Self-Driving Car Engineer Nanodegree

Deep Learning

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. Sections that begin with **'Implementation'** in the header indicate where you should begin your implementation for your project. Note that some sections of implementation are optional, and will be marked with **'Optional'** in the header.

In addition to implementing code, there will be questions that you must answer which relate to the project and your implementation. Each section where you will answer a question is preceded by a **'Question'** header. Carefully read each question and provide thorough answers in the following text boxes that begin with **'Answer:'**. Your project submission will be evaluated based on your answers to each of the questions and the implementation you provide.

> **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.

In [2]:

```
# Load pickled data
import pickle

# TODO: fill this in based on where you saved the training and testin
g data
training_file = "data/train.p"
testing_file = "data/test.p"

with open(training_file, mode='rb') as f:
    train = pickle.load(f)


X_train, y_train = train['features'], train['labels']
```

Step 1: Dataset Exploration

Visualize the German Traffic Signs Dataset. This is open ended, some suggestions include: plotting traffic signs images, plotting the count of each sign, etc. Be creative!

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

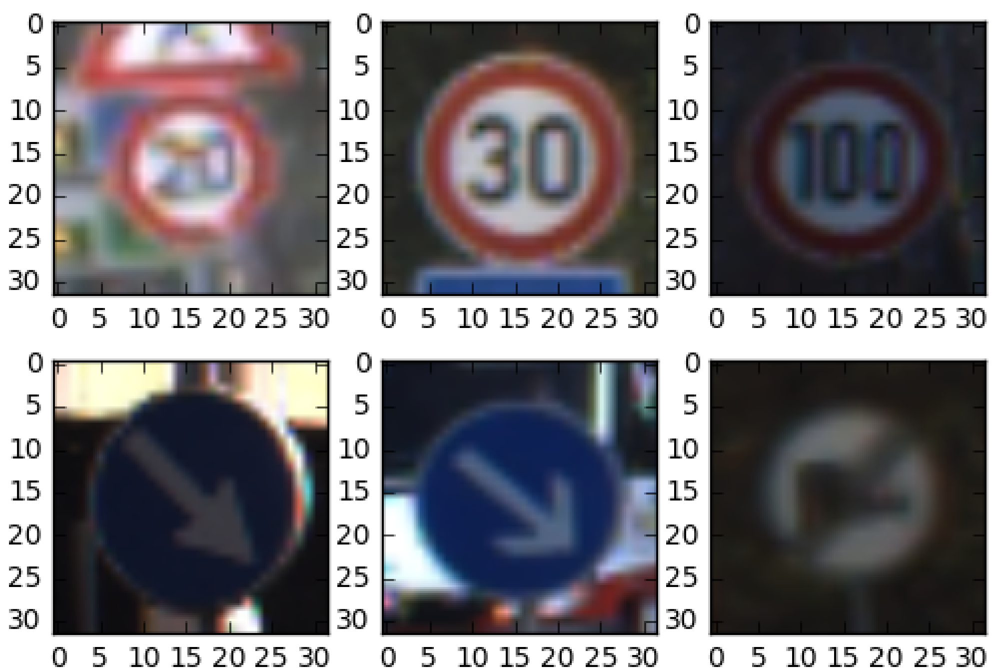
- features -> the images pixel values, (width, height, channels)
- labels -> the label of the traffic sign
- sizes -> the original width and height of the image, (width, height)
- coords -> coordinates of a bounding box around the sign in the image, (x1, y1, x2, y2). Based the original image (not the resized version).

In [3]:
```
n_train = len(X_train)
n_classes = len(set(y_train))
image_shape = X_train[0].shape

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

```
Number of training examples = 39209
Number of classes = 43
Image data shape = (32, 32, 3)
```

In [4]:
```
### Data exploration visualization goes here.
### Feel free to use as many code cells as needed.
%matplotlib inline
import matplotlib.pyplot as plt


fig = plt.figure()
fig.add_subplot(231)
plt.imshow(X_train[0])
fig.add_subplot(232)
plt.imshow(X_train[500])
fig.add_subplot(233)
plt.imshow(X_train[11600])
fig.add_subplot(234)
plt.imshow(X_train[-3010])
fig.add_subplot(235)
plt.imshow(X_train[-2050])
fig.add_subplot(236)
plt.imshow(X_train[-80])
```

Out[4]: <matplotlib.image.AxesImage at 0x7f8566d75048>



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 (http://benchmark.ini.rub.de/?section=gtsrb&subsection=dataset).

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

- Your model can be derived from a deep feedforward net or a deep convolutional network.
- 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 (http://yann.lecun.com/exdb/publis/pdf/sermanet-ijcnn-11.pdf). 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.

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.

In [5]:

```
from keras.preprocessing.image import ImageDataGenerator
from keras.models import Sequential, Model
from keras.layers import Dense, Dropout, Activation, Flatten, Merge
from keras.layers import Convolution2D, MaxPooling2D
from keras.optimizers import SGD
from keras.utils import np_utils

Y_train = np_utils.to_categorical(y_train, n_classes)
X_train = X_train.astype('float32')
X_train /= 255
```

```
Using TensorFlow backend.
```

In [6]:

```
from sklearn.model_selection import train_test_split
X_tr, X_val, Y_tr, Y_val = train_test_split(X_train, Y_train, test_si
ze=0.2, random_state=1)

datagen = ImageDataGenerator(
    rotation_range=3,
    width_shift_range=0.03,
    height_shift_range=0.03)
```

In [7]:
```
model = Sequential()

model.add(Convolution2D(32, 3, 3, border_mode='same',
                        input_shape=X_train.shape[1:]))
model.add(Activation('relu'))
model.add(Convolution2D(32, 3, 3))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Convolution2D(64, 3, 3, border_mode='same'))
model.add(Activation('relu'))
model.add(Convolution2D(64, 3, 3))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu'))
model.add(Dropout(0.5))
model.add(Dense(n_classes))
model.add(Activation('softmax'))

model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

In [12]:
```
from keras.callbacks import ModelCheckpoint
model.fit_generator(generator=datagen.flow(X_tr, Y_tr,
batch_size=35),
          samples_per_epoch=X_tr.shape[0],
          nb_epoch=35,
          validation_data=(X_val, Y_val),
          callbacks=
[ModelCheckpoint('model.h5',save_best_only=True)])
```

```
Epoch 1/35
31367/31367 [==============================] - 12s - loss: 2.4234 - a
cc: 0.3024 - val_loss: 0.7899 - val_acc: 0.7780
Epoch 2/35
31367/31367 [==============================] - 9s - loss: 0.5653 - ac
c: 0.8142 - val_loss: 0.1122 - val_acc: 0.9695
Epoch 3/35
31367/31367 [==============================] - 9s - loss: 0.2560 - ac
c: 0.9155 - val_loss: 0.0520 - val_acc: 0.9862
Epoch 4/35
31367/31367 [==============================] - 9s - loss: 0.1743 - ac
c: 0.9454 - val_loss: 0.0375 - val_acc: 0.9901
Epoch 5/35
31367/31367 [==============================] - 9s - loss: 0.1367 - ac
c: 0.9583 - val_loss: 0.0271 - val_acc: 0.9929
Epoch 6/35
31367/31367 [==============================] - 9s - loss: 0.1075 - ac
c: 0.9668 - val_loss: 0.0199 - val_acc: 0.9941
Epoch 7/35
31367/31367 [==============================] - 9s - loss: 0.0954 - ac
c: 0.9708 - val_loss: 0.0210 - val_acc: 0.9945
Epoch 8/35
31367/31367 [==============================] - 9s - loss: 0.0898 - ac
c: 0.9724 - val_loss: 0.0162 - val_acc: 0.9952
Epoch 9/35
31367/31367 [==============================] - 9s - loss: 0.0766 - ac
c: 0.9768 - val_loss: 0.0087 - val_acc: 0.9977
Epoch 10/35
31367/31367 [==============================] - 9s - loss: 0.0717 - ac
c: 0.9774 - val_loss: 0.0136 - val_acc: 0.9966
Epoch 11/35
31367/31367 [==============================] - 9s - loss: 0.0656 - ac
c: 0.9793 - val_loss: 0.0090 - val_acc: 0.9973
Epoch 12/35
31367/31367 [==============================] - 9s - loss: 0.0659 - ac
c: 0.9790 - val_loss: 0.0105 - val_acc: 0.9972
Epoch 13/35
31367/31367 [==============================] - 9s - loss: 0.0658 - ac
c: 0.9796 - val_loss: 0.0078 - val_acc: 0.9980
Epoch 14/35
31367/31367 [==============================] - 9s - loss: 0.0612 - ac
c: 0.9818 - val_loss: 0.0147 - val_acc: 0.9948
Epoch 15/35
