Behavioral Cloning Project

Model Architecture and Training Strategy

1. An appropriate model architecture has been employed

Initially I used LeNet architecture with 10 Epochs but the car was too much wavy going left and right even in a straight road, but still it was good enough to reach till the end. Anyways, I still created the Nvidia Autonomous Car Group model and the car drove completely fine through the first track with 3 epochs.

LeNet's architectural model summary is as follows:

Layer (type)	Output Shape	Param #
lambda_1 (Lambda)	(None, 160, 320, 3)	0
cropping2d_1 (Cropping2D)	(None, 90, 320, 3)	0
conv2d_1 (Conv2D)	(None, 86, 316, 6)	456
max_pooling2d_1 (MaxPooling2	(None, 43, 158, 6)	0
conv2d_2 (Conv2D)	(None, 39, 154, 6)	906
max_pooling2d_2 (MaxPooling2	(None, 19, 77, 6)	0
flatten_1 (Flatten)	(None, 8778)	0
dense_1 (Dense)	(None, 120)	1053480
dense_2 (Dense)	(None, 84)	10164
dense_3 (Dense)	(None, 1)	85

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dropout_1 (Dropout)   (None, 1)   0

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Total params: 1,065,091

Trainable params: 1,065,091

Non-trainable params: 0

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None

Nvidia's Autonomous car architectural model summary is as follows:

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Layer (type)   Output Shape   Param #

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lambda_1 (Lambda)   (None, 160, 320, 3)   0

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cropping2d_1 (Cropping2D)   (None, 90, 320, 3)   0

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conv2d_1 (Conv2D)   (None, 43, 158, 24)   1824

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conv2d_2 (Conv2D)   (None, 20, 77, 36)   21636

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conv2d_3 (Conv2D)   (None, 8, 37, 48)   43248

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conv2d_4 (Conv2D)   (None, 6, 35, 64)   27712

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conv2d_5 (Conv2D)   (None, 4, 33, 64)   36928

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flatten_1 (Flatten)   (None, 8448)   0

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dense_1 (Dense)   (None, 100)   844900

dense_2 (Dense)	(None, 50)	5050
dense_3 (Dense)	(None, 10)	510
dense_4 (Dense)	(None, 1)	11

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Total params: 981,819

Trainable params: 981,819

Non-trainable params: 0

None

2. Attempts to reduce overfitting in the model

Training and validation sets were used and was split as 80% and 20% respectively. LeNets architectural model was overfitting as the model's training loss was very less while the validation loss was too high. So, I added a dropout with a rate of 0.5 to reduce overfitting. Also, I collected more data through the same track and places were the car was going over the ledges. Also, by augmenting the data/flipping the image, the collected data just got doubled. I even used the side images along with the center images with 0.2 as the correction factor. This also increased the number of samples/data.

3. Model parameter tuning

The model used an Adam optimizer, so the learning rate was not tuned manually. Also, below are the hyper parameters which I used to fine tune the model.

```
# Hyper parameters to fine tune

input_shape = (160, 320, 3)
num_of_epochs = 3
lenet_conv_filters = 6
lenet_conv_kernel_size = (5, 5)
dropout_rate = 0.5
validation_split = 0.2  # 20% Validation and 80% Training
correction_factor = 0.2
correction = [0.0, correction_factor, -correction_factor]  # [center, left, right]
batch_size = 32
```

4. Appropriate training data

I generated the training data by using the simulator. With just the first track dataset, the car couldn't stay completely on the road as it went directly to the lake. So, I took more data in those areas where there are curves and where I felt that the car might go over the ledge. With the help of augmented data and side images, there were more data which helped the model to learn more. However, this led to overfitting the model and I had to use dropout to bring out a better model.

