Traffic_Sign_Classifier

December 23, 2018

1 Self-Driving Car Engineer Nanodegree

1.1 Deep Learning

1.2 Project: Build a Traffic Sign Recognition Classifier

```
In [1]: import os
```

```
In [2]: #check contents of data folder
        os.listdir("../data")
```

```
Out[2]: ['train.p', 'valid.p', 'test.p', '.ipynb_checkpoints']
```

1.3 Step 0: Load The Data

```
In [3]: # 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']
```

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 [4]:
```
### 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 examples
n_train = X_train.shape[0]

# TODO: Number of validation examples
n_validation = X_valid.shape[0]

# TODO: Number of testing examples.
n_test = X_test.shape[0]

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

# TODO: How many unique classes/labels there are in the dataset.
n_classes = np.unique(y_train).shape[0]

print("Number of training examples =", n_train)
print("Number of validation 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 validation examples = 4410
```

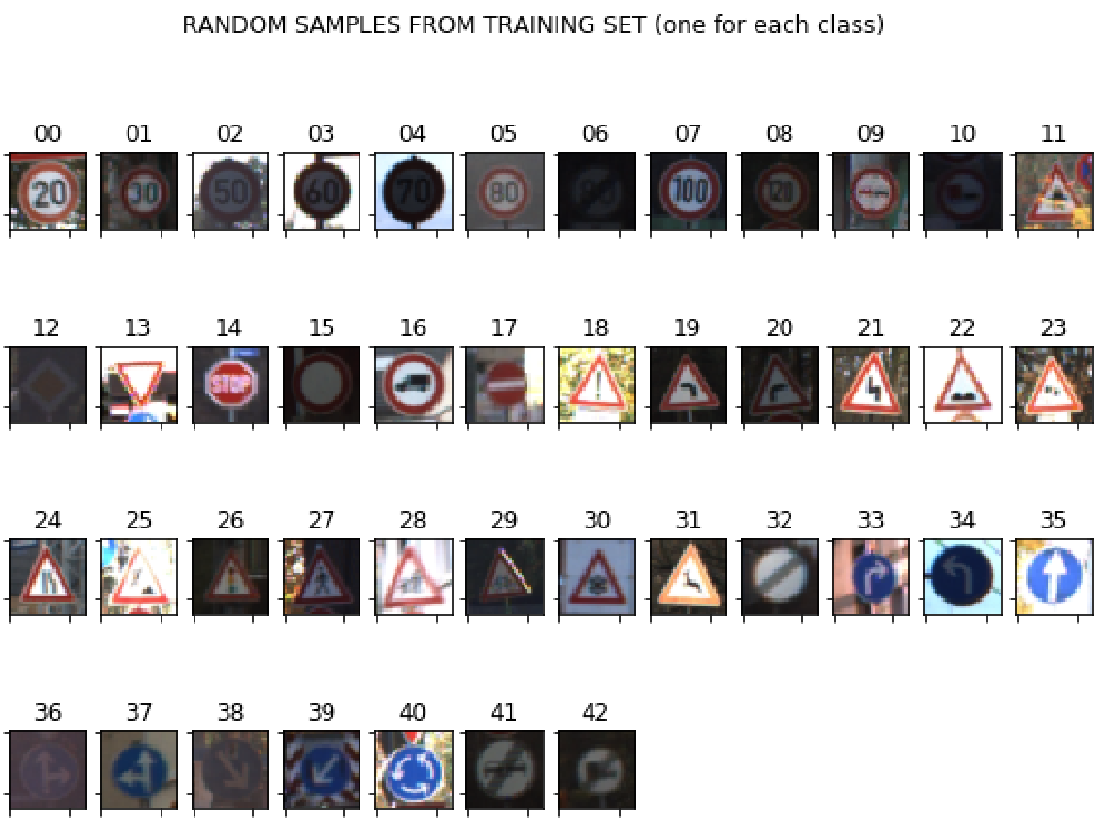
```
Number of testing examples = 12630
Image data shape = (32, 32, 3)
Number of classes = 43
```

1.4.2 Include an exploratory visualization of the dataset

Visualize the German Traffic Signs Dataset using the pickled file(s).

