15-883: Computational Models of Neural Systems

Lecture 1.1:

Brains and Computation

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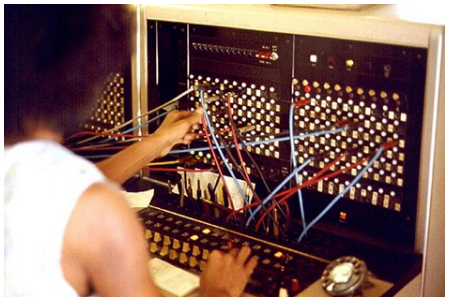
Models of the Nervous System

- Hydraulic network (Descartes): nerves = hoses that carry fluid to drive the muscles

- Clockwork: systematic and representational



- Telephone switchboard: communication

- Digital computer ("electronic brain"): computational

Metaphors can serve as informal theories.

Help to frame the discussion.

But limited in predictive power.

Why Do Modeling?

- Models help to organize and concisely express our thoughts about the system being modeled.

- Good models make testable predictions, which can help guide experiments.

- Sometimes a computational model must be implemented in a computer simulation in order to explore and fully understand its behavior.
  - Surprising behavior may lead to new theories.

Computers Made From Meat

The essential claim is this:

Brains perform computation.

Brains are also *organs* (i.e., metabolic systems) and *mechanical structures* (aqueducts, fiber tracts, etc.)

But they also perform computation. Therefore:

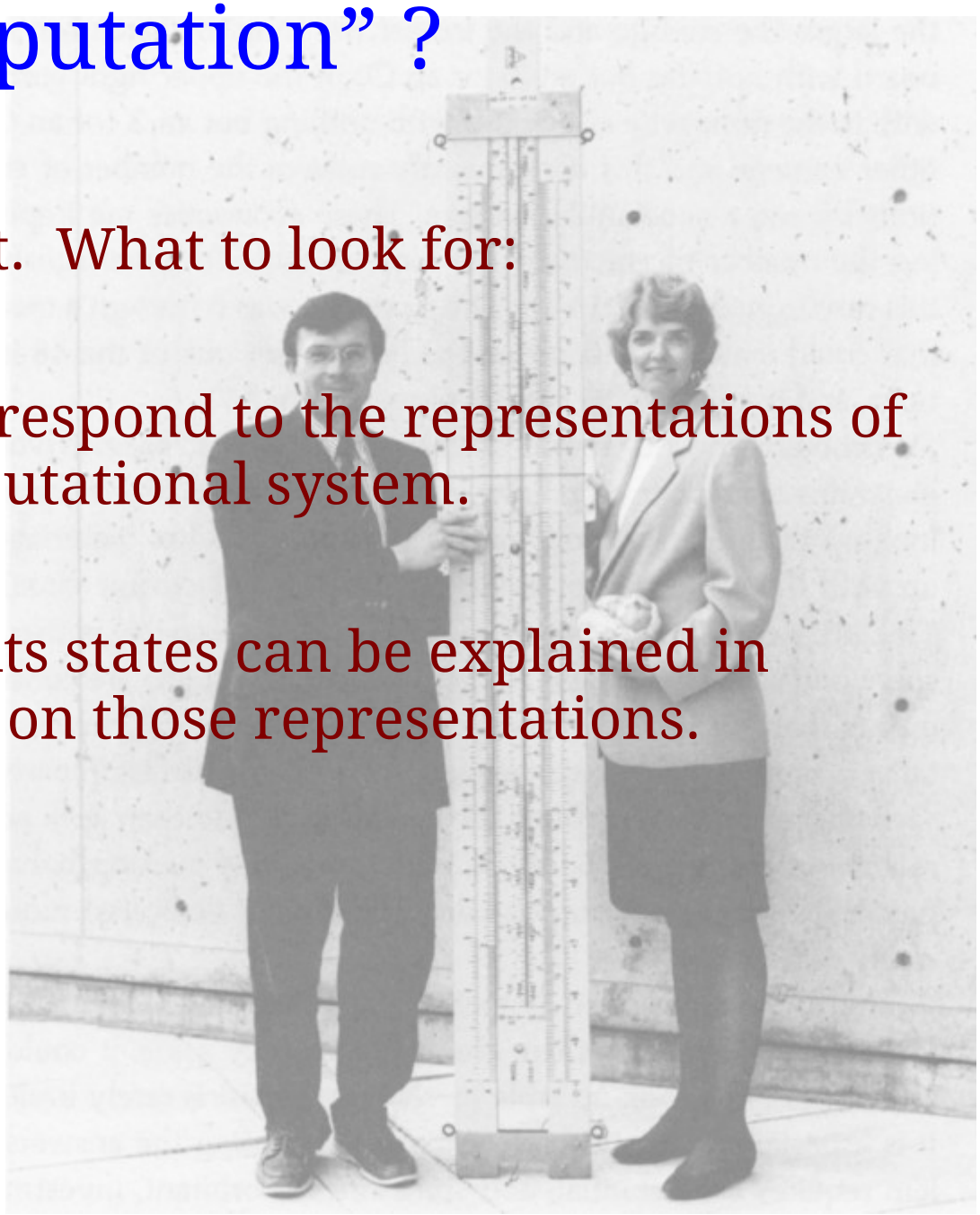
Computational theories can give insight into brain function.

Can A Physical System Perform "Computation" ?

It's a subjective judgment. What to look for:

1) Its physical states correspond to the representations of some abstract computational system.

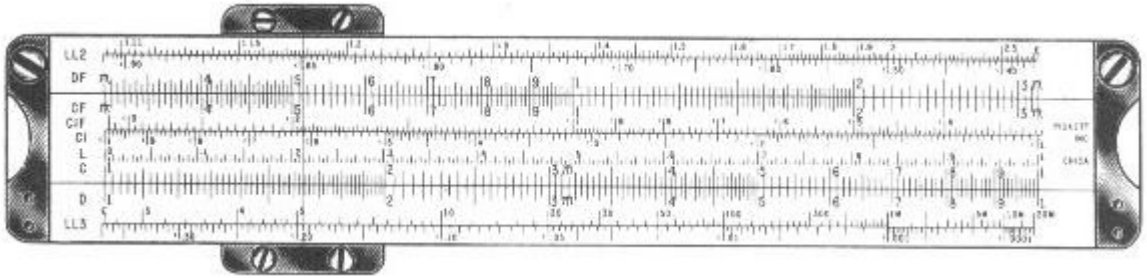
2) Transitions between its states can be explained in terms of operations on those representations.



