CSC411: Project #2

Due on Friday, March 10, 2017

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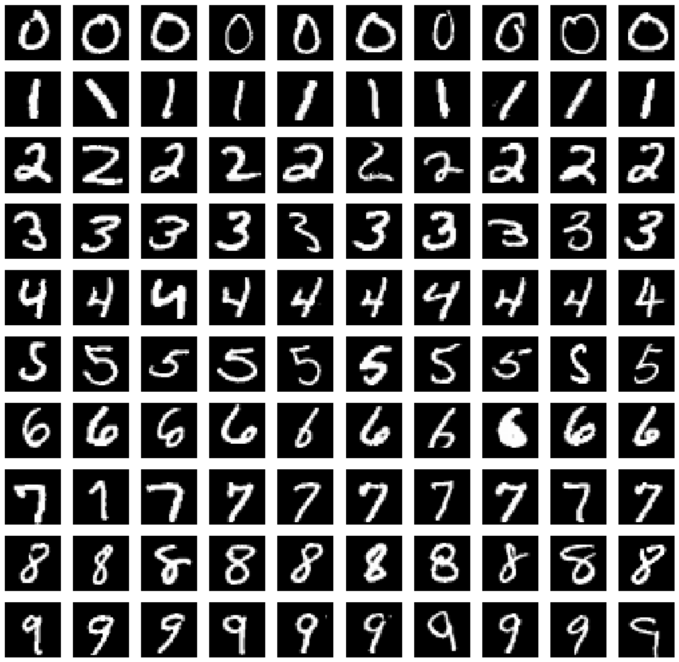
March 10, 2017

Part 1

Dataset description The dataset contained an even number of images per digit, having no more or less information the neural networks coud train off of determine one digit better apart from another. Each digit had multiple images of it where it was drawn with varying writing styles. Some digits were written with more loops and imperfections than others, had different thicknesses or were drawn slanted at different angles.Some digit images had discontinuous lines in the number shapes.
For example, in the images of the 0's some had a closed loop while others were perfect and had a small edge that jutted out near its top.

1. variety of angles
2. different styles of handwriting
3. gaps between continuous lines
4. different thickness levels



Part 2

Compute the network function by propagating forward and discarding intermediate results

```python
def compute_network(x, W0, b0, W1, b1):
    _,_, output = forward(x, W0, b0, W1, b1)
    return = argmax(output)
```

Part 3

1. We will use negative log-probabilities as our cost function, and find its gradient

```python
def cross_entropy(y, y_):
  return -sum(y_ * log(y))
```

2. Vectorized code for computing gradient of the cost function

```python
def deriv_multilayer(W0, b0, W1, b1, x, L0, L1, y, y_):
    dCdL1 = y - y_
    dCdW1 = dot(L0, dCdL1.T)
    dCdobydodh = dot(W1, dCdL1)
    diff = 1 - L0**2

    dCdW0 = tile(dCdobydodh, 28 * 28).T * dot(x, (diff.T))
    dCdb1 = dCdL1
    dCdb0 = dCdobydodh * diff

    return dCdW1, dCdb1, dCdW0, dCdb0
```

To verify gradient correctness we used finite differences to compare our output.

Method	approximation	gradient
W1	0.984191894531	0.984342670068
W0	0.0	-0.0
b1	0.000476837158203	0.000534144113772
b0	0.0	0.0

Part 4

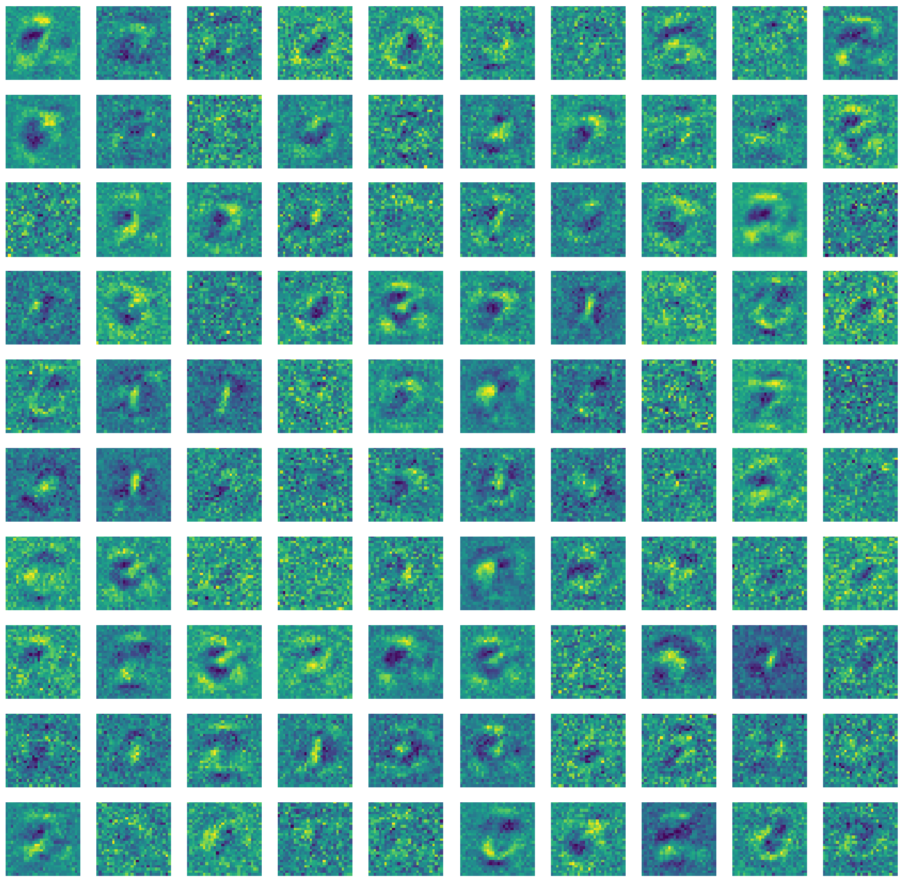
We start by loading sample weights from the pickle file. Then train it using mini-batch optimization to speed up training. Our training method works as follow:

