Practical Machine Learning, Causal Learning and Bayesian Belief Networks for System Simulation, Test and Predictive Maintenance

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Caveat: Slides are Notional for Distribution A

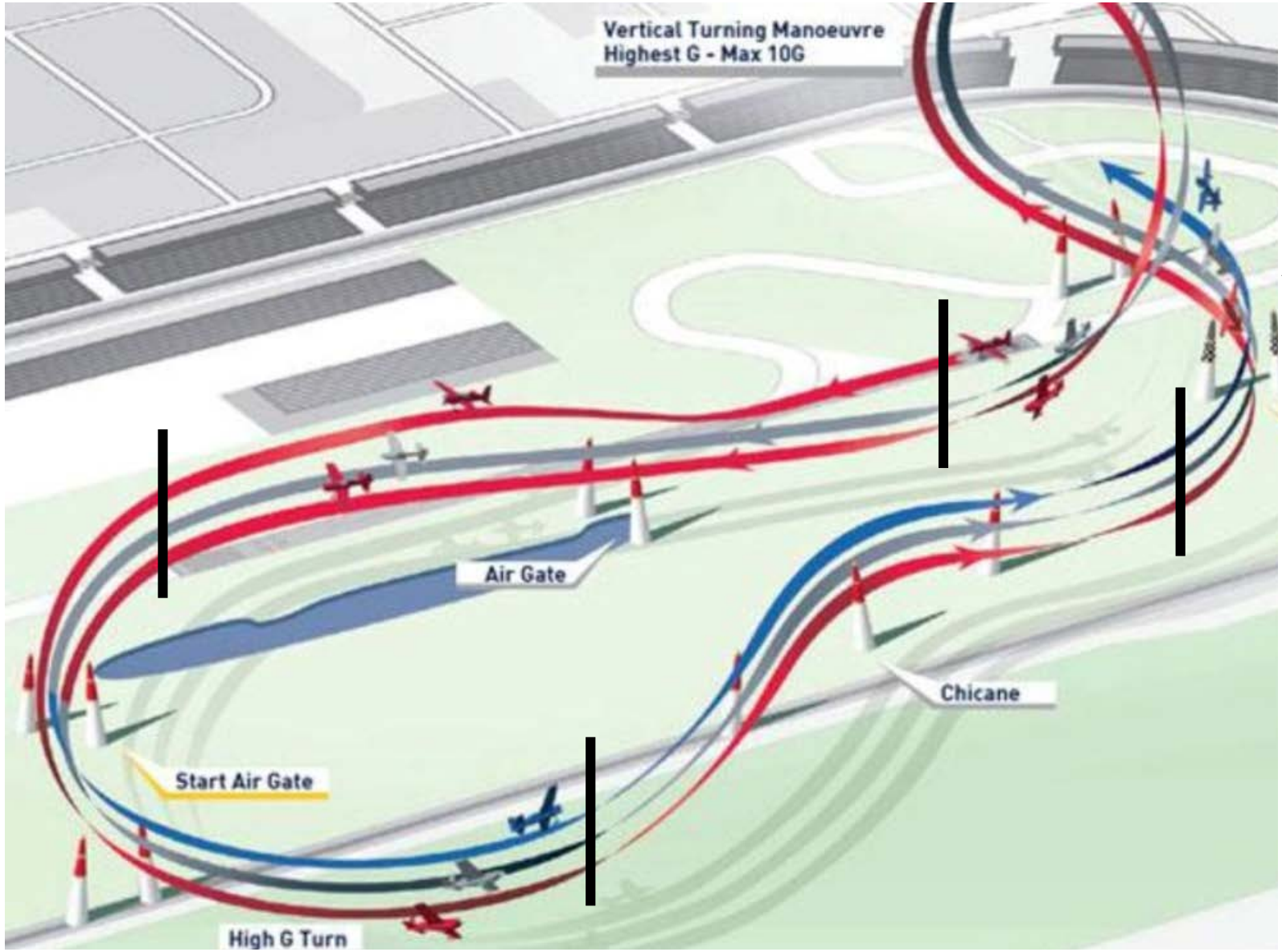
The following concepts represent current SEI research and customer support of programs within the USAF and Navy.

