

Using Data Science to Improve Air Safety



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TECHNOLOGY DRIVEN. WARFIGHTER FOCUSED.

Presented by:

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U.S. Army Aviation and Missile Research, Development, and Engineering Center

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Background

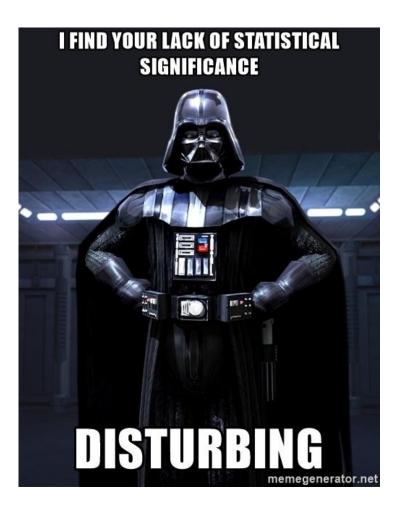


US Army Aviation Engineering Directorate

- Airworthiness Authority for the Army
- TRL 7-9 Development and Qualification

Dynamics Branch

- Health and Usage Monitoring Systems and Aviation Data Science Team Lead
- Bachelor and Master of Science in Mechanical Engineering
 - Dynamics & Modal Analysis
 - I'm not a
 - Researcher
 - Statistician or
 - Data scientist







U.S. Army Aviation and Missile Research, Development, and Engineering Center provides increased responsiveness to the nation's Warfighters through aviation and missile capabilities and life cycle engineering solutions.

- Headquartered at Redstone Arsenal, AL
- 5 Directorates
- 9,000 scientists & engineers
- \$2.45 billion in reimbursable funding, FY 16
- \$339 million in Science & Technology funding, FY 16

AMRDEC Priorities

Strategic Readiness – provide aviation and weapons technology and systems solutions to ensure victory on the battlefield

Future Force – develop and mature Science and Technology to provide technical capability to our Army's (and nation's) aviation and weapons systems

Soldiers & People – develop the engineering talent to support both Science and Technology and materiel enterprise



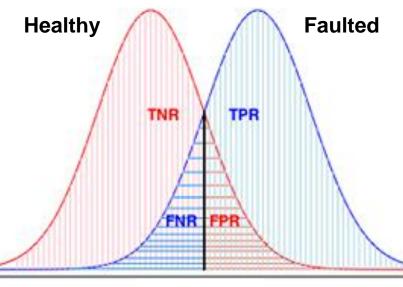


- Health and Usage Monitoring Systems (HUMS)
 - The child of FOQA (Flight Operations Quality Assurance)
- <u>True Positive</u>: Sensitivity; HUMS correctly identified a faulted state
 <u>False Negative</u>: Missed Detection
- <u>True Negative</u>: Specificity; HUMS correctly identified a healthy state
 - False Positive: False Alarm
- **Bookmakers Informedness** = TPR FPR
- Ground Truth

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U.S. ARMY

- Assets and Examples
- **ROC**: Receiver Operating Characteristic
- Epicyclic Transmission: Planetary Gearbox



Threshold



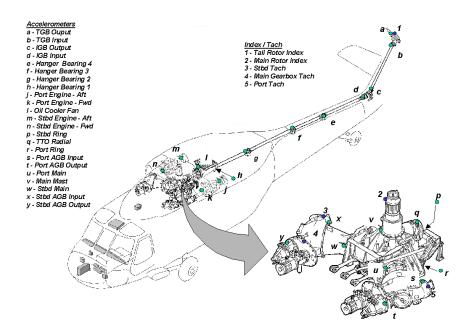
What is HUMS?



Health and Usage Monitoring System

Flight Operations Data (Parametric Data) e.g. altitude, pitch rate, engine torque

Sensor Data Burst data (High Frequency) e.g. accelerometers Continuous data (Low Frequency) e.g. oil debris monitor







What do we use it for?

- Univariate exceedance monitoring during flight
 - Oil debris monitoring
- Health/Usage monitoring
 - Drive train vibration
 - Rotor vibration
 - Flight regime classification
- Accident Investigation
 - Cockpit voice
 - Flight data recording





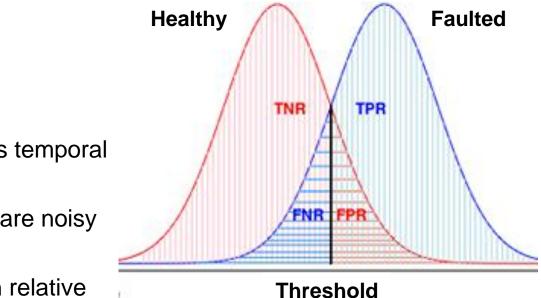








Exclusively uses univariate exceedance classification methods which are often prone to a False Positive/Negative problem.

