Self Driving Car Assignment Using keras

Loading Dataset

```
In [1]: from __future__ import division
        import os
        import numpy as np
        import random
        from scipy import pi
        import imageio
        import cv2
        from itertools import islice
        LIMIT = None
        DATA FOLDER = 'driving dataset'
        TRAIN_FILE = os.path.join(DATA FOLDER, 'data.txt')
        # the expected dimension is (tf ordering)
        # (None, 66, 200, 3)
        def return_data(split=.7):
           X = []
            y = []
            with open (TRAIN FILE) as fp:
                for line in islice(fp, LIMIT):
                    path, angle = line.strip().split()
                    full path = os.path.join(DATA FOLDER, path)
                    X.append(full path)
                    # using angles from -pi to pi to avoid rescaling th
        e atan in the network
                    y.append(float(angle) * pi / 180 )
            y = np.array(y)
            #images = np.array([np.float32(imageio.imread(im))/255 for
        im in X])
            images = np.array([np.float32(cv2.resize(imageio.imread(im,
        pilmode="RGB")[-150:], dsize=(200,66)))/255 for im in X])
            split index = int(split * len(X))
            train X = images[:split index]
            train_y = y[:split_index]
            test X = images[split index:]
            test_y = y[split_index:]
            return np.array(train X), np.array(train y), np.array(test
        X), np.array(test y)
```

Model Arcitecture

```
In [2]: from keras.layers import Convolution2D, Input
        from keras.layers.core import Dense, Flatten, Lambda, Activatio
        n, Dropout
        from keras.models import Model, Sequential
        from keras.optimizers import SGD
        import keras
        from keras.callbacks import ModelCheckpoint, ReduceLROnPlateau,
        RemoteMonitor, EarlyStopping
        from keras.layers import Conv2D, MaxPooling2D
        import tensorflow as tf
        11 11 11
        from tensorflow.compat.v1 import ConfigProto
        from tensorflow.compat.v1 import InteractiveSession
        config = ConfigProto()
        config.gpu_options.per_process_gpu_memory_fraction = 0.9
        sess = InteractiveSession(config=config)"""
        from keras import backend as K
        K.common.image_dim_ordering()
        # fina NVIDIA Architecture Model
        # reference: https://github.com/hdmetor/Nvidia-SelfDriving
        def NVIDA( lr rate, d rate, verbose=True ):
            nvidia model= Sequential()
            nvidia model.add(Convolution2D(24, kernel size=(5, 5),paddi
        ng='valid', activation='relu', strides=(2, 2), name='conv 1',in
        put shape=(66,200, 3) ))
            nvidia model.add(Convolution2D(36, kernel size=(5, 5),paddi
        ng='valid', activation='relu', strides=(2, 2), name='conv 2'))
            nvidia model.add(Convolution2D(48, kernel size=(5, 5),paddi
        ng='valid', activation='relu', strides=(2, 2), name='conv 3'))
            nvidia model.add(Convolution2D(64, kernel size=(3, 3),paddi
        ng='valid', activation='relu', strides=(1, 1), name='conv 4'))
            nvidia model.add(Convolution2D(64, kernel size=(3, 3),paddi
        ng='valid', activation='relu', strides=(1, 1), name='conv_5'))
            nvidia model.add(Flatten())
            nvidia_model.add(Dense(1164, activation="relu"))
            nvidia model.add(Dropout(rate=d rate))
            nvidia model.add(Dense(100, activation="relu"))
            nvidia model.add(Dropout(rate=d rate))
            nvidia model.add(Dense(50, activation="relu"))
            nvidia model.add(Dropout(rate=d rate))
            nvidia model.add(Dense(10, activation="relu"))
            nvidia model.add(Dropout(rate=d rate))
            nvidia model.add(Dense(1))
            nvidia model.add(Lambda(lambda x: keras.activations.tanh(x
        ))))
```

#optimiser inisilisation

```
ada=keras.optimizers.adam(lr_rate)

nvidia_model.compile(optimizer=ada,loss='mse')
if verbose:
    nvidia_model.summary()

return nvidia_model
```

Using TensorFlow backend.

