

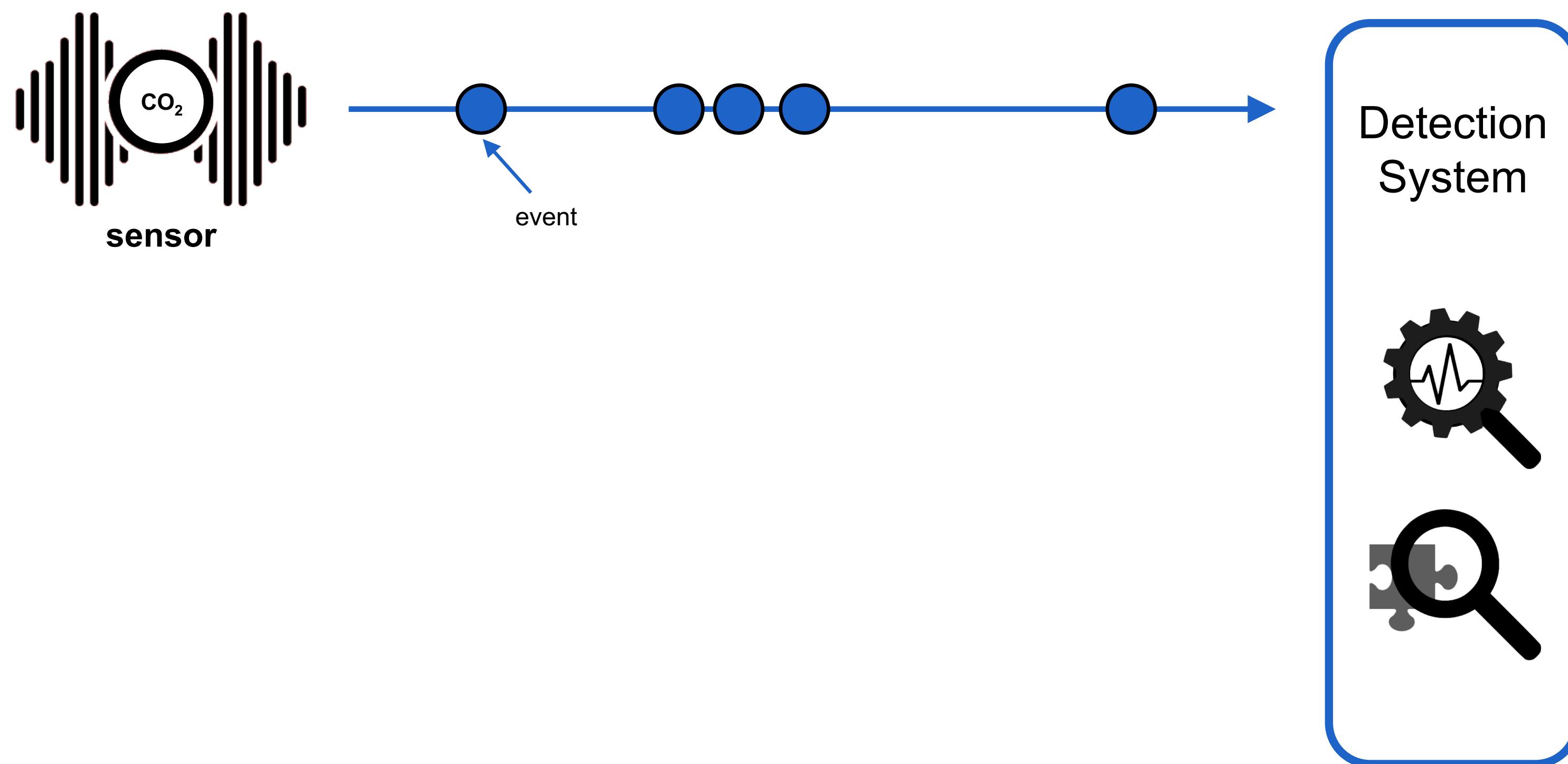
Adaptive anomaly detection and root cause analysis by fusing semantics and machine learning

Bram Steenwinckel

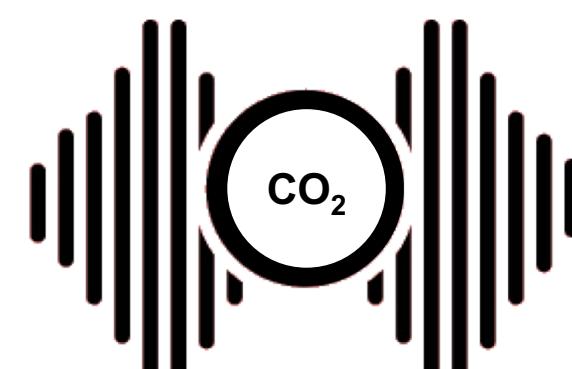
Promotors: Femke Ongenae & Filip De Turck

Mentor: Anna Lisa Gentile

SENSOR MONITORING



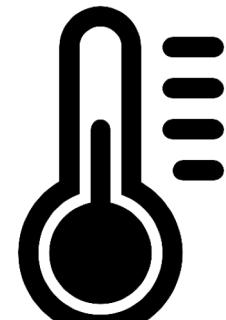
SENSOR MONITORING



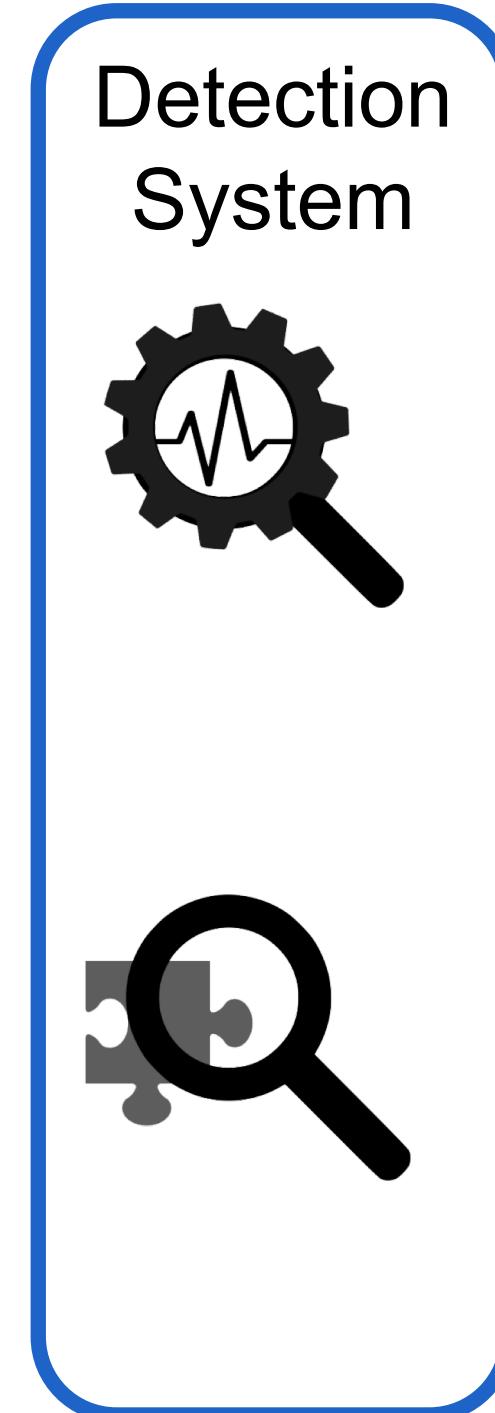
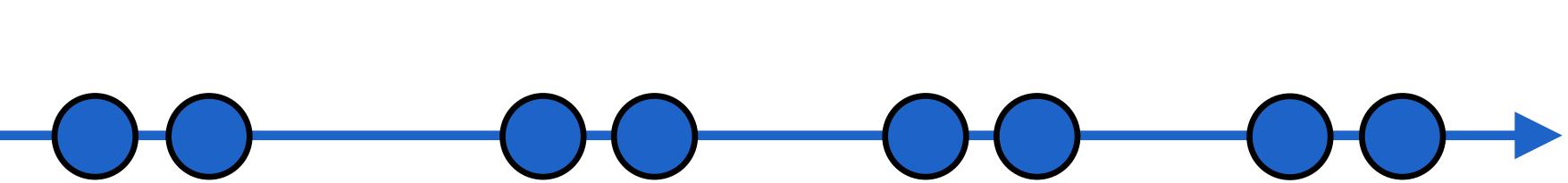
sensor



