Digital Twins: Introduction and Use Cases

Summer Student Lectures 2023

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interTwin is funded by Horizon Europe under grant agreement n° 101058386

NASA Apollo 13

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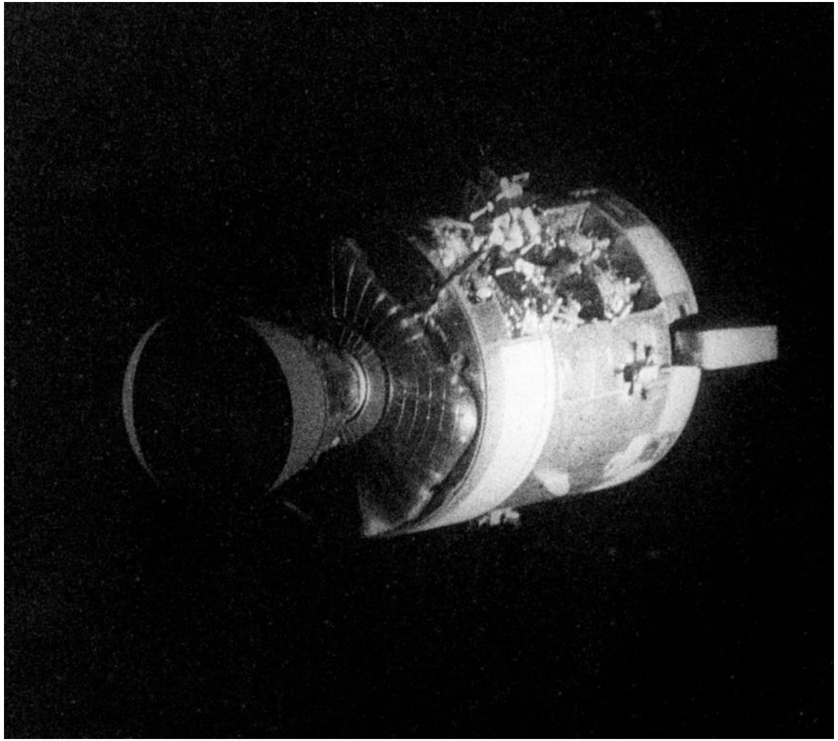
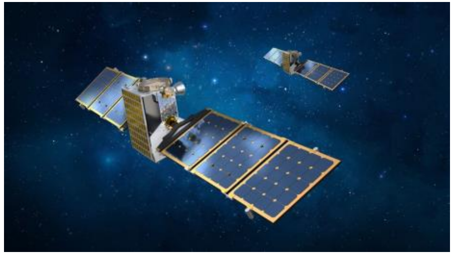


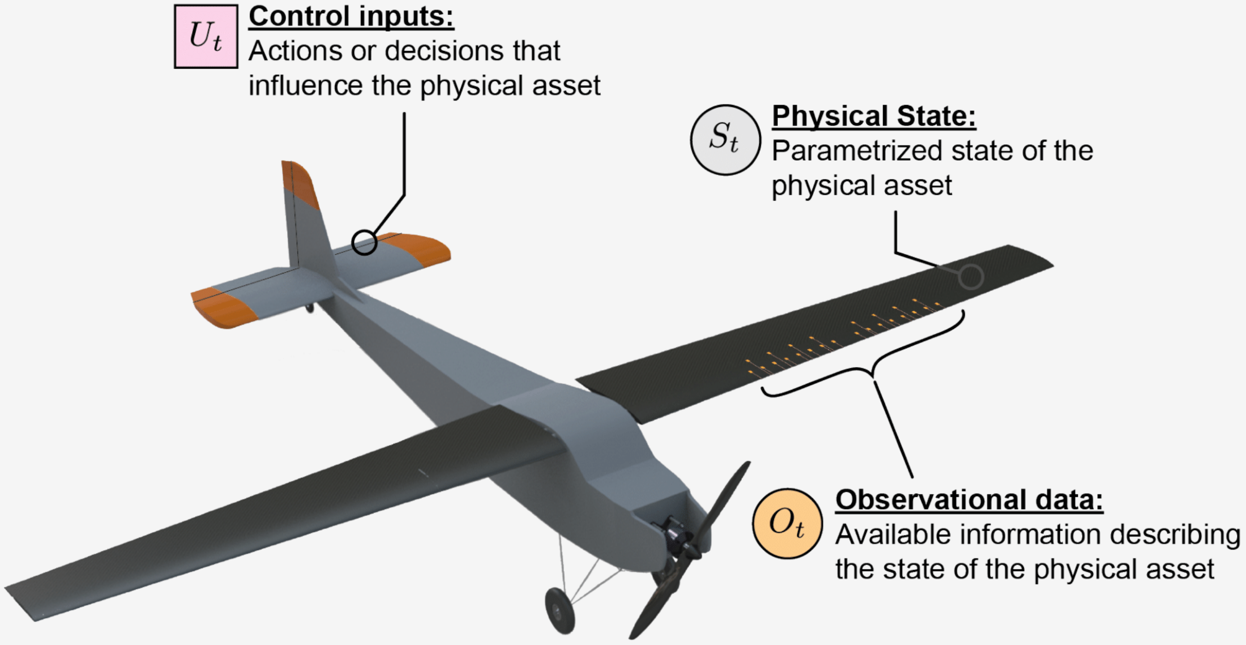
Digital Twin Industries



What is a Digital Twin?

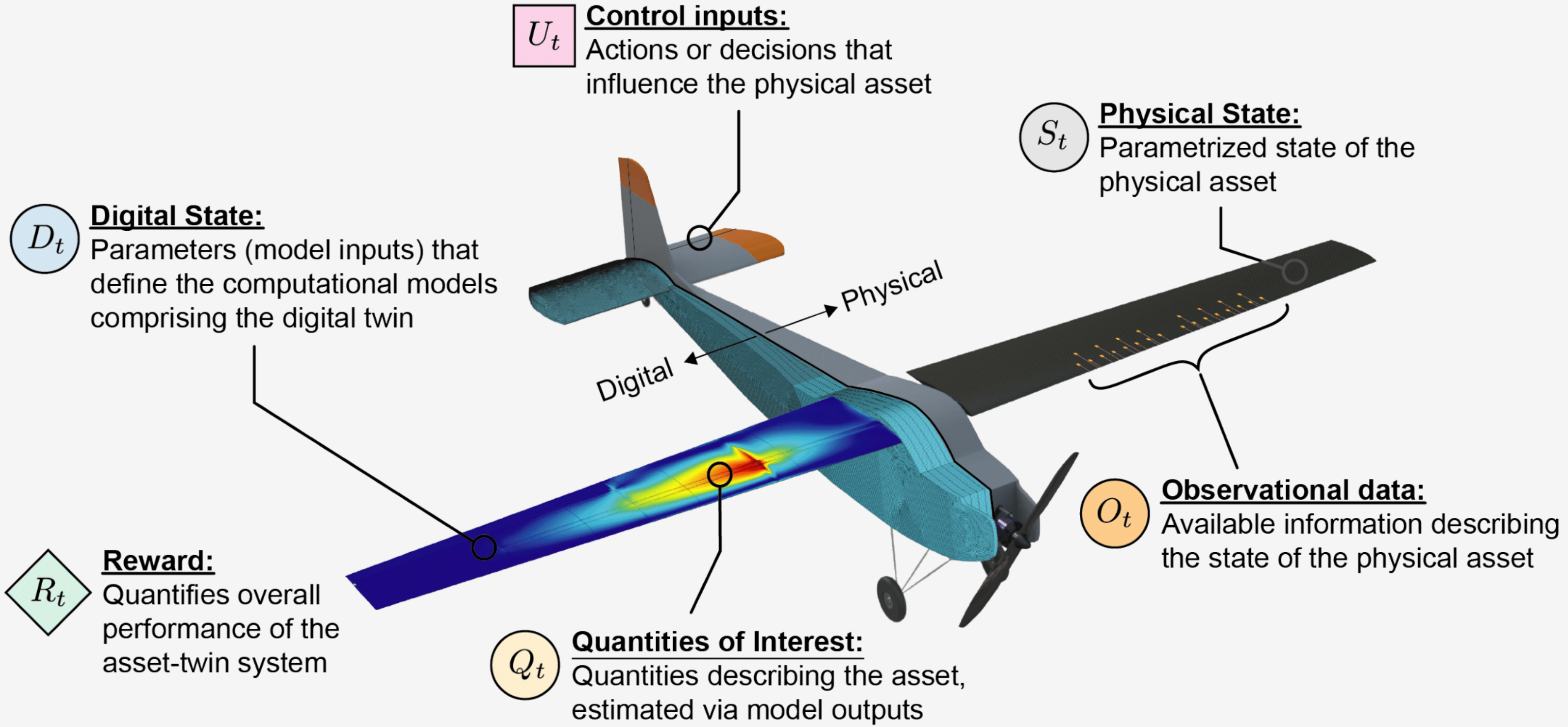
A digital twin is a virtual representation of an object or system helping in decision-making and prediction. It takes in real-time data and keeps track of the lifecycle of the object or system.

Digital Twin of UAV



[1] Willcox K. et al., Predictive Digital Twins, CIS Digital Twin Days, 2021

Digital Twin of UAV



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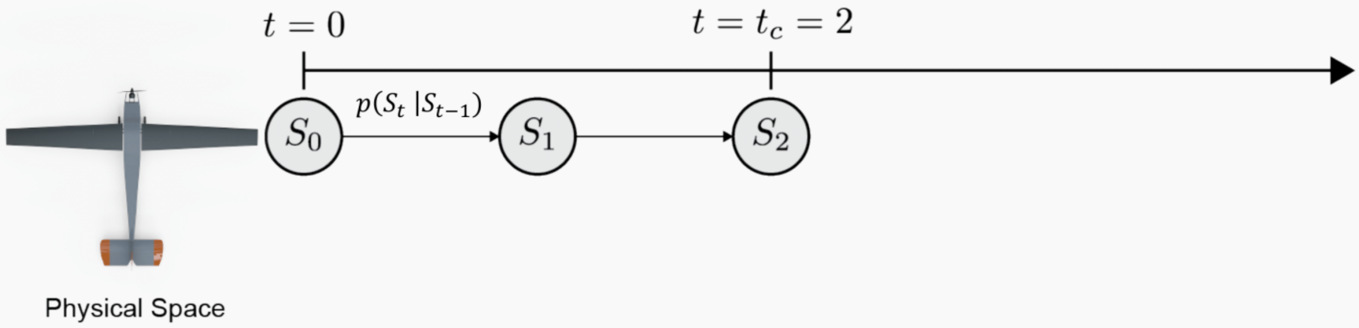
Digital Twin of UAV



