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 [13]:

```
# Load pickled data
import pickle
from sklearn.utils import shuffle

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

training_file = "./data/train.p"
validation_file= './data/valid.p'
testing_file = "./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)

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

assert(len(X_train) == len(y_train))
assert(len(X_valid) == len(y_valid))
assert(len(X_test) == len(y_test))

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

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 [14]:

```
### 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("Number of training examples =", n_train)
print("Number of validation examples =", len(X_valid))
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 [15]:

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


def getSignNames():
    return pd.read_csv('./data/signnames.csv').values

def plotImages(X, y, examples_per_sign=15, squeeze=False, cmap=None):
    samples_per_sign = np.bincount(y)
    for sign in getSignNames():
        print("{0}. {1} - Samples: {2}".format(sign[0], sign[1], samples_per_sign[sign[
0]]))
        sample_indices = np.where(y==sign[0])[0]
        random_samples = random.sample(list(sample_indices), examples_per_sign)
        fig = plt.figure(figsize = (examples_per_sign, 1))
        fig.subplots_adjust(hspace = 0, wspace = 0)
        for i in range(examples_per_sign):
            image = X[random_samples[i]]
            axis = fig.add_subplot(1,examples_per_sign, i+1, xticks=[], yticks=[])
            if squeeze: image = image.squeeze()
            if cmap == None: axis.imshow(image)
            else: axis.imshow(image.squeeze(), cmap=cmap)
        plt.show()
```

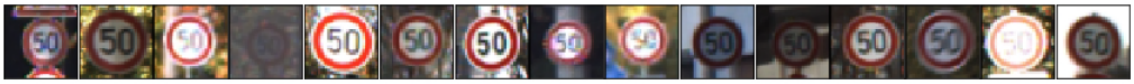
In [16]:

```
plotImages(X_train, y_train)
```

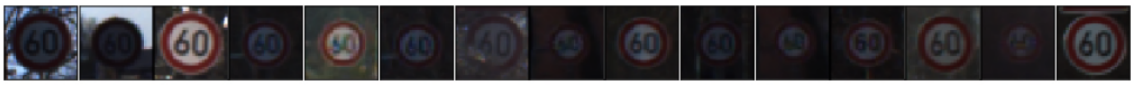
0. Speed limit (20km/h) - Samples: 180

1. Speed limit (30km/h) - Samples: 1980

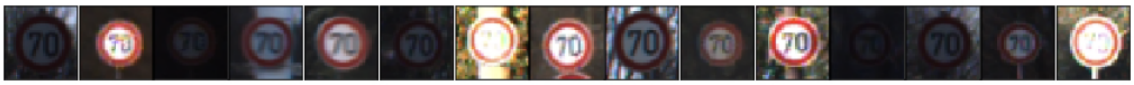
2. Speed limit (50km/h) - Samples: 2010



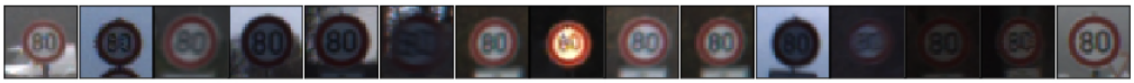
3. Speed limit (60km/h) - Samples: 1260



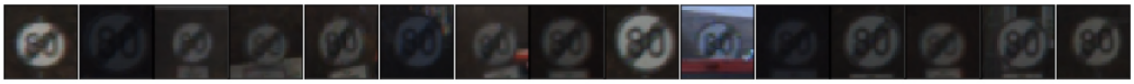
4. Speed limit (70km/h) - Samples: 1770



5. Speed limit (80km/h) - Samples: 1650

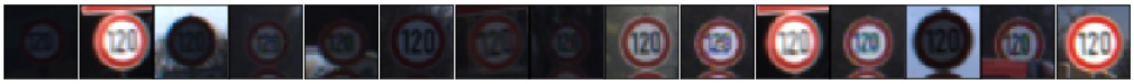


6. End of speed limit (80km/h) - Samples: 360

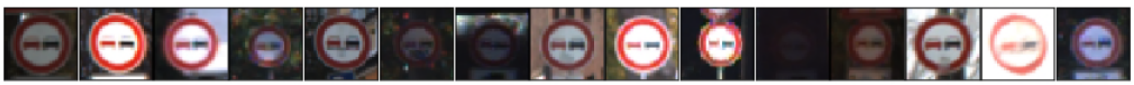


7. Speed limit (100km/h) - Samples: 1290

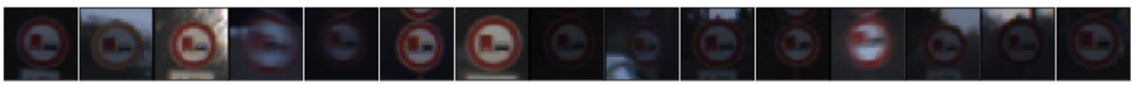
8. Speed limit (120km/h) - Samples: 1260



9. No passing - Samples: 1320

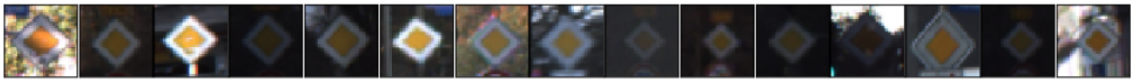


10. No passing for vehicles over 3.5 metric tons - Samples: 1800

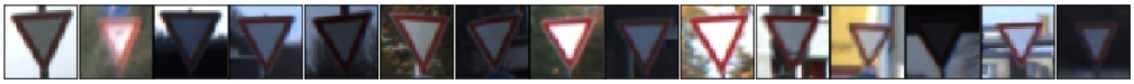


11. Right-of-way at the next intersection - Samples: 1170

12. Priority road - Samples: 1890

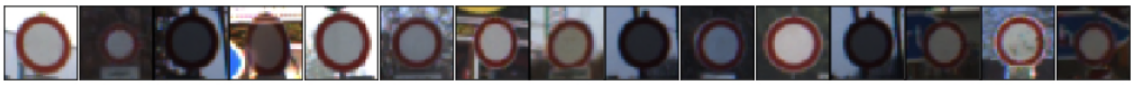


13. Yield - Samples: 1920



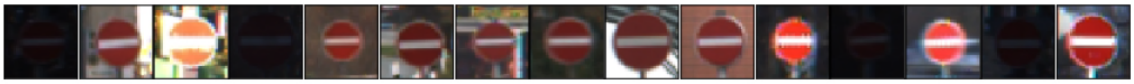
14. Stop - Samples: 690

15. No vehicles - Samples: 540



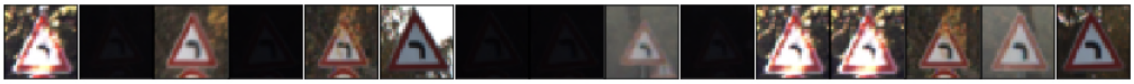
16. Vehicles over 3.5 metric tons prohibited - Samples: 360

17. No entry - Samples: 990

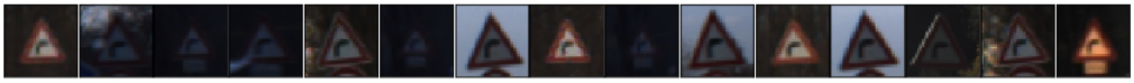


18. General caution - Samples: 1080

19. Dangerous curve to the left - Samples: 180



20. Dangerous curve to the right - Samples: 300



21. Double curve - Samples: 270

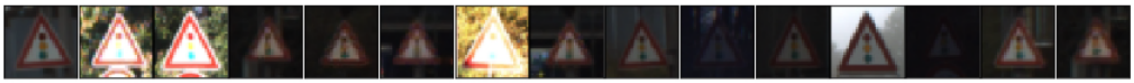
22. Bumpy road - Samples: 330

23. Slippery road - Samples: 450

24. Road narrows on the right - Samples: 240

25. Road work - Samples: 1350

26. Traffic signals - Samples: 540

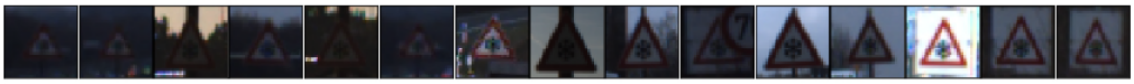


27. Pedestrians - Samples: 210

28. Children crossing - Samples: 480

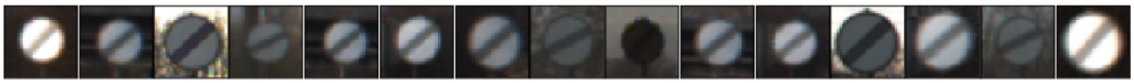
29. Bicycles crossing - Samples: 240

30. Beware of ice/snow - Samples: 390



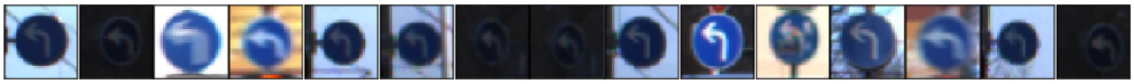
31. Wild animals crossing - Samples: 690

32. End of all speed and passing limits - Samples: 210



33. Turn right ahead - Samples: 599

34. Turn left ahead - Samples: 360

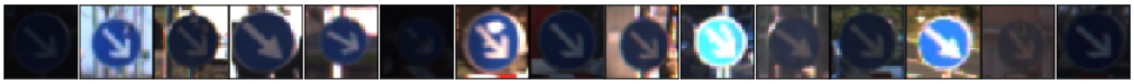


35. Ahead only - Samples: 1080

36. Go straight or right - Samples: 330

37. Go straight or left - Samples: 180

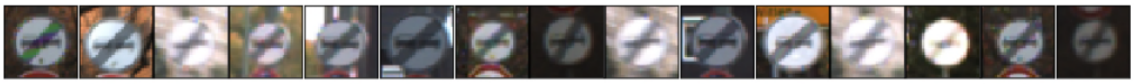
38. Keep right - Samples: 1860



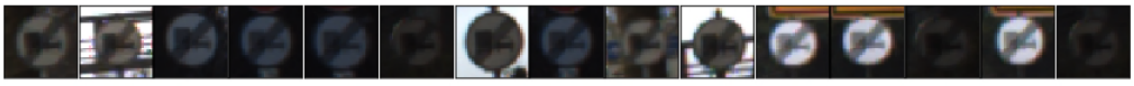
39. Keep left - Samples: 270

40. Roundabout mandatory - Samples: 300

41. End of no passing - Samples: 210

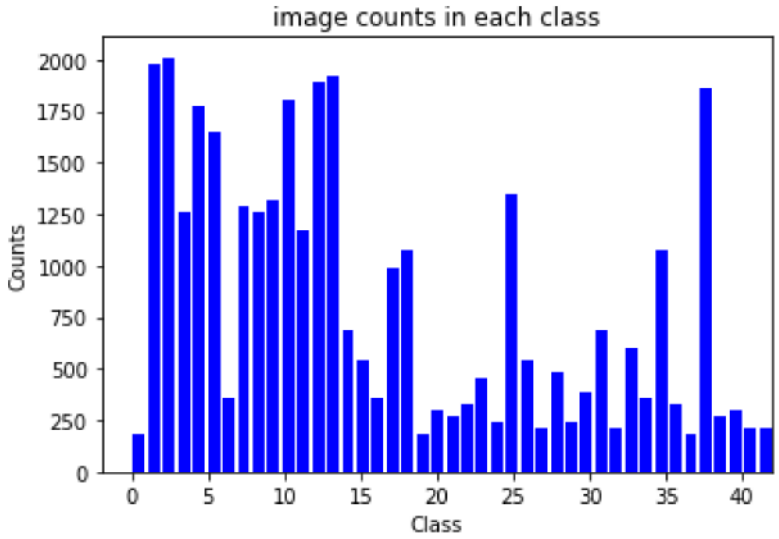


42. End of no passing by vehicles over 3.5 metric tons - Samples: 210



In [17]:

```
# plot the histogram
plt.hist(y_train, bins = n_classes, rwidth=0.8, facecolor='blue')
plt.xlim(xmax=n_classes-1)
plt.xlabel('Class')
plt.ylabel('Counts')
plt.title(r'image counts in each class')
plt.show()
```



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 [18]:

```
### Preprocess the data here. It is required to normalize the data. Other preprocessing
 steps could include
### converting to grayscale, etc.
### Feel free to use as many code cells as needed.
import matplotlib.pyplot as plt
import cv2

def getGrayScale(img):
    YCrCb = cv2.cvtColor(img, cv2.COLOR_RGB2YCrCb)
    return np.resize(YCrCb[:,:,0], (32,32,1))

def normalizeImage(img):
    a = -0.5
    b = 0.5
    minimum = 0
    maximum = 255
    return a + ((img - minimum) * (b - a)) / (maximum - minimum)

def preprocessImages(images):
    ret_array = []
    for img in images:
        img_tmp = img.copy()
        ret_array.append(normalizeImage(getGrayScale(img_tmp)))

    return ret_array


X_train = preprocessImages(X_train)
X_valid = preprocessImages(X_valid)
X_test = preprocessImages(X_test)

plotImages(X_train, y_train, squeeze=True, cmap='gray')
```

0. Speed limit (20km/h) - Samples: 180

1. Speed limit (30km/h) - Samples: 1980

2. Speed limit (50km/h) - Samples: 2010

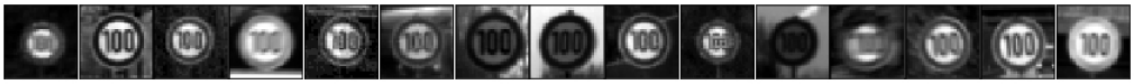
3. Speed limit (60km/h) - Samples: 1260

4. Speed limit (70km/h) - Samples: 1770

5. Speed limit (80km/h) - Samples: 1650

6. End of speed limit (80km/h) - Samples: 360

7. Speed limit (100km/h) - Samples: 1290



8. Speed limit (120km/h) - Samples: 1260

9. No passing - Samples: 1320

10. No passing for vehicles over 3.5 metric tons - Samples: 1800

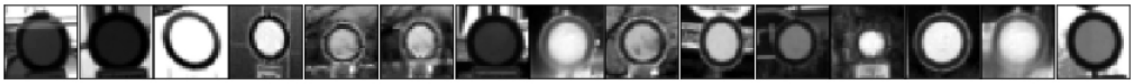
11. Right-of-way at the next intersection - Samples: 1170

12. Priority road - Samples: 1890

13. Yield - Samples: 1920

14. Stop - Samples: 690

15. No vehicles - Samples: 540



16. Vehicles over 3.5 metric tons prohibited - Samples: 360

17. No entry - Samples: 990

18. General caution - Samples: 1080

19. Dangerous curve to the left - Samples: 180

20. Dangerous curve to the right - Samples: 300

21. Double curve - Samples: 270

22. Bumpy road - Samples: 330

23. Slippery road - Samples: 450

24. Road narrows on the right - Samples: 240

25. Road work - Samples: 1350

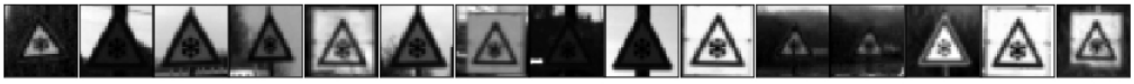
26. Traffic signals - Samples: 540

27. Pedestrians - Samples: 210

28. Children crossing - Samples: 480

29. Bicycles crossing - Samples: 240

30. Beware of ice/snow - Samples: 390



31. Wild animals crossing - Samples: 690

32. End of all speed and passing limits - Samples: 210

33. Turn right ahead - Samples: 599

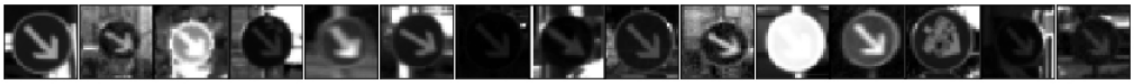
34. Turn left ahead - Samples: 360

35. Ahead only - Samples: 1080

36. Go straight or right - Samples: 330

37. Go straight or left - Samples: 180

38. Keep right - Samples: 1860



39. Keep left - Samples: 270

40. Roundabout mandatory - Samples: 300

41. End of no passing - Samples: 210

42. End of no passing by vehicles over 3.5 metric tons - Samples: 210

Model Architecture

In [19]:

```
### Define your architecture here.
### Feel free to use as many code cells as needed.
import os
import tensorflow as tf
from tensorflow.contrib.layers import flatten
from sklearn.utils import shuffle

def LeNet(x, num_labels):
    # Hyperparameters
    mu = 0
    sigma = 0.1

    # Convolutional Layer. Input = 32x32x1. Output = 28x28x48.
    conv1_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 1, 48), mean = mu, stddev
= sigma))
    conv1_b = tf.Variable(tf.zeros([48]))
    conv1 = tf.nn.conv2d(x, conv1_W, strides=[1, 1, 1, 1], padding='VALID') + conv1_b
    conv1 = tf.nn.relu(conv1)

    # Max Pooling. Input = 28x28x48. Output = 14x14x48.
    conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding=
'VALID', name='conv1')

    # Convolutional Layer. Output = 10x10x96.
    conv2_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 48, 96), mean = mu, stddev
 = sigma))
    conv2_b = tf.Variable(tf.zeros([96]))
    conv2 = tf.nn.conv2d(conv1, conv2_W, strides=[1, 1, 1, 1], padding='VALID') + con
v2_b
    conv2 = tf.nn.relu(conv2)

    # Max Pooling. Input = 10x10x96. Output = 5x5x96.
    conv2 = tf.nn.max_pool(conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding=
'VALID', name='conv2')

    # Convolutional Layer. Input = 5x5x96. Output = 3x3x172.
    conv3_W = tf.Variable(tf.truncated_normal(shape=(3, 3, 96, 172), mean = mu, stdde
v = sigma))
    conv3_b = tf.Variable(tf.zeros([172]))
    conv3 = tf.nn.conv2d(conv2, conv3_W, strides=[1, 1, 1, 1], padding='VALID') + con
v3_b
    conv3 = tf.nn.relu(conv3)

    # Max Pooling. Input = 3x3x172. Output = 2x2x172.
    conv3 = tf.nn.max_pool(conv3, ksize=[1, 2, 2, 1], strides=[1, 1, 1, 1], padding=
'VALID', name='conv3')

    # Flatten. Input = 2x2x172. Output = 688.
    fc1 = flatten(conv3)

    # Fully Connected. Input = 688. Output = 84.
    fc2_W = tf.Variable(tf.truncated_normal(shape=(688 , 84), mean = mu, stddev = sig
ma))
    fc2_b = tf.Variable(tf.zeros([84]))
    fc2 = tf.nn.xw_plus_b(fc1, fc2_W, fc2_b)
    fc2 = tf.nn.relu(fc2)

    # Fully Connected. Input = 84. Output = 43.
    fc3_W = tf.Variable(tf.truncated_normal(shape=(84, num_labels), mean = mu, stddev
```

```
 = sigma))
    fc3_b = tf.Variable(tf.zeros([num_labels]))
    logits = tf.nn.xw_plus_b(fc2, fc3_W, fc3_b)

    return logits


x = tf.placeholder(tf.float32, (None, 32, 32, 1))
y = tf.placeholder(tf.int32, (None))

y_one_hot = tf.one_hot(y, n_classes)
logits = LeNet(x, n_classes)
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits=logits, labels=y_one_h
ot)
loss_operation = tf.reduce_mean(cross_entropy)
optimizer = tf.train.AdamOptimizer(learning_rate = 0.001)
training_operation = optimizer.minimize(loss_operation)
```

