A Double-Helix Model for the V&V of Physical and Digital Twins

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What is a Digital Twin?

Digital Twins $\longrightarrow$ Digital Models

Digital Models $\nrightarrow$ Digital Twins

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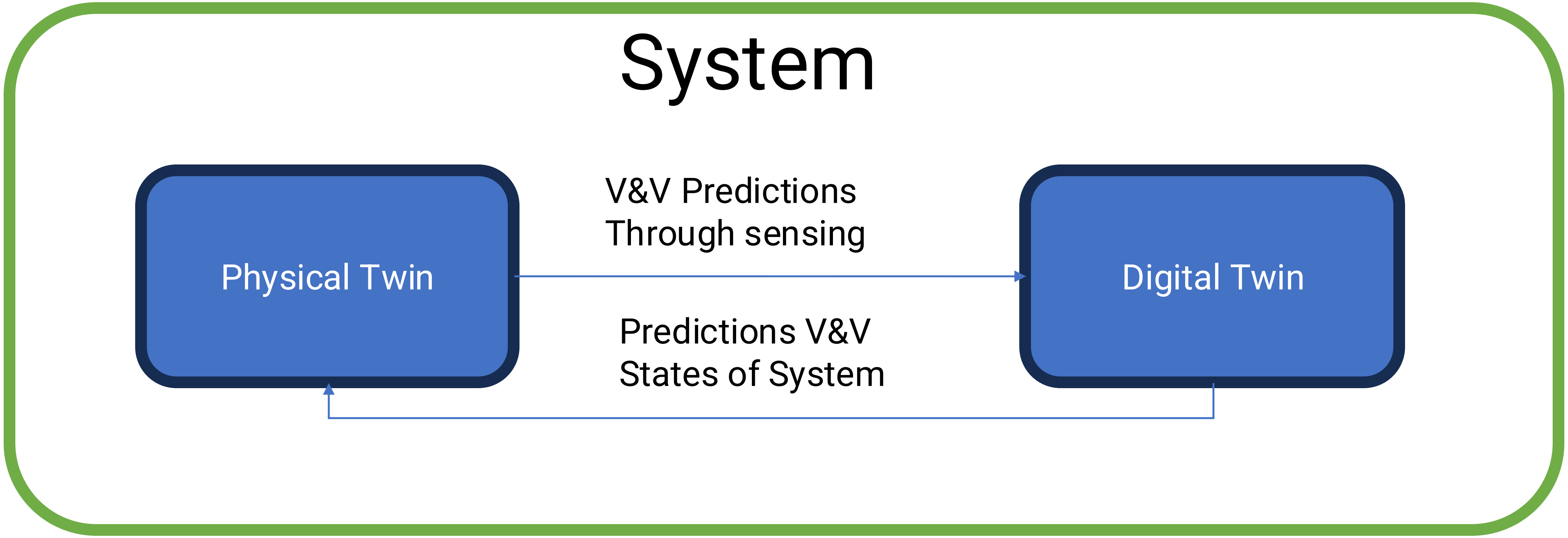
V&V Bi-directional Relationship



