Traffic_Sign_Classifier

January 15, 2019

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.

I have combined the Writeup with the Report itself, so that the reviewer don't have to search for multiple files while reviewing. It has also been suggested to be a good practice

---

1.3 Step 0: Load The Data

```
In [1]: # 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("Training keys: {}".format(train.keys()))
        print("X_train shape: {}, y_train shape: {}".format(X_train.shape, y_train.shape))
        print("X_valid shape: {}, y_valid shape:{}".format(X_valid.shape, y_valid.shape))
        print("X_test shape: {}, y_test shape:{}".format(X_test.shape, y_test.shape))
```

```
Training keys: dict_keys(['coords', 'labels', 'features', 'sizes'])
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

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

# TODO: Number of training, validation and testing examples
n_train      = X_train.shape[0]
n_validation = X_valid.shape[0]
n_test       = X_test.shape[0]

# TODO: What's the shape of a traffic sign image?
# TODO: How many unique classes/labels there are in the dataset.
image_shape  = X_train[0].shape
n_classes    = len(np.unique(y_train))

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

```
Number of training examples = 34799
Number of validating examples = 4410
Number of testing examples = 12630
Image data shape = (32, 32, 3)
Number of classes = 43
```

1.4.2 Discussion (1):

Data Set Summary

All datasets: Training, Validation and Testing Sets are present in "/data" folder in this Repository. From above, we get that: 1. There are 34799 training samples. 2. The validation set has 4410 samples. 3. The test set has 12630 samples. 4. Every sample is a (32x32x3) image of type "uint8" - an 8-bit image. 5. There are 43 different classes.

1.4.3 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?

```
In [3]: ### Data exploration visualization code goes here.
        ### Feel free to use as many code cells as needed.
        import matplotlib.pyplot as plt
        # Visualizations will be shown in the notebook.
        %matplotlib inline
```

Display a few random images Let's check a very small subset of, say 100 random images.

Every time the code in the cell below is executed, a significant fraction of the displayed images appears too dark to be recognized even by a human eye. Some images are pixelated, blurred, overexposed or underexposed which makes their classification somewhat challenging.

To examine the whole dataset like this, let's perform **histogram analysis** to detect the overexposure and under-exposure across the entire training dataset.

```
In [41]: ### Plot some random images from the training dataset.
         import numpy.random as rnd
         import matplotlib.gridspec as gridspec

         def plot_random_samples(images,n=100):
             sample_ids = rnd.randint(0,len(images),n)
             samples = images[sample_ids]

             grid_size = int(np.ceil(n/10))
             gs = gridspec.GridSpec(grid_size, 10, top=1., bottom=0., right=1., left=0., hspace=
             for index,g in enumerate(gs):
                 ax = plt.subplot(g)
                 ax.imshow(samples[index])
                 ax.set_xticks([])
                 ax.set_yticks([])
             plt.show()

         plot_random_samples(X_train)
```

Histogram Analysis (for Training Set)

- 1. The pixel intensity of each image is averaged over all three channels.
- 2. A histogram is then calculated over all images in the training set.

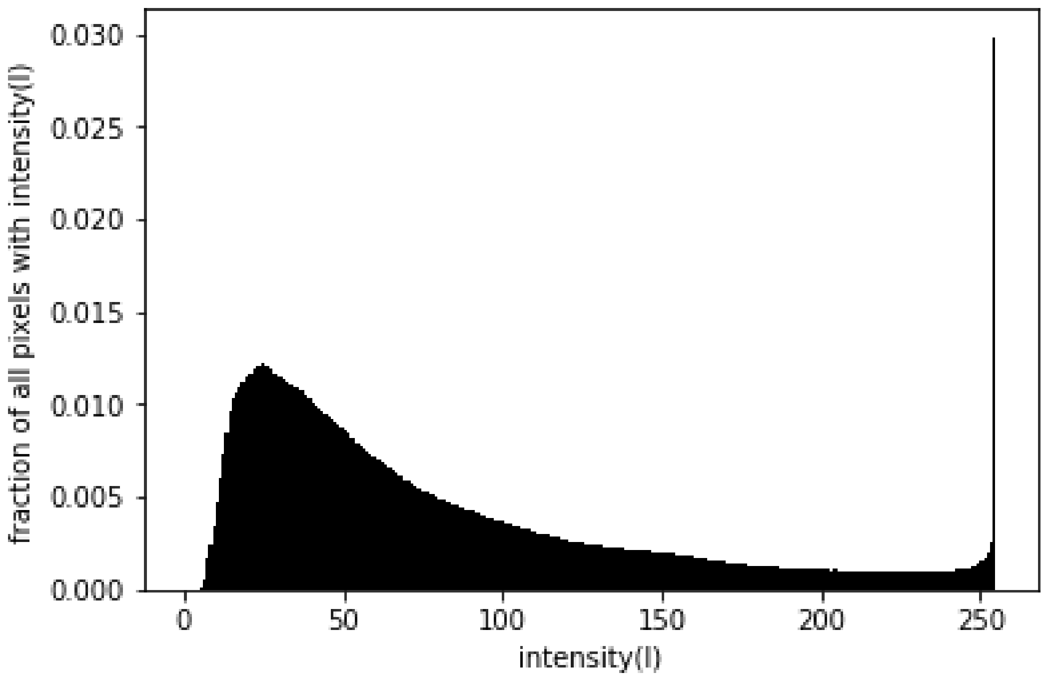
`Observation`: The histogram shows most of the intensity levels between '0-50' and a tall spike around the intensity level '255'.
`Inference`: There are a large number of images with very-dark pixels or very bright pixels.

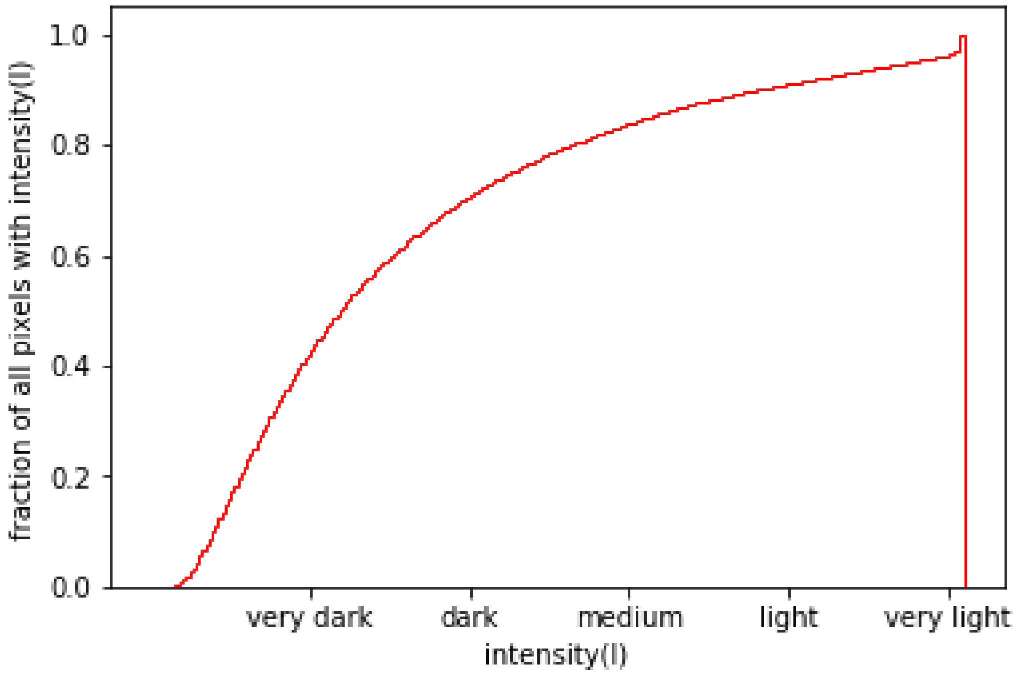
- 3. To more analyse the overall brightness spread over the dataset, a Cumulative Histogram is plotted.

`Observation`: If the intensity levels are divided into 5 parts - very dark, dark, medium, light and very light, nearly 60% of the pixels fall in the very dark & dark categories, while only about 10% of the pixels fall in the light & very light ones.
`Inference`: Underexposure is largely distributed over the training dataset. Histogram Equalization may improve this.

In [5]:
```
### Plot histogrm of all images in the training dataset.
### It's computed by averaging pixel intensities over all three channels.
def hist_img_data(X):
    plt.hist(np.mean(X,axis=3).flatten(), bins=range(256), color='k', normed=True)
```

