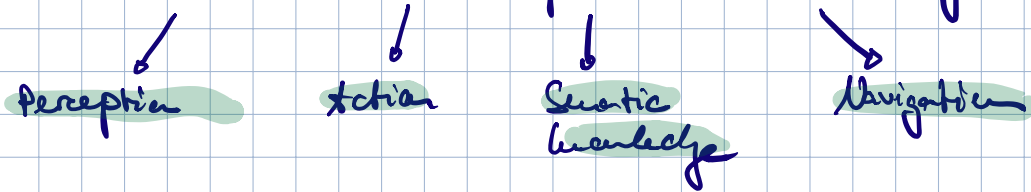


CCN - Day 3 - Máté Lengyel

- (Probabilistic Internal Models) -

INTERNAL MODEL = Mental representation surrounding world



Probabilistic perspective $\Rightarrow p_{\mu}(y) \rightarrow p(x|y) \rightarrow$ Interested in generative model: $p(x,y)$

↳ Central problem: Inverse $\Rightarrow p(y|x) \rightarrow$ How to do best?

↳ Model in alignment with "true" generating process

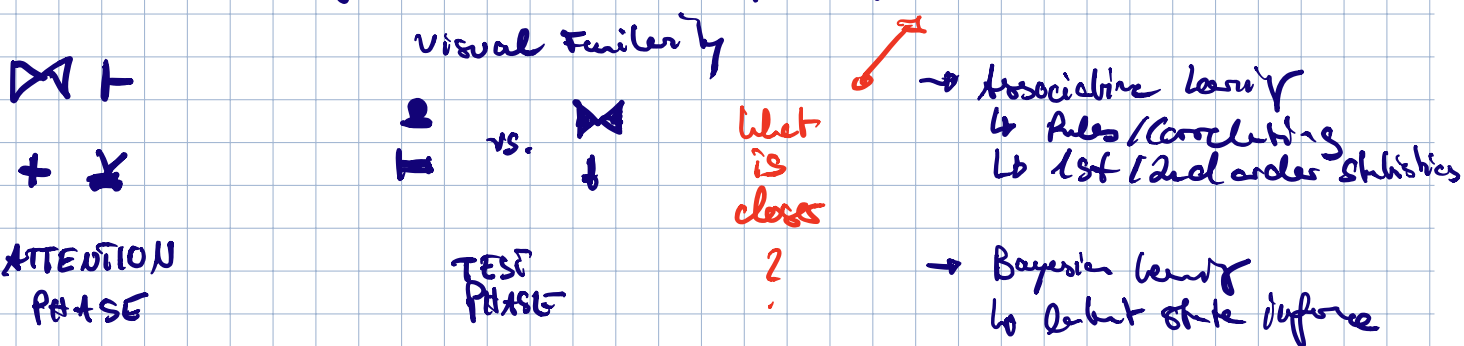
↳ Flexibility (!!!) \Rightarrow Using same internal model in multiple tasks!

Three parts:

- ① Env adaptation
- ② Task - Modality - Independence
- ③ Neural Substrates

ADAPTATION TO ENV

• Visual Action Learning (Söszegi Fiser) \rightarrow requires generalization via model identifi.



\Rightarrow **TRICK-HWBY**: As complexity of env/task increases

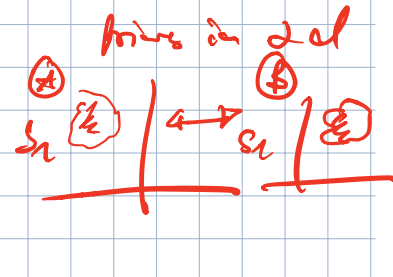
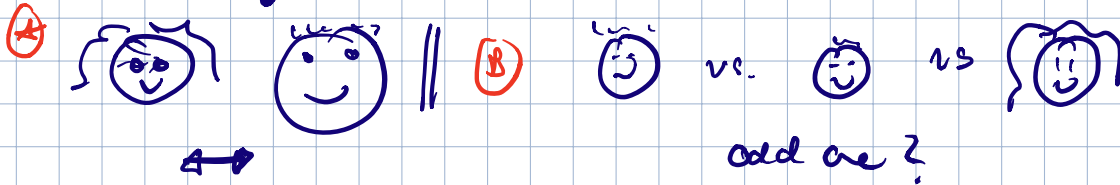
\rightarrow Bayesian learner fits performance best! \rightarrow Generalisation

• Climbing \rightarrow Haptic pull estimation to prev. task

\Rightarrow **TRICK-HWBY**: Zero-shot generalisation using extracted latent variables! \rightarrow to new haptic tool!

