



Virtual Mini Event, November 2021 **Systems Engineering Pathways to AI Now!**

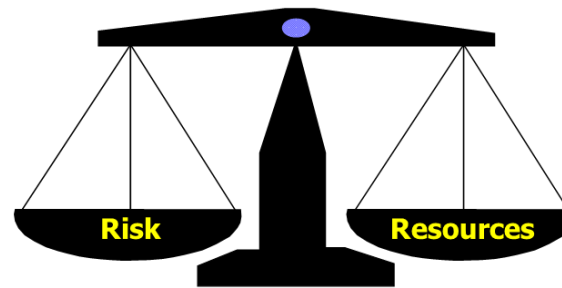
Causal Inference: Key for Opening the AI Black Box for Systems Engineering

Terril N Hurst, PhD

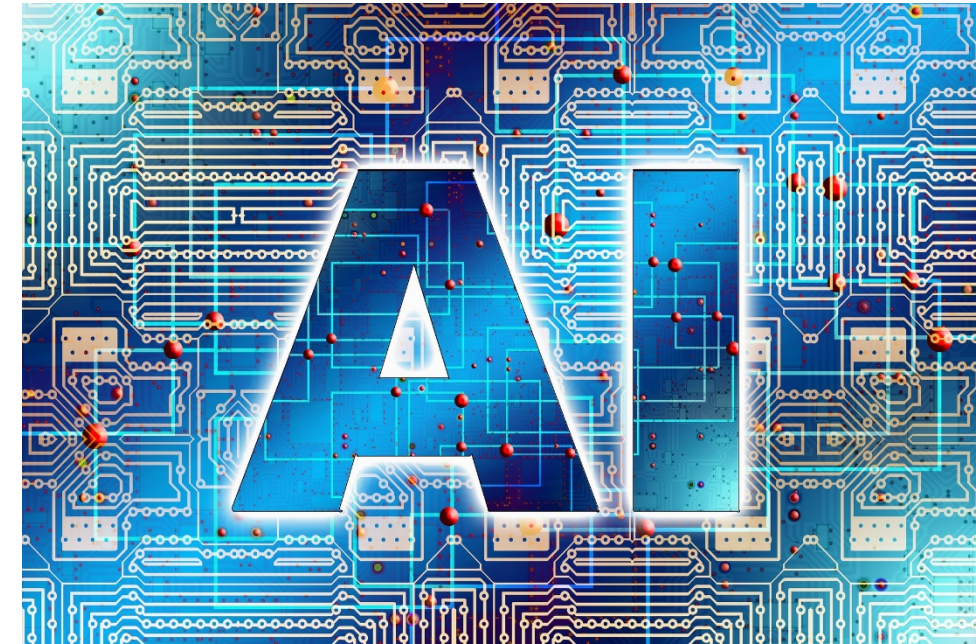
Scott A Goodman, PhD

Lawrence A Schneider

Raytheon Missiles & Defense



*Balancing the cost of knowing
against the risk of assuming*



Objectives of Presentation

- Reflect briefly on the boom/bust history of AI/ML
- Introduce *causal inference*, including examples that employ causal diagrams (CDs) and Bayesian Networks (BNs)
- Describe conditions necessary for adopting technologies/methods within systems engineering

Bottom Line Up Front: Causal inference reduces the hazard of poor decision-making due to spurious correlations, which can occur using black-box AI/ML techniques

The price: building a full probability model in order to answer a precise query

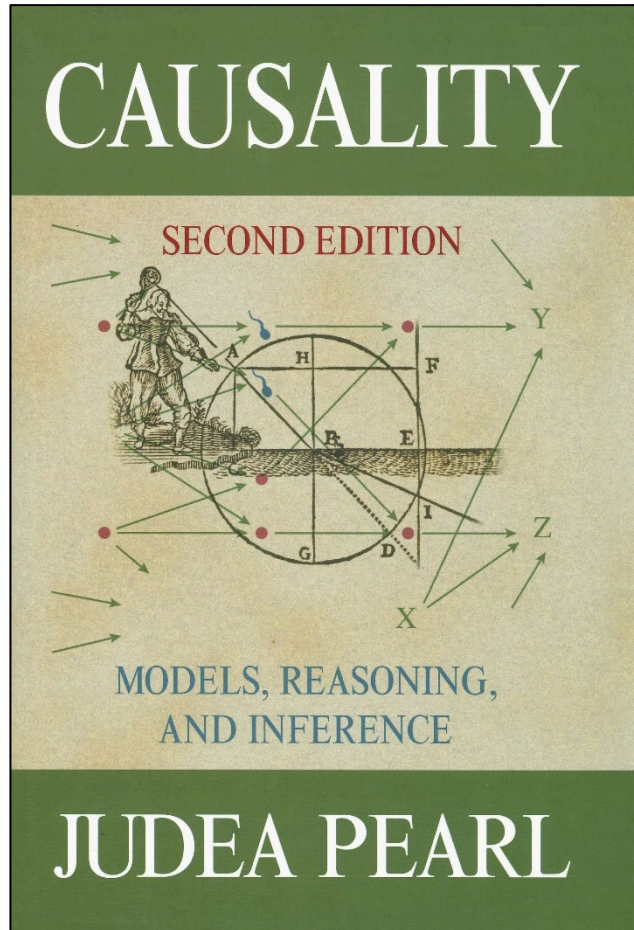
The boom/bust history of AI/ML – see [AI Winter](#)

