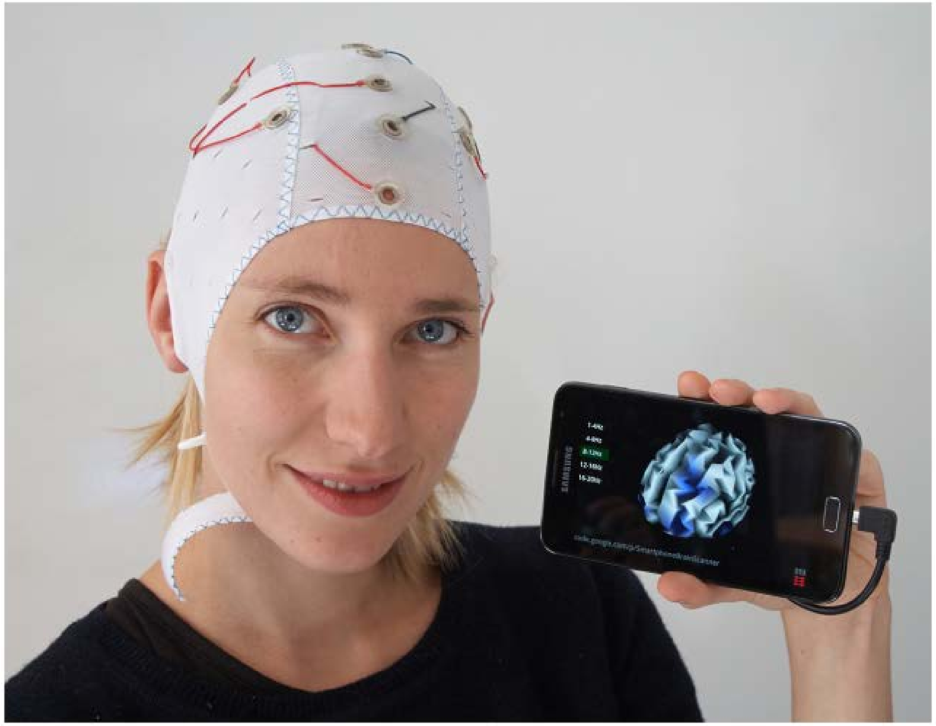
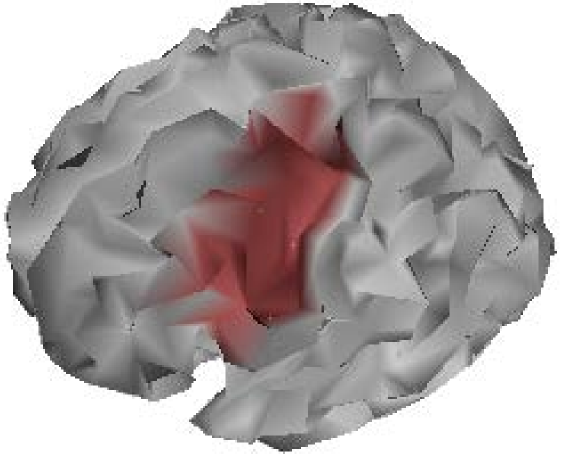
Oticon ESAB 2017

Neuroscience in the Wild

Neurotechnology for 24/7 brain state monitoring





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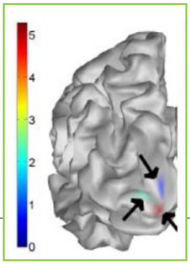
Quick intro

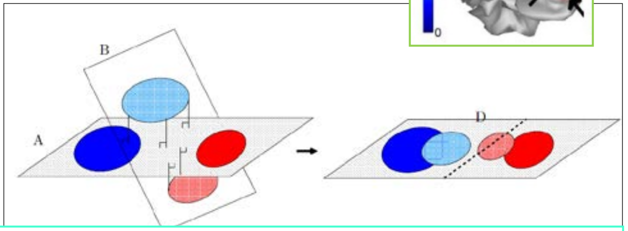
Head of Section for Cognitive Systems, DTU Compute, Technical University of Denmark

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



MLSP 2017: *”Deep Convolutional Neural Networks for Interpretable Analysis of EEG Sleep Stage Scoring… ”*

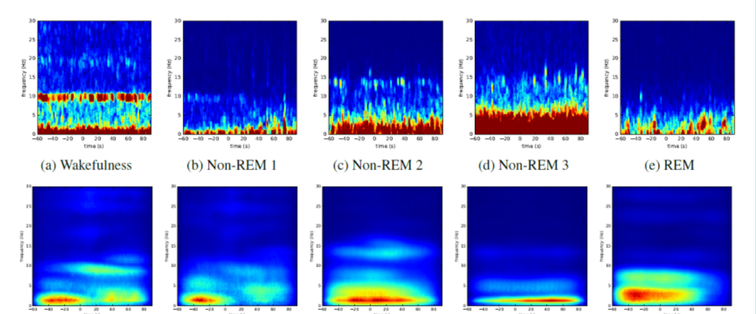


Fig. 1. Sensitivity analysis for subject 7. Top row shows characteristic sleep stage spectra; bottom row presents per-class sensitivity maps.

