



Taming Complexity: From Network Science to Control

Albert-László Barabási

NETWORKS SCIENCE INSTITUTE

NORTHEASTERN UNIVERSITY

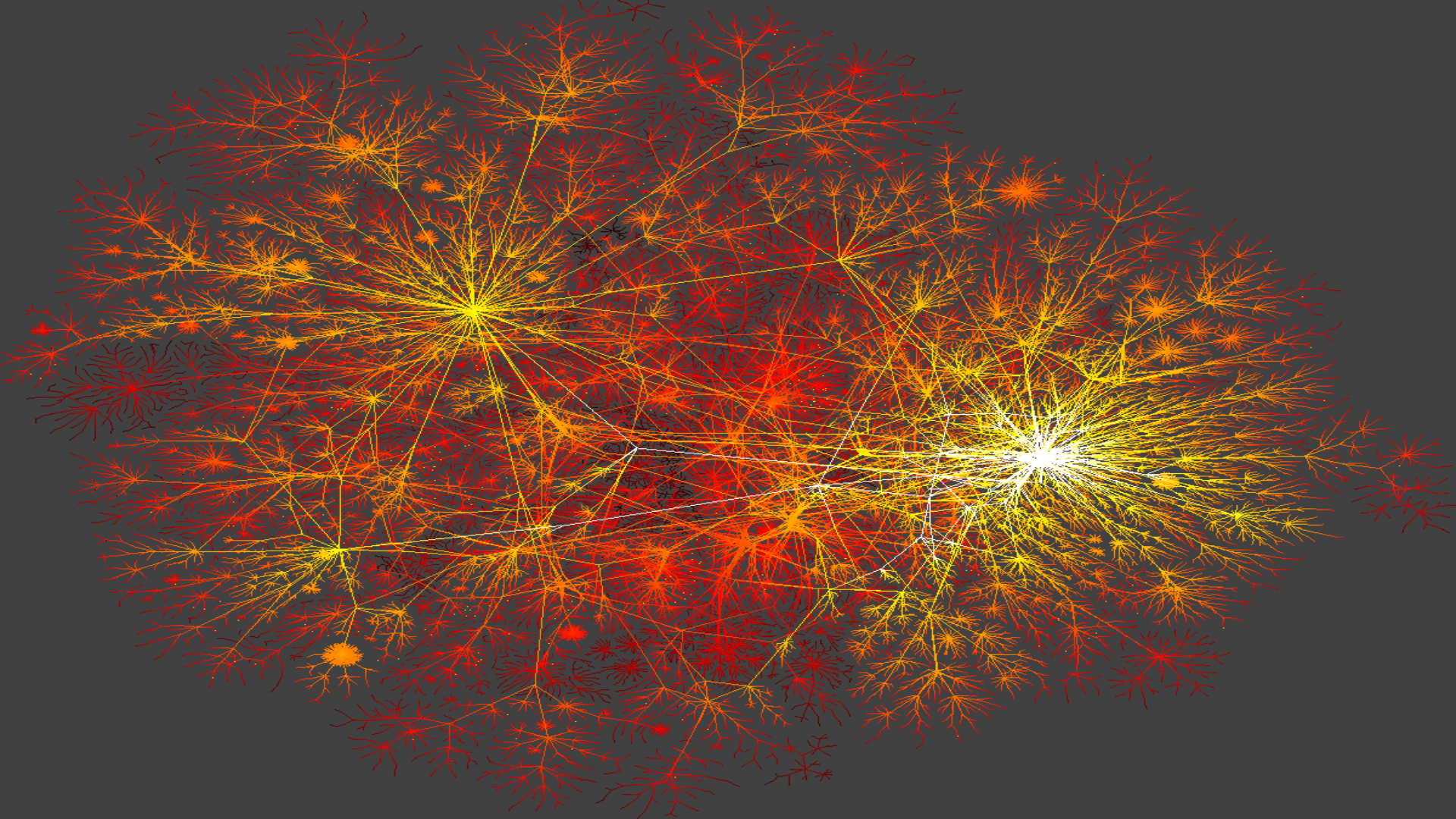
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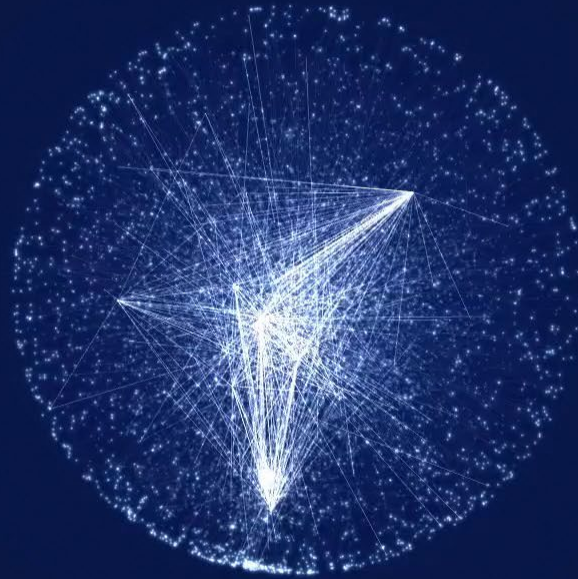
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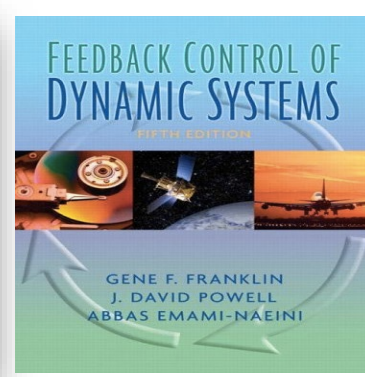
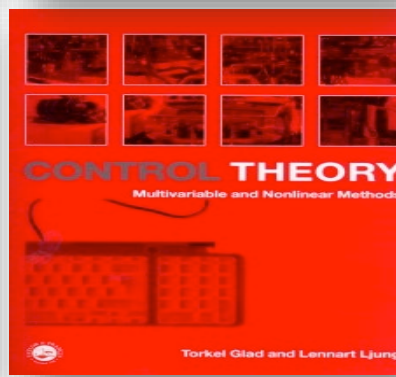
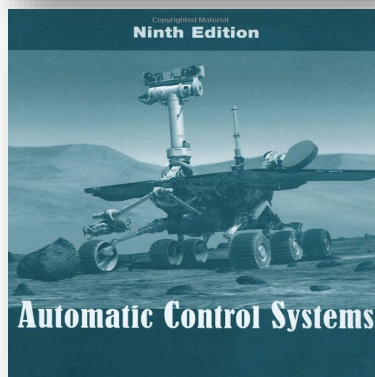
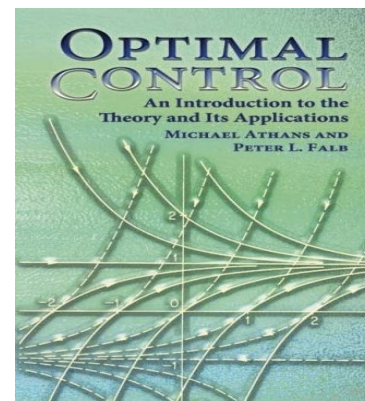
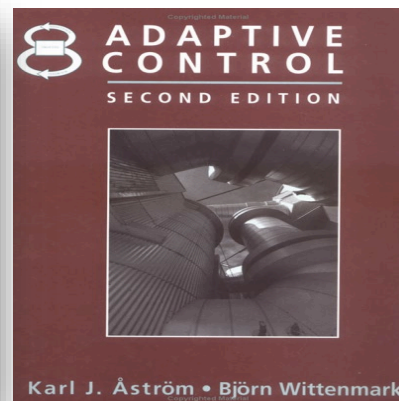
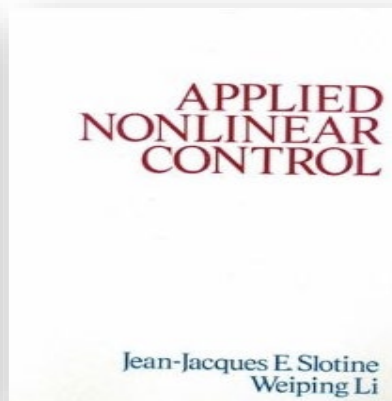
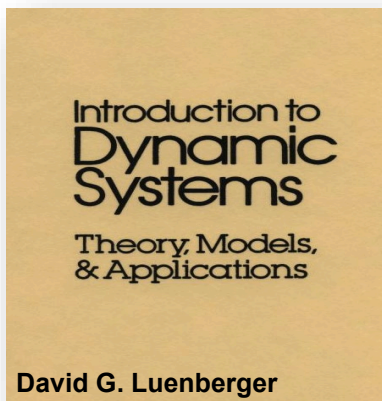
Understand

