GE RESEARCH

Abhinav Saxena, PhD

Fellow of the PHM Society
Senior Scientist, AI & Learning Systems GE Research, San Ramon CA
Adjunct Professor, Maintenance and Reliability Engineering, Lulea Technical University, Sweden
Editor, International Journal of Prognostics and Health Management (IJPHM)
asaxena@ge.com

AI-enabled Predictive Maintenance Digital Twins for Industrial Systems

Intelligent Maintenance Conference 2020

ETH Zurich

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- Dr. Hao Huang
- Mr. Achalesh Pandey, Executive Leader, Industrial AI Platforms
- Dr. Colin Parris, GE Digital
- and all members of the MLAI group at GE Research

Key References

- *Huang, H. Xu, C., Yoo, S., "Bi-Directional Causal Graph Learning through Weight-sharing and Low-rank Neural Network", IEEE International Conference on Data Mining (ICDM19) Nov 2019*
- *Chenxiao Xu, Hao Huang, and Shinjae Yoo. 2019. Scalable Causal Graph Learning through a Deep Neural Network. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19). Association for Computing Machinery, New York, NY, USA, 1853–1862. DOI:https://doi.org/10.1145/3357384.3357864*
- *Virani, N., Iyer, N. and Yang, Z., 2020. Justification-Based Reliability in Machine Learning. In AAAI (pp. 6078-6085)*
- *Bhushan, C., Yang, Z., Virani, N. and Iyer, N., 2020. Variational encoder-based reliable classification. arXiv preprint arXiv:2002.08289. (accepted at ICIP 2020)*
- *Publications on Uncertainty in PHM - https://ti.arc.nasa.gov/tech/dash/groups/pcoe/uncertainty-prognostics/publications/*

GRCTHINK

OUR MISSION ...
"Research to Reality"

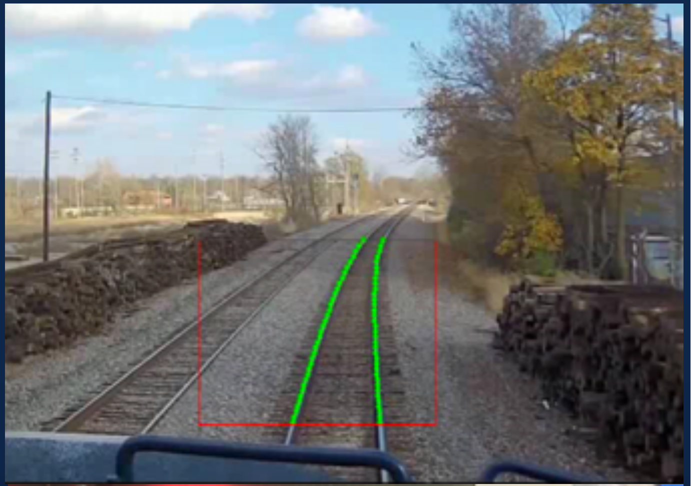
Gas Turbines	CT scanners	Engines	Wind turbines	Oil & Gas	Additive
12,000	**13,000**	**70,000**	**40,000**	**150,000+**	**1,400**

GE'S INNOVATION Ecosystem

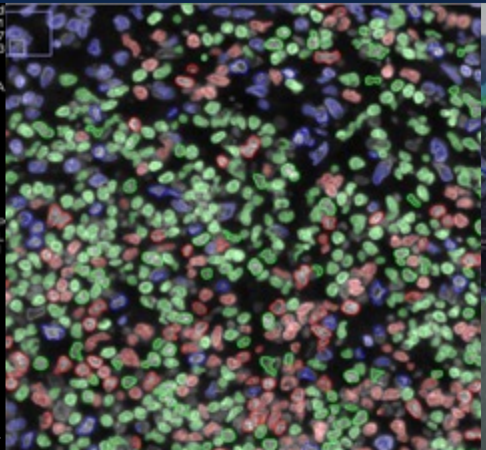
- **Ideas** to scale
- **1000+ Researchers -** 600+ PhDs
- **3,000** patents across the company each year, 60K+ portfolio
- **Contemporizing model** ... market test everything
- **Delivering** sustainable tech differentiation

Artificial Intelligence Group

GE Research



- 30+ years of Research, Development & Commercialization
- Over 50+ PhDs (computer vision, machine learning, knowledge representation, big data, & human system interaction)
- Broad spectrum of technology coverage:
  - Medical Image Analysis, Industrial Inspection, Aerial Inspection (drones & satellite-based) and Video Intelligence
  - Natural Language Processing, Knowledge Representation, and Reasoning
  - Diagnostics, Prognostics, Health Monitoring, and Time-series Analysis
  - AI-based Optimization & Controls and Workflow Automation
  - Science of AI: Robustness, Commonsense Reasoning, and Explainability.
- Integral partnerships with GE businesses, government, and academic institutions



Industry Value: Drivers and Dynamics

KEEP 300K PEOPLE IN THE SKY/HR.

1/3 OF THE WORLD ELECTRICITY

16 K SCANS PER MINUTE

DRIVERS

1 **INCREASED PRODUCTIVIT Y**

2 **FASTER GROWTH**

3 **RISK-MANAGED ADAPTABILITY**

4 **IMPROVED SAFETY**

DYNAMICS

Deeper customer engagement
E.g. Emirates, ENEL

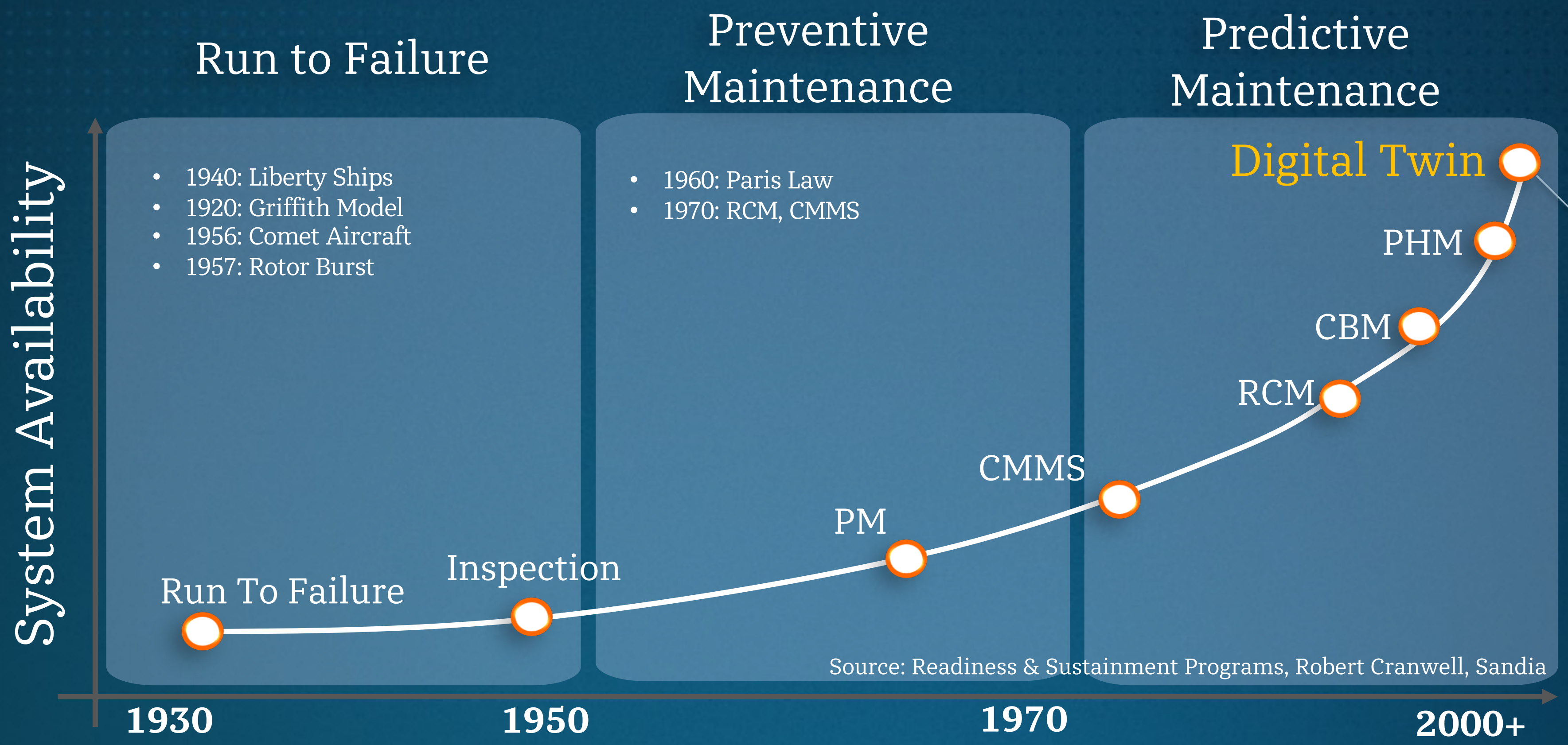
Blurring markets and government influences
E.g. Bezos, Musk, US/China

