Universality and Individuality in Recurrent Neural Networks

Niru Maheswaranathan, Alex Williams, Matthew D Golub, Surya Ganguli, David Sussillo

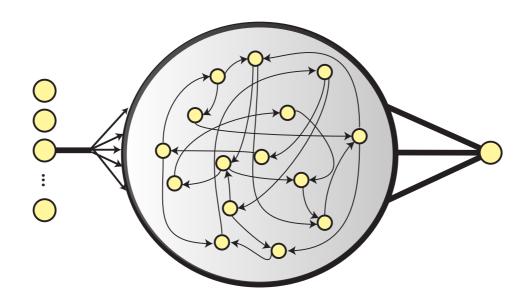
Google Brain & Stanford University

NeurlPS 2019

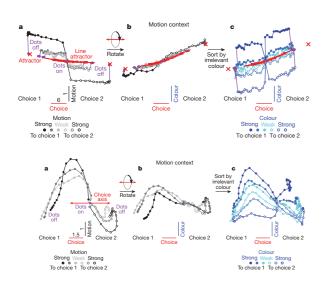
Artificial neural networks in neuroscience

Advantages:

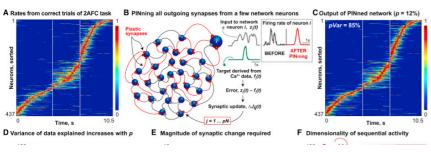
- Can train ANNs to accomplish tasks analogous to those studied in animals.
- Can inspect/probe/dissect artificial networks very easily.
- Can easily initiate a huge number of in silico studies



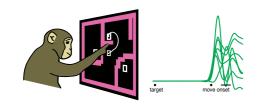
Artificial & biological neural networks



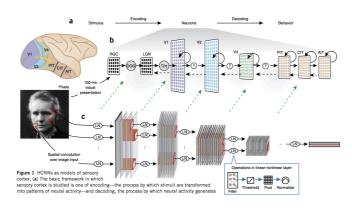
Mante & Sussillo et al. Nature 2013



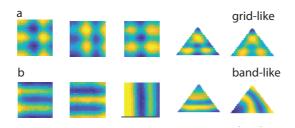
Rajan, Harvey, Tank, Neuron, 2016



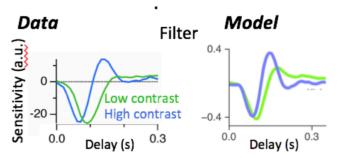
Sussillo et al., Nature Neuroscience, 2015



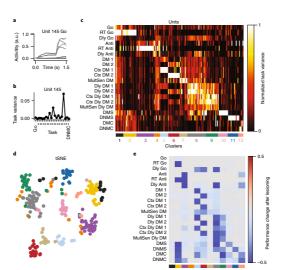
Yamins & DiCarlo, 2014

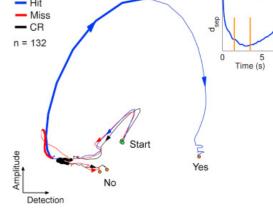


Cueva & Wei, ICLR, 2018



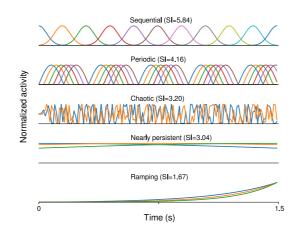
Maheswaranathan et al, 2018



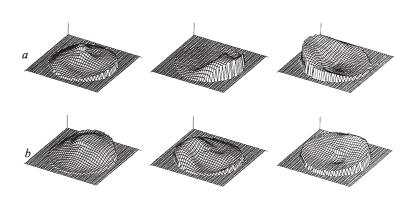


Carnevale et al, NEURON, 2015

Yang, et al., Nature Neuroscience 2019



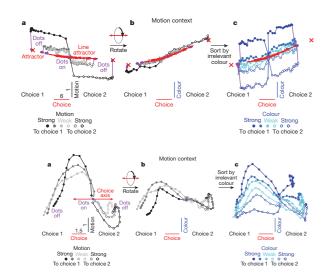
Orhan & Ma, Nature Neuroscience, 2019



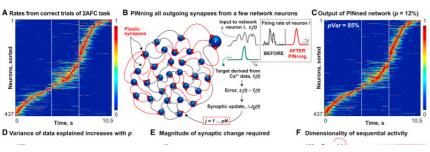
Zipser & Andersen, Science, 1988

Artificial & biological neural networks

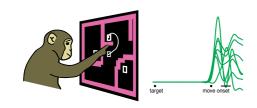
Networks have surprisingly similar representations...



