

What can AI contribute to neuroscience?

Caswell Barry, UCL.

Novel Computational Paradigms, Cambridge.

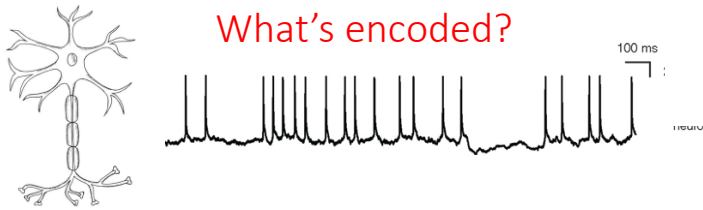
Neuroscience

- Encompasses many levels: from labs studying individual neurons to fMRI
- Aim: Understand how the brain generates cognitive phenomena (e.g. how do we remember?)
- Specific questions:
 - what information is present at different points in the brain – how it is represented?
 - how are stimuli encoded and behaviors affected?
 - what computations are performed by neural circuits?

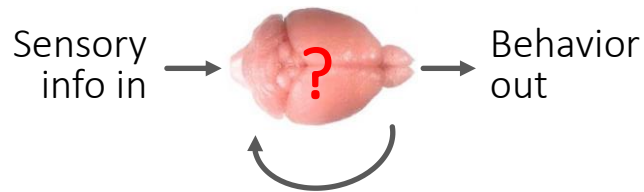


Two problems

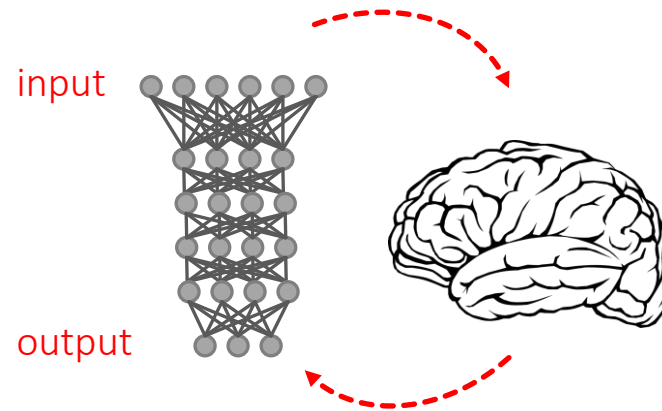
- **Bottom up** - the **data** problem:
 - fMRI (2GB per brain), electrodes (1GB/minute), microscopy (2GB+/minute)
 - what information is present, how it is encoded, what computations are performed?



- **Top down** - the **hypothesis & model** problem:

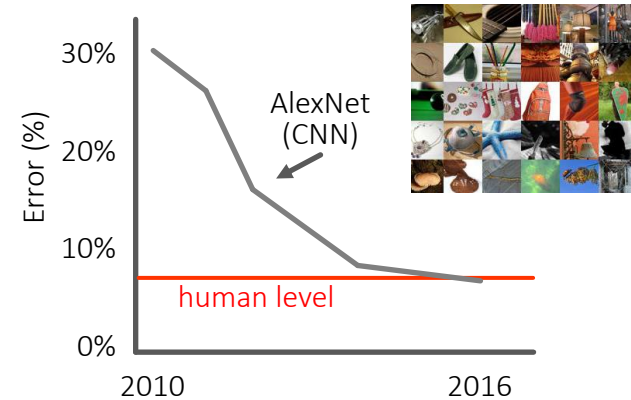


Deep networks (DNNs)



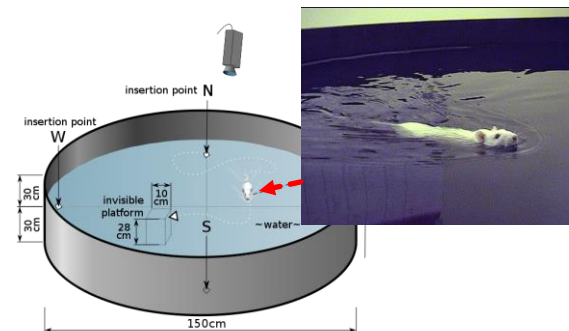
Bottom up

1. Deep learning is extremely good at mapping noisy input data to an output
 - e.g. stimuli to neural data
 - once trained a DNN can be interrogated



Top down

2. DNNs sometimes solve problems in a similar way to the brain – potentially **provides a good model system**
 - train to perform similar tasks to animals (e.g. visual recognition, navigation, limb control)



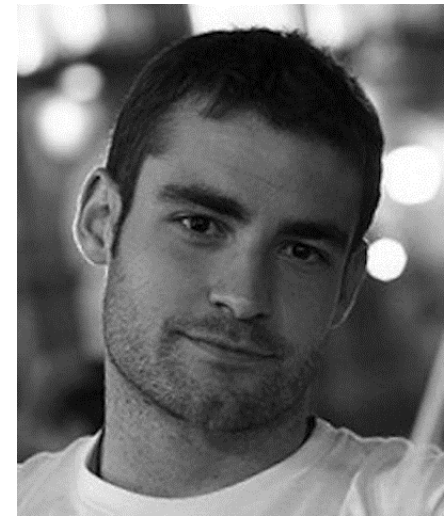
Top down (build a model)



Andrea Banino



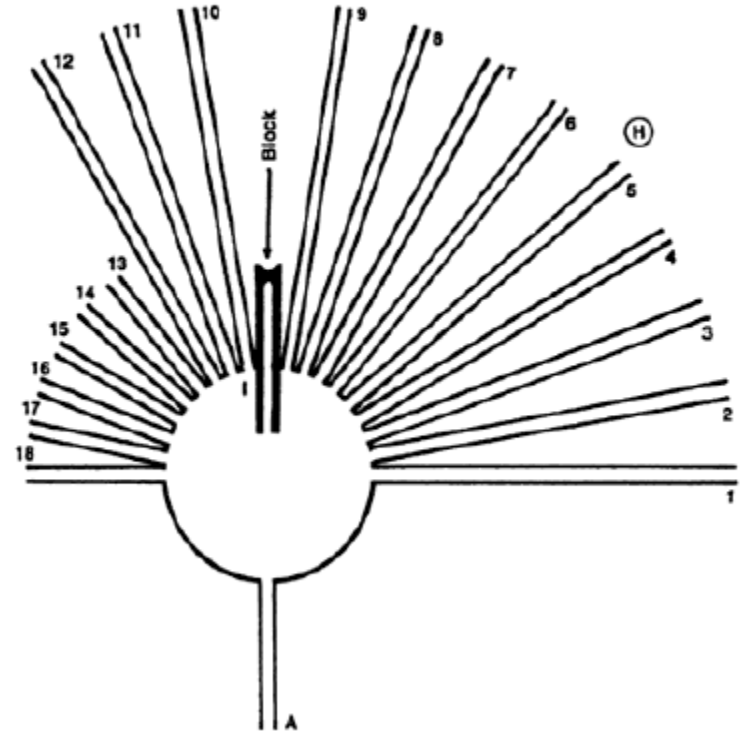
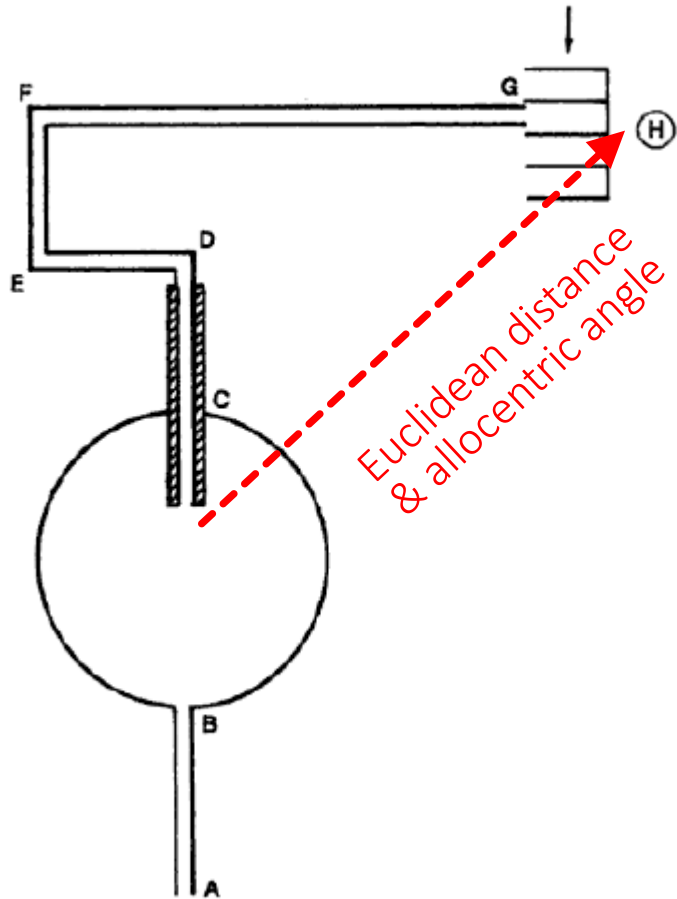
Dharshan Kumaran



