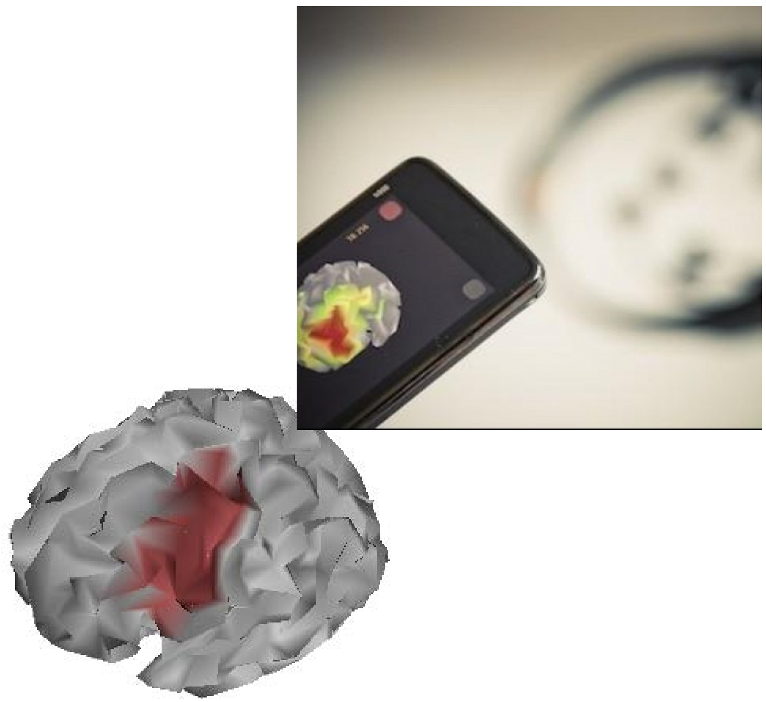
EEG in the Wild

Neurotechnology for 24/7 brain state monitoring



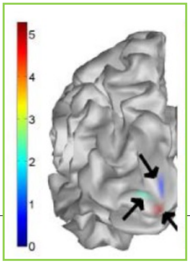
Lars Kai Hansen – lkai@dtu.dk
Technical University of Denmark

Quick intro

Physicist… a long, long time ago …

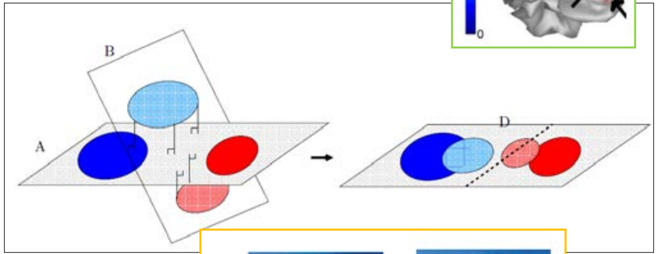
Head of Section for Cognitive Systems, DTU Compute, Technical University of Denmark

Invented the **ensemble method** with Peter Salamon… (IEEE PAMI, 1990).



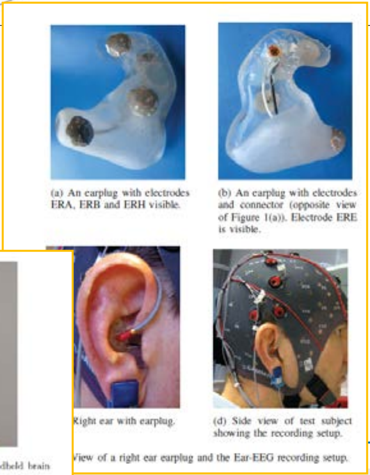
Since mid-90s work on systems neuroscience /neuroimaging:
First papers on mind reading (**PET**, 1994) and (**fMRI**, 1997)

Discovered "**Variance inflation**" (NIPS 2001) and fixed it for kPCA (JMLR, 2011) and SVMs (PRL, 2013).
Recovering structure from undersampling biases due to small samples in high-dimensional spaces

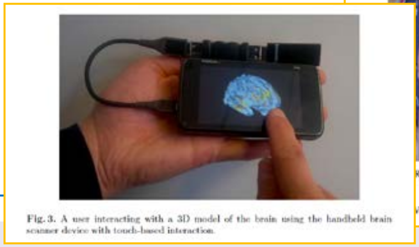


AISTATS 2016: *"Dreaming more data… "*
On deep learning with limited sample sizes

Promoting "EEG in the wild":



The Smartphone Brain Scanner
New Scientist Nov 2011: *"Now you can hold your brain in the palm of your hand"*



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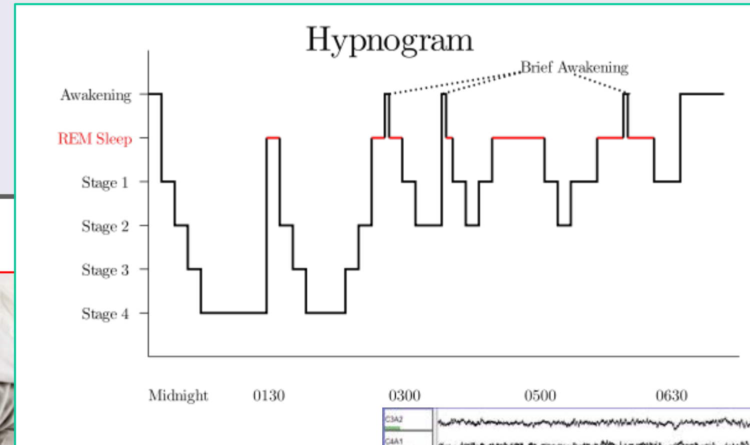
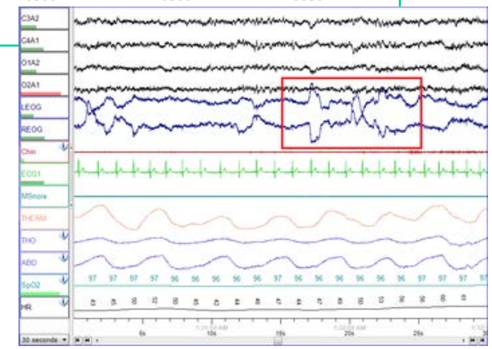
How did you sleep last night?



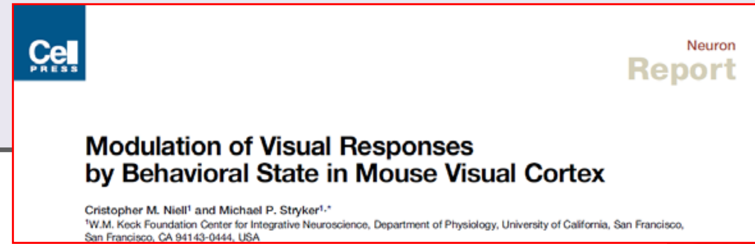


Science, social engineering and bio-medical innovation - all rooted in predictive, causal understanding of human behavior **- "the physics of behavior"**

Predictive modeling is realized by quantitative measures and active machine learning

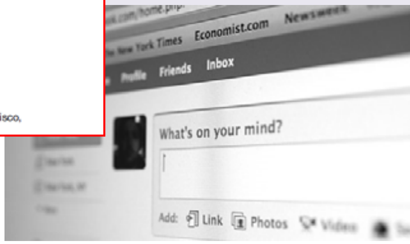
.. we have only limited quantitative self insight...

self-report is of limited use in science, engineering, bio-medicine...


Neuron
Report

Modulation of Visual Responses by Behavioral State in Mouse Visual Cortex

Cristopher M. Niell[1] and Michael P. Stryker[1,*]
[1]W.M. Keck Foundation Center for Integrative Neuroscience, Department of Physiology, University of California, San Francisco, San Francisco, CA 94143-0444, USA



Why in the wild?

A necessary science of the individual …

Human predictability – power laws …. need individual's data to predict

Brain is different in the wild …. even in lab motion matters: *'…most neurons showed more than a doubling of visually evoked firing rate as the animal transitioned from standing still to running..'* (Niell, Stryker, 2010)

Our current EEG in the wild tools:

Imaging with the smartphone brain scanner (SBS [YouTube link])

EarEEG non-invasive, discreet

Hyposafe's subcutaneous electrode device

Example SBS: engagement in the classroom

Example EarEEG: the scalp to ear link

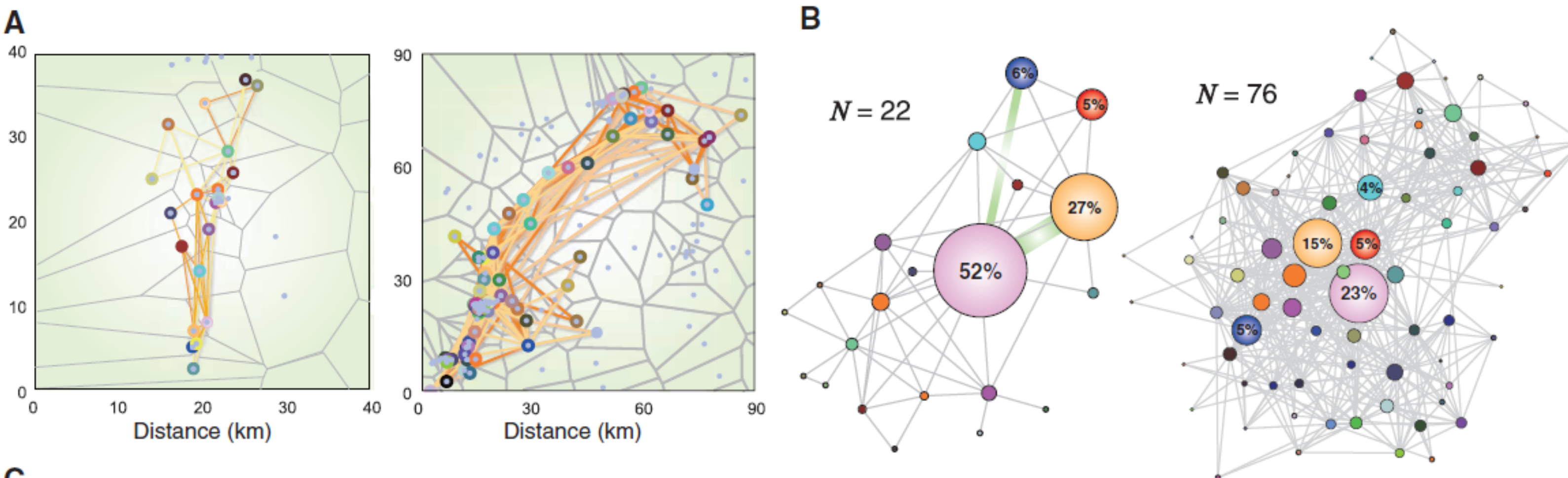
Example UNEEG Medical's Hyposafe device: 40+ days sampling in the wild