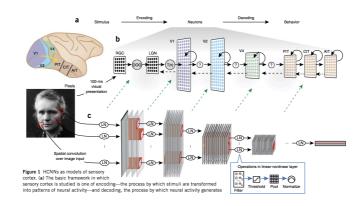
Mante & Sussillo et al. Nature 2013



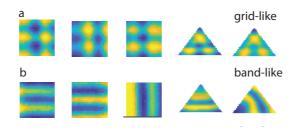
Rajan, Harvey, Tank, Neuron, 2016



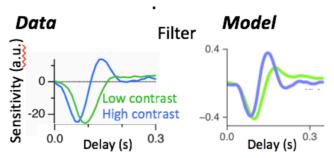
Sussillo et al., Nature Neuroscience, 2015



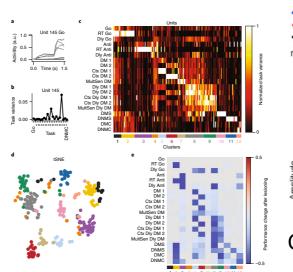
Yamins & DiCarlo, 2014

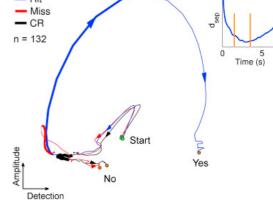


Cueva & Wei, ICLR, 2018



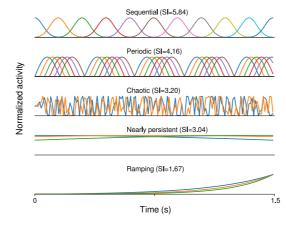
Maheswaranathan et al, 2018



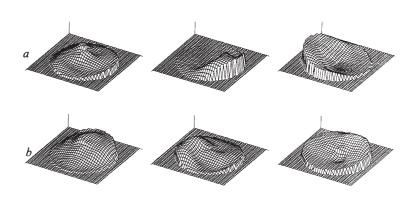


Carnevale et al, NEURON, 2015

Yang, et al., Nature Neuroscience 2019



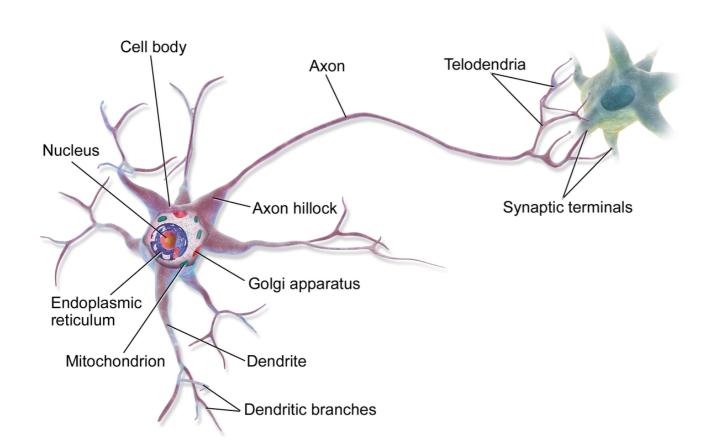
Orhan & Ma, Nature Neuroscience, 2019



Zipser & Andersen, Science, 1988

Artificial & biological neural networks

...but are composed of drastically different elements!



Biological neuron

 $y_i = \tanh(\sum_i W_{ij} \ x_j)$

Central question

When trained to perform the same **task**, why should we expect artificial and biological networks to be **similar**, given the drastic **differences in underlying mechanism**?

This work: an empirical approach

Network mechanisms

RNN architectures (e.g. LSTMs, GRUs, ...)
Nonlinearities (e.g. ReLU, tanh)
...

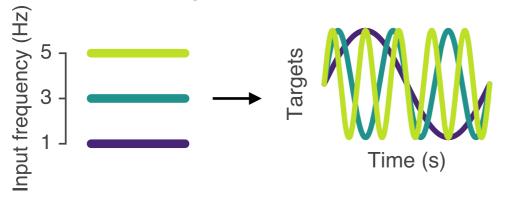
Similarity measures

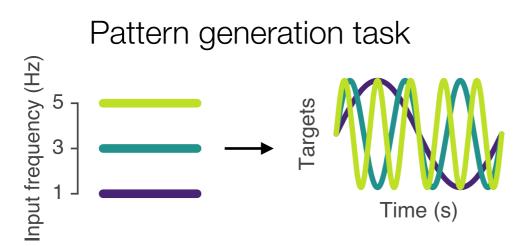
Canonical correlation analysis (CCA) Centered kernel alignment (CKA)