Terry Sejnowski and Patricia Churchland, authors of *The Computational Brain*

Physical Computation: The Slide Rule

- Abstract function being computed: multiplication
  - Input: a pair of numbers
  - Output: a number

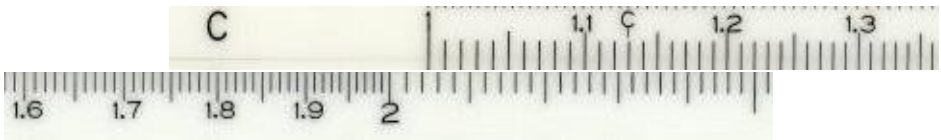


- Physical Realization:
  - First input = point on surface of the (fixed) D scale
  - Second input = point on surface of the (sliding) C scale
  - Output = point on surface of the (fixed) D scale

Slide Rule Computation: Multiply 2.05 by 3

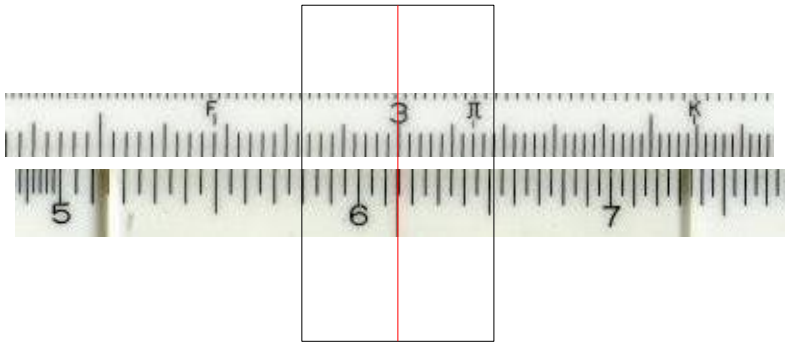
- Move the sliding C scale so that the digit “1” is at 2.05 on the D scale.

C
D



- Slide the cursor so that the red index is over the 3 on the C scale. Read the result 6.15 on the D scale.

C
D

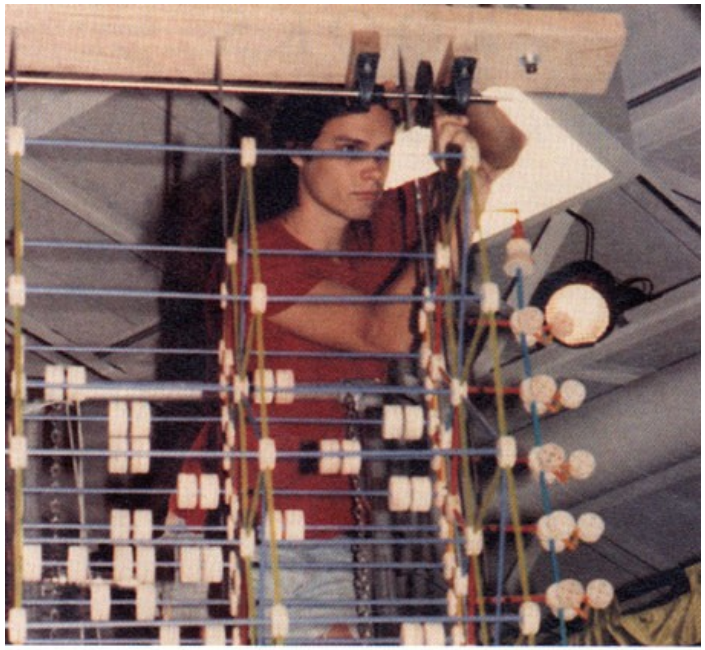


- Why does this work? Multiplication = adding logs.

