Automated, predictive, and interpretable modeling of *C. elegans* nociceptive escape dynamics

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Outline

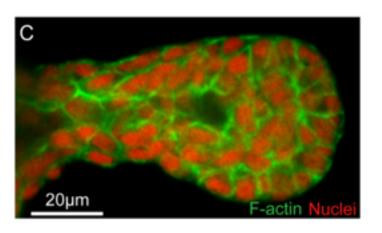
- What does my group do?
- Some philosophy
- Worms, take 1: statistics
- Worms, take 2: dynamics



- How biology processes information and learns?
 - -Neurons, individual cells, brains, populations...
 - What are the limits to our information processing capabilities?
 - What are the computational and biophysical mechanism used by biology to learn the environment?

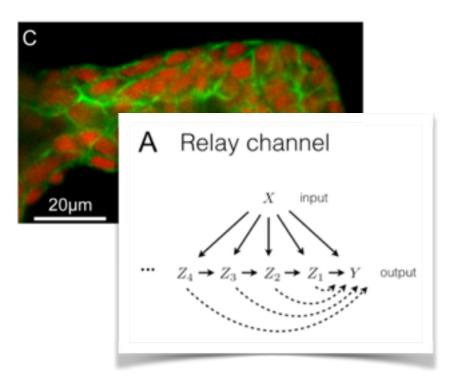


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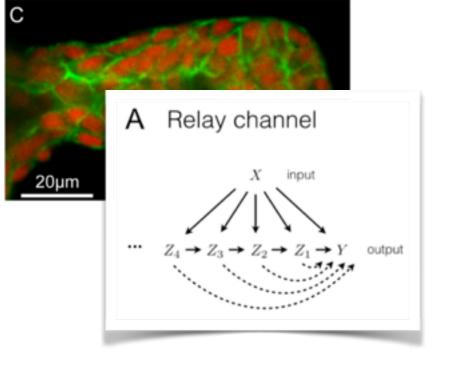


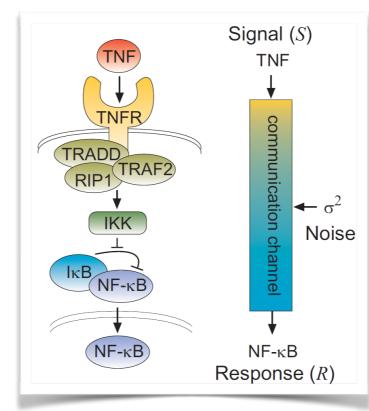
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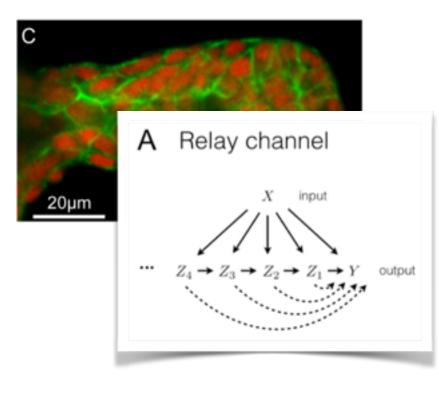
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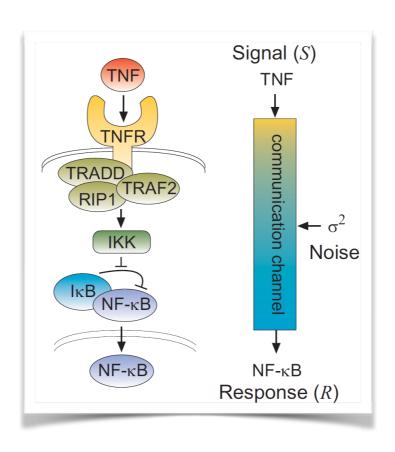


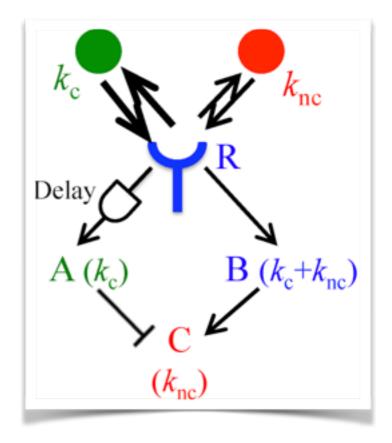




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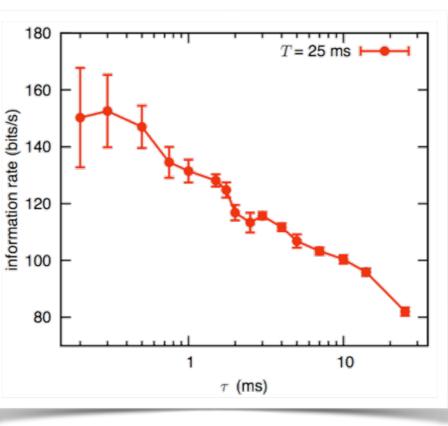
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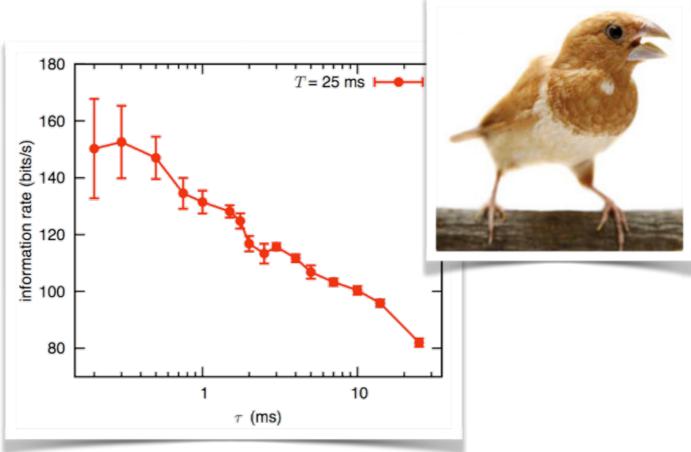






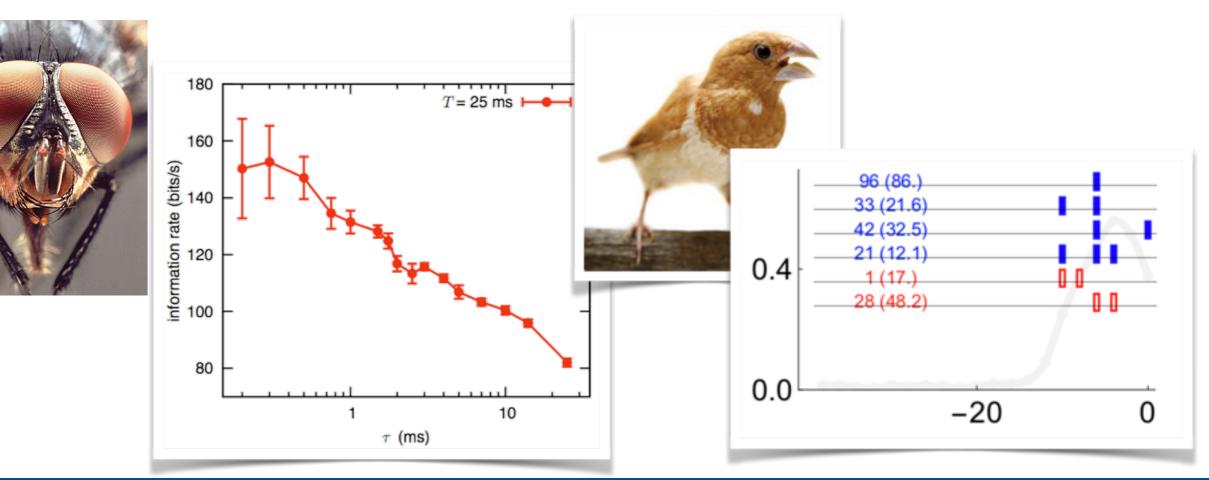
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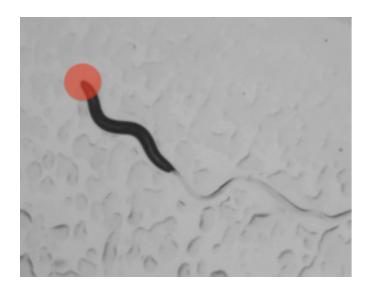


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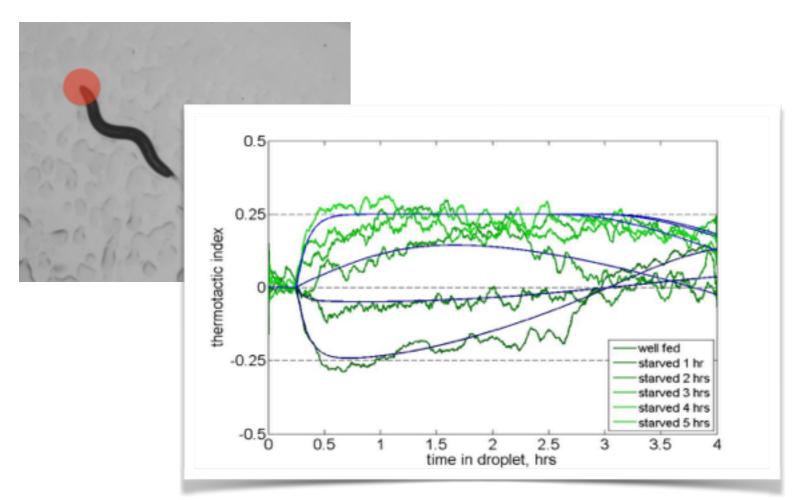


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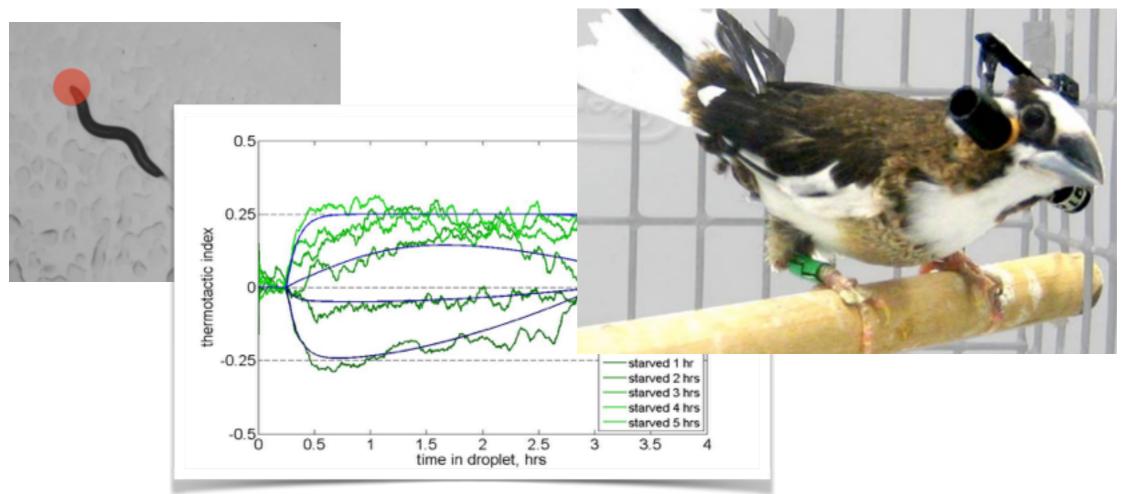