```
    plt.xlabel('intensity(I)')
    plt.ylabel('fraction of all pixels with intensity(I)')
    plt.show()

    plt.hist(np.mean(X,axis=3).flatten(), bins=range(256), color='r', normed=True, cumul
    plt.xlabel('intensity(I)')
    plt.xticks([50,100,150,200,250],['very dark', 'dark', 'medium','light','very light']
    plt.ylabel('fraction of all pixels with intensity(I)')
    plt.show()

hist_img_data(X_train)
```

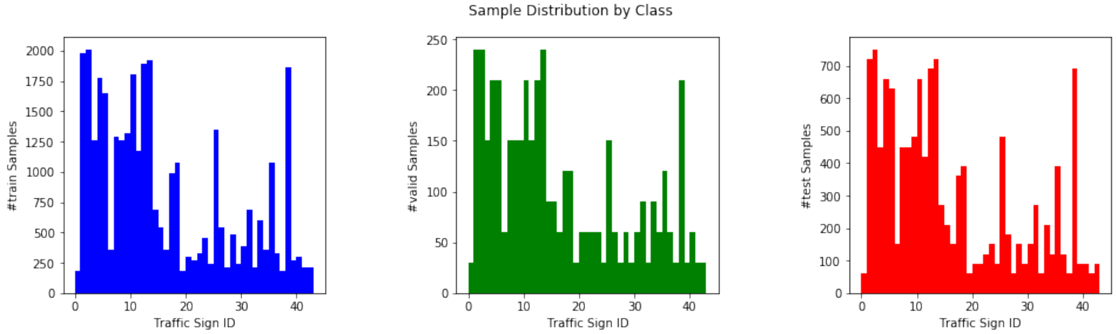




Analyze Data Skewness Checking for Data skewness would give a visualisation of spread of the image samples over different class labels. Histograms of class labels for training, validation and test sets are plotted below.

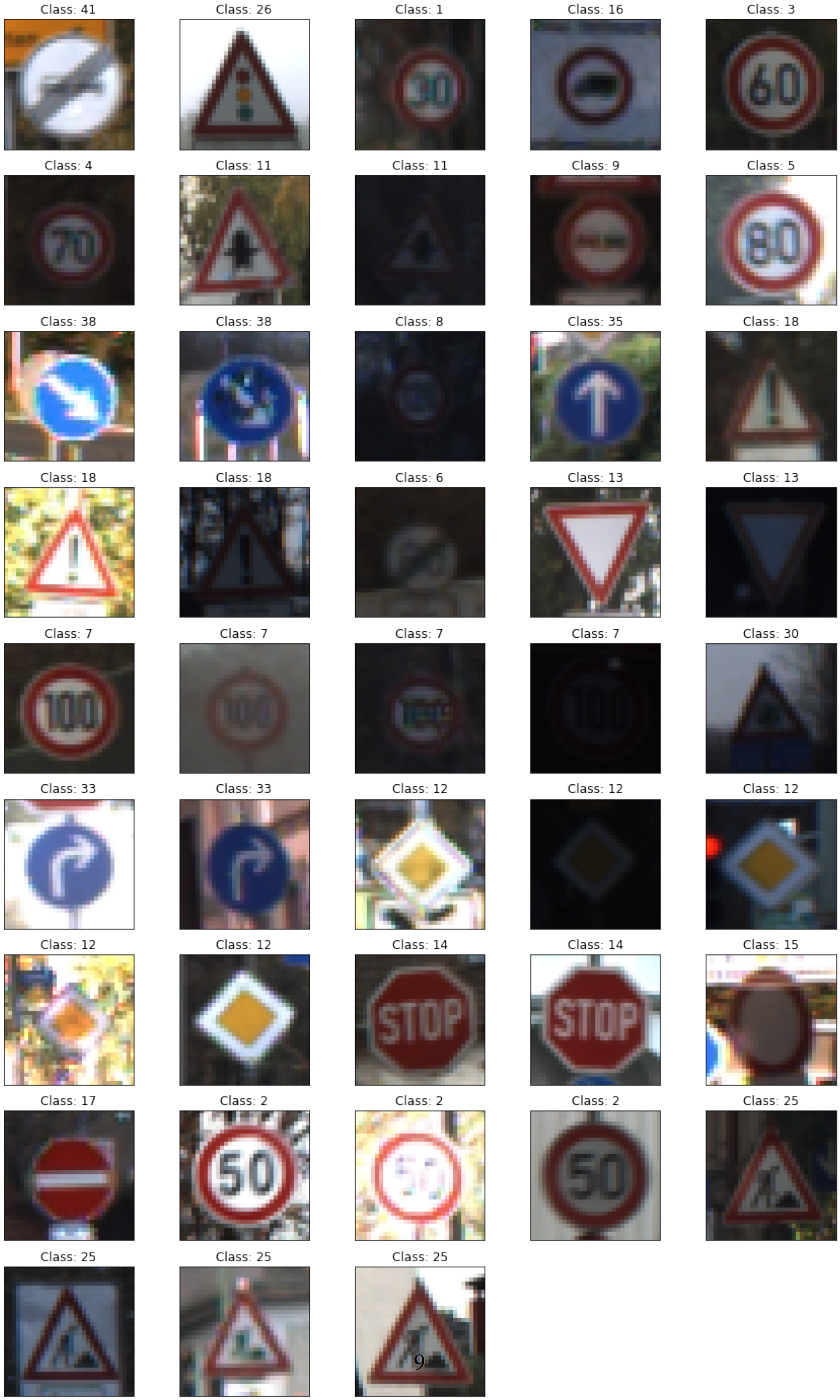
`Observation`: In all different sets, class distribution is not almost uniform. In the training set, a few labels have around 2000 samples while many other labels have a low sample count around or in range of 200-400. Similar skew happens to be present in other two datasets.
`Comment`: By some Data Augmentation techniques, we shall add more images to the class with low sample count.

```
In [6]: ## Plot frequency of each type of traffic sign in given different datasets.
        def hist_labels(datasets=None,ylabels=None,color=None):
            fig = plt.figure(figsize=(16,4))


            for i in range(len(datasets)):
                axis = fig.add_subplot(1,3,i+1)
                axis.hist(datasets[i], bins=range(n_classes+1), color=color[i])
                plt.xlabel('Traffic Sign ID')
                plt.ylabel('#{} Samples'.format(ylabels[i]))

            fig.subplots_adjust(wspace=0.5)
            plt.suptitle("Sample Distribution by Class")
            plt.show()

        hist_labels(datasets = [y_train,y_valid, y_test], ylabels = ['train','valid','test'], co
```



Display every class image This tells about the label and id of each given class.

In [7]:
```
import random

# Count samples in each class in training set
count_train = np.zeros(n_classes)

for i in range(n_train):
    idx = int(y_train[i])
    count_train[idx] += 1

# Count upper and lower bounds of classes
limbounds = np.zeros([n_classes,2])

limbounds[0,0] = 0
limbounds[0,1] = count_train[0]

for i in range(1,n_classes):
    limbounds[i,0] = limbounds[i-1,1]+1
    limbounds[i,1] = limbounds[i,0]+count_train[i]-1

c = 0
plt.figure(figsize=(15,25))

for i in range(n_classes):
    plt.subplot(9,5,i+1)
    index = random.randint(limbounds[i,0], limbounds[i,1])
    image = X_train[index].squeeze()
    plt.title('Class: ' + str(y_train[index]))

    fig = plt.imshow(image)

