Traffic_Sign_Classifier

September 13, 2017

1 Self-Driving Car Engineer Nanodegree

1.1 *Note: Project Rubric and Writeup is merged in this file as well*

1.2 Project: Build a Traffic Sign Recognition Classifier

1.2.1 Rubrik checkoff:

- Dataset Exploration
  - Section 2.2: The dataset has 34799 training samples, 4410 validation samples, and 12630 test samples. Every sample is a 32x32x3 image that can be classified into one of 43 labels.
  - Section 2.2.2
- Design and Test a Model Architecture
  - Section 2.3.1 and Section 2.4: The input data is normalized and grayscaled before training and inference. For training I have generated more samples by distorting the original inputs (rotation, translation, and scaling)
  - Section 2.5: The architecture is a modified LeNet-5 architecture with dropout in the fully connected layers. The dropout probability is a suject to optimization.
  - Section 2.5.1: Training is done with dropout = 0.3 (keep_prob=0.7), learning rate = 0.001 for 25 epochs. The epoch with the highest validation accuracy is saved.
  - Section 2.5.2: This approach achieves >98% accuracy on the validation set, and ~97% accuracy on the provided test set.
- Test a Model on New Images
  - Section 2.6.1: The new images are acquired and visualized. It is expected to be very hard to classify these images, because some of them are very noisy (some have part of another sign, some have very high salt-pepper noise, etc.)
  - Section 2.6.2: performance on newly acquired images is not that great (~75% accuracy).
  - Section 2.6.2

Final visualization and discussion provided Section 2.7.

1.3 #### POST REVIEW EDIT 1

- **How did you end up with this final architecture? Did you try out any other architectures?**

- I tried several different architectures, including deeper networks, and networks with bigger/smaller filters. However, the validation accuracy was only dropping from the original architecture. I am positive, LeNet is suboptimal, but at the same time there are just too many parameters, so I decided to improve upon existing architecture (the one shown in the lectures)

- **Why do you think that the final architecture is fit for the traffic sign classification problem?**
    - After visualizing the weights in the hidden layers, I realized that deeper network might not achieve better performance. The reason is that the traffic signs are more or less standardized, and are designed to be easily distinguishable between each other. However, it is important to use convolutional layers because signs could be distorted, and we need to extract important features. At the same time, traffic signs have several different features, which alone don't represent a single class. For example, if the sign is triangular, it could be "Bumpy road", "Pedestrian crossing", "Construction ahead", etc. it is he combination of features that make a sign what it is. That is why the number of filters in the convolution filters should be sufficiently high, and the number of combinations that we can make from them should also be high (that is in the fully-connected layer we need a lot of nodes).

- **Also provide a brief description of some design choices that you made - how did you tune the parameters, why was dropout used, how was the position of the dropout layer determined etc.**
    - Dropout was one of the first things I added. The problem was that I could get a 100% accuracy for training data for some architectures, but the validation accuracy was low. That forced me to use dropout. I tried using dropout in the convolutional layers, but it didn't seem like it had any effect at all on the performance. However, once I put the dropout after the FC, the performance increased almost immediately. Now the problem was to find the best number for the dropout.
    - The parameter tuning was the most tedious process. I used a "binary search" approach, where I would pick one of the layers and try two-three different parameters, and see which direction should I modify the parameter to. For example, I would run 3 processes with one of the FC layers having 100, 500, 1000 nodes. After that I would see which gives better performance, and repeat the process again -- in my case, 1000 nodes was better, so I would run 500, 1000, 1500, etc. This is not the best approach because For every modification I would do in a layer, I would have to recheck all other layers/hyperparameters. That took a lot of time: with n variables to check, (logn)^2 runs with every run being 1-3 minutes on my 1080Ti = around 8 hours of checking. Luckily this process is possible to automate :)

- **the rubric also requires you to specifically mention at least one characteristic of these images that might make it particularly easy/difficult for the classifier to classify them.**
    - These images were chosen because I thought they would be a little harder for my architecture, and I wanted to see what the performance would be.
    - There are 3 triangular and 4 circular signs were chosen: That would allow some confusion in the network (which is what happened)

- When choosing the signs, I wanted them to be as noisy as possible as well -- and not just the salt-and-pepper noise, but also the environemnt noise (light blicks, several shapes in the same picture, etc.). These inputs are exacly that.

- **Please be sure to also compare the accuracy of the model when tested on the new images and the accuracy on the original test set. Include the comparision in the writeup.**
  - The accuracy is provided in the original report for both validation and test datasets:
    * Original validation accurcy: ~98%
    * Original test accuracy: ~97%
    * New test accuracy: ~75%

---

2 Imports and Downloads

These auxiliary and support cells that load the dataset and appropriate packages.

```
In [1]: import csv
        import pickle
        import random
        import PIL

        import matplotlib.image as mpimg
        import matplotlib.pyplot as plt
        %matplotlib inline
        import numpy as np
        import tensorflow as tf

        import os.path
        import skimage.color
        import sklearn.utils
        import tensorflow.contrib.layers
        import IPython.core.display
```

```
/home/carnd/anaconda3/envs/carnd-term1/lib/python3.5/site-packages/matplotlib/font_manager.py:
  'Matplotlib is building the font cache using fc-list. '
```

```
In [2]: def get_data(folder, file_list, zip_url, zip_hash = None):
            import os, sys
            # For OS X:
            md5func = !which md5
            if len(md5func) == 0:
                # For Ubuntu
                md5func = !which md5sum
```

```python
    md5func = md5func[0]
else:
    md5func = md5func[0] + ' -r'

hash_cleanup = lambda h: h[0].split()[0]

def file_hash_valid():
    for file,file_hash in file_list.items():
        file_path = folder + '/' + file
        if not os.path.isfile(file_path):
            #raise IOError("File {} doesn't exist.".format(file_path))
            print("File {} doesn't exist.".format(file_path))
            return False
        # print ("*****Running ", md5func, file_path)
        md5func # Weird bug
        md5_compute = !$md5func $file_path
        md5_compute = hash_cleanup(md5_compute)
        # print (md5_compute, file_path)
        if md5_compute != file_hash:
            # raise RuntimeError("Hashes for file {} don't match.".format(file_pat
            print("Hashes for file {} don't match:".format(file_path))
            print("\t{} vs. {}".format(file_hash, hash_cleanup(md5_compute)))
            return False
    return True

zip_file_name = folder + '/' + zip_url.split('/')[-1]

need_download = False
need_extract = False

if os.path.isdir(folder) and file_hash_valid():
    print('All hashes valid')
    return
else:
    print('Need extraction')
    need_extract = True

if not os.path.isfile(zip_file_name):
    print('Need download and extraction')
    need_download = True
    need_extract = True
elif zip_hash is not None:
    md5_zip = !$md5func $zip_file_name
    md5_zip = hash_cleanup(md5_zip)
    need_download = md5_zip == zip_hash
    need_extract = need_extract or need_download

if need_download:
```

```
            !rm -f $zip_file_name
            !wget $zip_url -O $zip_file_name

        if need_extract:
            if zip_hash is not None:
                md5_zip = !$md5func $zip_file_name
                if hash_cleanup(md5_zip) != zip_hash:
                    raise ("Hash for downloaded file {} is off.".format(zip_file_name))
            cleanups = folder + '/*.p'
            !rm -f $cleanups
            !mkdir -p $folder
            !unzip $zip_file_name -d $folder

        if file_hash_valid():
            print ("All hashes valid")
```

2.1 Step 0: Load The Data

This cell loads the datasets and makes sure it is the correct one

```
In [3]: data_folder = './traffic_data'
        file_list = {
            'train.p': 'da9bc1eb32b045add8cae0e91a067f44',
            'valid.p': '3fa6f457c93d85ec3d1c3d6ad4d775b1',
            'test.p': '3d9d6e26048284e40a3f17a414b02981'
        }
        zip_url = 'https://d17h27t6h515a5.cloudfront.net/topher/2017/February/5898cd6f_traffic-

        get_data(data_folder, file_list, zip_url)


        training_file = data_folder+'/train.p'
        validation_file = data_folder+'/valid.p'
        testing_file = data_folder+'/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, sizes_train, coords_train = train['features'], train['labels'], train
        X_valid, y_valid, sizes_valid, coords_valid = valid['features'], valid['labels'], valid
        X_test, y_test, sizes_test, coords_test = test['features'], test['labels'], test['sizes
```

```
File ./traffic_data/test.p doesn't exist.
Need extraction
Need download and extraction
--2017-09-13 04:20:16--  https://d17h27t6h515a5.cloudfront.net/topher/2017/February/5898cd6f_t
Resolving d17h27t6h515a5.cloudfront.net (d17h27t6h515a5.cloudfront.net)... 54.230.141.54, 54.2
Connecting to d17h27t6h515a5.cloudfront.net (d17h27t6h515a5.cloudfront.net)|54.230.141.54|:443
HTTP request sent, awaiting response... 200 OK
Length: 123524425 (118M) [application/zip]
Saving to: ./traffic_data/traffic-signs-data.zip

./traffic_data/traf 100%[===================>] 117.80M  13.1MB/s    in 7.5s

2017-09-13 04:20:24 (15.6 MB/s) - ./traffic_data/traffic-signs-data.zip saved [123524425/12352

Archive:  ./traffic_data/traffic-signs-data.zip
  inflating: ./traffic_data/test.p
  inflating: ./traffic_data/train.p
  inflating: ./traffic_data/valid.p
All hashes valid
```

