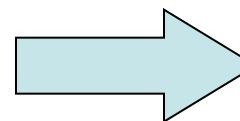
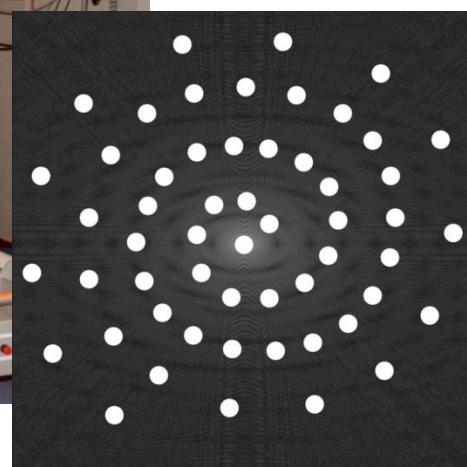
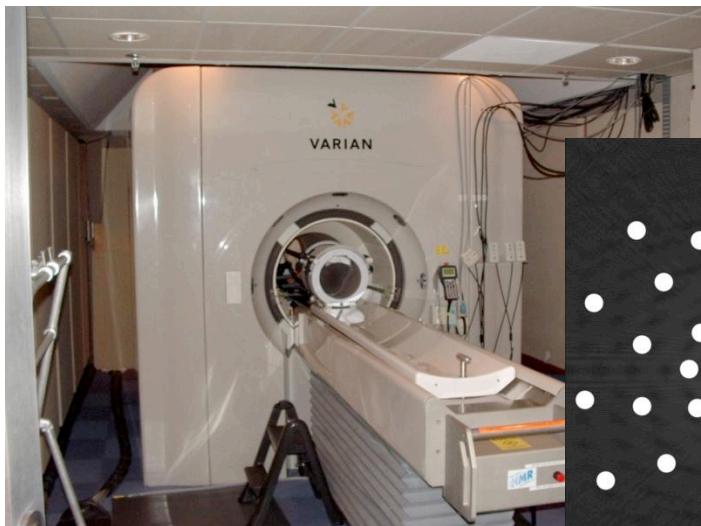
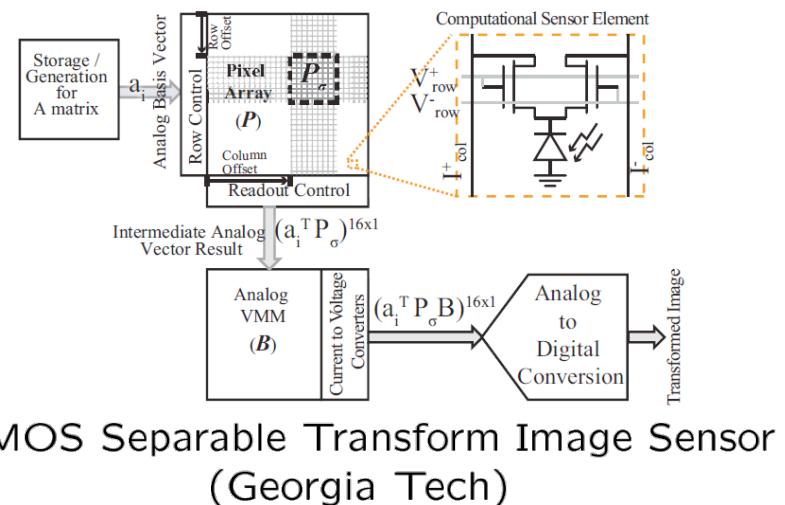
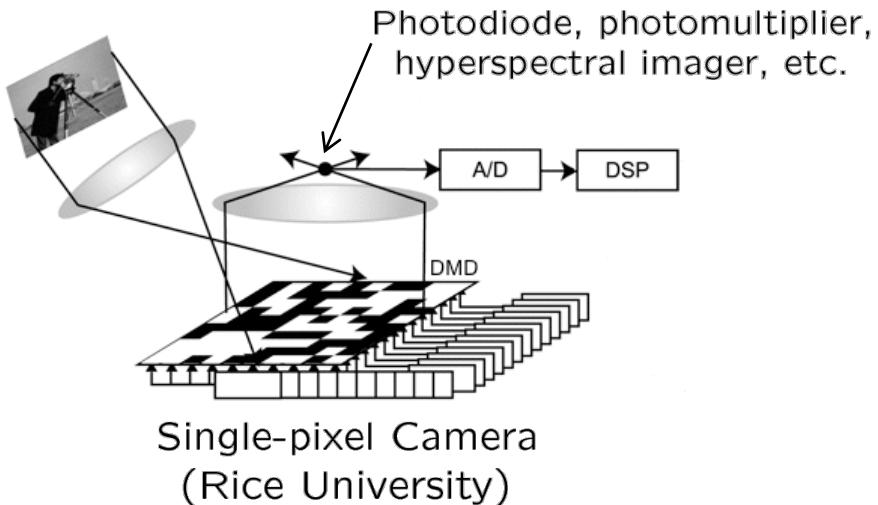


