Fifth Annual Conference on

Disruptive, Innovative, and Emerging Technologies in the Nuclear Industry

Leveraging Knowledge Graphs for Condition-Based Maintenance in Nuclear Systems

Speaker: Callum Paul Manning

PhD Student, Strathclyde University

November 27th-29th

Toronto, Ontario, Canada

Callum Paul Manning *

Dr. Andrew Young *
Dr. Graeme West *
Prof. Stephen McArthur *

* University of Strathclyde, Glasgow, UK

Email : callum.manning.2017@uni.strath.ac.uk

Why knowledge graphs for nuclear systems?

What is a knowledge Graph

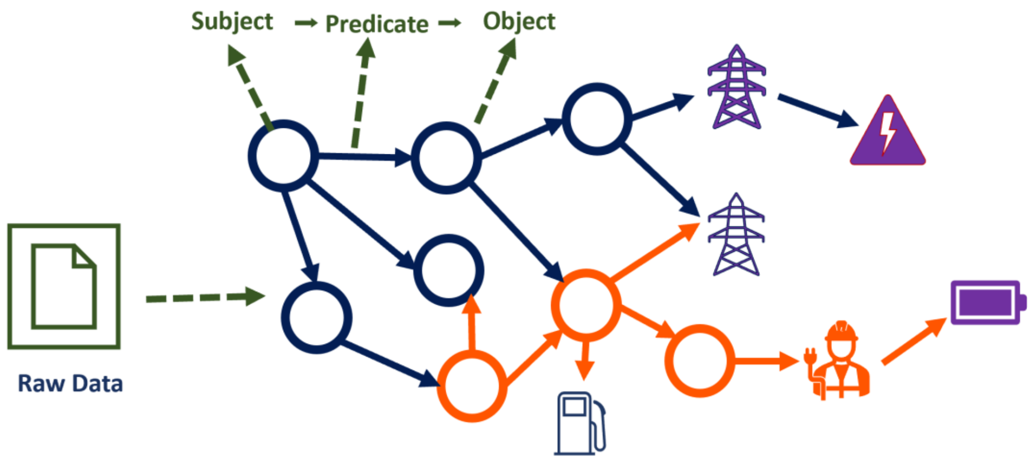
- A knowledge graph is a **data structure** that represents real-world entities and their relationships.
- It's like a network where **nodes are entities** and edges are connections between them.
- A **map of information**, where the connections reveal insights and patterns

Key Benefits

- **Natural Representation:** Mirrors how humans think and understand complex relationships.
- **Human-Centric:** Combines data with domain expertise, making information more accessible and understandable.
- **Data-Driven Insights:** Enables powerful data analysis and discovery of hidden connections.

Why they're key for critical Infrastructure

- Ongoing shift from **time based to condition-based** maintenance
- Need for **explainable** decision making
- Importance of **knowledge preservation in the long term**



- **By setting data into contextual relationships, we produce knowledge**
- **By applying or discerning some ontology of types we can develop and apply logical rules about data**