2.2 Step 1: Dataset Summary and 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**

The dataset seems to be a set of low resolution photos of the straffic symbols. It has minimal preprocessing:

- Crude centering of the images
- Reshape of images to 32x32x3

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

```
In [4]: n_train = X_train.shape[0]
        n_valid = X_valid.shape[0]
        n_test = X_test.shape[0]
```

```
image_shape = X_train.shape[1:]
n_classes = np.unique(np.concatenate((y_train, y_valid, y_test))).shape[0]

print("Number of training examples =", n_train)
print("Number of validation examples =", n_valid)
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 validation examples = 4410
Number of testing examples = 12630
Image data shape = (32, 32, 3)
Number of classes = 43
```

2.2.2 Include an exploratory visualization of the dataset

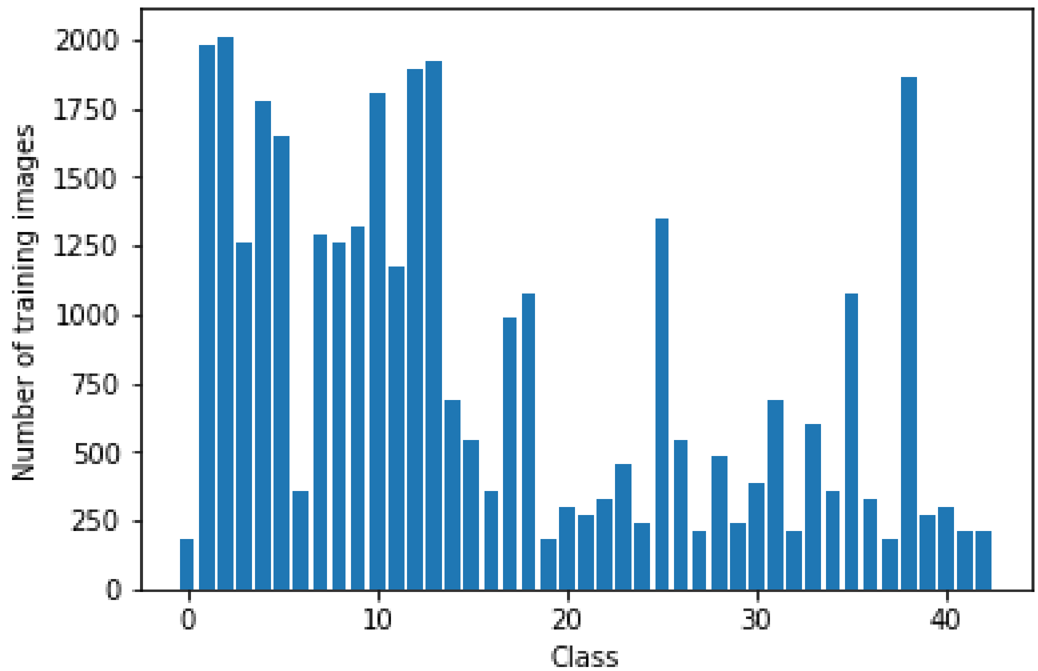
The visualization of the dataset is below.

This is the first level of the visualization on the original images only. It also includes the distribution bar-chart -- it shows what is the distribution of the inputs in the dataset. Note that the dataset is unbalanced, which might cause a problem when training the neural network.

In [5]:
```
def assort_indices_by_class(y):
    ret =  [[] for class_ in range(n_classes)]
    for i in range(y.shape[0]):
        ret[y[i]].append(i)
    return ret

def show_demo_grid(X, y, title):
    classes_to_show = 6
    samples_to_show = 16

    is_gray = (len(X.shape) == 3)

    height = X.shape[1]
    width = X.shape[2]
    if not is_gray:
        depth = X.shape[3]

    indices_by_class = assort_indices_by_class(y)

    if is_gray:
        grid_shape = (classes_to_show * height, samples_to_show * width)
    else:
        grid_shape = (classes_to_show * height, samples_to_show * width, depth)

    grid = np.empty(grid_shape, dtype=X.dtype)
```

```
    row = 0
    for c in random.sample(range(n_classes), classes_to_show):
        col = 0
        for i in random.sample(indices_by_class[c], samples_to_show):
            grid[row * height : (row+1) * height, col * width : (col+1) * width] = X[i]
            col = col + 1
        row = row + 1

    dpi = 32
    fig = plt.figure(0, (grid_shape[1] / dpi, grid_shape[0] / dpi))
    fig.suptitle(title, y=0.1)
    plt.axis("off")
    if is_gray:
        plt.imshow(grid, cmap='gray', vmin=-1, vmax=1)
    else:
        plt.imshow(grid)
    plt.show()

def show_samples_per_class(y):
    indices_by_class = assort_indices_by_class(y)
    plt.bar(range(n_classes), list(map(lambda i: len(indices_by_class[i]), range(n_cla
    plt.xlabel("Class")
    plt.ylabel("Number of training images")
    plt.show()

show_demo_grid(X_train, y_train, "Some images from the training set")
show_samples_per_class(y_train)
```

Some images from the training set



2.3 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.

I am using the LeNet-5 implementation shown in the classroom. The code works great out of the box, and requires minimum modifications.

The architecture achieves almost 97% accuracy on the test data. The modification on the LeNet architecture include only dropout, due to overfitting on the given dataset.

The dataset was also preprocessed (details below) and augmented. If the preprocessing step is obvious, the augmentation could be seen as another way of regularizing the network. At the same time, data augmentation allows us to create more datapoints, and make the dataset slightly more balanced.

2.3.1 Pre-process the Data Set

Preprocessing is fairly straight-forward, and includes two steps: normalization and grayscaling.

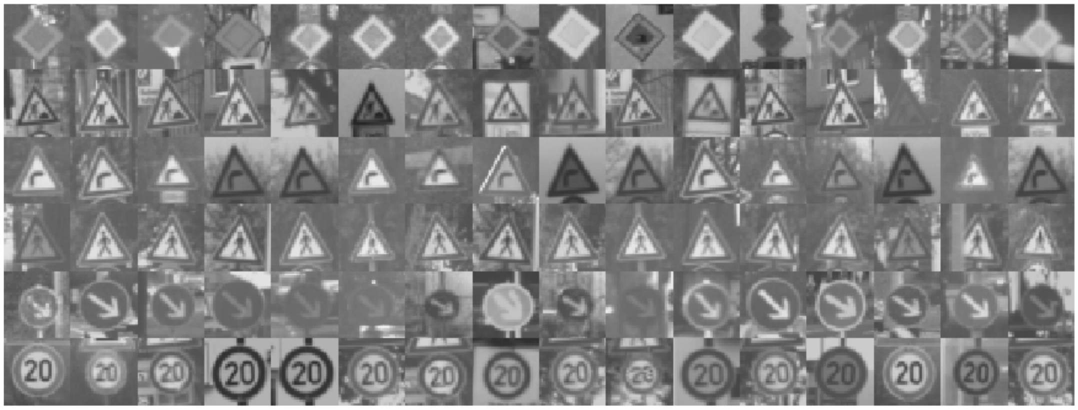
Normalization allows us standartize the input and constrain it to the range [0.-1.].

Grayscaling allows us to reduce the data dimensionality, while improving the accuracy. This might seem counter-intuitive, however, it was shown before that most of the time, color information is just noise unless processed by very deep convolutional layers.

```
In [6]: def normalize(img):
            min_ = np.percentile(img, 1)
```

```
    max_ = np.percentile(img, 99)
    img = np.clip(img, min_, max_)
    range_ = max_-min_
    if range_ == 0:
        range_ = 1
    img = (img-min_) / range_
    img = img - np.mean(img)
    return img

def preprocess(img):
    return normalize(skimage.color.rgb2gray(img))

def preprocess_all(images):
    res = np.empty((images.shape[0], images.shape[1], images.shape[2]), dtype=np.float3
    for i in range(images.shape[0]):
        if i % 1000 == 0:
            print('.', end='')
        res[i] = preprocess(images[i])
    return res

force_redo_preprocess = False
prep_file_name = data_folder+'/preprocessed.p'
if (not os.path.isfile(prep_file_name)) or force_redo_preprocess:
    X_train = preprocess_all(X_train)
    X_valid = preprocess_all(X_valid)
    X_test = preprocess_all(X_test)
    pickle.dump((X_train, X_valid, X_test), open(prep_file_name, "wb"))
else:
    (X_train, X_valid, X_test) = pickle.load(open(prep_file_name, "rb"))

show_demo_grid(X_train, y_train, "Images after preprocessing")
```

...