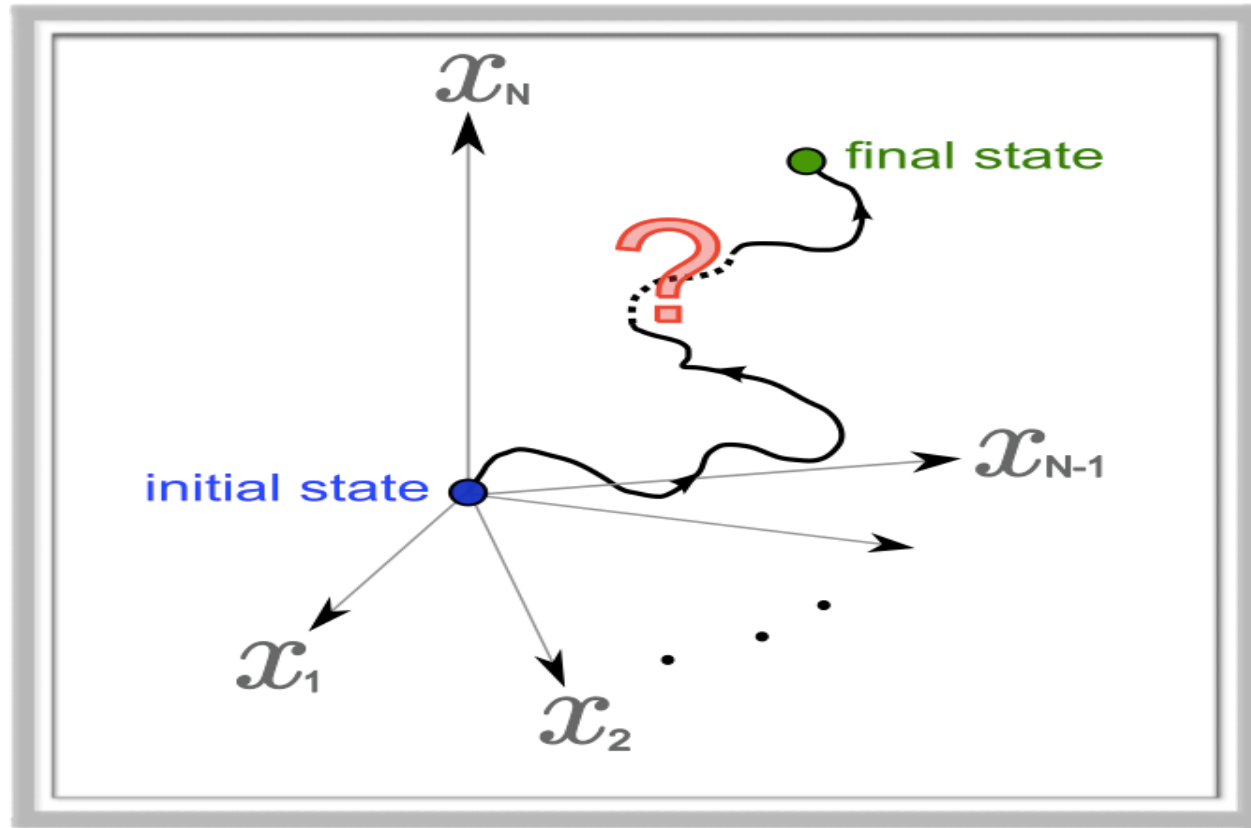
quantify

predict

control

Control Theory

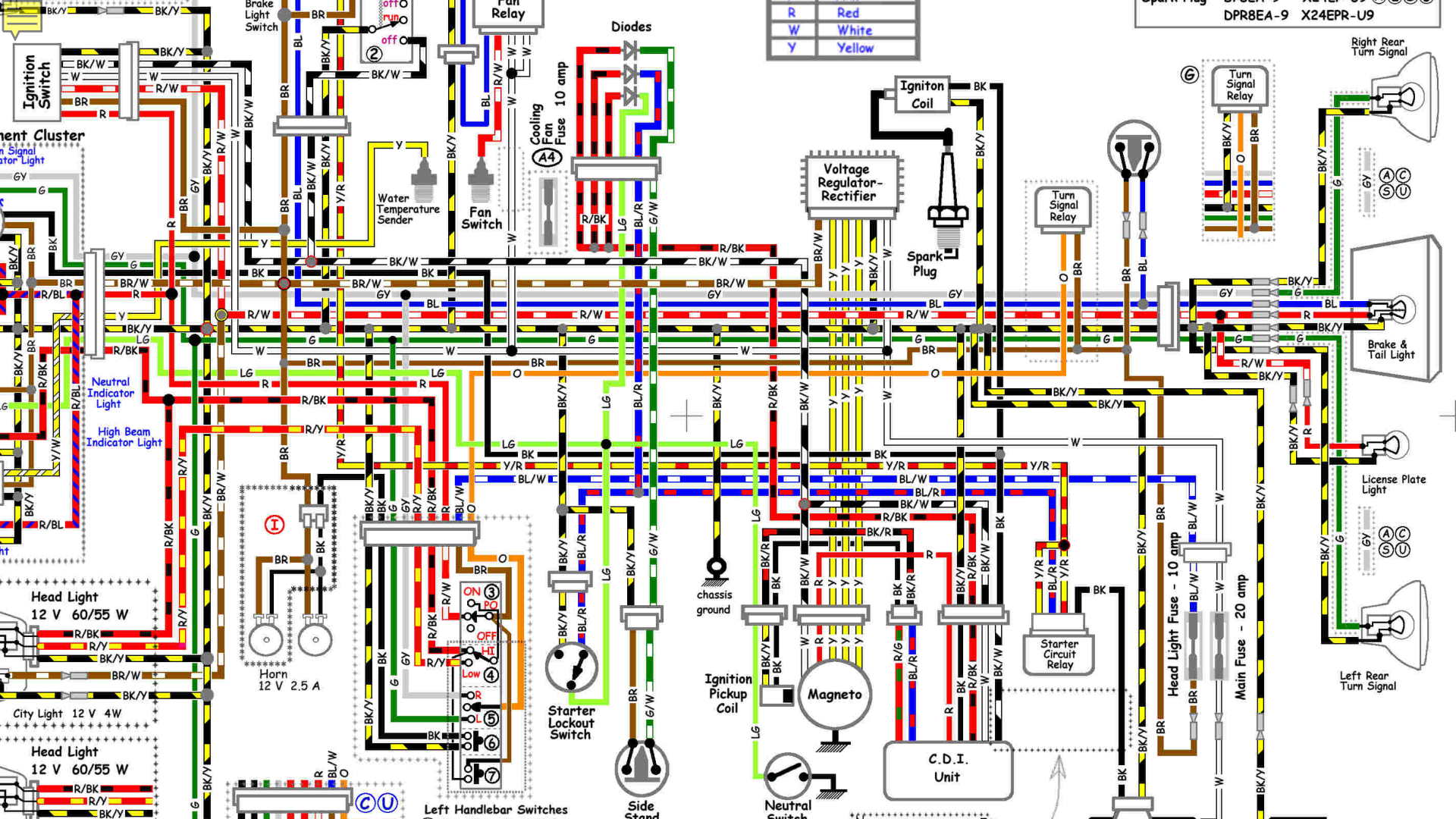




A system is controllable if it can be driven from any **initial state** to any desired **final state** in finite time.









Controllability of complex networks

Yang-Yu Liu^{1,2}, Jean-Jacques Slotine^{3,4} & Albert-László Barabási^{1,2,5}

The ultimate proof of our understanding of natural or technological systems is reflected in our ability to control them. Although control theory offers mathematical tools for steering engineered and natural systems towards a desired state, a framework to control complex self-organized systems is lacking. Here we develop analytical tools to study the controllability of an arbitrary complex directed network, identifying the set of driver nodes with time-dependent control that can guide the system's entire dynamics. We apply these tools to several real networks, finding that the number of driver nodes is determined mainly by the network's degree distribution. We show that sparse inhomogeneous networks, which emerge in many real complex systems, are the most difficult to control, but that dense and homogeneous networks can be controlled using a few driver nodes. Counterintuitively, we find that in both model and real systems the driver nodes tend to avoid the high-degree nodes.

