



Knowledge-guided Automation for Integrity Management of Aging Pipelines (KAI-MAP) for Hydrogen Transport

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Outline

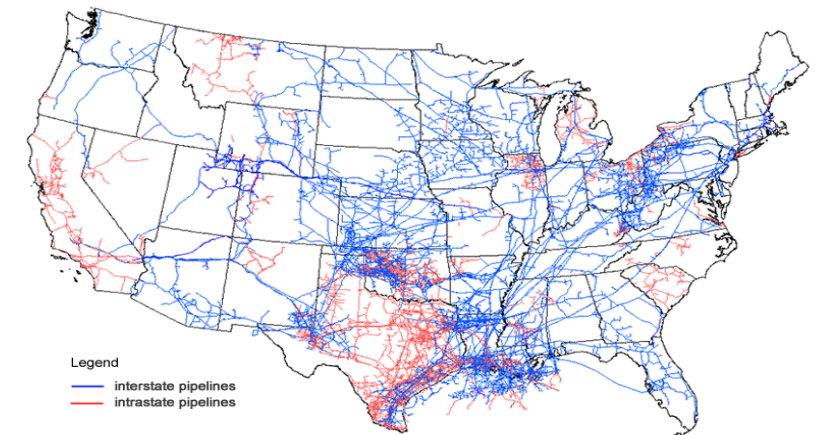
- **Background and objectives**
- **Statement of work**
 - Proposed research tasks
 - Program work schedule
 - External collaborations
- **Conclusions and Future Work**

Hydrogen Transportation using Existing natural gas pipeline

- Hydrogen can be transported in three ways:
 - pure hydrogen through dedicated pipeline
 - pure hydrogen through existing natural gas (NG) pipeline
 - mixture of hydrogen and NG through existing infrastructure
- Transporting hydrogen requires modifications to:
 - valves
 - meters
 - compressors, and others
- Several advantages in using existing infrastructure such as:
 - wider geographic reach
 - high capacity
 - interconnected

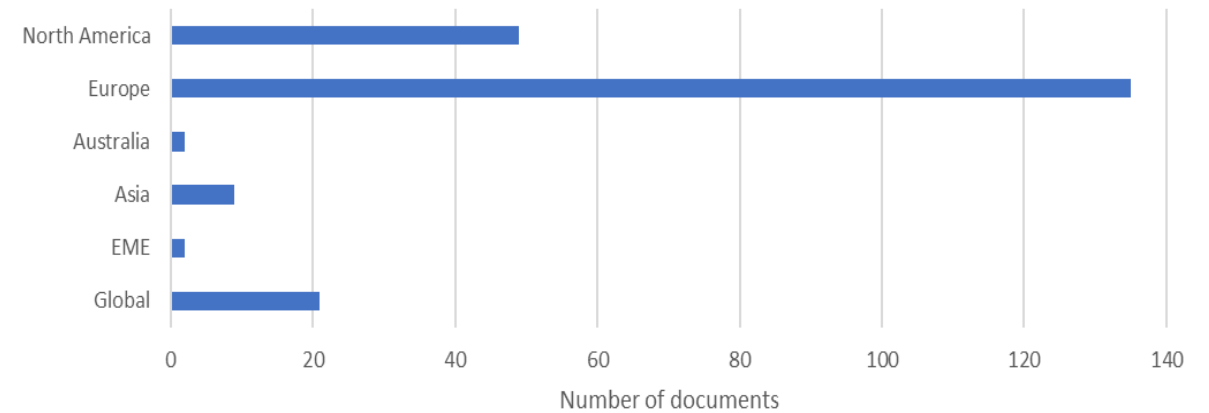
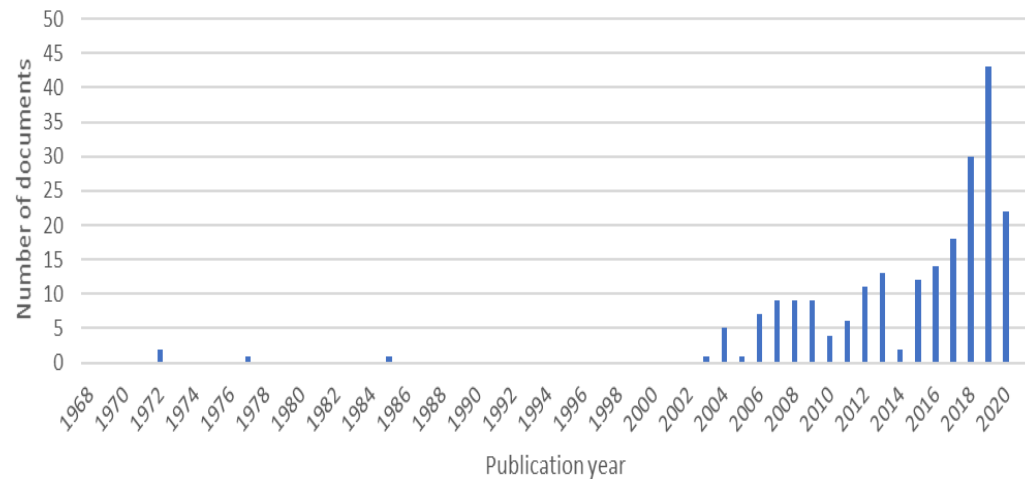


Map of U.S. interstate and intrastate natural gas pipelines



Source: U.S. Energy Information Administration, *About U.S. Natural Gas Pipelines*

Current status and motivation



- Rapid growth of related study in recent two decades
- US is relatively behind the worldwide infrastructure research and operational demonstration of hydrogen transport
- Quickly catch up via automatically knowledge discovery and information fusion



Identified critical gaps and objectives

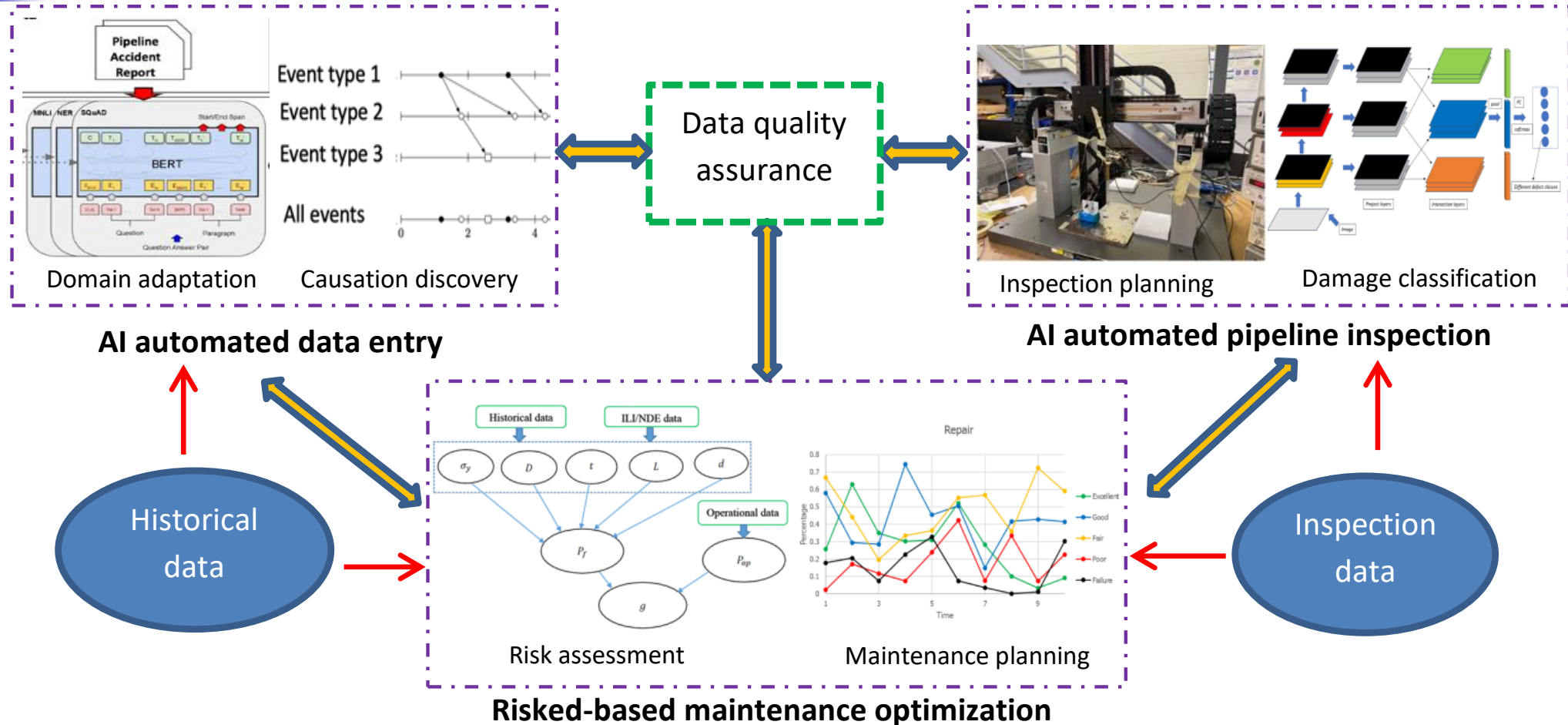
Research Question 1: How to include additional critical factors affecting the pipeline infrastructure for hydrogen transport, such as hydrogen embrittlement for corrosion and reduced fatigue performance of heated affected zone (HAZ)?