TSA - MODALITY INDEPENDENCE

- Familiarity vs. odd-one-out task



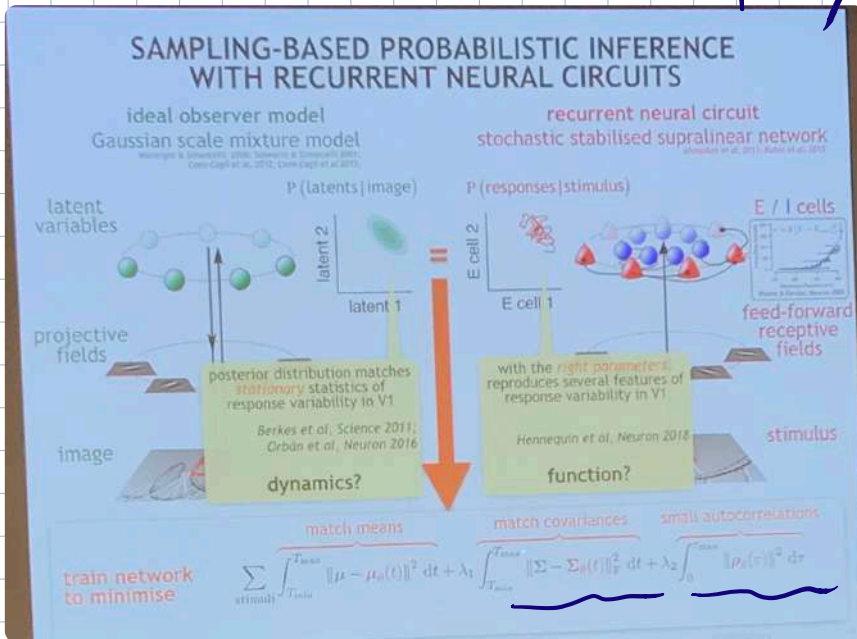
→ Natural prior identification for both tasks → ^{behavior} fitting!

⇒ TUG-tutty: Similar prior across task but different between subjects

- Cross-Validation → behavior prediction + prior prediction (across tasks)

NATURAL SUBSTRATES (Variability, Oscillations, Transients)

- Motivation → DL: Get biologically plausible dynamics!



→ Noise neural activity "noise"
Go models with latent vars!

↓
simplified figure

⇒ Probabilistic length scales → HMC!

Gaussian Scale Mixture Model

Stochastic Stabilised Supralinear Network

- Interested in resulting dynamics → hard-wired activity objectives
↳ anti-correlations ⇒ HMC

$$\hookrightarrow \delta_t = r_t + \sum_i [\gamma V_i(s_{t+1}) - V_i(s_t)] \rightarrow \delta_{i,t}$$

\Rightarrow DOPAMINE NEURON PER VALUE CHANNEL

\hookrightarrow Same model \rightarrow different mapping!

$$\sum_i \delta_{i,t} = \delta_t$$

model explains the Engelhard findings (1)

for arbitrary $\vec{\phi}$

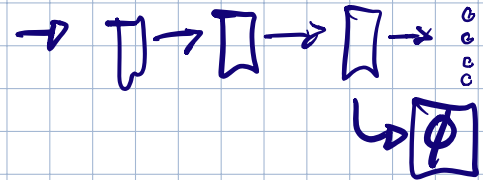
$$\delta_i(t) \approx \frac{r_t}{N} + w_i [\gamma \phi_i(s_{t+1}) - \phi_i(s_t)]$$

\rightarrow arbitrary input behavioral / sensory / task variables ϕ_i will correlate with different DA neurons

- either because ϕ_i is value-relevant (hence w_i is nonzero)
- or, even if not, due to slow/accidental fluctuations in w_i



• Put into DQN context:



\rightarrow Use to compute different "neuron"-specific RPEs

\hookrightarrow RELATIONSHIP TO DISTRIBUTIONAL RL ?!

• Facterization $\sum_i \delta_{i,t}$ can lead/imply distortions

why? what is this good for?

may just be a (serendipitous) side-effect of wiring

separation of channels could provide foundation for some **specificity of signaling** (e.g. multitasking, spatial credit assignment eg by effectors; Gershman et al 2009)

many modelers envision vector error signals to handle multiplicity in:

- outcome types, eg reward vs. punishment (Daw et al 2002; Lloyd & Dayan 2016)
- state uncertainty (Daw et al 2003; Rao 2010; Lak et al 2018)
- levels of abstraction (O'Reilly & Frank 2006; Botvinick et al 2009)
- timescales (Kurth-Nelson et al 2009), risk levels (Kurth-Nelson, Dabney, Uchida)
- effectors (Gershman et al 2009)
- predicted events other than reward (Dayan 1993; Gardner et al 2018)

... some of these may coexist, but do not appear to relate to these results

note also: other cases of heterogeneity (esp at larger region-region scale; Lee et al 2019; Menegas et al., 2018) is likely a different thing

• Learning of multiple value pt.?

conclusions

one example (of many) of heterogeneous dopamine responses

- **less than meets the eye:** we can easily reconcile this with scalar decision variables, no need to appeal to more structured multi-PE schemes (not mutually exclusive)
- **more than meets the eye:** heterogeneity inherited from population code for state, window into state representation in high-dimensional, continuous tasks
- general framework for feature-based value learning using arbitrary features
- whence the features? dovetails naturally with successor representation (Gershman), fancy map codes (Behrens), DQNs...