```
Jupyter Server URI:
http://localhost:8915/?token=aa83df93211dea532690c3f79a152d067d90e443b5374bcf
Python version:
3.7.3 (default, Mar 27 2019, 16:54:48) \n[Clang 4.0.1
(tags/RELEASE_401/final)]
/anaconda3/envs/IntroToTensorFlow/bin/python
Jupyter Notebook Version: (5, 7, 8)
```

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.

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

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

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

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

Step 0: Load The Data

[1]

```
from scipy.interpolate import interpolate...
```

```
/anaconda3/envs/IntroToTensorFlow/lib/python3.7/importlib/_bootstrap.py:219:
RuntimeWarning: compiletime version 3.6 of module
'tensorflow.python.framework.fast_tensor_util' does not match runtime version
3.7 return f(*args, **kwds)
```

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 of 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.

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

[2]

```
# Replace each question mark with the appropriate value....
```

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

Include an exploratory visualization of the dataset

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

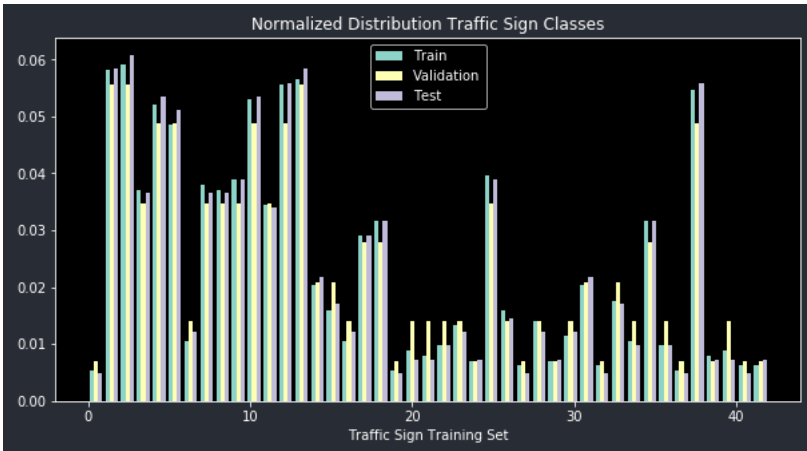
The Matplotlib examples and gallery pages are a great resource for doing visualizations in Python.

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

[3]

```
# Data exploration visualization code goes here....
```

```
/anaconda3/envs/IntroToTensorFlow/lib/python3.7/site-packages/matplotlib/axes/_axes.py:6521: MatplotlibDeprecationWarning: The 'normed' kwarg was deprecated in Matplotlib 2.1 and will be removed in 3.1. Use 'density' instead. alternative="'density'", removal="3.1")
<function matplotlib.pyplot.show(*args, **kw)>
```



Step 2: Design and Test a Model Architecture

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

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

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

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

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

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

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

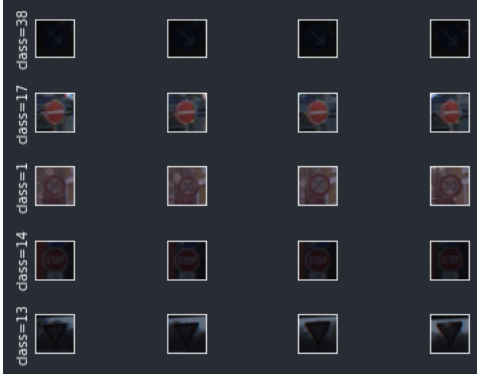
Minimally, the image data should be normalized so that the data has mean zero and equal variance. For image data, `(pixel - 128)/ 128` is a quick way to approximately normalize the data and can be used in this project.

