Machine Learning in Pipeline Inspection

Applications of supervised learning in non-destructive evaluation

Authors: Roberto H. HERRERA, Paul CHRISTENSEN, Adrianus ELVERS
UT Quality Inc. a RAE Energy Company; Edmonton, Canada

CINDE
CANADIAN INSTITUTE FOR NON-DESTRUCTIVE EVALUATION

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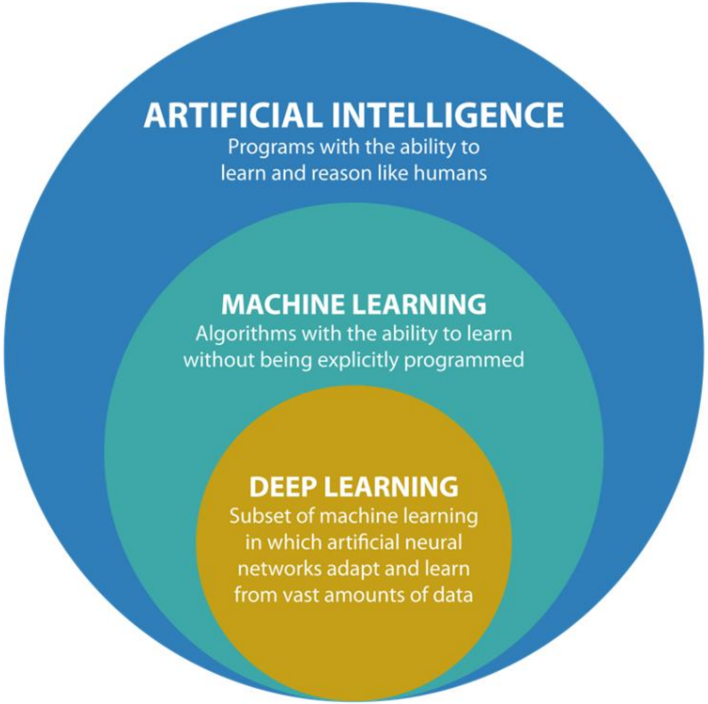
Machine Learning in Pipeline Inspection

- Supervised Learning
- Automatic Flaw Type Classification.
- Automatic Acceptance Criteria using Artificial Intelligence.

What is Machine Learning?

- Machine learning is a field of Artificial Intelligence that uses statistical techniques to give computer systems the ability to "learn"

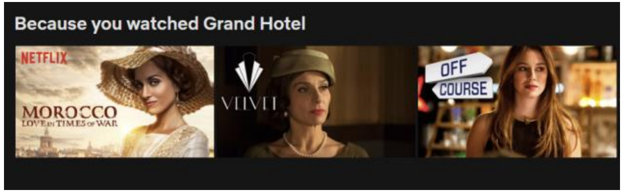
- Machine Learning is the science of getting computers to learn as well as humans do or better.



https://www.argility.com/argility-ecosystem-solutions/iot/machine-learning-deep-learning/

Data everywhere

- Machine learning algorithms find natural patterns in data that generate insight and help you make better decisions and predictions.
- Netflix

