Classifier

November 26, 2017

1 Self-Driving Car Engineer Nanodegree

1.1 Deep Learning

1.2 Project: Traffic Sign Recognition Classifier

1.2.1 Overview

This project's goal is to create traffic signs classifier using deep learning techniques and 'German traffic signs' dataset as a learning data. The code below is a process of creating such a classifier with explanations and visualizations for each step. These steps are: - Step 0: Import all the required dependencies - Step 1: Define a function for loading data - Step 2: Provide tools for displaying information about input dataset - Step 3. Process initial data and build a model for learning - Step 4. Train and validate the model - Step 5: Test a Model on New Images - Step 6. Visualize the result of prediction

Write up with all the explanations could be found in: ./writeup.pdf

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1.3 Step 0: Import all the required dependencies

```
In [78]: import functools
         from textwrap import wrap
         import pickle
         import numpy as np
         import pandas as pd
         import tensorflow as tf
         import matplotlib.pyplot as plt
         from matplotlib import gridspec
         import cv2 as cv
         from sklearn.utils import shuffle

         %matplotlib inline
```

1.4 Step 1: Define a function for loading data

```
In [41]: def load_data():
             loaded_data = {}
```

```
        training_file = './data/train.p'
        validation_file = './data/valid.p'
        testing_file = './data/test.p'
        labels_file = './signnames.csv'

        with open(training_file, mode='rb') as file:
            train = pickle.load(file)
        with open(validation_file, mode='rb') as file:
            valid = pickle.load(file)
        with open(testing_file, mode='rb') as file:
            test = pickle.load(file)

        loaded_data['x_train'] = train['features']
        loaded_data['y_train'] = train['labels']
        loaded_data['x_valid'] = valid['features']
        loaded_data['y_valid'] = valid['labels']
        loaded_data['x_test'] = test['features']
        loaded_data['y_test'] = test['labels']
        loaded_data['labels'] = np.array(pd.read_csv(labels_file, sep=',').values.tolist(
        loaded_data['labels_number'] = loaded_data['labels'].shape[0]

        return loaded_data
```

1.5 Step 2: Provide tools for displaying information about input dataset

1.5.1 Assert the equality of images sizes across dataset and print basic info

```
In [42]: def show_data_info(data):
             assert(
                 data['x_train'].shape[1:] == data['x_valid'].shape[1:] and
                 data['x_train'].shape[1:] == data['x_test'].shape[1:]
             )
             print('Total number of training images: {}'.format(data['x_train'].shape[0]))
             print('Total number of validation images: {}'.format(data['x_valid'].shape[0]))
             print('Total number of test images: {}'.format(data['x_test'].shape[0]))
             print('Total number of classes: {}'.format(data['labels_number']))
             print('Image size is {} across dataset'.format(data['x_train'].shape[1:]))
```

1.5.2 Display initial distribution of signs images across dataset and display some images from available subsets (train, valid, test)

```
In [43]: def show_signs_distribution(data):
             plt.subplots(figsize=(12, 15))
             plt.title('Signs distribution across dataset')
             plt.hist(
                 [
                     data['y_train'],
                     data['y_test'],
                     data['y_valid']
                 ],
                 bins=data['labels_number'],
                 color=('#1eb53a', '#f77f00', '#b80c09'),
                 orientation='horizontal',
                 rwidth=0.7,
                 label=('Train', 'Test', 'Valid')
             )
             plt.gca().invert_yaxis()
             plt.yticks(np.arange(data['labels_number']), data['labels'][:, 1])
             plt.xlabel('Number of examples')
             plt.legend(loc='lower right')
             plt.show()

         def show_signs(data, signs_per_row=5):
             gallery = {'train': [], 'valid': [], 'test':[]}

             signs_info_rows = np.copy(data['labels'])
             np.random.shuffle(signs_info_rows) #pylint: disable=E1101
             signs_info_rows = signs_info_rows[:5]

             for sign_info in signs_info_rows:
                 sign_id = int(sign_info[0])
                 sign_name = sign_info[1]

                 for key, value in gallery.items():
                     y_key = 'y_' + key
                     x_key = 'x_' + key
                     sign_image_indices = np.where(data[y_key] == sign_id)
                     sign_image_index = (sign_image_indices[0][0]
                         if isinstance(sign_image_indices, tuple)
                         else sign_image_indices[0])

                     image = data[x_key][sign_image_index]
                     gallery_item = [sign_name, image]
                     value.append(gallery_item)

             for key, value in gallery.items():
                 plt.figure(figsize=(15, 4))
                 plt.suptitle('{} dataset'.format(key.capitalize()), size=18)
                 for i in range(signs_per_row):
                     title, image = value[i]
                     plt.subplot(1, signs_per_row, i+1)
                     plt.title('\n'.join(wrap(title, 20)))
                     plt.imshow(image)

         def visualize_data(data):
             show_signs_distribution(data)
```

```
show_signs(data)
```

