



**University of
Zurich** UZH



Prediction of Psychiatric Multimorbidity in a Large Pediatric Sample



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Charité

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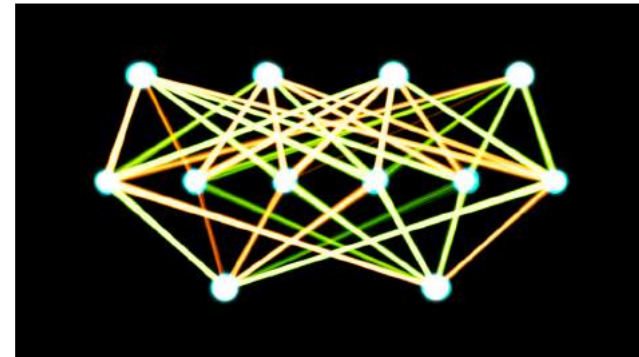
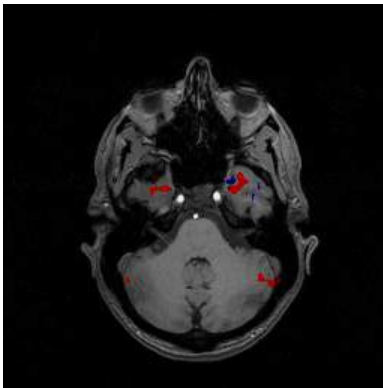
3rd meeting of FG-AI4H
EPFL SwissTech Convention Center,
Ecublens (Lausanne), Switzerland , 22-25
Jan. 2019

Outline

- Relevance
- Existing Work
- Current Challenges - Solutions
- Data availability
 - Sample
 - Data (neurophysiology (EEG), cognitive and behavior)
- Data Quality
 - Technical Validation
 - Test-retest preliminary results
- Benchmarking
- Organizers

The Final Goal: Biological Tests for Psychiatry

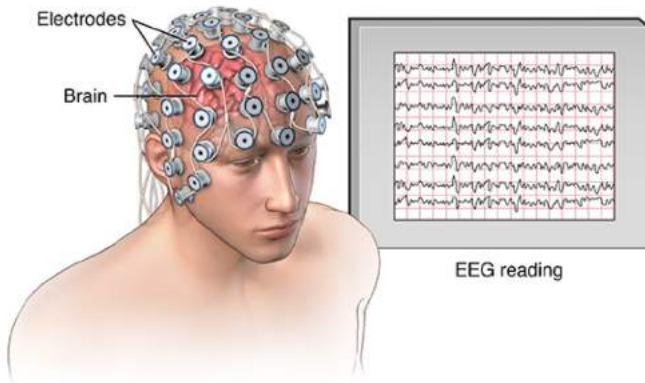
previous approaches with structural and functional MRI



Psychiatric Diagnosis

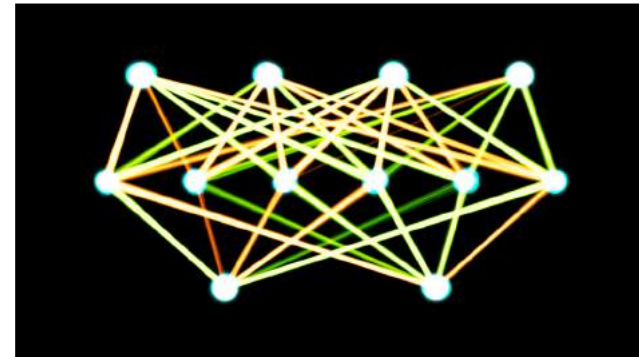
The Final Goal: Biological Tests for Psychiatry

Electroencephalography (EEG)



Why EEG:

- Low cost
- direct measurement of electrical brain activity
- good psychometric properties
- mobility (wide spread availability)



Psychiatric Diagnosis

Relevance of the proposal

- **Psychiatric disorders** are among the most common and debilitating illnesses across the lifespan.
- Epidemiologic studies indicate that 70% of all diagnosable psychiatric disorders **begin prior to age 24** (Kessler et al., 2005).
- **Diagnosing** psychiatric developmental disorders:
 - needs multiple prolonged interviews conducted by a psychiatrist with the child and its close relatives.
 - procedure is relatively costly.
 - remains highly subjective (low inter-rater reliability).
- **AI algorithms** promise to overcome the subjectivity of the manual diagnosis.
- An AI based/supported diagnosis would offer a **reliable, objective and cost-worthy** diagnostic method and finally potentially also **shorten the diagnosing time**.

Existing Work

- Neurophysiological (EEG) biomarkers:
 - Theta-beta ratio (TBR) in attention deficit hyperactivity disorder (e.g., Magee et al., 2005, Lenartowicz and Loo., 2014).
 - Frontal alpha asymmetry for depression (e.g. van der Vinne et al., 2017, Olbrich and Arns, 2013)
- The majority of existing studies have focused on differentiating between children with an **isolated psychiatric disorder** and typically developing children.
 - However, this line of research **does not reflect the real-life situation**:
 - over 75% of children with a clinical diagnosis have multiple psychiatric disorders = multimorbidities.
- Furthermore, most of the previous studies employ traditional univariate statistics. **Multivariate machine learning/AI approaches** have a great potential to overcome the limitations of univariate approaches.