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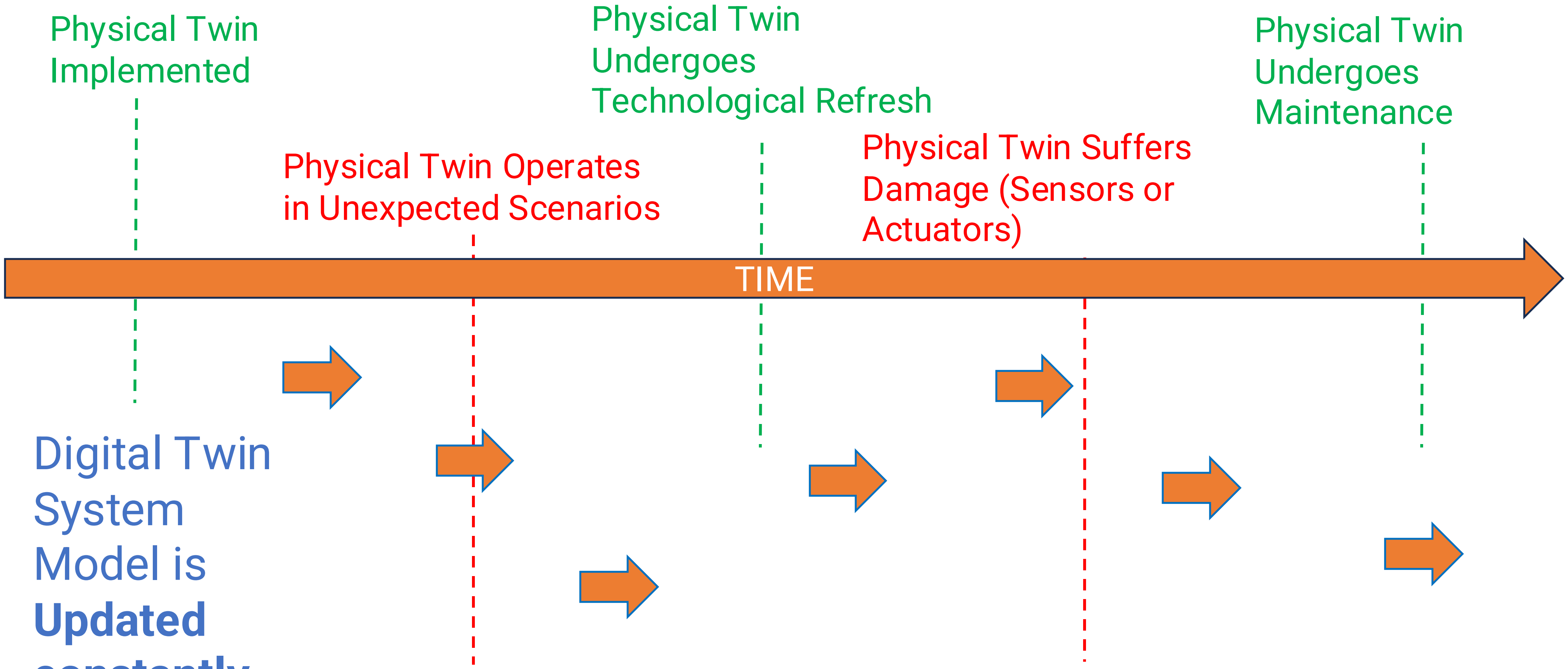
V&V for Digital Twins / Real – Time Updated Models for Digital Twins



Digital Twin System Model is **Updated constantly**

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Maturity Levels

No Digital Twin

Physical Asset

Digital Asset

Ideas + Concept

Analytical Models Without Data

Manufactured System

Models correlated with Data

Characterized System

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Maturity Levels

Physical Twin

Heavily Instrumented System for Real-Time Monitoring

Digital Twin

Real-Time Data Integration

Physics-Informed AI for Bridging Gaps

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Why Physics Informed AI

Analytical Models	AI Only Models
System Model Mis-specification	Subject to Data Quality
Lack of Adaptability	Requires Large Quantities of Data
	Not Interpretable

