Self_Driving_Car

June 29, 2019

```
In [1]: # import general purpose models
        import pandas as pd
        import numpy as np
        import os
        import math
        from datetime import datetime

        # package for train and test split
        from sklearn.model_selection import train_test_split

        # model evaluation package
        from sklearn.metrics import mean_squared_error

        # import model related packages
        import tensorflow as tf
        from tensorflow.core.protobuf import saver_pb2
        import cv2

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

        # for preparing tables for Results
        from prettytable import PrettyTable
```

1 Configs

```
In [2]: base_dir = '/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSets/CS09_SELF_DRIVING_CAR/drivi
        # op to write logs to Tensorboard
        logs_dir = './model/logs'
        save_dir = './model/save'

        # set number of epochs & batch size
        num_epochs = 50
        batch_size = 128
```

```
# set the number of samples for train
data_set_size = -1 # -1 for entire dataset

mp4_output_name = './results/driving_video.mp4'
```

2 Load dataset

```
In [3]: def create_path_df(base_dir):

            # declare two lists for input path, label value
            xs = list()
            ys = list()

            #read data.txt
            with open(os.path.join(base_dir, 'data.txt')) as f:
                for line in f:
                    # get the image path
                    xs.append(os.path.join(base_dir, line.split()[0]))
                    # convert the angle to radian value
                    ys.append(float(line.split()[1]))

            # create a path df and order its column
            path_df = pd.DataFrame({'Path' : xs, 'Label' : ys}, index=range(len(ys)))
            path_df = path_df[['Path', 'Label']]


            print('Total images: ', path_df.shape[0])

            return path_df

In [4]: def load_batch(df, batch_index, batch_size):

            # declare a list for holding input images
            x_out = list()

            # slice the data frame to required images
            start_index = batch_index * batch_size
            end_index = start_index + batch_size

            #print('Start & End index', start_index, end_index)

            temp_df = df.iloc[start_index : end_index, :]

            # load the images corresponding to the path in the temp_df
            y_out = temp_df['Label'].tolist()
```

```
        # fetch images one by one
        for index, row in temp_df.iterrows():
            # read the image & crop it
            #img = scipy.misc.imread(row.Path)[-150:]
            img = cv2.imread(row.Path)[-150:]
            # resize image & normalize it
            #img = scipy.misc.imresize(img, [66, 200]) / 255.0
            img = cv2.resize(img, (200, 66,)) / 255.0
            # append to list
            x_out.append(img)

        return x_out, y_out
```

In [5]:
```
path_df = create_path_df(base_dir)
path_df.head()
```

```
Total images:  45406
```

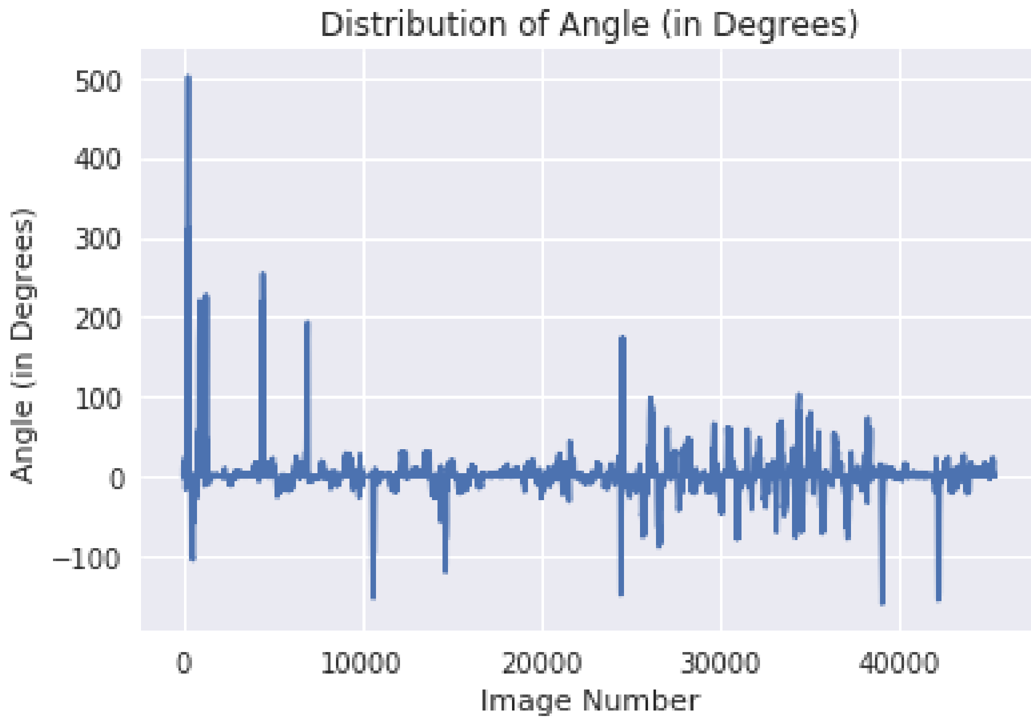
Out[5]:

	Path	Label
0	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
1	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
2	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
3	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
4	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0

