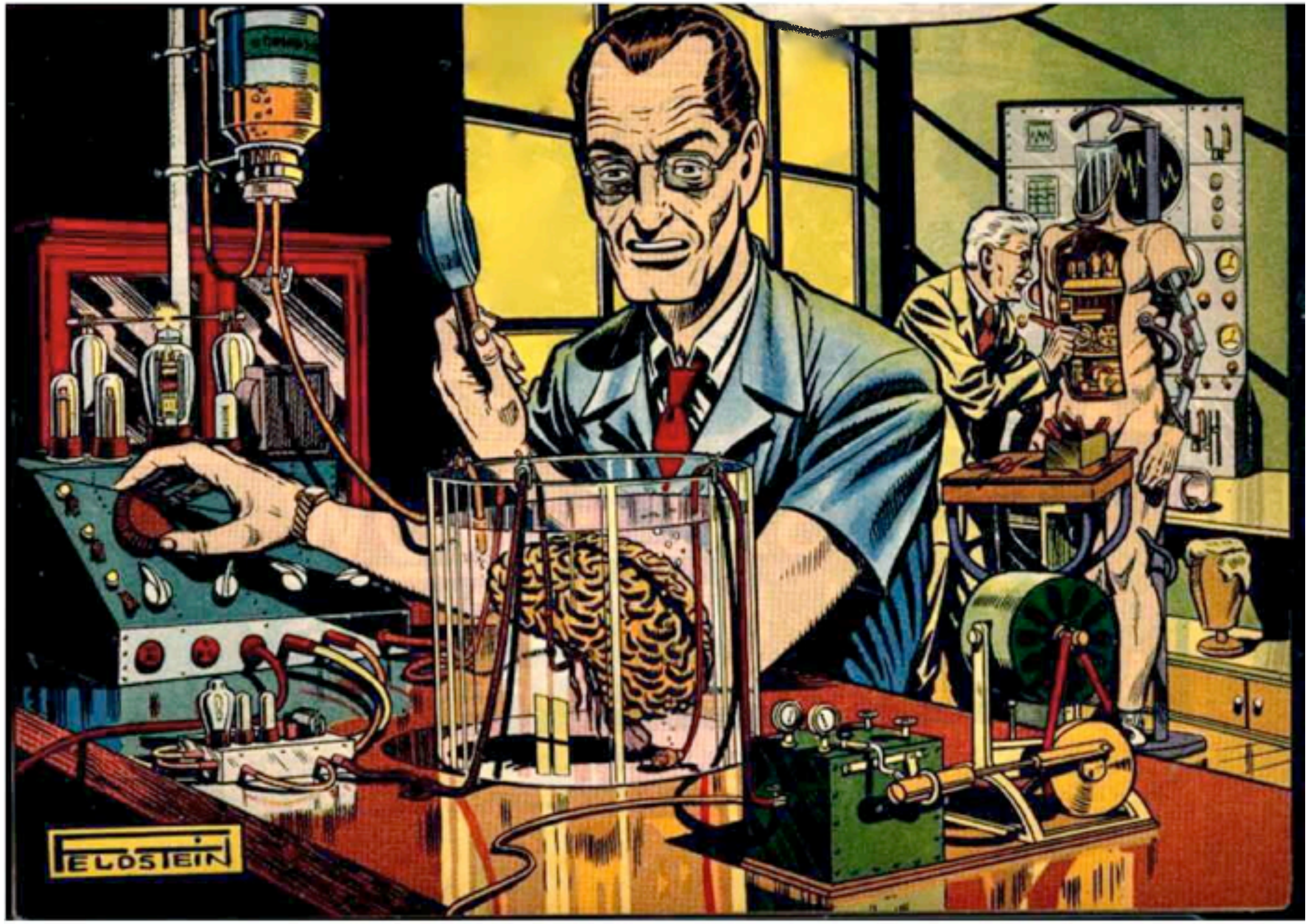
Active Sensing and Learning



ICASSP 2011, May 23, Prague

www.ece.wisc.edu/~nowak/ASL.html

Jarvis Haupt
www.ece.umn.edu/~jdhaupt

Rob Nowak
www.ece.wisc.edu/~nowak

Adaptive Information

Goal: Estimate an unknown object $x \in \mathcal{X}$ from scalar samples

Information: samples of the form $y_1(x), \ldots, y_n(x)$,
the values of certain functionals of x

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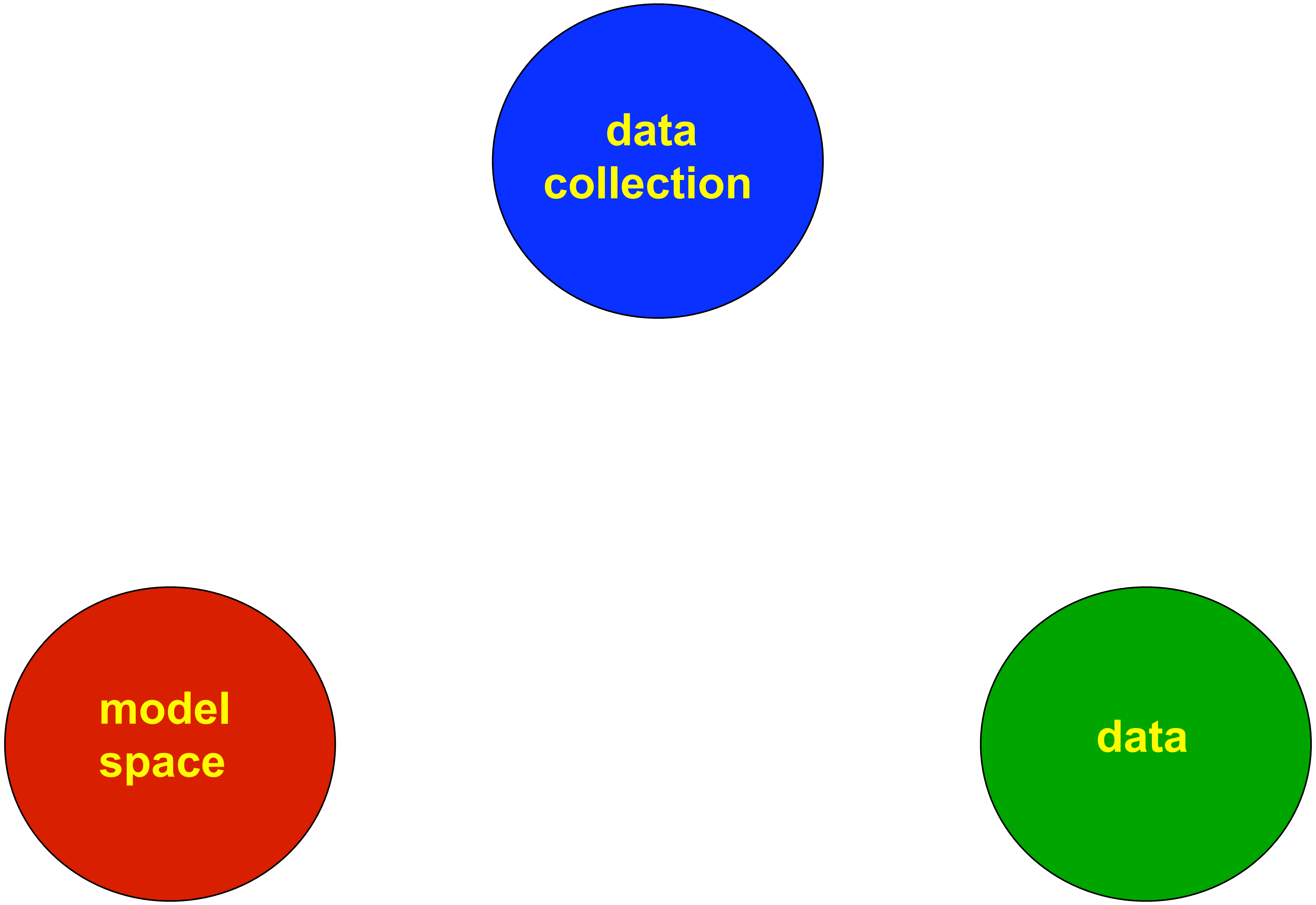
Does adaptivity help?

Feedback from Data Analysis to Data Collection

$\mathcal{Y}$: possible measurements/experiments

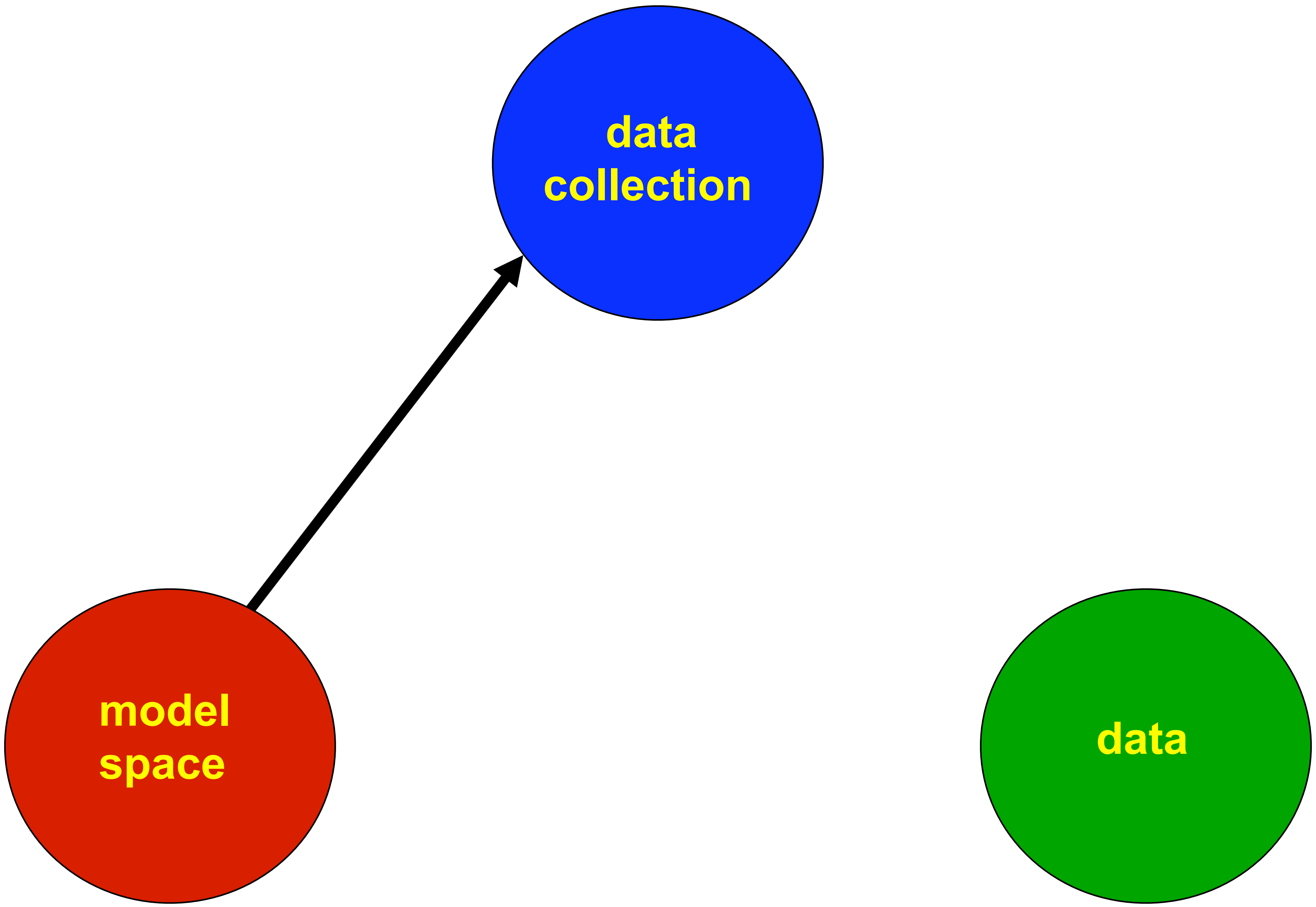


$\mathcal{X}$: models/hypotheses
under consideration

$y_1(x), y_2(x), \ldots$: information/data

Feedback from Data Analysis to Data Collection

$\mathcal{Y}$: possible measurements/experiments



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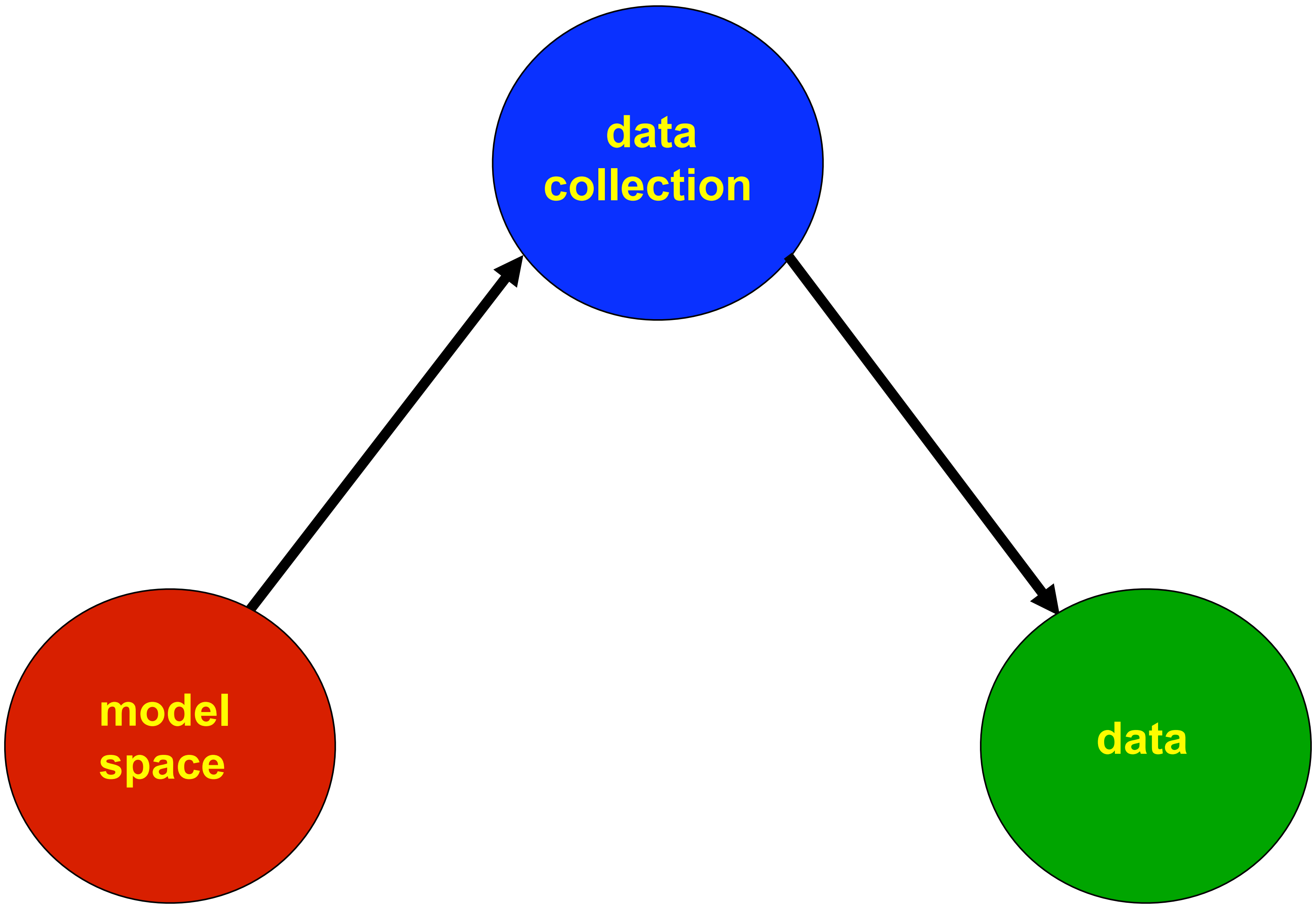

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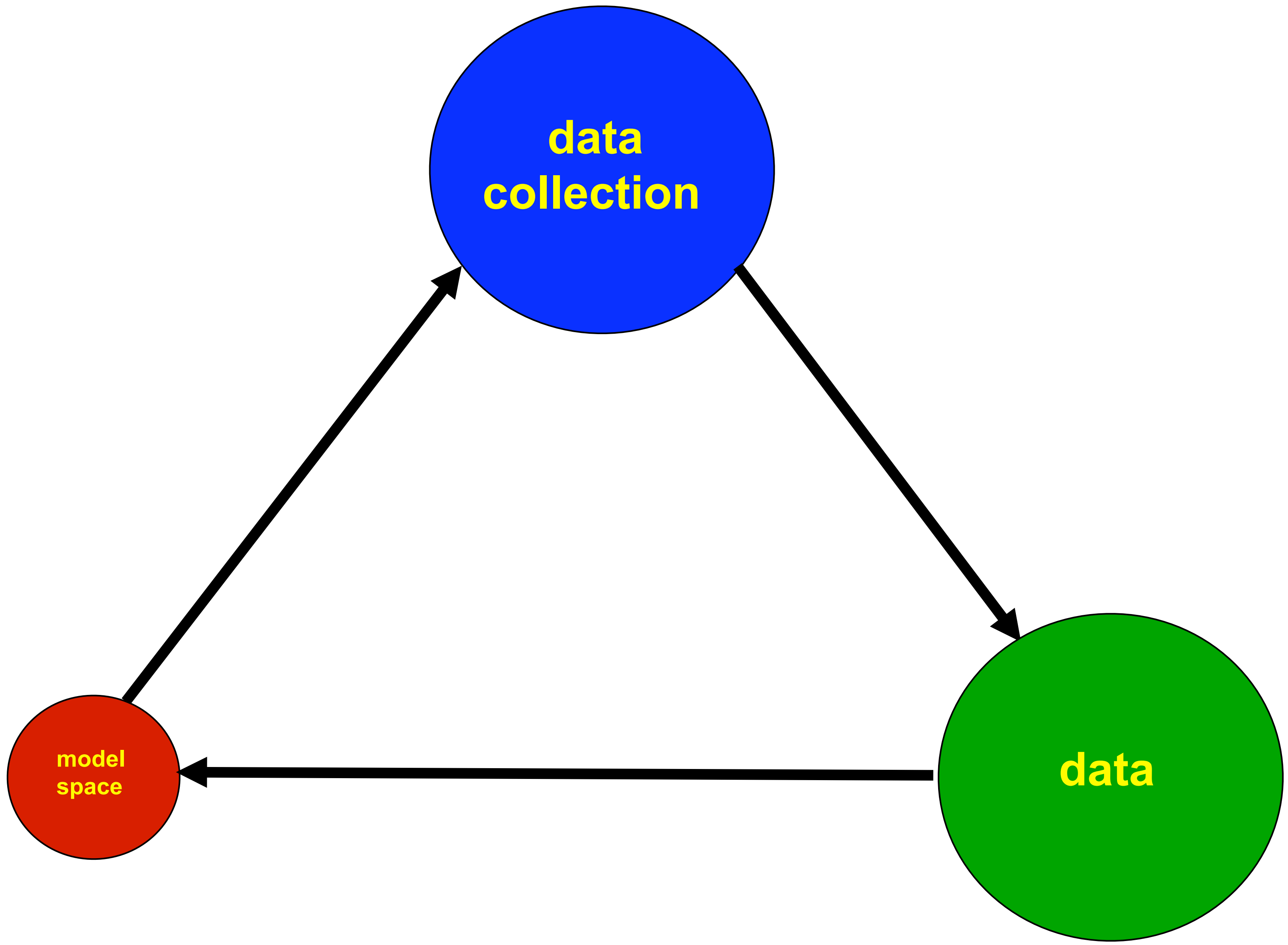

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Outline of Tutorial

Part 1: Introduction (Rob), 9:00-9:30

Part 2: Active Sensing (Jarvis), 9:30-10:30

Break, 10:30-10:45

Part 3: Active Learning (Rob), 10:45-11:45

Part 4: Conclusions and Future Directions, 11:45-12

Outline of Part 1:

Sequential Experimental Design

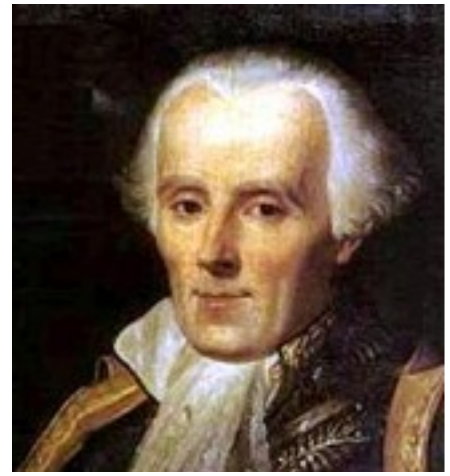
Adaptive Sensing for Sparse Recovery

Sensing and Inference in Large Networked Systems

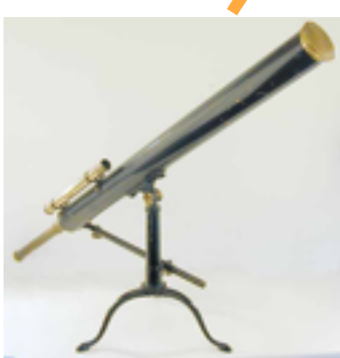
Active Learning in Machines and Humans

Mathematics of Active Sensing and Learning

Sequential Experimental Design



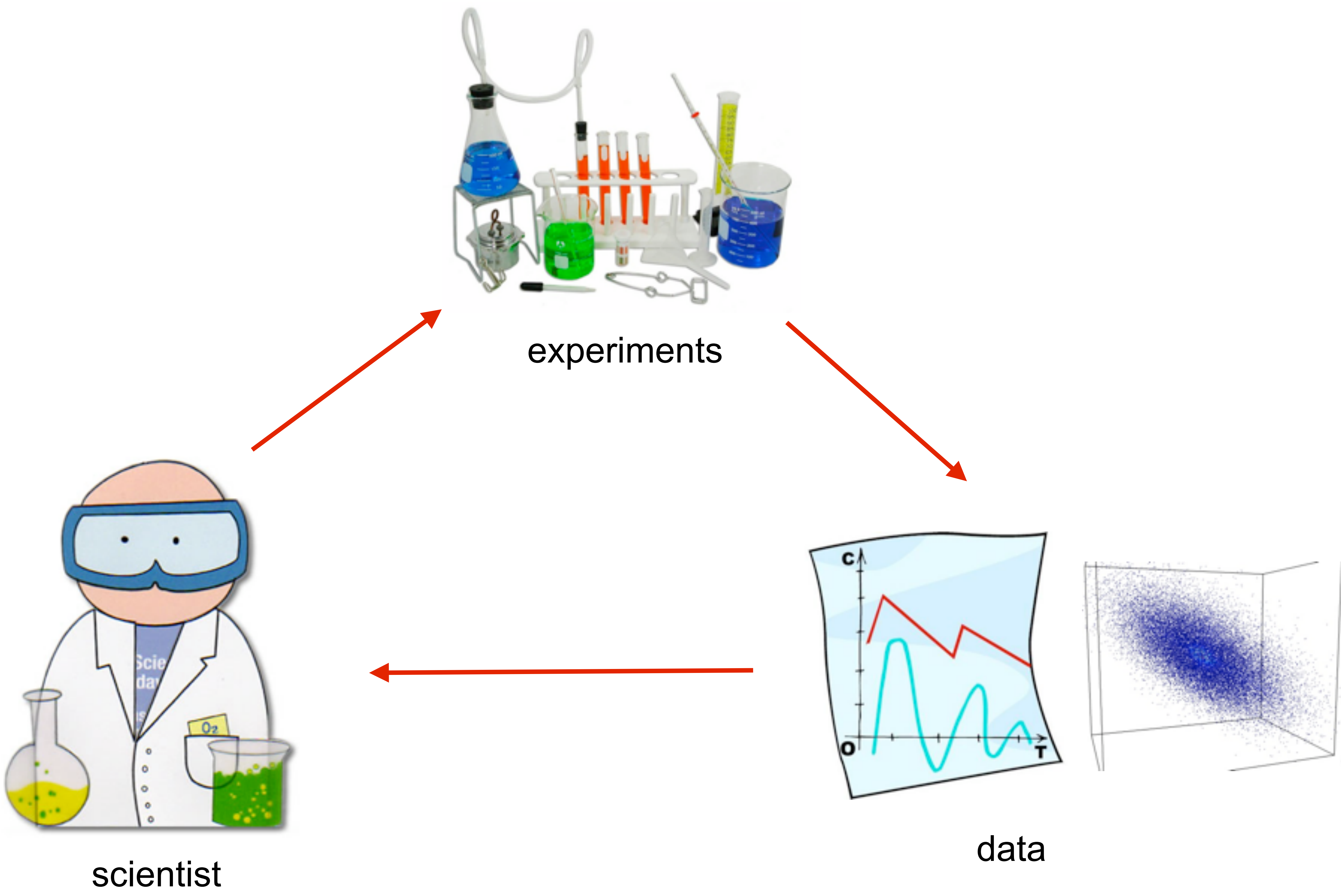
Decided to make new astronomical measurements when “the discrepancy between prediction and observation [was] large enough to give a high probability that there is something new to be found.” Jaynes (1986)



