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Intern Exit Presentation

Maximo Hierarchy Graph Data Visualization & Machine Learning for Time Series Predictive Maintenance

ALBERT GALIMOV

12/08/2025

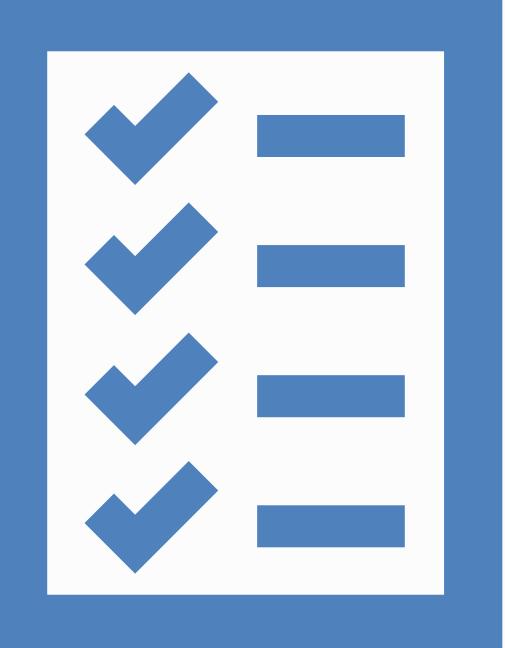
OSTEM INTERNSHIP PROGRAM



About Me

- Master's Student in Computer Science
 - University of Massachusetts (UMass), Amherst
- Automation and Control Engineer
 - Automated Traffic Control Systems, Russia
- Research Student Assistant
 - Fraunhofer, Germany
- AI Mentorship Program through UMass
 - Apple Team (Extern)
- NASA Langley Research Center Intern





Agenda

- Maximo Hierarchy Graph Data Visualization (Project 1)
- Machine Learning for Time Series Predictive Maintenance (Project 2)
- Potential Future Solutions for Predictive Maintenance (Project 3)
- Questions

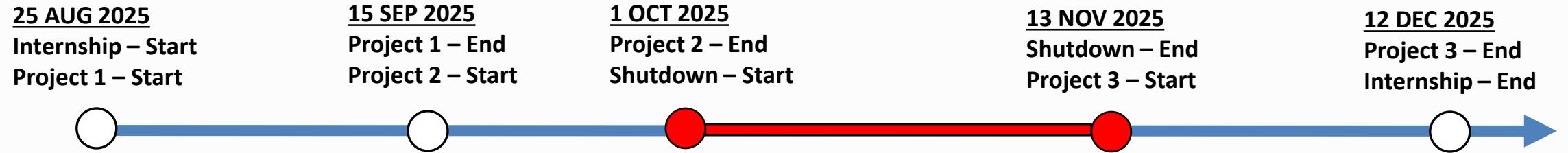
About NASA Langley Research Center (LaRC)

- Founded: July 17, 1917
- Location: Hampton, VA
- People: 3,400+
- Facilities: 200+
- Focus: aviation, expand understanding of Earth's atmosphere, and develop technology for space exploration



Resource: <https://www.nasa.gov/langley/>

Internship Timeline





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Maximo Hierarchy Graph Data Visualization

Maximo Hierarchy Graph Data Visualization

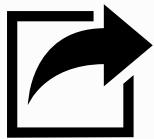


- **Current Challenge:** Data Management in Maximo Computerized Maintenance Management System (CMMS)

