Flexible Learning Reading Group @TU Berlin
10th Session: 23rd of January 2020

DEEP NEUROETHOLOGY OF A VIRTUAL RODENT

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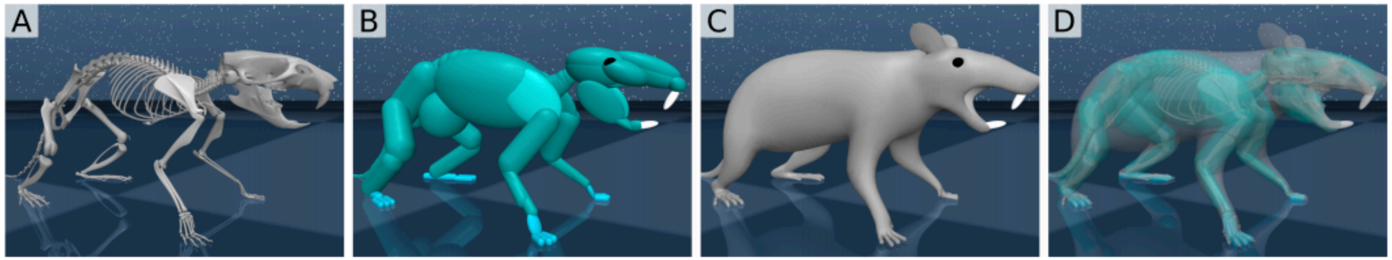
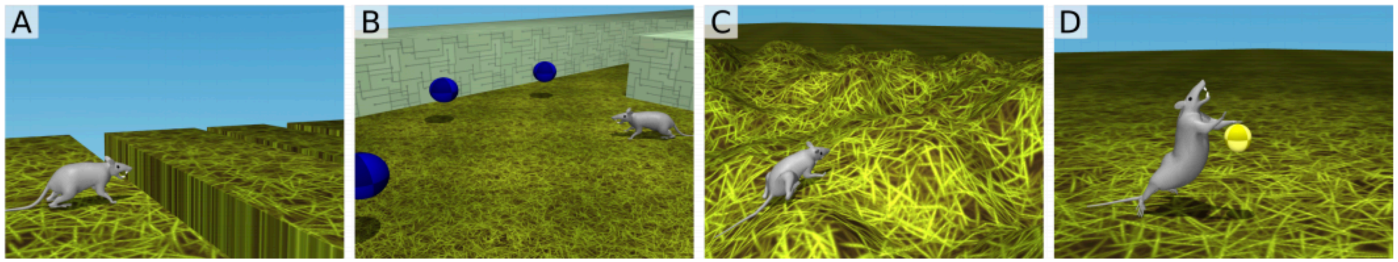
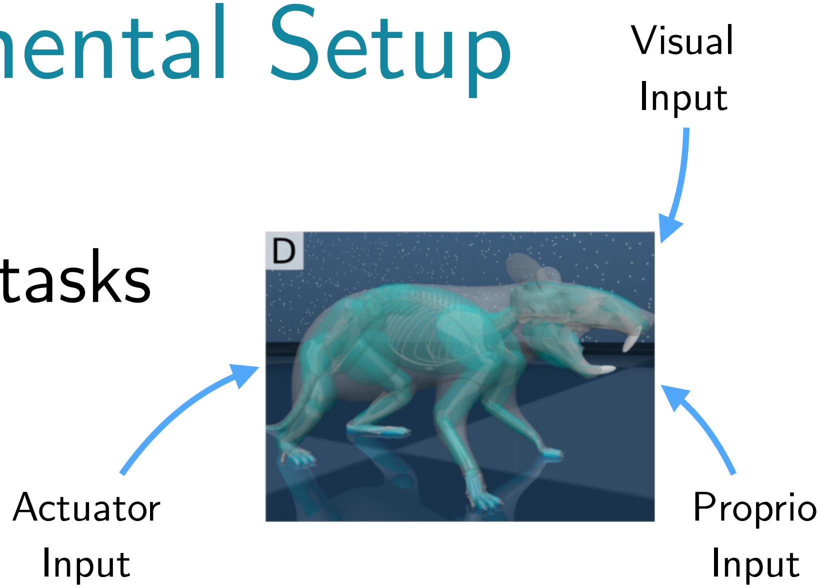




