Neurotechnologies and Machine Learning: from neurosurgery and neurology to neuroeducation and cybersport

Evgeny Burnaev
head of ADASE group
Skoltech

Joint with
Alexander Bernstein and Maxim Sharaev
Skoltech

ADASE

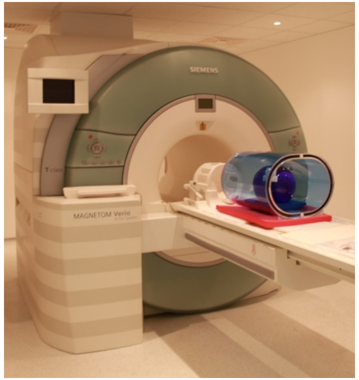
Skoltech
Skolkovo Institute of Science and Technology

Agenda

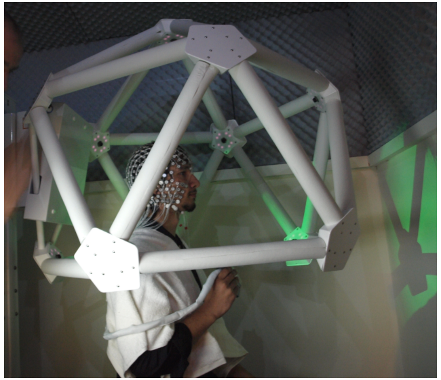
- Data sources
- Neuroimaging data peculiarities
- Biomedical problems based on neuroimaging data
- Neuroimaging data analysis
- Examples of using the developed methods for biomedical tasks
- Conclusions

Data Sources

MRI/
fMRI



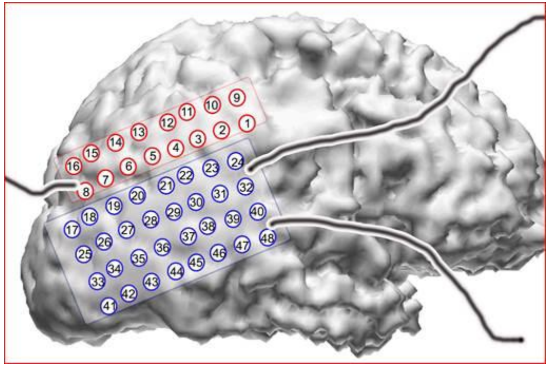
EEG



MEG

Eye-
tracking

iEEG



- Data sources
- Neuroimaging data peculiarities
- Biomedical problems based on neuroimaging data
- Neuroimaging data analysis
- Examples of using the developed methods for biomedical tasks
- Conclusions

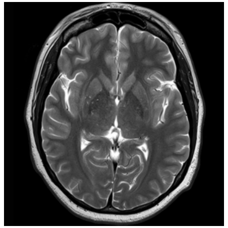
Neuroimaging data peculiarities: MRI

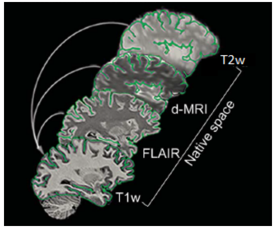
MRI: protocol of medical examination:

- structural MRI (sMRI)

in various modalities (T1, T2, DTI, FLAIR)

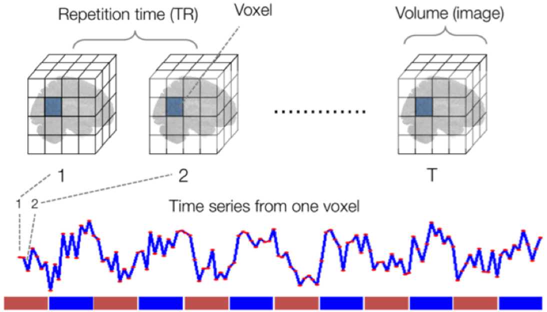
3D data
8×10^6 voxels
~100 Mb





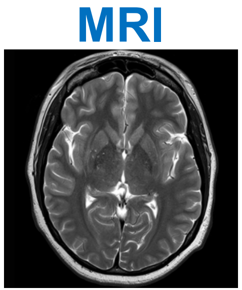
- functional MRI (fMRI)

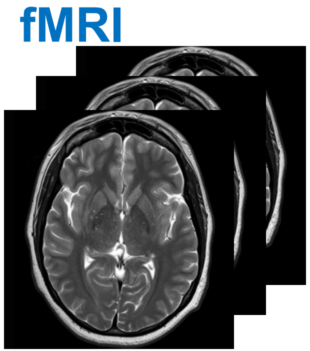
4D (3D time-dependent data)
1.5×10^6-dimensional MRI-measurements
received per a few seconds
>100 Mb



Skoltech
Skolkovo Institute of Science and Technology

Neuroimaging data peculiarities: MRI



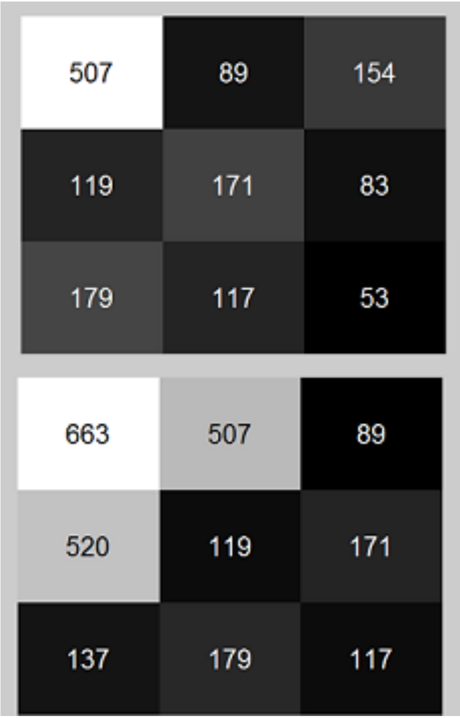


MRI: structural and functional

- High dimensional 3D/4D
- Good spatial, bad temporal resolution
- Noisy
- Different contrasts
- fMRI – correlational nature
- various Magnetic field strength characteristics (1.5T and 3T as usual, 7T maximum in clinics)
- various spatial characteristics (voxel size/image resolution), etc.

Noise and signal in fMRI data

- ❑ Up to 80-90% of noise in raw data
- ❑ Most common sources
  - **Non-physiological**
    1. Thermal noise
    2. Magnetic field inhomogenity
    3. Imperfection in RF pulse timings
    4. Many others
  - **Physiological**
    1. Cardiac noise
    2. Respiratory noise
  - **Motion**

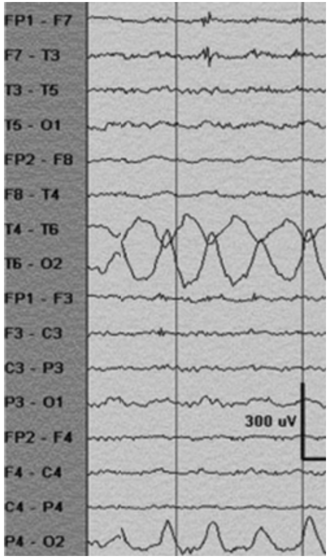


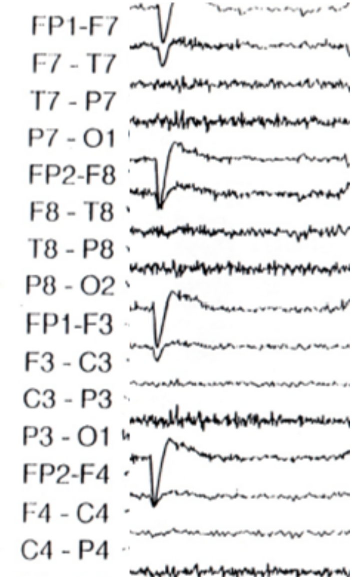
Skoltech
Skolkovo Institute of Science and Technology

Neuroimaging data peculiarities

Electroencephalography (EEG) data:

- various spatial characteristics (number of channels – 8, 16, … , 128)
- Good temporal, bad spatial resolution
- **Noisy:**
  - Eye movements
  - Muscular action potentials
  - Sweating
  - ECG
  - Poor electrode contact
  - Movement
  - Power supply (50Hz)





Summary: neuroimaging data

1) Different sources, data with different properties

2) Data is noisy

3) All data modalities reflect brain structure/function from different prospetives and are usually considered together by doctor/researcher (example – epilepsy diagnostics: MRI/fMRI/EEG/iEEG)

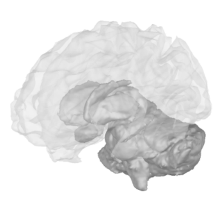
- Data sources
- Neuroimaging data peculiarities
- Biomedical problems based on neuroimaging data
- Neuroimaging data analysis
- Examples of using the developed methods for biomedical tasks
- Conclusions

Biomedical problems based on neuroimaging data

- Classification and regression tasks: diagnostics and treatment/outcome prediction
- Mapping and localization tasks: find specific brain areas (regions of interest, ROI)
- Correlational tasks: find dependencies between different indicators and discovered features

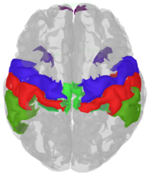
General pipeline for data analysis

1. Data acquisition



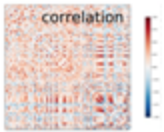
sMRI/fMRI

2. Data processing

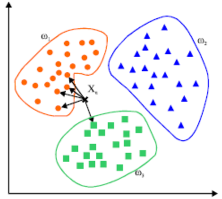


Data pre-processing,
Noise removal

3. Feature engineering



4. Machine Learning



5. Interpretation

Model interpretation:

Potential biomarkers

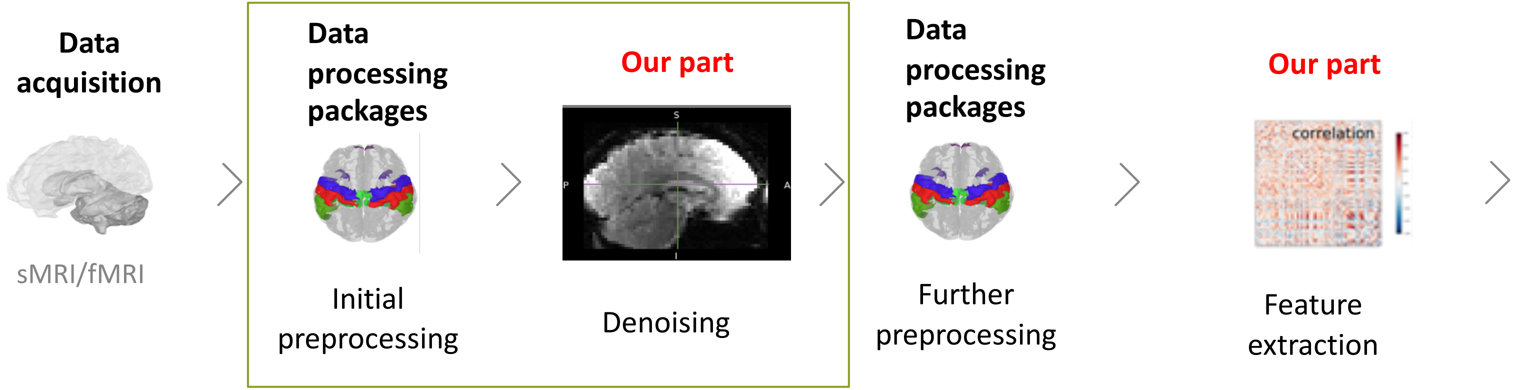
- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
    - Low-level, preprocessing
    - Mid-level, information extraction
    - High-level, inference
- **Examples of using the developed methods for biomedical tasks**
- **Conclusions**

- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
    - Low-level, preprocessing
    - Mid-level, information extraction
    - High-level, inference
- **Examples of using the developed methods for biomedical tasks**
- **Conclusions**

Skoltech
Skolkovo Institute of Science and Technology

Neuroimaging data analysis: low-level, preprocessing

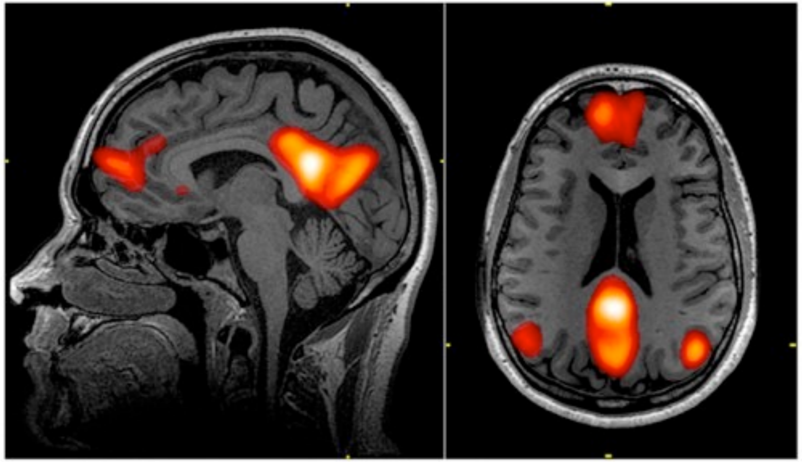
As an example, steps for fMRI data:
1) Filtering
2) Temporal corrections (i.e. different time for slice acquisition)
3) Coregistration, normalization, …
4) Denoising (details next)
5) Spatial smoothing, …



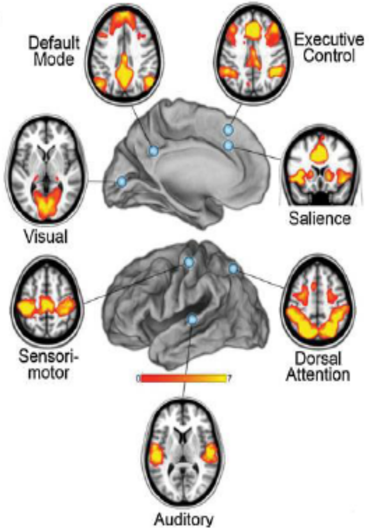
- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
  - Low-level, preprocessing
  - Mid-level, information extraction
  - High-level, inference
- **Examples of using the developed methods for biomedical tasks**
- **Conclusions**

Neuroimaging data analysis: mid-level, information extraction

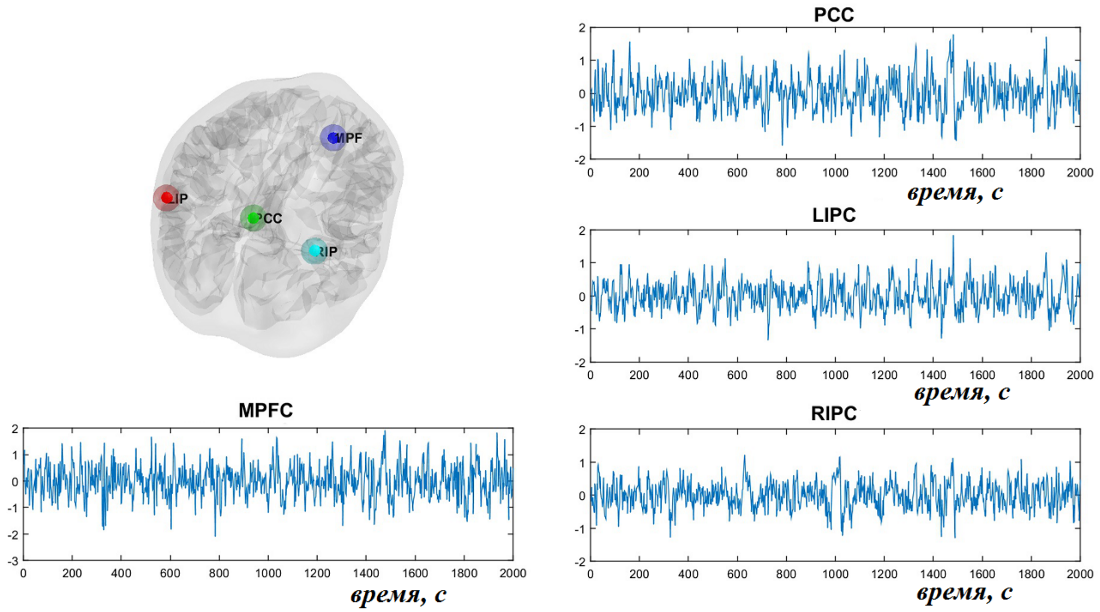
Resting-state fMRI: what is signal?