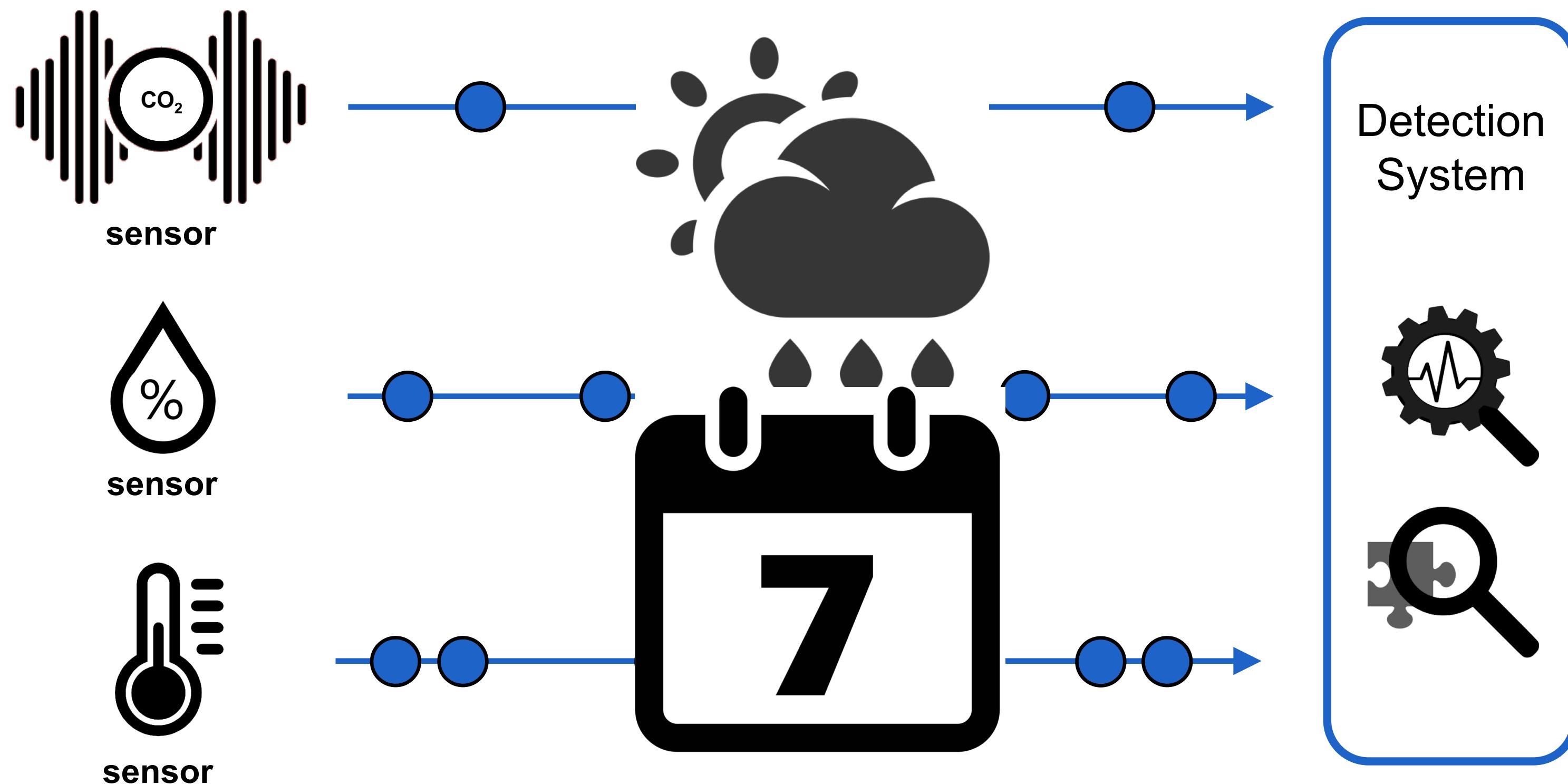
sensor



sensor



SENSOR MONITORING



COMMON TOOLS



Anomaly detection



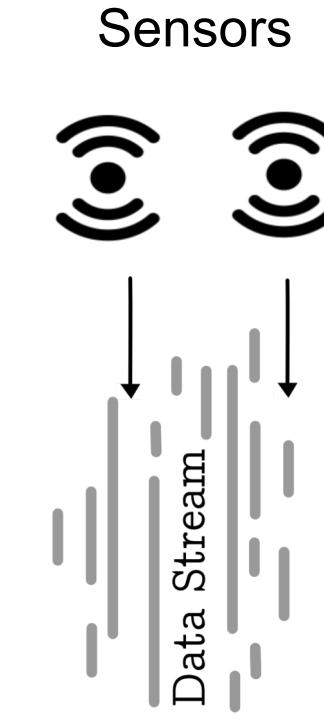
Root cause Analysis

DETECTION MECHANISMS TODAY

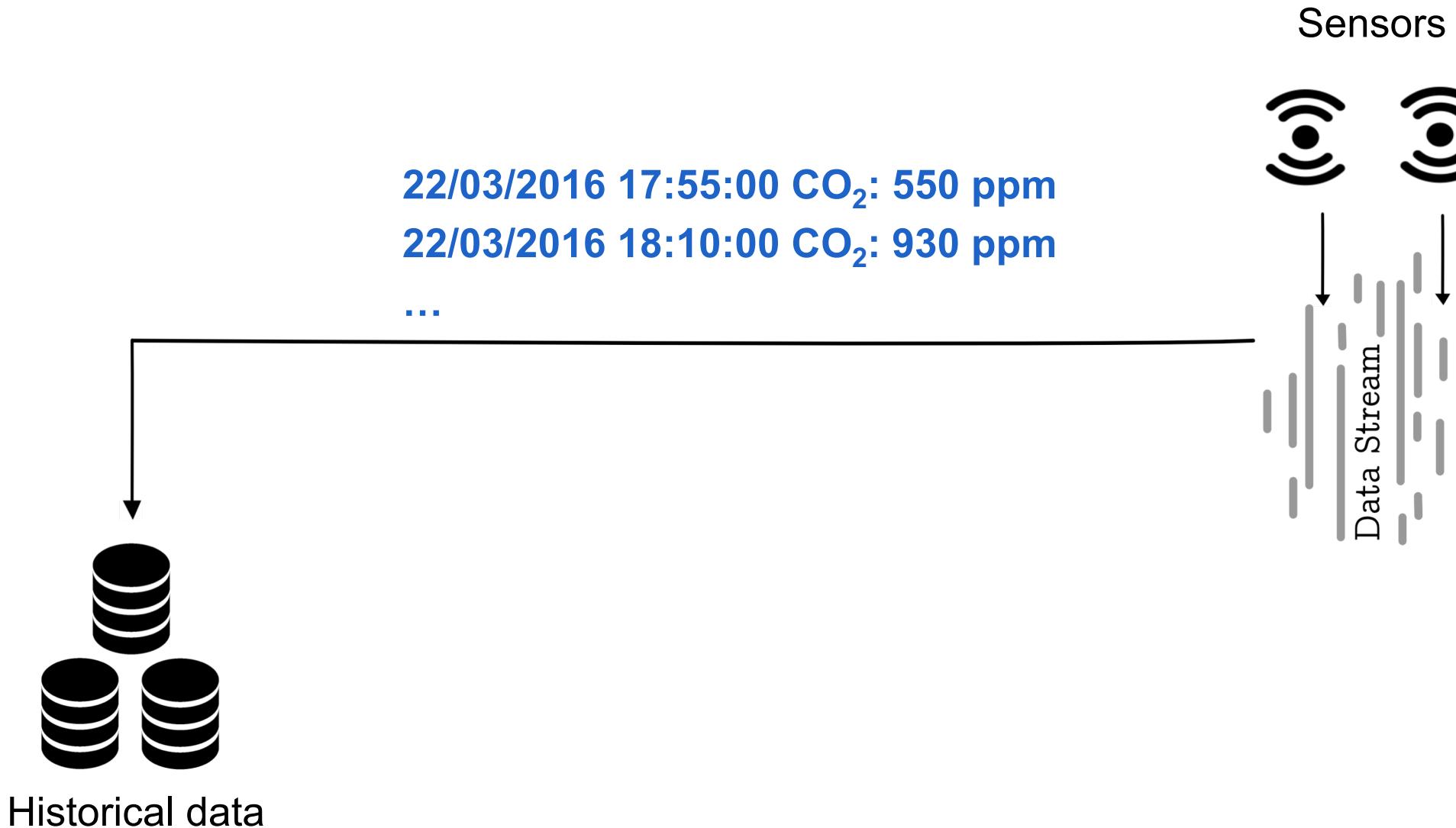
Sensors



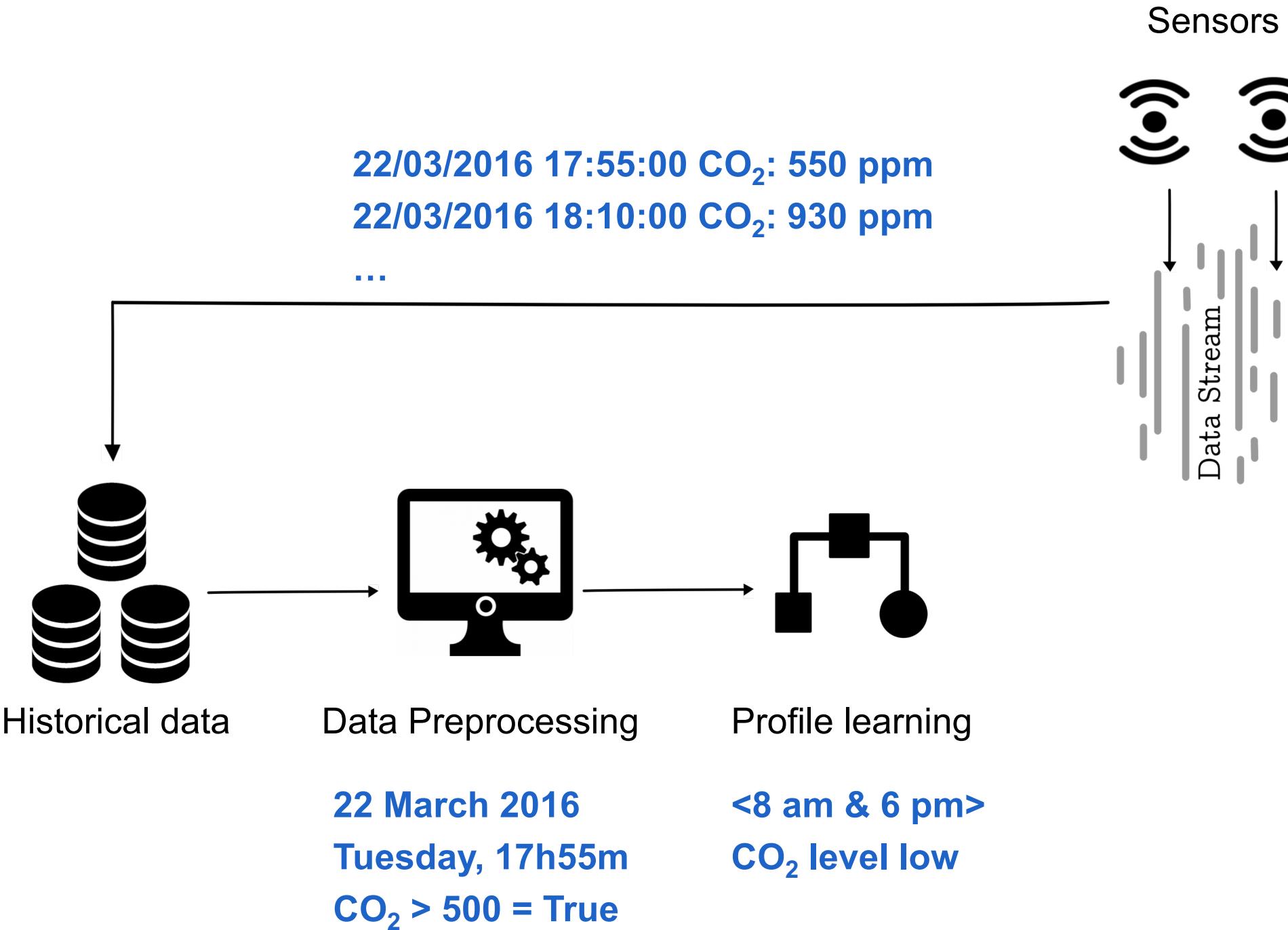
DETECTION MECHANISMS TODAY



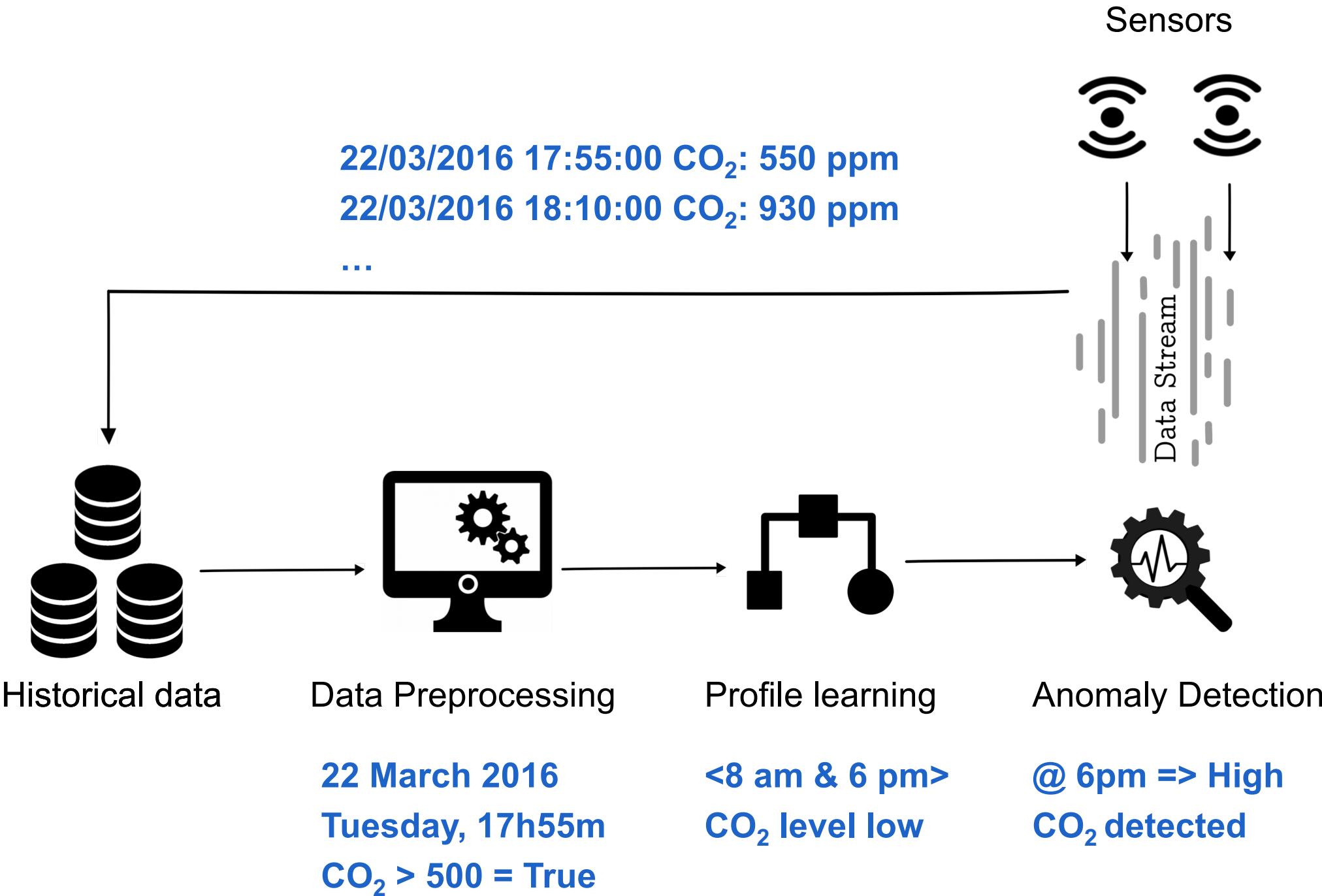
DETECTION MECHANISMS TODAY



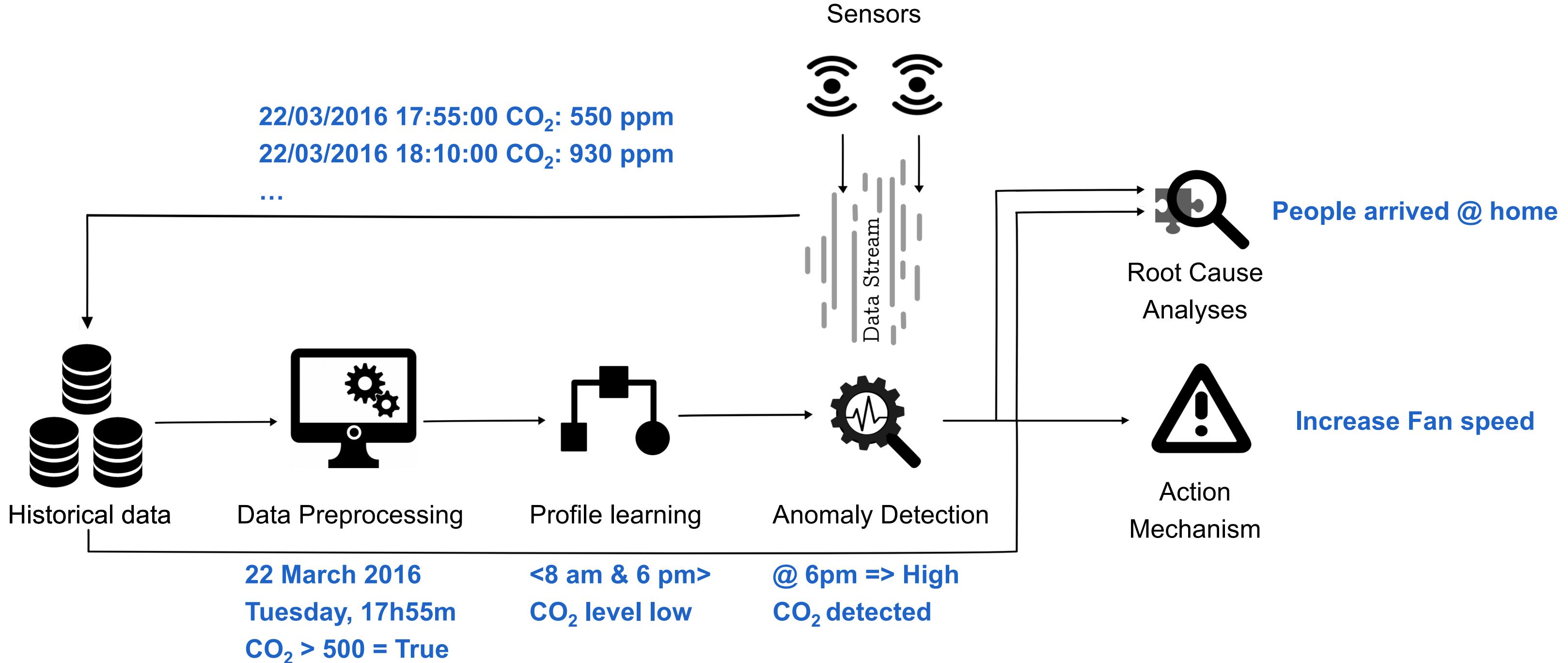
DETECTION MECHANISMS TODAY



