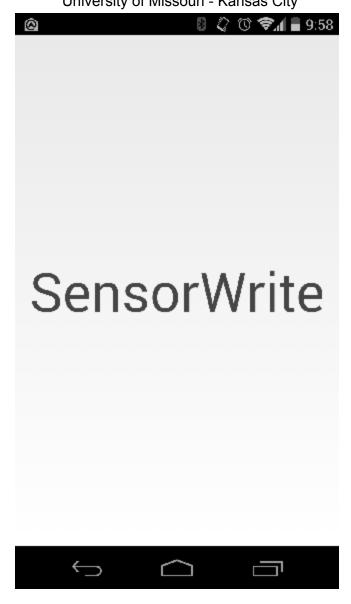
SensorWrite

Increment 4

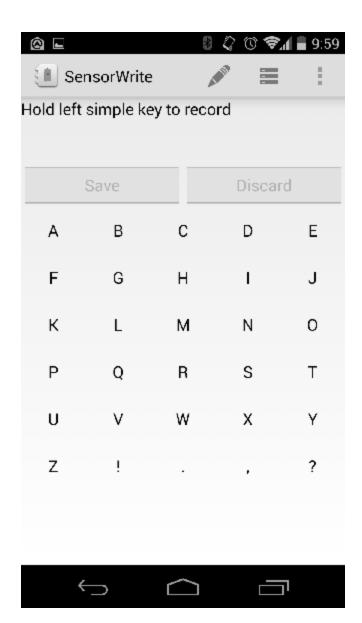
Group 7: James Clark, Anthony Sommer, Saitejasree Ramala, and James Wehmueller
CS 590BD: Big Data Analytics
Dr. Yugyung Lee
July 28, 2014
University of Missouri - Kansas City



Online Application:

This application uses the TI SensorTag to record the gestures of the user. In this application the user "air-writes" letters to an Android display using the TI SensorTag's accelerometer. The first phase of the application is to train the data. To do this the user selects the letter they want to train. When they are ready, they hold the left button on the tag (the one with four dots) and draw their letter, releasing when the letter is finished.

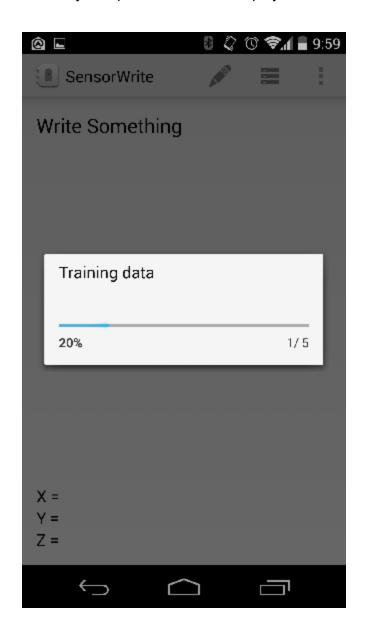


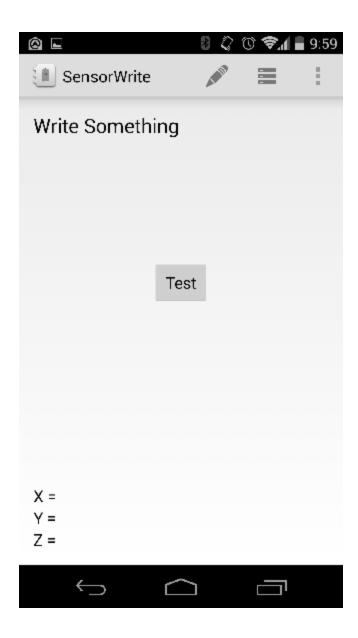


Initially the application doesn't actually learn the data, instead it simply stores it. When the application is booted, or when the testing screen is selected, then it goes through the stored data to train the system. It uses the Baum-Welch algorithm, which utilizes a Hidden Markov Model. This algorithm is explained here: http://en.wikipedia.org/wiki/Baum%E2%80%93Welch_algorithm.

Offline Application:

When testing for data, the user selects the "test" button, then when they're ready they hold down the left button on the tag and write their letter. When they let go of the button on the tag, the application uses the HMM to find which letter is most likely to represent it. It then displays this letter on the screen.