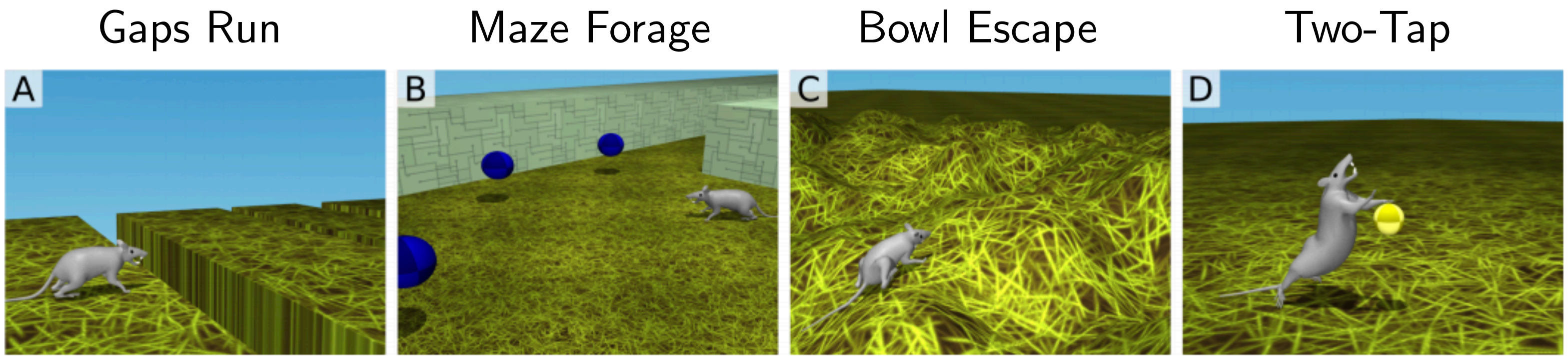
Picture Credits - Merel et al. (2020; ICLR)

Motivation & Experimental Setup

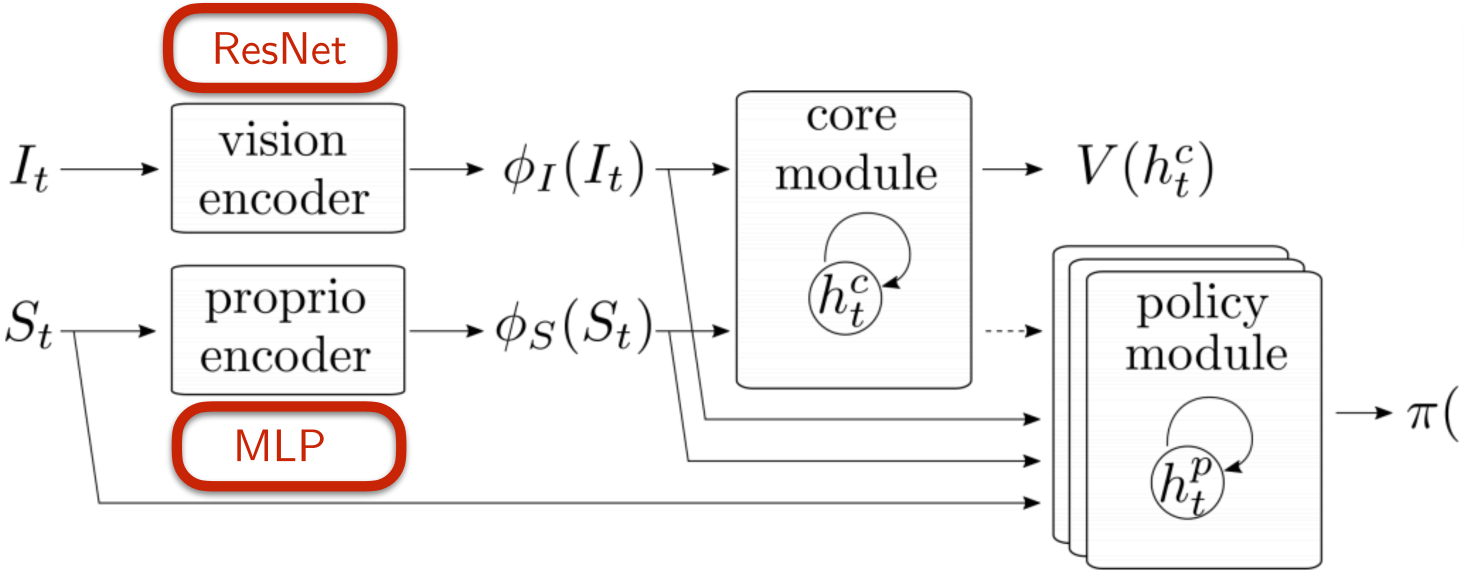
- Neuro - Claims based on single tasks
- DeepNets as ‚White-Boxes'
- Simulation = Flexibility