Research Question 2: US is behind the worldwide hydrogen transport research (see Fig. 1). How to catch up the progress by mapping worldwide projects and references?

Research Question 3: Adverse effect of hydrogen will deteriorate materials. How to develop new NDE capabilities for crack detection in situ and optimize the inspection frequencies to accommodate this new challenge?

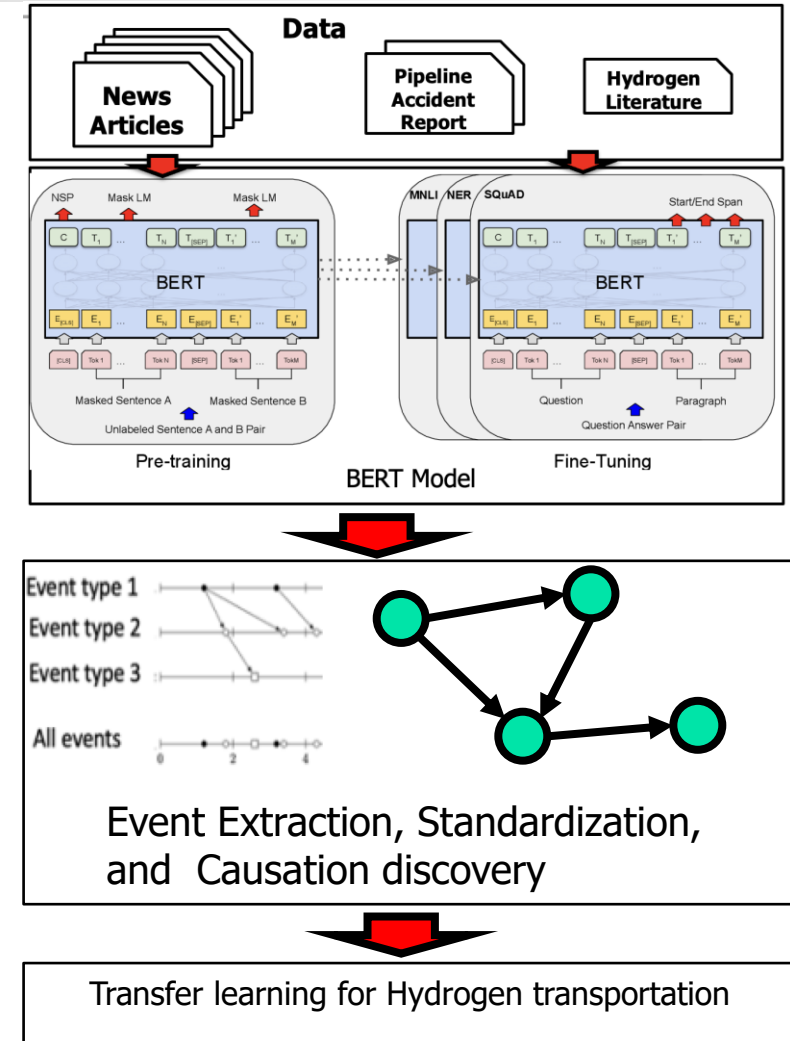
Research Question 4: Existing pipeline infrastructure has the potential to contribute to the emerging fuels. How to automate the knowledge transfer from past experiences to the new application of hydrogen transportation?

Proposed tasks



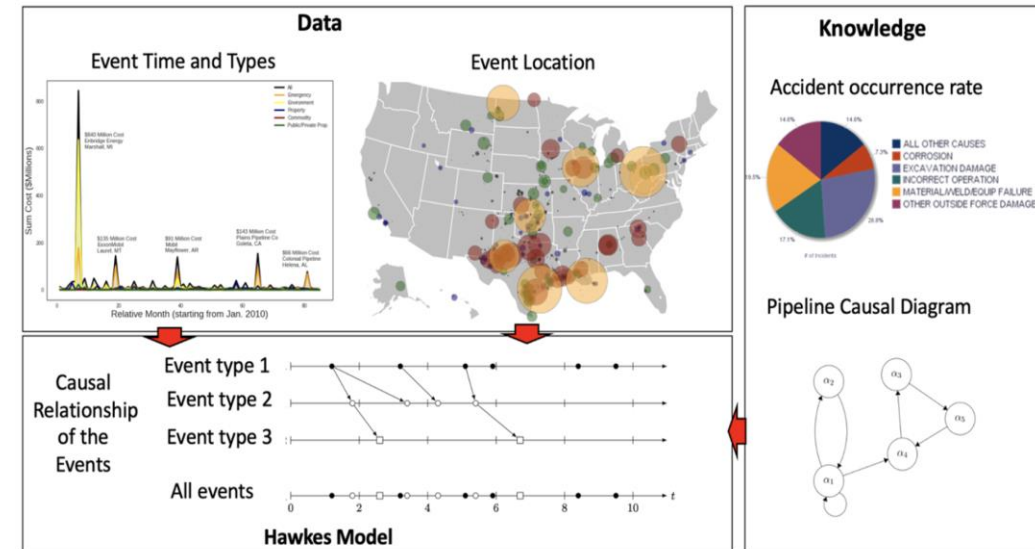
Accident Report Analysis and Event Extraction

- **Goal:** Read from the existing NTSB pipeline accident report to understand the causal relationship between events and accidents. Transfer knowledge from historic accidents to hydrogen transportation
- Proposed a three-step approach
 - Step 1: Automatic translate the accident report to accident events
 - Step 2: Causal Discovery of Accident Events (Understand the causal relationship between events)
 - Step 3: Use transfer learning to hydrogen event data.