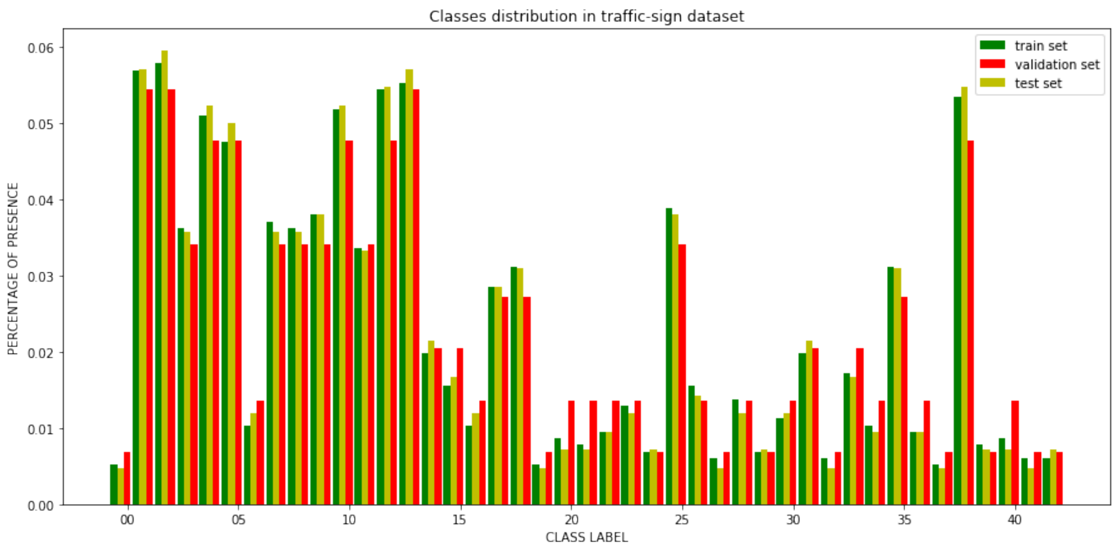
- First we can visualize some images sampled from training set:

```
In [5]: ### Data exploration visualization code goes here.
        ### Feel free to use as many code cells as needed.
        import matplotlib.pyplot as plt
        %matplotlib inline

        # show a random sample from each class of the traffic sign dataset
        rows, cols = 4, 12
        fig, ax_array = plt.subplots(rows, cols, figsize=(10,7))
        plt.suptitle('RANDOM SAMPLES FROM TRAINING SET (one for each class)')
        for class_idx, ax in enumerate(ax_array.ravel()):
            if class_idx < n_classes:
                # show a random image of the current class
                cur_X = X_train[y_train == class_idx]
                cur_img = cur_X[np.random.randint(len(cur_X))]
                ax.imshow(cur_img)
                ax.set_title('{:02d}'.format(class_idx))
            else:
                ax.axis('off')
        # hide both x and y ticks
        plt.setp([a.get_xticklabels() for a in ax_array.ravel()], visible=False)
        plt.setp([a.get_yticklabels() for a in ax_array.ravel()], visible=False)
        plt.draw()
```



- We can also get the idea of how these classes are distributed in both training and testing set

In [6]:
```
# bar-chart of classes distribution
train_distribution, test_distribution, validation_distribution = np.zeros(n_classes), np
for c in range(n_classes):
    train_distribution[c] = np.sum(y_train == c) / n_train
    test_distribution[c] = np.sum(y_test == c) / n_test
    validation_distribution[c] = np.sum(y_valid == c) / n_validation
fig, ax = plt.subplots(figsize=(15,7))
col_width = 0.3
bar_train = ax.bar(np.arange(n_classes)-col_width, train_distribution, width=col_width,
bar_test = ax.bar(np.arange(n_classes), test_distribution, width=col_width, color='y',al
bar_validation = ax.bar(np.arange(n_classes)+col_width, validation_distribution, width=c
ax.set_ylabel('PERCENTAGE OF PRESENCE')
ax.set_xlabel('CLASS LABEL')
ax.set_title('Classes distribution in traffic-sign dataset')
ax.set_xticks(np.arange(0, n_classes, 5)+col_width)
ax.set_xticklabels(['{:02d}'.format(c) for c in range(0, n_classes, 5)])
ax.legend((bar_train[0],bar_validation[0], bar_test[0]), ('train set', 'validation set',
plt.show()
```



From this plot we notice that there's a strong *imbalance among the classes*. Indeed, some classes are relatively over-represented, while some others are much less common. However, we see that the data distribution is almost the same between training, validation and testing set, and this is good news: looks like we won't have problem related to *dataset shift* when we'll evaluate our model on the test data.