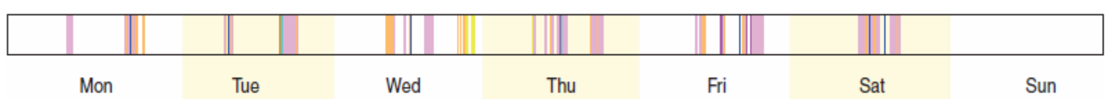
Engel, Andreas K., et al. "Where's the action? The pragmatic turn in cognitive science." *Trends in cognitive sciences* 17.5 (2013): 202-209.
Niell, Cristopher M., and Michael P. Stryker. "Modulation of visual responses by behavioral state in mouse visual cortex." *Neuron* 65.4 (2010): 472-479.

Limits of Predictability in Human Mobility

19 FEBRUARY 2010 VOL 327 SCIENCE

Chaoming Song,[1,2] Zehui Qu,[1,2,3] Nicholas Blumm,[1,2] Albert-László Barabási[1,2]*





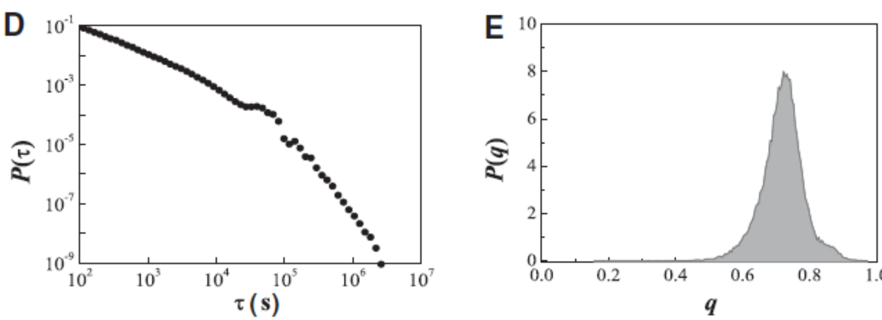


Fig. 1. (**A**) Trajectories of two anonymized mobile phone users who visited the vicinity of N = 22 and 76 different towers during the 3-month-long observational period. Each dot corresponds to a mobile phone tower, and each time a user makes a call, the closest tower that routes the call is recorded, pinpointing the user's approximate location. The gray lines represent the Voronoi lattice, approximating each tower's area of reception. The colored lines represent the recorded movement of the user between the towers. (**B**) Mobility networks associated with the two users shown in (A). The area of the nodes corresponds to the frequency of calls the user made in the vicinity of the respective tower, and the widths of line edges are proportional to the frequency of the observed direct movement between two towers. (**C**) A week-long call pattern that captures the time-dependent location of the user with N = 22. Each vertical line corresponds to a call, and its color matches the tower from where the call was placed. This sequence of locations serves as the basis of our mobility prediction. (**D**) The distribution of the time intervals between consecutive calls, τ, across the whole user population, documenting the nature of the call pattern as coming in bursts (*11*). (**E**) The distribution of the fraction of unknown locations, q, representing the hourly intervals when the user did not make a call, and thus his or her location remains unknown to us.

Short time predictability @ DTU (N=14)

B.S. Jensen, J.E. Larsen, K. Jensen, J. Larsen, L.K. Hansen: Estimating Human Predictability From Mobile Sensor Data
In Proc. IEEE International Workshop on Machine Learning for Signal Processing MLSP (2010).
B.S. Jensen, J.E. Larsen, K. Jensen, J. Larsen, L.K. Hansen: Predictability of mobile phone associations.
In Proc. 21st European Conference on Machine Learning, Mining Ubiquitous and Social Environments Workshop. Barcelona, Spain (2010).

Basic data collection with the ”Context Logger” tool (Nokia N95).

Sensor	Sampling	Data
Accelerometer	30/minute	3D Accelerometer values
GSM	1/minute	CellID of GSM base transceiver station
GPS	2–3/hour	Longitude, Latitude, and Altitude
Bluetooth	20–40/hour	Bluetooth MAC, friendly name, and device type
WLAN	1/minute	Access Point MAC address, SSID, and RX level
Phone activity	Event	Phone number and direction of call or message

Table 1. List of embedded mobile phone sensors used for collecting data

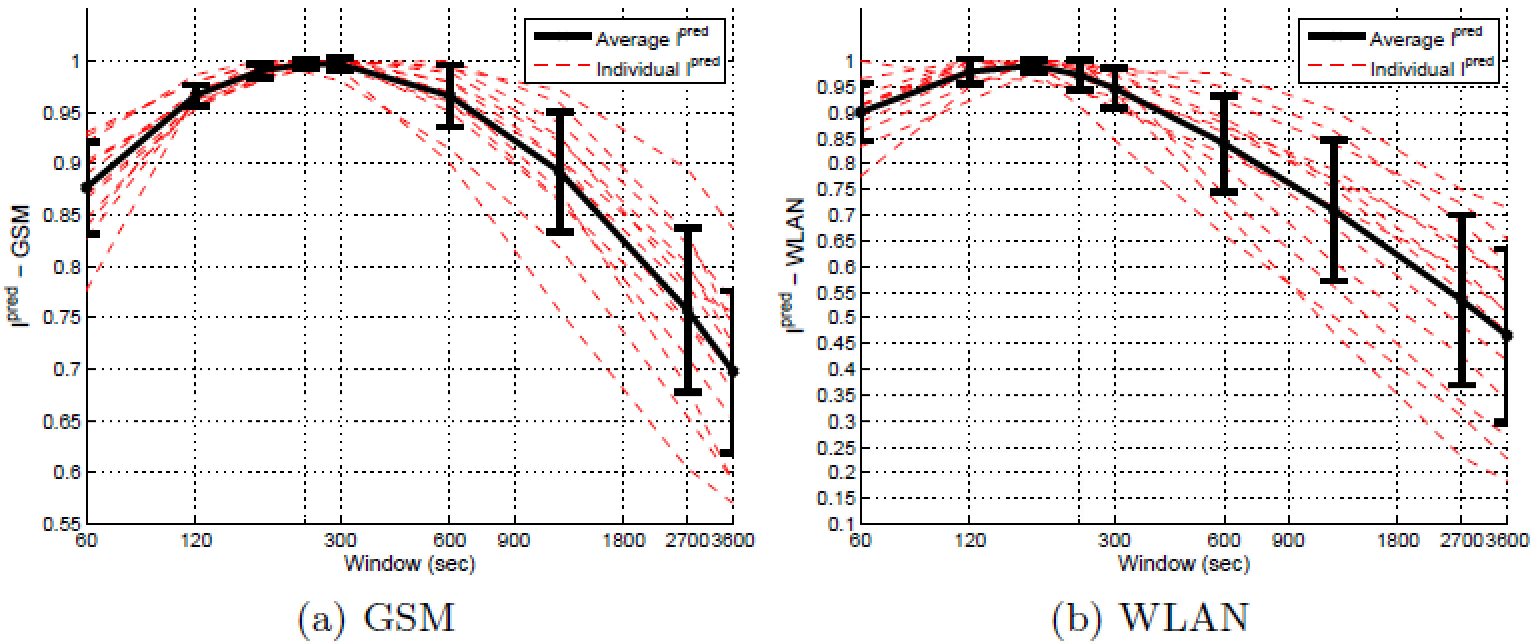
The experiment started October 28, 2008 and ended January 7, 2009.

N= 14 participants took part in the experiment between 31 to 71 days, resulting in approximately 472 days of data covering data collection periods totalling 676 days. The average duration was 48.2 days.

Current experimental platform “Copenhagen Network Study” is based on 1000 students!

Stopczynski, A., Sekara, V., Sapiezynski, P., Cuttone, A., Madsen, M. M., Larsen, J. E., & Lehmann, S. (2014). Measuring large-scale social networks with high resolution. *PloS one*, *9*(4), e95978.

Predictability vs time scale



(a) GSM (b) WLAN

Fig. 5. Predictive Information (normalized) vs. window length (log scale). Participant 3 is left out.

