AHA! an ‘Artificial Hippocampal Algorithm’ for Episodic Machine Learning

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Abstract

The majority of ML research concerns slow, statistical learning of i.i.d. samples from large, labelled datasets. Animals do not learn this way. An enviable characteristic of animal learning is ‘episodic’ learning - the ability to rapidly memorize a specific experience as a composition of existing concepts, without provided labels. The new knowledge can then be used to distinguish between similar experiences, to generalize between classes, and to selectively consolidate to long-term memory. The Hippocampus is known to be vital to these abilities. AHA is a biologically plausible computational model of the Hippocampus. Unlike most machine learning models, AHA is trained without any external labels and uses only local and immediate credit assignment. We demonstrate AHA in a superset of the Omniglot classification benchmark. The extended benchmark covers a wider range of known Hippocampal functions by testing pattern separation, completion, and reconstruction of original input. These functions are all performed within a single configuration of the computational model. Despite these constraints, results are comparable to state-of-the-art deep convolutional ANNs. In addition to the demonstrated high degree of functional overlap with the Hippocampal region, AHA is remarkably aligned to current macro-scale biological models and uses biologically plausible micro-scale learning rules.

1. Introduction

In recent years, machine learning has been applied to great effect across many problem domains. The solutions are predominantly based on slow statistical learning, require a very large amount of data, usually labelled, and need retraining rather than incremental learning to build on existing knowledge. Samples are typically assumed to be i.i.d (independent and identically distributed), implying an unchanging world. In contrast, animals learn new concepts quickly in dynamic environments without relearning of existing knowledge. Biological learning mechanisms confer a range of desirable qualities shown in Table 1:

- Being able to learn and reason about specific instances, even if they are very similar
- Generalise to other experiences
- Recognise complete entities robustly from partial cues
- Sample efficient (e.g. one-shot) learning
- Short-Term Memory of recent experiences
- Learn without labels
- Robustness to perturbations (e.g. noise and occlusion)
- Continual learning of new knowledge
- Selective retention of salient knowledge as Long Term Memory

Table 1: Qualities of biological learning.

These are desirable qualities for many systems. In particular, sample efficient learning would be of immediate benefit for many applications. The range of capabilities is particularly beneficial for an agent that acts within an environment.

It is difficult to imagine operating in the world without the ability to learn quickly enough to recall the specifics of the day, distinguish between similar experiences and objects and use new knowledge immediately. Imagine seeing every cup as a category rather than the cup that has your coffee! These skills also enable one to tell an autobiographical story and have a sense of identity, and by extension a sense of responsibility.

There has been growing interest in building ML systems that possess these qualities. One example is one-shot learning,
The motivation of this work is to understand and replicate hippocampal region functionality to achieve the range of qualities described in Table 1 using realistic sensor observations rather than highly abstract labels or symbols i.e. grounded high dimensional data generated by real world processes and used in real world tasks. This is challenging as many of the capabilities desired appear to be more amenable to symbolic reasoning. Additionally, we require grounding of internal representations to perform the equivalent of ‘consolidation’ for future inference, and enable generalization to future observations. Laying down longer term memories can then influence the way that the system perceives in the future.

Our approach is to build a biologically plausible computational model of the hippocampal region with modern ML techniques. Functionally, it should complement a slowly learned long term memory, analogous to the neocortex. We assume that the latter functionality is already sufficiently explored in the ML literature. Biological plausibility is chosen as biology has solved these challenges and modern ML techniques have been proven to be able to work at scale on these types of rich datasets. We choose to closely model the subfields of the hippocampal region because we believe this is the highest level of abstraction that will retain the desired functionality.

1A subfield is an anatomically and physiologically (functionally) distinct region.

The result is AHA - Artificial Hippocampal Algorithm. AHA can be used with real data and it provides insights into hippocampal function. This paper describes AHA and some experimental results.

AHA replicates the fast learning quality and 3 functional pathways of the hippocampal region. The pathways are: Pattern Separation (PS), being able to tell the difference between very similar patterns; Pattern Completion (PC), recognition of a complete pattern from partial cues; and Pattern Mapping (PM), reconstruction of the original complete pattern in a grounded form. The pathways must be integrated closely to be able to form unified representations. PS and PC functions are contradictory, making this unification challenging: separation of similar patterns into distinct representations at first glance appears to defeat completion.

The experiments are based on the classification test conducted by Lake et al. (2015) using Omniglot, a dataset of handwritten characters from a range of alphabets. “Compared to other common concepts, handwritten characters are simple and tractable enough to hope that machines, in the near future, will see most of the structure in the images that people do. For these reasons, Omniglot is an ideal testbed for developing more human-like learning algorithms” (Lake et al. 2019). The benchmark has many results for comparison and is a good basis for additional experiments that demonstrate other desired capabilities.

In the classification test, the algorithm is shown just one exemplar of a given character and is then required to identify another exemplar of the same character class in an unseen set of exemplars from numerous classes, without any explicit labels. We added an additional test for reasoning about singular instances, where the algorithm is required to distinguish between many samples of the same character class, referred to as ‘instance-classification’. In this case, the unseen exemplars are drawn from the same class as the character originally shown to the algorithm, hence they are very similar to each other. It can be understood that this task is very difficult for an algorithm that is also simultaneously able to complete the classification test.

In addition, the algorithm is shown and required to memorise a whole batch at a time for later comparison with the test batch, and both tests are run with increasing levels of noise and occlusion. These extensions capture many additional aspects of what we think of as ‘human-like learning’ (see Table 1). We encourage the community to adopt them into future one-shot studies.

The qualities we are seeking to achieve revolve around instantly learning a conjunction of concepts, which we define as an ‘episode’. In this sense, the Hippocampus enables Episodic Learning. It does not do this alone however, but through interplay with other brain regions. The Hip-
pocampus plays a role in semantic learning as well. See Appendix E for an in-depth discussion.

1.1. From sensors to symbols

For many of the insights in this paper it is necessary to make a distinction between two different types of data with very different qualities. We will refer to these as symbolic and non-symbolic data. They define an axis shown in Figure 1. Data can be partially symbolic when the relevant criteria are partially met. The figure shows defining characteristics of data on the axis from symbolic to non-symbolic.

We define symbolic data as discrete, perfect information, such as labels. Statistically, samples of a particular symbol value have low or zero variance and entropy making further compression difficult without loss of information. Samples of different symbol values are typically highly orthogonal (though not a necessary condition). Symbolic data tends to have fewer dimensions. Symbols are not ambiguous.