Arguments and debates on past and future of AI

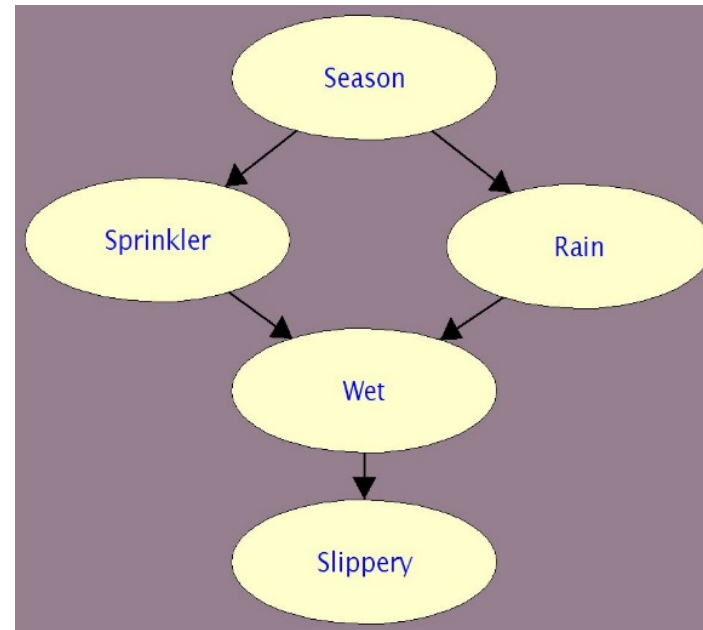
“Several philosophers, cognitive scientists and computer scientists have speculated on where AI might have failed and what lies in its future. [Hubert Dreyfus](#) highlighted [flawed assumptions of AI research in the past](#) and, as early as 1966, correctly predicted that the first wave of AI research would fail to fulfill the very public promises it was making. Other critics like [Noam Chomsky](#) have argued that AI is headed in the wrong direction, in part because of its heavy reliance on statistical techniques. Chomsky's comments fit into a larger debate with [Peter Norvig](#), centered around the role of statistical methods in AI.” [Wikipedia]

Awareness of the history of the science of AI is essential for recognizing when/where its technologies can be beneficial. We focus on *causal inference*, which augments conventional AI methods with Bayesian analysis. When combined with with AI's contributions based on formal logic, this provides a holistic, probabilistic decision-support paradigm

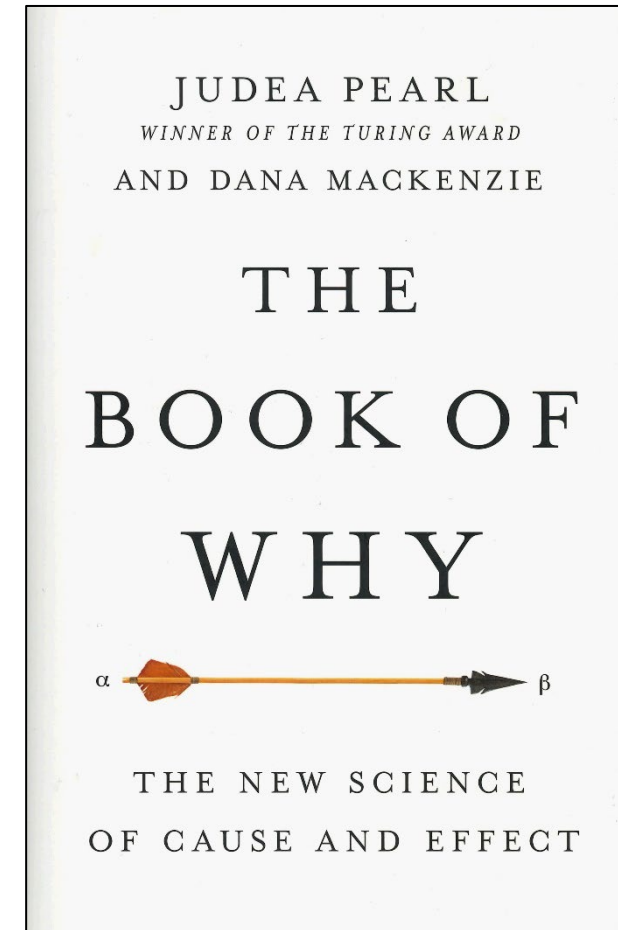
Pearl's work on the Science of Causality