Future Directions

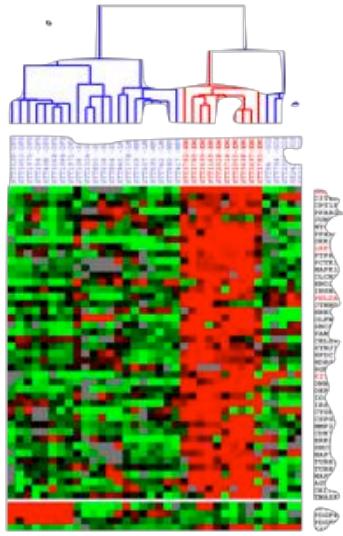
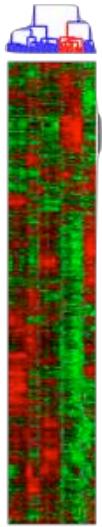
Agile Sensors and Stylized Applications



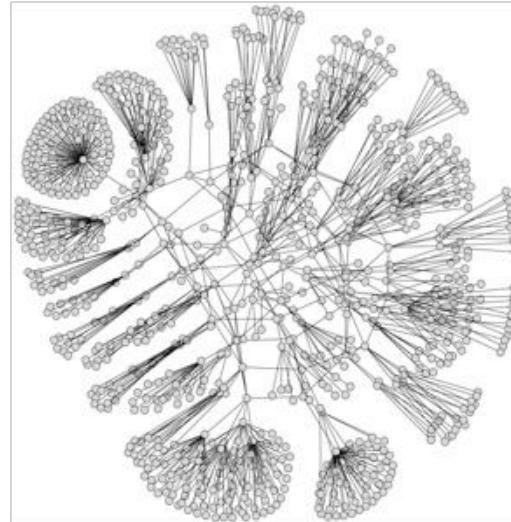
Measuring and Mapping Large Networks

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

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



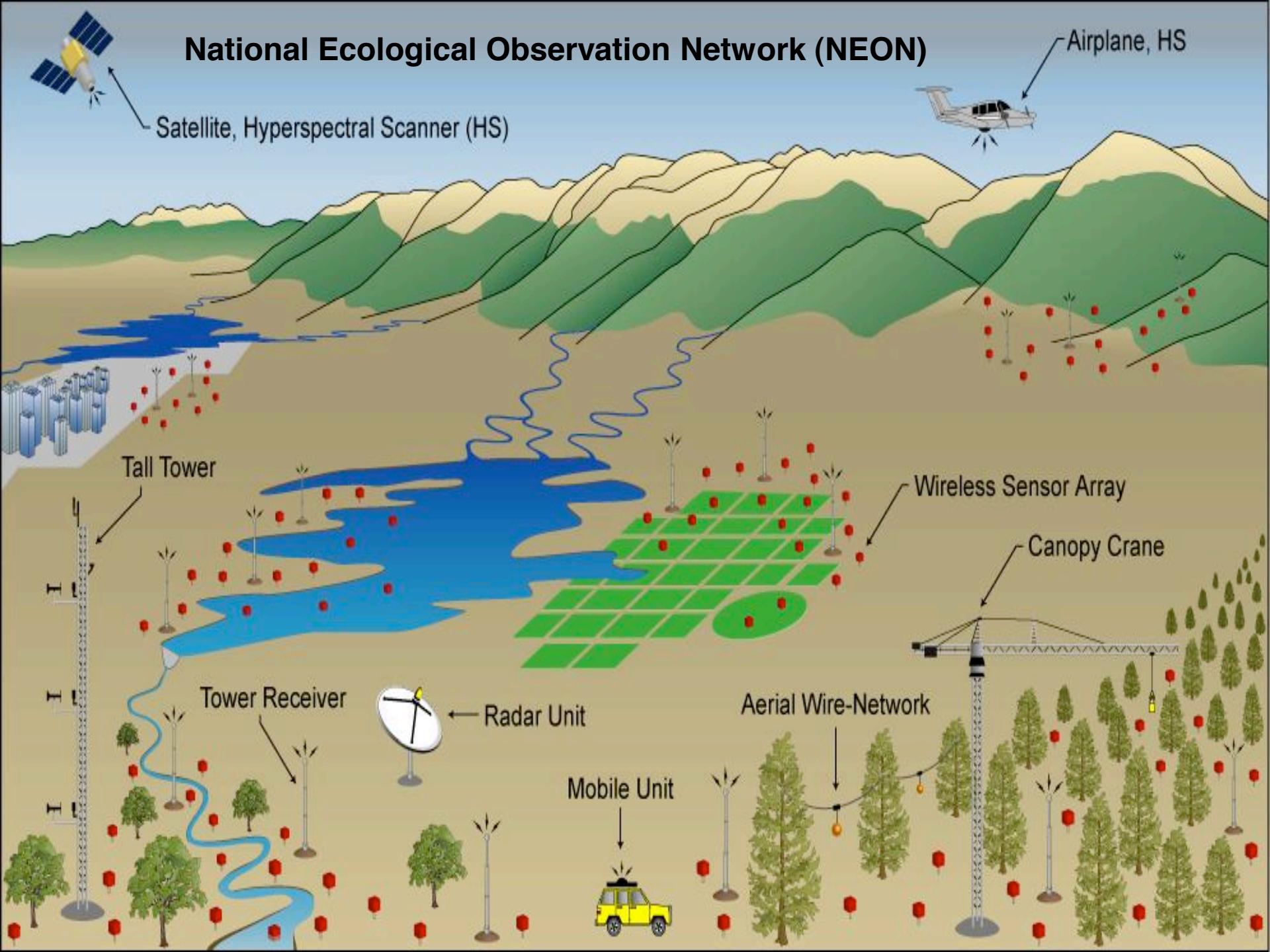
genes and expression/
interaction profiles



network routers and
traffic/distance profiles

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

National Ecological Observation Network (NEON)



Human Sensors and Social Networks



Active Learning with Human Sensors:

Suppose our machine learning algorithm wants to learn which glasses are the sexiest. It could tweet back to vpisteve asking “what type of glasses are the sexiest?”

This could be done automatically in response to any tweet containing words “glasses” and “sexy”.

