

# Traffic Sign Recognition

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# 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

## Data Set Summary & Exploration

### 1. A basic summary of the data set.

I used the pickle library to load the dataset ,then use numpy library to calculate summary statistics of the traffic signs data set:

The size of training set is:34799

The size of the validation set is:4410

The size of test set is:12630

The shape of a traffic sign image is:(32,32,1)

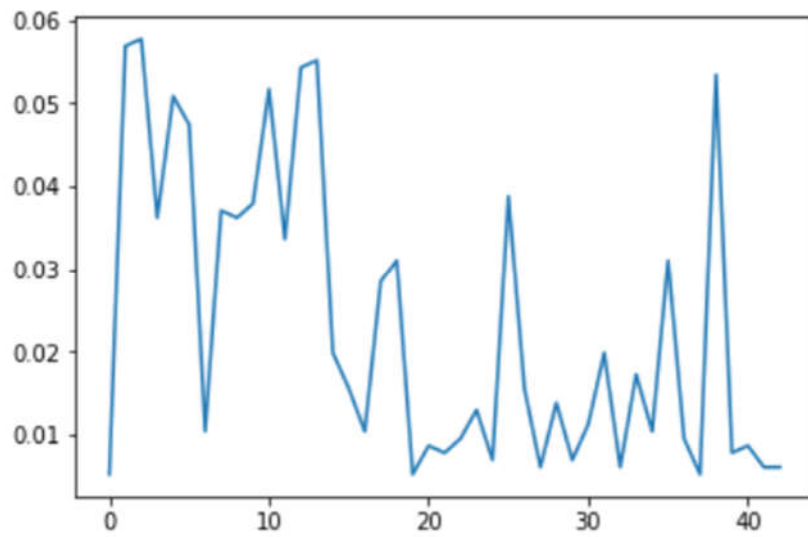
The number of unique classes/labels in the data set is:43

### 2. Exploratory visualization of the dataset.

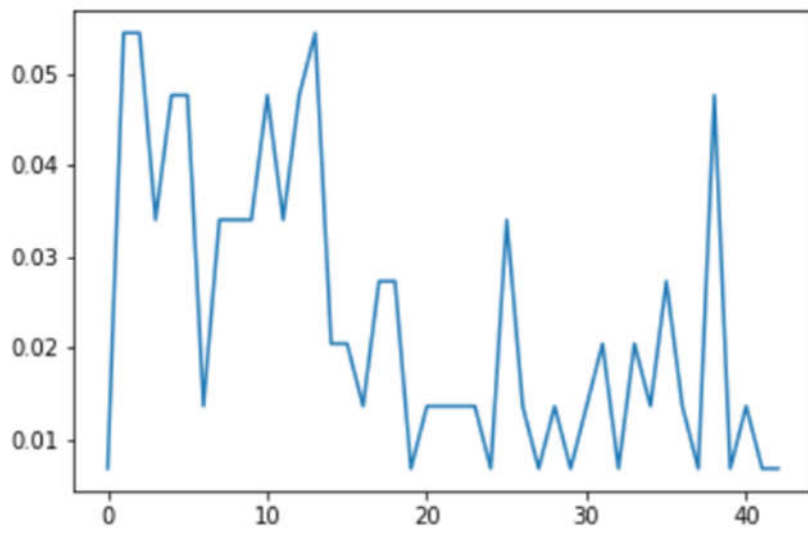
Random input images in X\_train dataset:



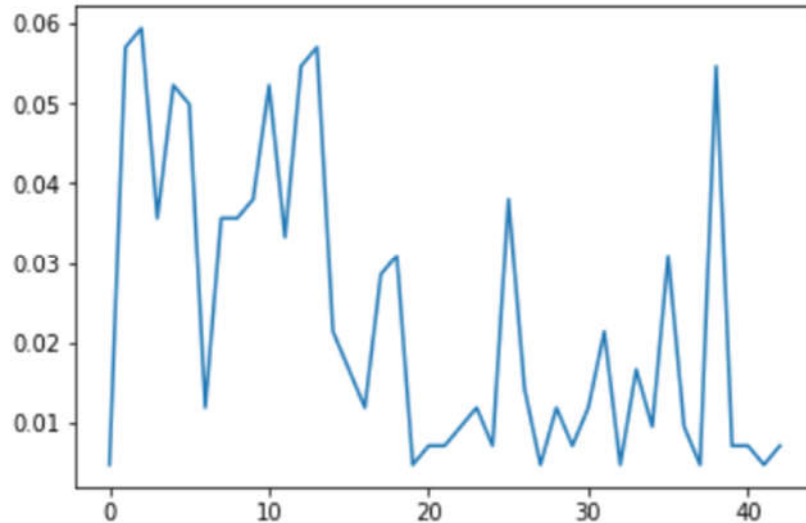
Class distribution in X\_train dataset:



Class distribution in X\_valid dataset:



Class distribution in X\_test dataset:



## Design and Test a Model Architecture

### 1. Preprocessed the image data.

#### 1.1 As a first step, I decided to convert the images to grayscale.

```
X_train_original = X_train  
X_train_gray = np.sum(X_train_original/3, axis=3, keepdims=True)
```

```
X_valid_original = X_valid  
X_valid_gray = np.sum(X_valid_original/3, axis=3, keepdims=True)
```

```
X_test_original = X_test  
X_test_gray = np.sum(X_test_original/3, axis=3, keepdims=True)
```

#### 1.2 Normalized the image data.

```
X_train_normalized = (X_train_gray - 128)/128  
X_valid_normalized = (X_valid_gray - 128)/128
```

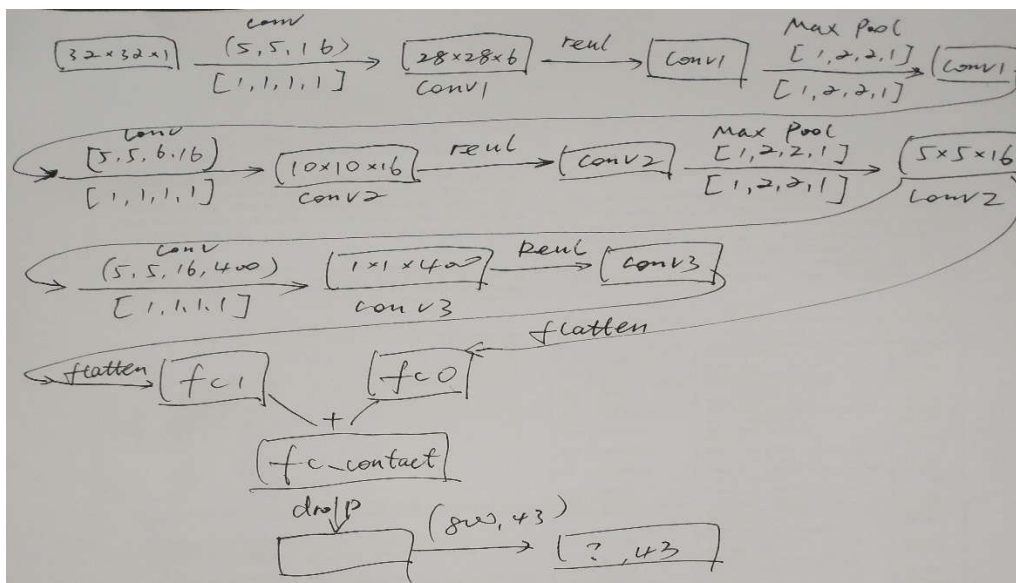
$X_{\text{test\_normalized}} = (X_{\text{test\_gray}} - 128)/128$

$X_{\text{train}} = X_{\text{train\_normalized}}$

$X_{\text{valid}} = X_{\text{valid\_normalized}}$

$X_{\text{test}} = X_{\text{test\_normalized}}$

## 2. Final model architecture looks like.



My final model consisted of the following layers:

```
conv1 shape: (?, 28, 28, 6)
conv1 after activation shape: (?, 28, 28, 6)
conv1 after pooling shape: (?, 14, 14, 6)
conv2 shape: (?, 10, 10, 16)
conv2 after activation shape: (?, 10, 10, 16)
conv2 after pooling shape: (?, 5, 5, 16)
fc0 shape: (?, 400)
conv3 shape: (?, 1, 1, 400)
conv3 after activation shape: (?, 1, 1, 400)
fc1 shape: (?, 400)
fc_contact fc0+fc1 shape: (?, 800)
fc_contact_drop shape: (?, 800)
logits shape: (?, 43)
```

Layer	Description
Input	32x32x1
Convolution (5, 5, 1, 6)	1x1 stride, valid padding, outputs 28x28x6
RELU	
Max pooling	2x2 stride, outputs 14x14x6
Convolution (5, 5, 6, 16)	1x1 stride, outputs 10x10x16
RELU	
Max Pooling	2x2 stride, outputs 5x5x16
Conv (5, 5, 16, 400)	1x1 stride, outputs 1x1x400
Flatten	fc0, fc1
contact	fc_contact
Drop	
Full connect	logits

### 3. Trained model.

To train the model, I used ....

