Tecnológico de Monterrey
Escuela de Ingeniería y Ciencias

Physiological-based Emotion Recognition

Objective Emotions for Real-time Environments

Workshop UH AccelNet - Tecnológico de Monterrey
4^{th} August, 2025

Milton Candela, milton.candela@exatec.tec.mx

Building Reliable Advances and BRAIN Innovations in Neurotechnology

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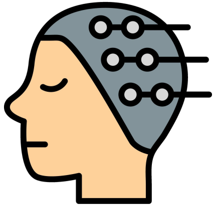
Overview

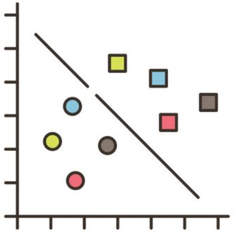
Biometrics

Computational Method

Cognitive State

EEG





Emotion

Statistics &
Machine Learning

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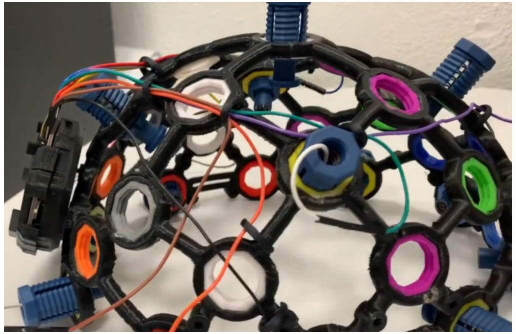
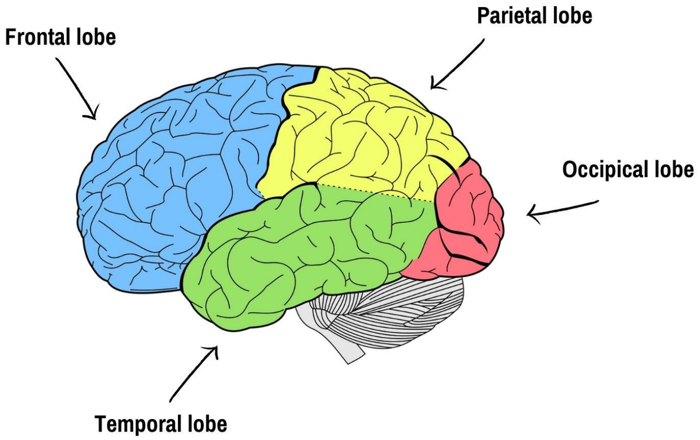
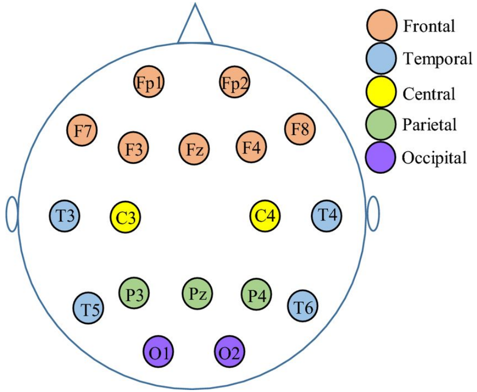
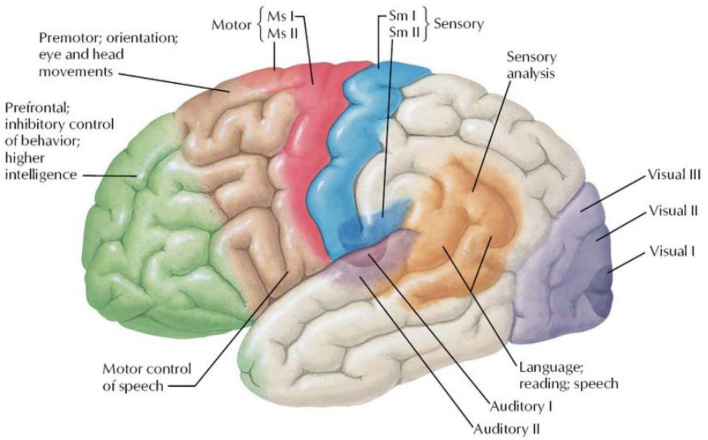
Electroencephalography (EEG) device

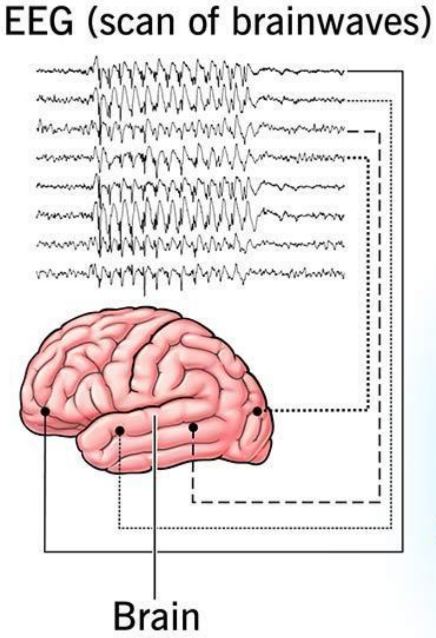
- **Ultracortex Mark IV**
  - Channels: 8
  - Business: OpenBCI
  - Sampling frequency (*fs*): 512 Hz
  - Default configuration: Fp1, Fp2, C3, C4, T7, T8, O1, O2
    - Reconfigurable electrodes
    - Dry electrodes (minimal setup)
    - USB dongle for bluetooth data transfer
    - OpenBCI GUI for impedance check
    - Python compatibility (through brainflow)