Optimization and Active Sensing/Learning

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

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

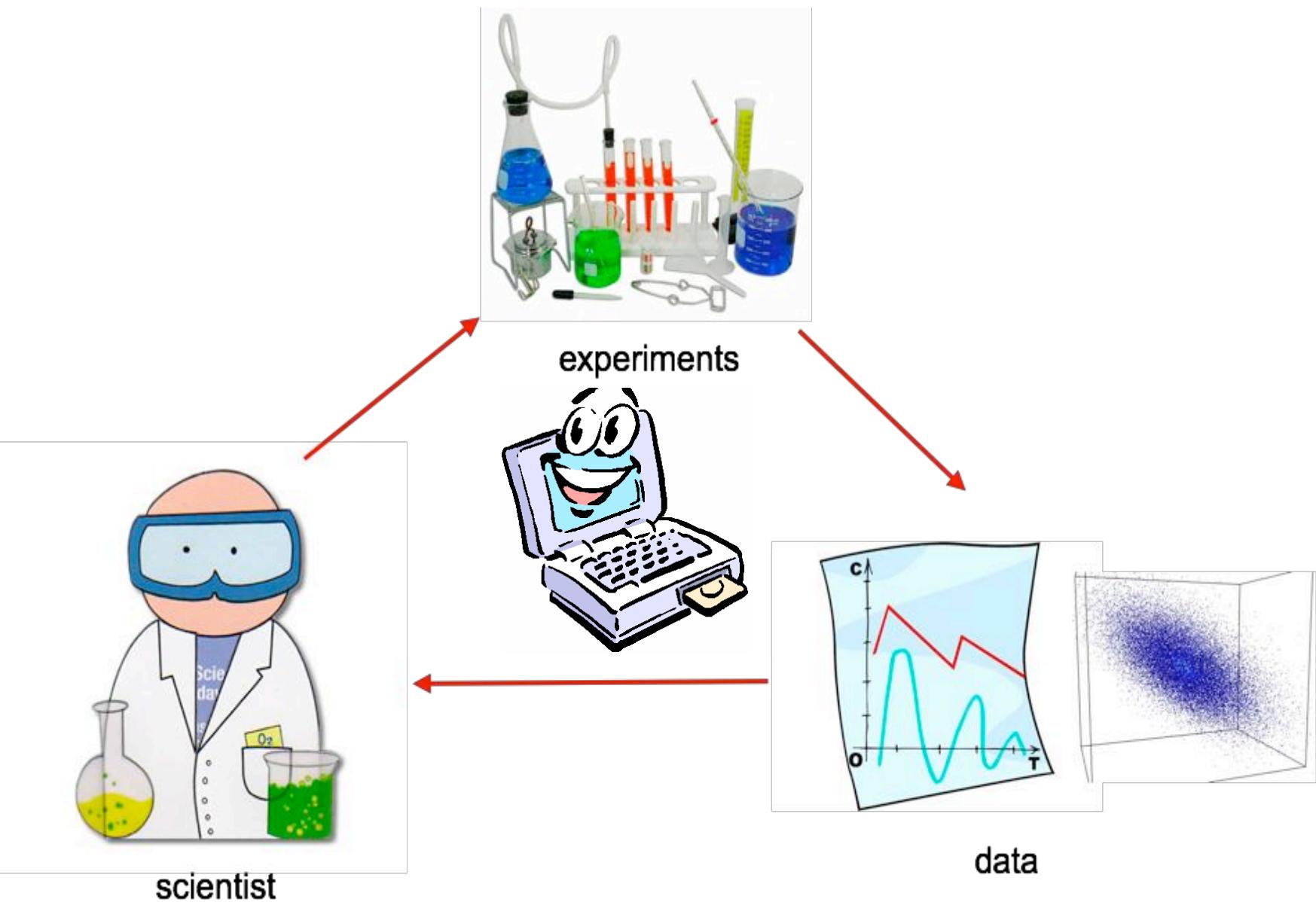
Adaptive Information: $y_1, y_2, \dots \in \mathcal{Y}$ are selected sequentially and y_i can depend on previously gathered information, i.e., $y_1(x), \dots, y_{i-1}(x)$

