13_CNN_on_MNIST_tensorflow_version

March 31, 2019

```
In [1]: # import CNN package
        import tensorflow as tf

        # import plot related functions
        import matplotlib.pyplot as plt
        import seaborn as sns
        sns.set()

        # 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):

            # 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):

            # 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 MODELS

```
In [5]: # declare placeholders for input and output
        X = tf.placeholder(tf.float32, [None, 28, 28, 1])
        y = tf.placeholder(tf.float32, [None, 10])
        keep_prob = tf.placeholder(tf.float32)
```

```
In [6]: X_test = mnist.test.images.reshape(mnist.test.images.shape[0], 28, 28, 1)
```

```
In [7]: def train_and_evaluate_model(custom_model, keep_prob_val, num_epochs = 2):

            """
            This function train and evaluate the CNN 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)
            X_train = X_train.reshape(X_train.shape[0], 28, 28, 1)

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


        # find predicted value, loss and accuracy for both train &test data sets
        X_train = mnist.train.images.reshape(mnist.train.images.shape[0], 28, 28, 1)
        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,))


        X_val = mnist.validation.images.reshape(mnist.validation.images.shape[0], 28
        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_prob : 1.
                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) CNN Model a - 3 Convs layers, 2 FC layers, Softmax

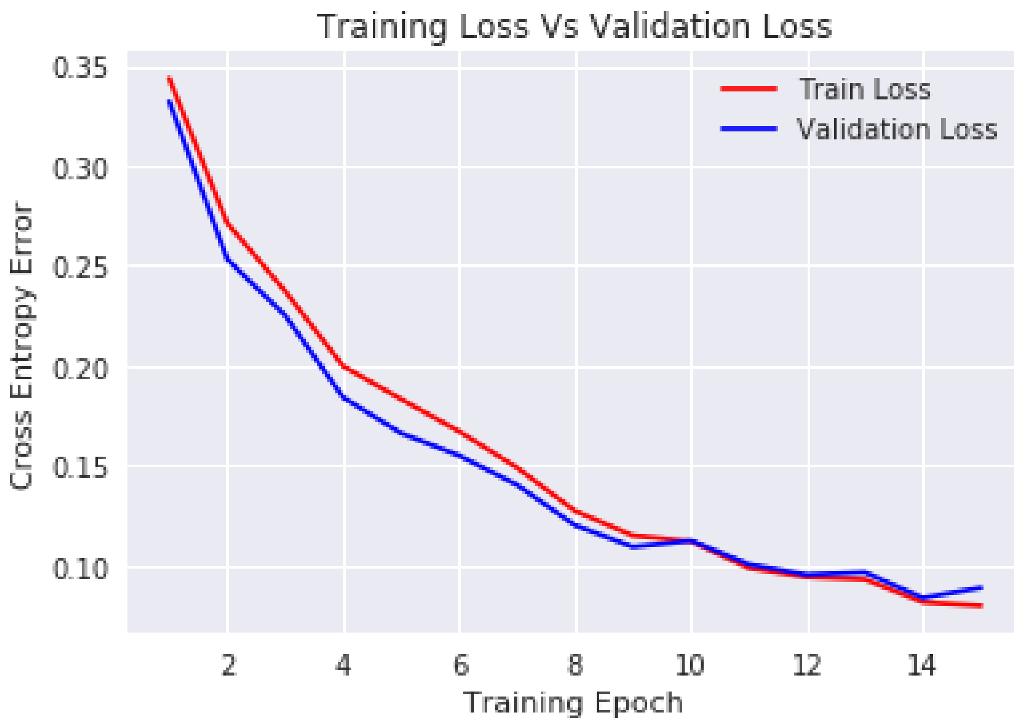
```
In [8]: def build_model_a(X):
            """
            This function defines an architecture for model
            """

            # =============================== Conv layer 1 ========================================

            # define filter and bias for each filter at layer 1
            filter_l1 = tf.Variable(tf.truncated_normal(shape=[5,5,1,12], stddev=0.1))
            bias_l1 = tf.Variable(tf.truncated_normal(shape=[12], stddev=0.1))

            # compute convolved output and actiation map for layer 1
            conv_out_1 = tf.nn.conv2d(X, filter_l1, strides=[1, 2, 2, 1], padding='SAME') + bias
            act_map_1 = tf.nn.relu(conv_out_1)

            print('Activation map 1', act_map_1)


            # ============================== Conv layer 2 ========================================
            # define filter and bias for each filter at layer 2
            filter_l2 = tf.Variable(tf.truncated_normal(shape=[3,3,12, 8], stddev=0.1))
            bias_l2 = tf.Variable(tf.truncated_normal(shape=[8], stddev=0.1))

            # compute convolved output and actiation map for layer 2
            conv_out_2 = tf.nn.conv2d(act_map_1, filter_l2, strides=[1, 2, 2, 1], padding='VALID
            act_map_2 = tf.nn.relu(conv_out_2)

            print('Activation map 2', act_map_2)

            # ============================== Conv layer 3 ========================================

            # define filter and bias for each filter at layer 2
            filter_l3 = tf.Variable(tf.truncated_normal(shape=[2,2,8, 6], stddev=0.1))
            bias_l3 = tf.Variable(tf.truncated_normal(shape=[6], stddev=0.1))
```

