# Fundamental Limits of Cyber-Physical and Hybrid System Modeling

Invited Talk

The 3nd International Workshop on Symbolic and Numerical Methods for Reachability Analysis (SNR) a satellite event of ETAPS 17, Uppsala, Sweden

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April 22, 2017



## **Background Paper**



#### Fundamental Limits of Cyber-Physical Systems Modeling

EDWARD A. LEE, EECS Department, UC Berkeley

This article examines the role of modeling in the engineering of cyber-physical systems. It argues that the role that models play in engineering is different from the role they play in science, and that this difference should direct us to use a different class of models, where simplicity and clarity of semantics dominate over accuracy and detail. I argue that determinism in models used for engineering is a valuable property and should be preserved whenever possible, regardless of whether the system being modeled is deterministic. I then identify three classes of fundamental limits on modeling, specifically chaotic behavior, the inability of computers to numerically handle a continuum, and the incompleteness of determinism. The last of these has profound consequences.

CCS Concepts: • Theory of computation  $\rightarrow$  Timed and hybrid models; • Computing methodologies  $\rightarrow$  Modeling methodologies; • Software and its engineering  $\rightarrow$  Domain specific languages

Additional Key Words and Phrases: Chaos, continuums, completeness

#### ACM Reference Format:

Edward A. Lee. 2016. Fundamental limits of cyber-physical systems modeling. ACM Trans. Cyber-Phys. Syst. 1, 1, Article 3 (November 2016), 26 pages.

DOI: http://dx.doi.org/10.1145/2912149

## Models vs. Reality



$$x(t) = x(0) + \int_0^t v(\tau)d\tau$$
$$v(t) = v(0) + \frac{1}{m} \int_0^t F(\tau)d\tau$$

The model

In this example, the modeling framework is calculus and Newton's laws.



The target (the thing being modeled)

Fidelity is how well the model and its target match

#### Deterministic Models



A model is deterministic if, given the initial *state* and the *inputs*, the model defines exactly one *behavior*.

Deterministic models have proved extremely valuable in the past:

- Differential equations
- Synchronous digital logic
- Instruction-set architectures
- Single-threaded imperative programs

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#### Deterministic Models



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#### Advantages:

- Enables testing
- Enables fault detection
- Makes simulation more effective
- Improves understanding
- Aligns with most of physics

### Newton's Cradle - The Model





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## Newton's Cradle - A Physical Realization





## Model Fidelity



- In *science*, the value of a model lies in how well its behavior matches that of the physical system.
- In *engineering*, the value of the physical system lies in how well its behavior matches that of the model.

In engineering, model fidelity is a two-way street.

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## Changing the Question for CPS



The question is not whether deterministic models can describe the behavior of cyber-physical systems (with high fidelity).

The question is whether we can build cyber-physical systems whose behavior matches that of a deterministic model (with high probability).

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## Cyber Models



#### Physical System:



#### Cyber Model:

```
/** Reset the output receivers, which are the inside receivers of
  the output ports of the container.
   @exception IllegalActionException If getting the receivers fails.
private void _resetOutputReceivers() throws IllegalActionException {
    List<IOPort> outputs = ((Actor) getContainer()).outputPortList():
    for (IOPort output : outputs) {
        if (_debugging) {
            _debug("Resetting inside receivers of output port: "
                    + output.getName());
        Receiver[7] receivers = output.getInsideReceivers():
        if (receivers != null) {
            for (int i = 0: i < receivers.length: i++) {
                if (receivers[i] != null) {
                    for (int j = 0; j < receivers[i].length; j++) {
                        if (receivers[i][j] instanceof FSMReceiver) {
                            receivers[i][i].reset();
```

We have learned how to create physical systems whose behavior matches this model extremely well.

### Faithful Physical Model of Newton's Cradle?



## Discrete modeling of collisions? Or continuous?

- localized plastic deformation
- viscous damping
- acoustic wave propagation

#### But:

- will it actually be more accurate?
- at what cost?



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I claim that an idealized model, with discrete collisions combined with simple continuous dynamics, is better for most engineering purposes than any more detailed model of the physics.

## Faithful Physical Model of Newton's Cradle?

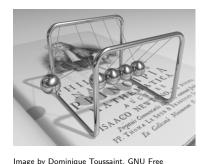


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## Fundamental Limits of Modeling



#### Outline of This Talk:

- Complexity
- Uncertainty
- Chaos
- Discretizing the Continuum
- Determinism is Incomplete
- Discreteness is Unavoidable

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## Complexity



"Iron wing" prototype of an Airbus A350.

