Traffic Sign Classifier

Write up

August 10th, Kenta Kumazaki

1. Purpose

The goals / steps of this 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

2. Output

- Make a pipeline that run deep learning to classify traffic signs.
  I used the Workspace in Udacity for this project.
- Reflect on my work in a written report.

3. Submission

(1) GitHub

https://github.com/kkumazaki/Self-Drivig-Car_Project3_Traffic-Sign-Classifier-Project.git

(2) Directory

<folder: main>

- **Writeup_of_Lesson14.pdf**: This file
- **Traffic_Sign_Classifier.ipynb**: Pipeline file (Jupyter Notebook)
- **Traffic_Sign_Classifier.html**: Pipeline file (HTML)
- Image files are saved as following:

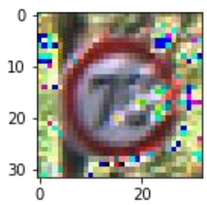
  <folder: Test_pics>

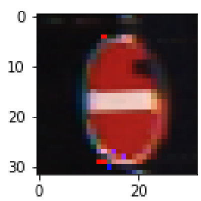
  Additional Test images downloaded by the following site.

  https://www.kaggle.com/meowmeowmeowmeowmeow/gtsrb-german-traffic-sign/version/1

  <folder: Test_results>

  Modified Test images for Traffic Sign Classification.





3. Reflection

(1)Description of my pipeline and results

My pipeline consisted of 4 steps as following, including the preparation Step: 0.

Step 0: Load the Data

Step 1: Dataset Summary & Exploration

Step 2: Design and Test a Model Architecture

Step 3: Test a Model on New Images

Step 0: Load the Data

Load the pre-uploaded datasets at the workspace.

```
# Load pickled data
import pickle

# 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']
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

At first, I check the dimensions of each necessary data.

```
### Replace each question mark with the appropriate value.
### Use python, pandas or numpy methods rather than hard coding the results

# Check whether the length of X, y are same.
assert(len(X_train) == len(y_train))
assert(len(X_valid) == len(y_valid))
assert(len(X_test) == len(y_test))

# 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.
import csv
with open('signnames.csv') as f:
    next(f)
    reader = csv.reader(f, delimiter=',')
    sign_names = [row for row in reader]

n_classes = len(sign_names)

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

```
Basic information:
Number of training examples = 34799
Number of testing examples = 12630
Image data shape = (32, 32, 3)
Number of classes = 43
```