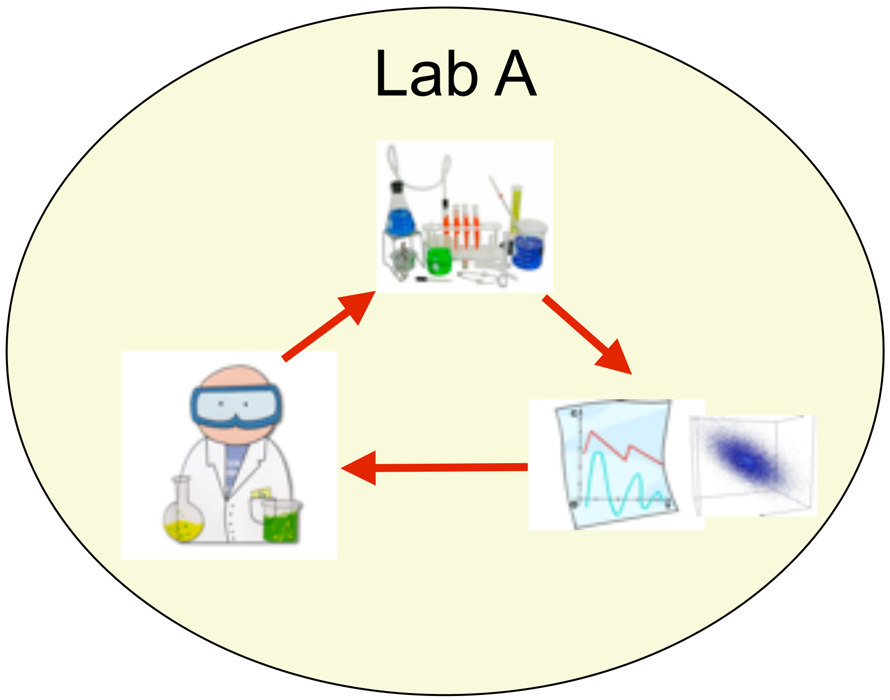
observe / infer → Discovery !

selective sensing

The Scientific Process in a Laboratory



The Scientific Process at Large



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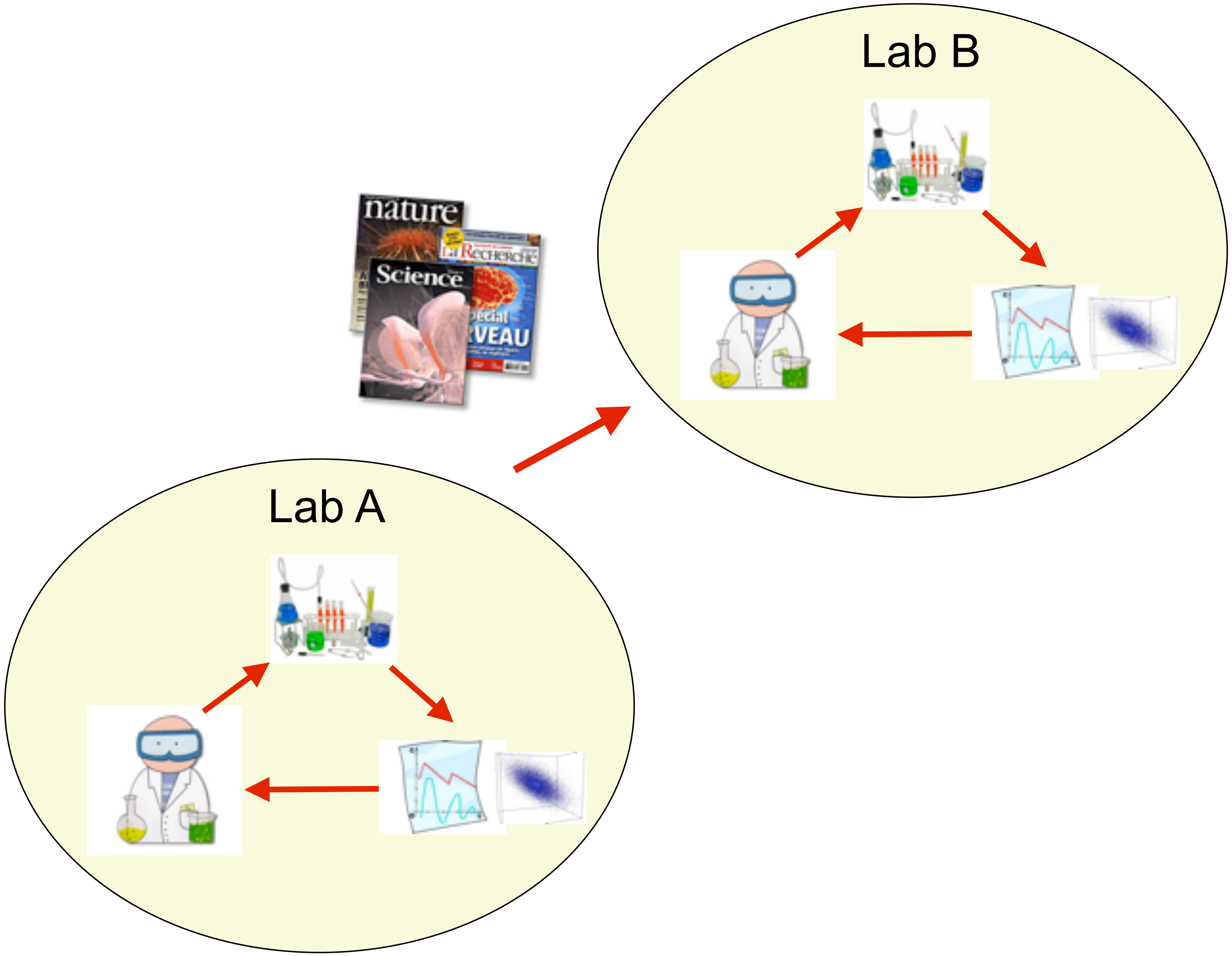

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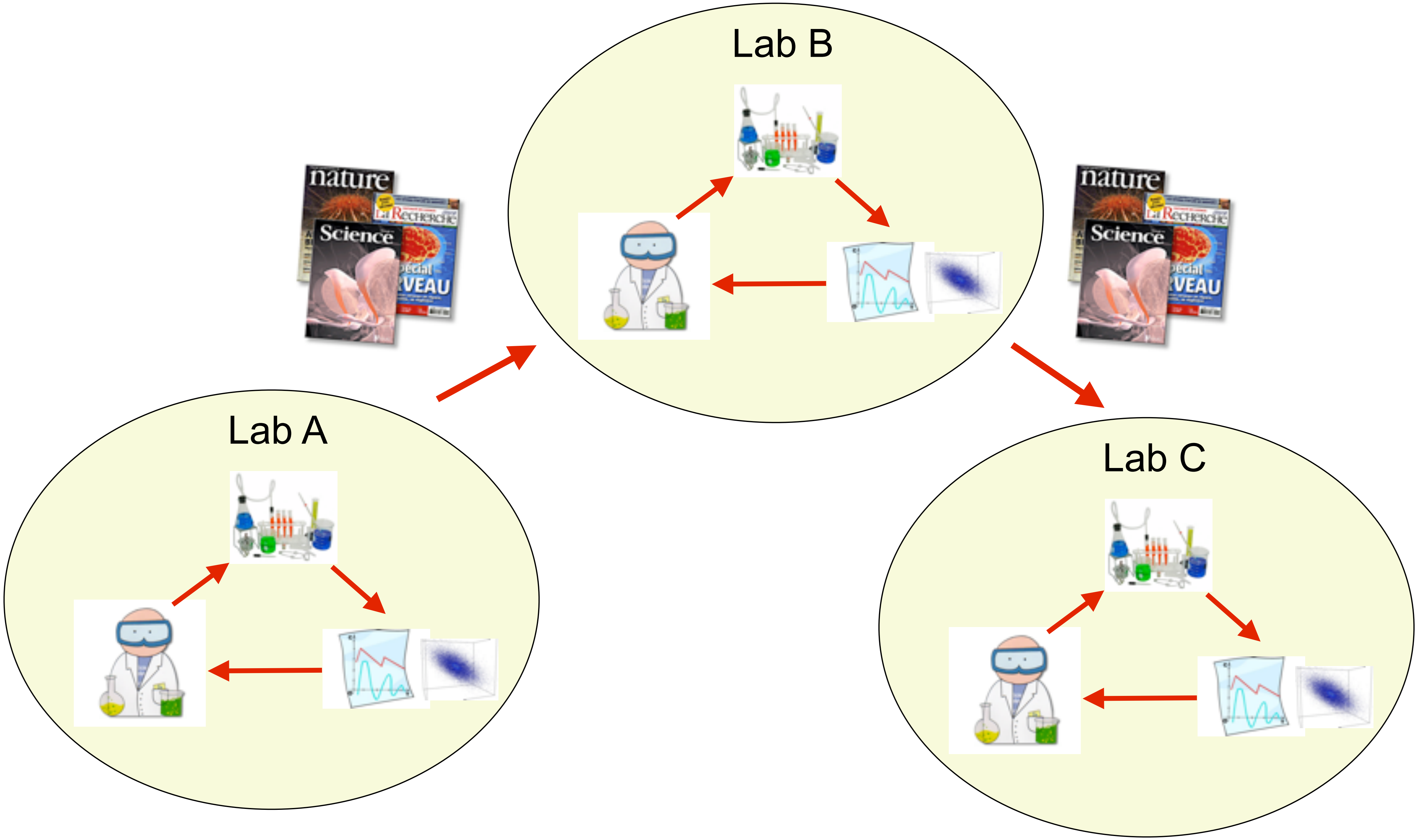

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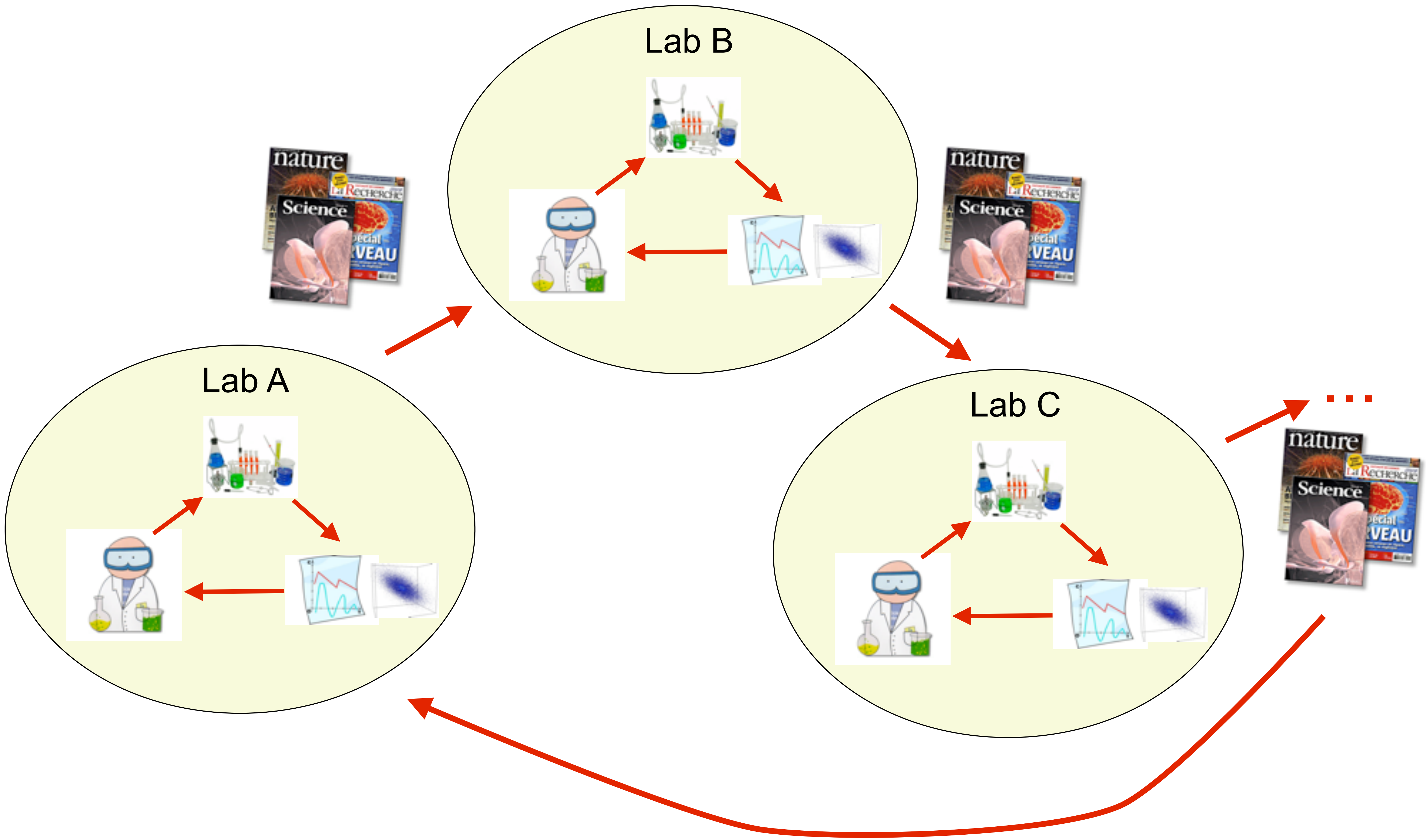

Motivation: Inferring Biological Pathways

Paul Alhquist
(Molecular Virology)

Audrey Gasch
(Genetics)

Motivation: Inferring Biological Pathways

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Audrey Gasch
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virus

fruit fly

Motivation: Inferring Biological Pathways

virus

13,071 single-gene
knock-down cell strains

fruit fly

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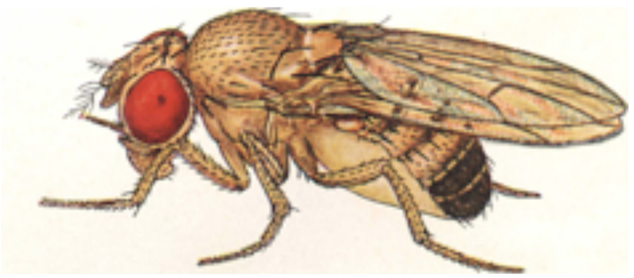

fruit fly

13,071 single-gene
knock-down cell strains

infect each strain
with fluorescing virus

microwell
array

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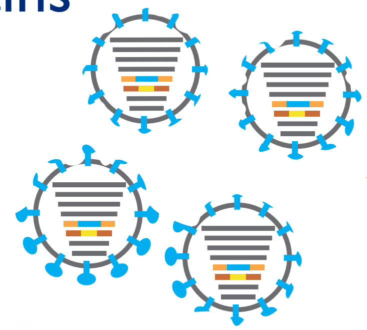

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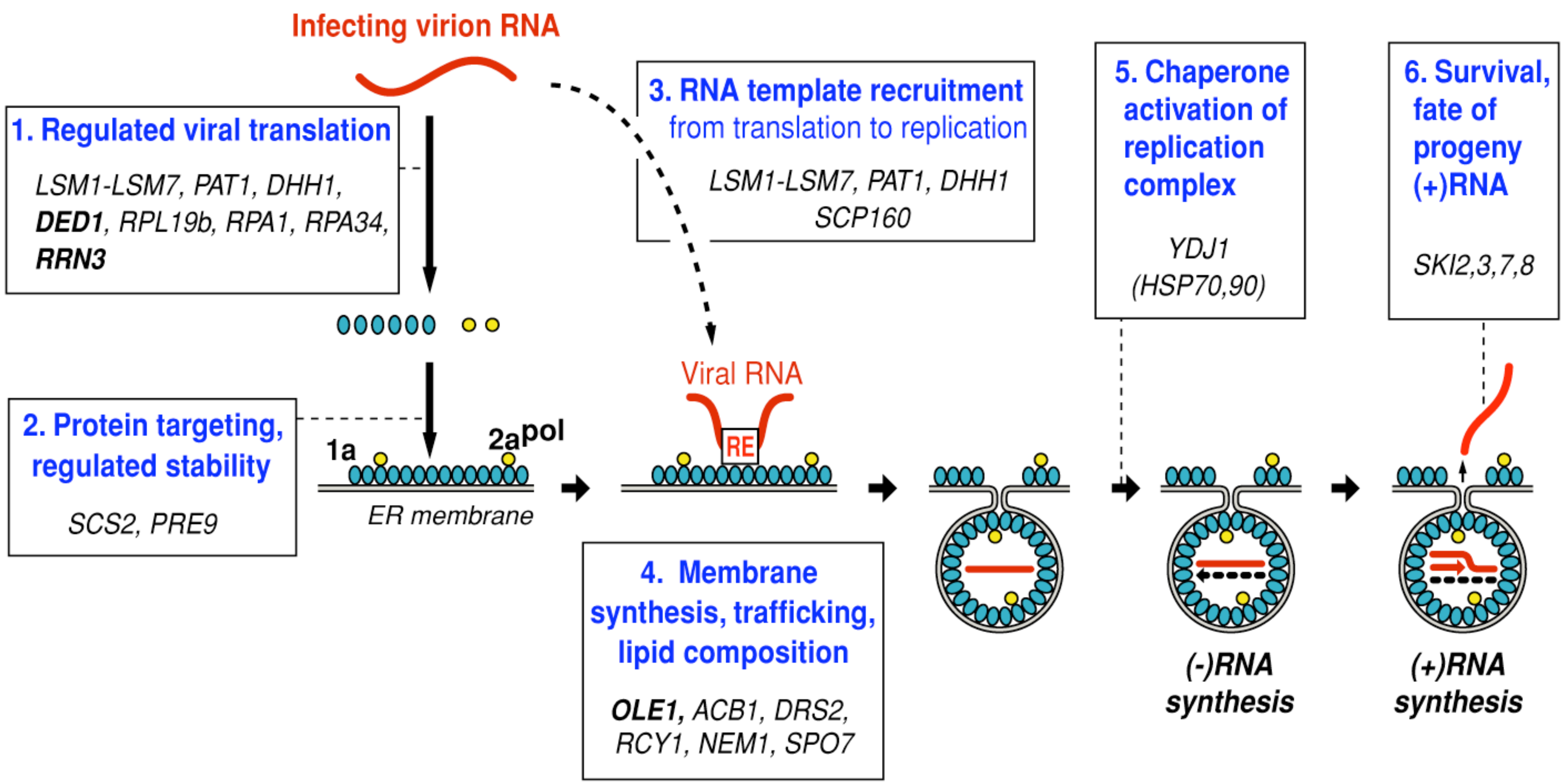

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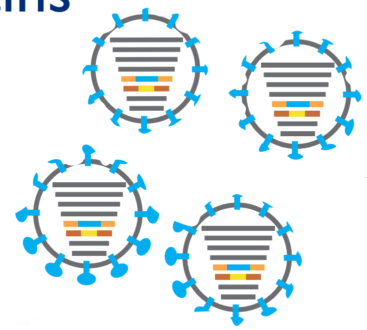

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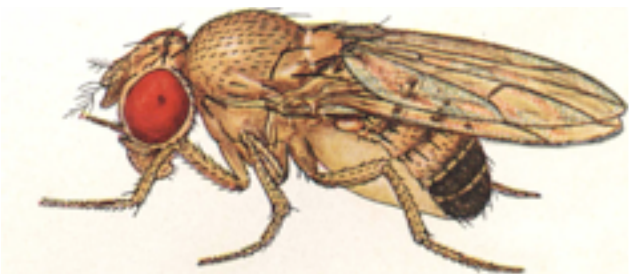

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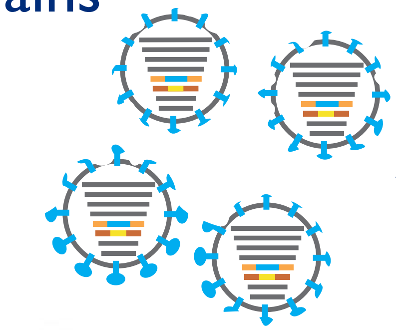

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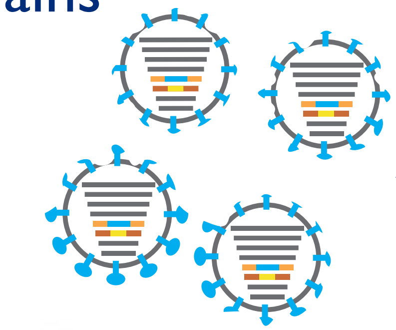

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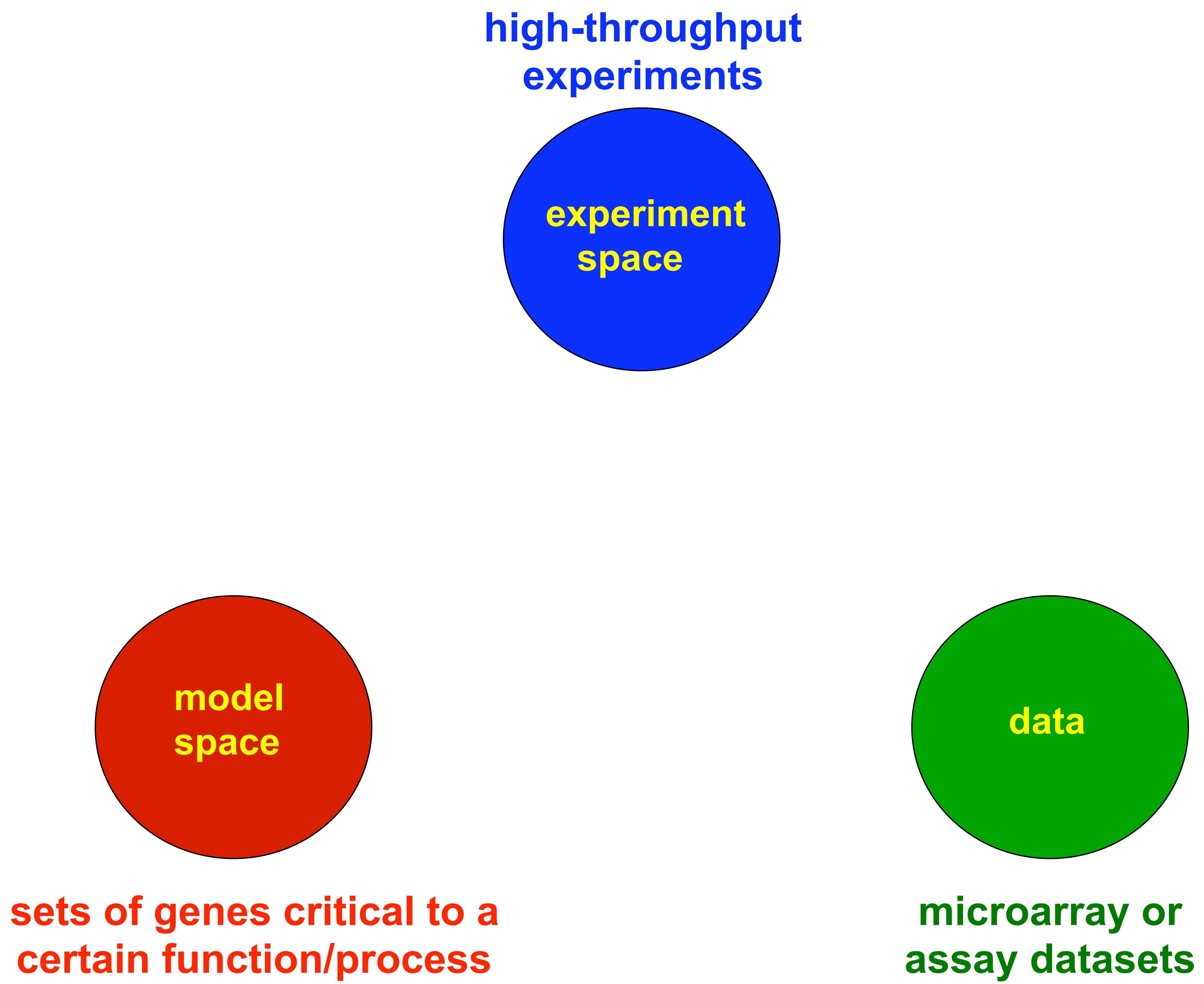
vastly more efficient that replicating all 13K experiments many times

