EVALUATION OF PIPELINE INSPECTION DATA AS A SHOWCASE FOR INDUSTRIAL DATA SCIENCE

ROSEN
empowered by technology

WHOAMI

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INTRODUCING THE ROSEN GROUP

ROSEN develops and manufactures equipment, software, and methods for the inspection, diagnosis, and protection of industrial structures in a wide range of industries.

Because damage can cause serious impacts!

INDUSTRIAL VS COMMERCIAL DATA SCIENCE

- Data Science practices and strategies can differ significantly between commercial and industrial Data Science applications
- Frequency of data input
- Cost of experiments and models
- Interpretability of data
- Demand on the accuracy of predictions

COMMERCIAL DATA SCIENCE

- Examples: online shop, click through rates, product recommendations, churn prediction
- E.g. identify and enforce preferable behavior, improve customer experience, increase revenue
- Usually large amount and high frequency of data input
- Data in general hard to misinterpret
- Allows real time experimentation (e.g. A/B testing)
- Predictions do not need to be very accurate due to high number of decisions
- Decisions of algorithm do need necessarily to be interpretable (although often desirable)

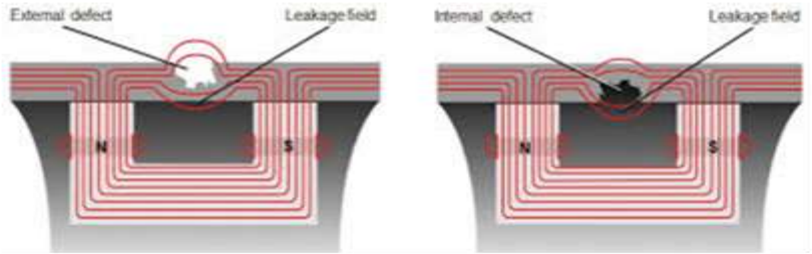
INDUSTRIAL DATA SCIENCE

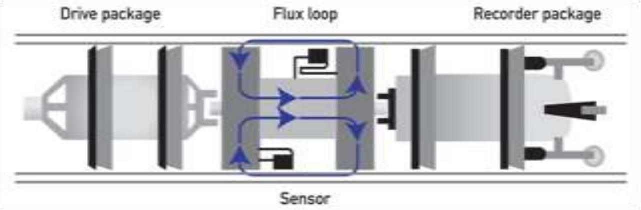
- Examples: Testing of devices, predictive maintenance of machines, planes, trains etc., (IoT applications)
- Data is often messy -> requires much more hands on management and analysis
- Create physical models using data sets
- Often time series data (sensors, successive measurements) -> restricts real time experimentation
- Automated testing is hard
- Predictions need to be very accurate, single prediction might be worth thousands of Euros
- -> a lot more money is allocated to single predictions, either by expensive algorithms or data collection/curation
- Models need to be interpretable
- (sometimes predictions need to be very fast, ‘on edge’)

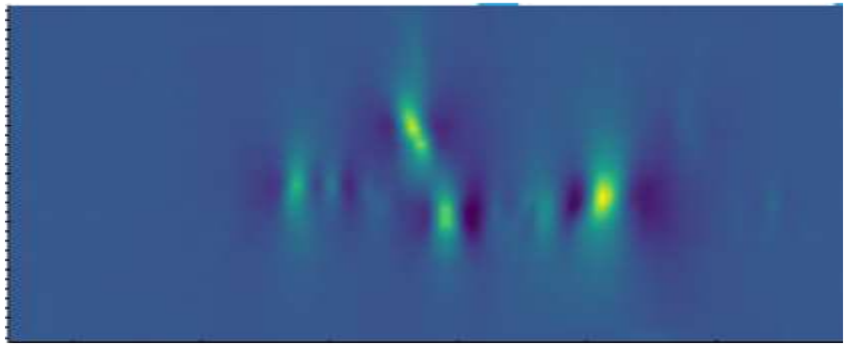
MAGNETIC FLUX LEAKAGE

- Measure volume loss in pipeline wall
- Indirect measurement principle
- Image-like data (2d array of amplitudes)

- Tasks: Detect, classify and estimate defect geometry from measured data.



