Knowledge Graphs for the use of capturing engineering expertise in industrial settings

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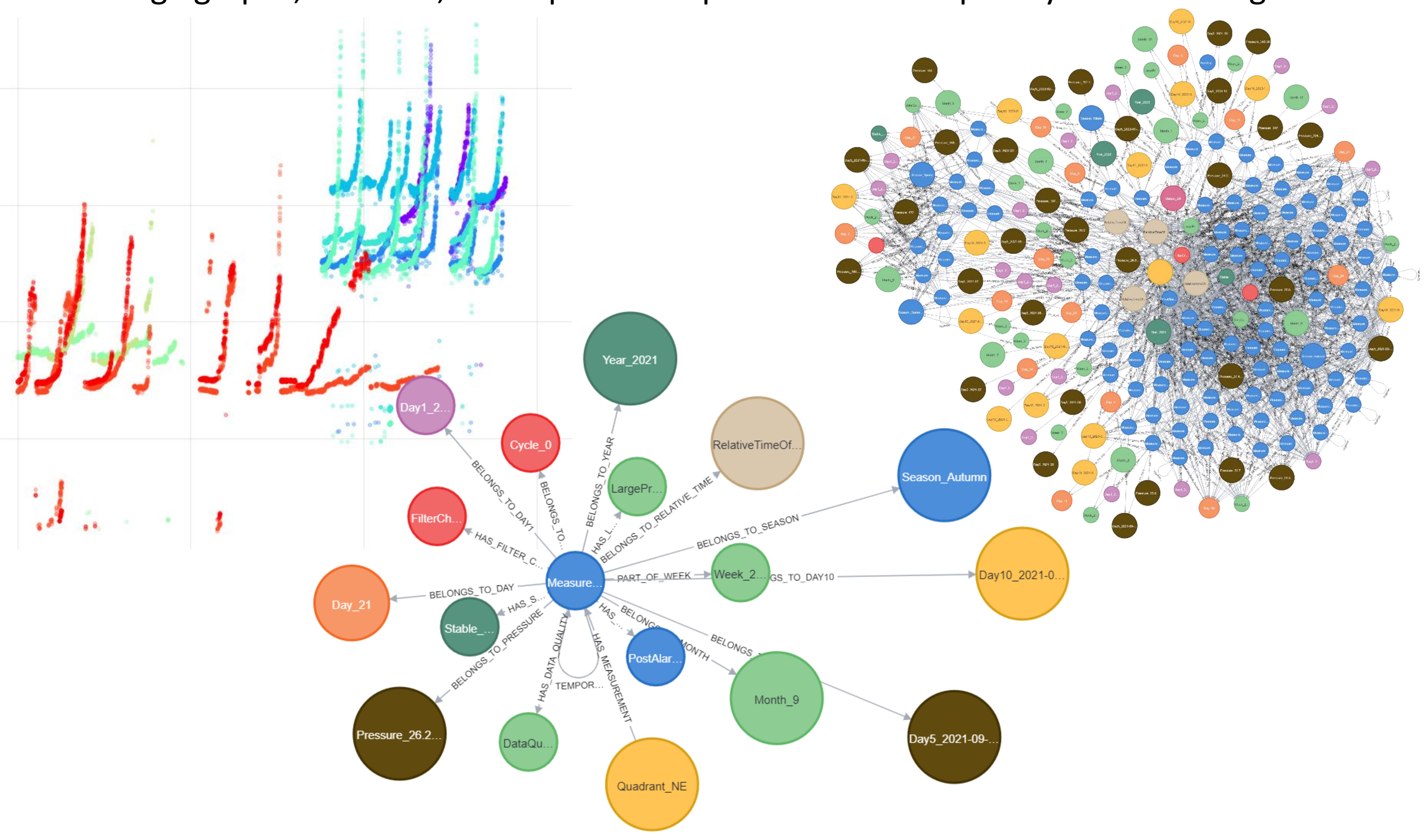
Introduction

- Knowledge graphs provide a reusable, explainable platform for encoding engineering knowledge.
- While traditional approaches to knowledge management in engineering often result in expertise becoming locked in specific implementations or static datasets, knowledge graphs offer a more flexible and powerful alternative.
- Knowledge graphs allow information to be coded in a way that is not just more semantically legible but richer in contextual information.
- This work seeks to leverage knowledge graphs to capture knowledge in an implementation agnostic format, capture data pipelines in the same format as the knowledge itself, provide traceable explanations for engineering decisions.

Beyond Traditional Data Representation

- The two figure below effectively store the same information
- When an engineer studies the time series data, they see more than just individual data points. They recognize patterns - peaks, troughs, and trends - that carry real-world significance. Traditional tabular data storage loses this rich contextual understanding. Knowledge graphs, however, can capture and preserve this deeper layer of meaning.



