

An EEG Workload Classifier for Multiple Subjects

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Overview

1. Challenge

2. Approach

3. Experiment

4. Discussion

5. Future Direction

Challenge

- * Large amount of noise
- * Large between-subject/day/trial variations

	Individual subject	8 subjects
NB	80%	45%
NN	80%	58%

Goal

A Classifier for
Multiple Subjects!

Stimulation

- * A subject-specific classifier

Trained and tested on individual subjects

- * A cross-subject classifier

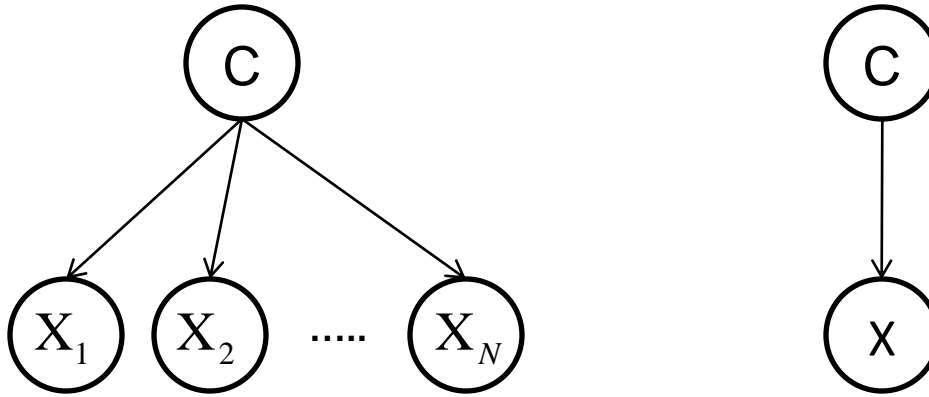
Trained on a group of subjects and tested on the same group of subjects

- * A subject-independent classifier

Trained on a group of subjects but tested on a novel subject that has not been trained on

Approach

Naïve Bayes Classifier



Likelihood

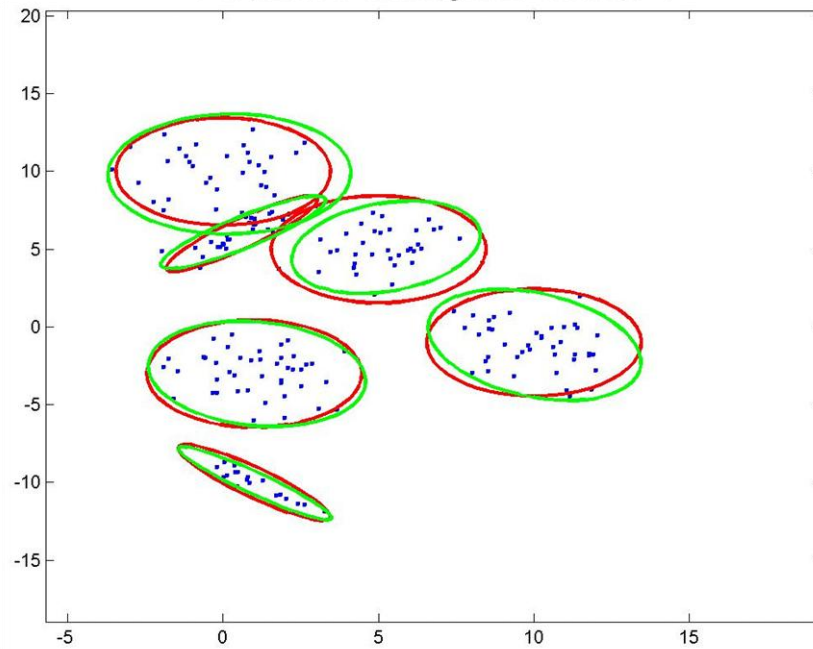
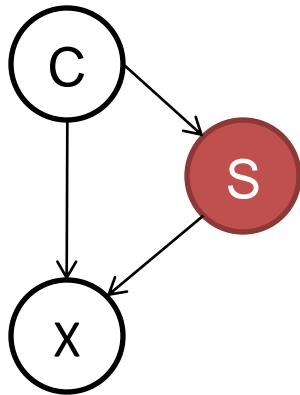
$$P(X_1, X_2, \dots, X_n | C) = \prod_{i=1}^n P(X_i | C)$$

