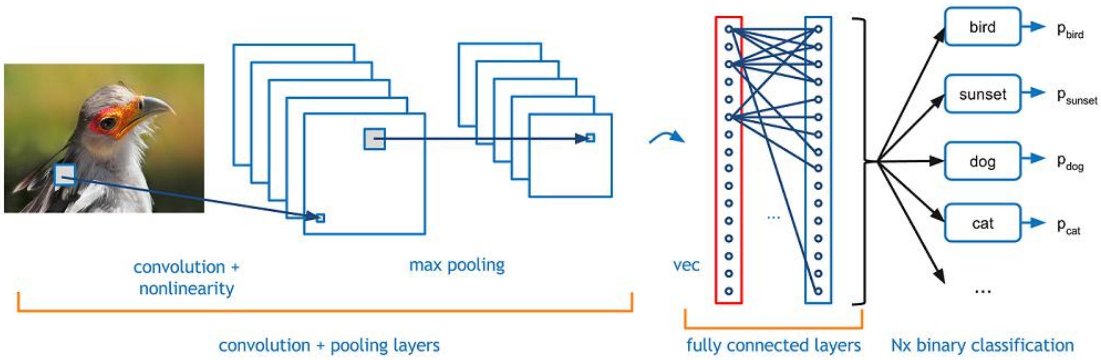
<u>**Machine Learning Lab 11**</u>

Convolutional Neural Networks

CNNs, like neural networks, are made up of neurons with learnable weights and biases. Each neuron receives several inputs, takes a weighted sum over them, pass it through an activation function and responds with an output. Unlike neural networks, where the input is a vector, here the input is a multi-channeled image and they are commonly applied to image processing tasks. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.



The dataset

For the convolutional neural networks I have performed my experiments on the Non-MNIST dataset, it is a dataset of characters and just like the MNIST dataset it is made of images of characters of the size of 28x28 pixels but the images are of the the english alphabets and not numbers. The images of these letters are in different fonts and the dataset contains 500,000 images in it, it contains 26 letters and each letter consists of 10 classes in itself.

"""Download a file if not present, and make sure it's the right size."""

Experiment

In this experiment I implemented a convolutional neural network using tensorflow and applied it to the task of character classification and achieved an accuracy of 89.8%

I started with downloading the Non-MNIST dataset and and parsing through it’s directory structure to extract the dataset and find the image. Next I load the image into the memory and preprocess them and save them into a pickle file.

Once the images are stored into a pickle file I load the pickle file and get the image in the form of numpy array from the pickle file. I randomize the data and reshape it to feed the neural network.

Next I create the CNN graph with tensorflow with two convolution layers, followed by relu and one fully connected layer. The CNN uses the softmax cross entropy loss and a gradient descent optimizer to train itself. With this network I am able to achieve an accuracy of 88.5%, next I increase the stride of the neural network 2 for both the kernel as well as the max pooling layers and make the kernel size as 2 and the accuracy increases to 89.8%.

The code and plots can be found in the accompanying jupyter notebook.

Convolutional Neural Networks

November 1, 2018

1 Lab 11

2 Convolutional neural networks

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2.2 Submitted by: Prateek Singh (15BCE1091)

```
In [1]: from __future__ import print_function
        import numpy as np
        import tensorflow as tf
        from six.moves import cPickle as pickle
        from six.moves import range
```

```
In [2]: url = 'https://commondatastorage.googleapis.com/books1000/'
        last_percent_reported = None
        data_root = '.' # Change me to store data elsewhere

        def download_progress_hook(count, blockSize, totalSize):
          global last_percent_reported
          percent = int(count * blockSize * 100 / totalSize)

          if last_percent_reported != percent:
            if percent % 5 == 0:
              sys.stdout.write("%s%%" % percent)
              sys.stdout.flush()
            else:
              sys.stdout.write(".")
              sys.stdout.flush()

            last_percent_reported = percent

        def maybe_download(filename, expected_bytes, force=False):
          """Download a file if not present, and make sure it's the right size."""
          dest_filename = os.path.join(data_root, filename)
          if force or not os.path.exists(dest_filename):
            print('Attempting to download:', filename)
            filename, _ = urlretrieve(url + filename, dest_filename, reporthook=download_progre
```

```
      print('\nDownload Complete!')
    statinfo = os.stat(dest_filename)
    if statinfo.st_size == expected_bytes:
      print('Found and verified', dest_filename)
    else:
      raise Exception(
        'Failed to verify ' + dest_filename + '. Can you get to it with a browser?')
    return dest_filename

  train_filename = maybe_download('notMNIST_large.tar.gz', 247336696)
  test_filename = maybe_download('notMNIST_small.tar.gz', 8458043)
```

```
Found and verified ./notMNIST_large.tar.gz
Found and verified ./notMNIST_small.tar.gz
```