'tf'

Loading and Traning and Hyperparameter Tuning

```
Hyperparameter Tuning
In [4]: import time
        import json
        import numpy as np
        import pickle
        print('Loading data...')
        train_x, train_y, test_x, test_y = return_data(split=0.7)
        print('Done')
          Loading data...
          Done
In [5]: print(f"train shape: {train x.shape}")
        print(f"test shape: {test_x.shape}")
          train shape: (31784, 66, 200, 3)
          test shape: (13622, 66, 200, 3)
In [20]: # Hyperparameter Tuning
        #checkpoint callback
        checkpointer = ModelCheckpoint(
           filepath="{epoch:02d}-{val_loss:.12f}.hdf5",
            verbose=1,
            save_best_only=True)
```

```
ng='valid', activation='relu', strides=(2, 2), name='conv 1',in
        put shape=(66,200, 3) ))
            nvidia model.add(Convolution2D(36, kernel size=(5, 5),paddi
        ng='valid', activation='relu', strides=(2, 2), name='conv 2'))
            nvidia_model.add(Convolution2D(48, kernel_size=(5, 5),paddi
        ng='valid', activation='relu', strides=(2, 2), name='conv 3'))
            nvidia model.add(Convolution2D(64, kernel size=(3, 3),paddi
        ng='valid', activation='relu', strides=(1, 1), name='conv 4'))
            nvidia_model.add(Convolution2D(64, kernel_size=(3, 3),paddi
        ng='valid', activation='relu', strides=(1, 1), name='conv 5'))
            nvidia model.add(Flatten())
            nvidia model.add(Dense(1164, activation="relu"))
            nvidia_model.add(Dropout(rate=params["d_rate"]))
            nvidia model.add(Dense(100, activation="relu"))
            nvidia model.add(Dropout(rate=params["d rate"]))
            nvidia model.add(Dense(50, activation="relu"))
            nvidia_model.add(Dropout(rate=params["d_rate"]))
            nvidia_model.add(Dense(10, activation="relu"))
            nvidia model.add(Dropout(rate=params["d rate"]))
            nvidia model.add(Dense(1))
            nvidia model.add(Lambda(lambda x: keras.activations.tanh(x
        )))
            #optimiser inisilisation
            ada=keras.optimizers.adam(learning rate=params["lr"])
            nvidia model.compile(optimizer=ada,loss='mse')
            history = nvidia model.fit(train x, train y,
                                validation data=[test x, test y],
                                batch size=params['batch size'],
                                epochs=params['epochs'],
                                verbose=0,
                                callbacks=[early_stopper,lr_plateau])
            # finally we have to make sure that history object and mode
        1 are returned
            return history, nvidia_model
In [21]: # making dict of hyperparameters
        p = { 'batch_size': (25,50,100,125), }
             'epochs': [100],
             'd rate':[0.5],
             "lr":[0.001,0.0001]}
           {'batch size': (25, 50, 100, 125),
            'epochs': [100],
            'd rate': [0.5],
            'lr': [0.001, 0.0001]}
```

nvidia_model.add(Convolution2D(24, kernel_size=(5, 5),paddi

In [22]: # hypertuning parameter using takos

```
t = talos.Scan(x=train_x,
         y=train_y,
         model=SDC,
         params=p,
          experiment_name='sdc_fnal')
   0%|
  | 0/50 [00:00<?, ?it/s]
   2%|
  | 1/50 [01:45<1:25:50, 105.11s/it]
   4%|
  | 2/50 [09:41<2:53:10, 216.46s/it]
   6%|
  | 3/50 [11:21<2:22:18, 181.68s/it]
   8%|
  | 4/50 [22:28<4:10:51, 327.21s/it]
  10%|
  | 5/50 [24:16<3:16:02, 261.39s/it]
  12%|
  | 6/50 [33:46<4:19:37, 354.04s/it]
```

import talos

14% | | 7/50 [35:26<3:18:57, 277.62s/it] 16%| | 8/50 [48:21<4:58:56, 427.05s/it] | 9/50 [49:57<3:43:56, 327.72s/it] 20%| | 10/50 [57:26<4:02:41, 364.05s/it] 22%| | 11/50 [59:10<3:06:00, 286.16s/it] 24%| | 12/50 [1:07:54<3:46:14, 357.24s/it] 26% | | 13/50 [1:09:28<2:51:39, 278.36s/it]