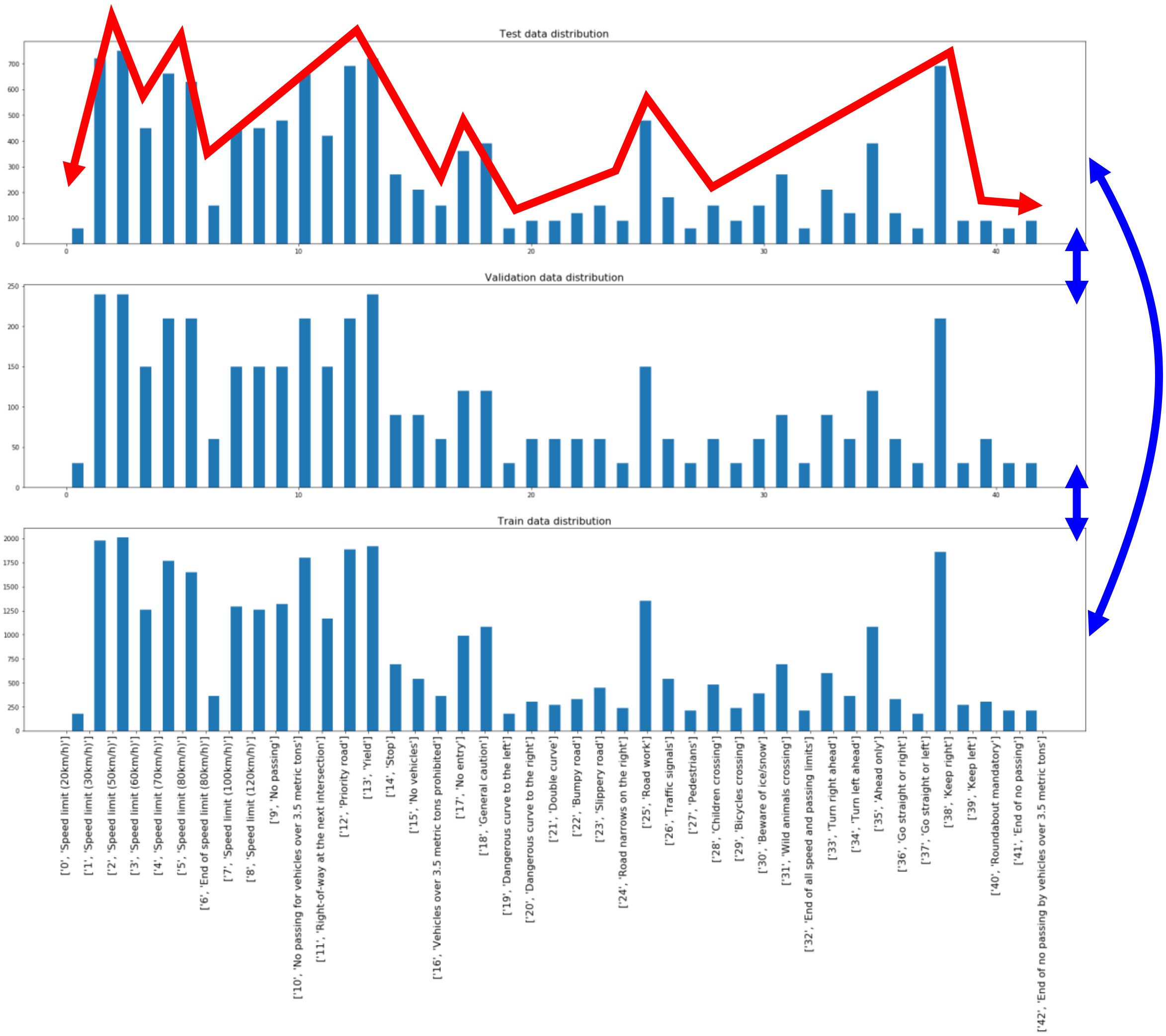
Next, I visualize the datasets with bar graphs.

```
### 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 random
import numpy as np

#Add here
import glob
import re
import cv2
import tensorflow as tf
from tensorflow.contrib.layers import flatten
from sklearn.utils import shuffle


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

```
#print("Visualize sumple picture:")
#plt.figure(figsize=(1, 1))
#plt.imshow(image)
#plot_index = y_train[index]
#print(plot_index)
#print(sign_names[plot_index])

#(1)Show dataset distribution
f,axes = plt.subplots(nrows=3, ncols=1,figsize=(30,20))
axes[2].hist(y_train, bins=n_classes, rwidth=0.5)
axes[2].set_title("Train data distribution",fontsize=16)
plt.xticks(np.arange(len(sign_names)),sign_names, rotation=90,fontsize=16)
axes[1].hist(y_valid, bins=n_classes, rwidth=0.5)
axes[1].set_title("Validation data distribution",fontsize=16)
axes[0].hist(y_test, bins=n_classes, rwidth=0.5)
axes[0].set_title("Test data distribution",fontsize=16)
```

The distributions of Test Data, Validation Data and Tran Data are shown below.

There's big disperse between each class (0 ~ 42), but there's small disperse between each datasets, so it will be OK to proceed.



```python
#(2)Show example image for each category
fig, axes = plt.subplots(nrows=9, ncols=n_classes//9+1,figsize=(20,20))
for i in range(n_classes):
    ind = np.min(np.where(y_train==i))
    image = X_train[ind].squeeze()
    axes[i//5][i%5].imshow(image)
    axes[i//5][i%5].set_title("%s, %s" % (sign_names[y_train[ind]], y_train[ind]))
fig.savefig("examples.png")
```

The following images are examples of Traffic Signs.

Step 2: Design and Test a Model Architecture

First in the Step2, I pre-process the Data Set.

I proceeded with the following steps:

[Test1] I trained the model without any preprocess nor any change from the original model,
and the Validation Accuracy was just 89.2%. Target Accuracy is 93%, so it's not good enough.

[Test2] I made the images from color to gray scale, and normalized them.
Validation Accuracy became 92.5%, but it's not good enough.

[Test3] I added training data by rotating the original training data by +15/-15 degree.
The number of training data became triple from original, which is 104,397.
Validation Accuracy became 93.7%, but it's better to make it more robust.

[Test4] I added training data by zooming up/down the original training data by +2/-2 pixels.
The number of training data became five times from original, which is 173,995.
Validation Accuracy became 94.3%, but it's not good enough because Test Accuracy was 92.4%.

I found that it's better to change the parameters of the model to get better results.

