Quantified living

Self-monitoring, brain monitoring

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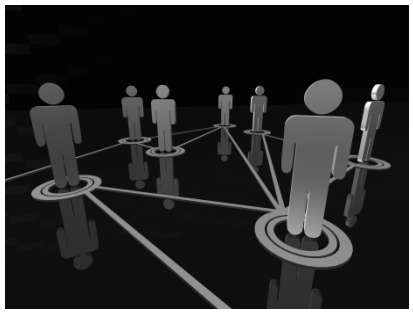
Cognitive Systems

10 faculty, 2 senior scientists
6 postdocs, 3 research assistants
25 Ph.D. students



Digital media

Social computing

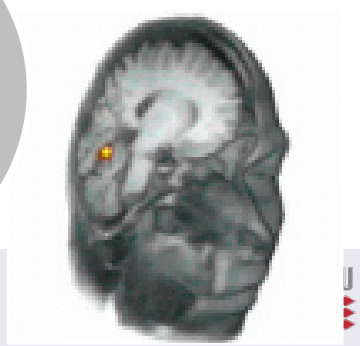
Statistical modeling

"Machine learning"

Cognitive Neuroscience

Mobile Systems

Neuro-informatics



Cimbi Center for integrated molecular brain imaging

Lars Kai Hansen
IMM, Technical University of Denmark

Did you sleep well last night?

More direct access to our state of mind will revolutionize the ways we understand and work with ourselves, our collaborators and our computers

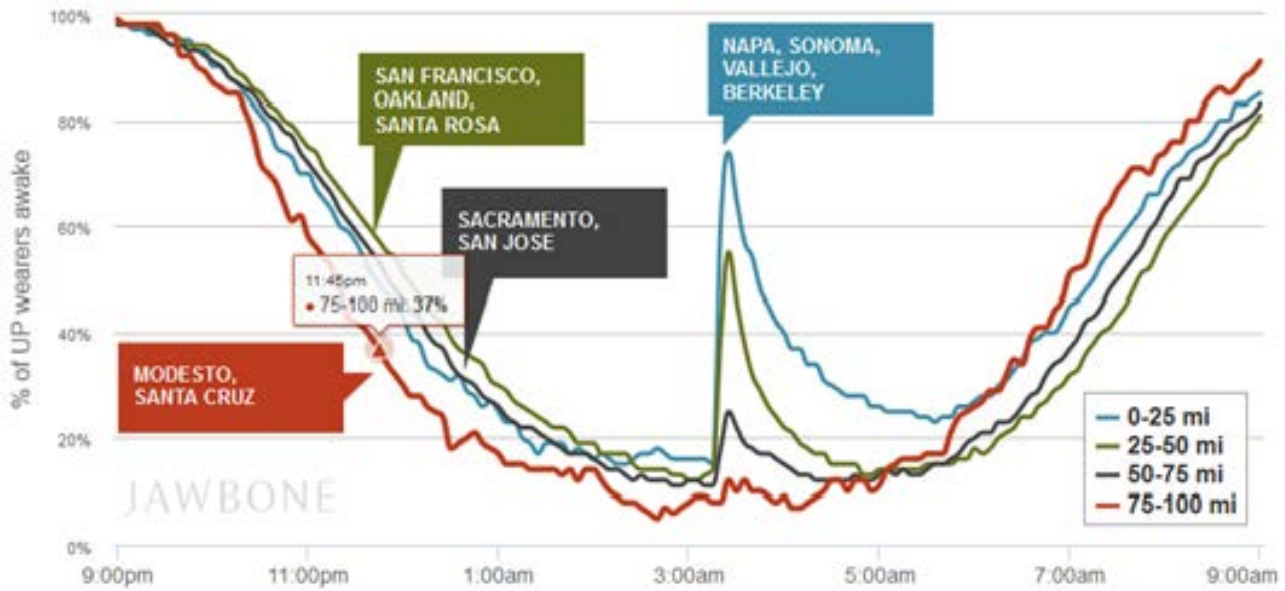
Mobile brain scanning can be used to read wishes and plans, to improve diagnosis, medication, and rehabilitation

At DTU Compute we have build the first truly mobile brains scanner. The scanner gives a 3D image og the instantaneous activity, we are currently working on making the system and realtime access to the brain useful for all.

Maybe we can help you to sleep better tonight?

Some friends did not sleep as well as they used to … the other night in Napa Valley

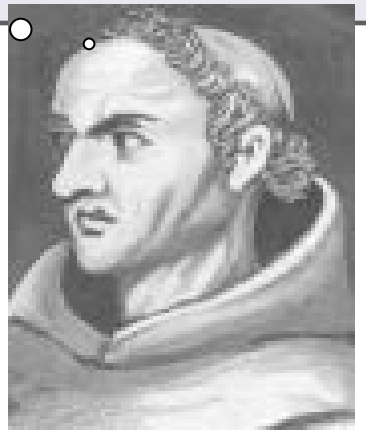
Below is a visualization prepared by our Senior Data Scientist Brian Wilt that shows how the South Napa Earthquake's effect on the UP wearers' sleep changes with the distance from the epicenter.



We wish all the people in the Bay Area who were affected by the earthquake a speedy recovery and a good night's sleep.

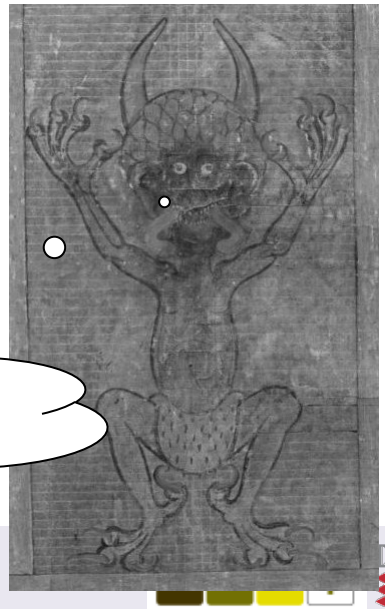
OUTLINE

Do not multiply causes!



