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

Rubric Points

Here I will consider the [rubric points]() individually and describe how I addressed each point in my implementation.

Files Submitted & Code Quality

1. 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
- writeup*report.md or writeup*report.pdf summarizing the results

2. 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`

3. Submission code is usable and readable

The model.py file contains the code for training and saving the convolution neural network. The file shows the pipeline I used for training and validating the model, and it contains comments to explain how the code works.

Model Architecture and Training Strategy

1. An appropriate model architecture has been employed

My final model consisted of following layers:

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Layer	Description
Input	160x320x3 RGB image
Cropping	Cropping 70 from top and 20 from bottom, Output = 70x320x3
Convolution 5x5	2x2 stride, relu activation, valid padding, Output = 32x163x24
Dropout	p=0.2, Output = 32x163x24
Convolution 5x5	2x2 stride, relu activation, valid padding, Output = 14x80x36
Dropout	p=0.2, Output = 14x80x36
Convolution 5x5	2x2 stride, relu activation, valid padding, Output = 5x38x48
Dropout	p=0.2, Output = 5x38x48
Convolution 3x3	1x1 stride, relu activation, valid padding, Output = 3x36x64
Dropout	p=0.2, Output = 3x36x64
Convolution 3x3	1x1 stride, relu activation, valid padding, Output = 1x34x64
Flatten	Output = 3x36x64
Dense	Output = 100
Dropout	p=0.5, Output = 100
Dense	Output = 50
Dropout	p=0.3, Output = 50
Dense	Output = 10
Dense	Output = 1

2. Attempts to reduce overfitting in the model

- The model contains several dropout layer
- The model was trained with data from many laps of track recording.
- The data includes several recovery instances when 🚗 is very close to track.

3. Model parameter tuning

- The model used an adam optimizer, so the learning rate was not tuned manually (model.py line 107).
- The model was tested on several correction for side camera but the value of 0.2 seemed to produce better result.
- Several epochs were tried from 1 to 20 but the loss seems to increase and decrease when the epochs are more. Three epochs of training produces satisfactory result.

4. Appropriate training data

- The data consist of many lap of driving.
- The data includes clockwise and counter clockwise driving.
- The data includes recovery driving when the 🚗 reaches very close to left or right lane boundary.
- The data is augmented as well.

Model Architecture and Training Strategy

1. Solution Design Approach

- First I tried using LeNet model but it did not produce great result.
- Later I tried the model developed by [Nvidia]() which seemed to work fine but the 🚗 went offside road after a while.
- The I started updating the model.
    - One obvious approach was to intoduce dropout.
    - Later I did experiment with different number of epochs.
    - I even tried varying the correcting angle for left and right 📸 images.
- The model seemed fine but it did not work perfectly.
- More data was collected and all the images (left, right and center) were flipped and a negative corresponding correction was applied.
- To test the model, `drive.py` was run with the saved `model.h5` and the simulator was launched in autonomous mode.
- The simulator seemed to work fine and the 🚙 did not move off the track.

2. Final Model Architecture

The final model architecture (model.py lines 88-106) consisted of a convolution neural network with the following layers and layer sizes:

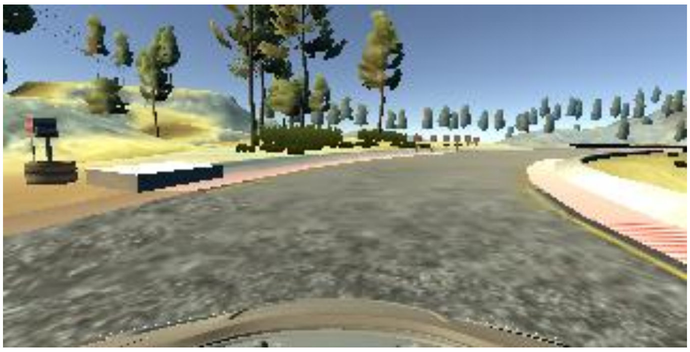
Layer	Description
Input	160x320x3 RGB image
Cropping	Cropping 70 from top and 20 from bottom, Output = 70x320x3
Convolution 5x5	2x2 stride, relu activation, valid padding, Output = 32x163x24
Dropout	p=0.2, Output = 32x163x24
Convolution 5x5	2x2 stride, relu activation, valid padding, Output = 14x80x36
Dropout	p=0.2, Output = 14x80x36
Convolution 5x5	2x2 stride, relu activation, valid padding, Output = 5x38x48
Dropout	p=0.2, Output = 5x38x48
Convolution 3x3	1x1 stride, relu activation, valid padding, Output = 3x36x64
Dropout	p=0.2, Output = 3x36x64
Convolution 3x3	1x1 stride, relu activation, valid padding, Output = 1x34x64
Flatten	Output = 3x36x64
Dense	Output = 100
Dropout	p=0.5, Output = 100
Dense	Output = 50
Dropout	p=0.3, Output = 50
Dense	Output = 10
Dense	Output = 1

3. Creation of the Training Set & Training Process

- The training data was captured over multiple laps of driving.

- The center lane driving was done for more than a lap.

- A lap of clockwise and counter-clockwise driving was also done.



- To simulate recovery the car was driving very close to left and right boundary.

- The data was also augmented by flipping the images.
- The data was then shuffled before training.
- A traing and validation set was created out of shuffled data.
- Training data was used to train the model while validataion data was used to determine how well model was.
- The model did underfit, so more data was collected.

- The dropout was also introduced in the model.
- The loss was increasing after certain number of epochs. three epochs seemed to give better result.
- The value of correction was also varied to find a better value but `0.2` seemed to work fine.
- `adam` optimizer was used to optimize learning rate.