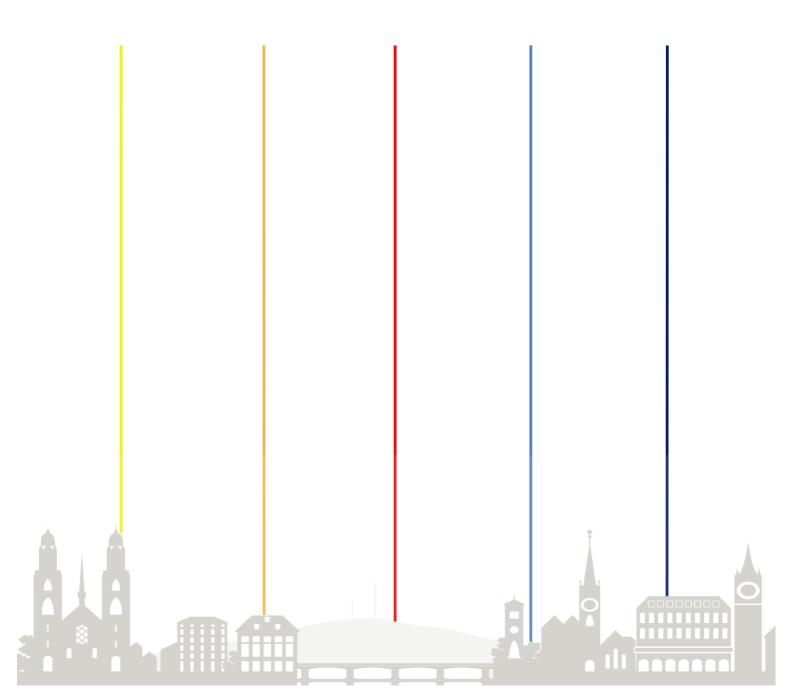


COMPUTATIONAL PSYCHIATRY COURSE

Participants' Guide

TNU, Zurich, 10.09. — 14.09.2018



CONTACT

CODE



Nicole Zahnd will help you with any issues. zahnd@biomed.ee.ethz.ch The code used for this course is open source. We encourage all participants to reuse and spread what they have learned and thereby advance the science.

2015: https://bitbucket.org/fpetzschner/cpc2015/ 2016: https://bitbucket.org/fpetzschner/cpc2016/ 2017: https://bitbucket.org/fpetzschner/cpc2017/ 2018: https://bitbucket.org/fpetzschner/cpc2018/

LECTURES

We record a podcast of all lectures given at the course.

2015: http://www.video.ethz.ch/lectures/d-itet/2015/autumn/227-0971-00L.html 2016: http://www.video.ethz.ch/lectures/d-itet/2016/autumn/227-0971-00L.html 2017: http://www.video.ethz.ch/lectures/d-itet/2017/autumn/227-0971-00L.html 2018: all talks will be recorded (access 1-2 months after the course)

SOCIAL

Free Sightseeing Tour through Zurich:

Start: Monday, 10.09.18, 17:30 Uhr, Meeting Point Polyterasse

Lunch Lottery: Tuesday, 11.09.18.

Find your 3 other lunch mates with the same number (see your name badge) in the entrance hall. Just talk to each other \odot

Sports:

You can get a free access pass to use the university sport facilities (ASVZ). Ask us for your pass.

Plenty of opportunities to hike, bike, climb, swim in and around Zurich (ask us!)

MEDIA

Facebook:

https://www.facebook.com/groups/1 481318692163550/

Twitter:

@CompPsychiatry
#CPC2018

Internet Access

Choose network named *public (or public-5)*.

cpc2018

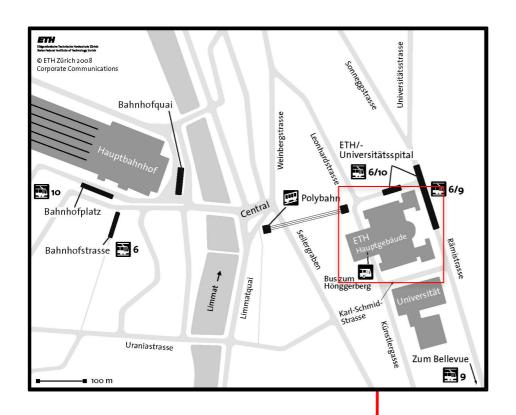
user name:

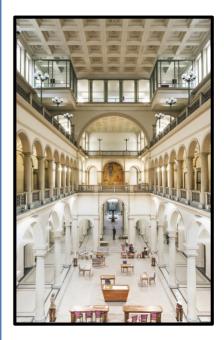
CPC_is_fun_2018

password:

WHERE

The course will take place at the main building of ETH, HG, Rämistrasse 101, 8092 Zürich, Registration and Catering: Foyer D Nord (follow the signs) Lecture hall: HG E3 (follow the signs) Practical Sessions: E33.3 and E33.5 (follow the signs)





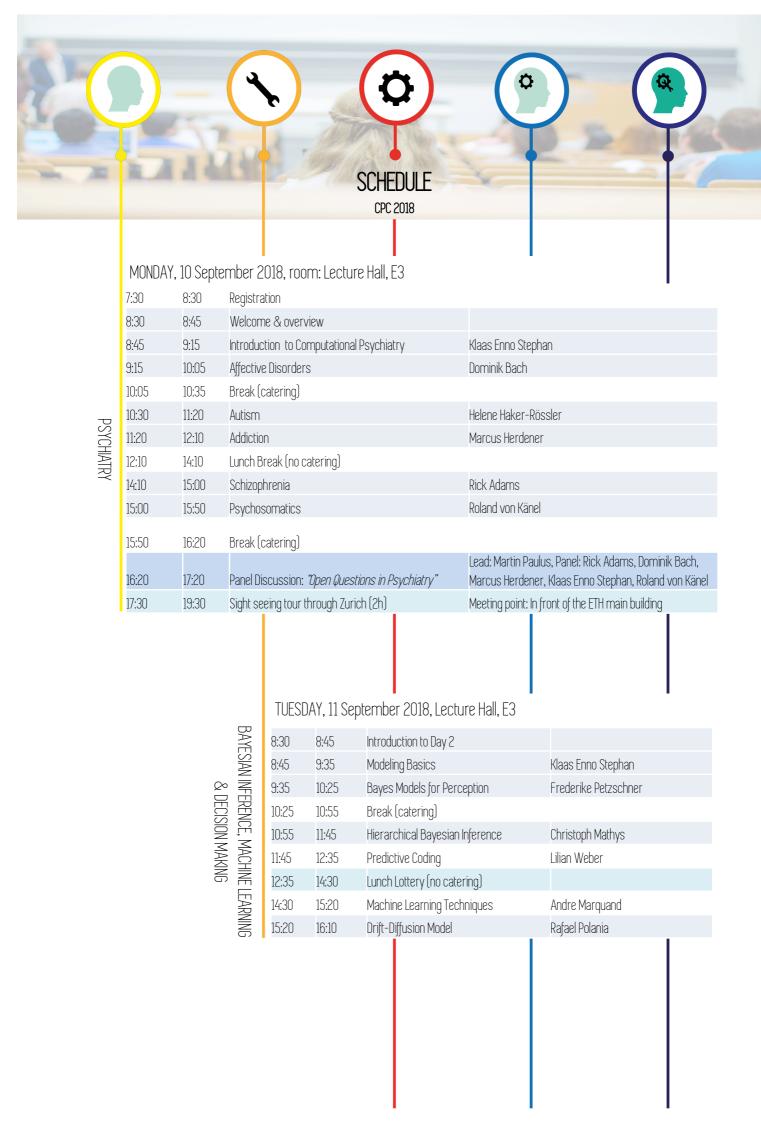
Zurich has excellent public transport opportunities.

The following tram numbers will take you to the ETH Centre. Rämistrasse 101:

- Tram 10 (from *Zürich, Bahnhofsplatz, HB* or *Zürich, Central*)
- Tram 6 (from Zürich, Bahnhofsplatz, HB or Zürich, Central)
- Polybahn (from *Zürich, Central*)
 The stop is called: *Zürich, ETH/Universitätsspital*

You can use www.sbb.ch/en to check the transportation schedule. A short 10-15mins walk will also take you to the University from the main station.