```
### 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.

#(1)Without normalization
#Test1: Only this, accuracy is 89.2%

#(3)Add rotated pictures in training data
#Test3: 93.7% with 104,397 training data
#import cv2
#(a)Initial parameters
height = X_train[0].shape[0]
width = X_train[0].shape[1]
center = (int(width/2), int(height/2))
scale = 1.0
angle1 = 15.0
angle2 = -15.0
trans1 = cv2.getRotationMatrix2D(center, angle1 , scale)
trans2 = cv2.getRotationMatrix2D(center, angle2 , scale)

X_train_base = np.copy(X_train)
y_train_base = np.copy(y_train)
```

```
X_train_trans1 = np.copy(X_train_base)
X_train_trans2 = np.copy(X_train_base)


#(b)Calculation
for i in range(n_train):
    X_train_trans1[i] = cv2.warpAffine(X_train[i], trans1, (width,height))
    X_train_trans2[i] = cv2.warpAffine(X_train[i], trans2, (width,height))

#(c)Append to the training data (Training size will be 3 times as original)
X_train = np.append(X_train, X_train_trans1, axis=0)
y_train = np.append(y_train, y_train_base, axis=0)

X_train = np.append(X_train, X_train_trans2, axis=0)
y_train = np.append(y_train, y_train_base, axis=0)

#(4)Zoom in/out pictures in training data
#Test4: % with  training data
#(a)Initial parameters
pixels = 2

X_train_zoomup = np.copy(X_train_base)
X_train_zoomout = np.copy(X_train_base)
#y_train_base = np.copy(y_train) # Already done
```

```python
zoomup_rate = (X_train_base[0].shape[0]+2*pixels)/X_train_base[0].shape[0]
zoomout_rate = (X_train_base[0].shape[0]-2*pixels)/X_train_base[0].shape[0]

#(b)Calculation
for i in range(n_train):
    zoom_img = cv2.resize(X_train_base[i], None, fx=zoomup_rate, fy=zoomup_rate, interpolation=cv2.INTER_CUBIC)
    X_train_zoomup[i] = zoom_img[pixels:pixels+X_train_base[0].shape[0], pixels:pixels+X_train_base[0].shape[0]]

    zoom_img = cv2.resize(X_train_base[i], None, fx=zoomout_rate, fy=zoomout_rate, interpolation=cv2.INTER_CUBIC)
    X_train_zoomout[i] = np.pad(zoom_img, ((pixels,pixels),(pixels,pixels), (0,0)), 'constant')

#(c)Append to the training data (Training size will be 5 times as original, after rotation and zoom in/out)
X_train = np.append(X_train, X_train_zoomup, axis=0)
y_train = np.append(y_train, y_train_base, axis=0)

X_train = np.append(X_train, X_train_zoomout, axis=0)
y_train = np.append(y_train, y_train_base, axis=0)
```

```python
#(2)Gray Scale and Normalization
#Test2: 92.5% with 34,799 training data
#import cv2
#(a)Gray Scale
for i in range(n_train):
    X_train[i] = np.expand_dims(cv2.cvtColor(X_train[i], cv2.COLOR_RGB2GRAY), axis=3)

for i in range(n_validation):
    X_valid[i] = np.expand_dims(cv2.cvtColor(X_valid[i], cv2.COLOR_RGB2GRAY), axis=3)

for i in range(n_test):
    X_test[i] = np.expand_dims(cv2.cvtColor(X_test[i], cv2.COLOR_RGB2GRAY), axis=3)

# Size change: 32x32x3 ---> 32x32x1
X_train = X_train[:, :, :, 0:1]
X_valid = X_valid[:, :, :, 0:1]
X_test = X_test[:, :, :, 0:1]
```

```python
#(b)Normalization
X_train = (X_train - np.mean(X_train)) / np.std(X_train)
X_valid = (X_valid - np.mean(X_valid)) / np.std(X_valid)
X_test = (X_test - np.mean(X_test)) / np.std(X_test)


#Confirmation
print("The shape of loaded X_train is ", X_train.shape)
print("The shape of loaded y_train is ", y_train.shape)
print("The shape of loaded X_valid is ", X_valid.shape)
print("The shape of loaded y_valid is ", y_valid.shape)
print("The shape of loaded X_test is ", X_test.shape)
print("The shape of loaded y_test is ", y_test.shape)