REVIEWS OF MODERN PHYSICS, VOLUME 88, JULY-SEPTEMBER 2016

Control principles of complex systems

Yang-Yu Liu

Channing Division of Network Medicine, Brigham and Women's Hospital, Harvard Medical School, Boston, Massachusetts 02115, USA and Center for Cancer Systems Biology, Dana-Farber Cancer Institute, Boston, Massachusetts 02115, USA

Albert-László Barabási

Center for Complex Network Research and Department of Computer Science and Biology, Boston, Massachusetts



Linear Time-Invariant Dynamics

$$\frac{d\mathbf{X}}{dt} = \mathbf{A} \cdot \mathbf{X}(t) + \mathbf{B} \cdot \mathbf{u}(t)$$

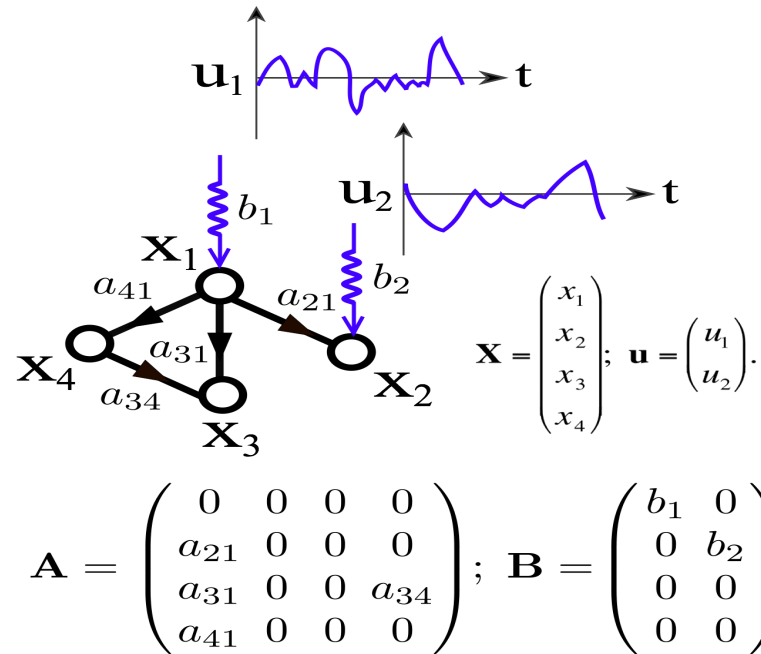
$\mathbf{A} \in R^{N \times N}$: weighted wiring diagram

$\mathbf{X}(t) \in R^{N \times 1}$: state vector.

$\mathbf{u}(t) \in R^{M \times 1}$: input vector ($M \leq N$).

$\mathbf{B} \in R^{N \times M}$: input matrix

(\Rightarrow control configuration).



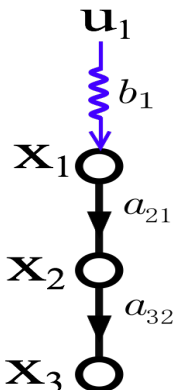
Kalman's Rank Condition:

A system is controllable iff its controllability matrix has full rank.

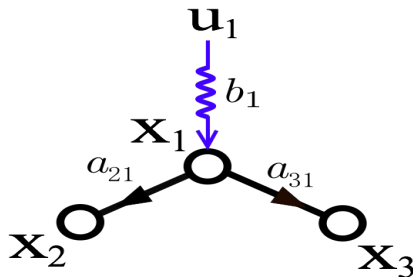
$$\text{rank } \mathbf{C} = N$$

$$\mathbf{C} = [\mathbf{B}, \mathbf{A} \cdot \mathbf{B}, \mathbf{A}^2 \cdot \mathbf{B}, \dots, \mathbf{A}^{N-1} \cdot \mathbf{B}]$$

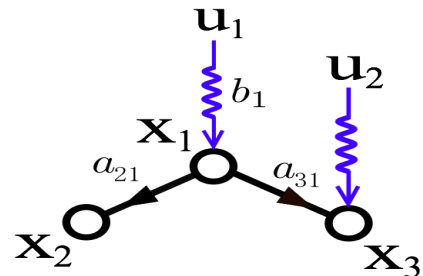
EXAMPLES: Controllable or not controllable?



Yes



No



Yes

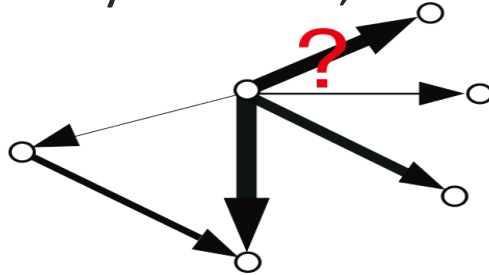
Problem: The Kálmán condition does not identify the control nodes.

It only tells us if our guess is correct.

Finding the control nodes requires $2N$ operations

Difficulties

1. Parameters (link weights): usually unknown.
e.g. gene regulatory network, Internet, etc.



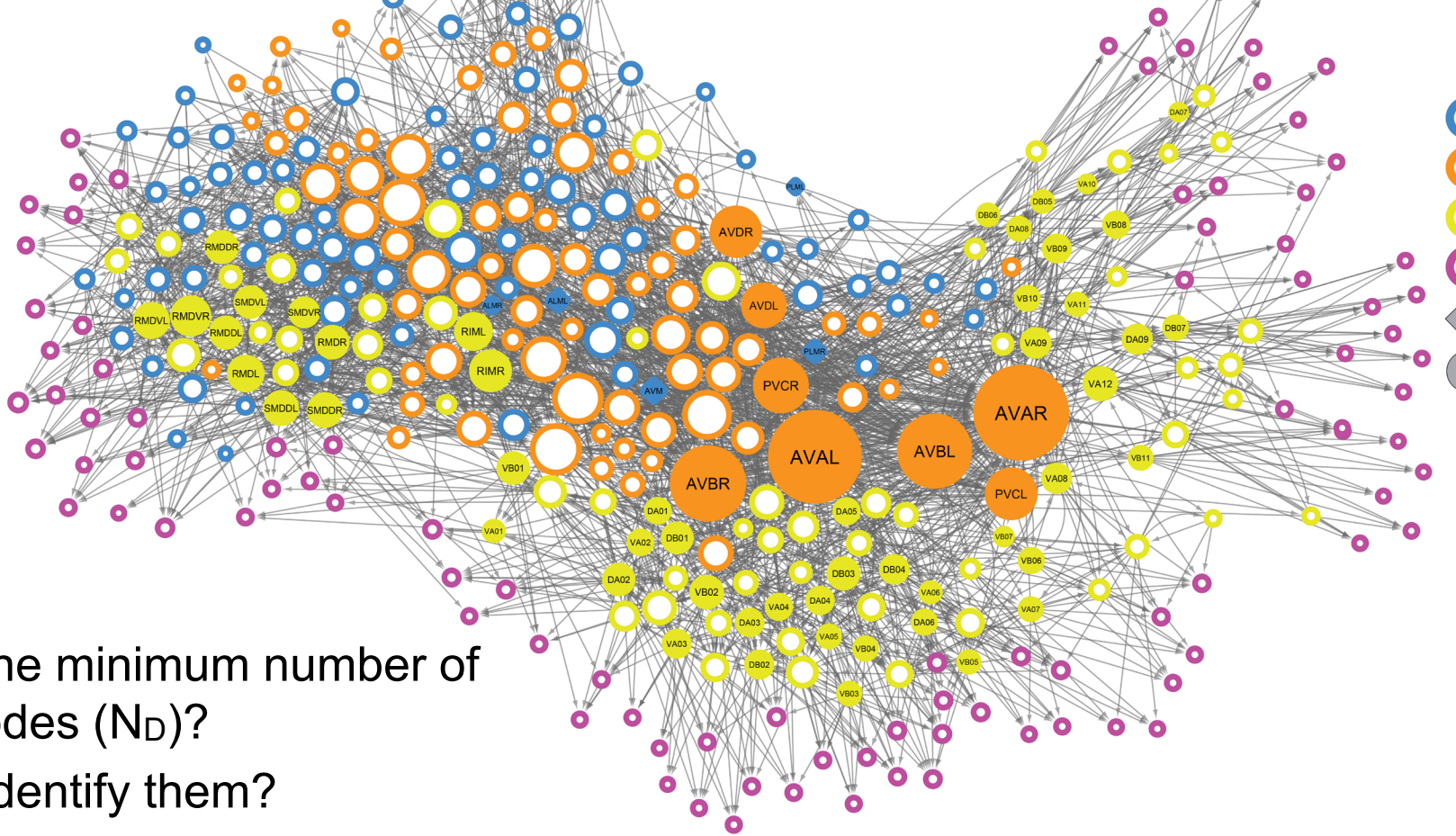
2. If brute-force search: $(2^N - 1)$ combinations.

