Questioning Questions in Computational Neuroscience

ECE Bio-Group Seminar

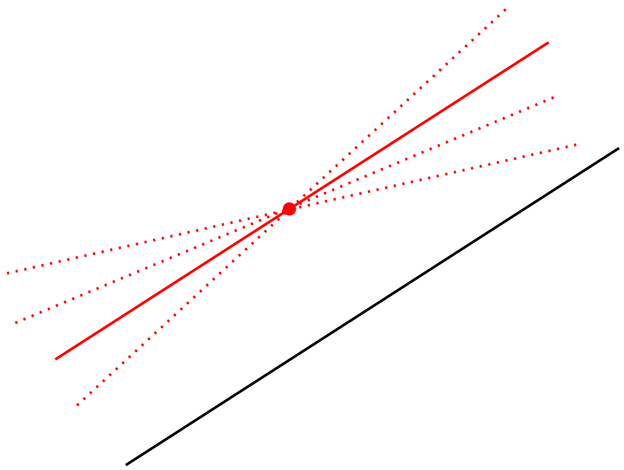
October 28, 2016

Yoonsuck Choe, Ph.D.

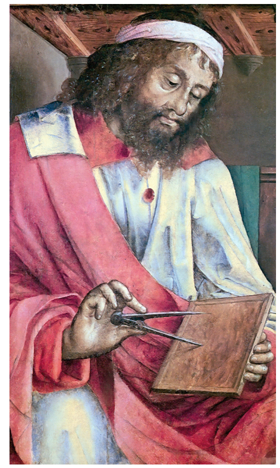
Department of Computer Science & Engineering

Texas A&M University

Asking the Right Question Is Critical



Parallel postulate



Euclid (circa BC 300)

Eugenio Beltrami (1985-1900)

Euclid's 5th postulate (parallel postulate).

- How can we prove the parallel postulates using ... ?

  Unsolvable. Unsolved for thousands of years.

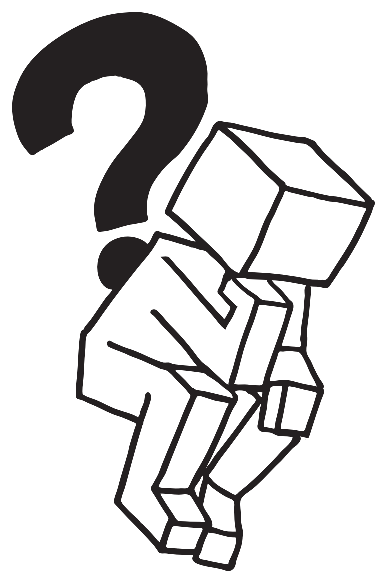
- ~~How~~ can we prove the parallel postulates using ... ?

  Solvable. The answer is "No" (Beltrami)

Image sources: Painting by Justus of Ghent; public domain photo.

Today's Topic

- Re-evaluating current questions in (computational) neuroscience.
- Showing how slight change in perspective can lead to new insights.



Background: Current Questions in Neuroscience

10 Unsolved Questions of Neuroscience

1. How is **information coded** in neural activity?
2. How are **memories stored** and retrieved?
3. What does the **baseline activity** in the brain represent?
4. How do brains **simulate the future**?
5. What are **emotions**?
6. What is **intelligence**?
7. How is **time represented** in the brain?
8. Why do brains **sleep and dream**?
9. How do the specialized systems of the brain **integrate** with one another?
10. What is **consciousness**?

Eagleman (2007)

23 Problems in Systems Neuroscience

1. Shall We Even Understand the **Fly's Brain**?
2. Can We Understand the Action of Brains in **Natural Environments**?
3. **Hemisphere Dominance** of Brain Function–Which Functions Are Lateralized and Why?
4. What Is the Function of the **Thalamus**?
5. What Is a **Neuronal Map**, How Does It Arise, and What Is It Good For?
6. What Is **Fed Back**?
7. How Can the Brain Be **So Fast**?
8. What Is the **Neural Code**?

Sejnowski and van Hemmen, Ed. (2006), styled after Hilbert's program.

23 Problems ... continued

9. Are Single Cortical Neurons **Soloists or** Are They Obedient Members of a Huge **Orchestra**?
10. What Is the Other **85 Percent of V1** Doing?
11. Which **Computation** Runs **in Visual Cortical Columns**?
12. Are Neurons **Adapted for Specific Computations**?
13. How Is **Time Represented** in the Brain?
14. How General Are **Neural Codes** in Sensory Systems?
15. How Does the Hearing System Perform **Auditory Scene Analysis**?
16. How Does Our Visual System Achieve **Shift and Size Invariance**?

23 Problems ... continued

17. What Is **Reflected in Sensory Neocortical Activity**: External Stimuli or What the Cortex Does with Them?
18. Do **Perception and Action** Result from Different Brain Circuits?
19. What Are the **Projective Fields** of Cortical Neurons?
20. How Are the Features of Objects **Integrated into Perceptual Wholes** That Are Selected by **Attention**?
21. Where Are the **Switches** on This Thing?
22. **Synesthesia**: What Does It Tell Us about the Emergence of Qualia, Metaphor, Abstract Thought, and Language?
23. What Are the **Neuronal Correlates of Consciousness**?

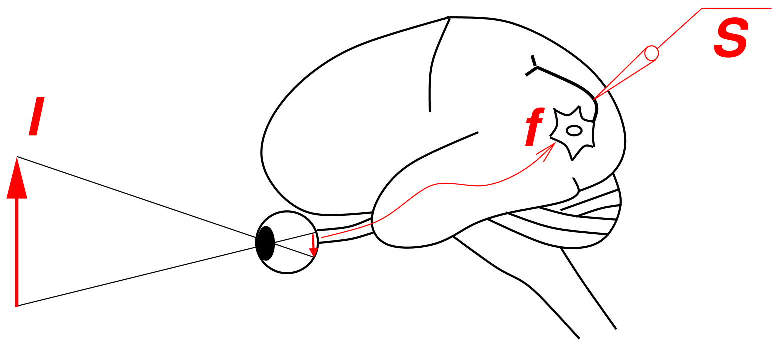
Outline

Questions to Consider

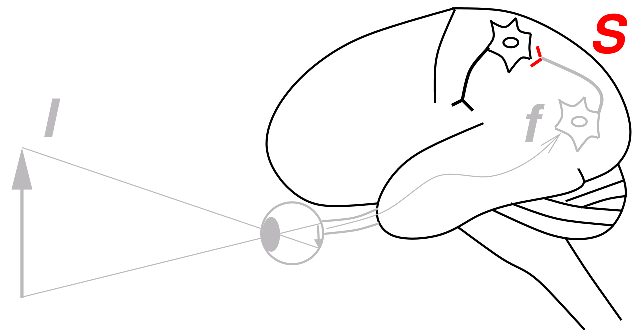
1. How to understand the neural code?
2. How did consciousness evolve?
3. How does the visual system process texture?
4. How to acquire the connectome?

1. How to Understand the Neural Code?

1. How to Understand the Neural Code?



(a) From the OUTSIDE



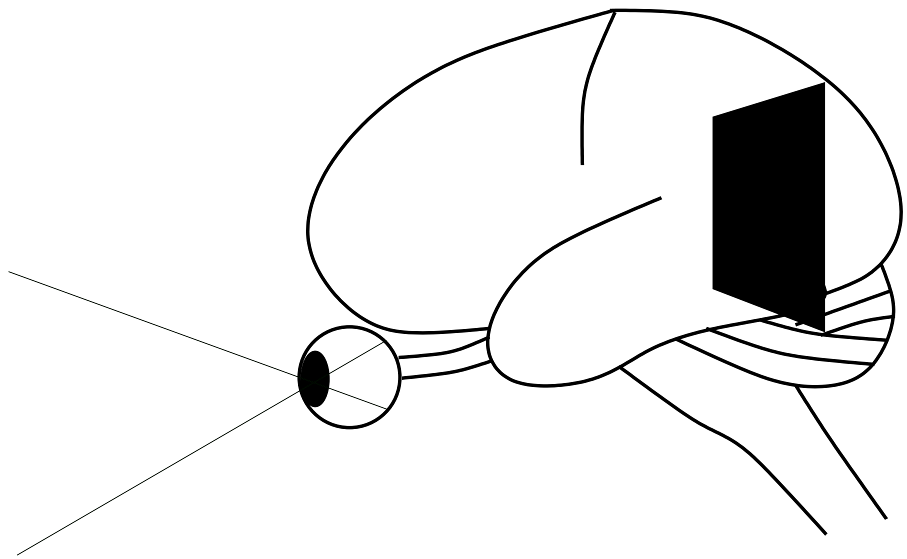
(b) From the INSIDE

- How can **we** understand the neural code? (X)
- How can **the brain itself** understand its neural code? (O)

Understanding the Neural Code, by the Brain

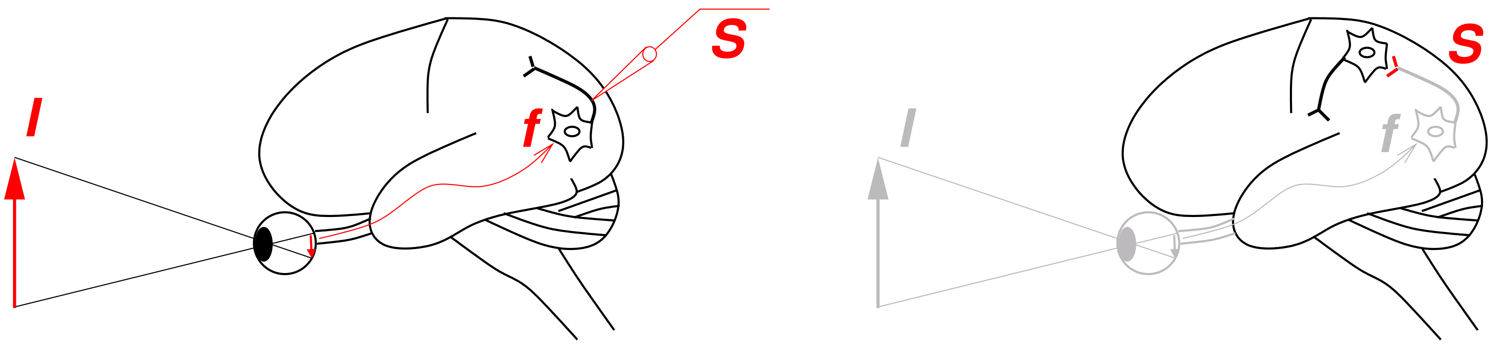
- What do these blinking lights mean?
- This is the BRAIN’s perspective.
  - Seems impossible to solve!

Understanding the Neural Code, by Us



- Now we can understand the meaning.
- This is OUR perspective.
  - However, this methodology is not available to the brain!

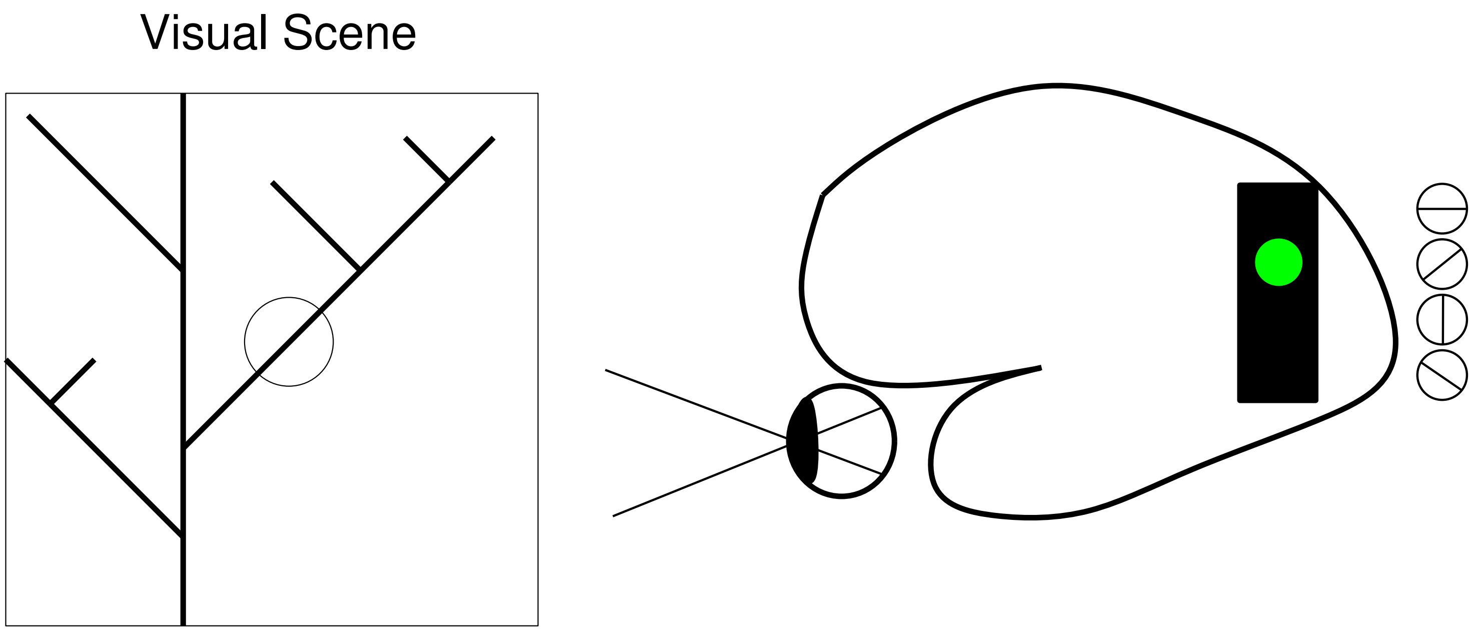
How to Understand the Neural Code?