#Save pickle
X_train_file = './augmented_X_train.p'
y_train_file = './augmented_y_train.p'
with open(X_train_file, mode='wb') as f:
    pickle.dump(X_train, f)
with open(y_train_file, mode='wb') as f:
    pickle.dump(y_train, f)
```

```
The shape of loaded X_train is  (173995, 32, 32, 1)
The shape of loaded y_train is  (173995,)
The shape of loaded X_valid is  (4410, 32, 32, 1)
The shape of loaded y_valid is  (4410,)
The shape of loaded X_test is  (12630, 32, 32, 1)
The shape of loaded y_test is  (12630,)
```

The following code shows the final model of this project.

[Test5] The original LeNet has output dimension: 10 (0, 1, 2, …, 8, 9), but our project has **output dimension 43**.

It's almost 4 times bigger than original one, so I made the depth of the hidden layers 4 times bigger than original.

```python
### Define your architecture here.
### Feel free to use as many code cells as needed.
#Try.2

#(1)Setup TensorFlow
#The EPOCH and BATCH_SIZE values affect the training speed and model accuracy.
#import tensorflow as tf

EPOCHS = 10
BATCH_SIZE = 128

#(2)Implement LeNet-5
#from tensorflow.contrib.layers import flatten

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

    # SOLUTION: Layer 1: Convolutional. Input = 32x32x1. Output = 28x28x24.# 4 times
    conv1_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 1, 24), mean = mu, stddev = sigma))# 4 times
    #conv1_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 3, 6), mean = mu, stddev = sigma)) # Color has 3 dimensions
    conv1_b = tf.Variable(tf.zeros(24))# 4 times
    conv1   = tf.nn.conv2d(x, conv1_W, strides=[1, 1, 1, 1], padding='VALID') + conv1_b

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

    # SOLUTION: Pooling. Input = 28x28x6. Output = 14x14x24.# 4 times
    conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='VALID')

    # SOLUTION: Layer 2: Convolutional. Output = 10x10x64.# 4 times
    conv2_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 24, 64), mean = mu, stddev = sigma))# 4 times
    conv2_b = tf.Variable(tf.zeros(64))# 4 times
    conv2   = tf.nn.conv2d(conv1, conv2_W, strides=[1, 1, 1, 1], padding='VALID') + conv2_b

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

    # SOLUTION: Pooling. Input = 10x10x16. Output = 5x5x64.# 4 times
    conv2 = tf.nn.max_pool(conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='VALID')

    # SOLUTION: Flatten. Input = 5x5x64. Output = 1600. # 4 times
    fc0   = flatten(conv2)

    # SOLUTION: Layer 3: Fully Connected. Input = 1600. Output = 480. # 4 times
    fc1_W = tf.Variable(tf.truncated_normal(shape=(1600, 480), mean = mu, stddev = sigma))# 4 times
    fc1_b = tf.Variable(tf.zeros(480))# 4 times
    fc1   = tf.matmul(fc0, fc1_W) + fc1_b

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

    # SOLUTION: Layer 4: Fully Connected. Input = 480. Output = 336. # 4 times
    fc2_W  = tf.Variable(tf.truncated_normal(shape=(480, 336), mean = mu, stddev = sigma))# 4 times
    fc2_b  = tf.Variable(tf.zeros(336))# 4 times
    fc2    = tf.matmul(fc1, fc2_W) + fc2_b

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

    # SOLUTION: Layer 5: Fully Connected. Input = 336. Output = 43.# 4 times
    #fc3_W  = tf.Variable(tf.truncated_normal(shape=(84, 10), mean = mu, stddev = sigma))
    fc3_W  = tf.Variable(tf.truncated_normal(shape=(336, 43), mean = mu, stddev = sigma)) # Output has 43 dimensions
    #fc3_b  = tf.Variable(tf.zeros(10))
    fc3_b  = tf.Variable(tf.zeros(43)) # Output has 43 dimensions
    logits = tf.matmul(fc2, fc3_W) + fc3_b

    return logits
```

```python
#(3)Features and Labels
#Train LeNet to classify MNIST data.
#x is a placeholder for a batch of input images. y is a placeholder for a batch of output labels.

x = tf.placeholder(tf.float32, (None, 32, 32, 1))
#x = tf.placeholder(tf.float32, (None, 32, 32, 3)) # Color has 3 dimensions
y = tf.placeholder(tf.int32, (None))
#one_hot_y = tf.one_hot(y, 10)
one_hot_y = tf.one_hot(y, 43) # Output has 43 dimensions