2008



A simple causal
Bayesian Network

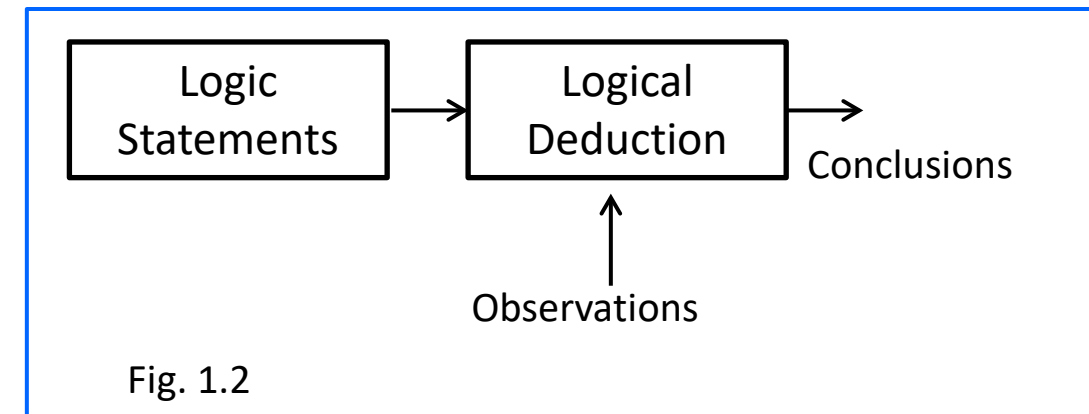
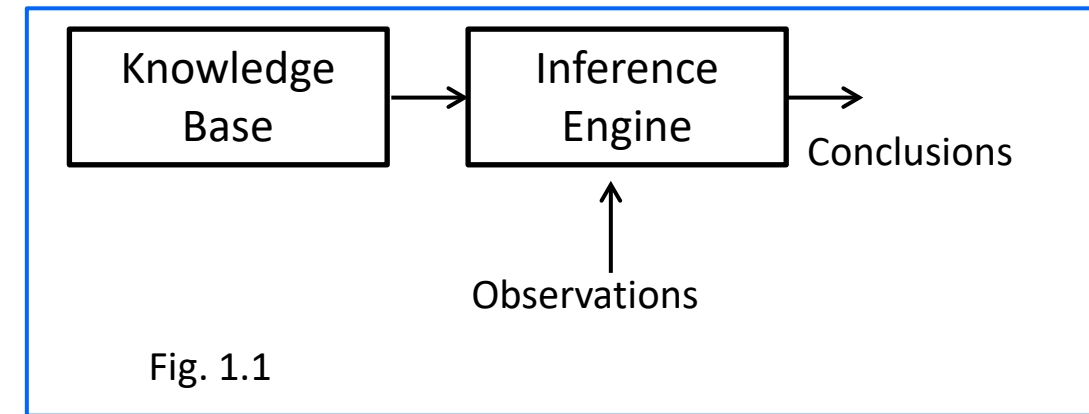


2018

Pearl's *Book of Why* made causal inference accessible to a broader audience

Origins of automated reasoning for AI/ML

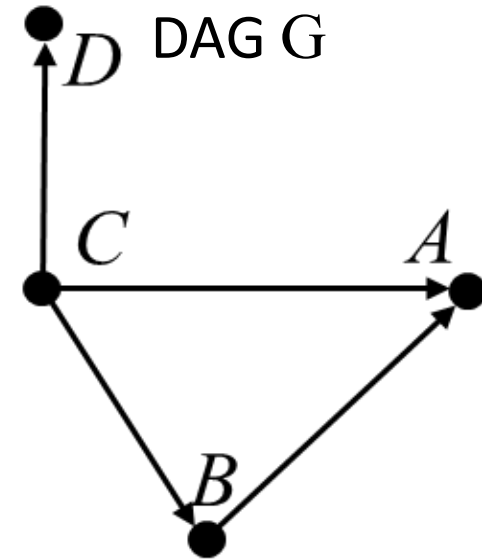
- In 1959, John McCarthy coined the term artificial intelligence (AI), and Arthur Samuel the term machine learning – 16 years(!) after neural networks were first proposed by McCulloch & Pitts
- Original AI proposal called for a 2-component system, separating what we know from how we think (Fig. 1.1):
 - Knowledge base KB
 - Inference engine IE (“reasoner”)
 - KB is domain-specific; IE is very general and therefore usually fixed
- Later, a more specific, 2-component system blurred this separation (Fig. 1.2):
 - Statements in logic
 - Logical deduction



