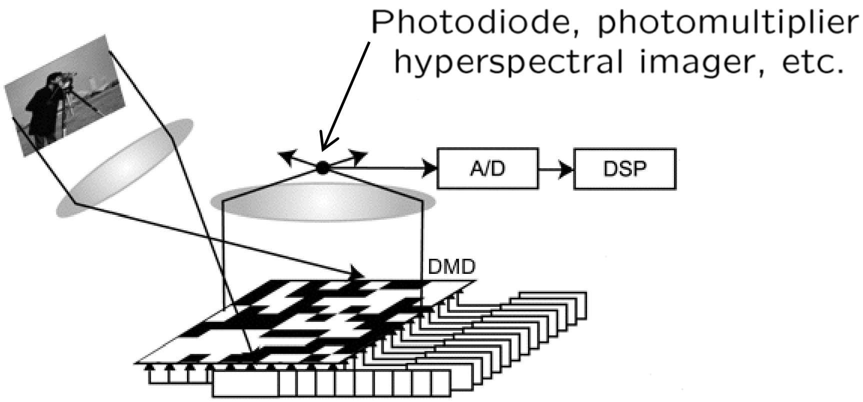
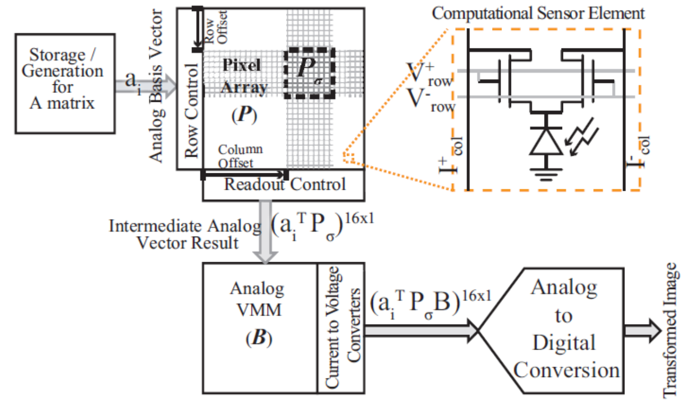
Future Directions