Will virtual prototyping ever reach a sufficient level of fidelity for such a system?

Cf. Electronic design automation, where virtual prototyping works fine for billion-transistor chips.



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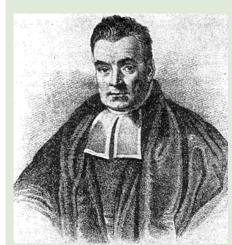
## Uncertainty



We can't construct deterministic models of what we don't know.

For this, nondeterminism is useful.

Bayesian probability (which is mostly due to Laplace) quantifies uncertainty.



Portrait of Reverend Thomas Bayes (1701 - 1761) that is probably not actually him.

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Determinism does not imply predictability.

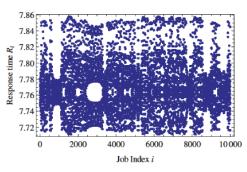


Fig. 15. Response time across jobs for the multi-resource scheduler with  $R_s(i-1)=7.76$  and  $R_s(i-2)=7.74$ .

(Lorenz, 1963; Thiele and Kumar, 2015)

### Chaos and the Butterfly Effect

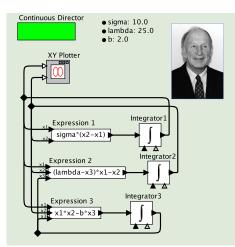


#### Lorenz attractor:

$$\dot{x}_1(t) = \sigma(x_2(t) - x_1(t)) 
\dot{x}_2(t) = (\lambda - x_3(t))x_1(t) - x_2(t) 
\dot{x}_3(t) = x_1(t)x_2(t) - bx_3(t)$$

This is a chaotic system, so arbitrarily small perturbations have arbitrarily large consequences.

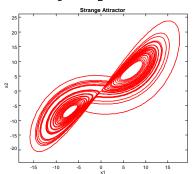
(Lorenz, 1963)



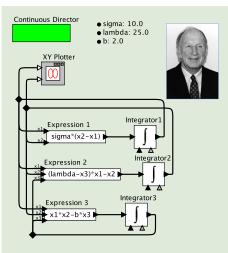
## Chaos and the Butterfly Effect



#### Plot of $x_1$ vs. $x_2$ :



The error in  $x_1$  and  $x_2$  due to numerical approximation is limited only by the stability of the system.



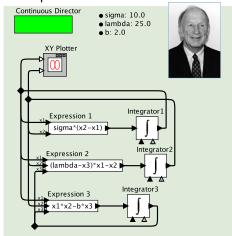
#### Models



#### Mathematical:

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#### Computational:



#### Models

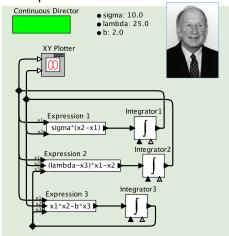


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Neither will match the behavior of a physical system being modeled.

#### Computational:



## Fundamental Limits of Modeling



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## Newton's Second Law with Impulsive Forces



Consider modeling collisions of masses in motion. Simple F = ma model:

$$x(t) = x(0) + \int_0^t v(\tau)d\tau$$
$$v(t) = v(0) + \frac{1}{m} \int_0^t F(\tau)d\tau$$

With an impulsive force at time T of magnitude  $F_i$ :

$$v(t) = v(0) + \frac{1}{m} \int_0^t (F(\tau) + F_i \delta(\tau - T)) d\tau$$

where  $\delta$  is the Dirac delta function.

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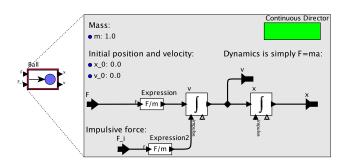
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## Computational Model

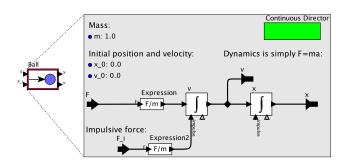




NOTE: The output v depends immediately on the input  $F_i$ , if it is present.

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## Direct Feedthrough



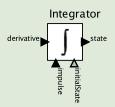
At time t, the state output is

$$v(t) = v(0) + \int_{t_0}^t \dot{v}(\tau) d\tau,$$

If the *impulse* input is present, then it adds immediately to v(t).