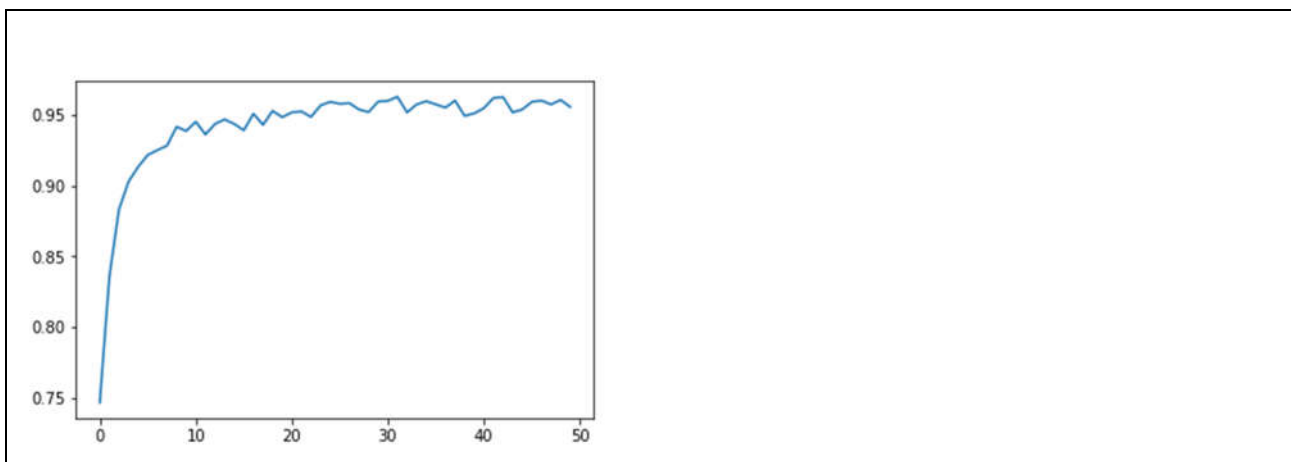
EPOCHS = 50

BATCH\_SIZE = 200

mu = 0

sigma = 0.1

rate = 0.001



EPOCH 1 ...  
Validation Accuracy = 0.746

EPOCH 2 ...  
Validation Accuracy = 0.836

EPOCH 3 ...  
Validation Accuracy = 0.883

EPOCH 4 ...  
Validation Accuracy = 0.903

EPOCH 5 ...  
Validation Accuracy = 0.913

EPOCH 6 ...  
Validation Accuracy = 0.922

EPOCH 7 ...  
Validation Accuracy = 0.925

EPOCH 8 ...  
Validation Accuracy = 0.928

EPOCH 9 ...  
Validation Accuracy = 0.942

EPOCH 10 ...  
Validation Accuracy = 0.939

EPOCH 11 ...  
Validation Accuracy = 0.945

EPOCH 12 ...  
Validation Accuracy = 0.936

EPOCH 13 ...  
Validation Accuracy = 0.944

EPOCH 14 ...  
Validation Accuracy = 0.947

EPOCH 15 ...  
Validation Accuracy = 0.944

EPOCH 16 ...  
Validation Accuracy = 0.939

EPOCH 17 ...  
Validation Accuracy = 0.951

EPOCH 18 ...  
Validation Accuracy = 0.943

EPOCH 19 ...  
Validation Accuracy = 0.953

EPOCH 20 ...  
Validation Accuracy = 0.949

EPOCH 21 ...  
Validation Accuracy = 0.952

EPOCH 22 ...  
Validation Accuracy = 0.953

EPOCH 23 ...  
Validation Accuracy = 0.949

EPOCH 24 ...  
Validation Accuracy = 0.957

EPOCH 25 ...  
Validation Accuracy = 0.959

EPOCH 26 ...  
Validation Accuracy = 0.958

EPOCH 27 ...  
Validation Accuracy = 0.959

EPOCH 28 ...  
Validation Accuracy = 0.954

EPOCH 29 ...  
Validation Accuracy = 0.952

EPOCH 30 ...