Digital – ↑ capabilities @ lower cost
E.g. Online, tele, autonomous

Maintenance Practices and Applications of AI

DESCRIPTIVE	DIAGNOSTICS	PREDICTIVE	PRESCRIPTIVE	AUTONOUMOUS
What Happened?	Why It Happened?	What Will Happen?	What Action to Take?	How to Manage Automatically?

Industry 1.0	Industry 2.0	Industry 3.0	Industry 4.0
Mechanization Steam and Water Power	Mass Production	Computers and Automation	IoT, AI, Cognitive, Personalization



Digital Twin
A continuously learning model

Remote Monitoring Today

High-Value Assets

- Aircraft Engines
- Power Plant Equipment
- Manufacturing Systems

Improve Safety

Sense

- Existing Sensors
- Inspection
- Advanced Sensors
- Advanced Inspection

Improve Availability

Predict

- Advanced Signal Processing
- Artificial Intelligence
- Model-Based Diagnostics
- Sensor & Data Fusion

Maximize Performance

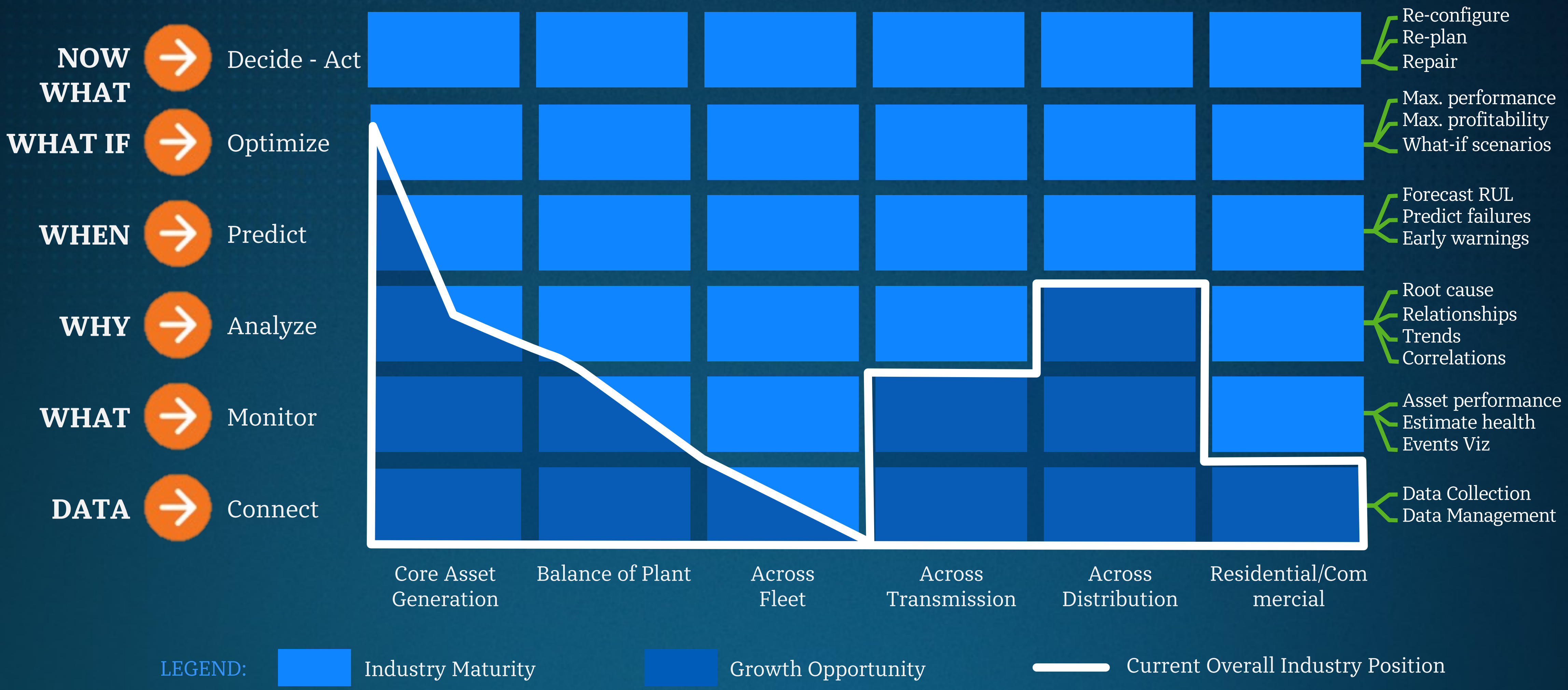
Assure

- Prevent Forced Outages
- Condition-Based Maintenance
- Performance Optimization

Improve Reliability

PHM Outcomes & Current State

Power Industry Example



Adapted from Power Digital Solutions Product Catalog

Digital Twin

definition

Engineering models that continuously add insights into each asset to deliver specific business outcomes

1. Per asset model
2. Business outcomes
3. Continuously tuned
4. Scalable
5. Adaptable

Inspection Optimization
- Inspection Delay & Avoidance

Work Planning
- Workscoping
  Maintenance, Repair, Inventory
- Workforce / Inventory Planning

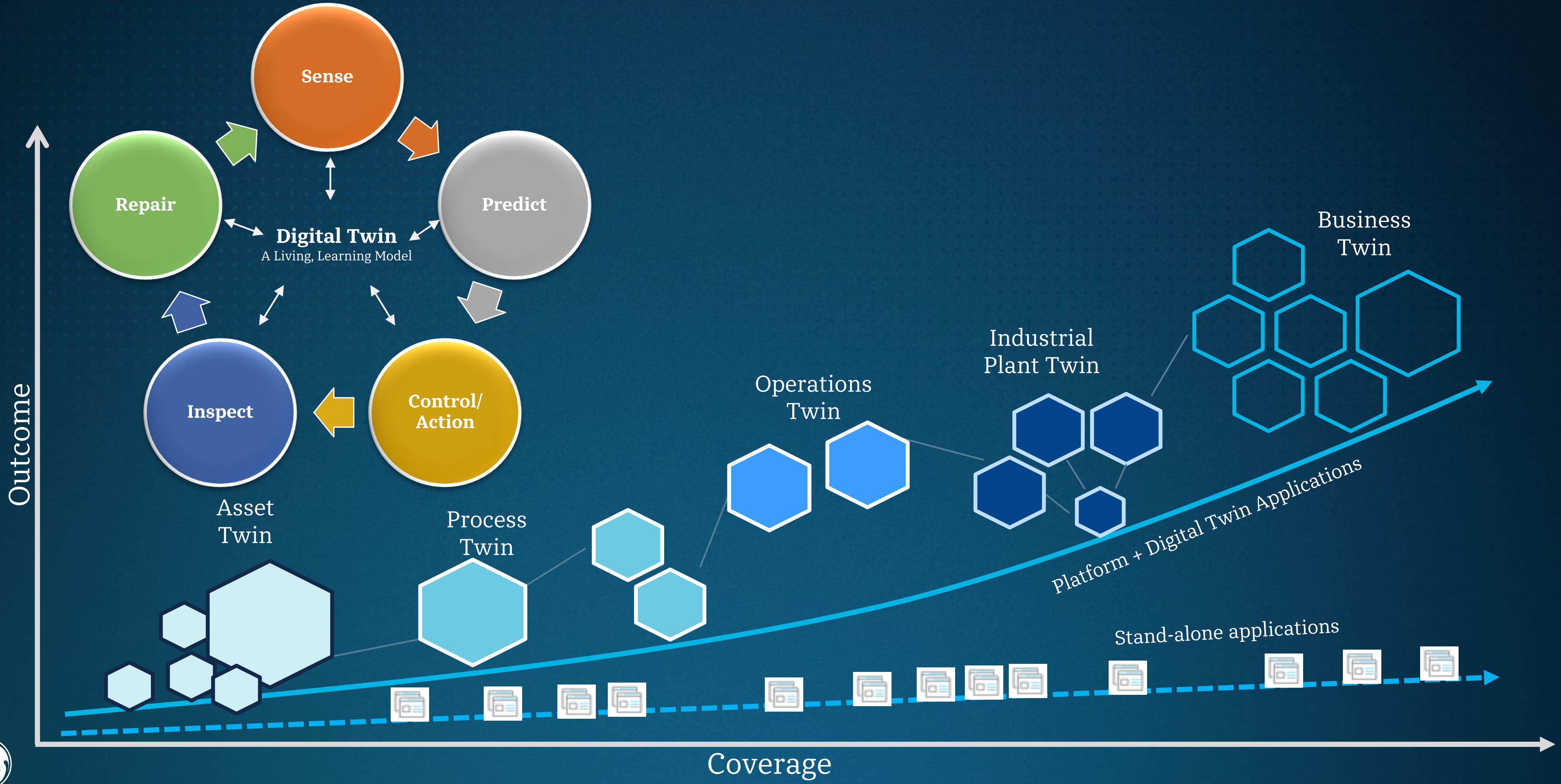
Work Optimization
- Optimize Shop Maintenance
- Outage Mgmt. & Reduction