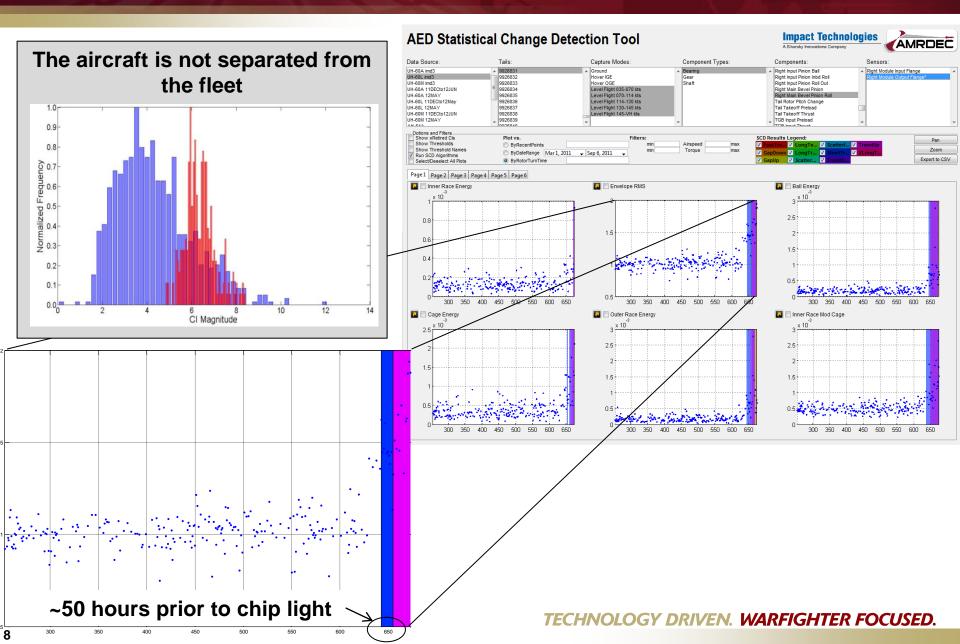


- The problem is temporal
- The variables are noisy
- Health is often relative
- Anomalous does not always mean broken or dangerous
- It does not account for other flight variables



An Example: Change Detection



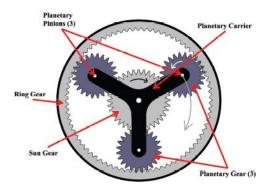


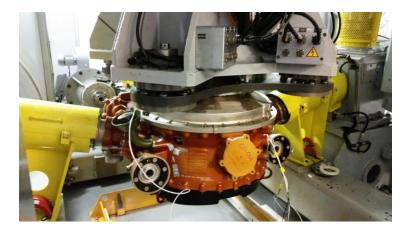


Case Study: Transmission Internal Failure



Epicyclic Transmission





Spiral Bevel Transmission

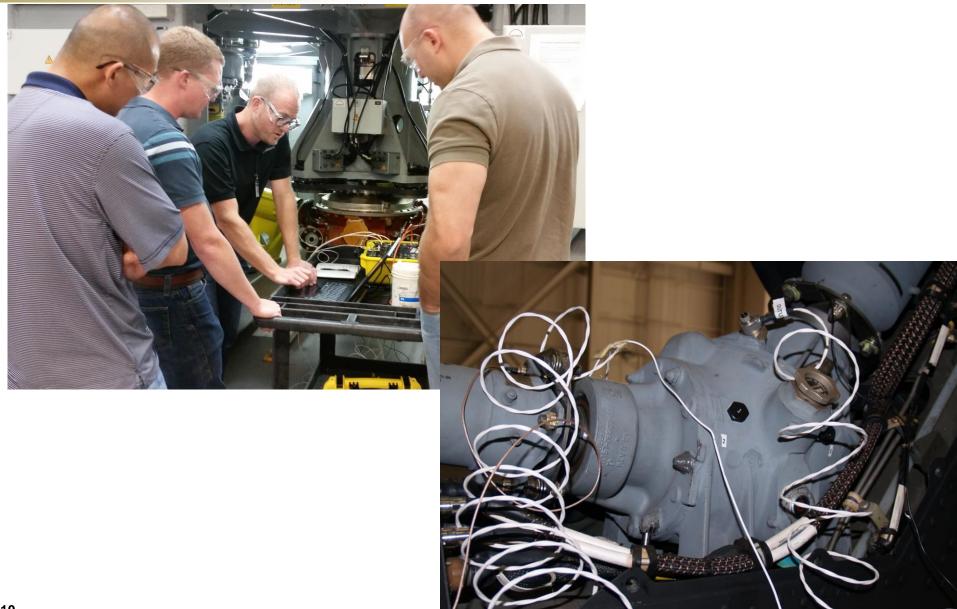






Can vibration transfer across an epicyclic transmission?