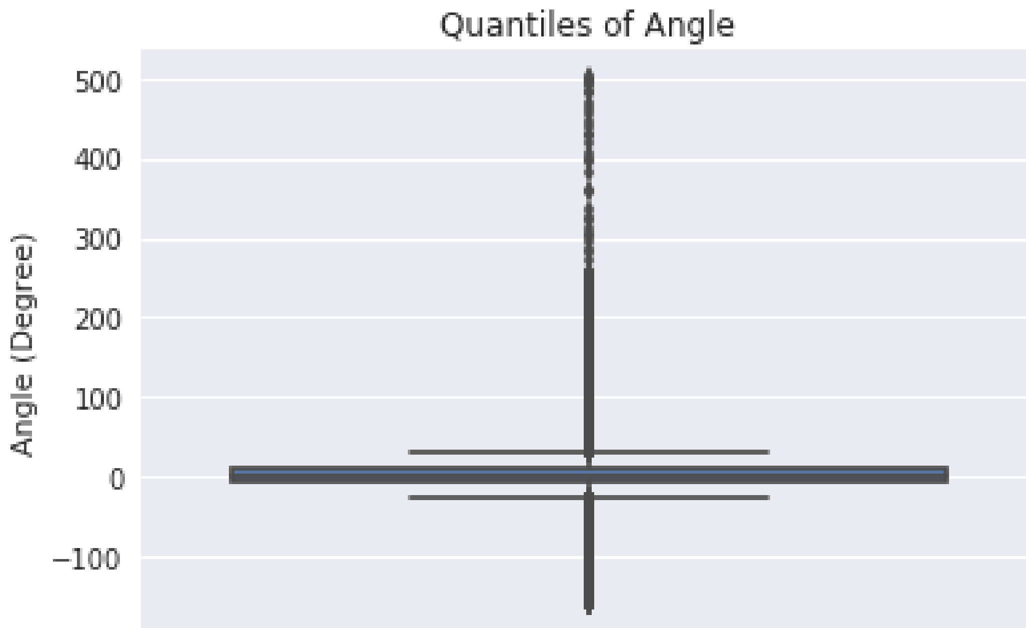
In [6]:
```
print('Angles in (Degree) Minimum : %f, Maximum : %f'%(path_df['Label'].min(),
                                                      path_df['Label'].max()))
```

```
Angles in (Degree) Minimum : -159.930000, Maximum : 501.780000
```

In [7]:
```
plt.plot(path_df['Label'])
plt.xlabel('Image Number')
plt.ylabel('Angle (in Degrees)')
plt.title('Distribution of Angle (in Degrees)')
plt.show()
```



In [8]:
```
# pick only those angles which is less than 720 degrees (2 rounds of rotation)
path_df = path_df[abs(path_df['Label']) <= 720]
sns.boxplot(data = path_df, y='Label')
plt.ylabel('Angle (Degree)')
plt.title('Quantiles of Angle')
plt.show()
```




```
In [9]: angle_series = path_df['Label']
        for percentile in np.arange(0, 1, 0.1):
            per_value = angle_series.quantile(q=percentile)
            print(' %f Percentile = %f'%(percentile * 100.0, per_value,))
```

```
0.000000 Percentile = -159.930000
10.000000 Percentile = -18.660000
20.000000 Percentile = -9.380000
30.000000 Percentile = -2.320000
40.000000 Percentile = 0.000000
50.000000 Percentile = 1.010000
60.000000 Percentile = 2.420000
70.000000 Percentile = 6.350000
80.000000 Percentile = 11.500000
90.000000 Percentile = 21.980000
```

```
In [10]: angle_series = path_df['Label']
         for percentile in np.arange(0.9, 1.0, 0.01):
             per_value = angle_series.quantile(q=percentile)
             print(' %f Percentile = %f'%(percentile * 100.0, per_value,))
```

```
90.000000 Percentile = 21.980000
91.000000 Percentile = 23.700000
92.000000 Percentile = 25.920000
93.000000 Percentile = 27.930000
```

```
 94.000000 Percentile = 30.026000
 95.000000 Percentile = 34.590000
 96.000000 Percentile = 42.760000
 97.000000 Percentile = 51.030000
 98.000000 Percentile = 65.850000
 99.000000 Percentile = 99.605000
```

```
In [11]: angle_series = path_df['Label']
         for percentile in np.arange(0.99, 1.0, 0.001):
             per_value = angle_series.quantile(q=percentile)
             print(' %f Percentile = %f'%(percentile * 100.0, per_value,))
```

```
 99.000000 Percentile = 99.605000
 99.100000 Percentile = 113.414550
 99.200000 Percentile = 136.121600
 99.300000 Percentile = 149.750000
 99.400000 Percentile = 166.690000
 99.500000 Percentile = 177.768250
 99.600000 Percentile = 190.690000
 99.700000 Percentile = 200.648500
 99.800000 Percentile = 217.820000
 99.900000 Percentile = 245.760900
 100.000000 Percentile = 501.780000
```

Observations

The steering angles at the begining is very large compared to the other . This is expected as the vehicle just stated to move

3 Convert Angle from Degree to Radian

```
In [12]: # convert the data to radian
         scaling_factor = np.pi / 180
         path_df['Label'] = path_df['Label'] * scaling_factor
```

4 Train , Validation, Test split of the Data

```
In [13]: if data_set_size > 0:
             path_df = path_df.iloc[0:data_set_size]

         train_df, test_df = train_test_split(path_df, test_size=0.30, shuffle=False)
         train_df, val_df = train_test_split(train_df, test_size=0.20, shuffle=False)
```

```
In [14]: print('Number of samples in train data: ', train_df.shape[0])
         print('Number of samples in  validation data: ', val_df.shape[0])
         print('Number of samples in  test data: ', test_df.shape[0])
```

```
Number of samples in train data:  25427
Number of samples in  validation data:  6357
Number of samples in  test data:  13622
```

In [15]:
```python
train_df.head()
```

Out[15]:

	Path	Label
0	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
1	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
2	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
3	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0
4	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	0.0

In [16]:
```python
val_df.head()
```

Out[16]:

	Path	Label
25427	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.144339
25428	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.140848
25429	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.140848
25430	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.139103
25431	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.139103

In [17]:
```python
test_df.head()
```

Out[17]:

	Path	Label
31784	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.478744
31785	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.494626
31786	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.503353
31787	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.519235
31788	/media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe...	-0.542099

5 Baseline Time Series Models

5.1 UTILS Functions

5.2 A1) Mean Model

In [18]:
```python
# get the mean angle from train data
mean_angle_train = train_df['Label'].mean()
```