Maximo: maintenance asset and work order tracking



- Assets taxonomic hierarchy lacking intuitive visualization

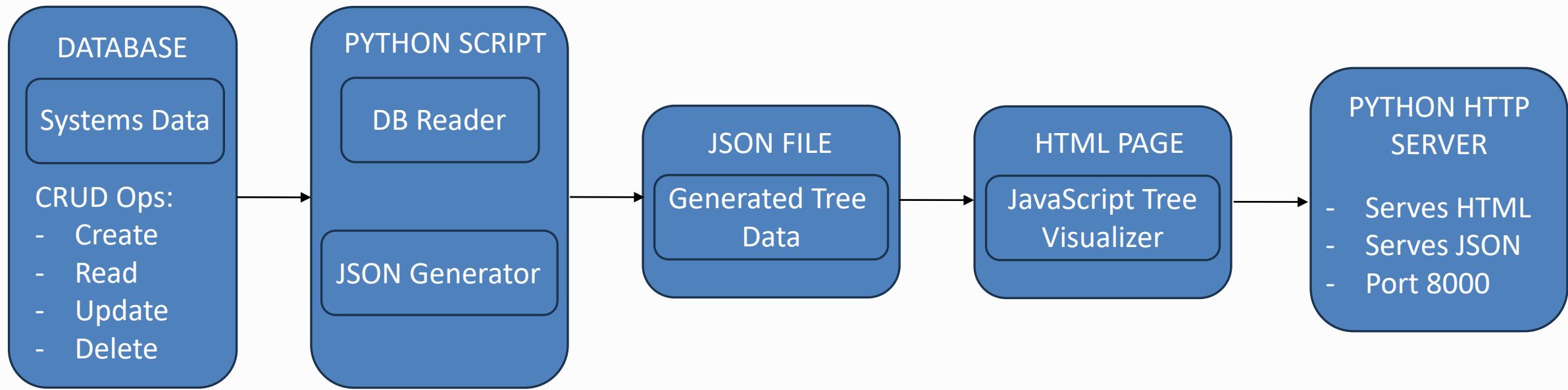


- NASA transition to *Enterprise CMMS (eCMMS)*



- **Goal:** develop intuitive Maximo hierarchy visualization mechanism to facilitate updates from LaRC's Maximo data to the new eCMMS schema

Web Application flow



Initial code for JavaScript Tree Visualizer provided by Braxton VanGundy

Web Application Back-end



Before update:

- BUILDING 100
- BUILDING 200

```
[  
  {  
    "file": "data\\BUILDING 100.json",  
    "name": "BUILDING 100"  
  },  
  {  
    "file": "data\\BUILDING 200.json",  
    "name": "BUILDING 200"  
  }  
]
```



After update:

- BUILDING 100
- BUILDING 200
- BUILDING 300
- BUILDING 400

```
[  
  {  
    "file": "data\\BUILDING 100.json",  
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  {  
    "file": "data\\BUILDING 400.json",  
    "name": "BUILDING 400"  
  }  
]
```

