SPE Workshop: Digital Asset Integrity Management (D-AIM)

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A Machine Learning Approach to Integrity Management of Pipelines

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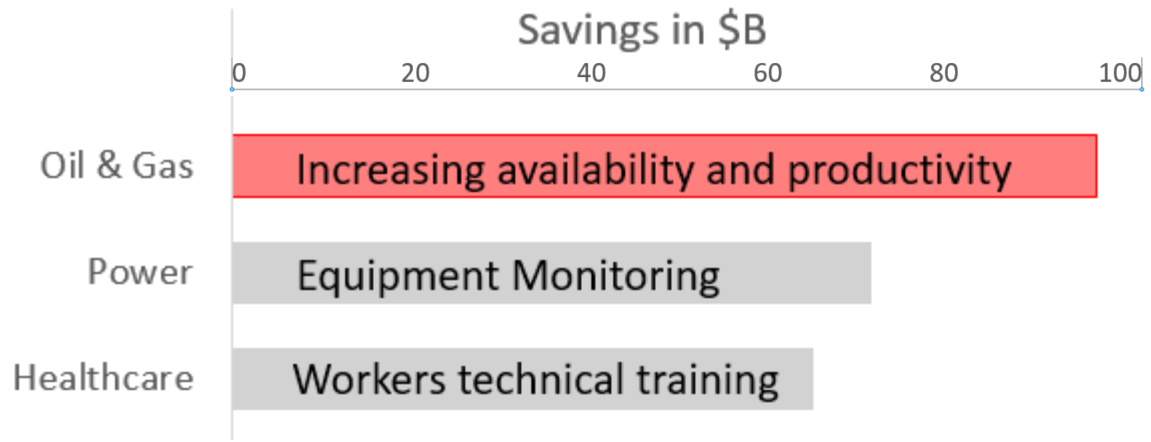
Outline

- Motivation and Definitions
- Prognostic and Health Management (PHM)
- Problem Definition
- Developed Approach
  - Global View of Pipeline PHM
  - Local View of Pipeline PHM
  - Remaining Useful Life (RUL) Estimation
- Examples of Results
- Summary

Motivation

Motivation

- Apply PHM to corrosion, the most prominent failure mechanisms in pipelines
- Only 1 % improvement in performance of systems saves billions



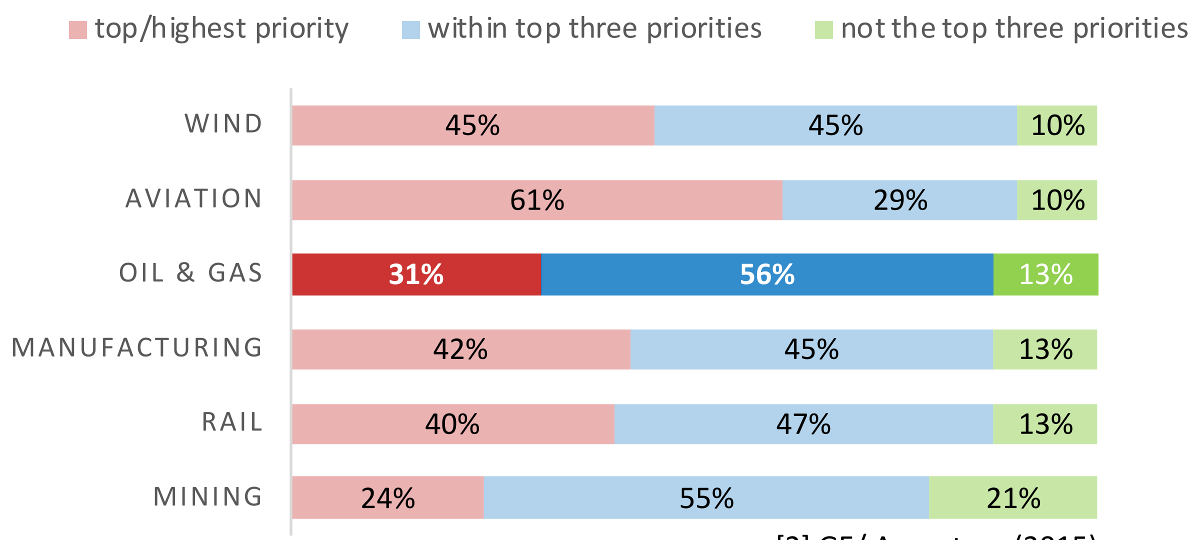
From: DOI 10.1007/978-3-319-44742-1

- Managing corrosion damage in oil and gas industry improves performance

What is the most efficient approach to manage pipelines corrosion failures?

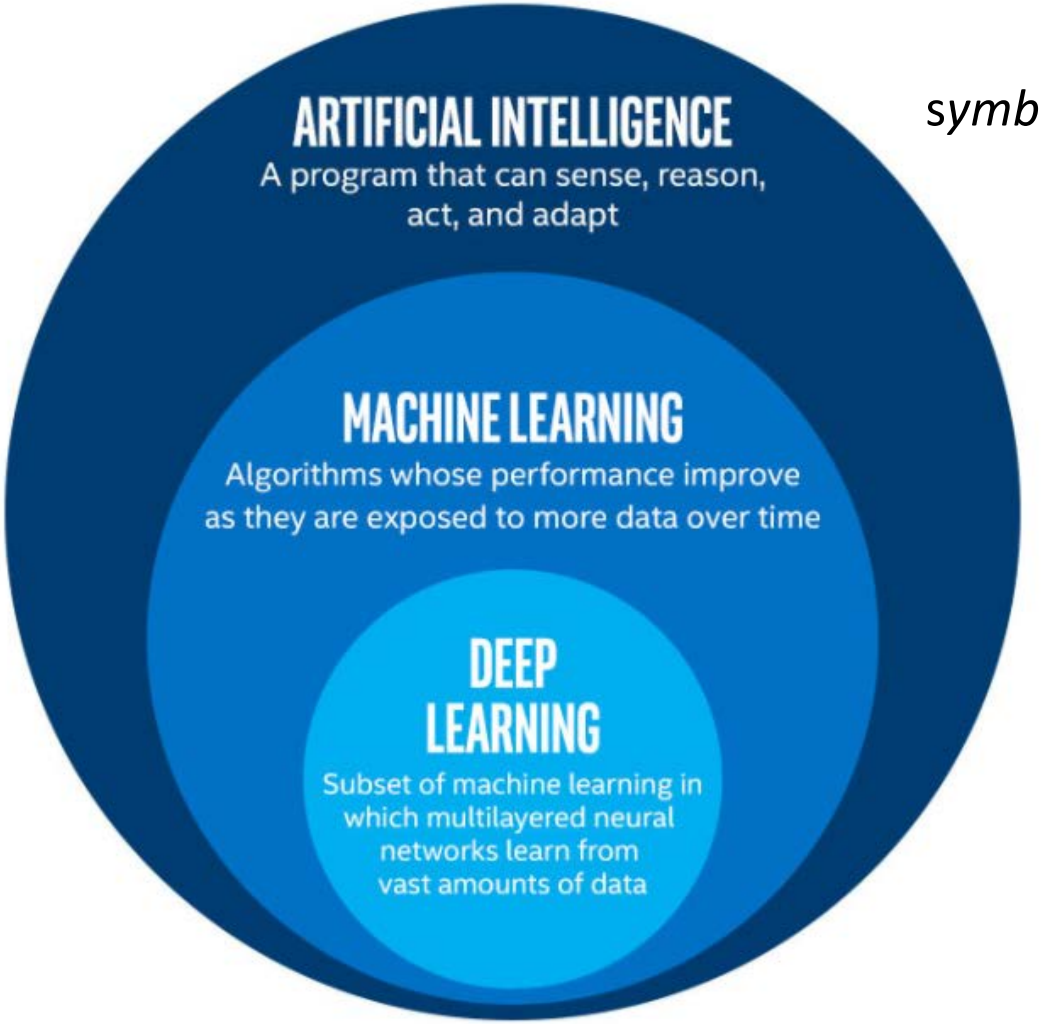
Motivation

- Significant progress in data analytics, machine learning and PHM
- Survey of key industries on relevance of data analytics :
  - How important is data analytics, machine learning relative to other priorities in your industry?