5.3 A2) Simple Moving Average Model

In [19]:
```python
def Simple_MA_Prediction(value_array, window_size):

    # if size less than 2 return as it is
    if len(value_array) < 2:
        return value_array
```

```
        # initialize predicted value list as empty
        predicted_values = list()

        # # process each element in the value list
        for index, value in enumerate(value_array):

           # case 1: We have already made atleast window_size predictions
            if index >=  window_size:
                predicted_value = np.mean(value_array[index - window_size : index])

            # case 2: We have just started prediction
            else:
                if index == 0:
                    predicted_value = value
                else:
                    predicted_value = np.mean(value_array[0 : index])

            # update the list
            predicted_values.append(predicted_value)

        # round the values to integers
        predicted_values = np.array([int(round(item)) for item in predicted_values])


        return np.array(predicted_values)
```

5.4 A3) Weighted Moving Average

```
In [20]: def WMA_Predictions(value_array, window_size):

        # if size less than 2 return as it is
        if len(value_array) < 2:
            return value_array

        # set the denominator
        denominator = (( window_size) * ( window_size + 1)) / 2

        # weights array
        window_weight_array = np.array(range(1, window_size + 1)) / denominator

        # initialize the predicted value with first element of value list
        predicted_values = list()

        # process each element in the value list
        for index, val in enumerate(value_array):

            # case 1: we have already made atleast window_size predictions
            if index >=  window_size:
```

```
            predicted_value = np.mean(window_weight_array * value_array[index - window_

        # case 2: we have just started prediction
        else:

            if index == 0:
                predicted_value = val
            else:
                # set the denominator
                denominator = (index * (index + 1)) / 2
                # weights array
                temp_weight_array = np.array(range(1, index + 1)) / denominator

                predicted_value = np.mean(temp_weight_array * value_array[0 : index])

        # update the list
        predicted_values.append(predicted_value)

    # round the values to integers
    predicted_values = np.array([int(round(item)) for item in predicted_values])

    return predicted_values
```

5.5 A4) Exponentially Weighted Moving Average

```
In [21]: def exp_weighted_MA_Predictions(value_array, alpha):

             # if size less than 2 return as it is
             if len(value_array) < 2:
                 return value_array

             # initialize as empty
             predicted_values = list()

             # predict for every time step
             for index, value in enumerate(value_array):

                 if index > 0:
                     predicted = alpha * value_array[index-1] + (1-alpha) * predicted_values[-1]
                 else:
                     predicted = value_array[0]

                 # update list
                 predicted_values.append(predicted)

             # round the values to integers
             predicted_values = np.array([int(round(item)) for item in predicted_values])
```

```
            return predicted_values
```

5.5.1 Hyperparam Tuning Util Functions

```
In [22]: def timeseries_model_prediction(df, window_size_sim, window_size_weight, alpha):

             # get the angles as a numpy array
             inp_array = df['Label'].values

             # get average predictions from all three methods

             # get simple moving average prediction
             simp_avg_pred = Simple_MA_Prediction(inp_array, window_size_sim)

             # get weighted moving average prediction
             weighted_avg_pred = WMA_Predictions(inp_array, window_size_weight)

             # get exponentially weighted moving average prediction
             exp_weighted_avg_pred = exp_weighted_MA_Predictions(inp_array, alpha)

             # form a return tuple
             ret_tuple = (simp_avg_pred, weighted_avg_pred, exp_weighted_avg_pred,)

             return ret_tuple
```

```
In [23]: def find_best_hyperparam(df):

             # try 10 different window sizes from 1 to 10
             window_size_list = list(range(1, 11))

             # try differnt alpah values from 0.3 to 0.99
             alpha_val_list = [0.20, 0.30, 0.40, 0.50, 0.65,
                               0.75, 0.82, 0.90, 0.95, 0.99]

             hyp_info_list = list()

             # evaluate each hyp value
             for window_size, alpha in zip(window_size_list, alpha_val_list):

                 # predict using this hyperparam
                 pred_info_tup = timeseries_model_prediction(df, window_size, window_size, alpha

                 # get actual values list
                 actual_values_list = df['Label'].values

                 # get predicted values list
                 predicted_values_list_sma = pred_info_tup[0]
                 predicted_values_list_wma = pred_info_tup[1]
```

```
            predicted_values_list_exp = pred_info_tup[2]

            # evaluate three models on this hyperparam
            sim_mse = mean_squared_error(actual_values_list, predicted_values_list_sma)
            wm_mse = mean_squared_error(actual_values_list, predicted_values_list_wma)
            exp_mse = mean_squared_error(actual_values_list, predicted_values_list_exp)

            # update hyp info list
            hyp_info_list.append((window_size, alpha, sim_mse, wm_mse, exp_mse,))

        # create the evaluation df
        eval_df = pd.DataFrame(hyp_info_list, columns=['Window', 'Alpha',
                                                       'SIM_MSE', 'WM_MSE','EXP_MSE'])

        # best index
        sim_model_best_index = eval_df['SIM_MSE'].idxmin()
        weight_model_best_index = eval_df['WM_MSE'].idxmin()
        exp_model_best_index = eval_df['EXP_MSE'].idxmin()

        print("""Hyper params (Window  for simple, weighted MA,
                 Alpha for Exponentailly weighted model) scores df: \n\n\n""", eval_df)

        # get the best hyperparam based on the MAPE lowest value
        sim_best_window = eval_df.loc[sim_model_best_index, 'Window']
        weight_best_window = eval_df.loc[weight_model_best_index, 'Window']
        exp_best_alpha = eval_df.loc[exp_model_best_index, 'Alpha']

        print('\n'*2)

        print('Best Window Size (Hyperparam) for Simple Moiving Average: ', sim_best_window
        print('Best Window Size (Hyperparam) for Weighted Moiving Average: ', weight_best_w
        print('Best Alpha (Hyperparam) for Exp. Weighted Moiving Average: ', exp_best_alpha



        return (sim_best_window, weight_best_window, exp_best_alpha,)
```