Although machine learning and deep learning are not novel in their application, our complement of causal learning to segregate true causal influence from spurious correlation enable us to go one step further in providing more actionable models.

The avionics system depicted in these slides could be any system. The methodology would be unchanged across domains.

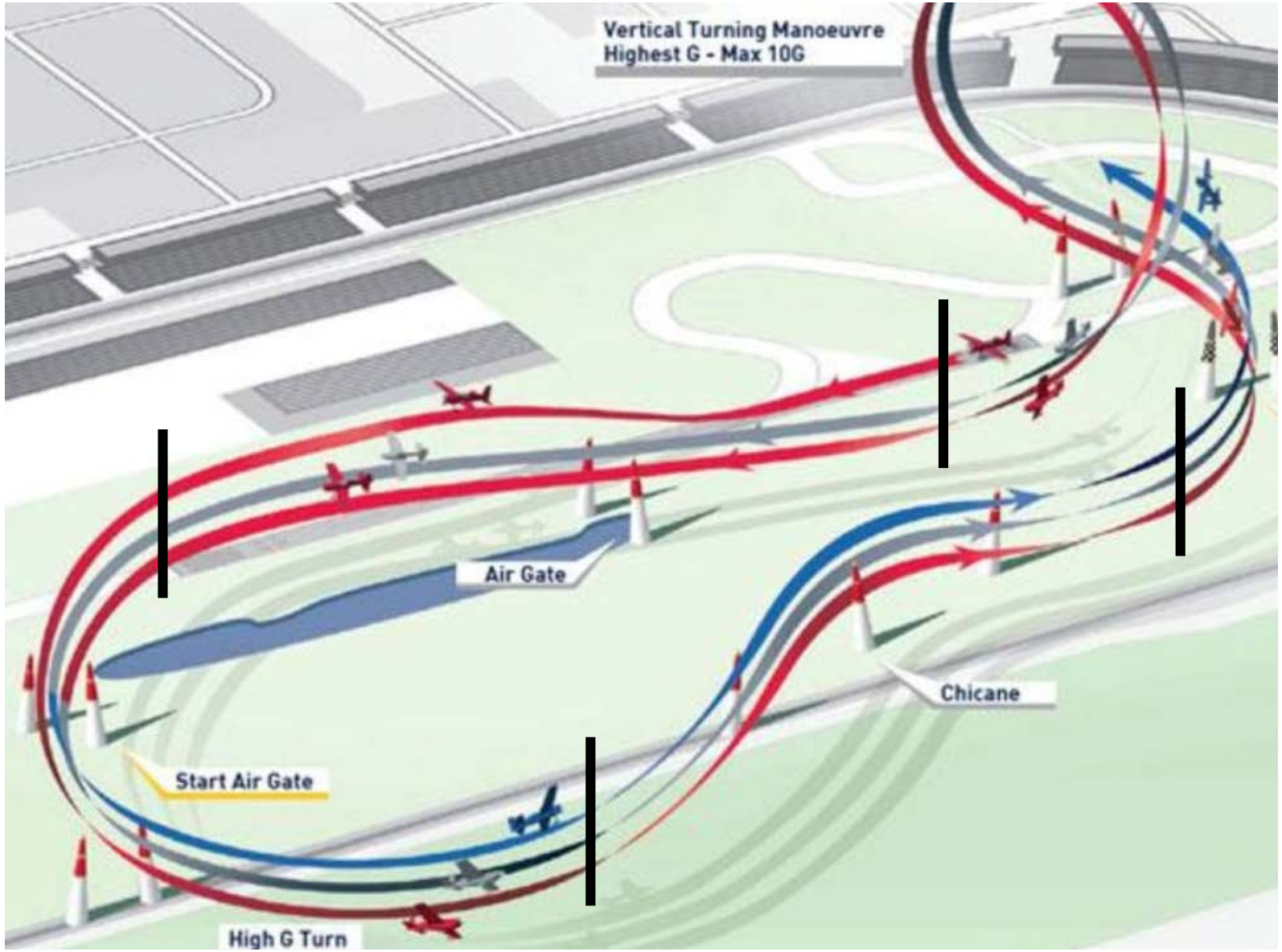
We first discuss potential improvement in system simulation and test via machine and causal learning followed by improvement in system diagnosis via BBNs informed from machine and causal learning.