At the other end of the scale, non-symbolic data is noisy, partially observable proxies of underlying concepts. Non-symbolic data may be ambiguous and uncertain. Clusters corresponding to different symbols are likely to overlap in a statistically significant way. Since symbols are not explicitly represented in non-symbolic data, but must be inferred from incidental observations, the number of dimensions is typically high. Overlap between symbols is not sufficient for the data to be categorised as non-symbolic e.g. two symbols expressed as random vectors, could have overlap.

The problem of associating symbols with sensor observations is known as the grounding problem. Powerful reasoning can be conducted with symbols, but to operate in complex, realistic environments, systems must be able to operate with grounded sensor data.

1.2. Biological plausibility criteria

For this work, we adopt the biological plausibility criteria from [Rawlinson et al. (2019)] with extensions:

- Only local credit assignment. No back-propagation of errors between cell-layers.
- Only immediate credit assignment. No synaptic memory beyond the current and/or next step.
- No time-travel, making use of past or future inputs or hidden states.
- No labelled data available for training.

As in [Rawlinson et al. (2019)], we do not claim these criteria are sufficient for complete biological plausibility. However, we aim to avoid the most implausible features of conventional machine learning.

The computational capabilities of single-layer networks are very limited, especially in comparison to two-layer networks. Biological neurons perform “dendrite computation”, involving integration and nonlinearities within dendrite sub-trees ([Guergiuev et al., 2016] [Tzilivaki et al., 2019]). This is computationally equivalent to 2 or 3 typical artificial neural network layers. For this reason we allow ourselves to use error backpropagation across two ANN layers, under the assumption that this could approximate dendrite computation within a single biological cell layer, and training signals propagated inside cells.

1.3. Contribution

Our primary contribution is to demonstrate several episodic memory functions in a unified model of the hippocampal region that has both close macro-scale agreement to known subfield connectivity, and biologically-plausible micro-scale learning rules able to operate on realistic unlabelled data.

There are finer-grained contributions to the computational modelling and machine learning fields.

1.3.1. Biological computational model of hippocampus

- Novel approach of implementing the subfields of the hippocampal region using modern ML techniques.
- Extends experiments focussed on pattern separation to generalisation and recognition of incomplete patterns.
- Demonstration using realistic sensor inputs, as opposed to synthetically generated vectors.

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Figure 1: A schematic depiction of the spectrum of information from sensor observations to the symbolic domain. The green overlay contextualises the components of the hippocampal region and AHA on the spectrum and is expanded later in the paper. The dashed arrow shows the flow of data through the system. EC is Entorhinal Cortex, the interface to the hippocampal region.
1.3.2. MACHINE LEARNING

A new heterogeneous architecture that can achieve a wide range of capabilities being:

- One shot learning without labels.
- Ability to distinguish between similar inputs.
- Short term memory of recent observations.
- Ability to ‘ground’ symbolic memories (for later consolidation).

2. Related work

There are three main areas of related work: computational models of the hippocampal region, one-shot learning in ML, and ML inspired by the hippocampal region. Each is expanded below.

2.1. Computational models of hippocampus

The hippocampal region has diverse functions in memory and learning. Attempts to define it can portray it has having contradictory roles, which is reflected in the computational models in the literature. This fact is expressed in an excellent review by Gluck & Myers (1993), where the authors divide the field into two broad approaches “(1) models of the role of the hippocampal region in incremental learning, which focus on the development of new representations that are sensitive to stimulus regularities and environmental context; (2) models that focus on the role of the hippocampal region in the rapid storage and retrieval of episodic memories”.

One of the most prominent models in the latter ‘episodic learning’ category is the Complementary Learning System (CLS). The central idea of CLS is that the neocortex and the hippocampus comprise complementary memory systems. The neocortex forms highly distributed and overlapping representations, excellent for robust inference and reasoning. The hippocampus forms much sparser, non-overlapping representations, excellent for robust inference and reasoning. The hippocampus forms much sparser, non-overlapping representations, and is specialised for fast learning. It facilitates interleaved replay which may mitigate a cause of catastrophic forgetting observed in neural network models. CLS was first introduced in McClelland et al. (1995) first implemented in Norman & O’Reilly (2003) and recently updated and explored in the context of Artificial Intelligence (Kumaran et al., 2016). CLS describes the function of individual subfields and their connectivity. Their function and role are described in [3.1] Their implementation is a simulation of the subfields, expressed at a neuronal level of detail. Hebbian learning is used to adapt synaptic weights. CLS has been a popular model, and there have since been several extensions. Greene et al. (2013) and Ketz et al. (2013) studied different aspects of CLS and extended it with LEABRA - a form of Hebbian learning that uses local error gradients, speeding up training and avoiding a pre-training step. Schapiro et al. (2017) extended CLS further with the introduction of ‘big-loop recurrence’, an important concept in hippocampal function, described in [3.1]. This paper also looked at how the hippocampal region could learn statistical regularities quickly (as opposed to episodic memories), forming something of a bridge between the two categories of models.

Another well received model was first published by Rolls at about the same time, and followed by many subsequent reports (Rolls, 2013). An early report of a working simulation is reported in Rolls (1995). It is qualitatively very similar to CLS with more detail on the neuroanatomy and functional consequences.

These studies aim to replicate known cognitive and behavioural phenomena in simplified tests and replicate measurable quantities characteristic of the subfields. The experiments test the ability of the model to ‘study’ and then ‘recall’ patterns for varying levels of pattern similarity. The input data are artificial vectors and the emphasis is on the ability to separate and recognise exact patterns, without generalization between ambiguous or intermediate patterns.

A prominent model in the first category ‘incremental learning’ was introduced by Gluck & Myers (1993). It captures another aspect of hippocampal function, prediction, and models a form of consolidation to long term memory.

Rather than modelling the subfields at a neural level, this work takes a top down approach and models the region as a whole. The central idea is that the “hippocampal region compresses (or makes more similar) the representations of inputs that co-occur or are otherwise redundant, and differentiates (or makes less similar) the representations of inputs that predict different future events” (Gluck et al., 2003). They use a ‘predictive autoencoder’ as a compressive bottleneck to learn such representations. The autoencoder is trained to reconstruct the next rather than current state, predicting future stimulus, including reward. A separate feedforward network forms a simple model of a combined cortex and cerebellum, forming long term memory. The compressed representations are stored in the separate long term memory to modify stimulus-response. The experiments focus on replicating ‘classical conditioning’ tests conducted in psychology, which test learning through association over many experiences.

