Research into Simulator Realism Gaps using Machine and Causal Learning

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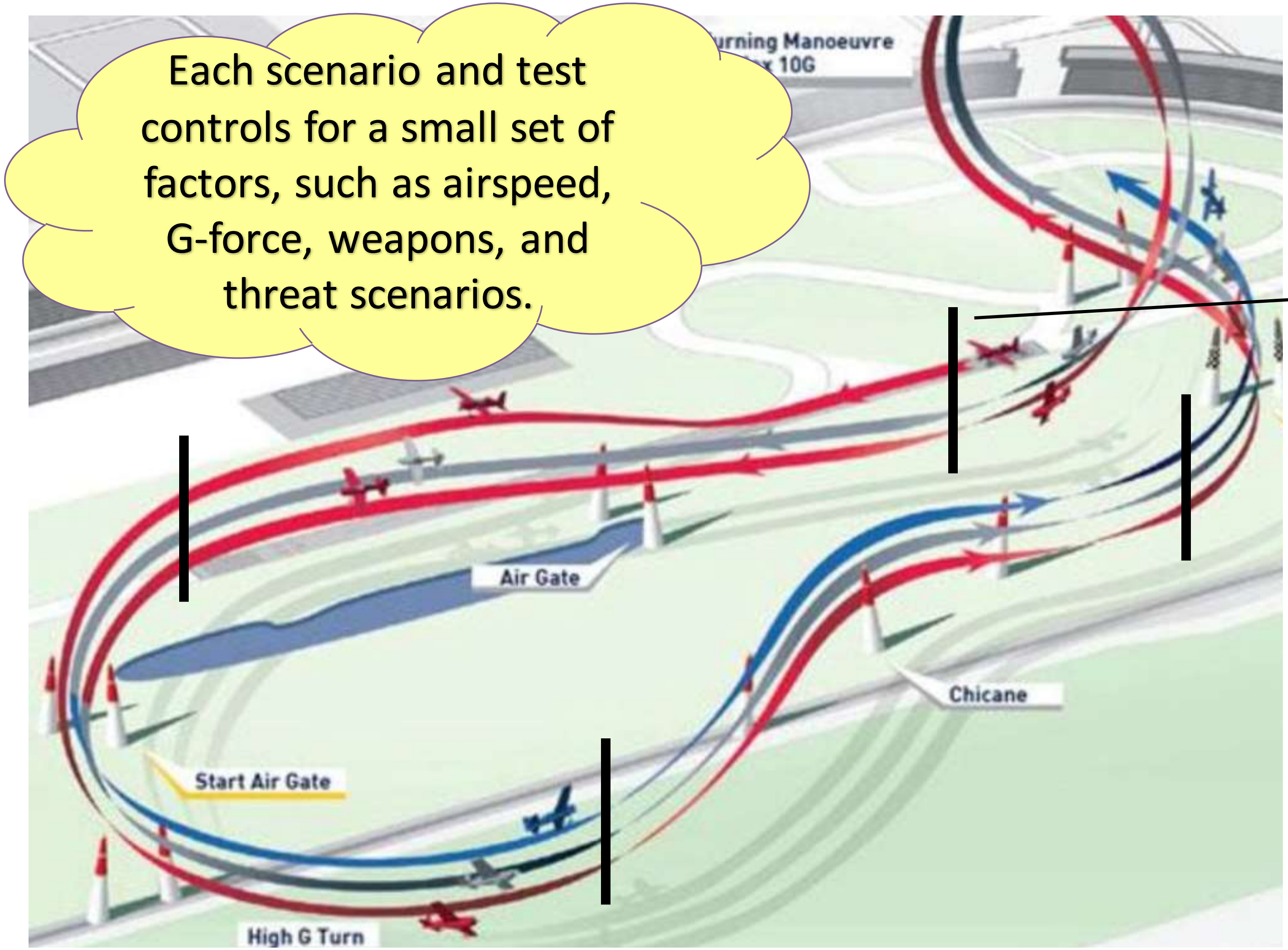
Simulation and Test Meets Machine and Causal Learning (SITEL)

Problem: USAF in prior years indicated (1) simulating realistic flight dynamics and tests for more complex system behavior is increasingly difficult, and (2) avionics changes can now require an unacceptable two years of regression testing. More efficient testing while maintaining realism is imperative. The technical limitation rests in the inability to analyze/simulate avionics system behavior, conditioned by hundreds of parameters, to achieve realistic flight dynamics and early identification of issues.

Solution: A new simulation and test evaluation platform which identifies behavior from flight testing, in terms of hundreds of parameters, that is not evident within existing avionics simulation and testing of aircraft. This evaluation platform will also specify the additional needed simulation scenarios and tests to achieve a more realistic behavior match with flight testing.