- Personal state decoding
  - William James and human behavior as habits
  - Human predictability: What happened February 2010?
- Big personal data
  - Open data, evidence based living
  - Quantified self
  - Privacy

- Mind reading in the wild
  - Danish Neurotechnology: HypoSafe, EarEEG
- Smartphone brain scanner
  - Engineering the SBS2
  - Applications: Neurofeedback, Bhutan experiment
- Future
  - A new era?



….Or I will haunt you with false positives

Why personal state decoding? Technical…

*"**Oticon Tego** is directed by the DecisionMaker system, driven by (AI) Artificial Intelligence that processes sound intelligently. This super advanced form of computer processing. Artificial Intelligence is the process of performing logical operations enthused by the human brain.*

The difference between AI-based and conventional instruments is distinct: AI-based instruments constantly adapt to particular situation where conventional instruments provide only a fixed response to selected types of sounds. AI-based, Oticon Tego evaluates the different sound processing options and selects the one guaranteed to give the clearest sound quality.

Just like the brain, OticonTego filters out the noise so you can concentrate on the speech you like to hear. The DecisionMaker system evaluates and decides exactly when and how to apply the various features to get the best speech understanding and sound quality in any situation. All the processing happens automatically, so you need not lift a finger at all! Completely hands-free Oticon Tego is an ideal hearing solution for the active you!"

should this not depend on the personal state?? e.g., attention

http://www.hearingaids123.com/oticon-tego

Why personal state decoding? To make up for cognitive biases

Human senses & brains are not optimal from a behavioral point of view...

See e.g. the list of cognitive biases in Wikipedia

Ambiguity effect	The tendency to avoid options for which missing information makes the probability seem "unknown."[8]
Anchoring or **focalism**	The tendency to rely too heavily, or "anchor," on one trait or piece of information when making decisions (usually the first piece of information that we acquire on that subject)[9][10]
Attentional bias	The tendency of our perception to be affected by our recurring thoughts.[11]
Availability heuristic	The tendency to overestimate the likelihood of events with greater "availability" in memory, which can be influenced by how recent the memories are or how unusual or emotionally charged they may be.[12]
Availability cascade	A self-reinforcing process in which a collective belief gains more and more plausibility through its increasing repetition in public discourse (or "repeat something long enough and it will become true").[13]
Backfire effect	When people react to disconfirming evidence by strengthening their beliefs.[14]
Bandwagon effect	The tendency to do (or believe) things because many other people do (or believe) the same. Related to groupthink and herd behavior.[15]
Base rate fallacy or **base rate neglect**	The tendency to ignore base rate information (generic, general information) and focus on specific information (information only pertaining to a certain case).[16]
Belief bias	An effect where someone's evaluation of the logical strength of an argument is biased by the believability of the conclusion.[17]
Bias blind spot	The tendency to see oneself as less biased than other people, or to be able to identify more cognitive biases in others than in oneself.[18]
Cheerleader effect	The tendency for people to appear more attractive in a group than in isolation.[19]

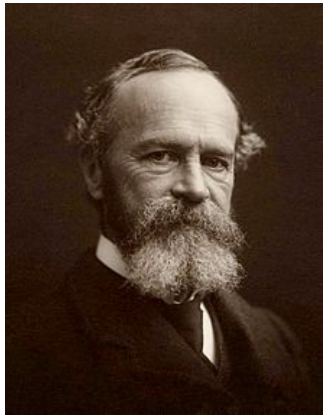
http://en.wikipedia.org/wiki/List_of_cognitive_biases

William James, The Principles of Psychology (1890)

CHAPTER IV "Habit"

"When we look at living creatures from an outward point of view, one of the first things that strike us is that they are bundles of habits."

"In wild animals, the usual round of daily behavior seems a necessity implanted at birth; in animals domesticated, and especially in man, it seems, to a great extent, to be the result of education. The habits to which there is an innate tendency are called instincts; some of those due to education would by most persons be called acts of reason."



"It thus appears that habit covers a very large part of life, and that one engaged in studying the objective manifestations of mind is bound at the very outset to define clearly just what its limits are."

Lifelogging for a quantified self

MyLifeBits is a Microsoft Research project.

Inspired by Vannevar Bush's hypothetical Memex computer system.

The project includes full-text search, text and audio annotations, and hyperlinks. The "experimental subject" of the project is computer scientist Gordon Bell, and the project will try to collect a lifetime of storage on and about Bell.

Jim Gemmell of Microsoft Research and Roger Lueder were the architects and creators of the system and its software.