(a) From the OUTSIDE (b) From the INSIDE

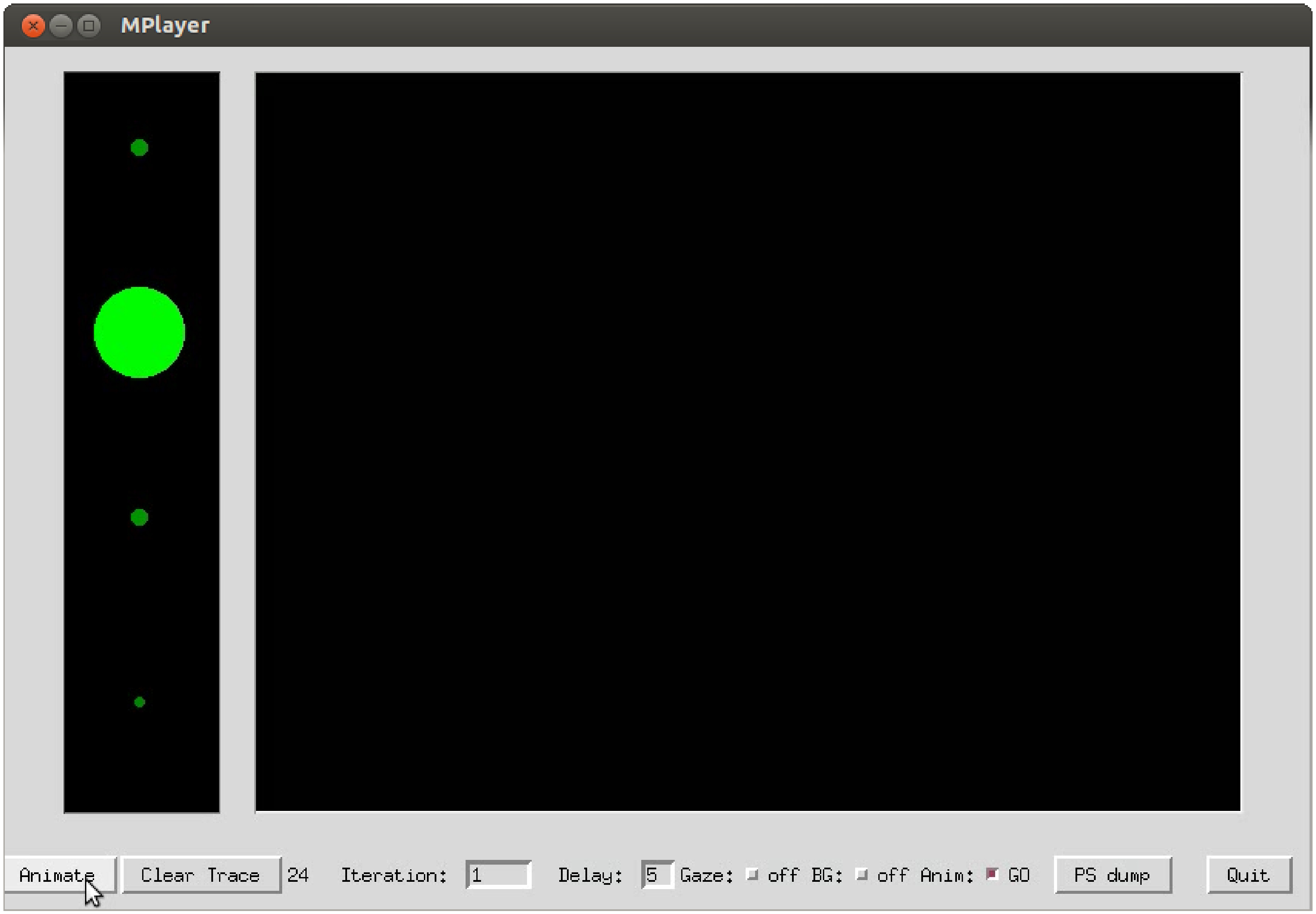
- How can **we** understand the brain? (X)
- How can **the brain itself** understand itself? (O)
  - Solution is through sensorimotor learning – not obvious when wrong question asked (Choe and Smith 2006; Choe et al. 2007).

Sensorimotor Learning to the Rescue



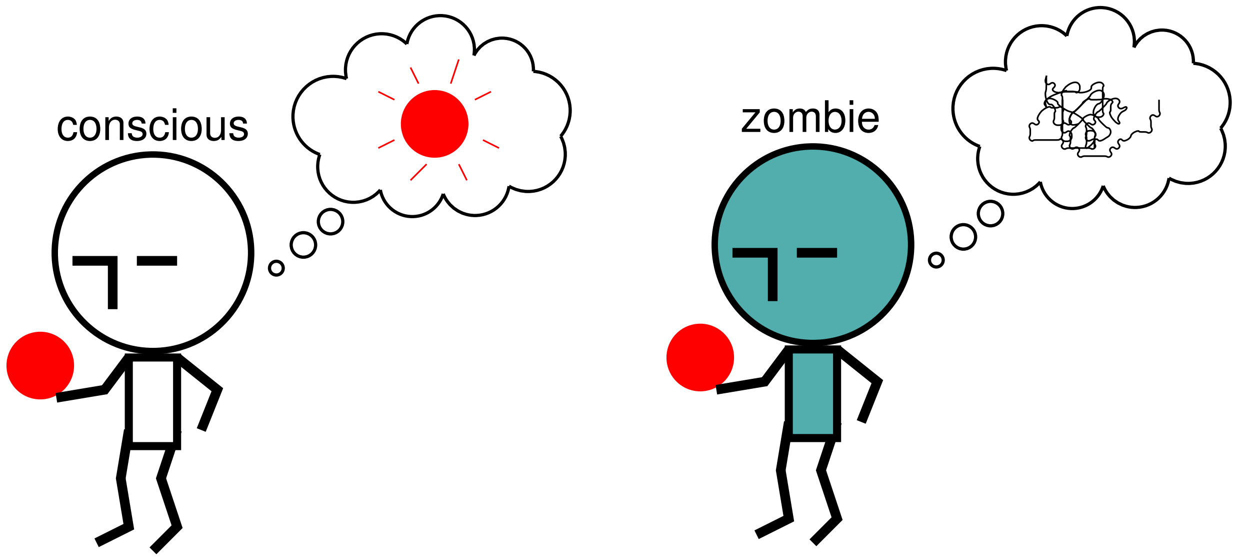
- Property of motor output that maintains internal state invariant
- Same as property of encoded sensory information.

Understanding, Inside the Brain



2. How did Consciousness Evolve?

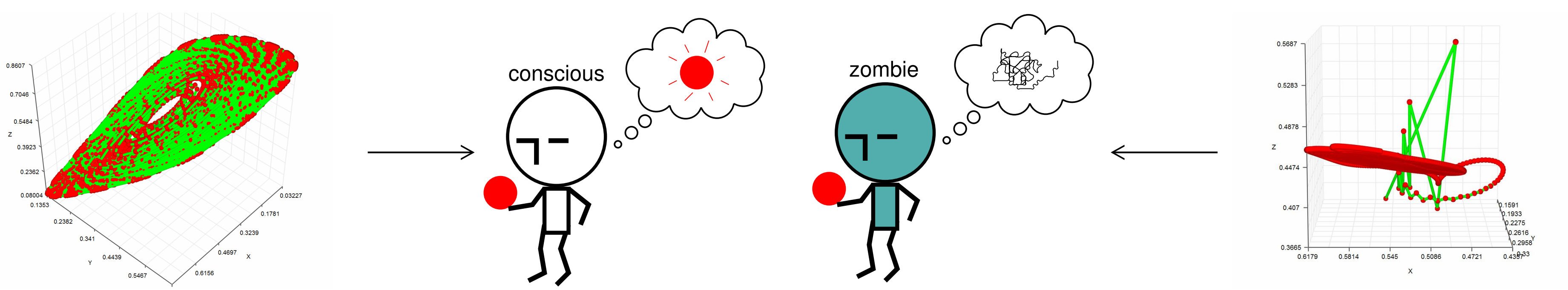
2. How did Consciousness Evolve?



- How did consciousness evolve? (X)
- How did the **necessary conditions** of consciousness evolve? (O)

2. How did Consciousness Evolve?

- How did consciousness evolve? (X)
- How did the **necessary conditions** of consciousness evolve? (O)
  - Former is subjective, latter is objective.
  - Predictive dynamics found to be key (Choe et al. 2012).



Necessary Condition for Consciousness

- Are there future events that are 100% predictable?

Necessary Condition for Consciousness

- Are there future events that are 100% predictable?
- What if I say there are such events?

Necessary Condition for Consciousness

- Are there future events that are 100% predictable?
- What if I say there are such events?
- I will clap my hands in the next 5 seconds.

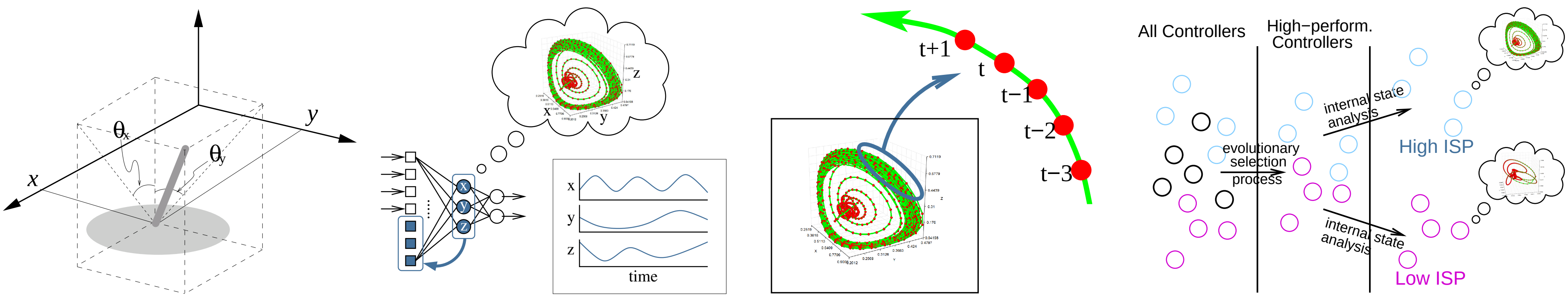
Necessary Condition for Consciousness

- Are there future events that are 100% predictable?
- What if I say there are such events?
- I will clap my hands in the next 5 seconds.
- “My” actions are 100% predictable, and this (authorship) is a key property of the self, the subject of consciousness.

Necessary Condition for Consciousness

- Are there future events that are 100% predictable?
- What if I say there are such events?
- I will clap my hands in the next 5 seconds.
- "My" actions are 100% predictable, and this (authorship) is a key property of the self, the subject of consciousness.
- Thus, the brain dynamics have to be predictable.