System Simulation and Test Operational Modes



Parametric data from avionics simulation and test are segregated by operational mode (suggested here as flight segments separated by vertical black lines)

Machine and Causal Learning within Modes



For each mode, Machine and Causal Learning models will be developed on both the flight data and simulation data.

This will enable us:

1) To evaluate realism of existing simulation and test, and
2) To generate more realistic scenarios at the parametric level for simulation and test.

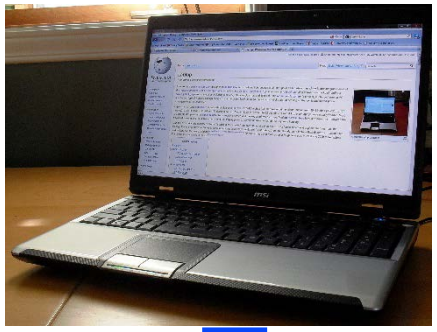
Scenarios in Flight Test missing from Simulator

Simulation

Simulation			Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Parameter
Operational Mode										
Time Snapshot										
1	1	09:01:01:05								
1	1	09:01:01:06								
1	1	09:01:01:07								
1	1	09:01:01:08								
1	1	09:01:01:09								
1	1	09:01:01:10								
1	1	09:01:01:11								
1	1	09:01:01:12								
1	1	09:01:01:13								
1	1	09:01:01:14								
1	1	09:01:01:15								
1	1	09:01:01:16								
1	1	09:01:01:17								
1	1	09:01:01:18								
1	1	09:01:01:19								
1	1	09:01:01:20								

Step 01

Simulation data is "learned" using Bayesia machine learning



Step 03

Bayesia multivariate "Outlier" (red row with red factors) drives new scenario to run in simulator

Simulation			Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Param
Operational Mode										
Time Snapshot										
1	1	09:01:01:05								
1	1	09:01:01:06								
1	1	09:01:01:07								
1	1	09:01:01:08								
1	1	09:01:01:09								
1	1	09:01:01:10								
1	1	09:01:01:11								
1	1	09:01:01:12								
1	1	09:01:01:13								
1	1	09:01:01:14								
1	1	09:01:01:15								
1	1	09:01:01:16								
1	1	09:01:01:17								
1	1	09:01:01:18								

Step 02

Flight Testing

Flight Test data is processed against the "learned" simulation data

			Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Parameter
Operational Mode										
Time Snapshot										
1	1	09:01:01:16								
1	1	09:01:01:17								
1	1	09:01:01:18								
1	1	09:01:01:19								
1	1	09:01:01:20								

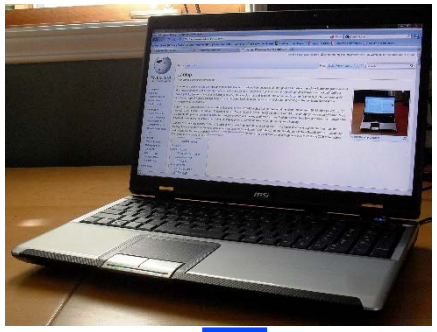
Scenarios in Simulator missing from Flight Test

Simulation

Simulation			Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Parameter
Operational Mode										
Time Snapshot										
1	1	09:01:01:05								
1	1	09:01:01:06								
1	1	09:01:01:07								
1	1	09:01:01:08								
1	1	09:01:01:09								
1	1	09:01:01:10								
1	1	09:01:01:11								
1	1	09:01:01:12								
1	1	09:01:01:13								
1	1	09:01:01:14								
1	1	09:01:01:15								
1	1	09:01:01:16								
1	1	09:01:01:17								
1	1	09:01:01:18								
1	1	09:01:01:19								
1	1	09:01:01:20								

Step 02

Simulation data is processed against the "learned" flight test data



Step 03

Bayesia multivariate "Outlier" (red row with red factors) identifies scenarios to be dropped or added to flight test

Simulation			Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Param
Operational Mode										
Time Snapshot										
1	1	09:01:01:05								
1	1	09:01:01:06								
1	1	09:01:01:07								
1	1	09:01:01:08								
1	1	09:01:01:09								
1	1	09:01:01:10								
1	1	09:01:01:11								
1	1	09:01:01:12								
1	1	09:01:01:13								
1	1	09:01:01:14								

