Build a Traffic Sign Recognition Classifier

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

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']
```

Step 1: Dataset Summary & Exploration

The summary of the dataset

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

In [2]:

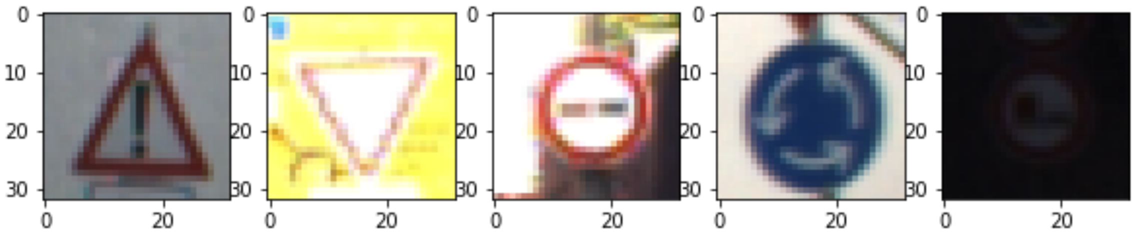
```
import numpy as np

# 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
```

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])
```



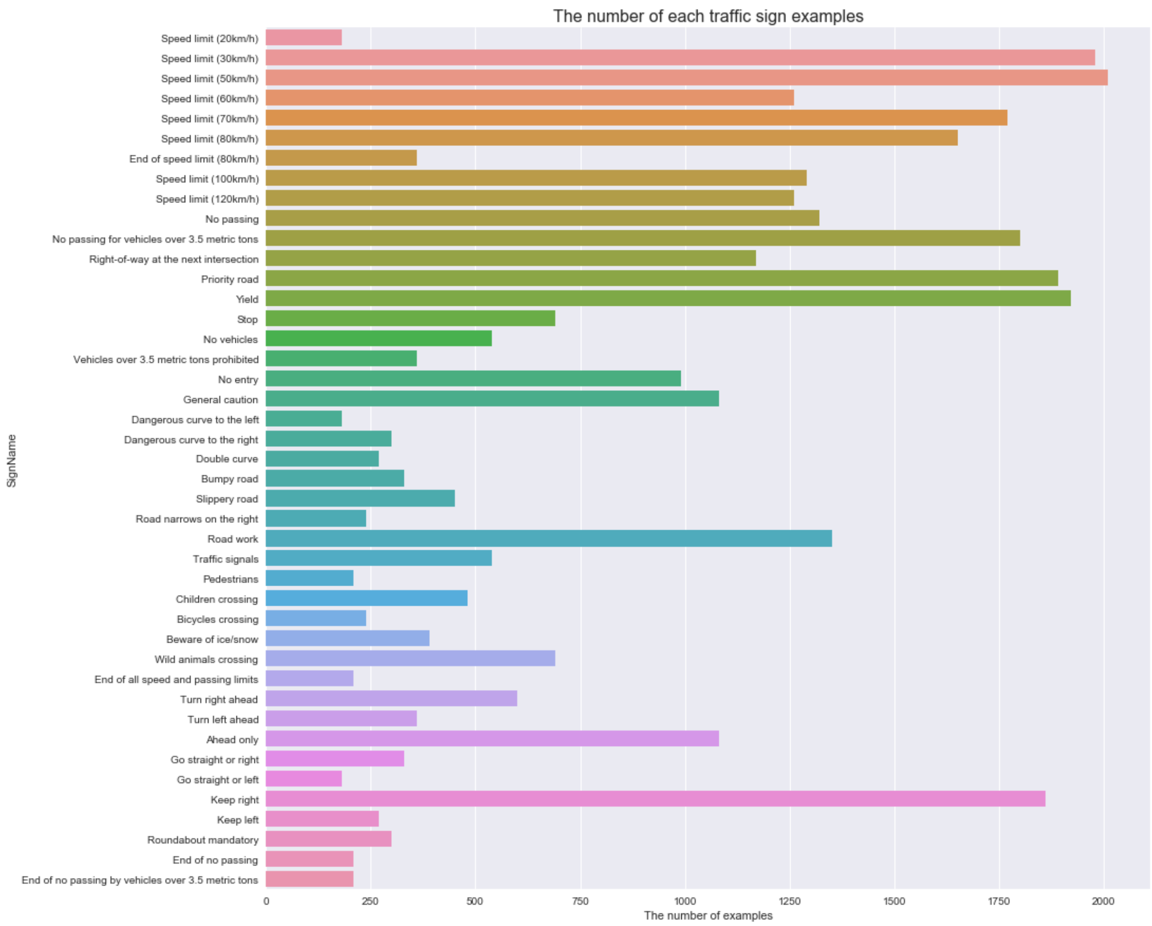
Visualize the number of each traffic sign examples

