

# FLANDERS MAKE

DRIVING INNOVATION IN MANUFACTURING

## AI lifecycle perspective

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## About me



**Bart Meyers**

Senior Research Engineer  
Digital Transformation

[View Profile](#)

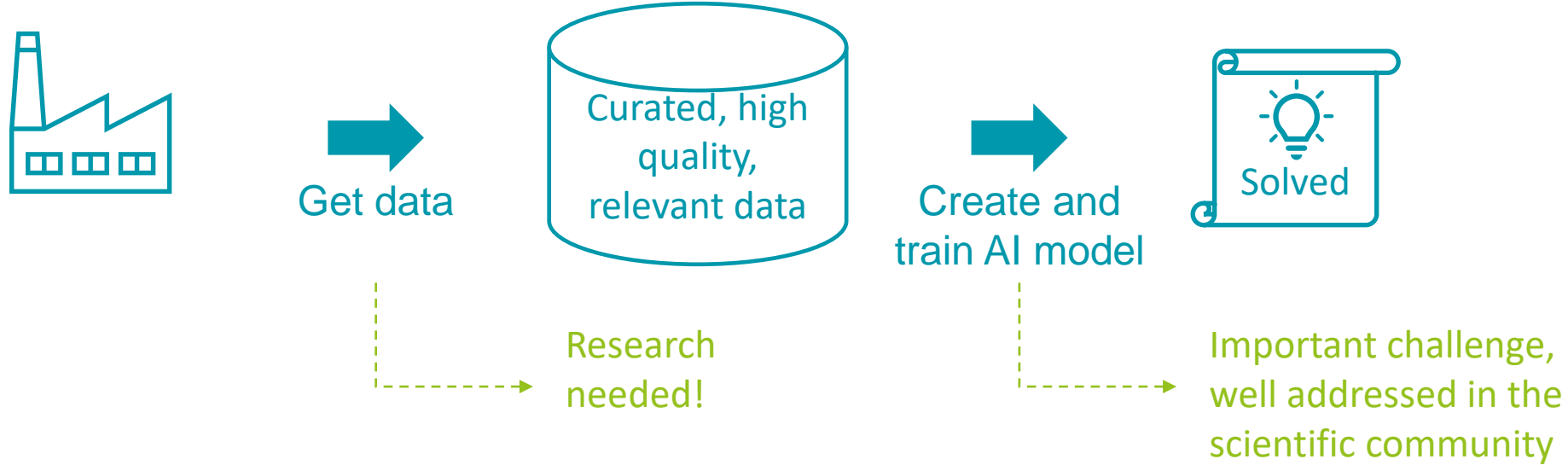
Background in computer science, modelling languages, architectures

Active in digitalization:

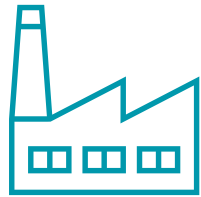
- Digital twins
- Internet of Things
- Applying AI in manufacturing
- Knowledge modeling
- Smart products/production

# Applying Artificial Intelligence in Manufacturing

## The life cycle for value-adding artificial intelligence



# Applying Artificial Intelligence in Manufacturing



Get data



If you want to ...  
You should look at ...



Production engineer

OK then perhaps  
look at ...

I need to  
make \$\$\$



Data scientist

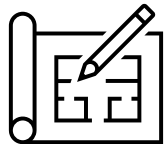
Yeah we have  
some data

But we do not  
have ...

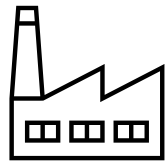
Those data are  
not yet  
ingested ...



Data engineer



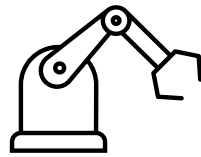
Product design



MES data

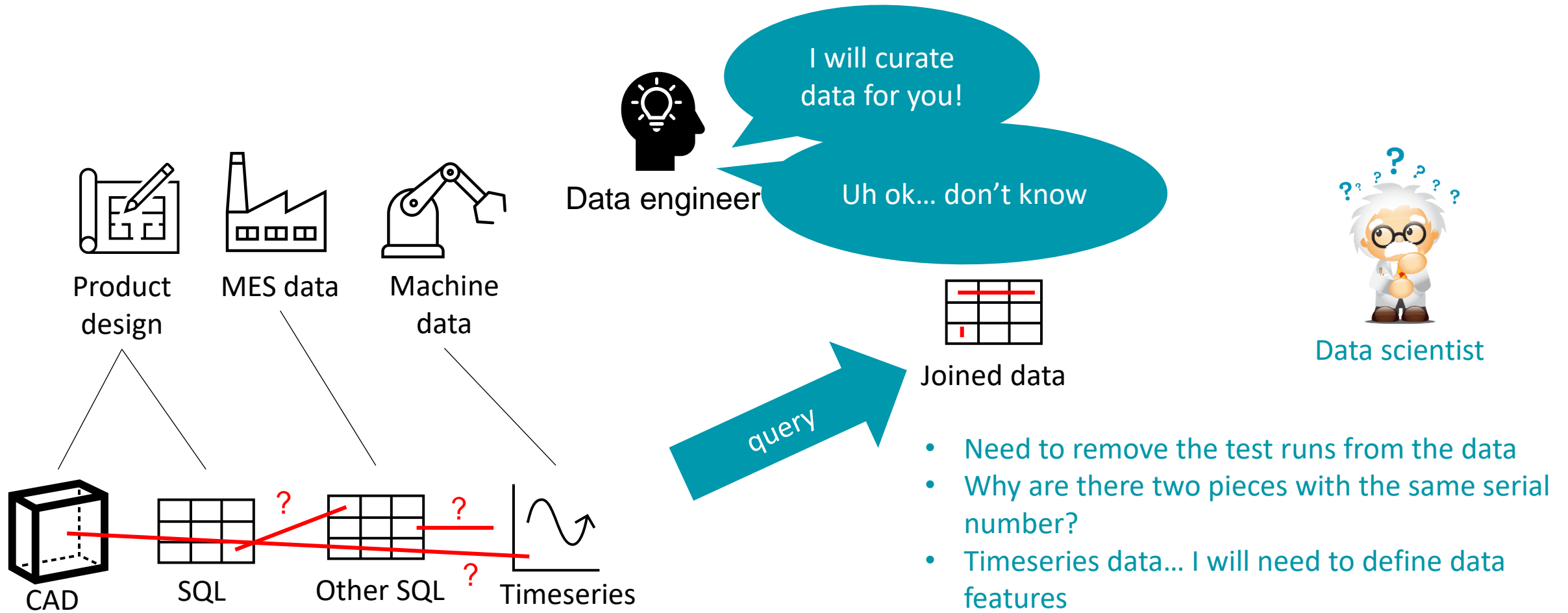


Sensor data



Machine data

# Applying Artificial Intelligence in Manufacturing



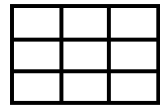
- Heterogeneous data silos
  - Location, query language, credentials needed
- Knowledge needed to make sense out of the data
  - "Join machine data with MES data via time stamps, in between half hour after manufacturing step"

- 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



**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!

The background is a vibrant green with a white grid pattern. Several palm trees are scattered across the scene, each with a cluster of coconuts at its base. The text is centered and rendered in a bold, dark blue, sans-serif font.

