THALAMUS: A BRAIN-INSPIRED ALGORITHM FOR BIOLOGICALLY-PLAUSIBLE CONTINUAL LEARNING AND DISENTANGLED REPRESENTATIONS

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Paper under double-blind review

ABSTRACT

Animals thrive in a constantly changing environment and leverage the temporal structure to learn well-factorized causal representations. In contrast, traditional neural networks suffer from forgetting in changing environments and many methods have been proposed to limit forgetting with different trade-offs. Inspired by the brain thalamocortical circuit, we introduce a simple algorithm that uses optimization at inference time to generate internal representations of the current task dynamically. The algorithm alternates between updating the model weights and a latent task embedding, allowing the agent to parse the stream of temporal experience into discrete events and organize learning about them. On a continual learning benchmark, it achieves competitive end average accuracy by mitigating forgetting, but importantly, the interaction between the weights dynamics and the latent dynamics organizes knowledge into flexible structures with a cognitive interface to control them. Tasks later in the sequence can be solved through knowledge transfer as they become reachable within the well-factorized latent space. The algorithm meets many of the desiderata of an ideal continually learning agent in open-ended environments, and its simplicity suggests fundamental computations in circuits with abundant feedback control loops such as the thalamocortical circuits in the brain

1 INTRODUCTION

Animals thrive in a constantly changing environmental demands at many time scales. Biological brains seem capable of using these changes advantageously and leverage the temporal structure to learn causal and well-factorized representations (Collins and Koechlin, 2012; Yu et al., 2021; Herce Castañón et al., 2021). In contrast, traditional neural networks suffer in such settings with sequential experience and display prominent interference between old and new learning limiting most training paradigms to using shuffled data (McCloskey and Cohen, 1989). Many recent methods advanced the flexibility of neural networks (for recent reviews, see Parisi et al. (2019); Hadsell et al. (2020); Veniat et al. (2021)). However, in addition to mitigating forgetting, several desirable properties in a continually learning agent have been recently suggested (Hadsell et al., 2020; Veniat et al., 2021) including: **accuracy** on many tasks at the end of a learning episode or at least **fast adaptation and recovery** of accuracy with minimal additional training. The ideal agent would also display **knowledge transfer** forward, to future tasks and backwards to previously learned tasks, but also transfer to tasks with slightly different computation and or slightly different input or output distributions (Veniat et al., 2021). The algorithm should **scale** favorably with the number of tasks and maintain **plasticity**, or the capacity for further learning, Finally, the agent should ideally able to function **unsupervised** and not rely on access to task labels and task boundaries (Hadsell et al., 2020; Rao et al., 2019). We argue for another critical feature: **contextual behavioral**, where the same inputs may require different responses at different times, a feature that might constrain the solution space to be of more relevance to brain function and to the full complexity of the world. A learning agent might struggle to identify reliable contextual signals in high dimensional input space, if they are knowable at all, and with many contextual modifiers it might not be feasible to experience all combinations sufficiently to develop associative responses. For example, to an object recognition network the answer to "what is this?" might not always be an "Apple" but rather can be "fruit",

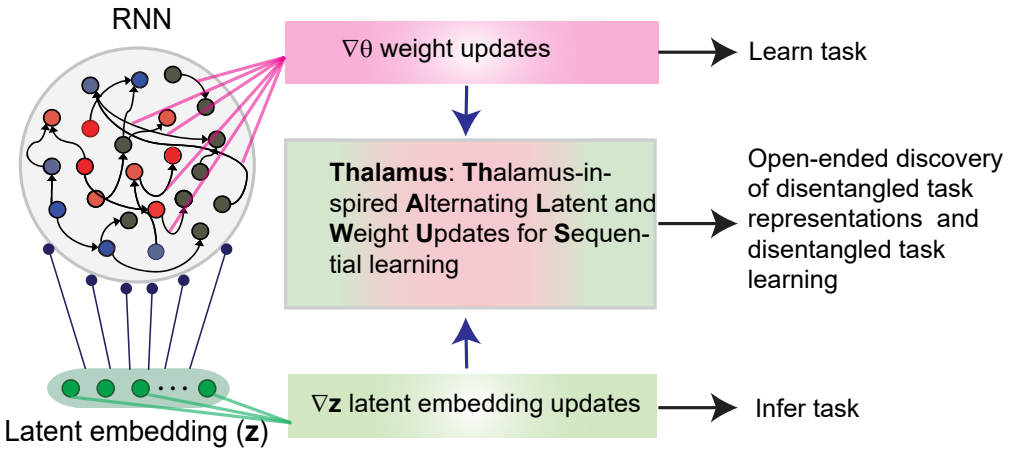

Figure 1: Thalamus (**Th**alamus-inspired **A**lternating **L**atent and **W**eight **U**pdates for **S**equential learning. Model schematic.

”food”, ”breakfast”, possibly a ”mistake” if you had ordered an orange, or ”sorry” if an annoyed partner points at an apple core on their desk. Until an agent has enough information on how to model these complexities, time acts as a reliable scaffold to discover these changing environmental demands.

Neuroscience experiments have revealed a thalamic role in cognitive flexibility and switching between behavioral policies (Schmitt, 2017; Mukherjee et al., 2021). The prefrontal cortex (PFC), linked to advanced cognition, shows representations of task variables and input to output transformations (Johnston et al., 2007; Mansouri et al., 2006; Rougier et al., 2005; Rikhye et al., 2018), while the medio-dorsal thalamus shows representations of the task being performed (Schmitt, 2017; Rikhye et al., 2018), and uncertainty about the current task (Mukherjee et al., 2021). The mediodorasal thalamus, devoid of recurrent excitatory connections, and with extensive reciprocal connections to PFC is thought to gate its computations by selecting task relevant representations to enable flexible behavioral switching (Wang and Halassa, 2021; Anonymous, 2022). The connections from cortex to thalamus engage in error feedback control to contextualize perceptual attention (Briggs, 2020), motor planning (Kao et al., 2021), and cognitive control (Halassa and Kastner, 2017; Wang and Halassa, 2021) and representations of error feedback can be observed in the thalamus (Ide and Li, 2011; Jakob et al., 2021; Wang et al., 2020).

In this paper, we take inspiration from the Thalamocortical circuit and develop a simple algorithm that uses optimization at inference time to produce internally generated contextual signals allowing the agent to parse its temporal experience into discrete events and organize learning about them (Fig. 1). Our contributions are as follows. We show that a network trained on tasks sequentially using the traditional *weight updates*, with task identifiers provided, can be used to identify tasks dynamically by taking gradient steps in the latent space (*latent updates*). We then consider unlabeled tasks and simply alternate weight updates and latent updates to arrive at Thalamus, an algorithm capable of parsing sequential experience into events (tasks) and contextualizing its response through the simple dynamics of gradient descent. The algorithm shows generalization to novel tasks and can discover temporal events at any arbitrary time-scale and does not require a pre-specified number of events or clusters. Additionally, it does not require distinction between a training phase or a testing phase and is accordingly suitable for open-ended learning.