Images after preprocessing

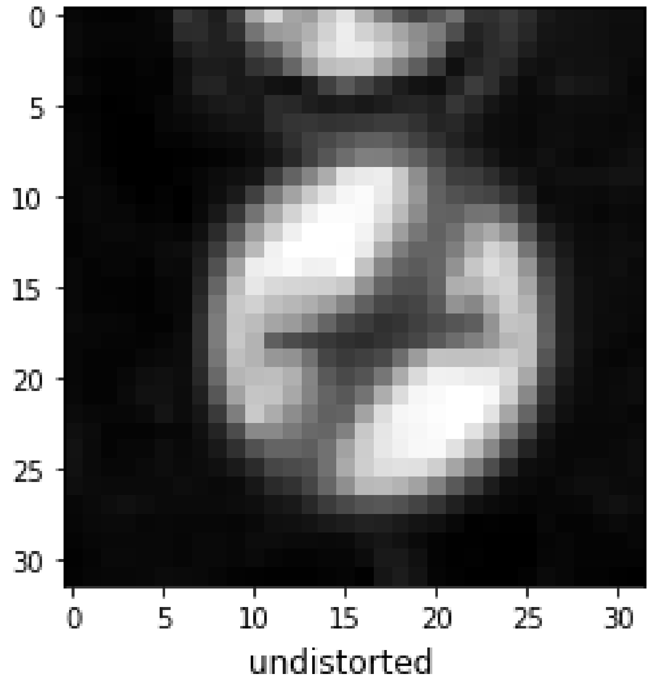
2.4 Data augmentation

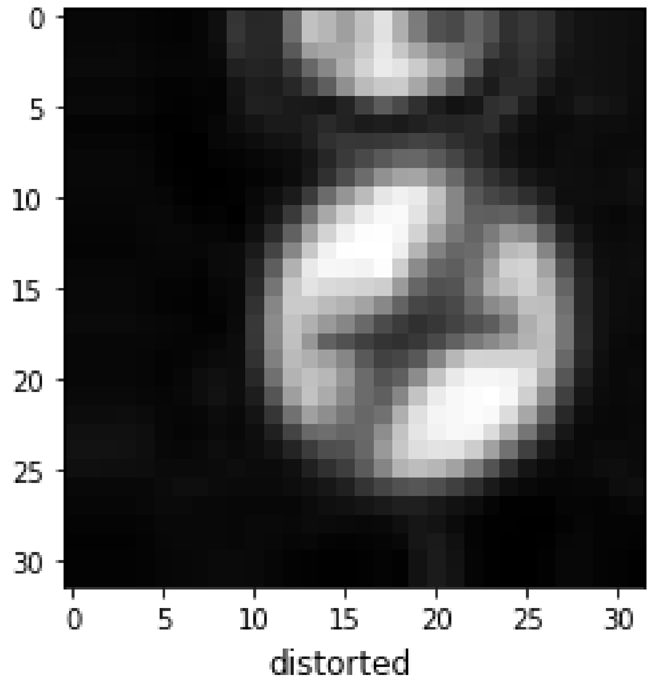
Data augmentation is a process where we change the original data to generate new inputs. The motivation is that if the original image is shifted or rotated a littel, the resulting label should not be affected. This is a very cheap and effective way of increasing the numbe rof inputs and balancing the data.

- Distort:
  - Rotate ś5 degrees
  - Translate ś0.1 of image size
  - Scale ś0.1 of the original shape

In [7]:
```
from skimage import transform
from skimage.transform import SimilarityTransform
from skimage.transform import warp

def distort(img):
    shift_y, shift_x = np.array(img.shape[:2]) / 2.

    shift = SimilarityTransform(translation=[-shift_x, -shift_y])
    tf = SimilarityTransform(
        rotation=np.deg2rad(random.uniform(-5.0, 5.0)),
        scale=random.uniform(0.9, 1.1),
        translation=(random.uniform(-0.1, 0.1)*img.shape[0], random.uniform(-0.1, 0.1)
    )
    shift_inv = SimilarityTransform(translation=[shift_x, shift_y])

    return warp(img, (shift + (tf + shift_inv)).inverse, mode='edge')

def distort_all(images):
    res = np.empty_like(images)
    for i in range(images.shape[0]):
        res[i] = distort(images[i])
    return res

# Sample images to show
plt.imshow(X_train[0], cmap='gray')
plt.suptitle('undistorted', y=0.05)
plt.show()
plt.imshow(distort(X_train[0]), cmap='gray')
plt.suptitle('distorted', y=0.05)
plt.show()

force_redo_augmentation = False
aug_file_name = data_folder+'/augmented.p'
if (not os.path.isfile(aug_file_name)) or force_redo_preprocess or force_redo_augmenta
    print("Augmenting...")
    X_train = np.concatenate((X_train, distort_all(X_train), distort_all(X_train)))
```

```
    y_train = np.concatenate((y_train, y_train, y_train))
    print("completed")
    pickle.dump((X_train, y_train), open(aug_file_name, "wb"))
else:
    (X_train, y_train) = pickle.load(open(aug_file_name, "rb"))
```






```
Augmenting...
completed
```

2.5 Model Architecture

The actual architecture consists of several layers

	Layer	Inputs	Outputs	Description
LAYER 1	Convolution 5x5	32x32x1	28x28x32	32 5x5 filters with 1-strides, and VALID padding
	ReLU			ReLU activation
	MaxPool	28x28x32	14x14x32	Maxpool with k=2, 1-strides, and VALID padding
LAYER 2	Convolution 5x5	14x14x32	10x10x64	64 5x5 filters with 1-strides, and VALID padding
	ReLU			ReLU activation
	MaxPool	28x28x64	5x5x64	Maxpool with k=2, 2-strides, and VALID padding
LAYER 3	Flatten	5x5x64	1600	Flattens the inputs to be used with MLPs (Not really a layer)
LAYER 4	Fully Connected	1600	120	Fully Connected layer with 1600 inputs and 120 outputs
	ReLU			ReLU activation

	Layer	Inputs	Outputs	Description
	Dropout			Dropout layer
LAYER 5	Fully Connected	120	84	Fully Connected layer with 120 inputs and 84 outputs
	ReLU			ReLU activation
	Dropout			Dropout layer
LAYER 6	Fully Connected	84	43	Output layer with 43 outputs

In [8]:
```
conv1_activation = None
conv2_activation = None

def MyNet(x):
    global conv1_activation, conv2_activation

    # Hyperparameters
    mu = 0
    sigma = 0.1

    # Layer 1: Convolutional. Input = 32x32x1. Output = 28x28x32.
    conv1_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 1, 32), mean = mu, stddev =
    conv1_b = tf.Variable(tf.zeros(32), name="conv1_b")
    conv1   = tf.nn.conv2d(x, conv1_W, strides=[1, 1, 1, 1], padding='VALID') + conv1_

    # Activation.
    conv1_activation = conv1 = tf.nn.relu(conv1)

    # Pooling. Input = 28x28x32. Output = 14x14x32.
    conv1 = tf.nn.max_pool(conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='V

    # Layer 2: Convolutional. Input = 14x14x32. Output = 10x10x64.
    conv2_W = tf.Variable(tf.truncated_normal(shape=(5, 5, 32, 64), mean = mu, stddev =
    conv2_b = tf.Variable(tf.zeros(64), name="conv2_b")
    conv2   = tf.nn.conv2d(conv1, conv2_W, strides=[1, 1, 1, 1], padding='VALID') + co

    # Activation.
    conv2_activation = conv2 = tf.nn.relu(conv2)

    # Pooling. Input = 10x10x64. Output = 5x5x64.
    conv2 = tf.nn.max_pool(conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='V

    # Layer 3 (not really): Flatten. Input = 5x5x64. Output = 1600.
    fc0   = tensorflow.contrib.layers.flatten(conv2)
    fc0 = tf.nn.dropout(fc0, keep_prob)

    # Layer 4: Fully Connected. Input = 1600. Output = 120.
    fc1_W = tf.Variable(tf.truncated_normal(shape=(1600, 120), mean = mu, stddev = sig
```

```
    fc1_b = tf.Variable(tf.zeros(120), name="fc1_b")
    fc1   = tf.matmul(fc0, fc1_W) + fc1_b

    # Activation.
    fc1 = tf.nn.relu(fc1)
    fc1 = tf.nn.dropout(fc1, keep_prob)

    # Layer 5: 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), name="fc2_b")
    fc2    = tf.matmul(fc1, fc2_W) + fc2_b

    # Activation.
    fc2 = tf.nn.relu(fc2)
    fc2 = tf.nn.dropout(fc2, keep_prob)

    # Layer 6: Fully Connected. Input = 84. Output = n_classes.
    fc3_W  = tf.Variable(tf.truncated_normal(shape=(84, n_classes), mean = mu, stddev =
    fc3_b  = tf.Variable(tf.zeros(n_classes), name="fc3_b")
    logits = tf.matmul(fc2, fc3_W) + fc3_b

    return logits
```