http://research.microsoft.com/en-us/projects/mylifebits/default.aspx

Gordon Bell

Quantified Self
self knowledge through numbers

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]*

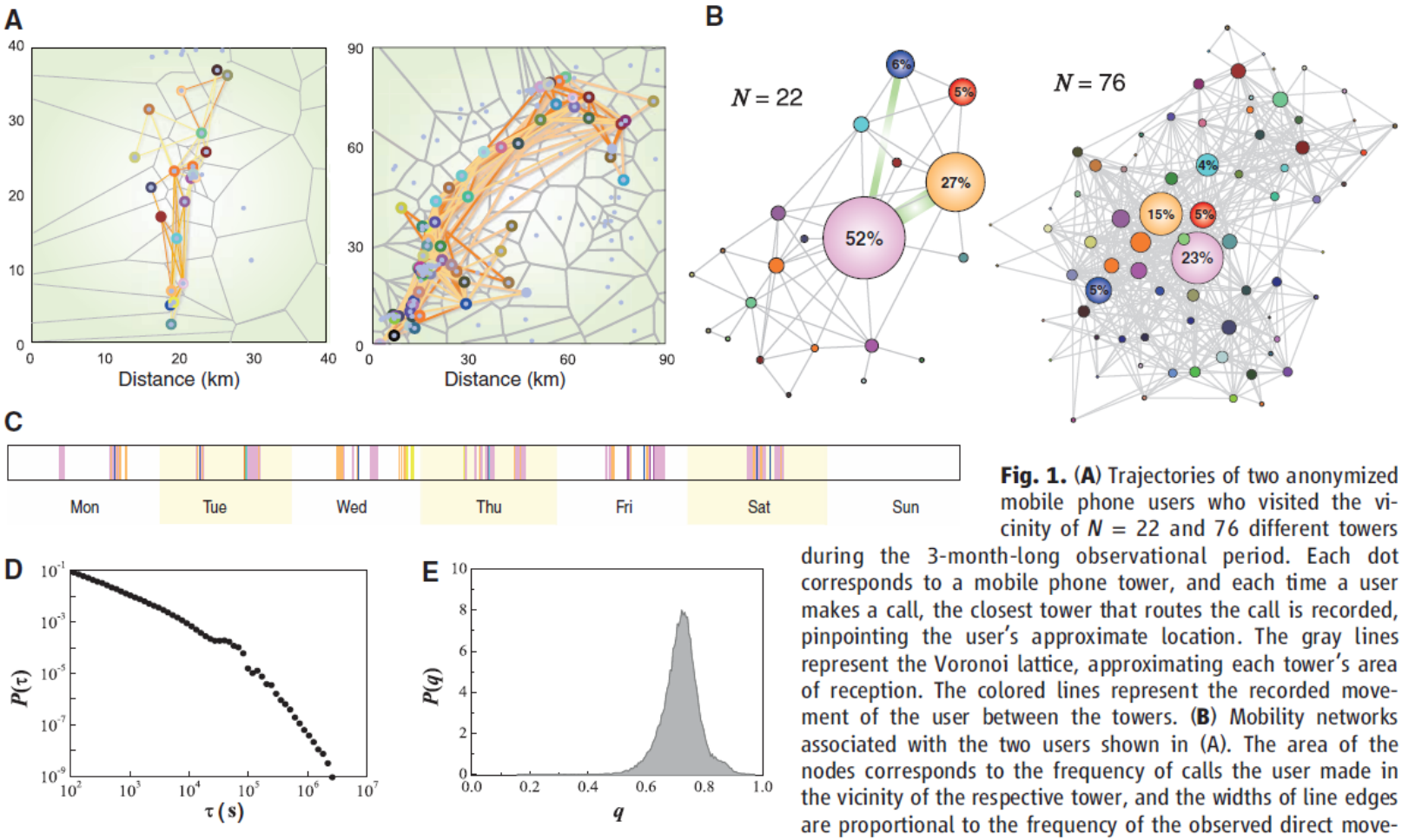


Fig. 1. (**A**) Trajectories of two anonymized mobile phone users who visited the vicinity of $N = 22$ and 76 different towers during the 3-month-long observational period. Each dot corresponds to a mobile phone tower, and each time a user makes a call, the closest tower that routes the call is recorded,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

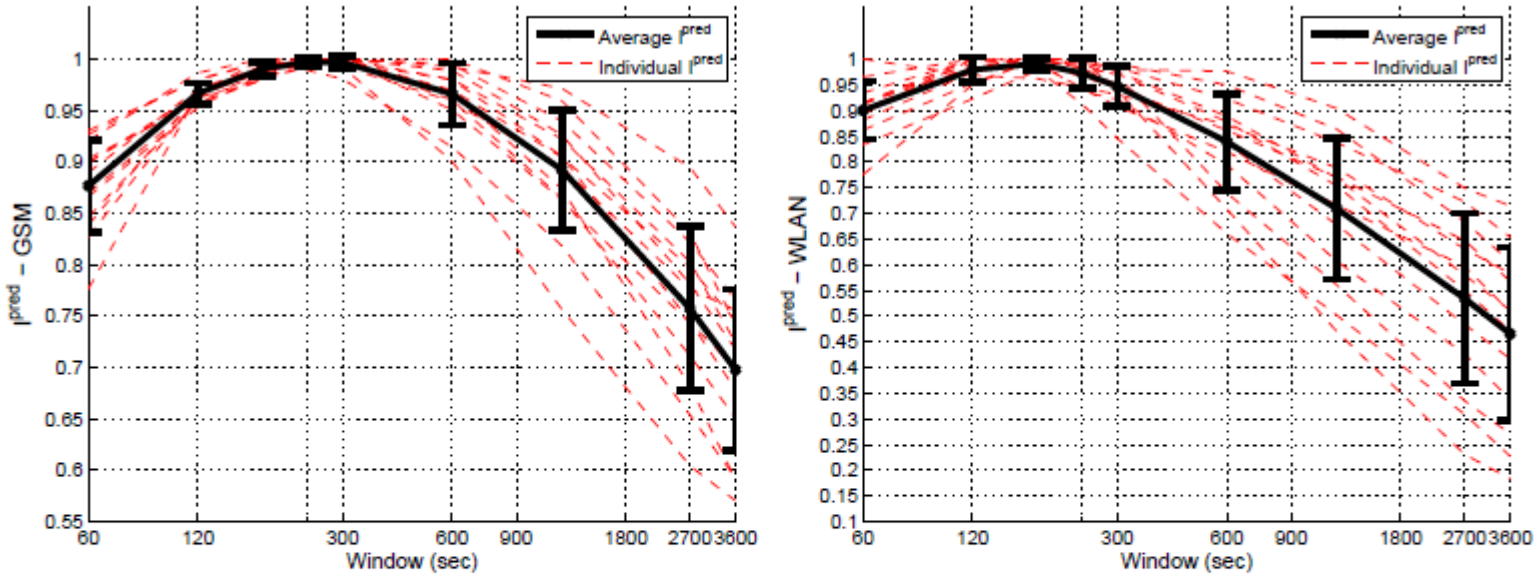
Participants were students and staff members from The Technical University of Denmark volunteering to be part of the experiment. Thus mainly situated in the greater Copenhagen area, Denmark.

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.

