Self-Driving Car Engineer Nanodegree

Deep Learning

Project: Build a Traffic Sign Recognition Classifier

In this notebook, a template is provided for you to implement your functionality in stages, which is required to successfully complete this project. If additional code is required that cannot be included in the notebook, be sure that the Python code is successfully imported and included in your submission if necessary.

> **Note**: Once you have completed all of the code implementations, you need to finalize your work by exporting the iPython Notebook as an HTML document. Before exporting the notebook to html, all of the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to \n", "**File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In addition to implementing code, there is a writeup to complete. The writeup should be completed in a separate file, which can be either a markdown file or a pdf document. There is a write up template (https://github.com/udacity/CarND-Traffic-Sign-Classifier-Project/blob/master/writeup_template.md) that can be used to guide the writing process. Completing the code template and writeup template will cover all of the rubric points (https://review.udacity.com/#!/rubrics/481/view) for this project.

The rubric (https://review.udacity.com/#!/rubrics/481/view) contains "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. The stand out suggestions are optional. If you decide to pursue the "stand out suggestions", you can include the code in this Ipython notebook and also discuss the results in the writeup file.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

Step 0: Load The Data

In [2]:
```
# Load pickled data
import pickle

# TODO: Fill this in based on where you saved the training and testing data

training_file = 'train.p'
validation_file='valid.p'
testing_file = 'test.p'

with open(training_file, mode='rb') as f:
    train = pickle.load(f)
with open(validation_file, mode='rb') as f:
    valid = pickle.load(f)
with open(testing_file, mode='rb') as f:
    test = pickle.load(f)

X_train, y_train = train['features'], train['labels']
X_valid, y_valid = valid['features'], valid['labels']
X_test, y_test = test['features'], test['labels']
```

Step 1: Dataset Summary & Exploration

The pickled data is a dictionary with 4 key/value pairs:

- `'features'` is a 4D array containing raw pixel data of the traffic sign images, (num examples, width, height, channels).
- `'labels'` is a 1D array containing the label/class id of the traffic sign. The file `signnames.csv` contains id -> name mappings for each id.
- `'sizes'` is a list containing tuples, (width, height) representing the original width and height the image.
- `'coords'` is a list containing tuples, (x1, y1, x2, y2) representing coordinates of a bounding box around the sign in the image. **THESE COORDINATES ASSUME THE ORIGINAL IMAGE. THE PICKLED DATA CONTAINS RESIZED VERSIONS (32 by 32) OF THESE IMAGES**

Complete the basic data summary below. Use python, numpy and/or pandas methods to calculate the data summary rather than hard coding the results. For example, the pandas shape method (http://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.shape.html) might be useful for calculating some of the summary results.

Provide a Basic Summary of the Data Set Using Python, Numpy and/or Pandas

In [3]:
```
### Replace each question mark with the appropriate value.
### Use python, pandas or numpy methods rather than hard coding the results
import numpy as np
# TODO: Number of training examples
n_train = len(X_train)

# TODO: Number of validation examples
n_validation = len(X_valid)

# TODO: Number of testing examples.
n_test = len(X_test)

# TODO: What's the shape of an traffic sign image?
image_shape = X_train[0].shape

# TODO: How many unique classes/labels there are in the dataset.
n_classes = len(np.unique(y_train))


#Print the data set summary
print("Number of training examples =", n_train)
print("Number of testing examples =", n_test)
print("Number of validation examples =", n_validation)
print("Image data shape =", image_shape)
print("Number of classes =", n_classes)
```

```
Number of training examples = 34799
Number of testing examples = 12630
Number of validation examples = 4410
Image data shape = (32, 32, 3)
Number of classes = 43
```

Include an exploratory visualization of the dataset

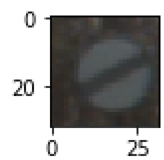
Visualize the German Traffic Signs Dataset using the pickled file(s). This is open ended, suggestions include: plotting traffic sign images, plotting the count of each sign, etc.

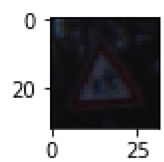
The Matplotlib (http://matplotlib.org/) examples (http://matplotlib.org/examples/index.html) and gallery (http://matplotlib.org/gallery.html) pages are a great resource for doing visualizations in Python.