Promoting ”Neuroscience in the Wild”:

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

Fig. 3. A user interacting with a 3D model of the brain using the handheld brain scanner device with touch-based interaction.

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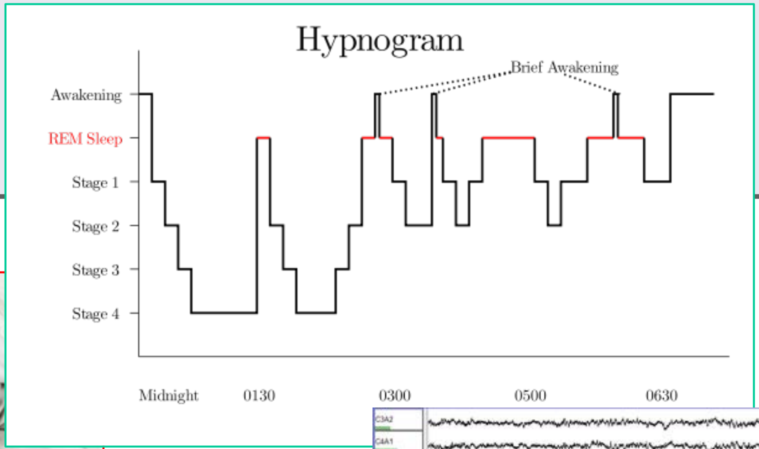
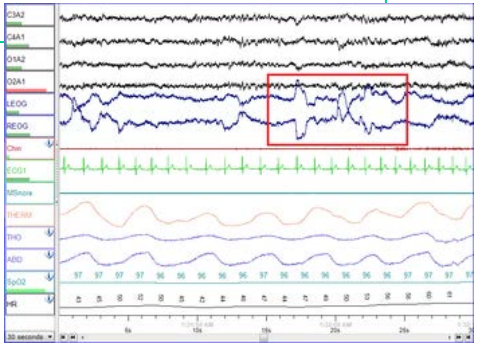
How did you sleep last night?



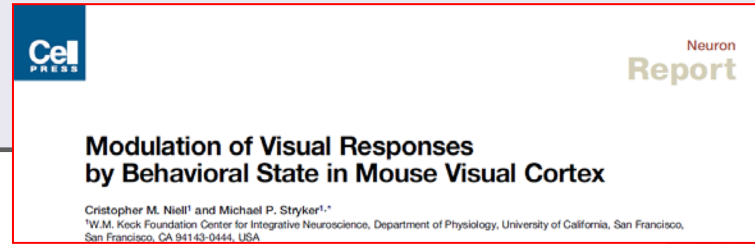


Science, social engineering and bio-medical innovation - all rooted in predictive, causal understanding of human behavior **- "the physics of behavior"**

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 the 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, SBS 2, SBS 3

EarEEG non-invasive, discreet

UNEEG Medical's subcutaneous electrode device

Example SBS 2: Engagement in the classroom

Example EarEEG: the scalp to ear link

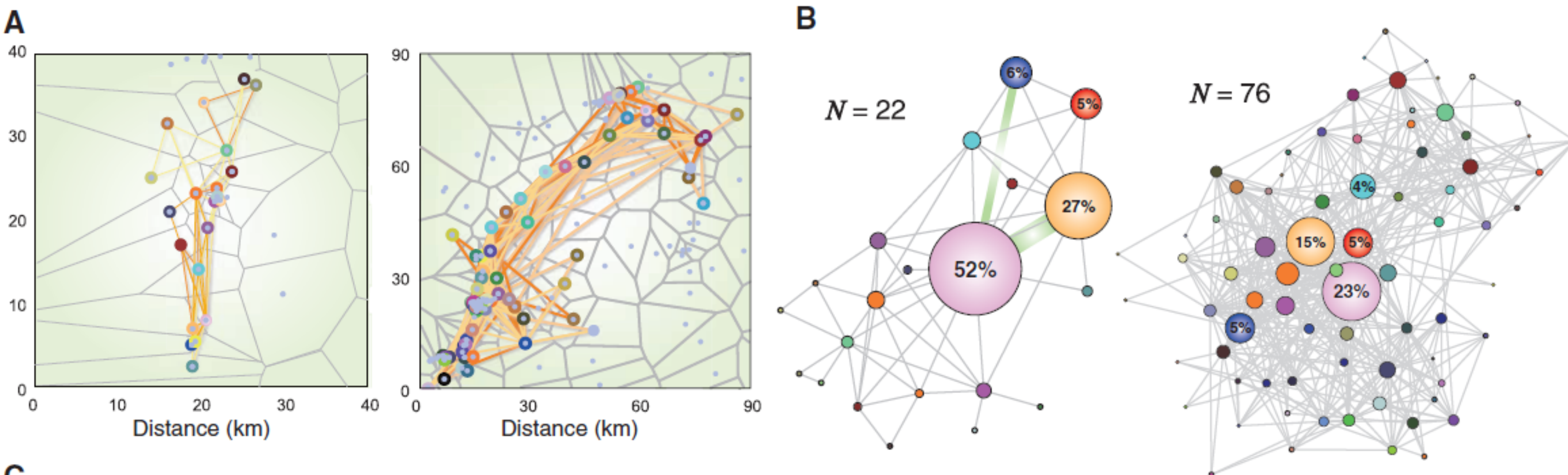
Example UNEEG Medical's Hyposafe device: 40+ days sampling in the wild