Current Challenges

- Focus on **one diagnosis vs. healthy controls**
 - in real life 70% multimorbidity
- Univariate vs. multivariate statistics
- **Small sample size** (not enough data)
- **No objective and standardized preprocessing** for EEG data
- Unknown **reliability** of EEG measures
- **Not enough computing power**
- **Too many variables for human mind/eye**
 - multi dimensional data space

nature
neuroscience

Building better biomarkers: brain models
in translational neuroimaging

Choong-Wan Woo¹⁻⁴, Luke J Chang⁵, Martin A Lindquist⁶ & Tor D Wager^{3,4}

 Molecular Psychiatry (2012) 17, 1174–1179
© 2012 Macmillan Publishers Limited All rights reserved 1359-4184/12
www.nature.com/mp

PERSPECTIVE

Why has it taken so long for biological psychiatry to develop
clinical tests and what to do about it?

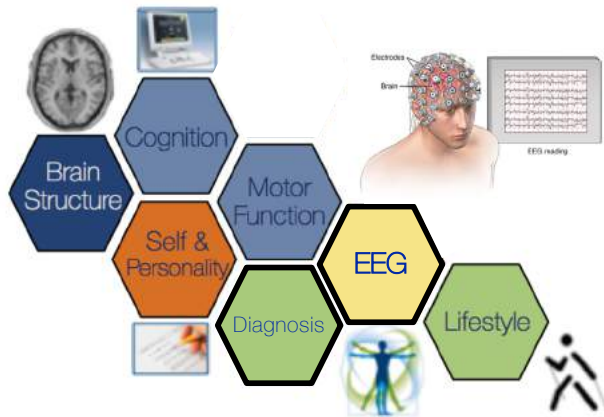
S Kapur¹, AG Phillips² and TR Insel³

Solution: AI & large representative samples

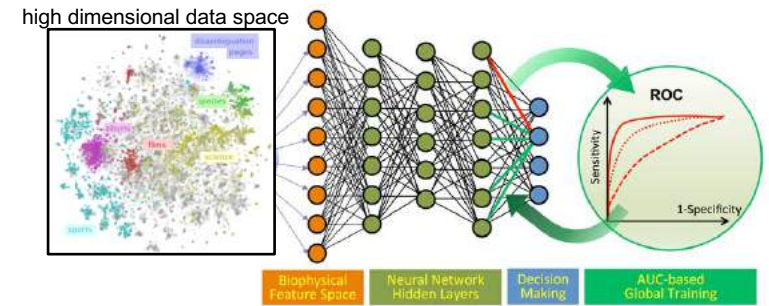
Availability of Big Data



Dr. Michael Milham



Advanced AI Algorithms



Growth in Computing Power



Data availability: Sample

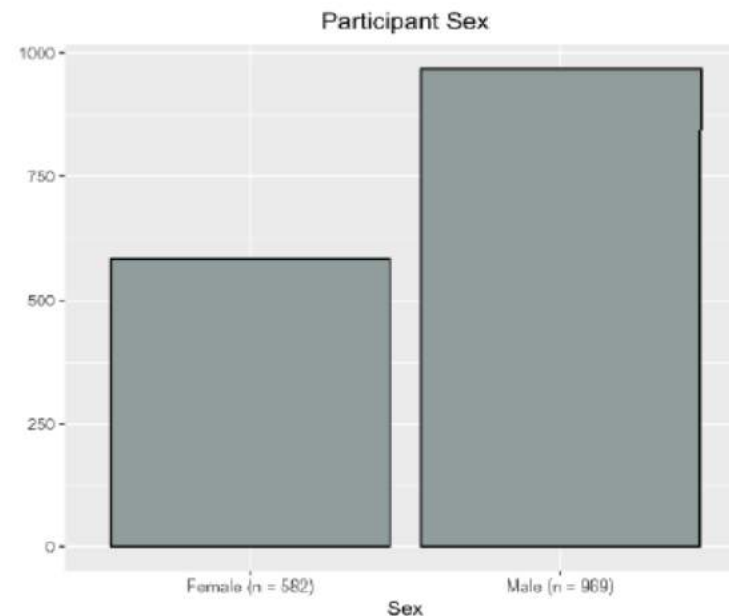
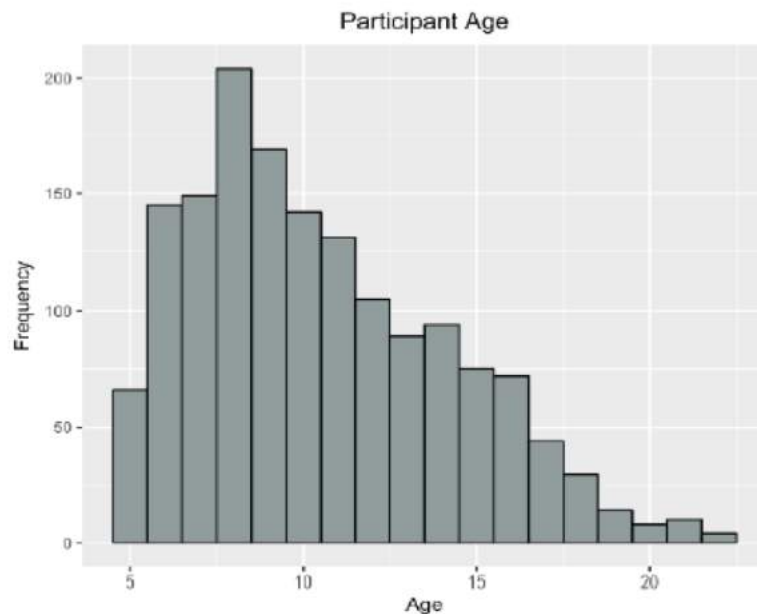
Healthy Brain Network (HBN) sample

