Introduction to Earth Engine and TensorFlow in Cloud Datalab

This notebook walks you through a simple example of using Earth Engine and TensorFlow together in Cloud Datalab.

Specifically, we will train a neural network to recognize cloudy pixels in a Landsat scene. For this simple example we will use the output of the Fmask cloud detection algorithm as training data.

Configure the Environment

We begin by importing a number of useful libraries.

In [1]:
```
import ee
from IPython import display
import math
from matplotlib import pyplot
import numpy
from osgeo import gdal
import tempfile
import tensorflow as tf
import urllib
import zipfile
```

Initialize the Earth Engine client. This assumes that you have already configured Earth Engine credentials in this Datalab instance. If not, see the "`Earth Engine Datalab Initialization.ipynb`" notebook.

In [2]:
```
ee.Initialize()
```

Inspect the Input Data

Load a Landsat image with corresponding Fmask label data.

In [3]:
```
input_image = ee.Image('LANDSAT/LT5_L1T_TOA_FMASK/LT50100551998003CPE00')
```

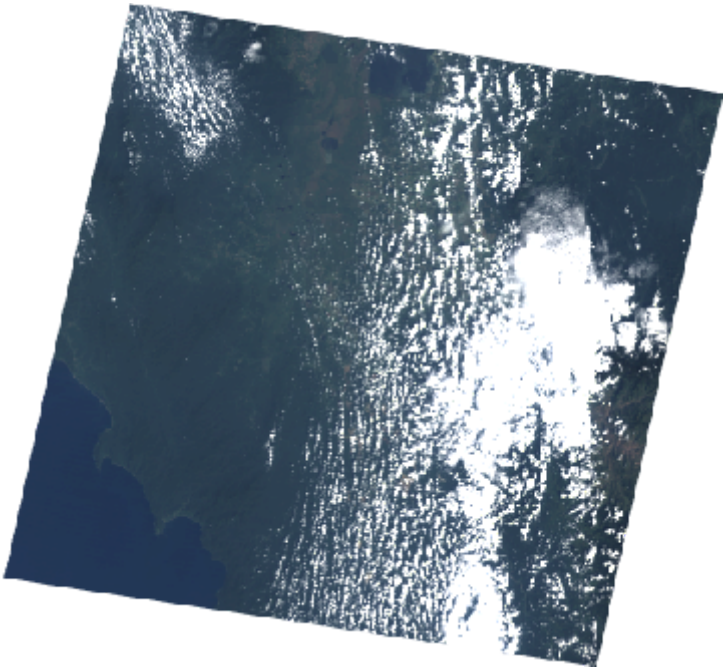
Let's define a helper function to make it easier to print thumbnails of Earth Engine images. (We'll be adding a library with utility functions like this one to the Earth Engine Python SDK, but for now we can do it by hand.)

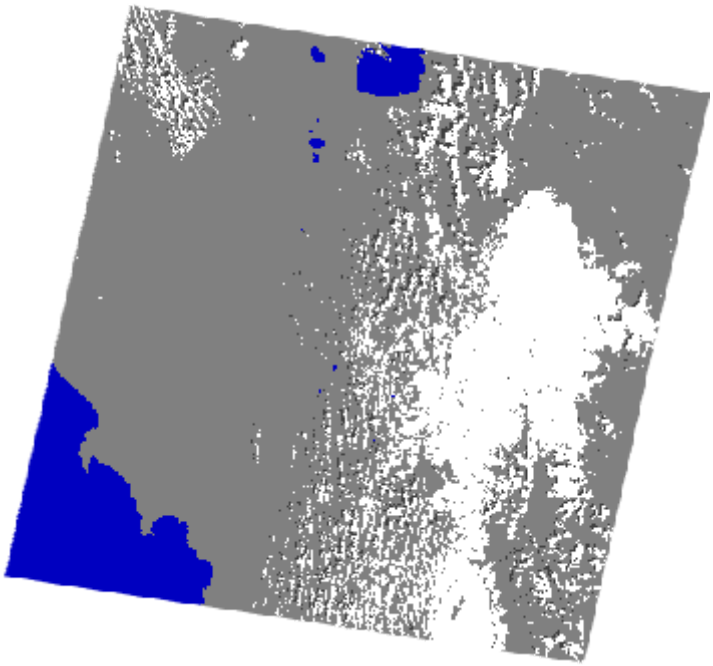
In [4]:
```
def print_image(image):
  display.display(display.Image(ee.data.getThumbnail({
      'image': image.serialize(),
      'dimensions': '360',
  })))
```