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.

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

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

1.5.1 Implementation

Use the code cell (or multiple code cells, if necessary) to implement the first step of your project. Once you have completed your implementation and are satisfied with the results, be sure to thoroughly answer the questions that follow.

Feature preprocessing

```
In [7]: ### 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.
```

```
import cv2

def preprocess_features(X, equalize_hist=True):

    # convert from RGB to YUV
    X = np.array([np.expand_dims(cv2.cvtColor(rgb_img, cv2.COLOR_RGB2YUV)[:, :, 0], 2) f

    # adjust image contrast
    if equalize_hist:
        X = np.array([np.expand_dims(cv2.equalizeHist(np.uint8(img)), 2) for img in X])

    X = np.float32(X)

    # standardize features
    X -= np.mean(X, axis=0)
    X /= (np.std(X, axis=0) + np.finfo('float32').eps)

    return X

X_train_norm = preprocess_features(X_train)
X_valid_norm = preprocess_features(X_valid)
X_test_norm = preprocess_features(X_test)
```

1.5.2 Question 1

Describe how you preprocessed the data. Why did you choose that technique?

Answer: Following this paper [Sermanet, LeCun] I employed three main steps of feature pre-processing:

1) *Each image is converted from RGB to YUV color space, then only the Y channel is used.* This choice can sound at first suprising, but the cited paper shows how this choice leads to the best performing model. This is slightly counter-intuitive, but if we think about it arguably we are able to distinguish all the traffic signs just by looking to the grayscale image.

2) *Contrast of each image is adjusted by means of histogram equalization*. This is to mitigate the numerous situation in which the image contrast is really poor.

3) *Each image is centered on zero mean and divided for its standard deviation*. This feature scaling is known to have beneficial effects on the gradient descent performed by the optimizer.

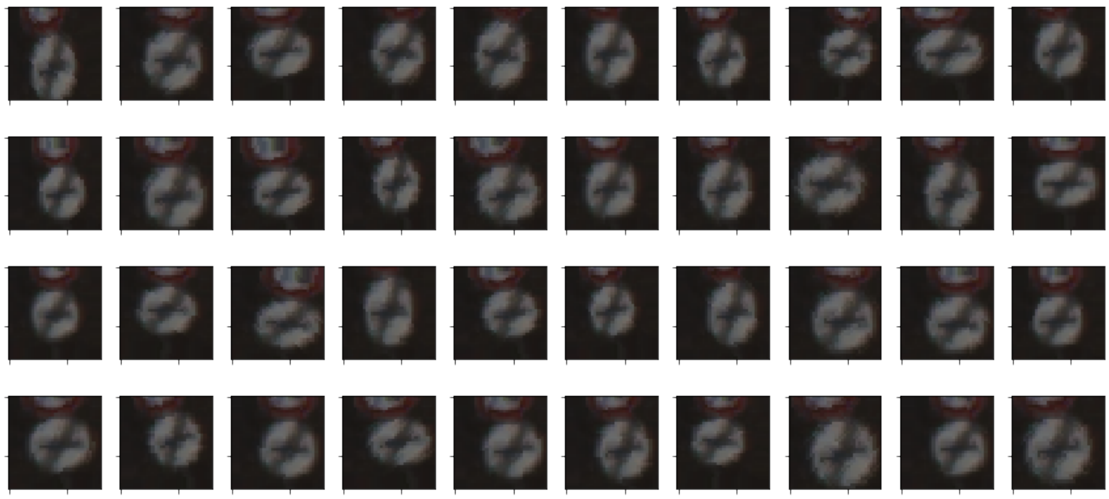
1.5.3 Data Agumentation

```
In [8]: from sklearn.model_selection import train_test_split
        from keras.preprocessing.image import ImageDataGenerator

        # create the generator to perform online data augmentation
        image_datagen = ImageDataGenerator(rotation_range=15.,
                                           zoom_range=0.2,
                                           width_shift_range=0.1,
```

```
                                          height_shift_range=0.1)

    # take a random image from the training set
    img_rgb = X_train[0]

    # plot the original image
    plt.figure(figsize=(1,1))
    plt.imshow(img_rgb)
    plt.title('Example of RGB image (class = {})'.format(y_train[0]))
    plt.show()

    # plot some randomly augmented images
    rows, cols = 4, 10
    fig, ax_array = plt.subplots(rows, cols, figsize=(15,7))
    for ax in ax_array.ravel():
        augmented_img, _ = image_datagen.flow(np.expand_dims(img_rgb, 0), y_train[0:1]).next
        ax.imshow(np.uint8(np.squeeze(augmented_img)))
    plt.setp([a.get_xticklabels() for a in ax_array.ravel()], visible=False)
    plt.setp([a.get_yticklabels() for a in ax_array.ravel()], visible=False)
    plt.suptitle('Random examples of data augmentation (starting from the previous image)')
    plt.show()
```

```
Using TensorFlow backend.
```