Training Data:

- current release: 1602 subjects
- Age 5-21 years
- Population: typical developing children and children with psychiatric developmental disorders (~70/ multimorbidities)

Test Data:

- Subsample of training data
- Future release: approx. 500 subjects / year



Data availability: Sample

Healthy Brain Network (HBN) sample

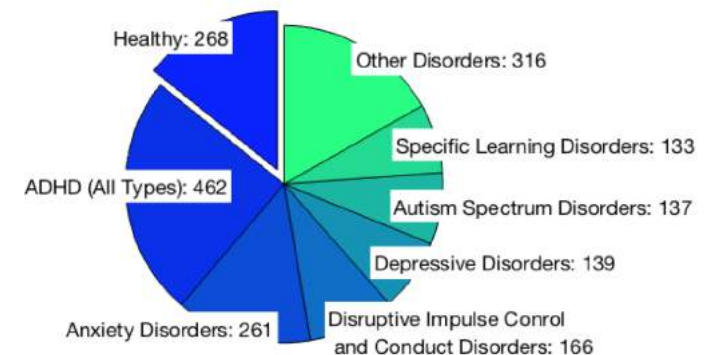
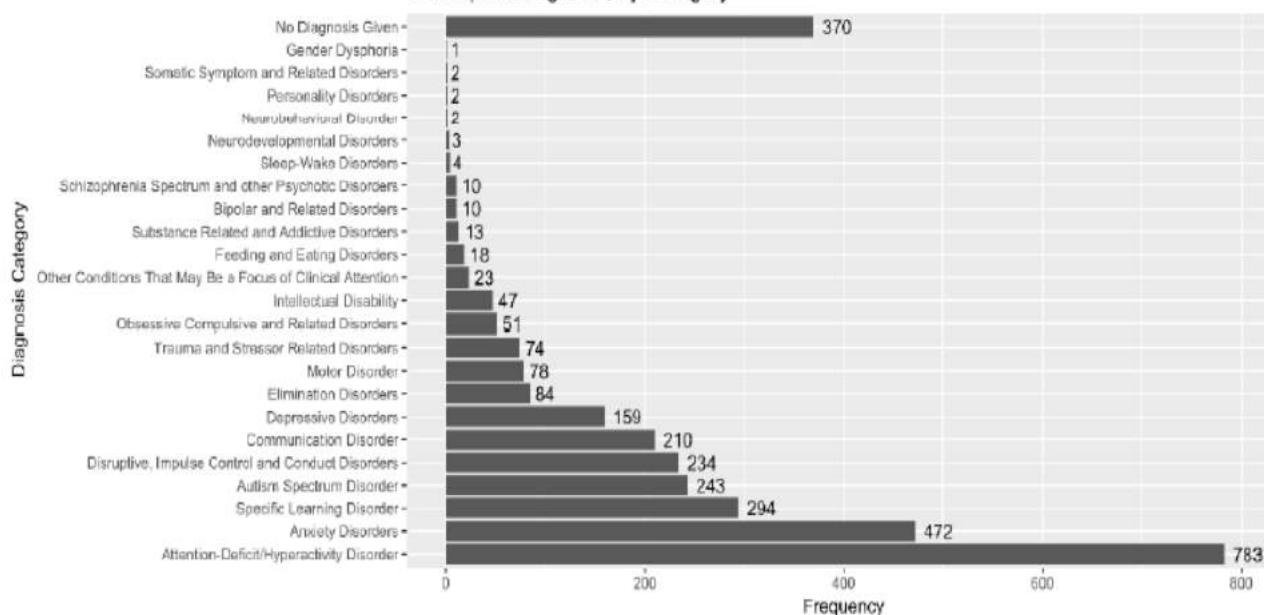
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Participant Diagnosis, by Category



Data availability: Data

- Demographics
 - Age, gender
- Cognitive Data
 - e.g. WISC
- Behavioral Data
 - Questionnaires (SWAN)
- resting EEG
 - Raw data
 - Preprocessed data
 - EEG features
 - e.g. theta-beta ratio, alpha asymmetry
- Possibly T1-weighted MRI images
 - Source reconstruction
 - Cortical thickness



- **Prediction of Diagnosis**
 - DSM-V consensus diagnosis
- **Annotation Quality:**
 - based on the decision of a clinical team
 - all interviews and materials conducted as basis for the DSM-5 consensus diagnosis
 - conducted by licensed clinicians

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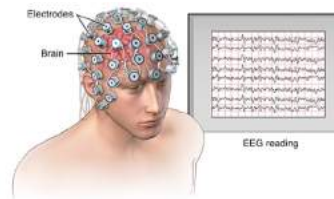
Cognitive & Behavioral Data:

- Demographics
- Cognition / Intelligence (e.g. WIAT, WISC-V, NIH-Toolbox)
- Medical History (e.g. addiction family history)
- Family Structure, Stress and Trauma (negative life events, parenting)
- Personality Traits (Big 5, self-esteem)
- Coping Strategies (communication skills, interpersonal factors)
- Physical Measures (e.g. bio-electric impedance analysis, BMI, Metabolic rate, heart rate, blood pressure, height, weight, handedness,...)
- Social Status (SES, parents education, family structure)