**MANU**  
**MONTHS LATER**



## Analysis results are hard to reuse



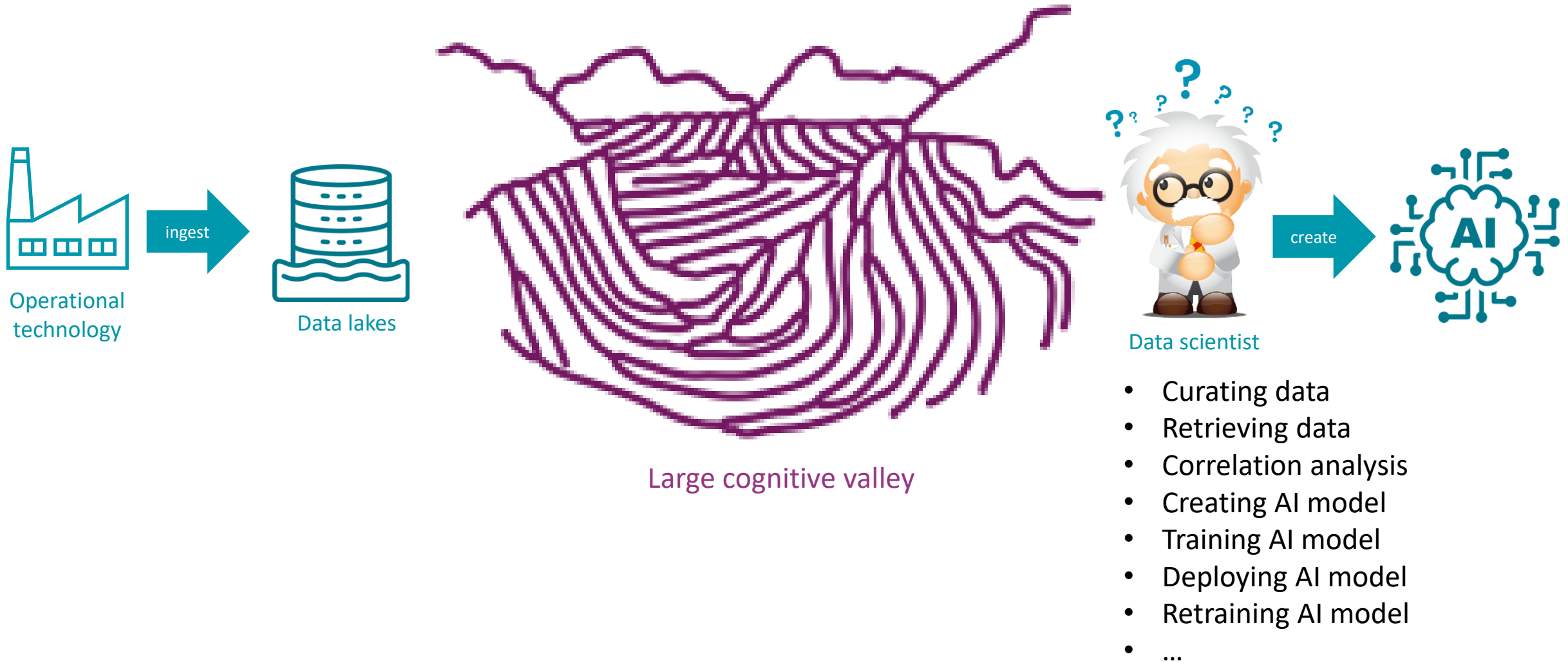
Other data scientist

Let's look into ...  
[very similar things  
as my colleague  
many months  
before]

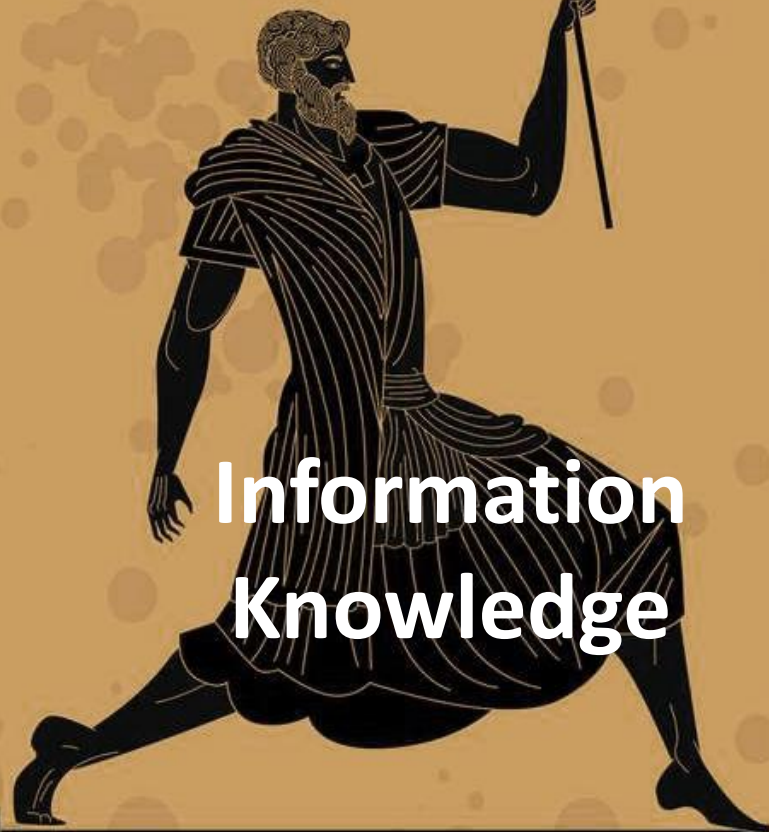
*Goes again through the same  
trials and tribulations as their  
colleague...*

