The Ghost in the Machine: Emergence of Computation through dynamics in CW-complexes

Renan Monteiro Barbosa[1]
[1]University of West Florida
rmb54f@students.uwf.edu

Abstract

The abstract paragraph should be indented ½ inch (3 picas) on both the left- and right-hand margins. Use 10 point type, with a vertical spacing (leading) of 11 points. The word **Abstract** must be centered, bold, and in point size 12. Two line spaces precede the abstract. The abstract must be limited to one paragraph.

Tempus quam pellentesque nec nam aliquam sem et tortor. Quam elementum pulvinar etiam non quam. Pretium aenean pharetra magna ac placerat vestibulum lectus mauris ultrices. Nunc aliquet bibendum enim facilisis. Lorem mollis aliquam ut porttitor leo a diam sollicitudin. Adipiscing elit pellentesque habitant morbi. Feugiat sed lectus vestibulum mattis ullamcorper velit sed ullamcorper morbi.

1 Introduction

Idea of papers to cite, that demonstrate progress in how we record and map neurons.

Advances in two-photon calcium imaging in larval zebrafish (Ahrens et al. 2012, Andalman et al. 2019, Naumann et al. 2016, Portugues et al. 2014), Drosophila (Kim et al. 2017 [7]), rodents (Allen et al. 2019, Chaudhuri et al. 2019, Stringer et al. 2019), and Caenorhabditis elegans (Kato et al. 2015, Nichols et al. 2017), as well as high channel count electrophysiology via NeuroPixels (e.g., Jun et al. 2017, Stringer et al. 2019, Trautmann et al. 2019), have enabled measuring and manipulating neural activity at unprecedented scale. We believe these technologies will present new opportunities to test the CTD framework.

(Must do a paper dump showcasing some advancements)

In the last few decades we have seen many advancements in neuroscience. It is now possible to record activity from every neuron in a zebrafish larva's brain while it is freely swimming and responding to stimuli Kim et al. 2017 [6]. We have a nearly complete map of one hemisphere of the fly brain, with every neuron and most of its synapses accounted for (Pipkin 2020 [10]). The neurons responsible for a mouse's memory of an event can be recorded, tagged, and replayed by laser stimulation, causing the mouse to behave as if the event had happened again (CarrilloReid et al. 2019 [2]; Ramirez et al. 2013 [12]).

Such advancements brought to light evidence for what was once only a theory, for example, Tolman in 1948 [15] argued that for Humans and other animals to make complex inferences from sparse observations and rapidly integrate new knowledge to control their behavior there should exist a systematic organization of such knowledge on what could be called a cognitive map.

But what was missing from these early studies, was a way to address the neuronal mechanisms that led information to be stored as memory. Further development has shown that place cells are part of a wider network of spatially modulated neurons, including grid, border, and head direction cells, each with distinct roles in the representation of space and spatial memory.

Preprint. Under review.

The combination of all these technological and theoretical developments demonstrated through evidence and theoretical models that there is indeed a mechanistic basis for memory formation, this was shown in the Nobel winning work done by May-Britt Moser, Edvard I. Moser [8]. This work has inspired new theories in theoretical-neuroscience that , likewise to Tolman, proposes the idea that relational memory and spatial reasoning might be related by a common mechanism (Eichenbaum and Cohen, 2014 [3]).

Some evidence, eventhough limited, has shown in recent work with grid cells, [4], by using simultaneous recordings from many hundreds of grid cells and subsequent topological data analysis that the joint activity of grid cells from an individual module (neuronal population) resides on a toroidal manifold as expected in a two-dimensional CAN (Continuous Attractor Network), supporting the argument that there is indeed a mechanism generating invariant representations. The positions are maintained between environments and from wakefulness to sleep, demonstrating to be invariant representations. This research demonstrated, with some limitations, network dynamics on a toroidal manifold and provided a population-level visualization of CAN dynamics in grid cells.

Even though the technological limitations to record population of neurons, these works provide growing evidence to hint that previous theories and intuitons formulated through theoretical neuro science were in the right path.

