Multi-task Learning for Commercial Brain Computer Interfaces

George Panagopoulos

gpanagopoulos@uh.edu, giorgospanagopoulos.github.io

Computational Physiology Lab, University of Houston, Houston, Texas 77204

Introduction

Problem

Improve subject generalization of passive economical Brain Computer Interfaces

Motivation:

Exploit the trade off between noisy individual recordings and increased number of subjects

Advantages:

Utilize knowledge shared between subjects during training

Extract patterns present in all subjects instead of explicit individuals

Methods

Discriminative MTL[1]

Logistic regression with group sparsity constraint on the K coefficients of all subjects T

\[
\min_{W} \frac{1}{N} \sum_{t=1}^{T} J(X_t, W_t, Y_t) + \lambda \sum_{k=1}^{K} |W_k|_2
\]

Rows of W are the feature coefficients \( w_t \) of each subject \( t \)

Each approach yields a different W:

- Subject Adaptive
- Multi-task
- Subject Invariant

Feature Coefficients

Subjects

The column average of multi-task W is the \( w_n \) of a new subject \( n \)

Data

Berkeley Experiment ¹

- 30 subjects
- One 5-minute session each
- Two types of stimuli during session
  - Math, memorizing colors, think of items
  - Listen to music, watch video ads, relax
- Cognitive state changes in the same session
- Classes: Mental activity or relaxation

Carnegie Mellon Experiment ²

- 9 subjects
- Ten 2-minute sessions with MOOC videos
- Self-classified levels of confusion for each session
- Cognitive state changes between sessions
- Classes: Confused or not

Results

MTL methods perform better as the number of subjects increases

MTL uncovers patterns that comply with the field’s literature

Conclusion

Multi-task algorithms are more robust than conventional pooled approaches to the subject generalization problem.

- Improved or steady accuracy with more subjects
- Consistent among datasets feature selection

References


Code

https://github.com/GiorgosPanagopoulos/Multi-task-Learning-for-Commercial-Brain-Computer-Interfaces