NOTE: It's recommended you start with something simple first. If you wish to do more, come back to it after you've completed the rest of the sections. It can be interesting to look at the distribution of classes in the training, validation and test set. Is the distribution the same? Are there more examples of some classes than others?

In [3]:
```
### Data exploration visualization code goes here.
### Feel free to use as many code cells as needed.
import matplotlib.pyplot as plt
import random
# Visualizations will be shown in the notebook.
%matplotlib inline
n=3
for i in range(0,3):
    index=random.randint(0,len(X_train))
    image=X_train[index].squeeze()
    plt.figure(figsize=(1,1))
    plt.imshow(image)
    print(y_train[index])
```

```
32
28
0
```





Step 2: Design and Test a Model Architecture

Design and implement a deep learning model that learns to recognize traffic signs. Train and test your model on the German Traffic Sign Dataset (http://benchmark.ini.rub.de/?section=gtsrb&subsection=dataset).

The LeNet-5 implementation shown in the classroom (https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/601ae704-1035-4287-8b11-e2c2716217ad/concepts/d4aca031-508f-4e0b-b493-e7b706120f81) at the end of the CNN lesson is a solid starting point. You'll have to change the number of classes and possibly the preprocessing, but aside from that it's plug and play!

With the LeNet-5 solution from the lecture, you should expect a validation set accuracy of about 0.89. To meet specifications, the validation set accuracy will need to be at least 0.93. It is possible to get an even higher accuracy, but 0.93 is the minimum for a successful project submission.

There are various aspects to consider when thinking about this problem:

- Neural network architecture (is the network over or underfitting?)
- Play around preprocessing techniques (normalization, rgb to grayscale, etc)
- Number of examples per label (some have more than others).
- Generate fake data.

Here is an example of a published baseline model on this problem (http://yann.lecun.com/exdb/publis/pdf/sermanet-ijcnn-11.pdf). It's not required to be familiar with the approach used in the paper but, it's good practice to try to read papers like these.

Pre-process the Data Set (normalization, grayscale, etc.)

Minimally, the image data should be normalized so that the data has mean zero and equal variance. For image data, `(pixel - 128)/ 128` is a quick way to approximately normalize the data and can be used in this project.

Other pre-processing steps are optional. You can try different techniques to see if it improves performance.

Use the code cell (or multiple code cells, if necessary) to implement the first step of your project.

Personal Note: The Epoch and batch_size are tuned so that the validation accuracy can reach a satisfactory level. The optimizaed value for the epoch is 30 and that of batch size is 115.

The code below shows the architecture of the CNN:

Layer 1: Convolutional. The input and output of the convolutional is 32x32x3 and 28x28x6, respectively. The relu activation, pooling, which has an input of 28x28x6 and output of 14x14x6.

Layer 2: Convolutional. The input and output of the convolutional is 14x14x6 and 10x10x16, respectively. The relu activation, pooling, which has an input of 10x10x16 and output of 5x5x16.

Then, flatten the output shape of the final pooling layer such that it's 1D instead of 3D, and the output is a 400 element 1D array.

Layer 3: Fully Connected. This has 120 outputs and then relu activation.

Layer 4: Fully Connected. This has 84 outputs and then relu activation.

Layer 5: Fully Connected. This has 43 outputs.