Now we can use our helper function to quickly visualize the image and label data. The Fmask values are:

0	1	2	3	4
Clear	Water	Shadow	Snow	Cloud

In [5]:
```
print_image(input_image.visualize(
    bands=['B3', 'B2', 'B1'],
    min=0,
    max=0.3,
))
print_image(input_image.visualize(
    bands=['fmask'],
    min=0,
    max=4,
    palette=['808080', '0000C0', '404040', '00FFFF', 'FFFFFF'],
))
```





Fetch the Input Data

First we define some helper functions to download raw data from Earth Engine as `numpy` arrays.

We use the `getDownloadId()` function, which only works for modestly sized datasets. For larger datasets, a better approach would be to initiate a batch Export from Earth Engine to Cloud Storage, which you could easily manage right here in Datalab too.

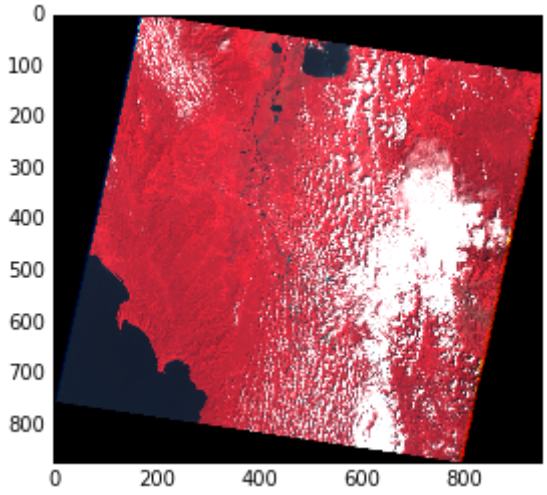
In [6]:
```
def download_tif(image, scale):
  url = ee.data.makeDownloadUrl(ee.data.getDownloadId({
        'image': image.serialize(),
        'scale': '%d' % scale,
        'filePerBand': 'false',
        'name': 'data',
  }))
  local_zip, headers = urllib.urlretrieve(url)
  with zipfile.ZipFile(local_zip) as local_zipfile:
    return local_zipfile.extract('data.tif', tempfile.mkdtemp())

def load_image(image, scale):
  local_tif_filename = download_tif(image, scale)
  dataset = gdal.Open(local_tif_filename, gdal.GA_ReadOnly)
  bands = [dataset.GetRasterBand(i + 1).ReadAsArray() for i in range(dataset.Rast
  return numpy.stack(bands, 2)
```

Now we can use that function to load the data from Earth Engine, including a valid data band, as a `numpy` array. This may take a few seconds. We also convert the Fmask band to a binary cloud label (i.e. `fmask=4`).

In [7]:
```
mask = input_image.mask().reduce('min')
data = load_image(input_image.addBands(mask), scale=240)
data[:,:,7] = numpy.equal(data[:,:,7], 4)
```

Display the local data. This time, for variety, we display it as an NRG false-color image. We can use `pyplot` to display local `numpy` arrays.

In [8]:
```
pyplot.imshow(numpy.clip(data[:,:,[3,2,1]] * 3, 0, 1))
pyplot.show()
```



Preprocess the Input Data

Select the valid pixels and hold out a fraction for use as validation data. Compute per-band means and standard deviations of the training data for normalization.

