FLANDERS MAKE
DRIVING INNOVATION IN MANUFACTURING

AI lifecycle perspective

Bart Meyers

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ASSISTANT

About me

Bart Meyers
Senior Research Engineer
Digital Transformation

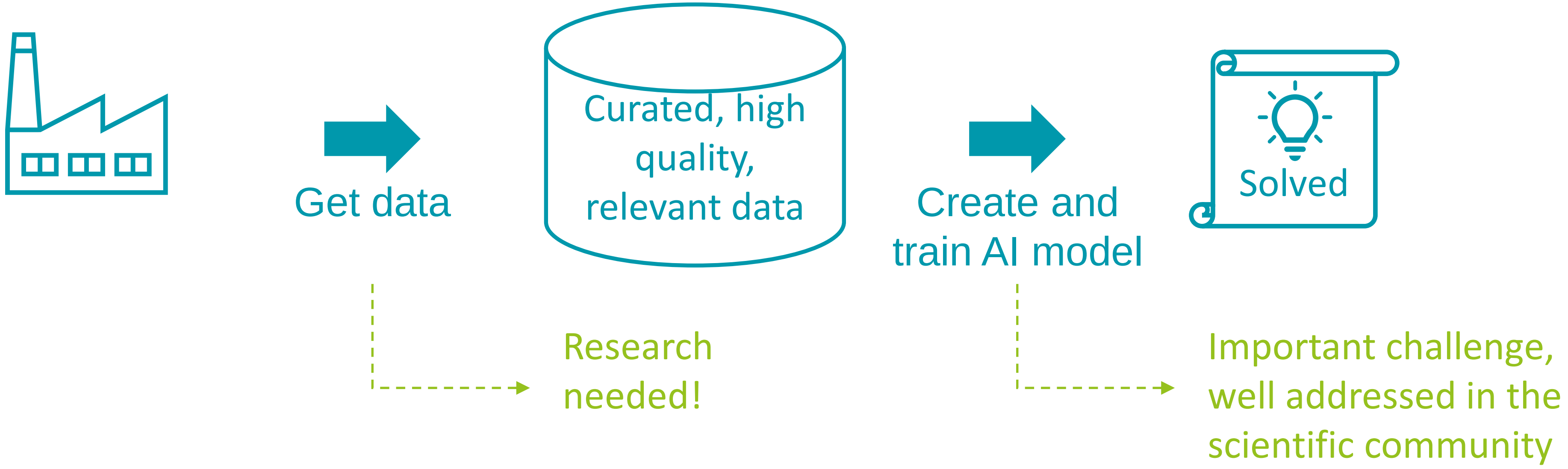
View Profile

Background in computer science, modelling languages, architectures

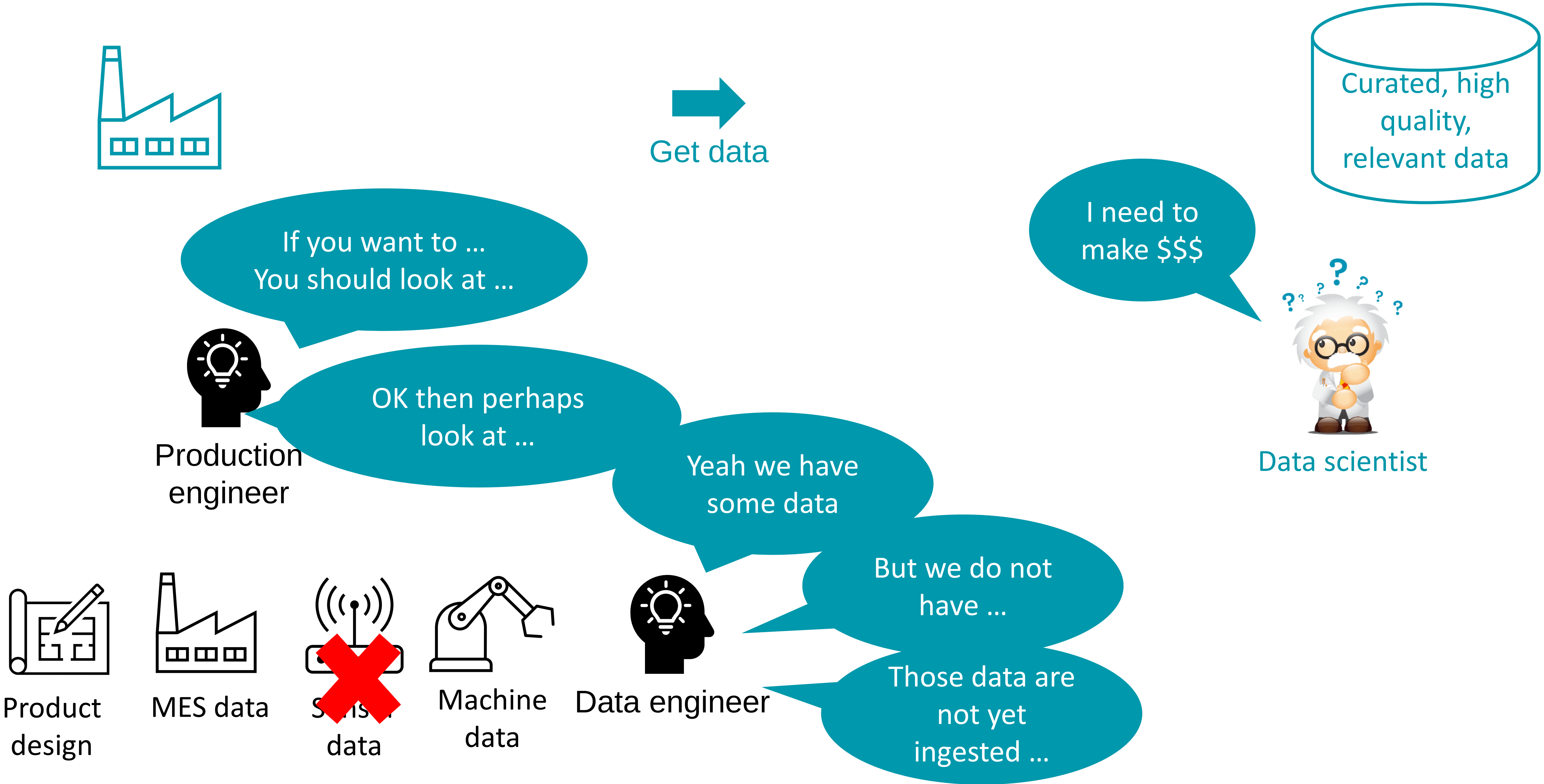
Active in digitalization:

- Digital twins
- Internet of Things
- Applying AI in manufacturing
- Knowledge modeling
- Smart products/production

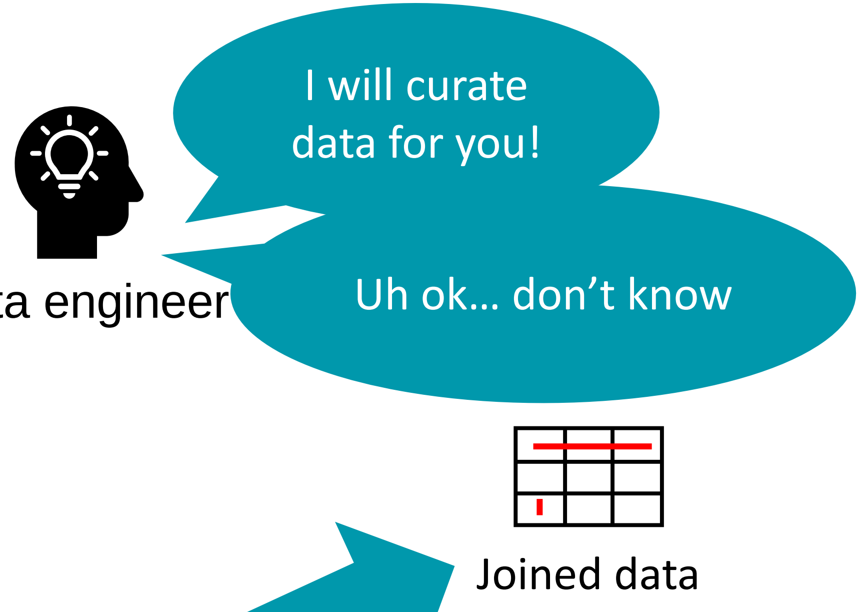
The life cycle for value-adding artificial intelligence