Service Optimization
- Shop & Region cost reduction + Per Asset Fleet Mgmt.

Design Impact
- Design for Service
- Design for Performance

New Service Creation
- Optimizing Controls
- Operations Optimization (N+1)
- Business Optimization (N+2)

Digital Transformation with Digital Twins



Consumer Sector Digital Transformation

Digital model / **Insights**	e.g. Demographic	Psychographic - Model of ONE
Business outcome / **System**	e.g. Segmentation	Profiling, prediction - P&L of ONE
Transformation & expansion / **Platform**	e.g. Books	New industries, services - platform for all

Digital model

Insights

e.g. Demographic

Psychographic - Model of ONE

Business outcome

System

e.g. Segmentation

Profiling, prediction - P&L of ONE

Transformation & expansion

Platform

e.g. Books

New industries, services - platform for all

GE's Industrial Digital Twin

Digital model

Insights

Flying in Asia-Europe Route

2-3 Service years

e.g. Fleet

Flying Singapore-London

Last inspection distress ranking < 2

Flies 80% between Coastal Airports

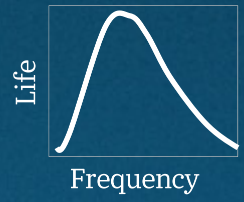
Temp. T49 delta < 10F

Due for overhaul in 7.1 months

Per Asset ... Per Flight - Model of ONE

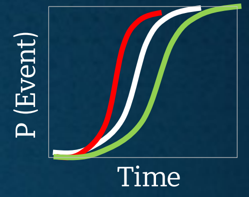
Business outcome

System



e.g. Fleet life and performance

Individual life and performance



Per Asset Analytics - P&L of ONE

Transformation & Expansion

Platform

e.g. Services & Products

Customized Optimizers

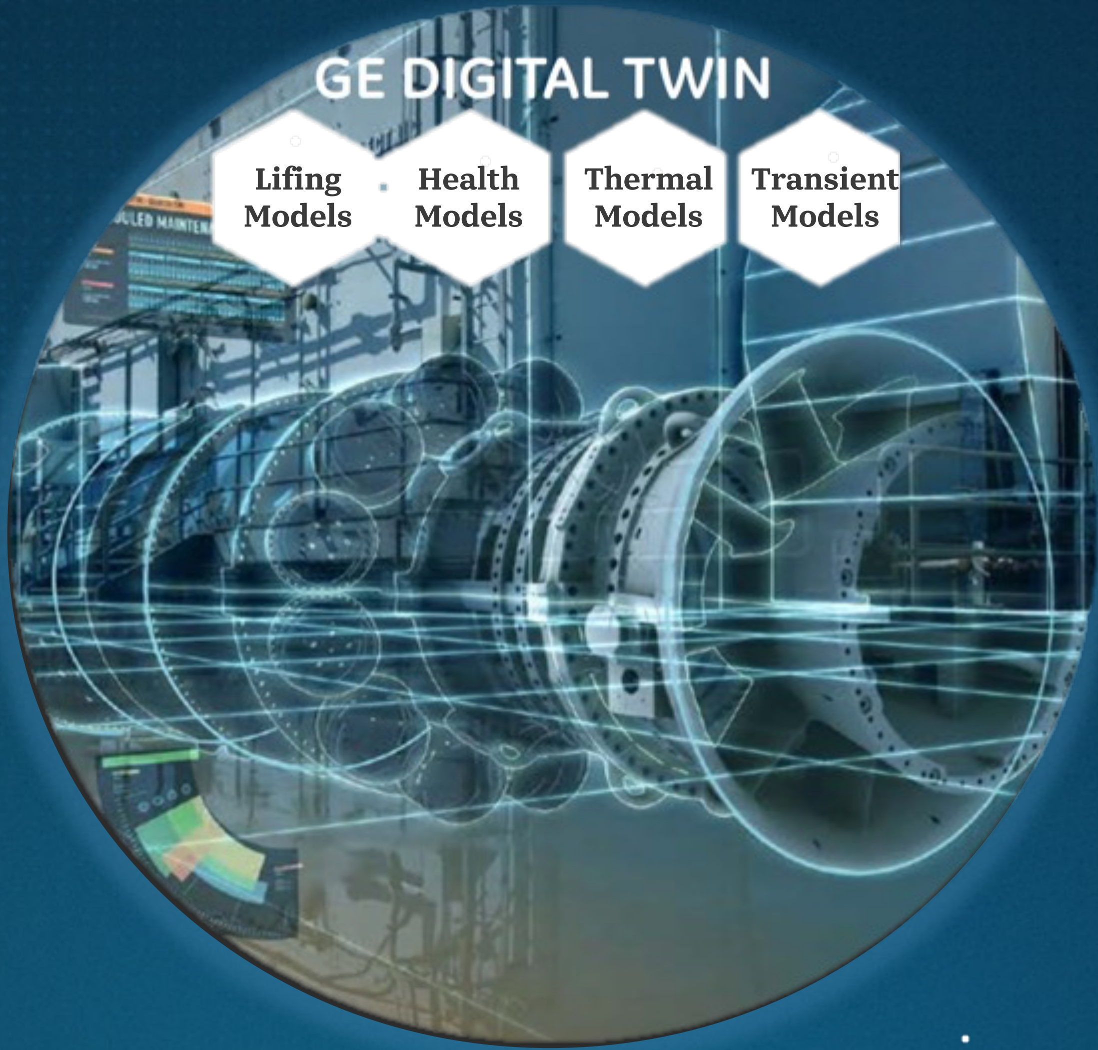
Digital Twin + Platform(s)