Nr. of features: ~270 (self-/ parent-/ teacher-report)

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Raw EEG:

- 5 min.
- Eyes closed (40 s) & eye open (20 s)
- 128 electrodes (Geodesic EGI system)
- sampling rate 500 Hz
- **Nr. of features: ~ 150'000**

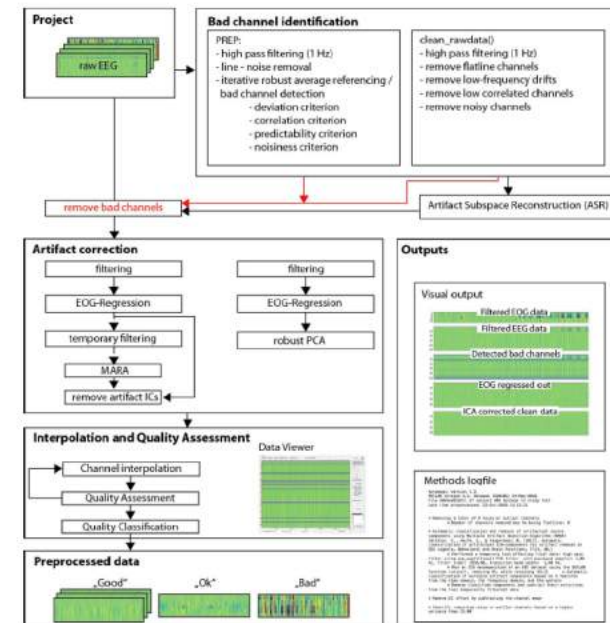
Prerequisite for Biomarker Research: Reliability of measures

Prerequisite for Reliability: Standardized Preprocessing

- Demographics
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Automagic

Pedroni, Bahreini Langer, (2018), biorXiv



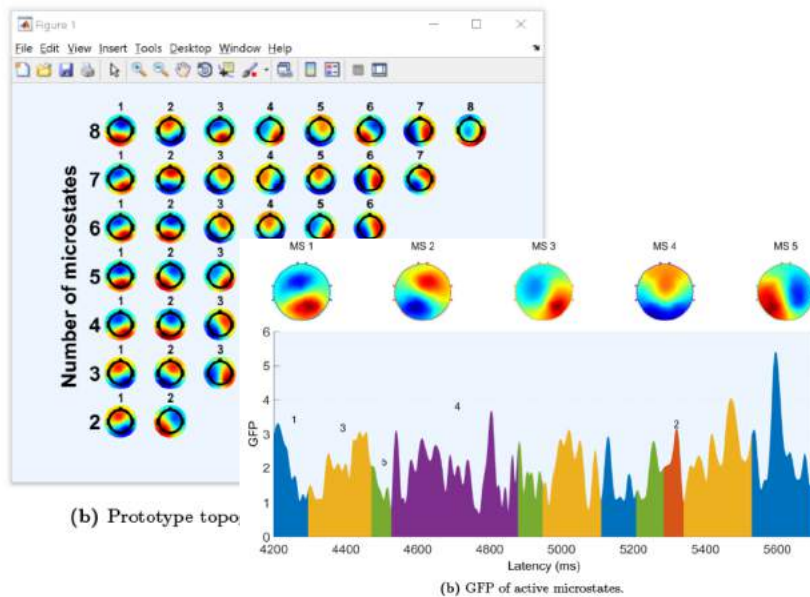
<https://github.com/methlabUZH/automagic>

Preprocessed EEG:

- Number of features: ~ 150'000

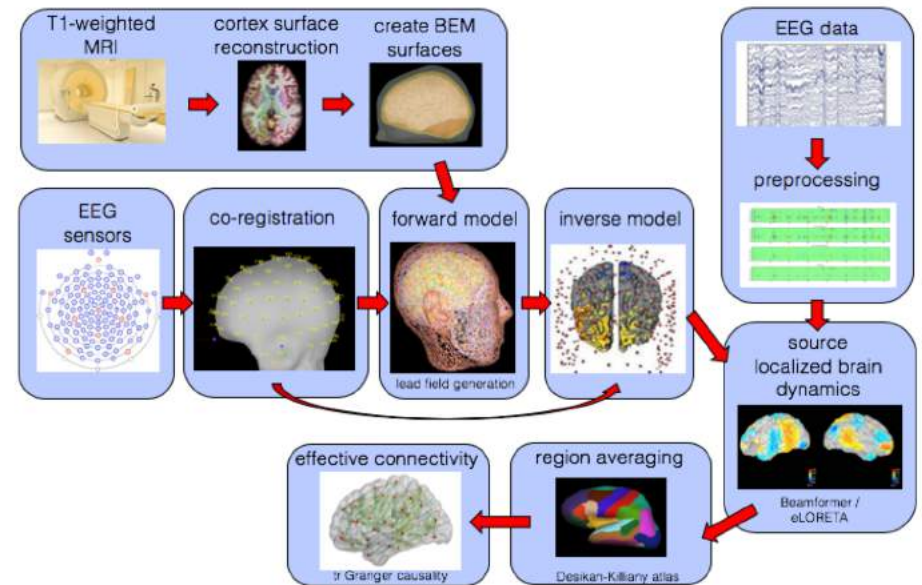
Developing Methods for EEG analysis

EEG Microstates Toolbox



Poulsen, Pedroni, Langer, Hansen (2018)

EEG Connectivity Analysis



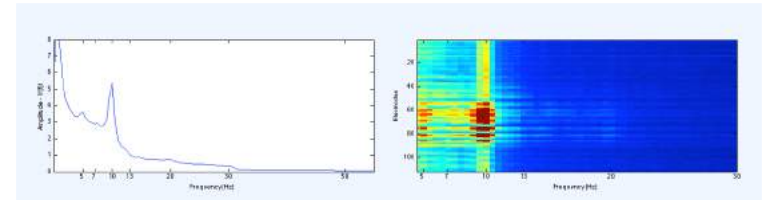
Haufe & Langer in prep.