    fig.axes.get_xaxis().set_visible(False)
    fig.axes.get_yaxis().set_visible(False)
```


Class: 41
Class: 26
Class: 1
Class: 16
Class: 3
Class: 4
Class: 11
Class: 11
Class: 9
Class: 5
Class: 38
Class: 38
Class: 8
Class: 35
Class: 18
Class: 18
Class: 18
Class: 6
Class: 13
Class: 13
Class: 7
Class: 7
Class: 7
Class: 7
Class: 30
Class: 33
Class: 33
Class: 12
Class: 12
Class: 12
Class: 12
Class: 12
Class: 14
Class: 14
Class: 15
Class: 17
Class: 2
Class: 2
Class: 2
Class: 25
Class: 25
Class: 25
Class: 25

1.4.4 Discussion (2):

Data Exploration/Visualization

1. Visualing Random Image Samples > Some 100 random samples from the training set are plotted above in a 10x10 grid. Among many of the reasons that make some of these samples hard to recognize are commonly 'Motion blur', 'images under low or very high light-exposure'. We can get simiar results for the random images by repeating this step.
2. Analyzing Image Exposure > A simple histogram and a cumulative histogram of all images in the training set are plotted above to find the extent of under/over-exposure. The Simple Histogram plot shows a massive hump centered around brightness level '30-35' and a tall spike at around brightness level '255'. The Cumulative Histogram plot shows that around 60-70% of pixels have brightness level below 100.
3. Dataset Skew Analysis > Histograms for Training, Validation and Testing Sets are plotted to visualise the frequency of class labels. All the plots show similar trend of sample distribution over classes, i.e. many classes have around 10 times fewer number of samples than those in other classes which have large number of sample. So, the data is mostly skewed and not good enough to train the model.

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.)

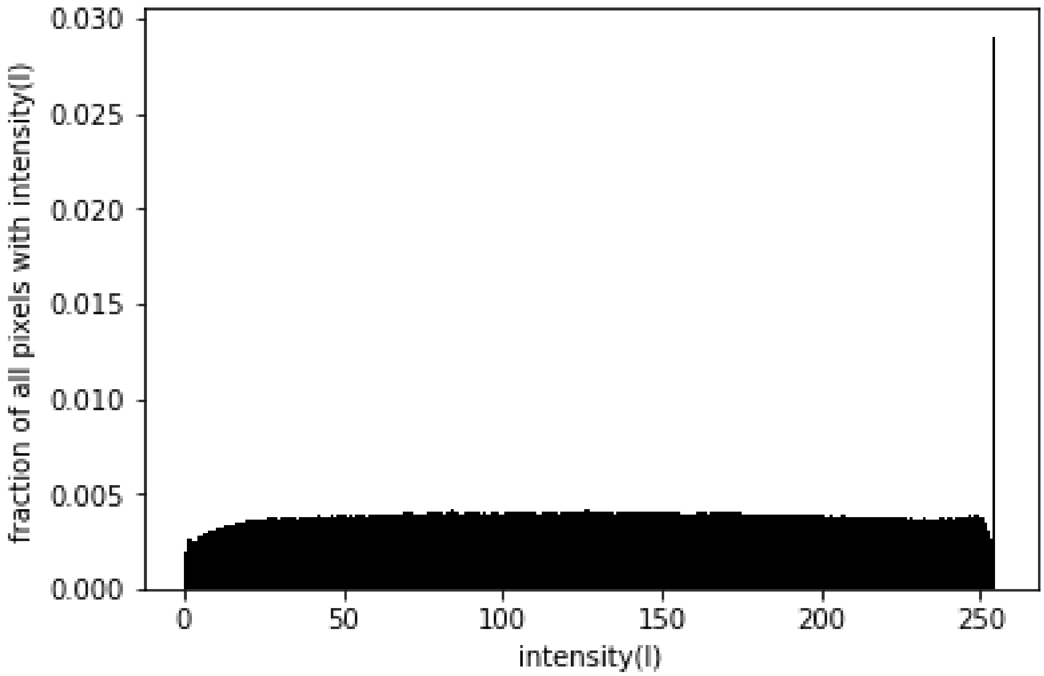
Minimally, the image data should be normalized so that the data has mean zero and equal variance. For image data, `(pixel - 128)/ 128` is a quick way to approximately normalize the data and can be used in this project. Other pre-processing steps are optional. You can try different techniques to see if it improves performance.

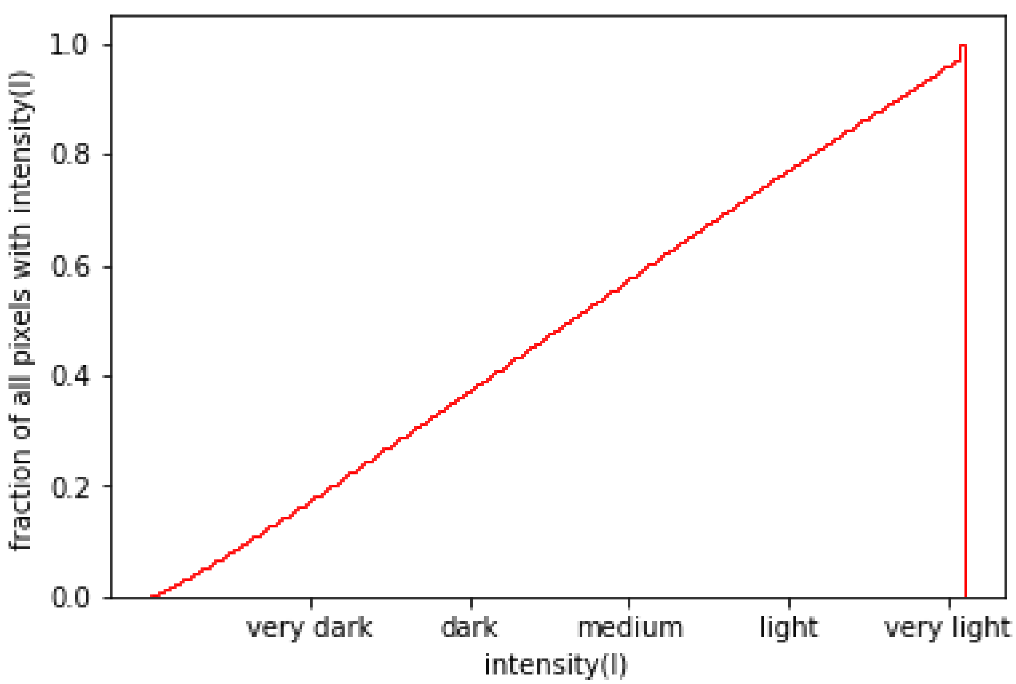
Use the code cell (or multiple code cells, if necessary) to implement the first step of your project.

```
In [8]: ### Preprocess the data here. It is required to normalize the data. Other preprocessing
        ### converting to grayscale, etc.
        ### Feel free to use as many code cells as needed.
```

Apply Histogram Equalization As told above, Histogram equalization is applied on all different datasets at hand. The modified histogram for training data is plotted. Random images from the dataset, now, look clearer to the naked eye.

```
In [9]: # Apply Histogram Equalization
        import cv2

        def hist_equalize(X):
            for i in range(X.shape[0]):
                img_rgb = X[i,:,:,:]
                img_yuv = cv2.cvtColor(img_rgb,cv2.COLOR_RGB2YUV)
                img_yuv[:,:,0] = cv2.equalizeHist(img_yuv[:,:,0])
                X[i,:,:,:] = cv2.cvtColor(img_yuv,cv2.COLOR_YUV2RGB)
            return X

        X_train = hist_equalize(X_train)
        X_valid = hist_equalize(X_valid)
        X_test  = hist_equalize(X_test)

        hist_img_data(X_train)
```






```
In [10]: # Visualise some random modified images from the training set.
         plot_random_samples(X_train)
```

Now that the images are modified to make it easy for the classifier and to positively contribute to its accuracy, Let's,

Augment the training dataset

> As the training dataset is largely skewed, i.e. most of the classes have very less example records as compared to other classes, it implies that the classifier model will not be accurately generalised to those down-sampled clases which will result in lower accuracy.

Therefore, - 1. More data is generated or augmented for every class such that every class has almost uniform number of samples. This is done by applying simple, "random affine transformations" to every (random) image in the training dataset. - 2. The number of copies generated per image depends on the number of existing samples in its class. This makes the number of samples in every class roughly of the same order.

In [11]:
```
import cv2

# Configuration Constants
MIN_ROTATION = -10.0
MAX_ROTATION =  10.0

MIN_OFFSET = -2
MAX_OFFSET = 2
```

```python
MIN_PIXEL_POSITION = 12
MAX_PIXEL_POSITION = 20

# Apply 'Random Transformations' on the images.
# These methods were suggested in the Project webinar.
def apply_random_affine(img,n):

    # Allocate an array for holding all transformed images.
    output  = np.zeros(shape=[n,*img.shape], dtype=img.dtype)

    # Generate random centers and angles for rotation.
    angles  = (MAX_ROTATION-MIN_ROTATION) * np.random.random(n) + MIN_ROTATION
    centers = np.random.randint(MIN_PIXEL_POSITION, MAX_PIXEL_POSITION+1, size=[n,2])

    # Generate random offsets for translation.
    offsets = np.random.randint(MIN_OFFSET, MAX_OFFSET+1, size=[n,2])

    # Generate transformed copies of input image.
    for i in range(n):
        M_rotate = cv2.getRotationMatrix2D(tuple(centers[i,:]), angles[i], 1)
        tmp = cv2.warpAffine(img, M_rotate, None)

        M_translate = np.float32([[1, 0, offsets[i,0]], [0, 1, offsets[i,1]]])
        output[i] = cv2.warpAffine(tmp, M_translate, img.shape[:2])

    return output

# Add Image Copies with Transformations.
def add_variants(X,y,n_copies):

    #Initialize output dataset with original data.
    X_out = np.copy(X)
    y_out = np.copy(y)

    # Generate copies for every image in the original dataset.
    # Append these copies and corresponding labels to output dataset.
    m = len(X)
    for i in range(m):
        variant_data = apply_random_affine(X[i], n_copies)
        X_out = np.vstack((X_out, variant_data))

        variant_labels = np.array([y[0]]*n_copies, dtype=y.dtype)
        y_out = np.concatenate((y_out, variant_labels))

    return (X_out, y_out)
```

```
def augment_data(X,y,MIN_EXAMPLE_COUNT = 1000):

    # Get sample count for every class label.
    # For np.histogram to work correctly with 0-based labels,
    # the number of bins has to be 1 more than the number of
    # classes.
    counts, labels = np.histogram(y, bins = range(n_classes+1))

    # Initilize empty output arrays. These will be filled with
    # original and transformed samples.
    data_shape = X.shape[1:]
    data_type  = X.dtype

    label_shape = y.shape[1:]
    label_type  = y.dtype

    X_out = np.empty(shape=[0,*data_shape],dtype=data_type)
    y_out = np.empty(shape=[0,*label_shape],dtype=label_type)

    # For every class, generate an appropriate number of synthetic samples.
    # np.histogram() above will generate one extra label
    # that we don't iterate over.
    for label in labels[:-1]:
        X_label = X[y==label]
        y_label = y[y==label]

        n_orig = len(y_label)

        if(counts[label] < 0.5 * MIN_EXAMPLE_COUNT):
            n_copies = MIN_EXAMPLE_COUNT//counts[label]
            X_label, y_label = add_variants(X_label, y_label, n_copies)

        n_total = len(y_label)

        X_out = np.concatenate((X_out, X_label))
        y_out = np.concatenate((y_out, y_label))

        print("Class label {}, original sample count {}, updated sample count {}"\
              .format(label,n_orig,n_total))

    return (X_out, y_out)
```

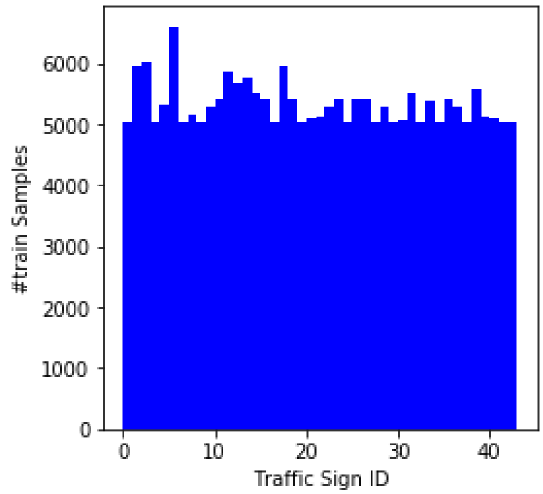
In [12]:
```
### Augment the Training Set.