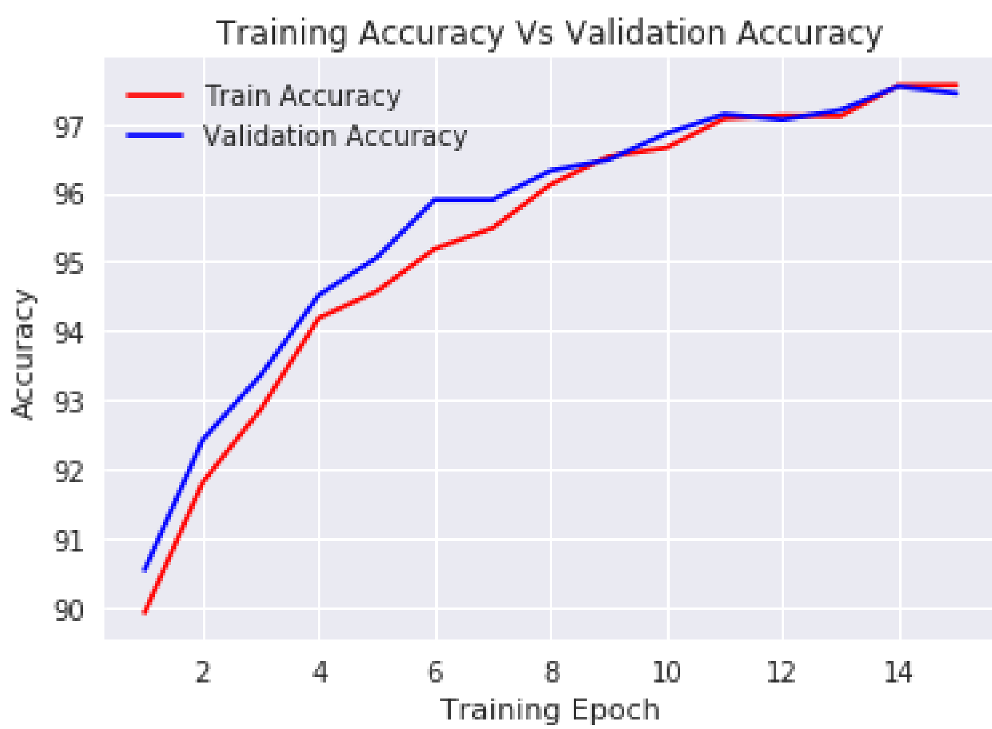
```
        # compute convolved output and actiation map for layer 2
        conv_out_3 = tf.nn.conv2d(act_map_2, filter_l3, strides=[1, 2, 2, 1], padding='VALID
        act_map_3 = tf.nn.relu(conv_out_3)

        print('Activation map 3', act_map_3)
        #==============================================================================


        # ================================ bottleneck layer ==================================
        bottle_neck_layer = tf.reshape(act_map_3, [-1, 54])


        # ============================== FC 1 ===============================================
        weight_fc_1 = tf.Variable(tf.truncated_normal(shape=[54, 28], stddev=0.1))
        bias_fc_1 = tf.Variable(tf.truncated_normal(shape=[28], stddev=0.1))
        # compute net ninput for FC1
        net_input_fc_1 = tf.matmul(bottle_neck_layer, weight_fc_1) +  bias_fc_1
        # compute activation
        output_fc_1 = tf.nn.relu(net_input_fc_1)

        # ============================= FC 2 ================================================
        weight_fc_2 = tf.Variable(tf.truncated_normal(shape=[28, 10], stddev=0.1))
        bias_fc_2 = tf.Variable(tf.truncated_normal(shape=[10], stddev=0.1))
        # compute net ninput for FC1
        net_input_fc_2 = tf.matmul(output_fc_1, weight_fc_2) +  bias_fc_2
        #==============================================================================

        # ================================== Softmax layer ==================================
        y_ = tf.nn.softmax(net_input_fc_2)

        return y_
```