2.5.1 Train, Validate and Test the Model

We will train for 25 epochs, and save the candidate with the highest validation accuracy. Although that might cause overfitting, if other regularization parameters are set correctly, the test accuracy will not be much lower than the validation accuracy.

```
In [9]: # This enables us to try the network on less train data
        used_ratio = 1.0

        if used_ratio < 1.0:
            used_n_train = int(used_ratio*X_train.shape[0])
            X_train, y_train = sklearn.utils.shuffle(X_train, y_train)
            X_train = X_train[0:used_n_train,:,:]
            y_train = y_train[0:used_n_train]

        X_train = np.expand_dims(X_train, axis=3)
        X_valid = np.expand_dims(X_valid, axis=3)
        X_test = np.expand_dims(X_test, axis=3)
```

```
In [10]: # Graph definition

         actual_learning_rate = 0.001
         actual_keep_prob = 0.7

         tf.reset_default_graph() # to avoid multiple variable declarations when we run this m
```

```
# input variables
keep_prob = tf.placeholder(tf.float32)
x = tf.placeholder(tf.float32, (None, X_train.shape[1], X_train.shape[2], X_train.shap
y = tf.placeholder(tf.int32, (None))
one_hot_y = tf.one_hot(y, n_classes)

# output operations
logits = MyNet(x)
softmax = tf.nn.softmax(logits)
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits=logits, labels=one_hot_
loss_operation = tf.reduce_mean(cross_entropy)
optimizer = tf.train.AdamOptimizer(learning_rate = actual_learning_rate)
training_operation = optimizer.minimize(loss_operation)
prediction_operation = tf.argmax(logits, 1)
correct_prediction = tf.equal(prediction_operation, tf.argmax(one_hot_y, 1))
accuracy_operation = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
top5_operation = tf.nn.top_k(softmax, 5)

# Construct Saver after graph definition and before starting any sessions
saver = tf.train.Saver()
```

In [11]:
```
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+BATC
        accuracy = sess.run(accuracy_operation, feed_dict={x: batch_x, y: batch_y, kee
        total_accuracy += (accuracy * len(batch_x))
    return total_accuracy / num_examples
```

In [12]:
```
# Training
EPOCHS = 25
BATCH_SIZE = 128

X_train2 = np.copy(X_train)
y_train2 = np.copy(y_train)

best_valid_acc = 0
force_train = False
if (not os.path.isfile(data_folder+'/mynet.ckpt.meta')) or force_redo_preprocess or fo
    with tf.Session() as sess:
        print("Initializing...")
        sess.run(tf.global_variables_initializer()) # to start from scratch
        #saver.restore(sess, "./model/mynet.ckpt")  # to continue training
        num_examples = len(X_train)
```

```
            print("Training...")
            print()
            for i in range(EPOCHS):
                X_train2, y_train2 = sklearn.utils.shuffle(X_train2, y_train2)
                for offset in range(0, num_examples, BATCH_SIZE):
                    end = offset + BATCH_SIZE
                    batch_x, batch_y = X_train2[offset:end], y_train2[offset:end]
                    sess.run(training_operation, feed_dict={x: batch_x, y: batch_y, keep_

                train_accuracy = evaluate(X_train, y_train)
                validation_accuracy = evaluate(X_valid, y_valid)
                print("EPOCH {} ...".format(i+1))
                print("Train Accuracy = {:.3f}".format(train_accuracy))
                print("Validation Accuracy = {:.3f}".format(validation_accuracy))
                if validation_accuracy > best_valid_acc and validation_accuracy > 0.97:
                    best_valid_acc = validation_accuracy
                    saver.save(sess, data_folder+'/mynet.ckpt')
                    print("Model saved")
                print()
```

```
Initializing...
Training...

EPOCH 1 ...
Train Accuracy = 0.915
Validation Accuracy = 0.915

EPOCH 2 ...
Train Accuracy = 0.970
Validation Accuracy = 0.963

EPOCH 3 ...
Train Accuracy = 0.986
Validation Accuracy = 0.974
Model saved

EPOCH 4 ...
Train Accuracy = 0.988
Validation Accuracy = 0.971

EPOCH 5 ...
Train Accuracy = 0.990
Validation Accuracy = 0.971

EPOCH 6 ...
Train Accuracy = 0.995
Validation Accuracy = 0.975
Model saved
```

```
EPOCH 7 ...
Train Accuracy = 0.997
Validation Accuracy = 0.978
Model saved

EPOCH 8 ...
Train Accuracy = 0.998
Validation Accuracy = 0.980
Model saved

EPOCH 9 ...
Train Accuracy = 0.998
Validation Accuracy = 0.978

EPOCH 10 ...
Train Accuracy = 0.998
Validation Accuracy = 0.980

EPOCH 11 ...
Train Accuracy = 0.999
Validation Accuracy = 0.983
Model saved

EPOCH 12 ...
Train Accuracy = 0.999
Validation Accuracy = 0.982

EPOCH 13 ...
Train Accuracy = 0.998
Validation Accuracy = 0.979

EPOCH 14 ...
Train Accuracy = 0.999
Validation Accuracy = 0.982

EPOCH 15 ...
Train Accuracy = 0.999
Validation Accuracy = 0.984
Model saved

EPOCH 16 ...
Train Accuracy = 0.999
Validation Accuracy = 0.981

EPOCH 17 ...
Train Accuracy = 0.999
Validation Accuracy = 0.982
```

```
EPOCH 18 ...
Train Accuracy = 1.000
Validation Accuracy = 0.984

EPOCH 19 ...
Train Accuracy = 1.000
Validation Accuracy = 0.981

EPOCH 20 ...
Train Accuracy = 0.999
Validation Accuracy = 0.981

EPOCH 21 ...
Train Accuracy = 1.000
Validation Accuracy = 0.981

EPOCH 22 ...
Train Accuracy = 0.998
Validation Accuracy = 0.982

EPOCH 23 ...
Train Accuracy = 0.999
Validation Accuracy = 0.980

EPOCH 24 ...
Train Accuracy = 1.000
Validation Accuracy = 0.984

EPOCH 25 ...
Train Accuracy = 0.999
Validation Accuracy = 0.983
```

2.5.2 Test on test set

The test accuracy is 97.2%, while the validation accuracy is 98.4%. We are overfitting a little, but that was expected/

```
In [18]: with tf.Session() as sess:
             saver.restore(sess, data_folder+"/mynet.ckpt")

             train_accuracy = evaluate(X_train, y_train)
             print("Training Accuracy = {:.3f}".format(train_accuracy))

             valid_accuracy = evaluate(X_valid, y_valid)
             print("Validation Accuracy = {:.3f}".format(valid_accuracy))
```

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

```
Training Accuracy = 0.999
Validation Accuracy = 0.984
Test Accuracy = 0.972
```

2.6 Step 3: Test a Model on New Images

The demo images acquired from one of the older cohorts. The top-5 is also show below. The accuracy is fairly low (~63%), however, this might be due to small number of instances. Note the "Turn right ahead" signal -- although the prediction is wrong, the second candidate is the correct prediction. More training examples, or more aggressive distortions during training might increase the accuracy.

2.6.1 The demo for new images is below

```
In [21]: def load_images(names):
             images = []
             for name in names:
                 images += [mpimg.imread(name)]
             return images

         def resize_down(img):
             pilimg = PIL.Image.fromarray(img)
             pilimg = pilimg.resize((image_shape[1], image_shape[0]), PIL.Image.ANTIALIAS)
             return np.array(pilimg)

         def process_input_image(img):
             img = resize_down(img)
             img = preprocess(img)
             return img

         classes = [32, 9, 25, 33, 19, 12, 1, 26]

         image_file_names = [
             data_folder + '/images/end-of-all-speed-limits.jpg',
             data_folder + '/images/no-passing-2.jpg',
             data_folder + '/images/road-work.jpg',
             data_folder + '/images/turn-right-ahead.jpg',
             data_folder + '/images/dangerous-turn-to-the-left.jpg',
             data_folder + '/images/my-privilaged-road.jpg',
             data_folder + '/images/my-speed-limit-30.jpg',
             data_folder + '/images/my-traffic-signals.jpg'
         ]
```

```
images = load_images(image_file_names)

fig, ax = plt.subplots(2, 4, sharex=True, sharey=True)
for idx in range(2):
    for jdx in range(4):
        image = process_input_image(images[idx*4+jdx])
        ax[idx][jdx].imshow(image, 'gray')
        ax[idx][jdx].axis("off")
plt.tight_layout()
```

2.6.2 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.