There is growing evidence to support that manifolds maintain a well-preserved covariance across tasks. These results support the view that complex computation emerges from the flexible activation of different combinations of “Neural modes” (Need to find a better term) which themselves arise from the Network Connectivity (reference to Hopfield is all you need and Transformers) (Cortical population activity within a preserved neural manifold underlies multiple motor behaviors, reference 8 for Emergence of universal computations through neural manifold dynamics)

In this paper we want to show that there exists a morphism between Neuroscience models and existing NN models, so we can approximately represent the Neural Manifolds with the Transformers.

Must note that, likewise Whittington [16] mentions, we are not saying the brain is closely related to transformers, instead we are using a mathematical relationship between the so popular transformers and the attractor neural networks that have been carefully formulated in neuroscience models as being an essential piece in forming invariant representations in a topological structure that facilitates the emergence of Computation Through Neural Population Dynamics.

(Cite the DeepSpeed-Megatron, Zero, SLURM, Scaling Laws and Nvidia research on training large models)

Additionally, we are exploiting this relationship by carefully crafting a modified transformers model so we can benefit from several technological advancements in how models are trained at scale ([11], [14], [9], [5]), these advancements have been matured and extensively tested at production given the popularity and widespread use of transformers. Further studies are required to develop and validate a better architecture that better represents Neural Population Dynamics.

2 Theory of Computing

Computing is not a new concept, there is historical evidence that the Greeks were already capable of performing computation to predict the astronomical movements giving a programmable input (Antikythera mechanism).

Start by defining Computing as Modelling, essential step to prove that the architecture is capable of Computing.

It is crucial to distinguish between the notions of computational model and simulation on the one hand and computing-as-modeling on the other

The computational model and simulation refer to the use of computers to model and simulate the behavior and processes of physical, biological, social, and other systems. They do not assume that modeling is an essential feature of computing; However, the claim is that computers can be, and are, used for modeling and simulating other phenomena.

In contrast, the notion of computing-as-modeling is indifferent as to the actual use of computers for the purposes of modeling or simulating other phenomena; rather, the claim is that modeling is an essential element of the characterization of computing.

The conclusion is that modeling is an essential element of physical computation, at least in current computational approaches in cognitive neuroscience.

At the book Shagrir - The Nature of Physical Computation [13]

A physical system P is a computing system just in case:

1. **Input-Output Mirroring**. The input-output function, g, of a given process in **P** preserves a certain relation, $\underline{R}$, in a target domain **T**: there is a mapping from **P** to **T** that maps g to $\underline{R}$, x to $\underline{x}$, y to $\underline{y}$, . . . , such that $g(x) = y$ iff $\langle \underline{x}, \underline{y} \rangle \ \epsilon \ \underline{R}$. This means that g and $\underline{R}$ share some formal relation **f**.
2. **Implementing**. This process of **P**, whose input-output function is g, implements some formalism **S** whose input-output (abstract) function is **f**.
3. **Representing**. The input variables x of **P** represent the entities $\underline{x}$ of **T**, and the output variables y of **P** represent the entities $\underline{y}$ of **T**.

The underlined italicized symbols (such as x and y) to signify properties of the target domain.

3 Why CW-complexes?

The far left panel is a simbplyfied cartoon depiction of a grid cell's firing pattern in a two-dimensional environment. Making a cut through the center of four fields provides a diamond shape (second panel), which comprises the base unit. The dashed whiteline illustrates running the "longdistance" in the diamond between the furthest two fields. By connecting the bottom edge to the top edge, two "half-fields" are generated (third panel) which becomes a single field when connecting the opened ends (far right panel). Note that there are three lines on the completed torus. The dashed black lines represent the original cuts along made in the first panel. The white line resembles the trajectory necessary to connect the two furthest points in the diamond. Note that it makes one revolution per rotation. That is, the trajectory travels through the interior of the torus as well as along the exterior.