24/7 Neurotechnology - Aim: Connect cognitive neuroscience and normal behaviors

Conventional EEG system

High-performance research and clinical EEG system

Wearable EEG system

Discreet, unobtrusive and user-friendly assistive devices for everyday life

Ear-EEG/Hyposafe device

Smartphone data

Brain state representations connected by machine learning

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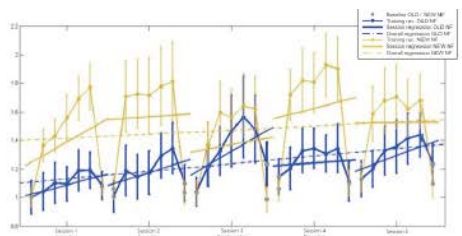
Smartphone brain scanner @ youtube

Mobility projects

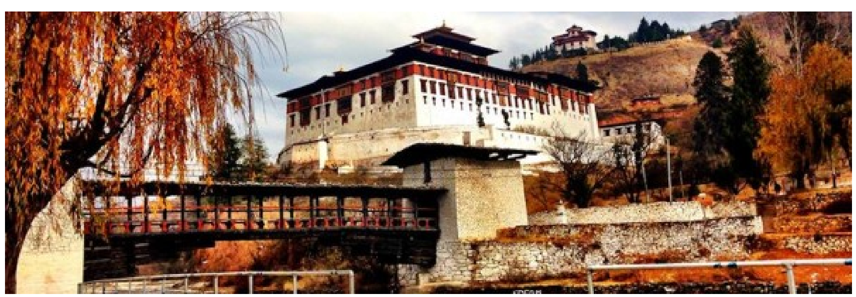
Simon Kamronn
Andreas Trier Poulsen

Social EEG-
- -Joint attention

Mobile real-time EEG Imaging
- -Neurofeedback
- -Digital media & emotion
- -Bhutan Epilepsy Project



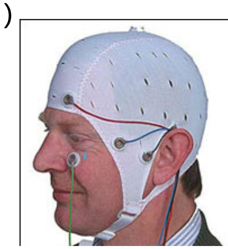
Camilla Falk



Farrah J. Mateen, Massachusetts General Hospital

Smartphone Brain Scanner

Based on the Emotiv wireless transmission mechanism w/ the EPOC head set or modified EasyCaps (Stefan Debener, Oldenburg)



Version SBS2.0 for generic Android platforms (Tested in Galaxy Note, Nexus 7,...)

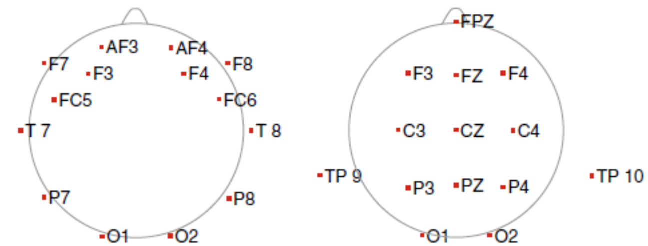
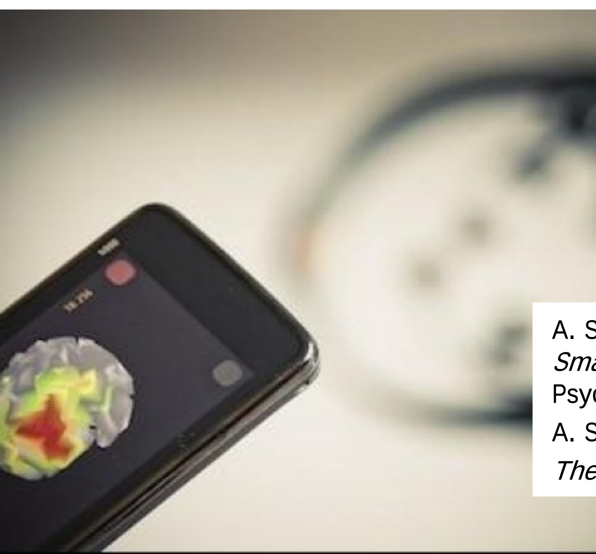


Fig. 5. Electrode locations for two mobile 16 channel EEG setups; the Emotiv neuroheadset using saline sensors positioned laterally (left), versus a standard gel-based Easycap EEG montage including central and midline positions (right).

https://github.com/SmartphoneBrainScanner



A. Stopczynski, C. Stahlhut, M.K. Petersen, J.E. Larsen, C.F. Jensen, M.G. Ivanova, T.S. Andersen, L.K. Hansen. *Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeed-back.* International Journal of Psychophysiology, (2014).

A. Stopczynski, C. Stahlhut, J.E. Larsen, M.K. Petersen, L.K. Hansen. *The Smartphone Brain Scanner: A Portable Real-Time Neuroimaging System.* PloS one 9 (2), e86733, (2014)

SBS2 functions

netexplo Global observatory on digital society

Real time system
- Bayesian minimum norm 3D reconstruction with a variety of forward models (N=1024).
- Adaptive SNR model (β,α) estimated every 10 sec.
- Update speed ~ 40 fps (Emotiv sample rate 128Hz, blocks of 8 samples)
- Selected frequency band option
- Spatial averaging in ”named” AAL regions

Mobile experiment set-ups, so far…
- Common spatial pattern- BCI
- Stimulus presentation options: video, image, text, audio
- Neuro-feedback

EEG imaging

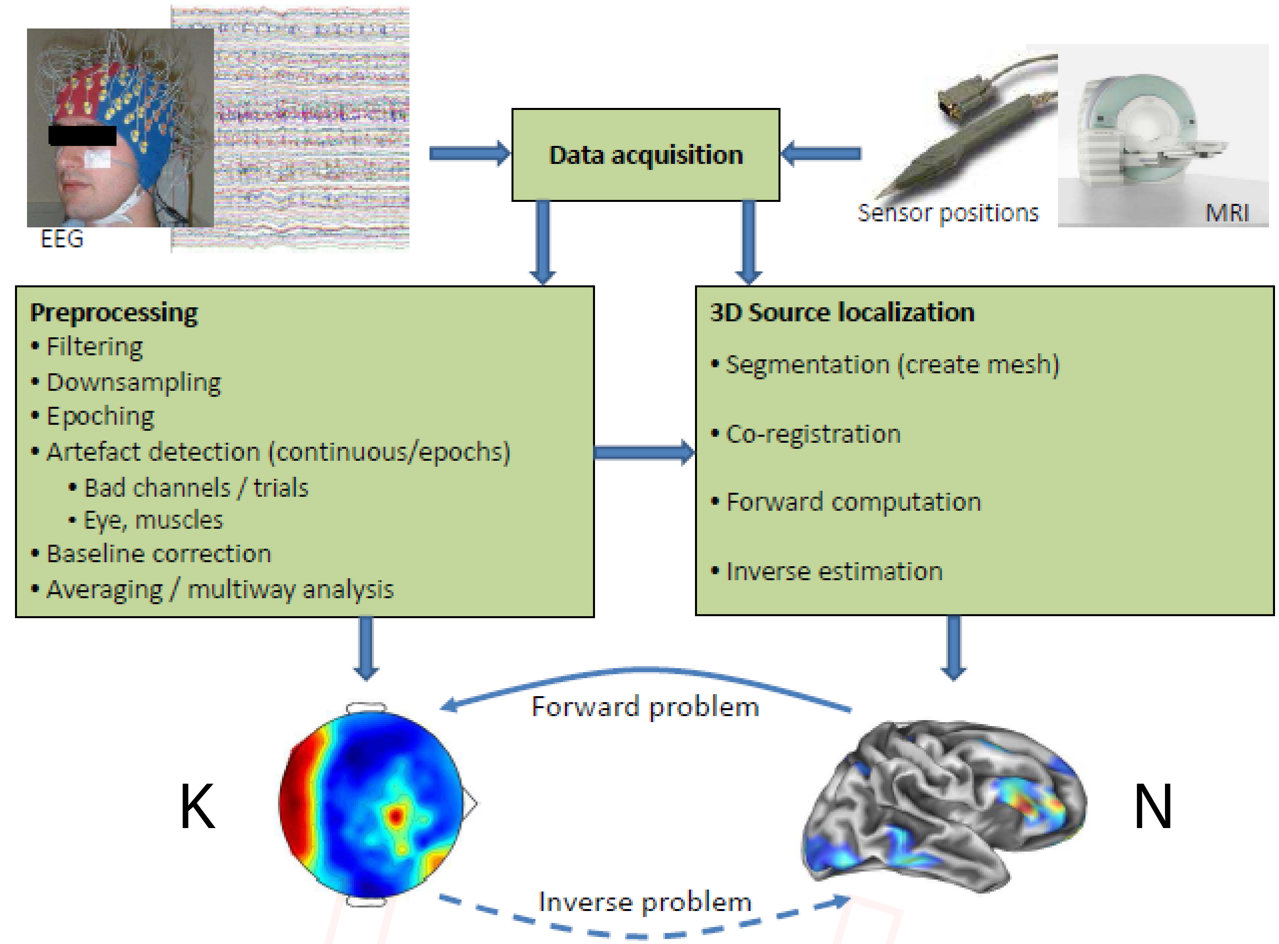
Linear ill-posed inverse problem

X: N x T
Y: K x T
A: K x N

N >> K

Need priors to solve!

