

University of Amsterdam

Multi-scale Networked Systems Research Group

# Data-Centric Analysis of Complex Industrial Systems

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# Why data-centric solutions?

- Modern systems in many domains are **data-rich ecosystems**  
=> Lots of **sensors**
- Computerisation  
=> Everything is a **computing platform**  
=> Strong presence of **software**
- Systems are continuously evolving during their lifecycle
- Dealing with **non-determinism**  
=> A common trait of CPS

# There are challenges ...

- Data scarcity
  - => Sometimes there is not enough data
  - => Not of the kind we need
  - => Gaps in data streams
- Data deluge
  - => Because of: Transfer limitations, processing limitations, latency
- Knowledge incorporation (more on this at the end ...)
- How to generalise?
  - => Oftentimes solutions are use-case specific

# **Example use-case:** Anomaly detection/identification

for semiconductor photolithography machines



# iDAPT Project

- *Interactive DSL for Composable EFB Adaptation using Bi-simulation and Extrinsic Coordination*
- National project funded by NWO
- Main project user: ASML Netherlands B.V.
- Other users: TNO, Thales, Radboud University Nijmegen



# Robustness

- Things go wrong, no matter how good the design (**design is not static**)
- This is about **detecting** that something is going wrong
  - => Unwanted behaviour
  - => Light turns on ...
- This is also about **distinguishing** between different unwanted behaviour
  - => Different things can go wrong in a complex system
  - => Different lights, different modes
- If we know about it, we can **fix** it, or reduce its effects
  - => Increased robustness

This is exactly what the solution is about!

# Robustness: Anomaly detection/identification

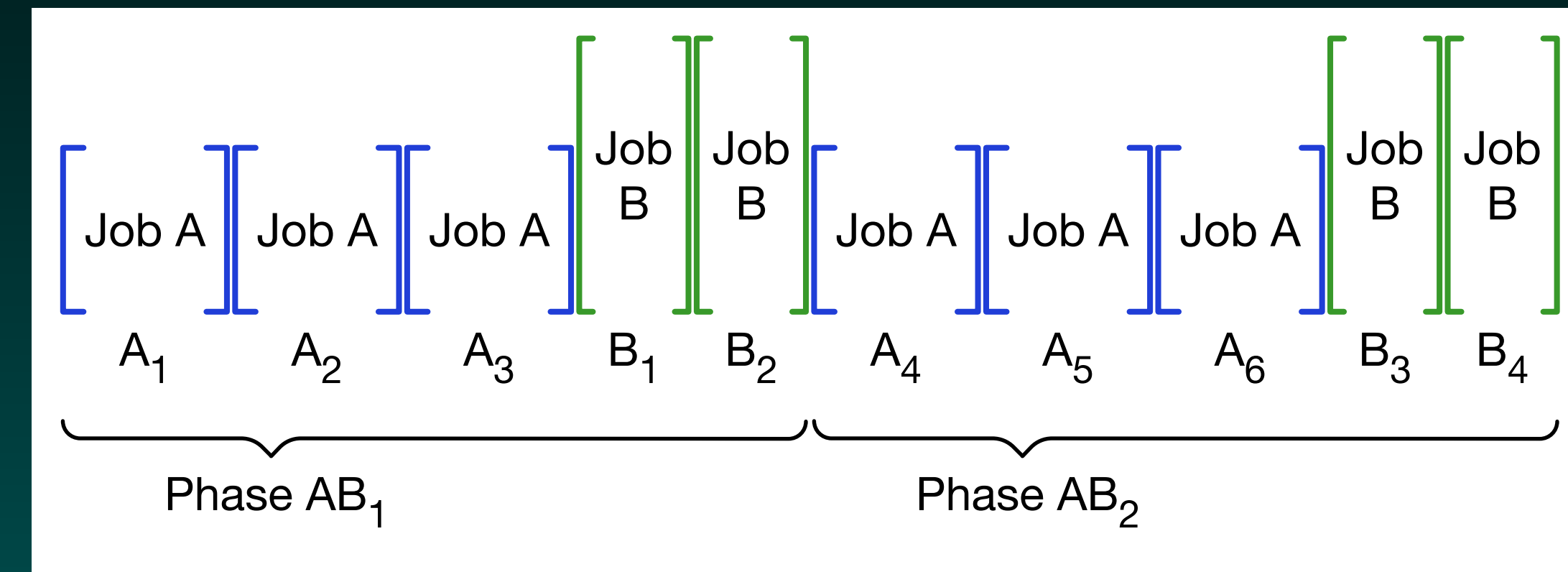
- Anomaly: A **readily** detectable deviation in system's normal behaviour  
=> A symptom
- Anomaly detection  
=> Behaviour is not as intended
- Anomaly identification  
=> What sort of trouble are we talking about?  
=> Which part? (subsystem)  
=> How bad? (severity)
- Predicting anomalous behaviour

It is all about normal behaviour vs anomalous behaviour.

# Industrial CPS and phases

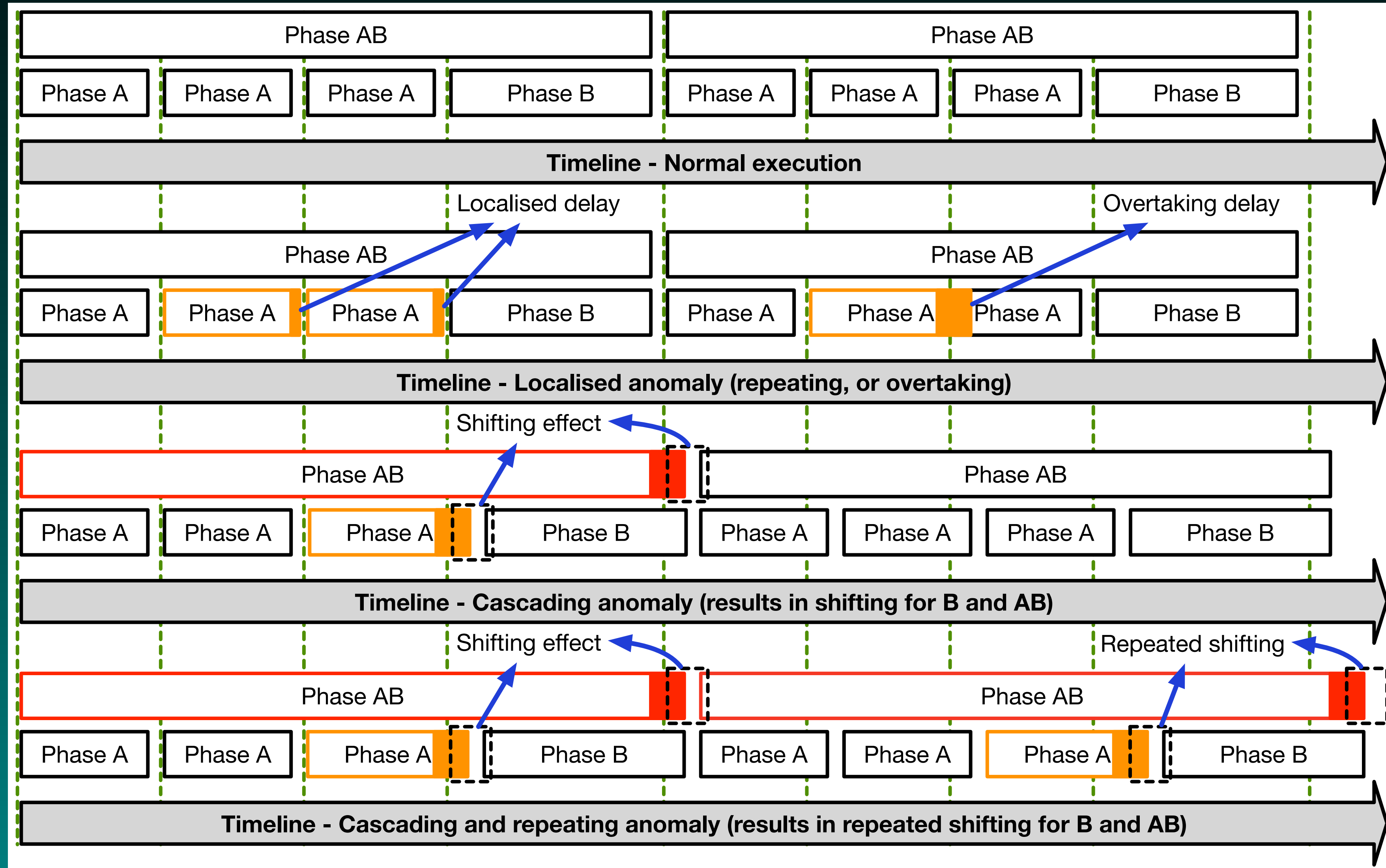
- Industrial CPS are **purpose-built**  
=> A limited domain of activities and tasks

- We want to exploit this repetitiveness for behavioural monitoring



- Execution phases => **Units of execution**
  - ➔ Atomic phases: Smallest **repetitive** unit of execution behaviour
  - ➔ Combo phases: **Repetitive** combinations of a collection of atomic phases
- Observation and analysis needs will determine phase granularity

# Anomalies and their effects



# Our subject: Industrial CPS

- We are not dealing with cars, or engines
- We are dealing with industrial machinery
  - => But, a specific breed, controlled by computers
- Characteristics of industrial CPS
  - => Bunch of computers working together, collectively!
  - => Different types of computers, heterogeneous
  - => Interaction with the environment
  - => Software, software, software, software, software, ...