How well are we actually doing?



Epicyclic Transmission 1	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN=100%	FP=0%	2
Actual Condition: Faulty	FN=100%	TP=0%	6
Sum of Assets:			8

Epicyclic Transmission 2	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN=100%	FP=0%	4
Actual Condition: Faulty	FN=100%	TP=0%	4
Sum of Assets:			8

Epicyclic Transmission 3 Built In HUMS	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN=0%	FP=100%	1
Actual Condition: Faulty	FN=100%	TP=0%	25
Sum of Assets:			26

Epicyclic Transmission 4	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN=91%	FP=9%	11
Actual Condition: Fault	FN=95%	TP=5%	21
	32		



Can we improve?



Epicyclic Transmission 3 Built In HUMS	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN=0%	FP=100%	1
Actual Condition: Faulty	FN=100%	TP=0%	25
Sum of Assets:			26

Epicyclic Transmission 3 Modified HUMS	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN=100%	FP=0%	1
Actual Condition: Faulty	FN=56%	TP=44%	25
Sum of Assets:			26



What about spiral bevel transmissions?



Tail Gearbox 1	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN=100%	FP=0%	4
Actual Condition: Faulty	FN=0%	TP=100%	3
Sum of Assets:			7

Tail Gearbox 2	HUMS Indicated Healthy	HUMS Indicated Fault	Assets
Actual Condition: Healthy	TN= 71%	FP=29%	7
Actual Condition: Fault	FN=13%	TP=87%	15
	S	oum of Assets:	22



What are we doing to fix the problem?



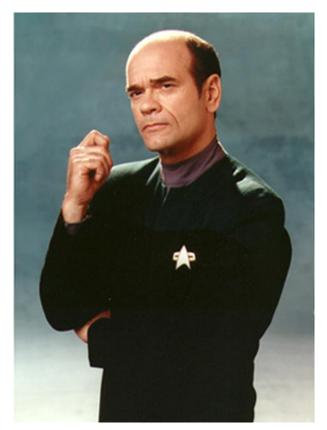
Remember the Emergency Medical Hologram?



What are we doing to fix the problem?



Remember the Emergency Medical Hologram?



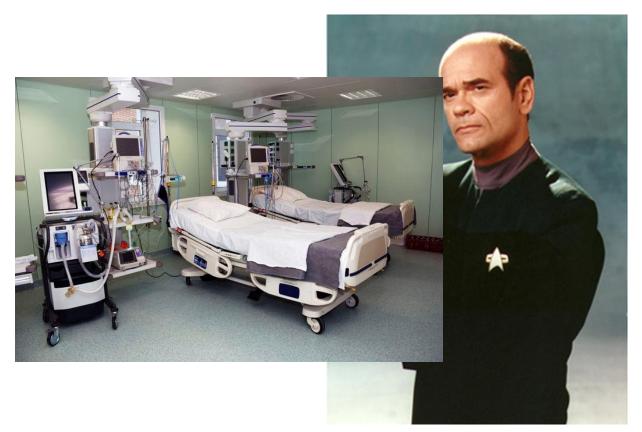
Please state the nature of the medical emergency



What are we doing to fix the problem?



Remember the Emergency Medical Hologram?



Please state the nature of the **engineering** emergency





We live in a common place with other industries when we talk about this topic:

- Medicine
- Nuclear Power
- Aviation

Development of multivariate machine learned diagnostics and prognostics requires

a process...



Our Machine Learning Process







Our Machine Learning Process



Our Machine Learning Axioms for Aviation

- Stirring the pile, is training
- Model evaluation, is training
- Model selection, is training
- Model validation, is training
- Looking under the hood, is training
- Stirring stops prior to testing
- Testing is done by the customer on a clean dataset

THIS IS YOUR MACHINE LEARNING SYSTEM?

YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.