Part.	Accel	BT.	BT.*	GPS	GSM	GSM*	Ann.	PA.	WLAN	WLAN*	Days
1	1474480	54349	2846	516	69458	529	533	544	224101	6387	71
2	2045773	38028	2478	1514	75669	603	596	1062	364272	6040	66
3	318597	27329	790	12	37217	98	222	21	125600	630	31
4	875287	7880	743	2	17750	228	134	620	186421	2394	52
5	1117147	13575	2373	4058	56206	227	386	277	251016	2347	48
6	711490	23702	1141	95	51702	235	82	839	92396	2119	50
7	1184457	13327	1765	3	45826	955	272	581	139466	4017	46
8	700258	42346	2080	614	74250	172	212	74	154108	3359	41
9	1101926	42346	1050	119	37393	100	104	497	104576	1804	38
10	1103086	21676	2104	419	63937	419	414	116	192338	2650	48
11	1122315	12492	655	929	46158	929	163	121	295716	2286	47
12	796452	30610	2317	40	51548	40	143	151	97769	2403	50
13	1024276	27550	1741	1114	49349	1114	137	949	171951	5463	51
14	971558	21502	1303	44	40017	44	149	686	118687	1263	36
Total	14547102	350879	20408	9479	716480	2837	3547	6538	2518417	28110	48.2

Table 2. Overview of collected data for each participant in the experiment: Participant, Accelerometer, Bluetooth, Unique Bluetooth devices, GPS, GSM, Unique GSM cells, Annotations, Phone Activity, WLAN Access Points, Unique WLAN Access Points, Duration in days.

Predictability vs time scale



(a) GSM (b) WLAN

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

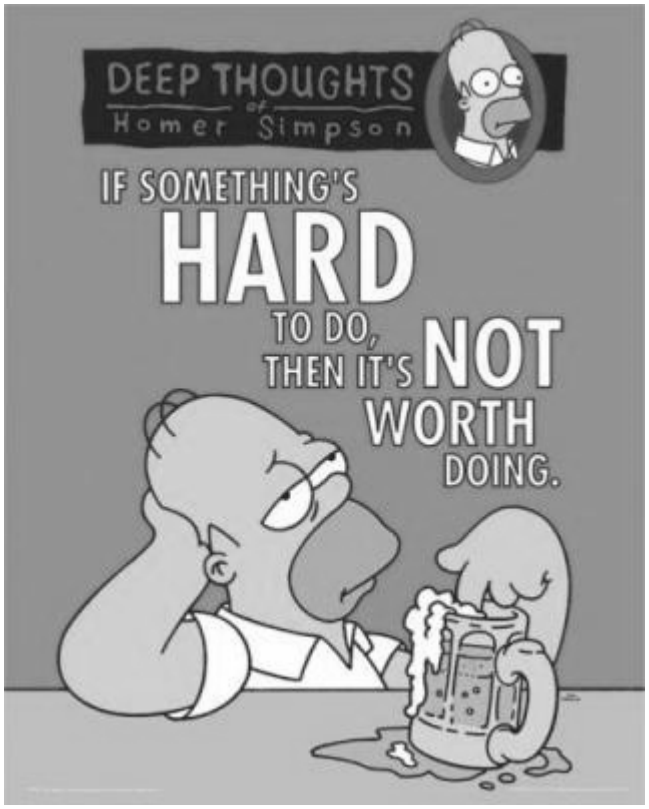
Personal state decoding

Aims to extract the mutual information between personal state and quantifiable behavior

- **Personal state**: Macroscopic variables, tags, behavioral categories ... *s(t)*
- **Sensed behaviors**: Micro/meso-scopic data/variables ... *x(t)*
- **Mutual information** is captured in the joint distribution ... *p(x,s).*

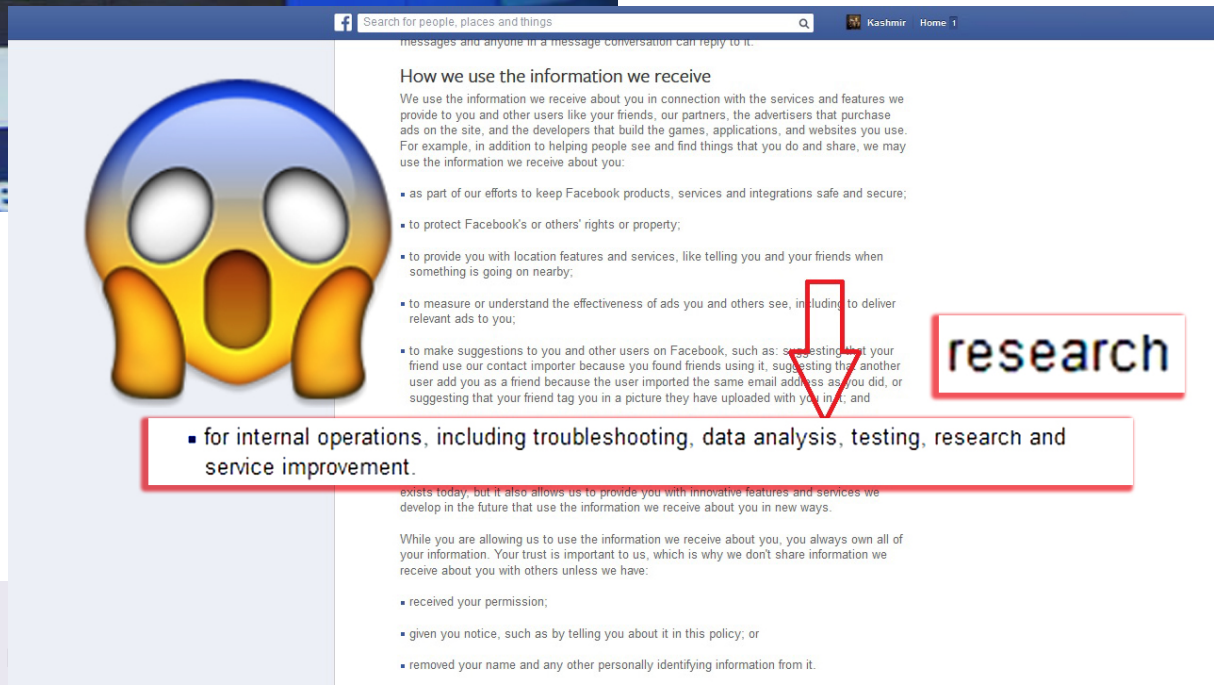
Supervised machine learning methods assume s(t) or parts of s(t) known ... unsupervised methods consider s(t) "hidden".....