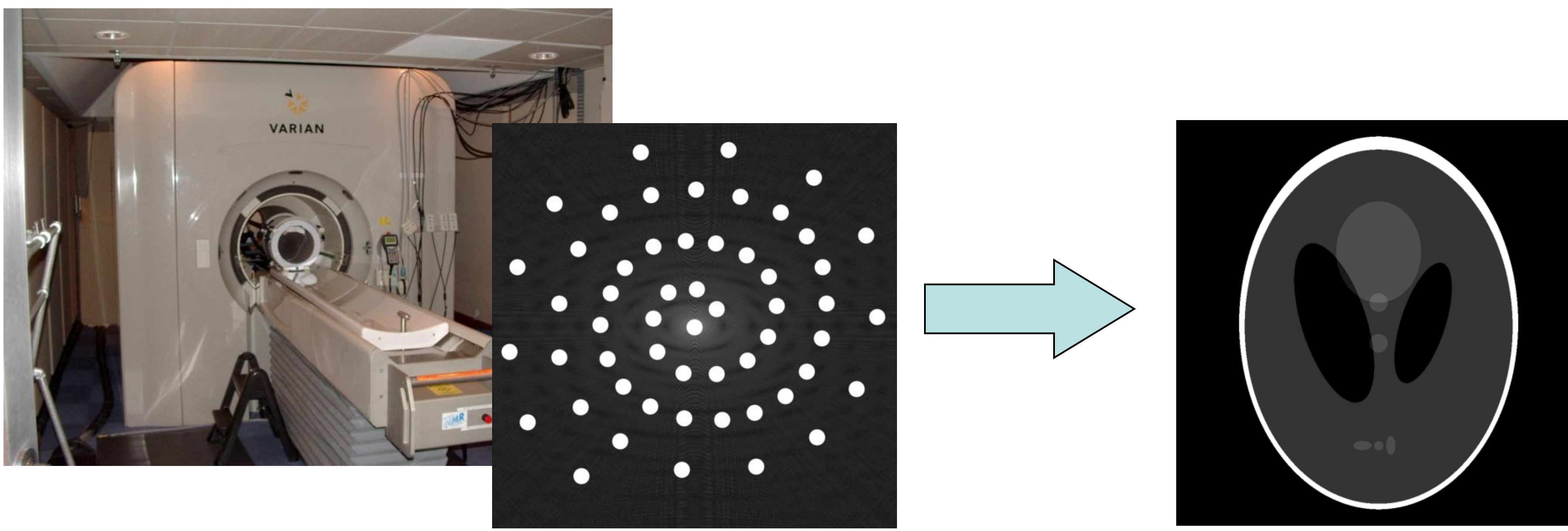
Agile Sensors and Stylized Applications



Single-pixel Camera
(Rice University)



CMOS Separable Transform Image Sensor
(Georgia Tech)



