Behavioral_Cloning

May 18, 2019

0.1 # Udacity Self-Driving Car Nano-Degree -- Behavioral Cloning

In this project the goal is to use a Unity car driving simulator (provided to me from Udacity) to take samples of images taken from a simulated, forward facing set of cameras, while traveling around a track under my control. From that data, I will train a neural network to map camera images to steering angles. If this is done with high enough accuracy, then the simulation should be able to steer itself successfully around the track, nearly cloning the steering behavior that I controlled the simulation with.

0.2 Taking the Data

The data for this project was generated by use of the Udacity driving simulator from which I collected driving data around a sample closed circuit track. The simulator allows the user to use WASD controls to accelerate, brake, and control the turning angle. Alternatively one can use mouse input for fine tuned steering control. I used the mouse support to take the data in the case studied here. I drove around the track a total of 3 times, once driving down the center of the lane, once with my left tire on the most left yellow lane marker as seen in the image below, and once with the right tire on the right most yellow lane marker.

The simulator samples images along the path the user takes, with three images taken for each sample. One image in the direct center of the car, one to the left of center of the car, and one to the right of center of the car. These images are stored in a directory that is generated during recording, along with a data dictionary. The data dictionary contains file paths for each image, along with the recorded steering wheel turning angle at the time of the samples. Left turning is represented as a negative turning angle, and right turning is taken as positive turning angle. The justification for my particular sampling method is explained in the sections below. Please note that this training data is not included in the git repo as it would make the repository too large, and the results in this notebook are demonstrations of the output when the training data is present.

[3]:
```
# Import all the required packages for this project
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

import cv2
from glob import glob
import os
```

```
import pickle

%matplotlib inline
```

[121]:
```
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split

from tensorflow.keras.models import Model,Sequential
from tensorflow.keras.layers import Lambda,Cropping2D,Input,Flatten
from tensorflow.keras.layers import␣
↪Convolution2D,GlobalAveragePooling2D,BatchNormalization
from tensorflow.keras.layers import Dense,Activation,Dropout
from tensorflow.keras.applications.resnet50 import ResNet50,preprocess_input
```

[5]:
```
import tensorflow as tf
```

0.3 ## Data Exploration and Processing

0.3.1 Unified Datasets

The first step in producing a model for this task, is understanding the data we have for this task. The data is segmented into 3 seperate directories and in 3 seperate data dictionaries. Our model will need to be trained on single images, and single steering angles, so we need to transform the form of the data into something useful for our neural network.

First I will be unifying all the data into a single record. The method of taking data provided by Udacity leaves each sessions image's stored in a separate directory labeled "IMG" and a data dictionary "driving_log.csv." There are 3 images for every sample, as described in the data taking section, but only one steering angle. We need to extract each image file path and map it to a steering angle that would keep the vehicle centered in the lane. Thus for data recorded on the center lane, the left camera should slightly correct the steering angle by turning in to the right, and the right camera should slightly steer into the left with respect to the recorded steering angle. This hopefully will allow the network to learn that seeing certain features that correspond to being left or right of center should be corrected to move toward the center.

Furthermore, because we know the neural networks typically perform well when tested in-sample, I recorded two other sets of data in addition to driving down the center of the lane. In one of the additional samples, I drove around the track with my left tire on the left-most lane marker, and in a third sample I drove around the track with the right tire on the right-most lane marker. These steering angles were modified such that, for the left tire data, the right camera should slightly correct to the right from the steering data, the center camera image should correct strongly toward the right from the steering data, and from the left camera we should correct most strongly toward the right from the steering data. The opposite is done with the right tire data.

The idea is that when we have samples for many possible positions along the width of the lane at all points on the track, the neural network should be able to generalize well for any position within the lane and interpolate the correct steering angle. One might imagine this method as sampling a vector field that represents the steering angle that moves the vehicle toward the lane center but still navigating the track at all points along the track as is visualized in the figure below:

In the image the distance from lane center is measured along the blue line, and the additional steering correction is represented by the red arrows, such that as you move away from lane center the intensity of steering correction also increases.

I implement these ideas in the code sample below. Please note that I did not include the data in the git repo as it would be too large but am showing the results in this notebook for my local results.