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

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

[4]

```
# Preprocess the data here. It is required to normalize the data. Other preprocessing
steps could include...
Updated Image Shape: (32, 32, 3)
```



Model Architecture

[5]

```
def LeNet(x, keep_prob):...
```

[6]

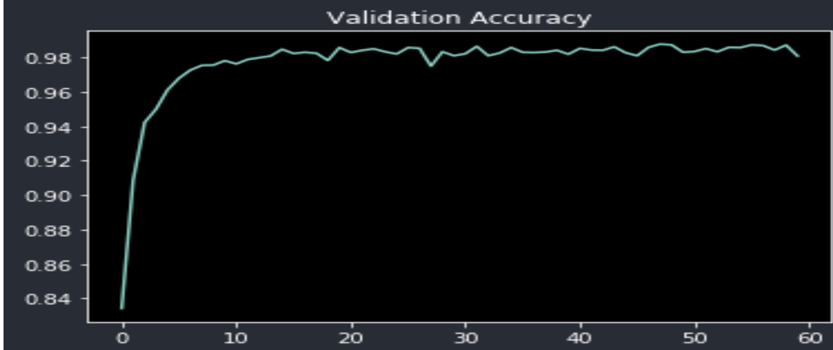
```
# Train your model here....
WARNING:tensorflow:From /anaconda3/envs/IntroToTensorFlow/lib/python3.7/site-
packages/tensorflow/python/framework/op_def_library.py:263: colocate_with
(from tensorflow.python.framework.ops) is deprecated and will be removed in a
future version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From /anaconda3/envs/IntroToTensorFlow/lib/python3.7/site-
packages/tensorflow/contrib/layers/python/layers/layers.py:1624: flatten
(from tensorflow.python.layers.core) is deprecated and will be removed in a
future version.
Instructions for updating:
Use keras.layers.flatten instead.
WARNING:tensorflow:From <ipython-input-5-8757814af4f3>:49: calling dropout
(from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be
removed in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 -
keep_prob`.
WARNING:tensorflow:From <ipython-input-6-b0bd01cb05fc>:19:
softmax_cross_entropy_with_logits (from tensorflow.python.ops.nn_ops) is
deprecated and will be removed in a future version.
Instructions for updating:

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

See `tf.nn.softmax_cross_entropy_with_logits_v2`.

Training...

EPOCH 1 ...
Validation Accuracy = 0.834
```

```
EPOCH 2 ...
Validation Accuracy = 0.909

EPOCH 3 ...
Validation Accuracy = 0.942

EPOCH 4 ...
Validation Accuracy = 0.950

EPOCH 5 ...
Validation Accuracy = 0.961

EPOCH 6 ...
Validation Accuracy = 0.968

EPOCH 7 ...
Validation Accuracy = 0.973

EPOCH 8 ...
Validation Accuracy = 0.975

EPOCH 9 ...
Validation Accuracy = 0.976

EPOCH 10 ...
Validation Accuracy = 0.978

EPOCH 11 ...
Validation Accuracy = 0.976

EPOCH 12 ...
Validation Accuracy = 0.979

EPOCH 13 ...
Validation Accuracy = 0.980

EPOCH 14 ...
Validation Accuracy = 0.981

EPOCH 15 ...
Validation Accuracy = 0.985

EPOCH 16 ...
Validation Accuracy = 0.982

EPOCH 17 ...
Validation Accuracy = 0.983

EPOCH 18 ...
Validation Accuracy = 0.982

EPOCH 19 ...
Validation Accuracy = 0.978

EPOCH 20 ...
Validation Accuracy = 0.986
```

```
EPOCH 21 ...
Validation Accuracy = 0.983

EPOCH 22 ...
Validation Accuracy = 0.984

EPOCH 23 ...
Validation Accuracy = 0.985

EPOCH 24 ...
Validation Accuracy = 0.983

EPOCH 25 ...
Validation Accuracy = 0.982

EPOCH 26 ...
Validation Accuracy = 0.986

EPOCH 27 ...
Validation Accuracy = 0.985

EPOCH 28 ...
Validation Accuracy = 0.975

EPOCH 29 ...
Validation Accuracy = 0.983

EPOCH 30 ...
Validation Accuracy = 0.981

EPOCH 31 ...
Validation Accuracy = 0.982

EPOCH 32 ...
Validation Accuracy = 0.986

EPOCH 33 ...
Validation Accuracy = 0.981

EPOCH 34 ...
Validation Accuracy = 0.983

EPOCH 35 ...
Validation Accuracy = 0.986

EPOCH 36 ...
Validation Accuracy = 0.983

EPOCH 37 ...
Validation Accuracy = 0.983

EPOCH 38 ...
Validation Accuracy = 0.983

EPOCH 39 ...
Validation Accuracy = 0.984
```

```
EPOCH 40 ...
Validation Accuracy = 0.982

EPOCH 41 ...
Validation Accuracy = 0.985

EPOCH 42 ...
Validation Accuracy = 0.984

EPOCH 43 ...
Validation Accuracy = 0.984

EPOCH 44 ...
Validation Accuracy = 0.986

EPOCH 45 ...
Validation Accuracy = 0.983

EPOCH 46 ...
Validation Accuracy = 0.981

EPOCH 47 ...
Validation Accuracy = 0.986

EPOCH 48 ...
Validation Accuracy = 0.988

EPOCH 49 ...
Validation Accuracy = 0.987

EPOCH 50 ...
Validation Accuracy = 0.983

EPOCH 51 ...
Validation Accuracy = 0.983

EPOCH 52 ...
Validation Accuracy = 0.985

EPOCH 53 ...
Validation Accuracy = 0.983

EPOCH 54 ...
Validation Accuracy = 0.986

EPOCH 55 ...
Validation Accuracy = 0.986

EPOCH 56 ...
Validation Accuracy = 0.987

EPOCH 57 ...
Validation Accuracy = 0.987

EPOCH 58 ...
Validation Accuracy = 0.984
```

```
EPOCH 59 ...
Validation Accuracy = 0.987

EPOCH 60 ...
Validation Accuracy = 0.981

Model Saved
```