New Services & Products – Platform for all

Example

INPUTS

- Atmospheric Data
- Operational Data
- Inspection & Repair
- Site Events

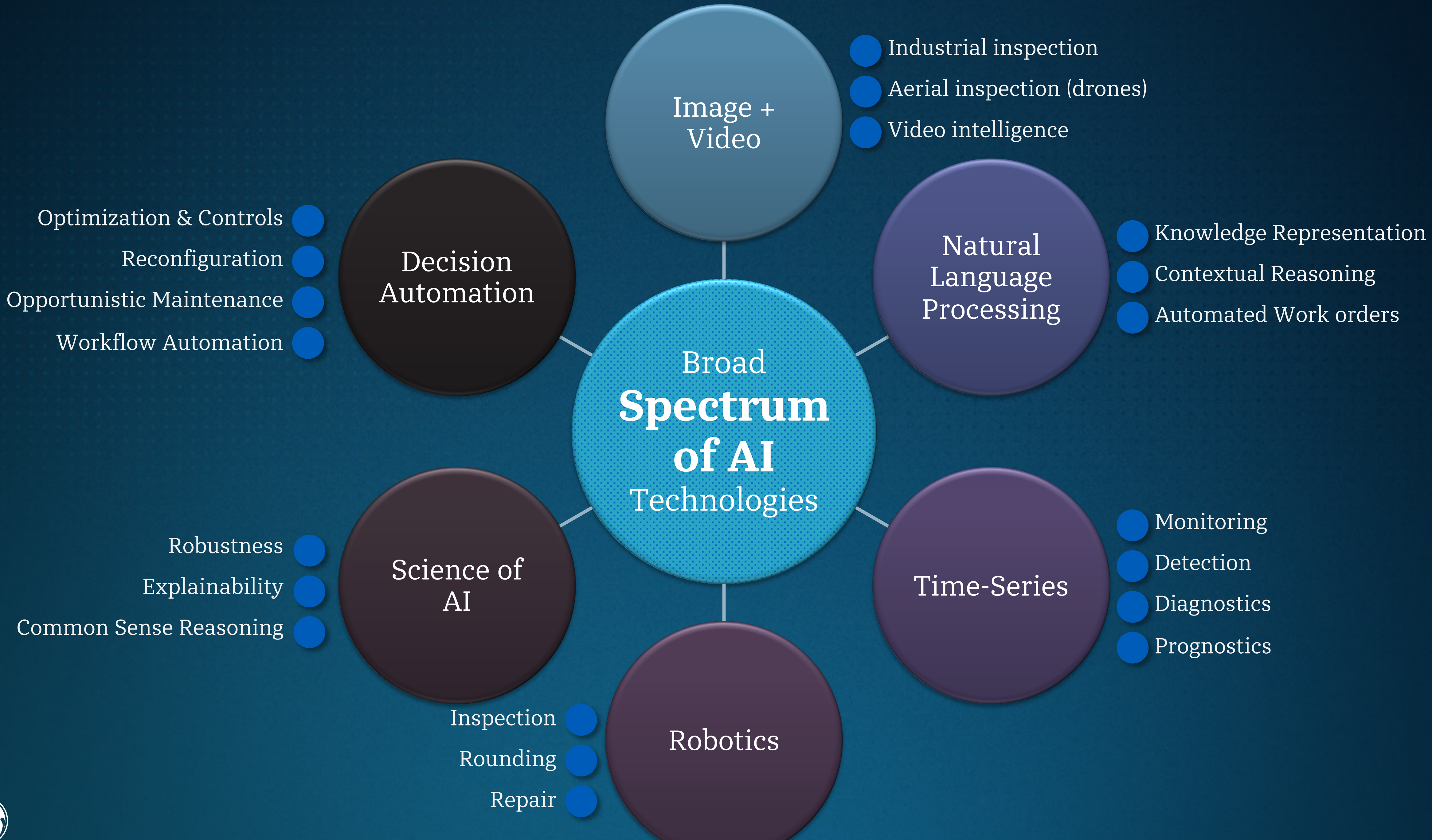


OUTCOMES

- Business Optimization
- Operations Optimization
- Asset Performance Management
- Advance Controls/Edge Computing
- Security

Reliability Capacity Emissions

CUSTOMER KPIs


Broad
Spectrum
of AI
Technologies
Image +
Video
Industrial inspection
Aerial inspection (drones)
Video intelligence
Natural
Language
Processing
Knowledge Representation
Contextual Reasoning
Automated Work orders
Time-Series
Monitoring
Detection
Diagnostics
Prognostics
Robotics
Inspection
Rounding
Repair
Science of
AI
Robustness
Explainability
Common Sense Reasoning
Decision
Automation
Optimization & Controls
Reconfiguration
Opportunistic Maintenance
Workflow Automation

Challenges in Predictive Maintenance → AI Opportunities

Contextual Reasoning

Industrial Data Quality

Explainability

Unstructured Information

Uncertainty and Trust

Information to Action - Automation

Continuous Learning

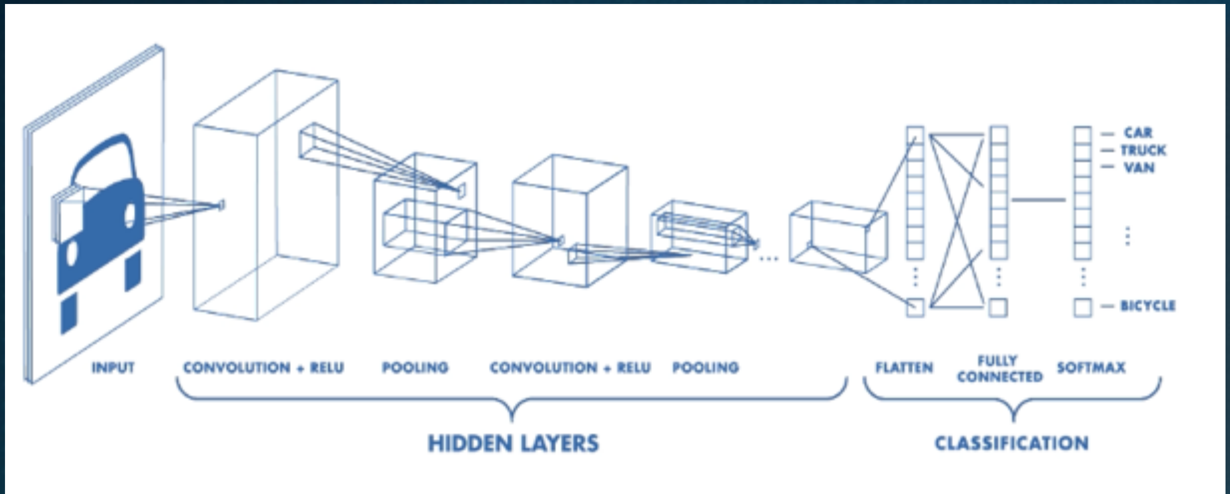
Edge-Cloud Continuity

Explainability

Deep Causal Learning

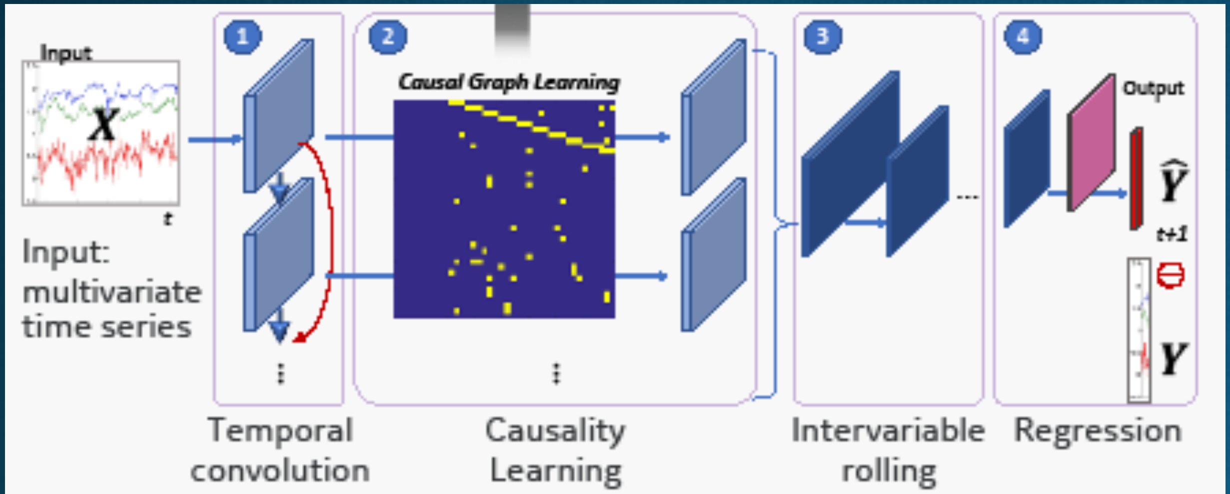
System-wide Monitor and Causality Analysis