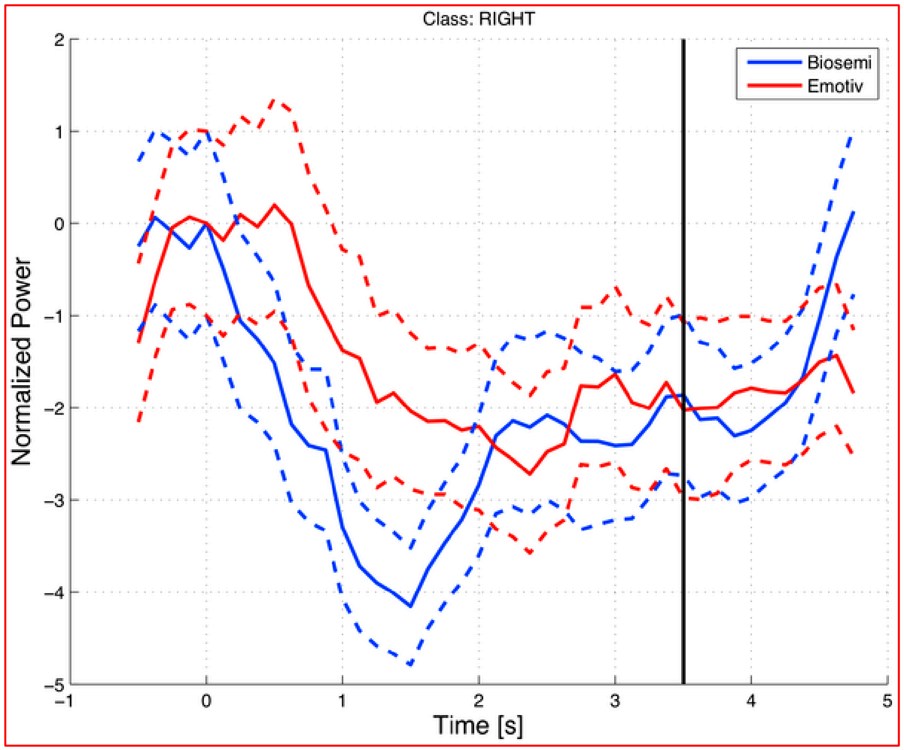
SBS: smoothness
 -minimum norm
Bayesian inference / 10 sec.



$$Y_{k,t} = \sum_{n=1}^{N} A_{k,n} X_{n,t} + E_{k,t}.$$

C. Stahlhut: Functional Brain Imaging by EEG: A Window to the Human Mind. PhD-Thesis (2011), DTU Informatics

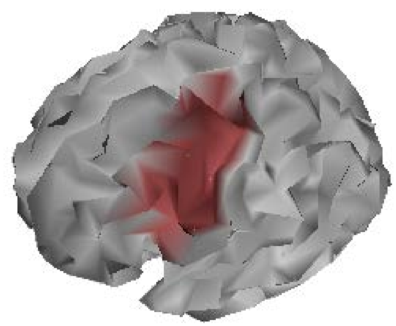
Do we get meaningful 3D reconstructions?

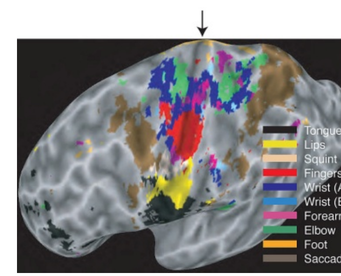


Imagined finger tapping

Left or <u>right</u> cued (at t=0)

Signal collected from an AAL region (n=80)





Meier, Jeffrey D., Tyson N. Aflalo, Sabine Kastner, and Michael SA Graziano. Complex organization of human primary motor cortex: a high-resolution fMRI study.Journal of neurophysiology 100(4) :800-1812 (2008).

A. Stopczynski, C. Stahlhut, M.K. Petersen, J.E. Larsen, C.F. Jensen, M.G. Ivanova, T.S. Andersen, L.K. Hansen. *Smartphones as pocketable labs: Visions for mobile brain imaging and neurofeedback.* International Journal of Psychophysiology, (2014).

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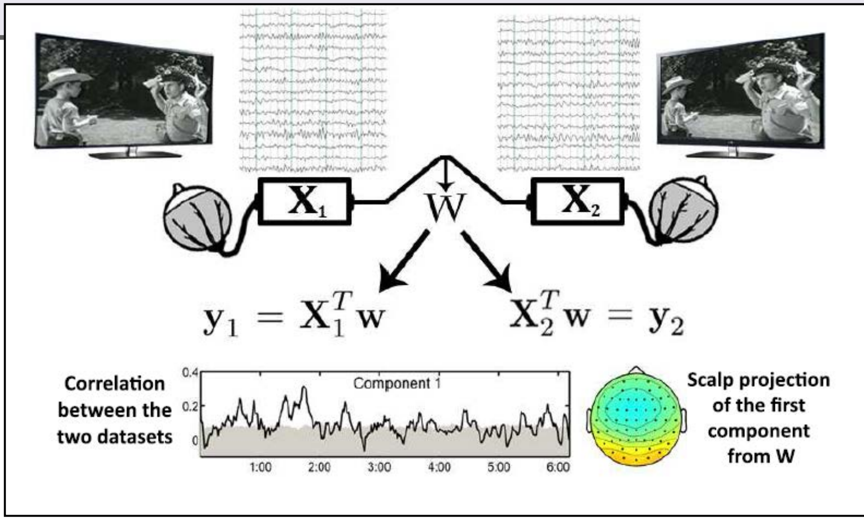
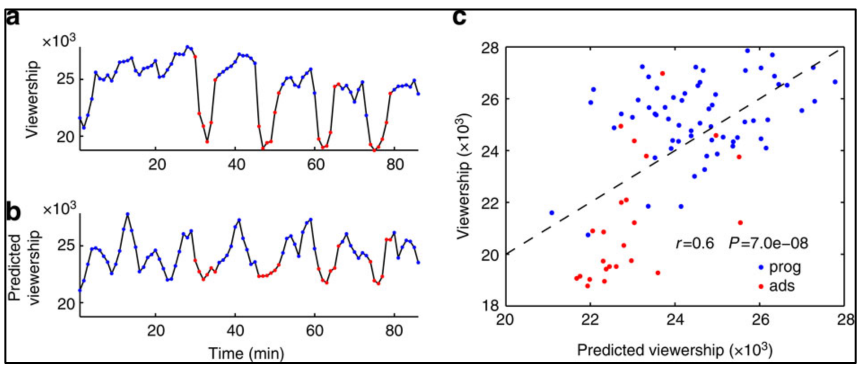
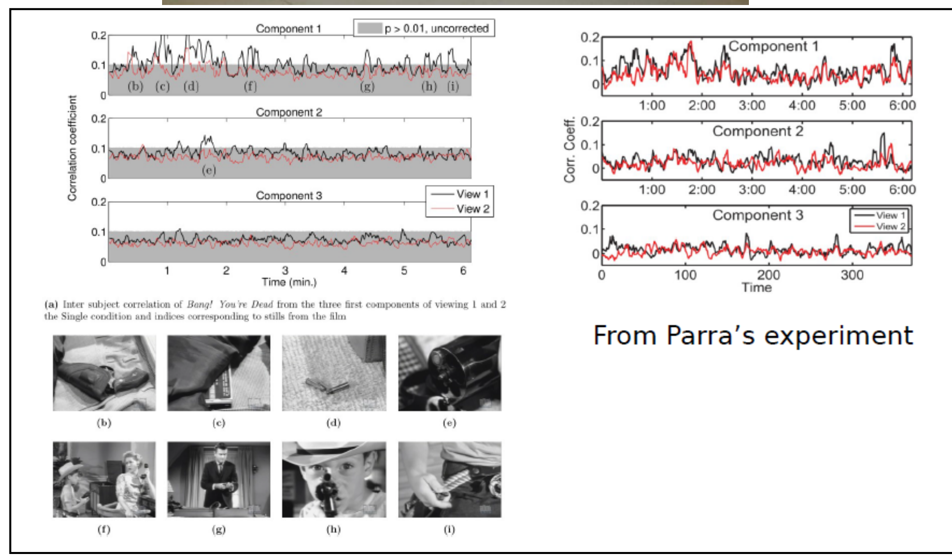
Imaging engagement in the classroom







JP. Dmochowski et al, "Correlated components of ongoing EEG point to emotionally laden attention a possible marker of engagement?" Frontiers of Human Neuroscience, 6:112, April 2012.

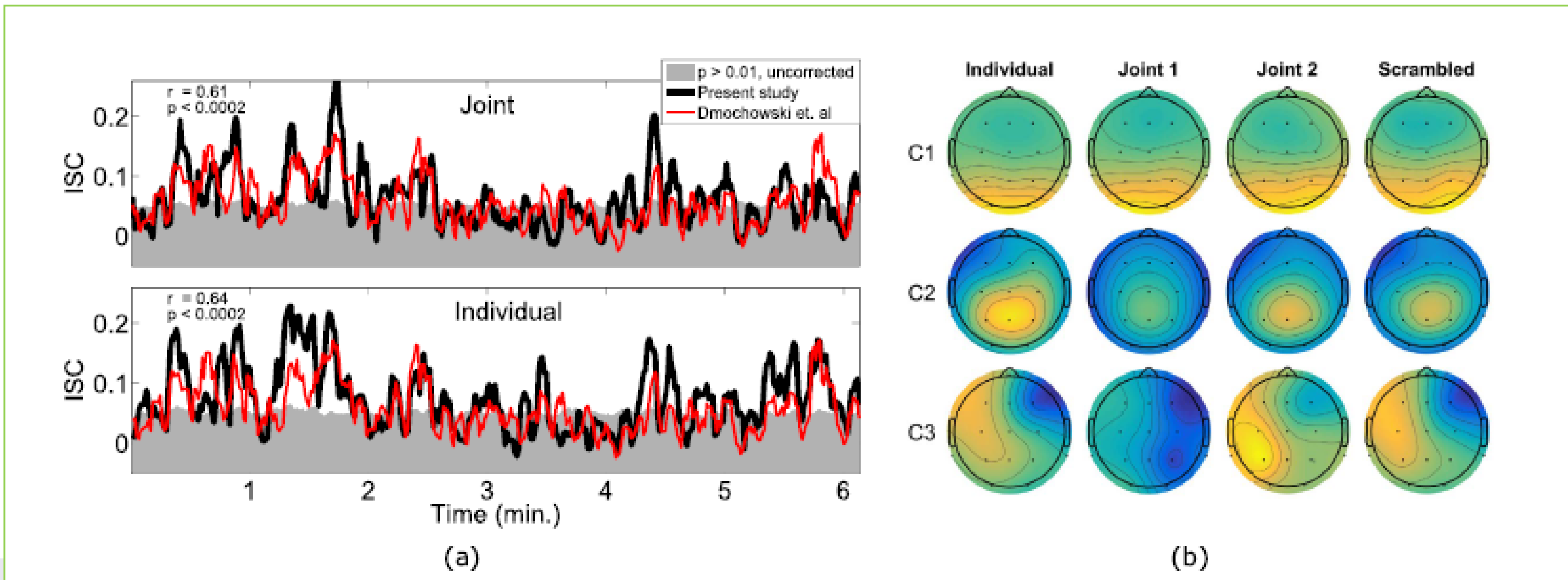
JP. Dmochowski et al, "Audience preferences are predicted by temporal reliability of neural processing", Nature Communications 5: 4567, July 2014.