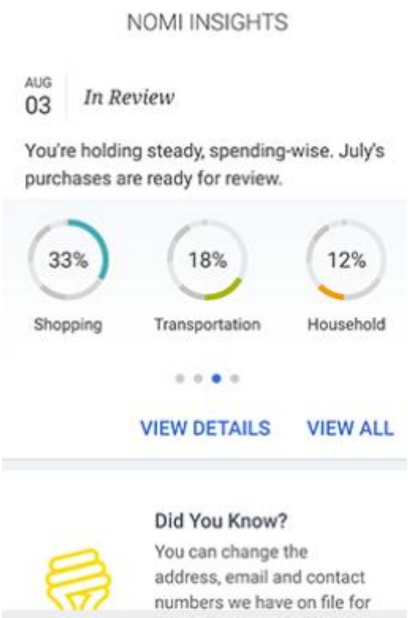


- Amazon Kindle

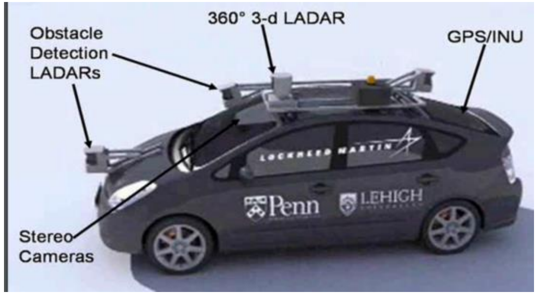
Some applications

- Web search
- Finance (Example RBC Canada)
- Space exploration
- Robotics
- Social Networks
- Autonomous cars
- Personal assistants (Google, Alexa, Siri)
- Non destructive Testing –

(The value will be on the data)

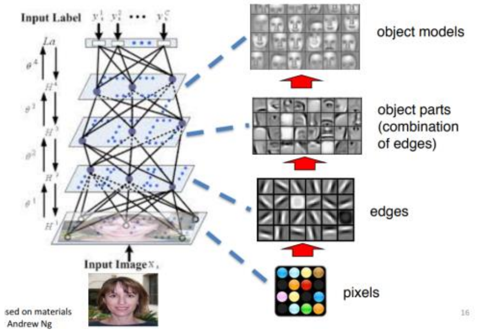


Using predictive technology, NOMI Find & Save does all the work for you, so you can save money without lifting a finger



Google now

Deep Belief Net on Face Images



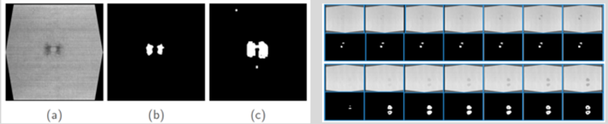
Some applications

NASA – Machine Learning

- Algorithms capable of learning from both data and human interaction to enable insights and make predictions

Aerospace Data Assistants Projects – 1 of 2

Anomaly Detection in Non-Destructive Evaluation of Materials Images



Develop techniques and algorithms to automatically detect anomalies during the nondestructive evaluation of materials

Goals

- Significantly reduce SME analysis time and assist experts in discovering additional anomalies
- Help to design better material compositions and structures

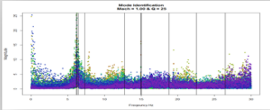
Techniques

- Two-Dimensional Regression designed to detect anomalous pixels
- Convolutional Neural Networks to classify the image data

Accomplishments & Next Steps

- Algorithms are validated with real data sets and further enhanced
- Deliver a tool with a good UI for SMEs to use as an 'Assistant' for anomaly detection of composite materials analysis

Predicting Flutter from Aeroelasticity Data



Semi-Span Super-Sonic Transport (S^4T) Model

Develop methods to automatically detect the onset of flutter during wind tunnel testing

Goals

- Find new ways of predicting flutter in the time domain
- Identify non-traditional predictor variables and unseen patterns
- Better understand precursors to flutter and improve configurations

Techniques

- Piecewise Regression to locate peaks, track coalescence of structural modes
- Time Series Motifs to identify signatures in the data that could represent precursors to flutter

Accomplishments & Next Steps

- Peak detection tested with multiple datasets
- Several significant time series motifs detected
- Testing with synthetic data for validation of algorithms