In [4]:

```
### Preprocess the data here. It is required to normalize the data. Other preproc
### converting to grayscale, etc.
### Feel free to use as many code cells as needed.
from sklearn.utils import shuffle

X_train, y_train = shuffle(X_train, y_train)

###convert color images to greyscale image

X_train =np.sum(X_train/3, axis=3, keepdims=True)
X_valid=np.sum(X_valid/3, axis=3, keepdims=True)
X_test=np.sum(X_test/3, axis=3, keepdims=True)

### Normalization of the train, valid and test images
X_train = (X_train- 127.5)/127.5
X_valid= (X_valid - 127.5)/127.5
X_test= (X_test - 127.5)/127.5


import tensorflow as tf

EPOCHS = 30
BATCH_SIZE = 115

from tensorflow.contrib.layers import flatten

def LeNet(x):
    # Arguments used for tf.truncated_normal, randomly defines variables for the 
    mu = 0
    sigma = 0.1

    # SOLUTION: Layer 1: Convolutional. Input = 32x32x1. Output = 28x28x6.
    conv1_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 1, 6), mean = mu, stdd
    conv1_b = tf.Variable(tf.zeros(6))
    conv1   = tf.nn.conv2d(x, conv1_W, strides=[1, 1, 1, 1], padding='VALID') + c

    # SOLUTION: Activation.
    conv1 = tf.nn.relu(conv1)

    # SOLUTION: Pooling. Input = 28x28x6. Output = 14x14x6.
    conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], paddi

    # SOLUTION: Layer 2: Convolutional. Output = 10x10x16.
    conv2_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 6, 16), mean = mu, std
    conv2_b = tf.Variable(tf.zeros(16))
    conv2   = tf.nn.conv2d(conv1, conv2_W, strides=[1, 1, 1, 1], padding='VALID')

    # SOLUTION: Activation.
    conv2 = tf.nn.relu(conv2)

    # SOLUTION: Pooling. Input = 10x10x16. Output = 5x5x16.
    conv2 = tf.nn.max_pool(conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], paddi

    # SOLUTION: Flatten. Input = 5x5x16. Output = 400.
    fc0   = flatten(conv2)
```

```
    # SOLUTION: Layer 3: Fully Connected. Input = 400. Output = 120.
    fc1_W = tf.Variable(tf.truncated_normal(shape=(400, 120), mean = mu, stddev =
    fc1_b = tf.Variable(tf.zeros(120))
    fc1   = tf.matmul(fc0, fc1_W) + fc1_b

    # SOLUTION: Activation.
    fc1    = tf.nn.relu(fc1)

    # SOLUTION: Layer 4: Fully Connected. Input = 120. Output = 84.
    fc2_W  = tf.Variable(tf.truncated_normal(shape=(120, 84), mean = mu, stddev =
    fc2_b  = tf.Variable(tf.zeros(84))
    fc2    = tf.matmul(fc1, fc2_W) + fc2_b

    # SOLUTION: Activation.
    fc2    = tf.nn.relu(fc2)

    # SOLUTION: Layer 5: Fully Connected. Input = 84. Output = 10.
    fc3_W  = tf.Variable(tf.truncated_normal(shape=(84, 43), mean = mu, stddev =
    fc3_b  = tf.Variable(tf.zeros(43))
    logits = tf.matmul(fc2, fc3_W) + fc3_b

    return logits
```

Model Architecture

Personal Note: The learning rate also plays a significant influence on the classifier accuracy, theoptimizaed learning rate for tihs case is 0.0025.

In [5]:
```
### Define your architecture here.
### Feel free to use as many code cells as needed.
x = tf.placeholder(tf.float32, (None, 32, 32, 1))
y = tf.placeholder(tf.int32, (None))
one_hot_y = tf.one_hot(y, 43)


rate = 0.0025

logits = LeNet(x)
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(labels=one_hot_y, logits=
loss_operation = tf.reduce_mean(cross_entropy)
optimizer = tf.train.AdamOptimizer(learning_rate = rate)
training_operation = optimizer.minimize(loss_operation)



correct_prediction = tf.equal(tf.argmax(logits, 1), tf.argmax(one_hot_y, 1))
accuracy_operation = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
saver = tf.train.Saver()

def evaluate(X_data, y_data):
    num_examples = len(X_data)
    total_accuracy = 0
    sess = tf.get_default_session()
    for offset in range(0, num_examples, BATCH_SIZE):
        batch_x, batch_y = X_data[offset:offset+BATCH_SIZE], y_data[offset:offset
        accuracy = sess.run(accuracy_operation, feed_dict={x: batch_x, y: batch_y
        total_accuracy += (accuracy * len(batch_x))
    return total_accuracy / num_examples
```

Train, Validate and Test the Model

A validation set can be used to assess how well the model is performing. A low accuracy on the training and validation sets imply underfitting. A high accuracy on the training set but low accuracy on the validation set implies overfitting.