Bayes nets adopt the *original* idea (Fig 1.1), but they incorporate probabilistic reasoning

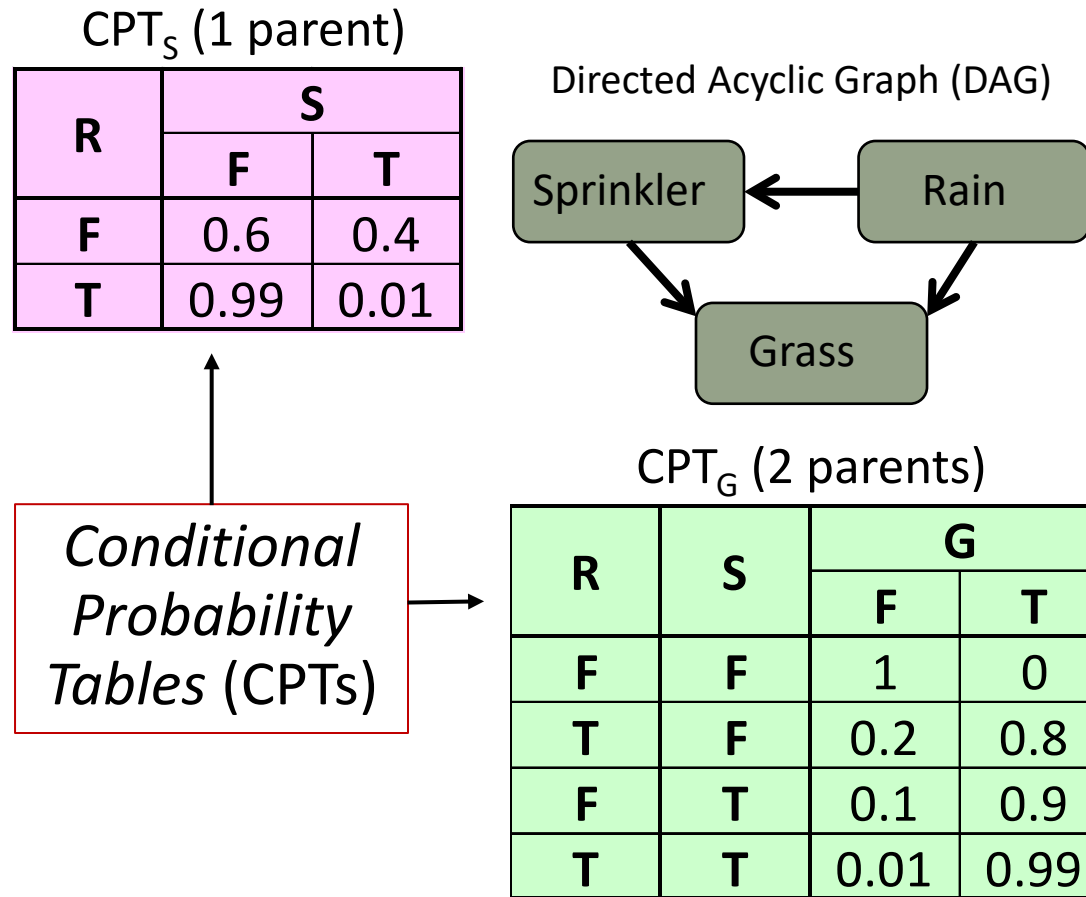
Reasoning with Causal Diagrams (CDs) & Bayes Nets (BNs)

- A graph G consists of a set V of vertices (or nodes) and a set E of edges (or links) connecting some pairs of vertices. CDs and BNs are comprised of directed acyclic graphs, (DAGs). In this DAG G , $\{A, B, C, D\} \in V$
- A path p in DAG G is a sequence of edges (e.g., $p: ((B, A), (A, C), (C, D))$ in G)
- A directed path in DAG G is a sequence of edges, each commencing with an arrow tail and ending with a head (e.g., $p: ((C, B), (B, A))$ in this DAG)



The power of CDs & BNs lies in their ability to reject spurious correlations, given evidence at specific nodes, which distinguishes them from neural networks

Wikipedia's introductory BN: Wet Grass, **G**; Sprinkler On **S**, Raining, **R**



CPT_R (0 parents)