Dynamic Programming: $K > 0$ measurement/experiment steps

$$\min_{\hat{x}, y_1, \dots, y_K} \max_{x \in \mathcal{X}} d(x, \hat{x}(y_1, \dots, y_K))$$

computationally prohibitive in all but very low-dimensional, simple problems

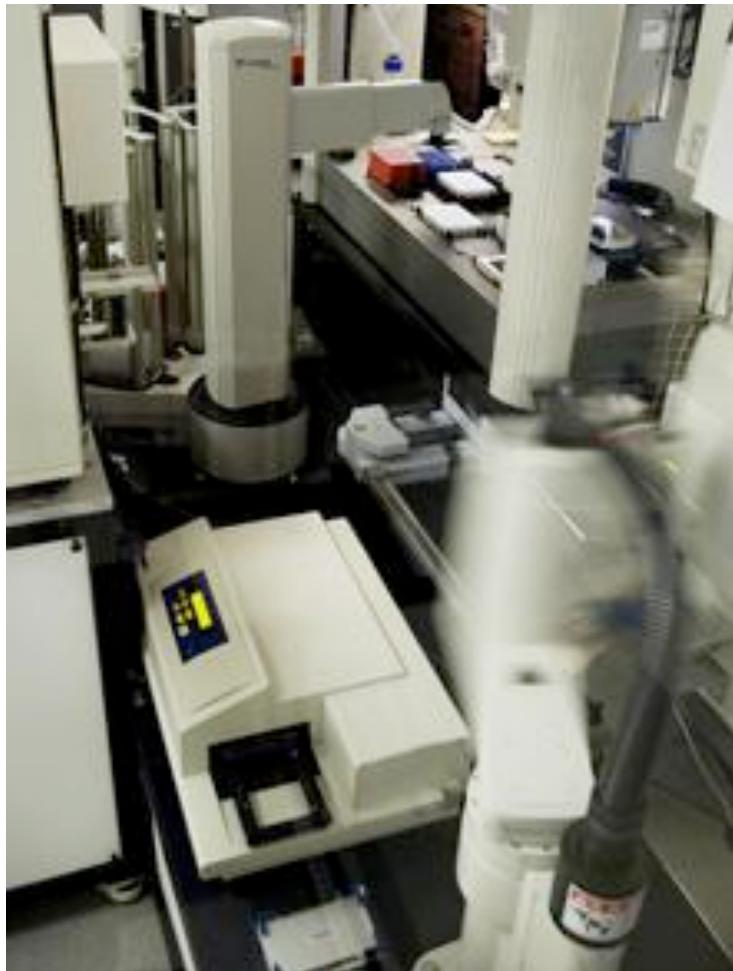
Automating Science





Robot Scientist

www.aber.ac.uk/compsci/Research/bio/robotsci/



Wired Magazine, April 2009:

For the first time, a robotic system has made a novel scientific discovery with virtually no human intellectual input.

Scientists designed "Adam" to carry out the entire scientific process on its own: formulating hypotheses, designing and running experiments, analyzing data, and deciding which experiments to run next. "It's a major advance," says David Waltz of the Center for Computational Learning Systems at Columbia University. "Science is being done here in a way that incorporates artificial intelligence. It's automating a part of the scientific process that hasn't been automated in the past."

Adam is the first automated system to complete the cycle from hypothesis, to experiment, to reformulated hypothesis without human intervention.

Scientific and Engineering Discovery is a Closed-loop Process

Do we have the right theory and methods for it ?

Paths forward:

- Closing the loop between data acquisition and analysis
- Do ‘more with less’ or ‘less with more’ data
(sublinear complexity algorithms)
- Integrating disparate information sources (including humans)
- Man-machine systems

Some Active Sensing and Learning References

(Not Comprehensive)

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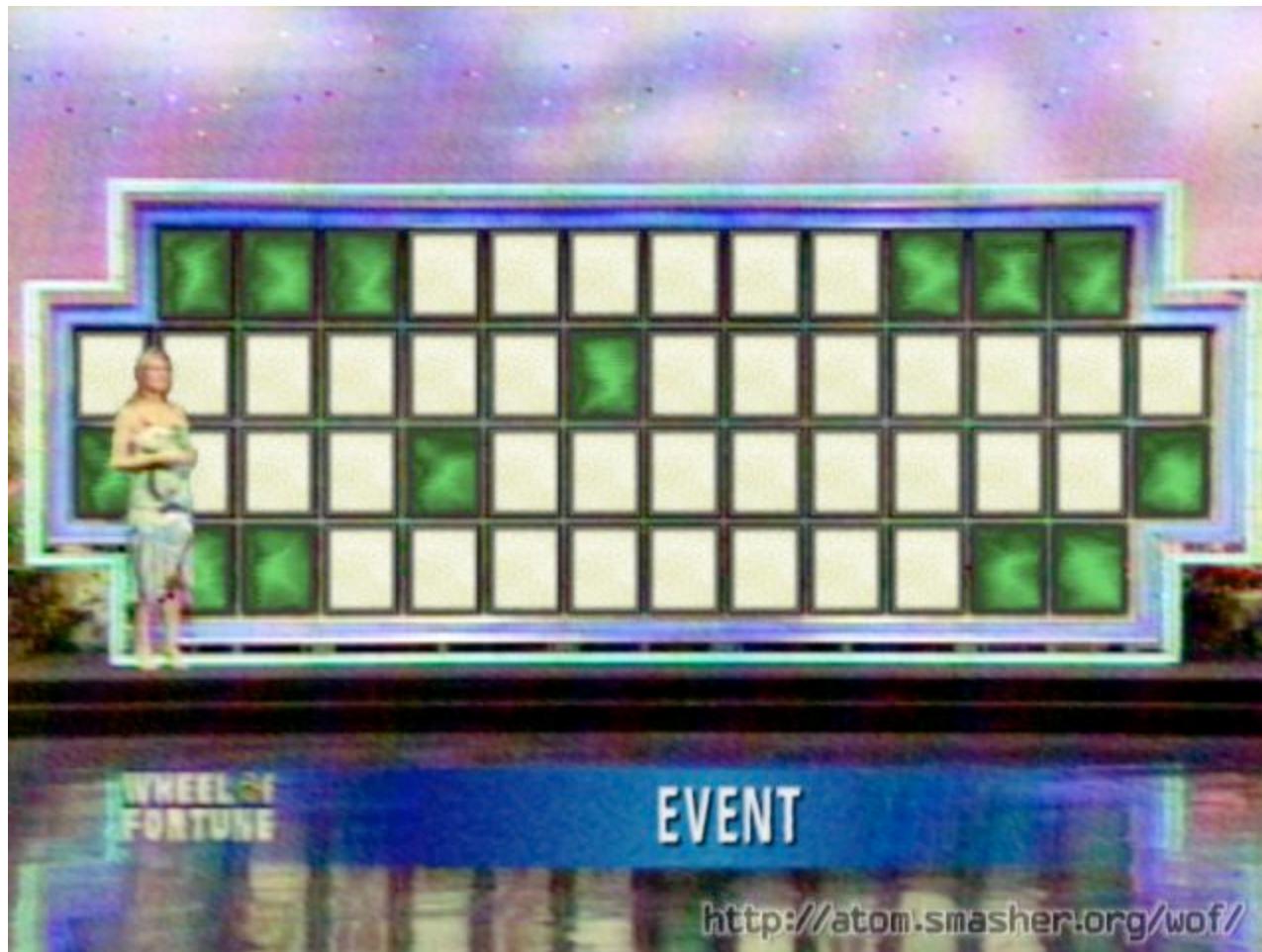
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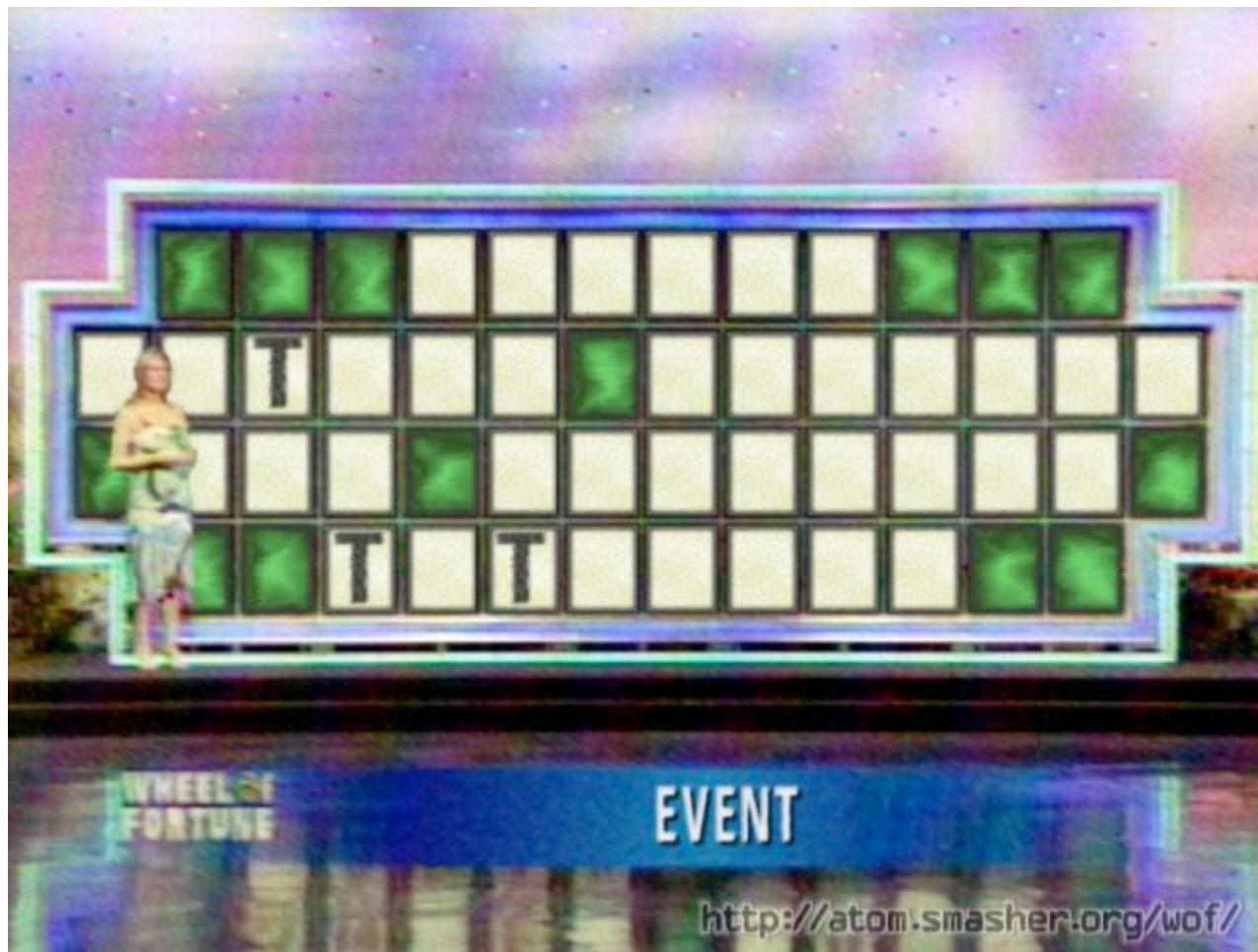
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“Active” Recreation...