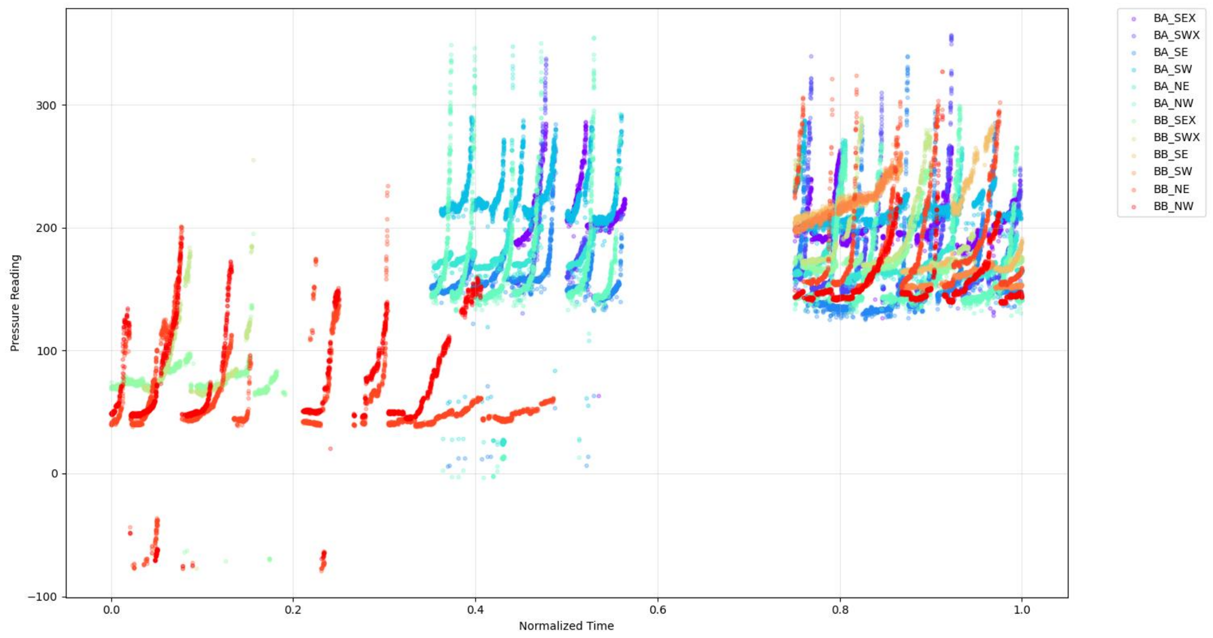
Real-world application & asset maintenance context

Real-World Application: Heavy water filters in CANDU reactors

- Currently relies on **time-based maintenance**.
- Filters degrade during use, not over time.
- Degradation is measured through **differential pressure**, which can be monitored using existing sensors.

Asset maintenance overview

- **Challenges:**
  - Misreading's in data and data gaps from system outages.
  - Subjectivity in asset lifespan assessments.
  - Filters often replaced early or surpassing expected pressure limits.
- **Data Issues:**
- Lack of segmented data for individual asset life.
- Hard-coded decisions limit adaptability.



Raw data from asset

Differential pressure across filter, showcasing challenge in segmenting and identifying individual filter lives

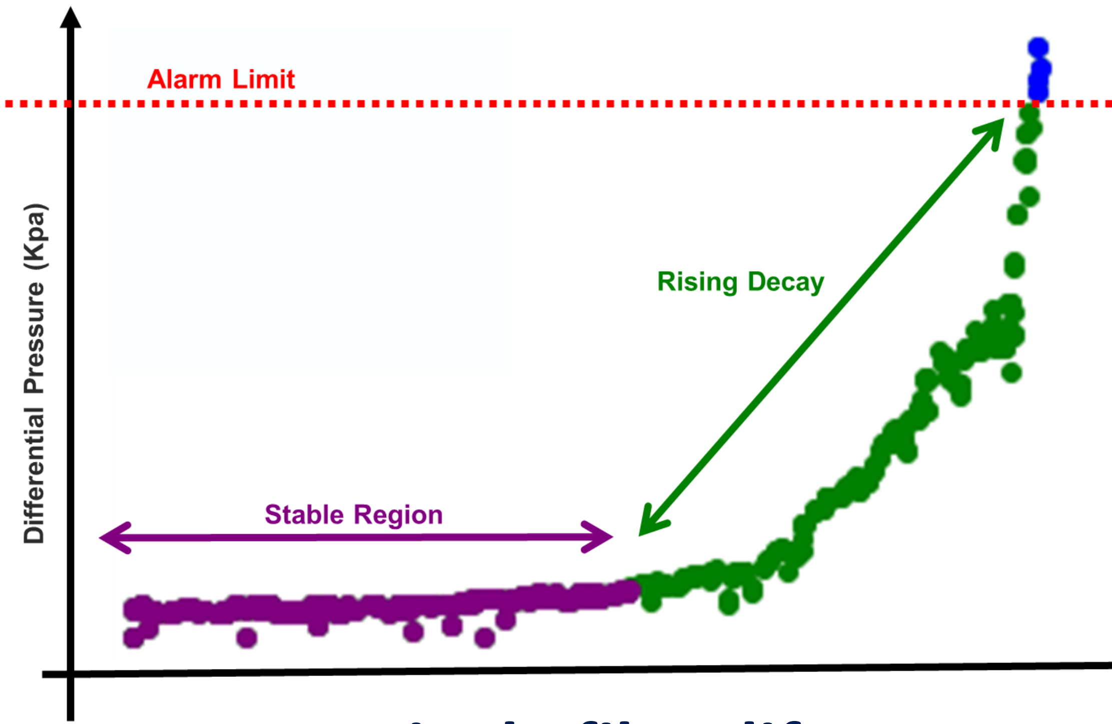
Maintenance strategies & knowledge approaches