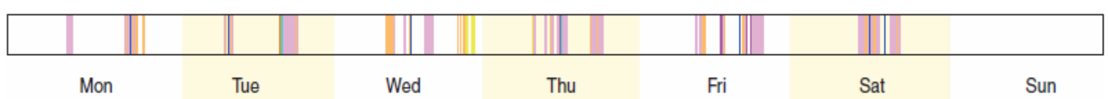
Engel, Andreas K., et al. "Where's the action? The pragmatic turn in cognitive science." *Trends in cognitive sciences* 17.5 (2013): 202-209.
Niell, Cristopher M., and Michael P. Stryker. "Modulation of visual responses by behavioral state in mouse visual cortex." *Neuron* 65.4 (2010): 472-479.

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]*





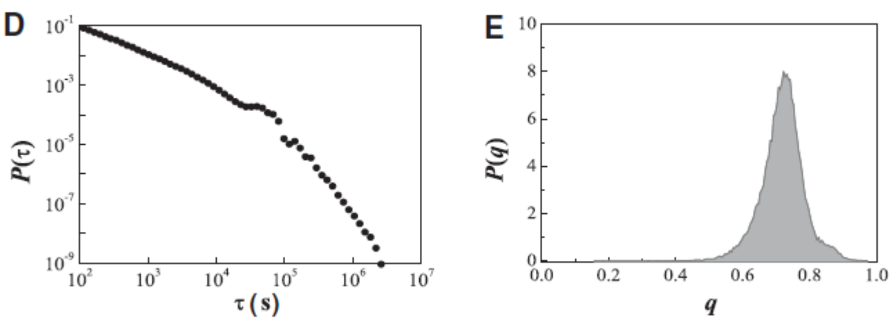


Fig. 1. (**A**) Trajectories of two anonymized mobile phone users who visited the vicinity of $N = 22$ and 76 different towers during the 3-month-long observational period. Each dot corresponds to a mobile phone tower, and each time a user makes a call, the closest tower that routes the call is recorded, 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.

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 AI

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Smartphone brain scanner
https://www.youtube.com/watch?v=i_66KAOzXhU

Mobility projects

Social EEG-

-Joint attention

Mobile real-time EEG Imaging

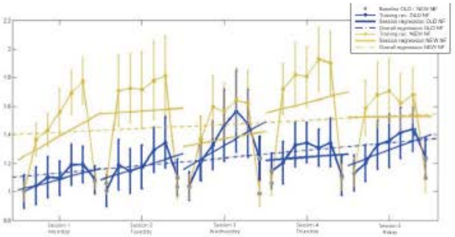
-Neurofeedback

-Digital media & emotion

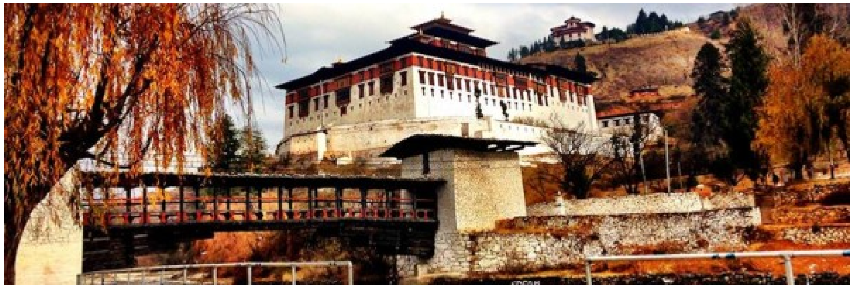
-Bhutan Epilepsy Project

Simon Kamronn

Andreas Trier Poulsen



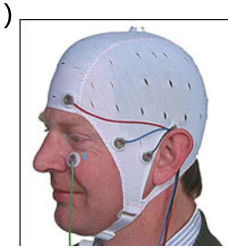
Camilla Falk



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,...)