5.6 Run each Base Model

5.6.1 Run A1

In [24]:
```
# compute validation & test loss
predicted_train = [mean_angle_train] * train_df.shape[0]
predicted_vals = [mean_angle_train] * val_df.shape[0]
predicted_test = [mean_angle_train] * test_df.shape[0]

# compute MSE from the mean model
mean_model_train_loss = round(mean_squared_error(train_df['Label'], predicted_train), 8
```

```
mean_model_val_loss = round(mean_squared_error(val_df['Label'], predicted_vals), 8)
mean_model_test_loss = round(mean_squared_error(test_df['Label'], predicted_test), 8)

print('Train loss: %f, Validation Loss : %f, Test Loss : %f'%(mean_model_train_loss,
                                                              mean_model_val_loss,
                                                              mean_model_test_loss))
```

```
Train loss: 0.310709, Validation Loss : 0.320283, Test Loss : 0.242241
```

5.6.2 Run A2, A3, A4

5.6.3 Step 1 : Find best window size

In [25]:
```
sim_best_window, weight_best_window, exp_best_alpha = find_best_hyperparam(train_df)
```

```
Hyper params (Window  for simple, weighted MA,
             Alpha for Exponentailly weighted model) scores df:
```

	Window	Alpha	SIM_MSE	WM_MSE	EXP_MSE
0	1	0.20	0.052800	0.052800	0.052793
1	2	0.30	0.049725	0.113120	0.049386
2	3	0.40	0.048355	0.166240	0.049105
3	4	0.50	0.048976	0.199472	0.048947
4	5	0.65	0.050010	0.220973	0.049268
5	6	0.75	0.050239	0.248035	0.050020
6	7	0.82	0.051470	0.272031	0.050854
7	8	0.90	0.052359	0.290254	0.052300
8	9	0.95	0.053458	0.297474	0.052915
9	10	0.99	0.054986	0.298939	0.052816

```
Best Window Size (Hyperparam) for Simple Moiving Average:  3
Best Window Size (Hyperparam) for Weighted Moiving Average:  1
Best Alpha (Hyperparam) for Exp. Weighted Moiving Average:  0.5
```

5.6.4 Step 2 : Predict using best window size

In [26]:
```
# Predict on Valiation Data
train_actual = train_df['Label'].values
train_predicted_sma = Simple_MA_Prediction(train_actual, sim_best_window)
train_predicted_wma = WMA_Predictions(train_actual, weight_best_window)
train_predicted_ewma = exp_weighted_MA_Predictions(train_actual, exp_best_alpha)


# Predict on Valiation Data
```

```
val_actual = val_df['Label'].values
val_predicted_sma = Simple_MA_Prediction(val_actual, sim_best_window)
val_predicted_wma = WMA_Predictions(val_actual, weight_best_window)
val_predicted_ewma = exp_weighted_MA_Predictions(val_actual, exp_best_alpha)

# Predict on Test Data
test_actual = test_df['Label'].values
test_predicted_sma = Simple_MA_Prediction(test_actual, sim_best_window)
test_predicted_wma = WMA_Predictions(test_actual, weight_best_window)
test_predicted_ewma = exp_weighted_MA_Predictions(test_actual, exp_best_alpha)
```

5.6.5 Step 3 : Evaluate the performace

```
In [27]: # Compute the MSE on train data
         train_mse_sma = round(mean_squared_error(train_actual, train_predicted_sma), 8)
         train_mse_wma = round(mean_squared_error(train_actual, train_predicted_wma), 8)
         train_mse_ewma = round(mean_squared_error(train_actual, train_predicted_ewma), 8)
         print('MSE of train data from Models SMA : %f, WMA : %f, EWMA : %f'%(train_mse_sma,
                                                    train_mse_wma, train_mse_ewma,))

         # Compute the MSE on validation data
         val_mse_sma = round(mean_squared_error(val_actual, val_predicted_sma), 8)
         val_mse_wma = round(mean_squared_error(val_actual, val_predicted_wma), 8)
         val_mse_ewma = round(mean_squared_error(val_actual, val_predicted_ewma), 8)
         print('MSE of validation data from Models SMA : %f, WMA : %f, EWMA : %f'%(val_mse_sma,
                                                    val_mse_wma, val_mse_ewma,))

         # Compute the MSE on test data
         test_mse_sma = round(mean_squared_error(test_actual, test_predicted_sma), 8)
         test_mse_wma = round(mean_squared_error(test_actual, test_predicted_wma), 8)
         test_mse_ewma = round(mean_squared_error(test_actual, test_predicted_ewma), 8)
         print('MSE of test data from Models SMA : %f, WMA : %f, EWMA : %f'%(test_mse_sma,
                                                    test_mse_wma, test_mse_ewma,))
```

```
MSE of train data from Models SMA : 0.048355, WMA : 0.052800, EWMA : 0.048947
MSE of validation data from Models SMA : 0.071728, WMA : 0.075981, EWMA : 0.071352
MSE of test data from Models SMA : 0.052458, WMA : 0.055134, EWMA : 0.053156
```

```
In [28]: row_sma_model = ('Simple-MA', 'Window=%d'%(sim_best_window,), train_mse_sma,
                          val_mse_sma, test_mse_sma,)
         row_wma_model = ('Weighted-MA', 'Window=%d'%(weight_best_window,), train_mse_wma,
                          val_mse_wma, test_mse_wma,)
         row_ewma_model = ('Exp-WMA', 'Alpha=%f'%(exp_best_alpha,) ,train_mse_ewma,
                           val_mse_ewma, test_mse_ewma,)
```

