



COMPUTATIONAL PHYSIOLOGY LAB

Multi-task Learning for Commercial Brain Compute Interfaces

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- Brain Computer Interfaces
- Subject-subject generalization
- Multi-task learning
- Experiment
- Future work

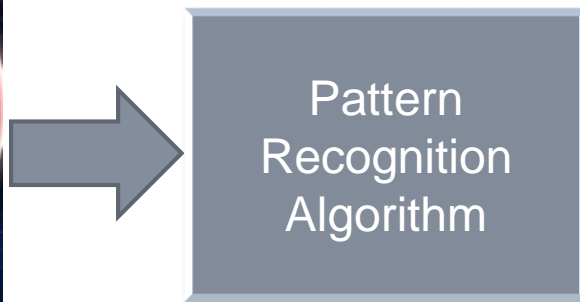
Brain Computer Interfaces

- Medical imaging devices, typically EEG-based
- Monitor the activity of certain areas of the brain
- Map certain recording patterns to specific activities (Active)
- Classify some aspect of the human's cognitive state (Passive)

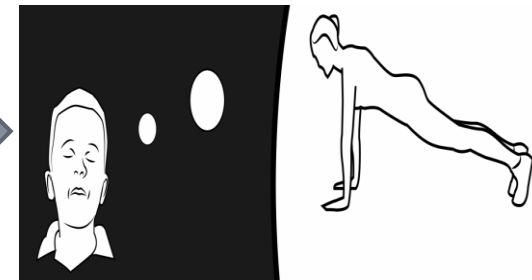
EEG signal



www.bio-signal.com



Classification



- BCI technology getting out of the lab
- Wireless headsets with EEG sensors and cool design

Advantages

- Economic
- Easy to use
- Application friendly
- Broader audience



Disadvantages

- Limited data
- Noisy signals

Subject-adaptive Algorithms

Train one specific model for each subject

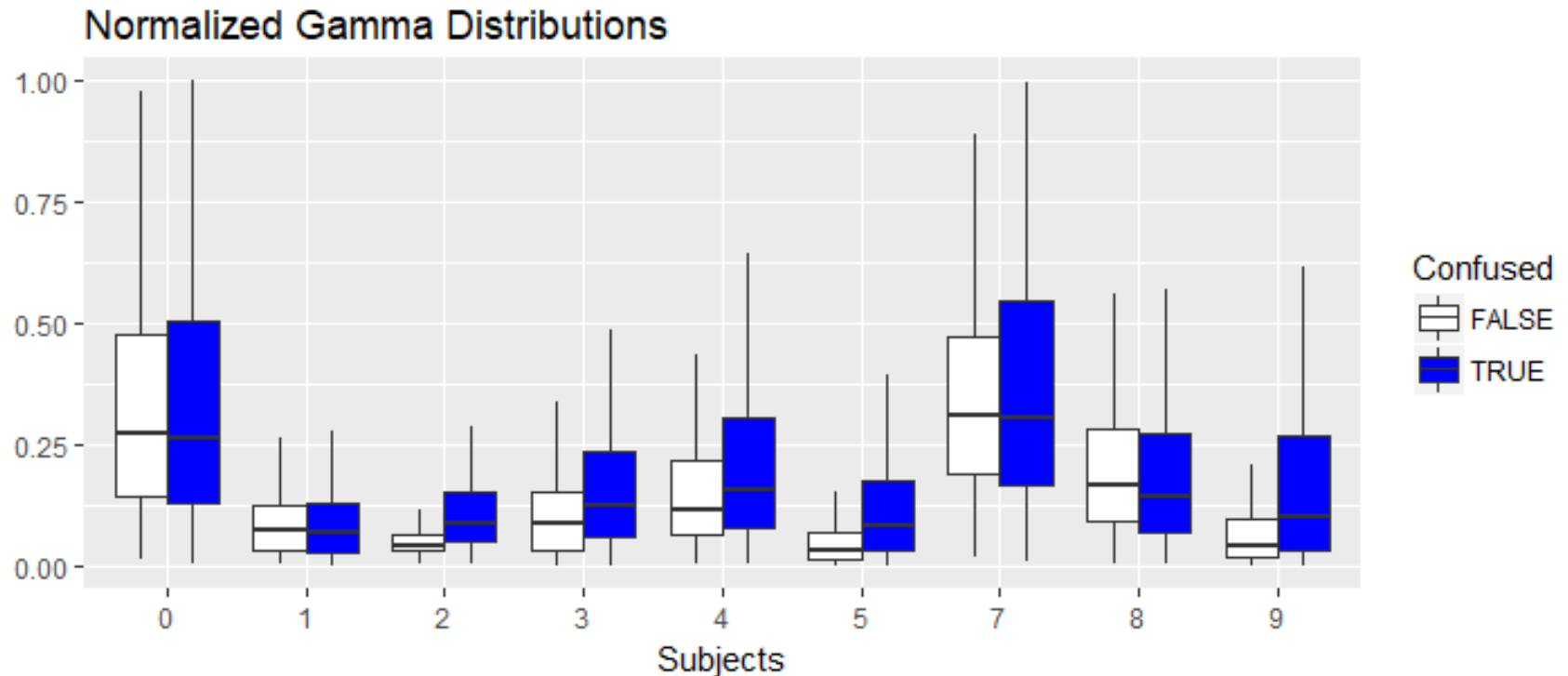
Problems:

- Need subject-specific training
- The algorithms adapt to noise
- Prior knowledge not utilized
- Knowledge extraction through different models, to derive general conclusions

Subject-invariant Algorithms

Train one model with data from all subjects (pooled)

Problem: Neural signals exhibit variability across brains



Multi-task Learning (MTL)

Learning on training tasks is performed simultaneously to capture intrinsic relatedness and share knowledge.

Advantages:

- Theoretically proved to increase accuracy in new tasks
- Extracts common patterns from all tasks
- Already used in clinical neuroimaging studies to overcome inter-subject variability issues

Regression with group sparsity constraint on the coefficients K of all tasks T

$$\min \frac{1}{N_t} \sum_{t=1}^T J(X_t, W_t, Y_t) + \lambda \sum_{k=1}^K |W_k|_2$$

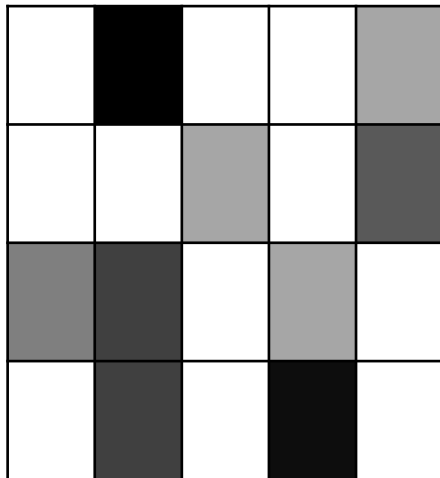
$$X_T \in R^{N_s \times K}, Y_s \in R^{N_s} \quad W = \begin{bmatrix} w_1^1 & \cdots & w_1^K \\ \vdots & \ddots & \vdots \\ w_T^1 & \cdots & w_T^K \end{bmatrix}$$

Difference in Coefficients

Each approach yields a different W :

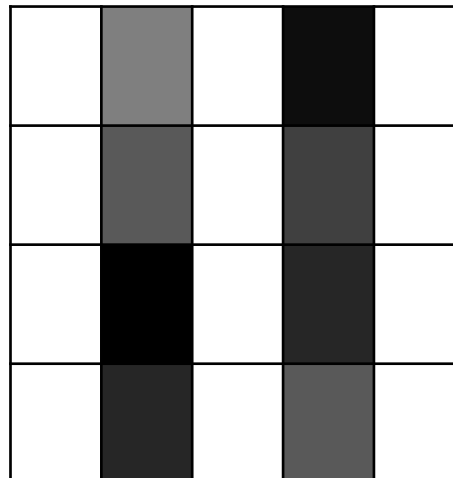
4 Subjects

Subject Adaptive



5 Features

Multi-task



Subject Invariant (pooled)



Bayesian estimation of the coefficients prior distribution, which is shared for all subjects

$$p(W; X, Y) \sim \prod_{t=1}^T p(y_t, X_t; w_t) p(w_t) \quad , \quad p(w_t) \sim N(\mu, \Sigma) \quad , \quad \forall t \in T$$

$$\min_{w_t, \mu, \Sigma} \frac{1}{\sigma^2} \sum_{t=1}^T \|X_t w_t - Y_t\|^2 + \frac{1}{2} \sum_{t=1}^T (w_t - \mu)^T \Sigma^{-1} (w_t - \mu) + \frac{T}{2} \log \det(\Sigma)$$

A coefficient vector w_n for a new subject is sampled from $N(\mu, \Sigma)$.

