

# Behavioral Cloning

## ➤ Behavioral Cloning Project

The goals / steps of this project are the following:

- Use the simulator to collect data of good driving behavior
- Build, a convolution neural network in Keras that predicts steering angles from images
- Train and validate the model with a training and validation set
- Test that the model successfully drives around track one without leaving the road
- Summarize the results with a written report

### Image References:

Image-1 : Autonomous mode driving visualization of model.h5 through simulator

Image-2 : Nvidia CNN architecture for autonomous vehicle

Image-3 : Centre lane driving image (a sample)

Image-4 : Total number of image captured for training/validation

Image-5 : Ideal epochs for training and snap of loss convergence

## ➤ Files Submitted & Code Quality

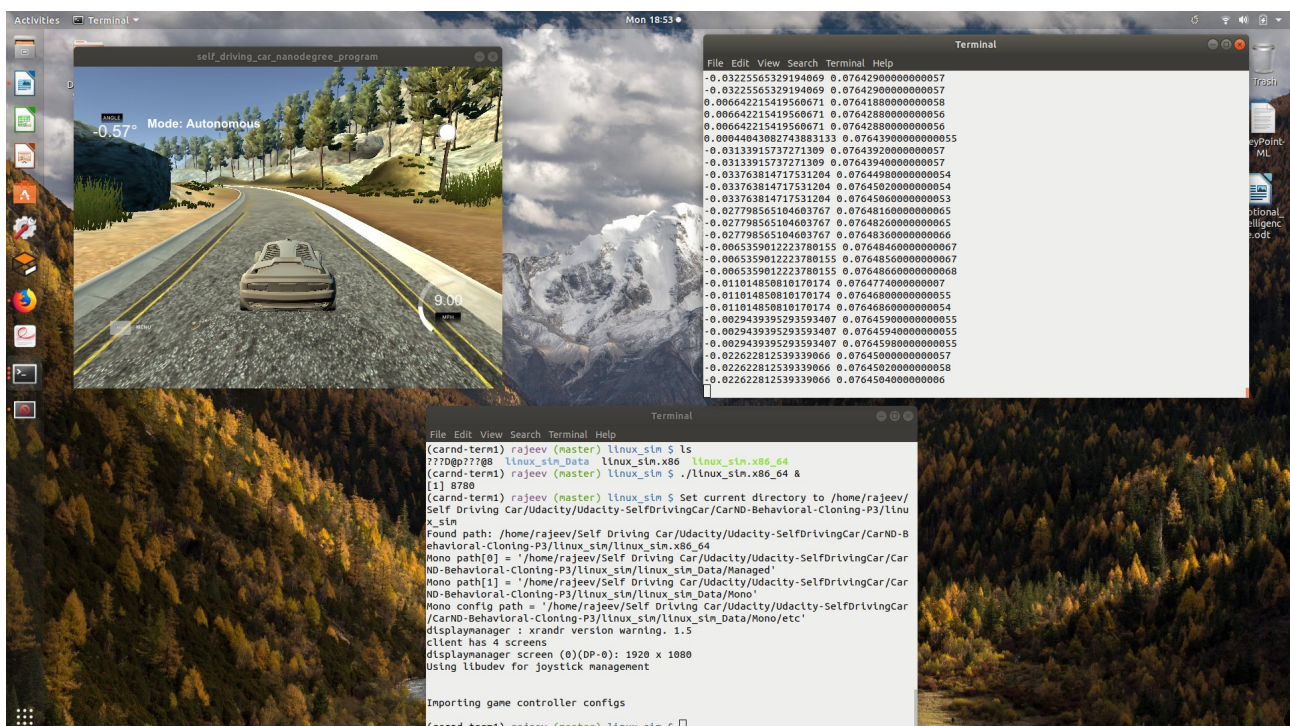
Submission includes all required files and can be used to run the simulator in autonomous mode, my project includes the following files:

- model.py : containing the script to create and train the model
- drive.py : for driving the car in autonomous mode
- model.h5 : containing a trained convolution neural network
- video.mp4 : containing a video of autonomous vehicle drive by trained model
- writeup\_report.md or writeup\_report.pdf summarizing the results

## ➤ Submission includes functional code

Using the Udacity provided simulator and my drive.py file, the car can be driven autonomously around the track by executing - “sh python drive.py model.h5”, also recorded video outcome as guided in class work.