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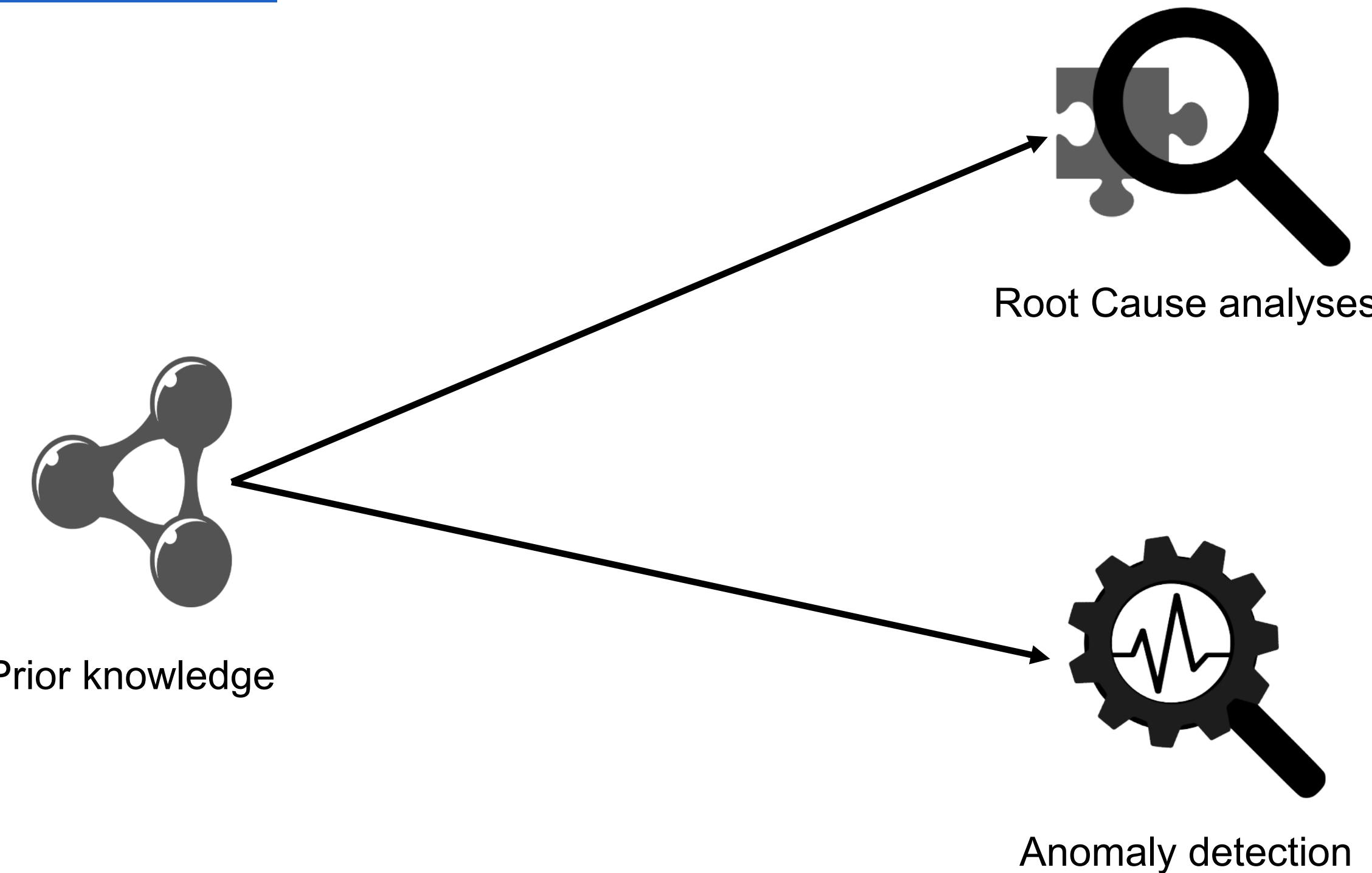
PROBLEM

“

The AD and RCA tools of today have difficulties
to adapt to changing environments without
a lot of human involvement...

”

GOAL?



- Reduce the human involvement
- Apply in streaming environment

- Increase detection rate for real time cases
- Reduce number of wrong detections (F1 score)

HOW TO EVALUATE?

1) RDF Datasets for classification (AM, AIFB, MUTAG)

⇒ Adapted to detect the minority class(es).