https://github.com/SmartphoneBrainScanner

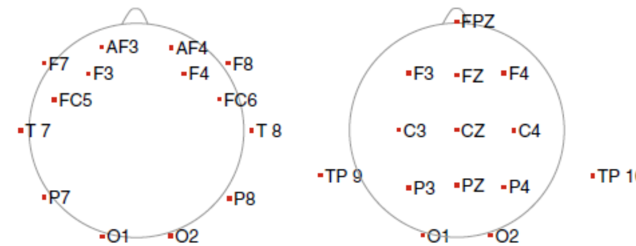
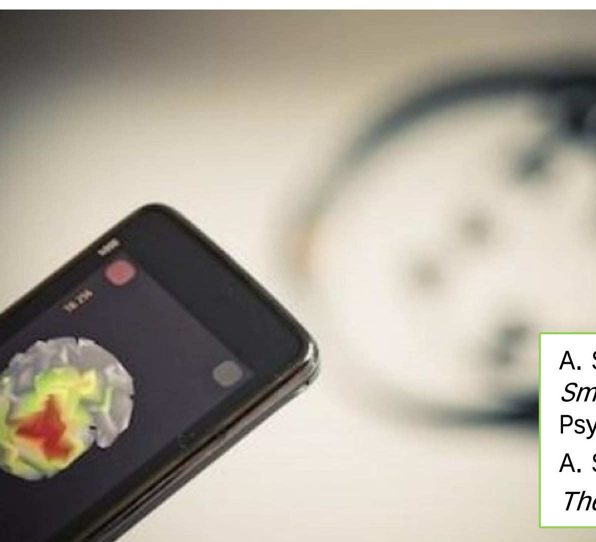


Fig. 5. Electrode locations for two mobile 16 channel EEG setups; the Emotiv neuroheadset using saline sensors positioned laterally (left), versus a standard gel-based Easycap EEG montage including central and midline positions (right).



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)

