SDCND Traffic Sign Recognition

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1 Intro

The project is a homework assignment for Udacity's **Self Driving Car Nano Degree**. The project is the third one called *Traffic Sign Classifier*.
The task is to train a neural network derived from or inspired by the LeNet-5 architecture to identify 43 classes of German traffic signs within 32x32x3 pictures. The goal accuracy is 93%.

1.1 Implementation

As mandated the actual code implementation is within the Ipython notebook provided with the project materials, that I adjusted/ expanded accordingly.

2 Rubric criteria

2.1 General remarks

Some of the criteria demand certain outputs by the notebook. Consequently the respective documentation can be found in the solution run of the notebook "Traffic_Sign_Classifier_20190409_04.html" together with the files of the corresponding directory (I will refer to it as the **solution-html**).

2.2 Criteria compliance

Dataset Summary :
see output within *solution-html*

Exploratory Visualization :
to get a better grip on the dataset I visualized the following:

- distribution of the frequencies of the different classes (say, the different signs) within the dataset and it's subsections (train, validate, test) as histograms
- differences of the relative frequencies between the subsections as histograms
- transformation of randomly chosen training images to other color spaces (HLS und LUV) and visualization of the various channels and some combination of channels

see the **actual output** within *solution-html*.
The idea was, to better understand how uniform the distribution of classes would be (I expected the training to be more difficult for non uniform distributions, since classes with few examples are harder to learn), how similar the distributions were (a test- dataset that is derived from an essentially different distribution compared to validation and training will result in a lower test- accuracy) and if I could identify maybe channels from color-spaces other than RGB and grayscale, that could help in preprocessing.

Preprocessing :
The preprocessing finally used is a transform to grayscale and normalization.
I did however experiment with the L- channel of the HLS space and with combinations of that with the L and V channels from LUV; the resulting performance was not good :-).

Model Architecture :
I did experiment with various details (e.g. including bias for the conv. layers or not, initialization of variables, ...) and number of layers, but not with the basic structure of the model:

- the front layers are pairs of convolutional layers with ReLU activation and pooling layers
- the rear layers are fully connected layers with optional ReLU and a dropout layer mixed in
- convolutional layers use "valid padding" and only stride=1
- pooling layers are max layers with "valid padding" and stride matching the kernel size

The detailed layer description of the *solution*:

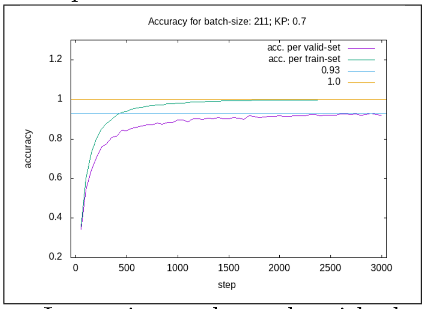
1. convolutional layer with 3x3 kernel, 8 output channels, bias unit and ReLU activation; 32x32x1 → 30x30x8
2. pooling layer with 2x2 kernel; 30x30x8 → 15x15x8
3. convolutional layer with 6x6 kernel, 21 output channels, bias unit and ReLU activation; 15x15x8 → 10x10x21
4. pooling layer with 2x2 kernel; 10x10x21 → 5x5x21
5. flatten- layer; 5x5x21 → 525
6. fully connected layer with bias and ReLU; 525 → 180
7. dropout layer
8. fully connected layer without bias (and no ReLU); 180 → 43
9. softmax layer

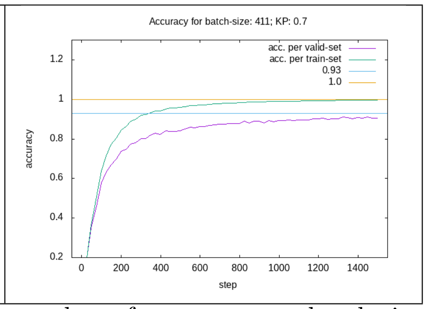
Note: with the preprocessing, the images fed to the NN were of technical dimension 32x32x1.