Simulating the region as a whole has the advantage of simplicity and scalability. Training an autoencoder with gradient descent is well suited to the statistical learning required for the ‘incremental learning’ category of hippocampal function. However, without sub-structures (such as analogues to the subfields), it is difficult to see how this model could
be extended to other episodic memory capabilities such as pattern separation. This is backed up by evidence through lesion studies that this type of incremental learning is actually accomplished by the Entorhinal Cortex, only one part of the region (Gluck et al., 2003). The style of consolidation to long term memory is unlike biology, where representations are uncompressed and consolidated to the same network in which they arose. The biological approach enables modification to future perception and is likely important for continual learning.

AHA fits most neatly into the ‘episodic learning’ category with a design that can be extended to ‘incremental learning’ in the future. It takes a mixed approach to the studies discussed, modelling the subfields but at a higher level of abstraction than individual neurons.

2.2. One-shot learning in ML

Historically, there has not been a lot of work on one-shot learning in ML/Al. Fei-Fei et al. (2003, 2006) conducted seminal work in which they defined a framework for pre-training with many classes, and then re-using the learned concepts to learn new classes quickly from a few examples (1-5). This was followed by Lake et al. (2011) with Bayesian Program Learning (BPL), inspired by a cognitive neuroscience approach. BPL “models the process of drawing characters generatively to decompose the image into small pieces …. to determine a structural explanation for the observed pixels” (Koch et al., 2015). Over multiple publications, these works introduced and established one-shot learning with Omniglot as a key benchmark - it is a real world task with well defined primitive ‘concepts’, yet is small and easy enough to be tractable with a variety of techniques.

The work culminated with a popular paper (Lake et al., 2015) in which the dataset was made openly available. That paper was notable in that it clearly defined a set of capabilities and corresponding tests to demonstrate fast and flexible one-shot learning that characterise human understanding such as classification, generation of novel exemplars and whole classes. One of those capabilities, one-shot classification, is relevant to this study. We believe the others are also important for higher order cognition.

BPL performs comparably to humans across the capabilities, by far outperforming other methods. By design it models the causal structure of the handwriting process with an in-built concept of the way to hierarchically decompose handwritten characters. It specialised for the task, requires stroke data at training time and is likely to be susceptible to occlusion and noise.

More recently, George et al. (2017) published a probabilistic generative vision model called Recursive Cortical Network (RCN). RCN incorporates neuroscientific principles from the visual cortex including hierarchy, top down and bottom up signal transmission, separate mechanisms for contour and appearance, and lateral connections for contour consistency. RCN was demonstrated on a range of problems, focussing on its ability to recognise text in the face of occlusion and noise using Captchas. It was also shown to be very competitive on the Omniglot one-shot classification task. The architecture is specialised for these types of visual processing tasks that require robust contour and topology modelling.

Other Omniglot solutions feature neural networks, beginning with an early paper (Koch et al. 2015) using a Siamese Neural Network. Some have exploited compositionality, others have aimed at learning quickly from scratch. The state of the field is well summarised in (Lake et al., 2019). Table 2 shows accuracy comparisons on the classification task later in this paper.

The most successful one-shot studies have exploited the idea of compositions of abstract concepts, consistent with the view of the hippocampal region as a learner of conjunctions of concepts that comprise an ‘episode’ e.g. a conversation about a specific topic at a specific time and location. However, each batch is assessed independently, rather than learning a combination of concepts as a composite concept and retaining that knowledge for future batches/experiences which would be a step toward continuous learning. None have explored one-shot recognition in the face of perturbations such as noise and occlusion or with very similar examples, such as exemplars (instances) of the same digit.

2.3. ML inspired by the hippocampal region

Wayne et al. (2018) developed MERLIN: ‘Memory, RL, and Inference Network’, an RL agent that incorporates the hippocampal model of Gluck & Myers (1993). Additional to the idea of predictive modelling, Wayne et al. (2018) introduced an external attentional memory that can be accessed with multiple read heads. The contents of the memory are the compressed representations from a variational autoencoder (VAE). The VAE is used for prediction as well as policy. This form of one-shot learning enables selectively attending to instance/s over extended time frames (in this case, longer than what is possible with BPTT) is consistent with hippocampal function.

Merlin was demonstrated to overcome limitations of other RL agents on partially observable environments perceived through high dimensional sensory data and where tasks require memory over long durations. Merlin was tested on a range of standard cognitive behavioural tests such as latent learning in a the T-Maze, the game of Memory and locating a hidden platform underwater using visual cues (Morris, 1983). The breadth and difficulty of the test suite constitute an impressive demonstration of an RL agent, and
of a hippocampal computational model.

The external memory is a core component of the model. However, as with (Gluck & Myers, 1993) above, memories do not effect future sensory perception, which may limit the potential for continual learning. It is unclear how well the algorithm would perform at differentiating similar stimuli. Symbol-Concept Association Network (SCAN) by Higgins et al. (2017) explores the idea that a small number of concepts can be used compositionally and hierarchically to describe a much larger set of concepts. SCAN does this by learning symbolic representations for grounded sensory input. A β-VAE (Kingma & Welling, 2013; Rezende et al., 2014) specialising in disentangled representations (Bengio et al., 2013) learns primitives from grounded visual input. Using an additional network, SCAN learns symbolic abstractions over the primitives as well as logical symbolic relations. Once in symbolic form, these relations are more easily learned and reasoned about. The symbols are provided explicitly, not inferred from sensor input, making this a form of supervised learning. The knowledge can be used bidirectionally, to generate images from symbols and vice versa, including symbolic descriptions of scenes it has not observed. The experiments are conducted in a simple 3d environment and with images of faces.

The hippocampal region is not referenced in the paper, but the idea of concept compositionality is consistent with our conception of hippocampal episodic learning. In SCAN, the reasoning occurs in an externally defined symbolic domain. In AHA, we show that symbols can be generated from unlabelled input. The disentangled representations have interesting similarities to pattern separation in the hippocampal region. It may prove to be a useful concept for building alternative hippocampal models.

3. Method

We constructed a computational model based on the work of Rolls and CLS (above), implemented with modern machine learning techniques and biological plausibility constraints (Section 1.2) for all parts of the architecture. This section describes our biological model followed by our AHA implementation of that model.

3.1. Biological Model

Our biological model of the hippocampal region is based on the models of Rolls (2013) and O’Reilly et al. (2014). It is shown in Figure 2. We give a high level description of details that we regard as relevant to understanding and replicating functionality, intentionally omitting details such as synaptic learning rules and numbers of neurons and connections.