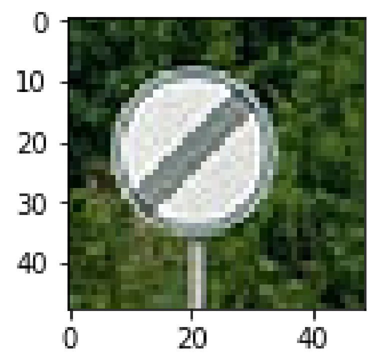
```
In [15]: class_name = [None] * n_classes
         with open(data_folder+'/signnames.csv', 'r') as csvfile:
             reader = csv.reader(csvfile, delimiter=',')
             for row in reader:
                 try:
                     class_name[int(row[0])] = row[1]
                 except ValueError:
```

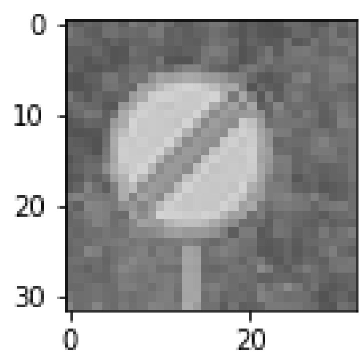
```
            pass

    def predict(X_data):
        num_examples = len(X_data)
        predictions = []
        sess = tf.get_default_session()
        for offset in range(0, num_examples, BATCH_SIZE):
            batch_x = X_data[offset:offset+BATCH_SIZE]
            prediction = sess.run(prediction_operation, feed_dict={x: batch_x, keep_prob:
            predictions.append(prediction)
        predictions = np.concatenate(predictions)

        return predictions

    def print_top5(img):
        img = np.expand_dims(img, axis=0)
        img = np.expand_dims(img, axis=3)

        top5 = sess.run(top5_operation, feed_dict={x: img, keep_prob: 1.0})
        plt.bar(top5.indices[0], top5.values[0])
        plt.xlabel("Class")
        plt.ylabel('Softmax probability')
        plt.show()
        for (v,i) in zip(top5.values[0], top5.indices[0]):
            print("{0:.4f} {1}".format(v, class_name[i]))

    def predict_name(img):
        img = np.expand_dims(img, axis=0)
        img = np.expand_dims(img, axis=3)

        pred = predict(img)
        return class_name[pred[0]]
```

In [16]:
```
print("Loading model...")
with tf.Session() as sess:
    saver = tf.train.Saver()
    saver.restore(sess, data_folder+"/mynet.ckpt")
    print("Model loaded.")

    goods = 0
    for (image, cls) in zip(images, classes):
        plt.figure(figsize=(2,2))
        plt.imshow(image)
        plt.show()
        image = process_input_image(image)
        plt.figure(figsize=(2,2))
        plt.imshow(image, cmap='gray', vmin=-1, vmax=1)
        plt.show()
```

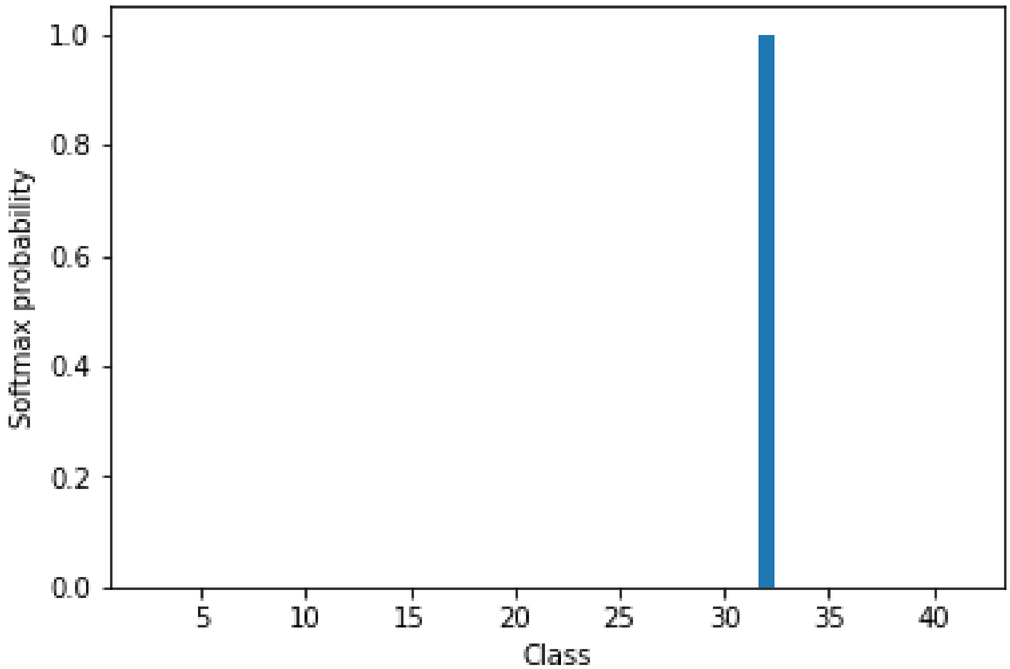
```python
            predictedName = predict_name(image)
            if predictedName == class_name[cls]:
                print('Predicted: {0} (CORRECT)'.format(predict_name(image)))
                goods = goods + 1
            else:
                print('Predicted: {0} (INCORRECT, expected: {1})'.format(predict_name(imag
            print_top5(image)
            IPython.core.display.display(IPython.core.display.HTML("<hr />"))

        print()
        print("Overall precision on the new images: {:.2f}%".format(100*goods/len(images)
```

```
Loading model...
Model loaded.
```



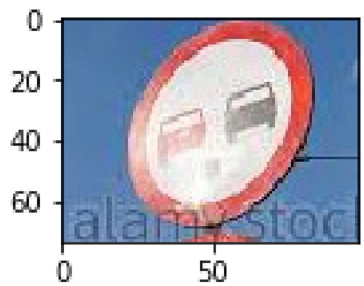


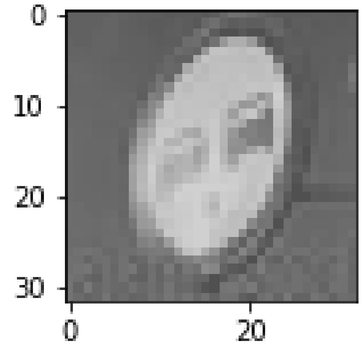

```
Predicted: End of all speed and passing limits (CORRECT)
```



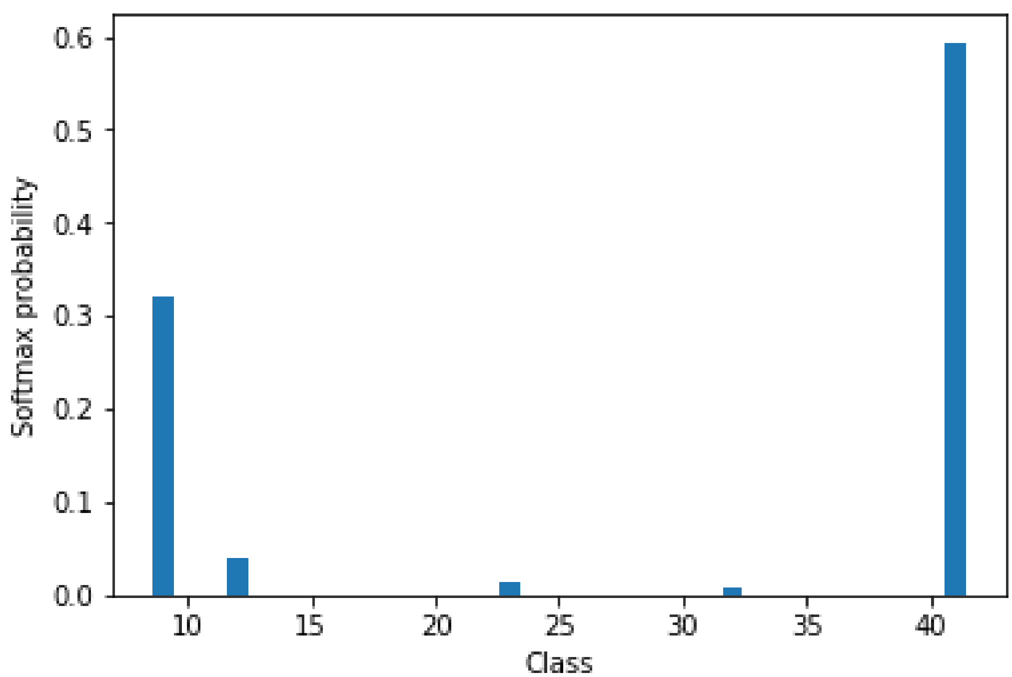

```
0.9998 End of all speed and passing limits
0.0001 End of no passing
0.0000 Children crossing
0.0000 End of speed limit (80km/h)
0.0000 Speed limit (60km/h)
```

```
<IPython.core.display.HTML object>
```