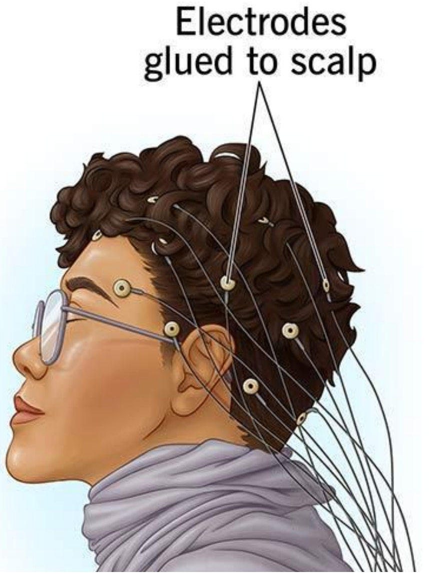












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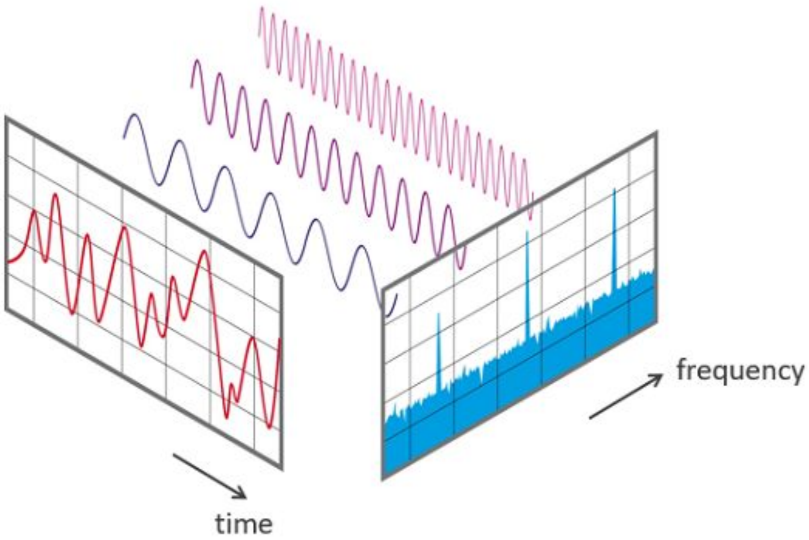
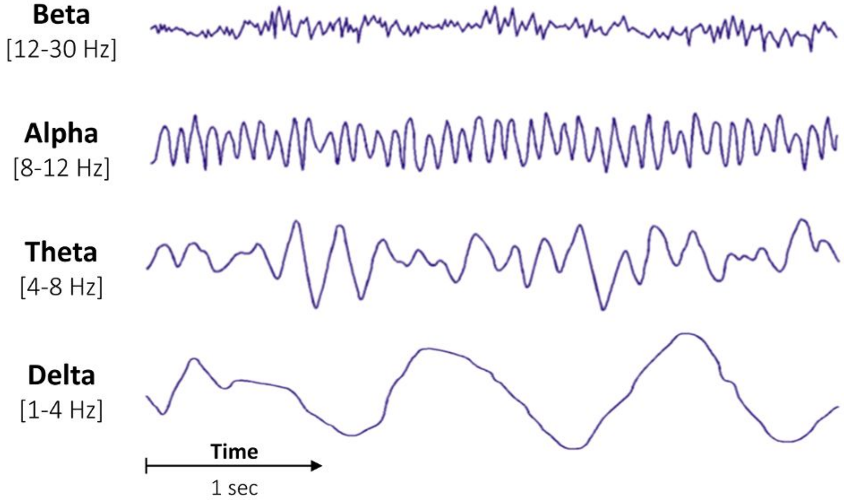
EEG frequency analysis (Fourier)





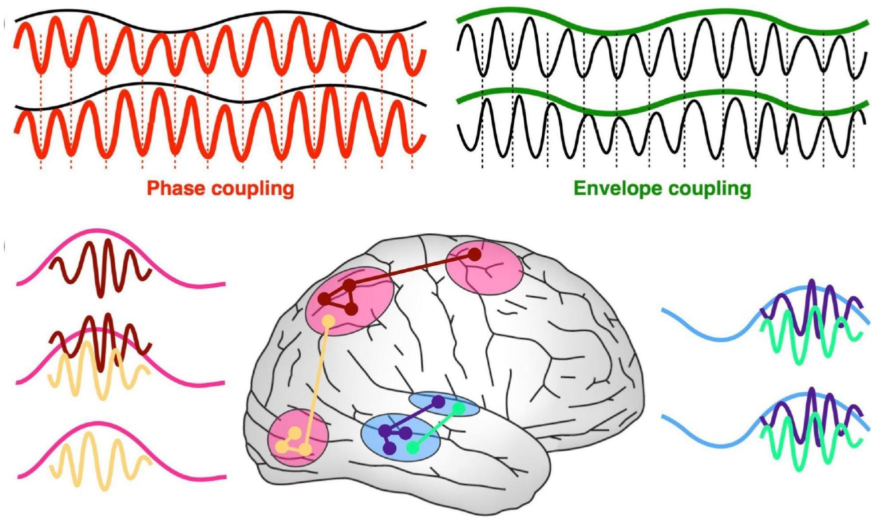
Active thinking

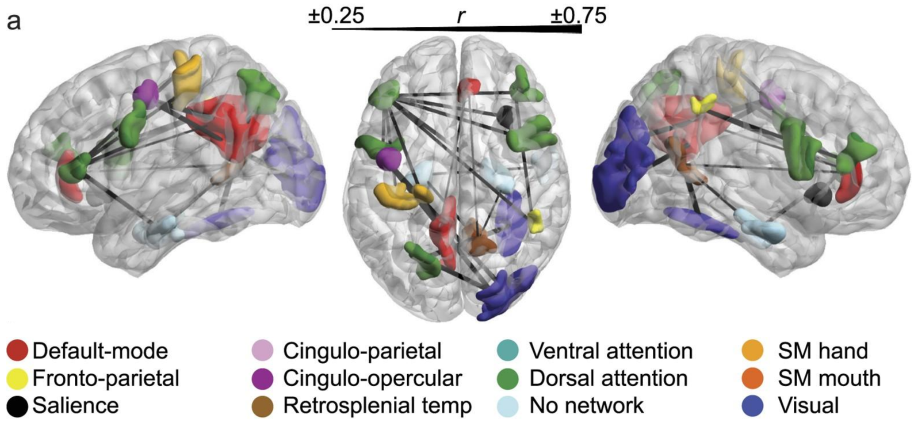
Attention

Sleeping

Deep Sleep

EEG functional connectivity analysis





Engel, AK. & Gerloff, C. *Trends Cogn Sci* (2022)
Hearne, LJ. et al. *Sci Rep* (2016)