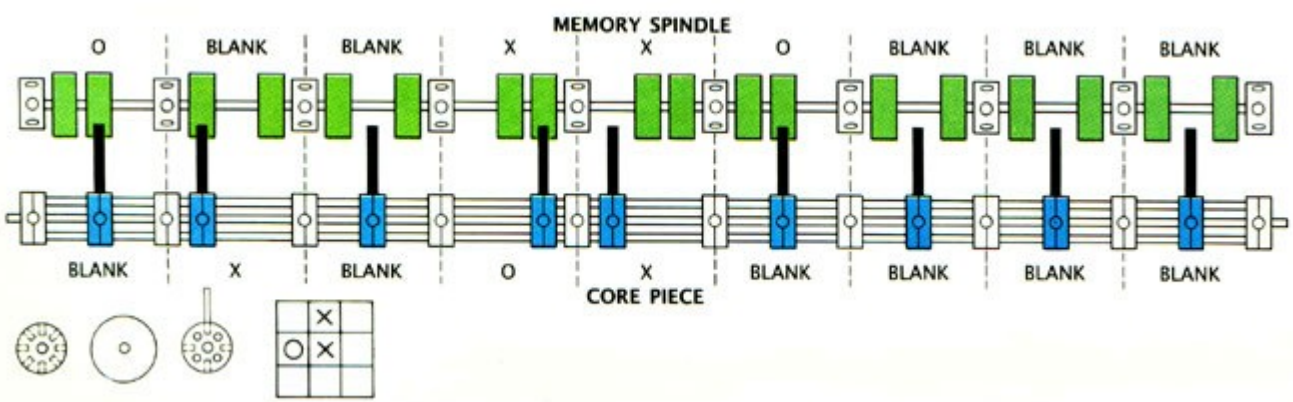
Tinkerytoy Tic-Tac-Toe Computer

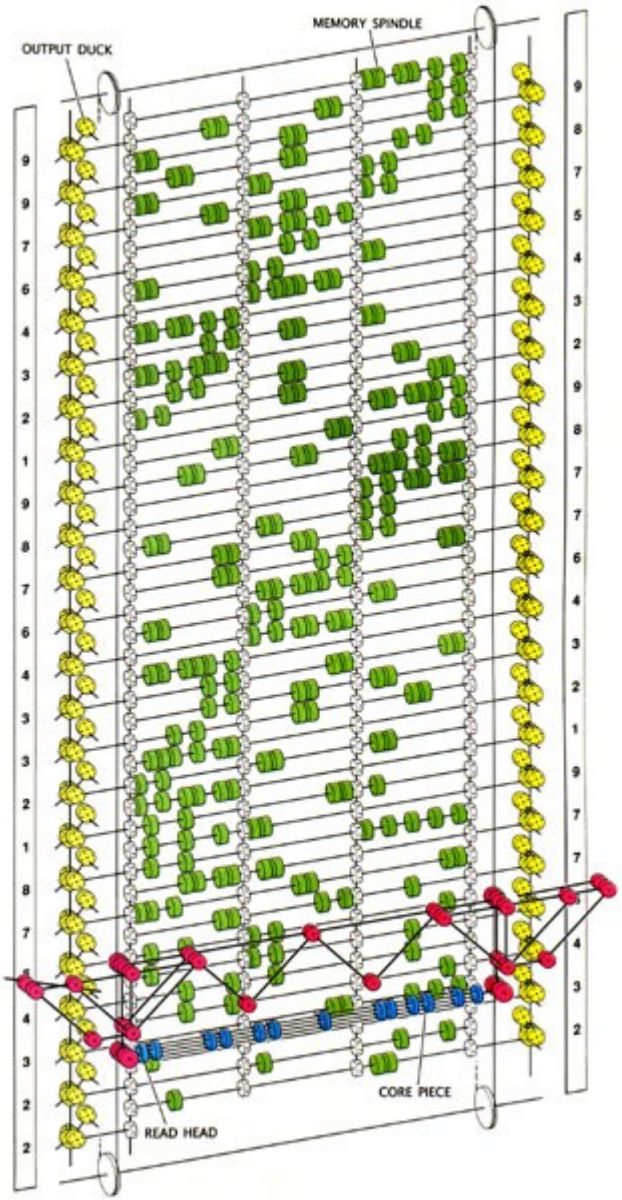
Designed by Danny Hillis at MIT.

See Scientific American article for details.



Edward Hardebeck helps to assemble the Tinkertoy computer





The Tinkertoy computer: ready for a game of tic-tac-toe

Do Brains Compute?

Most scholars believe the answer is “yes”.

- Brains are meat computers!

Some consider this conclusion demeaning.

- Computers are machines. I am not a machine!

Some try to find reasons the answer could be “no”.

- Example: if unpredictable quantum effects played a crucial role in what brains do, then the result would not be describable as a computable function.

How Big Are Meat Computers? Some Numbers

	Neurons	Synapses
Humans	10^{12}	10^{15}
Rats	10^{10}	10^{13}
1 mm^3 of cortex	10^5	10^9

A cortical neuron averages 4.12×10^3 synapses (cat or monkey.)

Demystifying the Brain (Cherniak, 1990)

- There are roughly 10^{13} synapses in cortex. Assume each stores one bit of information. That's 1.25 terabytes.
- The Library of Congress (80 million volumes, average 300 typed pages each) contains about 48 terabytes of data.
- The brain is complex, but not infinitely so.
- The cerebellum, concerned with posture and movement (and…?), contains four times as many neurons as the cortex, seat of language and conscious reasoning.

Computational Resources

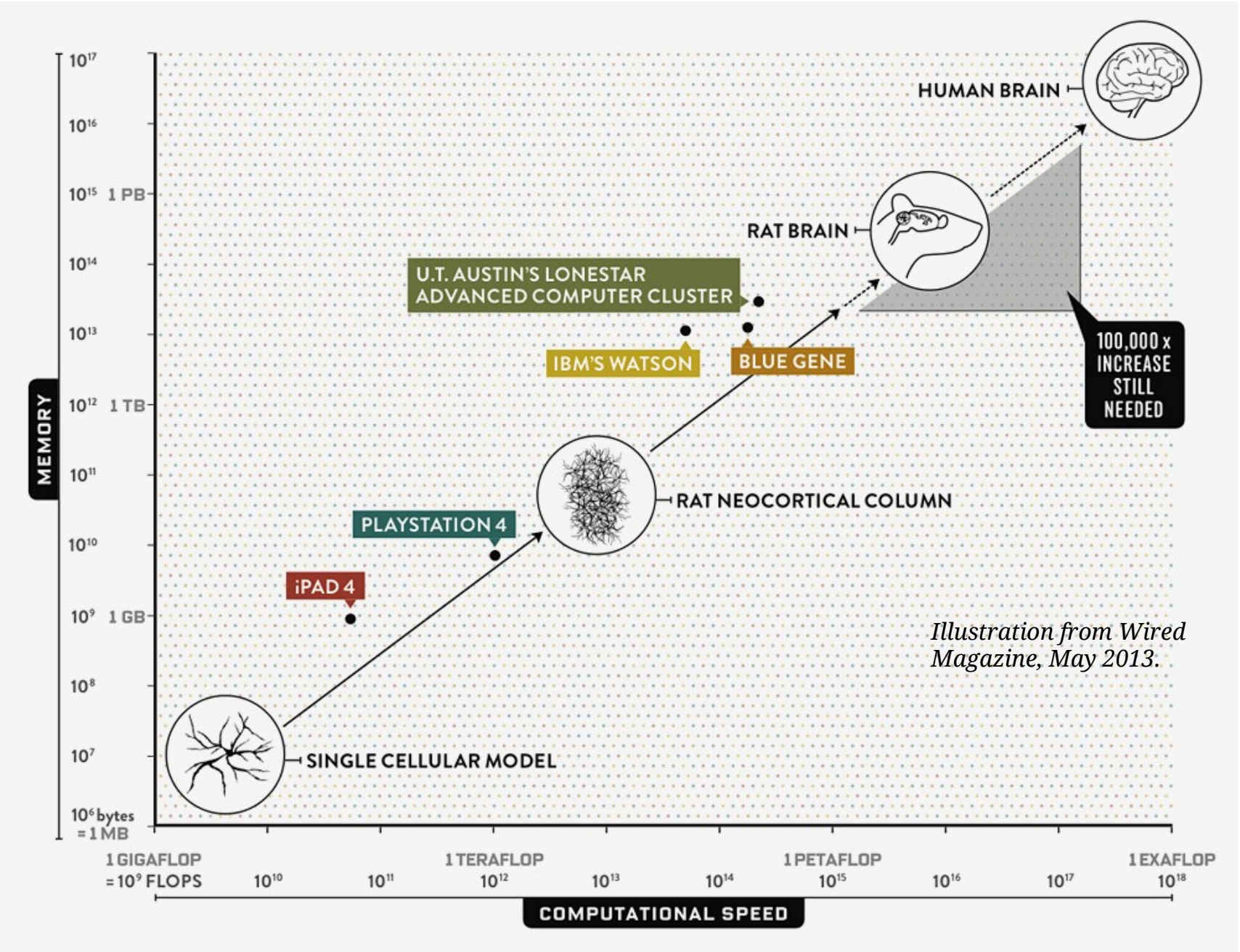


Illustration from Wired Magazine, May 2013.

