Project: Traffic Sign Recognition

Build a Traffic Sign Recognition Project

The goals / steps of this project are the following:

- Load the data set (see below for links to the project data set)
- Explore, summarize and visualize the data set
- Design, train and test a model architecture
- Use the model to make predictions on new images
- Analyze the softmax probabilities of the new images
- Summarize the results with a written report

Rubric Points

Here I will consider the rubric points individually and describe how I addressed each point in my implementation.

Data Set Summary & Exploration

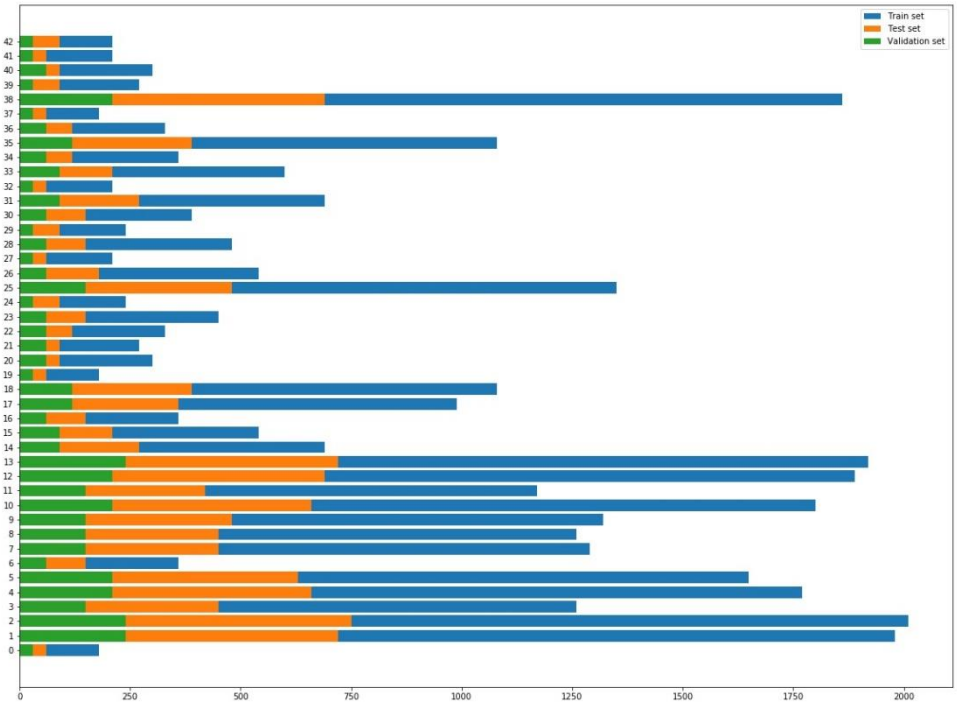
1. Basic summary of the data set.

Once the data sets are imported, I used the numpy library to calculate summary statistics of the traffic signs data set:

- The size of training set is 3799
- The size of the validation set is 4410
- The size of test set is 12630
- The shape of a traffic sign image is (32, 32, 3)
- The number of unique classes/labels in the data set is 43

2. Exploratory visualization of the dataset.

Here is a horizontal histogram chart showing how the three data sets are distributed along the diffent labels.



In order to have a better idea of the training set, for each label, I printed out 4 random images. The output is visible in the image below.

0 : Speed limit (20km/h)

1 : Speed limit (30km/h)

2 : Speed limit (50km/h)

3 : Speed limit (60km/h)

4 : Speed limit (70km/h)

5 : Speed limit (80km/h)

6 : End of speed limit (80km/h)

7 : Speed limit (100km/h)

8 : Speed limit (120km/h)

9 : No passing

10 : No passing for vehicles over 3.5 metric tons

11 : Right-of-way at the next intersection

12 : Priority road

13 : Yield

14 : Stop

15 : No vehicles

16 : Vehicles over 3.5 metric tons prohibited

17 : No entry

18 : General caution

19 : Dangerous curve to the left

20 : Dangerous curve to the right

21 : Double curve

22 : Bumpy road

23 : Slippery road

24 : Road narrows on the right

25 : Road work

26 : Traffic signals

27 : Pedestrians

28 : Children crossing

29 : Bicycles crossing

30 : Beware of ice/snow

31 : Wild animals crossing

32 : End of all speed and passing limits

33 : Turn right ahead

34 : Turn left ahead

35 : Ahead only

36 : Go straight or right

37 : Go straight or left

38 : Keep right

39 : Keep left

40 : Roundabout mandatory

41 : End of no passing

42 : End of no passing by vehicles over 3.5 metric tons

Design and Test a Model Architecture

2. Image data preprocess

As a first step, I converted the image to grayscale. I decided to grayscale them by simply averaging the Red Green and Blue values of the original image.