31367/31367 [==============================] - 9s - loss: 0.0588 - ac
c: 0.9816 - val_loss: 0.0057 - val_acc: 0.9985
Epoch 16/35
31367/31367 [==============================] - 9s - loss: 0.0556 - ac
c: 0.9827 - val_loss: 0.0062 - val_acc: 0.9983
Epoch 17/35
31367/31367 [==============================] - 9s - loss: 0.0567 - ac
c: 0.9830 - val_loss: 0.0084 - val_acc: 0.9977
Epoch 18/35
31367/31367 [==============================] - 9s - loss: 0.0533 - ac
c: 0.9836 - val_loss: 0.0046 - val_acc: 0.9986
Epoch 19/35
31367/31367 [==============================] - 10s - loss: 0.0512 - a
cc: 0.9856 - val_loss: 0.0109 - val_acc: 0.9960
```

```
Epoch 20/35
31367/31367 [==============================] - 9s - loss: 0.0500 - ac
c: 0.9848 - val_loss: 0.0032 - val_acc: 0.9996
Epoch 21/35
31367/31367 [==============================] - 9s - loss: 0.0472 - ac
c: 0.9857 - val_loss: 0.0065 - val_acc: 0.9989
Epoch 22/35
31367/31367 [==============================] - 9s - loss: 0.0489 - ac
c: 0.9854 - val_loss: 0.0055 - val_acc: 0.9986
Epoch 23/35
31367/31367 [==============================] - 10s - loss: 0.0458 - a
cc: 0.9861 - val_loss: 0.0052 - val_acc: 0.9982
Epoch 24/35
31367/31367 [==============================] - 9s - loss: 0.0445 - ac
c: 0.9864 - val_loss: 0.0066 - val_acc: 0.9983
Epoch 25/35
31367/31367 [==============================] - 9s - loss: 0.0456 - ac
c: 0.9864 - val_loss: 0.0060 - val_acc: 0.9986
Epoch 26/35
31367/31367 [==============================] - 10s - loss: 0.0437 - a
cc: 0.9872 - val_loss: 0.0061 - val_acc: 0.9985
Epoch 27/35
31367/31367 [==============================] - 9s - loss: 0.0448 - ac
c: 0.9863 - val_loss: 0.0068 - val_acc: 0.9981
Epoch 28/35
31367/31367 [==============================] - 9s - loss: 0.0406 - ac
c: 0.9883 - val_loss: 0.0063 - val_acc: 0.9986
Epoch 29/35
31367/31367 [==============================] - 9s - loss: 0.0483 - ac
c: 0.9862 - val_loss: 0.0050 - val_acc: 0.9989
Epoch 30/35
31367/31367 [==============================] - 9s - loss: 0.0420 - ac
c: 0.9882 - val_loss: 0.0050 - val_acc: 0.9986
Epoch 31/35
31367/31367 [==============================] - 9s - loss: 0.0437 - ac
c: 0.9877 - val_loss: 0.0053 - val_acc: 0.9992
Epoch 32/35
31367/31367 [==============================] - 9s - loss: 0.0427 - ac
c: 0.9875 - val_loss: 0.0026 - val_acc: 0.9991
Epoch 33/35
31367/31367 [==============================] - 9s - loss: 0.0407 - ac
c: 0.9885 - val_loss: 0.0059 - val_acc: 0.9986
Epoch 34/35
31367/31367 [==============================] - 9s - loss: 0.0396 - ac
c: 0.9891 - val_loss: 0.0037 - val_acc: 0.9989
Epoch 35/35
31367/31367 [==============================] - 9s - loss: 0.0426 - ac
c: 0.9883 - val_loss: 0.0032 - val_acc: 0.9992
```

Out[12]:
```
<keras.callbacks.History at 0x7fcd4ce05b38>
```

In [8]:
```
with open(testing_file, mode='rb') as f:
    test = pickle.load(f)

model.load_weights("model.h5")
X_test, y_test = test['features'], test['labels']

Y_test = np_utils.to_categorical(y_test, n_classes)
X_test = X_test.astype('float32')
X_test /= 255

score = model.evaluate(X_test, Y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
```

```
Test score: 0.0884608608286
Test accuracy: 0.98060174196
```

Question 1

Describe the techniques used to preprocess the data.

Answer:

I converted the feature data to float32 and one hot encoded the labels. I also jittered the images to create multiple perspectives of the feature data allowing for a more generalized model.

