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Modeling and Systems Principles

CMPLXSYS 270

Systems

All around us, interconnected systems determine how the world works

Modeling is a way of understanding the world, which makes us isolate and refine theories

Exploring what rules and components create what outcomes is a path to tackling modern problems

Today: foresee modeling pitfalls, gain intuition for dynamics

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Types of Models

<u>Static/“one-time” models</u>

- Given some examples, predict a value or label for a new piece of data
- Interpolation: predict value in between existing points
- Extrapolation: predict value beyond existing points
- Eg: Regressions (linear fit), classifiers (incl. machine learning)
- How most social science works
- <u>Correlation</u> based, but *suggestive*

<u>Dynamic/“simulation” models</u>

- Constructing *rules* for how a system evolves in time
- Hypothesizes and tests <u>causal</u> relationships between quantities
- Differential equations, or *difference equations* (discrete updates)
- Simulate with computers, or (rarely) analyze exactly with math
- Abstract total quantities evolving, or “agent-based” simulated individual elements

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Most “Data Science”

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My specialty

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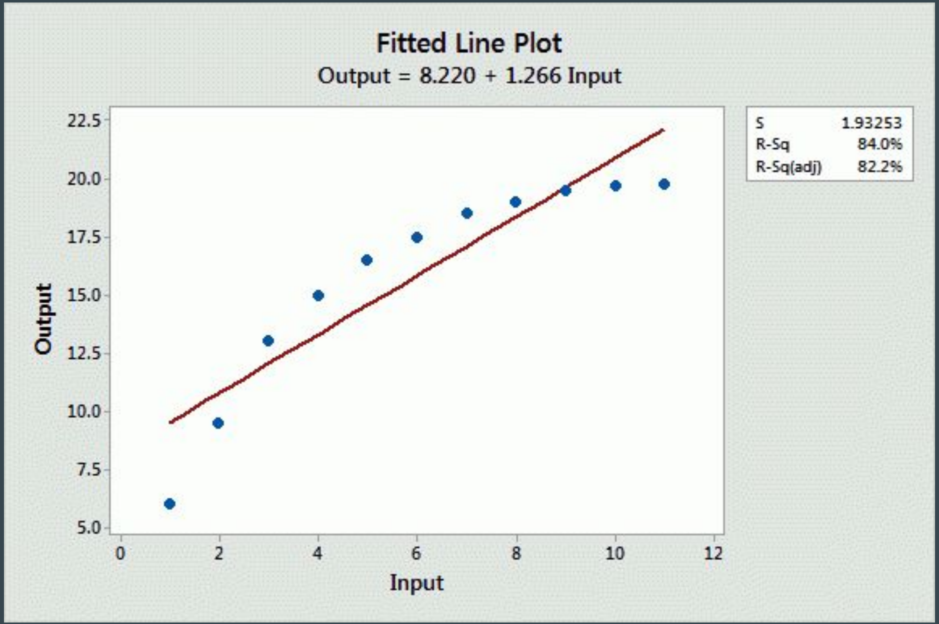
Static Modeling: A Balancing Act

<u>Complexity</u>

- Increases goodness of fit
    - Is the training data sufficiently well captured?

If model too coarse, results can be missing key structure, make bad predictions



Static Modeling: A Balancing Act

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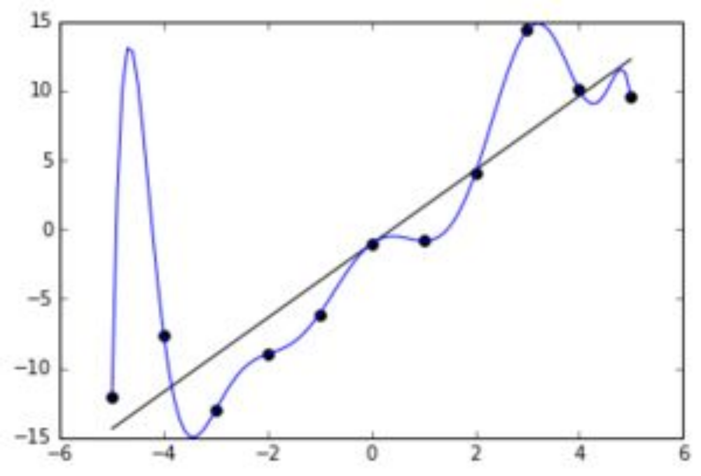

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predictions

Every added term in a functional model comes with 1+ parameter(s)

$Y = aX + bX^2 + c\mathrm{Sin}(kX) + d\mathrm{Log}(X) + \ldots$

Simplicity

- Clarity
  - What is the main relationship?
- Robustness
  - Less prone to overfitting

Static Modeling: A Balancing Act

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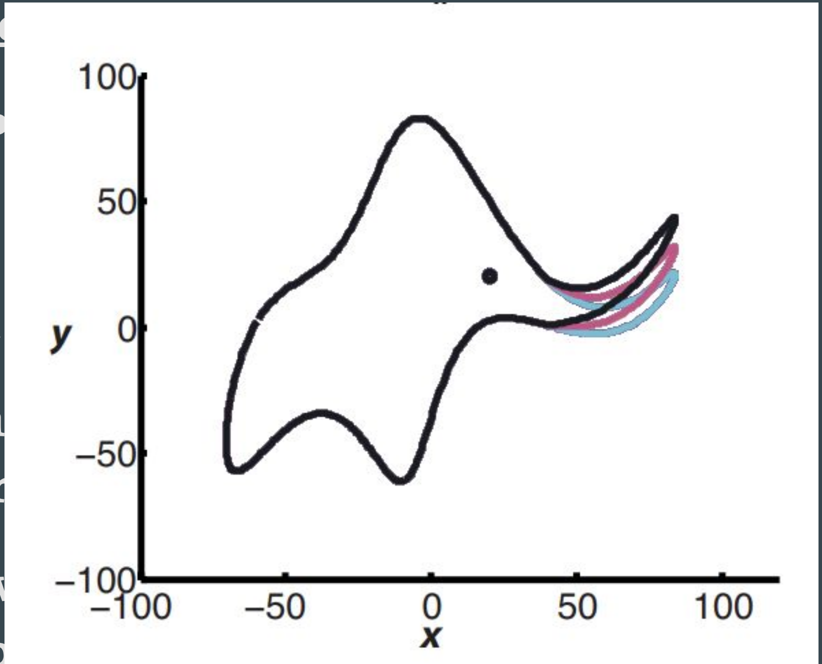

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- Intellectual honesty - many parameters "cheating"
  - "Four parameters->elephant, five->wiggle its trunk"

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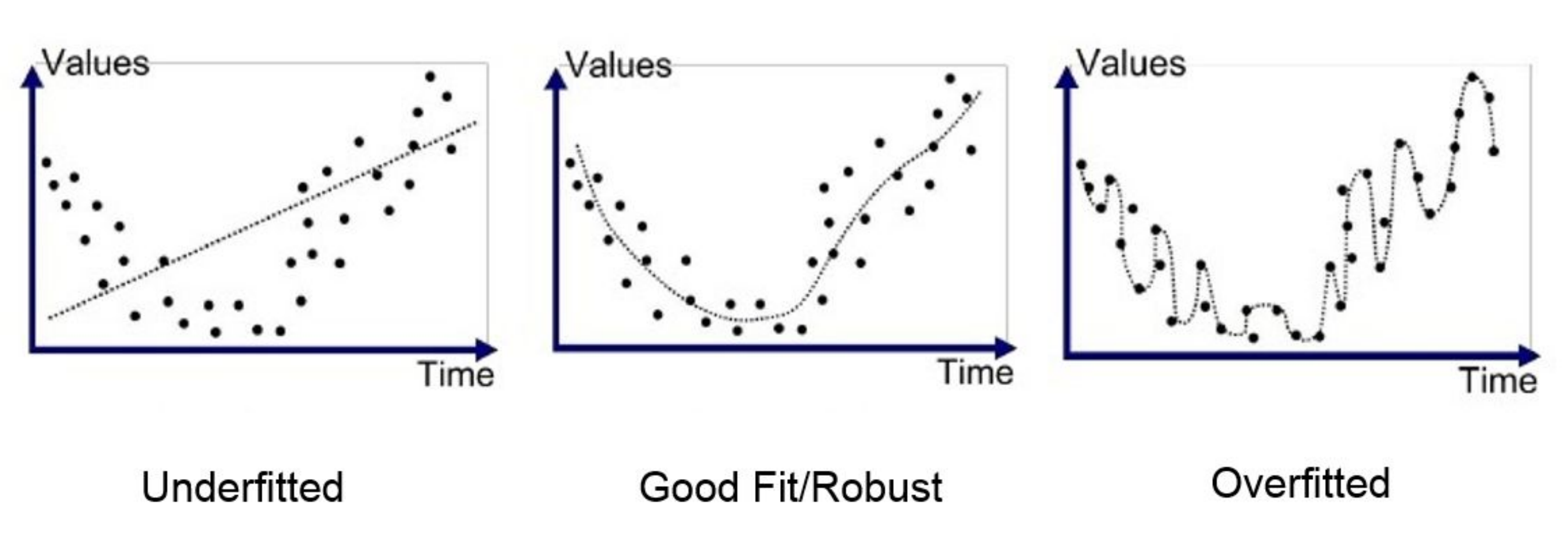
Goal: simplest model that reasonably represents your data!

Static Modeling: A Balancing Act



Dynamic Modeling: A Balancing Act

<u>Complexity</u>

- Realism/Accuracy
    - Is the system sufficiently well captured?

If core system not well represented, results meaningless or misleading

Every added mechanic in a model increases its complexity, # parameters

Identifying the most relevant elements of a system is an art!

<u>Simplicity</u>

- Understandability
    - Why does an outcome occur?
- Robustness* (usually)
    - Sensitivity to parameters?
- Practicality
    - Simulating a single droplet of water by its atoms?

Goal: simplest model that is good enough to capture your system!

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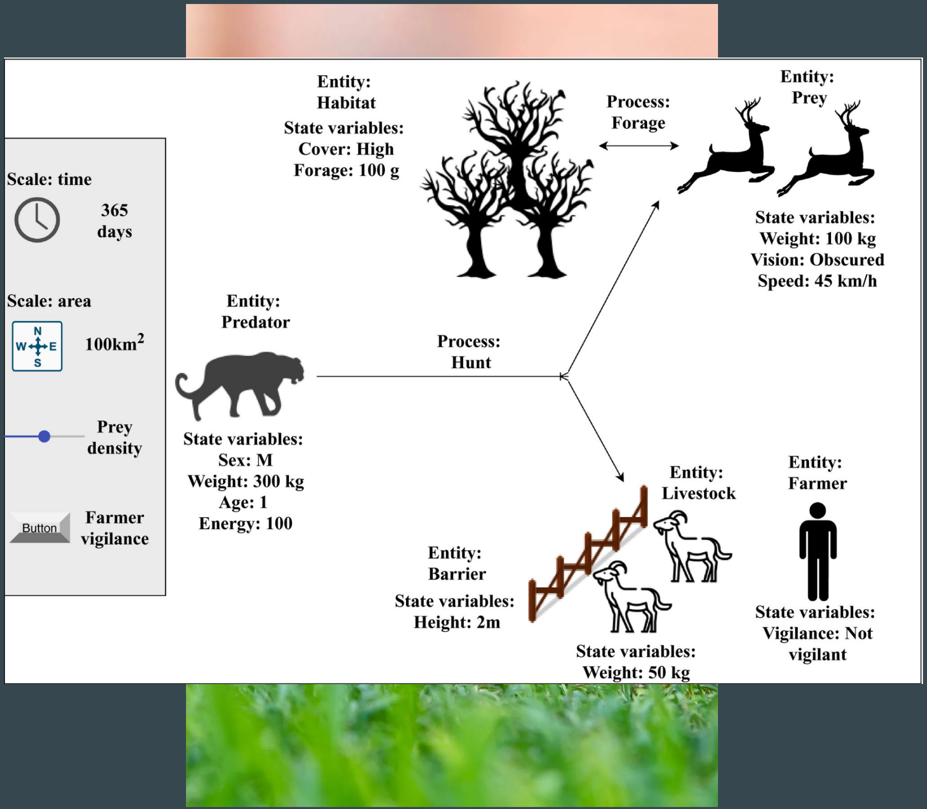
Dynamic Modeling: A Balancing Act

Example: Ecology (rabbit population):

Too simple: population growth proportional to current population (-->unbounded exponential growth)

Too Complex: Full habitat simulation with many competing species, predation simulated by sight and speed and distance-to-safety, familial food-sharing, day-night cycle, hibernation, . . .



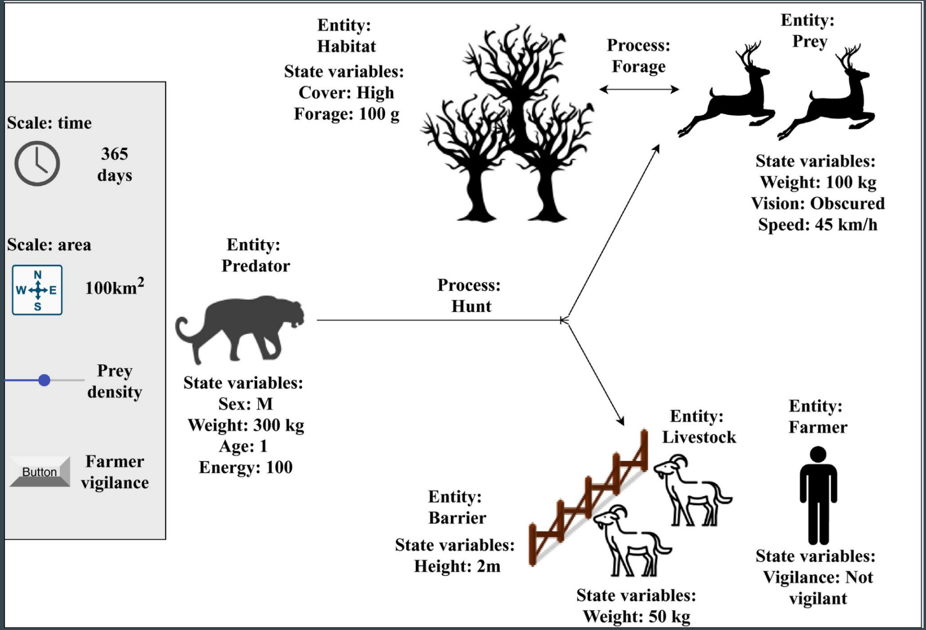
Dynamic Modeling: Agent-Based

ABM tends to fall on the "complex" side of the dynamic modeling spectrum.

It is very easy to make an ABM that is too complex to understand!

In general, there's no way to tell what an ABM will do until you run it (often many times)

But we can get some intuition by identifying types of feedback



Principles of Dynamic Systems: Positive Feedback

When something is "self-reinforcing"

Happens -> happens more

<u>Classic example</u>: Rabbits

- rate of growth proportional to current population

  -> exponential growth

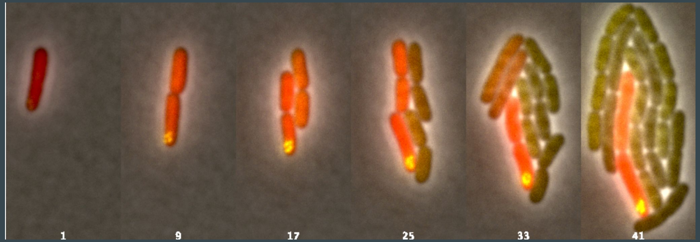
Necessary/fundamental to many systems

Dangerous (or just unrealistic) if unchecked

Can you think of examples?

Principles of Dynamic Systems: Positive Feedback

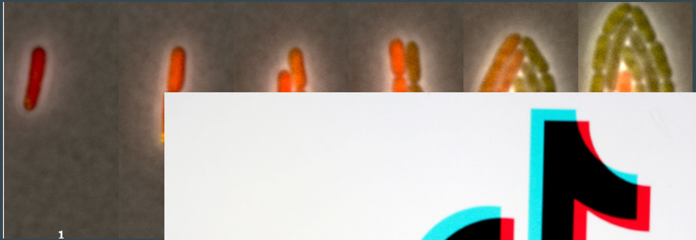
Examples: Reproduction



Principles of Dynamic Systems: Positive Feedback

Examples: Reproduction

Contagion (viral, social, etc)



Principles of Dynamic Systems: Positive Feedback

Examples: Reproduction

Contagion (viral, social, etc)

Super-intelligent AI

Principles of Dynamic Systems: Positive Feedback

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- Flood from Halo

Principles of Dynamic Systems: Positive Feedback

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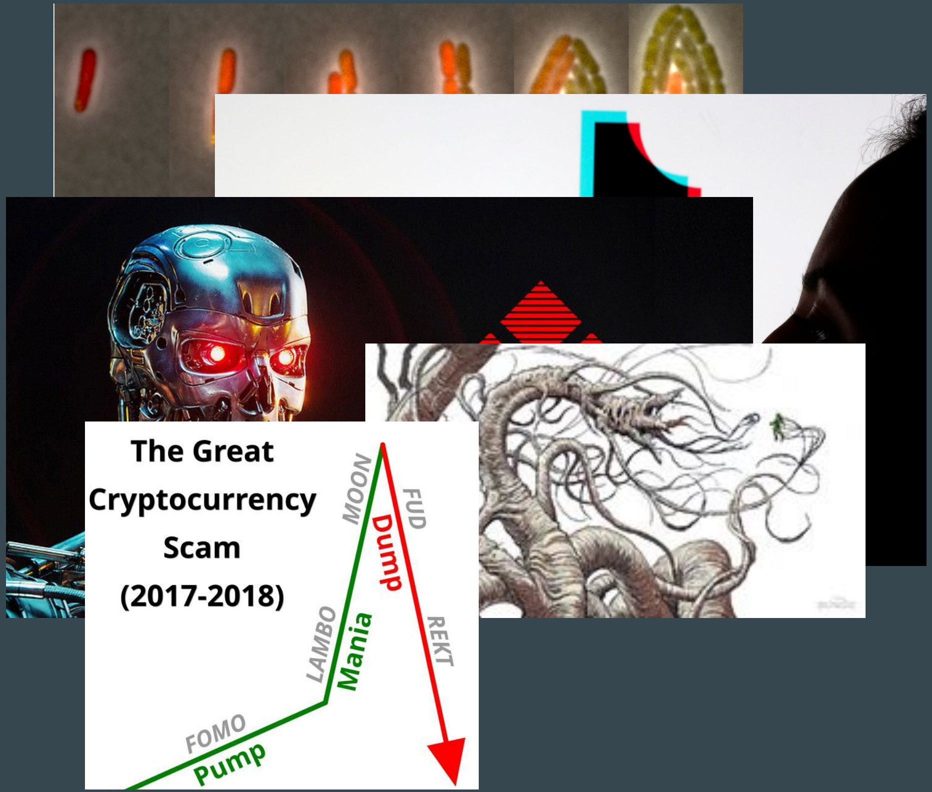
Speculative investments



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Hyperinflation

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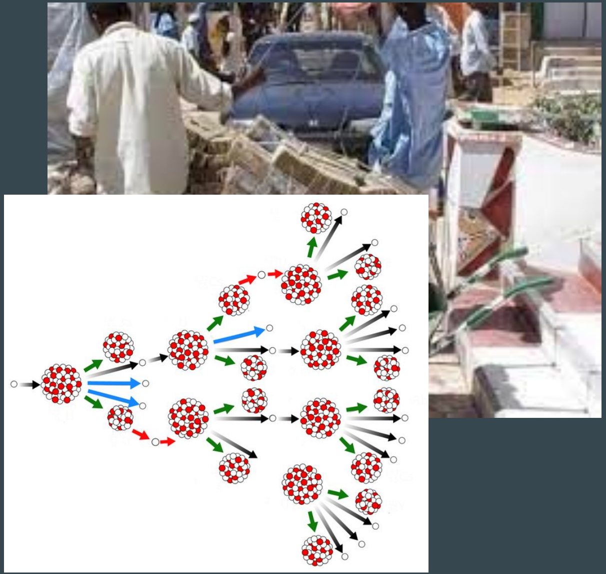
Nuclear fission/fusion



Principles of Dynamic Systems: Positive Feedback

Examples: Reproduction

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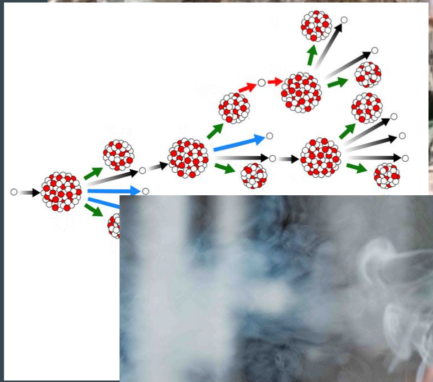
- Addiction



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Principles of Dynamic Systems: Positive Feedback

Examples: Reproduction

- Contagion (viral, social, etc)
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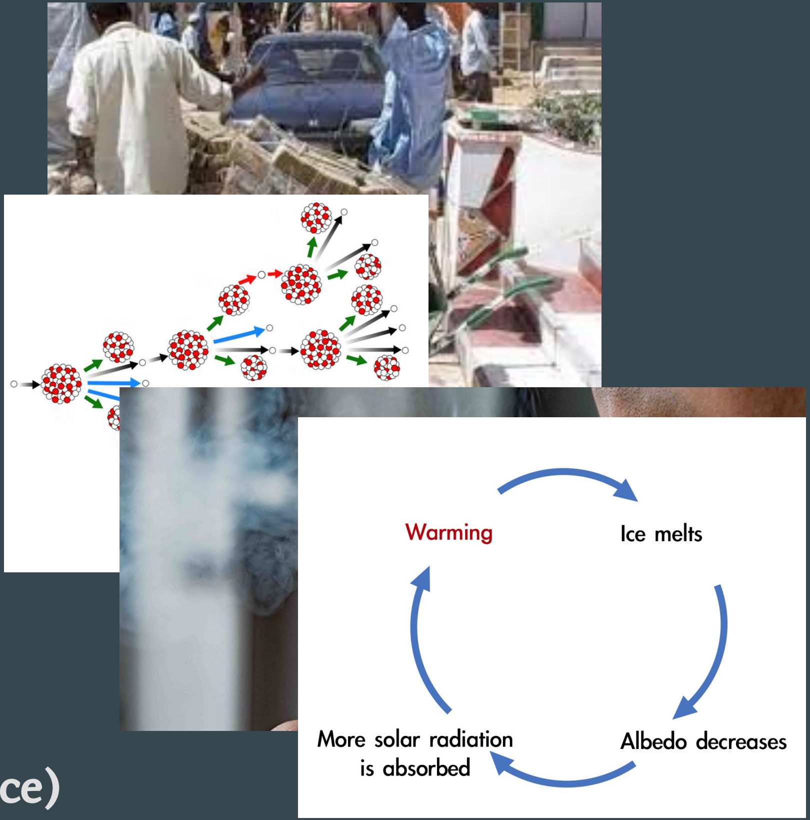
- Speculative investments
- Hyperinflation
- Nuclear fission/fusion
- Addiction
- Global temp w/ ice albedo (reflectance)



Principles of Dynamic Systems: Negative Feedback

When something is "self-defeating"

Happens -> happens less

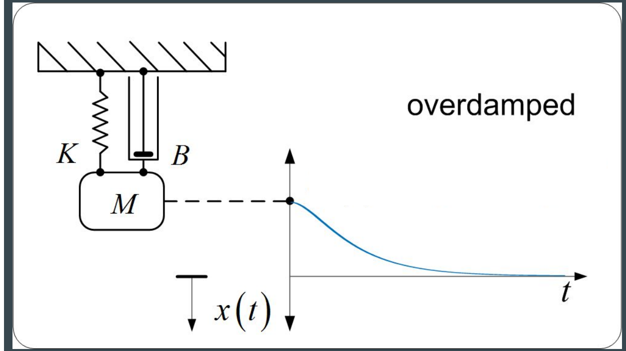
<u>Classic example:</u> mass on spring

- Force opposite current position leads to oscillation around equilibrium

Math note:

acceleration = -pos -> oscillation

velocity = -pos -> static equilibrium

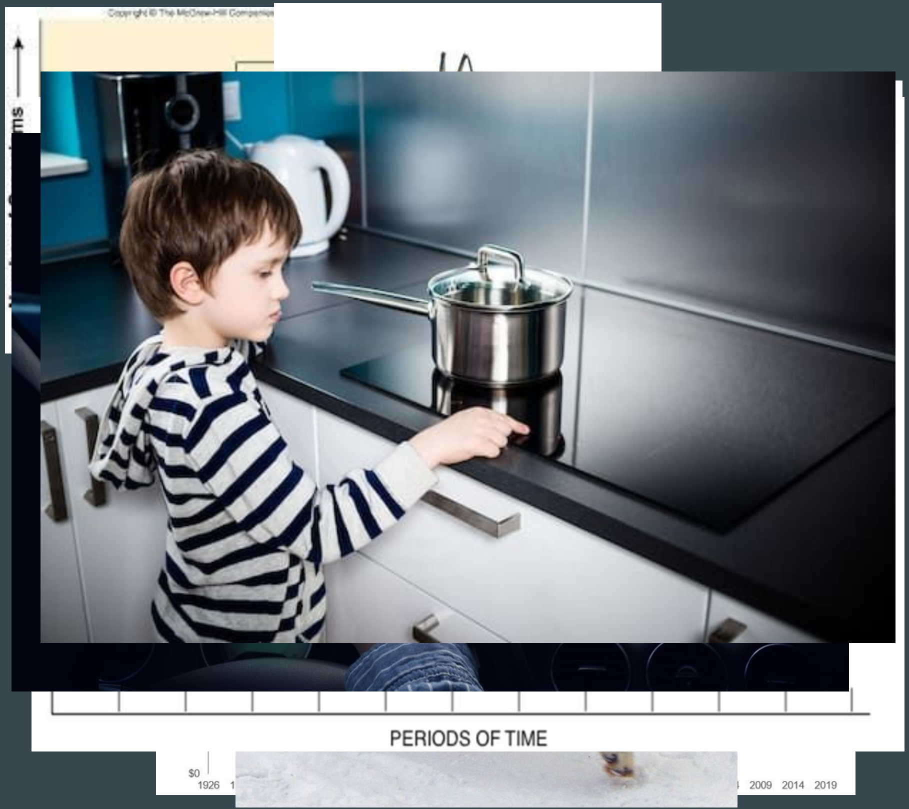


Can you think of examples?

Principles of Dynamic Systems: Negative Feedback

More examples:

- Populations with resource limits
- US political party power
- Wakefulness cycles
- Diseases/parasites/predators
- Temperature (radiative cooling)
- Boom/Bust cycles in economics
- Staying in your lane driving
- Learning from consequences



Precarious Positive and Negative Feedback: Early Earth

Oxygen catastrophes (2.4B-2B years ago)

1) Early life was only diverse around ocean vents
2) First non-sulfur photosynthetic organisms took over entire surface
3) Waste product (oxygen) toxic, but slowly removed by dissolved iron
4) 200M years of boom/bust cycles (banded iron in rocks)
5) Photosynthetic microbes evolve oxygen resistance... uh oh.

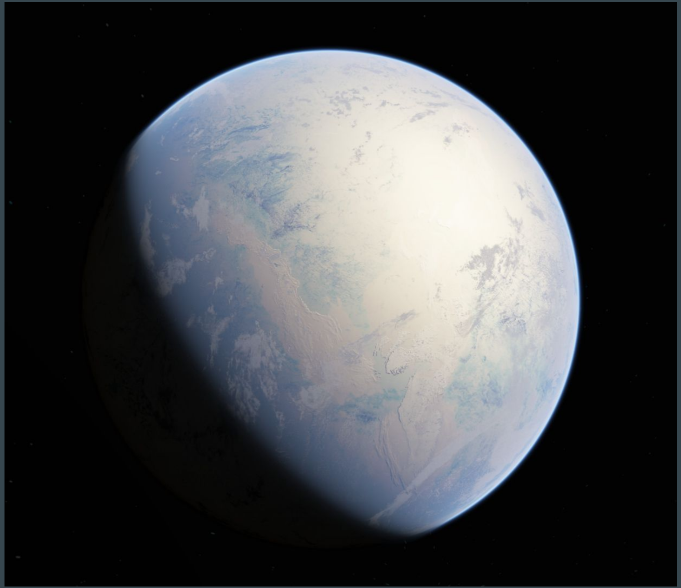
Dangerous Positive and Negative Feedback: Early Earth

6) Unchecked, they use up all the iron and poison the ocean and all other life with oxygen

7) oxygen leaking into the atmosphere turns methane into carbon dioxide, cooling the planet

8) ice albedo feedback → planet-wide ice age for 300M years (until volcanoes)

9) 99% of all life dead!



Sensitivity

Part of the issue with complex systems is that they're often *sensitive*

Three main kinds (dynamic models):

1) sensitive to starting conditions
2) sensitive to parameters
3) sensitive to model structure, implicit assumptions

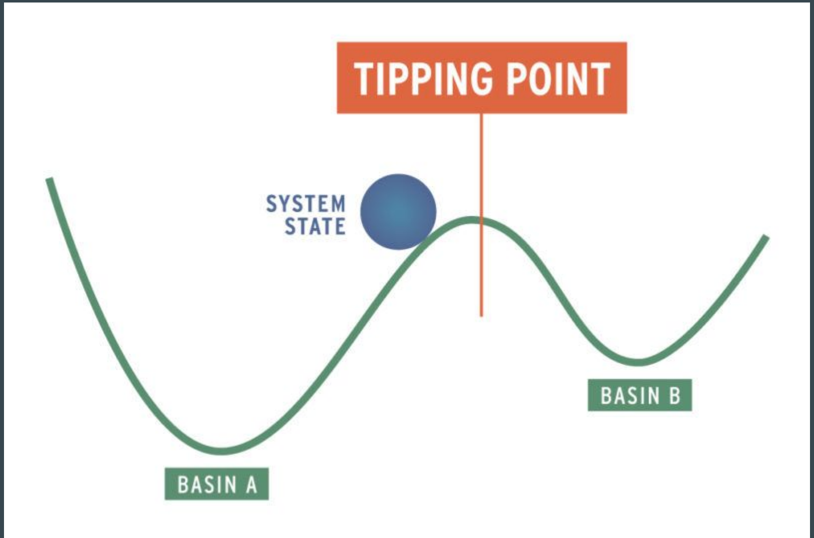
(in order of increasing subtlety and perniciousness)

Need to recognize and address/admit

Sensitivity: Starting conditions

Running the same simulation from different starting points can have wildly different results!

- no plants -> everything dies
- Two escaped weasels in New Zealand -> invasive boom
- Weather
- if you were born in 100,000 BC, your life would be much different!
- If asteroid aimed slightly different, no 65M BC extinction!



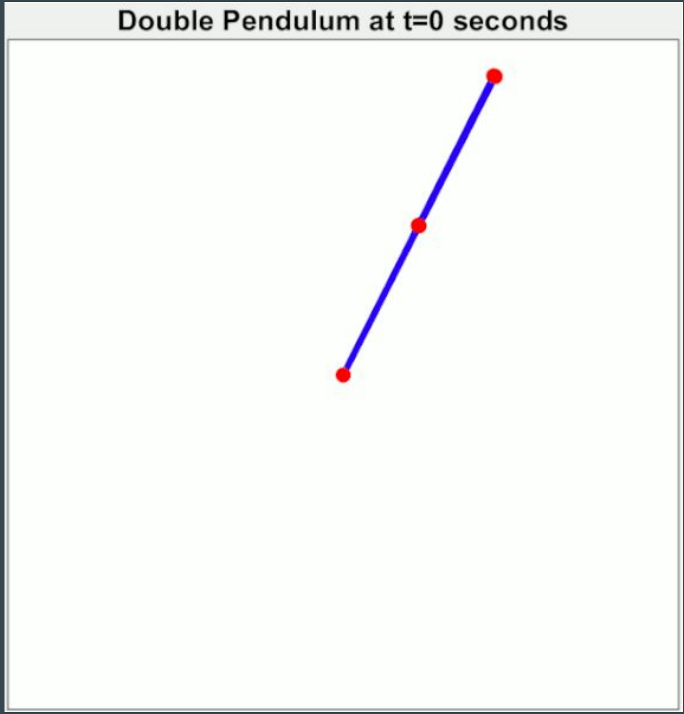
Sensitivity: Starting conditions

Math term: Chaotic systems have "sensitive dependence on initial conditions" (SDIC)

Classic chaotic systems:

- Fluid flow (water, atmosphere, etc)
- Neural activity
- Population dynamics
- Double pendulum
- Many more!

(more on this later, the math is really beautiful!)



Sensitivity: Parameters

The strength of different behavior is usually determined by parameters

- Each mechanic needs parameters to govern it

But the outcomes can be very different if you change parameters even a little!