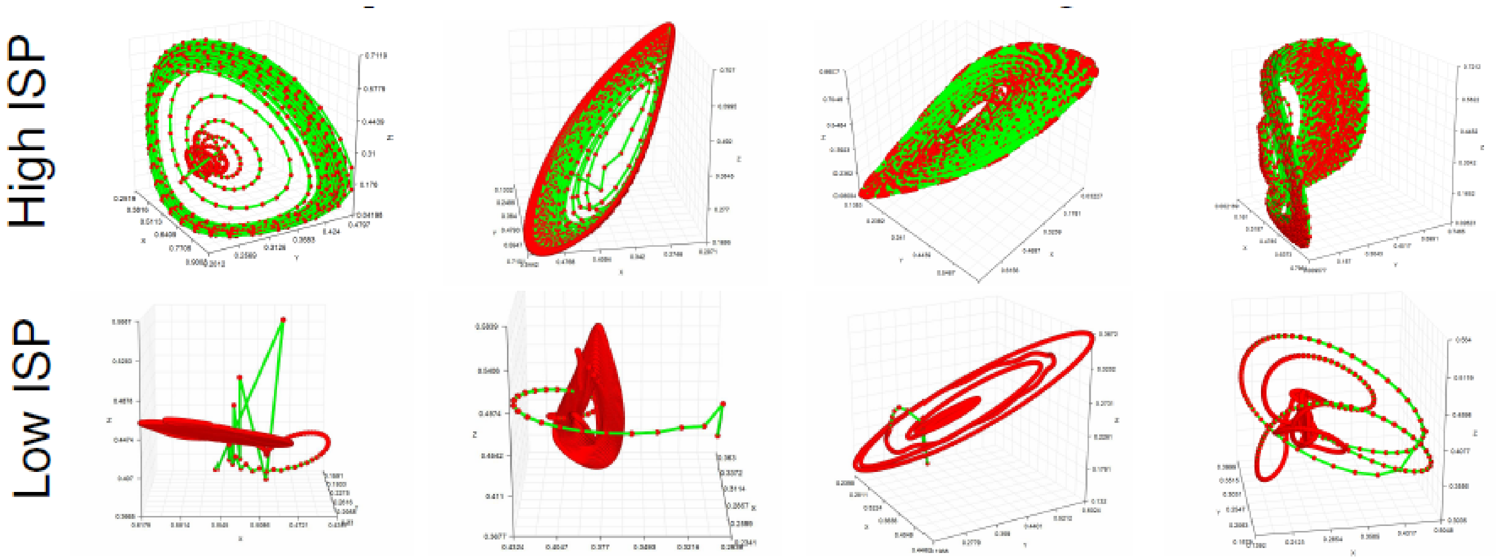
Could the Necessary Condition Evolve?



(a) Task (b) Controller (c) Measure ISP (d) Overview

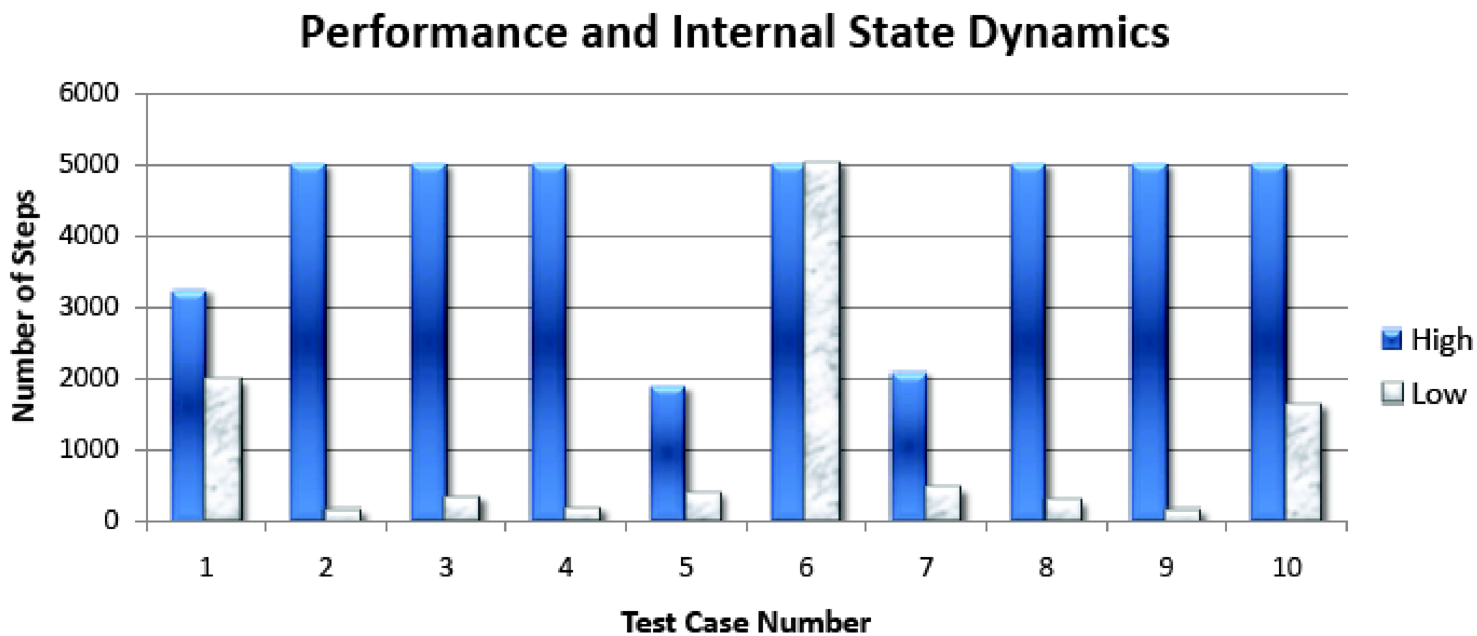
- Simulated evolution.
- Measure predictability of internal state dynamics.

Predictable vs. Unpredictable Internal Dyn.



- Internal dynamics of a simple pole-balancing controller neural network (Kwon and Choe 2008).

Predictable vs. Unpredictable Internal Dyn.



- Performance in controllers with high vs. low internal state predictability (Kwon and Choe 2008).
- Controllers with high ISP better fit in changing environment: Necessary condition can evolve!

3. How Does the Visual System Process Texture?

3. How Visual System Processes Texture?

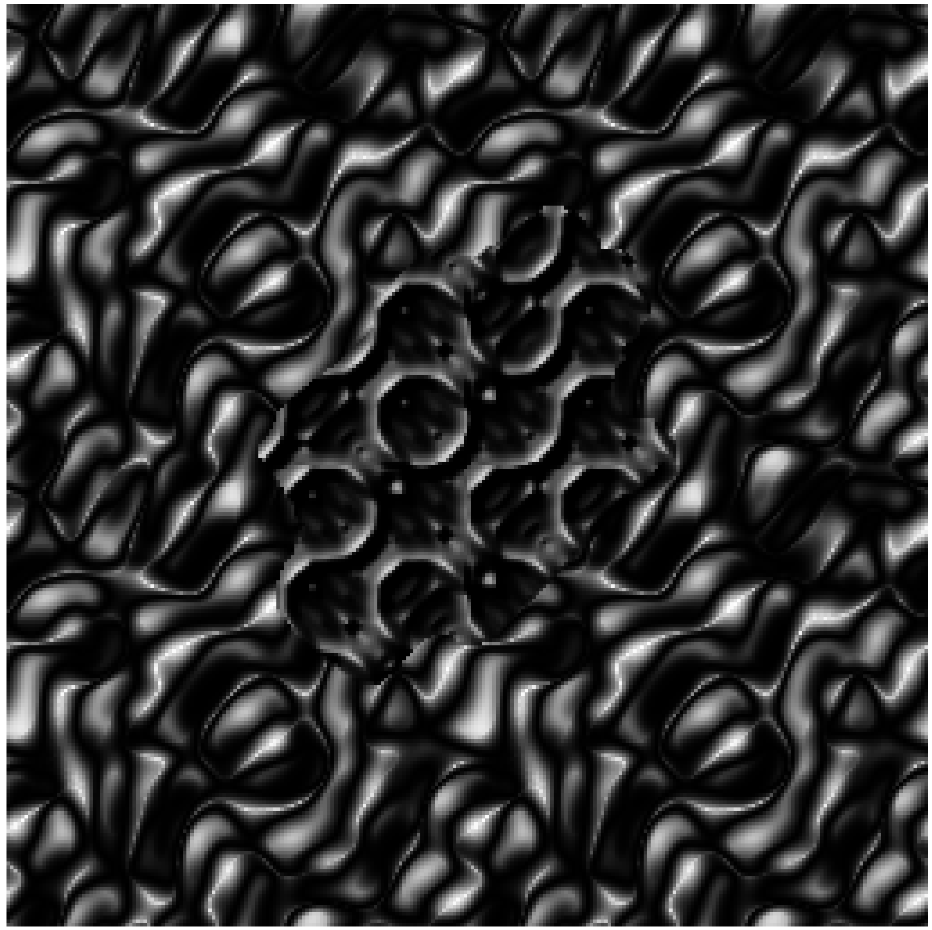
  

- How does the visual system process texture? (X)
- What is the nature of texture? (O)

How Visual System Processes Texture?

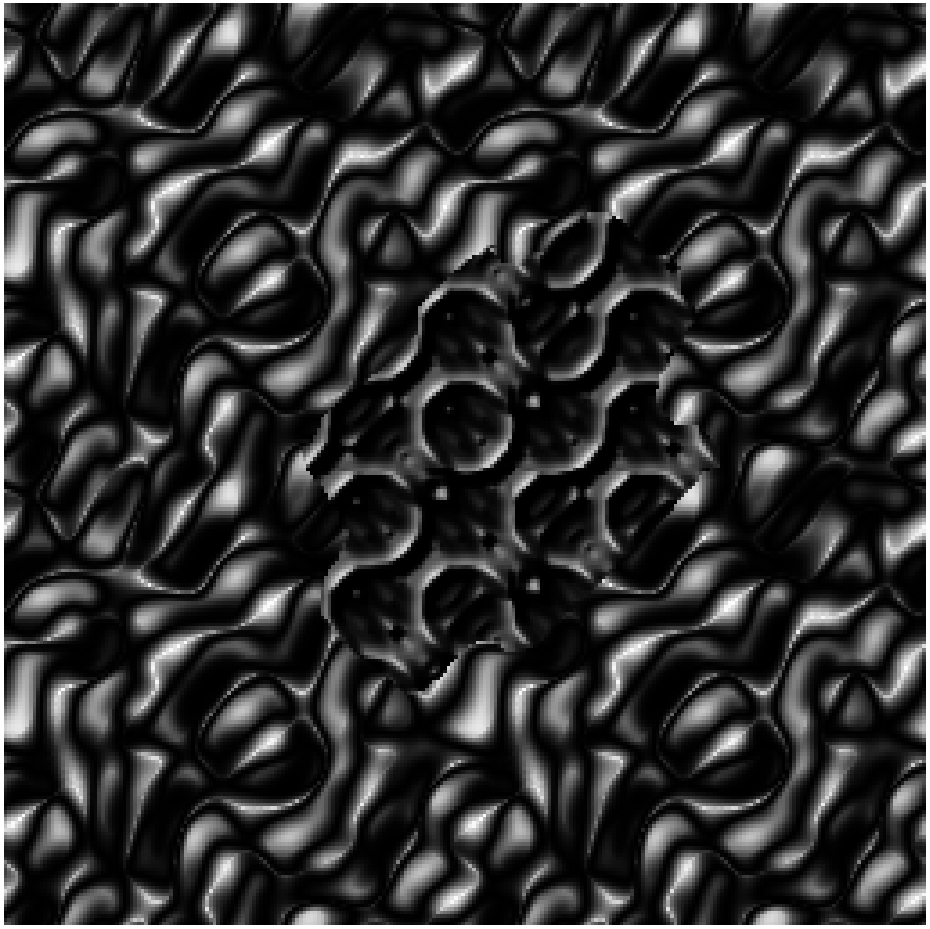
- How does the visual system process texture? (X)
- What is the nature of texture? (O)
  - Texture is a surface property and is thus tactile.
  - Tactile RFs more powerful than visual RFs (Bai et al. 2008; Park et al. 2009).

Texture in 2D



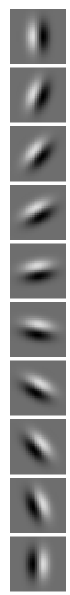
- Can you easily see the texture boundary?