28%| 14/50 [1:14:57<2:56:05, 293.49s/it]

30%| 15/50 [1:16:37<2:17:26, 235.61s/it]

32%| | 16/50 [1:26:52<3:17:56, 349.31s/it] 34%| | 17/50 [1:28:24<2:29:42, 272.19s/it] 36%| | 18/50 [1:41:28<3:47:04, 425.77s/it] 38%| | 19/50 [1:42:59<2:48:02, 325.23s/it] 40%| | 20/50 [1:51:54<3:14:04, 388.16s/it] | 21/50 [1:53:22<2:24:08, 298.23s/it] 44%| | 22/50 [2:02:41<2:55:35, 376.28s/it]

| 23/50 [2:04:48<2:15:46, 301.74s/it]

```
50%|
| 25/50 [2:17:13<2:10:16, 312.66s/it]
| 26/50 [2:26:22<2:33:25, 383.55s/it]
548
| 27/50 [2:27:59<1:54:05, 297.65s/it]
| 28/50 [2:39:34<2:32:50, 416.85s/it]
58%|
| 29/50 [2:41:22<1:53:25, 324.05s/it]
60%
| 30/50 [2:48:09<1:56:19, 349.00s/it]
62%|
| 31/50 [2:49:49<1:26:49, 274.16s/it]
64%|
```

| 32/50 [2:57:09<1:37:12, 324.04s/it]

| 24/50 [2:15:40<2:56:13, 406.68s/it]

66%| | 33/50 [2:58:56<1:13:22, 25 8.98s/it] 68%| | 34/50 [3:09:06<1:37:08, 36 4.30s/it] 70%| | 35/50 [3:10:30<1:10:02, 28 0.14s/it] 72%| | 36/50 [3:18:20<1:18:41, 33 7.22s/it] 74%| | 37/50 [3:19:51<57:00, 26 3.08s/it] 76%| | 38/50 [3:31:20<1:18:12, 391. 02s/it] 78%| | 39/50 [3:32:41<54:38, 298. 02s/it]

808

82%| | 41/50 [3:44:36<45:30, 30 3.44s/it] | 42/50 [3:55:08<53:36, 40 2.05s/it] | 43/50 [3:56:36<35:55, 30 7.95s/it] | 44/50 [4:07:51<41:47, 417. 90s/it] | 45/50 [4:09:27<26:46, 321. 30s/it] 92%| | 46/50 [4:17:33<24:42, 37 0.69s/it] | 47/50 [4:18:58<14:15, 28 5.17s/it]

69s/it]

| 40/50 [3:43:15<1:06:26, 398.

```
98%| | 49/50 [4:28:59<04:33, 27 3.53s/it]
```

```
100%| | 50/50 [4:37:15<00:00, 332. 72s/it]
```

```
In [27]: result = t.data
    result.head()
```

	round_epochs	val_loss	loss	lr	batch_size	d_rate	ер
0	11	0.319554	0.309572	0.0010	25	0.5	100
1	52	0.122518	0.127042	0.0001	25	0.5	100
2	11	0.319588	0.309542	0.0010	26	0.5	100
3	74	0.121853	0.121453	0.0001	26	0.5	100
4	12	0.319623	0.309552	0.0010	27	0.5	100

```
In [26]: # optimal hyperparameter
    result[result.val_loss==result.val_loss.min()]
```

	round_epochs	val_loss	loss	lr	batch_size	d_rate	ek
39	87	0.121049	0.125895	0.0001	44	0.5	10