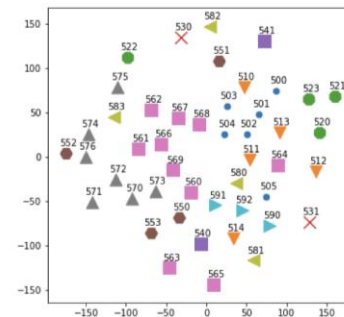


Event Causation Learning

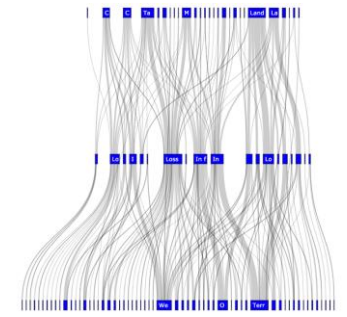
- Problem of Traditional Fault Tree Analysis
 - Static Tree and Reliability/probability is not updated with real-time observations
 - Need to manually specify the fault tree
- Proposed: Causal learning from spatio-temporal events using Hawkes Process and Bayesian Network
 - Bayesian Network is used to represent the relationship between different vents
 - Hawkes Process is used to learn the causation of the spatio-temporal events
 - We will utilize the Hawkes process to learn the causation between events for both traditional gas and hydrogen transport



Example of Event Trees for pipeline failures



Event Embedding

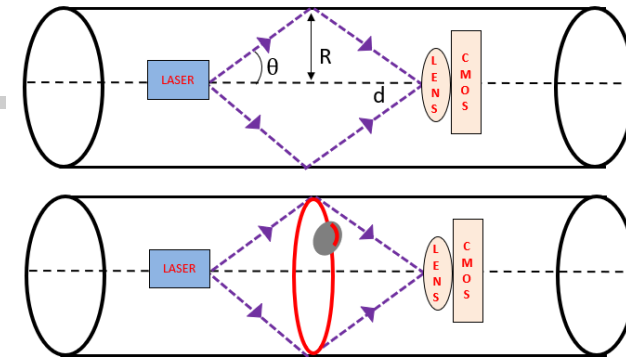
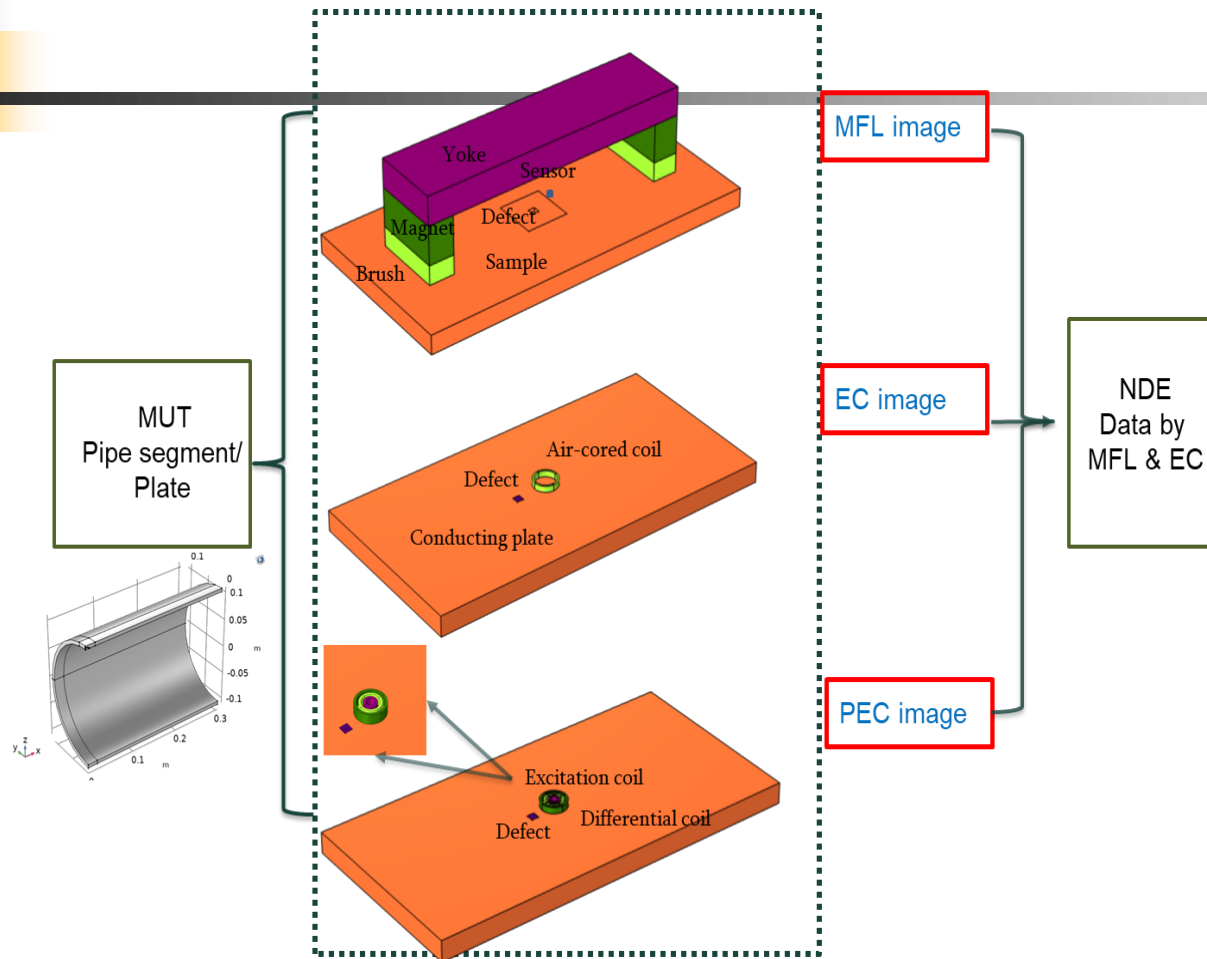