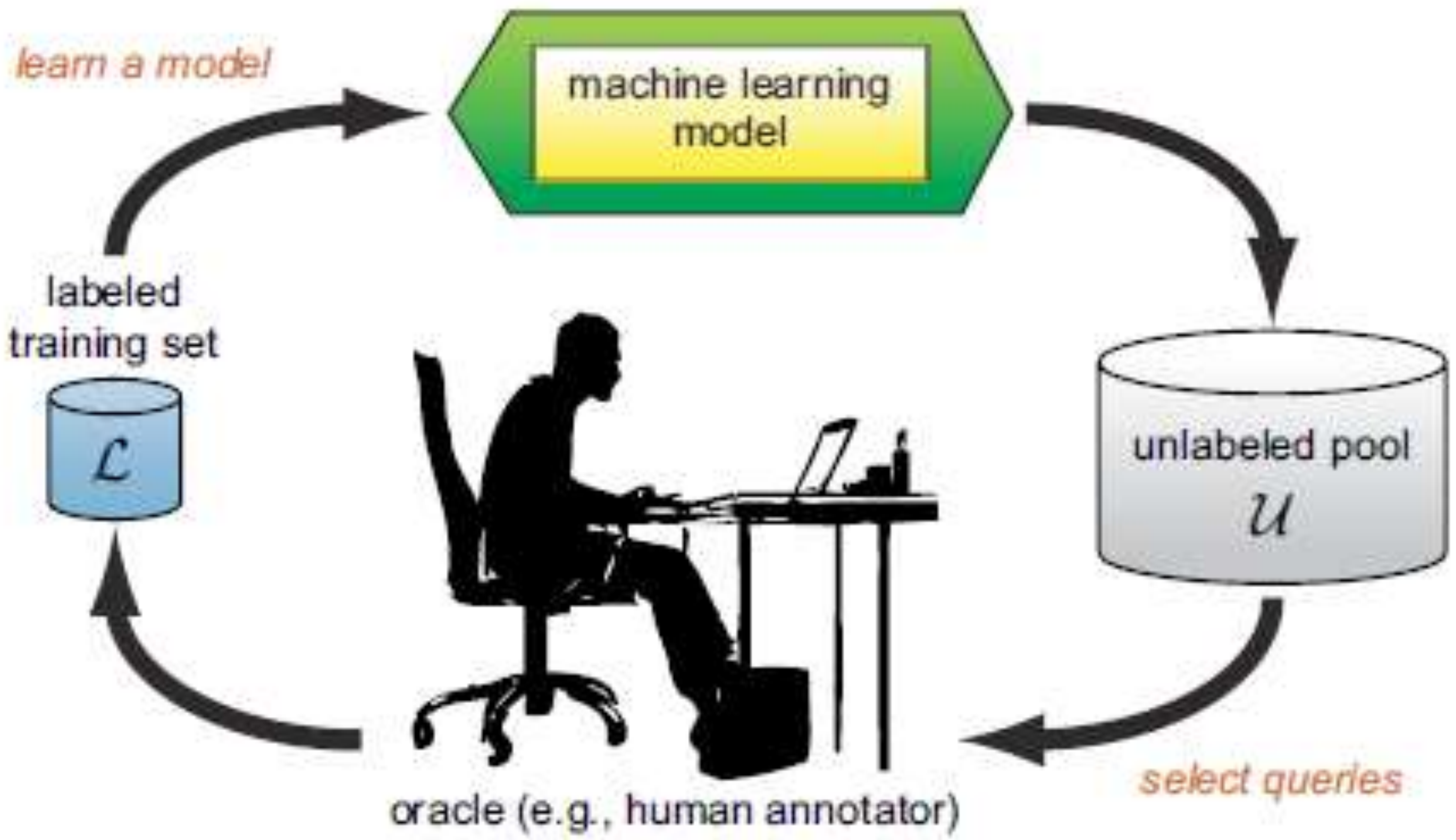




MOTIVATION FOR ACTIVE LEARNING

- Computer Vision problems
  - Large amounts of unlabeled data available
  - Human annotators can provide ground truth
  - Which instances to label?
  - Achieve high accuracy using as few labeled instances as possible

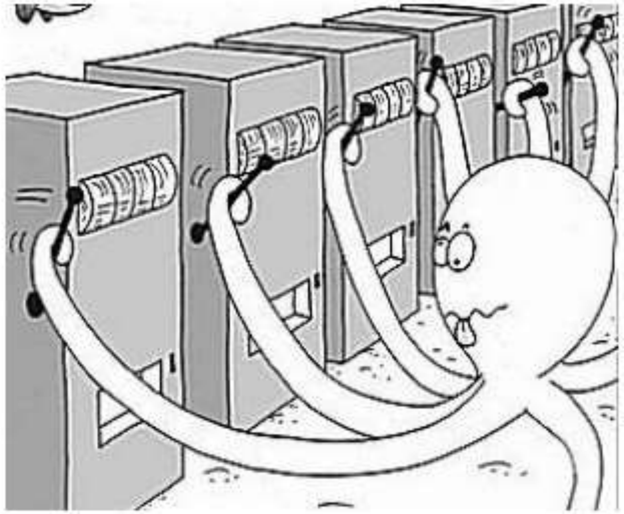
WHAT IS ACTIVE LEARNING?



Source: Settles, Burr (2010), "Active Learning Literature Survey", Computer Sciences Technical Report 1648. University of Wisconsin–Madison

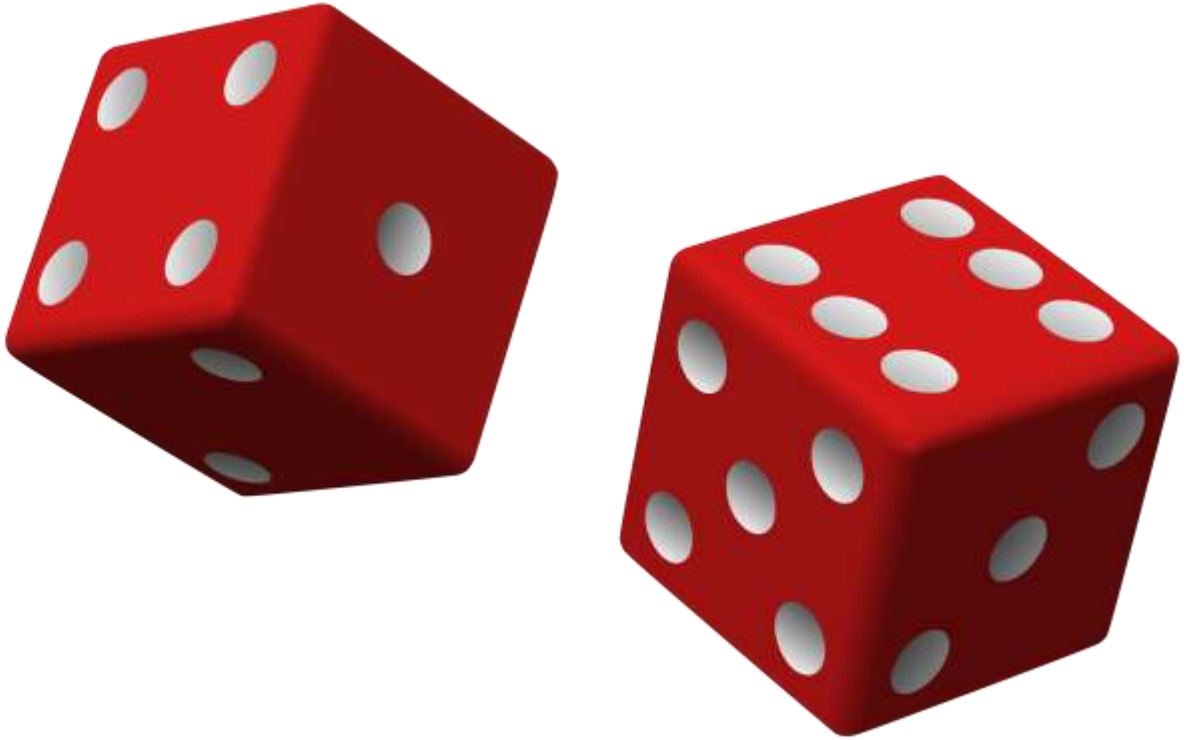
EXPLORATION VS EXPLOITATION DILEMMA

- How to design query algorithms?
  - Exploitation: make best decision based on currently available information
  - Exploration: gather more information



RANDOM QUERY

- Select instance to label randomly
- Good starting point
- Baseline algorithm : Compare other algorithms against random query