[17]:
```
# find how many directories are in the total data set,
# each with IMG, and driving_log.csv in each directory
data_dirs = glob(os.path.join("./train_data/*", ""))
print(data_dirs)
```

```
['./train_data/right/', './train_data/center/', './train_data/left/']
```

0.3.2 Unifying Data Directories Into Single (left,center,right,angle) Set

[37]:
```
np.random.seed(1337) # seed is set so you get consistant results for each run

def unify_data_set_samples(data_dirs):
    path = 'IMG'
    data_dict_path = 'driving_log.csv'

    # initialization of object to hold all file
    # paths and steering angles
    x_rows = []

    # for each directory, open the driving_log.csv
    for dir in data_dirs:
        csv_file = os.path.join(dir,data_dict_path)
        new_rows = []# init an empty list
        with open(csv_file, 'r') as f:
            rows = pd.read_csv(csv_file,
                               header=None,
                               skiprows=1)
            # assign column names to csv dataframe
            rows.columns = ['center','left','right','steering','t','b','c']
            # extract the numpy array
            rows = rows[['center','left','right','steering']].values

            #shuffle the dataset
            ridx = np.random.choice(range(len(rows)),len(rows),replace=False)
            rows = rows[ridx]

            # concatante all of the file paths and steering angles,
            # into a single numpy matrix
            for row in rows:
                img_c_path = os.path.join(dir,path,(row[0].split('/')[-1]).
↪strip())
```

```
                img_l_path = os.path.join(dir,path,(row[1].split('/')[-1]).
↪strip())
                img_r_path = os.path.join(dir,path,(row[2].split('/')[-1]).
↪strip())
                steering_center = float(row[3])

                new_row = np.
↪array([[img_c_path,img_l_path,img_r_path,steering_center]])
                new_rows.append(new_row)

        # combining object with the other objects
        x_rows.append(new_rows)

    #convert to numpy object
    x_rows = np.array(x_rows)
    x_rows = np.concatenate(x_rows).ravel()
    x_rows = x_rows.reshape(-1,4)
    return x_rows
```

[38]:
```
sample_paths = unify_data_set_samples(data_dirs)
```

[39]:
```
sample_paths.shape
```

[39]:
```
(10975, 4)
```

0.4 Reshape and Augment

With all of the data collected into a single numpy array, I need to form the data into, (file path, steer angle) pairs that will be used for training the neural network. In order to do that, I iterate through each row of the unified numpy array, and for each file path, if the file is coming from the left-tire data I modify the steering angle for each image in accordance with the method outlined above. For explicitness I choose the maximum angle correction to be about 22 degrees. I estimated the camera position where maximum steering correction would be required to be about 5 ft from the lane center (though the units don't play any role here). I assumed the distance between each camera was about 1 ft, e.g. for left-tire data, the left camera would be at 5 ft to the left of lane center, the center camera would be 4 ft to the left of lane center, and the right camera would be 3 ft of lane center in all images.

I used linear scaling such that for each camera position the steering angle would be given by, $\alpha' = \alpha_{\text{center}} + \left(\frac{22^\circ}{5\text{ ft}}\right) x_\perp$

where $x_\perp$ is the perpendicular (with respect to direction of travel) camera distance from lane center, with left of lane center represented by positive values of $x_\perp$ and right of lane center represented by negative values. The steering angle as recorded in the data is given by α_{center} and should represent the steering angle if maintaining the lane boundaries regardless of its lane-center distance.

The function below considers each image file path, makes appropriate adjustments to the steering angle and collects all data into (file path, steering angle) pairs.

[41]:
```python
def generate_img_path_angle_pairs(samples_path):
    nsamples = len(samples_path)

    # finding the corrective steering angles
    high_angle = 0.4 # 22 degrees is the max correction I would like to allow
    #find the corrections for each of the possible off lane center distances␣
 ↪recorded
    angle_cuts = high_angle/5*np.array([5,4,3,1])
    angle_cuts = angle_cuts[::-1]

    # shuffling the samples_path
    ridx = np.random.choice(range(nsamples),nsamples,replace=False)
    batch_samples = samples_path[ridx]

    # initialize empty lists for recording
    images = []
    angles = []

    for batch_sample in batch_samples:
        c_img = batch_sample[0]
        l_img = batch_sample[1]
        r_img = batch_sample[2]
        c_steering = float(batch_sample[3])
        directory = (batch_sample[0].split('/'))[-3] # check which correction␣
 ↪type should be used

        # apply aggressive steering to center correction
        if (directory == 'left'):
            # inside edge driving, correct steer right
            l_steering = c_steering+angle_cuts[3]
            r_steering = c_steering+angle_cuts[1]
            c_steering = c_steering+angle_cuts[2]
        elif (directory == 'right'):
            # outside edge driving, correct steer left
            l_steering = c_steering-angle_cuts[1]
            r_steering = c_steering-angle_cuts[3]
            c_steering = c_steering-angle_cuts[2]
        else:
            l_steering = c_steering+angle_cuts[1] #correct steer right
            r_steering = c_steering-angle_cuts[1] #correct steer left

        new_samples = np.array([c_img,l_img,r_img])
        new_angles = np.array([c_steering,l_steering,r_steering])

        images.append(new_samples)
        angles.append(new_angles)
```

```
    images = np.array(images)
    angles = np.array(angles)

    images = images.flatten()
    angles = angles.flatten()

    images,angles = shuffle(images,angles)

    return images,angles
```