A single datapoint within the graph contains much more embedded information

a) Top Left – Time Series Data, (b) Top Right – Full Knowledge Graph
(c) Single data point in graph

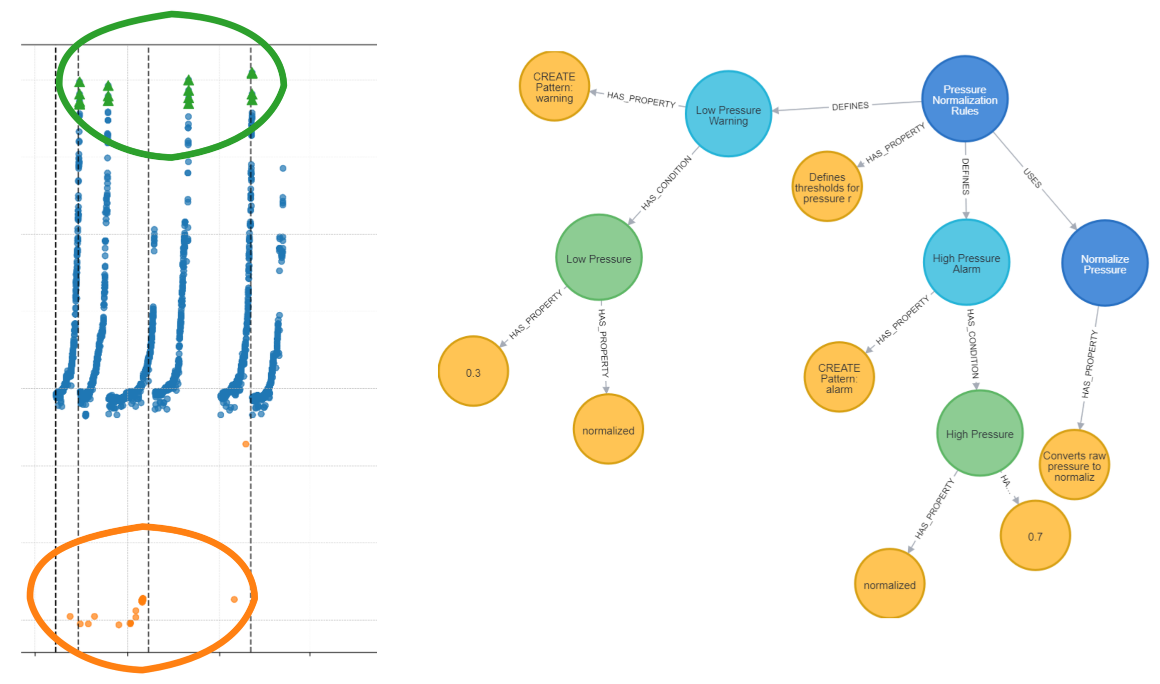
Case Study: Condition-Based Maintenance

- **Replacement of an asset in critical infrastructure – Heavy Water Filters**
  - An inexpensive asset but one which needs frequently replaced and which ideally must never run to failure.
  - Current method is a time-based replacement strategy, but degradation of this asset is 'use-based'.
  - Filter degradation measured through differential pressure monitoring
  - Despite being inexpensive it is still obviously safety critical
  - Only 8 documented cases of complete filter lifecycle data
- **Data Quality Issues:**
  - Frequent misreading and system outage gaps in sensor data
  - Subjective variations in asset lifespan assessments
  - Inconsistent replacement timing (both premature and delayed)Lack of properly segmented individual asset lifecycle data
  - Inflexible hard-coded decision processes
- **Comprehensive Data Integration**
  - Integration of all available sensor data into the knowledge graph structure
  - Preservation of engineering context and relationships
  - Capture of expert knowledge about degradation patterns
  - Incorporation of operational context and environmental factors
- **Analysis through Embeddings**
  - Translation of time-series data into graph-based representations
  - Use of embedding techniques to identify similar degradation patterns
  - Pattern matching across partial and complete lifecycle data
  - Integration of contextual factors in similarity calculations
- **Predictive Modelling Enhancement**
  - Development of shorter-term predictions using embedded pattern matching
  - Combination of similar historical patterns to project degradation trends
  - Real-time updating of predictions with new sensor data
  - Uncertainty quantification in predictions
- **Explainability through examination of clustered relationships**