2 Model

We consider the setting where tasks arrive sequentially and each task t is described by a dataset D^t of inputs, outputs, and task identifiers (x^t, y^t, i^t). We examine both settings where the task identifier is and is not available to the learning agent as input.

As a learning agent, we take a function f_θ with parameters θ that takes input x^t and latent embedding $\mathbf{z}$:

$$\hat{\mathbf{y}}^{\mathbf{t}} = f_\theta(\mathbf{x}^{\mathbf{t}}, \mathbf{z}) \tag{1}$$

We define some loss $\mathcal{L}$ as a function of predicted output $\hat{\mathbf{y}}$ and ground truth $\mathbf{y}$:

$$\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y}) \tag{2}$$

To optimize the model we define two updates of interest, updating the model parameters θ in the traditional sense according to their gradient $\Delta\theta$ (*weight update*), and updating the latent embedding $\mathbf{z}$ in the direction of the the error gradients $\Delta\mathbf{z}$ (*latent update*), by backpropagating gradients from $\mathcal{L}$ through f_θ, but keeping θ unchanged.

$$\Delta\theta \sim \frac{d\mathcal{L}}{d\theta}, \qquad \Delta\mathbf{z} \sim \frac{d\mathcal{L}}{d\mathbf{z}} \tag{3}$$

We showcase our algorithm by parametrizing f_θ with a vanilla RNN model, as an abstraction of PFC (although note applicability to any neural network architecture). Pre-activation of the RNN neurons $v(t)$ evolve in time as follows (bias terms excluded for clarity):

$$\tau_v \frac{\mathrm{d}}{\mathrm{d}t}\mathbf{v}(t) = -\mathbf{v}(t) + W^{in}\mathbf{x}(t) + W^r\phi(\mathbf{v}(t)) \odot W^z\mathbf{z} \tag{4}$$

Where v is the pre-nonlinearity activations, ϕ is a relu activation function, W^r is the recurrent weight matrix, i is the input to the network and W^{in} are the input weights, $\mathbf{z}$ is the latent embedding vector (representing the thalamus), and W^z are the weights from the latent embedding initialized from a Bernoulli distribution $w_{i,j} \sim B(p = 0.5)$ and kept fixed. These projections had a multiplicative effect, consistent with disinhibitory thalamocortical projections (Schmitt, 2017). Network output $\hat{\mathbf{y}}$ was a linear layer projection from the RNN neurons

$$\hat{\mathbf{y}} = relu(W^{out}r_{(t)}) \tag{5}$$

When task identifiers i^t were available they were input directly to the latent embedding $\mathbf{z}$ ($\mathbf{z} = i^t$) vector as one-hot encoded vectors. When task identifiers were not available, $\mathbf{z}$ was set to a uniform value. The set of RNN weights $RNN_\theta = \{W^r, W^{in}, W^{out}\}$ were trainable whereas the weights from the latent embedding W^z were kept fixed.

3 Experiments

We first describe continual learning dynamics in an RNN model trained with usual *weight update* paradigm, then we demonstrate the flexibility of taking gradient descent steps in the latent space (*latent update*) in the resulting pretrained model. Second, we consider unlabeled tasks stream and combine both updates in a simple algorithm capable of meeting most desiderata of an ideal continual learning agent, including learning disentangled representations that factorize along the structure of the environment (Fig. 1).

The algorithm was implemented in PyTorch and optimized with the Adam optimizer (Kingma and Ba, 2017) (learning rate 0.001 for weights updates and latent updates). Simulations were run at the *redacted for anonymity* computing cluster and we estimate in the order of 10^4 GPU hours were needed in developing the model. Code is available at *redacted for anonymity*.

3.1 Pretraining RNN with task identifiers, rehearsal, and training to criterion

We start by pretraining our vanilla RNN with task identifier input on a collection of 15 cognitive tasks commonly used in neuroscience and cognitive science experiments (Yang et al., 2019). The

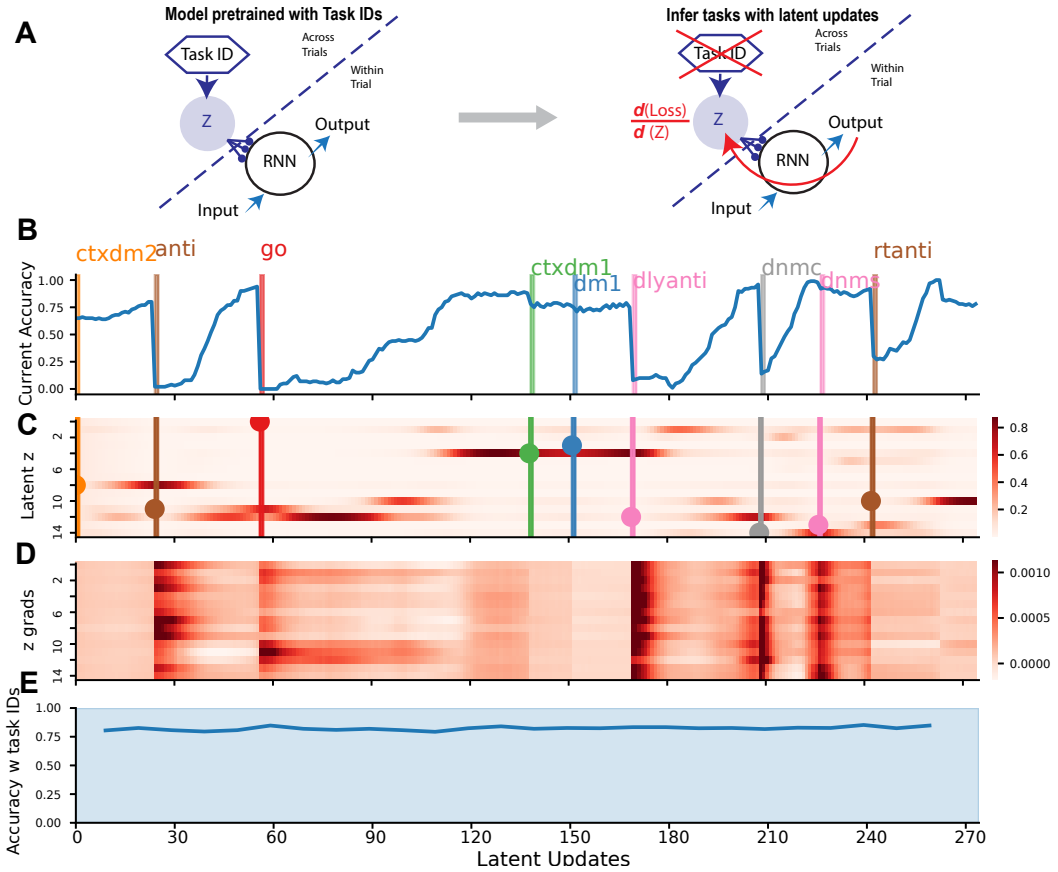

Figure 2: (A) Schematic of the experiment, model pretrained with task IDs and transitioning to identifying tasks through gradients backpropagated from the loss function to update the task embedding vector z (latent updates). (B) Current accuracy on current task as the network goes through multiple latent updates using only one batch from the current task. We switch to the next task once accuracy criterion is reached. (C) current values of the latent task embedding vector z. (D) gradients of loss with respect to z. (E) Average accuracy on all tasks if we were to use the original task IDs used during pretraining.