[42]:
```
X,y = generate_img_path_angle_pairs(sample_paths)
```

[43]:
```
X.shape
```

[43]: (32925,)

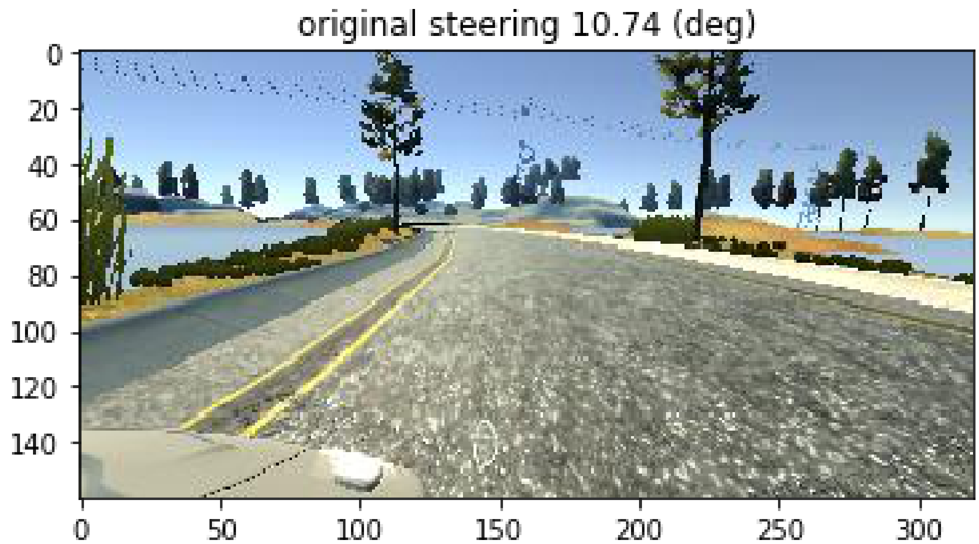
0.5 Data Augmentation to Help Generalization

One of the possible dangers we need to address is that it is possible that our network will be able to run in autonomous mode and correctly steer around the track in a particular direction (say traveling clockwise around the track circuit), but that is indistinguishable from simply recording a sequence of landmarks when to turn the car, or simply maintaining a constant, non-zero turn angle and getting lucky vs. actually learning to identify features of the images that allow it to learn to turn left or right on different tracks. In order to help our network be able to accomplish this task, we are going to augment the data such that for each image, it's mirror image about the central vertical axis will also be included in the dataset, along with the negative of the steering angle. This should be able to break any asymmetry in the steering angle distribution that would favor a particular turning angle from the car data.

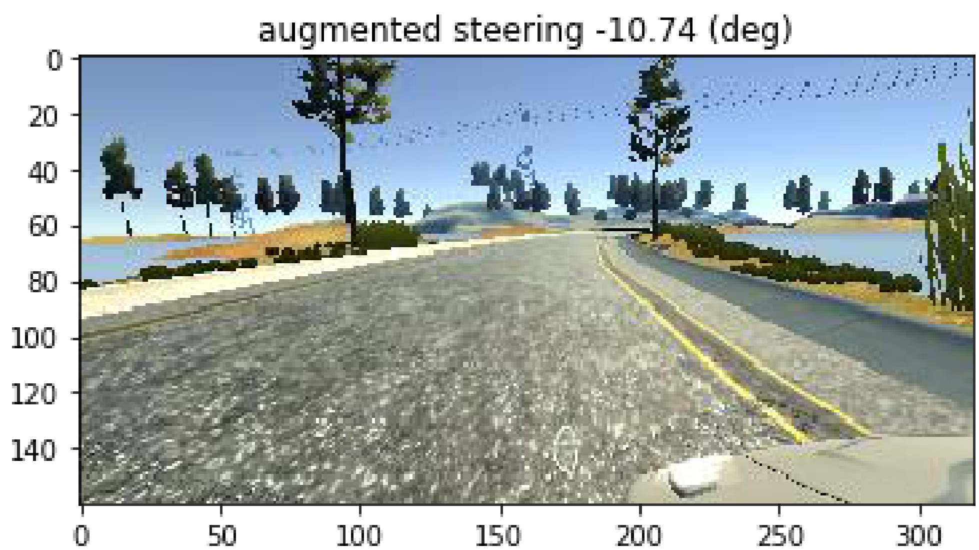
[44]:
```
def augment(X,y):
    X_flips = np.array([np.fliplr(xi) for xi in X])
    y_flips = np.array([-yi for yi in y])

    X_aug = np.concatenate((X,X_flips))
    y_aug = np.concatenate((y,y_flips))

    X_aug,y_aug = shuffle(X_aug,y_aug)

    return X_aug,y_aug
```