Traning using optimal hyper parameter

```
_best_weights=True)
# reduce learning rate plateau callback
lr_plateau = ReduceLROnPlateau(monitor='val_loss', factor=0.1,
patience=10, min_lr=0.000001, verbose=1, mode=min)
# optimal hyperparameter
epochs = 100
batch\_size = 44
lr=0.0001
d=0.5
print('Loading model')
nvidia = NVIDA(lr rate=lr, d rate=d)
print('Starting training')
history = nvidia.fit(train_x, train_y,
                    validation_data=(test_x, test_y),
                     nb epoch=epochs,
                     batch_size=batch_size,
                     verbose=2,
                     callbacks=[checkpointer])
with open( f'history_{time.time()}.pkl' , 'wb') as fp:
   # dict with np array as items are not serializable
    pickle.dump(dict((k, np.array(v).tolist()) for k, v in hist
ory.history.items()), fp)
print('Done')
```

Loading model

Model: "segmential 1"

conv 5 (Conv2D)

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Model: "sequential_1"		
Layer (type) aram #	Output Shape	P
======= conv_1 (Conv2D) 824	(None, 31, 98, 24)	1
conv_2 (Conv2D) 1636	(None, 14, 47, 36)	2
 conv_3 (Conv2D) 3248	(None, 5, 22, 48)	4
 conv_4 (Conv2D) 7712	(None, 3, 20, 64)	2

(None, 1, 18, 64)

flatten_1 (Flatten)	(None,	1152)	0
dense_1 (Dense) 342092	(None,	1164)	1
dropout_1 (Dropout)	(None,	1164)	0
dense_2 (Dense) 16500	(None,	100)	1
dropout_2 (Dropout)	(None,	100)	0
dense_3 (Dense)	(None,	50)	5
dropout_3 (Dropout)	(None,	50)	0
dense_4 (Dense)	(None,	10)	5
dropout_4 (Dropout)	(None,	10)	0
dense_5 (Dense)	(None,	1)	1
lambda_1 (Lambda)	(None,	1)	0
Total params: 1,595,511 Trainable params: 1,595,53 Non-trainable params: 0	11		
Starting training Train on 31784 samples, va Epoch 1/100 - 15s - loss: 0.3129 - va			
Epoch 00001: val_loss imp	roved from	inf to 0.24019,	savi

Epoch 00001: val_loss improved from inf to 0.24019, saving model to 01-0.240193529073.hdf5