# The Gap Between Manufacturing Environments and Artificial Intelligence

Conclusion: we need to bridge the gap



# Plato's Cave



**Information  
Knowledge**

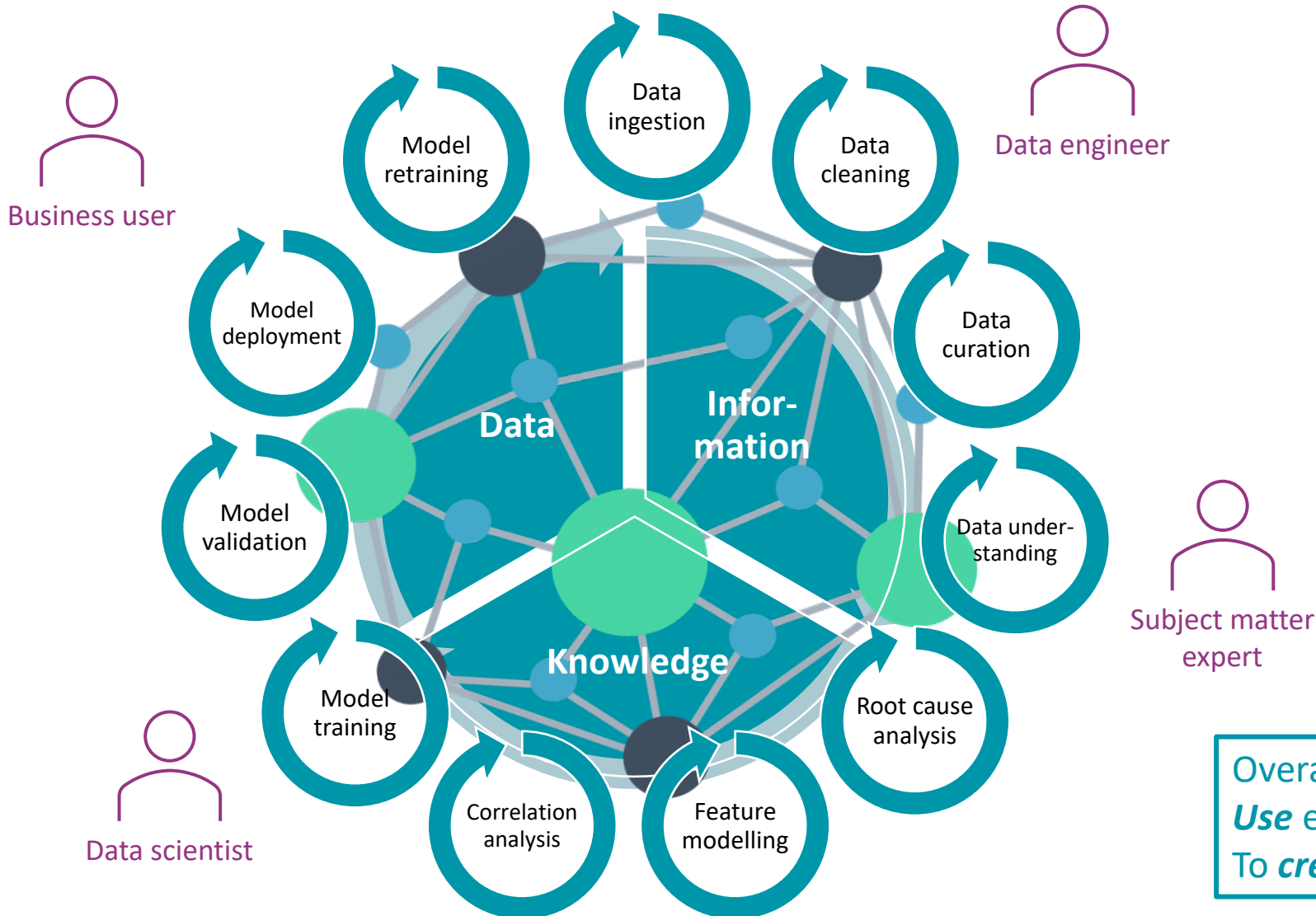


**Data**

or:  
impressions  
of reality

# Central data, information, knowledge management

## AI life cycle: iteratively and collaboratively build knowledge



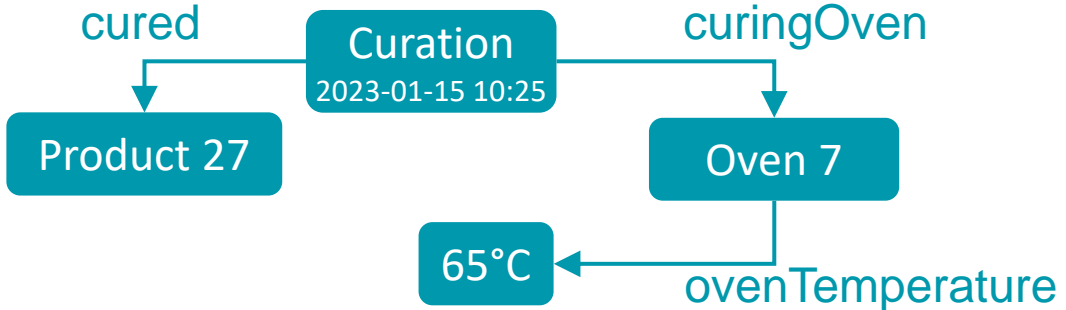
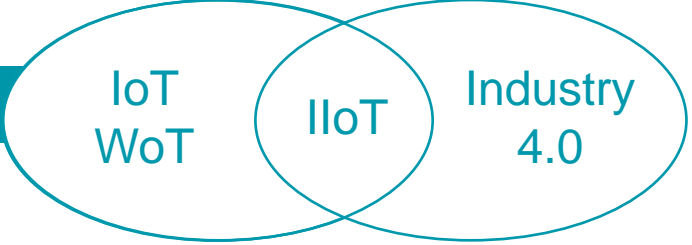
Overall goal:  
**Use** existing data, information and knowledge  
To **create** new insights (knowledge)

# Relationships Are The Future

1

Relationships are the future

# Relationships Are The Future



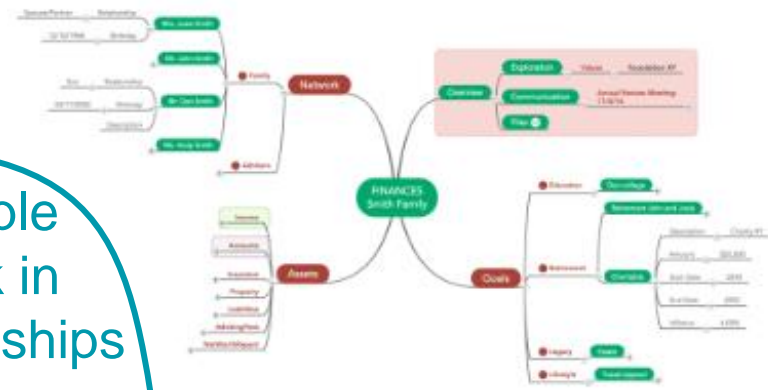
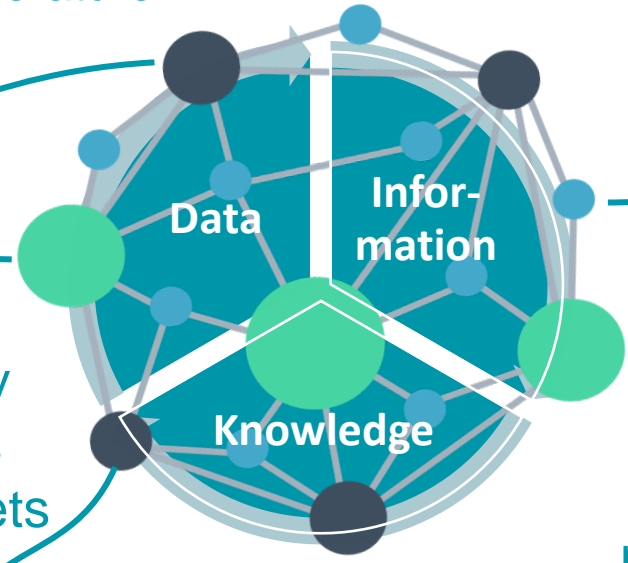
W3C  
Future  
Linked Data