[58]:
```
# example of the augment functionality
sample_x = plt.imread(X[100])
sample_y = y[100]
aug_x,aug_y = augment(np.array([sample_x]),np.array([sample_y]))
```

[59]:
```
plt.imshow(np.uint8(sample_x));
plt.title('original steering '+str(np.round(sample_y*180/3.14159,2))+' (deg)');
```



[60]:
```
plt.imshow(np.uint8(aug_x[0]));
plt.title('augmented steering '+str(np.round(aug_y[0]*180/3.14159,2))+' (deg)');
```

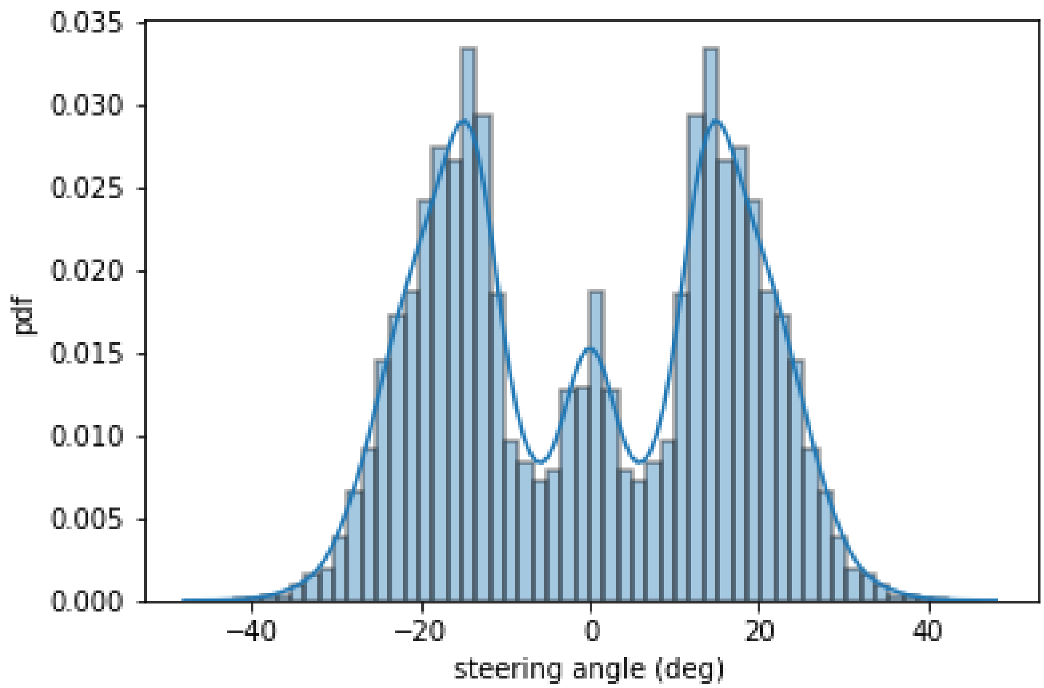


0.6 Steering Angle Distribution

As is the case in all machine learning tasks, we want to be confident our model is actually making use of the input features, and not learning a generalization of the univariate targets. In order to assess that, we look at the steering angle distribution and compute a base line mean-sqaure error (MSE) optimal value (the mean of the target data as the single optimal parameter) so that we can know if our model is significantly outperforming this value or making only slight use of the input features to find a correlation.