EEG imaging

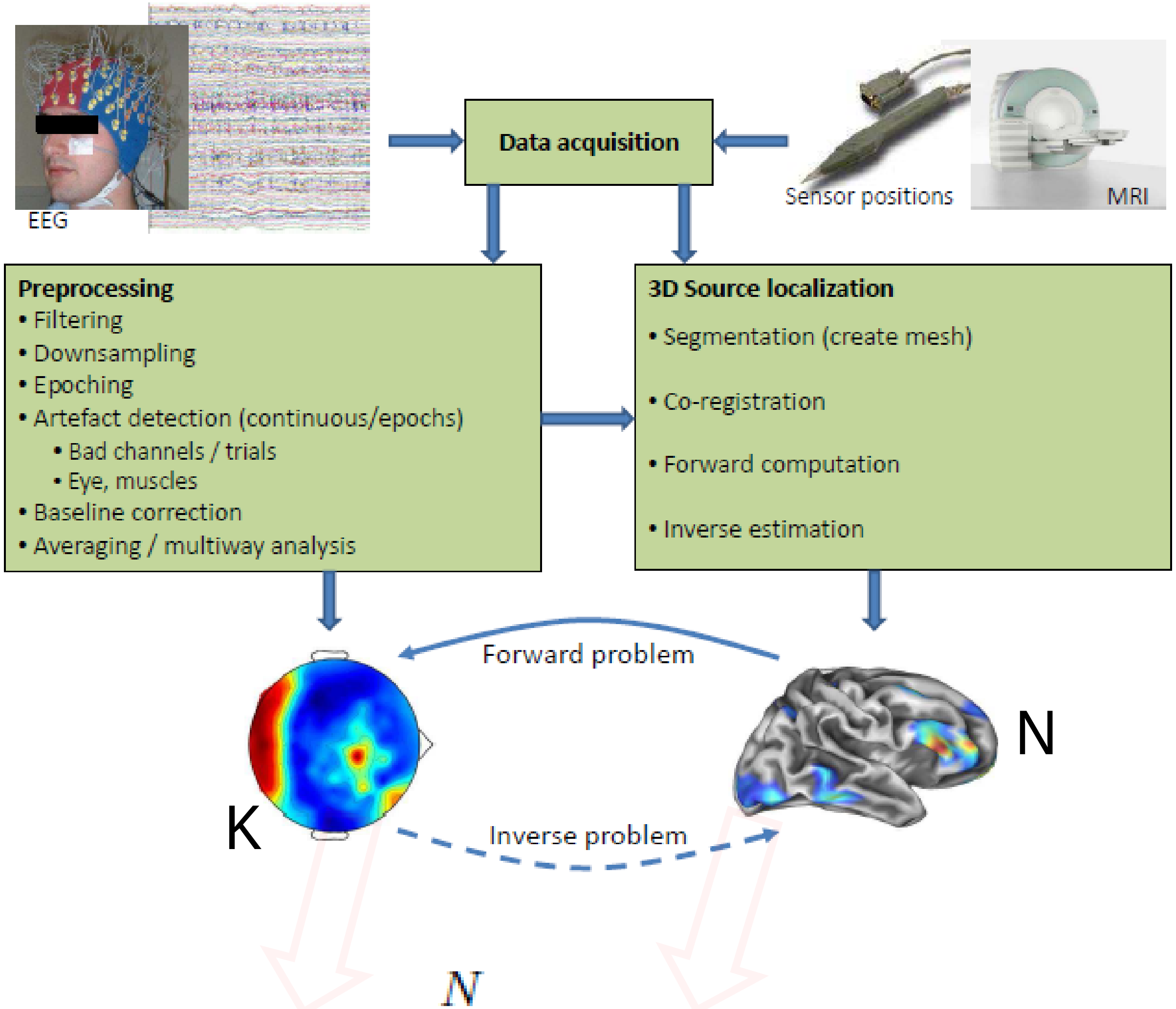
Linear ill-posed
inverse problem

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

N >> K

Need priors to solve!

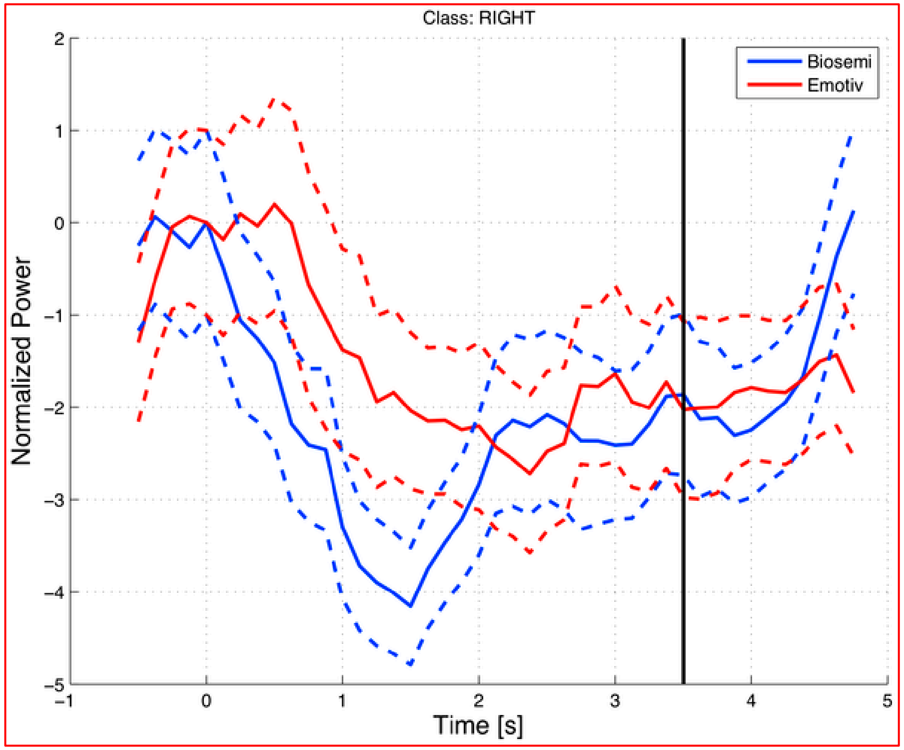
SBS: smoothness
-minimum norm like prior-
Bayesian inference / 10 sec.



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

ST Hansen, LK Hansen. Spatio-temporal reconstruction of brain dynamics from EEG with a Markov prior. NeuroImage, 148:274-283(2017).
ST Hansen, S Hauberg, LK Hansen. Data-driven forward model inference for EEG brain imaging. NeuroImage, 139(1):249-258 (2016).
RS Andersen, AU Eliasen, N Pedersen, MR Andersen, ST Hansen, LK Hansen. EEG source imaging assists decoding in a face recognition task. IEEE ICASSP (2017).
MR Andersen, A Vehtari, O Winther, LK Hansen. Bayesian inference for spatio-temporal spike and slab priors. arXiv:1509.04752. JMLR to appear (2017).

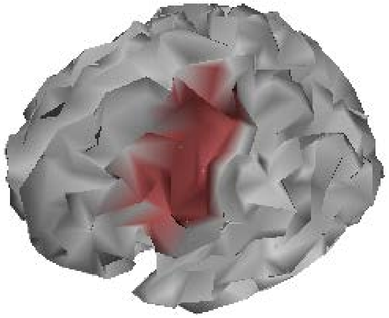
Do we get meaningful 3D reconstructions?