and builds predictive models of the relation



Why is predictability interesting: Nudging

The Facebook experiment



Cimbi Center for integrated molecular brain imaging
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IMM, Technical University of

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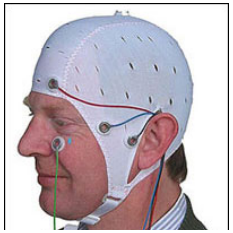
Based on the Emotiv wireless transmission mechanism w/ the EPOC head set or modified EasyCaps (Stefan Debener, Oldenburg)



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

https://github.com/SmartphoneBrainScanner

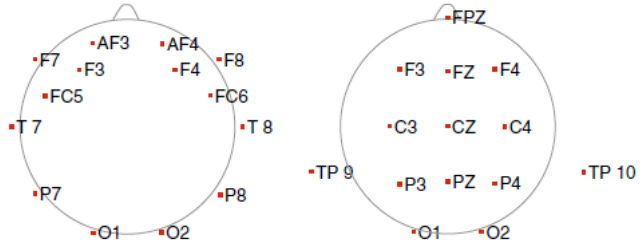
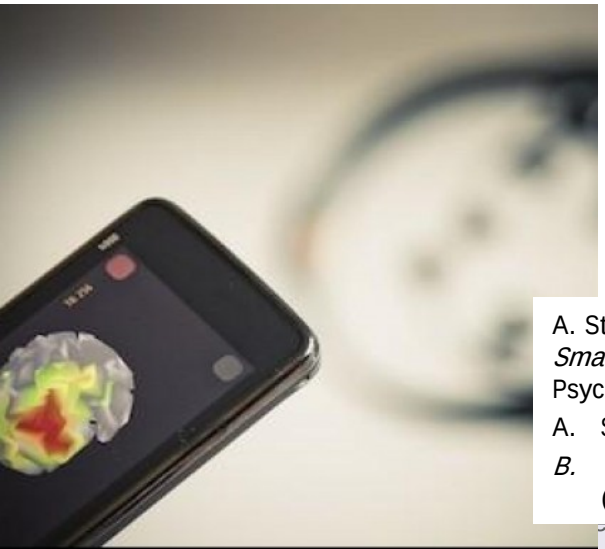


Fig. 5. Electrode locations for two mobile 16 channel EEG setups; the Emotiv neuroheadset using saline sensors positioned laterally (left), versus a standard gel-based Easycap EEG montage including central and midline positions (right).



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).

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B. The Smartphone Brain Scanner: A Portable Real-Time Neuroimaging System. PloS one 9 (2), e86733, (2014)

Stefan Debener: Taking your EEG for a walk…

Special issue:
"Towards mobile EEG"

International Journal of Psychophysiology 91 (2014) 46–53

Contents lists available at ScienceDirect

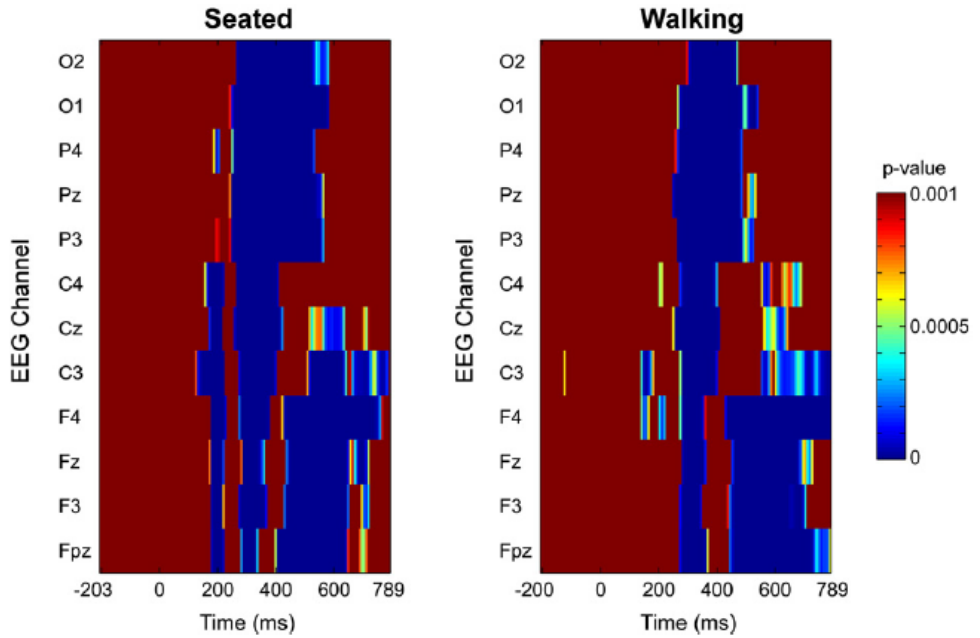
International Journal of Psychophysiology

journal homepage: www.elsevier.com/locate/ijpsycho

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).



Auditory odd ball detection: Control of Hearing instrument

Lars Kai Hansen
IMM, Technical University of Denmark

Evidence based living ”the quantified self”

More naturalistic conditions for brain imaging experiments

Long time recording in the wild:
Neurotechnology for 24/7 brain monitoring

EEG real time 3D imaging for bio-feedback and ”nudging”

Medical applications: Hypoglemia,

Illustration of
HypoSafe implantable device

(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.

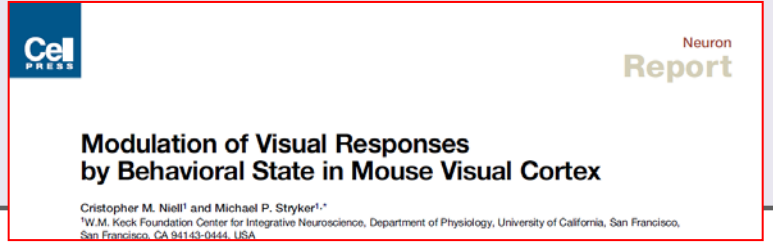
(c) Right ear with earplug.