Random examples of data augmentation (starting from the previous image)



1.5.4 Question 2

Describe how you set up the training, validation and testing data for your model. ***Optional****: If you generated additional data, how did you generate the data? Why did you generate the data? What are the differences in the new dataset (with generated data) from the original dataset?*

Answer: For the *train, validation and test split*, I just used the ones provided, composed by 34799, 4410 and 12630 examples respectively.

To get *additional data*, I leveraged on the `ImageDataGenerator` class provided in the Keras library. No need to re-invent the wheel! In this way I could perform data augmentation online, during the training. Training images are randomly rotated, zoomed and shifted but just in a narrow range, in order to create some variety in the data while not completely twisting the original feature content. The result of this process of augmentation is visible in the previous figure.

1.5.5 Model Architecture

```
In [9]: ### Define your architecture here.
        ### Feel free to use as many code cells as needed.

        import tensorflow as tf

        from tensorflow.contrib.layers import flatten


        def weight_variable(shape, mu=0, sigma=0.1):
            initialization = tf.truncated_normal(shape=shape, mean=mu, stddev=sigma)
            return tf.Variable(initialization)
```

```
def bias_variable(shape, start_val=0.1):
    initialization = tf.constant(start_val, shape=shape)
    return tf.Variable(initialization)


def conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME'):
    return tf.nn.conv2d(input=x, filter=W, strides=strides, padding=padding)


def max_pool_2x2(x):
    return tf.nn.max_pool(value=x, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SA


# network architecture definition
def my_net(x, n_classes):

    c1_out = 64
    conv1_W = weight_variable(shape=(3, 3, 1, c1_out))
    conv1_b = bias_variable(shape=(c1_out,))
    conv1 = tf.nn.relu(conv2d(x, conv1_W) + conv1_b)

    pool1 = max_pool_2x2(conv1)

    drop1 = tf.nn.dropout(pool1, keep_prob=keep_prob1)

    c2_out = 128
    conv2_W = weight_variable(shape=(3, 3, c1_out, c2_out))
    conv2_b = bias_variable(shape=(c2_out,))
    conv2 = tf.nn.relu(conv2d(drop1, conv2_W) + conv2_b)

    pool2 = max_pool_2x2(conv2)

    drop2 = tf.nn.dropout(pool2, keep_prob=keep_prob2)

    fc0 = tf.concat([flatten(drop1), flatten(drop2)],axis=1)

    fc1_out = 64
    fc1_W = weight_variable(shape=(fc0._shape[1].value, fc1_out))
    fc1_b = bias_variable(shape=(fc1_out,))
    fc1 = tf.matmul(fc0, fc1_W) + fc1_b

    drop_fc1 = tf.nn.dropout(fc1, keep_prob=keep_prob3)

    fc2_out = n_classes
    fc2_W = weight_variable(shape=(drop_fc1._shape[1].value, fc2_out))
    fc2_b = bias_variable(shape=(fc2_out,))
    logits = tf.matmul(drop_fc1, fc2_W) + fc2_b
```

```
    return logits


# placeholders
x = tf.placeholder(dtype=tf.float32, shape=(None, 32, 32, 1))
y = tf.placeholder(dtype=tf.int32, shape=None)
keep_prob1 = tf.placeholder(tf.float32)
keep_prob2 = tf.placeholder(tf.float32)
keep_prob3 = tf.placeholder(tf.float32)


# training pipeline
lr = 0.001
logits = my_net(x, n_classes=n_classes)
cross_entropy = tf.nn.sparse_softmax_cross_entropy_with_logits(logits=logits, labels=y)
loss_function = tf.reduce_mean(cross_entropy)
optimizer = tf.train.AdamOptimizer(learning_rate=lr)
train_step = optimizer.minimize(loss=loss_function)
```

1.5.6 Question 3

What does your final architecture look like? (Type of model, layers, sizes, connectivity, etc.)