Feedback from Data Analysis to Data Collection



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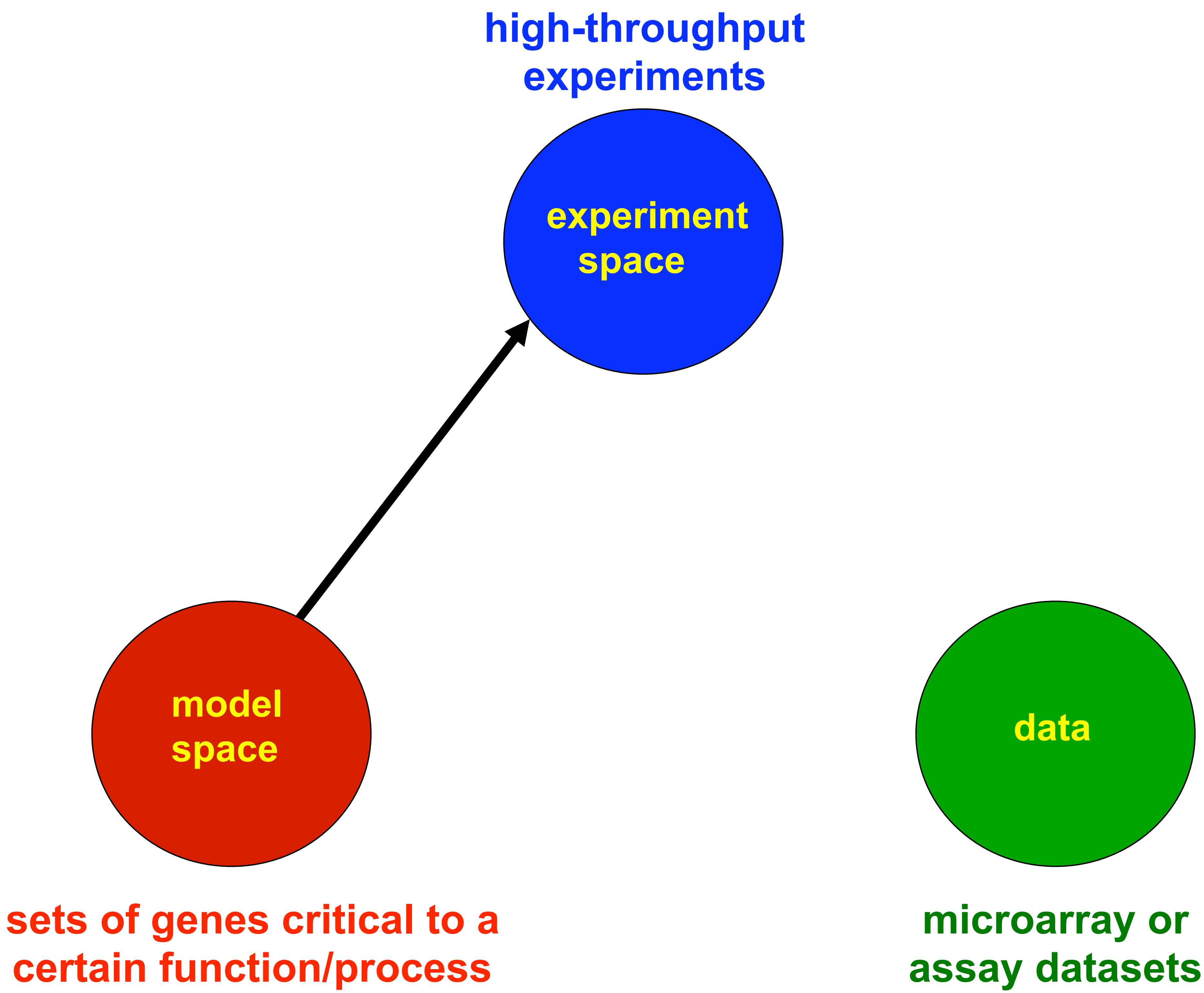

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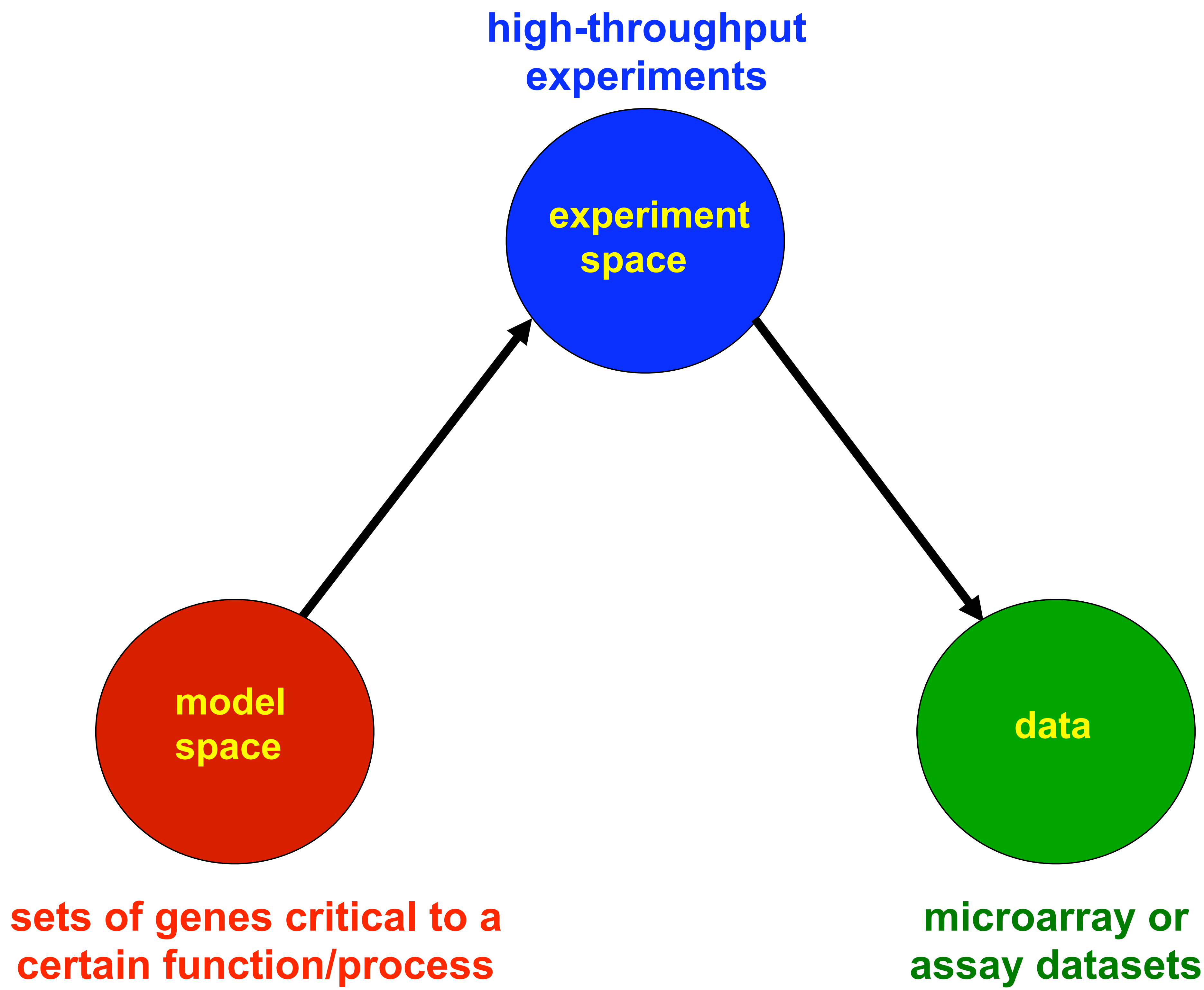

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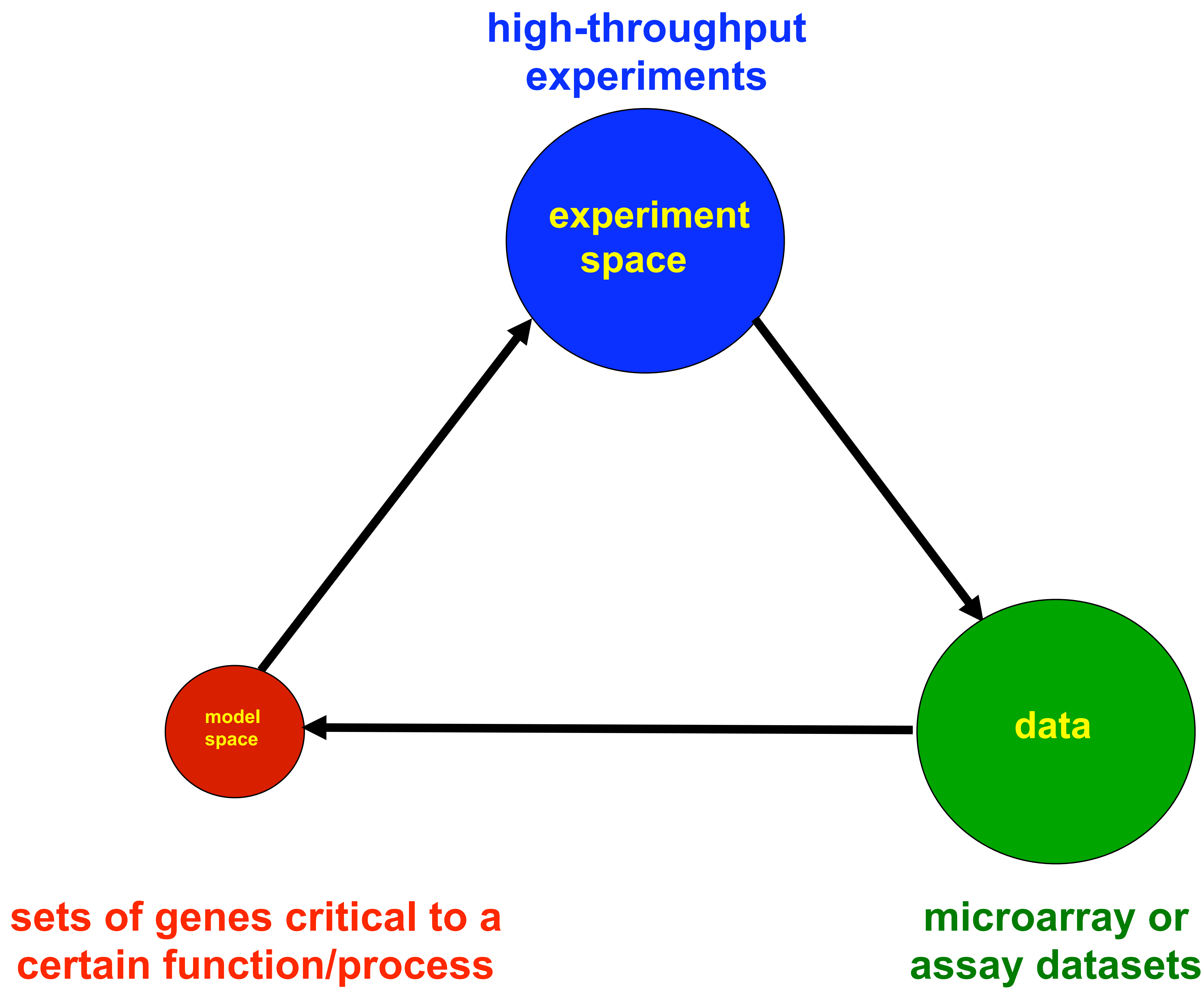
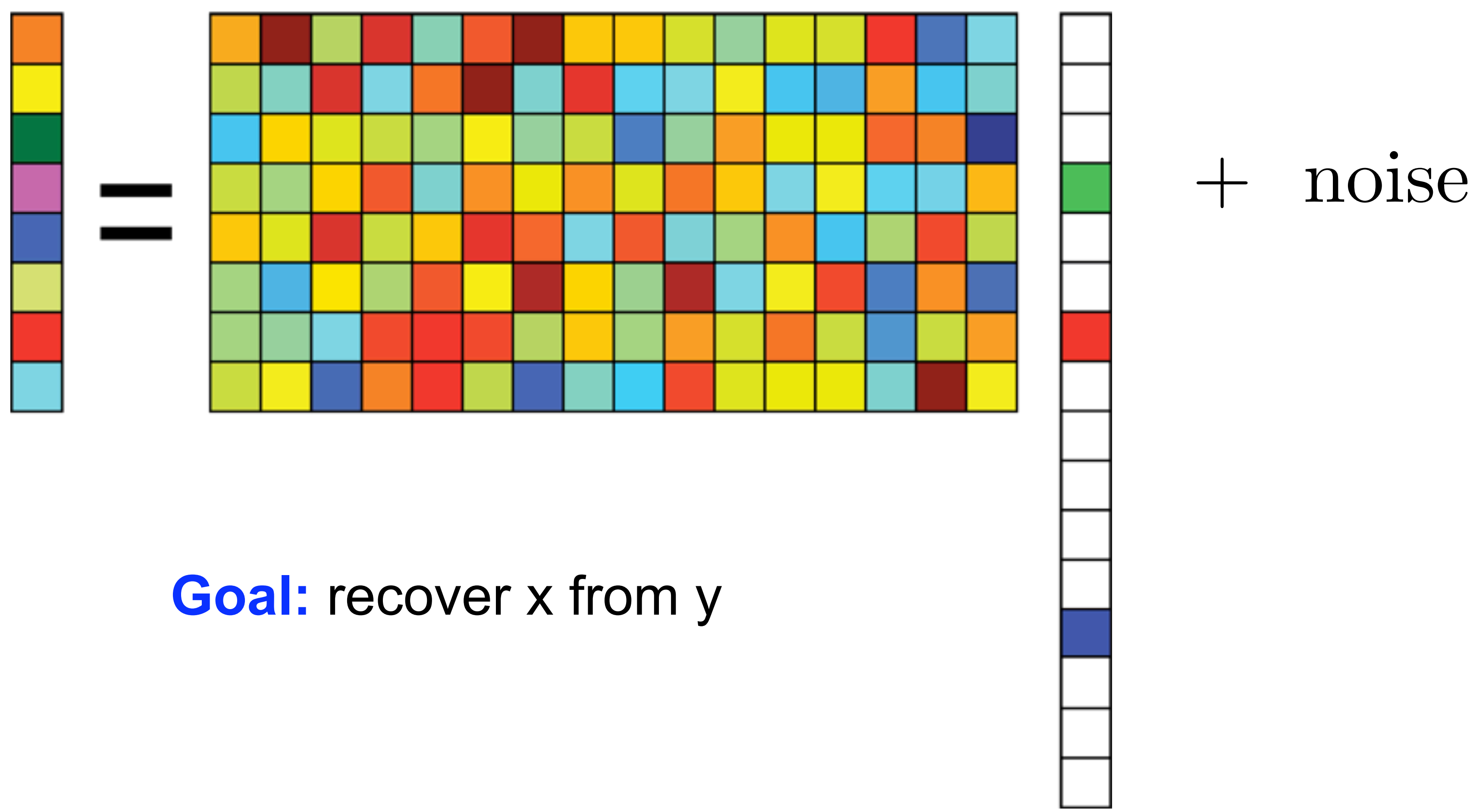


Adaptive Sensing for Sparse Recovery

(image reconstruction, compressed sensing, inverse problems)

$$y \;=\; A\,x \;+\; w \text{ , with } A \in \mathbb{R}^{m\times n},\ x \in \mathbb{R}^n \text{ (but sparse)},\ w \sim \mathcal{N}(0, I)$$



Goal: recover x from y

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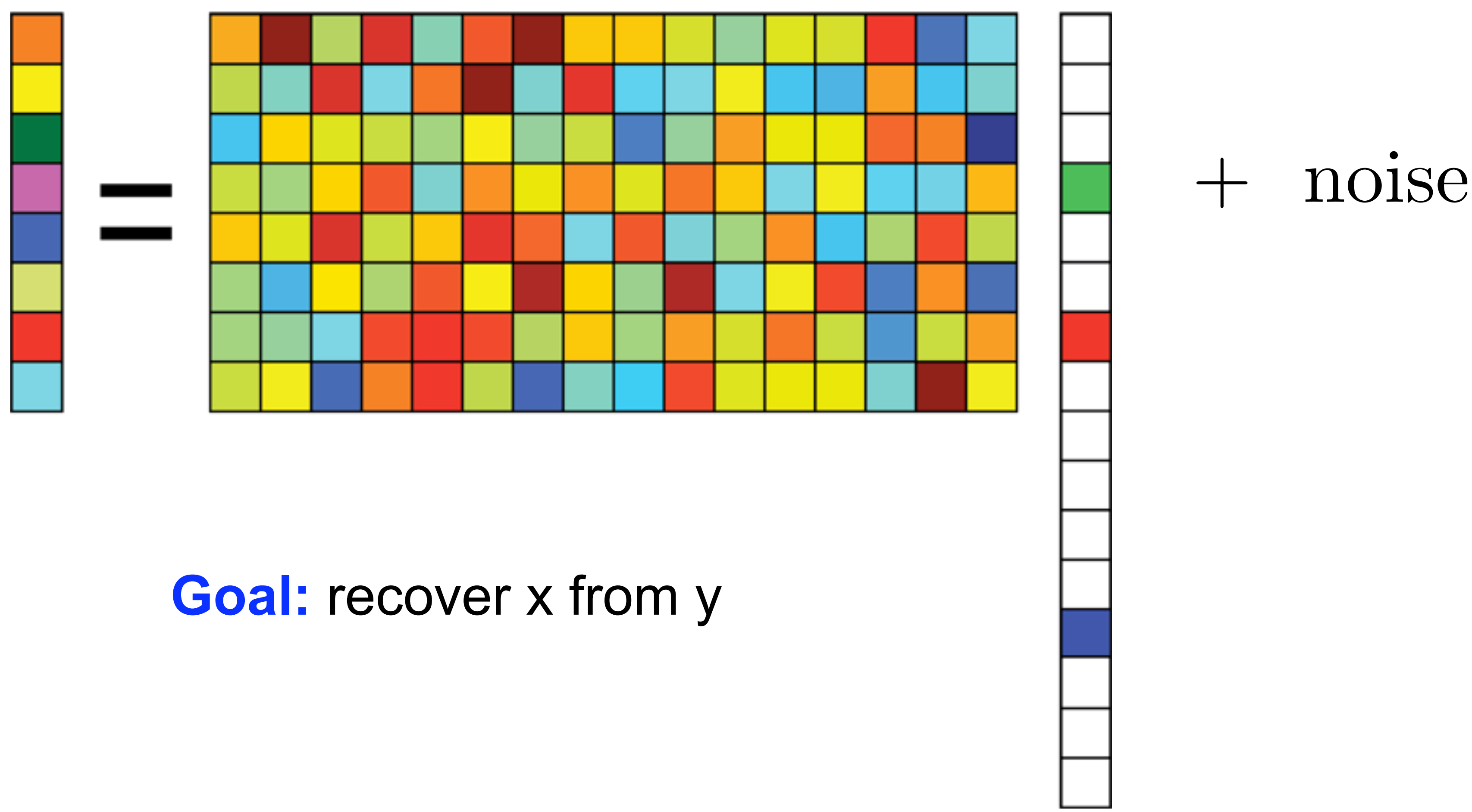


Goal: recover x from y

Is sequentially designing (rows of) A advantageous ?

Motivation: Randomized Experiments

$\widetilde{y}$ $=$  $\times$  $+$ 

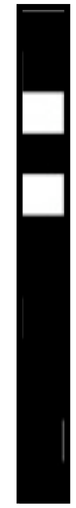
$k \times 1$

sparse signal

noise

indirect (randomized) measurement

Motivation: Randomized Experiments

$\underset{k \times 1}{\widetilde{y}} =$  $\times$  $+$ 

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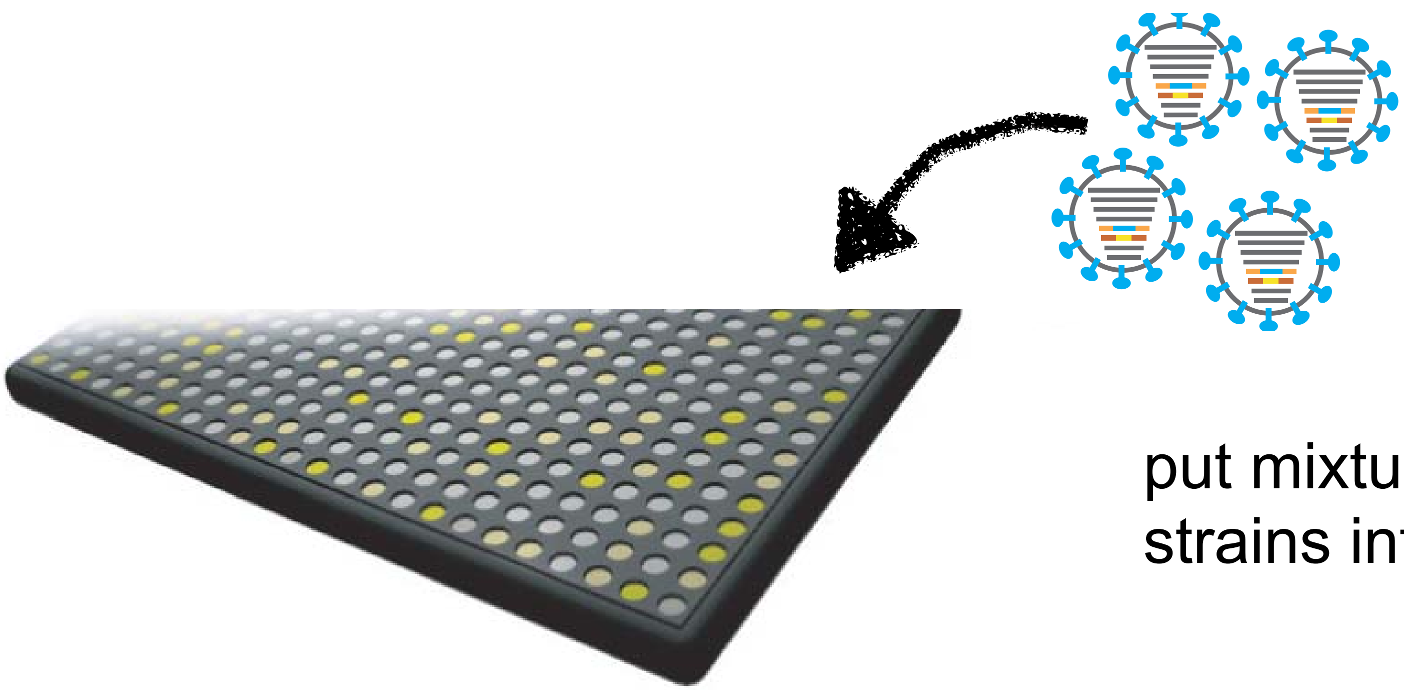

put mixtures of single-deletion strains into each well

Signal Processing Gear

back to shop

y = phi x (Dark T-Shirt)

$18.99

Fit: Standard

Not too tight, not too loose.

Fabric Thickness:

Thin Thick

1. Color: (Charcoal)
2. Size: Large Size Chart
3. Qty: 1

ADD TO CART

AVAILABILITY: In Stock.
Product Number: 030-469487567

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A visual representation of the math behind compressive sensing

Look cool without breaking the bank. Our durable, high-quality, pre-shrunk 100% cotton t-shirt is what to wear when you want to go comfortably casual. Preshrunk, durable and guaranteed.

