ENDOWING THE MACHINE WITH **ACTIVE INFERENCE**:

A GENERIC FRAMEWORK

TO IMPLEMENT **ADAPTIVE BCI**

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Outline:

PART I:

Generic framework for adaptive BCI

PART II:

Active Inference

PART III:

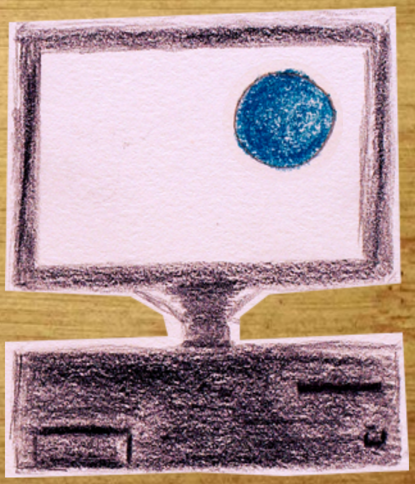
Application to the P300-speller

Brain–Computer Interface

Definition:

A system which enables a connection between a brain and a machine

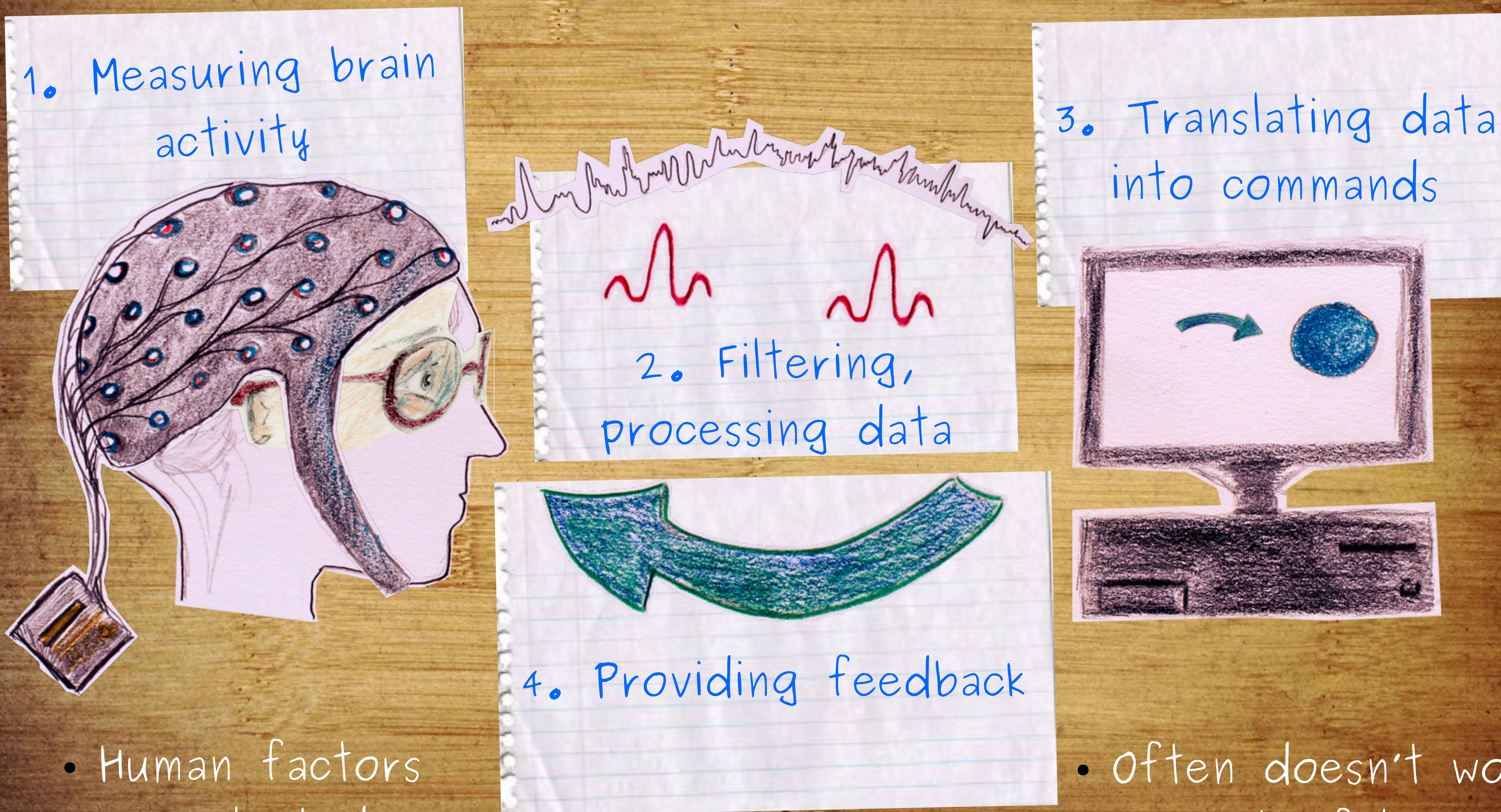
For communication, control, art, entertainment, neuro-rehabilitation, neuro-adaptive tech, passive monitoring…



often doesn't work outside of labs

[Brain–computer interfaces for communication and control, J.R. Wolpaw, 2002]

Human Brain–Computer Interface:



- Human factors neglected
- Often doesn't work out of labs

[Brain–computer interfaces for communication and control, J.R. Wolpaw, 2002]

Challenges/Motivation

Adaptive BCI methods:

Adjust to signal variabilities, and reduce them by influencing their causes;

Assist in learning, foster motivation, favor ergonomy, minimize fatigue….