S Kamronn Poulsen AT, Hansen LK. Multiview Bayesian correlated component analysis. Neural computation. 2015.

AT Poulsen, Kamronn S, Dmochowski J, Parra LC, Hansen LK. EEG in the classroom: Synchronised neural recordings during video presentation. Scientific Reports. 7:43916 2017.

Reproducing Parra's intersubject correlation with classroom EEG

Figure 1. Experimental setup for joint viewings. (**Left**) 9 subjects where placed on a line to induce a cinema-like experiences. (**Right**) Subjects seen from the back, watching films projected onto a screen. Tablets recording EEG are resting on the tables behind the subjects. The signal is transmitted wirelessly from each subject.



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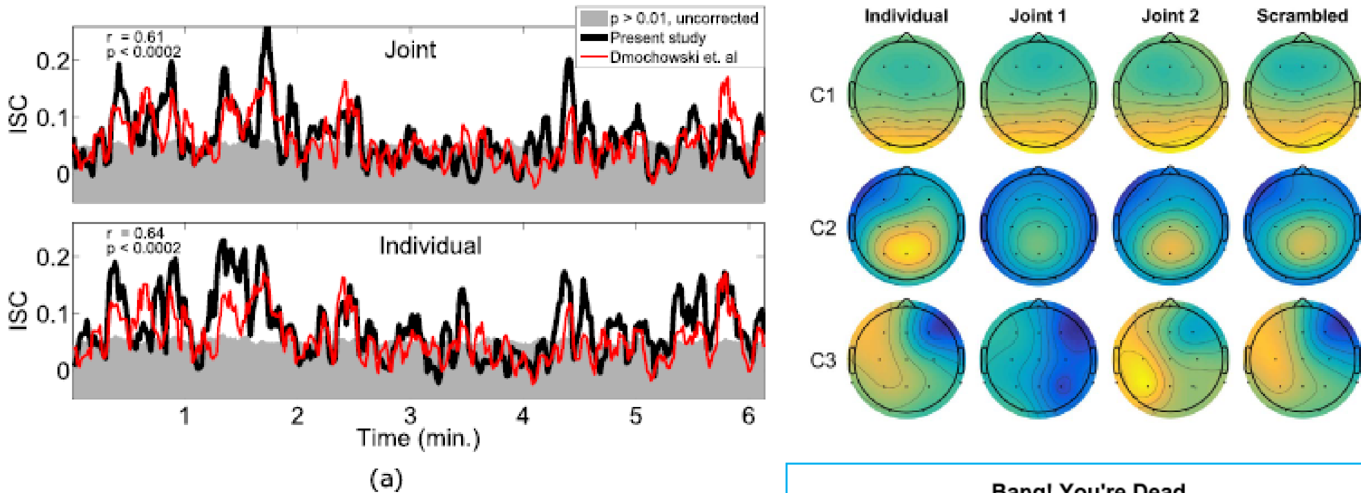
intersubject correlation ..towards a mechanism



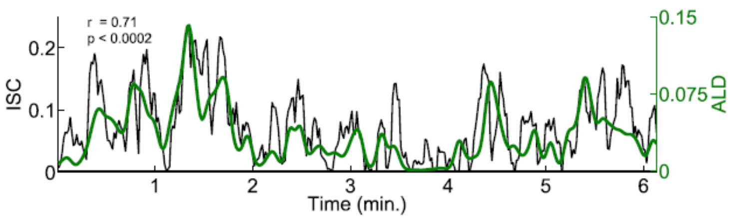


Figure 4. The ISC of the first CorrCA component is temporally correlated with the average luminance differences (ALD) of the film stimulus. ALD is calculated as the frame-to-frame difference in pixel intensity, smoothed to match the 5 s window of ISC, and mainly reflects the frequency of changes in camera position. Data computed from the neural responses of subjects watching *Bang You're Dead*.

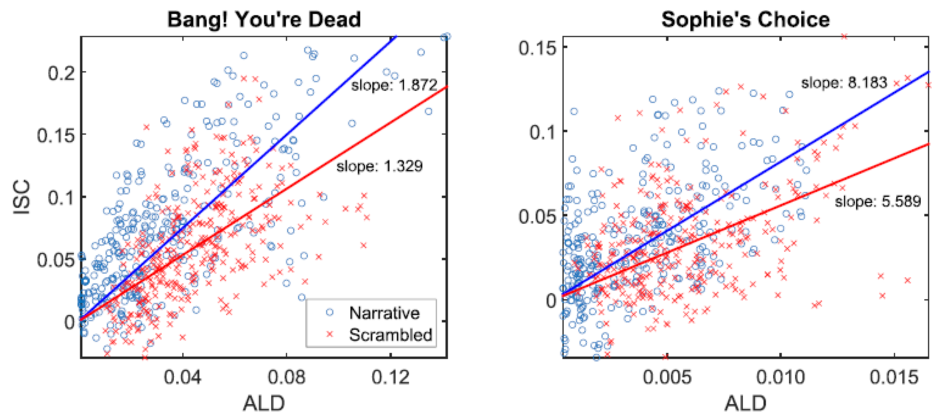


Figure 5. Relation between the ISC and the ALD for different conditions. Each point indicates a point in the ISC time course as seen in Fig. 2a (5 s windows, 80% overlap) and the corresponding ALD calculated from the visual stimulus. It is evident that time points with higher luminance fluctuations (hight ALD) result in higher correlation of brain activity across subjects (high ISC). The indicated "slope" is a least squares fit of the slope of lines passing through (0, 0). The slope indicates the strength of ISC for a given ALD value. For both films there is a significant drop in the slope ($p < 0.01$: block permutation test with block size $B = 25$ sec), thus the original narrative (blue) elicits higher ISC than the less engaging scrambled version of the films (red). Note that brightness of the scenes in *Sophie's Choice* is much lower than in *Bang! You're dead*, resulting in an ALD that is lower by almost a factor 10.

Müller, M. M. *et al.* "Feature-selective attention enhances color signals in early visual areas of the human brain". PNAS **103,** 14250–4 (2006).

Neurotech for 24 / 7 brain state monitoring: EarEEG

<u>Aim:</u>

A discreete, <u>non-invasive</u> solution for long time recording in the wild

<u>Status</u>

EarEEG is in well-working prototype

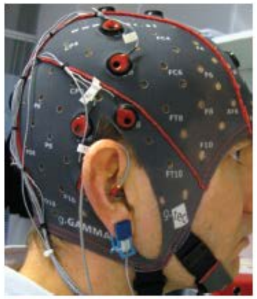
Classical EEG reproduced: Sustained and event related responses to audio and visual stimulus

High mutual information between ear and scalp EEG

(a) An earplug with electrodes ERA, ERB and ERH visible.

(b) An earplug with electrodes and connector (opposite view of Figure 1(a)). Electrode ERE is visible.

(c) Right ear with earplug.

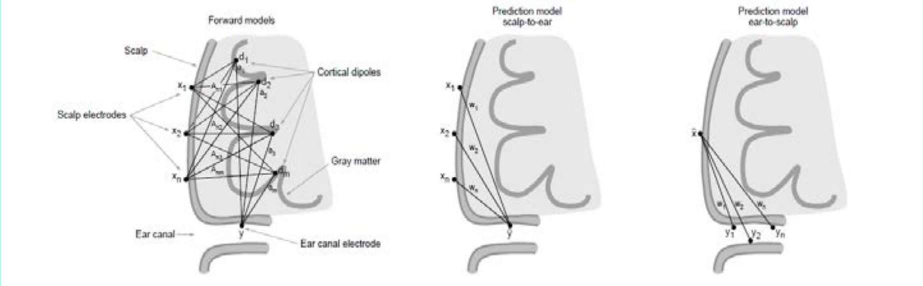


(d) Side view of test subject showing the recording setup.

Fig. 1. View of a right ear earplug and the Ear-EEG recording setup.

Kidmose, Preben, et al. "Ear-EEG from generic earpieces: A feasibility study." *Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE*. IEEE, 2013.

Neurotech for 24 / 7 brain state monitoring: EarEEG



On the keyhole hypothesis: High mutual information between Ear and Scalp EEG

Kaare B. Mikkelsen[a], Preben Kidmose[a,*], Lars Kai Hansen[b]

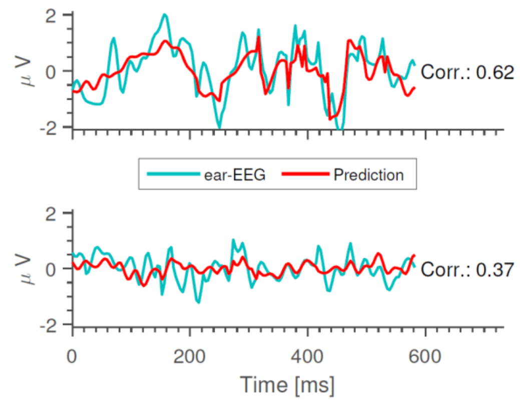


Figure 2: Short snippets of ear-EEG measurements together with their predictions.