Validation Accuracy = 0.960

EPOCH 31 ...

Validation Accuracy = 0.960

EPOCH 32 ...

Validation Accuracy = 0.963

EPOCH 33 ...

Validation Accuracy = 0.952

EPOCH 34 ...

Validation Accuracy = 0.958

EPOCH 35 ...

Validation Accuracy = 0.960

EPOCH 36 ...

Validation Accuracy = 0.958

EPOCH 37 ...

Validation Accuracy = 0.955

EPOCH 38 ...

Validation Accuracy = 0.960

EPOCH 39 ...

Validation Accuracy = 0.949

EPOCH 40 ...

Validation Accuracy = 0.951

EPOCH 41 ...

Validation Accuracy = 0.955

EPOCH 42 ...

Validation Accuracy = 0.962

EPOCH 43 ...

Validation Accuracy = 0.963

EPOCH 44 ...

Validation Accuracy = 0.952

```
EPOCH 45 ...  
Validation Accuracy = 0.954  
  
EPOCH 46 ...  
Validation Accuracy = 0.959  
  
EPOCH 47 ...  
Validation Accuracy = 0.960  
  
EPOCH 48 ...  
Validation Accuracy = 0.958  
  
EPOCH 49 ...  
Validation Accuracy = 0.961  
  
EPOCH 50 ...  
Validation Accuracy = 0.956
```

4. Describe the approach taken for finding a solution and getting the validation set accuracy to be at least 0.93.

My final model results were:  
training set accuracy of:1.000  
validation set accuracy of:0.956  
test set accuracy of:0.941

## Test a Model on New Images

1. Choose ten German traffic signs found on the web and provide them in the report.

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



## 2. The model's predictions on these new traffic signs.

input 	Top-1 guess: 11 (100.00%) 	Top-2 guess: 18 (0.00%) 	Top-3 guess: 27 (0.00%) 	Top-4 guess: 19 (0.00%) 	Top-5 guess: 30 (0.00%) 
input 	Top-1 guess: 13 (100.00%) 	Top-2 guess: 35 (0.00%) 	Top-3 guess: 11 (0.00%) 	Top-4 guess: 40 (0.00%) 	Top-5 guess: 2 (0.00%) 
input 	Top-1 guess: 1 (100.00%) 	Top-2 guess: 2 (0.00%) 	Top-3 guess: 0 (0.00%) 	Top-4 guess: 18 (0.00%) 	Top-5 guess: 14 (0.00%) 
input 	Top-1 guess: 25 (100.00%) 	Top-2 guess: 30 (0.00%) 	Top-3 guess: 29 (0.00%) 	Top-4 guess: 22 (0.00%) 	Top-5 guess: 24 (0.00%) 
input 	Top-1 guess: 28 (100.00%) 	Top-2 guess: 18 (0.00%) 	Top-3 guess: 11 (0.00%) 	Top-4 guess: 29 (0.00%) 	Top-5 guess: 6 (0.00%) 
input 	Top-1 guess: 29 (100.00%) 	Top-2 guess: 28 (0.00%) 	Top-3 guess: 3 (0.00%) 	Top-4 guess: 20 (0.00%) 	Top-5 guess: 23 (0.00%) 
input 	Top-1 guess: 31 (100.00%) 	Top-2 guess: 21 (0.00%) 	Top-3 guess: 25 (0.00%) 	Top-4 guess: 11 (0.00%) 	Top-5 guess: 1 (0.00%) 
input 	Top-1 guess: 35 (100.00%) 	Top-2 guess: 13 (0.00%) 	Top-3 guess: 36 (0.00%) 	Top-4 guess: 25 (0.00%) 	Top-5 guess: 20 (0.00%) 
input 	Top-1 guess: 33 (100.00%) 	Top-2 guess: 36 (0.00%) 	Top-3 guess: 26 (0.00%) 	Top-4 guess: 11 (0.00%) 	Top-5 guess: 38 (0.00%) 
input 	Top-1 guess: 39 (100.00%) 	Top-2 guess: 25 (0.00%) 	Top-3 guess: 40 (0.00%) 	Top-4 guess: 21 (0.00%) 	Top-5 guess: 37 (0.00%) 

The model was able to correctly guess 9 of the 10 traffic signs, which gives an accuracy of 90%.