Step 01

Flight Test data is "learned" using Bayesia machine learning

Flight Testing

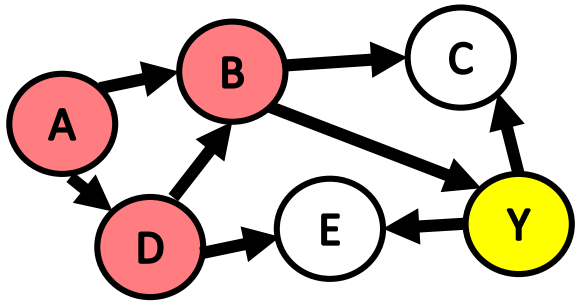
Operational Mode			Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Parameter
Time Snapshot										
1	1	09:01:01:16								
1	1	09:01:01:17								
1	1	09:01:01:18								
1	1	09:01:01:19								
1	1	09:01:01:20								

Learning Causal Patterns from Flight Test Stress Scenarios

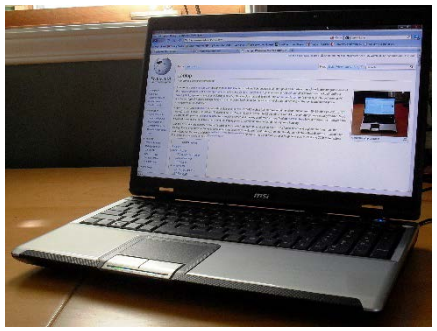
Simulation

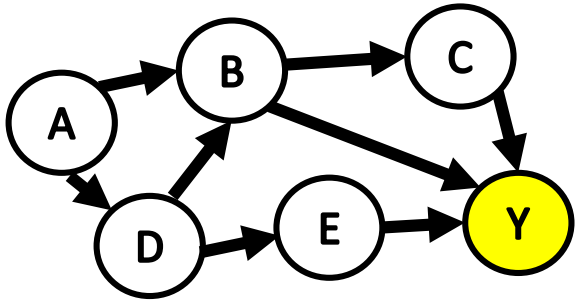
Step 03

Tetrad causal chains (red) for each Y stress factor clarify an essential scenario to be enacted



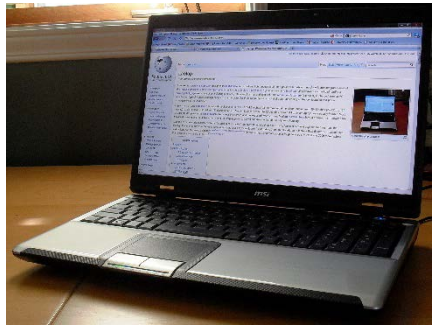
Bayesia





Bayesia results identify subset of factors for Causal Learning with Tetrad

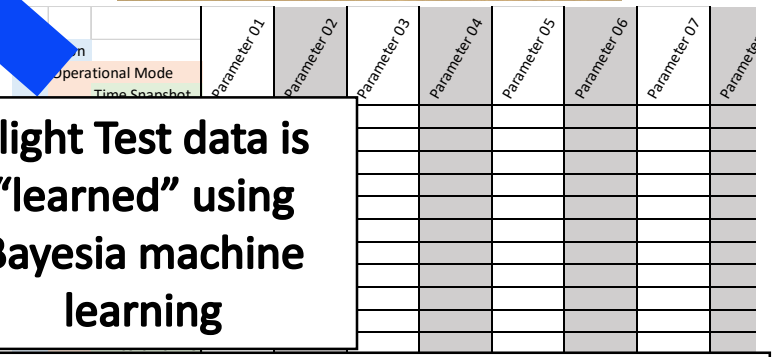
Tetrad



Step 02

Step 01

Flight Testing



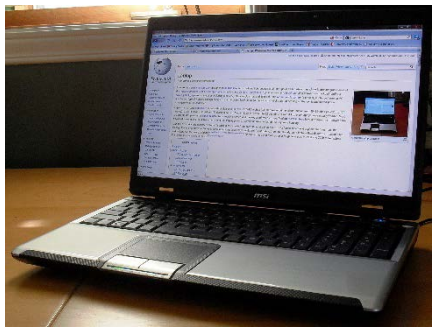
Flight Test data is "learned" using Bayesia machine learning

Yellow Y factors represent factors that are viewed as measures of different types of stress. So we conduct supervised machine learning on the Y factors individually.