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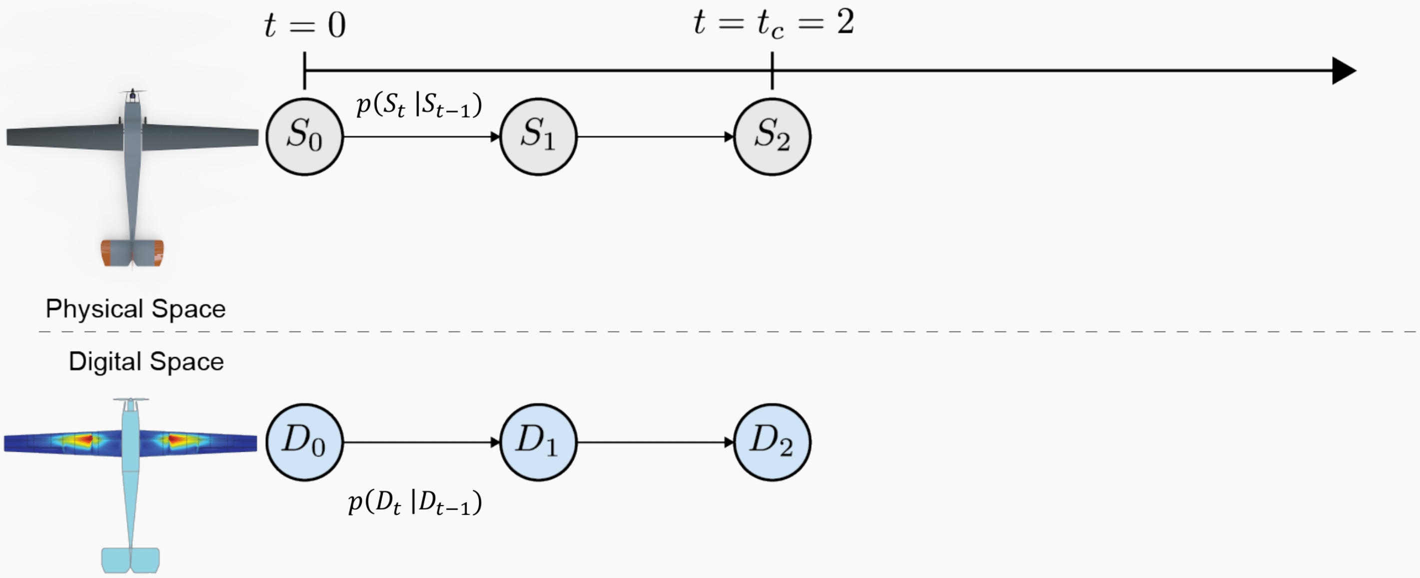
Digital Twin of UAV



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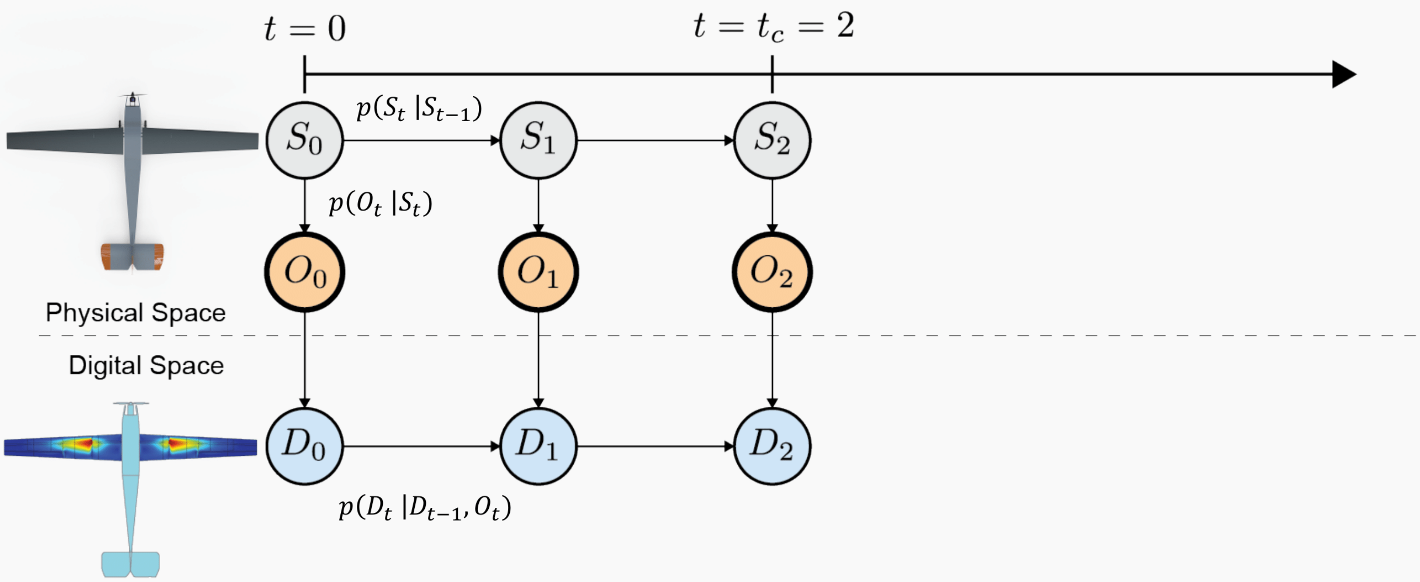
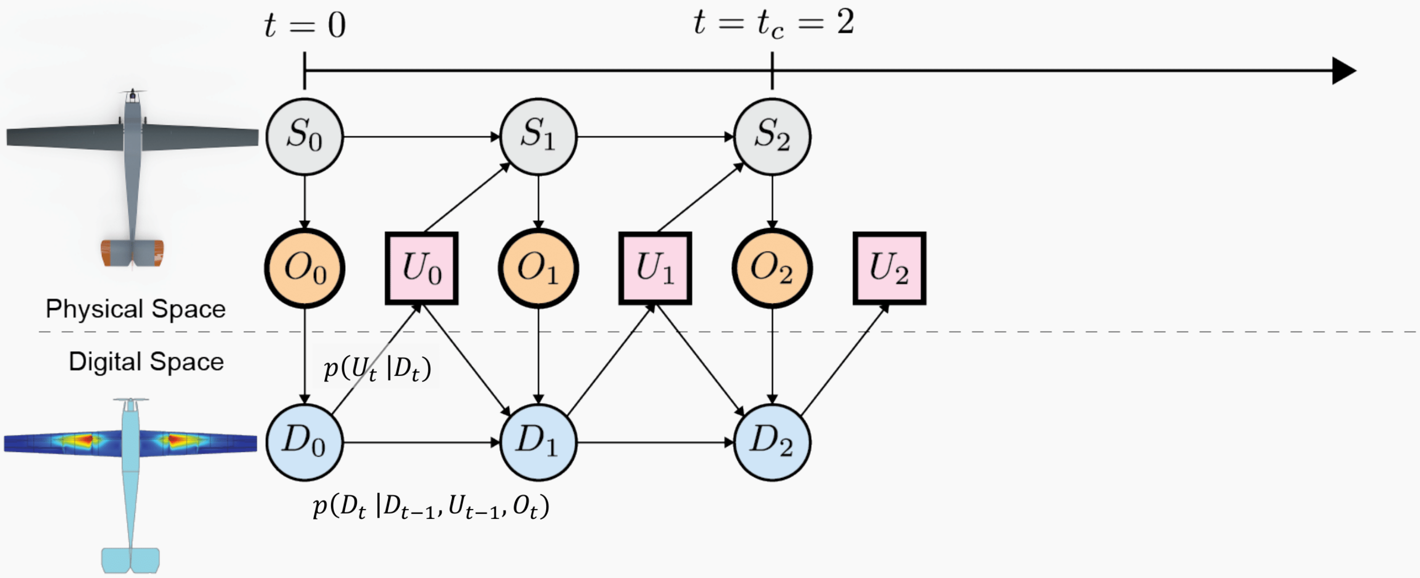

$t = 0$
$t = t_c = 2$
$p(S_t | S_{t-1})$
$p(O_t | S_t)$
S_0
S_1
S_2
O_0
O_1
O_2
Physical Space
Digital Space
D_0
D_1
D_2
$p(D_t | D_{t-1}, O_t)$



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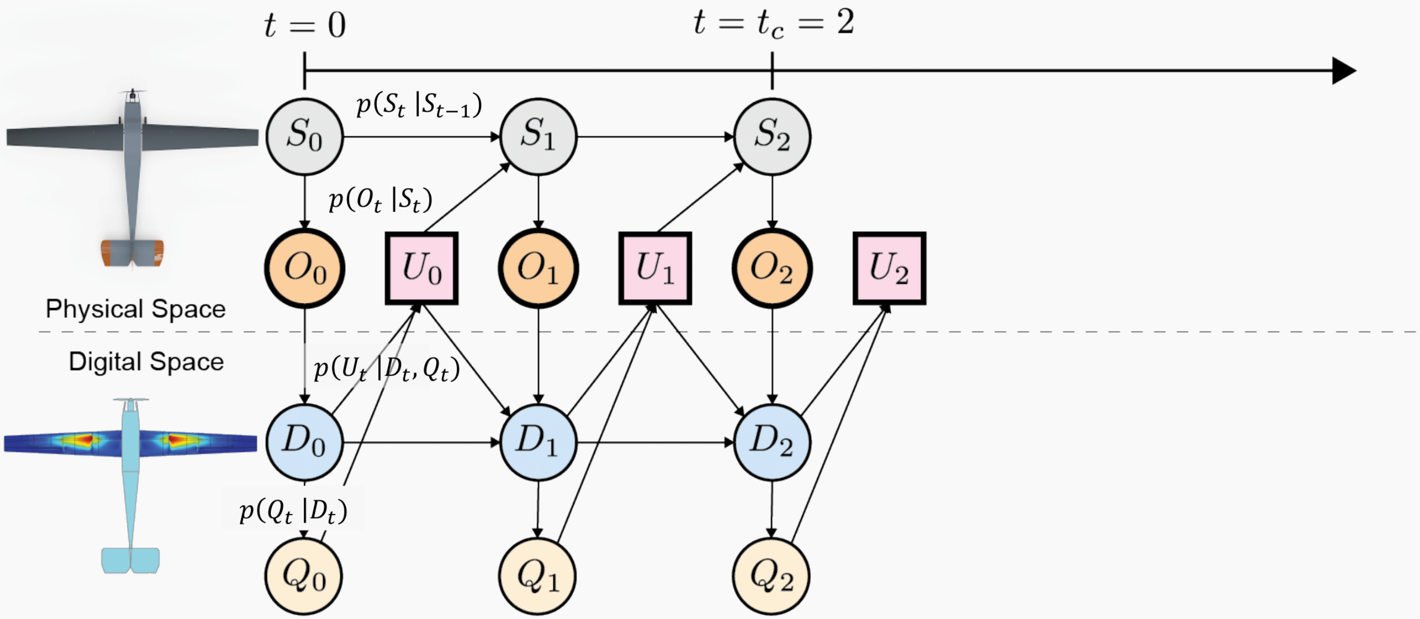
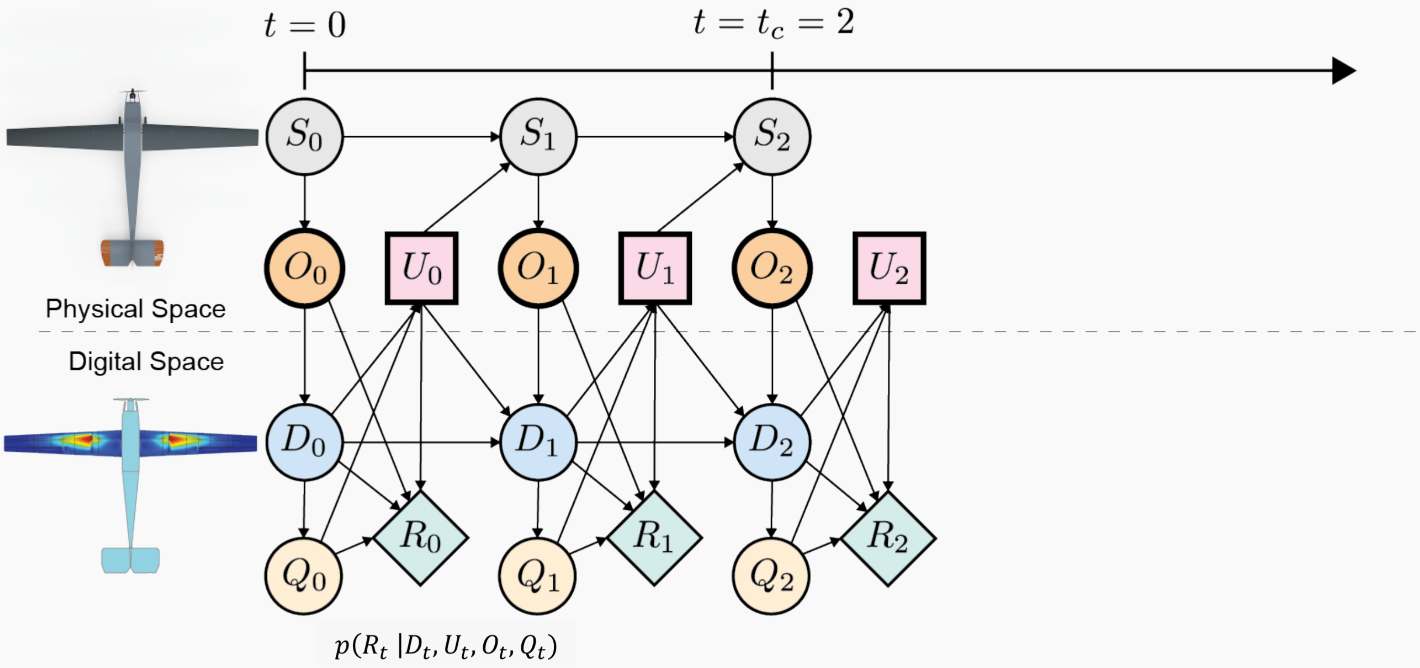