Posterior Probability

$$P(C | X_1, X_2, \dots, X_n) \propto \prod_{i=1}^n P(X_i | C) P(C)$$

Approach

1st Attempt to Deal with Between-Subject Variations

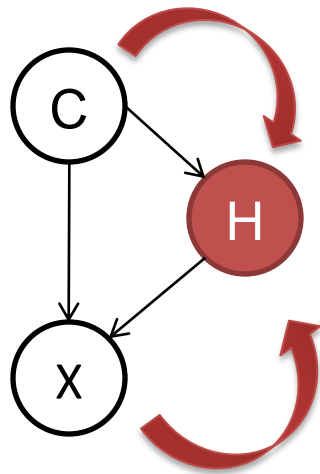


S is known during training but not testing

$$P(C | X) \propto \sum_S P(X | C, S) P(S | C) P(C)$$

Approach

2nd Attempt to Deal with Between-Subject Variations

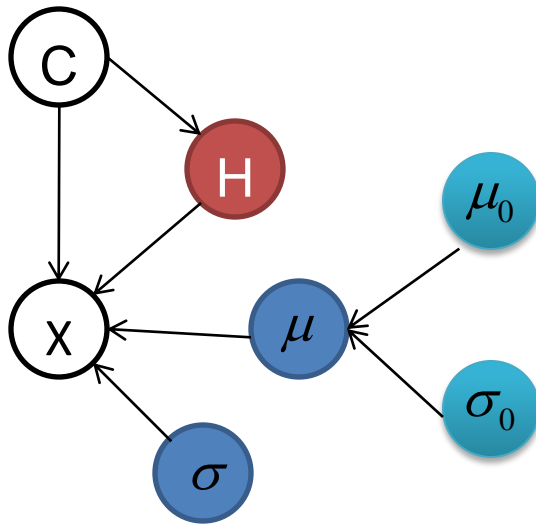


- * Factors including subject that could cause variations
- * Hidden Component

- H is unknown during both training and testing
- EM algorithm is used to uncover H node for training

Approach

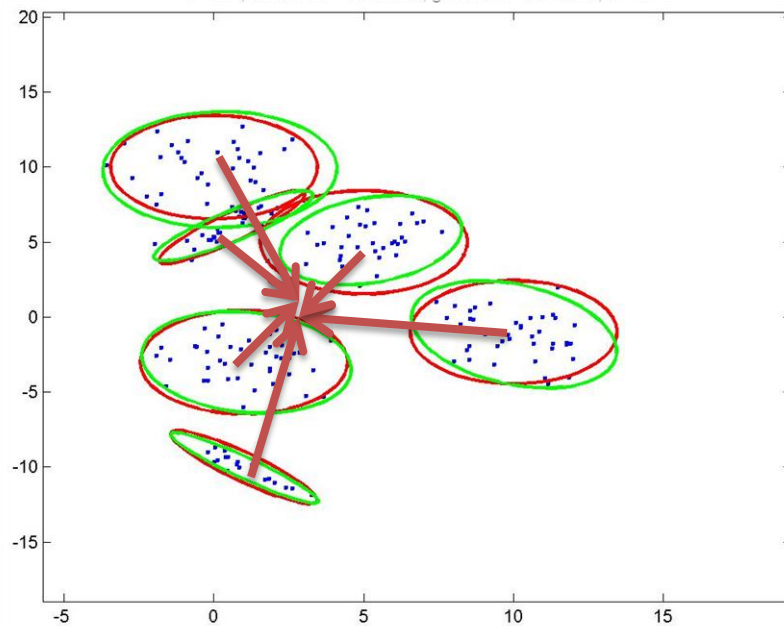
3rd Attempt to Deal with Between-Subject Variations



$$P(X | C, H) \sim N(\mu, \sigma)$$

$$\mu \sim N(\mu_0, \sigma_0)$$

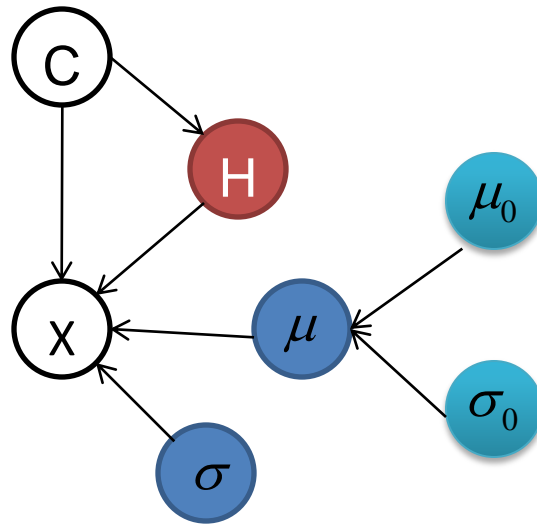
Constraints over parameters



Approach

Properties:

- * No a prior information is needed during both training and testing
- * Able to capture the between-subject variations automatically
- * Avoid overfitting by high level constraints



Experiment

Data

	Trial 1	Trial 2	Trial 12
Subject 1	L M H	L M H	L M H
Subject 2	L M H	L M H	L M H
Subject 3	L M H	L M H	L M H
.....
Subject 8	L M H	L M H	L M H

