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Identifying Actionable Relationships
Between IVHMS Sensor and Maintenance Event Datasets

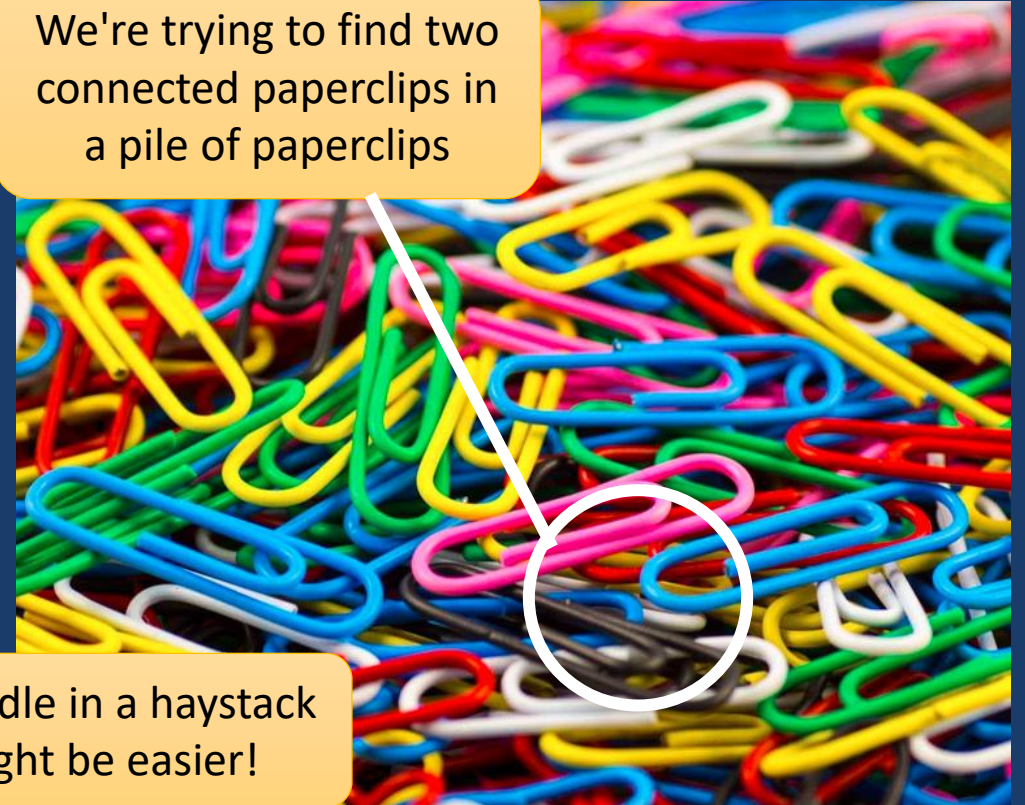
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- Software Engineer
- Support a supervised learning project for SRD RAM (CLARE)
 - Depends on unsupervised Natural Language Processing

Goal

- Identify relationships between distinct segments of IVHMS parametric data and maintenance events
- These relationships can then be used to train supervised applications (e.g., Virtual Signals, ASET) to proactively drive maintenance to increase aircraft availability.

We're trying to find two connected paperclips in a pile of paperclips



A needle in a haystack might be easier!

Agenda

- Datasets
- Assumptions
- Methodology
- Application

Datasets Used for Investigation

- Integrated Vehicle Health Management System (IVHMS) Data
 - Captured every power cycle
 - Parametric sensor data from a flight vehicle
 - High rate of capture: some channels may be 100Hz => 720,000 values for a 2 hours flight
 - Many continuous sensors
 - Engine Oil Pressure, Main Transmission Temperature, Altitude, etc.
 - Many boolean and discrete sensors
 - Built-in Tests, Landing Flag, Engines On, etc.
 - Both types of sensors can be composites of other sensors
 - Vibration values are discretized by the IVHMS into another continuous channel
 - Built-in Tests can be derived from continuous channels
 - Fleet-wide data capture results in a massive amount of data

Datasets Continued

- Maintenance
 - Captured every time a particular airframe is touched by maintenance
 - Maintenance records for a particular flight vehicle
 - Are scored to determine:
 - The impact of a maintenance driver
 - Mission Abort, Essential Maintenance Action, etc.
 - The changed or inspected functional group (FG)
 - Main Rotor, Cold Stage, Landing Gear, etc.
 - Again, fleet-wide capture results in a massive amount of data
 - 20,000,000+ maintenance records solely for H60M

We Assume:

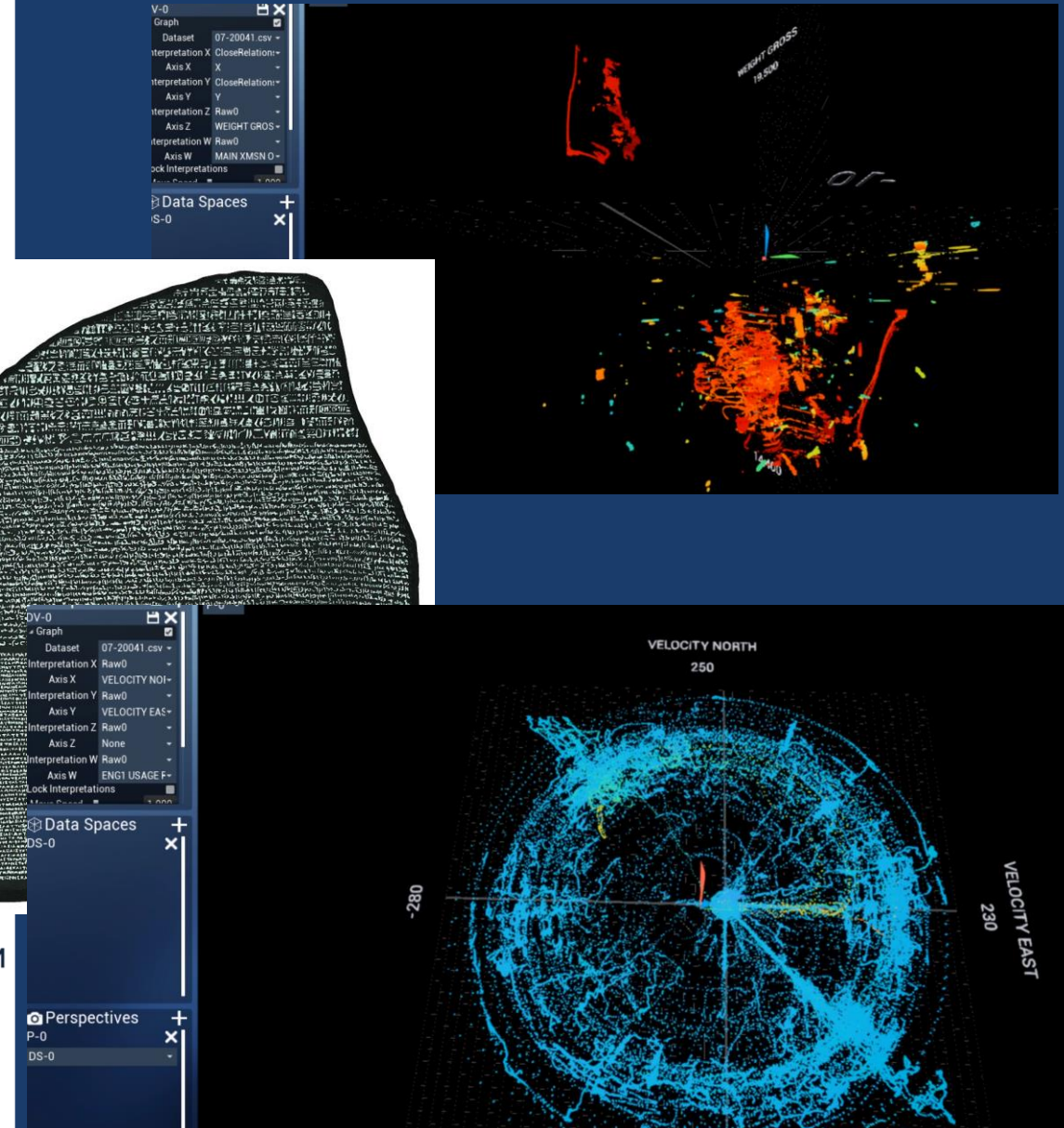
- That some faults requiring unscheduled maintenance will show degradation prior to actionable failure
- That some faults requiring unscheduled maintenance are preceded by operation in non-normative flight regimes
- That the IVHMS sensor space covers (or partly covers) the degradation or flight regimes for a subset of the faults above
- That degradation or flight regime indicators for faults will not greatly differ between different airframes of the same flight vehicle model
- Finally, that the methodology outlined in this brief, if applied to H60M data, will find these degradation or flight regime indications for faults

