Matthew Martin

998354224

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Project 3: Neural Networks (Connectionist Architectures and Ensemble Techniques)

Team Name: MatthewMartin

1.

The network that I chose is very simple. It consists of 3 layers: an input layer, a hidden layer, and an output layer. The input layer consists of 15360 (128 * 120) Sigmoid units, each corresponding to a pixel in the image. The greyscale values at the input layer are normalized (converted from [0, 255] to [0.0, 1.0]). The hidden layer consists of 16 Sigmoid units, each connected to all 15360 units in the input layer. The output layer consists of a single Sigmoid unit, connected to all 16 hidden units, where an output value of 0.0 maps to female and a value of 1.0 maps to male.

I chose this architecture because it was the simplest configuration I could think of, and it seems that simple is generally good when it comes to neural networks (in order to avoid overfitting). I decided on 16 units in the hidden layer after trial-and-error; A hidden layer of 16 units is large enough to achieve accurate predictions, but also small enough to avoid unneeded complexity (which makes decision surfaces overly complicated). Using a single output unit that maps to MALE or FEMALE is the naturally simple approach, so I chose it.

The model uses the standard stochastic gradient descent backpropagation scheme, and does not employ more complex variations.

The code consists of 8 java files: Display.java, FaceImage.java, ImageCollection.java, MatthewMartin.java, NeuralNetwork.java, NeuralNetwork_AllConnected.java, SigmoidUnit.java, and UnitLink.java. When "java MatthewMartin -train <MaleDir> <FemaleDir>" is run, a file called NeuralNetwork.data will be generated that contains all the trained weights. When "java MatthewMartin -test <TestDir>" is run, it will look for the NeuralNetwork.data file, load its contents, and feed each image in the <TestDir> directory into the neural network. The results are reported to stdout, one line per image, in lexographic order. The results consist of a prediction for each image, as well as the confidence value.

2.

The training data is divided into 5 folds, and one of these folds is chosen at random to be the "test fold." To ensure that there is equal male and female training data, the female data is duplicated four times. In the training set given, this results in 55 * 4 = 220 female faces and 218 male faces for a total of 220 + 218 = 438 training images. The neural network is trained only on the 4 non-test folds, and the test fold is passed into the network later as test data. I have defined "accuracy" to be 1.0 minus the difference from the expected result. If a MALE image is predicted to have a value of 0.7, the accuracy is

0.7. If a FEMALE is predicted to have a value of 0.7, the accuracy is 0.3. Thus, correct guesses have an accuracy of over 50%, and incorrect guesses have an accuracy below 50%.

The mean and standard deviation of the accuracy, as well as the number of guesses the network got correct, for 10 random 5-fold cross validation instances are shown in the table below:

Run Index	Mean of Accuracy	Std. Dev. of Accuracy	Guesses Correct
0	0.8789	0.1340	86/88
1	0.8829	0.1200	87/88
2	0.8724	0.1587	83/87
3	0.8752	0.1154	86/87
4	0.8687	0.1138	85/87
5	0.8837	0.1040	86/88
6	0.8721	0.1576	82/87
7	0.8780	0.1425	85/87
8	0.8673	0.1341	85/88
9	0.8758	0.1461	84/88

Note: Each fold has either 87 or 88 images in the training set given (438 images can be divided into 5 groups, 2 of which have 87 images and 3 of which have 88).

Of these ten 5-fold crossfold validation tests, 875 images were used in test folds. Of these 875, 849 were guessed correctly by the neural network after being trained on the remaining training folds. Thus, 97.03% of all guesses were made correctly.

Although the average “accuracy” is about 87%, this is the difference between the neural network result as a floating point number and the true value of an image (0.0 or 1.0). Therefore, if the neural network produces a value of 0.6 for a male, its accuracy is 60%, but it has still guessed the image correctly. Thus, the number of images that the network will guess correctly is higher than the reported “accuracy” value. According to the produced results, the neural network guesses approximately 97% of images correctly, and therefore has an approximate guessing error of 3%.