Web Application Interface

TREE VISUALIZATION

-- Select a file -- Visualize

↓

TREE VISUALIZATION

BUILDING 100 Visualize

-- Select a file --

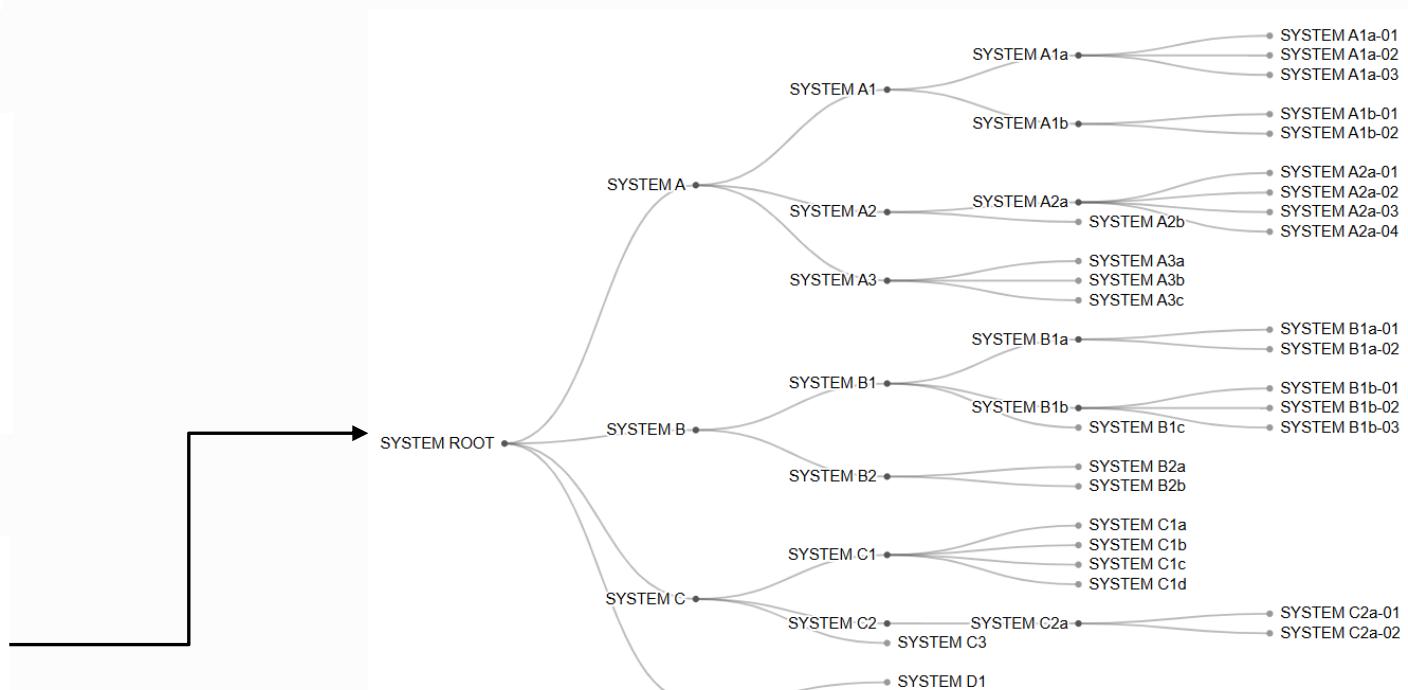
BUILDING 100
BUILDING 200

↓

TREE VISUALIZATION

BUILDING 100 Visualize

Select a Building and click "Visualize"



Results



- **Real-Time Visualization:** web interface displaying Maximo hierarchy data with building selectability



- **Optimized Data Pipeline:** lightweight pipeline handling data retrieval, updates, and reload operations for large-scale maintenance data



- **Scalable Architecture:** continuous improvement framework



- **Database Extensibility & Adaptability:** modular solution adaptable to any taxonomic hierarchy

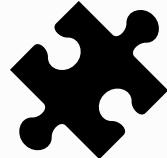


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Machine Learning for Time Series Predictive Maintenance

Machine Learning for Time Series Predictive Maintenance



- **Maintenance Timeline Opportunity:** develop ML models for expanded lead-time for predicting eminent maintenance system failures

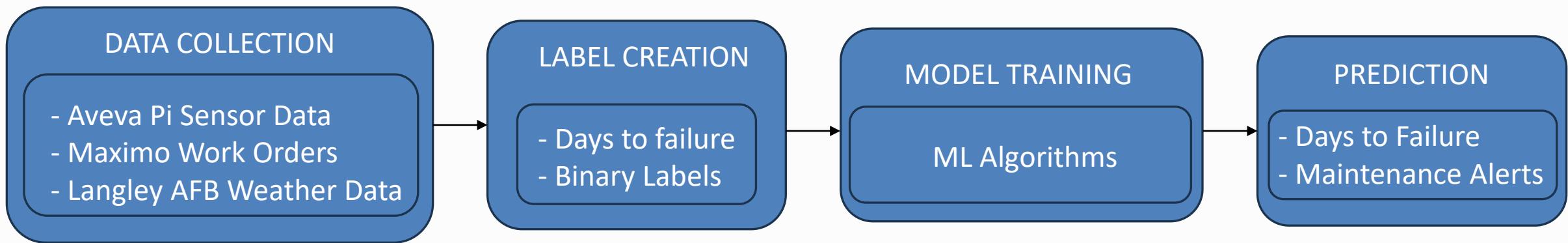


- **Operational Risk & Cost Impact:** Unexpected equipment failures compromise system reliability



- **Predictive Opportunity:** AI and Machine Learning (ML) for time series predict maintenance

Predictive Maintenance Pipeline



Data for Machine Learning Model

Aveva PI: Data Management Platform that collects and stores historical data

GB	Gearbox
InBrg	Inboard Bearing
OutBrg	Outboard Bearing
OB	Outboard
IB	Inboard
PeakVue	Method of measuring vibration
Overall	Another method of measuring vibration
PMPA	Pump A
PMPB	Pump B
CBM	Condition Based Maintenance
IOC	Integrated Operations Center
AlertFlag	Low setpoint for vibration measurements
AlarmFlag	Higher industry standard setpoint for vibration measurements
CTA	Cooling tower A

Maximo Data: Computerized Maintenance Management System (CMMS). Asset and work order tracking