In [6]:
```
### Train your model here.
### Calculate and report the accuracy on the training and validation set.
### Once a final model architecture is selected,
### the accuracy on the test set should be calculated and reported as well.
### Feel free to use as many code cells as needed.

with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    num_examples = len(X_train)

    print("Training...")
    print()
    for i in range(EPOCHS):
        X_train, y_train = shuffle(X_train, y_train)
        for offset in range(0, num_examples, BATCH_SIZE):
            end = offset + BATCH_SIZE
            batch_x, batch_y = X_train[offset:end], y_train[offset:end]
            sess.run(training_operation, feed_dict={x: batch_x, y: batch_y})

        validation_accuracy = evaluate(X_valid, y_valid)
        print("EPOCH {} ...".format(i+1))
        print("Validation Accuracy = {:.3f}".format(validation_accuracy))
        print()

    saver.save(sess, './lenet')
    print("Model saved")
```

```
Training...

EPOCH 1 ...
Validation Accuracy = 0.846

EPOCH 2 ...
Validation Accuracy = 0.889

EPOCH 3 ...
Validation Accuracy = 0.914

EPOCH 4 ...
Validation Accuracy = 0.897

EPOCH 5 ...
Validation Accuracy = 0.912

EPOCH 6 ...
Validation Accuracy = 0.922

EPOCH 7 ...
Validation Accuracy = 0.922

EPOCH 8 ...
Validation Accuracy = 0.932

EPOCH 9 ...
Validation Accuracy = 0.931

EPOCH 10 ...
```

```
Validation Accuracy = 0.927

EPOCH 11 ...
Validation Accuracy = 0.925

EPOCH 12 ...
Validation Accuracy = 0.924

EPOCH 13 ...
Validation Accuracy = 0.924

EPOCH 14 ...
Validation Accuracy = 0.928

EPOCH 15 ...
Validation Accuracy = 0.914

EPOCH 16 ...
Validation Accuracy = 0.922

EPOCH 17 ...
Validation Accuracy = 0.914

EPOCH 18 ...
Validation Accuracy = 0.941

EPOCH 19 ...
Validation Accuracy = 0.921

EPOCH 20 ...
Validation Accuracy = 0.917

EPOCH 21 ...
Validation Accuracy = 0.919

EPOCH 22 ...
Validation Accuracy = 0.927

EPOCH 23 ...
Validation Accuracy = 0.936

EPOCH 24 ...
Validation Accuracy = 0.941

EPOCH 25 ...
Validation Accuracy = 0.940

EPOCH 26 ...
Validation Accuracy = 0.930

EPOCH 27 ...
Validation Accuracy = 0.929

EPOCH 28 ...
Validation Accuracy = 0.941

EPOCH 29 ...
```

```
Validation Accuracy = 0.936

EPOCH 30 ...
Validation Accuracy = 0.939

Model saved
```

In [7]:
```
###Implement the model on the test data
with tf.Session() as sess:
    saver.restore(sess, tf.train.latest_checkpoint('.'))

    test_accuracy = evaluate(X_test, y_test)
    print("Test Accuracy = {:.3f}".format(test_accuracy))
```

```
INFO:tensorflow:Restoring parameters from .\lenet
Test Accuracy = 0.922
```

The validation accuracy after 30 epoches is 0.939, which means nearly 94% images in the valication set can be classified correctly.

Step 3: Test a Model on New Images

To give yourself more insight into how your model is working, download at least five pictures of German traffic signs from the web and use your model to predict the traffic sign type.

You may find `signnames.csv` useful as it contains mappings from the class id (integer) to the actual sign name.

There are five images picked to test the trained model. They were loaded and shown below. As is shown in the analyze performance block, the test accuracy of the five images with the trained model is 1, which means all the five images were classified correctly.

The first image is easy to classify;

The second is also easy but the background in the image has part of another traffic which may cause trouble to the classifier;

The third image is easy;

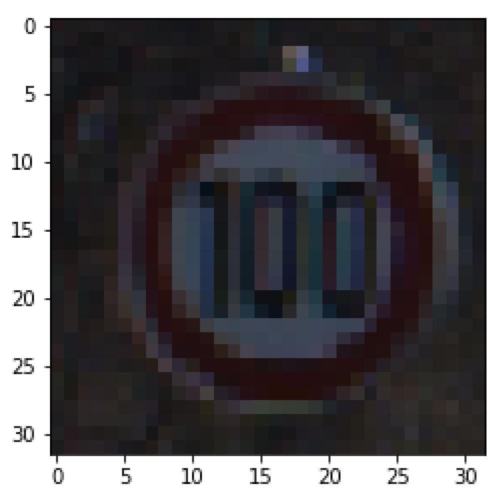
The fourth image is difficult. The sign is tilted and the background also has part of other sign;