Failure Tree

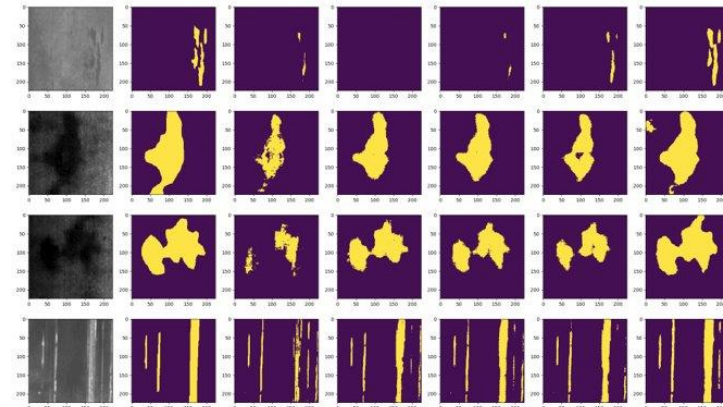
NDE for Pipeline Inspection

MFL, EC, PEC

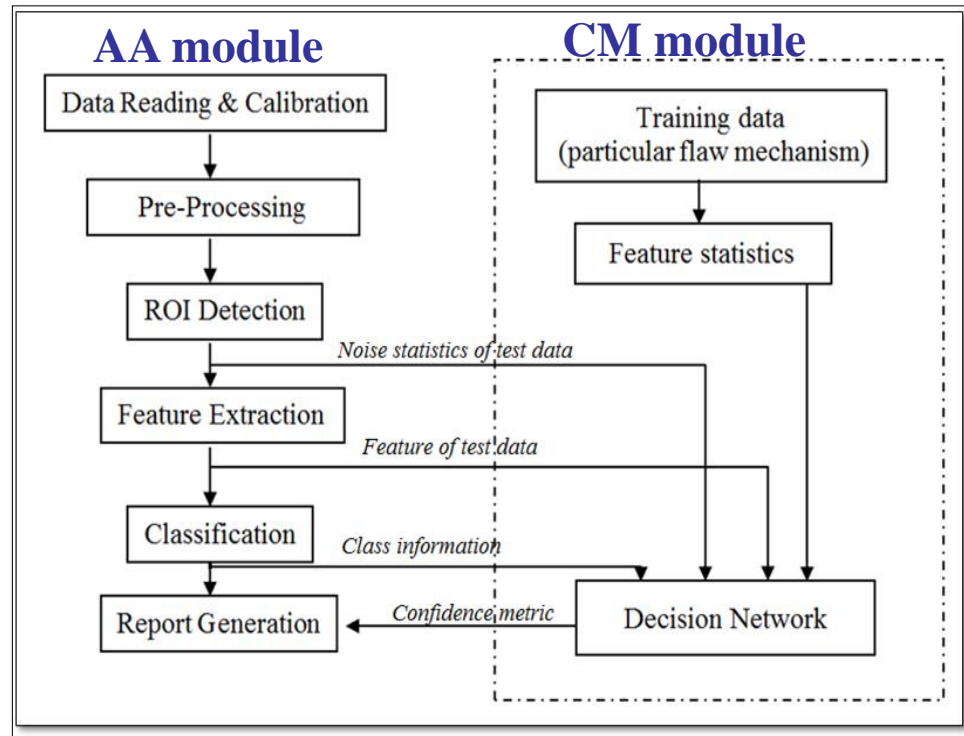
Structured light



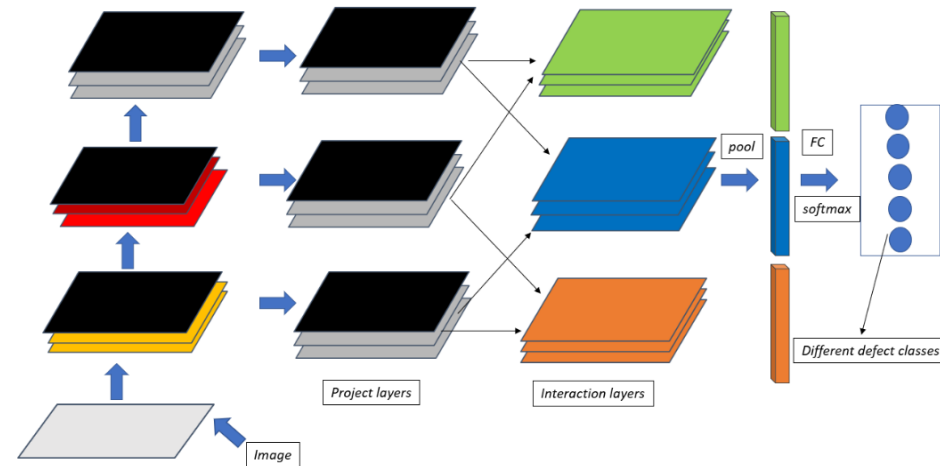
Laser projector as source, CMOS camera as detector, R : inner diameter of pipe wall, d : distance between source and detector, θ : angle of projection from source, deformation in red laser ring due to defect



Automated data processing and precursor identification – AI based techniques



CNN(Convolutional Neural Network) Hierarchical Bilinear pooling (HBP)



Column (a): Feature maps of different layers in CNN.
 Column (b): Features expanded to higher dimension by independent linear mapping
 Column (c): Element wise multiplication to model inter layer interaction

Data Quality Assessment & Enhancement

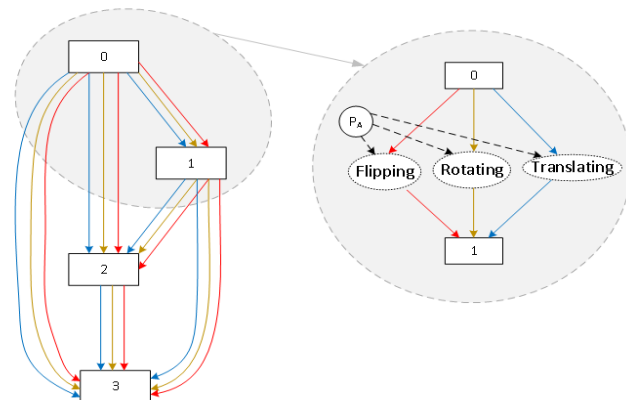
Problem: One of the biggest hurdles to integrating AI with NDE for pipeline inspection applications is the data limitation challenge where large volumes of training data is not available.

Our Solutions: In this project, we propose two AI techniques to tackle this challenge. These two techniques aim to tackle the challenge from two complementary perspectives.

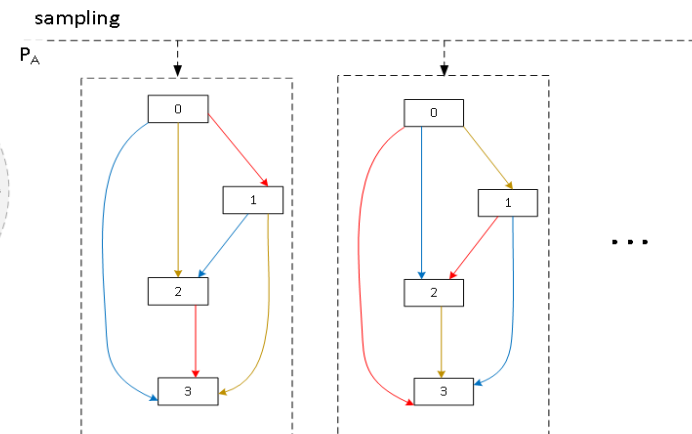
Technique 1: Data Augmentation (DA)

- In modern AI systems, data augmentation (DA) is an effective technique to increase both the amount and diversity of training data by applying augmenting operations on the original data samples in the training set.
- We propose to replace the manual design process with an automated process to find an effective data augmentation policy for the task of pipeline inspection.

(A)

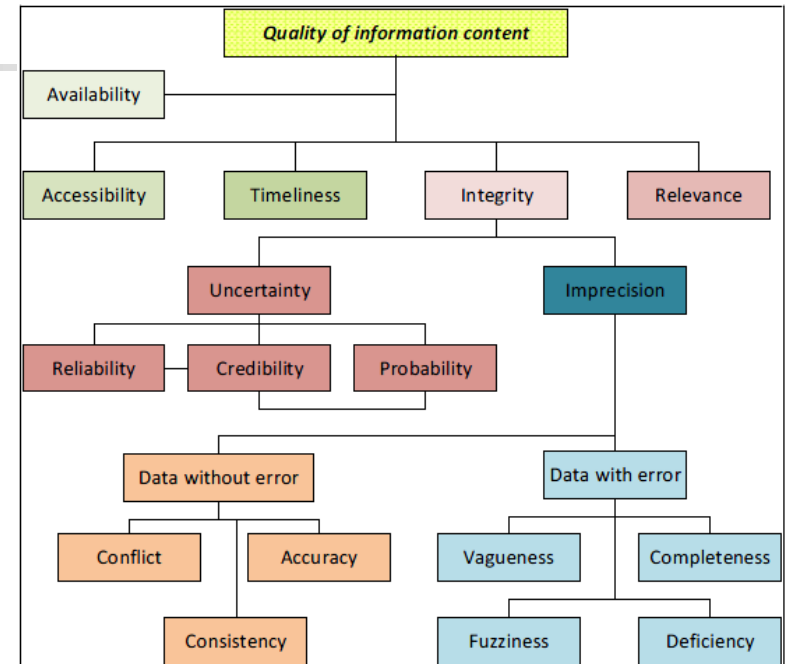


(B)