Extract the dataset from the compressed .tar.gz file. This would give us a set of directories, labeled A through J.

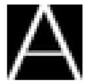
```
In [3]: num_classes = 10
        np.random.seed(133)

        def maybe_extract(filename, force=False):
          root = os.path.splitext(os.path.splitext(filename)[0])[0]  # remove .tar.gz
          if os.path.isdir(root) and not force:
            # You may override by setting force=True.
            print('%s already present - Skipping extraction of %s.' % (root, filename))
          else:
            print('Extracting data for %s. This may take a while. Please wait.' % root)
            tar = tarfile.open(filename)
            sys.stdout.flush()
            tar.extractall(data_root)
            tar.close()
          data_folders = [
            os.path.join(root, d) for d in sorted(os.listdir(root))
            if os.path.isdir(os.path.join(root, d))]
          if len(data_folders) != num_classes:
            raise Exception(
              'Expected %d folders, one per class. Found %d instead.' % (
                num_classes, len(data_folders)))
          print(data_folders)
          return data_folders

        train_folders = maybe_extract(train_filename)
        test_folders = maybe_extract(test_filename)
```

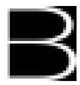
```
./notMNIST_large already present - Skipping extraction of ./notMNIST_large.tar.gz.
['./notMNIST_large/A', './notMNIST_large/B', './notMNIST_large/C', './notMNIST_large/D', './no
./notMNIST_small already present - Skipping extraction of ./notMNIST_small.tar.gz.
```

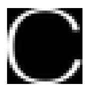
```
['./notMNIST_small/A', './notMNIST_small/B', './notMNIST_small/C', './notMNIST_small/D', './no
```

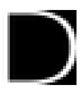
Looking at the dataset to ensure it's is sensible

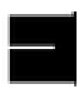
```
In [4]: for folders in train_folders:
            a = os.listdir(folders)
            display(Image(filename = folders + '/' + a[0]))
```

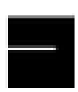


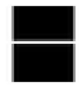


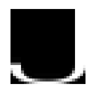












Loading the data in a more manageable format

We'll convert the entire dataset into a 3D array (image index, x, y) of floating point values, normalized to have approximately zero mean and standard deviation ~0.5 to make training easier down the road.