Model Training :
The actual training algorithm used is a simple one.
I used a standard Adam- optimizer with a cross-entropy- loss function and looped for a predetermined number of steps over one optimizer-step using a random batch of training examples of predefined size.
The program outputs the loss and accuracy of the current model **regarding the complete training- set and the complete validation-set** frequently to the screen/ browser and to a file; the actual model is also saved then, **if** the validation-accuracy is the best yet.
The random sampling of each batch is done using the complete training set. I used this approach because of it's simplicity and to make the implementation easy, but the approach does not guarantee that each training-example is used,

and it does not have the *epoch*- concept.
I would expect, such an approach has performance issues for very large datasets, that do not fit in memory, since the whole dataset is potentially accessed for each step.

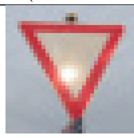
Solution Approach :
The approach I used is mainly one of trial and error. I implemented a NN-model derived as a mix from various different examples of a LeNet-5 like networks I researched on the WWW. I ran the training and evaluation with different parameters and also experimented a bit with the numbers and the sizes of layers. The output to a textfile of the validation and training accuracy once per *validation-step* steps allowed for the evaluation of the performance using a simple plot (using the gnuplot program).
Examples:





I experimented mostly with the number of steps to run, batch-size, dropout-rate and learning-rate (for the optimizer). E.g. I noticed, that the accuracy approached the *perfect score* of 1.0 for the training-set, but would lack for the validation-set; thus I presumed, the network was overfitting and adjusted dropout-rate.

Test a Model on New Images :
I downloaded various traffic sign pictures from the WWW and used 4 of these pictures plus 2 pictures I shot myself (for a total of 6) to test the model. :

 17: No entry	 13: Yield	 14: Stop
 5: Speed limit (80km/h)	 6: End of speed limit (80km/h)	 12: Priority road

In my expectation these pictures should have been not to hard to classify, since for all of them the lighting is quite good (not to dark) and can by readily recognized by a human. Only for "5: Speed limit (80km/h)" and "12: Priority road" I was uncertain whether additional objects directly connected to the signs (in fact fragments of other supplemental signs) might interfere with the identification.
To my surprise, the solution-model was only able to identify 4 of the 6 signs

correctly (see *solution-html* for details) and obviously not because of additional adjacent sign-fragments. The misidentified signs where:

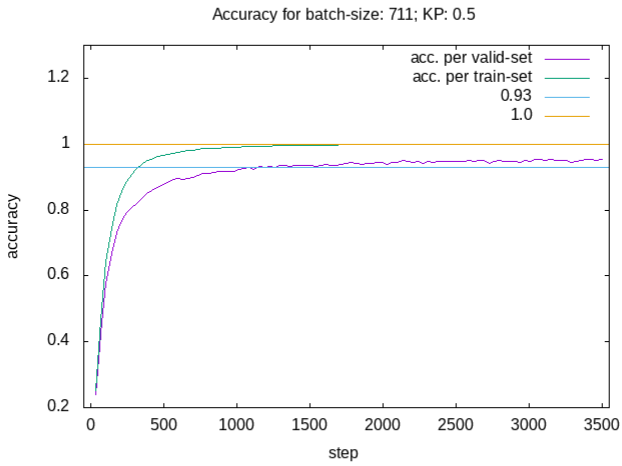
- the Stop- sign
  this was most puzzling, since it is such a distinct sign **and** the 5 top probabilities did not include the correct solution

- the Speed limit (80km/h) sign
  this seems to be a case of misidentified number, cause the highest probability assigned was also a speed limit sign, and there where 2 more among the top 5, but none with the correct number

As said, for further details refer to *solution-html*.

3 Solution

The solution used a *learning-rate* of 0.0009, a *batch-size* of 711 with a *dropout-rate* of 0.5 for 3500 steps.
The resulting accuracy of the model after the last step was 0.941 for the **test-set** (! it worked), 0.954 for the **validation-set** and 1.0 (0.999971) for the **training-set**.
(maybe the model is still overfitting the training set and we need to introduce additional dropout layers or other techniques)



"Solution files":

- `Traffic_Sign_Classifier.ipynb`
- `Traffic_Sign_Classifier_20190409_04.html`
- files in directory `Traffic_Sign_Classifier_20190409_04_files/`
- `results_20190409140717.txt`
- `results_20190409140717.png`