EEG-Based Control of a Computer Cursor Movement with Machine Learning. Part B

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Introduction

Brain-Computer Interface (BCI) systems have become a source of great interest in the recent years. Establishing a link with the brain will lead to many possibilities in the healthcare, robotics, or entertainment fields.

Instead of using invasive BCI, we are trying to understand user intention by classifying their Electroencephalography (EEG) result, which recorded electrical activities of the users' brain, with state-of-art machine learning technologies. Through this technique, more advanced prosthetic devices can be developed and handicapped patients can be benefited from it.

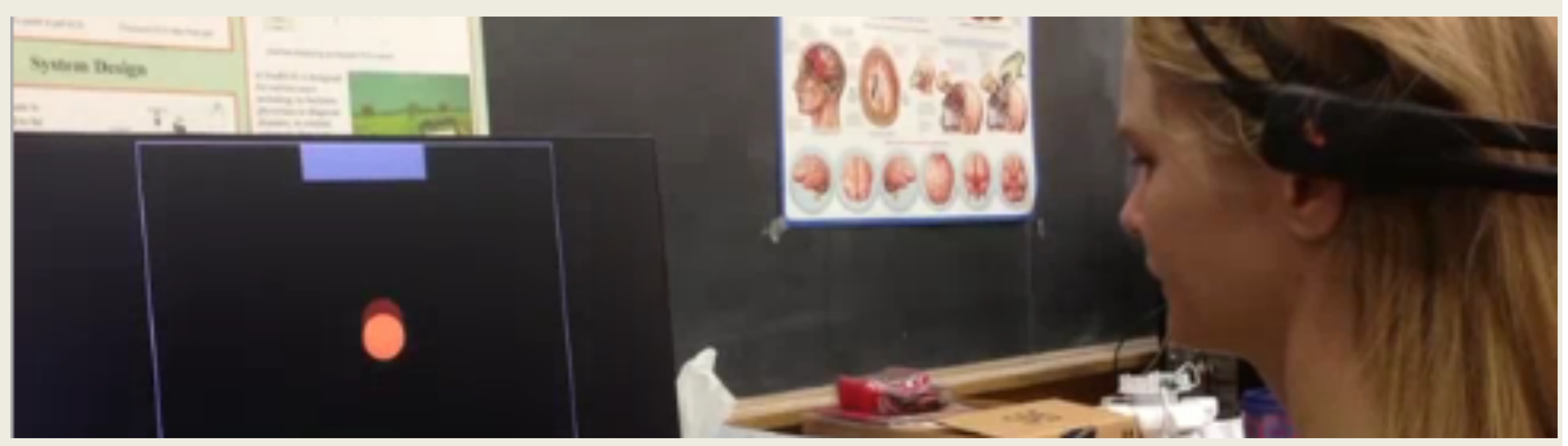


Figure 1: A picture captured during experiments [1]

Objectives

- To classify the user indenting cursor movement by using EEG signal with high accuracy, and
- To accelerate the process to acceptable speed

Formulized Problem

In the sense of machine learning, this is a supervised multiclass classification. The specification as follow:

- **Input**
  EEG data (time series) with 128 Hz and 14 channels
- **Prediction**
  The cursor movement direction at any given time point