A few images might not be readable, we'll just skip them.

```
In [5]: image_size = 28  # Pixel width and height.
        pixel_depth = 255.0  # Number of levels per pixel.

        def load_letter(folder, min_num_images):
          """Load the data for a single letter label."""
          image_files = os.listdir(folder)
          dataset = np.ndarray(shape=(len(image_files), image_size, image_size),
                               dtype=np.float32)
          print(folder)
          num_images = 0
          for image in image_files:
            image_file = os.path.join(folder, image)
            try:
              image_data = (imageio.imread(image_file).astype(float) -
                            pixel_depth / 2) / pixel_depth
              if image_data.shape != (image_size, image_size):
                raise Exception('Unexpected image shape: %s' % str(image_data.shape))
              dataset[num_images, :, :] = image_data
              num_images = num_images + 1
            except (IOError, ValueError) as e:
              print('Could not read:', image_file, ':', e, '- it\'s ok, skipping.')

          dataset = dataset[0:num_images, :, :]
          if num_images < min_num_images:
            raise Exception('Many fewer images than expected: %d < %d' %
```

```
                    (num_images, min_num_images))

  print('Full dataset tensor:', dataset.shape)
  print('Mean:', np.mean(dataset))
  print('Standard deviation:', np.std(dataset))
  return dataset

def maybe_pickle(data_folders, min_num_images_per_class, force=False):
  dataset_names = []
  for folder in data_folders:
    set_filename = folder + '.pickle'
    dataset_names.append(set_filename)
    if os.path.exists(set_filename) and not force:
      # You may override by setting force=True.
      print('%s already present - Skipping pickling.' % set_filename)
    else:
      print('Pickling %s.' % set_filename)
      dataset = load_letter(folder, min_num_images_per_class)
      try:
        with open(set_filename, 'wb') as f:
          pickle.dump(dataset, f, pickle.HIGHEST_PROTOCOL)
      except Exception as e:
        print('Unable to save data to', set_filename, ':', e)

  return dataset_names

train_datasets = maybe_pickle(train_folders, 45000)
test_datasets = maybe_pickle(test_folders, 1800)
```

```
./notMNIST_large/A.pickle already present - Skipping pickling.
./notMNIST_large/B.pickle already present - Skipping pickling.
./notMNIST_large/C.pickle already present - Skipping pickling.
./notMNIST_large/D.pickle already present - Skipping pickling.
./notMNIST_large/E.pickle already present - Skipping pickling.
./notMNIST_large/F.pickle already present - Skipping pickling.
./notMNIST_large/G.pickle already present - Skipping pickling.
./notMNIST_large/H.pickle already present - Skipping pickling.
./notMNIST_large/I.pickle already present - Skipping pickling.
./notMNIST_large/J.pickle already present - Skipping pickling.
./notMNIST_small/A.pickle already present - Skipping pickling.
./notMNIST_small/B.pickle already present - Skipping pickling.
./notMNIST_small/C.pickle already present - Skipping pickling.
./notMNIST_small/D.pickle already present - Skipping pickling.
./notMNIST_small/E.pickle already present - Skipping pickling.
./notMNIST_small/F.pickle already present - Skipping pickling.
./notMNIST_small/G.pickle already present - Skipping pickling.
./notMNIST_small/H.pickle already present - Skipping pickling.
./notMNIST_small/I.pickle already present - Skipping pickling.
```

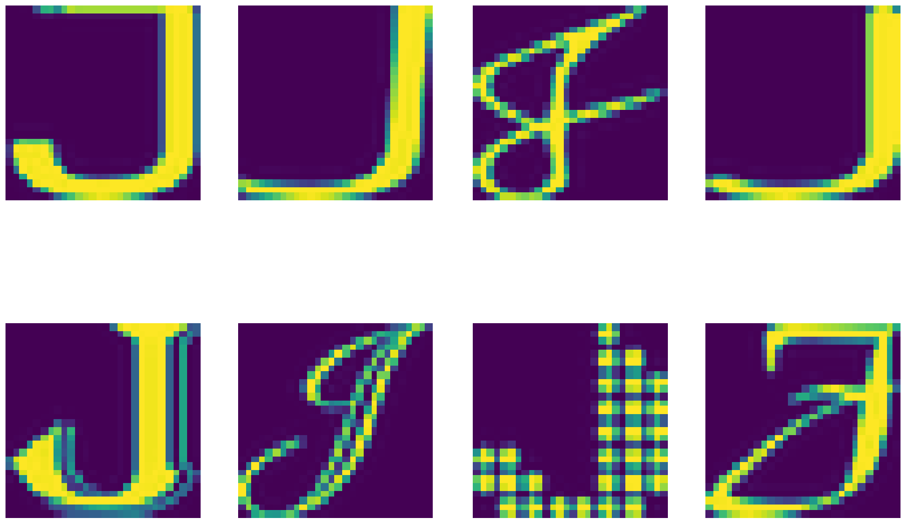
```
./notMNIST_small/J.pickle already present - Skipping pickling.
```