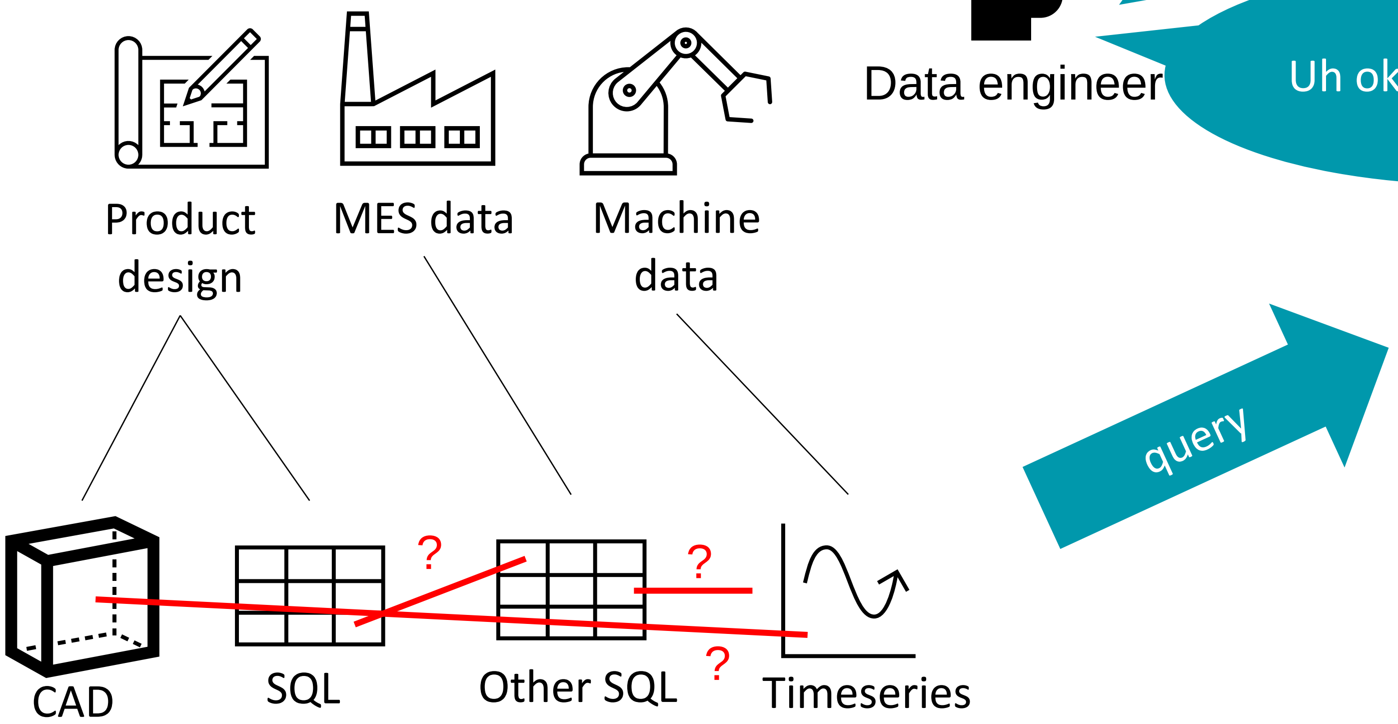


Applying Artificial Intelligence in Manufacturing



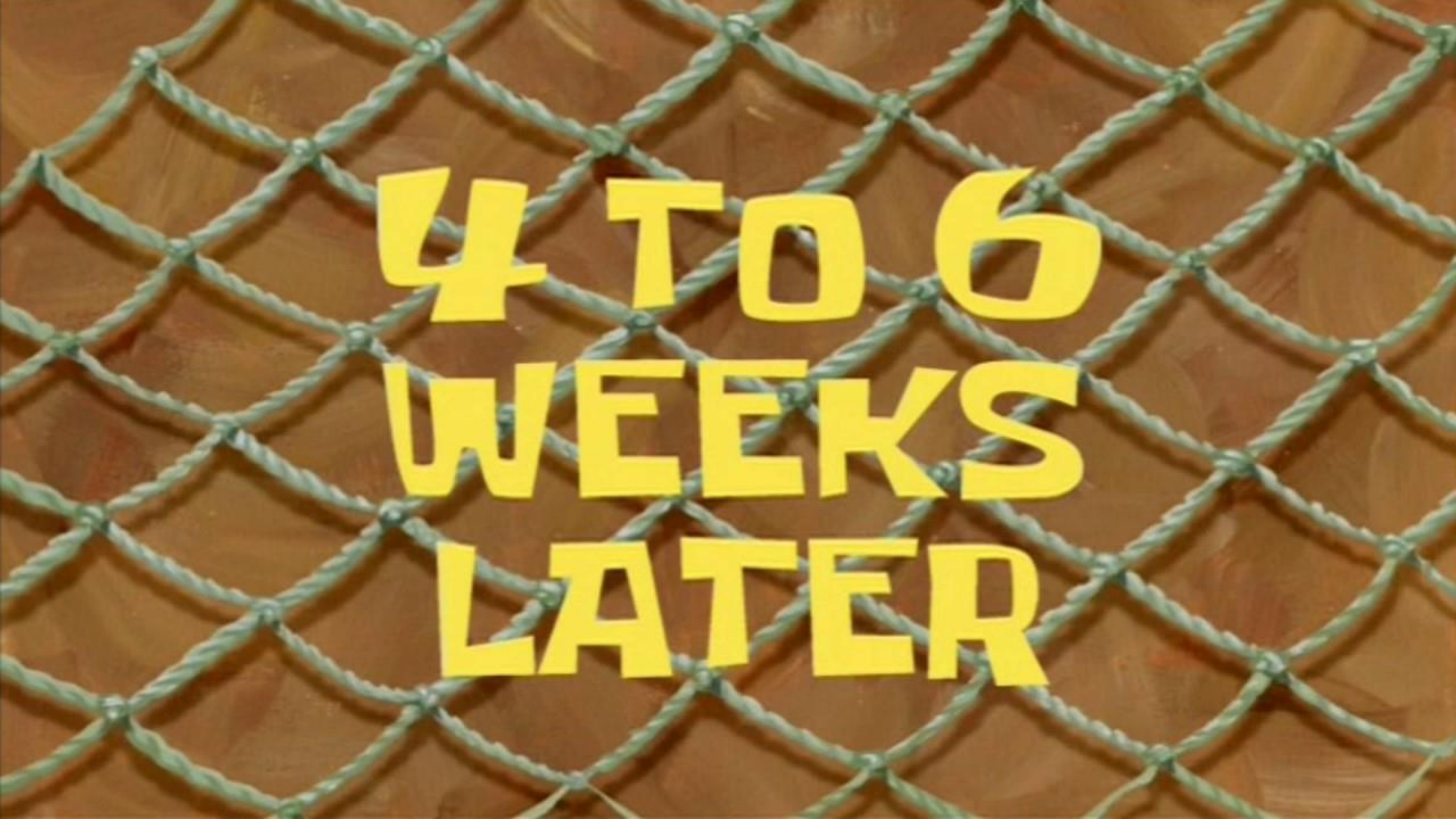
Applying Artificial Intelligence in Manufacturing



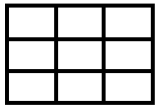


- Need to remove the test runs from the data
- Why are there two pieces with the same serial number?
- Timeseries data… I will need to define data features

- Heterogeneous data silos
  - Location, query language, credentials needed
- Knowledge needed to make sense out of the data
  - "Join machine data with MES data via time stamps, in between half hour after manufacturing step"


4 TO 6
WEEKS
LATER

Finally…



Joined data

Data scientist

But… the final data set is only 30 rows… ☹

Let’s do all of this again for a different product type!