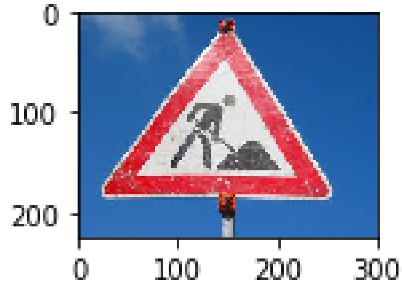


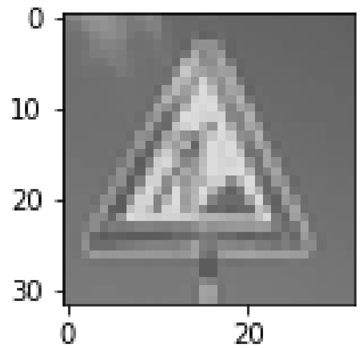
Predicted: End of no passing (INCORRECT, expected: No passing)



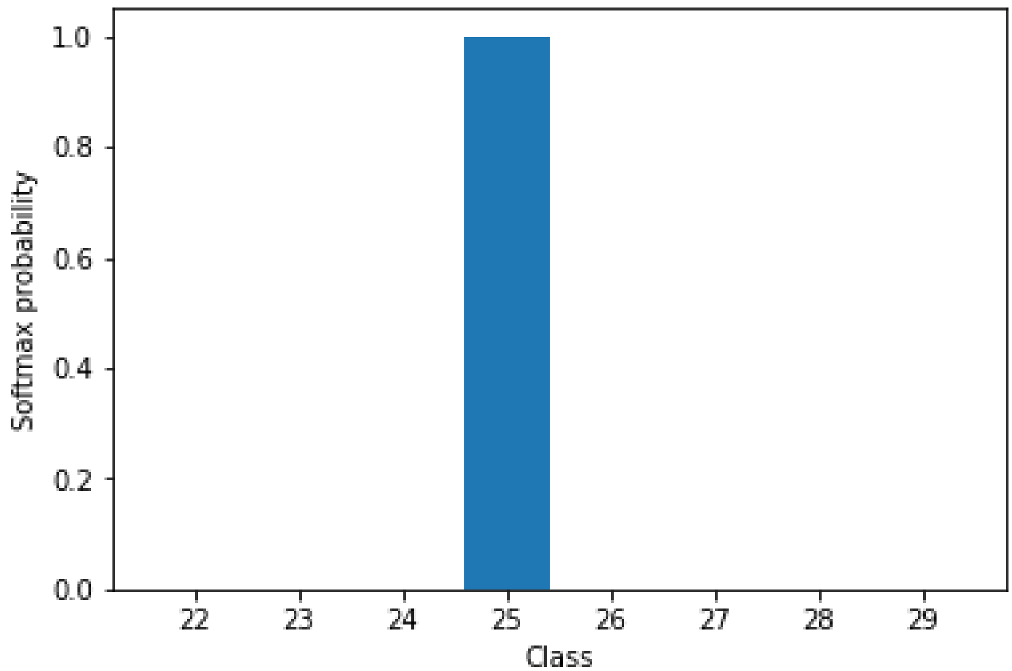
0.5937 End of no passing
0.3214 No passing
0.0392 Priority road
0.0131 Slippery road
0.0093 End of all speed and passing limits

<IPython.core.display.HTML object>



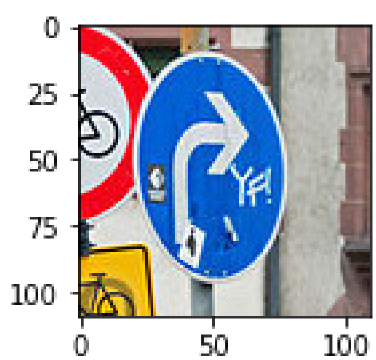


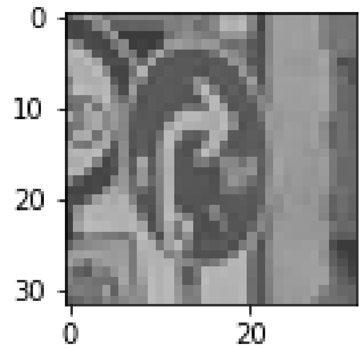
Predicted: Road work (CORRECT)



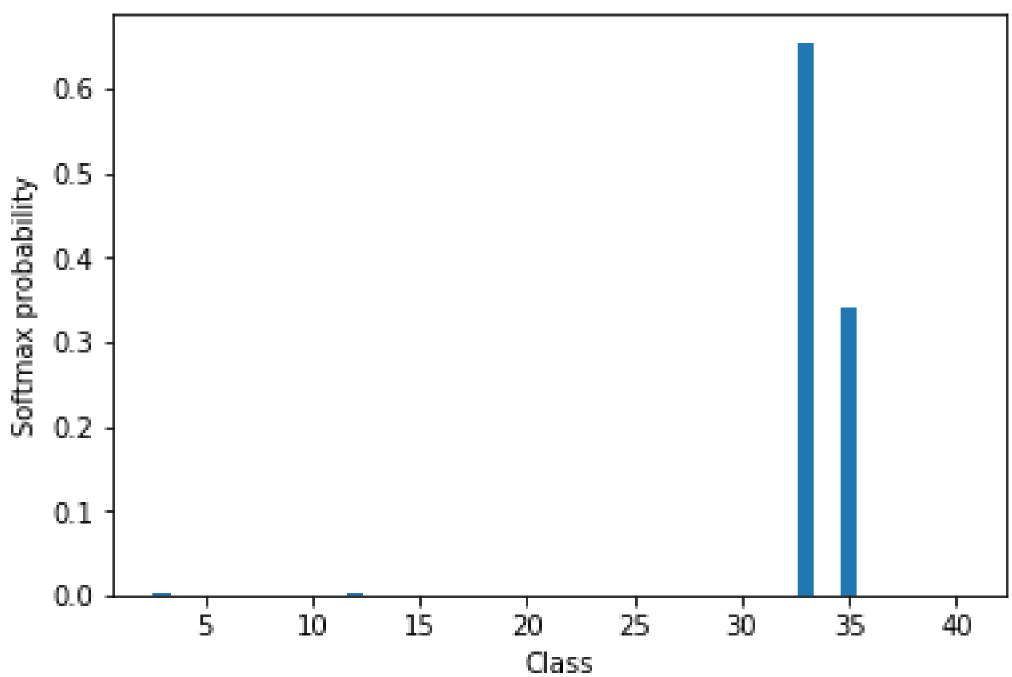

```
1.0000 Road work
0.0000 Bicycles crossing
0.0000 Bumpy road
0.0000 Road narrows on the right
0.0000 Traffic signals
```

```
<IPython.core.display.HTML object>
```



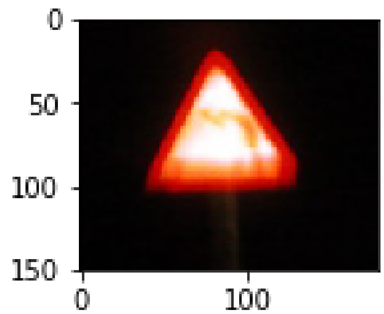


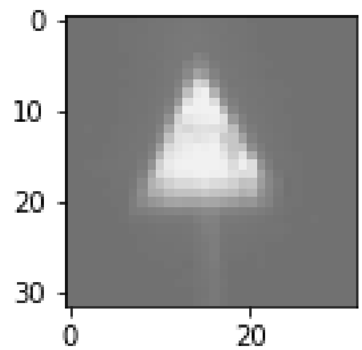

```
Predicted: Turn right ahead (CORRECT)
```



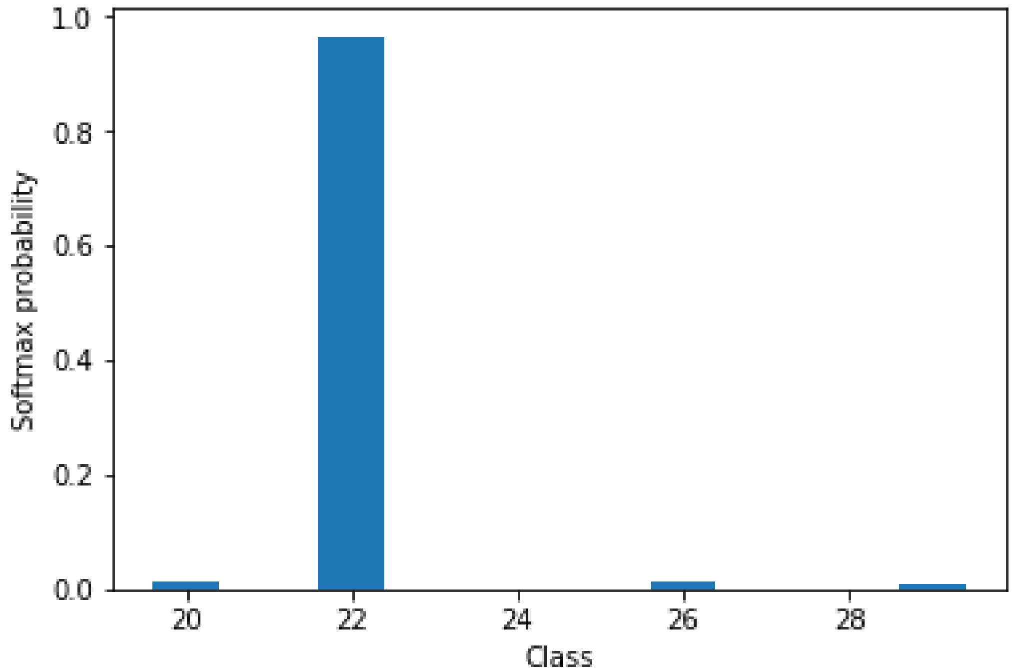

```
0.6548 Turn right ahead
0.3402 Ahead only
0.0025 Priority road
0.0013 Speed limit (60km/h)
0.0009 Roundabout mandatory
```

```
&lt;IPython.core.display.HTML object&gt;
```