Maintenance Strategies

- **Failure-Based Maintenance:** Corrective action after failure.
- **Planned Preventative Maintenance:** Scheduled actions at fixed intervals.
- **Condition-Based Maintenance:** Real-time monitoring and predictive analytics.
  - **Intelligent Condition Monitoring:** Leveraging sensor data, predictive modelling, and domain expertise.

Maintenance Approach Using Knowledge Graphs

- **Expert Knowledge Capture:** Encodes engineering insights for decision-making.
- **Data Integration:** Combines sensor data, historical records, and expert analysis.
- **Decision Support:** Provides actionable insights, reduces subjectivity, and enhances flexibility



A single filter life

Differential pressure across the lifespan of a single filter falls into broadly two stages a stable region, then an exponential degradation, these degrade with use

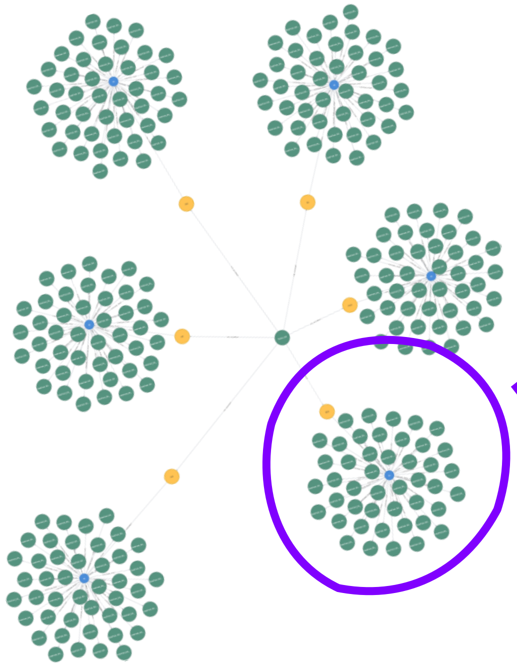
Knowledge-driven insights for filter life optimization

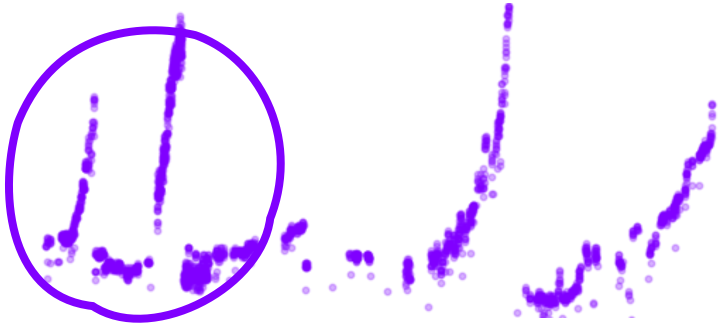
Leveraging Knowledge Graphs

- Make engineering expertise implementation-agnostic.
- Model and predict filter degradation and **remaining useful life**.
- Tailor maintenance actions using comprehensive analysis of sensor data and expert insights.