Emotion Models

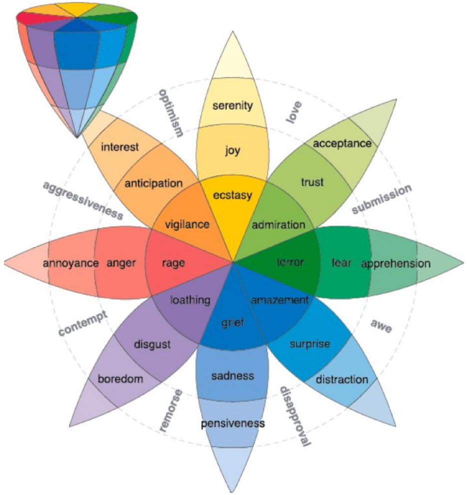
- **Discrete**
  - Binary
    - Positive, Negative [1]
  - Multi-class
    - 6 basic emotions: happiness, anger, fear, surprise, sadness, and disgust [2]
    - Social psychology emotions: joy, anger, sadness, fear, love, surprise [3]
- **Continuous**
  - 2D
    - Positive and Negative Affect Schedule (PANAS) [4]
    - Circumplex (HVHA, HVLA, LVHA, LVLA) [5]
  - 3D
    - Pleasure, Arousal, Dominance (PAD) or Valence, Arousal, Dominance (VAD) [6]

[1] Zheng & Lu (2015) *IEEE Trans. on Mental Development*
[2] Ekman & Oster (1979) *Annual Review of Psychology*
[3] Parrott (2001) *Emotions in Social Psychology*
[4] Watson et al. (1988) Personality and Social Psychology
[5] Russell (1980) *Personality and Social Psychology*
[6] Mehrabian (1996) *Current Psychology*

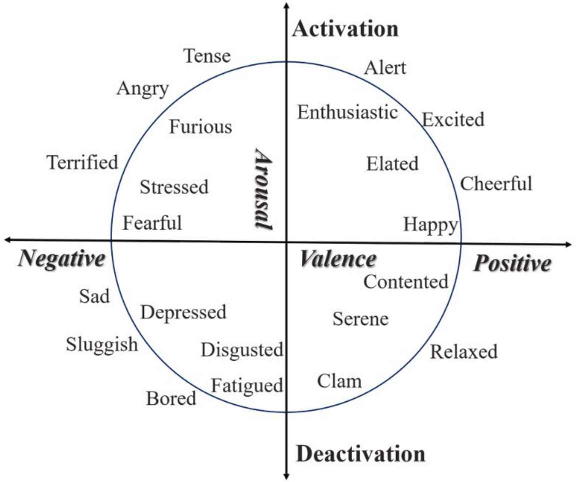
Emotion Models

Discrete

Continuous



Emotional wheel [1]



Circumplex [2]

Valence-Arousal-Dominance [3]

[1] Plutchik (1980) *Theories of Emotion*
[2] Russell (1980) *Personality and Social Psychology*
[3] Mehrabian (1996) *Current Psychology*

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Paper overview

- Published in *Frontiers in Human Neuroscience*
- Selected for the journal's Editor's pick eBook
    - Top 3% of all 2024 papers (16/510), top 2 in BCI topic

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Real-time EEG-based emotion recognition for neurohumanities: perspectives from principal component analysis and tree-based algorithms

Miguel Alejandro Blanco-Ríos[1†], Milton Osiel Candela-Leal[1,2†], Cecilia Orozco-Romo[1], Paulina Remis-Serna[1], Carol Stefany Vélez-Saboyá[3], Jorge de Jesús Lozoya-Santos[1], Manuel Cebral-Loureda[3] and Mauricio Adolfo Ramírez-Moreno[1]*

[1]School of Engineering and Sciences, Mechatronics Department, Tecnológico de Monterrey, Monterrey, Mexico, [2]Fetal-Neonatal Neuroimaging and Developmental Science Center, Boston Children's Hospital, Harvard Medical School, Boston, MA, United States, [3]School of Humanities and Education, Department of Humanistic Studies, Tecnológico de Monterrey, Monterrey, Mexico

Within the field of Humanities, there is a recognized need for educational innovation, as there are currently no reported tools available that enable individuals to interact with their environment to create an enhanced learning experience in the humanities (e.g., immersive spaces). This project proposes a solution to address this gap by integrating technology and promoting the development of teaching methodologies in the humanities, specifically by incorporating emotional monitoring during the learning process of humanistic context inside an immersive space. In order to achieve this goal, a real-time emotion recognition EEG-based system was developed to interpret and classify specific emotions. These emotions aligned with the early proposal by Descartes (Passions), including admiration, love, hate, desire, joy, and sadness. This system aims to integrate emotional data into the Neurohumanities Lab interactive

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Editor's pick eBook: highlighted research from Frontiers in Human Neuroscience 2024

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Jessica A. Turner, Srikantan S. Nagarajan, Mingzhou Ding, Julie Duque, Lutz Jäncke, Gernot R. Müller-Putz, Leonhard Schilbach, Jae Kun Shim and Kai Vogeley

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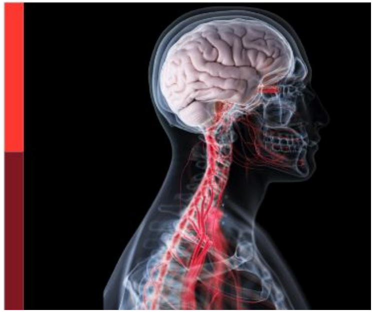
Frontiers in Human Neuroscience



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Real-time EEG-based Emotion Recognition for Neurohumanities

Perspectives from Principal Component Analysis and Tree-based Algorithms

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Within the field of Humanities, there is a recognized need for educational

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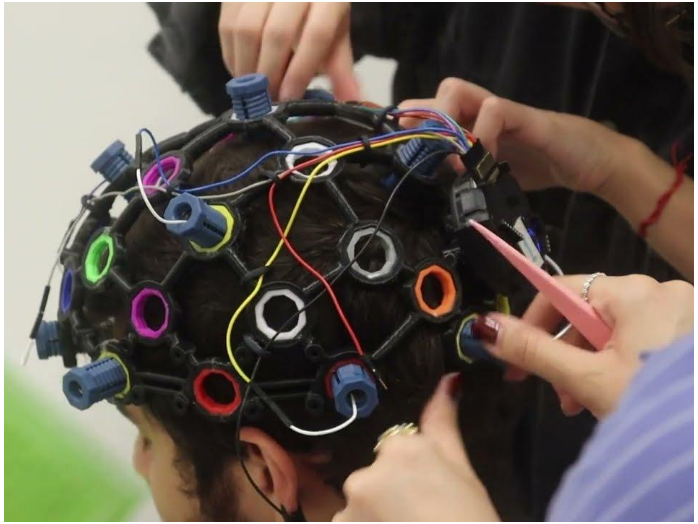
Motivation

- **Challenge:** Humanities teaching methodologies has been slower compared to other fields.
- **Solution:** ML + EEG in real-time to predict emotion and create adaptive learning experience.