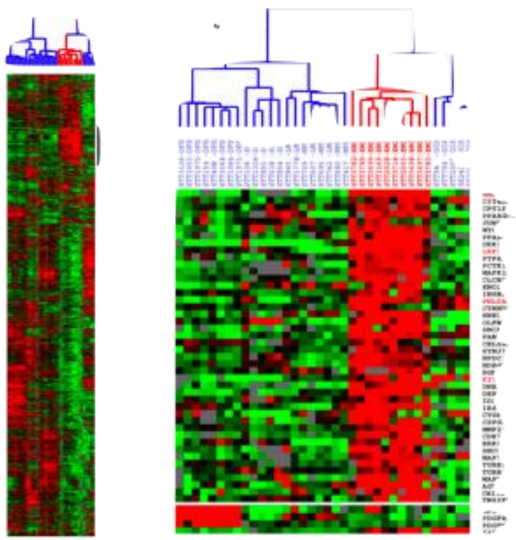
k-space

image

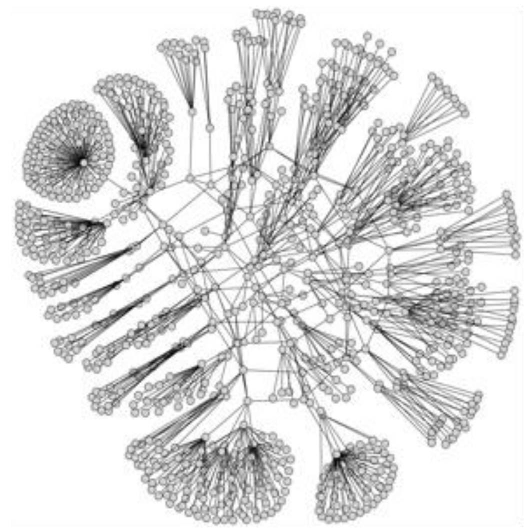
Measuring and Mapping Large Networks

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



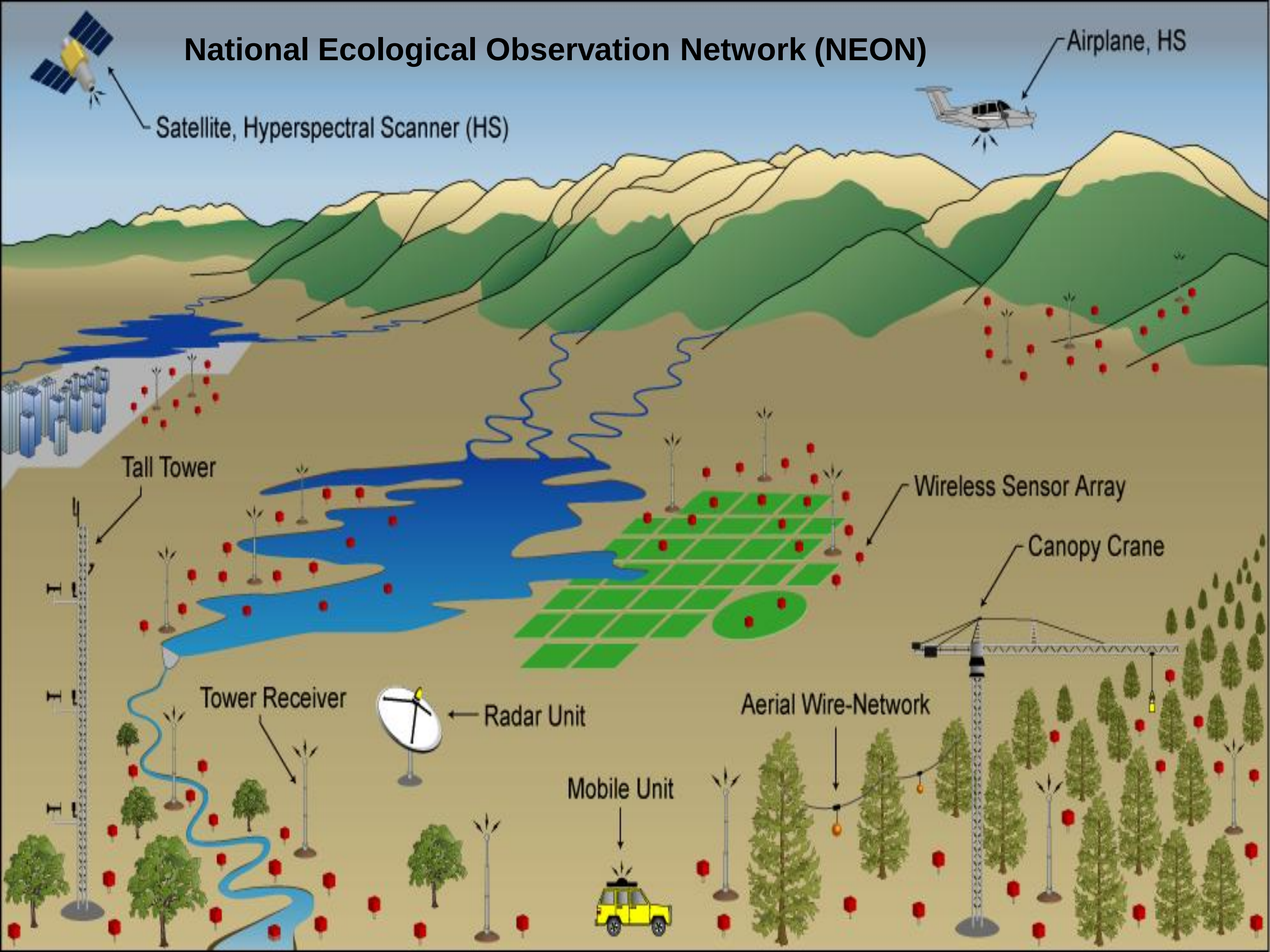
genes and expression/
interaction profiles



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

TwitterVision by Popvox LLC

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 $y_1(x), \ldots, y_n(x)$, the values of certain functionals of x

