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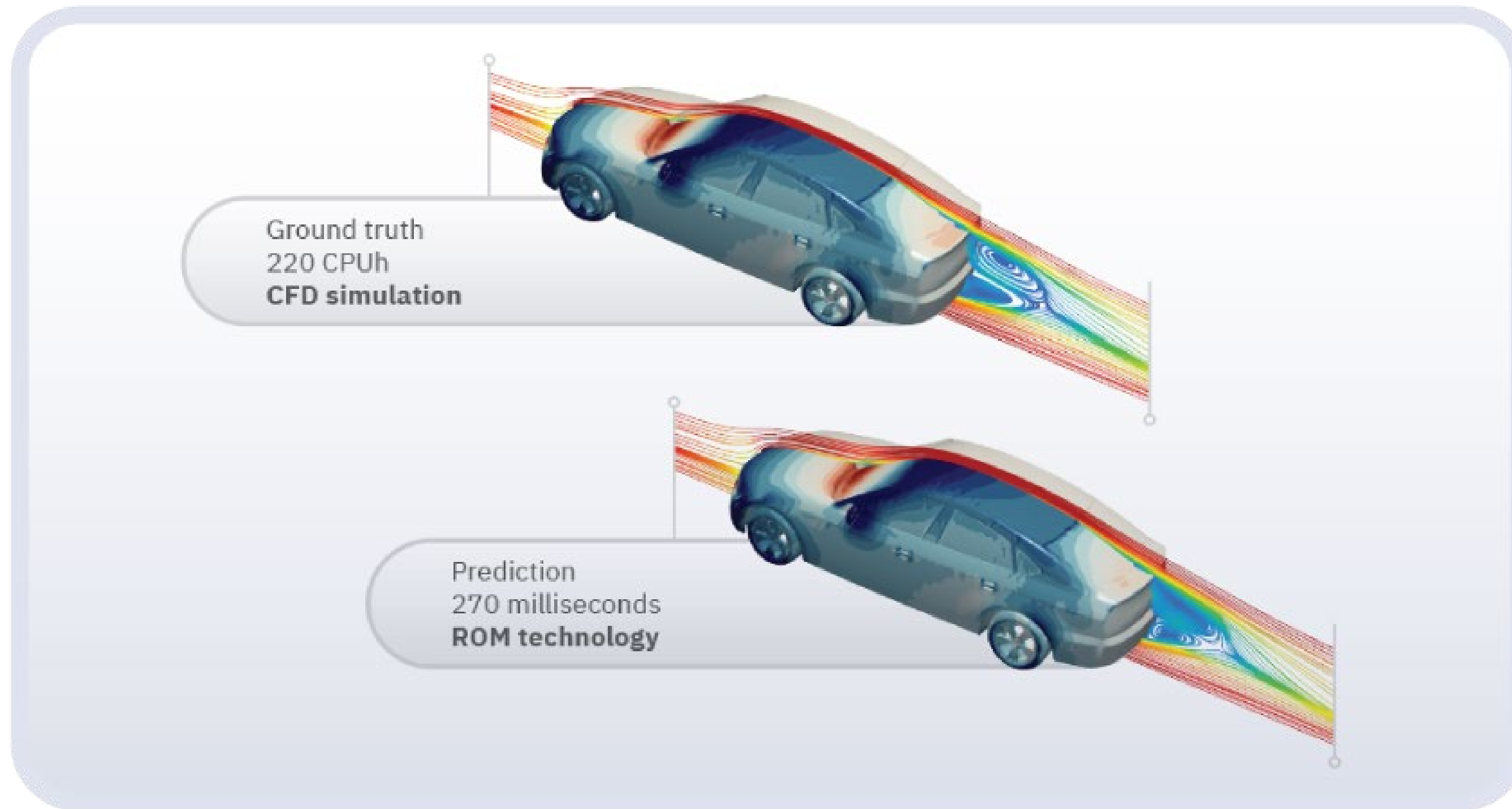
# Introducing nDAI

Bridging simulation and machine learning  
for instant design predictions

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Product Manager



# It is about Physics AI



# Engineering is getting tougher

## Create better products faster

The need for sharper tools to deliver high-fidelity simulations early in the design process.

## Impact of cost, time and expertise

High fidelity simulations are computationally expensive and require skilled engineers who usually work in the pre-production phase.

