FGAI4H-E-015-A1
Geneva, 30 May - 1 June 2019

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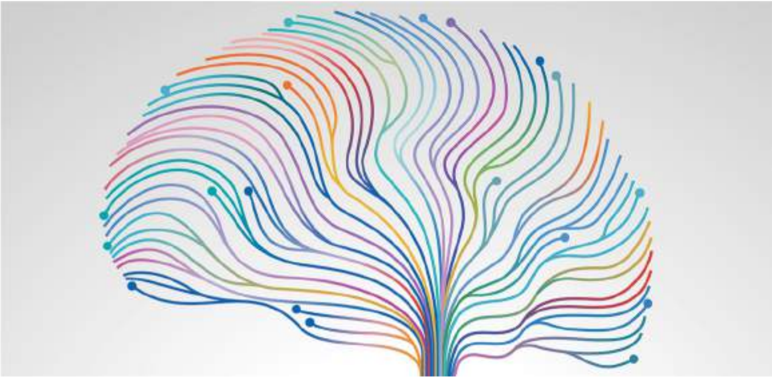
CHARITÉ
UNIVERSITÄTSMEDIZIN BERLIN

Topic Group: Psychiatry

Prediction of Psychiatric Multimorbidity in a Large Pediatric Sample



Prof. Nicolas Langer
University of Zurich
Department of Psychology
Methods of Plasticity Researcch

Dr. Stefan Haufe
Charité
Universitätsmedizin Berlin
Berlin Center for Advanced Neuroimaging (BCAN)

FG-AI4H
Meeting E: Geneva, Switzerland
Mai 30th-June 1st 2019

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.**

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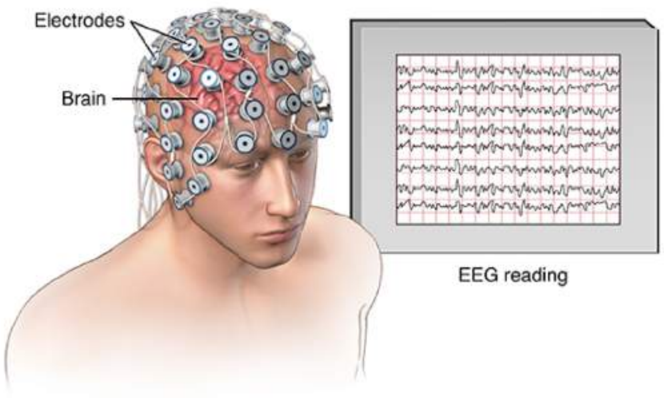
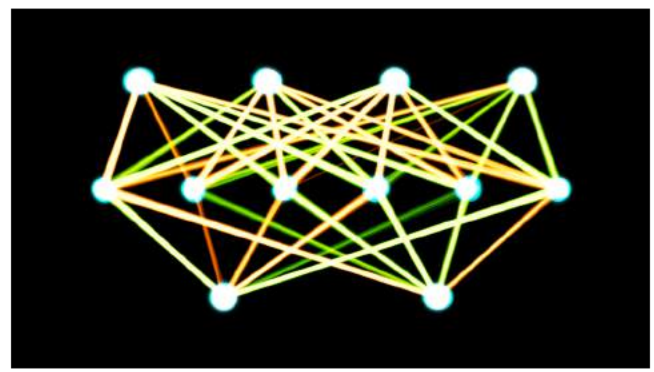
Subtopic: Prediction of Psychiatric Multimorbidity in a Large Pediatric Sample

Electroencephalography (EEG)



Why EEG:

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




SKID-I UND SKID-II
Strukturiertes Klinisches Interview für DSM-IV

DIPS
DIPS – Diagnostisches Interview bei psychischen Störungen

Psychiatric Diagnosis

Potential additional subtopic with MRI

- Structural MRI
- Resting state fMRI
- Diffusion Tensor Imaging (DTI)

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.