In [9]:
```
# buid the model a
cnn_a = build_model_a(X)

# train and evaluate the model
keep_prob_val = 1.0 # for dropout rate
num_epochs = 15
ts_loss_cnn_a, ts_acc_cnn_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)
```

```
Activation map 1 Tensor("Relu:0", shape=(?, 14, 14, 12), dtype=float32)
Activation map 2 Tensor("Relu_1:0", shape=(?, 6, 6, 8), dtype=float32)
```

```
Activation map 3 Tensor("Relu_2:0", shape=(?, 3, 3, 6), dtype=float32)
Test accuracy of model :97.470001, Test loss:0.083423
```





2.2 b) 4-Convs Layers, Dropout layer, FC layers, Softmax

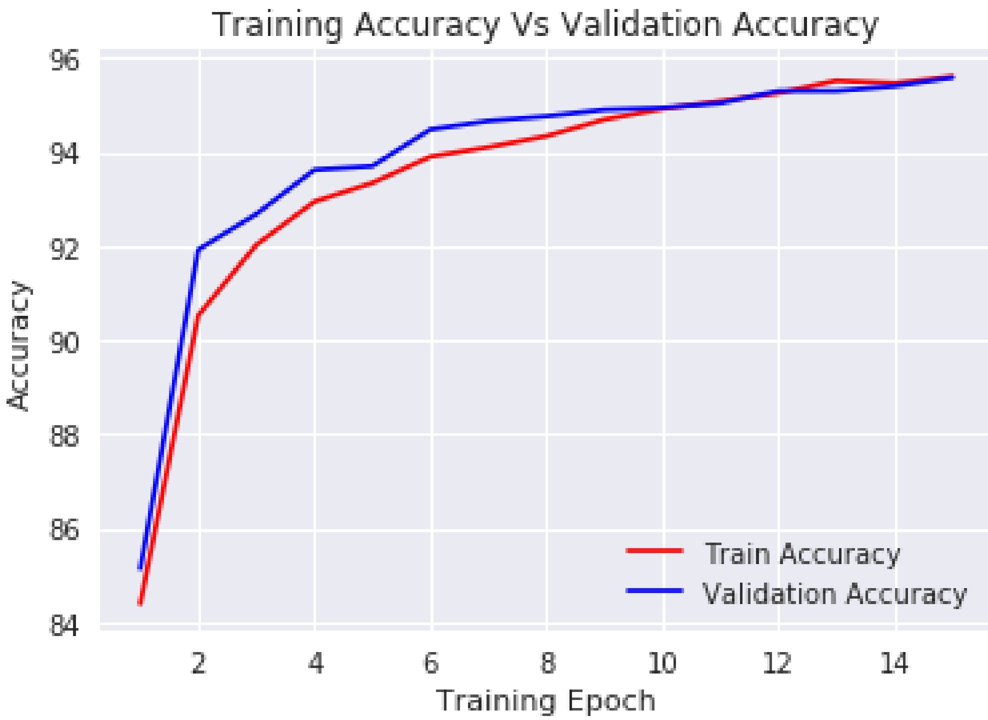
```
In [10]: def build_model_b(X):

             """
             This function defines an architecture for model
             """

             # Conv layer 1

             # define filter and bias for each filter at layer 1
             filter_l1 = tf.Variable(tf.truncated_normal(shape=[3,3,1,16], stddev=0.1))
             bias_l1 = tf.Variable(tf.truncated_normal(shape=[16], stddev=0.1))

             # compute convolved output and actiation map for layer 1
             conv_out_1 = tf.nn.conv2d(X, filter_l1, strides=[1, 2, 2, 1], padding='SAME') + bia
             act_map_1 = tf.nn.relu(conv_out_1)

             print('Activation map 1', act_map_1)


             # =============================== Conv layer 2 =====================================
             # define filter and bias for each filter at layer 2
             filter_l2 = tf.Variable(tf.truncated_normal(shape=[2,2,16, 10], stddev=0.1))
             bias_l2 = tf.Variable(tf.truncated_normal(shape=[10], stddev=0.1))

             # compute convolved output and actiation map for layer 2
             conv_out_2 = tf.nn.conv2d(act_map_1, filter_l2, strides=[1, 2, 2, 1], padding='SAME
             act_map_2 = tf.nn.relu(conv_out_2)

             print('Activation map 2', act_map_2)

             # =============================== Conv layer 3 =====================================

             # define filter and bias for each filter at layer 2
             filter_l3 = tf.Variable(tf.truncated_normal(shape=[2,2,10, 8], stddev=0.1))
             bias_l3 = tf.Variable(tf.truncated_normal(shape=[8], stddev=0.1))

             # compute convolved output and actiation map for layer 2
             conv_out_3 = tf.nn.conv2d(act_map_2, filter_l3, strides=[1, 2, 2, 1], padding='SAME
             act_map_3 = tf.nn.relu(conv_out_3)