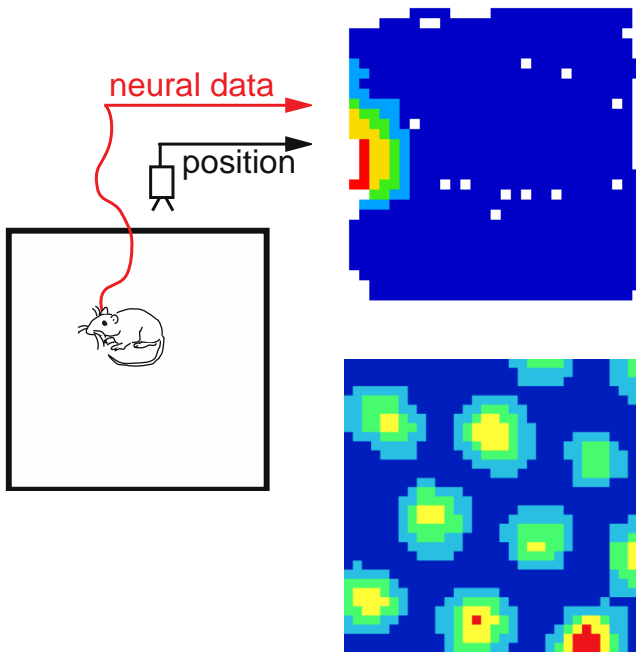
Benigno Uria



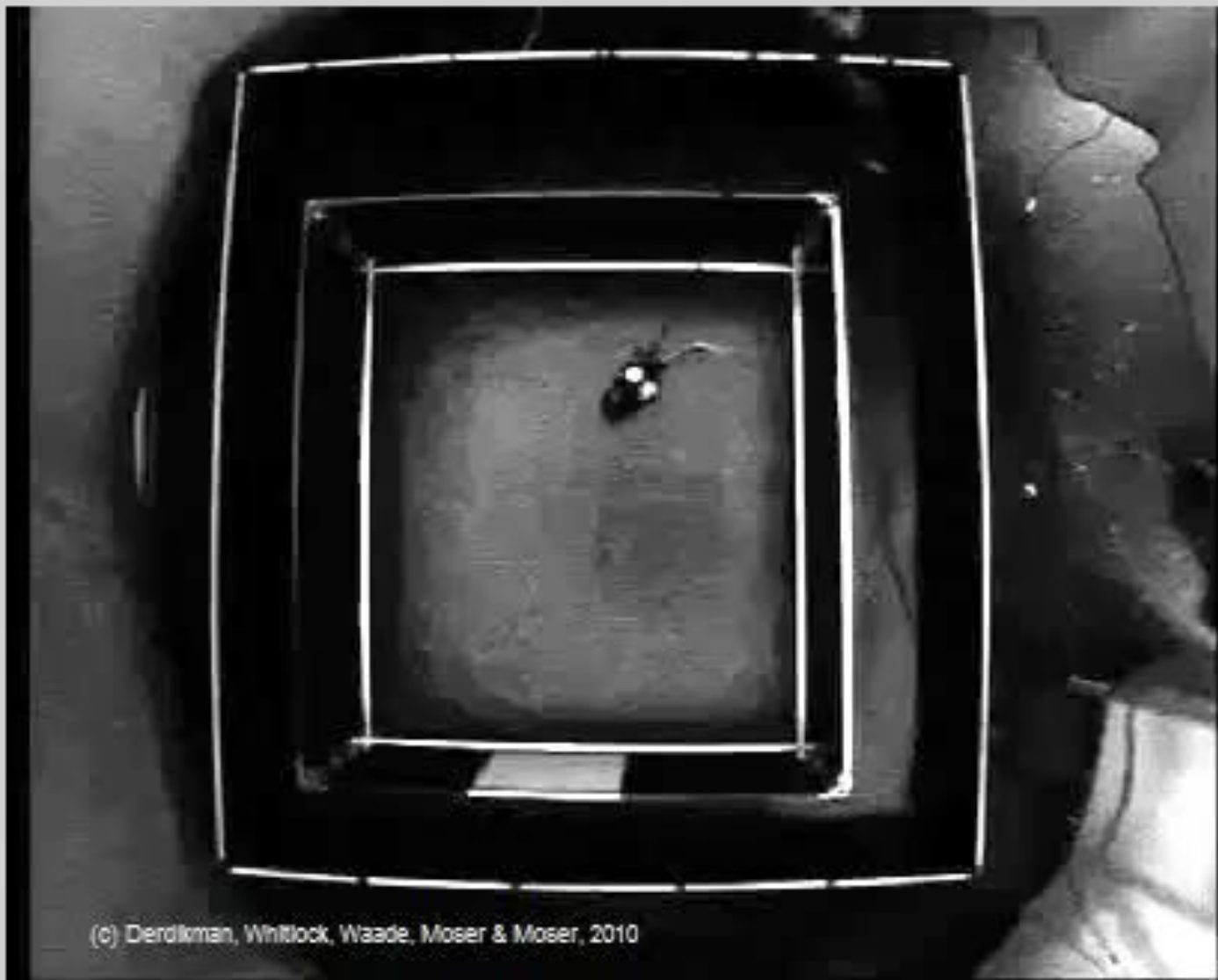
Tolman's Cognitive Map (1948)



Place cells & grid cells

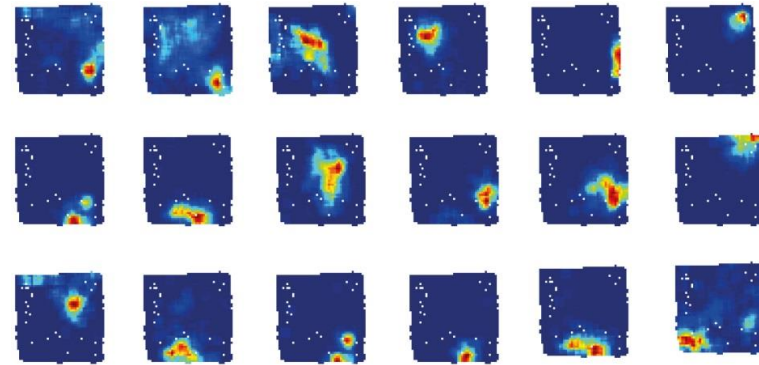
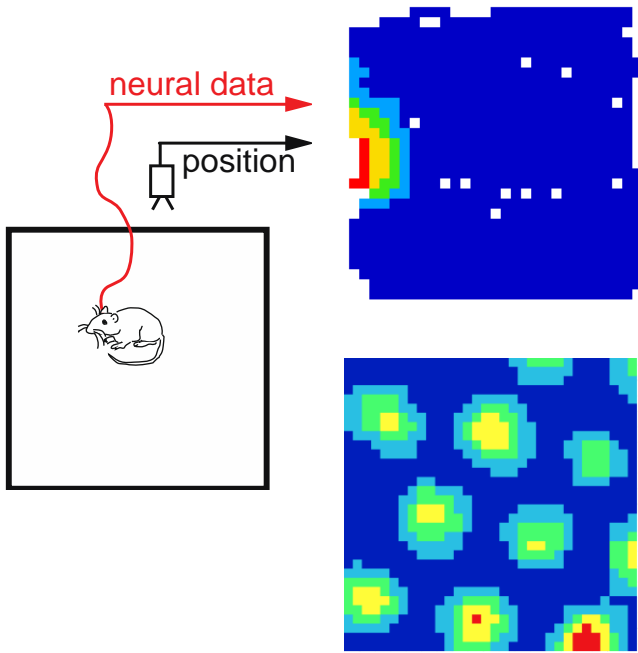


- Stably represent self-location
- Common to mammals (& possibly birds)

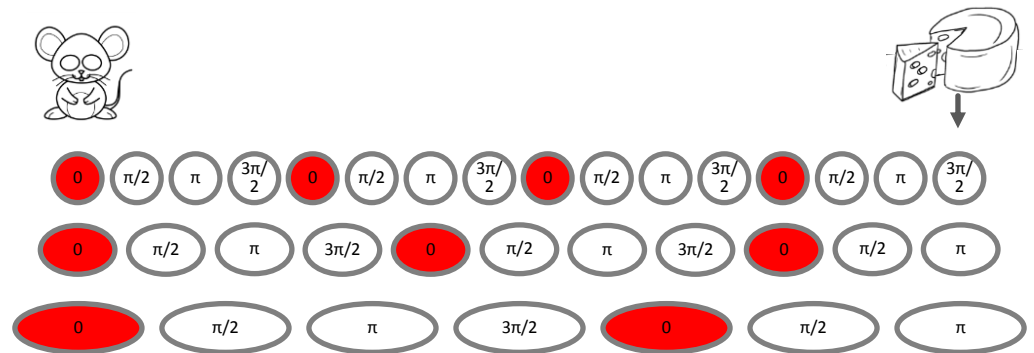


(c) Derdikman, Whitlock, Waade, Moser & Moser, 2010

Place cells & grid cells



- Stably represent self-location
- Common to mammals (& possibly birds)