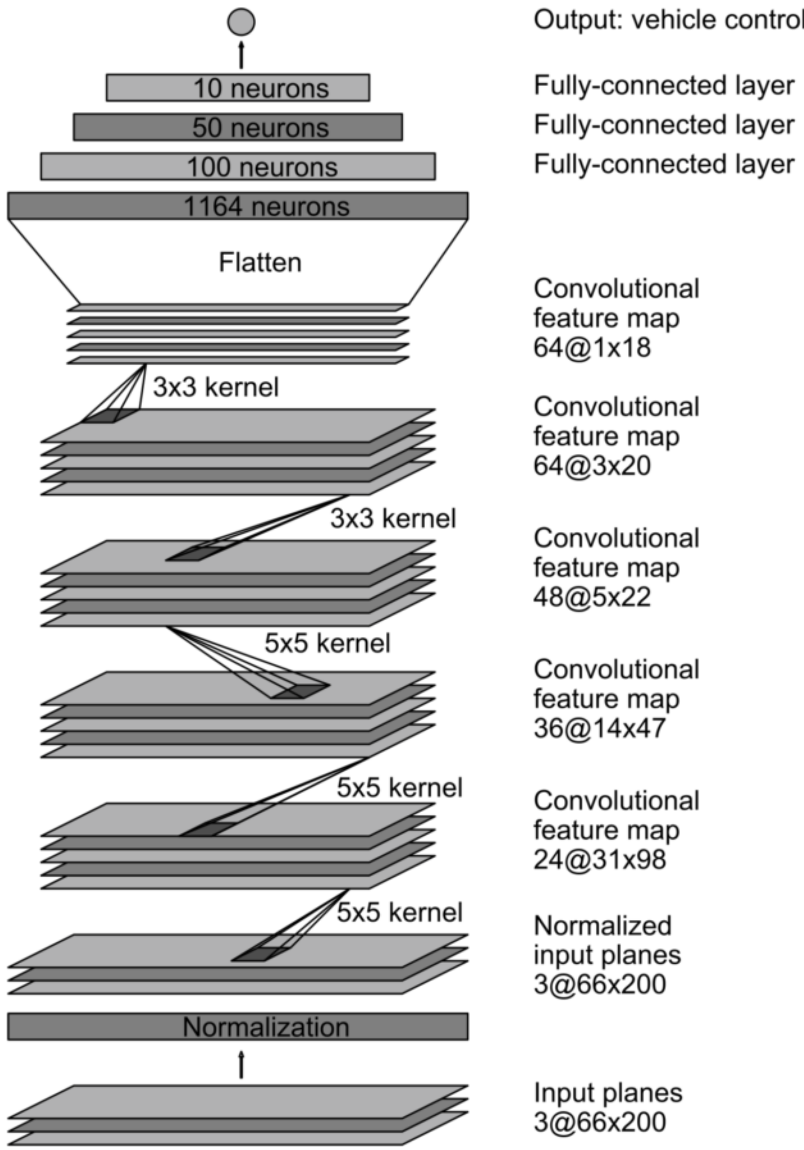
More Explanation

1. Solution Design Approach

My first step was to try the LeNet(http://yann.lecun.com/exdb/lenet/) model with 10 epochs and the training data obtained by driving properly in the center of the road. But the car went straight to the lake. Anyways, I included some data preprocessing by normalizing the data and then cropping the top and bottom of each image. However, even the data preprocessing did not help completely as it went directly to the second lake. Looking at the training and validation loss, I realized that the model is overfitting and added a dropout layer as well. The model got better but still couldn't make it till the end of the track. Finally, I generated some more training data, but this time I generated data from places where the car was making mistake by teaching it to swerve better while it is just about to roll over the ledge. This helped a lot as the model learned to escape during those situations and could complete the track properly. But the car was completely shaky/swervy throughout the track as I think the model keeps on predicting left and right even though it is a straight road. So, I started exploring Nvidia's architectural model and once I added that model and used the same datasets to train, the car could completely go till the end of the track with not that much wavy. So, the person sitting in that car would definitely experience a pleasant drive.