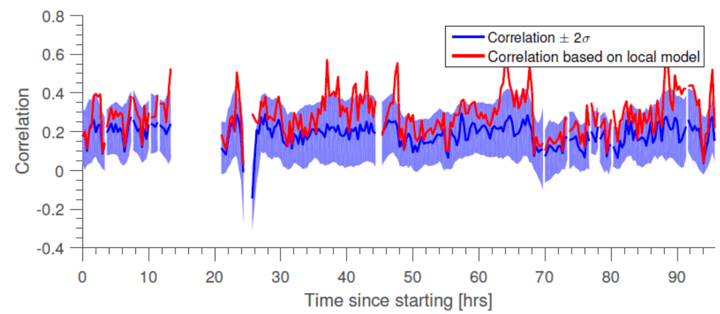
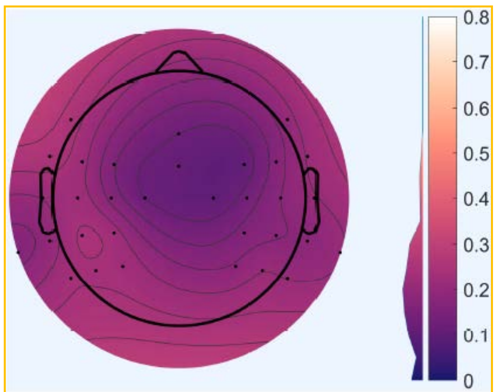
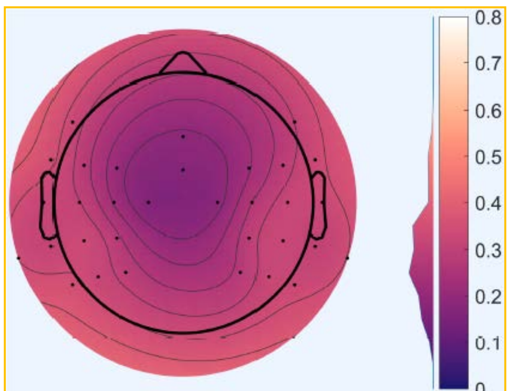


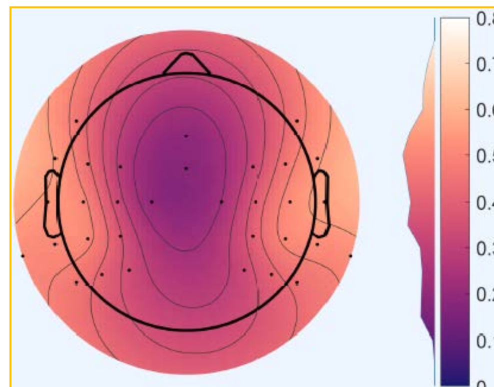
Figure 4: Prediction correlation, ρ, as a function of time since training (in blue). Shown in red is prediction correlation for a model trained on data within the last 10 minutes. Gaps correspond to data missing in the original data set.



(a) Using only the left ear.



(b) Decoupled ears.



(c) Coupled ears, with common reference.

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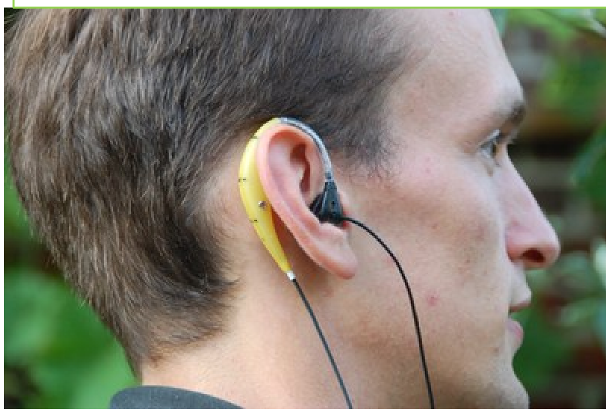
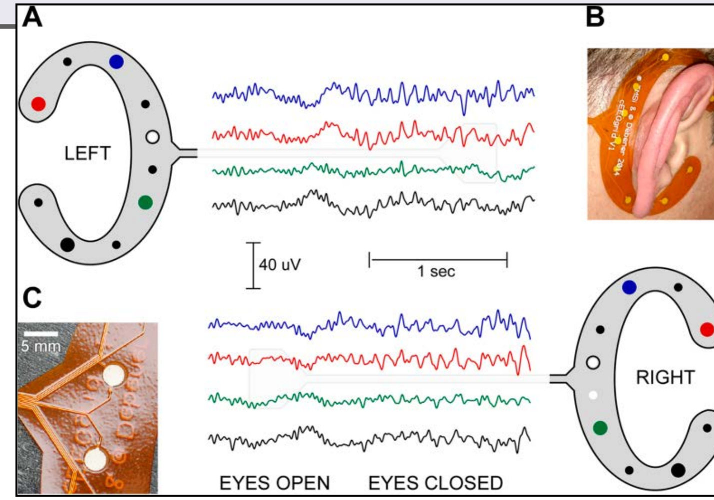
Debener & Vos's mobile EEG devices

Maarten De Vos, Oxford +
Neuropsychology at the University of Oldenburg,
CRITIAS and Sonomax, Canada.



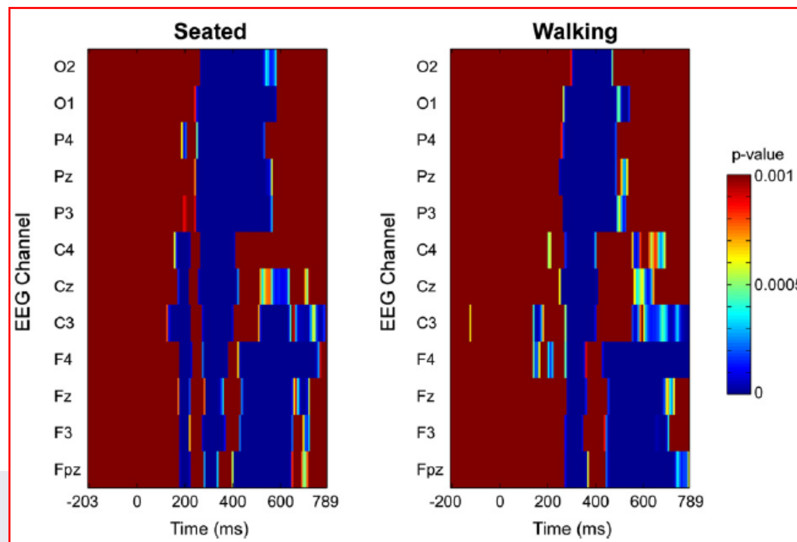


Stefan Debener, Maarten De Vos,
Neuropsychology at the University of Oldenburg,

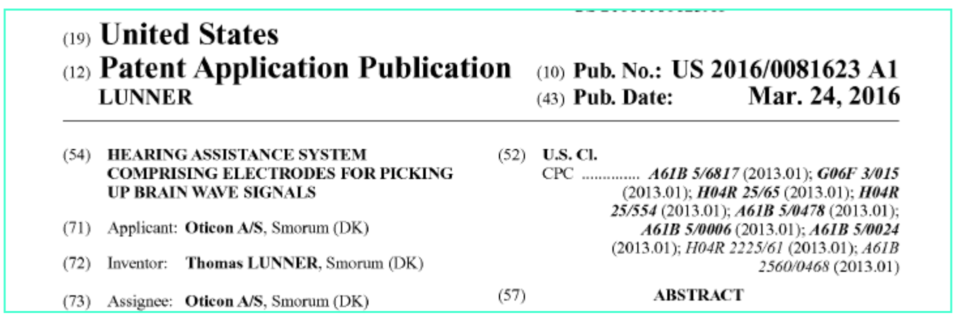
Towards a truly mobile auditory brain–computer interface: Exploring the P300 to take away

Maarten De Vos [a,b,c,*], Katharina Gandras [a], Stefan Debener [a,b,c]

Fig. 1. The mobile EEG system as proposed by Debener et al. (2012) consists of an amplifier-power supply unit, which is attached to the cap at the back of the head (weight 48 g, size 49 × 49 × 21 mm).