tasks are composed of trials with varying sequence lengths and input with brief noisy stimuli representing angles. The input-output computations require cognitive abilities such as working memory, perceptual decision making, contextual decision making amongst others, and importantly the same input may require opposite outputs depending on the task (example tasks given in Fig. A12). We train tasks only to criterion to prevent over-training and use rehearsal, a ubiquitous feature in animal learning, as they acquire expertise in new domains. The network achieves high end average accuracy on all tasks successfully (details of pretraining in Appendix A.2, Figs. A8, A9). This RNN trained with one-hot encoded task identifiers became proficient at all 15 tasks at the end of training, and we refer to it as the *pretrained network*.

3.2 Pretrained network can infer tasks through latent updates

To handle unlabeled tasks, one can possibly transition this pretrained network through weight updates and due to its accelerated ability at learning new tasks and rehearsing previous tasks (Fig. A8), it can adapt its weights rapidly to transition between tasks with a small number of batches (Fig. A10).

This is analogous to fine-tuning pretrained vision and language models to new data distributions. However, this assumes there is enough data to describe the new distribution fully (which is the case

in our simple dataset), and the network would have to constantly update weights as it transitions between distributions, making it prone to forgetting. Most critically, the network is not inferring a change in distribution and has no representation of it, but merely adapting the weights to it.

Here, we consider an alternative solution using latent updates to adapt to changing data distribution. By consuming only one batch, we take gradient steps in the latent space until accuracy reaches criterion again, and then allow the model to process incoming batches of the new task. Thereby the switch consumes only one batch (although other datasets and environments might require more data to accurately disambiguate context). We note several interesting aspects of this algorithm:

- The algorithm correctly switches the RNN to solve incoming tasks without forgetting any of its previous learning as evident by no decrease on its accuracy to perform all 15 tasks if given the task identifiers i^t again.

- At moments displays serial search behavior through several possible task labels before converging on the correct one, as a byproduct of Hamiltonian dynamics (Fig. 2C, e.g. in the solution of cxtdm1 from latent update 60 to 130).

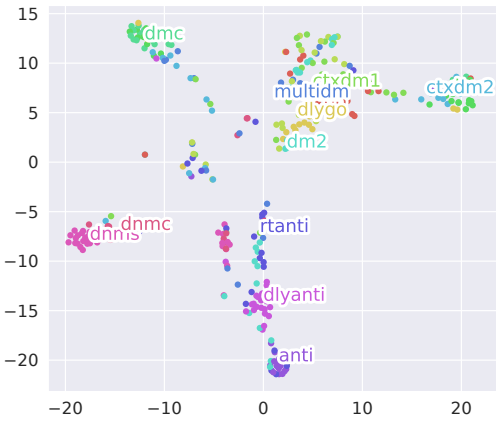

Figure 3: Dimensionality reduction with TSNE of the latent vectors after latent updates on each task. Data point colored by the ground truth task ID

- The algorithm might not solve the tasks using the embedding vectors it was pretrained on but rather using any latent vectors that perform well given its recent trajectory in the latent space. Interestingly, even though it was pretrained on uninformative latent space (equally distributed one-hot vectors), the latent updates retrieve a rich latent space that is functionally organized and clusters tasks according to similarity and compatibility (Fig. 3).

Pretraining the network however assumes one has access to data where data distribution changes are labelled across the correct dimensions. With this motivation, we next describe an algorithm that drops the requirement for any task labels.

3.3 Alternating weight and latent updates to discover task representations in unlabeled stream of tasks

We combine weight updates and latent updates in a simple algorithm that can recover the latent variables in the environment as it follows the dynamics of the data distribution in time. We start with a naive RNN attempting to solve a stream of incoming unlabeled tasks (Fig. 4). This network was freshly initialized and had no previous training on any tasks. It learns the first task through weight updates, and as the average accuracy begins to increase, any sudden drops from running average by more than a specified amount (0.1) would trigger switching to latent updates. We take as specified number of gradient descent steps in the latent space. If average accuracy has not recovered, the algorithm then goes back to learning through weight updates (see algorithm in 1). More intuitively, once the current latent embedding no longer solves the current task, use latent updates to reach at another

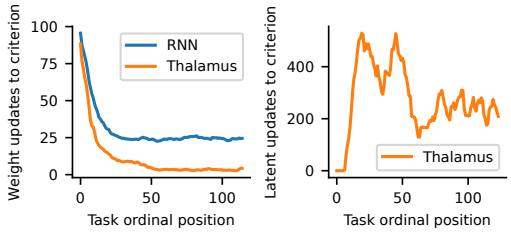

Figure 5: Comparing number of weight updates needed to solve tasks along the training sequence for Thalamus and baseline RNN. Right: Latent updates needed for each task in the sequence