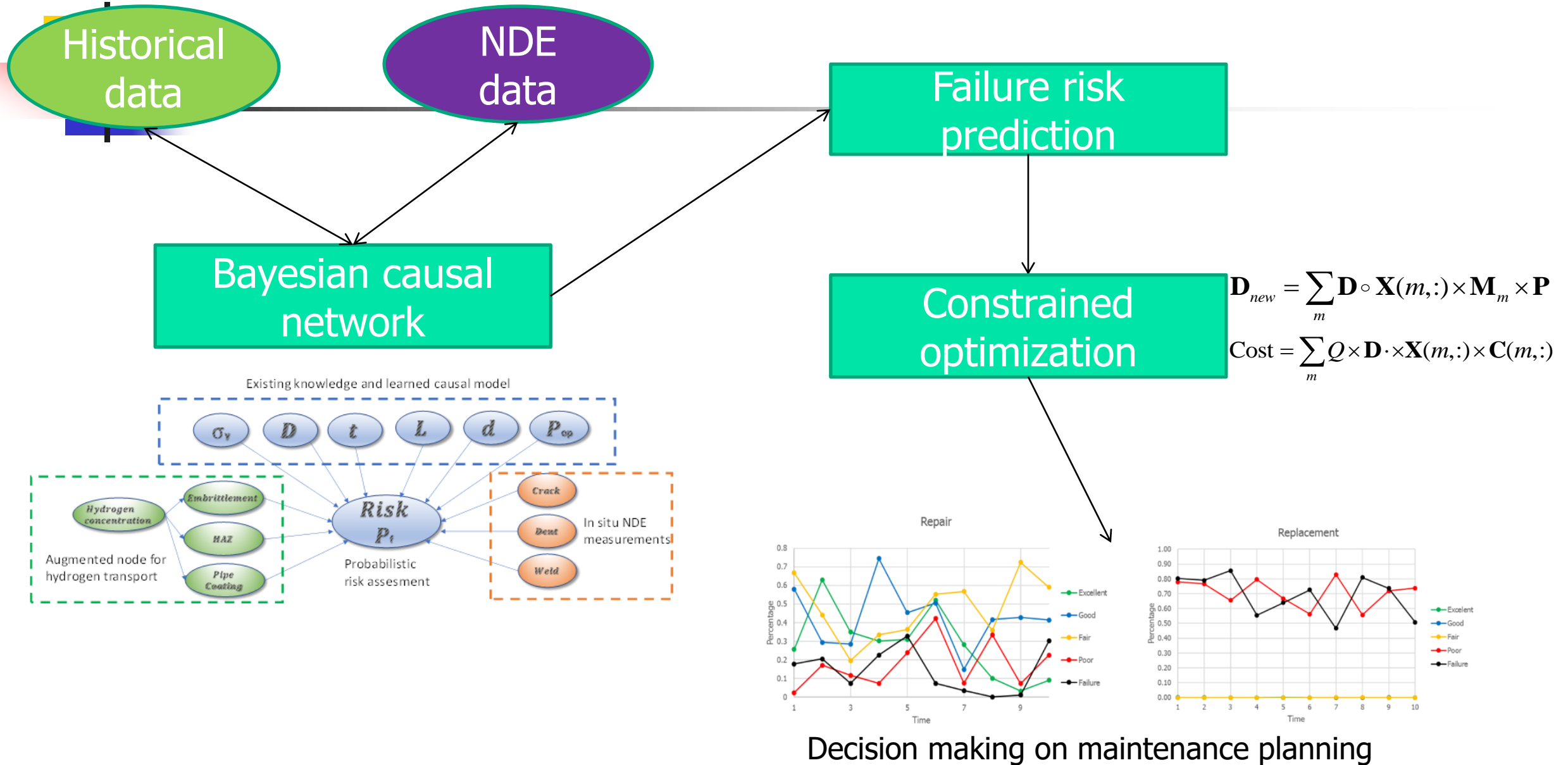
Data quality assessment for pipeline integrity management

| Quality Measure | Suggested Enhancement Technique |
|-----------------|---------------------------------|
| Accessibility | Techniques 1 and 2 |
| Timeliness | Data recollection |
| Relevance | Data recollection |
| Integrity | Technique 3 |
| Completeness | Technique 3 |
| Uncertainty | Data recollection |



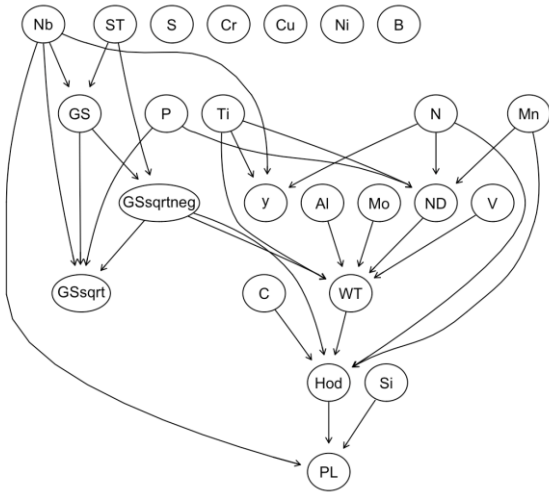
1. **Accessibility**: Accessibility is measured by the cost of obtaining information
2. **Timeliness**: Timeliness is determined by whether the data is available at the time it is needed
3. **Relevance**: Relevance is gauged by whether the data is related to the task of interests
4. **Integrity**: Integrity is measured by whether the data is accurate and consistent
5. **Completeness**: Completeness relates to whether all required data is present
6. **Uncertainty**: Uncertainty refers to whether the variability of the data is acceptable for the task of interest

Overall demonstration and validation

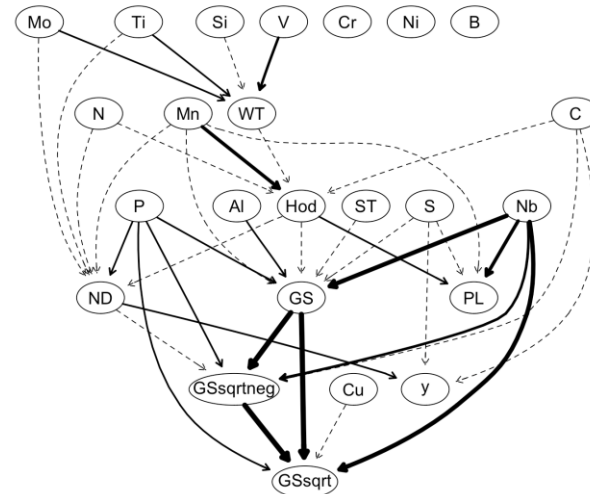


Case study: hydrogen impact on material strength - 1

| Index Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|----------------|----|----|----|----|-----|----|-----------|-----------|----|----|-----|----|
| | C | Mn | P | S | Al | Cr | Cu | Mo | Nb | Ni | sSi | Ti |
| Index Variable | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | |
| | V | B | N | PL | Hod | GS | GSsqrtneg | GSsqrtneg | ND | WT | ST | |



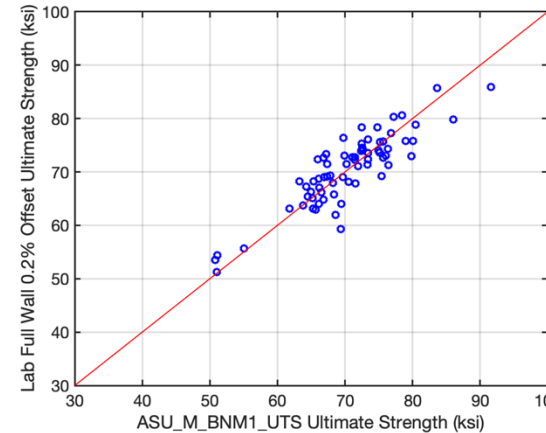
Bayesian network 1



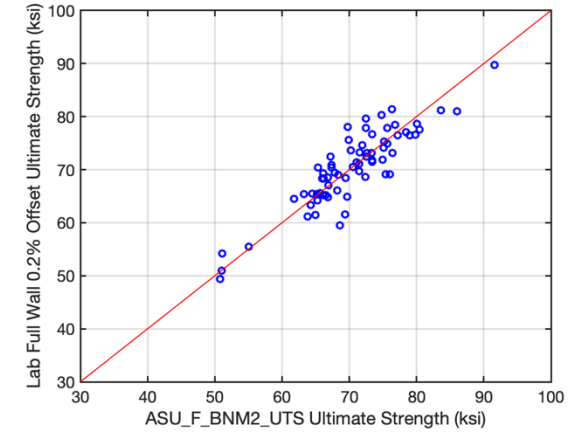
Bayesian network 2

Two Bayesian network can be learned from the same data depending on the modeling approach

Automated causation discovery?