UNCERTAINTY SAMPLING

- Most popular algorithm
- Query the instance which the classifier is most uncertain how to label
- Least confident prediction in terms of prediction probability

$$x^*_{LC} = \underset{x}{\operatorname{argmax}}\ 1 - P_\theta(\hat{y}|x)$$

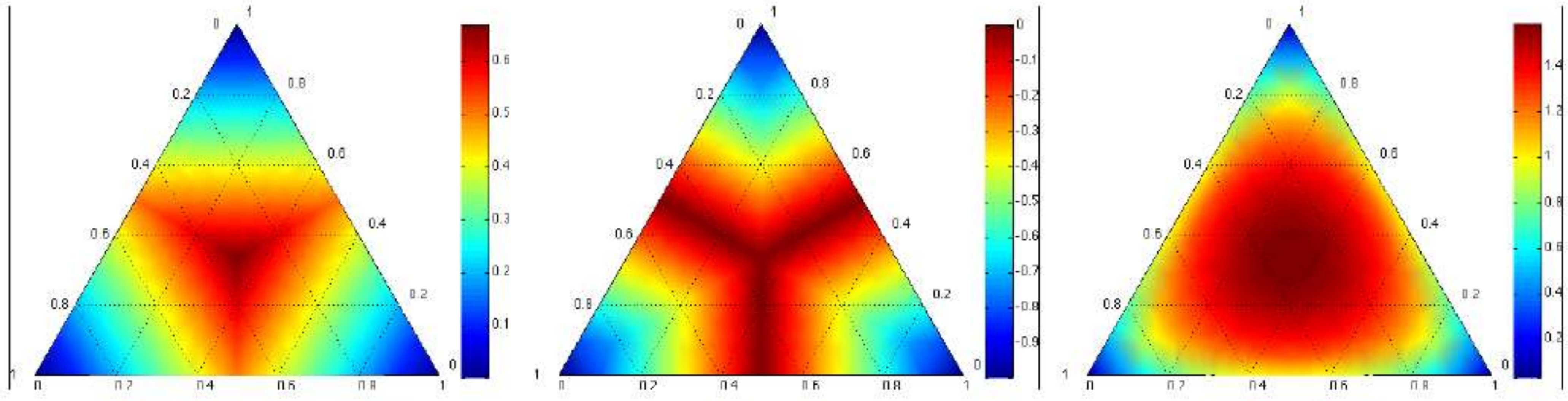
$$\hat{y} = \operatorname{argmax}_y P_\theta(y|x)$$

- Make use of margin between most probable classes or entropy of class prediction probabilities to capture the whole distribution

$$x^*_M = \underset{x}{\operatorname{argmin}}\ P_\theta(\hat{y}_1|x) - P_\theta(\hat{y}_2|x)$$

$$x^*_H = \underset{x}{\operatorname{argmax}} - \sum_i P_\theta(y_i|x) \log P_\theta(y_i|x)$$

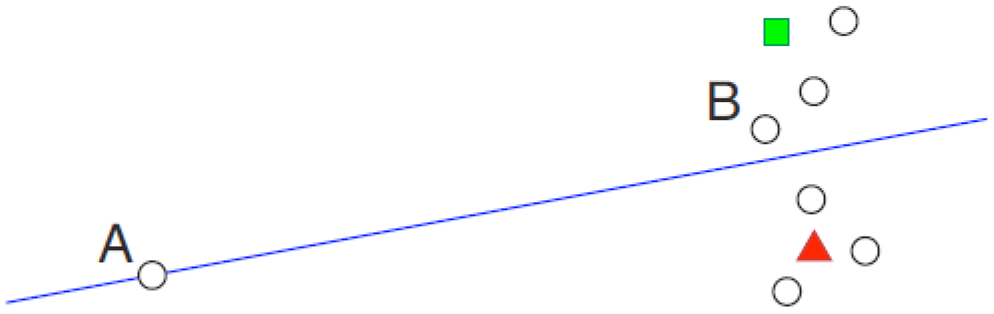
UNCERTAINTY SAMPLING



(a) least confident (b) margin (c) entropy

Source: Settles, Burr (2010), "Active Learning Literature Survey", Computer Sciences Technical Report 1648. University of Wisconsin–Madison

SHORTCOMINGS OF UNCERTAINTY SAMPLING



Source: Settles, Burr (2010), "Active Learning Literature Survey", Computer Sciences Technical Report 1648. University of Wisconsin–Madison

OTHER ALGORITHMS

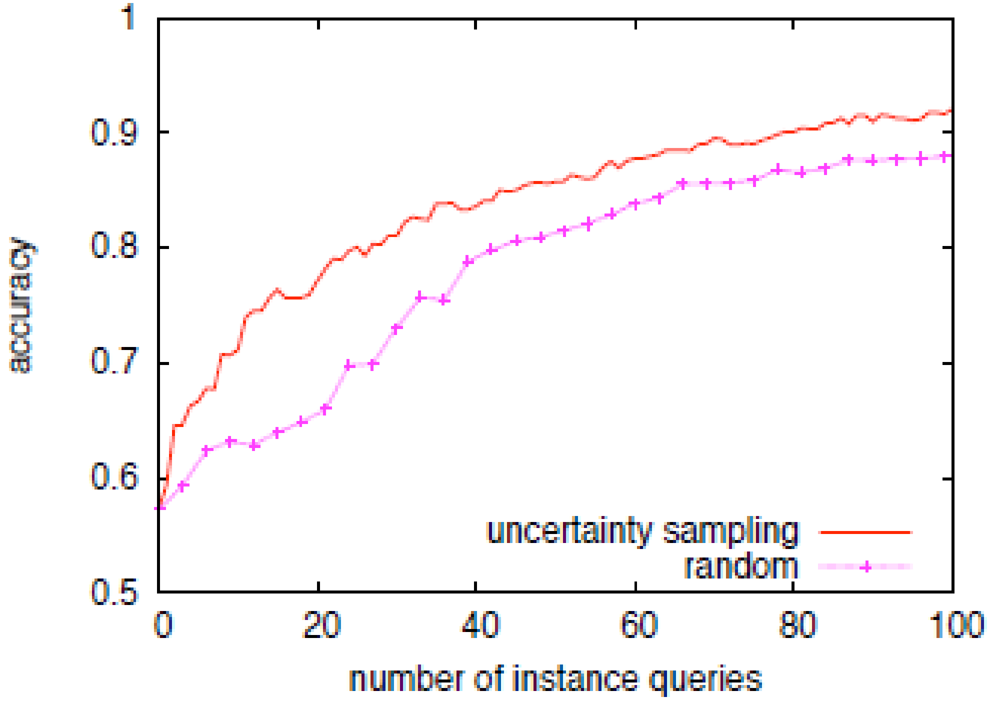
- Predict impact of model change when labeling a sample
- Predict expected error reduction induced by labeling a sample

WHICH ALGORITHM SHALL I USE?

