Dynamic Network Techniques for Autonomous Planning and Control
F49620-98-1-0376 – Final Report
(April 1, 1998 – November 30, 2000)
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1 Summary of research progress

Starting with functional description of physical mechanisms we were able to derive the standard probabilistic properties of Bayesian networks and to show:

- how the effects of unanticipated actions can be predicted from the network topology,
- how qualitative causal judgments can be integrated with statistical data,
- how actions interact with observations,
- how counterfactuals sentences can be interpreted and evaluated,
- how explanations and single-event causation can be defined in a given causal model.

Additionally, we have established an axiomatic characterization of causal dependencies, analogously to the characterization of informational dependencies. Finally, we have demonstrated that network-based identification techniques, in the presence of hidden variables, have a broad scope of new applications, ranging from skill acquisition by autonomous agents, to the analysis of treatment effectiveness in clinical trials.

The following specific results were obtained during the period of performance:

- Computer programs were developed to assist clinicians with assessing the efficacy of treatments in experimental studies for which subject compliance is imperfect [Chickering and Pearl, 1999].

- Methods were developed for selecting sufficient set of measurements that permit unbiased estimation of causal effects in observational studies [Greenland *et al.*, 1999].

- Polynomial algorithms were developed for finding *minimal separators* in a directed acyclic graphs, namely, finding a set S of nodes that d-separates a given pair nodes, such that no proper subset of S d-separates that pair. Versions of this problem include finding a minimal separator from a restricted set of nodes, finding a minimum-cost separator, and testing whether a given separator is minimal. We have confirmed the intuition that any separator which cannot be reduced by a single node must be minimal [Tian *et al.*, 1998].

- Methods for estimating or bounding counterfactual probabilities from statistical data were developed (e.g., John, who was treated and died, would have had 90% chance of survival had he not been treated) [Balke and Pearl, 1997].

- A formal model has been developed, based on *modifiable structural equations*, which generalizes and unifies the structural and counterfactual approaches to causal inference, explicates their conceptual and mathematical bases and resolves their technical difficulties [Galles and Pearl, 1998].

- It has been proven that the structural and counterfactual formalisms are equivalent in recursive causal models (i.e., systems without feedback) but not when feedback is considered possible. A simple rule was devised for translating a problem back and forth, between the structural and counterfactual representations [Galles and Pearl, 1998].

- Basic causal concepts such as "confounding" and "exogeneity" were given mathematically precise explication. It has been shown that, contrary to folklore, there is no statistical test for confounding. Traditional statistical criteria do not ensure unbiased effect estimates, nor do they follow from the requirement of unbiasedness [Greenland et al., 1999; Pearl, 2000].

- A new semantics for "actual causation" was developed based on a construct named "causal beam," that is, a minimally modified causal model, in reference to which the standard counterfactual criterion is adequate for identifying causes of singular events [Pearl, 1998a, 2000].

- Formal semantics was developed, based on structural models of counterfactuals, for the probabilities that event x is a *necessary* or *sufficient* cause (or both) of another event y [Pearl, 1999].
- Conditions were discovered under which probabilities of necessary and sufficient causation can be learned from data [Pearl, 1999; Tian and Pearl, 2000].
- New methods were developed for eliciting probabilities of causes from a combination of actions and observations. It was found that data from both experimental and nonexperimental studies can be combined to yield information that neither study alone can provide [Pearl, 1999].
- Universal bounds were established for probabilities of causation from both observational and experimental studies [Tian and Pearl, 2000].
- New definition of *causal explanation* was formulated in which explanation is treated as a fragment of knowledge needed to support causation [Halpern and Pearl, 2000].

2 List of publications resulting from the AFOSR grant (April 1, 1998 – November 30, 2000)

Pearl, J., "On the definition of actual cause," UCLA Computer Science Department, Technical Report (R-259), July 1998.

Pearl, J., "TETRAD and SEM," Commentary on "The TETRAD Project: Constraint Based Aids to Causal Model Specification" by R. Scheines, P. Spirtes, C. Glymour, C. Meek, and T. Richardson, in *Multivariate Behavioral Research*, Vol. 33 No. 1, 119–128, 1998.

Galles, D. & Pearl, J., "An Axiomatic Characterization of Causal Counterfactuals," *Foundations of Science*, Vol. 3, Issue 1, 151–182, 1998.

Pearl, J., "Graphs, Causality, and Structural Equation Models," *Sociological Methods and Research*, Vol. 27, No. 2, 226–284, November 1998.

Pearl, J., "Why There Is No Statistical Test For Confounding, Why Many Think There Is, and Why They Are Almost Right," UCLA Computer Science Department, Technical Report R-256, 1998.

Greenland, S., Pearl, J., and Robins, J., "Causal Diagrams for Epidemiological Research." *Epidemiology*, Vol. 1, No. 10, 37–48, January 1999.

Greenland, S., Robins, J., and Pearl, J. "Confounding and collapsibility in causal inference," *Statistical Science*, Vol. 14, No. 1, 29–46, 1999.

Tian, J., Paz, A., and Pearl, J., "Finding Minimal Separating Sets," UCLA Computer Science Department, Technical Report R-254, February 1998.

Pearl, J., "Simpson's paradox: An anatomy," UCLA Computer Science Department, Technical Report (R-264), March 1999.