$$\binom{N}{1} + \binom{N}{2} + \dots + \binom{N}{N} = 2^N - 1$$

3. Kalman's rank condition is hard to check for large system.

$$\text{rank } \mathbf{C} = N$$

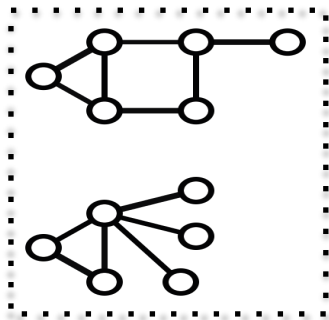
$$\mathbf{C} = [\mathbf{B}, \mathbf{A} \cdot \mathbf{B}, \mathbf{A}^2 \cdot \mathbf{B}, \dots, \mathbf{A}^{N-1} \cdot \mathbf{B}] \text{ has dimension } N \times NM.$$



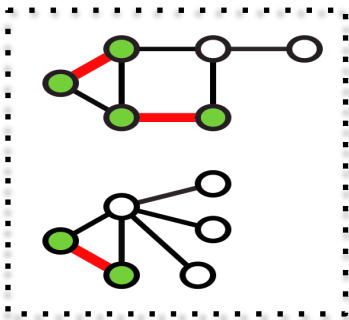
- What's the minimum number of driver nodes (N_D)?
- How to identify them?
- Which network characteristics determine N_D ?

Matching

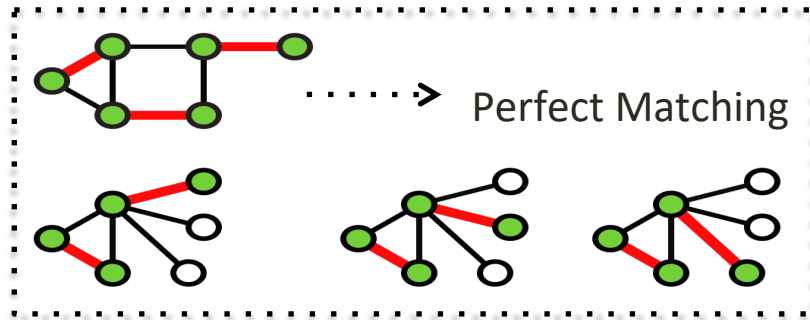
Network



Matching :
a set of edges without
common vertices.



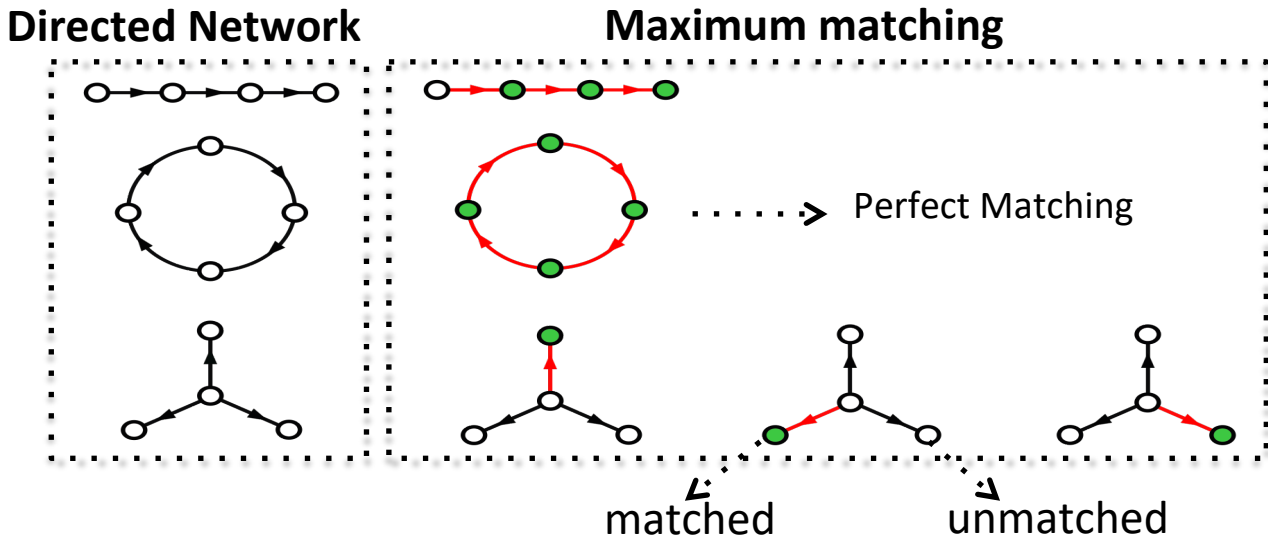
Maximum matching :
a matching of the largest size.





MATCHING IN DIRECTED NETWORKS:

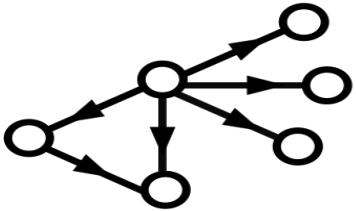
Matching: a set of edges **without common heads or tails.**



Minimum Input Theorem: Driver nodes = Unmatched nodes

EXAMPLES: Identifying the driver nodes

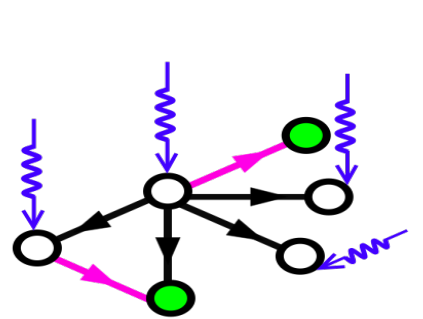
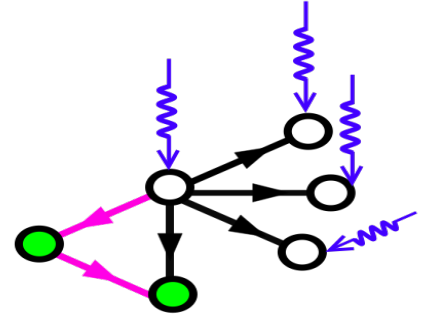
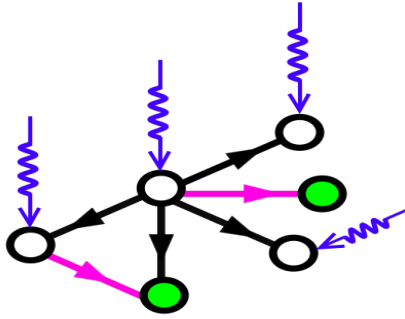
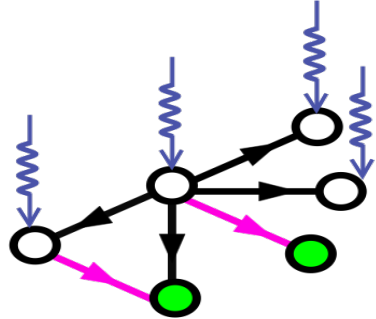
network