Answer: The final architecture is a relatively shallow network made by 4 layers. The first two layers are convolutional, while the third and last are fully connected. Following [Sermanet, LeCun] the output of both the first and second convolutional layers are concatenated and fed to the following dense layer. In this way we provide the fully-connected layer visual patterns at both different levels of abstraction. The last fully-connected layer then maps the prediction into one of the 43 classes.

```
In [10]: # metrics and functions for model evaluation
         correct_prediction = tf.equal(tf.argmax(logits, 1), tf.cast(y, tf.int64))
         accuracy_operation = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

         def evaluate(X_data, y_data):

             num_examples = X_data.shape[0]
             total_accuracy = 0

             sess = tf.get_default_session()
             for offset in range(0, num_examples, BATCHSIZE):
                 batch_x, batch_y = X_data[offset:offset+BATCHSIZE], y_data[offset:offset+BATCHS
                 accuracy = sess.run(accuracy_operation, feed_dict={x: batch_x, y: batch_y, keep
                 total_accuracy += accuracy * len(batch_x)

             return total_accuracy / num_examples

         # create a checkpointer to log the weights during training
         checkpointer = tf.train.Saver()
```

In [11]:
```
# training hyperparameters
BATCHSIZE = 128
EPOCHS = 30
BATCHES_PER_EPOCH = 5000
```

1.5.7 Train, Validate and Test the Model

In [19]:
```
# start training
with tf.Session() as sess:

    sess.run(tf.global_variables_initializer())

    for epoch in range(EPOCHS):

        print("EPOCH {} ...".format(epoch + 1))

        batch_counter = 0
        for batch_x, batch_y in image_datagen.flow(X_train_norm, y_train, batch_size=BA

            batch_counter += 1
            sess.run(train_step, feed_dict={x: batch_x, y: batch_y, keep_prob1: 0.5,kee

            if batch_counter == BATCHES_PER_EPOCH:
                break

        # at epoch end, evaluate accuracy on both training and validation set
        train_accuracy = evaluate(X_train_norm, y_train)
        val_accuracy = evaluate(X_valid_norm, y_valid)
        print('Train Accuracy = {:.3f} - Validation Accuracy: {:.3f}'.format(train_accu

        # log current weights
        #helps to load model with last best set of weights
        checkpointer.save(sess, save_path='../checkpoints/traffic_sign_model.ckpt', glo
```

```
EPOCH 1 ...
Train Accuracy = 0.947 - Validation Accuracy: 0.876
EPOCH 2 ...
Train Accuracy = 0.982 - Validation Accuracy: 0.918
EPOCH 3 ...
Train Accuracy = 0.991 - Validation Accuracy: 0.925
EPOCH 4 ...
Train Accuracy = 0.995 - Validation Accuracy: 0.949
EPOCH 5 ...
Train Accuracy = 0.996 - Validation Accuracy: 0.940
EPOCH 6 ...
Train Accuracy = 0.996 - Validation Accuracy: 0.945
EPOCH 7 ...
Train Accuracy = 0.996 - Validation Accuracy: 0.954
```

```
EPOCH 8 ...
Train Accuracy = 0.998 - Validation Accuracy: 0.956
EPOCH 9 ...
Train Accuracy = 0.997 - Validation Accuracy: 0.953
EPOCH 10 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.956
EPOCH 11 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.958
EPOCH 12 ...
Train Accuracy = 0.998 - Validation Accuracy: 0.961
EPOCH 13 ...
Train Accuracy = 0.998 - Validation Accuracy: 0.957
EPOCH 14 ...
Train Accuracy = 0.997 - Validation Accuracy: 0.952
EPOCH 15 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.955
EPOCH 16 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.962
EPOCH 17 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.961
EPOCH 18 ...
Train Accuracy = 0.996 - Validation Accuracy: 0.950
EPOCH 19 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.960
EPOCH 20 ...
Train Accuracy = 0.997 - Validation Accuracy: 0.956
EPOCH 21 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.959
EPOCH 22 ...
Train Accuracy = 0.998 - Validation Accuracy: 0.966
EPOCH 23 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.965
EPOCH 24 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.960
EPOCH 25 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.954
EPOCH 26 ...
Train Accuracy = 0.998 - Validation Accuracy: 0.961
EPOCH 27 ...
Train Accuracy = 0.998 - Validation Accuracy: 0.959
EPOCH 28 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.958
EPOCH 29 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.954
EPOCH 30 ...
Train Accuracy = 0.999 - Validation Accuracy: 0.959
```