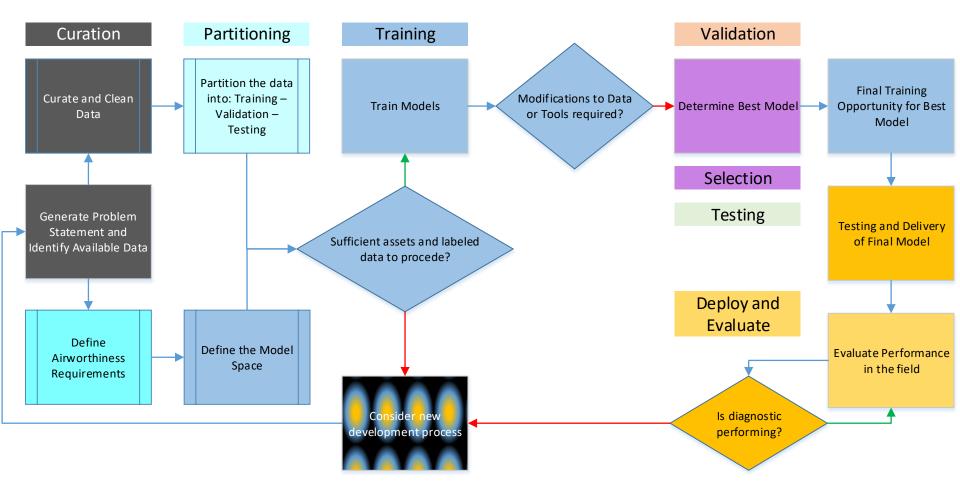




- We put together a general path forward we expect to see when we take on a machine learning task.
- Demonstrated in our NGB internal failure classification work
 - Cleanse
 - Partition
 - Train
 - Validate
 - Select
 - Test
 - Deploy
- We built a flow chart!

ROECOM Aviation Machine Learning Process

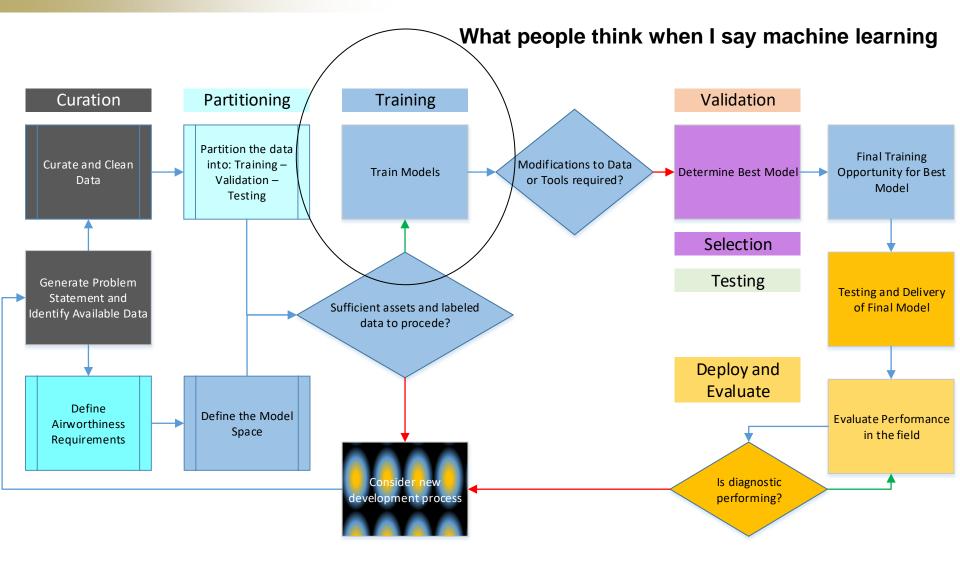




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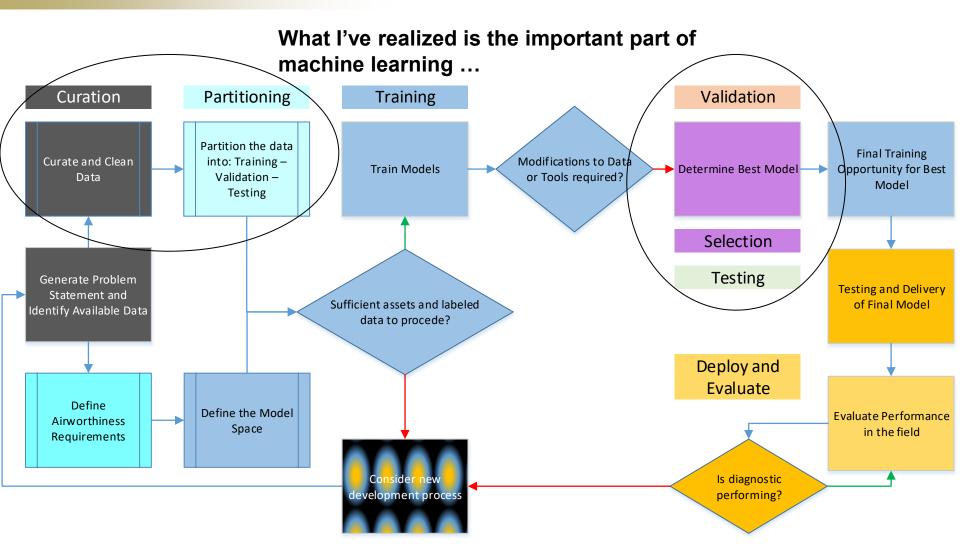
REFECON Aviation Machine Learning Process





