Traffic_Sign_Classifier

March 13, 2020

1 Self-Driving Car Engineer Nanodegree

1.1 Deep Learning

1.2 Project: Build a Traffic Sign Recognition Classifier

In this notebook, a template is provided for you to implement your functionality in stages, which is required to successfully complete this project. If additional code is required that cannot be included in the notebook, be sure that the Python code is successfully imported and included in your submission if necessary.

> **Note**: Once you have completed all of the code implementations, you need to finalize your work by exporting the iPython Notebook as an HTML document. Before exporting the notebook to html, all of the code cells need to have been run so that reviewers can see the final implementation and output. You can then export the notebook by using the menu above and navigating to ",”**File -> Download as -> HTML (.html)**. Include the finished document along with this notebook as your submission.

In addition to implementing code, there is a writeup to complete. The writeup should be completed in a separate file, which can be either a markdown file or a pdf document. There is a write up template that can be used to guide the writing process. Completing the code template and writeup template will cover all of the rubric points for this project.

The rubric contains "Stand Out Suggestions" for enhancing the project beyond the minimum requirements. The stand out suggestions are optional. If you decide to pursue the "stand out suggestions", you can include the code in this Ipython notebook and also discuss the results in the writeup file.

> **Note:** Code and Markdown cells can be executed using the **Shift + Enter** keyboard shortcut. In addition, Markdown cells can be edited by typically double-clicking the cell to enter edit mode.

1.3 Step 0: Load The Data

[1]:
```
# Python Imports
import cv2
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.pyplot import xticks
import matplotlib.image as mpimg
import random
from sklearn.utils import shuffle
from scipy import ndimage, misc
from math import pi
import copy
# from skimage import data
# from skimage.color import rgb2gray
import csv

import tensorflow as tf
# Tensorflow 1 compatibility
import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()
from tensorflow.compat.v1.layers import flatten

# 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']

# Print data shapes
print("Training, Validation, and Testing datasets.")
print("X_train shape:", X_train.shape)
print("y_train shape:", y_train.shape)
```

```
print("X_valid shape:", X_valid.shape)
print("y_valid shape:", y_valid.shape)
print("X_test shape:", X_test.shape)
print("y_test shape:", y_test.shape)
```

```
WARNING:tensorflow:From /home/ian/anaconda3/envs/carnd-term1/lib/python3.5/site-
packages/tensorflow_core/python/compat/v2_compat.py:88:
disable_resource_variables (from tensorflow.python.ops.variable_scope) is
deprecated and will be removed in a future version.
Instructions for updating:
non-resource variables are not supported in the long term
Training, Validation, and Testing datasets.
X_train shape: (34799, 32, 32, 3)
y_train shape: (34799,)
X_valid shape: (4410, 32, 32, 3)
y_valid shape: (4410,)
X_test shape: (12630, 32, 32, 3)
y_test shape: (12630,)
```

1.4 Step 1: Dataset Summary & Exploration

The pickled data is a dictionary with 4 key/value pairs:

- `'features'` is a 4D array containing raw pixel data of the traffic sign images, (num examples, width, height, channels).
- `'labels'` is a 1D array containing the label/class id of the traffic sign. The file `signnames.csv` contains id -> name mappings for each id.
- `'sizes'` is a list containing tuples, (width, height) representing the original width and height the image.
- `'coords'` is a list containing tuples, (x1, y1, x2, y2) representing coordinates of a bounding box around the sign in the image. **THESE COORDINATES ASSUME THE ORIGINAL IMAGE. THE PICKLED DATA CONTAINS RESIZED VERSIONS (32 by 32) OF THESE IMAGES**

Complete the basic data summary below. Use python, numpy and/or pandas methods to calculate the data summary rather than hard coding the results. For example, the pandas shape method might be useful for calculating some of the summary results.

1.4.1 Provide a Basic Summary of the Data Set Using Python, Numpy and/or Pandas

[2]:
```
### Replace each question mark with the appropriate value.
### Use python, pandas or numpy methods rather than hard coding the results

# TODO: Number of training examples
n_train = len(X_train)
```

```
# TODO: Number of validation examples
n_validation = len(X_valid)

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

# TODO: What's the shape of an traffic sign image?
image_shape = X_train[0].shape

# TODO: How many unique classes/labels there are in the dataset.
n_classes = len(np.unique(y_train))

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

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

1.4.2 Include an exploratory visualization of the dataset

Visualize the German Traffic Signs Dataset using the pickled file(s). This is open ended, suggestions include: plotting traffic sign images, plotting the count of each sign, etc.

The Matplotlib examples and gallery pages are a great resource for doing visualizations in Python.

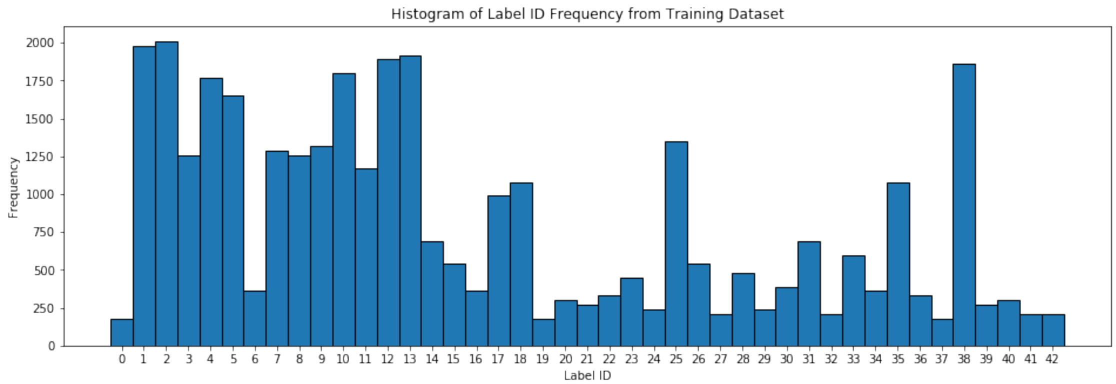
NOTE: It's recommended you start with something simple first. If you wish to do more, come back to it after you've completed the rest of the sections. It can be interesting to look at the distribution of classes in the training, validation and test set. Is the distribution the same? Are there more examples of some classes than others?

[3]:
```
### Data exploration visualization code goes here.
### Feel free to use as many code cells as needed.

# Shuffle Images
X_train, y_train = shuffle(X_train, y_train)

# Visualizations will be shown in the notebook.
%matplotlib inline

# Plot 15 random images from the training set with accompanying labels.
fig, ax = plt.subplots(3, 5, figsize=(15, 10))
fig.tight_layout(pad=3.0)
```

```
fig.suptitle('Random selection of 15 images from the training dataset.', fontsize=16)
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(15):
    index = random.randint(0, len(X_train))
    image = X_train[index]
    ax[i].imshow(image)
    ax[i].set_title('Label ID: ' + str(y_train[index]))
```

[4]:
```
# histogram of label frequency
plt.figure(figsize=(16, 5))
n, bins, patches = plt.hist(y_train, bins=range(n_classes+1), histtype='bar', align='left', alpha=1, edgecolor='black')
locs, labels = xticks()
xticks(np.arange(np.min(y_train), np.max(y_train)+1, step=1))
plt.xlabel('Label ID')
plt.ylabel('Frequency')
plt.title('Histogram of Label ID Frequency from Training Dataset')
plt.show()

print("{:>10s}".format("LabelID") + "\t" + "{:>10s}".format("Count"))
print("----------", "\t", "----------")
```

```python
for i in range(0, len(n)):
    print("{:>10d}".format(i) + "\t" + "{:>10d}".format(int(n[i])))
```



LabelID	Count
0	180
1	1980
2	2010
3	1260
4	1770
5	1650
6	360
7	1290
8	1260
9	1320
10	1800
11	1170
12	1890
13	1920
14	690
15	540
16	360
17	990
18	1080
19	180
20	300
21	270
22	330
23	450
24	240
25	1350
26	540

27	210
28	480
29	240
30	390
31	690
32	210
33	599
34	360
35	1080
36	330
37	180
38	1860
39	270
40	300
41	210
42	210

1.5 Step 2: Design and Test a Model Architecture

Design and implement a deep learning model that learns to recognize traffic signs. Train and test your model on the German Traffic Sign Dataset.

The LeNet-5 implementation shown in the classroom at the end of the CNN lesson is a solid starting point. You'll have to change the number of classes and possibly the preprocessing, but aside from that it's plug and play!

With the LeNet-5 solution from the lecture, you should expect a validation set accuracy of about 0.89. To meet specifications, the validation set accuracy will need to be at least 0.93. It is possible to get an even higher accuracy, but 0.93 is the minimum for a successful project submission.

There are various aspects to consider when thinking about this problem:

- Neural network architecture (is the network over or underfitting?)
- Play around preprocessing techniques (normalization, rgb to grayscale, etc)
- Number of examples per label (some have more than others).
- Generate fake data.

Here is an example of a published baseline model on this problem. It's not required to be familiar with the approach used in the paper but, it's good practice to try to read papers like these.

1.5.1 Pre-process the Data Set (normalization, grayscale, etc.)

Minimally, the image data should be normalized so that the data has mean zero and equal variance. For image data, `(pixel - 128)/ 128` is a quick way to approximately normalize the data and can be used in this project.

Other pre-processing steps are optional. You can try different techniques to see if it improves performance.

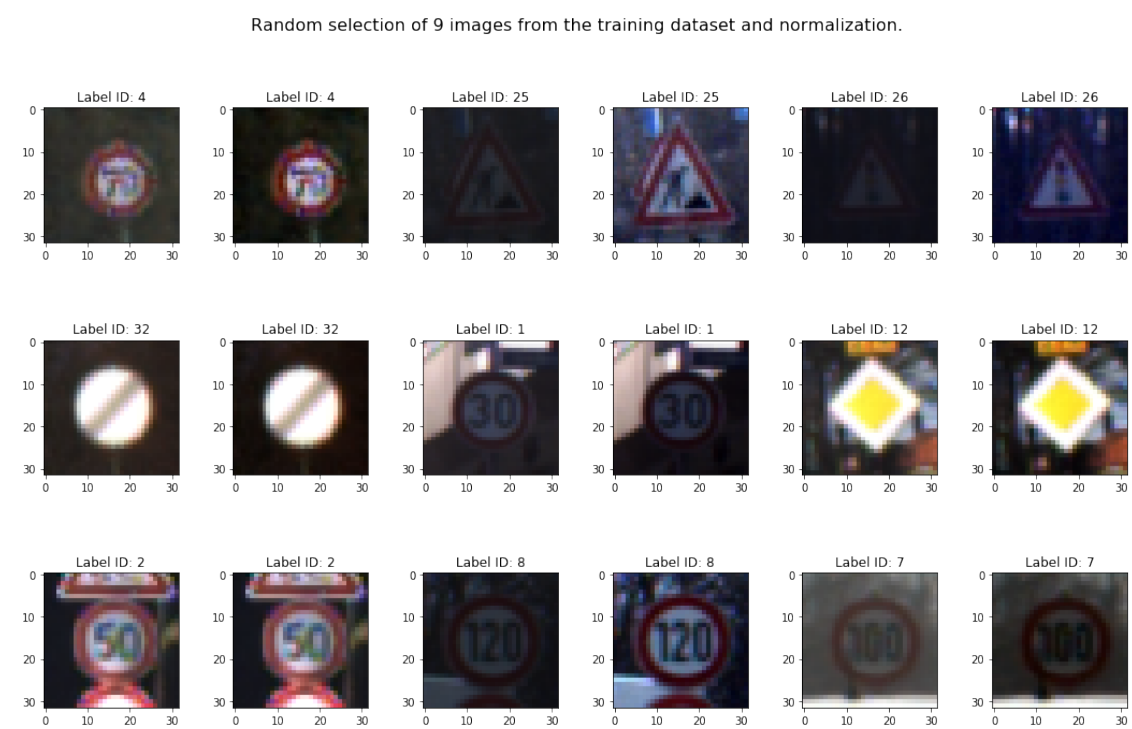
Use the code cell (or multiple code cells, if necessary) to implement the first step of your project.

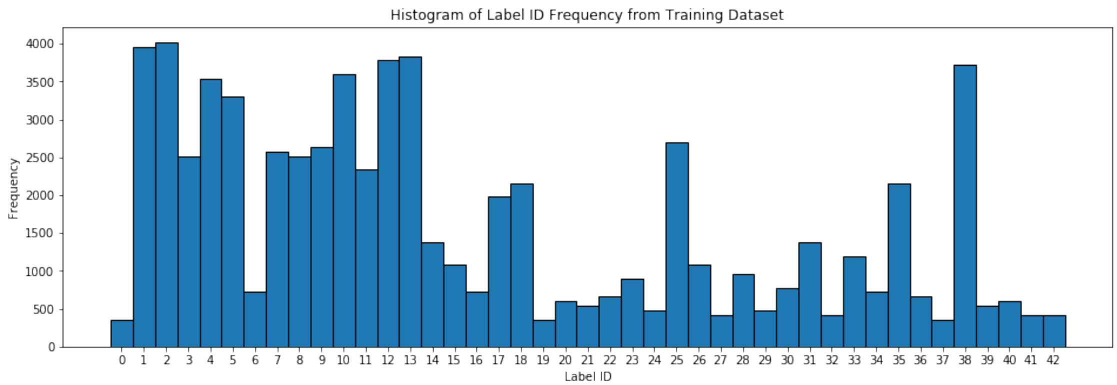
[5]:
```
### Preprocess the data here. It is required to normalize the data. Other␣
↪preprocessing steps could include
### converting to grayscale, etc.
### Feel free to use as many code cells as needed.
```

[6]:
```
# Create set of normalized images.
def normalize_image(img):
    img_norm = np.zeros_like(img)
    img_norm = cv2.normalize(img, img_norm, 0, 255, cv2.NORM_MINMAX)