6 B) CNN Model

6.1 Model Architecture

```
In [29]: def build_model(X, keep_prob):

             # First convolutional layer
             W_conv1 = tf.Variable(tf.truncated_normal([5, 5, 3, 24], stddev=0.1))
             b_conv1 = tf.Variable(tf.truncated_normal([24], stddev=0.1))
             net_conv1 = tf.nn.conv2d(X, W_conv1, strides=[1, 2, 2, 1], padding='VALID') + b_con
             h_conv1 = tf.nn.relu(net_conv1)


             # Second convolutional layer
             W_conv2 = tf.Variable(tf.truncated_normal([5, 5, 24, 36], stddev=0.1))
             b_conv2 = tf.Variable(tf.truncated_normal([36], stddev=0.1))
             net_conv2 = tf.nn.conv2d(h_conv1, W_conv2, strides=[1, 2, 2, 1], padding='VALID') +
             h_conv2 = tf.nn.relu(net_conv2)


             # Third convolutional layer
             W_conv3 = tf.Variable(tf.truncated_normal([5, 5, 36, 48], stddev=0.1))
             b_conv3 = tf.Variable(tf.truncated_normal([48], stddev=0.1))
             net_conv3 = tf.nn.conv2d(h_conv2, W_conv3, strides=[1, 2, 2, 1], padding='VALID') +
             h_conv3 = tf.nn.relu(net_conv3)

             # Fourth convolutional layer
             W_conv4 = tf.Variable(tf.truncated_normal([3, 3, 48, 64], stddev=0.1))
             b_conv4 = tf.Variable(tf.truncated_normal([64], stddev=0.1))
             net_conv4 = tf.nn.conv2d(h_conv3, W_conv4, strides=[1, 1, 1, 1], padding='VALID') +
             h_conv4 = tf.nn.relu(net_conv4)

             # Fifth convolutional layer
             W_conv5 = tf.Variable(tf.truncated_normal([3, 3, 64, 64], stddev=0.1))
             b_conv5 = tf.Variable(tf.truncated_normal([64], stddev=0.1))
             net_conv5 = tf.nn.conv2d(h_conv4, W_conv5, strides=[1, 1, 1, 1], padding='VALID') +
             h_conv5 = tf.nn.relu(net_conv5)

             # flatten the output layer
             h_conv5_flat = tf.reshape(h_conv5, [-1, 1152])


             #FCL 1
             W_fc1 = tf.Variable(tf.truncated_normal([1152, 1164], stddev=0.1))
             b_fc1 = tf.Variable(tf.truncated_normal([1164], stddev=0.1))
             net_fc1 = tf.matmul(h_conv5_flat, W_fc1) + b_fc1
             h_fc1 = tf.nn.relu(net_fc1)
             h_fc1_drop = tf.nn.dropout(h_fc1, keep_prob)
```

```
    #FCL 2
    W_fc2 = tf.Variable(tf.truncated_normal([1164, 100], stddev=0.1))
    b_fc2 = tf.Variable(tf.truncated_normal([100], stddev=0.1))
    net_fc2 = tf.matmul(h_fc1_drop, W_fc2) + b_fc2
    h_fc2 = tf.nn.relu(net_fc2)
    h_fc2_drop = tf.nn.dropout(h_fc2, keep_prob)

    #FCL 3
    W_fc3 = tf.Variable(tf.truncated_normal([100, 50], stddev=0.1))
    b_fc3 = tf.Variable(tf.truncated_normal([50], stddev=0.1))
    net_fc3 = tf.matmul(h_fc2_drop, W_fc3) + b_fc3
    h_fc3 = tf.nn.relu(net_fc3)
    h_fc3_drop = tf.nn.dropout(h_fc3, keep_prob)


    #FCL 4
    W_fc4 = tf.Variable(tf.truncated_normal([50, 10], stddev=0.1))
    b_fc4 = tf.Variable(tf.truncated_normal([10], stddev=0.1))
    net_fc4 = tf.matmul(h_fc3_drop, W_fc4) + b_fc4
    h_fc4 = tf.nn.relu(net_fc4)
    h_fc4_drop = tf.nn.dropout(h_fc4, keep_prob)


    #Output
    W_fc5 = tf.Variable(tf.truncated_normal([10, 1], stddev=0.1))
    b_fc5 = tf.Variable(tf.truncated_normal([1], stddev=0.1))
    net_fc5 = tf.matmul(h_fc4_drop, W_fc5) + b_fc5


    # declare final output layer
    #y_ = tf.atan(net_fc5) * 2 #scale the atan output
    y_ = net_fc5

    return y_
```

```
In [30]: def train_model(train_df, val_df):

    # Declare input, output layers size
    X = tf.placeholder(tf.float32, shape=[None, 66, 200, 3])
    y = tf.placeholder(tf.float32, shape=[None, 1]) # since it is a regression problem

    # declare dropout var
    keep_prob = tf.placeholder(tf.float32)

    # load the model architecture
    y_ = build_model(X, keep_prob)
```

```python
# define loss
loss = tf.reduce_mean(tf.square(tf.subtract(y, y_)))

print('X', X)
print('y', y)
print('keep_prob', keep_prob)
print('y_', y_)
print('loss', loss)


# declare a train step
train_step = tf.train.AdamOptimizer(1e-3).minimize(loss)

# declare a saver for saving the checkpoints (save only the best model)
saver =  tf.train.Saver(write_version = saver_pb2.SaverDef.V1)

# compute the number of batches
num_train_batches = math.ceil(train_df.shape[0] / batch_size)
num_val_batches = math.ceil(val_df.shape[0] / batch_size)


print('Number of train batches: %d, validation batches : %d\n\n'%(num_train_batches
                                                              num_val_batches,))


print('=' * 40 ,datetime.now(),  ' Training Started ', '='*40, '\n\n')

# initialize mean validation loss
prev_mean_val_loss = np.inf

global_step = 0

# open a session and run the graph
with tf.Session() as sess:

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

    # declare two lists for saving losess train & validation (epoch-wise)
    epoch_train_loss_list = list()
    epoch_val_loss_list = list()

    # run each training epoch
    for epoch in range(num_epochs):

        print(datetime.now(), ' Training epoch: {}'.format(epoch + 1))
```

```python
# declare two lists for saving losess train & validation (batch-wise)
batch_train_loss_list = list()
batch_val_loss_list = list()

# set validation id as zero
val_batch_id = 0

# run for every batch in this epoch
for tr_batch_id in range(num_train_batches):

    # load train batch data & train it
    xs, ys = load_batch(train_df, tr_batch_id, batch_size)
    ys = list(np.array(ys).reshape(-1,1))

    # trian on this batch
    _ , tr_loss = sess.run([train_step, loss],
                feed_dict={X: xs, y: ys, keep_prob: 0.8})

    # increment global step count
    global_step = global_step + 1

    # insert the loss to train loss list
    batch_train_loss_list.append(tr_loss)

# compute the mean train loss
mean_train_loss = np.mean(batch_train_loss_list)

# Evaluate validation loss batch-wise
for val_batch_id in range(num_val_batches):

    # load train batch data & train it
    xs, ys = load_batch(val_df, val_batch_id, batch_size)
    ys = list(np.array(ys).reshape(-1,1))

    # trian on this batch
    val_loss = sess.run([loss], feed_dict={X: xs, y: ys, keep_prob: 1.0})

    # insert the loss to train loss list
    batch_val_loss_list.append(val_loss)