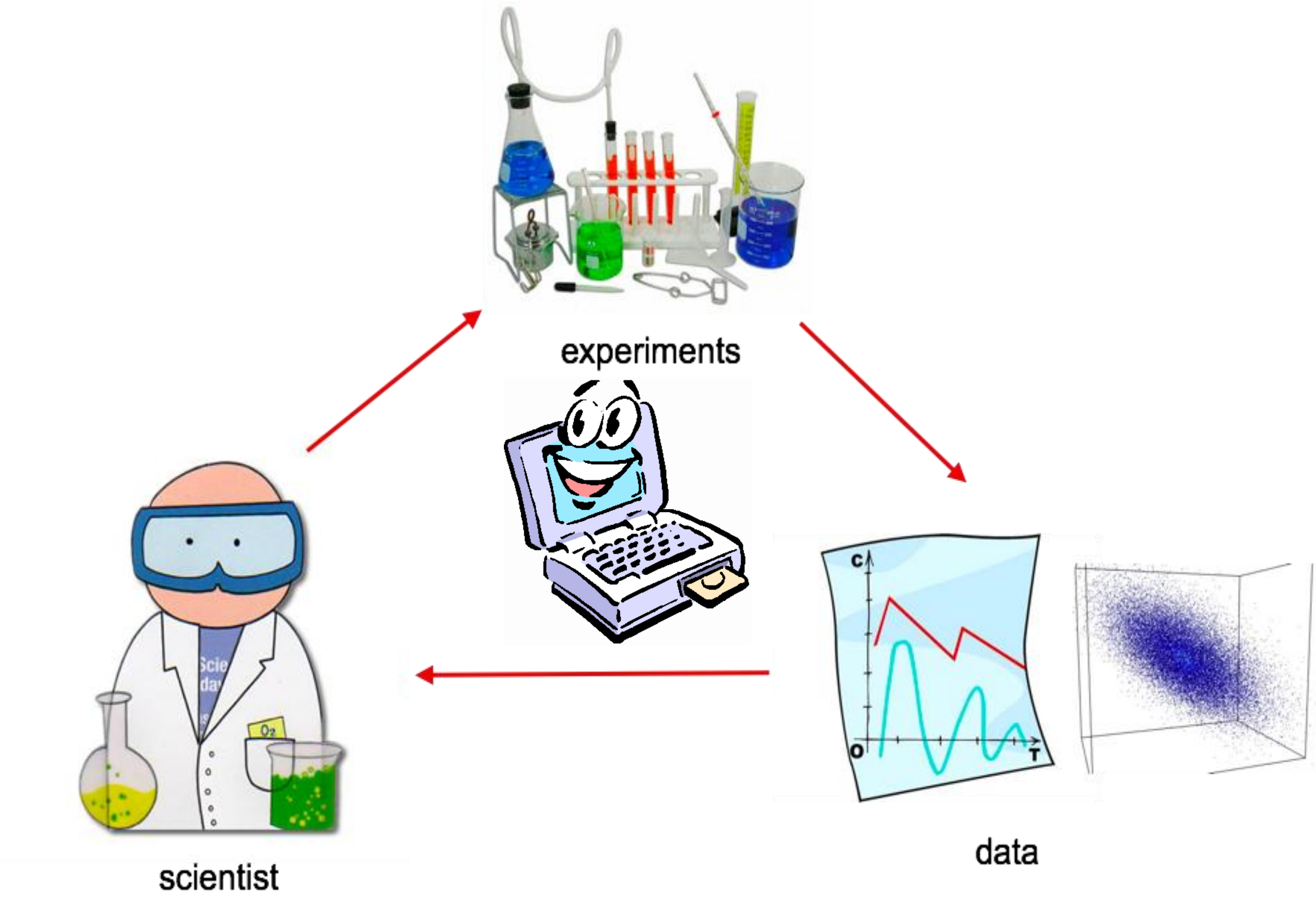
Adaptive Information: $y_1, y_2, \cdots \in \mathcal{Y}$ are selected sequentially and y_i can depend on previously gathered information, i.e., $y_1(x), \ldots, y_{i-1}(x)$

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

$$\min_{\widehat{x}\,,\, y_1,\ldots,y_K} \; \max_{x \in \mathcal{X}} \; d(x\,,\, \widehat{x}(y_1, \ldots, y_K))$$

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)

References

Adaptive and Sequential Compressive Sensing

* S. Ji, Y. Xue, and L. Carin, "Bayesian compressed sensing," *IEEE Trans. Signal Proc.,* vol. 56, no. 6, pp. 2346-2356, June 2008.

* R. Castro, J. Haupt, and R. Nowak, "Finding needles in noisy haystacks," *Proc. ICASSP,* pp. 5133-5136, 2008.

* M. Seeger and H. Nickisch, "Compressed sensing and Bayesian experimental design," *Proc. ICML,* 2008.

* A. Aldroubi, H. Wang, and K. Zarringhalam, "Sequential adaptive compressed sampling via Huffman codes," *preprint,* 2009.

