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 [1]:

```
# Load pickled data
import pickle

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

training_file = 'traffic-signs-data/train.p'
validation_file='traffic-signs-data/valid.p'
testing_file = 'traffic-signs-data/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)
```

In [2]:

```
X_train, y_train, x_train_sizes, x_train_coords = train['features'],
train['labels'], train['sizes'], train['coords']
X_validation, y_validation, x_valid_sizes, x_valid_coords = valid['feature
s'], valid['labels'], valid['sizes'], valid['coords']
X_test, y_test, x_test_sizes, x_test_coords = test['features'], test['label
s'], test['sizes'], test['coords']
```

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


# TODO: Number of training examples
n_train = len(y_train)

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

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

# TODO: What's the shape of an traffic sign image?
image_shape = X_train.shape[1:]

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

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

```
Number of training examples = 34799
Number of validation examples = 4410
Number of testing examples = 12630
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 [4]:

```
### Data exploration visualization code goes here.
### Feel free to use as many code cells as needed.
import matplotlib.pyplot as plt
# Visualizations will be shown in the notebook.
%matplotlib inline
import numpy as np
```

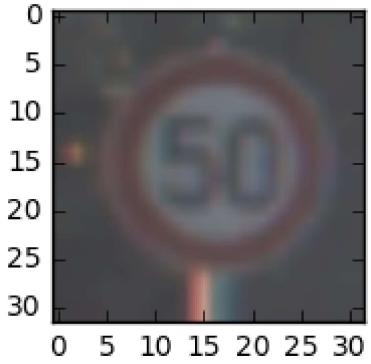
In [5]:

```
s_classes=set(y_train)
```

In [6]:

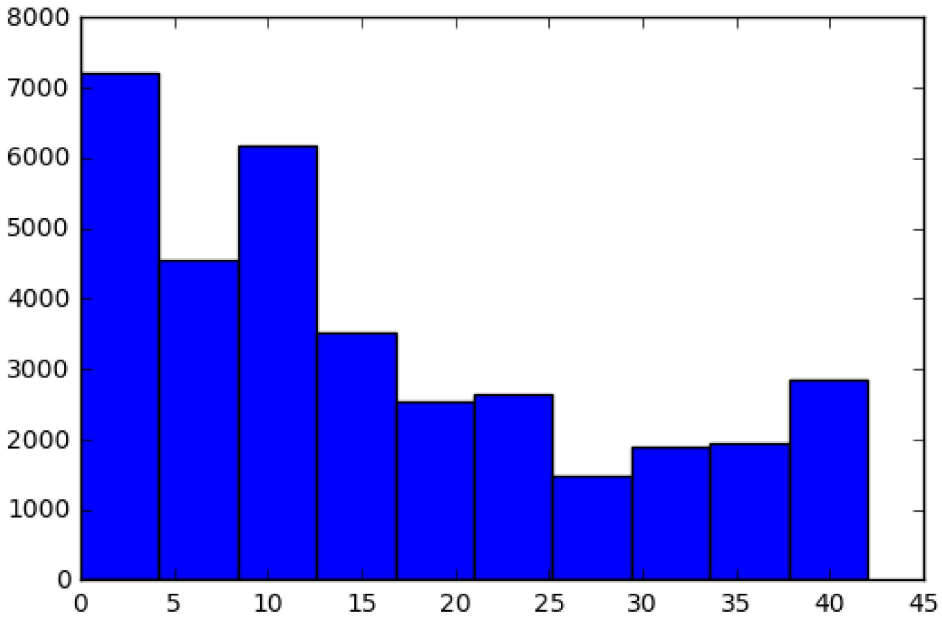
```
index = np.random.randint(0, len(X_train))
image = X_train[index].squeeze()

plt.figure(figsize=(2,2))
plt.imshow(image)
print(y_train[index])
```

```
2
```



In [7]:

```
plt.hist(y_train);
```



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.

In [8]:

```
def rgb2gray (rgb):
    return np.dot (rgb[...,:3], [0.299, 0.587, 0.144])

def imshow_gray (im):
    plt.figure(figsize=(2,2))
    plt.imshow (im, interpolation='nearest', cmap=plt.get_cmap ('gray'))

def rgb2gray_all(X):
    X_g = []
    for i in range(X.shape[0]):
        im0 = X[i]
        if len(im0.shape) == 3:
            im0=im0/128-1
            X_g.append(rgb2gray(im0))
    return np.expand_dims(X_g, axis=-1)
```

In [9]:

```
### Preprocess the data here. It is required to normalize the data. Other p
reprocessing steps could include
### converting to grayscale, etc.
### Feel free to use as many code cells as needed.
X_train = rgb2gray_all(X_train)
X_validation = rgb2gray_all(X_validation)
X_test = rgb2gray_all(X_test)
```

In [10]:

```
X_test.shape
```

Out[10]:

```
(12630, 32, 32, 1)
```

Model Architecture

In [11]:

```
### Define your architecture here.
### Feel free to use as many code cells as needed.
```

In [11]:

```
from sklearn.utils import shuffle

X_train, y_train = shuffle(X_train, y_train)
```

In [12]:

```
import tensorflow as tf
```

In [13]:

```
from tensorflow.contrib.layers import flatten

def LeNet(x):
    # Arguments used for tf.truncated_normal, randomly defines variables fo
r the weights and biases for each layer
    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, stddev = sigma))
    conv1_b = tf.Variable(tf.zeros(6))
    conv1   = tf.nn.conv2d(x, conv1_W, strides=[1, 1, 1, 1], padding='VALI
D') + conv1_b

    # 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],
 padding='VALID')

    # SOLUTION: Layer 2: Convolutional. Output = 10x10x16.
    conv2_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 6, 16), mean = m
u, stddev = sigma))
    conv2_b = tf.Variable(tf.zeros(16))
    conv2   = tf.nn.conv2d(conv1, conv2_W, strides=[1, 1, 1, 1], padding='V
ALID') + conv2_b

    # 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],
 padding='VALID')

    # 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, st
ddev = sigma))
    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, st
ddev = sigma))
    fc2_b  = tf.Variable(tf.zeros(84))
    fc2    = tf.matmul(fc1, fc2_W) + fc2_b

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

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

    return logits
```

In [14]:

```
x = tf.placeholder(tf.float32, (None, 32, 32, 1))
y = tf.placeholder(tf.int32, (None))
one_hot_y = tf.one_hot(y, n_classes)
keep_prob = tf.placeholder(tf.float32)
```

In [107]:

```
rate = 0.0005
dropout = 0.7
logits = LeNet(x)
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(labels=one_hot_y, l
ogits=logits)
loss_operation = tf.reduce_mean(cross_entropy)
optimizer = tf.train.AdamOptimizer(learning_rate = rate)
training_operation = optimizer.minimize(loss_operation)
```

In [108]:

```
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+BATCH_SIZE]
        accuracy = sess.run(accuracy_operation, feed_dict={x: batch_x, y: b
atch_y, keep_prob:1.})
        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 [109]:

```
### 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.
```

In [111]:

```
EPOCHS = 50
BATCH_SIZE = 128
```

In [112]:

```
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,
 keep_prob: dropout})

        validation_accuracy = evaluate(X_validation, y_validation)
        print("EPOCH {} ...".format(i+1))
        print("Validation Accuracy = {:.3f}".format(validation_accuracy))
        training_accuracy = evaluate(X_train, y_train)
        print("Training Accuracy = {:.3f}".format(training_accuracy))
        print()

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

```
Training...