Pearl, J. and Meshkat, P., "Testing Regression Models With Few Regressors," in D. Heckerman and J. Whittaker (Eds.), *Artificial Intelligence and Statistics 99*, Morgan Kaufmann, San Francisco, CA, 255–259, 1999.

Pearl, J., "Graphical Models for Probabilistic and Causal Reasoning," UCLA Computer Science Department, in D. Gabbay and P. Smets (Eds.), *Handbook on Defeasible Reasoning and Uncertainty Management Systems*, Vol. 1, 367–189, Kluwer Academic Publishers, the Netherlands, 1998.

Pearl, J., "Bayesian Networks," In R.A. Wilson and F. Keil (Eds.), *The MIT Encyclopedia of the Cognitive Sciences*, Cambridge, MA, 72–74, 1999.

Pearl, J., "Graphs, Structural Models and Causality," In C.N. Glymour and G.F. Cooper (Eds.), *Computation, Causation, and Discovery*, AAAI/MIT Press, Cambridge, MA, 95–138, 1999.

Chickering, D.M. and Pearl, J., "A Clinician's Tool for Analyzing Noncompliance," In C.N. Glymour and G.F. Cooper (Eds.), *Computation, Causation, and Discovery*, AAAI/MIT Press, Cambridge, MA, 407–424, 1999.

Pearl, J., "Reasoning with cause and effect," *Proceedings of the International Joint Conference on Artificial Intelligence* (IJCAI-99), Morgan Kaufmann, San Francisco, CA, 1437–1449, 1999.

Pearl, J., "Probabilities of causation: Three counterfactual interpretations and their identification," *Synthese*, Vol. 121, No. 1, 1999.

Pearl, J., *Causality: Models, Reasoning, and Inference*, Cambridge University Press, NY, 2000.

Tian, J. and Pearl, J., "Probabilities of causation: Bounds and identification," in Craig Boutilier and Moises Goldszmidt (Eds.), *Proceedings of the Sixteenth Conference on Uncertainty in Artificial Intelligence*, San Francisco, CA: Morgan Kaufmann, 589–598, 2000.

Pearl, J., "The logic of counterfactuals in causal inference (Discussion of 'Causal inference without counterfactuals' by A.P. Dawid)," in *Journal of American Statistical Association*, Vol. 95, No. 450, 428–435, June 2000.

Halpern, J.Y. and Pearl, J., "Actual Causality," UCLA Computer Science Department, Technical Report (R-266), July 2000.

Tian, J. and Pearl, J., "Probabilistic of causation: Bounds and identification," *Annals of Mathematics and Artificial Intelligence*, vol 28, 287-313, 2000.

Halpern, J.Y. and Pearl, J., "Causes and Explanations: A Structural Model Approach." UCLA Computer Science Department, Technical Report (R-266), November 2000.

Tian, J. and "A branch-and-bound algorithm for MDL Learning Bayesian Networks," In Craig Boutilier and Moises Goldszmidt (Eds.), *Proceedings of the Sixteenth Conference on Uncertainty in Artificial Intelligence*, San Francisco, CA: Morgan Kaufmann, 580–588, 2000.

Pearl, J., "Parameter identification: A new perspective," UCLA Computer Science Department, Technical Report (R-276), August 2000.

Pearl, J., and Russell S. "Bayesian Networks," UCLA Computer Science Department, Technical Report (R-277), August 2000. To appear in In M. Arbib (Ed.), *Handbook of Brain Theory and Neural Networks*, MIT Press, 2000.

Pearl, J., "Exogeneity and Superexogeneity: A no-tear perspective," UCLA Computer Science Department, Technical Report (R-278), September 2000.

Pearl, J., "On two pseudo-paradoxes in Bayesian analysis," UCLA Computer Science Department, Technical Report (R-279), September 2000. To appear in *Annals of Mathematics in Artificial Intelligence*, Special Issue on Representations of Uncertainty.

Pearl, J., " Direct and Indirect Effects," UCLA Computer Science Department, Technical Report (R-279), November, 2000.

Awards

J. Pearl received the 1999 IJCAI Award for Research Excellence, for his "fundamental work on heuristic search, reasoning under uncertainty, and causality."

J. Pearl received the 2000 AAAI Classic Paper Award, for his 1982 paper "Reverend Bayes on Inference Engines: A Distributed Hierarchical Approach." The paper was recognized for "revolutionizing uncertain reasoning through the introduction of efficient Bayesian inference methods."

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[Halpern and Pearl, 2000] J.Y. Halpern and J. Pearl. Actual causality. Technical Report R-266, Department of Computer Science, University of California, Los Angeles, CA, March 2000.

[Pearl, 1998] J. Pearl. On the definition of actual cause. Technical Report R-259, Department of Computer Science, University of California, Los Angeles, CA, 1998.

[Pearl, 1999] J. Pearl. Probabilities of causation: Three counterfactual interpretations and their identification. Technical Report R-261, Department of Computer Science, University of California, Los Angeles, CA, 1999. Forthcoming, *Synthese*, Vol. 121, No. 1, 2000.

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[Tian *et al.*, 1998] J. Tian, A. Paz, and J. Pearl. Finding minimal separating sets. Technical Report R-254, University of California, Los Angeles, CA, 1998.