→ Study behaviour/representations using neuro tools



Multi-Task Reinforcement Learning Setup

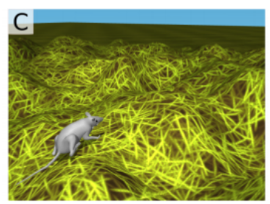


Maximum A Posteriori Policy Optimisation (Abdolmaleki et al., 2018):

„[…] assuming future success in maximising rewards, what are the actions most likely to have been taken?“

Kickstarting for Multi-Task RL (Schmitt et al., 2018):

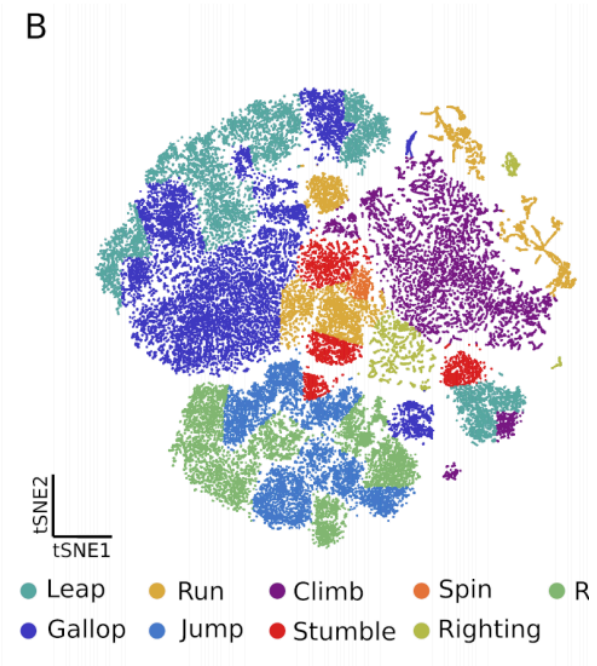
$$\mathcal{L}_{kick}^{k}(w, x, t) = \mathcal{L}_{MPO}(w, x, t) + \lambda_k \mathcal{H}\left(\pi_T(a|x_t)||\pi_S(a|x_t, w)\right)$$



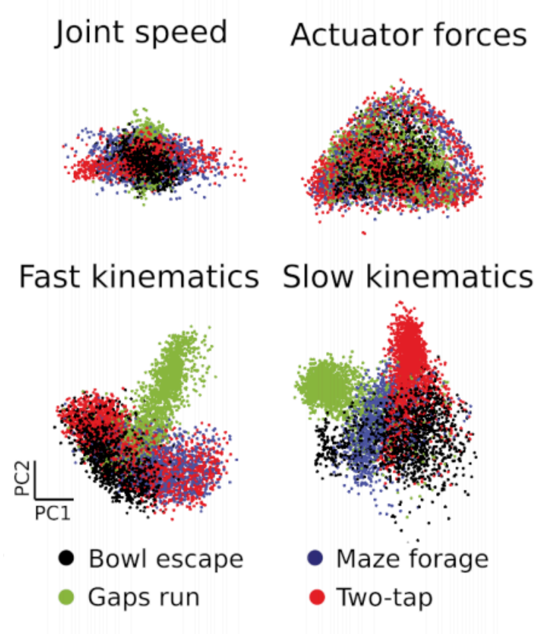
Behavioural Flexibility Through Timescales

Technique: tSNE

Behavioural Map



Timescale Differentiation



Different Timescales - (5-25Hz, 1-25Hz, 0.3-5Hz)