1.6 Step 3. Process initial data and build a model for learning

1.6.1 1) Provide logic for augmenting initial dataset

For augmenting dataset I've used next techniques of image processing: - image rotation combined with scaling. Angle is chosen randomly within predefined range. Scaling is used in order to avoid 'blind areas' of black pixels when we perform rotation. Image rotations was chosen because it is allows us to avoid network's overlearning on sign orientation criteria. - modifying the perspective of the image. For each image we randomly shift the corners so that result image skew its perspective. This techinque is used in order to prevent case when network relies on the correct form (circle, triangle and so on) of sign. Images can be skewed because of light refraction, not well-mounted sign, or simply because of position at which an image was taken - blurring image using GaussianBlur. This method was used because we can not rely on the assumption that image was not blurred because of speed or low camera resolution - combination of blurring and rotation - combination of blurring and modifying perspective

Note: combination of rotation and perspective modifications is not used, because both of these techniques leads to image scaling. So combinig them we potentially could face a case when image is "overscaled" and only part of sign is visible within initial frame

```
In [44]: def compose(*fns):
             return functools.reduce(lambda f, g: lambda x: f(g(x)), fns, lambda x: x)

         def generate_rotated_image(img, angle_delta=15, return_meta=False):
             height, width = img.shape[:2]
             angle = np.random.randint(-angle_delta, angle_delta + 1)
             scale = 1.25
             rotation_matrix = cv.getRotationMatrix2D((height / 2, width / 2), angle, scale)
             result_image = cv.warpAffine(img, rotation_matrix, (height, width))
             return ([result_image, angle, scale] if return_meta else result_image)

         def generate_perspective_transformed_image(img, dim_delta_percentage=.25, return_meta
             height, width = img.shape[:2]
             max_width_delta = dim_delta_percentage * width
             max_height_delta = dim_delta_percentage * height

             initial_points = np.float32([[0, 0], [width, 0], [0, height], [width, height]])
             out_points = np.copy(initial_points)

             for point in out_points:
                 x_coord, y_coord = point
                 p = np.random.rand(2)
                 modify_x, modify_y = np.where(p<0.4, True, False)
                 if modify_x:
                     x_delta = np.random.randint(0, max_width_delta)
                     point[0] = (x_coord + x_delta) if (x_coord > 0) else (x_coord - x_delta)
                 if modify_y:
                     y_delta = np.random.randint(0, max_height_delta)
```

```
                point[1] = (y_coord + y_delta) if (y_coord > 0) else (y_coord - y_delta)

        transform_matrix = cv.getPerspectiveTransform(initial_points, out_points)
        result_image = cv.warpPerspective(img, transform_matrix, (height, width))
        return ([result_image, out_points] if return_meta else result_image)

    def generate_blurred_image(img, return_meta=False):
        height, width = img.shape[:2]
        kernel = (7,7)
        blurred_image = cv.GaussianBlur(img, kernel, 0)
        return [blurred_image, kernel] if return_meta else blurred_image

    augmentations = [
        generate_blurred_image,
        generate_rotated_image,
        generate_perspective_transformed_image,
        compose(
            generate_blurred_image,
            generate_perspective_transformed_image
        ),
        compose(
            generate_blurred_image,
            generate_rotated_image
        )
    ]
```

1.6.2 2) Provide logic for data augmentation

For the initial dataset we perform augmentation "per sign", i.e. the more images available for current sign the less fake images we would create and vice versa. All the generated images as well as labels for them are concatenated with initial dataset

```
In [45]: def extend_dataset(initial_x, initial_y, labels, labels_total):
             images_per_sign_max = np.max(np.histogram(initial_y, labels_total)[0])
             out_x = np.copy(initial_x)
             out_y = np.copy(initial_y)
             generated_images = []
             generated_labels = []

             for i in range(labels_total):
                 sign_id = int(labels[i][0])
                 indices_of_sign = np.where(initial_y == sign_id)

                 if isinstance(indices_of_sign, tuple):
                     indices_to_concat = []
                     for indices_arr in indices_of_sign:
                         indices_to_concat.append(indices_arr)
                     indices_of_sign = np.concatenate(indices_to_concat)
```

```
            images_per_sign = indices_of_sign.shape[0]
            divident = 80000
            total_generated_images = int(divident / images_per_sign)
            input_indices = indices_of_sign[:total_generated_images]

            for counter in range(total_generated_images):
                index = np.random.choice(input_indices)
                initial_image = initial_x[index]
                augmentation = np.random.choice(augmentations)
                result_image = augmentation(initial_image)
                generated_images.append(result_image)
                generated_labels.append(sign_id)

        out_x = np.concatenate((out_x, generated_images))
        out_y = np.concatenate((out_y, generated_labels))

        return [out_x, out_y]
```

1.6.3 3) Provide logic for data preprocessing

Preprocess data in order to convert input images to the format required for neural network. Two techiques are used: - grayscaling is used in order to minimize the noise caused by different light conditions, ISO settings of camera and so on - normalization of pixel values, i.e. converting values so that they belong range from -1 to 1. This conversion is required in order to make the network treating all the features in the same unbiased manner