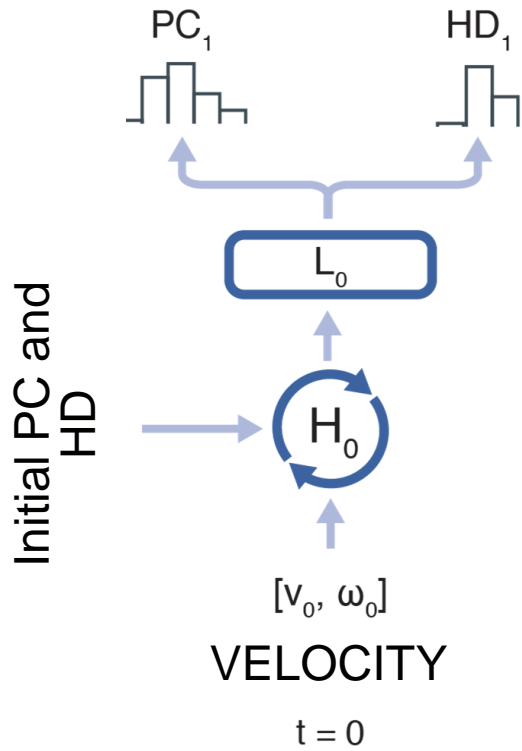


Goal distance = $[3\pi/2, \pi, \pi] = +75\text{cm}$

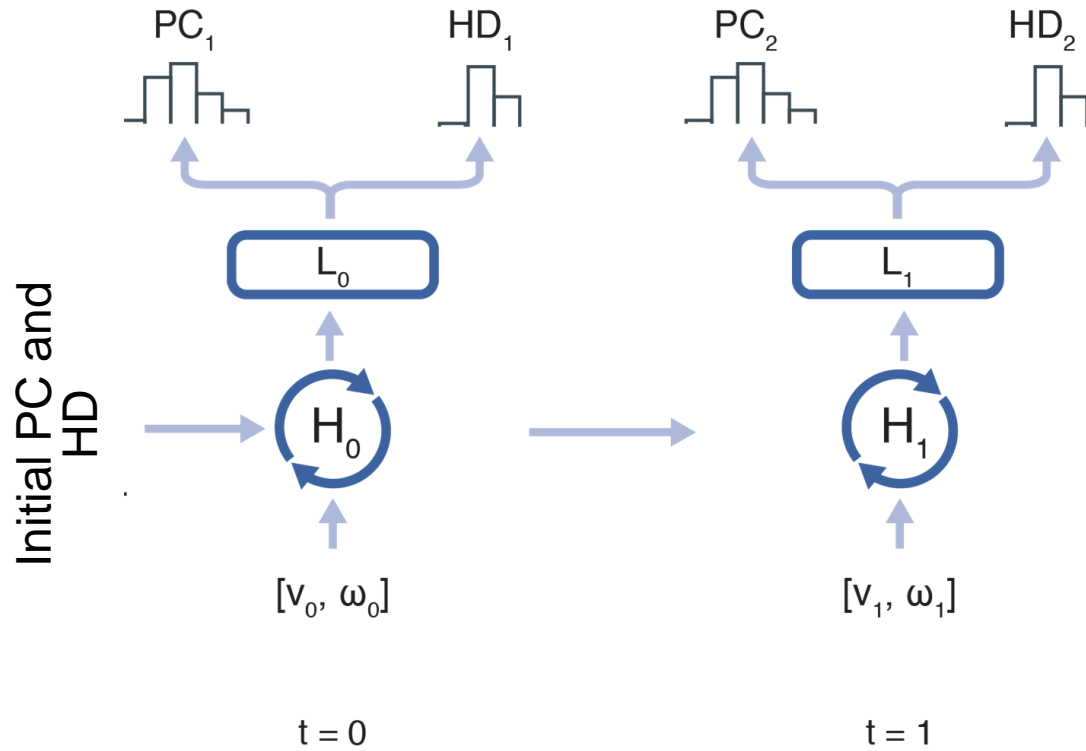
Aims

1. Test if mammalian-like **neural representations emerge** in a deep network trained to path integrate
2. Use such a network as a model system on which to conduct experiments
 - Demonstrate that **grid cells are an effective basis for vector based navigation**

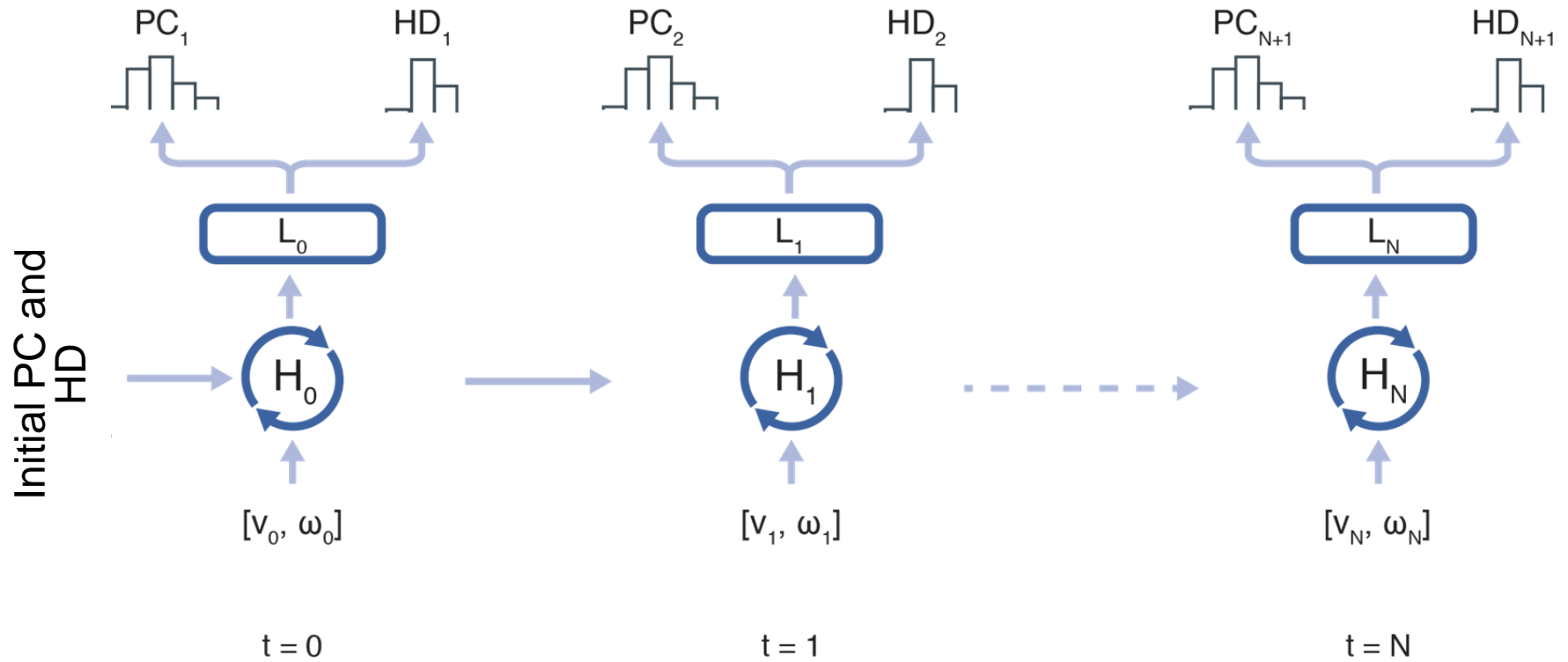
Supervised learning architecture



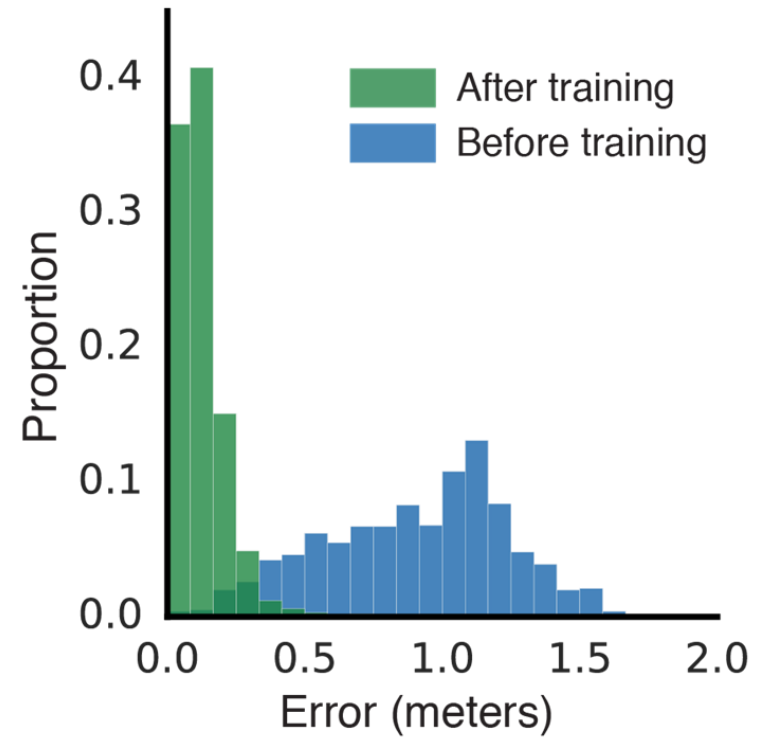
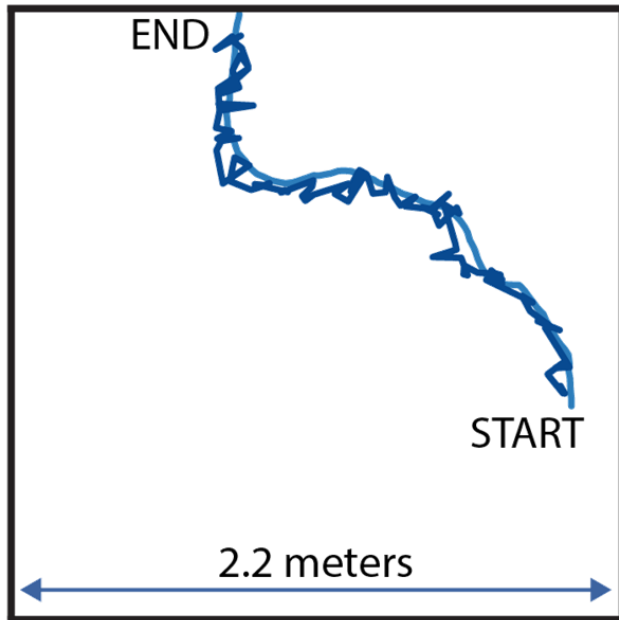
Supervised learning architecture



