

— 'Representing States and Spaces' —

- ① Thorndike → Law of effect \Rightarrow Pavlov / Skinner $\stackrel{②}{\Rightarrow}$ Reward-based learning \hookrightarrow STIMULUS
- ③ Tolman → Cognitive map \Rightarrow Value-based MF vs. Model-based
- ④ Harlow et al 1949 \Rightarrow Monkeys MB vs MF \Rightarrow learning sets!

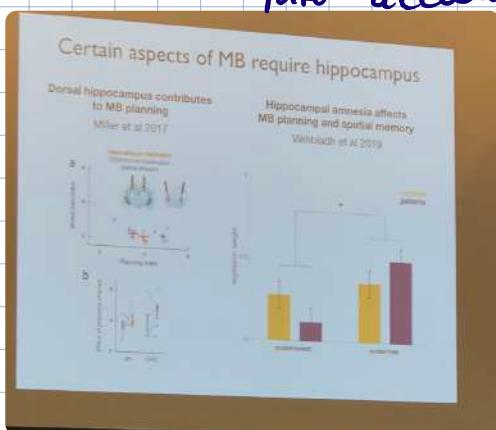


RL
Problem!

SECTION ON RL PROBLEM ① + ②

- Exploration prob: Optimistic init
 \hookrightarrow Set values high & always explore all actions in all states else!
- MF value propagation \Rightarrow simple inefficiency \hookrightarrow Improve by using the "right" state space representation!

- Schultz et al. \rightarrow Reward Predictive Error hypothesis \leftrightarrow Dopamine Firing Rate
- Model-based RL: Tolman! \rightarrow Simulated Model of Causal Predictive \rightarrow Johnson & Redlich (2005) \rightarrow hippocampal activity \rightarrow sweeps \hookrightarrow Especially at decision points! \Rightarrow short-wave ripple
- PFC \Rightarrow Model-based vs. Shrivastava \Rightarrow Model-Free
- Direct buffer peers of learning experimentally \rightarrow Duh et al. 11' \hookrightarrow Do you take transmissible structure 2-step task into account \Rightarrow receive after partial transmission

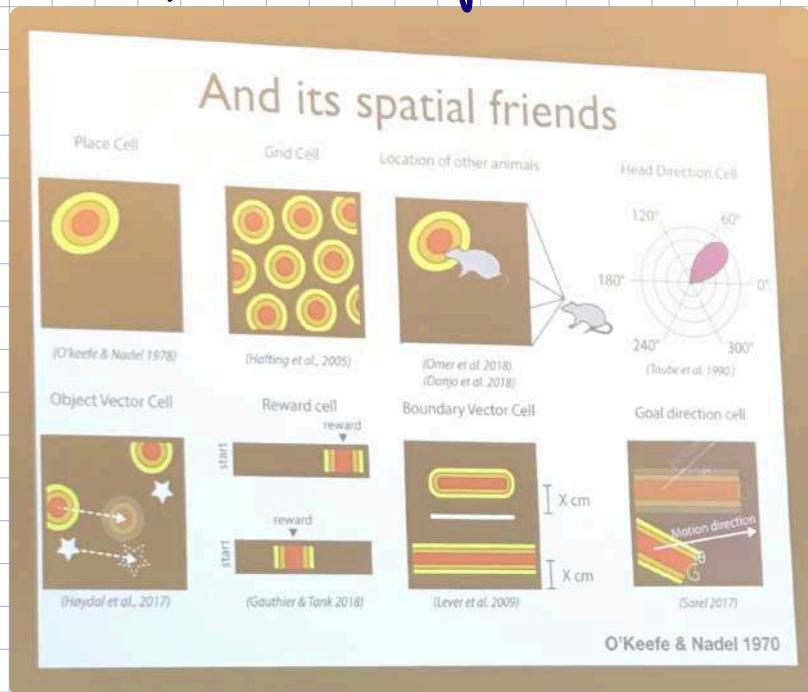


- How to integrate both systems!
- ① Abstraction: MF / MB both propose
- ② MB traces MF: Dynan - Seiden 81'
- ③ MC Trace - Search \Rightarrow Umarani et al 16'