- 5.6 oz. 100% cotton
- Standard fit

Other items by Signal Processing Gear:

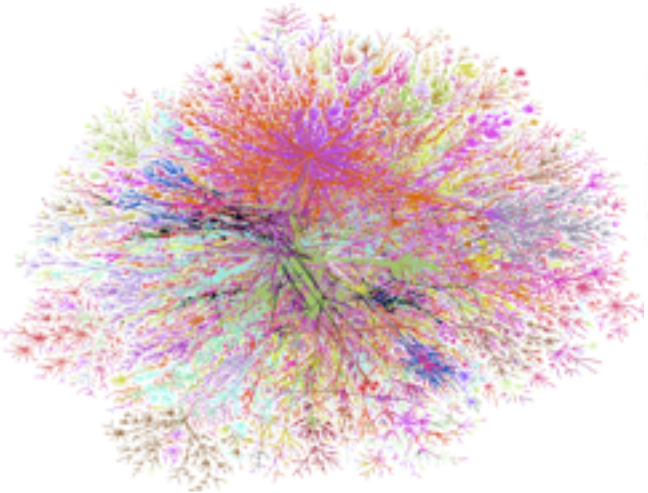
y = phi x (Mug)

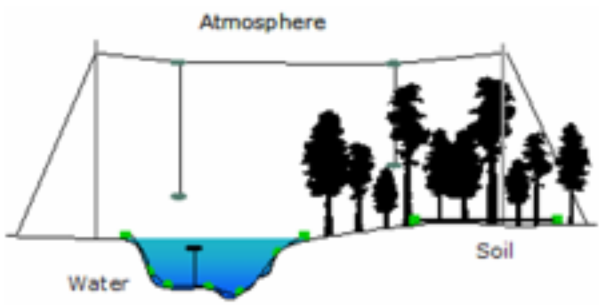
y = phi x (Large Mug)

y = phi x (Light T-Shirt)

Sensing and Inference in Large Networked Systems

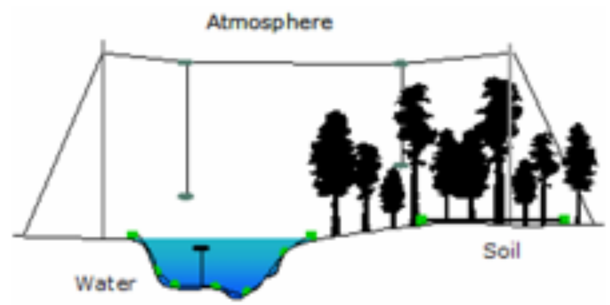
Sensing and Inference in Large Networked Systems





Technological Networks
(Internet Mapping Project, US power grid, UCLA CENS)

Sensing and Inference in Large Networked Systems



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Social Networks

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Technological Networks
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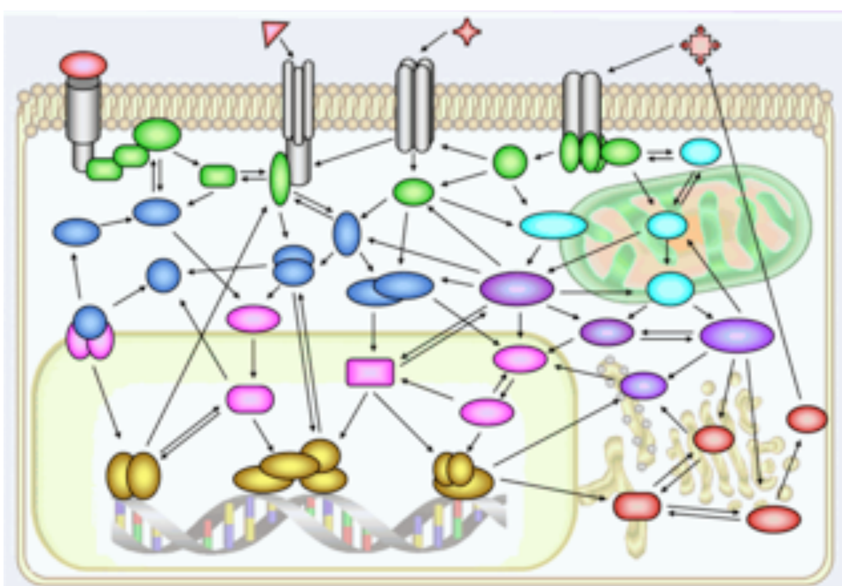
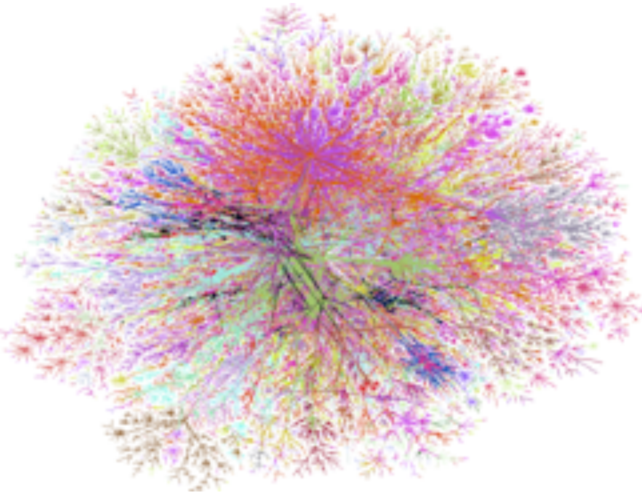
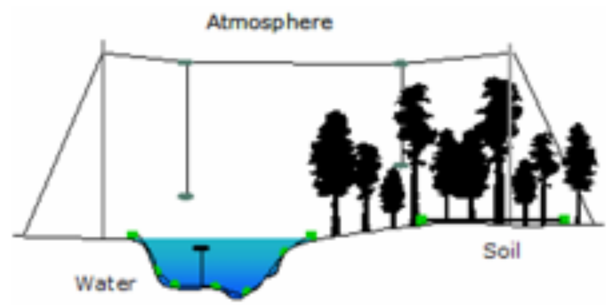
Social Networks



Biological Networks
(JMDBase)

Sensing and Inference in Large Networked Systems





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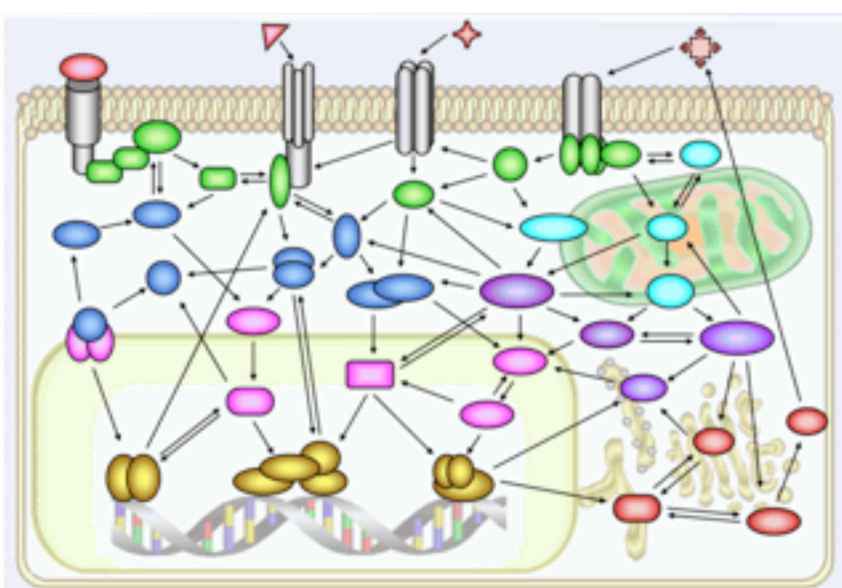

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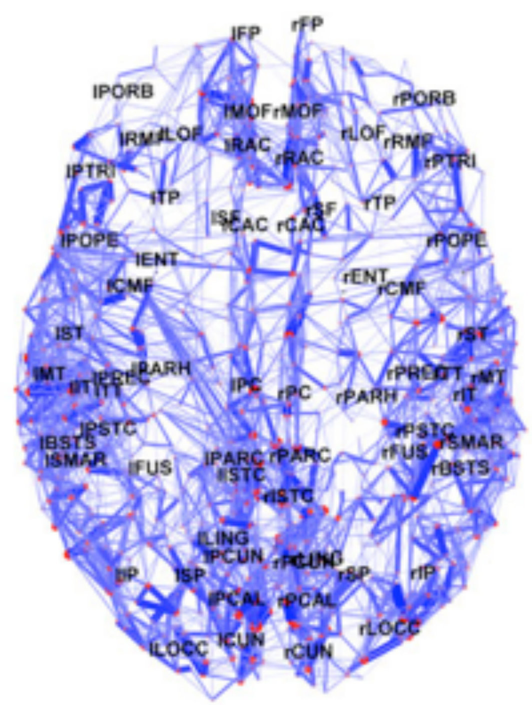

Brain Networks
(Worsley et al, 2005)

Sensing and Inference in Large Networked Systems

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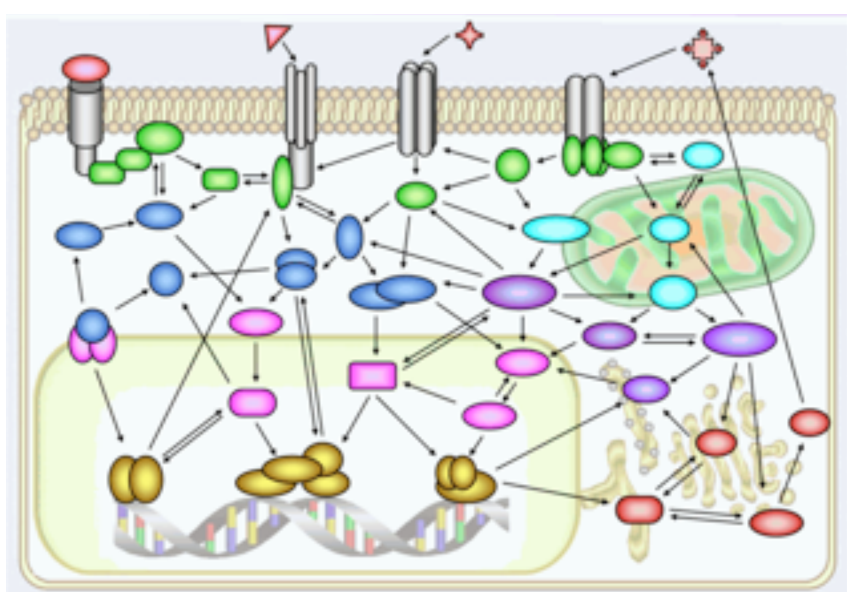

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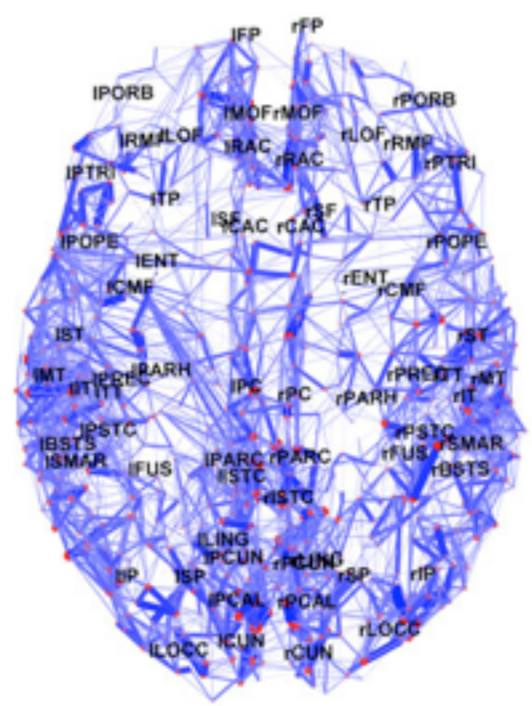


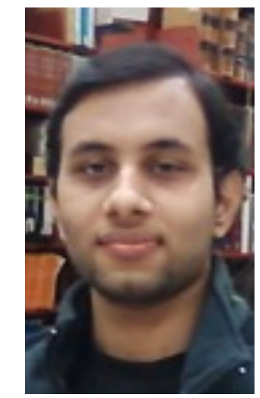
Brain Networks
(Worsley et al, 2005)

Challenges:

- Inferring structure & function of the system
- Optimized design & resource allocation
- Pattern analysis & anomaly detection

Network Structure and Clustering

Complex systems are not defined by the independent functions of individual components, rather they depend on the orchestrated interactions of these elements.



Gautam Dasarathy

Brian Eriksson

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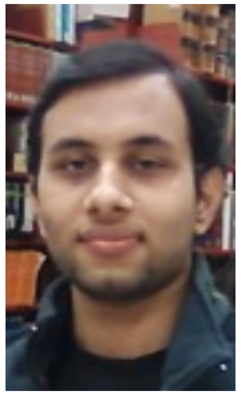
Network(s) of interactions can be revealed via **clustering** based on measured features



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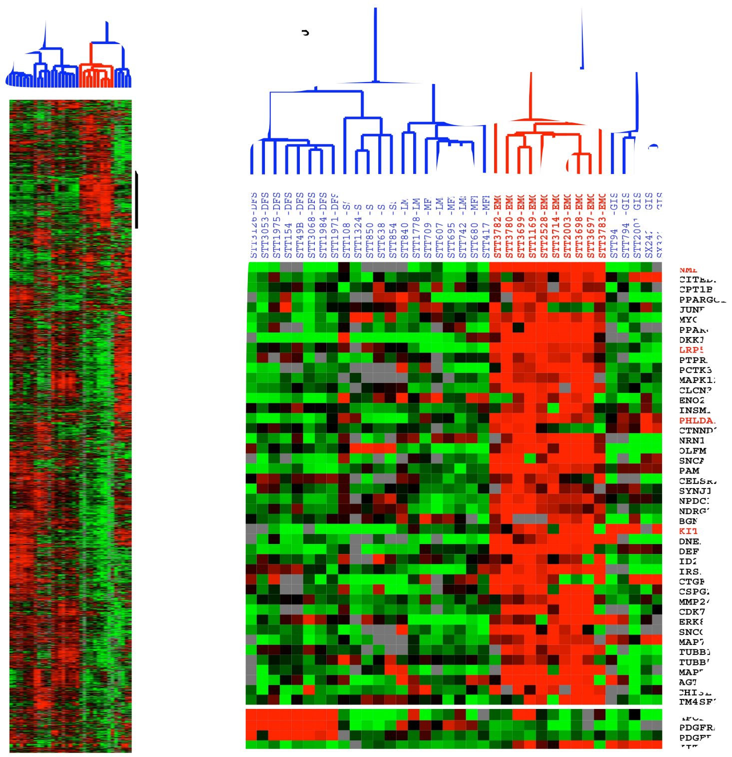
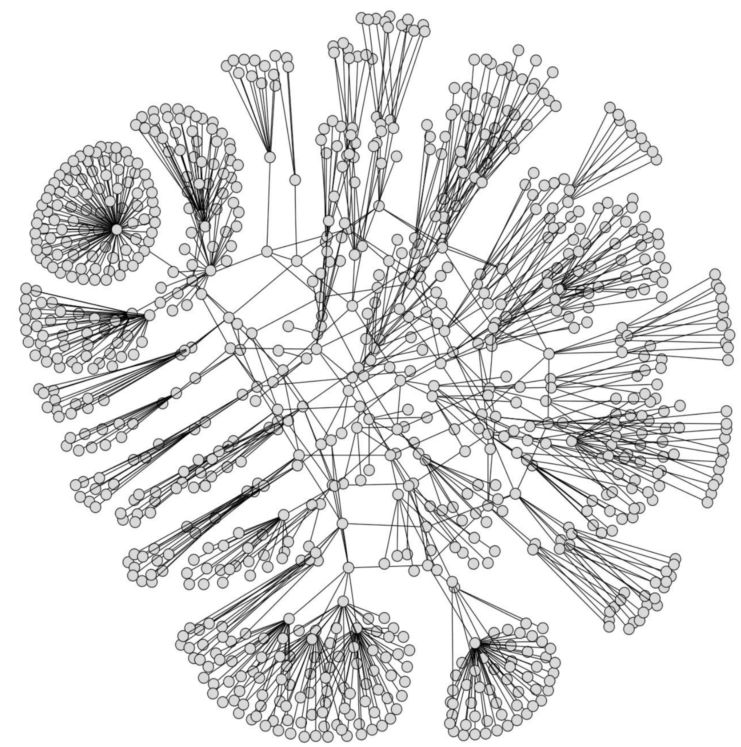
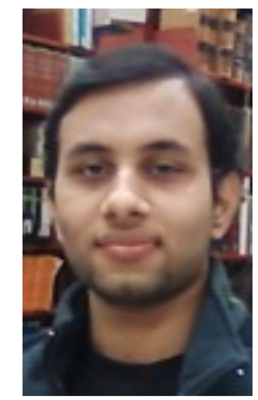


genes and expression/ interaction profiles



network routers and traffic/distance profiles



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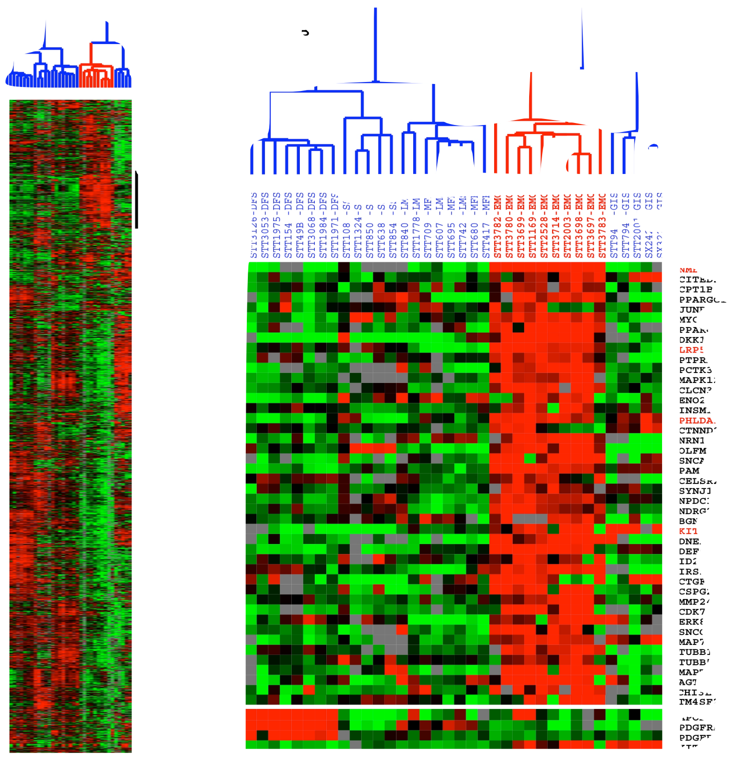

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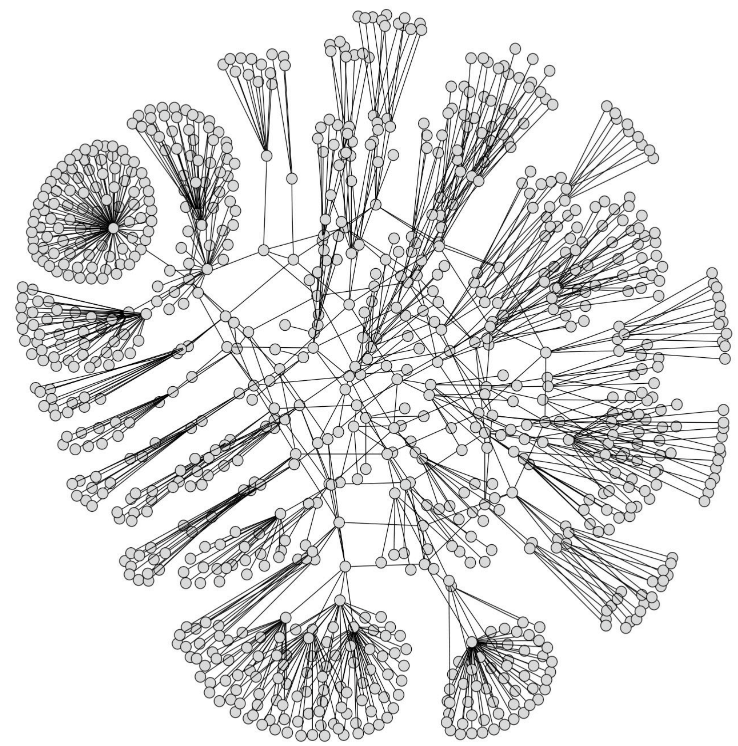

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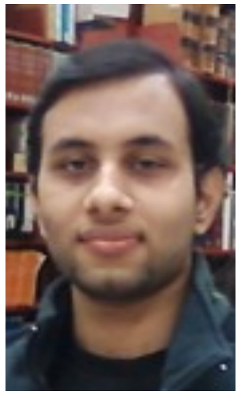

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Eriksson

Similarity-Based Clustering: Each component (gene/router) has an associated feature (measurement profile). Components can be clustered based on feature similarities.

Network Structure and Clustering

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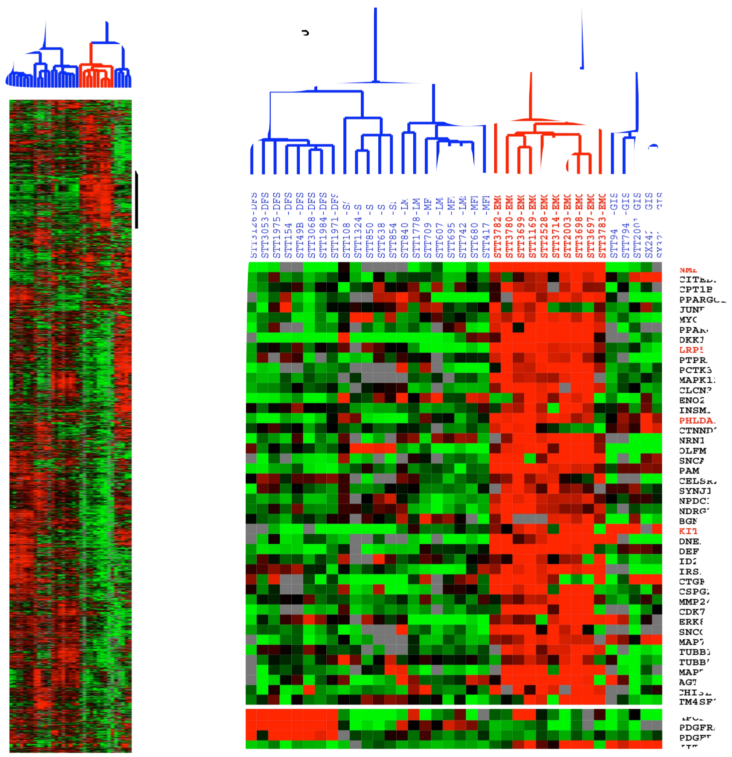

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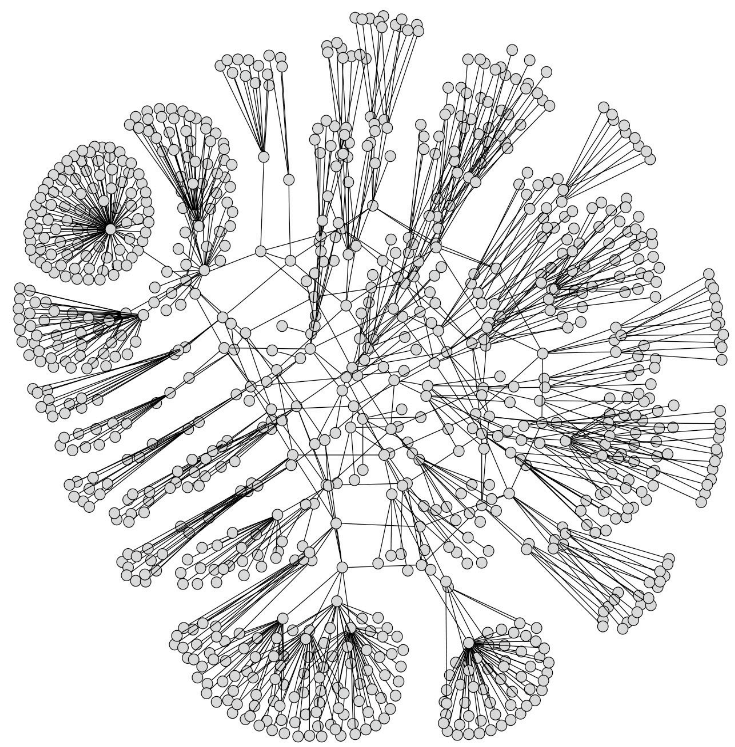

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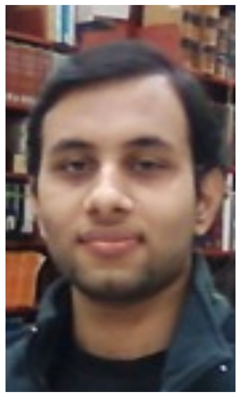

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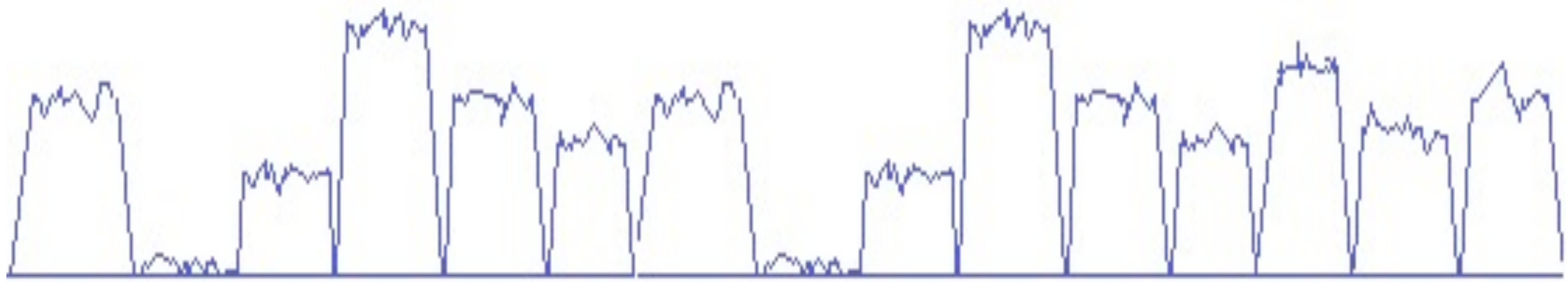
Brian
Eriksson

Similarity-Based Clustering: Each component (gene/router) has an associated feature (measurement profile). Components can be clustered based on feature similarities.

Recent Result: A sequential method for selecting "informative" similarities that produces accurate clusters from as few as $3N \log N$ similarities.