Industrial Cyber-Physical Systems (CPS) are highly repetitive systems

# Semiconductor photolithography machines

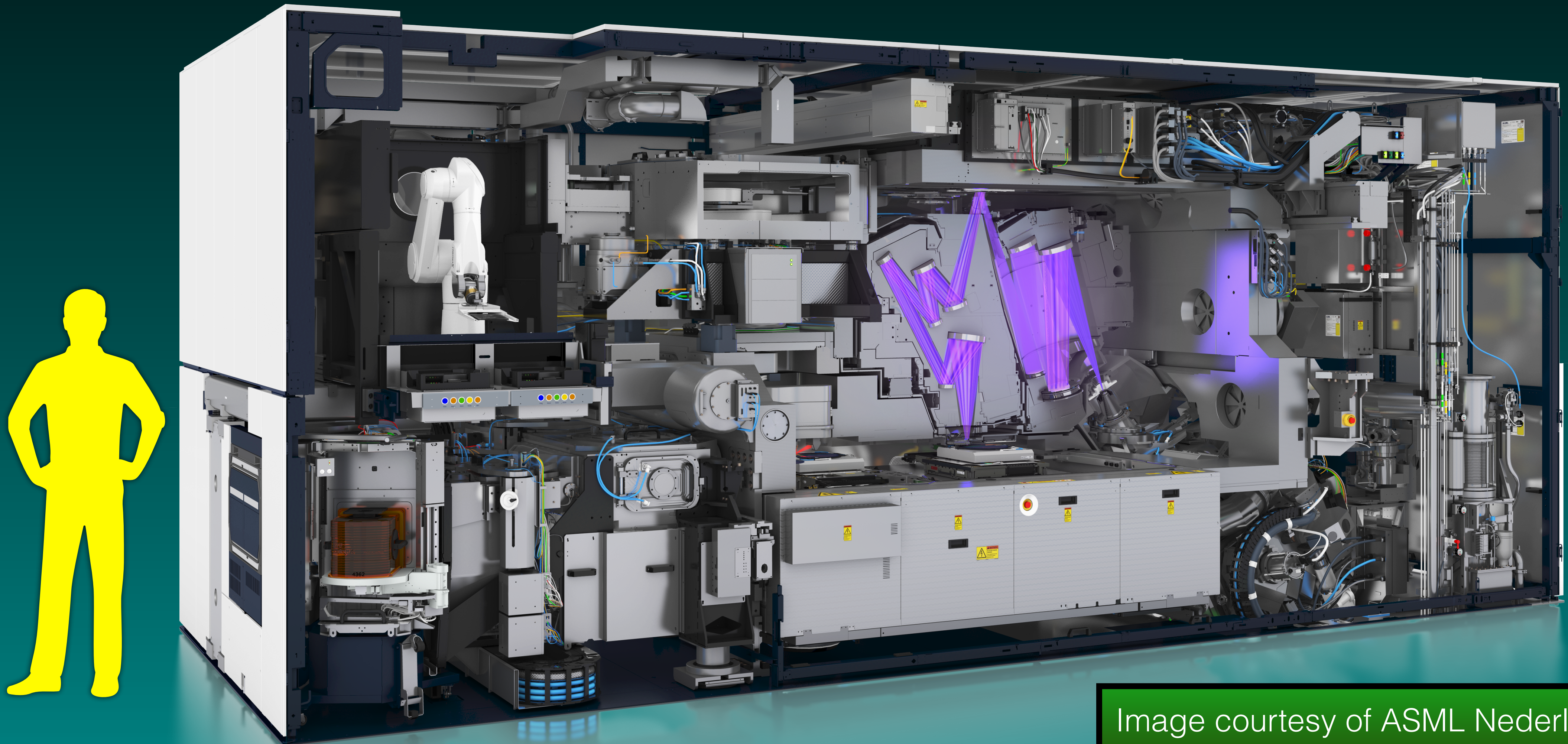
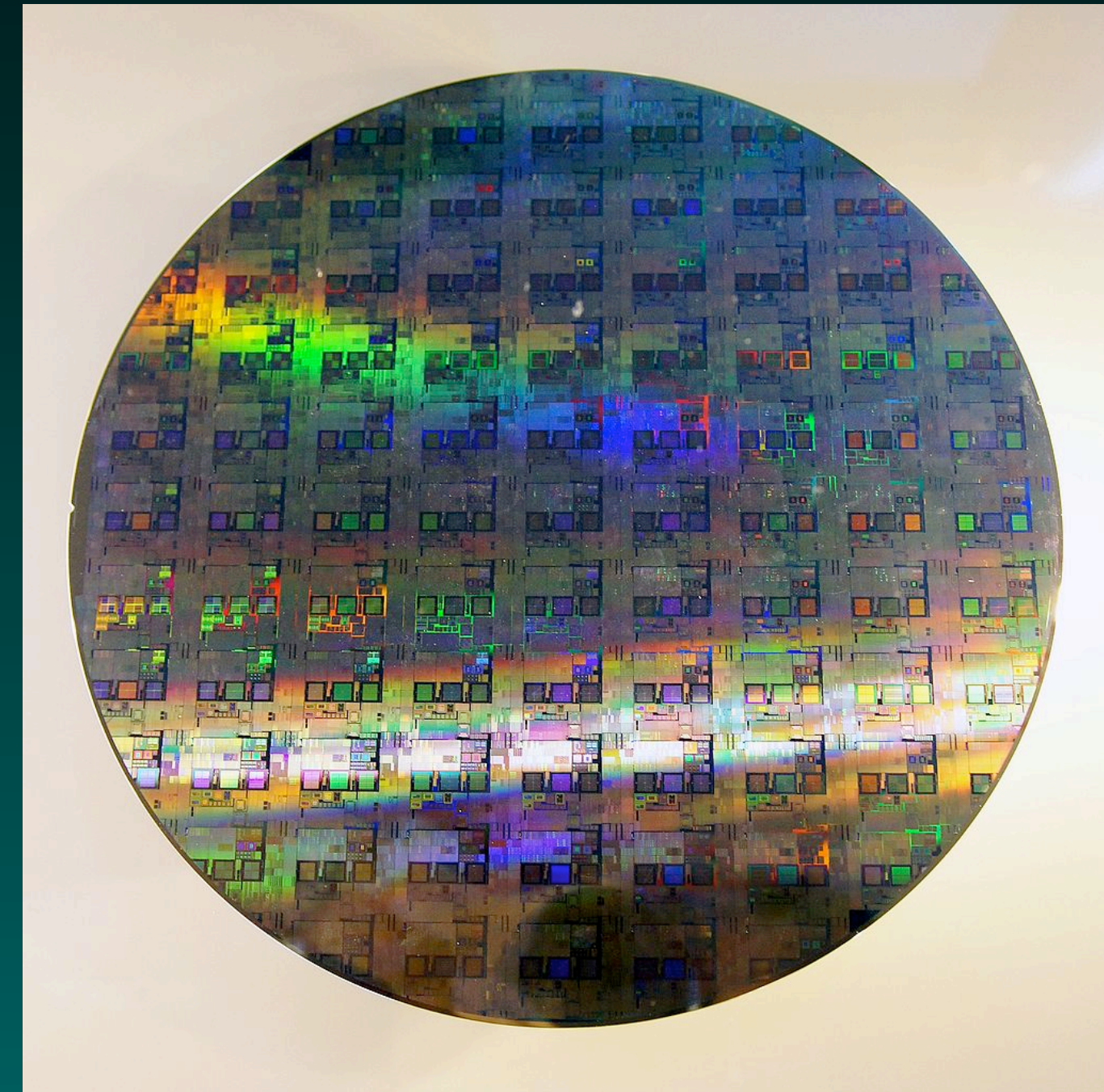


Image courtesy of ASML Nederlands B.V.