To do: enlarge literature for existing neuroimaging (structural and functional MRI), genetic, social media use, omics, AI solutions

Challenges of Existing AI Solutions

nature neuroscience

Building better biomarkers: brain models in translational neuroimaging

Choong-Wan Woo[1–4], Luke J Chang[5], Martin A Lindquist[6] & 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 Kapur[1], AG Phillips[2] and TR Insel[3]

General Topic Group:

- Focus on **one diagnosis vs. healthy controls**
    - in real life 70% multimorbidity
- **Small sample size** (not enough data)
- Not **enough computing power**

Subtopic: Prediction of Psychiatric Multimorbidity in a Large Pediatric Sample:

- **No objective and standardized preprocessing** for EEG data
- Unknown **reliability** of EEG measures

Description of Topic Group: Psychiatry

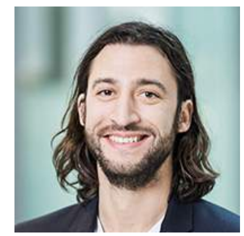
Collaboration with:

CHILD MIND® INSTITUTE
healthy brain network

Dr. Michael Milham

Topic Group Drivers

Stefan Haufe



Nicolas Langer

Available Data set(s):

Call for Topic Group Participation

INTERNATIONAL TELECOMMUNICATION UNION
TELECOMMUNICATION STANDARDIZATION SECTOR
STUDY PERIOD 2017-2020

FG-AI4H-E-005-A08
ITU-T Focus Group on AI for Health
Original: English

WG(s):	N/A	Geneva, 30 May – 1 June 2019
	DOCUMENT	
Source:	TG-Psy Driver	
Title:	Call for Topic Group Participation: Standardized benchmarking of AI in Psychiatry	
Purpose:	Engagement	

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CHILD MIND® INSTITUTE healthy brain network

Data availability: Sample

Healthy Brain Network (HBN) sample

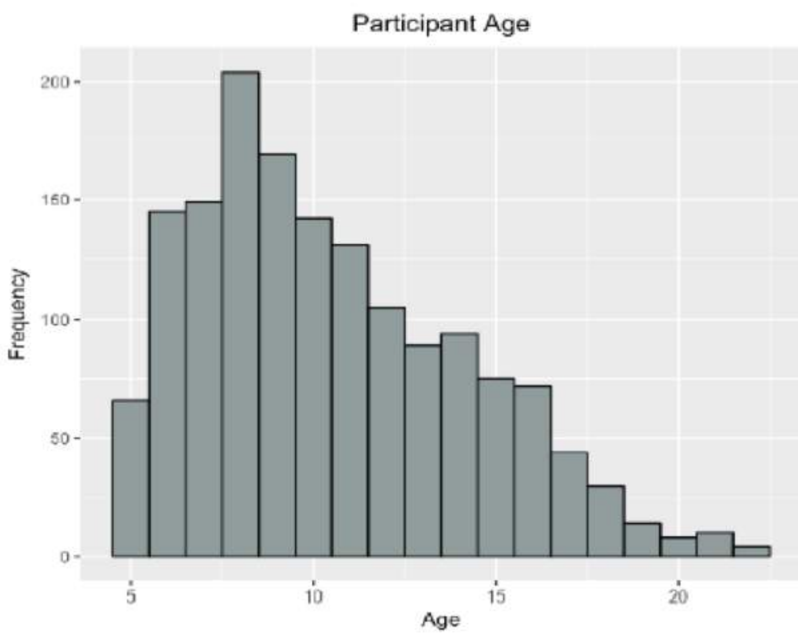
Update: continuation of data collection (currently ~1800 subjects)