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 0x129430e10>
```



Step 2: Design and Test a Model Architecture

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)
```

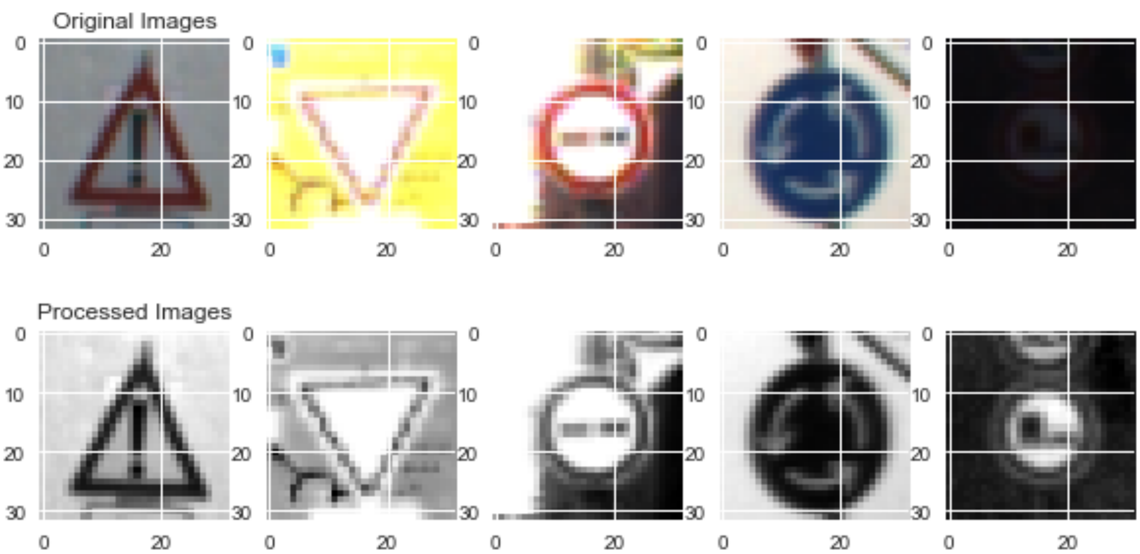
Here is some random examples of traffic sign images before and after processing.

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 0x11ffe9cf8>
```



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
"""
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)
"""

def brighten(img):
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    equ = cv2.equalizeHist(gray)
    return np.reshape(equ, (32, 32, 1))

# 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 = affine_transform(img)
        img = brighten(img)
        img = normalize(img)
        new_data.append(img)
    return new_data
```