X_train, y_train = augment_data(X_train, y_train, MIN_EXAMPLE_COUNT=5000)
# X_valid, y_valid = augment_data(X_valid, y_valid, MIN_EXAMPLE_COUNT=800)
```

```
Class label 0, original sample count 180, updated sample count 5040
Class label 1, original sample count 1980, updated sample count 5940
```

```
Class label 2, original sample count 2010, updated sample count 6030
Class label 3, original sample count 1260, updated sample count 5040
Class label 4, original sample count 1770, updated sample count 5310
Class label 5, original sample count 1650, updated sample count 6600
Class label 6, original sample count 360, updated sample count 5040
Class label 7, original sample count 1290, updated sample count 5160
Class label 8, original sample count 1260, updated sample count 5040
Class label 9, original sample count 1320, updated sample count 5280
Class label 10, original sample count 1800, updated sample count 5400
Class label 11, original sample count 1170, updated sample count 5850
Class label 12, original sample count 1890, updated sample count 5670
Class label 13, original sample count 1920, updated sample count 5760
Class label 14, original sample count 690, updated sample count 5520
Class label 15, original sample count 540, updated sample count 5400
Class label 16, original sample count 360, updated sample count 5040
Class label 17, original sample count 990, updated sample count 5940
Class label 18, original sample count 1080, updated sample count 5400
Class label 19, original sample count 180, updated sample count 5040
Class label 20, original sample count 300, updated sample count 5100
Class label 21, original sample count 270, updated sample count 5130
Class label 22, original sample count 330, updated sample count 5280
Class label 23, original sample count 450, updated sample count 5400
Class label 24, original sample count 240, updated sample count 5040
Class label 25, original sample count 1350, updated sample count 5400
Class label 26, original sample count 540, updated sample count 5400
Class label 27, original sample count 210, updated sample count 5040
Class label 28, original sample count 480, updated sample count 5280
Class label 29, original sample count 240, updated sample count 5040
Class label 30, original sample count 390, updated sample count 5070
Class label 31, original sample count 690, updated sample count 5520
Class label 32, original sample count 210, updated sample count 5040
Class label 33, original sample count 599, updated sample count 5391
Class label 34, original sample count 360, updated sample count 5040
Class label 35, original sample count 1080, updated sample count 5400
Class label 36, original sample count 330, updated sample count 5280
Class label 37, original sample count 180, updated sample count 5040
Class label 38, original sample count 1860, updated sample count 5580
Class label 39, original sample count 270, updated sample count 5130
Class label 40, original sample count 300, updated sample count 5100
Class label 41, original sample count 210, updated sample count 5040
Class label 42, original sample count 210, updated sample count 5040
```

In [13]:
```
# Plot Histogram for the newly modified Training set.
hist_labels(datasets = [y_train], ylabels = ['train'], color = ['b'])
```

Sample Distribution by Class



Normalizing pixel intensities In the original datasets, pixel values are in the range [0,255]. - 1. The values are normalized the subtracting channel-wise mean intensities and dividing by the corresponding pixel standard deviations. - 2. The mean and standard deviation are calculated from training data and used to normalize all given different datasets.

```
In [14]: ### Calculate per-channel pixel mean and std deviation.
         ### An alternative would be to use per channel mean image.

         pixel_means   = np.mean(X_train, axis=(0,1,2), dtype=np.float32)
         pixel_stddevs = np.std(X_train, axis=(0,1,2), dtype=np.float32)
         print ("For one training example,")
         print ("Channel-wise Mean: {} AND Channel-wise Standard Deviation: {}".format(pixel_mea

         X_train_norm  = X_train - pixel_means
         X_train_norm  = X_train_norm / (pixel_stddevs + 1e-6) # avoid division by 0

         X_valid_norm  = X_valid - pixel_means
         X_valid_norm  = X_valid_norm / (pixel_stddevs + 1e-6) # avoid division by 0

         X_test_norm   = X_test - pixel_means
         X_test_norm   = X_test_norm / (pixel_stddevs + 1e-6)  # avoid division by 0
```

```
For one training example,
Channel-wise Mean: 18.293291091918945 AND Channel-wise Standard Deviation: 68.43305206298828
```

1.5.2 Discussion (3):

Data Pre-processing

1. Applying Histogram Equalzation
   > Histogram equalization is applied to all the three sets to improve the brighness of images and thus, correct for exposure level.
   `Method:` Every RGB image is first converted to YUV format (taking reference from the paper link given in the instructions), then histogram correction is applied to the Y channel (channel 0 in a 32x32x3 YUV image) and finally the image is converted back to RGB. Some samples of histogram-corrected images are shown above. Now, they are almost easier to recognize manually. >
   > Correction for Brightness of image samples in the training set yielded about 2% improvement in the training accuracy.

2. Data Generation/Augmentation > For the initial training process, the training accuracy crossed 98% but validation accuracy was around 4% lower and test accuracy was around 7% lower than training accuracy. This implied a high variance issue in the model which was clear from the data skewness and additional data for low-sampled classes could help the model learn better. This would also help the model to give almost equal attention to these classes as well thus, improving on their misclassification. >
   > Additional data is generated by applying Affine Transfomations of random rotation and translation to every image in the training set. Images were rotated by random angles up to +/- 10ř around a random point near the center (12-20 pixels) then translated in both x and y directions by random offsets in the range +/-2 pixels.
   >
   > Since the dataset is already split, and the model needs have a 93% validation accuracy on the given validation set, no augmentation is done for the validation or test set. The number of extra samples generated for each class depends on the number of its existing samples and after augmentation each class has about 5000 samples. Thus, the augmented training set now has 229281 samples.

3. Data Normaization > Channel-wise means (Mu) and standard deviations (Sigma) are calculated over all images in the training set. The means are subtracted from all images in the three sets and the results are then divided by the standard deviations. >
   > Normalizing the data actually speeds up the training process.

1.5.3 Model Architecture

In [15]:
```
### Define your architecture here.
### Feel free to use as many code cells as needed.
```

In [16]:
```
### Ref.: https://github.com/aymericdamien/TensorFlow-Examples/blob/master/examples/3_N
### Wrappers/Functions for frequenty used layers.

import tensorflow as tf
import tensorflow.contrib.layers as layers

## Convolutional Layer
def conv(X,W,b,stride=1):
    out = tf.nn.conv2d(X, W, [1,stride,stride,1], padding='VALID')
    out = tf.nn.bias_add(out, b)
    return tf.nn.relu(out)
```

```
## Maxpooling on the Convolutional Layer
def maxpool(X,k,s):
    return tf.nn.max_pool(X, ksize=[1,k,k,1], strides=[1,s,s,1], padding='VALID')

## Flatten the last layer before the first Fully Connected Layer
def flatten(X):
    return layers.flatten(X)

## Logits from the Fully Connected Layers
def dense(x,W,B,squash=True):
    out = tf.matmul(x, W)
    out = tf.add(out, B)

    if squash == True:
        out = tf.nn.relu(out)
    return out
```

In [17]:
```
### Define hyper-parameters.
epochs = 130
batch_size = 128
learning_rate = 0.001
dropout_probability = 0.3

### Architecture for the Training Neural Network Model.
### Build LeNet like convolutional network.

# Mean and std. deviation for randomly initilized parameters.
mu    = 0
sigma = 0.1

# Define input plaeholders.
X = tf.placeholder(tf.float32,[None,32,32,3])
y = tf.placeholder(tf.uint8,[None])
keep_prob = tf.placeholder(tf.float32)

# Define parameters (weights and biases)
params = {
    # For Layer 1:
    # 5x5 convolution, input depth 3, output depth 6.
    'conv1':{
        'weights': tf.Variable(tf.truncated_normal([5,5,3,6], mu, sigma)),
        'biases' : tf.Variable(tf.zeros([6])),
        'stride': 1
    },
    # 2x2 pooling
    'pool1':{
        'kernel_sz': 2,
```

```
            'stride': 2
        },

        # For Layer 2:
        # 5x5 convolution, input depth 6, output depth 16.
        'conv2':{
            'weights':tf.Variable(tf.truncated_normal([5,5,6,16], mu, sigma)),
            'biases':tf.Variable(tf.zeros([16])),
            'stride':1
        },
        # 2x2 pooling
        'pool2':{
            'kernel_sz':2,
            'stride':2
        },

        # For Fully Connected Layer 1:
        # Previous Layer Size is : W = 5, H = 5, Depth (Channels) = 16 => So, Flattened Siz
        # 400 -> 120 dense layer
        'dense1':{
            'weights':tf.Variable(tf.truncated_normal([400,120],mu,sigma)),
            'biases':tf.Variable(tf.zeros([120]))
        },

        # For Fully Connected Layer 2:
        # 120 -> 84 dense layer
        'dense2':{
            'weights':tf.Variable(tf.truncated_normal([120,84],mu,sigma)),
            'biases':tf.zeros(([84]))
        },

        # For Output Layer:
        # 84 -> 43 (Number of Class Labels)
        'dense3':{
            'weights':tf.Variable(tf.truncated_normal([84,43],mu,sigma)),
            'biases':tf.zeros(([43]))
        }
    }

    # First Convolutional Layer with Max-pooling
    conv1_out = conv(X,params['conv1']['weights'], params['conv1']['biases'], params['conv1
    pool1_out = maxpool(conv1_out, params['pool1']['kernel_sz'], params['pool1']['stride'])

    # Second Convolutional Layer with Max-pooling
    conv2_out = conv(pool1_out, params['conv2']['weights'], params['conv2']['biases'], para
    pool2_out = maxpool(conv2_out, params['pool2']['kernel_sz'], params['pool2']['stride'])

    # Flatten the Last layer before the First Fully Connected Layer
```

```
flat_out   = flatten(pool2_out)