Interpretable Deep Learning Model



Typical Deep Learning Model

- Unconstrained low to high level connection
- Hard to interpret influencing factors

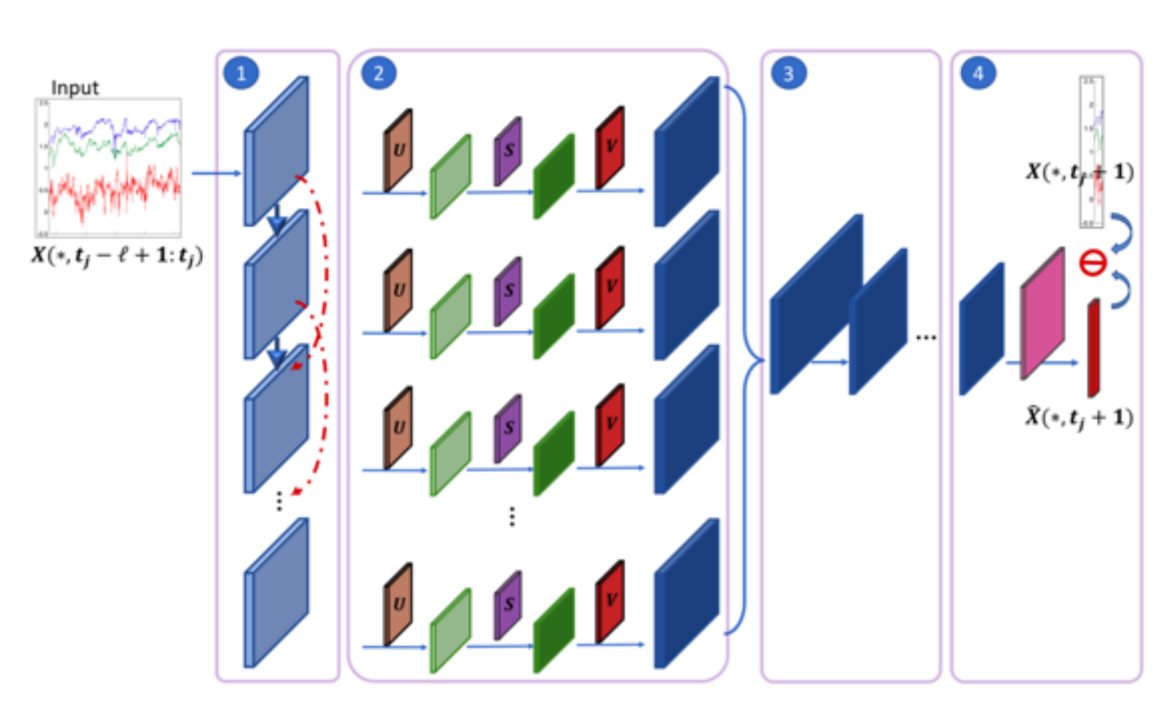


DANCE: Deep Analysis Net w/ Causal Embedding

- Constrained & structured low level to high level connection
- Can trace back influencing factors

Ref: Chenxiao Xu, Hao Huang, and Shinjae Yoo. 2019. Scalable Causal Graph Learning through a Deep Neural Network. In Proceedings of the 28th ACM International Conference on Information and Knowledge Management (CIKM '19). Association for Computing Machinery, New York, NY, USA, 1853–1862.