EEG features

- Demographics
 - Age, gender
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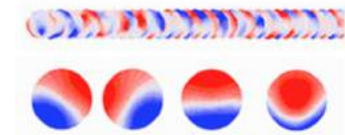
Frequency Domain:

- Frequency Power analysis
 - (e.g. theta/beta ratio; alpha asymmetry; 1/f noise, alpha peak)
- Number of features: ~ 122



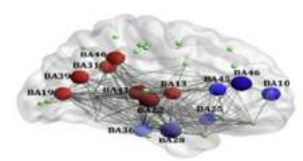
Time Domain:

- Microstates:
 - „MS are stable spatial configurations of the electric field. These spatially stationary microstates might be the basic building blocks of information processing.“ (Lehmann, 1978)
- Number of features: ~ 40



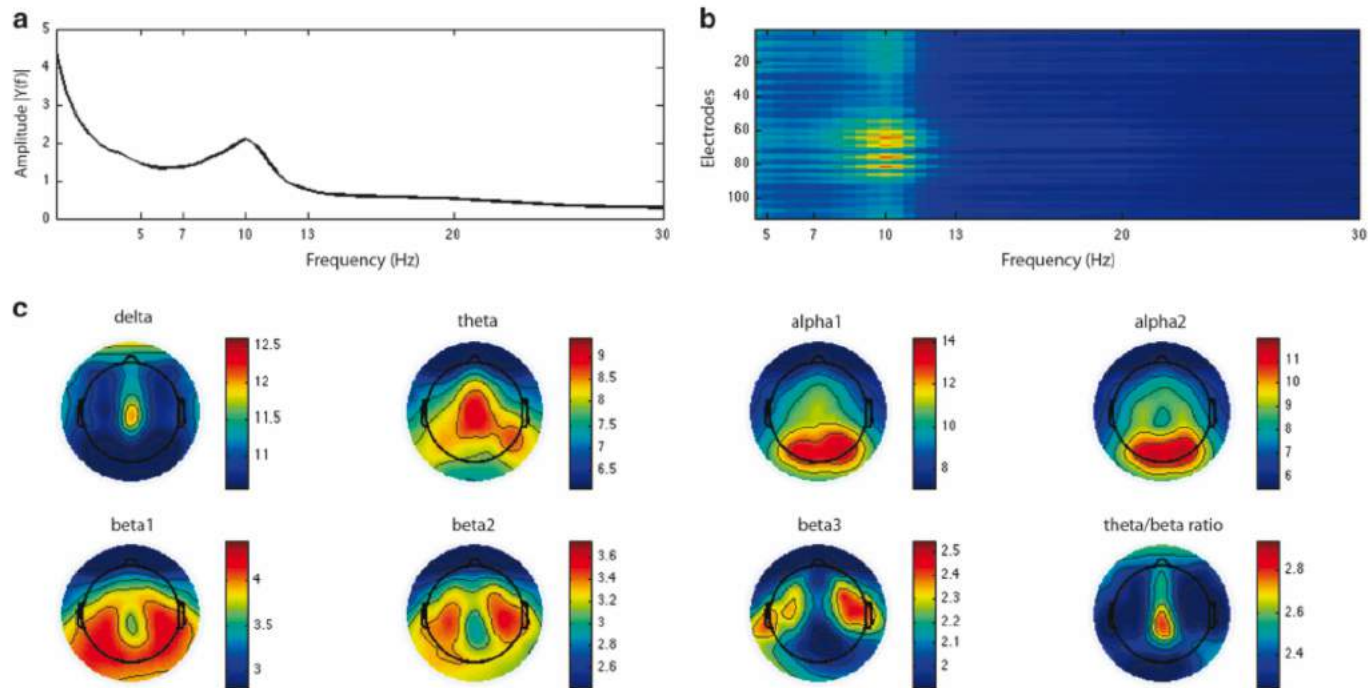
Functional Connectivity:

- Imaginary part of coherency
- Time-reversed Granger causality
- Number of features: ~ 9216