In [53]: os.listdir("../checkpoints")

```
Out[53]: ['checkpoint',
 'traffic_sign_model.ckpt-27.index',
 'traffic_sign_model.ckpt-29.meta',
 'traffic_sign_model.ckpt-29.data-00000-of-00001',
 'traffic_sign_model.ckpt-25.data-00000-of-00001',
 'traffic_sign_model.ckpt-26.data-00000-of-00001',
 'traffic_sign_model.ckpt-28.data-00000-of-00001',
 'traffic_sign_model.ckpt-25.meta',
 'traffic_sign_model.ckpt-27.meta',
 'traffic_sign_model.ckpt-26.meta',
 'traffic_sign_model.ckpt-26.index',
 'traffic_sign_model.ckpt-27.data-00000-of-00001',
 'traffic_sign_model.ckpt-28.meta',
 'traffic_sign_model.ckpt-29.index',
 'traffic_sign_model.ckpt-28.index',
 'traffic_sign_model.ckpt-25.index']
```

In [12]:
```
# testing the model
with tf.Session() as sess:

    # I don't know why checkpoints before 25 were not saved, so using other saved sessi
    checkpointer.restore(sess, '../checkpoints/traffic_sign_model.ckpt-28')

    test_accuracy = evaluate(X_test_norm, y_test)
    print('Performance on test set: {:.3f}'.format(test_accuracy))
```

```
INFO:tensorflow:Restoring parameters from ../checkpoints/traffic_sign_model.ckpt-28
Performance on test set: 0.953
```

1.5.8 Question 4

How did you train your model? (Type of optimizer, batch size, epochs, hyperparameters, etc.)

Answer: For the trainig I used *Adam optimizer*, which often proves to be a good choice to avoid the patient search of the right parameters for SGD. *Batchsize* was set to 128 due to memory constraint. Every 5000 batches visited, an evaluation on both training and validation set is performed. In order to avoid overfitting, both data augmentation and dropout (with different drop probability in different layers) are employed extensively.

1.5.9 Question 5

What approach did you take in coming up with a solution to this problem? It may have been a process of trial and error, in which case, outline the steps you took to get to the final solution and why you chose those steps. Perhaps your solution involved an already well known implementation or architecture. In this case, discuss why you think this is suitable for the current problem.

Answer: The network architecture is based on the paper [Sermanet, LeCun], in which the authors tackle the same problem (traffic sign classification), though using a different dataset. In section *II-A* of the paper, the authors explain that they found beneficial to feed the dense layers with the output of both the previous convolutional layers. Indeed, in this way the classifier is explicitly provided both the local "motifs" (learned by conv1) and the more "global" shapes and structure (learned by conv2) found in the features. I tried to replicate the same architecture, made by 2 convolutional and 2 fully connected layers.

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 [13]:
```
### Load the images and plot them here.
### Feel free to use as many code cells as needed.

### Load the images and plot them here.
import os

# load new images
new_images_dir = '../new_signs'
new_test_images = [os.path.join(new_images_dir, f) for f in os.listdir(new_images_dir)
new_test_images = [cv2.resize(cv2.imread(f), (32, 32)) for f in new_test_images]
new_test_images = [cv2.cvtColor(f, cv2.COLOR_BGR2RGB) for f in new_test_images]

# manually annotated labels for these new images
new_targets = [3, 25, 22, 17, 14]

# plot new test images
fig, axarray = plt.subplots(1, len(new_test_images))
for i, ax in enumerate(axarray.ravel()):
    ax.imshow(new_test_images[i])
    ax.set_title('{}'.format(i))
    plt.setp(ax.get_xticklabels(), visible=False)
    plt.setp(ax.get_yticklabels(), visible=False)
    ax.set_xticks([]), ax.set_yticks([])
```