Question 2

Describe how you set up the training, validation and testing data for your model. If you generated additional data, why?

Answer:

I used scit-kit learns train_test_split function to split 20% of the training data into a validation set and then kept the training and testing data seperate. I technically generated data by jittering the images, and I did this for the reasons stated in the answer to question 1.

Question 3

What does your final architecture look like? (Type of model, layers, sizes, connectivity, etc.) For reference on how to build a deep neural network using TensorFlow, see Deep Neural Network in TensorFlow (https://classroom.udacity.com/nanodegrees/nd013/parts/fbf77062-5703-404e-b60c-95b78b2f3f9e/modules/6df7ae49-c61c-4bb2-a23e-6527e69209ec/lessons/b516a270-8600-4f93-a0a3-20dfeabe5da6/concepts/83a3a2a2-a9bd-4b7b-95b0-eb924ab14432) from the classroom.

Answer:

I tested multiple architechture styles, and the most optimal solution was the one provided as an example in the Keras repo for CIFAR-10 (https://github.com/fchollet/keras/blob/master/examples/cifar10_cnn.py (https://github.com/fchollet/keras/blob/master/examples/cifar10_cnn.py)). It trained relatively fast compared to the two previous architechtures I tried to come up with, and it provided good results in and out of sample (~98% for both).

Question 4

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

Answer:

I used the adam optimizer, a batch size of 35, and trained with 35 epochs. Dropout for each layer of the network varied and I used what was recommended by the Keras repo.

Question 5

What approach did you take in coming up with a solution to this problem?

Answer:

I first tried to develop a model intuitively. However, this yieled slow training and not very accurate models. I then decided to rely on existing architechtures and that's when I came across the model from the Keras repo that I used.

Step 3: Test a Model on New Images

Take several pictures of traffic signs that you find on the web or around you (at least five), and run them through your classifier on your computer to produce example results. The classifier might not recognize some local signs but it could prove interesting nonetheless.

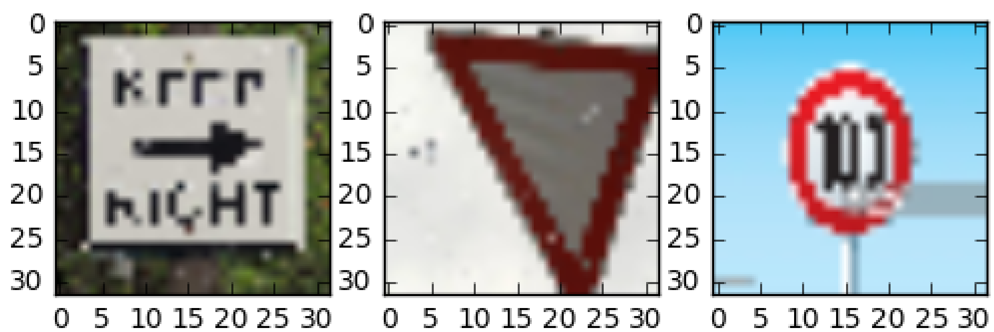
You may find `signnames.csv` useful as it contains mappings from the class id (integer) to the actual sign name.

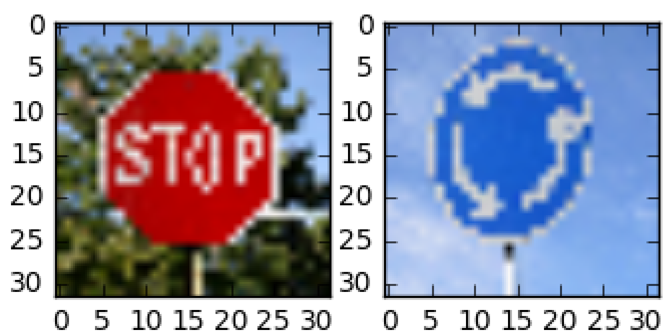
Implementation

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.

In [19]:
```
from keras.preprocessing.image import load_img
import matplotlib.pyplot as plt
import glob
import numpy as np
%matplotlib inline

path_list = glob.glob('new_images/*.png')
images = [load_img(filename) for filename in path_list]

images = [image.resize((32,32)) for image in images]

fig = plt.figure()
fig.add_subplot(131)
plt.imshow(images[0])
fig.add_subplot(132)
plt.imshow(images[1])
fig.add_subplot(133)
plt.imshow(images[2])

fig = plt.figure()
fig.add_subplot(131)
fig.add_subplot(131)
plt.imshow(images[3])
fig.add_subplot(132)
plt.imshow(images[4])
```

Out[19]: <matplotlib.image.AxesImage at 0x7f84dc59f748>





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 would be helpful to plot the images in the notebook.