             print('Activation map 3', act_map_3)
             # =============================== Conv layer 4 =====================================
```

```
    # define filter and bias for each filter at layer 2
    filter_l4 = tf.Variable(tf.truncated_normal(shape=[2,2,8, 6], stddev=0.1))
    bias_l4 = tf.Variable(tf.truncated_normal(shape=[6], stddev=0.1))

    # compute convolved output and actiation map for layer 2
    conv_out_4 = tf.nn.conv2d(act_map_3, filter_l4, strides=[1, 2, 2, 1], padding='SAME
    act_map_4 = tf.nn.relu(conv_out_4)

    print('Activation map 4', act_map_4)

    # flatten the output for creating bottleneck layer
    bottle_neck_layer = tf.reshape(act_map_4, [-1, 24])


    # ==================================== FC 1 ==========================================
    weight_fc_1 = tf.Variable(tf.truncated_normal(shape=[24, 18], stddev=0.1))
    bias_fc_1 = tf.Variable(tf.truncated_normal(shape=[18], stddev=0.1))
    # compute net ninput for FC1
    net_input_fc_1 = tf.matmul(bottle_neck_layer, weight_fc_1) +  bias_fc_1
    # compute activation
    output_fc_1 = tf.nn.relu(net_input_fc_1)
    # dropout layer
    output_fc_1 = tf.nn.dropout(output_fc_1, keep_prob)
    # =================================== FC 2 ===========================================
    weight_fc_2 = tf.Variable(tf.truncated_normal(shape=[18, 10], stddev=0.1))
    bias_fc_2 = tf.Variable(tf.truncated_normal(shape=[10], stddev=0.1))
    # compute net ninput for FC1
    net_input_fc_2 = tf.matmul(output_fc_1, weight_fc_2) +  bias_fc_2
    #==================================================================================


    # ================================= Softmax layer ===================================
    y_ = tf.nn.softmax(net_input_fc_2)

    return y_
```

In [11]:
```
# buid the model b
cnn_b = build_model_b(X)

# train and evaluate the model
keep_prob_val = 0.95 # for dropout rate
num_epochs = 15

ts_loss_cnn_b, ts_acc_cnn_b, train_metric_list, val_metric_list = train_and_evaluate_mo


# 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)
```

```
Activation map 1 Tensor("Relu_4:0", shape=(?, 14, 14, 16), dtype=float32)
Activation map 2 Tensor("Relu_5:0", shape=(?, 7, 7, 10), dtype=float32)
Activation map 3 Tensor("Relu_6:0", shape=(?, 4, 4, 8), dtype=float32)
Activation map 4 Tensor("Relu_7:0", shape=(?, 2, 2, 6), dtype=float32)
Test accuracy of model :95.820000, Test loss:0.138289
```