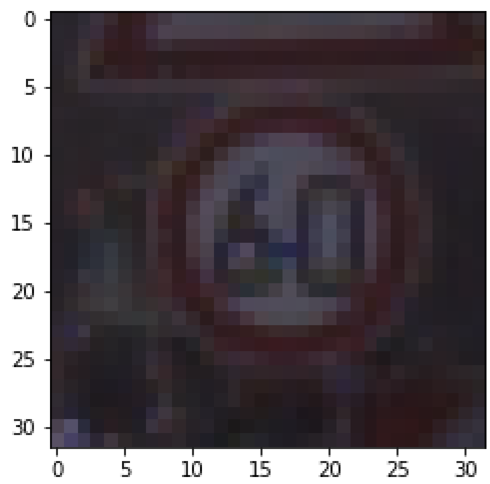
The fifth image is moderate, the contract with the background is low;

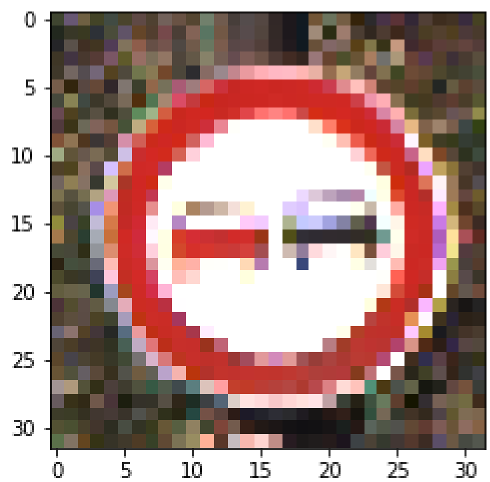
Load and Output the Images

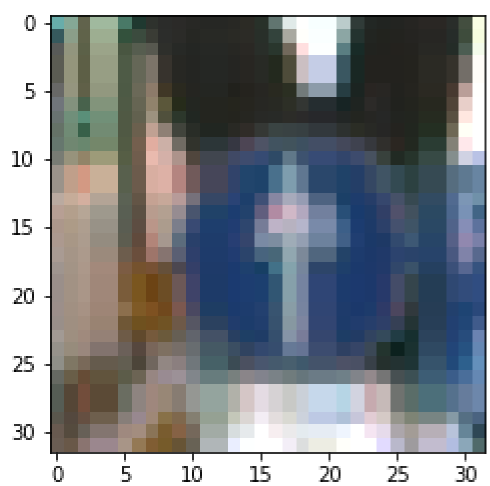
In [12]:

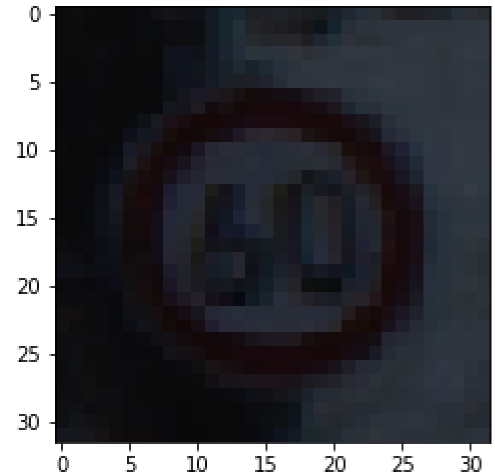
```
### Load the images and plot them here.
### Feel free to use as many code cells as needed.
#Import traffic signs class names
import csv
import glob
import os
import matplotlib.pyplot as plt
from PIL import Image

signs_class=[]
with open('signnames.csv', 'rt') as csvfile:
    reader = csv.DictReader(csvfile, delimiter=',')
    for row in reader:
        signs_class.append((row['SignName']))
New_images=[]
# Read all image into the folder
for filename in os.listdir("New Images"):
    img = Image.open(os.path.join("New Images", filename))
    img = img.resize((32, 32))
    plt.imshow(img)
    plt.show()
    img = np.array(img)
    New_images.append(img)
New_images=np.array(New_images,dtype=np.float32)
print(New_images.shape)


###convert color images to greyscale image

New_images =np.sum(New_images/3, axis=3, keepdims=True)


### Normalization of the train, valid and test images
New_images = (New_images- 128)/128

New_images_labels=[7,3,9,35,3]
```