$t = 0$
$t = t_c = 2$
$p(S_t | S_{t-1})$
$p(O_t | S_t)$
$p(U_t | D_t, Q_t)$
$p(Q_t | D_t)$
S_0 S_1 S_2
O_0 U_0 O_1 U_1 O_2 U_2
D_0 D_1 D_2
Q_0 Q_1 Q_2
Physical Space
Digital Space



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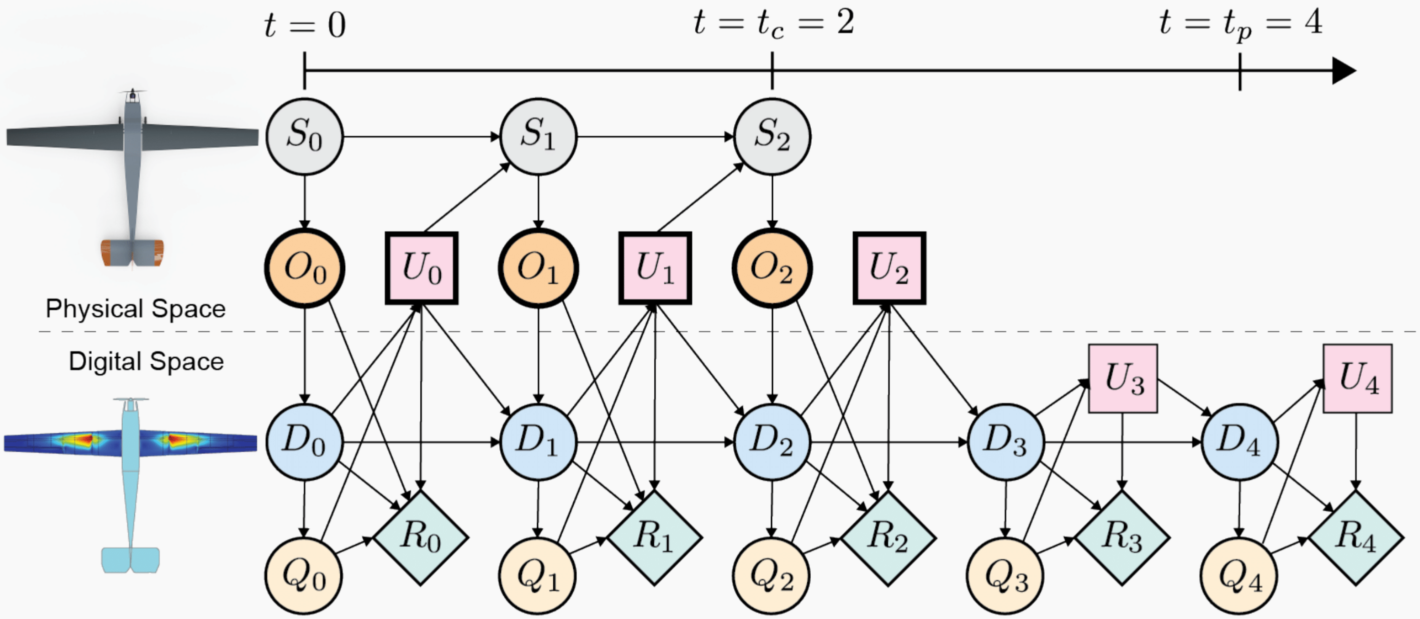

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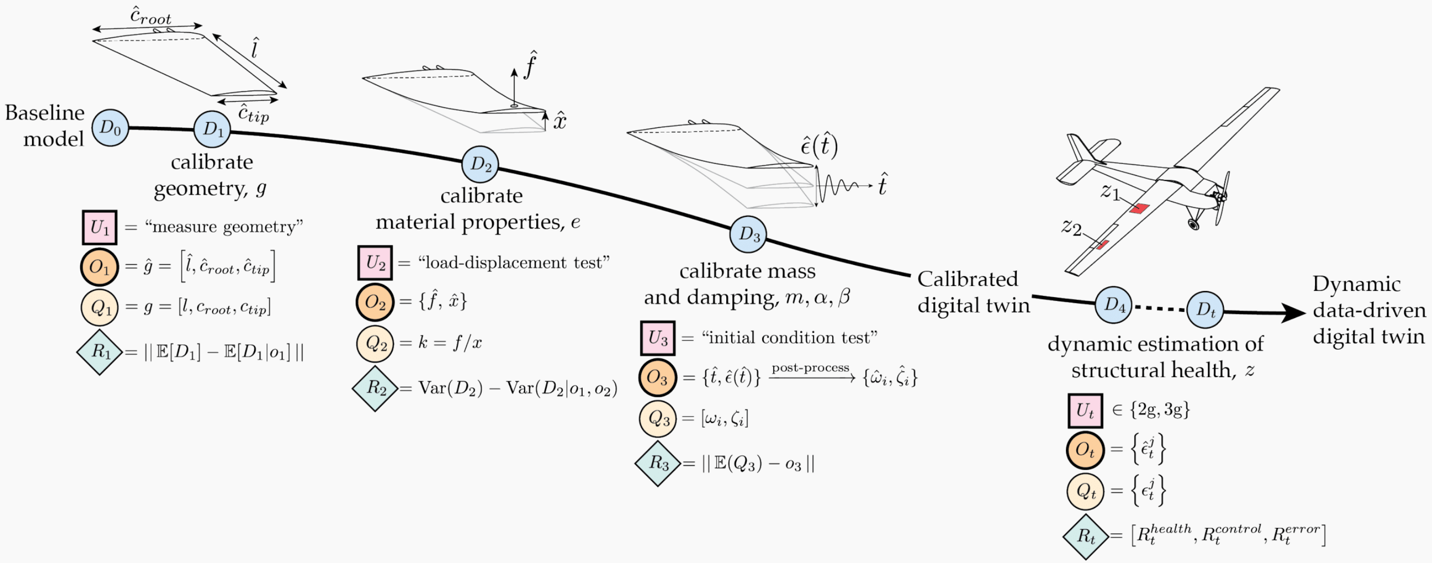
Graph represents joint probability distribution: $p\left(D_0, \dots, D_{t_p}, Q_0, \dots, Q_{t_p}, R_0, \dots, R_{t_p}, U_{t_c+1}, \dots, U_{t_p} \;\middle|\; o_0, \dots, o_{t_c}, u_0, \dots, u_{t_c}\right)$

Creating and evolving a structural digital twin
for an unmanned aerial vehicle



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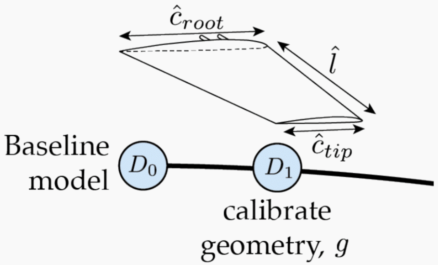


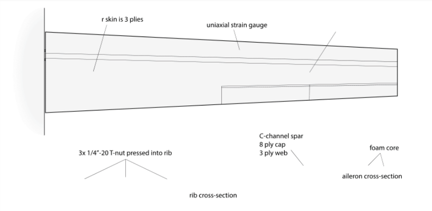
U_1 = "measure geometry"

$O_1 = \hat{g} = \left[\hat{l}, \hat{c}_{root}, \hat{c}_{tip}\right]$

$Q_1 = g = [l, c_{root}, c_{tip}]$

$R_1 = || \mathbb{E}[D_1] - \mathbb{E}[D_1|o_1] ||$

Prior



Observation

D_t	c_{root} [mm]	c_{tip} [mm]	l [mm]
Prior information	$\mathcal{N}(435.6, 1.3)$	$\mathcal{N}(261.1, 1.3)$	$\mathcal{N}(1828.8, 1.3)$
Posterior estimate	433	260	1828

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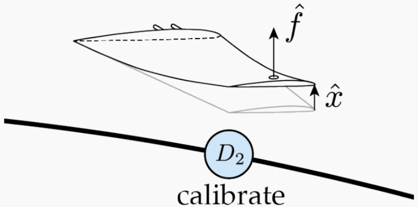
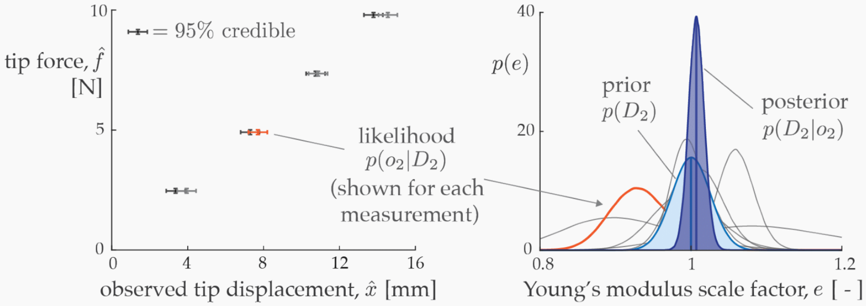


calibrate
material properties, e

- U_2 = "load-displacement test"
- O_2 = $\{\hat{f}, \hat{x}\}$
- Q_2 = $k = f/x$
- R_2 = $\mathrm{Var}(D_2) - \mathrm{Var}(D_2|o_1, o_2)$



D_t	c_{root} [mm]	c_{tip} [mm]	l [mm]	e [-]
Prior information	$\mathcal{N}(435.6, 1.3)$	$\mathcal{N}(261.1, 1.3)$	$\mathcal{N}(1828.8, 1.3)$	$\mathcal{N}(1.0, 0.026)$
Posterior estimate	433	260	1828	1.0073 (0.0103)

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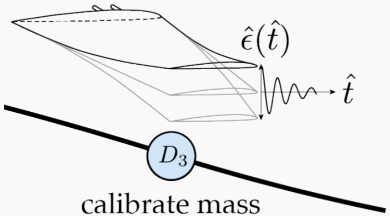