1.6.2 Predict the Sign Type for Each Image

```
In [15]: ### 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.

         # first things first: feature preprocessing
         new_test_images_norm = preprocess_features(new_test_images)

         with tf.Session() as sess:

             # restore saved session
             checkpointer.restore(sess, '../checkpoints/traffic_sign_model.ckpt-28')

             # predict on unseen images
             prediction = np.argmax(np.array(sess.run(logits, feed_dict={x: new_test_images_norm

         for i, pred in enumerate(prediction):
             print('Image {} - Target = {:02d}, Predicted = {:02d}'.format(i, new_targets[i], pr

         print('> Model accuracy: {:.02f}'.format(np.sum(new_targets==prediction)/len(new_target
```

```
INFO:tensorflow:Restoring parameters from ../checkpoints/traffic_sign_model.ckpt-28
Image 0 - Target = 03, Predicted = 03
Image 1 - Target = 25, Predicted = 25
Image 2 - Target = 22, Predicted = 22
Image 3 - Target = 17, Predicted = 14
Image 4 - Target = 14, Predicted = 14
> Model accuracy: 0.80
```

1.6.3 Question 6

Choose five candidate images of traffic signs and provide them in the report. Are there any particular qualities of the image(s) that might make classification difficult? It could be helpful to plot the images in the notebook.

Answer: All the previous 5 images are taken from web, some of them have bad lighting and are hazy.

1.6.4 Question 7

Is your model able to perform equally well on captured pictures when compared to testing on the dataset? The simplest way to do this check the accuracy of the predictions. For example, if the model predicted 1 out of 5 signs correctly, it's 20% accurate.

Answer: Evaluated on these 5 newly captured pictures, the model accuracy results 80%. While it's true that the performance drop w.r.t. the test set is high (around 15%), we must keep in mind that 5 images are too few to be of any statistical significance.

1.6.5 Analyze Performance

1.6.6 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.