## Organizing simulation data and insights

Designers need access to democratized tools over methods for collaborative data-driven decisions.



# Physics AI's strategic role



## Shift left

Bring forward the usage of high-fidelity tools in the design process, this implies an increase of cost

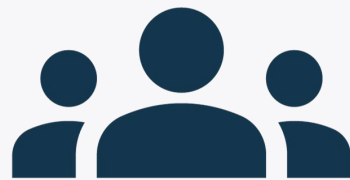


## Push right

Leverage historical data and insights, apply them directly to accelerate the next project.

# Physics AI adoption barriers

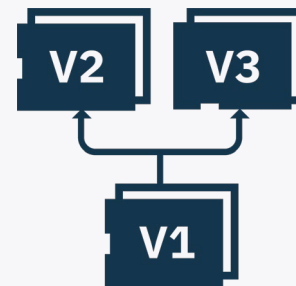
## Cultural gap between engineers and data scientists



Engineers struggle to imagine how to integrate ML in their everyday work.

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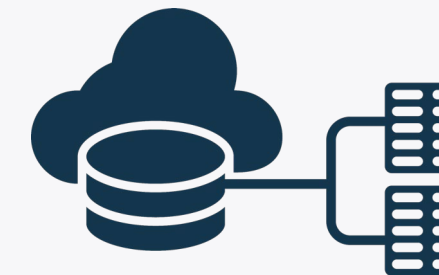
## Data is dynamic and requires governance



ML models have a short lifespan, putting the governance over the ML stack is a demanding task.

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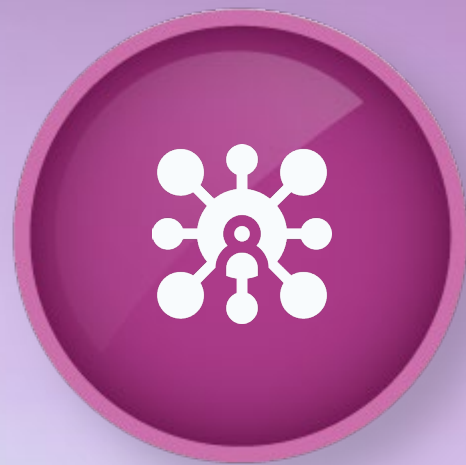
## Infrastructure



AI/ML Training requires data to be moved to the right hardware. And trained models should be accessible to other stakeholders.

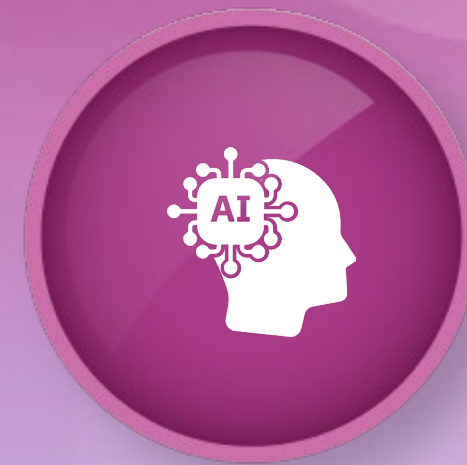
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# Imagine an AI platform powered by these capabilities



## Solver, problem, and data agnostic

- Pure data-driven
- 0D, 1D, 2D, 3D + 1 (time)
- No pre-trained models



## Multiple model architectures

- ROM and CNN
- Train and tune ML models
- Compare ML models



## Distributed architecture and data federation

- Cloud-based architecture
- Locally, HPC or cloud execution
- Data source from file system / APIs