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

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

P. Kidmose et al. Auditory Evoked Responses from Ear-EEG Recordings. IEEE EMBS (2012)

DTU mobility projects


Neuron
Report

Modulation of Visual Responses
by Behavioral State in Mouse Visual Cortex

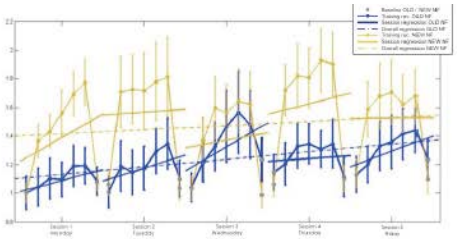
Cristopher M. Niell[1] and Michael P. Stryker[1,*]
[1]W.M. Keck Foundation Center for Integrative Neuroscience, Department of Physiology, University of California, San Francisco, San Francisco, CA 94143-0444, USA

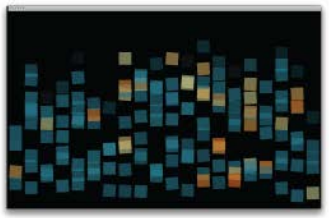
Social EEG-
- -Leaders and followers
- -Joint attention

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

Simon Kamronn

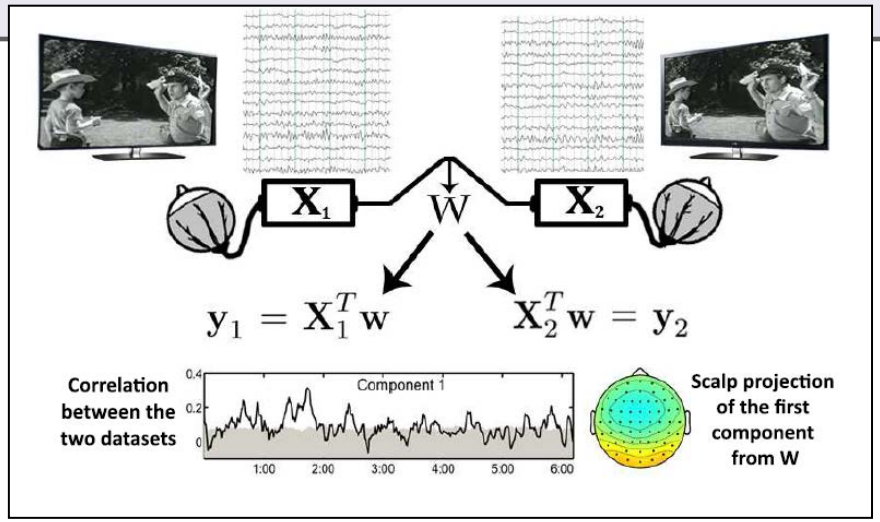
Andreas Trier Poulsen

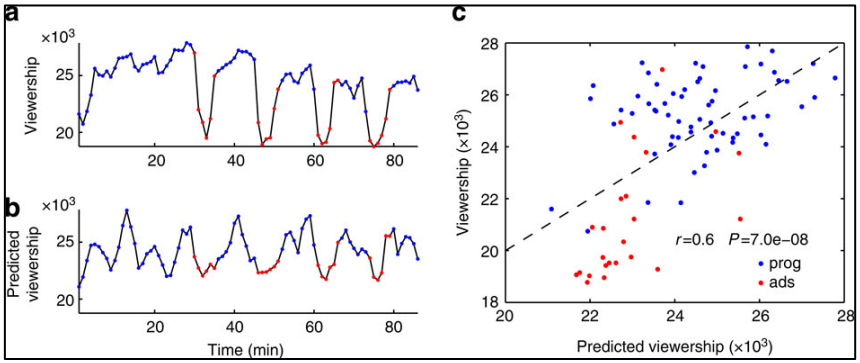


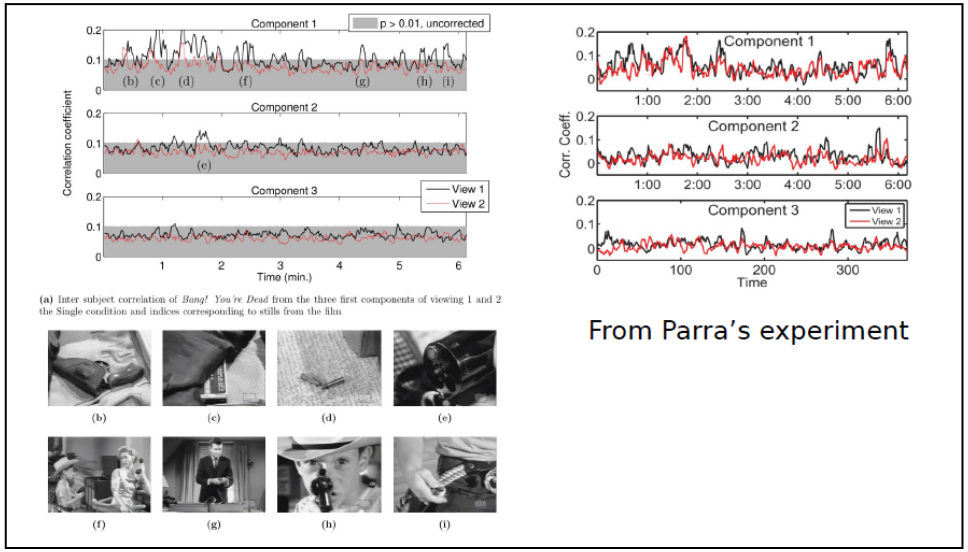


Camilla Falk

Joint attention to digital media (Parra et al.)