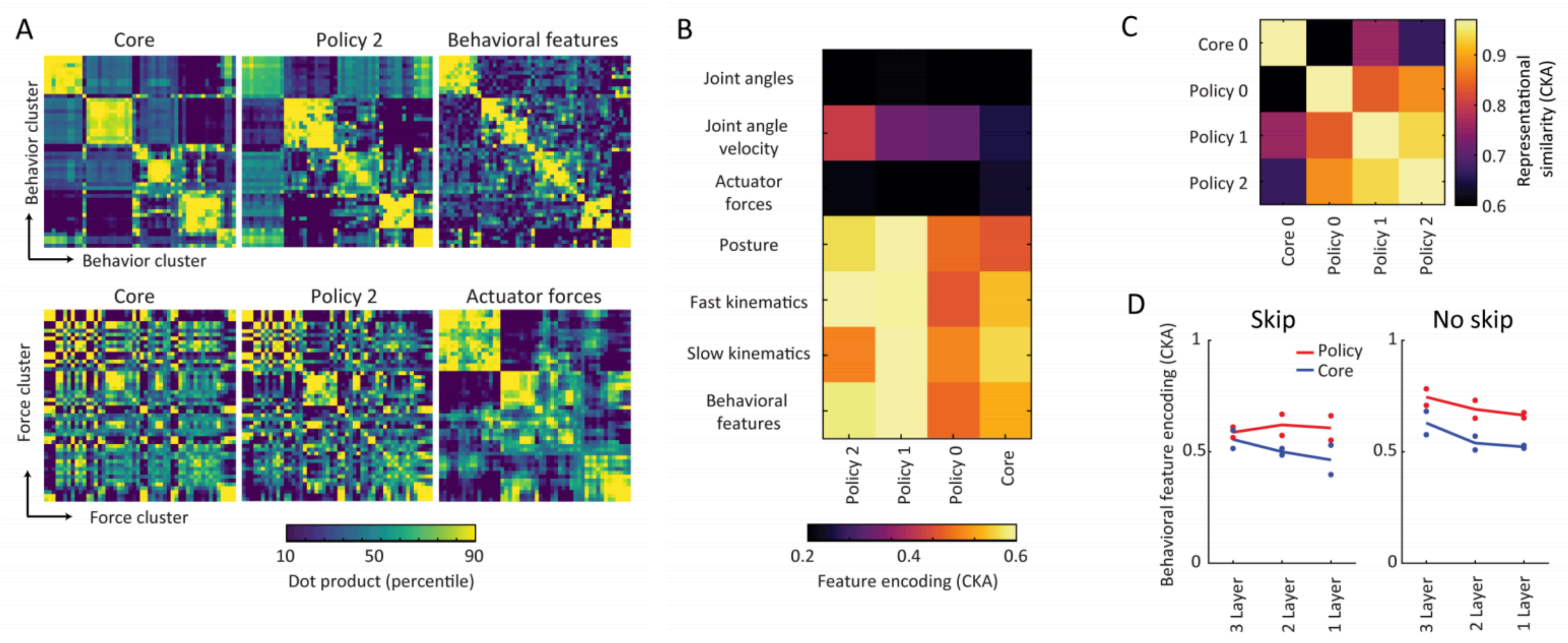
Task Differentiation More Profound on Longer Timescale