    return img_norm



X_train_norm = np.zeros_like(X_train)

for i in range (0, len(X_train_norm)):
    X_train_norm[i] = normalize_image(X_train[i])

# Plot 9 random images from the training set with accompanying labels.
fig, ax = plt.subplots(3, 6, figsize=(15, 10))
fig.tight_layout(pad=2.0)
fig.suptitle('Random selection of 9 images from the training dataset and␣
↪normalization.', fontsize=16)
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(0, 18, 2):
    index = random.randint(0, len(X_train))
    img = X_train[index]
    img_norm = X_train_norm[index]
    ax[i].imshow(img)
    ax[i].set_title('Label ID: ' + str(y_train[index]))
    ax[i+1].imshow(img_norm)
    ax[i+1].set_title('Label ID: ' + str(y_train[index]))

print("X_train, y_train shapes BEFORE concatenating normalized images:", X_train.
↪shape, y_train.shape)
print("Adding", len(X_train_norm), "images")

# Add normalized images to X_train dataset
X_train = np.concatenate((X_train, X_train_norm), axis=0)
y_train = np.concatenate((y_train, y_train), axis=0)

print("X_train, y_train shapes AFTER concatenating normalized images:", X_train.
↪shape, y_train.shape)
```

```python
#Clear arrays to free up memory
X_train_norm = []

# Updated histogram of label frequency
plt.figure(figsize=(16, 5))
n, bins, patches = plt.hist(y_train, bins=range(n_classes+1), histtype='bar',␣
↪align='left', alpha=1, edgecolor='black')
locs, labels = xticks()
xticks(np.arange(np.min(y_train), np.max(y_train)+1, step=1))
plt.xlabel('Label ID')
plt.ylabel('Frequency')
plt.title('Histogram of Label ID Frequency from Training Dataset')
plt.show()

print("{:>10s}".format("LabelID") + "\t" + "{:>10s}".format("Count"))
print("----------", "\t", "----------")

for i in range(0, len(n)):
    print("{:>10d}".format(i) + "\t" + "{:>10d}".format(int(n[i])))
```

```
X_train, y_train shapes BEFORE concatenating normalized images: (34799, 32, 32,
3) (34799,)
Adding 34799 images
X_train, y_train shapes AFTER concatenating normalized images: (69598, 32, 32,
3) (69598,)
```





LabelID	Count
0	360
1	3960
2	4020
3	2520
4	3540
5	3300
6	720
7	2580
8	2520
9	2640
10	3600
11	2340
12	3780
13	3840
14	1380
15	1080
16	720
17	1980
18	2160
19	360
20	600
21	540
22	660
23	900
24	480
25	2700
26	1080
27	420
28	960

```
29       480
30       780
31      1380
32       420
33      1198
34       720
35      2160
36       660
37       360
38      3720
39       540
40       600
41       420
42       420
```

[7]:

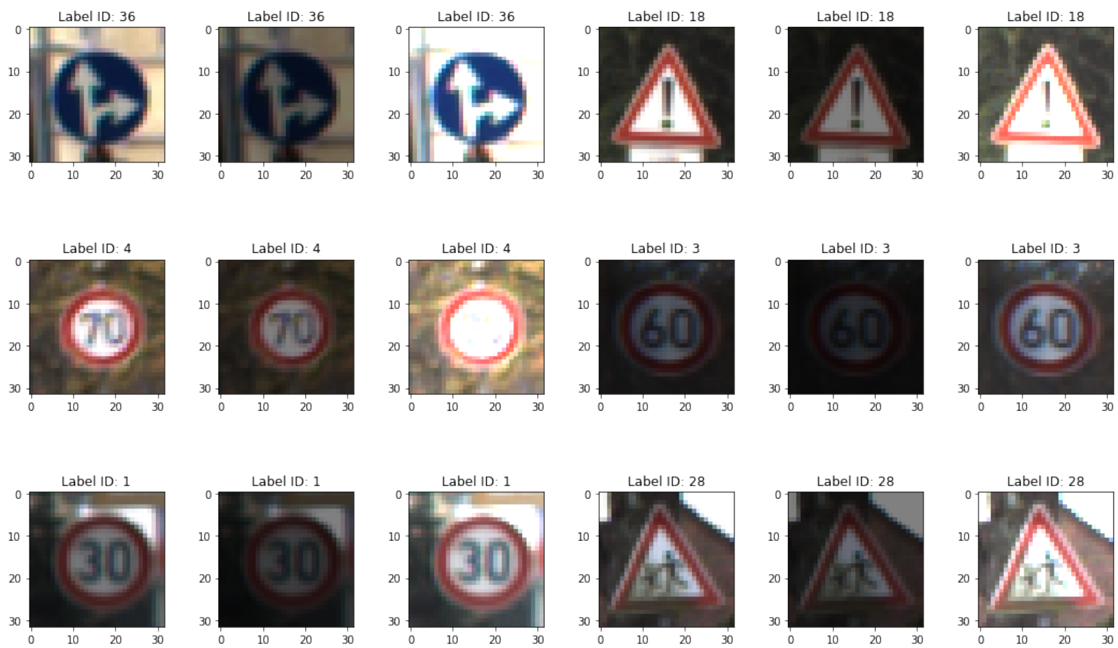
```
def add_gaussian_noise(X_imgs, alpha, beta, gamma):
    gaussian_noise_imgs = []
    row, col, _ = X_imgs[0].shape
    # Gaussian distribution parameters
    mean = 0
    var = 0.1
    sigma = var ** 0.5

    for X_img in X_imgs:
        gaussian = np.random.random((row, col, 1)).astype(np.float32)
        gaussian = np.concatenate((gaussian, gaussian, gaussian), axis = 2)
        gaussian_img = cv2.addWeighted(X_img, alpha, 0.25 * gaussian, beta,␣
 ↪gamma, dtype = cv2.CV_8U)
        gaussian_noise_imgs.append(gaussian_img)

    gaussian_noise_imgs = np.array(gaussian_noise_imgs, dtype=np.uint8)

    return gaussian_noise_imgs



X_train_gauss_darken = add_gaussian_noise(X_train, alpha=0.50, beta=0.25,␣
 ↪gamma=0)
X_train_gauss_brighten = add_gaussian_noise(X_train, alpha=1.75, beta=0.25,␣
 ↪gamma=10)
y_train_gauss = np.copy(y_train)

# Plot 6 random images from the training set with accompanying labels.
fig, ax = plt.subplots(3, 6, figsize=(15, 10))
fig.tight_layout(pad=2.0)
fig.suptitle('Random selection of 6 images from the training dataset and␣
 ↪darkened/brightened adjustments.', fontsize=16)
```

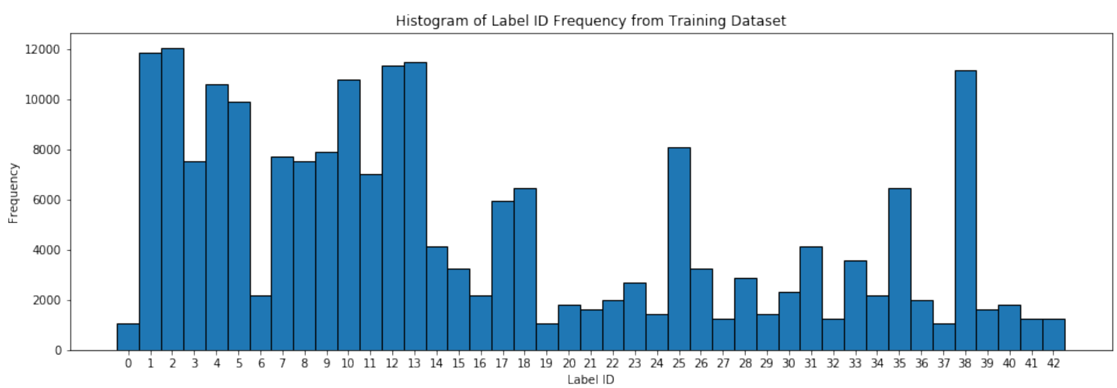
```
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(0, 18, 3):
    index = random.randint(0, len(X_train))
    ax[i].imshow(X_train[index])
    ax[i].set_title('Label ID: ' + str(y_train[index]))
    ax[i+1].imshow(X_train_gauss_darken[index])
    ax[i+1].set_title('Label ID: ' + str(y_train[index]))
    ax[i+2].imshow(X_train_gauss_brighten[index])
    ax[i+2].set_title('Label ID: ' + str(y_train[index]))

print("X_train, y_train shapes BEFORE concatenating darkened and brightened␣
 ↪images:", X_train.shape, y_train.shape)
print("Adding", len(X_train) * 2, "images")

# Add darkened and brightened images to X_train dataset
X_train = np.concatenate((X_train, X_train_gauss_darken), axis=0)
y_train = np.concatenate((y_train, y_train_gauss), axis=0)
X_train = np.concatenate((X_train, X_train_gauss_darken), axis=0)
y_train = np.concatenate((y_train, y_train_gauss), axis=0)

print("X_train, y_train shapes AFTER concatenating darkened and brightened␣
 ↪images:", X_train.shape, y_train.shape)

#Clear unnecessary arrays to free up memory
X_train_gauss_darken = []
X_train_gauss_brighten = []
y_train_gauss = []

# Updated histogram of label frequency
plt.figure(figsize=(16, 5))
n, bins, patches = plt.hist(y_train, bins=range(n_classes+1), histtype='bar',␣
 ↪align='left', alpha=1, edgecolor='black')
locs, labels = xticks()
xticks(np.arange(np.min(y_train), np.max(y_train)+1, step=1))
plt.xlabel('Label ID')
plt.ylabel('Frequency')
plt.title('Histogram of Label ID Frequency from Training Dataset')
plt.show()

print("{:>10s}".format("LabelID") + "\t" + "{:>10s}".format("Count"))
print("----------", "\t", "----------")

for i in range(0, len(n)):
    print("{:>10d}".format(i) + "\t" + "{:>10d}".format(int(n[i])))
```

```
X_train, y_train shapes BEFORE concatenating darkened and brightened images:
```