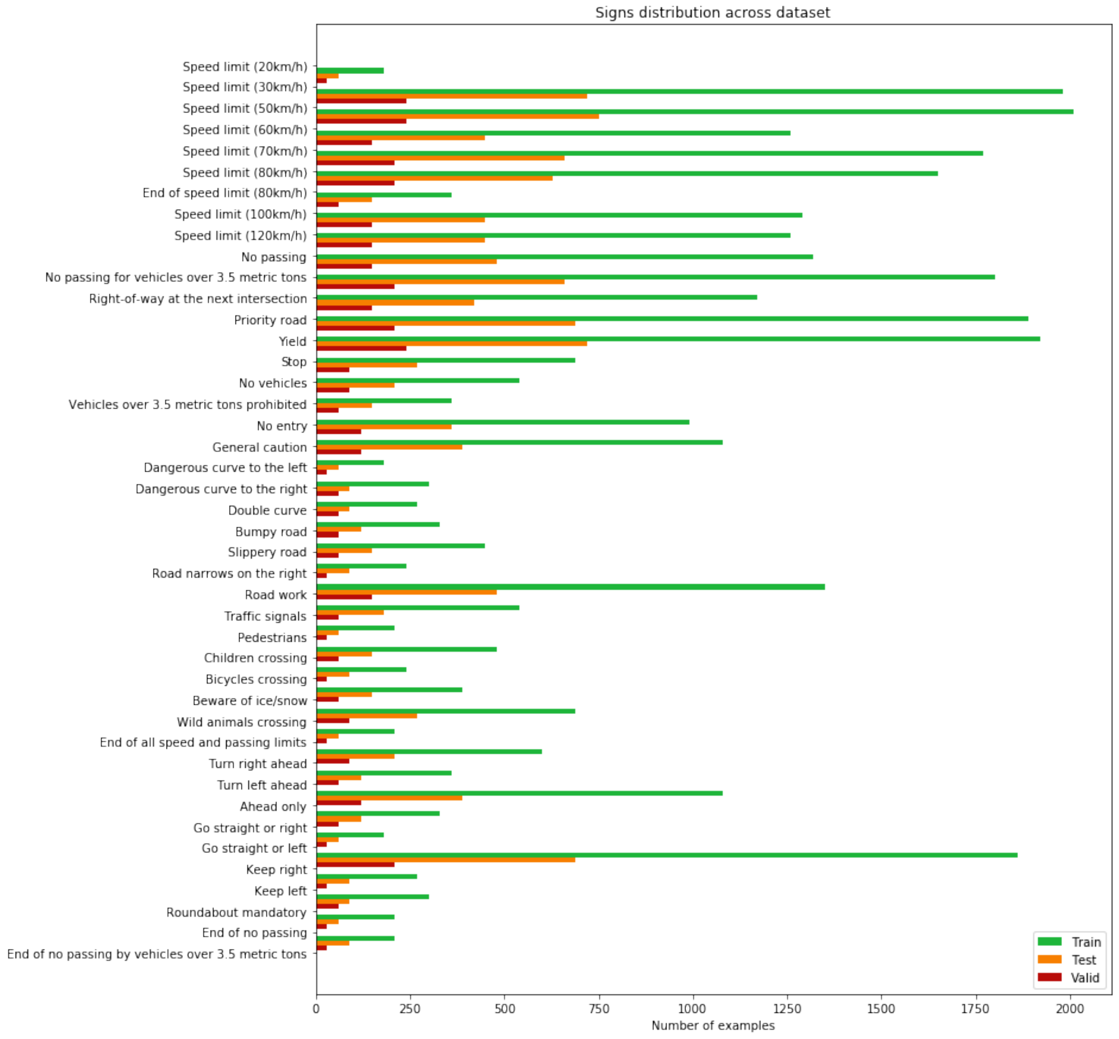
```
In [46]: def grayscale(image):
             gray_image = cv.cvtColor(image, cv.COLOR_RGB2GRAY)
             return np.array(gray_image).astype(np.float32)

         def normalize_gray(gray_image):
             flatten = gray_image.flatten()
             normalized = ((flatten - 128) / 128).reshape((32, 32, 1))
             return normalized

         preprocess_image = compose(normalize_gray, grayscale)

         def preprocess_data(raw_data):
             out_data = {}

             for key, value in raw_data.items():
                 if key == 'x_train':
                     extended_x, extended_y = extend_dataset(
                         raw_data['x_train'],
                         raw_data['y_train'],
                         raw_data['labels'],
                         raw_data['labels_number']
```