- Finding which parameters which are robust, and which are sensitive is a whole discipline!
    - (Sensitivity Analysis)

The Curse of Many Parameters

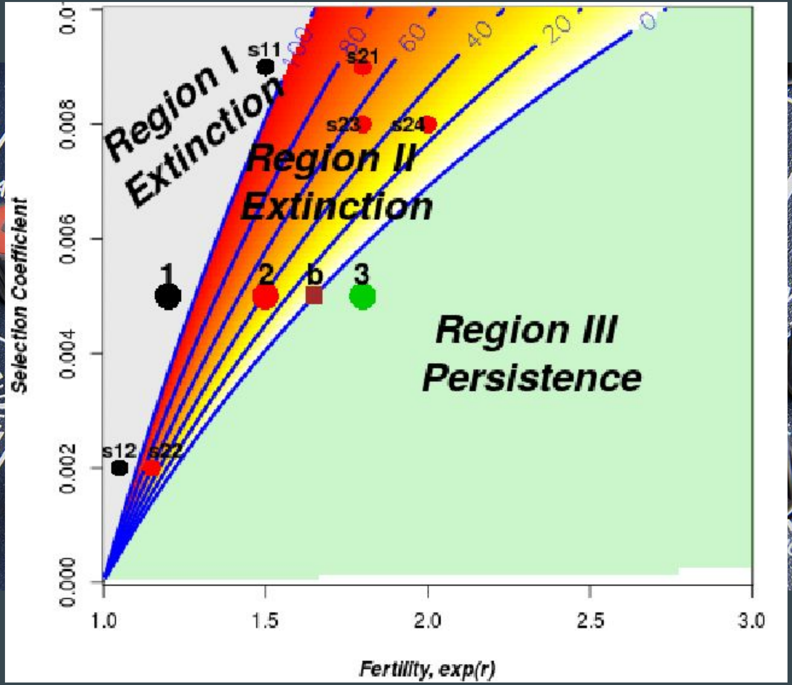
One solution is to run the simulation for all parameter values and map out what happens

BUT:

Imagine 6 parameters, try 10 values of each:

- -> 1 million simulations
  - each with many agents interacting with each other per time-step
    - For many time-steps
    - For many start states?

Quickly gets infeasible!



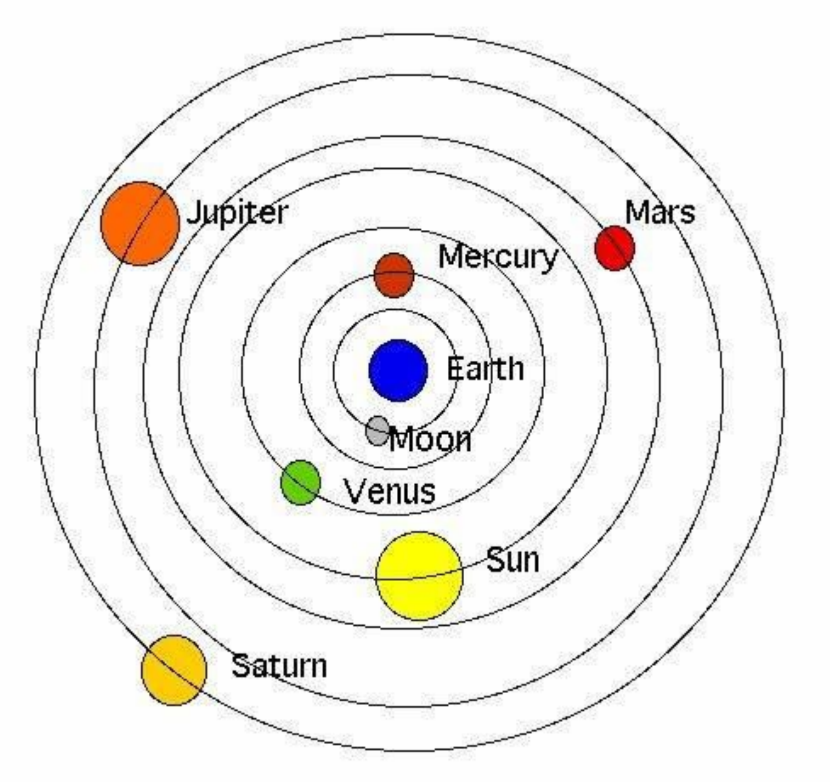
Sensitivity: Model Structure

The most subtle thing to account for are the conceptual choices made by the modeler—how to frame it, what to include, etc.

Does the model represent the phenomenon? How else could it be represented?

Have all the relevant feedback processes been captured?

Models could be valid in the short term, but behave differently on different time-scales



Modeling: A (Worthwhile) Balancing Act

Modeling is fraught with potential pitfalls and inaccuracies, but despite this it works pretty well!

All of science can be seen as developing models for the rules of our world

- Better models → progress!

Many remaining modern problems have to do with emergent behavior of complex systems → ABM a natural tool

Still plenty of areas to explore, and room to improve!

Summary

We want to capture as many relevant aspects of a system as possible

- Think about any positive and negative feedback dynamics keeping the system balanced
- But, adding too much can make the system hard to understand and balance
- Keep in mind the different kinds of sensitivity a model might exhibit
- Nothing's perfect, but even imperfect models can point towards interesting truths!