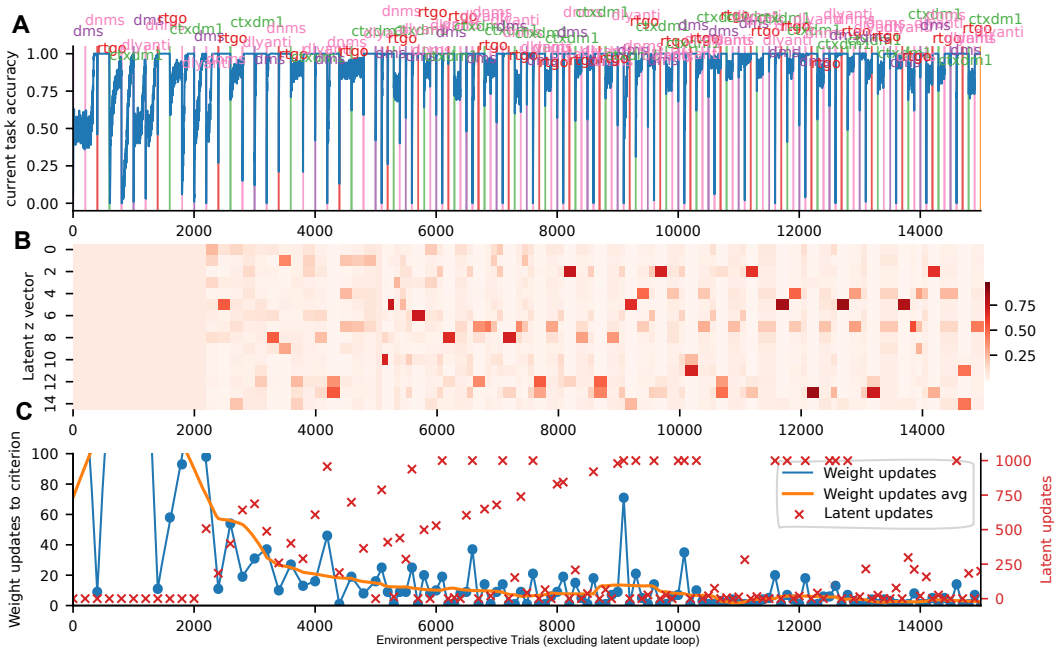

Figure 4: Newly initialized network learning unlabelled tasks using the Thalamus algorithm. Training begins with exposure to each task for 200 batches, and then for 100 for visualization purposes. Note that as opposed to Fig.2.A here we only show batches of new data points and omit latent update loops (A) Accuracy on current task. Vertical lines label transition between tasks. (B) latent vector representation. (C) Weight updates (left axis) and Latent updates (right) to reach accuracy criterion.

one. If the task was seen before likely this will solve the current task and you move on. If not, then it is likely a new task and gradient descent arrived at an untrained embedding. The algorithm then goes back to weight updates and learns the task with the loaded embedding. These dynamics allow the algorithm to successfully uncover the latent structure of the environment (discrete stream of tasks) without supervision, while remaining invariant to the time scale and not requiring a predefined number of clusters or events. Successful convergence leads the algorithm to require fewer weight updates and eventually, handle the stream of unlabelled tasks through latent updates only (Figs. 4, 5).

For quantitative comparison with other models, we noted that continual learning models were not designed to handle contextual behavior. For example, methods for task-agnostic continual learning (Rao et al., 2019; Zeno et al., 2021; Achille et al., 2018) have a task inference network that maps from inputs to task identity, and this network would have to be trained by weight updates to handle transitions between opposing tasks. Accordingly, we compare to other methods on an established continual learning benchmark in the next section. To quantify results on cognitive tasks, we use an RNN in training mode to transition between tasks with weight updates as a proxy (Table 1, Fig. 5). We noted that towards the end of the learning sequence Thalamus required far fewer weight updates and had higher average accuracy due to recovering promptly from the dip in accuracy at task transitions. These benefits come at the cost of a higher number of passes through the model for latent updates. While Thalamus requires higher number of model runs, due to latent updates, by biasing the model to adapt with latent updates it produces a well-factorized latent space that allows solving 27% of unseen tasks (Table 1, See quantification on a continual learning benchmark next section).

A vexing finding in brains is that despite internal consistency and intact function, recordings show that, to an outside observer, brain representations seem to drift and change over days and weeks (for e.g. see Marks and Goard (2021)), causing difficulties, for example, in designing a brain controller interface (BCI) (Mridha et al., 2021). By training a classifier to predict task identifier from latent

Table 1: Model comparison on NeuroGym tasks: Thalamus vs. RNN, from the last 20 blocks in a 5-task sequence learning over 20 random choice of tasks and model initializations.

Model	Weight updates	Avg accuracy	Total updates (compute)	Ratio novel tasks solved (¿0.8)
RNN	23.73 ± 1.21	0.91 ± 0.00	23.73 ± 1.21	0.21 ± 0.12
Thalamus	3.64 ± 0.50	0.96 ± 0.00	271.56 ± 55.28	0.27 ± 0.14

Table 2: End average accuracy (tested on all 5 tasks, mean ($\pm$ SEM)) on the split MNIST binary classification tasks. Performance results from Ven and Tolias (2019)

Method	Accuracy	Prompt with a training batch
Upper bound (iid)	98.42 ($\pm$ 0.06)	No
EWC	63.95 ($\pm$ 1.90)	No
SI	65.36 ($\pm$ 1.57)	No
LwF	71.50 ($\pm$ 1.63)	No
DGR	95.72 ($\pm$ 0.25)	No
RtF	97.31 ($\pm$ 0.11)	No
Thalamus (Ours)	97.71 ($\pm$ 0.13)	Yes

z vector, we show that the internal-generated representations in our model reveal similar dynamics (Fig. 6).

3.4 Comparison on external benchmark: split MNIST

We compare our model to other continual learning methods on a popular continual learning benchmark that splits MNIST digits into 5 pairs, making each pair into a binary classification task (0 or 1, chosen arbitrarily) (LeCun and Cortes, 2010), (referred to as 'domain incremental learning' Ven and Tolias (2019)). Models are shown an image at a time from each task and are required to classify it as 0 or 1. Importantly, models have no access to task identifiers and are trained on the 5 tasks sequentially. As Thalamus embodies a slightly different paradigm meant to operate in dynamic environments, testing its performance on a task requires prompting with a batch from the training-set of the same task, so it can adapt its latent embedding z through latent updates. (i.e. it requires feedback from the environment whether as a supervised signal or a reinforcement reward). Thalamus shows competitive end average accuracy (Table 2) when compared to the popular regularization-based methods synaptic intelligence (SI) (Zenke et al., 2017), elastic weight consolidation (EWC) (Kirkpatrick et al., 2017) although these methods are at a great disadvantage here as they generally require access to task labels and task boundaries. We also compare to three generative rehearsal methods that are of relevance to neuroscience theories: deep generative replay (DGR) (Shin et al., 2017), learning without forgetting (LwF) (Li and Hoiem, 2018), and the model with the current state of the art, replay through feedback (RtF) (Ven and Tolias, 2019) (Table 2). Of note, other more recent works do not report results on MNIST and moved on to more complex datasets requiring specific optimizers, data augmentations, and loss functions making comparison to their core architecture difficult (Pham et al., 2021; He and Zhu, 2021), and as we argue here, not all desiderata of continual learning have been met for the simpler MNIST-based tasks. Further experimental details can be found in Appendix A.1.