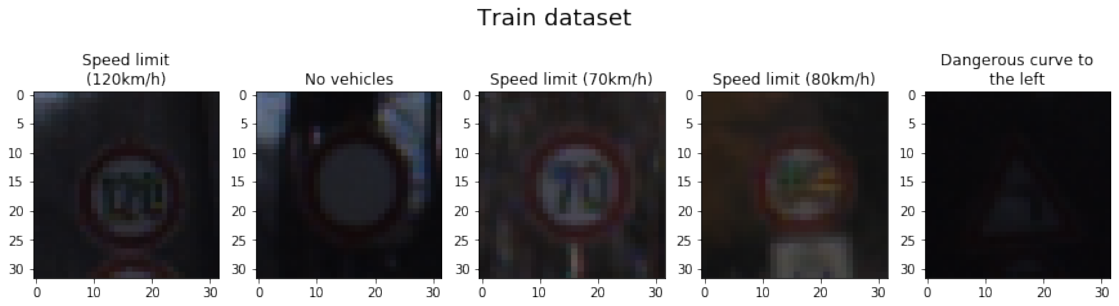
```
                )
                out_data['x_train'] = np.array(list(map(preprocess_image, extended_x)))
                out_data['y_train'] = extended_y
                continue

            if key == 'y_train':
                continue

            if key[0] == 'x':
                out_data[key] = np.array(list(map(preprocess_image, value)))
                continue

            out_data[str(key)] = value

        return out_data
```

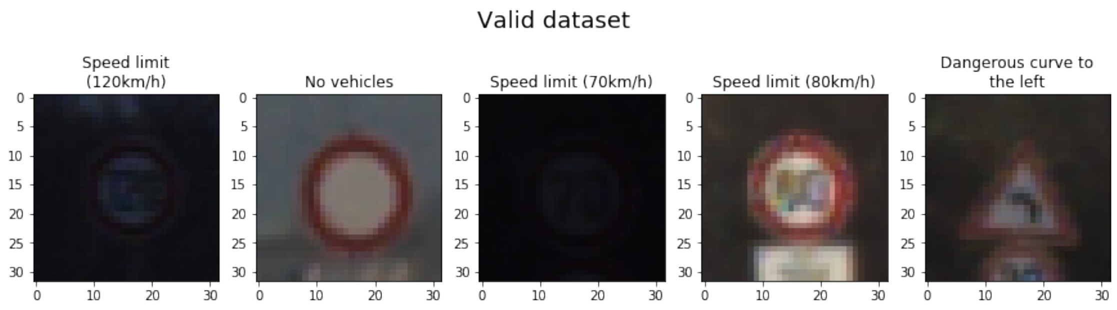
1.6.4 4) Load data, show info and preprocess it using functions defined above

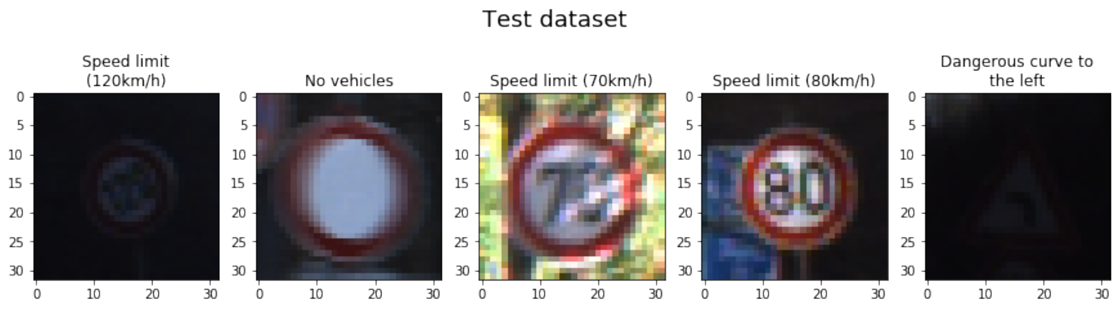
```
In [47]: input_data = load_data()
         show_data_info(input_data)
         visualize_data(input_data)
         preprocessed_data = preprocess_data(input_data)
```

```
Total number of training images: 34799
Total number of validation images: 4410
Total number of test images: 12630
Total number of classes: 43
Image size is (32, 32, 3) across dataset
```


Signs distribution across dataset
Speed limit (20km/h)
Speed limit (30km/h)
Speed limit (50km/h)
Speed limit (60km/h)
Speed limit (70km/h)
Speed limit (80km/h)
End of speed limit (80km/h)
Speed limit (100km/h)
Speed limit (120km/h)
No passing
No passing for vehicles over 3.5 metric tons
Right-of-way at the next intersection
Priority road
Yield
Stop
No vehicles
Vehicles over 3.5 metric tons prohibited
No entry
General caution
Dangerous curve to the left
Dangerous curve to the right
Double curve
Bumpy road
Slippery road
Road narrows on the right
Road work
Traffic signals
Pedestrians
Children crossing
Bicycles crossing
Beware of ice/snow
Wild animals crossing
End of all speed and passing limits
Turn right ahead
Turn left ahead
Ahead only
Go straight or right
Go straight or left
Keep right
Keep left
Roundabout mandatory
End of no passing
End of no passing by vehicles over 3.5 metric tons
Train
Test
Valid
0
250
500
750
1000
1250
1500
1750
2000
Number of examples