Entorhinal Cortex (EC), the main gateway between the neocortex and hippocampus, has an input and output layer. The hippocampal region ‘reconstructs’ the input pattern in the output layer. The hippocampal region learns to reconstruct the input pattern in one-shot, enabling you to recall your day after only living it once, and to distinguish between the similar experiences you have had. It retains memories over the short term and selectively consolidates the memories to the neocortex for long term storage.

The EC forms a sparse and distributed overlapping pattern that combines input from all over the neocortex and subcortical structures. This pattern becomes sparser and less overlapping through Dentate Gyrus (DG) to CA3 with increasing inhibition and compression. That provides independent representations for similar inputs and therefore an ability to separate patterns, important for learning about specific episodes or conjunctions of input concepts, as opposed to generalities. The DG-CA3 connections (Mossy fibres) are sparse, contributing to the sparsening of the signal, and are responsible for memorization in CA3. The EC-CA3 connections form a pattern association network and are responsible for providing a cue for recall from CA3 (Rolls, 2013) (not a feature of CLS). Recurrent connections in CA3 create an autoassociative memory with basins of attraction storing multiple patterns. Any part of a stored pattern can be presented as a cue to recall a crisp version of the closest pattern. CA1 and the CA3-CA1-EC connectivity forms a hierarchical pattern associative network that maps back to EC to present the original pattern for replay to the cortex via reciprocal feedback connections, for recall and consolidation. The independent patterns stored in CA3 are replayed in an interleaved fashion, allowing slow learning in the cortex without catastrophic forgetting.
‘Big-loop’ recurrence occurs when a reconstructed EC pattern is transmitted back into the hippocampal region as the EC input. This process has received little attention in the computational modelling literature. It appears to be important for the hippocampal region to learn statistical information in the form of higher order patterns across episodes (Schapiro et al., 2017; Koster et al., 2018). That capability, and therefore ‘big-loop’ recurrence, is out of scope for this study.

3.2. AHA Model

AHA is a complementary component to statistical learning. Since this work uses a simple visual task, we use a simple Vision Component VC(EC) to represent a combined neocortex/EC. In the following sections we use a special Functional(Biological) notation to clearly identify the functional instantiations of each biological component. VC(EC) is pre-trained to recognise common visual features of the dataset, mimicking an assumed complementary memory using slow statistical learning. AHA produces VC(EC) representations for unseen samples without any additional training. Figure 3 shows the components and connectivity of AHA used to implement the biological model in 2. A more detailed figure is shown in E.1.

3.2.1. PS(DG) - Pattern Separation

PS(DG) is implemented with a sparse autoencoder based on Makhzani & Frey (2014; 2015) (see Appendix A.1) to produce the increasingly sparse and orthogonal representations observed in the EC-DG-CA3 pathway. There are 225 units, with a sparsity of 10 active units at a time.

Sparsity is implemented as a ‘top-k’ ranking per mini-batch, emulating a local competitive process via inhibitory interneurons. Smaller values for k are enough to produce less overlapping outputs, but orthogonality is further improved by replicating the sparse connectivity observed between DG-CA3 (as discussed in Section 3.1). A portion of the incoming connections are removed by setting weights to zero (similar to the sparsening technique of Ahmad & Scheinkman (2019)). Additionally, after a neuron fires (i.e. it is amongst the top-k), it is temporarily inhibited, mimicking the refractory period observed in biological neurons.

The first step is to calculate the weighted sum $z_i$ for each neuron $i$. The inhibition term $\phi_i$ is applied with an element-wise multiplication and then a mask. $M$ is calculated for the topk elements. We use an operator topk(a, b) that returns a ‘1’ for the top $b$ elements in argument $a$, and ‘0’ otherwise.

$$M = \text{topk}(\phi \cdot z, k)$$

The mask is applied with an elementwise multiplication to select the ‘active’ cells that have a non-zero output.

$$y = M \cdot z$$

Inhibition decays exponentially with the hyperparameter $0 \leq \gamma \leq 1$ determining the inhibition decay rate.

$$\phi_i(t + 1) = \phi_i(t) \cdot \gamma$$

PS(DG) is initialised with (uniformly distributed) random weights and does not undergo any training, similar to an Extreme Learning Machine (A et al., 2014). The signal is conditioned to be optimised for memorisation in a Hopfield network, explained in Appendix A.2.

The idealized function of PS(DG) is similar to a hashing function: similar inputs should produce dissimilar outputs. There have been other explorations of hashing with ANNs, such as chaotic neural networks (Lian et al., 2007; Li et al., 2011), however they tend to be complex, multi-layered and do not fit our biological plausibility constraints. The PS(DG) version which we coin a Random Sparse Autoencoder (RSA), may be useful in other contexts where orthogonality or pseudorandom non-clashing outputs is required.

3.2.2. PC(CA3) - Pattern Completion

PC(CA3) is implemented with a Hopfield network (Hopfield, 1982). The Hopfield network is a biologically-inspired auto-associative content-addressable memory. It can store multiple patterns and recall crisp versions of them from partial cues.

PC(CA3)’s role is dedicated to storage and autoassociative recall, and does not perform pattern recognition. As such,
PC(CA3) has the same number of neurons as PS(DG) (225 neurons) and there is a unique one-to-one connectivity between them. PS(DG) effectively encapsulates the biological connectivity between DG and CA3 neurons.

Unlike a standard Hopfield network, there are separate pathways for memorization and recall. PS(DG) patterns are memorized by learning the appropriate recurrent weights for a given input pattern. The recall cue is provided via the PR(EC-CA3) network and full explanation is given in that section below.

We used graded neurons with tanh activation function and a gain of $\lambda$. A small portion $n$ of all neurons are updated at each step (of $N = 70$ iterations), which speeds up convergence without any practical consequences (i.e. 1 per step guarantees convergence). The Pseudoinverse learning rule \cite{Pal1996} was used to learn the feedback recurrent weights. It was chosen for convenience in that it increases capacity and is calculated in one time step. Weights can be learnt with more biologically realistic alternatives such as the original Hebbian learning or the Storkey learning rule \cite{Storkey1997}. As with the biological case, the learning occurs rapidly within one exposure to an external stimulus.

3.2.3. PR(EC-CA3) - Pattern Retrieval

PR(EC-CA3) models the connectivity between EC and CA3 with a fully connected neural network. It’s role is to retrieve appropriate PS(DG) patterns stored in PC(CA3). As with PS(DG), it has the same number of units as PC(CA3) with 1 to 1 direct connections.