Default **M**ode **N**etwork [Graner et al., 2013]



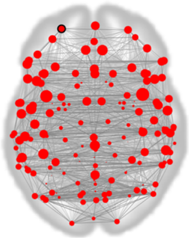
FMRI: time-series extraction from regions



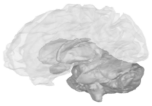
fMRI data example –signal from active regions

Dimensionality reduction and feature extraction

- Statistical methods: PCA, ICA, manifold learning, and etc. – problems with interpretation, not always capture clinically meaningful information
- Domain-specific methods:
    - vectorized features (volumes, curvatures, thicknesses from MRI - Freesurfer),
    - matrix features (correlation matrices from fMRI/EEG data) also could be considered as connectivity graphs – CONN, Nilearn

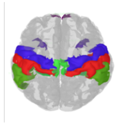


Data acquisition



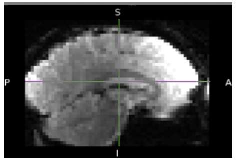
sMRI/fMRI

Data processing packages



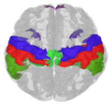
Initial preprocessing

Our part



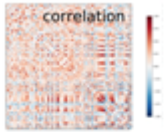
Denoising

Data processing packages



Further preprocessing

Our part

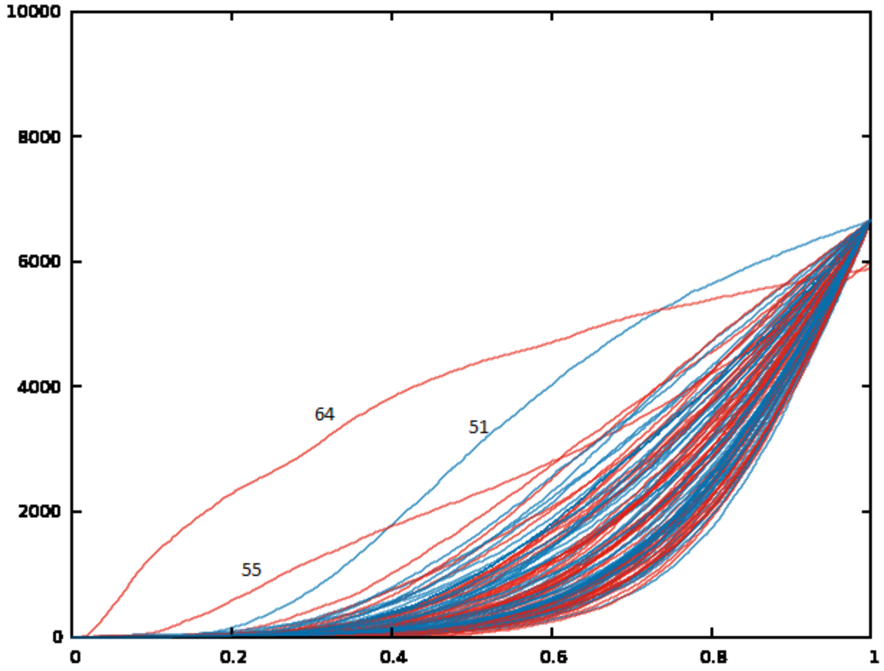


Feature extraction

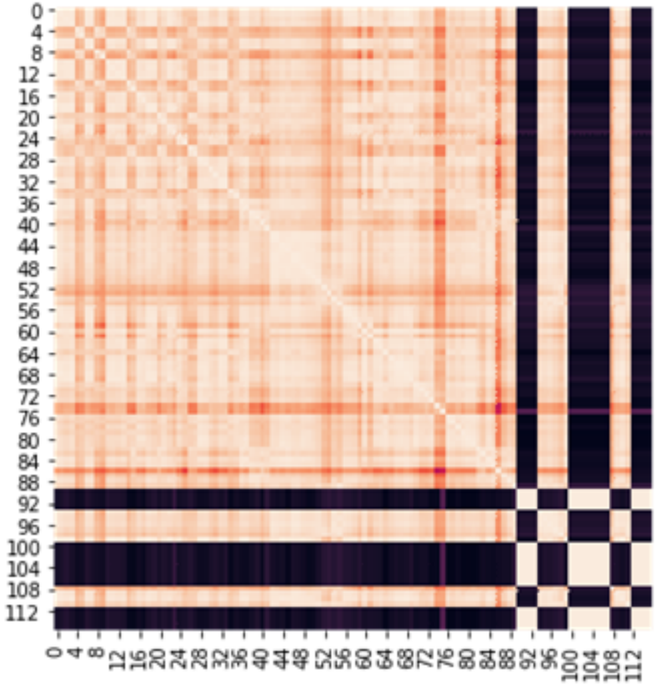
High-level tasks

Skoltech
Skolkovo Institute of Science and Technology

Anomalies detection via Topological Data Analysis: Betti numbers [ongoing research]



Patient 64



- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
  - Low-level, preprocessing
  - Mid-level, information extraction
  - High-level, inference
- **Examples of using the developed methods for biomedical tasks**
- **Conclusions**

Neuroimaging data analysis: high-level, inference

Final step, where ML algorithms are applied

- detecting the objects of interest
- recognition of the detected objects
- finding relations between the objects
- classification, etc.

- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
- **Examples of using the developed methods for biomedical tasks**
  - Noise elimination
  - Connectivity analysis and feature extraction
  - fMRI data decomposition in a Pre-surgical planning task
  - Classification tasks for clinics and education
  - Cybersport research
- **Conclusions**

Skoltech Biomedical Initiative: partners

Год основания 1914

НИИ НЕЙРОХИРУРГИИ
имени академика Н.Н.Бурденко

ВЫСШАЯ ШКОЛА ЭКОНОМИКИ

НАЦИОНАЛЬНЫЙ ИССЛЕДОВАТЕЛЬСКИЙ
УНИВЕРСИТЕТ

ЦЕНТР ПАТОЛОГИИ РЕЧИ
И НЕЙРОРЕАБИЛИТАЦИИ

- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
- **Examples of using the developed methods for biomedical tasks**
    - Noise elimination
    - Connectivity analysis and feature extraction
    - fMRI data decomposition in a Pre-surgical planning task
    - Classification tasks for clinics and education
- **Conclusions**

Noise elimination

1) Equipment/acquisition: B0 inhomogenity, heat, RF coils, subject motion and etc. – **very different from signal, not informative**

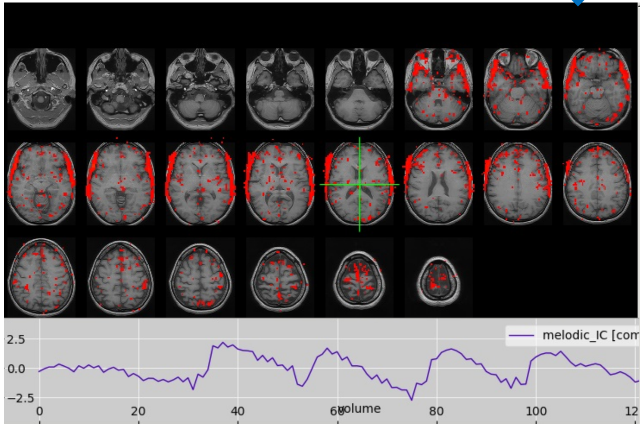
2) Physiological: cardiac, respiratory, CSF fluctuations – could **look like signal, might be informative**

Most sources of noise are assumed to be independent from signal and from each other -> ICA

Noise detection and elimination [ongoing research]

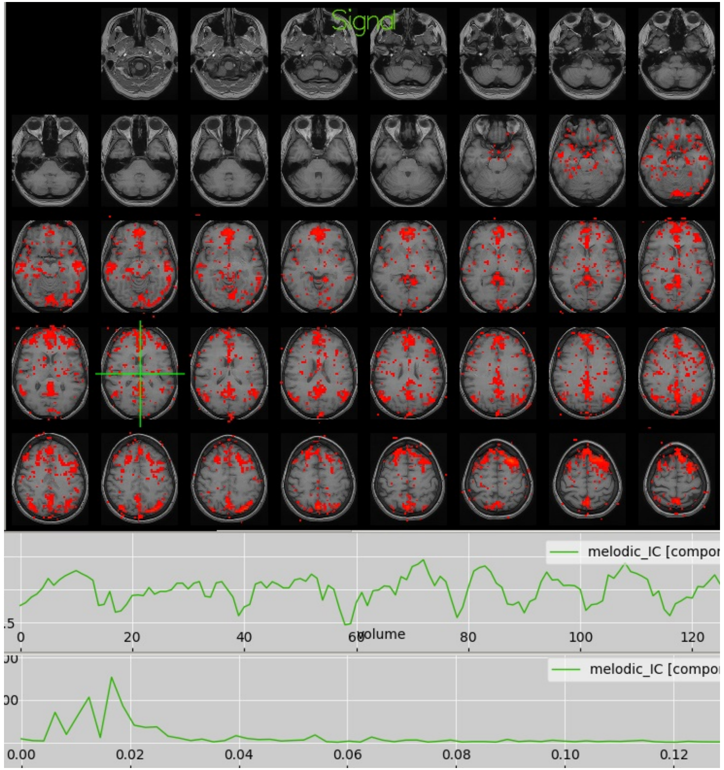
- ❑ ICA decomposition
- ❑ Noise differ from neuronal signal in spatial and temporal patterns of ICs

Now IC classification is performed **manually** by experts or **by trained classifier** (FSL FIX) – need for labelled data, highly dependent on specific scanner and parameters.



We introduce metrics based on physics of process and work on making it less dependent on a particular scanner (HF component, Correlation with motion, EDGE fraction, CSF fraction)

Signal: DMN

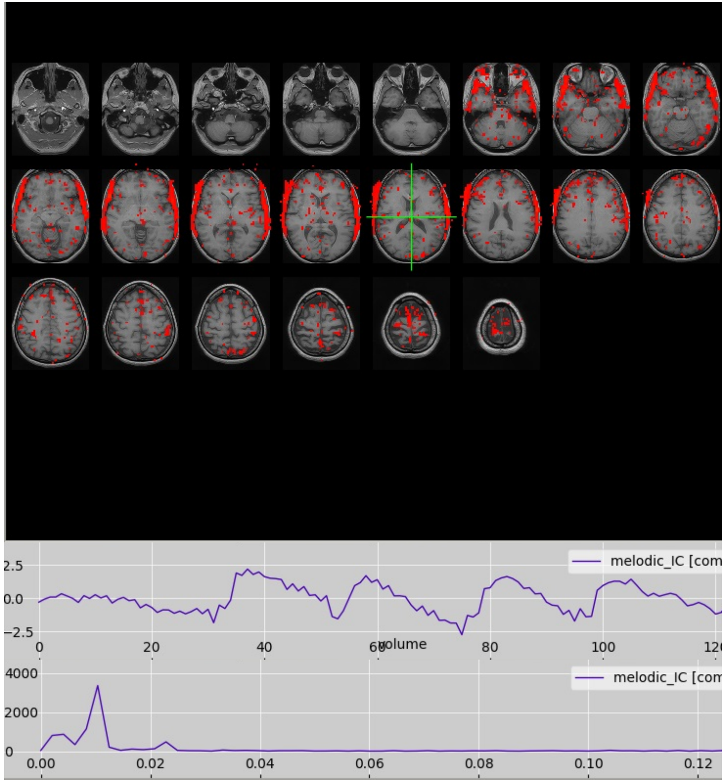


ICA Spatial maps

ICA time-series

ICA spectrum

Noise: motion



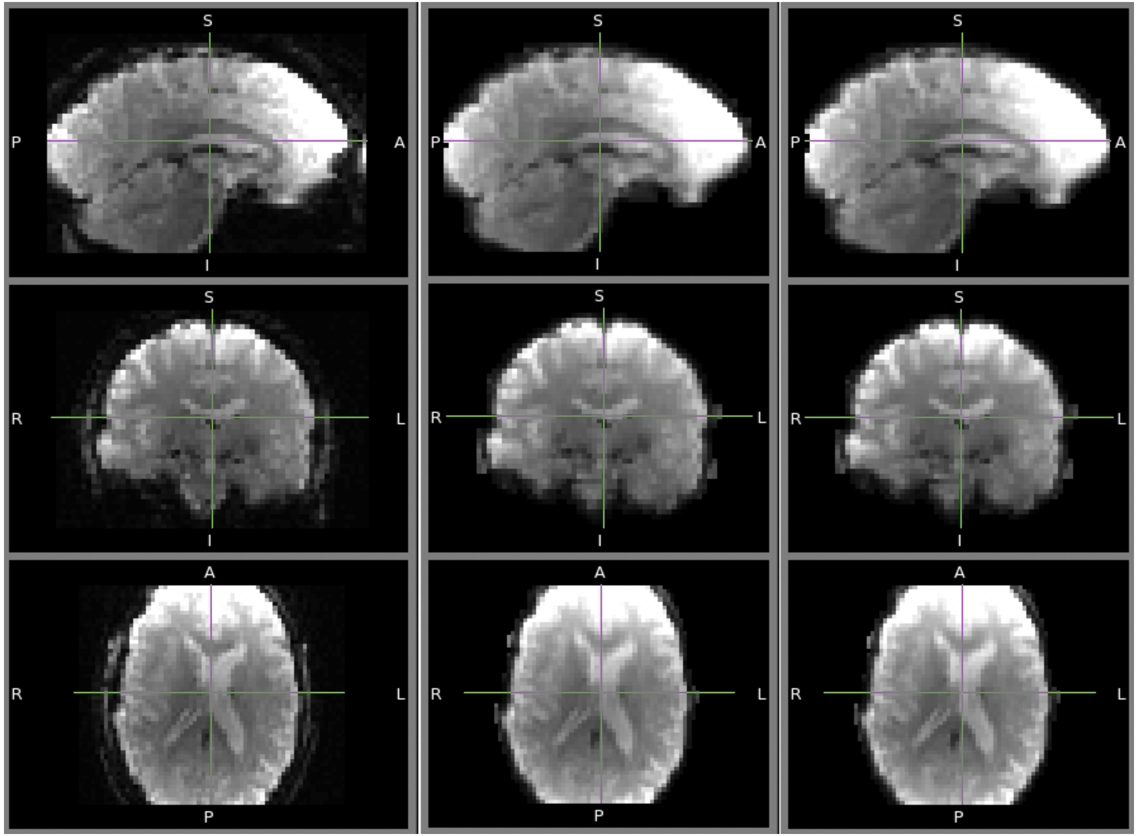
ICA Spatial maps

EDGE fraction

ICA time-series

ICA spectrum

Noise detection and elimination: example

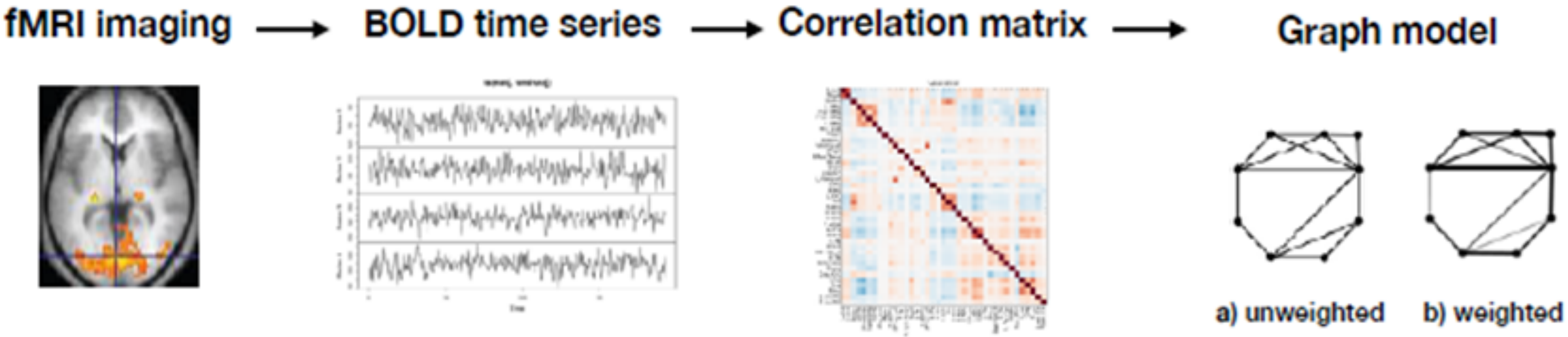


Result: 5-20% increase of AUC

- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
- **Examples of using the developed methods for biomedical tasks**
  - Noise elimination
  - Connectivity analysis and feature extraction
  - fMRI data decomposition in a Pre-surgical planning task
  - Classification tasks for clinics and education
  - Cybersport research
- **Conclusions**

Skoltech
Skolkovo Institute of Science and Technology

Connectivity analysis and feature extraction



“Descriptor” of
brain networks

Correlational connectivity

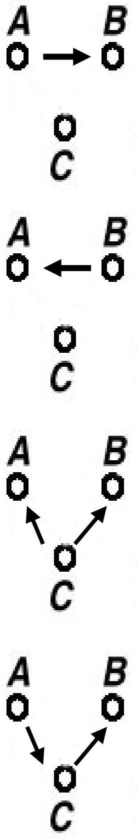
** Pros:

- Easy to compute;

** Cons:

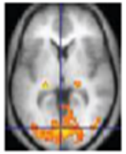
- no mechanistic insight
- interpretation of resulting patterns is difficult / arbitrary, i.e. false correlations;

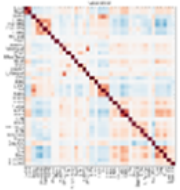
→ Causal (Effective) connectivity



Methods to assess effective connectivity

fMRI imaging → ?? → causation matrix

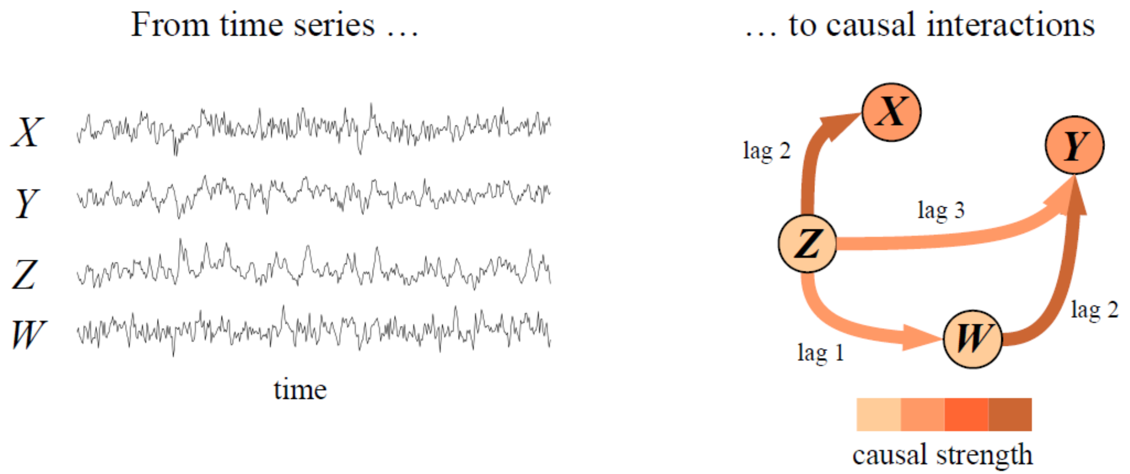




Causality "Descriptor" of brain networks

- Time-series analysis
  - Can dynamics of region A be predicted better using past values of region A and region B as opposed to using past values of region A alone, e.g. **Granger Causality, Transfer Entropy**
- Methods based on (non)linear dynamic models
  - Dynamic Causal Modelling (DCM)

Transfer entropy: model-free approach to assess causality [ongoing research]



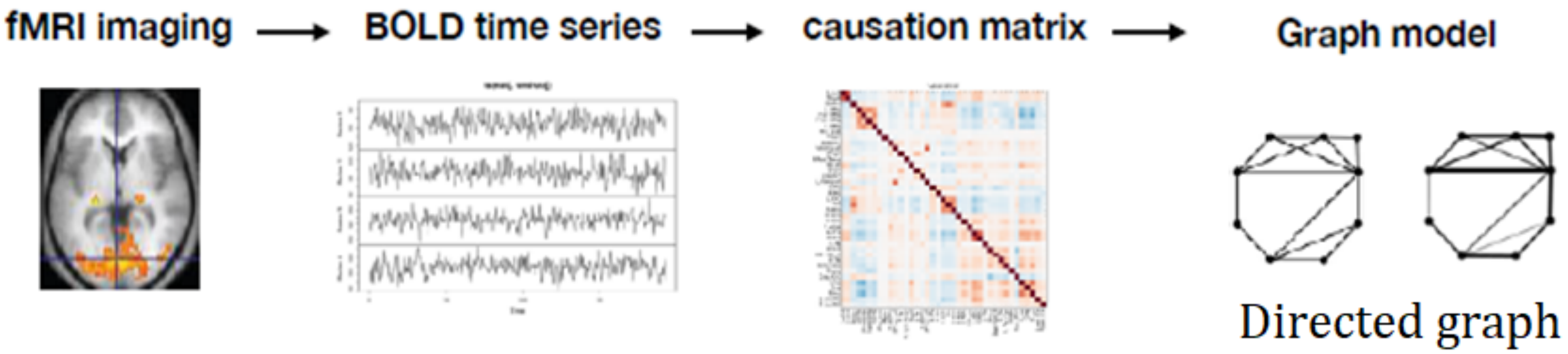
$$p(Y_n|Y_n^-, X_n^-) = p(Y_n|Y_n^-)$$

Markovian independence

$$TE_{X\to Y} = \sum p(Y_n, |Y_n^-, X_n^-) log \frac{p(Y_n|Y_n^-, X_n^-)}{p(Y_n|Y_n^-)}$$

Transfer Entropy (TE) – deviation from equality (KL distance)

Connectivity analysis and feature extraction [ongoing research]



Analysis of directed weighted graphs!

- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
- **Examples of using the developed methods for biomedical tasks**
  - Noise elimination
  - Connectivity analysis and feature extraction
  - fMRI data decomposition in a Pre-surgical planning task
  - Classification tasks for clinics and education
  - Cybersport research
- **Conclusions**

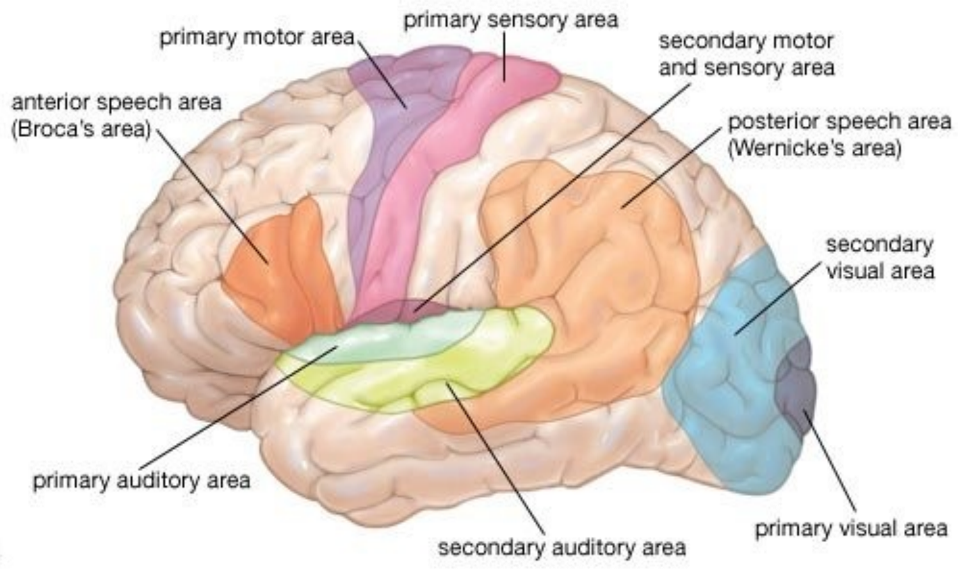
Mapping and localization tasks for presurgical planning: brain functional areas

Brain functional areas in patients with gliomas

- **Medical partner**: N.N. Burdenko National Scientific and Practical Center for Neurosurgery

- Before operation - pre-operative mapping; during the operation precise mapping (Electrocorticography, ECoG)

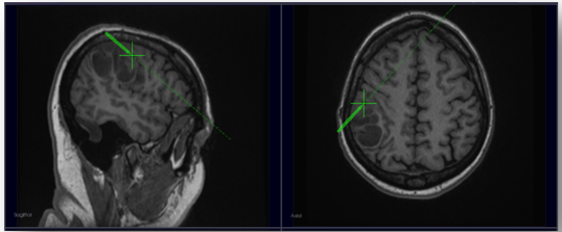
- **3T** MR scanner
- T1, rs-**fMRI** modalities, brain function

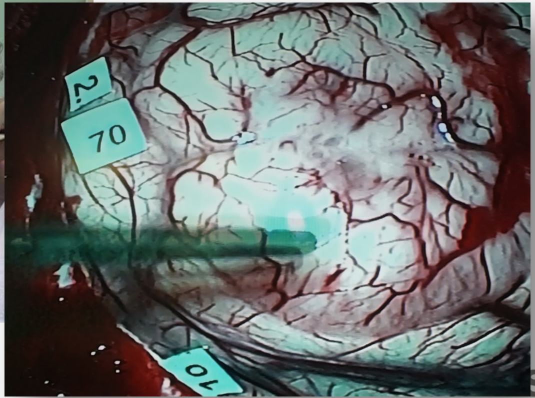


*from https://www.britannica.com

Brain cortex mapping

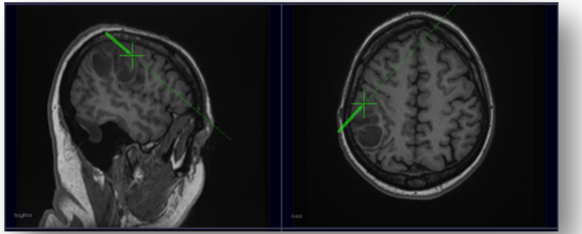
- Invasive
  - intraoperative cortical stimulation mapping (CSM)

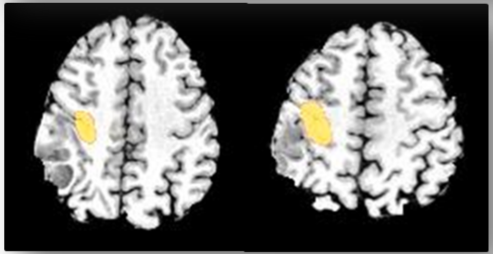




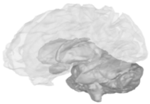
Brain cortex mapping

- Invasive
  - intraoperative cortical stimulation mapping (CSM)
- Non-invasive
  - task-based functional MRI





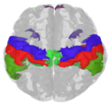
Neuroimaging data



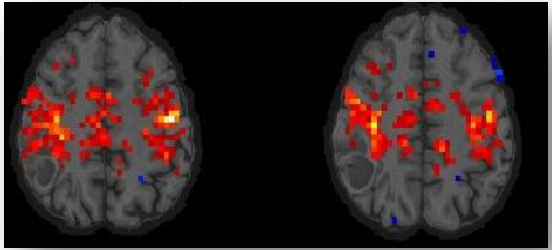
sMRI/fMRI

??

Localization



Brain cortex mapping: resting-state fMRI



Resting-state functional MRI

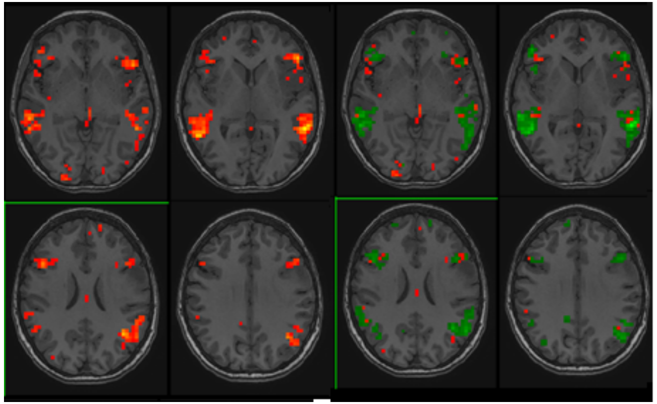
- Reflects all brain networks
- We need one concrete
- Localization in healthy subjects is known
- This prior information could be used for search

Spatial masks and constrained ICA: flow

- **Step 1:** Create universal spatial maps for visual, motor and language areas based on “90 ROIs” functional brain atlas
- **Step 2:** Create individual spatial maps based on fMRI images (coregistration and spatial normalization)
- **Step 3**: Use individual spatial maps as spatial constrains for ICA decomposition

Presurgical planning in patients with brain gliomas

- **Step 1** (completed): statistical methods (constrained ICA) on individual fMRI
  - Now used by neurosurgeons as a preliminary analysis



2018 IEEE International Conference on Data Mining Workshops (ICDMW)

Functional Brain Areas Mapping in Patients with Glioma based on Resting-State fMRI Data Decomposition

1st Maksim Sharaev, *CDISE, Skolkovo Institute of Science and Technology*, Moscow, Russia, m.sharaev@skoltech.ru

2nd Alexander Smirnov, *N.N. Burdenko National Scientific and Practical Center for Neurosurgery*, Moscow, Russia, asmirnof@nsi.ru

3rd Tatiana Melnikova-Pitskhelauri, *N.N. Burdenko National Scientific and Practical Center for Neurosurgery*, Moscow, Russia, melpitz@nsi.ru

4th Vyacheslav Orlov, *National Research Center "Kurchatov Institute"*, Moscow, Russia, ptica89@bk.ru

5th Evgeny Burnaev, *CDISE, Skolkovo Institute of Science and Technology*, Moscow, Russia, e.burnaev@skoltech.ru

6th Igor Pronin, *N .N. Burdenko National Scientific and Practical Center for Neurosurgery*, Moscow, Russia, pronin@nsi.ru

7th David Pitskhelauri, *N .N. Burdenko National Scientific and Practical Center for Neurosurgery*, Moscow, Russia, dav@nsi.ru

8th Alexander Bernstein, *CDISE, Skolkovo Institute of Science and Technology*, Moscow, Russia, a.bernstein@skoltech.ru

***Abstract*—In current work we propose a three-step approach to automatic and efficient functional brain areas mapping as well demonstrate in case studies on three patients with gliomas the potential applicability of constrained source separation technique (semiblind Independent Component Analysis, ICA) to brain networks discovery and the similarity of task-based-fMRI (t-fMRI) and resting state-fMRI (rs-fMRI) results.**

Blind and semiblind ICA-analysis was applied for both methods t-fMRI and rs-fMRI. To measure similarity between spatial maps we used Dice coefficient, which shows the ratio of overlapping voxels and all active voxels in two compared maps for each patient

I. Introduction

In surgical practice, if the tumor is very close to the cortex or the associative pathways responsible for language or motor function, the surgeon must balance the radicality of resection and the preservation of functionally significant brain regions. The advantages of broad resection should be compared with the degree of neurological deficiency that arise due to the destruction of functionally significant cortical areas. Since the degree of individual anatomical variability of these areas

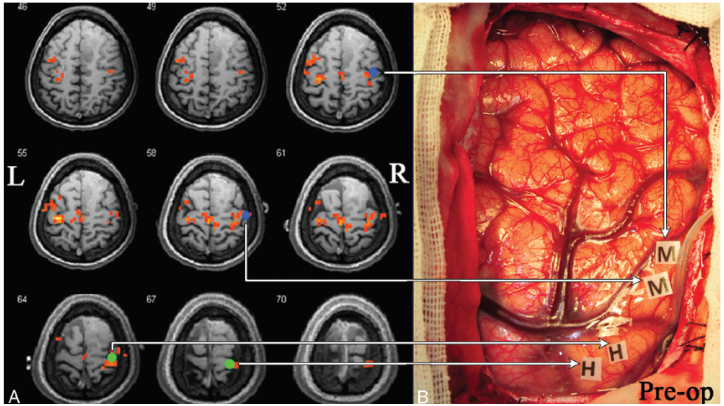
2375-9259/18/$31.00 ©2018 IEEE
DOI 10.1109/ICDMW.2018.00049

IEEE computer society

Skoltech
Skolkovo Institute of Science and Technology

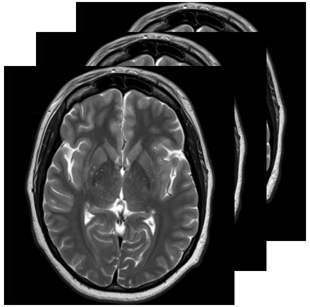
Presurgical planning in patients with brain gliomas

- **Step 2** (started): ICA + ML methods + data fusion
  - Intraoperative data is used as ground truth to improve model quality



Blind source separation (ICA) and fMRI

fMRI



Observed

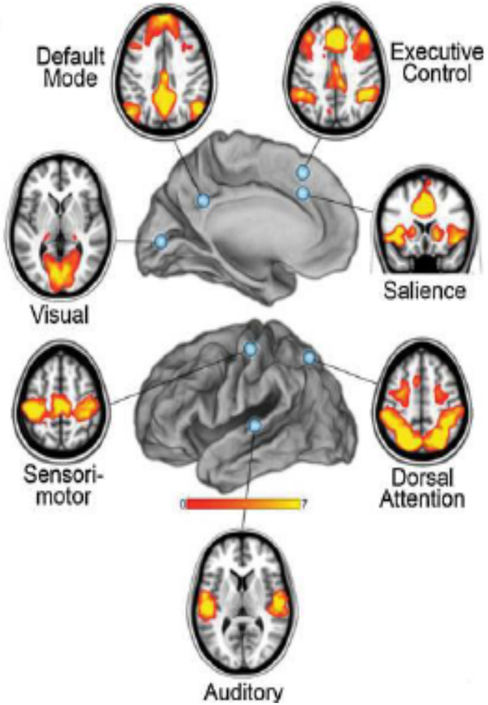
$$\mathbf{x} = (x_1, x_2, \dots, x_n)^{\mathrm{T}}$$

Sources $\mathbf{s} = (s_1, s_2, \dots, s_n)^{\mathrm{T}}$

$$\mathbf{x} = \mathbf{As}$$

Estimate $\boldsymbol{s} = \mathbf{Wx},\ \boldsymbol{s} = (s_1, s_2, \dots, s_m)^{\mathrm{T}}$

Same as cocktail party problem!



Constrained ICA briefly

Observed $\mathbf{x} = (x_1, x_2, \dots, x_n)^{\mathrm{T}}$ Sources $\mathbf{s} = (s_1, s_2, \dots, s_n)^{\mathrm{T}}$ $\mathbf{x} = \mathbf{A}\mathbf{s}$

Estimate $\boldsymbol{s} = \mathbf{W}\mathbf{x}$, $\boldsymbol{s} = (s_1, s_2, \dots, s_m)^{\mathrm{T}}$ $J(\boldsymbol{s}) = H\left(\boldsymbol{s}_{\mathbf{gauss}}\right) - H(\boldsymbol{s}) \rightarrow \max$

Subject to:

$\mathbf{g}(\mathbf{s}\!:\mathbf{W}) \leq 0$ where $\mathbf{g}(\mathbf{s}\!:\mathbf{W}) = [g_1(\mathbf{s}\!:\mathbf{W}), g_2(\mathbf{s}\!:\mathbf{W}), \dots, g_{\mathrm{p}}(\mathbf{s}\!:\mathbf{W})]^{\mathrm{T}}$

