HL, 3-Dropout, 4-BN	0.9	0.08025092	97.86
MLP-c	5-HL, 3-Dropout, 4-BN	0.94	0.070729315	98.009995

5 Conclusion

In this assignment, various architecture of MLPs have been tried and evaluated on MNIST data set

All models showed test accuracy above 97%

Batch Normalization version showed less deviation between train, validation loss

The network with more layeres and complicated architectures (model_b, moidel_c) showed a tendacy to overfit when compared with simple model_a

For MNIST dataset, simple model (model_a) can be used as it showed relatively small loss and good accuracy