Oticon mobile EEG device



(19) **United States**
(12) **Patent Application Publication**
LUNNER

(10) **Pub. No.: US 2016/0081623 A1**
(43) **Pub. Date: Mar. 24, 2016**

(54) **HEARING ASSISTANCE SYSTEM COMPRISING ELECTRODES FOR PICKING UP BRAIN WAVE SIGNALS**

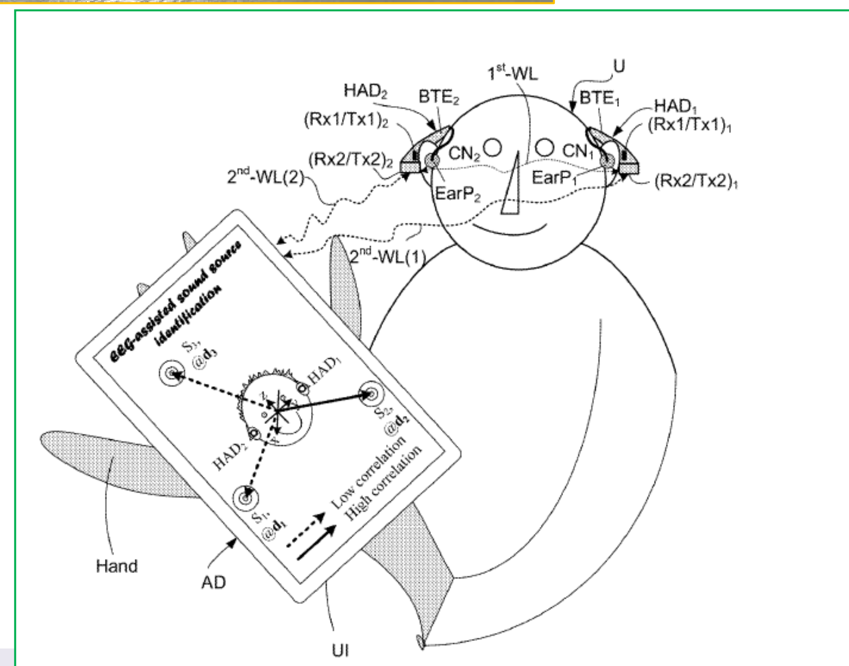
(71) Applicant: **Oticon A/S**, Smorum (DK)

(72) Inventor: **Thomas LUNNER**, Smorum (DK)

(73) Assignee: **Oticon A/S**, Smorum (DK)

(52) **U.S. Cl.**
CPC ***A61B 5/6817*** (2013.01); ***G06F 3/015*** (2013.01); ***H04R 25/65*** (2013.01); ***H04R 25/554*** (2013.01); ***A61B 5/0478*** (2013.01); ***A61B 5/0006*** (2013.01); ***A61B 5/0024*** (2013.01); *H04R 2225/61* (2013.01); *A61B 2560/0468* (2013.01)

(57) **ABSTRACT**



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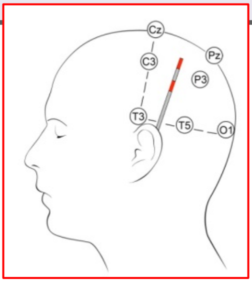
Neurotech for 24/7 brain state monitoring: UNEEG Medical



<u>Aim:</u>

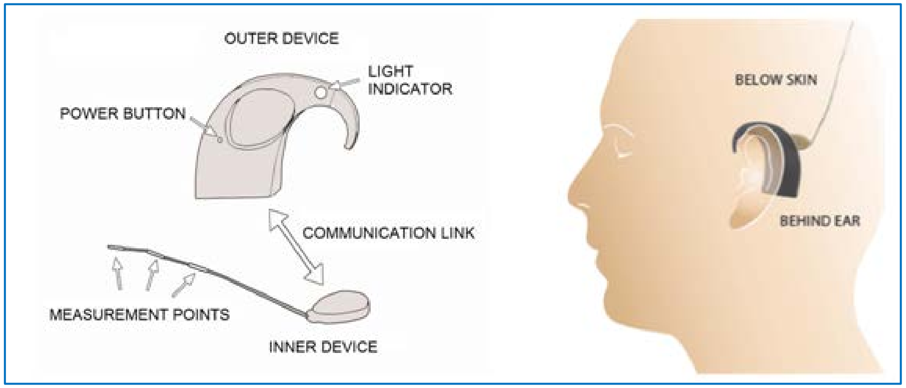
Permanent recording in the wild - Decoding hypoglaemia risk

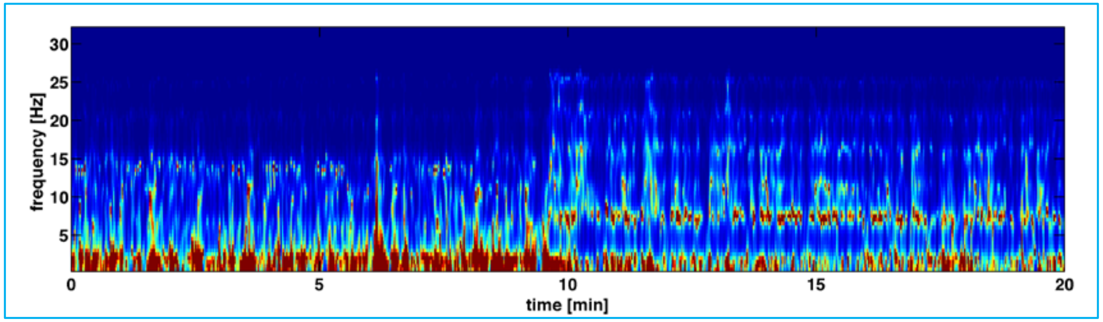
<u>Status</u>

Very stable subcutaneous electrode

Magnetic coupling (signal / power) with outside ear piece

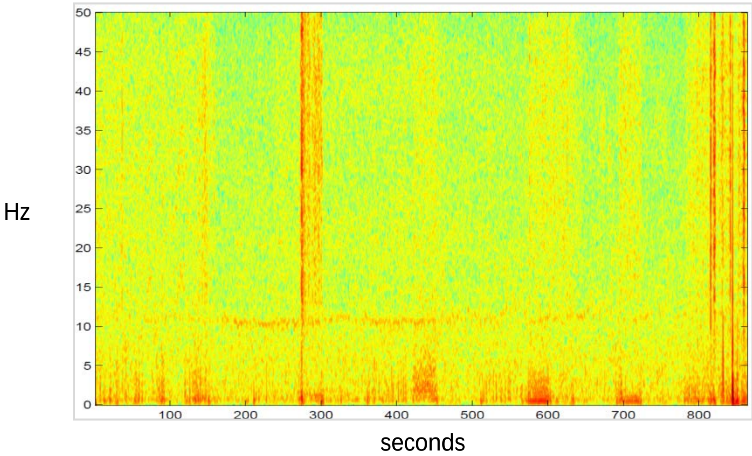
Signal is highly correlated with surface electrode in same location

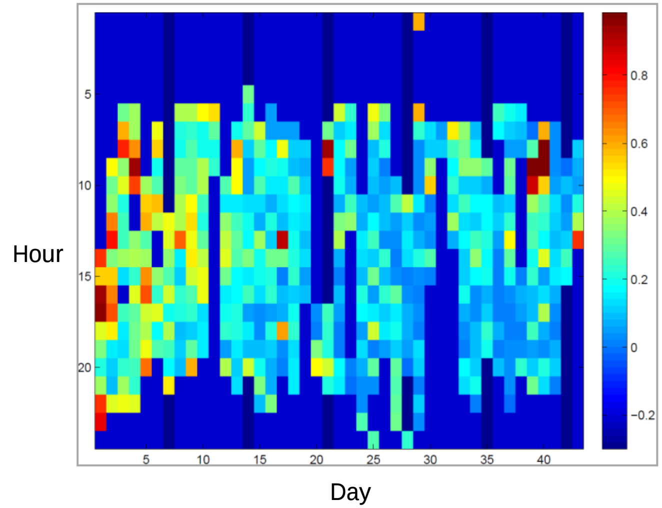




Duun-Henriksen, Jonas, et al. "EEG Signal Quality of a Subcutaneous Recording System Compared to Standard Surface Electrodes." *Journal of Sensors* (2015).
Elsborg, R., Juhl, C., Beck-Nielsen, H., & Remvig, L. (2011). Detecting hypoglycemia by using the brain as a biosensor. INTECH Open Access Publisher.

Ultra long term brain decoding in healthy control: Hyposafe / UNEEG Medical device

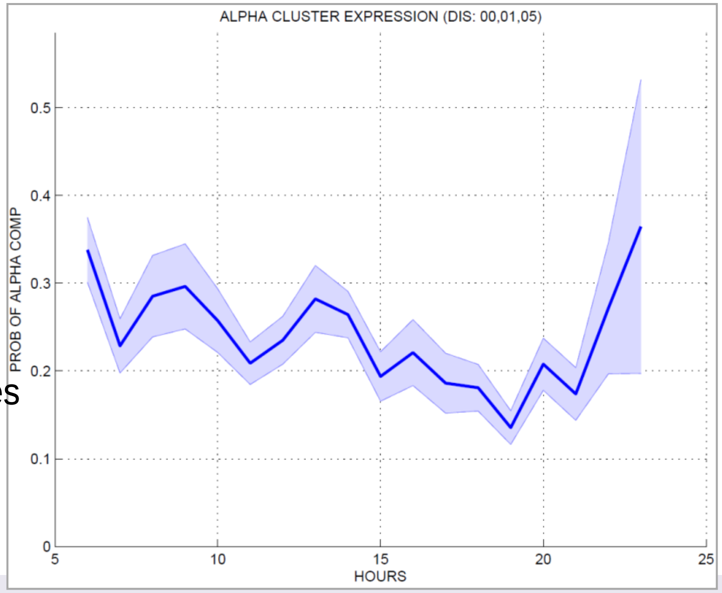




How does (partial) mind wandering vary during the day?

How does a brain on vacation differ from a working brain?