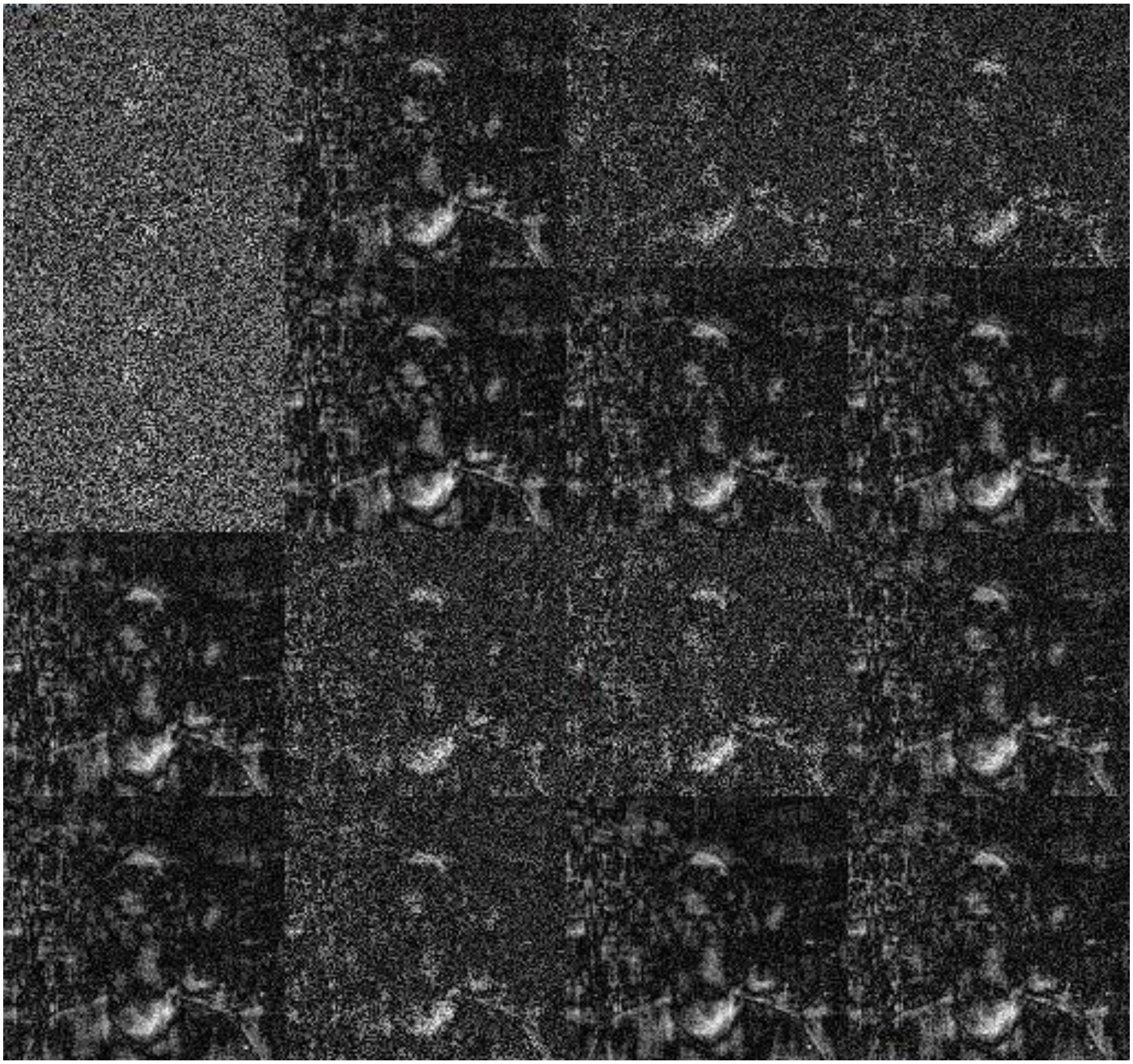
3.

The file MatthewMartin.predictions has been included, which contains a line for each of the 40 test images. The neural network was trained with an arbitrary seed (the neural network uses the seed to randomly shuffle the training data) using all given training data (/Male and /Female directories). Next, each image in the test set was fed into the trained network. Each line of the file has the prediction that was made by the neural network, as well as its confidence in each prediction.

My neural network has a single output unit that produces a floating-point number in the interval [0.0, 1.0]. If this number is below 0.5 the image is classified as FEMALE; if it is above 0.5 it is classified as MALE (a result of exactly 0.5 results in “UNDECIDED,” but this is so rare it will likely never occur in practice). The confidence (similar to the accuracy) of a given result is defined as simply 1.0 minus the distance from the guessed result (1.0 for MALE, 0.0 for FEMALE). For instance, if a value of 0.7 is produced, it will be classified as MALE with a confidence of 0.7. If a value of 0.1 is produced, it will be classified as FEMALE with a confidence of 0.9. Thus, the confidence will never fall below 0.5 (if the neural network is 40% sure that an image is male, it is 60% sure that it is female so it will be classified as such).

4.

The following image is the result of visualizing each hidden layer unit. Each of the 16 squares corresponds to a hidden unit:



In this visualization, dark areas correspond to areas where the weight is close to zero and lighter areas correspond to areas where the weight is further from zero. From the image, we can see that the neural network places a higher value on areas around the mouth, forehead, eyes, cheeks, and neck. Interestingly, the network places perhaps the largest value on the neck area. This suggests that the network is checking for the presence of an Adam's Apple to differentiate males. The neural network is also observing differences in male and female lips, eye placement, and cheek structure in order to make an accurate prediction.