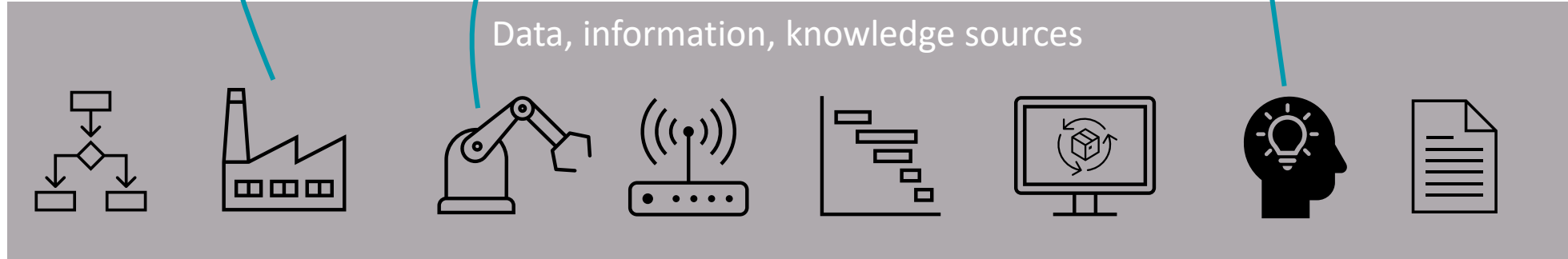
Relationships  
are context

One company  
• many silos  
• many assets

People think in relationships

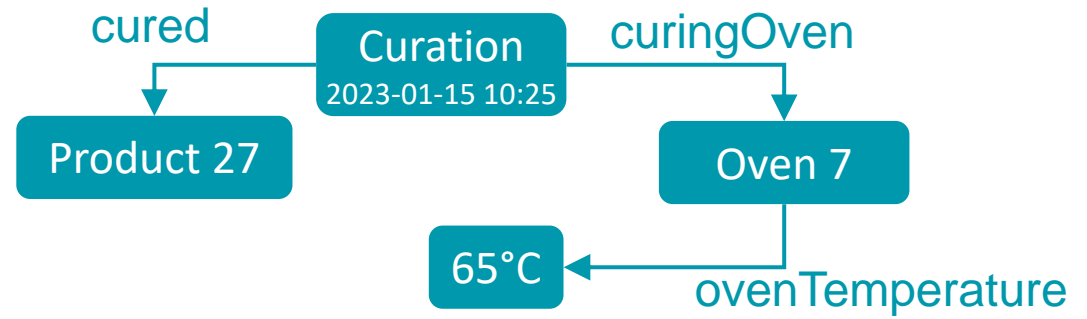


Data, information, knowledge sources



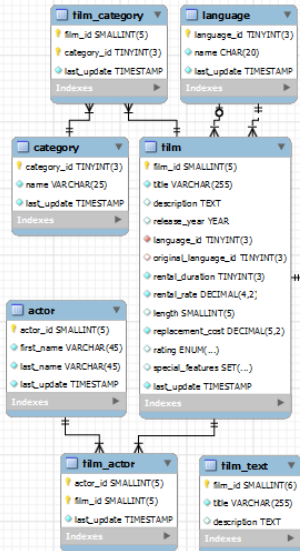
# User Domain vs Technical Domain

1 Relationships are the future

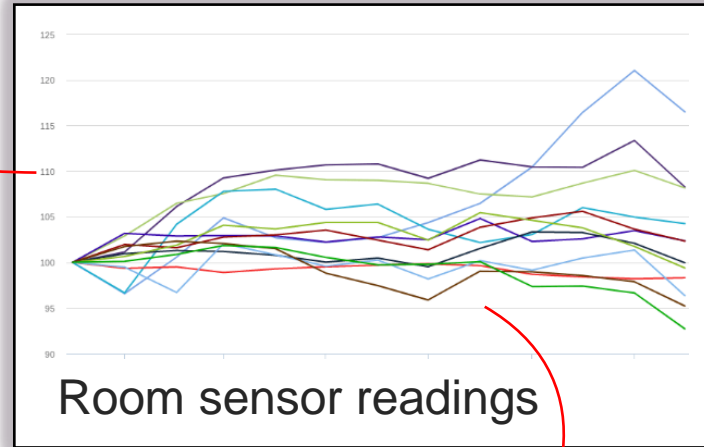


2 User domain vs technical domain

# User Domain vs Technical Domain



Product structure



Room sensor readings

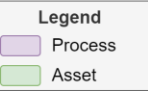
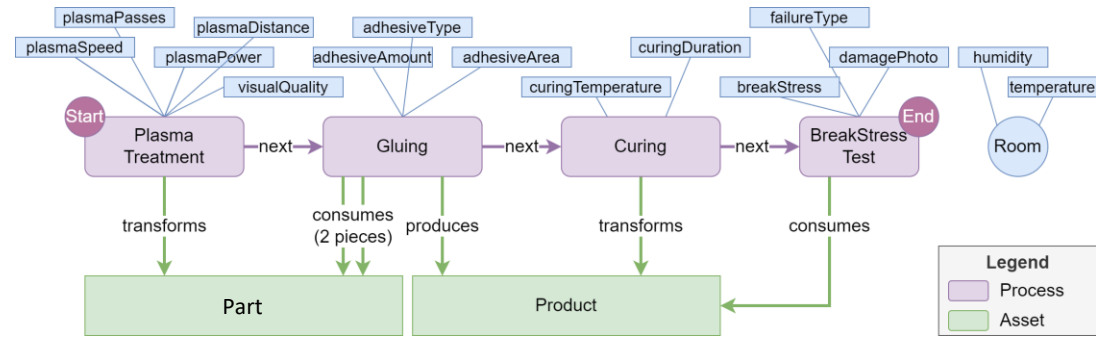
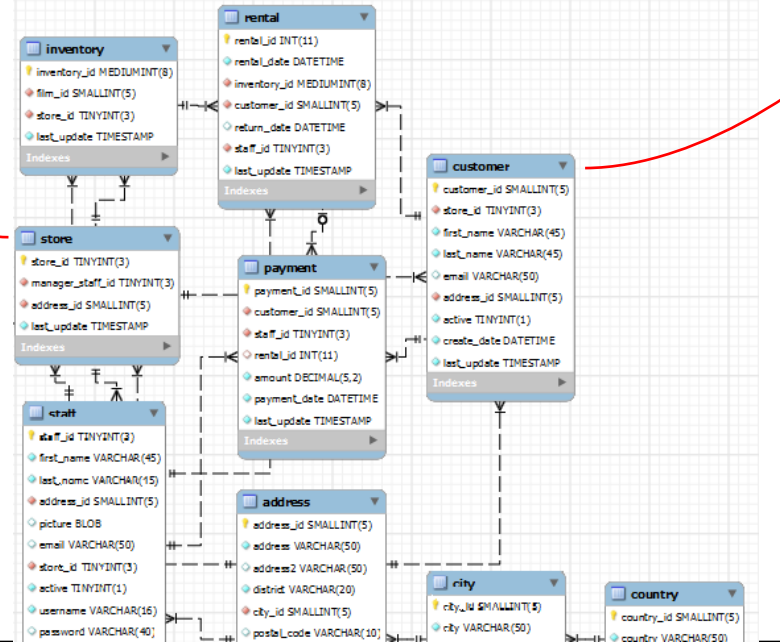


This is data...