Answer:

Two of the signs are American and not german. However, the images are close enough to the german signs that it should guess correctly. (stop sign, keep right)

In [22]:
```
X = np.array([np.array(image).astype('float32')/255 for image in imag
es])
preds = model.predict(X)
```

Question 7

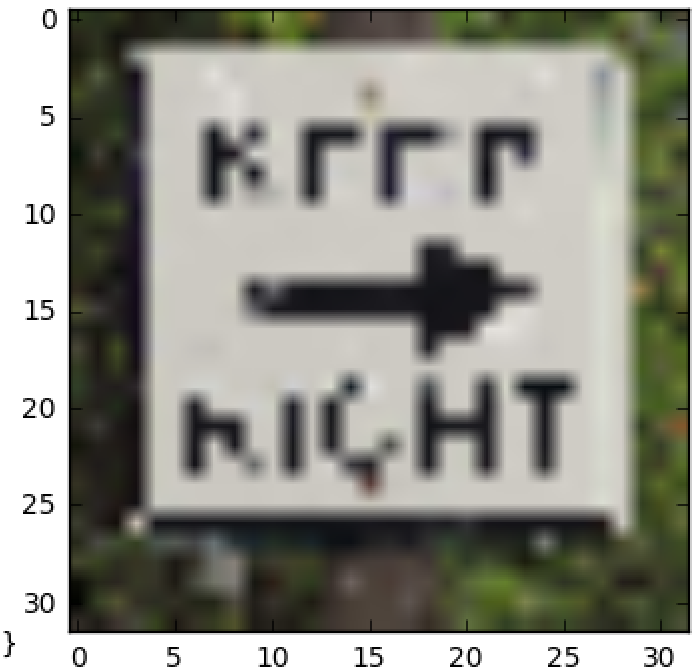
Is your model able to perform equally well on captured pictures or a live camera stream when compared to testing on the dataset?

Answer:

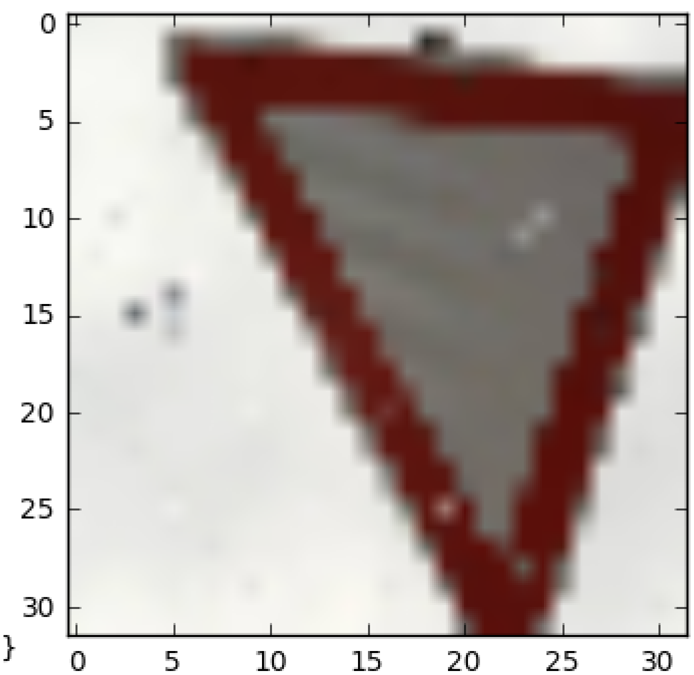
The model was able to correctly guess all capture pictures. Live camera stream was not tested.