Verifying that the data still looks good. Displaying a sample of the labels and images from the ndarray.

```
In [6]: import random
        def disp_8_img(imgs, titles):
          """Display subplot with 8 images or less"""
          for i, img in enumerate(imgs):
            plt.subplot(2, 4, i+1)
            plt.title(titles[i])
            plt.axis('off')
            plt.imshow(img)

        def disp_sample_pickles(data_folders):
          folder = random.sample(data_folders, 1)
          pickle_filename = ''.join(folder) + '.pickle'
          print(folder)
          print(data_folders)
          try:
            with open(pickle_filename, 'rb') as f:
              dataset = pickle.load(f)
          except Exception as e:
            print('Unable to read data from', pickle_filename, ':', e)
            return
          # display
          plt.suptitle(''.join(folder)[-1])
          for i, img in enumerate(random.sample(list(dataset), 8)):
            plt.subplot(2, 4, i+1)
            plt.axis('off')
            plt.imshow(img)

        disp_sample_pickles(train_folders)
```

```
['./notMNIST_large/J']
['./notMNIST_large/A', './notMNIST_large/B', './notMNIST_large/C', './notMNIST_large/D', './no
```

J



checking for the data to be balanced across classes.

```
In [7]: def disp_number_images(data_folders):
          for folder in data_folders:
            pickle_filename = ''.join(folder) + '.pickle'
            try:
              with open(pickle_filename, 'rb') as f:
                dataset = pickle.load(f)
            except Exception as e:
              print('Unable to read data from', pickle_filename, ':', e)
              return
            print('Number of images in ', folder, ' : ', len(dataset))

        disp_number_images(train_folders)
        disp_number_images(test_folders)
```

```
Number of images in  ./notMNIST_large/A  :  52909
Number of images in  ./notMNIST_large/B  :  52911
Number of images in  ./notMNIST_large/C  :  52912
Number of images in  ./notMNIST_large/D  :  52911
Number of images in  ./notMNIST_large/E  :  52912
Number of images in  ./notMNIST_large/F  :  52912
Number of images in  ./notMNIST_large/G  :  52912
Number of images in  ./notMNIST_large/H  :  52912
Number of images in  ./notMNIST_large/I  :  52912
Number of images in  ./notMNIST_large/J  :  52911
```

```
Number of images in  ./notMNIST_small/A  :  1872
Number of images in  ./notMNIST_small/B  :  1873
Number of images in  ./notMNIST_small/C  :  1873
Number of images in  ./notMNIST_small/D  :  1873
Number of images in  ./notMNIST_small/E  :  1873
Number of images in  ./notMNIST_small/F  :  1872
Number of images in  ./notMNIST_small/G  :  1872
Number of images in  ./notMNIST_small/H  :  1872
Number of images in  ./notMNIST_small/I  :  1872
Number of images in  ./notMNIST_small/J  :  1872
```

In [8]:
```
def make_arrays(nb_rows, img_size):
  if nb_rows:
    dataset = np.ndarray((nb_rows, img_size, img_size), dtype=np.float32)
    labels = np.ndarray(nb_rows, dtype=np.int32)
  else:
    dataset, labels = None, None
  return dataset, labels

def merge_datasets(pickle_files, train_size, valid_size=0):
  num_classes = len(pickle_files)
  print(pickle_files)
  valid_dataset, valid_labels = make_arrays(valid_size, image_size)
  train_dataset, train_labels = make_arrays(train_size, image_size)
  vsize_per_class = valid_size // num_classes
  tsize_per_class = train_size // num_classes

  start_v, start_t = 0, 0
  end_v, end_t = vsize_per_class, tsize_per_class
  end_l = vsize_per_class+tsize_per_class
  for label, pickle_file in enumerate(pickle_files):
    try:
      with open(pickle_file, 'rb') as f:
        letter_set = pickle.load(f)
        # let's shuffle the letters to have random validation and training set
        np.random.shuffle(letter_set)
        if valid_dataset is not None:
          valid_letter = letter_set[:vsize_per_class, :, :]
          valid_dataset[start_v:end_v, :, :] = valid_letter
          valid_labels[start_v:end_v] = label
          start_v += vsize_per_class
          end_v += vsize_per_class

        train_letter = letter_set[vsize_per_class:end_l, :, :]
        train_dataset[start_t:end_t, :, :] = train_letter
        train_labels[start_t:end_t] = label
        start_t += tsize_per_class
```

```
            end_t += tsize_per_class
        except Exception as e:
          print('Unable to process data from', pickle_file, ':', e)
          raise

      return valid_dataset, valid_labels, train_dataset, train_labels


    train_size = 200000
    valid_size = 10000
    test_size = 10000

    valid_dataset, valid_labels, train_dataset, train_labels = merge_datasets(
      train_datasets, train_size, valid_size)
    _, _, test_dataset, test_labels = merge_datasets(test_datasets, test_size)

    print('Training:', train_dataset.shape, train_labels.shape)
    print('Validation:', valid_dataset.shape, valid_labels.shape)
    print('Testing:', test_dataset.shape, test_labels.shape)
```

```
['./notMNIST_large/A.pickle', './notMNIST_large/B.pickle', './notMNIST_large/C.pickle', './notM
['./notMNIST_small/A.pickle', './notMNIST_small/B.pickle', './notMNIST_small/C.pickle', './notM
Training: (200000, 28, 28) (200000,)
Validation: (10000, 28, 28) (10000,)
Testing: (10000, 28, 28) (10000,)
```