AIAA Conference – Big Data Session_ Final – Jan 2016

Types of learning

Machine Learning

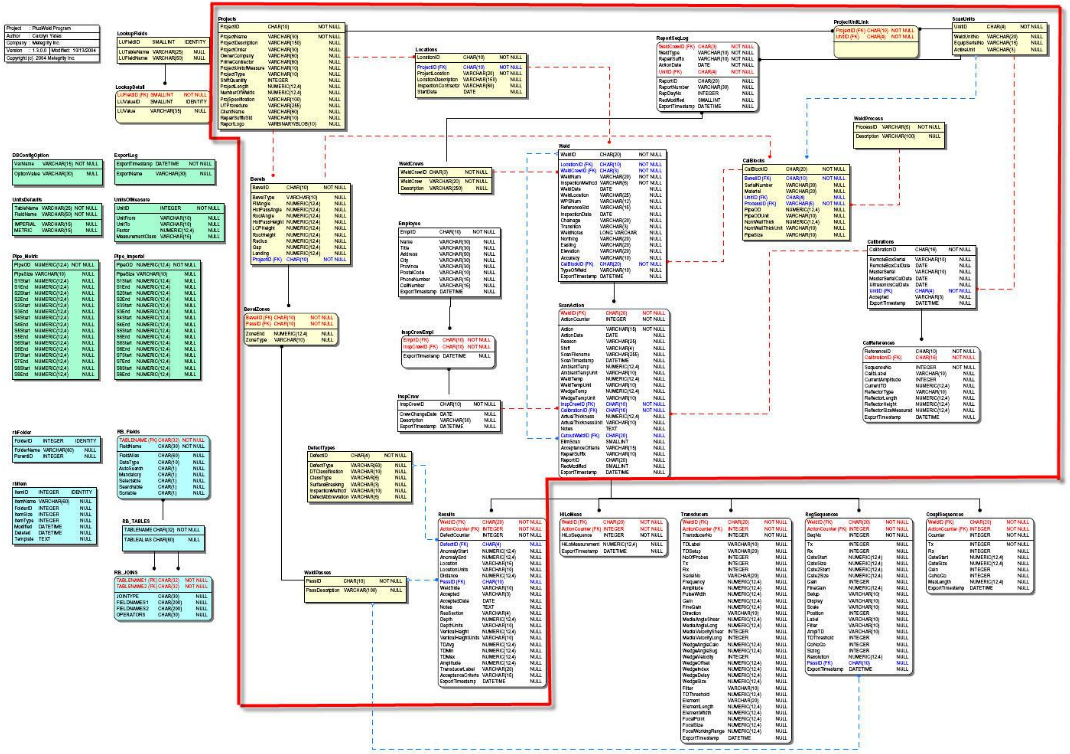
- **Supervised**: Task driven (Regression / Classification)
- **Unsupervised**: Data driven (Clustering)
- **Reinforcement**: Algorithm learns to react to an environment

Google AI

Pipeline inspection data:

- The perfect case

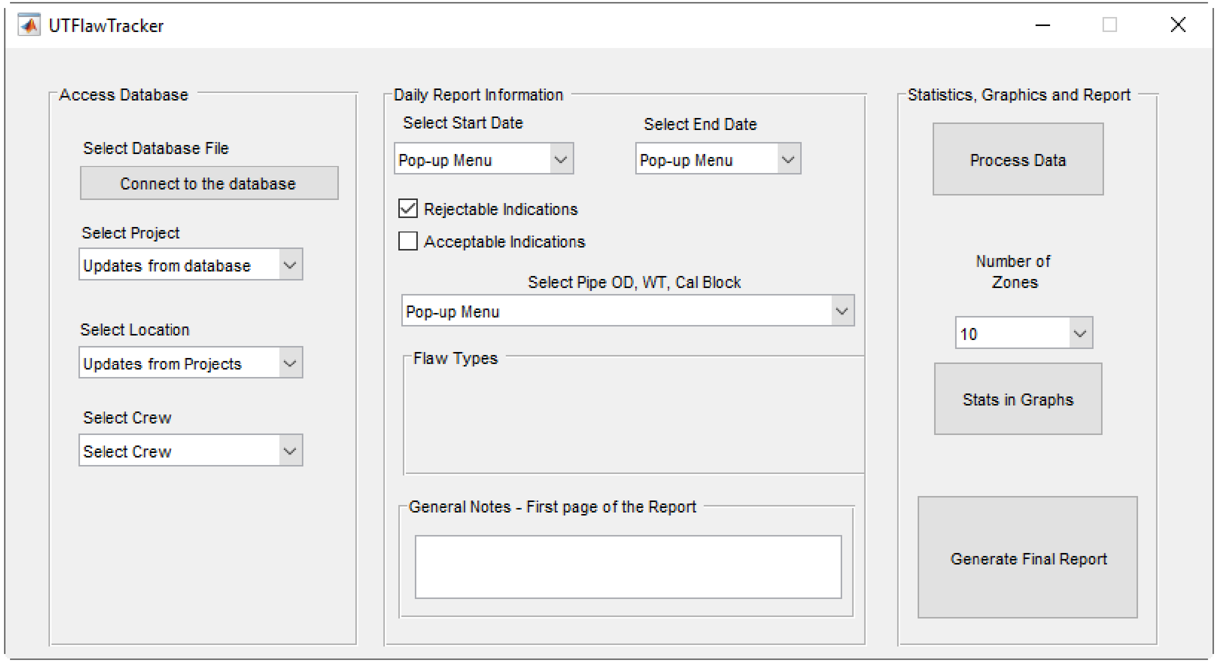
UTQ Flaw Tracker



Pipeline inspection data:

UTQ Flaw Tracker

- UT Flaw Tracker©, filters the dataset to feed the proper data into the ML algorithm.



Getting your data ready for Machine Learning

- The Flaw Tracker Report

WeldNum	Flaw	DefectCounter	Result	Class	Ident	Channel	WeldSide	Start	End	Length	Depth	Height	WallThickness	ScanDateTime
Weld_001	1	1	Accepted	LB	IF	TOFD	N/A	274	278	4	11.2	1	19.1	2017-09-29 22:16
Weld_002	1	2	Accepted	LB	IF	TOFD	N/A	234	238	4	8	1	19.1	2017-09-29 22:16
Weld_...	1	3	Accepted	LB	IF	TOFD	N/A	202	206	4	7.5	1	19.1	2017-09-29 22:16
...	1	1	Accepted	LB	IF	TOFD	N/A	150	158	8	15.2	1	19.1	2017-09-29 22:30
...	1	2	Accepted	LB	IF	TOFD	N/A	178	183	5	15.2	1	19.1	2017-09-29 22:30
...	1	3	Accepted	LB	IF	TOFD	N/A	196	202	6	15.7	1	19.1	2017-09-29 22:30
...	1	4	Accepted	LB	IF	TOFD	N/A	238	252	14	15.8	1.2	19.1	2017-09-29 22:30
...	1	5	Accepted	LB	IF	TOFD	N/A	274	280	6	16	1	19.1	2017-09-29 22:30
...	1	1	Accepted	LB	IF	TOFD	N/A	522	526	4	10.5	1	19.1	2017-09-29 22:36
Weld_957	1	2	Accepted	LB	IF	TOFD	N/A	172	176	4	16.8	1	19.1	2017-09-29 22:36

Getting your data ready for Machine Learning

Each indication has the following parameters:

- Operator's inputs (subjective)

  - WeldNum – Fixed Input data
  - Flaw – Software Flaw Tracker
  - DefectCounter – Software Flaw Tracker
  - Result – Operator's decision (Accept/Reject)
  - Class – Operator's input (LB, VR, etc.)
  - Identification – Operator's input (Flaw Type: Geometry, IF- incomplete fusion, Porosity, etc.)

- Direct results from the measurement system UT Scan (objective)

  - Channel – UT Scan software
  - WeldSide – UT Scan software
  - Start – Operator's marked but the indication comes from the UT Scan
  - End – Idem
  - Length – Idem
  - Depth – Idem
  - Height – Idem
  - WallThickness – Physical data
  - ScanDateTime – Fixed data

How to apply Machine Learning to our data?