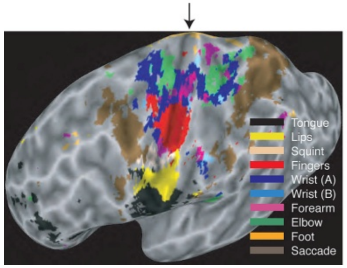


Imagined finger tapping

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).

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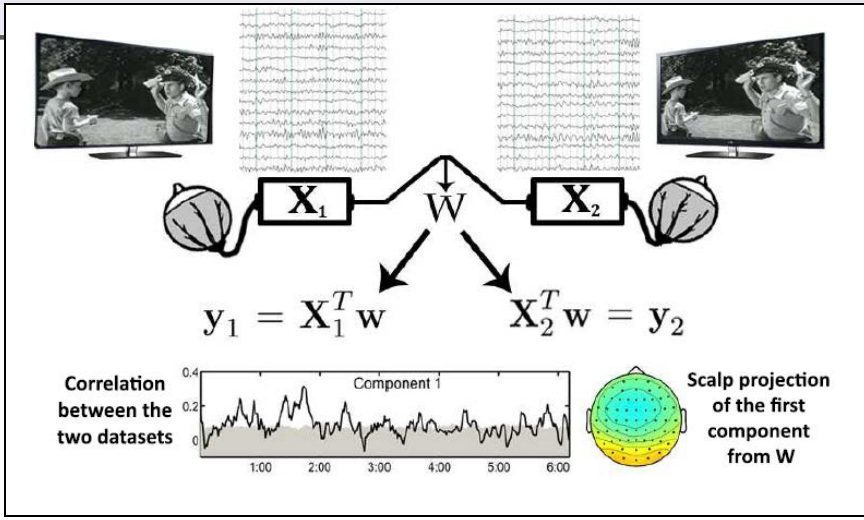
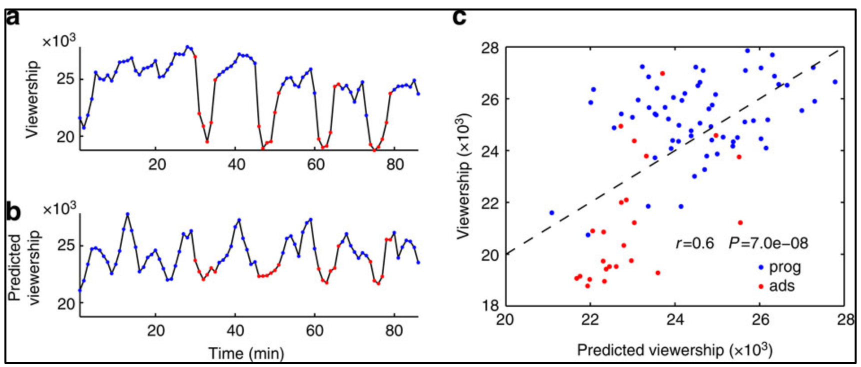
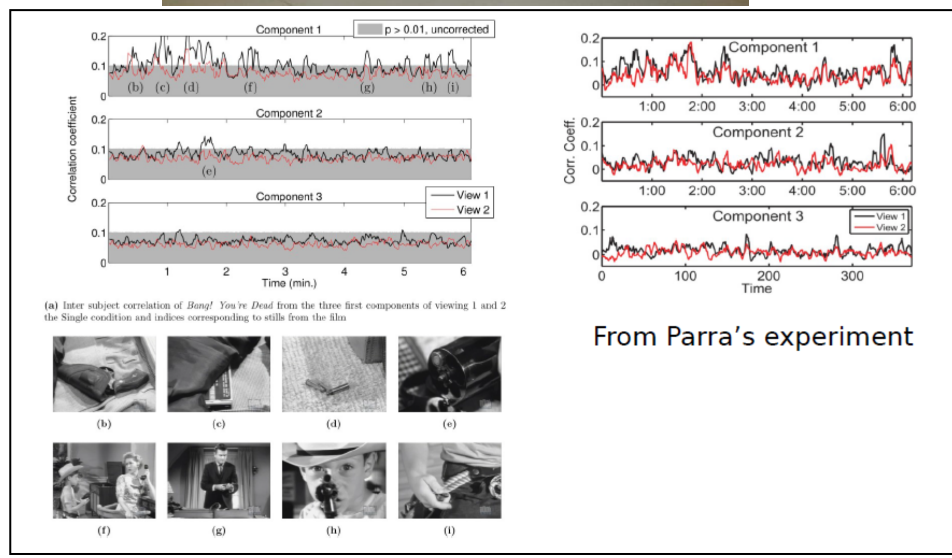
Imaging engagement in the classroom