Consider causes of signal variability

The equipment and experimental environment:

1. Equipment sensitivity or magnetic field present in the environment (Niedermeyer & da Silva, 2005, Maby 2016)

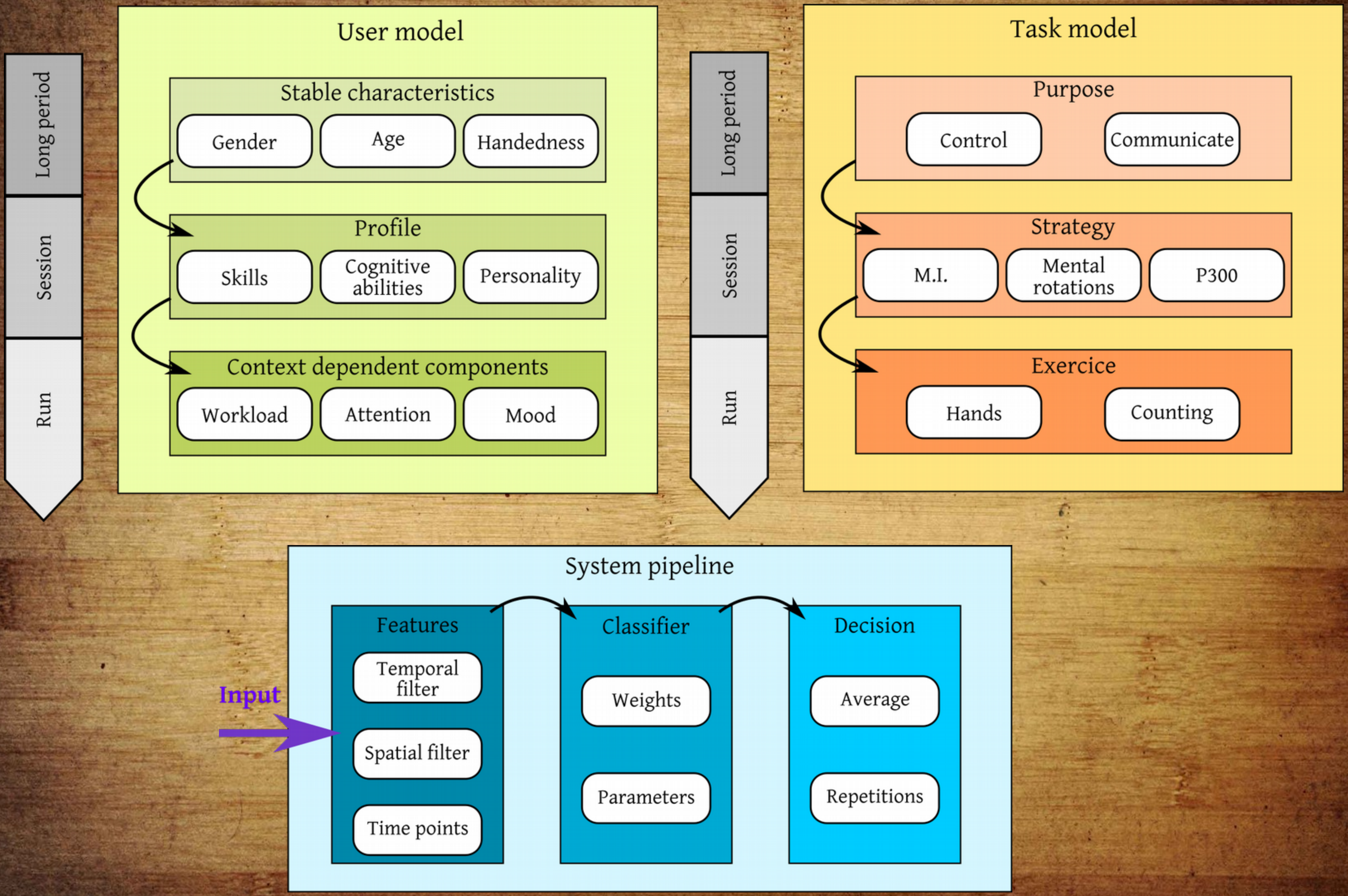
2. Quality of the instructions given to the user to follow through the task (Neuper 2005)

Short term user factors:

1. Attention, mood (Nijboer 2008, Jeunet 2016) muscle tension (Schumacher 2015)
2. User's mental command, e.g. for MI – kinesthetic or visual motor imagery (Neuper 2005)

Long term user factors:

3. User's learning capacity depending on e.g. memory span, intrinsic motivation, imagination and skills (Jeunet 2016)

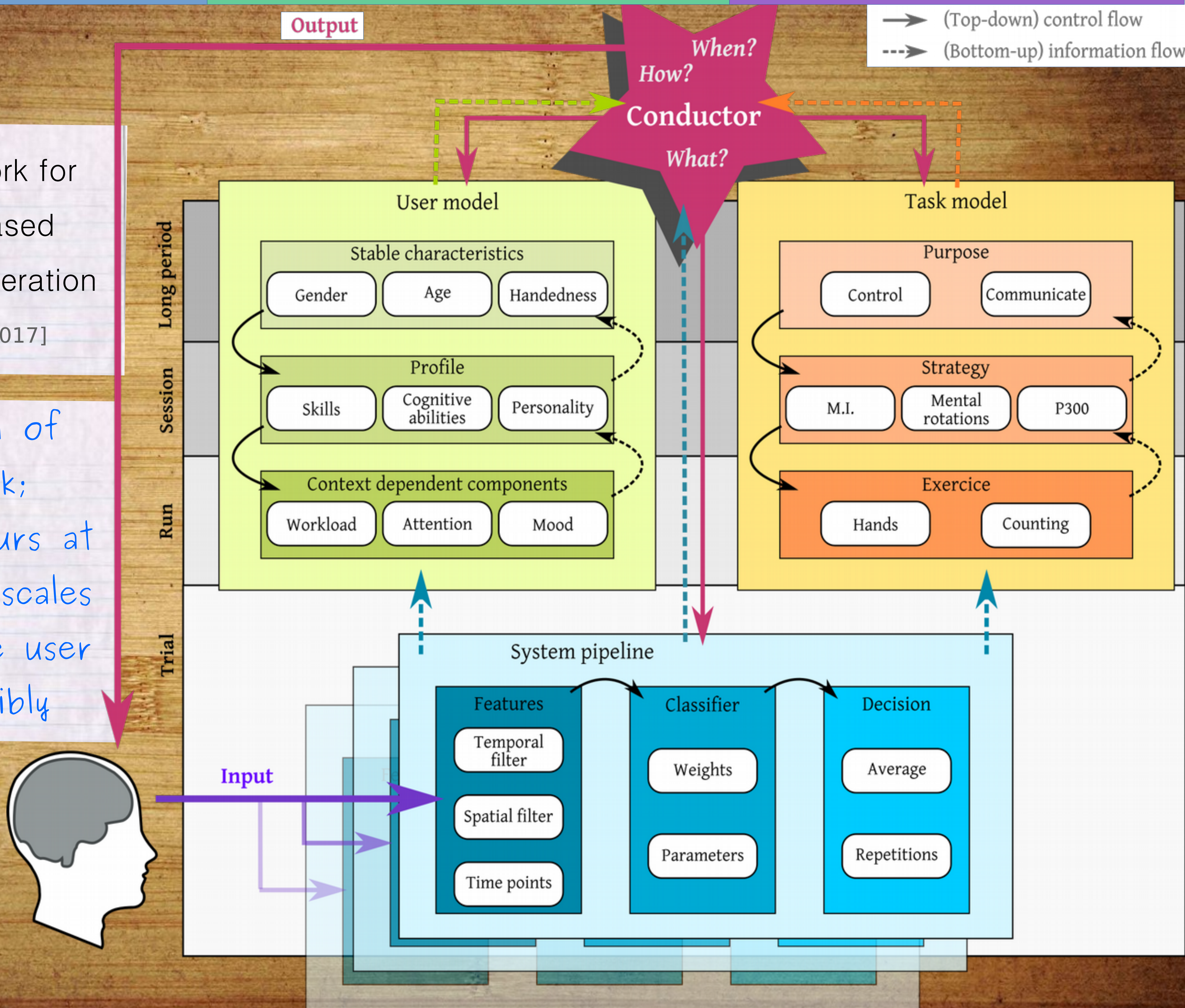


Long period
Session
Run
User model
Stable characteristics
Gender
Age
Handedness
Profile
Skills
Cognitive abilities
Personality
Context dependent components
Workload
Attention
Mood
Long period
Session
Run
Task model
Purpose
Control
Communicate
Strategy
M.I.
Mental rotations
P300
Exercice
Hands
Counting
System pipeline
Input
Features
Temporal filter
Spatial filter
Time points
Classifier
Weights
Parameters
Decision
Average
Repetitions

A generic framework for adaptive EEG-based BCI training and operation

[Mladenovic et al. 2017]

- Explicit model of user and task;
- Adaptation occurs at different time scales
- learn about the user and act flexibly



What about a (generic) computational framework?

Active Inference

A computational neuroscience approach on how an adaptive system like the brain should implement perception, learning and action.

Importantly, such a system
- Implements a model of its environment
- Optimizes its interactions through both making inference (about the environment) and acting (upon the environment)
- Inference and Action both rest on optimizing a single cost function called Free energy

We propose to endow the BCI system with Active Inference in order to optimize cooperation with BCI user. This entails endowing the BCI system with an explicit model of the user and task, as prescribed by our framework for adaptive BCI.

Reminder of a P300-speller

A communication device

Examples:

- Basic: row/column protocol, spell after n flashes
- optimal stopping, i.e. spell when enough evidence has been accumulated

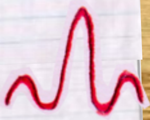
Principle:

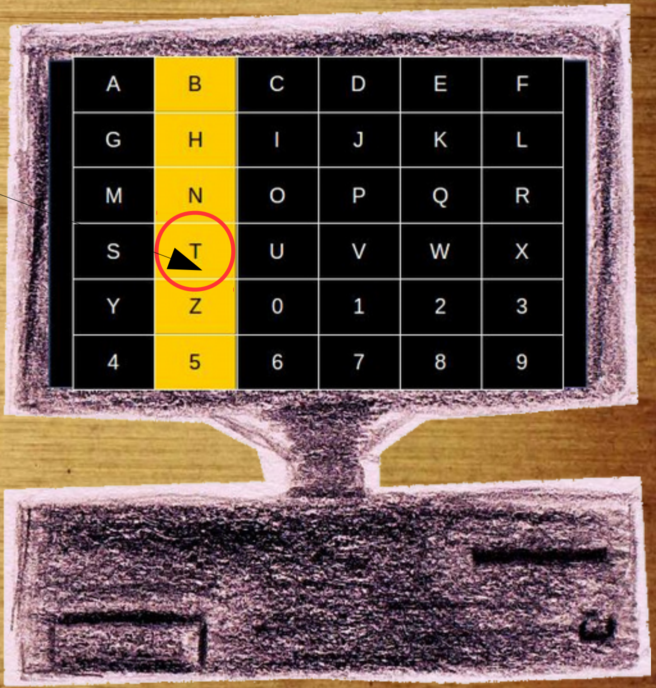
Reactive BCI

Items are flashed

ERP or P300

Visual oddball paradigm





Applying Active Inference on a P300-speller

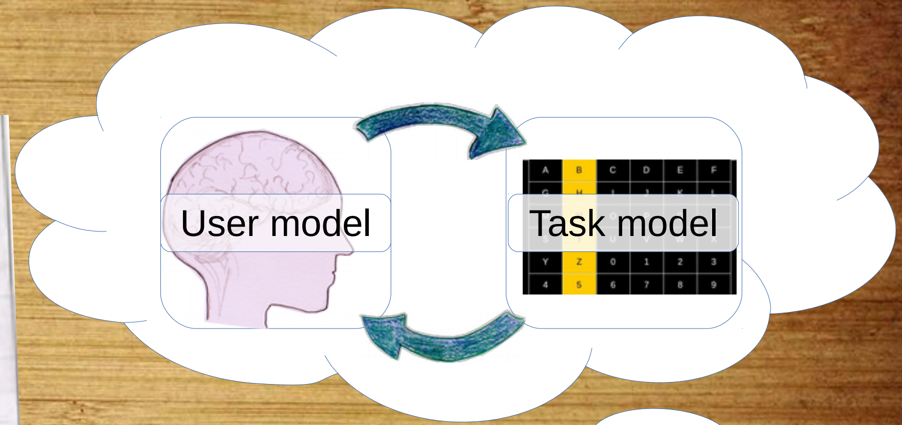
ACTION/PERCEPTION

FOCUS ON A LETTER;

SPELL A WORD;