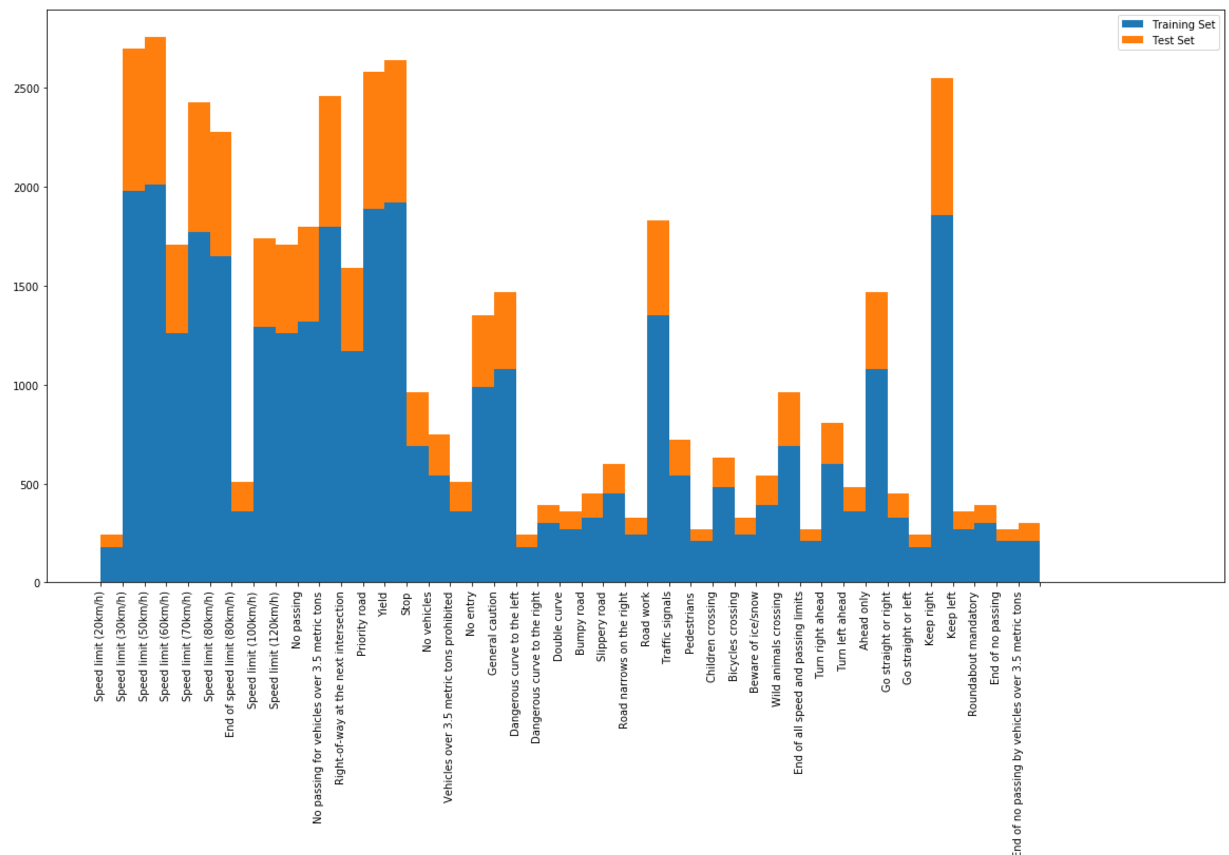

```
(5, 32, 32, 3)
```

Analyze Performance

In [38]:
```
### Calculate the accuracy for these 5 new images.
### For example, if the model predicted 1 out of 5 signs correctly, it's 20% accu
###Implement the model on the test data
with tf.Session() as sess:
    saver.restore(sess, tf.train.latest_checkpoint('.'))

    test_accuracy = evaluate(New_images, New_images_labels)
    print("Test Accuracy = {:.3f}".format(test_accuracy))
```

```
INFO:tensorflow:Restoring parameters from .\lenet
Test Accuracy = 1.000
```

In [43]:
```
#exploratory visualization of the data set:
import csv
import pylab as pl

with open('signnames.csv') as f:
    reader = csv.reader(f)
    class_names_raw = list(reader)
    class_names = [i[1] for i in class_names_raw][1::]
    labels = [i[0] for i in class_names_raw][1::]

#Plotting
fig = pl.figure(None, figsize=(20,10))

pl.hist([y_train, y_test], bins = range(0,50), histtype='bar', stacked=True)

pl.xticks(np.array(range(0,44)), class_names, rotation='vertical')
pl.legend(['Training Set', 'Test Set'])
pl.show()
```



The dataset structure of the training and test images are shown in the figure above.

Output Top 5 Softmax Probabilities For Each Image Found on the Web

For each of the new images, print out the model's softmax probabilities to show the **certainty** of the model's predictions (limit the output to the top 5 probabilities for each image). `tf.nn.top_k` (https://www.tensorflow.org/versions/r0.12/api_docs/python/nn.html#top_k) could prove helpful here.

The example below demonstrates how tf.nn.top_k can be used to find the top k predictions for each image.

`tf.nn.top_k` will return the values and indices (class ids) of the top k predictions. So if k=3, for each sign, it'll return the 3 largest probabilities (out of a possible 43) and the correspoding class ids.

Take this numpy array as an example. The values in the array represent predictions. The array contains softmax probabilities for five candidate images with six possible classes. `tf.nn.top_k` is used to choose the three classes with the highest probability:

```
# (5, 6) array
a = np.array([[ 0.24879643,  0.07032244,  0.12641572,  0.34763842,  0.078
93497,
         0.12789202],
       [ 0.28086119,  0.27569815,  0.08594638,  0.0178669 ,  0.18063401,
         0.15899337],
       [ 0.26076848,  0.23664738,  0.08020603,  0.07001922,  0.1134371 ,
         0.23892179],
       [ 0.11943333,  0.29198961,  0.02605103,  0.26234032,  0.1351348 ,
         0.16505091],
       [ 0.09561176,  0.34396535,  0.0643941 ,  0.16240774,  0.24206137,
         0.09155967]])
```

Running it through `sess.run(tf.nn.top_k(tf.constant(a), k=3))` produces:

```
TopKV2(values=array([[ 0.34763842,  0.24879643,  0.12789202],
       [ 0.28086119,  0.27569815,  0.18063401],
       [ 0.26076848,  0.23892179,  0.23664738],
       [ 0.29198961,  0.26234032,  0.16505091],
       [ 0.34396535,  0.24206137,  0.16240774]]), indices=array([[3, 0,
 5],
       [0, 1, 4],
       [0, 5, 1],
       [1, 3, 5],
       [1, 4, 3]], dtype=int32))
```

Looking just at the first row we get `[ 0.34763842,  0.24879643,  0.12789202]`, you can confirm these are the 3 largest probabilities in a. You'll also notice `[3, 0, 5]` are the corresponding indices.

In [39]:
```
### Print out the top five softmax probabilities for the predictions on the Germa
### Feel free to use as many code cells as needed.
with tf.Session() as sess:

    # Apply softmax function to the output
    softmax = tf.nn.softmax(output)

    # Show the top 5 prediction
    TopKV5 = sess.run(tf.nn.top_k(softmax, k=5))
    print (TopKV5)
```

```
TopKV2(values=array([[ 0.03084971,  0.03055597,  0.0282121 ,  0.02820078,  0.02
763416],
       [ 0.02960551,  0.0291388 ,  0.0277476 ,  0.02710027,  0.02671392],
       [ 0.03836574,  0.03466478,  0.03391736,  0.03266291,  0.03102477],
       [ 0.03063273,  0.02852163,  0.02839184,  0.02673925,  0.0265878 ],
       [ 0.0310782 ,  0.03066145,  0.02827515,  0.02804025,  0.02729589]], dtyp
e=float32), indices=array([[38, 22, 32,  1,  5],
       [38, 22, 32,  1,  5],
       [29, 38,  5, 32, 42],
       [22, 32, 38, 29, 19],
       [38, 22, 32,  1, 17]]))
```

Project Writeup

Once you have completed the code implementation, document your results in a project writeup using this template (https://github.com/udacity/CarND-Traffic-Sign-Classifier-Project/blob/master/writeup_template.md) as a guide. The writeup can be in a markdown or pdf file.