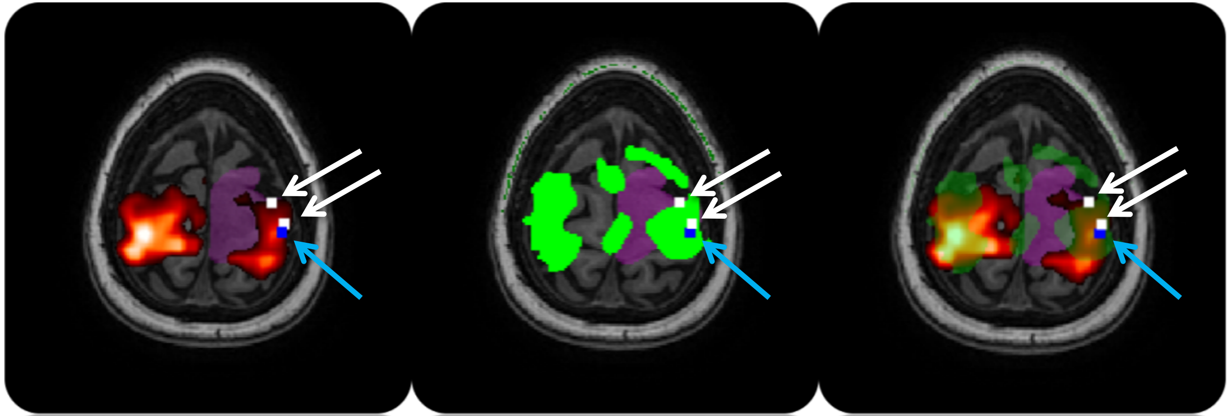
Here

$$g_i(s_i\!:\mathbf{w}_i) = \varepsilon(s_i, r_i) - \xi_i \leq 0$$

* Based on Lin Q.H. et al., 2010

Composing task-based fMRI, resting-state fMRI, CSM

Patient A., 31 y.o., glioma grade IV. Seizures, loss of consciousness



Rs-fMRI

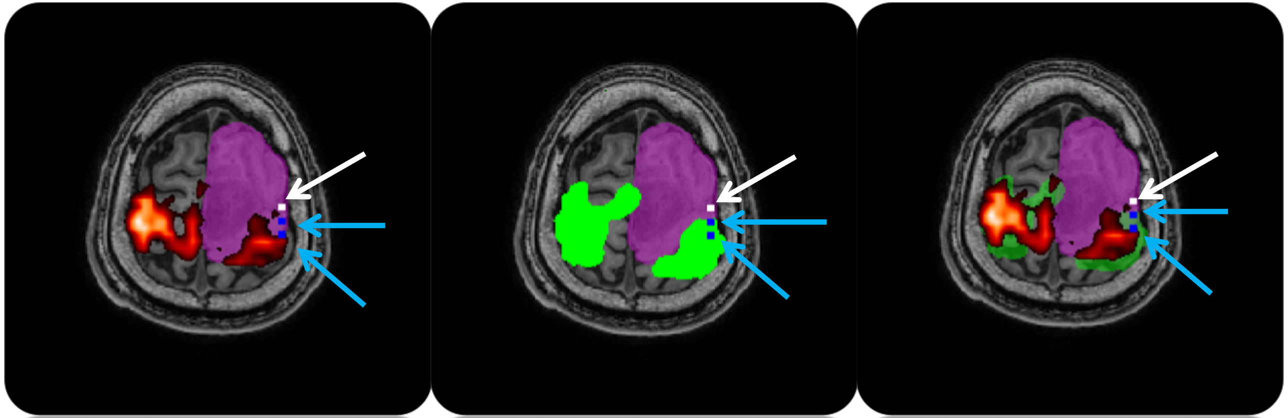
Tb-fMRI

Rs&Tb-fMRI

- tumor
- positive CSM
- negative CSM

Composing task-based fMRI, resting-state fMRI, CSM

Patient B., 39 y.o., glioma grade II. Seizures, loss of consciousness



Rs-fMRI | Tb-fMRI | Rs&Tb-fMRI

- tumor
- positive CSM
- negative CSM

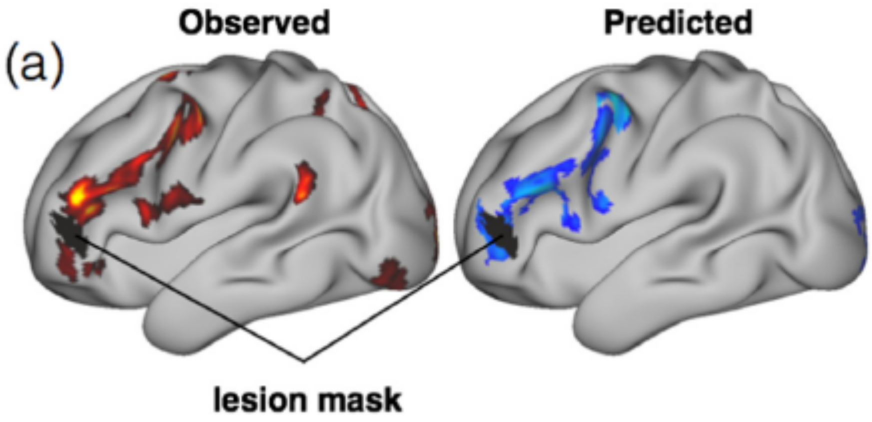
Results

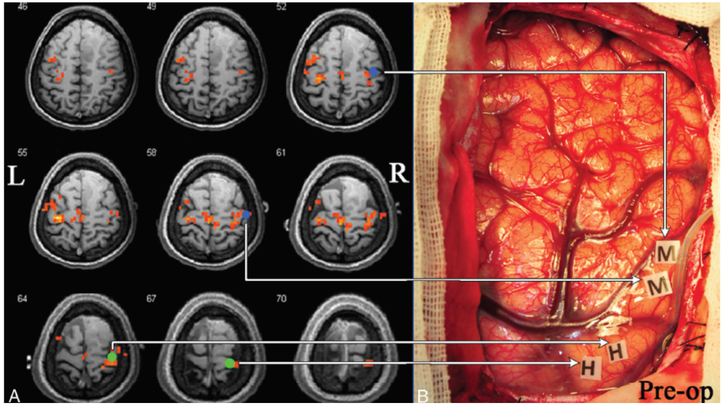
Overlap between CSM and sensorimotor resting-state network

Subj.	Total positive points	Total negative points	Positive	Negative
1	5	4	100%	25%
2	3	4	100%	0%
3	4	4	100%	25%
4	6	11	100%	64%
5	4	4	100%	50%
6	4	4	100%	0%
7	3	3	100%	0%

Presurgical planning: extension

1) We receive **unique** intraoperative data
2) In healthy subjects it is possible to predict brain activation by resting-state activity (Tavor et al., 2016). **Human Connectome Project**





Presurgical planning: extension

- **Step 3** (planned):
  - new data is obtained during the operation
  - Model precision decreases due to tissue move

Integration is needed with neuronavigation system for **online** mapping and correcting the offline predictions, based on ECoG information during the operation.

- **Medical partners**: N.N. Burdenko National Scientific and Practical Center for Neurosurgery
- Potentially: BrainLAB (Germany), AUTOPLAN (Russia)

- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
- **Examples of using the developed methods for biomedical tasks**
  - Noise elimination
  - Connectivity analysis and feature extraction
  - fMRI data decomposition in a Pre-surgical planning task
  - Classification tasks for clinics and education
  - Cybersport research
- **Conclusions**

Skoltech
Skolkovo Institute of Science and Technology

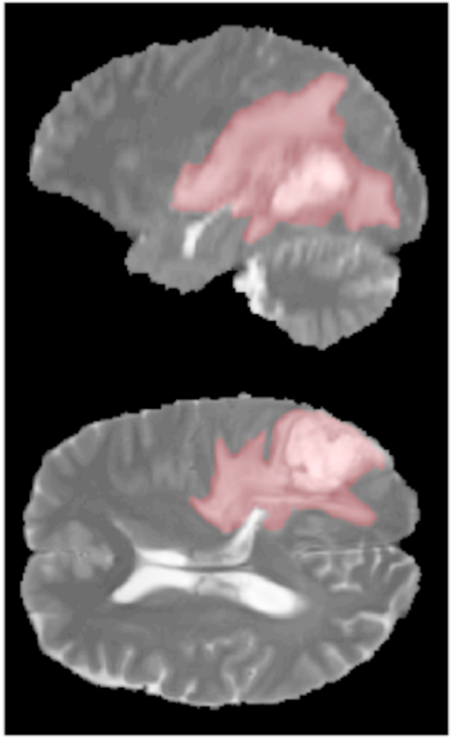
Deep Bayesian Generative Models for Knowledge Transfer and MRI Processing

accepted to Frontiers in Neuroscience, 2019: arxiv 1908.05480
accepted to ISNN proc., 2019: arxiv 1905.07855
preprint 2019: arxiv 1908.11853

Magnetic resonance imaging (MRI) — medical imaging technique used in radiology to form pictures of the body anatomy

MRI semantic segmentation applications in medicine:

- Tumors (e.g. brain, liver) analysis and monitoring
- Multiple sclerosis plaques detection
- White matter hyperintesities detection



MRI with labelled brain tumor

1. Scarce data

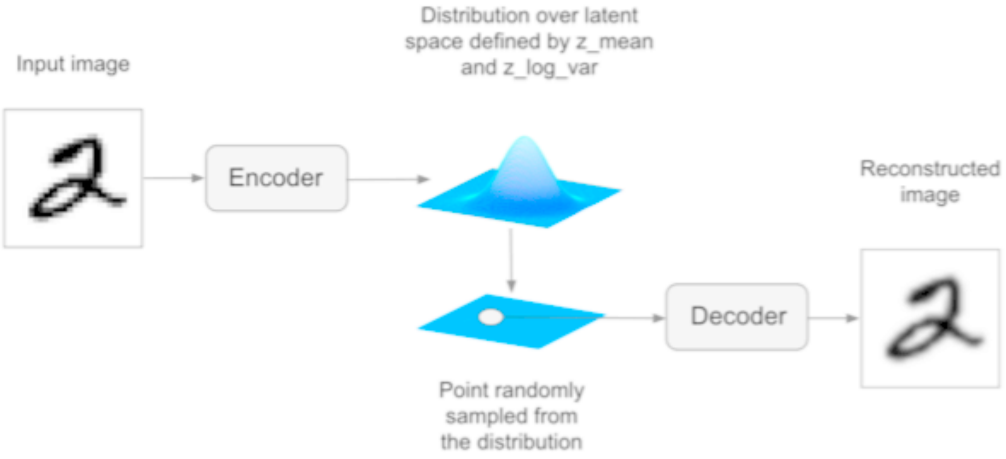
- Expensive annotation
- Privacy concerns
- Bad performance of transfer learning due to disease specificity

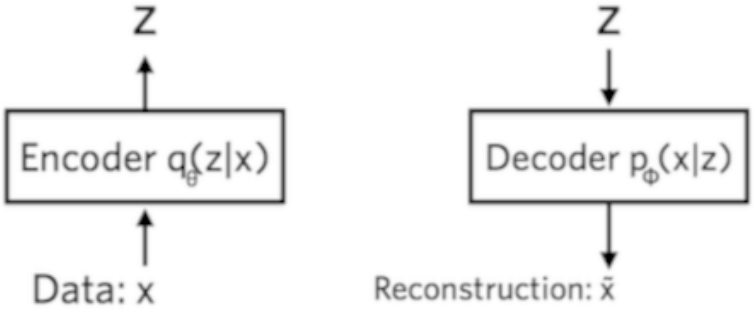
2. High dimensionality

- 3D images
- Memory issues

Solution for 1:
Transfer Learning under Bayesian Approach

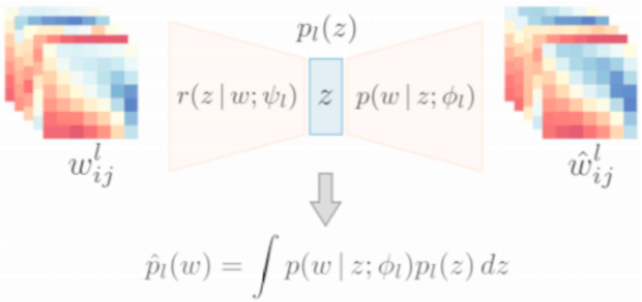
Variational Autoencoder





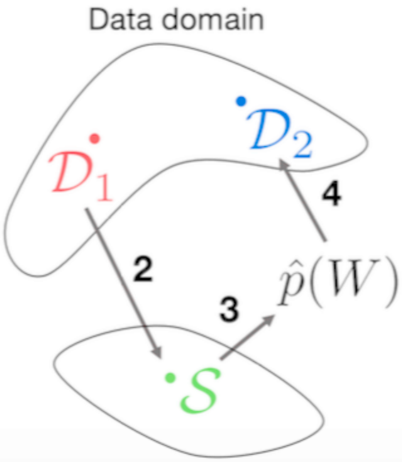
Main Idea

Use VAE model to learn implicit prior distribution over convolutional filters of each layer



Algorithm

1. Train network on the bootstrapped source dataset ($\mathcal{D}_1$)
2. Collect learned filters
3. Train implicit prior distribution (VAE)
4. Use trained prior for variational inference on the target dataset ($\mathcal{D}_2$)



Experimental Set-Up

Datasets

- 285 MRI of patients with brain tumor (BRATS18)
- 170 MRI of patients with multiple sclerosis (MS)

Prepocessing:

- Scaling
- Alignment
- Scull-stripping

Task:

Binary semantic segmentation

Metrics:

Dice Similarity Coefficient:

$$DSC = \frac{2TP}{2TP + FP + FN}$$

Intersection over Union:

$$IOU = \frac{TP}{TP + FP + FN}$$

Example of MRI slices and ground truth segmentation

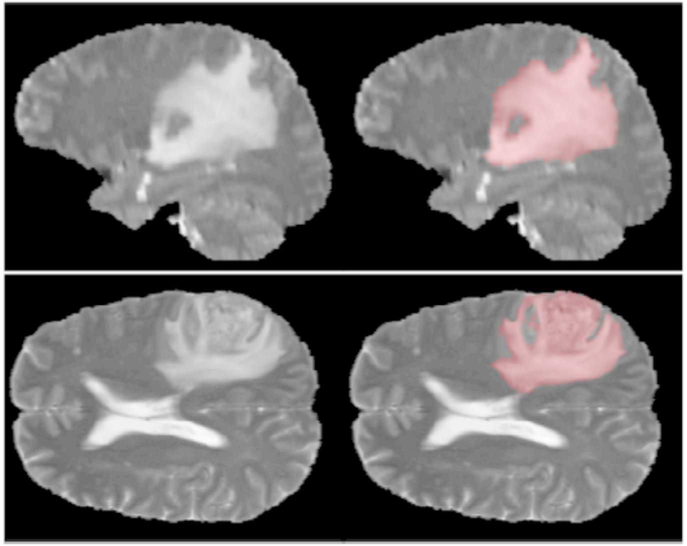


Figure: BRATS18 dataset

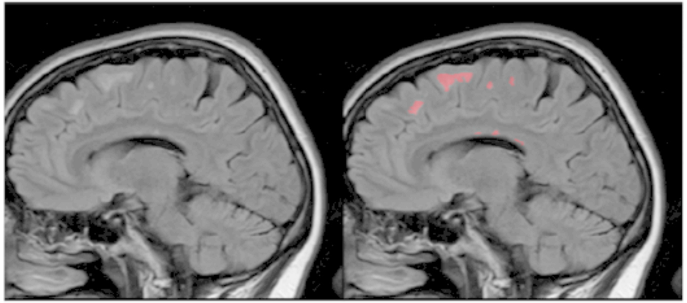
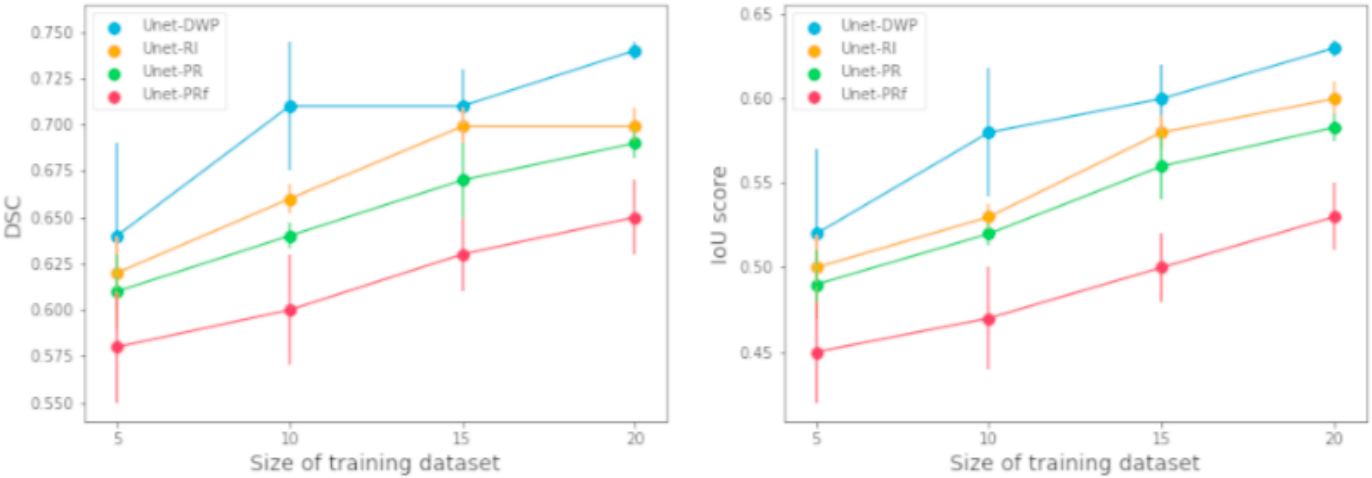


Figure: MS dataset

Experimental Set-Up [2]

- Train Unet models on the full MS dataset
  - Use bootstrapped sample from the initial dataset
  - Weights are randomly initialized
- Collect filters from the trained models
  - Use cycling learning rate to expand set of learned filters
- Train VAE for each layer / set of consecutive layers
- Do variational inference with implicit prior (VAE) on subset of BRATS18 dataset (5-20 images)

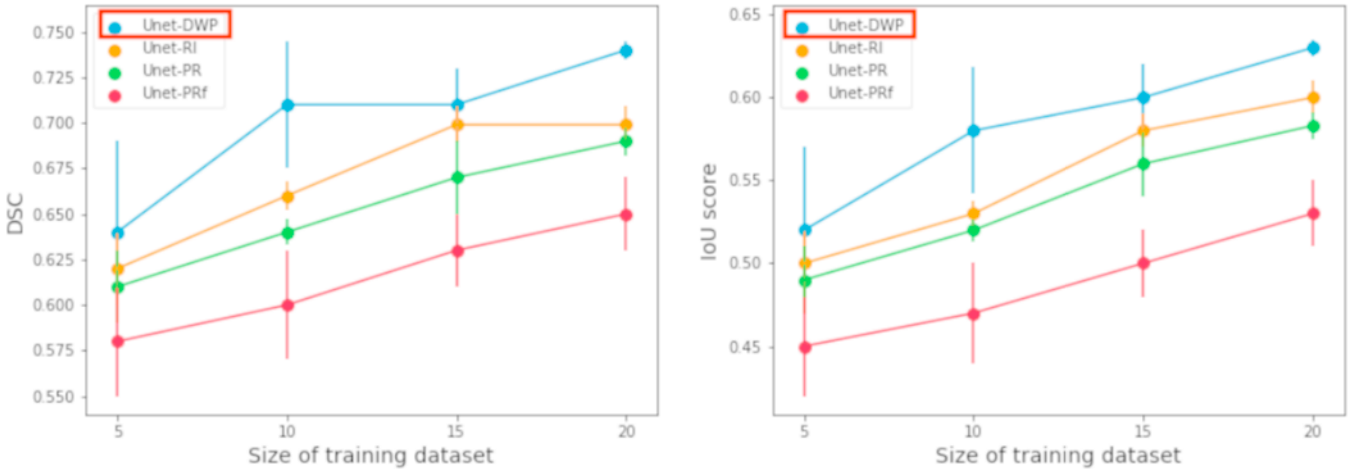
Results



- **Unet-RI** (orange): without transfer learning
- **Unet-PR** (green): fine-tuning of the whole network
- **Unet-PRf** (red): fine-tuning of the input and output block

ech
ce and Technology

Results



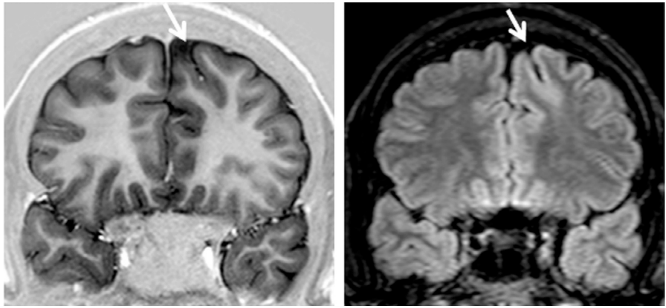
- **Unet-RI** (orange): without transfer learning
- **Unet-PR** (green): fine-tuning of the whole network
- **Unet-PRf** (red): fine-tuning of the input and output block