2) Proof of concept case studies:



Pervasive healthcare

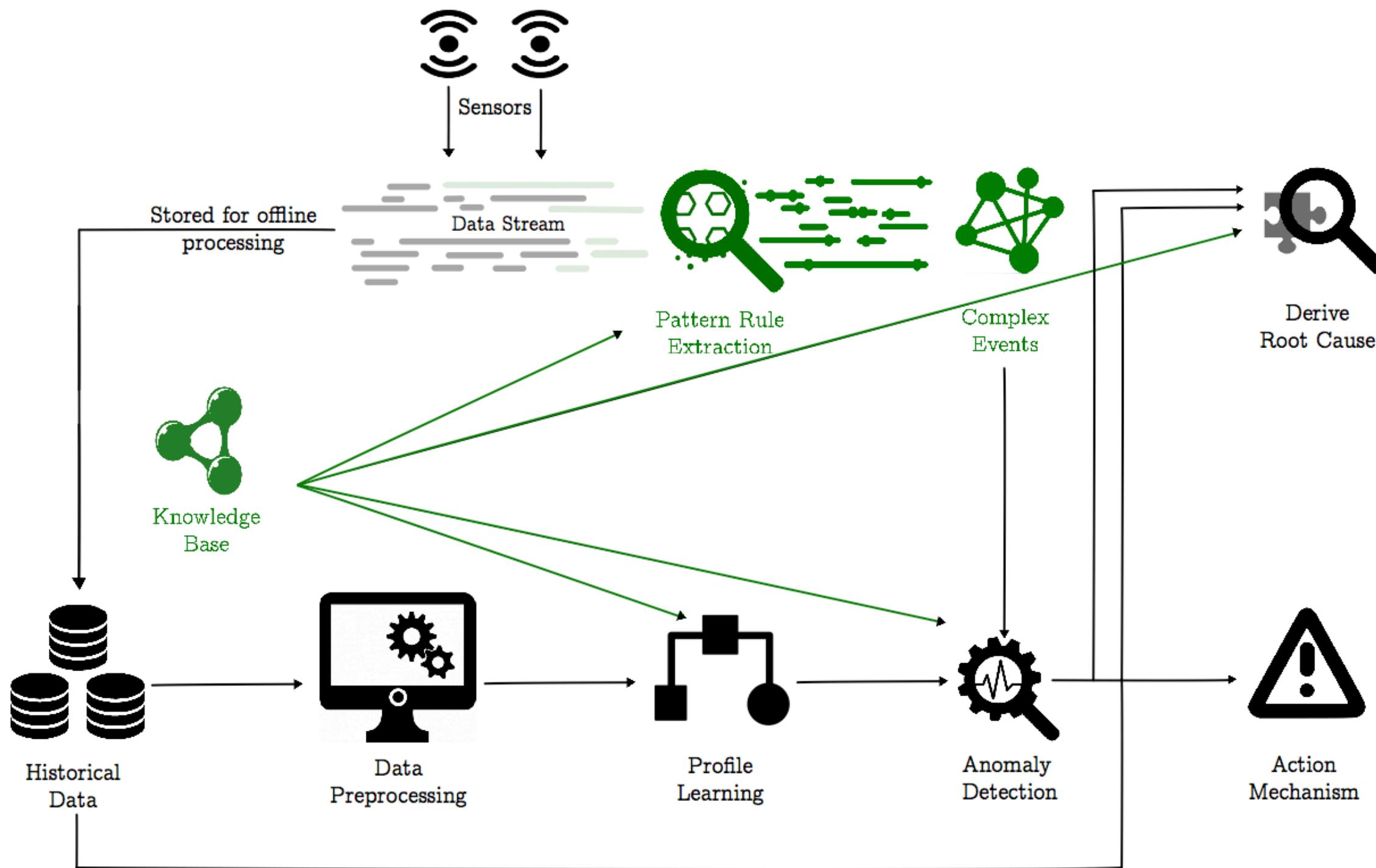


Predictive maintenance

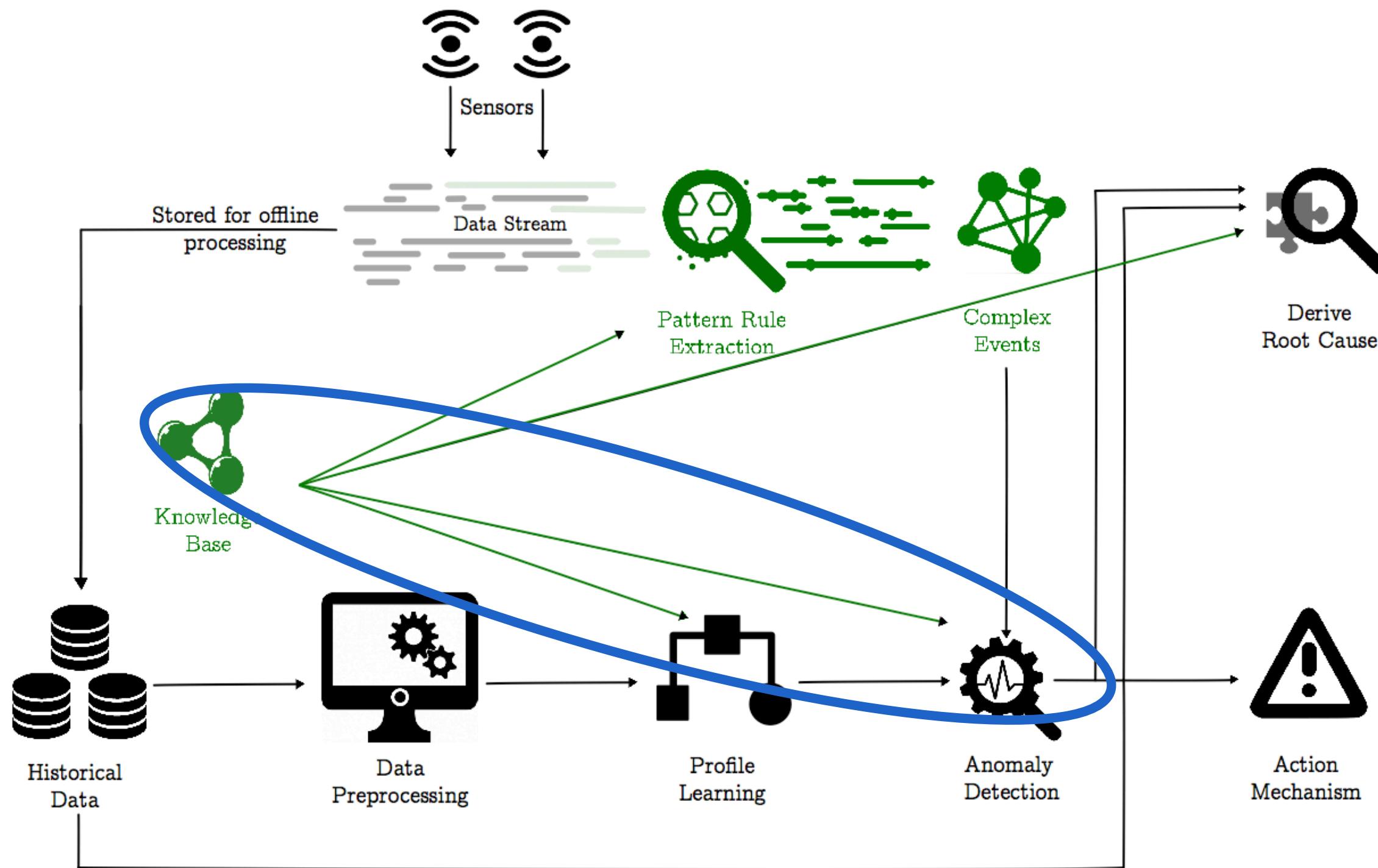
OUTLINE

1. Introduction
2. Feature importance with knowledge learning
3. Interpretable knowledge for cause detection
4. Adaptive stream detection
5. Additions & conclusion

