

An Automated Process for Recognizing Handwriting with Accelerometers

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Abstract

The objective of this project is to develop an automated method for recognizing handwriting using accelerometers and to determine the factors that improve its accuracy.

One traces out individual block letters using an accelerometer. The acceleration versus time data from each letter is converted into an image using discrete double integration.

Machine Learning is used to classify the images as letters. Different parameters are changed to determine their effects.

The most successful model had an 90.00% accuracy in guessing EMINST letters and 10.26% for accelerometer written letters.

Introduction

Each recording produces a data point with 4 elements: time and acceleration in each direction. The i^{th} data point would be:

$$p_i = (t_i, a_{i1}, a_{i2}, a_{i3})$$

The velocity and position are calculated with discrete double integration:

$$x_i = x_{i-1} + v_i(t_i - t_{i-1})$$

$$v_i = v_{i-1} + a_i(t_i - t_{i-1})$$

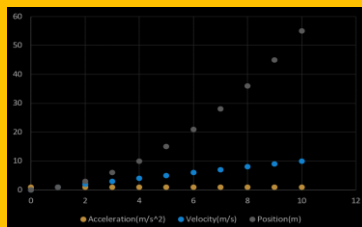


Figure 1: Example Acceleration, Velocity and Position vs Time (s) graphs with obtained by discrete double integration

The neural network takes information about individual letters as input neurons. In one iteration of training, the network randomly assigns the input layer values to values of neurons in one or many layers between the first layer and last layer. Over many iterations of this process, the weights and biases are updated in order to improve the model's accuracy.

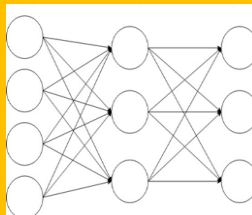


Figure 2: Graphic representation of neural network with Input (Left), Hidden (Middle), and Output (Right) neurons

Materials and Methods

The neural network was trained with several configurations using EMNIST Letters data.

By default the parameters were set as :

- 3 Hidden Layers – Size 100
- 50 Maximum Iterations
- Alpha of 0.1
- SGD Solver
- Tolerance of 0.0001
- Initial Learning Rate 0.1



Figure 3: Samples from the EMNIST 'letters' Dataset

The default configuration was tested with the following changes:

- 1, 2, 3, 4, 5, 6, 7, 8, and 10 Layers.
- Layer Sizes of 10, 50, 100, 150, 200, 250, and 300.
- Alpha Values of 0.0001, 0.001, 0.01, 0.1, 1, and 10.
- SGD, Adam and LBFGS Solvers.
- 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 Random States.
- Initial Learning Rates of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, and 0.8.

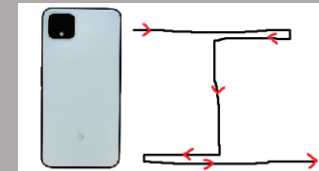


Figure 4: Illustration of the Pixel 4 Taking a Path to draw the letter 'I'

Fifteen Copies of the English Alphabet were traced using the accelerometers from an iPhone 7 and a Google Pixel 4. These were converted into images using discrete double integration. The best performing model with EMNIST was tested on this data for accuracy.



Figure 5: Graphs of an 'I' drawn by Accelerometer from the Pixel 4

Discussion and Future Work

- Increasing the number of layers increases testing accuracy
- Increasing the size of layers increases testing accuracy
- An Alpha value of 0.1 produced the highest testing set score
- The SGD solver performs the best.
- Changing the number of random states had little effect on the accuracy of the model
- Increasing the initial learning rate decreases the testing score

The best performing model with EMNIST (default without random states) was tested on the accelerometer drawn images for accuracy. The score is 10.2564%. Since EMNIST letters look different from Accelerometer letters, it might be more effective to use an Accelerometer made data set to train the neural network in the future.

Conclusions

For recognizing handwriting with SKLearn's Multilayer Perceptron Classifier, optimal accuracy can be obtained by using:

- Many Large Layers
- Alpha Value of 0.1
- The SGD Solver
- 0 Random States
- Low Initial Learning Rate

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This research would not have been possible without this course's coordinator Roberta Šilerová, my research supervisor Chris Larnder and my research partners Jerome Chabert, Hoang Anh Nguyen and Adamo Orsini.

References:

Cohen, G., Afshar, S., Tapson, J., & van Schaik, A. (2017). EMNIST: an extension of MNIST to handwritten letters. Retrieved from <http://arxiv.org/abs/1702.05373>
sklearn.neural_network.MLPClassifier. Retrieved from https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html

Results

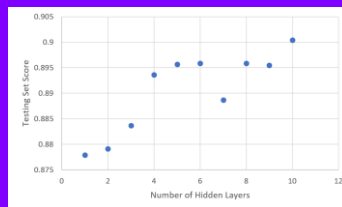


Figure 6: Testing Set Score using Different Numbers of Hidden Layers

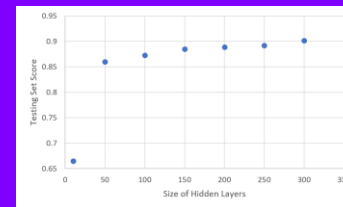


Figure 7: Testing Set Score using Different Amounts of Hidden Layers

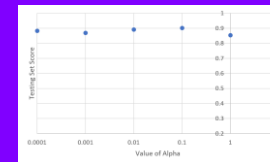


Figure 8: Testing Set Score using Different Alpha Values

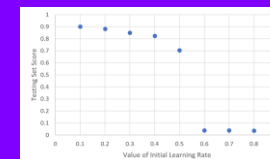


Figure 9: Testing Set Score using Different Initial Learning Rates