R	
F	T
0.8	0.2

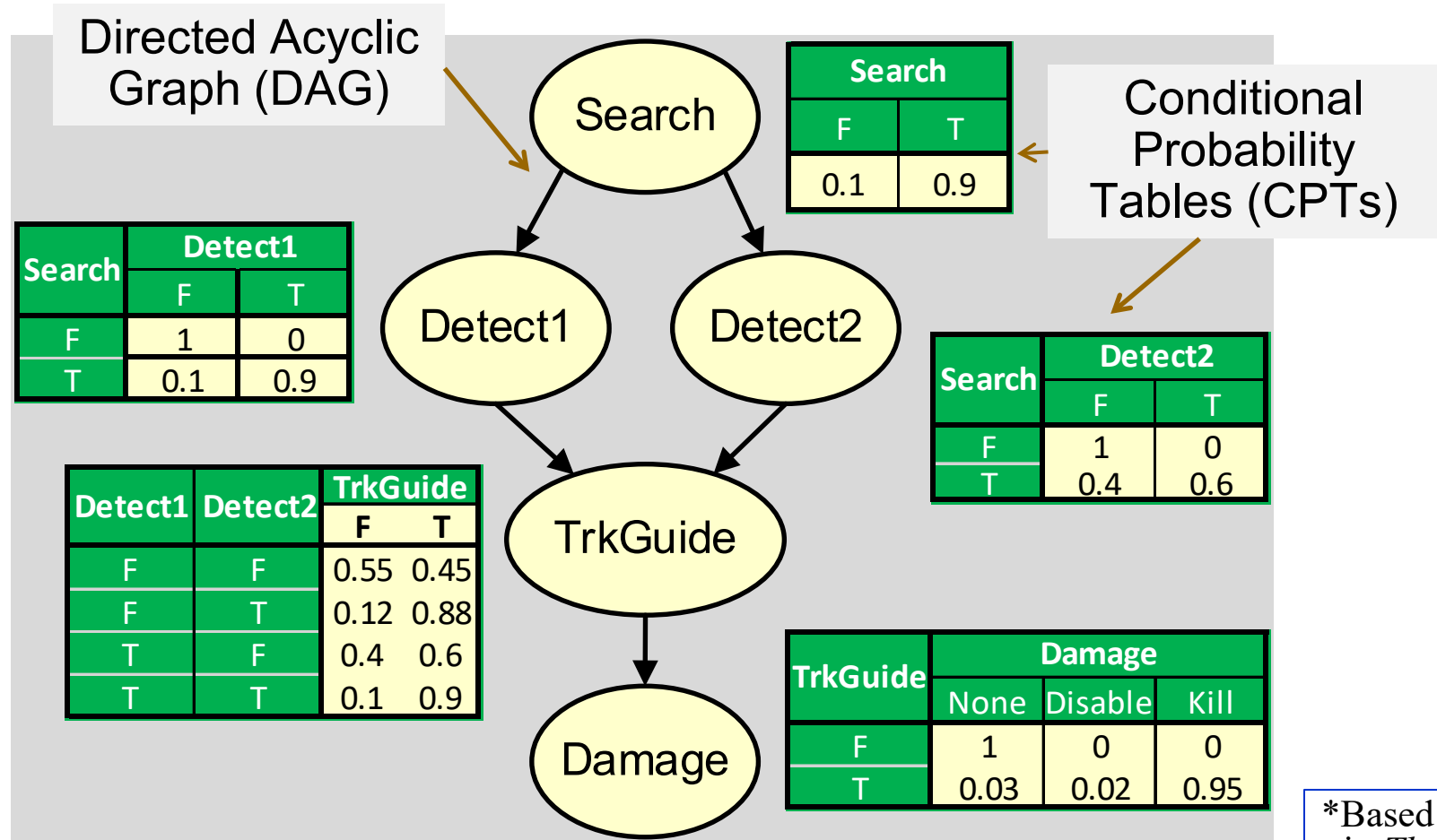
BNs employ 3 different types of probability distributions:

- Joint Probability Distribution JPD, $f(x_1, x_2, \dots, x_n)$
- Conditional Probability Distributions CPDs (as listed in these CPTs), $f(x_1 | x_2, x_3)$
- Marginal Probability Distributions MPDs, $f(x_1)$, i.e., “averaging out” other variables

BNs employ the logic of probability to compute answers to specific questions, e.g., “What’s the probability it’s raining given that my grass is wet?” $Pr(R = T | G = T)$