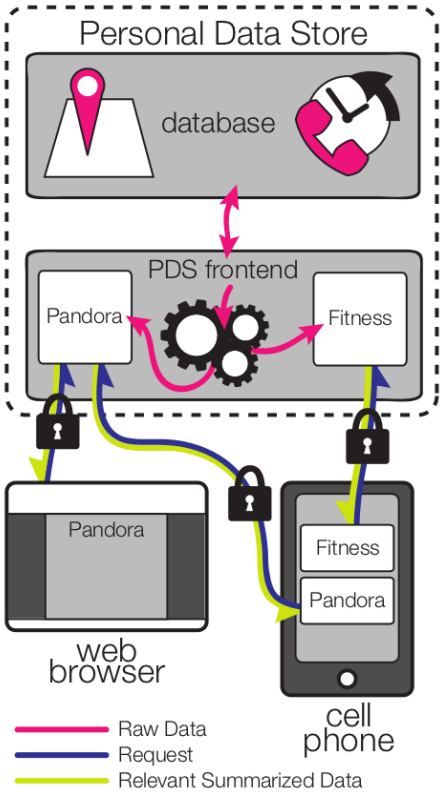


Jacek P. Dmochowski, Paul Sajda, Joao Dias, Lucas C. Parra, "Correlated components of ongoing EEG point to emotionally laden attention - a possible marker of engagement?" Frontiers of Human Neuroscience, 6:112, April 2012.

Jacek P. Dmochowski, Matthew A. Bezdek, Brian P. Abelson, John S. Johnson, Eric H. Schumacher, Lucas C. Parra, "Audience preferences are predicted by temporal reliability of neural processing", Nature Communications 5: 4567, July 2014.

Poulsen, A. T., Kamronn, S., Parra, L. C., & Hansen, L. K. (2014, June). Bayesian Correlated Component Analysis for inference of joint EEG activation. In *Pattern Recognition in Neuroimaging, 2014 International Workshop on* (pp. 1-4). IEEE.

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

Arkadiusz Stopczynski[1,2], Dazza Greenwood[2], Lars Kai Hansen[1], Alex Sandy Pentland[2]
1 Technical University of Denmark
2 MIT Media Lab
arks@dtu.dk, dazza@civics.com, lkai@dtu.dk, sandy@media.mit.edu

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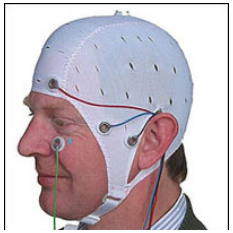

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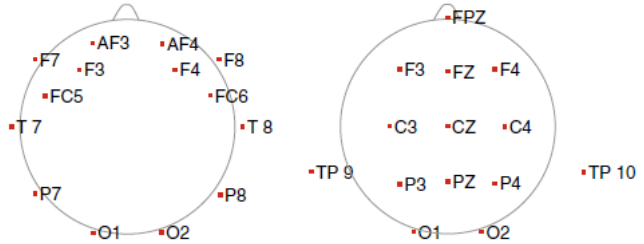

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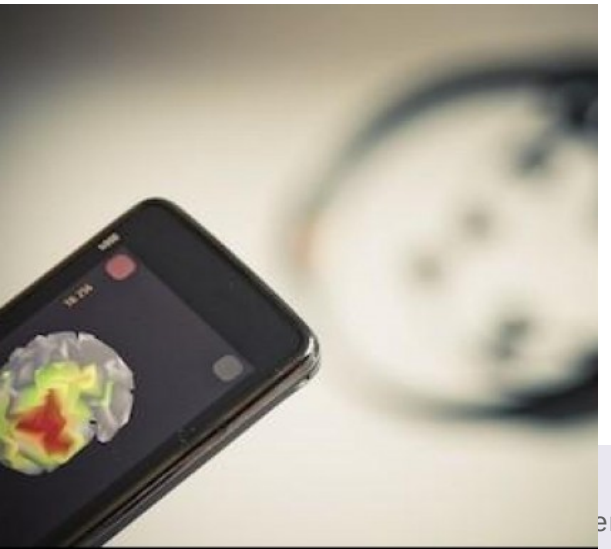

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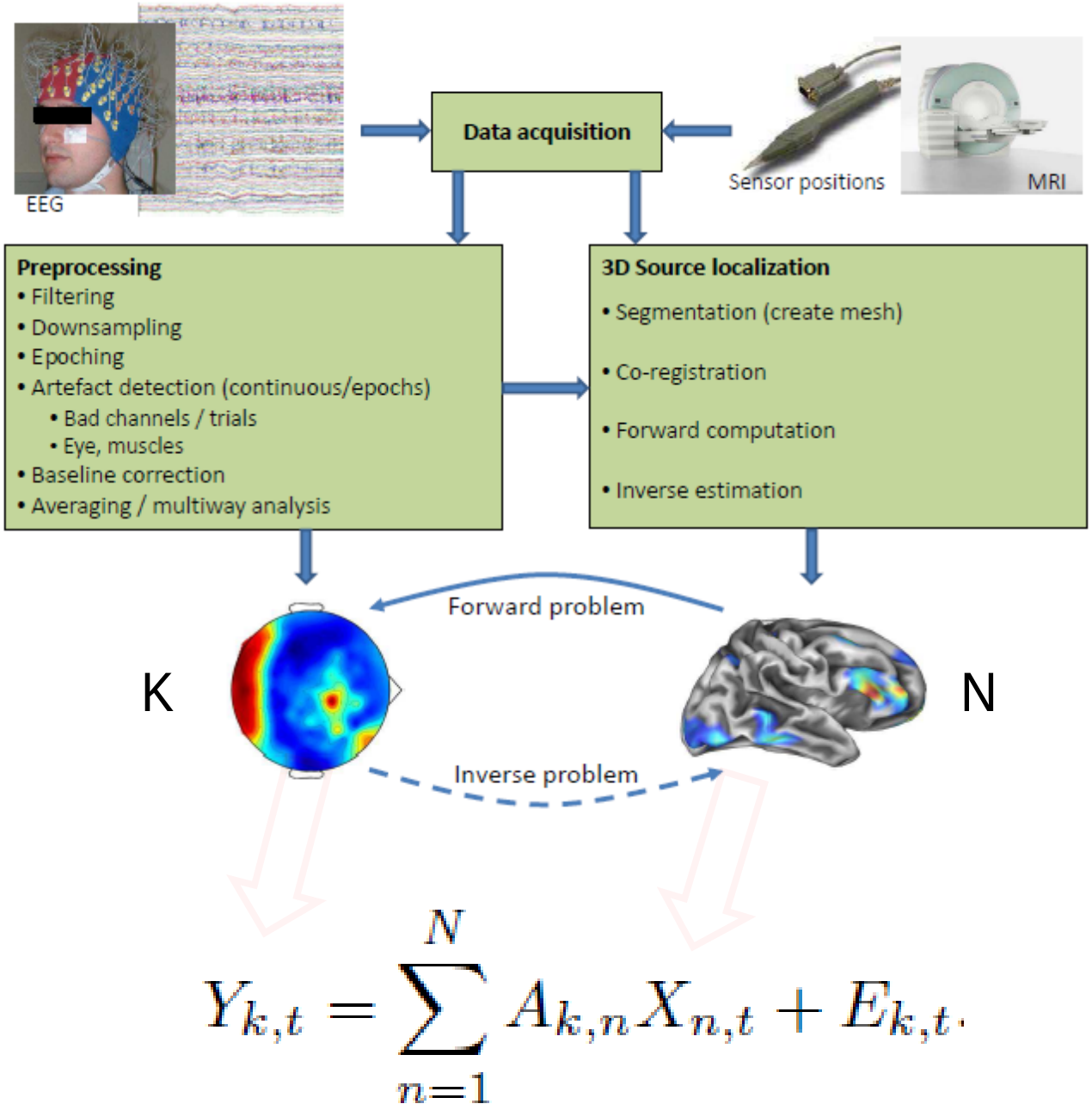
EEG imaging