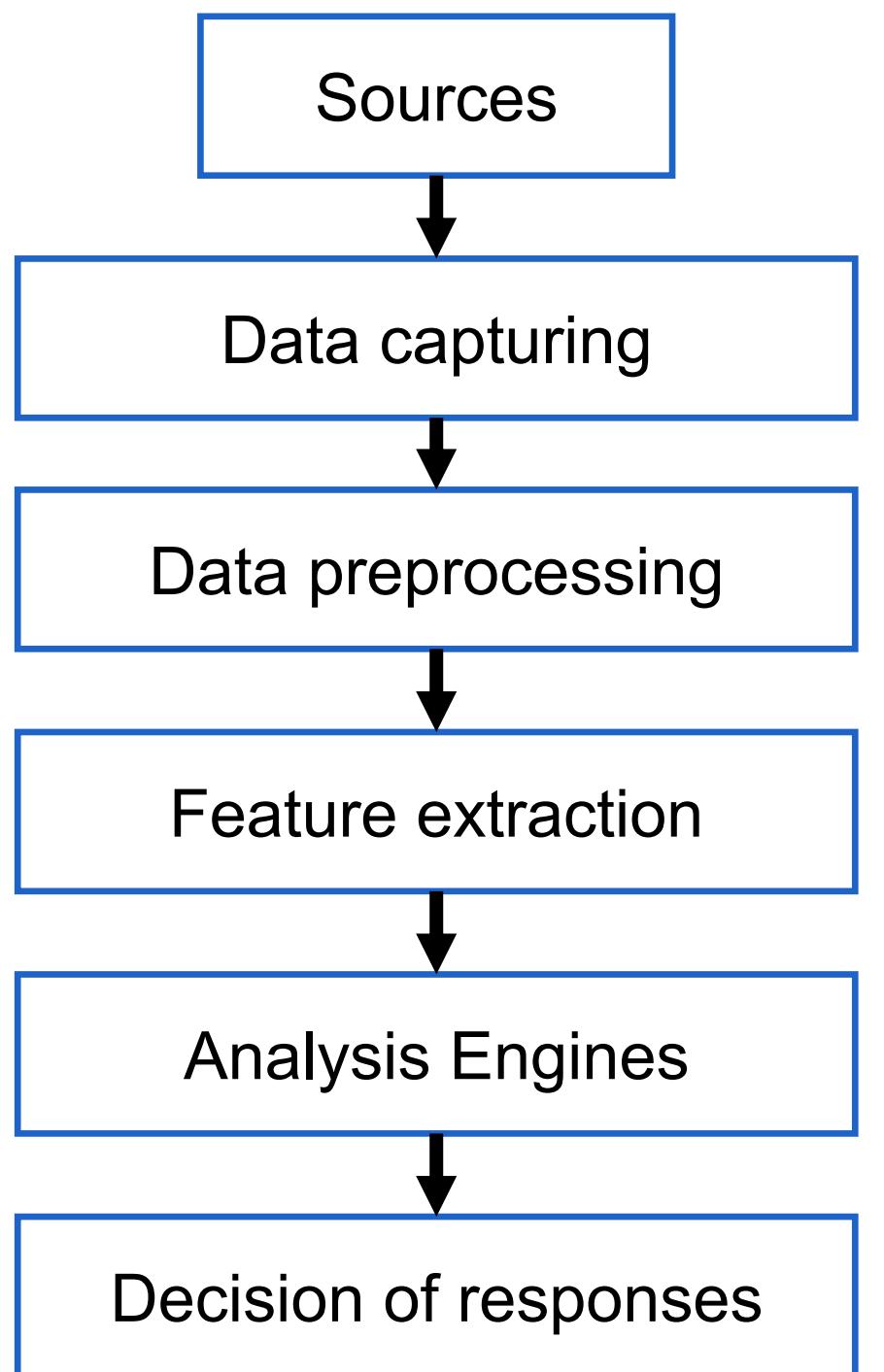
OVERVIEW



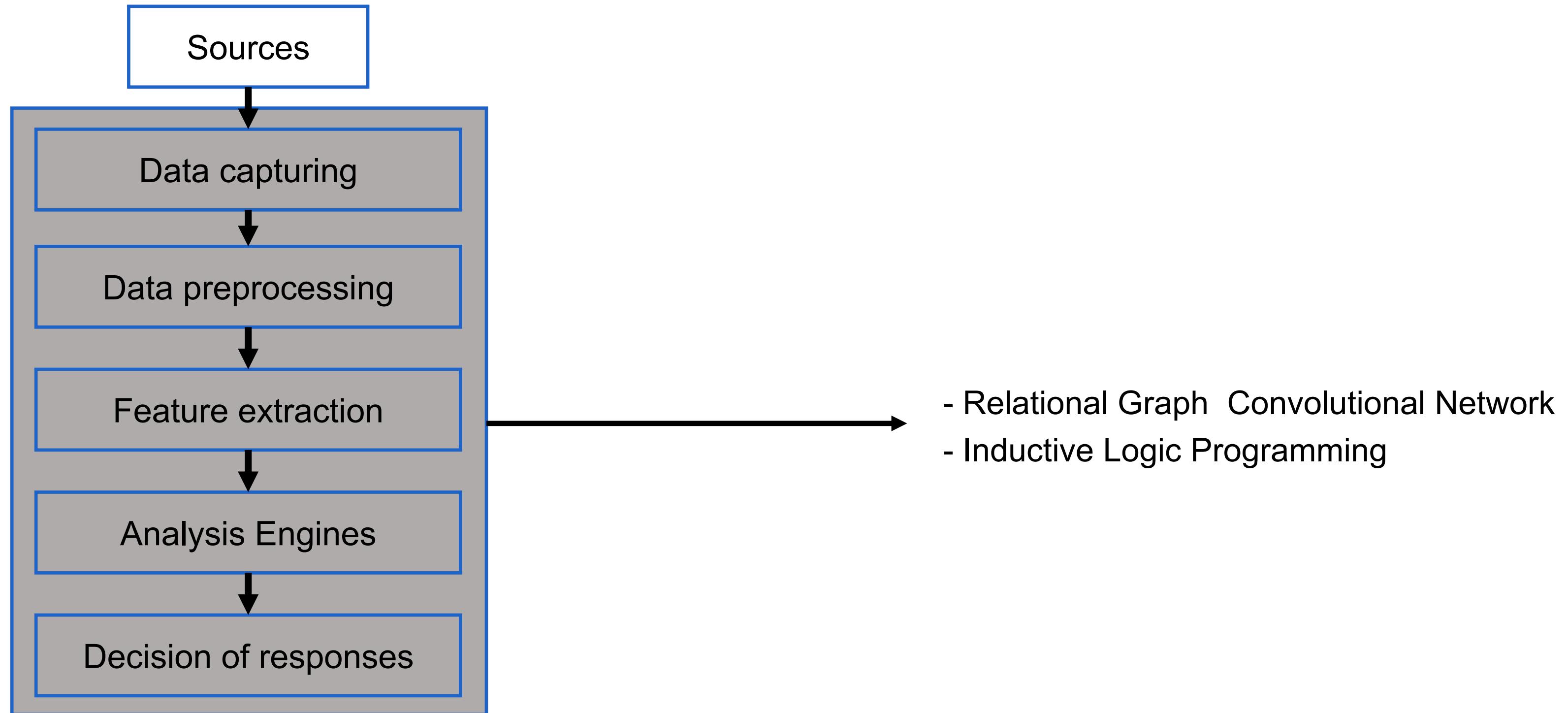
KNOWLEDGE INSIDE ML-BASED AD



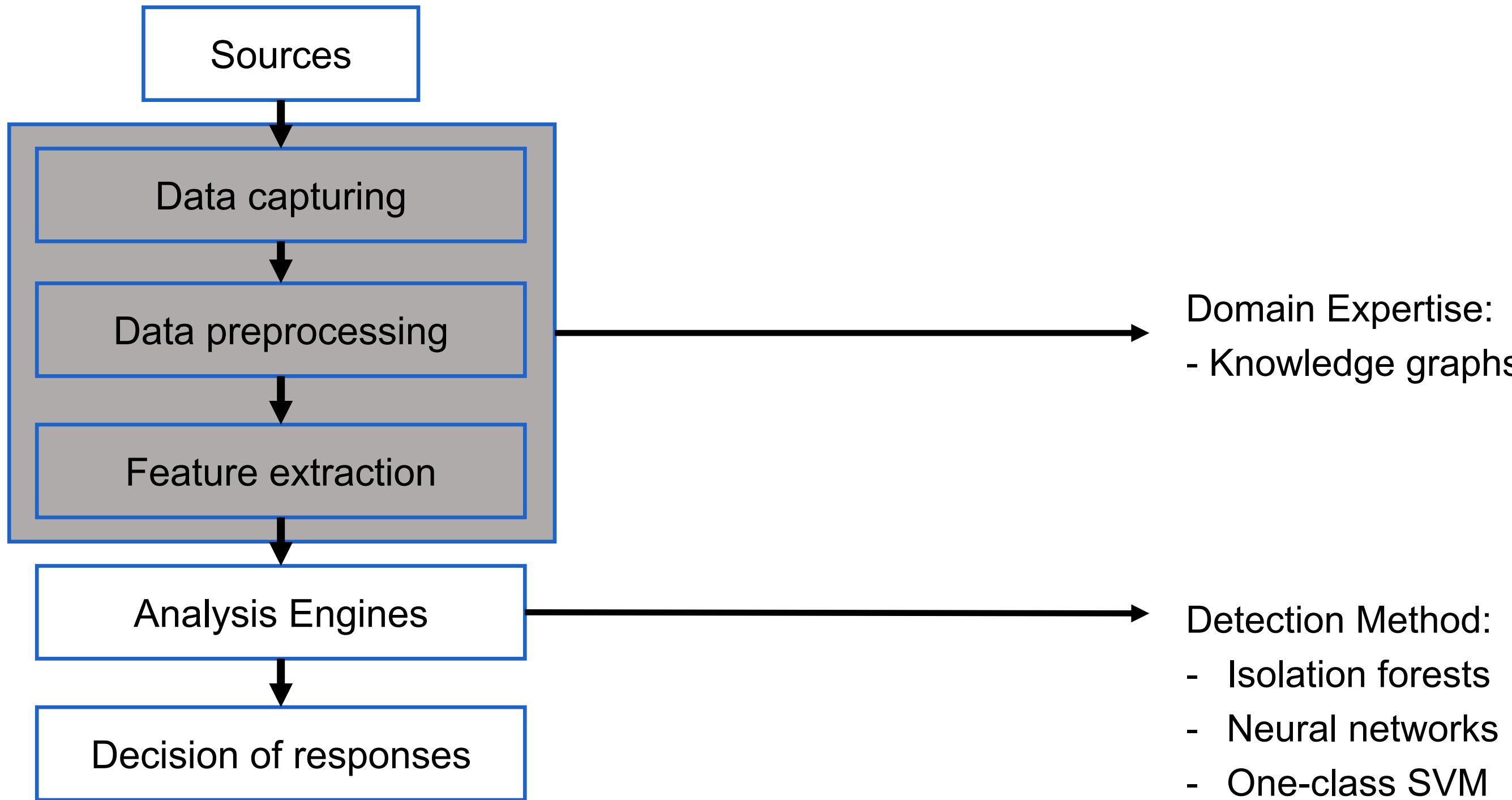
ML PROCESS



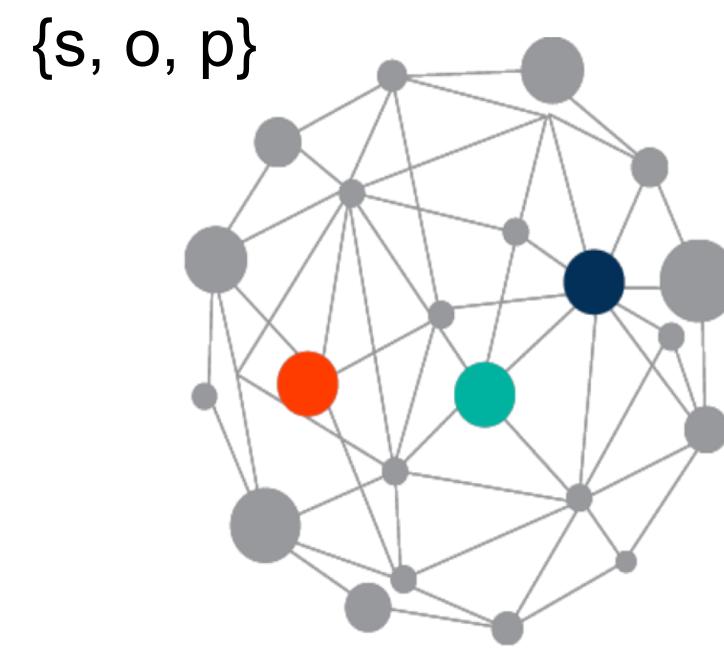
SOTA: KNOWLEDGE INSIDE ML-BASED AD



SOTA: KNOWLEDGE INSIDE ML-BASED AD

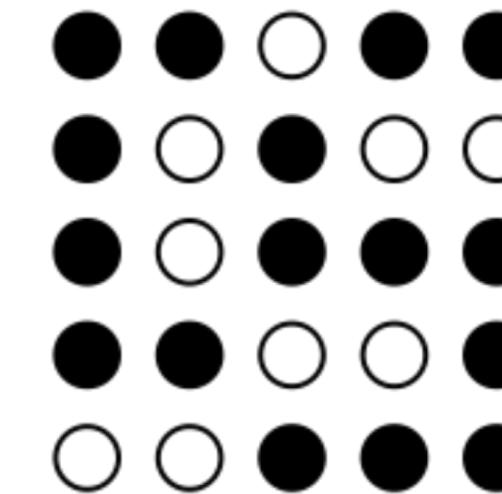


SOTA: EMBEDDING