* S. Deutsch, A. Averbuch, and S. Dekel, "Adaptive compressed image sensing based on wavelet modeling and direct samplng," *Proc. 8th Intl. Conf. on Sampling Theory and Applications,* 2009.

References

Adaptive and Sequential Compressive Sensing (Continued)

* M. Seeger, H. Nickisch, R. Pohmann, and B. Schoelkopf, "Optimization of k-space trajectories for compressed sensing by Bayesian experimental design," *Magnetic Resonance in Medicine,* vol. 63, pp. 116-126, 2009.

* J. Haupt, R. Baraniuk, R. Castro, and R. Nowak, "Compressive distilled sensing: Sparse recovery using adaptivity in compressive measurements," *Proc. Asilomar Conf.,* pp. 1551-1555, 2009.

* M. Iwen and A. Tewfik, "Adaptive group testing strategies for target detection and localization in noisy environments," *submitted*, 2010.

* D. Malioutov, S. Sanghavi, and A. Willsky, "Sequential compressed sensing," *IEEE Journal of Sel. Topics in Signal Proc.,* vol. 4, no. 2, pp. 435-444, April 2010.

References

Bayesian Experimental Design

* D. Lindley, “On the measure of the information provided by an experiment,” *Annals of Mathematical Statistics,* vol. 27, no. 4, pp. 986-1005, 1956.

* M. DeGroot, “Uncertainty, information, and sequential experiments,” *Annals of Mathematical Statistics,* vol. 33, no. 2, pp. 404-419, 1962.

* M. Seeger, “Bayesian inference and optimal design in the sparse linear model,” *Journal of Machine Learning Research*, vol. 9, pp. 759-813, 2008.

References

Multistage methods in genomics

* J. Satagopan and R. Elston, "Optimal two-stage genotyping in population-based association studies," *Genetic Epidemiology,* vol. 25, no. 2, pp. 149-157, 2003.

* S. Zehetmayer, P. Bauer, and M. Posch, "Two-stage designs for experiments with large number of hypotheses," *Bioinformatics,* vol. 21, no. 19, pp. 3771-3777, 2005.

* S. Zehetmayer, P. Bauer, and M. Posch, "Optimized multi-stage designs controlling the false discovery or the family-wise error rate," *Statistics in Medicine,* vol. 27, no. 21, pp. 4145-4160, 2008.

References

Adpative sensing methods in signal processing

* E. Bashan, R. Raich, and A. Hero, “Optimal two-stage search for sparse targets using convex criteria,” *IEEE Trans. Signal Processing,* vol. 56, no. 11, pp. 5389-5402, 2008.

* G. Newstadt, E. Bashan, and A. Hero, “Adaptive search for sparse targets with informative priors,” *Proc. ICASSP,* pp. 3542-3545, 2010.

* J. Haupt, R. Castro, and R. Nowak, “Distilled sensing: Adaptive sampling for sparse detection and estimation,” *IEEE Trans. Information Theory,* to appear, 2011.

* M. Malloy and R. Nowak, “Sequential analysis in high dimensional multiple testing and sparse recovery,” *Proc. Intl. Symposium on Information Theory,* to appear, 2011.

References

Adpative sensing methods in signal processing

* A. Tajer, R. Castro, and X. Wang, “Adaptive Sensing of Multiple Spectrum Bands, *IEEE Transactions on Information Theory*, submitted, 2010.

* B. Eriksson, G. Dasarthy, A. Singh, and R. Nowak, “Active Clustering: Robust and Efficient Hierarchical Clustering using Adaptively Selected Similarities,” submitted, 2011.

References

Active learning – Channel coding with feedback

* M. Horstein, “Sequential decoding using noiseless feedback,” *IEEE Trans. Information Theory,* vol. 9, no. 3, 1963.

* M. Burnashev and K. Zigangirov, “An interval estimation problem for controlled observations,” *Problems in Information Transmission,* vol. 10, 1974.

References

Active learning – Sequential experimental design

* D. Cohn, R. Atlas, and A. Ladner, “Improving generalization with active learning,” *Machine Learning,* vol. 15, no. 2, 1994.