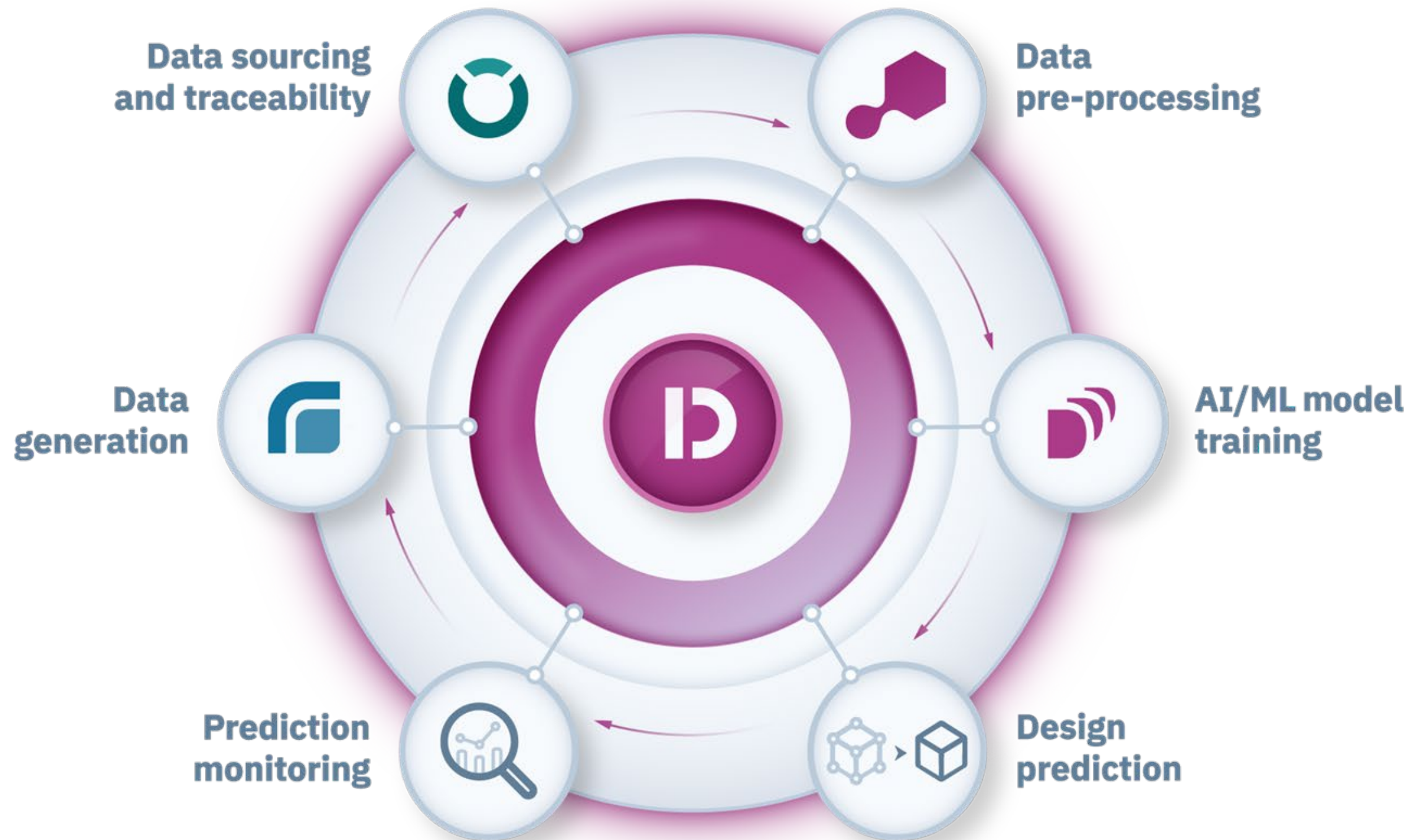
## Governance and democratization

- Traceability of training data
- Versioning