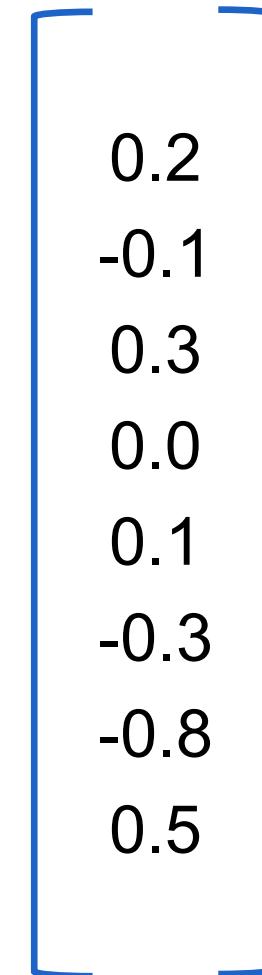
Knowledge graph

Transformation



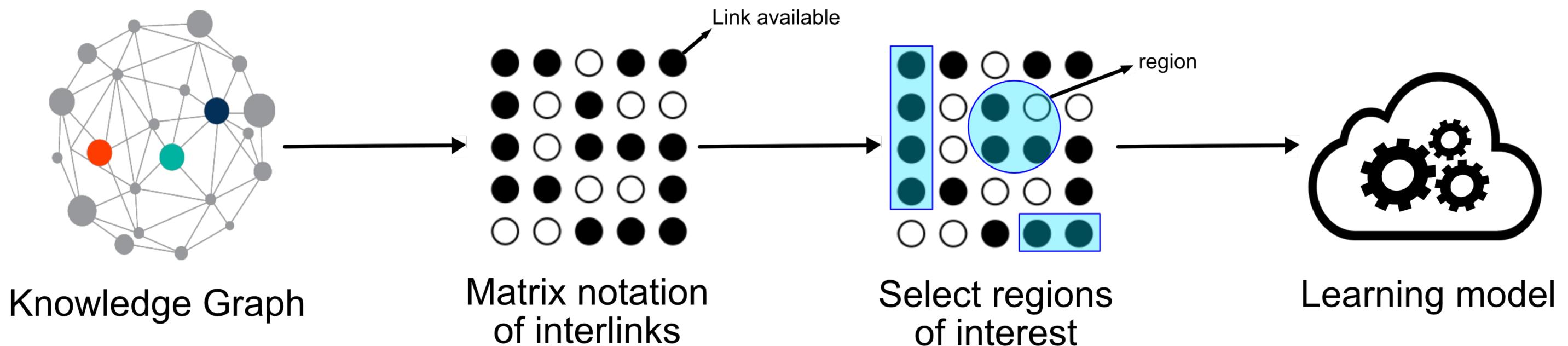
Matrix notation of
interlinks

Transformation



Vector

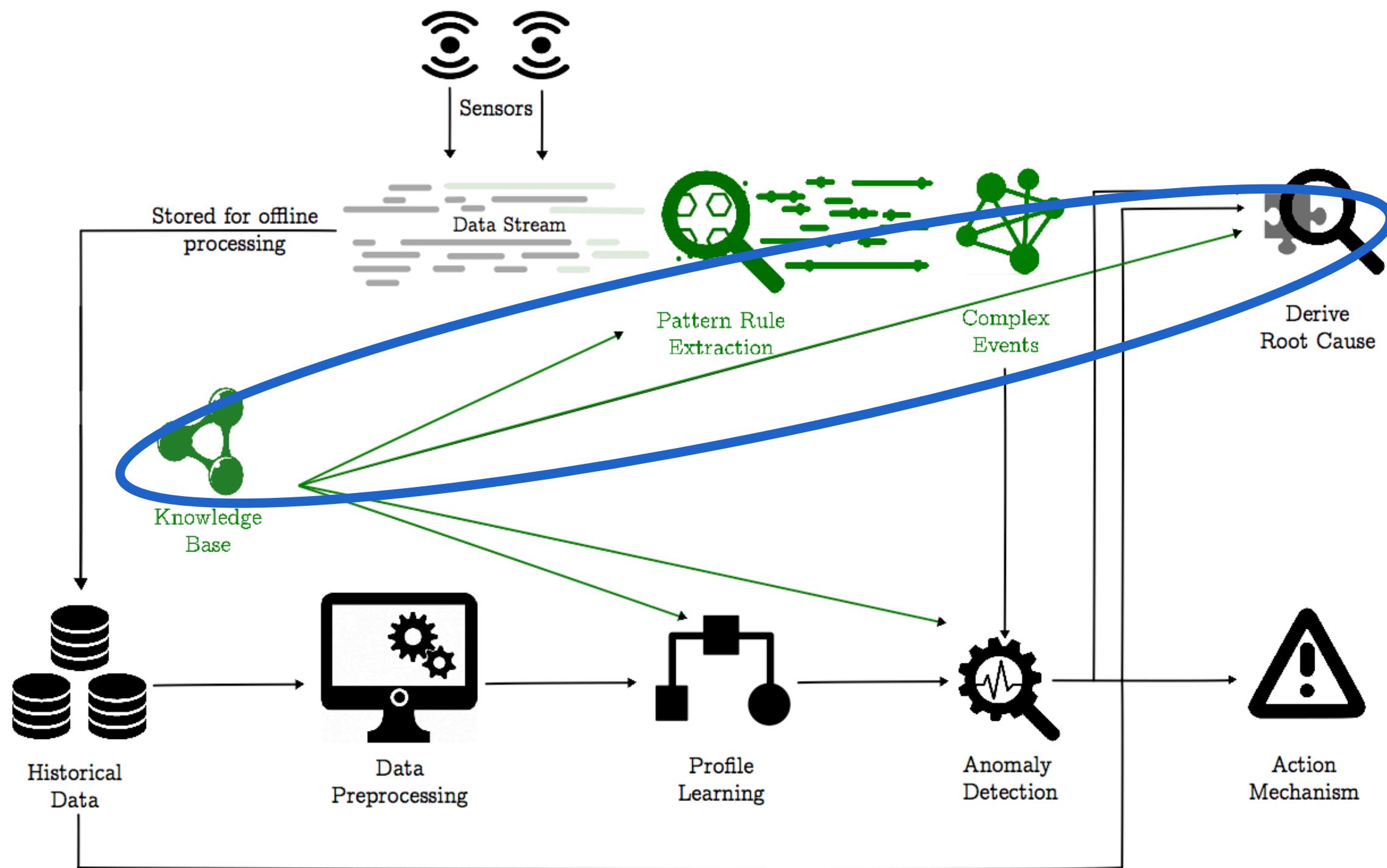
IMPROVED FEATURE GENERATION



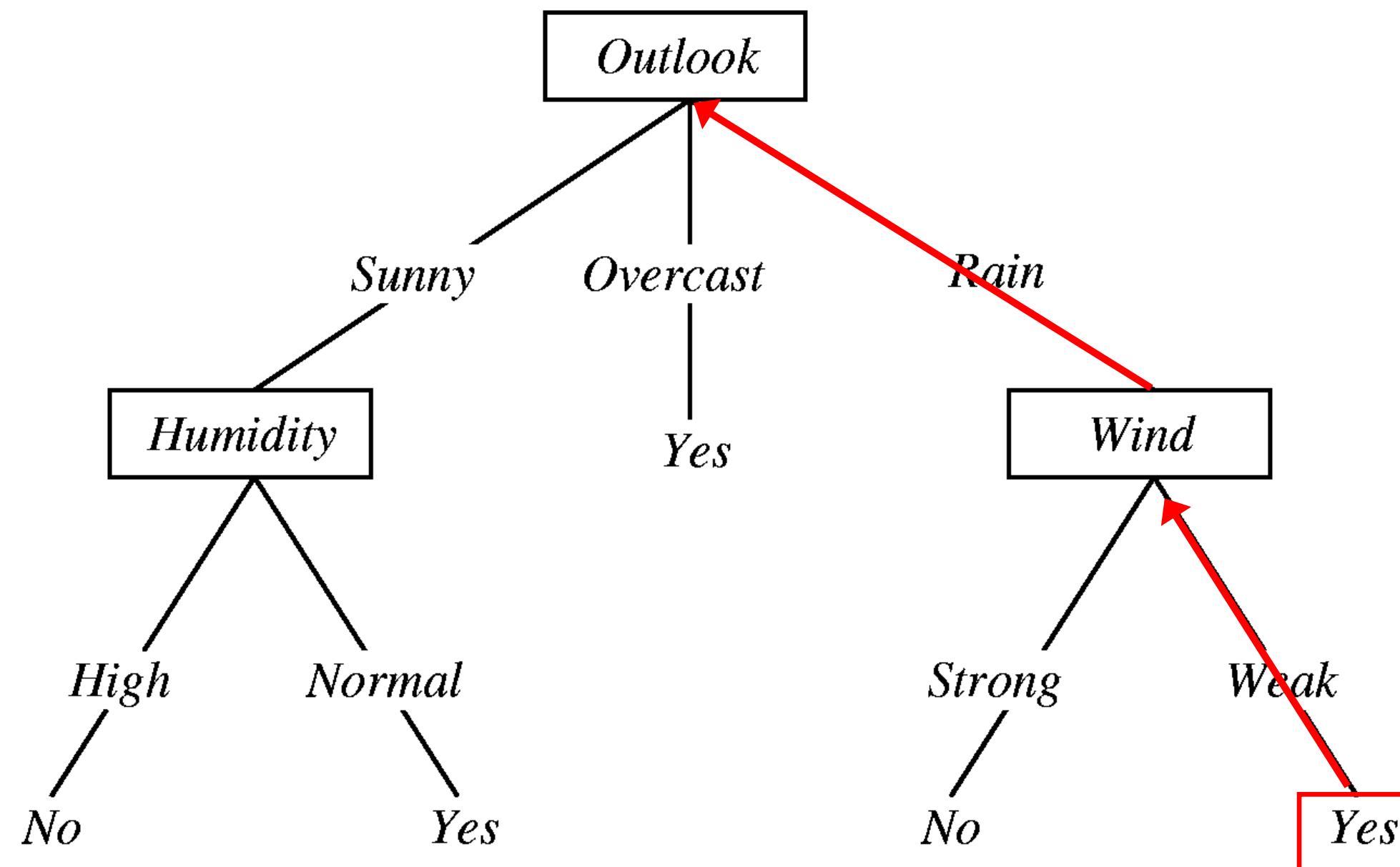
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CAUSE DETECTION