```
(69598, 32, 32, 3) (69598,)
Adding 139196 images
X_train, y_train shapes AFTER concatenating darkened and brightened images:
(208794, 32, 32, 3) (208794,)
```

Random selection of 6 images from the training dataset and darkened/brightened adjustments.





LabelID	Count
0	1080
1	11880
2	12060
3	7560

```
4      10620
5       9900
6       2160
7       7740
8       7560
9       7920
10     10800
11      7020
12     11340
13     11520
14      4140
15      3240
16      2160
17      5940
18      6480
19      1080
20      1800
21      1620
22      1980
23      2700
24      1440
25      8100
26      3240
27      1260
28      2880
29      1440
30      2340
31      4140
32      1260
33      3594
34      2160
35      6480
36      1980
37      1080
38     11160
39      1620
40      1800
41      1260
42      1260
```

[8]:

```
##### Rotation (at finer angles) #####

IMAGE_SIZE = 32

# # TensorFlow 1.0 Method.  Not backward compatible.
# def rotate_images(X_imgs, start_angle, end_angle, n_images):
#     X_rotate = []
```

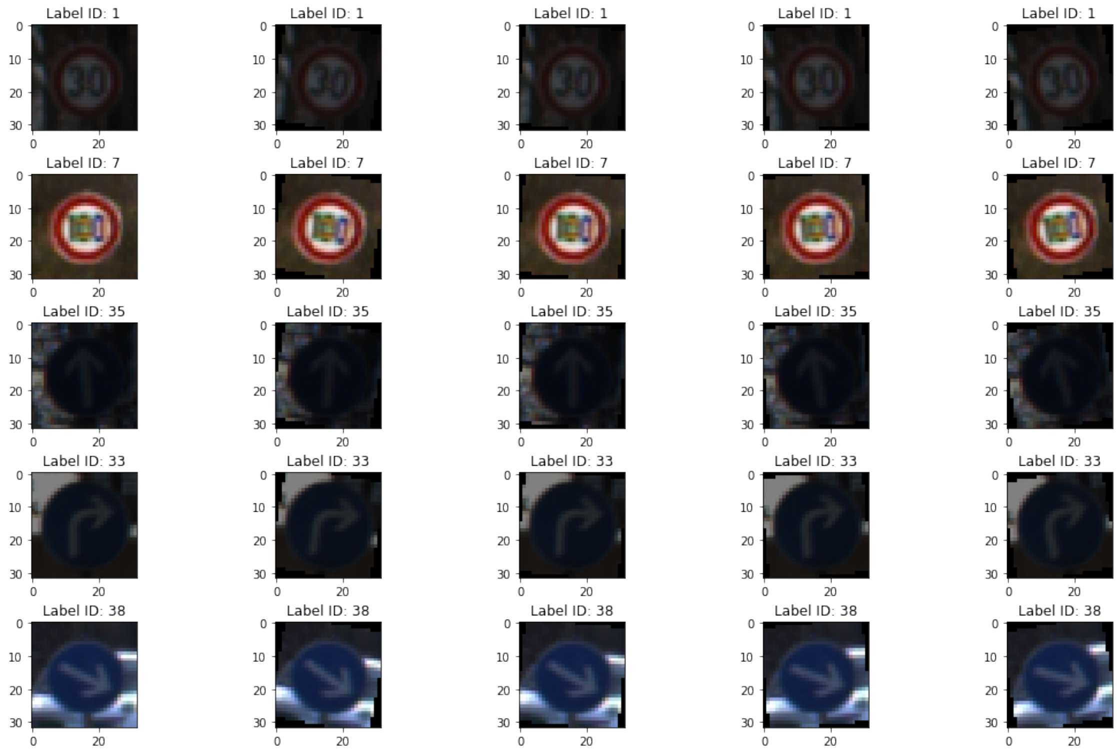
```
#     iterate_at = (end_angle - start_angle) / (n_images - 1)

#     tf.reset_default_graph()
#     X = tf.placeholder(tf.float32, shape = (None, IMAGE_SIZE, IMAGE_SIZE, 3))
#     radian = tf.placeholder(tf.float32, shape = (len(X_imgs)))
#     tf_img = tf.contrib.image.rotate(X, radian)
#     with tf.Session() as sess:
#         sess.run(tf.global_variables_initializer())

#         for index in range(n_images):
#             degrees_angle = start_angle + index * iterate_at
#             radian_value = degrees_angle * pi / 180  # Convert to radian
#             radian_arr = [radian_value] * len(X_imgs)
#             rotated_imgs = sess.run(tf_img, feed_dict = {X: X_imgs, radian:␣
 ↪radian_arr})
#             X_rotate.extend(rotated_imgs)

#     X_rotate = np.array(X_rotate, dtype = np.float32)
#     return X_rotate



# Start rotation at -90 degrees, end at 90 degrees and produce totally 14 images
# rotated_imgs = rotate_images(X_imgs, -90, 90, 14)
############################################################


# Produce rotated images of -10, -5, 5, and 10 degress of original image.␣
 ↪[Training dataset]
X_train_05deg_neg = np.zeros_like(X_train)
X_train_05deg_pos = np.zeros_like(X_train)
X_train_10deg_neg = np.zeros_like(X_train)
X_train_10deg_pos = np.zeros_like(X_train)
y_train_deg = np.copy(y_train)

for i in range (0, len(X_train)):
    X_train_05deg_neg[i] = ndimage.rotate(X_train[i], -5, reshape=False)
    X_train_05deg_pos[i] = ndimage.rotate(X_train[i], 5, reshape=False)
    X_train_10deg_neg[i] = ndimage.rotate(X_train[i], -10, reshape=False)
    X_train_10deg_pos[i] = ndimage.rotate(X_train[i], 10, reshape=False)

# Plot 5 random images from the training set with accompanying labels.
fig, ax = plt.subplots(5, 5, figsize=(15, 10))
fig.tight_layout(pad=2.0)
fig.suptitle('Random selection of 5 images from the training dataset and rotated␣
 ↪adjustments.', fontsize=16)
fig.subplots_adjust(top=0.90)
```

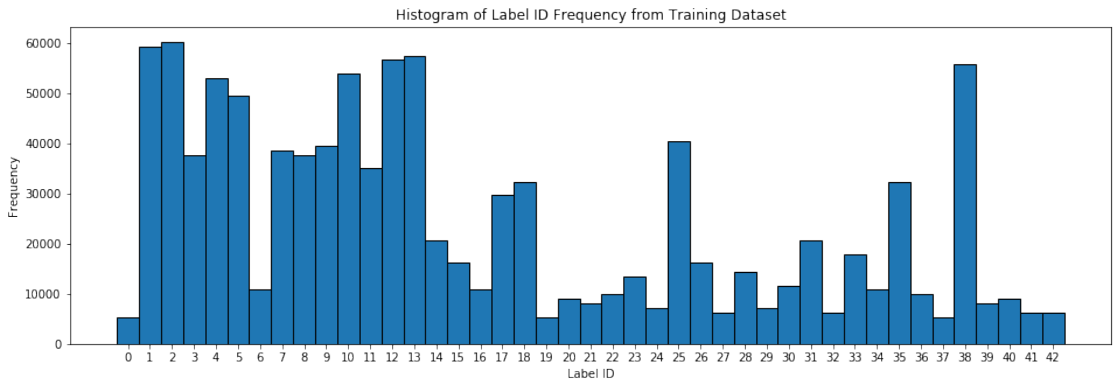
```
ax = ax.ravel()
for i in range(0, 25, 5):
    index = random.randint(0, len(X_train))
    ax[i].imshow(X_train[index])
    ax[i].set_title('Label ID: ' + str(y_train[index]))
    ax[i+1].imshow(X_train_10deg_neg[index])
    ax[i+1].set_title('Label ID: ' + str(y_train[index]))
    ax[i+2].imshow(X_train_05deg_neg[index])
    ax[i+2].set_title('Label ID: ' + str(y_train[index]))
    ax[i+3].imshow(X_train_05deg_pos[index])
    ax[i+3].set_title('Label ID: ' + str(y_train[index]))
    ax[i+4].imshow(X_train_10deg_pos[index])
    ax[i+4].set_title('Label ID: ' + str(y_train[index]))

print("X_train, y_train shapes BEFORE concatenating rotated images:", X_train.
 ↪shape, y_train.shape)
print("Adding", len(X_train) * 4, "images")

# Add darkened and brightened images to X_train dataset
X_train = np.concatenate((X_train, X_train_10deg_neg), axis=0)
y_train = np.concatenate((y_train, y_train_deg), axis=0)
X_train = np.concatenate((X_train, X_train_05deg_neg), axis=0)
y_train = np.concatenate((y_train, y_train_deg), axis=0)
X_train = np.concatenate((X_train, X_train_05deg_pos), axis=0)
y_train = np.concatenate((y_train, y_train_deg), axis=0)
X_train = np.concatenate((X_train, X_train_10deg_pos), axis=0)
y_train = np.concatenate((y_train, y_train_deg), axis=0)

print("X_train, y_train shapes AFTER concatenating rotated images:", X_train.
 ↪shape, y_train.shape)

# Clear unnecessary arrays to free up memory
X_train_10deg_neg = []
X_train_05deg_neg = []
X_train_05deg_pos = []
X_train_10deg_pos = []
y_train_deg = []

# Updated histogram of label frequency
plt.figure(figsize=(16, 5))
n, bins, patches = plt.hist(y_train, bins=range(n_classes+1), histtype='bar',␣
 ↪align='left', alpha=1, edgecolor='black')
locs, labels = xticks()
xticks(np.arange(np.min(y_train), np.max(y_train)+1, step=1))
plt.xlabel('Label ID')
plt.ylabel('Frequency')
plt.title('Histogram of Label ID Frequency from Training Dataset')
```

```
plt.show()

print("{:>10s}".format("LabelID") + "\t" + "{:>10s}".format("Count"))
print("----------", "\t", "----------")

for i in range(0, len(n)):
    print("{:>10d}".format(i) + "\t" + "{:>10d}".format(int(n[i])))
```

```
X_train, y_train shapes BEFORE concatenating rotated images: (208794, 32, 32, 3)
(208794,)
Adding 835176 images
X_train, y_train shapes AFTER concatenating rotated images: (1043970, 32, 32, 3)
(1043970,)
```

Random selection of 5 images from the training dataset and rotated adjustments.





LabelID	Count
0	5400
1	59400
2	60300
3	37800
4	53100
5	49500
6	10800
7	38700
8	37800
9	39600
10	54000
11	35100
12	56700
13	57600
14	20700
15	16200
16	10800
17	29700
18	32400
19	5400
20	9000
21	8100
22	9900
23	13500
24	7200
25	40500
26	16200
27	6300
28	14400
29	7200
30	11700
31	20700

```
32        6300
33       17970
34       10800
35       32400
36        9900
37        5400
38       55800
39        8100
40        9000
41        6300
42        6300
```

[9]:

```
##### Perspective Transform #####

def get_mask_coord(imshape, pov):
    # Perspective Right
    if pov=='right':
        vertices = np.array([[(0, imshape[0]),              # Bottom-Left Corner
                              (0, 0),                       # Top-Left Corner
                              (imshape[1]-1, 0+5),          # Top-Right Corner
                              (imshape[1]-1, imshape[0]-5), # Bottom-Right Corner
                              ]], dtype = np.int32)
    # Perspective Left
    elif pov=='left':
        vertices = np.array([[(0+1, imshape[0]-5),      # Bottom-Left Corner
                              (0+1, 0+5),               # Top-Left Corner
                              (imshape[1], 0),          # Top-Right Corner
                              (imshape[1], imshape[0]), # Bottom-Right Corner
                              ]], dtype = np.int32)
    # Perspective Left
    elif pov=='top':
        vertices = np.array([[(0, imshape[0]),          # Bottom-Left Corner
                              (0+5, 0+1),               # Top-Left Corner
                              (imshape[1]-5, 0+1),      # Top-Right Corner
                              (imshape[1], imshape[0]), # Bottom-Right Corner
                              ]], dtype = np.int32)
    # Perspective Left
    elif pov=='bottom':
        vertices = np.array([[(0+5, imshape[0]-1),              # Bottom-Left␣
↪Corner
                              (0, 0),                       # Top-Left Corner
                              (imshape[1], 0),          # Top-Right Corner
                              (imshape[1]-5, imshape[0]-1), # Bottom-Right Corner
                              ]], dtype = np.int32)
    # No Perspective Change
    else:
        vertices = np.array([[(0, imshape[0]),            # Bottom-Left Corner
```

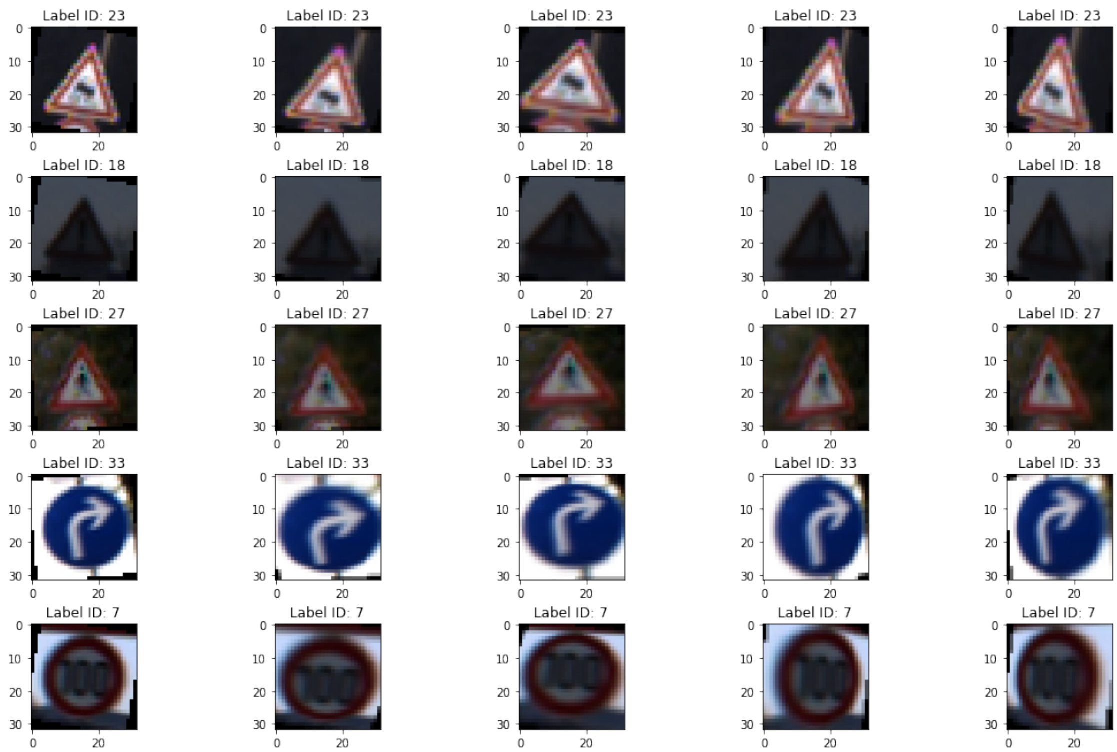
```
                              (0, 0),                    # Top-Left Corner
                              (imshape[1], 0),           # Top-Right Corner
                              (imshape[1], imshape[0]),  # Bottom-Right Corner
                              ]], dtype = np.int32)
    return vertices



def get_perspective_matrices(X_img, pov):
    offset = 0
    img_size = (X_img.shape[1], X_img.shape[0])

    # Estimate the coordinates of object of interest inside the image.
    src = np.float32(get_mask_coord(X_img.shape, pov))
    dst = np.float32([[offset, img_size[1]], [offset, 0], [img_size[0] - offset,
 →0],
                      [img_size[0] - offset, img_size[1]]])

    perspective_matrix = cv2.getPerspectiveTransform(src, dst)
    return perspective_matrix



def perspective_transform(X_img, pov):
    # Doing only for one type of example
    perspective_matrix = get_perspective_matrices(X_img, pov)
    warped_img = cv2.warpPerspective(X_img, perspective_matrix,
                                     (X_img.shape[1], X_img.shape[0]),
                                     flags = cv2.INTER_LINEAR)
    return warped_img

#######################################################################################

max_count = 50000
X_train_lowcount = []
y_train_lowcount = []
n_counter = copy.deepcopy(n)

# Get list of images to process
for i in range (0, len(X_train)):
    if n_counter[y_train[i]] < max_count:
        # Add image to new list or array
        # Add label to new list or array
        X_train_lowcount.append(X_train[i])
        y_train_lowcount.append(y_train[i])
        # Increment n_counter
        n_counter[y_train[i]] += 1
```

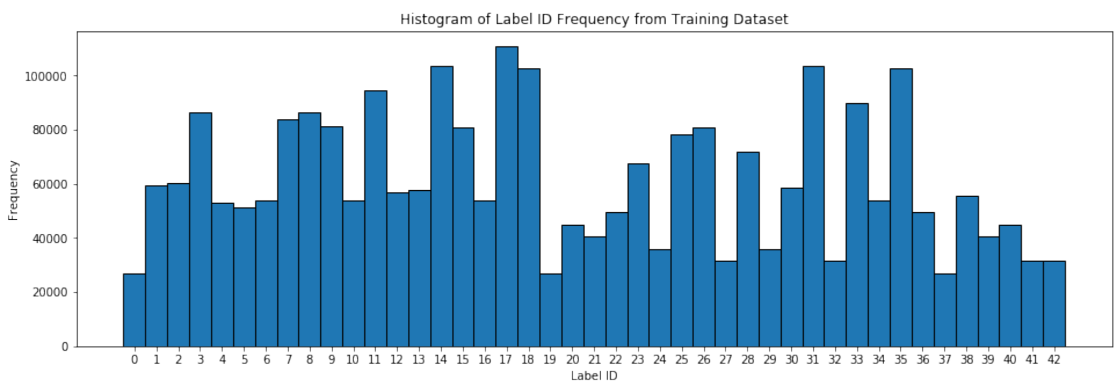
```
X_train_lowcount = np.array(X_train_lowcount)
y_train_lowcount = np.array(y_train_lowcount)

X_train_xfm_top = np.zeros_like(X_train_lowcount)
X_train_xfm_bottom = np.zeros_like(X_train_lowcount)
X_train_xfm_left = np.zeros_like(X_train_lowcount)
X_train_xfm_right = np.zeros_like(X_train_lowcount)
y_train_xfm = np.copy(y_train_lowcount)

# Perspective Transforms
for i in range (0, len(X_train_lowcount)):
    X_train_xfm_top[i] = perspective_transform(X_train_lowcount[i], pov='top')
    X_train_xfm_bottom[i] = perspective_transform(X_train_lowcount[i],␣
 ↪pov='bottom')
    X_train_xfm_left[i] = perspective_transform(X_train_lowcount[i], pov='left')
    X_train_xfm_right[i] = perspective_transform(X_train_lowcount[i],␣
 ↪pov='right')

# Plot 5 random images from the training set with accompanying labels.
fig, ax = plt.subplots(5, 5, figsize=(15, 10))
fig.tight_layout(pad=2.0)
fig.suptitle('Random selection of 5 images from the training set and perspective␣
 ↪transform adjustments.', fontsize=16)
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(0, 25, 5):
    index = random.randint(0, len(X_train_lowcount))
    ax[i].imshow(X_train_lowcount[index])
    ax[i].set_title('Label ID: ' + str(y_train_lowcount[index]))
    ax[i+1].imshow(X_train_xfm_top[index])
    ax[i+1].set_title('Label ID: ' + str(y_train_xfm[index]))
    ax[i+2].imshow(X_train_xfm_bottom[index])
    ax[i+2].set_title('Label ID: ' + str(y_train_xfm[index]))
    ax[i+3].imshow(X_train_xfm_left[index])
    ax[i+3].set_title('Label ID: ' + str(y_train_xfm[index]))
    ax[i+4].imshow(X_train_xfm_right[index])
    ax[i+4].set_title('Label ID: ' + str(y_train_xfm[index]))

print("X_train, y_train shapes BEFORE concatenating perspective transformed␣
 ↪images:", X_train.shape, y_train.shape)
print("Adding", len(X_train_lowcount) * 4, "images")

# Add perspective transformed to X_train dataset
X_train = np.concatenate((X_train, X_train_xfm_top), axis=0)
X_train_xfm_top = []
y_train = np.concatenate((y_train, y_train_xfm), axis=0)
```

```
X_train = np.concatenate((X_train, X_train_xfm_bottom), axis=0)
X_train_xfm_bottom = []
y_train = np.concatenate((y_train, y_train_xfm), axis=0)

X_train = np.concatenate((X_train, X_train_xfm_left), axis=0)
X_train_xfm_left = []
y_train = np.concatenate((y_train, y_train_xfm), axis=0)

X_train = np.concatenate((X_train, X_train_xfm_right), axis=0)
X_train_xfm_right = []
y_train = np.concatenate((y_train, y_train_xfm), axis=0)

print("X_train, y_train shapes AFTER concatenating rotated images:", X_train.
 ↪shape, y_train.shape)

# Clear unnecessary lists and arrays to free up memory
X_train_lowcount = []
y_train_lowcount = []
y_train_xfm = []

# Updated histogram of label frequency
plt.figure(figsize=(16, 5))
n, bins, patches = plt.hist(y_train, bins=range(n_classes+1), histtype='bar',␣
 ↪align='left', alpha=1, edgecolor='black')
locs, labels = xticks()
xticks(np.arange(np.min(y_train), np.max(y_train)+1, step=1))
plt.xlabel('Label ID')
plt.ylabel('Frequency')
plt.title('Histogram of Label ID Frequency from Training Dataset')
plt.show()

print("{:>10s}".format("LabelID") + "\t" + "{:>10s}".format("Count"))
print("----------", "\t", "----------")

for i in range(0, len(n)):
    print("{:>10d}".format(i) + "\t" + "{:>10d}".format(int(n[i])))
```

```
X_train, y_train shapes BEFORE concatenating perspective transformed images:
(1043970, 32, 32, 3) (1043970,)
Adding 1600280 images
X_train, y_train shapes AFTER concatenating rotated images: (2644250, 32, 32, 3)
(2644250,)
```

Random selection of 5 images from the training set and perspective transform adjustments.





LabelID	Count
0	27000
1	59400
2	60300
3	86600
4	53100
5	51500