Vertical	Left	Right	No Movement
Horizontal	Up	Down	No Movement

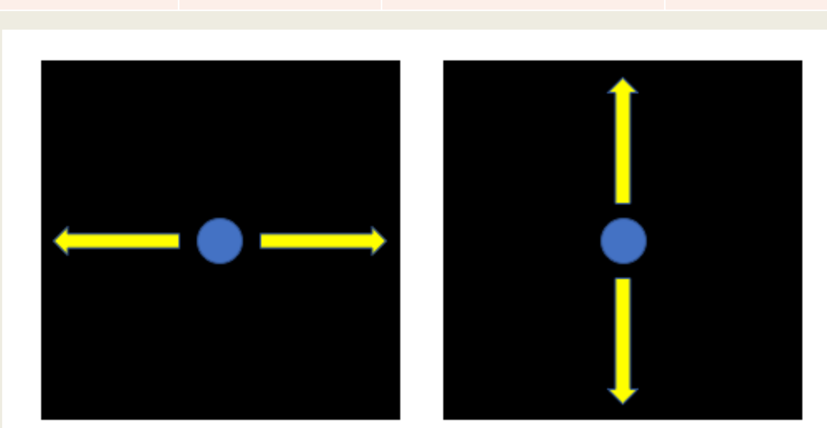
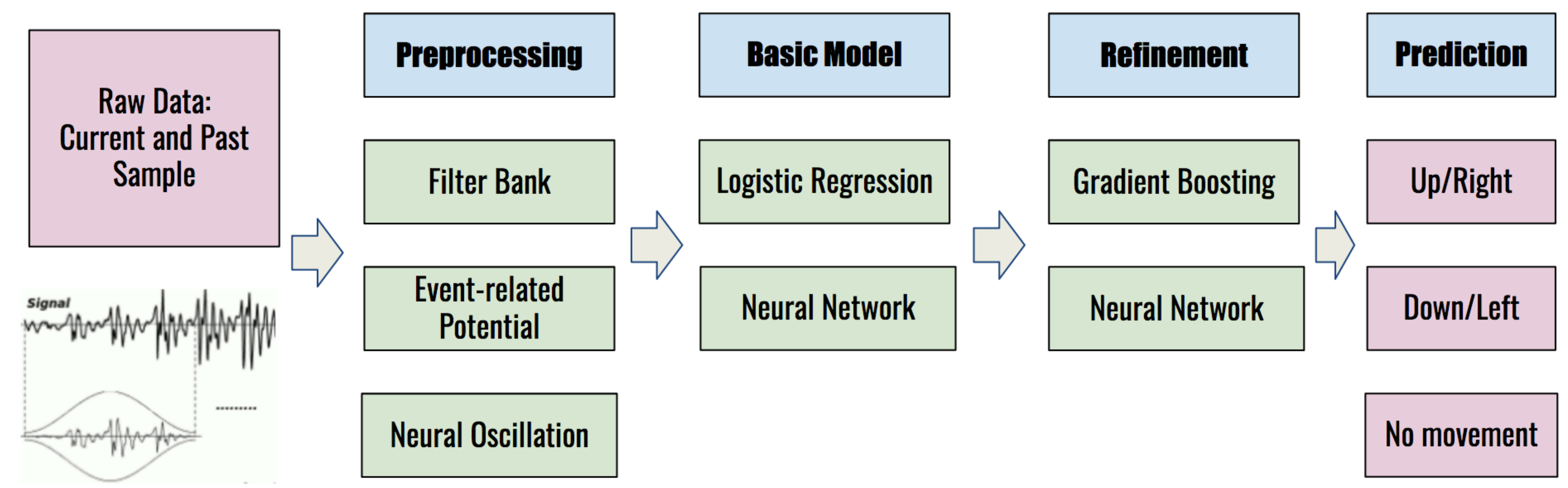


Figure: Outline of training task using one dimensional movement

Overview of the Models



Features Extraction: Filter Bank

Low freq. → High freq.

Psychological or Physiological State	Changes in EEG Waves
Deep sleep	Predominance of the delta wave
Concentrated	Suppression of the alpha wave
Vigilant	Generation of beta wave
Recognition of sensory stimuli	Changes in gamma wave

Figure: Changes in EEG Waves and Psychological and Physiological States are Related [2]

