

# Fiete Lab 2020 Trimester 1 Goals

Prof. Ila Fiete, Dr. Leenoy Meshulam, Rylan Schaeffer January 28, 2020

See Leenoy's presentation from last week's Theory Meeting https://drive.google.com/drive/u/1/folders/ 1IuUrhOhq1S18MBfCQkXGkLwz1OnKXDZ7

#### Goals:

1. Understand how neurally-plausible mechanistic models solve IBL task

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 What computation(s) do plausible neural models execute to solve the same IBL task solved by mice?

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- What computation(s) do plausible neural models execute to solve the same IBL task solved by mice?
- How do model design choices (e.g. learning rules, size, connectivity, noise) affect the learnt solution, and why?

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#### Research Questions

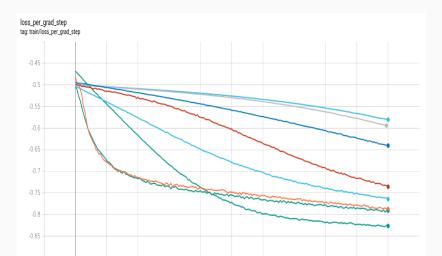
- What computation(s) do plausible neural models execute to solve the same IBL task solved by mice?
- How do model design choices (e.g. learning rules, size, connectivity, noise) affect the learnt solution, and why?
- How does gradient descent on a high dimensional error landscape enable learning the IBL task's structure?

#### **Project 2 - Implementation Details**

- Loss: Cross Entropy
- ullet Stimuli sampled from  $\mathcal{N}(-1,1)$  and  $\mathcal{N}(1,1)$  plus block prior
- Architectures: RNN (tanh), LSTM, GRU
- Number of stacked layers: 1
- Hidden dimension: 10, 20, 50, 100, 200
- Weight Initializations: Uniform  $\pm \frac{1}{\text{hidden state size}}$ , Identity
- Optimizer: SGD with LR=0.01, no momentum

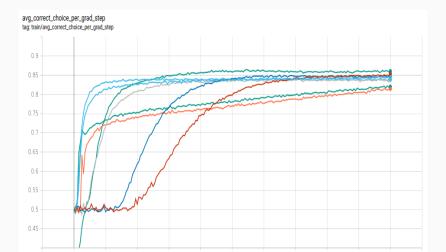
Models appear to learn task:

Figure 1: Loss vs Grad Step



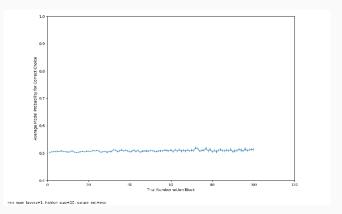
Models appear to learn task:

Figure 2: P(Correct Choice) vs Grad Step



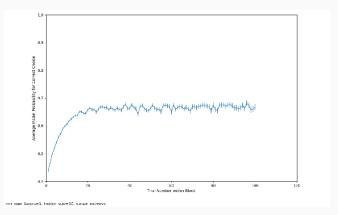
Models appear to learn task's block structure:

Figure 3: P(Correct Action) vs Trial Number within Block



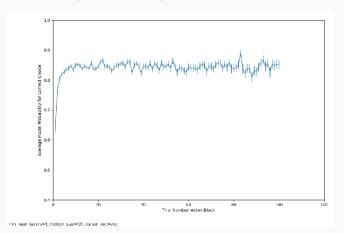
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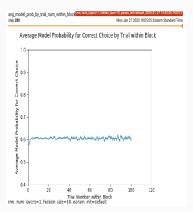
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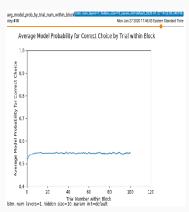
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Architecture appears to effect learning strategy.

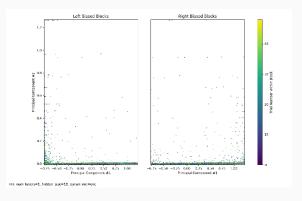
Consider P(Correct Action) after first indication that model recognizes block structure:





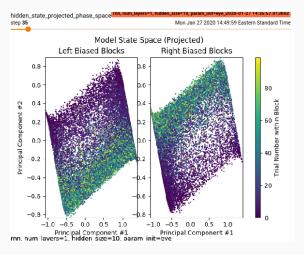
Models (sometime) reveal 2D manifold reflecting task structure:

Figure 4: RNN Phase State projected onto first two PCs



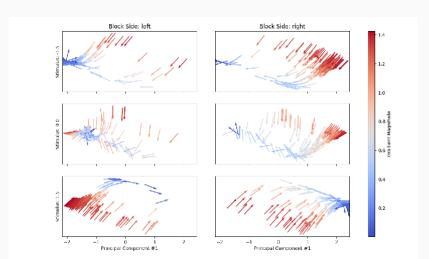
Models (sometime) reveal 2D manifold reflecting task structure:

Figure 4: RNN Phase State projected onto first two PCs



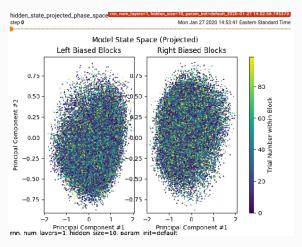
Movement in projected phase space for left, neutral, right stimuli:

Figure 5: P(Correct Choice) vs Grad Step



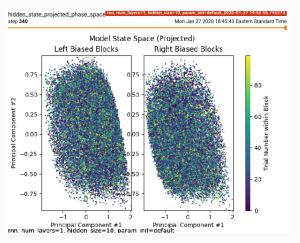
Models (sometime) do not appear to learn 2D manifold:

Figure 6: RNN Phase State projected onto first two PCs

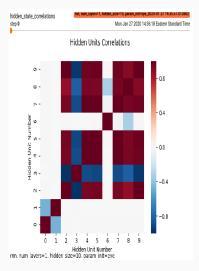


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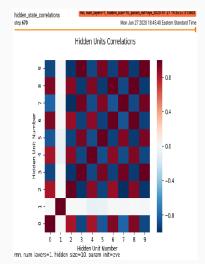
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**Figure 7:** Hidden units correlations before learning.

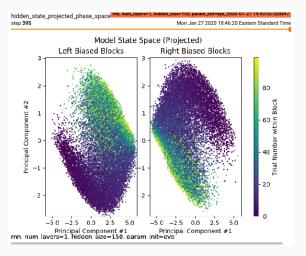


**Figure 8:** Hidden units correlations after learning.



Other manifolds,

Figure 9: RNN Phase State projected onto first two PCs



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