Cognitive Radio Spectrum Sensing

"primary" users have preference over "secondary" users



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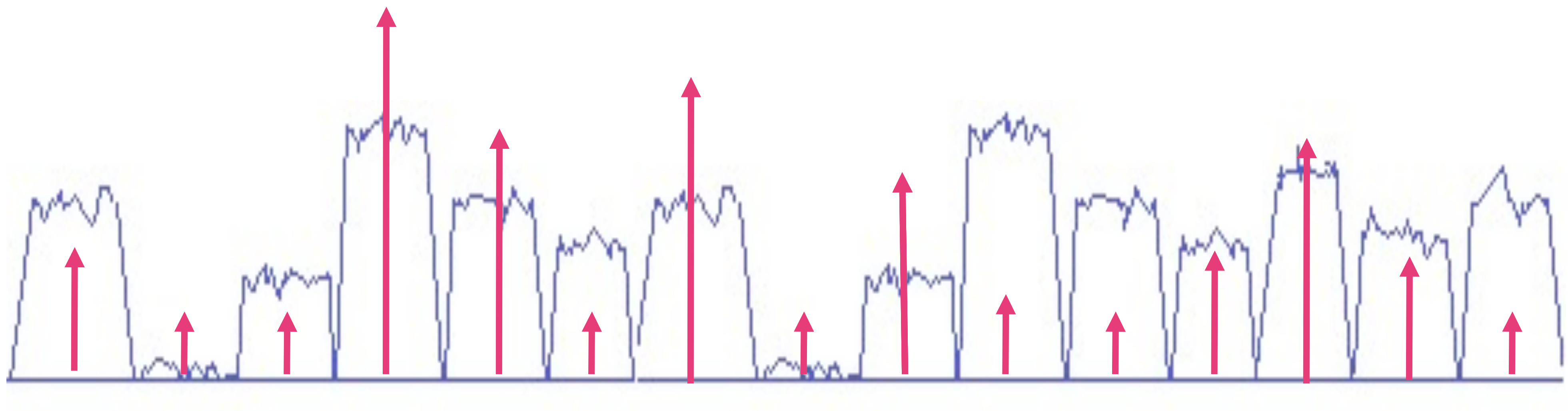

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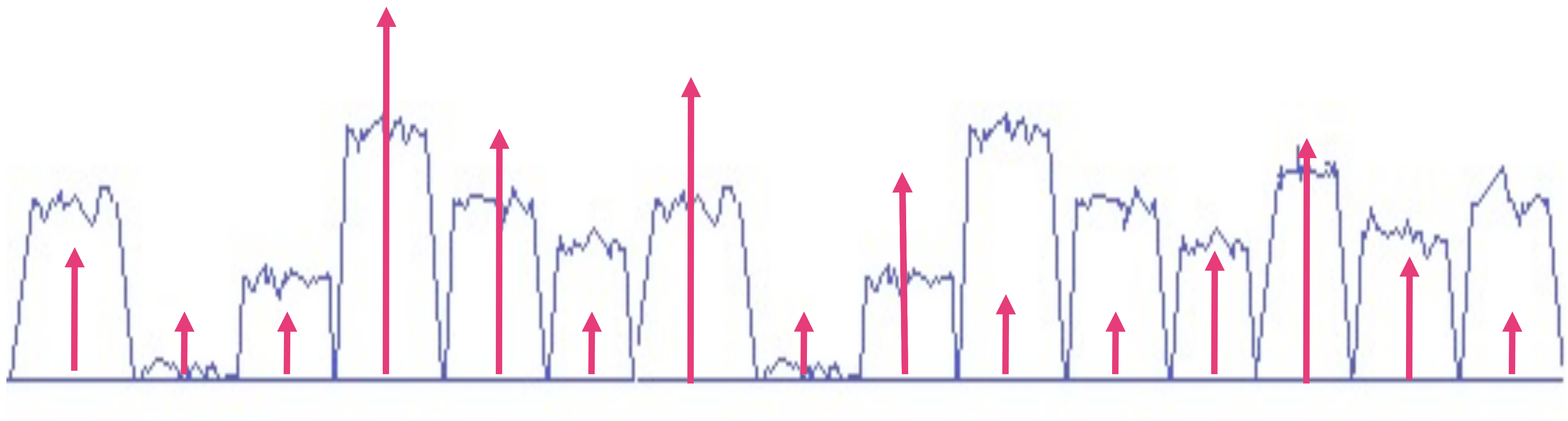

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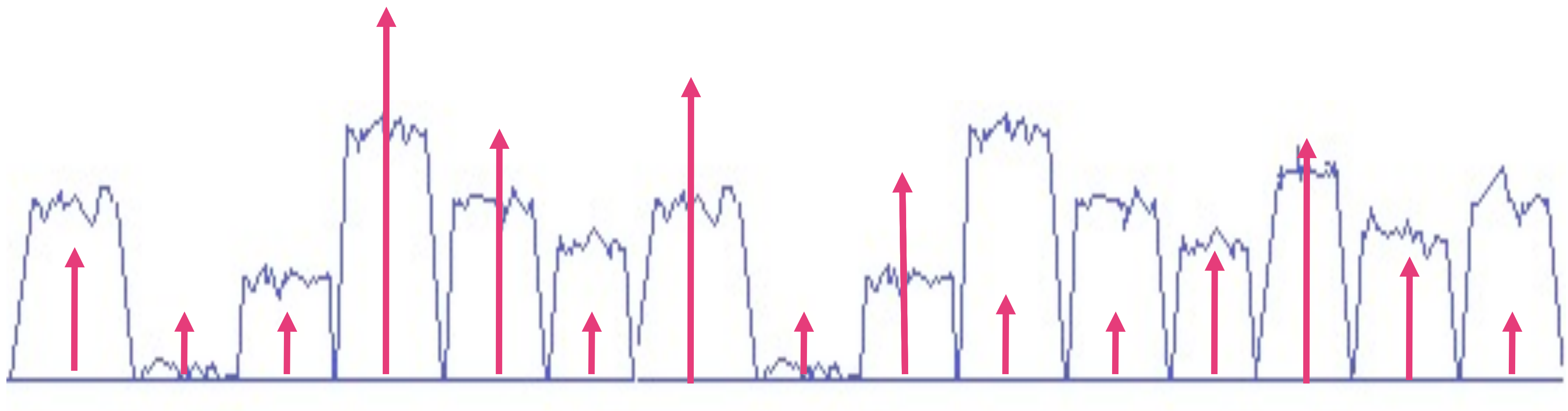

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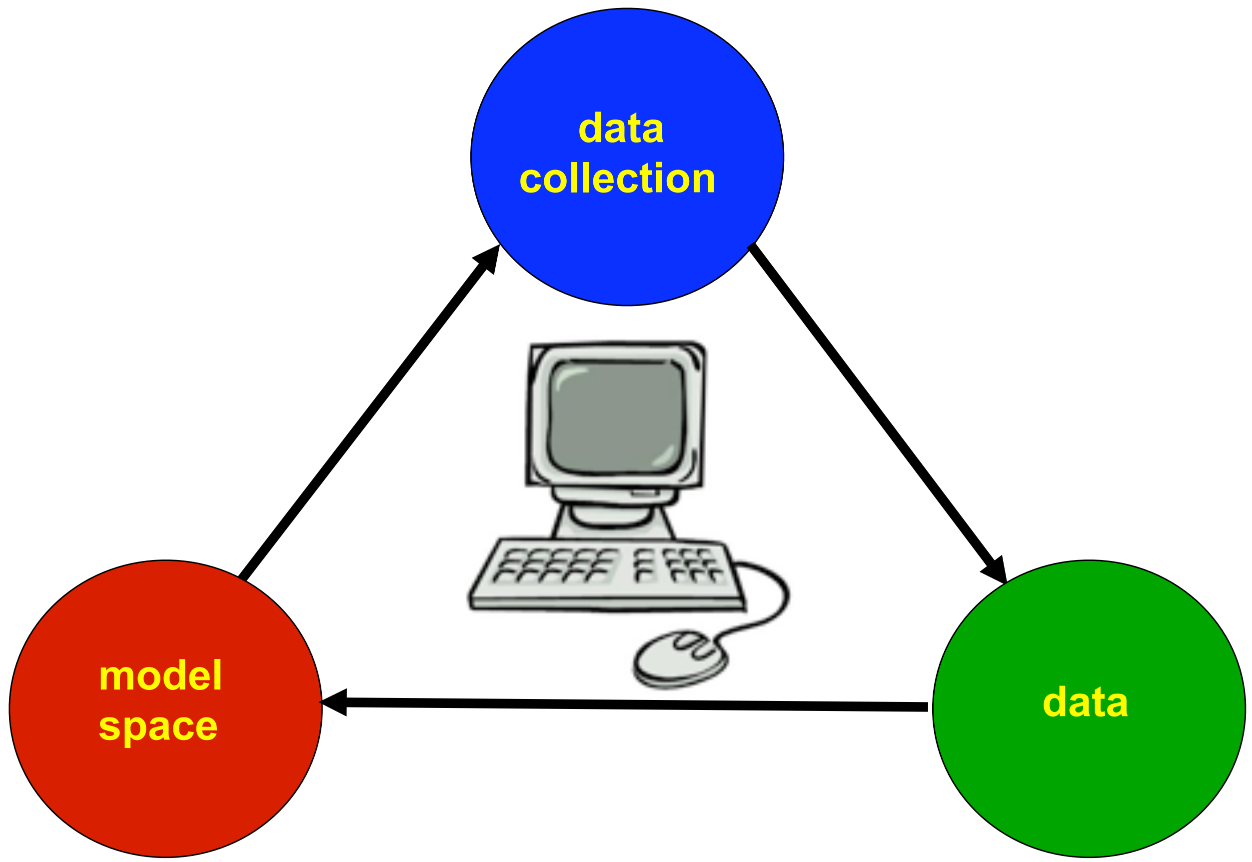
adaptive spectrum sensing is significantly more time-efficient than fixed sensing

Active Learning in Machines and Humans



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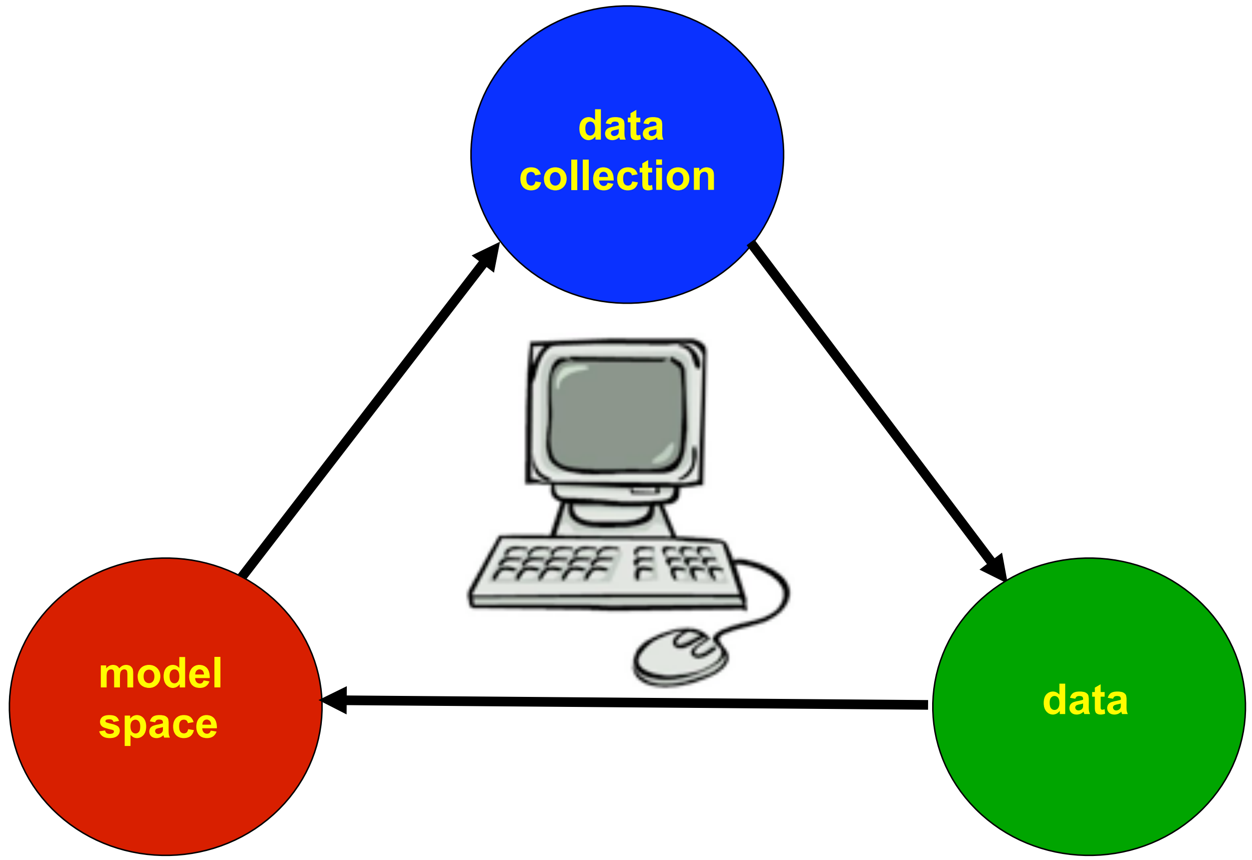
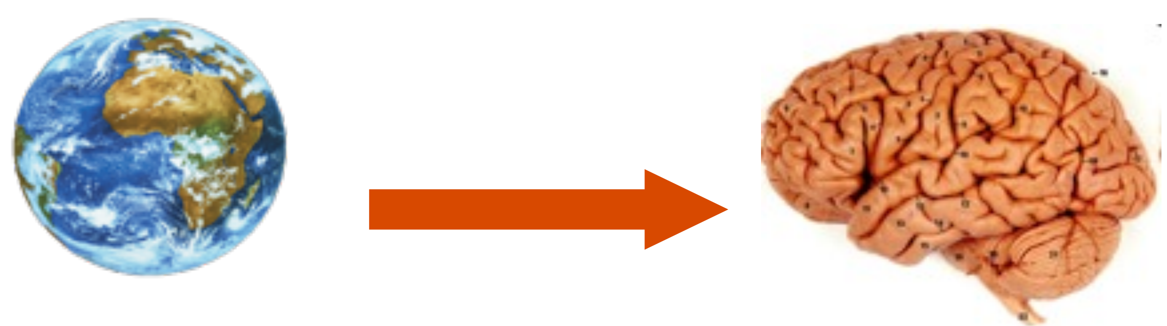
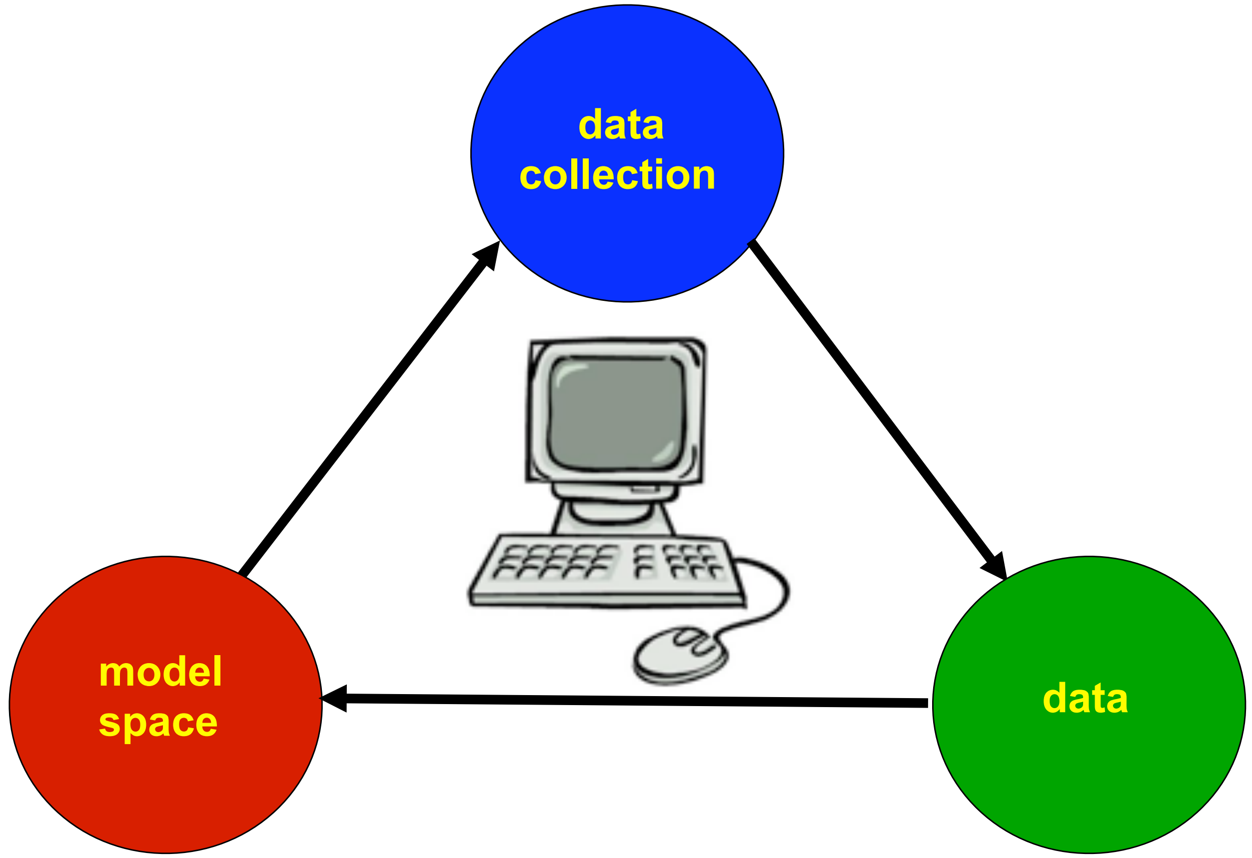


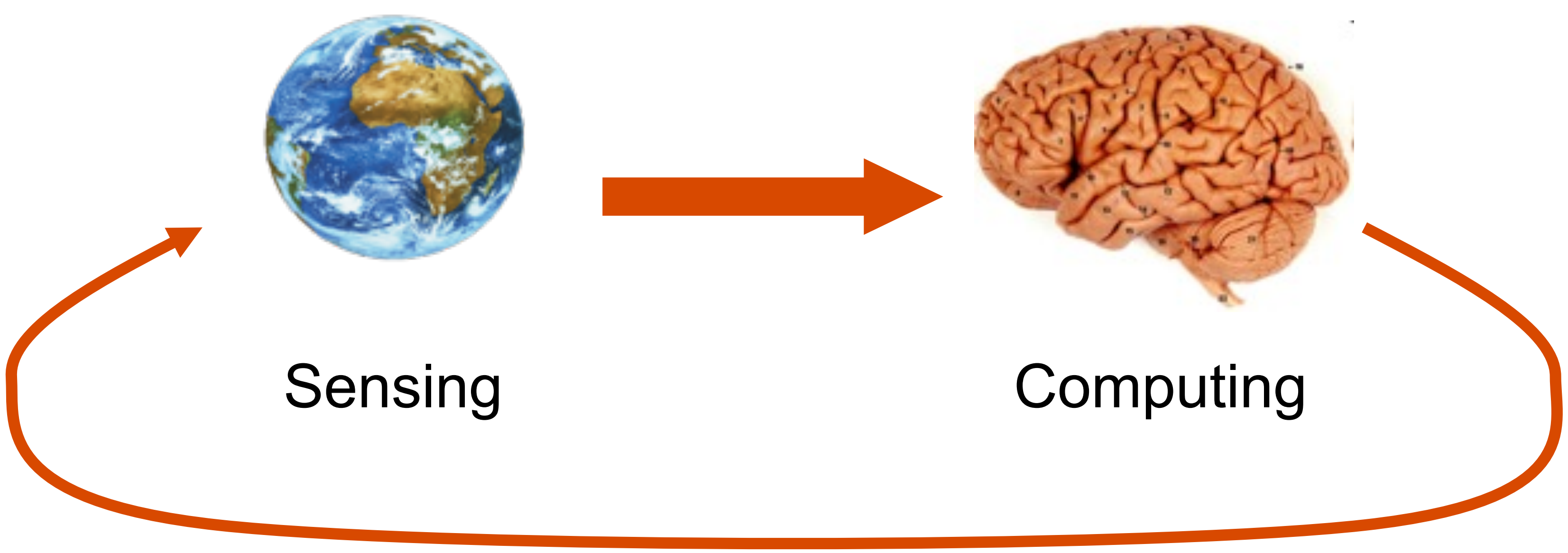


Sensing

Computing

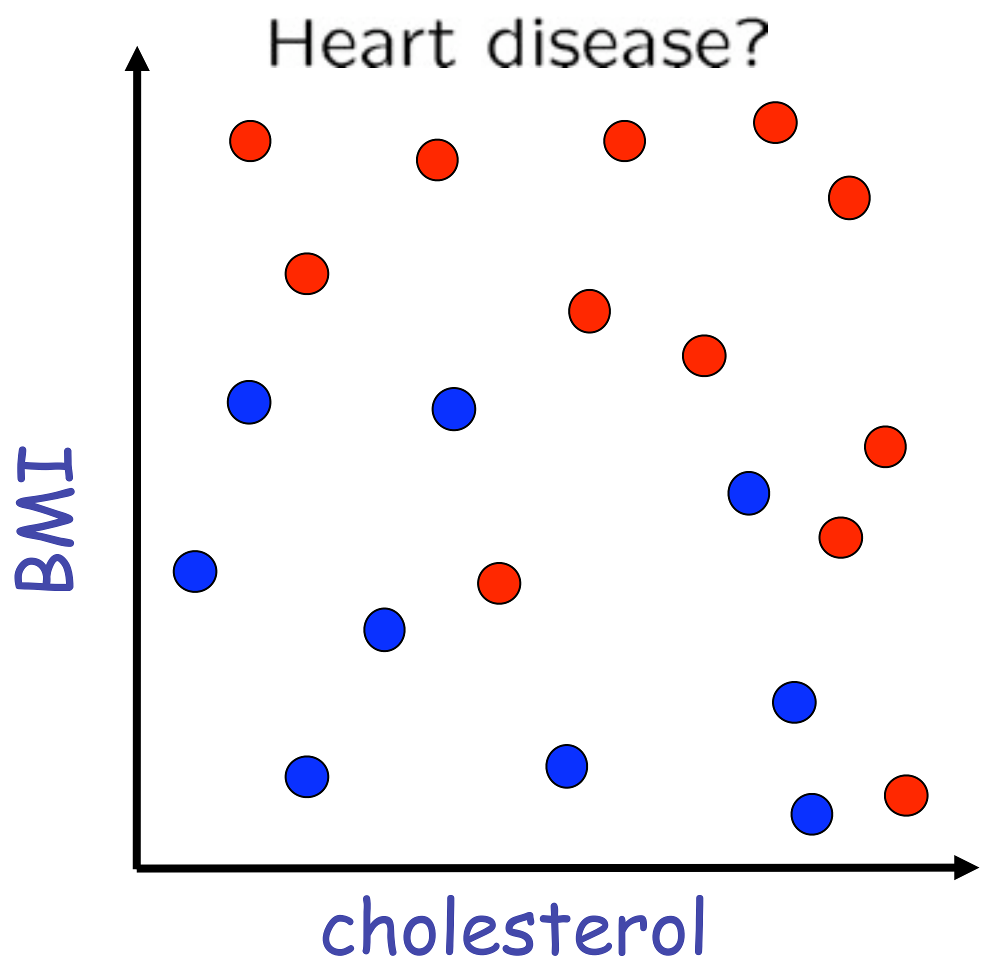
Active Learning in Machines and Humans





Active Learning

Learn to predict labels y from features x based on training examples $\{(x_i, y_i)\}_{i=1}^n$