```
6           54000
7           83900
8           86600
9           81200
10          54000
11          94700
12          56700
13          57600
14         103500
15          81000
16          54000
17         110900
18         102800
19          27000
20          45000
21          40500
22          49500
23          67500
24          36000
25          78500
26          81000
27          31500
28          72000
29          36000
30          58500
31         103500
32          31500
33          89850
34          54000
35         102800
36          49500
37          27000
38          55800
39          40500
40          45000
41          31500
42          31500
```

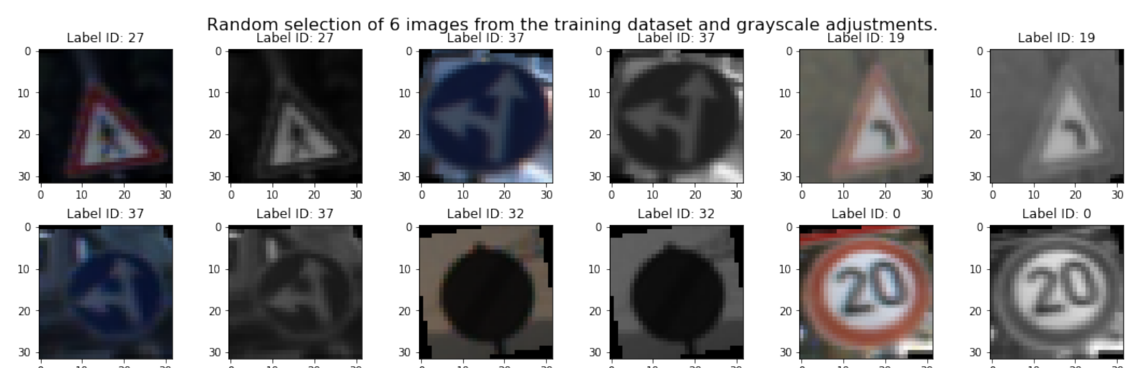
[10]:

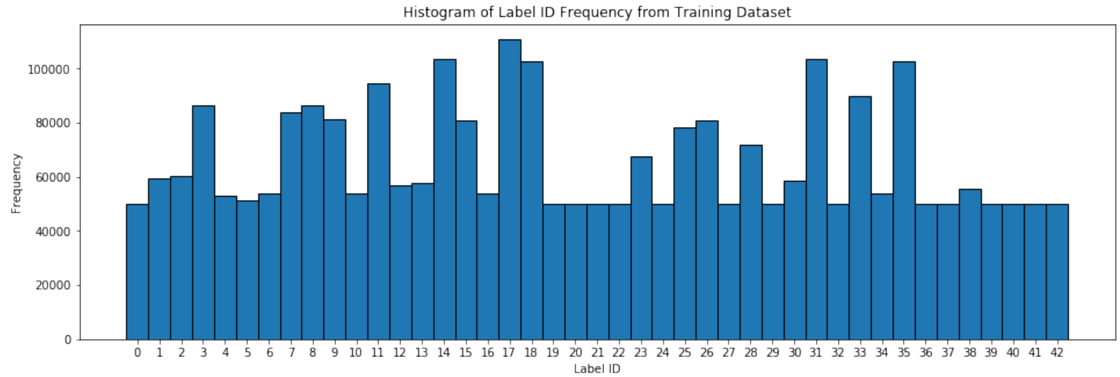
```
## Grayscale Images #####

max_count = 50000
X_train_lowcount = []
y_train_lowcount = []
n_counter = copy.deepcopy(n)

# Get list of images to process
for i in range (0, len(X_train)):
```

```
    if n_counter[y_train[i]] < max_count:
        # Add image to new list or array
        # Add label to new list or array
        X_train_lowcount.append(X_train[i])
        y_train_lowcount.append(y_train[i])
        # Increment n_counter
        n_counter[y_train[i]] += 1

X_train_lowcount = np.array(X_train_lowcount)
y_train_lowcount = np.array(y_train_lowcount)

# X_train_gray = np.zeros_like(X_train_lowcount)
X_train_gray = np.zeros(X_train_lowcount.shape[:-1])
y_train_gray = np.copy(y_train_lowcount)

# Convert to single-channel grayscale
for i in range(X_train_lowcount.shape[0]):
    X_train_gray[i] = cv2.cvtColor(X_train_lowcount[i], cv2.COLOR_BGR2GRAY)

# Convert to 3-channel BGR
X_train_gray_stacked = np.zeros_like(X_train_lowcount)

for i in range(0, len(X_train_gray)):
    X_train_gray_stacked[i] = np.stack((X_train_gray[i],)*3, axis=-1)

# Plot 6 random images from the training set with accompanying labels.
fig, ax = plt.subplots(2, 6, figsize=(15, 5))
fig.tight_layout(pad=2.0)
fig.suptitle('Random selection of 6 images from the training dataset and␣
 ↪grayscale adjustments.', fontsize=16)
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(0, 12, 2):
    index = random.randint(0, len(X_train_lowcount))
    ax[i].imshow(X_train_lowcount[index])
    ax[i].set_title('Label ID: ' + str(y_train_lowcount[index]))
    ax[i+1].imshow(X_train_gray_stacked[index], cmap='gray')
    ax[i+1].set_title('Label ID: ' + str(y_train_gray[index]))

print("X_train, y_train shapes BEFORE concatenating perspective transformed␣
 ↪images:", X_train.shape, y_train.shape)
print("Adding", len(X_train_lowcount), "images")

# Add perspective transformed to X_train dataset
X_train = np.concatenate((X_train, X_train_gray_stacked), axis=0)
X_train_gray = []
X_train_gray_stacked = []
```

```
y_train = np.concatenate((y_train, y_train_gray), axis=0)

print("X_train, y_train shapes AFTER concatenating rotated images:", X_train.shape, y_train.shape)

# Clear unnecessary lists and arrays to free up memory
X_train_lowcount = []
y_train_lowcount = []
y_train_gray = []

# Updated histogram of label frequency
plt.figure(figsize=(16, 5))
n, bins, patches = plt.hist(y_train, bins=range(n_classes+1), histtype='bar', align='left', alpha=1, edgecolor='black')
locs, labels = xticks()
xticks(np.arange(np.min(y_train), np.max(y_train)+1, step=1))
plt.xlabel('Label ID')
plt.ylabel('Frequency')
plt.title('Histogram of Label ID Frequency from Training Dataset')
plt.show()

print("{:>10s}".format("LabelID") + "\t" + "{:>10s}".format("Count"))
print("----------", "\t", "----------")

for i in range(0, len(n)):
    print("{:>10d}".format(i) + "\t" + "{:>10d}".format(int(n[i])))
```

```
X_train, y_train shapes BEFORE concatenating perspective transformed images:
(2644250, 32, 32, 3) (2644250,)
Adding 201000 images
X_train, y_train shapes AFTER concatenating rotated images: (2845250, 32, 32, 3)
(2845250,)
```





LabelID	Count
0	50000
1	59400
2	60300
3	86600
4	53100
5	51500
6	54000
7	83900
8	86600
9	81200
10	54000
11	94700
12	56700
13	57600
14	103500
15	81000
16	54000
17	110900
18	102800
19	50000
20	50000
21	50000
22	50000
23	67500
24	50000
25	78500
26	81000
27	50000
28	72000
29	50000
30	58500
31	103500

```
32          50000
33          89850
34          54000
35         102800
36          50000
37          50000
38          55800
39          50000
40          50000
41          50000
42          50000
```

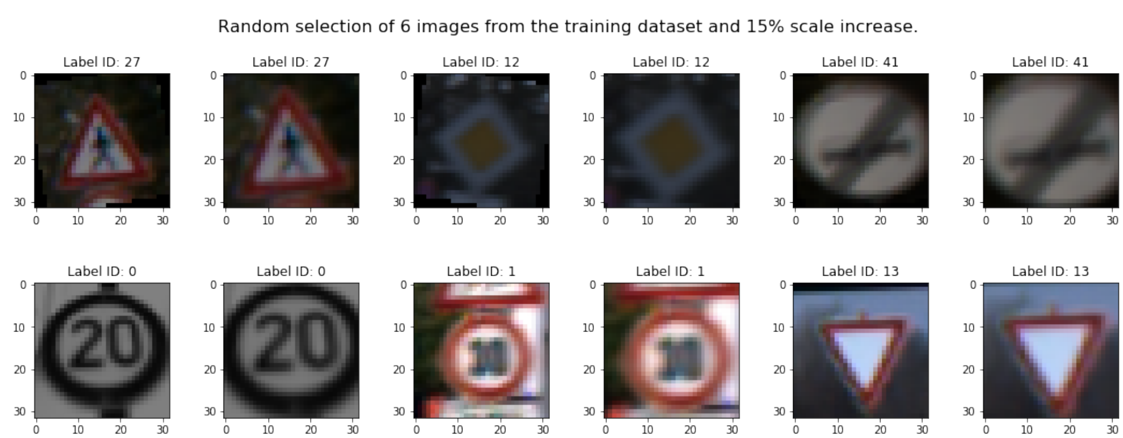
[11]:

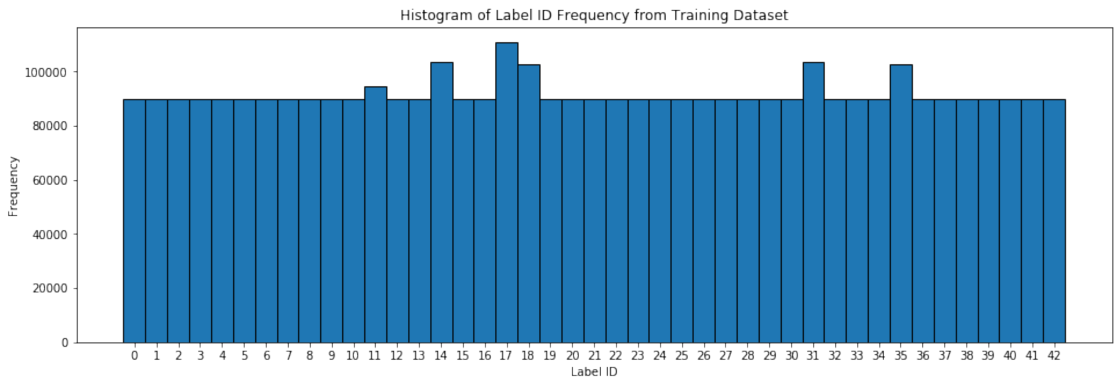
```
##### Scale Up #####

def central_scale_images(X_imgs, scales):
    # Various settings needed for Tensorflow operation
    boxes = np.zeros((len(scales), 4), dtype = np.float32)
    for index, scale in enumerate(scales):
        x1 = y1 = 0.5 - 0.5 * scale # To scale centrally
        x2 = y2 = 0.5 + 0.5 * scale
        boxes[index] = np.array([y1, x1, y2, x2], dtype = np.float32)
    box_ind = np.zeros((len(scales)), dtype = np.int32)
    crop_size = np.array([IMAGE_SIZE, IMAGE_SIZE], dtype = np.int32)

    X_scale_data = []
    tf.reset_default_graph()
    X = tf.placeholder(tf.float32, shape = (1, IMAGE_SIZE, IMAGE_SIZE, 3))
    # Define Tensorflow operation for all scales but only one base image at a
 ↪time
    tf_img = tf.image.crop_and_resize(X, boxes, box_ind, crop_size)
    with tf.Session() as sess:
        sess.run(tf.global_variables_initializer())

        for img_data in X_imgs:
            batch_img = np.expand_dims(img_data, axis = 0)
            scaled_imgs = sess.run(tf_img, feed_dict = {X: batch_img})
            X_scale_data.extend(scaled_imgs)

    X_scale_data = np.array(X_scale_data, dtype = np.float32)
    return X_scale_data

# Produce each image at scaling of 90%, 75% and 60% of original image.
# scaled_imgs = central_scale_images(X_imgs, [0.90])



max_count = 90000
```

```python
X_train_lowcount = []
y_train_lowcount = []
n_counter = copy.deepcopy(n)

# Get list of images to process
for i in range (0, len(X_train)):
    if n_counter[y_train[i]] < max_count:
        # Add image to new list or array
        # Add label to new list or array
        X_train_lowcount.append(X_train[i])
        y_train_lowcount.append(y_train[i])
        # Increment n_counter
        n_counter[y_train[i]] += 1

X_train_lowcount = np.array(X_train_lowcount)
y_train_lowcount = np.array(y_train_lowcount)

X_train_scaled = central_scale_images(X_train_lowcount, [0.85])
X_train_scaled = X_train_scaled.astype('uint8')
y_train_scaled = np.copy(y_train_lowcount)

# Plot 6 random images from the training set with accompanying labels.
fig, ax = plt.subplots(2, 6, figsize=(15, 6))
fig.tight_layout(pad=2.0)
fig.suptitle('Random selection of 6 images from the training dataset and 15%␣
 ↪scale increase.', fontsize=16)
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(0, 12, 2):
    index = random.randint(0, len(X_train_lowcount))
    ax[i].imshow(X_train_lowcount[index])
    ax[i].set_title('Label ID: ' + str(y_train_lowcount[index]))
    ax[i+1].imshow(X_train_scaled[index])
    ax[i+1].set_title('Label ID: ' + str(y_train_scaled[index]))

print("X_train, y_train shapes BEFORE concatenating perspective transformed␣
 ↪images:", X_train.shape, y_train.shape)
print("Adding", len(X_train_lowcount), "images")