Texture in 3D

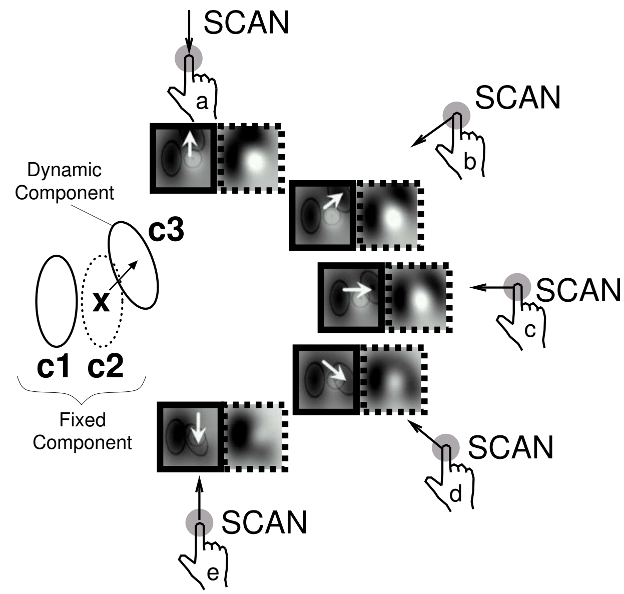


- Now can you see the boundary?

Preprocessing with Visual vs. Tactile RF



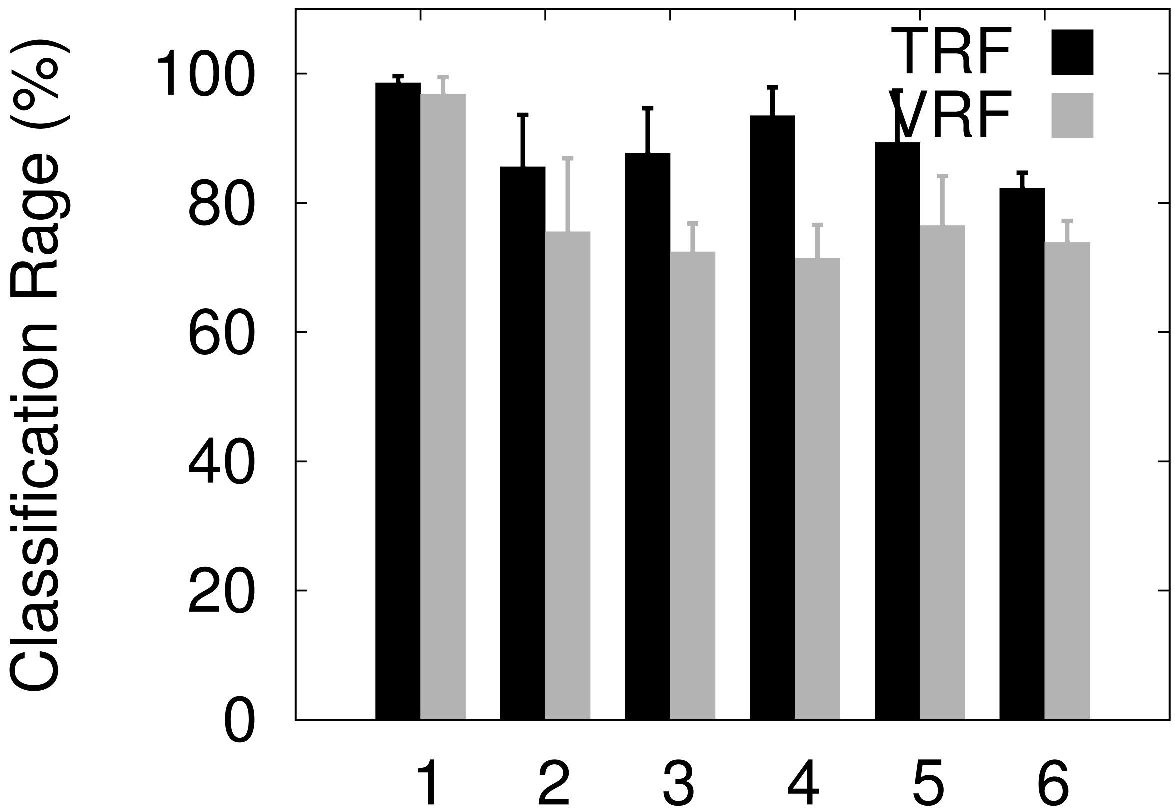
(a) Visual RFs



(b) Tactile RFs

- Preprocess texture with visual vs. tactile receptive field.
- Run classifier on result.

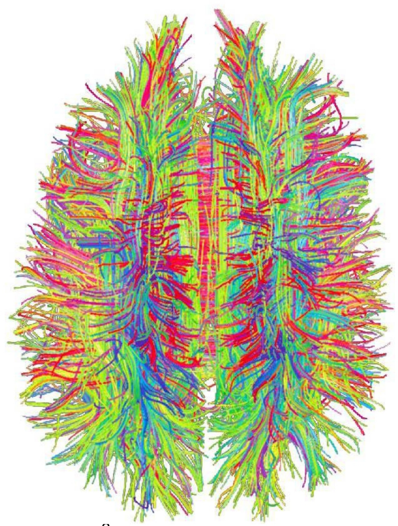
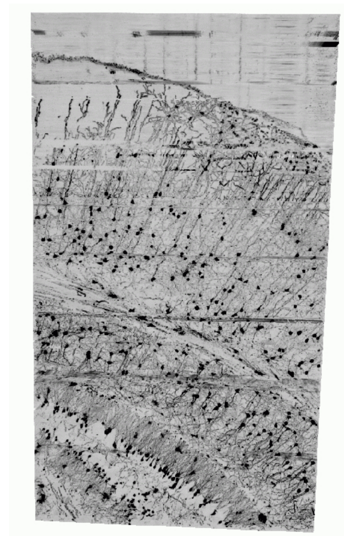
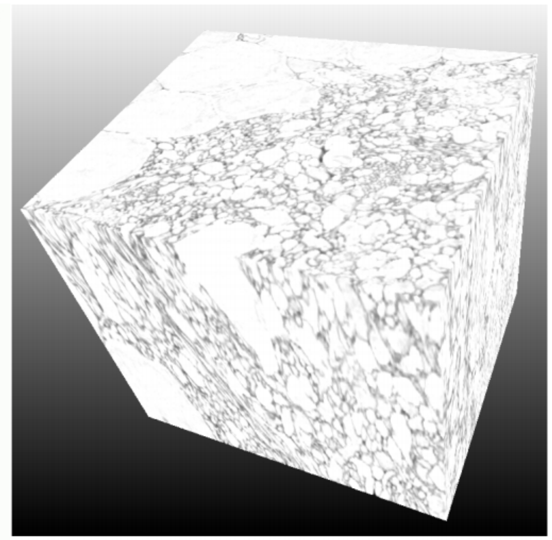
Tactile vs. Visual Texture Processing



- Tactile filter better than visual filter (Bai et al. 2008).
- Texture may be more intimately related to touch.

4. How to Acquire the Connectome

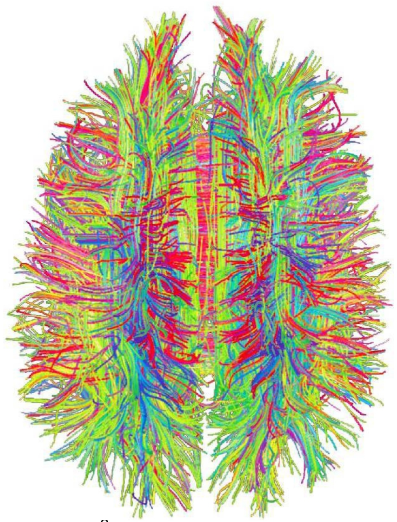
4. How to Acquire the Connectome

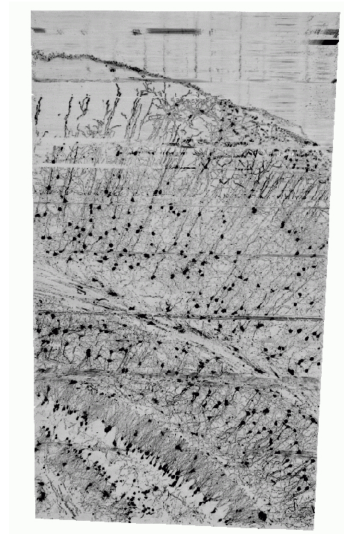




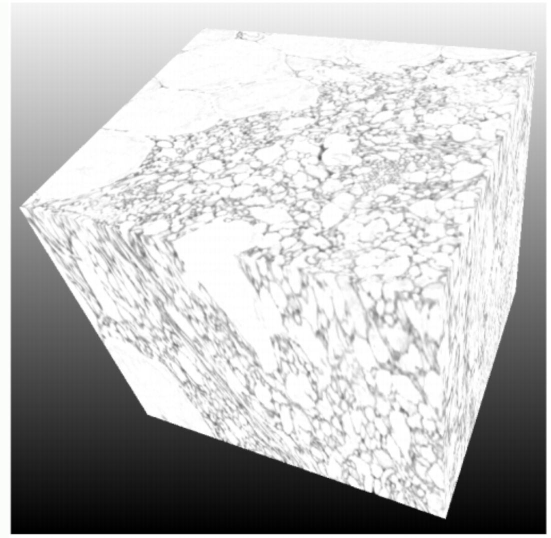
Imaging:	Diffusion Tensor Imaging	Light Microscopy	Electron Microscopy
Scale:	~ 10 cm cube	~ 1 cm cube	~ 100 um cube
Resolution:	~ 1 mm cube	~ 1 um cube	~ 10 nm cube
	Hagmann et al. (2007)	Mayerich et al. (2008)	Denk and Horstmann (2004)

- How to acqiure the connectome? (X)
- What if the connectome is available today? (O)

4. How to Acquire the Connectome







Imaging:	Diffusion Tensor Imaging	Light Microscopy	Electron Microscopy
Scale:	$\sim$ 10 cm cube	$\sim$ 1 cm cube	$\sim$ 100 um cube
Resolution:	$\sim$ 1 mm cube	$\sim$ 1 um cube	$\sim$ 10 nm cube
	Hagmann et al. (2007)	Mayerich et al. (2008)	Denk and Horstmann (2004)

- How to acqiure the connectome? (X)
- What if the connectome is available today? (O)
  - Test analysis methods with synthetic connectome.

What if Connectome is Available Today?

- *C. elegans* connectome is available (White et al. 1986).
  - Without activity and behavior data, progress is slow.
- Izquierdo and Beer (2013): used genetic algorithm to search for the parameters.
- Sohn et al. (2011): used cluster analysis to identify functional modules.

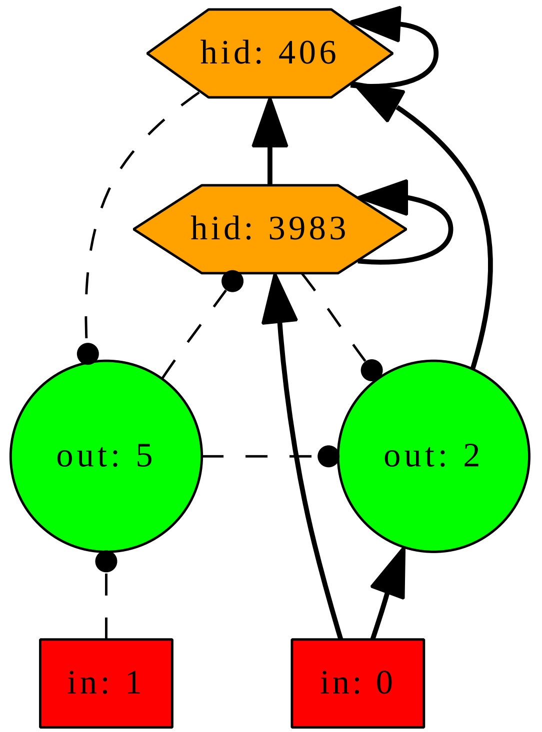
Analysis of the Connectome

- Neuroimaging-based
  - Park et al. (2014): Used graph-ICA to identify task-sepecific subnetworks.
  - van den Heuvel and Sporns (2011): Rich club
- EM-level connectome
  - Seung and Sümbül (2014): Cell types, connectivity, and function (direction selectivity) in the retina.