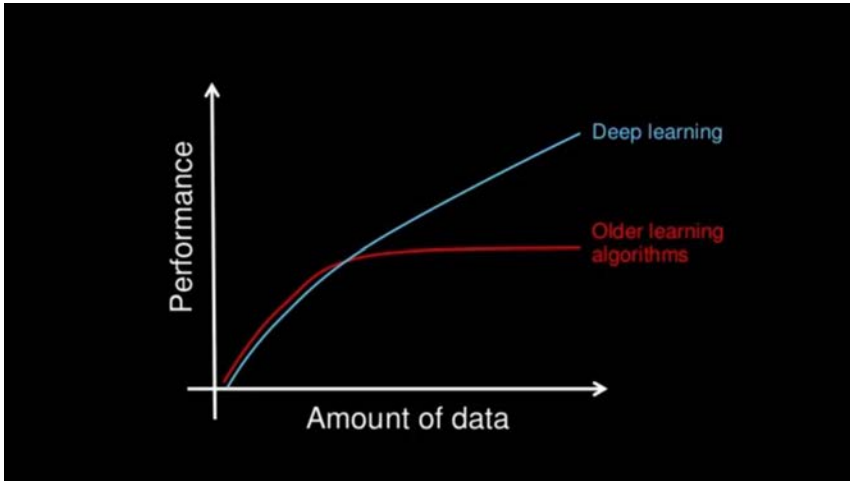


[2] GE/ Accenture (2015)

AI, Machine Learning, Deep Learning



symbolic vs. *connectionist approaches to AI*

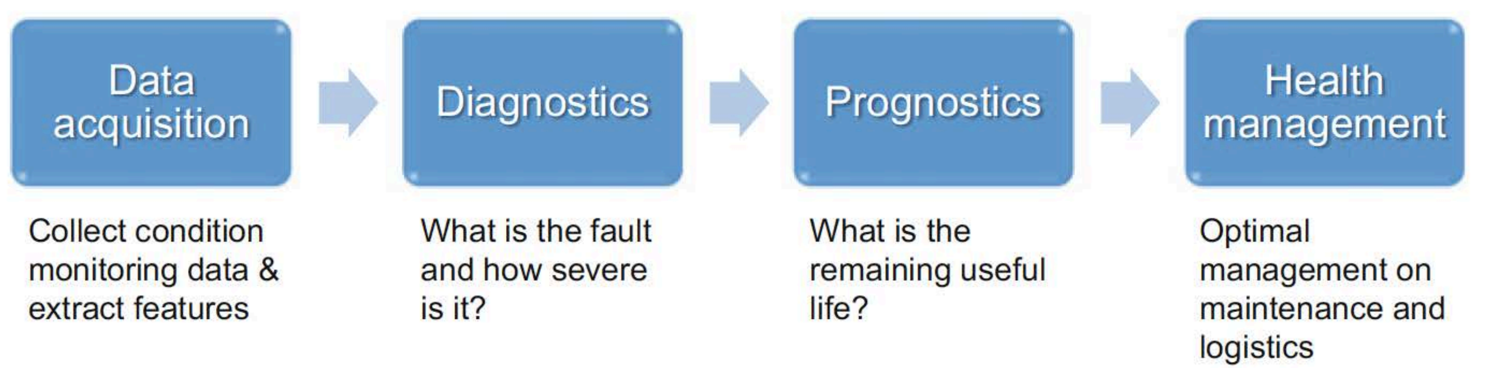


From: https://towardsdatascience.com/cousins-of-artificial-intelligence-dda4edc27b55

Data Analytics and Machine Learning in Pipeline Integrity Management

- Prognosis and health management (PHM) is the field where data analytics is applied
  - Cost effective and conditioned based pipeline integrity management

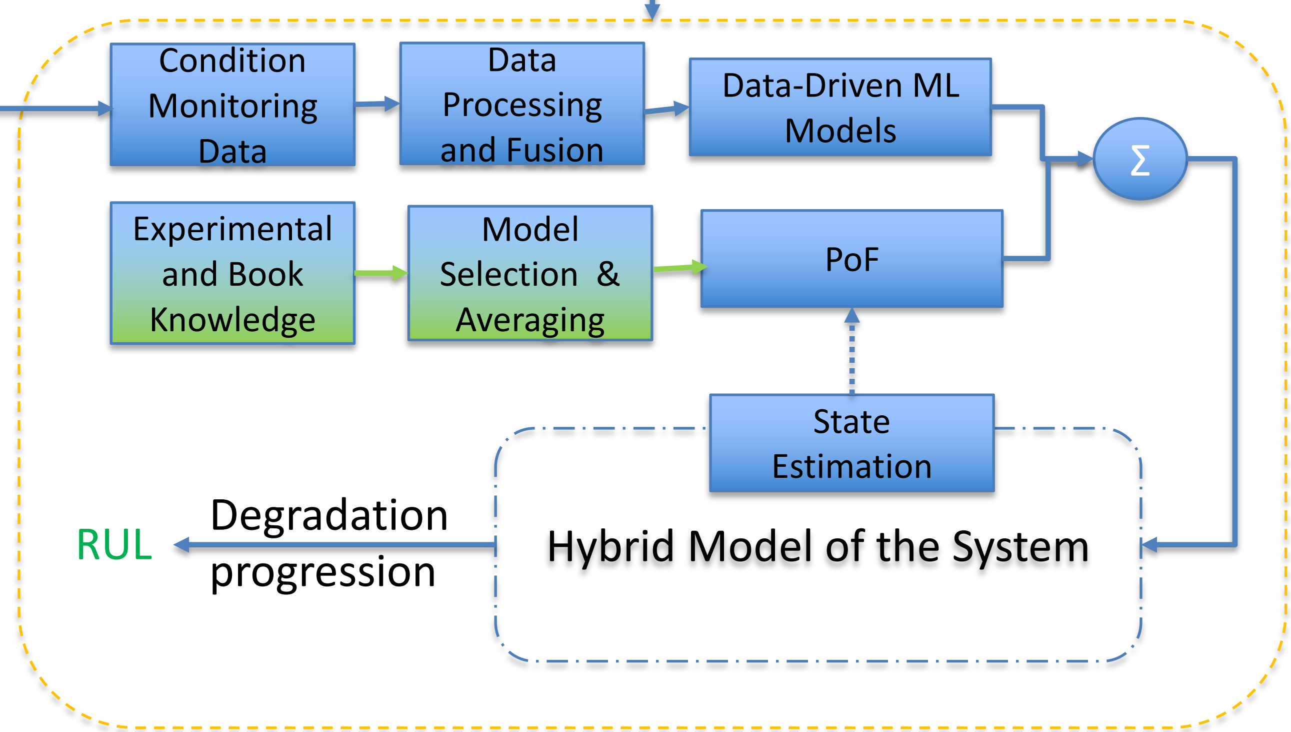
- What is PHM?



[From:DOI 10.1007/978-3-319-44742-1

Data Analytics and Machine Learning in Pipeline Integrity Management

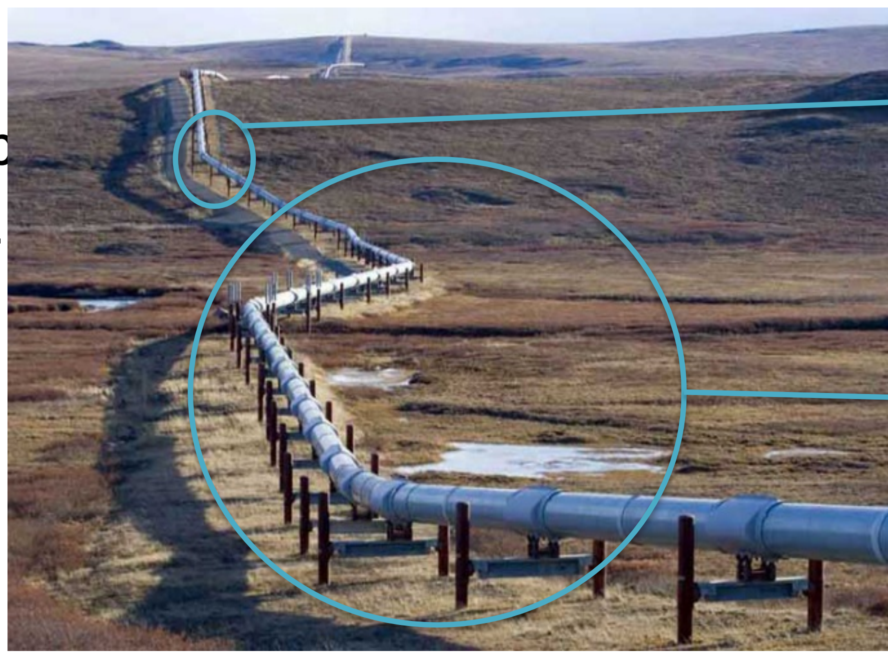
- PHM categories
  - Data-driven models
  - Physics of Failure-based models (PoF)
  - **Hybrid models**



Problem Definition

Problem Definition

- Available data for a corroded pipeline:
  - Noisy and expensive offline large scale data/information
  - Corrosion growth physics of failure (PoF) information
  - Accurate and inexpensive online local data



- Ob
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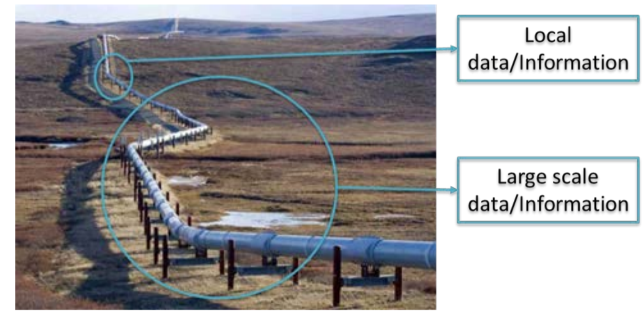
  - odel for high-confidence

Developed Approach

Overall View



The approach involves two levels:

- Local level: an optimal arrangement of sensors and inspection areas was mathematically investigated:
  - Minimizing health monitoring cost
  - Maximizing probability of detection of corrosion damages

- Large scale level: data and information gathered through different techniques were fused to:
  - Developed and updated a hybrid corrosion growth model including measurement uncertainties to estimate RUL

Overall View

Local

Sensor Network $\xrightarrow{\text{Recurrent Neural Net}}$ E_S

Human Inspection $\xrightarrow{\text{Convolutional Neural Net}}$ E_H

E_S, E_H $\xrightarrow{\text{Recurrent Neural Net}}$ E_1

Large scale

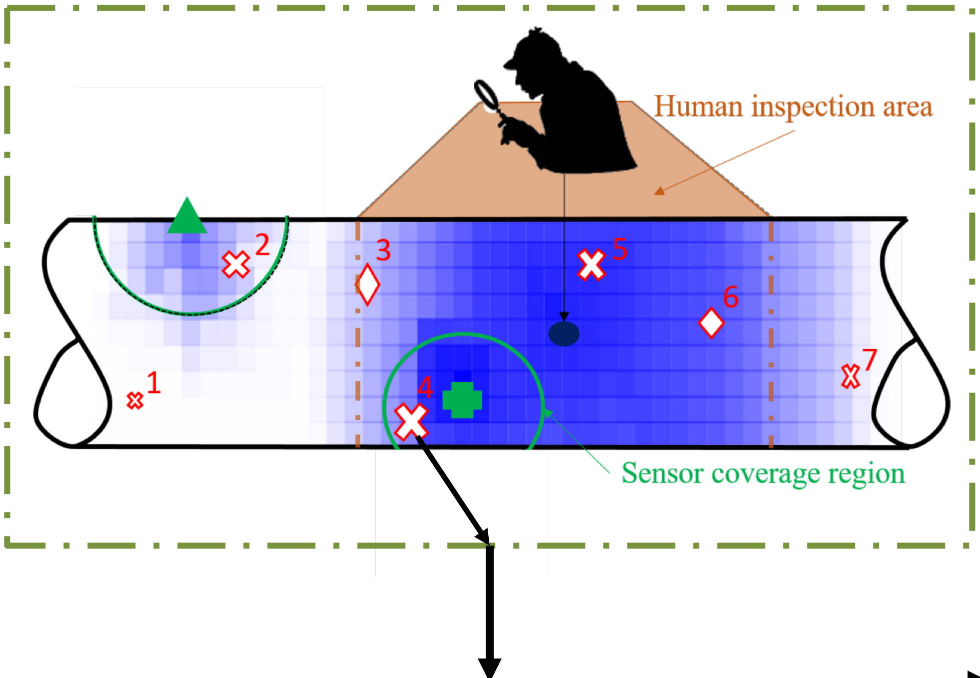
In-Line Inspection $\xrightarrow{\text{Hierarchical Bayesian}}$ E_I

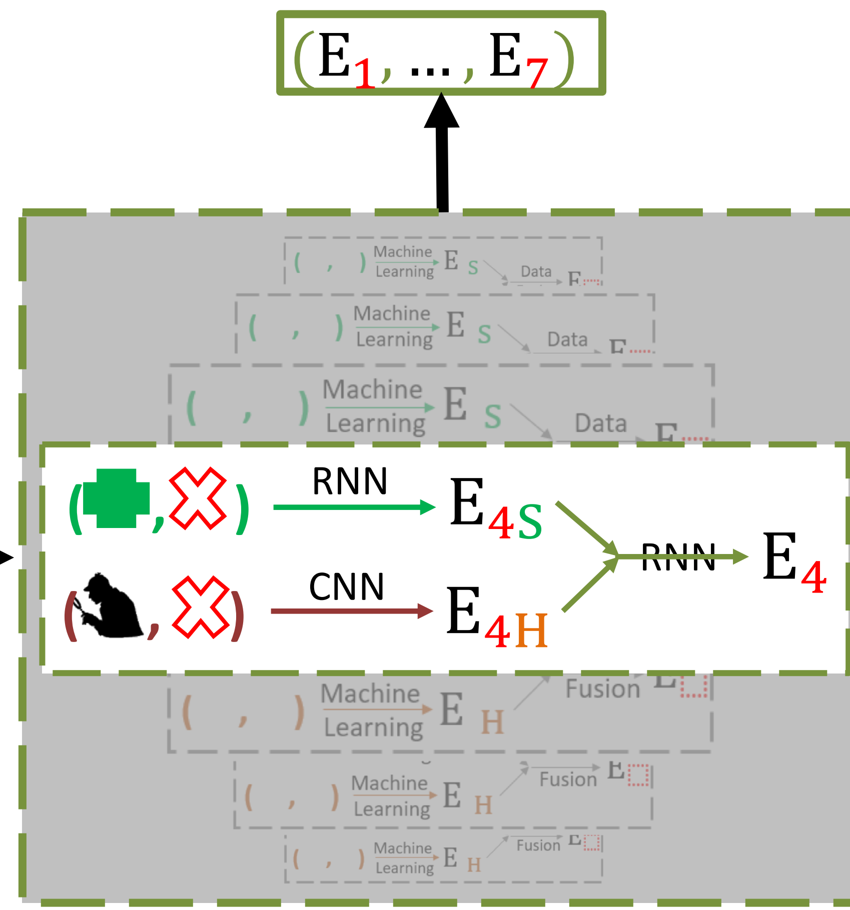
[Sensor Network $\xrightarrow{\text{Recurrent Neural Net}}$ E_S; Human Inspection $\xrightarrow{\text{Convolutional Neural Net}}$ E_H; $\xrightarrow{\text{Recurrent Neural Net}}$ E_1 (Local)] $\xrightarrow{\text{Augmented Particle Filtering}}$ E_{PF}

E_I, E_{PF} $\xrightarrow{\text{Augmented Particle Filtering}}$ $E_F \rightarrow$ RUL

E_H : Estimated corrosion damage size based on human inspection
S: Sensor, H: Human Inspection, I: ILI, F: final, PF: particle filtering

Detailed View – Local Level





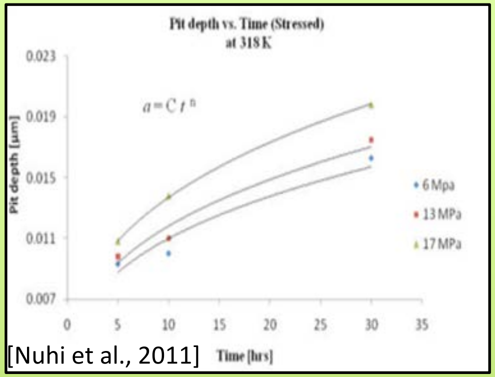
- Damage type 1
- Damage type 2
- Sensor type 1
- Sensor type 2
- Human inspection type 1
- E_{4S} Estimated size of damage 4 based on sensor data
- E_{4H} Estimated size of damage 4 based on human inspection

Detailed View – Large Scale Level

ILI data

[iectech.org]

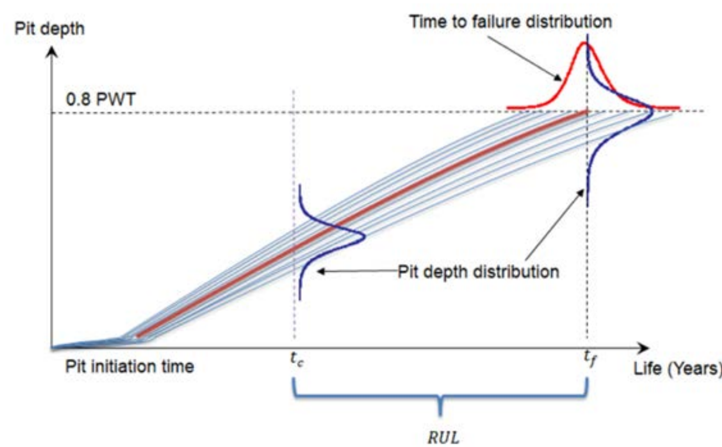
PoF model



[Nuhi et al., 2011]