[61]:
```
y_targs = np.concatenate((y,-y))
```

[63]:
```
sns.distplot((y_targs*180/np.pi),norm_hist=True,hist_kws=dict(edgecolor="k",␣
 ↪linewidth=1.5));
plt.xlabel("steering angle (deg)");
plt.ylabel("pdf");
```



[64]:
```
mean_targs = np.mean(y_targs)
base_mse = np.mean((y_targs-mean_targs)**2)
print('Base MSE score from mean steering angle: ', np.round(base_mse,2))
```

```
Base MSE score from mean steering angle:  0.09
```

[65]:
```
# optional pickling of the data
with open('./imgs_steer_paths.pkl','wb') as f:
    pickle.dump(sample_paths,f)
```

[ ]:
```
# optional load of pickled data
with open('./imgs_steer_paths.pkl','rb') as f:
    sample_paths = pickle.load(f)
```

0.7 Train and Validation Data Split

I used 20% of the data as validation data and didn't generate any test set as this isn't going to be used in production, so knowing how it would perform "in the wild" isn't really necessary for this task.

[67]:
```
# spliting into a train,validation set, split arrays
# or matrices into random train and test subsets
train_img_paths,valid_img_paths,train_angles,valid_angles =␣
↪train_test_split(X,y,test_size=0.2,random_state=1337)
```

0.8 Creating a Runtime Data Generator

Each image in the data set is stored by matplotlib's imread function as a $160 \times 320 \times 3$ array where each value can take a value between 0 and 255. This would mean the total dataset after augmentation would take up about 75 GB alone! Obviously we can't load all the data into single machine memory, so to overcome this issue we are going to use a data generator, such that a mini-batch of images is loaded into memory used along with a stochastic gradient decent method, we can train our model and immediately release the image data in RAM and continuously load new images from the training data using a single machine.

To do this we create a data generator using the `yield` command from python in the function below, such that mini-batch of size `2*batch_rows` of randomized images is returned with the associated steering angle targets. As a final note, the RGB color channels are converted to YUV color channels before being input to the network, for reasons explained in the next section.

[86]:
```
def data_generator_from_file(paths,targs,batch_rows=32):
    num_rows = len(paths)
    samples,targs = shuffle(paths,targs)

    while 1: # Loop forever so the generator never terminates
        for offset in range(0, num_rows, batch_rows):
            batch_samples = samples[offset:offset+batch_rows]
            batch_targs = targs[offset:offset+batch_rows]

            #initialize batch arrays
            images = []
            angles = []

            for sample,steer in zip(batch_samples,batch_targs):
                img = plt.imread(sample)
                #img = cv2.cvtColor(img, cv2.COLOR_RGB2YUV) #color channel␣
↪convert turned off in the notebook
                images.append(img)
                angles.append(steer)

            images = np.array(images)
            angles = np.array(angles)

            # apply the augmentation steps
```

```
            X_train_batch,y_train_batch = augment(images,angles)

            yield X_train_batch, y_train_batch
```

[103]:
```
#generate an example mini-batch
for x_samples,y_samples in␣
 ↪data_generator_from_file(train_img_paths,train_angles,2):
    break
```

[118]:
```
# visualize some samples from the generator
fig = plt.figure(figsize=(5,10))
fig.subplots_adjust(left=0,right=1,bottom=0,top=1,hspace=0.25,wspace=0.05)

for i,x_sample,y_sample in zip(range(4),x_samples,y_samples):
    title ='steering '+str(np.round(y_sample*180/3.14159,2))+' (deg)'
    img = np.uint8(x_sample)
    axis = fig.add_subplot(4,1,i + 1, xticks=[], yticks=[])
    plt.title(title,fontsize=20)
    axis.imshow(img,aspect="auto")

plt.show()
```

steering 25.93 (deg)

steering 18.18 (deg)

steering -18.18 (deg)

steering -25.93 (deg)