→ Indicates Selective Representation Reuse for Flexibility

Network Activity: Behaviour not Forces

Technique:
RSA-CKA

$$CKA(XX^T, YY^T) = \frac{\|XY^T\|_F}{\|XX^T\|_F \|YY^T\|_F}$$

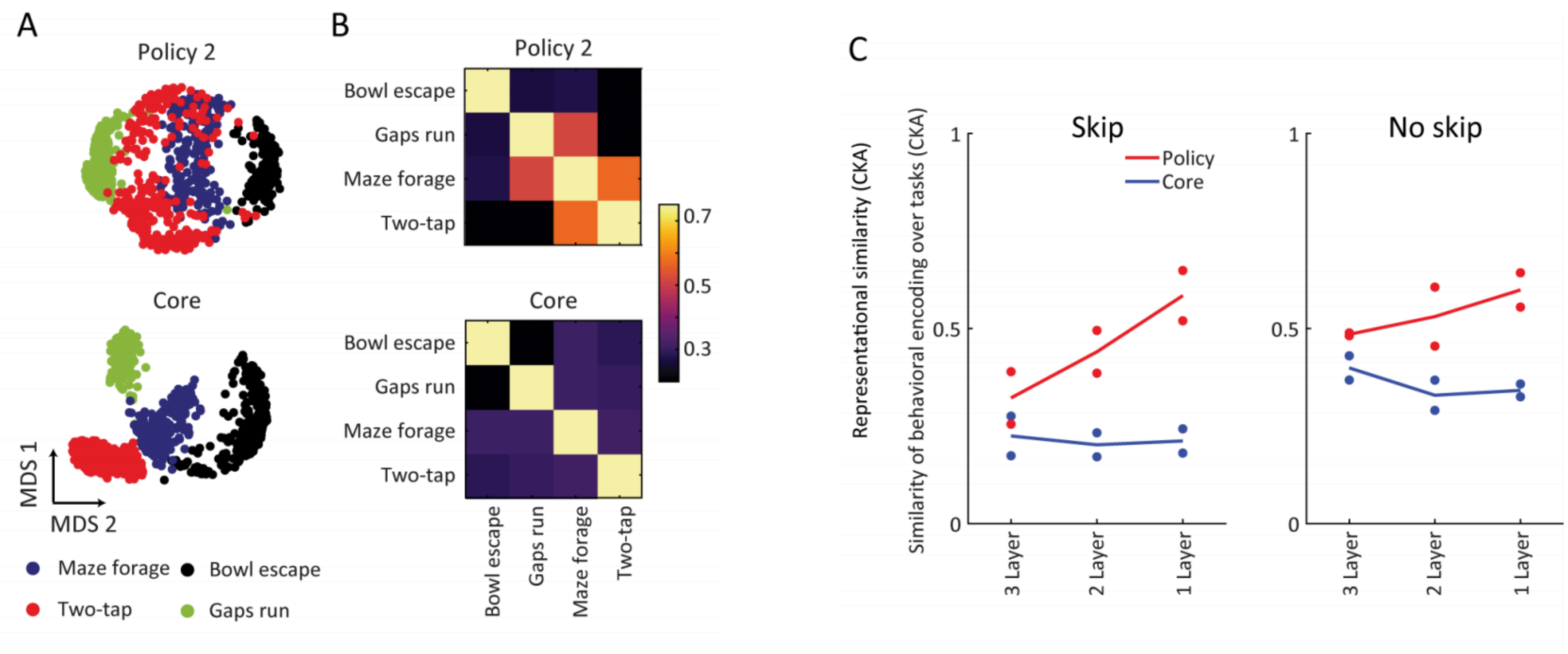


→ Core & Policy Encode Distinct Behavioural Features

Degrees of Representation Sharing

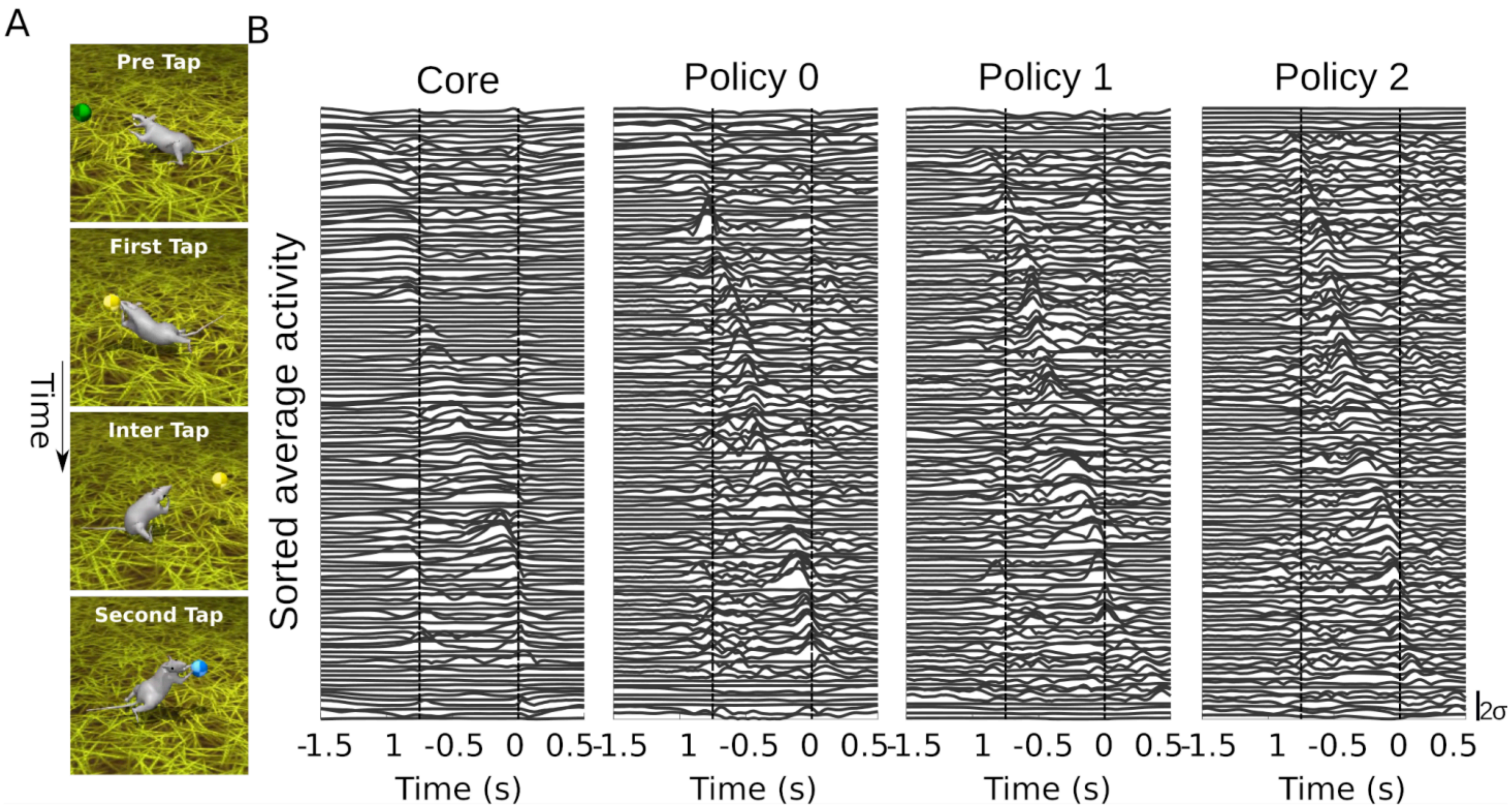
Technique: MDS

2-D embedding of population activity across layers



→ Core more distinct & Policy more overlap + Capacity!

Population Dynamics Synchronize Behaviour



→ Mechanism: Core = Integrates Task Context

Policy = Executes Patterns Task Independent

ICLR OpenReview

- Reviewer 1

„An appendix explaining with notation how the behavioral ‚features' were computed, for example, would have been helpful."

„[…] what would add a lot to this paper would be side-by-side comparisons of real neural data with "neural" data from the artificial rodent."