Do you understand the process?

- Technically inspired -
- Multiple data/knowledge silos -

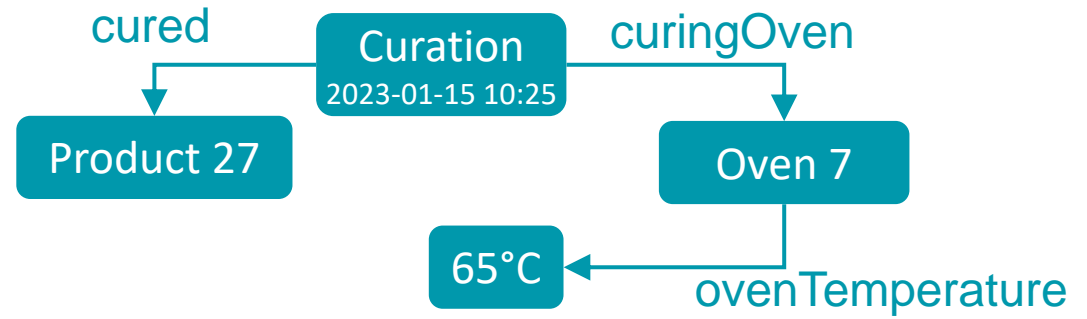
Production order executions (MES)