Expected Benefits

- Improved reliability through precise maintenance.
- Reduced over-maintenance and failures.
- Enhanced ability to adapt strategies to evolving operational conditions



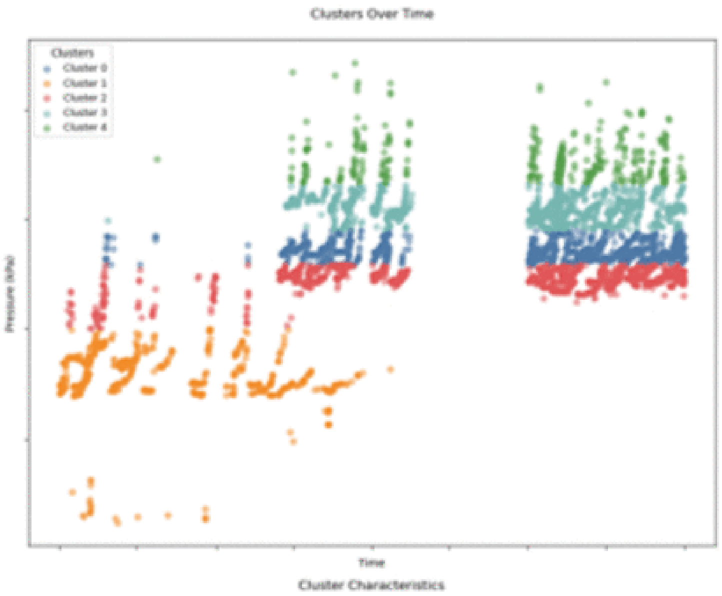


Temporal data in the graph

The graph holds time series data in relation to station and filter

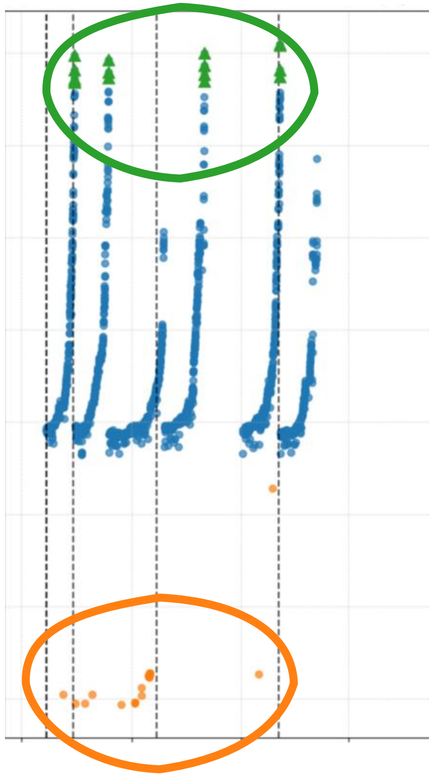
Clustering and path traversing

Can use clustering to find how pressure values relate across stations and quadrants