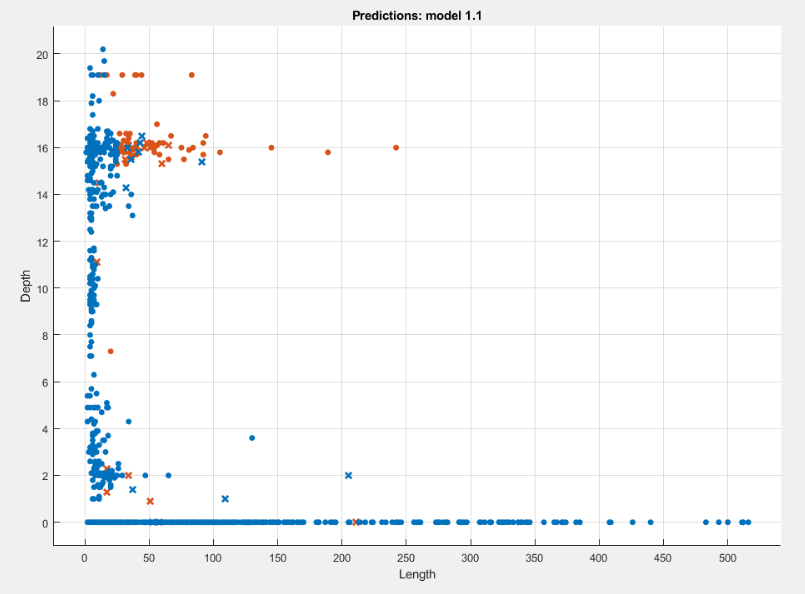
- We can "train" a computer to "learn" from the Physical Data (objective) to infer the **classification of the indications**
  - With the same accuracy as humans do or higher.

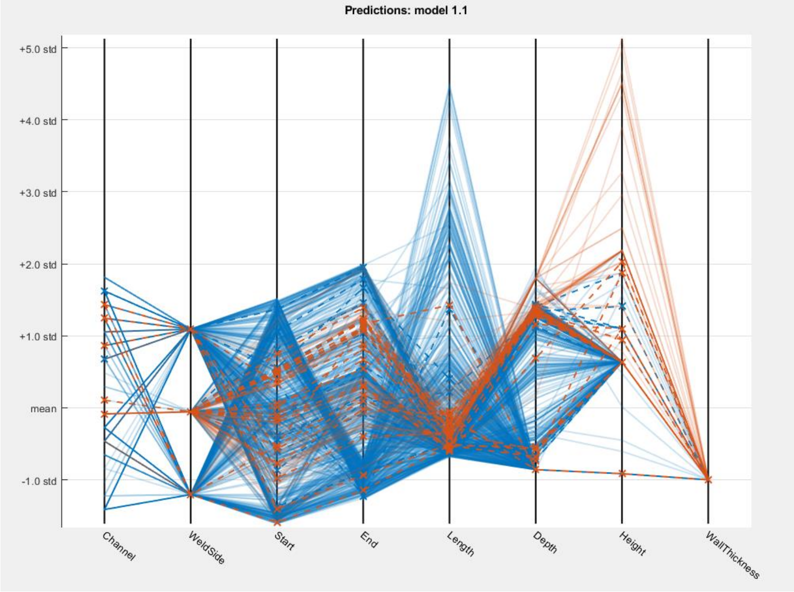
The task can be described as:

- **Given the Measured Data from the UT Scan:**
  - Channel – UT Scan software
  - WeldSide – UT Scan software
  - Start – Operator's marked but the indication comes from the UT Scan
  - End – Idem
  - Length – Idem
  - Depth – Idem
  - Height – Idem
  - WallThickness – Physical data
  - ScanDateTime – Fixed data
- **Classify the Flaw Types as: Geometry, Incomplete Fusion, Porosity, etc. and …**
- **BTW let me know if I should Accept it or Reject it.**
- **Another condition is to be consistent and with an accuracy close to 100%.**
  - **Independently of your mood, the weather, your vision or any other physiological motivation.**

Feed the Machine Learning algorithm with data.

- We have trained a Machine Learning algorithm in a dataset of
  - 766 Indications





Data conditioning

- The Confusion Matrix.

The algorithm "learned" to classify Accepted or Rejected indications with an accuracy of 97%

Processing new datasets

Once the Machine Learning algorithm produces a reasonable result, process the new dataset with the Trained Algorithm

- A database from a recent project (2018) was used as a testing dataset.
- We ran the trained model over the 657 indications in this new dataset,
- Hiding the labels and evaluation performed by the operators (flaw types and evaluation: accepted or rejected).

What is the accuracy? Are the results consistent?