Involved Classification Techniques

Neural Network

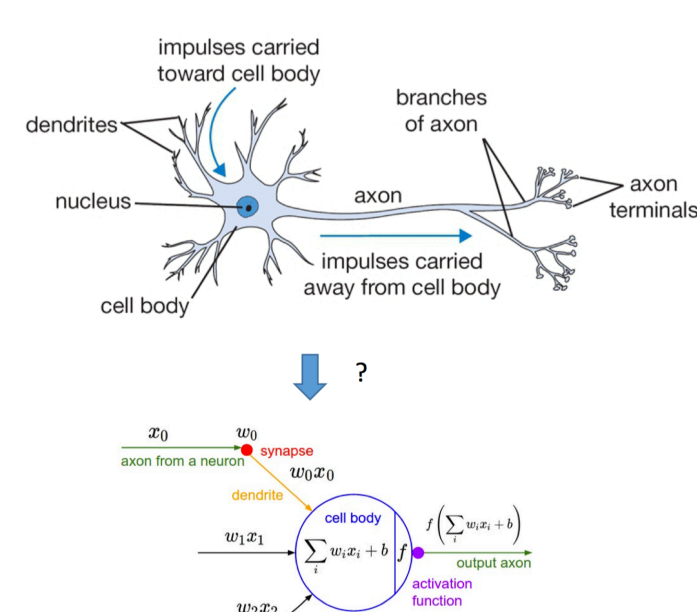


Figure: The basic principle of NN [2]

Gradient Boosting

Gradient Boosting = Gradient Descent + Boosting

Adaboost

$$H(x) = \sum_t \rho_t h_t(x)$$

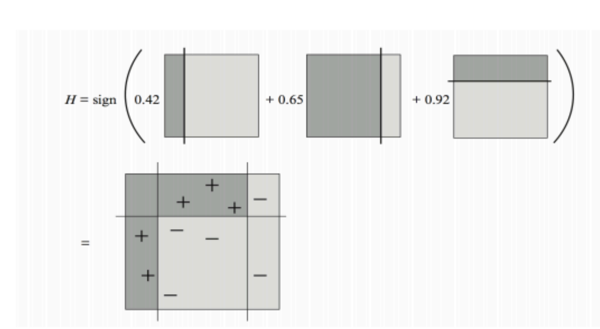


Figure: AdaBoost. Source: Figure 1.2 of [Schapire and Freund, 2012]

Figure: An intuitive explanation of GB [3]

Experiment Setup

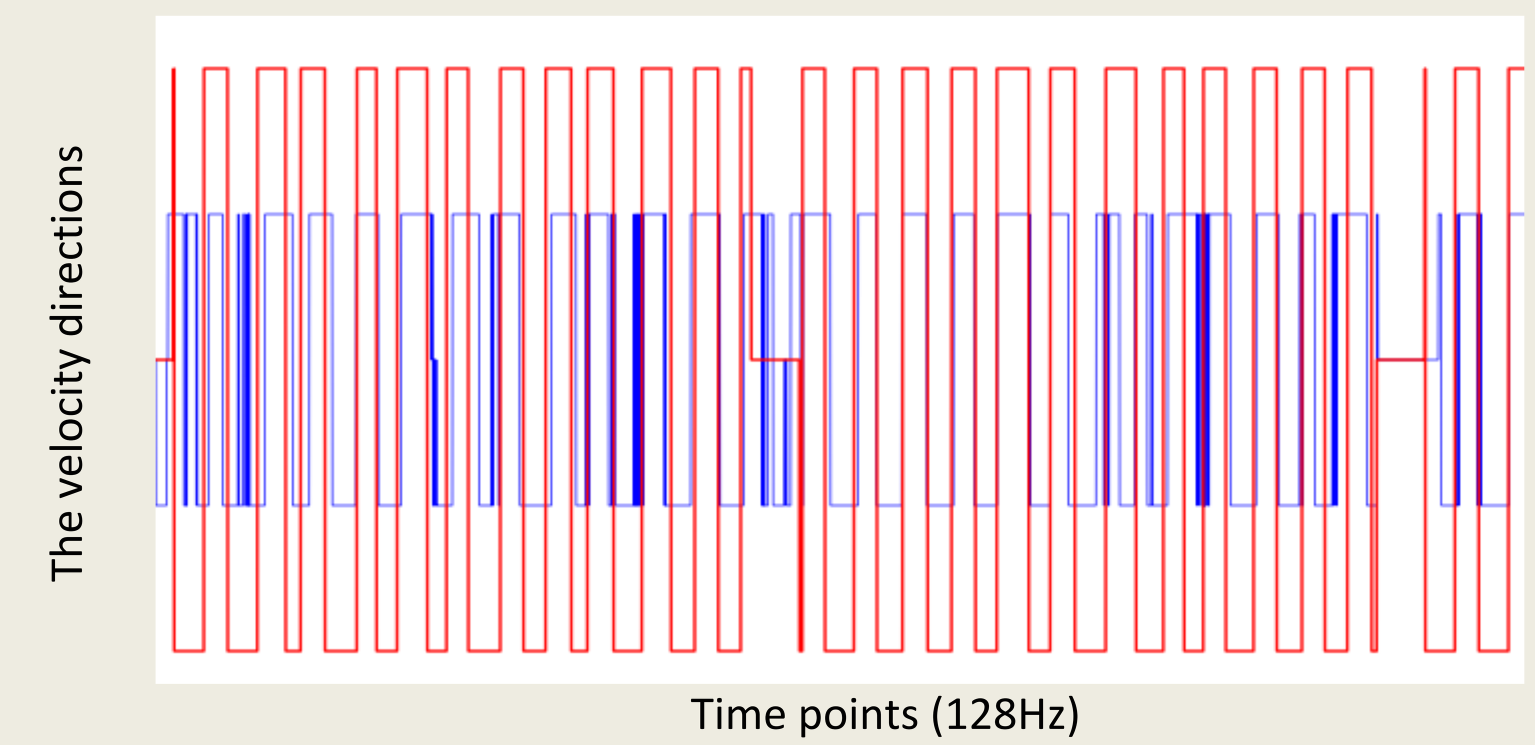
- 12 Subjects' data were used
- Each of them has 5 trials about horizontal / vertical movements