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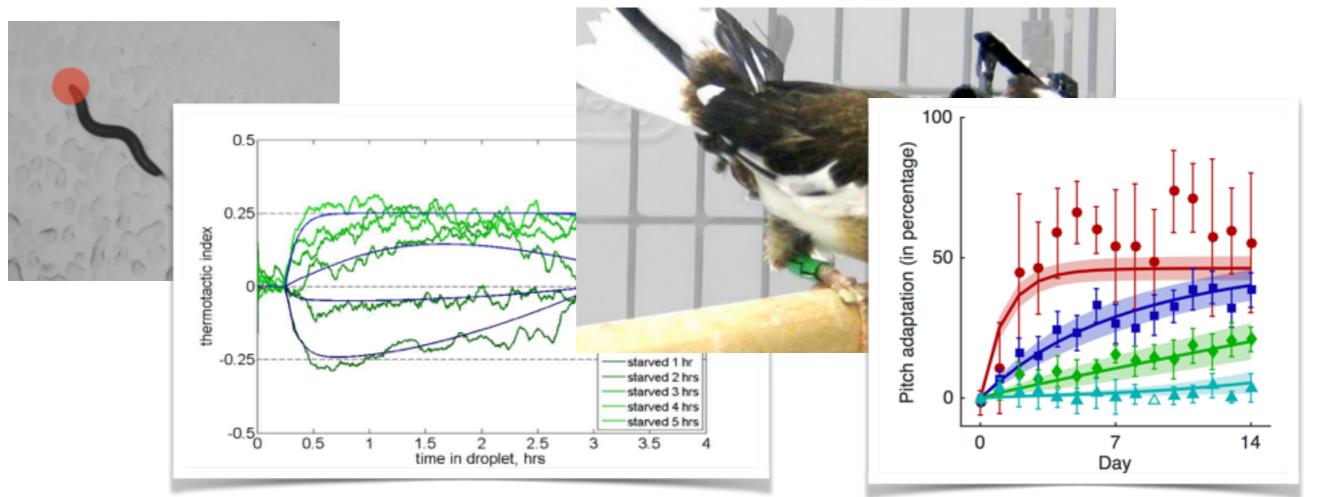


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Why do we study this?



Ilya Nemenman, KITP-SNAV 8/2018

Why do we study this?

"Studying string theory cannot be more exciting than studying the brain that can study string theory."



Thanks

- Bryan Daniels (Arizona State)
- Will Ryu (Toronto)
- KaWai (George) Leung (data science somewhere in Boston)
- Aliya Mohammadi (Toronto)

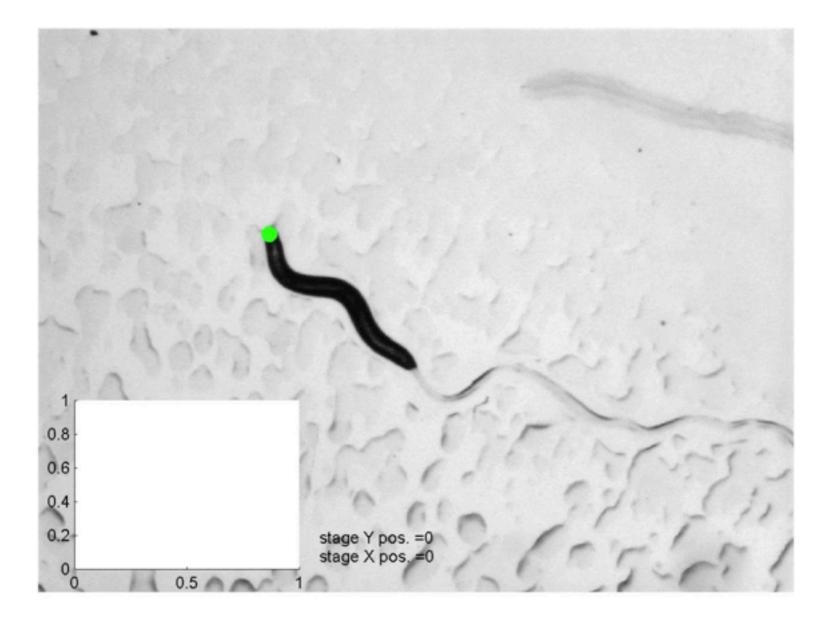


Successes of q-bio

- We know that circuits (neural, genetic, signaling) can be understood mathematically.
- Noise and individual variability are not just "...it happens," but can also be modeled.
- We (often) understand why the circuits are the way they are from control-theoretic, information-theoretic, evolutionary, and optimization principles.
- There is probably no "paradigm change", no "new physics" at the small circuits level: putting enough experiments, stat mech, and nonlinear dynamics together, we can understand every circuit.
- Measuring 1000s of variables is relatively easier than knowing what to do with the measurements.
- And yet, more is different, and we don't know how to deal with it.

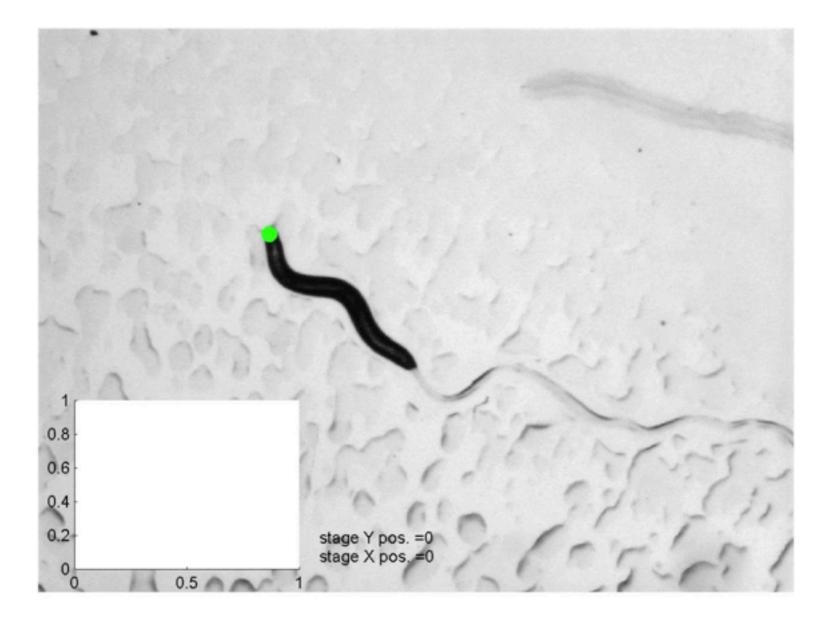


How do we model this?





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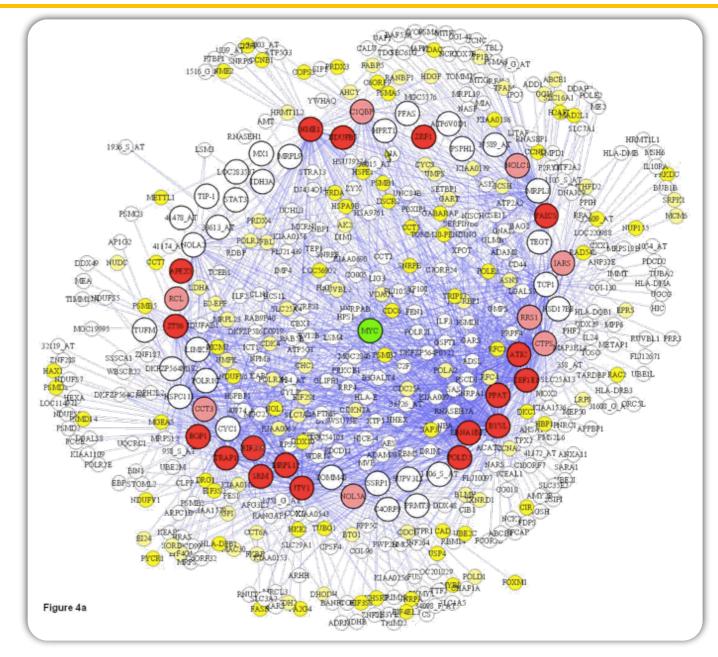




How do we go from circuits to organisms?

A culture's icons are a window onto its soul. Few would disagree that, in the culture of molecular biology that dominated much of the life sciences for the last third of the 20th century, the dominant icon was the double helix. In the present, post-modern, 'systems biology' era, however, it is, arguably, the hairball.

A.D. Lander. BMC Biology 2010, 8:40





Of exactitude in science

...In that Empire, the craft of Cartography attained such Perfection that the Map of a Single province covered the space of an entire City, and the Map of the Empire itself an entire Province. In the course of Time, these Extensive maps were found somehow wanting, and so the College of Cartographers evolved a Map of the Empire that was of the same Scale as the Empire and that coincided with it point for point. Less attentive to the Study of Cartography, succeeding Generations came to judge a map of such Magnitude cumbersome, and, not without Irreverence, they abandoned it to the Rigours of sun and Rain. In the western Deserts, tattered Fragments of the Map are still to be found, Sheltering an occasional Beast or beggar; in the whole Nation, no other relic is left of the Discipline of Geography.

> From Travels of Praiseworthy Men (1658) by J. A. Suarez Miranda (a fictional reference). By Jorge Luis Borges and Adolfo Bioy Casares. English translation quoted from J. L. Borges, A Universal History of Infamy, Penguin Books, London, 1975.





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 Theories must loose details and must be developed to explain limited sets of phenomena.



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- "Don't model bulldozers with quarks." (Goldenfeld and Kadanoff, 1999)
 Theories must loose details and must be developed to explain limited sets of phenomena.
- Otherwise: The best material model of a cat is another, or preferably the same, cat. (*Philosophy of Science*, Wiener and Rosenblueth, 1945)



Without loosing details, biology ceases to be science

- Western scientific tradition:
 - There are laws (of nature, of god, whatever). A rock is a rock everywhere. It falls the same in Pisa and in Atlanta.
 - There're causes and there are effects.
 - There is "useless information" (Oscar Wilde).
 - But this belief requires closing one's eyes to minor discrepancies
 - Two balls dropped from the Leaning Tower didn't actually land simultaneously.
 - "If we had the STM in the 1920s, there wouldn't be the Debye theory of solids." (H. Levine)

• Non-western tradition, e.g., buddhism

Pratityasamutpada: dependent origination: "Pratitya samutpada is sometimes called the teaching of cause and effect, but that can be misleading, because we usually think of cause and effect as separate entities, with cause always preceding effect, and one cause leading to one effect. According to the teaching of Interdependent Co-Arising, cause and effect co-arise (samutpada) and everything is a result of multiple causes and conditions... " — Thich Nhat Hanh



So...

- Are there phenomenological, coarse-grained, and yet functionally accurate representations of activity of (some) biological systems, or are we forever doomed to every detail mattering?
 - Such models would not answer *every* question, but specific questions on coarse scales.
 - How can we learn such phenomenological models directly from data?

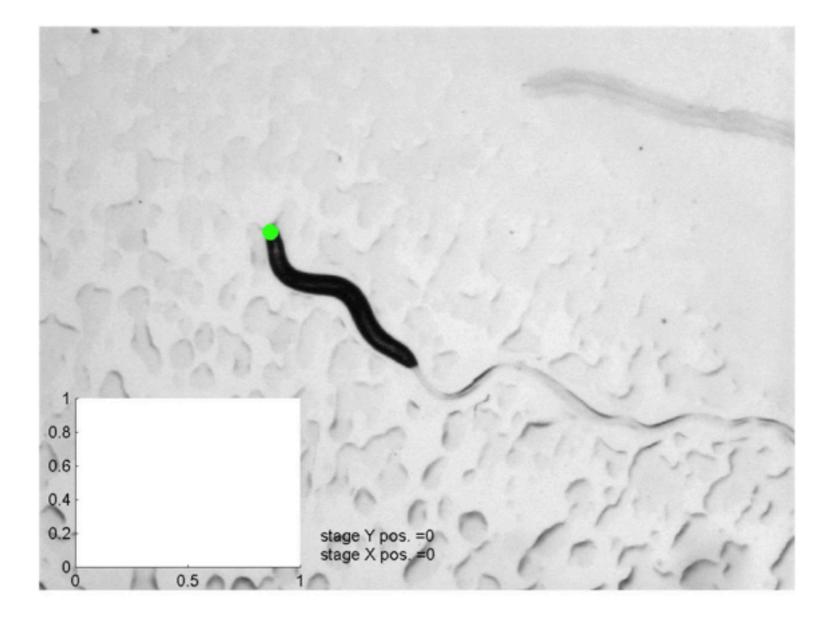


In this talk

- We will study one data set of nociceptive escape response in the worm.
- We will first build a purely phenomenological model of this process, designed specifically to answer behavioral questions.
- We will then build a dynamical model of the same data using an automated inference system.

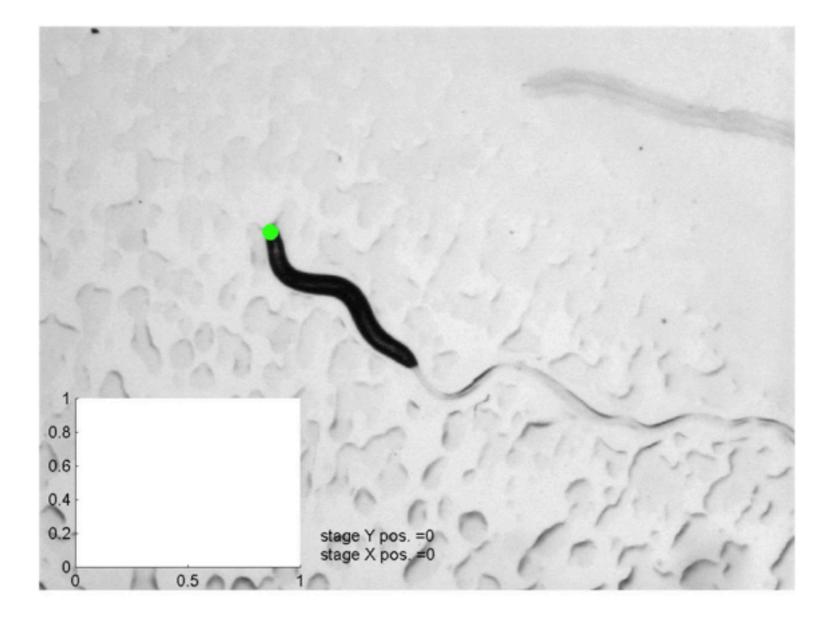


Getting back to the worms





Getting back to the worms



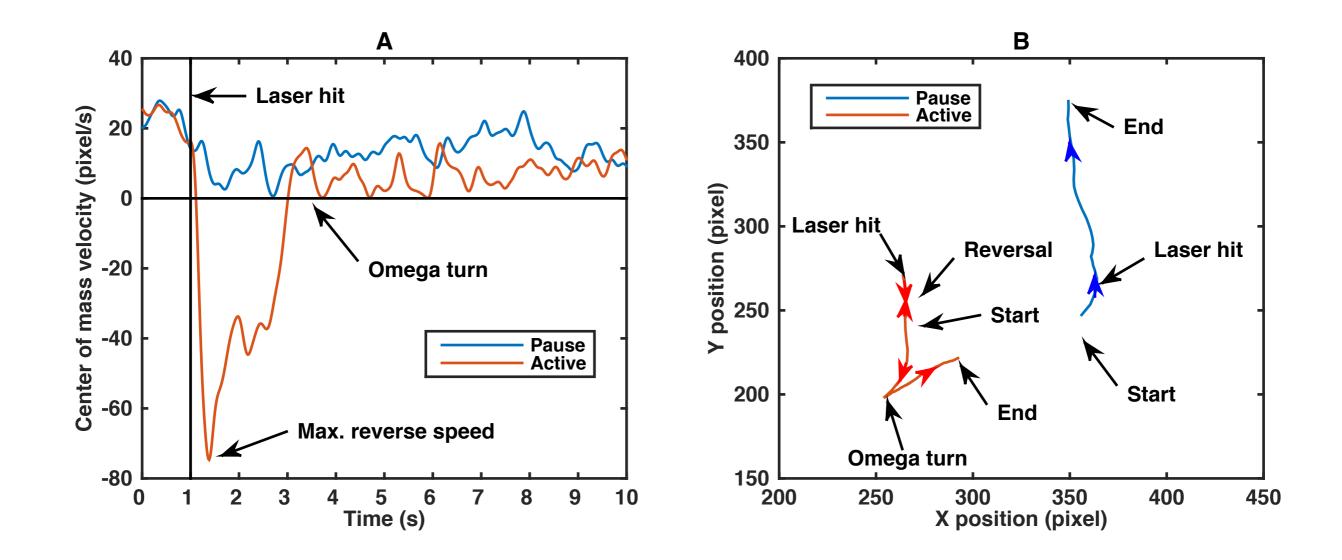


Questions

- How does the sensory information influence the behavior?
 - Can we predict the behavior from the sensory signals?
 - Can we postdict the sensory signals from the behavior?
- Nociception
 - Can't ask an animal "Could you please rate the pain you experience on the scale of 1-10?"
 - How do we test **analgesics** using animal models?
- How to distinguish analgesic effects of drugs from effects on motor behavior?
 - An old joke: how do you prove that a roach hears with its legs?
- How to model complex behaviors?
 - Detailed, mechanistic modeling, from molecules to neurons to behavior over long time scales is *unlikely to work*.
 - Need phenomenological models.

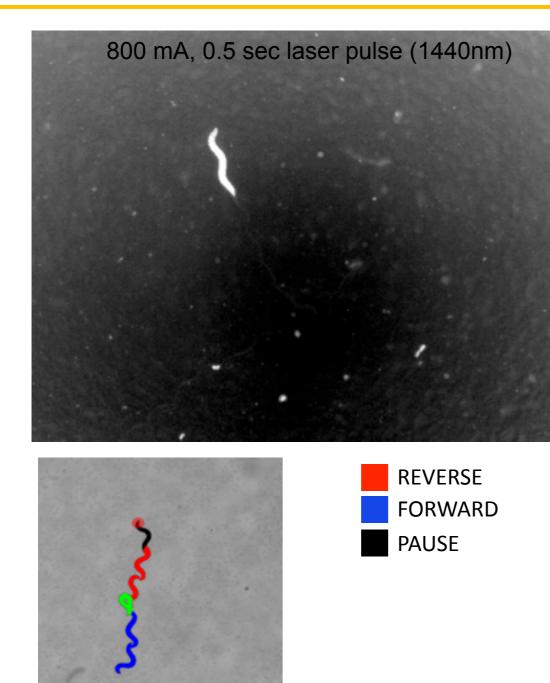


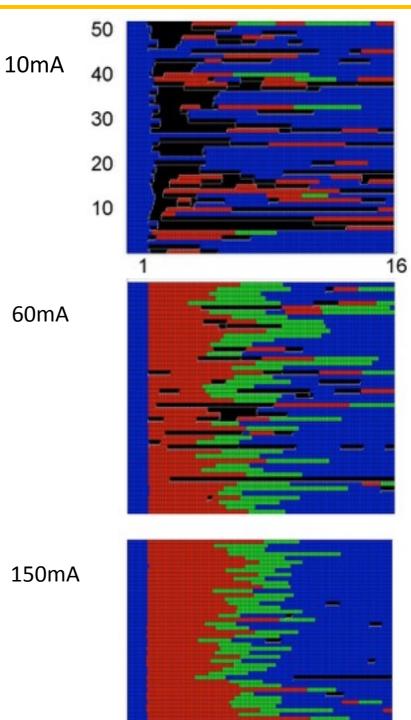
Typical center of mass trajectories





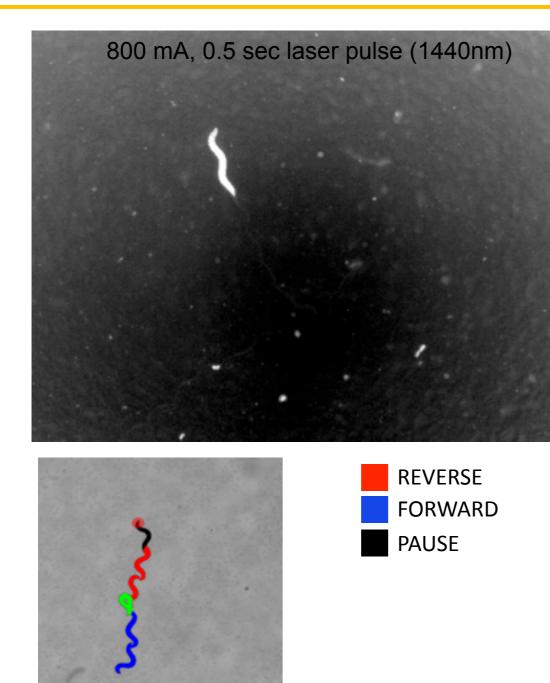
Properties of the escape behavior: Statistics of states depends on stimuli

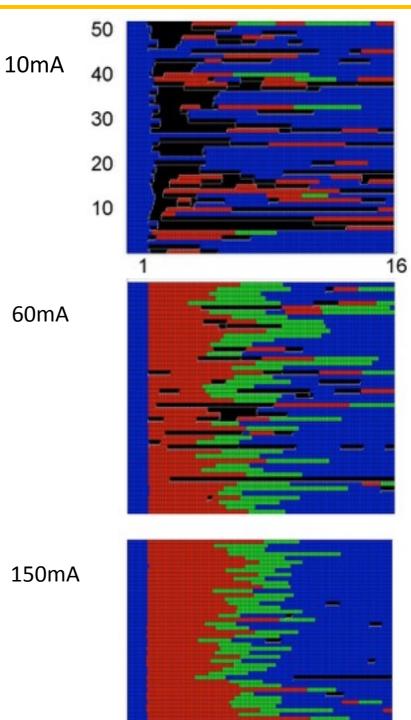






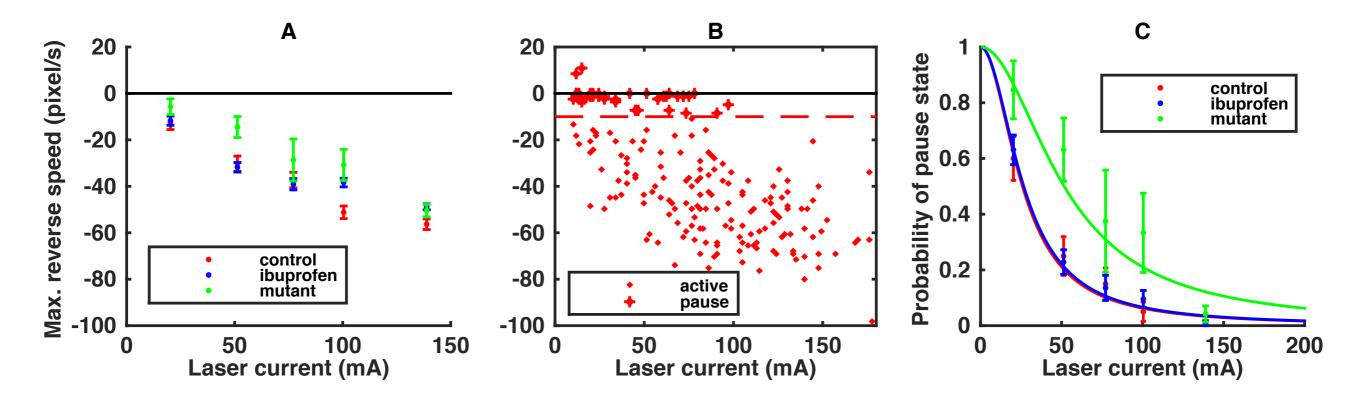
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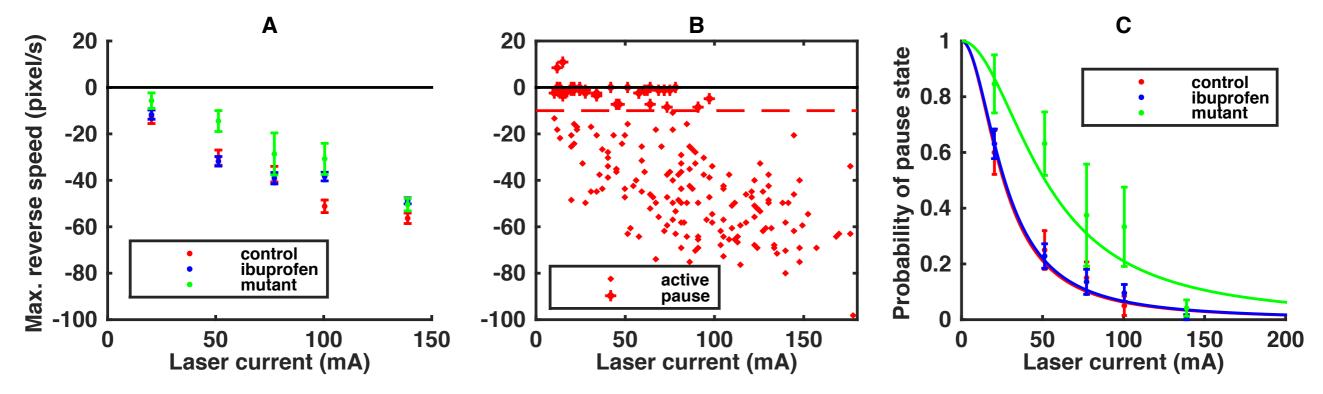


Simple statistical characterizations are insufficient: Need whole behavior quantification





Simple statistical characterizations are insufficient: Need whole behavior quantification



- Max escape velocity shows little predictive power.
- Analysis made complicated by having paused and active escaping worms.
- Simple statistics show little power to distinguish effects of perturbations, which are visually significant.



Modeling whole behavior: Bayes to the rescue

$$P(I|\mathbf{v}) = \frac{P(\mathbf{v}|I)P(I)}{P(\mathbf{v})} = \frac{1}{Z}P(\mathbf{v}|I)P(I)$$

$$P(\mathbf{v}|I) = P(\mathbf{v}|s=p,I)P(s=p|I) + P(\mathbf{v}|s=a,I)P(s=a|I).$$

$$P(s = a | I, \mathcal{I}_0) = 1 - P(s = p | I, \mathcal{I}_0) = \frac{(I/\mathcal{I}_0)^2}{1 + (I/\mathcal{I}_0)^2}$$



Modeling whole behavior: Templated escape response

$$P(\mathbf{v}|a,I) = \frac{1}{(2\pi)^{\frac{T}{2}} |\Sigma_a|^{\frac{1}{2}}} \times \exp\left[-\frac{1}{2}(\mathbf{v} - f_{\mathcal{I}_1,\mathcal{I}_2}(I)\mathbf{u}_a)^{\mathrm{T}}\Sigma_a^{-1}(\mathbf{v} - f_{\mathcal{I}_1,\mathcal{I}_2}(I)\mathbf{u}_a)\right]$$

$$f(I) \equiv f_{\mathcal{I}_1,\mathcal{I}_2}(I) = \mathcal{I}_1 + \frac{I}{1 + I/\mathcal{I}_2}$$



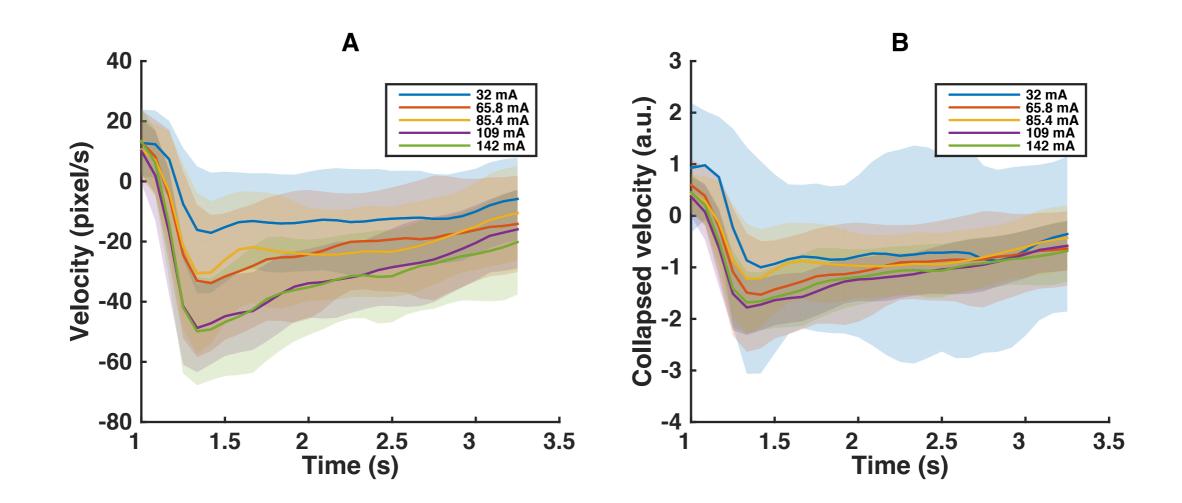
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$$\begin{split} P(\mathbf{v}|a,I) &= \frac{1}{(2\pi)^{\frac{T}{2}} |\Sigma_a|^{\frac{1}{2}}} \times \exp\left[-\frac{1}{2}(\mathbf{v} - f_{\mathcal{I}_1,\mathcal{I}_2}(I)\mathbf{u}_a)^{\mathrm{T}}\Sigma_a^{-1}(\mathbf{v} - f_{\mathcal{I}_1,\mathcal{I}_2}(I)\mathbf{u}_a)\right] \\ f(I) &\equiv f_{\mathcal{I}_1,\mathcal{I}_2}(I) = \mathcal{I}_1 + \frac{I}{1 + I/\mathcal{I}_2} \end{split}$$

Similar templating (but without rescaling) for pausing.

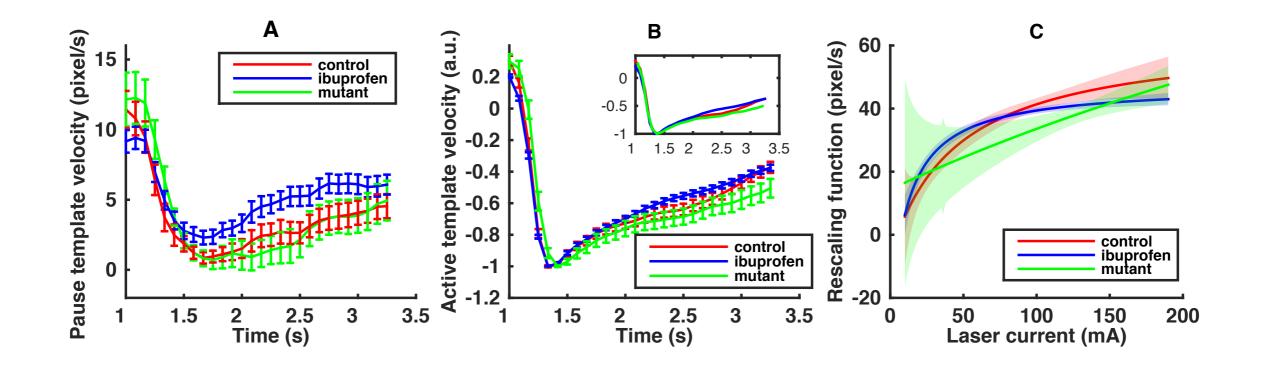


How does the templating assumption work?





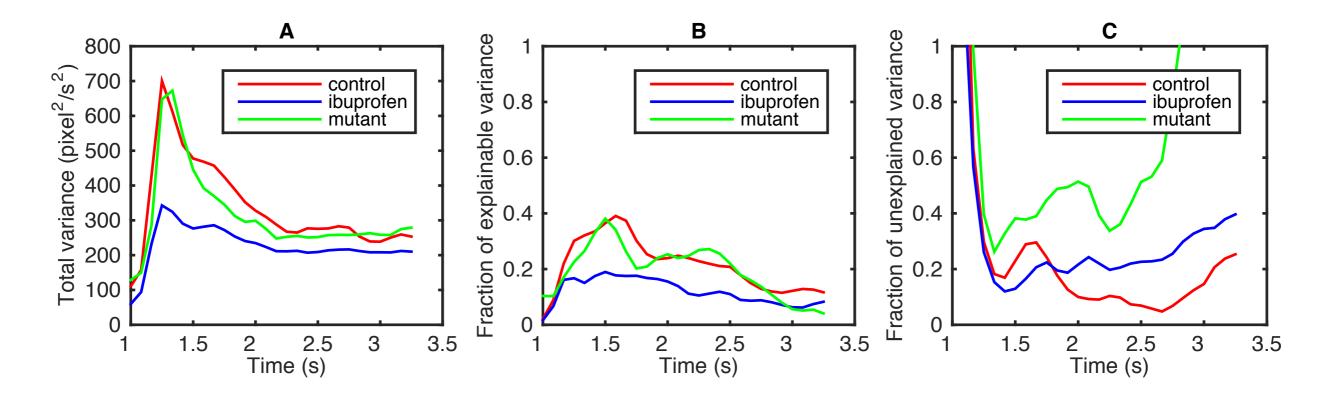
The templates and the scaling functions



- Ibuprofen treatment does not change the template, and only changes parameters of the scaling function.
- Mutant changes the template and changes the shape of the scaling function!



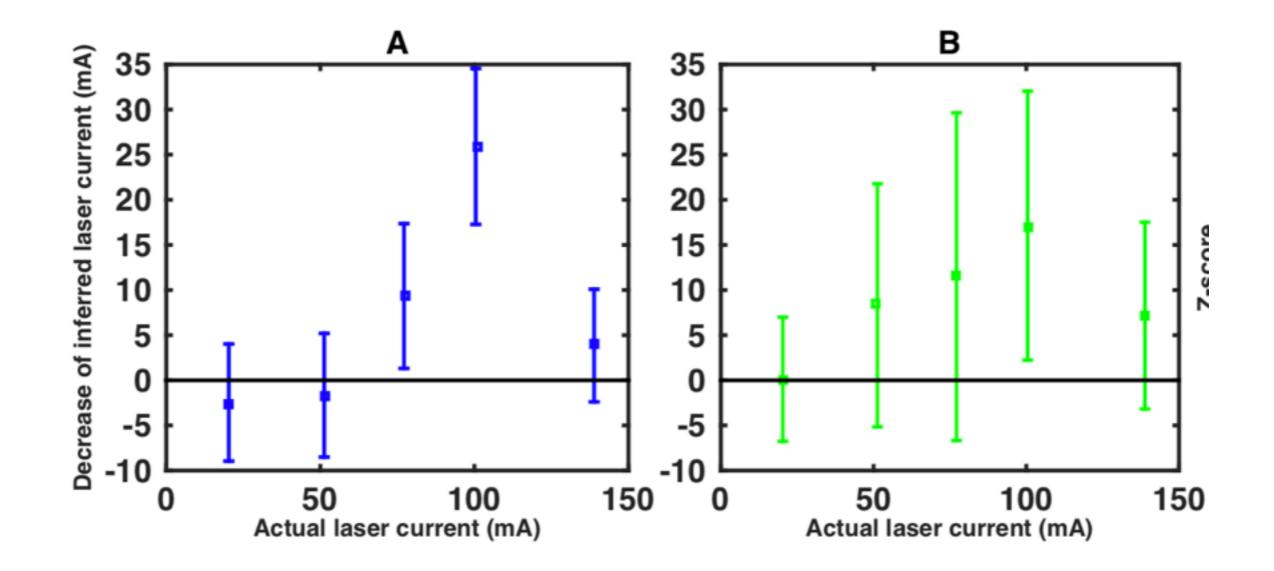
Explanatory power of the template model



- The model has a much worse explanatory power for the mutant. Mutant changes the worm behavior qualitatively.
- Conclusion: mutant is not an analgesic/sensory mutant only.



Can quantify analgesic effects





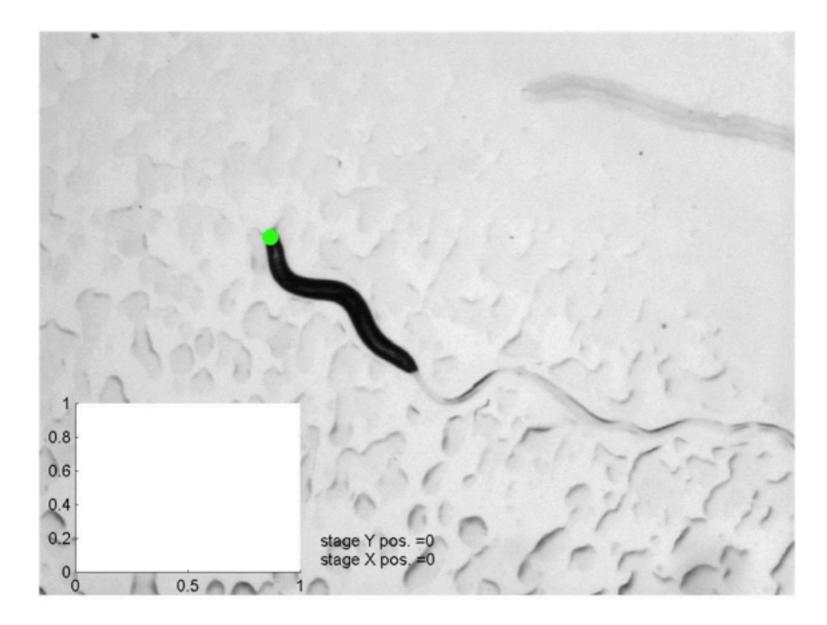
Summary I:

- Can relate stimulus to behavior in a quantitative model.
- Can quantify analgesic effects.
- Can say if the effect is more than analgesic.

• But: can we automate the modeling?

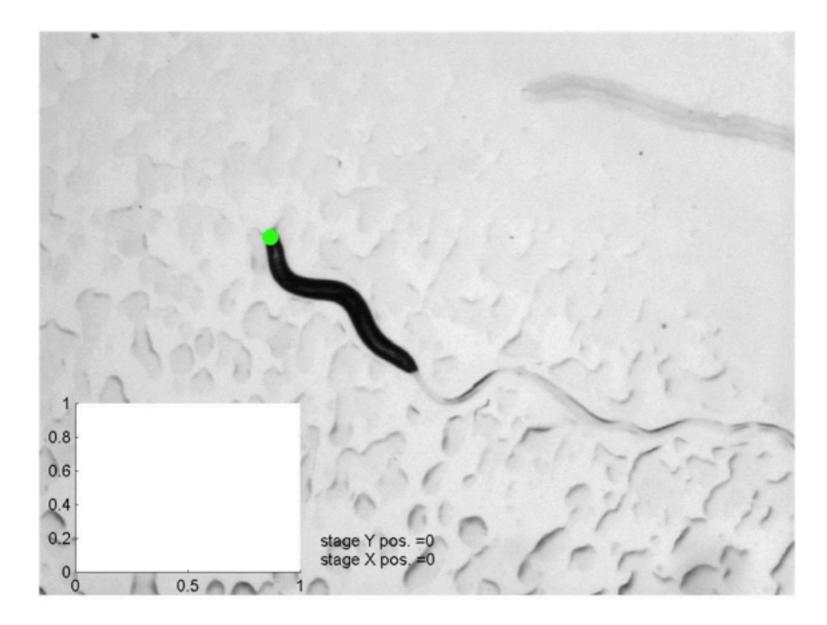


Can we infer the equations governing the worm's dynamics?





Can we infer the equations governing the worm's dynamics?





First steps for dynamics (and keep the worm in mind)

- Assume that dynamics of cellular networks is temporally local, given by ordinary differential equations.
 - Do not fit curves; fit dynamics.
- Neglect stochasticity, and spatial structure for now

$$\begin{cases} \frac{dx_1}{dt} = f_1(x_1, x_2, \dots, x_n) \\ \dots \\ \frac{dx_n}{dt} = f_n(x_1, x_2, \dots, x_n) \end{cases}$$



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- Can we automatically fit these functions f_i from data?
 - How do we enumerate the set of all possible multivariate functions?
 - How do we search through this list?
 - How do we not overfit?



The field (and we) has worked on this problem for a while

- Bottom-up methods, reducing a known microscopic, mechanistic network (not the easiest path).
- Top-down methods that build phenomenological models from data directly, and without reconstructing a mechanistic network as an intermediate step
 - Crutchfield and McNamara, Compl Syst 1987
 - Voit et al, Theor Biol Med Model 2006
 - Lillacci and Khammash, PLoS CB 2010
 - Munsky, et al., MSB 2009, Science 2013
 - Lipson et al., Science 2009, Phys Biol 2011 EUREQA
 - Brunton et al., 2016 SINDY
 - AutomatedStatistician.com

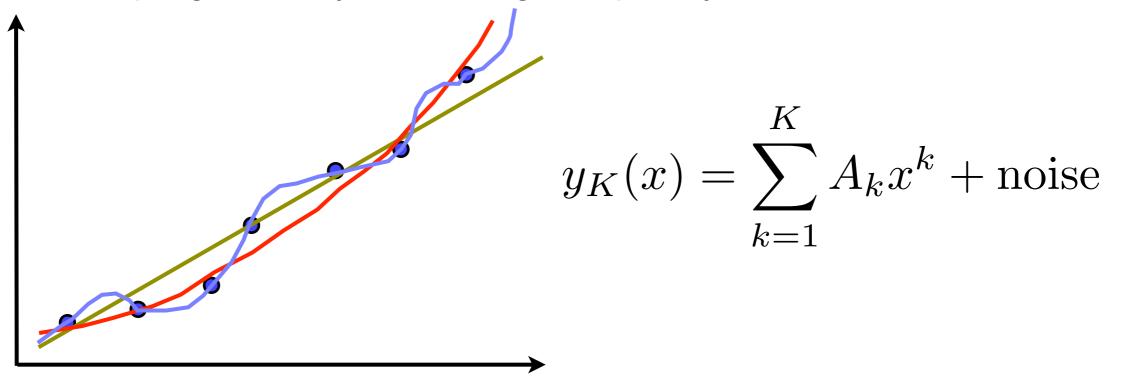


Can we avoid the exhaustive search and the need for the correct basis?



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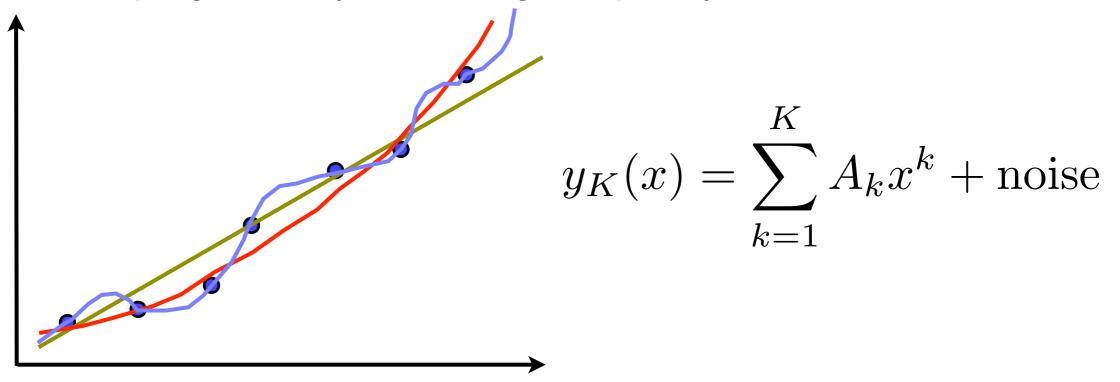
 Do not need an exhaustive search or exact fits when fitting dimensional curves with progressively increasing complexity





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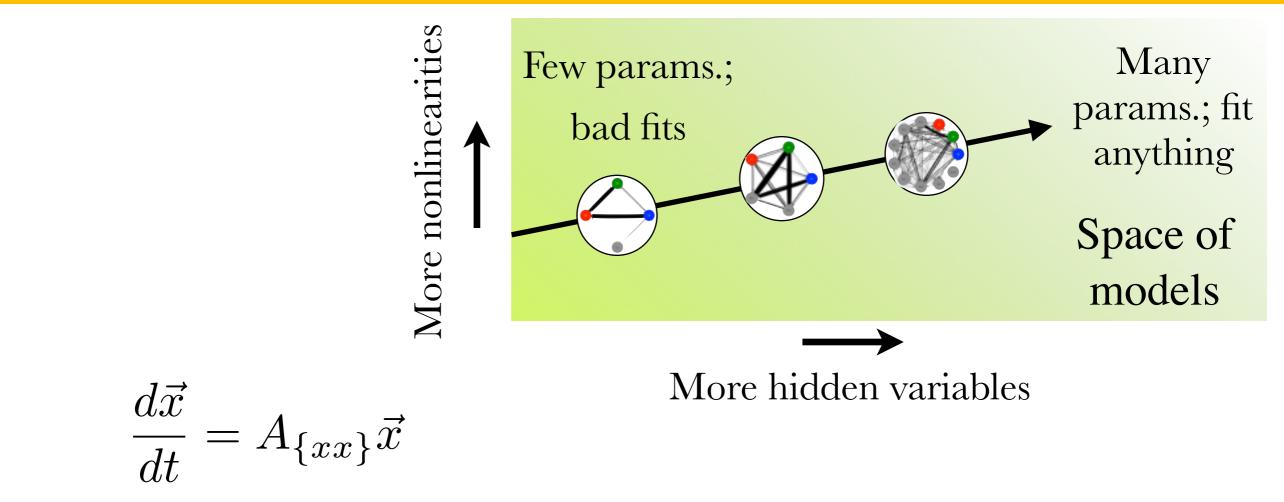
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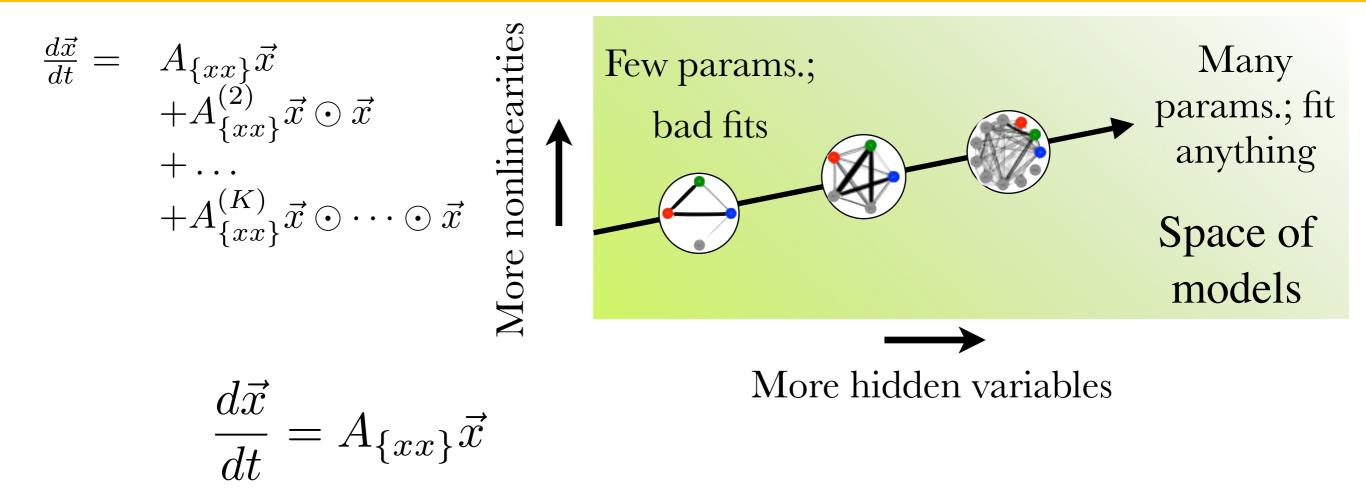
- Use **nested**, **complete** model families, e.g., Taylor series.
- Use Bayesian model selection to limit the complexity of the search space (the value of maximum K).

Schwartz, Ann Stat 1978; MacKay, Neural Comp, 1992 Balasubramanian, Neural Comp, 1996; Nemenman, Neural Comp, 2005

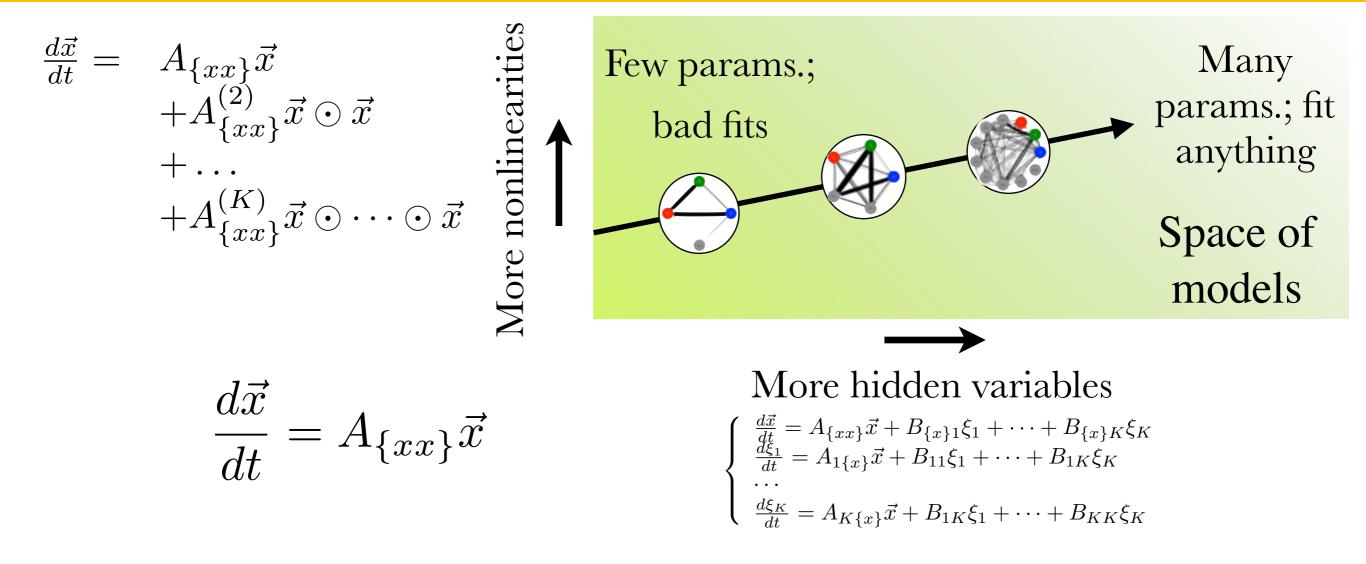




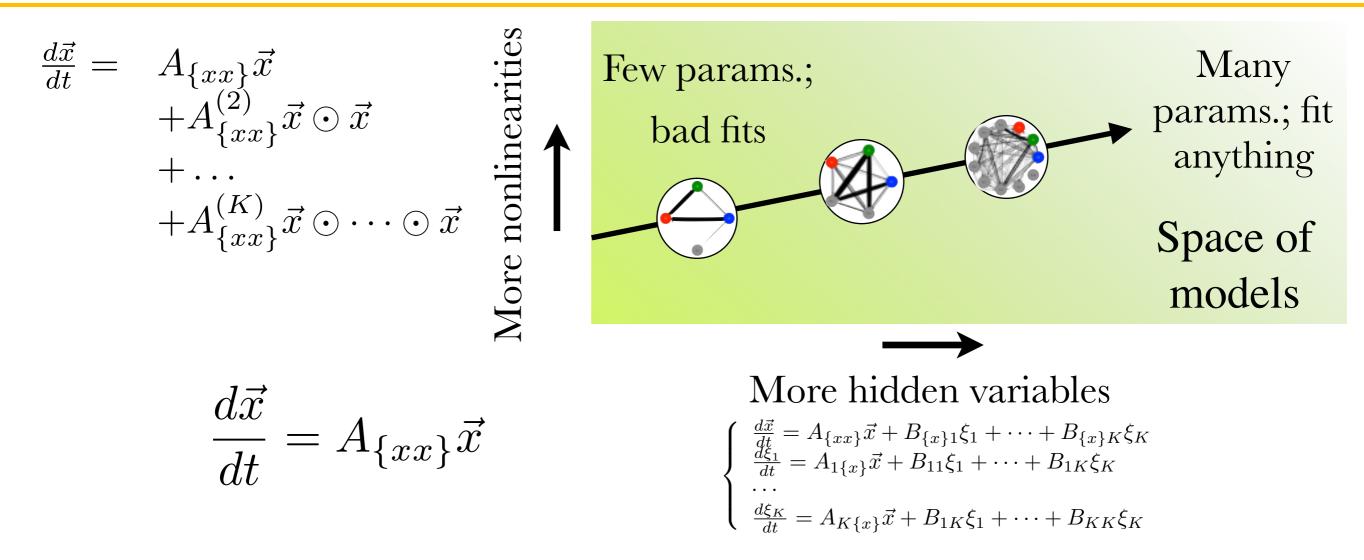












- Hidden degrees of freedom and nonlinearities breaks nestedness -- no consistency.
- Choose any (reasonable) **complete** path through the model space
 - Good choice good fits with little data; Bad choice not worse than exhaustive search.



Two types of model families

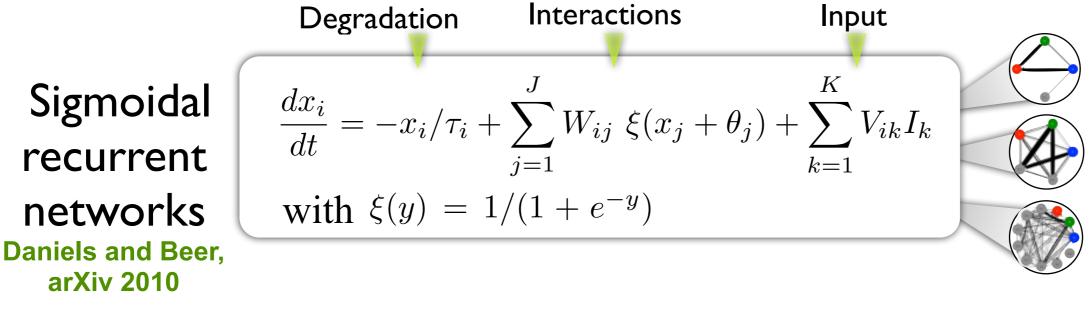
- Both nested and complete.
- Account for nonlinearities and hidden variables.
- Biologically reasonable.

Daniels and Nemenman, Nature Comm 2015; PLoS ONE 2015



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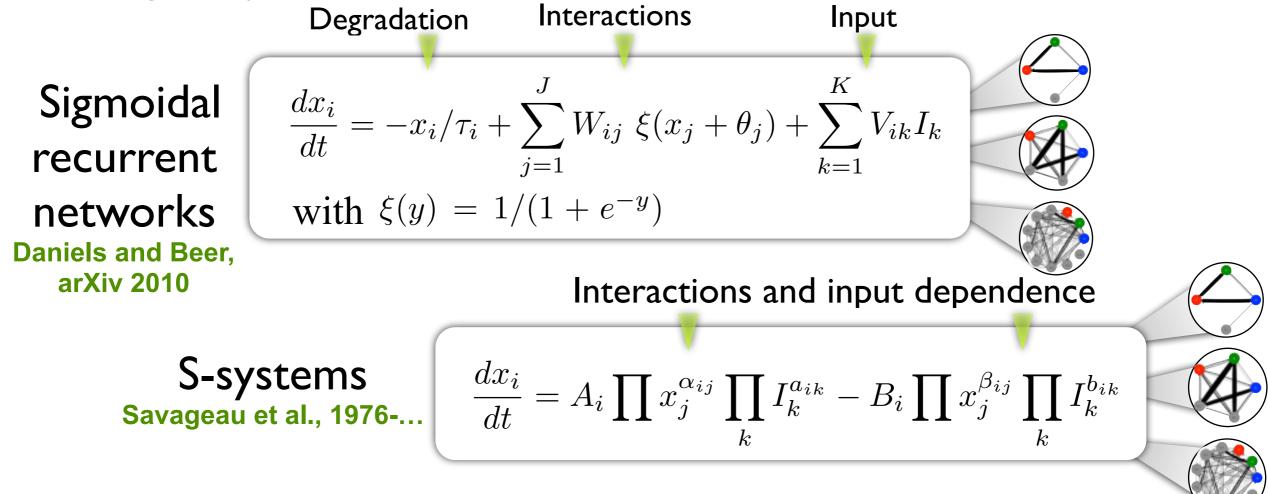


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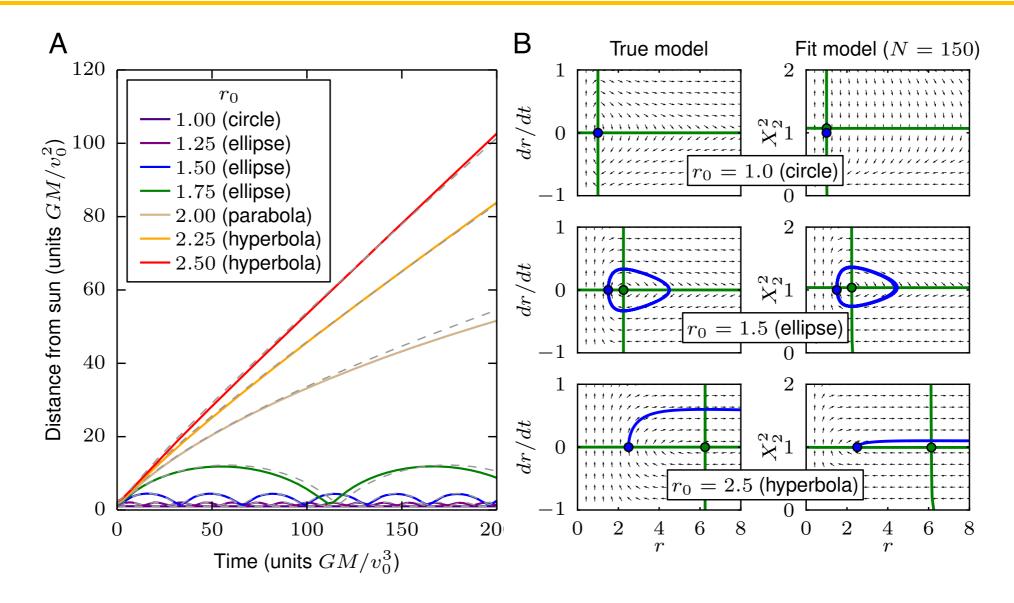
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Finding laws that we already know: An automated Sir Isaac (Sirlsaac on GitHub)

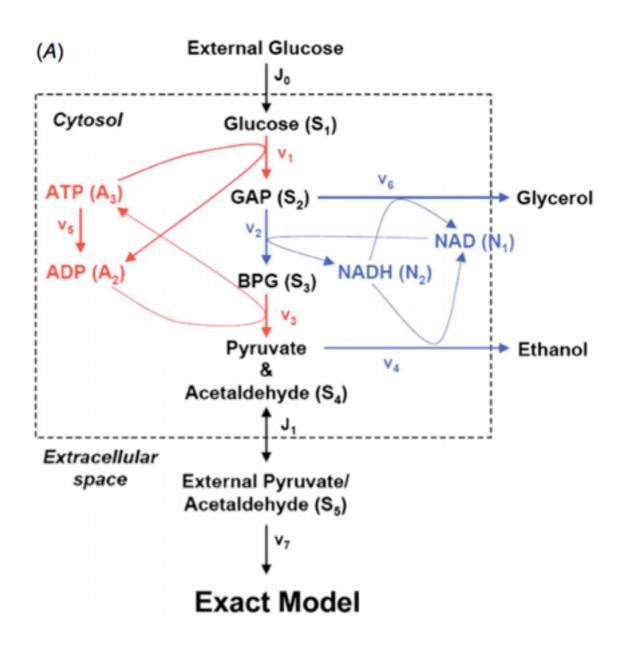


- Finds the hidden variable needed to account for the Newton's laws.
- Accounts for different classes of trajectories.

Daniels and Nemenman, Nature Comm 2015, PLoS ONE 2015



Test Model: Yeast Glycolytic Oscillator



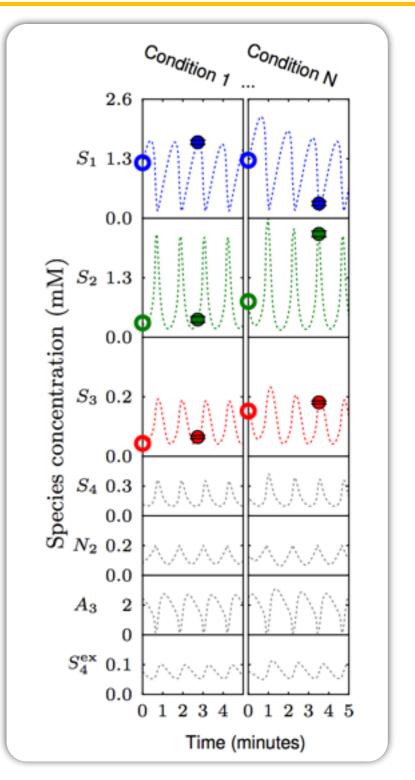
- 7 species, 28 parameters
- Complex rational dynamical laws

Ruoff et al., 2003



The yeast glycolytic oscillations: Complex dynamics needing complex structure

- Observe only 3/7 of variables; add 10% noise.
- Data: N samples of structure
 - Initial condition of the 3 species;
 - Some random time later;
 - The value of these 3 species at that time.





Results

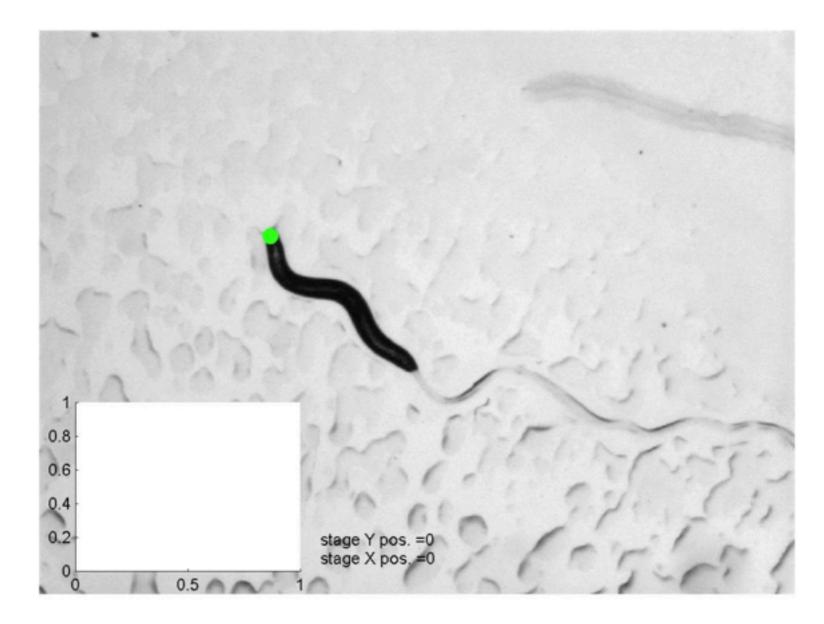
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Condition 1 ... Condition N Condition M Condition 1 ... 2.62.6 $S_1 \, 1.3$ $S_1 \, 1.3$ -300-3500.00.04 -400-450 $\begin{array}{c} S_2 \ 1.3 \\ 0.0 \\ S_3 \ 0.2 \\ 0.0 \\ S_4 \ 0.3 \\ 0.0 \\ N_2 \ 0.2 \end{array}$ $S_2 \, 1.3$ 1.0Out-of-sample correlation 0.80.6 0.00.40.2 $S_3 \ 0.2$ 0.020 40 60 0 Number of parameters 0.0 X_4 _ Num. measurements N X_5 0 248 40Mean out-of-sample correlation 1.00.0-40.8 $X_6 - 1$ A_3 $\mathbf{2}$ 0.6-20 0.40 234012345 1 S_4^{ex} 0.1 0.20.0Time (minutes) 0.0 $\mathbf{2}$ 3 0 0 2 3 $0 \ 1$ 3 Computational effort Time (minutes)

(×10⁸ model evals)

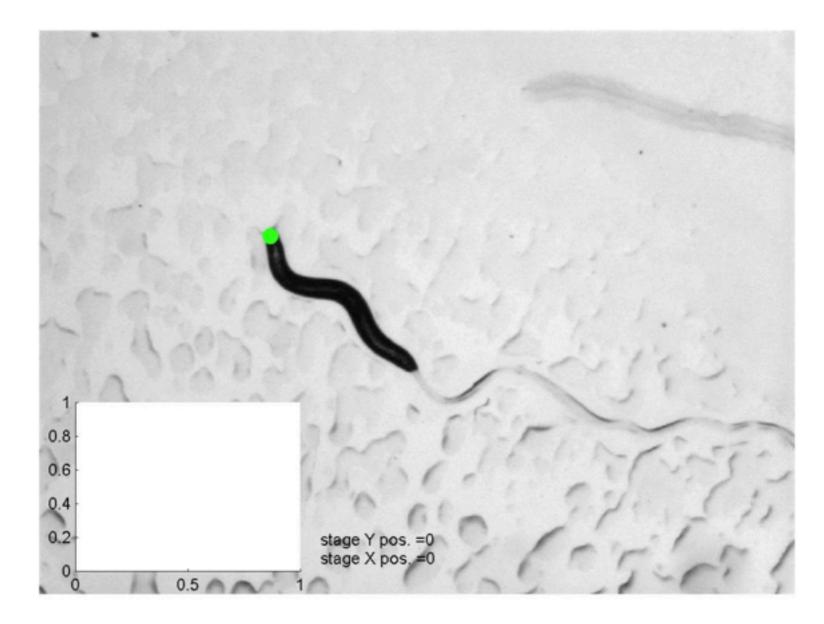
- ~100x fewer evaluations for the same accuracy compared to full search.
- ~1000x fewer data points than full search.
- Better accuracy than curve fitting.
- Linear scaling with the amount of data and with the number of variables.
- Finds conservation laws.

Modeling *C. elegans* temperature nociception escape response



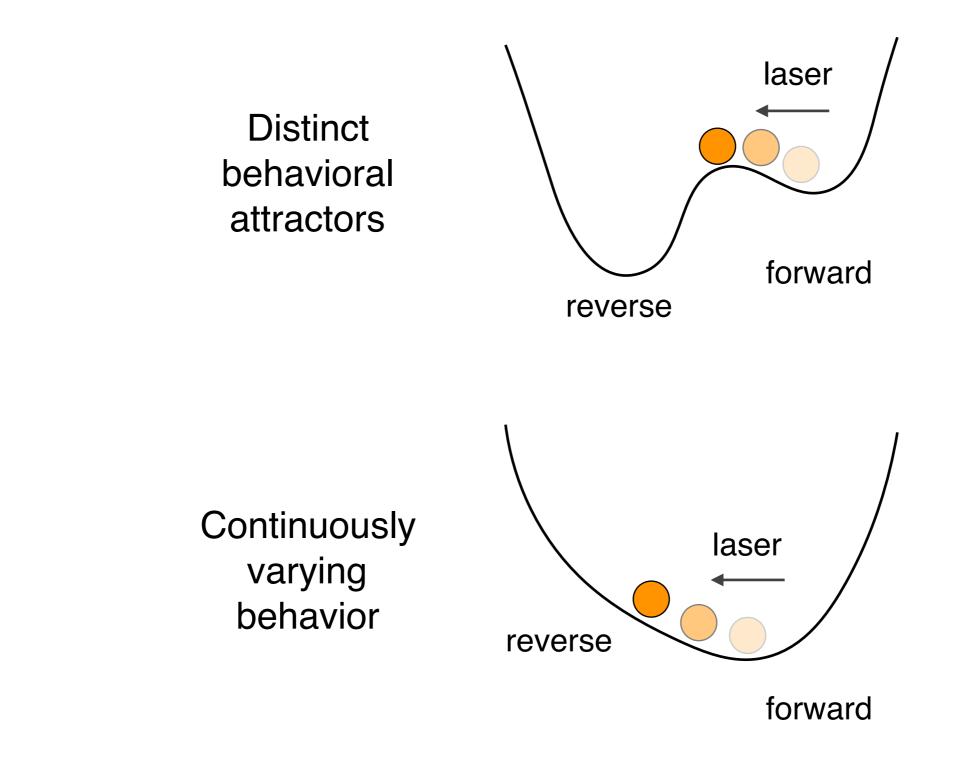


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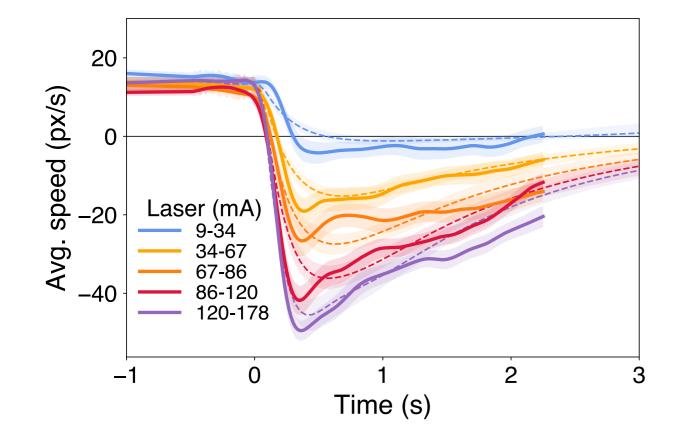


Question: what is the logic of this behavior?

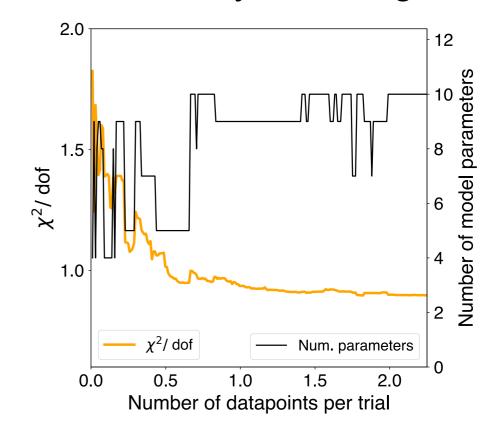




Worm nociception: Data and fits



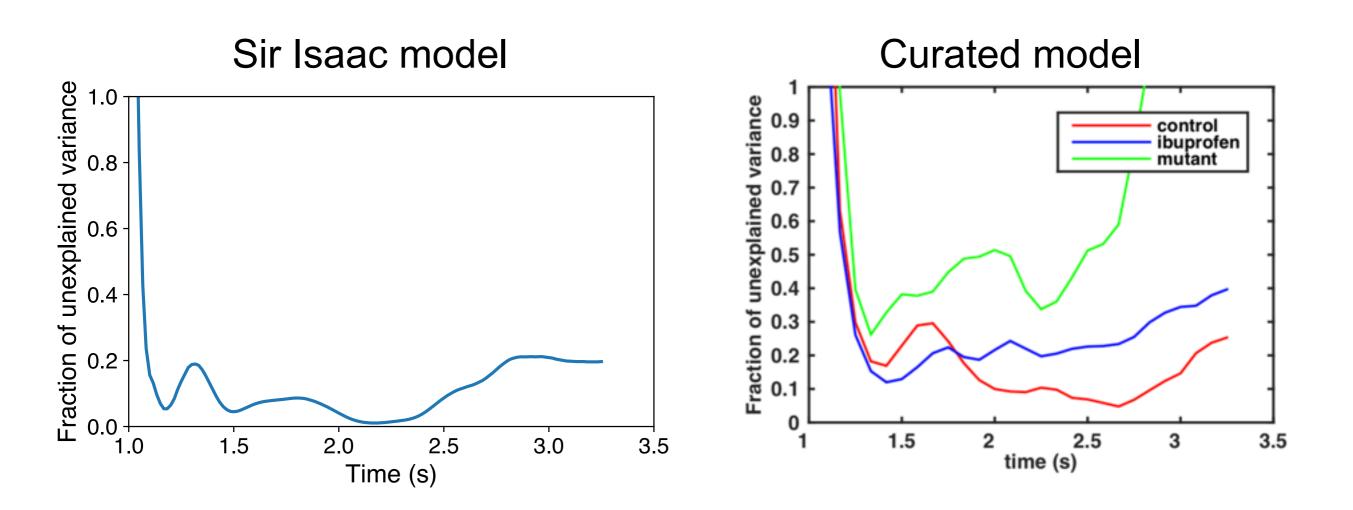
SGD style training



Daniels, Ryu, IN, in prep.

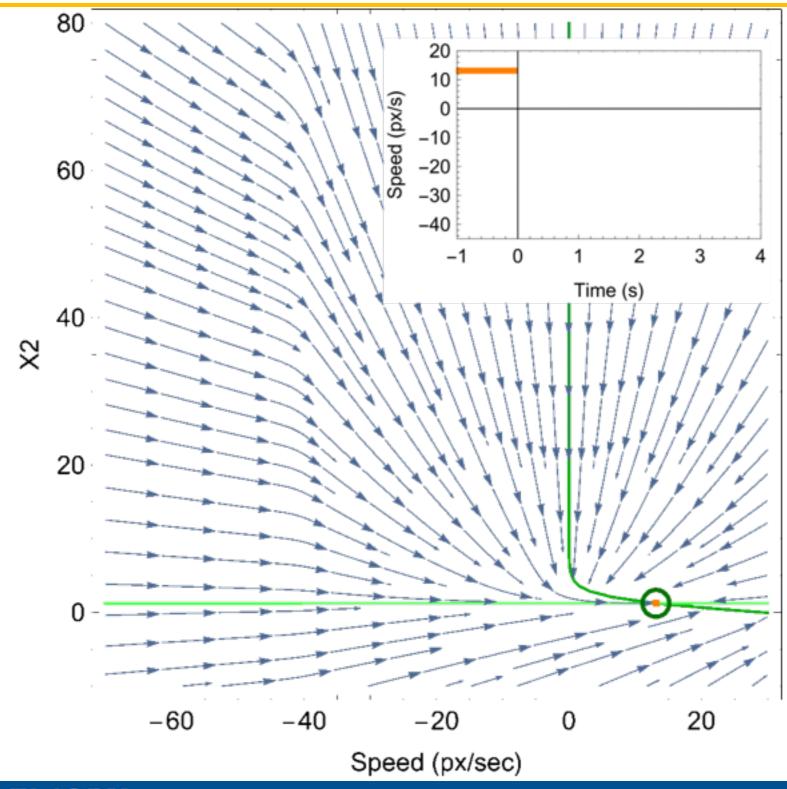


Comparing to hand-curated model





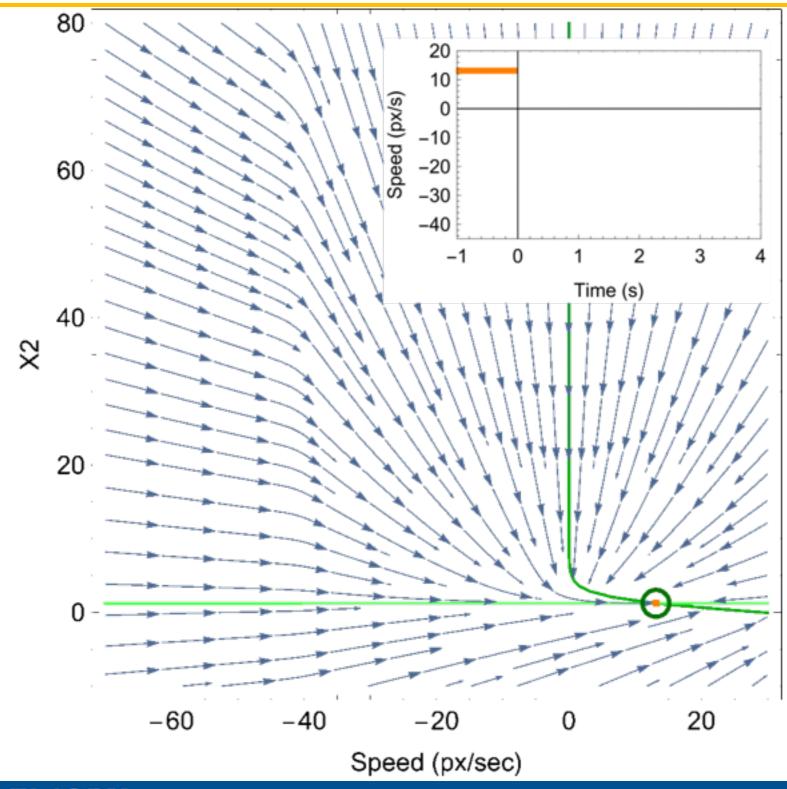
What is the logic of the behavioral dynamics? A single attractor



Continuously varying behavioral attractor



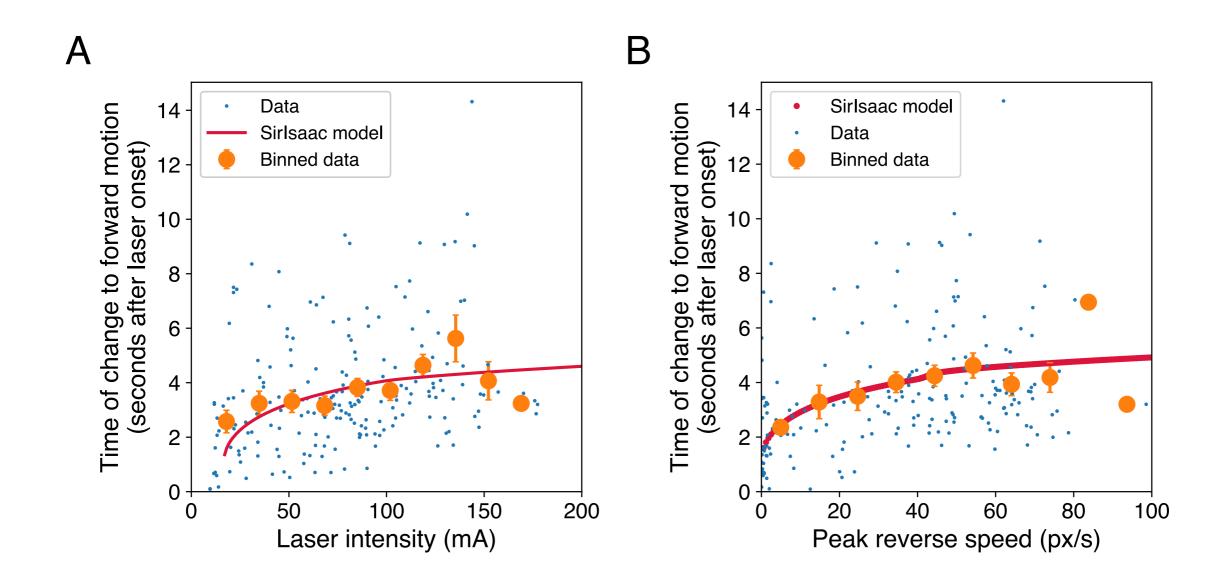
What is the logic of the behavioral dynamics? A single attractor



Continuously varying behavioral attractor



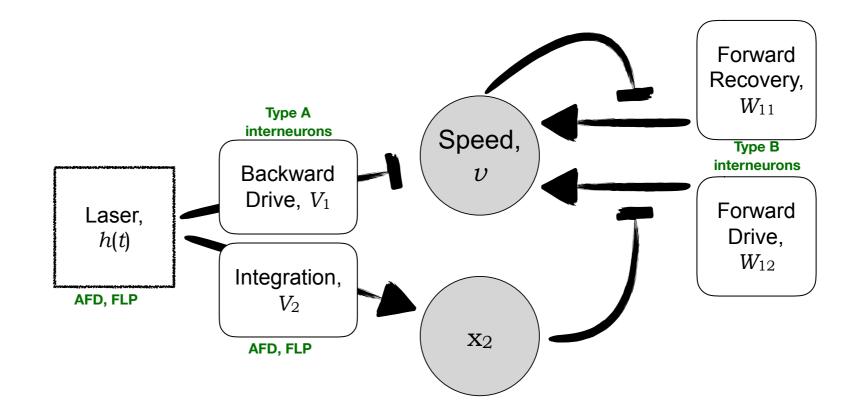
Why should you believe our model? The predictions





Interpreting the model

$$\frac{dv}{dt} = -\frac{v}{\tau_1} + V_1 h(t) + \frac{W_{11}}{1 + e^{v + \theta_1}} + \frac{W_{12}}{1 + e^{x_2}},$$
$$\frac{dx_2}{dt} = -x_2 + V_2 h(t).$$





Summary II



Summary II

- Deemphasize "truth" of a model, focus on accuracy of prediction and on refining (not coarse-graining)
 phenomenological dynamics.
- Complete, nested model families of dynamics allow to use Bayesian model selection to adapt model complexity.
- Such phenomenological models make accurate and interpretable predictions, at least for the worms.
- Why do this? Go from models to phenomenological theories
 - Repeat Hookean approach in biology: build effective models of similar systems and look for patterns (e.g., chemotaxis in *C. elegans* and *E. coli*).