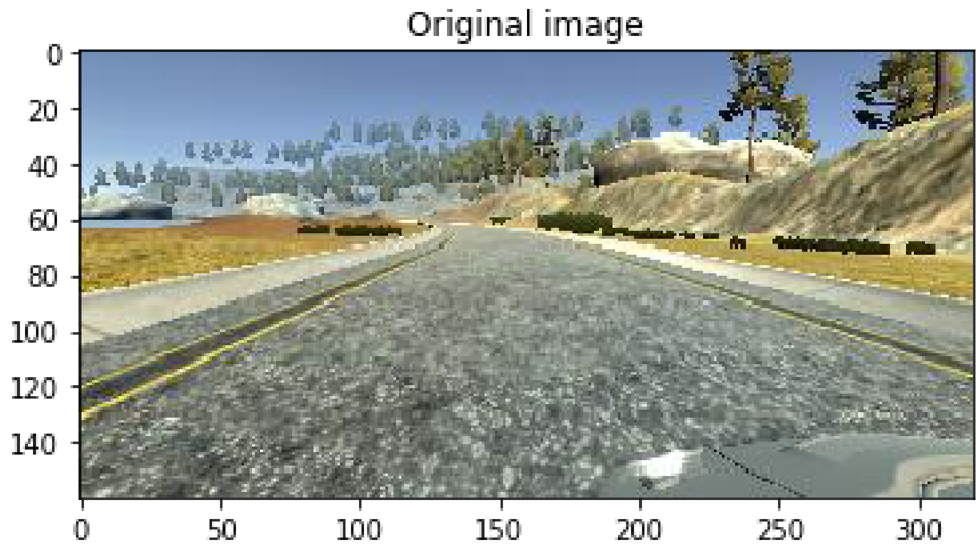
[ ]:
```
# Make the data generator objects for training and validation datasets
# Set our batch size
batch_size = 128 #so we will have 256 images and targets per mini-batch

# compile and train the model using the generator function
train_generator_obj =␣
↪data_generator_from_file(train_img_paths,train_angles,batch_size)
validation_generator_obj =␣
↪data_generator_from_file(valid_img_paths,valid_angles,batch_size)
```

0.9 Model Generation

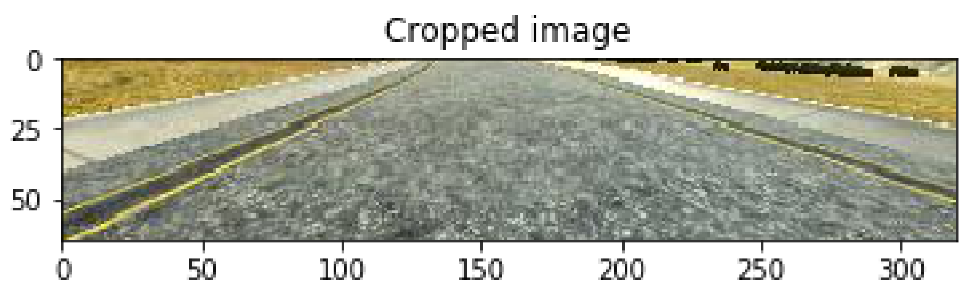
In order to go from center camera image to steering angle, a convolutional neural network nearly identical to the model described here End to End Learning for Self-Driving Cars used by Nvidia researchers M. Bojarski *et al*, to map simulated and real world images to steering angles is employed. The Nvidia model explicitly mentions use of the YUV color channels rather than RGB color channels. This likely helps the network identify lane markings as useful features in various lighting conditions and therefore is used in my network, though I did not check if it empirically made any difference in network performance. The only modification to the network is that data standardization along with image cropping to an area of interest is done within the network, as well as the inclusion of batch normalization layers through out. The batch normalization layers, both speed up training and act as regularizers for the generalization of the driving task. An image of the network architecture is provided below where I've omitted the cropping and standardization step.

The area of interest cropping, is done in such a way that the image is focusing on the road way directly in front of the vehicle such that distant features or features found in the sky can not play a role in determining steering angle. The side effect of this is that this network can only perform well on roads that have almost no inclinations, as you can imagine a case where the cropped image will inadvertently contain the road-sky horizon when approaching the top of a hill. I do not know how the network would react to a strong horizontal gradient like that and it would be an out-of-sample result. I show below a sample of an original input image, and its cropped version so you can see what section of the road is being analyzed during the training.

[92]:
```
ridx = 0
plt.imshow(np.uint8(x_sample[ridx]));
plt.title('Original image');
```



[93]:
```
plt.imshow(np.uint8(x_sample[ridx][65:-30,:]));
plt.title('Cropped image');
```



I suspect that since this network is used on a much larger data set in the Nvidia trial that this network is major overkill as it has 560, 211 free parameters on something like 65, 850 images and one area of additional research would be to reduce the network complexity to find the minimal functioning model for the task.