Approach: SEI will work to develop software (Java, C; 1553 Bus & Ethernet) required to access and manage the parametric data from flight data recorders for consumption by Bayesia and Tetrad. SEI will also develop software to interface with the simulation and test environments to implement SEI recommended flight scenarios. SEI will conduct machine learning of the existing simulation scenarios (Bayesia). Then, SEI will process flight testing parametric data and identify the "outlier" behavior in terms of parameter settings not represented in the simulation and test. The "outlier" behavior becomes the basis for recommending additional simulation scenarios and tests. SEI will also conduct causal learning on the flight test data (Tetrad) to further discover patterns and chains of parameter behavior representing additional scenarios to include in simulation and test.

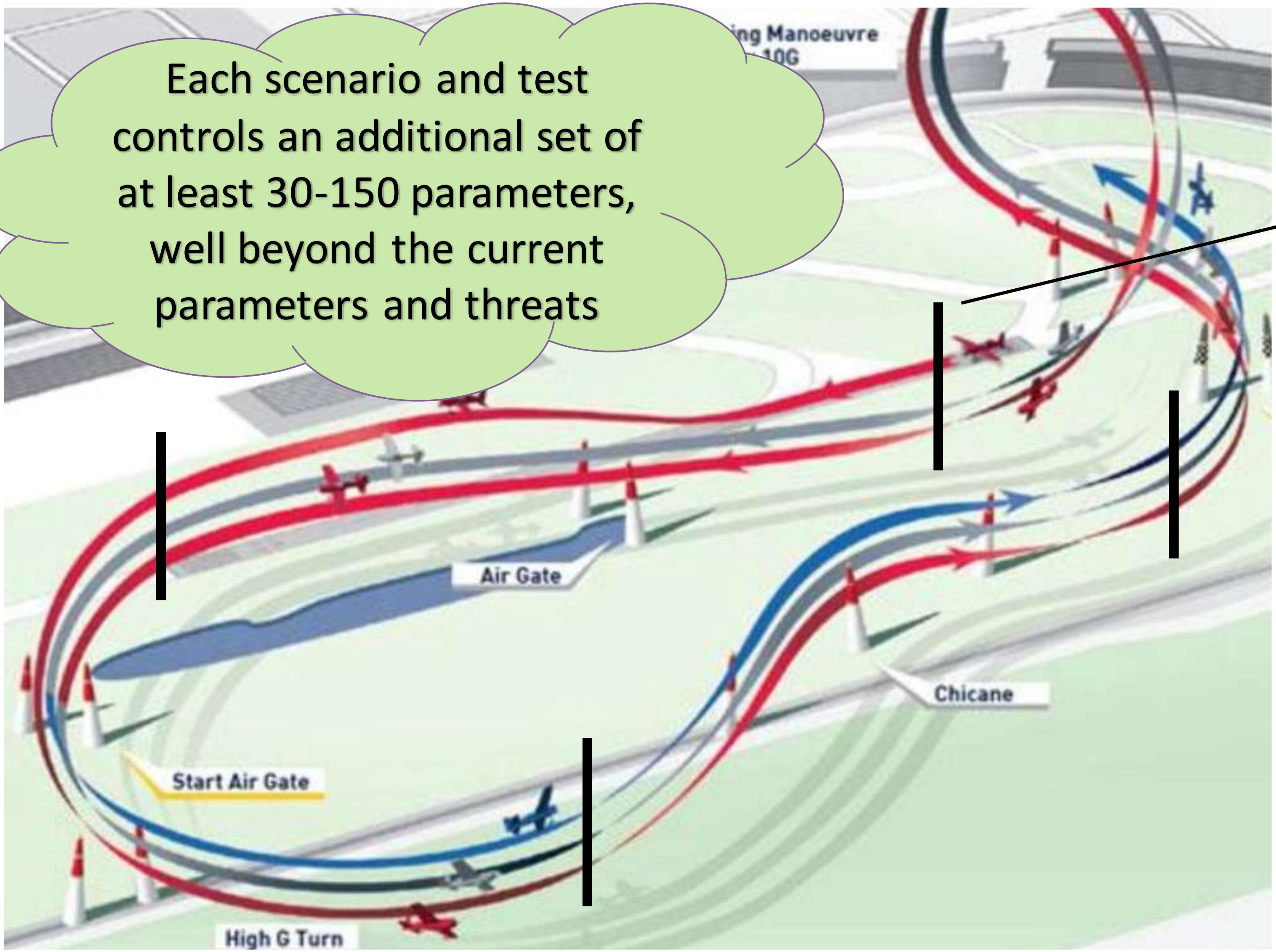
Current: Simulation and Test



Avionics simulation scenarios and tests are developed per operational mode, shown here as flight segments separated by vertical black lines.