Sensor data

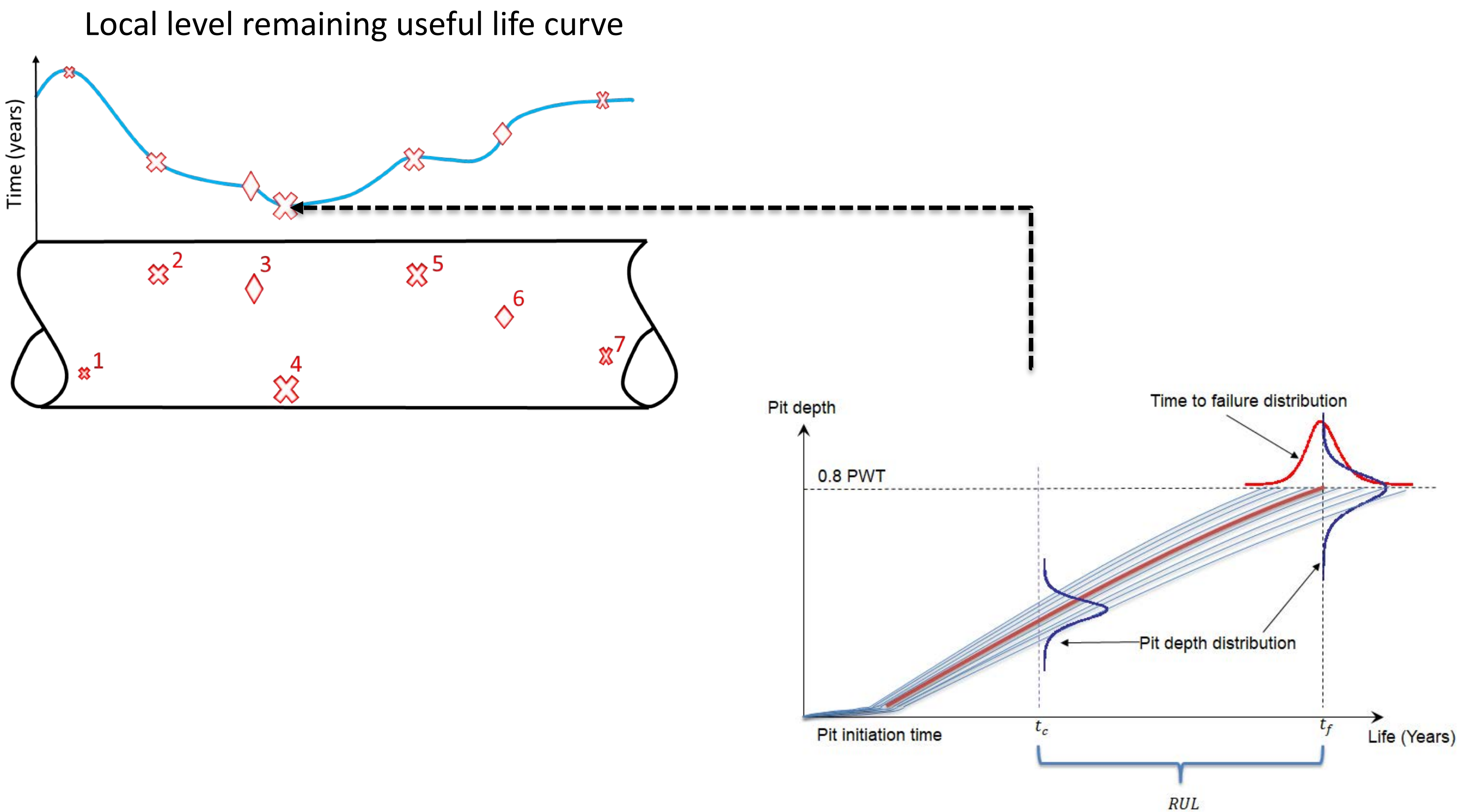
The picture can't be displayed.



Fusing ILI, sensor data and PoF information to estimate a high-confidence RUL for all corrosion damages.

•Nuhi, M., Seer, T. A., Al Tamimi, A. M., Modarres, M., & Seibi, A. (2011). Reliability analysis for degradation effects of pitting corrosion in carbon steel pipes. Procedia Engineering, 10, 1930–1935.

RUL estimation for all corrosion damages



PWT: Pipe wall thickness

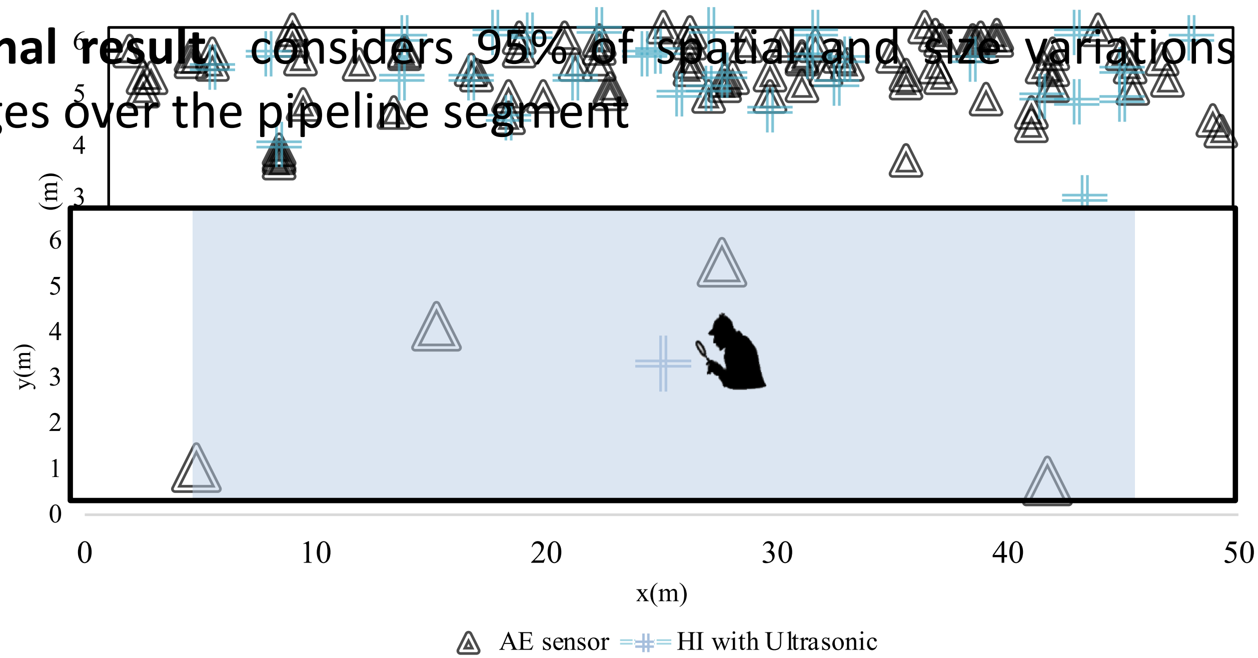
t_c: Current time, t_f: Failure time

Examples of Results

Results-Local Level

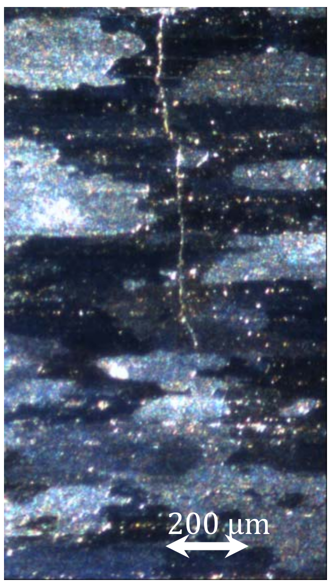
- 46 synthetic realizations of pitting corrosion damages over a pipeline segment were considered
- Corresponding optimal arrangements were aggregated
  - Acoustic Emission Sensors (Triangle sign)
  - Human Inspection With Ultrasound tool (plus sign)

- **The final result** considers 95% of spatial and size variations of corrosion damages over the pipeline segment

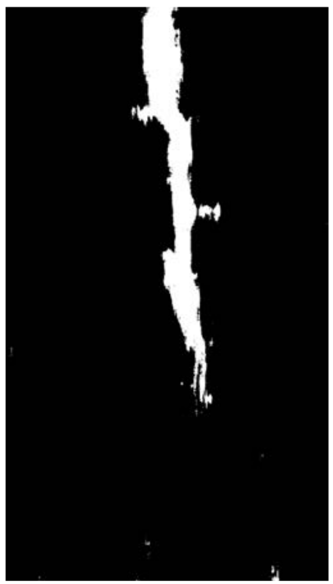


Results- Local Level

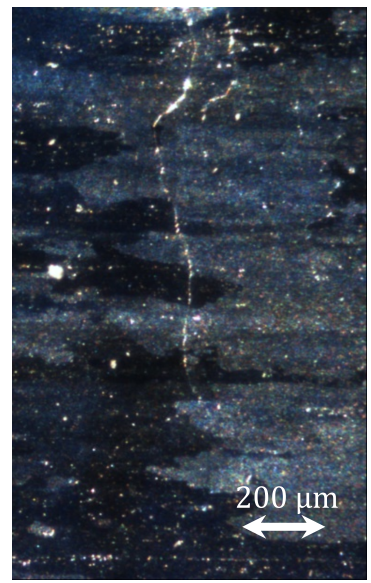
- Automated crack length estimation using CNNs
  - Images correspond to experiments conducted at Center for Risk and Reliability.