After, I normalized the images in order to have the grayscale values inside the range [-1, 1].

Keeping the gray values inside this range instead of [0, 255] is fundamental for the training operation in order to get good performances of the model.

Then I shuffled the data using the specific function.

Note: in the first project submission, I decided to omit the grayscaling process since in terms of accuracy it does not give us better result.

Thanks to the reviewer I realized that this method helps to drastically reduce the image dimension and the computational load. In fact, keeping approximately the same accuracy, the images to be processed have 1/3 of the original RGB image dimension.

2. Model architecture

My final model consisted of a standard LeNet architecture and, in particular, is made of the following layers:

Layer	Description
Input	32x32x3 RGB image
Convolution 1	1x1 stride, VALID padding, output: 28x28x6
RELU	
Max pooling 1	2x2 stride, VALID padding, output: 14x14x6
Convolution 2	1x1 stride, VALID padding, output: 10x10x16
RELU	
Max pooling 2	2x2 stride, VALID padding, output: 5x5x16
Flatten	Output: 400
Fully connected	input: 400, output: 120
RELU	
Fully connected	input: 120, output: 84
RELU	
Fully connected	input: 84, output: 43

3. Model training

To train the model, after some tuning, I decided to use the following hyperparameters:

- Epochs = 20
- Batch size = 128
- Learning rate = 0.001

For the training optimization, I used the softmax_cross_entropy_with_logits function which compares the evaluated logits with the one hot end labels.

This gives the cross entropy which is a measure of how different the logits are from the ground truth training labels.

Next, the cross-entropy values are averaged along all the training images.

Then, I minimize the loss function using the AdamOptimizer function which is similar to the stochastic gradient descent method.

4. Results

My final model results were:

- training set accuracy of 0.993
- validation set accuracy of 0.976
- test set accuracy of 0.891

These results satisfy the minimum requests for the project completion.

Test a Model on New Images

1. Chosen images

Here are five German traffic signs that I found on the web:

In these images, I picked signs that might have some additional difficulty in the prediction.

For example, the third image 'Go straight or left' is taken from a steep angle.

In addition, the fourth image 'Road work' presents sone differences from the one in the dataset. In fact, the background is yellow instead of white.

2. Model's predictions on the new traffic signs.

Here are the results of the prediction on the new images:

	Image	Prediction
1	Yield	Yield
2	Dangerous curve to the right	Dangerous curve to the right
3	Go straight or left	Go straight or left
4	Road work	Road work
5	Road narrows to the right	Road narrows to the right

The model was able to correctly guess all the 5 traffic signs, which gives an accuracy of 100%. This result is compatible with the one obtained evaluating the accuracy on the given training set.

3. Softmax probabilities

Analyzing the top five softmax probabilities for each prediction allows to understand how the model works. For most of the images, the model recognizes with absolute precision the traffic signs.

In the last two images, the correct prediction does not have 100% probability but it is still close to it.

Image 1: Yield	
Probability	**Prediction**
100%	Yield
0%	Ahead only
0%	No vehicles
0%	No passing
0%	Speed limit (50km/h)

Image 2: Dangerous curve to the right	
Probability	**Prediction**
99.87%	Dangerous curve to the right
0.10%	Slippery road
0%	Road work
0%	Right-of-way at the next intersection
0%	Children crossing

Image 3 : Go straight or left	
Probability	**Prediction**
100%	Go straight or left
0%	Dangerous curve to the left
0%	Keep left
0%	No passing for vehicles over 3.5 metric tons
0%	Traffic signals

Image 4: Road work	
Probability	**Prediction**
51.42%	Road work
47.19%	Priority road
1.39%	Right-of-way at the next intersection
0%	Speed limit (50km/h)
0%	Speed limit (80km/h)

Image 5: Road narrow to the right	
Probability	**Prediction**
93.85%	Road narrows to the right
5.81%	Bicycles crossing
0.23%	Speed limit (50km/h)
0.07%	Children crossing
0.03%	Road work

Conclusions

The trained model has a high prediction accuracy and it is also robust since it correctly works with other images taken from internet.

The overall result might be improved by applying some changes:

- use more sophisticate architectures
- apply data augmentation (rotation, translation, zoom, flips, and/or color perturbation) in order to have a better view of the signs
- use more layers on the LeNet architecture