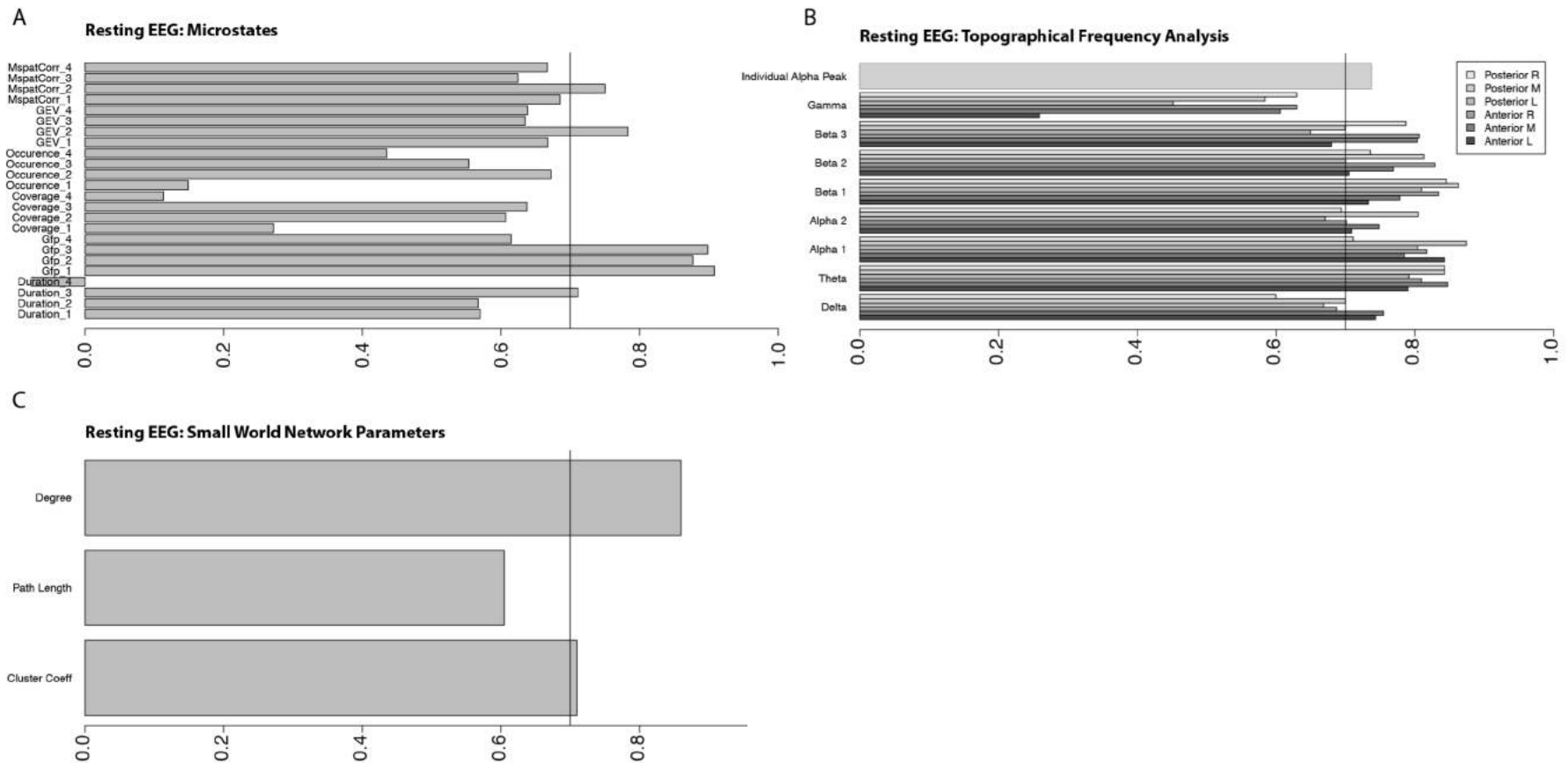
Data Quality: Validation Analysis

Technical Validation (N = 126)



Data Quality: Test-retest Reliability

Preliminary results (N = 30)



Benchmarking

Task: prediction of multiple disorders from demographic, phenotypical (cognitive and behavioral) and EEG data

Training: on public HBN data

Benchmarking: on future releases of HBN data sets (approx. 500 subjects / year)

Implementation: participants submit executable code

- Standardized input (data folder) and output (binary classification matrix)
- Container architecture (docker/kubernetes)
 - Free choice of development tools for participants
 - Safe for organizers
- Cloud computing: GCP/AWS or similar
- Challenge platform: crowdai.org/Kaggle etc.



kubernetes



kaggle

Performance metrics

		D disorders					D disorders		
Y^{true} : true test labels	N subjects	1	1	1	Y^{pred} : predicted labels	N subjects	0	1	1
		1	1	1			0	0	1
		0	0	0			0	0	0
		0	1	1			1	1	1
		1	1	1			0	1	0
		1	1	0			1	1	0
		1	0	1			1	1	1

Main metric (used for ranking): multi-task accuracy

$$\text{ACC} = 1 - \frac{1}{ND} \sum_{n=1}^N \sum_{d=1}^D |Y_{n,d}^{\text{true}} - Y_{n,d}^{\text{pred}}|$$

