Behavioral Cloning

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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

```
python drive.py model.h5
```

```
You can run Track 1 with a speed of 30 and Track 2 with a speed of 15.
```

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 model consists of a convolution neural network that is largely based on the architecture of NVIDIA (https://devblogs.nvidia.com/deep-learning-self-driving-cars/) and has been extended by some dropouts between the fully connected layers.

From line 97 (function "build_NVIDIA ()") the model is created.

2. Attempts to reduce overfitting in the model

The model contains dropout layers in order to reduce overfitting (model.py lines 108, 110, 112).

3. Model parameter tuning

The model used an adam optimizer, so the learning rate was not tuned manually (model.py line 115).

4. Appropriate training data

The training data consists of a separate set of training images of track 1 and track 2. All 3 images (left, center, middle) were used.

Model Architecture and Training Strategy

1. Solution Design Approach

The overall strategy for deriving a model architecture was to use an existing architecture and adapt it to my training data.

The first step was to use a convolution neural network similar to the NVIDIA. This is due to documented success a good starting position.

In order to gauge how well the model was working, I split my image and steering angle data into a training and validation set. I found that my first model had a low mean squared error on the training set but a high mean squared error on the validation set. This implied that the model was overfitting.

To combat the overfitting, I modified the model so that I add additional dropout layers.

The final step was to run the simulator to see how well the car was driving around track one. There were a few spots where the vehicle fell off the track. to improve the driving behavior in these cases, I record more training data for this spots.

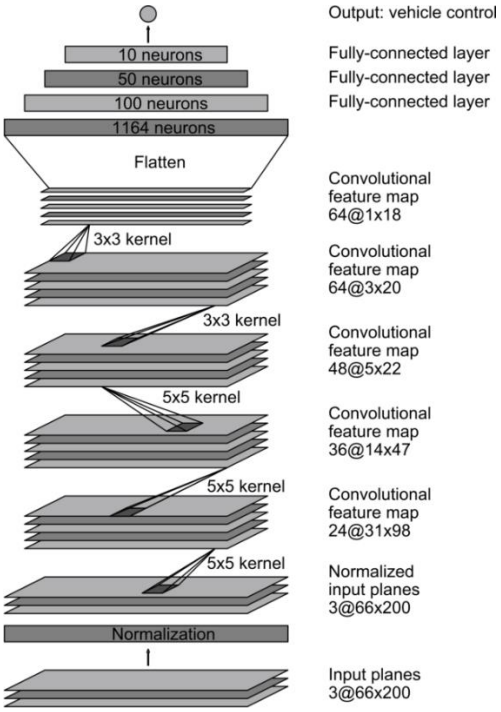
At the end of the process, the vehicle is able to drive autonomously around the track without leaving the road.

2. Final Model Architecture

The final model architecture (model.py lines 97-118) consisted of a convolution neural network with the following layers and layer sizes:

Layer	Description
Input	200x66x3 color Image
Convolution 5x5	2x2 stride, valid padding, RELU activation
Convolution 5x5	2x2 stride, valid padding, RELU activation
Convolution 5x5	2x2 stride, valid padding, RELU activation
Convolution 3x3	1x1 stride, valid padding, RELU activation
Convolution 3x3	1x1 stride, valid padding, RELU activation
Flatten	Output 1164
Fully connected layer	Output 100, RELU activation
Dropout	Rate 0.2
Fully connected layer	Output 50, RELU activation
Dropout	Rate 0.2
Fully connected layer	Output 10, RELU activation
Dropout	Rate 0.2
Output	Output 1 (Steering)

Here is a visualization of the original NVIDIA architecture:



3. Image Preprocessing

Preprocessing the images takes 2 steps:
- cropping (to remove unnecessary image data, e.g. Trees, the horizon, etc.)
- resizing (to fit the 200x66 input size for NVIDIA architecture)

original Image

cropped image

resized image

4. Creation of the Training Set & Training Process

To capture good driving behavior, I first recorded two laps on each track using center lane driving. Here are example images of left, center and right lane driving (from Track 2):

I repeated this process on both tracks in order to get more data points.
In addition to that, I also did the tracks counter-clockwise.

To modified the data, I flipped the images in 50% of the cases in which driving was not straight ahead.

I finally randomly shuffled the data set and put 20% of the data into a validation set (model.py line 116).

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 3 with a batch size of 128. I used an adam optimizer so that manually training the learning rate wasn't necessary. Here's the plot of my „model mean squared error loss".