Epoch 2/100

```
- 10s - loss: 0.3081 - val loss: 0.2352
Epoch 00002: val loss improved from 0.24019 to 0.23518,
saving model to 02-0.235184571388.hdf5
Epoch 3/100
- 10s - loss: 0.2909 - val loss: 0.2353
Epoch 00003: val loss did not improve from 0.23518
Epoch 4/100
- 10s - loss: 0.2593 - val loss: 0.2522
Epoch 00004: val loss did not improve from 0.23518
Epoch 5/100
- 10s - loss: 0.2199 - val loss: 0.2094
Epoch 00005: val loss improved from 0.23518 to 0.20940,
saving model to 05-0.209404710160.hdf5
Epoch 6/100
- 10s - loss: 0.1965 - val loss: 0.1984
Epoch 00006: val loss improved from 0.20940 to 0.19845,
saving model to 06-0.198446688075.hdf5
Epoch 7/100
- 10s - loss: 0.1771 - val loss: 0.2066
Epoch 00007: val loss did not improve from 0.19845
Epoch 8/100
- 10s - loss: 0.1660 - val loss: 0.2009
Epoch 00008: val loss did not improve from 0.19845
Epoch 9/100
- 10s - loss: 0.1595 - val loss: 0.1861
Epoch 00009: val loss improved from 0.19845 to 0.18613,
saving model to 09-0.186132975735.hdf5
Epoch 10/100
- 10s - loss: 0.1499 - val loss: 0.2067
Epoch 00010: val loss did not improve from 0.18613
Epoch 11/100
- 10s - loss: 0.1459 - val loss: 0.1854
Epoch 00011: val loss improved from 0.18613 to 0.18538,
saving model to 11-0.185376542353.hdf5
Epoch 12/100
- 10s - loss: 0.1417 - val loss: 0.1766
Epoch 00012: val loss improved from 0.18538 to 0.17664,
saving model to 12-0.176639022486.hdf5
Epoch 13/100
- 10s - loss: 0.1401 - val loss: 0.1903
```

```
Epoch 00013: val loss did not improve from 0.17664
Epoch 14/100
 - 10s - loss: 0.1392 - val loss: 0.2066
Epoch 00014: val loss did not improve from 0.17664
Epoch 15/100
 - 10s - loss: 0.1376 - val loss: 0.2198
Epoch 00015: val loss did not improve from 0.17664
Epoch 16/100
- 10s - loss: 0.1351 - val loss: 0.2273
Epoch 00016: val loss did not improve from 0.17664
Epoch 17/100
- 10s - loss: 0.1339 - val loss: 0.1885
Epoch 00017: val loss did not improve from 0.17664
Epoch 18/100
- 10s - loss: 0.1357 - val loss: 0.2245
Epoch 00018: val loss did not improve from 0.17664
Epoch 19/100
- 10s - loss: 0.1334 - val loss: 0.2149
Epoch 00019: val loss did not improve from 0.17664
Epoch 20/100
- 10s - loss: 0.1310 - val loss: 0.2186
Epoch 00020: val loss did not improve from 0.17664
Epoch 21/100
- 10s - loss: 0.1332 - val loss: 0.2124
Epoch 00021: val loss did not improve from 0.17664
Epoch 22/100
- 10s - loss: 0.1306 - val loss: 0.2022
Epoch 00022: val loss did not improve from 0.17664
Epoch 23/100
- 10s - loss: 0.1316 - val loss: 0.2015
Epoch 00023: val loss did not improve from 0.17664
Epoch 24/100
- 10s - loss: 0.1304 - val loss: 0.2275
Epoch 00024: val loss did not improve from 0.17664
Epoch 25/100
- 10s - loss: 0.1307 - val loss: 0.1889
Epoch 00025: val loss did not improve from 0.17664
Epoch 26/100