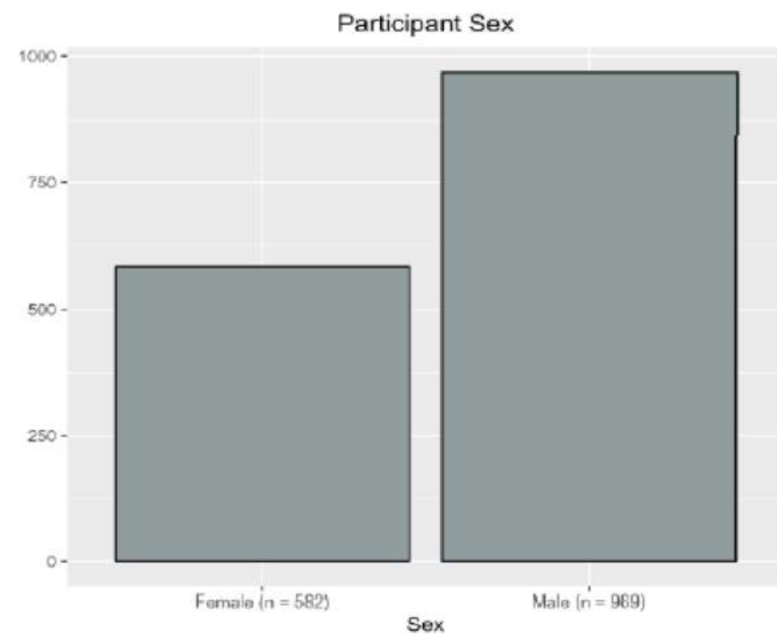
Training Data:

- current release: 1602 subjects
- Age 5-21 years
- Population: typical developing children and children with psychiatric developmental

Test Data:

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





Data availability: Sample

Healthy Brain Network (HBN) sample

Training Data:

- current release: 1602 subjects
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- Population: typical developing children and children with psychiatric developmental disorders (~70% multimorbidities)

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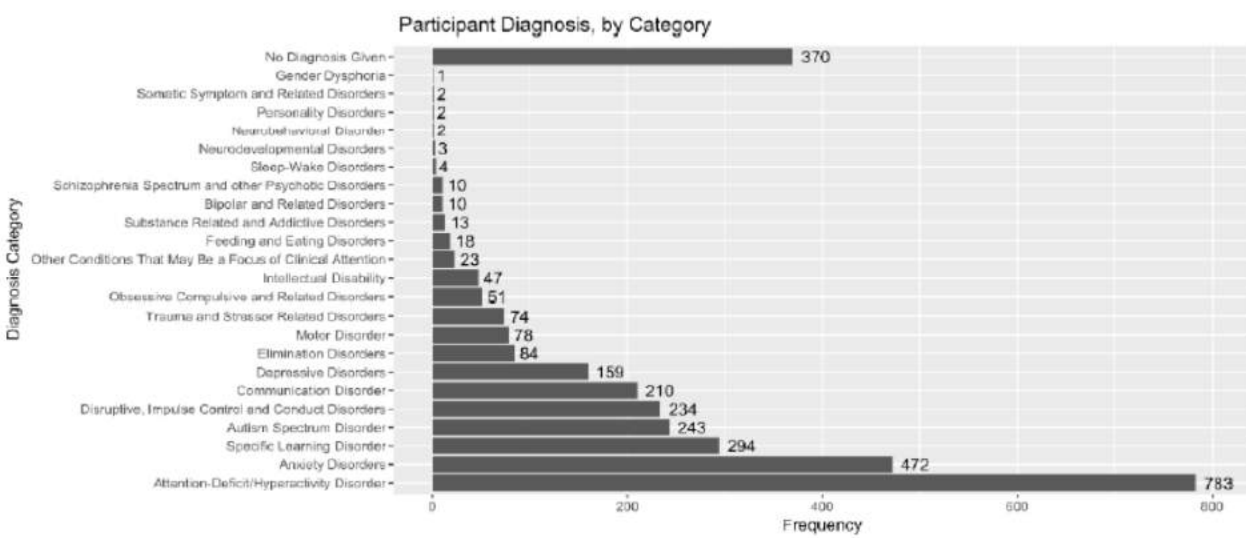
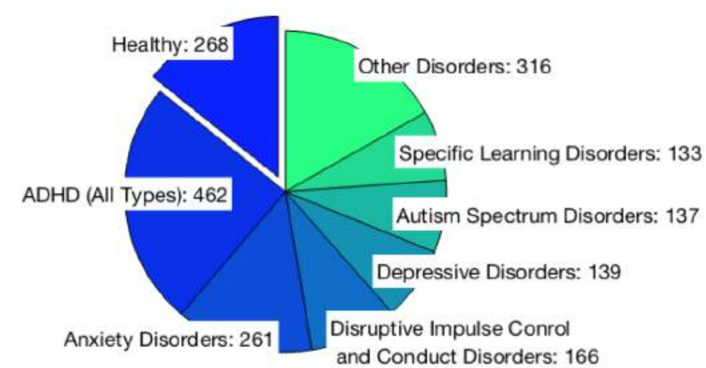
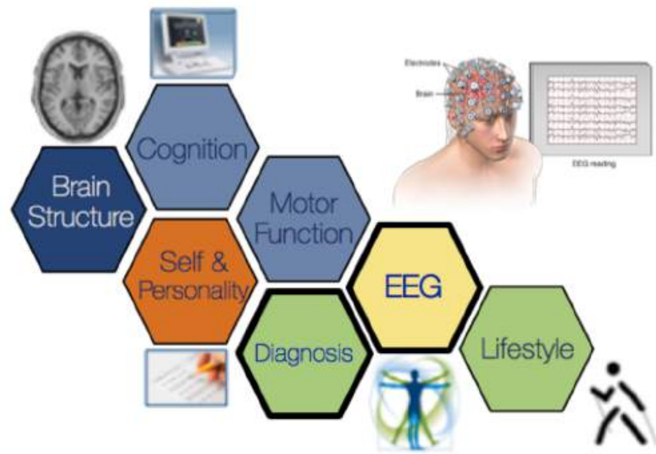