Original



CNN prediction

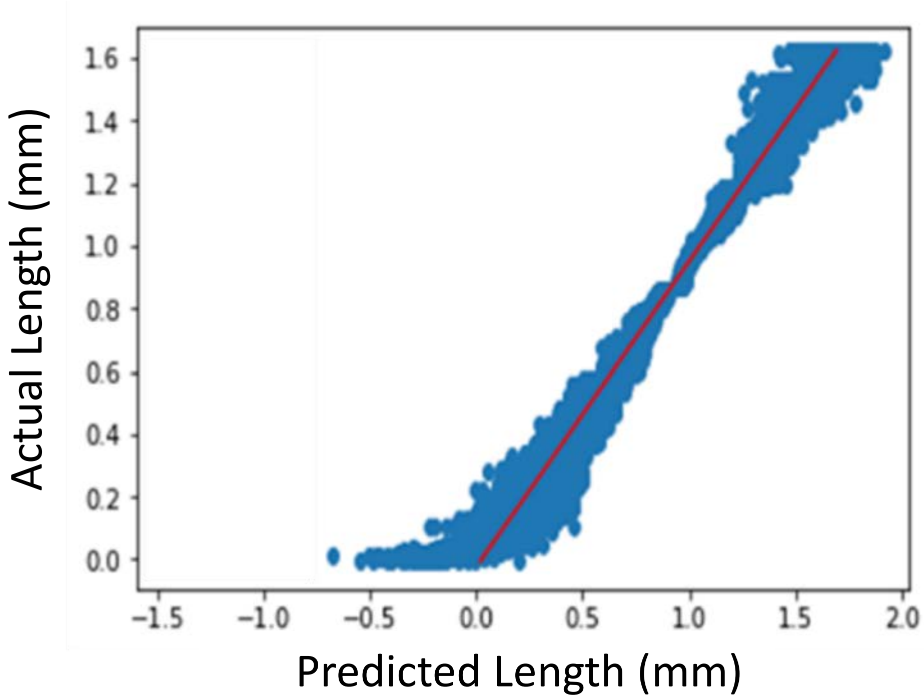


Original

CNN prediction

Results- Local Level

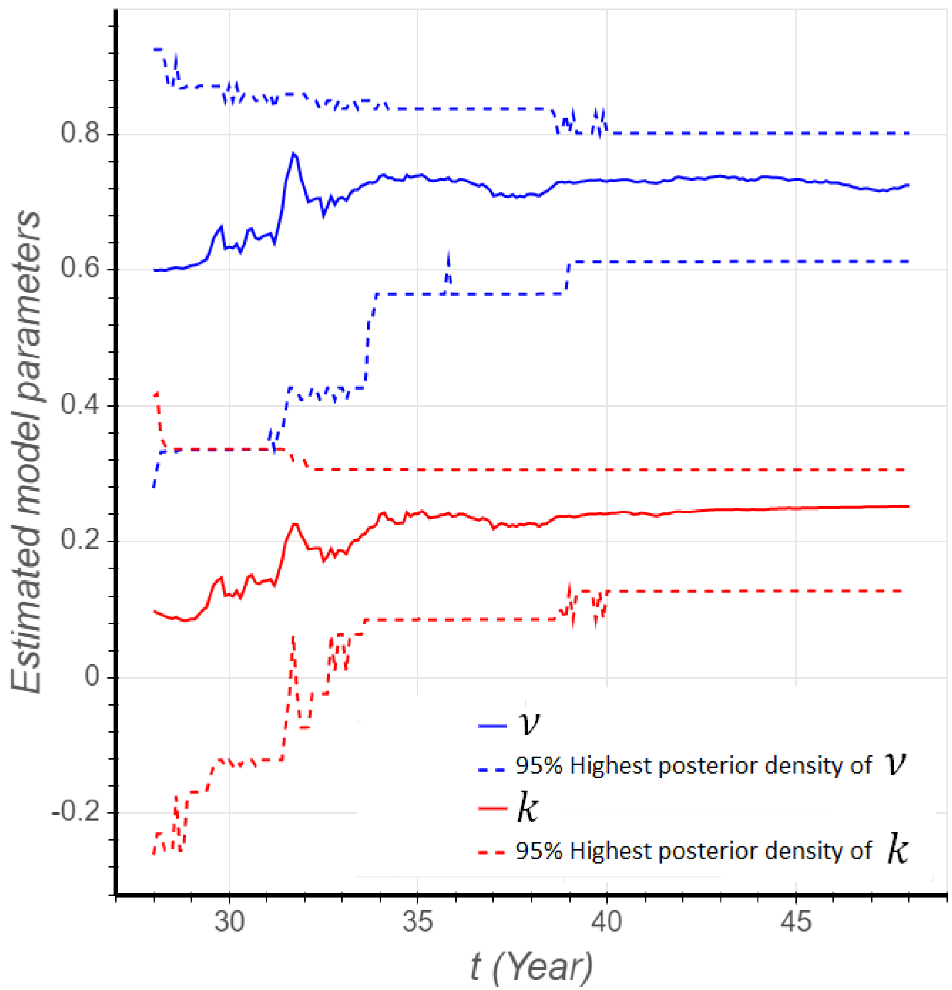
- Online crack growth (length) estimation using RNNs inferred from acoustic emission signals



*Red line: Identity line of actual length

Results- Local Level

Estimation of pitting corrosion growth model parameters by augmented particle filtering



PoF - based pitting corrosion growth model
[Nuhi et al, 2011]

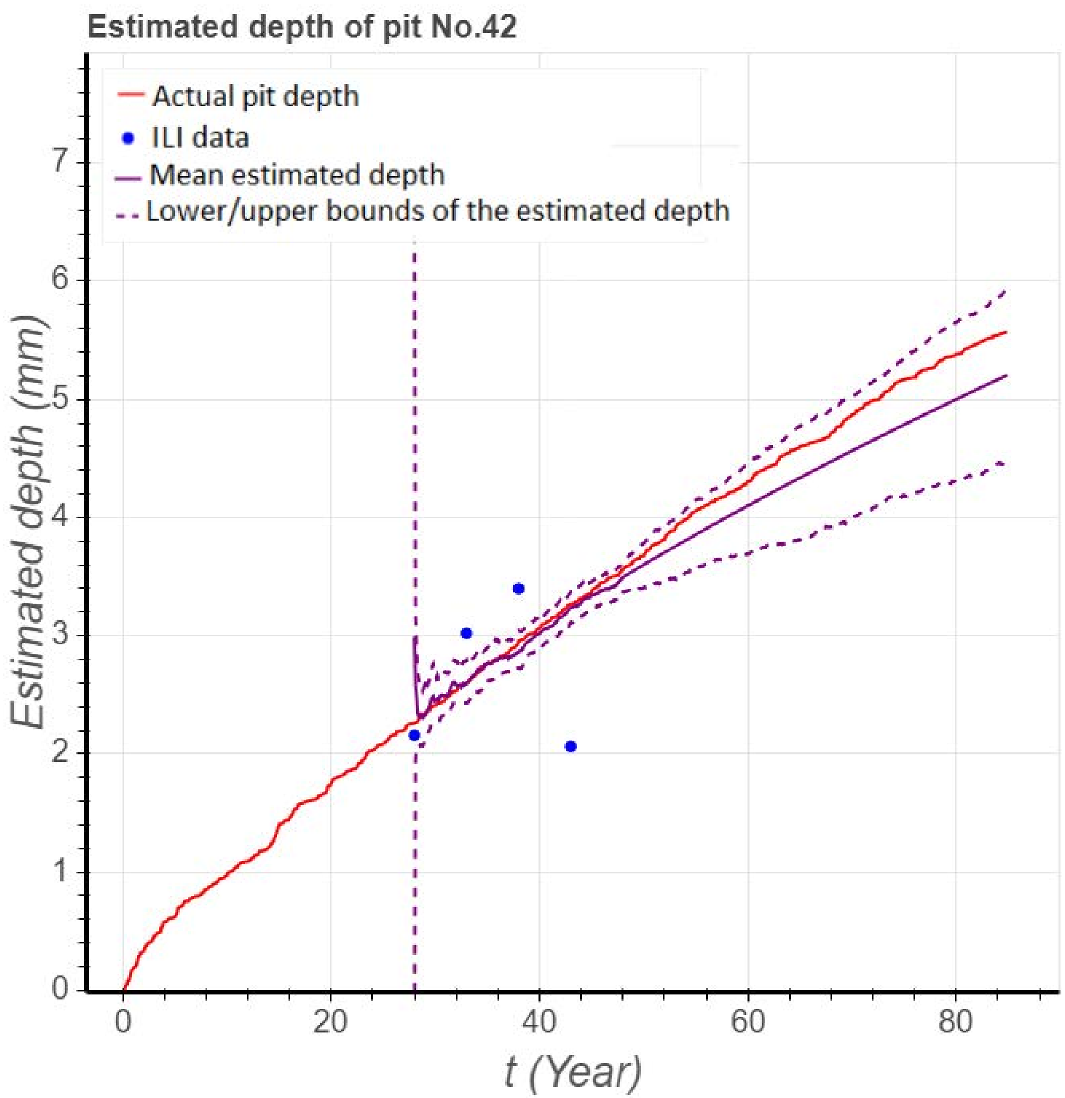
$$d = k(t - t_0)^{\nu}$$

d = pit depth
t : operation time
t_0 : Operation initiation time
k & ν : growth model parameters

•Nuhi, M., Seer, T. A., Al Tamimi, A. M., Modarres, M., & Seibi, A. (2011). Reliability analysis for degradation effects of pitting corrosion in carbon steel pipes. Procedia Engineering, 10, 1930–1935.