3.5 Knowledge transfer and contextual behavior

To assess knowledge transfer we use the split MNIST task but limit the model to learning only the first 4 tasks and then test on the last unseen task. The model requires one batch from the training set of the last task to update its latent z, and achieves a 91.14 ± 3.73 accuracy on the last task (avg accuracy on all tasks 93.62 ($\pm$ 0.30)) (example run in Fig. A11). Through learning the first four tasks the MLP and the latent z become a function parametrizable along relevant dimensions to solve related tasks. To highlight this difference compared to other methods we plot the accuracy on task 5 as models learn the tasks sequentially (Fig. 7). This generalization relies on balancing learning between the weights and the latent embedding. To showcase these effects we consider that continual

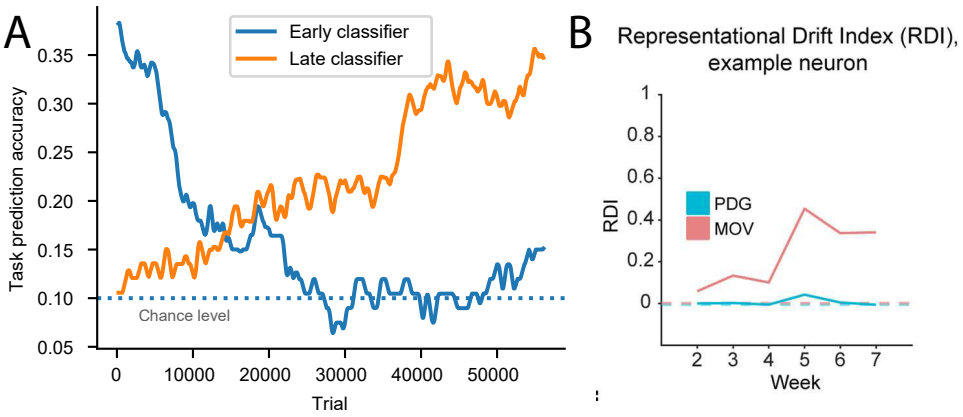

Figure 6: (A) Representational drift in the network trained on 10 tasks, measured by training a logistic regression classifier to predict task identity from the latent z embeddings, either from early (first 1000 batches) or late batches and tested accuracy on all. (B) Drift measured in the responses of a visual cortex neuron in response to natural movie (MOV) or passive drifting gratings (PDG). Adapted from Marks and Goard (2021)

learning literature recommends using stochastic gradient descent (SGD) with momentum and a low learning rate to limit interference in weight updates thereby limiting forgetting of earlier tasks (Hsu et al., 2019; Mirzadeh et al., 2020). Thalamus shows the opposite effect, overall accuracy drops (to 83%) but we see a disproportionately higher drop in accuracy of the unseen fifth task (drops to 67%) when using SGD with 10^4 learning rate.

Contextual split MNIST: Finally, we introduce a new challenge by taking the first 3 tasks from split MNIST but then adding task 4 and 5 by using images from tasks 1 and 2 but flipping the labels. It is trivial to show that other continual learning methods, which rely on input images to infer context, achieve a ceiling accuracy around 59%, but Thalamus maintains similar accuracy (96.09 $\pm$0.83).

4 Related Work

Our work adds to a growing continual learning literature, we refer the reader to recent reviews (Hadsell et al., 2020; Parisi et al., 2019), and only discuss papers of specific relevance to our algorithm. Continual learning of unlabeled tasks: several methods have been proposed for continual learning when task boundaries and task identities are not known and most methods use a variational inference approach (Rao et al., 2019; Zeno et al., 2021; Achille et al., 2018) to infer tasks and map current data points to a categorical variable representing task identity. Most methods require learning a task inference network to a latent space, running inference on the latent space and decoding to output. To handle new tasks, they keep a buffer of unexplained data points and instantiate a new categorical task once the buffer fills. In contrast, Thalamus relies on simply training a network to solve a given task. Task inference is done by inverting the network computations, presumably through the same credit assignment mechanisms that underlie learning in the brain, though these are yet to be fully understood. The shape of the latent space inferred by latent updates is fully specified by the forward network weights. Additionally, by using a continuous vector to represent tasks, it can handle an open ended number of tasks naturally. A critical difference is that these methods are unable to handle contextual behavior which maps the same input to different outputs in different contexts.

Thalamus is intimately related to the theory of predictive coding in neuroscience (Rao and Ballard, 1999) and our gradient descent updates to the thalamus vector are conceptually similar to propagation of prediction errors. The algorithm also connects to adaptive learning from behavioral science (Yu et al., 2021), and to perspectives in neuroscience that consider learning as interaction between

learning in the 'weight space' and 'activity space' (Sohn et al., 2021; Heald et al., 2021). Our work instantiates these concepts by learning by using gradient descent for latent updates. Similar use of gradient descent to update latent variables was proposed as model for schizophrenia by Yamashita and Tani (2012) and more recently to retrieve language instructions for cognitive tasks (Riveland and Pouget, 2022). Our work uses these methods as a component in a continually learning agent to learn disentangled representations.

The concept of fast weights also prescribes changes in the model parameters at inference time to adapt computations to recent context (Ba et al., 2016), however our model extends this to fast changes in the neural space and uses credit assignment and gradient descent at inference time. RL^2 algorithm uses meta-learning to instantiate an RNN that can eventually adapt itself to a changing environment (Duan et al., 2016). In common with Thalamus, it also instantiates a learning system that operates in neural activity space to adapt its computations to ongoing task demands. Hypernetworks utilize one network that generates parameters of another network to similarly adapt its computations (Ha et al., 2016). Both algorithms use gradient flow through the task loss to determine the optimal neural activity, however they use gradients heavily during the extensive training of the meta-learner (hypernetwork) and use only forward propagation during inference. Our algorithm combines use of gradient updates with forward propagation at inference time resulting in a much simpler algorithm and continued adaptability with no specified training phase. Deep feedback control operates on similar concepts by calculating an inverse of a neural network computation and allowing a deep feedback controller to dynamically guide the network at inference time (Meulemans et al., 2022). Our model uses back-propagation through the neural network and operates on gradients instead of estimating a function inverse. Finally, the algorithm is also related to energy-based models that also rely on optimization-based inference (Mordatch, 2018) but our algorithm does not require the lengthy training with negative samples to train the energy-based model.

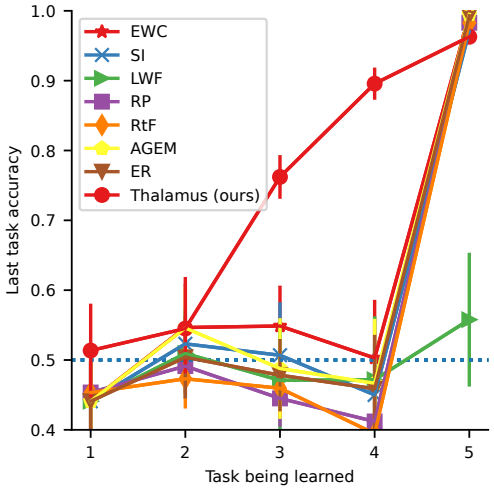

Figure 7: Measuring accuracy of the last task only as various models learned the sequence of tasks from 1 to 5. Simulations run as specified in Ven and Tolias (2019).

5 Conclusions

Thalamus is a relatively simple algorithm that can label ongoing temporal experience and then adapt to future similar events by retrieving those internally generated labels. The algorithm advances the role of optimization for inference as a natural extension to neural network architectures. A notable limitation is since we use a simple latent space, the form of knowledge transfer between tasks is quite limited conceptually to adapting the same computations if they apply to a new or old task. A richer form of knowledge transfer would emerge with a latent space that allows for compositionality over computational primitives. Future work will consider latent spaces with hierarchical or recurrent structures. While the algorithm in this preliminary work will require further development to operate at scale, it shows several conceptually interesting properties, and the representations it might learn from more complex and naturalistic datasets will be of interest to compare to brain representations.