Data availability

- 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

AI Input Data Structure: Life style and Cognition

- 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
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  - Cortical thickness

<u>Cognitive & Behavioral Data:</u>

- 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)

Data format: .csv file

AI Input Data Structure: resting EEG raw 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
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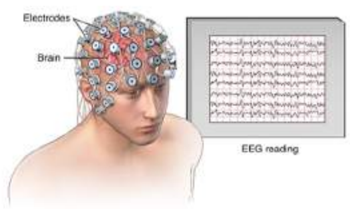


<u>Raw EEG:</u>

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

Data format: .mat file MATLAB

(also possible share it as .csv)

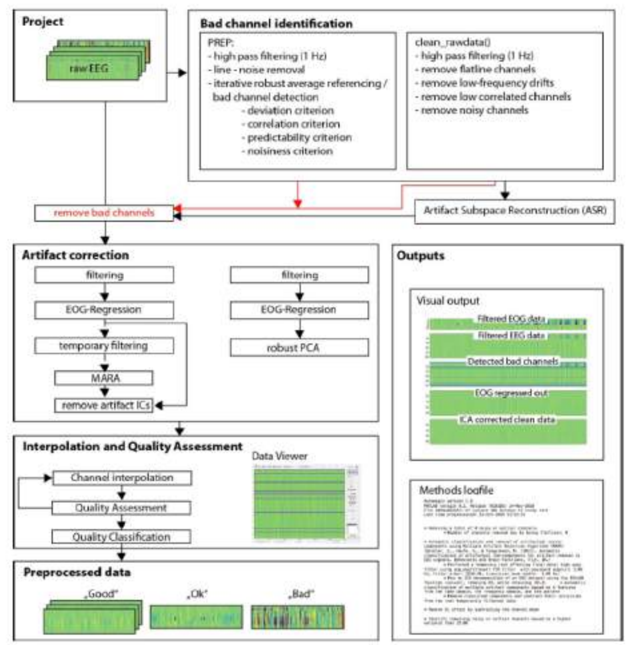
Update:
- Preprocessed all data

AI Input Data Structure: resting EEG preprocessed 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

Automagic

Pedroni, Bahreini Langer, (2018), biorXiv



https://github.com/methlabUZH/automagic

Preprocessed EEG:

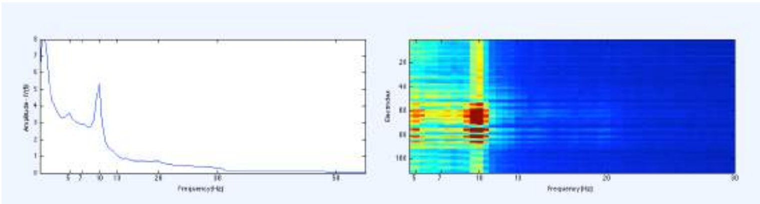
- Number of features: ~ 150'000

AI Input Data Structure: derivative EEG 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

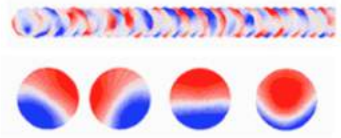
Frequency Domain:

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



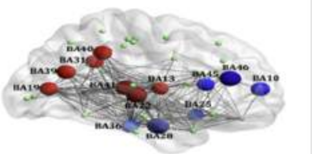
Time Domain:

- 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 format: .mat file MATLAB

(also possible share it as .csv)

Overview of 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.

Performance metrics

Y^{true} : true test labels

N subjects

D disorders

1	1	1
1	1	1
0	0	0
0	1	1
1	1	1
1	1	0
1	0	1

Y^{pred} : predicted labels

N subjects

D disorders

0	1	1
0	0	1
0	0	0
1	1	1
0	1	0
1	1	0
1	1	1

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

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

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

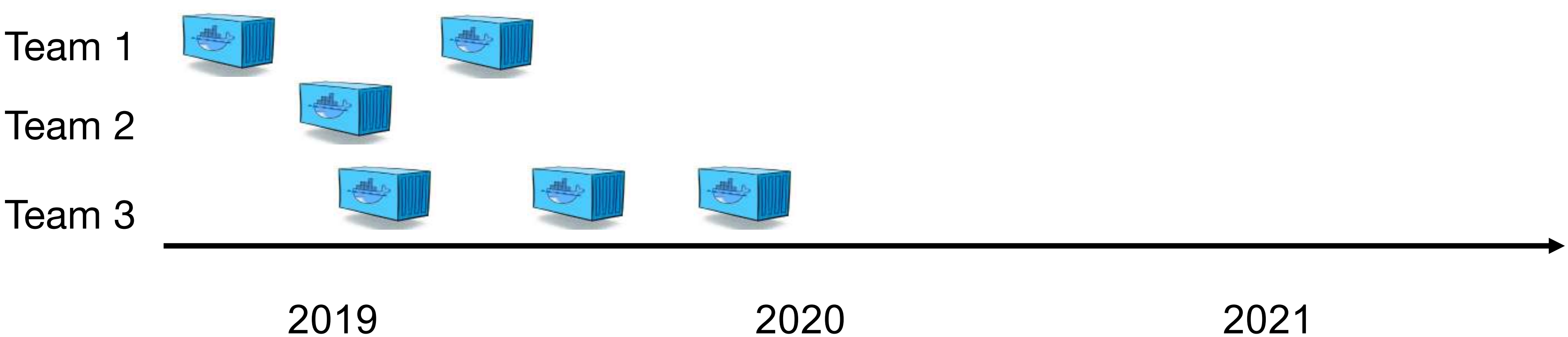
Multi-task metrics for continuous labels (severity scores) available.