Experiment

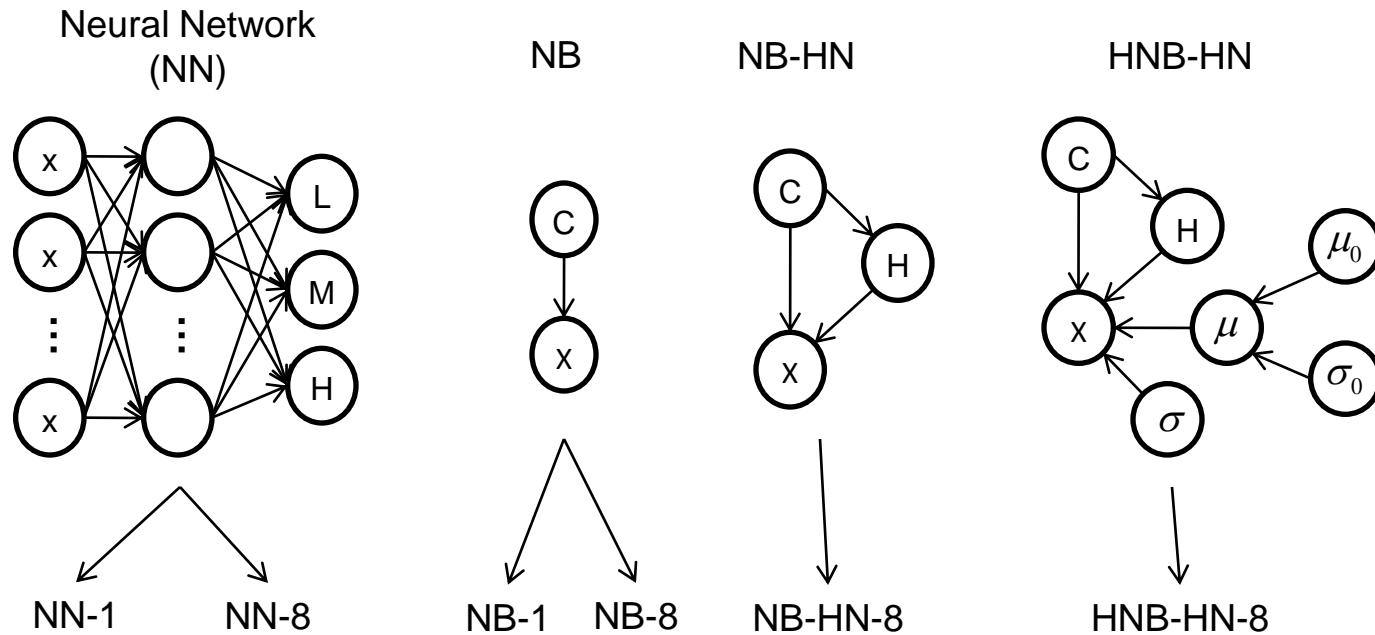
Feature

- * **19 EEG channels**
- * **Down sampled to 128 Hz**
- * **No artifact correction or rejection**
- * **Short-term Fourier transform**
- * **40s windows with 35s of overlap**
- * **No taper function was applied to the windows**
- * **Magnitude of 5 standard clinical bands**
- * **Delta [2-4Hz], theta [5-8Hz], alpha [9-13Hz], beta [14-32Hz], gamma [33-43Hz], expanded gamma [33-57Hz], [63-100Hz]**
- * **A total of 133 input features**

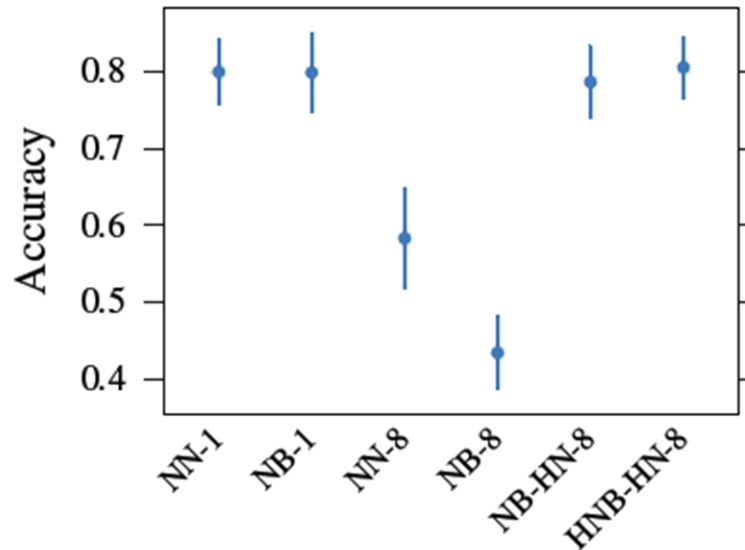
Experiment

Classifiers

- * **'-1': classifier that is trained and tested on individual subjects**
- * **'-8': classifier that is trained on all 8 subjects but tested on individual subjects**



Discussion



- * As expected, NN-8 and NB-8 performs much worse than NN-1 and NB-1 when presented to a group of subjects
- * NB with a hidden node performs as well as subject specific classifiers NN-1 and NB-1
- * Constraints on the parameters led to further improvement

Future Direction

- * Cross-trial, cross-day workload classification
- * A subject-independent classifier

For more details, you can also refer to our paper in the NeuroImage journal:

<http://dx.doi.org/10.1016/j.neuroimage.2011.07.094>

The work was supported in part by grant N0001410019 to Wayne D. Gray from the Office of Naval Research, Dr. Ray Perez, Project Officer.

Questions?