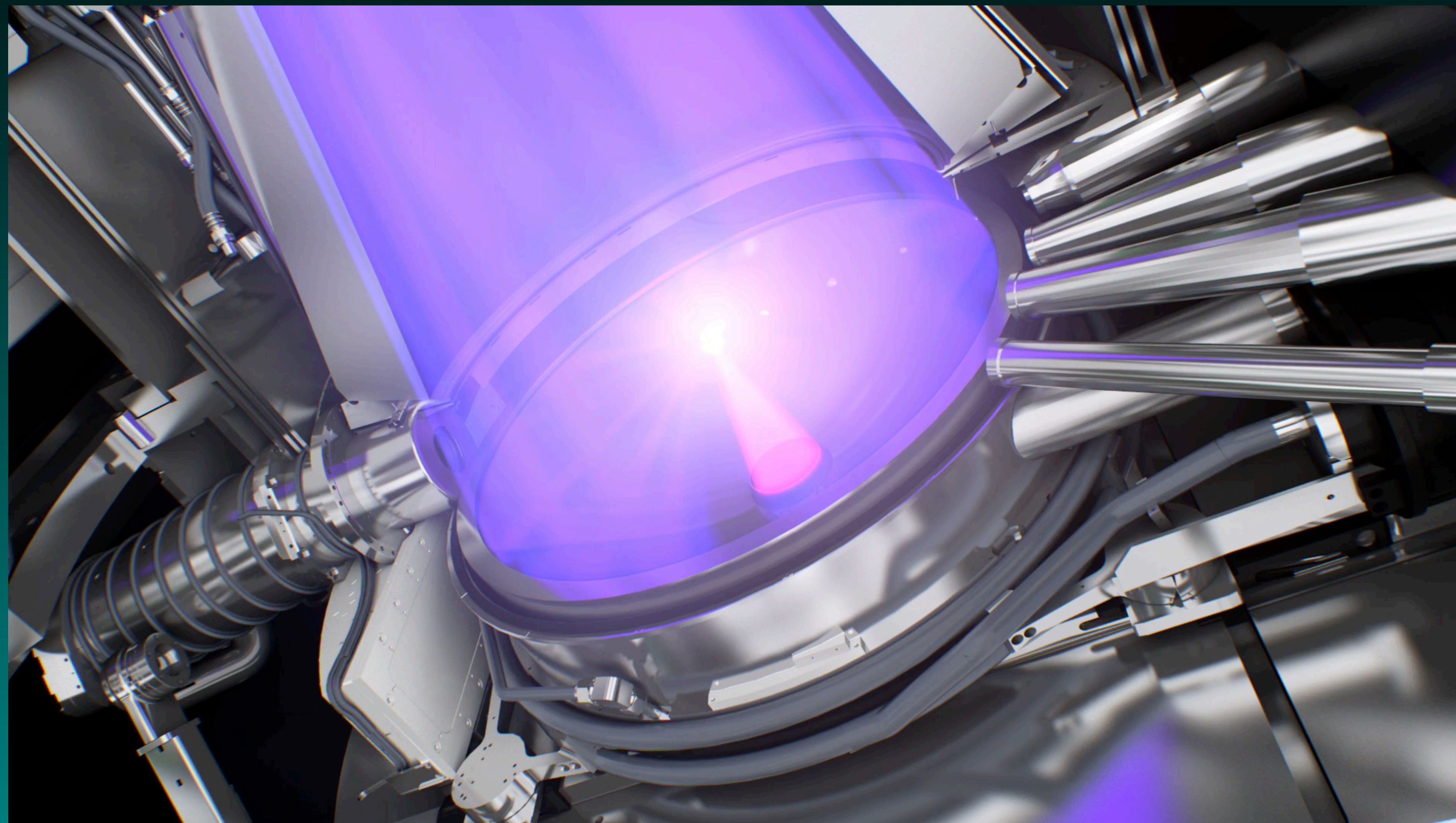
# Semiconductor photolithography machines

- Very similar to photography
- Involves light (EUV) and therefore, a **light source**
- Involves film (**wafer**) with **photosensitive material**
- Involves patterns to be applied (**reticle**)
- Involves chemical developers
- Has to be done at scale, otherwise a smartphone will cost €10000 ...



# Photolithography

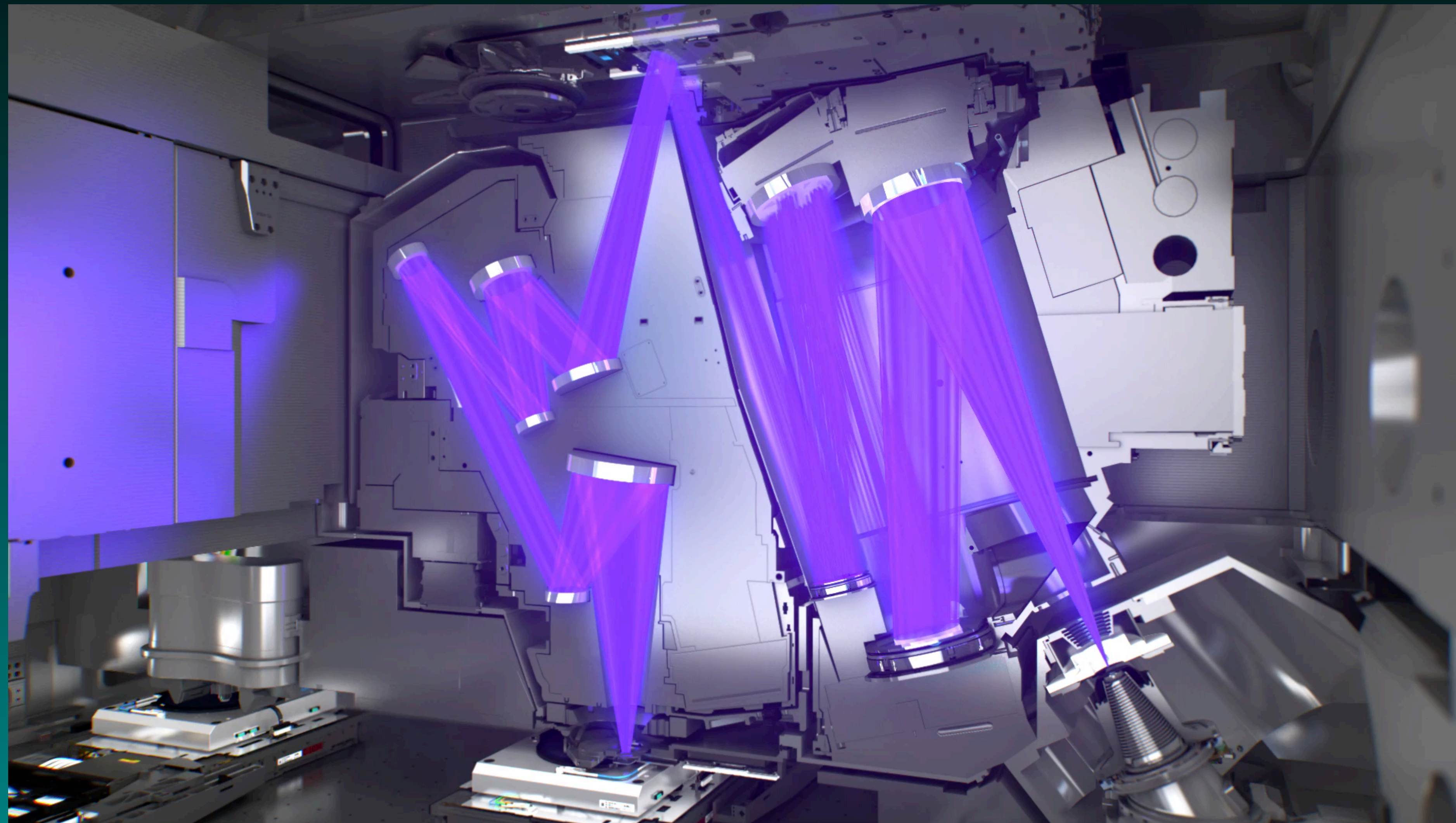
EUV generation - The light source



Video courtesy of  
ASML Netherlands B.V.

# Photolithography

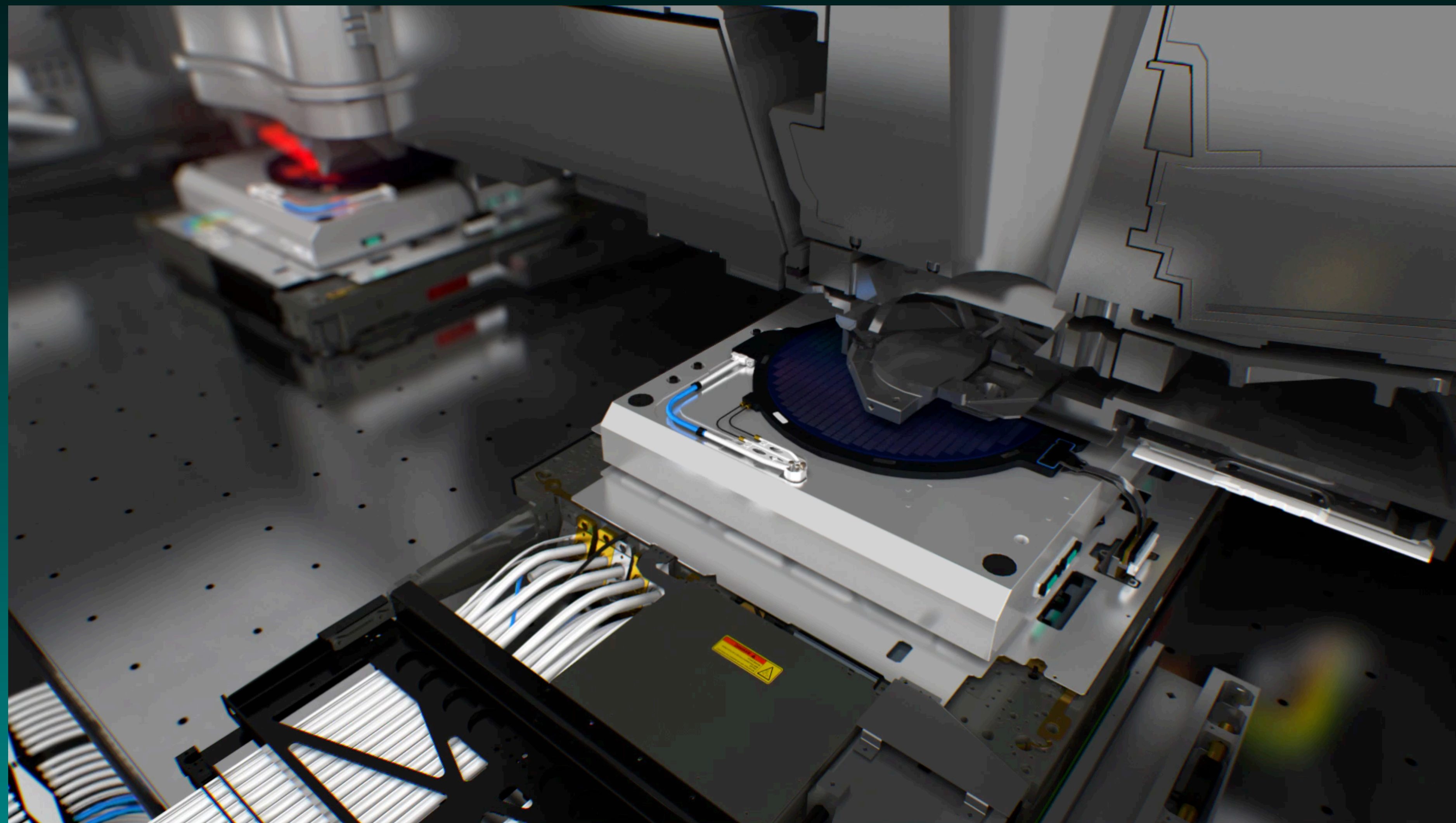
Light path and patterns



Video courtesy of  
ASML Nederlands B.V.