[122]:
```
def generate_nvidia_model():
    in_rows,in_cols = 160,320
    # define the CNN you want to use with preprocessing layers
    model = Sequential()
    #preprocessing
    model.add(Lambda(lambda x: (x-127.5)/127.5,input_shape=(in_rows,in_cols,3)))
    model.add(Cropping2D(cropping=((65,30),(0,0))))

    #NETWORK
    #conv_layer1
```

```
    model.
↪add(Convolution2D(filters=24,kernel_size=5,strides=(2,2),padding='same'))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    #conv_layer2
    model.add(Convolution2D(filters=36,kernel_size=5,strides=(2,2)))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    #conv_layer3
    model.add(Convolution2D(filters=48,kernel_size=5,strides=(2,2)))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    #conv_layer4
    model.add(Convolution2D(filters=64,kernel_size=3,strides=(1,1)))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    #conv_layer5
    model.add(Convolution2D(filters=64,kernel_size=3,strides=(1,1)))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    #FC layers
    # stack outputs in a flattened vector
    model.add(Flatten())

    model.add(Dense(100))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    model.add(Dense(50))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    model.add(Dense(10))
    model.add(BatchNormalization())
    model.add(Activation('relu'))

    #steering angle
    model.add(Dense(1))

    return model
```

[123]:
```
my_model = generate_nvidia_model()
```

```
WARNING:tensorflow:From /Users/bvlcek/anaconda2/envs/py3/lib/python3.7/site-
packages/tensorflow/python/ops/resource_variable_ops.py:435: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Colocations handled automatically by placer.
```

[124]:
```
my_model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lambda (Lambda)              (None, 160, 320, 3)       0
_________________________________________________________________
cropping2d (Cropping2D)      (None, 65, 320, 3)        0
_________________________________________________________________
conv2d (Conv2D)              (None, 33, 160, 24)       1824
_________________________________________________________________
batch_normalization_v1 (Batc (None, 33, 160, 24)       96
_________________________________________________________________
activation (Activation)      (None, 33, 160, 24)       0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 15, 78, 36)        21636
_________________________________________________________________
batch_normalization_v1_1 (Ba (None, 15, 78, 36)        144
_________________________________________________________________
activation_1 (Activation)    (None, 15, 78, 36)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 6, 37, 48)         43248
_________________________________________________________________
batch_normalization_v1_2 (Ba (None, 6, 37, 48)         192
_________________________________________________________________
activation_2 (Activation)    (None, 6, 37, 48)         0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 4, 35, 64)         27712
_________________________________________________________________
batch_normalization_v1_3 (Ba (None, 4, 35, 64)         256
_________________________________________________________________
activation_3 (Activation)    (None, 4, 35, 64)         0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 2, 33, 64)         36928
_________________________________________________________________
batch_normalization_v1_4 (Ba (None, 2, 33, 64)         256
_________________________________________________________________
activation_4 (Activation)    (None, 2, 33, 64)         0
_________________________________________________________________
flatten (Flatten)            (None, 4224)              0
```

```
_________________________________________________________________
dense (Dense)                (None, 100)               422500
_________________________________________________________________
batch_normalization_v1_5 (Ba (None, 100)               400
_________________________________________________________________
activation_5 (Activation)    (None, 100)               0
_________________________________________________________________
dense_1 (Dense)              (None, 50)                5050
_________________________________________________________________
batch_normalization_v1_6 (Ba (None, 50)                200
_________________________________________________________________
activation_6 (Activation)    (None, 50)                0
_________________________________________________________________
dense_2 (Dense)              (None, 10)                510
_________________________________________________________________
batch_normalization_v1_7 (Ba (None, 10)                40
_________________________________________________________________
activation_7 (Activation)    (None, 10)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 11
=================================================================
Total params: 561,003
Trainable params: 560,211
Non-trainable params: 792
_________________________________________________________________
```

0.10 Model Training

I trained this model on a Nvidia Tesla K80 GPU provided to me by Udacity, using the keras built ADAM optimizer along with mean square error of steering angle as the loss function for this network. Without a GPU this would take a very long time to compute the network parameters, however the code to do so is provided below should you want to execute it. After training for 4 epochs, which took 16 minutes, my final result was a training loss of 0.0022 and a validation loss of 0.0029, which obviously is better than the baseline error. The learning chart shows only slight overfitting but more epochs would be needed to confirm this.