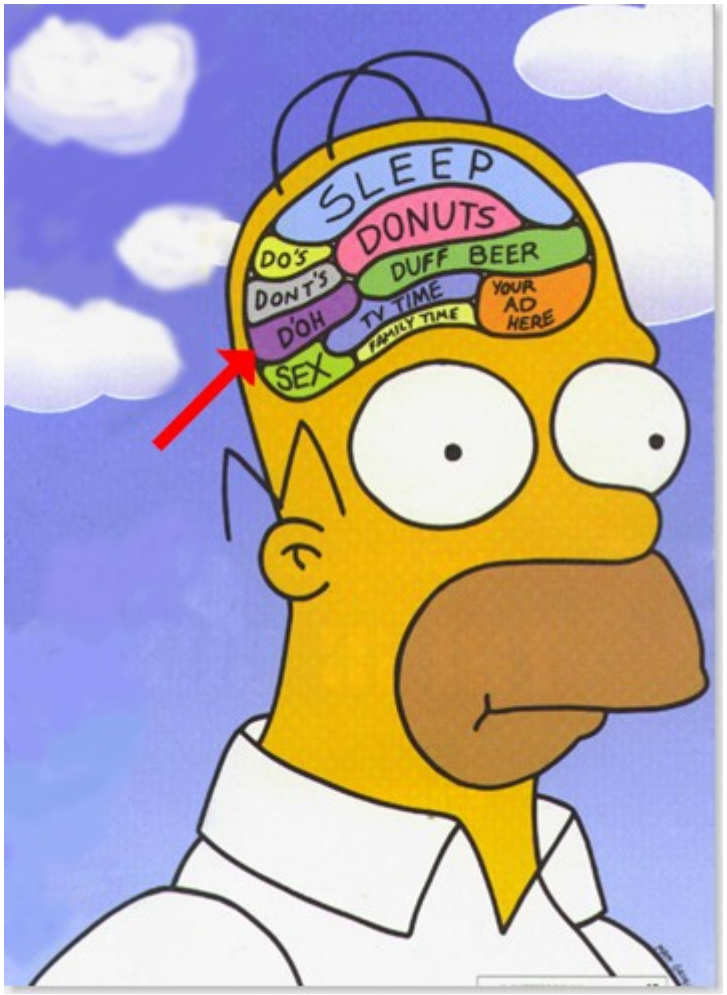
Computational Processes Posited in the Brain

- Table lookup / associative memory.
- Competitive learning; self-organizing maps.
- Principal components analysis.
- Gradient descent error minimization learning.
- Temporal difference learning.
- Dynamical systems (attractor networks, parallel constraint satisfaction).

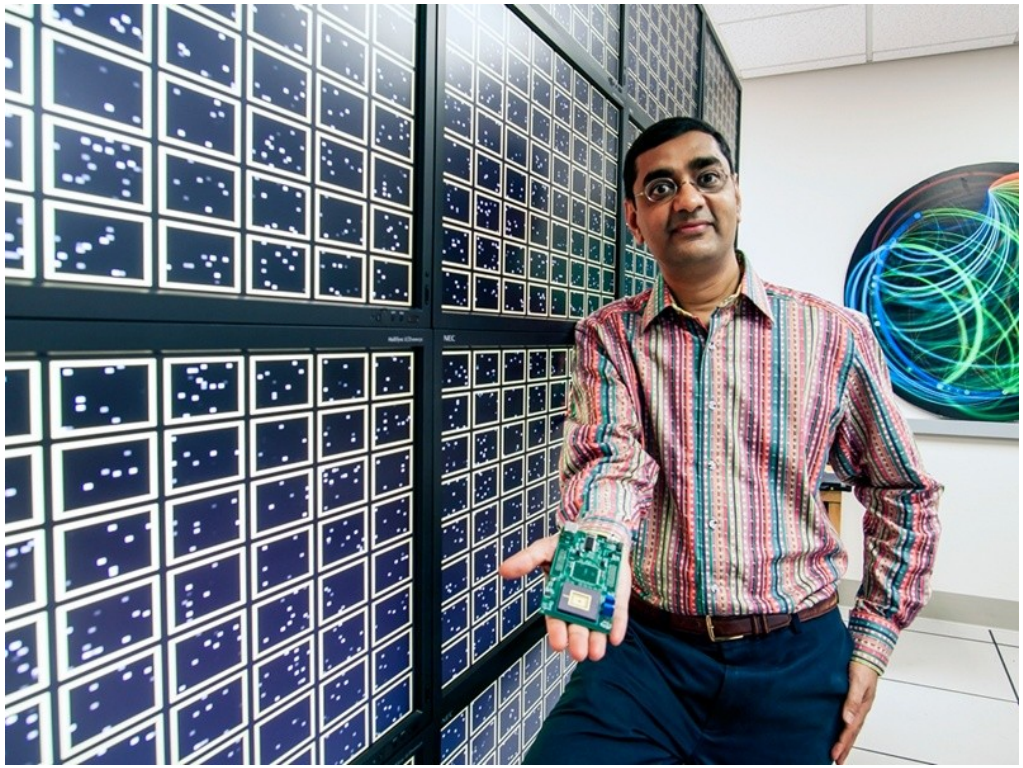
This course will explore these models and how they apply to various brain structures: hippocampus, basal ganglia, cerebellum, cortex, etc.

Want to Build a Brain?
Some Bad News:

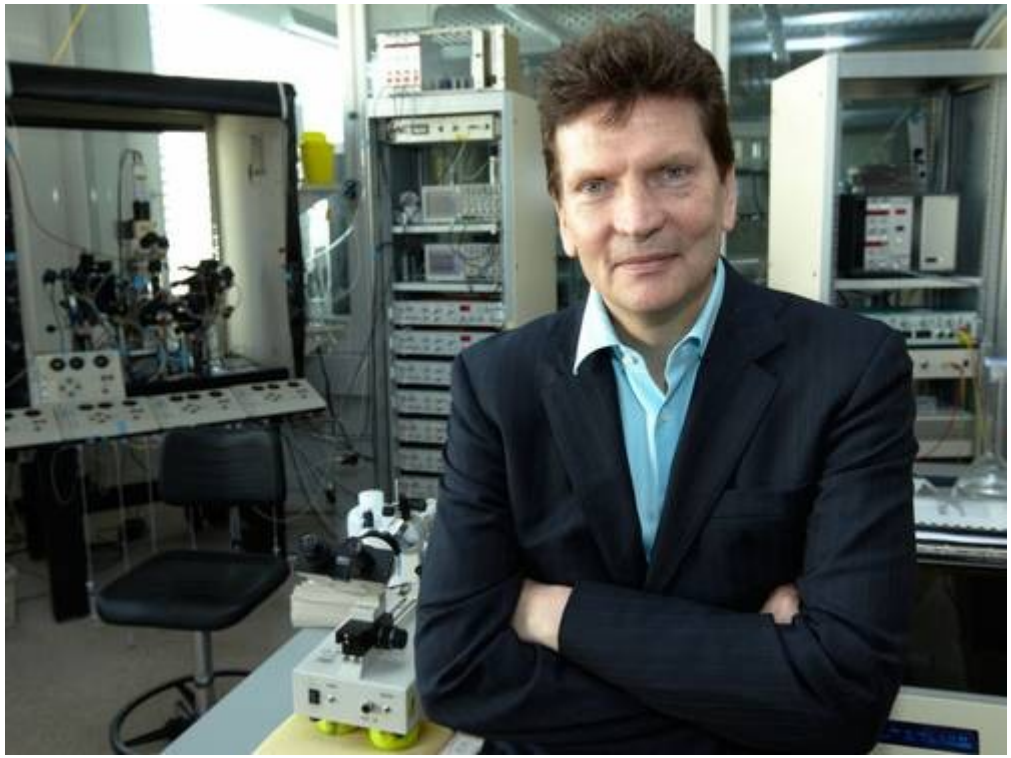
- We're still in the early days of neural computation.
- Our theories of brain function are vague and wrong.



“Building A Brain”



IBM's Dharmendra Modha



EPFL's Henry Markram

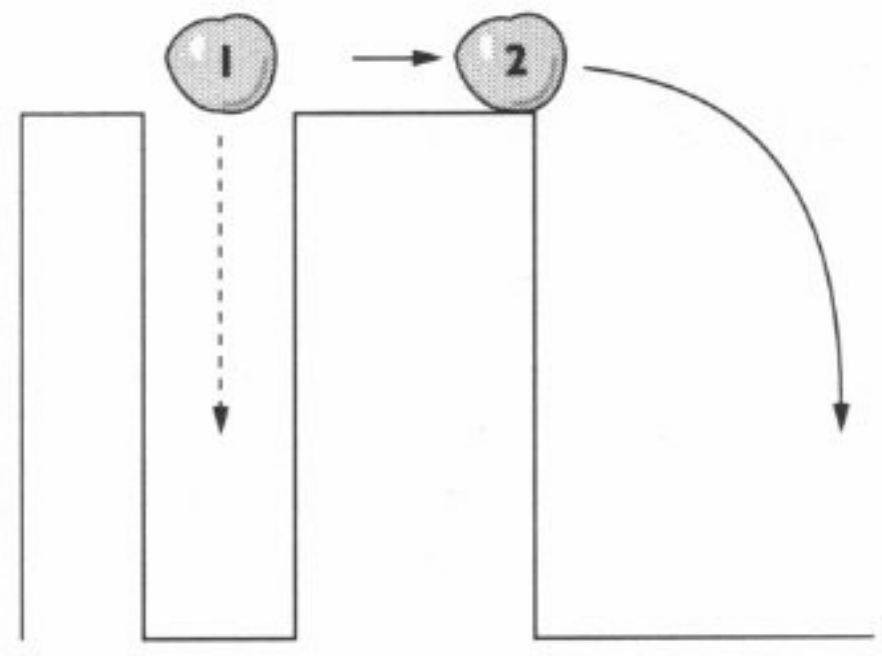
Science vs. Engineering

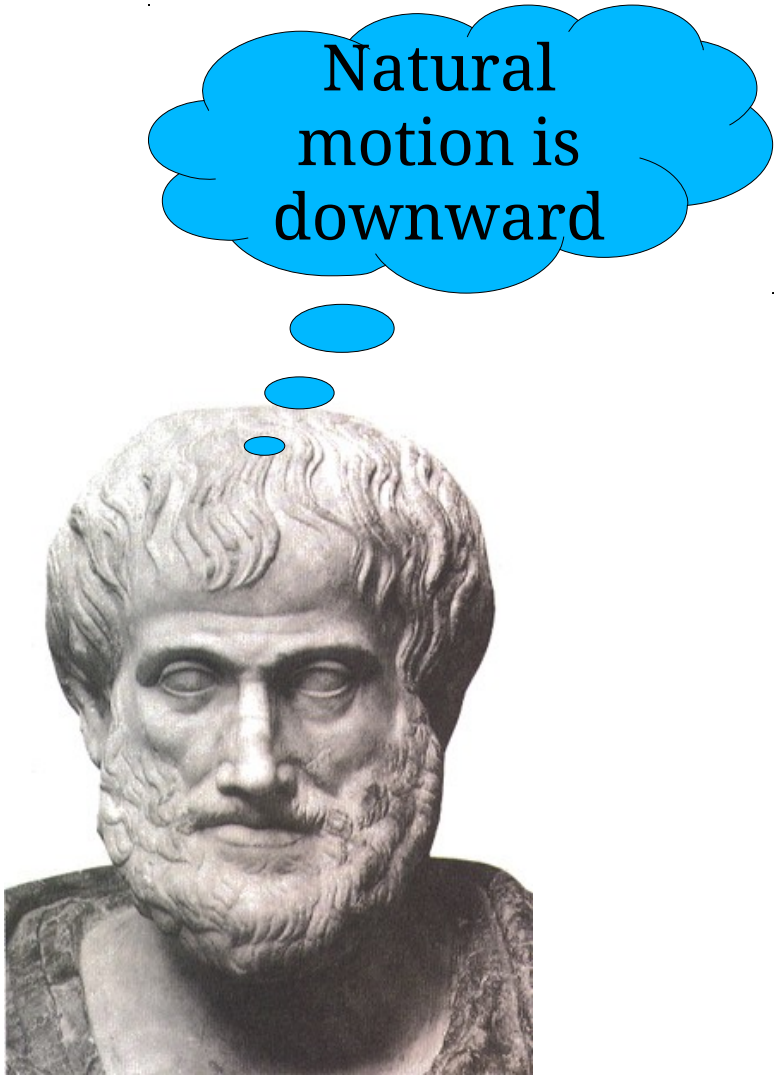
- Science: figure out how nature works.
  - Good models are as simple as possible.
  - Models should reflect reality.
  - Models should be falsifiable (make predictions).
- Engineering: figure out how to make useful stuff.
  - “Good” means performs a task faster/cheaper/more reliably.
  - Making a system more “like the brain” doesn't in itself make it better.
- Holy grail for CS/AI people: use insights from neuroscience to solve engineering problems in perception, control, inference, etc.
  - Hard, because we don't know how brains work yet.