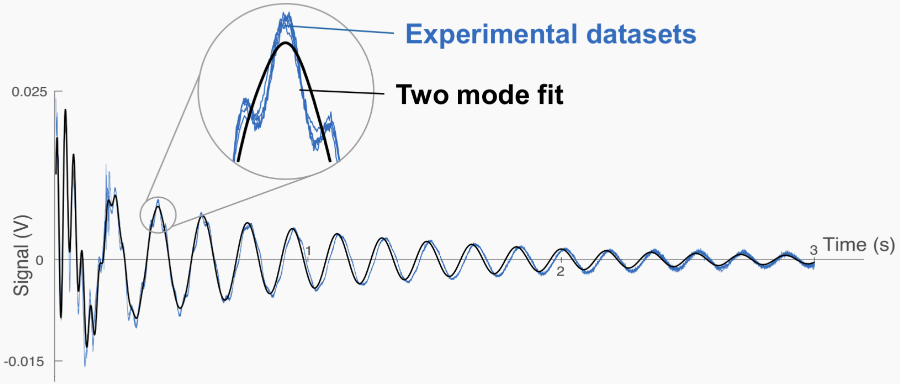
calibrate mass and damping, m, α, β

U_3 = "initial condition test"

$O_3 = \{\hat{t}, \hat{\epsilon}(\hat{t})\} \xrightarrow{\text{post-process}} \{\hat{\omega}_i, \hat{\zeta}_i\}$

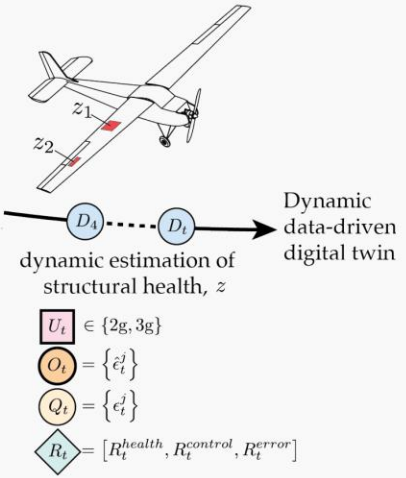
$Q_3 = [\omega_i, \zeta_i]$

$R_3 = || \mathbb{E}(Q_3) - o_3 ||$

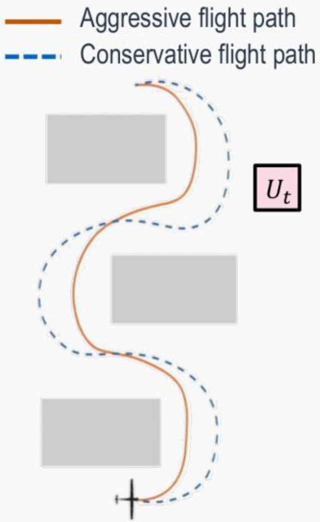


D_t	c_{root} [mm]	c_{tip} [mm]	l [mm]	e [-]	m_{servo} [g]	α [s^{-1}]	β [s]
Prior information	$\mathcal{N}(435.6, 1.3)$	$\mathcal{N}(261.1, 1.3)$	$\mathcal{N}(1828.8, 1.3)$	$\mathcal{N}(1.0, 0.026)$	$2m_{servo}+m_{pitot}=472$ $m_{servo}, m_{pitot} \geq 0$	0	0
Posterior estimate	433	260	1828	1.0073 (0.0103)	169.1 (3.9)	1.030 (0.001)	7.66×10^{-4} (6.18×10^{-7})

[1] Willcox K. et al., Predictive Digital Twins, CIS Digital Twin Days, 2021



- Aircraft undergoes in-flight structural health degradation
- 24 wing-mounted sensors provide noisy strain data O_t
- Digital twin is dynamically updated and used to drive mission re-planning
- Scenarios are simulated in ROS



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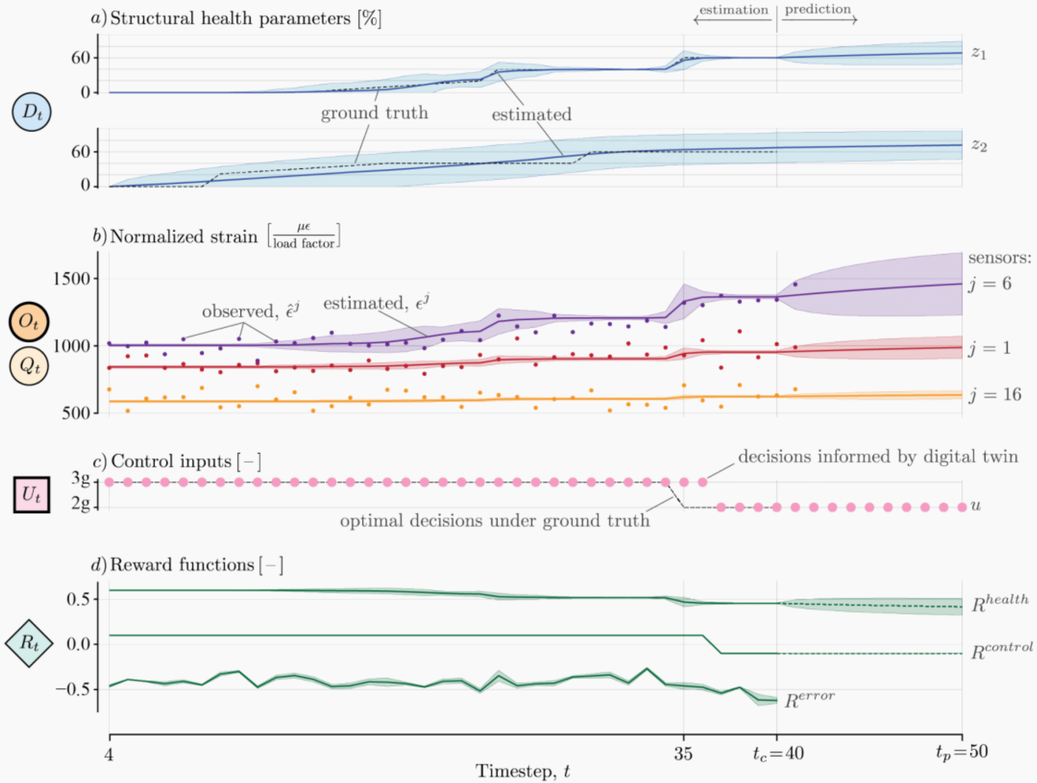

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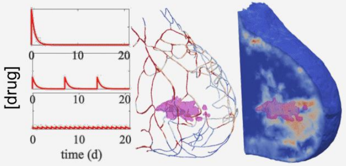
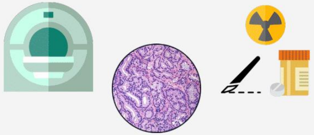
Digital Twin of Patient

D_t Digital Twin State
Tumor dynamics, mechanics

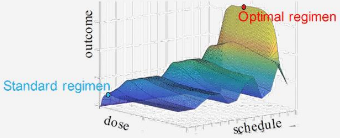


U_t Control inputs
MRI studies, biopsies, treatment regimens

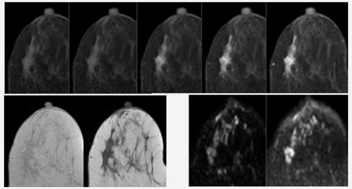


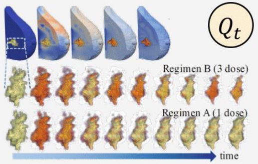
S_t Physical State
Anatomy & morphology, mechanical & physiological state

R_t Reward
Patient outcomes: treatment efficacy, toxicity



O_t Observational data
Anatomy, perfusion, permeability, cell density, metabolism





Q_t Quantities of Interest
Distribution of therapies, tumor shape, cell density

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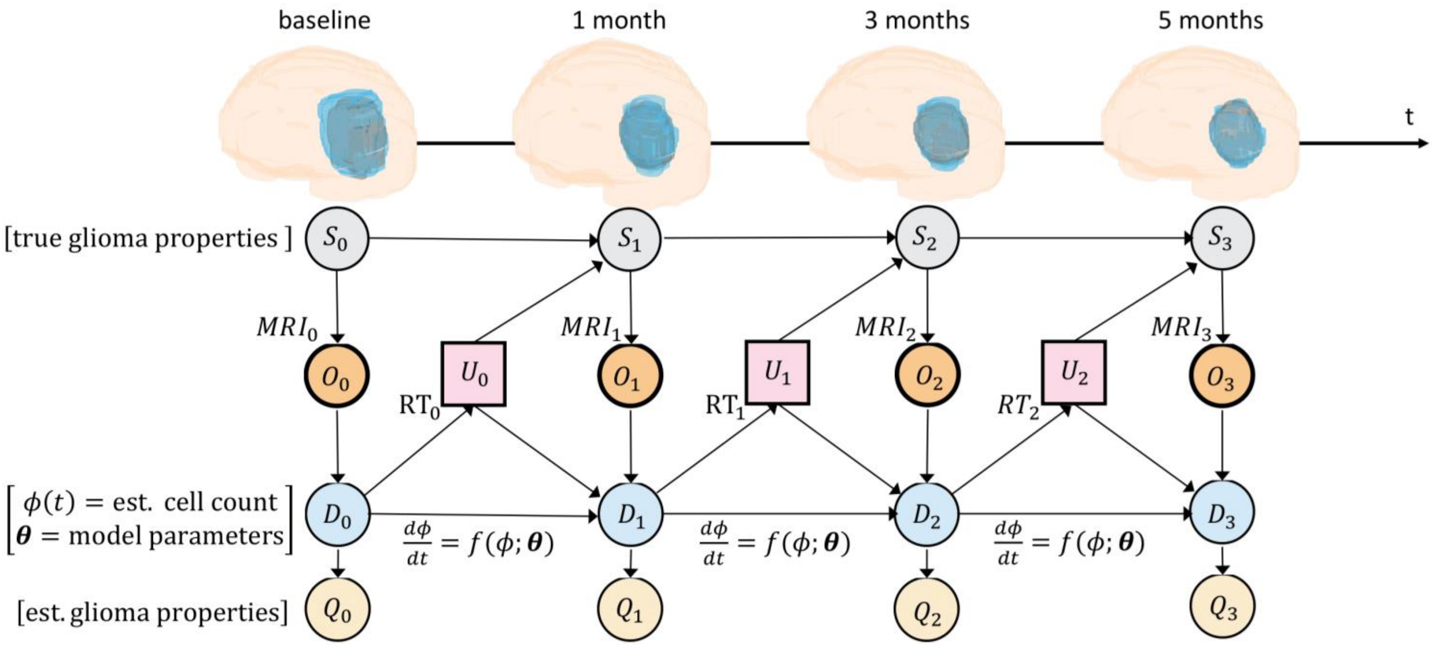
Digital Twin of Patient



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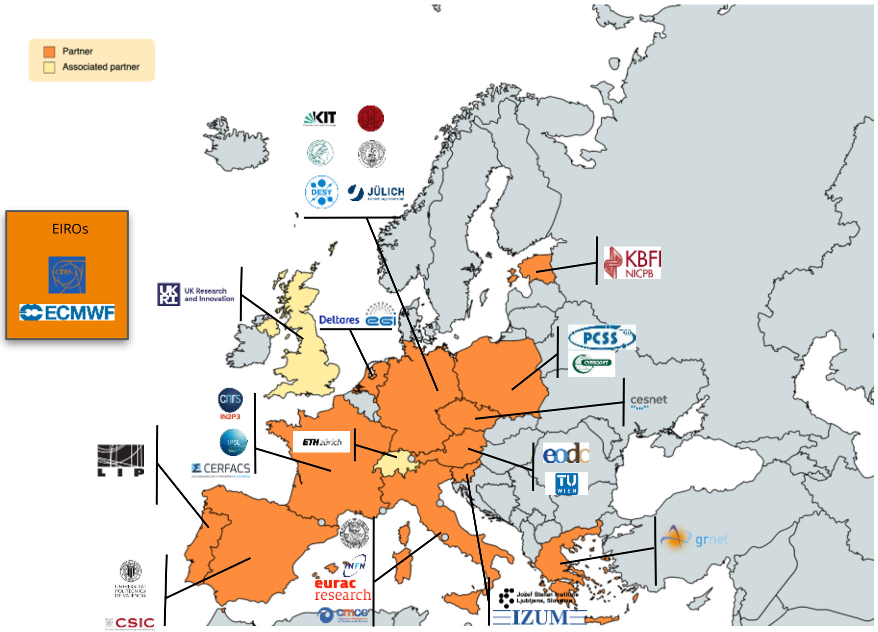
interTwin overall objective

Co-design and implement the prototype of an interdisciplinary Digital Twin Engine.