BN for allocating/verifying algorithm requirements

Weapon kill-chain model for anti-aircraft missile*

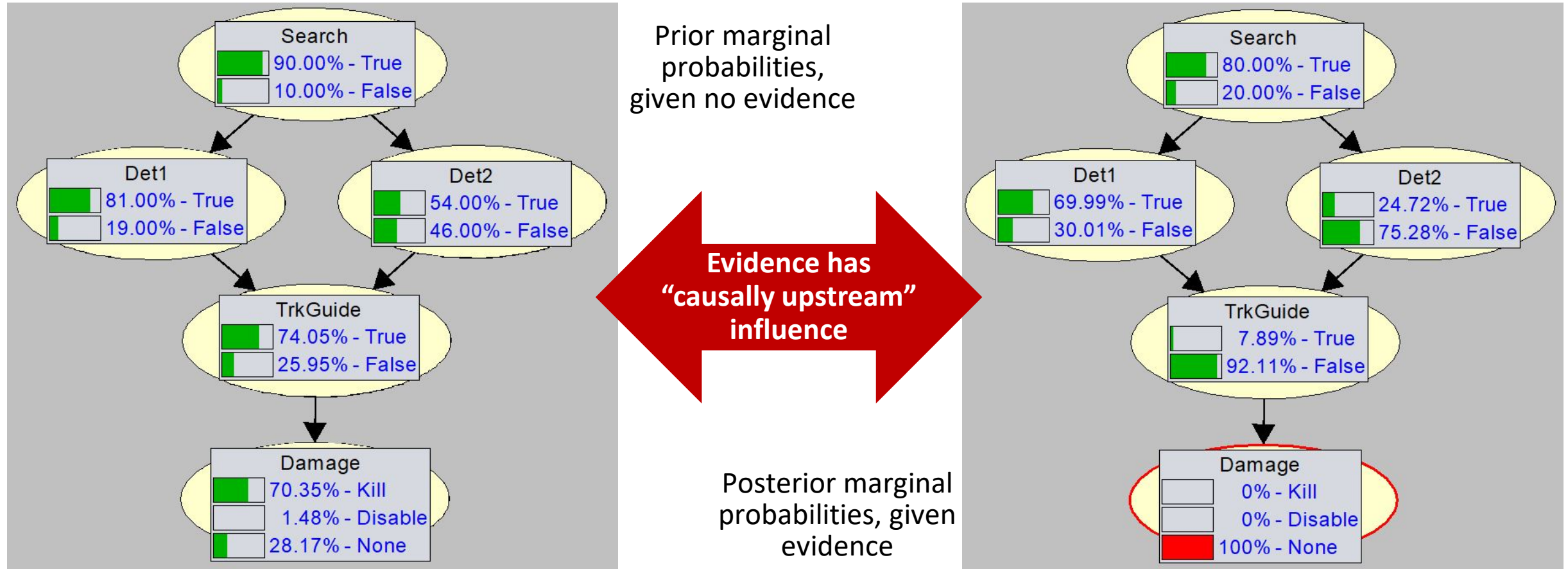


The DAG creates the structure for populating CPTs with values using available data and SME knowledge

*Based on Ball's example in *The Fundamentals of Aircraft Combat Survivability Analysis & Design* (AIAA, 2nd ed., 2003)

Samlam demo: Prior & Posterior Marginal Probabilities

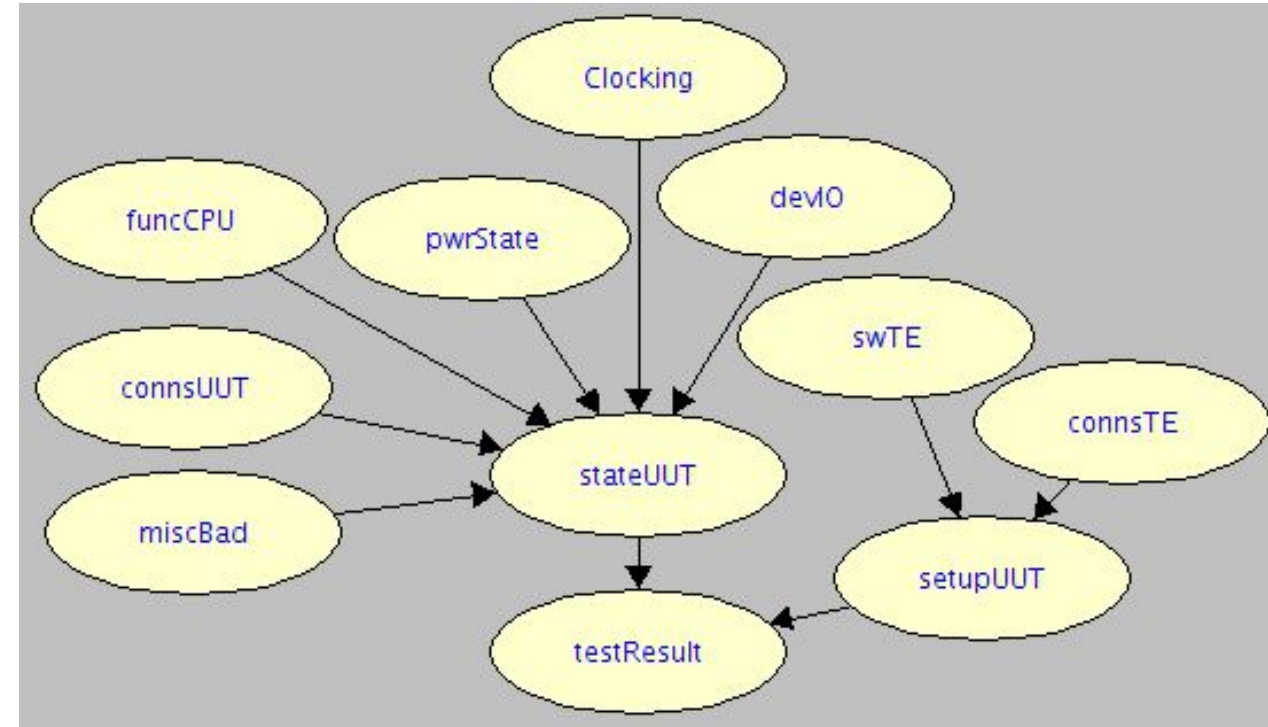
Once populated with data/knowledge, we use BN logic to answer a query, e.g., “what is the probability that Detector1 failed given that we missed the target?”