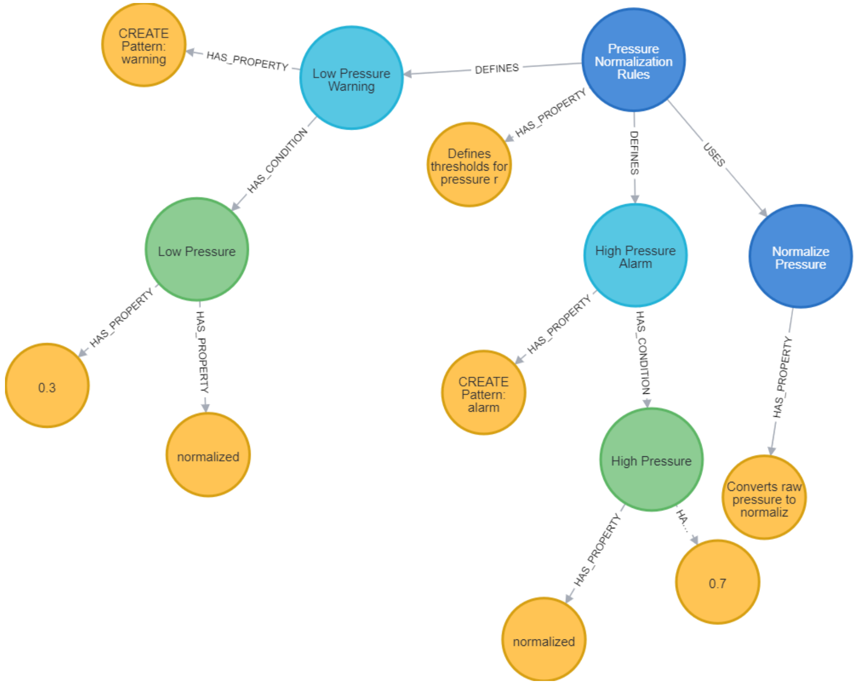
Capturing expert knowledge

- **Knowledge Elicitation Process**
  - Expertise is gathered from domain experts (e.g., thresholds for normalized pressure or operational rules in reactors). Interviews or literature help define key entities, relationships, and constraints.
- **Converting Expertise to Graph Structure**
  - Expert knowledge is represented as nodes (e.g., DomainExpertise, Rule, DataPoint), attributes (e.g., thresholds, conditions), and relationships (e.g., TRIGGERED, RESULTED_IN).
- **Types of Captured Knowledge**
  - Includes domain concepts (e.g., "normal pressure range"), rules (e.g., "pressure > 0.7 triggers alarm"), and functions (e.g., data normalization, classification).
- **Validation Mechanisms**
  - Patterns in data are tested against rules (Rule nodes) to validate accuracy, ensuring that alarms or classifications align with domain knowledge.



Extract of plot showing low- and high-pressure extremes

Datapoints are marked and annotated

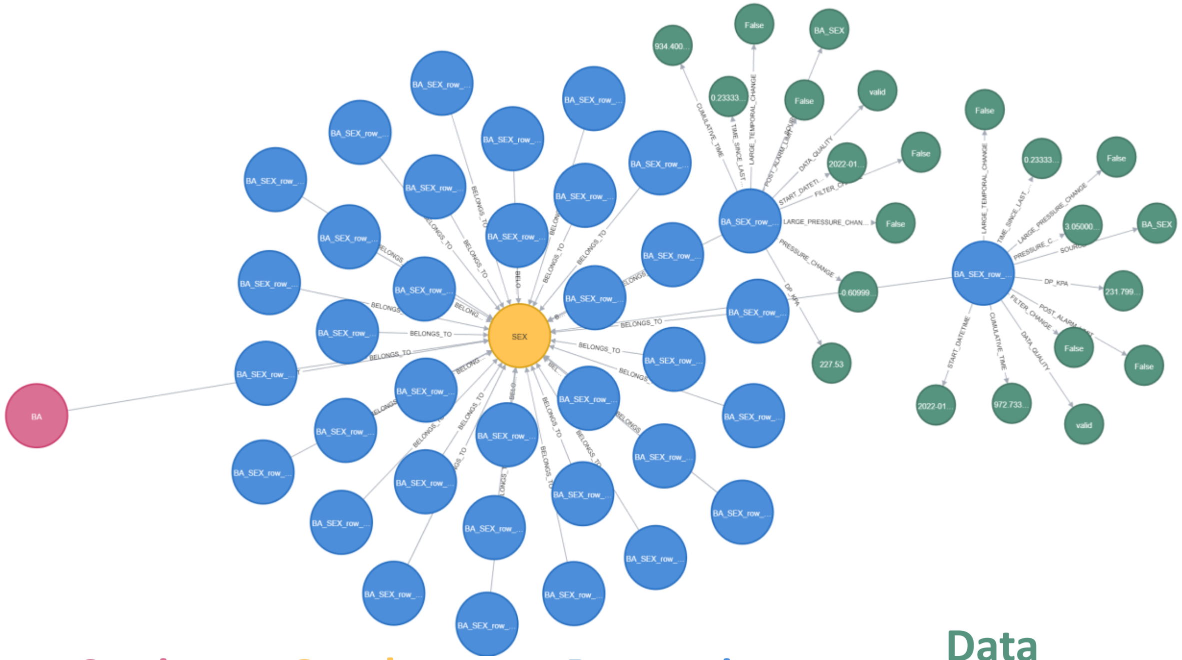


Knowledge Graph Capturing logic around annotation

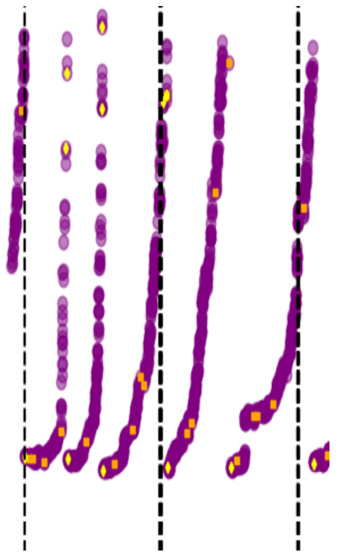
Knowledge Graph doesn't just capture data but the decision making structure as well