Expected Results:

- Identification of relationships that are:
 - Already known and proven
 - SME physics-based approach
 - Already known, but not proven
 - Maintainer institutional knowledge
 - Unknown
 - Relationships that might be non-human-intuitive

Drafting a Rosetta Stone

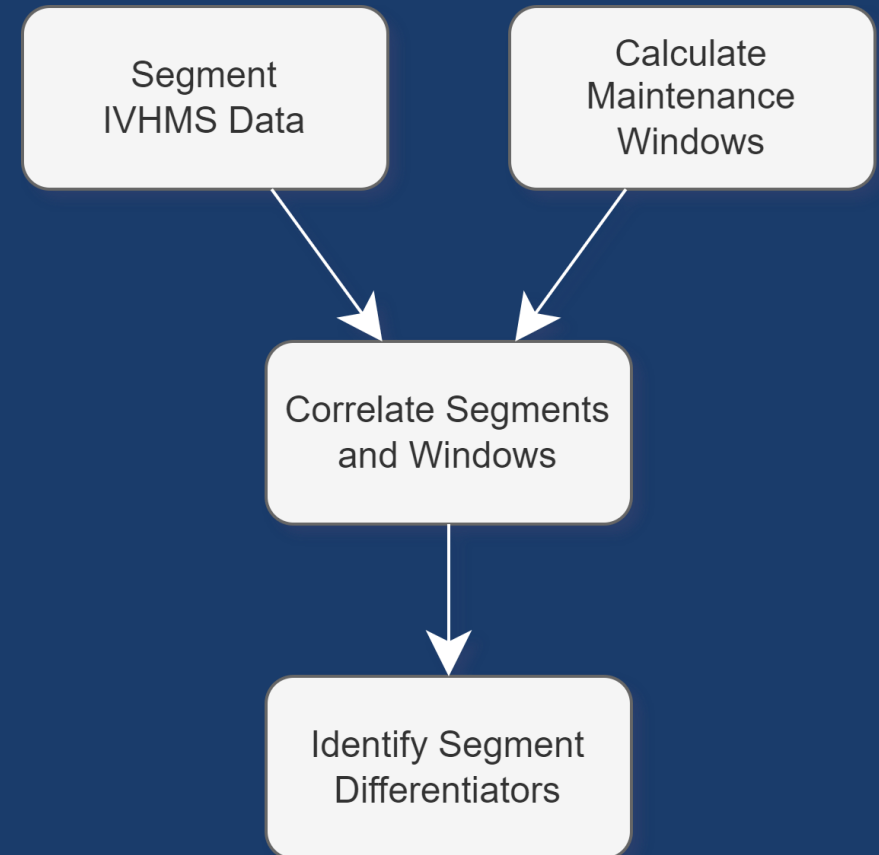
- In order to create the relationship engine, we must first understand the data
- We explored the dataset with IRTC's CompreheND™ viewer
- The relationships we found drove the development of a method to find the desired relationships



COMPREHEND™

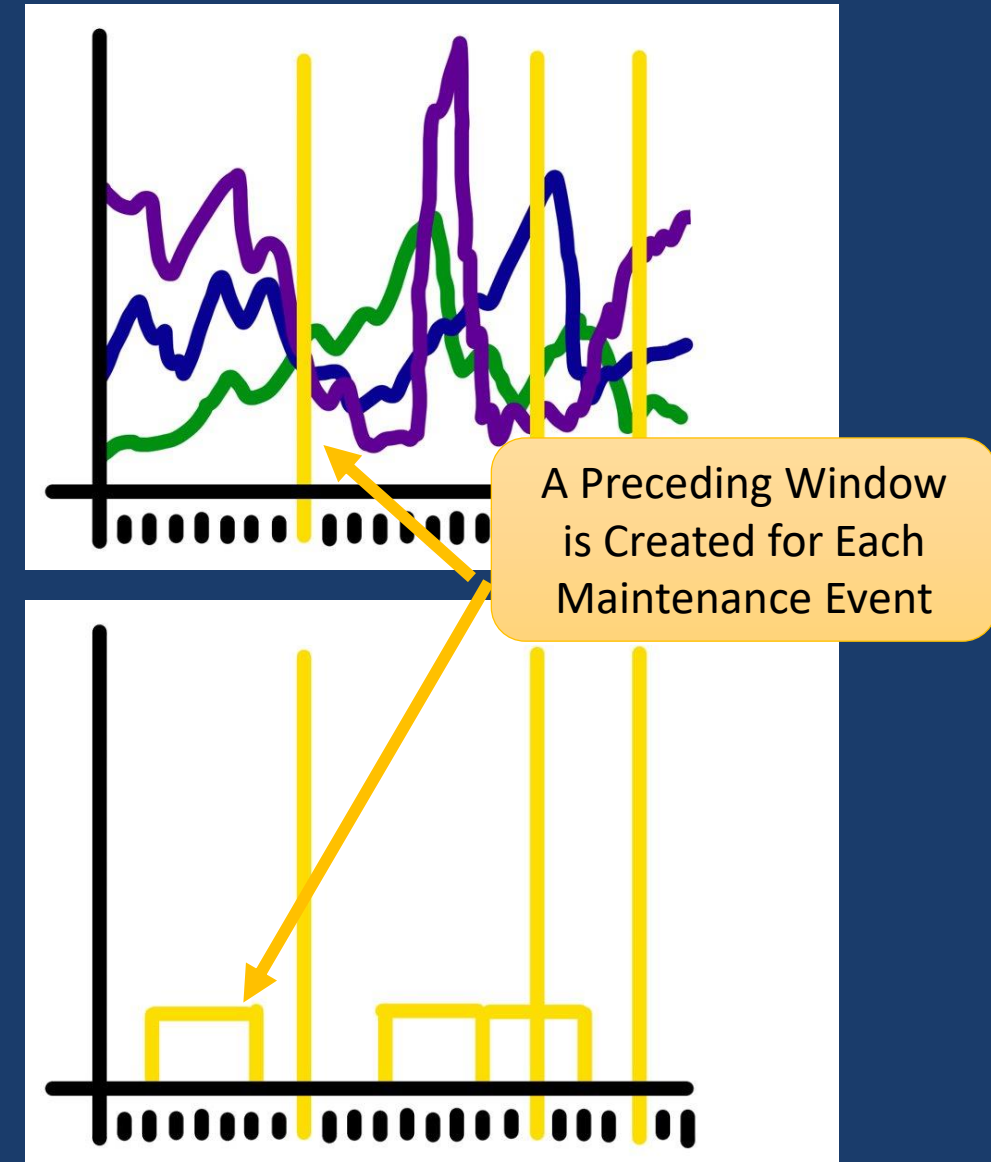
Methodology Overview

- Calculate Maintenance Windows
- Define Indicator Segments
 - Manual Segmentation
 - Regimes
 - Manual clustering on reduced data
 - Automated Segmentation
 - Clustering on raw or reduced data
- Correlate Indicator Sources to Maintenance Timelines
 - Manual correlation
 - Automated correlation
- Identify Segment Differentiators
- Verify Indicators