Acknowledgments

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Table 3: hyperparameters used

Parameter	**Neurogym RNN**	**split MNIST MLP**
Weight update learning rate	0.001	0.001
Latent Update learning rates	0.01	0.001
Latent Update $\mathcal{L}_2$ regularization	0.0001	0.1
Latent size	15	10
Max latent updates	min(1000, $batchno$)	
W^z sparsity	0.5	0.8

A APPENDIX

A.1 TRAINING DETAILS AND HYPERPARAMTERS FOR THALAMUS TRAINING WITH NO TASK IDENTIFIERS

For the neurogym dataset, we used a 356-dimensional RNN and a dt of 100ms and tau of 200ms. Recurrent weight matrix initialized as an identity matrix (Le et al., 2015; Yang et al., 2019). Multiplicative binary projections from z to the RNN had sparsity of 0.5. We initially present the tasks to be learned in the same order twice for 200 batches each and allow the model to adapt with weight updates only. The model then sees the same sequence repeatedly and allowed to make both weight and latent updates, until it converges (defined as the running average of weight updates needed dropping below the no of tasks in the sequence). The first 3 repetitions are with a block size of 200 and then we lower it to 100 for efficiency and easier visualization. For the split MNIST dataset and comparison with other models, we employ the same architecture and hyperparameters reported in Ven and Tolias (2019); Hsu et al. (2019). The classifer network had two fully-connected layers with 400 ReLU units and a 2-unit output layer. We used a 10 dimensional latent z embedding space that projected multiplicative binary gates with 0.8 sparsity. The same gating weights were used for both layers for simplicity. For this dataset we follow a more incremental sequencing of the tasks to align better with other methods on the same dataset. Tasks are incrementally added and the tasks seen so far is rehearsed twice after each new task.

A.2 PRETRAINING THE NETWORK FOR SECTIONS 3.1 AND 3.2 WITH TASK IDENTIFIERS

We provide an example learning session of a sequence of 15 tasks with rehearsal and training to criterion (Fig. 9). During training, accuracy on all other tasks was tested every 10 batches using the task IDs as input to indicate the testing task. Ablations show that task identifiers, training to criterion and rehearsal are the minimal components for this network and this dataset. As the network learns more tasks we see a decrease in the batches needed to acquire new tasks or rehearse early ones (8), consistent with previous literature (Goudar et al., 2021; Davidson and Mozer, 2020).

A.3 RAPID ADAPTATION OF PRETRAINED NETWORK

We provide an example of training the network using weight updates. After pretraining with task IDs it can now transition its behavior without task IDs, by adapting its parameters rapidly to handle oncoming tasks and requiring few updates to achieve criterion performance on each task (Fig. 10). But see main text for discussion of the limitations of this approach to adaptable behavior.

A.4 THALAMUS ALGORITHM

For completeness we provide the algorithm details below in Algorithm 1.

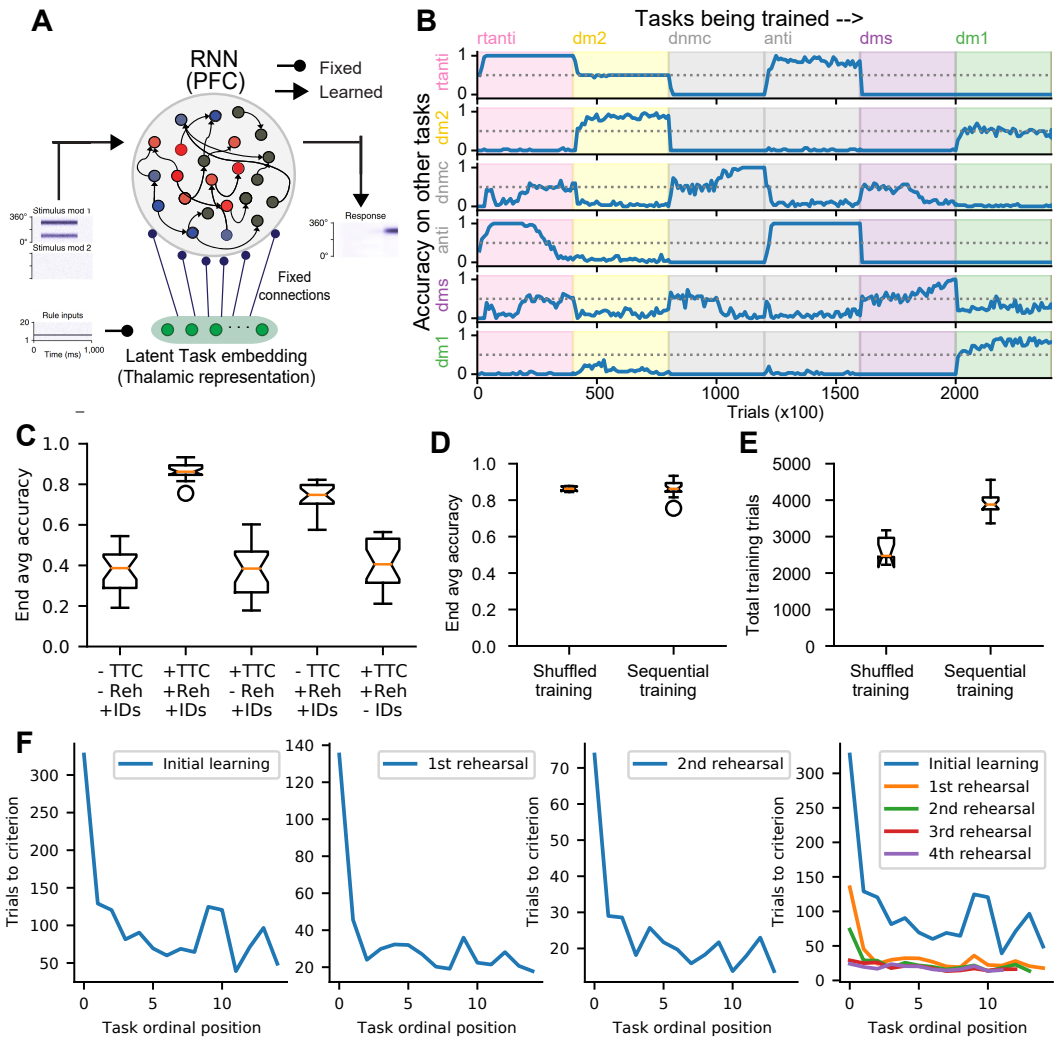

Figure 8: (A) Network schematic. (B) Accuracy on all tasks as the network learns them sequentially. (C) Accuracy at the end of the training session averaged across all 15 tasks, measured over 10 random orderings of the tasks. The x axis labels indicate which components were used in the training paradigm. TTC indicates training each task to criterion, Reh, indicates rehearsal of previous tasks after each new task, and IDs indicates whether task identity was input to the network. The combination of the three components was necessary for optimal accuracy. (D) For comparison, we train the network using shuffled data until it achieves similar accuracy and (E) compare the number of batches needed using shuffle training and sequential training. (F) Decreased batches to criterion as a function of the order of which task was learned in the initial learning and in subsequent rehearsals. The right subplot is the same lines overlaid to show progression.