Tasks

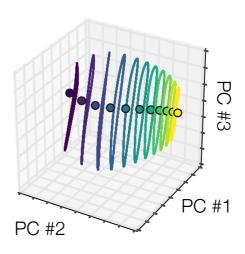
Decision making Pattern generation Working memory

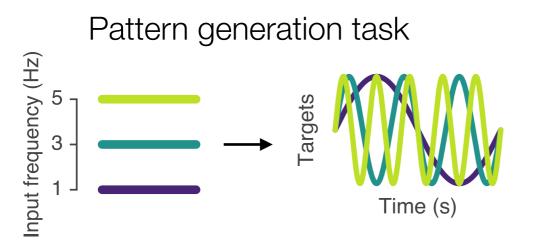
Pattern generation task



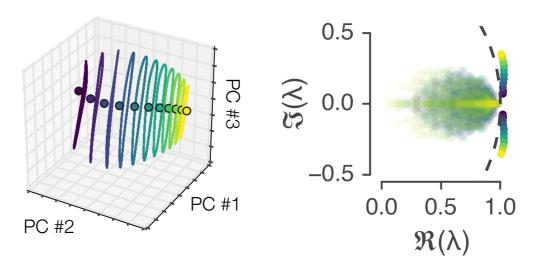


Analyzing trained networks

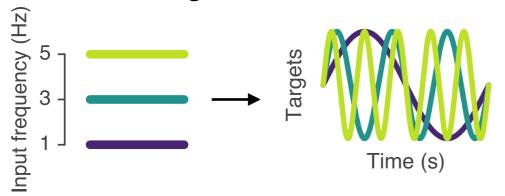




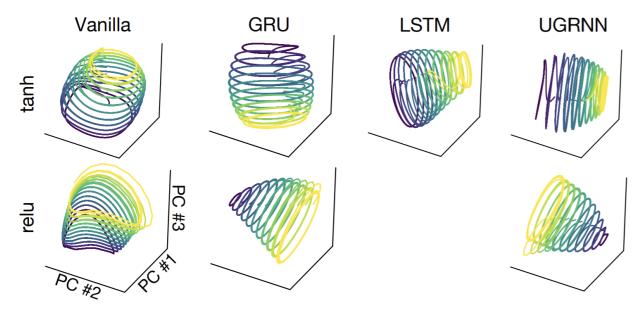
Analyzing trained networks



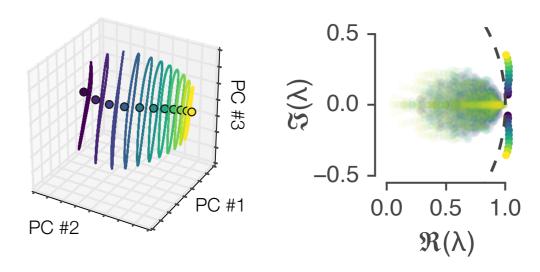
Pattern generation task



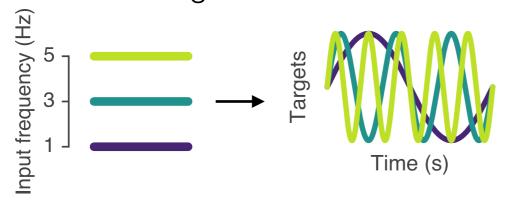
Network representations show individuality