Train dataset
Speed limit (120km/h)
No vehicles
Speed limit (70km/h)
Speed limit (80km/h)
Dangerous curve to the left





1.6.5 5) Define a model for learning

As a starting point LeNet model architecture have been used. But after experimenting with different values and parameters several changes were made: - number of epochs was increased to 25 - after second convolution dropout was added - number of convolution layers' channels was increased - sigmoid was used instead of "relu" activation function for the last fully connected layers

```
In [48]: EPOCHS = 25
         BATCH_SIZE = 128
         mu = 0
         sigma = 0.1
         features_total = preprocessed_data['labels_number']

         def model(x):
             padding_conv = 'VALID'
             padding_pool = 'SAME'

             strides = {
                 'conv_1': [1, 1, 1, 1],
                 'conv_2': [1, 1, 1, 1],
                 'pool_1': [1, 2, 2, 1],
                 'pool_2': [1, 2, 2, 1]
             }
```

```
weights = {
    'conv_1': tf.Variable(tf.truncated_normal([5, 5, 1, 16], mean=mu, stddev=sigma
    'conv_2': tf.Variable(tf.truncated_normal([5, 5, 16, 32], mean=mu, stddev=sig
    'ful_1': tf.Variable(tf.truncated_normal([800, 300], mean=mu, stddev=sigma)),
    'ful_2': tf.Variable(tf.truncated_normal([300, 70], mean=mu, stddev=sigma)),
    'ful_3': tf.Variable(tf.truncated_normal([70, features_total], mean=mu, stdde
}

biases = {
    'conv_bias_1': tf.Variable(tf.zeros(16)),
    'conv_bias_2': tf.Variable(tf.zeros(32)),
    'ful_bias_1': tf.Variable(tf.zeros(300)),
    'ful_bias_2': tf.Variable(tf.zeros(70)),
    'ful_bias_3': tf.Variable(tf.zeros(features_total)),
}

kernels = {
    'pool_1': [1, 2, 2, 1],
    'pool_2': [1, 2, 2, 1]
}

conv_1 = tf.nn.conv2d(x, weights['conv_1'], strides['conv_1'], padding_conv)
conv_1 = tf.nn.bias_add(conv_1, biases['conv_bias_1'])
activation_1 = tf.nn.relu(conv_1)
pool_1 = tf.nn.max_pool(activation_1, kernels['pool_1'], strides['pool_1'], paddi
layer_1 = pool_1

conv_2 = tf.nn.conv2d(layer_1, weights['conv_2'], strides['conv_2'], padding_conv
conv_2 = tf.nn.bias_add(conv_2, biases['conv_bias_2'])
activation_2 = tf.nn.relu(conv_2)
pool_2 = tf.nn.max_pool(activation_2, kernels['pool_2'], strides['pool_2'], paddi
layer_2 = pool_2
layer_2 = tf.nn.dropout(layer_2, 0.75)

flattened = tf.contrib.layers.flatten(layer_2)

layer_3 = tf.matmul(flattened, weights['ful_1'])
layer_3 = tf.nn.bias_add(layer_3, biases['ful_bias_1'])
layer_3 = tf.nn.relu(layer_3)

layer_4 = tf.matmul(layer_3, weights['ful_2'])
layer_4 = tf.nn.bias_add(layer_4, biases['ful_bias_2'])
layer_4 = tf.nn.sigmoid(layer_4)

layer_5 = tf.matmul(layer_4, weights['ful_3'])
layer_5 = tf.nn.bias_add(layer_5, biases['ful_bias_3'])
```

```
        logits = layer_5

        return logits
```