Digital Twin Engine

- It is an **open-source platform** based on open standards.
- It offers the capability to integrate with **application-specific Digital Twins**.
- Its functional specifications and implementation are based on
  - a **co-designed interoperability framework**
  - conceptual model of a DT for research - **the DTE blueprint architecture**.

Consortium Overview



EGI Foundation as coordinator

29 **Participants**, including 1 affiliated entity and 2 associated partners

Consortium at a glance

10 Providers	11 Technology providers	14 Community representants
cloud, HTC , HPC resources and access to Quantum systems	delivering the DTE infrastructure and horizontal capabilities	from 5 scientific areas; requirements and developing DT applications and thematic modules

Link with Destination Earth

- **Collaboration with ECMWF**
  Demonstrators of **data handling across interTwin and DestinE DTs** for the Extremes and Climate in production-type configurations.

- **Collaboration with DestinE**
  Development of **common software architecture concepts** that are also **applicable to other major DTs initiatives**.

Requirements

- **Online Learning**
  The DTE shall enable handling **stream of data** larger than 10MB/s

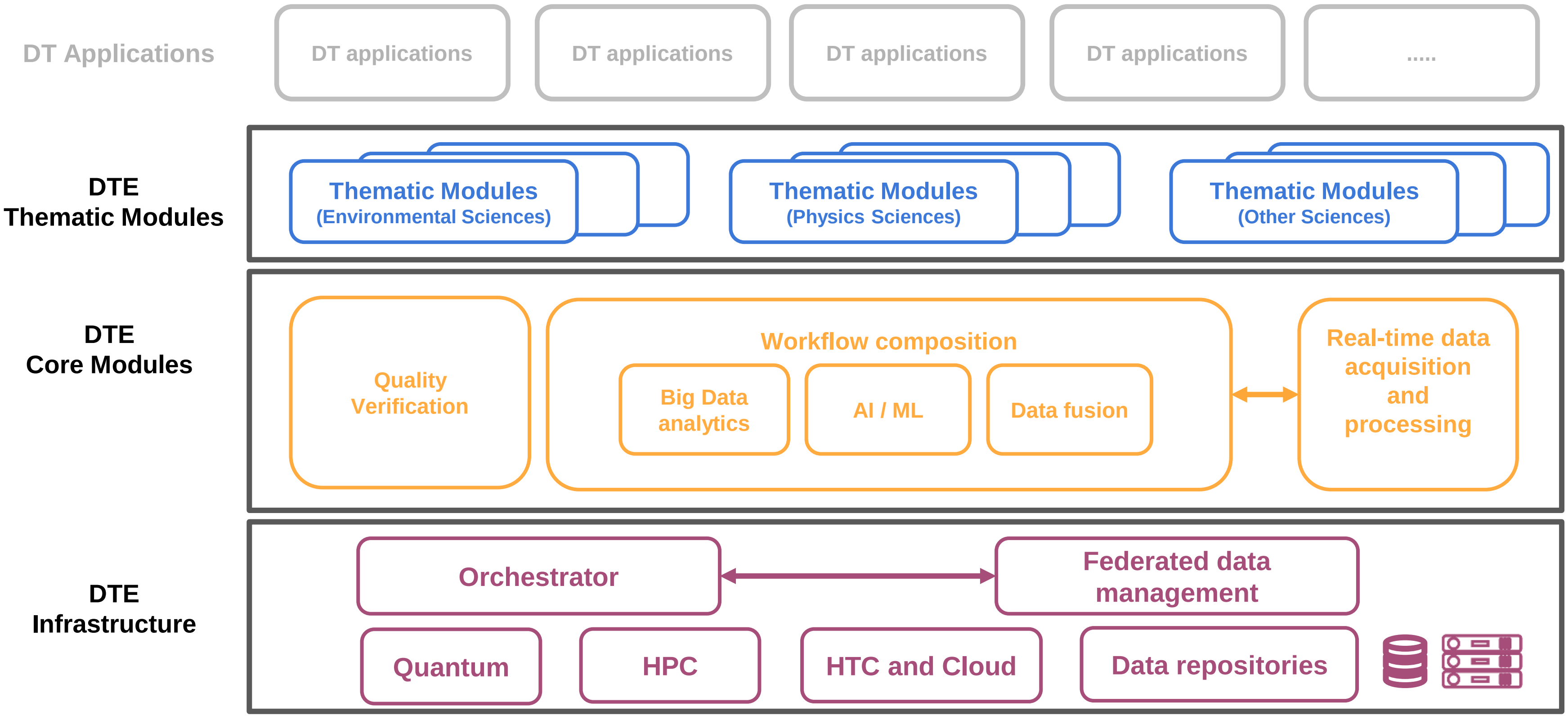
- **Federated Learning**
  The DTE shall to able to **transmit/receive data synchronically** (at least aperiodically) between different HPC providers

- **Hyperparameter Optimization**
  The DTE shall support HPO frameworks (RayTune, etc).

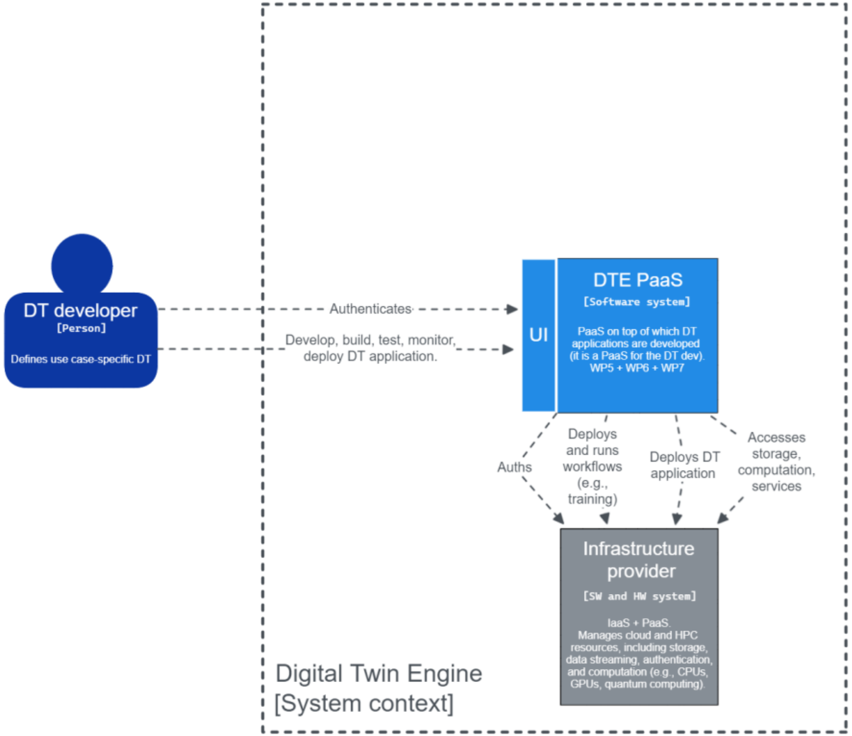
- **Unified access to infrastructure**
  DTE shall enable **homogeneous security and access policies**, resource accounting to HPC, HTC and cloud providers

- **Bridge difference in infrastructure needs**
  The DTE shall be usable by sciences with **vast differences in compute/storage** needs