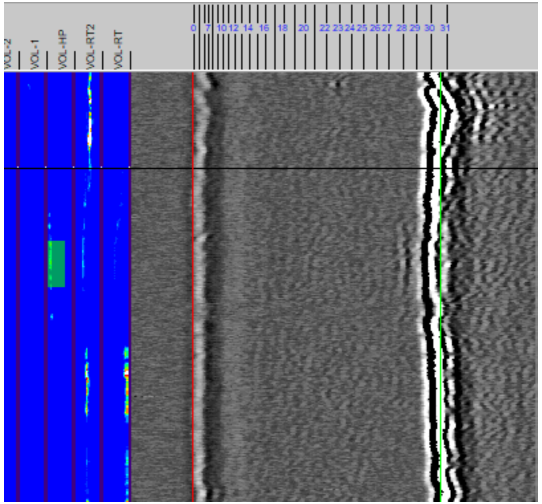
- From 657 Indications, the ML algorithm correctly classified 654 in Accepted or Rejected for an accuracy of 99.5%.
- Accuracy 99.5%.
- Only three indications were accepted that the algorithm thinks we should reject.

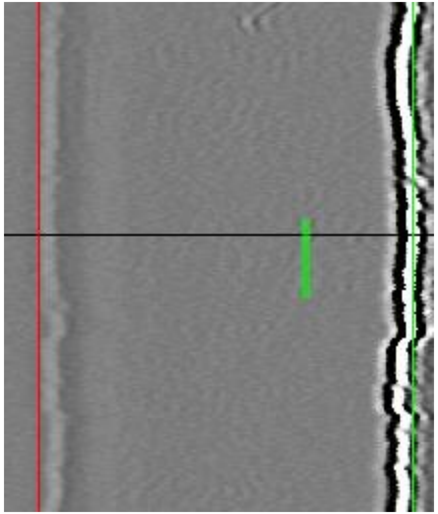
- Note: After consultation with the specialist, these were close-calls. These indications were correctly classified by the operators but were so close to the acceptable limit that another operator could have had a different opinion.

WeldNum	Flaw	DefectCounter	Result	Class	Ident	Channel	WeldSide	Start	End	Length	Depth	Height	WallThickness	ScanDateTime
'BS-07-071'	1	2	'Accepted'	'NA'	't-IF'	'VOL-HP'	'UpStream'	127	162	36	27.5	1	29.8	10/1/2018 4:42:53 PM
'BS-07-074'	1	3	'Accepted'	'NA'	't-IF'	'TOFD'	'N/A'	121	160	40	25.6	0.5	29.8	10/1/2018 5:04:53 PM

- From 657 indications 2 are not in agreement with the “ground data”.

  - Only two indications were accepted that the algorithm thinks we should reject:





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What about the flaw types? Multiple class classification.

- From 657 Indications the Algorithm correctly classified 641 with the correct Flaw Type
- Accuracy 97.6%.
- These are the misclassified Flaw Types
- Geo as IF and IF as Geo
- Actual Accuracy – 99.7%

Operator	ML Algorithm
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'Geo'}	{'IF' }
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'Geo'}	{'NC'}
{'Geo'}	{'NC' }
{'Geo'}	{'NC'}
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'Geo'}	{'NC' }
{'IF' }	{'Geo' }

Results are in good agreement

- See the Original and Estimated side by side

```
>> [yOrig{:,1} yEstimated]

ans =

  657×2 cell array

    {'Geo'}    {'Geo'}
    {'IF' }    {'IF' }
    {'Geo'}    {'Geo'}
    {'Geo'}    {'Geo'}
    {'Geo'}    {'Geo'}
    {'Geo'}    {'Geo'}
    {'Geo'}    {'Geo'}
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    {'Geo'}    {'Geo'}
    {'Geo'}    {'Geo'}
    {'IF' }    {'IF' }
    {'Geo'}    {'NC' }
    {'Geo'}    {'Geo'}
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    {'Geo'}    {'Geo'}
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    {'Geo'}    {'Geo'}
    {'Geo'}    {'Geo'}
    {'Geo'}    {'Geo'}
    {'IF' }    {'IF' }
```

Conclusions

- How to integrate ML into current systems?

- Machine Learning will be a complement to the Flaw Type classification.
- Acceptance criteria could be validated by the AI algorithm.
- The Machine Learning functionality will be added to the current version of the UTQ Flaw Tracker as a validating method.