MANY
MONTHS LATER

Analysis results are hard to reuse

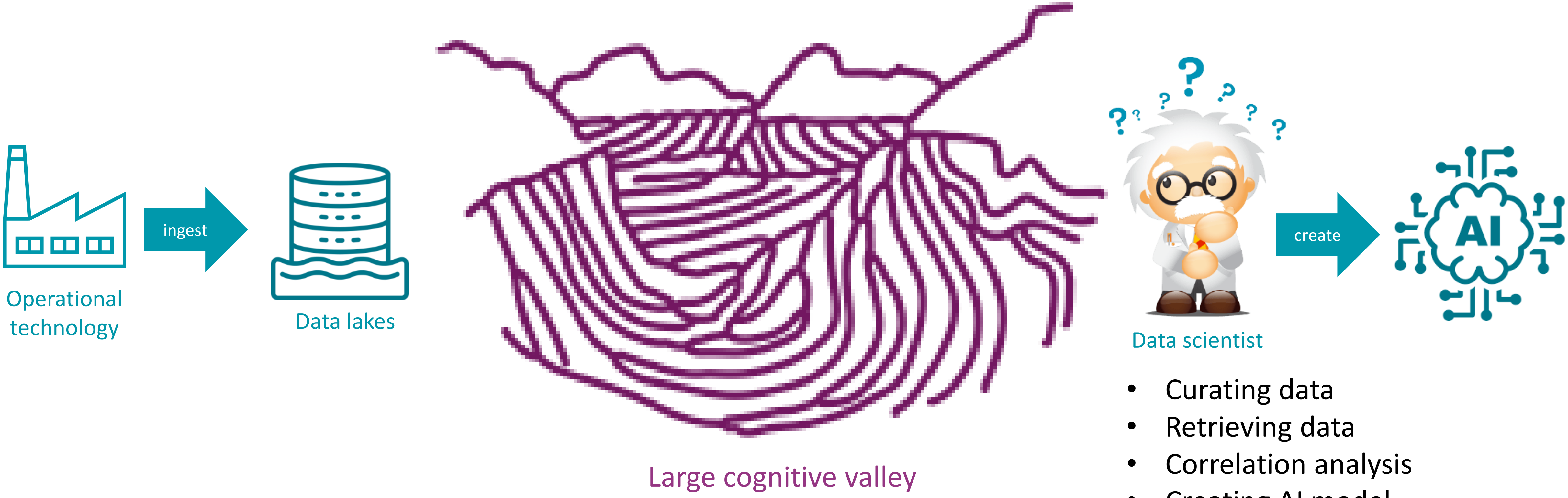
Let’s look into … [very similar things as my colleague many months before]

Other data scientist

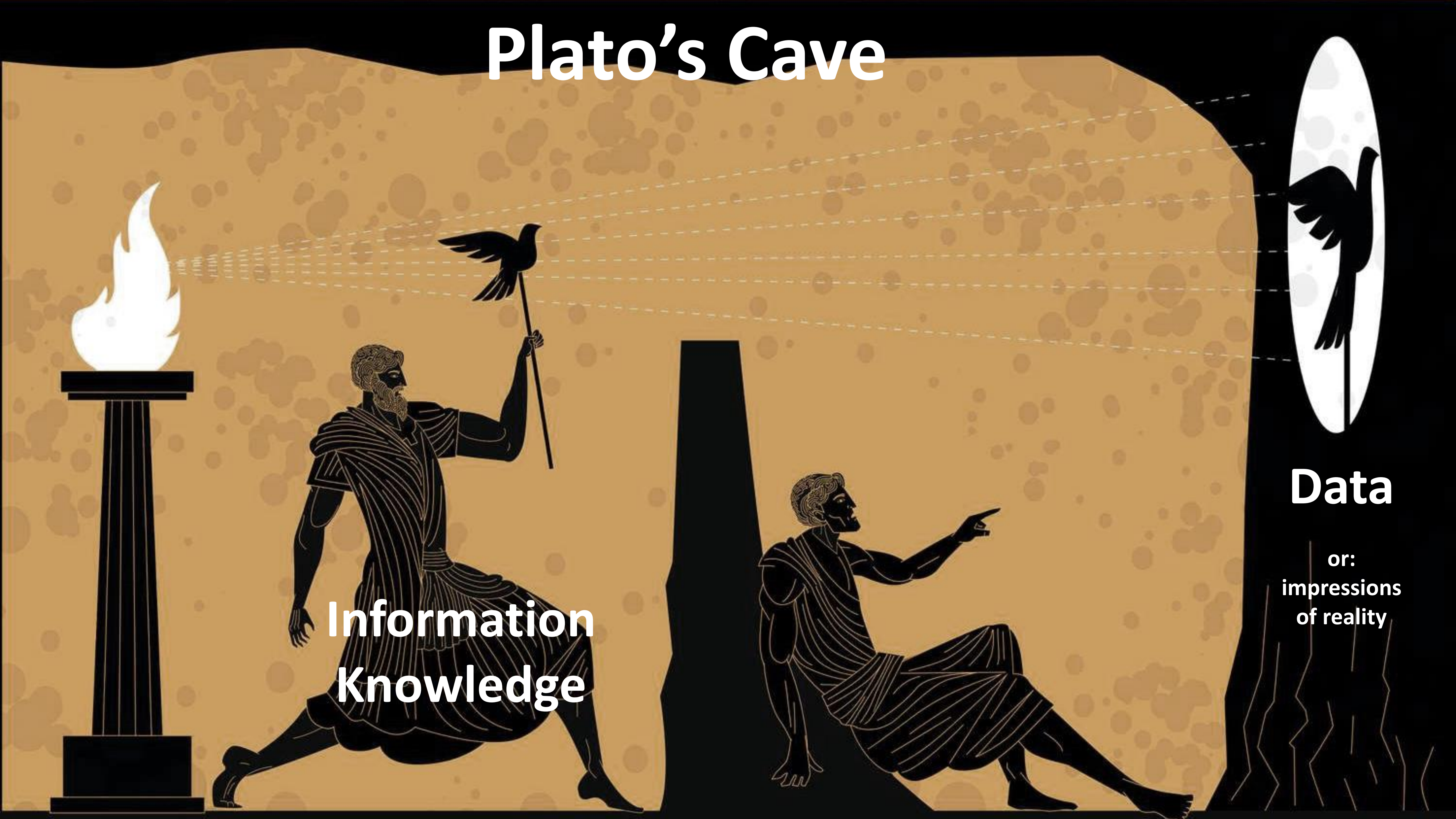
Goes again through the same trials and tribulations as their colleague…