Linear ill-posed inverse problem

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

N >> K

Need priors to solve!



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

SBS2 functions current

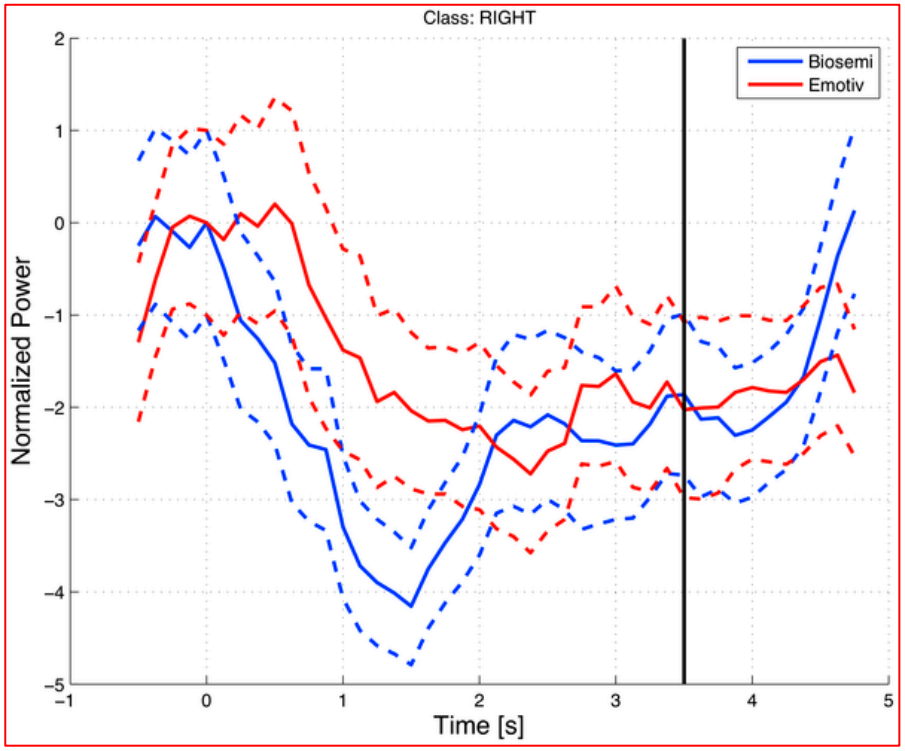
Real time system

- 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

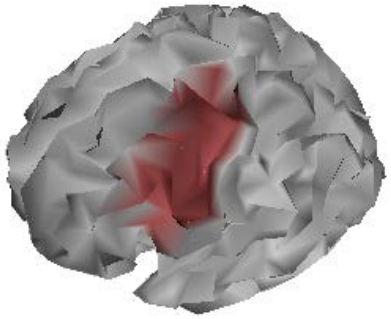
Do we get meaningful 3D reconstructions?

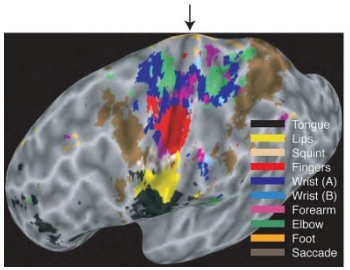


Imagined finger tapping

Left or right cued (at t=0)

Signal collected from an AAL region (n=80)





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Conclusion

Human behavior <u>is</u> quantified, modeled and predicted

The key technology is **<u>machine learning</u>**, not ”big data”

Decoding the brain is around the corner: Simple brain states can be decoded with high accuracy…

… More complex mechanisms may be revealed with non-linear decoders even in high dimensional settings … and some care!

Bring it to the masses: Mobility and ecological validity are challenging -

- minimally invasive devices and Ear technology are good candidates

Conclusion: An evidence based living?

Tracking/prediction technology can be used to

+ help humanity to cope with a sub-optimal brain
+ support recovery from physical or mental challenges
+ better understand the goals and actions of friends
+ create better, state dependent services

- Exercise mental control: Information -> power (M.J. Lynch)
- Decrease human autonomy
- Convert citizens to consumers

Acknowledgments

Lundbeck Foundation (www.cimbi.org)
Danish Research Councils