EPOCH 1 ...
Validation Accuracy = 0.572
Training Accuracy = 0.633

EPOCH 2 ...
Validation Accuracy = 0.766
Training Accuracy = 0.834

EPOCH 3 ...
Validation Accuracy = 0.837
Training Accuracy = 0.908

EPOCH 4 ...
Validation Accuracy = 0.861
Training Accuracy = 0.935

EPOCH 5 ...
Validation Accuracy = 0.884
Training Accuracy = 0.955

EPOCH 6 ...
Validation Accuracy = 0.899
Training Accuracy = 0.954

EPOCH 7 ...
Validation Accuracy = 0.896
Training Accuracy = 0.971

EPOCH 8 ...
Validation Accuracy = 0.915
Training Accuracy = 0.977

EPOCH 9 ...
Validation Accuracy = 0.910
Training Accuracy = 0.977

EPOCH 10 ...
Validation Accuracy = 0.919
Training Accuracy = 0.985

EPOCH 11 ...
Validation Accuracy = 0.927
Training Accuracy = 0.985

EPOCH 12 ...
Validation Accuracy = 0.919
Training Accuracy = 0.987
```

```
EPOCH 13 ...
Validation Accuracy = 0.919
Training Accuracy = 0.988

EPOCH 14 ...
Validation Accuracy = 0.920
Training Accuracy = 0.988

EPOCH 15 ...
Validation Accuracy = 0.933
Training Accuracy = 0.991

EPOCH 16 ...
Validation Accuracy = 0.932
Training Accuracy = 0.990

EPOCH 17 ...
Validation Accuracy = 0.931
Training Accuracy = 0.992

EPOCH 18 ...
Validation Accuracy = 0.936
Training Accuracy = 0.992

EPOCH 19 ...
Validation Accuracy = 0.930
Training Accuracy = 0.994

EPOCH 20 ...
Validation Accuracy = 0.930
Training Accuracy = 0.995

EPOCH 21 ...
Validation Accuracy = 0.939
Training Accuracy = 0.996

EPOCH 22 ...
Validation Accuracy = 0.927
Training Accuracy = 0.995

EPOCH 23 ...
Validation Accuracy = 0.936
Training Accuracy = 0.996

EPOCH 24 ...
Validation Accuracy = 0.932
Training Accuracy = 0.997

EPOCH 25 ...
Validation Accuracy = 0.934
```

```
Training Accuracy = 0.997

EPOCH 26 ...
Validation Accuracy = 0.945
Training Accuracy = 0.997

EPOCH 27 ...
Validation Accuracy = 0.933
Training Accuracy = 0.998

EPOCH 28 ...
Validation Accuracy = 0.931
Training Accuracy = 0.997

EPOCH 29 ...
Validation Accuracy = 0.935
Training Accuracy = 0.998

EPOCH 30 ...
Validation Accuracy = 0.938
Training Accuracy = 0.997

EPOCH 31 ...
Validation Accuracy = 0.942
Training Accuracy = 0.999

EPOCH 32 ...
Validation Accuracy = 0.940
Training Accuracy = 0.999

EPOCH 33 ...
Validation Accuracy = 0.939
Training Accuracy = 0.999

EPOCH 34 ...
Validation Accuracy = 0.934
Training Accuracy = 0.999

EPOCH 35 ...
Validation Accuracy = 0.936
Training Accuracy = 0.999

EPOCH 36 ...
Validation Accuracy = 0.935
Training Accuracy = 0.999

EPOCH 37 ...
Validation Accuracy = 0.936
Training Accuracy = 0.999
```

```
EPOCH 38 ...
Validation Accuracy = 0.935
Training Accuracy = 0.999

EPOCH 39 ...
Validation Accuracy = 0.942
Training Accuracy = 0.999

EPOCH 40 ...
Validation Accuracy = 0.937
Training Accuracy = 0.999

EPOCH 41 ...
Validation Accuracy = 0.933
Training Accuracy = 0.999

EPOCH 42 ...
Validation Accuracy = 0.936
Training Accuracy = 0.999

EPOCH 43 ...
Validation Accuracy = 0.939
Training Accuracy = 0.998

EPOCH 44 ...
Validation Accuracy = 0.935
Training Accuracy = 0.998

EPOCH 45 ...
Validation Accuracy = 0.943
Training Accuracy = 1.000

EPOCH 46 ...
Validation Accuracy = 0.941
Training Accuracy = 1.000

EPOCH 47 ...
Validation Accuracy = 0.943
Training Accuracy = 0.999

EPOCH 48 ...
Validation Accuracy = 0.934
Training Accuracy = 0.999

EPOCH 49 ...
Validation Accuracy = 0.937
Training Accuracy = 1.000

EPOCH 50 ...
Validation Accuracy = 0.932
```

```
Training Accuracy = 1.000

Model saved
```

In [113]:

```
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 .\traffic_sign
Test Accuracy = 0.926
```

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.

Load and Output the Images

In [114]:

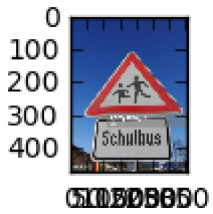
```
### Load the images and plot them here.
### Feel free to use as many code cells as needed.
```

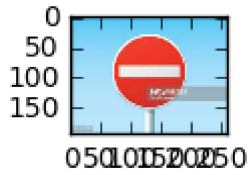
In [115]:

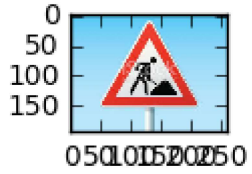
```
import glob
from PIL import Image
from scipy.misc import imresize

X_sample=[]
sample_images = glob.glob('./samples/*')
```

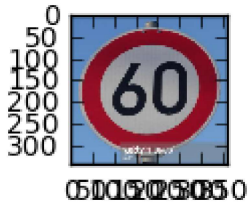
In [116]:

```
for fp in sample_images:
    im = Image.open(fp, 'r')
    plt.figure(figsize=(1,1))
    plt.imshow(im)
```









In [117]:

```
y_sample = [28, 17, 25,  1,  3]
```

In [118]:

```
for fp in sample_images:
    im0 = imresize(np.asarray (Image.open(fp, 'r')), (32, 32))
    if len(im0.shape) == 3:
        im0=im0/128-1
        X_sample.append(rgb2gray(im0))
X_sample = np.expand_dims(X_sample, axis=-1)
```

Predict the Sign Type for Each Image

In [119]:

```
### Run the predictions here and use the model to output the prediction for
 each image.
### Make sure to pre-process the images with the same pre-processing pipeli
ne used earlier.
### Feel free to use as many code cells as needed.
```

In [120]:

```
with tf.Session() as sess:
    saver.restore(sess, tf.train.latest_checkpoint('.'))
    logits_sample = sess.run(logits, feed_dict={x: X_sample, keep_prob:
1.})
```

```
INFO:tensorflow:Restoring parameters from .\traffic_sign
```

In [121]:

```
classes_samples = np.argmax(logits_sample, 1)
```

In [122]:

```
classes_samples
```

Out[122]:

```
array([28, 17, 25,  1,  3], dtype=int64)
```

In [87]:

```
import pandas as pd
```

In [88]:

```
df = pd.read_csv('signnames.csv')
df[df['ClassId'].isin(classes_samples)]
```

Out[88]:

	ClassId	SignName
1	1	Speed limit (30km/h)
3	3	Speed limit (60km/h)
17	17	No entry
25	25	Road work

Analyze Performance

In [89]:

```
### Calculate the accuracy for these 5 new images.
### For example, if the model predicted 1 out of 5 signs correctly, it's 2
0% accurate on these new images.
```

In [123]:

```
with tf.Session() as sess:
    saver.restore(sess, tf.train.latest_checkpoint('.'))

