Traffic_Sign_Classifier

June 20, 2018

1 Build a Traffic Sign Recognition Classifier

1.0.1 The goals of my project are the following:

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

1.1 Step 0: Load The Data

In [1]:
```
# Load pickled data
import pickle
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)

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

1.2 Step 1: Dataset Summary & Exploration

1.2.1 The summary of the dataset

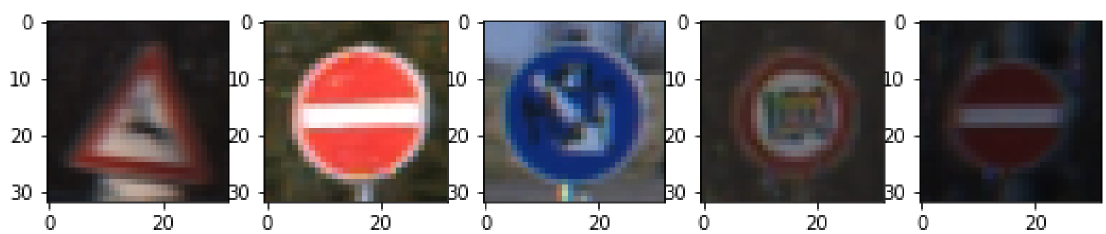
I used the numpy library to calculate summary statistics of the traffic signs data set

```
In [2]: import numpy as np

        # Number of training examples
        n_train = len(X_train)

        # Number of validation examples
        n_validation = len(X_valid)

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

        # The shape of an traffic sign image
        image_shape = (X_train.shape[1:4])

        # Number of 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 valid 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 valid examples = 4410
Number of testing examples = 12630
Image data shape = (32, 32, 3)
Number of classes = 43
```

1.2.2 Choose 5 images from training set randomly and show them

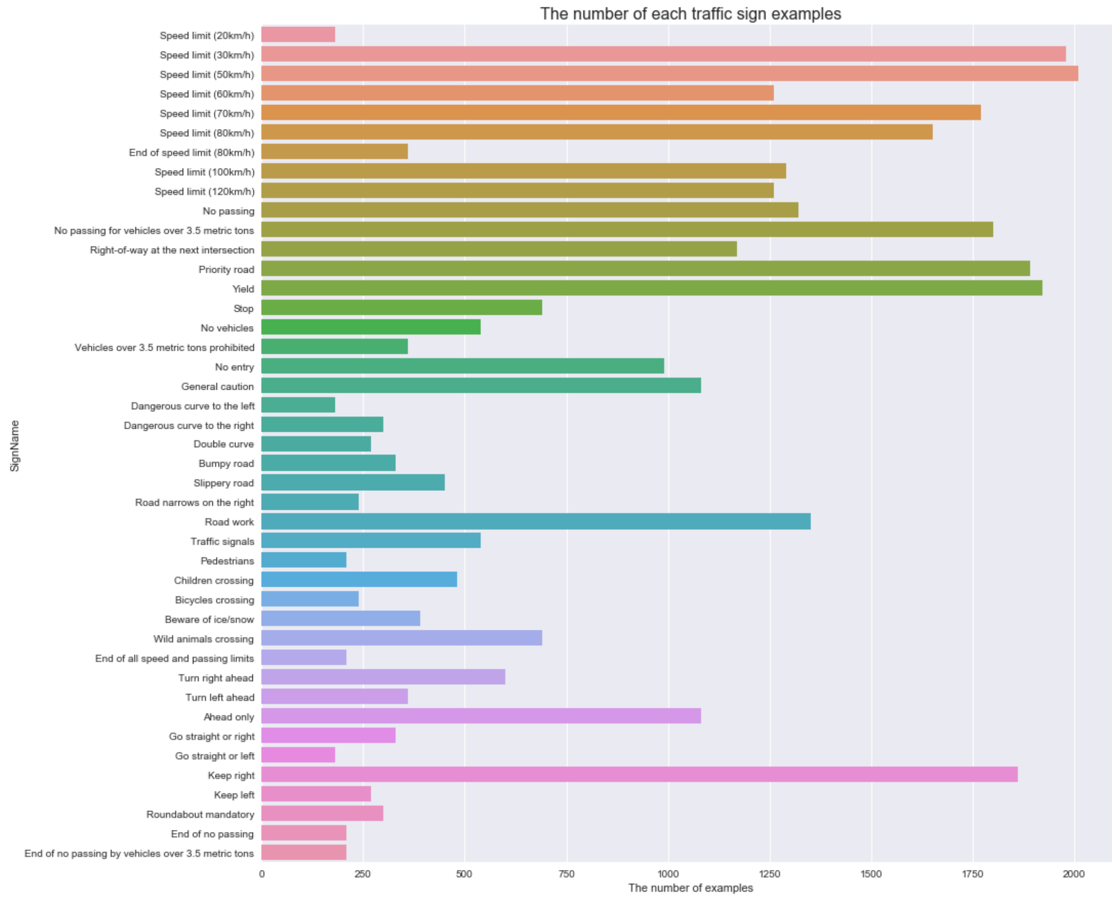
```
In [3]: import matplotlib.pyplot as plt
        %matplotlib inline