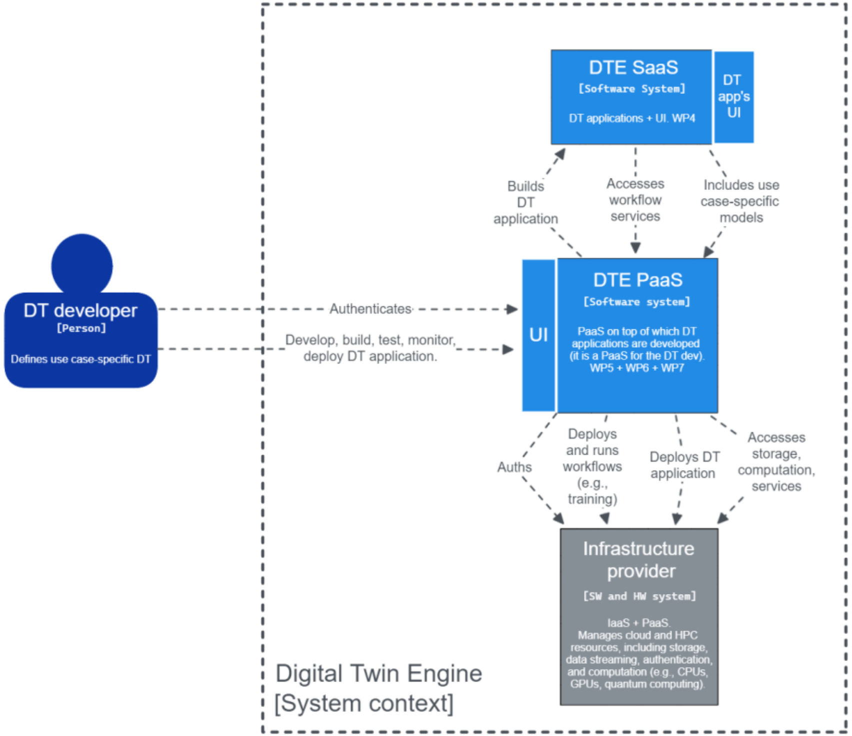
interTwin components



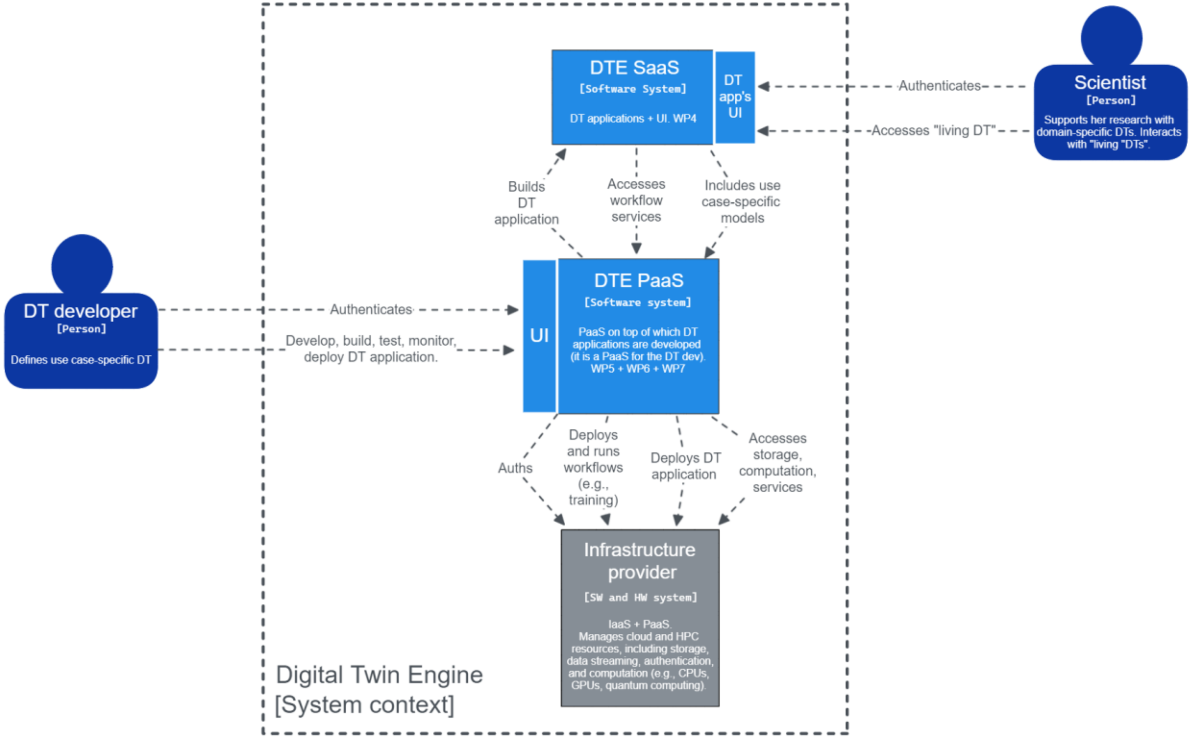
Digital Twin Engine



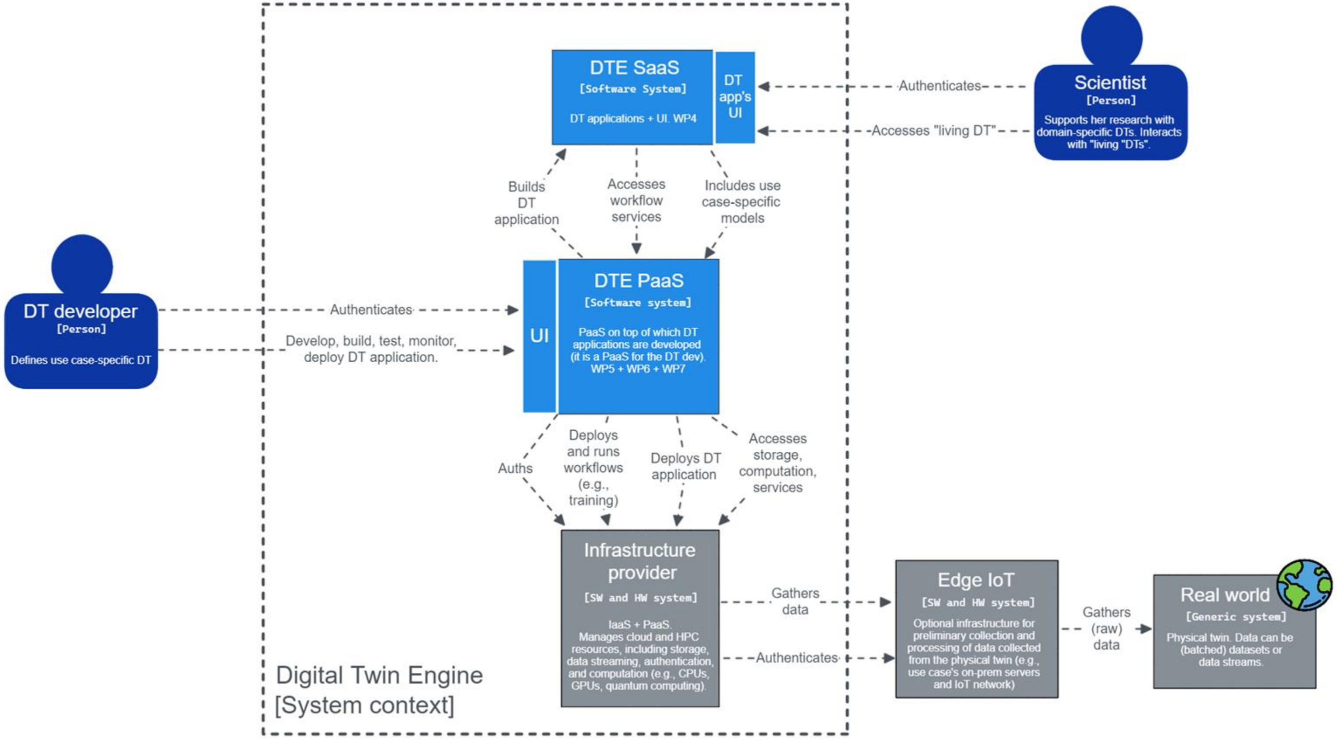
Digital Twin Engine (2)



Digital Twin Engine (3)

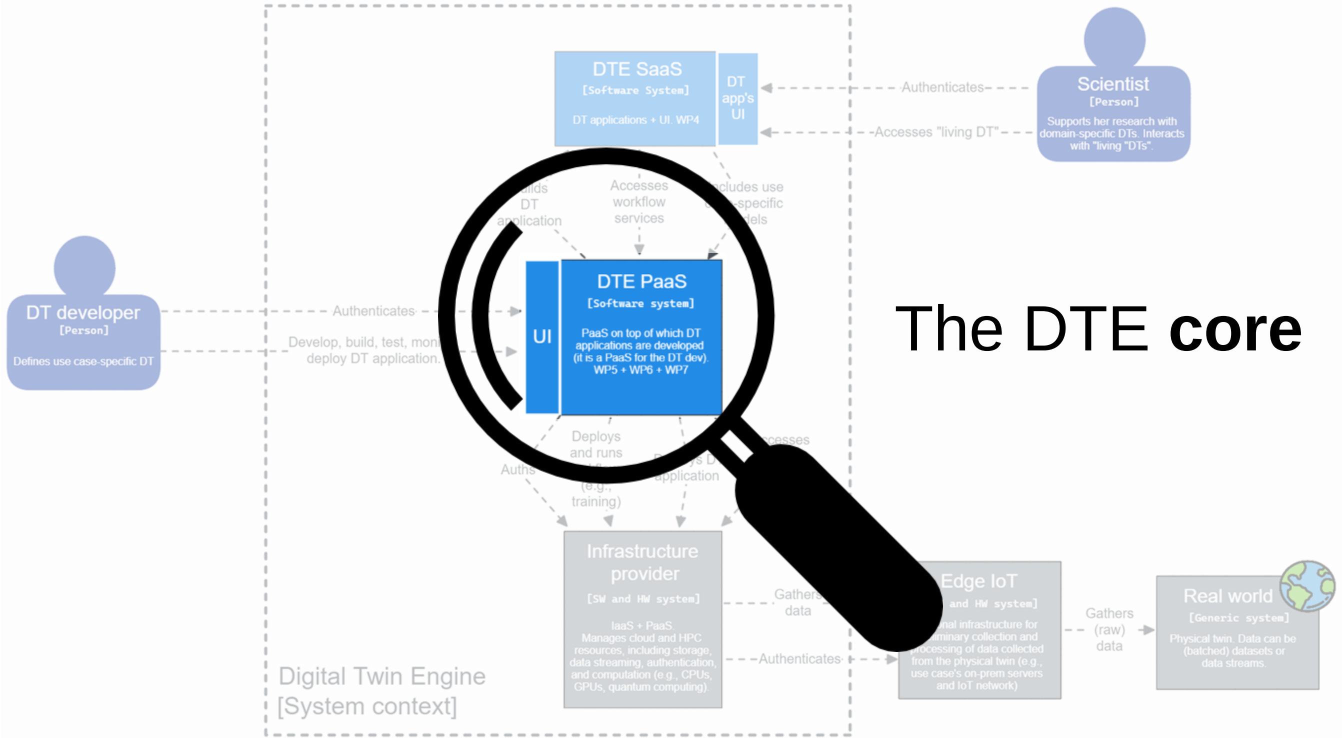


Digital Twin Engine (4)



Zoomable version: https://cernbox.cern.ch/s/EBandsayghMcFtG

Digital Twin Engine (4)