Skoltech
Skolkovo Institute of Science and Technology

Mapping and localization tasks for presurgical planning: brain epileptogenic foci

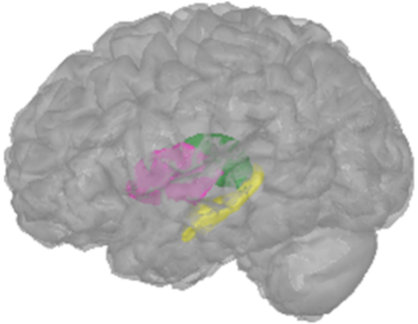
Foci of epileptogenic activity localization

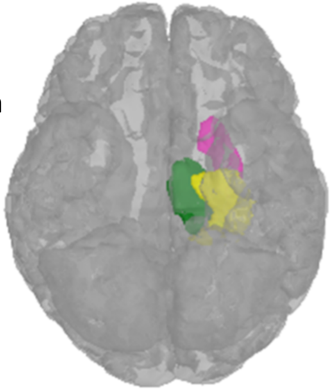
- **Medical partner**: V.I. Kulakov Research Center for Obstetrics, Gynecology and Perinatology
- Often treatment with drugs is ineffective
- Removal of foci of epileptogenic activity leads to recovery
- MRI positive/negative is subjective
- Radiologists with different level of qualification



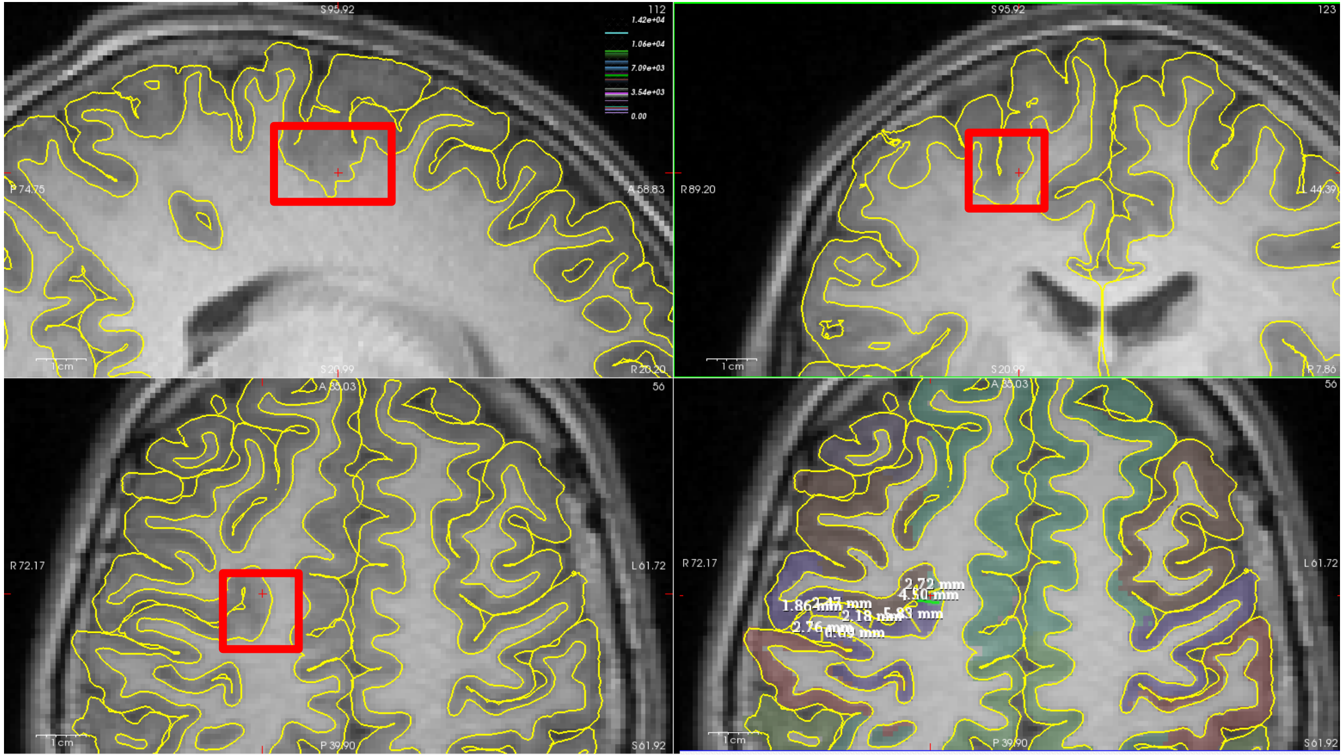
Segmented and labelled data to train models

Left Hippocampus, Thalamus, Putamen

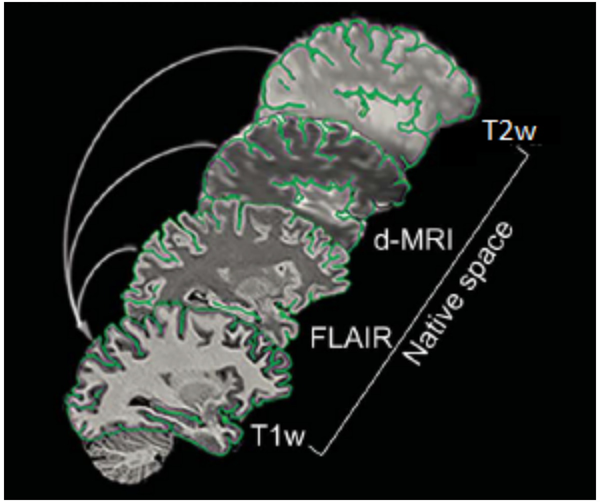




Brain tissue segmentation: epileptogenic focus



Data labelling and weakly supervised learning



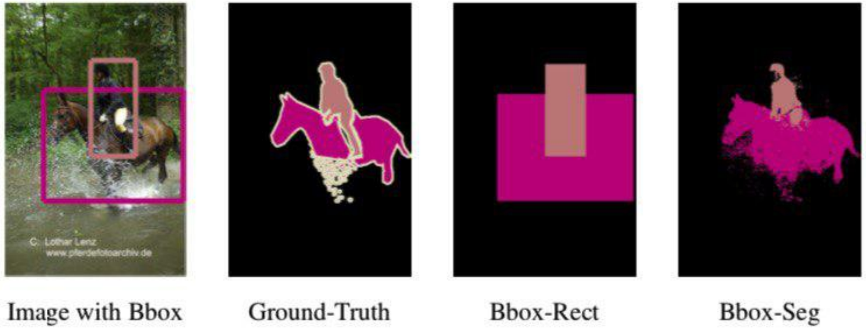
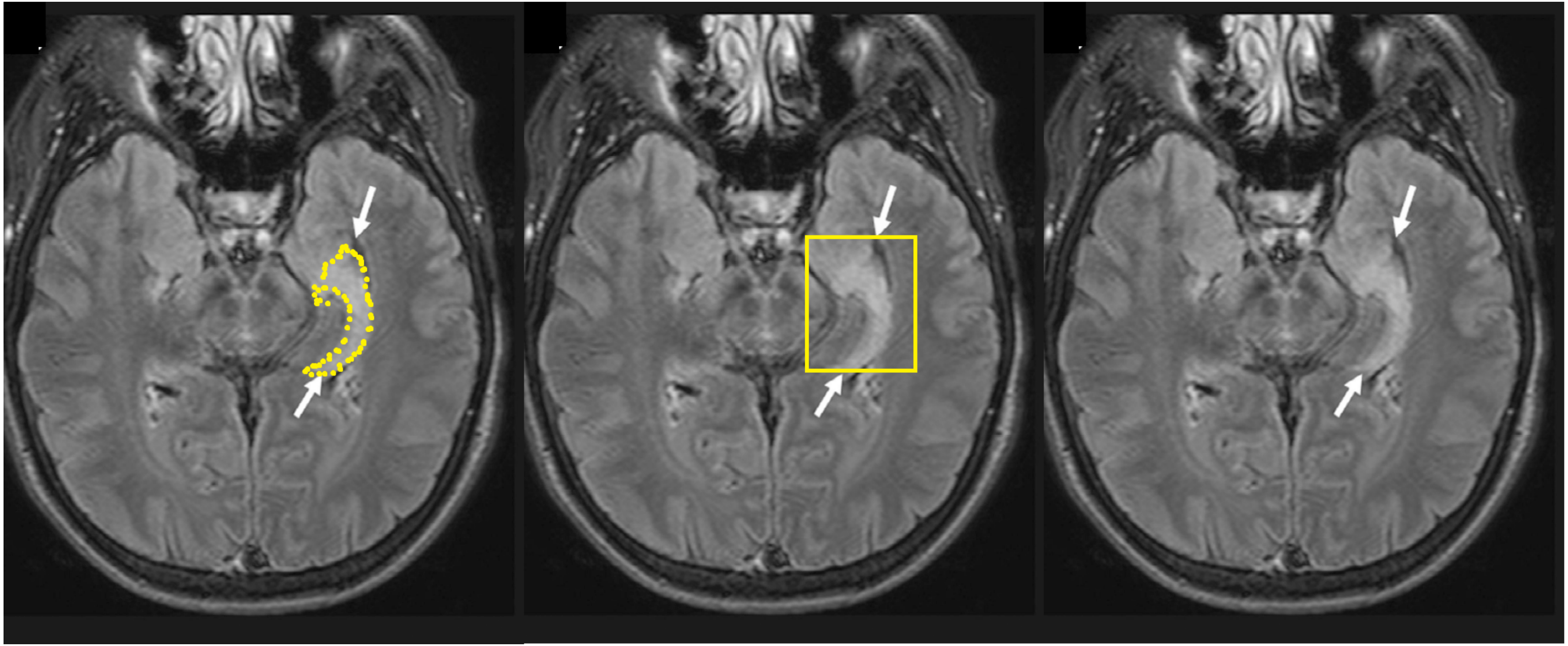


Figure 4. Estimated segmentation from bounding box annotation.

*Weakly- and Semi-Supervised Learning of a Deep Convolutional Network for Semantic Image Segmentation, 2015

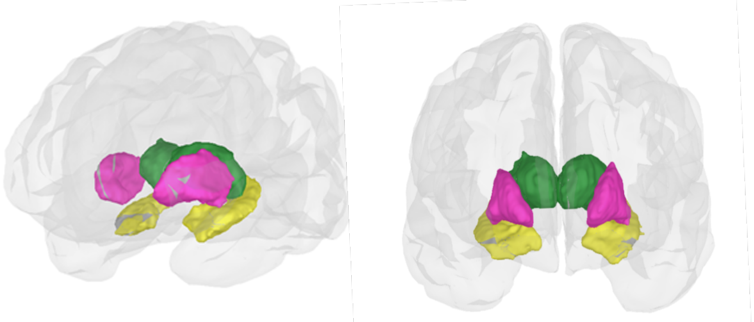
Data labelling and weakly supervised learning



MRI-based epilepsy diagnostics and foci

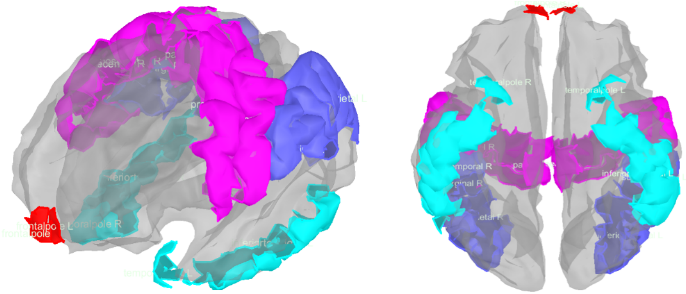
Classification	Data type	Accuracy	FPR (fixed), %	Sensitivity, %	Specificity (TPR),%
Epilepsy	**1.5T** Structural MRI	0.82	20	80.0	80.0

Subcortical epilepsy biomarkers



Biomarkers: Hippocampus Left/Right, Thalamus Left/Right, and Putamen Left/Right

Cortical epilepsy biomarkers



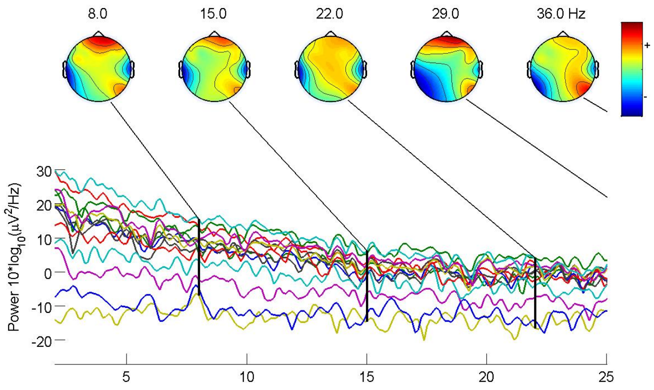
Biomarkers: Postcentral, Precentral, Paracentral, Para hippocampal, Temporal gyri and Frontal and Temporal poles

Skoltech
Skolkovo Institute of Science and Technology

Depression diagnostics based on EEG data

Depression types diagnostics

- ❑ **Medical partner**: V.P. Serbsky Moscow Research Institute of Psychiatry
- ❑ 128-channel EEG data on depression
- ❑ Aims:
  - to develop an algorithm that could be used as additional source of information at initial depression diagnostics
  - to develop an algorithm that could be used to distinguish between different types of depression



Used features

- Magnitudes of rhythm bands – mediocre results

- Coherence – good results

$$Coh_{xy}(f) = \frac{S_{xy}(f)}{\sqrt{S_x(f)S_y(f)}}$$

- Imaginary Coherence – poor results

$$ImCoh_{xy}(f) = Im(Coh_{xy}(f))$$

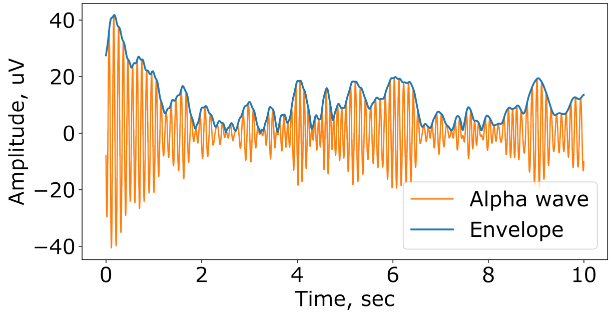
- Phase Lag Index – poor results

$$PLI_{xy}(f) = \left|\frac{1}{n}\sum sign(\varphi_x(f) - \varphi_y(f))\right|$$

- Phase Slope Index – poor results

- Alpha/beta band envelopes – good results

Alpha/beta band filtering
Hilbert transform and envelope extraction
Calculation of correlation between channels



Skoltech
Skolkovo Institute of Science and Technology

Selected results

Model	ROC-AUC (Repeated 10-fold CV)
Rhythm features, best linear model	0.72
Coherence, best linear model	**0.88**
Coherence, best XGB model	0.83
Envelopes, best linear model	**0.89**
Envelopes, best XGB model	0.80
All features, final model	**0.98**
Neural Nets on raw signal	0.5

Correlational tasks

Neuroeducation: motivation

“Adaptive Learning Startup Squirrel AI Raises CN¥1B (US$150 million)”

“Squirrel AI uses customized resources and learning activities to identify and address the **unique needs** of each learner based on their **profiles, learning level, strengths and weaknesses**—an educational method is known as AI Adaptive Learning”

*from https://medium.com

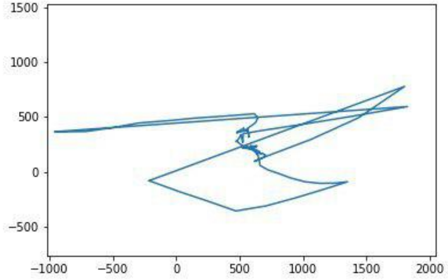
Neuroeducation

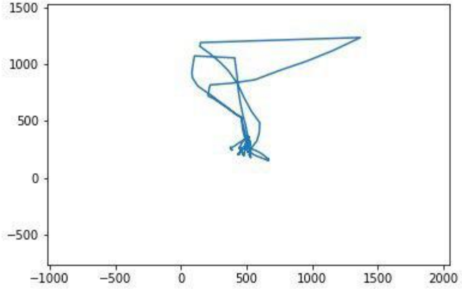
- Behavioral indexes (like accuracy and reaction time) and neuroimaging markers
- Are objective markers
- We aim at finding these correlates as well as their dependencies on study programs

Skoltech
Skolkovo Institute of Science and Technology

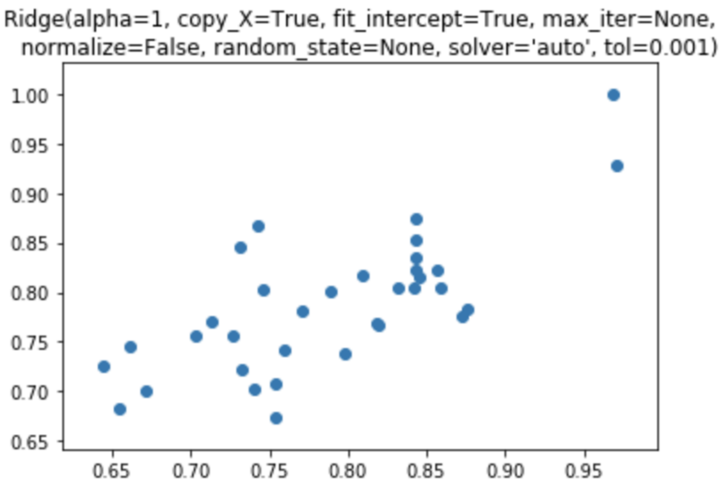
Neuroeducation

Test performance prediction based on eye-tracking data





Mean performance prediction



	method	MSE	baseline(MSE)
0	linearRegression(normalize=True)	0.0493907	0.0680758
1	linear_model.Lasso(alpha=0.05)	0.0456625	0.0680758
2	linear_model.Ridge(alpha=0.025)	0.0459179	0.0680758