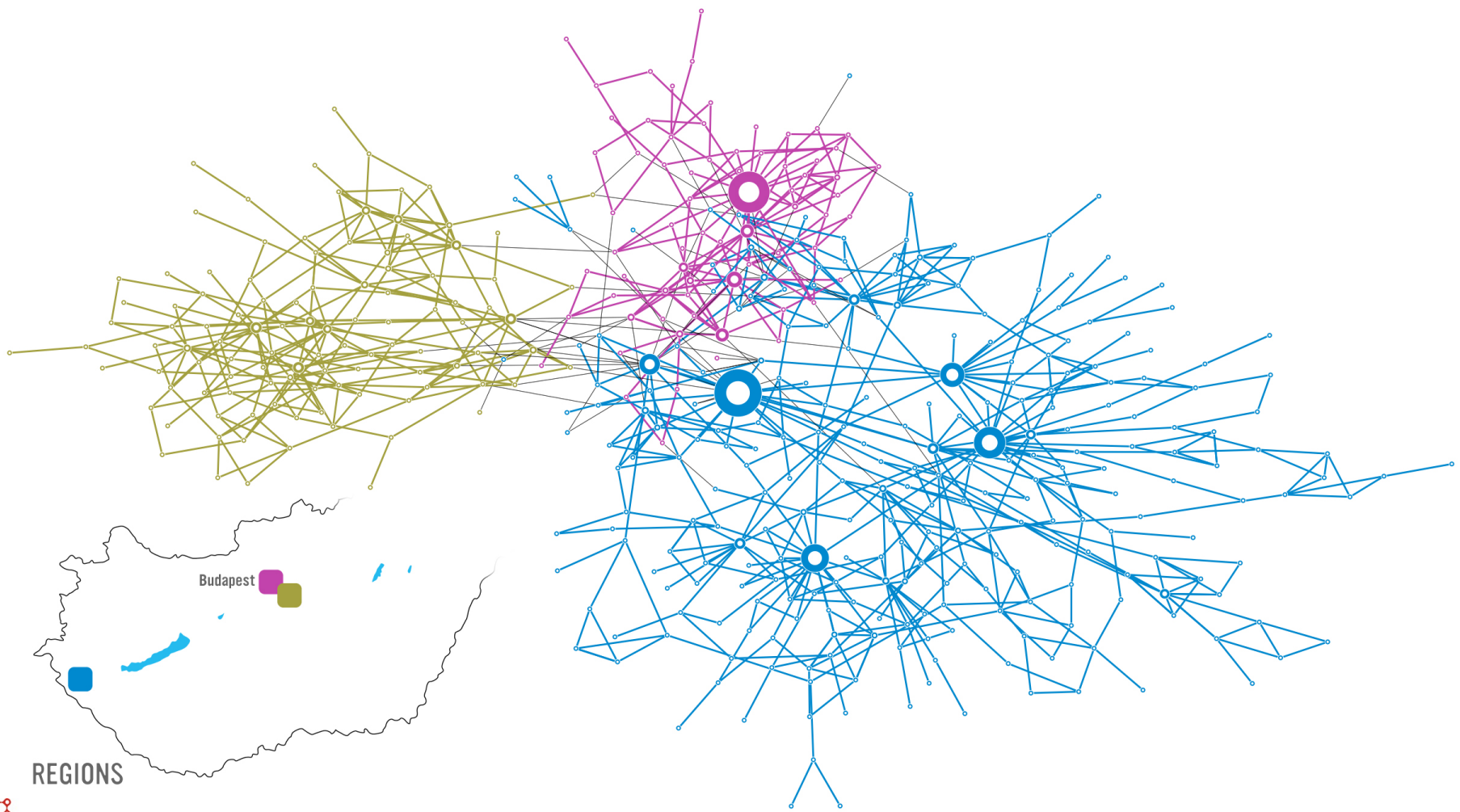


Brute-force search
 $O(2^N) \sim 10^{30}$ for $N=100$.
Hopeless!

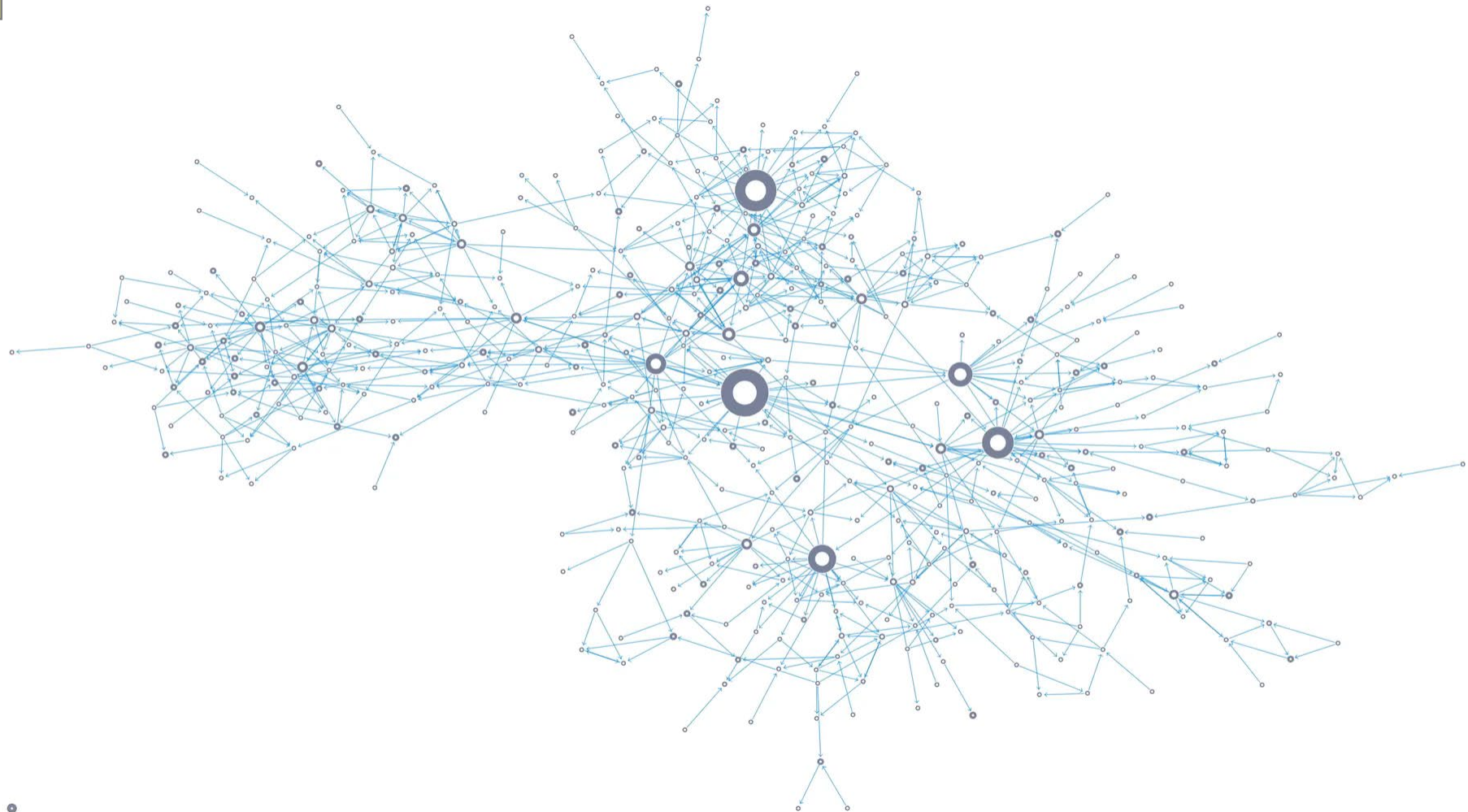
Hopcroft-Karp Algorithm
 $O(N^{1/2}L)$ Polynomial!
Fast even for $N \sim 10^6$.