# First Fully Connected Layer
fc1_out    = dense(flat_out, params['dense1']['weights'], params['dense1']['biases'])
fc1_out    = tf.nn.dropout(fc1_out, keep_prob)

# Second Fully Connected Layer
fc2_out    = dense(fc1_out, params['dense2']['weights'], params['dense2']['biases'])
fc2_out    = tf.nn.dropout(fc2_out, keep_prob)

# Output Layer
fc3_out    = dense(fc2_out, params['dense3']['weights'], params['dense3']['biases'], squ

# Logits from the Output Layer
logits = fc3_out
```

1.5.4 Discussion (4):

Architecture of the Selected Neural Network Model

I have used a model architecture similar to the LeNet5 architecture, except that the output layer has size 43 instead of 10. This architecture seems to have performed well enough so no other modifications were done.

My model has following sequental layers:

Layer	Description
Input	32x32x3 RGB image
L1: Convolution 5x5	1x1 stride, VALID padding, outputs 28x28x6
L1: Max Pooling 2x2	2x2 stride, VALID padding, outputs 14x14x6
L1: RELU	outputs 14x14x6
L2: Convolution 3x3	1x1 stride, VALID padding, outputs 10x10x16
L2: Max Pooling 2x2	2x2 stride, VALID padding, outputs 5x5x16
L2: RELU	outputs 5x5x16
Flatten	outputs 400
L3: Fully connected	outputs 120
L4: Fully connected	outputs 84
L5: Output/Softmax	outputs 43

1. The model uses softmax layer to compute the classification probabilities.
2. A cross-entropy cost funtion is used for the training process.
3. The cost function or loss is optimized using the "Adam optimizer".

1.5.5 Train, Validate and Test the Model

Checking Model Performance: Validation set is used to assess the performace.

Criteria for Performance: (Based on Model Accuracy)

1. Underfitting: Low Accuracy on Training Set and Validation Set 2. Overfitting: High Accuracy on Training Set and Low Accuracy on Validation Set

NOTE: Overfitting on Training Set implies that the Model is not generalised for examples other than the ones in Training Set. Care is taken so that, Validation Set doesn't bleed in the Training Set.

In [20]:
```
one_hot_y = tf.one_hot(y, n_classes, on_value=1, off_value=0)

# Define cost function (minimization objective) and minimization algorithm.
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits=logits, labels=one_hot_y
training_loss = tf.reduce_mean(cross_entropy)
optimizer     = tf.train.AdamOptimizer(learning_rate=learning_rate)
optimization  = optimizer.minimize(training_loss)

# Define accuracy.
correct_predictions = tf.equal(tf.argmax(logits,1),tf.argmax(one_hot_y,1))
accuracy_calculation = tf.reduce_mean(tf.cast(correct_predictions,tf.float32))
```

In [21]:
```
# Define evaluation function.
def evaluate(sess,X_data,y_data):
    num_examples = X_data.shape[0]
    net_accuracy = 0.0;
    n_batches = num_examples // batch_size
    for offset in range(0, num_examples, batch_size):
        X_batch = X_data[offset:offset+batch_size]
        y_batch = y_data[offset:offset+batch_size]
        batch_accuracy = sess.run(accuracy_calculation, feed_dict={X: X_batch, y: y_bat
        net_accuracy += batch_accuracy

    return net_accuracy / n_batches
```

In [22]:
```
### 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.
```

In [23]:
```
# Define training function
from sklearn.utils import shuffle
from tqdm import tqdm

def train(sess):
    sess.run(tf.global_variables_initializer())

    for e in tqdm(range(epochs)):
        global X_train, X_train_norm, y_train
        X_train, X_train_norm, y_train = shuffle(X_train, X_train_norm, y_train)
        for offset in range(0, n_train, batch_size):
            X_batch = X_train_norm[offset:offset+batch_size]
            y_batch = y_train[offset:offset+batch_size]
```

```
                sess.run(optimization, feed_dict={X: X_batch, y: y_batch, keep_prob: 1-drop

            if (e+1) % 10 == 0:
                train_accuracy = evaluate(sess, X_train_norm, y_train)
                valid_accuracy = evaluate(sess, X_valid_norm, y_valid)
                print("Epochs {}, training accuracy {:.3f}, validation accuracy {:.3f}"\
                    .format(e+1,train_accuracy,valid_accuracy))
```

In [24]:
```
model_file_prefix = './saved_model'

def run_training(sess):
    print("Training started!")
    train(sess)
    print("Training completed!")

    print("Evaluating model on test data...")
    print("Test accuracy {:.3f}".format(evaluate(sess, X_test_norm, y_test)))

    print("Saving model data to file...")
    saver = tf.train.Saver()
    saver.save(sess, model_file_prefix)
    print("Model saved!")
```

In [25]:
```
import os.path

# Run training or load exiting model.
use_existing = False

session = tf.Session(config=tf.ConfigProto(log_device_placement=True))

if use_existing == False:
    # Run and Save the model
    run_training(session)

elif (use_existing == True) and (not os.path.isfile(model_file_prefix+'.meta')):
    print("Saved model file doens't exist! Running training again...")
    # Run and Save the model
    run_training(session)

else:
    #Load the Saved model.
    print("Reloading existing model...")
    saver = tf.train.Saver()
    saver.restore(session, tf.train.latest_checkpoint('.'))
    print("Model loading finished!")
```

```
Training started!
```

```
  8%|         | 10/130 [00:47<11:13,  5.61s/it]

Epochs 10, training accuracy 0.921, validation accuracy 0.942

 15%|        | 20/130 [01:33<10:05,  5.51s/it]

Epochs 20, training accuracy 0.955, validation accuracy 0.968

 23%|       | 30/130 [02:18<09:08,  5.49s/it]

Epochs 30, training accuracy 0.971, validation accuracy 0.972

 31%|       | 40/130 [03:04<08:15,  5.50s/it]

Epochs 40, training accuracy 0.976, validation accuracy 0.981

 38%|      | 50/130 [03:49<07:16,  5.46s/it]

Epochs 50, training accuracy 0.980, validation accuracy 0.988

 46%|     | 60/130 [04:35<06:26,  5.53s/it]

Epochs 60, training accuracy 0.985, validation accuracy 0.990

 54%|    | 70/130 [05:21<05:32,  5.54s/it]

Epochs 70, training accuracy 0.980, validation accuracy 0.993

 62%|   | 80/130 [06:06<04:35,  5.51s/it]

Epochs 80, training accuracy 0.986, validation accuracy 0.986

 69%|   | 90/130 [06:52<03:39,  5.49s/it]

Epochs 90, training accuracy 0.987, validation accuracy 0.994

 77%|  | 100/130 [07:37<02:44,  5.49s/it]

Epochs 100, training accuracy 0.989, validation accuracy 0.989

 85%| | 110/130 [08:23<01:49,  5.49s/it]
```

```
Epochs 110, training accuracy 0.989, validation accuracy 0.997


 92%|| 120/130 [09:09<00:55,  5.56s/it]

Epochs 120, training accuracy 0.991, validation accuracy 0.999


100%|| 130/130 [09:55<00:00,  5.54s/it]

Epochs 130, training accuracy 0.984, validation accuracy 0.993
Training completed!
Evaluating model on test data...




Test accuracy 0.936
Saving model data to file...
Model saved!
```

1.5.6 Discussion (4):

Training the Model, and Approaching an acceptable Solution

The functions **train()** and **evaluate()** are used to train and evaluate the model, respectively.

> The hyper-parameters have been finalized from analyzing the performance on the validation set.
> 1. Learning rate of 0.001 seems fine for the Adam optimizer. Higher learning rates though caused the model to train faster initially however, in later stages (epochs), this resulted in downgrading the training accuracy. On the other hand, lower learning rate, like 0.0001, slowed the training significantly in later stages. 2. Batch size of '128' is selected keeping in mind the large number of training examples. The main consideration was training speed as final accuracies didn't seem to be affected by batch size. 3. Droupout is added to minimize the overfitting. Without any dropout, validation accuracy would plateau even as training accuracy would keep improving. A keep-probability of 0.3 gave good enough results. Higher values caused training to become slow. 4. Number of epochs vary from 100-130. It was observed that after data augmentation, training took significantly longer than just 30 epochs being used with the original dataset. The improvement in accuracy also slowed down exponentially with the number of iterations, as can be seen from above. We can see that training accuracy reached ~97% by 30 epochs but 99% accuracy could only be attained by or after 100 epochs.

The final accuracies are: 1. Training set accuracy of 98.4% 2. Validation set accuracy of 99.3% 3. Test set accuracy of 93.6%

While doing the project, I also came to read about other Models like GoogleNet Inception Modules (Class just gives a hint about it), ResNets etc. But, as suggested in the project instruction, I started with LeNet architecture for my first Neural Networks project, and this seems to have given me pretty good results.

1.5.7 Analyze: Model Performance

Compute the confusion matrix. Find the "precision and recall" rates for Testing Set. (as per Suggestion points in the Rubrics)

In [26]:
```
# Compute key metrics.
from tqdm import tqdm

def compute_key_metrics(sess, X_data, y_data):
    confusion_matrix = np.zeros([n_classes,n_classes], np.int32)
    predicted_labels = np.zeros_like(y_data)

    n_examples = X_data.shape[0]
    for offset in tqdm(range(0, n_examples, batch_size)):
        X_batch = X_data[offset:offset+batch_size]
        y_batch = y_data[offset:offset+batch_size]

        y_predicted = sess.run(tf.argmax(logits, 1), feed_dict={X: X_batch, y: y_batch,
        np.add.at(confusion_matrix, [y_batch,y_predicted], 1)

        predicted_labels[offset:offset+batch_size] = y_predicted

    # True positives live on the main diagonal. Extract them.
    true_postives = confusion_matrix[[range(n_classes)],[range(n_classes)]]