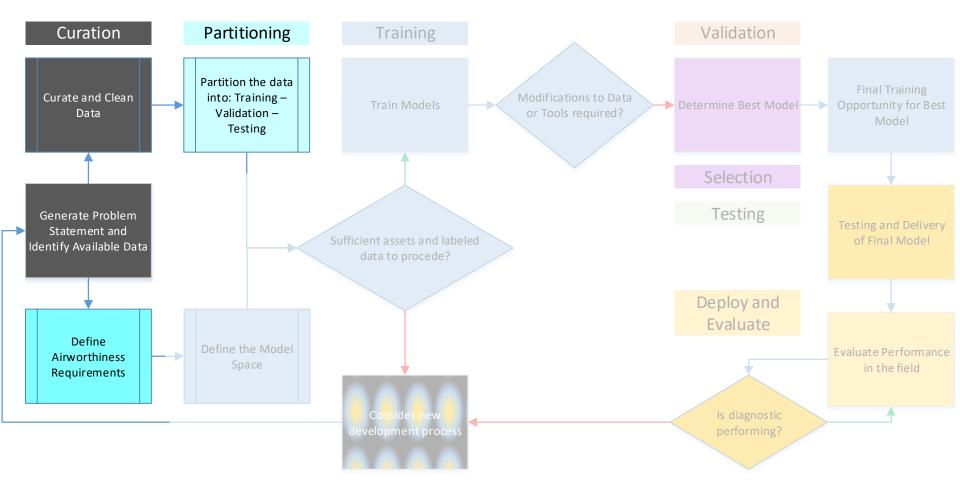
ROECOM Aviation Machine Learning Process





Rolecom
 Aviation Machine Learning Process

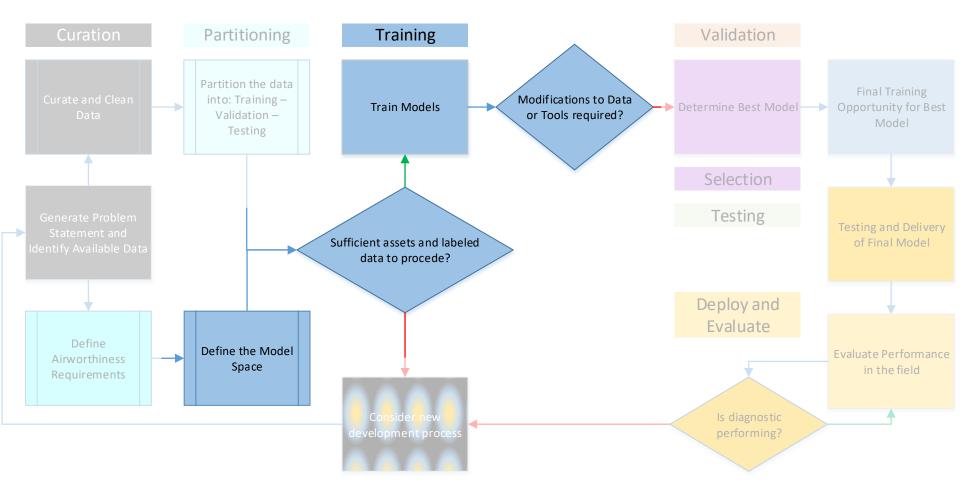




TECHNOLOGY DRIVEN. WARFIGHTER FOCUSED.