Secondary metrics: F1-score, sensitivity, specificity, precision, recall

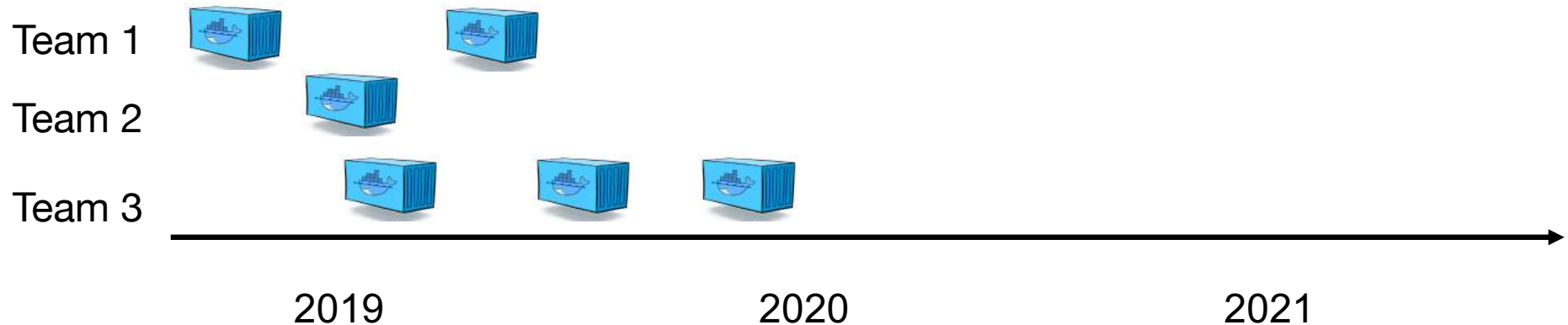
Multi-task metrics for continuous labels (severity scores) available.

Timeline

Idea: continuous prediction challenge

- Participant teams can refine and upload containers any time
- Benchmarking of most recent containers each time new data are released
- Time stamp system allows public release of test set without delay
- Tracking progress over time as new releases become available