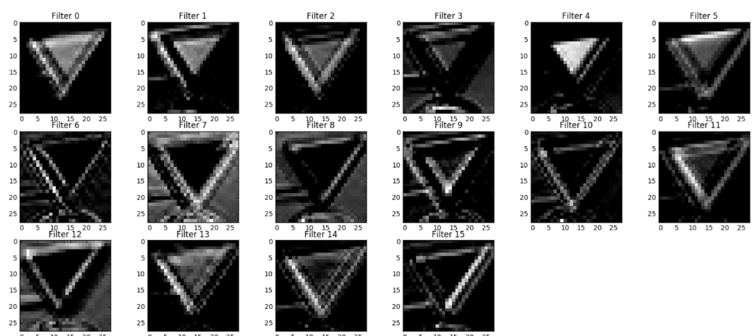
> **Note**: Once you have completed all of the code implementations and successfully answered each question above, you may finalize your work by exporting the iPython Notebook as an HTML document. You can do this by using the menu above and navigating to \n", "**File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

Step 4 (Optional): Visualize the Neural Network's State with Test Images

This Section is not required to complete but acts as an additional excersise for understaning the output of a neural network's weights. While neural networks can be a great learning device they are often referred to as a black box. We can understand what the weights of a neural network look like better by plotting their feature maps. After successfully training your neural network you can see what it's feature maps look like by plotting the output of the network's weight layers in response to a test stimuli image. From these plotted feature maps, it's possible to see what characteristics of an image the network finds interesting. For a sign, maybe the inner network feature maps react with high activation to the sign's boundary outline or to the contrast in the sign's painted symbol.

Provided for you below is the function code that allows you to get the visualization output of any tensorflow weight layer you want. The inputs to the function should be a stimuli image, one used during training or a new one you provided, and then the tensorflow variable name that represents the layer's state during the training process, for instance if you wanted to see what the LeNet lab's (https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/601ae704-1035-4287-8b11-e2c2716217ad/concepts/d4aca031-508f-4e0b-b493-e7b706120f81) feature maps looked like for it's second convolutional layer you could enter conv2 as the tf_activation variable.

For an example of what feature map outputs look like, check out NVIDIA's results in their paper End-to-End Deep Learning for Self-Driving Cars (https://devblogs.nvidia.com/parallelforall/deep-learning-self-driving-cars/) in the section Visualization of internal CNN State. NVIDIA was able to show that their network's inner weights had high activations to road boundary lines by comparing feature maps from an image with a clear path to one without. Try experimenting with a similar test to show that your trained network's weights are looking for interesting features, whether it's looking at differences in feature maps from images with or without a sign, or even what feature maps look like in a trained network vs a completely untrained one on the same sign image.



Your output should look something like this (above)

In [ ]:

```
### Visualize your network's feature maps here.
### Feel free to use as many code cells as needed.

# image_input: the test image being fed into the network to produce the feature m
# tf_activation: should be a tf variable name used during your training procedure
# activation_min/max: can be used to view the activation contrast in more detail,
# plt_num: used to plot out multiple different weight feature map sets on the sam

def outputFeatureMap(image_input, tf_activation, activation_min=-1, activation_ma
    # Here make sure to preprocess your image_input in a way your network expects
    # with size, normalization, ect if needed
    # image_input =
    # Note: x should be the same name as your network's tensorflow data placehold
    # If you get an error tf_activation is not defined it may be having trouble a
    activation = tf_activation.eval(session=sess,feed_dict={x : image_input})
    featuremaps = activation.shape[3]
    plt.figure(plt_num, figsize=(15,15))
    for featuremap in range(featuremaps):
        plt.subplot(6,8, featuremap+1) # sets the number of feature maps to show
        plt.title('FeatureMap ' + str(featuremap)) # displays the feature map num
        if activation_min != -1 & activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vm
        elif activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vm
        elif activation_min !=-1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vm
        else:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", cm
```