* V. Fedorov, “Theory of Optimal Experiments,” New York: Academic Press, 1972.

* Y. Freund, H. Seung, E. Shamir, and N. Tishby, “Selective sampling using the query by committee algorithm,” *Machine Learning,* vol. 28, no. 2-3, 1997.

* D. Mackay, “Information-based objective functions for active data selection,” *Neural Computation,* vol. 4, 1991.

* D. Cohn, “Active learning with statistical models,” *Journal of Artificial Intelligence Research,* 1996.

References

Active learning – Sequential experimental design (continued)

* N. Cesa-Bianchi, A. Conconi, and C. Gentile, "Learning probabilistic linear threshold classifiers via selective sampling," *Proc. COLT,* 2003.

* A. Korostelev, "On minimax rates of convergence in image models under sequential design," *Statistics and Probability Letters*, vol. 43, 1999.

* J. Kim and A. Korostelev, "Rates of convergence for the sup-norm risk in image models under sequential designs," *Statistics and Probability Letters,* vol. 46, 2000.

* P. Hall and I. Molchanov, "Sequential methods for design-adaptive estimation of discontinuities in regression curves and surfaces," *Annals of Statistics,* vol. 31, no. 3, 2003.

* R. Castro, R. Willett, and R. Nowak, "Faster rates in regression via active learning," *NIPS,* 2005.

References

Active learning – Sequential experimental design (continued)

* Dasgupta, "Analysis of a greedy active learning strategy," *NIPS,* 2004.

* Dasgupta, Hsu, and Monteleoni, "A general agnostic active learning algorithm," *NIPS*, 2007.

* Balcan, Beygelzimer, and Langford, "Agnostic active learning," *ICML,* 2006.

* Hanneke, "Teaching dimension and the complexity of active learning," *COLT,* 2007.

* Hanneke, "A bound on the label complexity of agnostic active learning," *ICML,* 2007.

* Kaariainen, "Active learning in the non-realizable case," *ALT,* 2006.

References

Active learning – Sequential experimental design (continued)

* Castro and Nowak, “Minimax bounds for active learning,” *IEEE Trans. on Information Theory,* vol. 54, no. 5, 2008.

* Hanneke, “Adaptive rates of convergence in active learning,” *COLT*, 2009.

* R. Castro, C. Kalish, R. Nowak, R. Qian, T. Rogers, and X. Zhu, “Human active learning,” *NIPS*, 2008

References

Active learning – Learning with queries

* Hegedus, “Generalized teaching dimensions and the query complexity of learning,” *COLT,* 1995.

* R. Nowak, “Generalized binary search,” *Proc. Allerton*, 2008.

* Kulkami, Mitter, and Tsitsiklis, “Active learning using arbitrary binary valued queries,” *Machine Learning*, 1993.

* Karp and Kleinberg, “Noisy binary search and its applications,” *SODA*, 2007.

* Angluin, “Queries revisited,” Springer Lecture Notes in Computer Science: Algorithmic Learning Theory, pp. 12-31, 2001.

* Hellerstein, Pillaipakkamnatt, Raghavan, and Wilkins, “How many queries are needed to learn?,” *J. ACM*, vol. 43, no. 5, 1996.

References

Active learning – Learning with queries (continued)

* Garey and Graham, “Performance bounds on the splitting algorithm for binary testing,” *Acta Inf.,* 1974.

* Hyafil and Rivest, “Constructing optimal binary decision trees is NP-complete,” *Inf. Process. Letters*, 1976.