Maintenance Windows

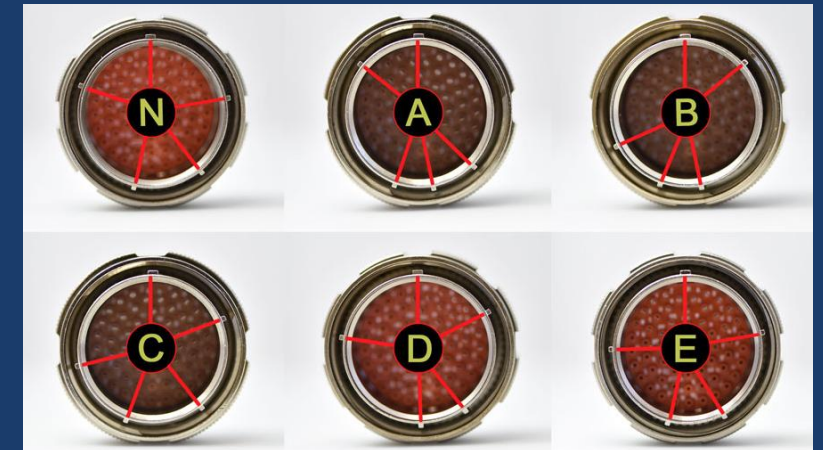
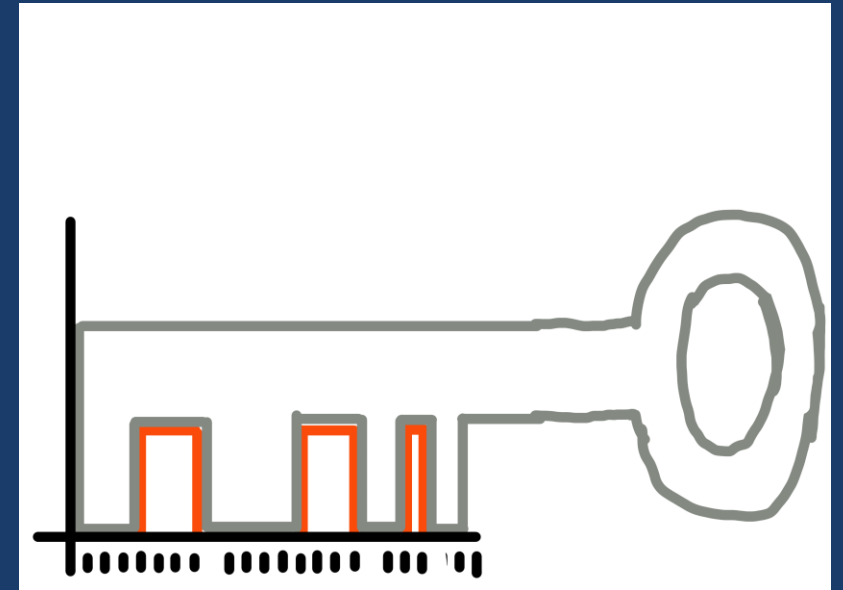
- Build windows of interest using the time of occurrence of maintenance actions for a particular functional group
- Maintenance actions occur at discrete points in time, always between flights
- For each action on a particular functional group, a window of time before that action is selected
 - Multiple maintenance events for a functional group generate a 'key'.
 - With more maintenance events, the confidence in a result alignment rises



Single or Multiple Events?

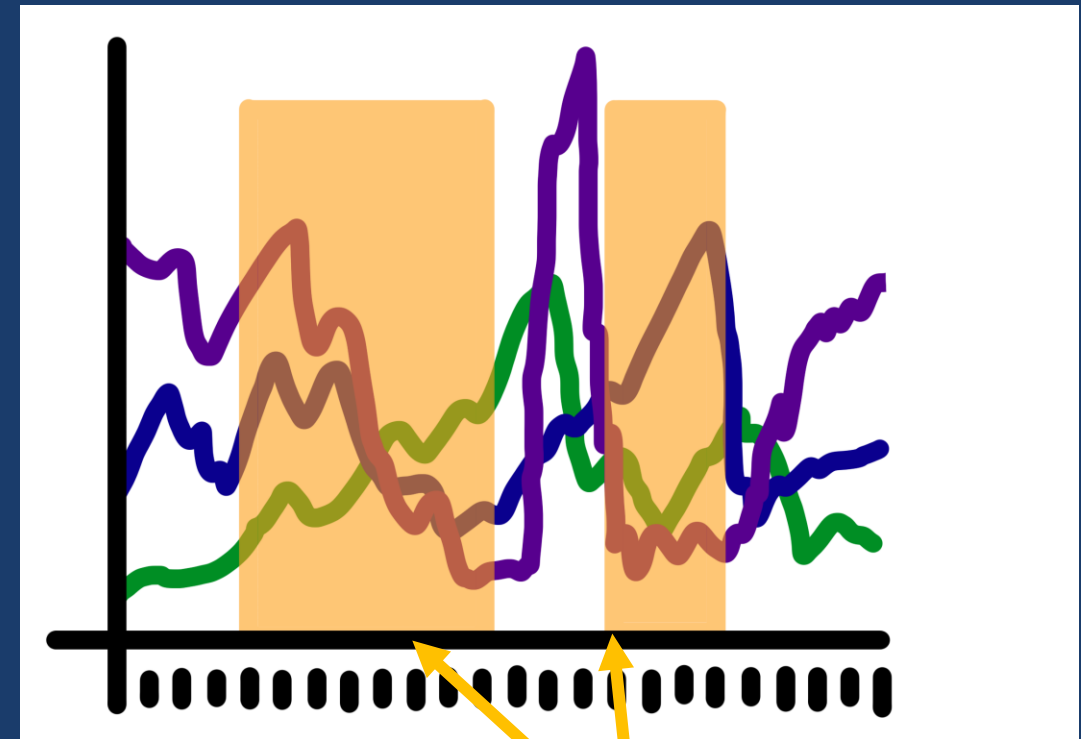
- A single window and a contiguous IVHMS segment can always be aligned, though it may take a long time to find it
 - If allowed any width or distance, they will always line up
- Multiple windows will only fully align to a non-contiguous IVHMS segment
 - The multiple windows act as a 'keying' mechanism like in D38999 mil spec connectors

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Manual Segmentation

- Define ranges of parameters to identify segments of the parametric data
- Physics-based and Human-driven
- Examples:
 - High gross weight, aggressive maneuvering
 - Should show wear on drive train and rotors
 - Cumulative Vibration
 - Leads to Electronics Failure
- Some anecdotal relationships are known but not necessarily proven

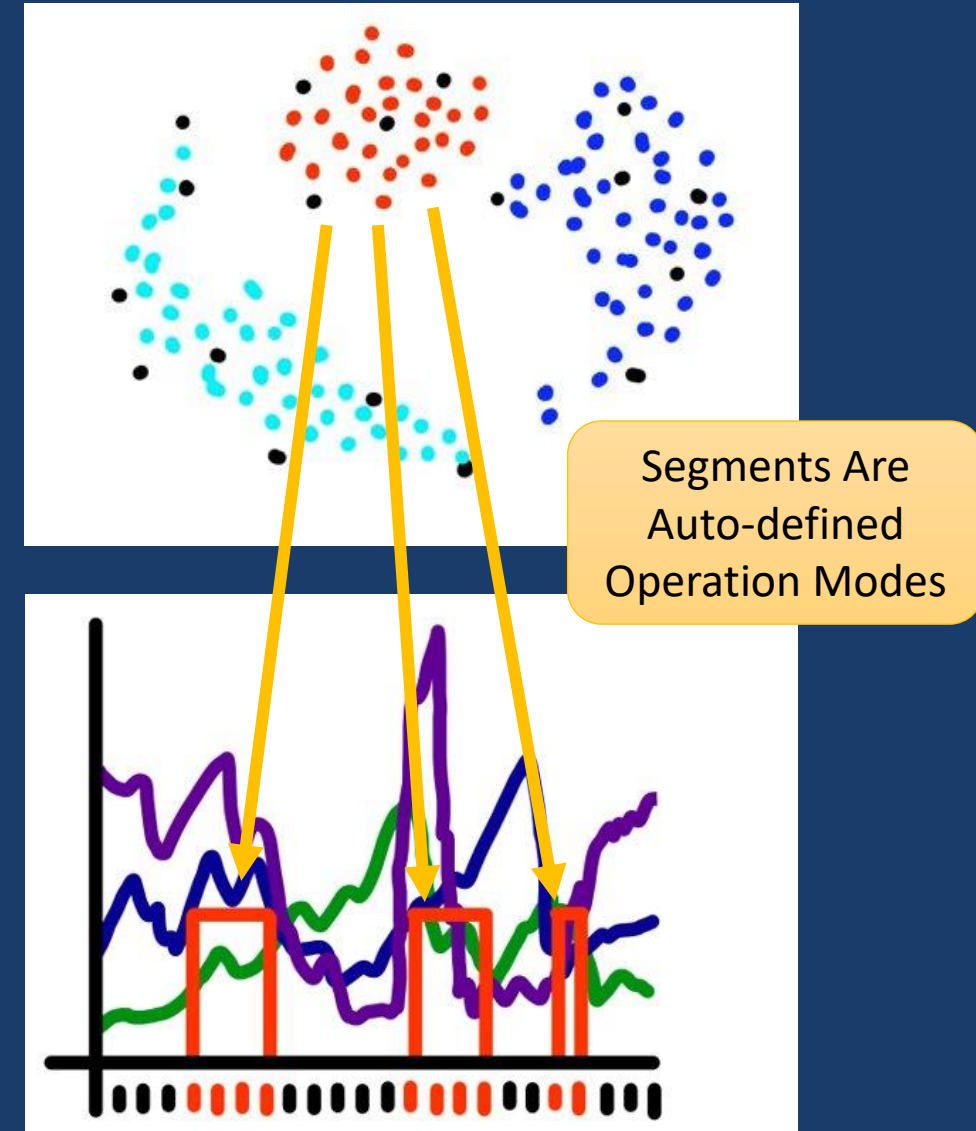


Regions of a
Defined
Operation Mode

Clustering

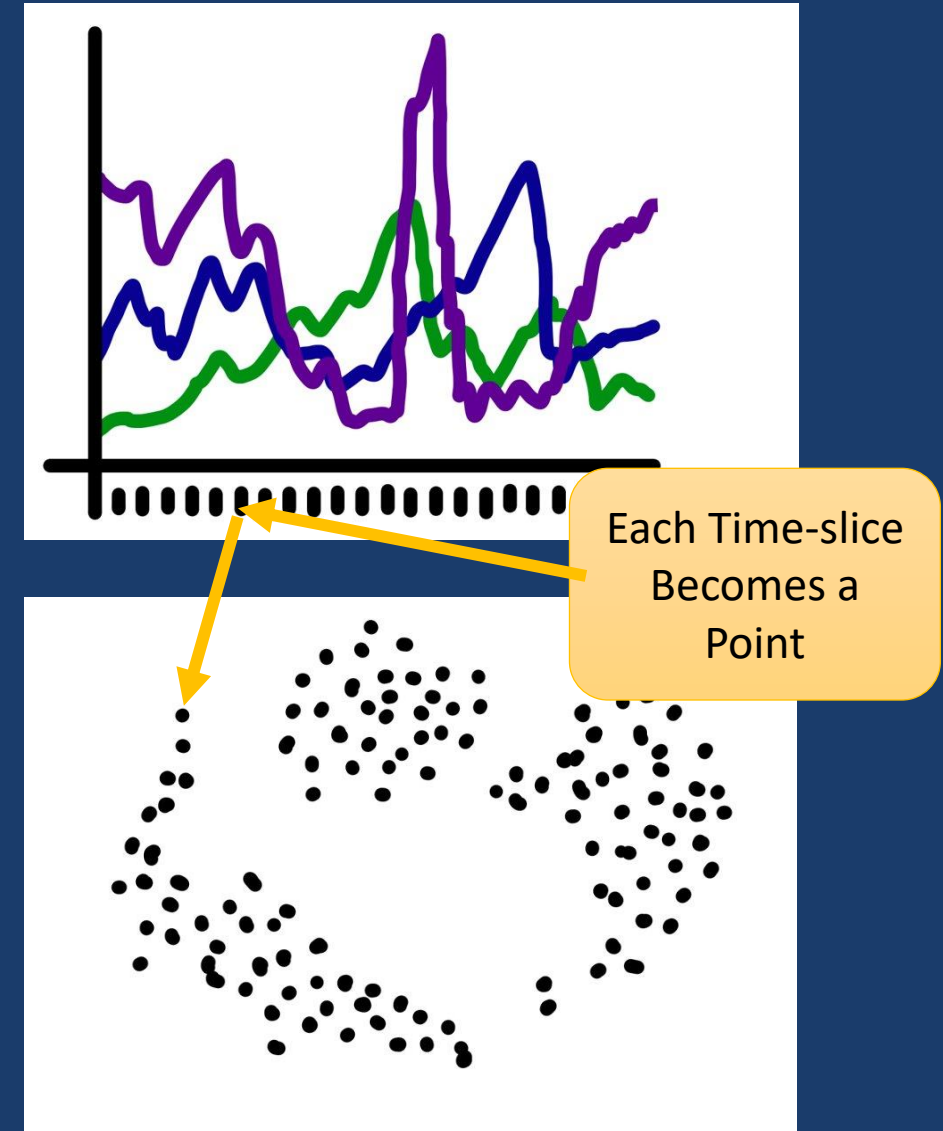
- Segments a dataset into subsets
 - Each subset is distinct from other subsets
 - Each segment can be 1-many timestamp windows
- Manual
 - Human Pattern Recognition can be used on dimensionally reduced data to pick clusters
- Automated
 - Industry standard algorithms like K-Means or DBSCAN (or HDBSCAN) can create segments of data items without human intervention

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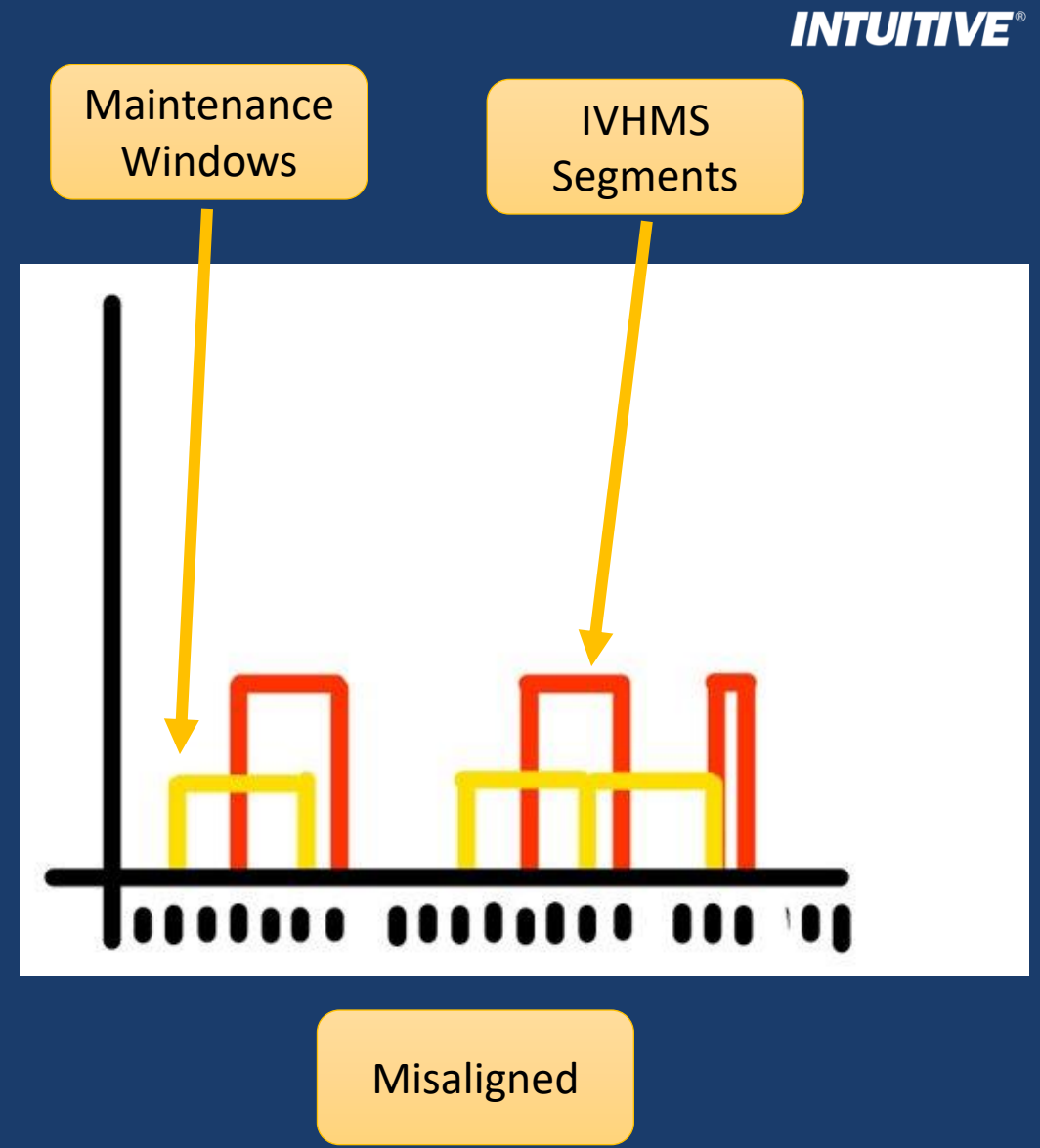
Dimensional Reduction

- Enhances continuous structure
 - Used for visualization as well as enhancing clustering algorithms
- Take a set of points in N dimensional space and (intelligently) project them into a lower $(N-k)$ dimensional space
- In example right, each timestamp is a particular point in the dimensionally reduced plot
- Industry standard algorithms include tSNE and Umap



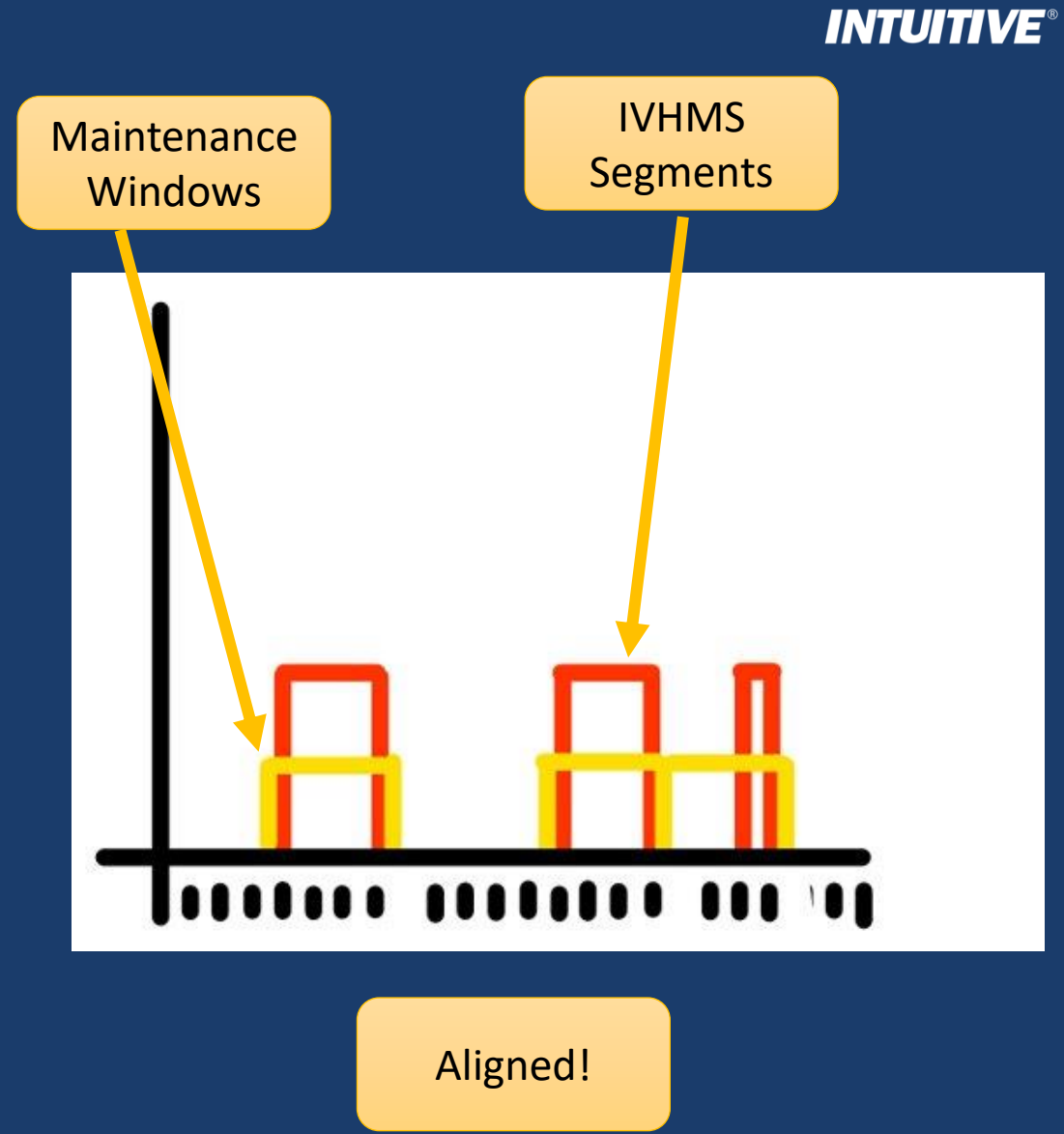
Correlation – Manual

- It is possible, if tedious, to manually compare all combinations of IVHMS segments with maintenance windows
- This is impractical due to the large number of possible maintenance windows and the large number of segments possible through tunable ML clustering



Correlation – Automated

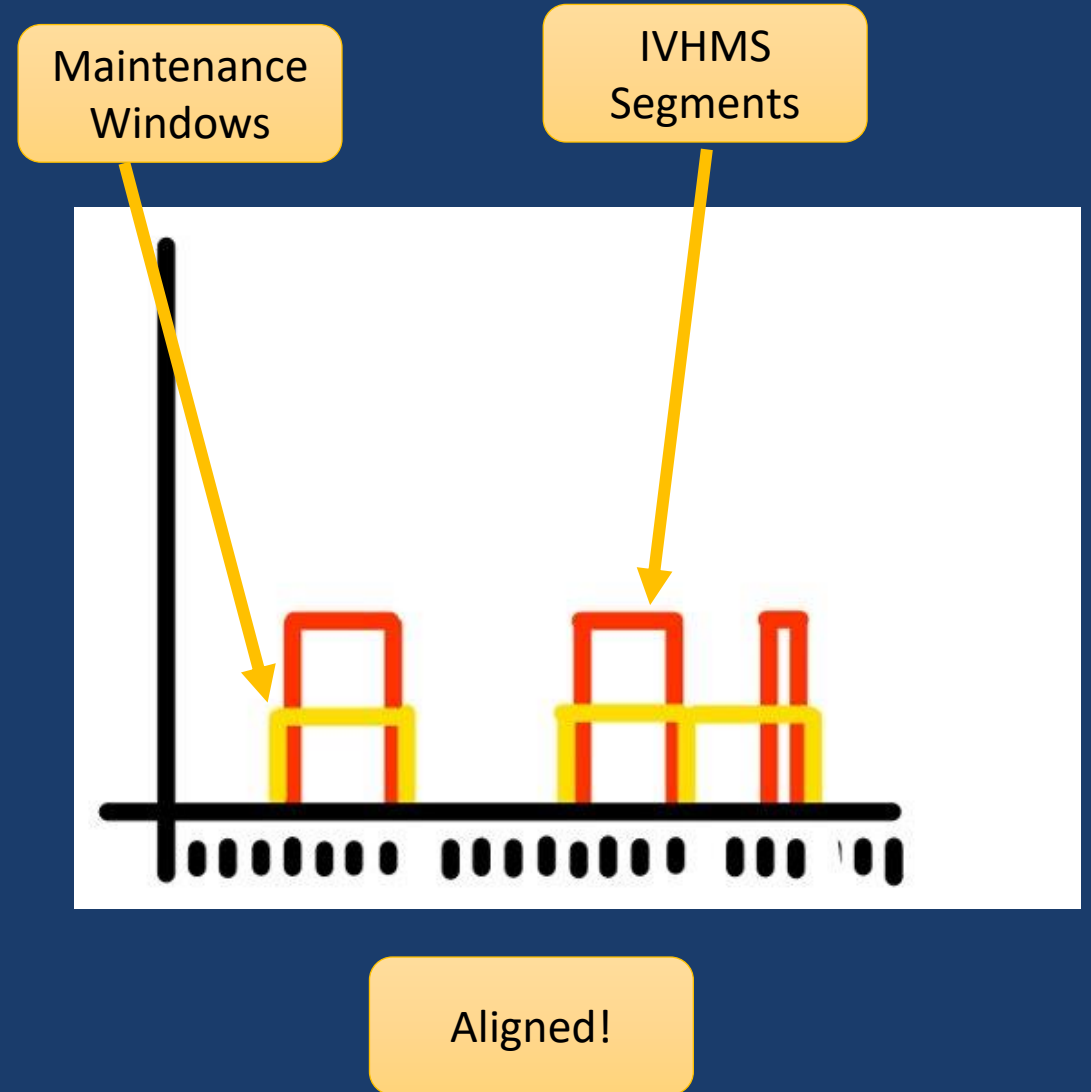
- The correlation task can be automated to leverage the power of computers
- Many millions of correlations can be evaluated in minutes, where a human would have taken weeks
- Automated correlation allows for creation of a greater number of candidate windows and segments



Correlation – Automated

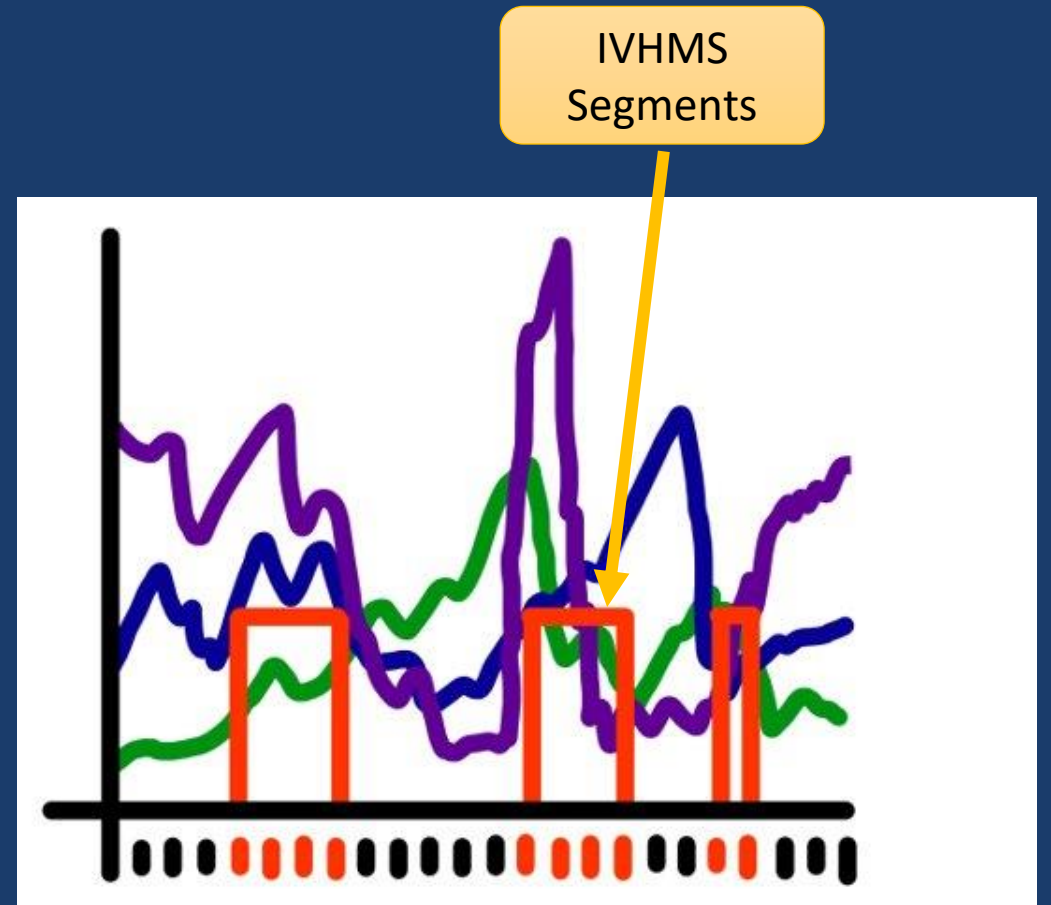
- Correlations are ranked according to a fitness value
- The highest 'fitness' values are the best correlations
- Currently using how much of a cluster segment is contained in a maintenance window (as a percentile) as the fitness value
 - IHVMS maintenance drivers can vary in duration, precedence is most important

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Identify Segment Differentiators

- What is driving this segment to separate from the rest of the IVHMS data?
- It is straightforward for manually defined regimes/segments
- Automatically created segments require some other analysis
- Algorithms exist for this type of analysis: PCA, Shapley Values, etc.



Indicator Verification

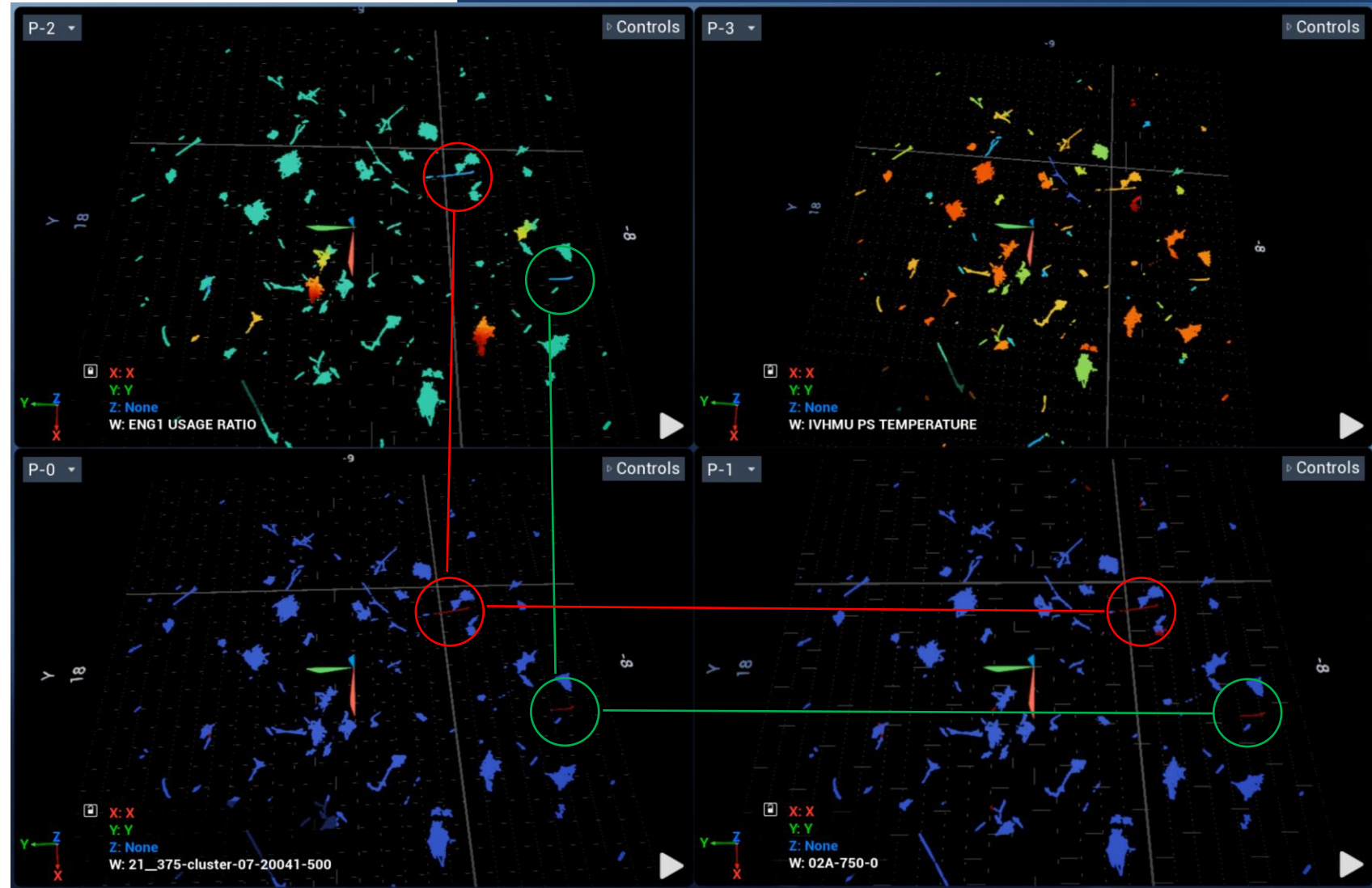
- Identify other airframes with an IVHMS segment similar to a set of indicators developed on a particular airframe
- Investigate whether those airframes with matching segments exhibit the same maintenance events in the same time windows
- Repeatability

Results

- 04A FG (Engine) events associated to:
 - Running in a low fuel mode
 - FUEL 1 PRESS LO
 - MAIN TANK 1 FUEL QTY
 - Running in a hot environment / mode
 - ENG 1 OIL TEMP
 - IVHMU PS TEMPERATURE
- 02A FG (Fuselage) events associated to:
 - High Yaw Torque
 - RUDDER PEDAL