Next, we'll randomize the data. It's important to have the labels well shuffled for the training and test distributions to match.

```
In [9]: def randomize(dataset, labels):
          permutation = np.random.permutation(labels.shape[0])
          shuffled_dataset = dataset[permutation,:,:]
          shuffled_labels = labels[permutation]
          return shuffled_dataset, shuffled_labels
        train_dataset, train_labels = randomize(train_dataset, train_labels)
        test_dataset, test_labels = randomize(test_dataset, test_labels)
        valid_dataset, valid_labels = randomize(valid_dataset, valid_labels)
```

```
In [2]: pickle_file = 'notMNIST.pickle'

        with open(pickle_file, 'rb') as f:
          save = pickle.load(f)
          train_dataset = save['train_dataset']
          train_labels = save['train_labels']
          valid_dataset = save['valid_dataset']
          valid_labels = save['valid_labels']
          test_dataset = save['test_dataset']
          test_labels = save['test_labels']
```

```
    del save  # hint to help gc free up memory
    print('Training set', train_dataset.shape, train_labels.shape)
    print('Validation set', valid_dataset.shape, valid_labels.shape)
    print('Test set', test_dataset.shape, test_labels.shape)
```

```
Training set (200000, 28, 28) (200000,)
Validation set (10000, 28, 28) (10000,)
Test set (10000, 28, 28) (10000,)
```

Reformat into a TensorFlow-friendly shape: - convolutions need the image data formatted as a cube (width by height by #channels) - labels as float 1-hot encodings.

```
In [3]: image_size = 28
        num_labels = 10
        num_channels = 1 # grayscale

        import numpy as np

        def reformat(dataset, labels):
          dataset = dataset.reshape(
            (-1, image_size, image_size, num_channels)).astype(np.float32)
          labels = (np.arange(num_labels) == labels[:,None]).astype(np.float32)
          return dataset, labels
        train_dataset, train_labels = reformat(train_dataset, train_labels)
        valid_dataset, valid_labels = reformat(valid_dataset, valid_labels)
        test_dataset, test_labels = reformat(test_dataset, test_labels)
        print('Training set', train_dataset.shape, train_labels.shape)
        print('Validation set', valid_dataset.shape, valid_labels.shape)
        print('Test set', test_dataset.shape, test_labels.shape)
```

```
Training set (200000, 28, 28, 1) (200000, 10)
Validation set (10000, 28, 28, 1) (10000, 10)
Test set (10000, 28, 28, 1) (10000, 10)
```

```
In [4]: def accuracy(predictions, labels):
          return (100.0 * np.sum(np.argmax(predictions, 1) == np.argmax(labels, 1))
                  / predictions.shape[0])
```