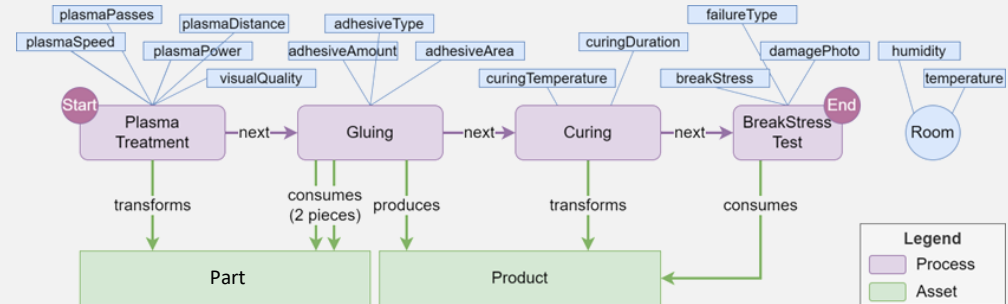


# Explicitize & Reuse Knowledge

1 Relationships are the future

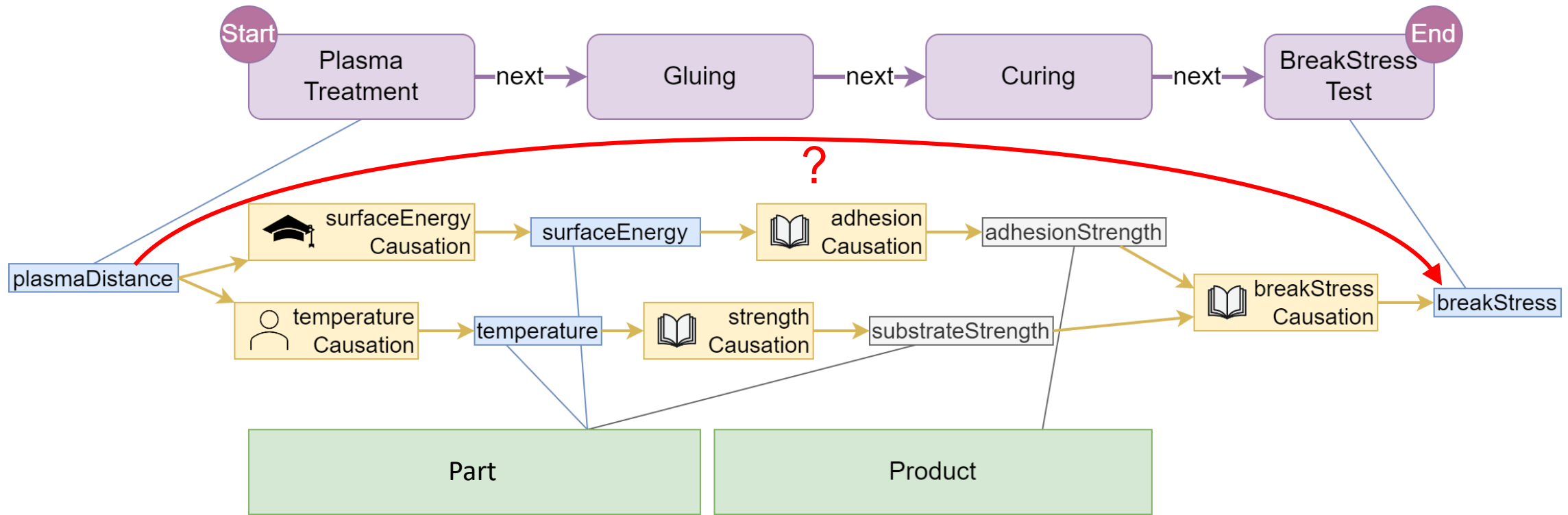


2 User domain vs technical domain



3 Explicitize, store and reuse knowledge

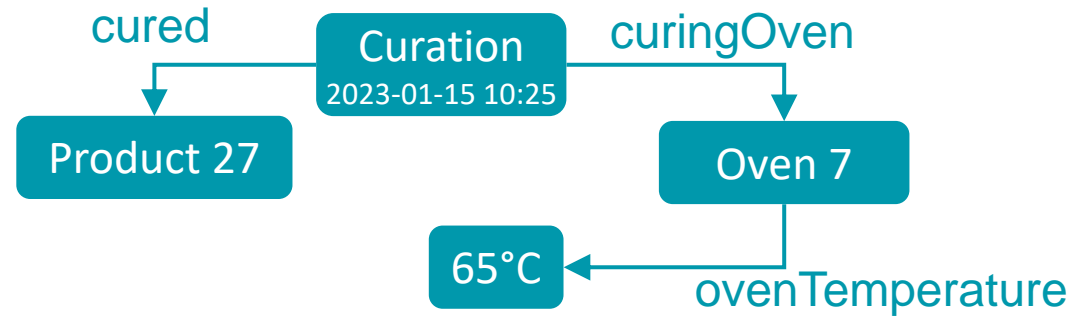
# Explicitize, Store & Reuse Knowledge



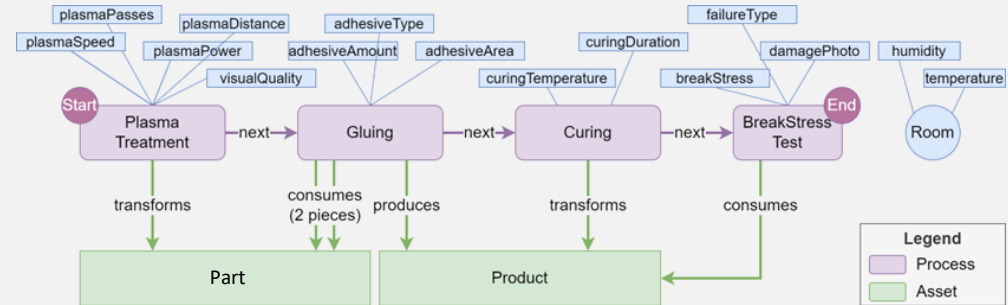
- Knowledge
- Explicit & accessible
  - Iteratively defined and stored
  - Contributed by process engineer, data scientist, ...
  - Graph/relationship nature by default
  - Can be exploited by logical reasoning

# Key Enablers for AI life cycle support

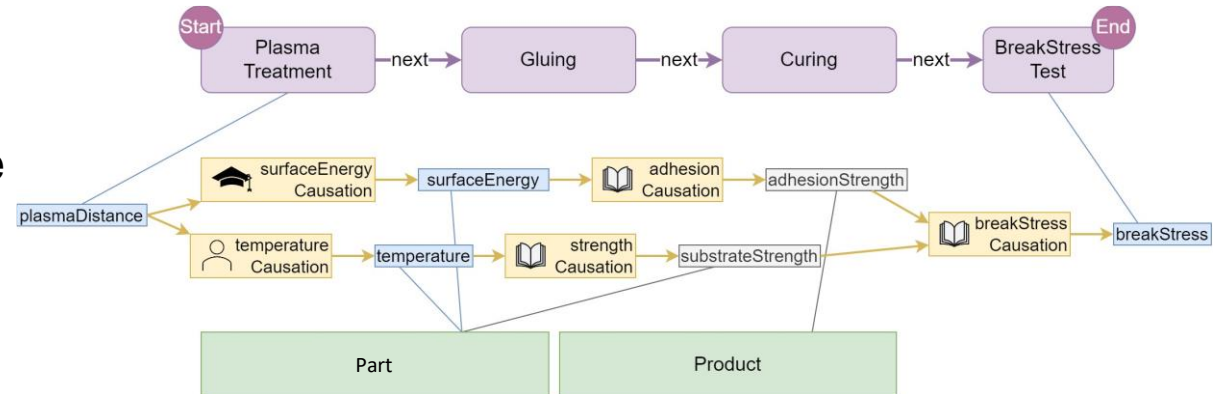
1 Relationships are the future



2 User domain vs technical domain



3 Explicitize, store and reuse knowledge



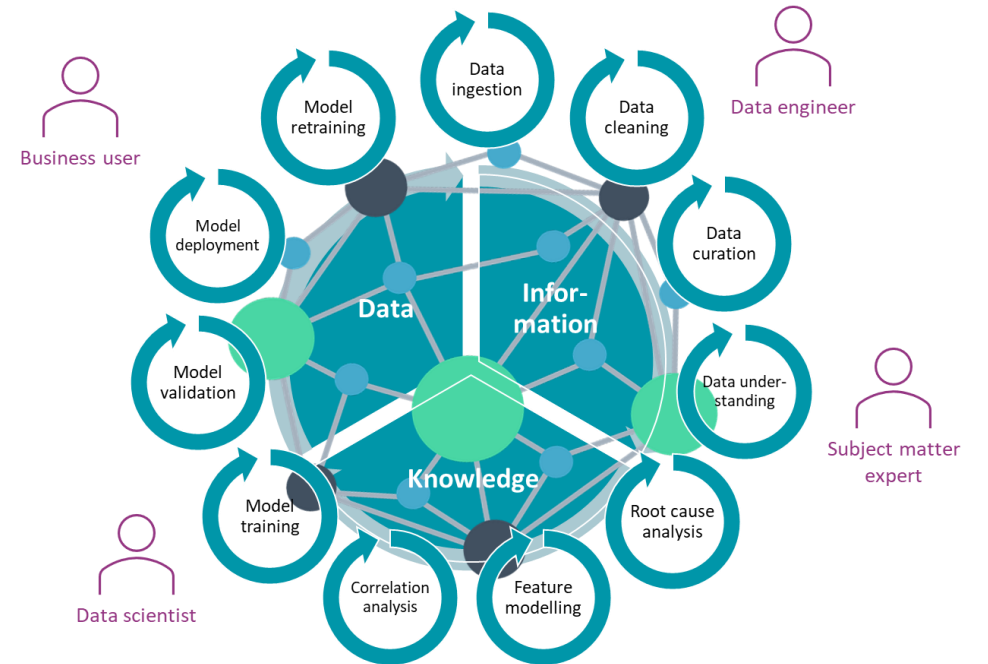
# Conclusions

Enable AI by enabling **AI lifecycle**

What's missing?