ROECOM Aviation Machine Learning Process

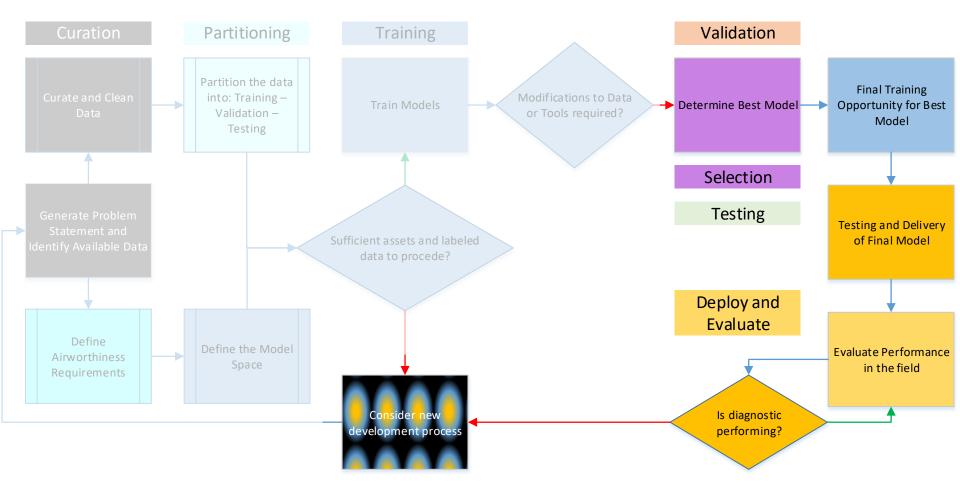




TECHNOLOGY DRIVEN. WARFIGHTER FOCUSED.

ROTECOM Aviation Machine Learning Process





TECHNOLOGY DRIVEN. WARFIGHTER FOCUSED.





METRICS

Description: Bagged Logistic Regression over history-max plus FRF-CI's Justification for inclusion in pretest: "Simplest" model on generalization (CV informedness) list

	Train	CV	Pretest
Measurment Informedness	0.812	0.856	0.596
Measurment TPR	0.860	_	0.618
Asset TPR	0.478	_	0.286
Asset FPR	0.174	_	0.147
Asset TPR (M oo N)	0.826	_	0.429
Asset FPR (M oo N)	0.090	_	0.032
Asset Unpredicted Positives	0.000	_	0.125
Asset Unpredicted Negatives	0.000	_	0.004
Asset MooN Unpredicted Positives	0.000	_	0.125
Asset MooN Unpredicted Negatives	0.000	_	0.004

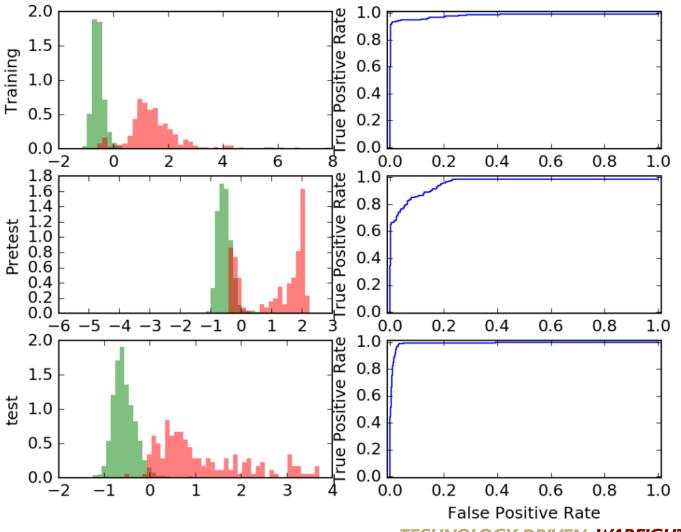
Training	Real Positives	Real Negatives	
Predicted Positives	313.0	674.0	
Predicted Negatives	51.0	13528.0	