Synthetic Connectomics

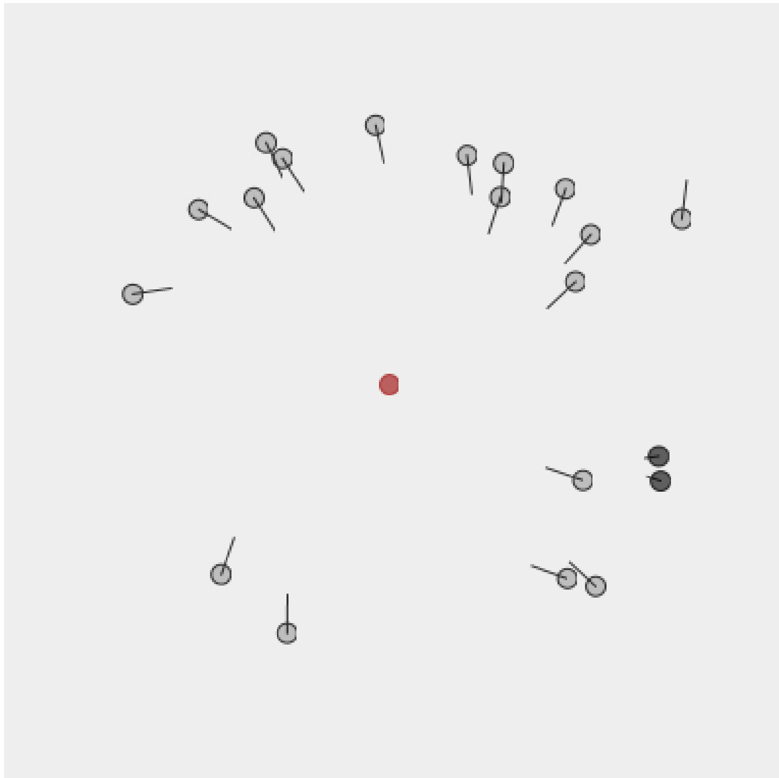
- Simulated evolution of neural network controllers.
- Use a topological evolution algorithm (NEAT, Stanley and Miikkulainen 2002).
- Full access to connectivity, weight, activity, and behavior.

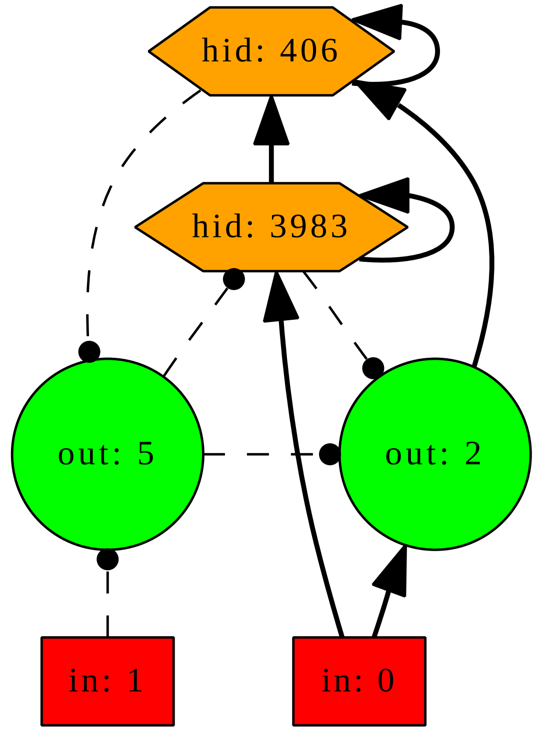
Example: Analyze This!



- Simple circuit evolved using Neuroevolution (NEAT).
  – Hard to know what it does without sensorimotor linkage: Brain in a vat.

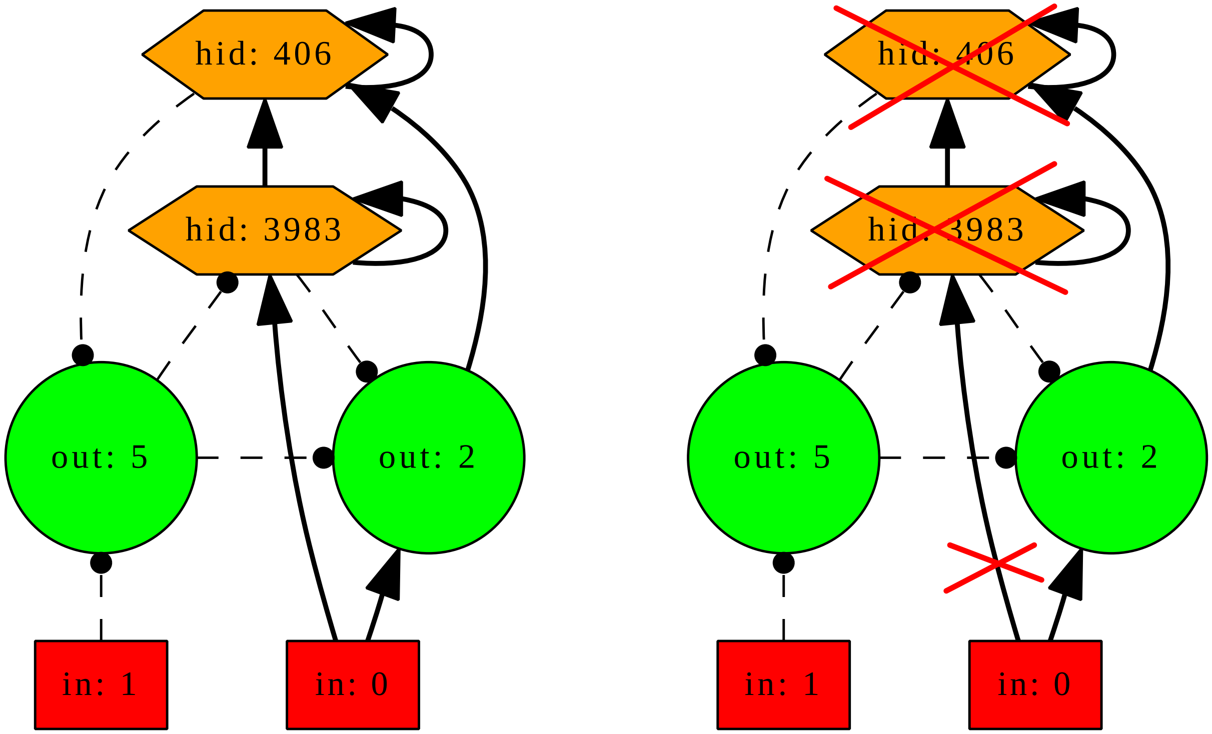
Example: Context





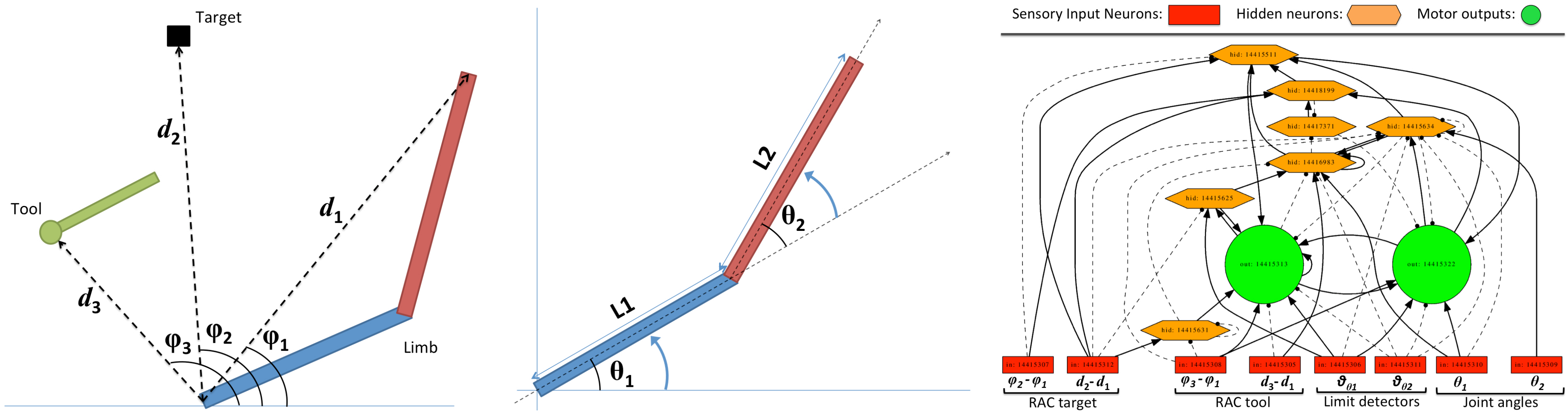
- Task: Navigation to goal.
- Input: fixed input (bias) and angle to goal.
- Output: thrust and angle adjust.

Approach: Lesion Study



- Observe behavior after eliminating connections or neurons.
- Result: works well with almost everything gone!
  - Need to study behavior in a social context to fully

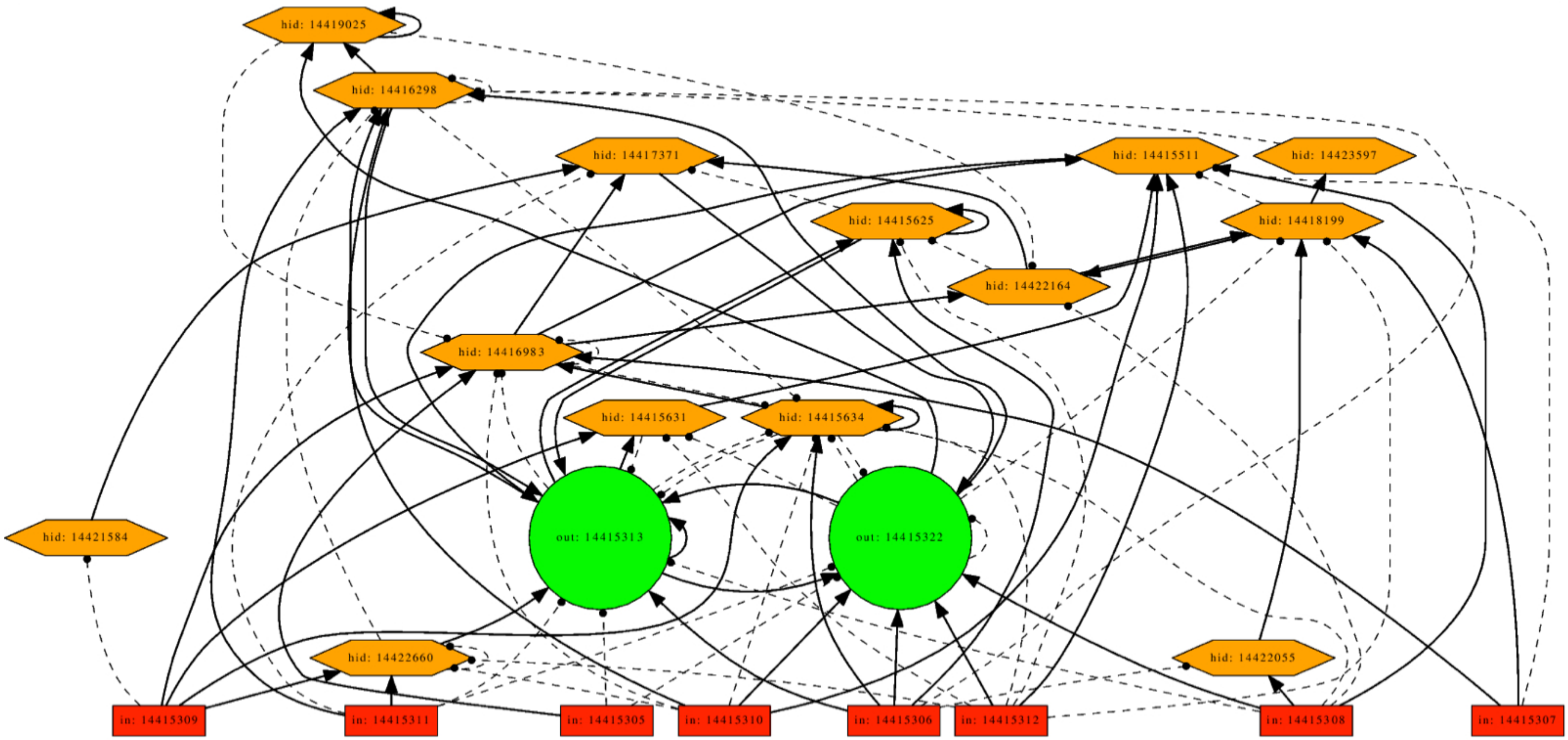
Example 2: Tool Use



- Articulated arm.
- Tool (green bar) pick up and reach goal.
- Evolved neural network controller.