building a small network with two convolutional layers, followed by one fully connected layer. Convolutional networks are more expensive computationally, so we'll limit its depth and number of fully connected nodes.

```
In [6]: batch_size = 16
        patch_size = 5
        depth = 16
        num_hidden = 64
```

```python
graph = tf.Graph()

with graph.as_default():

  # Input data.
  tf_train_dataset = tf.placeholder(
    tf.float32, shape=(batch_size, image_size, image_size, num_channels))
  tf_train_labels = tf.placeholder(tf.float32, shape=(batch_size, num_labels))
  tf_valid_dataset = tf.constant(valid_dataset)
  tf_test_dataset = tf.constant(test_dataset)

  # Variables.
  layer1_weights = tf.Variable(tf.truncated_normal(
      [patch_size, patch_size, num_channels, depth], stddev=0.1))
  layer1_biases = tf.Variable(tf.zeros([depth]))
  layer2_weights = tf.Variable(tf.truncated_normal(
      [patch_size, patch_size, depth, depth], stddev=0.1))
  layer2_biases = tf.Variable(tf.constant(1.0, shape=[depth]))
  layer3_weights = tf.Variable(tf.truncated_normal(
      [image_size // 4 * image_size // 4 * depth, num_hidden], stddev=0.1))
  layer3_biases = tf.Variable(tf.constant(1.0, shape=[num_hidden]))
  layer4_weights = tf.Variable(tf.truncated_normal(
      [num_hidden, num_labels], stddev=0.1))
  layer4_biases = tf.Variable(tf.constant(1.0, shape=[num_labels]))

  # Model.
  def model(data):
    conv = tf.nn.conv2d(data, layer1_weights, [1, 2, 2, 1], padding='SAME')
    hidden = tf.nn.relu(conv + layer1_biases)
    conv = tf.nn.conv2d(hidden, layer2_weights, [1, 2, 2, 1], padding='SAME')
    hidden = tf.nn.relu(conv + layer2_biases)
    shape = hidden.get_shape().as_list()
    reshape = tf.reshape(hidden, [shape[0], shape[1] * shape[2] * shape[3]])
    hidden = tf.nn.relu(tf.matmul(reshape, layer3_weights) + layer3_biases)
    return tf.matmul(hidden, layer4_weights) + layer4_biases

  # Training computation.
  logits = model(tf_train_dataset)
  loss = tf.reduce_mean(
    tf.nn.softmax_cross_entropy_with_logits(labels=tf_train_labels, logits=logits))

  # Optimizer.
  optimizer = tf.train.GradientDescentOptimizer(0.05).minimize(loss)

  # Predictions for the training, validation, and test data.
  train_prediction = tf.nn.softmax(logits)
  valid_prediction = tf.nn.softmax(model(tf_valid_dataset))
  test_prediction = tf.nn.softmax(model(tf_test_dataset))
```

```
In [7]: num_steps = 1001

        with tf.Session(graph=graph) as session:
          tf.global_variables_initializer().run()
          print('Initialized')
          for step in range(num_steps):
            offset = (step * batch_size) % (train_labels.shape[0] - batch_size)
            batch_data = train_dataset[offset:(offset + batch_size), :, :, :]
            batch_labels = train_labels[offset:(offset + batch_size), :]
            feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
            _, l, predictions = session.run(
              [optimizer, loss, train_prediction], feed_dict=feed_dict)
            if (step % 50 == 0):
              print('Minibatch loss at step %d: %f' % (step, l))
              print('Minibatch accuracy: %.1f%%' % accuracy(predictions, batch_labels))
              print('Validation accuracy: %.1f%%' % accuracy(
                valid_prediction.eval(), valid_labels))
          print('Test accuracy: %.1f%%' % accuracy(test_prediction.eval(), test_labels))
```

```
Initialized
Minibatch loss at step 0: 3.252700
Minibatch accuracy: 0.0%
Validation accuracy: 9.9%
Minibatch loss at step 50: 1.850138
Minibatch accuracy: 31.2%
Validation accuracy: 48.7%
Minibatch loss at step 100: 1.010035
Minibatch accuracy: 62.5%
Validation accuracy: 64.9%
Minibatch loss at step 150: 1.289849
Minibatch accuracy: 68.8%
Validation accuracy: 72.0%
Minibatch loss at step 200: 0.505446
Minibatch accuracy: 81.2%
Validation accuracy: 75.6%
Minibatch loss at step 250: 1.345587
Minibatch accuracy: 56.2%
Validation accuracy: 69.6%
Minibatch loss at step 300: 0.695081
Minibatch accuracy: 75.0%
Validation accuracy: 77.0%
Minibatch loss at step 350: 0.638521
Minibatch accuracy: 75.0%
Validation accuracy: 78.8%
Minibatch loss at step 400: 0.511915
Minibatch accuracy: 81.2%
Validation accuracy: 78.8%
Minibatch loss at step 450: 0.779062
```

```
Minibatch accuracy: 75.0%
Validation accuracy: 78.7%
Minibatch loss at step 500: 0.602857
Minibatch accuracy: 81.2%
Validation accuracy: 78.8%
Minibatch loss at step 550: 1.071783
Minibatch accuracy: 75.0%
Validation accuracy: 80.2%
Minibatch loss at step 600: 0.966325
Minibatch accuracy: 56.2%
Validation accuracy: 80.5%
Minibatch loss at step 650: 0.564390
Minibatch accuracy: 81.2%
Validation accuracy: 81.5%
Minibatch loss at step 700: 0.549062
Minibatch accuracy: 81.2%
Validation accuracy: 81.0%
Minibatch loss at step 750: 0.473424
Minibatch accuracy: 87.5%
Validation accuracy: 81.4%
Minibatch loss at step 800: 0.421251
Minibatch accuracy: 87.5%
Validation accuracy: 80.3%
Minibatch loss at step 850: 0.261832
Minibatch accuracy: 93.8%
Validation accuracy: 81.6%
Minibatch loss at step 900: 0.716957
Minibatch accuracy: 68.8%
Validation accuracy: 82.2%
Minibatch loss at step 950: 0.280484
Minibatch accuracy: 93.8%
Validation accuracy: 82.5%
Minibatch loss at step 1000: 0.360719
Minibatch accuracy: 93.8%
Validation accuracy: 81.6%
Test accuracy: 88.5%
```