#(4)Settnig for Training Pipeline
rate = 0.001

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

```python
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
```

```python
### 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.
#Try.2

#(6)Train the Model
#Run the training data through the training pipeline to train the model.
#Before each epoch, shuffle the training set.
#After each epoch, measure the loss and accuracy of the validation set.
#Save the model after training.

#This needs GPU.

#from sklearn.utils import shuffle
```

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

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

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

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

The results of Validation Accuracy is shown below. Final Validation Accuracy is **94.4%**, which is better than the Target Accuracy: 93%. It can have better result by Early Termination at **EPOCH 7~9**, but it may have better results with other Test Data, so I proceed by taking this trained model.

```
Training...

EPOCH 1 ...
Validation Accuracy = 0.926

EPOCH 2 ...
Validation Accuracy = 0.941

EPOCH 3 ...
Validation Accuracy = 0.955

EPOCH 4 ...
Validation Accuracy = 0.945

EPOCH 5 ...
Validation Accuracy = 0.945

EPOCH 6 ...
Validation Accuracy = 0.948

EPOCH 7 ...
Validation Accuracy = 0.958

EPOCH 8 ...
Validation Accuracy = 0.957

EPOCH 9 ...
Validation Accuracy = 0.958

EPOCH 10 ...
Validation Accuracy = 0.944

Model saved
```

I evaluated the Model with Test Data.

Test Accuracy is 94.3%, so it passes the Target Accuracy.

```
#(7)Evaluate the Model
#Once you are completely satisfied with your model, evaluate the performance of the model on the test set.
#Be sure to only do this once!
#If you were to measure the performance of your trained model on the test set, then improve your model,
# and then measure the performance of your model on the test set again, that would invalidate your test results.
#You wouldn't get a true measure of how well your model would perform against real data.

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

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

