A neuro-inspired architecture for unsupervised continual learning based on online clustering and hierarchical predictive coding

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Abstract

We propose that the Continual Learning desiderata can be achieved through a neuro-inspired architecture, grounded on Mountcastle's cortical column hypothesis (Mountcastle, 1997). The proposed architecture involves a single module, called Self-Taught Associative Memory (STAM), which models the function of a cortical column. STAMs are repeated in multi-level hierarchies involving feedforward, lateral and feedback connections. STAM networks learn in an unsupervised manner, based on a combination of online clustering and hierarchical predictive coding. This short paper only presents the architecture and its connections with neuroscience. A mathematical formulation and experimental results will be presented in an extended version of this paper.

1 Connection with neuroscience

Instead of providing directly an algorithmic description of STAMs (that would hide the connection to neuroscience and cortical columns), we first give a sequence of points about cortical columns that the design of STAMs is based on. We should note that the following points are still an active area of research and debate among neuroscientists - they should not be viewed as proven facts. In the same way that computer science has created useful ANNs based on a crude model of a neuron’s function, we may also find out that STAMs are useful in practice even though they may be only a caricature of how cortical columns, and the cortex in general, work.

1) The cerebral cortex consists of the same six-layer module, referred to as cortical column, repeated throughout the cortex with minor anatomical differences. The "canonical cortical circuit" by Douglas and Martin (see Fig.[1]) captures what is currently known about this module at the level of connections between the six cortical layers (Douglas et al., 1989; Douglas and Martin, 2004). The complete connectome of a cortical column, at the level of individual neurons and synapses, is not yet known.

2) If the same cortical module is used in brain regions associated with very different function (e.g., the columns of V1 "see" visual features, the columns of A1 "hear" sounds, the columns of the prefrontal cortex make plans), we are led to the hypothesis that the cortical column performs a very general but powerful computational function. The neuroscience literature is sparse in offering hypotheses about what this common function may be. In the following, we refer to this unknown computational function of cortical columns as \( \Phi(x) \), where \( x \) is a vector that represents the collection of inputs into a column. We propose a specific function \( \Phi(x) \) in Section[2]

3) The structure of cortical columns is such that it can be viewed as a module with two input channels: a feedforward input channel from lower brain regions (such as the thalamus) or from lower-level
Figure 1: The canonical cortical circuit as represented by Douglas and Martin in (Douglas and Martin, 2004). The diagram shows two instances of the circuit, one in “Area-a” and another in “Area-b”. The layer number (e.g., L4) represents the layer where the soma is located. Red arrows represent excitatory projections between neurons of the same column, while blue arrows represent inhibitory projections (they are mostly between neurons of the same layer). The black arrows represent connections between different columns (or other brain regions). Feedforward inputs enter primarily into L4. L4 neurons project to L2/3 neurons. The feedforward outputs originate from L2/3 (pyramidal) neurons. Information from L2/3 neurons is also sent to the deep layers (L5 and L6), where the feedback outputs originate from. L6 neurons also project their (intracolumn) feedback back to the input L4 neurons. External feedback connections from other cortical columns project mostly to L3 neurons.

cortical regions (e.g., V1 columns projecting to V2 columns), and a feedback input channel from higher-level cortical regions (e.g., from V2 columns to V1 columns). Symmetrically, a cortical column has two output channels: the feedback outputs towards lower-level cortical regions and other parts of the brain, and the feedforward outputs towards higher cortical regions. These feedforward/feedback channels are used to create hierarchies of cortical columns in which most connections are reciprocal. Based on this distinction, we revise our notation as \( \Phi(x_f, x_b) \), where \( x_f \) is the feedforward input vector and \( x_b \) is the feedback input vector.

4) The internal connectivity of neurons at a cortical column is relatively dense (compared to the connection density between different columns) and forms multiple feedback loops. In particular, there are recurrent circuits of excitatory and inhibitory neurons at layer-4 (where \( x_f \) enters the column), at layers 2/3 (where \( x_b \) enters the column, and the feedforward output \( y_f \) exits the column) and at layers 5/6 (where the feedback output \( y_b \) exits the column). There are also internal feedback circuits from the output neurons at layers 5/6 to the input neurons at layer-4. Such recurrent circuits and feedback paths from outputs to inputs are common in artificial networks implementing sequential/stateful computations, such as associative memory networks (Lansner, 2009). In other words, the highly recurrent structure of cortical columns implies that their function is probably more complex than stateless computations (such as filtering, feature detection or any other memoryless mathematical transformation of their inputs). In fact, it has been shown that recurrent neural networks with rational weights are Turing-complete (Siegelmann, 2012).