Comparing Flight Test Behavior across Aircraft and Pilots

Simulation

Bayesia



Flight Testing

Step 04

Step 02

Step 01

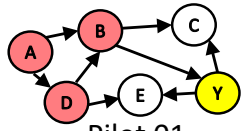
Step 03

Understanding "causal differences" between pilots and aircraft also inform scenarios

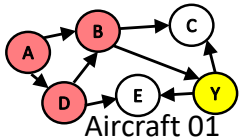
Differences "outliers" between pilots or between aircraft inform scenarios

Bayesia helps target causal modeling

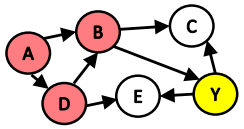
Flight Test data is "learned" using Bayesia machine learning, for each aircraft and for each pilot



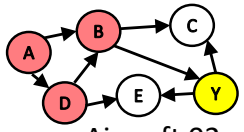
Pilot 01



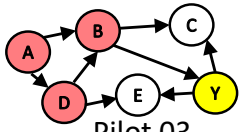
Aircraft 01



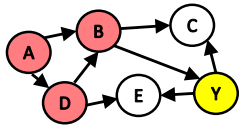
Pilot 02



Aircraft 02

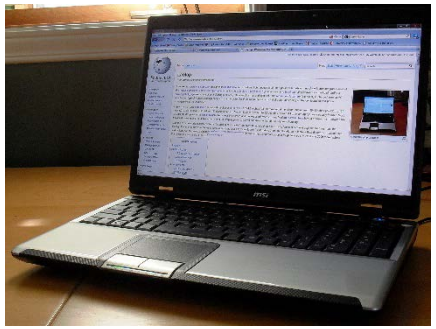


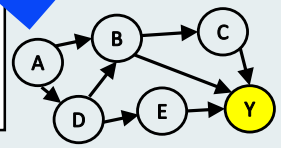
Pilot 03



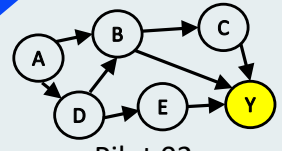
Aircraft 03

Tetrad

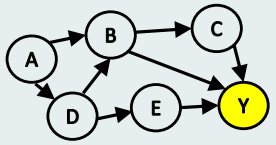




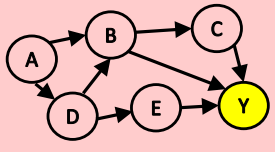
Pilot 01



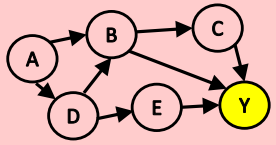
Pilot 02



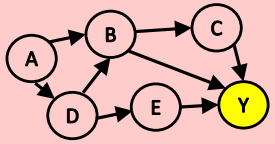
Pilot 03