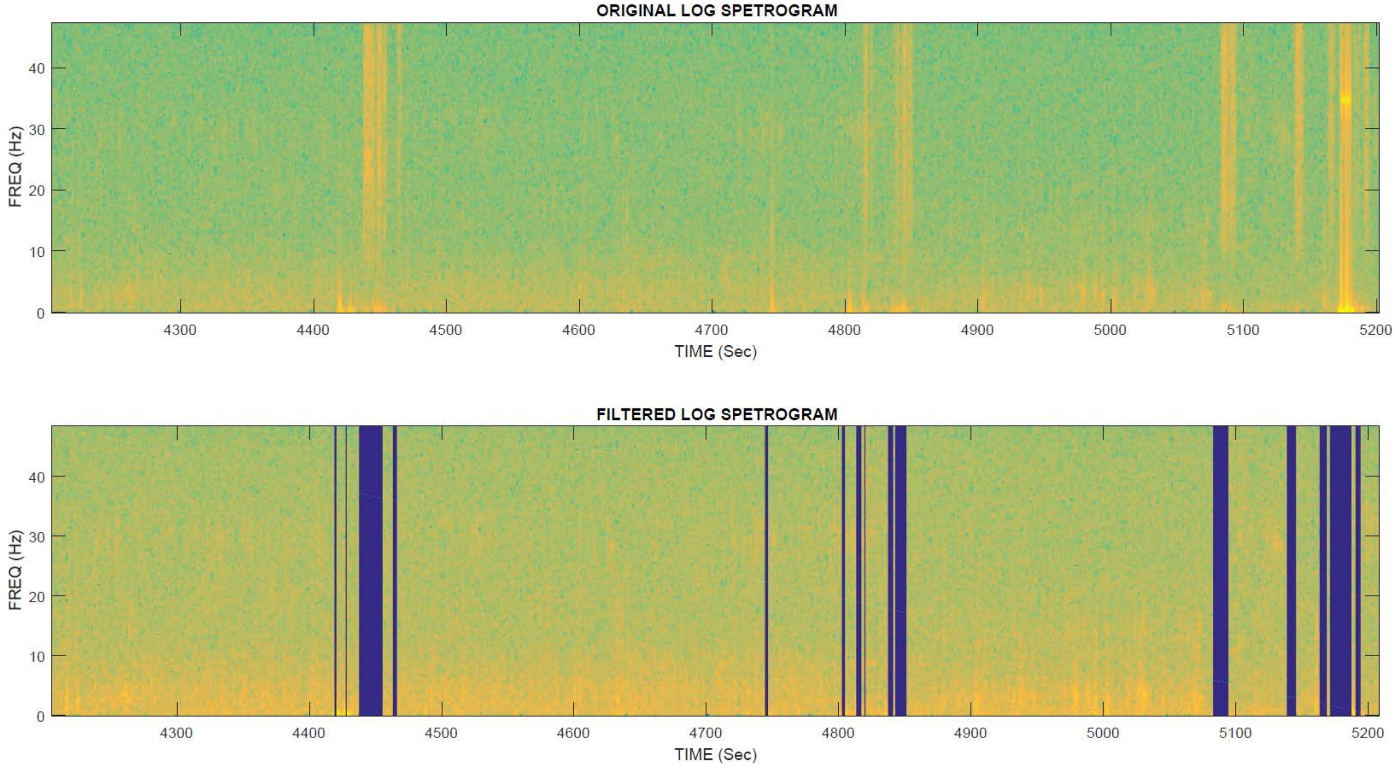
Methods:
Power spectrum over 3 sec win / 2 sec overlap as basic features
Clustering. Manually identify (2) alpha clusters;
Assign power spectra over 45 days to clusters...



Killingsworth, Matthew A., and Daniel T. Gilbert.
"A wandering mind is an unhappy mind." *Science* 330.6006 (2010): 932-932.

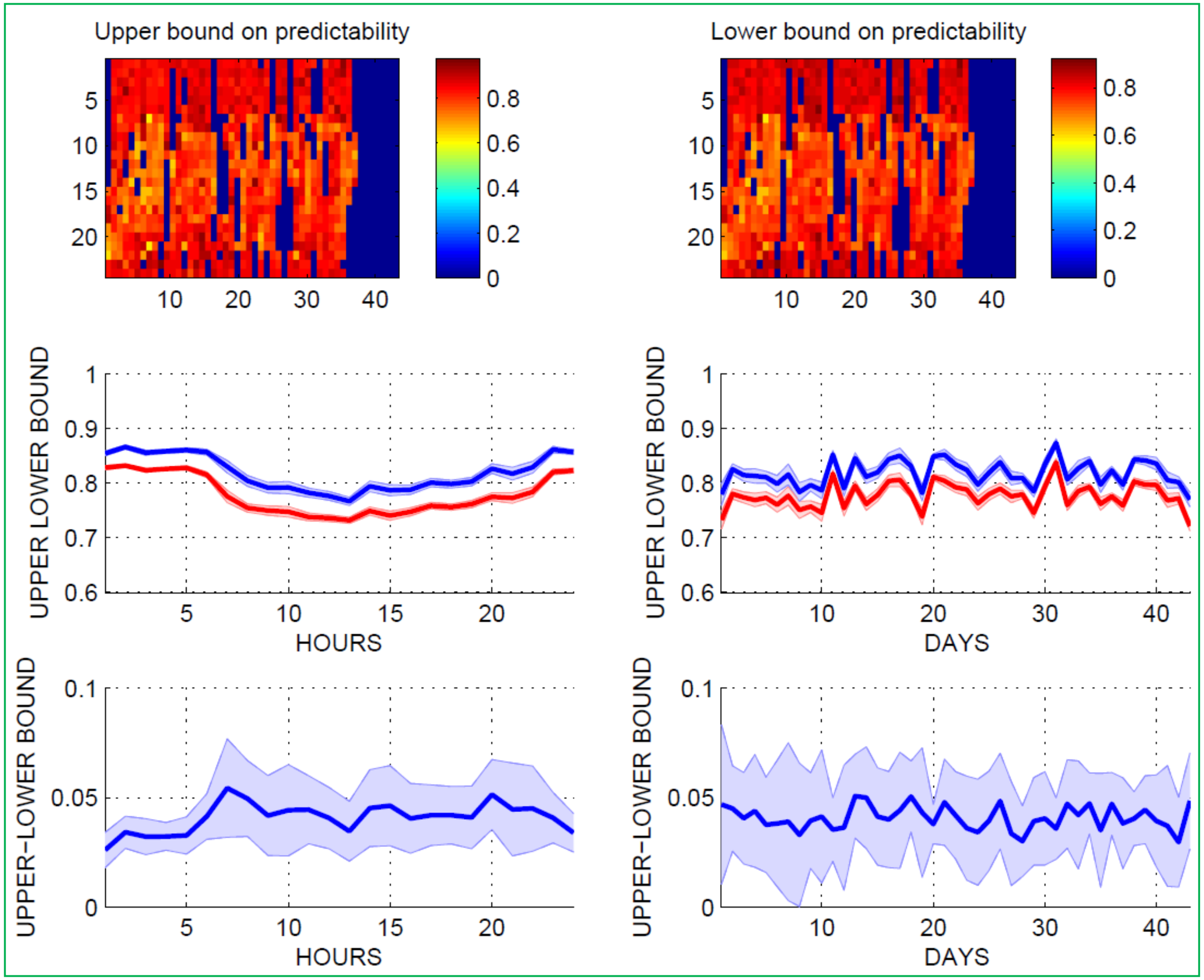
Analytic strategy

Challenge: Ultra-long sequences, seasonal, non-stationary data, with significant artefactual episodes and ”missing data”



Short term predictability

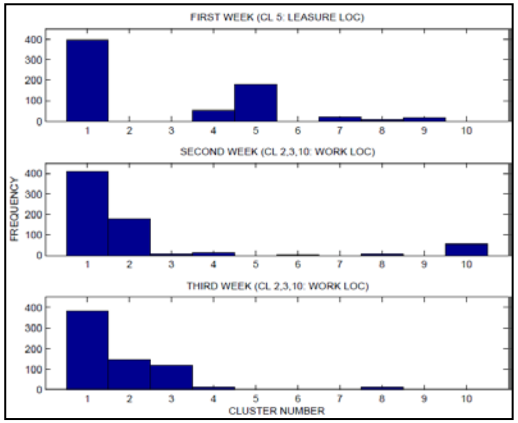
Fano Ineq. Bound on predictability of spectral microstates (ts=1 sec)



Predictability

High at night,

lowest during ”leisure time”



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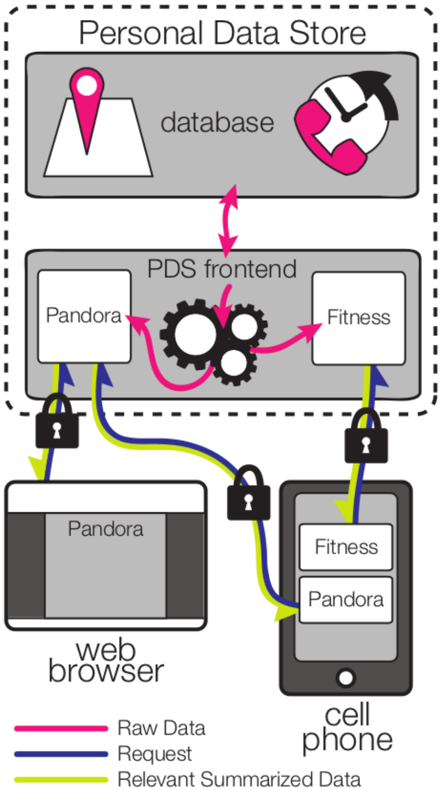
Privacy… it's human to share



Intuitive data

Images, speech, economical, commercial, location, individual thoughts

Non-intuitive data

Health: diet, complete motion patterns

Physiology: heart beat, skin resistance, gaze, brain data, your mind set

Sandy Pentland calls for "**a new deal on data**" with three basic tenets:

1) you have the right to possess your data,
2) to control how it is used,
3) to destroy or distribute it as you see fit.

Privacy for Personal Neuroinformatics

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Acknowledgment - Q&A

Lundbeck Foundation (CIMBI, CINS)
Novo Nordisk Foundation (BASICS project)
Innovation Foundation Denmark (NeuroTech 24/7)