/

CLASSIFIER OUTPUT

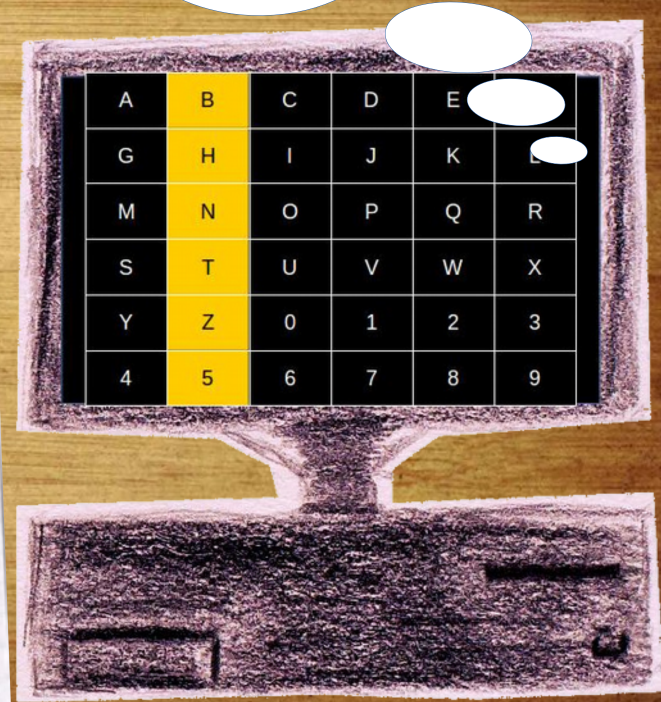


PERCEPTION/ACTION

P300 OR

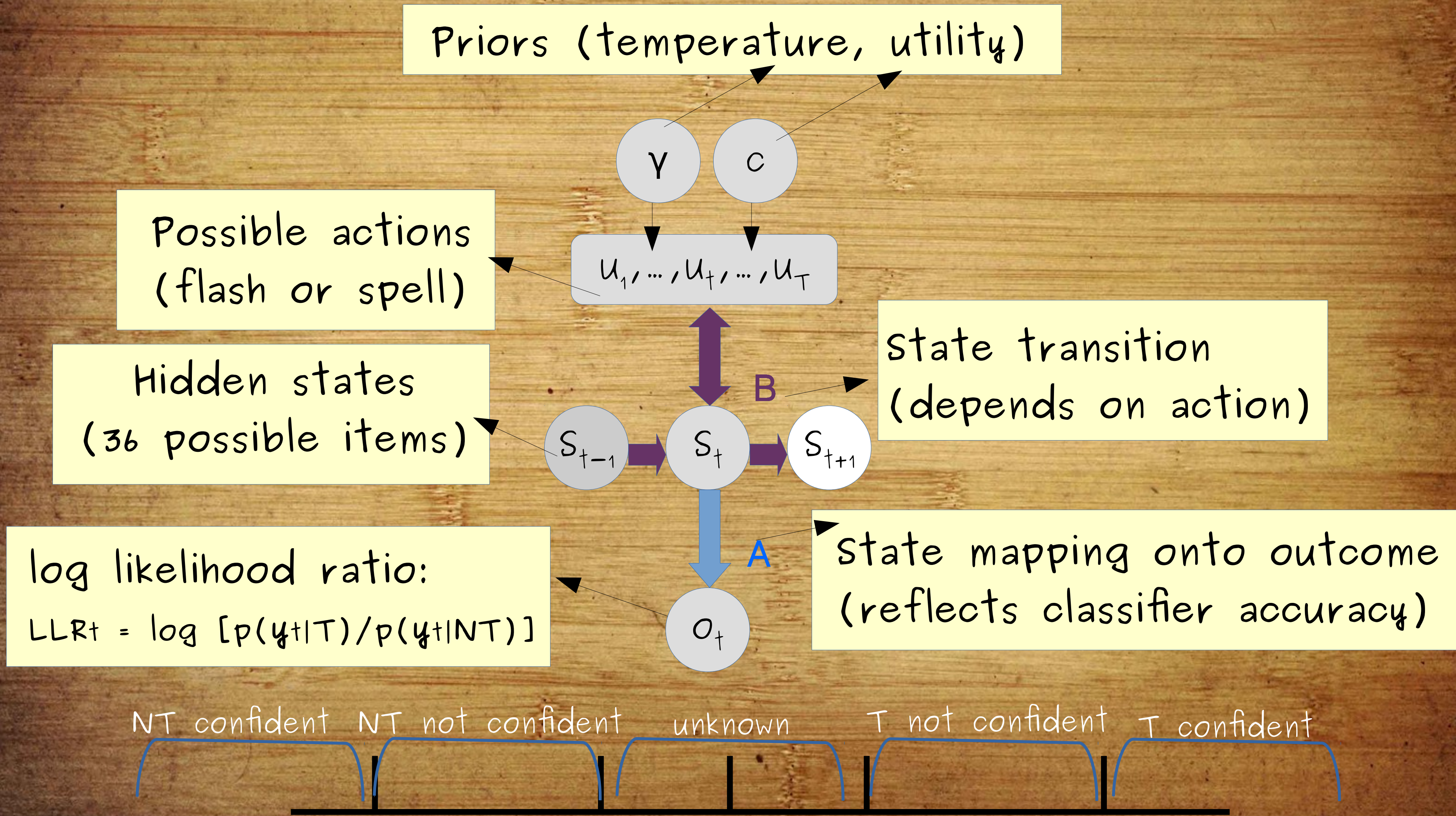
ERROR POTENTIALS /

FLASHING OR SPELLING



What can be the choice of rows/columns to flash to reveal the target?

Generic Framework for P300-speller



[Mladenovic et al. 2017]

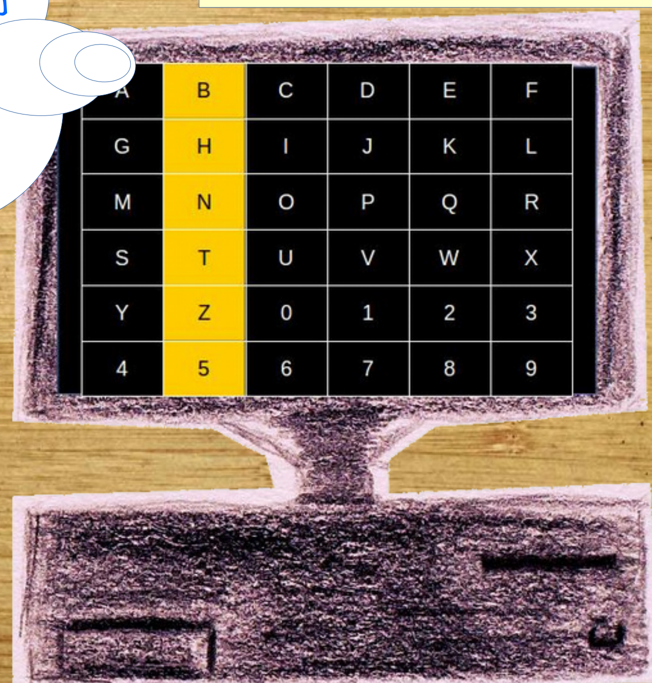
P300-speller
optimal stopping + flashing

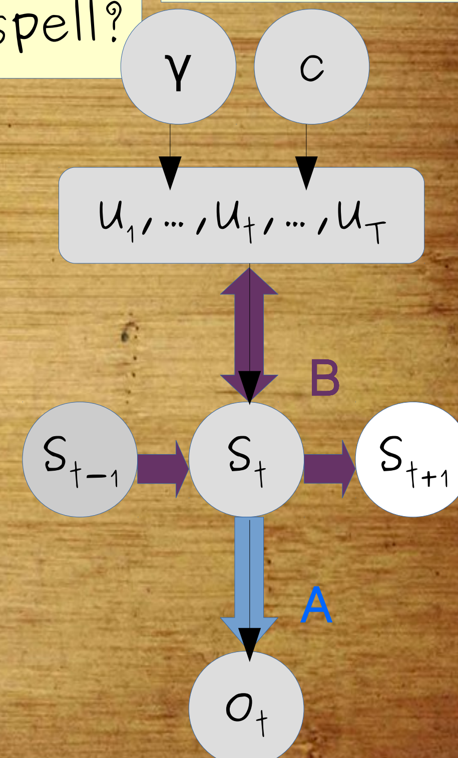
optimal stopping
- Should I go on flashing or spell?

optimal flashing
- Which items should I flash?

How confident I want to be before I spell?

Which outcome do I favor?





Which action minimizes Free Energy?

preliminary RESULTS:

Comparing Simulations between Active Inference with and without Optimal Flashing

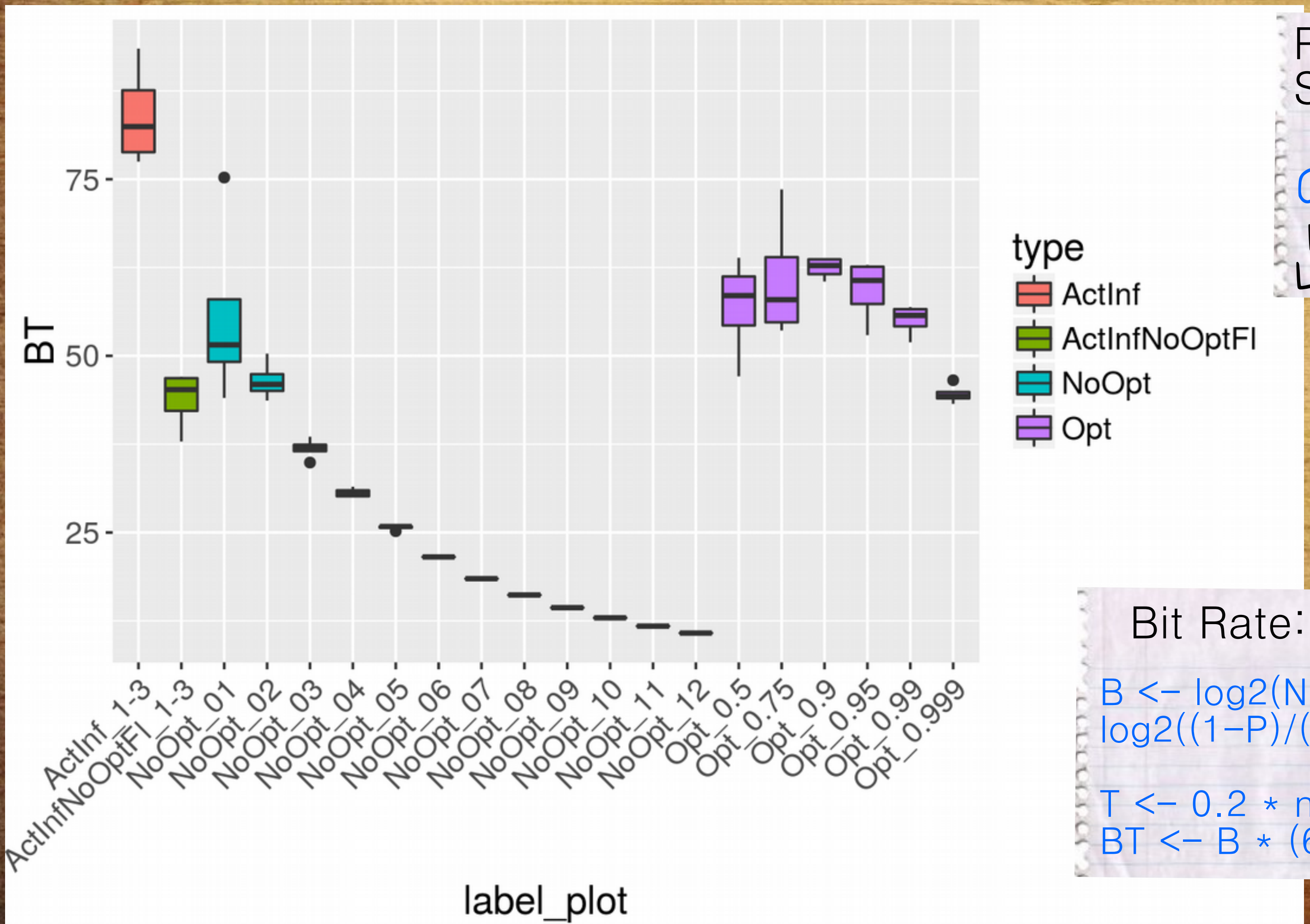
Optimal stopping & flashing showed increased accuracy in reduced time

- Optimal stopping: 20.1±9 flashes / 80.6% accuracy
- Optimal stop & flashing: 15.8±6 flashes / 85.2% accuracy

[Mladenovic et al. 2017]

preliminary RESULTS 2:

Compared real data between ActInf (OptFlash and NoOptFlash) basic, and optimal stopping P300-speller (good, average, bad subject)



Real data from Subject 13:

Classif output:

LLR T > 3,1

LLR NT <-3,-1

Bit Rate:

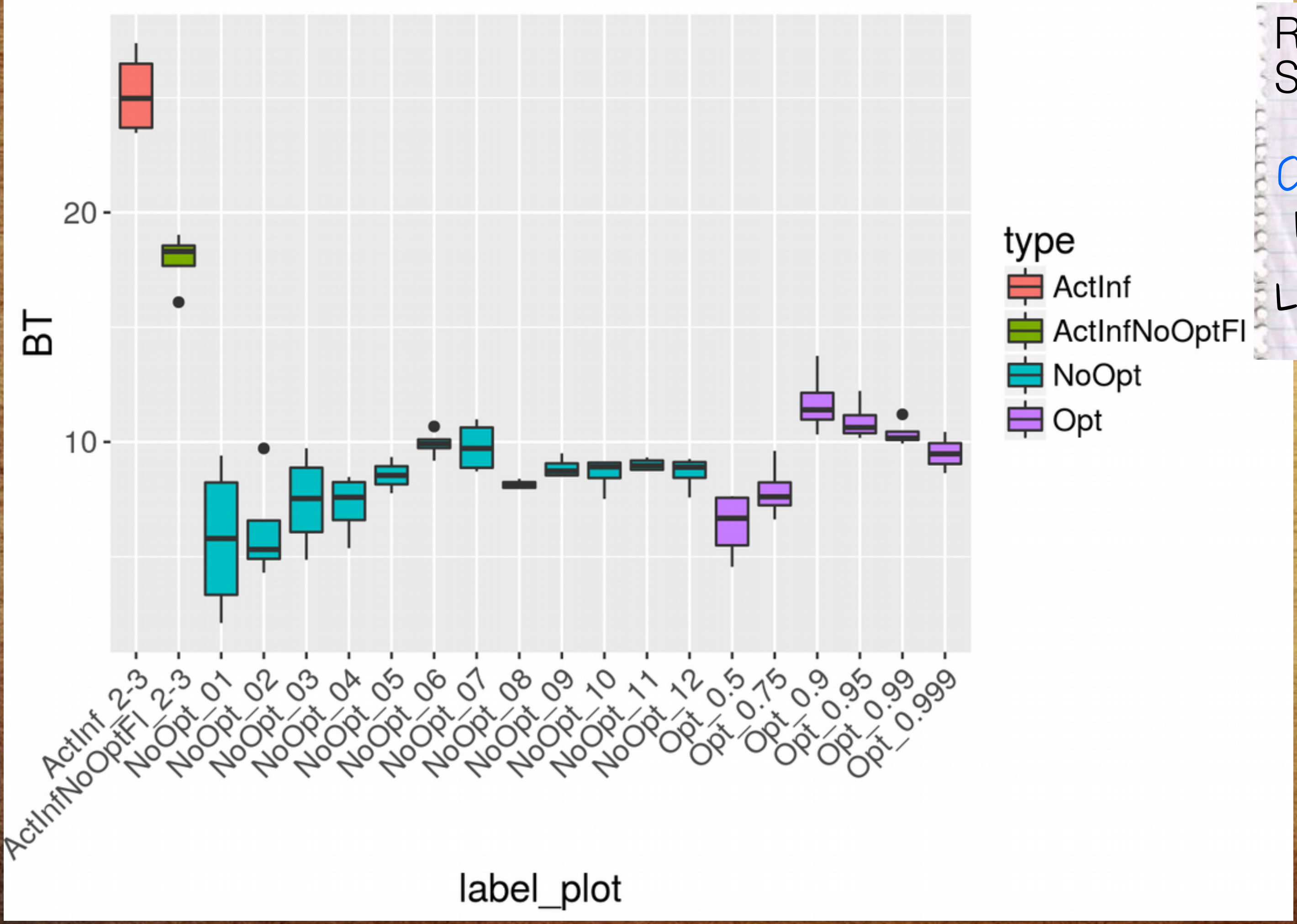
B <- log2(N) + P * log2(P) – (1–P) * log2((1–P)/(N–1))