The Gap Between Manufacturing Environments and Artificial Intelligence

Conclusion: we need to bridge the gap

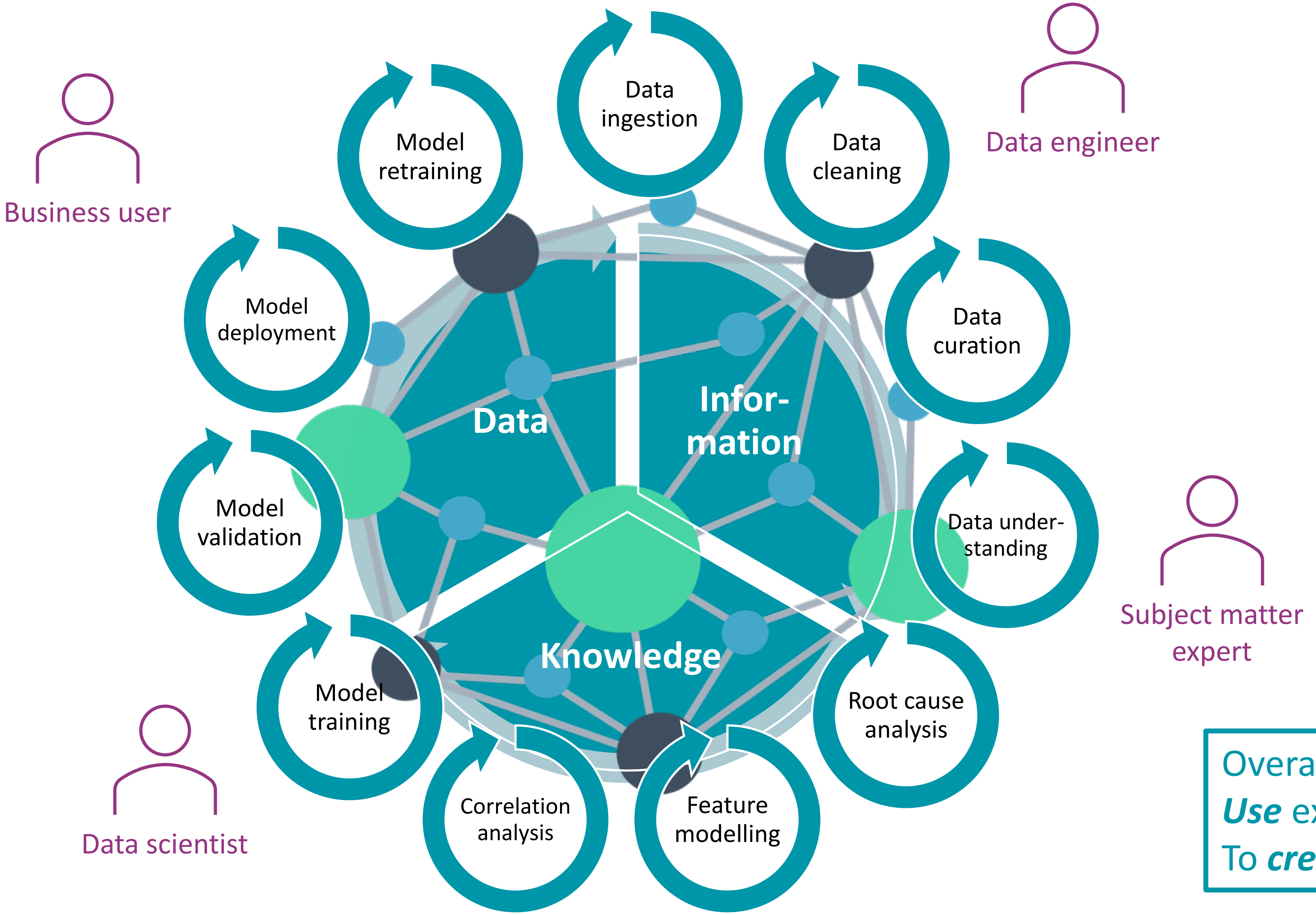


- Curating data
- Retrieving data
- Correlation analysis
- Creating AI model
- Training AI model
- Deploying AI model
- Retraining AI model
- …


Plato’s Cave
Information
Knowledge
Data
or:
impressions
of reality

Central data, information, knowledge management

AI life cycle: iteratively and collaboratively build knowledge

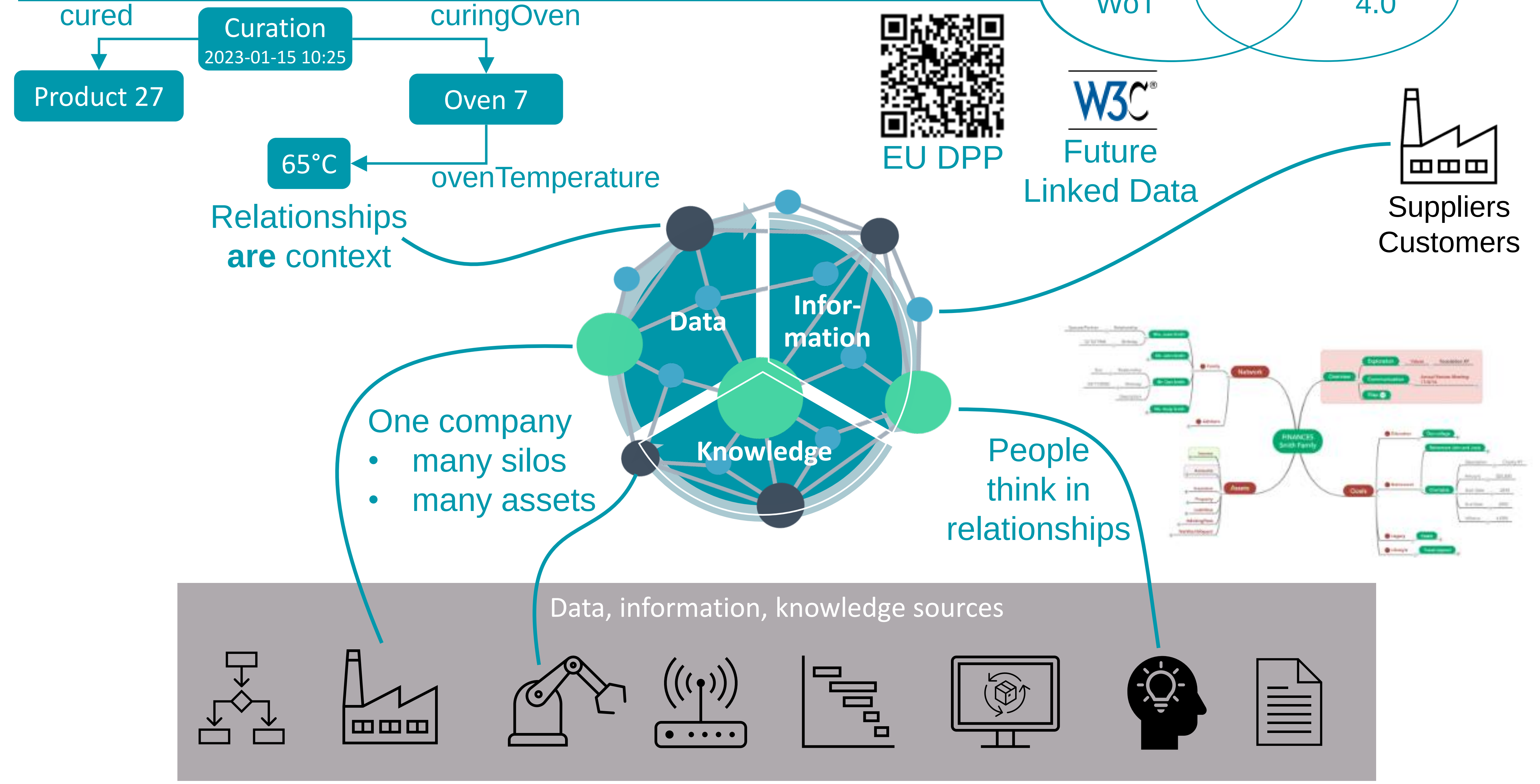


Overall goal:
Use existing data, information and knowledge
To ***create*** new insights (knowledge)