Prediction using Bayesian network 1



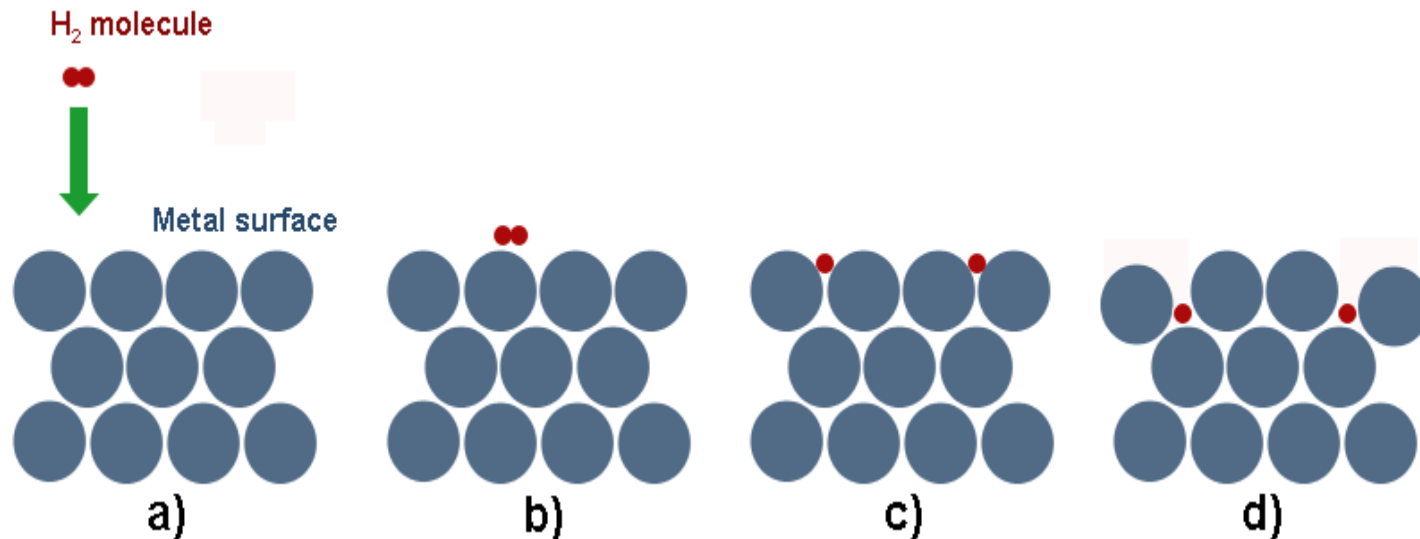
Prediction using Bayesian network 2

Two Bayesian networks provide different prediction accuracy/errors

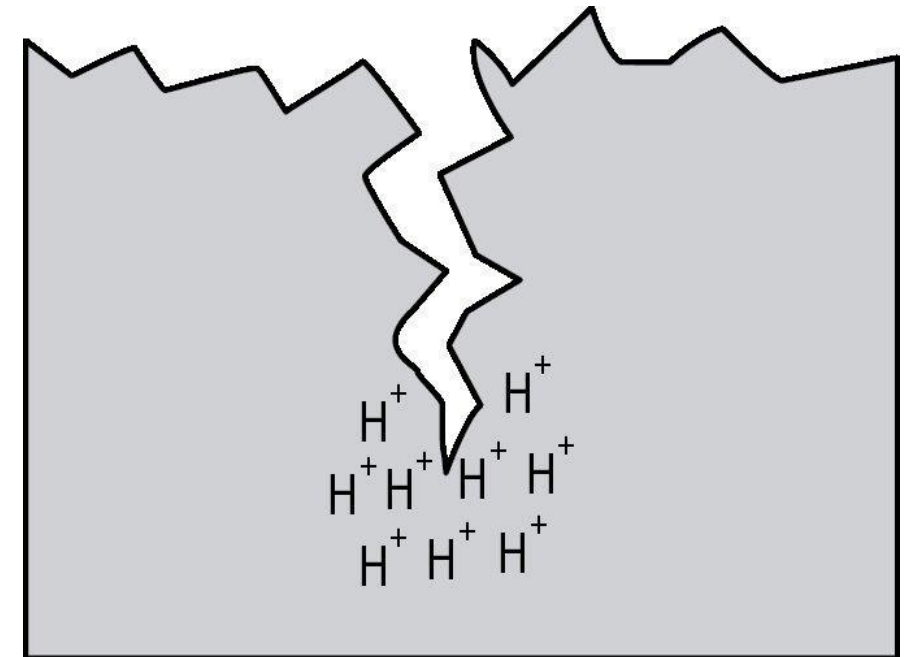
Quality Assessment?

Case study: hydrogen impact on material strength - 2

- Hydrogen molecules adsorb on metal surface to form atomic hydrogen
- Atomic hydrogen intrude between crystal lattices causing Hydrogen Embrittlement

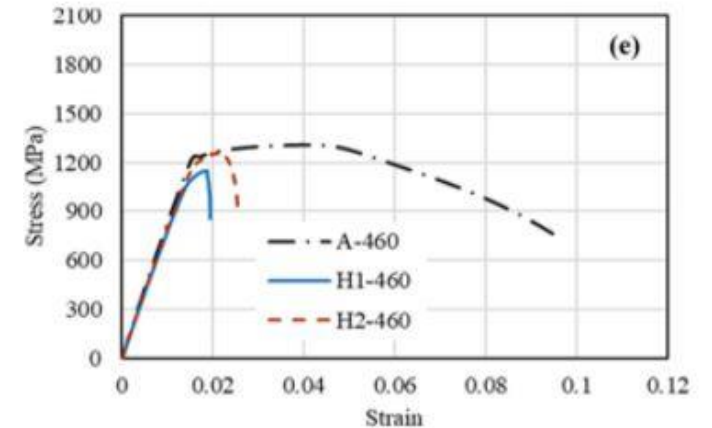
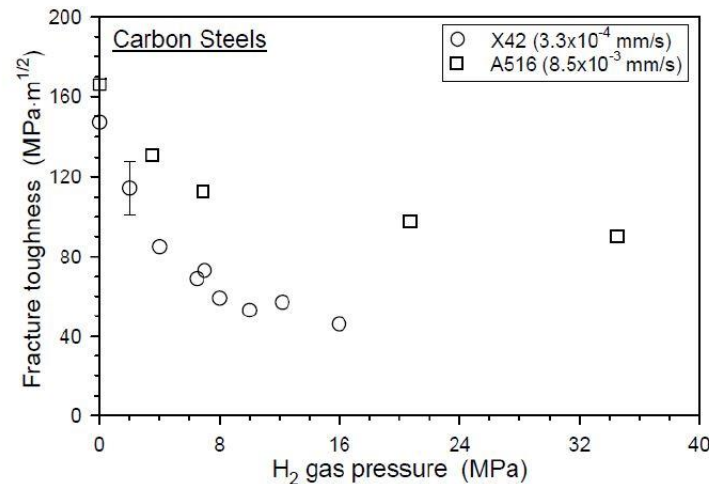
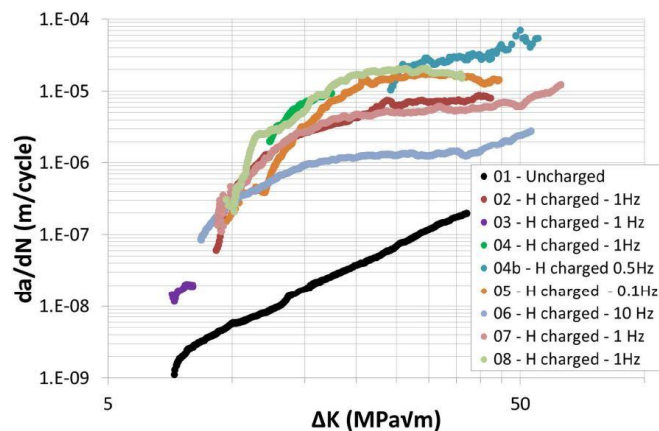


- Severity of hydrogen embrittlement depends on:
 - i) gas pressure
 - ii) hydrogen concentration in mixture
 - iii) localized concentration of hydrogen at stress risers, and others