# Photolithography

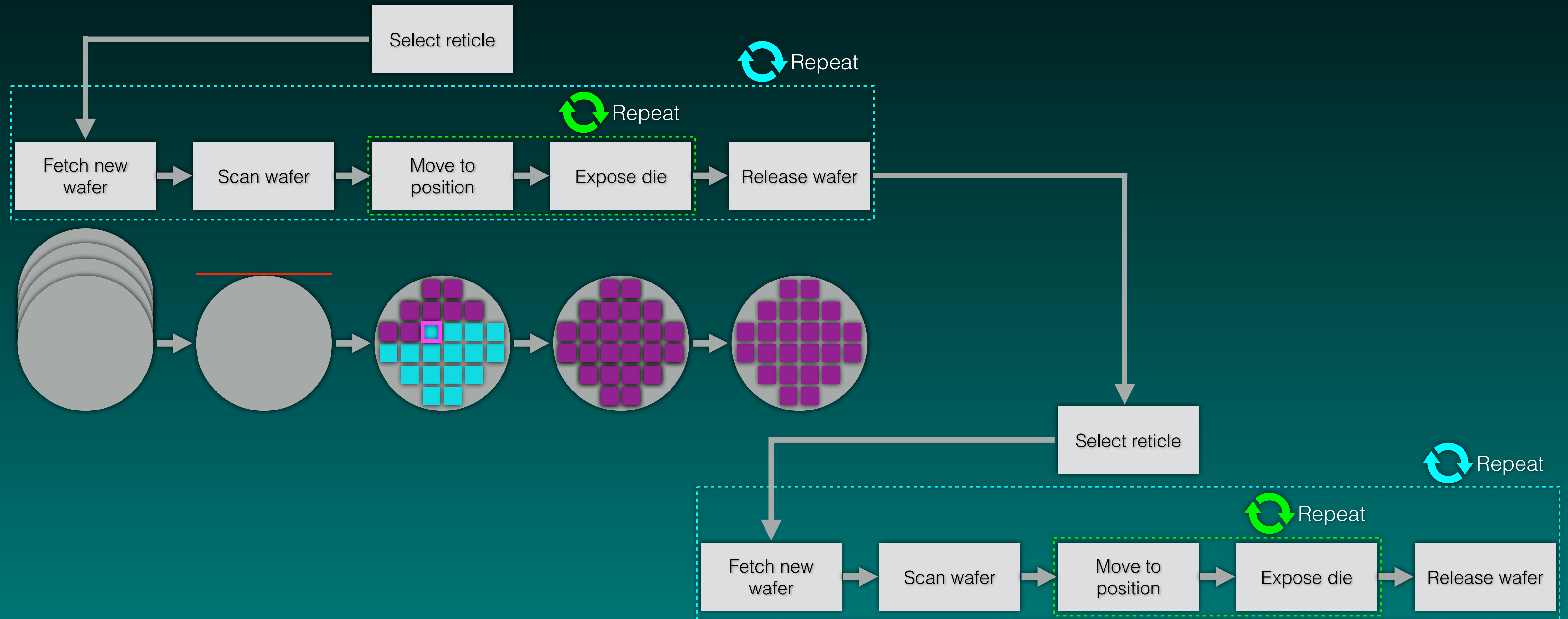
Stepper unit exposing photosensitive material



Video courtesy of  
ASML Nederlands B.V.

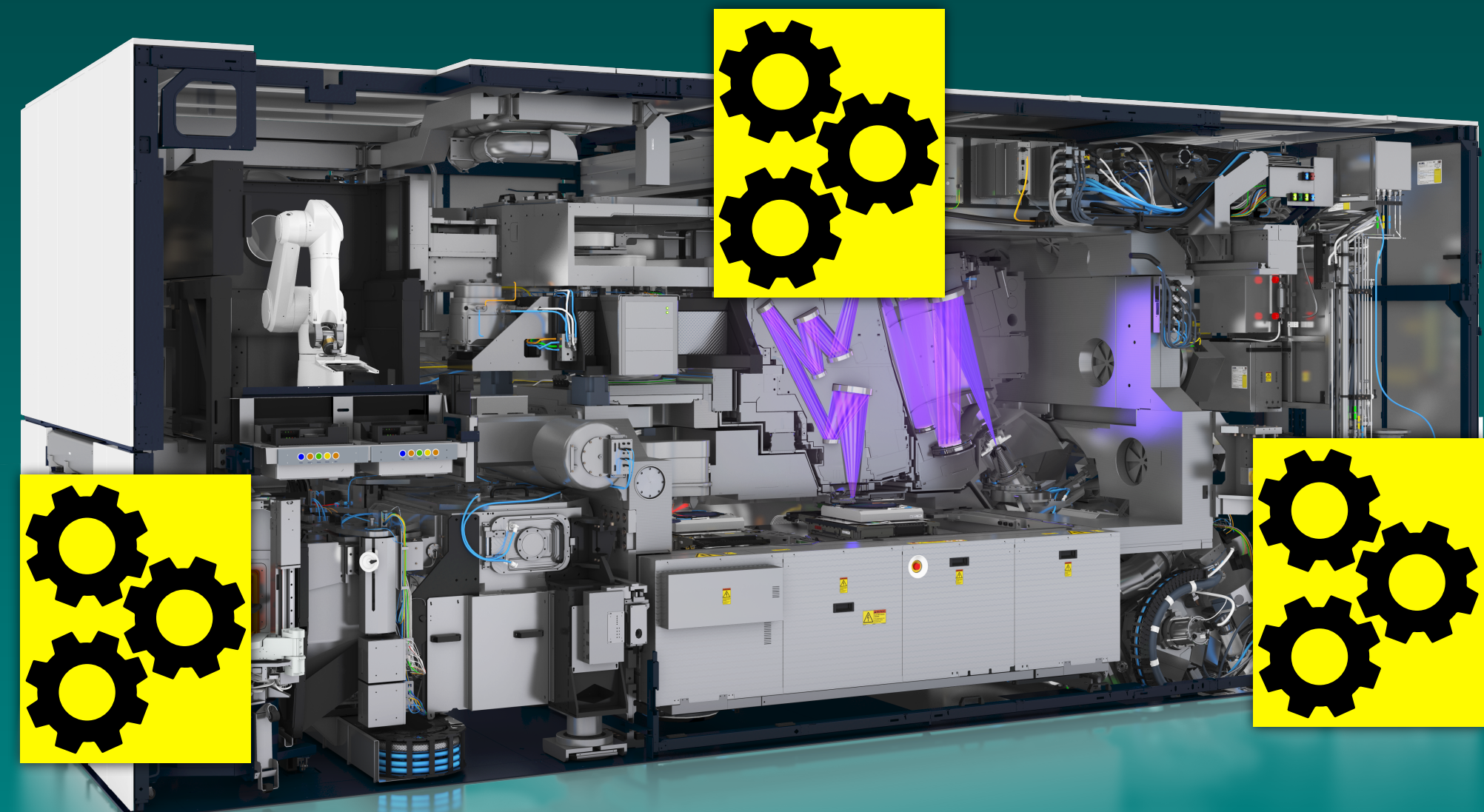
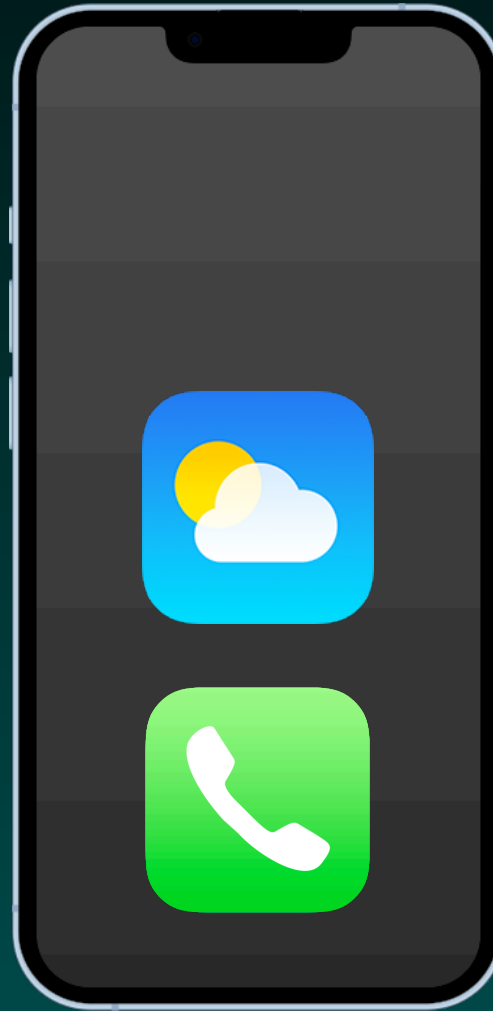
# Characteristics of industrial CPS