0	mean_RESPONSE_TIME_by_participant	0.0594819	-1
9	PREVIOUS_SAC_AVG_VELOCITY_by_participant	0.0406355	-1
1	mean_TRIAL_FIXATION_TOTAL_by_participant	0.0313184	1
5	CURRENT_FIX_BLINK_AROUND_BOTH_by_participant	0.030871	-1
2	mean_CURRENT_FIX_DURATION_by_participant	0.0295631	1
10	PREVIOUS_SAC_AMPLITUDE_by_participant	0.023081	1
3	mean_CURRENT_FIX_MSG_TIME_1_by_participant	0.0124428	1
4	CURRENT_FIX_BLINK_AROUND_NONE_by_participant	0.0112081	1
11	PREVIOUS_SAC_ANGLE_by_participant	0.0087276	1
8	CURRENT_FIX_PUPIL_mean_by_participant	0.00530635	1
6	CURRENT_FIX_BLINK_AROUND_BEFORE_by_participant	0.00272534	1
7	CURRENT_FIX_BLINK_AROUND_AFTER_by_participant	0.0022988	1
12	PREVIOUS_SAC_DURATION_by_participant	0.000195068	-1

Baseline – mean performance over all participants

Skoltech
Skolkovo Institute of Science and Technology

- **Data sources**
- **Neuroimaging data peculiarities**
- **Biomedical problems based on neuroimaging data**
- **Neuroimaging data analysis**
- **Examples of using the developed methods for biomedical tasks**
    - Noise elimination
    - Connectivity analysis and feature extraction
    - fMRI data decomposition in a Pre-surgical planning task
    - Classification tasks for clinics and education
    - Cybersport research
- **Conclusions**

Evolution of Players

Amateur Player
Have **fun**

Hardcore Player
Wants to **win**

PRO Player
It is a **job**

Not Only Gaming, but Big Money and Audience

MARKET DATA
eSPORTS: ENJOYING GREAT MOMENTUM

$700M
Spent in eSports (2017)

12M
Attend live events in US & Europe

385M
Viewers & enthusiasts worldwide

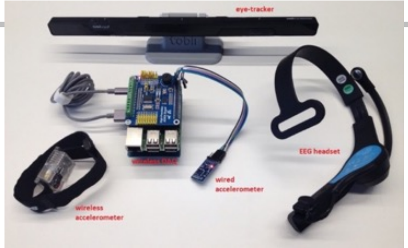
$24.7M
Prize pool of the 2017 International (DOTA 2)

NEWZOO, SUPERDATA, REDEF

There are no available tools for the eSports professional trainers to assess physical and mental conditions

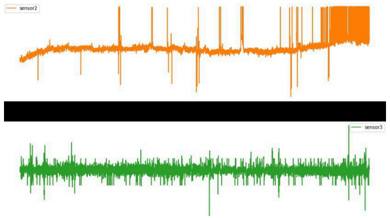
of an e-athlete!

Cybersportsmen psychophysiological state monitoring (joint work with A. Somov, A. Cichocki, A. Phan)



<u>Goal</u>: Construct an intelligent equipment to assess

- ✓ Whether reaction is quick under pressure
- ✓ Sustained concentration over time
- ✓ Mental resources allocation



Skoltech CyberAcademy

Founded in 2018

- Research
  - Understanding psycho-emotional conditions of eSports athletes
  - Brain-to-brain
  - Datasets collection
- Professional team: Monolith ; Disciplines: CS:GO, Fortnite
- Innovation – startups:
  - HEAD KRAKEN
  - ESAcademy

eSports Research Group

Andrey Somov
Assistant Professor

Evgeny Burnaev
Associate Professor

Andrey Lange
Sr. Research Engineer

Anton Stepanov
Research Engineer

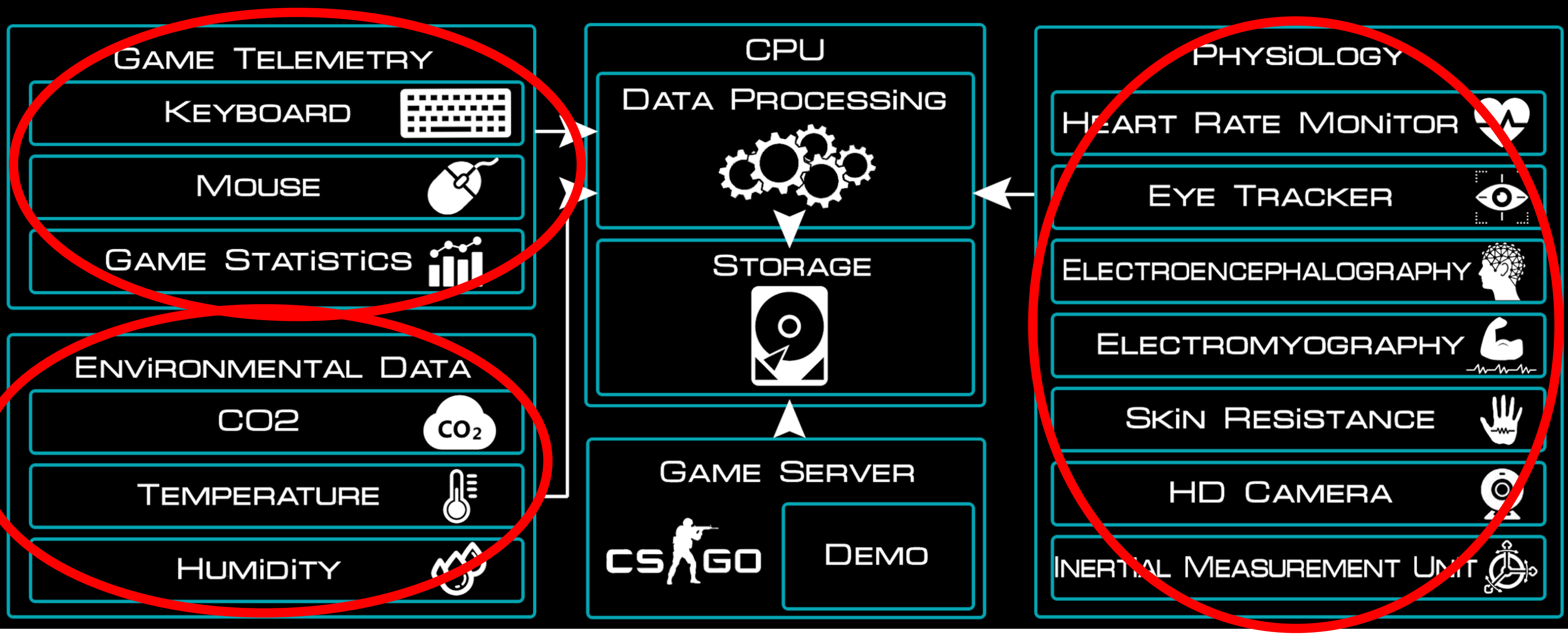
Dmitry Nikolaev
Research Engineer

Alexander Korotin
PhD student

Some our papers

1. A. Smerdov, A. Kiskun, R. Shaniiazov, A. Somov, E. Burnaev. Understanding Cyber Athletes Behaviour Through a Smart Chair: CS:GO and Monolith Team Scenario. IEEE 5th World Forum on Internet of Things (WF-IoT), April, 15-18, 2019, Limerick, Ireland.
2. A. Smerdov, A. Somov, E. Burnaev. eSports Pro-Players Behavior During the Game Events: Statistical Analysis of Data Obtained Using the Smart Chair. The 5th IEEE International Conference on Internet of People, August 19-23, 2019, Leicester, UK.
3. A. Korotin, N. Khromov, A. Stepanov, A. Lange, E. Burnaev, A. Somov. Towards Understanding of eSports Athletes Potentialities: Sensing System for Data Collection and Analysis. The 5th IEEE International Conference on Internet of People, August 19-23, 2019, Leicester, UK.
4. A. Stepanov, A. Korotin, N. Khromov, A. Lange, E. Burnaev, A. Somov. Sensors and Game Synchronization for Data Analysis in eSports. IEEE International Conference on Industrial Informatics (INDIN), July 22-25, 2019, Helsinki-Espoo, Finland.
5. N. Khromov, A. Korotin, A. Lange, A. Stepanov, E. Burnaev, A. Somov. Esports Athletes and Players: a Comparative Study. IEEE Pervasive Computing
6. B. B. Velichkovsky, N. Khromov, A. Korotin, E. Burnaev, A. Somov. Visual Fixations Duration as an Indicator of Skill Level in eSports. International Conference on Human-Computer Interaction (INTERACT). September 2-6, 2019, Paphos, Cyprus.

Experimental Testbed



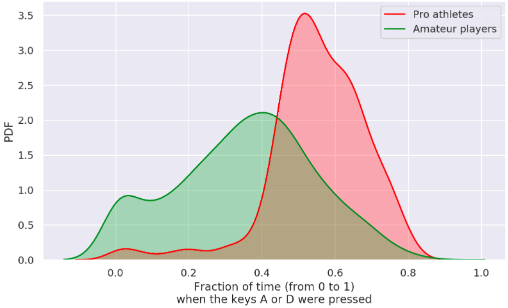
Experimental test bed

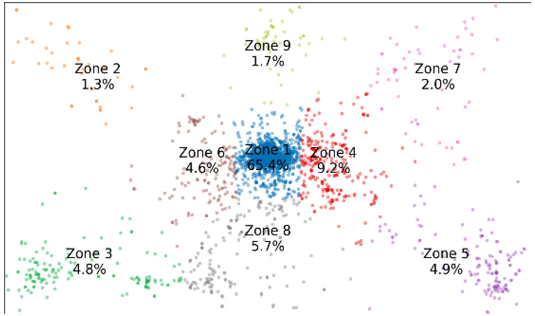
Data Collection - Challenges

- ➢ Professional Players' Data!
  - a) Active Cyber-Athlete Data (professional team required) - **Monolith** (Sk)
- ➢ Diverse Data (10+ data streams)
  - a) Sensor specificity (proper sensors set up & calibration required)
  - b) Different collection mechanisms (real-time synchronisation required!)
  - c) Continuous data collection (real-time data integrity monitoring required!)
- ➢ Black-Box-Generated Game Data
  - a) Logs are typically generated on server (access to server required!)
  - b) Typically, specific game scenario needed (server set up required!)

Machine Learning

1) Determine physiological/in-game features that affect the performance
   a) Determine causal dependencies between features ("decompose" performance)
   b) Find most important and explainable features
2) Predict player's (team's) future short/long-term
   a) Performance;
   b) Pitfalls/problems;
3) Give advice for skill development/improvement.
   a) For player;
   b) For coach;



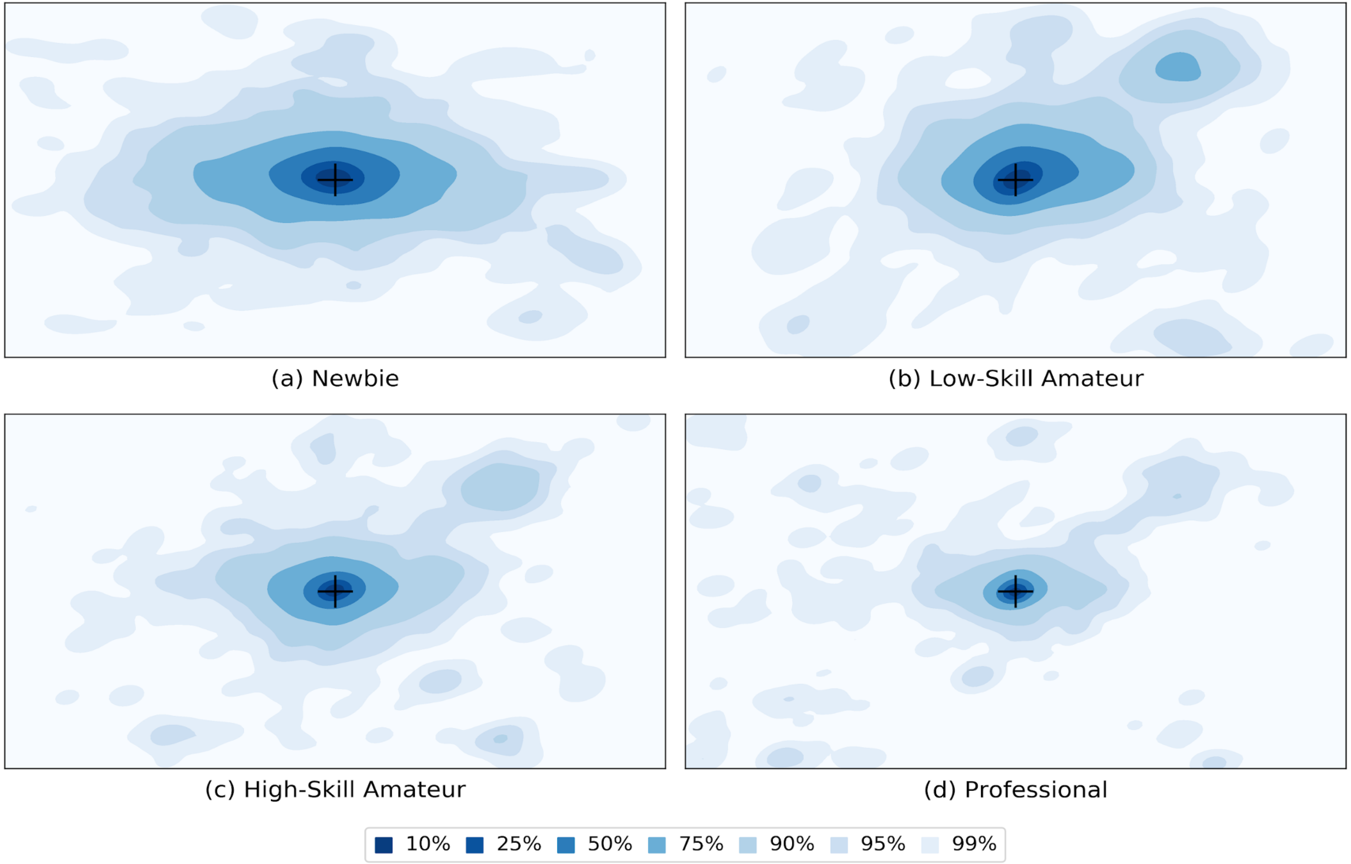


Skoltech
Skolkovo Institute of Science and Technology

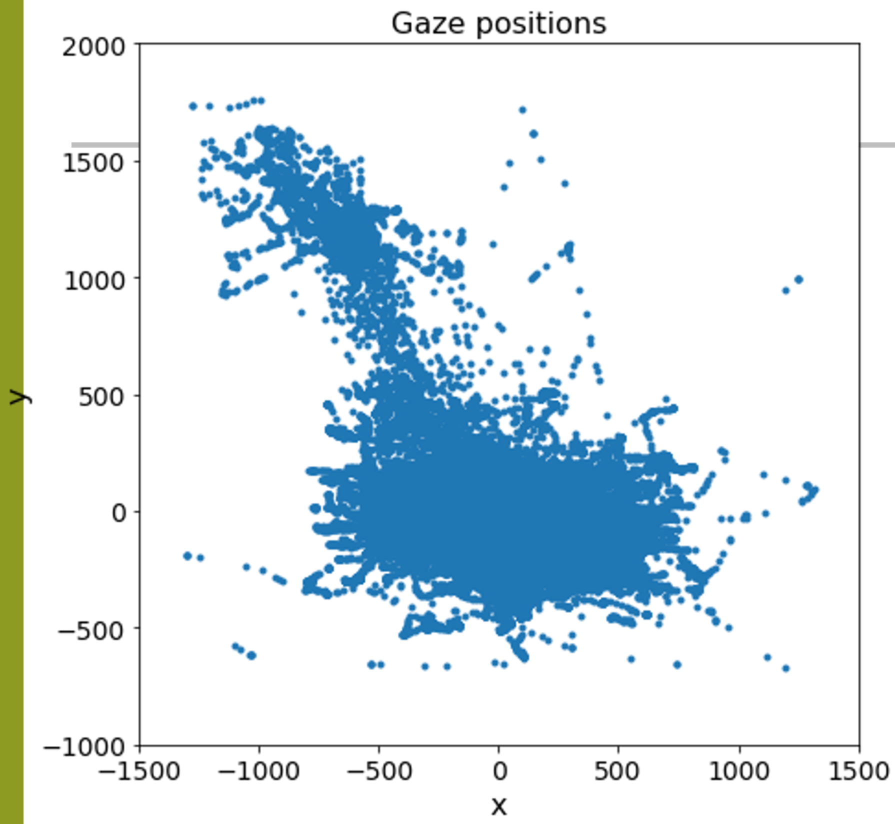
9 ZONES OF INTEREST

Skoltech
Skolkovo Institute of Science and Technology

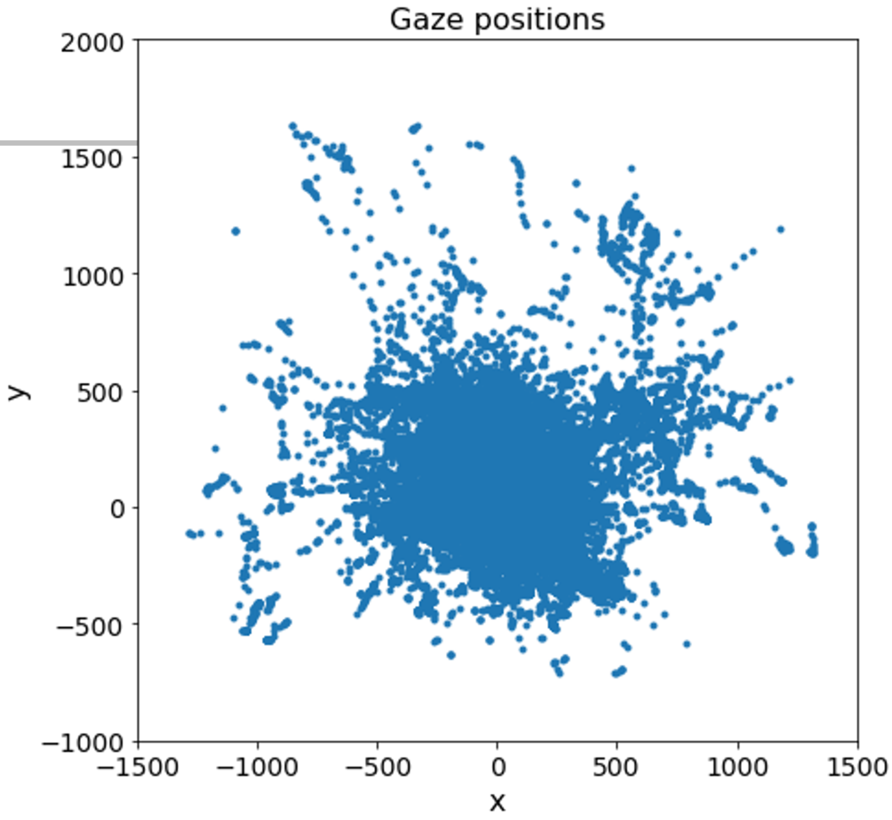
Heat-map results: newbies vs amateurs vs pros