1.6.6 Step 4. Train and validate the model

As well as for LeNet's model training AdamOptimizer is used, but I've added decaying learning rate - it allows to make learning process smoother especially when the validation accuracy is coming closer to the target value.

```
In [49]: x = tf.placeholder(tf.float32, (None, 32, 32, 1))
         y = tf.placeholder(tf.int32, (None))
         one_hot_y = tf.one_hot(y, features_total)

         rate = 0.001
         global_step = tf.Variable(0, trainable=False)
         learning_rate = tf.train.exponential_decay(0.001, global_step, 800, 0.8, staircase=Tr

         logits = model(x)
         cross_entropy = tf.nn.softmax_cross_entropy_with_logits(labels=one_hot_y, logits=logi
         loss_operation = tf.reduce_mean(cross_entropy)
         optimizer = tf.train.AdamOptimizer(learning_rate=learning_rate)
         training_operation = optimizer.minimize(loss_operation, global_step=global_step)

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

         def evaluate(x_data, y_data):
             num_examples = len(x_data)
             total_accuracy = 0
             sess = tf.get_default_session()
             for offset in range(0, num_examples, BATCH_SIZE):
                 batch_x, batch_y = x_data[offset:offset+BATCH_SIZE], y_data[offset:offset+BAT
                 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:
             sess.run(tf.global_variables_initializer())
             num_examples = len(preprocessed_data['x_train'])

             print("Training...")
             print()
             for i in range(EPOCHS):
                 X_train, y_train = shuffle(preprocessed_data['x_train'], preprocessed_data['y
                 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(preprocessed_data['x_valid'], preprocessed_data

            print("EPOCH {} ...".format(i+1))
            print('Learning rate = {}'.format(sess.run(learning_rate)))
            print("Validation Accuracy = {:.3f}".format(validation_accuracy))
            print()

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


        final_accuracy = evaluate(preprocessed_data['x_test'], preprocessed_data['y_test']
        print("TEST SET ACCURACY = {:.3f}".format(final_accuracy))
```

```
Training...

EPOCH 1 ...
Learning rate = 0.0010000000474974513
Validation Accuracy = 0.759

EPOCH 2 ...
Learning rate = 0.0010000000474974513
Validation Accuracy = 0.895

EPOCH 3 ...
Learning rate = 0.000800000037997961
Validation Accuracy = 0.910

EPOCH 4 ...
Learning rate = 0.000800000037997961
Validation Accuracy = 0.926

EPOCH 5 ...
Learning rate = 0.0006400001002475619
Validation Accuracy = 0.935

EPOCH 6 ...
Learning rate = 0.0006400001002475619
Validation Accuracy = 0.940

EPOCH 7 ...
Learning rate = 0.0006400001002475619
Validation Accuracy = 0.942
```

```
EPOCH 8 ...
Learning rate = 0.0005120000569149852
Validation Accuracy = 0.941

EPOCH 9 ...
Learning rate = 0.0005120000569149852
Validation Accuracy = 0.944

EPOCH 10 ...
Learning rate = 0.00040960003389045596
Validation Accuracy = 0.943

EPOCH 11 ...
Learning rate = 0.00040960003389045596
Validation Accuracy = 0.941

EPOCH 12 ...
Learning rate = 0.00032768002711236477
Validation Accuracy = 0.950

EPOCH 13 ...
Learning rate = 0.00032768002711236477
Validation Accuracy = 0.944

EPOCH 14 ...
Learning rate = 0.00032768002711236477
Validation Accuracy = 0.952

EPOCH 15 ...
Learning rate = 0.00026214405079372227
Validation Accuracy = 0.950

EPOCH 16 ...
Learning rate = 0.00026214405079372227
Validation Accuracy = 0.954

EPOCH 17 ...
Learning rate = 0.00020971523190382868
Validation Accuracy = 0.953

EPOCH 18 ...
Learning rate = 0.00020971523190382868
Validation Accuracy = 0.950

EPOCH 19 ...
Learning rate = 0.00020971523190382868
Validation Accuracy = 0.949
```

```
EPOCH 20 ...
Learning rate = 0.000167772188433446
Validation Accuracy = 0.951

EPOCH 21 ...
Learning rate = 0.000167772188433446
Validation Accuracy = 0.951

EPOCH 22 ...
Learning rate = 0.00013421774201560766
Validation Accuracy = 0.954

EPOCH 23 ...
Learning rate = 0.00013421774201560766
Validation Accuracy = 0.949

EPOCH 24 ...
Learning rate = 0.00010737420234363526
Validation Accuracy = 0.952

EPOCH 25 ...
Learning rate = 0.00010737420234363526
Validation Accuracy = 0.954

Model saved
TEST SET ACCURACY = 0.934
```

1.7 Step 5: Test a Model on New Images

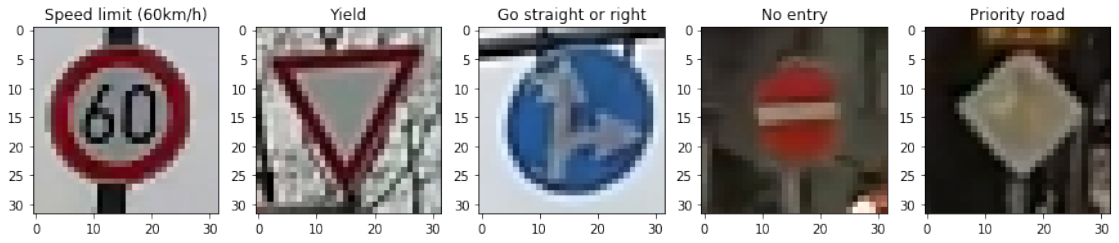
1) Provide a logic for downloading saved and visualiztion of images In order to test a model 5 images has been downloaded. All of the images were taken as a screenshots from this video: https://www.youtube.com/watch?v=r4I_4aP2Xd0