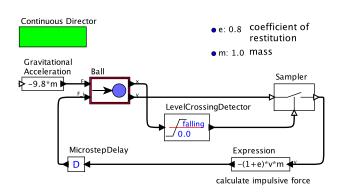
The output at time *t* depends on the *impulse* input at time *t*, but not on the *derivative* input.

Ptolemy II Integrator has "impulse" input:



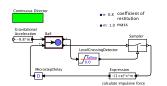
## Bouncing Ball Model



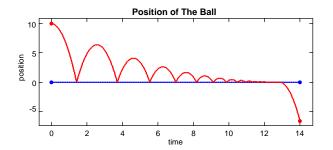


## **Bouncing Ball Execution**



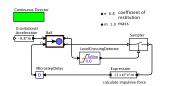


The velocity and position of the ball ie in a continuum. The surface is modeled as discrete.

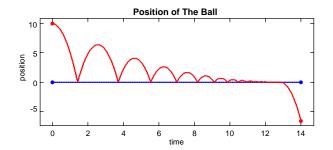


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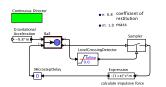


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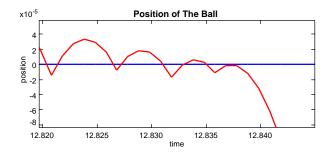


# **Bouncing Ball Execution**





Level-crossing can only be done up to some precision, and the resulting error will inevitably be large enough that the ball tunnels through the surface.



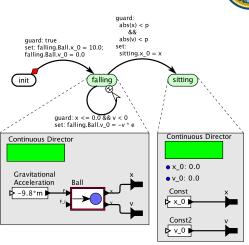
# Regimes of Validity of a Model



All models are wrong, some are useful.

(Box and Draper, 1987)

Modal models (switched systems) split models into modes, and a transition system ensures that a mode is active only when the model in that mode is valid



not tunnel.

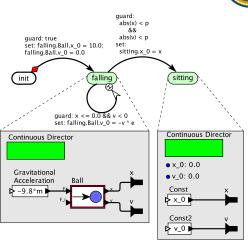


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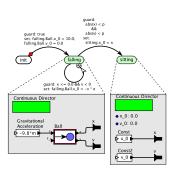
Modal models (switched systems) split models into *modes*, and a transition system ensures that a mode is active only when the model in that mode is valid.



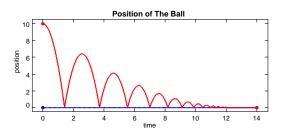
Modal model of the bouncing ball that does not tunnel.

# Regimes of Validity of a Model





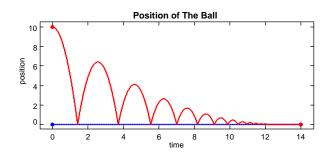
Switch out of the free-fall mode when that model is no longer valid.



### A Second Issue: Zeno Conditions



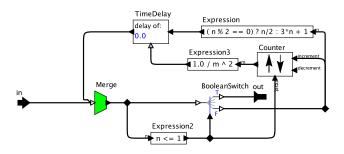
In theory, without the modal model, the ideal model prescribes an infinite number of bounces in finite time:



# Detecting Zeno Conditions is Hard



The following model exhibits Zeno behavior if the Collatz Conjecture is false, and otherwise does not:



Collatz Conjecture: For any natural number  $n \ge 1$ , if n is even, divide it by 2; if n is odd multiply it by 3 and add 1. Repeat the process indefinitely. The conjecture is that no matter what number you start with, you will always eventually reach 1. (due to Ben Lickly)

# Fundamental Limits of Modeling



#### Outline of This Talk:

- Complexity
- Uncertainty
- Chaos
- Discretizing the Continuum
- Determinism is Incomplete
- Discreteness is Unavoidable

# Collisions + Continuous Dynamics



Discrete and continuous, cyber and physical.



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Even purely physical models illustrate the subtleties.



### Determinism is Incomplete



Any set of deterministic models rich enough to encompass Newton's laws plus discrete transitions is incomplete.

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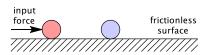
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## Collisions: Mixing Discrete and Continuous





#### Conservation of momentum:

$$m_1v_1'+m_2v_2'=m_1v_1+m_2v_2.$$

Conservation of kinetic energy:

$$\frac{m_1(v_1')^2}{2} + \frac{m_2(v_2')^2}{2} = \frac{m_1(v_1)^2}{2} + \frac{m_2(v_2)^2}{2}.$$

We have two equations and two unknowns,  $v'_1$  and  $v'_2$ .