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

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

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,
 0.07893497,
         0.12789202],
       [ 0.28086119,  0.27569815,  0.08594638,  0.0178669 ,  0.18063
401,
         0.15899337],
       [ 0.26076848,  0.23664738,  0.08020603,  0.07001922,  0.11343
71 ,
         0.23892179],
       [ 0.11943333,  0.29198961,  0.02605103,  0.26234032,  0.13513
48 ,
         0.16505091],
       [ 0.09561176,  0.34396535,  0.0643941 ,  0.16240774,  0.24206
137,
         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 [91]:

```
### Print out the top five softmax probabilities for the predictions on the
 German traffic sign images found on the web.
### Feel free to use as many code cells as needed.
```

In [126]:

```
softmax = tf.nn.softmax(logits)
```

In [127]:

```
with tf.Session() as sess:
    saver.restore(sess, tf.train.latest_checkpoint('.'))
    top_5 = sess.run(tf.nn.top_k(softmax, k=5), feed_dict={x: X_sample, kee
p_prob:1.})
```

```
INFO:tensorflow:Restoring parameters from .\traffic_sign
```

In [128]:

```
top_5
```

Out[128]:

```
TopKV2(values=array([[  9.35004592e-01,   4.17103358e-02,   1.
39959399e-02,
          4.67969058e-03,   2.94811046e-03],
       [  9.99812663e-01,   1.75454159e-04,   1.19657607e-05,
          6.12733497e-13,   2.71687349e-13],
       [  9.99884248e-01,   1.05057617e-04,   9.25233326e-06,
          1.40355428e-06,   1.71061287e-09],
       [  9.99999881e-01,   1.32206125e-07,   9.30244326e-09,
          8.71579420e-10,   4.64542088e-13],
       [  1.00000000e+00,   5.64761475e-12,   7.07278311e-13,
          9.28081593e-18,   5.46240794e-18]], dtype=float32),
 indices=array([[28, 29, 30,  3, 23],
       [17, 34,  9, 28,  3],
       [25, 21, 30, 31, 20],
       [ 1,  5,  0,  3,  4],
       [ 3,  2,  1, 36, 38]]))
```

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.

In [ ]:

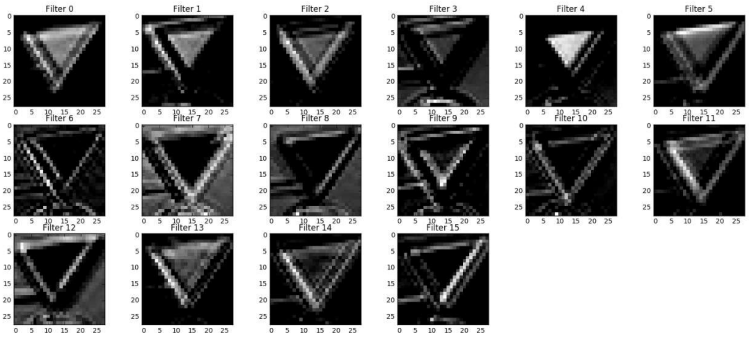
```

```

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 fea
ture maps
# tf_activation: should be a tf variable name used during your training pro
cedure that represents the calculated state of a specific weight layer
# activation_min/max: can be used to view the activation contrast in more d
etail, by default matplot sets min and max to the actual min and max values
 of the output
# plt_num: used to plot out multiple different weight feature map sets on t
he same block, just extend the plt number for each new feature map entry

def outputFeatureMap(image_input, tf_activation, activation_min=-1, activat
ion_max=-1 ,plt_num=1):
    # Here make sure to preprocess your image_input in a way your network e
xpects
    # with size, normalization, ect if needed
    # image_input =
    # Note: x should be the same name as your network's tensorflow data pla
ceholder variable
    # If you get an error tf_activation is not defined it may be having tro
uble accessing the variable from inside a function
    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 on each row and column
        plt.title('FeatureMap ' + str(featuremap)) # displays the feature m
ap number
        if activation_min != -1 & activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="neares
t", vmin =activation_min, vmax=activation_max, cmap="gray")
        elif activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="neares
t", vmax=activation_max, cmap="gray")
        elif activation_min !=-1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="neares
t", vmin=activation_min, cmap="gray")
        else:
            plt.imshow(activation[0,:,:, featuremap], interpolation="neares
t", cmap="gray")
```