***Model knowledge explicitly***

- Relationships first
- Model problem domain
- Model tacit knowledge



# FLANDERS MAKE

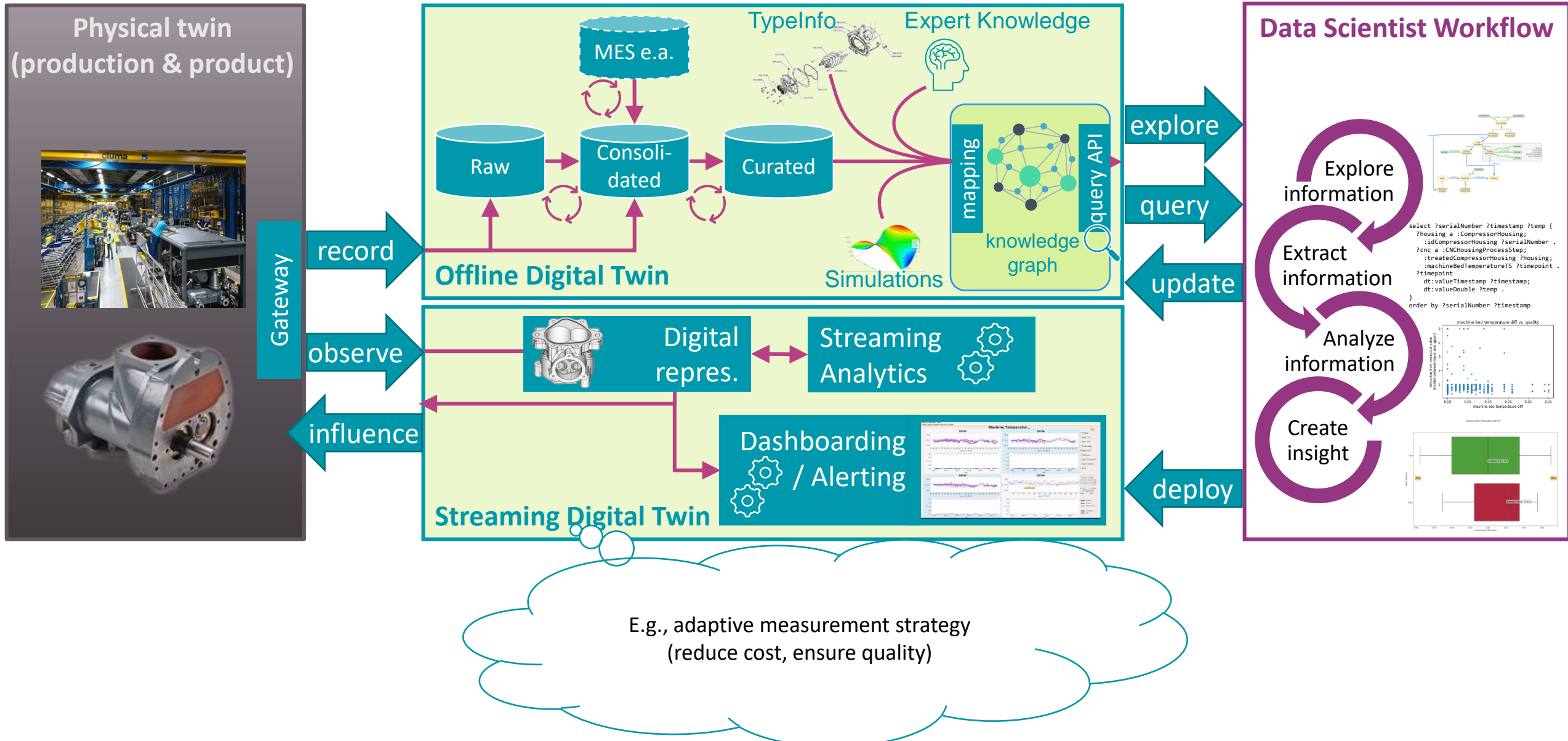
DRIVING INNOVATION IN MANUFACTURING

**Thank you!**

This research was supported by Flanders Make, the strategic research center for the manufacturing industry. This research was partially funded by the DTDesign ICON (Flanders Innovation and Entrepreneurship FM/ICON :: HBC.2019.0079) project. This work is partially funded by the European Commission under the framework program Horizon 2020, grant agreement number 101000165, project name ASSISTANT.



# Digital twin design workflow



Physical twin  
(production & product)



Gateway

record

observe

influence

Offline Digital Twin

Streaming Digital Twin

MES e.a.

Raw

Consolidated

Curated

TypeInfo

Expert Knowledge

Simulations

mapping

knowledge graph

query API

explore

query

update

deploy

Data Scientist Workflow

Explore information

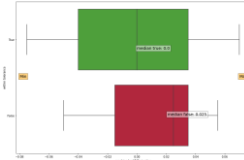
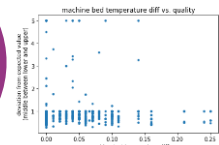
Extract information

Analyze information

Create insight



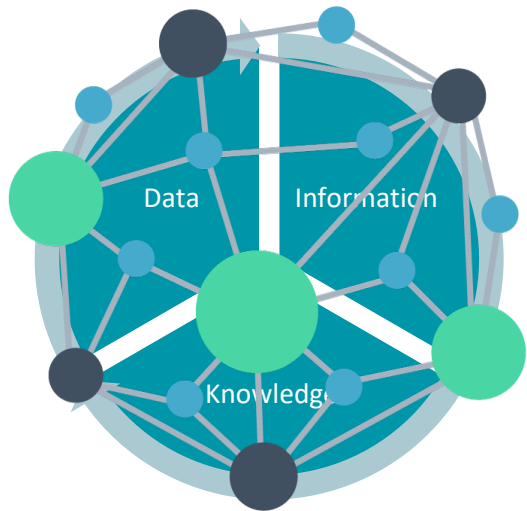
```
select ?serialNumber ?timestamp ?temp {
  ?housing a :CompressorHousing;
  ?cnc a :CNC HousingProcessStep;
  ?treatedCompressorHousing ?housing;
  ?machineBedTemperatureTS ?timestamp;
  ?timepoint
  dt:valueTimestamp ?timestamp;
  dt:valueDouble ?temp .
}
order by ?serialNumber ?timestamp
```



E.g., adaptive measurement strategy  
(reduce cost, ensure quality)

# 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

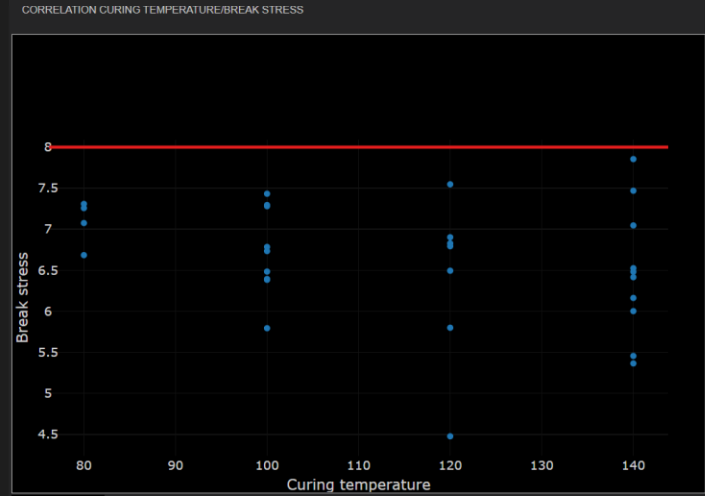
# Demo

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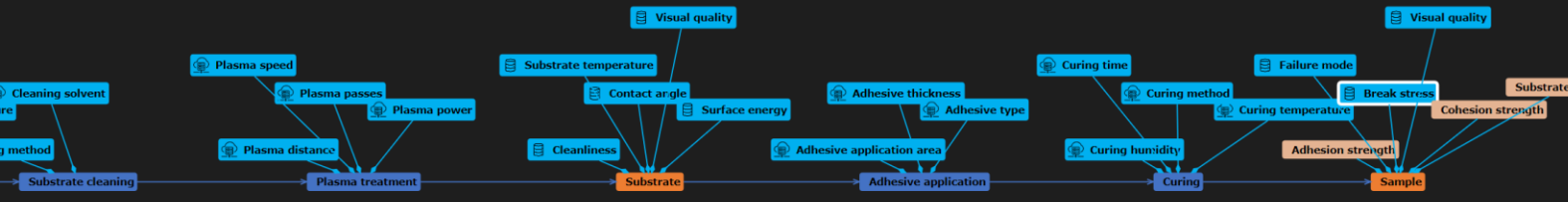