    # For false positives take column-wise sum excluding the row of the target class.
    false_positives = np.sum(confusion_matrix, axis=0) - true_postives

    # For false negatives take row-wise sum exclding the column of the target class.
    false_negatives = np.sum(confusion_matrix, axis=1) - true_postives

    # True negatives are all values in the matrix excluding the row and column of a cla
    true_negatives  = np.sum(confusion_matrix) - (true_postives+false_positives+false_n

    precision = np.squeeze(true_postives / (true_postives+false_positives+1e-6))
    recall    = np.squeeze(true_postives / (true_postives+false_negatives+1e-6))
    specificity = np.squeeze(true_negatives / (true_negatives+false_positives+1e-6))

    return {
        'confmat': confusion_matrix,
        'predicted_labels': predicted_labels,
        'precision': precision,
        'recall': recall,
        'specificity': specificity
    }
```

In [27]:
```
metrics = compute_key_metrics(session,X_test_norm,y_test)
```

```
100%|| 99/99 [00:03<00:00, 24.95it/s]
```

Inspecting some Misclassified Samples Below, first 100 misclassified examples alongwith their target labels are plotted.

`Observation`: 1. Some of these images have much poor quality which a naked eye, as well, will not be able classify correctly. 2. A few others are easily confusable, like the 60km/h and 80 km/h signs, as they have almost same appearance. 3. In some cases, it's not clear what might have thrown the model off course.

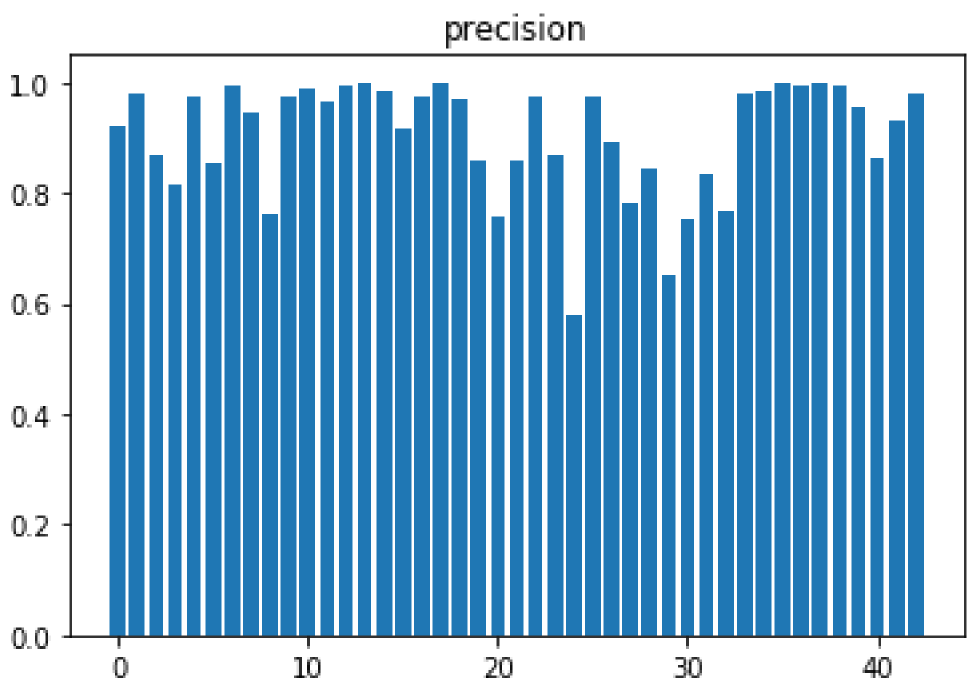
```
In [28]: import pandas

         sign_names = pandas.read_csv('signnames.csv')
         sign_names = sign_names.as_matrix()
         predicted_labels = metrics['predicted_labels']
```

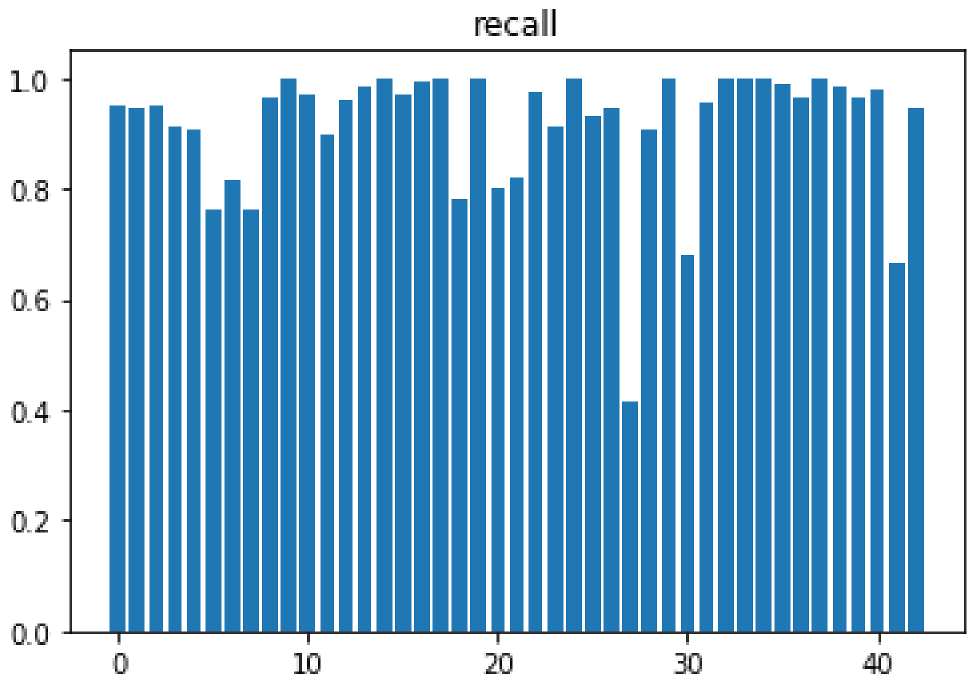
```
In [29]: misclassified_idx = np.where(np.not_equal(y_test, metrics['predicted_labels']))
         M = X_test[misclassified_idx][:100]

         gs = gridspec.GridSpec(25, 4, top=8., bottom=0., right=2., left=0., hspace=1, wspace=0.

         for i,g in enumerate(gs):
             ax = plt.subplot(g)
             ax.imshow(M[i])
             ax.set_title("Actual {}\nPredicted {}".format(sign_names[y_test[misclassified_idx][
                                                           sign_names[predicted_labels[mis
             ax.set_xticks([])
             ax.set_yticks([])

         plt.show()
```


Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (80km/h)
Predicted Speed limit (60km/h)
Actual Beware of ice/snow
Predicted Children crossing
Actual General caution
Predicted Bicycles crossing
Actual Road work
Predicted Wild animals crossing
Actual No vehicles
Predicted Speed limit (80km/h)
Actual Children crossing
Predicted Bicycles crossing
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Beware of ice/snow
Predicted Wild animals crossing
Actual Beware of ice/snow
Predicted Wild animals crossing
Actual Speed limit (60km/h)
Predicted No passing for vehicles over 3.5 metric tons
Actual Road work
Predicted Dangerous curve to the right
Actual General caution
Predicted Double curve
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Beware of ice/snow
Predicted Children crossing
Actual No passing for vehicles over 3.5 metric tons
Predicted Wild animals crossing
Actual Priority road
Predicted Road work
Actual General caution
Predicted Road narrows on the right
Actual Speed limit (70km/h)
Predicted Speed limit (20km/h)
Actual End of speed limit (80km/h)
Predicted End of all speed and passing limits
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Keep right
Predicted Road work
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual End of no passing
Predicted No passing
Actual Speed limit (50km/h)
Predicted Speed limit (80km/h)
Actual Speed limit (50km/h)
Predicted Speed limit (60km/h)
Actual Speed limit (70km/h)
Predicted Speed limit (100km/h)
Actual Dangerous curve to the right
Predicted Slippery road
Actual Right-of-way at the next intersection
Predicted Beware of ice/snow
Actual End of speed limit (80km/h)
Predicted Speed limit (100km/h)
Actual Speed limit (70km/h)
Predicted Priority road
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Beware of ice/snow
Predicted Slippery road
Actual Beware of ice/snow
Predicted Bicycles crossing
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual End of speed limit (80km/h)
Predicted Speed limit (80km/h)
Actual Speed limit (70km/h)
Predicted Speed limit (80km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (70km/h)
Actual Right-of-way at the next intersection
Predicted Beware of ice/snow
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Pedestrians
Predicted Right-of-way at the next intersection
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (80km/h)
Predicted Speed limit (120km/h)
Actual Yield
Predicted Speed limit (60km/h)
Actual Beware of ice/snow
Predicted Bicycles crossing
Actual Speed limit (60km/h)
Predicted Speed limit (80km/h)
Actual Children crossing
Predicted Bicycles crossing
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (30km/h)
Predicted Speed limit (50km/h)
Actual Traffic signals
Predicted General caution
Actual Speed limit (30km/h)
Predicted Speed limit (50km/h)
Actual Pedestrians
Predicted Road narrows on the right
Actual Right-of-way at the next intersection
Predicted Double curve
Actual Speed limit (60km/h)
Predicted Speed limit (80km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual No passing for vehicles over 3.5 metric tons
Predicted Wild animals crossing
Actual Yield
Predicted Speed limit (60km/h)
Actual Pedestrians
Predicted Road narrows on the right
Actual General caution
Predicted Wild animals crossing
Actual Speed limit (80km/h)
Predicted Speed limit (60km/h)
Actual Speed limit (80km/h)
Predicted Speed limit (60km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Keep right
Predicted Keep left
Actual Speed limit (80km/h)
Predicted Speed limit (60km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Speed limit (70km/h)
Predicted Speed limit (20km/h)
Actual General caution
Predicted Road narrows on the right
Actual Priority road
Predicted Speed limit (50km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Right-of-way at the next intersection
Predicted Beware of ice/snow
Actual Keep left
Predicted Turn right ahead
Actual Right-of-way at the next intersection
Predicted Road narrows on the right
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Speed limit (70km/h)
Predicted Speed limit (120km/h)
Actual Speed limit (50km/h)
Predicted Speed limit (30km/h)
Actual Speed limit (120km/h)
Predicted Speed limit (60km/h)
Actual General caution
Predicted Wild animals crossing
Actual Stop
Predicted Speed limit (60km/h)
Actual Speed limit (80km/h)
Predicted Speed limit (100km/h)
Actual Speed limit (70km/h)
Predicted Speed limit (50km/h)
Actual Children crossing
Predicted Bicycles crossing
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Road work
Predicted Double curve
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Speed limit (70km/h)
Predicted Speed limit (50km/h)
Actual General caution
Predicted Traffic signals
Actual Beware of ice/snow
Predicted Dangerous curve to the right
Actual Pedestrians
Predicted Children crossing
Actual Dangerous curve to the right
Predicted Children crossing
Actual Speed limit (60km/h)
Predicted Speed limit (80km/h)
Actual General caution
Predicted Children crossing
Actual Priority road
Predicted No vehicles
Actual Speed limit (80km/h)
Predicted Speed limit (50km/h)
Actual Speed limit (100km/h)
Predicted Speed limit (120km/h)
Actual Keep right
Predicted No passing for vehicles over 3.5 metric tons

Analyse the class-wise Precision & Recall This tells that how the model worked in general (General Behavior), and we get to know the classes with very low precision or recall values. Then, inspect such class samples to see which other images they get confused with.