Relationships Are The Future

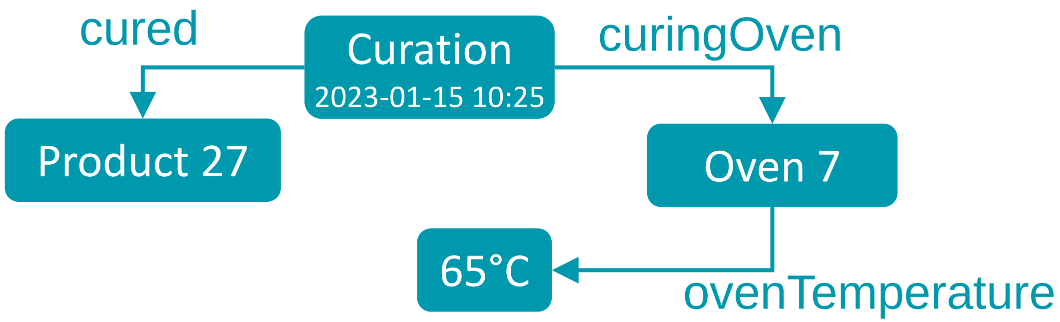
1. Relationships are the future

Relationships Are The Future



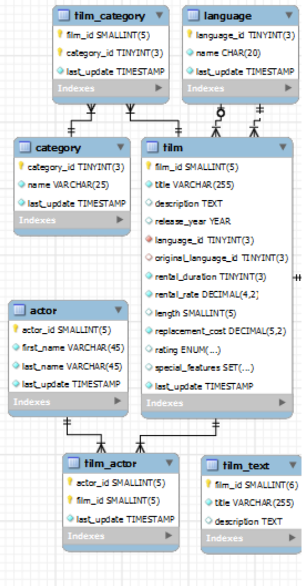
User Domain vs Technical Domain

1 Relationships are the future



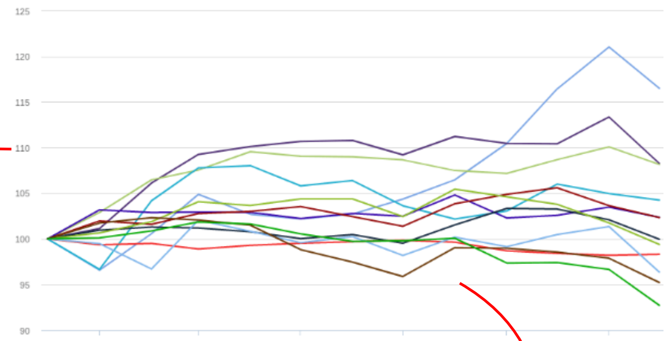
2 User domain vs technical domain

User Domain vs Technical Domain



Product structure

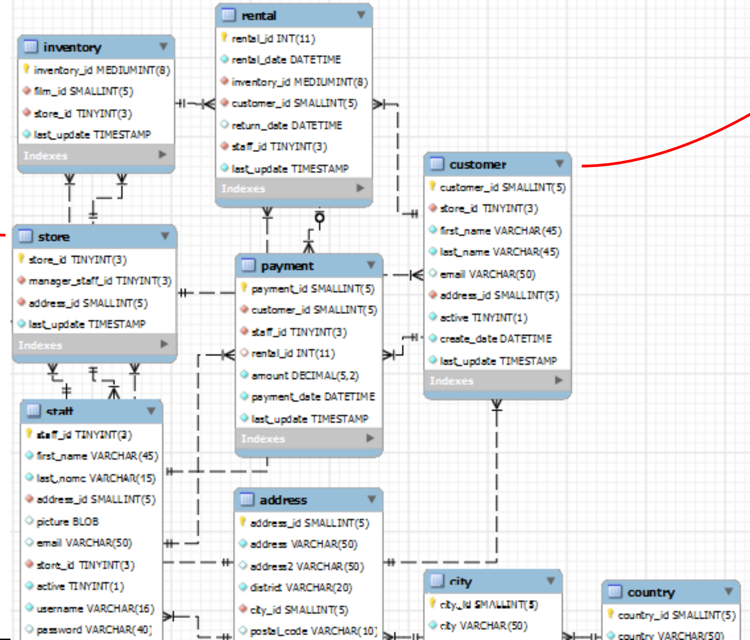
?



Room sensor readings

?

Production order executions (MES)



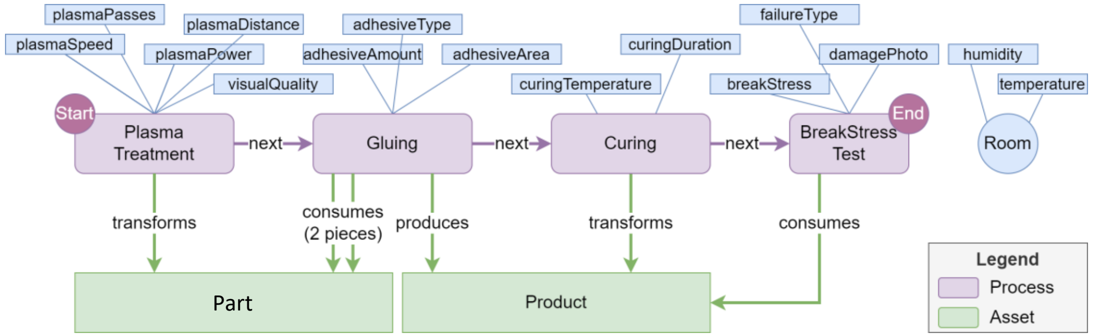
?

This is data…

Do you understand the process?