# Ad hoc correlation analysis



Energy Optimization experiments 3 - After Surface Energy Optimization



```

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

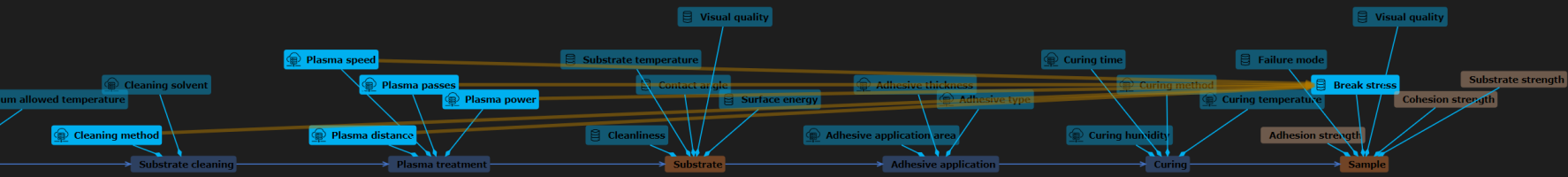
SELECT ?c ?v1 ?v2 ?phase ?v1Label ?v2Label
WHERE {
  ?i1 rdf:type jml:CuringPS;
  jml:curingTemperature ?v1;
  jml:context ?c.
  optional {
    ?v1 rdfs:label ?v1Label.
  }
  bind (datatype(?v1) as ?v1Type).
  ?i2 rdf:type jml:Sample;
  jml:breakStress ?v2;
  jml:context ?c.
  optional {
    ?v2 rdfs:label ?v2Label.
  }
  bind (datatype(?v2) as ?v2Type).

  # The phase is always associated to both instances,
  # but one is enough.
  ?i1 jml:phase ?phase.
  }
  
```

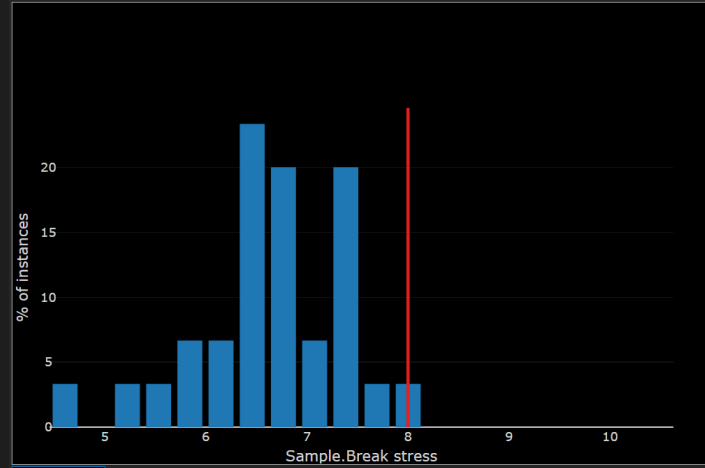
## Exploration and data visualization

## Query generation

ion 2 - Surface Energy Optimization experiments 3 - After Surface Energy Optimization



DISTRIBUTION BREAK STRESS



Show Query

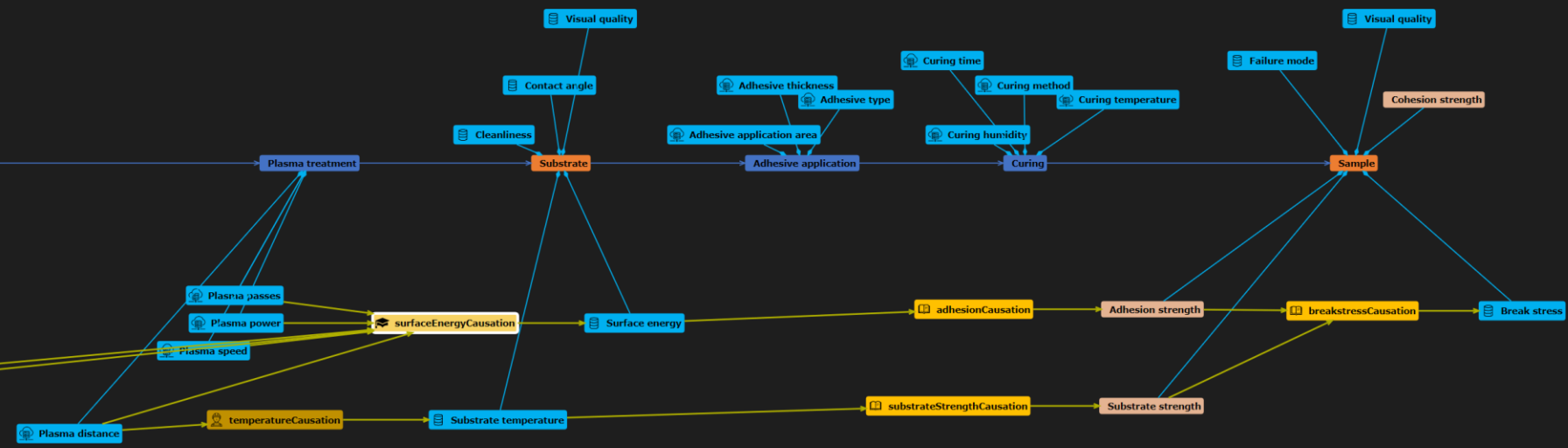
```

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

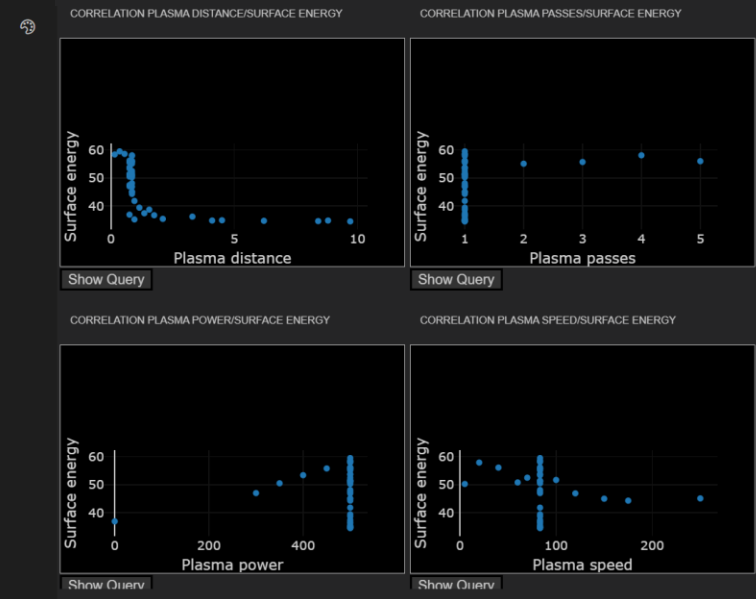
select ?inst ?val ?phase ?dType ?valLabel {
  ?inst rdf:type jml:Sample;
  jml:breakStress ?val;
  jml:phase ?phase.
  bind (datatype(?val) as ?dType).
  optional {
    ?val rdfs:label ?valLabel
  }
} order by ?phase
  
```

Reasoning on influence factors

3 - After Surface Energy Optimization



Root cause analysis support



## Further Watching