Case study: hydrogen impact on material strength - 3

- Manifestation of hydrogen embrittlement is enhanced susceptibility to fracture
- Hydrogen reduces:
 - i) tensile strength
 - ii) ductility
 - iii) fracture toughness
 - iv) corrosion resistance
- Hydrogen accelerates fatigue crack propagation
- Materials become susceptible to time-dependent crack propagation in hydrogen environment



Case study: hydrogen impact on material strength - 4

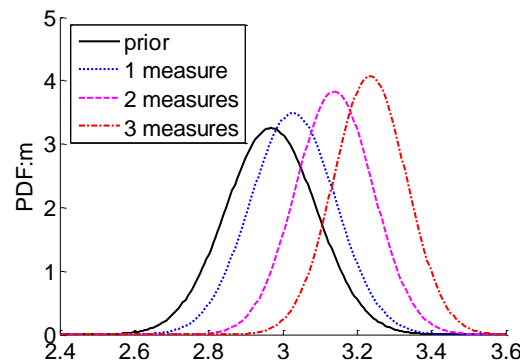
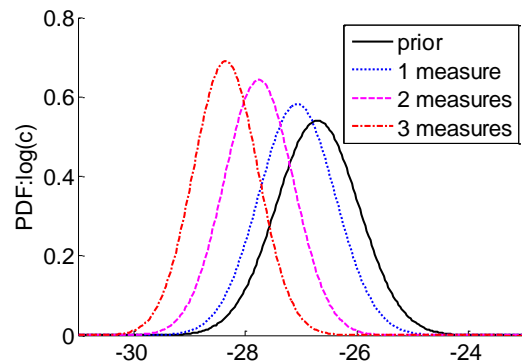
- Bayesian updating: update the belief of “existing knowledge” given “new information”

Diagram illustrating the Bayesian updating process:

- Posterior (New knowledge)
- Likelihood Model
- Prior (Existing knowledge)

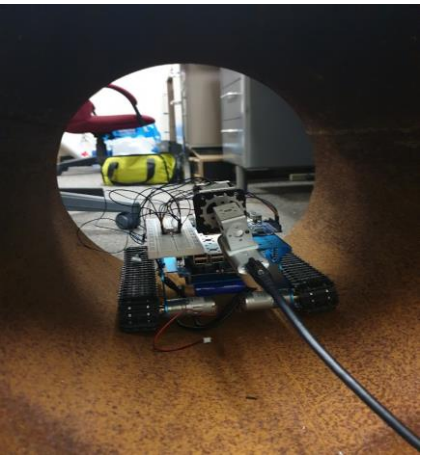
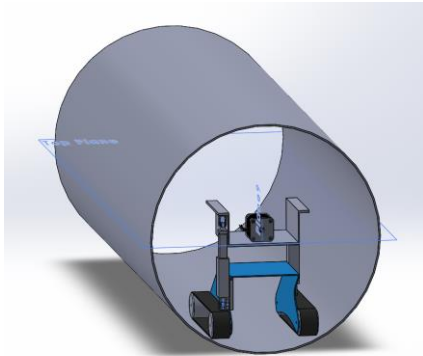
$$P(\theta | x') = \frac{P(x' | \theta)P(\theta)}{P(x')}$$

Normalizing constant

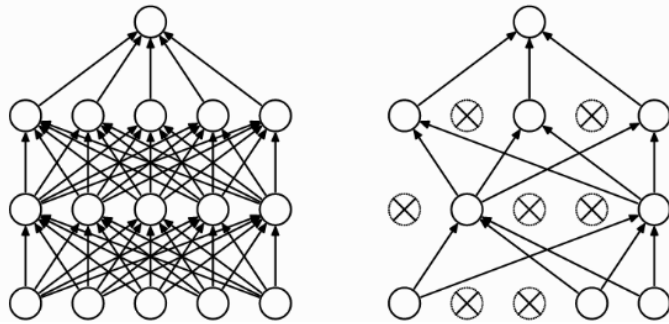
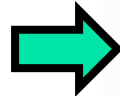


Thomas Bayes

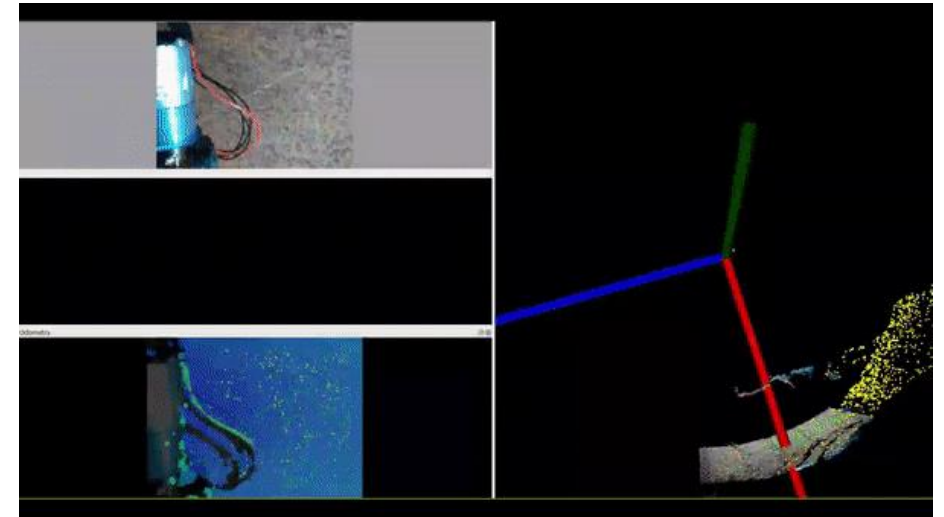
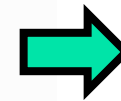
Case study: hydrogen impact on material strength – 5



Wired RGB-D camera that captures pipe wall at 1280x720 pixels and 30fps.

