Machine Learning and Brain-Computer Interfaces

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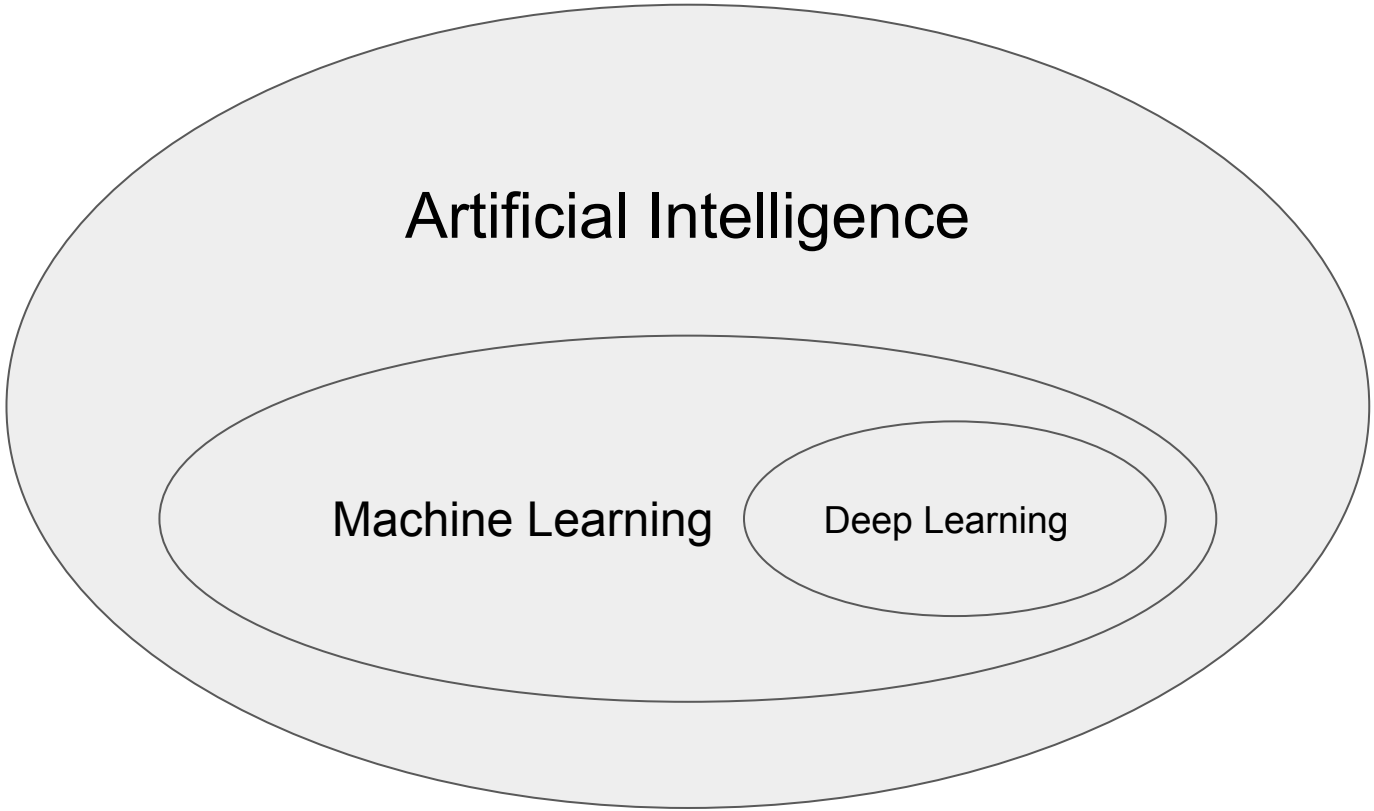
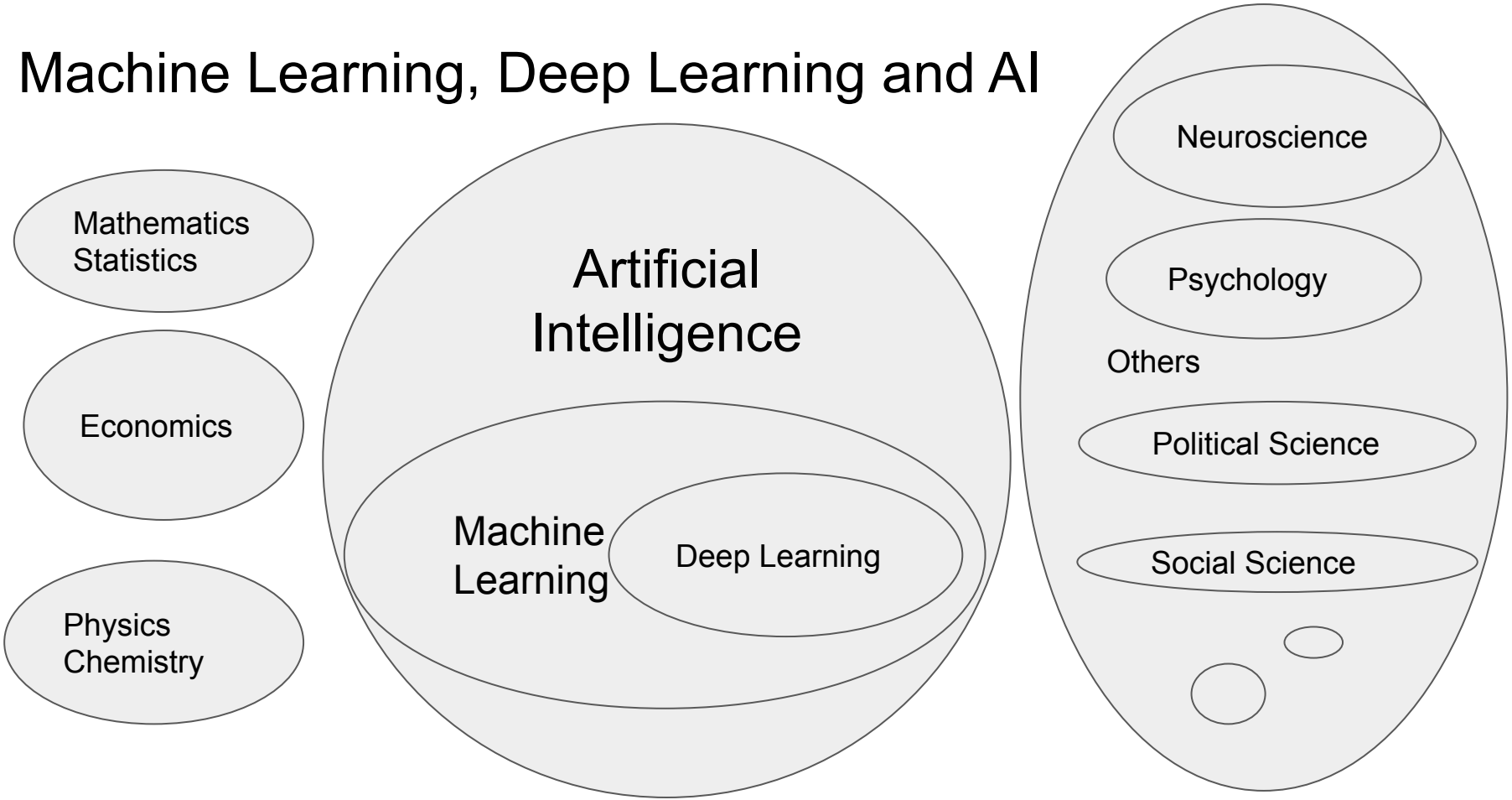
Fall 2022