PC(CA3) stores the orthogonal patterns from PS(DG) and must be able to recall the appropriate pattern from a corresponding VC(EC) pattern which is unlikely to be exactly the same or an exact subset (without the use of synthetic data). If PS(DG) is effective, then small differences in VC(EC) result in orthogonal outputs and it will not provide a meaningful cue to PC(CA3). The direct connectivity between EC and CA3 constitutes a pattern recognition network that allows exploitation of the overlapping representation in EC which contain information about underlying concepts.

The implementation is informed by the way it is accomplished in the hippocampal region. As mentioned, this pathway is used for recall of the memorized patterns (from DG). At the time of memorization, DG causes activation of pyramidal neurons in CA3. The EC-CA3 connections are learned associatively between the co-active EC neurons. The process is illustrated in Figure 4.

In the context of AHA, the VC(EC) is mapped to a cue to recall a stored pattern in PC(CA3). The mapping is achieved with PR(EC-CA3), a fully connected 2-layer ANN with a ‘leaky ReLU’ activation function in the first layer, ‘sigmoid’ for the second, and L2 regularization. The VC(EC) is input and the PS(DG) output is used as internally generated labels for self-supervised training. The learning is posed as multi-label with a cross entropy loss.

PR(EC-CA3) constitutes feedforward connectivity to the neurons of PC(CA3). As with the rapid learning of PC(CA3) recurrent connections, PR(EC-CA3) learns completely within one stimulus exposure. The learning process during that exposure is implemented as $N = 40$ mini-batches with constant input. Refer to Appendix B for more details on PR(EC-CA3).

3.2.4. PM(CA1) - Pattern Mapping

PM(CA1), the CA1 equivalent, is trained to reconstruct the VC(EC) pattern that served as input to the other pathways. It is a fully connected 2-layer ANN with ‘leaky ReLU’ activation function, MSE loss function and L2 and denoising regularization. In this case, PC(CA3) is the input and the VC(EC) signal is the target ‘output’, another internally generated pattern used for self-supervised training. PM(CA1) is effectively learning to ground the ‘symbolic’ representation for re-‘experiencing’ and consolidation. As per PR(EC-CA3), PM(CA1) converges over $N = 40$ mini-batches.

3.2.5. VC(EC) - Vision Component

The role of the VC(EC) is to process high dimensional sensor input and provide relatively abstract (semi-symbolic) visual features that can be used compositionally. A single layer convolutional sparse autoencoder based on Makhzani & Frey \cite{Makhzani2015} (see Appendix D.1) provides an embedding in terms of primitive visual features. However, in Omniglot there is a lot of empty background. Lacking an attention mechanism, this detracts from compositionality of foreground features. To suppress encoding of the background, we added an ‘Interest Filter’ mechanism.

The ‘Interest Filter’ loosely mimics known retinal processing. The retina possesses centre-surround inhibitory and
excitatory cells that can be well approximated with a Difference of Gaussians (DoG) kernel [Enroth-Cugell & Robson, 1966; Young, 1987; McMahon et al., 2004]. See Appendix D.3 for our implementation.

3.3. AHA Insights

3.3.1. The Importance of Pattern Retrieval (EC-CA3 Connectivity)

Pattern completion by CA3 is conventionally attributed to the recurrent connections. In AHA, we found that the feed-forward connections (PR(EC-CA3)) were even more important as predicted in [Cheng, 2013]. The requirements of PR(EC-CA3) to retrieve an appropriate cue to PC(CA3) from non-symbolic observations, means that it retrieves whole patterns, performing a large amount of completion. The recurrent connections in PC(CA3) are still vital for additional completion and sharpening so that it can be effectively reconstructed by PMi(CA1) for re-activation of the originating cortical representation. It is possible that previous computational studies were not faced with this limitation because the experiments focussed on a narrower problem set - recognition of a few symbolic but incomplete patterns, where the cue at EC is a perfect subset of the memorised pattern. There are other factors to consider such as the division of EC into discrete receptive fields and capacity difference between PR(EC-CA3) and PC(CA3) equivalent networks [Rolls, 2013]. However, the importance of PR(EC-CA3) in AHA suggests that the connectivity is more important than previously acknowledged.

3.3.2. Unifying Separation and Completion

Separation and completion are conflicting capabilities requiring separate pathways. It is difficult to achieve both within a unified representation. Without a unified representation, it is difficult to combine both capabilities in the same task. Note that both separation and completion are necessary for the two reported experiments, even though the importance of ‘separation’ is more obvious in the Instance-classification test. Separation allows storage of a unique form of the memory, and completion recalls the most ‘similar’ memorized form. It does not matter whether observational variation is caused by occlusion, noise or different exemplars of the same class.

AHA accomplishes unified representation through the flow and transformation of information from non-symbolic observations, to symbolic form and back again (Figure 1). As information moves up the processing hierarchy of the neocortex, overlapping representations grounded in the high dimensional sensory processing become more separate and stable - gradually becoming more symbolic, in our definition. PS(DG) achieves the most significant jump towards the symbolic end of the axis. Effectively random, non-overlapping outputs no longer represent concepts as grounded in perceptual processing but instead internally generated labels.

Unification of the pathways is achieved with the use of the symbolic pattern as the target for supervised learning in PR(EC-CA3) (discussed in Section 3.2.3). There is no need for externally provided labels. The approach is a form of self-supervised learning [Gidaris et al., 2019] which uses a self-generated goal to supervise learning. However, usually a pre-conceived goal such as rotation is used with the motivation of learning generalisable representations. In the case of AHA, the goal is also self-generated and the motivation is separability. As such, orthogonal labels are very effective. Anti-correlation between patterns also increases the capacity of the Hopfield network and enables symbol compositionality.

3.3.3. Symbols are Task Dependent

Symbols are useful if they are abstractions over some range of variation that allows more effective reasoning. The symbolic representations in AHA are flexible and depend on the task. For the instance-classification test, the symbol generalizes over versions of the same exemplar (subject to noise and occlusion). This is the standard definition of episodic learning. For the classification test, the symbol learnt generalizes over multiple exemplars of the same class (additionally subject to noise and occlusion). This is the standard definition for generalization in classification.