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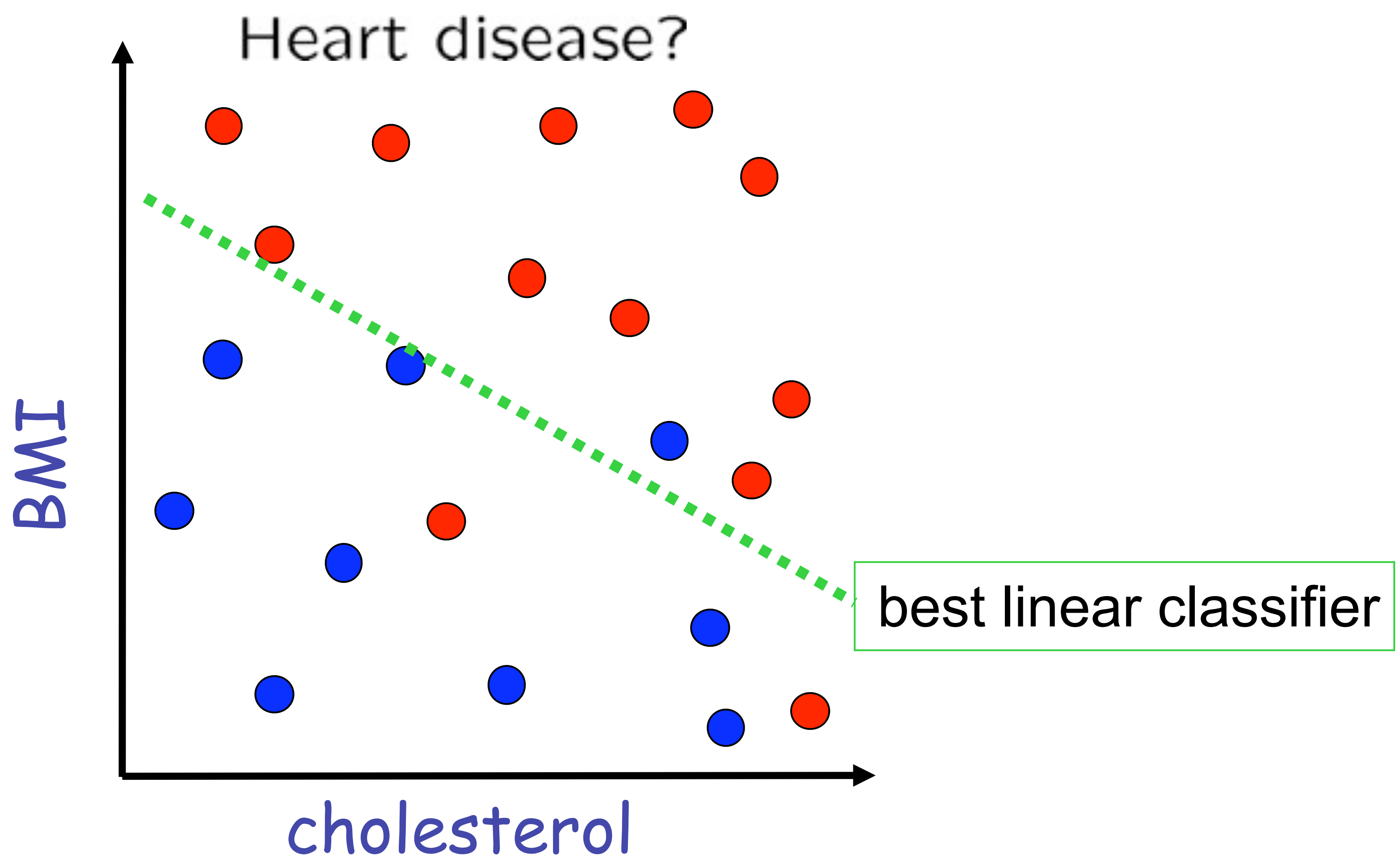

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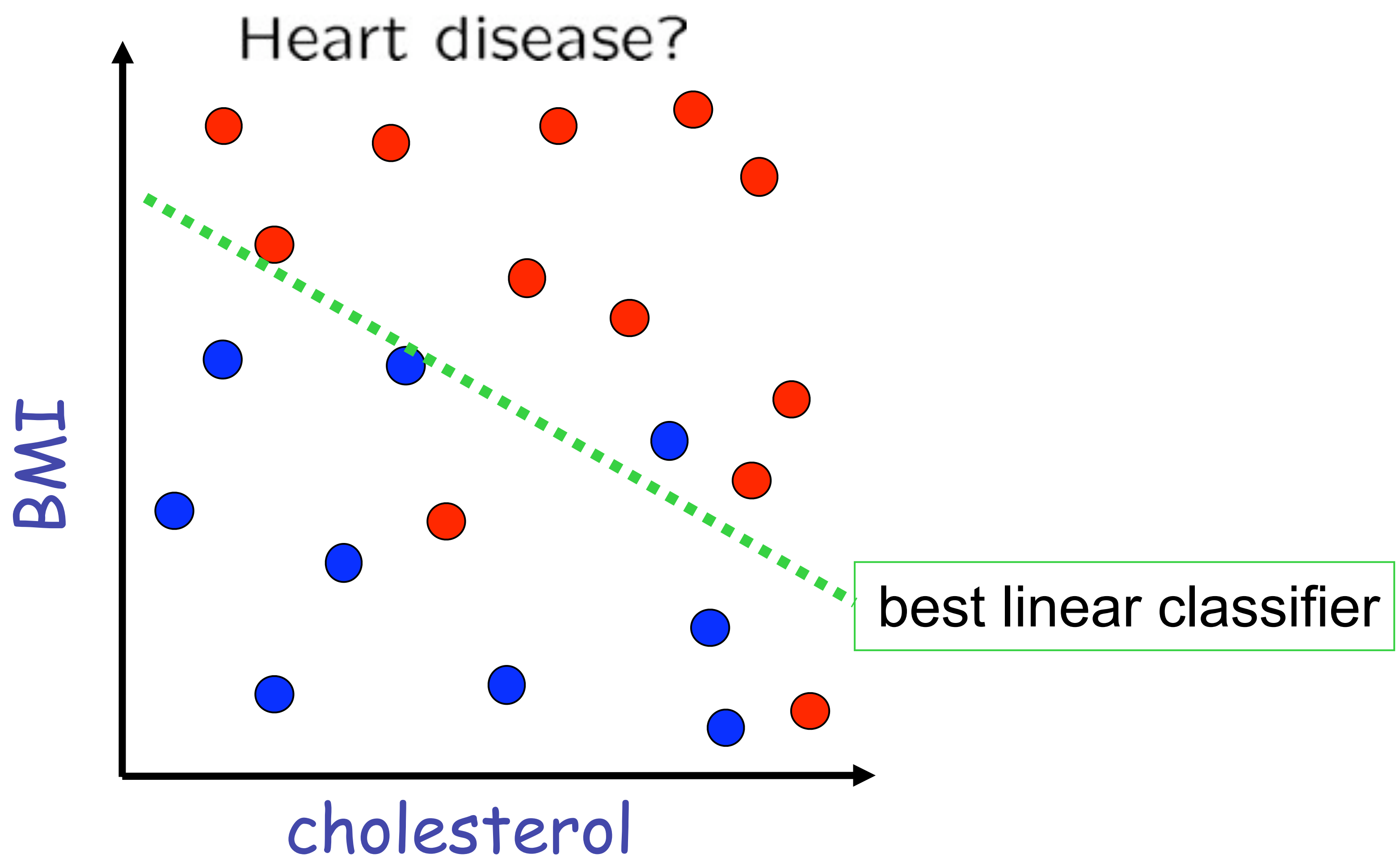

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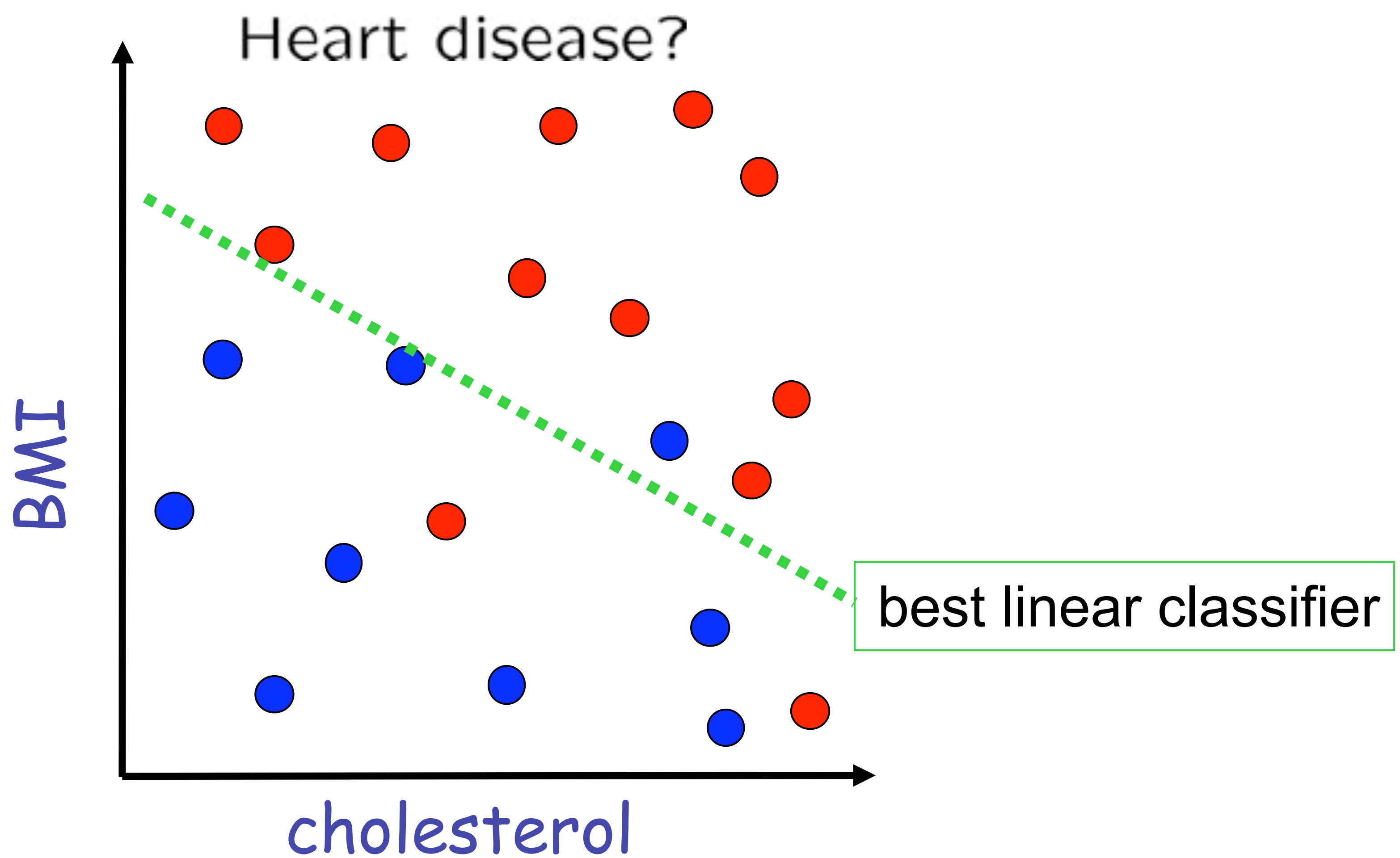

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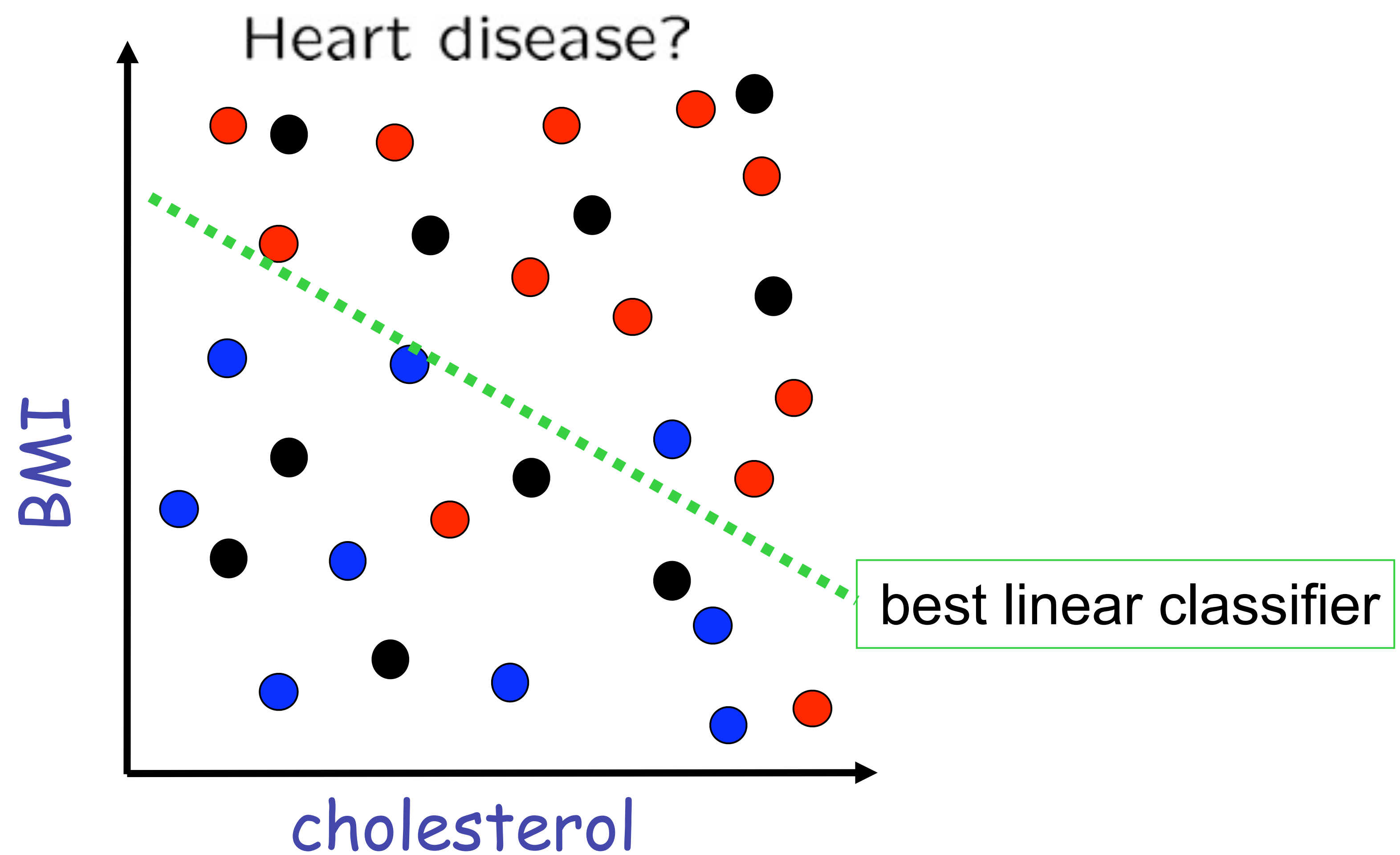

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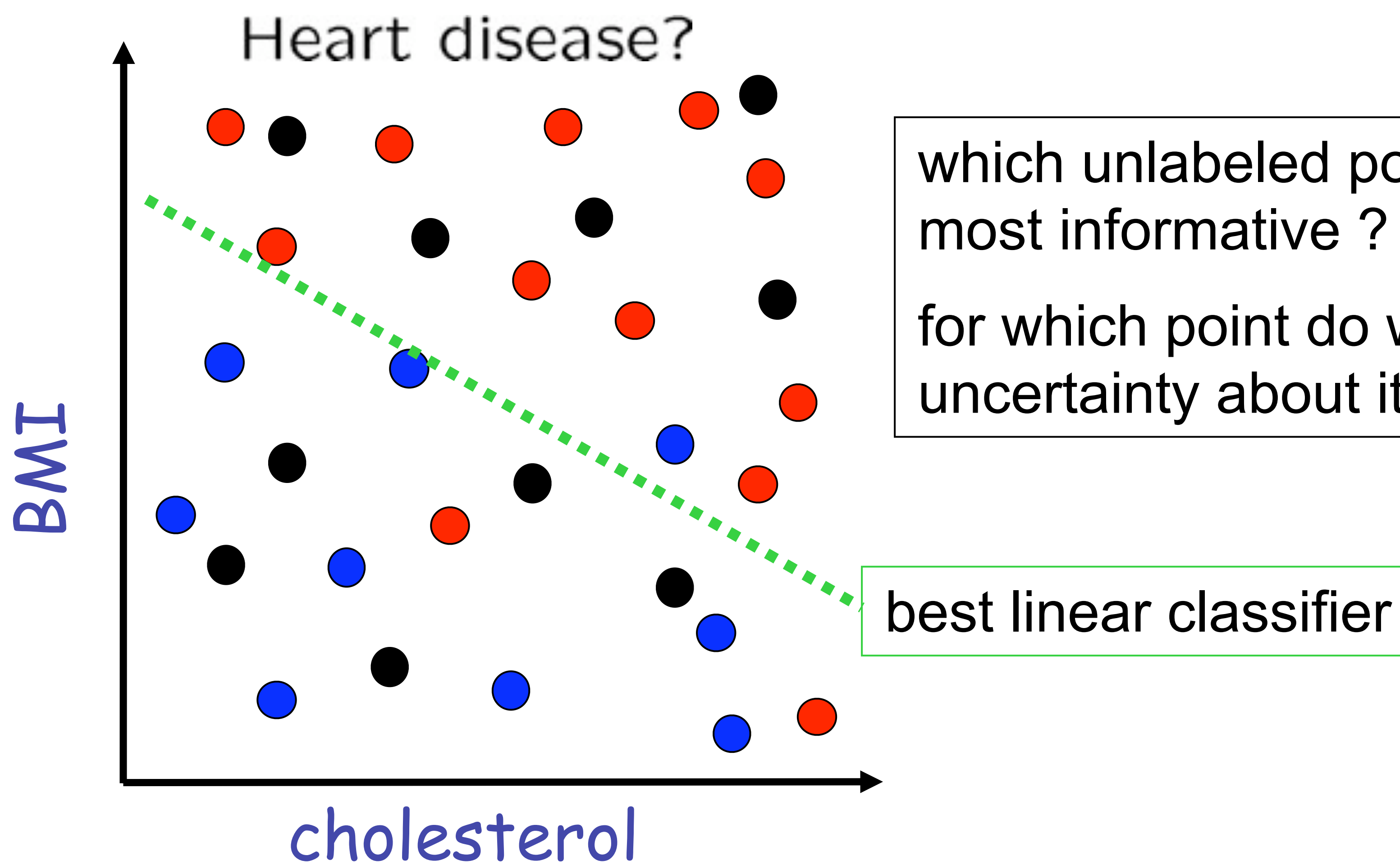

which unlabeled point is likely to be most informative ?

for which point do we have the greatest uncertainty about its label ?

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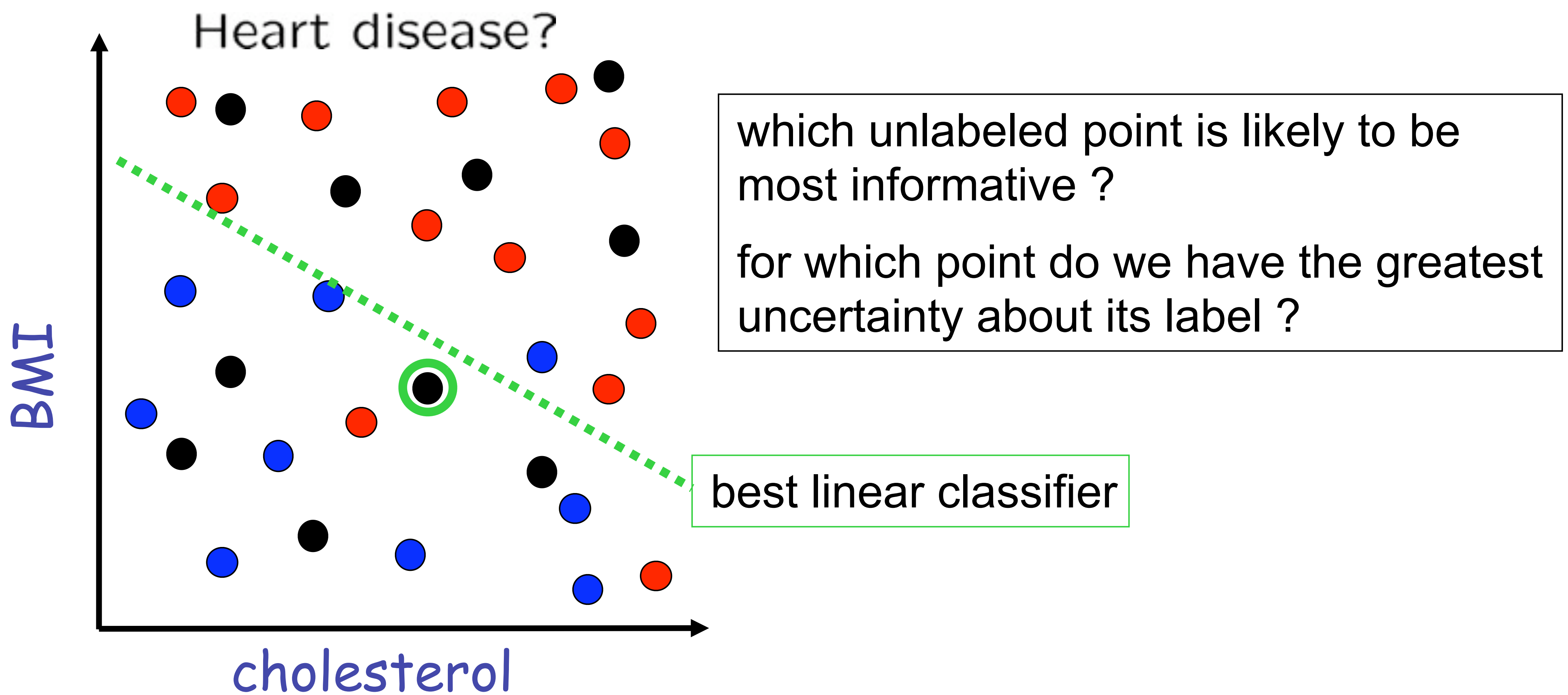

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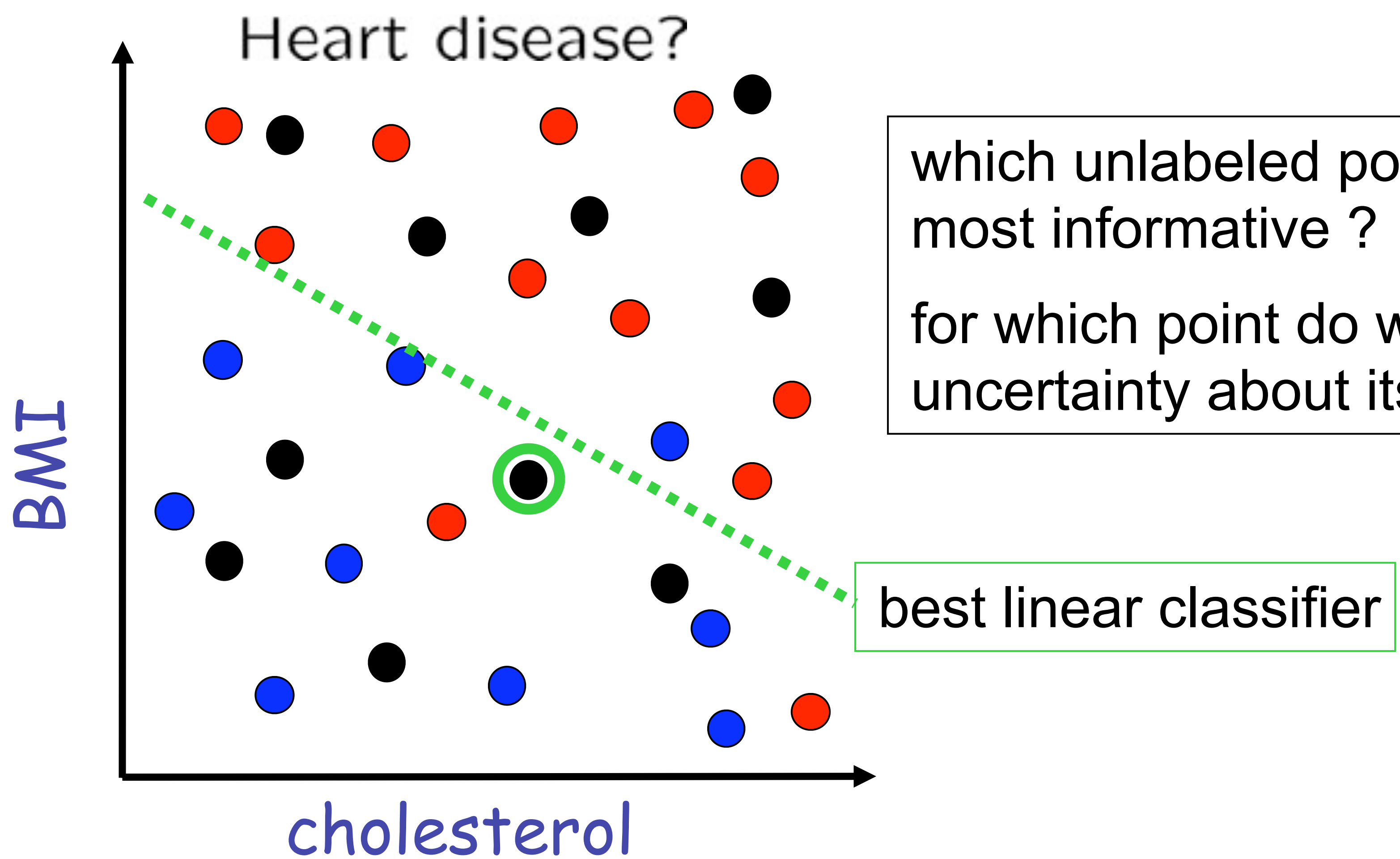

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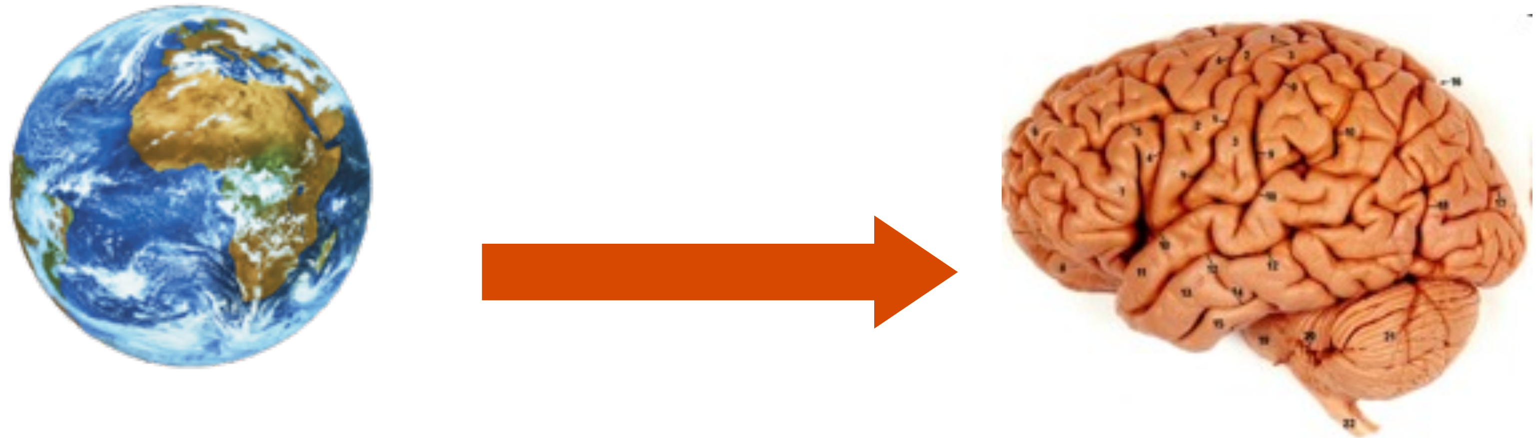
Active learning can very effectively "narrow down" the location of the optimal decision boundary

The Theory of the Organism-Environment System: III. Role of Efferent Influences on Receptors in the Formation of Knowledge*

TIMO JARVILEHTO
Department of Behavioral Sciences, University of Oulu, Finland

Abstract—The present article is an attempt to give—in the frame of the theory of the organism-environment system (Jarvilehto, 1998a)—a new interpretation to the role of efferent influences on receptor activity and to the functions of senses in the formation of knowledge. It is argued, on the basis of experimental evidence and theoretical considerations, that the senses are not transmitters of environmental information, but create a direct connection between the organism and the environment, which makes the development of a dynamic living system, the organism-environment system, possible. In this connection process, the efferent influences on receptor activity are of particular significance because, with their help, the receptors may be adjusted in relation to the parts of the environment that are most important in achieving behavioral results. Perception is the process of joining of new parts of the environment to the organism-environment system; thus, the formation of knowledge by perception is based on reorganization (widening and differentiation) of the organism-environment system, and not on transmission of information from the environment. With the help of the efferent influences on receptors, each organism creates its own peculiar world that is simultaneously subjective and objective. The present considerations have far-reaching influences as well on experimental work in neurophysiology and psychology of perception as on philosophical considerations of knowledge formation.