# Add perspective transformed to X_train dataset
X_train = np.concatenate((X_train, X_train_scaled), axis=0)
X_train_scaled = []
y_train = np.concatenate((y_train, y_train_scaled), axis=0)

print("X_train, y_train shapes AFTER concatenating rotated images:", X_train.
 ↪shape, y_train.shape)
```

```python
# Clear unnecessary lists and arrays to free up memory
X_train_lowcount = []
y_train_lowcount = []
y_train_scaled = []

# Updated histogram of label frequency
plt.figure(figsize=(16, 5))
n, bins, patches = plt.hist(y_train, bins=range(n_classes+1), histtype='bar',␣
↪align='left', alpha=1, edgecolor='black')
locs, labels = xticks()
xticks(np.arange(np.min(y_train), np.max(y_train)+1, step=1))
plt.xlabel('Label ID')
plt.ylabel('Frequency')
plt.title('Histogram of Label ID Frequency from Training Dataset')
plt.show()

print("{:>10s}".format("LabelID") + "\t" + "{:>10s}".format("Count"))
print("----------", "\t", "----------")

for i in range(0, len(n)):
    print("{:>10d}".format(i) + "\t" + "{:>10d}".format(int(n[i])))
```

```
WARNING:tensorflow:From <ipython-input-11-c99041dfb9bb>:17: calling
crop_and_resize_v1 (from tensorflow.python.ops.image_ops_impl) with box_ind is
deprecated and will be removed in a future version.
Instructions for updating:
box_ind is deprecated, use box_indices instead
X_train, y_train shapes BEFORE concatenating perspective transformed images:
(2845250, 32, 32, 3) (2845250,)
Adding 1102950 images
X_train, y_train shapes AFTER concatenating rotated images: (3948200, 32, 32, 3)
(3948200,)
```





LabelID	Count
0	90000
1	90000
2	90000
3	90000
4	90000
5	90000
6	90000
7	90000
8	90000
9	90000
10	90000
11	94700
12	90000
13	90000
14	103500
15	90000
16	90000
17	110900
18	102800
19	90000
20	90000
21	90000
22	90000
23	90000
24	90000
25	90000
26	90000
27	90000
28	90000
29	90000
30	90000
31	103500

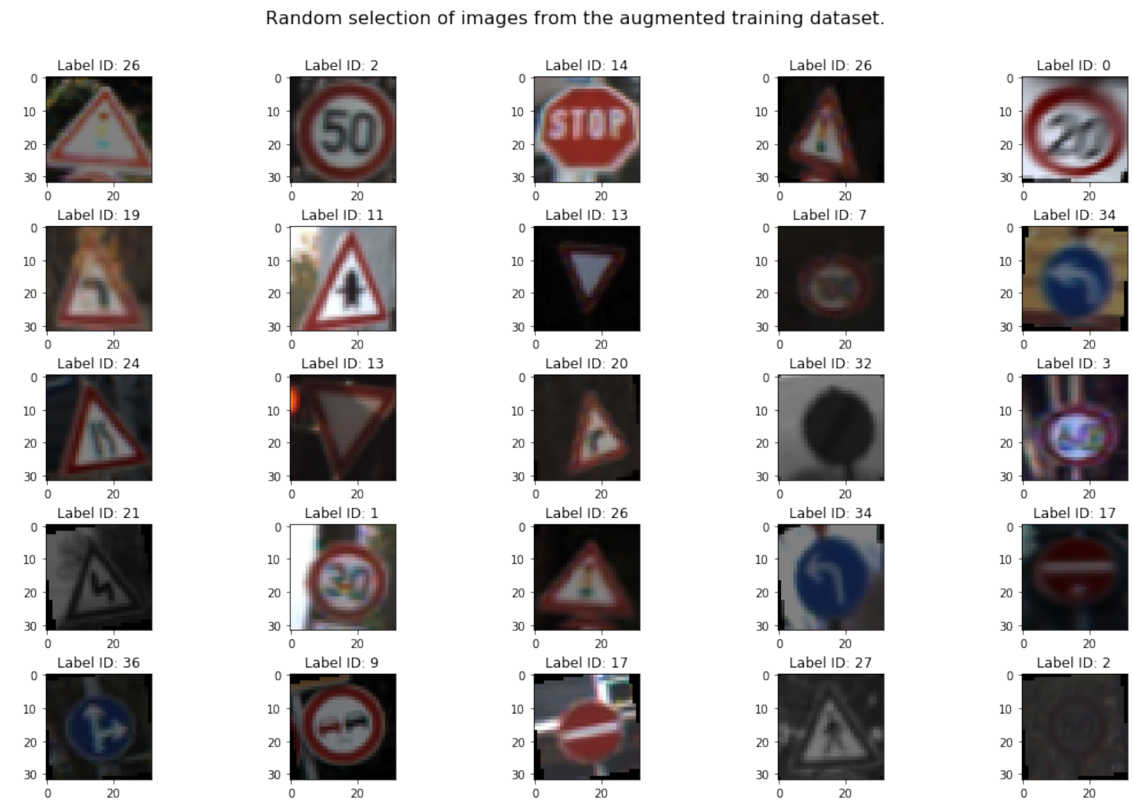
```
32          90000
33          90000
34          90000
35         102800
36          90000
37          90000
38          90000
39          90000
40          90000
41          90000
42          90000
```

[12]:
```
# Clear unecessary arrays--just in case!
X_train_norm = []
X_train_gauss_darken = []
X_train_gauss_brighten = []
X_train_05deg_neg = []
X_train_05deg_pos = []
X_train_10deg_neg = []
X_train_10deg_pos = []
X_train_xfm_top = []
X_train_xfm_bottom = []
X_train_xfm_left = []
X_train_xfm_right = []

y_train_norm = []
y_train_gauss_darken = []
y_train_gauss_brighten = []
y_train_05deg_neg = []
y_train_05deg_pos = []
y_train_10deg_neg = []
y_train_10deg_pos = []
y_train_xfm_top = []
y_train_xfm_bottom = []
y_train_xfm_left = []
```

[13]:
```
# Shuffle Images
X_train, y_train = shuffle(X_train, y_train)

print('Images Shuffled')
print("X_train, y_train shapes of augmented dataset:", X_train.shape, y_train.
 ↪shape)

# Plot random images from the training set with accompanying labels.
fig, ax = plt.subplots(5, 5, figsize=(15, 10))
fig.tight_layout(pad=2.0)
```

```
fig.suptitle('Random selection of images from the augmented training dataset.',␣
↪fontsize=16)
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(0, 25):
    index = random.randint(0, len(X_train))
    ax[i].imshow(X_train[index])
    ax[i].set_title('Label ID: ' + str(y_train[index]))
```

```
Images Shuffled
X_train, y_train shapes of augmented dataset: (3948200, 32, 32, 3) (3948200,)
```



1.5.2 Input

The LeNet architecture accepts a 32x32xC image as input, where C is the number of color channels. The dataset is a collection of RGB color and grayscale images with channels C=3 and C=1, respectively.

1.5.3 Model Architecture

LeNet-5 neural network architecture was used as the base architecture for training the model. Modifications to this architecture are ***emphasized below***.

Layer 1: Convolutional. The output shape is 28x28x6.

Activation. ReLU.

Pooling. The output shape is 14x14x6.

Layer 2: Convolutional. The output shape is 10x10x16.

Activation. ReLU.

Pooling. The output shape is 5x5x16.

Dropout. *A dropout layer is added after the previous pooling layer. The probability of keeping the output is dictated by the* `keep_prob` *variable.*

Flatten. Flatten the output shape of the final pooling layer such that it's 1D instead of 3D. The easiest way to do is by using `tf.contrib.layers.flatten`.

Layer 3: Fully Connected. This has 120 outputs.

Activation. ReLU.

Layer 4: Fully Connected. This has 84 outputs.

Activation. ReLU.

Layer 5: Fully Connected (Logits). This has 43 outputs–one for each traffic sign label.

1.5.4 Output

Return the result of the 2nd fully connected layer. The output of the first and second convolution layers are also output for visualization at the end of this notebook.

[14]:
```
### Define your architecture here.
### Feel free to use as many code cells as needed.

EPOCHS = 20
BATCH_SIZE = 512

# Architecture: LeNet-5, modified
def LeNet(x):
    # Arguments used for tf.truncated_normal, randomly defines variables for the␣
 ↪weights and biases for each layer
#     Defaults
#     mu = 0
#     sigma = 0.1

    mu = 0.0
```

```
    sigma = 0.05

#     Additional layers did not seem to improve performance from default␣
↪settings.
#     Only one additional dropout layer was kept in the model after the second␣
↪fully connected layer (fc2)
#     # Layer 0: Convolutional. Input = 32x32x3. Output = 32x32x3.
#     # output_height = (input_height - filter_height + 1) / vertical_stride =␣
↪(32 - 1 + 1) / 1 = 32
#     # output_width = (input_width - filter_width + 1) / horizontal_stride =␣
↪(32 - 1 + 1) / 1 = 32
#     conv0_W = tf.Variable(tf.truncated_normal(shape=(1, 1, 3, 3), mean=mu,␣
↪stddev=sigma))
#     conv0_b = tf.Variable(tf.zeros(3))
#     conv0 = tf.nn.conv2d(x, conv0_W, strides=[1, 1, 1, 1], padding='SAME') +␣
↪conv0_b

#     # Activation.
#     conv0 = tf.nn.relu(conv0)

#     # Pooling. Input = 32x32x3. Output = 32x32x3.
#     conv0 = tf.nn.max_pool(conv0, ksize=[1, 2, 2, 1], strides=[1, 1, 1, 1],␣
↪padding='SAME')

    # TODO: Layer 1: Convolutional. Input = 32x32x3. Output = 28x28x6.
    # output_height = (input_height - filter_height + 1) / vertical_stride = (32␣
↪- 5 + 1) / 1 = 28
    # output_width = (input_width - filter_width + 1) / horizontal_stride = (32␣
↪- 5 + 1) / 1 = 28
    conv1_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 3, 6), mean=mu,␣
↪stddev=sigma))
    conv1_b = tf.Variable(tf.zeros(6))
    conv1 = tf.nn.conv2d(x, conv1_W, strides=[1, 1, 1, 1], padding='VALID') +␣
↪conv1_b

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

    # TODO: Pooling. Input = 28x28x6. Output = 14x14x6.
    conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1],␣
↪padding='VALID')

#     # Dropout
#     conv1 = tf.nn.dropout(conv1, keep_prob)

    # TODO: Layer 2: Convolutional. Output = 10x10x16.
```

```
    conv2_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 6, 16), mean=mu,␣
↪stddev=sigma))
    conv2_b = tf.Variable(tf.zeros(16))
    conv2 = tf.nn.conv2d(conv1, conv2_W, strides=[1, 1, 1, 1], padding='VALID')␣
↪+ conv2_b

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

    # TODO: Pooling. Input = 10x10x16. Output = 5x5x16.
    conv2 = tf.nn.max_pool(conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1],␣
↪padding='VALID')

    # Dropout
    conv2drop = tf.nn.dropout(conv2, keep_prob)

    # TODO: Flatten. Input = 5x5x16. Output = 400.
    fc0 = flatten(conv2drop)

    # TODO: Layer 3: Fully Connected. Input = 400. Output = 120.
    fc1_W = tf.Variable(tf.truncated_normal(shape=(400, 120), mean=mu,␣
↪stddev=sigma))
    fc1_b = tf.Variable(tf.zeros(120))
    fc1 = tf.matmul(fc0, fc1_W) + fc1_b

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

#     # Dropout
#     fc1 = tf.nn.dropout(fc1, keep_prob)

    # TODO: Layer 4: Fully Connected. Input = 120. Output = 84.
    fc2_W = tf.Variable(tf.truncated_normal(shape=(120, 84), mean=mu,␣
↪stddev=sigma))
    fc2_b = tf.Variable(tf.zeros(84))
    fc2 = tf.matmul(fc1, fc2_W) + fc2_b