- Reviewer 2

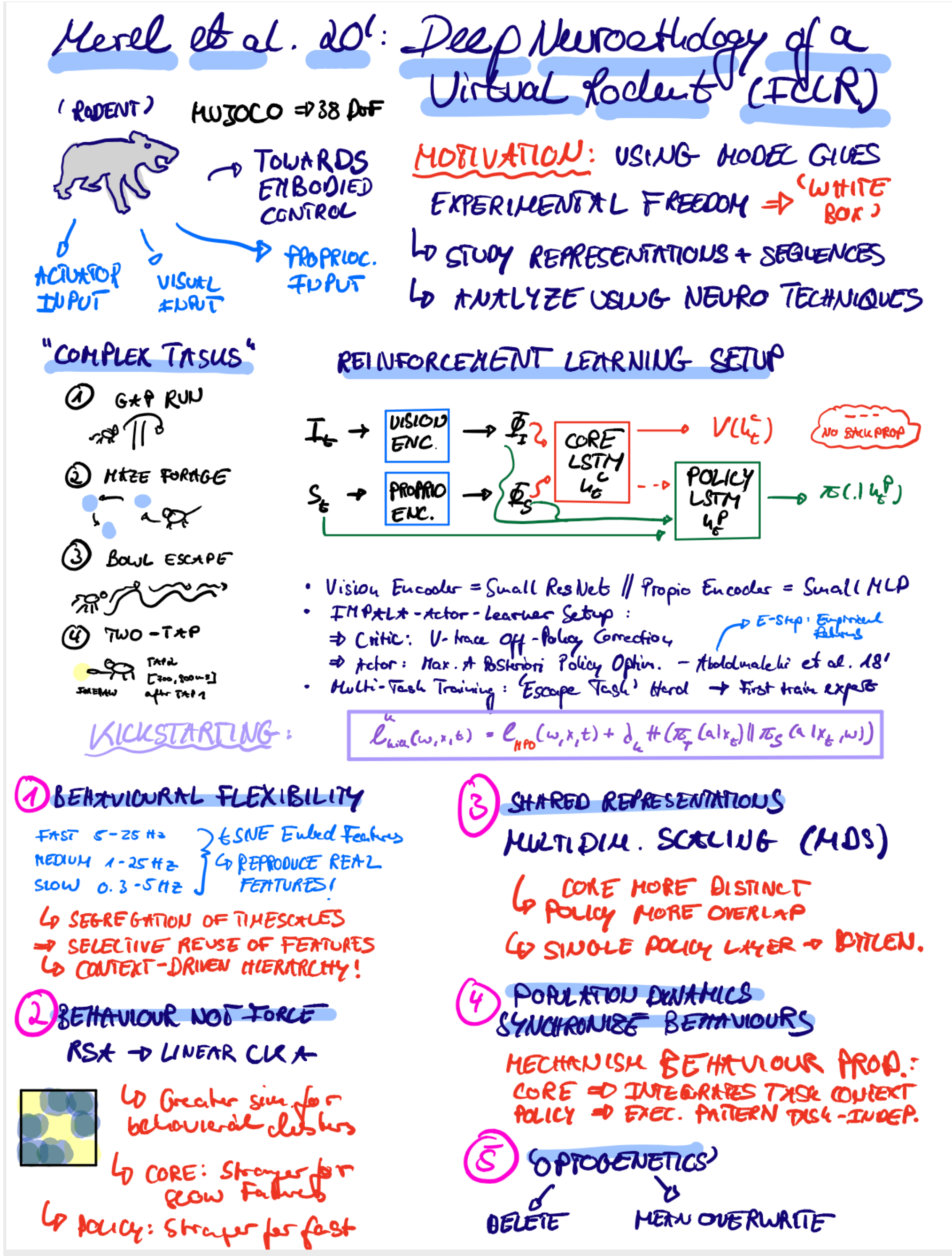
„given the architecture choice made in the paper, most of the main results do not seem very surprising. […] the architecture choice itself is not motivated well enough. The differences between […] the core and policy networks entirely depend on the fact that the core network is trained separately from the policy network."

- Reviewer 3

„The actual analysis is a bit of a letdown - not because it seems to be wrong or incompetently done, rather the opposite - but in that there is so little to learn from it."

Key Contribution/Insights - Merel et al., 20'

- MuJoCo Virtual Rodent + IMPALA/MPO/Kickstart
- Timescale Differentiation: Selective Representation Reuse
- Greater encoding similarity for behavioural than force features
- Shared representations: Core distinct - Policy overlap
- Dynamics: C integrates context - P executes indep.



Session 11: 5th of February 2020

On the Measure of Intelligence

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Abstract

To make deliberate progress towards more intelligent and more human-like artificial systems, we need to be following an appropriate feedback signal: we need to be able to define and evaluate intelligence in a way that enables comparisons between two systems, as well as comparisons with humans. Over the past hundred years, there has been an abundance of attempts to define and measure intelligence, across both the fields of psychology and AI. We summarize and critically assess these definitions and evaluation approaches, while making apparent the two historical conceptions of intelligence that have implicitly guided them. We note that in practice, the contemporary AI community still gravitates towards benchmarking intelligence by comparing the *skill* exhibited by AIs and humans at specific tasks, such as board games and video games. We argue that solely measuring skill at any given task falls short of measuring intelligence, because skill is heavily modulated by prior knowledge and experience: unlimited priors or unlimited training data allow experimenters to "buy" arbitrary levels of skills for a system, in a way that masks the system's own generalization power. We then articulate a new formal definition of intelligence based on Algorithmic Information Theory, describing intelligence as *skill-acquisition efficiency* and highlighting the concepts of *scope*, *generalization difficulty*, *priors*, and *experience*, as critical pieces to be accounted for in characterizing intelligent systems. Using this definition, we propose a set of guidelines for what a general AI benchmark should look like. Finally, we present a new benchmark closely following these guidelines, the Abstraction and Reasoning Corpus (ARC), built upon an explicit set of priors designed to be as close as possible to innate human priors. We argue that ARC can be used to measure a human-like form of general fluid intelligence and that it enables fair general intelligence comparisons between AI systems and humans.