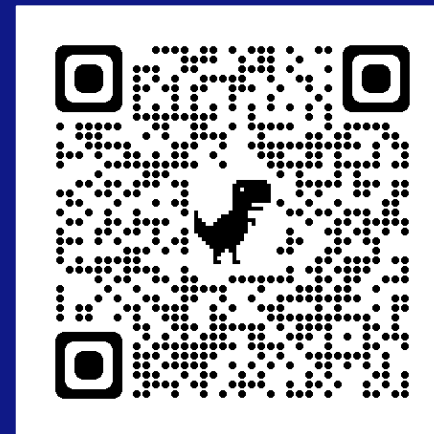




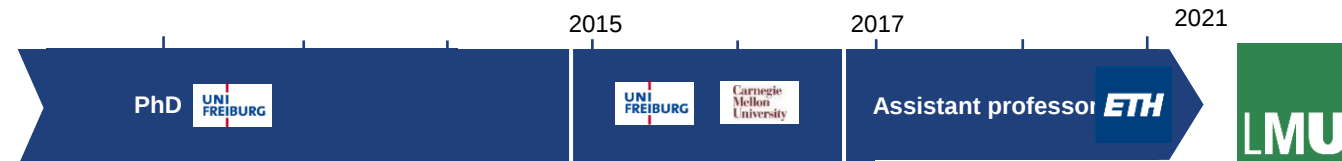
Bringing AI into business management

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Solving management problems with artificial intelligence (AI)



What defines our research

1

Information

We solve management problems of **relevance** by using data science

2

Innovation

We develop **new** algorithms from the area of AI (statistics, computer science, etc.)

3

Impact

We evaluate the added value of our tools **rigorously** in management practice

We see 3 challenges for bringing AI into business management



01

Missing accountability of AI decisions

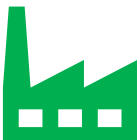
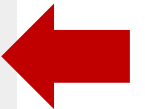
- Clarify boundaries of AI interventions
- Implement governance structures
- Establish risk management frameworks



02

Incomplete frameworks for human-in-the-loop analytics

- Develop human-in-the-loop frameworks from user perspective
- **Promote frameworks for human learning and exploration**
- Advance prescriptive algorithms

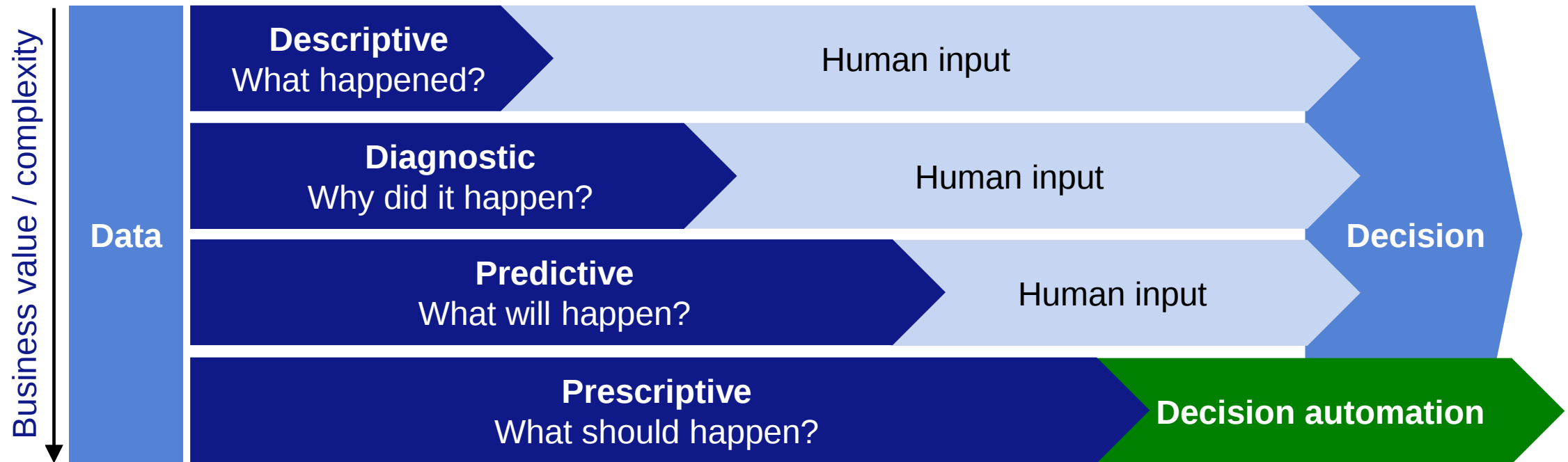


03

Organizational inertia

- Appoint transformation workforce
- Encourage managers to explore and experiment
- Incentivize adoption

What's next in AI for business decision-making: From predictions to decisions

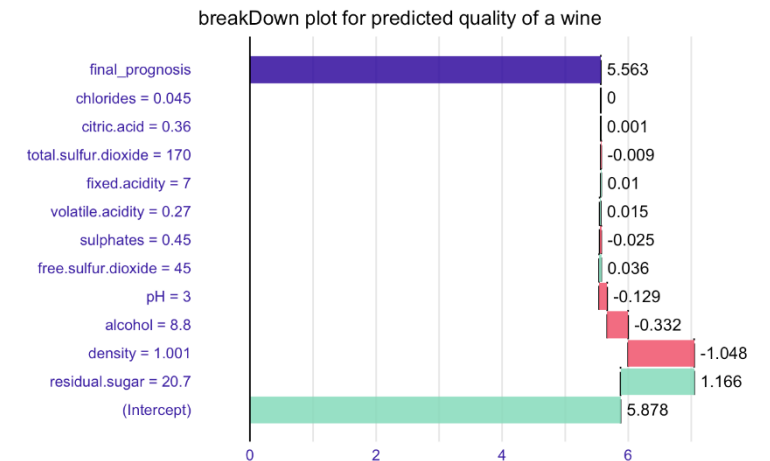
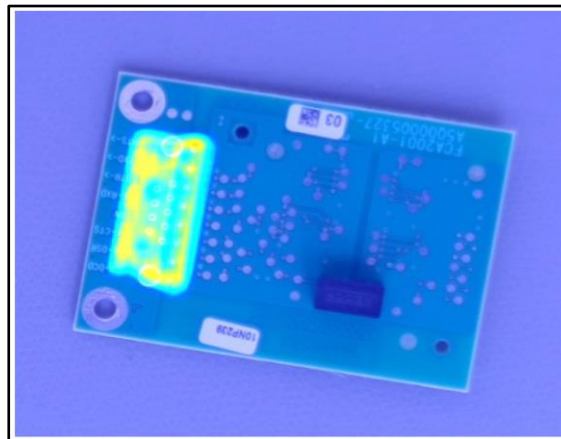
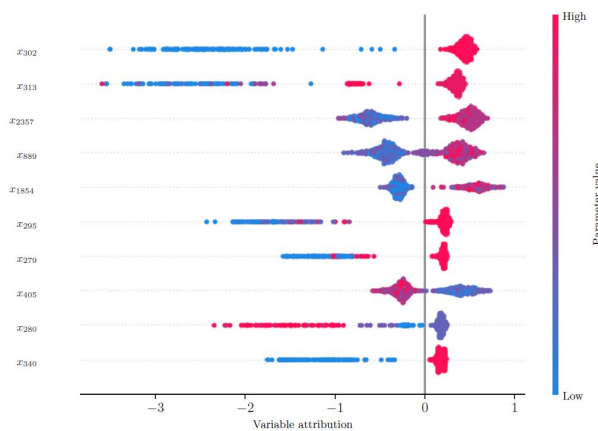


Explainable AI («XAI») can close the gap between predictions and decisions

Explainable AI („XAI“)

Explainable AI refers to tools that reduce the black-box nature of predictions and makes them more opaque

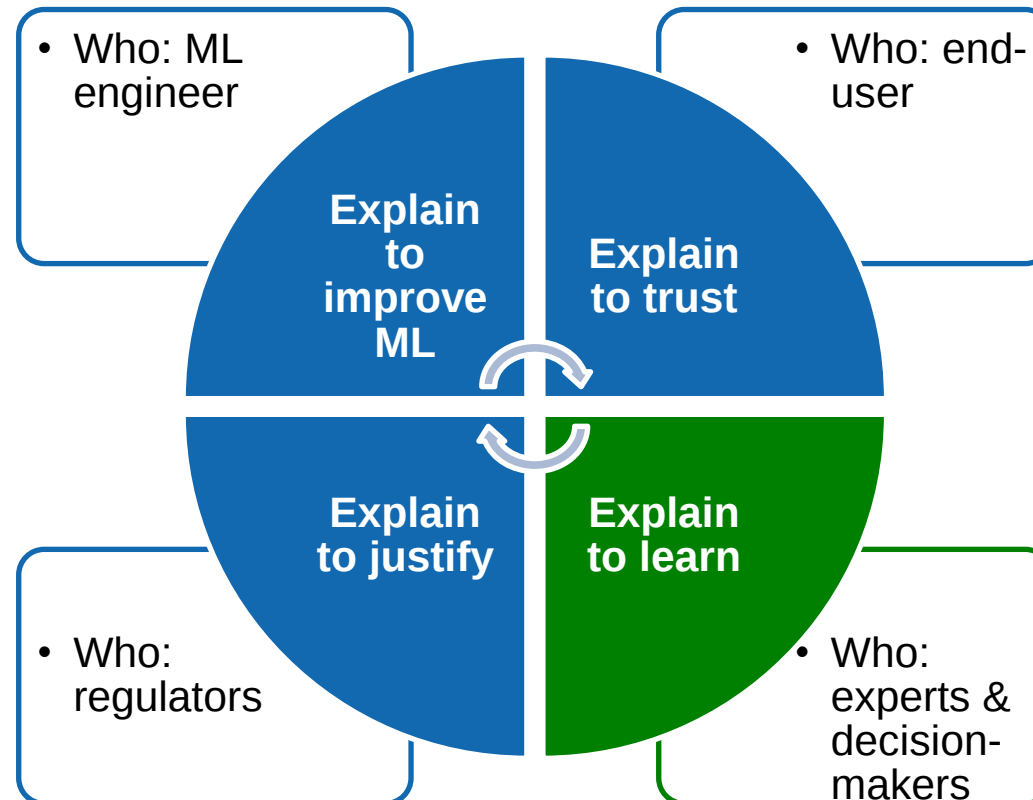
$$y = \alpha + \beta_1 x_1 + \dots + \beta_k x_k$$



IF a patient (has an age ≤ 60 **AND** a weight ≤ 80 kg **AND** has mild symptoms)
OR (has an age ≤ 40 **AND** a weight ≤ 80 kg **AND** has severe symptoms)
OR (has an age ≤ 30 **AND** a weight ≤ 100 kg **AND** has severe symptoms)
THEN treat with drug

XAI can have various motivations – but: it can also promote human learning through “learn-to-explain”

Why to aim for explainability?



Enabling better decision-making for industrial problems

Mining company data for human learning

- **Problem:** existing company data is vast and often not systematically processed
- **Complication:** most company data not in tabular form but as text (e.g., reports, invoices, etc.)
- **Solution:** knowledge extraction from raw text

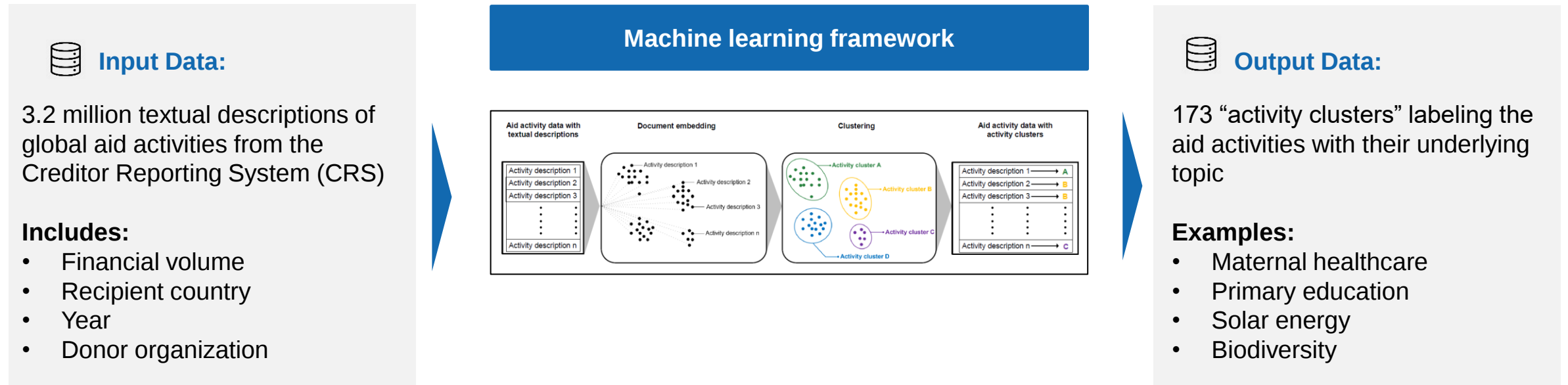
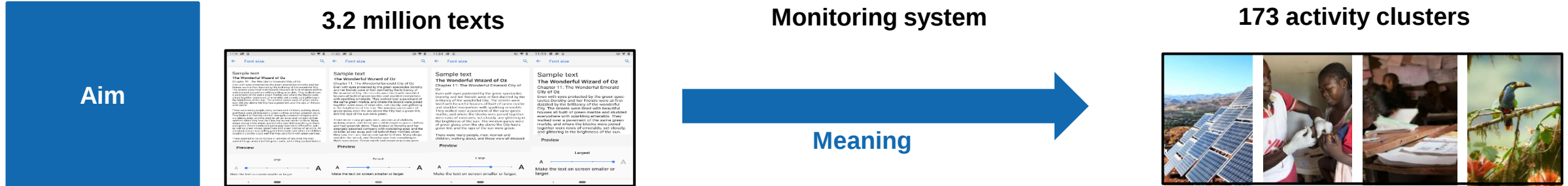
Promotes human learning but managers remain fully in driver seat

Generating new evidence for human-in-the-loop decisions

- **Problem:** company data is digitized but monitoring does not inform best actions
- **Complication:** high-dimensional, non-linear data
- **Solution:** explainable AI (XAI) to create new evidence as a decision aid

Guides human decisions-making by prioritizing decisions and improving task performance (+trust)

XAI can cluster development aid projects to generate real-time monitoring and promote human learning



Using explainable artificial intelligence to improve process quality: Evidence from semiconductor fabrication

Motivation

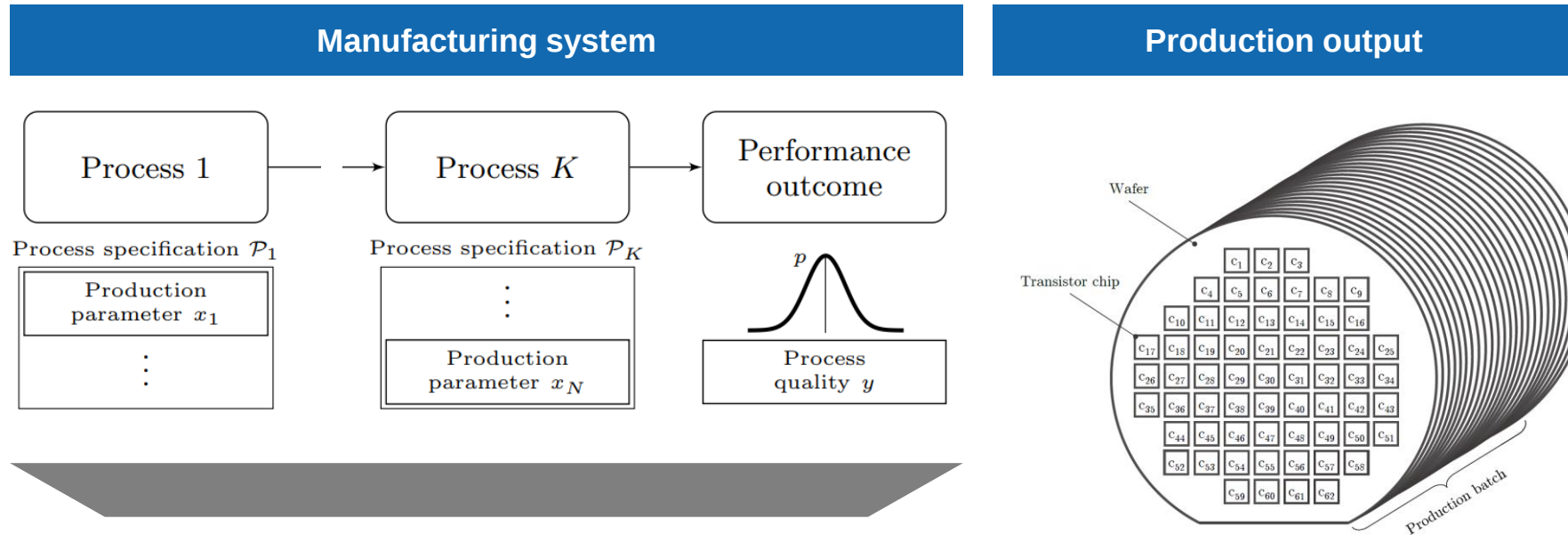
- Nonconformance is a key cost driver in manufacturing
- 10% to 15% of operating expenses
- Extensive sensor measurements but identifying quality drivers challenging

Proposed framework

- New data-driven framework based on “**explainable AI**”
- Designed for complex, non-linear relationships between quality drivers and quality variation



Prescriptive framework must adapt to constraints of real-world setting

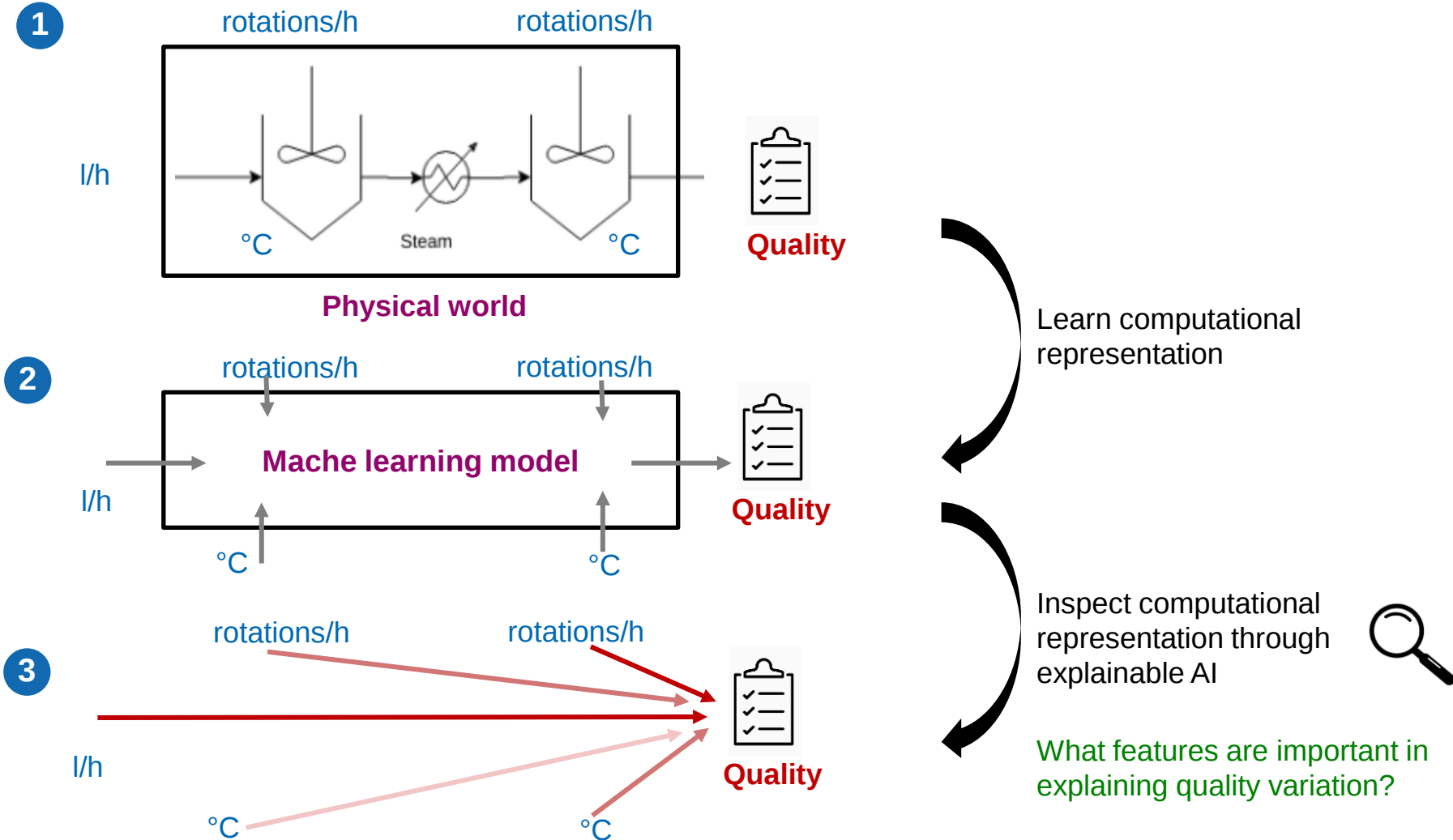


Challenges

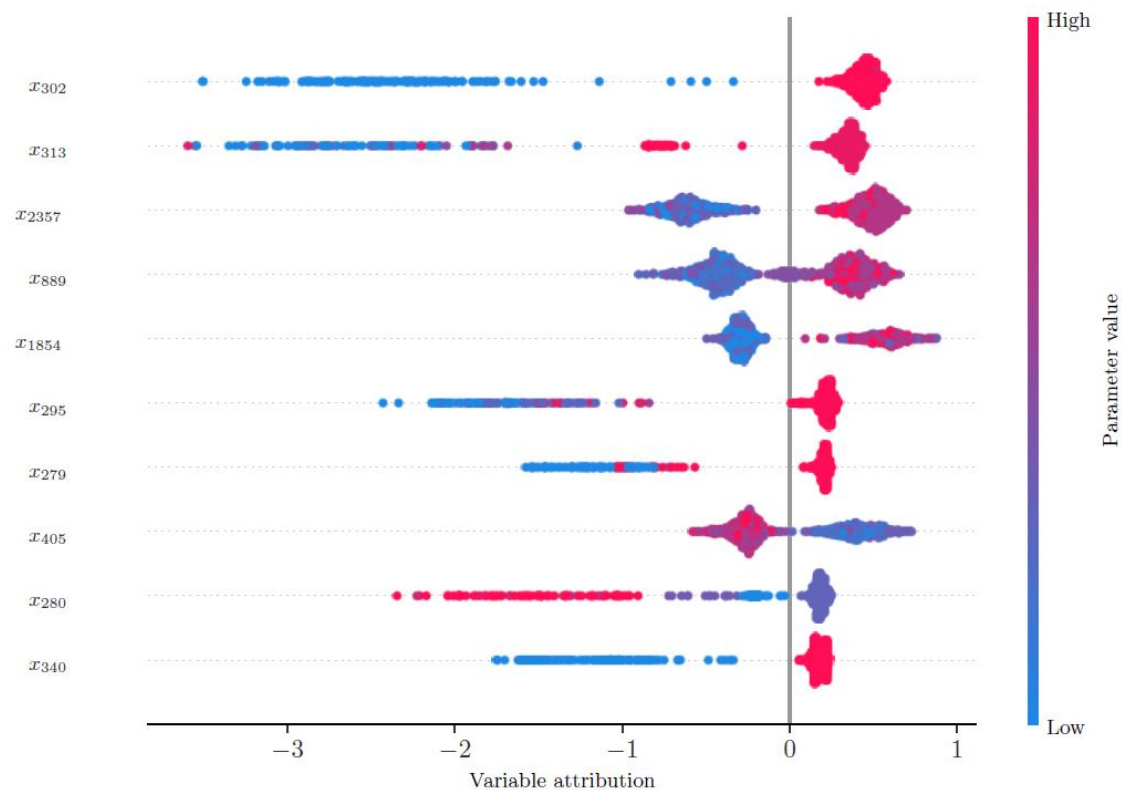
- High-dimensional setting
- Complex non- linearities driving process quality

But: state-of-the-art are linear models

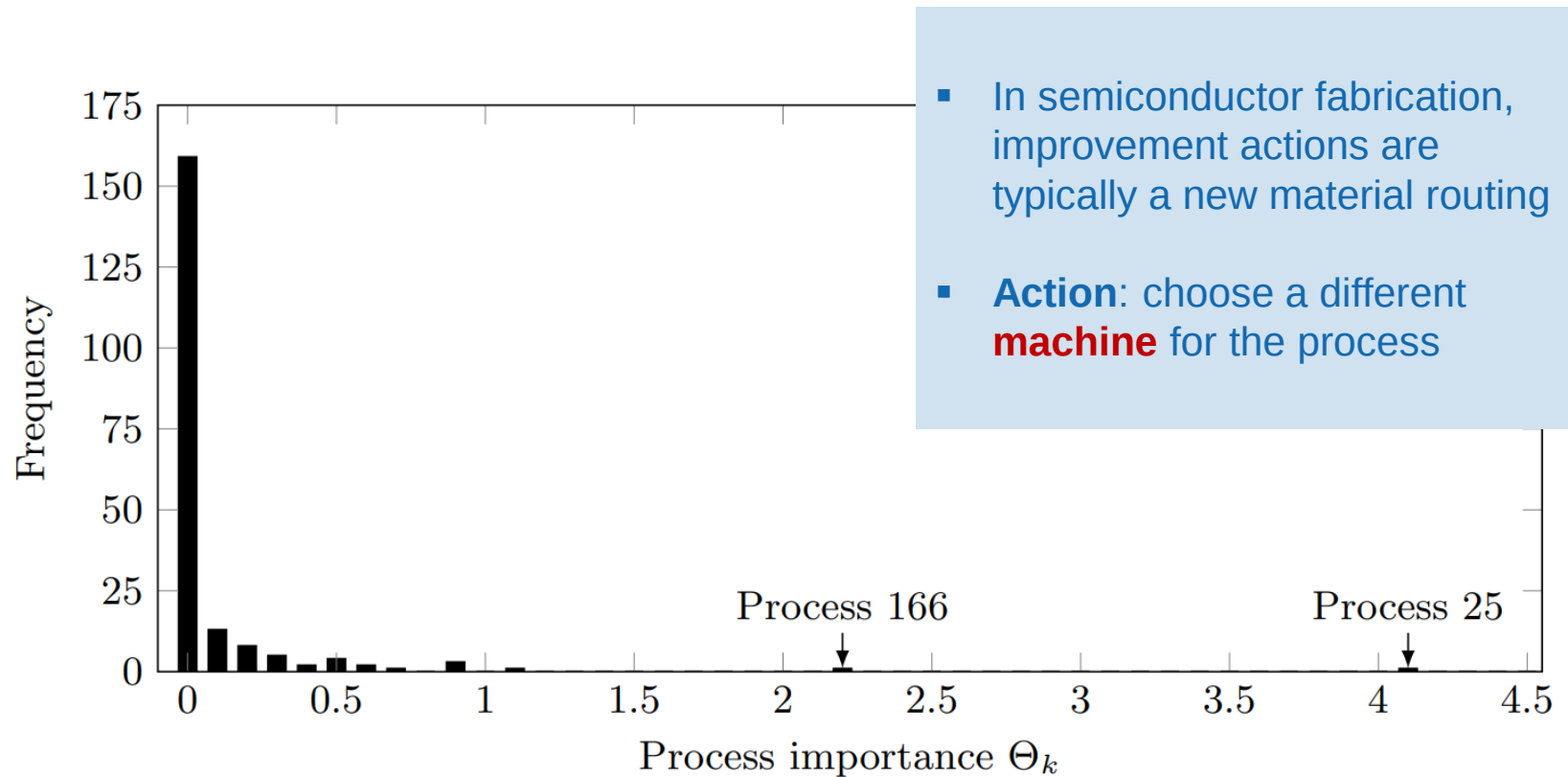
Learning a 'digital twin' to identify quality drivers and remove root causes



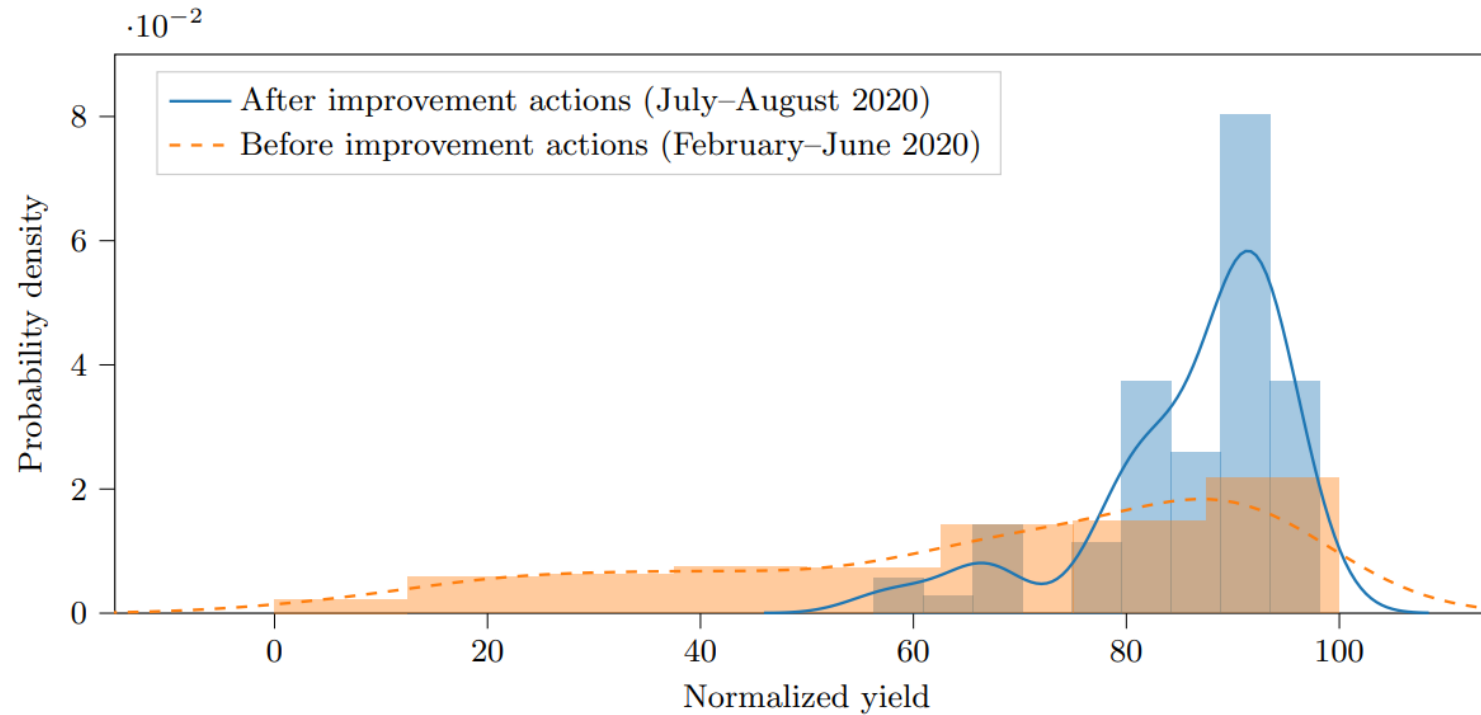
Feature attribution at parameter level (=“standard SHAP plot”)



Process importance identifies processes with large contribution to quality variation (“quality drivers”)



Actual roll-out in July-August 2020 shows significant yield improvements



Yield loss reduced by **51.3%** ($p < 0.001$)

Explainable AI as an effective human-in-the-loop approach

Limitations / robustness

- Explainable AI finds **correlation, not causations**
→ requires rigorous experimental testing
- Can only select improvement actions that are **captured in the data** (i.e., observed and with variation)
→ manufactures introduce controlled variation (Design of Experiments; Fisher 1935)
- **Robust results** (same conclusion with other machine learning models)

Conclusion

- One of first papers on explainable AI in Management Science
- Promotes human learning: AI identified quality drivers that were **previously unknown** to the process engineers
- Applicability to other domains (drivers of customer churn, health outcomes, etc.)

XAI is well aligned to address AI hurdles around the technological, managerial, and organizational level



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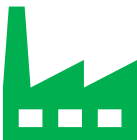
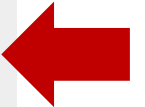
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Artificial intelligence | Impact