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Why Physics Informed AI

Adaptable

Physics-Informed AI Models

Less subject to Data Quality

Interpretable

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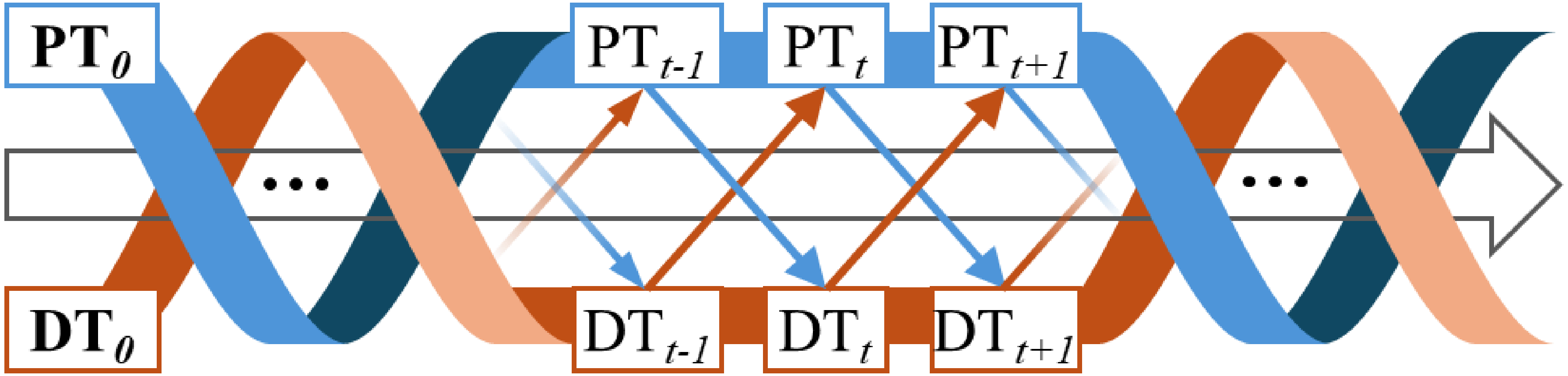
Dynamical Nature of Physical/Digital Twins



- **Recognize the dual verification** of the Physical to Digital Twin verification (Associated System verifies associated models). Digital Twin verifies the physical system (System model verifies the system).
- Identify **expected and unexpected changes** in underlying system dynamics **over time** and study the impact of such changes in the **correctness of the Twins**.
- Twins Verification is **dynamic and should happen constantly over time**.

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THANK **YOU**

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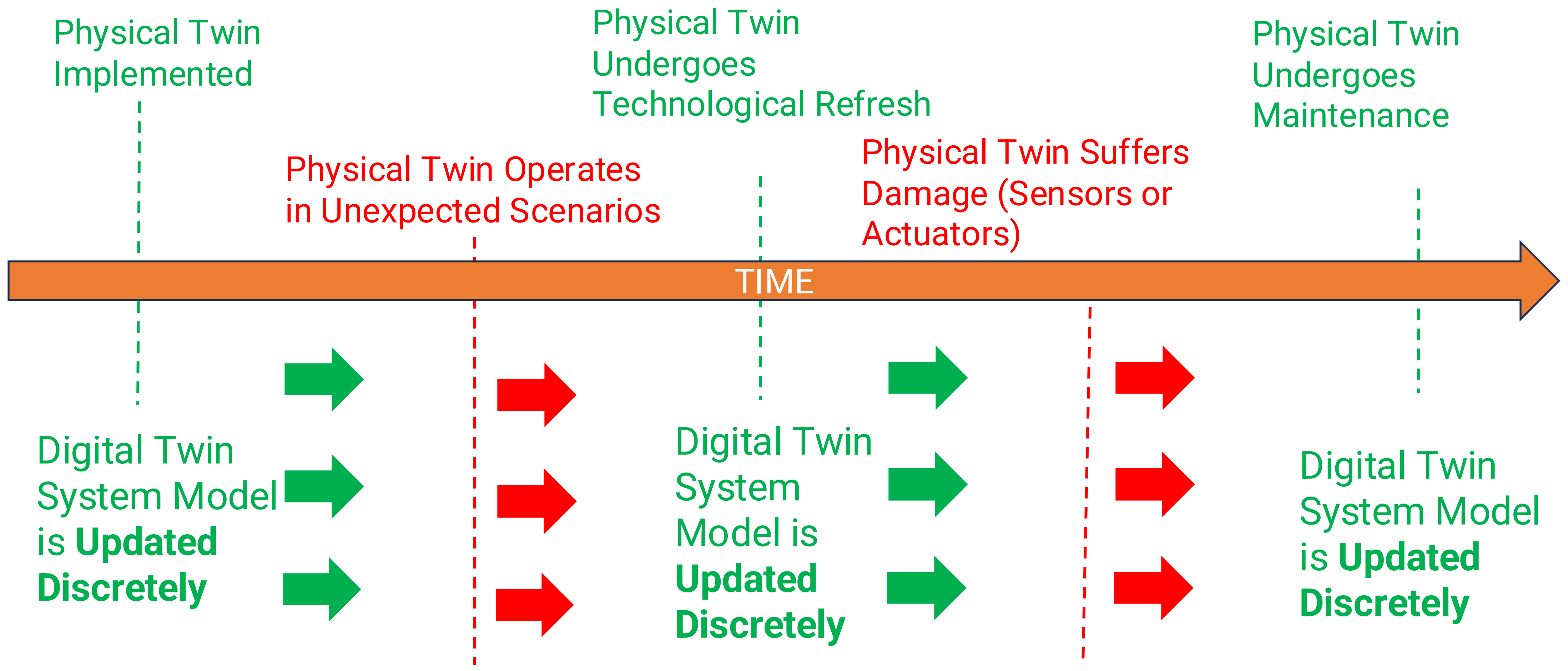
V&V for Digital Twins / Analytical Models for Digital Twin