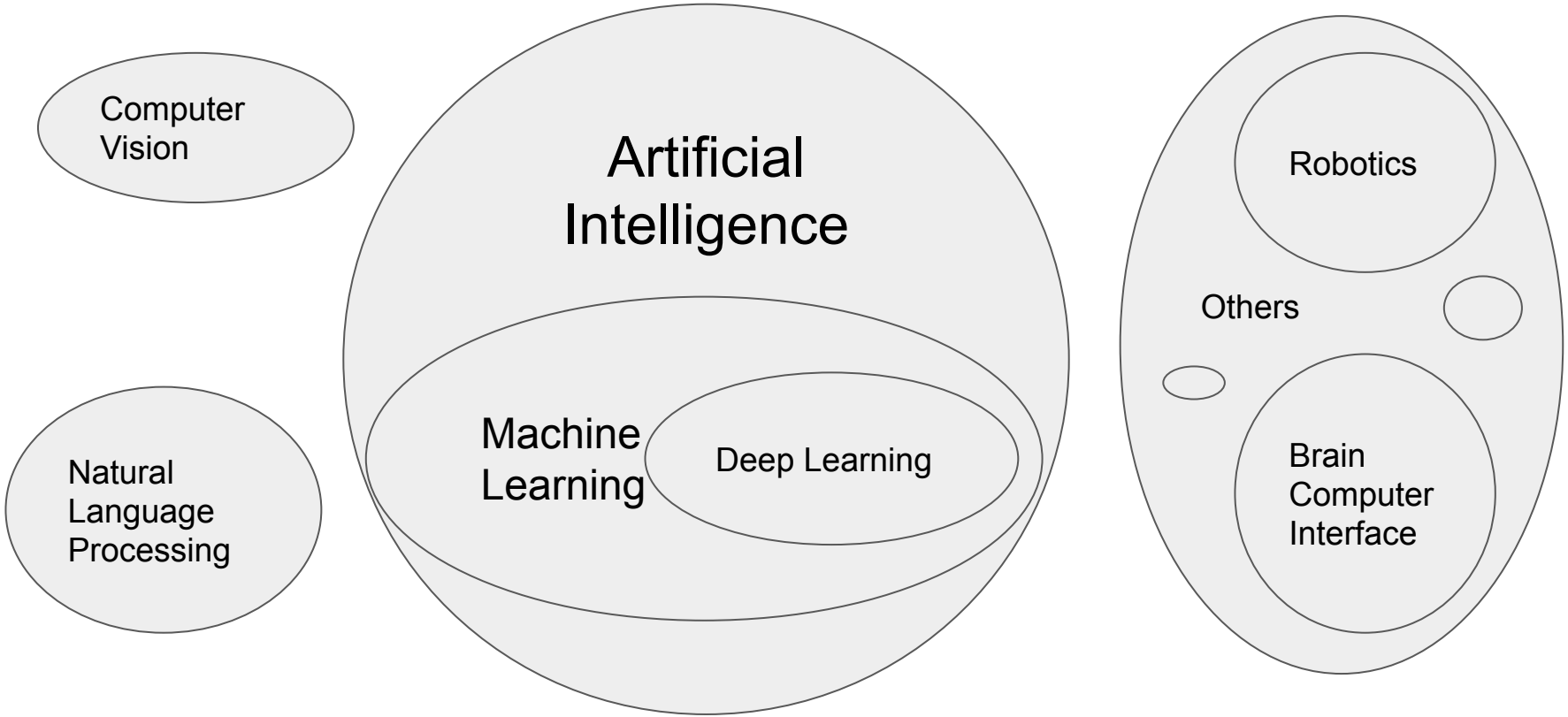
Machine Learning, Deep Learning and AI



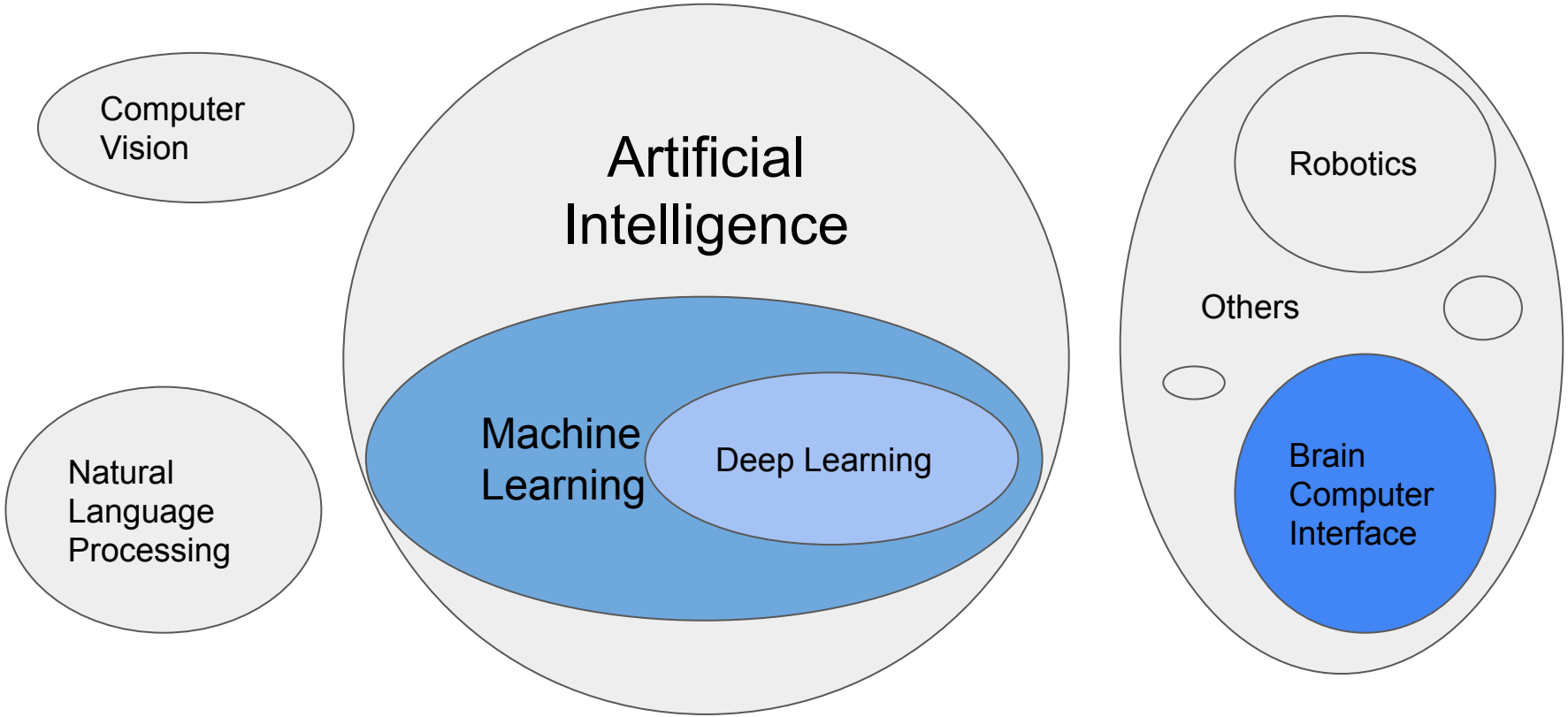
Machine Learning, Deep Learning and AI



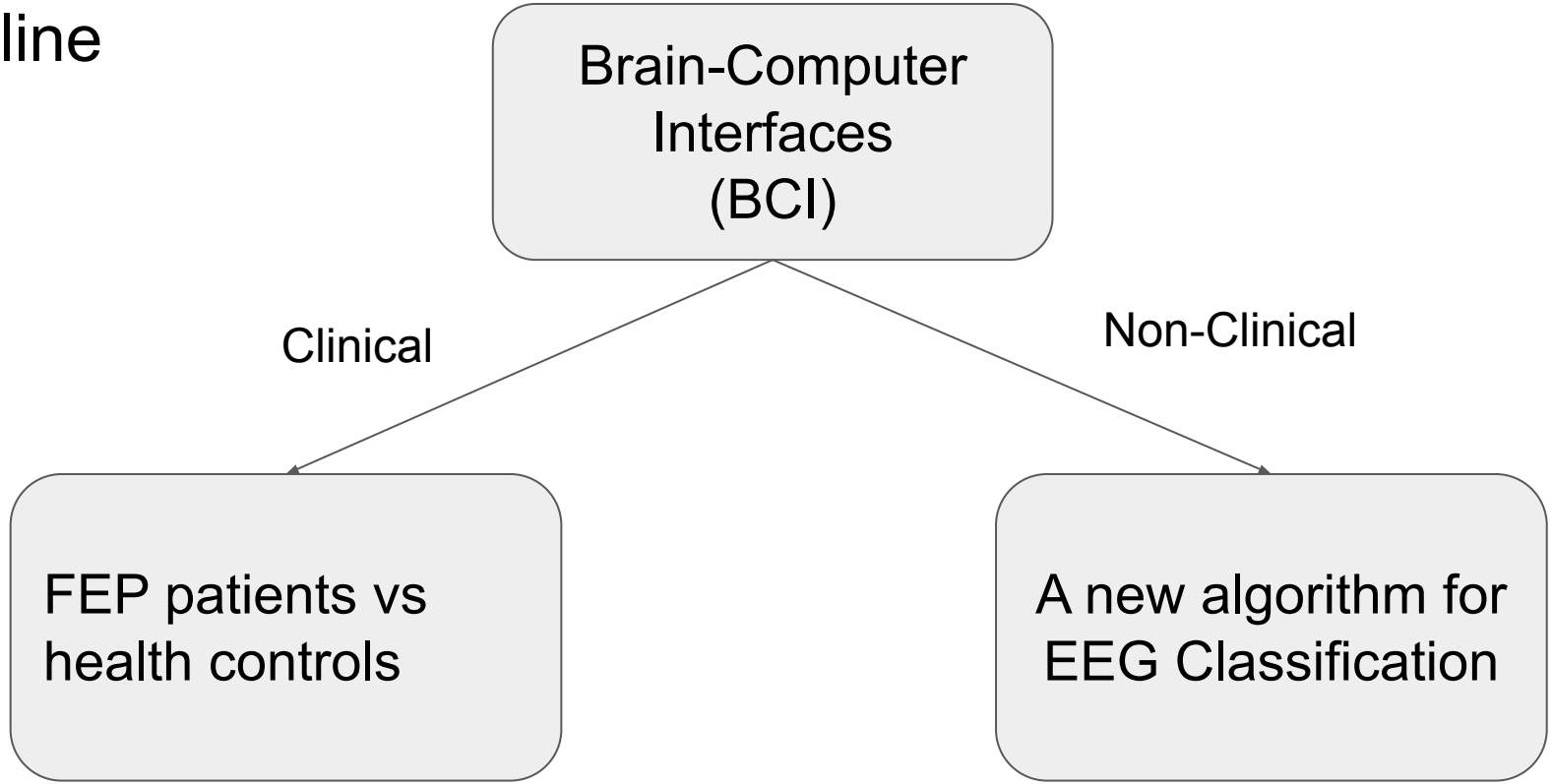
Machine Learning, Deep Learning and AI



Machine Learning, Deep Learning and AI



Outline

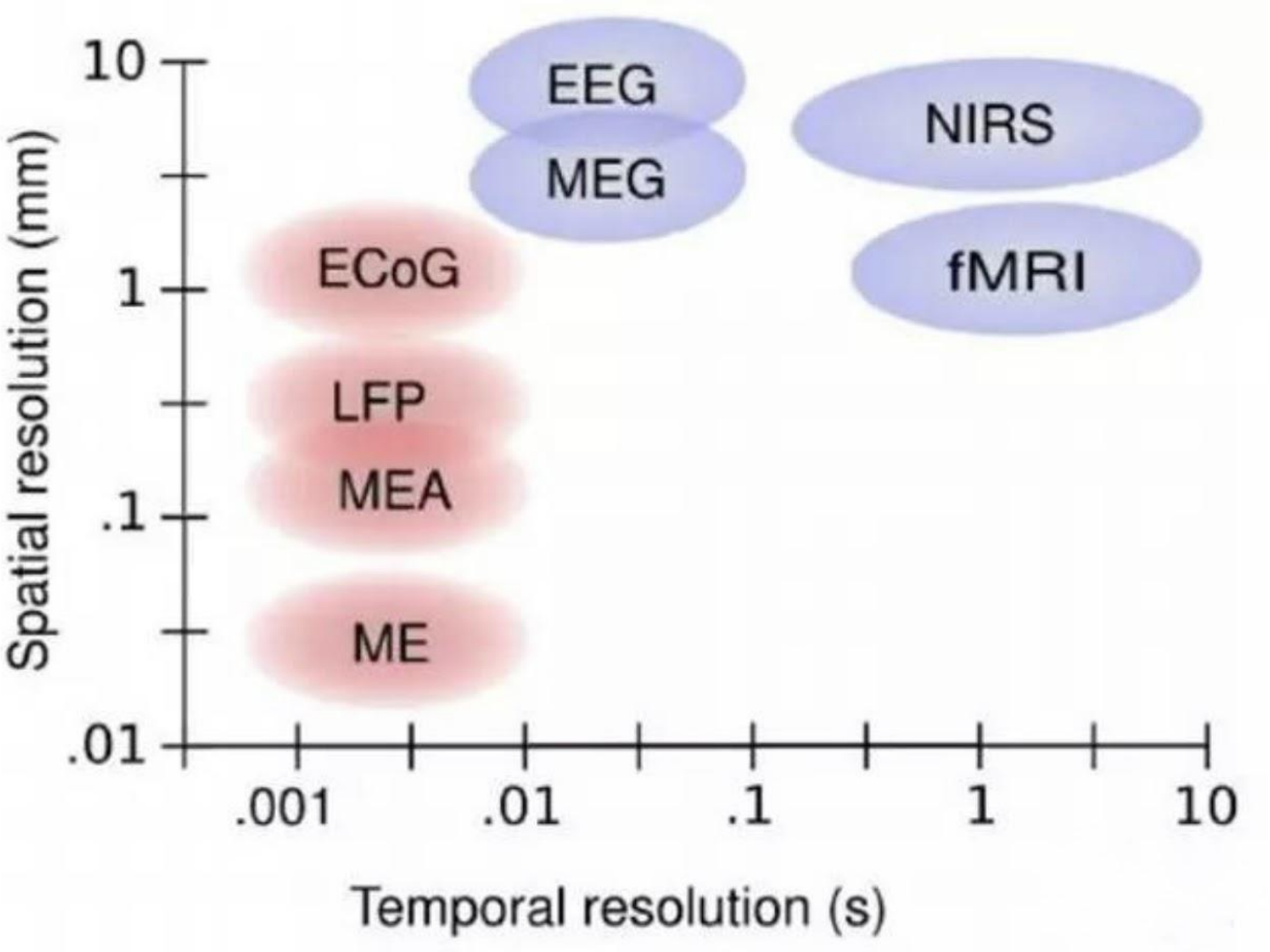

Brain-Computer Interfaces (BCI)
Clinical
Non-Clinical
FEP patients vs health controls
A new algorithm for EEG Classification