The only preprocessing measure that was taken is cropping the image so that it has a square shape. All the rest (converting to 32x32x1, grayscale and so on) is performed in the code.

```
In [ ]: def load_images():
            images_folder = './new_images'
            images = np.array([
                '1.png', # Speed limit (60km/h)
                '2.png', # Yield
                '3.png', # Go straight or right
                '4.png', # No entry
                '5.png' # Priority road
            ])
            labels = np.array([
                3, # Speed limit (60km/h)
                13, # Yield
                36, # Go straight or right
                17, # No entry
                12 # Priority road
            ])

            load_image = lambda img_name: cv.imread('{folder}/{file}'.format(folder=images_fol
            convert_to_rgb = lambda img: cv.cvtColor(img, cv.COLOR_BGR2RGB)
            resize = lambda img: cv.resize(img, (32, 32))

            converted_images = list(map(compose(resize, convert_to_rgb, load_image), images))

            new_data = {}
            new_data['x_new'] = np.array(converted_images)
            new_data['y_new'] = labels
            new_data['labels'] = input_data['labels']
            new_data['labels_number'] = input_data['labels_number']

            return new_data

        def get_sign_name(sign_id, labels):
            get_sign = lambda acc, item: (item[1] if int(item[0]) == sign_id else None) if acc
            name = functools.reduce(get_sign, labels, None)
            return name

        def show_images(new_data):
            plt.figure(figsize=(15,5))
            for i in range(len(new_data['x_new'])):
                image = new_data['x_new'][i]
                sign_id = new_data['y_new'][i]
                get_sign = lambda acc, item: (item[1] if int(item[0]) == sign_id else None) if
                title = get_sign_name(sign_id, new_data['labels'])
                plt.subplot(1, 5, i+1)
                plt.title(title)
                plt.imshow(image)
            plt.show()
```

2) Load images and display them with labels

```
In [84]: new_data = load_images()
         show_images(new_data)
```



3) Preprocess data and evaluate the model Here we also define variables for accuracy and predictions that are made by the model. We'll use them later.

```
In [59]: preprocessed_new_data = preprocess_data(new_data)

         predictions = tf.nn.top_k(tf.nn.softmax(logits), k=5)
         new_accuracy = None
         new_predictions = None

         with tf.Session() as sess:
             sess.run(tf.global_variables_initializer())
             saver = tf.train.import_meta_graph('./lenet.meta')
             saver.restore(sess, "./lenet")
             new_accuracy = evaluate(
                 preprocessed_new_data['x_new'],
                 preprocessed_new_data ['y_new']
             )
             new_predictions = sess.run(predictions, feed_dict={
                 x: preprocessed_new_data['x_new'],
                 y: preprocessed_new_data ['y_new']
             })
```

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

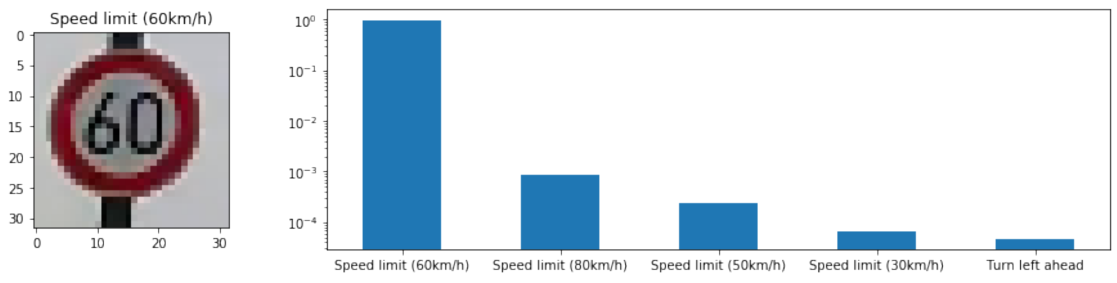
1.8 Step 6. Visualizing the result of prediction

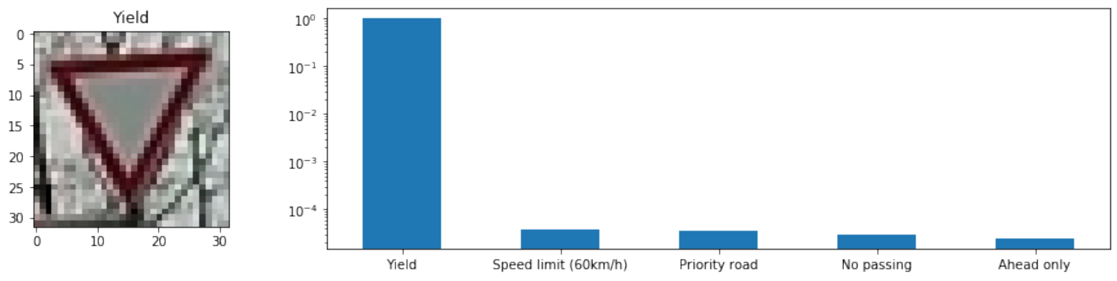
Here we display the most probable predictions as the bar chart. Log scale is used because the difference between the major result and all the other ones is huge