# compute the mean train loss
mean_val_loss = np.mean(batch_val_loss_list)


# update the loss list declared for epochs
epoch_train_loss_list.append(mean_train_loss)
epoch_val_loss_list.append(mean_val_loss)
```

```
                # check if validation score improved or not, if yes save the model
                if mean_val_loss < prev_mean_val_loss:
                    # update previous mean val loss
                    prev_mean_val_loss = mean_val_loss

                    # write the checkpoint files to disk
                    checkpoint_path = os.path.join(save_dir, 'model.ckpt')
                    filename = saver.save(sess, checkpoint_path)
                    print(datetime.now(),' Validation loss improved, Model saved in file: %


        return (epoch_train_loss_list, epoch_val_loss_list,)
```

```
In [31]: def test_model(test_df):

        # set the number of batches
        num_test_batches = math.ceil(test_df.shape[0] / batch_size)

        # Evaluate the model on Test dataset
        batch_test_loss_list = list()
        predicted_list = list()

        # open a session
        with tf.Session() as sess:

            #First let's load meta graph and restore weights
            saver = tf.train.import_meta_graph(os.path.join(save_dir, 'model.ckpt.meta'))
            saver.restore(sess, tf.train.latest_checkpoint(save_dir))

            print('Model restored successfully ...')

            # get input & output
            graph = tf.get_default_graph()
            X = graph.get_tensor_by_name('Placeholder:0')
            y = graph.get_tensor_by_name('Placeholder_1:0')
            keep_prob = graph.get_tensor_by_name('Placeholder_2:0')
            y_ = graph.get_tensor_by_name('add_9:0')
            loss = graph.get_tensor_by_name('Mean:0')

            print('Fetching All tensors Completed ...')

            # run test batch by batch
            for test_batch_id in range(num_test_batches):

                # load train batch data & train it
                xs, ys = load_batch(test_df, test_batch_id, batch_size)
                ys = list(np.array(ys).reshape(-1,1))
```

```
                    # trian on this batch
                    test_predicted, test_loss = sess.run([y_, loss], feed_dict={X: xs, y: ys,
                                                                                keep_prob: 1.0}

                    predicted_list.extend(list(test_predicted.flatten()))

                    # insert the loss to train loss list
                    batch_test_loss_list.append(test_loss)

                # compute the mean train loss
                mean_test_loss = np.mean(batch_test_loss_list)
                print('Test loss (MSE) mean of all batches: ', mean_test_loss)

                print('Done !!!')

                return (mean_test_loss, predicted_list,)
```

```
In [32]: cnn_tr_loss_list, cnn_val_loss_list = train_model(train_df, val_df)
```

```
X Tensor("Placeholder:0", shape=(?, 66, 200, 3), dtype=float32)
y Tensor("Placeholder_1:0", shape=(?, 1), dtype=float32)
keep_prob Tensor("Placeholder_2:0", dtype=float32)
y_ Tensor("add_9:0", shape=(?, 1), dtype=float32)
loss Tensor("Mean:0", shape=(), dtype=float32)
Number of train batches: 199, validation batches : 50


======================================== 2019-06-23 01:42:15.779995  Training Started  =========


2019-06-23 01:42:15.860833  Training epoch: 1
WARNING:tensorflow:*******************************************************
WARNING:tensorflow:TensorFlow's V1 checkpoint format has been deprecated.
WARNING:tensorflow:Consider switching to the more efficient V2 format:
WARNING:tensorflow:   `tf.train.Saver(write_version=tf.train.SaverDef.V2)`
WARNING:tensorflow:now on by default.
WARNING:tensorflow:*******************************************************
2019-06-23 02:01:16.126146  Validation loss improved, Model saved in file: ./model/save/model.ck
2019-06-23 02:01:16.126377  Training epoch: 2
2019-06-23 02:05:58.203249  Training epoch: 3
2019-06-23 02:10:40.169323  Training epoch: 4
2019-06-23 02:15:22.087529  Training epoch: 5
2019-06-23 02:20:04.020628  Training epoch: 6
2019-06-23 02:24:46.210286  Training epoch: 7
2019-06-23 02:29:29.537741  Training epoch: 8
2019-06-23 02:34:11.284825  Training epoch: 9
2019-06-23 02:38:53.408465  Training epoch: 10
```

```
2019-06-23 02:43:38.063824  Training epoch: 11
2019-06-23 02:48:21.829722  Training epoch: 12
2019-06-23 02:53:04.528596  Training epoch: 13
2019-06-23 02:57:45.923086  Training epoch: 14
2019-06-23 03:02:28.514844  Training epoch: 15
2019-06-23 03:07:09.935979  Training epoch: 16
2019-06-23 03:11:52.528969  Training epoch: 17
2019-06-23 03:16:33.882348  Training epoch: 18
2019-06-23 03:21:16.301000  Training epoch: 19
2019-06-23 03:25:57.546858  Training epoch: 20
2019-06-23 03:30:39.893613  Training epoch: 21
2019-06-23 03:35:21.299538  Training epoch: 22
2019-06-23 03:40:03.874281  Training epoch: 23
2019-06-23 03:44:45.300449  Training epoch: 24
2019-06-23 03:49:27.899014  Training epoch: 25
2019-06-23 03:54:09.472686  Training epoch: 26
2019-06-23 03:58:52.036918  Training epoch: 27
2019-06-23 04:03:33.375882  Training epoch: 28
2019-06-23 04:08:15.925852  Training epoch: 29
2019-06-23 04:12:57.333068  Training epoch: 30
2019-06-23 04:17:39.806784  Training epoch: 31
2019-06-23 04:22:21.062941  Training epoch: 32
2019-06-23 04:27:03.418157  Training epoch: 33
2019-06-23 04:31:44.570691  Training epoch: 34
2019-06-23 04:36:27.082862  Training epoch: 35
2019-06-23 04:41:08.424885  Training epoch: 36
2019-06-23 04:45:50.906094  Training epoch: 37
2019-06-23 04:50:32.257147  Training epoch: 38
2019-06-23 04:55:14.602202  Training epoch: 39
2019-06-23 04:59:55.686838  Training epoch: 40
2019-06-23 05:04:38.214084  Training epoch: 41
2019-06-23 05:09:19.377030  Training epoch: 42
2019-06-23 05:14:01.749569  Training epoch: 43
2019-06-23 05:18:42.956870  Training epoch: 44
2019-06-23 05:23:25.364501  Training epoch: 45
2019-06-23 05:28:06.573913  Training epoch: 46
2019-06-23 05:32:49.122646  Training epoch: 47
2019-06-23 05:37:30.374801  Training epoch: 48
2019-06-23 05:42:12.845136  Training epoch: 49
2019-06-23 05:46:54.208547  Training epoch: 50
```