In [9]:
```
HOLDOUT_FRACTION = 0.1

# Reshape into a single vector of pixels.
data_vector = data.reshape([data.shape[0] * data.shape[1], data.shape[2]])

# Select only the valid data and shuffle it.
valid_data = data_vector[numpy.equal(data_vector[:,8], 1)]
numpy.random.shuffle(valid_data)

# Hold out a fraction of the labeled data for validation.
training_size = int(valid_data.shape[0] * (1 - HOLDOUT_FRACTION))
training_data = valid_data[0:training_size,:]
validation_data = valid_data[training_size:-1,:]

# Compute per-band means and standard deviations of the input bands.
data_mean = training_data[:,0:7].mean(0)
data_std = training_data[:,0:7].std(0)
```

In [10]:
```
valid_data.shape
```

Out[10]:
```
(587713, 9)
```

Build the TensorFlow Model

We start with a helper function to build a simple TensorFlow neural network layer.

In [11]:
```
def make_nn_layer(input, output_size):
  input_size = input.get_shape().as_list()[1]
  weights = tf.Variable(tf.truncated_normal(
      [input_size, output_size],
      stddev=1.0 / math.sqrt(float(input_size))))
  biases = tf.Variable(tf.zeros([output_size]))
  return tf.matmul(input, weights) + biases
```

Here we define our TensorFlow model, a neural network with two hidden layers with tanh() nonlinearities. The main network has two outputs, continuous-valued “logits” representing non-cloud and cloud, respectively. The binary output is intepreted as the argmax of these outputs.

We define a training step, which uses Kingma and Ba's Adam algorithm to minimize the cross-entropy between the logits and the training data. Finally, we define a simple overall percentage accuracy measure.

In [12]:
```
NUM_INPUT_BANDS = 7
NUM_HIDDEN_1 = 20
NUM_HIDDEN_2 = 20
NUM_CLASSES = 2

input = tf.placeholder(tf.float32, shape=[None, NUM_INPUT_BANDS])
labels = tf.placeholder(tf.float32, shape=[None])

normalized = (input - data_mean) / data_std
hidden1 = tf.nn.tanh(make_nn_layer(normalized, NUM_HIDDEN_1))
hidden2 = tf.nn.tanh(make_nn_layer(hidden1, NUM_HIDDEN_2))
logits = make_nn_layer(hidden2, NUM_CLASSES)
outputs = tf.argmax(logits, 1)

int_labels = tf.to_int64(labels)
cross_entropy = tf.nn.sparse_softmax_cross_entropy_with_logits(logits, int_labels
train_step = tf.train.AdamOptimizer().minimize(cross_entropy)

correct_prediction = tf.equal(outputs, int_labels)
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
```

Train the Neural Network

Now train the neural network, using batches of training data drawn randomly from the training data pool. We periodically compute the accuracy against the validation data. When we're done training, we apply the model to the complete input data set.

This simple notebook performs all TensorFlow operations locally. However, for larger analyses you could bring up a cluster of TensorFlow workers to parallelize the computation, all controlled from within Datalab.

