Prognostics for Systems Health Management - Model and Hybrid Based Approaches. Where are we heading?

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Acknowledgement

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Collaborators

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Prognostics

- Enables:
  - Adopting condition-based maintenance strategies, instead of time-based maintenance
  - Optimally scheduling maintenance
  - Optimally planning for spare components
  - Reconfiguring the system to avoid using the component before it fails
  - Prolonging component life by modifying how the component is used (e.g., load shedding)
  - Optimally plan or replan a mission
- System operations can be optimized in a variety of ways

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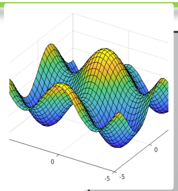
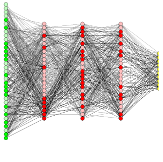
Current Approaches



Results tend to be intuitive
Models can be reused
If incorporated early enough in the design process, can drive sensor requirements
Computationally efficient to implement
Model development requires a thorough understanding of the system
High-fidelity models can be computationally intensive



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Data-Driven Methods

Pros

- Easy and Fast to implement
  - Several off-the-shelf packages are available for data mining
- May identify relationships that were not previously considered
  - Can consider all relationships without prejudice

Cons

- Requires lots of data and a “balanced” approach
  - Most of the time, lots of run-to-failure data are not available
  - High risk of “over-learning” the data
  - Conversely, there’s also a risk of “over-generalizing”
- Results may be counter- (or even un-)intuitive
  - Correlation does not always imply causality!
- Can be computationally intensive, both for analysis and implementation

Example techniques

- Regression analysis
- Neural Networks (NN)
- Bayesian updates
- Relevance vector machines (RVM)

Physics-Based Methods

Description of a system's underlying physics using suitable representation

Some examples:

- Model derived from "First Principles"
  - Encapsulate fundamental laws of physics
    - PDEs
    - Euler-Lagrange Equations
- Empirical model chosen based on an understanding of the dynamics of a system
  - Lumped Parameter Model
  - Classical 1^{st} (or higher) order response curves
- Mappings of stressors onto damage accumulation
  - Finite Element Model
  - High-fidelity Simulation Model

Something in the model correlates to the failure mode(s) of interest

Physics-Based Models

Pros
- Results tend to be intuitive
  - Based on modeled phenomenon
  - And when they're not, they're still instructive (e.g., identifying needs for more fidelity or unmodeled effects)
- Models can be reused
  - Tuning of parameters can be used to account for differences in design
- If incorporated early enough in the design process, can drive sensor requirements (adding or removing)
- Computationally efficient to implement

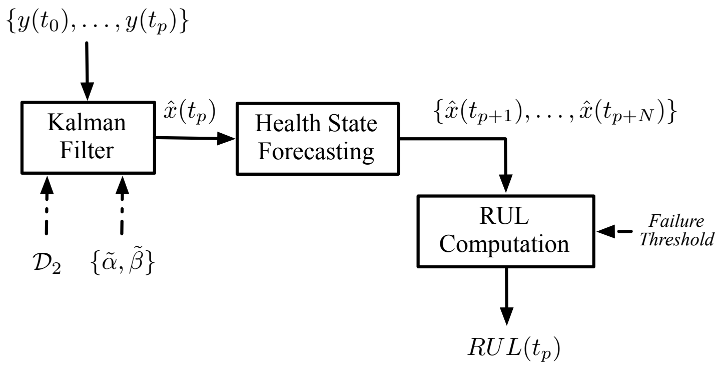
Cons
- Model development requires a thorough understanding of the system
- High-fidelity models can be computationally intensive

Examples
- Paris-Erdogan Crack Growth Model
- Taylor tool wear model
- Corrosion model
- Abrasion model