Repetition in a semiconductor photolithography machine



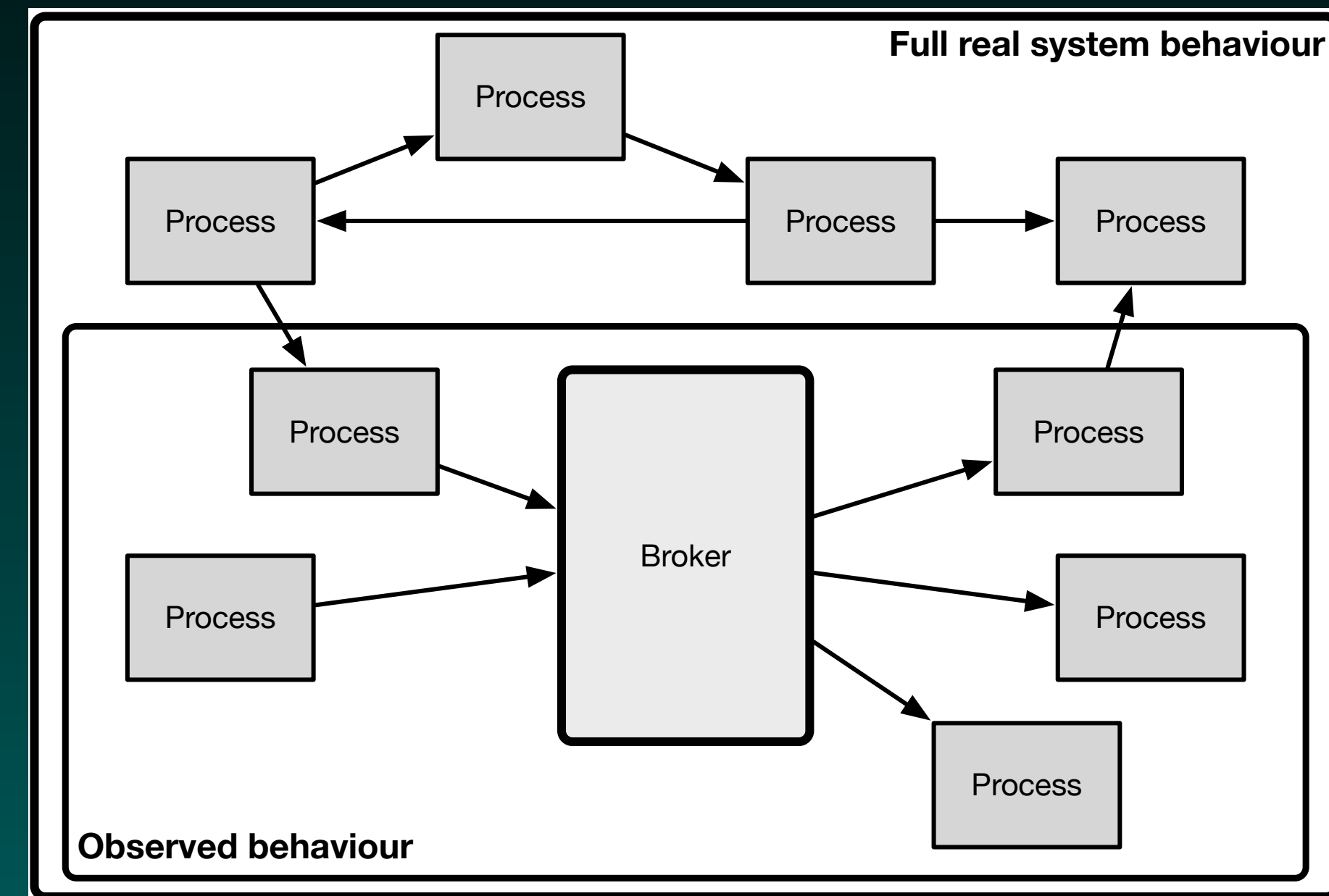
# Software is taking over

- Everything is being computerised, industrial CPS included
- Computers are platforms for software  
=> Software can be added or removed  
=> New or extended software, extended functionality
- Software is a big source of data  
=> We can take advantage of sensors and collect
- Software is getting too large  
=> Complexity, extremely costly to get it right at design time



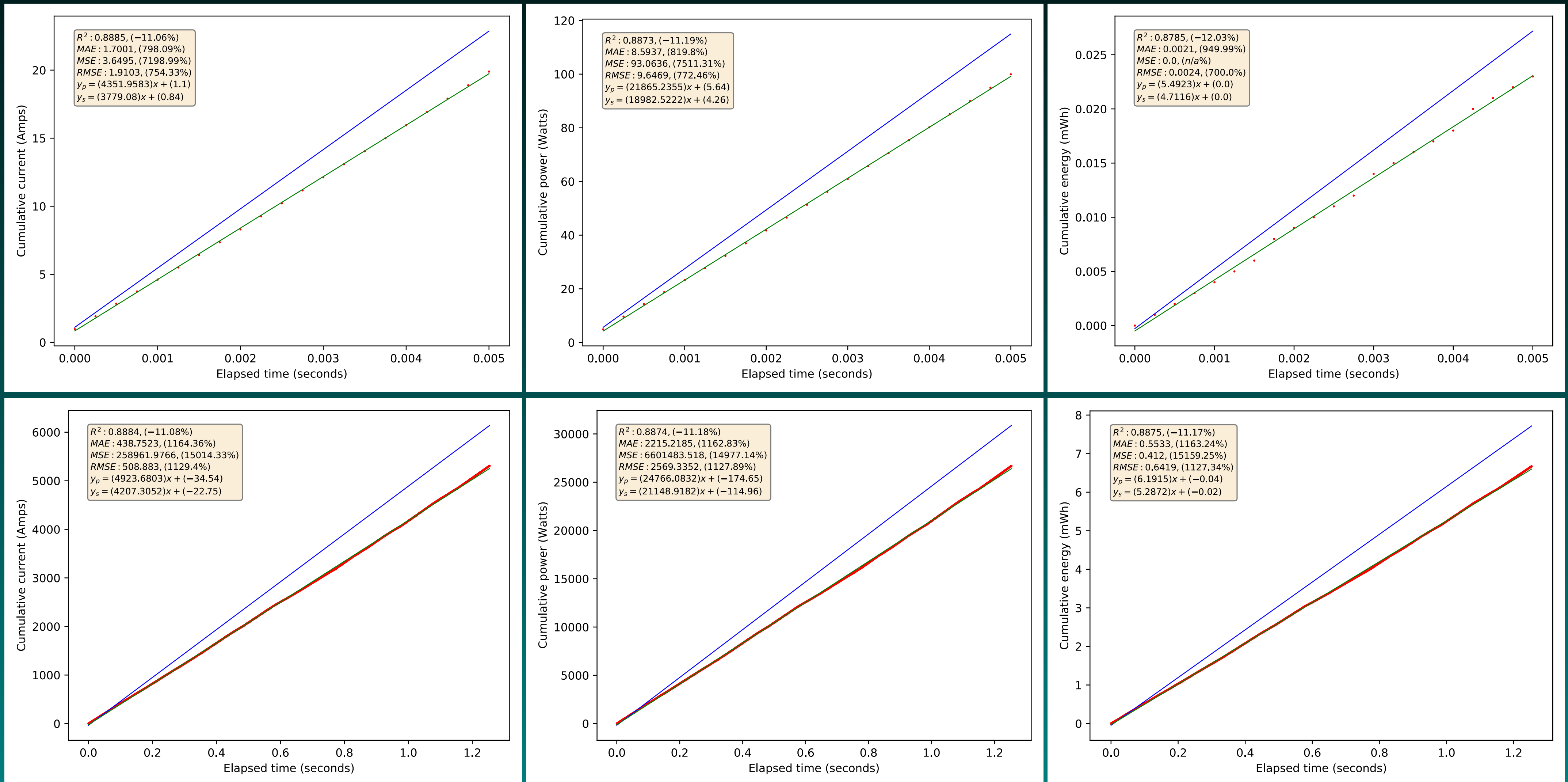
# Minimal, but extensive enough data

- We look into efficient collection of data
  - => Enough to understand what is going on (understand the behaviour)
  - => Be efficient, not too much data
- Process the data in different ways
  - => Ability to generate **fingerprints** for the behaviour
  - => Ability to compare different fingerprints
  - => Take advantage of Artificial Intelligence (AI)