A STEVEN SPIELBERG FILM
READY PLAYER ONE

Elon Musk's Neuralink monkey brain demo explained

283,116 views • Apr 9, 2021

4.6K 135 SHARE SAVE


EEG
MEG
NIRS
fMRI
ECoG
LFP
MEA
ME
10
1
.1
.01
Spatial resolution (mm)
.001
.01
.1
1
10
Temporal resolution (s)

FEP patients vs health controls

Clinical, non-invasive, wired

Electroencephalography (EEG)

Biomarkers, machine learning

Human cognitive tasks and mental states

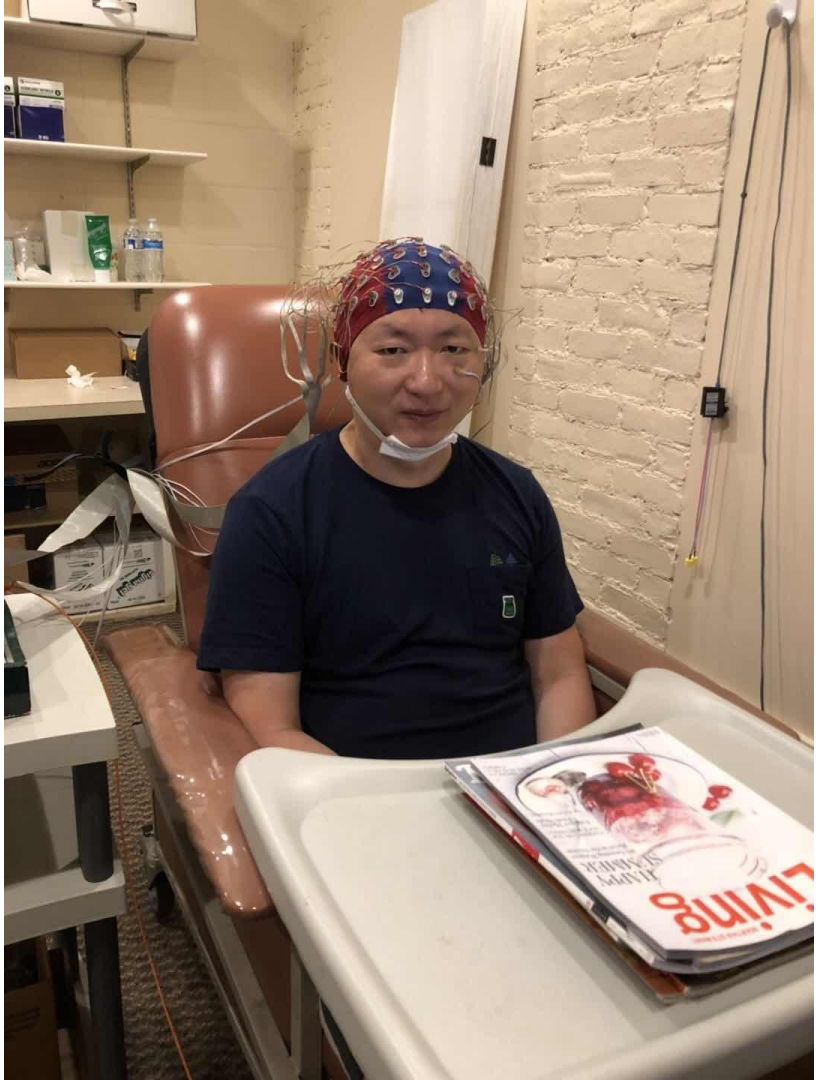
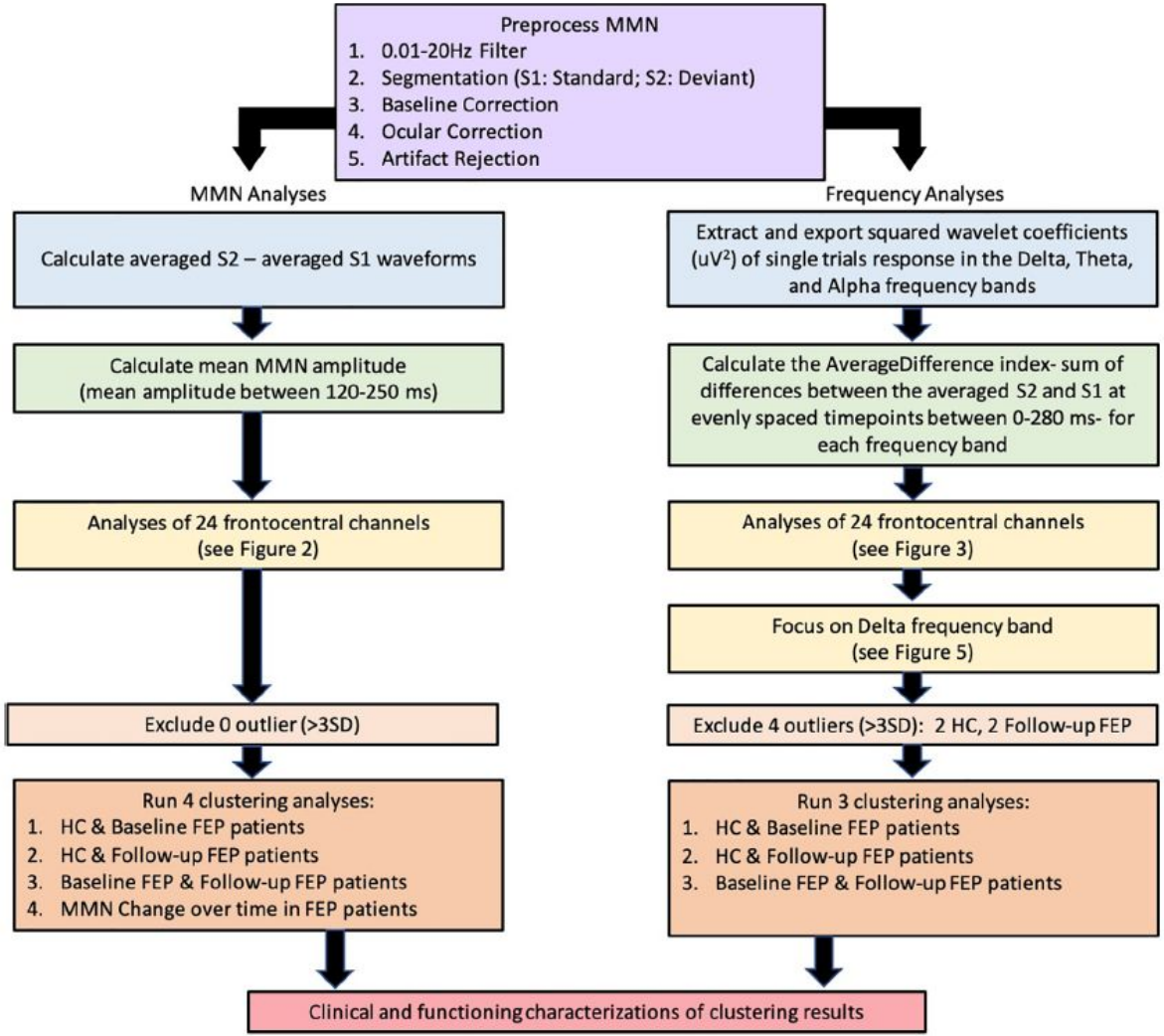
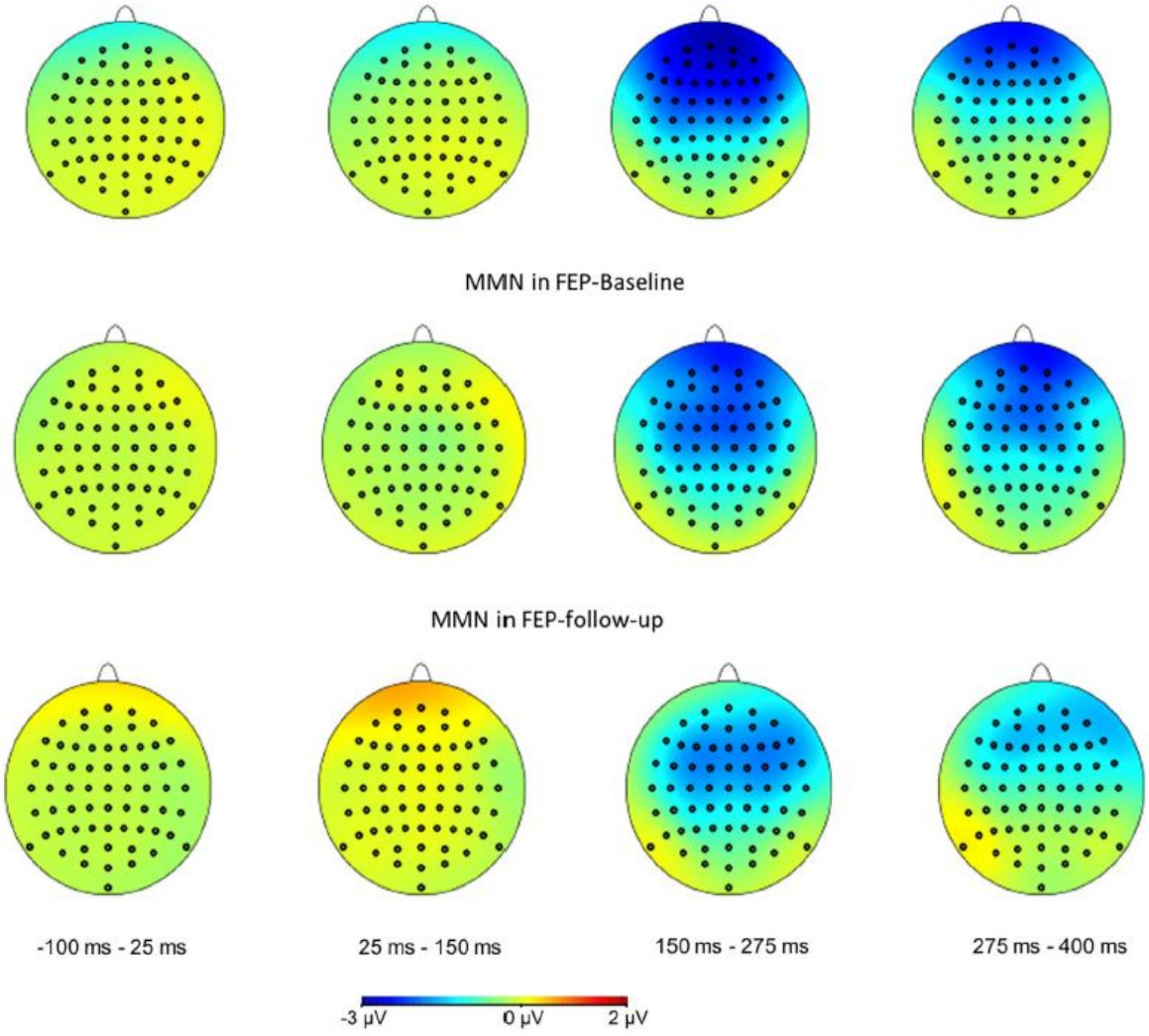