Algorithm 1 Thalamus algorithm

Init $\mathbf{z}$ to a uniform value
repeat
  Sample x^t, y^t from D^t in sequential blocks
  $\hat{\mathbf{y}}^{\mathbf{t}} = f_\theta(\mathbf{x}^{\mathbf{t}}, \mathbf{z})$
  Accuracy = $\mathcal{L}(\hat{y}^t, y^t)$
  if Running mean accuracy - Accuracy ≥ 0.1 **then**
    while remaining latent updates AND Accuracy $<$ Criterion **do** ▷ latent updates ramp up to a max of 1000
      $\Delta\mathbf{z} \leftarrow \alpha^z \frac{d\mathcal{L}}{d\mathbf{z}} + \mathcal{L}_2 reg$ ▷ α^z learning rate was 0.01
      $\hat{\mathbf{y}}^{\mathbf{t}} = f_\theta(\mathbf{x}^{\mathbf{t}}, \mathbf{z})$
      Accuracy = $\mathcal{L}(\hat{\mathbf{y}}^t, \mathbf{y}^t)$
    end while
  end if
  if Running mean accuracy - Accuracy ≥ 0.1 **then**
    $\Delta\mathbf{W} \leftarrow \alpha^W \frac{d\mathcal{L}}{d\mathbf{W}}$ ▷ Update weights only if accuracy not recovered
  end if
  Update Running mean accuracy
until Converged: not requiring any weight updates for the all tasks tested

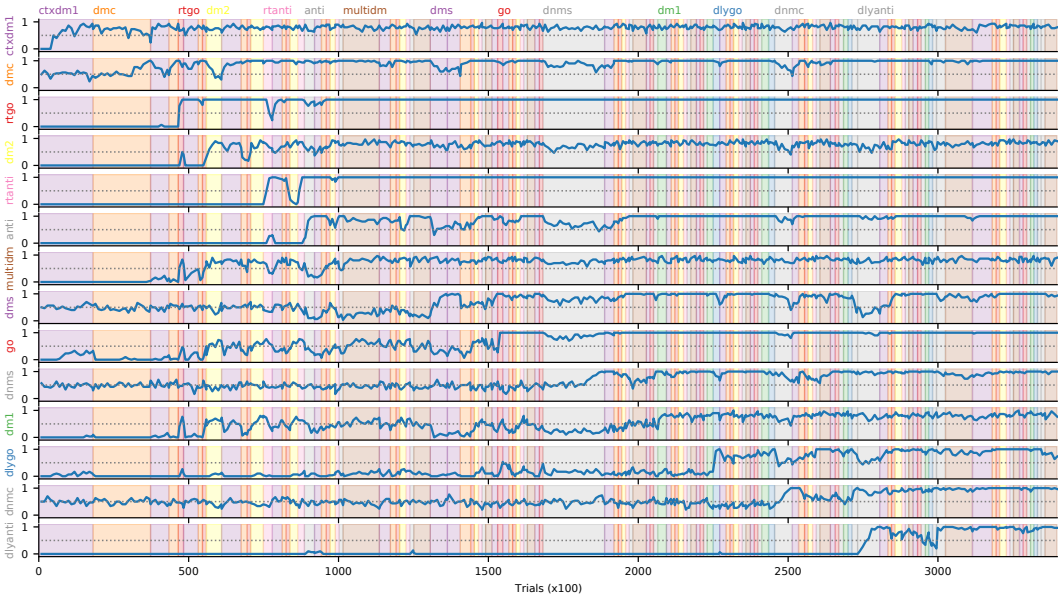

Figure 9: Training on all 15 tasks with rehearsal and training to criterion.

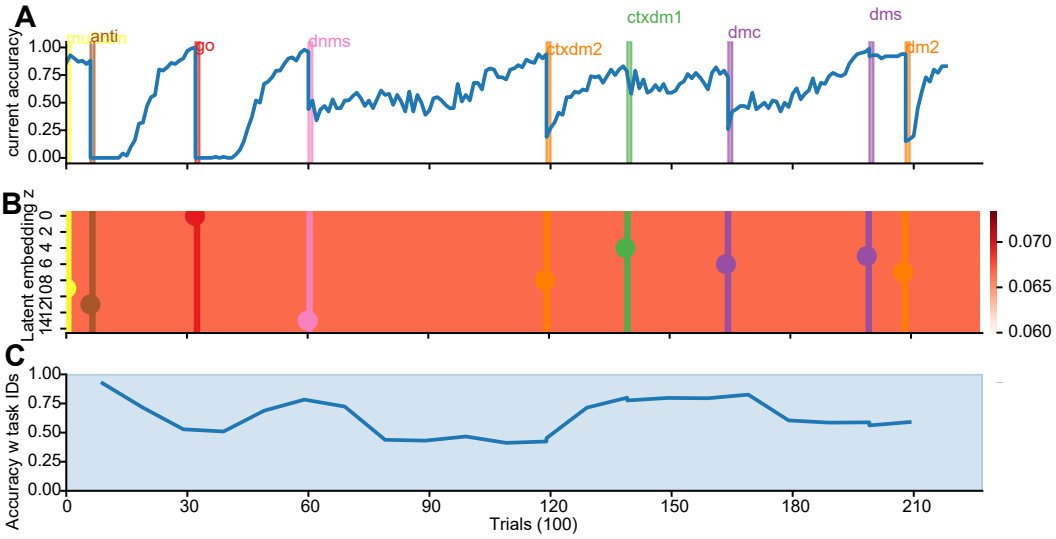

Figure 10: Pretrained network adapts rapidly to changing tasks. (A) solving a stream of tasks by rapidly fine-tuning the weights. (B) Latent task embedding z kept uninformative and uniform with the network no longer receiving task IDs as input. (C) the network begins to no longer respond to the pretraining task IDs, and accuracy on all tasks drops with progressive adaptation of the weights.