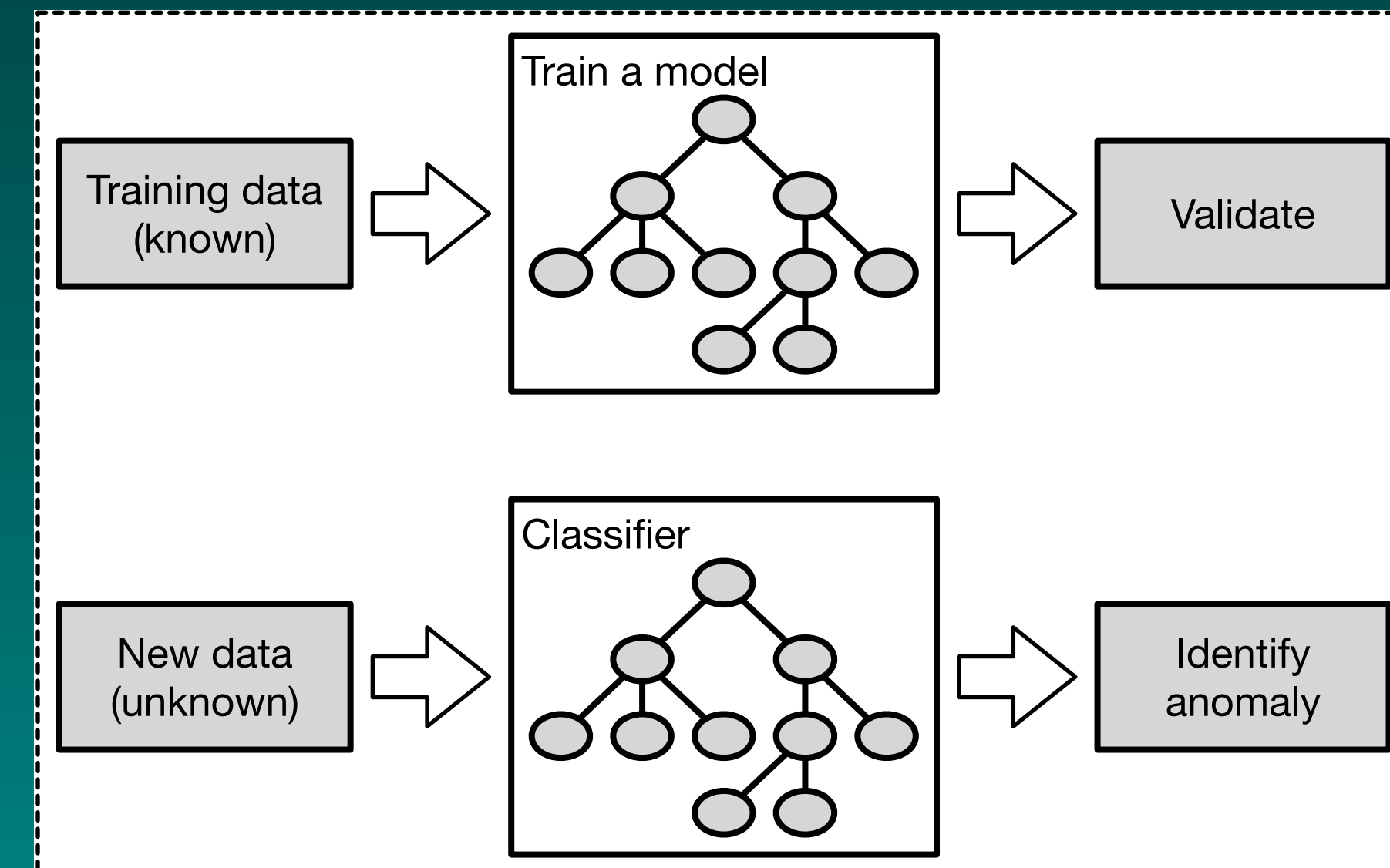
It is all about data and what we can learn from it.

# How about those fingerprints?



# Where there is data, there is AI

- AI models are trained with known data and can react to unknown data  
=> Based on what they have learned
- Specifically for us: Classifiers  
=> Use known data to train the model  
=> Teach it different behavioural categories  
=> Use the model to classify unknown behaviour
- There are different types of classifiers  
=> Traditional models, e.g., Decision Trees  
=> And deep learning models, specifically, Convolutional Neural Networks (CNN)