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

#     # Dropout
#     fc2 = tf.nn.dropout(fc2, keep_prob)

    # TODO: Layer 5: Fully Connected. Input = 84. Output = 43 (classes of␣
↪traffic signs).
    output_classes = 43
```

```
    fc3_W = tf.Variable(tf.truncated_normal(shape=(84, output_classes), mean=mu,␣
↪stddev=sigma))
    fc3_b = tf.Variable(tf.zeros(output_classes))
    logits = tf.matmul(fc2, fc3_W) + fc3_b

    return logits, conv1, conv2



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, keep_prob: 1.0})
        total_accuracy += (accuracy * len(batch_x))
    return total_accuracy / num_examples



# Features and Labels
# One-Hot encoding
x = tf.placeholder(tf.float32, (None, 32, 32, 3))
y = tf.placeholder(tf.int32, (None))
keep_prob = tf.placeholder(tf.float32)
one_hot_y = tf.one_hot(y, 43)

rate = 0.001

# Training Pipeline
logits, tf_activation1, tf_activation2 = 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)

# Model evaluation
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()
```

```
WARNING:tensorflow:From <ipython-input-14-efbce179c0b4>:60: calling dropout
(from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be
```

```
removed in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 -
keep_prob`.
WARNING:tensorflow:From <ipython-input-14-efbce179c0b4>:63: flatten (from
tensorflow.python.layers.core) is deprecated and will be removed in a future
version.
Instructions for updating:
Use keras.layers.Flatten instead.
WARNING:tensorflow:From /home/ian/anaconda3/envs/carnd-term1/lib/python3.5/site-
packages/tensorflow_core/python/layers/core.py:332: Layer.apply (from
tensorflow.python.keras.engine.base_layer) is deprecated and will be removed in
a future version.
Instructions for updating:
Please use `layer.__call__` method instead.
WARNING:tensorflow:From <ipython-input-14-efbce179c0b4>:120:
softmax_cross_entropy_with_logits (from tensorflow.python.ops.nn_ops) is
deprecated and will be removed in a future version.
Instructions for updating:

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

See `tf.nn.softmax_cross_entropy_with_logits_v2`.
```

1.5.5 Train, Validate and Test the Model

A validation set can be used to assess how well the model is performing. A low accuracy on the training and validation sets imply underfitting. A high accuracy on the training set but low accuracy on the validation set implies overfitting.

[15]:
```
### 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.

# The accuracy measured against the validation set
validation_accuracy = 0.0

# Measurements use for graphing loss and accuracy
epochs_list = []
loss_ep = []
train_acc_ep = []
valid_acc_ep = []
```

```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,␣
 ↪keep_prob: 0.5})

        training_accuracy = evaluate(X_train, y_train)
        validation_accuracy = evaluate(X_valid, y_valid)

        train_acc_ep.append(training_accuracy)
        valid_acc_ep.append(validation_accuracy)
        epochs_list.append(i+1)

        print("EPOCH {} ...".format(i+1))
        print("Training Accuracy   = {:.3f}".format(training_accuracy))
        print("Validation Accuracy = {:.3f}".format(validation_accuracy))
        print()

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

print('Validation accuracy at {}'.format(validation_accuracy))
```

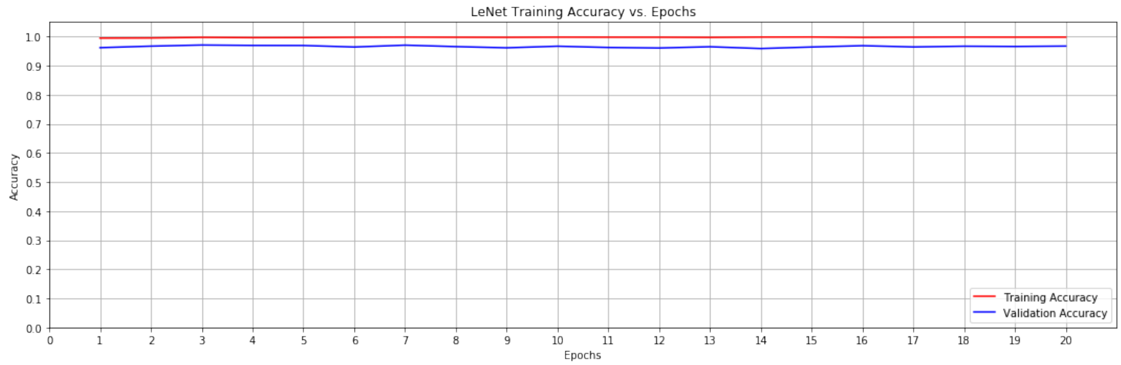
```
Training...

EPOCH 1 ...
Training Accuracy   = 0.995
Validation Accuracy = 0.962

EPOCH 2 ...
Training Accuracy   = 0.995
Validation Accuracy = 0.967

EPOCH 3 ...
Training Accuracy   = 0.997
Validation Accuracy = 0.971
```

```
EPOCH 4 ...
Training Accuracy   = 0.996
Validation Accuracy = 0.969

EPOCH 5 ...
Training Accuracy   = 0.996
Validation Accuracy = 0.969

EPOCH 6 ...
Training Accuracy   = 0.997
Validation Accuracy = 0.964

EPOCH 7 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.970

EPOCH 8 ...
Training Accuracy   = 0.997
Validation Accuracy = 0.965

EPOCH 9 ...
Training Accuracy   = 0.997
Validation Accuracy = 0.961

EPOCH 10 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.967

EPOCH 11 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.962

EPOCH 12 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.961

EPOCH 13 ...
Training Accuracy   = 0.997
Validation Accuracy = 0.965

EPOCH 14 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.959

EPOCH 15 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.964
```

```
EPOCH 16 ...
Training Accuracy   = 0.997
Validation Accuracy = 0.968

EPOCH 17 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.964

EPOCH 18 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.967

EPOCH 19 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.966

EPOCH 20 ...
Training Accuracy   = 0.998
Validation Accuracy = 0.967

Model saved
Validation accuracy at 0.9671201834873278
```

[16]:

```
plt.figure(figsize=(15, 5))
plt.title('LeNet Training Accuracy vs. Epochs')
plt.plot(epochs_list, train_acc_ep, 'r', label='Training Accuracy')
plt.plot(epochs_list, valid_acc_ep, 'b', label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.ylim([0, 1.05])
plt.xlim([0, epochs_list[-1]+1])
plt.xticks(np.arange(0,21,1))
plt.yticks(np.arange(0,1.1,0.1))
plt.legend(loc=4)
plt.grid(True)
plt.tight_layout()
plt.show()
```



1.6 Evaluate the Model Against the Testing Dataset

Evaluate the performance of the model on the test set.

Note: 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.

[17]:
```
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 ./Traffic_Sign_Classifier_lenet
Test Accuracy = 0.950
```

1.7 Step 3: Test a Model on New Images

To give yourself more insight into how your model is working, download at least five pictures of German traffic signs from the web and use your model to predict the traffic sign type.

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

1.7.1 Load and Output the Images

[18]:
```
### Load the images and plot them here.
### Feel free to use as many code cells as needed.

import glob

X_newimg_list = []
y_newimg_list = []

for i, img in enumerate(glob.glob('./trafficsignimages/32x32x3/*.png')):
    image = cv2.imread(img)
    image = cv2.cvtColor(image, cv2.COLOR_BGR2RGB)
    X_newimg_list.append(image)

y_newimg_list = [21, 12, 17, 4, 12,
                 25, 33, 13, 5, 25,
                 1, 26, 2, 19, 23,
                 40, 38, 31, 15, 9,
                 10, 1, 37, 18, 28,
                 14, 17, 26, 27, 36 ]

X_newimg = np.array(X_newimg_list)
y_newimg = np.array(y_newimg_list)

# Show new images in the order they appear in the list (not random)
fig, ax = plt.subplots(6, 5, figsize=(15, 12))
fig.tight_layout(pad=2.0)
fig.suptitle('Traffic sign images found on the internet.', fontsize=16)
fig.subplots_adjust(top=0.90)
ax = ax.ravel()
for i in range(0, len(X_newimg_list)):
#     index = random.randint(0, len(X_train))
    ax[i].imshow(X_newimg[i])
    ax[i].set_title('Label ID: ' + str(y_newimg[i]))
```

1.7.2 Predict the Sign Type for Each Image

The ground truth and predicted label ID for each image is shown below. In instances that the ground truth and predicted labels do not match, the text above the image will appear red.

[19]:
```python
### 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.

fig, ax = plt.subplots(6, 5, figsize=(15, 22))
fig.tight_layout(pad=2.0)
fig.suptitle('Traffic sign images found on the internet--Predictions from trained model.', fontsize=16)
fig.subplots_adjust(top=0.95)
```

```python
ax = ax.ravel()

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

    for i in range(0, len(X_newimg)):
        X_newimg1 = np.array(X_newimg[i])
        X_newimg1_arr = np.expand_dims(X_newimg1, axis=0)
        y_newimg1 = np.array(y_newimg[i])
        y_newimg1_arr = np.expand_dims(y_newimg1, axis=0)

        y_prediction = sess.run(logits, feed_dict={x: X_newimg1_arr, keep_prob:
 ↪1.0})
        y_prediction_label = list(y_prediction[0]).index(max(y_prediction[0]))

        ax[i].imshow(X_newimg1)

        if y_newimg1 == y_prediction_label:
            ax[i].set_title('Label ID: ' + str(y_newimg1) + '\nPrediction: ' +
 ↪str(y_prediction_label))
        else:
            ax[i].set_title('Label ID: ' + str(y_newimg1) + '\nPrediction: ' +
 ↪str(y_prediction_label), color='r')
```

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


Traffic sign images found on the internet--Predictions from trained model.
Label ID: 21
Prediction: 21
Label ID: 12
Prediction: 12
Label ID: 17
Prediction: 17
Label ID: 4
Prediction: 4
Label ID: 12
Prediction: 12
Label ID: 25
Prediction: 25
Label ID: 33
Prediction: 33
Label ID: 13
Prediction: 13
Label ID: 5
Prediction: 1
Label ID: 25
Prediction: 25
Label ID: 1
Prediction: 0
Label ID: 26
Prediction: 26
Label ID: 2
Prediction: 2
Label ID: 19
Prediction: 19
Label ID: 23
Prediction: 23
Label ID: 40
Prediction: 40
Label ID: 38
Prediction: 33
Label ID: 31
Prediction: 31
Label ID: 15
Prediction: 15
Label ID: 9
Prediction: 9
Label ID: 10
Prediction: 10
Label ID: 1
Prediction: 1
Label ID: 37
Prediction: 37
Label ID: 18
Prediction: 18
Label ID: 28
Prediction: 28
Label ID: 14
Prediction: 14
Label ID: 17
Prediction: 17
Label ID: 26
Prediction: 26
Label ID: 27
Prediction: 18
Label ID: 36
Prediction: 36

1.7.3 Analyze Performance

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

count_correct = 0

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

    newimg_accuracy = evaluate(X_newimg, y_newimg)
    print("New Image Accuracy = {:.3f}".format(newimg_accuracy))

    for i in range(0, len(X_newimg)):
        X_newimg1 = np.array(X_newimg[i])
        X_newimg1_arr = np.expand_dims(X_newimg1, axis=0)
        y_newimg1 = np.array(y_newimg[i])
        y_newimg1_arr = np.expand_dims(y_newimg1, axis=0)

        y_prediction = sess.run(logits, feed_dict={x: X_newimg1_arr, keep_prob:␣
↪1.0})
        y_prediction_label = list(y_prediction[0]).index(max(y_prediction[0]))

        ax[i].imshow(X_newimg1)

        if y_newimg1 == y_prediction_label:
            count_correct += 1

newimg1_accuracy = count_correct / len(X_newimg)

print('\nCalculated accuracy by individual image analysis:')
print('\tTotal image count from internet dataset:', len(X_newimg))
print('\tCorrect label prediction count from internet dataset:', count_correct)
print('\tAccuracy: {:.2f}%'.format(newimg1_accuracy*100))
```

```
INFO:tensorflow:Restoring parameters from ./Traffic_Sign_Classifier_lenet
New Image Accuracy = 0.867

Calculated accuracy by individual image analysis:
        Total image count from internet dataset: 30
        Correct label prediction count from internet dataset: 26
        Accuracy: 86.67%
```

1.7.4 Output Top 5 Softmax Probabilities For Each Image Found on the Web

For each of the new images, print out the model's softmax probabilities to show the **certainty** of the model's predictions (limit the output to the top 5 probabilities for each image). `tf.nn.top_k` could prove helpful here.