- Algorithm for cold start when no classifier is available (random query, deterministic query)
- Balance exploration and exploitation
- Combine different selection strategies
- Test test test

TESTING QUERY ALGORITHM

- Active learning can be simulated on a fully labeled data set
- Human annotator is simulated by giving the correct label
- Compare performance over number of labeled instances against random query



Source: Settles, Burr (2010), "Active Learning Literature Survey", Computer Sciences Technical Report 1648. University of Wisconsin–Madison

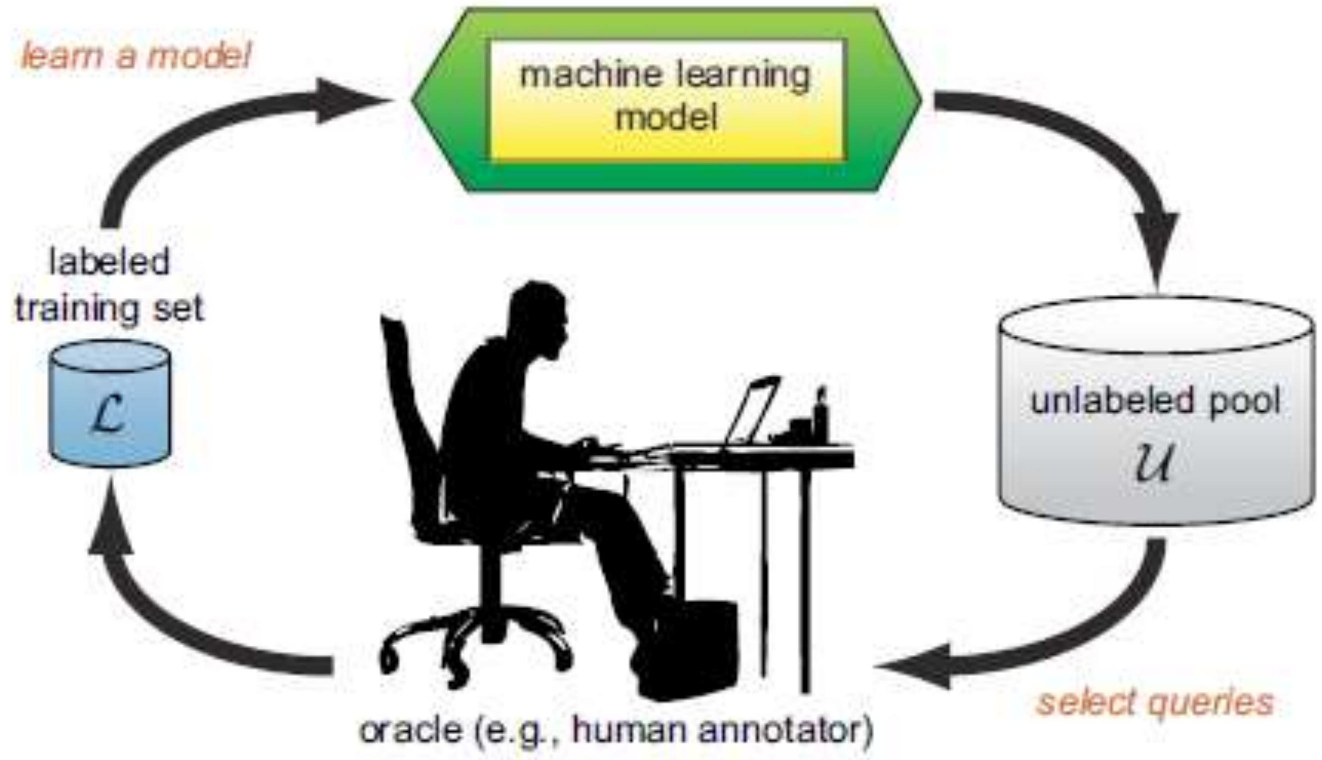
CONVERGENCE

- When to stop labeling?
  - Costs
  - Human annotator notices convergence
  - Stopping criterion

CONCLUSION

- Active learning can help you if you have a huge amount of unlabeled data and humans can provide ground truth
- There is no best query algorithm
- There is no best way to measure convergence

- Problems to consider:
  - Noisy human annotators
  - Class discovery
  - Training speed of ml algorithms



Source: Settles, Burr (2010), "Active Learning Literature Survey", Computer Sciences Technical Report 1648. University of Wisconsin–Madison