```
In [30]: plt.bar(range(n_classes), metrics['precision'])
         plt.title('precision')
         plt.show()
         plt.bar(range(n_classes), metrics['recall'])
         plt.title('recall')
         plt.show()
```






```
In [31]: low_precision_classes = np.argsort(metrics['precision'])[:3]
         low_recall_classes    = np.argsort(metrics['recall'])[:3]
         print("Low precision classes:", low_precision_classes)
         print("Low recall classes:", low_recall_classes)
```

```
Low precision classes: [24 29 30]
Low recall classes: [27 41 30]
```

For each low precision classes, find the class that gives maximum false positives. > These are found in columns of the confusion matrix.

For each low recall classes, find the class that gives maximum false negatives. > These are found in rows on the confusion matrix.

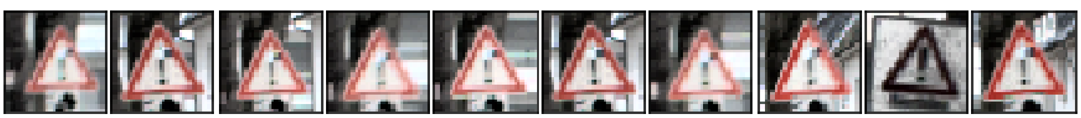
```
In [32]: # Get a copy of the confusion matrix excluding true positives.
         conf_mat = np.copy(metrics['confmat'])
         np.fill_diagonal(conf_mat,0)

         # For each class with low precision, get class that causes most false positives.
         false_positive_classes = np.argmax(conf_mat[:, low_precision_classes], axis=0)
         print("False positive classes:", false_positive_classes)

         # For each class with low recall, get class that causes most false negatives.
         false_negative_classes = np.argmax(conf_mat[low_recall_classes,:], axis=1)
         print("False negative classes:", false_negative_classes)
```

```
False positive classes: [18 28 11]
False negative classes: [24 32 29]
```

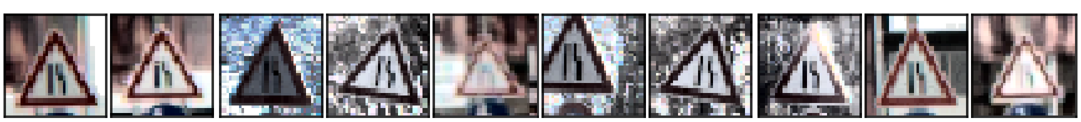
Below, Low Precision Classes

```
In [42]: for i in range(len(low_precision_classes)):
             # Get misclassified samples from false positive class.
             fp_idx = np.logical_and(np.squeeze(y_test==false_positive_classes[i]),
                                     np.squeeze(predicted_labels==low_precision_classes[i]))

             fp_samples = X_test[fp_idx]

             # Get (representative) samples from the target class.
             target_idx = np.where(y_test == low_precision_classes[i])
             target_samples = X_test[target_idx]

             print("Actual class:", sign_names[false_positive_classes[i]])
             plot_random_samples(fp_samples,10)
             print("Predicted as class:", sign_names[low_precision_classes[i]])
             plot_random_samples(target_samples, 10)
             print("\n\n")
```

```
Actual class: [18 'General caution']
```

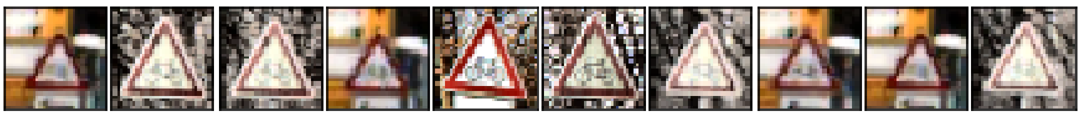


```
Predicted as class: [24 'Road narrows on the right']
```



```
Actual class: [28 'Children crossing']
```

Predicted as class: [29 'Bicycles crossing']



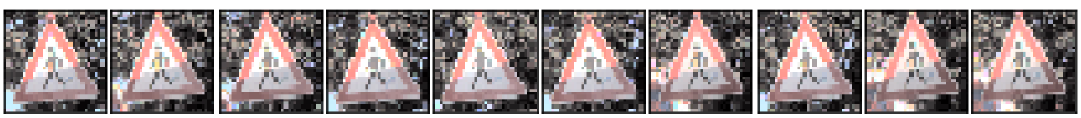
Actual class: [11 'Right-of-way at the next intersection']

Predicted as class: [30 'Beware of ice/snow']

Below, Low Recall Classes

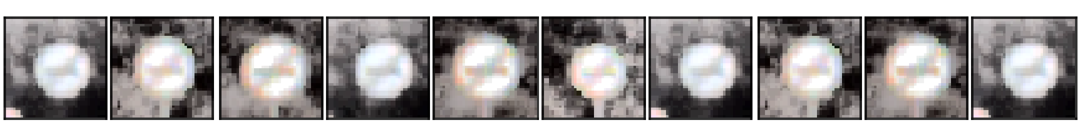
In [43]:
```
for i in range(len(low_recall_classes)):
    # Get misclassified samples from target class.
    target_idx = np.logical_and(np.squeeze(y_test==low_recall_classes[i]),
                                np.squeeze(predicted_labels==false_negative_classes[i])

    target_samples = X_test[target_idx]

    # Get (representative) samples from the false negative class.
    fp_idx = np.where(y_test == false_negative_classes[i] )
    fp_samples = X_test[fp_idx]

    print("Actual class:", sign_names[low_recall_classes[i]])
    plot_random_samples(target_samples, 10)
    print("Predicted as class:", sign_names[false_negative_classes[i]])
    plot_random_samples(fp_samples, 10)
    print("\n\n")
```

```
Actual class: [27 'Pedestrians']
```

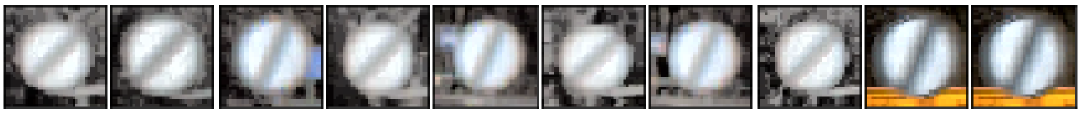


```
Predicted as class: [24 'Road narrows on the right']
```

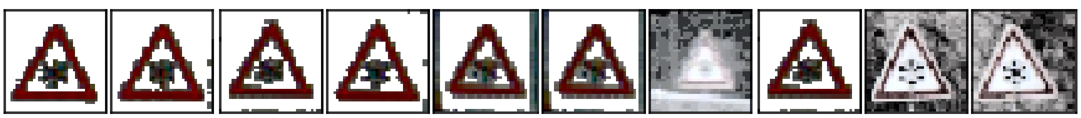
```
Actual class: [41 'End of no passing']
```



Predicted as class: [32 'End of all speed and passing limits']



Actual class: [30 'Beware of ice/snow']



Predicted as class: [29 'Bicycles crossing']

1.5.8 Discussion (5):

Analyzing the Model Performance

Because the validation set is small and not augmented either, a high validation set accuracy (~99%) didn't translate into as good a test accuracy (~93%). Above, some misclassified samples have been plotted aloghwith their target labels. For many examples, why the misclassfication would have occured or why the model got confused seems obvious like: Motion Blur, pixelation, Over-exposure etc. As discussed above, e.g., The sign of Speed Limit 60 km/h could be easily confused with that of 80 km/h in a blurred image as the digits would almost look alike in shape.

More insight is obtained by computing the confusion matrix, and precision and recall values. Some finer high-level features seem to be overlooked by the model. E.g., 'General Caution' with an exclaimation mark and 'Pedestrian' with a human in the middle, both, have been confused with 'Road narrows on the right'.

1.6 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.

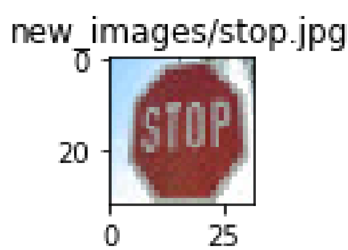
1.6.1 Load and Output the Images