oltech
tute of Science and Technology



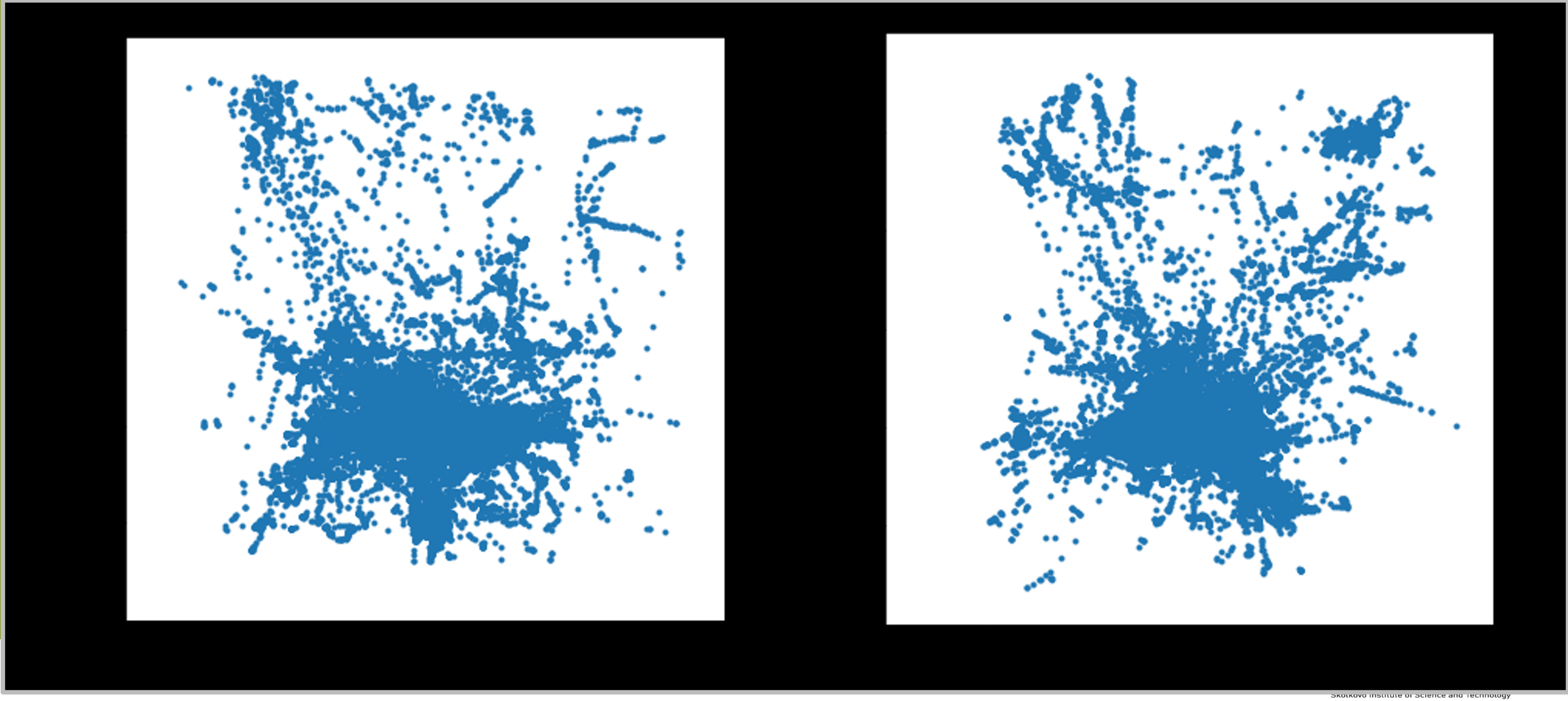
Player



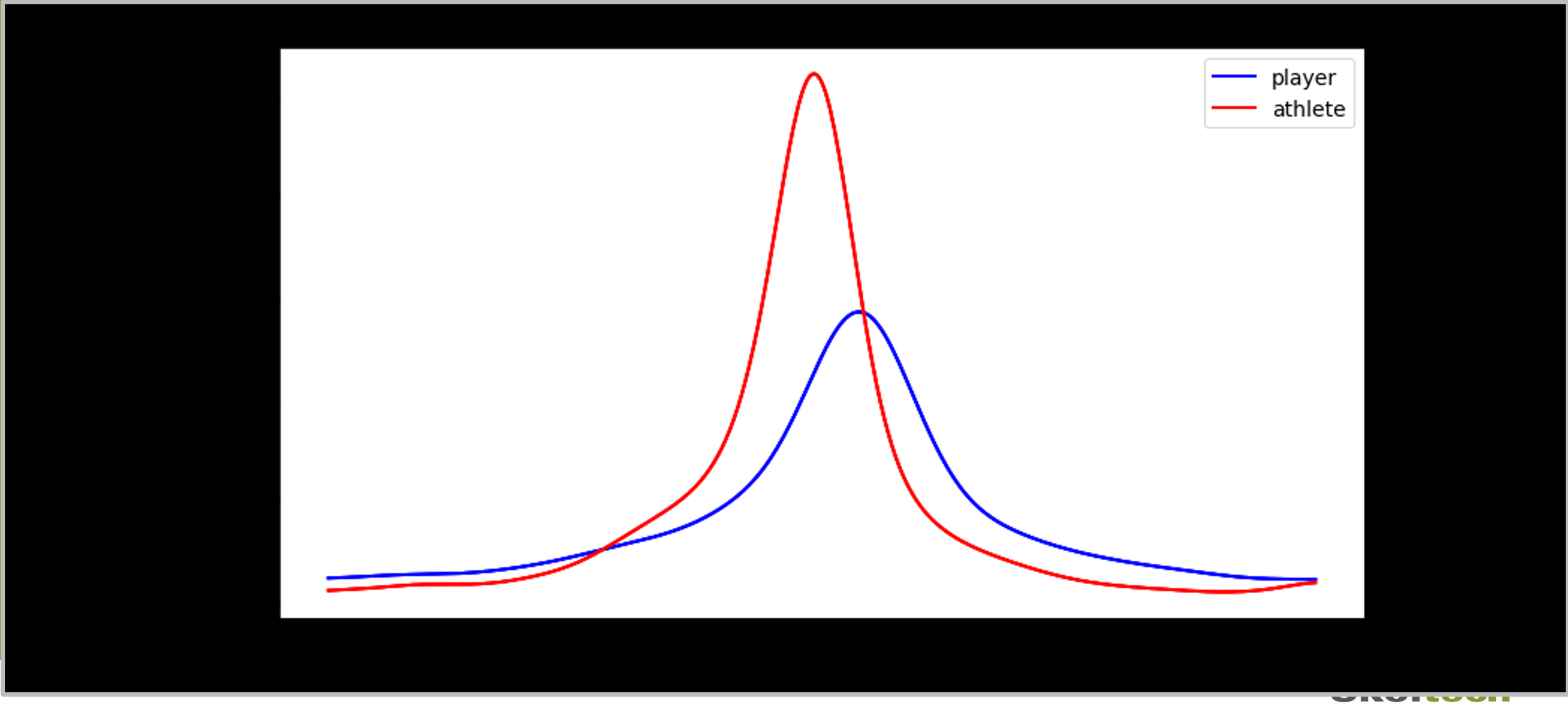
Athlete

Skoltech
Skolkovo Institute of Science and Technology

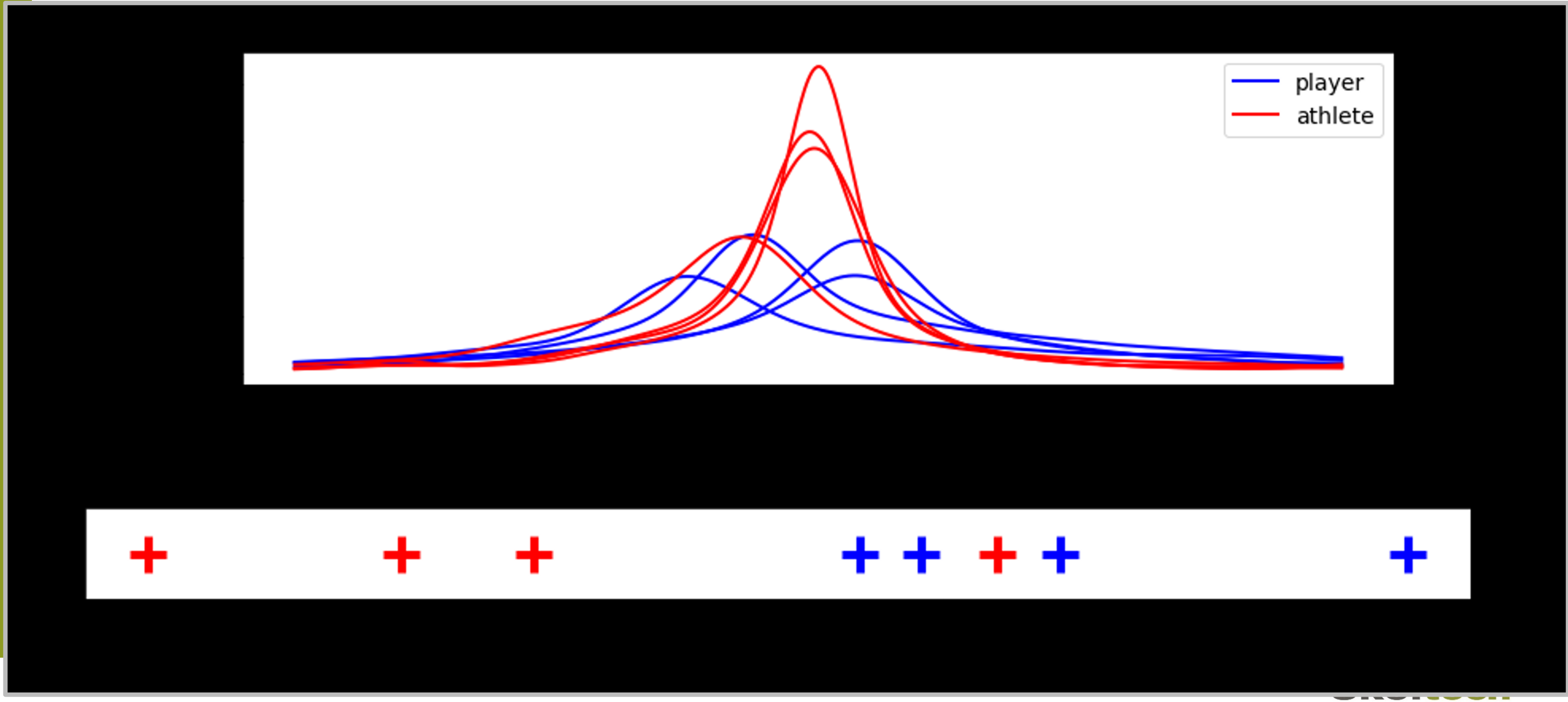
And How Do we Classify These Two?



Any Ideas?



Gaze Variance is a Good Feature!



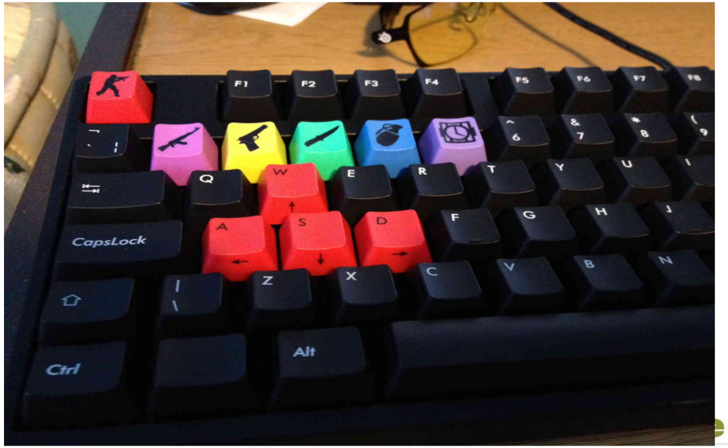
What about key controls? Are them sensors?

Skoltech
Skolkovo Institute of Science and Technology

Keyboard/mouse

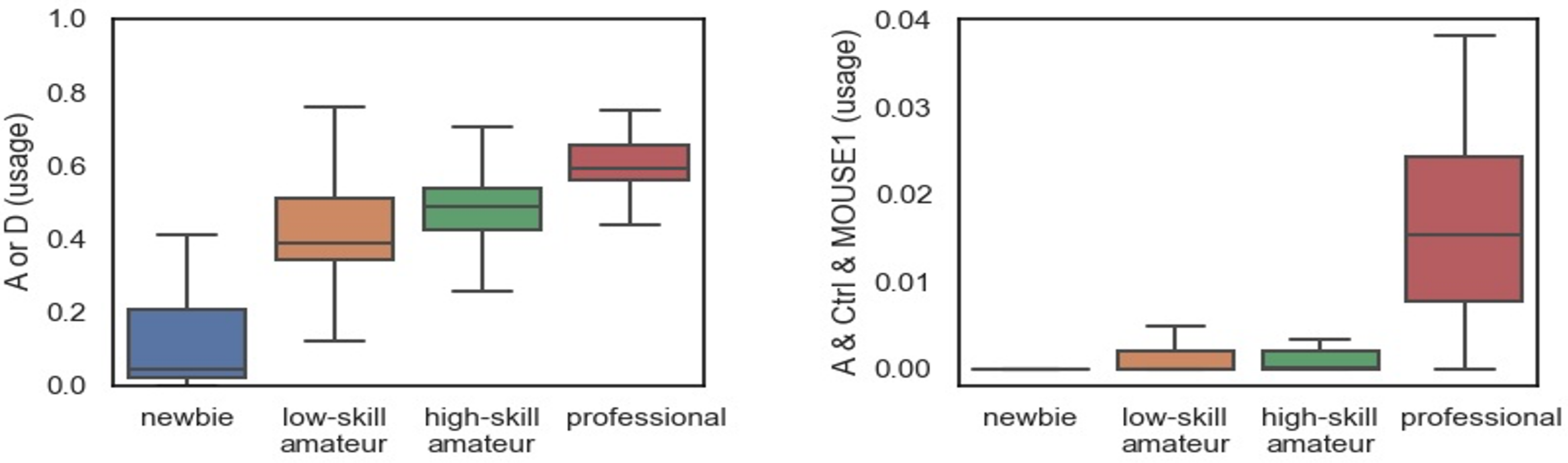
Pro's:
1. no hw required
2. "always on" devices
3. high-speed tracking is possible
4. game independent sensors

Con's:
1. requires recording software
2. different "binds"
3. different mouse sensitivity



Sensors details: keyboard/mouse

Key/mouse: newbies vs amateurs vs pros



Skoltech
Skolkovo Institute of Science and Technology

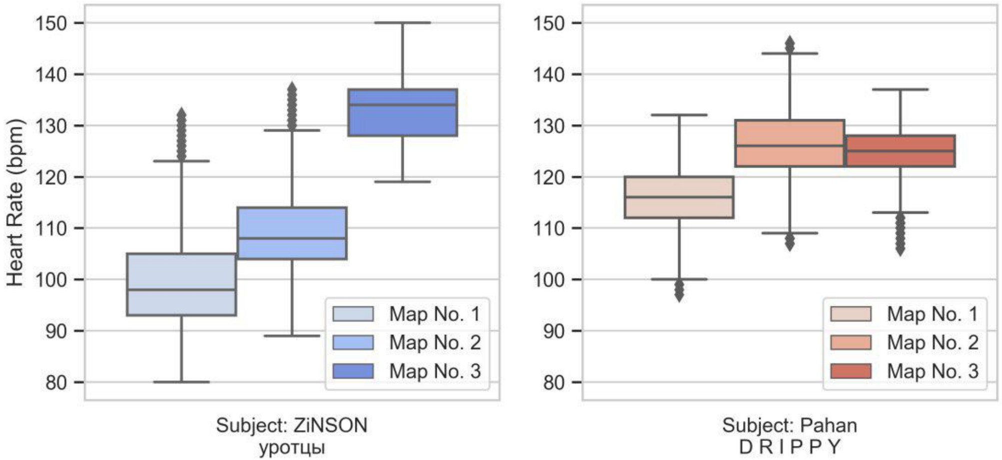
Design and Implementation of Real-World Experiment

Proof-of-concept: Moscow LAN TF2

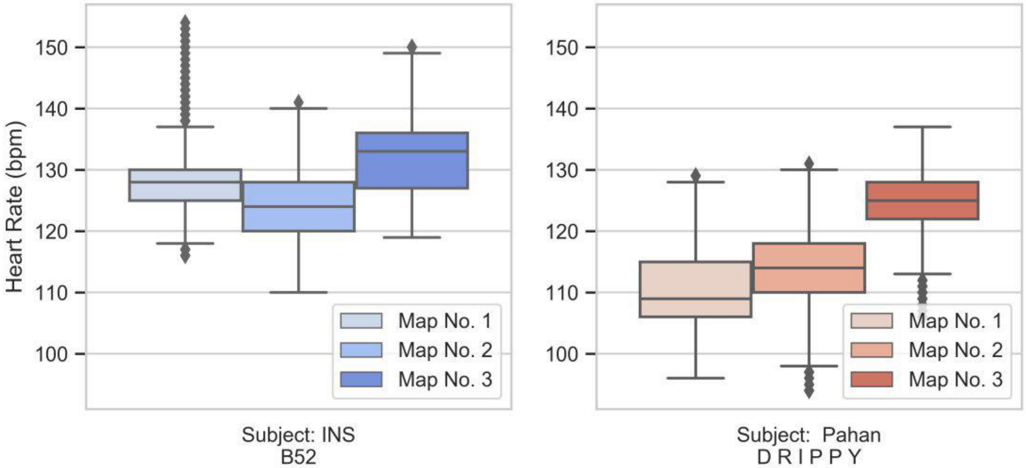
Live-stream with captains HRM overlay on twitch.tv/kritzkast