```
INFO:tensorflow:Restoring parameters from ./lenet
Test Accuracy = 0.943
```

Step 3: Test a Model on New Images

I downloaded **10 new Test Images** by the following Website, and evaluated the Model with them.

https://www.kaggle.com/meowmeowmeowmeowmeow/gtsrb-german-traffic-sign/version/1

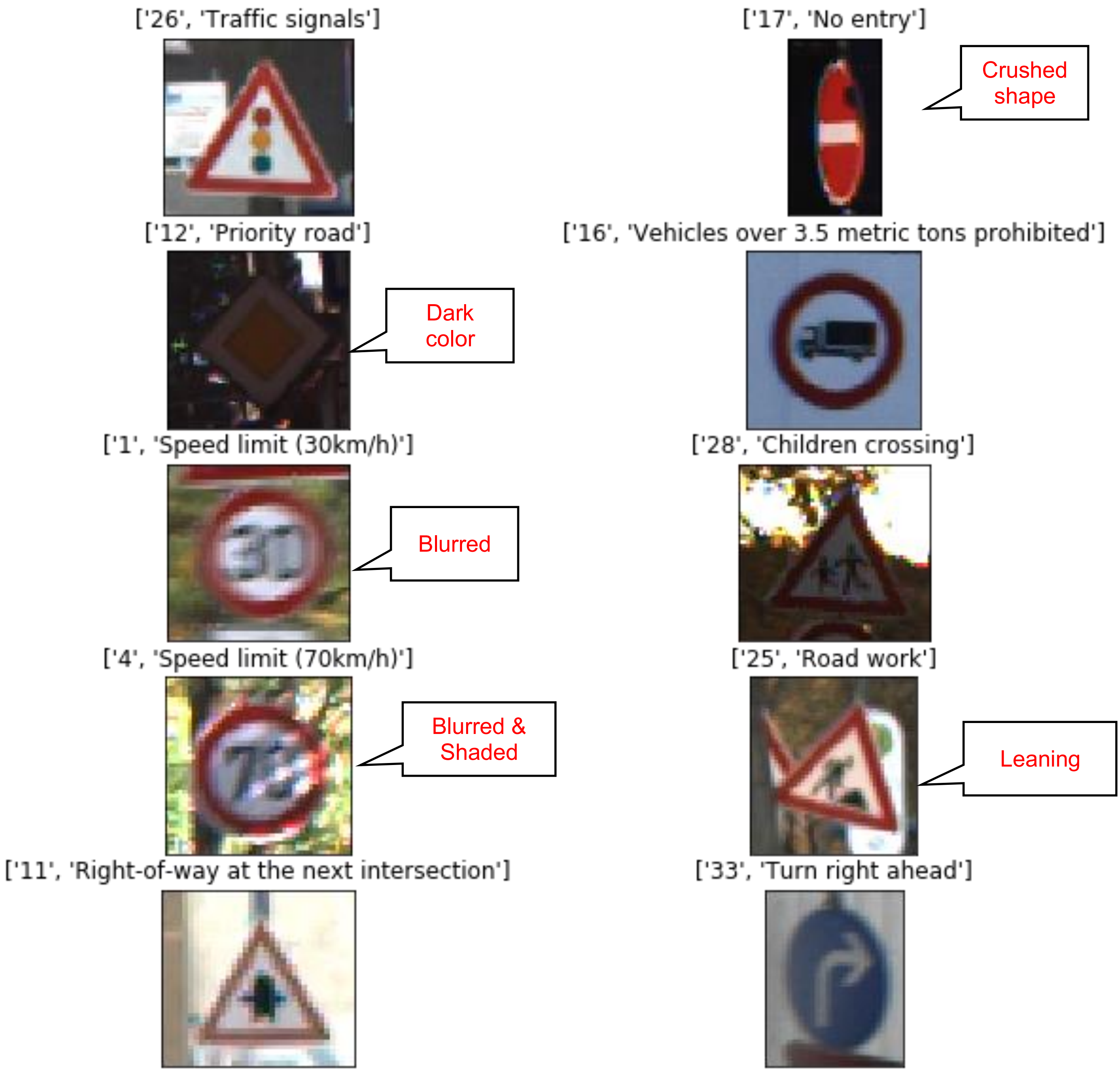
These images have different image size and data type is float, so I modified them into good data type with the Model. The size of Test Data by new images is **10(image numbers)x32x32(size)x3(RGB colors)**.

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

#Download Source: https://www.kaggle.com/meowmeowmeowmeowmeow/gtsrb-german-traffic-sign/version/1
#There are 2 points to modify with these data as below:
#(a)Data size: ** x ** x 3 --> 32 x 32 x 3
#(b)Data type: float --> int conversion

#(1)Import pictures
#import glob
#import re
#import cv2

Test_pics = np.array(glob.glob('Test_pics/*.png'))
new_test_images = [plt.imread(file) for file in Test_pics]

#(2)Initialize
#new_test_modify = np.zeros([32, 32, 3])
X_data = np.zeros([1, 32, 32, 3])
y_data = []
```

```
#(3)Test
#print(Test_pics)
#classes= re.findall(r"¥d+", Test_pics[9])[0]
#print(classes)
```

```
#(4)Modify raw data and make Test data
plt.figure(figsize=(10,10))
for i, image in enumerate(new_test_images):
    xrate = 32./new_test_images[i].shape[1]
    yrate = 32./new_test_images[i].shape[0]
    new_test_resize = cv2.resize(new_test_images[i], None, fx=xrate, fy=yrate, interpolation=cv2.INTER_CUBIC) #(a)Data size modification
    new_test_modify = (new_test_resize * 256).astype(np.uint8) #(b)Data type conversion

    X_data = np.append(X_data, np.expand_dims(new_test_modify,axis=0), axis=0)
    classes= int(re.findall(r"¥d+", Test_pics[i])[0])
    y_data.append(classes)

    plt.subplot(5,len(Test_pics)//5,i+1)
    plt.title("%s" % (sign_names[classes]))
    plt.imshow(image)
    plt.xticks([])
    plt.yticks([])

plt.show()

# (N+1)x32x32xC ---> Nx32x32xC
X_data = X_data[1: , ...].astype(np.uint8)

print('X_data shape:', np.array(X_data).shape)

X_data shape: (10, 32, 32, 3)
```

I chose 10 images. **Some of them are challenging for classification**.