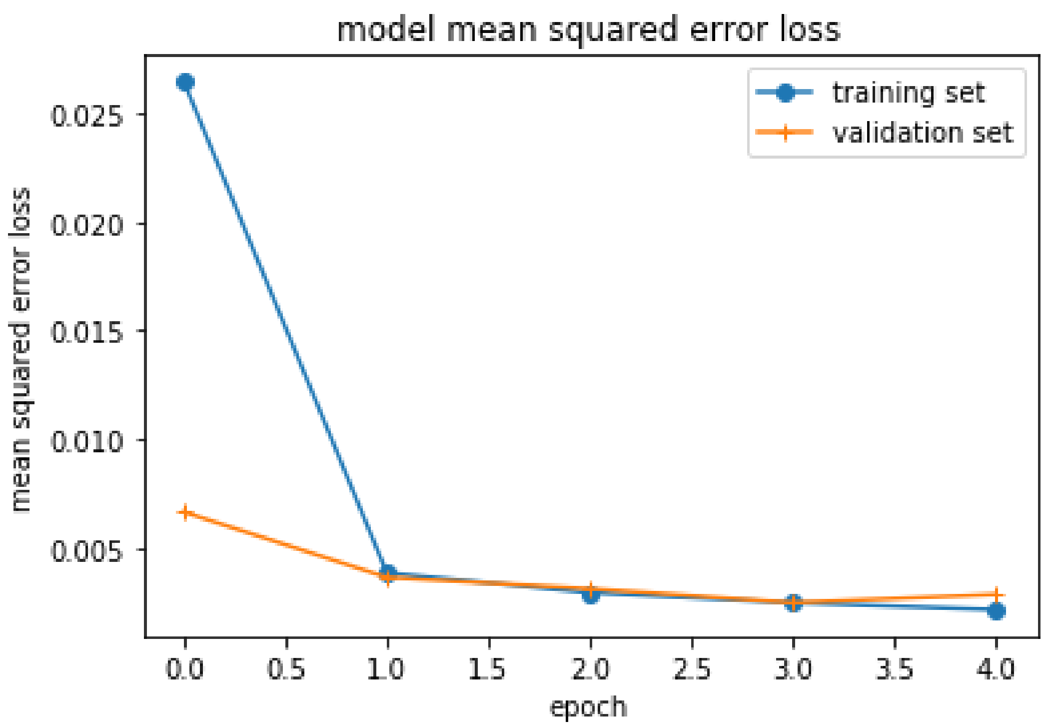
[432]:
```
model.compile(loss='mse',optimizer='adam')
```

[ ]:
```
history_object = model.fit_generator(train_generator_obj,
                                     steps_per_epoch=np.
 ↪ceil(len(train_sample_paths)/batch_size),
                                     validation_data=validation_generator_obj,
                                     validation_steps=np.
 ↪ceil(len(valid_sample_paths)/batch_size),
                                     epochs=1,
                                     verbose=1)
```

[152]:
```
# load of pickled training data from cloud training session
with open('./train_history.pkl','rb') as f:
```

```
    history = pickle.load(f)
```

[157]:
```
# plot the training and validation loss for each epoch from the pickled
# training results from the Nvidia Tesla K80
plt.plot(history[0],marker='o')
plt.plot(history[1],marker='+')
plt.title('model mean squared error loss')
plt.ylabel('mean squared error loss')
plt.xlabel('epoch')
plt.legend(['training set', 'validation set'], loc='upper right')
plt.show()
```



0.11 Model Validation

In order to properly test network performance, Udacity provides a script `drive.py` which when provided a HDF5 file of a trained network, will connect to the driving simulator and feed center camera images to the network and send steering commands to the car as well as maintain a 9 mph vehicle speed (different from that of the training data).

The car was able to successfully navigate the track, though, in some areas the car performs in a way that I would not enjoy as a person riding in the car (rapid steering corrections). A video of the autonomous driving was generated using the `video.py` script and is provided here, note the playback is twice the speed.

I believe because the track is brightly lit in the majority of the training images, that the network's inexperience with shadows make it behave less than ideally in these situations and further augmentation by random lightening and darkening of images, or additional training data with more samples of shadows would eliminate this behavior. I also believe incorporating steering angle smoothing to the controller (such as exponential smoothing method) would reduce this behavior such that a sequence of images is what the controller uses for input rather than single frame steering inputs. As a final validation check of this network, I also positioned the car in the opposite direction of the training data so that the circuit would need to be transervsed in the anti-clockwise direction. The car was able to successfully navigate the track in the opposite direction as well.

0.12 Final Notes

The model does perform the task well and drives the track with out the aid of a human, however, I would be surprised if the model would generalize well to other tracks that have significant elevation changes, road texture different from the training set, significant number of shadows over the roadway, and/or significantly different lighting conditions. To overcome all of these issues I believe a lane finding + vanishing point finding algorithm would need to be used to find appropriate cropping areas, after cropping a resizing will take place so the image to the network is a standardized size. Further training data would be needed for the network to overcome shadow effects, and different lighting conditions. Though random darkening and brightening of training data could help with the training for different lighting conditions without the need of recording further samples. It would also be interesting to reduce the network down to its bare minimum number of layers and find what are the convolution feature maps that the network finds useful for insight to making this type of network perform better in more varied situations.