T <- 0.2 * nFlash

BT <- B * (60/T)

preliminary RESULTS 2:

Compared real data between ActInf (optFlash and NoOptFlash) basic, and optimal stopping P300-speller (good, average, bad subject)



Real data from Subject 05:

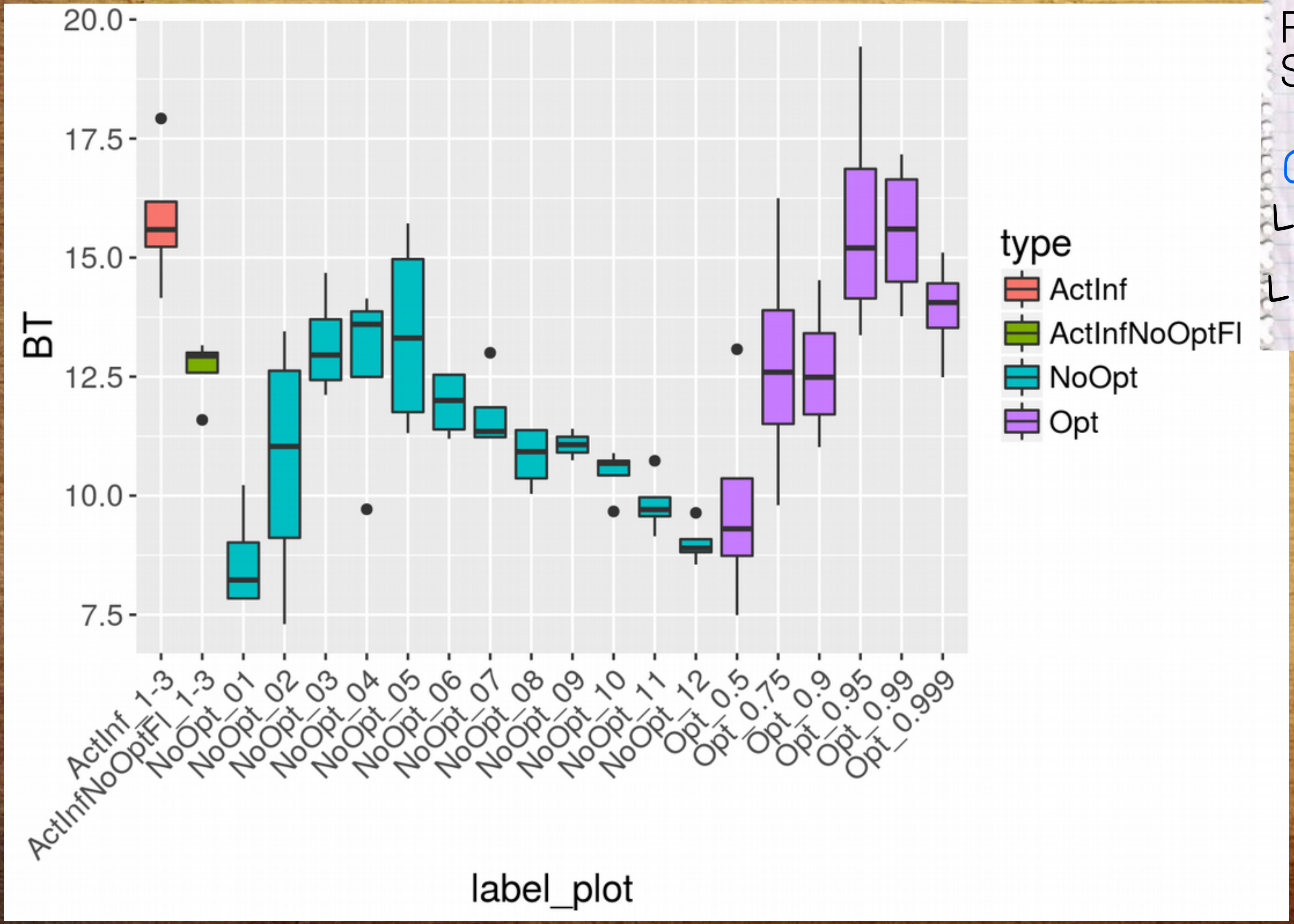
Classif output:

LLR T > 3,2

LLR NT <-3,-2

preliminary RESULTS 2:

Compared real data between ActInf(optFlash and NoOptFlash), basic, and optimal stopping P300-speller (good, average, bad subject)