Controlled network



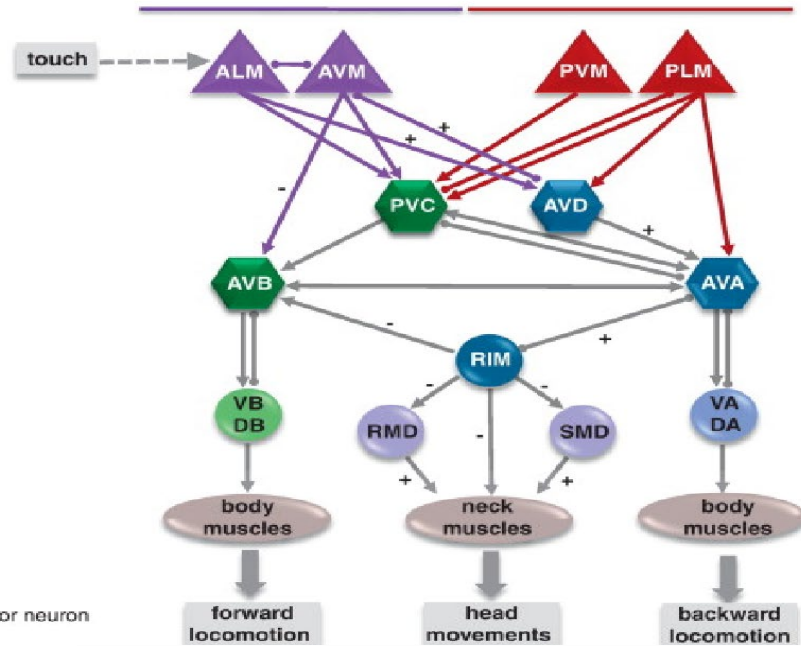
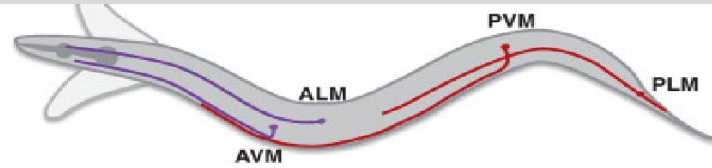