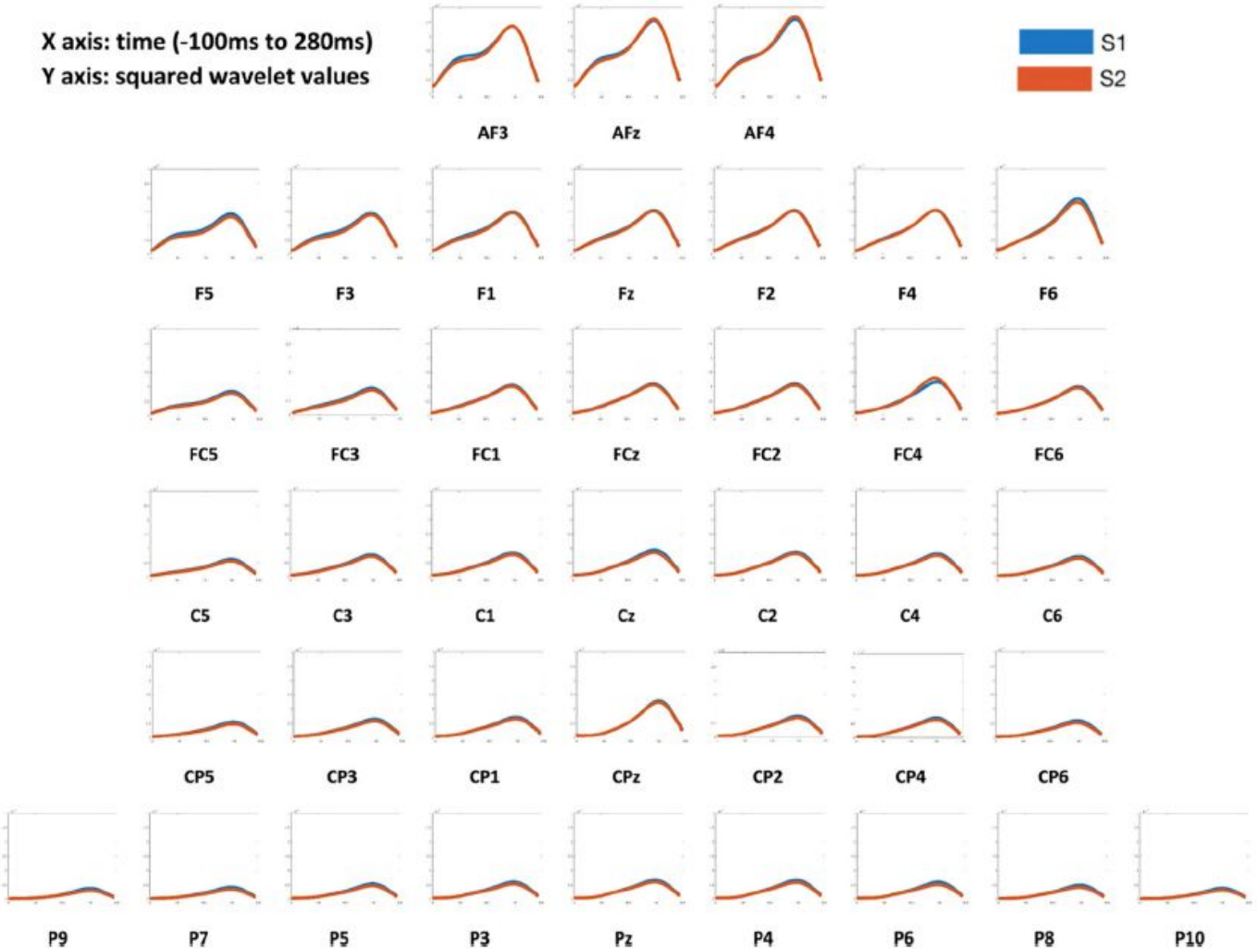
TABLE 1 | Comparisons between controls, baseline patients, and 6-month follow-up patients.

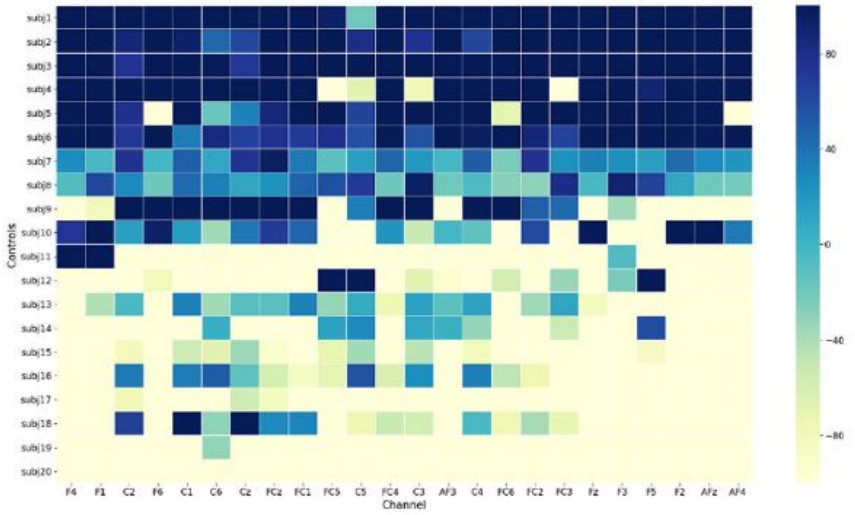
Variables	Controls (N=33)	Baseline Patients (N=20)	6m Follow-up Patients (N=18)	Statistics P value
	Mean (Std Errors)	Mean (Std Errors)	Mean (Std Errors)	
Age	22.91 (3.9)	22.7 (3.2)	23.39 (3.3)	F = 0.19 p = 0.83
Females (count, %)	12 (36.36%)	7 (35.00%)	6 (33.33%)	χ = 0.05 p = 0.98
Education (years)	15.55 (1.7)	14.95 (1.6)	15.06 (1.6)	F = 0.97 p = 0.388
UPSA total score	83.45 (8.3)	79.99 (10.9)	82.52 (12.0)	F = 0.58 p = 0.56
MCAS total score	54.75 (0.6)	48.1 (5.8)	48.0 (6.2)	F = 17.38 p <0.0001
MATRICS Neurocognitive Composite Score	50.45 (5.2)	46.21 (6.4)	48.63 (8.1)	F = 2.70 p = 0.07
MATRICS Social Subscore	54.52 (6.6)	53.58 (11.5)	55.33 (13.8)	F = 0.13 p = 0.88
TASIT	55.77 (4.5)	53.69 (6.4)	54.67 (5.2)	F = 0.579 p = 0.46
PANSS positive	N/A	14.45 (6.8)	13.18 (5.4)	t = 0.62 p = 0.27
PANSS negative	N/A	12.5 (3.8)	10.41 (3.5)	t = 1.70 p = 0.048
PANSS general	N/A	30.6 (7.9)	26.70 (8.4)	t = 1.45 p = 0.08
PANSS total	N/A	57.55 (16.7)	50.29 (16.1)	t = 1.33 p = 0.09
Chlorpromazine equivalents	N/A	226.51 (234.3)	292.45 (241.6)	t = -0.74 p = 0.77

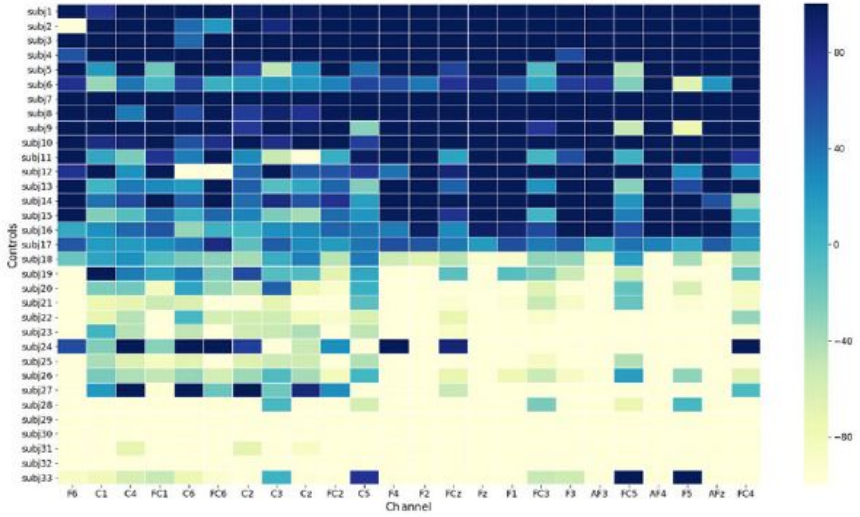
Means with standard deviations in parentheses unless specified otherwise; UPSA, UCSD Performance-based Skills Assessment; MCAS, Multnomah Community Ability Scale; MATRICS, Measurement and Treatment Research to Improve Cognition in Schizophrenia; TASIT, The Awareness of Social Inference Test; PANSS, Positive and Negative Syndrome Scale; CPZ, chlorpromazine equivalents.