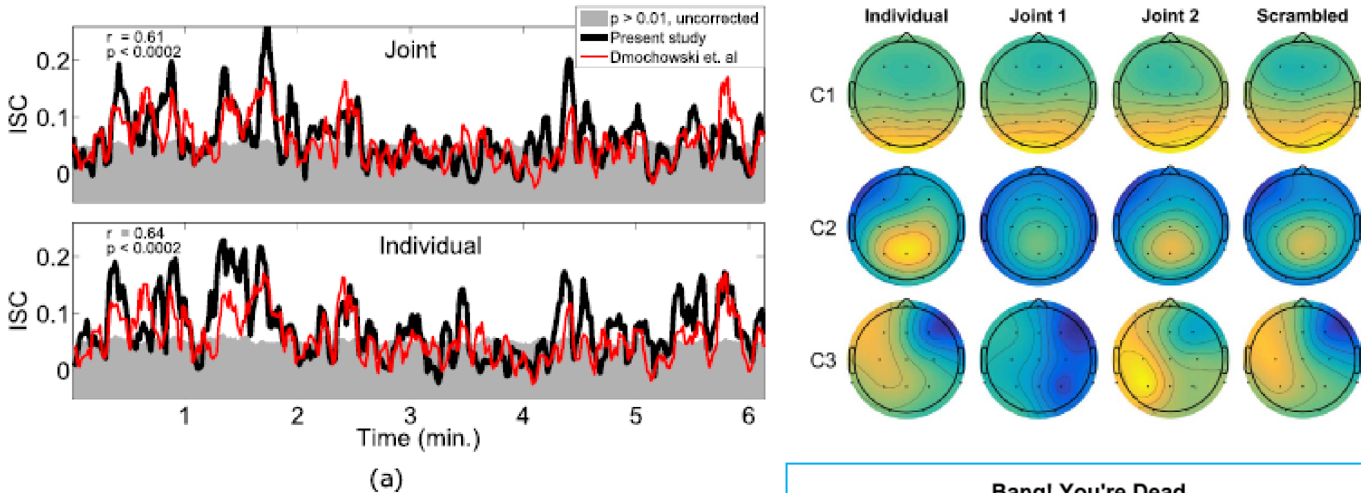
JP. Dmochowski et al, "Correlated components of ongoing EEG point to emotionally laden attention a possible marker of engagement?" Frontiers of Human Neuroscience, 6:112, April 2012.

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.

intersubject correlation ..towards a mechanism



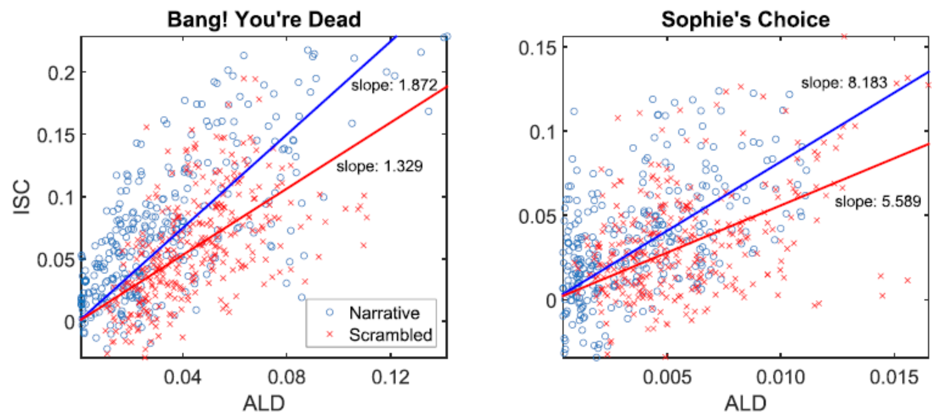


Figure 5. Relation between the ISC and the ALD for different conditions. Each point indicates a point in the ISC time course as seen in Fig. 2a (5 s windows, 80% overlap) and the corresponding ALD calculated from the visual stimulus. It is evident that time points with higher luminance fluctuations (hight 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.