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.

Load and Output the Images

Load the images and plot them here. Feel free to use as many code cells as needed.

[7]

```
import  csv...
```

```
['Speed limit (20km/h)', 'Speed limit (30km/h)', 'Speed limit (50km/h)',
'Speed limit (60km/h)', 'Speed limit (70km/h)'] ...
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
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floats or [0..255] for integers).
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Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
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Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
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floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```

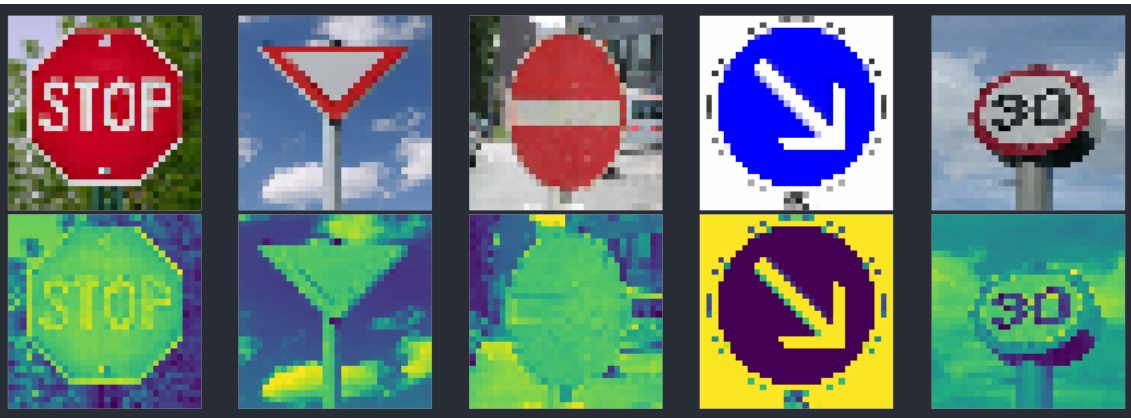

Predict the Sign Type for Each Image

[8]

```
from PIL import Image...
```

```
WARNING:tensorflow:From /anaconda3/envs/IntroToTensorFlow/lib/python3.7/site-packages/tensorflow/python/training/saver.py:1266: checkpoint_exists (from tensorflow.python.training.checkpoint_management) is deprecated and will be removed in a future version. Instructions for updating: Use standard file APIs to check for files with this prefix. INFO:tensorflow:Restoring parameters from ./model
```

[9]

```
# Run the predictions here and use the model to output the prediction for each image...
```

Analyze Performance

[10]

```
with tf.Session() as sess:...
```

```
INFO:tensorflow:Restoring parameters from ./model Test Accuracy = 0.92
```

[11]

```
# Calculate the accuracy for these 5 new images....
```

[12]

```
# Print out the top five softmax probabilities for the predictions on the German traffic sign images found on the
web....
```

```
(5, 32, 32, 3) INFO:tensorflow:Restoring parameters from ./model Test Set Accuracy = 0.600 INFO:tensorflow:Restoring parameters from ./model
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for floats or [0..255] for integers).
```