Model-based prognostics

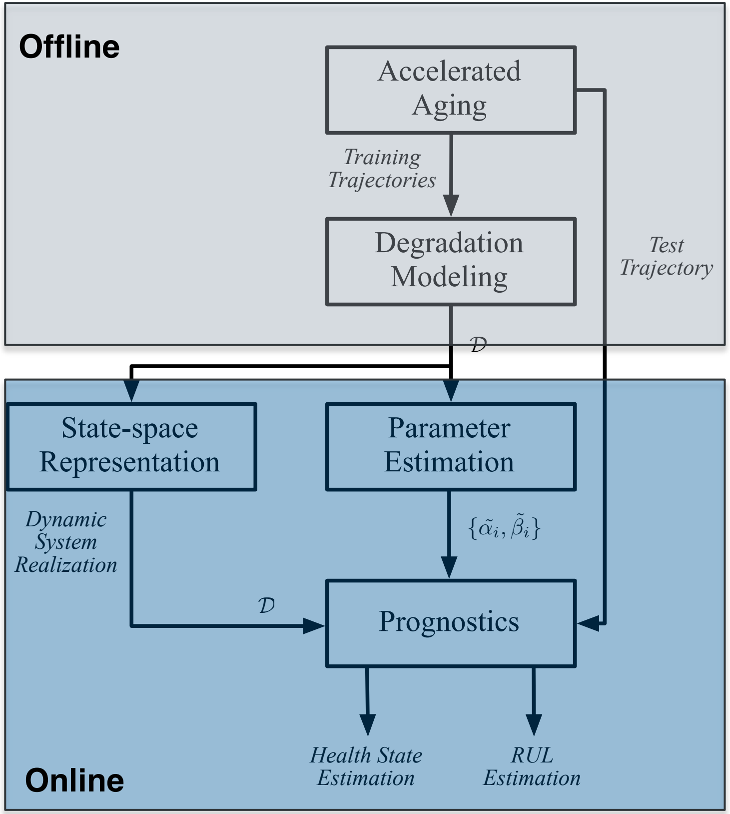
- State vector includes dynamics of normal and degradation process

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$
$$y_k = Hx_k + v_k$$



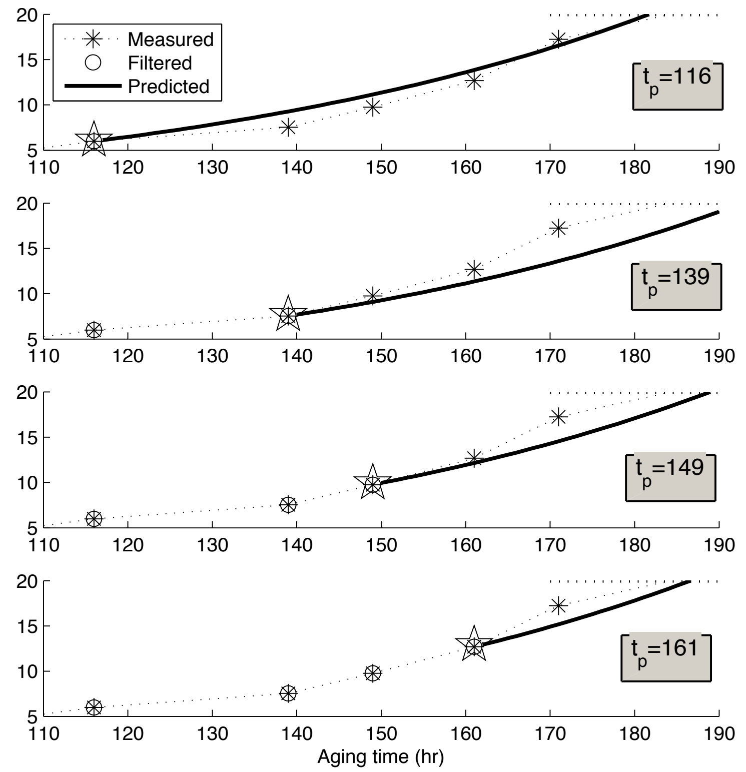
- EOL defined at time in which performance variable cross failure threshold