Dynamic functionality

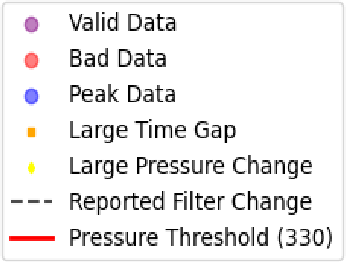
- **Nodes hold references to**
  - data
  - functions
  - rules
  - subgraphs
- These nodes hold a record of data processing
  - **Explainability** through traceability
- **Functions** pull information from the nodes within the graph produce new nodes
- **Rules** evaluated logical conditions within the graph, allow graph modification
- In this case rules within the graph allow us to mark up the existing data based on queries and functions.



Station Quadrant Data point Data annotation



Annotated Plot

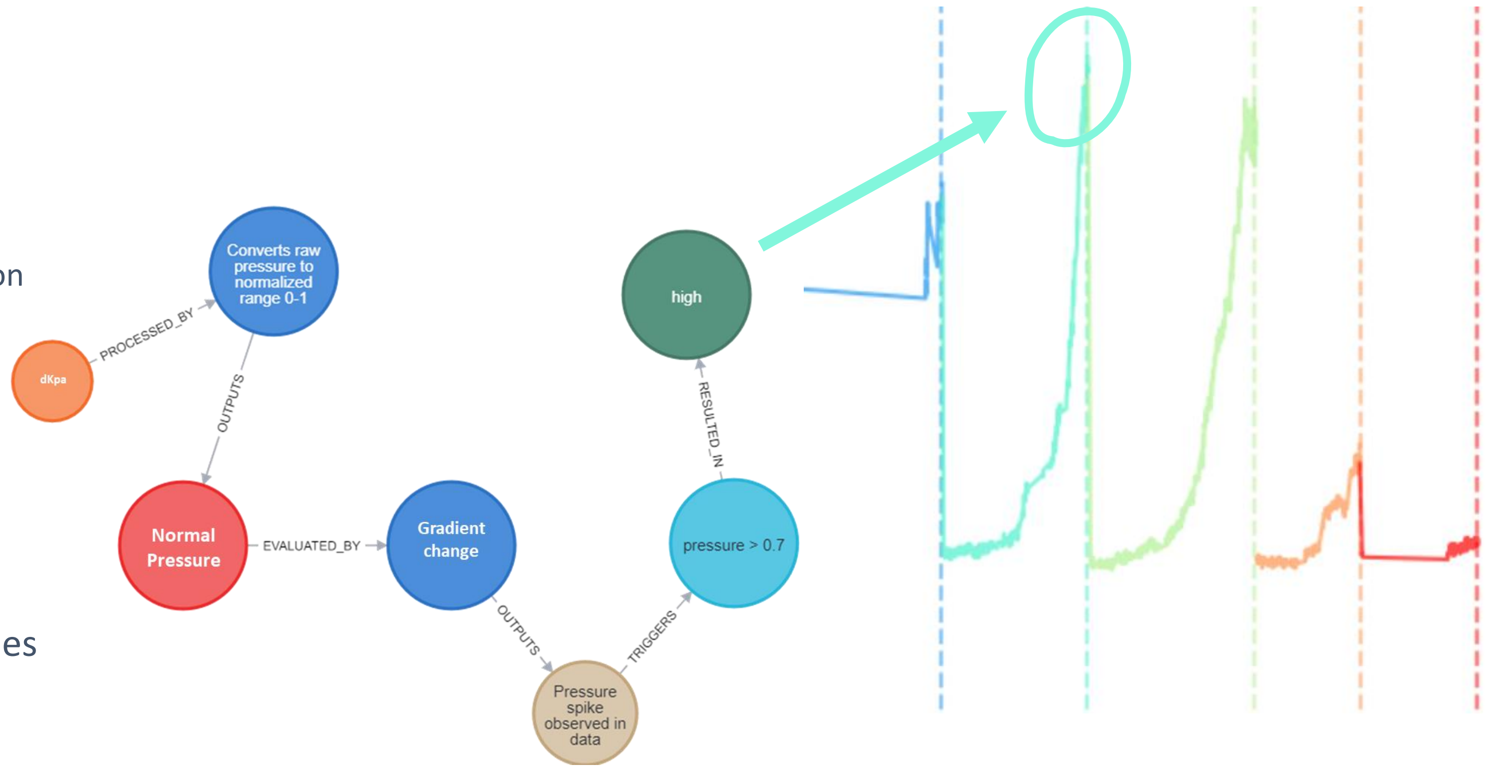


Analysis then annotation

We query the graph to identify key features and traits and annotate nodes with descriptions of those features

Explainable data pipelines

- Pipeline structure
  - Data flows through a chain of functions
  - In this example :
    - Normalization -> Spike detection -> Rule evaluation
- Traceability
  - Each step is represented by nodes and relationships
  - Queryable database of decisions
- Connection to domain concepts
  - Rule nodes link back to domain knowledge, rules are aligned with experts in the field.
- Real-time explanations
  - Clear paths for explaining decisions can be traced through graph

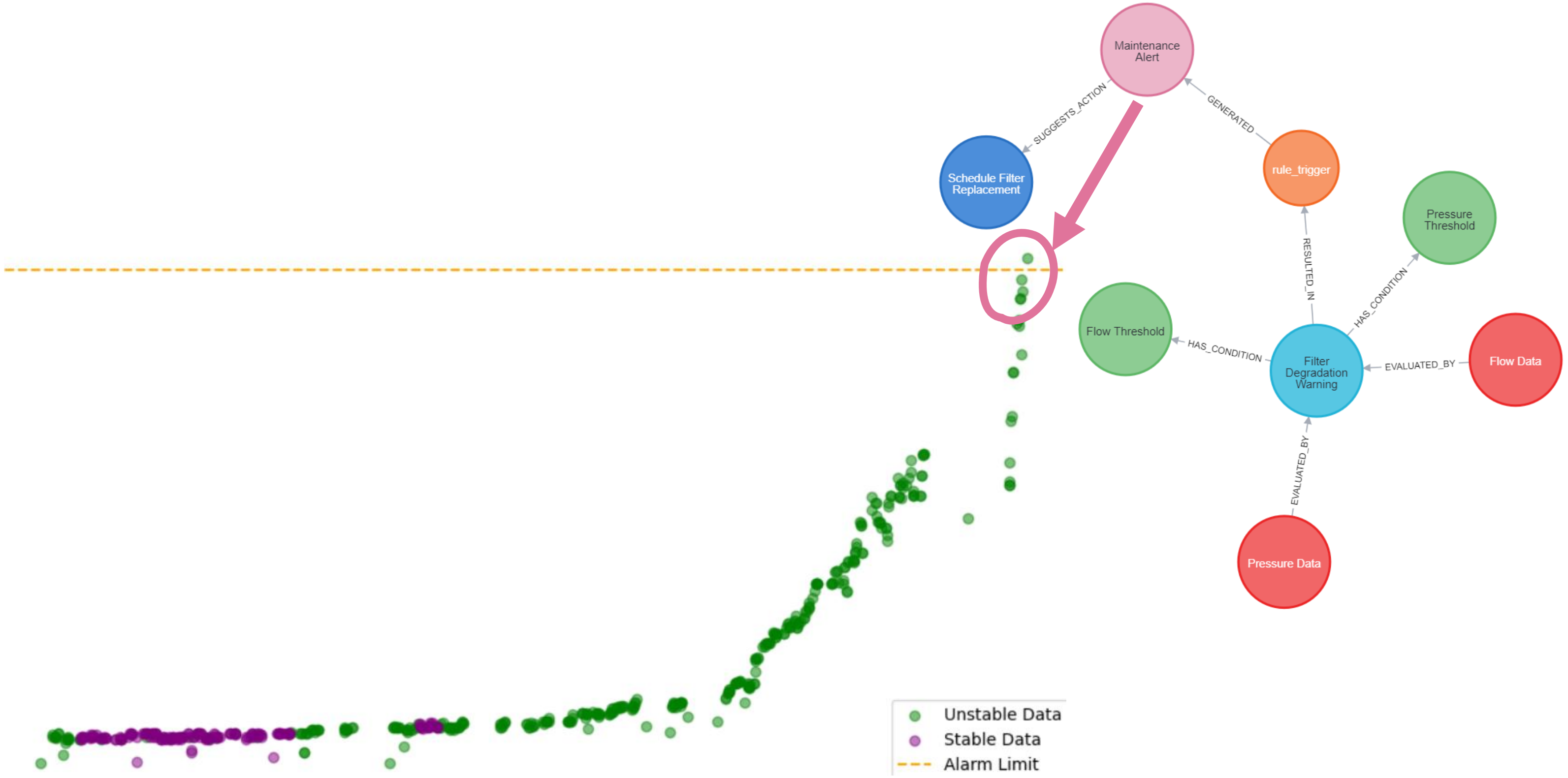


Explainability through traceability

We can trace explainability through the graph. The reason some point is marked as the end of the filter is based on a record of functions and logic

Integrating reasoning into maintenance

- **Knowledge is used to find insights**
  - Generates Clear recommendations linked directly to detected issues
  - Enables operators to focus on prioritized maintenance tasks
- **Dynamic rule management**
  - Rules can be adjusted dynamically within the system allowing flexibility
  - Complex multi-condition rules can model real world problems more effectively
- **Domain-ppecific adaptability**
  - The system supports specialized domains (e.g., nuclear reactors) by encoding expert knowledge into rules and thresholds.
  - Easily scalable for other industries with complex monitoring needs.



A single filter life

Finally we have isolated the single filter life, using the graph structure we can trace decisions from inception to finally raising the alarm

Benefits for the nuclear sector

Enhanced safety through better monitoring

- Continuous data collection and real-time anomaly detection reduce the risk of unexpected failures.
- Complex rules (e.g., pressure and temperature thresholds) enable early identification of potential issues.
- Alerts and insights support quick, informed decision-making during critical situations

Improved maintenance scheduling

- Proactive identification of asset degradation allows maintenance to be planned ahead of time.
- Reduces downtime by ensuring components are replaced or repaired only when necessary.