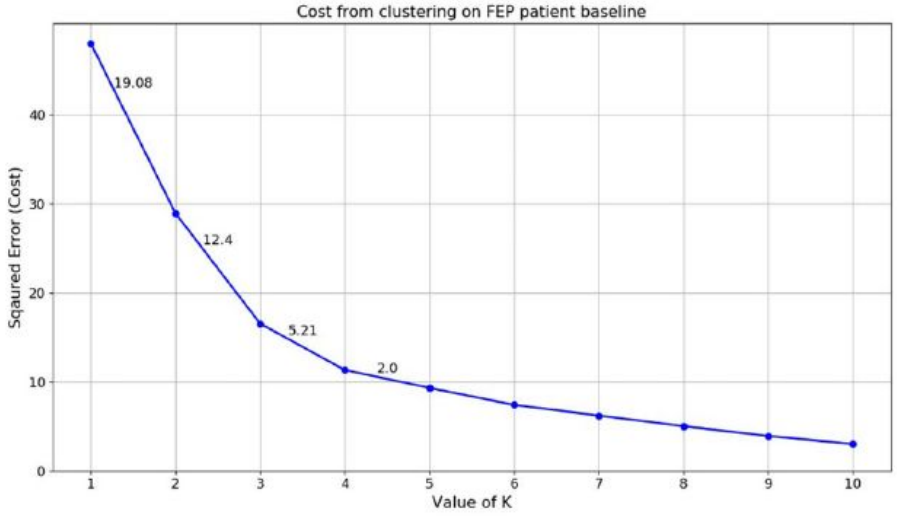

Preprocess MMN
1. 0.01-20Hz Filter
2. Segmentation (S1: Standard; S2: Deviant)
3. Baseline Correction
4. Ocular Correction
5. Artifact Rejection
MMN Analyses
Frequency Analyses
Calculate averaged S2 – averaged S1 waveforms
Extract and export squared wavelet coefficients (uV²) of single trials response in the Delta, Theta, and Alpha frequency bands
Calculate mean MMN amplitude (mean amplitude between 120-250 ms)
Calculate the AverageDifference index- sum of differences between the averaged S2 and S1 at evenly spaced timepoints between 0-280 ms- for each frequency band
Analyses of 24 frontocentral channels (see Figure 2)
Analyses of 24 frontocentral channels (see Figure 3)
Focus on Delta frequency band (see Figure 5)
Exclude 0 outlier (>3SD)
Exclude 4 outliers (>3SD): 2 HC, 2 Follow-up FEP
Run 4 clustering analyses:
1. HC & Baseline FEP patients
2. HC & Follow-up FEP patients
3. Baseline FEP & Follow-up FEP patients
4. MMN Change over time in FEP patients
Run 3 clustering analyses:
1. HC & Baseline FEP patients
2. HC & Follow-up FEP patients
3. Baseline FEP & Follow-up FEP patients
Clinical and functioning characterizations of clustering results

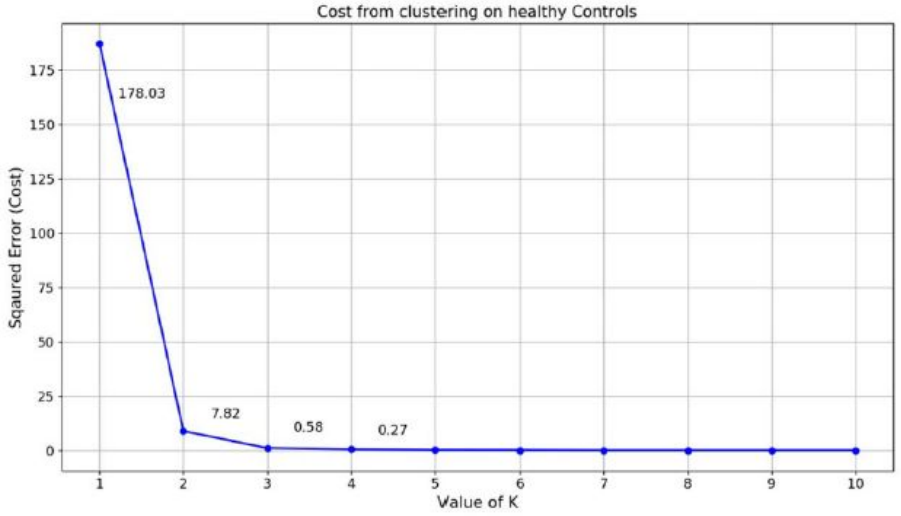

MMN in FEP-Baseline
MMN in FEP-follow-up
-100 ms - 25 ms
25 ms - 150 ms
150 ms - 275 ms
275 ms - 400 ms
-3 µV
0 µV
2 µV


X axis: time (-100ms to 280ms)
Y axis: squared wavelet values
S1
S2
AF3
AFz
AF4
F5
F3
F1
Fz
F2
F4
F6
FC5
FC3
FC1
FCz
FC2
FC4
FC6
C5
C3
C1
Cz
C2
C4
C6
CP5
CP3
CP1
CPz
CP2
CP4
CP6
P9
P7
P5
P3
Pz
P4
P6
P8
P10


Controls
Channel
F4 F1 C2 F6 C1 C6 C2 FC2 FC1 FC5 C5 FC4 C3 AF3 C4 FC6 FC2 FC3 Fz F3 F5 F2 AFz AF4


Controls
Channel
F6 C1 C4 FC1 C6 FC6 C2 C3 C2 FC2 C5 F4 F2 FCz Fz F1 FC3 F3 AF3 FC5 AF4 F5 AFz FC4


Cost from clustering on FEP patient baseline
Sqaured Error (Cost)
Value of K
19.08
12.4
5.21
2.0


Cost from clustering on healthy Controls
Sqaured Error (Cost)
Value of K
178.03
7.82
0.58
0.27

Multi-Class Time Continuity Voting for EEG Classification

Non-Clinical, Non-invasive, wireless

Everyone can use it everyday

Human-In-The-Loop Machine Learning

Interpretable results

MUSE headband by InteraXon

Tasks

From Neuroscience:

learning, memory, behavior, perception, and consciousness

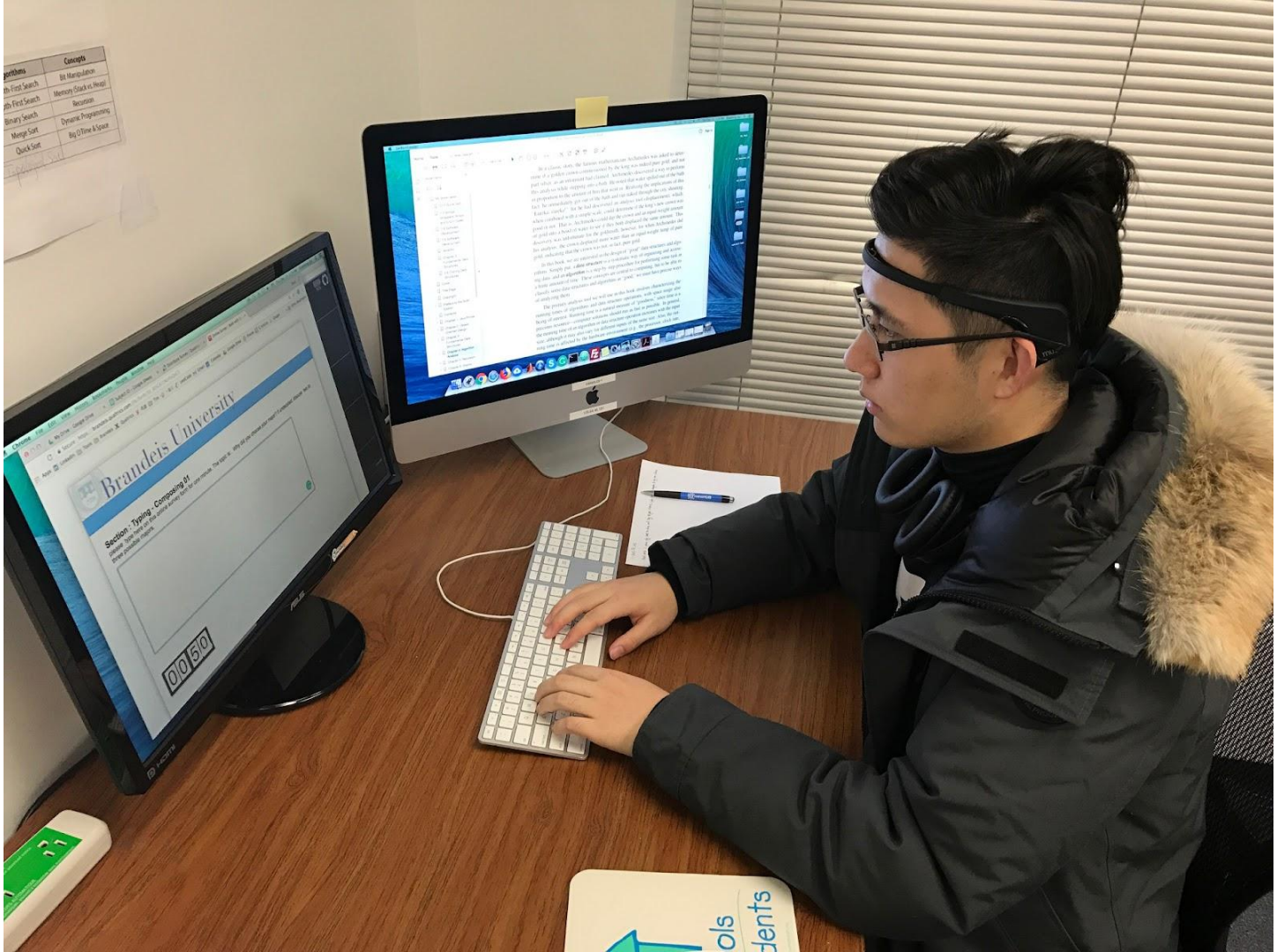
From four basic language skills:

listening, speaking, reading, and writing; [speaking -> noise]

What we have done:

reading, writing, typing, thinking, recalling, counting, drawing, solving math problems, and programming


muse
PROBABILISTIC GRAPHICAL MODELS
PRINCIPLES AND TECHNIQUES


Concepts
Bit Manipulation
Memory (Stack vs. Heap)
Recursion
Dynamic Programming
Big O Time & Space
Brandeis University
Section - Typing - Composing 01
0 0 5 0