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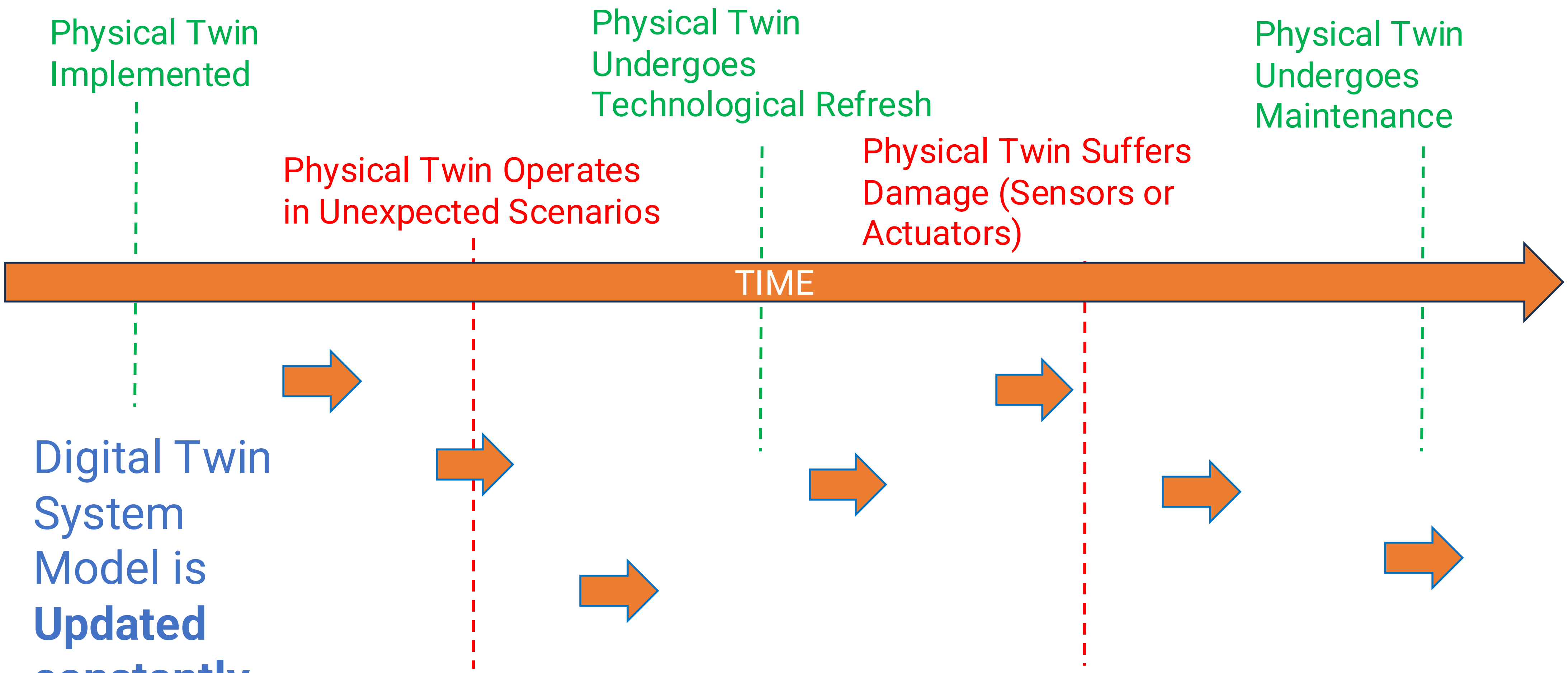
V&V for Digital Twins / Black Box Models for Digital Twin