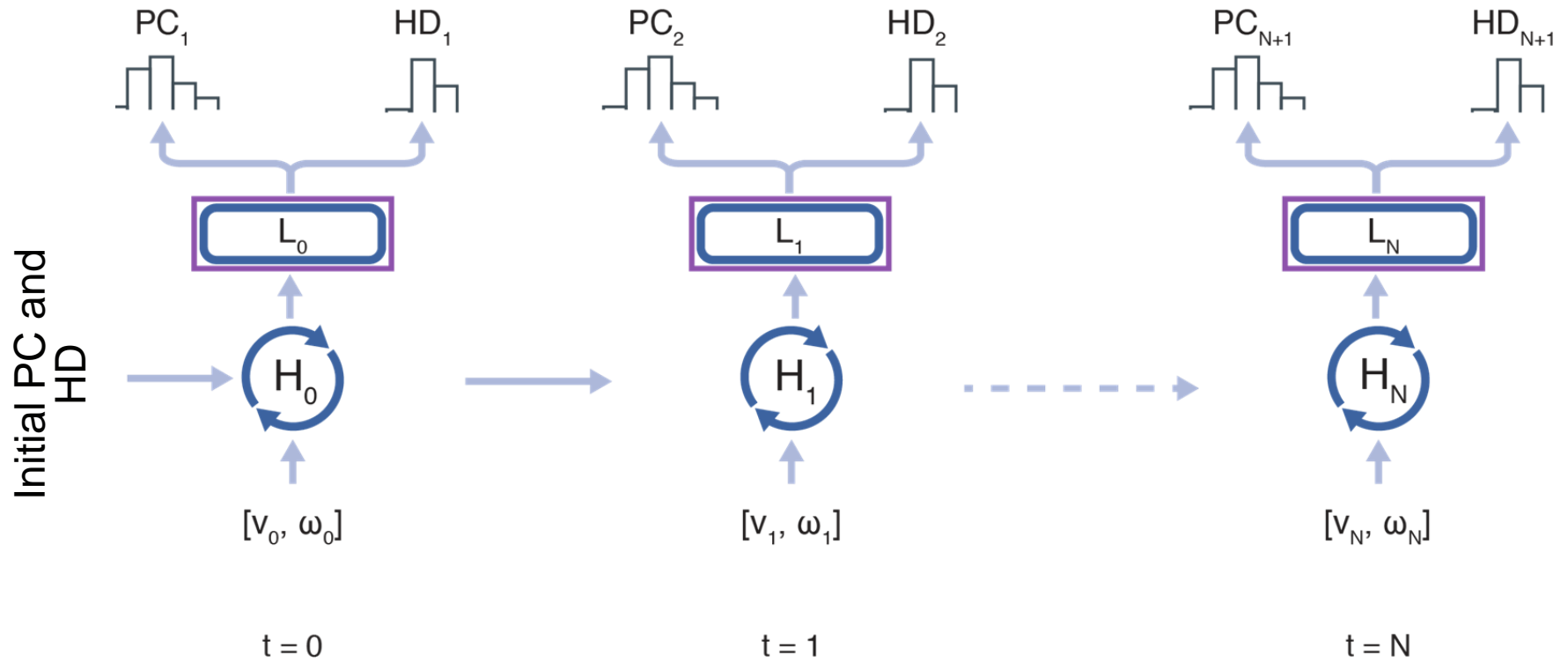
Supervised learning architecture



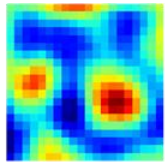
Path integration task



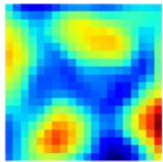
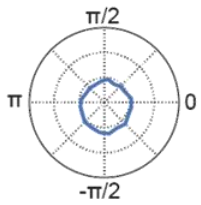
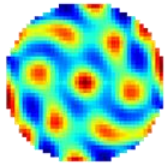
Analysis of linear layer



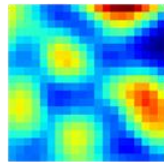
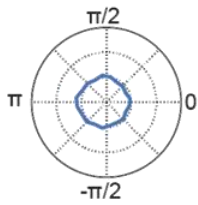
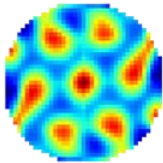
Linear layer activations



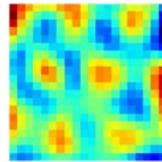
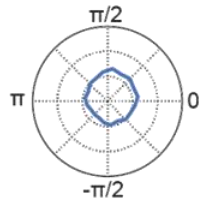
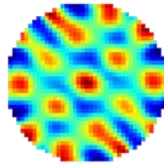
1.18



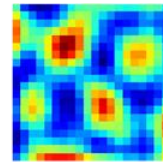
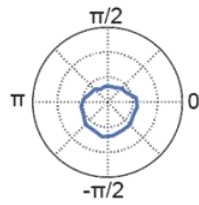
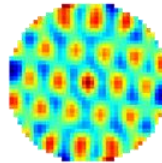
1.15



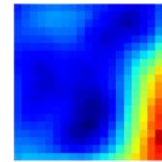
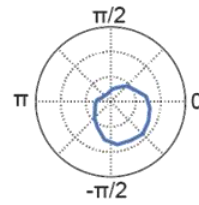
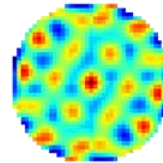
0.52



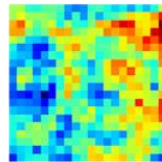
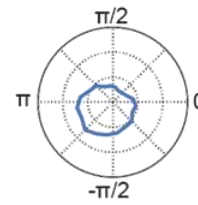
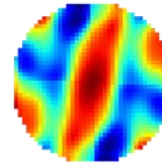
0.83



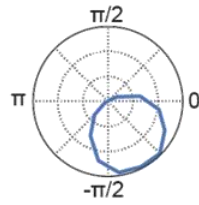
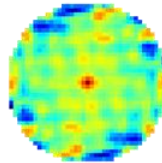
0.66