Worktype	Description
CBMF	Condition-Based Maintenance Find
REPR	Repair
PM	Preventative Maintenance
PTIF	Predictive Testing & Inspection Find
SSR	Service Support Request
PMF	Preventative Maintenance Find
REPR	Repair
TC	Trouble Call
MREA	Maintenance & Reliability Engineering (or Effects) Analysis

Previous Intern Work

- Previous intern work was implemented combining XGBoost Algorithm which uses gradient boosting for ensemble learning, along with cross validation and hyperparameter tuning

Results of previous work:

Naïve Benchmark: **39.43 days remaining useful life (RUL)**

Model Overall Average: **~41 days RUL**

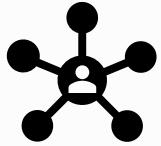
A Naïve baseline is the simplest possible model that serves as a performance benchmark (represents predicting the underlying probability distribution of the predicted value)

Model is similar to the Naïve estimation, indicating poor current performance

New approach



- Recurrent Neural Network (RNN) for capturing temporal patterns

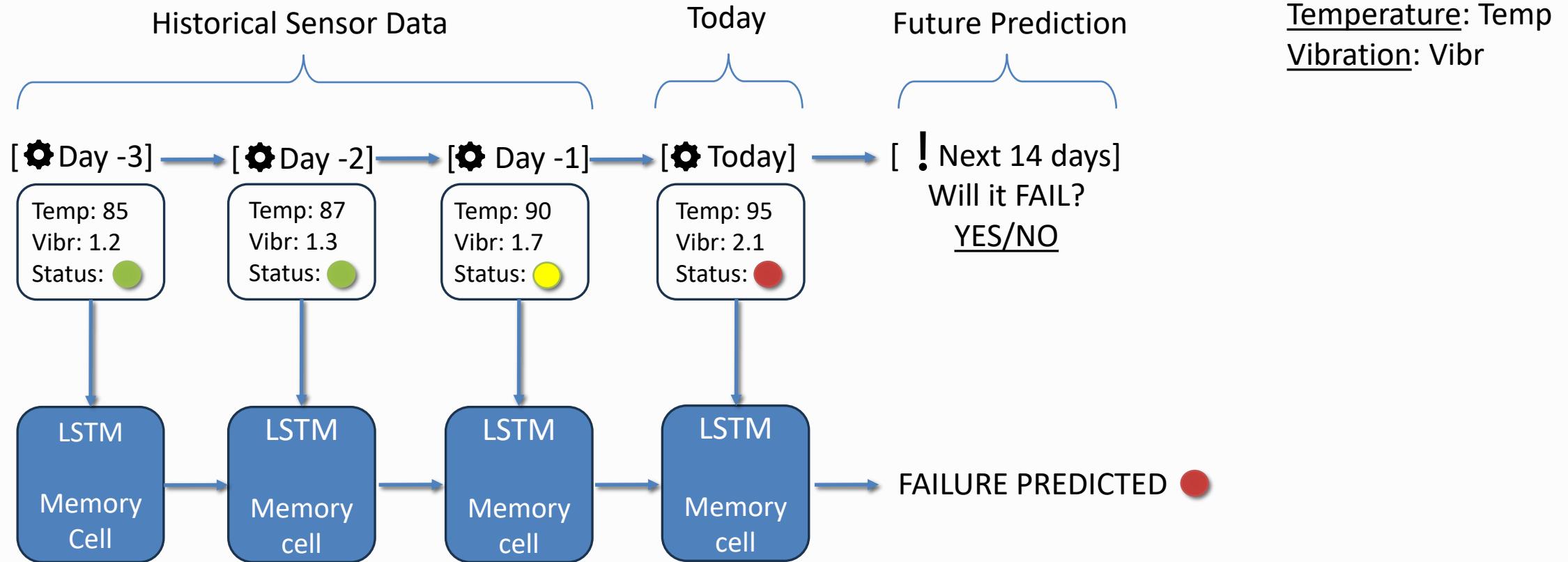


- Long Short-Term Memory as RNN approach - long-term patterns for early failure detection

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- Binary classification approach - predict failure within 14 days vs. continuous time-to-failure estimation

Long Short-Term Memory (LSTM)