Undisclosed Data Set Collection

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



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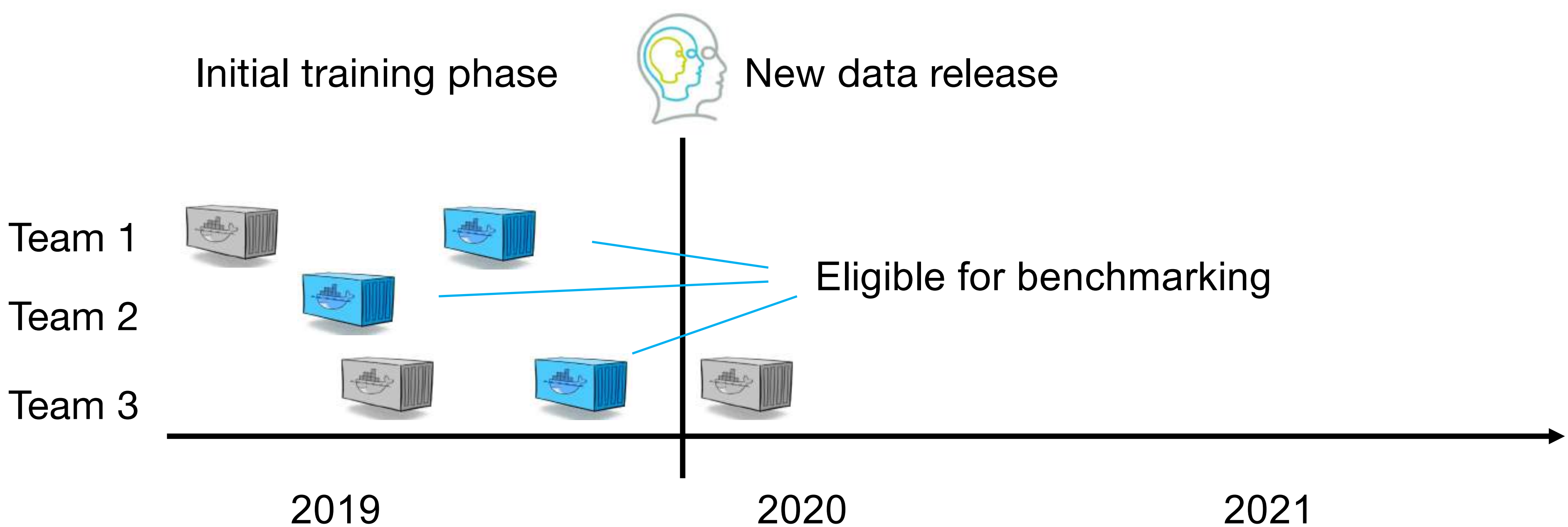

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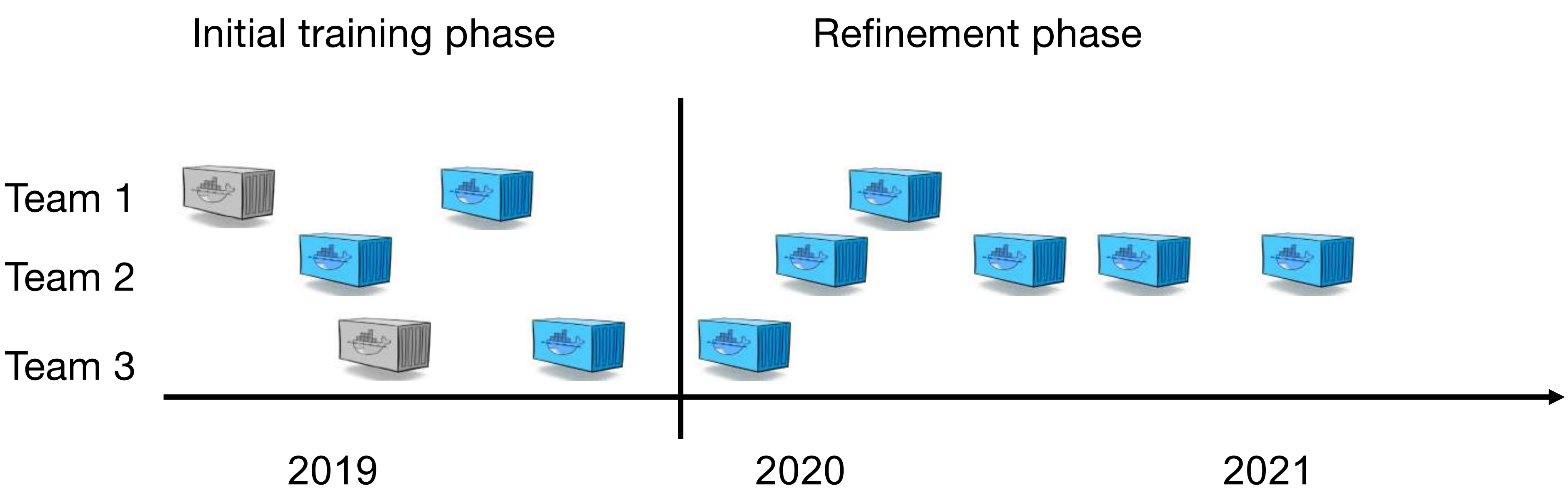