ROC Curves



ROC curves



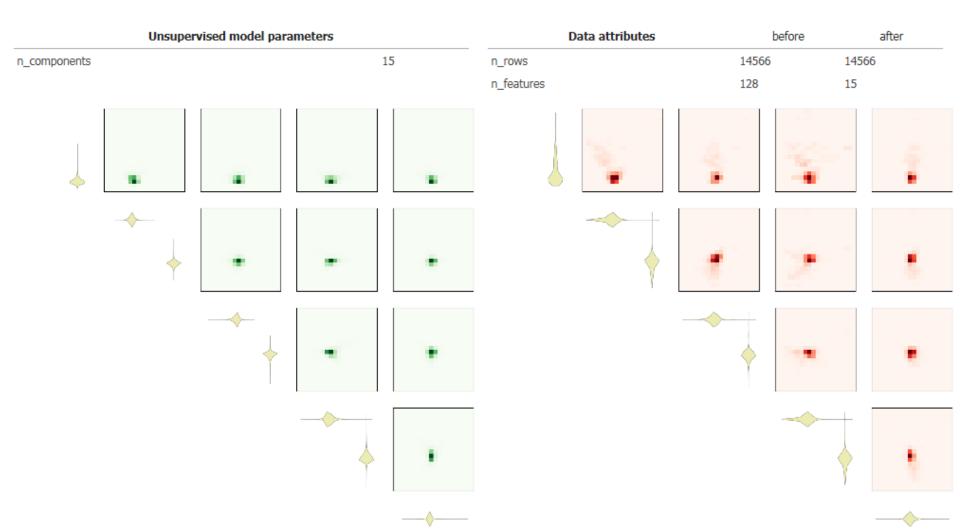
Temporal Assessment of Performance







RandomizedPCA on STA:64D-NX-SF-NX-10



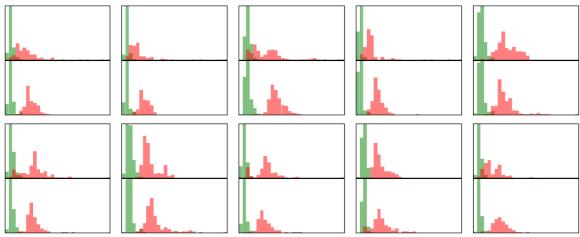


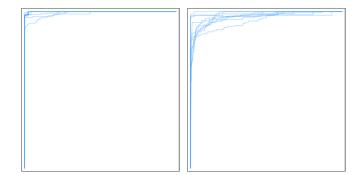
How did it perform in cross validation?



CROSS-VALIDATION w/ 10 FOLDS

Fold #	True Positive Rate	False Positive Rate	True Positive Accuracy	True Negative Accuracy	Informedness
Fold #0	1.00	0.08	0.22	1.00	0.92
Fold #1	0.84	0.06	0.26	1.00	0.78
Fold #2	0.90	0.02	0.50	1.00	0.87
Fold #3	1.00	0.06	0.34	1.00	0.94
Fold #4	1.00	0.07	0.23	1.00	0.93
Fold #5	0.98	0.07	0.24	1.00	0.92
Fold #6	1.00	0.06	0.29	1.00	0.94
Fold #7	0.83	0.02	0.55	1.00	0.82
Fold #8	0.99	0.03	0.49	1.00	0.96
Fold #9	0.82	0.02	0.52	0.99	0.79

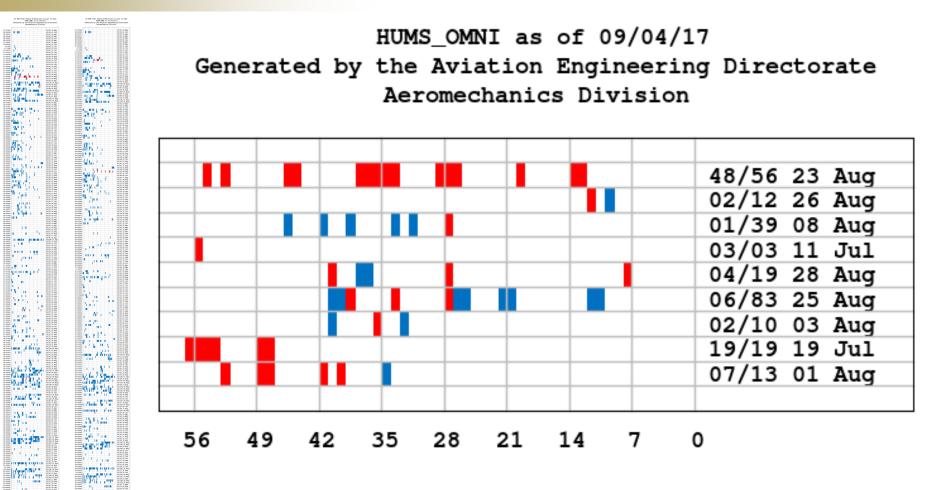






Enterprise Data Analytics Report





TECHNOLOGY DRIVEN. WARFIGHTER FOCUSED.

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- Yes, but it needs some adjustments:
 - Metrics need to be computed across the maximum data for the life of the aircraft
 - Sampling techniques are ok for training but not when reporting performance
 - Post Mortem indicates we picked almost the best choice but not the best choice
 - We could have an improvement of up to 10% informedness
- Does it *automate away* the engineer?
 - No, but it sure does give them a great place to focus
 - 650 aircraft and you have confidence that you will be focused on the select 9 or 10 that need your attention
 - Still has a **FP rate** that needs engineering assistance





- Thanks to the great government and contractor team:
 - AMRDEC
 - Andrew
 - Jeremy
 - Matt
 - Jamie
 - Avion
 - Shawn

- PEO-AVN
 - Frances
- Honeywell
 - Andrew
 - Abe
 - Raj
- RMCI
 - Lance
 - Nate
 - Steve