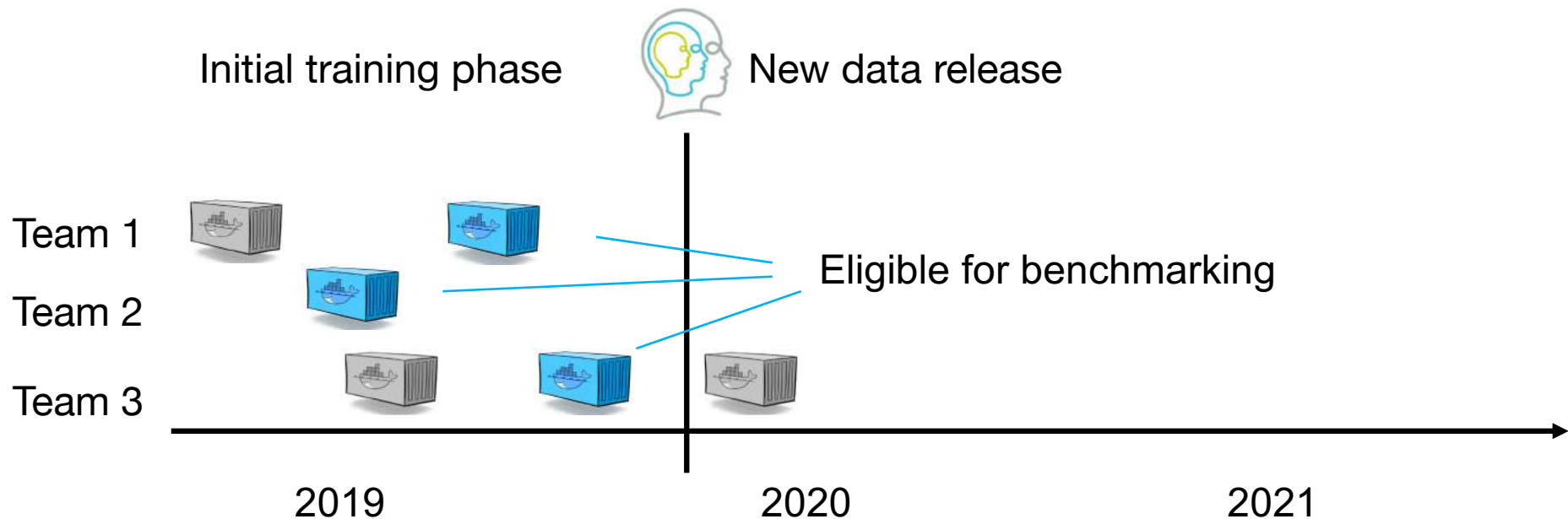
Initial training phase



Timeline

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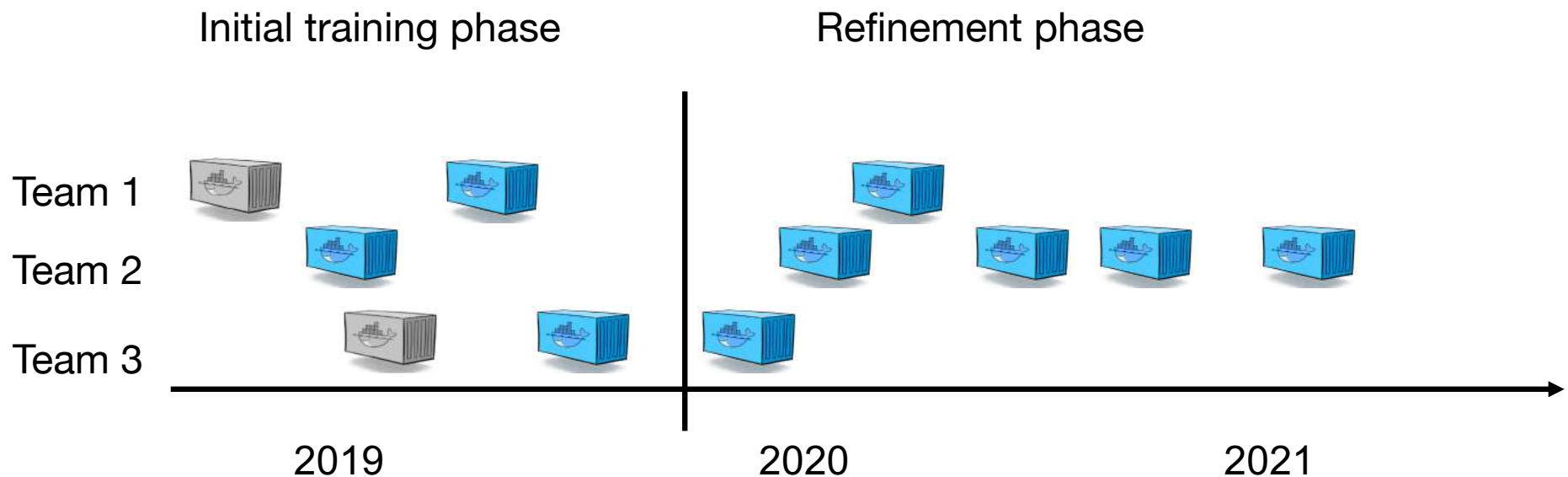
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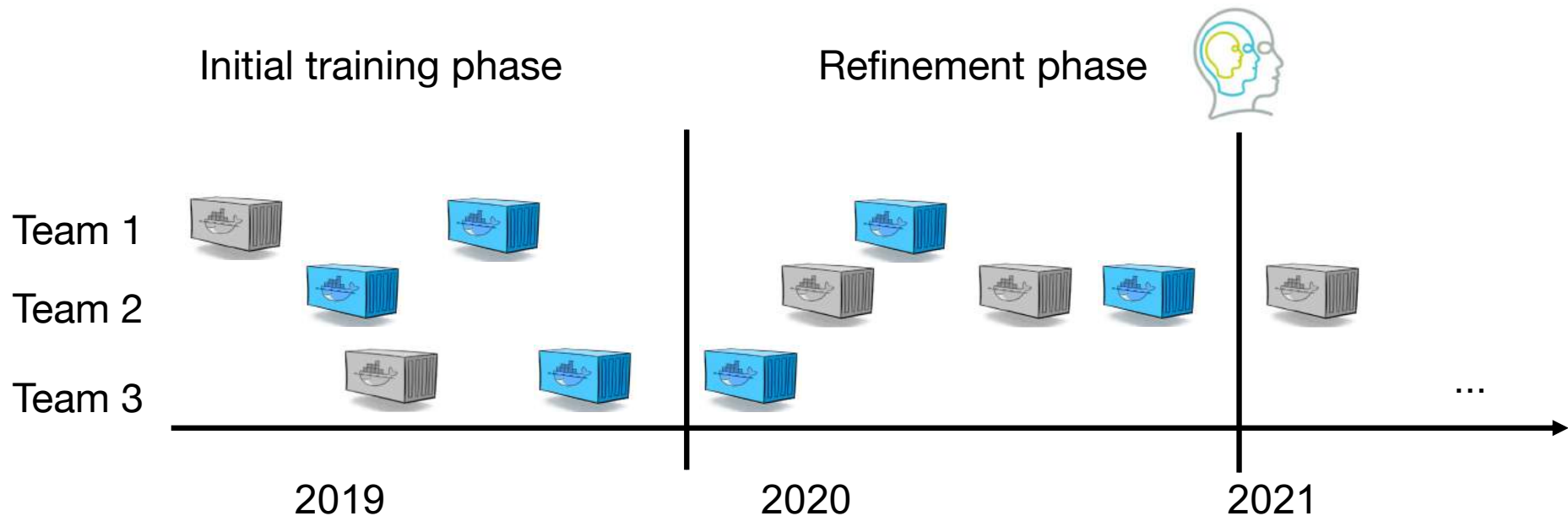
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Feasibility

- Close collaboration with the ongoing HBN initiative (support of Dr. Michael Milham)
- Training data already publicly available
- Good data quality
- Expertise regarding signal processing of EEG and statistical analyses
- Previous studies have demonstrated predictive value of EEG data to discriminate between children with an isolated psychiatric developmental disorder and control children

Organizers

Prof. Nicolas Langer



Bio:

- PhD in Neuroscience & Psychology at University of Zurich
- Postdoctoral Fellow at Harvard Medical School
- Endeavor Scientist at Child Mind Institute
- Now: Assistant Professor with Tenure Track at University of Zurich

Research interest: development of new methods for neuroimaging, EEG, eye-tracking

- design multi-level, multi-modal paradigms to study cognitive performance and perception
- Clinical focus: psychiatric developmental disorders (e.g. ADHD)
- Open Science Advocate (open software, open data)

Interested in solving big data neuro-health problems using AI as part of a collaborative/community driven effort.

Organizers

Dr. Stefan Haufe

Bio:

- PhD in Computer Science/Machine Learning at TU Berlin
- Marie Curie Postdoctoral Fellow at Columbia University
- Now ERC Research Group Leader at Charité



Research interest: analysis of EEG data using signal processing/AI

- Reconstruction of brain sources and estimation of brain connectivity
- Prediction of mental/clinical states using AI, interpretation of AI models
- Clinical focus: psychiatric and neurological disorders

Interested in solving big data neuro-health problems using AI
as part of a collaborative/community driven effort.

THANK YOU FOR YOUR ATTENTION

Prof. Nicolas Langer and Dr. Stefan Haufe have no conflict of interest