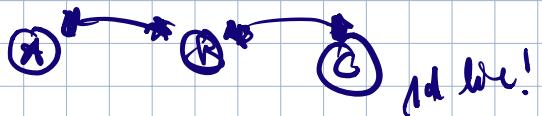
- Haider & Dan 18' \Rightarrow Optimal backups for flyover
 - \hookrightarrow Gain from Taxes!
 - \hookrightarrow Select transitions based on effect on policy update! (+)
 - \hookrightarrow Explains variability in hippocampus ripples!
 - ↳ how important are states!
- THETA SWEEPS \rightarrow happen when animal traveling!
 - STAR WAVE RIPPLES (SWR) \rightarrow rest/sleep!
 - \hookrightarrow Hypothesis: During sleep model-based system trains HF system

SECTION ON STATE SPACES (3) + (4)

- Geometry exploitation vs. Past experience replacement
 - \hookrightarrow Statistics of roadmaps! \Rightarrow Disentangle perf! \rightarrow global vector
 - \rightarrow Hippocampus as cognitive map \Rightarrow O'Keefe & Nadel 1870
 - \hookrightarrow place cells, grid cells, other animals, etc.

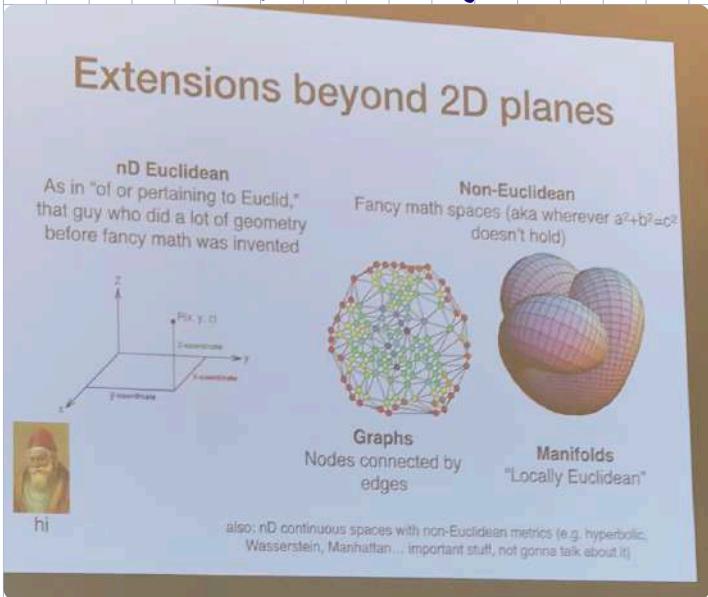


- Remapping \Rightarrow different dyres
 - \hookrightarrow Transfer of topological maps across cells \Rightarrow Hippo without losses of connectivity
 - \hookrightarrow Redundancy in recordings!
 - \hookrightarrow Context vs. Structure of env!

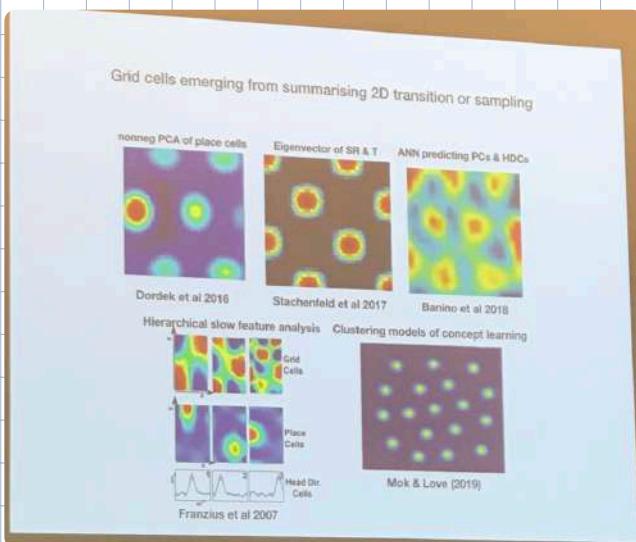


- Dusek et al 97' \Rightarrow Relational Inference in hippocampus \Rightarrow Tractrix
- Hexagonal fire neurons across different types of cells!
 - ↳ in PFC: Jacobs et al 13' \Rightarrow Grid cells! \rightarrow Maps outside hippocampus