2.3 c) CNN Model 4 -Conv Layer, Dropout, Batch Norm, FC, Softmax

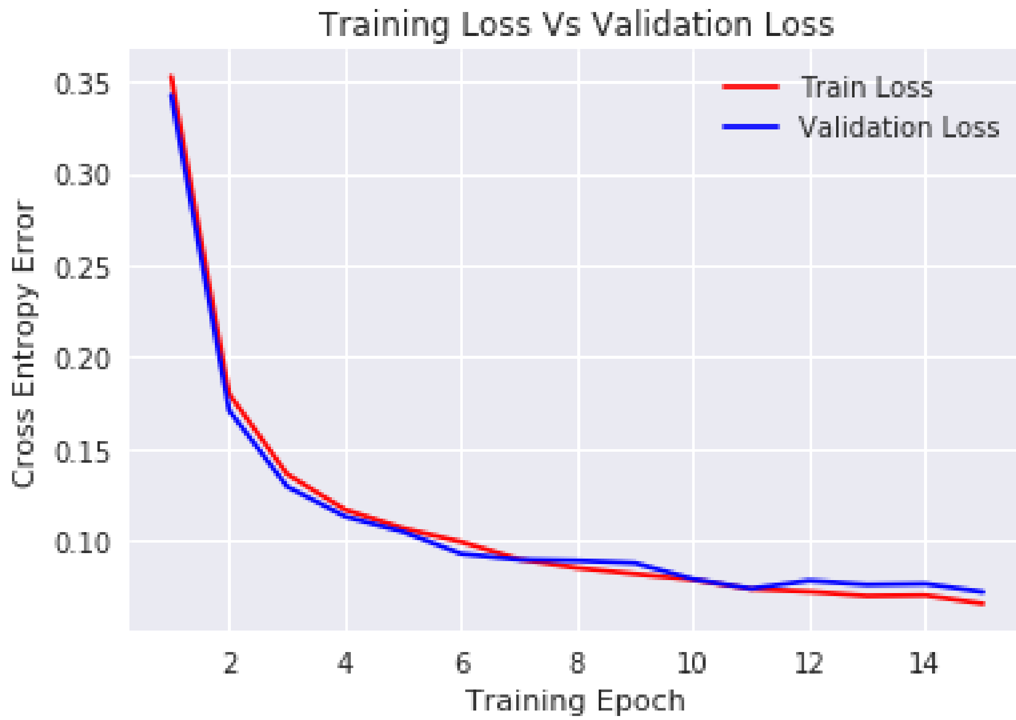
```
In [12]: def build_model_c(X):

             """
             This function defines an architecture for model
             """

             # Conv layer 1

             # define filter and bias for each filter at layer 1
             filter_l1 = tf.Variable(tf.truncated_normal(shape=[3,3,1,16], stddev=0.1))
             bias_l1 = tf.Variable(tf.truncated_normal(shape=[16], stddev=0.1))

             # compute convolved output and actiation map for layer 1
             conv_out_1 = tf.nn.conv2d(X, filter_l1, strides=[1, 2, 2, 1], padding='SAME') + bia
             act_map_1 = tf.nn.relu(conv_out_1)

             print('Activation map 1', act_map_1)

             # =============================== Conv layer 2 ====================================
             # define filter and bias for each filter at layer 2
             filter_l2 = tf.Variable(tf.truncated_normal(shape=[3,3,16, 10], stddev=0.1))
```