SOTA: CAUSE DETECTION



SOTA: CAUSE DETECTION

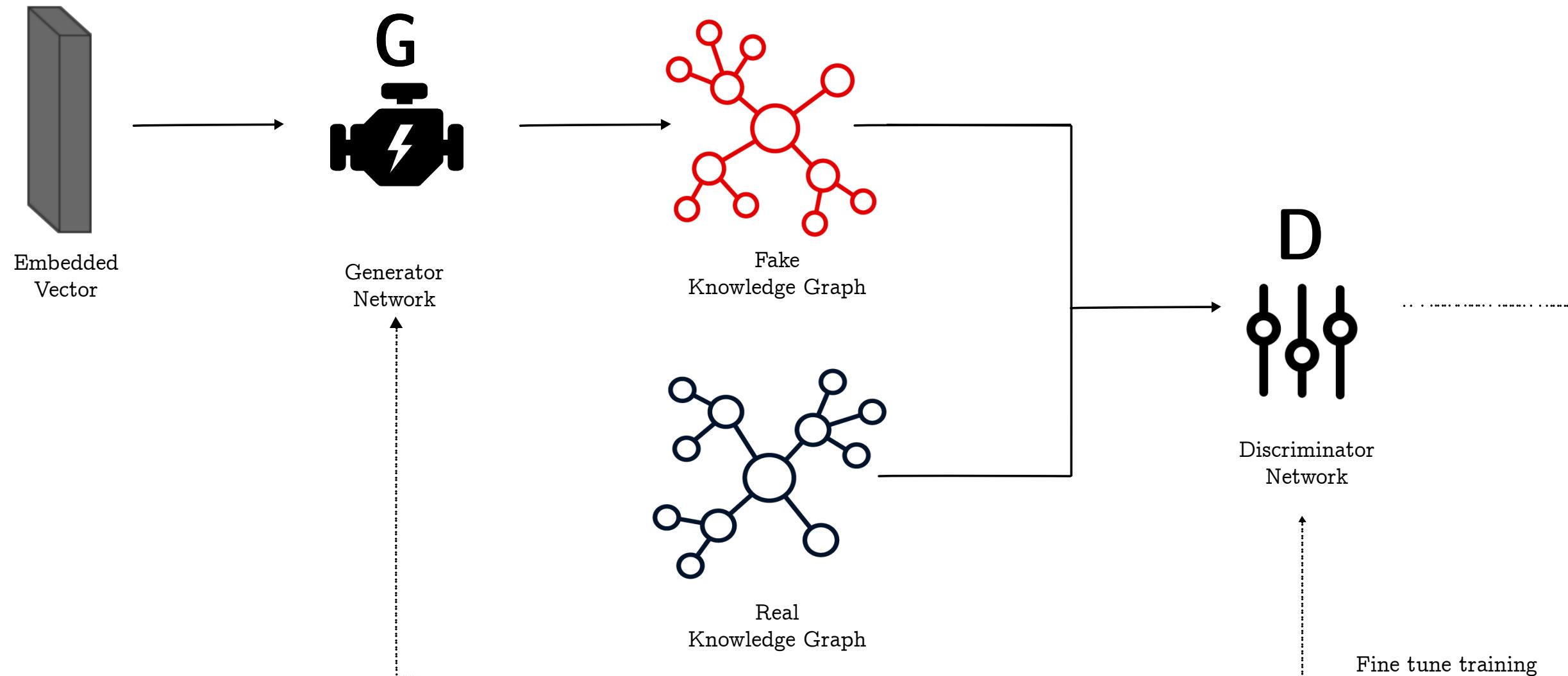
But:

- Models not always trees...
- Features not always interpretable (embeddings)
- Causes fixed (only from learned behavior)

=> Original knowledge graphs have however high interpretability and reasoning capacities

CAUSES FROM KNOWLEDGE

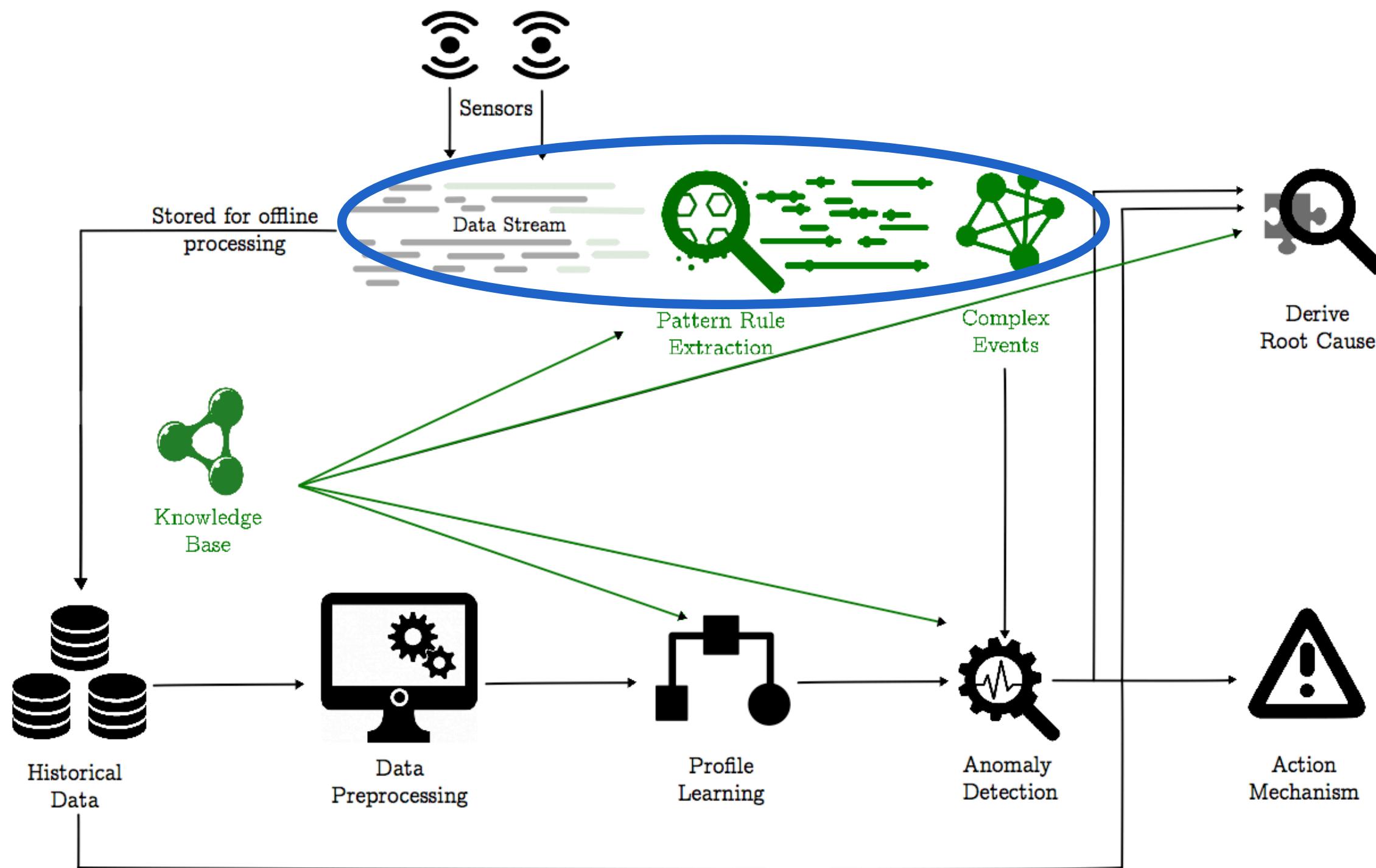
Generative Adversarial Network transforming the embeddings back to knowledge “graphs”



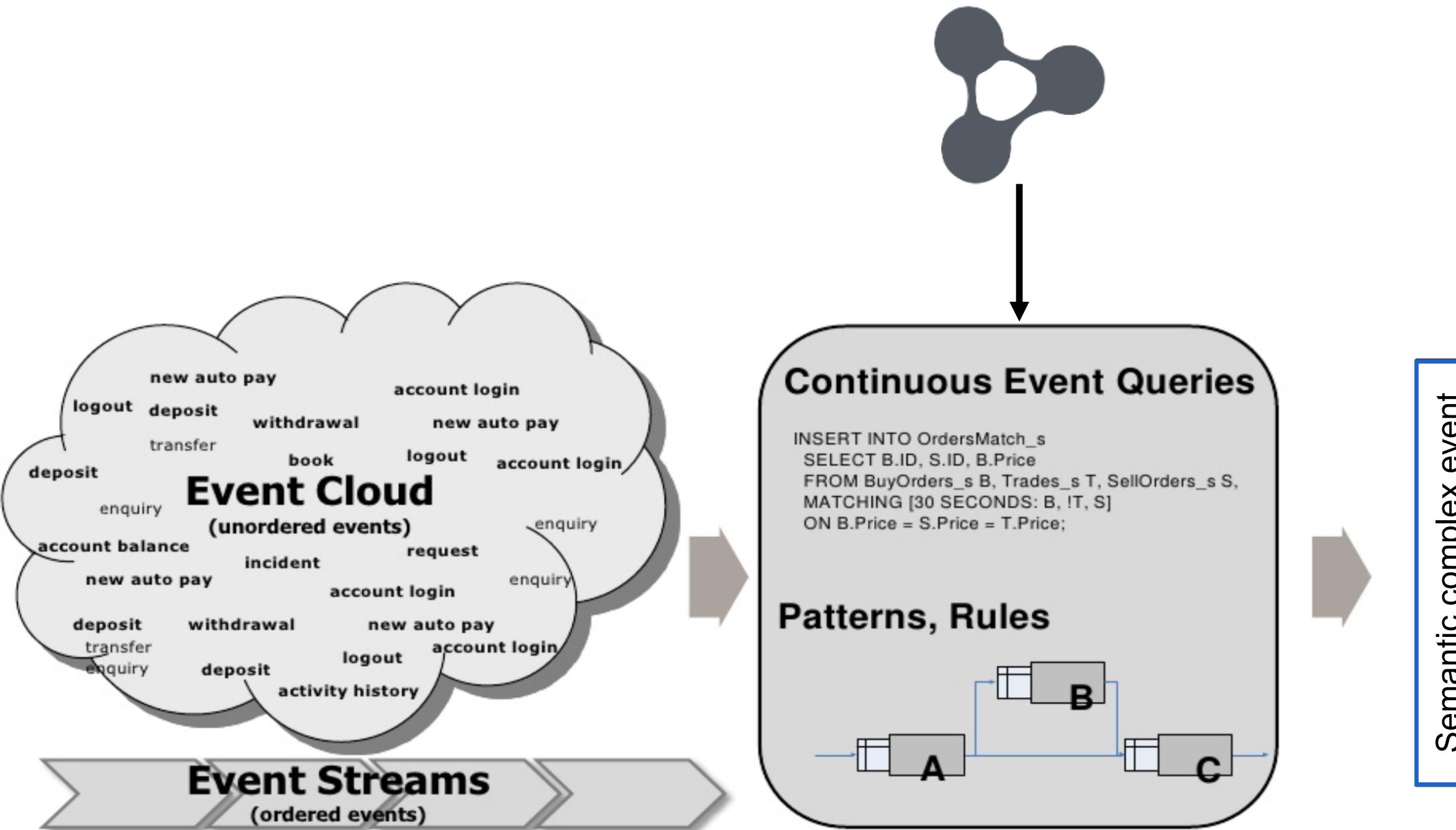
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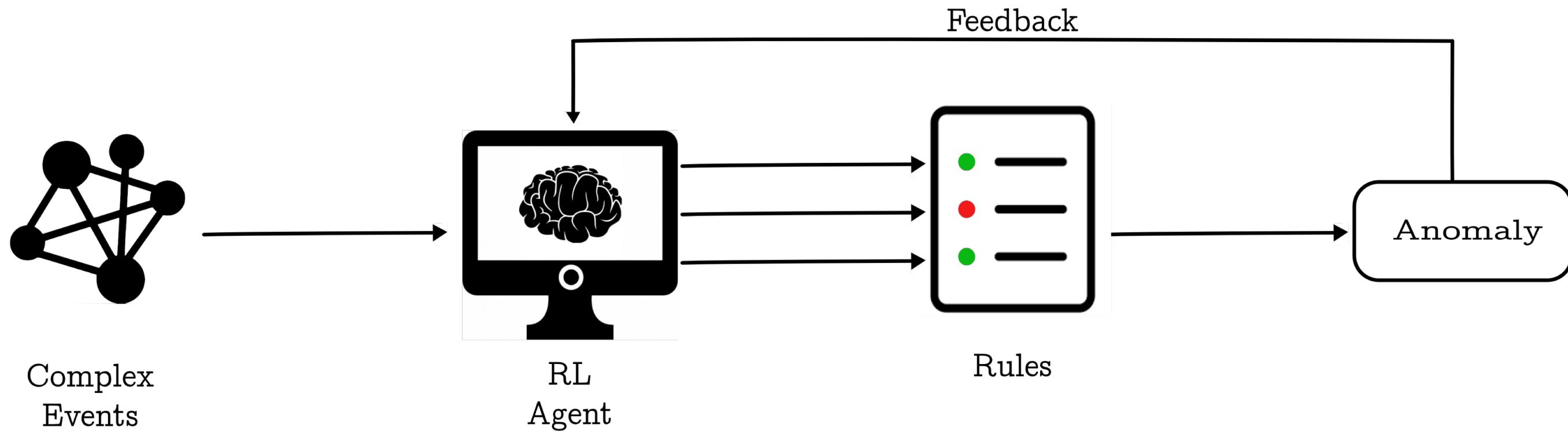
KNOWLEDGE INSIDE RULE-BASED SYSTEMS