Image-1 : Autonomous mode driving visualization of model.h5 through simulator



➤ **Submission code is usable and readable**

The model.py file contains the code for training and saving the convolution neural network (model.h5). The file shows the pipeline i used for training and validating the model, and it contains eloborative comments to explain how the code works. Code has modularity, independent functions and only system defined parameters (to avoid hardcodings).

## **Model Architecture and Training Strategy**

➤ **Solution Design Approach**

The overall strategy for deriving a model architecture was to first try out very simple architecture (one convolution & connected layer) as explained in curriculam to understand impact of various parameters thereafter try out complex model LeNet and Nvidia model architecture.

While tried very simple architecture and unprocessed input data, trained model was able to drive vehicle for a short distance then derailed from track in any direction. While introduced pre-processing mechanism as follows, performance improved a bit:

- Grayscale - RGB to BGR images processing (model.py code line : 52)
- Normalization – i.e. Lambda normalization and cropping (model.py code line : 64 – 68)

However trained models couldn't drive vehicle efficiently so decided to move on slightly complex model i.e LeNet architecture (model.py code line : 71 - 81). Outcome improved slightly but model was not able to drive vehicle on sharp turns, leaving track and went in undesired space.

Eventually as suggested in course lectures to achieve project objectives, I decided to move on Nvidia architecture model and implemented same (model.py code line : 84 - 96). This model worked well on whole track though at a few occassions go in extreme left/right, also once strike with roadside object.

### **Appropriate training data**

- Training data was chosen to keep the vehicle driving on the road. I used a combination of center lane driving, recovering from the left and right sides of the road.
- For details about how I created the training data, see the next section (model.py code line : 47)
- Than decide to increase training data (reverse track data input for training) and fine tunning of hyper parameters.

At the end of the process with Nvidia model, vehicle is able to drive autonomously around the track without leaving the road.

### **Model parameter tuning**

- The model used an adam optimizer, so the learning rate was not tuned manually (model.py line 100).
- Increase learning iteration to 10 (model.py code line : 33) because training and validation loss was dropping.

### **Attempt to reduce overfitting in the model**

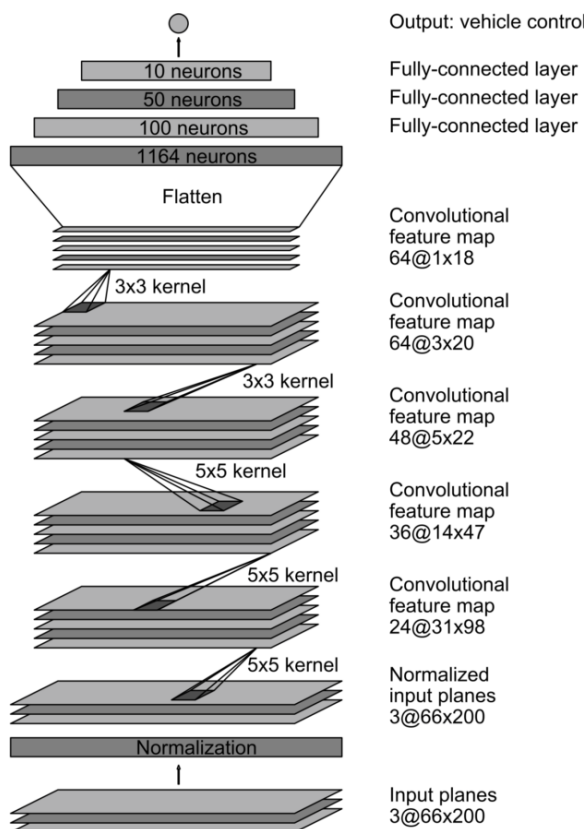
- The model was trained and validated on different data sets to ensure that the model was not overfitting (model.py code line 34), 25% data kept for validation.
- The model was tested by running it through the simulator and ensuring that the vehicle could stay on the track.