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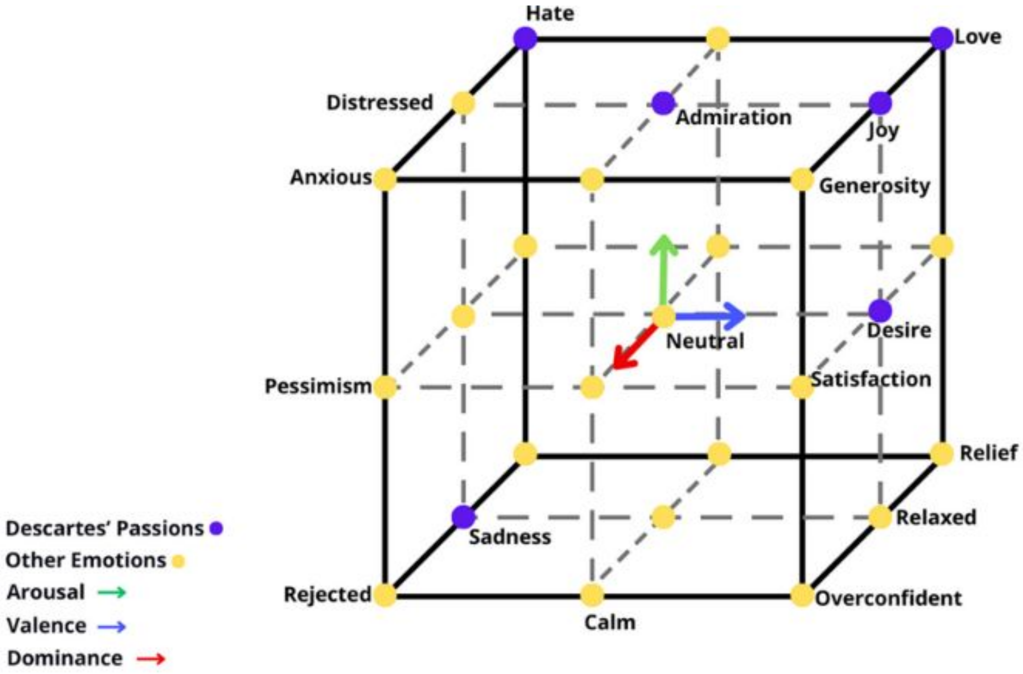
VAD emotion model



Blanco-Ríos & Candela-Leal et al. (2024)
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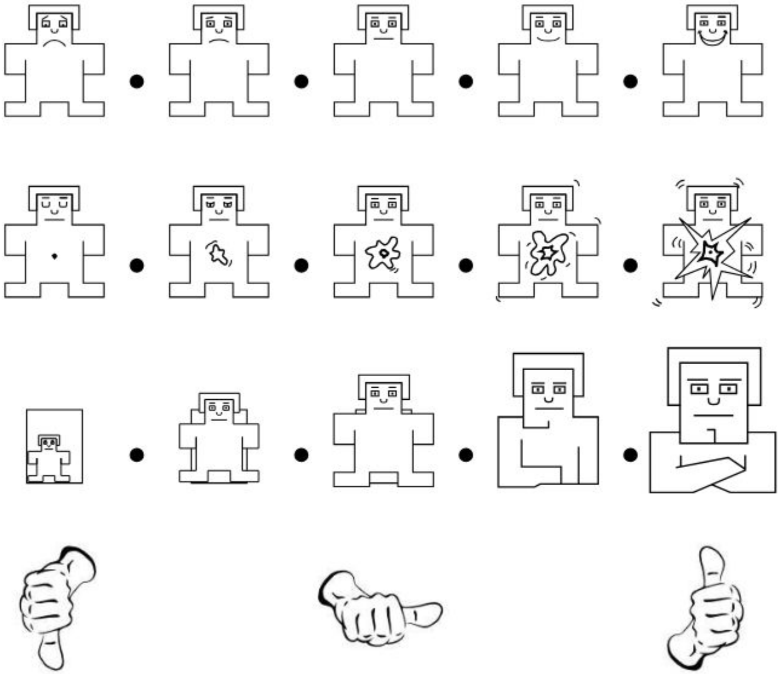
Self-Assessment Manikin (SAM)

- 1-9 Likert scale ratings
- **Valence:** Unpleasant (stressed) to happy (elated).
- **Arousal:** Uninterested (bored) to excited (alert).
- **Dominance:** Helpless (without control) to empowered (in control).



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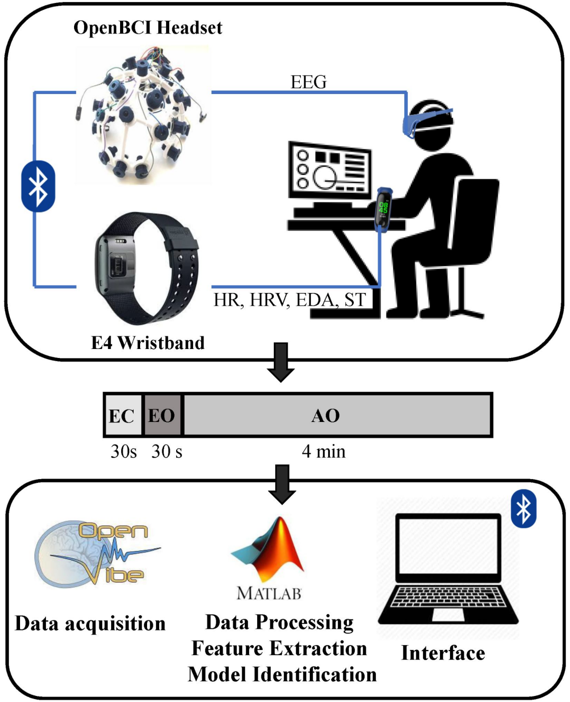
Koelstra et al. (2012) *IEEE Transactions on Affective Computing*