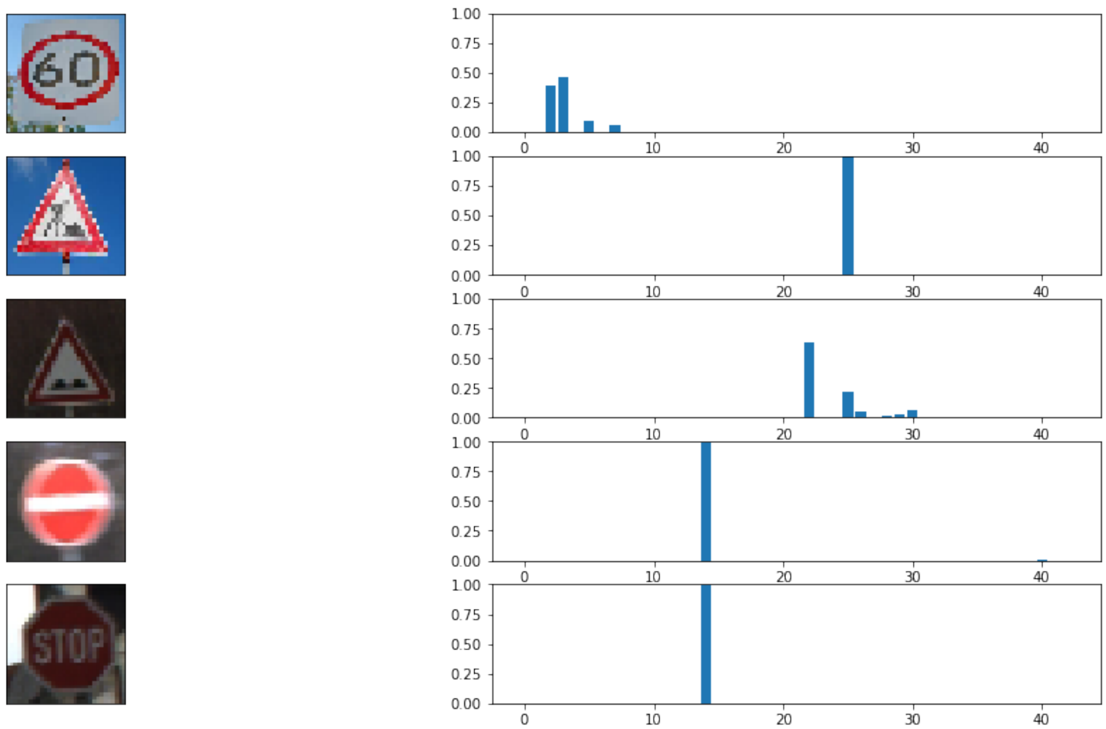
```
In [18]: ### Print out the top five softmax probabilities for the predictions on the German traf
         ### Feel free to use as many code cells as needed.
```

```python
# visualizing softmax probabilities
with tf.Session() as sess:

    # restore saved session
    checkpointer.restore(sess, '../checkpoints/traffic_sign_model.ckpt-28')

    # certainty of predictions
    K = 3
    top_3 = sess.run(tf.nn.top_k(logits, k=K), feed_dict={x: new_test_images_norm, keep

    # compute softmax probabilities
    softmax_probs = sess.run(tf.nn.softmax(logits), feed_dict={x: new_test_images_norm,

# plot softmax probs along with traffic sign examples
n_images = new_test_images_norm.shape[0]
fig, axarray = plt.subplots(n_images, 2, figsize = (17,9))
plt.suptitle('Visualization of softmax probabilities for each example', fontweight='bol
for r in range(0, n_images):
    axarray[r, 0].imshow(np.squeeze(new_test_images[r]))
    axarray[r, 0].set_xticks([]), axarray[r, 0].set_yticks([])
    plt.setp(axarray[r, 0].get_xticklabels(), visible=False)
    plt.setp(axarray[r, 0].get_yticklabels(), visible=False)
    axarray[r, 1].bar(np.arange(n_classes), softmax_probs[r])
    axarray[r, 1].set_ylim([0, 1])

# print top K predictions of the model for each example, along with confidence (softmax
for i in range(len(new_test_images)):
    print('Top {} model predictions for image {} (Target is {:02d})'.format(K, i, new_t
    for k in range(K):
        top_c = top_3[1][i][k]
        print('   Prediction = {:02d} with confidence {:.2f}'.format(top_c, softmax_pro
```

```
INFO:tensorflow:Restoring parameters from ../checkpoints/traffic_sign_model.ckpt-28
Top 3 model predictions for image 0 (Target is 03)
   Prediction = 03 with confidence 0.46
   Prediction = 02 with confidence 0.38
   Prediction = 05 with confidence 0.10
Top 3 model predictions for image 1 (Target is 25)
   Prediction = 25 with confidence 1.00
   Prediction = 28 with confidence 0.00
   Prediction = 30 with confidence 0.00
Top 3 model predictions for image 2 (Target is 22)
   Prediction = 22 with confidence 0.63
   Prediction = 25 with confidence 0.21
   Prediction = 30 with confidence 0.06
Top 3 model predictions for image 3 (Target is 17)
   Prediction = 14 with confidence 1.00
```

```
    Prediction = 40 with confidence 0.00
    Prediction = 17 with confidence 0.00
Top 3 model predictions for image 4 (Target is 14)
    Prediction = 14 with confidence 0.99
    Prediction = 02 with confidence 0.00
    Prediction = 01 with confidence 0.00
```

Visualization of softmax probabilities for each example



1.6.7 Question 8

Use the model's softmax probabilities to visualize the ***certainty*** *of its predictions,* `tf.nn.top_k` *could prove helpful here. Which predictions is the model certain of? Uncertain? If the model was incorrect in its initial prediction, does the correct prediction appear in the top k? (k should be 5 at most)*

Answer: As immediately emerges from the plot above, our model is quite sure of which class the second and fifth traffic signs belong, but it's slightly confused on the first and third. Indeed, in the fourth image the model is not only able to predict the right class, but shows also an high confidence, in this case example (no-entry sign) model's prediction is wrong, nonetheless the correct target appears in the top 3 predictions, which is encouraging.

In the first image of (Speed limit (60km/h)) the model got confused with (Speed limit 50km/h) and (Speed limit 80km/h) signs. In third image the confidence for right class is quite higher than other confused classes.