- Hexagonal coding \rightarrow 2D \rightarrow 2D comprise! \Rightarrow Klüske et al 19'



- Graph \Rightarrow State as Node!
- \Rightarrow Transition as Weight/Edge



Modelling work on europe \Rightarrow off grid cells

\hookrightarrow transition matrix \Rightarrow top eigenvalues

↳ Find grid cells in fMRI! \Rightarrow grid code similarity = repr. similarity

- Method abstraction \rightarrow Cognitively \Leftrightarrow Cubert vs Henry
 \hookrightarrow cognitive load reduced!
- Male stickleback fish \rightarrow male = real under belly \Leftrightarrow sharp belly
- Learning of abstract representation space \Leftrightarrow Experience (active inference)
 \rightarrow latent states \Rightarrow OFC! \rightarrow Wilson & Nir, Schul & Nir 16, 19'
- Hippocampal splitting \rightarrow Wood et al 2000 \rightarrow cubert (adult - double activity!)
- Generalization of states \Rightarrow hippocampus \rightarrow Subregions from all others!

What is a good representation?

Prodictive

Dispersed

Low-Dim

Hierarchical

Transfer

Reliable

Successor
representation

Separate
rewards

Easier to learn
less

if
level of
abstraction

if
more
tasks

Task
Connectivity

PREDICTIVE

- Successor Representations in Hippocampus → Saksena et al. 18'

↳ Transfer!

Transfer of
Value locations!

↳ Successor vs. Eligibility

LOW-DIM

- Context Cold!
- Eigenvectors ↗ Eigenvalues
↳ longest EV captures most variance in specific matrix
⇒ moment!

- PCA, etc. (dim. reduction) ⇒ Generalizability

✓ faynside Seibert → Lam ⊕ invert generative model

- Helenholtz Machine → Hinton, Dayan (1998) → competitive
- VAEs → Kingma & Welling 13' → have latent transfer structures
↳ HOLISTIC RL → add memory element // hippocampus

Beliefs
Reinforcement!

Further Reading

Example works with learned representations

Grid Cells, Place Cells, and Geodesic Generalization for Spatial Reinforcement Learning. Gustafson & Daw PLoS Comput Biol (2011).

Performance-optimized hierarchical models predict neural responses in higher visual cortex. Yamins, Cadieu, Solomon, Seibert, DiCarlo. PNAS (2014).

Reinforcement Learning in Multidimensional Environments Relies on Attention Mechanisms. Niv, Daniel, Geana, Gershman, Leong, Radulescu, Wilson. J Neurosci (2015).

The successor representation in human reinforcement learning. Momennejad, Russek, Cheong, Botvinick, Daw. Nat Human Behav (2017).

Vector-based navigation using grid-like representations in artificial agents. Banino, Barry et al. Nature (2018).

Prefrontal cortex as a meta-reinforcement learning system. Wang, Kurth-Nelson, Kumaran, Tirumala, Soyer, Leibo, Hassabis, Botvinick. Nat Neurosci (2018).

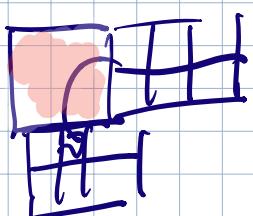
Rethinking dopamine as generalized prediction error. Gardner, Schoenbaum, Gershman. Proc Royal Society (2018).

See keynote
tomorrow!

Liz Spelke - 'From core systems to new concepts of knowledge'

- Infant/kid learning \Rightarrow Highest general intelligence \rightarrow 0-5 year old kids
 - \hookrightarrow high variability across nature of tasks that kids have to master!
 - \hookrightarrow across cultures and subjective endorsement!
- Fast & flexible learning \rightarrow Herz: Developmental Psychology PvV

- Eleanor Gibson - Visual Cliff \Rightarrow Developmental psychophysics



\rightarrow visual depth (sees w. plexiglass)

\hookrightarrow Goettl: From birth

\hookrightarrow Ratti: First vis. exp.

\hookrightarrow Infants: From crowded

\hookrightarrow Carlo: Perceptual learning over time!

of objects!

\Rightarrow Depth perception is innate, not shaped by experience length

\Rightarrow ancient Mechanism / Visual Exploration / Time

FUFTNT CORE KNOWLEDGE SYSTEMS

Six systems of core knowledge

		The systems center on abstract, interconnected concepts.
objects (continuity, contact)	agents (cause, cost, value...)	They are limited.
		They activate specific systems in human and animal brains.
persons (shared experience)	places (distance, direction)	They are shared by other animals and therefore are ancient.
		They are innate.
forms (rel. length, medial axes?)	number (comparison, addition...)	They emerge early and are present throughout life.

suggests kids' learning

all are related



Ancient

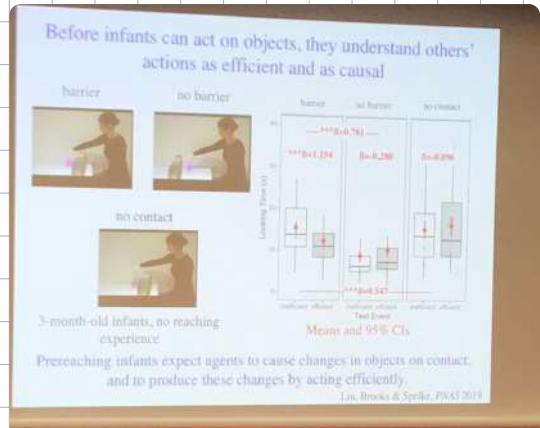


Heba -
Lewy

- Plays \Rightarrow abstract concepts \rightarrow limited \Rightarrow support of learning
 - \hookrightarrow discrete + relative abstractions relevant // not color/shape!
 - \hookrightarrow Navigator follows after perception \Rightarrow Not directly
 - \hookrightarrow But how is this learned?! \Rightarrow End-to-end?!
 - \hookrightarrow series of experiments by Lee & Spelke
 - \hookrightarrow How is action planning learned? \rightarrow Hard to study some process seems to be very slow!
 - \hookrightarrow place cells \rightarrow grid cells \rightarrow border cells [DEVELOP]
 - \hookrightarrow LEARNING / EXPLORATION REQUIRED!
 - \hookrightarrow learning supports \Rightarrow Re-orientation \rightarrow self-supervised!
 - \Rightarrow Not evolutionary but affects!

\Rightarrow EUCLIDEAN NATURE OF WORLD \rightarrow CONSTANT ACROSS EVOL.

- Universally useful abstractions will emerge early on \rightarrow help most!
 - \rightarrow Open-ended systems of concepts \Rightarrow generated by productive rules
- Important point in time when kids realize that numbers are exact representations \Rightarrow Superb symbolic manipulative realization
- Tool use — End of 1st year
 - \rightarrow detection vs. usage of object features \rightarrow not incentive!
 - \rightarrow 7 month: assoc. moment with specific objects
 - \rightarrow but no direct functionality assert.



\rightarrow Lee, Brodsky, Spelke PNAS 19' \Rightarrow causal + Effec

\hookrightarrow Required to learn! \Rightarrow OBSERVER

- Language \Rightarrow Person / Object / Form / Function
- \hookrightarrow COMPOSITION OF CORE SYSTEMS

Grammars → More general interpretation → follow by logic/
Symbolic rules of Nature!

Generalizing the hypothesis

Language gives our species a unique system for composing new concepts from core concepts, in accord with productive rules.

- a single, open-ended stock of words
- rules for forming new expressions based only on the grammatical properties of words, not their meanings.
- compositional semantics
- pragmatics (relevance)

These properties enable children to learn new words and expressions rapidly, from language alone (ex: "I've got *two pets*: a dog and a cat.")

Only humans learn like this (c.f. word-learning dogs).

Language learning supports rapid, productive, flexible concept learning, because (a) language rules generate an infinite set of concepts, (b) words & phrases provide an economical way to represent them, and (c) children learn their language from others in their culture, who speak about things they find useful and relevant.

Spelke, LangLrngDev 2017