Modeling

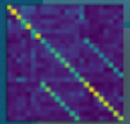


Data Preparation

Original n-dimensional time series

Sample i

Test Sample

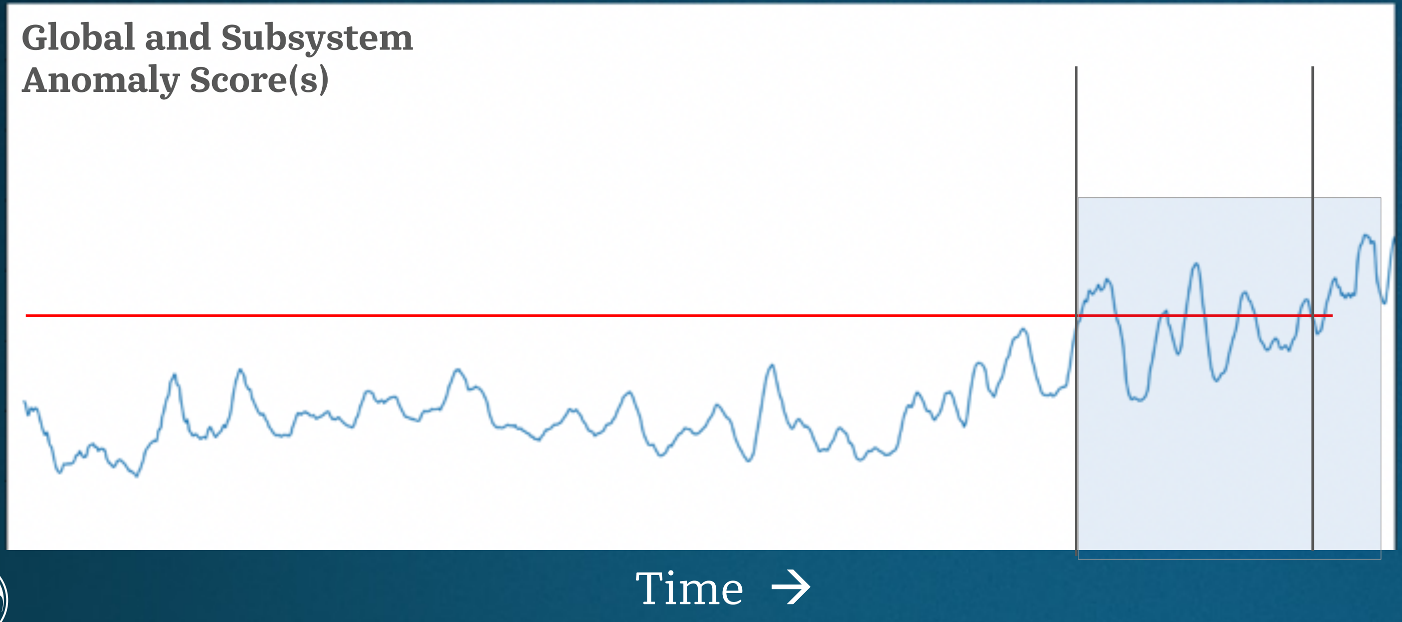


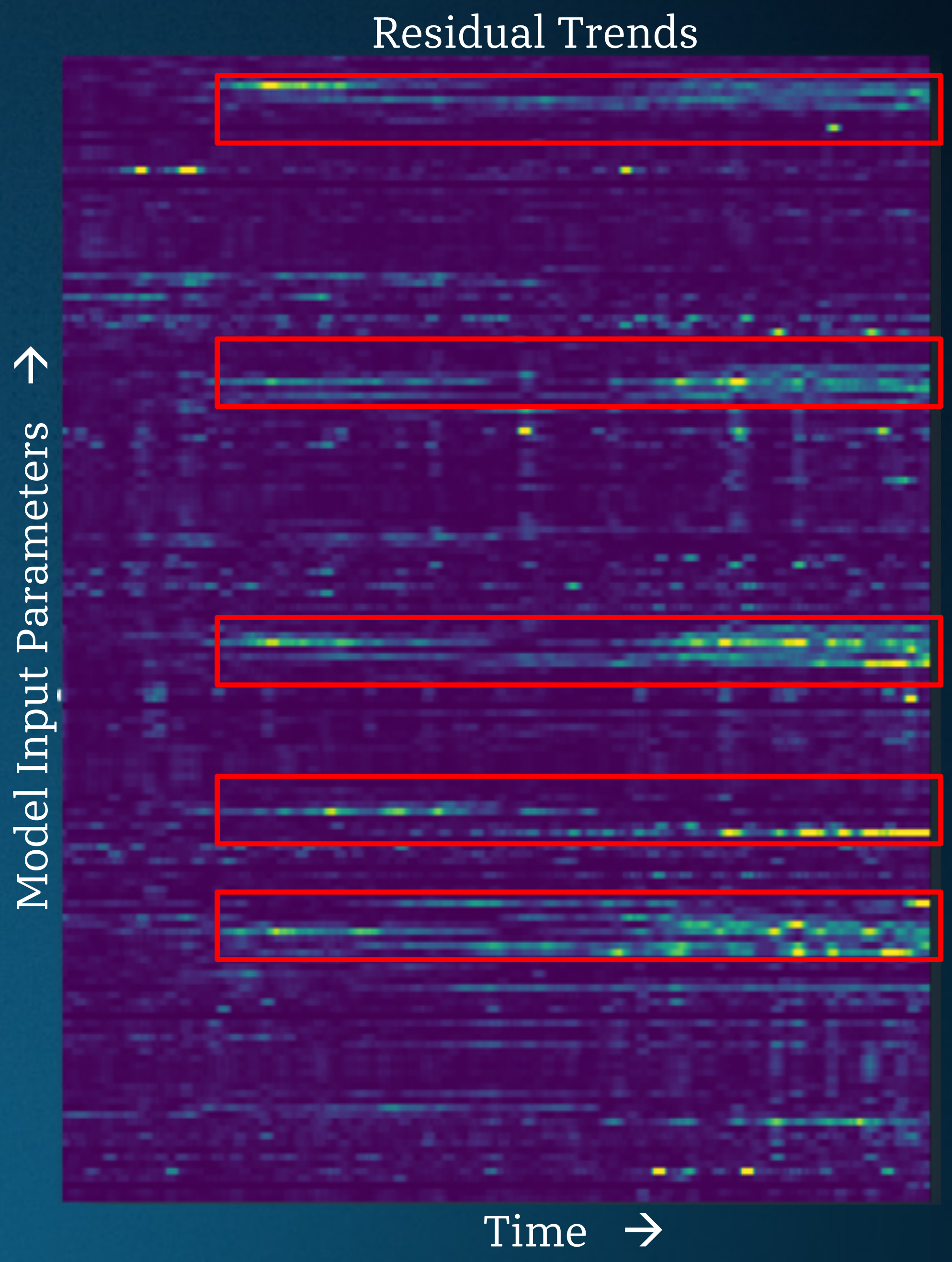
Trained model

Residuals + Factors
(Anomalies)

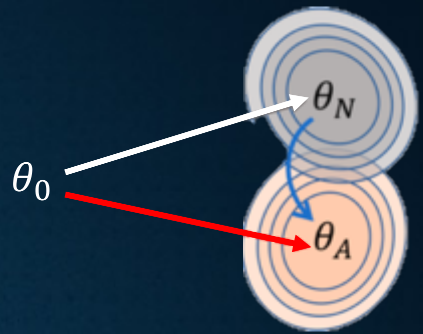
System-wide Coverage (1)
e.g. Aircraft Jet Engine

Deep Causal Learning
- Models causal relationship between parameters of the system
- Does not require parameter subset selection prior to modeling
- Does not require identification of nominal set *apriori*
- Applicable to a variety of time-series formats
- Applicable across fleets, asset models,

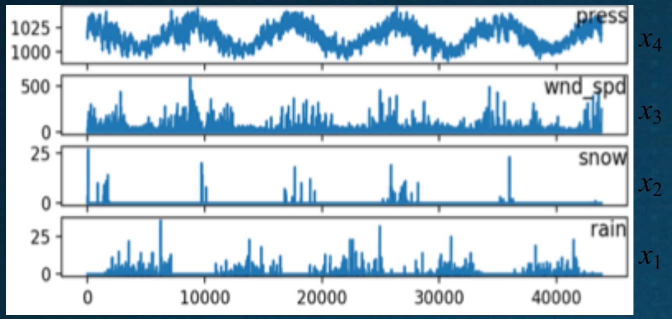




Causality/Correlation Matrix

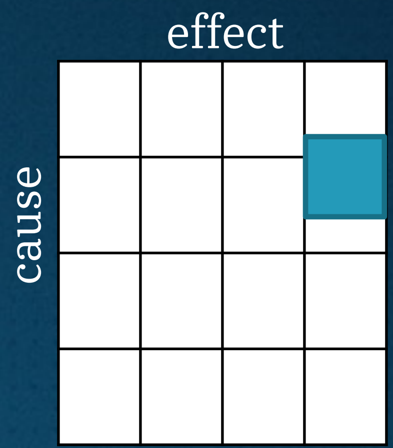


Input: Multivariate time series



$$X(t) = \sum_{\tau=1}^{L} A_\tau X(t-\tau) + \varepsilon(t),$$

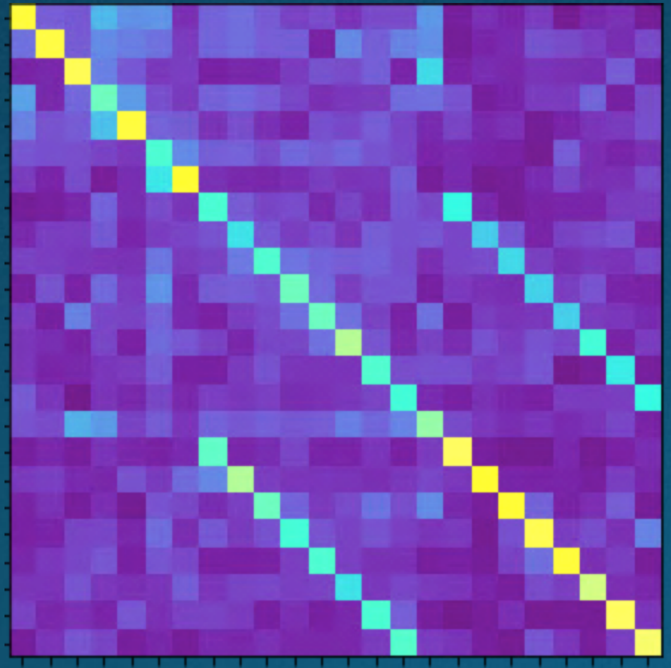
Granger Causality, Multivariate Linear



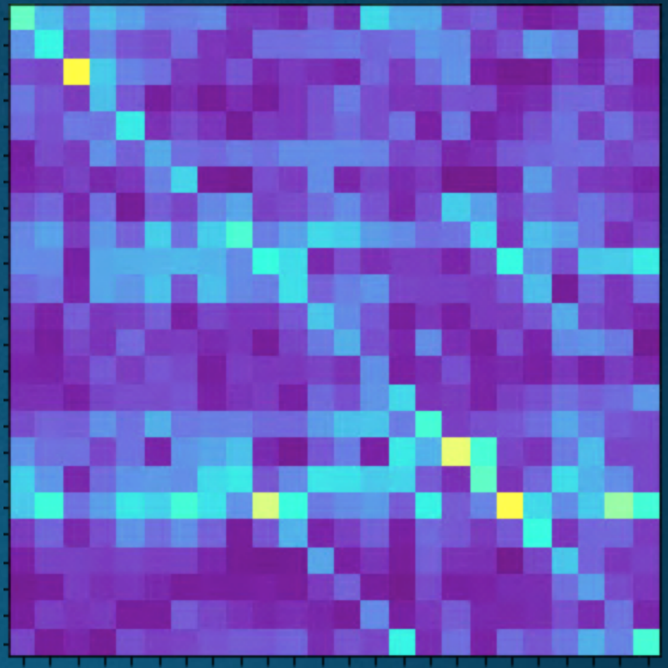
Output: Relationships between timeseries

