## Mail from Stefano

Hi,

Thanks for today's meeting.

Here is the references we discussed:

- General motivation of why open-endedness is important for the future AI: <a href="https://www.oreilly.com/radar/open-endedness-the-last-grand-challenge-youve-never-heard-of/">https://www.oreilly.com/radar/open-endedness-the-last-grand-challenge-youve-never-heard-of/</a>
- Description of long-term dynamics in CA and some measures (like the simple one counting the number of cells of each type), the CA type is not relevant for this project as it is embedding the evolution in the cells (this can be skipped): Long-term evolutionary dynamics in heterogeneous cellular automata. Medernach at al. (2013)
- Other ways to quantify the dynamic computation in CA, here several methods are proposed but the one that is interesting to me is the one based on autoencoders <a href="https://arxiv.org/abs/2104.01008">https://arxiv.org/abs/2104.01008</a>

You will be targeting homogeneous CA (that is those where the rules to update the cells' state are the same for all the cells).

My suggestion on the two types to look at are:

- Neural CA (CA where the rules are replaced by neural networks)
- Continuous CA (where the states are not discrete but continuous)

Let me know if you think of any other CA types we may want to use.

## Neural CA

There are several implementations and usages, but it is perhaps a good idea to start with a single neuron (or few neurons) per cell. To increase the complexity of the rules it could be possible to increase the size of the "neighborhood". Here some implementations (you do not need to read those papers, they may be useful references, perhaps just have a look at the main idea):

- https://ieeexplore.ieee.org/document/8004527
- <a href="https://distill.pub/2020/growing-ca/">https://distill.pub/2020/growing-ca/</a> (there are a few related papers in the same journal)
- https://arxiv.org/abs/2101.07627
- you find many more recent papers on neural CA, such as using attention mechanisms  $\bigcirc$

## Continuos CA

The most popular and used at the moment is Lenia. The main papers are <a href="https://arxiv.org/pdf/1812.05433.pdf">https://arxiv.org/pdf/1812.05433.pdf</a> and <a href="https://arxiv.org/pdf/2005.03742.pdf">https://arxiv.org/pdf/1812.05433.pdf</a> and <a href="https://arxiv.org/pdf/2005.03742.pdf">https://arxiv.org/pdf/1812.05433.pdf</a> and <a href="https://arxiv.org/pdf/2005.03742.pdf">https://arxiv.org/pdf/1812.05433.pdf</a> and <a href="https://arxiv.org/pdf/2005.03742.pdf">https://arxiv.org/pdf/2005.03742.pdf</a>

However, I suggest you get an idea on how it works from here instead <a href="https://developmentalsystems.org/sensorimotor-lenia/">https://developmentalsystems.org/sensorimotor-lenia/</a> (at least there is a nice explanation on how Lenia works and a simple video named "animation of Lenia step")

A couple of (unrelated, no need to read unless you find it fun) recent references on developments of Lenia are <a href="https://sites.google.com/view/flowlenia/">https://sites.google.com/view/flowlenia/</a> and <a href="https://google-research.github.io/self-organising-systems/">https://google-research.github.io/self-organising-systems/</a> <a href="particle-lenia/">particle-lenia/</a>

Best,

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Stefano