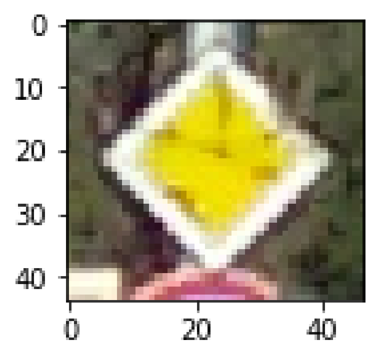


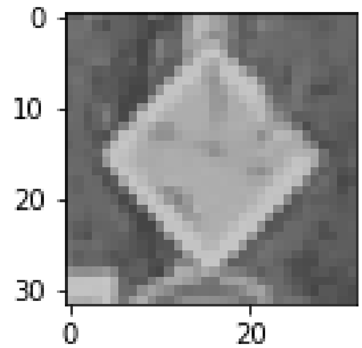

```
Predicted: Bumpy road (INCORRECT, expected: Dangerous curve to the left)
```



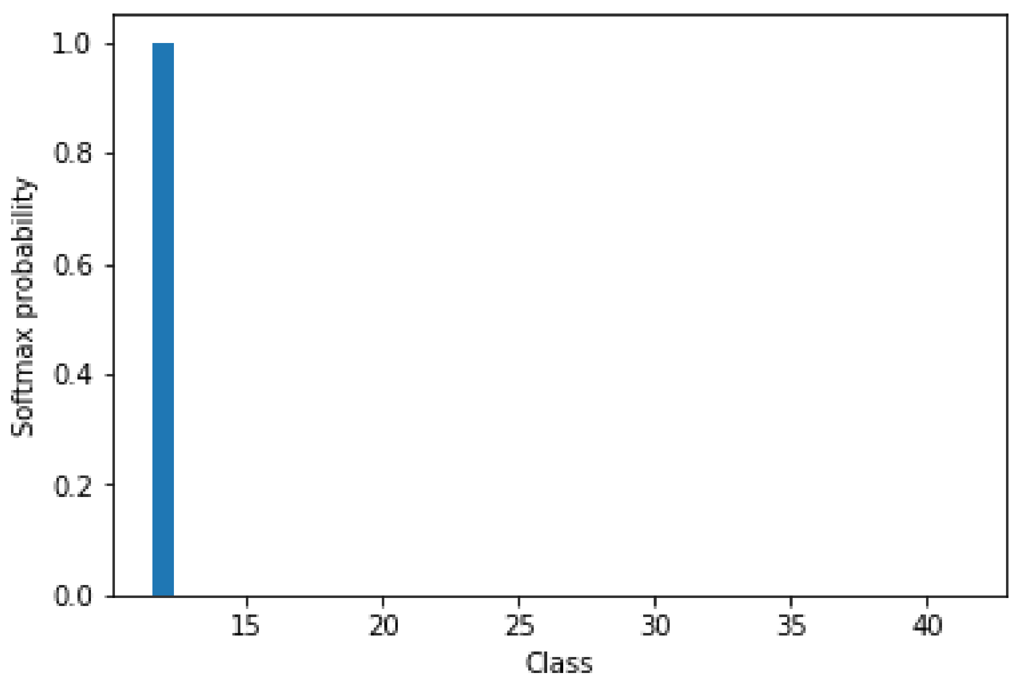

```
0.9652 Bumpy road
0.0129 Traffic signals
0.0111 Dangerous curve to the right
0.0081 Bicycles crossing
0.0011 Road work
```

```
<IPython.core.display.HTML object>
```



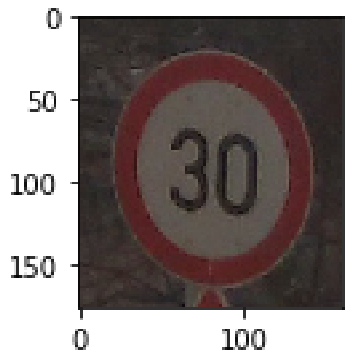


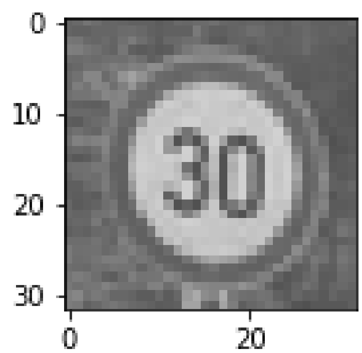
Predicted: Priority road (CORRECT)



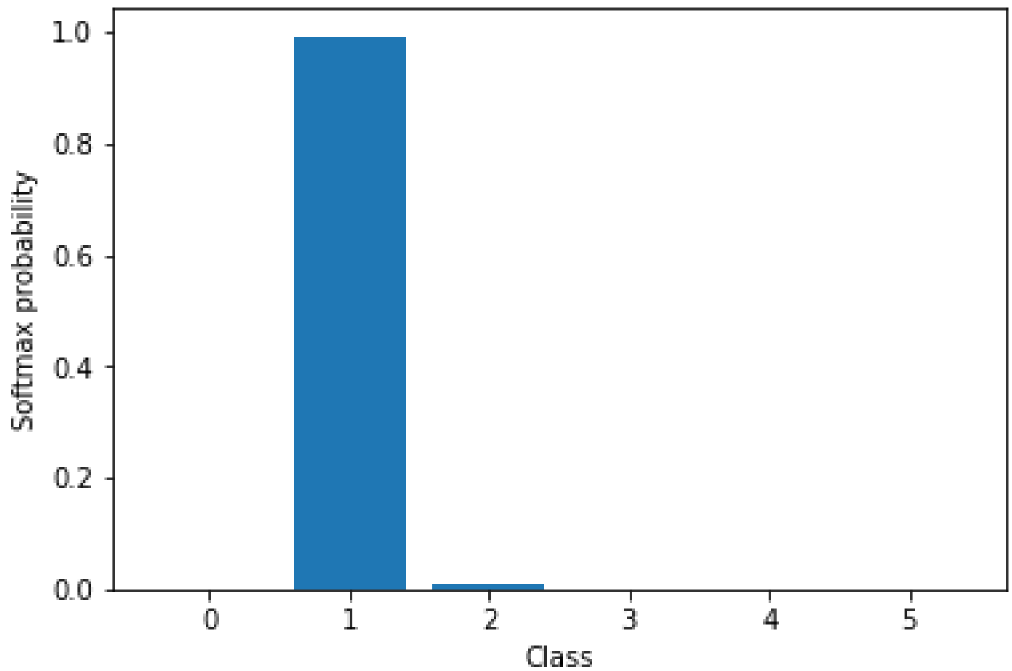

```
1.0000 Priority road
0.0000 Roundabout mandatory
0.0000 Yield
0.0000 Keep right
0.0000 End of no passing
```

<IPython.core.display.HTML object>



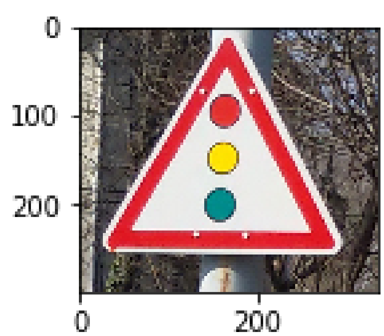


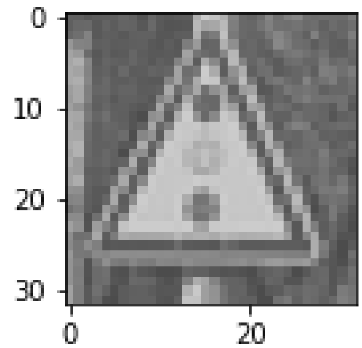
Predicted: Speed limit (30km/h) (CORRECT)