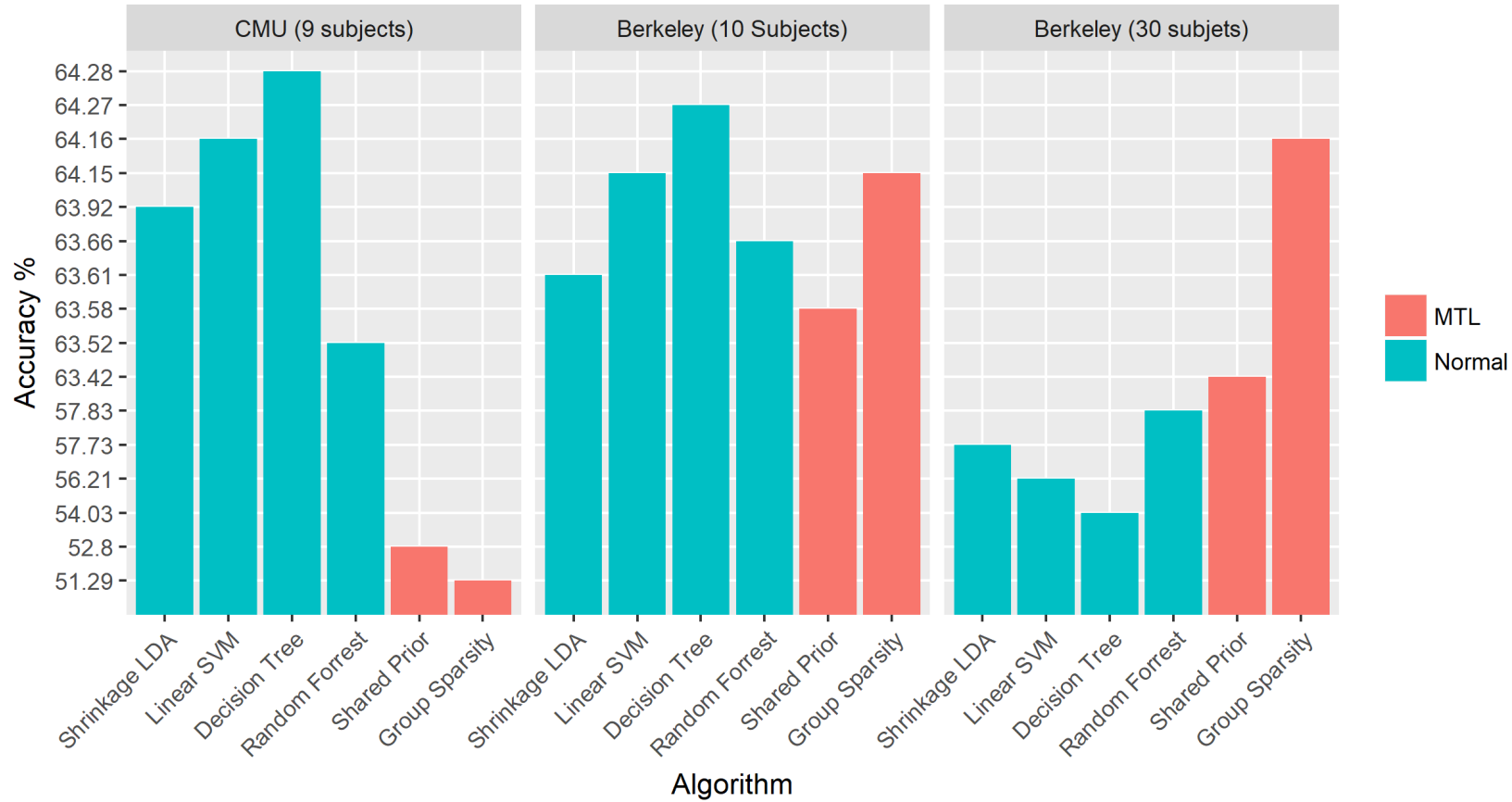
Carnegie Mellon Experiment

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

Berkeley Experiment

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

10-fold subject cross validation

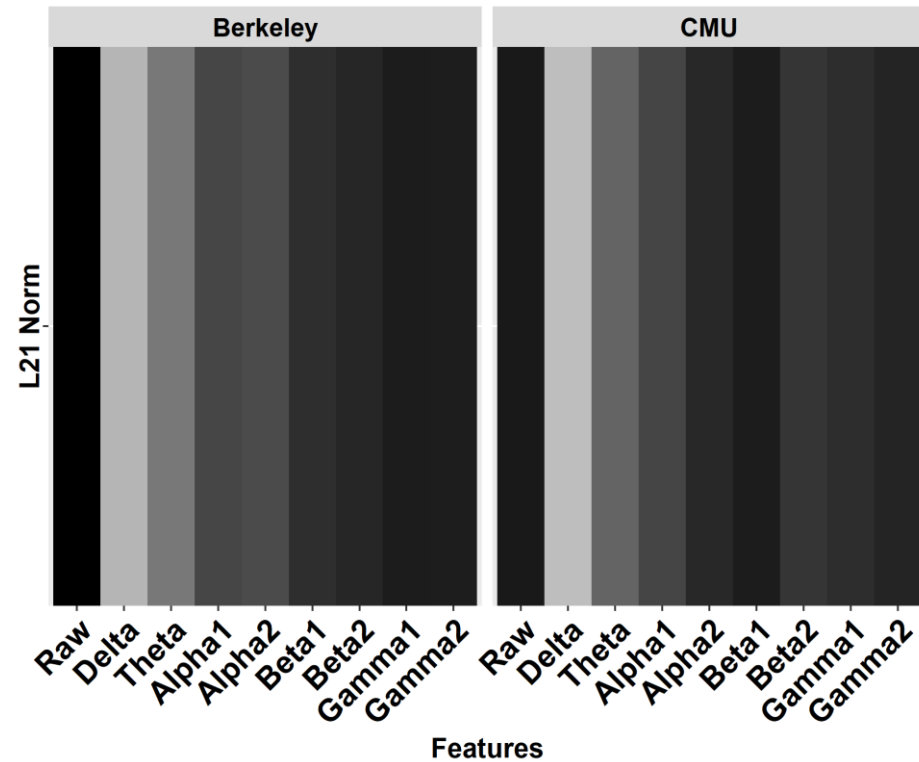
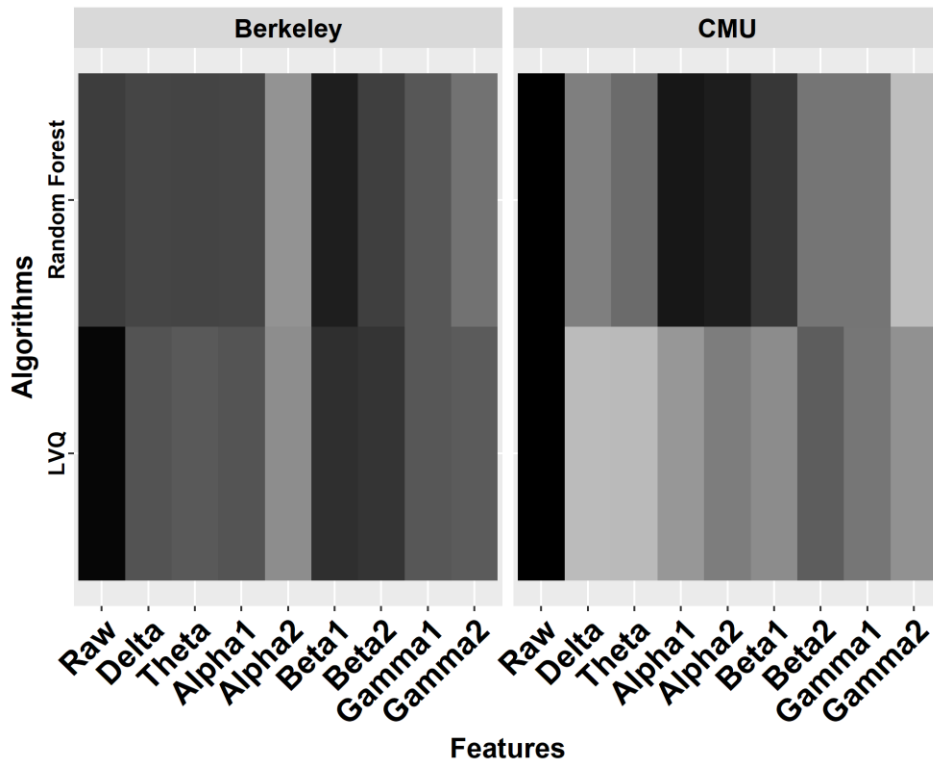


Also used: MLP, RBF NN, LVQ, KNN, XGBOOST and Ensemble of NN

Consistent pattern extraction agreeing with the field's literature

Pooled

Multi-task



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

- Steady or increase accuracy as the number of subjects increases
- Consistent feature selection

This may apply to all studies that include humans

Address session-session generalization:

- Compare fully adaptive and multi-task learning approaches to same subject recordings
- Use the models derived for each subject in MTL to new recordings of that subject

Sequential multi-task learning

- Exploit the sequential nature of the data to achieve more accuracy results

To reproduce the experiment

Pipeline (R and MATLAB) with run instructions in:
<https://github.com/GiorgosPanagopoulos/Multi-task-Learning-for-Commercial-Brain-Computer-Interfaces>



Thank you

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<https://giorgospanagopoulos.github.io>