1. First forward method - passes flattened image through the network keeping all intermediate results
2. Then we compute the gradient with respect to $W0, b0, W1, b1$
3. We keep accumulating error values and then update our parameters $W0, b0, W1, b1$ over a single batch and repeat

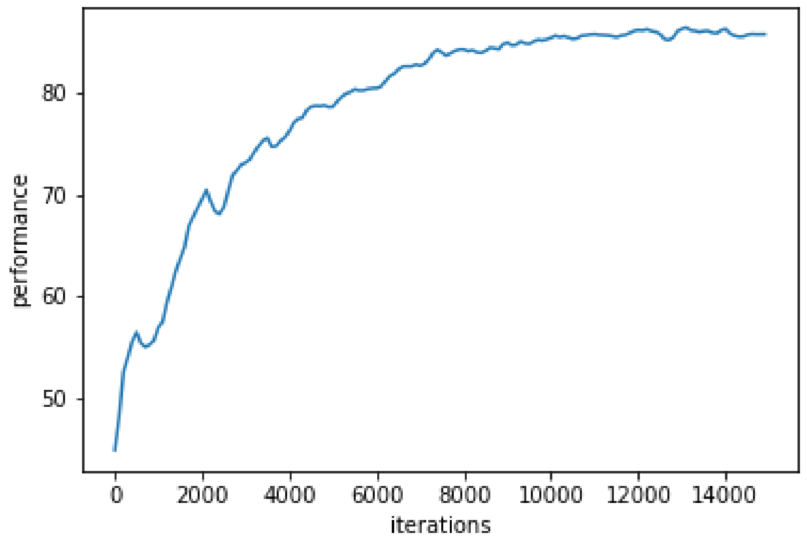
```python
def train(plot=False):
    global W0, b0, W1, b1
    global plot_iters, plot_performance
    plot_iters = []
    plot_performance = []
    alpha = 1e-3
    for i in range(150):
        X, Y, examples_n = get_batch(i * 5,10)

        update = np.zeros(4)

        for j in range(examples_n):
            y = Y[j].reshape((10, 1))
            x = X[j].reshape((28 * 28, 1)) / 255.
            L0, L1, output = forward(x, W0, b0, W1, b1)
            gradients = deriv_multilayer(W0, b0, W1, b1, x, L0, L1, output, y)
            update = [update[k] + gradients[k] for k in range(len(gradients))]

        # update the weights
        W1 -= alpha * update[0]
        b1 -= alpha * update[1]
        W0 -= alpha * update[2]
        b0 -= alpha * update[3]
        if plot:
            plot_iters.append(i * examples_n)
            plot_performance.append(test_perf())
    return plot_iters,plot_performance
train(plot=True)
```

```
def get_batch(offset,example_per_class=5):
    # 5 examples per class
    classes_num = 10
    x_batch = np.zeros((example_per_class * classes_num, 28 * 28))
    y_batch = np.zeros((example_per_class * classes_num, classes_num))
    for i in range(classes_num):
        for j in range(example_per_class):
            x_batch[i * example_per_class + j] = M['train' + str(i)][j +
                                                                        offset]
            y_batch[i * example_per_class + j][i] = 1
    return x_batch, y_batch, example_per_class * classes_num
```

visualizing weights:



performance graph:

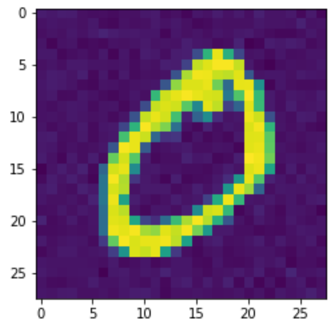


Part 5

So as discussed in lecture large errors are penalized quadratically in linear regressions. So our multinomial regression doesn't suffer from it. We start with generating a noise for our data set.

```
# generate noise and N(0,σ^2)
noise = scipy.stats.norm.rvs(scale=5,size=784*50*10)
noise = noise.reshape(500,784)
X,Y,n = get_batch(offset=0,examples=50)
X += noise
```

After modifying our data set with noise - we get images that look like this



Part 6

Part 7

To construct the neural network, we trained on 5400 images with 90 images per actor. Each image was cropped to a bounding box that was resized to a 60×60 array containing only the actor's face. Images were serialized in a dictionary that mapped the actors' names to an array list of their whole RGB images saved in a three-dimensional numpy array.

```
actor_imgs = {
'Steve Carell': [carell_1, carell_2, ..., carell_n],
'Fran Drescher': [drescher_1, drescher_2, ..., drescher_n]
 }
```

This dictionary was read from a file called `actor_imgs.p` using the `pickle` module to create a unique training, validation and test set.
Each image passed through the neural network was preprocessed to standardize its values and characteristics so we could compare images on the same physical conditions as closely as possible.
To preprocess each image we did the following:

- grayscale the image to convert the 3D RGB image to a 2D array `rgb2gray()` function given in class.
- flattening the image array to a 1×786 vector stored in a NumPy array
- normalize the image's pixels, their values are limited to values 0 to 1. This will allow us to compare images by standardizing the range of their pixel intensities

Neural Network Performance