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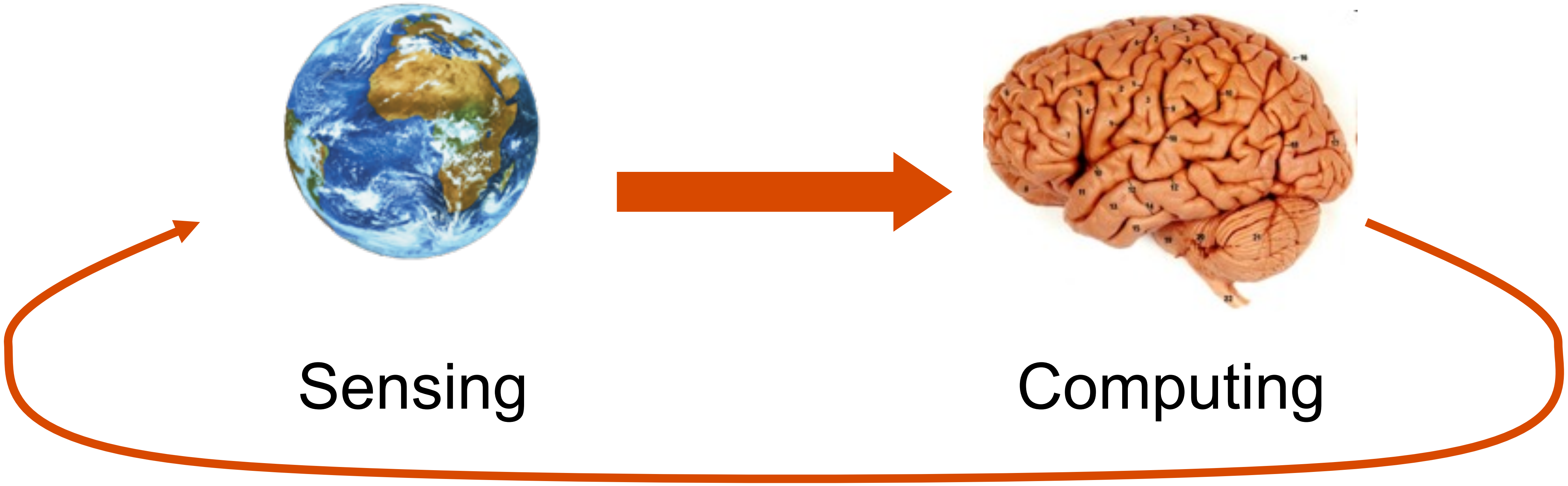

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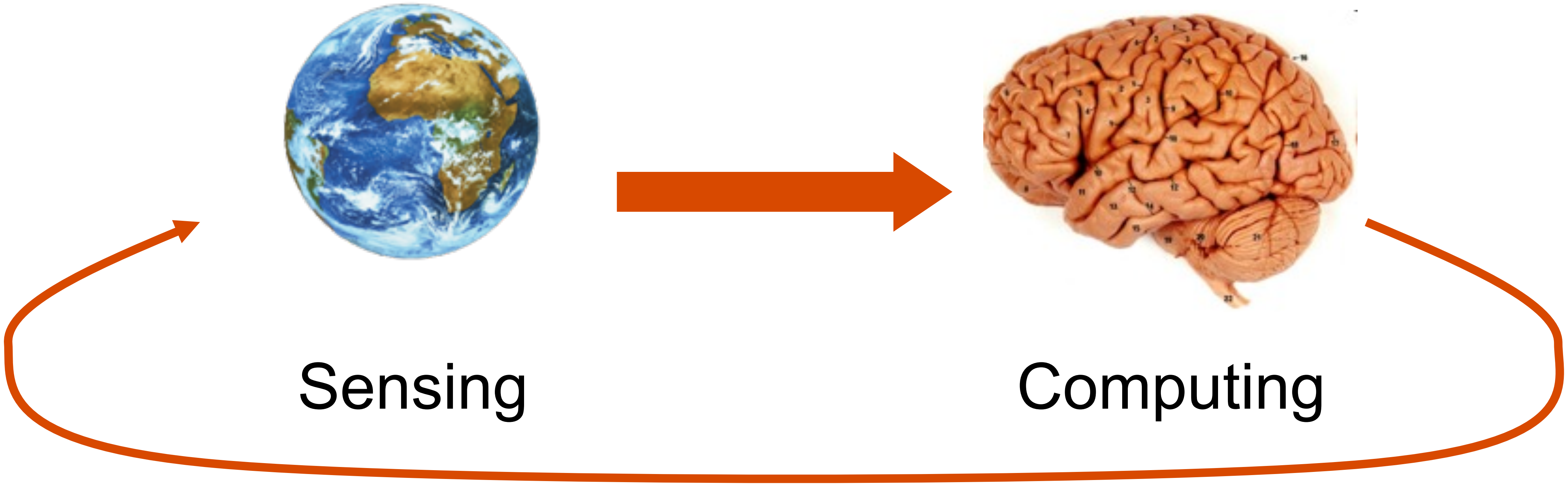

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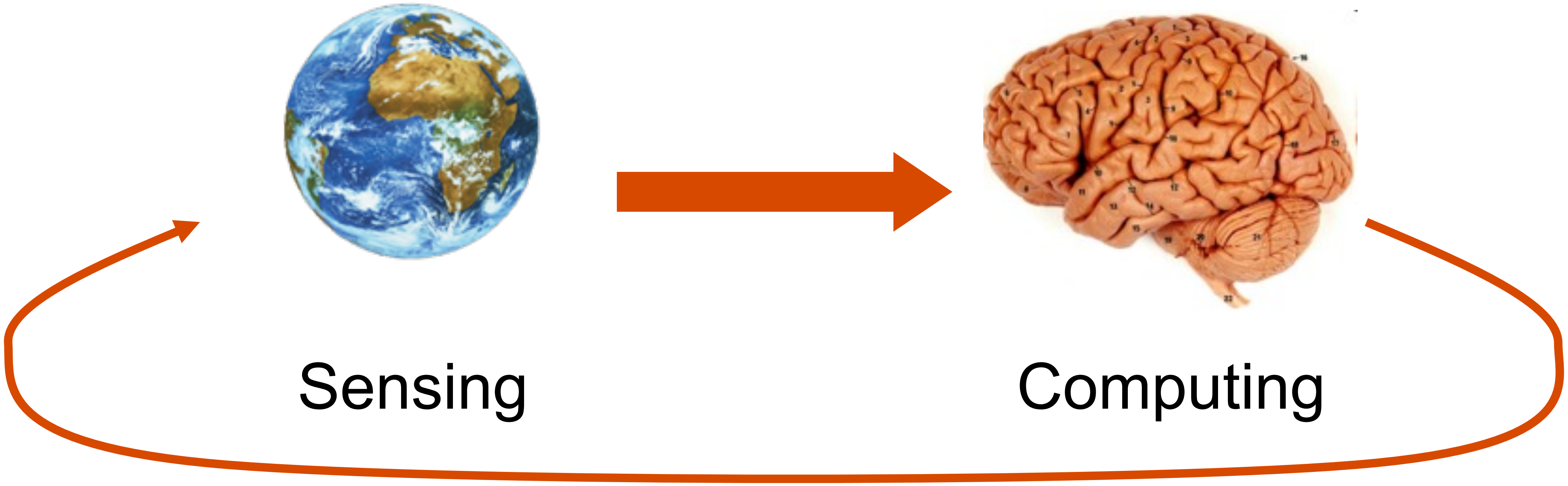

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Visual Perception

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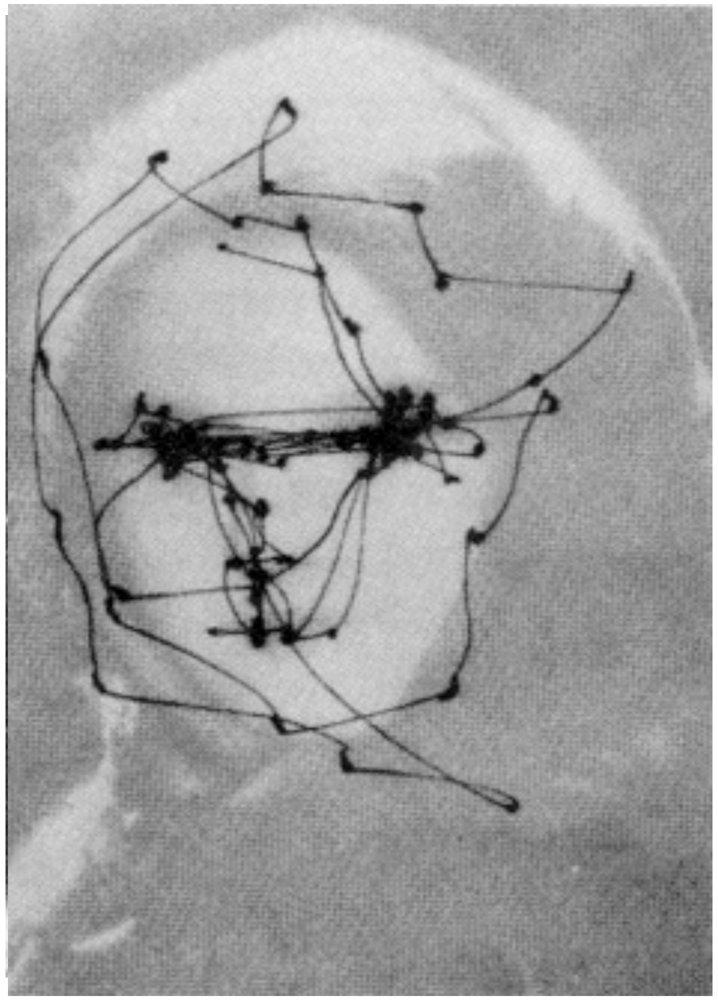
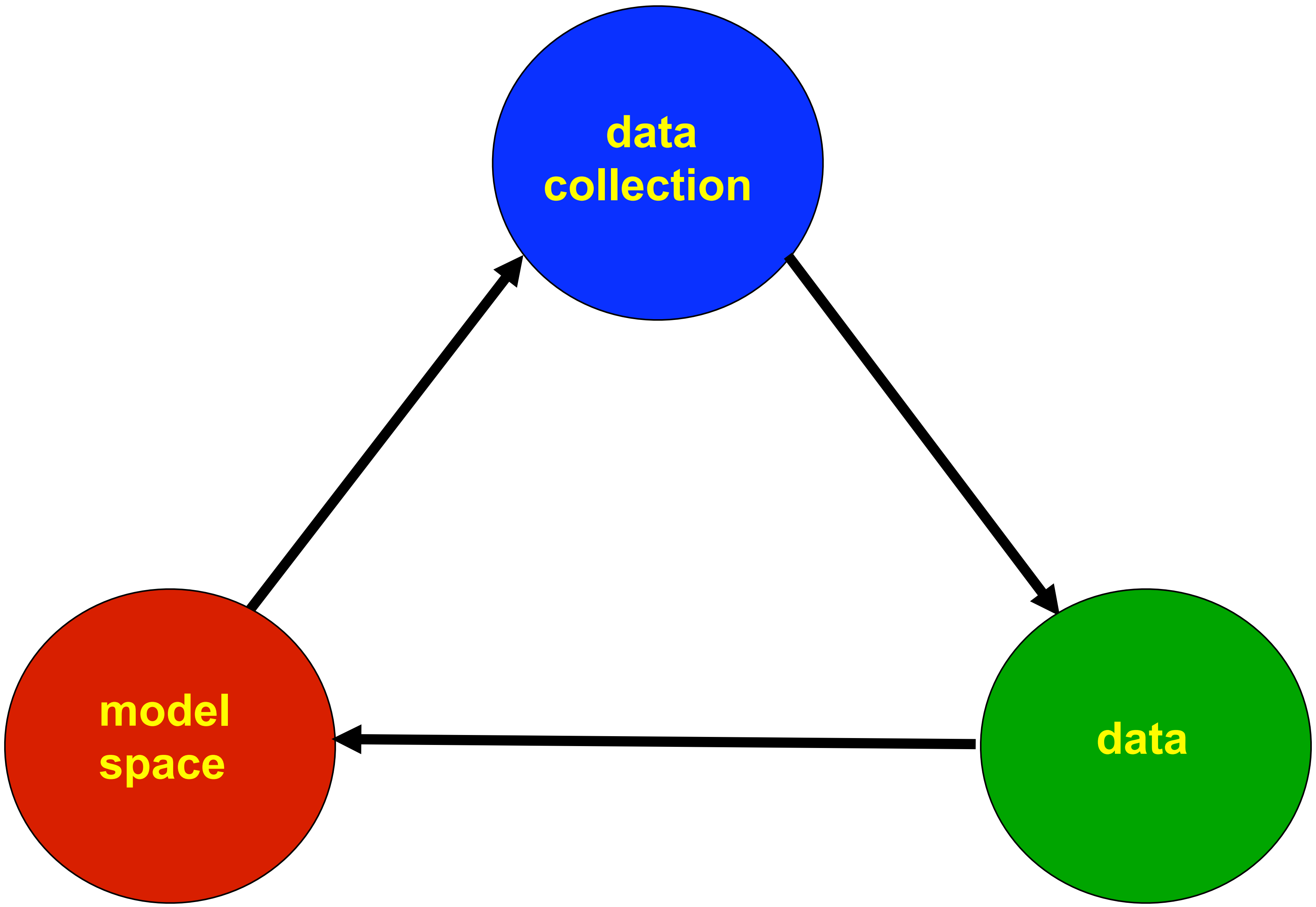



S

Mathematical Theory of Active Sensing and Learning

$\mathcal{Y}$: possible measurements/experiments



$\mathcal{X}$: models/hypotheses
under consideration

$y_1(x), y_2(x), \ldots$: information/data

Adaptive vs. Non-Adaptive: Three Situations

The "bare minimum" number of measurements depends on intrinsic complexity of $\mathcal{X}$. In practice, the minimum number depends on jointly on $\mathcal{X}$ and $\mathcal{Y}$.

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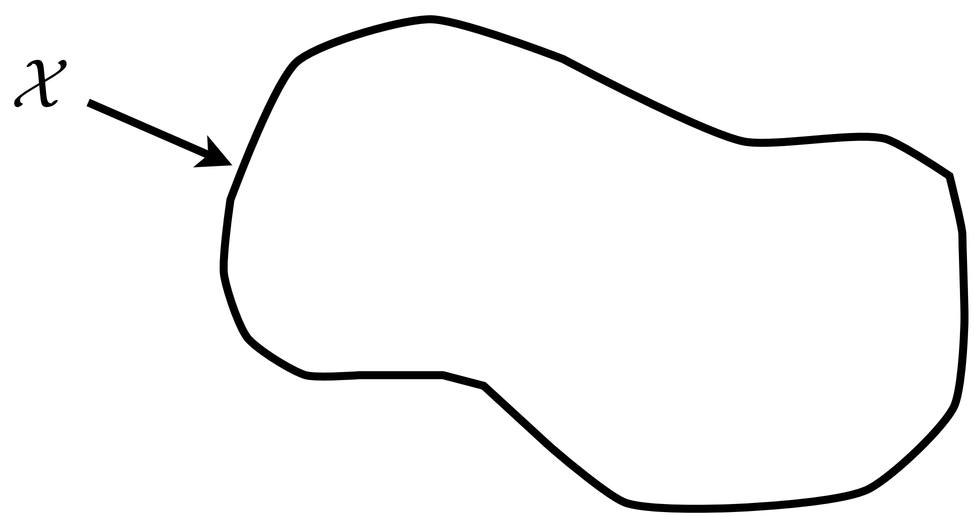
Good and Bad: adaptive requires bare minimum number of measurments, non-adaptive requires many more

The Bare Minimum

Assume $\mathcal{X}$ is equipped with metric d and is compact.



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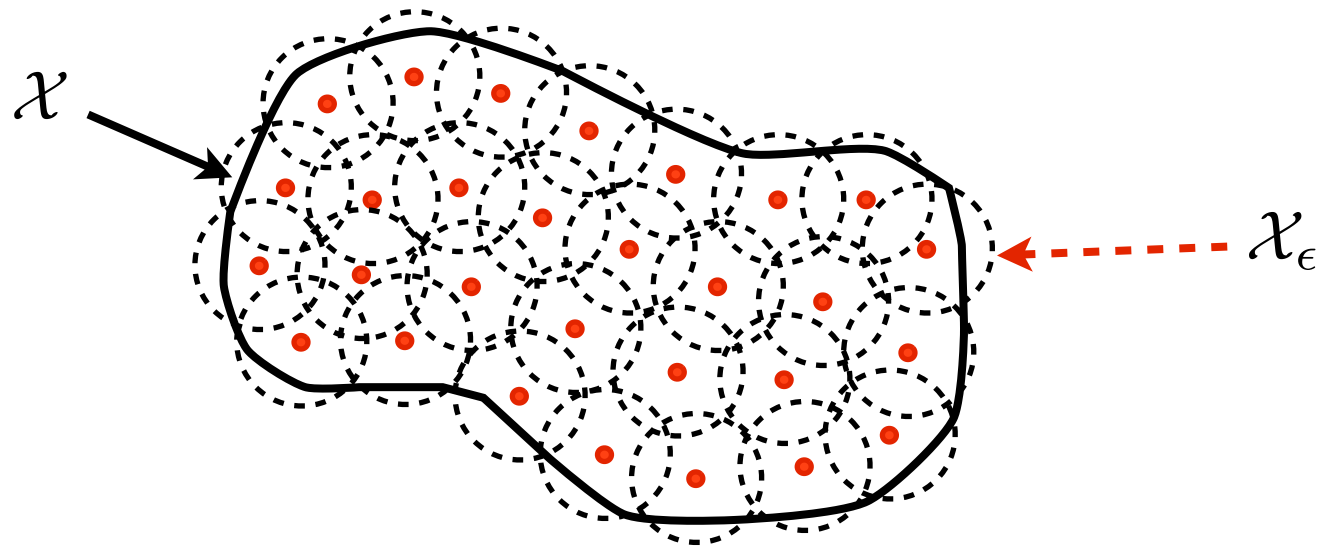

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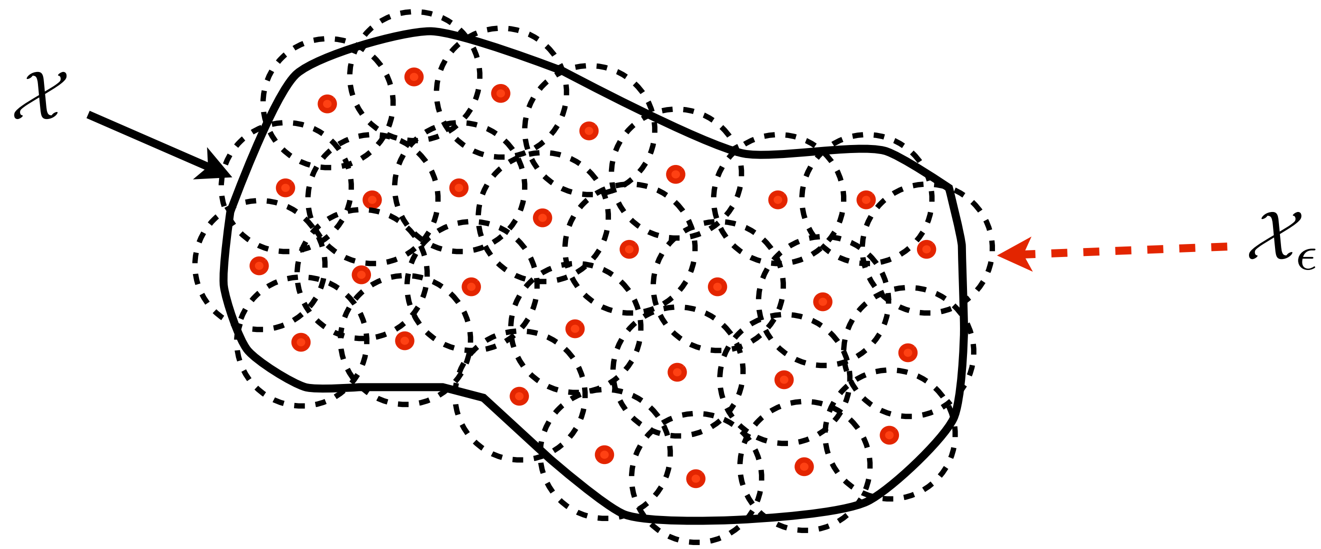

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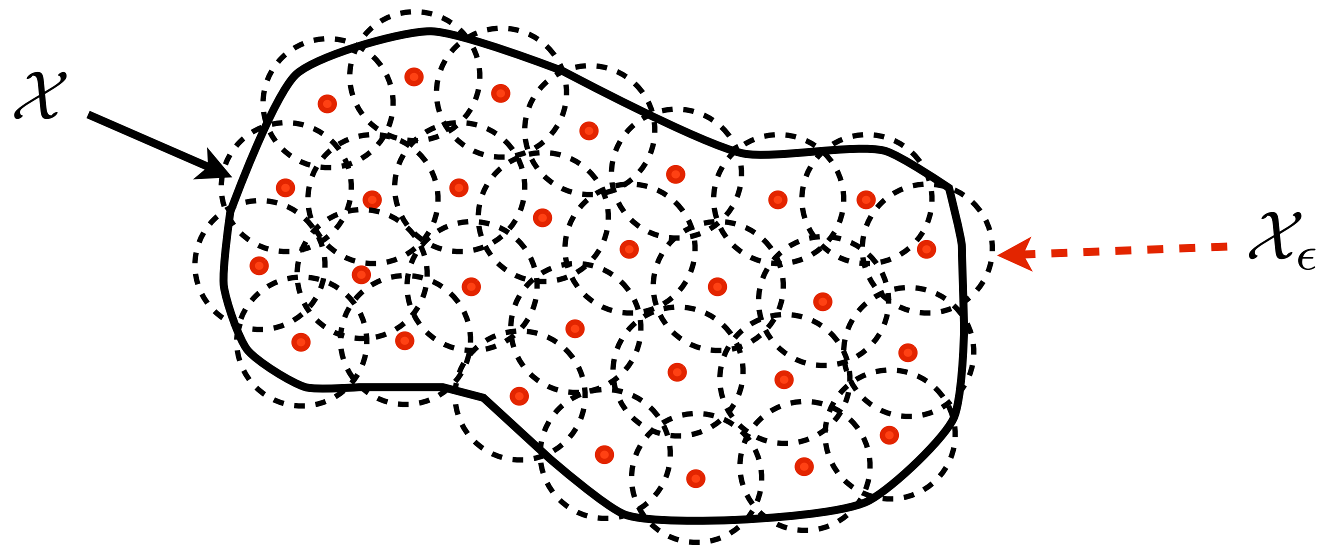

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Ex. suppose $\mathcal{X} = [0,1]^d$. we can take a uniform grid of points spaced ϵ apart as our cover. Then $N_\epsilon = (\frac{1}{\epsilon})^d$ and $\log N_\epsilon = d \log(1/\epsilon)$.