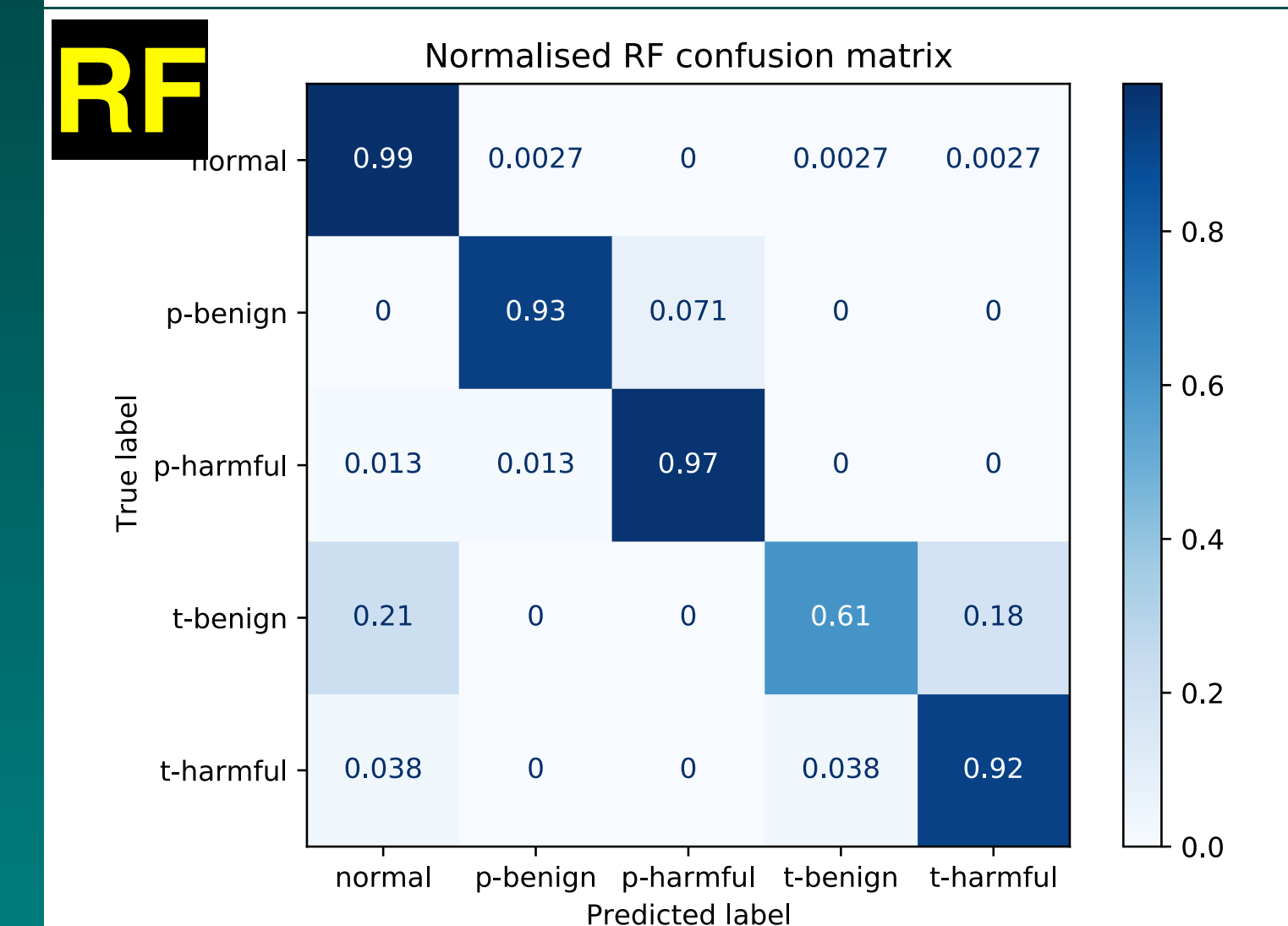
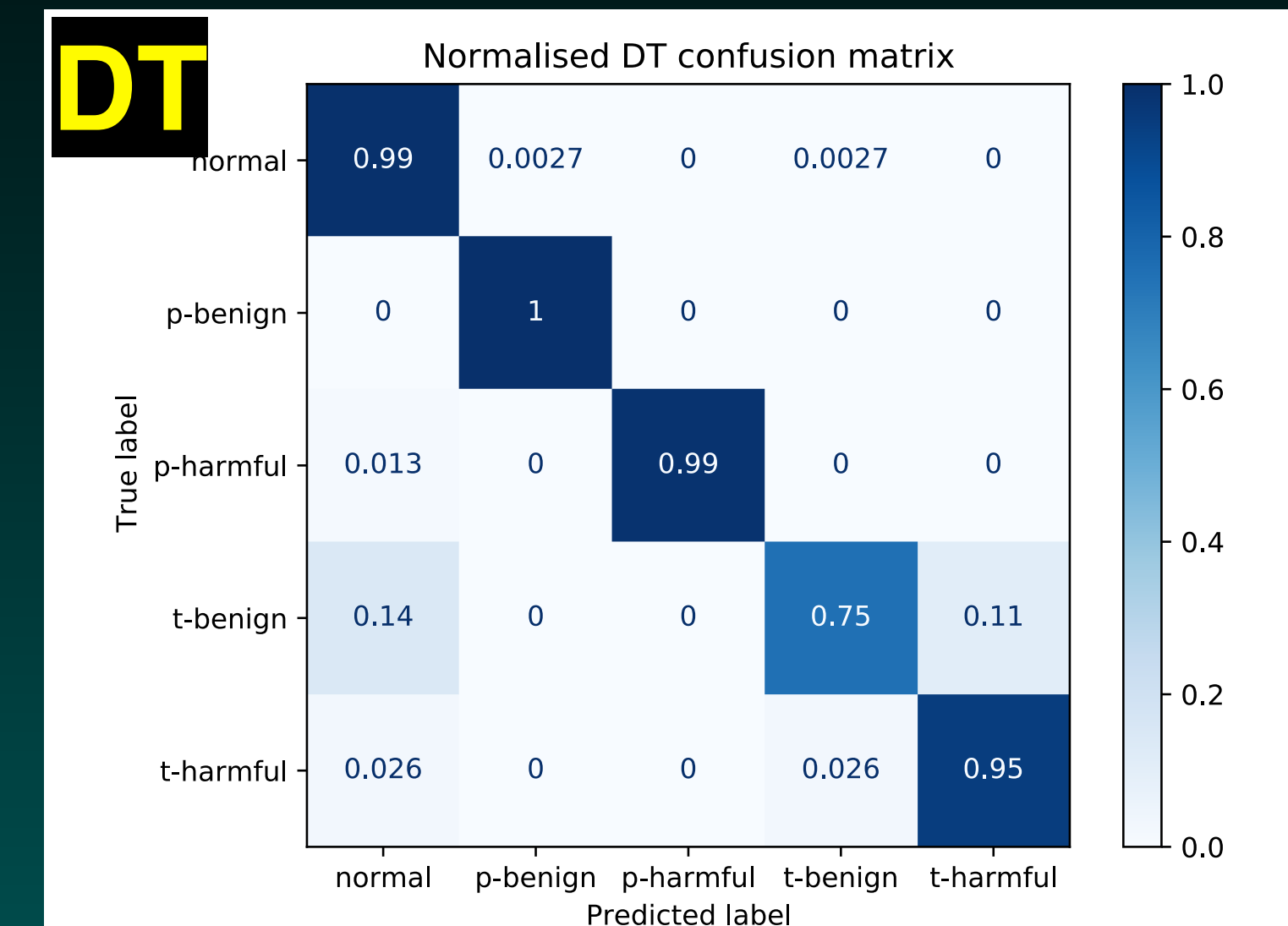
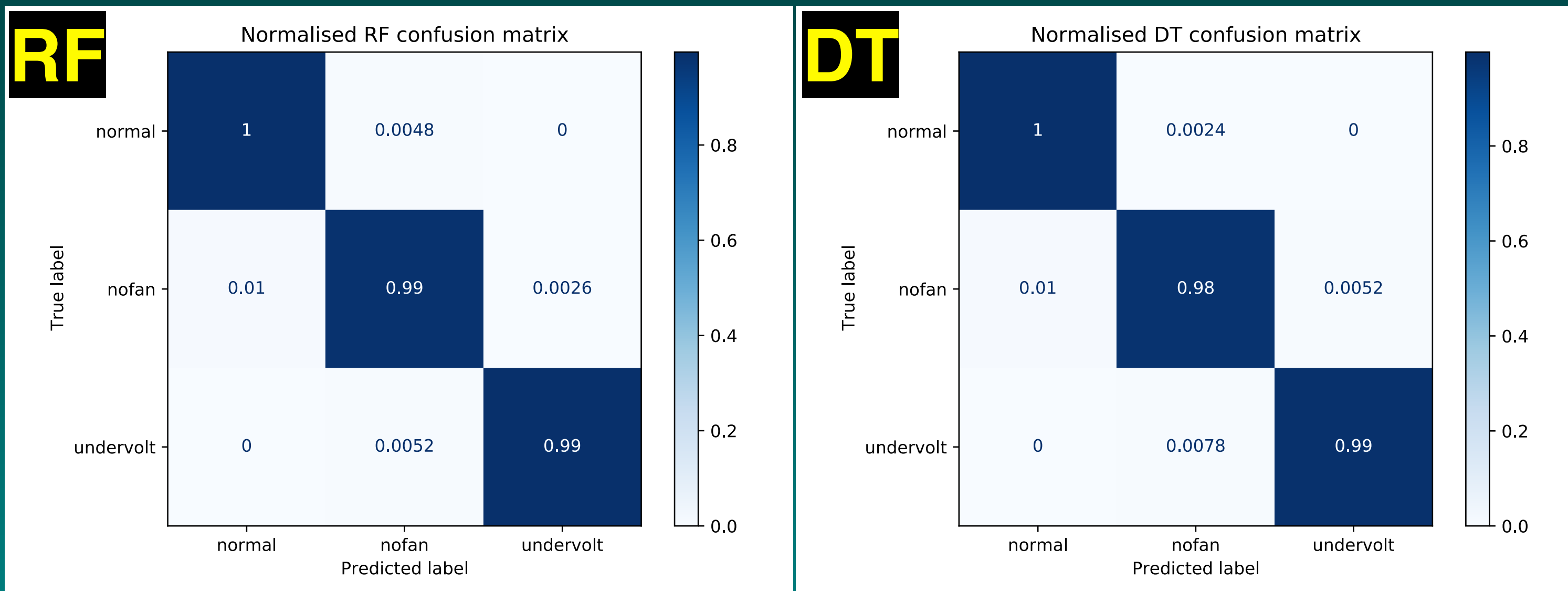


# Where there is data, there is AI

- How good is a classifier?
  - => This is evaluated by the accuracy of its predictions
  - => Classifiers learn from known data
  - => Learning performance varies
- Correct classification rates:
  - => Solution using traditional ML: **99.23%**
  - => Solution using DL with CNN: **94.85%**  
(with room to improve ...)

# Where there is data, there is AI

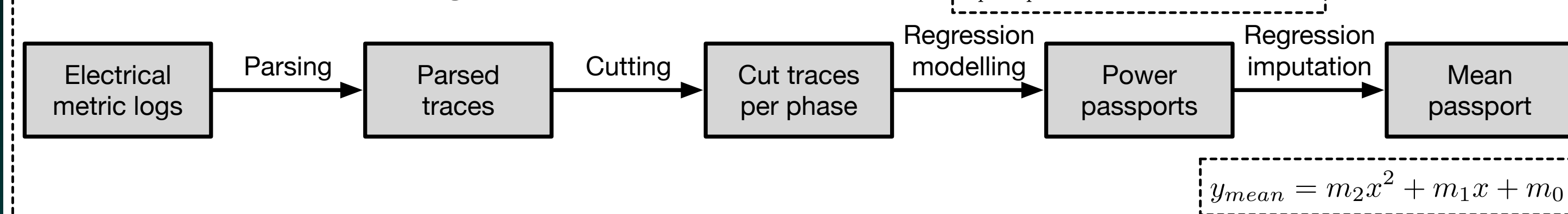
- How good is a classifier?
  - => Evaluated by the accuracy of predictions
  - => Classifiers learn from data
  - Known data for supervised ...
  - => Learning performance varies



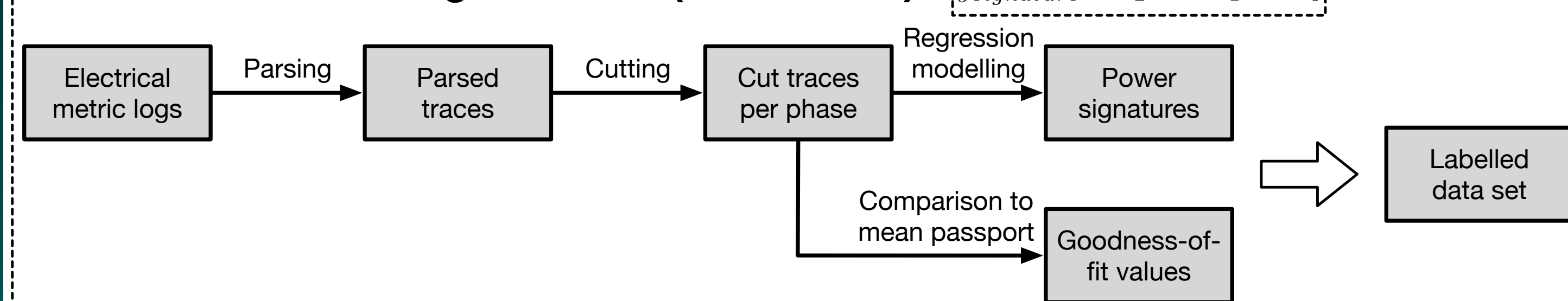
# Complete solution 1

- The solution combines fingerprinting techniques with AI techniques
- Different solutions addressing different information positions