WEDNESDAY, 12 September 2018, room: Lecture Hall, E3

MOELS OF PLANNING, BIOPHYSICAL MODELS & MODEL INVERSION

8:30	8:45	Introduction to Day 3	
8:45	09:35	Markov Decision Processes	Frederike Petzschner & Lionel Rigoux
09:35	10:25	Reinforcement Learning	Woo-Young Ahn
10:25	10:55	Break (catering)	
10:55	11:45	Active Inference	Philipp Schwartenbeck
11:45	12:35	Dynamic Causal Modeling for fMRI	Jakob Heinzle
12:35	14:30	Lunch (no catering)	
14:30	15:20	Dynamic Causal Modeling for EEG	Dario Schöbi
15:20	16:10	Bayesian Model Selection and Averaging	Stefan Frässle
16:10	16:40	Break (catering)	
16:40	17:30	Model inversion: Markov Chain Monte Carlo and Variational Bayes	Lionel Rigoux

THURSDAY, 13 September 2018, room: Lecture Hall, E3

8:30	8:45	Klaas Enno Stephan
8:45	9:35	Read Montague
9:35	10:05	Break (catering)
10:05	10:55	Hanneke den Ouden
		Panel Discussion: <i>"The Future of Computational Psychiatry"</i> Lead: Klaas Enno Stephan Panel: Jean Zarate, Peter Stern, Read Montague, Stephen Fleming, Adam Chekroud,
10:55	11:55	David Redish, Valerie Voon, Hanneke den Ouden
11:55	14:00	Lunch Break (no catering)
14:00	14:50	Stephen Fleming
14:50	15:40	Adam Chekroud
15:40	16:10	Break (catering)
16:10	17:00	David Redish
17:00	17:50	Valerie Voon
17:50	18:00	Closing remarks

MODEL APPLICATION



FRIDAY, 14 September 2018 (optional)

8:30	9:30	Practical A (Lecture Hall E33.3): Bayesian Learning using the <u>Hierarchical Gaussian Filter</u> (Tore Erdmann & Lilian Weber)	Practical B (Lecture Hall E33.5): Active inference using the Active Inference Toolbox (Philipp Schwartenbeck & Andreea Diaconescu)
9:30	10:00	Break (catering)	
10:00	11:30	Practical A (Part 2)	Practical B (Part 2)
11:30	13:30	Lunch Break (no catering)	
13:30	15:00	Practical C (room E33.3): Model Inversion using the Variational Bayes Toolbox (Lionel Rigoux & Eduardo Aponte)	Practical Session D (room E33.5): Reinforcement Learning using the hBayesDM Package (Woo-Young Ahn)
15:00	15:30	Break (catering)	
15:30	17:00	Practical C (Part 2)	Practical D (Part 2)

FURTHER READING

Variational Bayes

Chapter 1 and 2

http://www.cse.buffalo.edu/faculty/mbeal/thesis/

Bayesian Model Selection & Averaging

Bayesian model selection for group studies Stephan KE, Penny WD, Daunizeau J, Moran RJ, Friston KJ Neuroimage (2009) 46(4): 1004-1017

http://www.sciencedirect.com/science/article/pii/S1053811909002638

Markov Chain Monte Carlo

A quick introduction to Markov chains and Markov chain Monte Carlo

Waagepetersen R

http://people.math.aau.dk/~rw/Papers/mcmc_intro.pdf

Chapter on sampling methods in the book "pattern recognition and machine learning" Bishop

Hierarchical Gaussian Filter

Uncertainty in perception and the Hierarchical Gaussian Filter
Mathys CD, Lomakina, El, Daunizeau J, Iglesias S, Brodersen KH, Friston, KJ, & Stephan KE
Frontiers in Human Neuroscience (2014) 8:825
http://doi.org/10.3389/fnhum.2014.00825

Markov Decision Models

Planning and acting in partially observable stochastic domains
Kaelbling LP, Littman ML & Cassandra AR
Artificial Intelligence (1998),101(1-2): 99—134
https://www.cis.upenn.edu/~mkearns/papers/barbados/klc-pomdp.pdf

Dynamic Causal Modeling for fMRI

Understanding DCM: Ten simple rules for the clinician
Kahan J, Foltynie T
Neuroimage (2013) 83: 542-549
http://www.sciencedirect.com/science/article/pii/S105381191300760X

Analyzing effective connectivity with functional magnetic resonance imaging. Stephan KE and Friston KJ, WIREs Cognitive Sience (2010), 1:446-459, http://www.fil.ion.ucl.ac.uk/spm/doc/papers/Stephan_WIREsCognSci_1_446_2010.pdf

Dynamic Causal Modeling for EEG

Losing Control Under Ketamine: Suppressed Cortico-Hippocampal Drive Following Acute Ketamine in Rats, Moran RJ, Jones MW, Blockeel AJ, Adams RA, Stephan KE & Friston KJ Neuropsychopharmacology (2015) 40: 268–277

http://www.nature.com/npp/journal/v40/n2/abs/npp2014184a.html

FURTHER READING

Bayesian Models for Perception

A Bayesian perspective on Magnitude Estimation.

