SDCND Behavioral Cloning

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1 Intro

The project is a homework assignment for Udacity's **Self Driving Car Nano Degree**. The project is the 4th one called *Behavioral Cloning*.
The task is to train a neural network to mimic the driving recorded by driving through a car- track simulation. The goal accuracy is to be able to drive a whole lap within the simulation "autonomously", meaning by letting the (convolutional) neural network do the driving (the NN actually only controls the steering angle, not all possible input parameters).

2 The project

2.1 Result files

The project contains 2 sets of results, both of which actually manage to do the autonomously lap. There are 2 slightly different models, the actual training and validation data used was the same (a dataset named "test04").

model-file	model-program	video
`test04.cnn.model`	`model.py`	`model_test04.mp4`
`test04.cnn.model2`	`model2.py`	`model2_test04.mp4`

The second model is way bigger and github would not let me upload it, so I did split the actual model file which could be reconstructed with:
"`cat test04.cnn.model2??  > test04.cnn.model2`"
I copied the model-file and video of the 1st model to "model.h5" and "video.mp4" as these were the defined expected file names.

2.2 Implementation and experimentation

I choose to implement everything on my local computer.

Step 1, acquiring training/validation data this was done locally several times by driving a few laps in the sim and renaming the resulting simulation-log file.

Step 2, preprocessing I first wrote a preprocessing script (`preprocess.py`) that would gather data from selected simulation runs (by taking the respective file names as input) under a specified "training-set-name" and generate randomly shuffled training/validation/test subsets thereof (70/20/10

Step 3, regression I then wrote a script (`simple_regression.py`) that would try to learn a simple regression model from the training data, that I could run with the simulation.
I hoped to get a better "feel" for the setup with this. But the my regression models would not work as hoped in the simulation (the car kept driving of the track) and I abandoned the regression model.

Step 4, the CNN models I then implemented a CNN model heavily inspired by the network I implemented for the traffic signs. I did change some of the parameters. I first tried to use a NN without dropout, but that would heavily

overfit so I (re-) inserted drop-out layers.
I also used the recommended flip- the image approach to get double the input data and transformed the images to RGB colour space (as used by "drive.py"). Both model implementations use the adam- optimizer to do the training for simplification reasons.

Step 5, more training data At first I had difficulties with getting to the full lap (the car drove into the water after half of it). I decided to heed the suggestion and collected more training data by doing a training simulation where I explicitly drove towards the sides of the track almost leaving it before I corrected the steering, hoping the NN would learn to "drive back to the middle of the track" by example.
This seemed to have worked! as the resulting model would achieve the desired lap after using the new data *in addition* to the previously used data.

1st CNN model version :
The python source `model.py` contains the first successful version of the model I implemented, meaning the first version while playing with the models layers (size, number, types of layers and their respective parameters), that I could use to save a model that could steer the demanded full lap in autonomous mode.

Basic model features:

- starts with cropping and normalization layers (the lambda- approach, that was recommended)
- some conv.- layers with ReLU activation and following max- pooling
- some dense/ fully connected layers with ReLU activation and following dropout
- final dense layer without activation

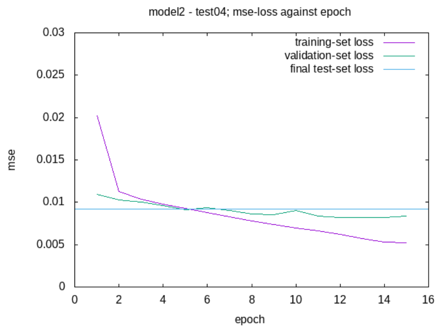
2nd CNN model version :
The python source `model2.py` contains a slightly different model architecture based on the first one and reflecting further experiments I carried out.
Here I used more layers, varied some of the size parameters and used only one dropout layer (between the flattening- layer after the last conv.- layer before the first dense- layers instead of between dense layers).

2.3 Additional results

Loss per episode the following graphics show the training and validation- loss per episode for one example each of the 2 model versions (the dataset "test05" is smaller one and the resulting model is not as good a driver as when using "test04" data).
I found it remarkable, that the validation- loss starts below the training- loss even though my usage of "mse" as a loss function should be independent on size and I expected that the loss would always be smaller for the data used to train the model.
Also, the progression of the loss suggests, that there is still overfitting, but I

guess the best approach here would be to use just lots more training data (I did not have).

2nd model version “test04” dataset



1st model version with “test05”