Improving Feedback in Massive Open Online Course (MOOC) Learning through EEG Analysis

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Overview

Original Paper Introduction Wang, Li, et. al 2011

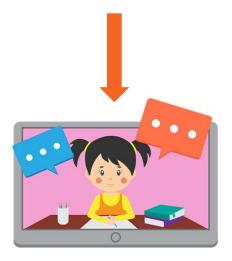
Goals

- Determine reproducibility
- Improve results with different model(s)
- Improve preprocessing and feature selection



Original Paper

Goals



- Determine if EEG can detect confusion
- Determine if EEG can detect confusion better than human observers
- End goal: provide feedback about student confusion level during remote learning





Original Paper - Setup

Design & Data Collection

- 10 students wore a **single-channel MindSet headset**
- Watched videos assumed to be confusing or not confusing
 - Confusing = quantum mechanics, stem cell research
 - Not confusing = geometry, algebra
- Self-reported confusion on scale of 1-7
 - Videos were also predefined as confusing or not confusing (second target variable)

Original Paper - Models

Gaussian Naive Bayes Classifier

- Good for sparse & noisy training set
- Two targets (predefined/student-defined confusion)
- Used various features captured from EEG data
 - O Not much said about dimensionality reduction or feature selection
 - No scaling of data

Original Paper - Models

Student Specific

- Single student as dataset
- Training on half the student's videos
- Testing on the other half of the student's videos

Student Independent

- Leave one out cross validation:
 - Training on all but 1 student
 - Testing on the left out student

Original Paper Results

Student Specific:

- 67% pre-defined confusion
- 56% user-defined confusion

Student Independent

- 57% pre-defined confusion
- 51% user-defined confusion

Room for Improvement

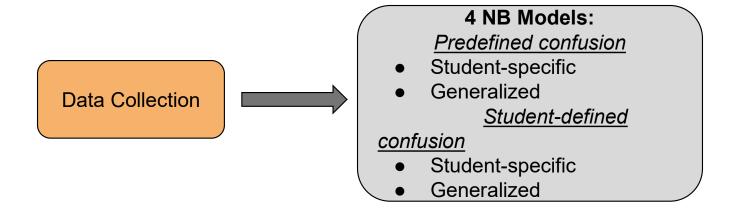
Data

- No feature selection
- Student-defined confusion is convoluted
- No data standardization
- VERY small dataset + one sample corrupted
- Age range narrow (24-31)

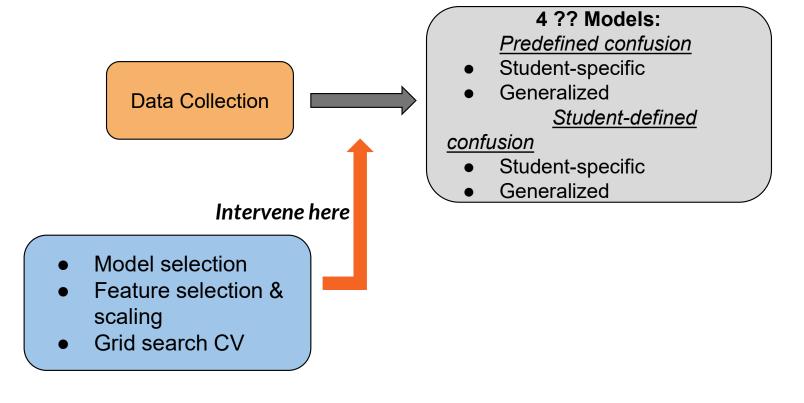
Model Selection/Usage

- No testing of various models
- No grid search or hyperparameter tuning

How do we improve??



How do we improve??