EEG Indices

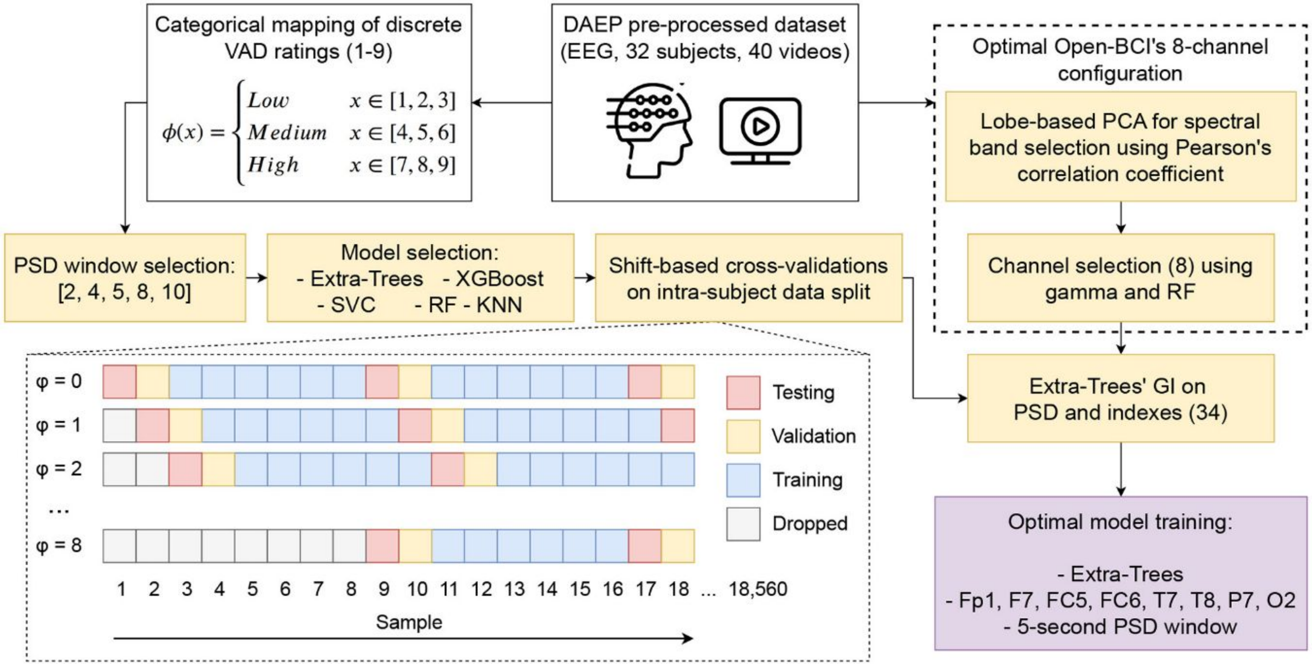
Combine frequency bands to determine an explainable behavior:

- **Engagement:** β/(θ+α) [1]
    - Cognitive processing in contrast to a more passive state.
- **Fatigue:** α/θ [2]
    - Mental weariness; required at sustained attention.
- **Excitement:** β/α [3]
    - High alert and attentive; excitement or increased interest.



[1] Ismail & Karwowski (2020) *PLOS ONE*, 15(12)
[2] Ramírez-Moreno et al., (2021) *IJERPH*, 18(22)
[3] Kislov et al. (2022) *Brain Sciences*, 13(1)

Methodology



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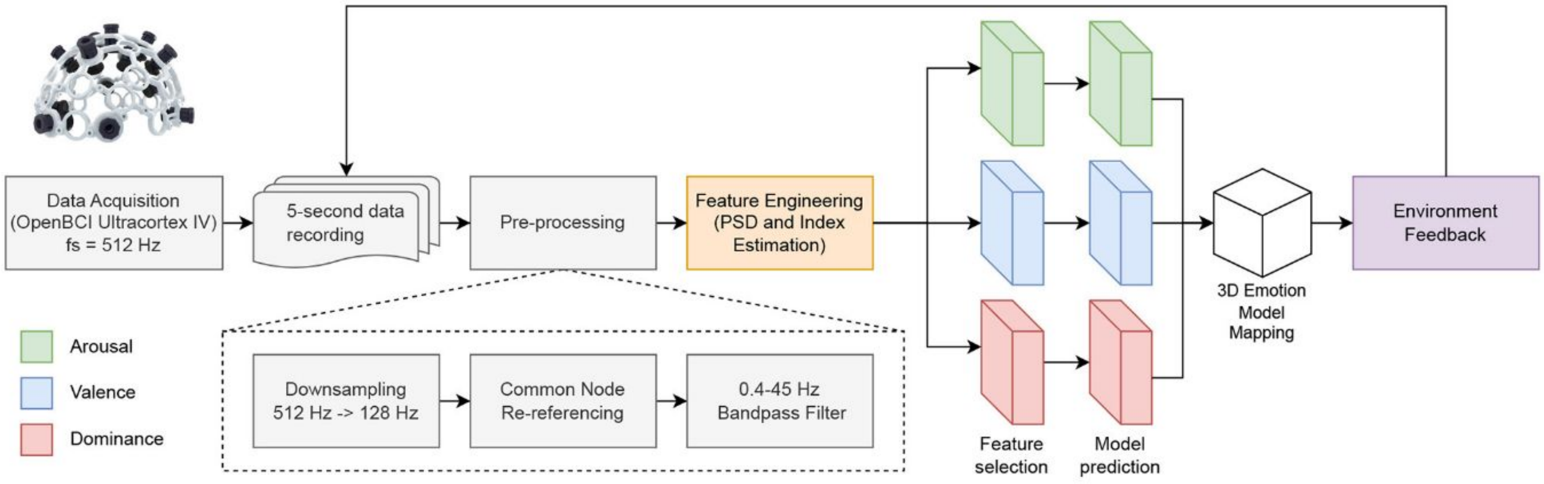
Flow diagram of real-time prediction