Skoltech

Semi-Final

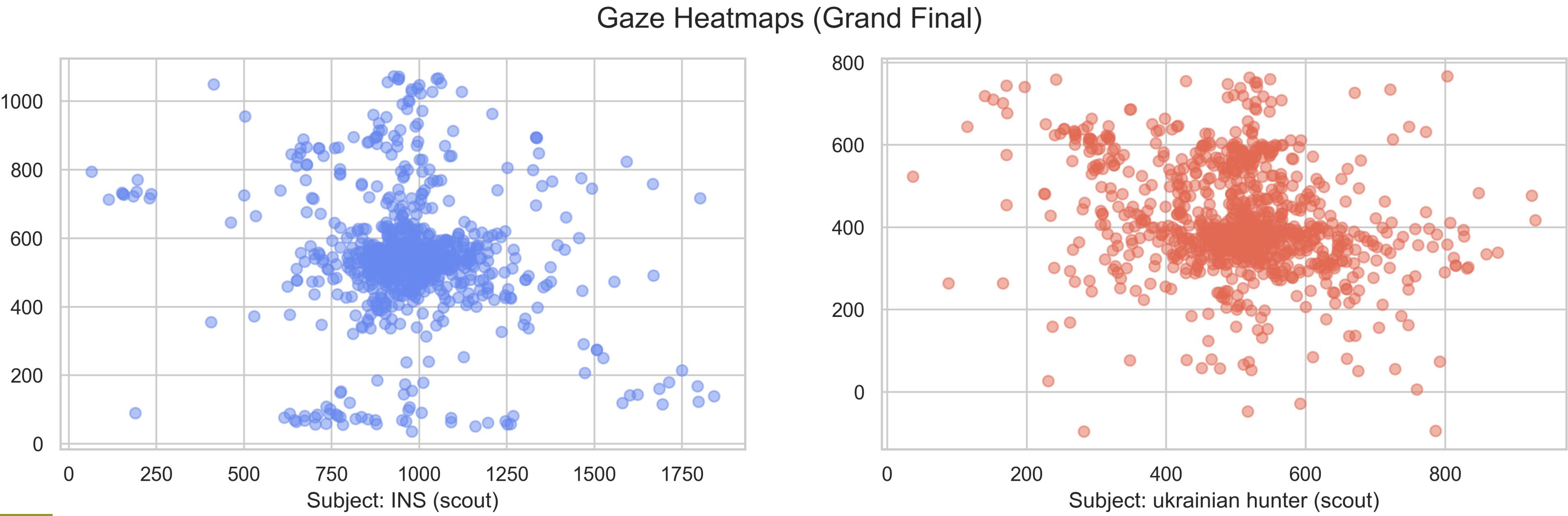


Grand Final



Skoltech
Skolkovo Institute of Science and Technology

Eye-tracker Heatmap



Skoltech
Skolkovo Institute of Science and Technology

Technology for the implementation of neuro projects

- Many projects with similar steps
- Need to create a technology to automate routine operations, compare results and etc.
- 1st step: develop a scheme of projects (pipeline) – is already been used in CDISE
- 2nd step: move all research to CoBrain Analytics platform
    - Six Algorithmic Chains were implemented on the platform Cobrain Analytics in 2018
    - Five Algorithmic Chains are being implemented on the platform Cobrain Analytics now

CoBrain Analytics

Skoltech
Skolkovo Institute of Science and Technology

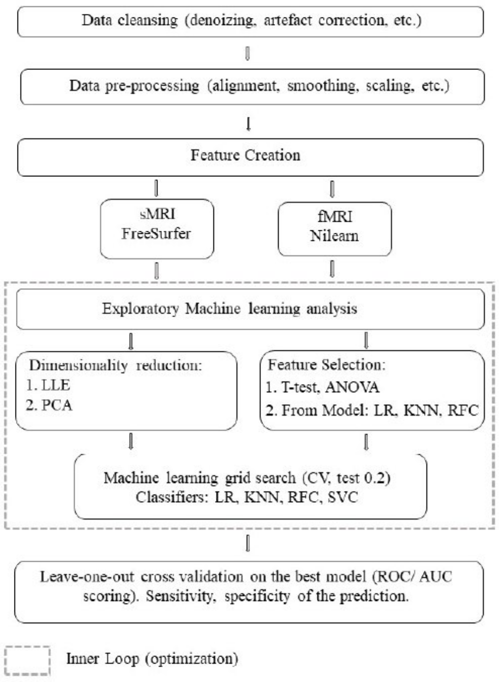
Pipeline for neuroscientific research “SBI-technologies”

- Lots of multimodal datasets
- Similar preprocessing and analysis methods

- Routine work should be automatized (less labor, less errors)

- We introduce a block-pipeline, meta-data is saved on each step

Multimodal data input → Data preprocessing → Analysis and inference → Results visualization



Conclusions

- Neuroimaging data are the basis for solving biomedical problems and fundamental tasks of AI

- Neuroimaging data have peculiarities, due to both the complexity of the object (brain) and data acquisition methods

- Standard data processing methods, including denoising and feature extraction should use domain knowledge and models; CDISE's experience has demonstrated this

- To work in this area people need new specialization

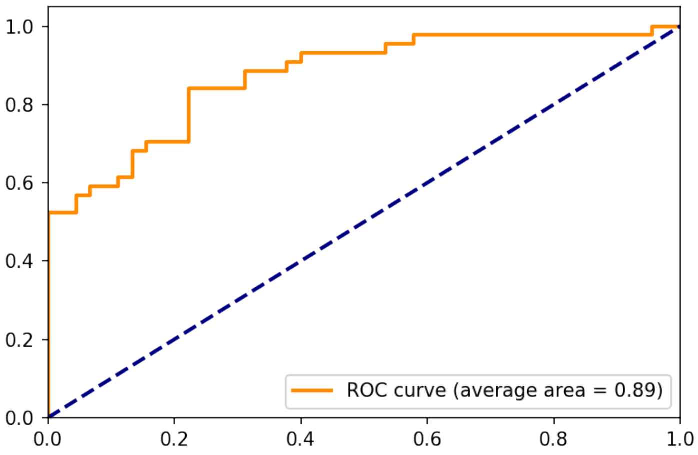
Thanks for attention!

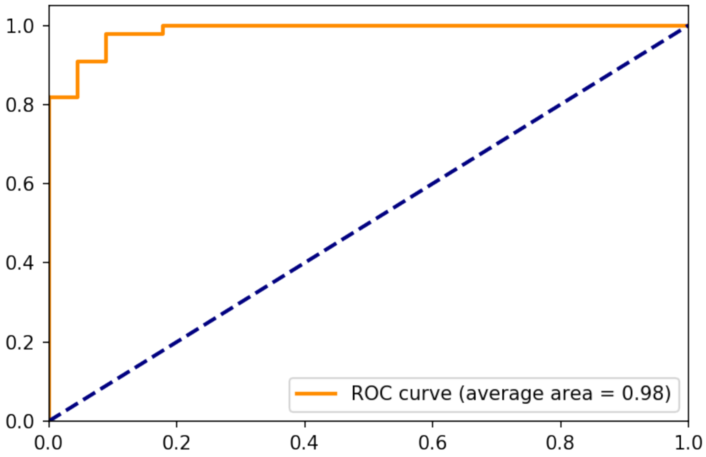
Receiver Operator Characteristic

Only envelopes correlation (alpha)

All features

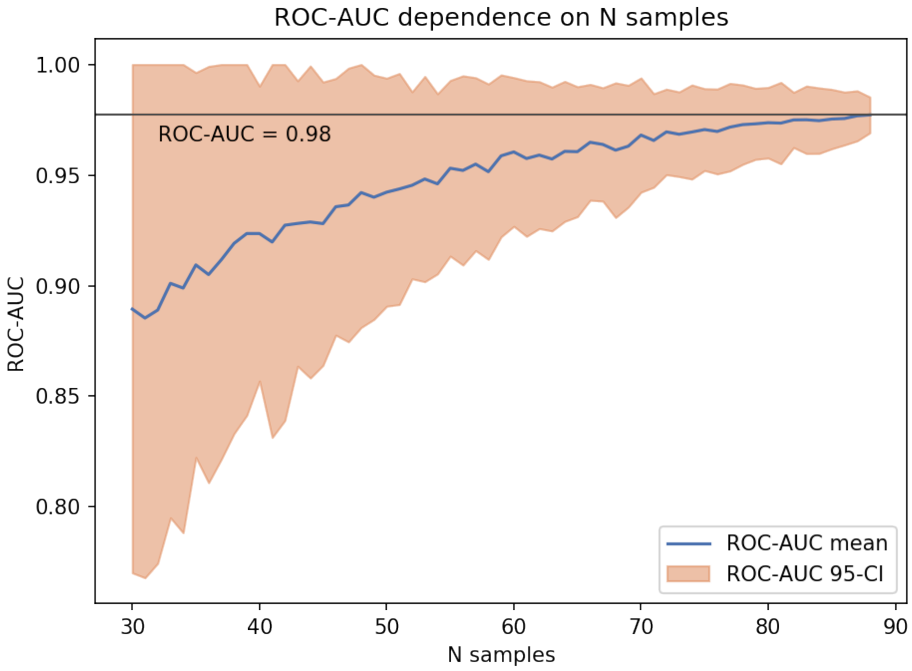
Sensitivity
= Recall
= TP /
(TP + FN)



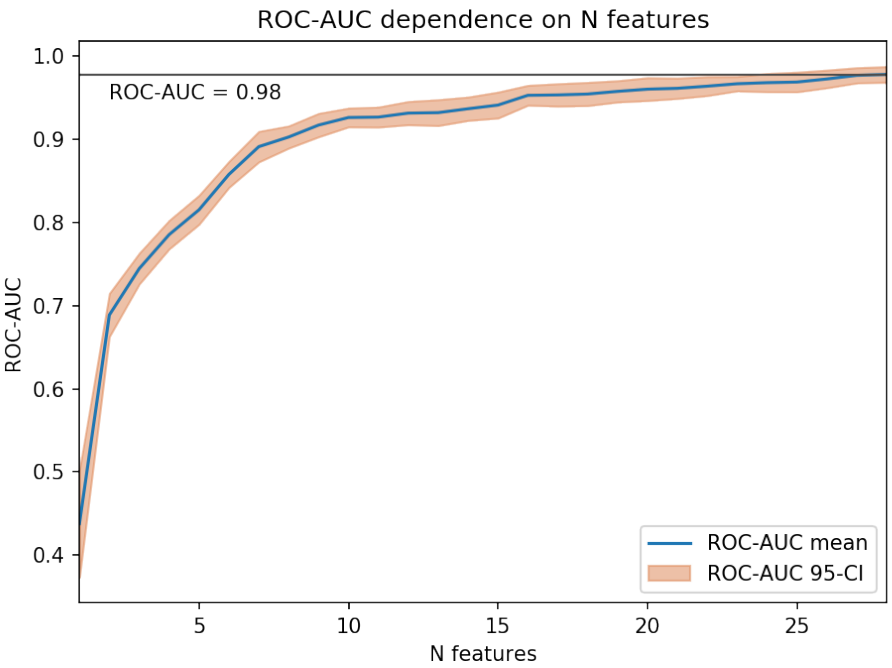


1 - Specificity
= False Negative Rate
= FN / (TP + FN)

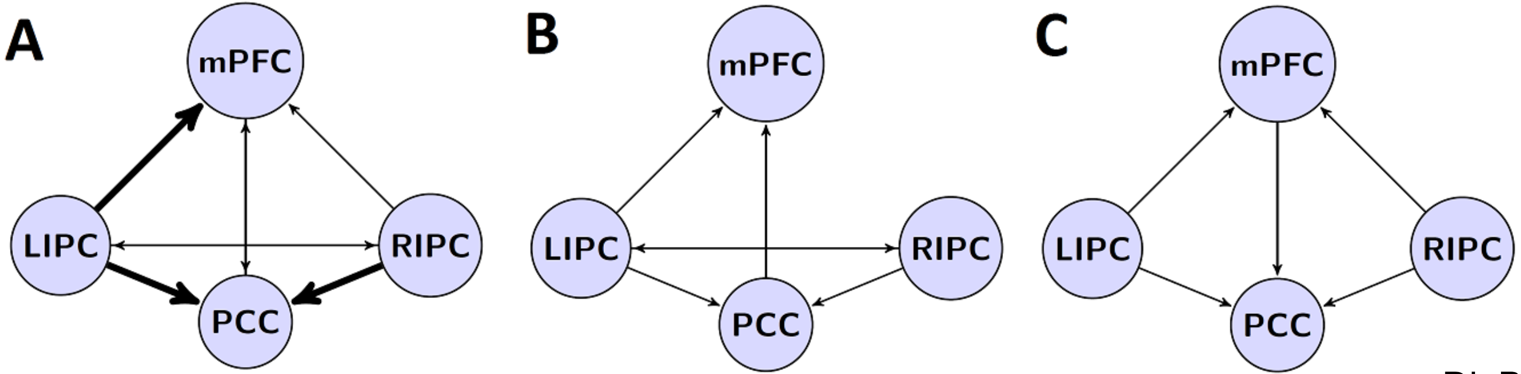
Dependence on sample size



Dependence on N features



Next steps: MDD subtypes classification, source reconstruction, electrode clustering, applying neural networks and graph classification approaches.



Razi, Friston, 2015

Di, Biswal, 2014

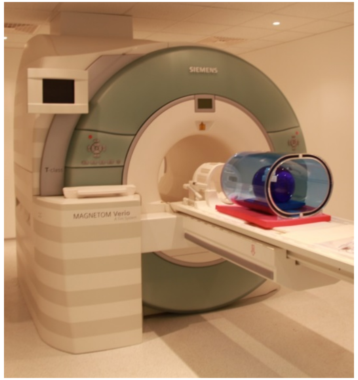
Appendix

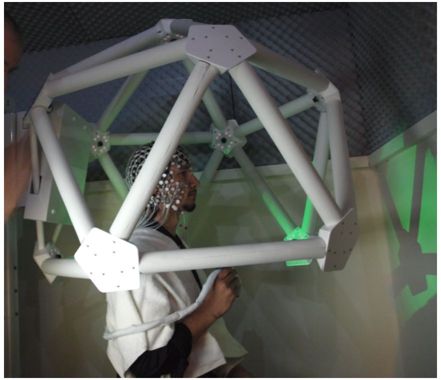
Dynamic Causal Modelling

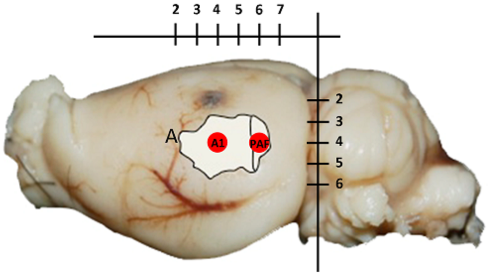
Generative model

$$\dot{x} = f(x, u, \theta) + \omega$$
$$y = g(x, u, \theta) + v$$

Experimental data







= Silverball electrode, diameter: 1 mm

Resting-state fMRI modelling

→ $\dot{\boldsymbol{x}}(\boldsymbol{t}) = \boldsymbol{A}\boldsymbol{x}(\boldsymbol{t}) + \boldsymbol{v}(\boldsymbol{t})$

→ Coupled dynamical systems with no external input

→ $$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \vdots \\ \dot{x}_n \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} & \cdots & A_{1n} \\ A_{21} & A_{22} & \cdots & A_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ A_{n1} & A_{n2} & \cdots & A_{nn} \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}$$

n regions

Aij - Extrinsic effective connectivity parameters

DCM: pros&cons

PROS:

1. Neurobiologically plausible
2. Easy to interpret parameter values
3. Parameter priors could be derived from anatomical data, tractography, invasive study, laser Doppler flowmetry and etc.

CONS:

1. Model-based
2. Parameter estimation procedures

Connectomes for brain fundamental research

frontiers in Human Neuroscience

ORIGINAL RESEARCH
published: 01 February 2016
doi: 10.3389/fnhum.2016.00014

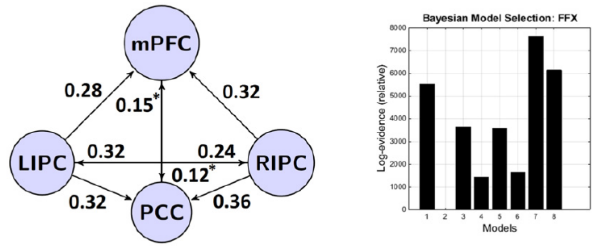


FIGURE 3 | The winning model at the group level and its connectivity parameters (in Hz). Left: the winning model and its non-trivial significant ($p < 0.05$) connections. Right: bayesian model selection (BMS) results—models and their (relative) log-evidences. Models legend: 1–lateral modulation with (w) direct connections between bilateral LIPC and RIPC, 2–lateral modulation without (wo) direct connections between bilateral LIPC and RIPC, 3–mPFC modulation (w), 4–mPFC modulation (wo), 5–PCC modulation (w), 6–PCC modulation (wo), 7–full connected (w), 8–full connected (wo). *Non-significant after Bonferroni correction.

Effective Connectivity within the Default Mode Network: Dynamic Causal Modeling of Resting-State fMRI Data

Maksim G. Sharaev[1,2,3], Viktoria V. Zavyalova[1,4], Vadim L. Ushakov[1,5], Sergey I. Kartashov[1,5] and Boris M. Velichkovsky[1,6]*

Collaboration with **fundamental research centers** (IHNA RAS, Kurchatov Institute) and a growing number of open international **Neuroimaging databases** helps to discover brain macroscopic functional architecture

Skoltech
Skolkovo Institute of Science and Technology