0.17

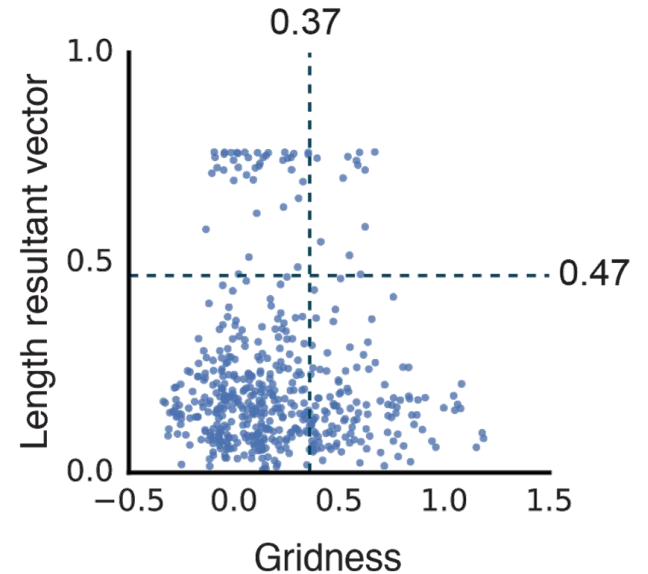
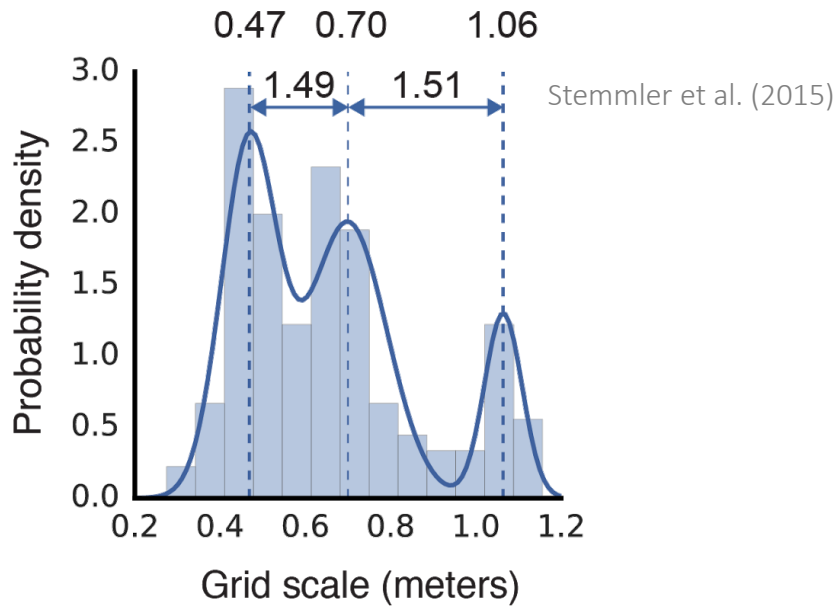
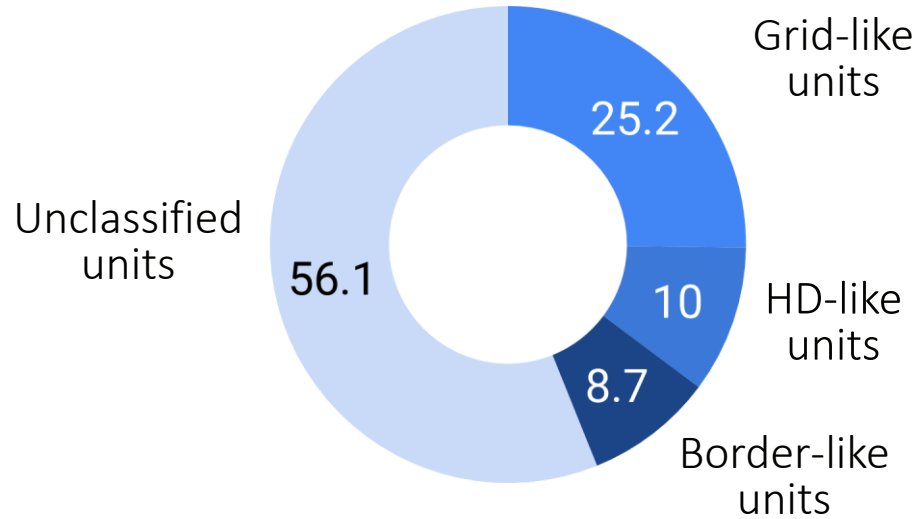


-0.05



Linear layer: properties

% of all units (n=512)



Grid cell agent: architecture

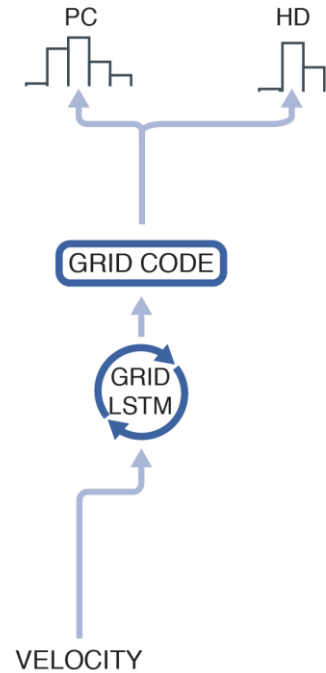


“Morris Water Maze”

Grid cell agent: architecture



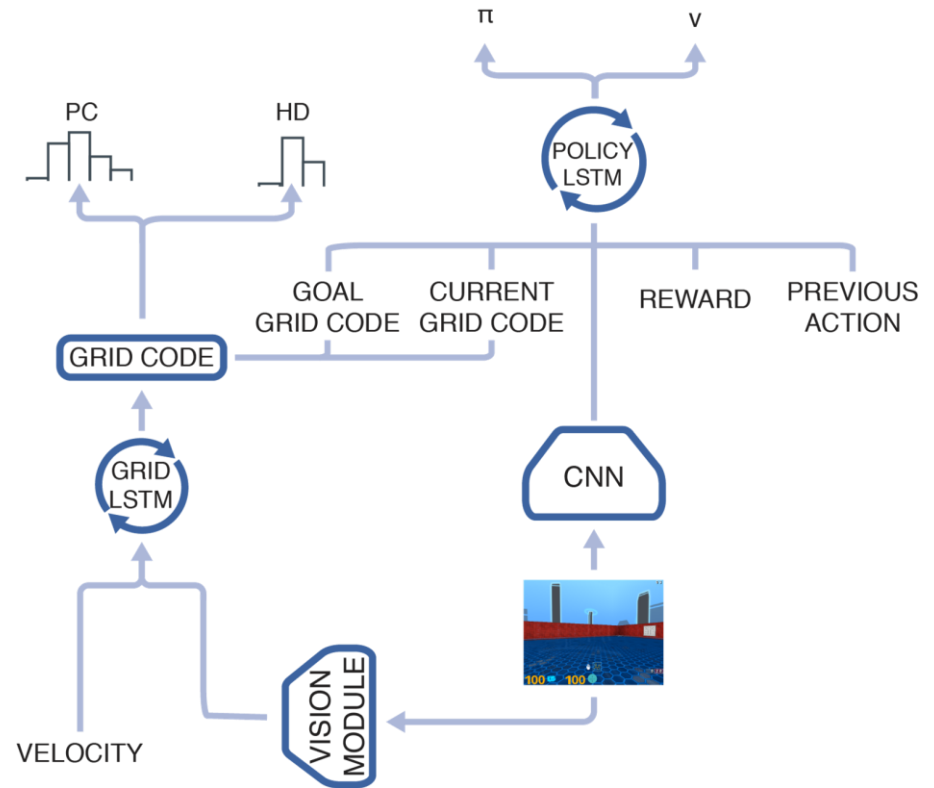
“Morris Water Maze”



Grid cell agent: architecture



“Morris Water Maze”

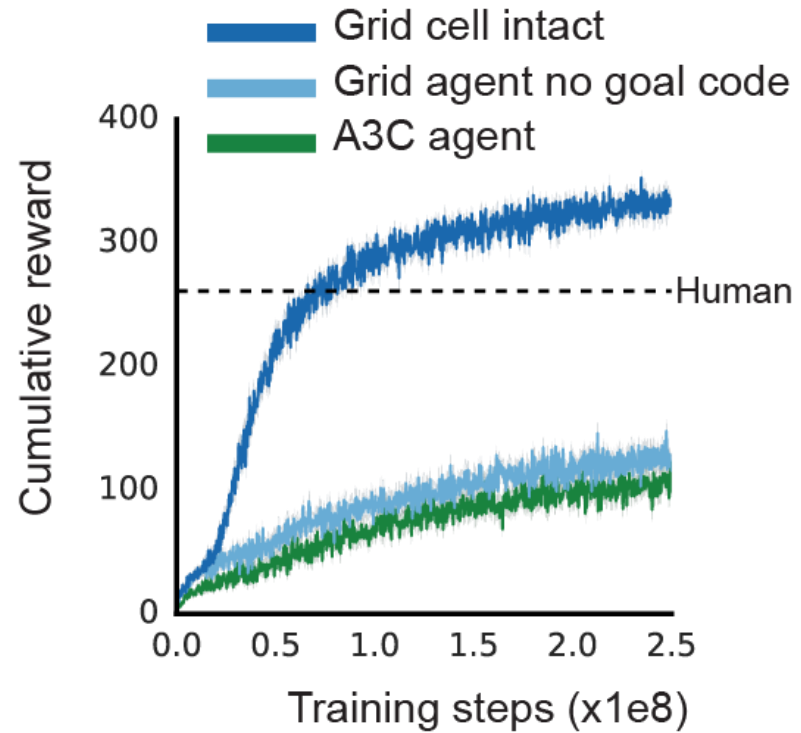
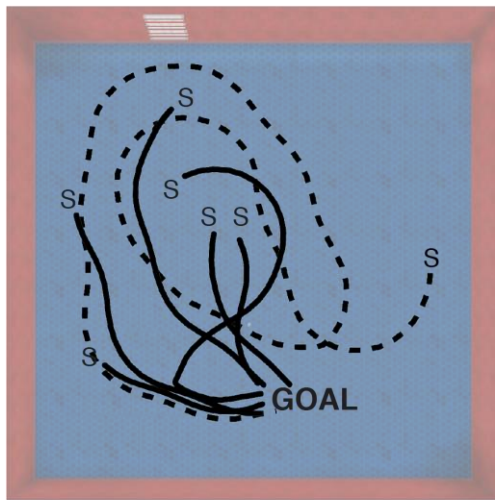


Goal: maximise expected cumulative discounted future reward

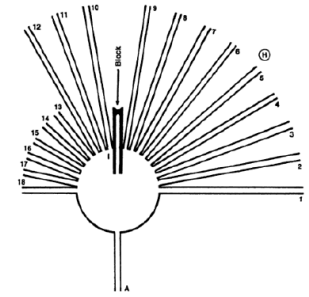
$$G_t = \mathbb{E}\left[\sum_{j=1}^{\infty} \gamma^{j-1} R_{t+j}\right]$$