5) It has been previously hypothesized, based on the structure of the cortical circuit, that the function of cortical columns is to perform predictive coding (Bastos et al., 2012). In that framework, feedback projections between columns transfer predictions while feedforward projections between prediction errors (Rao and Ballard, 1999). A column acts as a generative model that can predict its feedforward inputs based on its own priors (stored locally) and also based on predictions that are fed back
from higher-level columns. Note that the predictive coding hypothesis does not propose a specific algorithm for generating these predictions - it is only a framework that specifies the type of information (predictions and prediction errors) that flow in the feedback and feedforward paths, respectively. Our STAM model can be thought of as a specific implementation of the predictive coding hypothesis, as described in Section 2.

6) Cortical columns have the capability to incrementally learn from their inputs, storing internal representations that can generalize from few exemplars to useful invariants, at least after some initial "development stage". For instance, each column of the Inferior Temporal (IT) visual region responds to different orientations or partial views of specific animate or inanimate objects (e.g., faces) (Tanaka 1996). Each column is highly selective (e.g., it only responding to faces) but it is also has strong generalization abilities (e.g., responds to same face independent of rotation, light, occlusions). In other words, it appears that a cortical column stores related "prototypes", and exemplars that are similar to that prototype are recognized by that column (Kiani et al. 2007; Kriegeskorte et al., 2008). From the computational perspective, this is essentially an online clustering operation: an input vector is mapped to its nearest cluster centroid (according to some distance metric). Additionally, the centroid of the chosen cluster is adjusted incrementally with every new exemplar so that it comes a bit closer to that input vector - this is how an online clustering module gradually learns the structure of the input data.

7) An online clustering algorithm that is similar to k-means (and asymptotically equivalent to k-means) can be implemented with a rather simple recurrent neural network of excitatory and inhibitory spiking neurons, as shown recently (Pehlevan et al., 2018). That circuit models the olfactory system in *Drosophila* but similar recurrent E/I circuits are also present in layer-4 of cortical columns. We hypothesize that the main function of the E/I circuits at layer-4 is also to perform online clustering of that column’s feedforward inputs.

2 STAM architecture

Putting the previous seven points together, we now describe the computational function $\Phi(x_f, x_b)$ that we associate with cortical columns, and describe the proposed STAM module in more detail.

A STAM module receives two input channels (feedforward $x_f$ and feedback $x_b$) and it produces the corresponding two output channels. The first function of a STAM is to perform online clustering of the feedforward input vector $x_f$ that it receives. We hypothesize that this is also the main function of the E/I circuits at layer-4 of a cortical column, similar to the neural circuit of (Pehlevan et al., 2018). The number of clusters in STAMs is dynamically adjusted driven by “novelty detection” (if the new input is far from any existing centroid, add a new cluster) and “overlap detection” (if two centroids are quite close, merge the two clusters) - we are still investigating how these two mechanisms are implemented in the brain.

The centroid $c(x_f)$ that is closest to the given exemplar $x_f$ is then compared to the predicted centroid that arrives from a higher-level STAM through feedback connections (see Fig 2). In cortical columns, this comparison is probably performed at layers 2/3 because that is where neurons receive projections from both layer-4 and projections from higher-level columns (Fig 1). In STAMs, this comparison results in the difference $c(x_f) - x_b$ between the local centroid and what the next-level STAM predicts for the corresponding receptive field. It is this difference (prediction error) that constitutes the feedforward output of the STAM. In cortical columns, we hypothesize that this corresponds to the output projections from layers 2/3. Returning to STAMs, this prediction error is then transformed to the feedback that will be sent back to each of the lower-level STAMs, so that each STAM will only receive the feedback that corresponds to its own receptive field. In cortical columns, we hypothesize that this is the function of neurons at layers 5/6 (Fig 1).