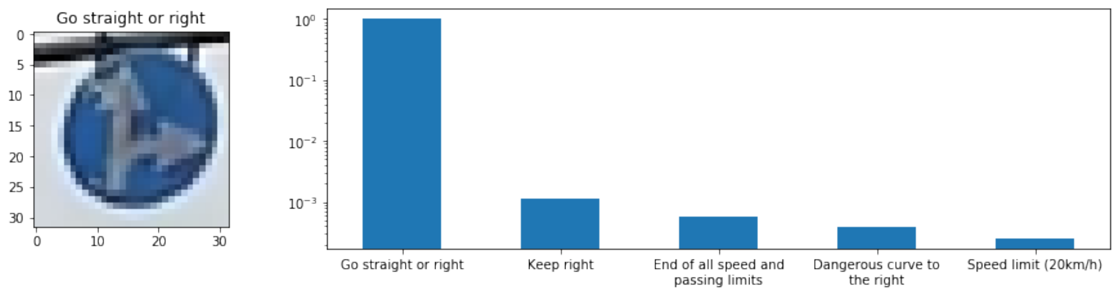
```
In [92]: def show_predictions(data, predictions, accuracy):
             images_total = len(data['x_new'])

             print('\nPredictions accuracy (for images from the web): {}'.format(accuracy))

             plt.figure(figsize=(15, 4 * images_total))
             grid = gridspec.GridSpec(images_total, 2, width_ratios=[1, 4])
```

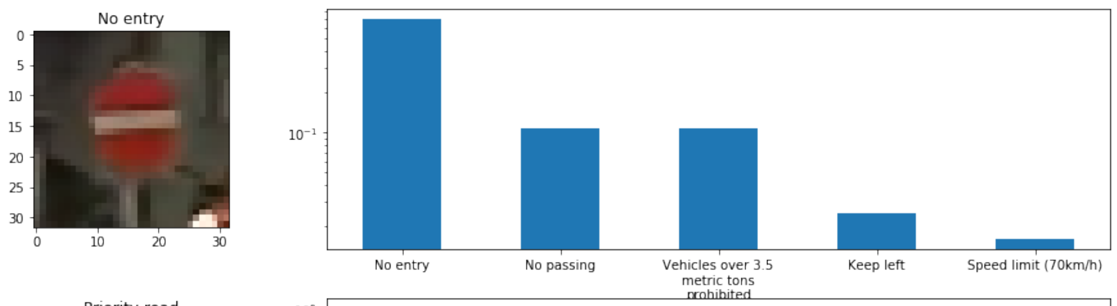
```
    for i in range(images_total):
        image = data['x_new'][i]
        sign_id = data['y_new'][i]
        title = get_sign_name(sign_id, data['labels'])

        plt.subplot(grid[2 * i])
        plt.title(title)
        plt.imshow(image)

        plt.subplot(grid[2 * i + 1])
        x = np.arange(5)
        plt.bar(x, predictions[0][i], log=True, width=0.5)
        labels = []
        for prediction in predictions[1][i]:
            label = get_sign_name(prediction, data['labels'])
            label = ('\n'.join(wrap(label, 20)))
            labels.append(label)
        plt.xticks(x, labels)

    plt.show()

show_predictions(new_data, new_predictions, new_accuracy)
```

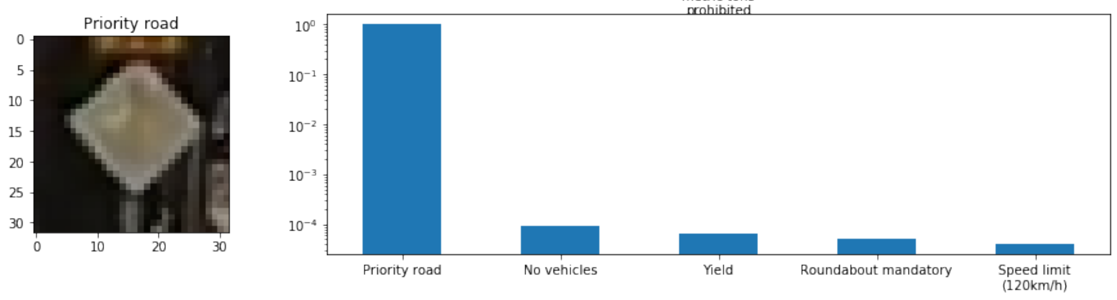
```
Predictions accuracy (for images from the web): 1.0
```


Speed limit (60km/h)
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
Speed limit (60km/h)
Speed limit (80km/h)
Speed limit (50km/h)
Speed limit (30km/h)
Turn left ahead


Yield
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
Yield
Speed limit (60km/h)
Priority road
No passing
Ahead only


Go straight or right
10^0
10^{-1}
10^{-2}
10^{-3}
Go straight or right
Keep right
End of all speed and passing limits
Dangerous curve to the right
Speed limit (20km/h)


No entry
10^{-1}
No entry
No passing
Vehicles over 3.5 metric tons prohibited
Keep left
Speed limit (70km/h)


Priority road
10^0
10^{-1}
10^{-2}
10^{-3}
10^{-4}
Priority road
No vehicles
Yield
Roundabout mandatory
Speed limit (120km/h)