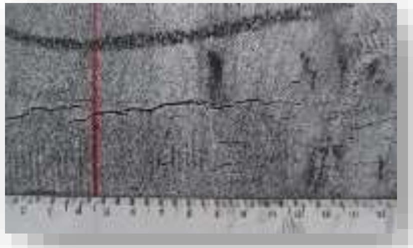
EMAT CRACK DETECTION AND COATING ASSESSMENT

22-24" EMAT ILI tool

Crack Detection

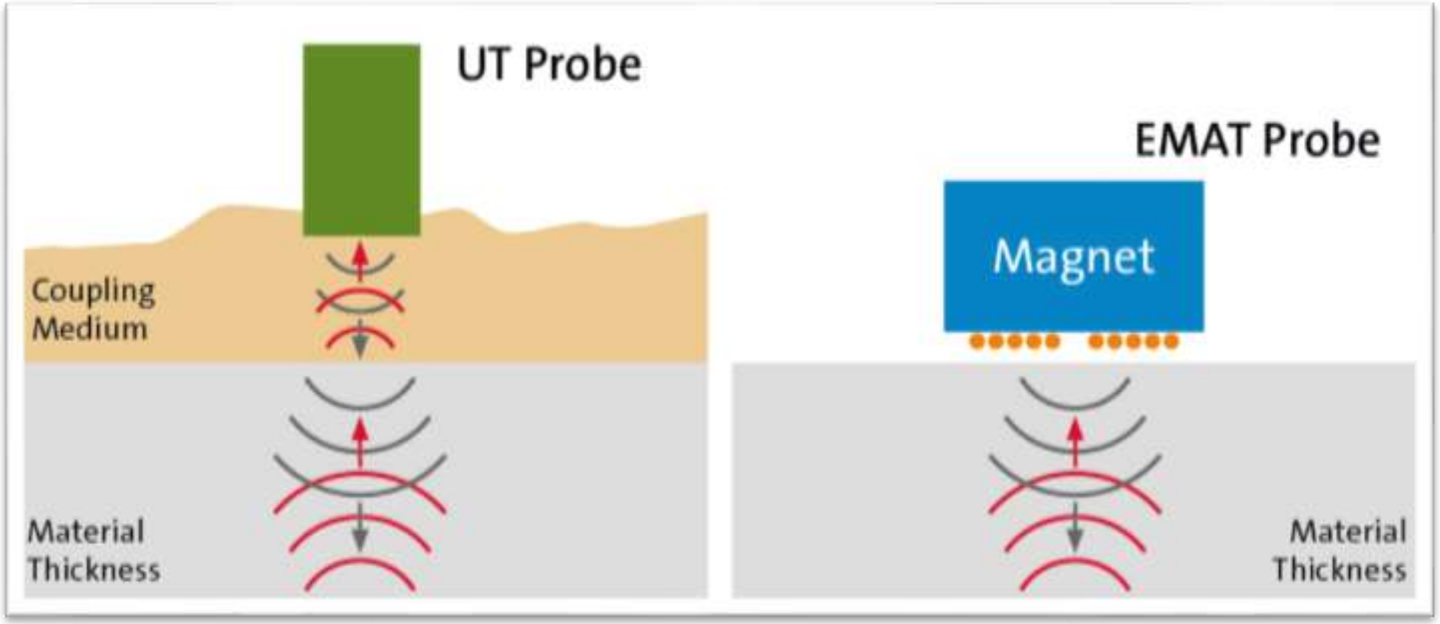
Coating Disbondment

Coating Identification

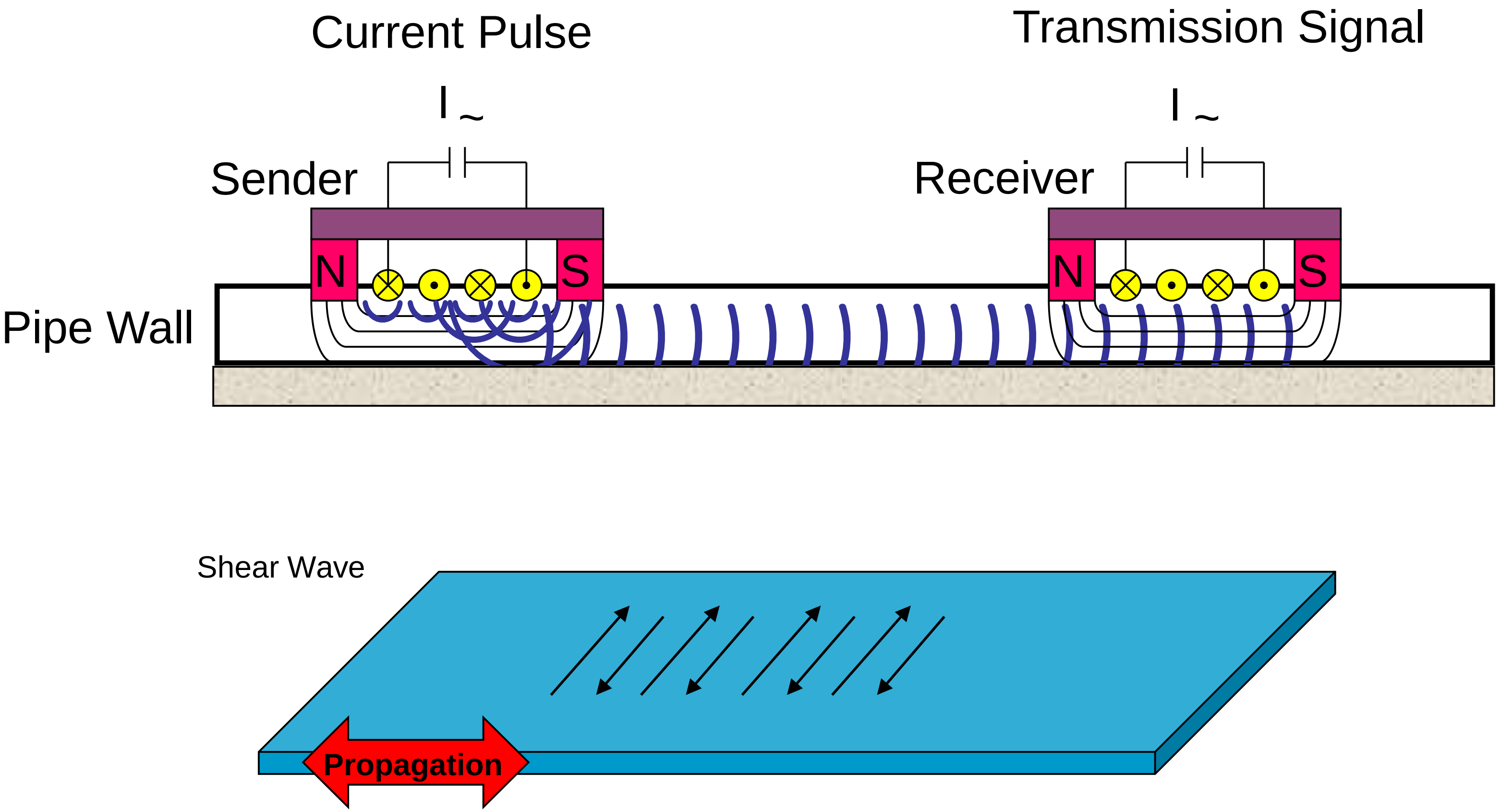


EMAT: COUPLANT-FREE ULTRASONIC INSPECTION

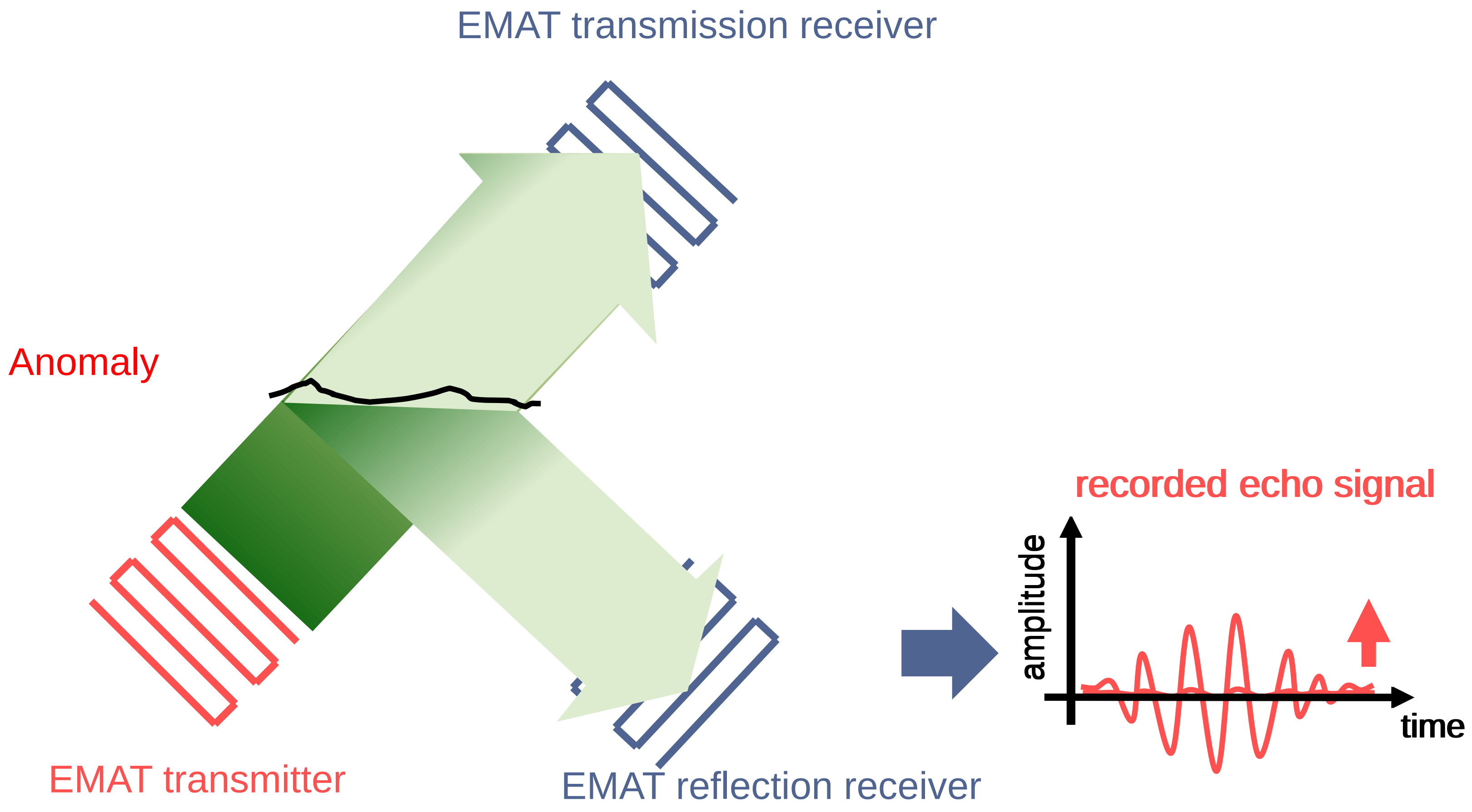
- EMAT: Electro Magnetic Acoustic Transducer
  - Applies forces to metal surface without direct contact
  - Detects movement in a metal surface without direct contact