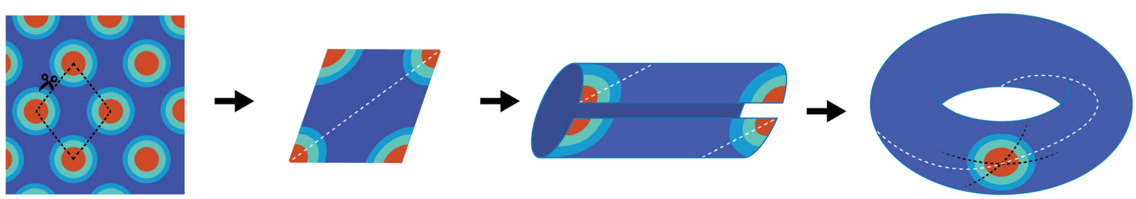


Figure 1: Schematic depiction of why grid cells map to a torus.

4 Conclusions

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed eiusmod tempor incidunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquid ex ea commodi consequat. Quis aute iure reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint obcaecat cupiditat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

5 experimenting with Editing

Advancements in the last few decades have brought us to a point at which what was thought to only be theorized by Tolman in 1948 [15] as he argued that for Humans and other animals to make complex inferences from sparse observations and rapidly integrate new knowledge to control their behavior there should exist a systematic organization of such knowledge on what could be called a cognitive map. (note, try to make it sound like the theory of computing)

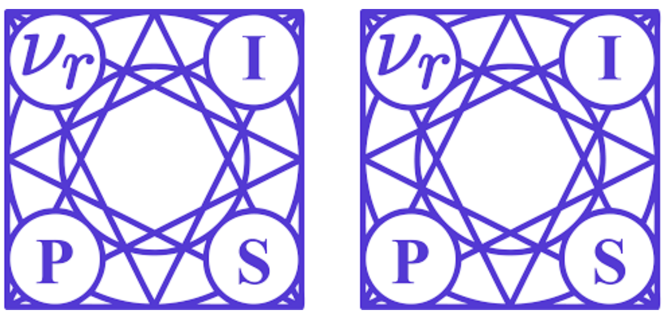
But what was missing from these early studies, was a way to address the neuronal mechanisms that led information to be stored as memory. Further development has shown that place cells are part of a wider network of spatially modulated neurons, including grid, border, and head direction cells, each with distinct roles in the representation of space and spatial memory.

Bringing to surface a mechanistic basis for memory formation (Nobel prize winning Place Cells, Grid Cells, and Memory) which later has been suggested that relational memory and spatial reasoning might be related by a common mechanism (Eichenbaum and Cohen, 2014 [3]).

[1]

6 Multiple images

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed eiusmod tempor incidunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquid ex ea commodi consequat. Quis aute iure reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint obcaecat cupiditat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum. Fig. 1 shows the NeurIPS logo as well as Fig. 2.



(a) (b)

Figure 2: Examples for sub-images

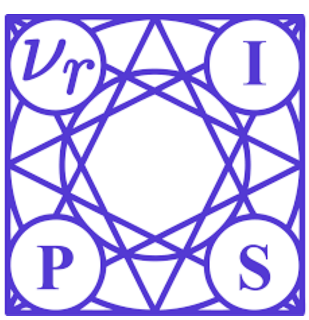


Figure 3: Logo image

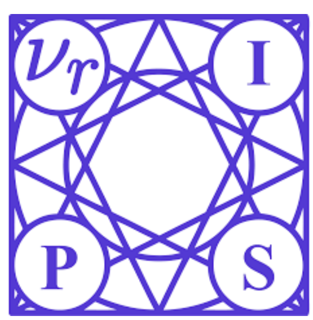


Figure 4: Logo image

7 Some other Section

Citations examples used to be here

8 Tables

Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed eiusmod tempor incidunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquid ex ea commodi consequat. Quis aute iure reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint obcaecat cupiditat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum. The Table 1 shows an example of a table.

Table 1: Sample table title

Part		
Name	Description	Size (μm)
Dendrite	Input terminal	$\sim$100
Axon	Output terminal	$\sim$10
Soma	Cell body	up to 10^6

Acknowledgments

Use unnumbered third level headings for the acknowledgments. All acknowledgments go at the end of the paper. Do not include acknowledgments in the anonymized submission, only in the final paper. This example was prepared by Dennis Núñez Fernández.