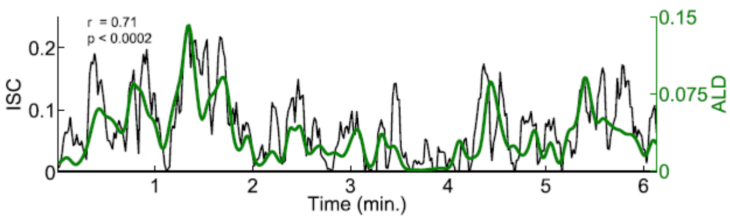
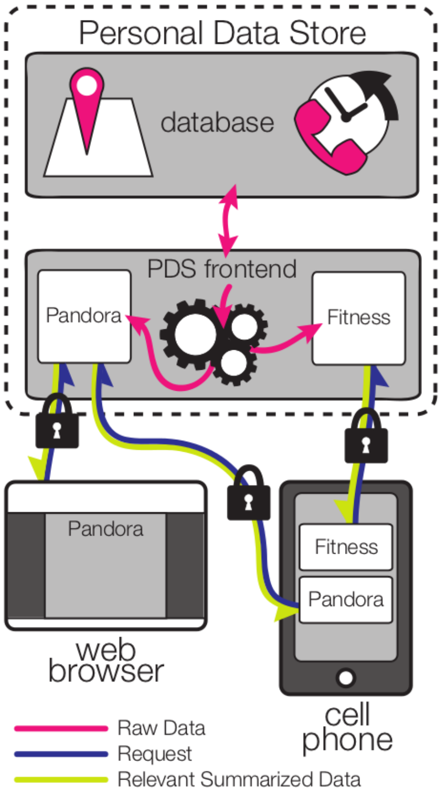


Figure 4. The ISC of the first CorrCA component is temporally correlated with the average luminance differences (ALD) of the film stimulus. ALD is calculated as the frame-to-frame difference in pixel intensity, smoothed to match the 5 s window of ISC, and mainly reflects the frequency of changes in camera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

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

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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2 MIT Media Lab
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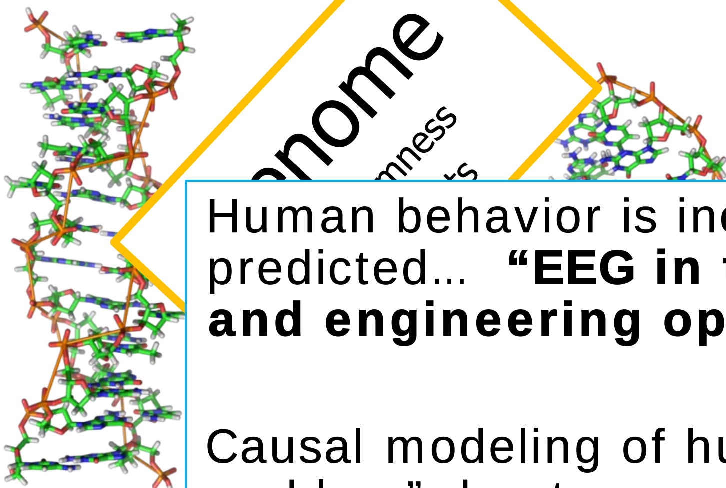
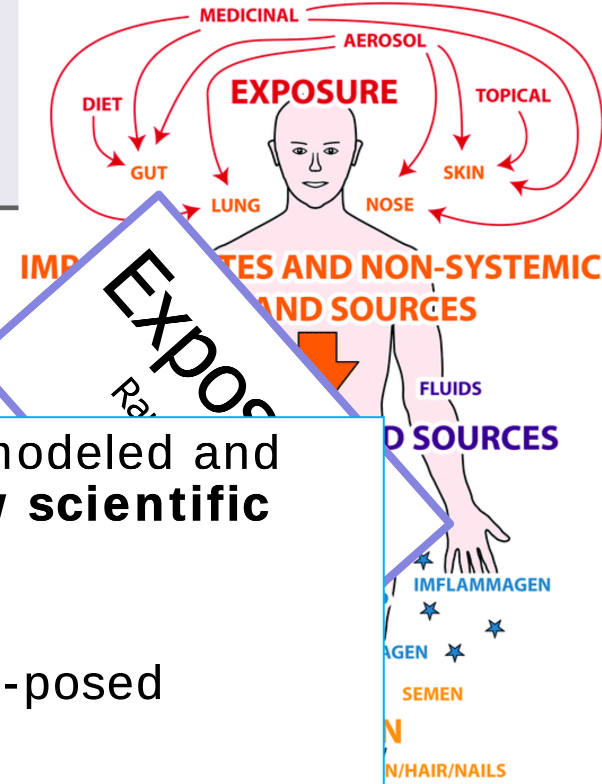
Outlook.. The personal baseline





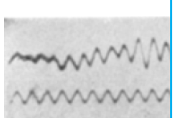
Human behavior is increasingly quantified, modeled and predicted... **“EEG in the wild will add new scientific and engineering opportunities”**

Causal modeling of human behavior is an ”ill-posed problem” due to massive undersampling

Design variability is increasingly quantified: **Genomics** ...

Personal history variability: **Exposome** ...smartphone data, social media, etc.

Intrinsic brain variability: **The Cognitome** ...**will be soon be collected from a brain near you**



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Acknowledgment - Q&A

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Innovation Foundation Denmark (NeuroTech 24/7)

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