In summary, a STAM module integrates three computational functions: online clustering, associative memory formation (i.e., learning and updating the location of the centroids), and hierarchical predictive coding. The online clustering component groups together similar inputs, allowing the STAM to generalize. The patterns that a STAM learns are the centroids of each cluster – all previously inputs/exemplars are discarded. That centroid $c(x)$ becomes the "recalled memory" when that STAM is presented with vector $x$. Even if the vector $x$ is noisy or partially observed, the centroid $c(x)$ should remain the same as long as $x$ falls in the basin of attraction of $c(x)$. Finally, the proposed STAM hierarchies, including the reciprocal projections between successive levels, implement hierarchical
predictive coding: lower-level STAMs reduce the dimensionality of the input data and at the same time they are regulated by higher-level STAMs that “see the bigger picture” (i.e., they have a larger receptive field but potentially in a lower resolution) aggregating information from lower-level STAMs.

3 Connection with Continual Learning

Let us now examine how the proposed architecture addresses the desiderata that is often associated with Continual Learning (CL):

1. **Online learning:** STAMs constantly update their centroids with every example. There is no separate training stage, and there is no specific task for which the network optimizes the features it learns. Any tasks that require classification will of course require one or few labeled examples so that the corresponding clusters that were formed previously are now associated with the name of a class.

2. **Transfer learning:** The hierarchical nature of the proposed architecture means that features learned (in an unsupervised manner) at lower-level STAMs can be reused in different tasks that higher-level STAMs perform. Through hierarchical predictive coding, this process is also taking place in the top-down direction: for instance, if the visual data shift at some point from bright to dark images, but the objects are still the same (e.g., animals), the centroids of the higher-level STAMs will remain the same, modulating the lower-level STAMs to darken their centroids instead of learning new prototypes.

3. **Resistance to catastrophic forgetting:** If the system does not operate at full capacity (see next point), the introduction of a new prototype will lead to the creation of new clusters at some STAMs in the hierarchy (e.g., layer-1 STAMs will learn new elementary visual features if we start feeding them natural images instead of MNIST examples – while a STAM at a higher-level would create a new cluster when it first starts seeing examples of scooters but without affecting the cluster associated with bicycles).

4. **Bounded system size:** The learning capacity of a STAM architecture depends on two factors: the number of STAMs and the maximum number of centroids that each STAM can store. These two capacity constraints require the system to forget past prototypes that have not been recently updated with new exemplars because the corresponding cluster centroids will gradually shift towards
more recently exemplars of different prototypes. This is a graceful forgetting process however (e.g.,
gradaulr forgetting the facial characteristics of our children when they were ten years younger).

5. No direct access to previous experience: A STAM only needs to store the centroids of the clusters
it has learned so far. Those centroids correspond to prototypes, allowing the STAM to generalize. All
previously seen exemplars are discarded.

4 Related work and discussion

Our main premise is that the cortical column represents the main anatomical and functional module
in the cortex. This premise is inspired by the groundbreaking work of V. Mountcastle (Mountcastle,
1978, 1997), by follow up work by Martin, Douglas, and colleagues (Douglas et al., 1989; Douglas
and Martin, 2004), and by more recent findings such as (Kaschube et al., 2010; Kaas, 2012; Reid,
2012; Miller, 2016). It should be noted that this hypothesis is not adopted by everyone in neuroscience
- there are many “contrarian voices” that question whether the structure of cortical columns is the
same throughout the cortex (Molnar, 2013) or whether there is actually a common function behind
this structure (Horton and Adams, 2005). We believe that this debate reflects the importance of this
question in neuroscience. We hope to contribute to this debate by exploring the continual learning
capabilities of hierarchical networks of cortical columns computationally, modeling cortical columns
as STAMs.