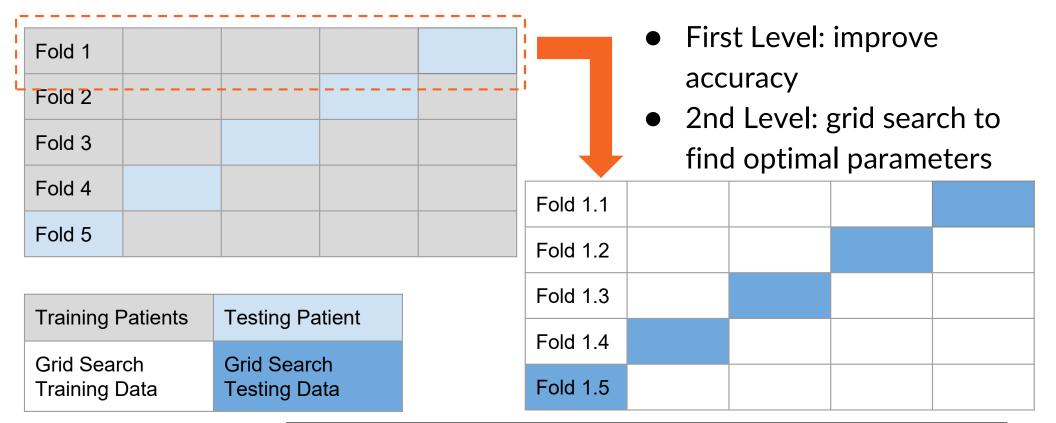
Improving Model Selection and Usage

Models Tested

- Logistic regression
- K Nearest Neighbors
- Support VectorMachine
- Random Forest
- Decision Tree

- Why these models?
- Considered the best for classification problems
- Compare their performance with naive bayes

Cross Validation



Model Results - Student Specific

Model	Average Pre-defined Confusion Label Accuracy	Average User-defined Confusion Label Accuracy
Their Naive Bayes	67%	56%
Naive Bayes	55%*	73%
Logistic regression	49%*	65%
K Nearest Neighbors	51%*	79%
Support Vector Machine	41%*	71%*
Random Forest	57%	80%
Decision Tree	58%*	83%*

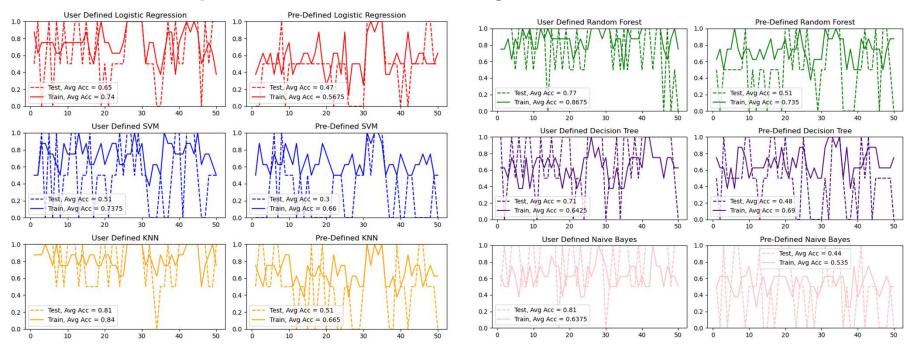
^{* =} Model improved by a combination of feature selection + scaling

Model Results - Student Independent

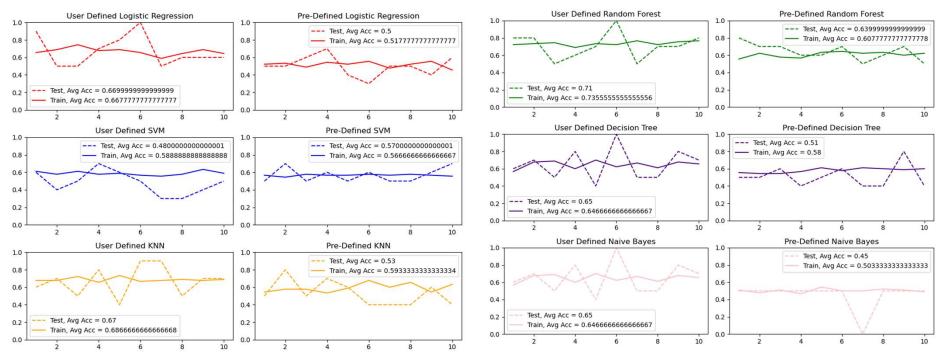
Model	Average Pre-defined Confusion Label Accuracy	Average User-defined Confusion Label Accuracy
Their Naive Bayes	57%	51%
Naive Bayes	50%*	67%*
Logistic regression	50%	67%
K Nearest Neighbors	65%*	70%*
Support Vector Machine	52%*	65%*
Random Forest	65%*	74%
Decision Tree	62%*	72%