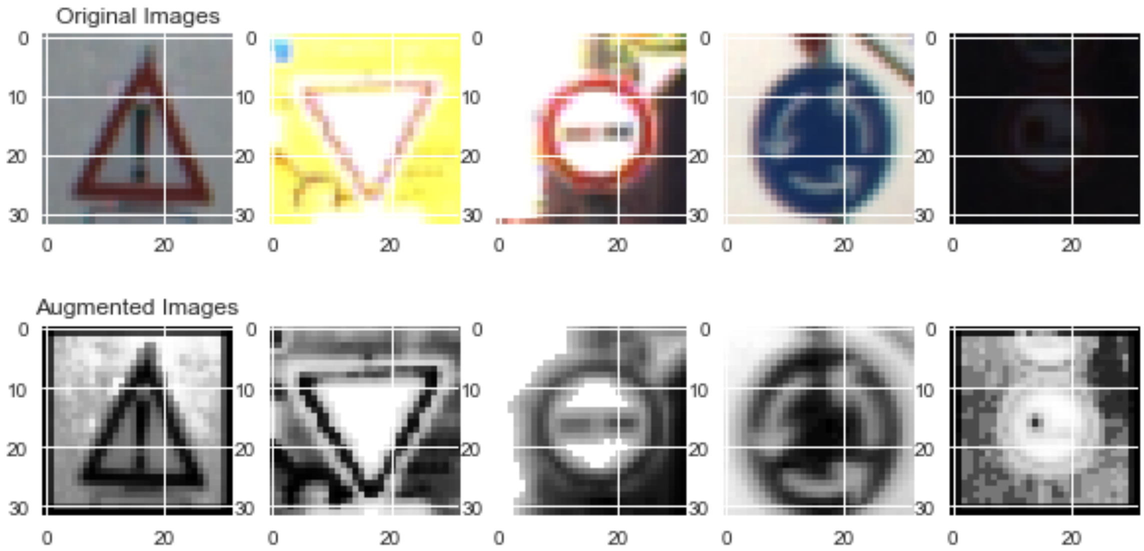
Here is some random examples of original images and augmented images:

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(np.reshape(transform(X_train)[index], (h, w)), cmap="gray")
ax[0][0].set_title("Original Images")
ax[1][0].set_title("Augmented Images")
```

Out[8]:

```
<matplotlib.text.Text at 0x10c7f1e48>
```



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)

X_ = np.vstack((processing(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, ra
ndom_state=0)

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

```
(74497, 32, 32, 1) (3921, 32, 32, 1)
```

In [11]:

```
# Process the features
X_test = processing(X_test)
```

Model Architecture

- I used LeNet Model Archititeture because it has small size and high accuracy. It could keep the image features well.
- I tried something different on activation layer, using ELU instead of ReLU to get the network faster and more accurate. I also Added a dropout of 50% to the fully connected layer in order to avoid overfitting.
- The model architecture consists of the following layers:

Layer	Description
Input	32x32x1 Gray Image
Convolution 5x5	1x1 stride, valid padding, outputs 28x28x6
ELU	
Max pooling	2x2 stride, valid padding, outputs 14x14x6
Convolution 5x5	1x1 stride, valid padding, outputs 10x10x16
ELU	
Max pooling	2x2 stride, valid padding, outputs 5x5x16
Flatten	outputs 400
Fully connected	outputs 120
ELU	
Fully connected	outputs 84
ELU	
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=[
1,2,2,1], keep_prob=0.5, padding="VALID"):

    # layer1, convolutional
    w1 = tf.Variable(tf.truncated_normal(shape=(5, 5, 1, 6), mean=mu, stddev=sig
ma))
    b1 = tf.Variable(tf.zeros(6))
    conv1 = tf.nn.conv2d(x, w1, strides, padding) + b1
    conv1 = tf.nn.elu(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=si
gma))
    b2 = tf.Variable(tf.zeros(16))
    conv2 = tf.nn.conv2d(conv1, w2, strides, padding) + b2
    conv2 = tf.nn.elu(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.elu(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.elu(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
```

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, lo
gits=logits))
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 = 0.845