Trials	1st, 2nd and 3rd	4th	5th
Basic Models	Training Data	Validation	Validation
Ensemble Models	-	2-fold Valid	2-fold Valid

The Computation ran on XSEDE-Bridges 16 Cores + GPU (P100)

Results

The comparison of prediction and ground truth of each time points

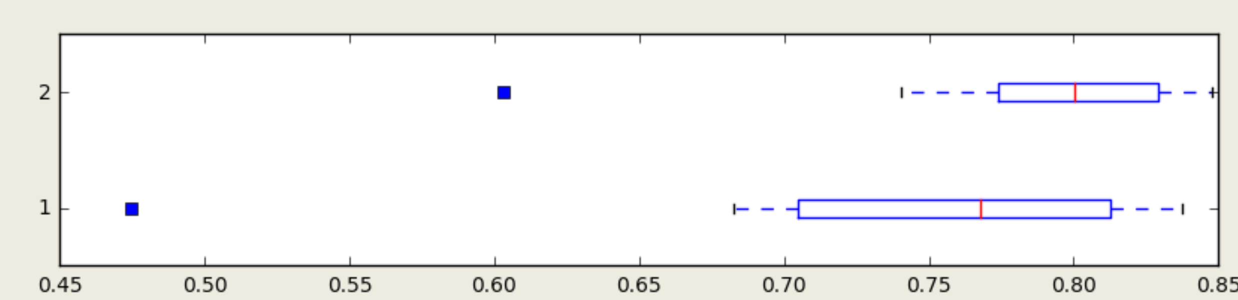


Red: Ground Truth **Blue: Our Classification**

Prediction	AUC	Accuracy
Horizontal	0.92	80%
Vertical	0.74	60%

AUC is the area under the ROC curve and mainly uses to estimate the classifiers' capability of discrimination.

The boxplot of the mean accuracy of each subject



Although the accuracy of the models varies from subjects to subjects, our models can perform well on most of the subjects.

Future Work

- Accelerating the process by converting to C programs
- Integrating the models to Brain-Computer Interfaces

Acknowledgements

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References

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[2] KatarzynaBlinowska, Piota Durka. ELECTROENCEPHALOGRAPHY (EEG) [Online]. Available: http://users.rowan.edu/~polikar/CLASSES/ECE504/EEG.pdf
[3] From a Lecture (10) PowerPoint of CUHK IERG4160 (2017 Spring)
[4] Cheng Li. Northeastern University. A Gentle Introduction to Gradient Boosting.