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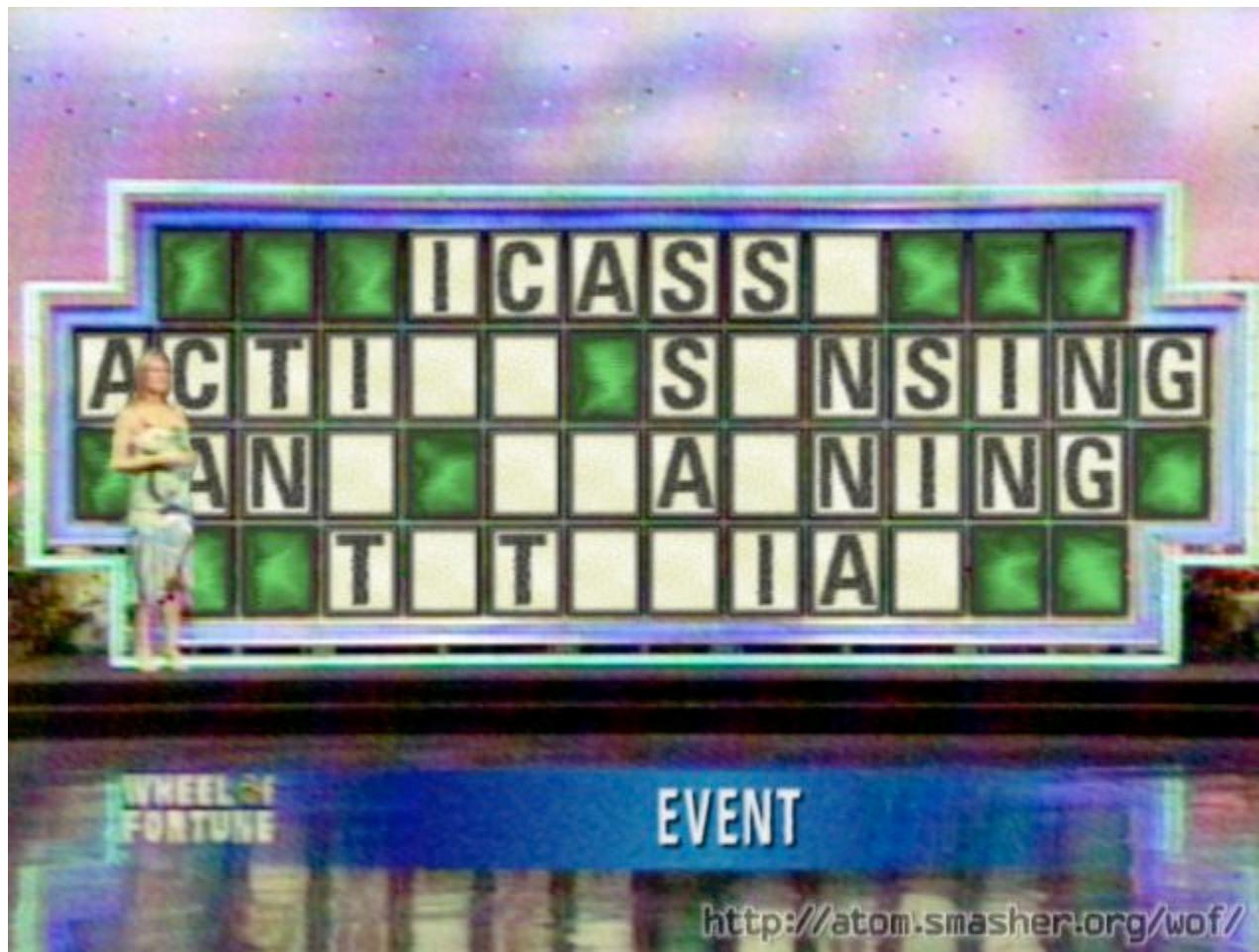
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