Ability to condition on evidence blends formal logic with the reality of real-world uncertainty for credible decision-making

Simple BN: Unit Under Test (UUT) in Test Equipment (TE)

Node	States	Data Source
funcCPU	Yes; No	longTextDB
pwrState	inSpec; outSpec	longTextDB
Clocking	inSpec; outSpec	longTextDB
connsUUT	OK; notOK	longTextDB
devIO	OK; notOK	longTextDB
miscBad	No; Yes	SME Estimate
swTE	OK; notOK	SME Estimate
connsTE	OK; notOK	SME Estimate
setupUUT	OK; notOK	SME Estimate
stateUUT	OK; notOK	onlineDB
testUUT	Pass; Fail	onlineDB



Conditional Probability Tables not shown

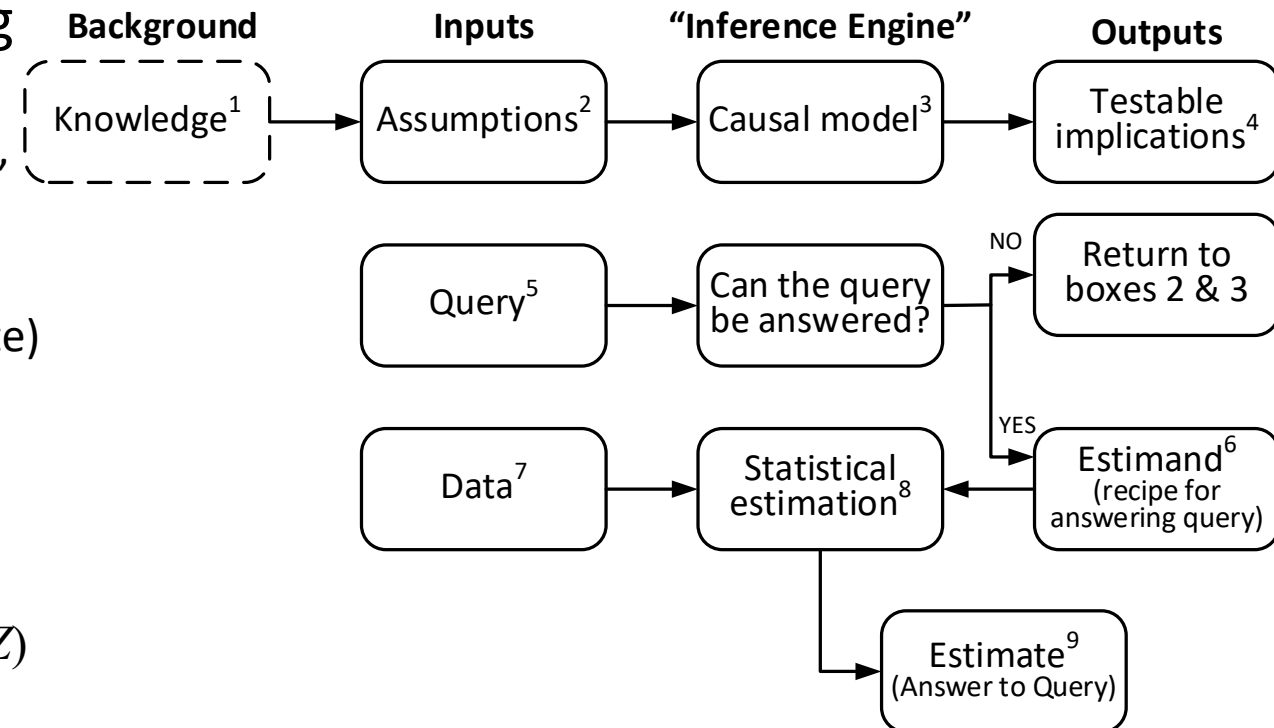
BNs can blend available data with SME knowledge to compensate for missing or noisy data

Pearl's Causal-Model Inference Engine unlocks the black box

Example Query: “What is the effect of including Subsystem S on System Effectiveness E ?”