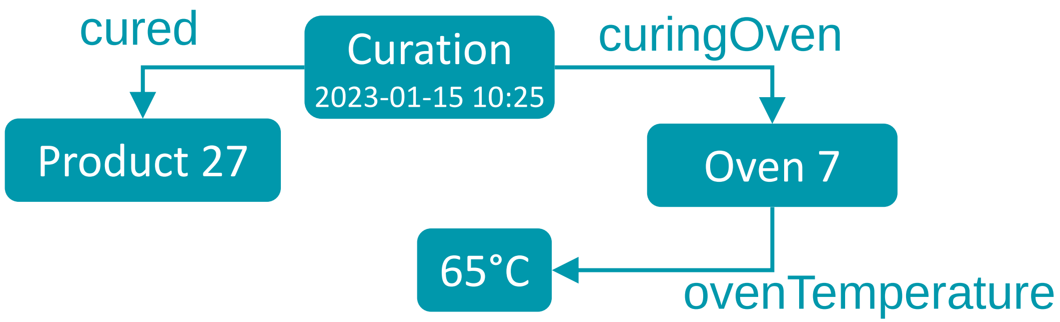
- Technically inspired –

- Multiple data/knowledge silos -

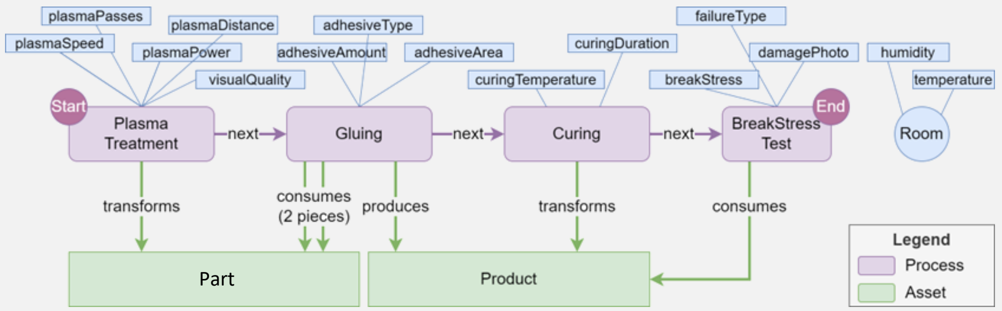


Explicitize & Reuse Knowledge

1 Relationships are the future

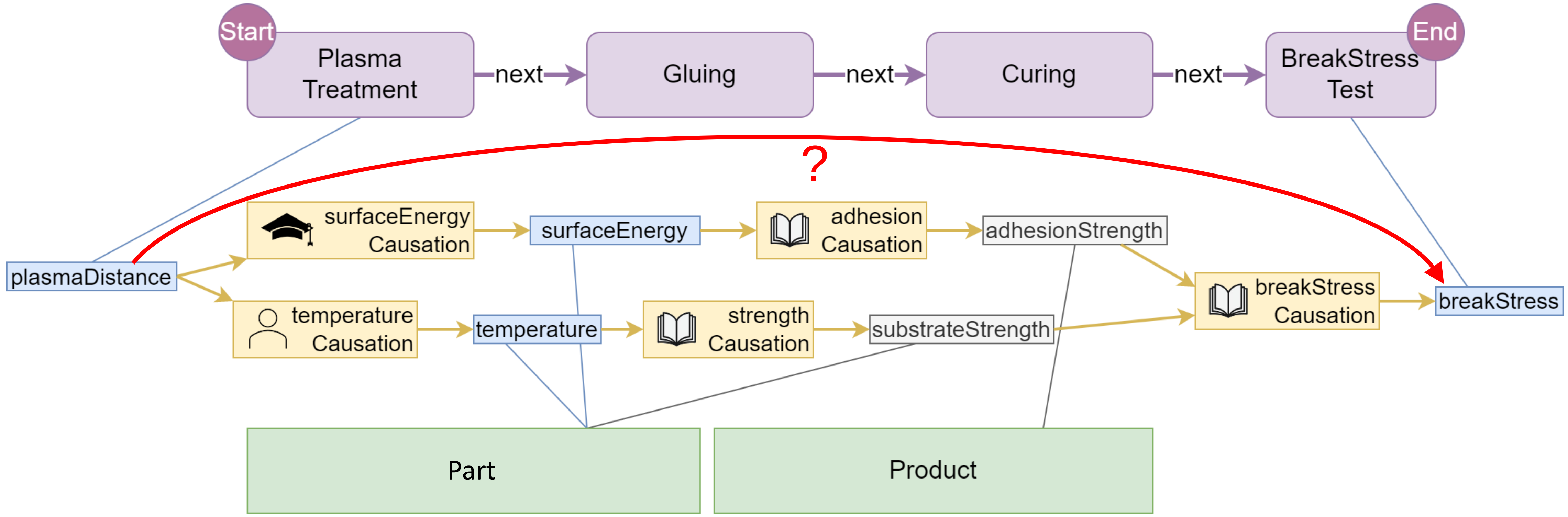


2 User domain vs technical domain



3 Explicitize, store and reuse knowledge

Explicitize, Store & Reuse Knowledge

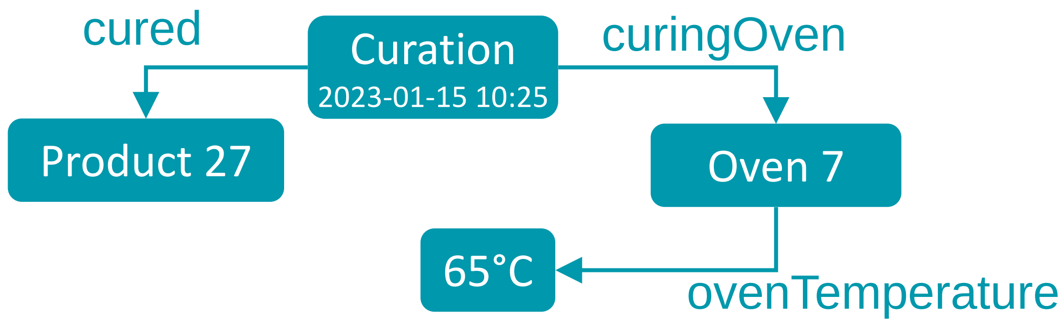


Knowledge

- Explicit & accessible
- Iteratively defined and stored
- Contributed by process engineer, data scientist, …
- Graph/relationship nature by default
- Can be exploited by logical reasoning

Key Enablers for AI life cycle support

1 Relationships are the future



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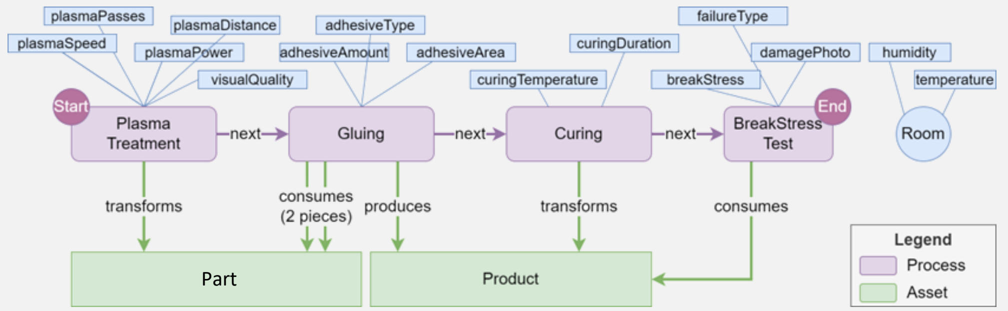

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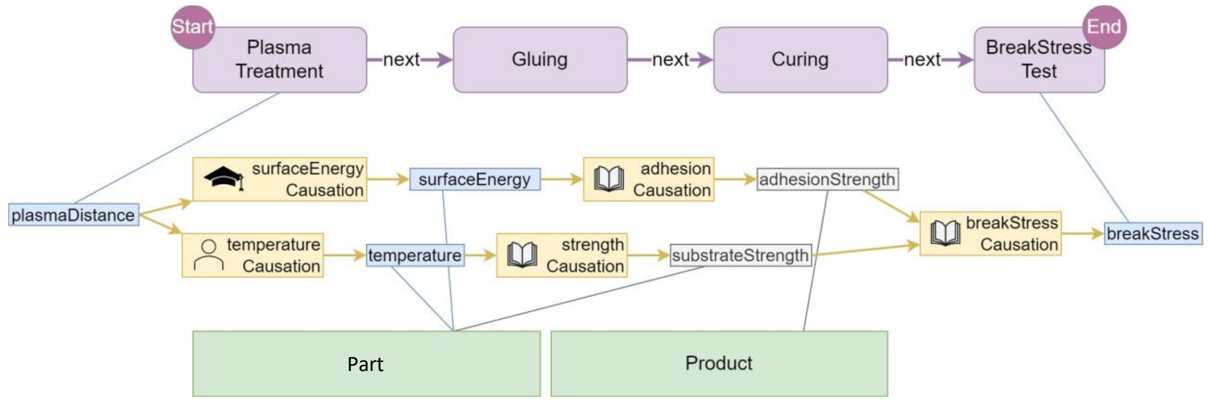


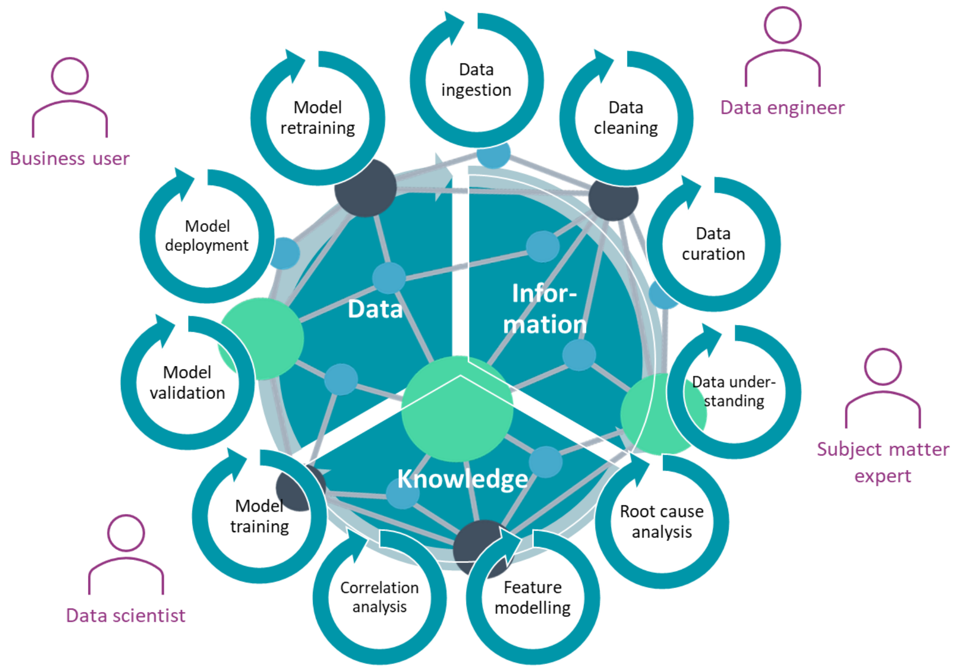
Conclusions

Enable AI by enabling **AI lifecycle**

What's missing?