REGIONS





C Elegans: Light Body Touch Circuit

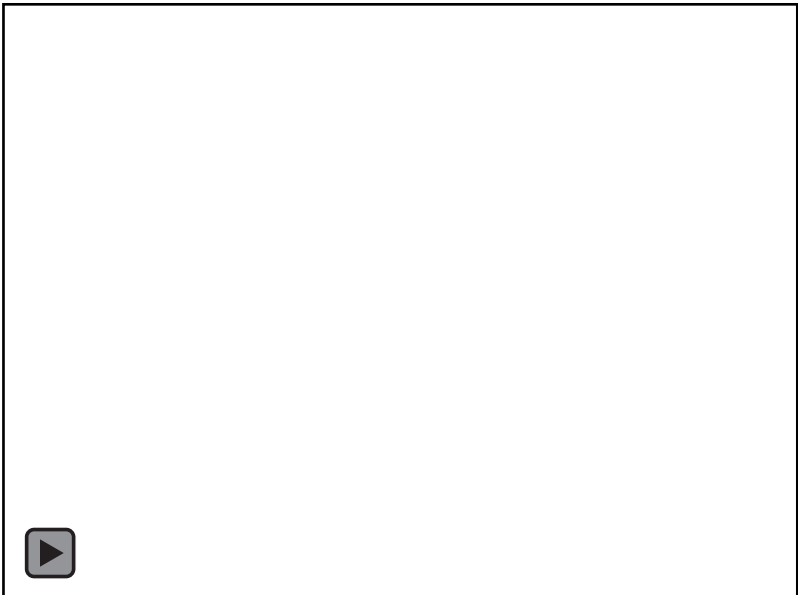


Sensory input

Control system

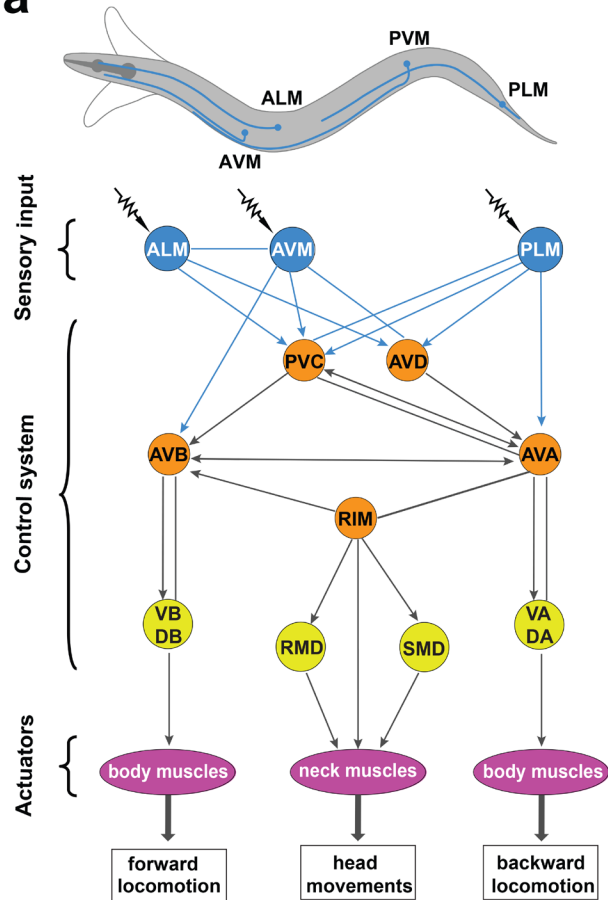
Actuators to be controlled

○ motor neuron



C Elegans: Light Body Touch Circuit

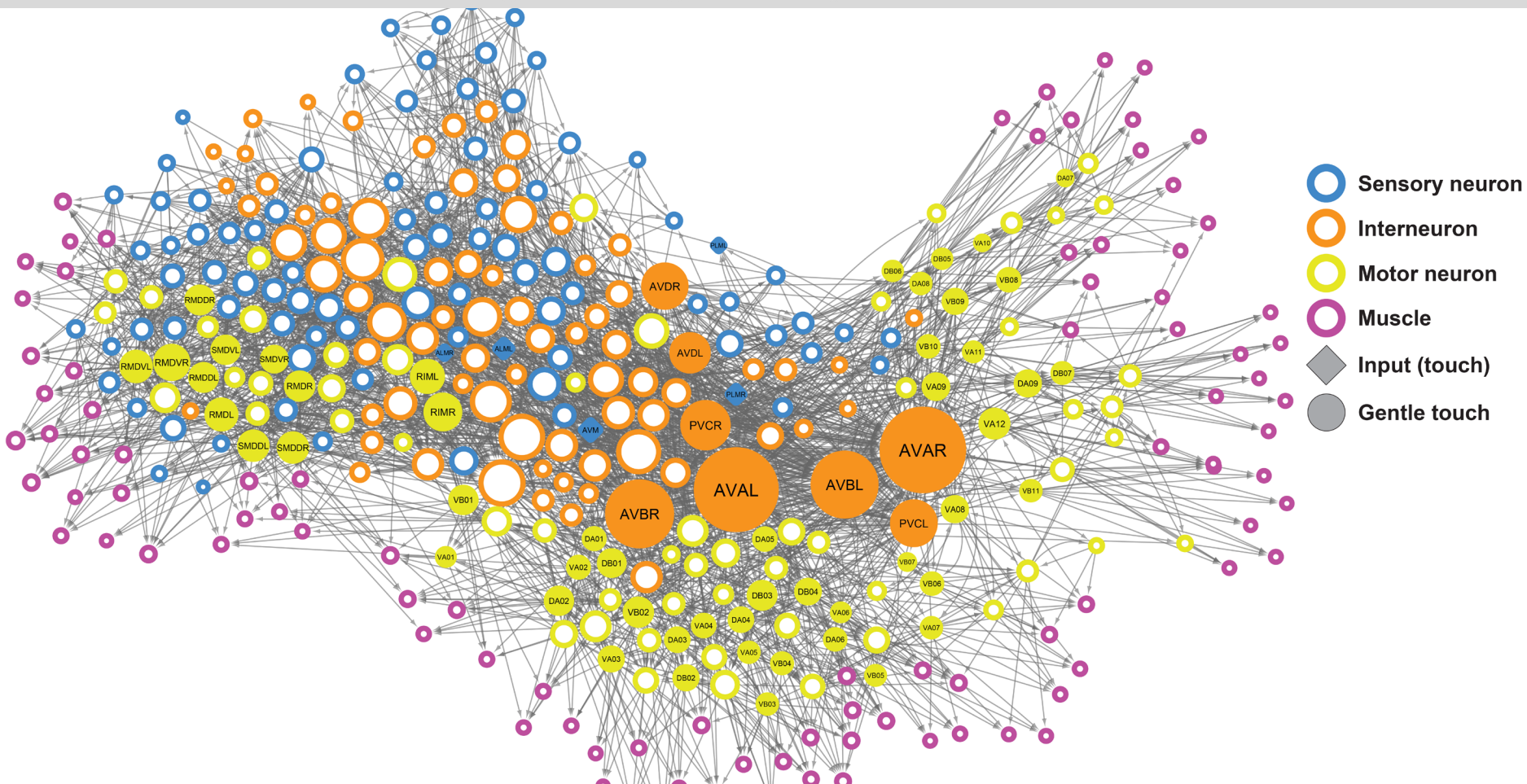
a

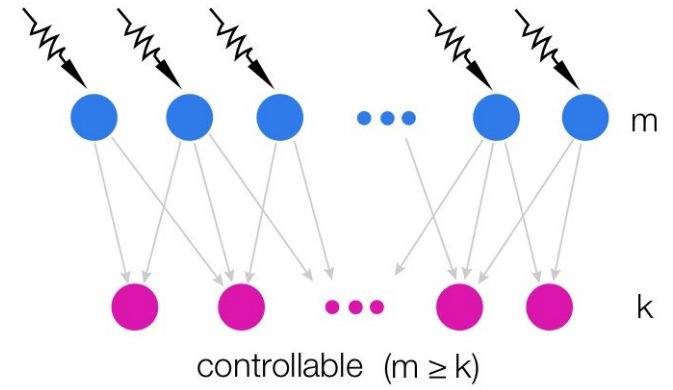
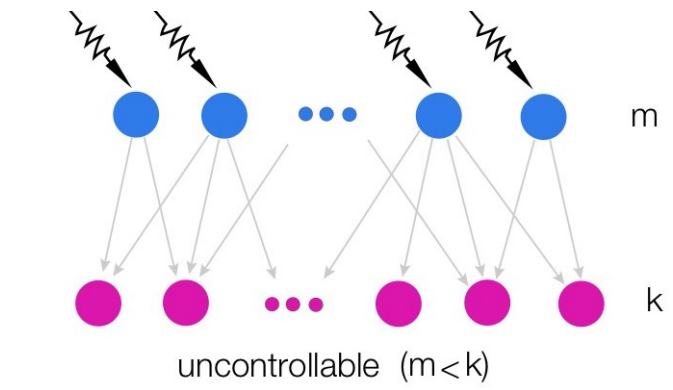
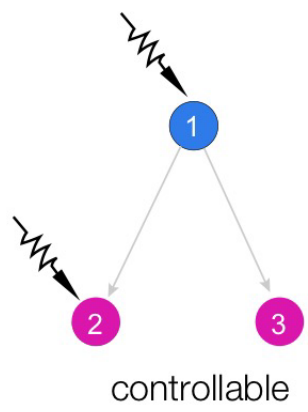
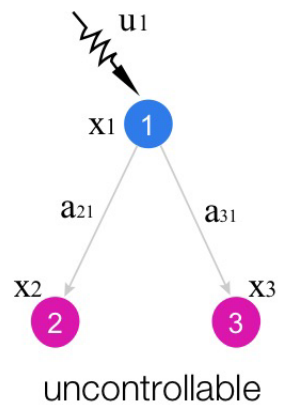


b

	Control	Predicted Neuron Classes	Experimental Facts
Control Muscles		DA, DB	loss of backward/forward locomotion
		DD	uncoordinated motion
		AVA	uncoordinated motion
		VA, VB, VD, AS	likely loss of locomotion
Control Motor Neurons		AVA, AVB	uncoordinated motion
		AVD	loss of reversal response
		PVC	loss of reversal response

C *Elegans*: Light Body Touch Circuit

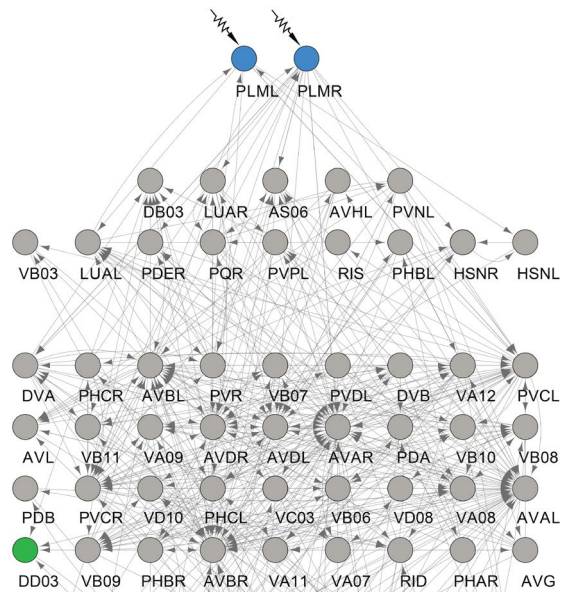




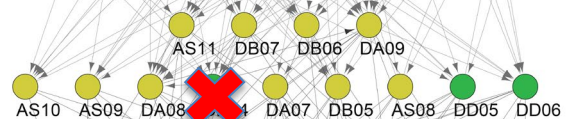


DD Class

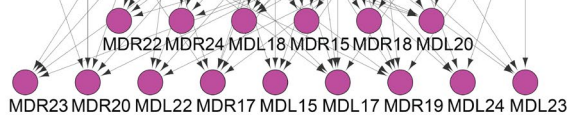
Receptor
Neurons



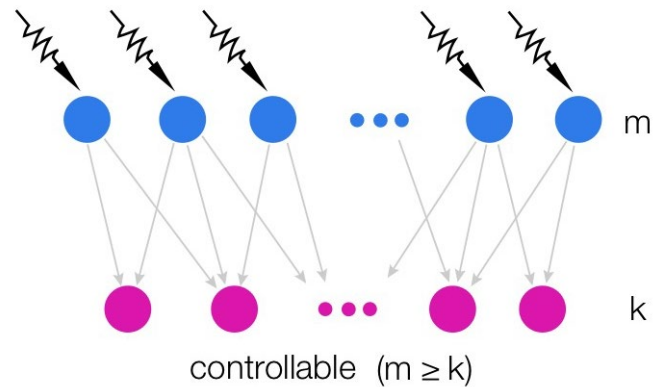
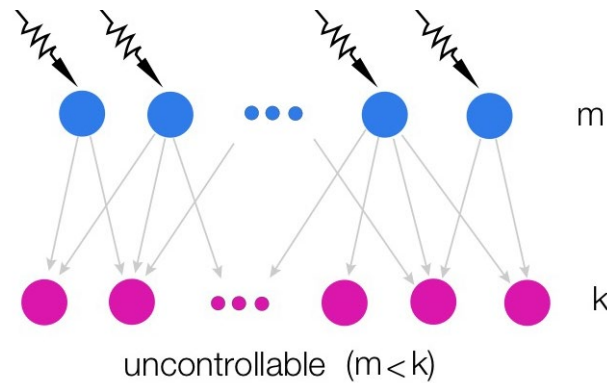
Muscles'
Neighbours



Muscles



● Assessed Neuronal Class



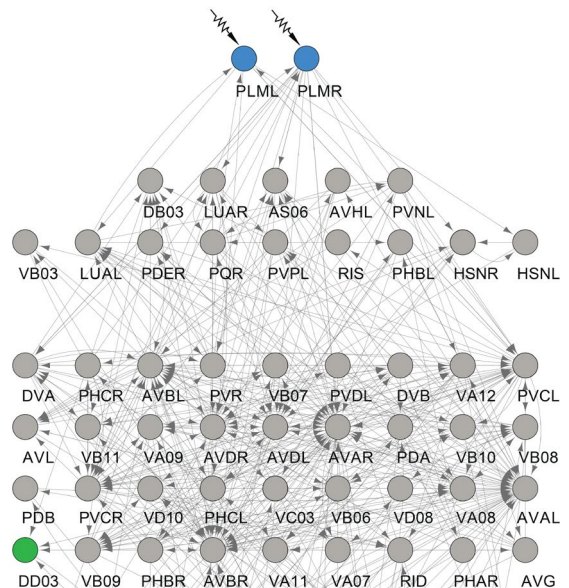
9 → 8

15 → 14

Yan, Vertes, Towlson, Chew, Walker, Schafer, Barabási, Nature (20



Receptor
Neurons



Muscles'
Neighbours

9 → 8

15 → 14

● Assessed Neuronal Class

The vast majority of neurons, if 'ablated' do not alter muscle controllability.

Of 279 neurons, only 12 neuronal classes affect muscle control.