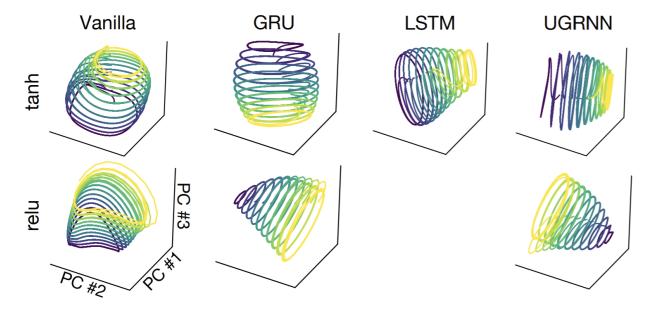
Analyzing trained networks



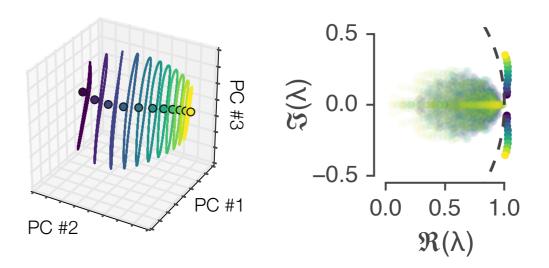
Pattern generation task



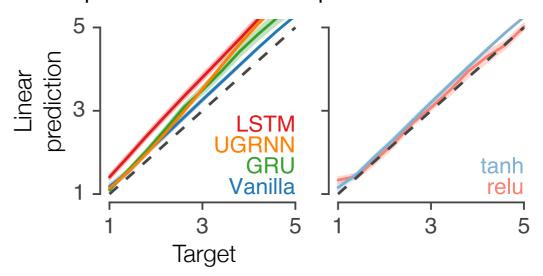
Network representations show individuality



Analyzing trained networks



but aspects of the computation are universal



Learn more at Poster #179

Extracting universal algorithmic principles from large populations of recurrent networks

1907.08549

Niru Maheswaranathan**, Alex H. Williams***, Matthew D. Golub*, Surya Ganguli **, David Sussillo** // Google Brain 🧇 & Stanford University \$

Motivation

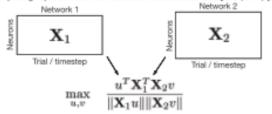
Comparing brains and artificial neural networks (ANNs) [1-4]:

- · Why should we trust comparisons between biological brains and artificial neural networks?
- . Do networks trained on the same task find universal or unique solutions?
- · Are these comparisons sensitive to modeling choices, such as neural network architectures?

Methods

Trained ~1000s of networks with different architectures on a several tasks. Vanita RNN Update Gate RNN Gated Recurrent Unit (GRU) Long-short term memory (LSTM) (Collins et al 2017)

1. Comparing representations: canonical correlation analysis (CCA) [5,6]



2. Comparing algorithms: fixed point analysis [7,8] RNN defines a nonlinear map: $h^{t+1} = F(h^t, x^t)$

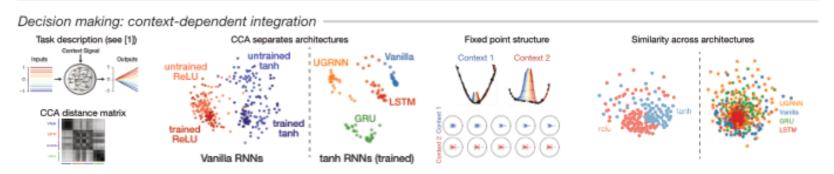
Computing (approximate) fixed points: $\operatorname{argmin} \|F(h, 0) - h\|_2^2$

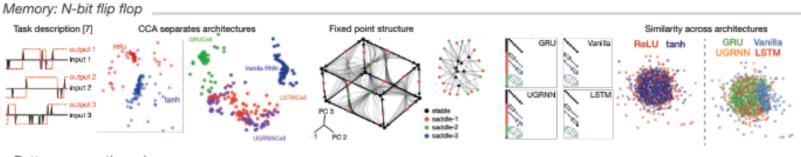
Linearizing around fixed points: $h^{t+1} - h^* \approx J (h^t - h^*)$

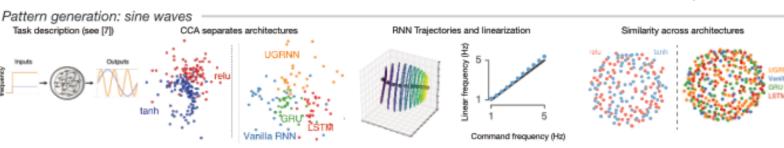
References

- Mante, Sussilio et al. (2013) Nature. 503: 78-84.
- Yamins et al. (2014). Proc Natl Acad Sci USA. 111(23): 8619.
 Kriegeskorte (2015). Annual Rev of Vis Sci. 1:417.
- Barak (2017), Curr Opin Neurbiol, 46:1.
- Raghu et. al. (2017). Neural Information Processing Systems. arxiv.org/abs/1706.05806
- [6] Wang et. al. (2018). axiv.org/abs/1812.02598
 [7] Sussillo & Barak. (2013). Neural computation 25.3: 626-649.
 [8] Golub & Sussillo. JOSS. (2018): 1003.

Results







Conclusions

- . Depending on how you quantify similarity, networks trained on the same task can look identical or different!
- · Geometry of artificial neural representations are architecture dependent, but algorithms are more universal

Contact @nirum@google.com y @niru_m

arxiv:1907.08549 Poster #179