In [46]:
```
caption = []
for (image, (answer, confs)) in zip(images, zip(list(map(np.argmax, p
reds)), preds)):
    caption.append({answer:confs[answer]})

for cap, image in zip(caption, images):
    fig = plt.figure()
    fig.text(0,.1, cap)
    plt.imshow(image)
```

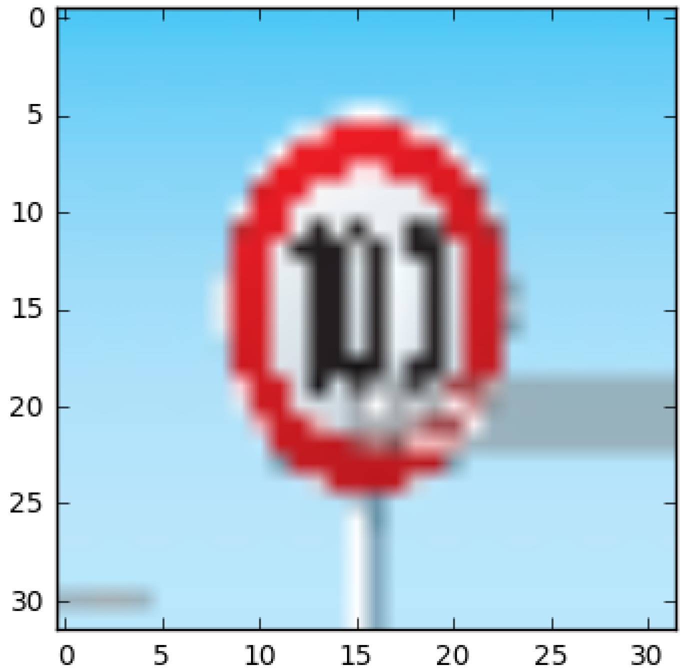
```
[{12: 0.87700701}, {13: 0.99999952}, {7: 0.65676087}, {14: 1.0}, {40:
 1.0}]
```