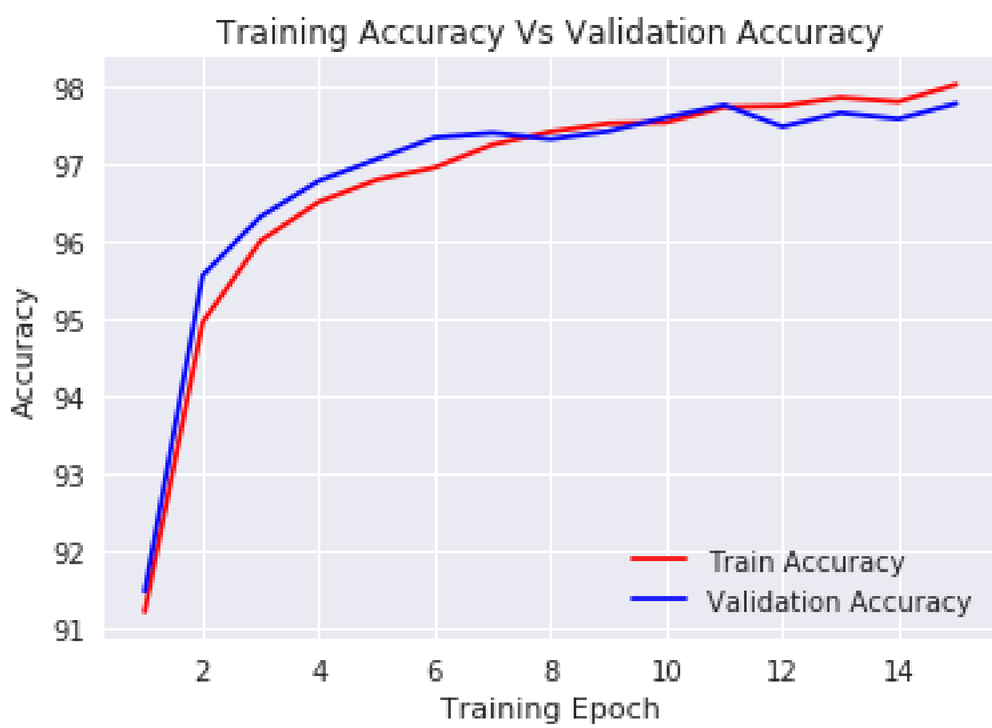
```
bias_l2 = tf.Variable(tf.truncated_normal(shape=[10], stddev=0.1))

# compute convolved output and actiation map for layer 2
conv_out_2 = tf.nn.conv2d(act_map_1, filter_l2, strides=[1, 2, 2, 1], padding='SAME
act_map_2 = tf.nn.relu(conv_out_2)

print('Activation map 2', act_map_2)

# ================================ Conv layer 3 =====================================

# define filter and bias for each filter at layer 2
filter_l3 = tf.Variable(tf.truncated_normal(shape=[2,2,10, 8], stddev=0.1))
bias_l3 = tf.Variable(tf.truncated_normal(shape=[8], stddev=0.1))

# compute convolved output and actiation map for layer 2
conv_out_3 = tf.nn.conv2d(act_map_2, filter_l3, strides=[1, 2, 2, 1], padding='SAME
act_map_3 = tf.nn.relu(conv_out_3)

print('Activation map 3', act_map_3)

# ================================ Conv layer 4 =====================================

# define filter and bias for each filter at layer 2
filter_l4 = tf.Variable(tf.truncated_normal(shape=[2,2,8, 6], stddev=0.1))
bias_l4 = tf.Variable(tf.truncated_normal(shape=[6], stddev=0.1))

# compute convolved output and actiation map for layer 2
conv_out_4 = tf.nn.conv2d(act_map_3, filter_l4, strides=[1, 2, 2, 1], padding='SAME
act_map_4 = tf.nn.relu(conv_out_4)

print('Activation map 4', act_map_4)

# flatten the output for creating bottleneck layer
bottle_neck_layer = tf.reshape(act_map_4, [-1, 24])


# ===================================== FC 1 ========================================
weight_fc_1 = tf.Variable(tf.truncated_normal(shape=[24, 16], stddev=0.1))
bias_fc_1 = tf.Variable(tf.truncated_normal(shape=[16], stddev=0.1))
# compute net ninput for FC1
net_input_fc_1 = tf.matmul(bottle_neck_layer, weight_fc_1) +  bias_fc_1

# apply batch normalization
# Calculate the mean and variance of x.
batch_mean_fc_1, batch_var_fc_1 = tf.nn.moments(net_input_fc_1, [0])

alpha_fc_1 = tf.Variable(tf.ones([16]))
beta_fc_1 = tf.Variable(tf.zeros([16]))
```

```
        # do batch normalization on net input
        epsilon = 1e-03
        net_input_fc_1 = tf.nn.batch_normalization(net_input_fc_1, batch_mean_fc_1, batch_v
                                                   beta_fc_1, alpha_fc_1, epsilon)

        # compute activation
        output_fc_1 = tf.nn.relu(net_input_fc_1)
        # dropout layer
        output_fc_1 =  tf.nn.dropout(output_fc_1, keep_prob)

        # =================================== FC 2 ==========================================
        weight_fc_2 = tf.Variable(tf.truncated_normal(shape=[16, 10], stddev=0.1))
        bias_fc_2 = tf.Variable(tf.truncated_normal(shape=[10], stddev=0.1))
        # compute net ninput for FC1
        net_input_fc_2 = tf.matmul(output_fc_1, weight_fc_2) +  bias_fc_2
        #=================================================================================


        # ================================= Softmax layer ==================================
        y_ = tf.nn.softmax(net_input_fc_2)

        return y_
```

```
In [13]: # buid the model c
         cnn_c = build_model_c(X)

         # train and evaluate the model
         keep_prob_val = 0.95 # for dropout rate
         num_epochs = 15
         ts_loss_cnn_c, ts_acc_cnn_c, train_metric_list, val_metric_list = train_and_evaluate_mo



         # 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)
```

```
Activation map 1 Tensor("Relu_9:0", shape=(?, 14, 14, 16), dtype=float32)
Activation map 2 Tensor("Relu_10:0", shape=(?, 7, 7, 10), dtype=float32)
Activation map 3 Tensor("Relu_11:0", shape=(?, 4, 4, 8), dtype=float32)
Activation map 4 Tensor("Relu_12:0", shape=(?, 2, 2, 6), dtype=float32)
Test accuracy of model :97.669998, Test loss:0.066673
```