- Model consumption by non-experts

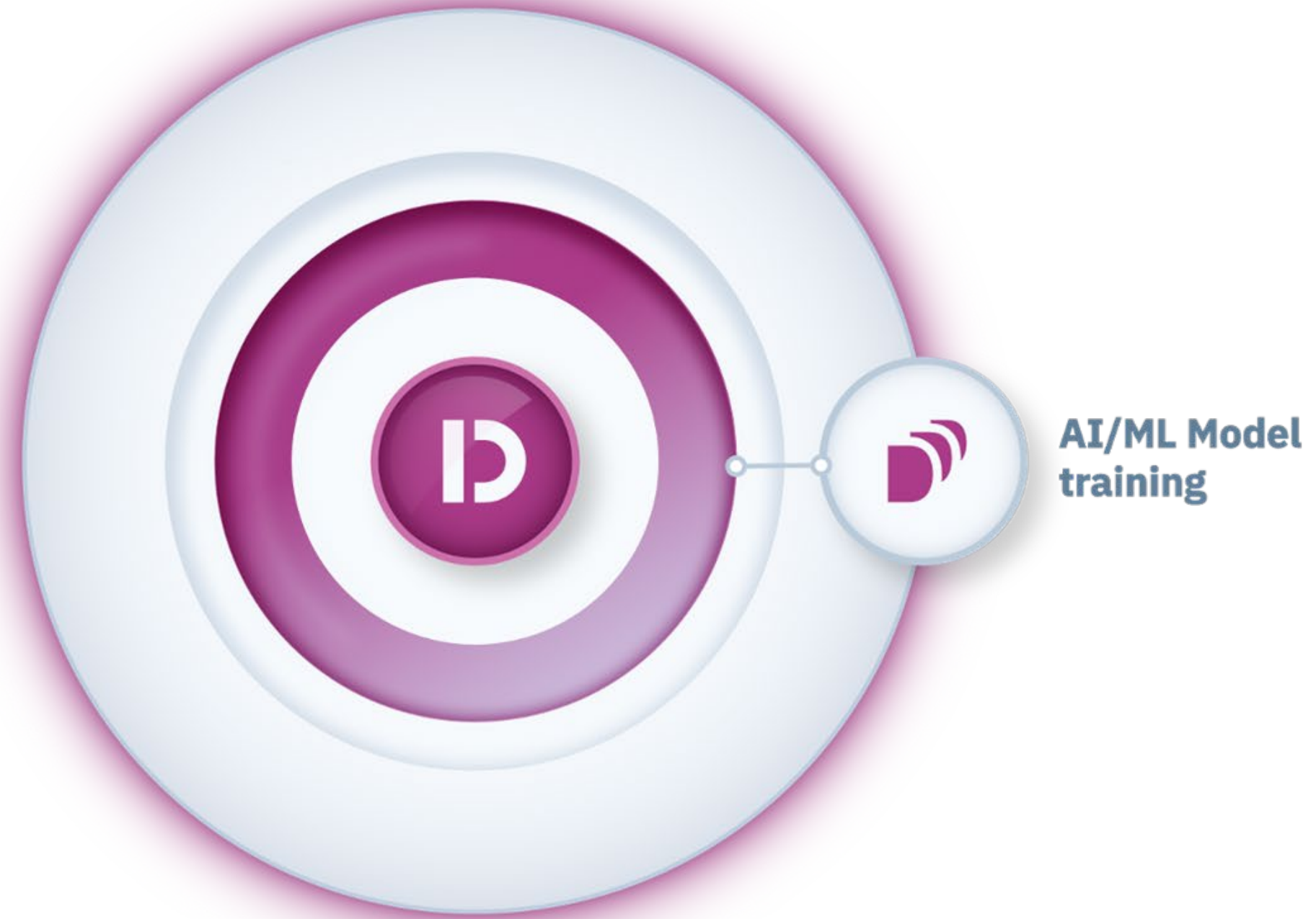
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# Introducing nDAI