Petzschner FH, Glasauer S, Stephan KE

Trends in Cognitive Sciences (2015). 19(5):285–293

Perception as Bayesian Inference. Knill CD & Richards W, 2008

Predictive Coding & Active Inference

Computational psychiatry: the brain as a phantastic organ. Friston KJ, Stephan KE, Montague R, Dolan RJ Lancet Psychiatry (2014) 1:148—158

Optimal inference with suboptimal models: Addiction & active Bayesian inference .

Schwartenbeck P , FitzGerald THB, Mathys C, Dolan R, Wurst F, Kronbichler M, Friston K.

Medical Hypotheses (2015) 84:109—117

Reinforcement Learning

Decision-theoretic psychiatry.

Huys QJM, Guitart-Masip M, Dolan RJ and Dayan P

Clin Psychol Sci (2015) 3(3):400-421

Sutton & Barto, Reinforcement learning, MIT Press, 1998

Machine Learning

From estimating activation locality to predicting disorder: A review of pattern recognition for neuroimaging-based psychiatric diagnostics. Wolfers T, Buitelaar JK, Beckmann CF, Franke B, Marquand AF Neuroscience & Biobehavioral Reviews (2015) 57: 328-349

Cross-validation failure: Small sample sizes lead to large error bars. Gaël Varoquaux Neurolmage (2017) in press

Addiction

The role of learning-related dopamine signals in addiction vulnerability. Huys QJM, Tobler PT, Hasler G, Flagel SB. Progress in Neurobiology (2014): 211:31-77

Schizophrenia

What We Know: Findings That Every Theory of Schizophrenia Should. MacDonald, Schulz Schizophrenia Bulletin, 2009

Autism

Can Bayesian Theories of Autism Spectrum Disorder Help Improve Clinical Practice? Haker H, Schneebeli M, Stephan KE. Front. Psychiatry, 2016

Bayesian inference: a method of inferring upon properties of the underlying distribution generating a set of data using Bayes' theorem. In this method, both the likelihood of a data set and prior distributions on the sufficient statistics of the underlying data distribution are incorporated in the inference process.

Bayesian: adjective describing methods that employ Bayes' rule, including prior information in the statistical process.

Bounded rationality: the idea that decision-makers are limited by various constraints (time, information, cognitive limitations, etc) and thus make rational decisions insofar as these constraint allow.

Dynamical system: set of differential equations that describes, for example, how a set of neuronal populations changes activity as a function of input. It can include complicated non-linear dynamics and interactions between the nodes.

Dynamical systems theory: area of maths used to describe time-evolving systems using differential equations or difference equations, depending on whether the systems states are continuous or discrete.

Effective connectivity: causal and, therefore, directed influences between neurons, or neuronal populations, as opposed to purely anatomical or functional (statistical dependencies) connectivity.

Free energy: in statistics, the lower bound on log model evidence. In physics, the total amount of work extractable from a statistical system. In cognition, a functional representing the trade-off between information and constraint; a model of bounded rationality.

Good regulator theorem: a theorem proved by Conant & Ashby (1970) stating that in order for an agent to be maximally both successful at regulating its environment and simple, it must have a model of its environment. This means that the brain must necessarily develop a model of its environment.

Hemodynamics: in fMRI hemodynamics stands for all the neuronally induced changes in blood flow, volume and oxygenation. These changes lead to the observed signal, also called the blood oxygen level dependent (BOLD) signal, and are characterized by the hemodynamic response to an input stimulus.

CHEAT SHEET

Hierarchical Gaussian Filter (HGF): a set of prescriptions for updating beliefs about the state of an agent's environment. In response to a time series of observations, an agent can use the HGF to update its beliefs about environmental states including - crucially - its uncertainty about states. This allows such an agent dynamically to adapt its learning rate in order to minimize surprise. There is mounting empirical evidence that the quantities relevant to HGF updates have correlates in neural activity.

Inverse problem: an inverse problem in science is the process of calculating from a set of observations the causal factors that produced them. It is called an inverse problem because it starts with the results and then calculates the causes. This is the inverse of a forward problem, which starts with the causes and then calculates the results.

Kullback-Leibler (KL) divergence: a non-symmetric non-negative measure of the dissimilarity of two probability densities; zero if the two densities are identical and increasingly positive with growing dissimilarity.