Binary Search

$$\mathcal{X} = \{\,\text{subsets } [0, \tfrac{1}{N}], [0, \tfrac{2}{N}], \ldots, [0, 1]\,\}$$
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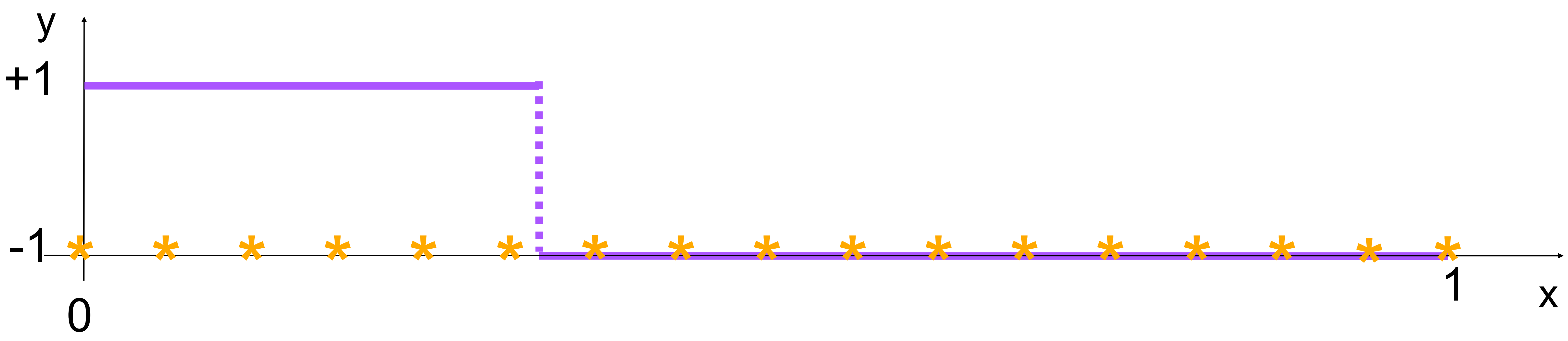

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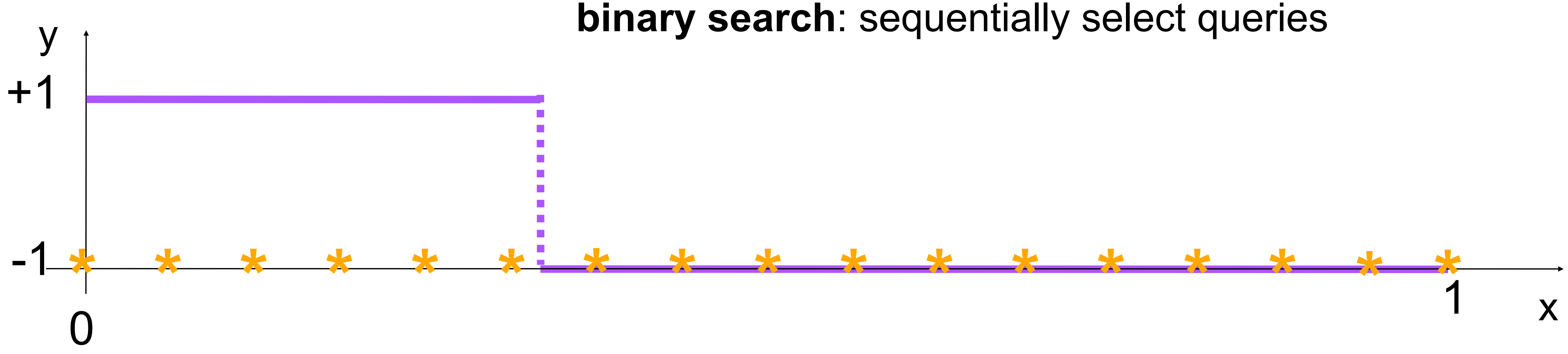

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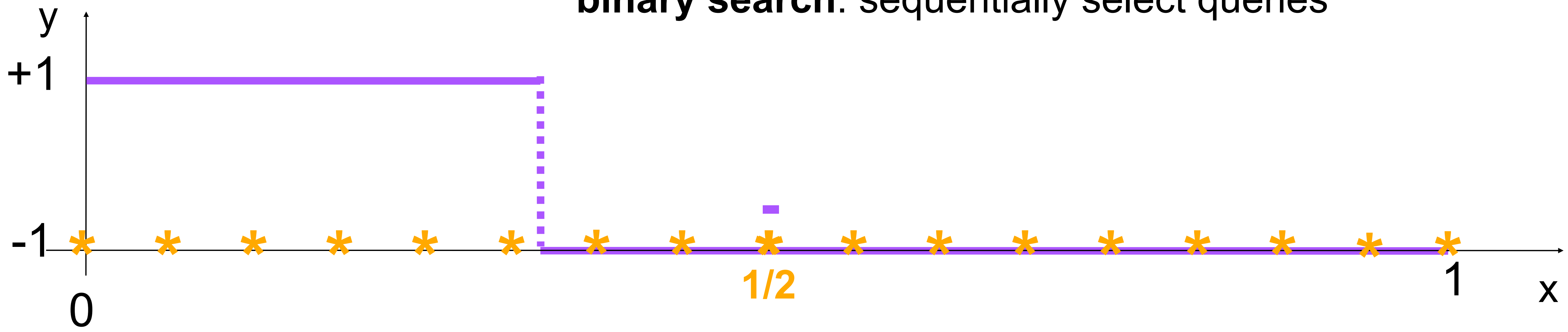

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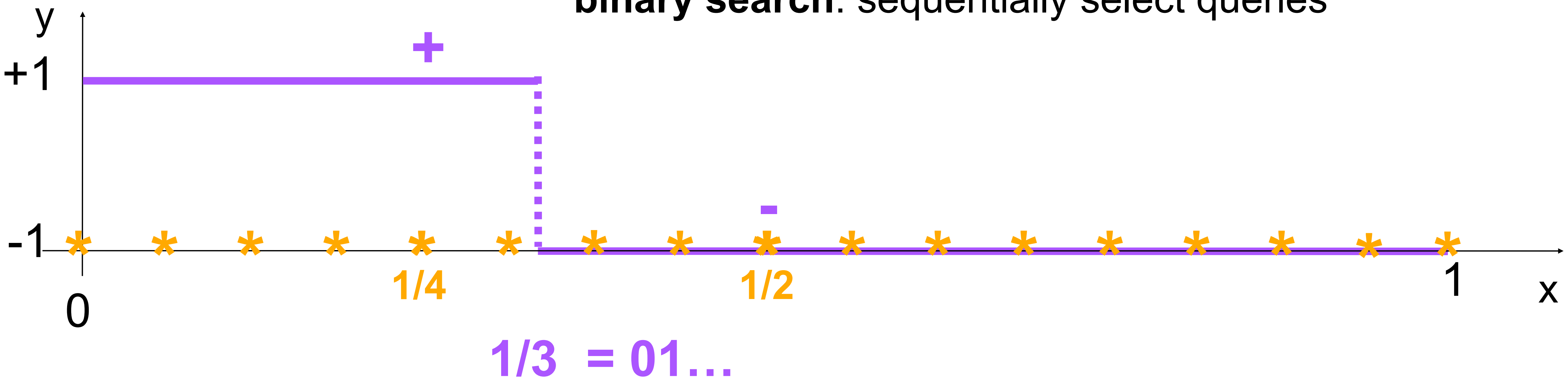

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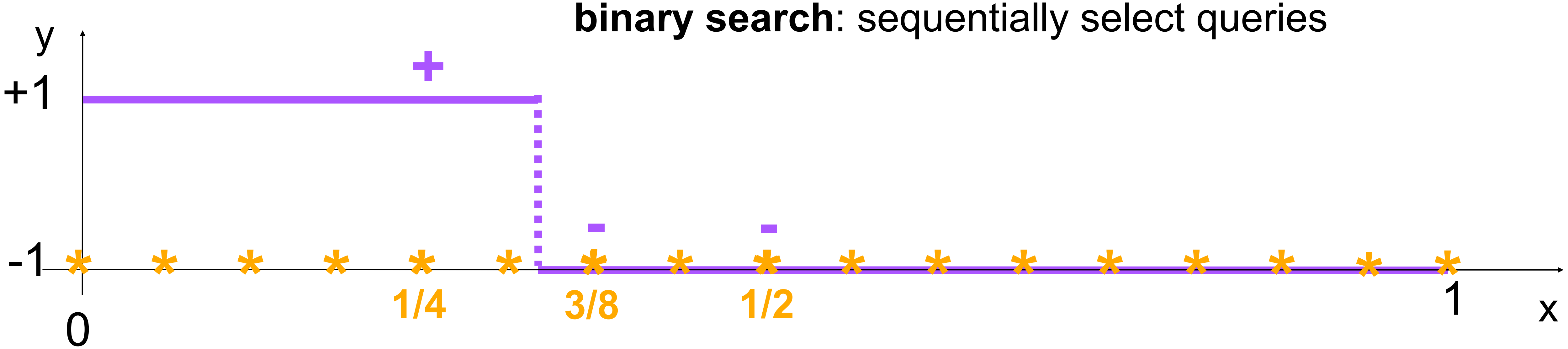

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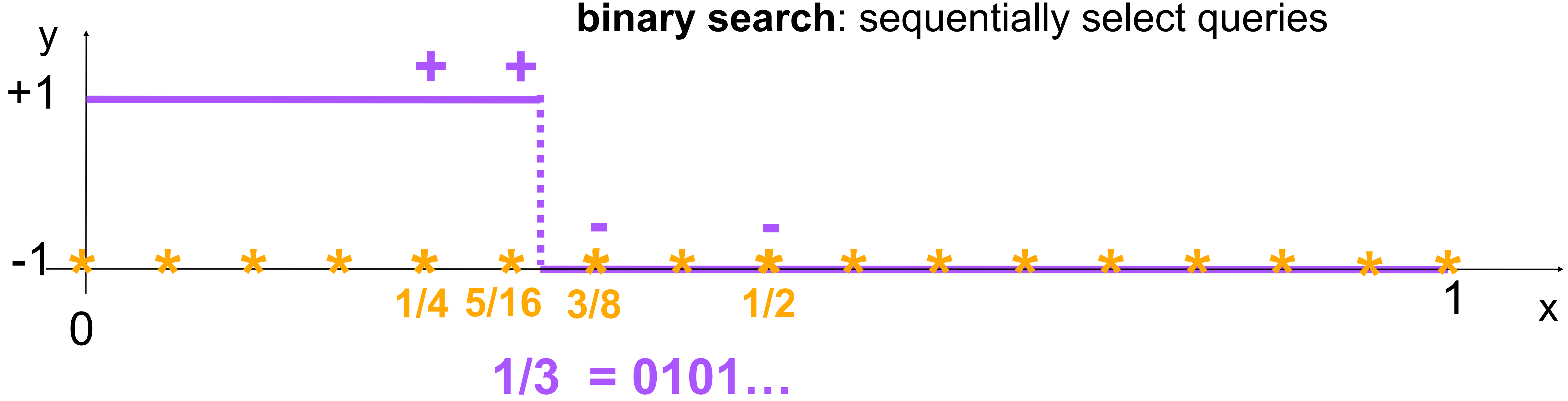

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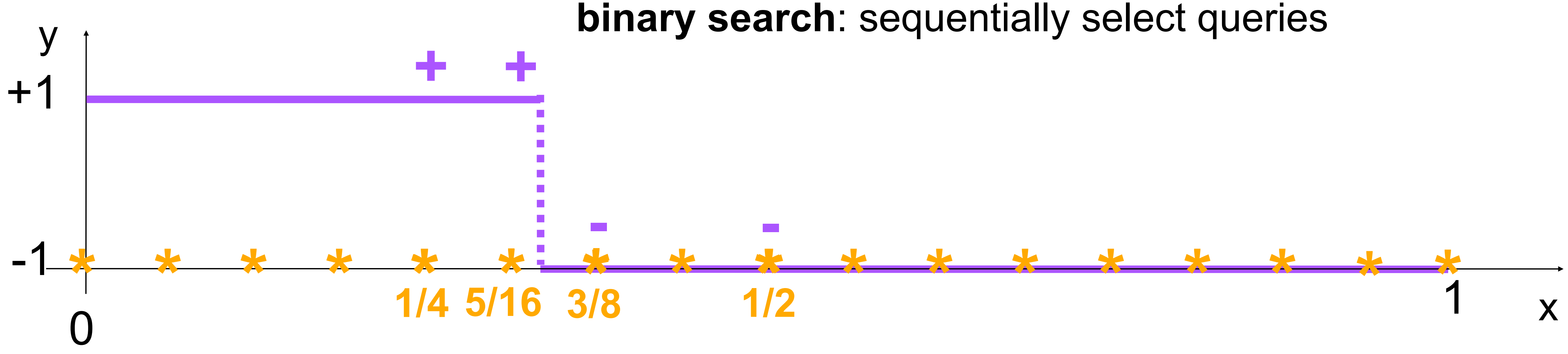

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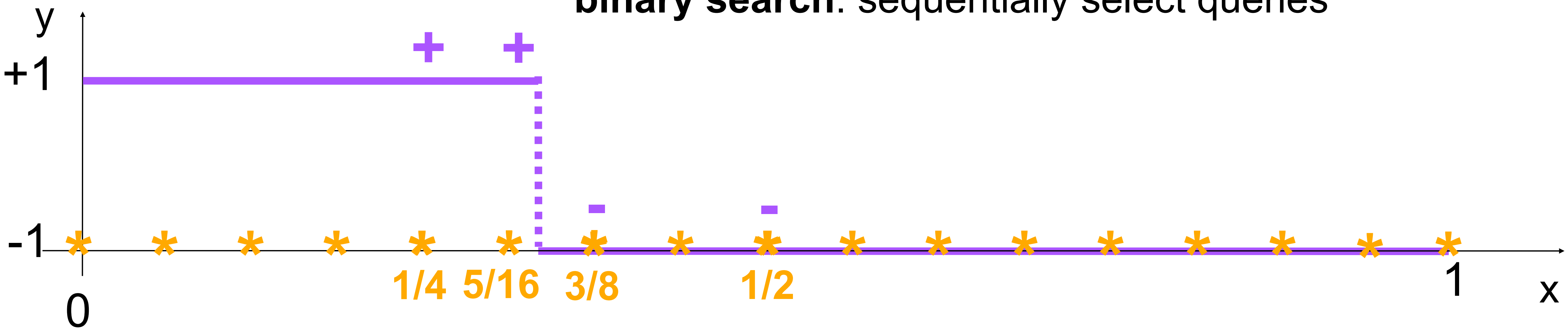

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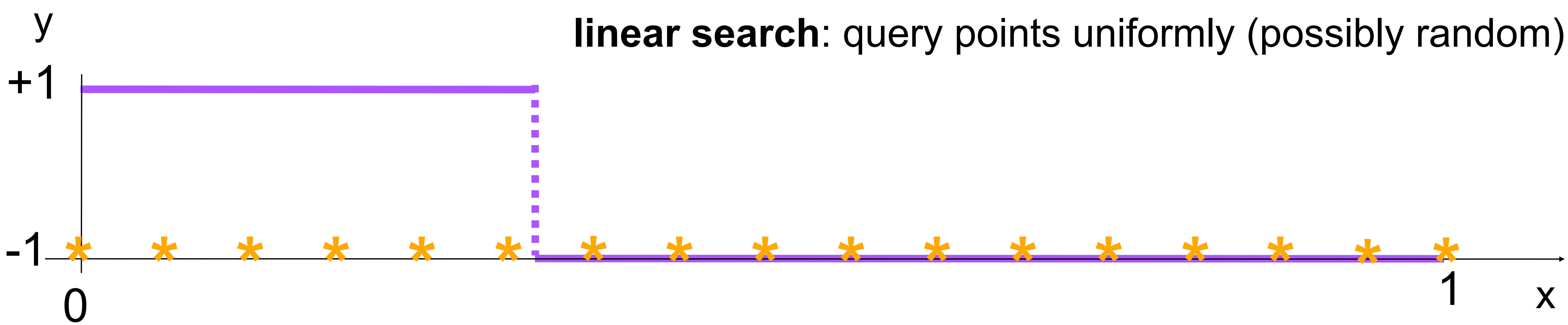
linear search: query points uniformly (possibly random)



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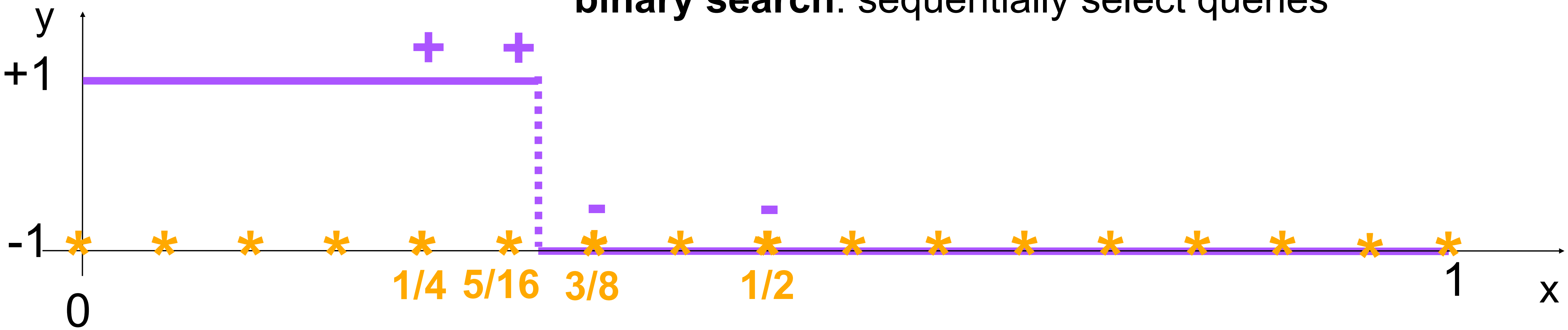

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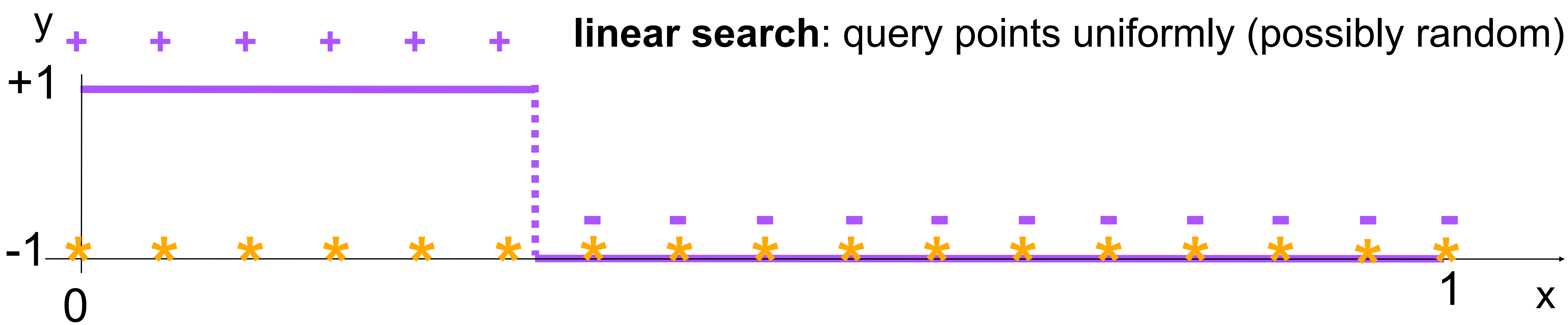
requires $\log_2 N$ queries

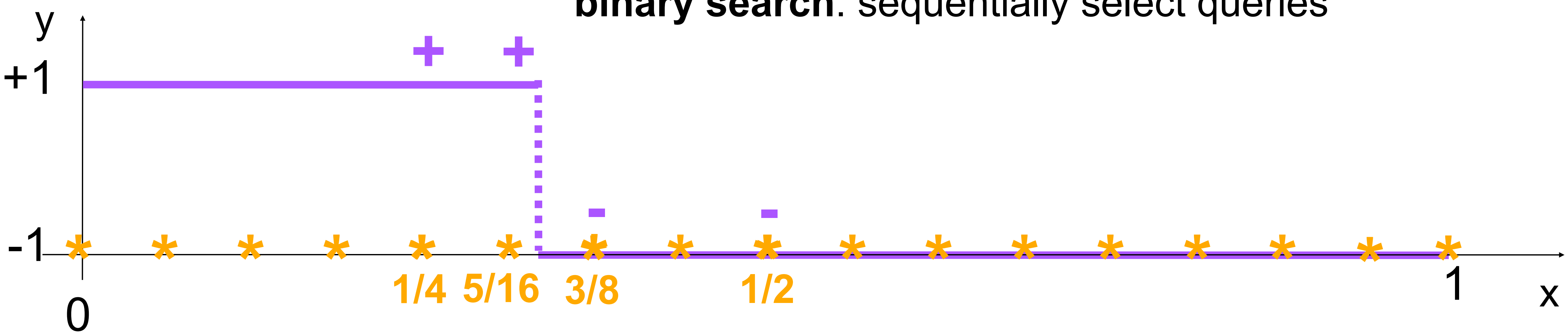
linear search: query points uniformly (possibly random)



Binary Search

$$\mathcal{X} = \{\,\text{subsets } [0, \tfrac{1}{N}], [0, \tfrac{2}{N}], \ldots, [0, 1]\,\}$$
$$\mathcal{Y} = \text{“membership queries”}$$

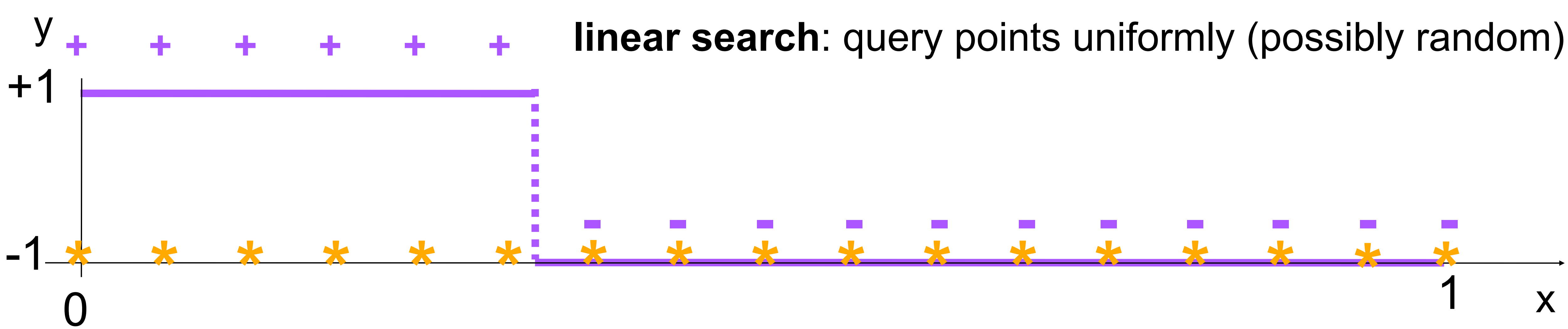
binary search: sequentially select queries



1/3 = 0101…

requires $\log_2 N$ queries

linear search: query points uniformly (possibly random)



requires $O(N)$ queries

Outline of Tutorial

Part 1: Introduction (Rob), 9:00-9:30

Part 2: Active Sensing (Jarvis), 9:30-10:30

Break, 10:30-10:45

Part 3: Active Learning (Rob), 10:45-11:45

Part 4: Conclusions and Future Directions, 11:45-12