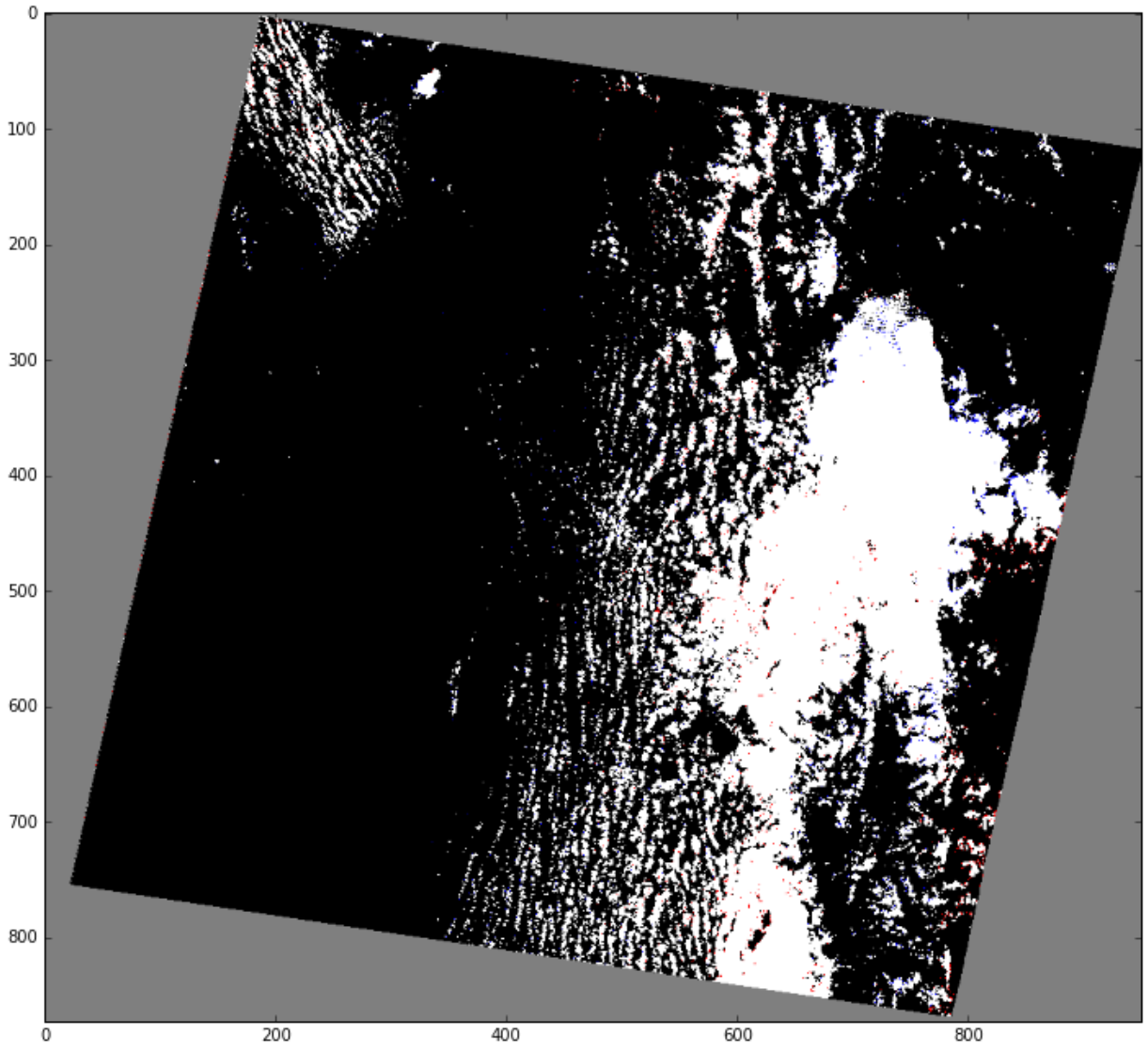
In [13]:
```
BATCH_SIZE = 1000
NUM_BATCHES = 1000

with tf.Session() as sess:
  sess.run(tf.initialize_all_variables())

  validation_dict = {
    input: validation_data[:,0:7],
    labels: validation_data[:,7],
  }

  for i in range(NUM_BATCHES):
    batch = training_data[numpy.random.choice(training_size, BATCH_SIZE, False),:
    train_step.run({input: batch[:,0:7], labels: batch[:,7]})

    if i % 100 == 0 or i == NUM_BATCHES - 1:
      print('Accuracy %.2f%% at step %d' % (accuracy.eval(validation_dict) * 100,

  output_data = outputs.eval({input: data_vector[:,0:7]})
```

```
Accuracy 91.95% at step 0
Accuracy 97.37% at step 100
Accuracy 98.17% at step 200
Accuracy 98.59% at step 300
Accuracy 98.82% at step 400
Accuracy 98.91% at step 500
Accuracy 99.07% at step 600
Accuracy 99.15% at step 700
Accuracy 99.29% at step 800
Accuracy 99.32% at step 900
Accuracy 99.38% at step 999
```