S/T	1	2	3	4	5
1	T	C	R	B	D
2	B	T	C	R	D
3	T	B	R	D	C
4	T	C	R	B	D
5	C	T	R	D	B
6	T	C	B	R	D

Fig. 2. Session (S) with Task (T) order shuffled

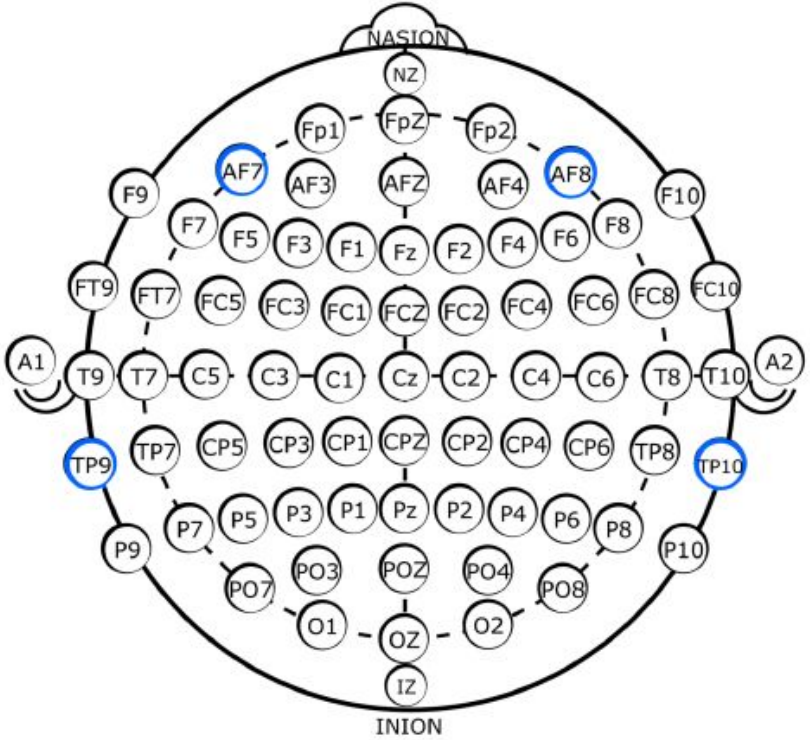
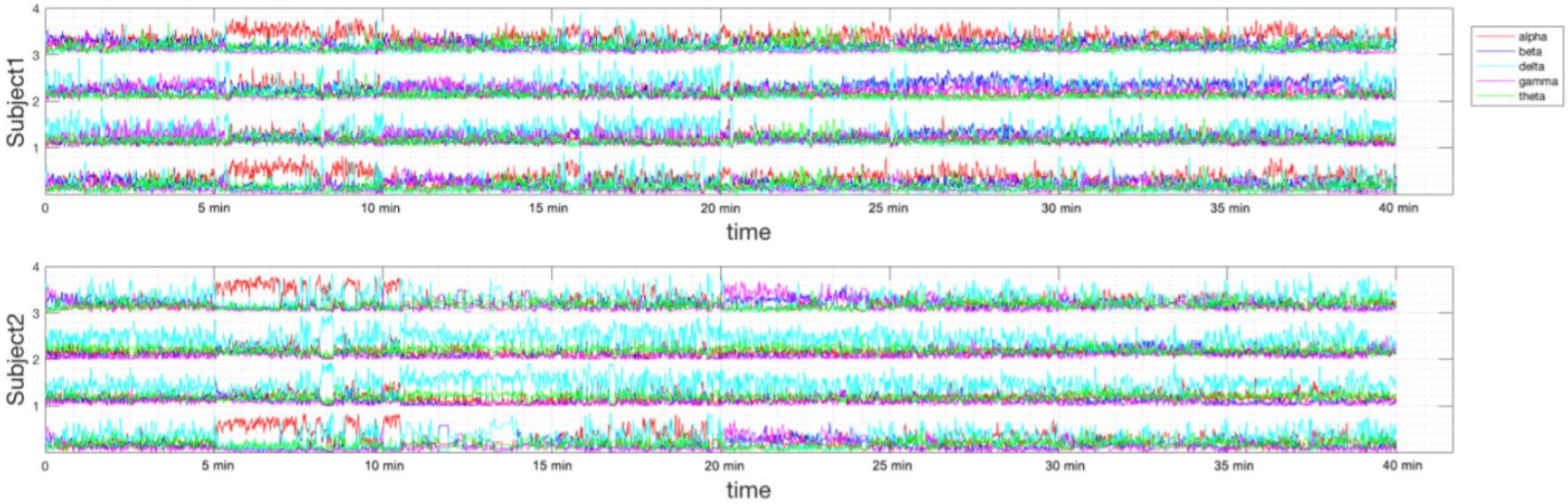
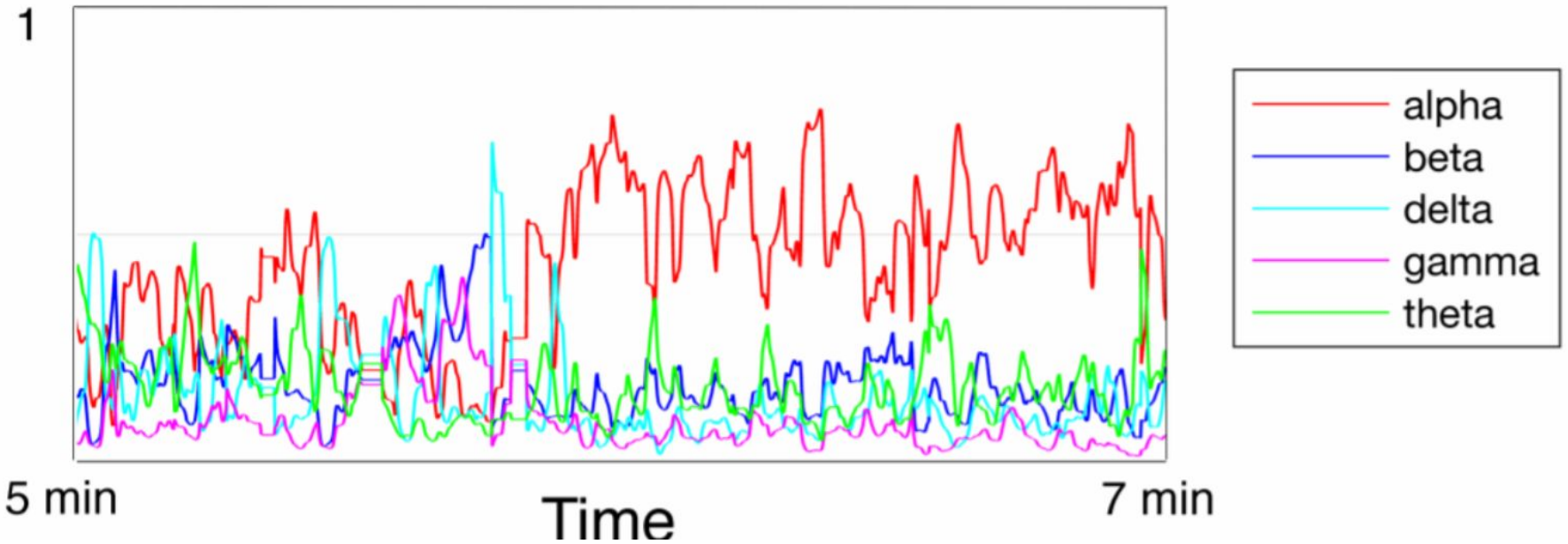


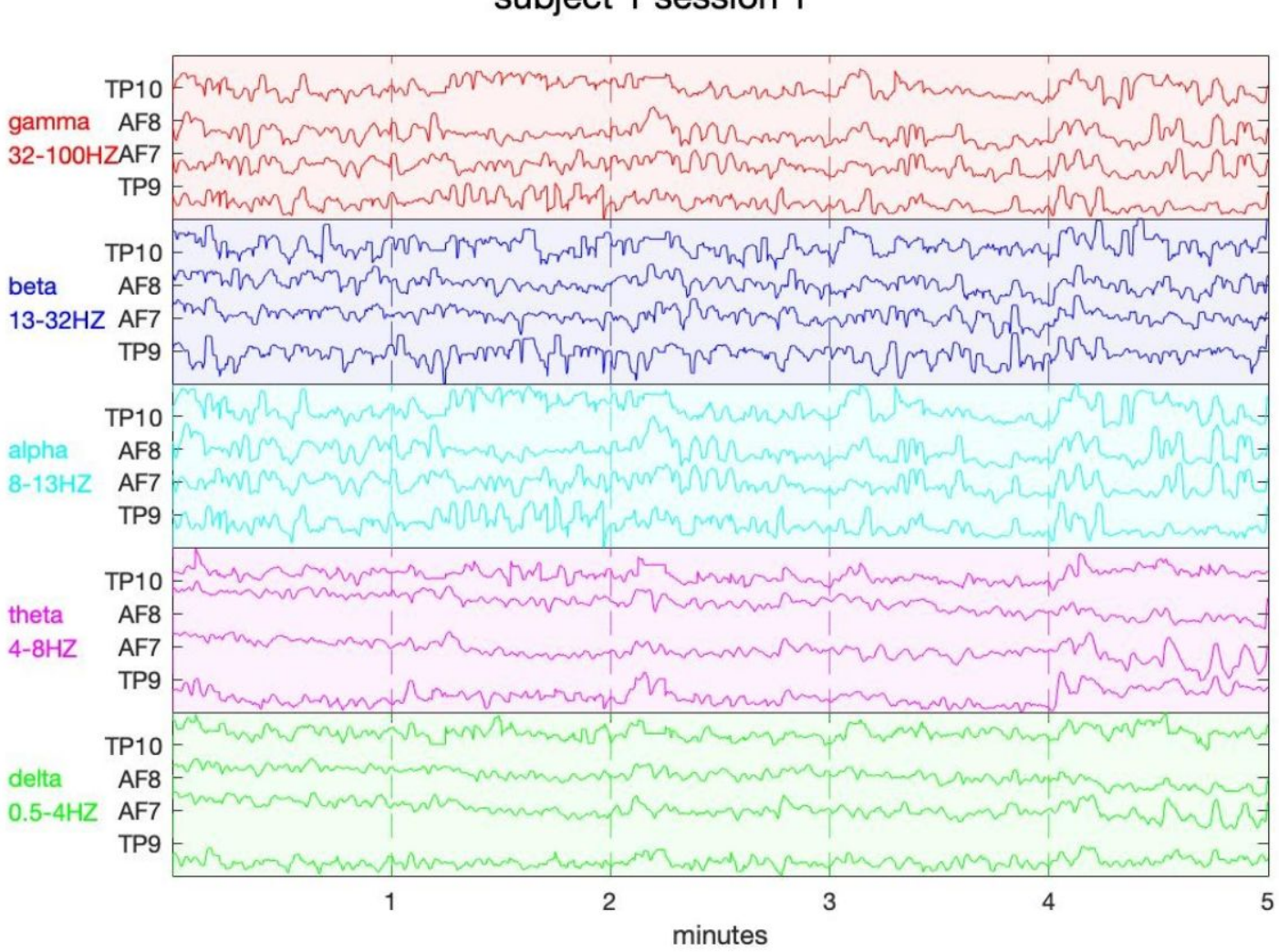
Fig. 3. 10-20 System, four electrodes used on Muse Headset were highlighted