 - 10s - loss: 0.1301 - val loss: 0.1980
```

```
Epoch 00026: val loss did not improve from 0.17664
Epoch 27/100
 - 10s - loss: 0.1288 - val loss: 0.1848
Epoch 00027: val loss did not improve from 0.17664
Epoch 28/100
- 10s - loss: 0.1300 - val loss: 0.1861
Epoch 00028: val loss did not improve from 0.17664
Epoch 29/100
- 10s - loss: 0.1307 - val loss: 0.2009
Epoch 00029: val loss did not improve from 0.17664
Epoch 30/100
- 10s - loss: 0.1280 - val loss: 0.1991
Epoch 00030: val_loss did not improve from 0.17664
Epoch 31/100
- 10s - loss: 0.1280 - val loss: 0.2047
Epoch 00031: val loss did not improve from 0.17664
Epoch 32/100
 - 10s - loss: 0.1302 - val loss: 0.1833
Epoch 00032: val loss did not improve from 0.17664
Epoch 33/100
- 10s - loss: 0.1279 - val loss: 0.1958
Epoch 00033: val loss did not improve from 0.17664
Epoch 34/100
- 10s - loss: 0.1274 - val loss: 0.1641
Epoch 00034: val loss improved from 0.17664 to 0.16414,
saving model to 34-0.164143860230.hdf5
Epoch 35/100
- 10s - loss: 0.1297 - val loss: 0.1818
Epoch 00035: val loss did not improve from 0.16414
Epoch 36/100
- 10s - loss: 0.1289 - val loss: 0.1928
Epoch 00036: val loss did not improve from 0.16414
Epoch 37/100
- 10s - loss: 0.1277 - val loss: 0.2068
Epoch 00037: val loss did not improve from 0.16414
Epoch 38/100
 - 10s - loss: 0.1283 - val loss: 0.1896
Epoch 00038: val loss did not improve from 0.16414
Epoch 39/100
- 10s - loss: 0.1270 - val loss: 0.1952
```

```
Epoch 00039: val loss did not improve from 0.16414
Epoch 40/100
 - 10s - loss: 0.1266 - val loss: 0.2016
Epoch 00040: val loss did not improve from 0.16414
Epoch 41/100
- 10s - loss: 0.1274 - val loss: 0.1749
Epoch 00041: val loss did not improve from 0.16414
Epoch 42/100
- 10s - loss: 0.1263 - val loss: 0.1723
Epoch 00042: val loss did not improve from 0.16414
Epoch 43/100
 - 10s - loss: 0.1265 - val loss: 0.1759
Epoch 00043: val loss did not improve from 0.16414
Epoch 44/100
- 10s - loss: 0.1268 - val loss: 0.1844
Epoch 00044: val loss did not improve from 0.16414
Epoch 45/100
- 10s - loss: 0.1282 - val_loss: 0.1597
Epoch 00045: val loss improved from 0.16414 to 0.15974,
saving model to 45-0.159739194284.hdf5
Epoch 46/100
- 10s - loss: 0.1277 - val loss: 0.1662
Epoch 00046: val loss did not improve from 0.15974
Epoch 47/100
- 10s - loss: 0.1256 - val loss: 0.1766
Epoch 00047: val loss did not improve from 0.15974
Epoch 48/100
- 10s - loss: 0.1266 - val loss: 0.1851
Epoch 00048: val loss did not improve from 0.15974
Epoch 49/100
- 10s - loss: 0.1255 - val loss: 0.1852
Epoch 00049: val loss did not improve from 0.15974
Epoch 50/100
- 10s - loss: 0.1269 - val loss: 0.1895
Epoch 00050: val loss did not improve from 0.15974
Epoch 51/100
- 10s - loss: 0.1268 - val loss: 0.1685
Epoch 00051: val loss did not improve from 0.15974
```