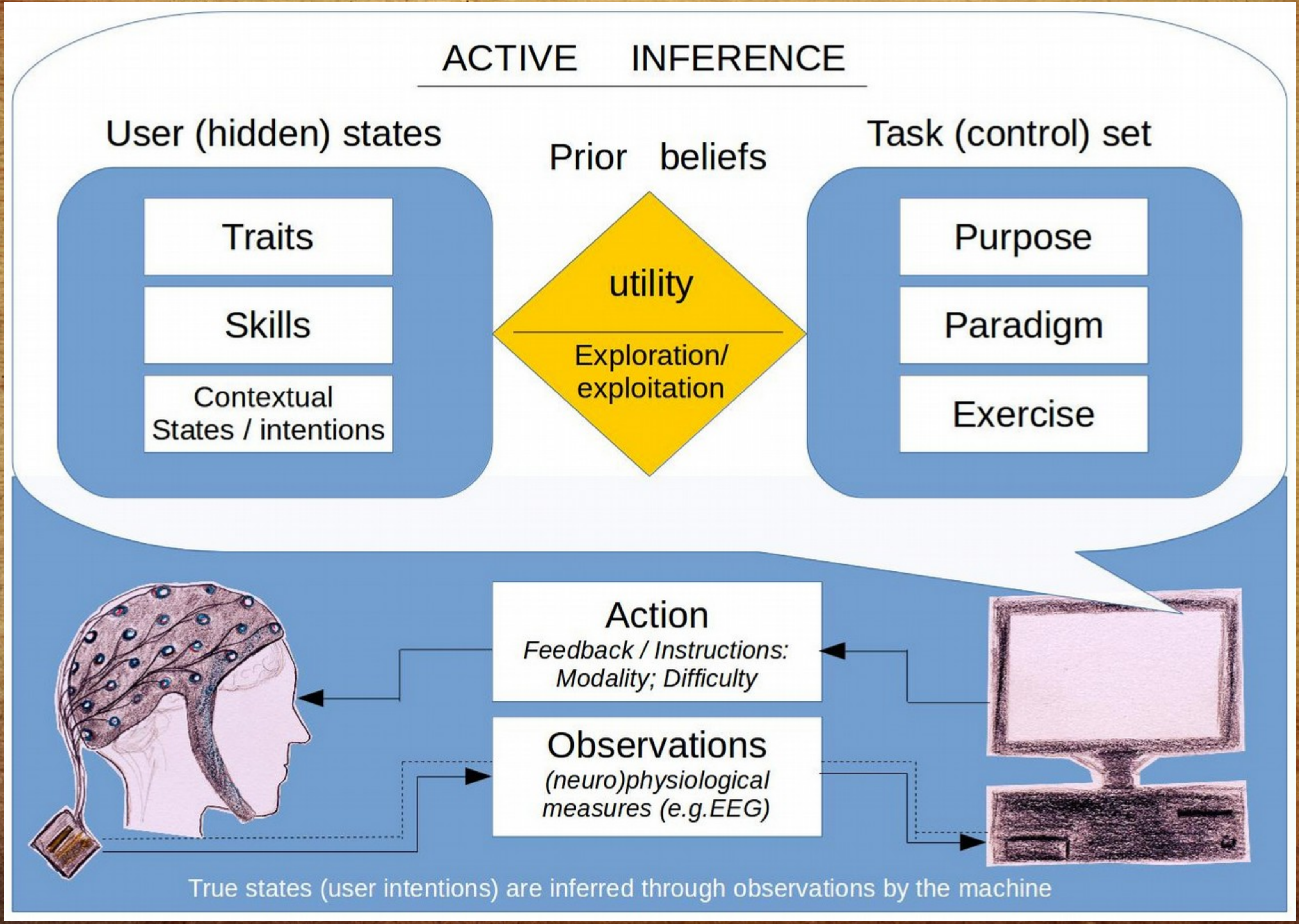
Real data from Subject 04:

Classif output:

LLR T > 3,1

LLR NT <−3,−1

Active Inference for adaptive BCI

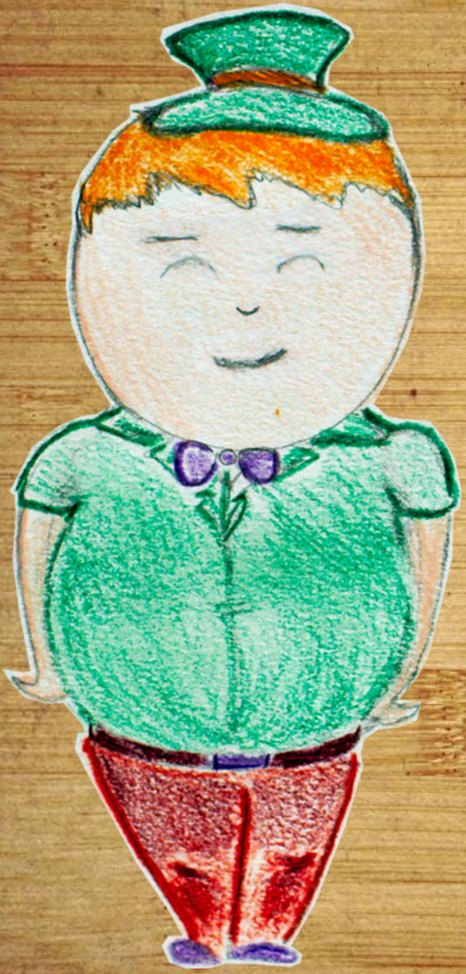


Conclusion:

- Adaptive methods adjust to signal variabilities
  - Identify the causes and influence them
- Conceptualize a framework for adaptive BCI
  - Implement it with Active Inference
- Application on P300-speller, preliminary results
- Active Inference can be extended for a fully adaptive BCI

Acknowledgments:

Thank You!



Questions?