Model knowledge explicitly

- Relationships first
- Model problem domain
- Model tacit knowledge



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Thank you!

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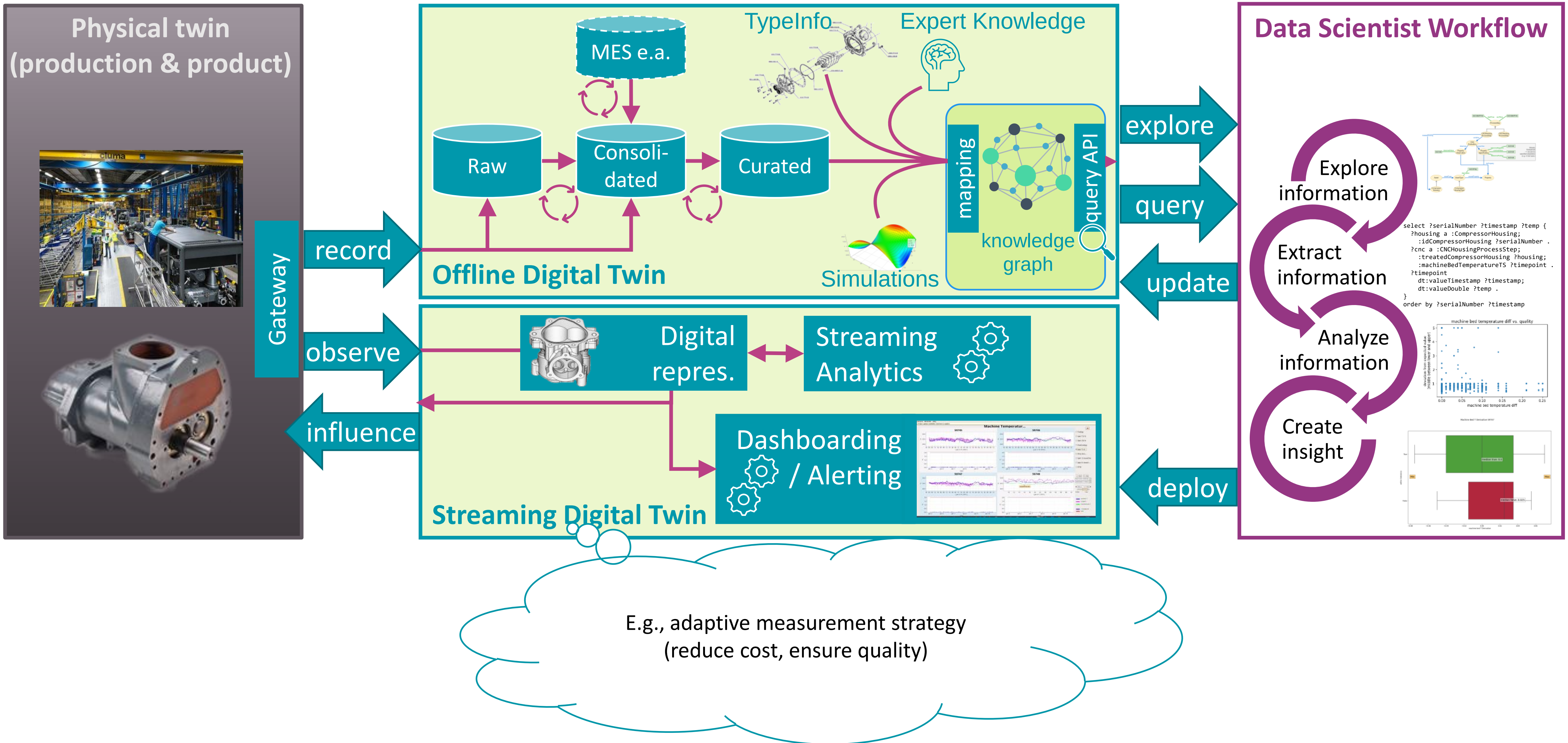
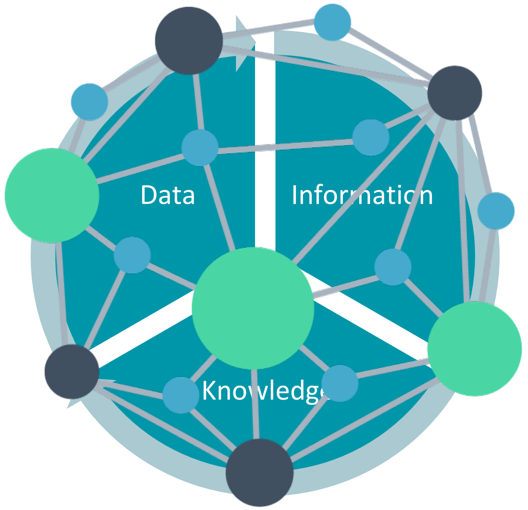
Digital twin design workflow



Functions of Knowledge Graph

Three main functions that allow you to get value out of your data and knowledge



Knowledge Graph

Understand data

- Link heterogeneous data and provide abstraction layer
- Explore and query

+

Model (tacit) knowledge

- Company-specific production knowledge
- Influence factors, uncertainties, simulations, …