The concepts represented in the EC are the primitives for composition. Primitives can be composed into new concepts, which get consolidated back into the slow-learning Long-Term Memory. In turn the LTM can perceive these new concepts again as primitives for a subsequent stage of learning. This theoretically confers an ability to build more abstract concepts hierarchically. One can visualise this in Figure 1 as the dotted line of EC gradually moving to the right towards the symbolic domain. It need not be fixed at any one point in time however. If the statistical learning component is itself hierarchical, an attentional mechanism could shift the dotted line left and right dynamically. This is an exciting prospect for future work and prompts a re-evaluation of traditional class boundaries and a recognition that concepts exist on a spectrum of varying abstraction. It is also further motivation for abstractions that can be used combinatorially (compositionally) in ways not experienced during learning, such as disentangled representations [Bengio et al., 2013] and equivariances [Sabour et al., 2017].

4. Experiments

As mentioned in the Introduction, the experiments are based on the one-shot learning framework in [Lake et al., 2015]. We took the classification test, and extended it to varying
levels of noise and occlusion. Robustness to perturbations is one of the objectives (Table 1) and an area that is not solved well by conventional neural network architectures (Ahmad & Scheinkman, 2019). We also added a variant for instance learning requiring an ability to distinguish between very similar exemplars from the same class. They are referred to as Classification and Instance-classification experiments respectively. The Omniglot dataset is used, a set of handwritten characters from 50 alphabets.

In a single experimental run, the algorithm is shown a set of 20 unique ‘train’ characters. It is then shown a batch of 20 ‘test’ characters of the same classes, written by a different person. It must then match the corresponding train and test exemplars. This is known as 20-way classification. The characters and alphabets are selected to maximize difficulty through confusion of similar characters. In the biological literature, train and test are often referred to as study and recall respectively. Correct recall is referred to as recognition, or as we say, an AHA moment!

The images for the runs are drawn from the ‘evaluation’ set consisting of 30 alphabets and 964 classes, and the VC(EC) pre-training was conducted on the ‘background’ split, 20 alphabets. Pre-training was done with 2000 batches and a batch size of 128.

Other studies that have extended earlier work on one-shot learning have used only 5 alphabets, tested recall between (as opposed to within) alphabets, and used augmented datasets, making the problem significantly easier (Lake et al., 2019).

Occlusion is achieved with randomly placed circles, completely contained within the image. Circle pixel intensity is set to the background value. The diameter is expressed as a fraction of the image side length was set between 0 and 0.8 in increments of 0.1.

Noise is introduced by replacing a proportion of the pixels with a uniformly distributed random value within the pixel intensity range. The proportion of pixels is varied and is expressed as a fraction of the side length of the image.

Test-time performance is measured by iterating over each train sample, and identifying the best matching sample in the test batch. The metric for best match is simply the minimum MSE (note no labels are ever provided to AHA). A correct classification is one where the best match is the correct exemplar and accuracy is calculated using the rate of correct classifications.

We refer to accuracy as ‘Recognition’. However, we only consider it to be a true AHA moment if the system is able to recall (and reconstruct) the appropriate memory. We can intuitively identify with this phenomenon and it is essential for consolidation and ‘big-loop’ recurrence (both future work). AHA is evaluated in two ways: recognition rate which is quantitatively compared to other methods, and qualitatively on the reconstruction of a retrieved complete memory in grounded, observational form.

5. Results

5.1. Recognition Rate

The recognition rate is plotted versus occlusion for classification in Figure 5a and instance-classification in Figure 6a. Likewise versus noise for classification in Figure 5b and instance-classification in Figure 6b. Recognition is measured using output patterns from different parts of the algorithm: VC(EC), PR(EC-CA3) and PC(CA3).

VC(EC) constitutes a baseline performance without the assistance of AHA. For the classification experiment, the pattern retrieval network, PR(EC-CA3), boosts performance significantly by over 10% to 86.0% at no noise or occlusion.

For occlusion, the margin is maintained until the occlusion becomes significant (~0.7 diameter). Then as the task becomes too difficult the rates begin to converge. PC(CA3) recognition is no better than VC(EC).

The trend is different when the perturbation is due to noise. PC(CA3) recognition is again no better than VC(EC), but PR(EC-CA3) maintains a relatively constant advantage, and the performance of all metrics follows a predominantly linear trend i.e. it does not drop off rapidly at high levels of noise.

To put it into context, AHA performance is contrasted with other state-of-the-art approaches in Table 2. The values are reproduced from Lake et al. (2019).

| Algorithm       | Citation          | Accuracy |
|-----------------|-------------------|----------|
| Human           | (Lake et al., 2019) | 95.5%    |
| BPL             | (Lake et al., 2019) | 96.7%    |
| RCN             | (George et al., 2017) | 92.7%    |
| Simple Conv Net | (Lake et al., 2019) | 86.5%    |
| Prototypical Net| (Lake et al., 2019) | 86.3%    |
| AHA             |                   | 86.0%    |
| VHE             | (Hewitt et al., 2018) | 81.3%    |

Table 2: Comparison of algorithms for classification, without perturbations.

In the case of occlusion, a similar trend is observed for instance-classification, as for classification, although they are quite different. The task is achievable with 100% recognition until occlusion has become significant at approximately 0.25 circular diameter. Then the relative advantage
of PR(EC-CA3) grows until the task becomes too difficult and like with classification, they begin to converge. The peak advantage is over 25% at a high level of occlusion, where PR(EC-CA3) is still performing well at over 75%. Note also that in this case, which is the focus of most episodic work in computational models, PC(CA3) does indeed confer a significant advantage that grows with occlusion until it converges as the task becomes too difficult.

The case of noise in the instance-classification experiment shows the same relative advantage of VC(EC), PR(EC-CA3) and PC(CA3) as for classification. However, like with classification, increased noise did not cause a rapid drop in performance.

5.2. Qualitative analysis

The patterns are shown as they propagate through the components of AHA, for typical scenarios, in Figures 7a to 8c.

The legend for those figures is shown in Table 3.

| Row | Pattern                        |
|-----|--------------------------------|
| 1   | Train samples                  |
| 2   | PS(DG) output                  |
| 3   | Test samples                   |
| 4   | PR(EC-CA3) output              |
| 5   | PC(CA3) output                 |
| 6   | PM(CA1) output (VC(EC) reconstruction) |

Table 3: Legend for Figures 7a to 8c

6. Discussion

Referring to Table 2, BPL and RCN are significantly ahead of other methods, and are similar to human performance. This is expected for BPL, as it exploits domain-specific prior knowledge about handwriting via stroke formation. RCN, by virtue of the design which is modelled on the visual cortex, is also specialised for this type of visual task. It is less clear how it could be applied to other datasets and problems where contours are less distinct. The Simple Conv Net (CNN) represents a standard approach from the state-of-the-art in deep learning. Surprisingly, AHA is almost as good...
Figure 7: Classification test patterns as they propagate through AHA, see Table 3 for legend.
Figure 8: Instance-classification test patterns as they propagate through AHA, see Table 3 for legend.
AHA performed extremely well on the instance-classification test. The recognition rate is almost perfect up to occlusion diameter of 0.5, and degrades gracefully, remaining above 50% until almost 0.75. Likewise for noise it remains high near or above 0.75. While instance learning itself should be easy, under noise and occlusion, PC(CA3) and PR(EC-CA3) is distinctly advantageous. In addition, instance learning in a system that also generalizes is quite difficult due to the conflicting demands of these two capabilities.