$$R(t_p) = t_{EOL} - t_p$$

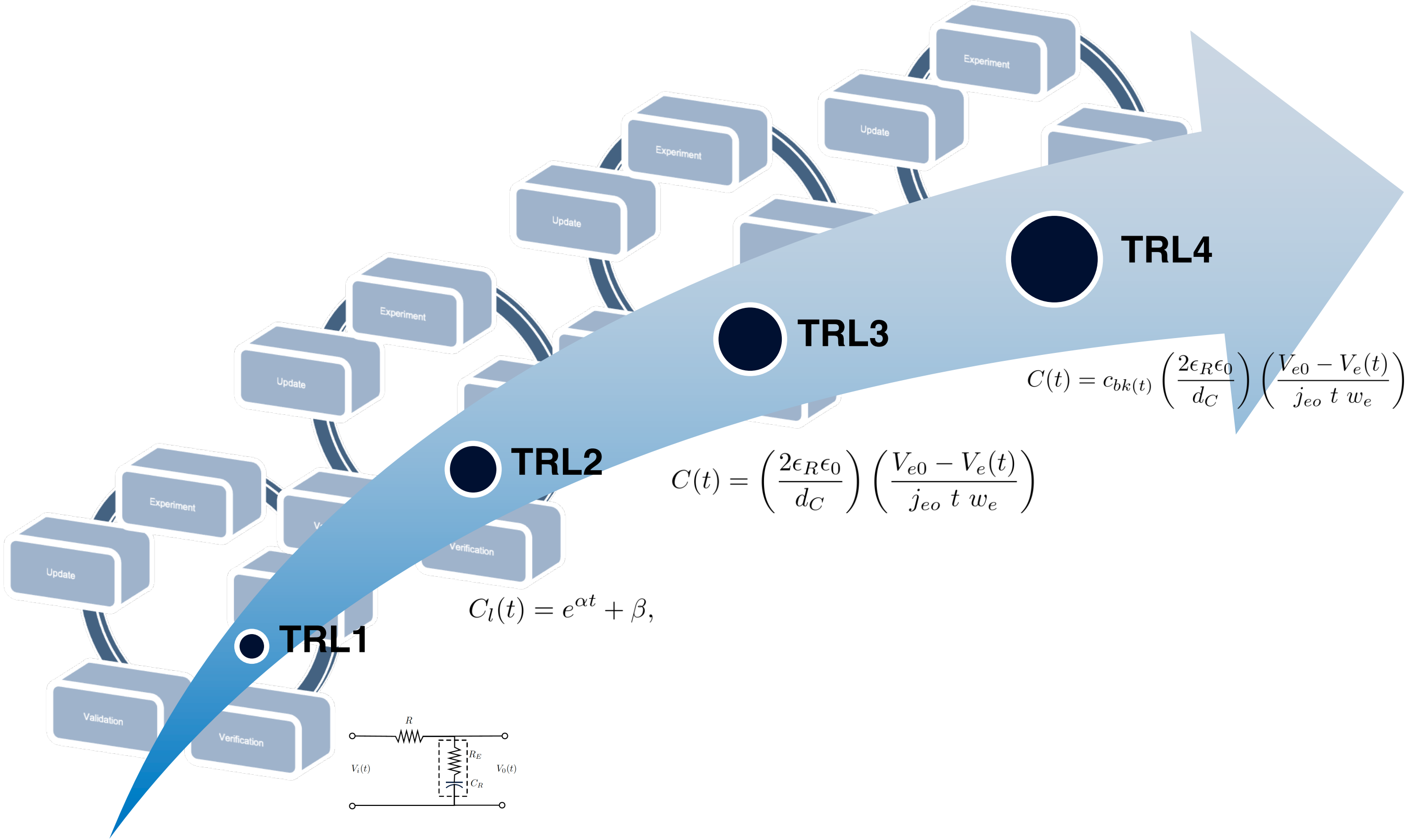


Model-based prognostics

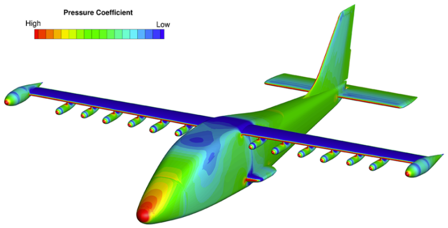
- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed

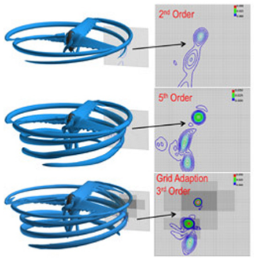


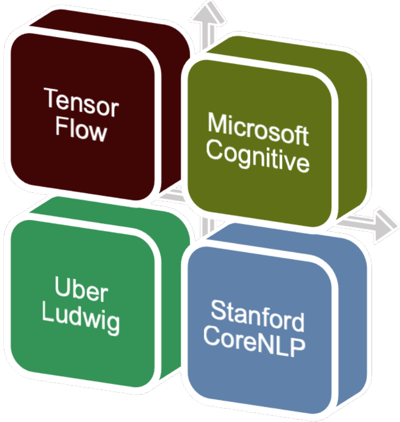
Algorithm and Model Development TRL

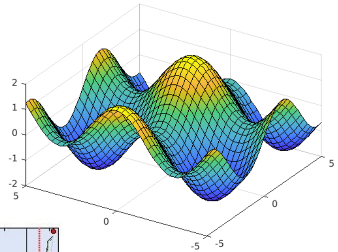


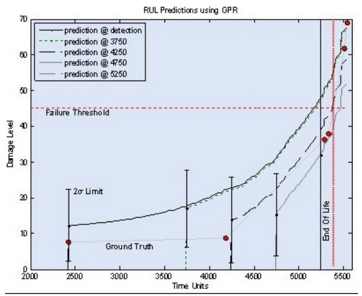
Machine Learning underlying physics parameter

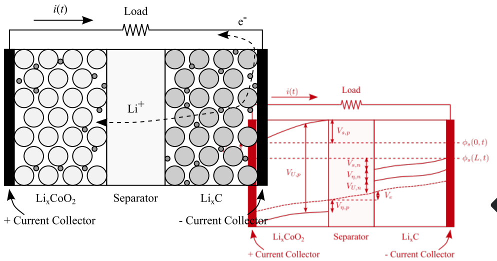


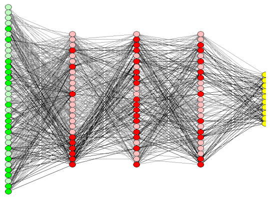






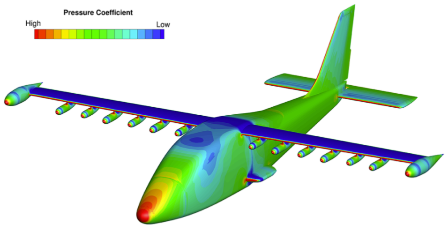


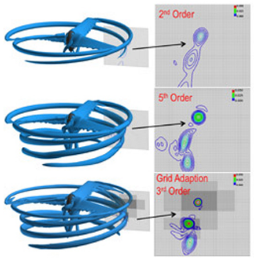


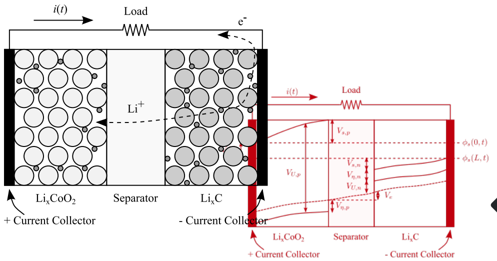


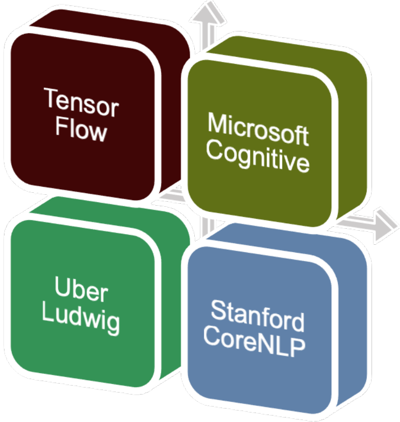
Understanding and Learning underlying Physics for Complex Systems