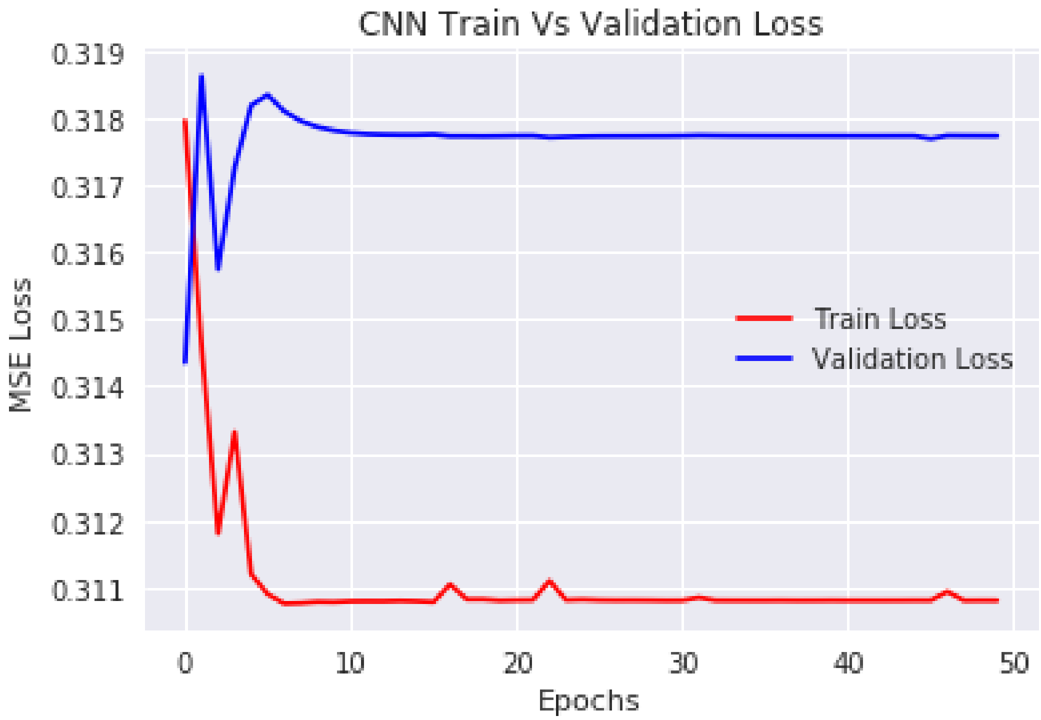
```
In [33]: cnn_test_loss, cnn_predicted_list_test = test_model(test_df)
         cnn_test_loss = round(cnn_test_loss, 8)
```

```
INFO:tensorflow:Restoring parameters from ./model/save/model.ckpt
Model restored successfully ...
Fetching All tensors Completed ...
```

```
Test loss (MSE) mean of all batches:  0.23867664
Done !!!
```

7 Plot Train vs Validation losess

```
In [34]: plt.plot(list(range(len(cnn_tr_loss_list))), cnn_tr_loss_list, label='Train Loss', colo
         plt.plot(list(range(len(cnn_val_loss_list))), cnn_val_loss_list, label='Validation Loss
         plt.legend()
         plt.xlabel('Epochs')
         plt.ylabel('MSE Loss')
         plt.title('CNN Train Vs Validation Loss')
         plt.show()
```



Observations
Validation loss tends plateau after epoch 10
Train loss keeps decreasing over epoch
Early stopping is used to pick the best model, the model is saved only if the loss is improved

8 Save Driving Video File

```
In [35]: test_df = test_df[['Path', 'Label']]
         print('Number of predicted angles', len(cnn_predicted_list_test))
         print('Test df shape', test_df.shape)
```

```
Number of predicted angles 13622
Test df shape (13622, 2)
```