Pilot subjective assessments from within the simulator provide feedback on the realism of the simulation and test.

Solution: Simulation and Test



Each scenario and test controls an additional set of at least 30-150 parameters, well beyond the current parameters and threats

Parametric data are captured by flight recorders during actual flight testing of each operational mode. A set of parameters are also captured during simulation.

Machine and causal learning are applied to each mode:

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

Example Additional Parameters to Analyze and Model

- Angle of attack
- Altitude
- Trim surface settings … (multitude)
- Engine thrust, pressure, temperature, speed, vibration, … (30-100 parameters)
- Atmospheric conditions …. (multitude)
- Timings of all settings…… (multitude)
- Sequencing of controllable settings……(multitude)

Modern aircraft have upwards of 1000+ parameters captured by the flight data recorder

Identifying Scenarios in Flight Test missing from Simulator

Simulation

Simulation	Operational Mode	Time Snapshot	Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Paramete
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	Operational Mode	Time Snapshot	Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Param
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								

Flight Testing

Step 02

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

n	Operational Mode	Time Snapshot	Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Paramete
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								

Identifying Scenarios in Simulator missing from Flight Test

Simulation

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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 <u>or</u> added to flight test

Simulation	Operational Mode	Time Snapshot	Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Param
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								

Flight Testing

Step 01

Flight Test data is "learned" using Bayesia machine learning

n	Operational Mode	Time Snapshot	Parameter 01	Parameter 02	Parameter 03	Parameter 04	Parameter 05	Parameter 06	Parameter 07	Paramete
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 for Stress Scenarios

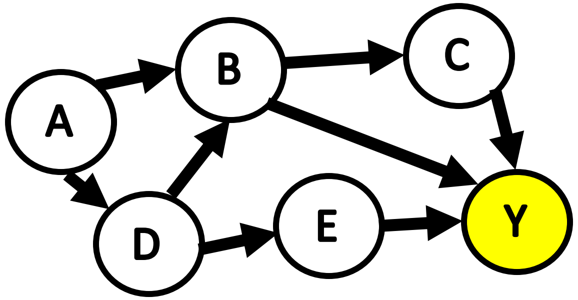
Simulation

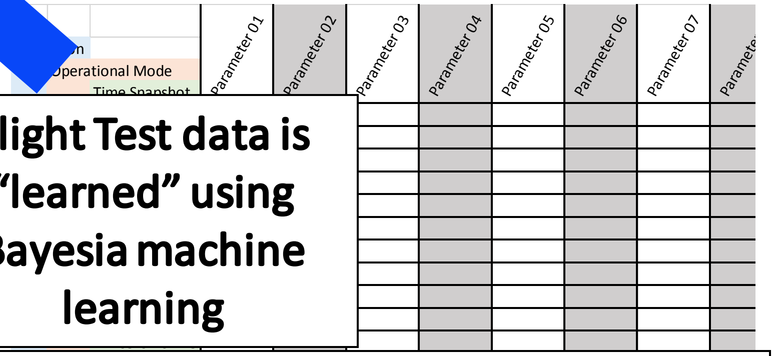
Bayesia

Flight Testing

Step 03

Step 01





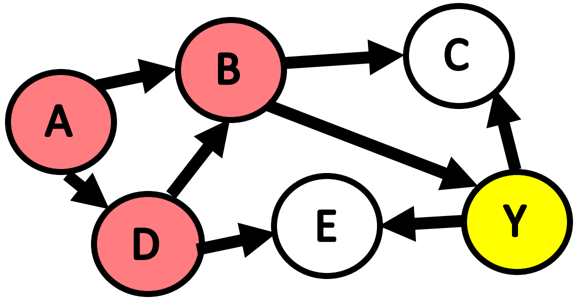
Tetrad discovered and estimated causal chains (red) for each Y stress factor clarify an essential scenario