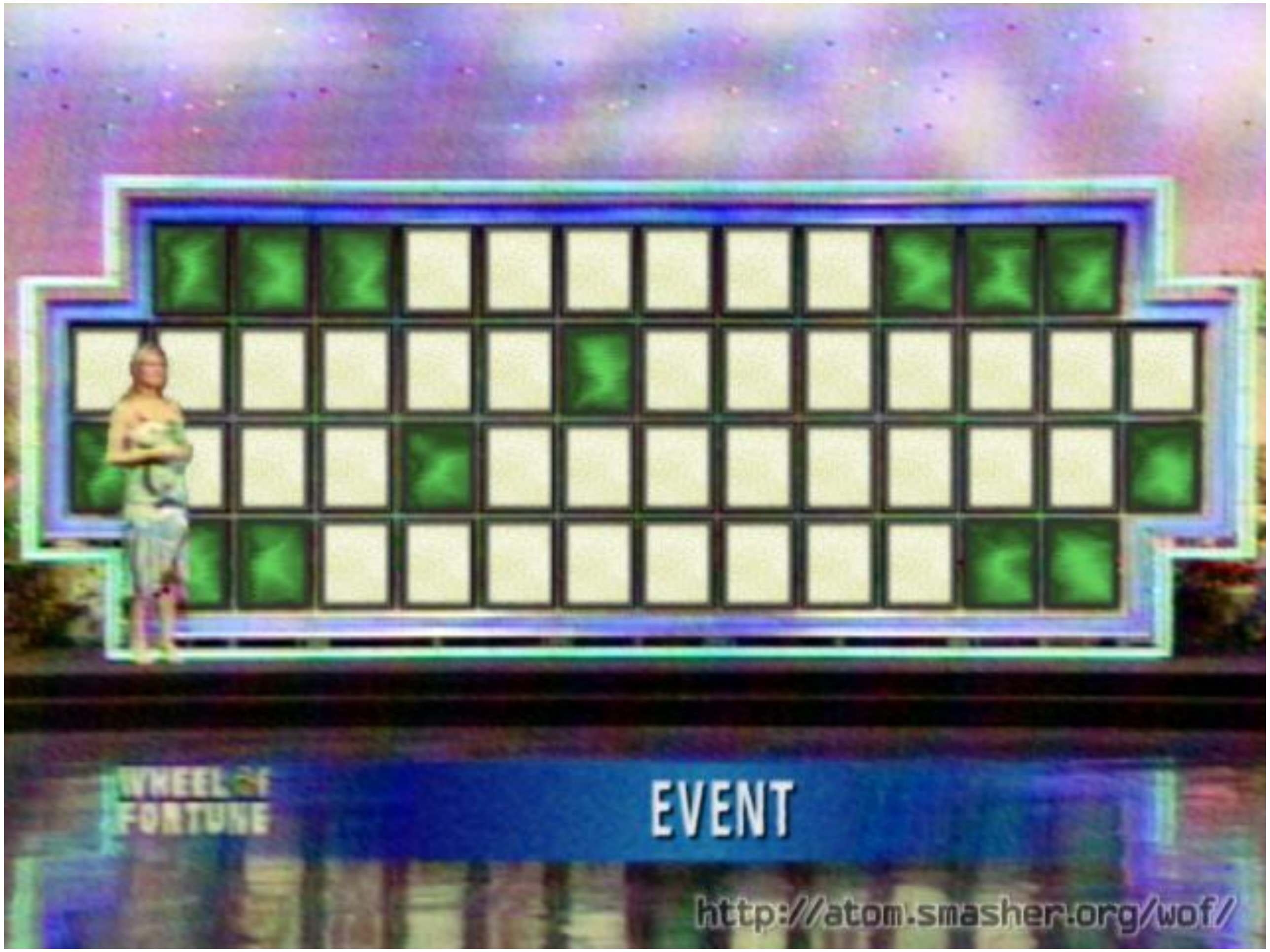
References

Book chapters

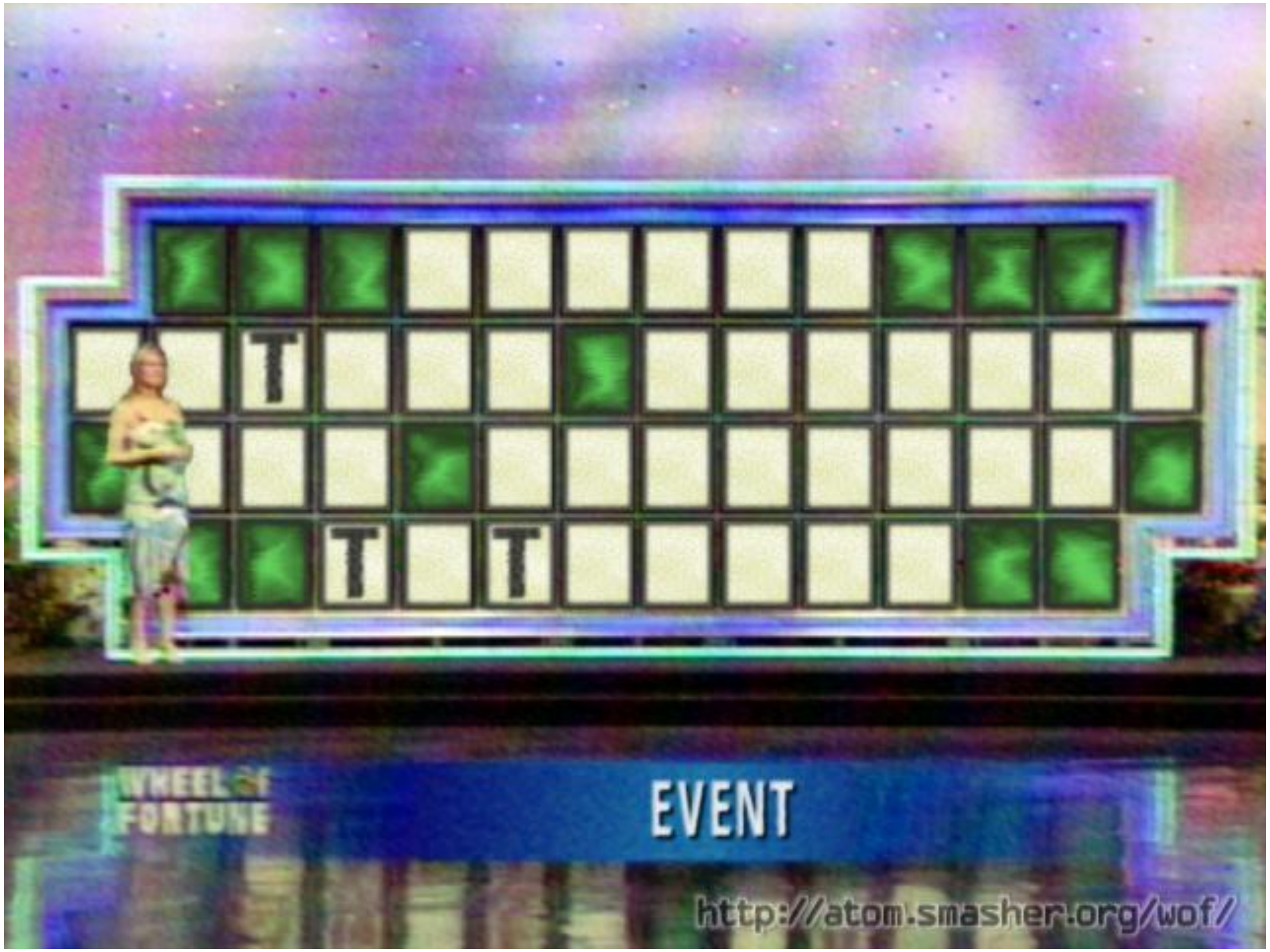
* R. Castro and R. Nowak, “Active sensing and learning,” in *Foundations and Applications of Sensor Management*, A. Hero, D. Castanon, D. Cochran, and K. Kastella (Eds.), pp. 177-200, Springer-Verlag, 2007.

* J. Haupt and R. Nowak, “Adaptive sensing for sparse recovery,” *Compressed Sensing: Theory and Applications*, Y. Eldar and G. Kutyniok (Eds.), Cambridge University Press, to appear.

“Active” Recreation…



“Active” Recreation…



“Active” Recreation…

“Active” Recreation…

“Active” Recreation…

“Active” Recreation…

“Active” Recreation…

“Active” Recreation…

“Active” Recreation…