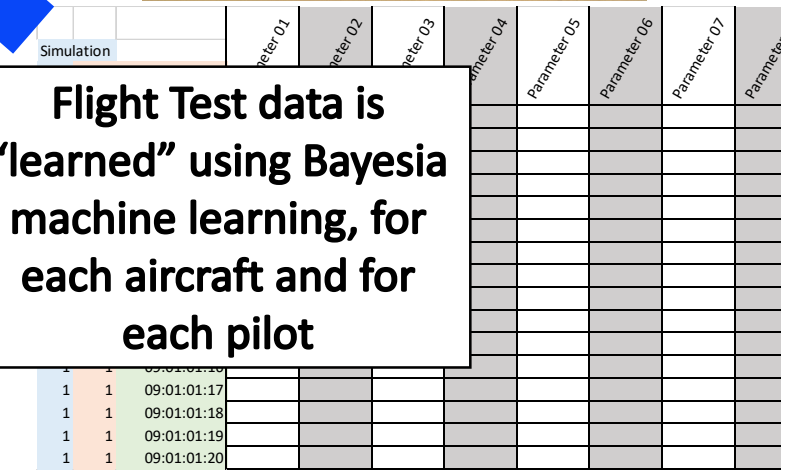
Aircraft 01



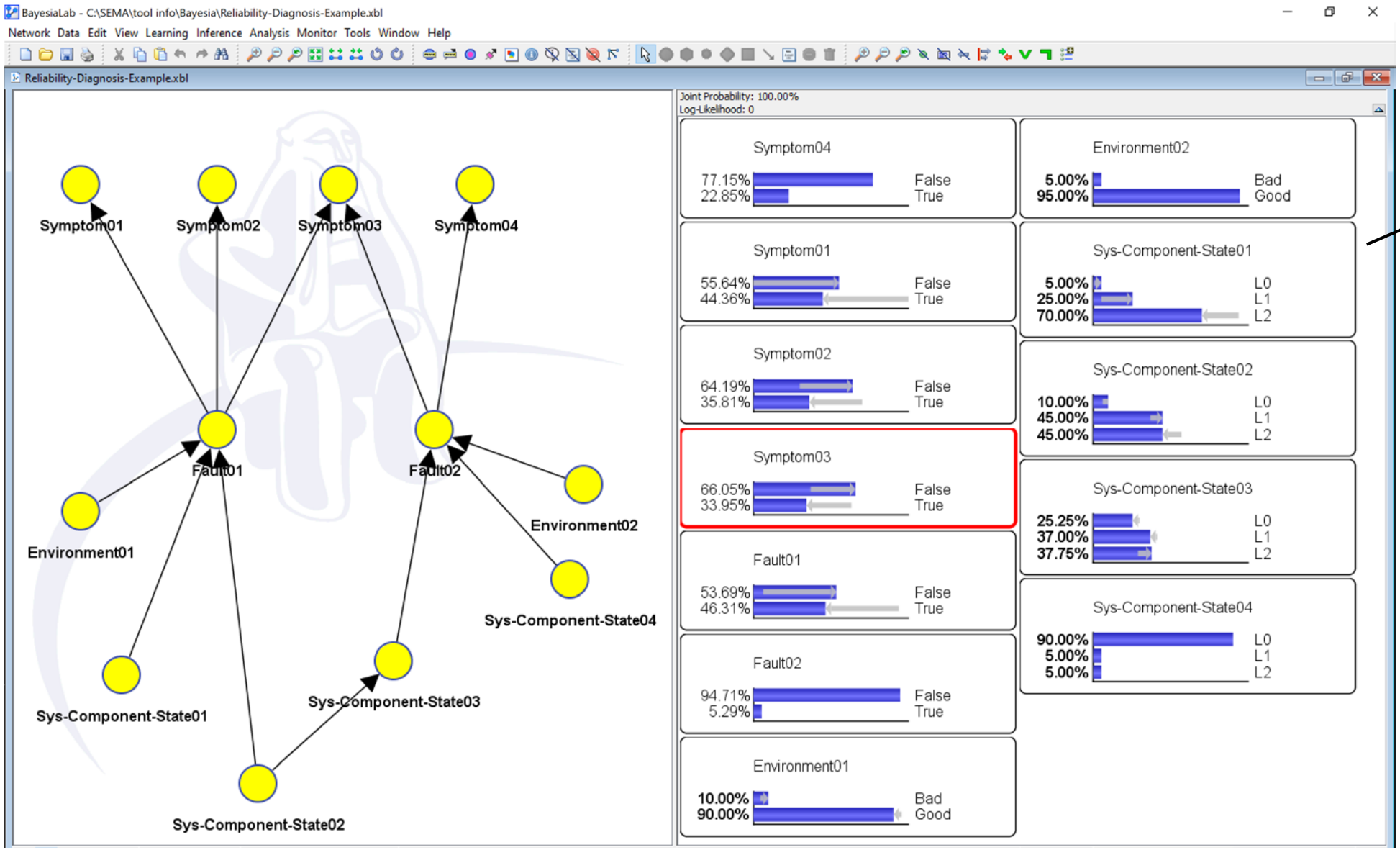
Aircraft 02



Aircraft 03

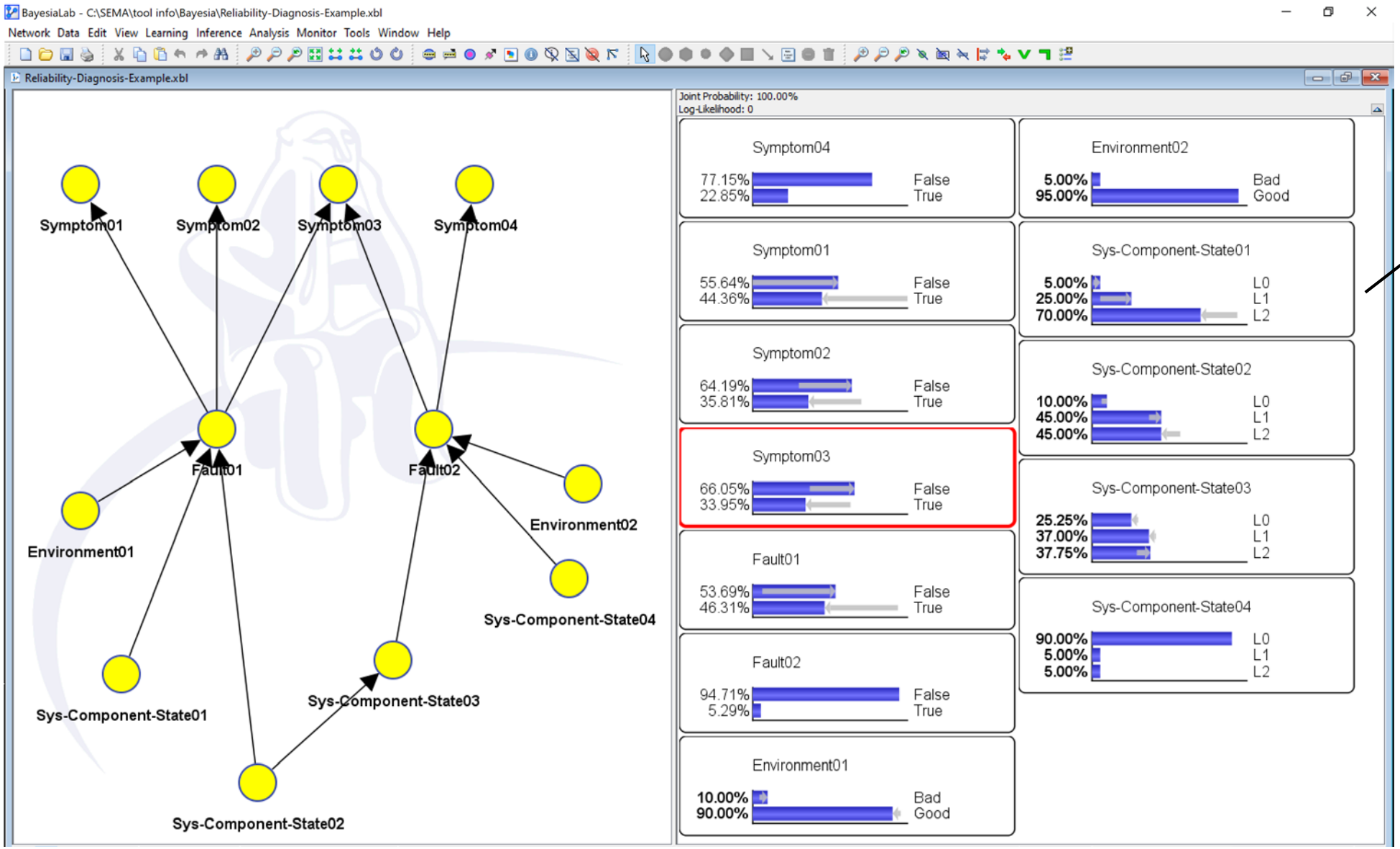


Bayesian Belief Networks (BBNs) for Predictive Maintenance



BBN concept linking System Behavior States with Potential Faults and Potential Symptoms

Bayesian Belief Networks (BBNs) for Predictive Maintenance



Such a BBN may be constructed thru both Machine and Causal Learning. The BBN machinery brings together causal learning and prior knowledge to guide maintenance decision.