Markov chain Monte Carlo (MCMC): a class of algorithms for sampling from a probability distribution based on constructing a Markov chain that has the desired distribution as its equilibrium distribution. The state of the chain after a number of steps is then used as a sample of the desired distribution. The quality of the sample improves as a function of the number of steps.

Markov Decision Process: provide a mathematical framework for modeling decision making in situations where outcomes are partly random and partly under the control of a decision maker.

Minimization of Shannon surprise: the Shannon surprise associated with an observation is the negative logarithm of the probability of that observation under a given model. This means that impossible observations lead to infinite surprise, while entirely certain observations lead to no surprise at all. A model that makes good predictions minimizes Shannon surprise.

Model evidence: the conditional probability of the data given the model and the denominator from Bayes theorem; represents the decisive quantity for Bayesian model comparison and selection; its log can be decomposed into a trade-off between model fit and model complexity.

Negative free energy: a lower bound approximation to the log evidence which derives from a variational perspective; maximising the negative free energy not only yields an estimate of the log evidence, but also provides an estimate of the posterior by minimising the KL divergence between an approximate posterior and the true posterior.

Neural Mass Model: model that describes the average activity of a subset of neurons, using a small number of state variables that summarize the average activity of millions of interacting neurons.

Neuronal Oscillations: repetitive neural activity in the CNS, driven by either the activity of a single neuron or interactions within a population of neurons.

ODE (ordinary differential equation): differential equation that is a function of only one independent variable and its derivatives.

Optimality: a term used to describe perfectly rational decision making in the absence of constraint. Mathematically, this is often described by maximum expected utility or maximum likelihood.

Policy: the method or system of principles used by a agent to quide his or her decision process.

Posterior predictive distribution: distribution of unobserved states conditional on observed data, equivalent to the expectation of the probability of the new data point given the model parameters, taken over the posterior distribution.

Precision-weighted prediction error (PWPE): under mild assumptions, Bayesian inference (i.e., inference according to the rules of probability) can be reduced to belief-updating by PWPEs. Hereby, a previous statistic is updated by adding to it the difference between a new observation and the previous statistic, after this difference has been weighted by a ratio of precisions, namely that of the precision of the precision to the precision of the current belief.

Precision: term used to describe the dispersion of a distribution. The precision is $1/\sigma^2$, where σ is the standard deviation of the distribution.

Predictive Coding: The predictive coding account of perceptual inference assumes that sensory cortex infers the most likely causes of incoming (noisy) sensory inputs. It suggests a hierarchical neural architecture where each level tries to predict the state of the level below (prediction units) and evaluates the discrepancy with the actual inputs from the lower level (prediction error units, PE). Inference corresponds to adjusting neuronal states and learning refers to adjusting connection strengths, both serving to minimize PE at all levels of the hierarchy.

Transition probabilities: the probability with which one state changes into another state. Usually used in the context of state space models, in which a process is described as a set of transitions between a number of states.

LUNCH	I OPTIONS		
On ETH	1 campus:		
5	Tannenbar	Bistro (Sandwiches, etc.)	Mon-Fri (07:00-17:00)
6	Clausiusbar	Asian food	Mon-Fri (07:30-16:30)
7	Mensa Polyterrasse	Different lunch menus (also vegi), buffet, salade etc. / Dinner	Mon-Fri (11:15-19:15)
8	Cafeteria Einstein	Bistro (Sandwiches, etc.)	Mon-Fri (06:45- 19:45)
9	bQm	Bistro / Student bar	Mon-Thu (11:45-23:00, Fri-22:00)
11	Polysnack	Italian food	Mon-Fri (07:30-17:00)
an	d close by:		
Klara's Kitchen Bio,		Bio, vegetarian, vegan, gluten-free,	Mon-Fri (08:00-18:30)
Hot Pasta D		Different Italian Pasta	Mon - Fri (08:30-24:00)

HOL Pasta Dijjerent italian Pasta Mon - Fri (U8:3U-24:UU)

Sat (09:00-24:00)