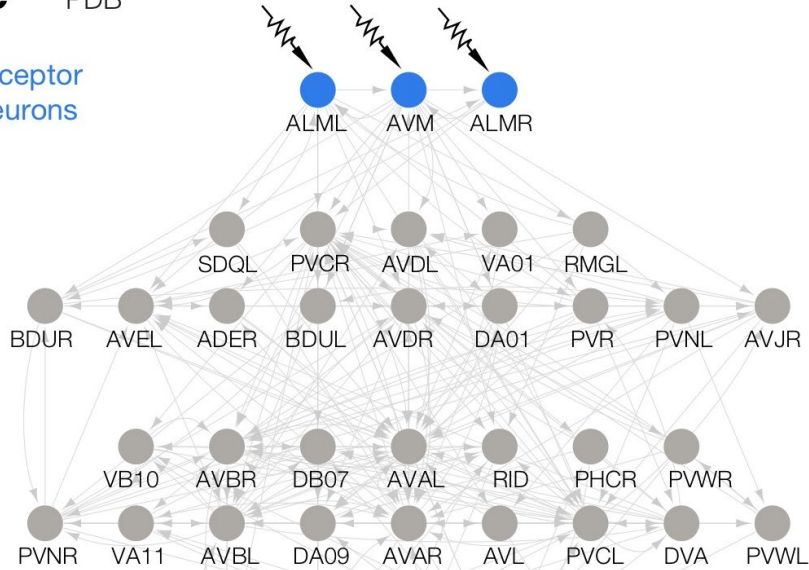


Neuron classes indispensable for network control (predictions)

Control	Predicted Neuron Classes	Experimental Facts
Control Muscles	DA, DB	loss of backward/forward locomotion
	DD	uncoordinated motion
	AVA	uncoordinated motion
	VA, VB, VD, AS	likely loss of locomotion
Control Motor Neurons	AVA, AVB	uncoordinated motion
	AVD	loss of reversal response
	PVC	loss of reversal response

e PDB

receptor
neurons



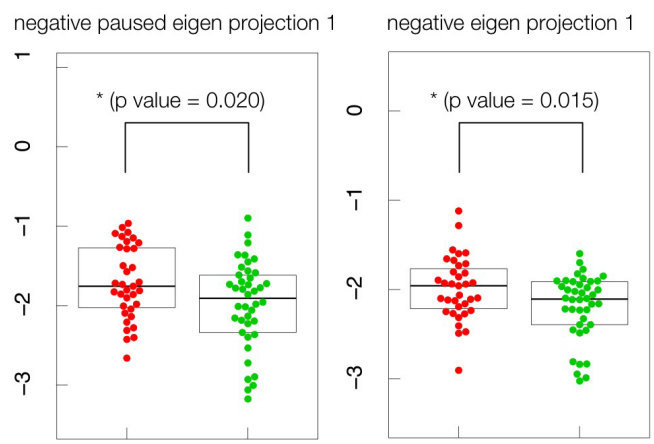
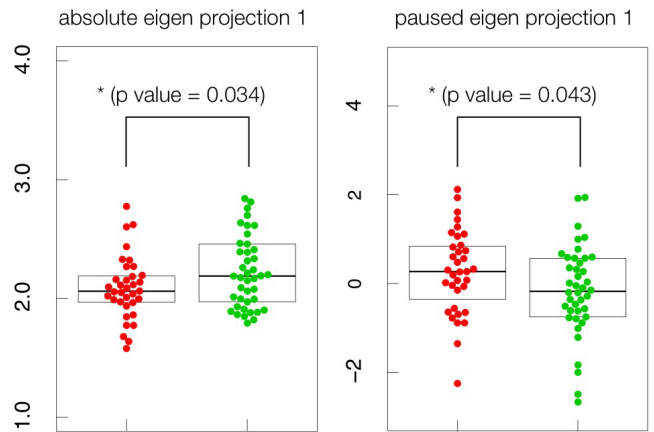
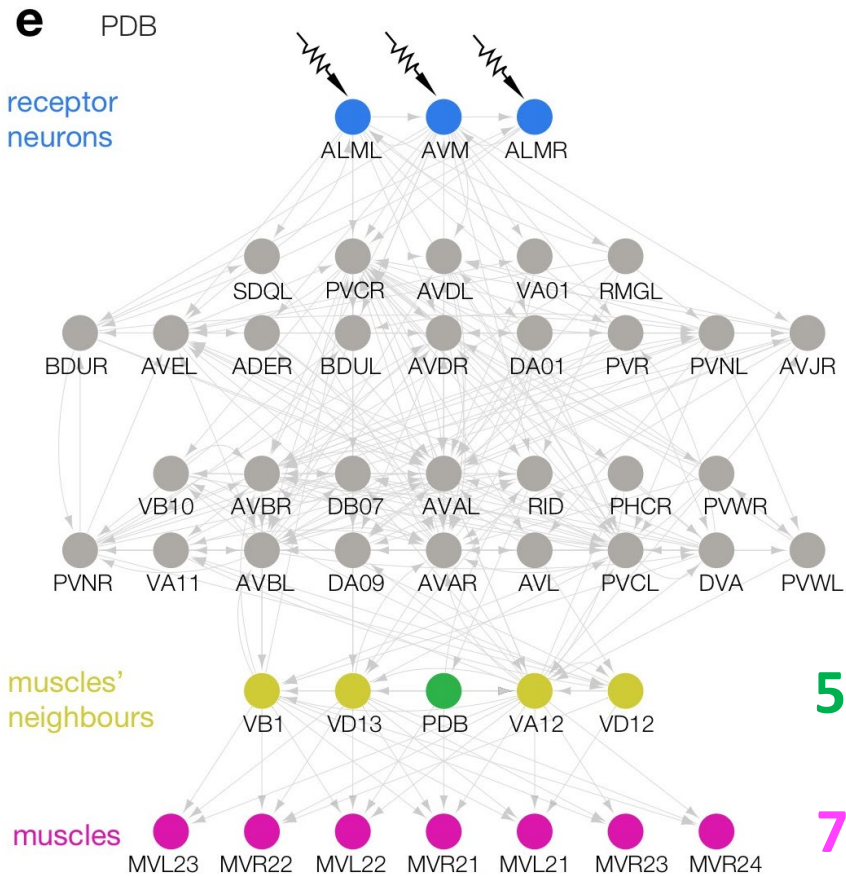
muscles'
neighbours

5 → 4

muscles

7 → 6

MVL23 MVR22 MVL22 MVR21 MVL21 MVR23 MVR24



• mock-ablated • PDB-ablated

Ablation effects of neuron classes on locomotion

Control	Predicted Neuron Classes	Experimental Facts
Control Muscles	DA, DB	loss of backward/forward locomotion
	DD	uncoordinated motion
	AVA	uncoordinated motion
	VA, VB, VD, AS	likely loss of locomotion
	PDB	verified by new experiments
Control Motor Neurons	AVA, AVB	uncoordinated motion
	AVD	loss of reversal response
	PVC	loss of reversal response



Network Science: Structure determines function.



Structure matters:

Robustness

Spreading processes

Controllability

Observability



Boston



Yang-Yu Liu
Harvard



Jean-Jacques Slotine
MIT



Gang Yan



Emma Towlson

Univ. of Cambridge



Petra Vértés



William R. Schafer



Yee Lian Chew



Denise S. Walker

We are looking for new lab members!

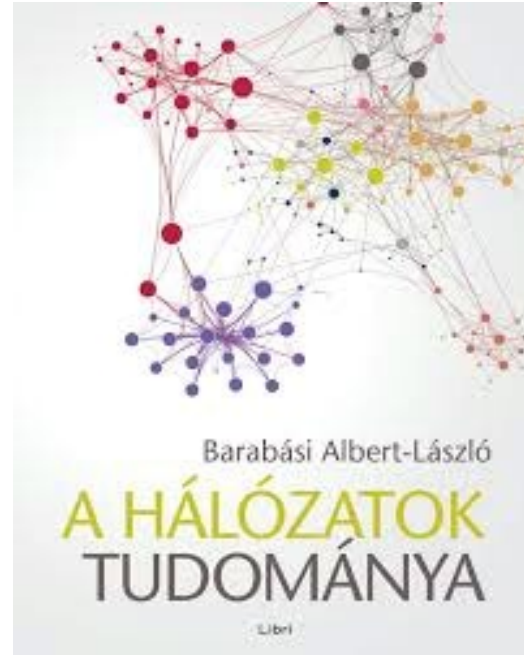


Talk to me if interested, or email: barabasi@gmail.com



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NETWORK SCIENCE



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