### ➤ Final Model Architecture

The final model architecture (model.py lines 84 -96) consisted of a convolution neural network with the following layers and layer sizes :

- Image-1 visualize architecture of Nvidia CNN model adopted by nvidia autonomous vehicle team. Same advance model we realized in our project to achieve expected objectives. Model has 5 convolutional layers, 3 fully connected layers, one pre-processing layer along with input/output layers.
- Five 2D convolutional layers have sizes:
  - 24, 5, 5, subsample=(2,2), activation="relu"
  - 36, 5, 5, subsample=(2,2), activation="relu"
  - 48, 5, 5, subsample=(2,2), activation="relu"
  - 64, 3, 3, activation="relu"
  - 64, 3, 3, activation="relu"

Image-2 : Nvidia CNN architecture for autonomous vehicle



### ➤ Creation of the Training Set & Training Process

To capture good driving behavior,

- I first recorded one laps on track one using center lane driving
- Thereafter one lap on track in reverse direction
- Randomly shuffled the data set and put 25% of the data into a validation set.
- I used an adam optimizer so that manually training the learning rate wasn't necessary
- 3439 vehicle training sample data point gathered (at unique time instances)
- Date pre-processing done (explained earlier)

Here is an example image of center lane driving:



Image-3 : Centre lane driving image (a sample)

After collection process, I had **3439** number of data points for each camera (left, centre and right – file driving\_log.csv columns). The total number of camera images = **10288** , as depicted in image-4