  - Makes use of electromagnetic induction across air gap
  - Advantages: Contactless, Dry inspection, Usable at high temperatures and pressures, High volume coverage



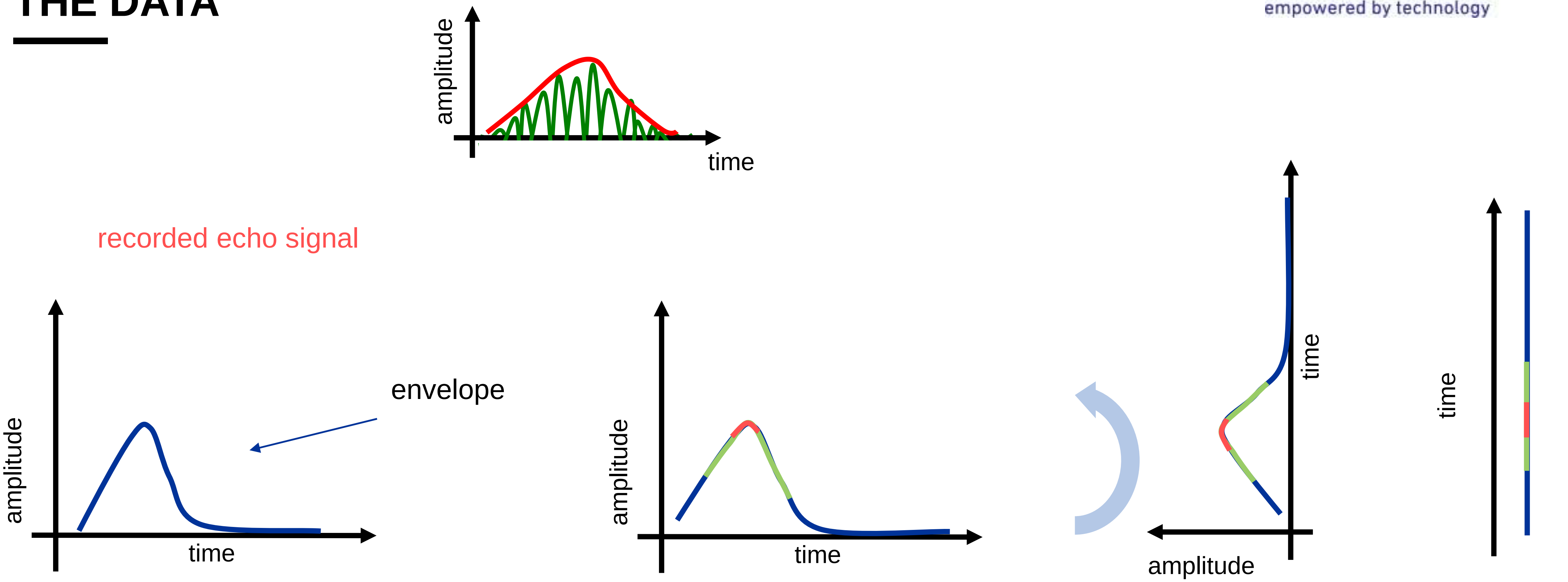
OVERALL SETUP



EMAT ANOMALY DETECTION



THE DATA


amplitude
time
recorded echo signal
envelope
amplitude
time
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time
time
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time