2. Final Model Architecture

The model architecture which was chosen is Nvidia Autonomous car Group's architectural model and is shown in the below image:

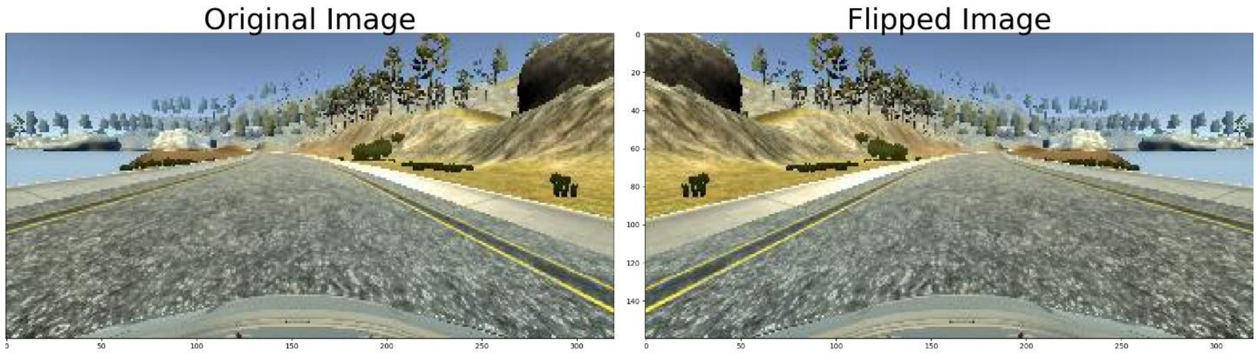


Taken from https://devblogs.nvidia.com/deep-learning-self-driving-cars/

The summary of the model which I used was explained earlier in the 1st point.

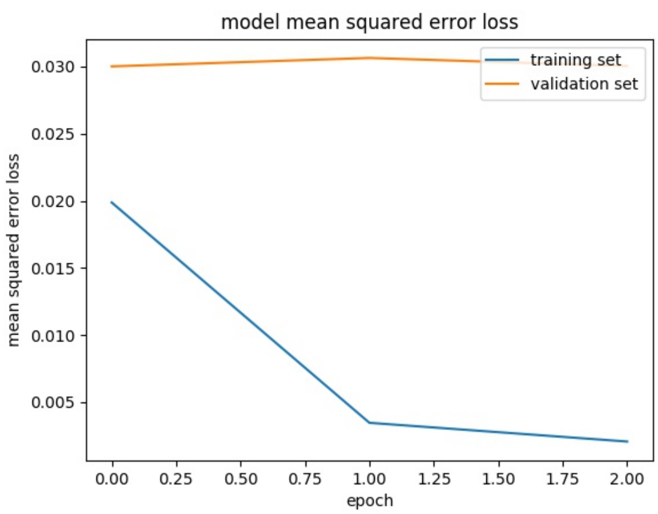
3. Creation of the Training Set & Training Process

To have more data, data was augmented/flipped, thus helping the car not to be left biased always. Below is an example image used to obtain a flipped image.



Apart from flipping the image, the side images along with center images were used with a correction factor of 0.2. This along with augmenting, gave about 21432 samples.

All these data was used for training the model with three epochs. The data was shuffled randomly. The following picture visualizes the mean squared error loss vs epoch for both training and validation set:



4. Code Explanation:

```
# Enabling/Disabling switches
ENABLE_SIDE_IMAGES = 1
ENABLE_FLIPPING_IMAGES = 1
ENABLE_PICKLE = 1
ENABLE_FOR_PC = 1
```

Above are switches to enable or disable it. Only with ENABLE_SIDE_IMAGES and ENABLE_FLIPPING_IMAGES being set, I could get a better accuracy. Also, I used Pickle file to work locally in my laptop while training the model as it was faster to load from a pickle file rather than parsing the csv file and then augmenting and adding the images/measurements to the list. This can be enabled by setting ENABLE_PICKLE which will check for “images.p” or “measurements.p” and if either of them is not found, it creates them from scratch. ENABLE_FOR_PC switch is required to set the image path while training the model in my laptop and it needs to be disabled while training in the workspace.

“create_model” is the function which takes in the samples and the type of model (‘LeNet’ or ‘Nvidia’). Based on the type, the appropriate model is created, compiled and saved as my_model_LeNet.h5 or my_model_Nvidia.h5. The model which I have submitted is obtained from Nvidia’s model as the name says. Also, generator with batch size of 32 were used to generate the training and validation samples required for the model.

Also, the directory “working_model” has all the different models I tried and found to be working for the first track along with one video which I generated. The directory “final_run” has all the images of the drive.py which I used to make the video.mp4.