Epcho 2...
Validation Accuracy = 0.912

Epcho 3...
Validation Accuracy = 0.938

Epcho 4...
Validation Accuracy = 0.945

Epcho 5...
Validation Accuracy = 0.951

Epcho 6...
Validation Accuracy = 0.956

Epcho 7...
Validation Accuracy = 0.961

Epcho 8...
Validation Accuracy = 0.959

Epcho 9...
Validation Accuracy = 0.973

Epcho 10...
Validation Accuracy = 0.967

Epcho 11...
Validation Accuracy = 0.966

Epcho 12...
Validation Accuracy = 0.971

Epcho 13...
Validation Accuracy = 0.973

Epcho 14...
Validation Accuracy = 0.977

Epcho 15...
Validation Accuracy = 0.978

Epcho 16...
Validation Accuracy = 0.978

Epcho 17...
Validation Accuracy = 0.977

Epcho 18...
Validation Accuracy = 0.974

Epcho 19...
Validation Accuracy = 0.979

Epcho 20...
Validation Accuracy = 0.979
```

```
Epcho 21...
Validation Accuracy = 0.979

Epcho 22...
Validation Accuracy = 0.978

Epcho 23...
Validation Accuracy = 0.974

Epcho 24...
Validation Accuracy = 0.979

Epcho 25...
Validation Accuracy = 0.980

Epcho 26...
Validation Accuracy = 0.983

Epcho 27...
Validation Accuracy = 0.981

Epcho 28...
Validation Accuracy = 0.978

Epcho 29...
Validation Accuracy = 0.981

Epcho 30...
Validation Accuracy = 0.984

Epcho 31...
Validation Accuracy = 0.980

Epcho 32...
Validation Accuracy = 0.984

Epcho 33...
Validation Accuracy = 0.979

Epcho 34...
Validation Accuracy = 0.981

Epcho 35...
Validation Accuracy = 0.981

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 = 0.996
Validation Accuracy = 0.982
Test Accuracy = 0.935
```

Validation accuracy and test accuracy are all above 0.9, so the model works well.

First time I used ReLU as the activation method, and accuracy on training data, validation data, and test data are the following:

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

The second time I used ELU which the teacher suggested, and accuracy are a little higher, as the following:

- Train Accuracy = 0.996
- Validation Accuracy = 0.984
- Test Accuracy = 0.934

The third time I tried histogram equalization instead of image enhance brightness to enhance image contrast, and the accuracy are the following:

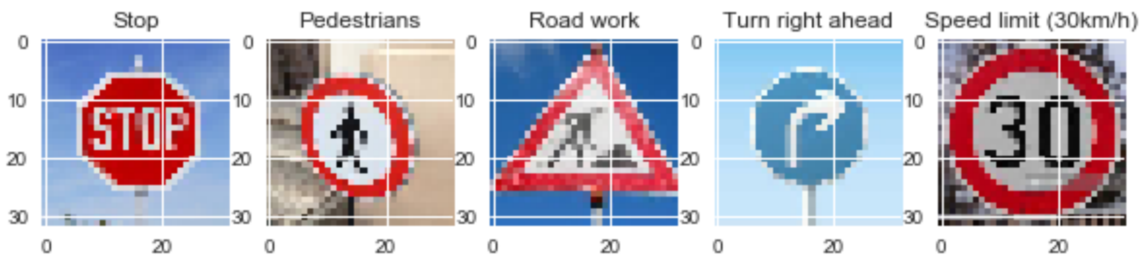
- Train Accuracy = 0.996
- Validation Accuracy = 0.982
- Test Accuracy = 0.935

Step 3: Test a Model on New Images

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])
```