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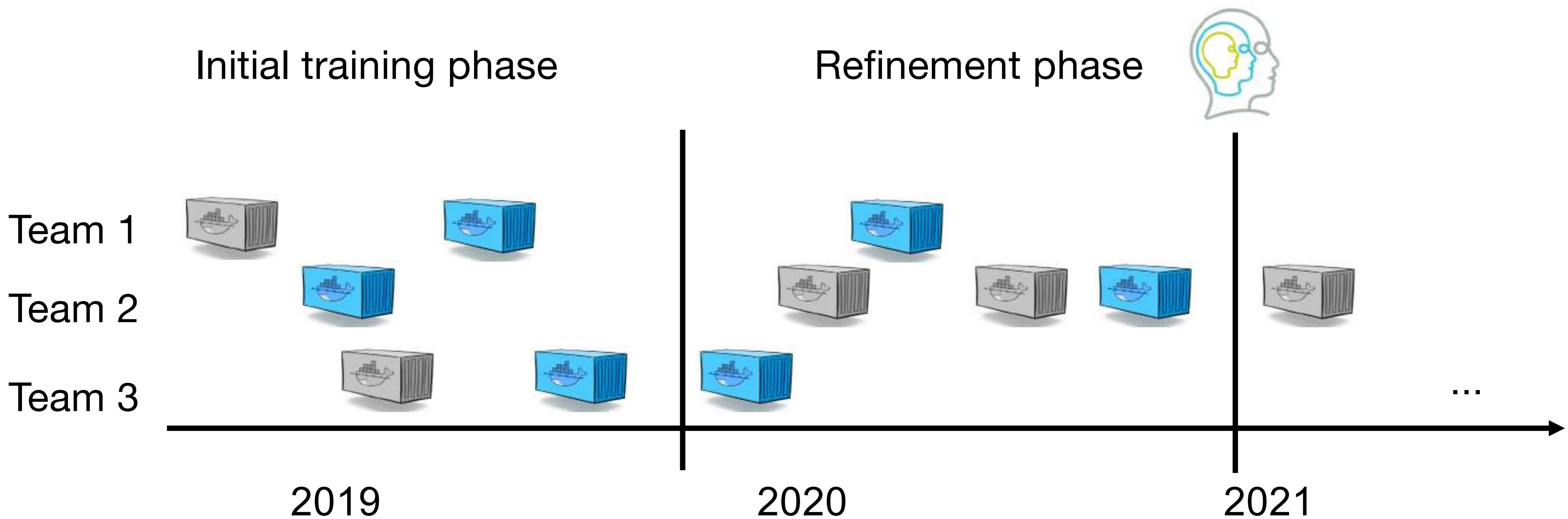

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Ongoing Work:

- Working on Topic Description Document (TDD) (1st version submitted)
- Working on infrastructure for data handling & management
  - data format (cognitive and lifestyle data: .csv; neurophysiological data: .mat)
  - Anonymization may lead to informative data loss
- Scores and Metrics: Quantifying uncertainty
- Potential merging (or collaboration) with TG neuro-cognitive disorders

Other validation data sets:

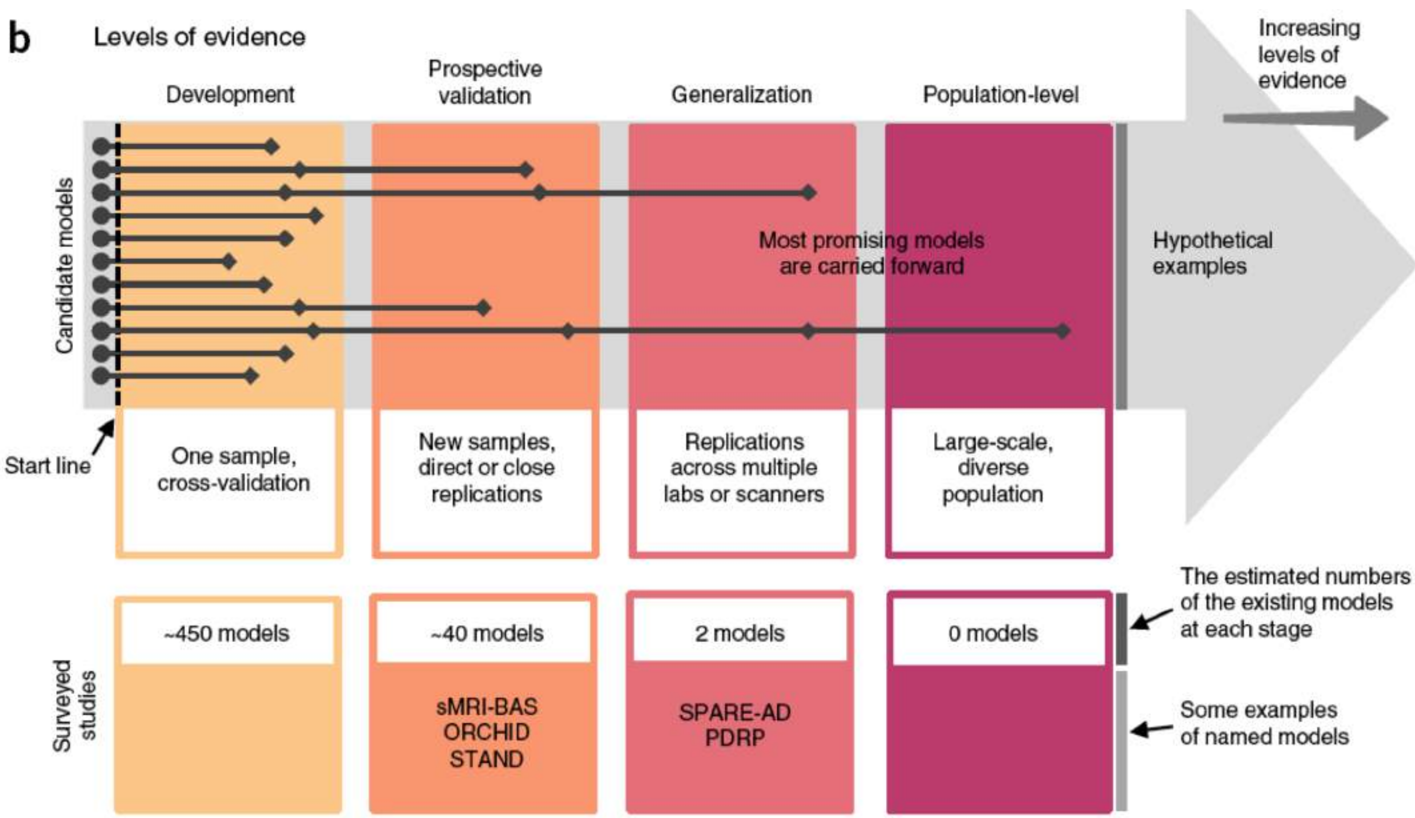
- RDOC db
  - ≥6000 neurophysiological data EEG
  - High heterogeneity (different labs contributed); unknown clinical population

New subtopic data set?

- Adolescent Brain Cognitive Development (ABCD) Study
  - planned 10'000 subjects (currently ≥1000 psychiatric patients)
  - cognitive and neuroimaging data
  - longitudinal

Call for group participation (neuroscience conference OHBM 2019)

Generalizability



Woo et al., 2017, Nature Neuroscience

THANK YOU FOR YOUR ATTENTION