```
/home/chencan/anaconda3/envs/tensorflow_gpu_r17/lib/python3.6/site-package
s/h5py/__init__.py:36: FutureWarning: Conversion of the second argument of
issubdtype from `float` to `np.floating` is deprecated. In future, it will
be treated as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
```

```
WARNING:tensorflow:From /home/chencan/anaconda3/envs/tensorflow_gpu_r17/li
b/python3.6/site-packages/tensorflow/contrib/learn/python/learn/datasets/b
ase.py:198: retry (from tensorflow.contrib.learn.python.learn.datasets.bas
e) is deprecated and will be removed in a future version.
Instructions for updating:
Use the retry module or similar alternatives.
WARNING:tensorflow:From <ipython-input-19-b92b5b366429>:62: softmax_cross_
entropy_with_logits (from tensorflow.python.ops.nn_ops) is deprecated and
will be removed in a future version.
Instructions for updating:

Future major versions of TensorFlow will allow gradients to flow
into the labels input on backprop by default.

See tf.nn.softmax_cross_entropy_with_logits_v2.
```

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 [21]:

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

EPOCHS = 22
BATCH_SIZE = 128

# sess = tf.get_default_session()
# accuracy = sess.run(accuracy_operation, feed_dict={x: batch_x, y: batch_y})
# equals -->
# accuracy = accuracy_operation.eval(feed_dict={x: batch_x, y: batch_y})
# only if there is only one evaluated tensor

def evaluate(X_data, y_data):
    num_examples = len(X_data)
    total_accuracy = 0
    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 = accuracy_operation.eval(feed_dict={x: batch_x, y: batch_y})
        total_accuracy += (accuracy * len(batch_x))
    return total_accuracy / num_examples


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

    print("Training...")
    for i in range(EPOCHS):
        print("EPOCH {} ... ".format(i+1), end='')
        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})
        train_accuracy = evaluate(X_valid, y_valid)
        print("Train Accuracy = {:.3f}".format(train_accuracy))

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

```
Training...
EPOCH 1 ... Train Accuracy = 0.859
EPOCH 2 ... Train Accuracy = 0.900
EPOCH 3 ... Train Accuracy = 0.930
EPOCH 4 ... Train Accuracy = 0.939
EPOCH 5 ... Train Accuracy = 0.934
EPOCH 6 ... Train Accuracy = 0.941
EPOCH 7 ... Train Accuracy = 0.943
EPOCH 8 ... Train Accuracy = 0.954
EPOCH 9 ... Train Accuracy = 0.924
EPOCH 10 ... Train Accuracy = 0.939
EPOCH 11 ... Train Accuracy = 0.953
EPOCH 12 ... Train Accuracy = 0.964
EPOCH 13 ... Train Accuracy = 0.955
EPOCH 14 ... Train Accuracy = 0.965
EPOCH 15 ... Train Accuracy = 0.947
EPOCH 16 ... Train Accuracy = 0.950
EPOCH 17 ... Train Accuracy = 0.965
EPOCH 18 ... Train Accuracy = 0.961
EPOCH 19 ... Train Accuracy = 0.969
EPOCH 20 ... Train Accuracy = 0.971
EPOCH 21 ... Train Accuracy = 0.974
EPOCH 22 ... Train Accuracy = 0.972
Model saved
```

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.

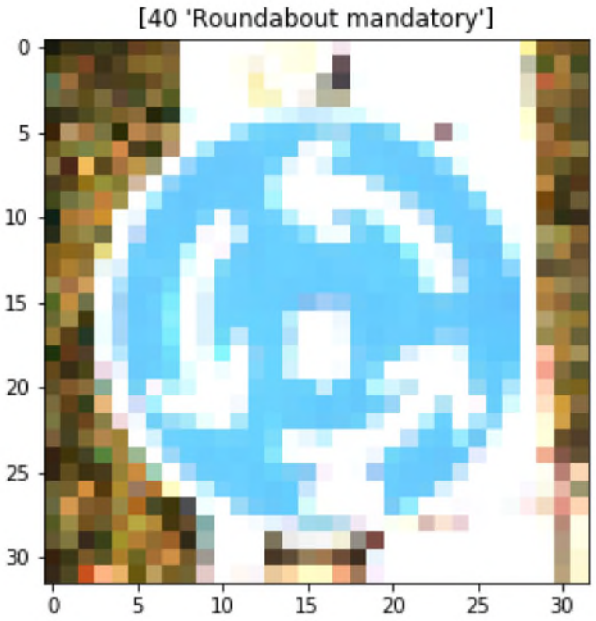
You may find `signnames.csv` useful as it contains mappings from the class id (integer) to the actual sign name.

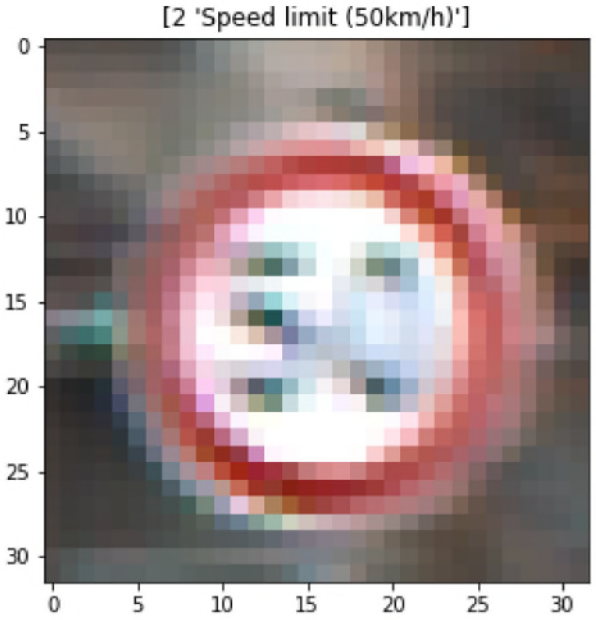
Load and Output the Images

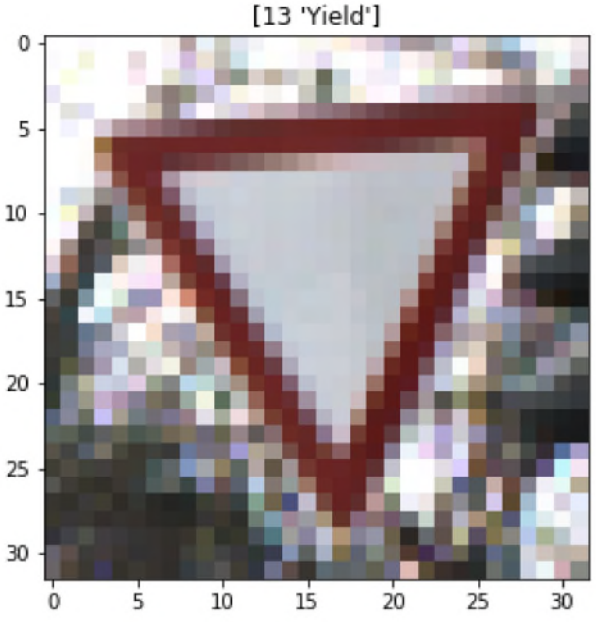
In [39]:

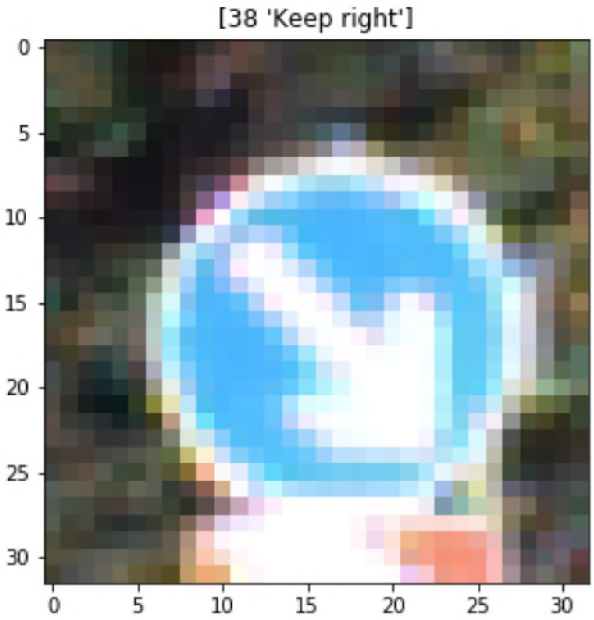
```
### Load the images and plot them here.
### Feel free to use as many code cells as needed.
import glob
import random
import numpy as np
import cv2
import pandas as pd