Mon-Fri (08:00-**21:00**) Migros Supermarket with a restaurant

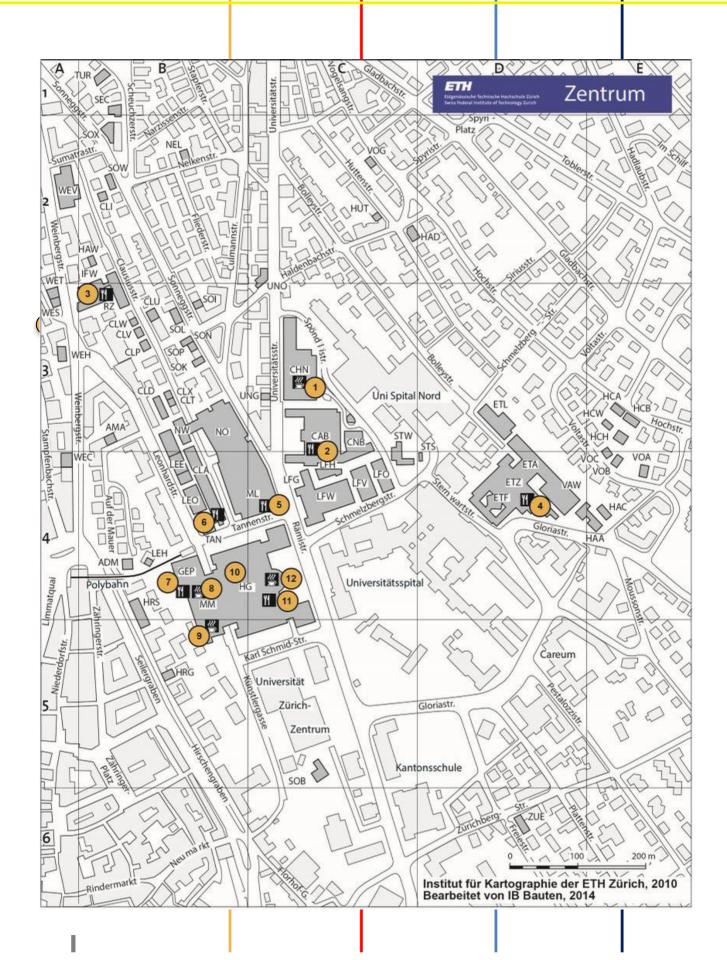
Sat (09:00-**21:00**)

Mon-Fri (06:30-18:30) Bäckerei Wüst Bakery

Sat & **Sun** (07:00-17.00)

Do not forget to bring along your **student identification card**. You will get a **discount** in all **ETH** restaurants.

LUNCH OPTIONS



ORGANIZER

Translational Neuromodeling Unit Prof. Klaas Enno Stephan, MD Dr. med. PhD Dr. Frederike Petzschner Heidi Brunner Nicole Zahnd contact: cpcourse@biomed.ee.ethz.ch









SPEAKERS

Rick Adams. UCL. London

Woo-Young Ahn, Seoul National University, South Korea

Eduardo Aponte, University of Zurich & ETH Zurich, Zurich, Switzerland

Dominik Bach, University of Zurich, Zurich, Switzerland

Adam Chekroud, Spring Health, New York, USA

Andreea Diaconescu, University of Basel, Basel, Switzerland

Tore Erdmann, SISSA, Trieste, Italy Stephen Fleming, UCL London, UK

Stefan Frässle, University of Zurich & ETH Zurich, Zurich, Switzerland

Helene Haker-Rössler, University of Zurich & ETH Zurich, Zurich, Switzerland

Jakob Heinzle, University of Zurich & ETH Zurich, Zurich, Switzerland

Marcus Herdener, University of Zurich, Zurich, Switzerland

Roland von Känel, University of Zurich, University Hospital Zurich, Zurich, Switzerland

Christoph Mathys, SISSA, Trieste, Italy

Andre Marquand, Donders Institute, Nijmegen, Netherlands

Read Montague, Virginia Tech, USA

Hanneke den Ouden, Radboud University, Netherlands

Martin Paulus, Laureate Institute, Tulsa, USA

Frederike Petzschner, University of Zurich & ETH Zurich, Zurich, Switzerland

Rafael Polania, ETH Zurich, Zurich, Switzerland David Redish, University of Minnesota, USA

Lionel Rigoux, Max Planck Institute for Metabolism Research, Cologne, Germany

Dario Schöbi, University of Zurich & ETH Zurich, Zurich, Switzerland

Philipp Schwartenbeck, UCL, London & Oxford University, UK

Klaas Enno Stephan, University of Zurich & ETH Zurich, Zurich, Switzerland

Peter Stern, Science Magazine, Washington DC, USA

Valerie Voon, University of Cambridge, UK

Lilian Weber, University of Zurich & ETH Zurich, Zurich, Switzerland

Jean Zarate. Nature Neuroscience. New York. USA

ETH zürich





MSc & Doctoral Program Biomedical Engineering

Institute for Biomedical Engineering