```
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
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floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
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floats or [0..255] for integers).
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floats or [0..255] for integers).
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floats or [0..255] for integers).
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floats or [0..255] for integers).
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floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
Clipping input data to the valid range for imshow with RGB data ([0..1] for
floats or [0..255] for integers).
```

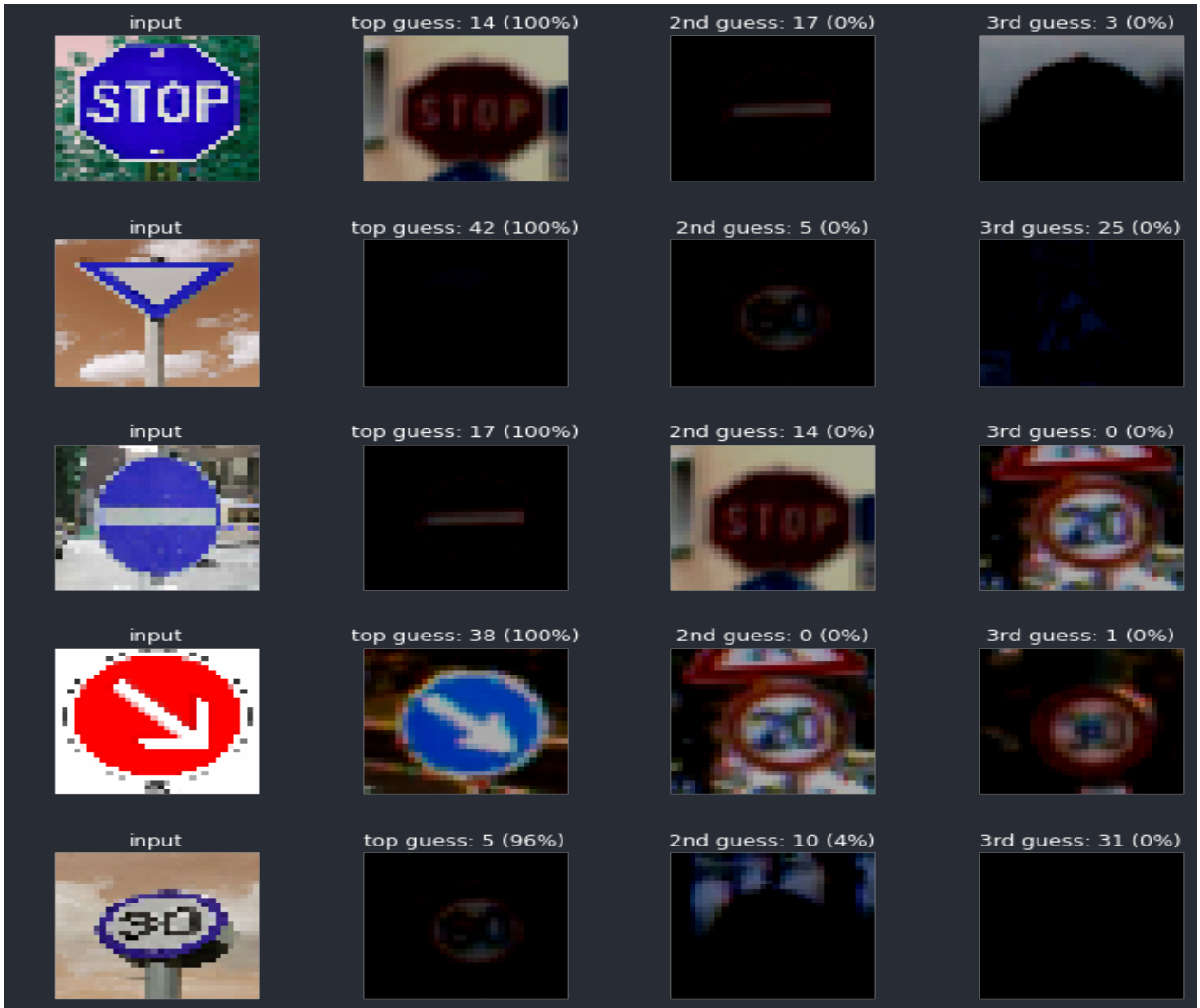

Project Writeup

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

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

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

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

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

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