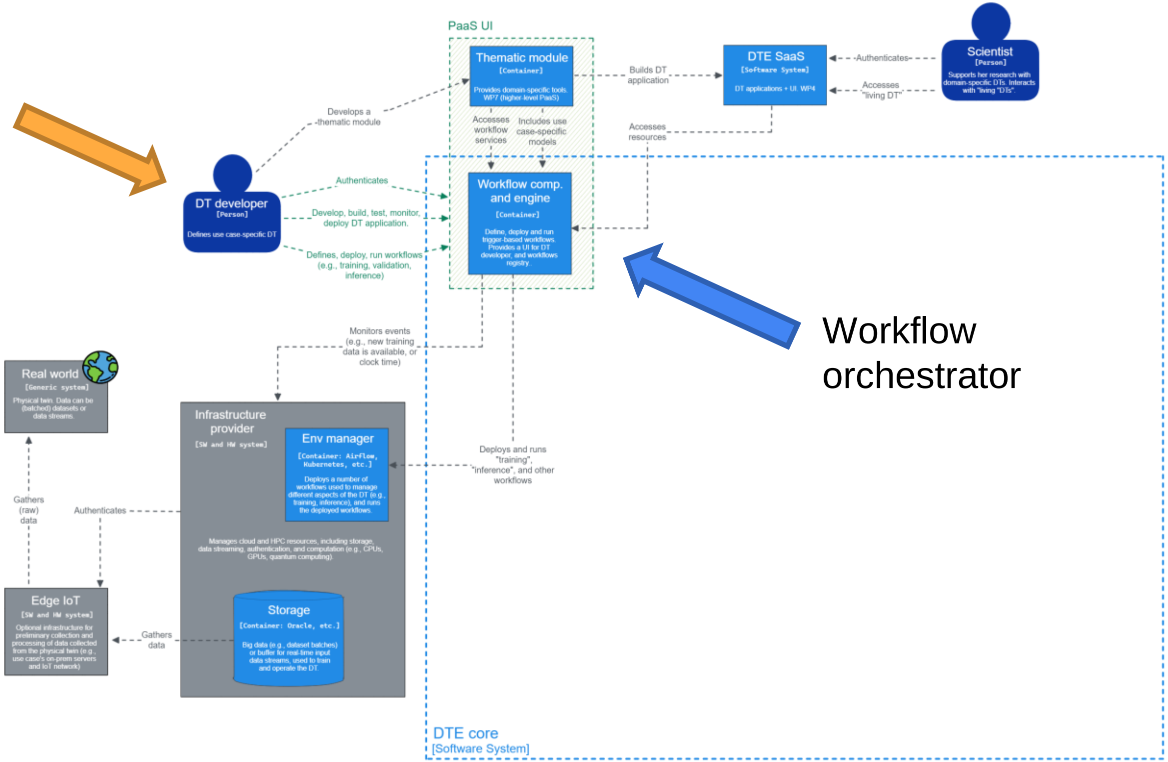


The DTE **core**

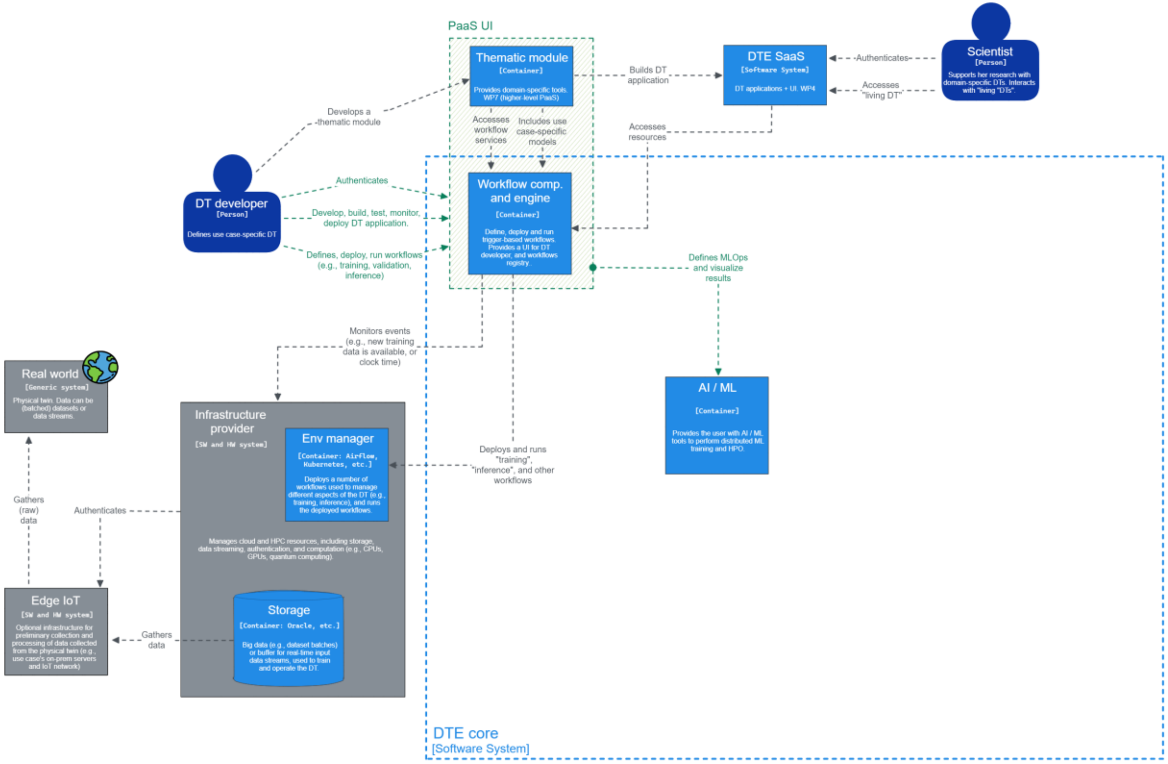
DT workflow composition

DT developer

Workflow orchestrator



DT workflow composition (2)



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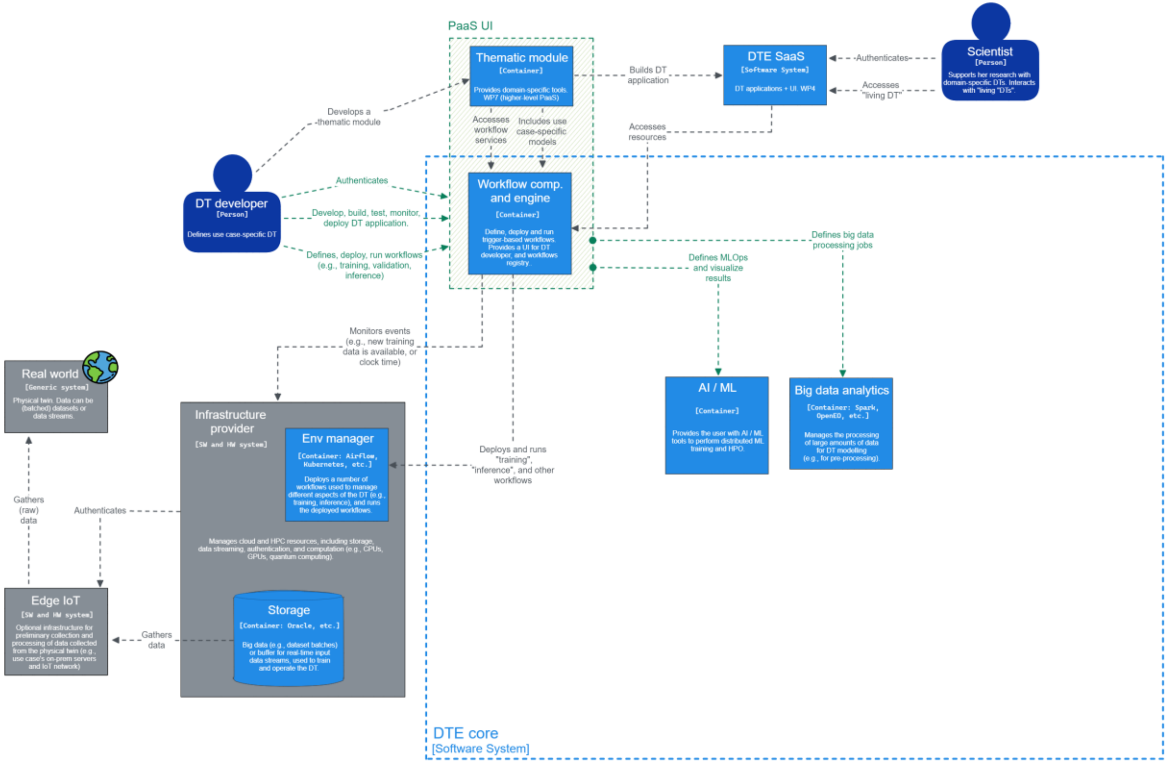
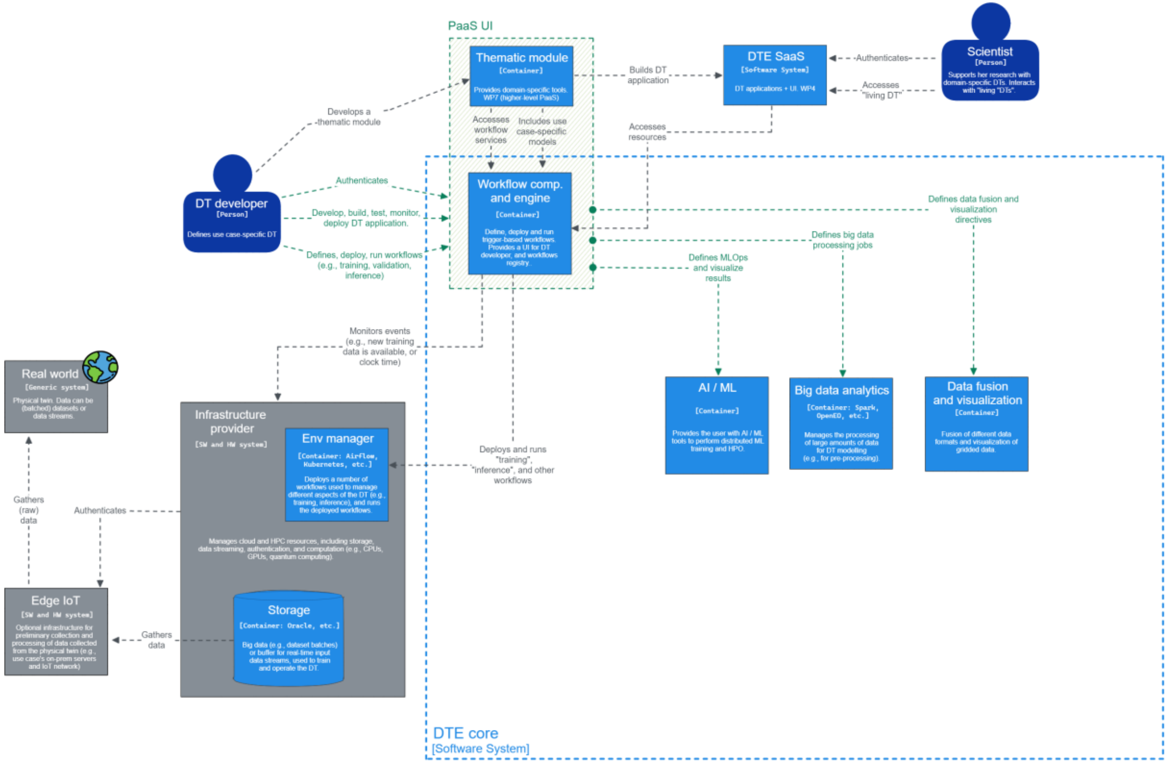
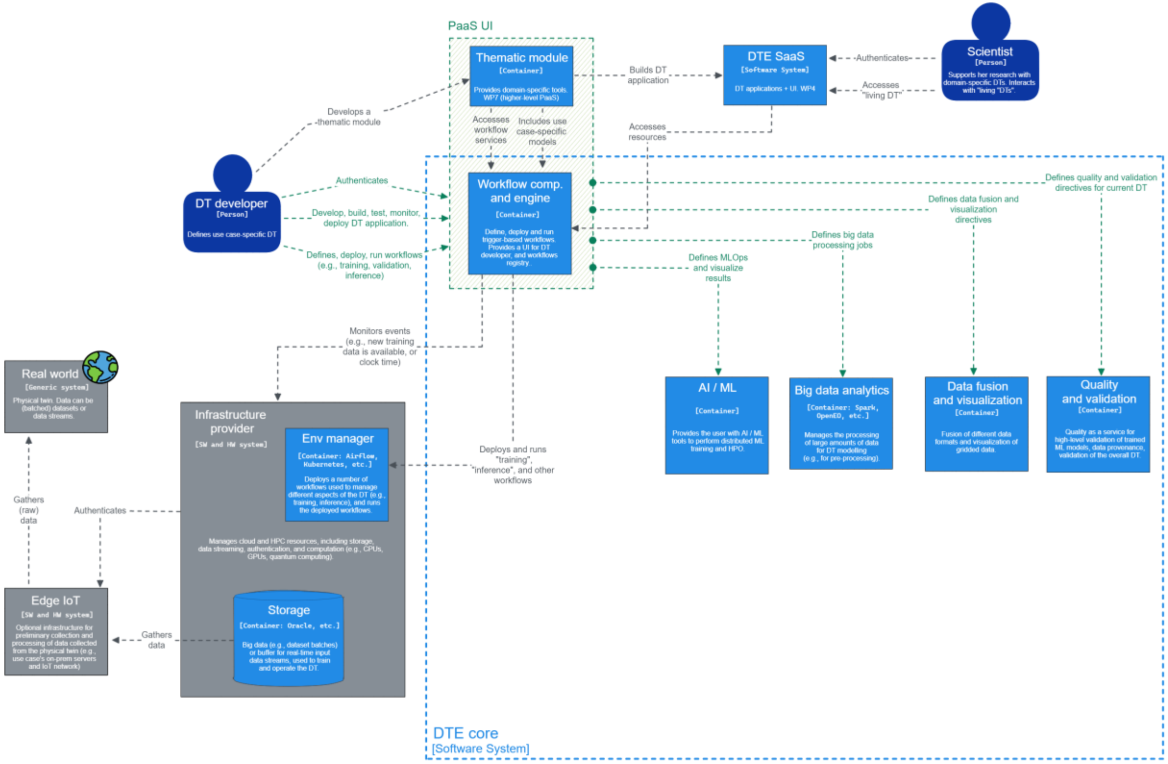