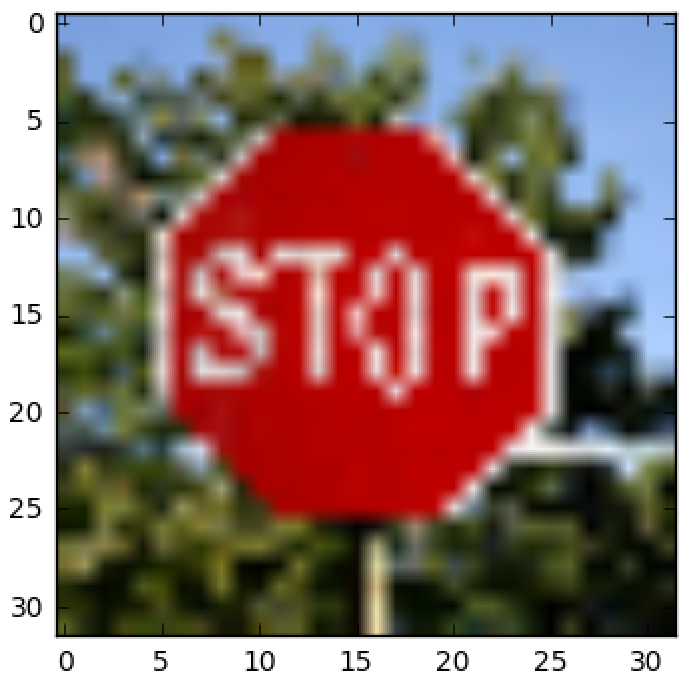
{12: 0.87700701}



{13: 0.99999952}

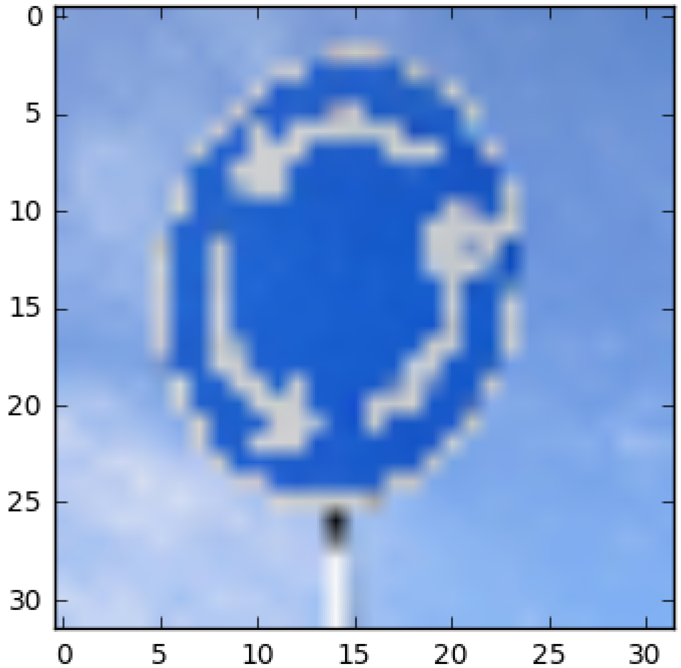


{7: 0.65676087}



{14: 1.0}

{40: 1.0}



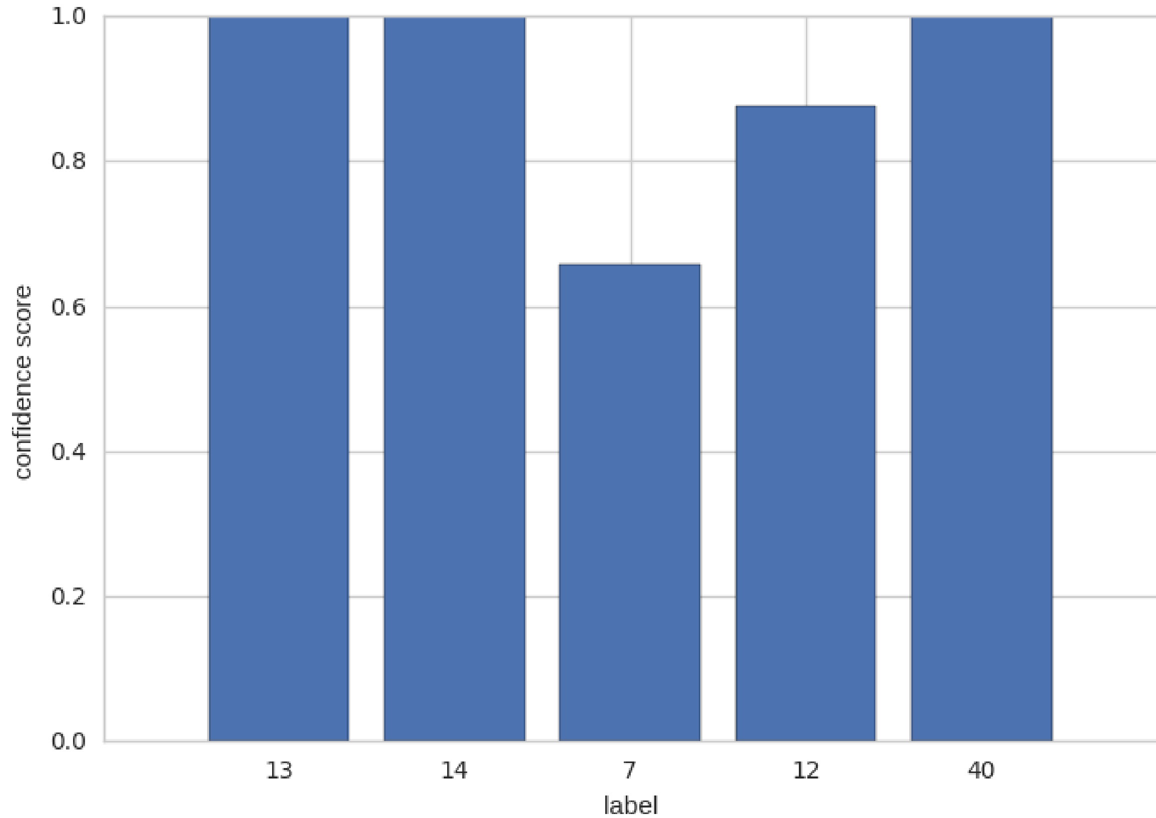
Question 8

*Use the model's softmax probabilities to visualize the **certainty** of its predictions, [`tf.nn.top_k`](https://www.tensorflow.org/versions/r0.11/api_docs/python/nn.html#top_k) (https://www.tensorflow.org/versions/r0.11/api_docs/python/nn.html#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:

Three of the five images had a 100% confidence score while the other two had scores above 50%. All images were classified correctly.

In [59]:
```
import matplotlib.pyplot as plt
data = {}
for (img, (answer, confs)) in zip(small_images, zip(list(map(np.argma
x, preds)), preds)):
    data.update({str(answer):confs[answer]})
plt.bar(range(len(data)), data.values(), align='center')
plt.xticks(range(len(data)), data.keys())
plt.ylabel('confidence score')
plt.xlabel('label')
plt.show()
```



Question 9

If necessary, provide documentation for how an interface was built for your model to load and classify newly-acquired images.

Answer: I acquired images through Google search, resized them, converted them to float32 and normalized them just like I did with the training set.

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