- Wilson, A., Wade, D., Albarado, K., Partain, J., and Statham, M., "A Classifier Development Process for Mechanical Health Diagnostics on US Army Rotorcraft", Proceedings of the ML and PHM Workshop, SIGKDD 2016, San Francisco, CA, August 2016.
- Wilson, A., and Wade, D., "Reconstructing Spectra from IVHMS Condition Indicators," Proceedings of the 73rd American Helicopter Society Annual Forum, Fort Worth, TX, May 2017.
- 3. Wilson, A., Wade, D., Ling, J., Chowdhary, K., Davis, W., Barone, M., and Fike, J., "Convolutional Neural Networks for Frequency Response Predictions," Proceedings of the Verification and Validation Symposium, Las Vegas, NV, May 2017.
- Wade, D., and Wilson, A., "Applying Machine Learning-Based Diagnostic Functions to Rotorcraft Safety", Proceedings of the Tenth Australian Defence Science and Technology Group International Conference on Health and Usage Monitoring Systems, Melbourne, VIC, Australia, February 2017.
- Wade, D. et al, "Measurement of Vibration Transfer Functions to Inform Machine Learning Based HUMS Diagnostics," Proceedings of the 72nd Annual Forum of the American Helicopter Society, May 2016.





- Cal Tech: "Learning From Data"
 - FREE on YouTube
 - <u>https://work.caltech.edu/telecourse</u>
- NASA work in Flight Operations Data and the Future ATC System
 - <u>https://www.nasa.gov/content/air-traffic-operations-lab-answering-big-questions-about-the-future-of-air-travel</u>
- Journal of Aerospace Information Systems
 - <u>https://arc.aiaa.org/loi/jais</u>
- SIGKDD (Association for Computing Machinery: Special Interest Group on Knowledge Discovery and Data Mining)
 - <u>http://www.kdd.org/</u>
- ASME V&V Symposium
 - <u>https://www.asme.org/events/vandv</u>





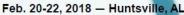
Upcoming Events







AIRWORTHINESS, CBM, and HUMS Technical Meeting Call for Papers



The Redstone Chapter of AHS International will be sponsoring a Technical Meeting on Airworthiness, Condition Based Maintenance (CBM), and Health and Usage Monitoring (HUMS) on February 20-22, 2018 in Huntsville, Alabama. The Technical Meeting will present applicable technologies that are new to continued airworthiness, current and potential processes, and hardware required for military and civil aircraft airworthiness.

Abstracts are to be submitted to <u>abstracts@ahsredstone.org</u>_no later than October 13, 2017. It is strongly encouraged that abstracts be submitted in a .pdf format and not be any larger than 2MB. They should be approximately 1,000 words, present the status of the background data to be used, summarize figures and illustrations to be used (with samples), and include a summary of important conclusions. Abstracts will be accepted in a variety of technical disciplines related to commercial or military aircraft Airworthiness, Condition Based maintenance, Health-Monitoring Technologies, or Certification/Qualification of vertical flight aircraft. Papers are solicited on the following topics:

- HUMS/SUMS for maintenance credits
- Measuring the Return on Investment of HUMS installation, analysis, and data retention
- Using HUMS to improve logistics and decrease aircraft downtime
- Low-cost HUMS solutions
- Improvement of data flow on and off board aircraft
- Civil and Military Regulatory Advancements and Recommendations related to HUMS
- Flight Data Analysis (FOQA/FDM)
- Aviation Data Science
- Next Generation HUMS
- HUMS sensors, architecture improvements, and technologies
- Maintainer, Pilot, and Operator experiences and feedback
 Using HUMS to influence Future Vertical Lift design
- Fault Modeling and Simulation for HUMS development and qualification



-Machine learning on scientific and engineer data

-Surrogate modeling

-Image processing/ comp vision

-Classification Problems

-Unraveling Buzz Words

-What is "Big Data"

-IT Infrastructure and storage

-Developing internal data science talent

-Public release and hosting competitions

RADS Redstone Arsenal

Data Science Working Group

Open Announcement and Call for Participation

Pockets of engineers and analysts across Redstone Arsenal are applying data science methods to government data. Many of these groups may have common problems even though they have different datasets.

How do we leverage existing knowledge and parallel efforts to improve efficiency and maximize capability? If you think you may fall into this category, join us!

This free event is cosponsored by AMRDEC and MSIC. The planned format is a single auditorium with short talks and panel discussions. We are soliciting interested individuals to participate in this event through submission of short abstracts for talks or panels as related to the listed topics.

If you are interested in this event, please submit your abstracts or questions to the listed organizers. Agenda and attendance information is forthcoming.

This event is unclassified and is intended for government employees and government sponsored onsite support contractors only. Please contact a POC below for detailed information.

> Join us! 7 November 2017 MSIC Auditorium





Thank you for your time and attention





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