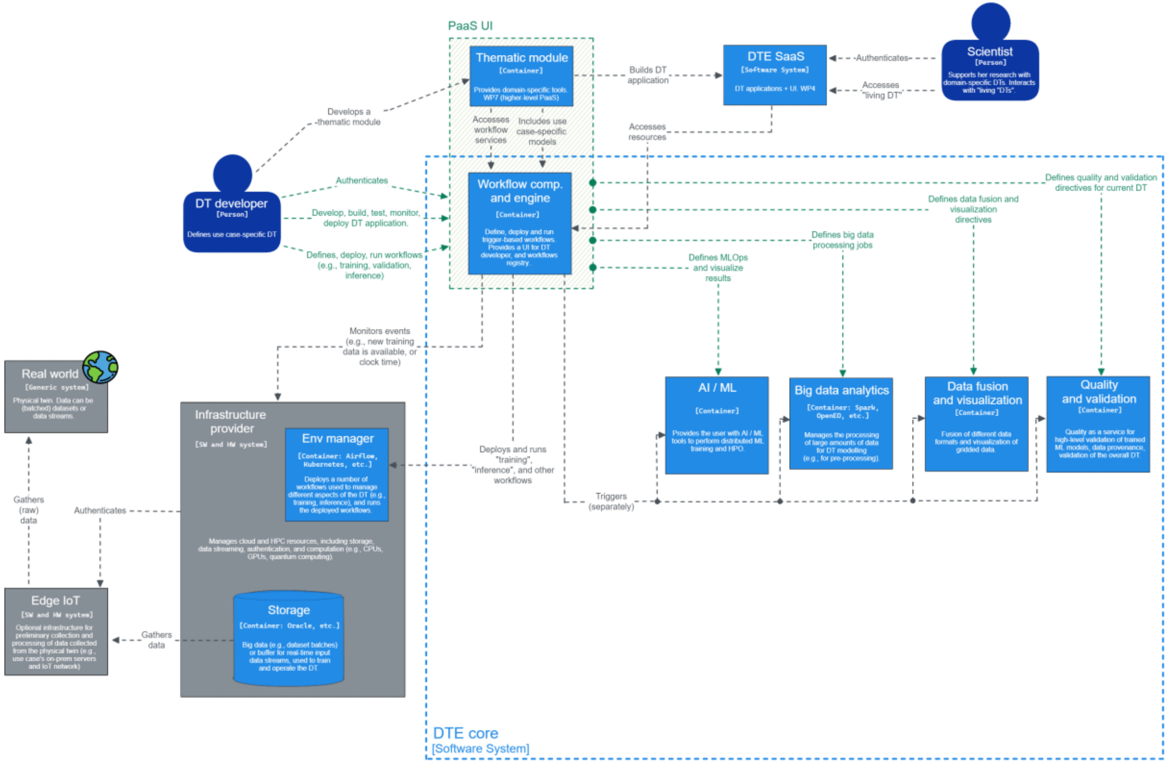
DT workflow composition (4)



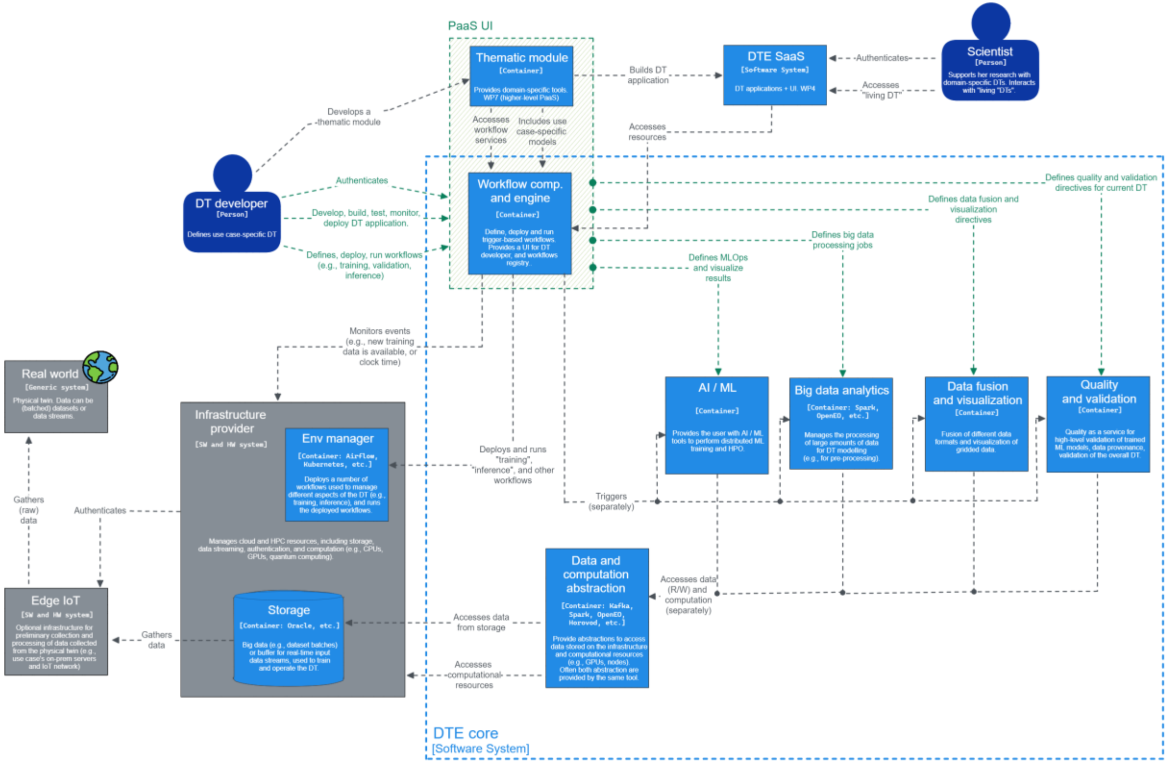
DT workflow composition (5)



DT workflow composition (6)



DT workflow composition (7)



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Earth Observation

Cyclone Classification

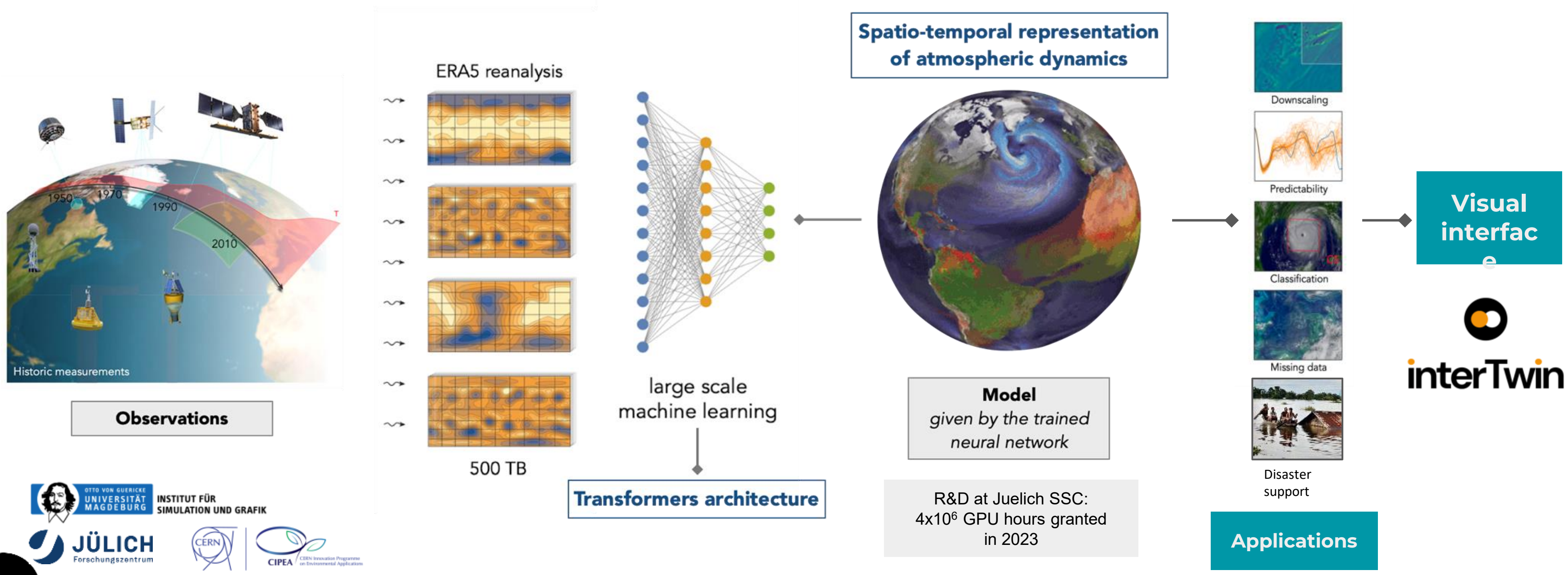
Fire Hazard Map Generation

Early Flood Warnings

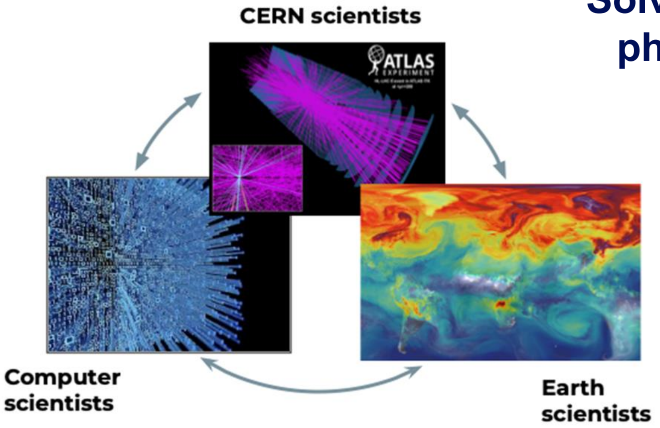
Drought Prediction

EMP^2: Environmental Modelling and prediction platform

First proof-of-concept of a machine-learning based global environmental model trained on terabytes of observational data



Why CERN?



Solve common scientific challenge(s) in high-energy physics and weather/climate science using AI/ML

Model complex, nonlinear phenomena and improve current simulations

Access multi-scale dependencies of a given process

Earth science: eg. better understand convection phenomena

CERN: eg. particle-jet showers reconstruction

Condense dataset information in a compact representation

better handle the information in downstream applications.

eg. condense the info in a few GB rather than TB

Explore potential of unsupervised learning for scientific applications

Extract new information directly from data

eg. learn unknown correlation patterns

Earth science: eg. early detection of extreme events

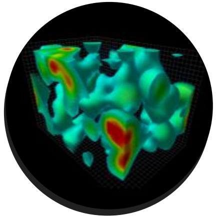
CERN: eg. anomaly detection

Common Goal:

Develop a proof of concept of representation learning for scientific applications based on observations

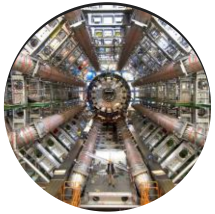
Physics

Radio Astronomy



Quantum Field Theory

Gravitational Wave Astronomy



High Energy Physics

Thank you!

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References

- [1]: Sharma, Angira, Edward Kosasih, Jie Zhang, Alexandra Brintrup, and Anisoara Calinescu. ‘Digital Twins: State of the Art Theory and Practice, Challenges, and Open Research Questions’. *Journal of Industrial Information Integration* 30 (1 November 2022): 100383. https://doi.org/10.1016/j.jii.2022.100383.
- [2]: [EPFL] Predictive Digital Twins: From Physics-Based Modeling to Scientific Machine Learning, n.d. https://www.youtube.com/watch?v=ZuSx0pYAZ_I&ab_channel=CenterforIntelligentSystemsCISEPFL