Epoch 52/100

```
- 10s - loss: 0.1258 - val loss: 0.2059
Epoch 00052: val loss did not improve from 0.15974
Epoch 53/100
- 10s - loss: 0.1264 - val loss: 0.1745
Epoch 00053: val loss did not improve from 0.15974
Epoch 54/100
- 10s - loss: 0.1275 - val loss: 0.1541
Epoch 00054: val loss improved from 0.15974 to 0.15406,
saving model to 54-0.154061736122.hdf5
Epoch 55/100
- 10s - loss: 0.1261 - val loss: 0.1741
Epoch 00055: val loss did not improve from 0.15406
Epoch 56/100
- 10s - loss: 0.1270 - val loss: 0.1858
Epoch 00056: val loss did not improve from 0.15406
Epoch 57/100
- 10s - loss: 0.1260 - val_loss: 0.1670
Epoch 00057: val loss did not improve from 0.15406
Epoch 58/100
- 10s - loss: 0.1267 - val loss: 0.1836
Epoch 00058: val loss did not improve from 0.15406
Epoch 59/100
- 10s - loss: 0.1281 - val loss: 0.1600
Epoch 00059: val loss did not improve from 0.15406
Epoch 60/100
- 10s - loss: 0.1249 - val loss: 0.1636
Epoch 00060: val loss did not improve from 0.15406
Epoch 61/100
- 10s - loss: 0.1258 - val loss: 0.1758
Epoch 00061: val loss did not improve from 0.15406
Epoch 62/100
- 10s - loss: 0.1255 - val loss: 0.1867
Epoch 00062: val loss did not improve from 0.15406
Epoch 63/100
- 10s - loss: 0.1255 - val loss: 0.1721
Epoch 00063: val loss did not improve from 0.15406
Epoch 64/100
- 10s - loss: 0.1258 - val loss: 0.1903
Epoch 00064: val loss did not improve from 0.15406
```

```
Epoch 65/100
 - 10s - loss: 0.1249 - val loss: 0.1901
Epoch 00065: val loss did not improve from 0.15406
Epoch 66/100
- 10s - loss: 0.1264 - val loss: 0.1904
Epoch 00066: val loss did not improve from 0.15406
Epoch 67/100
- 10s - loss: 0.1261 - val loss: 0.1569
Epoch 00067: val loss did not improve from 0.15406
Epoch 68/100
- 10s - loss: 0.1261 - val loss: 0.1663
Epoch 00068: val loss did not improve from 0.15406
Epoch 69/100
- 10s - loss: 0.1249 - val loss: 0.1701
Epoch 00069: val loss did not improve from 0.15406
Epoch 70/100
- 10s - loss: 0.1261 - val loss: 0.1830
Epoch 00070: val loss did not improve from 0.15406
Epoch 71/100
- 10s - loss: 0.1253 - val loss: 0.1857
Epoch 00071: val loss did not improve from 0.15406
Epoch 72/100
- 10s - loss: 0.1259 - val loss: 0.1692
Epoch 00072: val loss did not improve from 0.15406
Epoch 73/100
- 10s - loss: 0.1240 - val loss: 0.1654
Epoch 00073: val loss did not improve from 0.15406
Epoch 74/100
- 10s - loss: 0.1249 - val loss: 0.2063
Epoch 00074: val loss did not improve from 0.15406
Epoch 75/100
- 10s - loss: 0.1245 - val loss: 0.1846
Epoch 00075: val loss did not improve from 0.15406
Epoch 76/100
- 10s - loss: 0.1248 - val loss: 0.1919
Epoch 00076: val loss did not improve from 0.15406
Epoch 77/100
- 10s - loss: 0.1247 - val loss: 0.1815
Epoch 00077: val loss did not improve from 0.15406
```

```
Epoch 78/100
 - 10s - loss: 0.1255 - val loss: 0.1861
Epoch 00078: val loss did not improve from 0.15406
Epoch 79/100
- 10s - loss: 0.1254 - val loss: 0.1843
Epoch 00079: val loss did not improve from 0.15406
Epoch 80/100
- 10s - loss: 0.1249 - val loss: 0.1749
Epoch 00080: val loss did not improve from 0.15406
Epoch 81/100
- 10s - loss: 0.1260 - val loss: 0.1854
Epoch 00081: val loss did not improve from 0.15406
Epoch 82/100
- 10s - loss: 0.1269 - val loss: 0.2101
Epoch 00082: val loss did not improve from 0.15406
Epoch 83/100
- 10s - loss: 0.1252 - val loss: 0.1990
Epoch 00083: val loss did not improve from 0.15406
Epoch 84/100
- 10s - loss: 0.1239 - val loss: 0.2022
Epoch 00084: val loss did not improve from 0.15406
Epoch 85/100
- 10s - loss: 0.1245 - val loss: 0.2097
Epoch 00085: val loss did not improve from 0.15406
Epoch 86/100
- 10s - loss: 0.1251 - val loss: 0.2044
Epoch 00086: val loss did not improve from 0.15406
Epoch 87/100
- 10s - loss: 0.1244 - val loss: 0.1768
Epoch 00087: val loss did not improve from 0.15406
Epoch 88/100
- 10s - loss: 0.1236 - val loss: 0.1631
Epoch 00088: val loss did not improve from 0.15406
Epoch 89/100
- 10s - loss: 0.1262 - val loss: 0.1679
Epoch 00089: val loss did not improve from 0.15406
Epoch 90/100
- 10s - loss: 0.1246 - val loss: 0.2443
Epoch 00090: val loss did not improve from 0.15406
```

```
Epoch 91/100
           - 10s - loss: 0.1265 - val loss: 0.2047
          Epoch 00091: val loss did not improve from 0.15406
          Epoch 92/100
           - 10s - loss: 0.1249 - val loss: 0.2127
          Epoch 00092: val loss did not improve from 0.15406
          Epoch 93/100
           - 10s - loss: 0.1243 - val loss: 0.1958
          Epoch 00093: val loss did not improve from 0.15406
          Epoch 94/100
           - 10s - loss: 0.1240 - val loss: 0.1762
          Epoch 00094: val loss did not improve from 0.15406
          Epoch 95/100
           - 10s - loss: 0.1250 - val loss: 0.2092
          Epoch 00095: val loss did not improve from 0.15406
          Epoch 96/100
           - 10s - loss: 0.1243 - val loss: 0.1988
          Epoch 00096: val loss did not improve from 0.15406
          Epoch 97/100
           - 10s - loss: 0.1240 - val loss: 0.1836
          Epoch 00097: val loss did not improve from 0.15406
          Epoch 98/100
           - 10s - loss: 0.1245 - val loss: 0.1998
          Epoch 00098: val loss did not improve from 0.15406
          Epoch 99/100
           - 10s - loss: 0.1245 - val loss: 0.1929
          Epoch 00099: val loss did not improve from 0.15406
          Epoch 100/100
           - 10s - loss: 0.1254 - val loss: 0.1744
          Epoch 00100: val loss did not improve from 0.15406
In [31]: # Loading best model checkpoint
```

```
In [31]: # Loading best model checkpoint

nvidia = NVIDA(lr_rate=lr, d_rate=d, verbose=0)

nvidia.load_weights("41-0.148576635343.hdf5")
scores = nvidia.evaluate(test_x, test_y, verbose=0)
print(f"{nvidia.metrics_names}: {scores}")
```