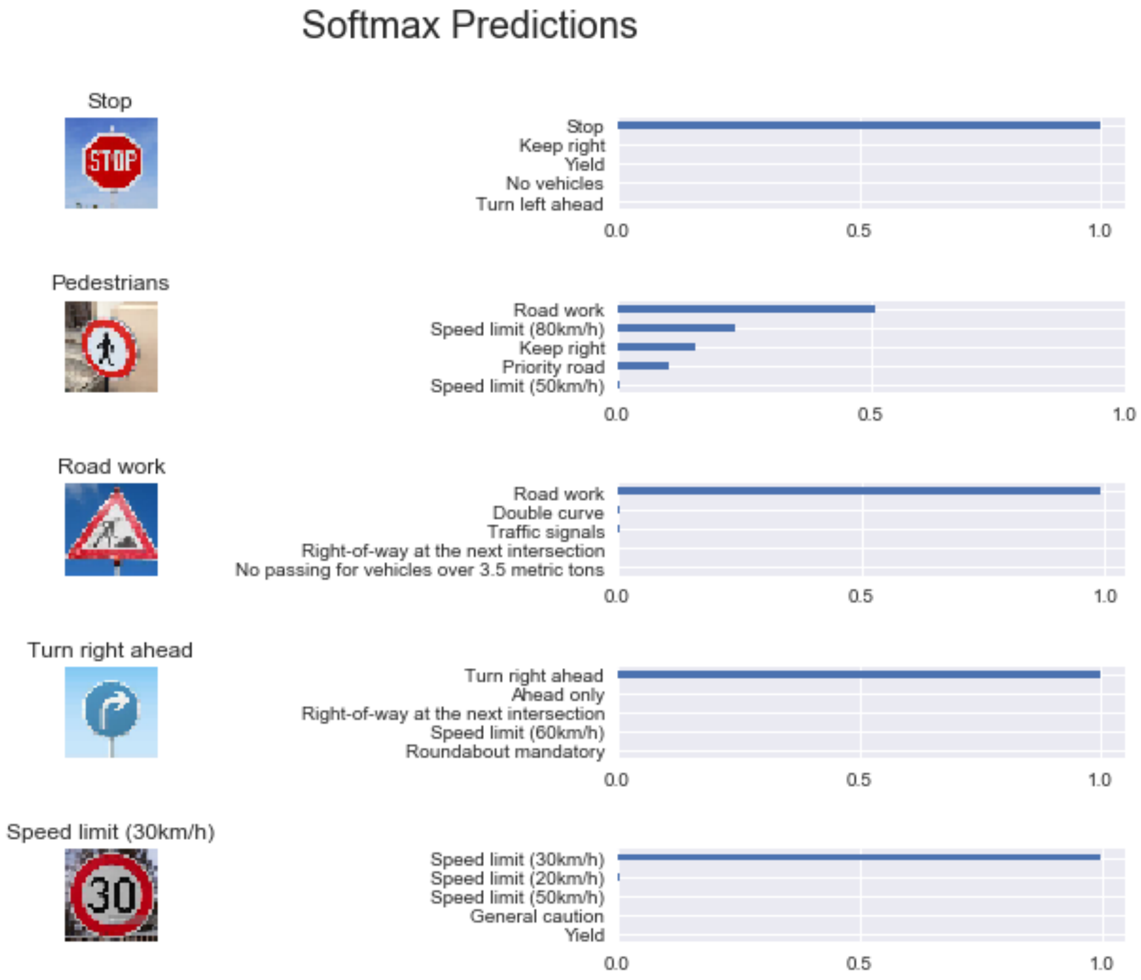
My images are all bright, but the second image might be difficult to classify because the sign is a little bit of perspective.

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 Ge
rman traffic sign images found on the web.
    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]], predictions.values[i][j]))


    # Visualize the results
    fig, ax = plt.subplots(nrows=5, ncols=2, figsize=(12, 8))
    plt.subplots_adjust(wspace =0.5, hspace =1)
    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, predic
tions.indices, predictions.values)):
        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 : Road work
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
Keep right: 0.000
Yield: 0.000
No vehicles: 0.000
Turn left ahead: 0.000

Image2 top 5 Soft Probabilites:
Road work: 0.508
Speed limit (80km/h): 0.233
Keep right: 0.153
Priority road: 0.101
Speed limit (50km/h): 0.005

Image3 top 5 Soft Probabilites:
Road work: 0.991
Double curve: 0.004
Traffic signals: 0.003
Right-of-way at the next intersection: 0.001
No passing for vehicles over 3.5 metric tons: 0.000

Image4 top 5 Soft Probabilites:
Turn right ahead: 1.000
Ahead only: 0.000
Right-of-way at the next intersection: 0.000
Speed limit (60km/h): 0.000
Roundabout mandatory: 0.000

Image5 top 5 Soft Probabilites:
Speed limit (30km/h): 0.997
Speed limit (20km/h): 0.003
Speed limit (50km/h): 0.000
General caution: 0.000
Yield: 0.000
```



Summerize

- At last, the predictions accuracy on new images is 0.8, which is lower than the original test set accuracy. However, the web image samples are too few, and its reference value is not high.
- Except the second image, other's predictions are quite certain, some are even 100% accuracy. It is very good.