```
In [36]: ### Load the images and plot them here.
         ### Feel free to use as many code cells as needed.

         import scipy.ndimage as ndimage

         new_files=['new_images/bumpy.jpg','new_images/caution.jpg',
                    'new_images/no-vehicles.jpg','new_images/stop.jpg','new_images/work.jpg']

         X_new = np.zeros([len(new_files),32,32,3], dtype=np.uint8)
         y_new = np.array([22,18,15,14,25], dtype=np.uint8) # Known Label Ids from the Signnames

         for i in range(len(new_files)):
             X_new[i] = ndimage.imread(new_files[i])

             plt.figure(figsize=(1,1))
             plt.imshow(X_new[i])
             plt.title(new_files[i])
             plt.show()
```


new_images/bumpy.jpg
0
20
0
25


new_images/caution.jpg
0
20
0
25


new_images/no-vehicles.jpg
0
20
0
25


new_images/stop.jpg
0
STOP
20
0
25

1.6.2 Predict the Sign Type for Each Image

```
In [37]: ### 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 earl
         ### Feel free to use as many code cells as needed.
```

```
In [38]: X_new = hist_equalize(X_new)
         X_new_norm = X_new - pixel_means
         X_new_norm = X_new_norm / (pixel_stddevs + 1e-6) #avoid division by 0

         new_images_metrics = compute_key_metrics(session, X_new_norm, y_new)
```

```
100%|| 1/1 [00:00<00:00, 20.57it/s]
```

1.6.3 Analyze Performance

```
In [44]: ### Calculate the accuracy for these 5 new images.
         ### For example, if the model predicted 1 out of 5 signs correctly, it's 20% accurate o

         print("Acuracy for new test images: ", np.sum(new_images_metrics['predicted_labels']==y
```

```
Acuracy for new test images:  0.8
```

1.6.4 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]])
```

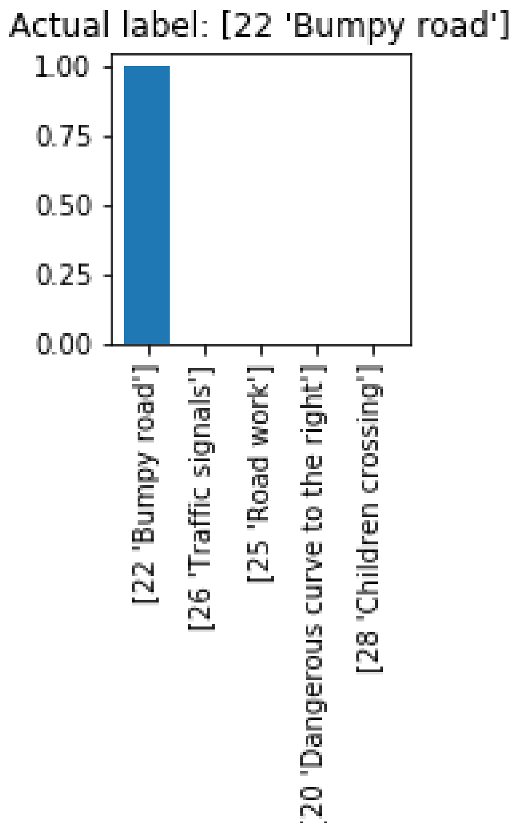
Running it through `sess.run(tf.nn.top_k(tf.constant(a), k=3))` produces:

```
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))
```

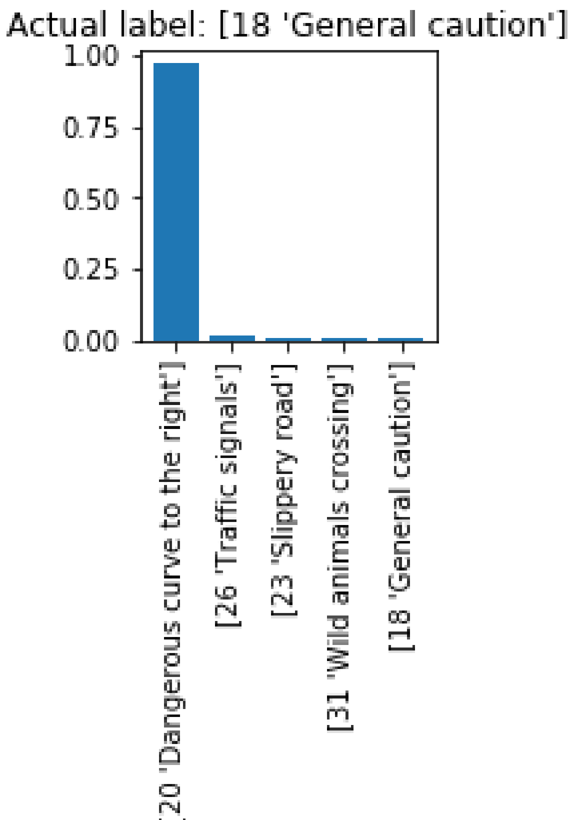
Looking just at the first row we get `[ 0.34763842,  0.24879643,  0.12789202]`, you can confirm these are the 3 largest probabilities in a. You'll also notice `[3, 0, 5]` are the corresponding indices.

In [45]:
```
### Print out the top five softmax probabilities for the predictions on the German traf
### Feel free to use as many code cells as needed.

top5 = session.run(tf.nn.top_k(tf.nn.softmax(logits), 5), feed_dict={X: X_new_norm, y:

for i in range(len(y_new)):
    print("Actual label: {}".format(sign_names[y_new[i]]))
    print("Predicted classes and probabilities ", list(zip(top5[1][i], np.round(top5[0]
    plt.figure(figsize=(1,1))
    plt.imshow(X_new[i])
    plt.title(new_files[i])
    plt.show()
    plt.figure(figsize=(2,2))
    plt.bar(range(5), top5[0][i])
    plt.title("Actual label: {}".format(sign_names[y_new[i]]))
    plt.xticks(range(5), sign_names[top5[1][i]], rotation='vertical')
    plt.show()
    print("------------------------------------------------------")
```

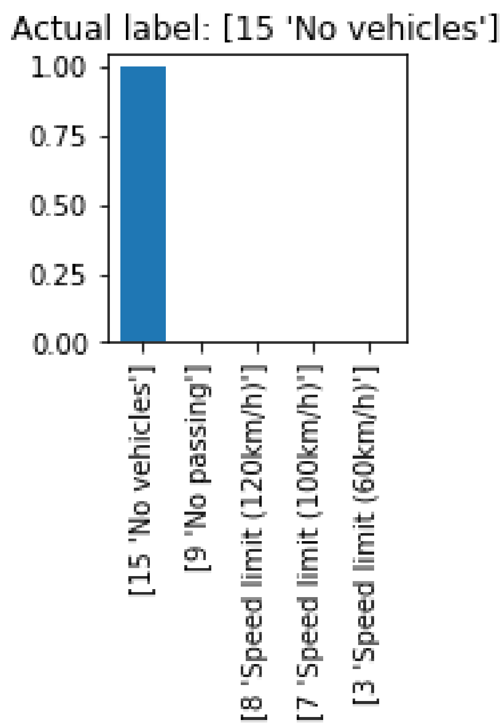
```
Actual label: [22 'Bumpy road']
Predicted classes and probabilities  [(22, 1.0), (26, 0.0), (25, 0.0), (20, 0.0), (28, 0.0)]
```



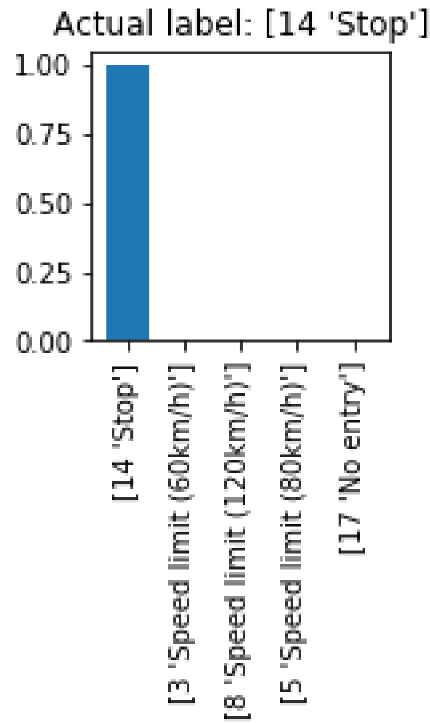

```
-----------------------------------------------------
Actual label: [18 'General caution']
Predicted classes and probabilities  [(20, 0.97000003), (26, 0.0099999998), (23, 0.0), (31, 0.0)
```




```
------------------------------------------------------
Actual label: [15 'No vehicles']
Predicted classes and probabilities  [(15, 1.0), (9, 0.0), (8, 0.0), (7, 0.0), (3, 0.0)]
```




```
----------------------------------------------------
Actual label: [14 'Stop']
Predicted classes and probabilities  [(14, 1.0), (3, 0.0), (8, 0.0), (5, 0.0), (17, 0.0)]
```




```
------------------------------------------------------
Actual label: [25 'Road work']
Predicted classes and probabilities  [(25, 1.0), (22, 0.0), (29, 0.0), (19, 0.0), (20, 0.0)]
```