        imgs_index = np.random.randint(len(X_train), size=5)

        fig, ax = plt.subplots(nrows=1, ncols=5, figsize=(10,10))
        for i, index in enumerate(imgs_index):
            ax[i].imshow(X_train[index])
```



1.2.3 Visualize the number of each traffic sign examples

```
In [4]: import pandas as pd
        import seaborn as sns

        # Read the signnames file
        signnames = pd.read_csv("./signnames.csv")

        # Count the number of each traffic sign examples
        counts = []
        for i in signnames["ClassId"]:
            count = list(y_train).count(i)
            counts.append(count)
        signnames["Counts"] = counts

        # Visualize the counts
        fig, ax = plt.subplots(figsize=(15, 15))
        sns.set_color_codes("muted")
        sns.barplot(x="Counts", y="SignName", data=signnames)
        ax.set_xlabel('The number of examples')
        ax.set_title('The number of each traffic sign examples', fontsize=16)
```

```
Out[4]: <matplotlib.text.Text at 0x1298c4e10>
```



1.3 Step 2: Design and Test a Model Architecture

1.3.1 Process the data set

First I converted the images to grayscale because color is helpless to identify objects in images and grayscale could reduce the computing effort. Secondly I normalized the image data because scaling feature values in a similar range could make gradients in control.

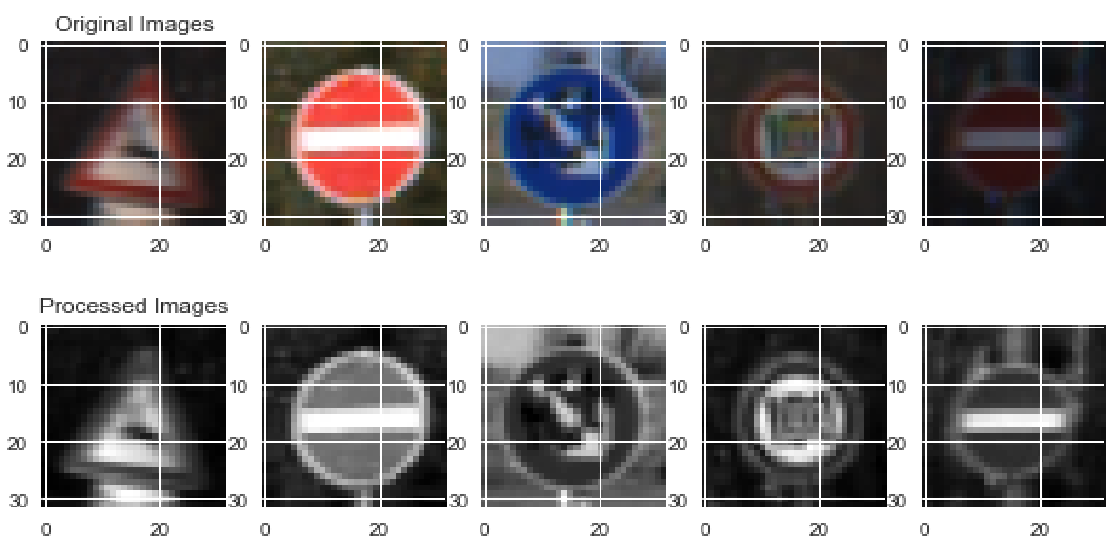
```
In [5]: # Grayscale method
        def grayscale(img):
            return np.sum(img/3, axis=2, keepdims=True)

        # Normalize method
        def normalize(img):
            return img/255

        def processing(data):
            new_data = []
```

```
    for img in data:
        img = grayscale(img)
        img = normalize(img)
        new_data.append(img)
    return np.array(new_data)
```

Here is some random examples of traffic sign images before and after processing.