Fleet of 600+ engines
18 months of data
260+ parameters

Fleet

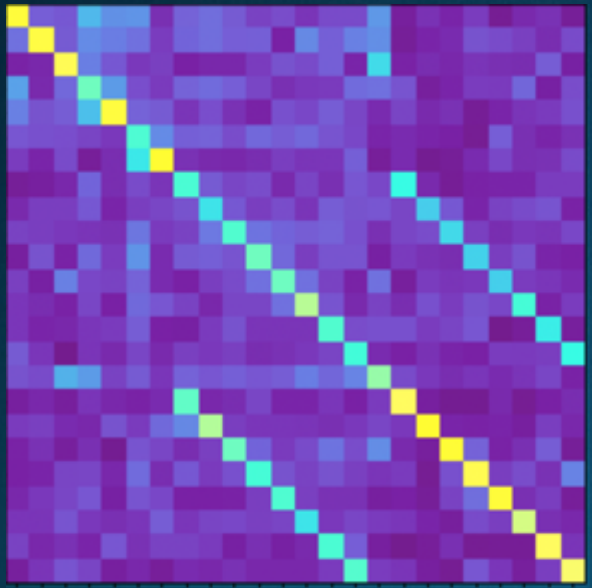


Unhealthy Asset

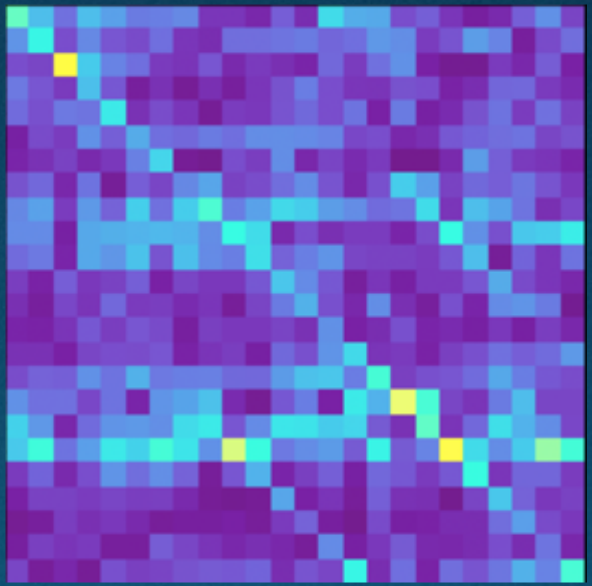


Causality/Correlation Matrix - 2

Fleet



Unhealthy Asset



EXAMPLES

(1) Corrected Altitude = measures altitude as a f(total pressure, total air temperature)

(2) Computed Airspeed is subject to air-density changes,

(3) Adjustment of fan air flowrate is f(fan speed), explains desired cooling outlet temperature.

(4) Fan speed ,f(engine rotational speeds) is affected by Pressure and Bleed Position.

(5) Outflow Valve is the actuator of the Cabin Pressure Regulating System.

(6) The change of Valve Position is triggered by the change of altitude and outlet temperature.

$$L_{\hat{N}} = \frac{1}{nmc} \sum_{t=1}^{n} \sum_{i=1}^{m} \sum_{k=1}^{c} \left(X^{(t)}(i, t_{j+k}) - \hat{X}^{(t)}(i, t_{j+k}) \right)^2 + \lambda \|\hat{N}\|_2,$$

$$L_{\hat{A}} = \frac{1}{n'mc} \sum_{t=1}^{n'} \sum_{i=1}^{m} \sum_{k=1}^{c} \left(X'^{(t)}(i, t_{j+k}) - \hat{X}'^{(t)}(i, t_{j+k}) \right)^2 + \lambda \|\hat{A}\|_2 + \gamma \|\hat{A} - \hat{N}\|_2,$$

$$\left|\hat{A} - \hat{N}\right| = Anomaly\ causal\ factors$$

Information to Action & **Trust**

Humble AI

Understand Model Competence and Region of Trust for Safe Prescriptive Analytics – EXTRAPOLATION?

Motivating Examples from Industry

humility...

Fault Classification for Wind Turbines

I know this is fault class 1, please authorize to take appropriate actions.

The wind turbine generator might have fault 1 or 3, but not 2, I need more evidence to resolve confusion.

Treatment Prescription or More Tests?

Ultrasound

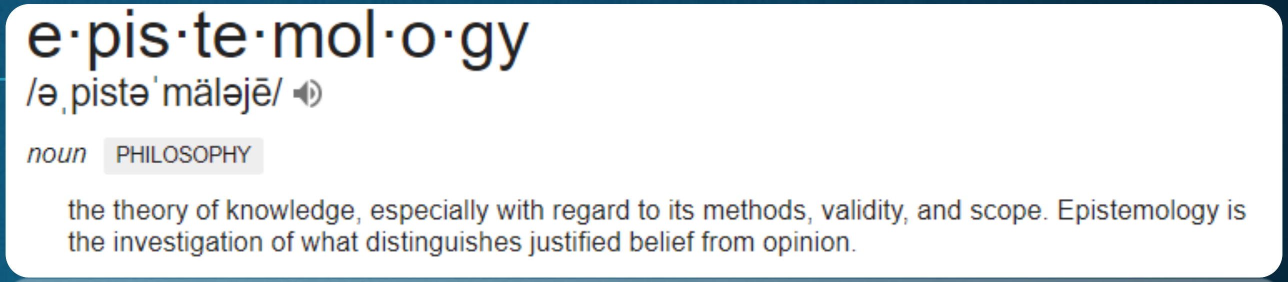
The patient has symptoms of disease x, here is the evidence, I recommend to begin treatment.

The patient might have symptoms of disease x, but I need more evidence, please collect more data.

I don’t know if patient has symptoms of disease x, partner can you look into it.

Identification of Model Competence

Context	Example of Conceptual Approach
On input side	Anomaly detection based on training distribution
On output side	Size of prediction intervals to detect unstable extrapolation
Jointly with input and output	Concept drift detection using residuals between actual and predicted outcomes
Internal model parameters	Epistemic models


e·pis·te·mol·o·gy
/əˌpistəˈmäləjē/

noun PHILOSOPHY

the theory of knowledge, especially with regard to its methods, validity, and scope. Epistemology is the investigation of what distinguishes justified belief from opinion.

Why Look at Epistemology of ML?

“How can we theoretically characterize what an AI "knows" and what it doesn’t?”

Epistemology is the study of the nature of knowledge, justification, and the rationality of belief for humans and human psychology, we explore to extend it for machine learning systems

Machine learning provides statistically impressive results which might be individually unreliable

- ✘ “My validation accuracy was high, so trust my belief”
- ✘ “Soft-max value for predicted class is high, so trust my belief”

Can we understand the limitations of ML due to:

- Observability (or separability)?
- Unreliable or brittle extrapolation?

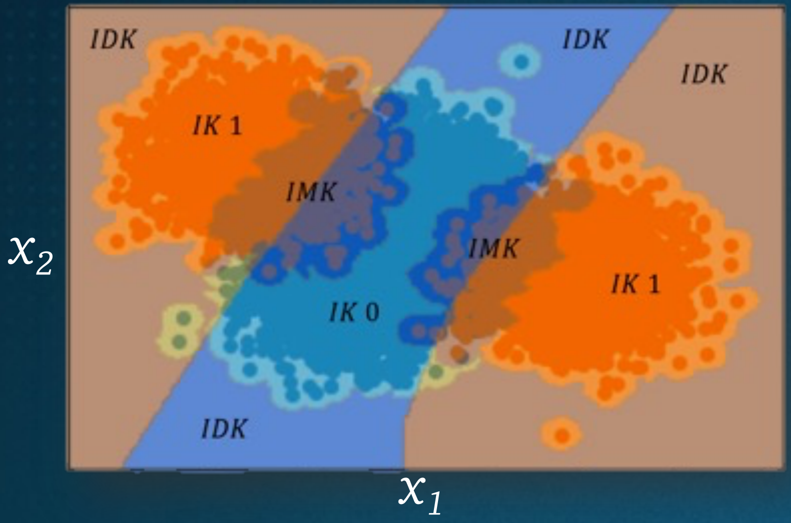
If AI is aware of its own knowledge and limitations, then it can provide that information for reliability/safety as well as ask for help (Humble AI)