Flight Test data is "learned" using Bayesia machine learning

Bayesia results identify subset of factors for Causal Learning with Tetrad

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

Tetrad



Step 02

Comparing Flight Test Behavior across Aircraft and Pilots

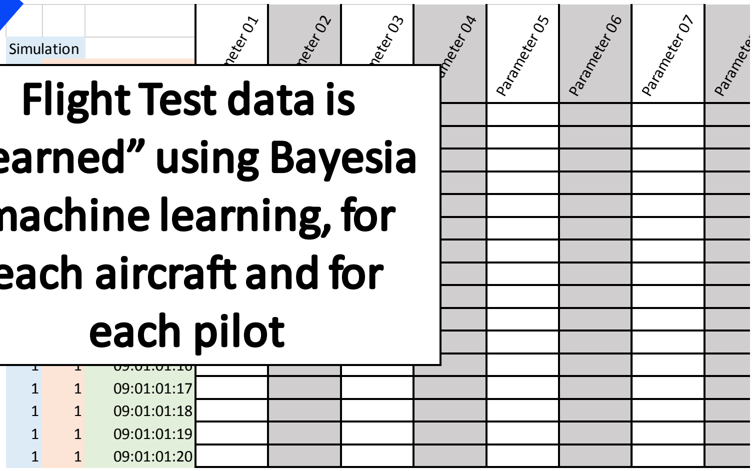
Simulation

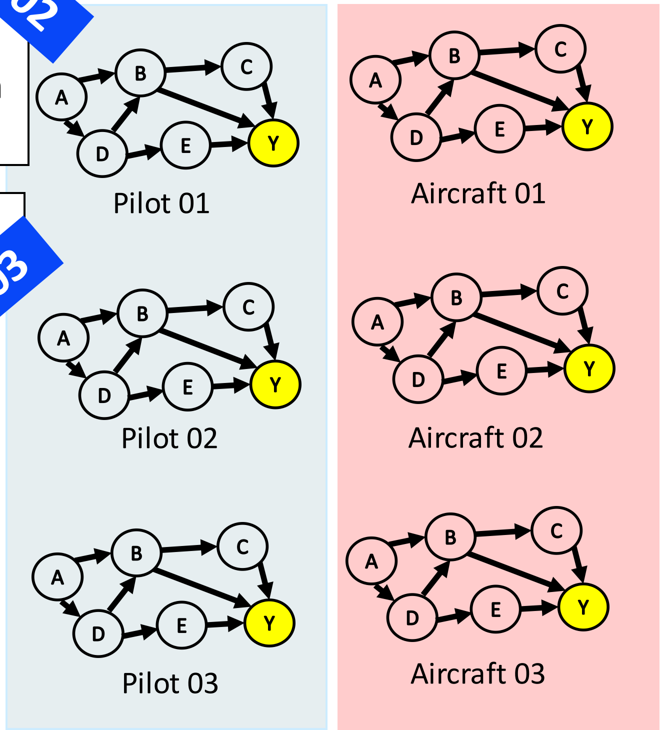
Bayesia

Flight Testing

Step 01

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





Step 02

Differences "outliers" between pilots or between aircraft inform scenarios

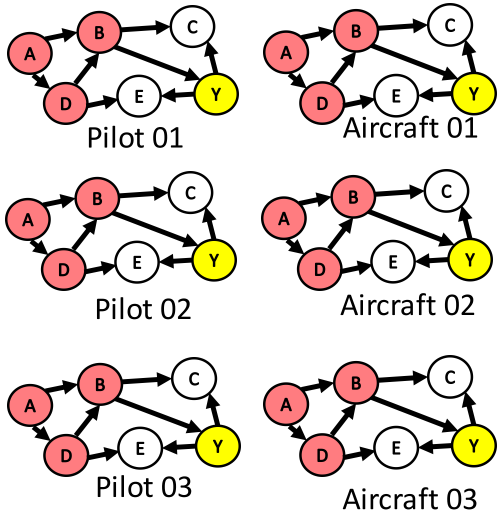
Step 03

Bayesia helps target causal modeling

Tetrad

Step 04

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



Approach to Evaluate and Improve Realism of Existing Simulation and Test

1) Per operational mode during simulation, collect parametric data; apply machine learning producing a “learning” of behavior for each simulated mode
2) Download actual flight test parametric data from flight recorders; evaluate the data set for “outliers” using the simulation “learning” as a reference baseline
3) Each “outlier” will represent realistic behavior not contained within the simulation
4) Each “outlier” will be associated with a time snapshot and a set of parameters which collectively represent the “outlier” behavior
5) The set of parameter values forming each “outlier” will then be recommended as a scenario to be added to the simulation and test
6) Lastly, apply causal learning to the flight test parametric data to decipher true causal chains of parametric behavior which will inform more realistic simulation scenarios and test, <u>including scenarios that may not have occurred in flight test or thought of by the active duty pilots</u>

Success Measures

What measure(s) will be used to help indicate success?