- Historical data and trends support optimization of maintenance schedules for efficiency and cost savings

Knowledge preservation

- Expert rules and thresholds are encoded in the graph, ensuring they are preserved even as staff changes occur.
- The graph structure enables training and onboarding of new personnel, providing them with a clear view of decision pathways.
- Historical records of events and insights create a valuable resource for continuous improvement and regulatory compliance.

Future potential

NeuroSymbolic integration	Graph learning elements	Guiding model building
• Combine symbolic reasoning from the knowledge graph with machine learning to enhance interpretability and adaptability. • Use the graph to encode explicit domain knowledge (e.g., rules, thresholds) alongside learned patterns from neural networks. • Facilitate hybrid decision-making where rules guide the machine learning process and ML models handle complex, non-linear patterns	• Leverage the graph structure for advanced learning tasks like Graph Neural Networks (GNNs). • Predict asset degradation trends by learning directly from graph-structured data. • Use relationships (e.g., CONTAINS, TRIGGERS, RESULTED_IN) to understand system-wide impacts and interactions	• Input Design: Use graph relationships to define features and inputs for ML models. • Example: Incorporate "normalized pressure" and "temperature" thresholds as constraints for learning algorithms. • Model Interpretation: Use graph pathways to explain how machine learning models arrive at predictions. • Feedback Integration: Dynamically adjust graph rules and structures based on ML outputs to improve accuracy over time.

Thank you!

5 minutes for Q+A