Noise did not cause a rapid drop in performance like it did for occlusion because it effects all topological features equally and gradually. Whereas increased occlusion increases the likelihood of suddenly removing topological features that were important.

The results show that PR(EC-CA3) performs classification significantly better than PC(CA3). This is evidence for our hypothesis that it is more important than previously thought, and that PC(CA3)’s primary role is for completion and mapping back to EC, as discussed in Section 3.3 PC(CA3) performs its assigned role very well, but that role is not classification.

As shown in Figures 7a to 8c PS(DG) (row 2) effectively produces non-overlapping patterns from the train batch samples, even where the samples are extremely similar (different exemplars of the same class). PR(EC-CA3) outputs are in most cases, recognizable retrievals of the correct pattern, however they are noisy and unevenly attenuated. PC(CA3) then converges to a crisp recall of one of the memorised patterns i.e. a basin of attraction in the Hopfield network, not always the correct one. The sharp, complete version is used by PM(CA1) to create a high quality reconstruction of the corresponding training sample. There is a small amount of shadowing and fainter sections, but the character is clearly identifiable, showing that the original complete VC(EC) pattern has been reconstructed which could be used for consolidation or recalled for use in a task.

In the presence of occlusion a complete train sample is still recalled in most cases (one exception in the examples shown in the Results). In addition, the recall is mainly correct even when the occluded portion disrupts the topology of the sample (e.g. columns 1, 10, 11, 13, 20 in Figure 7b and columns 1, 7, 11, 12, 13, 19 in Figure 8b). Recall tends to fail gracefully, recalling similar samples. Take column 8, Figure 7b. The recalled character has a large circular form with a dot in the middle. It shares many of the feature cues with the correct character. In other failure cases such as column 6b the occlusion has not damaged the sample significantly, but PR(EC-CA3) appears to have recalled multiple patterns that converge to the wrong train sample. It is not obvious from visual inspection of the train and test samples, if ambiguous visual features have contributed to the error, or if it is due to the representational and generalizational capacity of PR(EC-CA3). It is possible that ‘big-loop’ recurrence could assist in disambiguation leading to a correct outcome in these cases.

PR(EC-CA3) outputs a superposition of possible patterns, which enhances the chance of a lucky match via our MSE metric. PC(CA3) is designed to retrieve a single, sharp complete sample and in doing so is unable to hedge its bets. We believe this is one cause of lower PC(CA3) classification accuracy compared to PR(EC-CA3).

7. Conclusions

This paper presented AHA, a novel computational model of the hippocampal region and subfields (functional and anatomical sub-regions). AHA uses biologically-plausible, local learning rules without external labels. AHA performs fast learning, separation and completion functions within a unified representation. The symbolic representations generated within AHA can be grounded - mapped back to the original sensor input. We describe how this architecture can complement the slow statistical learning of popular ML methods. AHA could extend their abilities to more animal-like learning, such as one-shot learning of a conjunction of primitives (an episode). This could enable ML to perform more sample-efficient learning, and reason about specific instances.

The system was tested on visual recognition tasks featuring realistic, non-symbolic data. We posed a new benchmark based on the visual one-shot classification task in [Lake et al., 2015]. A instance-classification test was introduced, testing ability to reason about specific instance/s. Noise and occlusion were added. The results show that subfield functionality matches biological observations, and demonstrates a range of capabilities. AHA can memorise a set of samples, learn in one-shot, perform classification requiring generalisation and identify specific instances (reason about specifics) in the face of occlusion or noise. It can accurately reconstruct the original input samples which can be used for consolidation of long term memories to influence future perception. AHA one-shot classification accuracy is comparable to existing ML methods that do not exploit domain-specific knowledge about handwriting.

Labelling is known to be a burdensome cost that limits the practical application of ML. AHA explores how information flow from sensor observations to increasingly symbolic
representations and back again can result in learning new concepts as compositions of existing concepts, a possible path to lifelong or continual learning. During this process, external labels are not required.

The experiments expanded the scope of previous biological computational model studies, shedding light on role and interplay of the subfields and aiding in understanding functionality of the hippocampal region as a whole.

8. Future Work

In future we will explore two ways that AHA could augment slowly learned ML models. Firstly, the use of grounded non-symbolic VC(EC) reconstructions from PM(CA1) to selectively consolidate memories so that they can affect future perception. Secondly, AHA could directly and immediately augment slow-learning ML models by interpolating rapidly learned classification or predictions from AHA with the slow-learning model. This approach is compatible with a wide variety of models and would make them more responsive to rapidly changing data, or where fewer labelled samples are available.

We would also like to investigate how these representations can be fed back through AHA in ‘big-loop’ recurrence to learn statistical regularities across episodes (see Section 2.1) and to resolve ambiguous inputs.

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Author Contributions

GK and DR devised the concept and experiments. GK, DR and AA wrote the code. GK, DR and AA executed the experiments. GK, DR and AA wrote the paper.

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A. PS(DG)

A.1. Sparse autoencoder

Our fully-connected sparse autoencoder is based on the $k$-sparse autoencoder [Makhzani & Frey, 2014]. The top-$k$ active cells are chosen for a sample, and the rest set to 0. We replace the sparsity schedule with the lifetime sparsity rule from [Makhzani & Frey, 2015]. For a given filter, the $k\%$ largest activations across the mini-batch samples are retained and the rest set to 0. We set $k$ to a lifetime of 1 sample per mini-batch. Note that the two sparsity rules are combined with an OR logic, so the lifetime rule ensures that each filter is trained at least once per mini-batch.

A.2. Signal conditioning

The PS(DG) output $X$ is conditioned for memorization into the Hopfield network, which benefits from binary vectors in the range $[-1, 1]$. The conditioning function is:

$$X = 2 \text{sgn}(X) - 1$$

It is implied that $X$ must be unit range.