Do We Have All the Math We Need to Understand the Brain?

- Probably not yet.
- People have tried all kinds of things:
  - Chaos theory
  - Dynamical systems theory
  - Particle filters
  - Artificial neural networks (many flavors)
  - Quantum mechanics
- We can explain simple neural reflexes, but not memory or cognition.
- Current theories will probably turn out to be as wrong as Aristotelian physics.

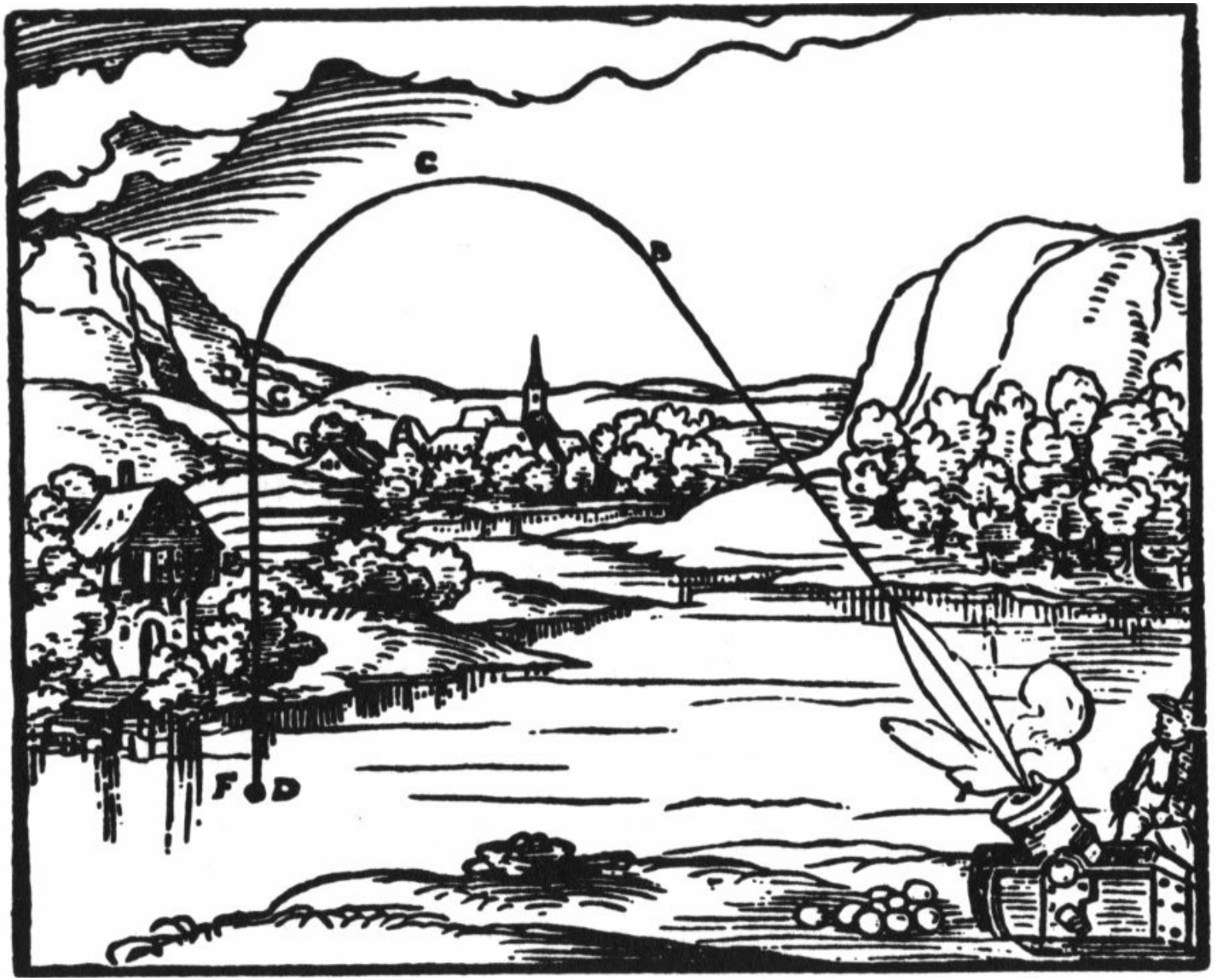
Which Rock Hits the Ground First?