Knowledge Graphs as a Solution

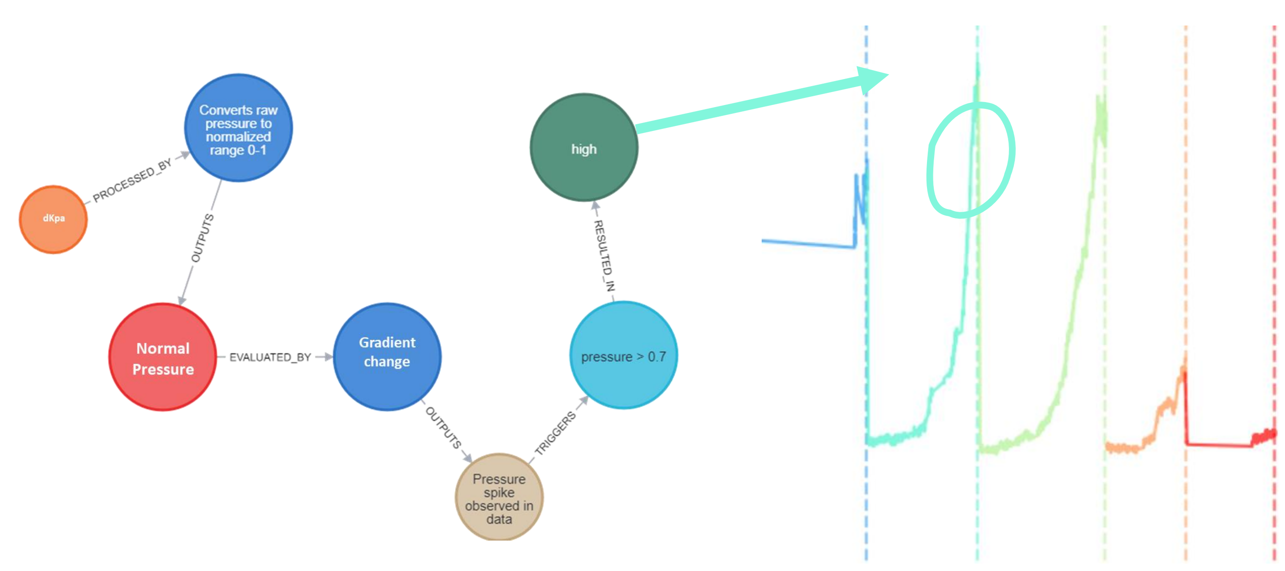
Knowledge graphs offer several key capabilities that make them ideal for engineering applications:

- 1. Data Organization and Context
  - Can sort and structure large amounts of engineering data
  - Preserve relationships and context between different data elements
  - Enable flexible querying and exploration of complex datasets
- 2. Pipeline and Reasoning Integration
  - Describe and manage data pipelines
  - Integrate reasoning tools directly into the knowledge structure
  - Enable automated validation and common sense checking
- 3. Sparse Data Enhancement
  - Transform sparse data problems into partially labeled problems
  - Leverage existing knowledge to enhance limited datasets
  - Enable transfer learning across similar engineering scenarios



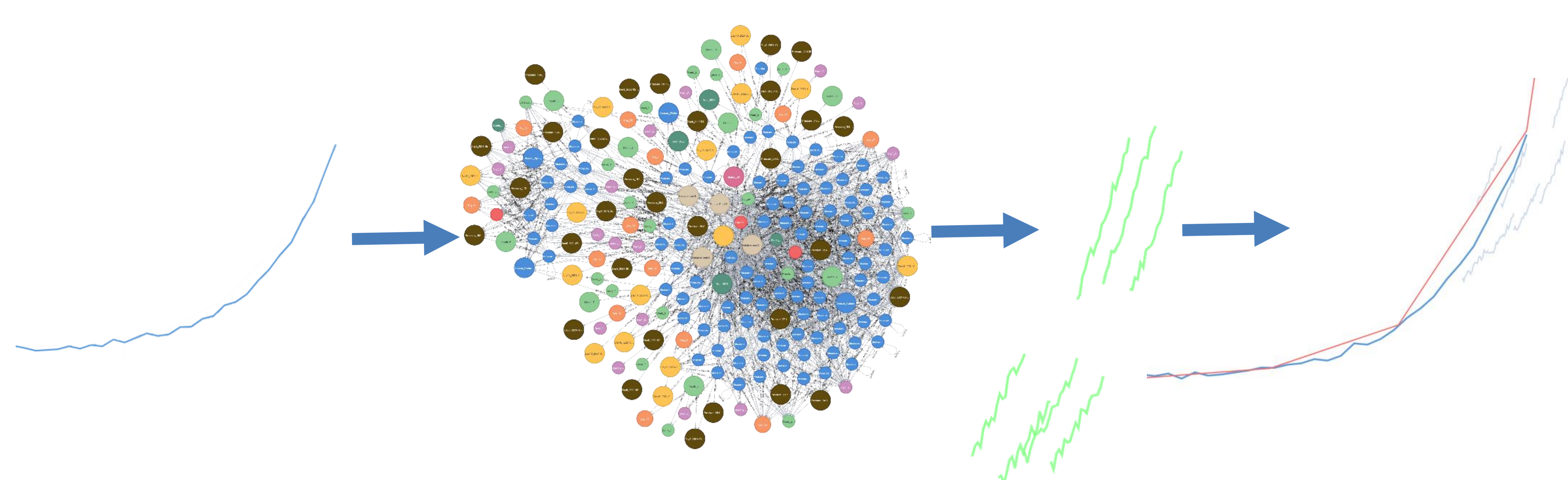
Knowledge Graph Capturing logic around data annotation and context

Datapoints are marked and annotated, according to logic described in graph



Pipeline and reasoning integration

The data pipeline and logic can be captured in the graph



NeuroSymbolic Sparse Data enhancement

We take an ordinary time series plot, embed it into our graph, cluster to find it's nearest neighbours, use these to predict the degradation of the asset.

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