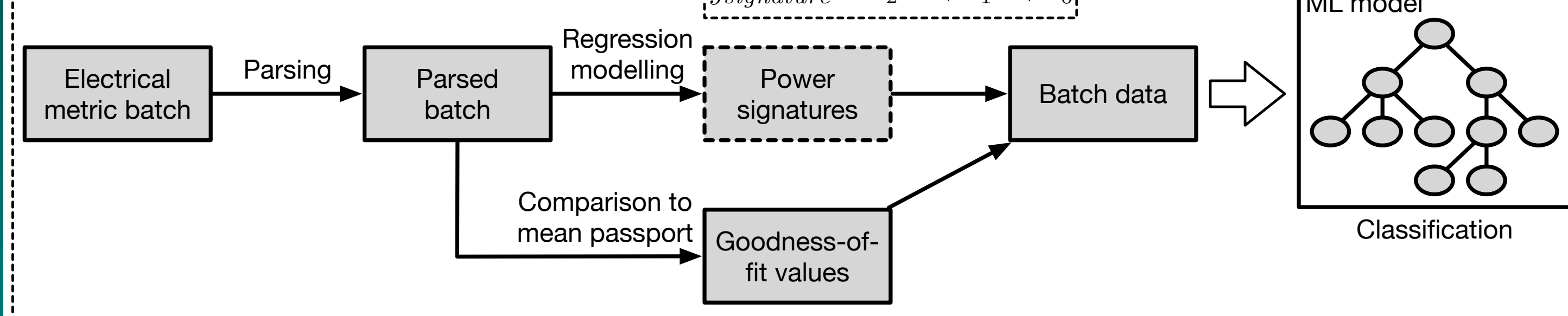
## Classic ML: Data set generation (reference)



## Classic ML: Data set generation (anomalous)

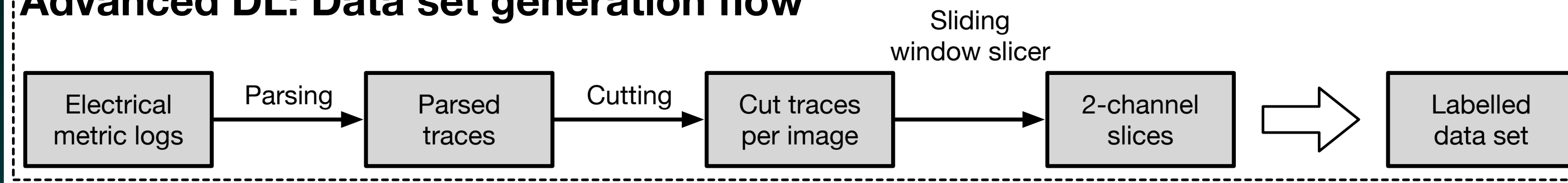


## Classic ML: Classification flow

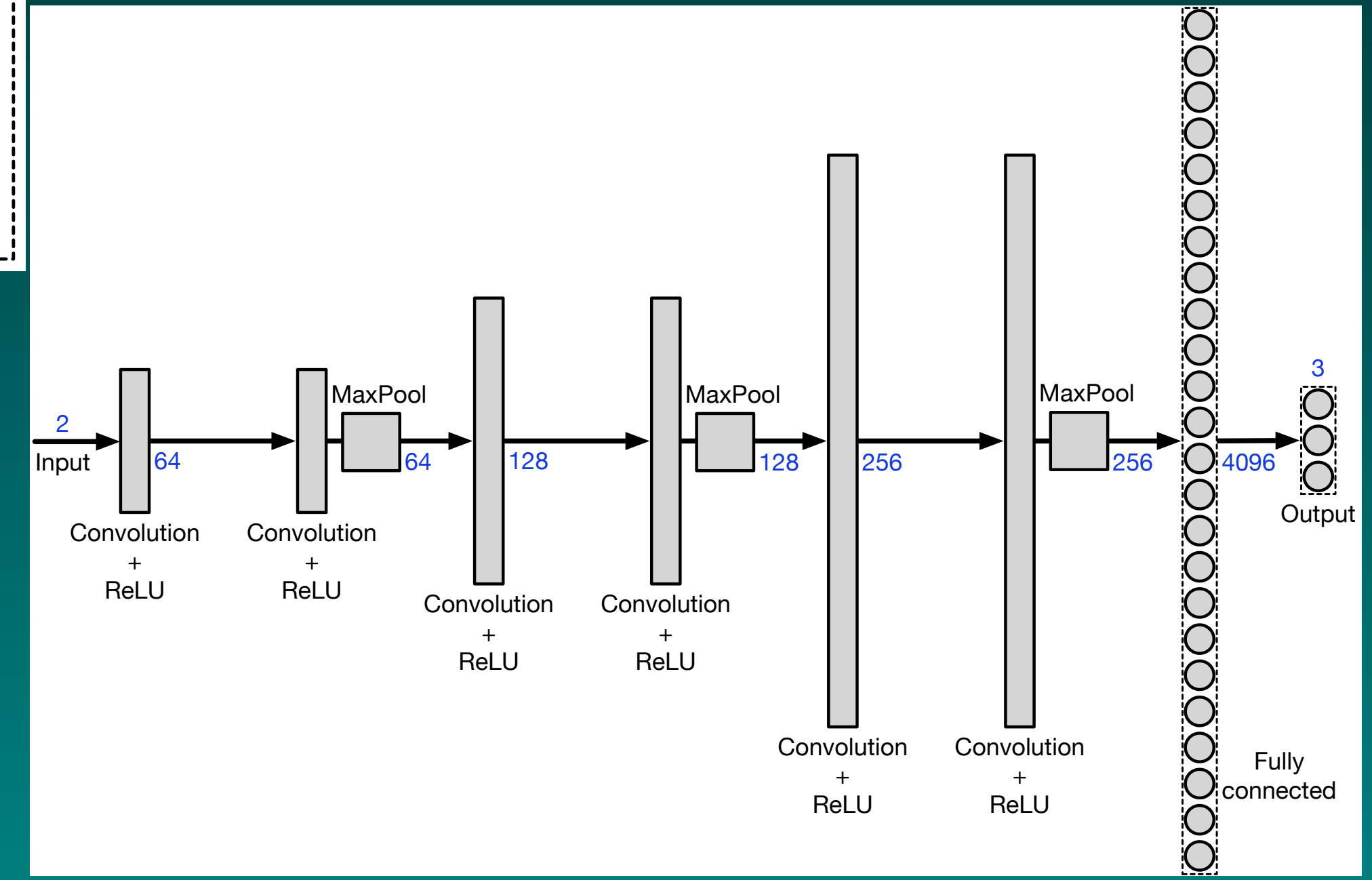
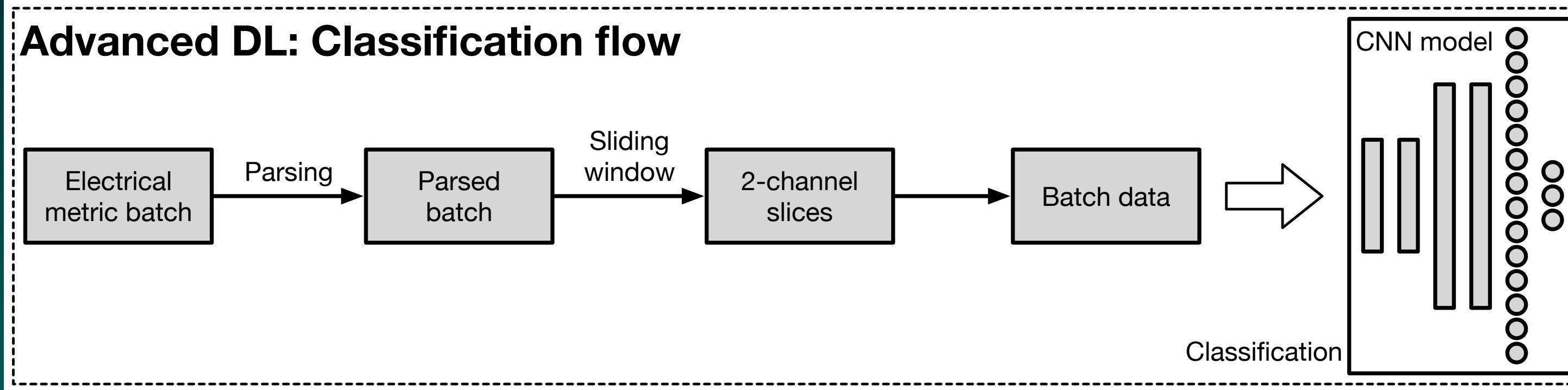


# Complete solution 2

## Advanced DL: Data set generation flow



## Advanced DL: Classification flow



# Comparison

Classic ML vs Advanced DL

- Classic ML advantages:
  - => Exceptional accuracy -> **99.23%**
  - => Very fast training and inference (after preprocessing)
  - => Explainable output (take a look at the DT and backtrack)
- Advanced DL:
  - => Good accuracy -> **94.85%** (can be even better)
  - => Minimal preprocessing (just proper formatting)
  - => Can be relatively quickly put together

To be compared:

- Training speed, classification speed, accuracy, overhead
- Reduction in feature engineering, CNN model design effort

# Incorporation of knowledge

- Different information positions will define:
  - => Solution specifics
  - => Type of model
  - => Achievable performance (model performance, speed, ...)
- Two types of knowledge
  - => **Readily** available
  - => **Extracted** from data
- Can we develop a framework? Generalise?

		Knowledge position		
		White	Grey	Black
Data position	White	White-White (WW)	White-Grey (WG)	White-Black (WB)
	Grey	Grey-White (GW)	Grey-Grey (GG)	Grey-Black (GB)
	Black	Black-White (BW)	Black-Grey (BG)	Black-Black (BB)

# Science does not happen in vacuum

- **UvA:**

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Thank you!