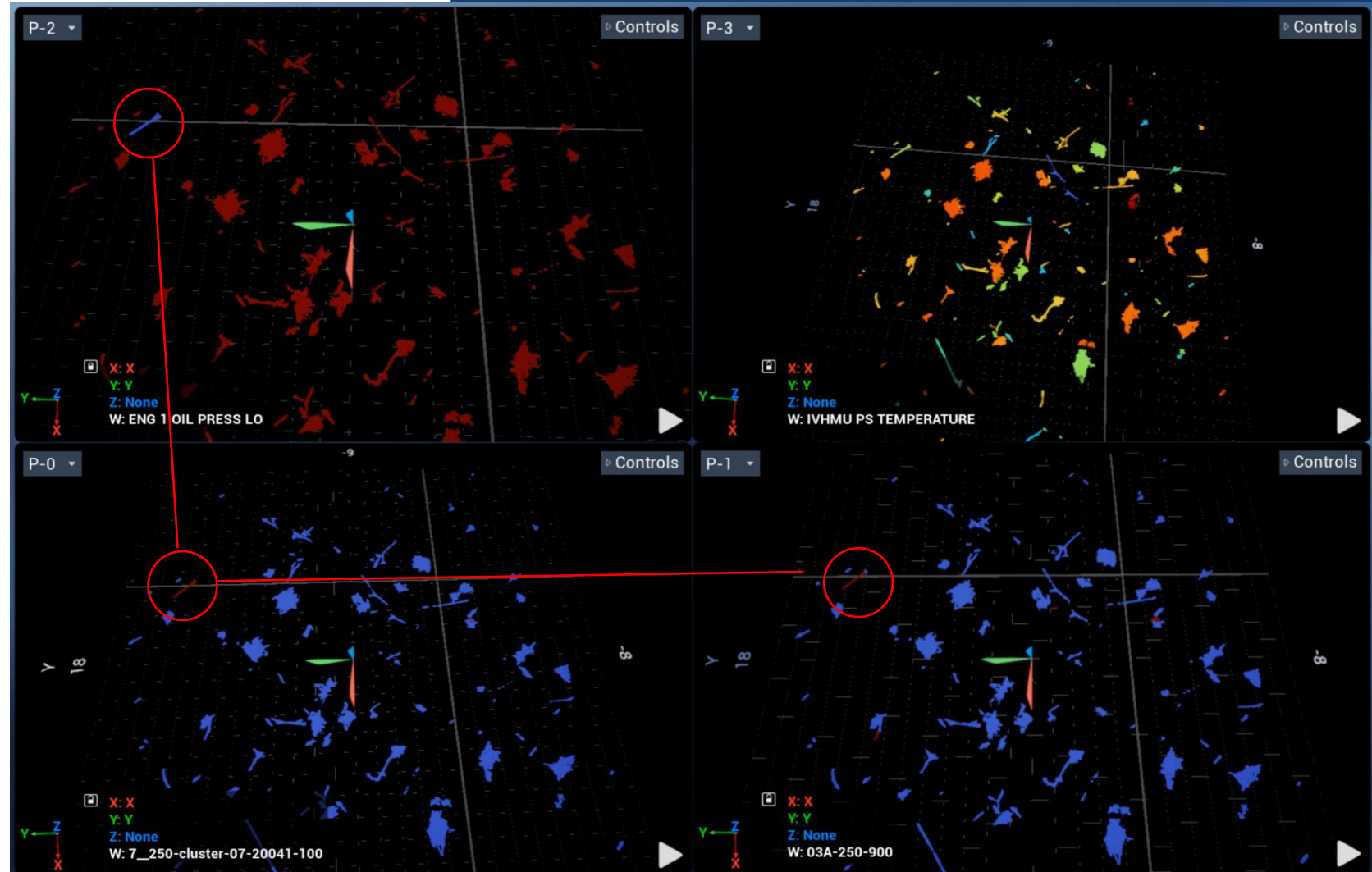
Exposing the Black Box I

- AI/ML solutions are often black boxes: their inner workings are hidden from the user
- Dimensional Reduction allows visualization of the large multivariate space



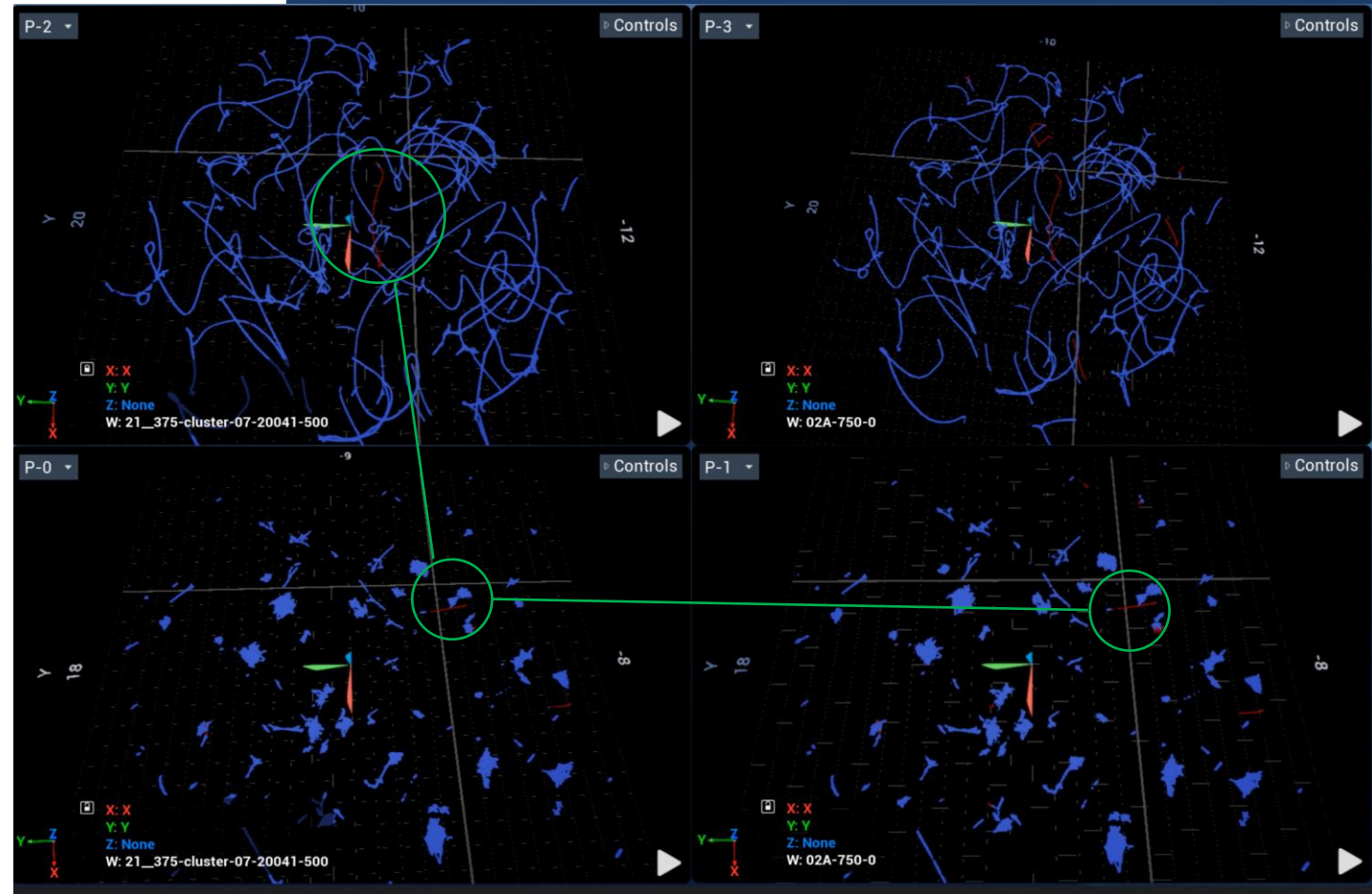
Exposing the Black Box II

- We can examine 'why' the AI is choosing particular clusters
- In example right, the ENG1 OIL PRESS LO flag was the primary driver for 250-cluster-100, which preceded an 03A event



Exposing the Black Box III

- Different hyper-parameters, as well as different preprocessing, reduce the data to different modes
- Each reduction will promote different structure in the clustering algorithm
- Some are more human-readable, while others are more AI-readable



Application I

- IVHMS/Maintenance relationships could be used to plan for maintenance costs and efforts before they occur
 - Squadrons can preorder parts for expected maintenance if they know they will be flying in a particular maintenance-causing regime
 - Costly inspections can be stepped forward into phase maintenance if the IVHMS data indicates a problem will occur in the near future



Application II

- This insight into increased maintenance costs can be executed at multiple levels
 - If an aircraft encounters an IVHMS indicator region, inspection and maintenance could be accelerated for that one aircraft
 - If a group knows they are going to execute missions in flight regimes that indicate maintenance, they can prepare in advance by preordering the maintenance parts and scheduling the maintenance that they know they will need.



Conclusion / What's Next

- We have shown a capability of automated finding of IVHMS/Maintenance relationships on the micro level
 - An extreme subset of both datasets
 - One aircraft for one year
 - Maintenance events separated only down to the functional group
- In the future, this can (and will) be applied to the entire datasets
 - All aircraft over all years
 - Separation of maintenance events to their full resolution