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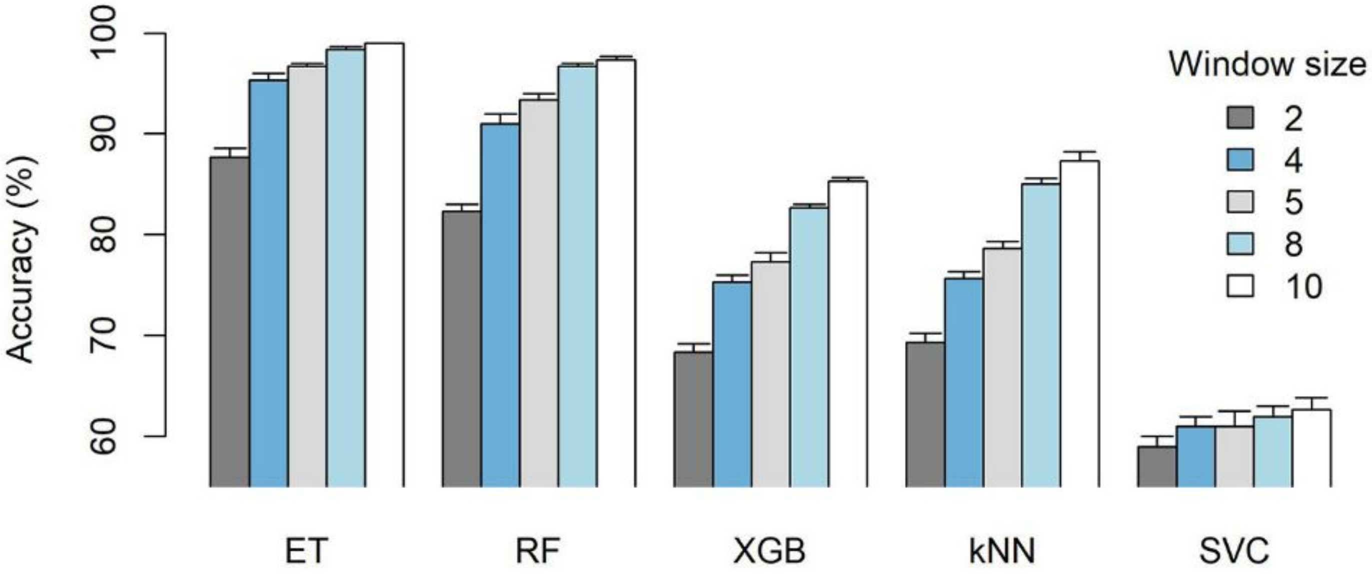
Window size selection



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Frequency band-lobe pair most related to emotion

f_{band}	Lobe	Arousal	Valence	Dominance	Σ
δ	F	0.0472	0.0447	0.0422	0.1341
	T	0.0511	0.0455	0.0436	0.1402
	P	0.05	0.0435	0.0445	0.138
	O	0.0438	0.0423	0.0426	0.1287
	C	0.0511	0.043	0.0447	0.1388
	CP	0.0456	0.0446	0.0406	0.1308
θ	F	0.0877	0.0795	0.0778	0.245
	T	0.0954	0.0804	0.0785	0.2543
	P	0.0971	0.083	0.0833	0.2634
	O	0.0946	0.0762	0.0794	0.2502
	C	0.0945	0.0783	0.0812	0.254
	CP	0.0839	0.083	0.0773	0.2442
α	F	0.1146*	0.0686	0.0763	0.2595
	T	0.1123	0.073	0.078	0.2633
	P	0.1138	0.087	0.0845	0.2853
	O	0.1233	0.0883*	0.0844	0.296
	C	0.1182*	0.0828*	0.0836	0.2846
	CP	0.1108	0.0815	0.08	0.2723
β	F	0.1642	0.0989	0.1065	0.3696
	T	0.1684	0.0988	0.1183	0.3855
	P	0.1894	0.1113	0.1184	0.4191
	O	0.1797	0.1072	0.1094	0.3963
	C	0.1788*	0.0985	0.1207	0.398
	CP	0.1696*	0.1083	0.1084	0.3863
γ	F	0.1868*	0.1228	0.1176*	**0.4272**
	T	0.188*	0.1226*	**0.1327**	**0.4433**
	P	0.2005	**0.1316***	0.1264	**0.4585**
	O	**0.2011**	0.1295	0.1257	**0.4563**
	C	0.1958	0.1178	0.1307	**0.4443**
	CP	0.1783*	0.1281	0.1187	**0.4251**

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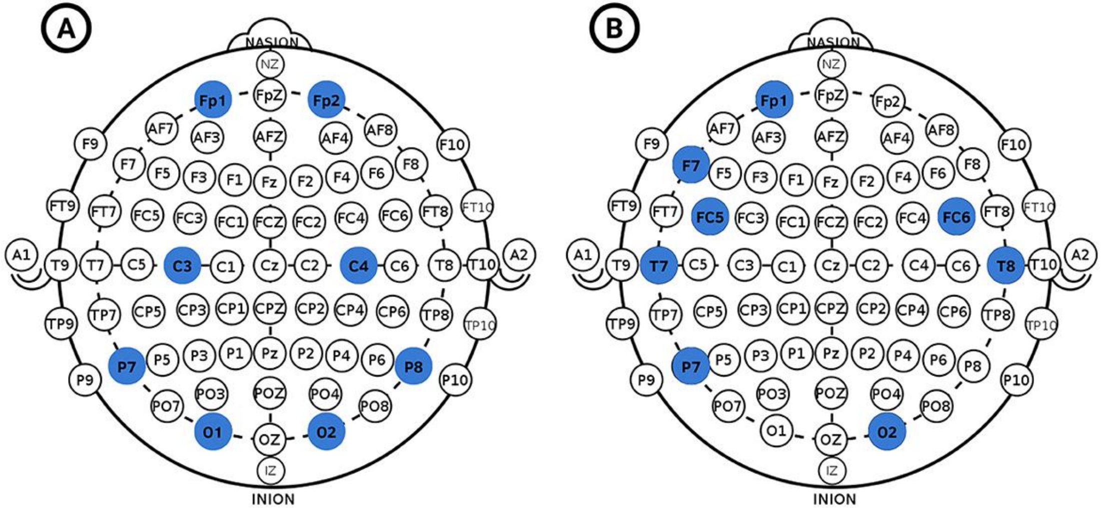
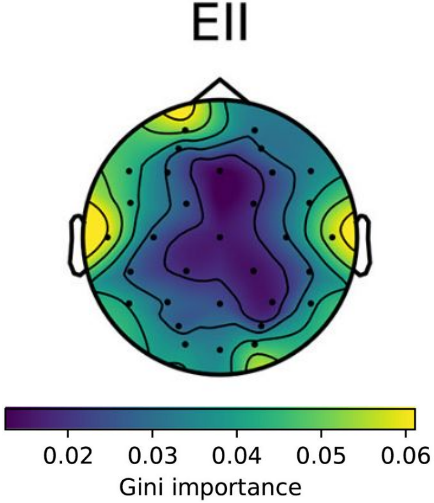
Optimal channel configuration (gamma)