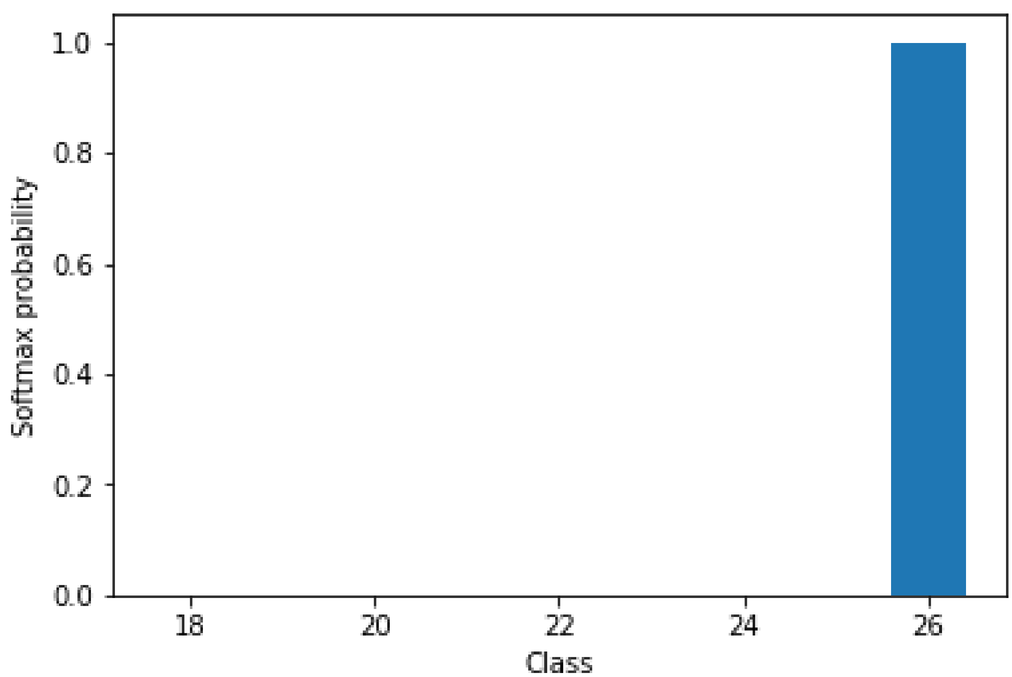

```
0.9921 Speed limit (30km/h)
0.0067 Speed limit (50km/h)
0.0011 Speed limit (20km/h)
0.0000 Speed limit (80km/h)
0.0000 Speed limit (70km/h)
```

```
<IPython.core.display.HTML object>
```






```
Predicted: Traffic signals (CORRECT)
```




```
1.0000 Traffic signals
0.0000 General caution
0.0000 Bumpy road
0.0000 Road work
0.0000 Dangerous curve to the left
```

```
<IPython.core.display.HTML object>
```

```
Overall precision on the new images: 75.00%
```

2.7 Step 4: Visualize the Neural Network's State with Test Images

Visualization is shown here for individual neurons. This visualization clearly shows what each individual layer focuses on while looking at an image.

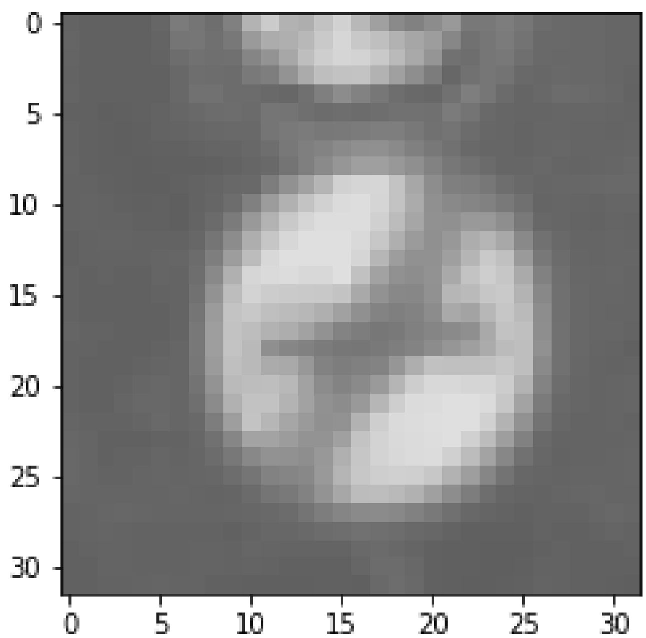
In the visualization of the activations of the first convolutional layer, I have seen that different feature maps look for different edges, for example the 7th feature map is activated by diagonal edges, and the 8th feature map is activated by horizontal edges.

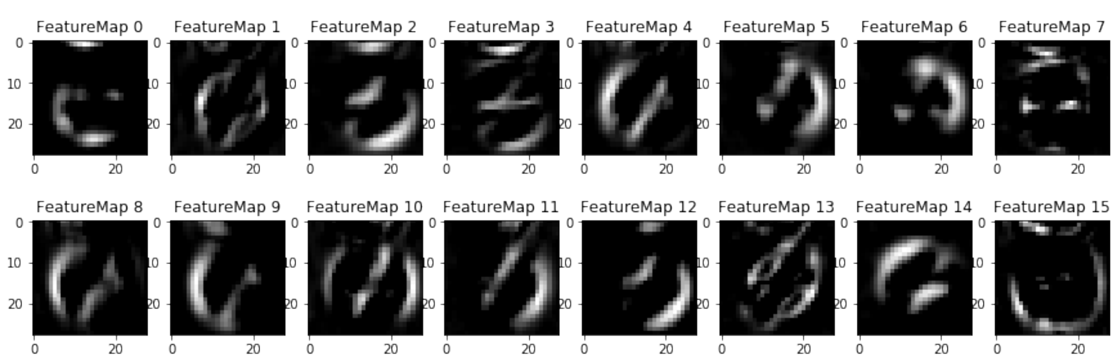
The visualization of the second convolutional layer is not easy to understand for humans.

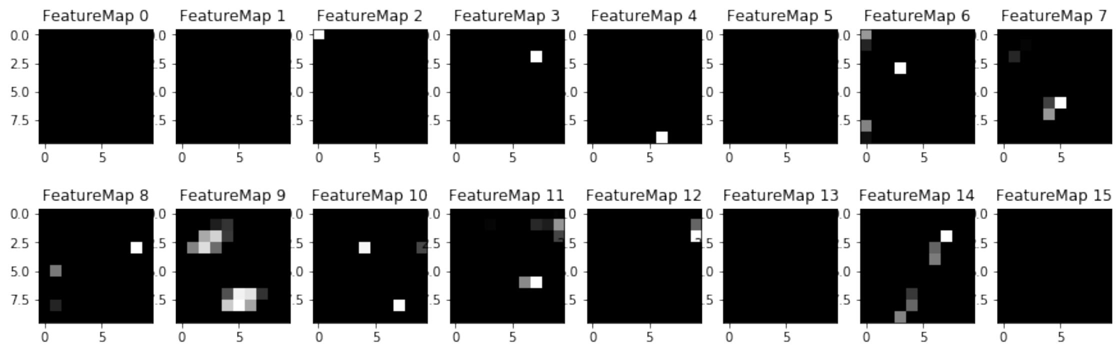
In [17]:
```
### Visualize your network's feature maps here.
### Feel free to use as many code cells as needed.

# 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 tha
# activation_min/max: can be used to view the activation contrast in more detail, by
# plt_num: used to plot out multiple different weight feature map sets on the same bl

def outputFeatureMap(image_input, tf_activation, activation_min=-1, activation_max=-1
    activation = sess.run(tf_activation, feed_dict={x: image_input, keep_prob: 1.0})
    featuremaps = activation.shape[3]
    plt.figure(plt_num, figsize=(15,15))
    for featuremap in range(min([featuremaps, 16])):
        plt.subplot(6,8, featuremap+1) # sets the number of feature maps to show on e
        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 =a
        elif activation_max != -1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmax=ac
        elif activation_min !=-1:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", vmin=ac
        else:
            plt.imshow(activation[0,:,:, featuremap], interpolation="nearest", cmap="g
    plt.show()

def myOutputFeatureMap(img):
    img = np.expand_dims(img, axis=0)
    outputFeatureMap(img, conv1_activation)
    outputFeatureMap(img, conv2_activation)

print("Loading model...")
```

```
with tf.Session() as sess:
    saver = tf.train.Saver()
    saver.restore(sess, data_folder + "/mynet.ckpt")
    print("Model loaded.")

    print()
    print(class_name[y_train[0]])
    plt.imshow(np.squeeze(X_train[0], axis=2), cmap='gray', vmin=-1, vmax=1)
    plt.show()
    myOutputFeatureMap(X_train[0])
```

```
Loading model...
Model loaded.

End of no passing
```






FeatureMap 0
FeatureMap 1
FeatureMap 2
FeatureMap 3
FeatureMap 4
FeatureMap 5
FeatureMap 6
FeatureMap 7
FeatureMap 8
FeatureMap 9
FeatureMap 10
FeatureMap 11
FeatureMap 12
FeatureMap 13
FeatureMap 14
FeatureMap 15

```
In [ ]:
```