Digital Twin System Model is **Updated constantly**

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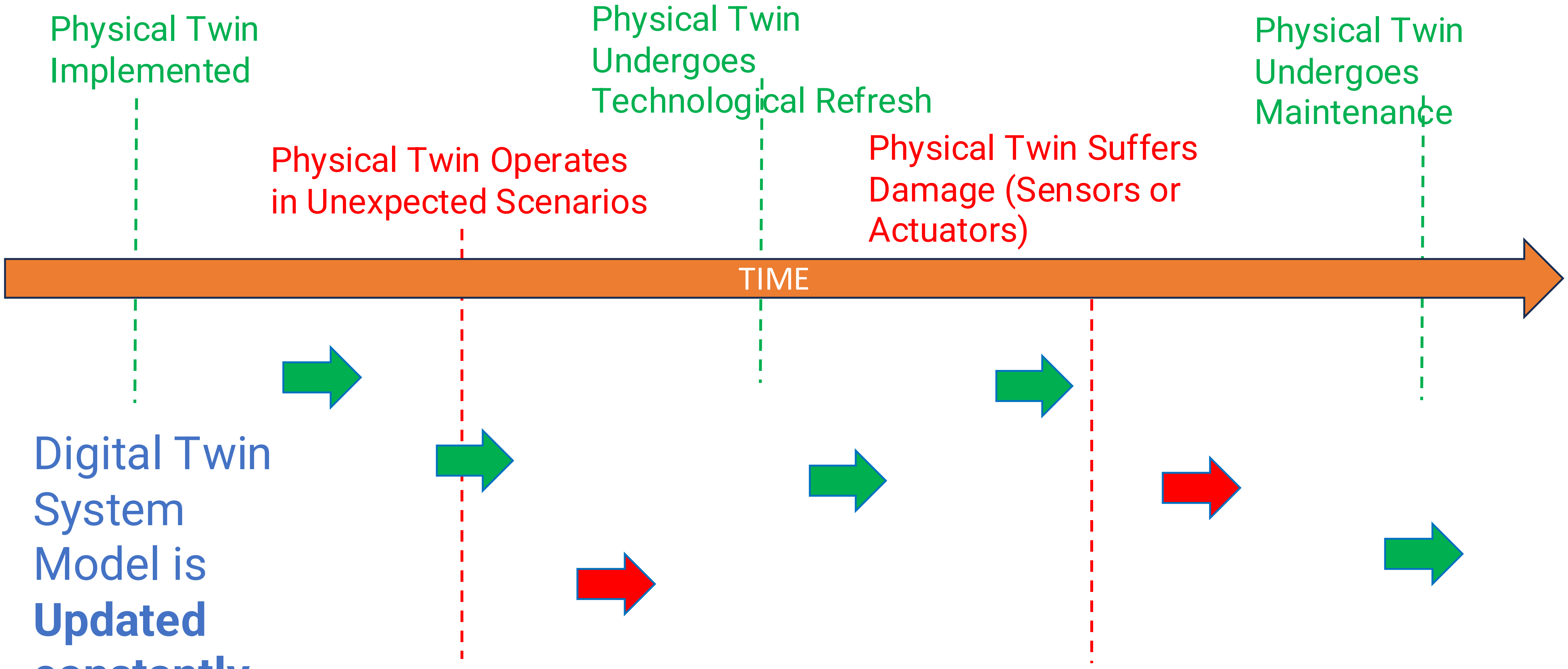
V&V for Digital Twins / Conditional Model Based Neural Networks for Digital Twin



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Analytical Models

Fixed Models: Crafted when system is deployed once and for all

Trainable Parameters: Can be updated as data is gathered

Bayesian Parameters: Can be updated as data is gathered. Characterizes uncertainty of the predictions

- Can adapt to any function in the function space defined by the relationships in the model.
- Totally Interpretable.