Training Loss Vs Validation Loss
Train Loss
Validation Loss
Cross Entropy Error
0.35
0.30
0.25
0.20
0.15
0.10
2
4
6
8
10
12
14
Training Epoch


Training Accuracy Vs Validation Accuracy
Train Accuracy
Validation Accuracy
Accuracy
98
97
96
95
94
93
92
91
2
4
6
8
10
12
14
Training Epoch

3 Results Summary

```
In [14]: from prettytable import PrettyTable

In [15]: ptable = PrettyTable()
         ptable.title = 'Comparison of CNN Models'
         ptable.field_names = ['Model', 'Architecure', 'Loss', 'Accuracy']

In [16]: ptable.add_row(['CNN-a', '3-Convs, 2-FC', ts_loss_cnn_a, ts_acc_cnn_a, ])
         ptable.add_row(['CNN-b', '4-Convs, 1-Dropout, 2-FC', ts_loss_cnn_b, ts_acc_cnn_b, ])
         ptable.add_row(['CNN-c', '4-Convs, 1-BN, 1-Dropout, 2-FC', ts_loss_cnn_c, ts_acc_cnn_c,

In [17]: print(ptable)
```

```
+-----------------------------------------------------------------+
|                    Comparison of CNN Models                     |
+-------+--------------------------------+------------+----------+
| Model |          Architecure           |    Loss    | Accuracy |
+-------+--------------------------------+------------+----------+
| CNN-a |         3-Convs, 2-FC          | 0.08342285 |  97.47   |
| CNN-b |    4-Convs, 1-Dropout, 2-FC    | 0.13828881 |  95.82   |
| CNN-c | 4-Convs, 1-BN, 1-Dropout, 2-FC | 0.06667277 |  97.67   |
+-------+--------------------------------+------------+----------+
```

4 Conclusion

All CNN models gave accuracy above 95% on test dataset

The deviation of train, validation curve is very less for model c i.e the model with batch normalization method

As the number of layers increases the batch normalization model showed improved results (Model b & Model c both have 6 layers and the performance of c (with batch normalization) is better)