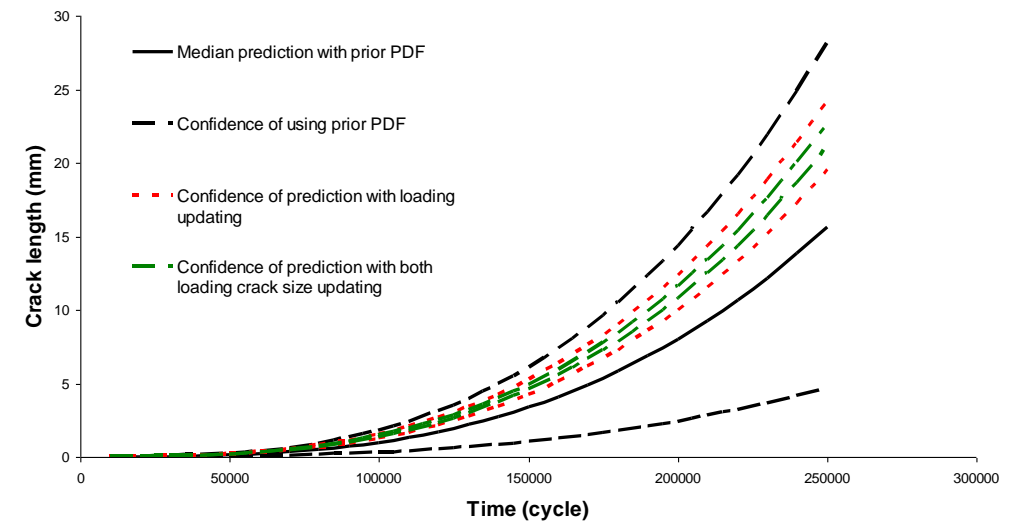
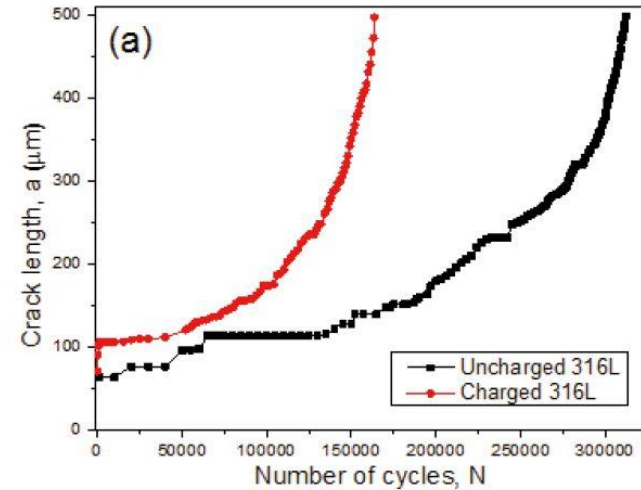
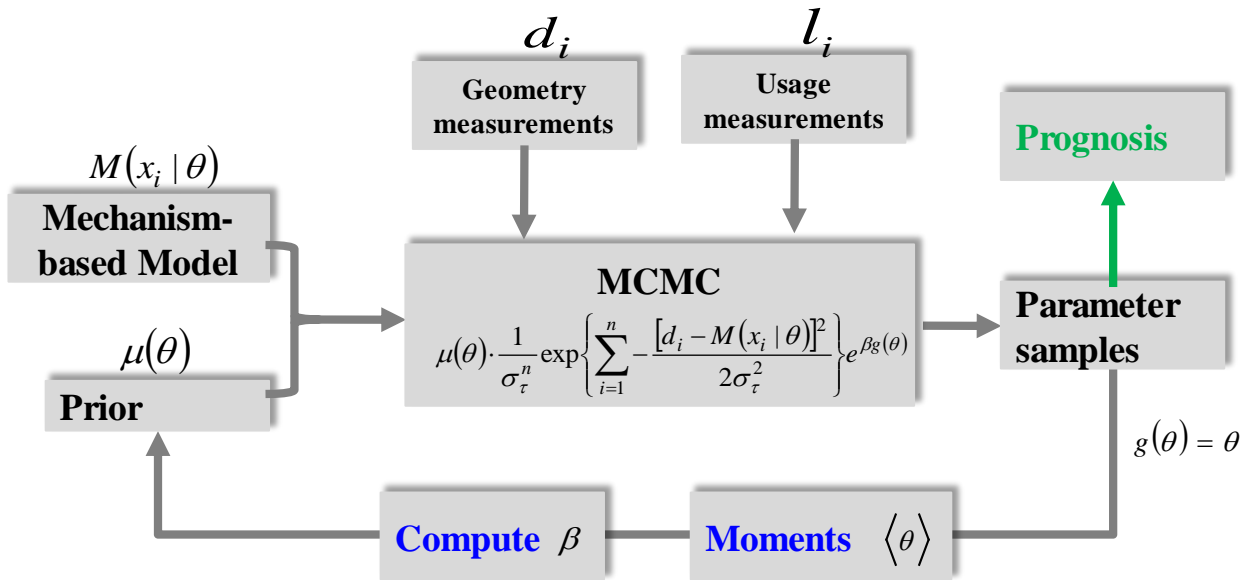


Machine learning-based detection and quantification



Pipe mapping demonstration for a corroded metallic pipe using the RTAB-Map package, that performs RGB-D Simultaneous Localization & Mapping (SLAM)

Case study: hydrogen impact on material strength - 6



Case study: hydrogen impact on material strength - 6

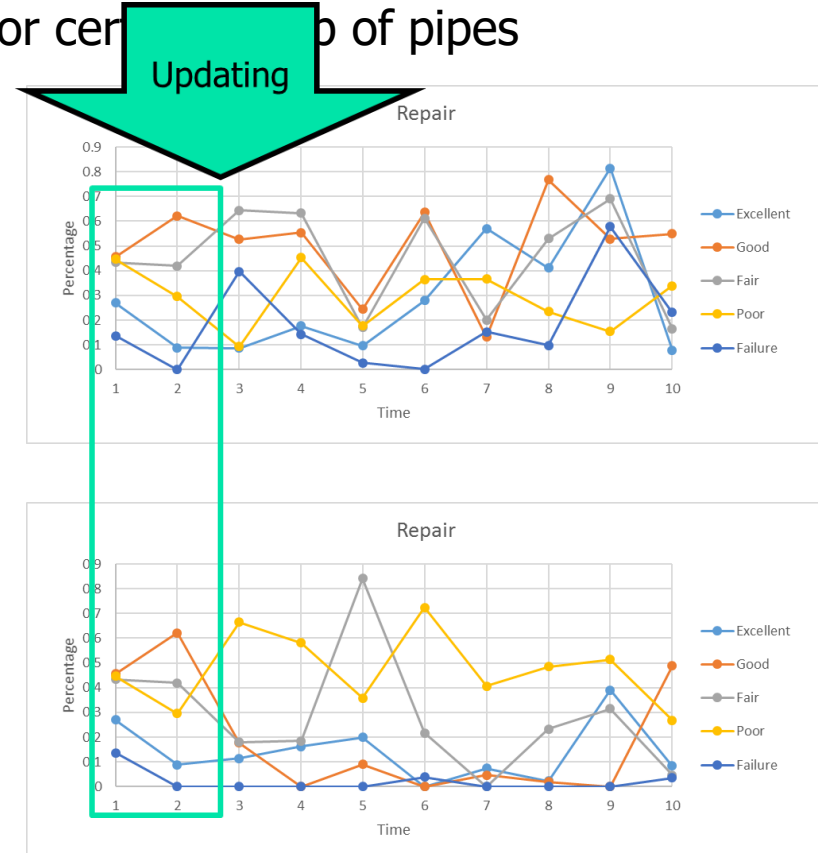
- The changed crack growth curve would lead to change in transition matrix:

$$P' = \begin{bmatrix} 0.6068 & 0.3922 & 0.0010 & 0 & 0 \\ 0 & 0.5072 & 0.4726 & 0.0184 & 0.0017 \\ 0 & 0 & 0.3764 & 0.5882 & 0.0354 \\ 0 & 0 & 0 & 0.4098 & 0.5902 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$



$$P = \begin{bmatrix} 0.5285 & 0.4612 & 0.0067 & 0.0028 & 0.0007 \\ 0 & 0.4248 & 0.5301 & 0.0388 & 0.0063 \\ 0 & 0 & 0.3006 & 0.6430 & 0.0564 \\ 0 & 0 & 0 & 0.3814 & 0.6186 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

- The changed transition matrix will affect the maintenance suggestions for certain group of pipes





Educational Objective

- Guide and train graduate students at ASU/MSU in pipe integrity assessment and risk mitigation;
- Leverage existing undergraduate research programs at ASU/MSU to include pipe industry research as part of the curriculum and potential areas of professional interest for future engineers;
- Enhance ASU courses (MAE 523 Fracture Mechanics and MAE 548 Probabilistic Methods for Engineering Analysis and Design) based on results and insights derived from this research;
- Invite industry experts (see support letters) to deliver seminar/workshops to undergraduate/graduate students on challenges and opportunities in the gas and pipeline industry;
- Encourage involved students to apply for internships at USDOT and related industry to gain practical experience and engage in potential technology transfer activities based on this work.



Project Personnel

- **PI: Dr. Yongming Liu, co-PI: Dr. Hao Yan, ASU**
 - Responsible for the overall progress of the project
 - Lead research activities on automated knowledge discovery, Bayesian causal modeling, quality assurance, maintenance planning
 - Advise student research
- **Co-PIs: Dr. Yiming Deng, Dr. Mi Zhang, Dr. Lalita Udpa**
 - Lead research activities on NDT techniques, quality assurance, and AI-assisted data analytics
 - Advise student research
- **Technical Advisory Panel (TAP) – PRCI: Gary Hines, Gary Choquette, Jeff Whitworth; GTI: Ernest Lever; EWI – Tom McGaughy**
 - Provide comments and suggestions on the suitability and feasibility of the proposed study
 - Provide in-kind support for the proposed project, if possible (e.g., sharing inspection report/data)



THANK YOU

Acknowledgement

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If you have additional questions, please contact yongming.liu@asu.edu