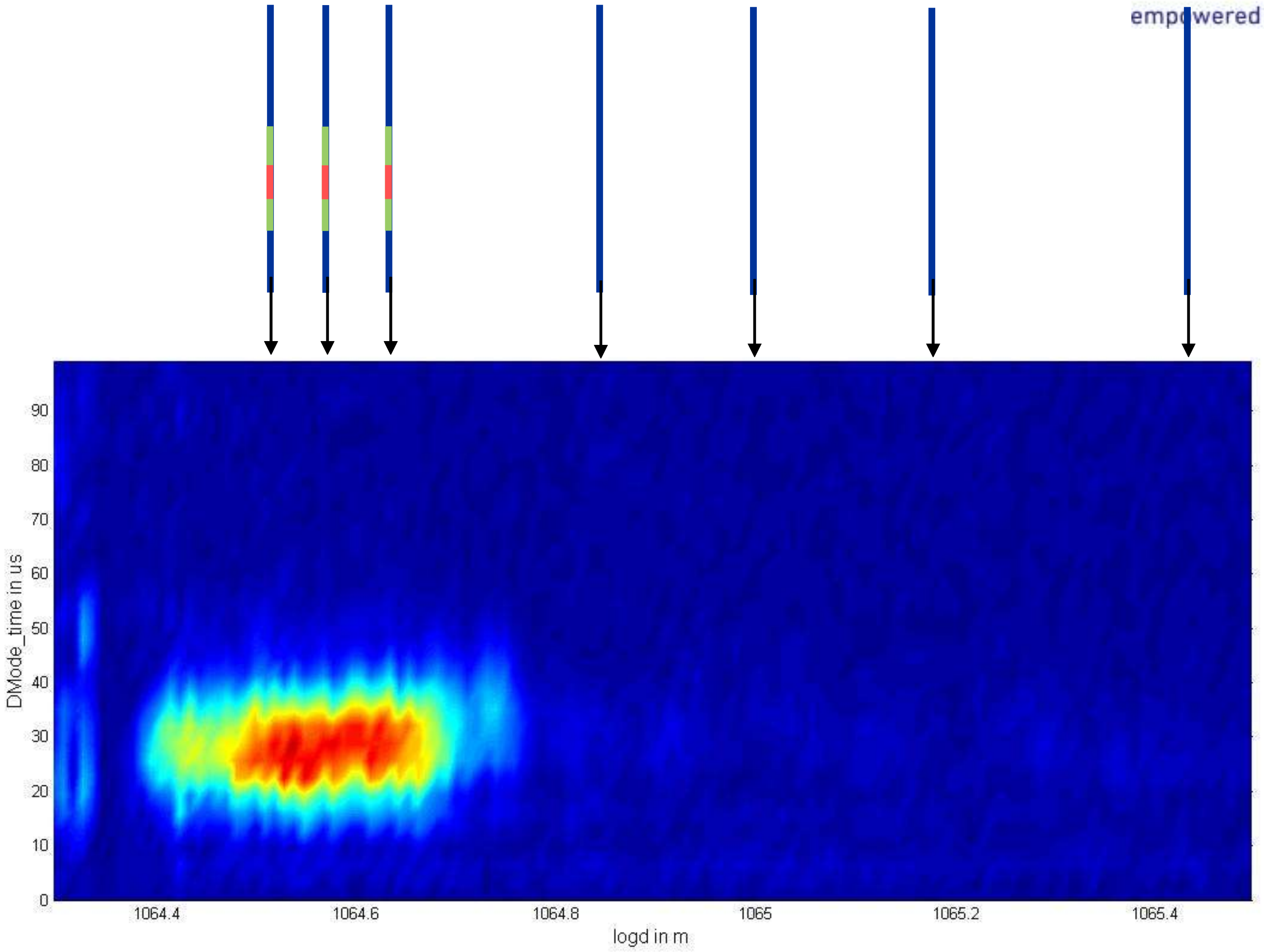
3D DATA

One channel:

2d image

Multiple channels

3D Data

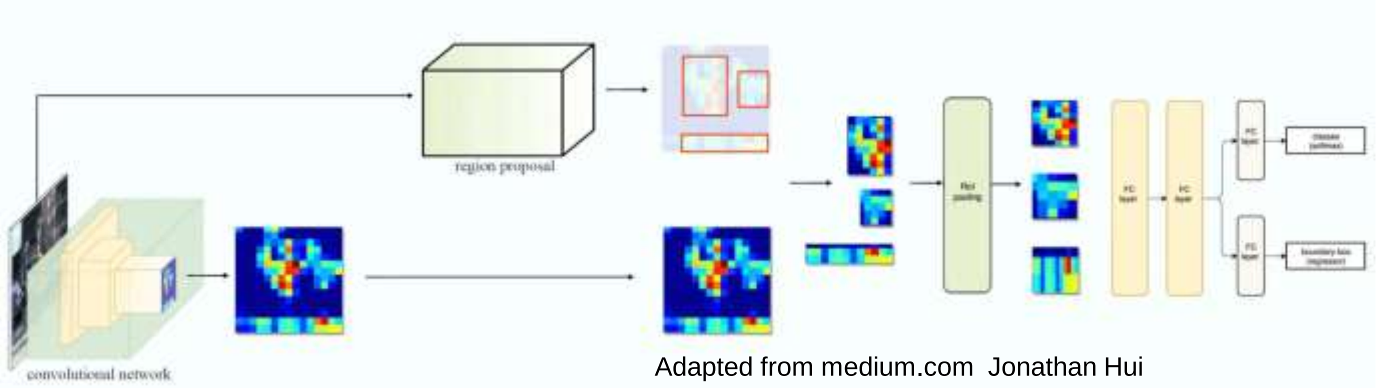


THE CHALLENGE

- Detect anomalies (objects, patterns) in 2D/3D data and classify anomalies
  - In principle a computer vision problem
  - Anomaly localization and classification
  - Object detection
  - Need labeled data
  - Provided by inhouse domain experts
  - Dig up campaigns
  - Recent breakthroughs in Deep learning