In the context of modeling cortical columns with STAMs, the most relevant prior work has appeared
in the theoretical neuroscience literature, in the context of hierarchical Bayesian inference (Lee and
Mumford, 2003) and predictive coding (Rao and Ballard, 1999; Bastos et al., 2012). D. Mumford had
proposed a similar model of how the cortex works based on Grenader’s “pattern theory” (without
using the term “predictive coding” though) (Mumford, 1992) – that model associates cortical feedback
paths with “analysis by synthesis”, i.e., higher level cortical regions generate hypotheses for the
inputs received by lower level regions. Similar ideas have been proposed by S. Ullman (ascending
and descending cortical streams performing “pattern search”) (Ullman, 1995), and by S. Grossberg
in a model of “laminar cortical circuits”, which consider the connectivity between layers in cortical
columns, and bidirectional “adaptive resonance” networks that model the effect of top-down attention
mechanisms (Grossberg, 2007). More recently, K. Miller has proposed that two operations performed
by cortical columns are a “feedforward computation of selectivity” (similar to clustering operations in
STAMs) and a recurrent computation of adaptive gain control between external stimuli and competing
internally generated signals (similar to the STAM operation of comparing the result of local clustering
with predictions from higher-levels) (Miller, 2016). The idea that cortical columns constitute the
building block of associative memory networks, which is also central in our STAMs architecture, was
first presented by Lansner and colleagues (Fransen and Lansner, 1998; Lansner, 2009).

In the context of machine learning and artificial neural networks, the STAM architecture has simi-
larities with several unsupervised methods. First, there is a large body of work in clustering-based
methods for unsupervised learning – see (Caron et al., 2018) for a recent review. For instance, the
work of Coates and Ng has shown that k-means clustering is not only simpler and faster than methods
based on sparse autoencoders or Gaussian mixtures – it also performs better in feature learning as
long as the model has enough hidden nodes (centroids in the clustering case) and the receptive field
(i.e., input dimensionality) is sufficiently small (Coates et al., 2011). For tasks in which the input
dimensionality is large, clustering can be used as the basic building block of deep hierarchies (Coates
and Ng, 2012) – similar to the feedforward aspect of the STAM architecture.

The previous clustering-based methods, however, do not include the feedback component of the
STAM architecture, which is inspired by the recurrent connectivity in the brain. Machine learning
methods such as Helmholtz machines (Dayan et al., 1995) and Deep Predictive Coding (Lotter et al.,
2016) are similar to the STAM architecture in terms of how they use feedback connections - but they
are not based on clustering and they have not been developed in the context of continual learning
tasks, meaning that they assume a mostly stationary environment.

Another approach to model the function of cortical columns, and to construct hierarchies based
on that model, has been pursued by J. Hawkins and colleagues at Numenta (George and Hawkins,
2009). Even though our high-level position is the same (namely, that the basic building block of
artificial neural networks should be a functional model of the cortical column, rather than individual
neurons), the Numenta architecture (“Hierarchical Temporal Memory”) is significantly different
than the STAMs architecture. One major difference is that the former is based on a hierarchy of coincidence detectors while the latter combines online clustering and predictive coding.

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References

Andre M Bastos, W Martin Usrey, Rick A Adams, George R Mangun, Pascal Fries, and Karl J Friston. Canonical microcircuits for predictive coding. Neuron, 76(4):695–711, 2012. ISSN 0896-6273.

Mathilde Caron, Piotr Bojanowski, Armand Joulin, and Matthijs Douze. Deep clustering for unsupervised learning of visual features. arXiv preprint arXiv:1807.05520, 2018.

Adam Coates and Andrew Y Ng. Learning feature representations with k-means, pages 561–580. Springer, 2012.

Adam Coates, Andrew Ng, and Honglak Lee. An analysis of single-layer networks in unsupervised feature learning. In Proceedings of the fourteenth international conference on artificial intelligence and statistics, pages 215–223, 2011.

Peter Dayan, Geoffrey E Hinton, Radford M Neal, and Richard S Zemel. The helmholtz machine. Neural computation, 7(5):889–904, 1995. ISSN 0899-7667.

R. J. Douglas and K. A. C. Martin. Neuronal circuits of the neocortex. Annual Review of Neuroscience, 27:419–452, 2004.

R.J. Douglas, K.A.C. Martin, and D. Whitteridge. A canonical microcircuit for neocortex. Neural Computation, 1:480–488, 1989.

Erik Fransén and Anders Lansner. A model of cortical associative memory based on a horizontal network of connected columns. Network: Computation in Neural Systems, 9(2):235–264, 1998. ISSN 0954-898X.

Dileep George and Jeff Hawkins. Towards a mathematical theory of cortical micro-circuits. PLoS computational biology, 5(10):e1000532, 2009. ISSN 1553-7358.