The convolutional model above uses convolutions with stride 2 to reduce the dimensionality. Replacing the strides by a max pooling operation (`nn.max_pool()`) of stride 2 and kernel size 2.

```
In [8]: batch_size = 16
        patch_size = 5
        depth = 16
        num_hidden = 64

        graph = tf.Graph()
```

```python
with graph.as_default():

  # Input data.
  tf_train_dataset = tf.placeholder(
    tf.float32, shape=(batch_size, image_size, image_size, num_channels))
  tf_train_labels = tf.placeholder(tf.float32, shape=(batch_size, num_labels))
  tf_valid_dataset = tf.constant(valid_dataset)
  tf_test_dataset = tf.constant(test_dataset)

  # Variables.
  layer1_weights = tf.Variable(tf.truncated_normal(
      [patch_size, patch_size, num_channels, depth], stddev=0.1))
  layer1_biases = tf.Variable(tf.zeros([depth]))
  layer2_weights = tf.Variable(tf.truncated_normal(
      [patch_size, patch_size, depth, depth], stddev=0.1))
  layer2_biases = tf.Variable(tf.constant(1.0, shape=[depth]))
  layer3_weights = tf.Variable(tf.truncated_normal(
      [image_size // 4 * image_size // 4 * depth, num_hidden], stddev=0.1))
  layer3_biases = tf.Variable(tf.constant(1.0, shape=[num_hidden]))
  layer4_weights = tf.Variable(tf.truncated_normal(
      [num_hidden, num_labels], stddev=0.1))
  layer4_biases = tf.Variable(tf.constant(1.0, shape=[num_labels]))

  # Model.
  def model(data):
    conv1 = tf.nn.conv2d(data, layer1_weights, [1, 1, 1, 1], padding='SAME')
    bias1 = tf.nn.relu(conv1 + layer1_biases)
    pool1 = tf.nn.max_pool(bias1, [1, 2, 2, 1], [1, 2, 2, 1], padding='SAME')
    conv2 = tf.nn.conv2d(pool1, layer2_weights, [1, 1, 1, 1], padding='SAME')
    bias2 = tf.nn.relu(conv2 + layer2_biases)
    pool2 = tf.nn.max_pool(bias2, [1, 2, 2, 1], [1, 2, 2, 1], padding='SAME')
    shape = pool2.get_shape().as_list()
    reshape = tf.reshape(pool2, [shape[0], shape[1] * shape[2] * shape[3]])
    hidden = tf.nn.relu(tf.matmul(reshape, layer3_weights) + layer3_biases)
    return tf.matmul(hidden, layer4_weights) + layer4_biases

  # Training computation.
  logits = model(tf_train_dataset)
  loss = tf.reduce_mean(
    tf.nn.softmax_cross_entropy_with_logits(labels=tf_train_labels, logits=logits))

  # Optimizer.
  optimizer = tf.train.GradientDescentOptimizer(0.05).minimize(loss)

  # Predictions for the training, validation, and test data.
  train_prediction = tf.nn.softmax(logits)
  valid_prediction = tf.nn.softmax(model(tf_valid_dataset))
  test_prediction = tf.nn.softmax(model(tf_test_dataset))
```