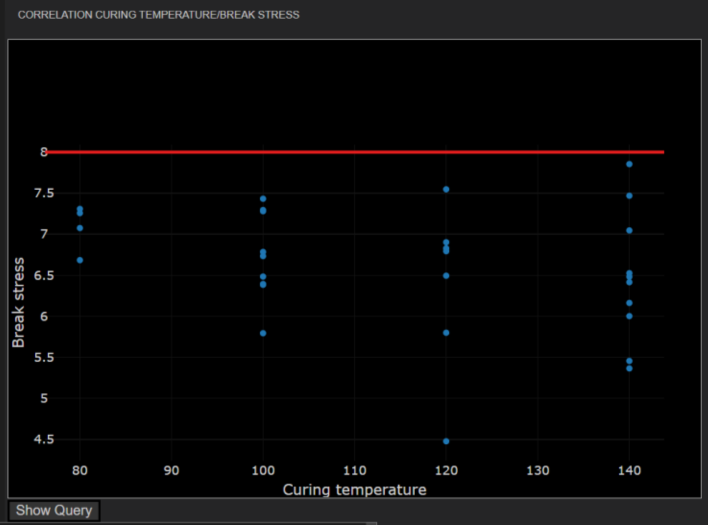
=

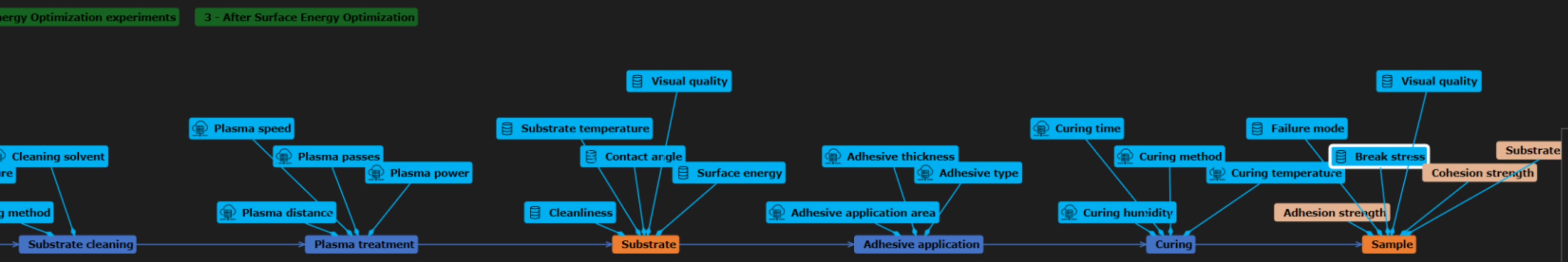
Generate insights

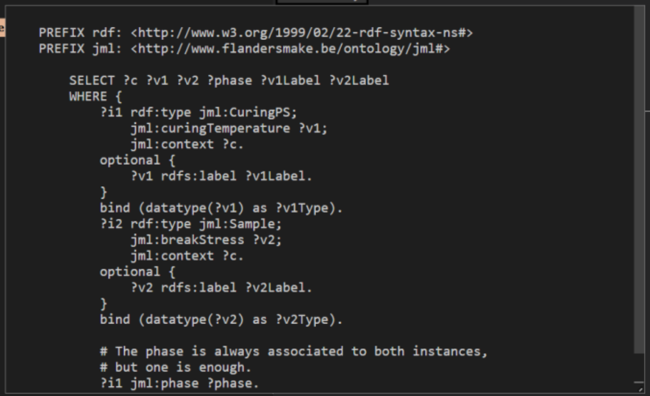
- Feature analysis, correlation analysis, root cause analysis
- Predictive and prescriptive data analytics

Demo

Ad hoc correlation analysis

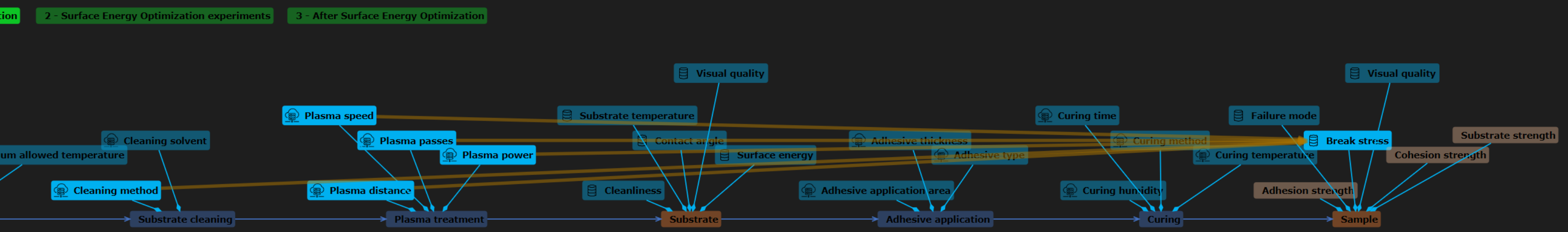


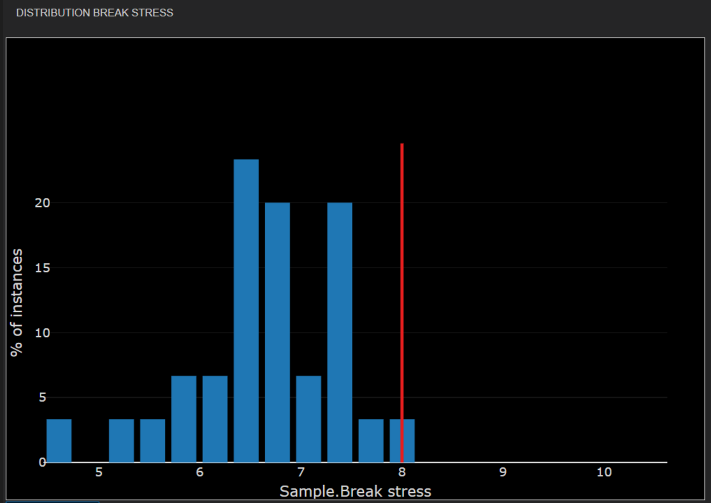




Exploration and data visualization

Query generation

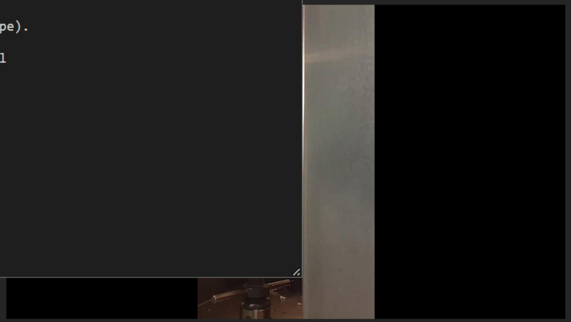




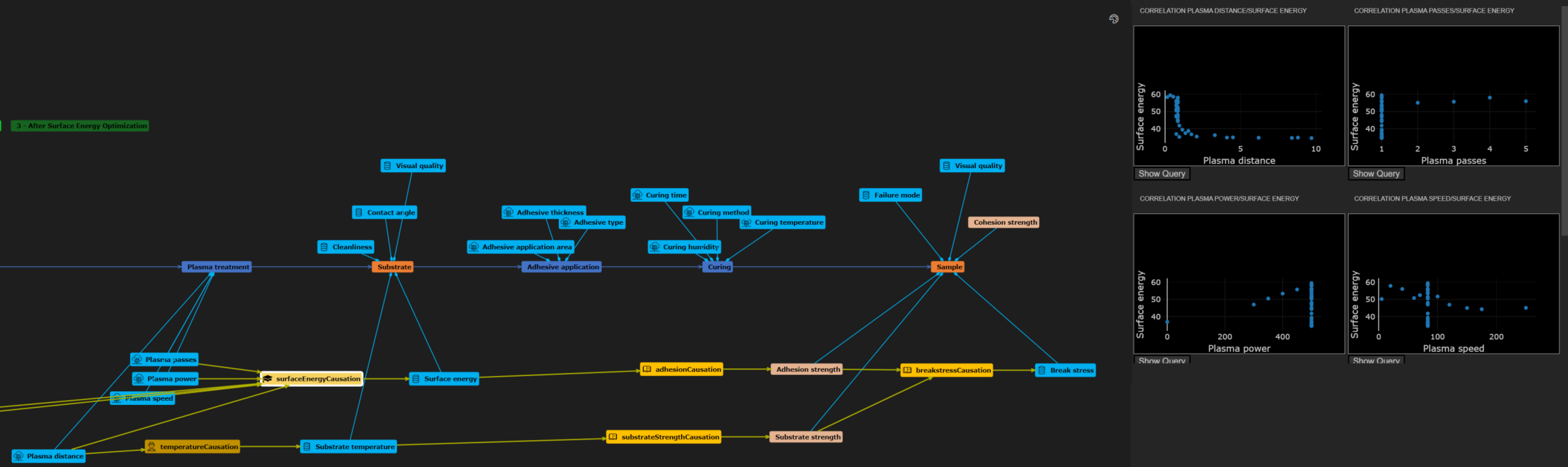
Show Query

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX jml: <http://www.flandersmake.be/ontology/jml#>

        select ?inst ?val ?phase ?dType ?valLabel {
            ?inst rdf:type jml:Sample;
                  jml:breakStress ?val;
                  jml:phase ?phase.
            bind (datatype(?val) as ?dType).
            optional {
                ?val rdfs:label ?valLabel
            }
        } order by ?phase
```



Reasoning on influence factors



Root cause analysis support

Further Watching