Increased number of simulation scenarios and tests recommended from machine and causal learning along with the coverage percentage of total realistic flight test scenarios

Subjective value statements of the new scenarios and tests from both Simulation/Test staff and active duty pilots (survey assessing confidence in realism of simulated scenarios)

Percentage of recommended simulation scenarios and tests implemented

Percentage of recommended simulation scenarios and tests which identify future issues when compared to the percentage computed for the baseline simulation at start of the research (long term)

Relevant Work - 01

Published research exists in the use of machine learning, statistical cluster approaches to multivariate time series, and Bayesian/Neural Networks to model complex, avionics system performance. However, the limited research of applications of machine learning and causal discovery in the field of avionics simulation and test suggest the field may be relatively immature, and would benefit from detailed, successful case studies.

Melnyk, I., Banerjee, A., Matthews, B., & Oza, N. (2016). Semi-Markov Switching Vector Autoregressive Model-based Anomaly Detection in Aviation Systems. *arXiv preprint arXiv:1602.06550*.

Gil Casals, S., Owezarski, P., & Descargues, G. (2012). Risk Assessment for Airworthiness Security (pp. 25–36). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-33678-2_3

Sampigethaya, K., Poovendran, R., & Bushnell, L. (2008). Secure Operation, Control, and Maintenance of Future E-Enabled Airplanes. *Proceedings of the IEEE*, *96*(12), 1992–2007. https://doi.org/10.1109/JPROC.2008.2006123

Ali, M. S., Bhagavathula, R., & Pendse, R. (n.d.). Airplane data networks and security issues. In *The 23rd Digital Avionics Systems Conference (IEEE Cat. No.04CH37576)* (p. 8.E.1-81-12). IEEE. https://doi.org/10.1109/DASC.2004.1390773

Davies, M. D., & Limes, G. (2011). Finding system-level failures in flight-critical software systems. In *2011 IEEE/AIAA 30th Digital Avionics Systems Conference* (p. 7C5-1-7C5-10). IEEE. https://doi.org/10.1109/DASC.2011.6096125

Famili, F., & Letourneau, S. (n.d.). Monitoring of aircraft operation using statistics and machine learning. In *Proceedings 11th International Conference on Tools with Artificial Intelligence* (pp. 279–286). IEEE Comput. Soc. https://doi.org/10.1109/TAI.1999.809800

Relevant Work - 02

Although beneficial use of causal modeling is documented, the literature is devoid of causal learning in system sustainment and specifically, validation of highly complex systems undergoing change.

Scheines, Richard. Causal Modeling Workshop. 2015. http://www.hss.cmu.edu/philosophy/casestudiesworkshop.php

Morgan, Stephen & Winship, Christopher. Counterfactuals and Causal Inference: Methods and Principles for Social Research. 2nd Edition. November 2014. Cambridge University Press.

Pearl, Judea. Causality: Models, Reasoning and Inference. 2nd Edition. September 2009. Cambridge University Press.

Pearl, Judea & Glymour, Madelyn. Causal Inference in Statistics: A Primer. 1st Edition. March 2016. Wiley.

Spirtes, Peter & Glymour, Clark & Scheines, Richard. Causation, Prediction, and Search, 2nd Edition. January 2001. MIT Press, A Bradford Book.

Tetrad V software program. Department of Philosophy, Carnegie Mellon University. http://www.phil.cmu.edu/tetrad/

Danks, D. (2106). *Why Causal Discovery and Modeling Should be in Your Research Design,* SEI Brown Bag Presentation, \\ad\dfs\Groups\OCOS\IT\Common\MediaServices, File “2016-02-18DDanksBrownBag-big”.

Intended Artifacts & Results

Research and transition artifacts include:

1) Automated machine learning algorithms which represent realistic dynamic flight profiles,
2) Causal models of parameter relationships useful for designing simulation scenarios and test cases,
3) Documented simulation scenarios programmed in the Hill AFB simulation environment,
4) Documented test cases and procedures programmed in the Hill AFB test environment,
5) Guidance on the update of the machine and causal learning in anticipation of additional avionics systems labs.

Intended publications and venues include:

1) Aircraft Airworthiness & Sustainment Conference,
2) International Conference on Software Engineering (ICSE),
3) ACM SIGMETRICS International Conference on Measurement and Modeling of Computer Systems, and
4) IEEE Prognostics and Health Management (PHM) Conference and Journal [lead to IEEE stds work?].

Tools and algorithms include:

1) Scenario evaluation tool to be integrated with the Hill AFB Simulators and Test Lab equipment,
2) Bayesia “machine learned” probabilistic structural equation models; Tetrad causal discovery models.

Data collection repositories to be created include:

1) New data repositories to be owned and maintained by the Hill AFB Data Analytics and Post Flight Test teams,

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