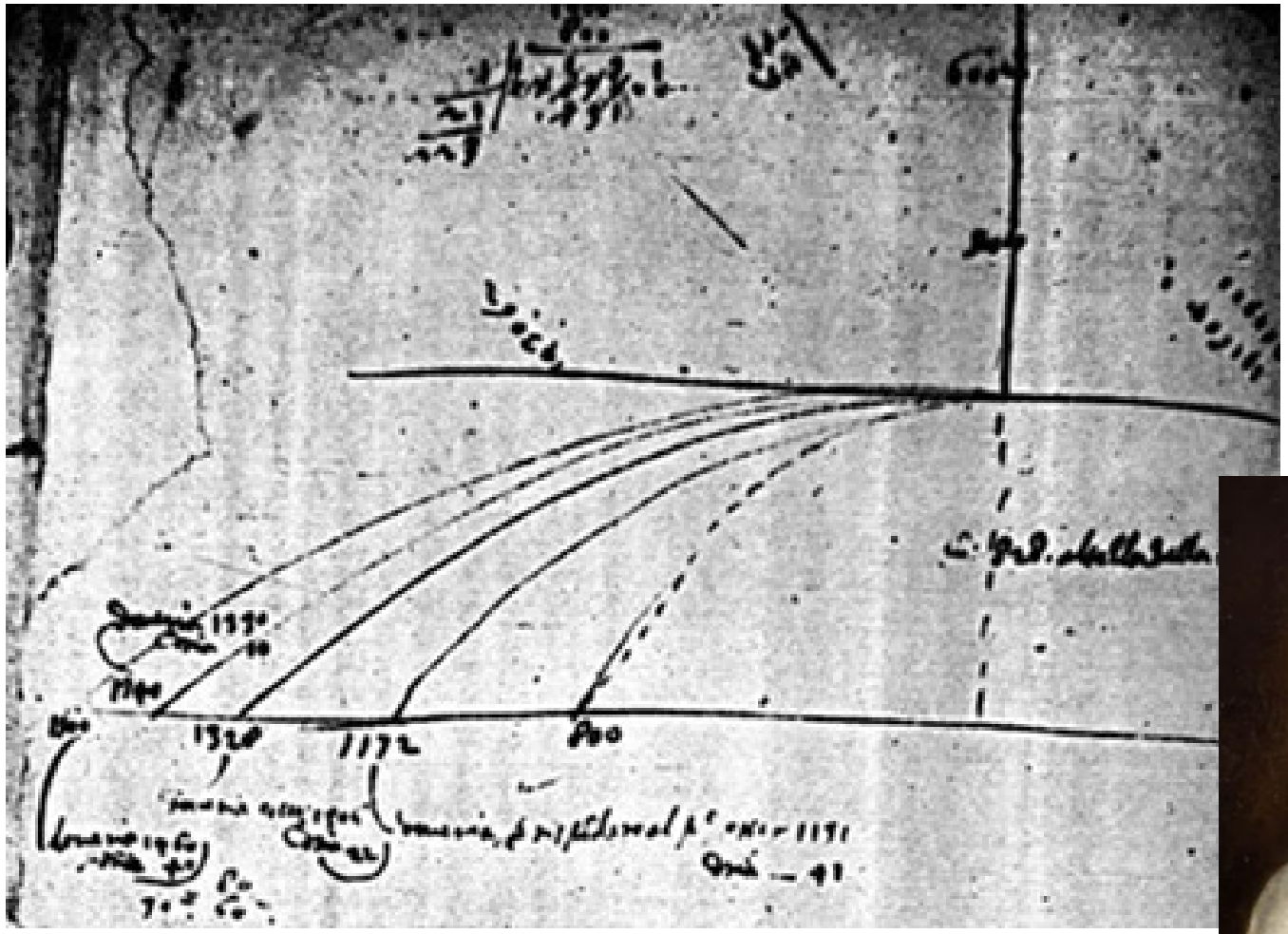


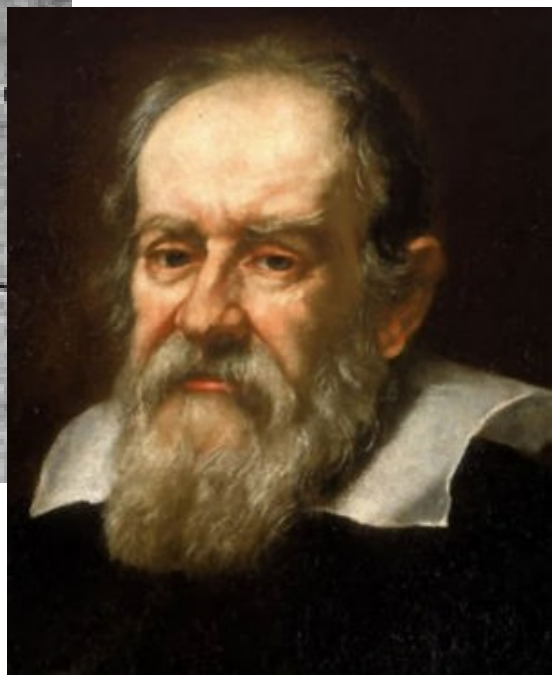
Aristotle (384-322 BCE)

Aristotelian Motion



Galileo: Motion is Parabolic and Independent of Mass





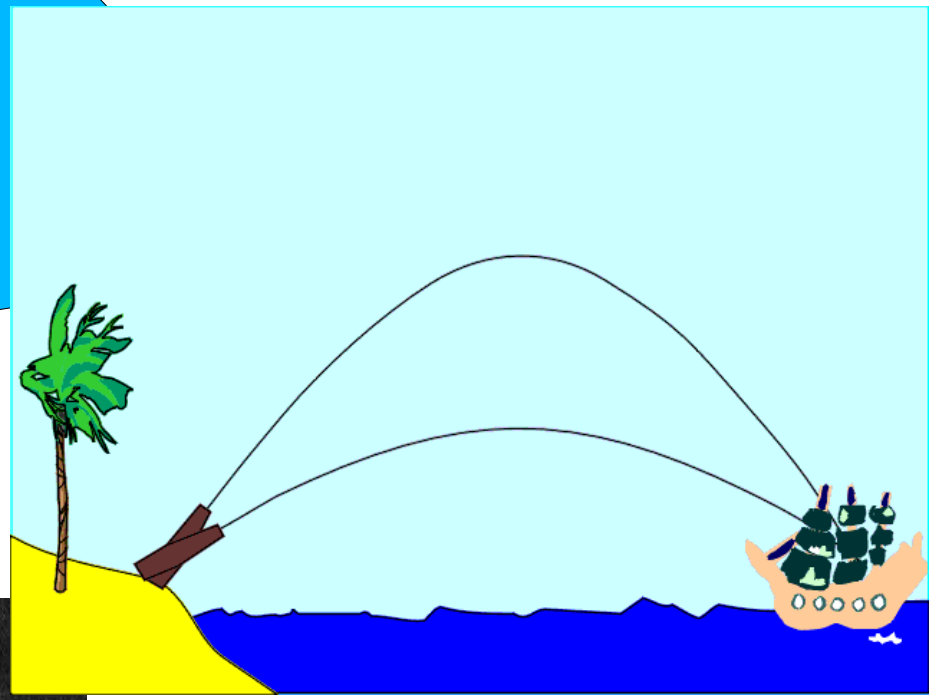
Galileo Galilei (1564-1642)