Results- Large Scale Level

An example of the estimated depth



Results- Large Scale Level

Comparison between our results and the results of Maes model**:

Performance metric	Developed approach	Maes model**
RMSE	0.334	0.556
Metric N*	24.5%	60.55%

*Metric N: percentage of pits that their predicted depth is out of $\pm 10\%$ bounds of their actual depth.
** Maes model: State of the art pitting corrosion growth model for in-line inspected pits available in the literature which is validated by field data.

Summary

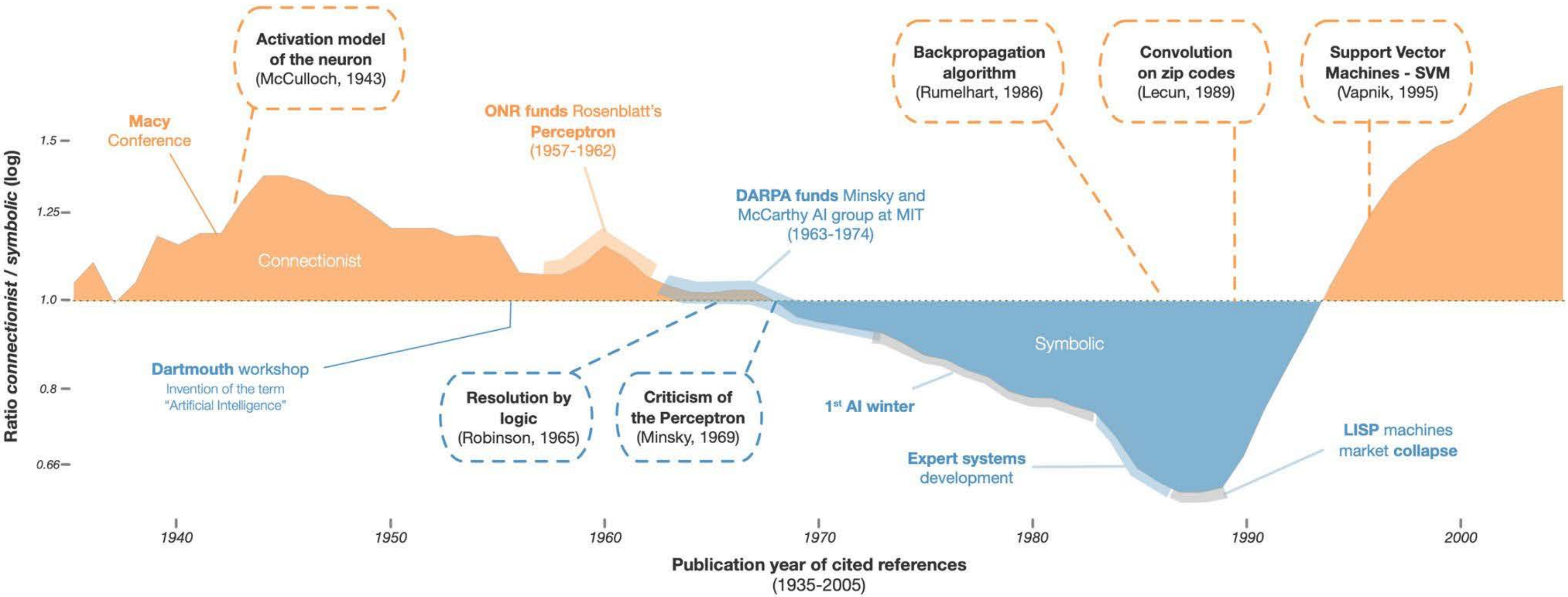
Summary

- A new machine learning based approach for RUL estimation of corroded pipelines is developed
- This approach considers local and large scale data/information for a high confidence RUL estimation
  - Local data are gathered using an optimal arrangement of sensors and inspection areas
  - Large scale data are gathered using in-line inspection
  - Local data are used to mitigate the uncertainties regarding large scale data
  - A fusion of local and large scale data are used to update physics of failure model parameters
- Future works:
  - Dynamic sensor placement based on data fusion results
  - Finding an optimal maintenance policy including optimal maintenance actions and schedule for each pipeline segment
  - Optimal next ILI time

Thank you

Questions?

AI in History



Case study:

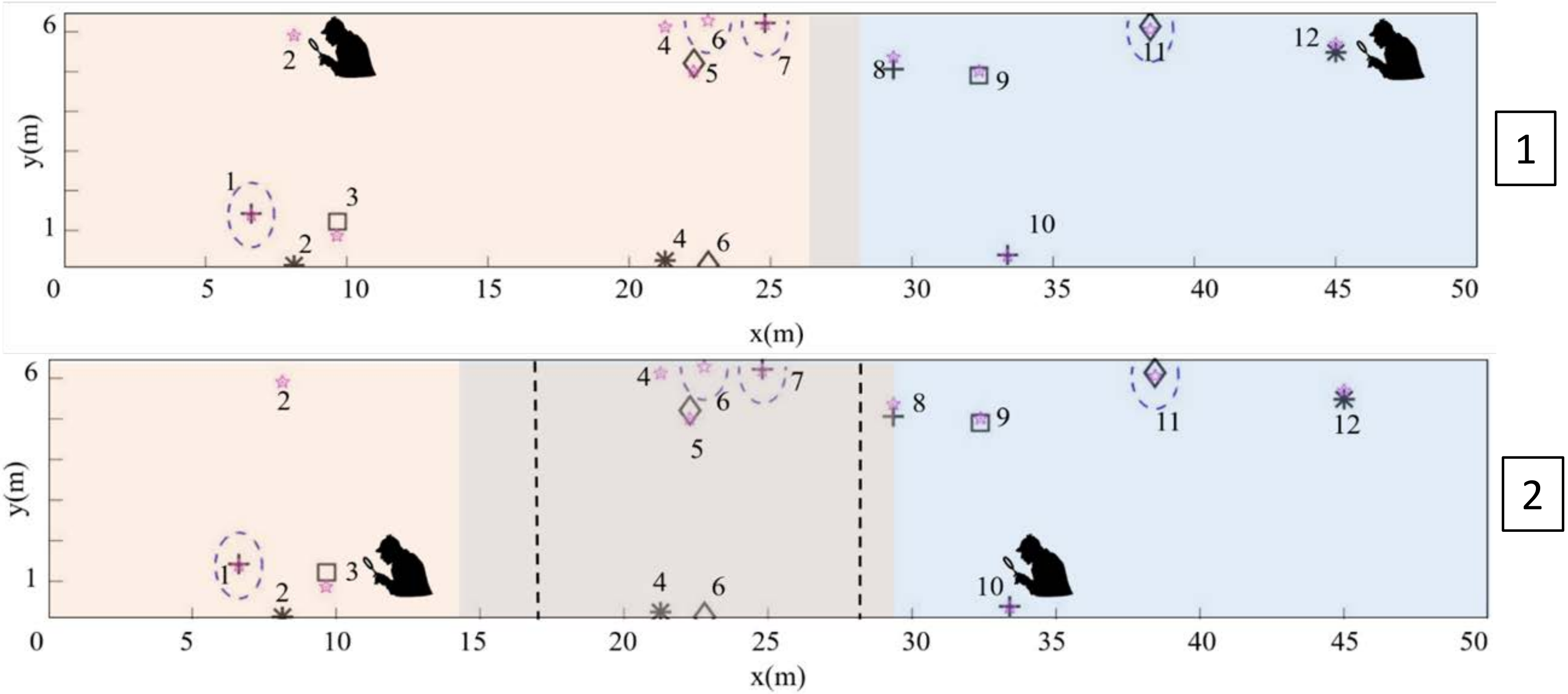
Assumptions and Pipeline Specifications

- A short pipeline segment is considered to illustrate the proposed approach
  - Length=50 m, Radius=1 m
- Internal pitting corrosion
  - Pit depth as the damage size
- Generated 46 **synthetic** samples
- Models from the literature are used for pitting damage density and size distributions
  - Longitudinal pitting density: **0.2 pit/meter**
- Detection methods: Acoustic emission sensors & Human inspection with ultrasonic tools

Case study:

Layout for one Pitting Corrosion Sample

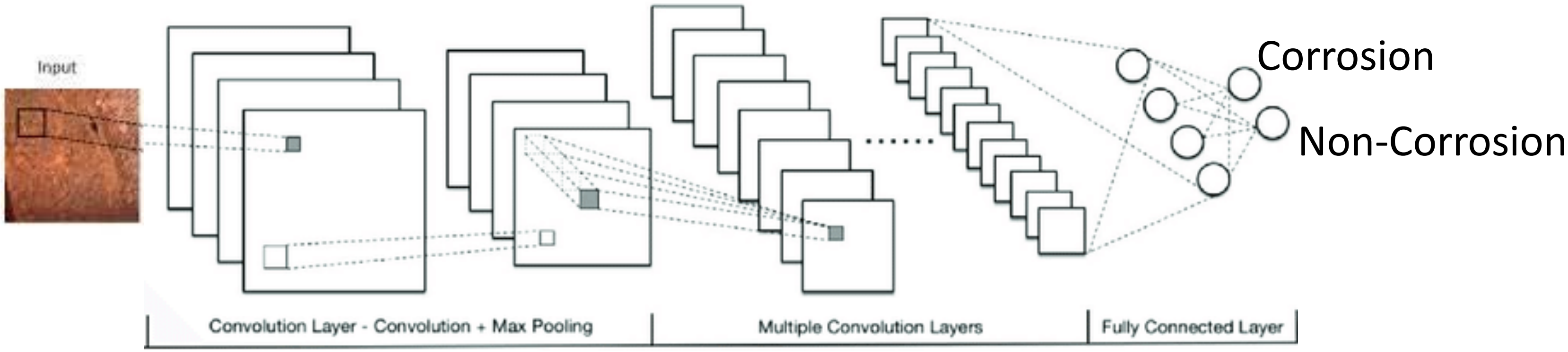
- 142 continues variables, 198 binary variables