References

[1] Manuel Beiran, Nicolas Meirhaeghe, Hansem Sohn, Mehrdad Jazayeri, and Srdjan Ostojic. Parametric control of flexible timing through low-dimensional neural manifolds. *Neuron*, 111(5):739–753, 2023.

[2] Luis Carrillo-Reid, Shuting Han, Weijian Yang, Alejandro Akrouh, and Rafael Yuste. Controlling visually guided behavior by holographic recalling of cortical ensembles. *Cell*, 178(2):447–457, 2019.

[3] Howard Eichenbaum and Neal J Cohen. Can we reconcile the declarative memory and spatial navigation views on hippocampal function? *Neuron*, 83(4):764–770, 2014.

[4] Richard J Gardner, Erik Hermansen, Marius Pachitariu, Yoram Burak, Nils A Baas, Benjamin A Dunn, May-Britt Moser, and Edvard I Moser. Toroidal topology of population activity in grid cells. *Nature*, 602(7895):123–128, 2022.

[5] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. Scaling laws for neural language models. *CoRR*, abs/2001.08361, 2020.

[6] Dal Hyung Kim, Jungsoo Kim, João C Marques, Abhinav Grama, David GC Hildebrand, Wenchao Gu, Jennifer M Li, and Drew N Robson. Pan-neuronal calcium imaging with cellular resolution in freely swimming zebrafish. *Nature methods*, 14(11):1107–1114, 2017.

[7] Sung Soo Kim, Hervé Rouault, Shaul Druckmann, and Vivek Jayaraman. Ring attractor dynamics in the drosophila central brain. *Science*, 356(6340):849–853, 2017.

[8] May-Britt Moser, David C Rowland, and Edvard I Moser. Place cells, grid cells, and memory. *Cold Spring Harbor perspectives in biology*, 7(2):a021808, 2015.

[9] Deepak Narayanan, Mohammad Shoeybi, Jared Casper, Patrick LeGresley, Mostofa Patwary, Vijay Korthikanti, Dmitri Vainbrand, Prethvi Kashinkunti, Julie Bernauer, Bryan Catanzaro, Amar Phanishayee, and Matei Zaharia. Efficient large-scale language model training on GPU clusters. *CoRR*, abs/2104.04473, 2021.

[10] Jason Pipkin. Mapping the mind of a fly. *Elife*, 9:e62451, 2020.

[11] Samyam Rajbhandari, Jeff Rasley, Olatunji Ruwase, and Yuxiong He. Zero: Memory optimization towards training A trillion parameter models. *CoRR*, abs/1910.02054, 2019.

[12] Steve Ramirez, Xu Liu, Pei-Ann Lin, Junghyup Suh, Michele Pignatelli, Roger L Redondo, Tomás J Ryan, and Susumu Tonegawa. Creating a false memory in the hippocampus. *Science*, 341(6144):387–391, 2013.

[13] Oron Shagrir. *The nature of physical computation*. Oxford University Press, 2022.

[14] Shaden Smith, Mostofa Patwary, Brandon Norick, Patrick LeGresley, Samyam Rajbhandari, Jared Casper, Zhun Liu, Shrimai Prabhumoye, George Zerveas, Vijay Korthikanti, Elton Zheng, Rewon Child, Reza Yazdani Aminabadi, Julie Bernauer, Xia Song, Mohammad Shoeybi, Yuxiong He, Michael Houston, Saurabh Tiwary, and Bryan Catanzaro. Using deepspeed and megatron to train megatron-turing NLG 530b, A large-scale generative language model. *CoRR*, abs/2201.11990, 2022.

[15] Edward C Tolman. Cognitive maps in rats and men. *Psychological review*, 55(4):189, 1948.

[16] James CR Whittington, Joseph Warren, and Timothy EJ Behrens. Relating transformers to models and neural representations of the hippocampal formation. *arXiv preprint arXiv:2112.04035*, 2021.