1. Knowledge: Traces of the reasoning agent's past experience, e.g., observations, actions, education, culture, etc.
2. Explicit, simplifying Assumptions
3. CD (other causal model forms exist, but this is Pearl's favorite)
4. Testable implications; data contradictions $\rightarrow$ modify the CD
5. Causal Query: the question we wish to answer; it must be formulated using the causal* vocabulary – e.g., $P(E \mid do(S))$
6. Estimand: from Latin, “that which is to be estimated”; the recipe for answering the Causal Query, e.g., $P(E \mid E, Z) \times P(Z)$
7. Data (observations): Ingredients going into the Estimand recipe, e.g., $P(E \mid S, Z)$
8. Estimation: Based upon finite data
9. Answer to Query; example: “Including subsystem S increases System Effectiveness E by $30\% \pm 20\%$.” If correct, add to Box 1; else re-do Step 3 (CD)

*If observational (not DOE) data, use do-calculus to convert S to $do(S)$



“Notice that, unlike traditional statistical inference, we collect data only after we posit the causal model, and after we state the query we wish to answer, and after we derive the estimand.”

- Pearl 2018

The Three P's of Successful Systems Engineering

Any technology for systems engineering must support People, Pipes, & Protocols

- **People:** “You are smarter than your data” (Judea Pearl, *The Book of Why*)
 - Neural networks can help users to perform causal reasoning, but causal models do that at the outset
 - Since the causal inference engine (earlier slide) provides testability prior to collecting any data, it is extremely adaptable. It is not fitting a function to data
- **Pipes:** networks, connecting both people and linked data
 - Causal models naturally accommodate the ontologies used in systems engineering
 - The Bayesian analysis protocol opens clear communication channels for system stakeholders
- **Protocols:** Organized, pre-planned ways of generating/sending/receiving credible data at the right time for decision-making. The iterative Bayesian analysis protocol (from Gelman):
 1. Build a full probability model, describing the nature of the sample and prior (external) knowledge
 2. Collect data (see Pearl's inference engine); then update the probability model (Bayes' Theorem)
 3. Critically evaluate sensitivity of conclusions to assumptions made in probability model; then iterate

Causal inference aids understanding & applying AI/ML in all three P's

Facilitating adoption of AI into engineering workflows

- Adopting both “hard technologies” (e.g., hardware/algorithms/software) and “soft technologies” (e.g., protocols, rewards/measurements) require awareness of people’s talent, motivation and willingness to teach/learn new ways of doing things
- Empowering causal inference within decision-making requires commitments to
 - apply credible modeling, simulation, & analysis (MSA) of (sub)systems & components
 - place observational data (e.g., reliability) on the same causal grounds as data from designed experiments via the [*do-calculus*](#)
 - quantify uncertainty at each decision-making point

Pearl: “Data do not understand causes and effects; humans do. I hope that the new science of causal inference will enable us to better understand how we do it.”

References

1. Ben-Gal, I., “Bayesian Networks,” in Ruggeri, F. et al, *Encyclopedia of Statistics in Quality & Reliability*, Wiley & Sons (2007) <http://www.eng.tau.ac.il/~bengal/BN.pdf>
2. Darwiche, A., *Modeling and Reasoning with Bayesian Networks*, Cambridge (2009). See also <http://reasoning.cs.ucla.edu/>
3. Darwiche, A., “Human-Level Intelligence or Animal-Like Abilities?” <https://arxiv.org/abs/1707.04327>
4. Gelman, A. et al, *Bayesian Data Analysis*, 3rd ed., CRC Press, 2014 <http://www.stat.columbia.edu/~gelman/book/>
5. Hurst, T.N. J.J. Ballantyne, and A.T.Mense, “Building Requirements-Flow Models using Bayesian Networks and Designed Simulation Experiments, 2014 Conference on Applied Statistics in Defense.
6. Hurst, T.N., J.J. Ballantyne, and A.T. Mense, “Learning Bayesian Network Structure from Designed Simulation Experiments,” 2015 Conference on Applied Statistics in Defense.
7. Jaynes, E.T., *Probability Theory: The Logic of Science* ([Cambridge](#)), 2003.
8. Pearl, J., *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, Morgan Kaufmann (San Mateo, CA), 1988 <https://dl.acm.org/doi/book/10.5555/534975>
9. Pearl, J., *Causality: Models, Reasoning, and Inference*, 2nd ed., ([Cambridge](#)), 2009.
10. Pearl, J., [The Book of Why](#): *The New Science of Cause and Effect*, 2018.