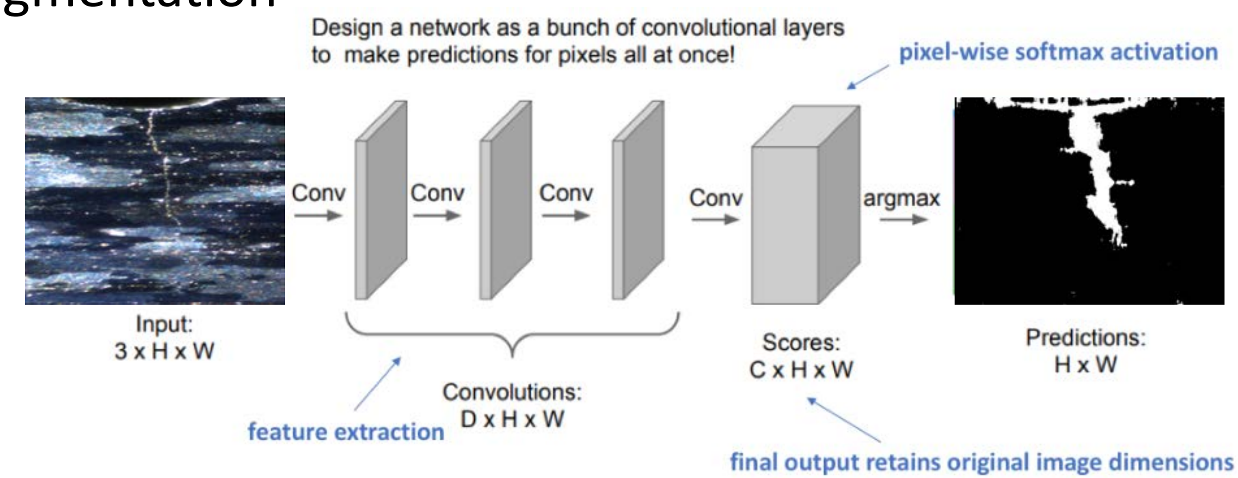
1: without clustering, 2: with clustering