SOTA: COMPLEX EVENT PROCESSING



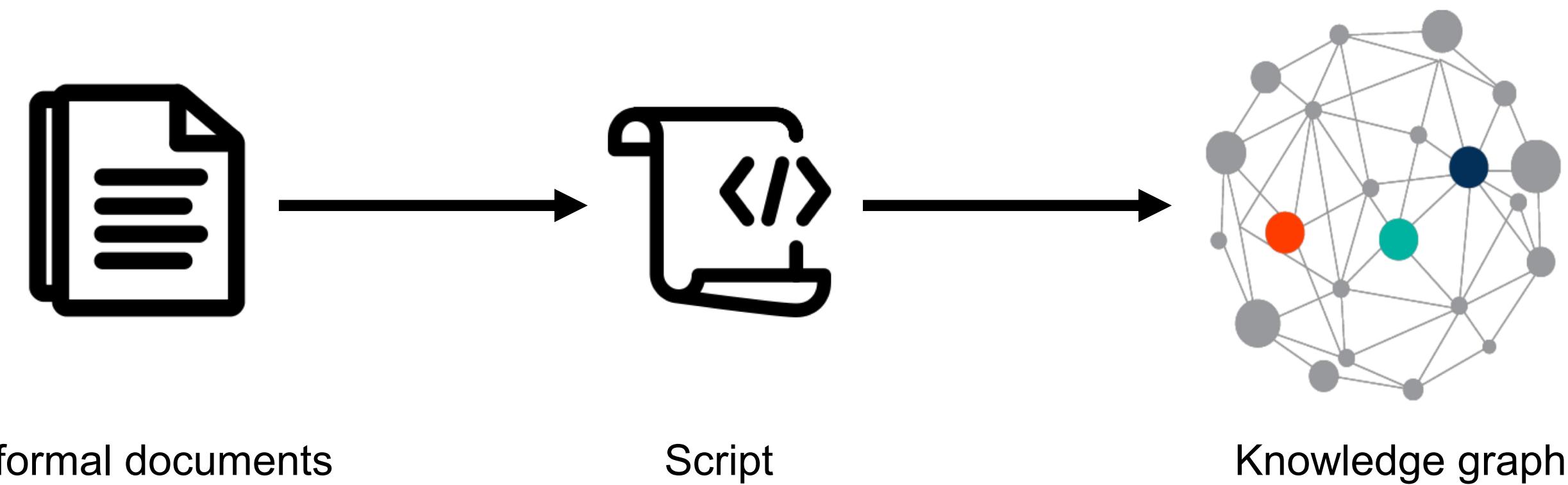
ADAPTIVE STREAM DETECTION



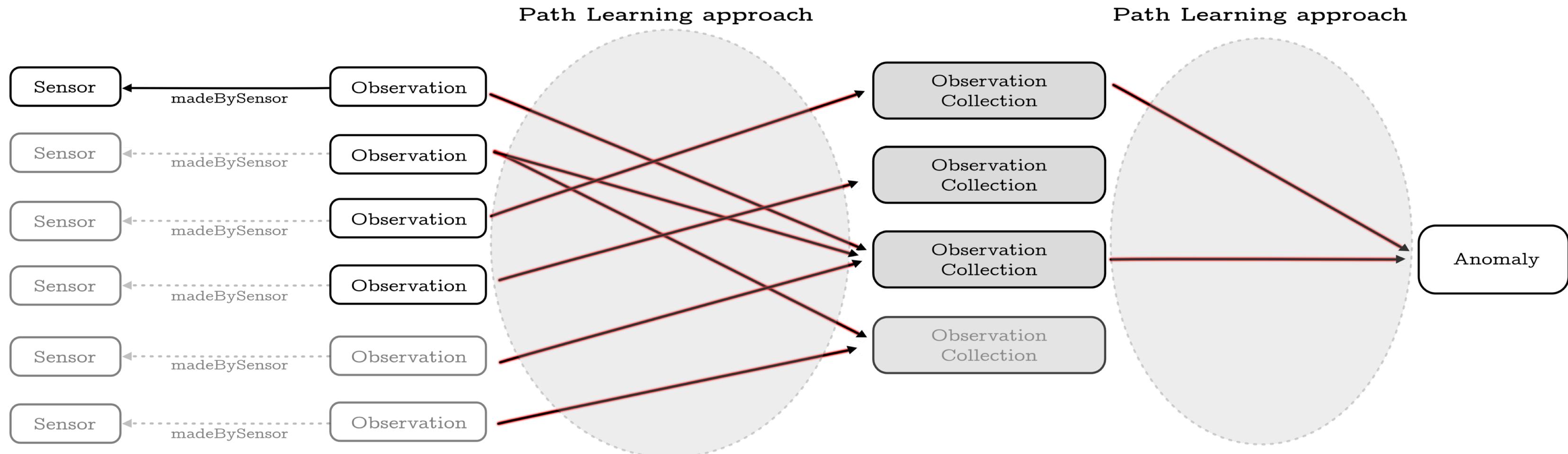
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FROM KNOWLEDGE TO GRAPH



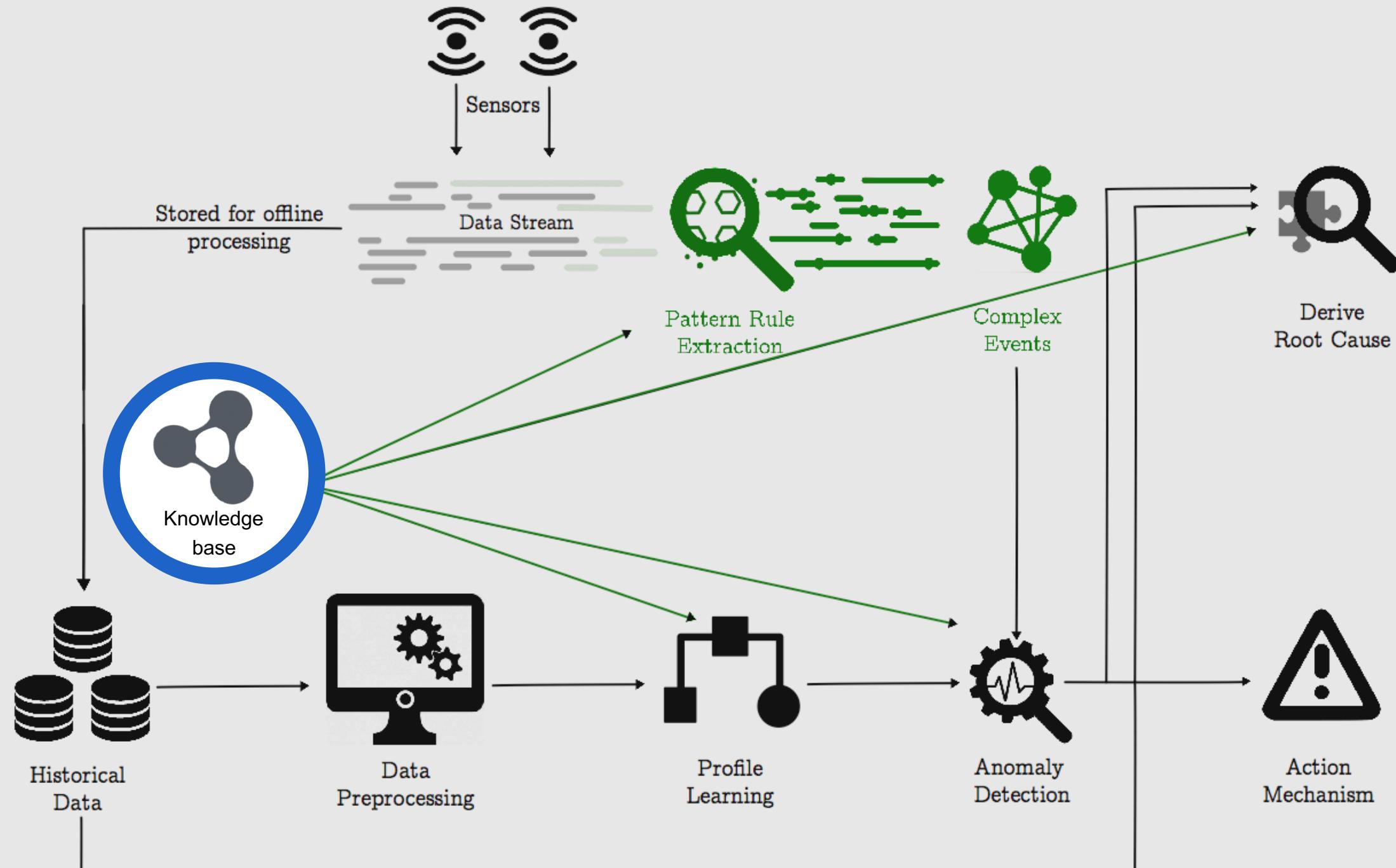
LEARNING THE CAUSE OF AN OBSERVATION



CONCLUSION

- Hypothesis:
 1. Outperform detection rate by incorporating knowledge
=> **by extracting the knowledge in a closed loop with the models**
 2. Reduce F1 score, the number of false detects, with knowledge
=> **by limiting the effect of the frequently used accuracy metric**
 3. Reduce the human involvement drastically
=> **By deriving the causes from the available knowledge**
 4. Make techniques available for streaming environments
=> **By adaptively adding the model-based rules**

CONCLUSION



THANK YOU!

Acknowledgements:

- Reviewers & organizing committee
- My mentor: Anna Lisa Gentile
- My promotores: Filip De Turck & Femke Ongenae
- Industry partner: imec, Televic & Renson



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