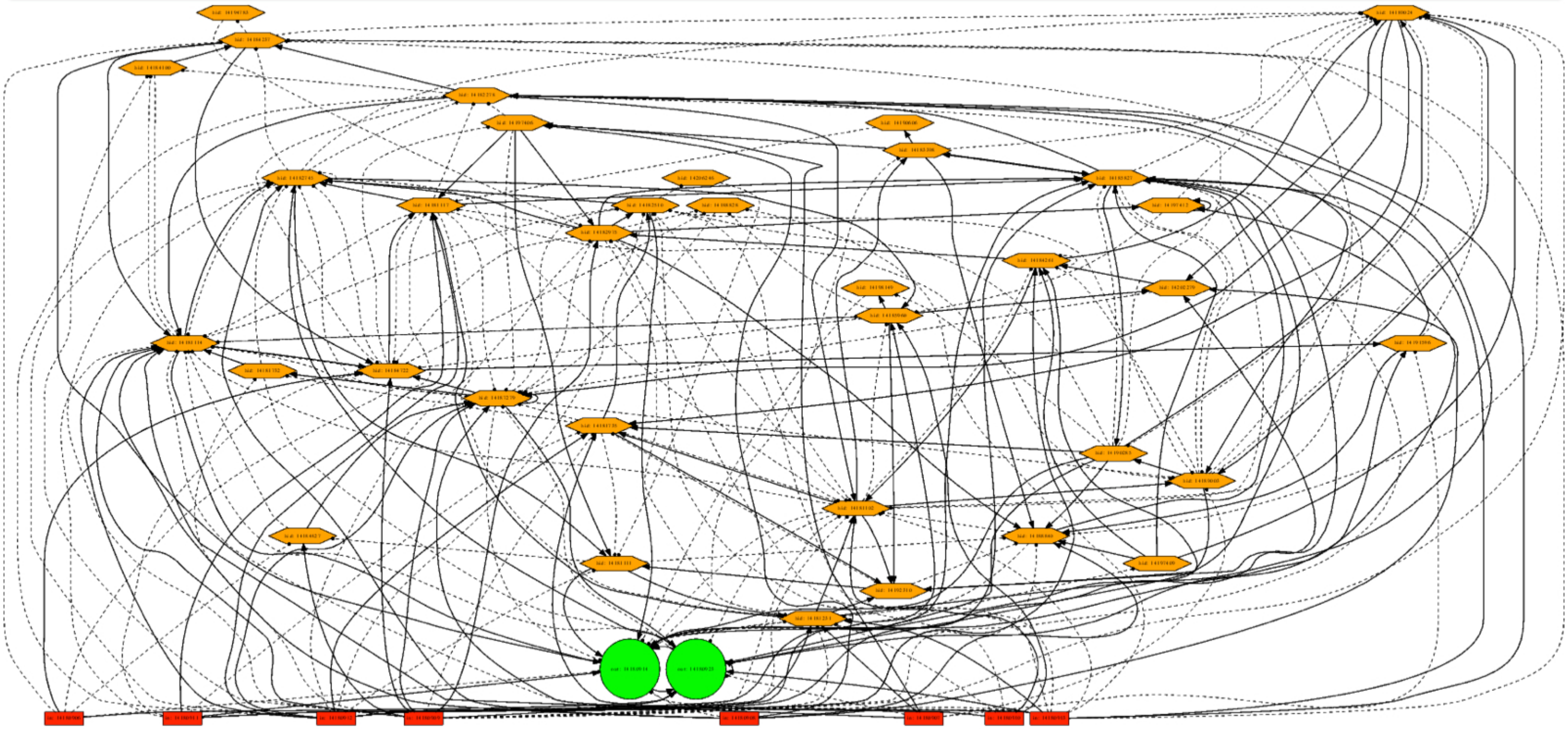
Evolved Circuits: S^{2}T

Sensory Input Neurons: Hidden neurons: Motor outputs:



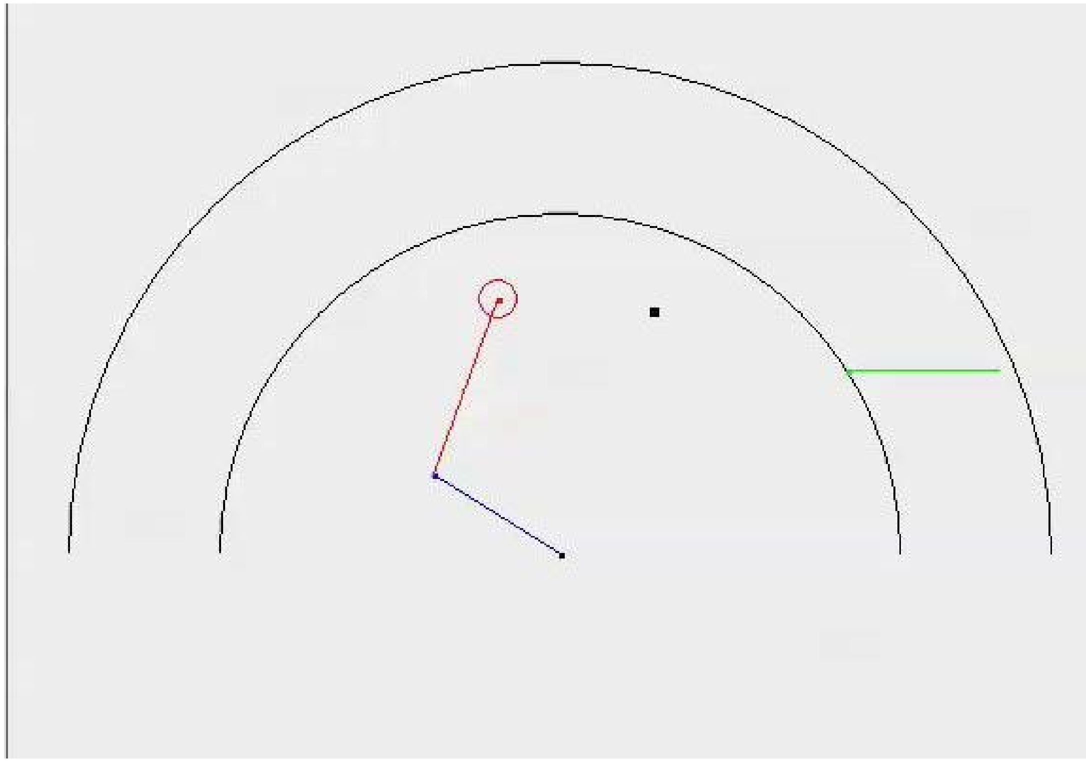
- Complexity depends on fitness criterion used.

Evolved Circuits: DS



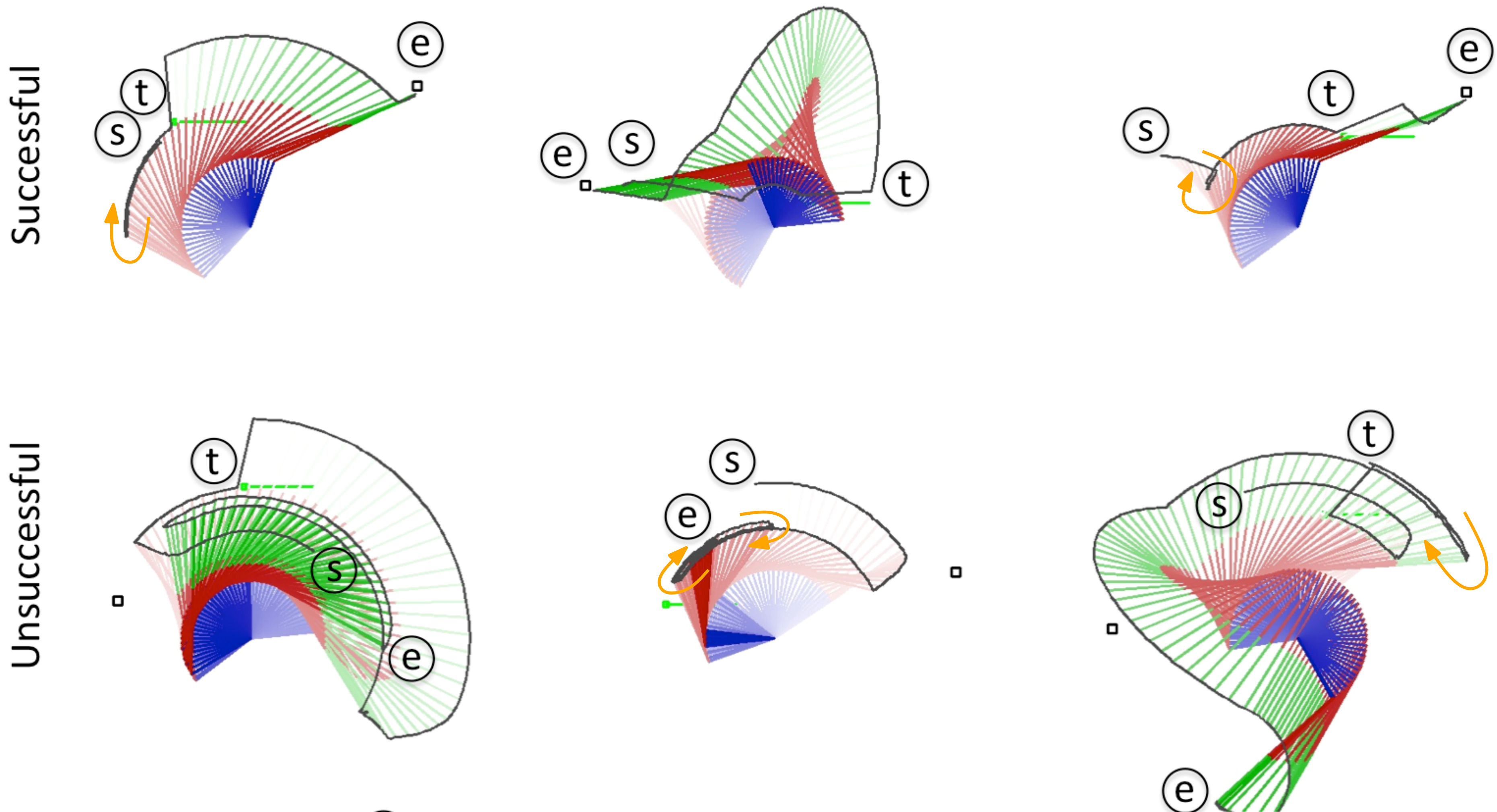
- Complexity depends on fitness criterion used.
- How can we analyze these circuits?

Tool Use Behavior



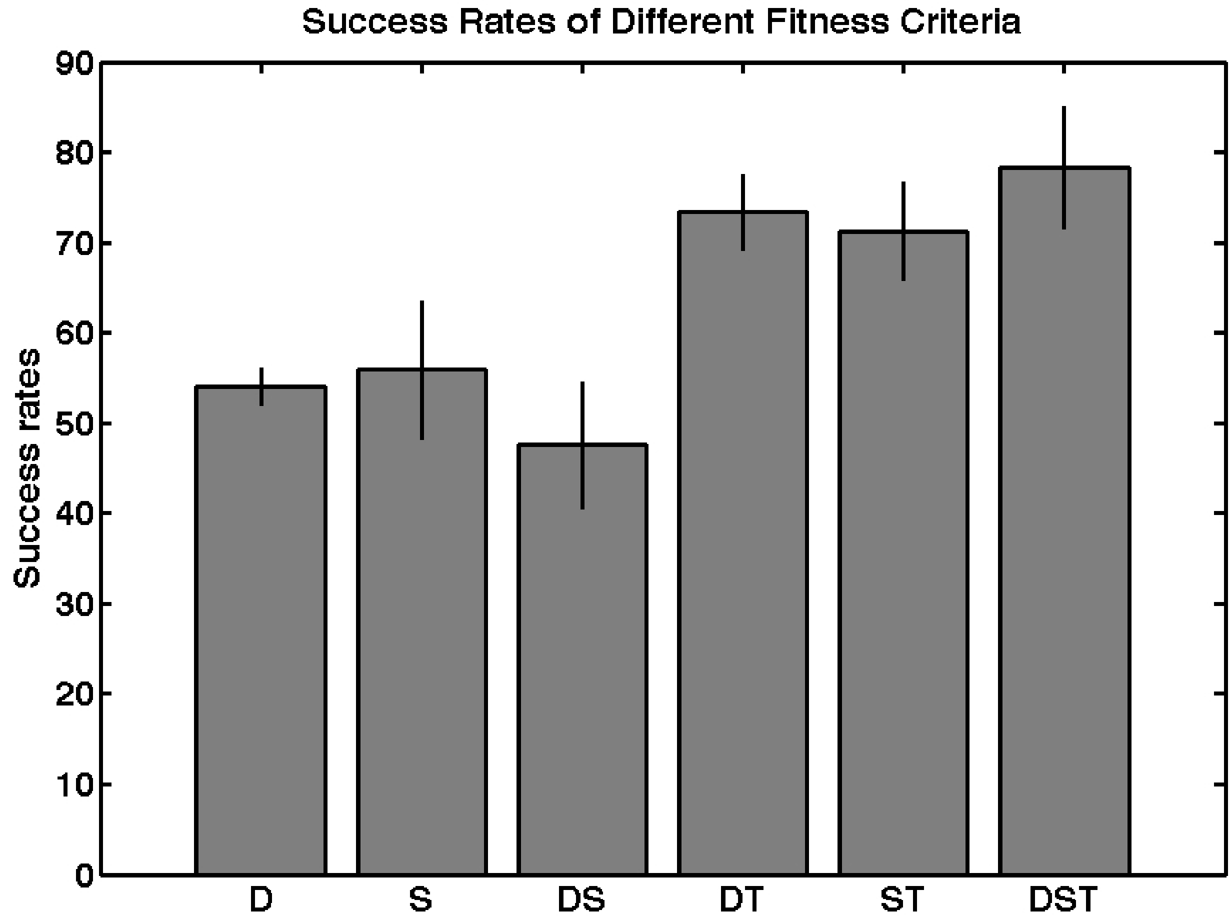
- Articulated arm.
- Tool (green bar) pick up and reach goal.