- **EII**: Emotion Importance Index, calculated for each emotion *e*

$$EII(c) = \frac{1}{E}\sum_{e=1}^{E} GI(c, e)$$





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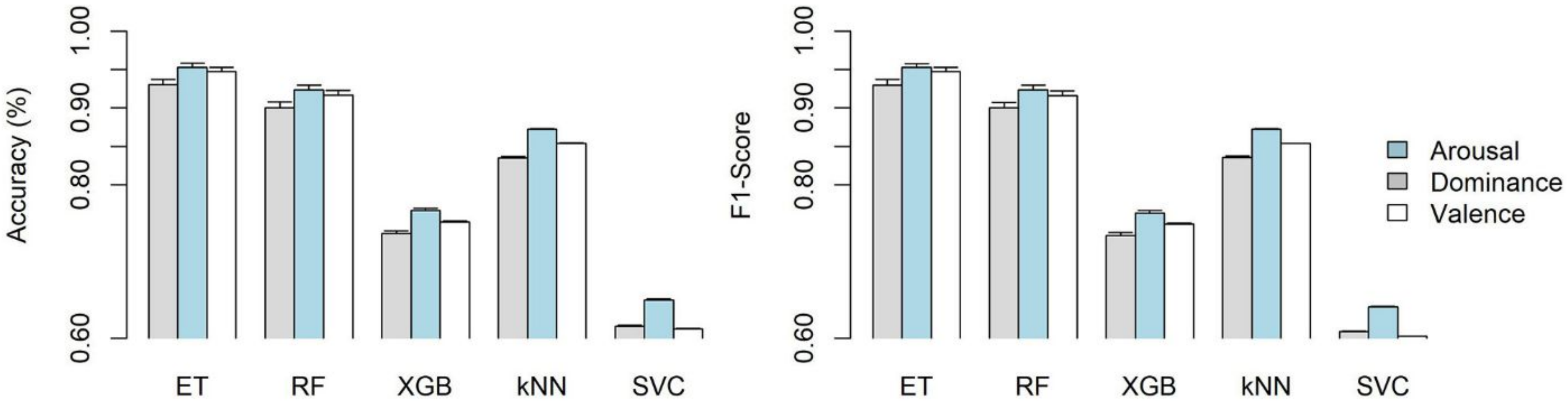
ML model selection & feature importance

- **ET**: Extra-Trees, **RF**: Random Forest, **XGB**: XGBoost
  kNN: k-Nearest Neighbors, **SVC**: Support Vector Classifier



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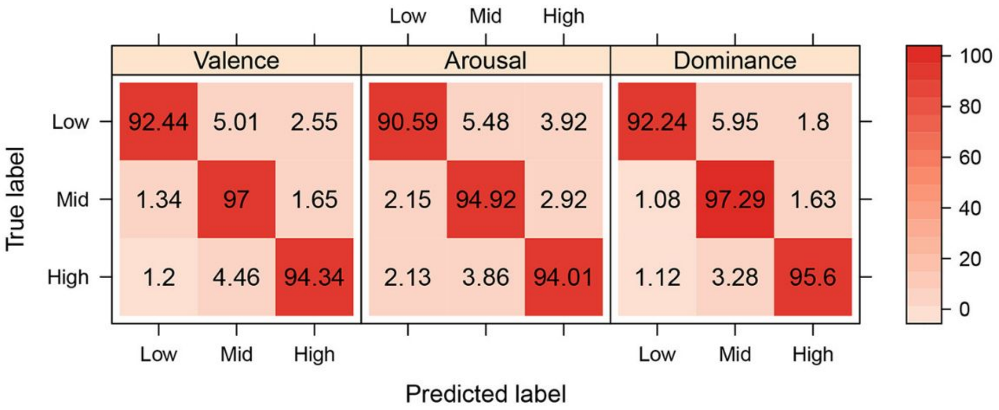
Conclusion

- 8-channel EEG real-time emotion recognition is feasible and accurate
  - VAD model is capable of mapping further emotions
    - Changing the current learning environment based on student's state
- **Adaptive environments improves engagement and learning**