Epistemology in Machine Learning

Support from Geometric Neighborhoods

Characterizing region of trust, region of overlap, and region of extrapolation to generate Justification-based Reliability
KNOWLEDGE = JUSTIFIED TRUE BELIEF

Inference Problem



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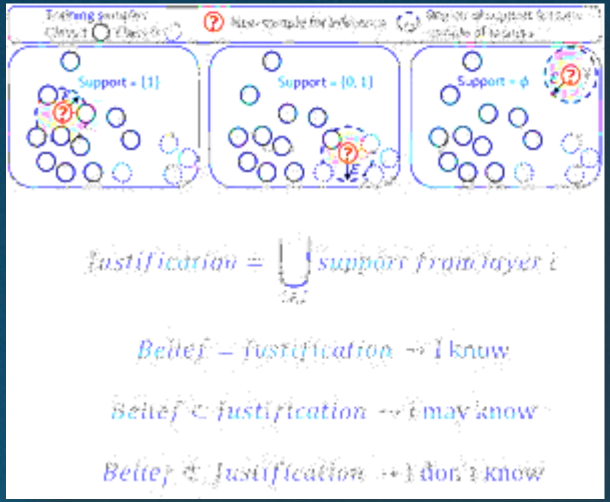
Geometric Support



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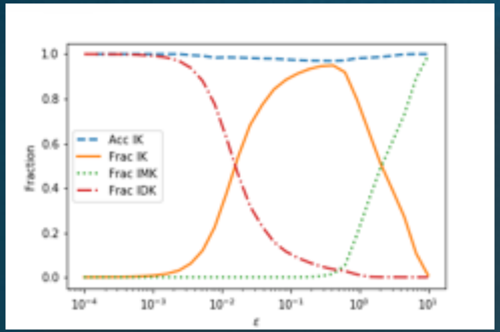
Levels of Epistemic Certainty

What AI **knows** → regions IK
- *region of trust*

What AI **may know** → regions IMK
- *region of overlap*

What AI **does not know** → regions IDK
- *region of extrapolation*



Behavior of IK, IMK, and IDK regions as a function of e

References:
- *Virani, N., Iyer, N. and Yang, Z., 2020. Justification-Based Reliability in Machine Learning. In AAAI (pp. 6078-6085)*
- *Bhushan, C., Yang, Z., Virani, N. and Iyer, N., 2020. Variational encoder-based reliable classification. arXiv preprint arXiv:2002.08289. (accepted at ICIP 2020)*

Learning-based Optimization for Wind Turbines

Wind Farm

Sensor data

Get the right data

Machine learning-based predictive and prescriptive models with continual learning

Find optimal decisions

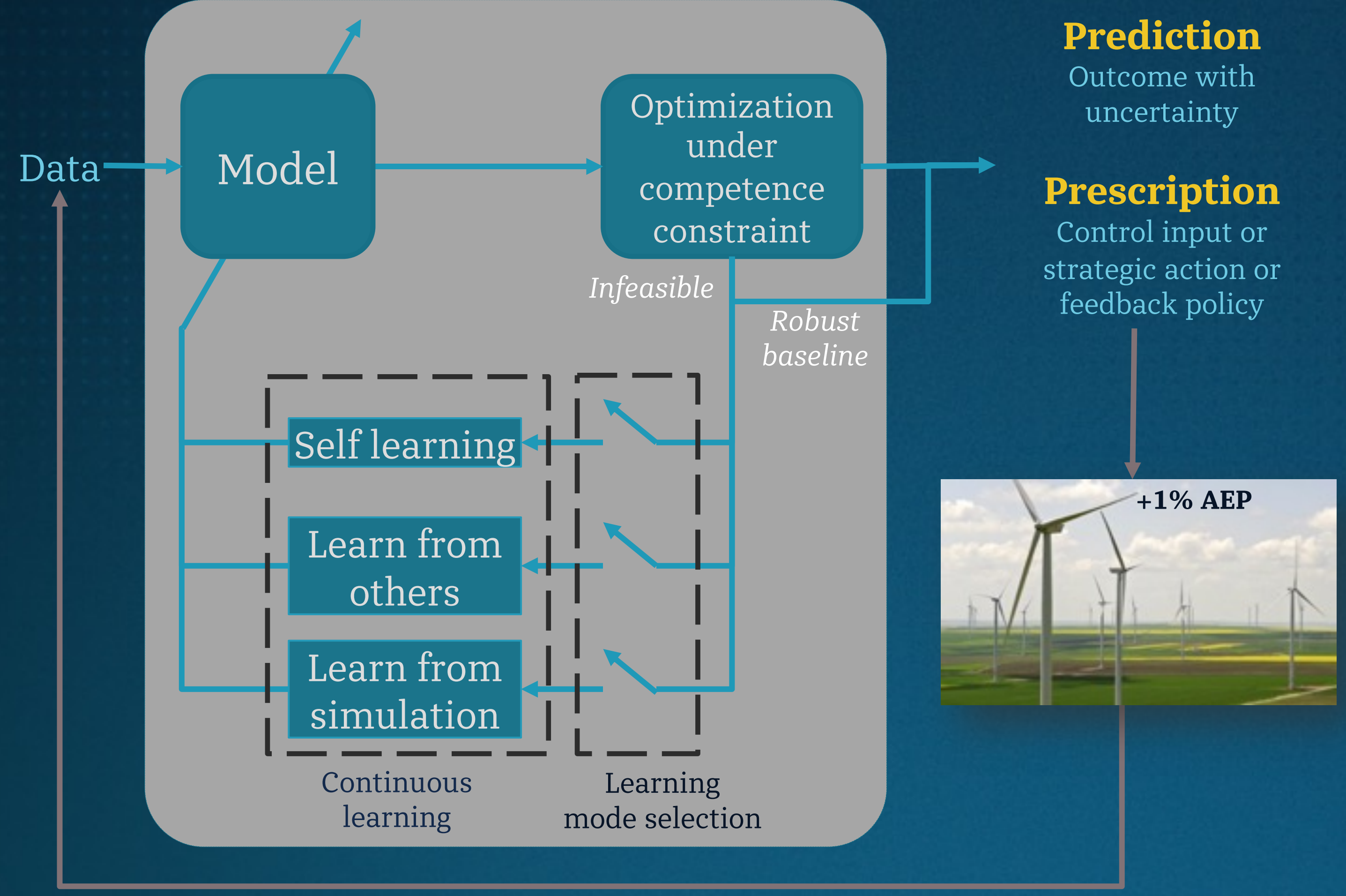
Deploy action

Control signals

Humble AI with Digital Twin

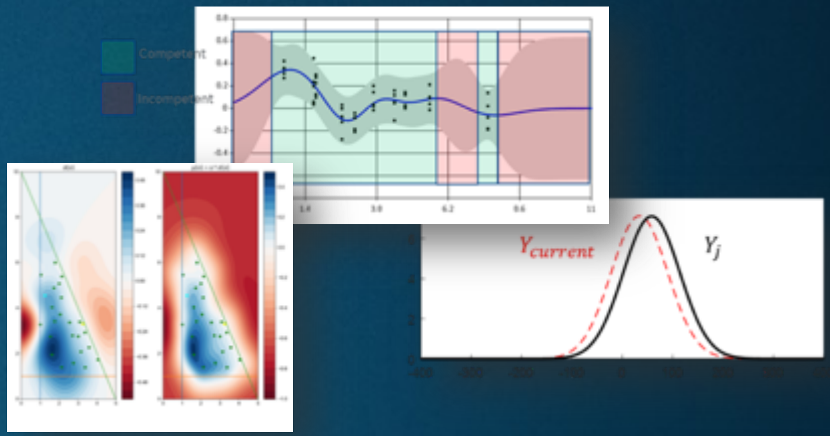
Realizing full value of data-driven analytics by putting information to action

Humble AI



Defining capabilities

- understand region of trust
- quantify uncertainty
- ask for help when incompetent
- continuous learning from multiple sources



Final thoughts...

AI is already starting to create significant value

Trust is key to adoption

- Data quality and assurance
- Model assurance
- Explainability

Leverage physics and domain knowledge for AI

- Improves accuracy and capability
- Adds Explainability