Tool Use Behavior: Various Patterns



(s) : start (t) : pick up tool (e) : end

Performance

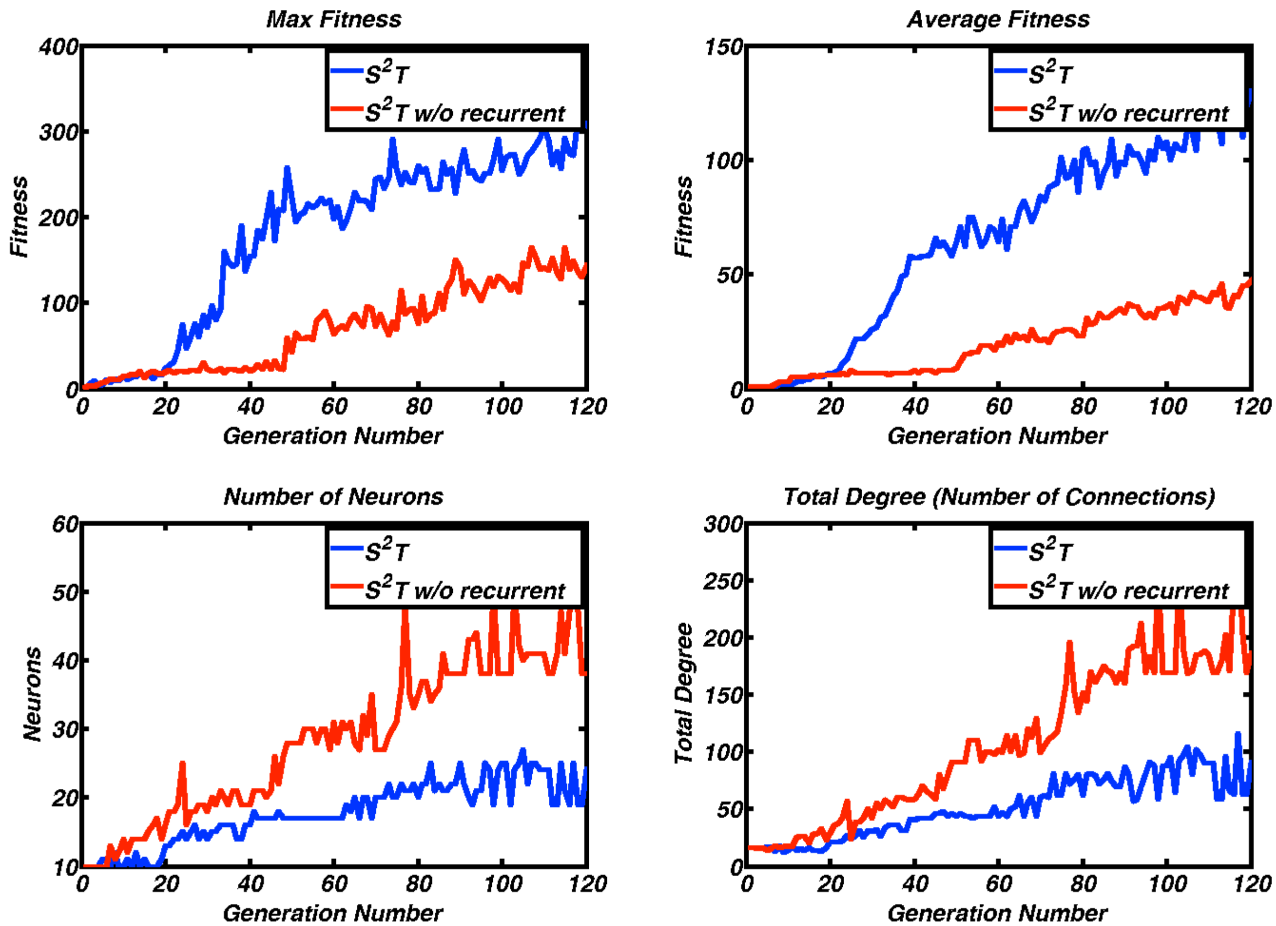


- D: distance, S: speed, T: tool pick up frequency
- Decent performance, bettwe with “T”.

How to Understand the Evolved Networks?

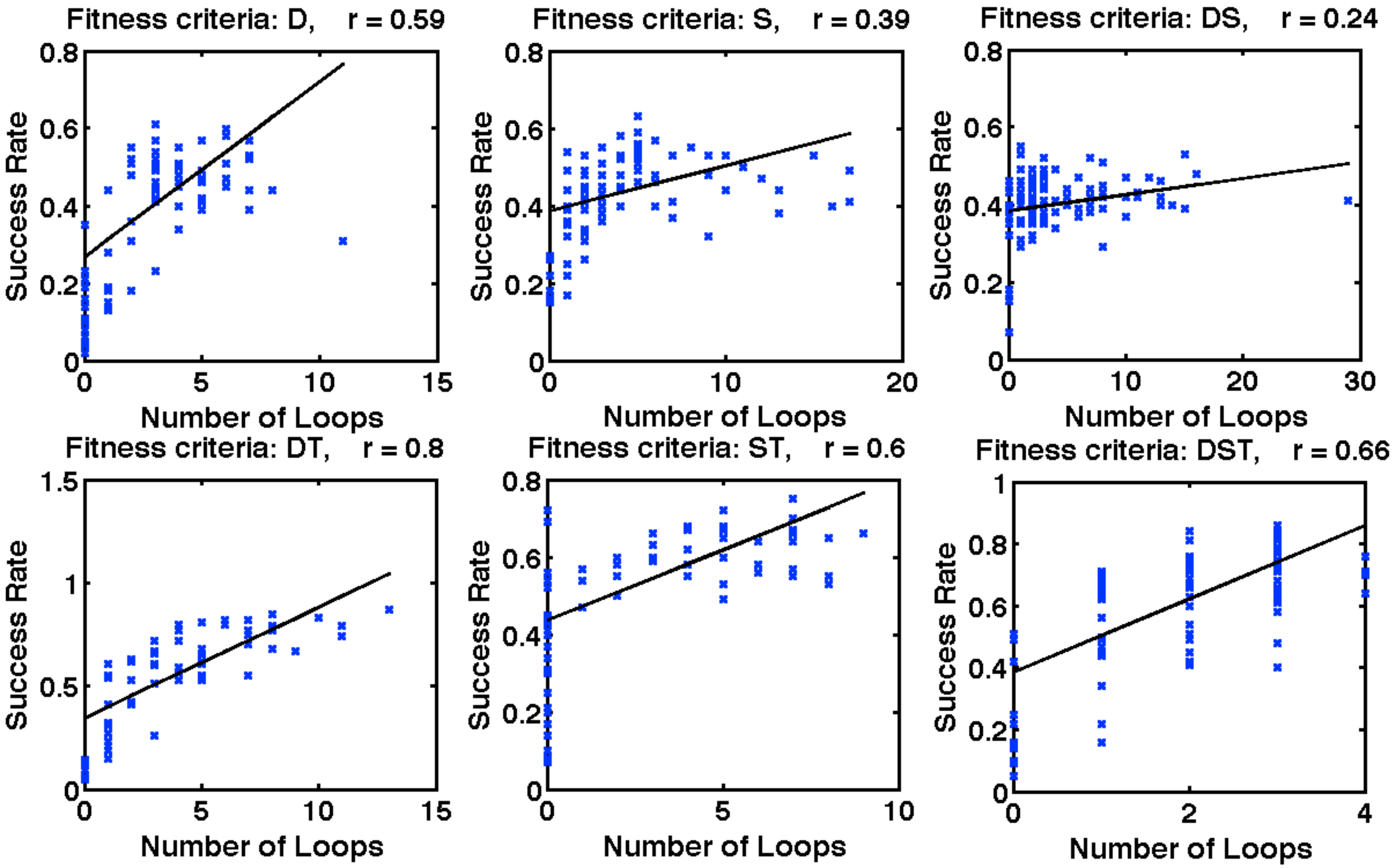
- Analyze recurrent loops (cycles in the connectivity).
- Clustering of activation dynamics.
- Correlated behavior and activation dynamics.
- Mostly preliminary work at this point.

Importance of Recurrent Connections



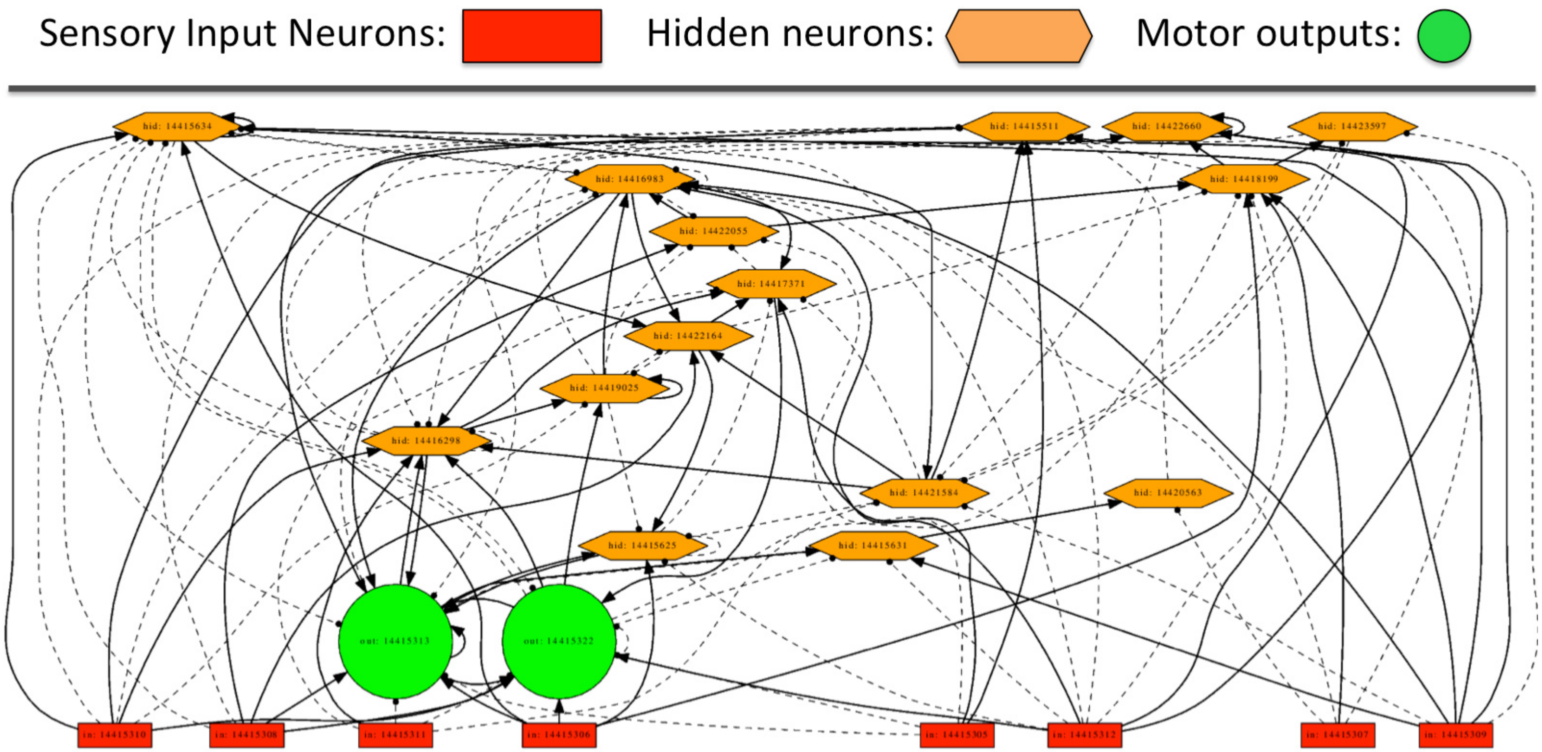
- Faster evolution (top), more compact networks (bottom).