img_names = []
img_labels = []

sign_names = pd.read_csv('./data/images/GT-online_test.csv').values
for single in sign_names:
    split = single[0].split(';')
    img_names.append(split[0])
    img_labels.append(int(split[-1]))


imgs = []
labels = []

img_files = glob.glob('./data/images/*.ppm')

for img_path in img_files:
    img = cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB)
    img_resized = cv2.resize(img, (32, 32))
    imgs.append(img_resized)

    for i in range(len(img_names)):
        if img_names[i] == img_path.split('/')[-1]:
            labels.append(img_labels[i])

print(labels)

label_names = getSignNames()

def draw_images(data, images_per_line=1, squeeze=False, cmap=None):
    for offset in range(0, len(data), images_per_line):
        batch = data[offset:offset + images_per_line]
        fig = plt.figure(figsize = (25,5))
        for i in range(images_per_line):
            axis = fig.add_subplot(1, images_per_line, i + 1)
            if labels[offset+i] < len(sign_names):
                axis.set_title(label_names[labels[offset+i]])
            else:
                axis.set_title('unknown')

            image = batch[i].copy()
            if squeeze: image = image.squeeze()
            if cmap == None: axis.imshow(image)
            else: axis.imshow(image.squeeze(), cmap=cmap)

        plt.show()


draw_images(imgs)
print(labels)
```

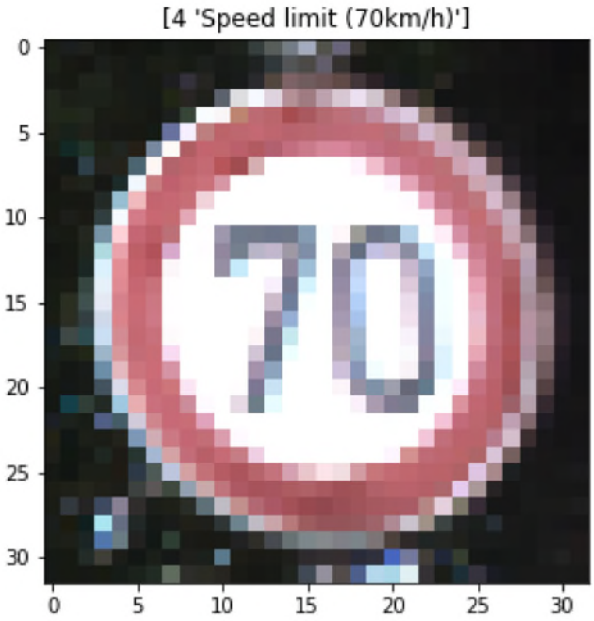
```
[40, 2, 13, 38, 4]
```











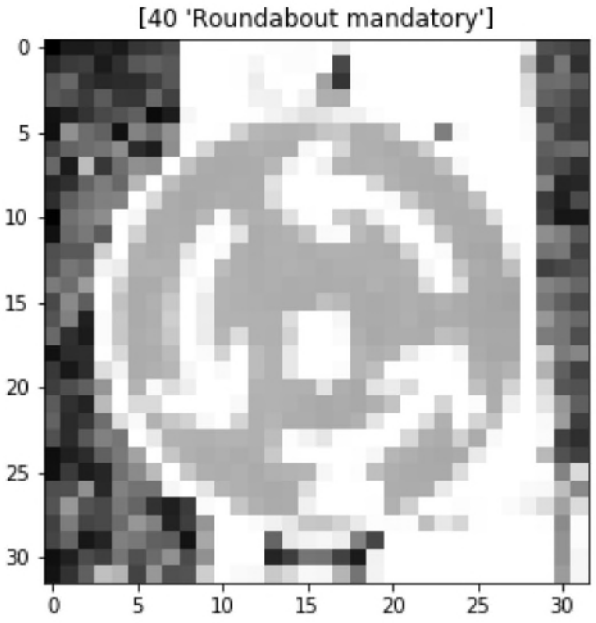