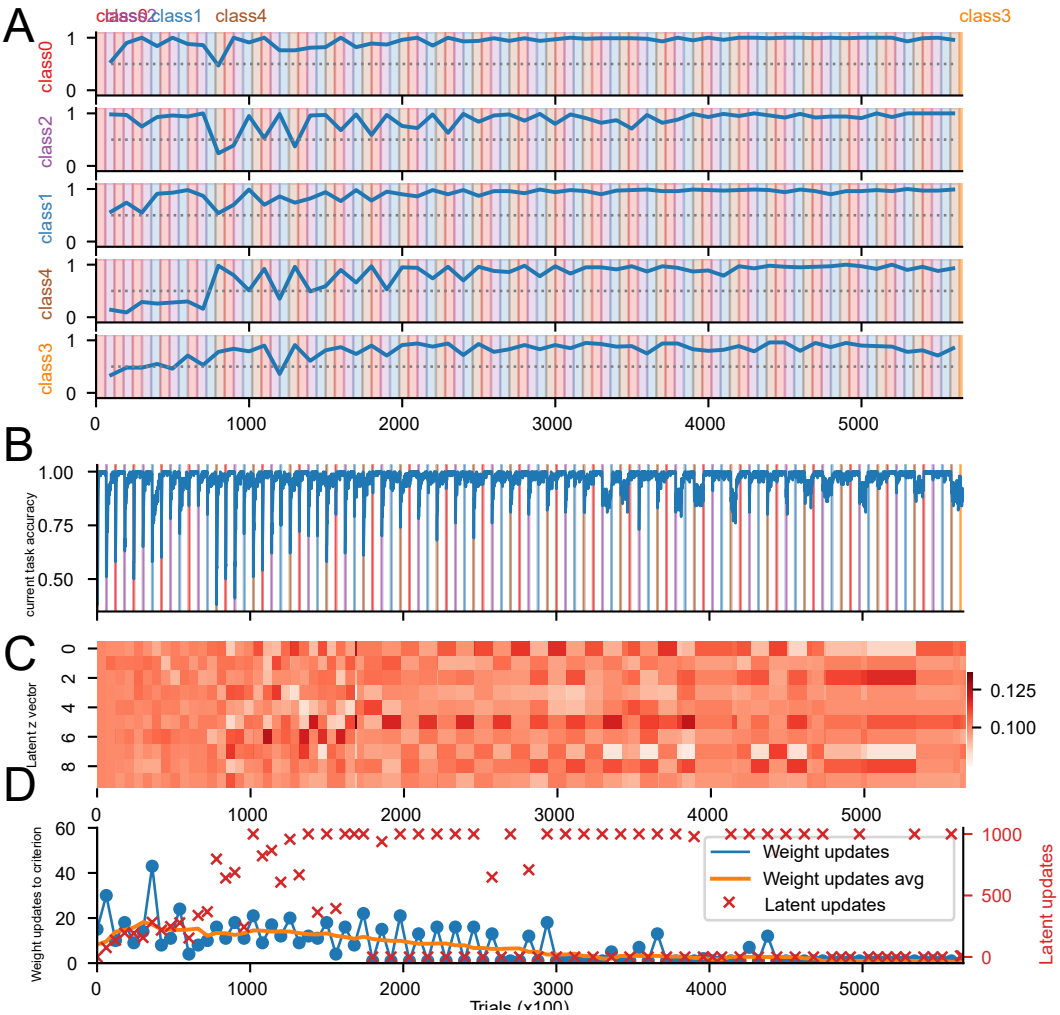

Figure 11: Example run of Thalamus on split MNIST tasks. We provide an example where the 5th task "task 3" was not seen until much later in the training but performance on it increases after the model forms latent representations of the other tasks.

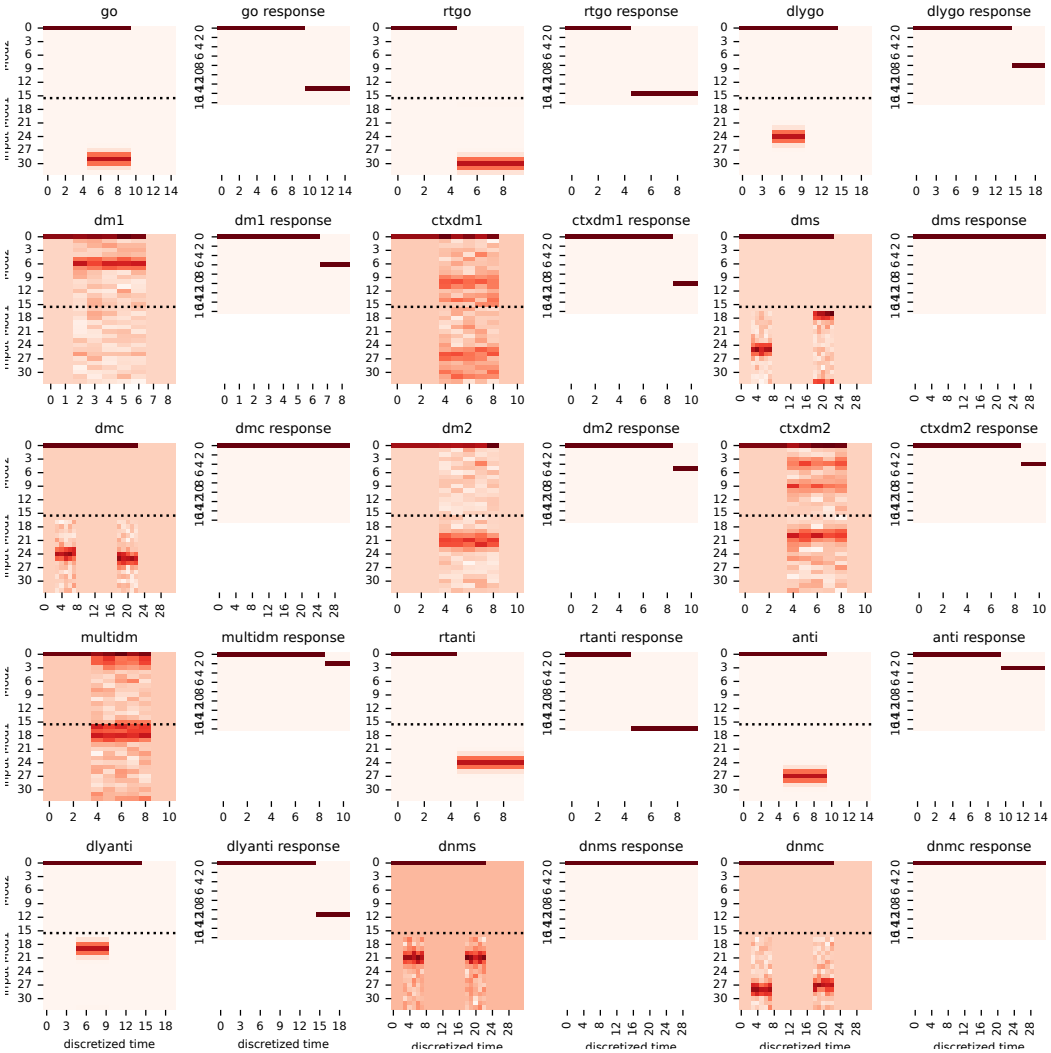

Figure 12: Visualizing the inputs and the ground truth responses for neurogym tasks. See Yang et al. (2019) for details and descriptions