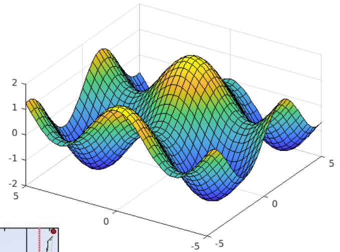
Machine Learning underlying physics parameter

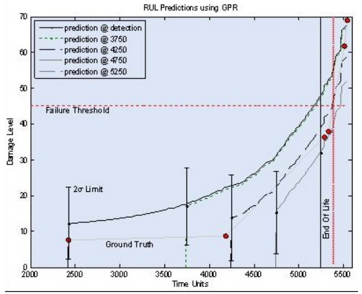


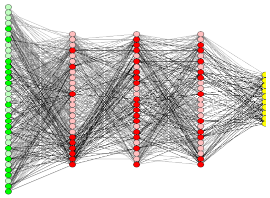




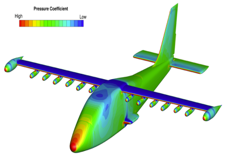


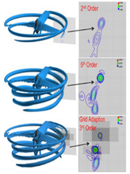


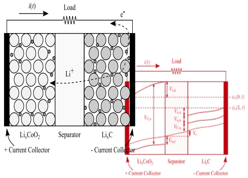




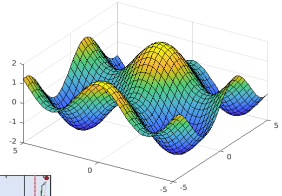
Understanding and Learning underlying Physics for Complex Systems

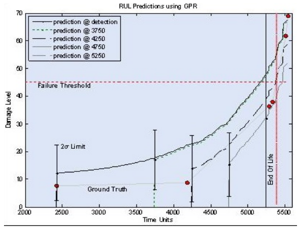

Pressure Coefficient
High
Low

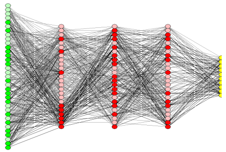



Load
Separator
+ Current Collector
- Current Collector

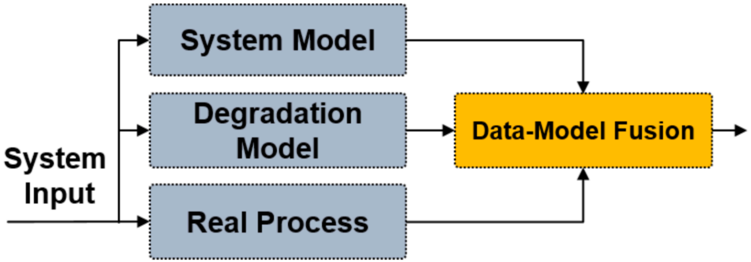
+



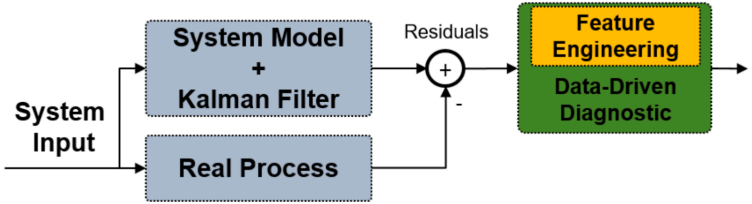

RUL Predictions using GPR
prediction @ detection
prediction @ 3750
prediction @ 4250
prediction @ 4750
prediction @ 5250
Failure Threshold
Ground Truth
End Of Life
Damage Level
Time Units