```
In [6]: h, w = X_train.shape[1:3]

        fig, ax = plt.subplots(nrows=2, ncols=5, figsize=(10,5))
        for i, index in enumerate(imgs_index):
            ax[0][i].imshow(X_train[index])
            ax[1][i].imshow(np.reshape(processing(X_train)[index], (h,w)), cmap="gray")
        ax[0][0].set_title("Original Images")
        ax[1][0].set_title("Processed Images")
```

```
Out[6]: <matplotlib.text.Text at 0x120559d68>
```



I decided to generate additional data because more data might help to improve model accuracy. To add more data to the the data set, I used brightening because I noticed some of original images are very dark, and improving the image contrast might help to fine edges of the image. Another technique I used is affine transform because a little perspective might be closer to the reality.

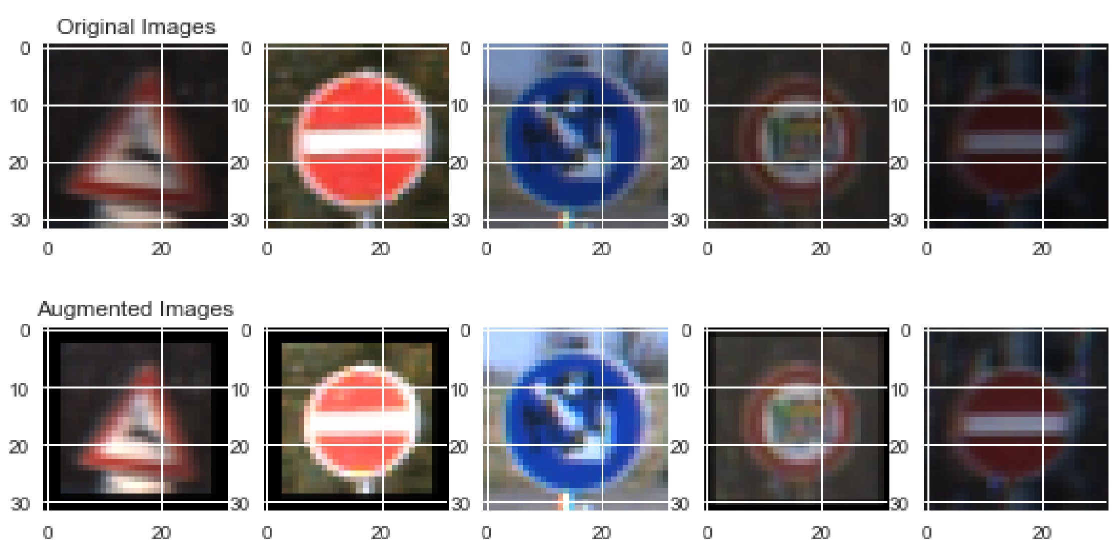
```
In [7]: from PIL import Image
        from PIL import ImageEnhance
        import cv2

        # Brighten method
```

```python
def brighten(img, brightness=1.5):
    img = Image.fromarray(img)
    enh_bri = ImageEnhance.Brightness(img)
    img_brightened = enh_bri.enhance(brightness)
    return np.array(img_brightened)

# Affine transform method
def affine_transform(img):
    pts1 = np.float32([[5,5], [27,5], [5,27]])
    rd = np.random.randint(-3,3)
    pts2 = np.float32([[5+rd,5+rd], [27-rd,5+rd], [5+rd,27-rd]])
    M = cv2.getAffineTransform(pts1, pts2)
    img_transformed = cv2.warpAffine(img,M,(32, 32))
    return img_transformed

def transform(data):
    new_data = []
    for img in data:
        img = brighten(img)
        img = affine_transform(img)
        new_data.append(img)
    return np.array(new_data)
```

Here is some random examples of original images and augmented images:

```python
In [8]: fig, ax = plt.subplots(nrows=2, ncols=5, figsize=(10,5))
        for i, index in enumerate(imgs_index):
            ax[0][i].imshow(X_train[index])
            ax[1][i].imshow(transform(X_train)[index])
        ax[0][0].set_title("Original Images")
        ax[1][0].set_title("Augmented Images")
```

```
Out[8]: <matplotlib.text.Text at 0x112c84cf8>
```



In [9]:
```
# Combine the training set and validation set
X_ = np.append(X_train, X_valid, axis=0)
y_ = np.append(y_train, y_valid, axis=0)

# Process the features
X_ = np.vstack((X_, transform(X_)))
y_ = np.tile(y_, 2)
```

In [10]:
```
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split

# Shuffle and Split the data into training and validation subsets
X_, y_= shuffle(X_, y_)
X_train, X_valid, y_train, y_valid = train_test_split(X_, y_, test_size=0.05, random_s

print(X_train.shape, X_valid.shape)
```

```
(74497, 32, 32, 3) (3921, 32, 32, 3)
```

In [11]:
```
X_train = processing(X_train)
X_valid = processing(X_valid)
X_test = processing(X_test)
```

1.3.2 Model Architecture

I used LeNex Model Architeture which consists of the following layers:

Layer	Description
Input	32x32x1 Gray Image
Convolution 5x5	1x1 stride, valid padding, outputs 28x28x6
RELU	
Max pooling	2x2 stride, valid padding, outputs 14x14x6
Convolution 5x5	1x1 stride, valid padding, outputs 10x10x16
RELU	
Max pooling	2x2 stride, valid padding, outputs 5x5x16
Fully connected	outputs 400
Fully connected	outputs 120
RELU	
Fully connected	outputs 84
RELU	
Dropout	50% keep
Fully connected	outputs 43

```
In [12]: import tensorflow as tf
         from tensorflow.contrib.layers import flatten

         def LeNet(x, mu=0, sigma=0.1, strides=[1,1,1,1], ksize=[1,2,2,1], pool_strides=[1,2,2

             # layer1, convolutional
             w1 = tf.Variable(tf.truncated_normal(shape=(5, 5, 1, 6), mean=mu, stddev=sigma))
             b1 = tf.Variable(tf.zeros(6))
             conv1 = tf.nn.conv2d(x, w1, strides, padding) + b1
             conv1 = tf.nn.relu(conv1)
             conv1 = tf.nn.max_pool(conv1, ksize, pool_strides, padding)

             # layer2, convolutional
             w2 = tf.Variable(tf.truncated_normal(shape=(5, 5, 6, 16), mean=mu, stddev=sigma))
             b2 = tf.Variable(tf.zeros(16))
             conv2 = tf.nn.conv2d(conv1, w2, strides, padding) + b2
             conv2 = tf.nn.relu(conv2)
             conv2 = tf.nn.max_pool(conv2, ksize, pool_strides, padding)

             # fully conneted
             fc0 = flatten(conv2)

             # layer3, fully conneted
             w3 = tf.Variable(tf.truncated_normal(shape=(400, 120), mean=mu, stddev=sigma))
             b3 = tf.Variable(tf.zeros(120))
             fc1 = tf.matmul(fc0,w3) + b3
             fc1= tf.nn.relu(fc1)

             # layer4, fully conneted and dropout half outputs
             w4 = tf.Variable(tf.truncated_normal(shape=(120, 84), mean=mu, stddev=sigma))
             b4 = tf.Variable(tf.zeros(84))
             fc2 = tf.matmul(fc1,w4) + b4
             fc2 = tf.nn.relu(fc2)
             fc2 = tf.nn.dropout(fc2, keep_prob)

             # layer5, fully conneted
             w5 = tf.Variable(tf.truncated_normal(shape=(84, 43), mean=mu, stddev=sigma))
             b5 = tf.Variable(tf.zeros(43))
             logits = tf.matmul(fc2,w5) + b5

             return logits
```

1.3.3 Train, Validate and Test the Model

To train the model, I used hyperparameters as the following:

```
In [13]: epochs = 35
         batch_size = 128
```

```
lr = 0.001
```

In [14]:
```
x = tf.placeholder(tf.float32, (None, 32, 32, 1))
y = tf.placeholder(tf.int32, (None))
targets = tf.one_hot(y, 43)
```

In [15]:
```
logits = LeNet(x)
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(labels=targets, logits=l
optimizer = tf.train.AdamOptimizer(learning_rate = lr)
training_operation = optimizer.minimize(cost)
```

In [16]:
```
correct_prediction = tf.equal(tf.argmax(logits, 1), tf.argmax(targets, 1))
accuracy_operation = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
saver = tf.train.Saver()

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

In [17]:
```
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    n_examples = len(X_train)

    print("Training...")
    print()
    for each in range(epochs):
        X_train, y_train = shuffle(X_train, y_train)
        for i in range(0, n_examples, batch_size):
            j = i + batch_size
            batch_x, batch_y = X_train[i:j], y_train[i:j]
            sess.run(training_operation, feed_dict={x:batch_x, y:batch_y})
        validation_accuracy = evaluate(X_valid, y_valid)
        print("Epcho {}...".format(each+1))
        print("Validation Accuracy = {:.3f}".format(validation_accuracy))
        print()

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

```
Training...

Epcho 1...
Validation Accuracy = 0.737
```

```
Epcho 2...
Validation Accuracy = 0.850

Epcho 3...
Validation Accuracy = 0.890

Epcho 4...
Validation Accuracy = 0.892

Epcho 5...
Validation Accuracy = 0.929

Epcho 6...
Validation Accuracy = 0.929

Epcho 7...
Validation Accuracy = 0.943

Epcho 8...
Validation Accuracy = 0.947

Epcho 9...
Validation Accuracy = 0.949

Epcho 10...
Validation Accuracy = 0.949

Epcho 11...
Validation Accuracy = 0.950

Epcho 12...
Validation Accuracy = 0.953

Epcho 13...
Validation Accuracy = 0.967

Epcho 14...
Validation Accuracy = 0.958

Epcho 15...
Validation Accuracy = 0.967

Epcho 16...
Validation Accuracy = 0.965

Epcho 17...
Validation Accuracy = 0.963
```

```
Epcho 18...
Validation Accuracy = 0.967

Epcho 19...
Validation Accuracy = 0.970

Epcho 20...
Validation Accuracy = 0.966

Epcho 21...
Validation Accuracy = 0.969

Epcho 22...
Validation Accuracy = 0.967

Epcho 23...
Validation Accuracy = 0.973

Epcho 24...
Validation Accuracy = 0.977

Epcho 25...
Validation Accuracy = 0.972

Epcho 26...
Validation Accuracy = 0.971

Epcho 27...
Validation Accuracy = 0.975

Epcho 28...
Validation Accuracy = 0.975

Epcho 29...
Validation Accuracy = 0.973

Epcho 30...
Validation Accuracy = 0.973

Epcho 31...
Validation Accuracy = 0.975

Epcho 32...
Validation Accuracy = 0.977

Epcho 33...
Validation Accuracy = 0.978
```

```
Epcho 34...
Validation Accuracy = 0.980

Epcho 35...
Validation Accuracy = 0.978

Model saved
```

In [18]:
```
with tf.Session() as sess:
    saver.restore(sess,  './traffic_sign_classifer')
    print("Train Accuracy = {:.3f}".format(evaluate(X_train, y_train)))
    print("Validation Accuracy = {:.3f}".format(evaluate(X_valid, y_valid)))
    print("Test Accuracy = {:.3f}".format(evaluate(X_test, y_test)))
```

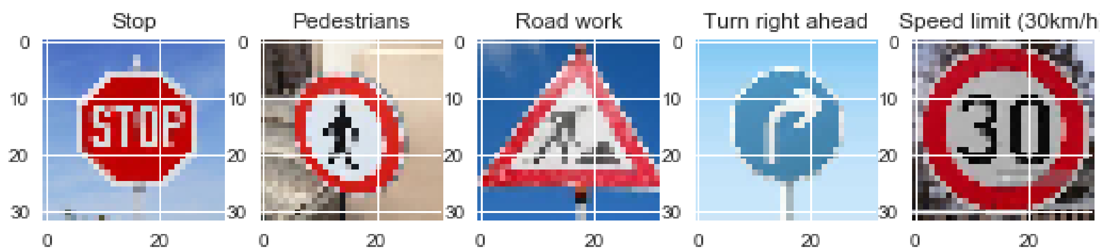
```
Train Accuracy = 0.989
Validation Accuracy = 0.977
Test Accuracy = 0.931
```

1.4 Step 3: Test a Model on New Images

1.4.1 Load and Output the Images

In [19]:
```
# Load the German traffic sign images downloaded from web
import os
web_images = os.listdir("web_images/")

web_imgs_X = []
for im_file in web_images:
    if im_file == ".DS_Store":
        continue
    img = plt.imread("web_images/"+ im_file)
    img = cv2.resize(img, (32, 32))
    web_imgs_X.append(img)