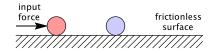


#### After a Collision



Quadratic problem has two solutions.

**Solution 1:** 
$$v'_1 = v_1$$
,  $v'_2 = v_2$  (ignore collision).



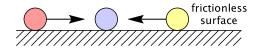
#### Solution 2:

$$v'_1 = \frac{v_1(m_1 - m_2) + 2m_2v_2}{m_1 + m_2}$$
 $v'_2 = \frac{v_2(m_2 - m_1) + 2m_1v_1}{m_1 + m_2}$ 

Note that if  $m_1 = m_2$ , then the two masses simply exchange velocities (Newton's cradle).



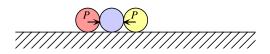
Consider this scenario:



Simultaneous collisions where one collision does not cause the other.



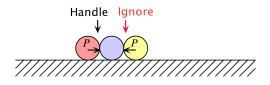
One solution: nondeterministic interleaving of the collisions:



At superdense time  $(\tau,0)$ , we have two simultaneous collisions.



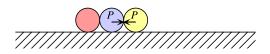
One solution: nondeterministic interleaving of the collisions:



At superdense time  $(\tau,1)$ , choose arbitrarily to handle the left collision.



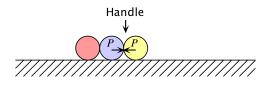
One solution: nondeterministic interleaving of the collisions:



After superdense time  $(\tau, 1)$ , the momentums are as shown.



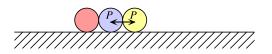
One solution: nondeterministic interleaving of the collisions:



At superdense time  $(\tau, 2)$ , handle the new collision.



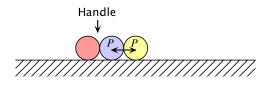
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After superdense time  $(\tau, 2)$ , the momentums are as shown.



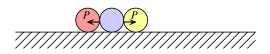
One solution: nondeterministic interleaving of the collisions:



At superdense time  $(\tau, 3)$ , handle the new collision.



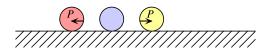
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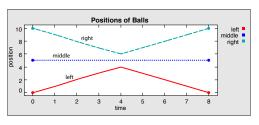


The balls move away at equal speed (if their masses are the same!)

## Arbitrary Interleaving



Arbitrary interleaving of the collisions yields the right result (for any choice of interleaving), but only if the masses are the same!

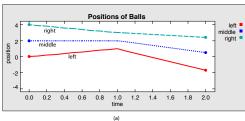


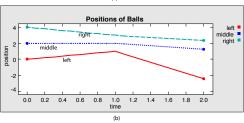
CollisionSimultaneous.xml

## Arbitrary Interleaving Yields Nondeterminism



If the masses are different, the behavior depends on which collision is handled first!



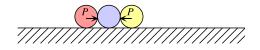


# Recall the Heisenberg Uncertainty Principle



We cannot simultaneously know the position and momentum of an object to arbitrary precision.

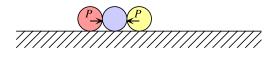
But the reaction to these collisions depends on knowing position and momentum precisely.



# Heisenberg Uncertainty Principle



Arbitrary interleaving and nondeterministic results appear to be defensible on physical grounds.

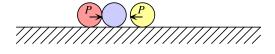


## Is Determinism Incomplete?



Let au be the time between collisions. Consider a sequence of models for au>0 where  $au\to0$ . Sequence of models is Cauchy. Then consider au<0 and  $au\to0$ . Sequence is again Cauchy.

Every model in each sequence is deterministic, but the limit model is not.



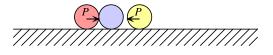
In Lee (2014), I show that a direct description of this scenario results in a *non-constructive* model. The nondeterminism arises in making this model constructive.

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# Fundamental Limits of Modeling



#### Outline of This Talk:

- Complexity
- Uncertainty
- Chaos
- Discretizing the Continuum
- Determinism is Incomplete
- Discreteness is Unavoidable

Deterministic models may become nondeterministic at the limits when mixing discrete and continuous behaviors.