I adapted Gray scale and Normalization to the new 10 images same as other image data, and I ran the prediction of the Sign Type for each image.

```
### 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 earlier.
### Feel free to use as many code cells as needed.

#(0)Initialize
X_data_test = np.copy(X_data)

#(1)Gray Scale and Normalization
#(a)Gray Scale
for i in range(len(X_data)):
    X_data_test[i] = np.expand_dims(cv2.cvtColor(X_data_test[i], cv2.COLOR_RGB2GRAY), axis=3)

# Size change: 32x32x3 ---> 32x32x1
X_data_test = X_data_test[:, :, :, 0:1]

#(b)Normalization
X_data_test = (X_data_test - np.mean(X_data_test)) / np.std(X_data_test)
```

The result of prediction matched the labeled answer **100%**, so my Model is well trained for new images as well.

```
#(2)Run predictions

with tf.Session() as sess:
    saver.restore(sess, './lenet')
    #saver = tf.train.import_meta_graph('lenet.meta') #doesn't work well
    #saver.restore(sess, tf.train.latest_checkpoint('./')) #doesn't work well
    predicted_logits = sess.run(logits, feed_dict={x: X_data_test})
    predicted_labels = np.argmax(predicted_logits, axis=1)

    print("Result of prediction: ¥n", predicted_labels)

print("Answer: ¥n", y_data)
```

```
INFO:tensorflow:Restoring parameters from ./lenet
Result of prediction:
 [26 17 12 16  1 28  4 25 11 33]
Answer:
 [26, 17, 12, 16, 1, 28, 4, 25, 11, 33]
```

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

length = len(y_data)
score = 0

for i in range(length):
    if (y_data[i] == predicted_labels[i]):
        score += 1

accuracy = score/length * 100
print("Accuracy for the new images is :" + str(accuracy) + "%.")
```

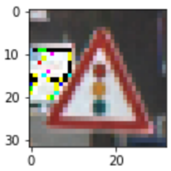
```
Accuracy for the new images is :100.0%.
```

Finally, I show the Output Top 5 Softmax Probabilities for each image found on the Web site.

```
### 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.
with tf.Session() as sess:
    softmax = tf.nn.softmax(predicted_logits)
    results = sess.run(tf.nn.top_k(softmax, k=5))

for x in range(len(y_data)):
    print("Original Image (size is random): " + str(x+1))
    plt.figure(figsize=(2,2))
    plt.imshow(new_test_images[x])
    plt.show()
    print("Modified Image (size: 32x32x3): " + str(x+1))
    plt.figure(figsize=(2,2))
    plt.imshow(X_data[x])
    plt.show()
    if(sign_names[y_data[x]] == sign_names[predicted_labels[x]]):
        print("{0}{1}:".format('Correct prediction: ' , sign_names[y_data[x]]))
    else:
        print("{0}{1}:".format('Incorrect prediction: ' , sign_names[y_data[x]]))
    for y in range(5):
        print("{:s}: {:.2f}%".format(str(sign_names[results[1][x][y]]), results[0][x][y]*100))

    print()
```

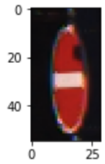
Original Image (size is random): 1

Modified Image (size: 32x32x3): 1

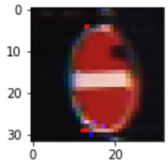


Correct prediction: ['26', 'Traffic signals']:
['26', 'Traffic signals']: 100.00%
['18', 'General caution']: 0.00%
['37', 'Go straight or left']: 0.00%
['35', 'Ahead only']: 0.00%
['5', 'Speed limit (80km/h)']: 0.00%

Original Image (size is random): 2

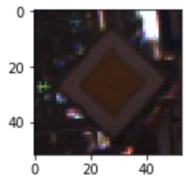


Modified Image (size: 32x32x3): 2

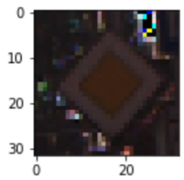


Correct prediction: ['17', 'No entry']:
['17', 'No entry']: 100.00%
['38', 'Keep right']: 0.00%
['9', 'No passing']: 0.00%
['40', 'Roundabout mandatory']: 0.00%
['20', 'Dangerous curve to the right']: 0.00%

Original Image (size is random): 3

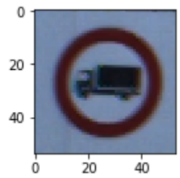


Modified Image (size: 32x32x3): 3

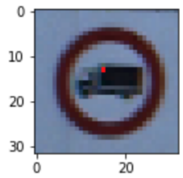


Correct prediction: ['12', 'Priority road']:
['12', 'Priority road']: 100.00%
['13', 'Yield']: 0.00%
['5', 'Speed limit (80km/h)']: 0.00%
['9', 'No passing']: 0.00%
['15', 'No vehicles']: 0.00%

Original Image (size is random): 4

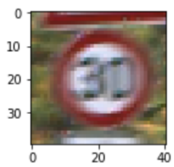


Modified Image (size: 32x32x3): 4

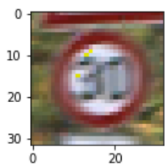


Correct prediction: ['16', 'Vehicles over 3.5 metric tons prohibited']:
['16', 'Vehicles over 3.5 metric tons prohibited']: 100.00%
['40', 'Roundabout mandatory']: 0.00%
['7', 'Speed limit (100km/h)']: 0.00%
['41', 'End of no passing']: 0.00%
['37', 'Go straight or left']: 0.00%

Original Image (size is random): 5

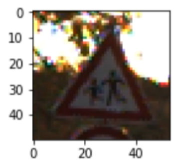


Modified Image (size: 32x32x3): 5

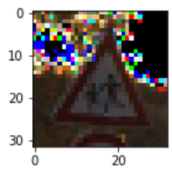


Correct prediction: ['1', 'Speed limit (30km/h)']:
['1', 'Speed limit (30km/h)']: 100.00%
['4', 'Speed limit (70km/h)']: 0.00%
['40', 'Roundabout mandatory']: 0.00%
['0', 'Speed limit (20km/h)']: 0.00%
['8', 'Speed limit (120km/h)']: 0.00%

Original Image (size is random): 6

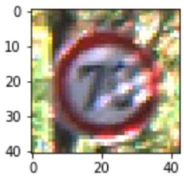


Modified Image (size: 32x32x3): 6

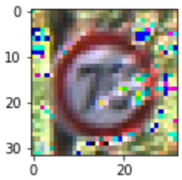


Correct prediction: ['28', 'Children crossing']:
['28', 'Children crossing']: 100.00%
['24', 'Road narrows on the right']: 0.00%
['29', 'Bicycles crossing']: 0.00%
['11', 'Right-of-way at the next intersection']: 0.00%
['5', 'Speed limit (80km/h)']: 0.00%