Inspect the Results

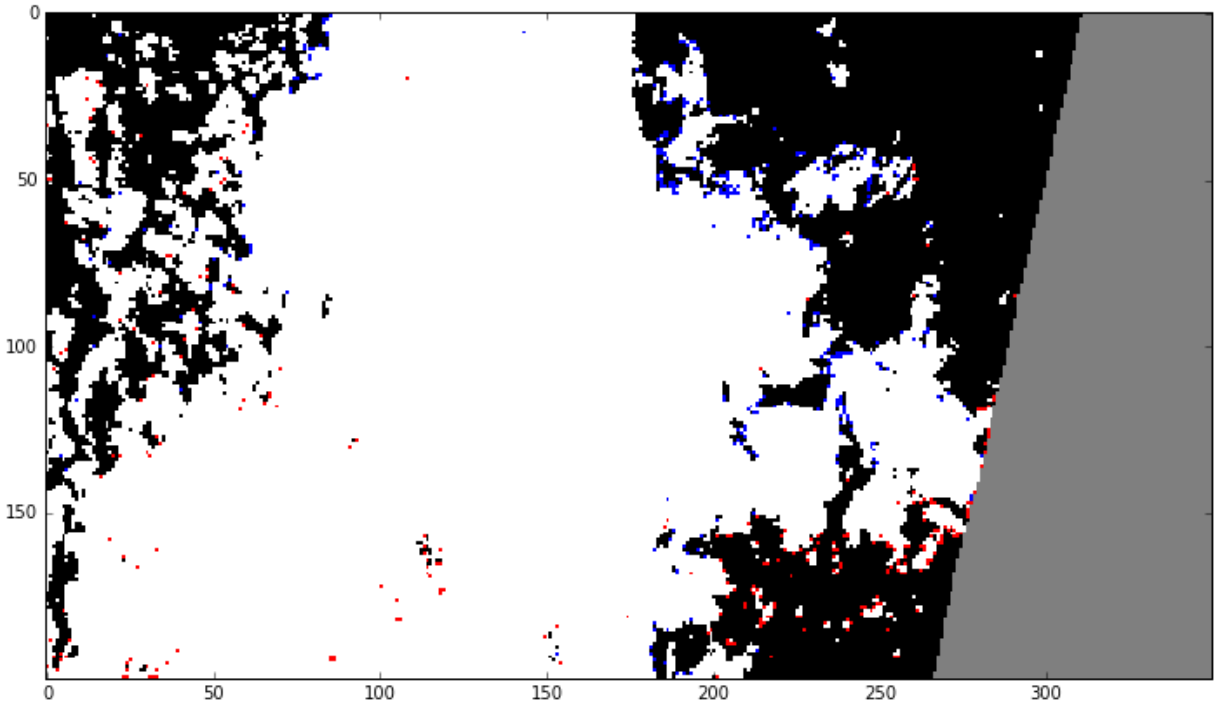
Here we dislay the results. The red band corresponds to the TensorFlow output and the blue band corresponds to the labeled training data, so pixels that are red and blue correspond to disagreements between the model and the training data. (There aren't many: look carefully around the fringes of the clouds.)

In [14]:
```
output_image = output_data.reshape([data.shape[0], data.shape[1]])
red = numpy.where(data[:,:,8], output_image, 0.5)
blue = numpy.where(data[:,:,8], data[:,:,7], 0.5)
green = numpy.minimum(red, blue)

comparison_image = numpy.dstack((red, green, blue))
pyplot.figure(figsize = (12,12))
pyplot.imshow(comparison_image)
pyplot.show()
```



We can zoom in on a particular region over on the right side of the image to see some of the disagreements. Red pixels represent comission errors and blue pixels represent omission errors relative to the labeled input data.

In [15]:
```
pyplot.figure(figsize = (12,12))
pyplot.imshow(comparison_image[300:500,600:,:], interpolation='nearest')
pyplot.show()
```



In [ ]: