Behavioral Cloning

Ara Patapoutian, July 2017

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

Rubric Points

Files Submitted & Code Quality

1. Submission files:

My project includes the following files:

- **model.ipynb** & **model.py** containing the script to create and train the model
    - I used Jupyter notebook (ipynb) to generate code and at the end, converted to Python (py), since the project requested a python format
    - This file contains the code for training and saving the neural network
    - I did not use generators code since my computer memory was large 32 GB, and could handle the 4.8 GB size of training images
    - cell-1 (ipynb) includes all the parameters I could tune, I started the network as the NVIDIA network

    ```
    # parameters used
    FLIP_FLAG   = True    # if True adds flipped images for training
    CROP_FLAG   = True    # if True cropps undesired portions of an image
    NORM_FLAG   = True    # if True normalizes the input to network
    RL_IM_FLAG  = True    # if True uses the left and right images as well
    ```

```
IMAGE_SHAPE      = (160, 320, 3)
TOP_CROP         = 62      # where to crop at top of image
BOTTOM_CROP      = 24      # where to crop at bottom of image
CAMERA_DELTA     = 0.002   # distance between cameras, assuming vertical distance is normalized 1
PROB_LR          = 0.6     # probability of using a left/right image
SAVED_FN         = "model.h5"
EPOCHS           = 3
BATCH_SIZE       = 64
VALIDATION_SPLIT = 0.25
KP               = 0.3     # keep prob

# NVIDIA Network config: K=kernel, F=features, S=stride
K = [5,  5,  5,  3,  3]
F = [24, 36, 48, 64, 64]
S = [2,   2,  2,  1,  1]
FC= [100, 50, 10]
```

- **drive.py** for driving the car in autonomous mode
  - I ended up changing the velocity from 9 mph to 20 mph to stress the system
- **model.h5** containing a trained convolution neural network
  - Using the Udacity provided simulator and my drive.py file, the car can be driven autonomously around the track by executing >>> python drive.py model.h5
- **p3.md** summarizing the results
  - It is this report and covers for README file as well
- **run1.mp4** is the video capturing 1 rev of the track

Model Architecture and Training Strategy

1. Model architecture has been employed

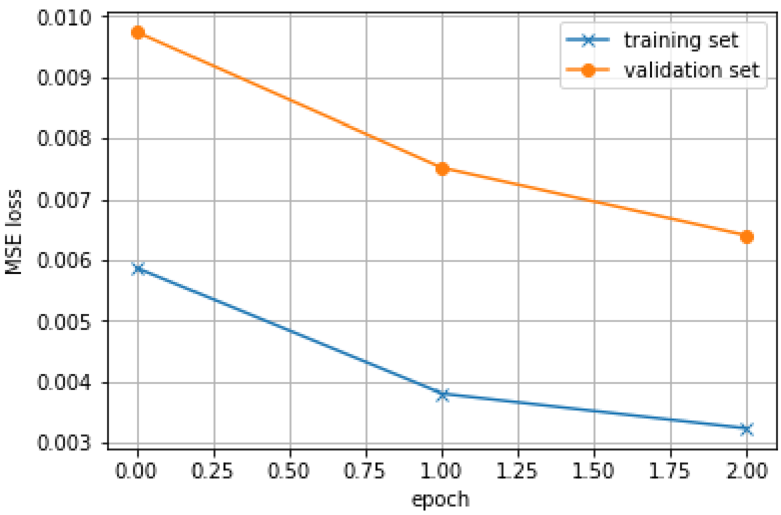
- I used the NVIDIA architecture, discussed in Section 14 of the class project and covered by the NVIDIA paper *End to End Learning for Self-Driving Cars* by M. Bojarski et al. (from now on referred as NVIDIA paper)
- This model has 5 convolution layers followed by 3 fully connected (FC) layers
  - The model includes RELU activation on all convolution and fully connected layers
- I parameterized the layer variables to easily change them if needed, see cell-1 content above
- I did an analysis on trainable parameters and obtained 346 K parameters (cell-12)
  - the NVIDIA paper reports 250 K such parameters versus my 346 K
  - I attributed the difference to the input image size 66×200 for NVIDIA, versus 74×320 for my project (after cropping)
- The code has the option to normalized the input, by using a Keras lambda layer (cell-11) using the flag NORM_FLAG
  - I tried running without normalization. I observed slower convergence and poorer car performance
  - as a result I set NORM_FLAG = True

2. Attempts to reduce overfitting in the model

- I added dropout to all fully connected layers except output (cell-11)
- I tried dropout on the last convolution layer but did not help
  - Ended up not using dropout on any convolution layer
- I increased training data in multiple ways as described below

3. Model parameter tuning

- The model used an **adam** optimizer, so the learning rate was not tuned manually (cell-12)
- I used **25% of available data** for validation
- played with BATCH_SIZE, did not make much of a difference, ended up using **BATCH_SIZE=64**
- To minimize validation loss ended up using **EPOCHS=3**
  - I choose this by observing training cost versus validation cost behaviors, an example plot is shown here



4. Appropriate training data

- Training data was chosen to keep the vehicle driving on the road
  - validation cost was useful in training a specific network but not that useful in deciding what training data to use
  - in other words, certain data makes validation cost higher but yet the driving experience improves
- I did not use the second track because I had difficulty navigating the track and therefore had difficulty properly training the network
- To diversify data:
  1. I used numpy's fliplr() function that doubled my repository
  2. I trained the car both counterclockwise and clockwise
  3. I used some of the left and right images provided during training

For details about how I created the training data, see the next section.

Model Architecture and Training Strategy

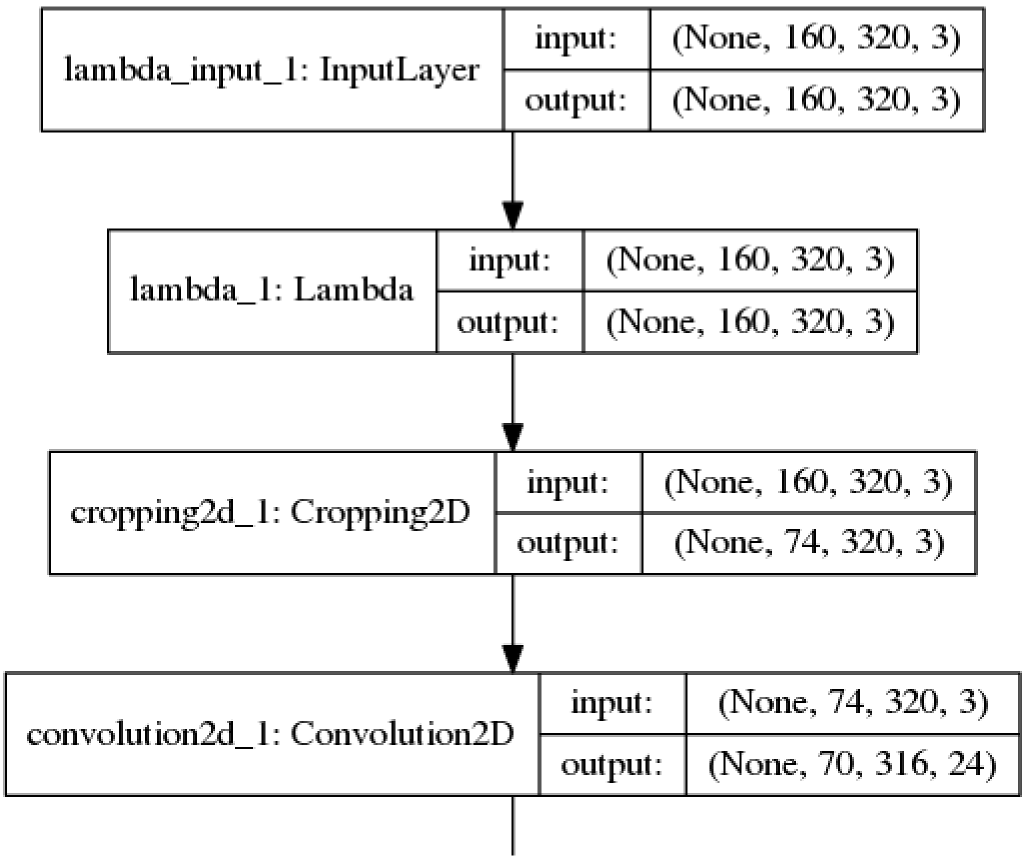
1. Solution Design Approach

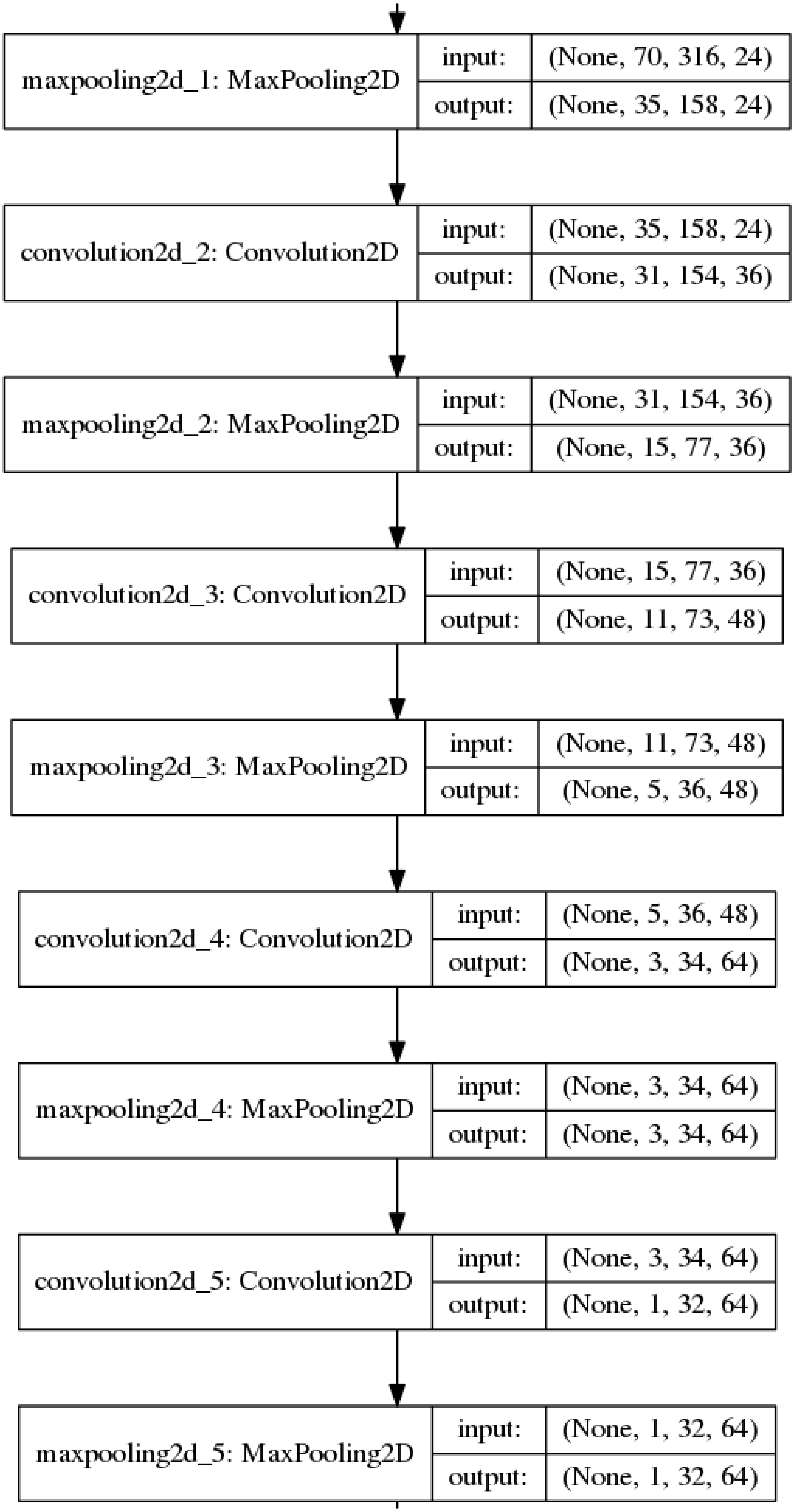
- After duplicating the instructor's attempts by starting with simple networks, my initial serious starting point was the NVIDIA network as described by NVIDIA paper
    - NVIDIA's network with dropout worked well from start, and as a result I focused on training data set preparation rather than network optimization
- The overall strategy for deriving a model architecture was for the car not to approach the side lanes
    - To stress the system I increase the car set-velocity to **20 mph** inside drive.py
        - as the car speed increased, two effects were observed:
            1. the car oscillated more (right/left) on straight lanes
            2. the car started missing sharp turns
        - Furthermore, these two impairments are highly correlated: as I increase the left/right camera steering angle shifts (see Appendix), the sharp turns got better but the oscillations got worst
        - Also, when I reduced the fraction of left/right camera pictures, oscillations got better but sharp turn performance degraded
        - In doing such trade-offs, I found out the validation loss not to be very helpful, I had to test drive the car after each modification
        - I ended up using small angle shifts (**a=0.0002**, see Appendix) for the side cameras, and used **60%** of the side camera images, which I picked randomly (cell-5)

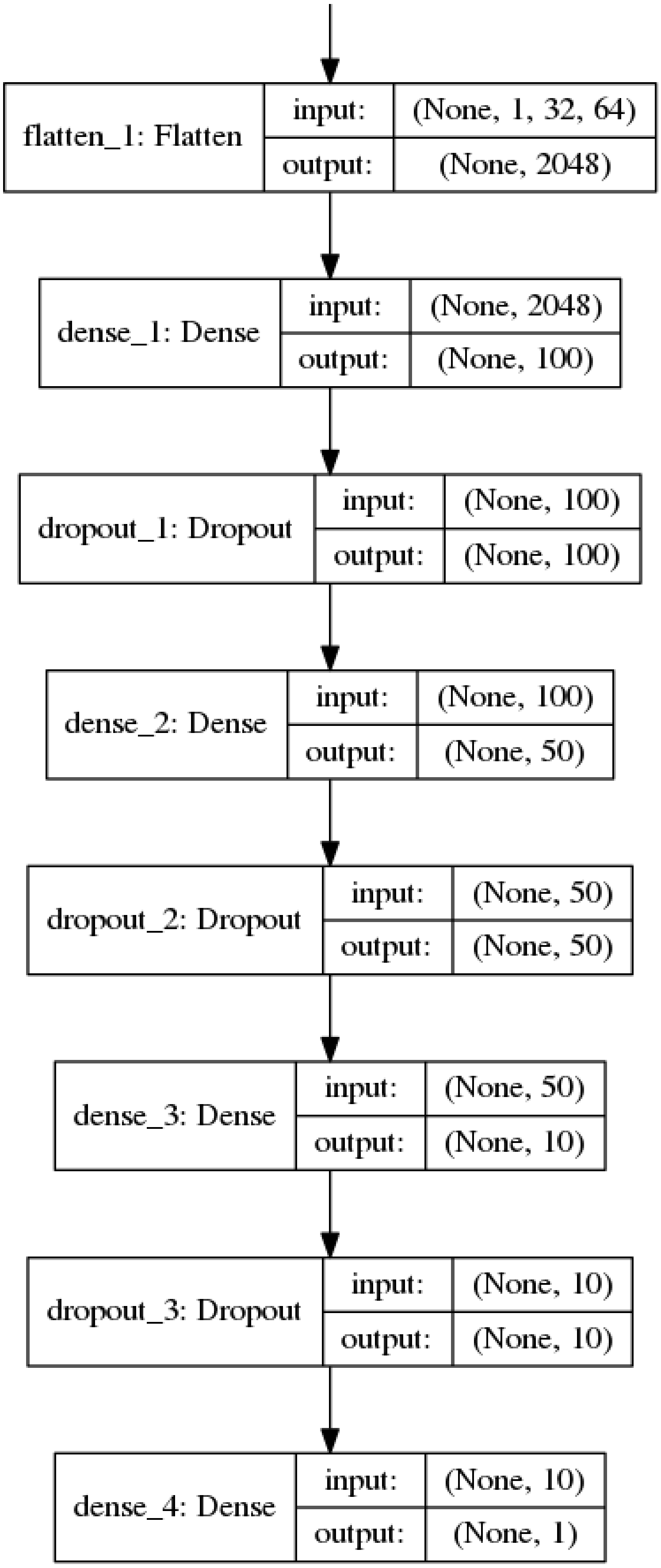
2. Final Model Architecture

- Not counting normalization and cropping I had 5 convolution layers and 3 FC layers (cell-11)

Here is a visualization of the architecture that I obtained by using Keras SCG() function




maxpooling2d_1: MaxPooling2D
input: (None, 70, 316, 24)
output: (None, 35, 158, 24)
convolution2d_2: Convolution2D
input: (None, 35, 158, 24)
output: (None, 31, 154, 36)
maxpooling2d_2: MaxPooling2D
input: (None, 31, 154, 36)
output: (None, 15, 77, 36)
convolution2d_3: Convolution2D
input: (None, 15, 77, 36)
output: (None, 11, 73, 48)
maxpooling2d_3: MaxPooling2D
input: (None, 11, 73, 48)
output: (None, 5, 36, 48)
convolution2d_4: Convolution2D
input: (None, 5, 36, 48)
output: (None, 3, 34, 64)
maxpooling2d_4: MaxPooling2D
input: (None, 3, 34, 64)
output: (None, 3, 34, 64)
convolution2d_5: Convolution2D
input: (None, 3, 34, 64)
output: (None, 1, 32, 64)
maxpooling2d_5: MaxPooling2D
input: (None, 1, 32, 64)
output: (None, 1, 32, 64)

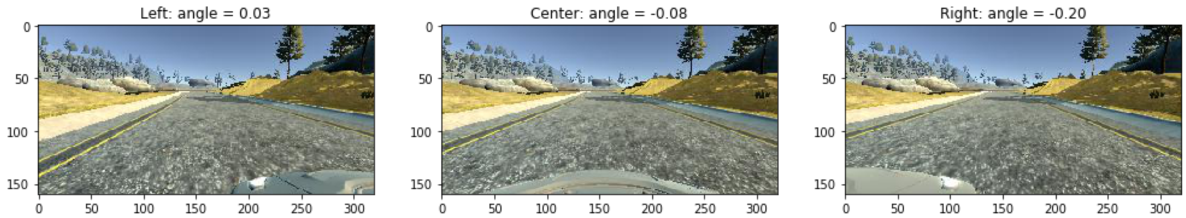


- The number if trainable parameters are calculated in cell-12

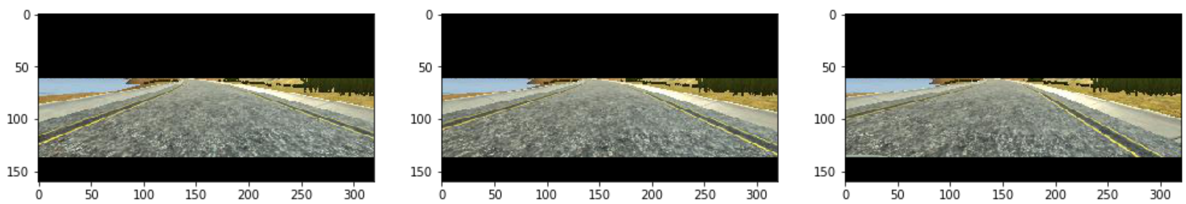
Conv layer 1 complexity = 1875
Conv layer 2 complexity = 22200
Conv layer 3 complexity = 44100
Conv layer 4 complexity = 28080
Conv layer 5 complexity = 37440
Conv complexity = 133695
FC layer 1 complexity = 206848
FC layer 2 complexity = 5100
FC layer 3 complexity = 550
FC complexity = 212498
Total trainable parameters = **346,193**

3. Creation of the Training Set & Training Process

- Original capture:
  - 2 laps on track counterclockwise
  - 1 lap on track clockwise
  - some sharp turns
  - for a total of 9767 images
- Doubled data set by using left-right flip function np.fliplr()
  - for a total of $9767 \times 2 = 19,534$ images
- Increased original data by 60% by incorporating some left and right camera images
  - for a total of $31,287$ images
  - originally, I also applied right/left flip on the side cameras but then decided to not use them since I was trying to limit the side camera images, in order to control oscillations (as discussed above)
  - here is an image from the three cameras



  - I calculated the left and right steering angles from center angle as discussed in Appendix
- To minimize clutter, cropped images
  - TOP_CROP = 62 # where to crop at top of image
  - BOTTOM_CROP = 24 # where to crop at bottom of image
  - the cropped image has $160 - 62 - 24 = 74$ rows of pixels
  - here is the cropped images from the three cameras



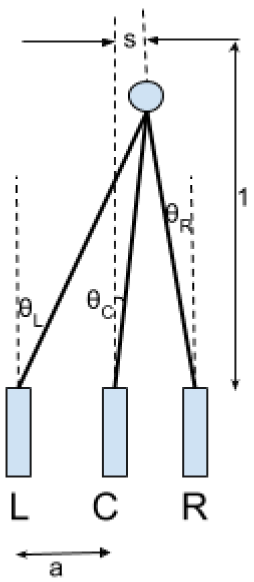
- I finally randomly shuffled the data set and put 25% of the data into a validation set

Concluding Remarks

- Since the car stayed within lanes, I had to push the the speed limit from 9 to 20 mph
    - Containing oscillations and sharp turns were the main challenges I was struggling with
    - The car still oscillates on a straight line, but well within the lane lines
    - The car also performs sharp turns at high speeds
    - All this can be watched on run1.mp4
- It was interesting to observe how important the training data is for the network to be a successful one
- Other attempts
    - I tried to train on second track but could not stay center, even at low speeds
    - I tried to put a PI and P controller on steering angle (rather than the speed), to control oscillations, without much success, a PID system may be more promising

Appendix

- The model is shown below



- Normalized the vertical distance from cameras to point of interest to be 1
- Denoted by s, the horizontal displacement from center camera corresponding to the steering angle θ_C,
    - θ_C and s are related as follows

$$\theta_C = \frac{180}{\pi}\tan(s) \Rightarrow s = \arctan\left(\frac{\pi}{180}\theta\right)$$

- If the side cameras are a units to the left & right of center camera, then the associated angles θ_L & θ_R are given respectively as

$$\theta_L = \frac{180}{\pi}\tan(s + a)$$

$$\theta_R = \frac{180}{\pi}\tan(s - a)$$

- In summary, the parameter to be calibrated is a, and given a, the right and left angles can be calculated from θ_C in 2 steps:
    1. from $\theta_C \to s$
    2. from $s, a \to \theta_L, \theta_R$