# Name the images
web_imgs_y = np.array([14, 27, 25, 33, 1])
web_imgs_signnames = []
for i in web_imgs_y:
    web_imgs_signnames.append(signnames["SignName"][i])

# Normalize the images
web_imgs_X_p = processing(web_imgs_X)

# Plot the images
```

```
fig, ax = plt.subplots(nrows=1, ncols=5, figsize=(10,4.5))
for i in range(len(web_imgs_X)):
    ax[i].set_title(web_imgs_signnames[i])
    ax[i].imshow(web_imgs_X[i])
```



My images are all bright, but the second image might be difficult to classify because the sign is a little bit of perspective.

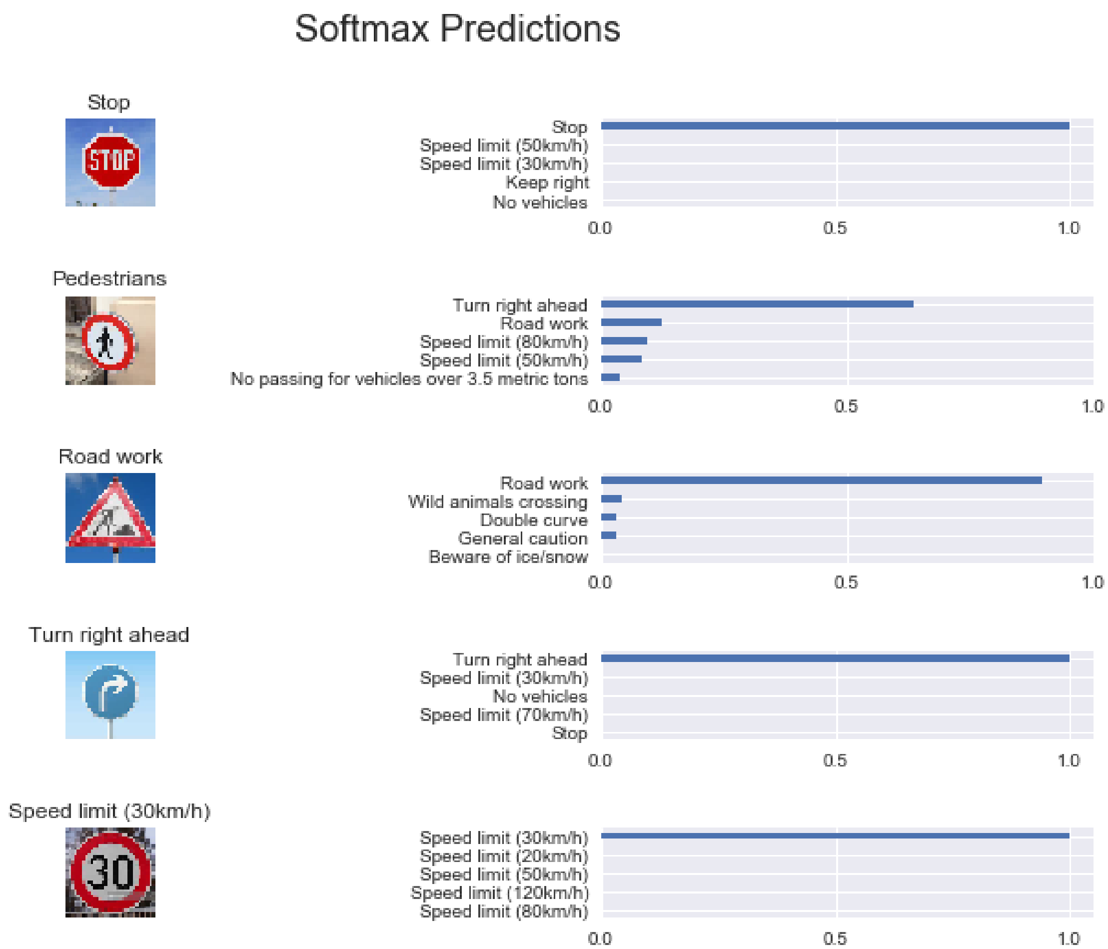
1.4.2 Predict the Sign Type for Each Image

In [20]:
```
# Assess the prediction accuracy for each image
with tf.Session() as sess:
    saver.restore(sess,'./traffic_sign_classifer')
    logits = sess.run(tf.nn.softmax(logits), feed_dict={x: web_imgs_X_p})
    n_predictions = 5
    predictions = sess.run(tf.nn.top_k(logits, n_predictions))