Recurrent Loops vs. Performance



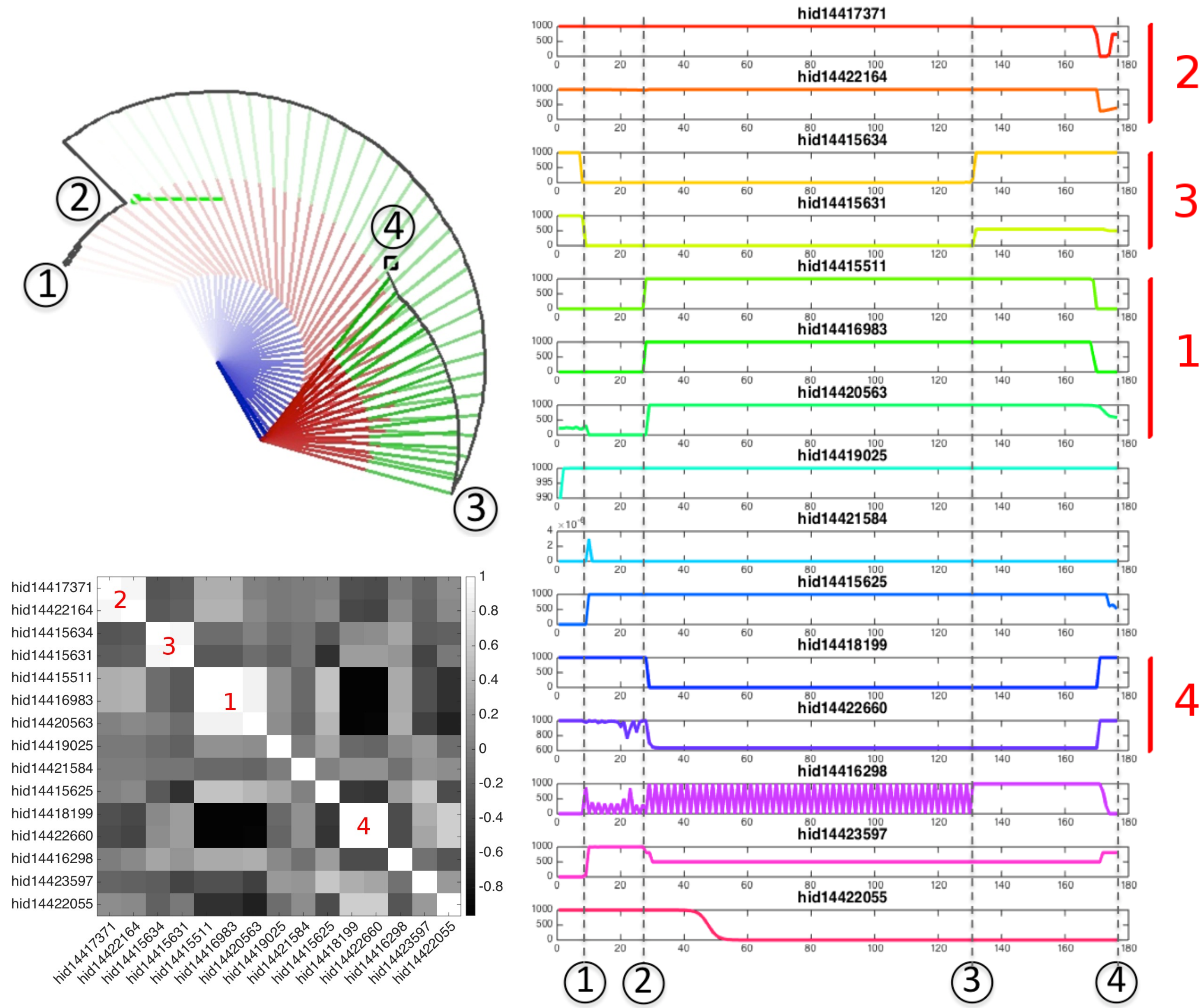
- Number of loops positively correlated with performance.

Example Network



- A representative successful network.

Activation of Neurons and Behavior



Synthetic Connectomics Techniques to be Explored

- Behavior categorization
- Internal dynamics categorization
- Systematic lesion studies and causality analysis
- Individual vs. social context comparison
- Circuit module identification through phylogenetic profiling
- Task-circuit mapping through black-box transfer learning

Discussion and Conclusion

Discussion: More Questions

- How are memories stored and retrieved? (X)
  - Assumes memory is about the past.
  - Assumes that memory is internal.
- How memories are used to predict? (O)
  - Memory is for the future (Lim and Choe 2006b, 2005, 2006a, 2008).
- How are the processings of internal and external memory related? (O)
  - Memory can be inside AND outside (Chung and Choe 2011).

Discussion: Yet More Questions

- How does the brain process information? (X)
  - Information has meaning only relative to an observer.
  - Shannon's information: No semantics, by definition.
- How does the brain process meaning? (O)
  - Meaning/semantics should be inherent to the brain.
- How does the brain optimize speed/accuracy/quantity? (X)
- How does the brain optimize quality? (O)

Conclusion

- Taking the brain's own perspective.
- Questioning the nature of things.
- Reducing to tractable, objective necessary conditions.
- Do we have powerful enough tools, if full data is given?

Acknowledgments

- Neural coding: Bhamidipati (2004); Choe and Bhamidipati (2004); Choe and Smith (2006); Choe et al. (2007); Choe (2011); Choe et al. (2008)
- Consciousness: Kwon and Choe (2008); Choe et al. (2012); Chung et al. (2012)
- Texture: Bai et al. (2008); Park et al. (2009); Bai (2008); Park (2009)
- Synthetic connectomics: Li et al. (2015).

References

Bai, Y. H. (2008). *Relative Advantage of Touch over Vision in the Exploration of Texture*. Master's thesis, Department of Computer Science, Texas A&M University, College Station, Texas.

Bai, Y. H., Park, C., and Choe, Y. (2008). Relative advantage of touch over vision in the exploration of texture. In *Proceedings of the 19th International Conference on Pattern Recognition (ICPR 2008)*, 1–4, 10.1109/ICPR.2008.4760961. **Best Scientific Paper Award**.

Bhamidipati, S. K. (2004). *Sensory invariance driven action (SIDA) framework for understanding the meaning of neural spikes.*. Master's thesis, Department of Computer Science, Texas A&M University.

Choe, Y. (2011). Action-based autonomous grounding. In Modayil, J., Precup, D., and Singh, S., editors, *AAAI-11 Workshop on Lifelong Learning from Sensorimotor Experience*, 56–57. Palo Alto, CA: AAAI Press. AAAI Workshop Technical Report WS-11-15.

Choe, Y., and Bhamidipati, S. K. (2004). Autonomous acquisition of the meaning of sensory states through sensory-invariance driven action. In Ijspeert, A. J., Murata, M., and Wakamiya, N., editors, *Biologically Inspired Approaches to Advanced Information Technology*, Lecture Notes in Computer Science 3141, 176–188. Berlin: Springer.

Choe, Y., Kwon, J., and Chung, J. R. (2012). Time, consciousness, and mind uploading. *International Journal on Machine Consciousness*, 4:257–274.

Choe, Y., and Smith, N. H. (2006). Motion-based autonomous grounding: Inferring external world properties from internal sensory states alone. In Gil, Y., and Mooney, R., editors, *Proceedings of the 21st National Conference on Artificial Intelligence(AAAI 2006)*, 936–941.

Choe, Y., Yang, H.-F., and Eng, D. C.-Y. (2007). Autonomous learning of the semantics of internal sensory states based on motor exploration. *International Journal of Humanoid Robotics*, 4:211–243.

Choe, Y., Yang, H.-F., and Misra, N. (2008). Motor system's role in grounding, receptive field development, and shape recognition. In *Proceedings of the Seventh International Conference on Development and Learning*, 67–72. IEEE.

Chung, J. R., and Choe, Y. (2011). Emergence of memory in reactive agents equipped with environmental markers. *IEEE Transactions on Autonomous Mental Development*, 3:257–271.

Chung, J. R., Kwon, J., Mann, T. A., and Choe, Y. (2012). Evolution of time in neural networks: From the present to the past, and forward to the future. In Rao, A. R., and Cecchi, G. A., editors, *The Relevance of the Time Domain to Neural Network Models, Springer Series in Cognitive and Neural Systems 3*, 99–116. New York: Springer.

Denk, W., and Horstmann, H. (2004). Serial block-face scanning electron microscopy to reconstruct three-dimensional tissue nanostructure. *PLoS Biology*, 19:e329.

Hagmann, P., Kurant, M., Gigandet, X., Thiran, P., Wedeen, V. J., Meuli, R., and Thiran, J.-P. (2007). Mapping human whole-brain structural networks with diffusion MRI. *PLoS ONE*, 2:e597.

Izquierdo, E. J., and Beer, R. D. (2013). Connecting a connectome to behavior: an ensemble of neuroanatomical models of c. elegans klinotaxis. *PLoS computational biology*, 9(2):e1002890.

Kwon, J., and Choe, Y. (2008). Internal state predictability as an evolutionary precursor of self-awareness and agency. In *Proceedings of the Seventh International Conference on Development and Learning*, 109–114. IEEE.

Li, Q., Yoo, J., and Choe, Y. (2015). Emergence of tool use in an articulated limb controlled by evolved neural circuits. In *Proceedings of the International Joint Conference on Neural Networks*. DOI: 10.1109/IJCNN.2015.7280564.

Lim, H., and Choe, Y. (2005). Facilitatory neural activity compensating for neural delays as a potential cause of the flash-lag effect. In *Proceedings of the International Joint Conference on Neural Networks*, 268–273. Piscataway, NJ: IEEE Press.

Lim, H., and Choe, Y. (2006a). Delay compensation through facilitating synapses and STDP: A neural basis for orientation flash-lag effect. In *Proceedings of the International Joint Conference on Neural Networks*, 8385–8392. Piscataway, NJ: IEEE Press.

Lim, H., and Choe, Y. (2006b). Facilitating neural dynamics for delay compensation and prediction in evolutionary neural networks. In Keijzer, M., editor, *Proceedings of the 8th Annual Conference on Genetic and Evolutionary Computation, GECCO-2006*, 167–174.

Lim, H., and Choe, Y. (2008). Extrapolative delay compensation through facilitating synapses and its relation to the flash-lag effect. *IEEE Transactions on Neural Networks*, 19:1678–1688.

Mayerich, D., Abbott, L. C., and McCormick, B. H. (2008). Knife-edge scanning microscopy for imaging and reconstruction of three-dimensional anatomical structures of the mouse brain. *Journal of Microscopy*, 231:134–143.

Park, B., Kim, D.-S., and Park, H.-J. (2014). Graph independent component analysis reveals repertoires of intrinsic network components in the human brain. *PloS one*, 9(1):e82873.

Park, C. (2009). *Performance, Development, and Analysis of Tactile vs. Visual Receptive Fields in Texture Tasks*. PhD thesis, Department of Computer Science, Texas A&M University.

Park, C., Bai, Y. H., and Choe, Y. (2009). Tactile or visual?: Stimulus characteristics determine receptive field type in a self-organizing map model of cortical development. In *Proceedings of the 2009 IEEE Symposium on Computational Intelligence for Multimedia Signal and Vision Processing*, 6–13. **Best Student Paper Award**.

Seung, H. S., and Sümbül, U. (2014). Neuronal cell types and connectivity: Lessons from the retina. *Neuron*, 83(6):1262–1272.

Sohn, Y., Choi, M.-K., Ahn, Y.-Y., Lee, J., and Jeong, J. (2011). Topological cluster analysis reveals the systemic organization of the *caenorhabditis elegans* connectome. *PLoS Computational Biology*, 7:e1001139.

Stanley, K. O., and Miikkulainen, R. (2002). Evolving neural networks through augmenting topologies. *Evolutionary Computation*, 10:99–127.

van den Heuvel, M. P., and Sporns, O. (2011). Rich-club organization of the human connectome. *The Journal of neuroscience*, 31(44):15775–15786.

White, J. G., Southgate, E., Thomson, J. N., and Brenner, S. (1986). The structure of the nervous system of the nematode caenorhabditis elegans. *Philosophical Transactions of the Royal Society of London B*, 314:1–340.