CAUSALITY

Models, Reasoning, and Inference

Judea Pearl

Development of Western science is based on two great achievements: the invention of the formal logical system (in Euclidean geometry) by the Greek philosophers, and the discovery of the possibility to find out causal relationships by systematic experiment (during the Renaissance).

— A. Einstein, April 23, 1953

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