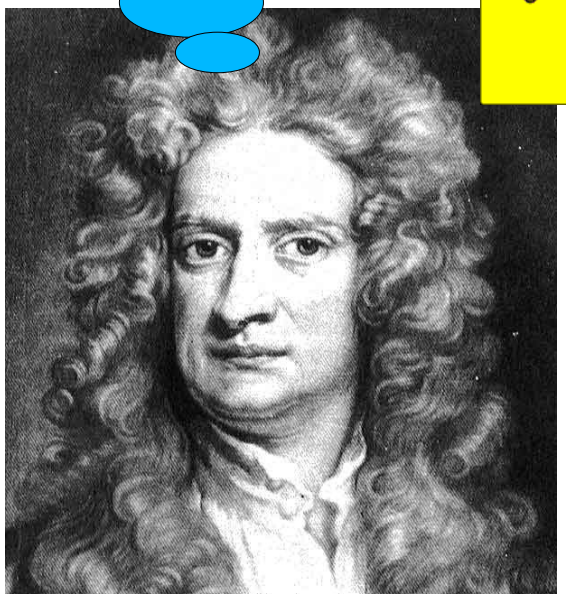
Why a Parabola? Need Calculus

$$a(t) = -9.8\, m/s^2$$

$$v(t) = \int a(t)\, dt = -9.8\, t + v_0$$

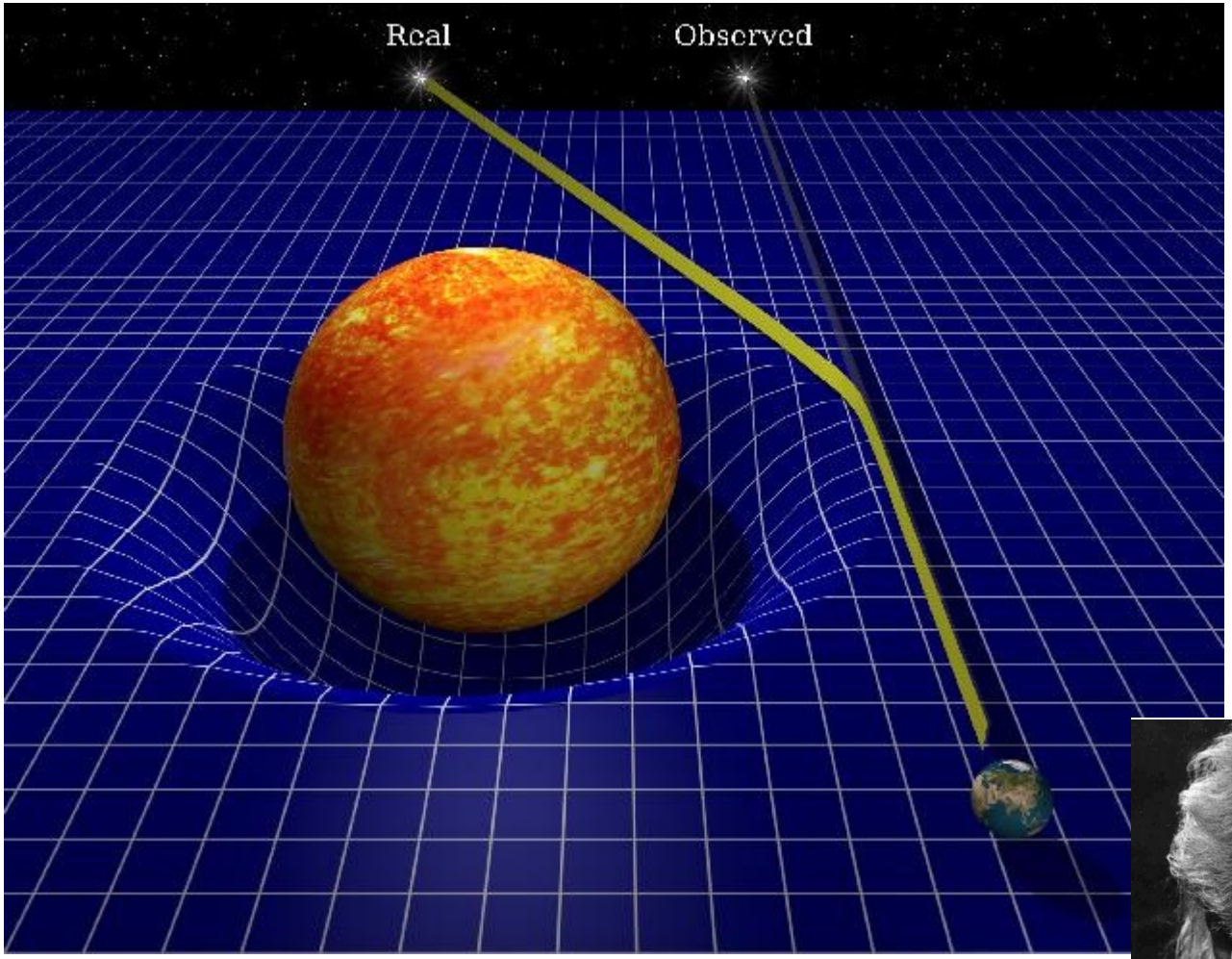
$$h(t) = \int v(t)\, dt = -9.8\, t^2/2 + v_0 t + h_0$$



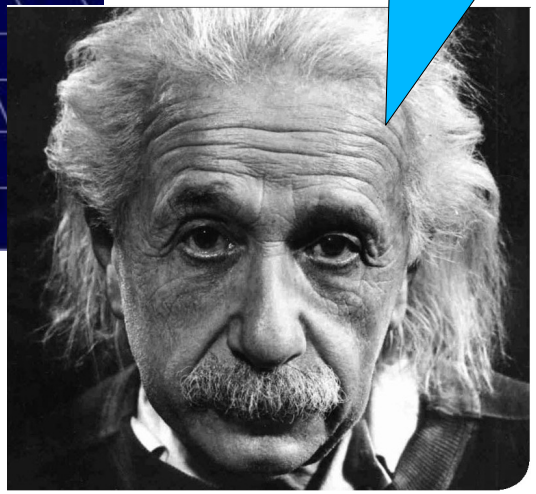


Isaac Newton (1643-1727)

Relativistic Motion: Curved Spacetime



For this theory you need tensor calculus.



Albert Einstein (1879-1955)

The Misunderstood Brain

- We know **a lot** about what makes neurons fire.
- We know **a good deal** about wiring patterns.
- We know **only a little** about how information is represented in neural tissue.
  - Where are the “noun phrase” cells in the brain?
- We know **almost nothing** about how information is processed.
- This course explores what we do know. There is progress every month.
- It's an exciting time to be a computational neuroscientist.

Some Representative Successes

- Dopamine cells fire in response to rewards, but also in response to neutral stimuli that have become associated with rewards. But they can also stop firing with further training, or they can pause when a reward is missed. Why should they do that?
  - Temporal difference learning, a type of *reinforcement learning*, neatly explains much of the data.
- Most cells in primary visual cortex get input from both eyes but have a dominant eye that they respond more to. Staining shows zebra-like “ocular dominance” stripes. How does this structure emerge?
  - Competitive learning algorithms, a type of *unsupervised learning*, can account for the formation of ocular dominance and orientation selectivity in V1.