```
[40, 2, 13, 38, 4]
```

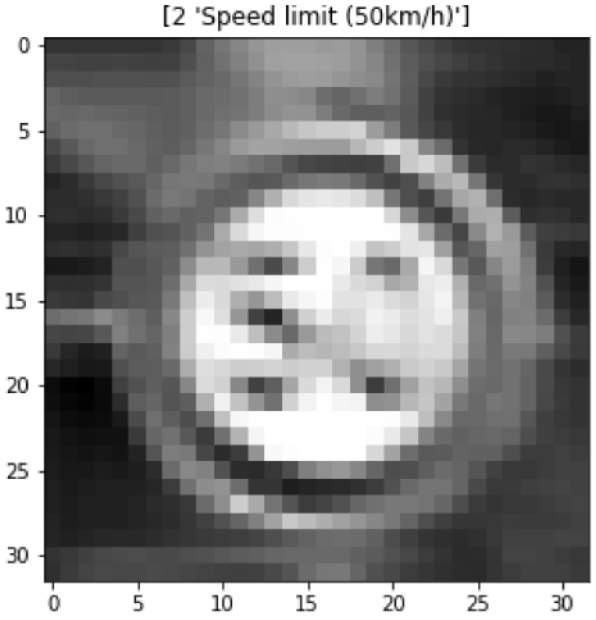
Predict the Sign Type for Each Image

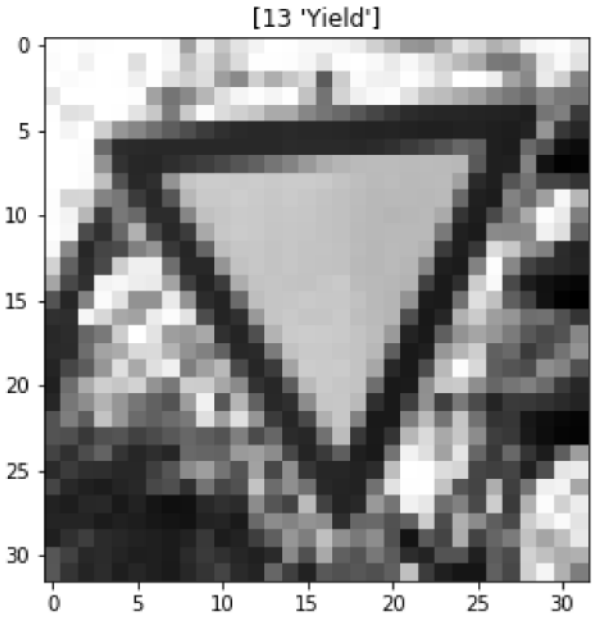
In [41]:

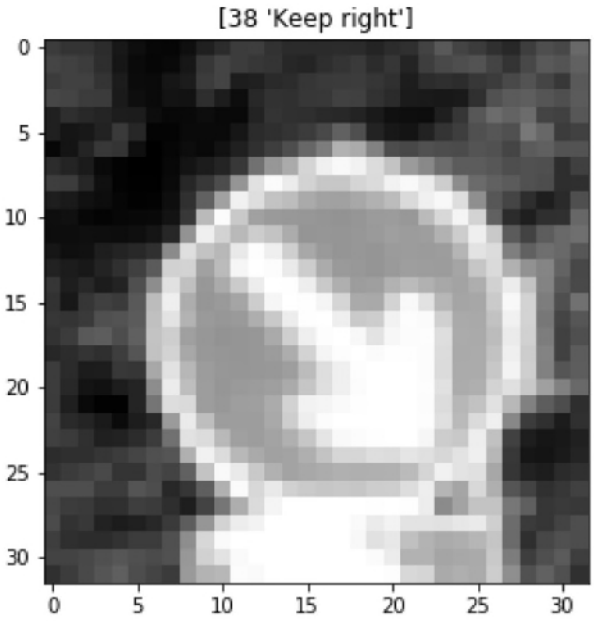
```
### Run the predictions here and use the model to output the prediction for each image.
### Make sure to pre-process the images with the same pre-processing pipeline used earl
ier.
### Feel free to use as many code cells as needed.
print(labels)
signs_proccessed = preprocessImages(imgs)
draw_images(signs_proccessed, squeeze=True, cmap='gray')
```

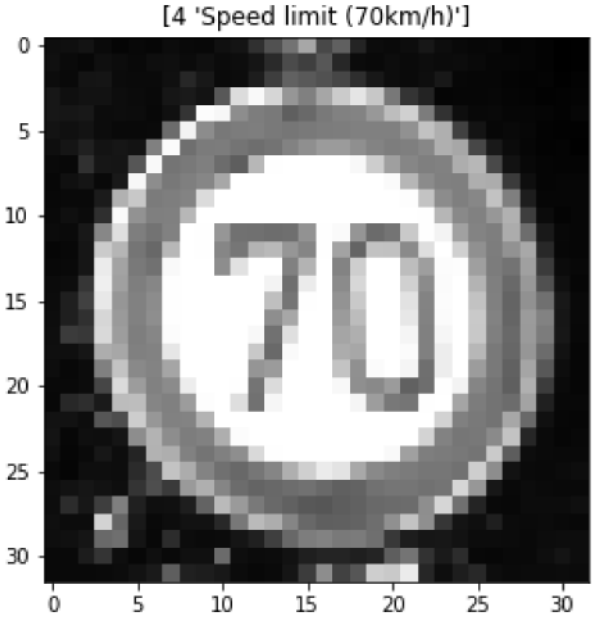
```
[40, 2, 13, 38, 4]
[40, 2, 13, 38, 4]
```












```
[40, 2, 13, 38, 4]
```

Analyze Performance

In [42]:

```
### Calculate the accuracy for these 5 new images.
### For example, if the model predicted 1 out of 5 signs correctly, it's 20% accurate o
n these new images.

correct_prediction = tf.equal(tf.argmax(logits, 1), tf.argmax(y_one_hot, 1))
accuracy_operation = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
saver = tf.train.Saver()
BATCH_SIZE = 128

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: batch_y})
        total_accuracy += (accuracy * len(batch_x))
    return total_accuracy / num_examples

with tf.Session() as sess:
    saver.restore(sess, tf.train.latest_checkpoint('./model/'))
    print(labels)
    test_accuracy = evaluate(signs_proccessed, labels)
    print("Test Accuracy = {:.3f}".format(test_accuracy))
```

```
INFO:tensorflow:Restoring parameters from ./model/model
[40, 2, 13, 38, 4]
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 ,  0.18063401,
         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:

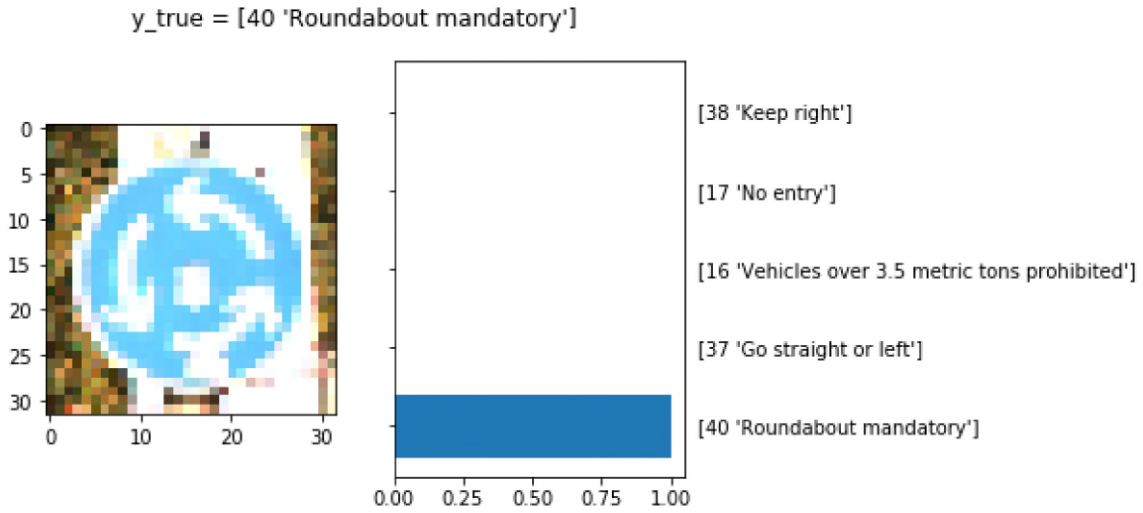
```
TopKV2(values=array([[ 0.34763842,  0.24879643,  0.12789202],
       [ 0.28086119,  0.27569815,  0.18063401],
       [ 0.26076848,  0.23892179,  0.23664738],
       [ 0.29198961,  0.26234032,  0.16505091],
       [ 0.34396535,  0.24206137,  0.16240774]]), indices=array([[3, 0, 5],
       [0, 1, 4],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

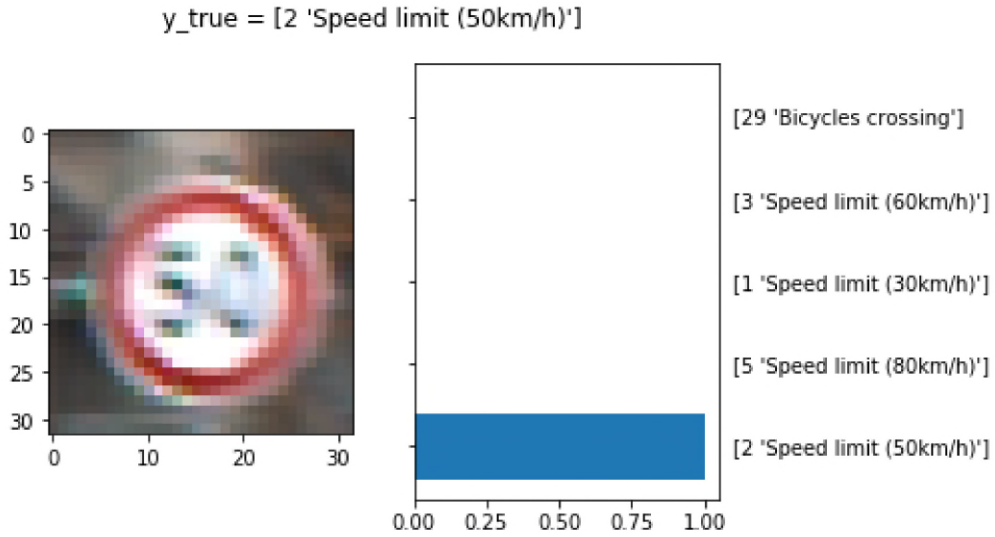
Looking just at the first row we get `[ 0.34763842,  0.24879643,  0.12789202]`, you can confirm these are the 3 largest probabilities in `a`. You'll also notice `[3, 0, 5]` are the corresponding indices.

In [44]:

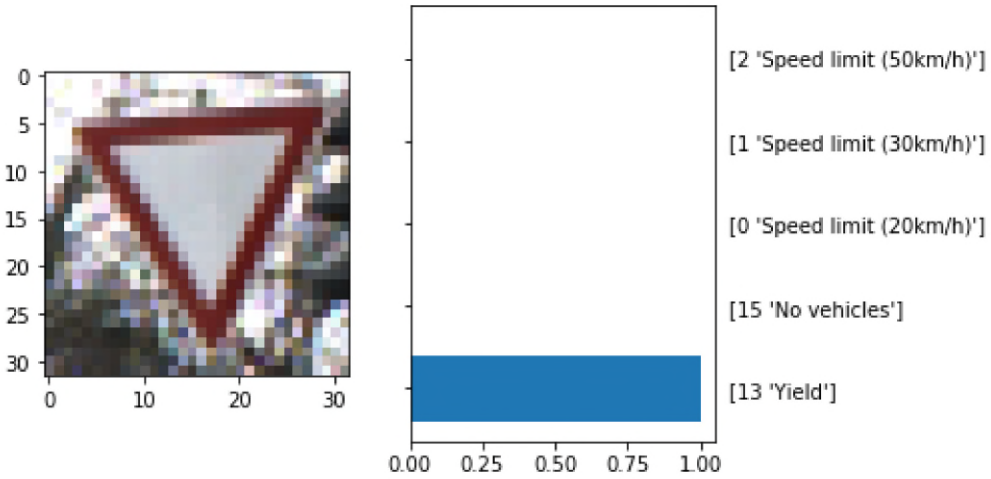
```
### Print out the top five softmax probabilities for the predictions on the German traf
fic sign images found on the web.
### Feel free to use as many code cells as needed.
TOP_K = 5
with tf.Session() as sess:
    saver.restore(sess, tf.train.latest_checkpoint('./model/'))
    top = sess.run(tf.nn.top_k(tf.nn.softmax(logits), k=TOP_K), feed_dict={x:signs_proc
essed})

for i in range(len(img_files)):
    f, (ax1, ax2) = plt.subplots(1, 2, sharey=False, sharex=False)
    f.suptitle("y_true = {}".format(label_names[labels[i]]))
    ax1.imshow(imgs[i])
    print('prediction: ', top.values[i])
    ax2.barh(range(TOP_K), top.values[i], align='center')
    ax2.set_yticks(range(TOP_K))
    ax2.set_yticklabels( label_names[top[1][i].astype(int)])
    ax2.tick_params(labelleft=False , labelright=True)
```

```
INFO:tensorflow:Restoring parameters from ./model/model
prediction:  [1.0000000e+00 8.0199997e-10 2.5352900e-10 3.8923781e-11 1.85
82882e-11]
prediction:  [1.0000000e+00 2.0870240e-18 7.5639494e-19 1.5299802e-30 2.30
76776e-32]
prediction:  [1.0000000e+00 2.4487744e-38 0.0000000e+00 0.0000000e+00 0.00
00000e+00]
prediction:  [1.0000000e+00 3.9018636e-22 3.3661048e-23 1.8455502e-23 5.49
76518e-26]
prediction:  [1.0000000e+00 2.2304778e-22 1.1162017e-23 6.7667221e-32 3.91
94295e-33]
```

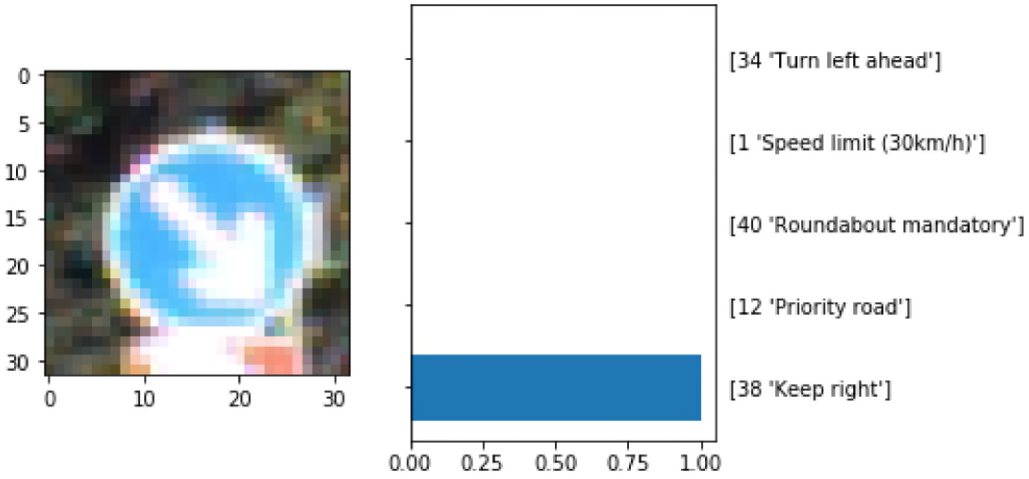




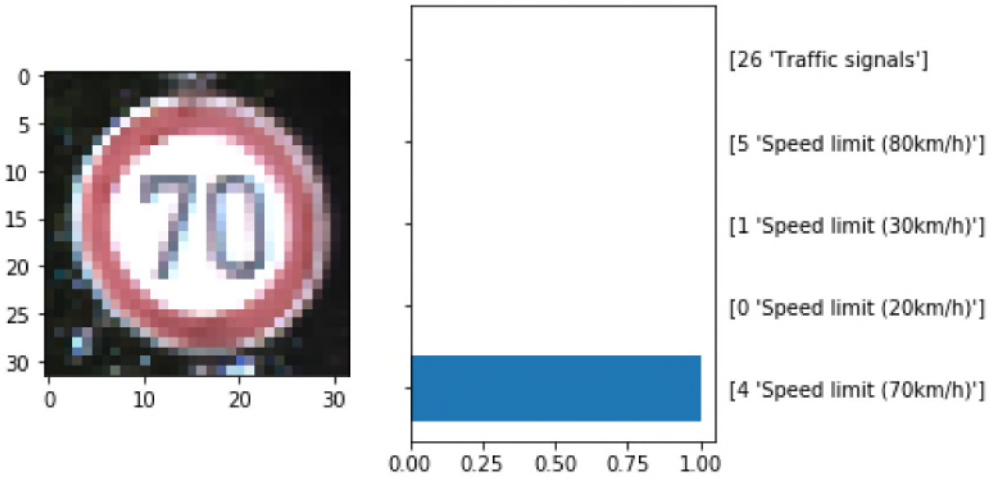
y_true = [13 'Yield']



y_true = [38 'Keep right']



y_true = [4 'Speed limit (70km/h)']



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.

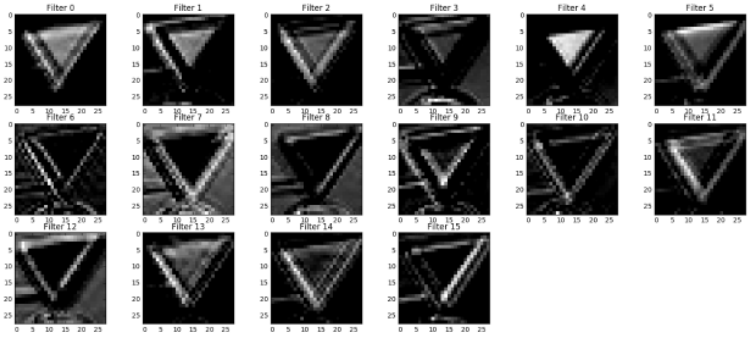
> **Note**: Once you have completed all of the code implementations and successfully answered each question above, you may finalize your work by exporting the iPython Notebook as an HTML document. You can do this by using the menu above and navigating to \n", "**File -> Download as -> HTML (.html)**. 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 [31]:

```
### 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 maps
# tf_activation: should be a tf variable name used during your training procedure that
 represents the calculated state of a specific weight layer
# activation_min/max: can be used to view the activation contrast in more detail, by de
fault 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 the same bloc
k, just extend the plt number for each new feature map entry

def outputFeatureMap(image_input, tf_activation, activation_min=-1, activation_max=-1 ,
plt_num=1):
    # 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 placeholder var
iable
    # If you get an error tf_activation is not defined it may be having trouble accessi
ng 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(16,8, featuremap+1) # sets the number of feature maps to show on ea
ch row and column
        plt.title('FeatureMap ' + str(featuremap)) # displays the feature map number
        if activation_min != -1 & activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmin =ac
tivation_min, vmax=activation_max, cmap="gray")
        elif activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmax=act
ivation_max, cmap="gray")
        elif activation_min !=-1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmin=act
ivation_min, cmap="gray")
        else:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", cmap="gr
ay")

with tf.Session() as sess:
    graph = X_train[0:BATCH_SIZE]
    saver.restore(sess, tf.train.latest_checkpoint('./model/'))
    conv1 = sess.graph.get_tensor_by_name('conv1:0')
    outputFeatureMap(graph,conv1, activation_min=-1, activation_max=-1, plt_num=1)
    conv2 = sess.graph.get_tensor_by_name('conv2:0')
    outputFeatureMap(graph,conv2, activation_min=-1, activation_max=-1, plt_num=2)
```

```
INFO:tensorflow:Restoring parameters from ./model/model
```