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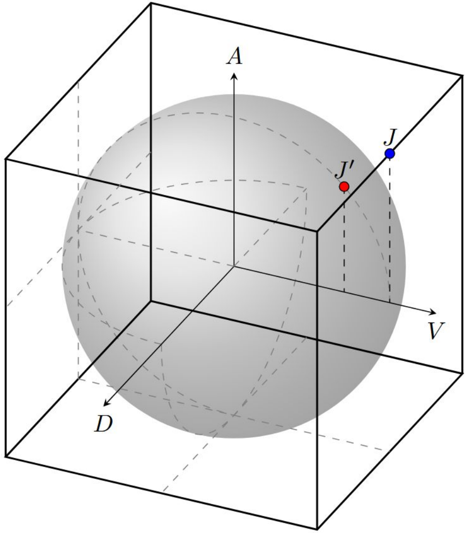
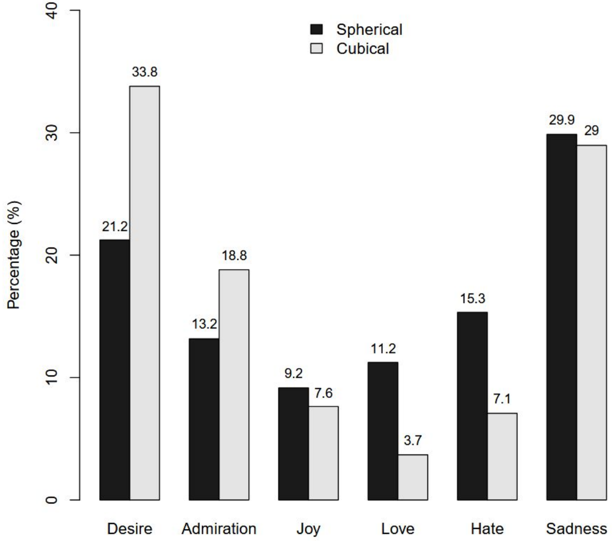
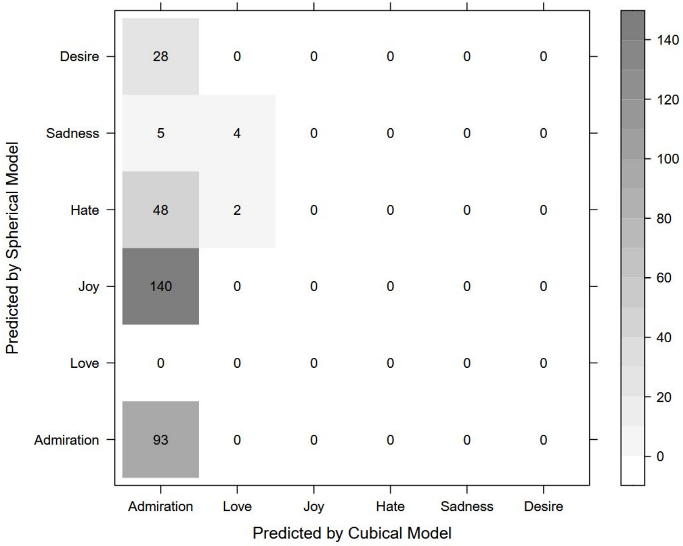
Future Directions on VAD modeling

- Spherical Model for an equidistant modeling of predicted VAD values







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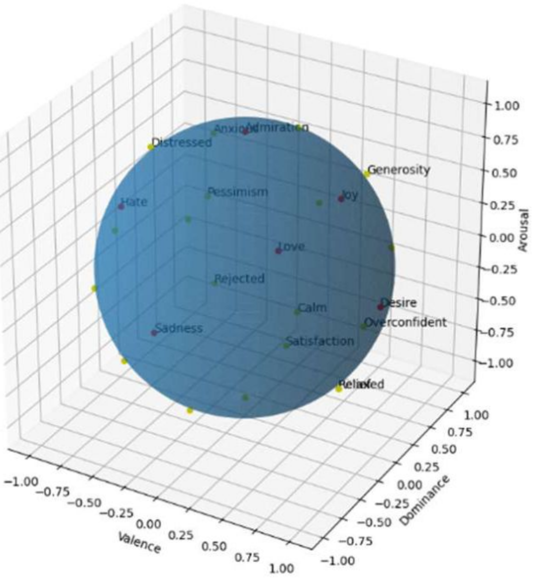
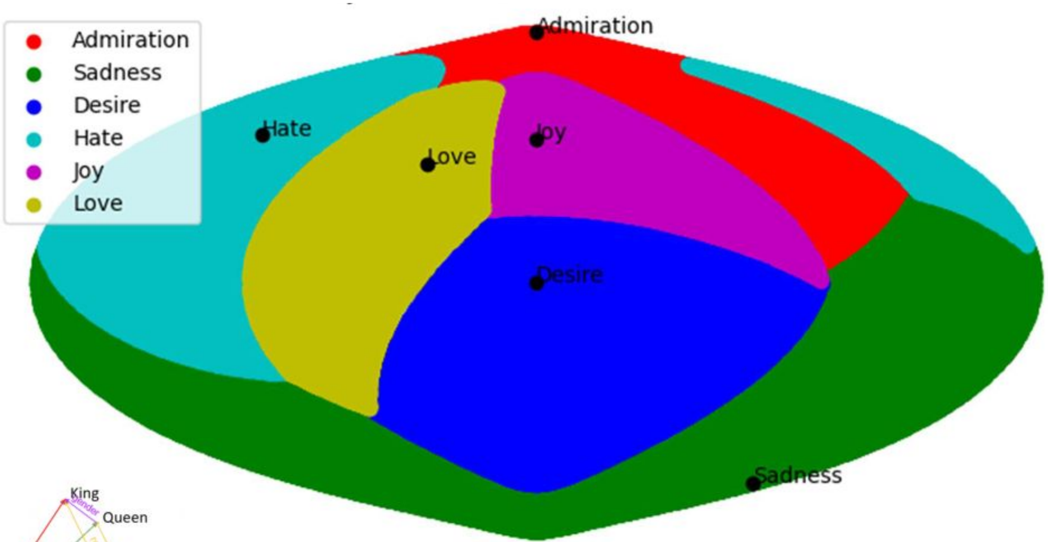
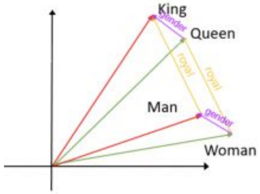




$$\vec{A} \cdot \vec{B} = |\vec{A}||\vec{B}| \cos \theta$$



Thanks

Any questions?

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Future Directions on VAD prediction

- Instead of normalization based on dataset, considering n >>, normalization based on
  - Short 3-second trial baseline prior to stimuli
  - Global features according to inter-subject LOO data division
  - Normalized PSD using BrainFlow rather than bandpower using PyEEG
- Reduce overfit by
  - Include bias-reducted ML models such as histGBR instead of RF
  - Select proper window size that captures emotion features but for real-time
  - Reducing the amount of features by adding emotion-specific feature selection
  - Hybrid classification + regression model for overall and refined VAD prediction
  - Prediction performance based on R2 and correlation for comprehensive performance
  - Inter-subject data division with Cross-Validation rather than intra-subject data division