```
Original Image (size is random): 7
```

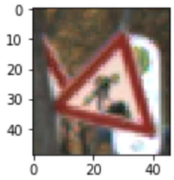



```
Modified Image (size: 32x32x3): 7
```

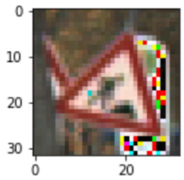



```
Correct prediction: ['4', 'Speed limit (70km/h)']:
['4', 'Speed limit (70km/h)']: 100.00%
['24', 'Road narrows on the right']: 0.00%
['0', 'Speed limit (20km/h)']: 0.00%
['1', 'Speed limit (30km/h)']: 0.00%
['2', 'Speed limit (50km/h)']: 0.00%
```

```
Original Image (size is random): 8
```

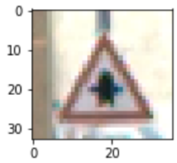



```
Modified Image (size: 32x32x3): 8
```

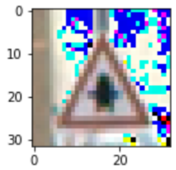



```
Correct prediction: ['25', 'Road work']:
['25', 'Road work']: 85.34%
['33', 'Turn right ahead']: 14.66%
['20', 'Dangerous curve to the right']: 0.00%
['11', 'Right-of-way at the next intersection']: 0.00%
['37', 'Go straight or left']: 0.00%
```

```
Original Image (size is random): 9
```

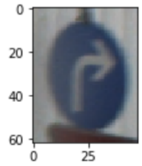



```
Modified Image (size: 32x32x3): 9
```

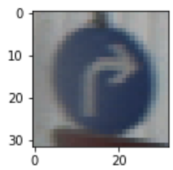



```
Correct prediction: ['11', 'Right-of-way at the next intersection']:
['11', 'Right-of-way at the next intersection']: 100.00%
['27', 'Pedestrians']: 0.00%
['30', 'Beware of ice/snow']: 0.00%
['24', 'Road narrows on the right']: 0.00%
['28', 'Children crossing']: 0.00%
```

```
Original Image (size is random): 10
```




```
Modified Image (size: 32x32x3): 10
```




```
Correct prediction: ['33', 'Turn right ahead']:
['33', 'Turn right ahead']: 100.00%
['39', 'Keep left']: 0.00%
['37', 'Go straight or left']: 0.00%
['35', 'Ahead only']: 0.00%
['20', 'Dangerous curve to the right']: 0.00%
```

1st prediction is 85.3% and 2nd prediction is 14.7% with No.8, but **mostly the 1st prediction is 100%.**