Prior Work



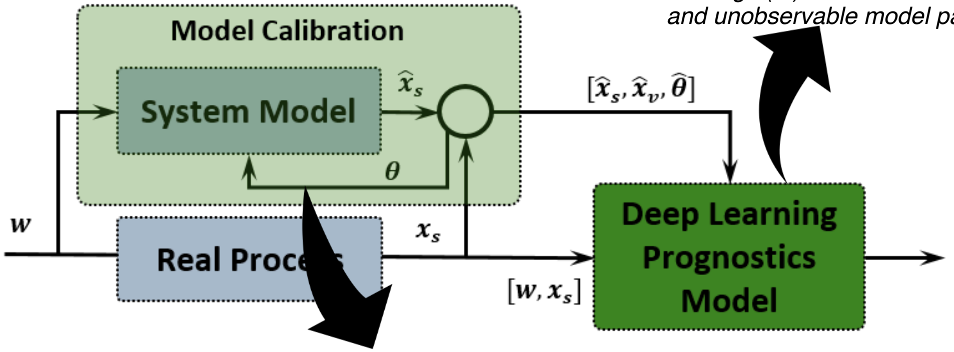
(Hanachi et al., 2017). A particle filter is used as a fusion mechanism to aggregate the diagnostic results from measurement signals and degradation models.



Overall architecture of the residual-based hybrid diagnostics in (Rausch et al., 2005). Feature engineering is carried out for the residuals between Kalman Filter estimates and sensor readings and are used as input to an SVM classifier.

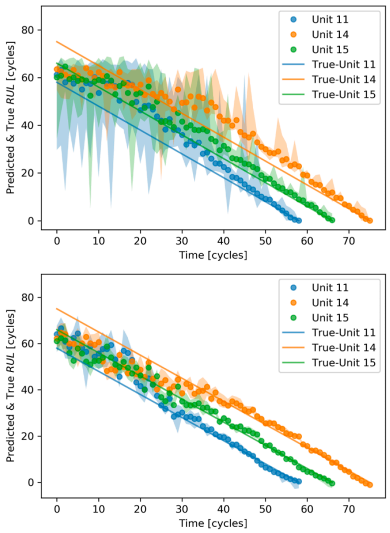
Deep Learning + Physics Model Calibration

The deep learning prognostics model receives as input the scenario-descriptor operating conditions (w), sensor readings ($\hat{x}_s$), estimates of the sensor readings ($\hat{x}_s$) and the virtual sensors ($\hat{x}_v$) and unobservable model parameters (θ)



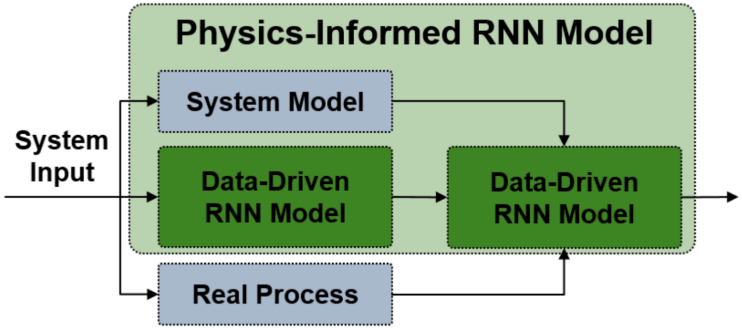
Feedback arrow to the system model represents the calibration process for updating unobservable model parameters .

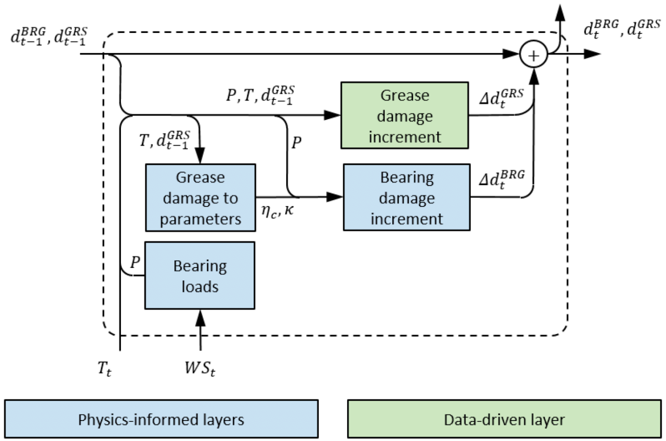
Overall architecture of the hybrid prognostics framework fusing physics-based and deep learning models.



Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) : True and predicted RUL of the baseline model (top) and the proposed hybrid approach (bottom) for each test unit

Physics + RNN (Nascimento & Viana, 2019)





Overall architecture of the physics-informed recurrent neural network in

Y. A. Yucesan and F. A. C. Viana, "A physics-informed neural network for wind turbine main bearing fatigue," International Journal of Prognostics and Health Management, Vol. 11 (1), 2020. (ISSN: 2153-2648).

Next Steps : Looking Ahead

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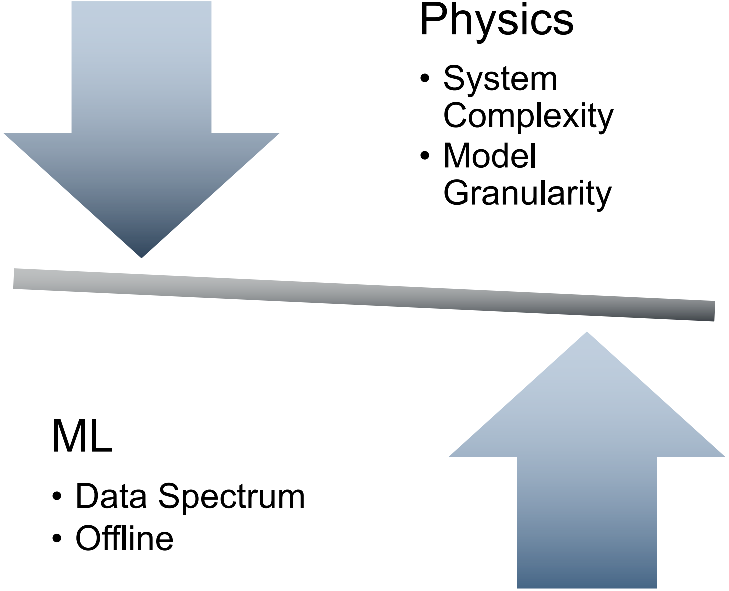


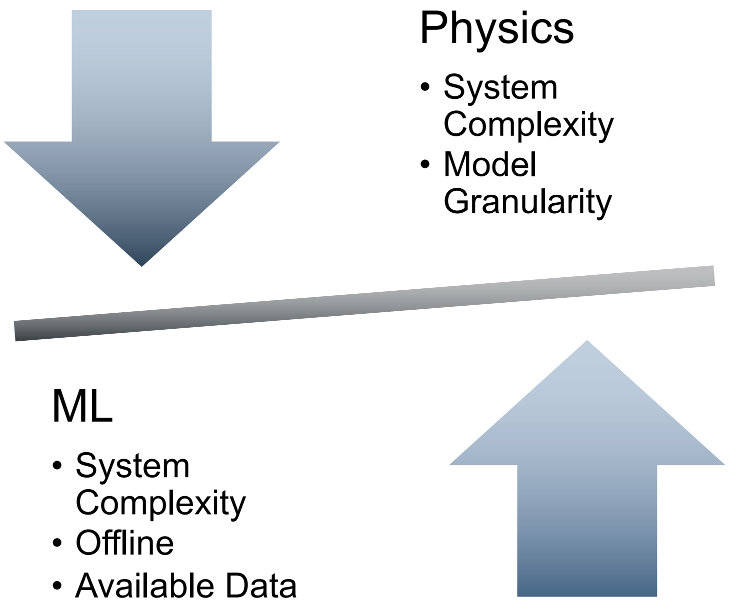
Physics

- System Complexity
- Model Granularity

ML

- Data Spectrum
- Offline

Next Steps : Looking Ahead



Thank You