8.0.1 Add the predicted labels to the data frame

In [36]:
```python
test_df['Predicted_Radian'] = cnn_predicted_list_test
# convertt to angle
test_df['Predicted_Degree'] = test_df['Predicted_Radian'] * (180 / np.pi)
test_df.head()
```

Out[36]:
```
                                                    Path     Label  \
31784  /media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe... -0.478744
31785  /media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe... -0.494626
31786  /media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe... -0.503353
31787  /media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe... -0.519235
31788  /media/amd_3/20DAD539DAD50BC2/DSET_REPO/DataSe... -0.542099

       Predicted_Radian  Predicted_Degree
31784          0.015313          0.877369
31785          0.014013          0.802885
31786          0.011122          0.637258
31787          0.016339          0.936142
31788          0.014668          0.840434
```

In [37]:
```python
def save_driving_video(test_df):

    # Read steering wheel image
    steering_img = cv2.imread('steering_wheel_image.jpg',0)
    steering_rows, steering_cols = steering_img.shape

    # set font size for text
    font = cv2.FONT_HERSHEY_SIMPLEX

    # padding for steering
    padding = np.zeros((8, 240, 3))
    height, width, = 256, 695
    size = (width, height)

    smoothed_angle = 0

    # declare an videocapture object
    vid_out = cv2.VideoWriter(mp4_output_name, cv2.VideoWriter_fourcc(*'DIVX'), 15, siz

    # for
    for index, row in test_df.iterrows():
        # set road image path
        img_road = cv2.imread(row.Path)
```

```
            # get predicted degree
            degrees = row.Predicted_Degree
            # rotate the steering
            smoothed_angle += (0.2 * pow(abs((degrees - smoothed_angle)), 2.0 / 3.0) *
                               (degrees - smoothed_angle) / abs(degrees - smoothed_angle))

            M = cv2.getRotationMatrix2D((steering_cols/2,steering_rows/2),-smoothed_angle,1
            dst = cv2.warpAffine(steering_img, M, (steering_cols,steering_rows))

            # padded sequence
            stacked_img = np.stack((dst,)*3, axis=-1)
            padded_steering = np.concatenate([padding, stacked_img, padding])

            # combine steering & road image
            combined_img = np.concatenate([img_road, padded_steering], axis=1)

            # add text to the data
            cv2.putText(img=combined_img, text='{0:.4f} o'.format(degrees), org=(500,128),
                        fontFace=font, fontScale=1.0,
                        color=(0, 0, 255), thickness=5)

            # write & read the image back
            cv2.imwrite('temp.jpg', combined_img)
            combined_img = cv2.imread('temp.jpg')

            #print(combined_img.shape)
            vid_out.write(combined_img)

        vid_out.release()
```

In [38]:
```
save_driving_video(test_df)
```

9 Results

In [39]:
```
# get CNN mean value of loss train, validation
cnn_train_loss = round(np.mean(cnn_tr_loss_list), 8)
cnn_val_loss = round(np.mean(cnn_val_loss_list), 8)

row_mean_model = ('Mean Model', 'array size:N', mean_model_train_loss, mean_model_val_l
                  mean_model_test_loss,)
row_cnn_model = ('CNN Model', '5 Convs, 5 FCL,\n Linear output', cnn_train_loss,
                 cnn_val_loss, cnn_test_loss,)
```

In [40]:
```
Pret_table = PrettyTable()
Pret_table.field_names = ['Model', 'Hyper Param', 'Train MSE', 'Validation MSE', 'Test
Pret_table.title = 'Self Driving Car - MSE of Models'

# basic time series model results
```

```python
Pret_table.add_row(row_mean_model)
Pret_table.add_row(row_sma_model)
Pret_table.add_row(row_wma_model)
Pret_table.add_row(row_ewma_model)

# CNN model result
Pret_table.add_row(row_cnn_model)
print(Pret_table)
```

```
+-----------------------------------------------------------------------------+
|                        Self Driving Car - MSE of Models                     |
+-------------+-----------------+------------+----------------+------------+
|    Model    |   Hyper Param   | Train MSE  | Validation MSE |  Test MSE  |
+-------------+-----------------+------------+----------------+------------+
|  Mean Model |   array size:N  | 0.31070876 |   0.32028271   | 0.24224142 |
|  Simple-MA  |     Window=3    | 0.04835476 |   0.07172848   | 0.05245807 |
| Weighted-MA |     Window=1    | 0.05280013 |   0.07598096   | 0.05513379 |
|   Exp-WMA   |  Alpha=0.500000 | 0.04894741 |   0.07135225   | 0.05315572 |
|  CNN Model  | 5 Convs, 5 FCL, | 0.3111167  |   0.31766912   | 0.23867664 |
|             |   Linear output |            |                |            |
+-------------+-----------------+------------+----------------+------------+
```

10 Procedure Summary

Basic EDA is done on the steering anlge

Classical time series models such as simple moving average, weigted moving averge exponentially weighted moving average are used as reference models.

The dataset is partioned into batches considering the timestamp order

CNN Architecute is designed

The angle is conveted into radian (number format) from degrees .

Hyperparam tuning is done for classical time series models

Testing of classical time series models are done

Training & testing of CNN is done

The train, validation loss is plotted for CNN

11 Conclusion

The classical time series model outperformed CNN model

The CNN model is slightly better than mean model

The input to CNN is fed based on time step order

The performace of CNN is not great when compared to classical time series model, this is expected as the CNN totally ignores the time sequence inforamtion

Given a single image it is difficult to make a decision to turn left or right, we need to consider few previous images and also buffer few upcoming images in order to decide whether to turn left or right

The models which can handle time series information can be used to improve the MSE further.

LSTM model which uses CNN features can be used to improve the performace
The architecture & hyperparam of CNN can be tuned to furter improve the results