['loss']: 0.14857663764049028

In [32]: pred_angle = nvidia.predict(test_x)

pred angle[:15]

visualisation of predicted angle

```
In [39]: # visualisation predicted angle result
         #pip3 install opencv-python
         import scipy.misc
         import cv2
         from subprocess import call
         import math
         import imageio
         import time
         img = cv2.imread('steering wheel image.jpg',0)
         rows, cols = img.shape
        smoothed angle = 0
        #read data.txt
        xs = []
        ys = []
        with open("driving dataset/data.txt") as f:
            for line in f:
                 xs.append("driving dataset/" + line.split()[0])
                 #the paper by Nvidia uses the inverse of the turning ra
        dius,
                 #but steering wheel angle is proportional to the invers
         e of turning radius
                #so the steering wheel angle in radians is used as the
         output
                ys.append(float(line.split()[1]) * scipy.pi / 180)
         #get number of images
        num_images = len(xs)
         i = math.ceil(num images*0.8)
```

```
print("Starting frameofvideo:" +str(i))
while (cv2.waitKey(10) != ord('q')):
    full_image = imageio.imread("driving_dataset/" + str(i) +
".jpg", pilmode="RGB")
    image = cv2.resize(full image[-150:], dsize=(200,66)) / 25
    degrees = (nvidia.predict(image.reshape(1,66,200,3))[0][0]*
180.0 )/scipy.pi
   cv2.imshow("frame", cv2.cvtColor(full image, cv2.COLOR RGB2
BGR))
    #make smooth angle transitions by turning the steering whee
1 based on the difference of the current angle
    #and the predicted angle
   smoothed angle += 0.2 * pow(abs((degrees - smoothed angle)))
)), 2.0 / 3.0) * (degrees - smoothed_angle) / abs(degrees - smo
othed_angle)
    #print("Steering angle: " + str(degrees) + " (pred)\t" + st
r(ys[i]*180/scipy.pi) + " (actual)")
    #print("smoothed_angle: ",smoothed_angle)
   M = cv2.getRotationMatrix2D((cols/2,rows/2),-smoothed angle
,1)
   dst = cv2.warpAffine(img,M,(cols,rows))
   cv2.imshow("steering wheel", dst)
   time.sleep(0.02)
   i += 1
cv2.destroyAllWindows()
```

Starting frameofvideo:36325

Observation

1. Although traning data was not very large still Nvidia end to end model is doing quite well in prediction angle of stering wheels (ofcourse not near close to use in real life).

END:)