    count = 0
    for i in range(len(web_imgs_X)):
        prediction_type = signnames["SignName"][predictions.indices[i][0]]
        print("Image{} Prediciton : {}".format(i+1, prediction_type))
        # Calculate the accuracy for these 5 new images.
        if predictions.indices[i][0] == web_imgs_y[i]:
            count += 1
    print()
    print("Web Images Prediction Accuracy = ", count/len(logits))
    print()

    # Calculate the top five softmax probabilities for the predictions on the German
    for i in range(len(web_imgs_X)):
        print("\nImage{} top 5 Soft Probabilites: ".format(i+1))
        for j in range(n_predictions):
            print("{}: {:.3f}".format(signnames["SignName"][predictions.indices[i][j]


    # Visualize the results
    fig, ax = plt.subplots(nrows=5, ncols=2, figsize=(12, 8))
    plt.subplots_adjust(wspace =0.5, hspace =1)
```

```python
        fig.suptitle('Softmax Predictions', fontsize=20)


        margin = 0.05
        index = np.arange(n_predictions)
        width = (2. - 2. * margin) / n_predictions

        for i, (img, pred_indicies, pred_values) in enumerate(zip(web_imgs_X, predictions
            pred_names = [signnames["SignName"][j] for j in pred_indicies]
            correct_name = web_imgs_signnames[i]

            ax[i][0].imshow(img)
            ax[i][0].set_title(correct_name)
            ax[i][0].set_axis_off()

            ax[i][1].barh(index + margin, pred_values[::-1], width)
            ax[i][1].set_yticks(index + margin)
            ax[i][1].set_yticklabels(pred_names[::-1])
            ax[i][1].set_xticks([0, 0.5, 1.0])
```

```
Image1 Prediciton : Stop
Image2 Prediciton : Turn right ahead
Image3 Prediciton : Road work
Image4 Prediciton : Turn right ahead
Image5 Prediciton : Speed limit (30km/h)

Web Images Prediction Accuracy =  0.8


Image1 top 5 Soft Probabilites:
Stop: 1.000
Speed limit (50km/h): 0.000
Speed limit (30km/h): 0.000
Keep right: 0.000
No vehicles: 0.000

Image2 top 5 Soft Probabilites:
Turn right ahead: 0.635
Road work: 0.123
Speed limit (80km/h): 0.093
Speed limit (50km/h): 0.084
No passing for vehicles over 3.5 metric tons: 0.038

Image3 top 5 Soft Probabilites:
Road work: 0.894
Wild animals crossing: 0.039
```

```
Double curve: 0.030
General caution: 0.029
Beware of ice/snow: 0.002

Image4 top 5 Soft Probabilites:
Turn right ahead: 1.000
Speed limit (30km/h): 0.000
No vehicles: 0.000
Speed limit (70km/h): 0.000
Stop: 0.000

Image5 top 5 Soft Probabilites:
Speed limit (30km/h): 1.000
Speed limit (20km/h): 0.000
Speed limit (50km/h): 0.000
Speed limit (120km/h): 0.000
Speed limit (80km/h): 0.000
```



1.5 Summerize

- The predictions on new images except the second one are quite certain, some were even 100% accuracy. It is very good.
- Actually I used the same data to run the LeNex three times, and the results were different. The test on web images also had a quite diffent performance. First time the prediction accuracy was 0.8, only the pedestrain sign prediciton was wrong. Second time the prediction accuracy was 0.2, only the stop sign prediction was right. And the third time performance was similar to the first time.