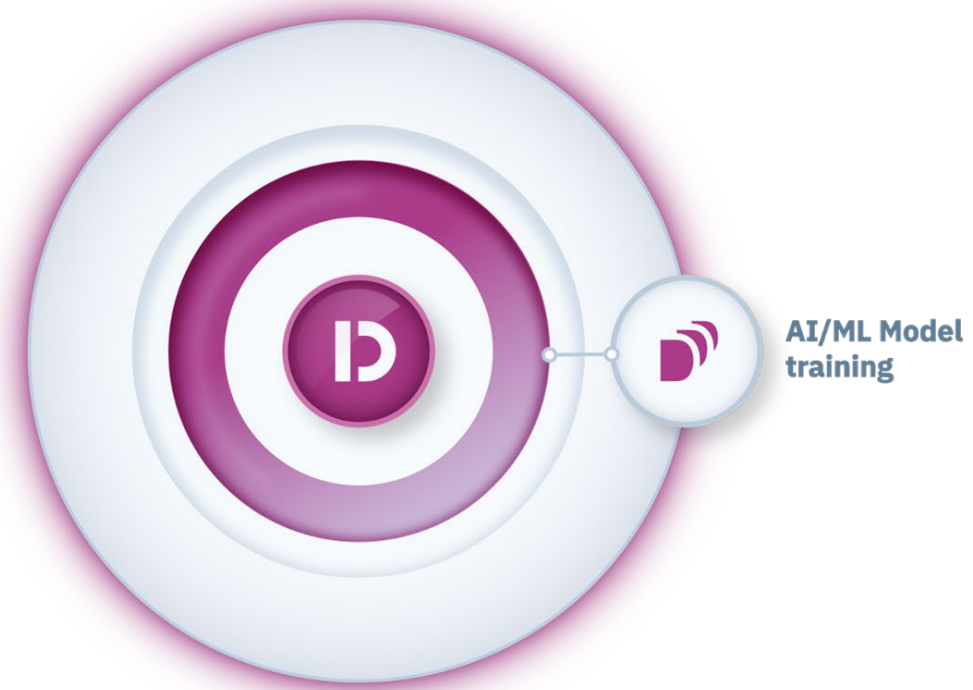




# nD Modeler

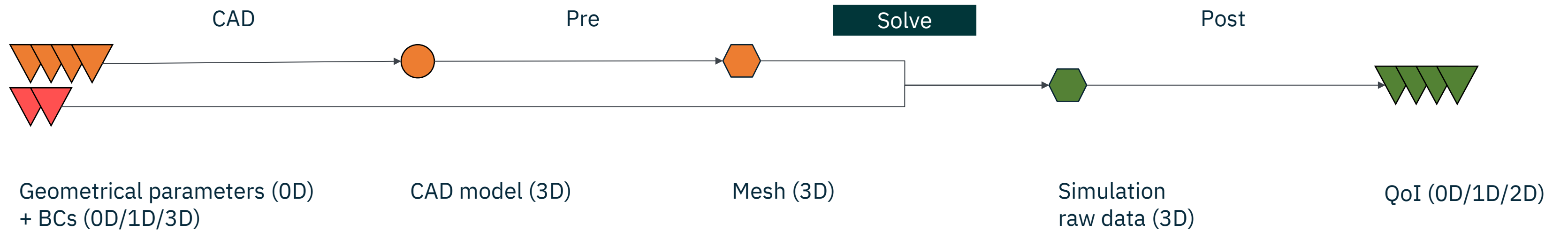


# nD Modeler