# Fundamental Limits of Modeling



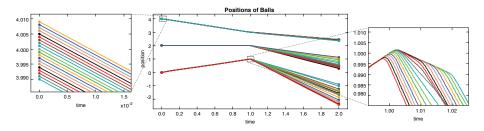
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### Continuous Models of Collisions



For the ball collision example, we could defensibly reject discrete models and model the balls as squishy, springy objects. The resulting model is chaotic:



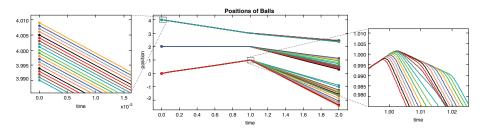
But in general, discreteness cannot be avoided without also rejecting causality.



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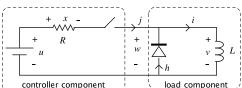


But in general, discreteness cannot be avoided without also rejecting causality.



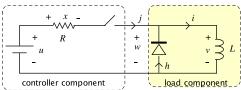


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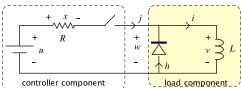


If the diode is reverse biased,

$$j(t) = \frac{1}{L} \int_0^t w(\tau) d\tau,$$



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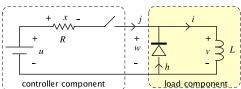
If the diode is reverse biased,

$$j(t) = \frac{1}{L} \int_0^t w(\tau) d\tau,$$

Hence, for the load component, w is an input and j is an output. The environment cannot arbitrarily set the current j independent of the history.



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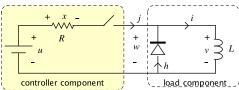
If the diode is reverse biased,

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Moreover, the output j does not depend immediately on the input w (there is no direct feedthrough).



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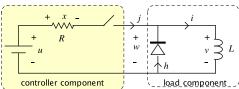


If the switch is closed, by Ohm's law,

$$w(t) = u(t) - j(t)R$$



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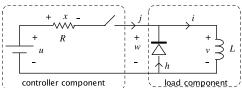
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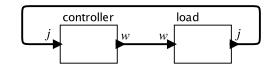
so we can consider j to be the input and w to be the output. In this case, there is direct feedthrough.



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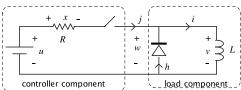


Hence, with the switch closed and the diode reverse biased, we have a constructive model with causality as shown below:

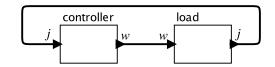




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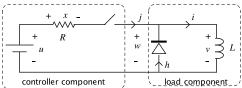


This model is constructive.





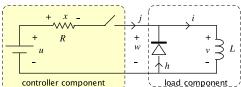
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When the switch is opened, the current j is forced to zero and the diode becomes forward biased.



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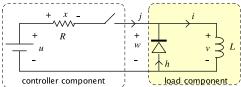


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In this case, j has to be the *output* of the controller, not the input, and its output j does not depend on the input w (there is no direct feedthrough.



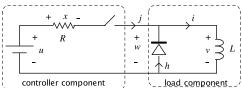
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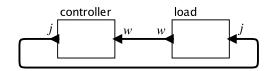
The load component also reverses causality, where j becomes the input and w becomes the output, because w equals the voltage drop of a forward-biased diode.



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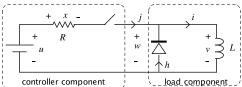


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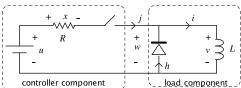
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When the switch goes from closed to open, the causality and direct feedthrough properties of the two components reverse.



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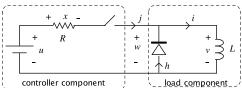


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There is no logic that can transition from A causes B to B causes A smoothly without passing through non-constructive models.



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Discreteness is unavoidable!



- Scientists and engineers use models differently.
- Deterministic models are useful.
- Chaotic deterministic models have limited predictive power.
- All models have a limited regime of validity
- Modal models makes these regimes explicit.
- Discrete models may exhibit Zeno conditions.
- Detecting Zeno conditions is hard.
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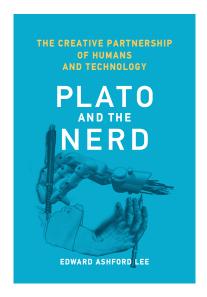
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### Forthcoming Book — MIT Press, Fall 2017





This book explores how engineers use models. I argue that these models are not discovered preexisting truths, but rather are invented in a fundamentally human creative process.

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