Evaluation:

To test this data we had a single user input training data (J.W) and tested the data three times, twice with James, and once with J.W. We trained 5 letters (A, B, C, D, and E), training each one with 10. For the tests we used 10 repetitions for each letter.

Data:

First test (User: James)

| Actual\Predicted | A | В | С | D | Е |
|------------------|---|---|---|---|---|
| Α | 4 | 5 | 0 | 0 | 1 |
| В | 0 | 9 | 0 | 1 | 0 |
| С | 3 | 0 | 6 | 0 | 1 |
| D | 0 | 7 | 0 | 3 | 0 |
| E | 0 | 5 | 0 | 0 | 5 |

| | A | В | С | D | Е |
|-----------|-----|------|-----|-----|-----|
| Precision | .57 | .35 | 1 | .75 | .71 |
| Recall | .4 | .9 | .6 | .3 | .5 |
| F-Measure | .47 | .504 | .75 | .43 | .59 |

Second test (User: James)

| Actual\Predicted | A | В | С | D | Е |
|------------------|---|----|---|---|---|
| Α | 3 | 7 | 0 | 0 | 0 |
| В | 0 | 10 | 0 | 0 | 0 |
| С | 2 | 0 | 5 | 0 | 3 |
| D | 0 | 3 | 0 | 7 | 0 |
| E | 0 | 2 | 0 | 0 | 7 |

| | A | В | С | D | Е |
|-----------|----|-----|-----|-----|----|
| Precision | .6 | .59 | 1 | 1 | .7 |
| Recall | .3 | 1 | .5 | .7 | .7 |
| F-Measure | .4 | .74 | .67 | .82 | .7 |

| Actual\Predicted | A | В | С | D | E |
|------------------|----|---|----|---|----|
| A | 10 | 0 | 0 | 0 | 0 |
| В | 0 | 6 | 0 | 4 | 0 |
| С | 0 | 0 | 10 | 0 | 0 |
| D | 0 | 4 | 0 | 6 | 0 |
| E | 0 | 0 | 0 | 0 | 10 |

| | A | В | С | D | E |
|-----------|---|----|---|----|---|
| Precision | 1 | .6 | 1 | .6 | 1 |
| Recall | 1 | .6 | 1 | .6 | 1 |
| F-Measure | 1 | .6 | 1 | .6 | 1 |

Fourth test (User: Teja)

| Actual\Predicted | A | В | С | D | E |
|------------------|----|---|---|---|----|
| Α | 10 | 0 | 0 | 0 | 0 |
| В | 0 | 8 | 0 | 2 | 0 |
| С | 0 | 0 | 9 | 0 | 1 |
| D | 0 | 3 | 0 | 7 | 0 |
| E | 0 | 0 | 0 | 0 | 10 |

| | A | В | С | D | E |
|-----------|---|-----|-----|-----|-----|
| Precision | 1 | .8 | .9 | .7 | 1 |
| Recall | 1 | .72 | 1 | .77 | .9 |
| F-Measure | 1 | .75 | .94 | .73 | .94 |

Evaluation:

As one would expect, J.W.'s and Teja's results were much more accurate than James'. Other than the confusion between B and D, J.W. was perfect. Teja also had some confusion between B and D, but only had one other error. James had inconsistent, and somewhat poor, results.

This analysis has many limitations.

- 1. We took much care to be certain we were holding the sensor as straight as possible during training and testing. The issue of the tag orientation is an important one for our application. If the user turns the tag while writing, it can affect the data in significant ways. We were originally going to address this issue by normalizing the data using the gyroscope, but we found out that the gyroscope wasn't sufficient for this task. This problem could also be solved by using a sufficient number of training data, but we simply didn't have time to do hundreds of training sets.
- 2. We only tested 5 letters, If we were to include all letters then the number of errors would likely increase significantly, since there are more letters to confuse it with.
- 3. We only tested and trained with 10 attempts for each letter. If we were to use more training data our results would almost certainly be more accurate. Also the fact that we only tested with a small sample means our statistical results have a large margin of error.
- 4. We only had one person train the data for each test. While this would increase the accuracy for a user like James to include other training data (even if it wasn't his own), it would likely decrease J.W.'s and Teja's performance.

YouTube Video

https://www.youtube.com/watch?v=qGfQpRyzSGQ&feature=youtu.be