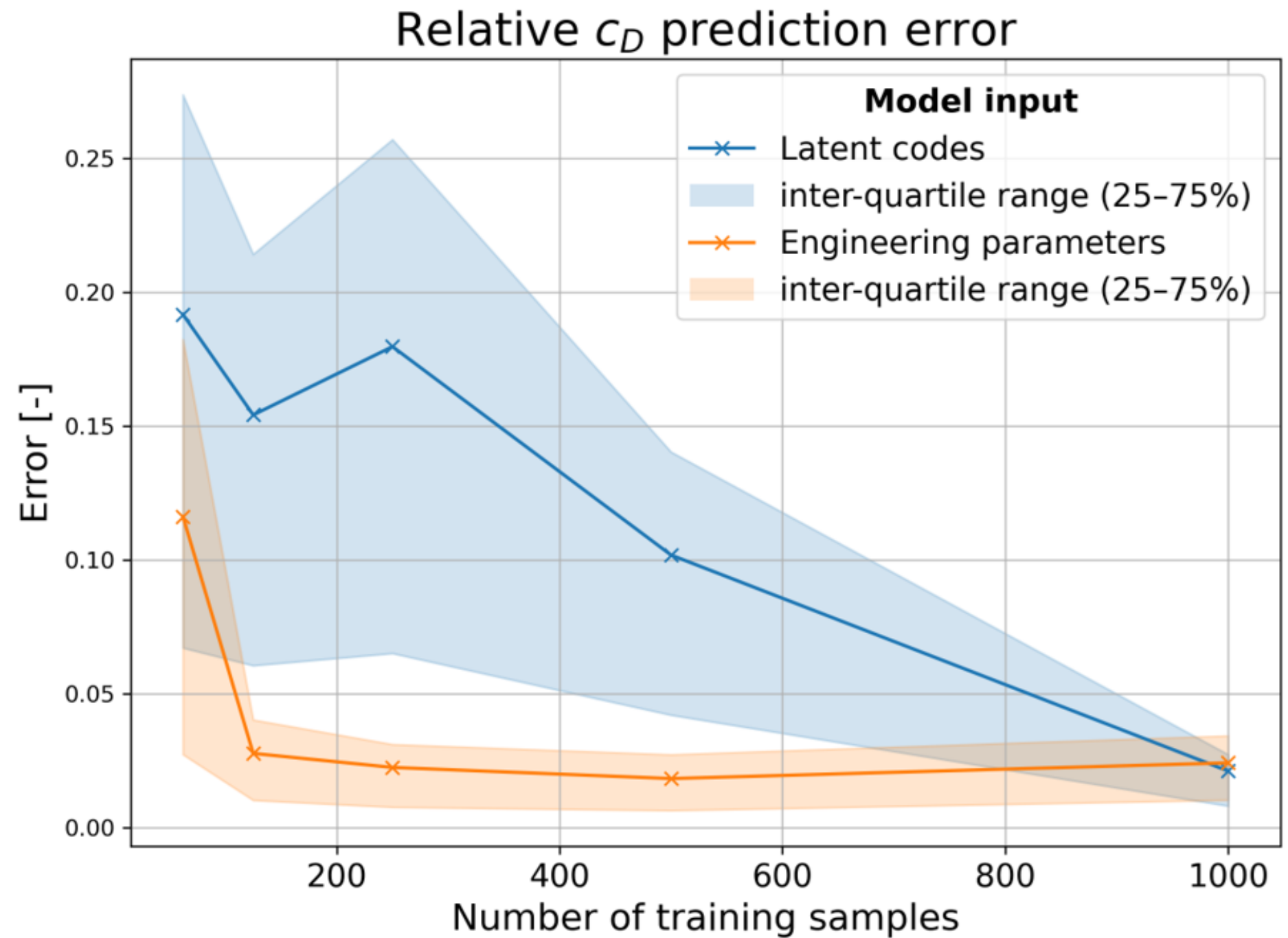
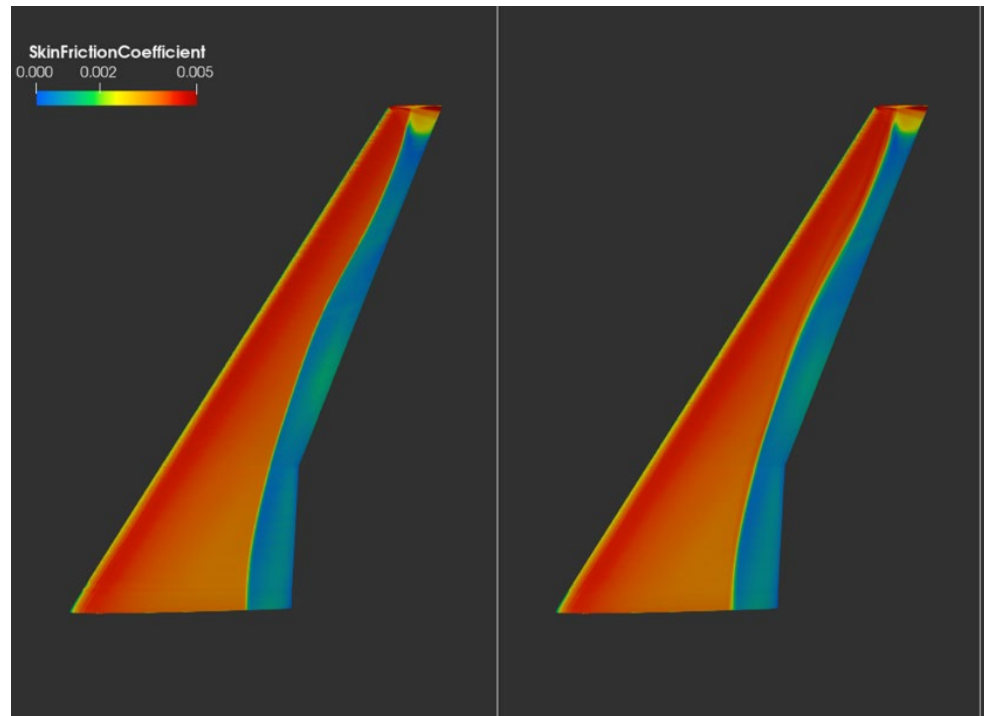
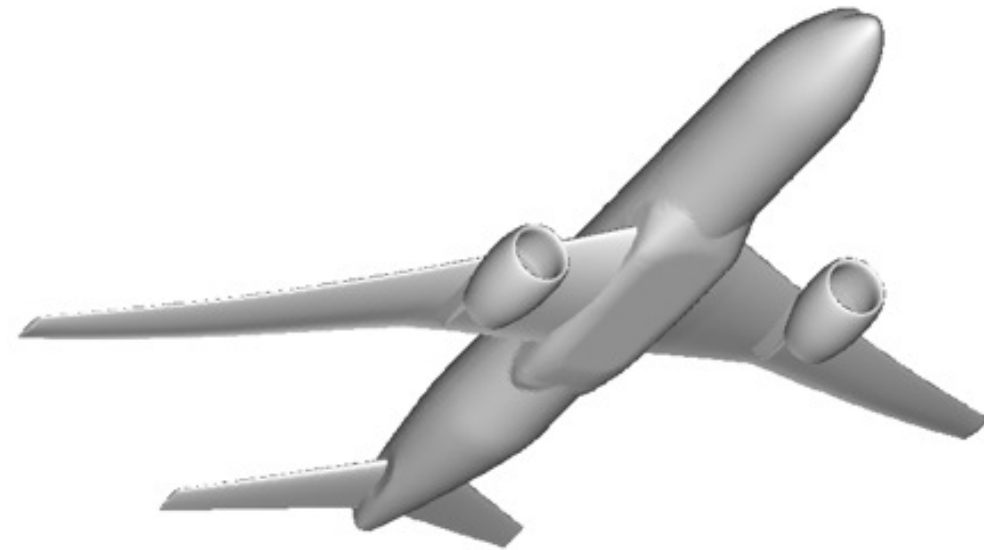