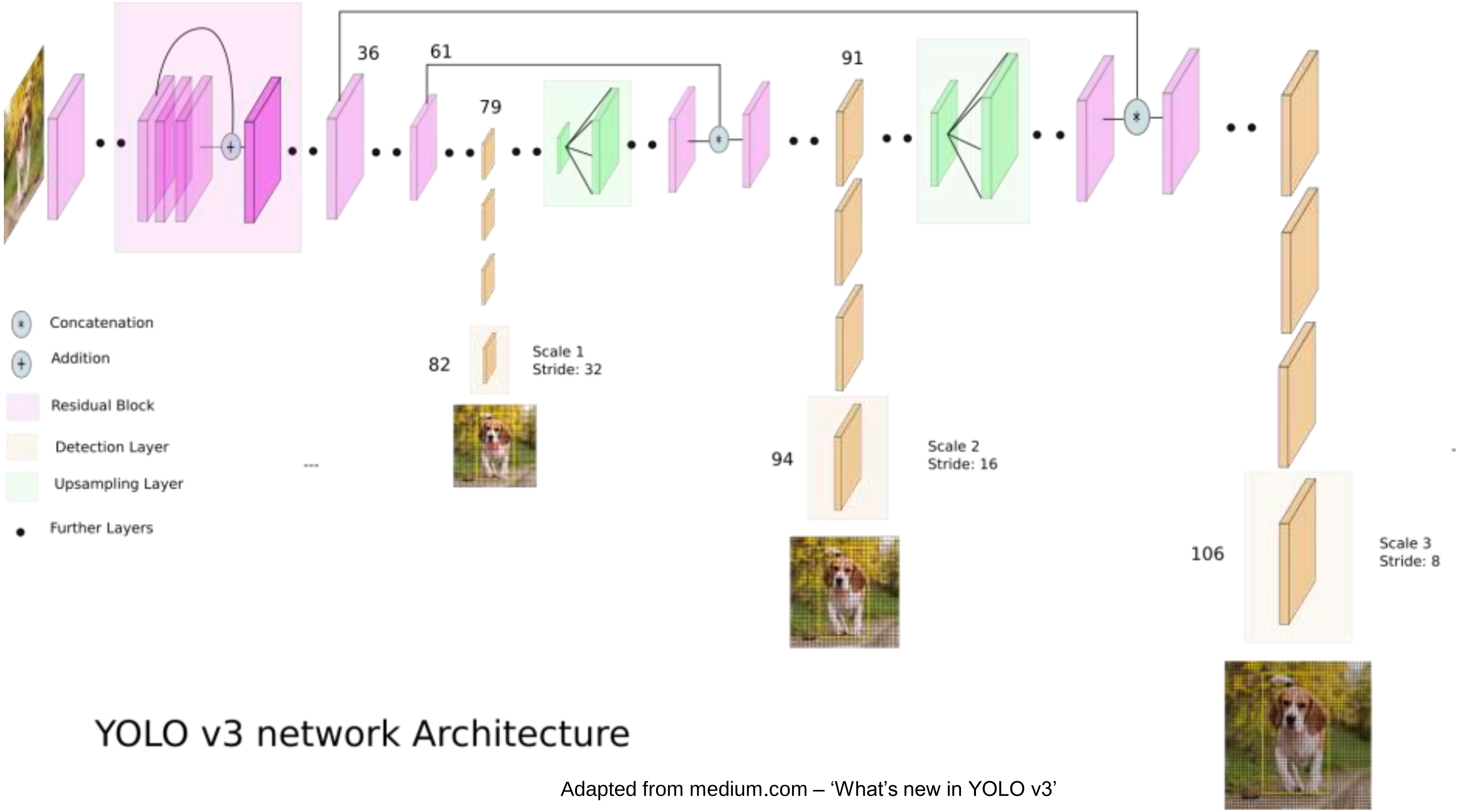
OBJECT DETECTION ALGORITHMS

- Modern Object detection algorithms are based almost exclusively on convolutional neural architectures
  - Easiest Problem: Image classification, e.g. cat/dog, t = (c1, c2, …, cN)
  - Object localization: where in the image is the object? t = (p, x, y, h, w, c1, c2, …, cN)
  - Object detection: Localize multiple objects in image
  - Image segmentation: classify each pixel according to class membership
  - Two types of networks: Single shot networks (e.g. YOLO) (fast!) and networks with region proposals (e.g. Faster RCNN) (precise!)
  - Method can be easily extended to include multiple information channels (c.f. multiple color channels)



Adapted from medium.com Jonathan Hui

EXAMPLE: YOLO



Adapted from medium.com – ‘What’s new in YOLO v3’

PERFORMANCE METRICS

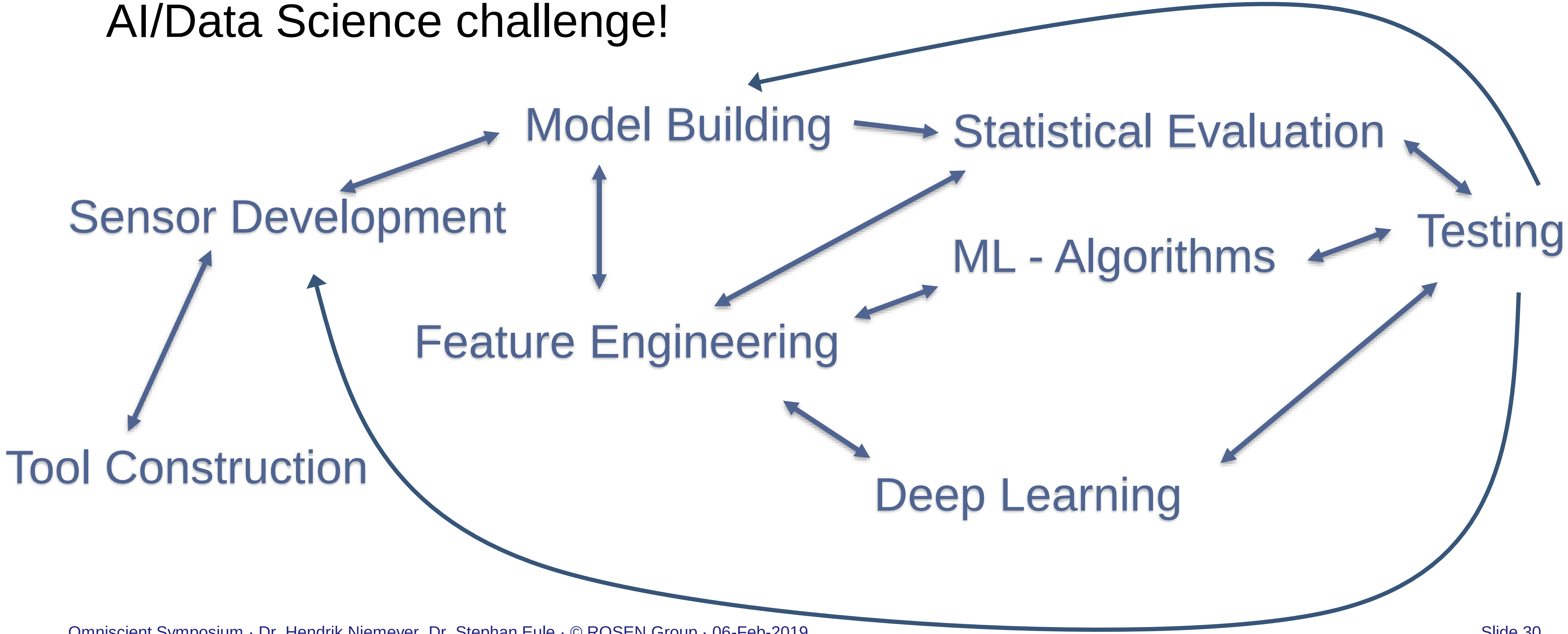
Maximize Precision: $\frac{TP}{TP+FP} = \frac{TP}{\text{all detections}}$

Constraint: Recall $\frac{TP}{TP+FN} = \frac{TP}{\text{all ground truth}} \cong 1$

Approach: First detect anomalies, second classify anomalies, last quantify anomalies

CONCLUSION

- Pipeline Inspection at ROSEN is an extremely interesting industrial AI/Data Science challenge!



THANK YOU FOR JOINING THIS PRESENTATION.

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