Stephen Grossberg. Towards a unified theory of neocortex: laminar cortical circuits for vision and cognition. Progress in brain research, 165:79–104, 2007. ISSN 0079-6123.

Jonathan C Horton and Daniel L Adams. The cortical column: a structure without a function. Philosophical Transactions of the Royal Society of London B: Biological Sciences, 360(1456):837–862, 2005. ISSN 0962-8436.

Jon H. Kaas. Evolution of columns, modules, and domains in the neocortex of primates. Proceedings of the National Academy of Sciences, 109(Supplement 1):10655–10660, 2012. doi: 10.1073/pnas.1201892109. URL [http://www.pnas.org/content/109/suppl.1/10655.abstract](http://www.pnas.org/content/109/suppl.1/10655.abstract)

Matthias Kaschube, Michael Schnabel, Siegrid Löwel, David M. Coppola, Leonard E. White, and Fred Wolf. Universality in the evolution of orientation columns in the visual cortex. Science, 330 (6007):1113–1116, 2010. doi: 10.1126/science.1194869. URL [http://www.sciencemag.org/content/330/6007/1113.abstract](http://www.sciencemag.org/content/330/6007/1113.abstract)

Roozbeh Kiani, Hossein Esteky, Koorosh Mirpour, and Keiji Tanaka. Object category structure in response patterns of neuronal population in monkey inferior temporal cortex. Journal of neurophysiology, 97(6):4296–4309, 2007. ISSN 0022-3077.
Nikolaus Kriegeskorte, Marieke Mur, Douglas A Ruff, Roozbeh Kiani, Jerzy Bodurka, Hossein Esteky, Keiji Tanaka, and Peter A Bandettini. Matching categorical object representations in inferior temporal cortex of man and monkey. *Neuron*, 60(6):1126–1141, 2008. ISSN 0896-6273.

Anders Lansner. Associative memory models: from the cell-assembly theory to biophysically detailed cortex simulations. *Trends in neurosciences*, 32(3):178–186, 2009. ISSN 0166-2236.

Tai Sing Lee and David Mumford. Hierarchical bayesian inference in the visual cortex. *JOSA A*, 20(7):1434–1448, 2003. ISSN 1520-8532.

William Lotter, Gabriel Kreiman, and David Cox. Deep predictive coding networks for video prediction and unsupervised learning. *arXiv preprint arXiv:1605.08104*, 2016.

Kenneth D. Miller. Canonical computations of cerebral cortex. *Current Opinion in Neurobiology*, 37:75–84, 2016. ISSN 0959-4388. doi: http://dx.doi.org/10.1016/j.conb.2016.01.008. URL http://www.sciencedirect.com/science/article/pii/S095943881600009X

Z Molnár. *Cortical columns*, pages 109–129. Elsevier, 2013.

V.B. Mountcastle. The columnar organization of the neocortex. *Brain*, 120(4):701–722, 1997.

Vernon Mountcastle. An organizing principle for cerebral function: the unit module and the distributed system. *The mindful brain*, 1978.

David Mumford. On the computational architecture of the neocortex. *Biological cybernetics*, 66(3):241–251, 1992. ISSN 0340-1200.

Cengiz Pehlevan, Alexander Genkin, and Dmitri B. Chklovskii. A clustering neural network model of insect olfaction. *bioRxiv*, 2018. URL http://biorxiv.org/content/early/2018/01/27/226746.abstract

Rajesh PN Rao and Dana H Ballard. Predictive coding in the visual cortex: a functional interpretation of some extra-classical receptive-field effects. *Nature neuroscience*, 2(1):79, 1999. ISSN 1546-1726.

R. Clay Reid. From functional architecture to functional connectomics. *Neuron*, 75(2):209–217, 2012. ISSN 0896-6273. URL http://linkinghub.elsevier.com/retrieve/pii/S0896627312005934

Hava T Siegelmann. *Neural networks and analog computation: beyond the Turing limit*. Springer Science and Business Media, 2012. ISBN 146120707X.

Keiji Tanaka. Inferotemporal cortex and object vision. *Annual review of neuroscience*, 19(1):109–139, 1996. ISSN 0147-006X.

Shimon Ullman. Sequence seeking and counter streams: a computational model for bidirectional information flow in the visual cortex. *Cerebral cortex*, 5(1):1–11, 1995. ISSN 1460-2199.