- How should I approach my problem?
- Which model is appropriate for my scope?
- Do I have enough training data?
- What accuracy can be expected?

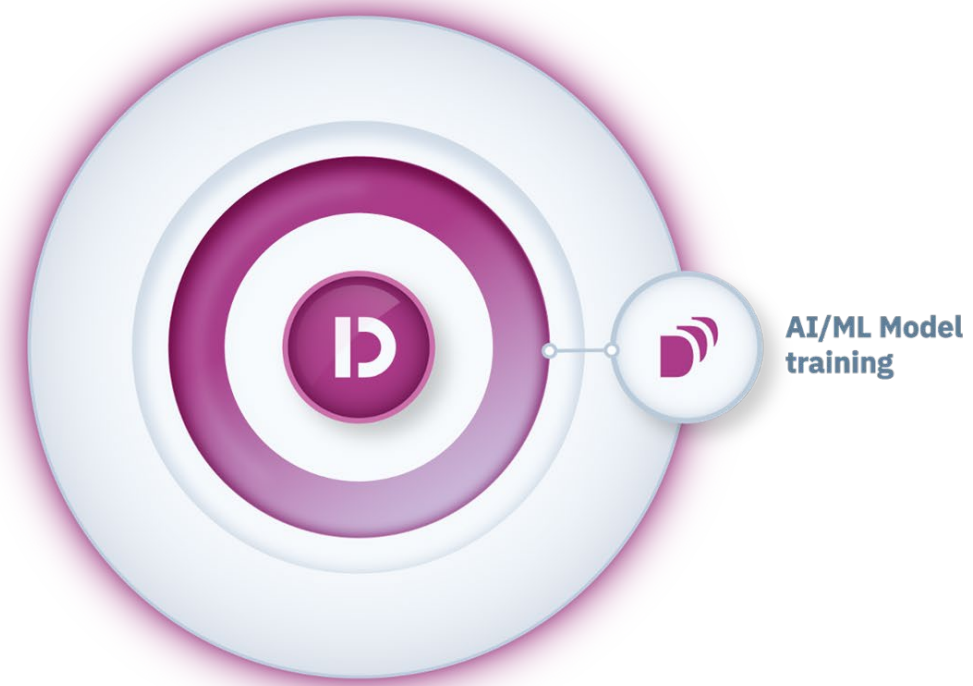
# Choosing the model domain is not obvious