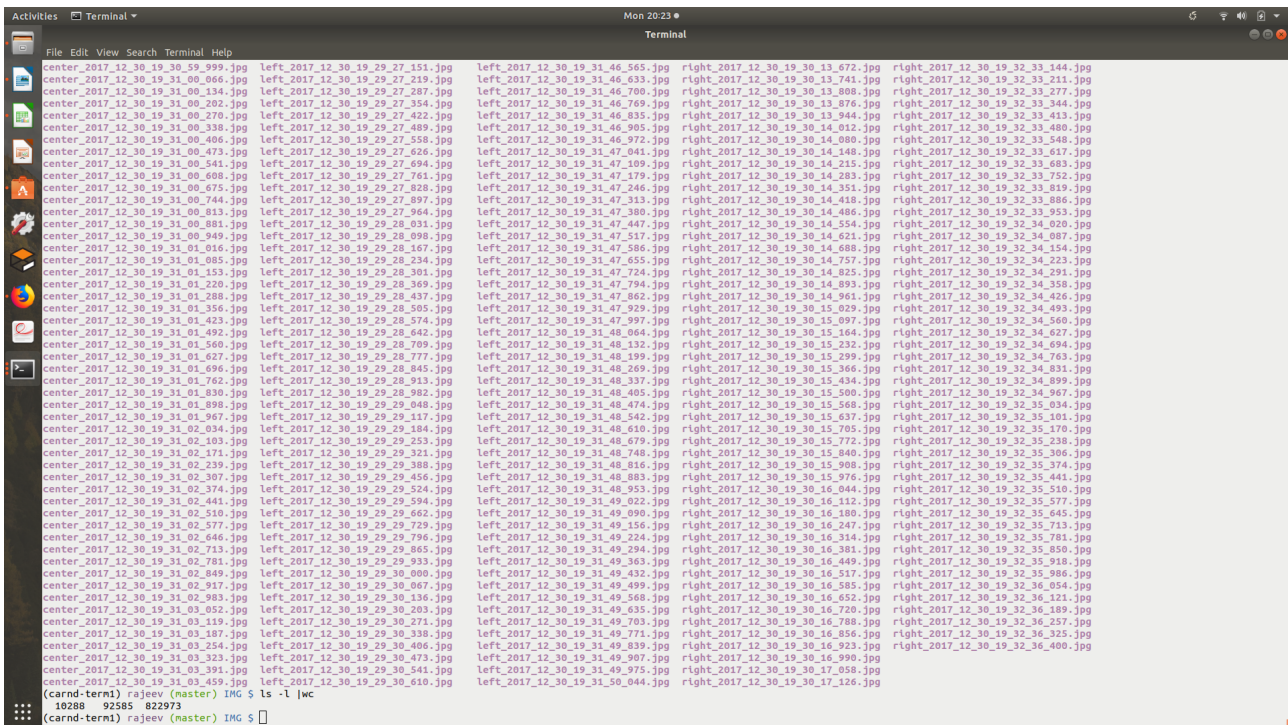


Image-4 : Total number of image captured for training/validation

I used this training data for training the model. The validation set helped determine if the model was over or under fitting.

The ideal number of epochs was 10 as evidenced by image-5 (Outcome slightly varied for each training)

```
Activities Terminal Mon 20:37
Terminal
File Edit View Search Terminal Help
(carnd-term1) rajeev (master) Data $ python model.py
Using TensorFlow backend.
Loading images
preprocessed images
size of image = (160, 320)
Training model
Train on 7715 samples, validate on 2572 samples
Epoch 1/10
2018-01-01 20:36:25.401283: I tensorflow/core/platform/cpu_feature_guard.cc:137] Your CPU supports instructions that this TensorFlow binary was not compiled to use: SSE4.1 SSE4.2 AVX AVX2 FMA
2018-01-01 20:36:25.529530: I tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:892] successful NUMA node read from SysFS had negative value (-1), but there must be at least one NUMA node, so returning NUMA node zero
2018-01-01 20:36:25.529753: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1030] Found device 0 with properties:
name: GeForce GTX 1060 major: 6 minor: 1 memoryClockRate(GHz): 1.6705
pciBusID: 0000:01:00.0
totalMemory: 5.92GiB freeMemory: 5.11GiB
2018-01-01 20:36:25.529766: I tensorflow/core/common_runtime/gpu/gpu_device.cc:1120] Creating TensorFlow device (/device:GPU:0) -> (device: 0, name: GeForce GTX 1060, pci bus id: 0000:01:00.0, compute capa
bility: 6.1)
7715/7715 [=====] - 7s - loss: 0.0434 - val_loss: 0.0382
Epoch 2/10
7715/7715 [=====] - 6s - loss: 0.0405 - val_loss: 0.0509
Epoch 3/10
7715/7715 [=====] - 6s - loss: 0.0344 - val_loss: 0.0332
Epoch 4/10
7715/7715 [=====] - 6s - loss: 0.0282 - val_loss: 0.0249
Epoch 5/10
7715/7715 [=====] - 6s - loss: 0.0240 - val_loss: 0.0280
Epoch 6/10
7715/7715 [=====] - 6s - loss: 0.0240 - val_loss: 0.0246
Epoch 7/10
7715/7715 [=====] - 6s - loss: 0.0218 - val_loss: 0.0256
Epoch 8/10
7715/7715 [=====] - 6s - loss: 0.0238 - val_loss: 0.0279
Epoch 9/10
7715/7715 [=====] - 6s - loss: 0.0207 - val_loss: 0.0264
Epoch 10/10
7715/7715 [=====] - 6s - loss: 0.0203 - val_loss: 0.0274
Model saved in file model.h5
Exception ignored in: <bound method BaseSession.__del__ of <tensorflow.python.client.session.Session object at 0x7f1c411a1710>
Traceback (most recent call last):
  File "/home/rajeev/anaconda3/envs/carnd-term1/lib/python3.5/site-packages/tensorflow/python/client/session.py", line 696, in __del__
TypeError: 'NoneType' object is not callable
(carnd-term1) rajeev (master) Data $
```

Image-5 : Ideal epochs for training and snap of loss convergence

### Summary:

Model.py, captured training set and above mentioned tuned hyper parameters able to generate a model.h5 outcome which efficiently drive autonomous vehicle. Mostly vehicle remain in centre of the road, never being erratic in driving and speed remained nearly 10mph. The video outcome is available with submission for review. All execution done Ubuntu 17.10, GPU (GeForce GTX 1060)/CPU grade machine and compute execution being fairly fast.