Morris Water Maze

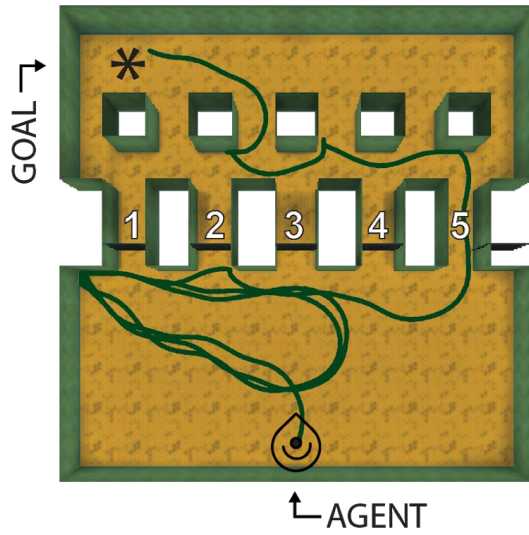
- First Trajectory
- Subsequent Trajectories



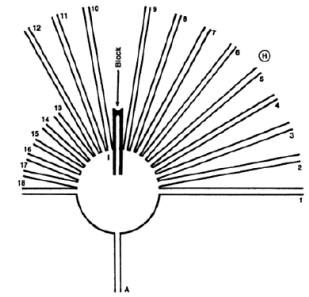
Shortcut linearized sunburst



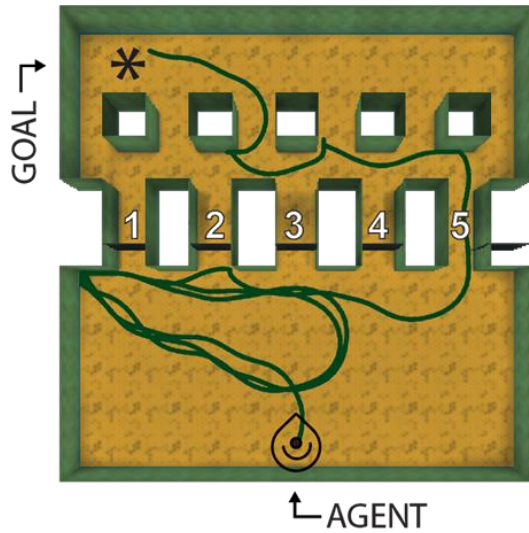
First trajectory



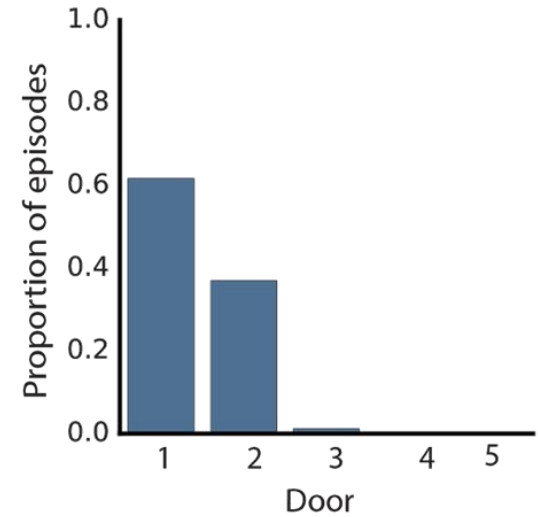
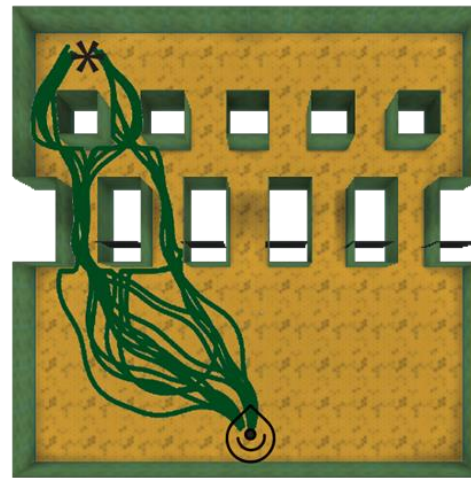
Shortcut linearized sunburst



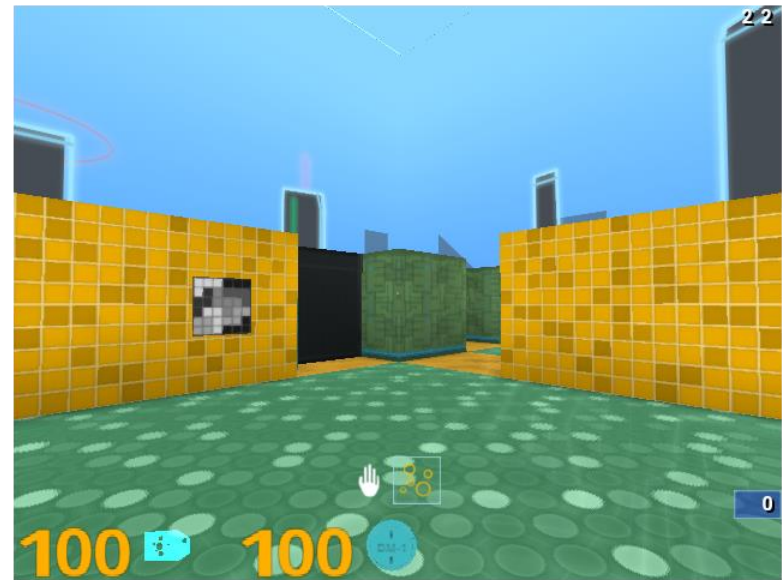
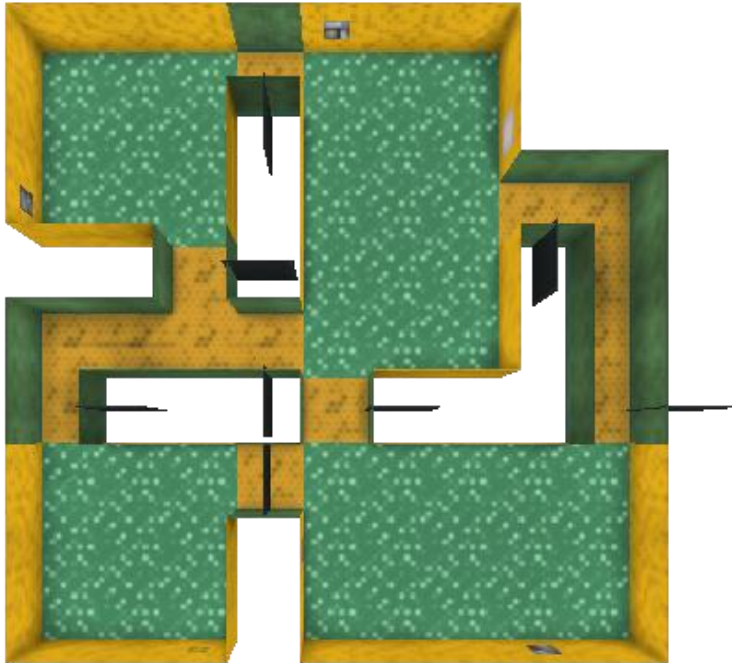
First trajectory



Subsequent trajectories

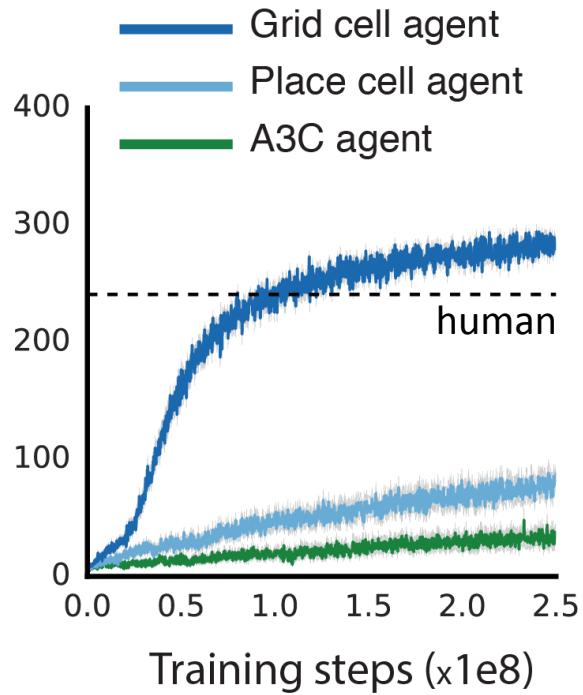


Complex maze: stochastic doors

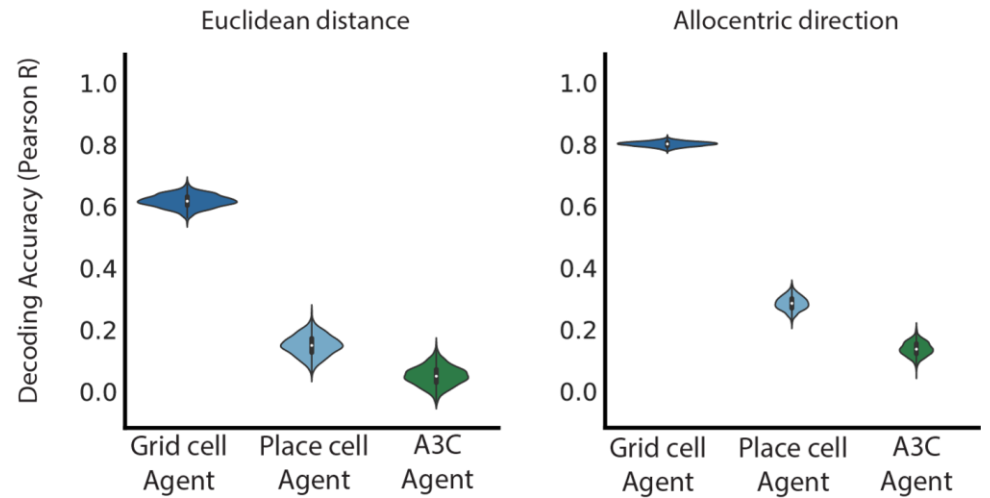
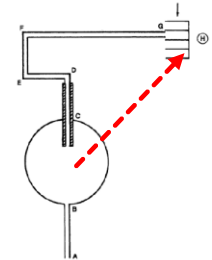


A novel maze configuration (colours, wall position, goal location) is generate for each episode

Complex maze: analysis

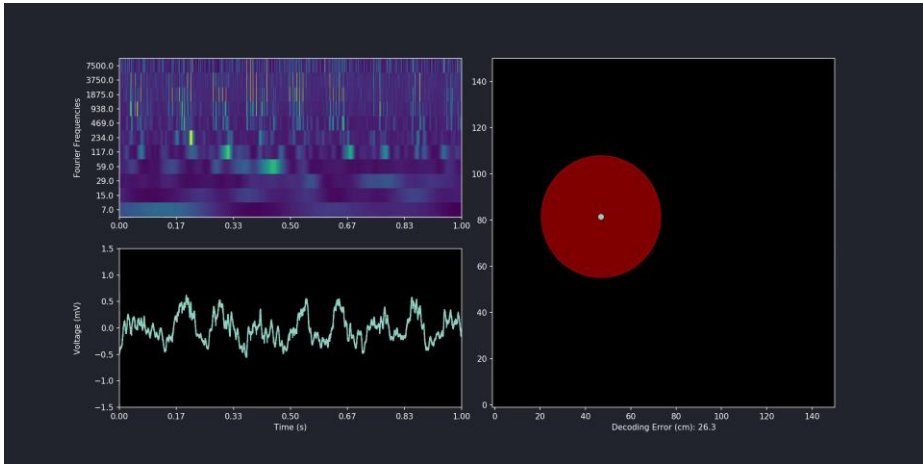
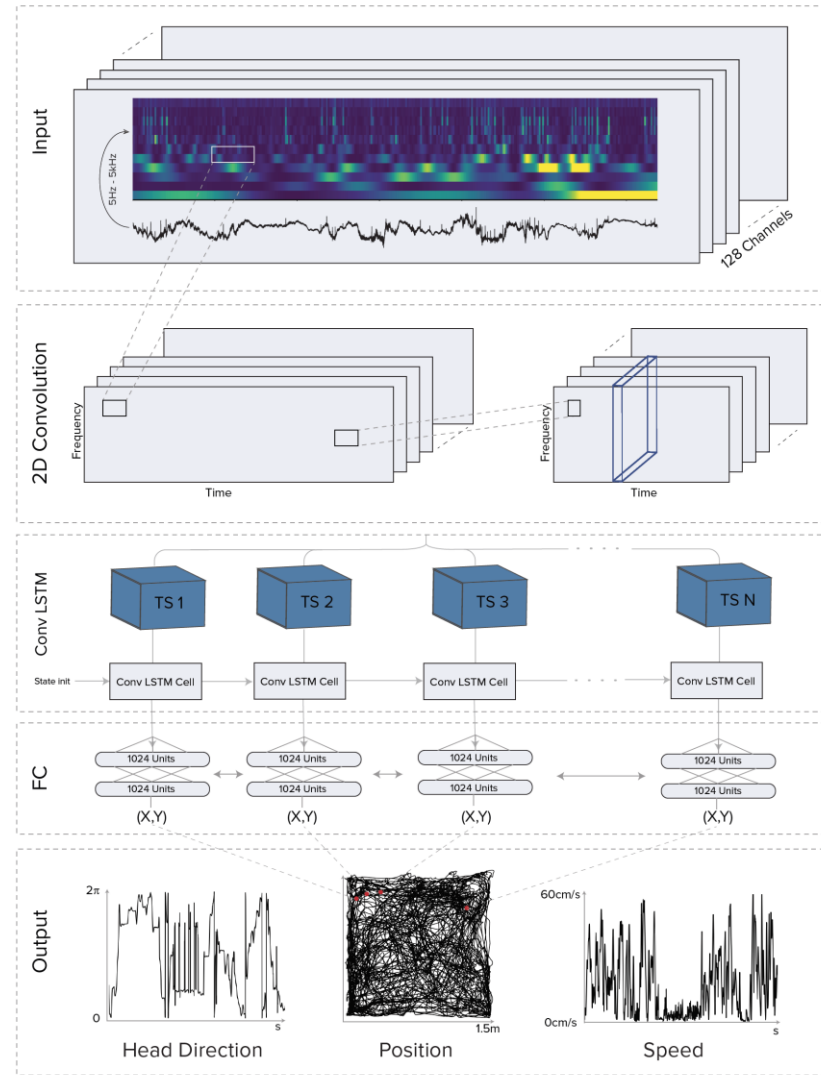


Multivariate decoding

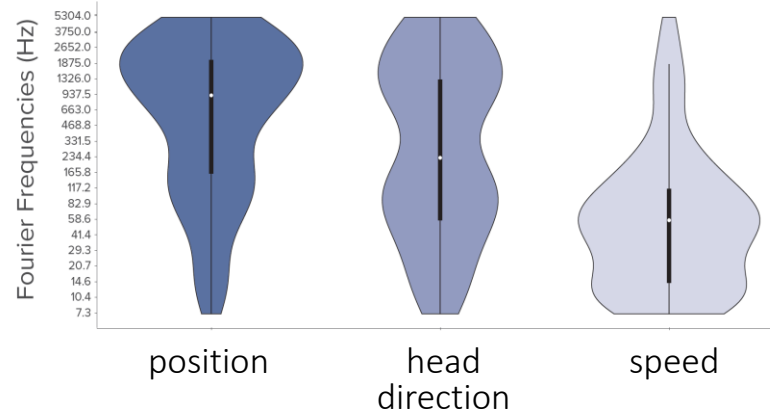
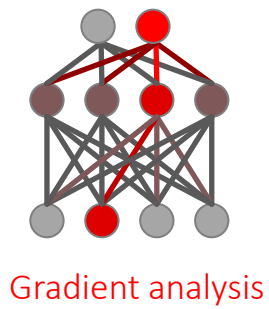
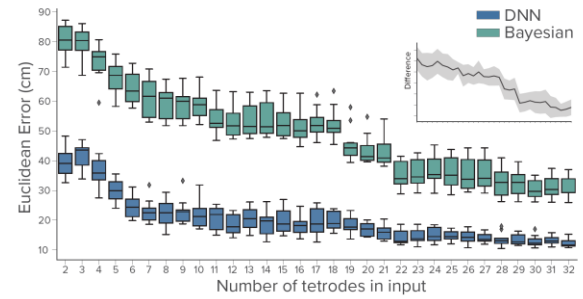
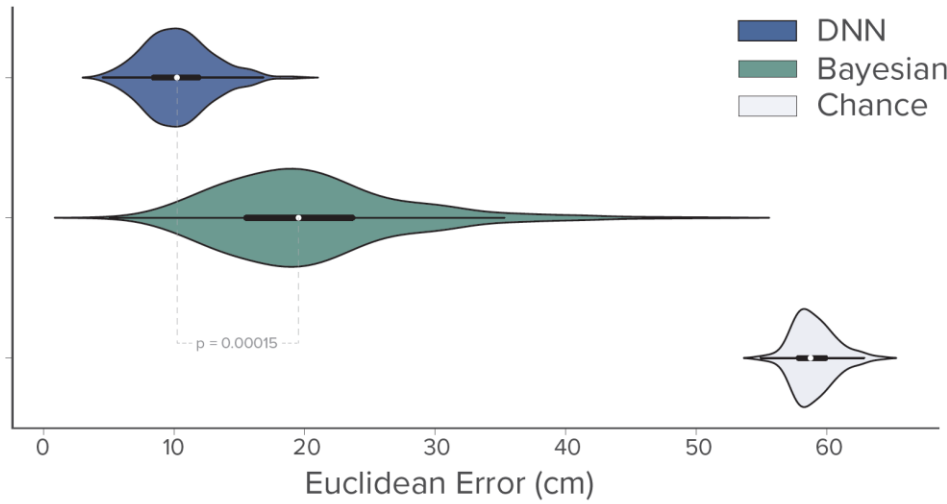


Bottom up (data focused)

Decoding wide-band neural data with DNNs



DNN comfortably outperforms standard decoding methods



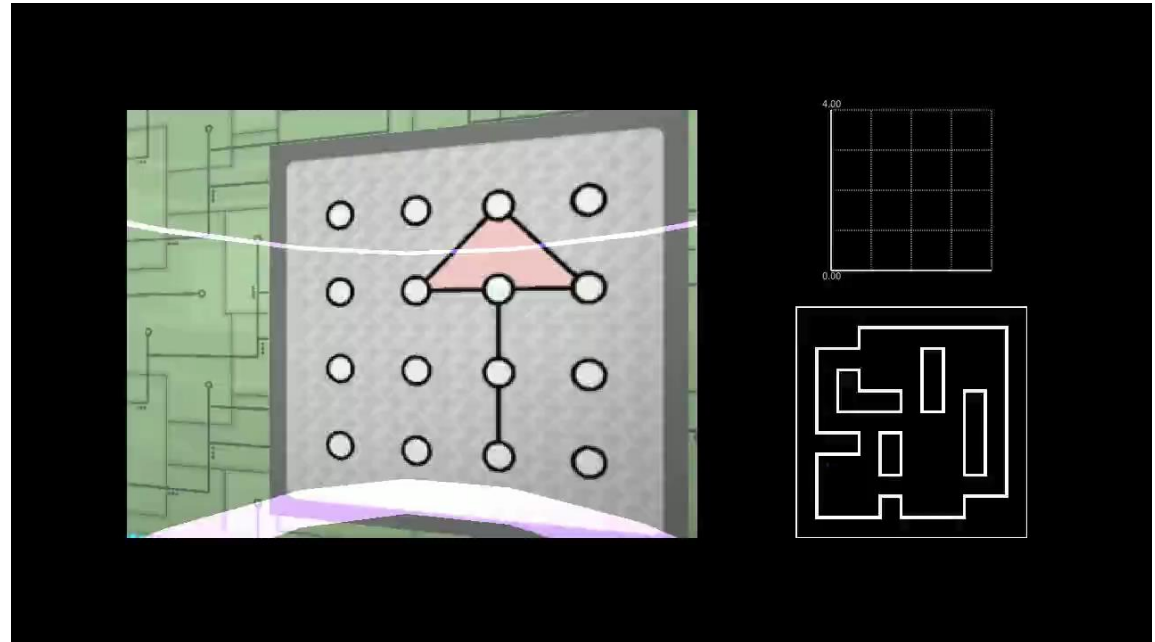
Conclusions

- Grid-like units **emerge spontaneously** when performing self localization and match many properties of mammalian spatially modulated neurons
- Emergent grid-like representations provides a **Euclidean spatial metric** and associated vector operations
 - supporting proficient navigation
- DNNs provide a powerful tool for **interrogating neural codes**
 - understand what is encode, how, & when

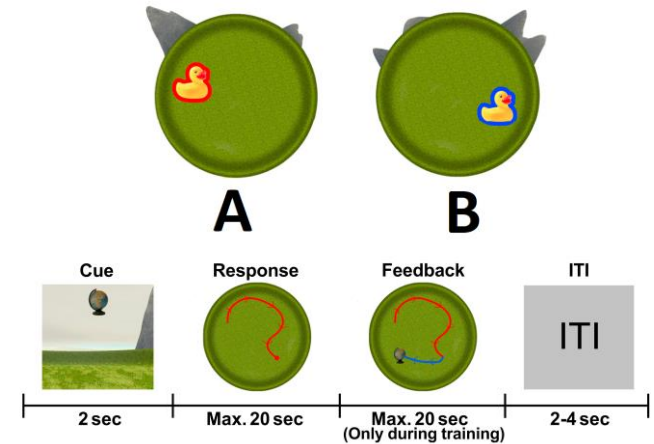
Thanks

- Andrea Banino
- Beni Uri
- Dharsh Kumaran

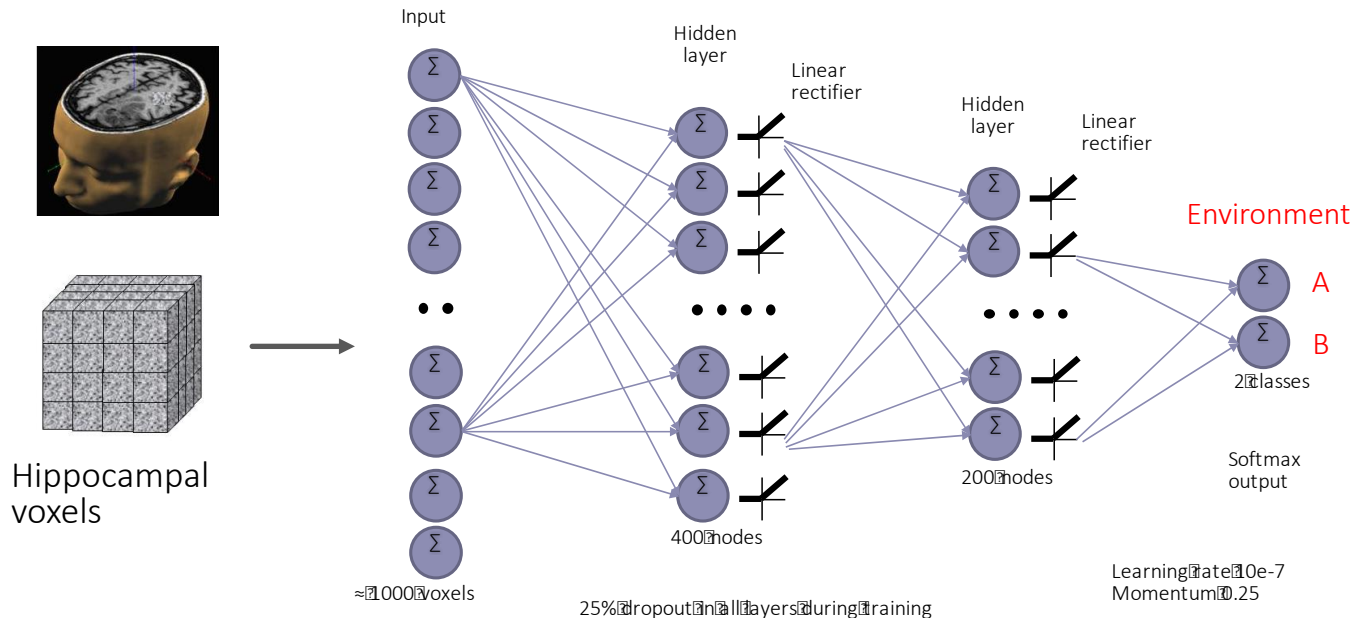
- Sander Tanni
- Markus Frey
- Christian Doeller

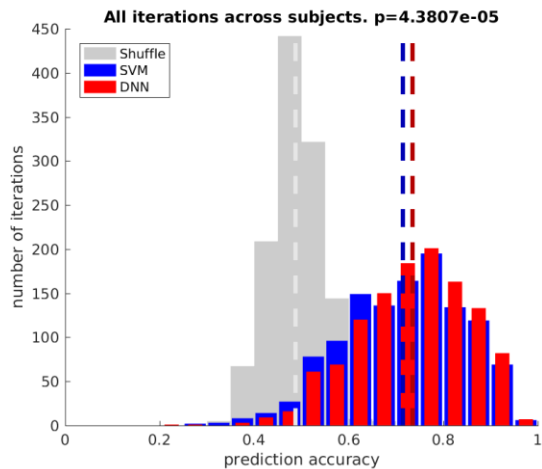


Can we decode location from human data?

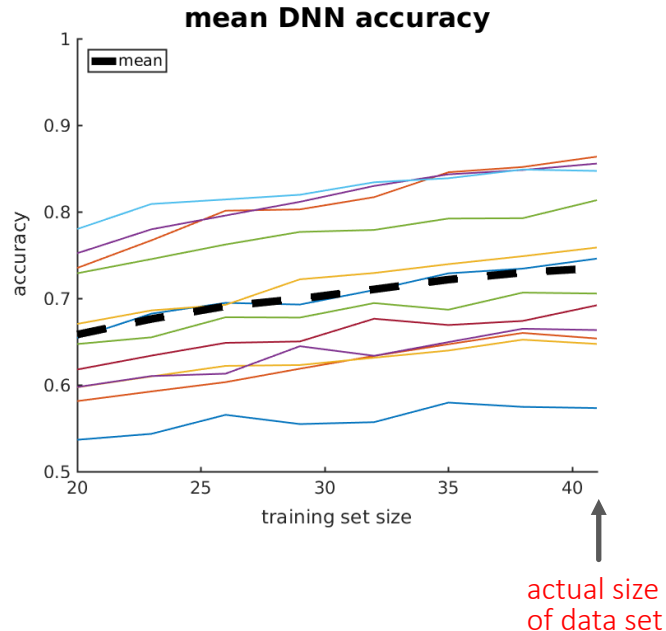


- 18 subjects perform a simple spatial memory task in the scanner
 - learn location of objects in two environments that are disambiguated by back ground
 - ~35 minutes of data per person





- Based solely on hippocampal voxels:
 - performance exceeds SVM (just)
 - 73% correct vs 71%
- But categorization is hard:
 - hippocampus is a small deep structure
 - subjects might not be accurate themselves – don't know what max score is



- Do we have enough data?
 - subsampled data indicates not
 - with more data DNN performance increases further above SVM (e.g. 1 hour plus)
- We need to investigate methods for augmenting the existing data
- Next steps:
 - explore which voxels are informative
 - how information is distributed & encoded etc.