In [9]:
```
num_steps = 1001

with tf.Session(graph=graph) as session:
  tf.global_variables_initializer().run()
  print('Initialized')
  for step in range(num_steps):
    offset = (step * batch_size) % (train_labels.shape[0] - batch_size)
    batch_data = train_dataset[offset:(offset + batch_size), :, :, :]
    batch_labels = train_labels[offset:(offset + batch_size), :]
    feed_dict = {tf_train_dataset : batch_data, tf_train_labels : batch_labels}
    _, l, predictions = session.run([optimizer, loss, train_prediction], feed_dict=feed
    if (step % 50 == 0):
      print('Minibatch loss at step %d: %f' % (step, l))
      print('Minibatch accuracy: %.1f%%' % accuracy(predictions, batch_labels))
      print('Validation accuracy: %.1f%%' % accuracy(
        valid_prediction.eval(), valid_labels))
  print('Test accuracy: %.1f%%' % accuracy(test_prediction.eval(), test_labels))
```

```
Initialized
Minibatch loss at step 0: 3.045946
Minibatch accuracy: 12.5%
Validation accuracy: 10.0%
Minibatch loss at step 50: 1.833991
Minibatch accuracy: 31.2%
Validation accuracy: 46.6%
Minibatch loss at step 100: 1.044222
Minibatch accuracy: 56.2%
Validation accuracy: 62.4%
Minibatch loss at step 150: 1.086824
Minibatch accuracy: 68.8%
Validation accuracy: 70.6%
Minibatch loss at step 200: 0.626718
Minibatch accuracy: 81.2%
Validation accuracy: 73.7%
Minibatch loss at step 250: 1.310024
Minibatch accuracy: 62.5%
Validation accuracy: 74.4%
Minibatch loss at step 300: 0.477789
Minibatch accuracy: 75.0%
Validation accuracy: 77.4%
Minibatch loss at step 350: 0.495264
Minibatch accuracy: 81.2%
Validation accuracy: 79.5%
Minibatch loss at step 400: 0.597861
Minibatch accuracy: 75.0%
Validation accuracy: 79.2%
Minibatch loss at step 450: 0.637514
Minibatch accuracy: 81.2%
```

```
Validation accuracy: 80.6%
Minibatch loss at step 500: 0.441908
Minibatch accuracy: 87.5%
Validation accuracy: 80.2%
Minibatch loss at step 550: 0.707909
Minibatch accuracy: 75.0%
Validation accuracy: 81.6%
Minibatch loss at step 600: 1.103696
Minibatch accuracy: 75.0%
Validation accuracy: 82.0%
Minibatch loss at step 650: 0.399387
Minibatch accuracy: 87.5%
Validation accuracy: 83.0%
Minibatch loss at step 700: 0.450146
Minibatch accuracy: 87.5%
Validation accuracy: 82.2%
Minibatch loss at step 750: 0.412422
Minibatch accuracy: 87.5%
Validation accuracy: 82.6%
Minibatch loss at step 800: 0.354055
Minibatch accuracy: 87.5%
Validation accuracy: 83.0%
Minibatch loss at step 850: 0.240893
Minibatch accuracy: 93.8%
Validation accuracy: 83.3%
Minibatch loss at step 900: 0.460379
Minibatch accuracy: 93.8%
Validation accuracy: 83.8%
Minibatch loss at step 950: 0.301897
Minibatch accuracy: 87.5%
Validation accuracy: 84.6%
Minibatch loss at step 1000: 0.424297
Minibatch accuracy: 87.5%
Validation accuracy: 83.5%
Test accuracy: 89.8%
```