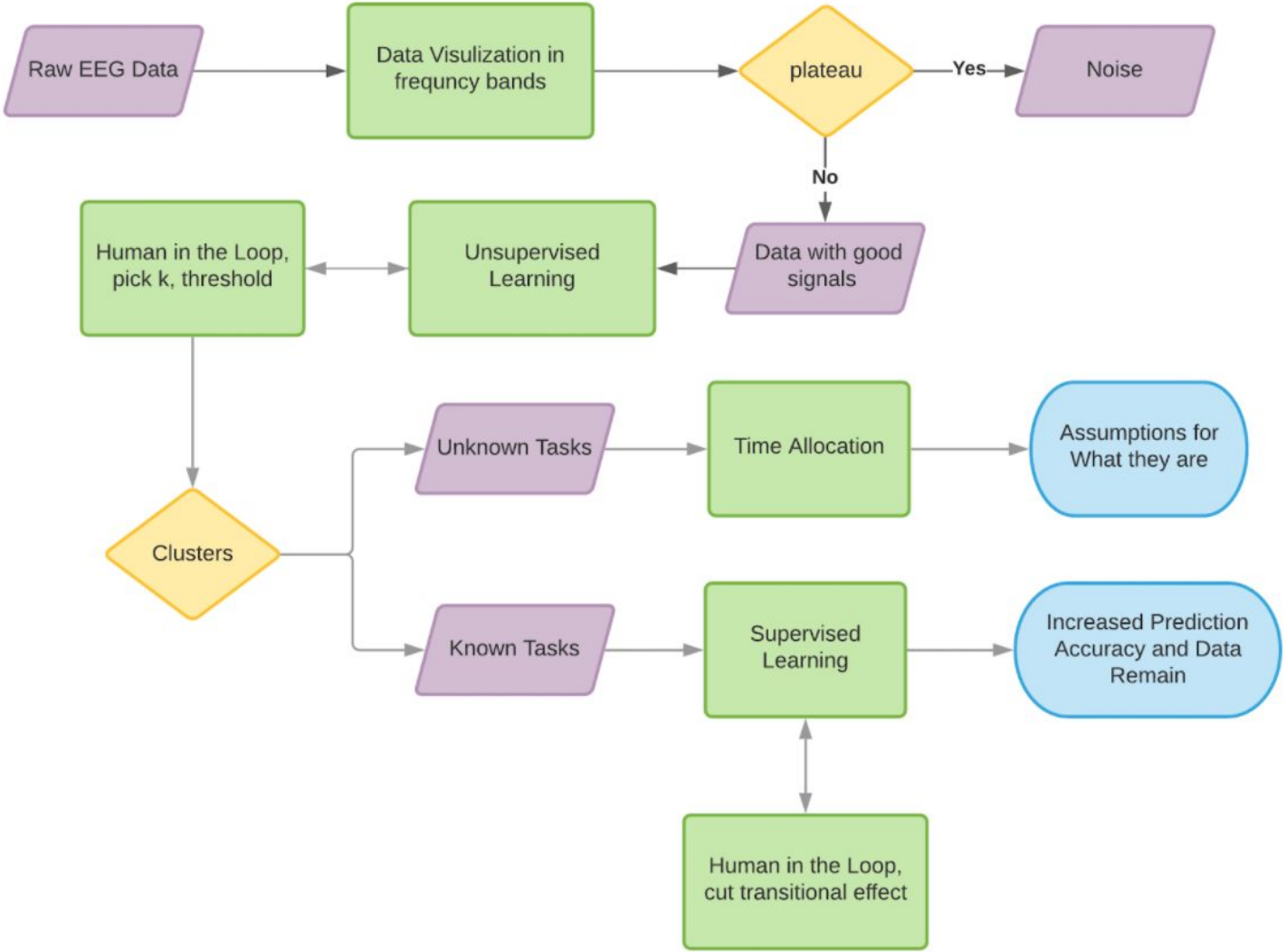
Relative EEG bands for Subjects 1 and 2

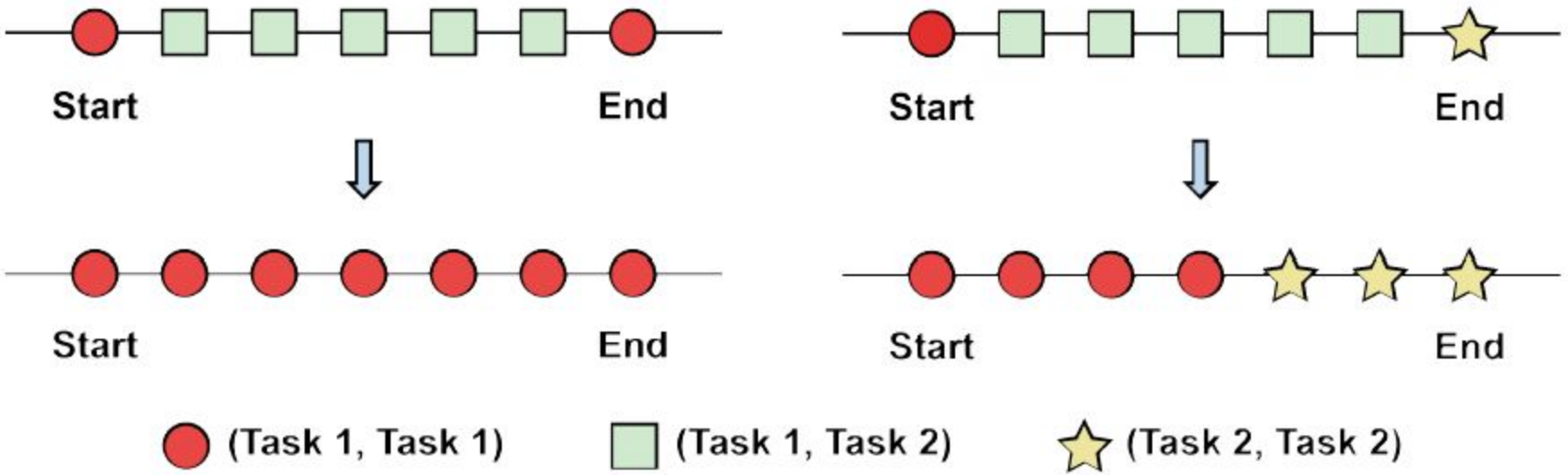


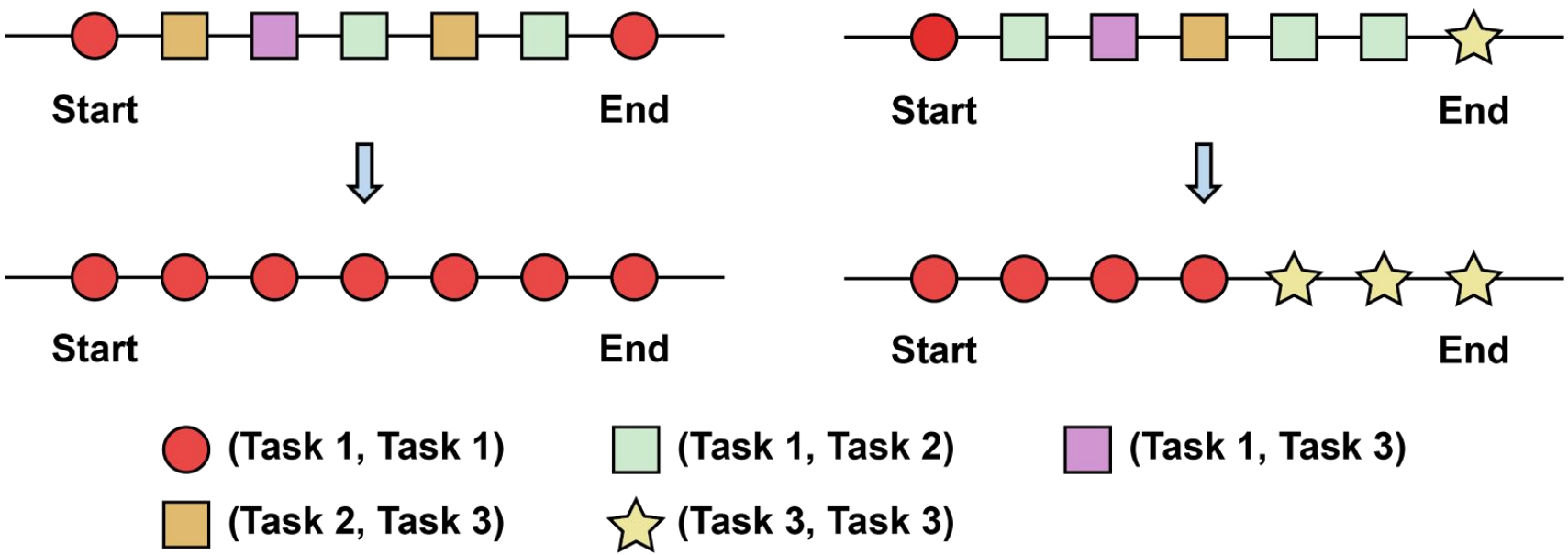
Relative EEG bands for Subject 1

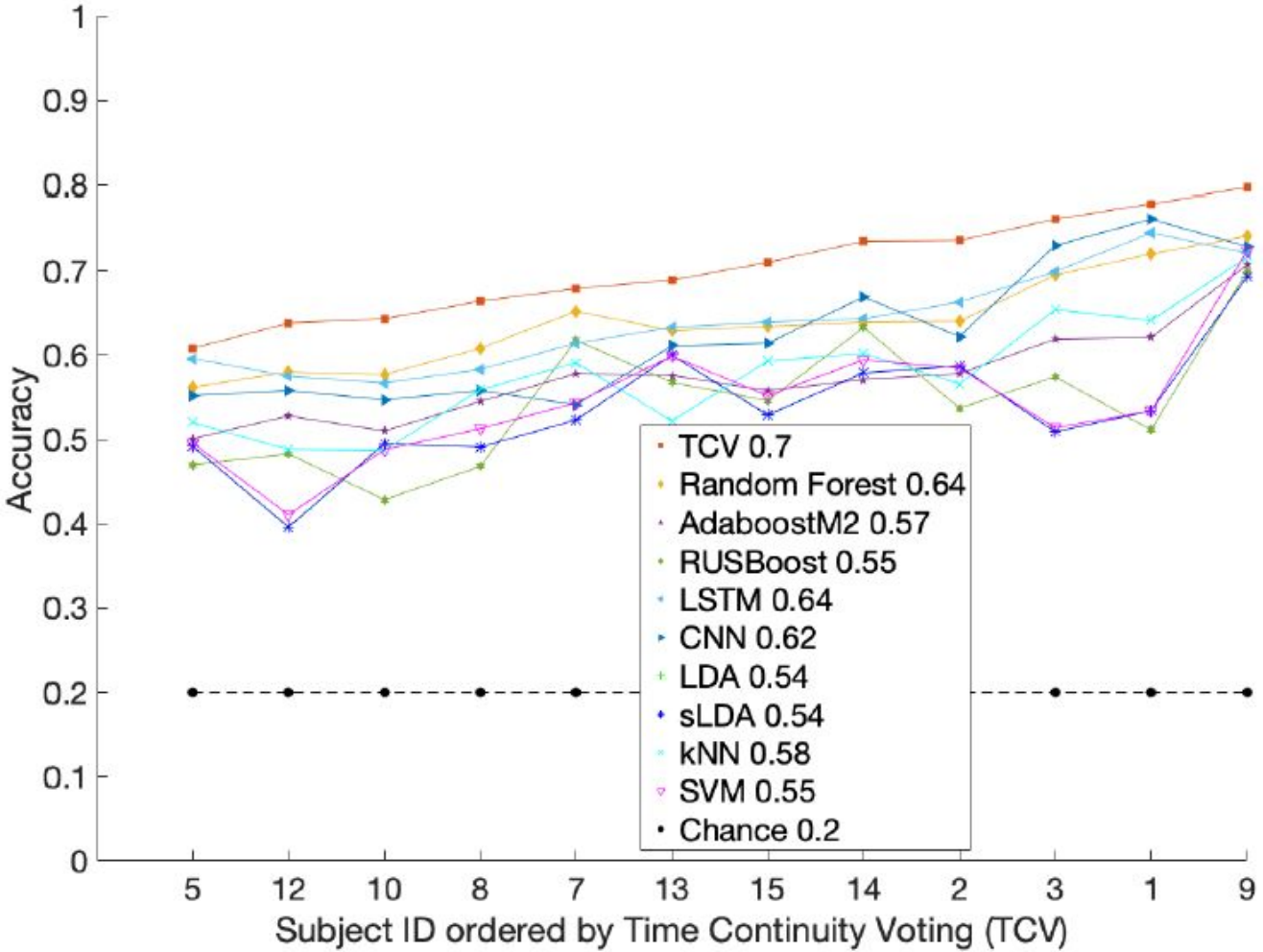



subject 1 session 1
gamma
32-100HZ
beta
13-32HZ
alpha
8-13HZ
theta
4-8HZ
delta
0.5-4HZ
TP10
AF8
AF7
TP9
1
2
3
4
5
minutes


Raw EEG Data
Data Visulization in frequncy bands
plateau
Yes
Noise
No
Data with good signals
Unsupervised Learning
Human in the Loop, pick k, threshold
Clusters
Unknown Tasks
Time Allocation
Assumptions for What they are
Known Tasks
Supervised Learning
Increased Prediction Accuracy and Data Remain
Human in the Loop, cut transitional effect


Start
End
Start
End
Start
End
Start
End
(Task 1, Task 1)
(Task 1, Task 2)
(Task 2, Task 2)


Start
End
Start
End
Start
End
Start
End
(Task 1, Task 1)
(Task 1, Task 2)
(Task 1, Task 3)
(Task 2, Task 3)
(Task 3, Task 3)


Accuracy
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
TCV 0.7
Random Forest 0.64
AdaboostM2 0.57
RUSBoost 0.55
LSTM 0.64
CNN 0.62
LDA 0.54
sLDA 0.54
kNN 0.58
SVM 0.55
Chance 0.2
5
12
10
8
7
13
15
14
2
3
1
9
Subject ID ordered by Time Continuity Voting (TCV)

Compare

Machine Learning (**Single Algorithms**)

LDA, SVM, KNN etc. - Adequate Accuracy - Runtime low (Fast)