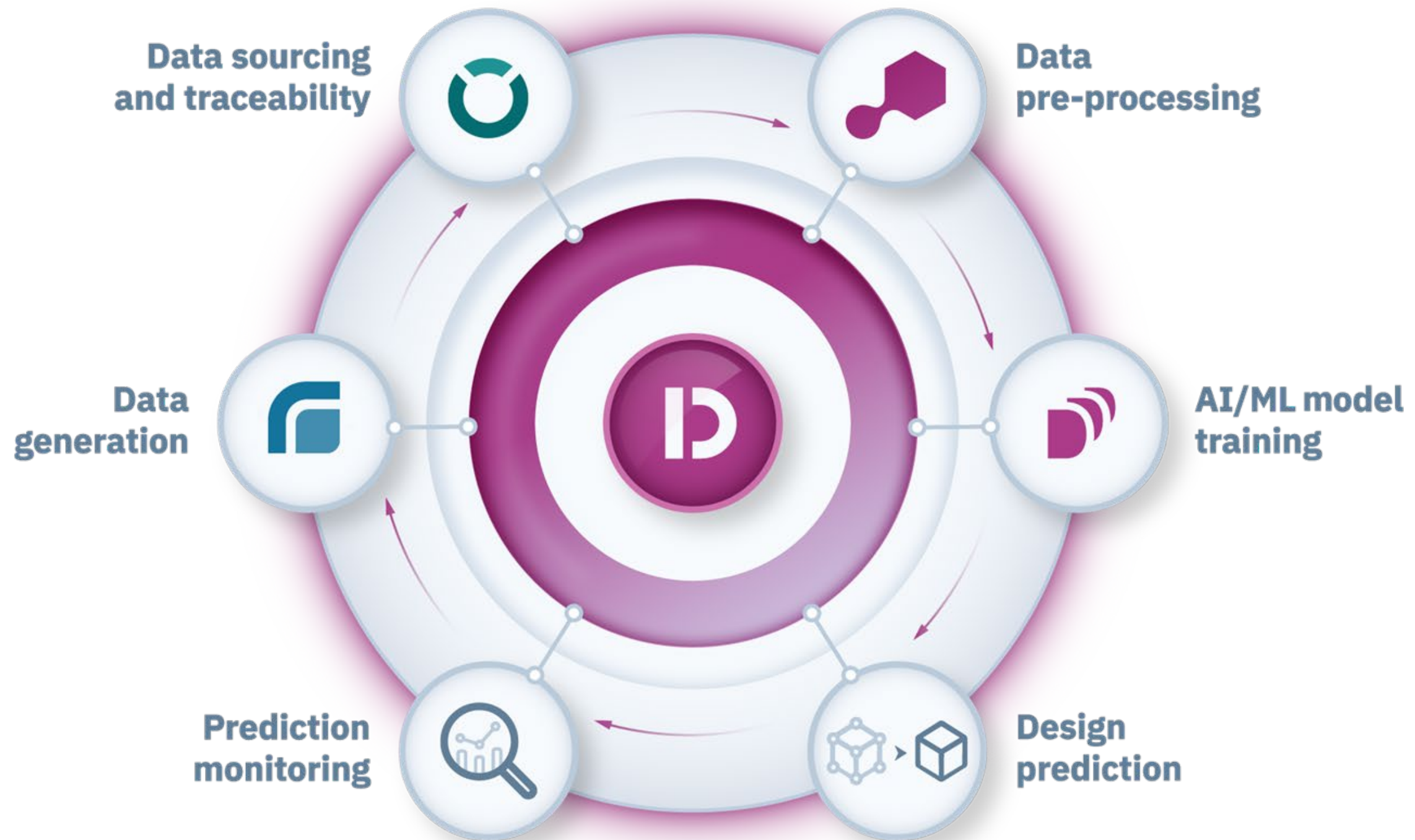
# Choosing the model architecture is not trivial



# nD Modeler



- Train, validate and track surrogates.
- Compare different ML architectures
- Quantify accuracy-efficiency trade-offs
- Deploy the trained model for production



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# Looking forward and conclusion



# What's coming next

## Mimic integration

Streamline the interaction  
nD Modeler – mimic for  
data preparation

Preprocessing automatic included  
during inference

## Geometric Deep Learning

From data warehouses  
to data lakes

Native CAD integration

## nDAI in VOLTA

Governance of models

Traceability of data and processes

Execution at scale

# Committed to deliver impact

## **Sustainable engineering**

Time-to-market

Exploit enterprise knowledge

## **Democratization**

Breaking silos

Improve collaboration

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# Thank you

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