^{* =} Model improved by a combination of feature selection + scaling

Evaluating Overfitting and generalizability: Student Specific



Evaluating Overfitting and generalizability: Student Independent

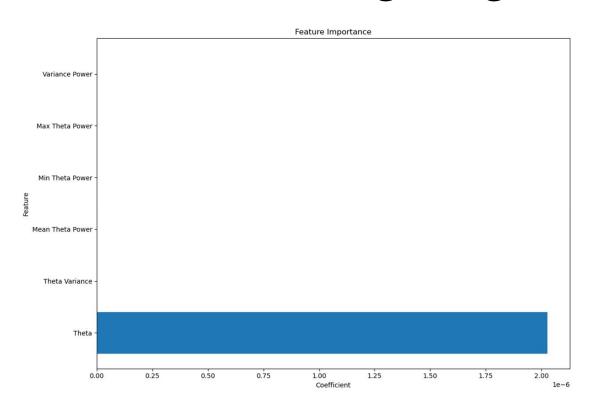


Improving Data

How can we improve the data?

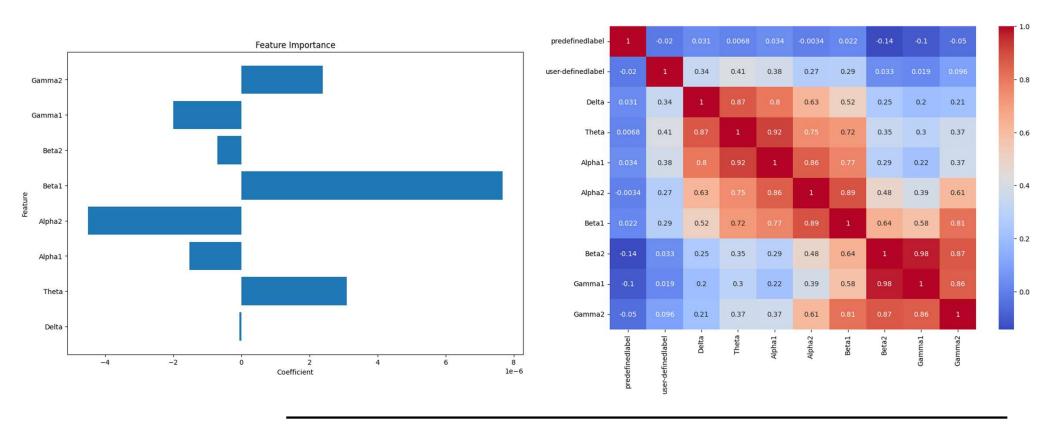
- Paper's researchers speculated that theta signal played important role
 - O In neuroscience theta wave correlated with:
 - Memory, learning and spatial navigation
 - O Can we generate more useful features from the theta band?
- Can we improve the features used in the models with better/more feature engineering?
- Will data normalization help with performance and overfitting?

Investigating Theta Features

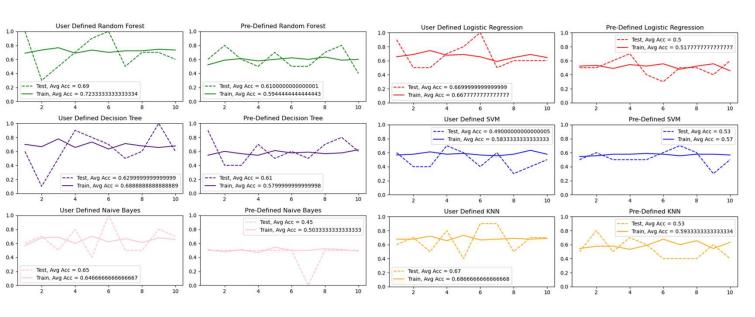


- Generated statistical features from theta band
- Performed LASSO
 Regression fit to
 determine if feature
 were important in
 classification
- Theta features not significant

Investigating Feature Importance



Does data regularization improve model performance and overfitting?



- Improved model performance?
 - o Yes
- Improved fit?
 - o Yes

Conclusions and Discussion

Best Performing Model(s)

- Model:
 - Student Specific: Decision Tree (27% inc.)
 - Student Independent: Random Forest (23% inc)
- Means of channels are features
- Regularization of data? Yes

Best Performing Model + Data Combo: Results

Student Specific:

- % pre-defined confusion
- % user-defined confusion

Student Independent:

- % pre-defined confusion
- % user-defined confusion

How we would design the for MOOC Feedback

Modeling:

- Label: student/user defined confusion
- Model: Random Forest
- Data normalization

Data Collection:

- Collect more data
- Take into account major(s) of students for video selection
- Wider age range of students (avg 27.9)

Thank you! Any Questions?