Machine Learning (**Ensemble Methods**)

Random Forest, Adaboost, XGBoost, etc - Better Accuracy - Runtime increased

Machine Learning (**Deep Learning)**

CNN, RNN, Transformer, etc. - higher Accuracy - Require Big Data & GPU (Slow)

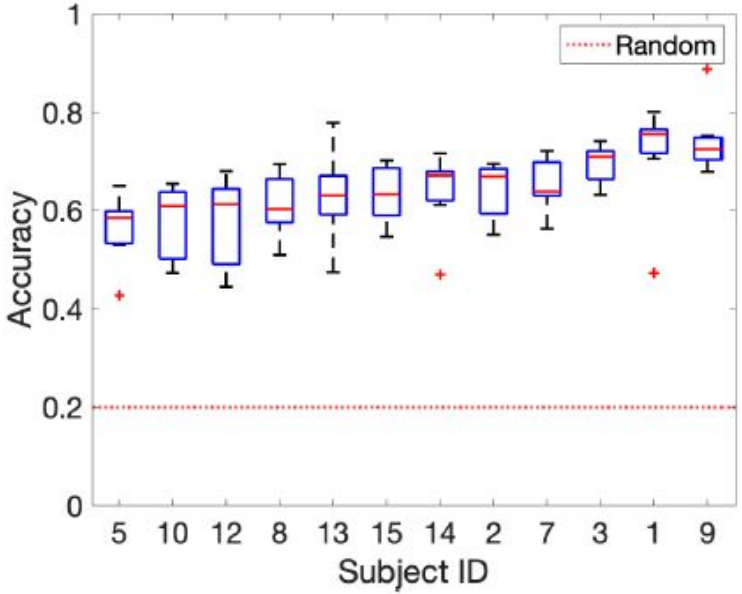


Fig. 7. Subject Difference

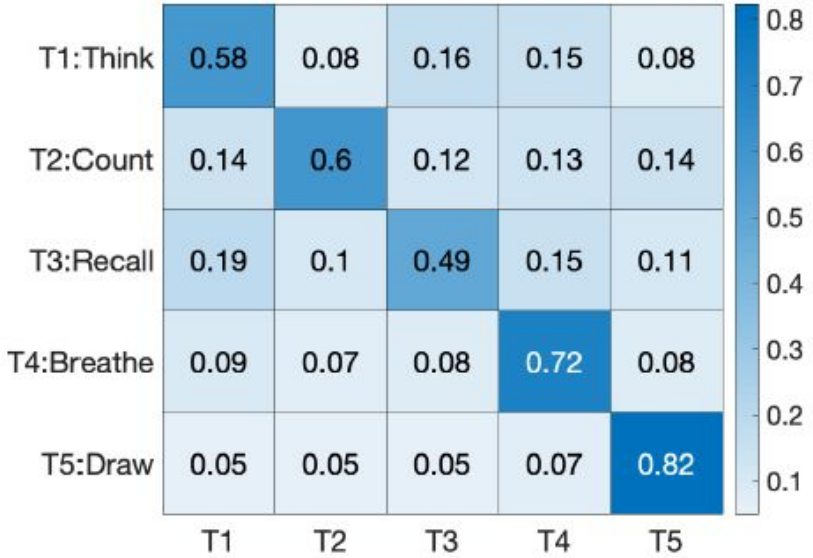
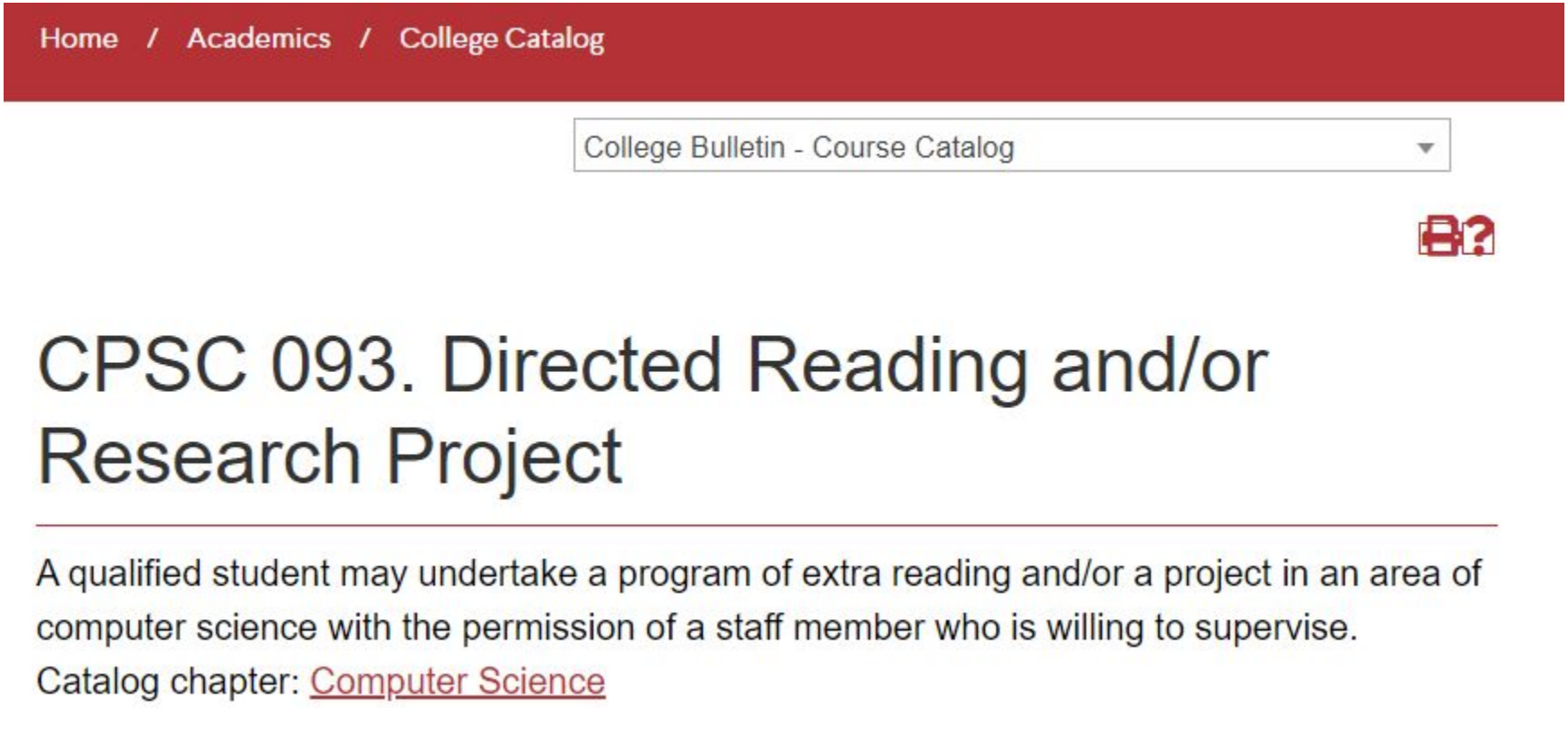


Fig. 8. Task Prediction Accuracy, average of all twelve subjects.

Sample Publications with Swarthmore Students

- **Congratulations!**
- Abdelrahman Abdelmonsef and Brian Xiang got a paper accepted at KDD 2022 Undergraduate Consortium, SIGKDD, the top conference in Data Mining and Analysis.
- Too Fine or Too Coarse? The Goldilocks Composition of Data Complexity for Robust Left-Right Eye-Tracking Classifiers
- **More Student Papers**
- (Selected from HCI International, one of the top twenty conferences in Human Computer Interaction)
- S014: Advances in Augmented Cognition - I
- It's Easy as ABC Framework for User Feedback, Sydney Levy, Alexandra Fischmann
- High-Powered Ocular Artifact Detection with C-LSTM-E, Ian McDiarmid-Sterling, Luca Cerbin

CS 093, half credit, Fall 22 (and possibly Spring 23)



Questions?

More Details on my profile:
cs.swarthmore.edu/~xqu1/

Thank you so much!