The example below demonstrates how tf.nn.top_k can be used to find the top k predictions for each image.

`tf.nn.top_k` will return the values and indices (class ids) of the top k predictions. So if k=3, for each sign, it'll return the 3 largest probabilities (out of a possible 43) and the correspoding class ids.

Take this numpy array as an example. The values in the array represent predictions. The array contains softmax probabilities for five candidate images with six possible classes. `tf.nn.top_k` is used to choose the three classes with the highest probability:

```
# (5, 6) array
a = np.array([[ 0.24879643,  0.07032244,  0.12641572,  0.34763842,  0.07893497,
         0.12789202],
       [ 0.28086119,  0.27569815,  0.08594638,  0.0178669 ,  0.18063401,
         0.15899337],
       [ 0.26076848,  0.23664738,  0.08020603,  0.07001922,  0.1134371 ,
         0.23892179],
       [ 0.11943333,  0.29198961,  0.02605103,  0.26234032,  0.1351348 ,
         0.16505091],
       [ 0.09561176,  0.34396535,  0.0643941 ,  0.16240774,  0.24206137,
         0.09155967]])
```

Running it through `sess.run(tf.nn.top_k(tf.constant(a), k=3))` produces:

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

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

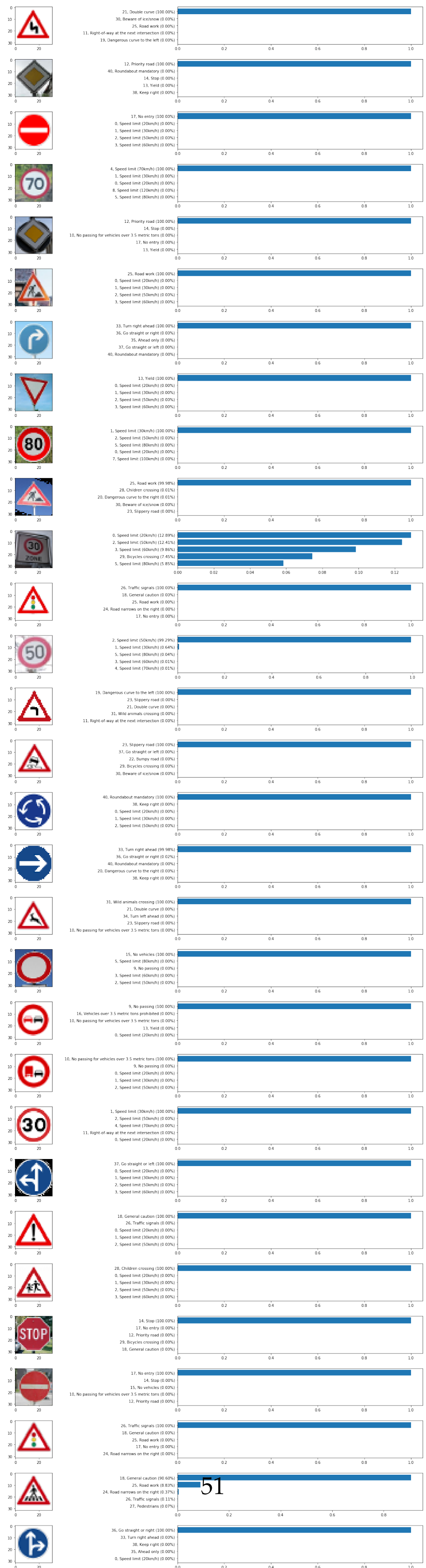
[21]:
```
### Print out the top five softmax probabilities for the predictions on the␣
↪German traffic sign images found on the web.
### Feel free to use as many code cells as needed.

signnames_labelIDs = []
signnames_labels = []
```

```python
# Save sign labels and names to lists
with open('signnames.csv') as csv_file:
    csv_reader = csv.reader(csv_file, delimiter=',')
    line_count = 0
    for row in csv_reader:
        if line_count == 0:
            line_count += 1
        else:
            signnames_labelIDs.append(int(row[0]))
            signnames_labels.append(row[1])
            line_count += 1


softmax_logits = tf.nn.softmax(logits)
k = 5
top_k = tf.nn.top_k(softmax_logits, k=k)

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

    newimg_softmax_logits = sess.run(softmax_logits, feed_dict={x: X_newimg,␣
 ↪keep_prob: 1.0})
    newimg_top_k = sess.run(top_k, feed_dict={x: X_newimg, keep_prob: 1.0})

    fig, ax = plt.subplots(len(X_newimg), 2, figsize=(20, 60))
    fig.tight_layout(pad=2.0)
    fig.suptitle('Top five softmax probabilities for the predictions on the␣
 ↪German traffic sign images found on the internet.', fontsize=16)
    fig.subplots_adjust(top=0.97)
    ax = ax.ravel()

    labels = []
    widths = []

    for i in range(0, len(X_newimg)):
        ax[i*2].imshow(X_newimg[i])

        for j in range(len(newimg_top_k[0][0])-1, -1, -1):
            labels.append(str(newimg_top_k[1][i][j]) + str(', ') +
                          str(signnames_labels[newimg_top_k[1][i][j]]) + str('␣
 ↪(') +
                          str('{:0.2f}'.format(100*newimg_top_k[0][i][j])) +␣
 ↪str('%)'))
            widths.append(newimg_top_k[0][i][j])

        ax[i*2+1].barh(labels, widths, align='center')
```

```
        labels = []
        widths = []

##### Reference
#         print(len(newimg_top_k[0][0])) # Number of softmax probabilities per␣
 ↪image.
#         print(newimg_top_k[1][0][i]) # Label ID
#         print(newimg_top_k[0][0][i]) # Probability
#         print(signnames_labels[newimg_top_k[1][0][i]]) # Label Name
```

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

Top five softmax probabilities for the predictions on the German traffic sign images found on the internet.



1.7.5 Project Writeup

Once you have completed the code implementation, document your results in a project writeup using this template as a guide. The writeup can be in a markdown or pdf file.

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

1.8 Step 4 (Optional): Visualize the Neural Network's State with Test Images

This Section is not required to complete but acts as an additional excersise for understaning the output of a neural network's weights. While neural networks can be a great learning device they are often referred to as a black box. We can understand what the weights of a neural network look like better by plotting their feature maps. After successfully training your neural network you can see what it's feature maps look like by plotting the output of the network's weight layers in response to a test stimuli image. From these plotted feature maps, it's possible to see what characteristics of an image the network finds interesting. For a sign, maybe the inner network feature maps react with high activation to the sign's boundary outline or to the contrast in the sign's painted symbol.

Provided for you below is the function code that allows you to get the visualization output of any tensorflow weight layer you want. The inputs to the function should be a stimuli image, one used during training or a new one you provided, and then the tensorflow variable name that represents the layer's state during the training process, for instance if you wanted to see what the LeNet lab's feature maps looked like for it's second convolutional layer you could enter conv2 as the tf_activation variable.

For an example of what feature map outputs look like, check out NVIDIA's results in their paper End-to-End Deep Learning for Self-Driving Cars in the section Visualization of internal CNN State. NVIDIA was able to show that their network's inner weights had high activations to road boundary lines by comparing feature maps from an image with a clear path to one without. Try experimenting with a similar test to show that your trained network's weights are looking for interesting features, whether it's looking at differences in feature maps from images with or without a sign, or even what feature maps look like in a trained network vs a completely untrained one on the same sign image.

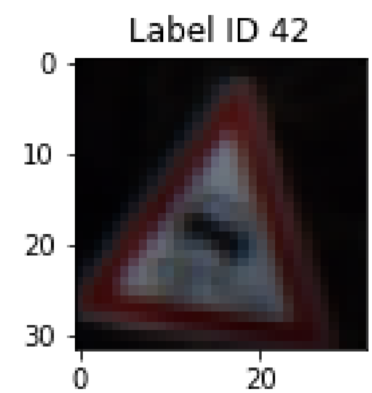
Your output should look something like this (above)

[22]:
```
### Visualize your network's feature maps here.
### Feel free to use as many code cells as needed.
```

```
# image_input: the test image being fed into the network to produce the feature maps
# tf_activation: should be a tf variable name used during your training procedure that represents the calculated state of a specific weight layer
# activation_min/max: can be used to view the activation contrast in more detail, by default matplot sets min and max to the actual min and max values of the output
# plt_num: used to plot out multiple different weight feature map sets on the same block, just extend the plt number for each new feature map entry

def outputFeatureMap(image_input, tf_activation, activation_min=-1, activation_max=-1 ,plt_num=1):
    # Here make sure to preprocess your image_input in a way your network expects
    # with size, normalization, ect if needed
    # image_input =
    # Note: x should be the same name as your network's tensorflow data placeholder variable
    # If you get an error tf_activation is not defined it may be having trouble accessing the variable from inside a function
    activation = tf_activation.eval(session=sess,feed_dict={x : image_input})
    featuremaps = activation.shape[3]
    plt.figure(plt_num, figsize=(15,15))
    for featuremap in range(featuremaps):
        plt.subplot(6,8, featuremap+1) # sets the number of feature maps to show on each row and column
        plt.title('FeatureMap ' + str(featuremap)) # displays the feature map number
        if activation_min != -1 & activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmin =activation_min, vmax=activation_max, cmap="gray")
        elif activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmax=activation_max, cmap="gray")
        elif activation_min !=-1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmin=activation_min, cmap="gray")
        else:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", cmap="gray")

# image_input = image
img_index = random.randint(0, len(X_train)-1)
image_input = X_train[img_index]
image_input = np.array(image_input).reshape(1, 32, 32, 3)
```

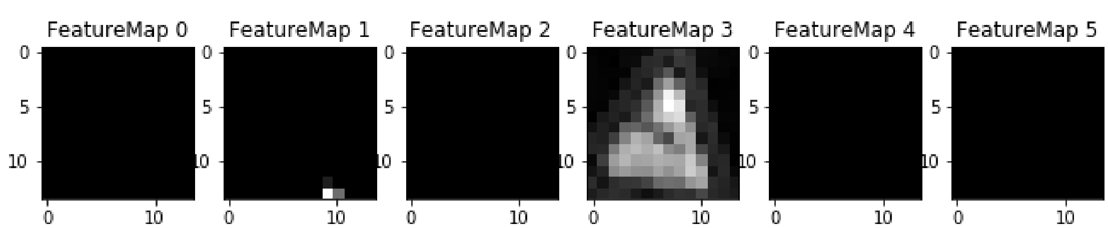
```python
# Note: that to get access to tf_activation, the session should be interactive␣
↪which can be achieved with the following commands.
sess = tf.InteractiveSession()
sess.as_default()
init = tf.global_variables_initializer()
sess.run(init)

# Show original image
fig, ax = plt.subplots(1, 1, figsize=(2,2))
ax.imshow(X_train[img_index])
ax.set_title('Label ID ' + str(y_train[index]))

print('Original Image')
```

```
Original Image
```



[23]:
```python
print('Feature map of the first activation layer (first convolution layer)')

outputFeatureMap(image_input, tf_activation1, activation_min=-1,␣
↪activation_max=-1 ,plt_num=1)
```

```
Feature map of the first activation layer (first convolution layer)
```



[24]:
```
print('Feature map of the second activation layer (second convolution layer)')

outputFeatureMap(image_input, tf_activation2, activation_min=-1,␣
↪activation_max=-1 ,plt_num=1)
```

```
Feature map of the second activation layer (second convolution layer)
```