B. PR(EC-CA3)

The PR(EC-CA3) output $Y$ is optimized for the classification task. To present a valid cue for Hopfield convergence, additional conditioning is required. First, a norm is applied per sample $i$ out of $K$ samples, with a gain term $\gamma = 10$.

$$Y_i = \gamma \cdot Y_i \cdot \left(\frac{1}{K} \sum_{j=1}^{K} Y_j\right)$$

Next, the range is transformed to the Hopfield operating range of $[-1, 1]$ and finally an offset $\Theta$ is applied per sample. Intuitively, $\Theta$ shifts the output distribution to straddle zero, with at least $k$ bits $> 0$, where $k$ is the fixed sparsity of the stored patterns from PS(DG).

$$Y = (2Y - 1) + \Theta$$

Given that it is in range $[-1, 1]$, anything negative acts as inhibition, so the balance is very important. The inputs are relatively sparse, dominated by background (negative). To allow some elements to reach an active status before the many inhibitory elements dominate, it’s necessary to initialize the distribution as described.

C. PM(CA1)

Denoising consists of salt and pepper noise over a fraction $\eta_f$ of the input elements.

D. VC(EC)

D.1. Sparse convolutional autoencoder

Our sparse convolutional autoencoder is based on the winner-take-all autoencoder [Makhzani & Frey, 2015]. To select the top-$k$ active cells per mini-batch sample, we use a convolutional version of the original rule from [Makhzani & Frey, 2014]. The top-$k$ cells are selected independently at each convolutional position by competition over all the filters. We use a lifetime of 1 sample per mini-batch as described above. We found that a single autoencoder layer with tied weights was sufficient for the Omniglot character encoding. However, additional layers could have been trained with local losses without violating our biological plausibility rules. To reduce the dimensionality of the VC(EC) output, we applied max-pooling to the convolutional output.

D.2. Pre-training

Pre-training of the sparse convolutional autoencoder develops filters that detect a set of primitive visual concepts that consist of straight and curved edges, sometimes with junctions (Figure S1).

D.3. Interest Filter

As shown in Figure S2, positive and negative DoG filters are used to enhance positive and negative intensity transitions. The filter output is subject to local non-maxima suppression to merge nearby features and a ‘top-$k$’ function creates a mask of the most significant features globally. Positive and negative masks are combined by summation giving a final ‘Interest Filter’ mask that is applied to all channels of the convolutional output volume. A smoothing operation is then applied to provide some tolerance to feature location. There is a final max-pooling stage to reduce dimensionality. Refer
E. Memory Systems

Memory is multi-faceted. It is often divided into Working, Declarative and Non-declarative as shown in Figure S3.

In this study, we are interested in Declarative memory. “Explicit memory (or declarative memory) is one of the two main types of long-term human memory. It is the conscious, intentional recollection of factual information, previous experiences, and concepts” (Ullman 2004). Declarative memory is further divided into Semantic and Episodic memory.

It is conventionally understood that semantic memories are generic, whereas episodic memories are specific or ‘singular’ memories. A more nuanced taxonomy, proposed by Goldberg (2009), is shown in Figure S4.

Semantic memories can be about singular concepts, such as “Paris is the capital of France”, as well as generic concepts such as “tomatoes are red”. Episodic memories are only about singular events or things, which is why they can support ‘autobiographical’ content, but are sometimes too narrowly defined as being solely autobiographical content.

In the neocortex, declarative memories are believed to comprise cliques of active neurons, jointly representing some concept as a distributed representation. All declarative knowledge is stored this way. The distinction between Generic or Singular knowledge types only concerns the content of the information. It does not necessitate a fundamentally different learning mechanism.

The conventional understanding is that the Hippocampus is the short term storage of declarative memory. This knowledge is then replayed and consolidated in the neocortex over time. The more salient memories are consolidated, but the less important are not, and are forgotten.

By extension, it is likely that ‘singular’ knowledge (both semantic and episodic) is also learnt slowly in the neocortex via repeated replay. Hippocampus would therefore be the gatekeeper to all forms of declarative knowledge, enabling both semantic and episodic learning according to the conventional definitions.

E.1. System design

The full architecture of AHA is shown in Figure S5. The hyperparameters used in our experiments are shown in Table 4. We used the Adam optimizer (Kingma & Ba 2014) in all experiments.
Figure S5: Architecture details (the hyperparameters shown are for the experiments after pre-training the VC).
| Model                  | Parameter                          | Value         |
|------------------------|------------------------------------|---------------|
| **PS(DG)** - Pattern Separation with RSA** | k (sparsity)                      | 10            |
|                        | h (number of units)                | 225           |
| **PC(CA3)** - Pattern Completion with Hopfield Network | λ (gain)                         | 2.7           |
|                        | n (cells updated per step)         | 20            |
|                        | N (iterations)                     | 70            |
|                        | h (number of units)                | 225           |
| **PR(EC-CA3)** - Pattern Retrieval with Fully Connected ANN | h (number of units hidden layer) | 800           |
|                        | o (number of output units)         | 225           |
|                        | λ (l2 regularization)              | 0.000025      |
| **PR(EC-CA3)** - Signal Conditioning | γ (gain)                         | 10            |
| **PM(CA1)** - Pattern Mapping with Fully Connected ANN | h (number of units hidden layer) | 100           |
|                        | o (number of output units)         | 100           |
|                        | λ (l2 regularization)              | 0.0004        |
|                        | ηf (denoising fraction)            | 0.25          |
| **VC(EC)** - Vision Component Sparse Convolutional Autoencoder | k (sparsity) ()=pre-training | (1), 4        |
|                        | f (number of filters)              | 121           |
|                        | fw (filter width)                 | 10            |
|                        | fh (filter height)                | 10            |
|                        | fs (filter stride)                | (5), 1        |
|                        | Batches (pre-training)             | 200           |
|                        | Batch size (pre-training)          | 128           |
| **VC(EC)** - Vision Component Interest Filter | DoG kernel size                | 7             |
|                        | DoG kernel std                     | 0             |
|                        | DoG kernel k                       | 1.6           |
|                        | Non maxima suppression size        | 5             |
|                        | Non maxima suppression stride      | 1             |
|                        | Smoothing size                     | 15            |
|                        | Smoothing encoding std             | 2.375         |
|                        | k (number of features)             | 15            |
| **VC(EC)** - Vision Component | Resize                           | 0.5           |
|                        | Max Pooling size                   | 4             |
|                        | Max Pooling stride                 | 4             |

Table 4: Hyperparameter values for reported experiments.