CNN

- CNN for corrosion detection

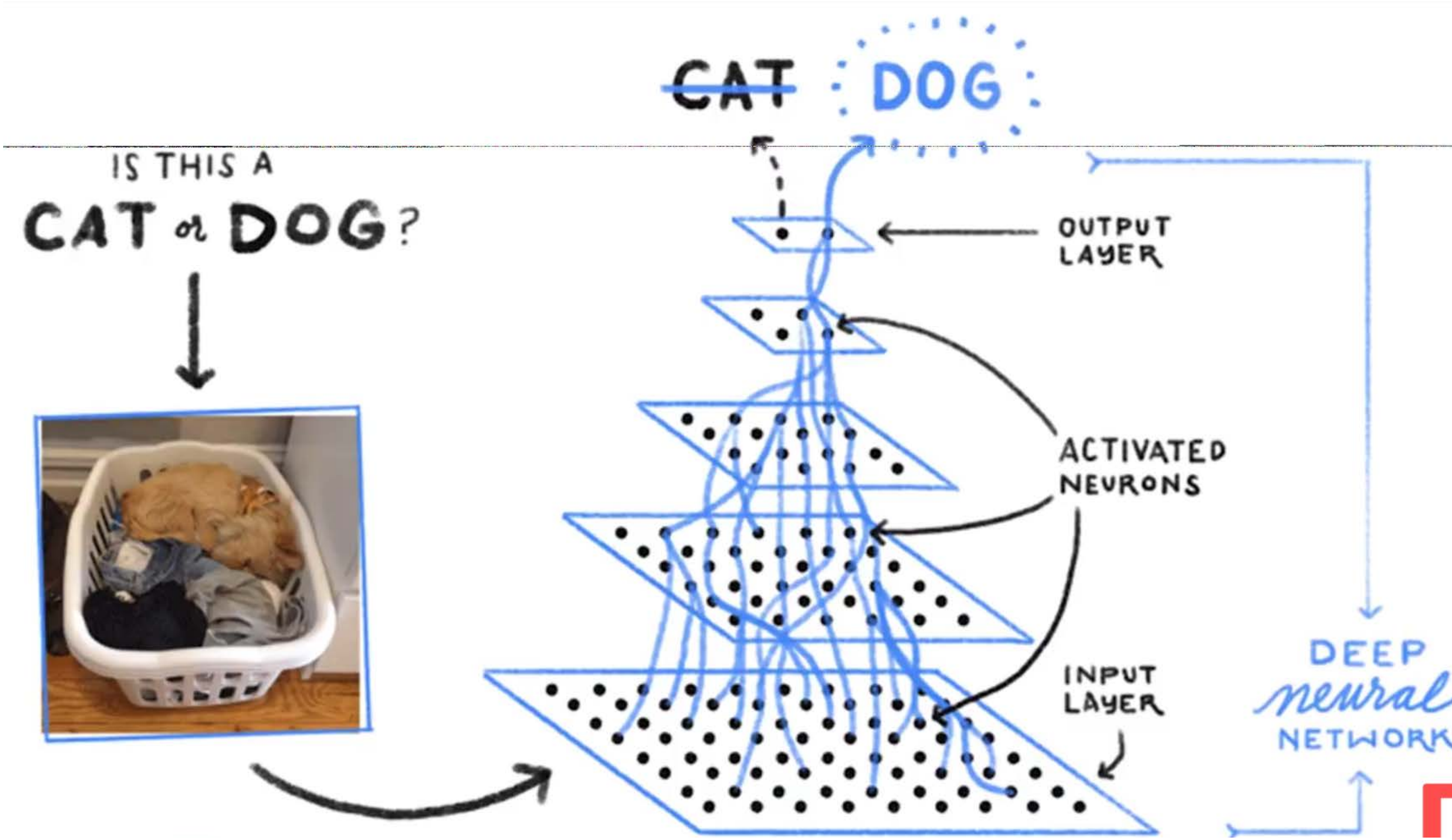


- Semantic Image Segmentation



https://www.jeremyjordan.me/semantic-segmentation/

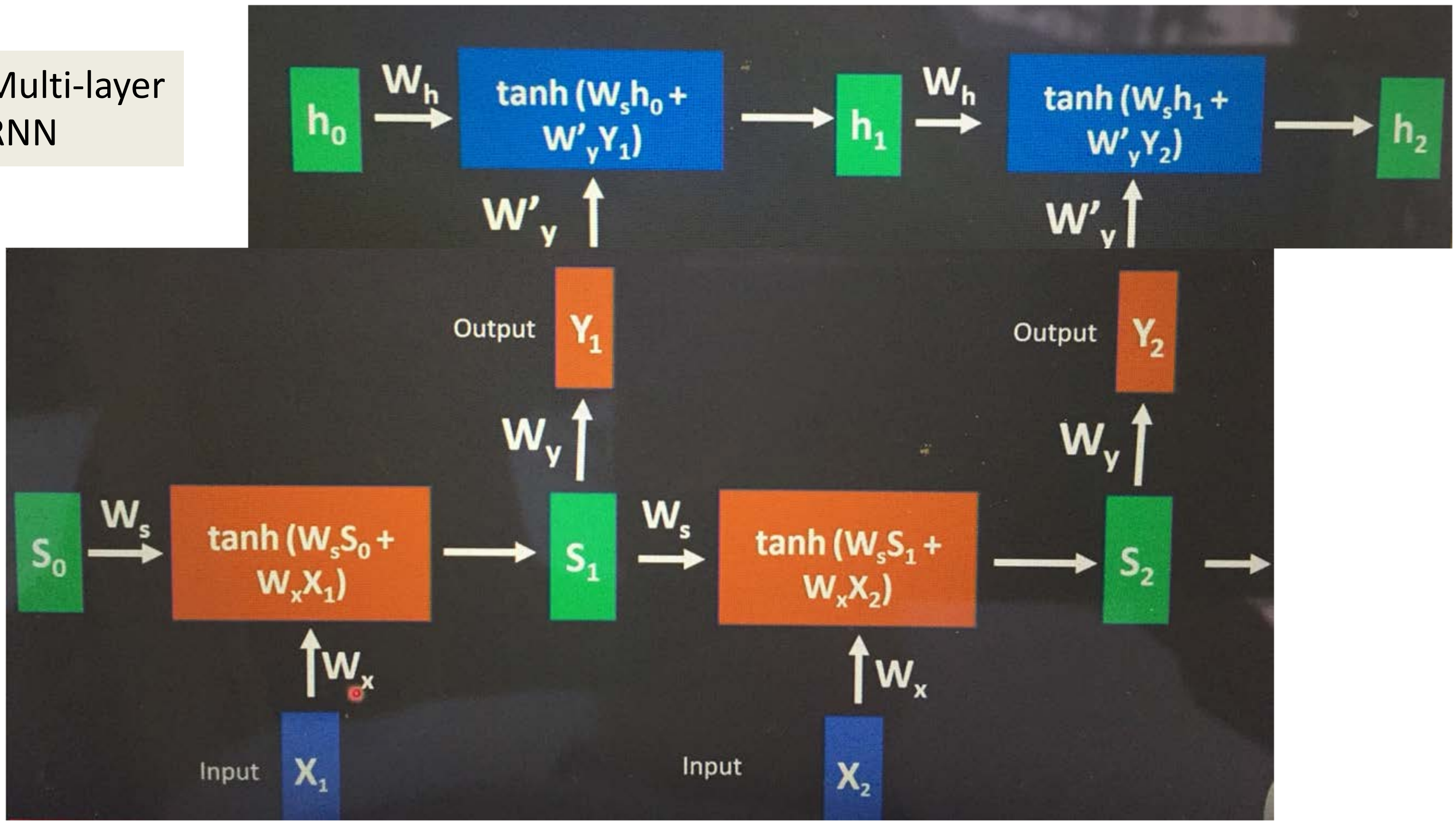
CNN 9cont.0



IS THIS A
CAT or DOG?
~~CAT~~
DOG
OUTPUT LAYER
ACTIVATED NEURONS
INPUT LAYER
DEEP neural NETWORK

RNN

Multi-layer RNN

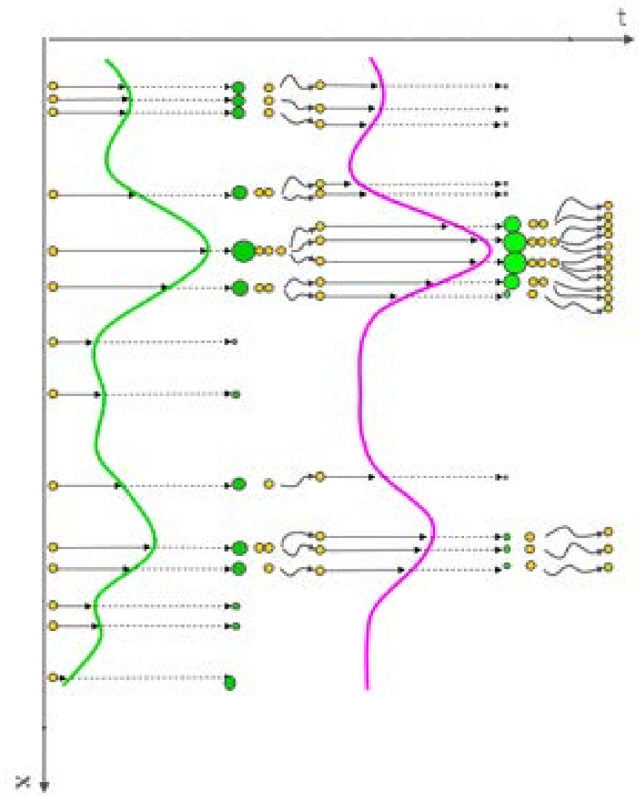


Particle Filtering

- Particle Filtering is a sequential Monte Carlo methods for on-line learning within a Bayesian framework.
- The key idea in PF is to approximate the posterior density function of the state of the system with a discrete weighted distribution of some random samples (i.e., particles)

$$Pr(d_j|y_{1:j}) \simeq \sum_{p=1}^{P} w_j^p \delta(d_j - d_j^p)$$

$d_j = actual\ state\ of\ the\ system\ at\ time\ step\ j$
$y_{1:j} = noisy\ measurments\ from\ time\ step\ 0\ to\ j$
$w_j^p = updated\ weight\ of\ p^{th}\ particle\ at\ time\ step\ j$
$\delta = Dirac's\ delta\ function$
$P = number\ of\ particles$



Particle Filtering

In order to perform PF, P number of samples or particles are generated from initial pdf of the state of the system and then at each time step, those particles are evolved by using the process model (prediction step). Subsequently, the measurements corresponding to that time step will be used to update the assigned weight to each particle (updating step)

Process Model: $d_j = f\left(D_{j-1}, V_{j-1}\right) \rightarrow P(d_j|d_{j-1})$

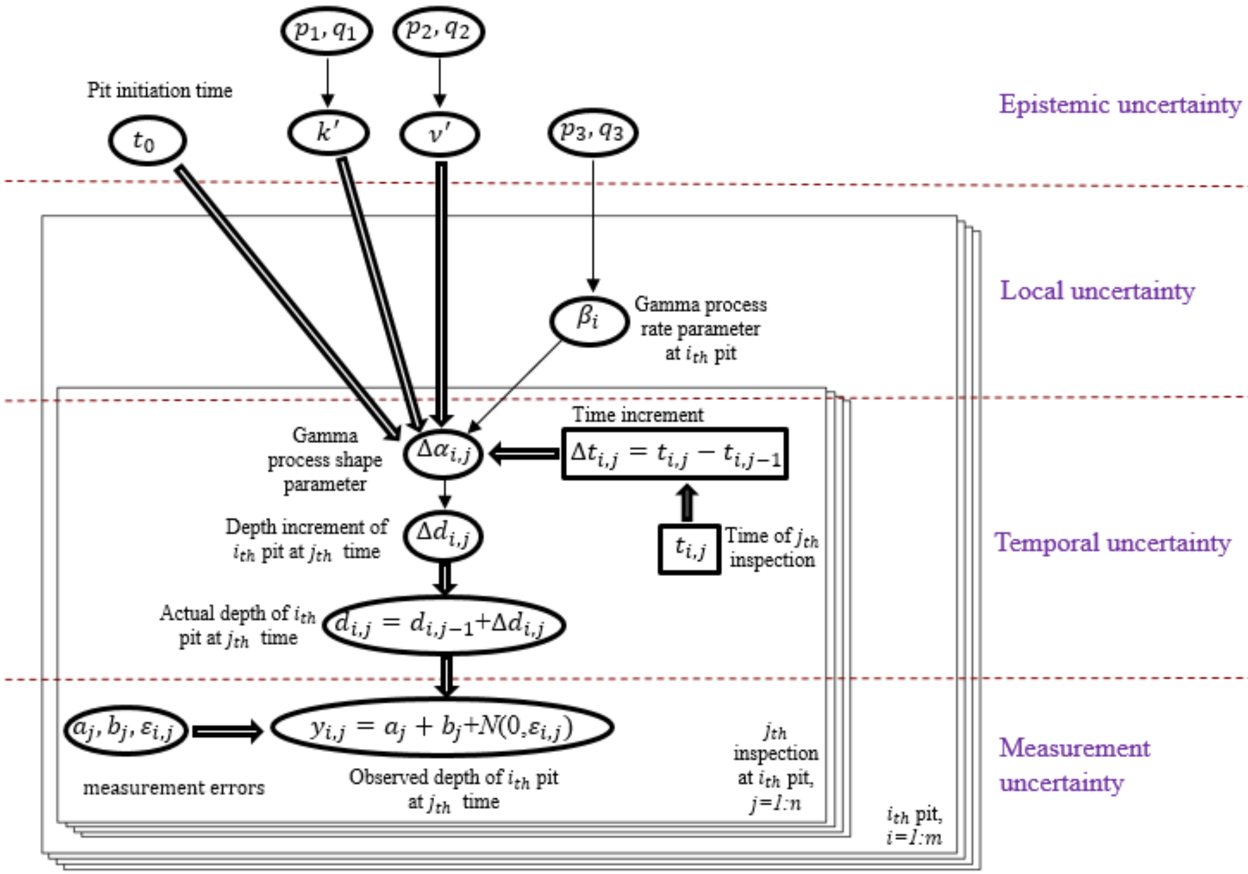
Where d_j is state at time step *j*, V is called process noise and f is the evolution function.

Measurement Model: $y_j = h\left(d_j, W_j\right) \rightarrow P(y_j|d_j)$

Where y_j is state at time step *j*, W_j is called measurement noise and h is the evolution function.

In the standard PF, it is assumed that the parameters of the process model are known. However, for most of the practical cases, those parameters are unknown, but the form of the process model is known based on the physics of the process. In that case, augmented particle filtering (APF) can be used to estimate the state of the system and the process model parameters.

Hierarchical Bayesian



Another method that is a used in this approach is a hierarchical Bayesian (HB) method based on a non-homogeneous gamma process. HB modeling is an appropriate method to make scientific inference about a population, based on many individuals. This method has been used to fuse ILI data of various pits along the pipeline.