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Black-Box Models

Fixed Models: Crafted when system is deployed once and for all → Trainable Parameters: Can be updated as data is gathered → Bayesian Parameters: Can be updated as data is gathered. Characterizes uncertainty of the predictions

- Can adapt to any function through Universal Approximation Guarantees.
- Predictability Robustness.
- Lack of Interpretability.

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Conditional Models

$$P_{black|white} = \frac{P_{white,black}}{P_{white}}$$

$$f_{black|white} = \mathbb{E}[\mathrm{P}_{black|white}]$$

- If Analytical Models and Black-Box models are defined probabilistically, a conditional model can be developed.
- The conditional model uses the robustness of the Black-Box models while allowing to discriminate when are both models agreeing or disagreeing.

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Conclusions

- Acknowledging the dual feedback V&V loop between the Physical and Digital twins provides a better framework for defining the V&V activities of the integrated system.
- Acknowledging the dynamic nature of the underlying dynamics of the system should guide the V&V activities of the twins.
- Using trainable Bayesian models improves not only the robustness of the models by allowing them to accommodate newly acquired data but also it allows the user to understand how certain the model is.
- The use of conditional models leverages the benefits of analytical and black-box models in a principled way.

Current Verification Strategies

- Static Verifications:

Physical Twin Verification

$$\hat{f}(i_t) = \{\hat{a}_{t+1}, \hat{s}_{t+1}, \hat{o}_{t+1}\}$$

$$|\hat{s}_{t+1}| \leq \epsilon_s, |\hat{o}_{t+1}| \leq \epsilon_o$$

The digital twin verifies that predicted next states and outputs are bounded given a prescription

Digital Twin Verification

$$|s_{t+1} - \hat{s}_{t+1}| \leq \epsilon_{s_{t+1}}, |o_{t+1} - \hat{o}_{t+1}| \leq \epsilon_{o_{t+1}}$$

The sensed states and outputs from the physical twin verify that the predictions of the digital twin are not too far from reality.

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Current Validation Strategies

- Static Validation:

Physical Twin Validation

$$\epsilon_{c_{lb}} \leq f_c(\hat{a}_{t+1}, \hat{s}_{t+1}, \hat{o}_{t+1}) \leq \epsilon_{c_{ub}}$$

The realized actions, states and outputs by the physical twin are constrained as per the system objectives.

Digital Twin Validation

$$\epsilon_{p_{lb}} \leq f_p(a_{t+1}, s_{t+1}, o_{t+1}) \leq \epsilon_{p_{ub}}$$

The performance metrics of the integrated system are meet.

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Current Verification/Validation Strategies

- Failure under Static vision

$$\left|f_{s_t} - f_{s_{t+n}}\right| \geq 0, \left|f_{o_t} - f_{o_{t+n}}\right| \geq 0$$

If the underlying dynamics evolve, the condition above holds true and the verified/validated twins are no longer correct.

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Allowing Trainable Models

- Trainable Parameters in White Box models (analytical models)
- Trainable Parameters in Black Box models (artificial intelligence models)
- Probabilistic Modeling through Bayesian Updates

Some preliminary results…

- Sample data from the harmonic and the dumped harmonic oscillator.

$$(t, y_1) \in \mathcal{D}_1, t \in [0,10], y_1 = x_0 \cos(\omega t) + \frac{v_0}{\omega} \sin(\omega t)$$

$$(t, y_2) \in \mathcal{D}_2, y_2 = e^{-\gamma t}\left(x_0 \cos(\omega_d t) + \frac{v_{0+x_0\gamma}}{\omega_d} \sin(\omega_d t)\right)$$

- Use the harmonic oscillator as the system model and let the MCMC algorithm discover the posterior distribution of the parameters driving the system model.
- Construct the CMBBNN and observe if the Bayesian System Model properly informs the predictions of the Bayesian Neural Network.

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Some preliminary results