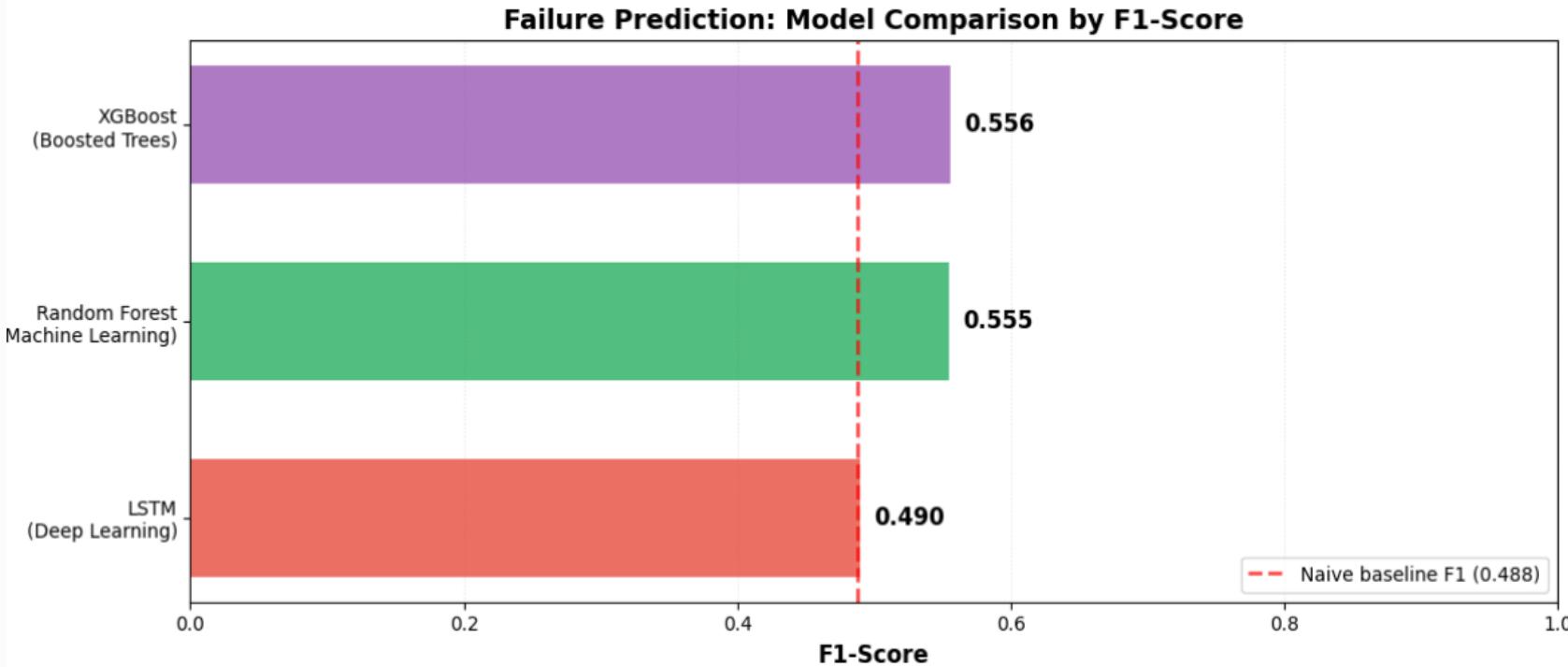
Labels generation

- **Approach 1:** Predict days until failure
- **Approach 2:** Create binary labels if failure happens within specific window days

Equipment ID	Days until failure	Failure within 14 days?
Pump-001	45 days	No
Pump-002	12 days	Yes
Pump-003	78 days	No
Pump-004	3 days	Yes
Pump-005	32 days	No

Result

Note: experiments with various dataset configurations, labeling approaches, and ML models presenting results from three representative models.



The F1 score is a measurement of accuracy that balances two factors and ranges from 0 to 1:

- How many correct positive results your model found (recall)
- How many of your model's positive predictions were actually correct (precision)

Conclusion



- Insufficient predictive signal with ML models performing only marginally better than naive baselines



- Future work: explore additional sensor modalities and data collection strategies, guided by subject matter expertise

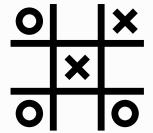


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Potential Future Solutions for Predictive Maintenance

Potential Future Solutions for Predictive Maintenance



Current approach: amplitude-based accelerometer measurements

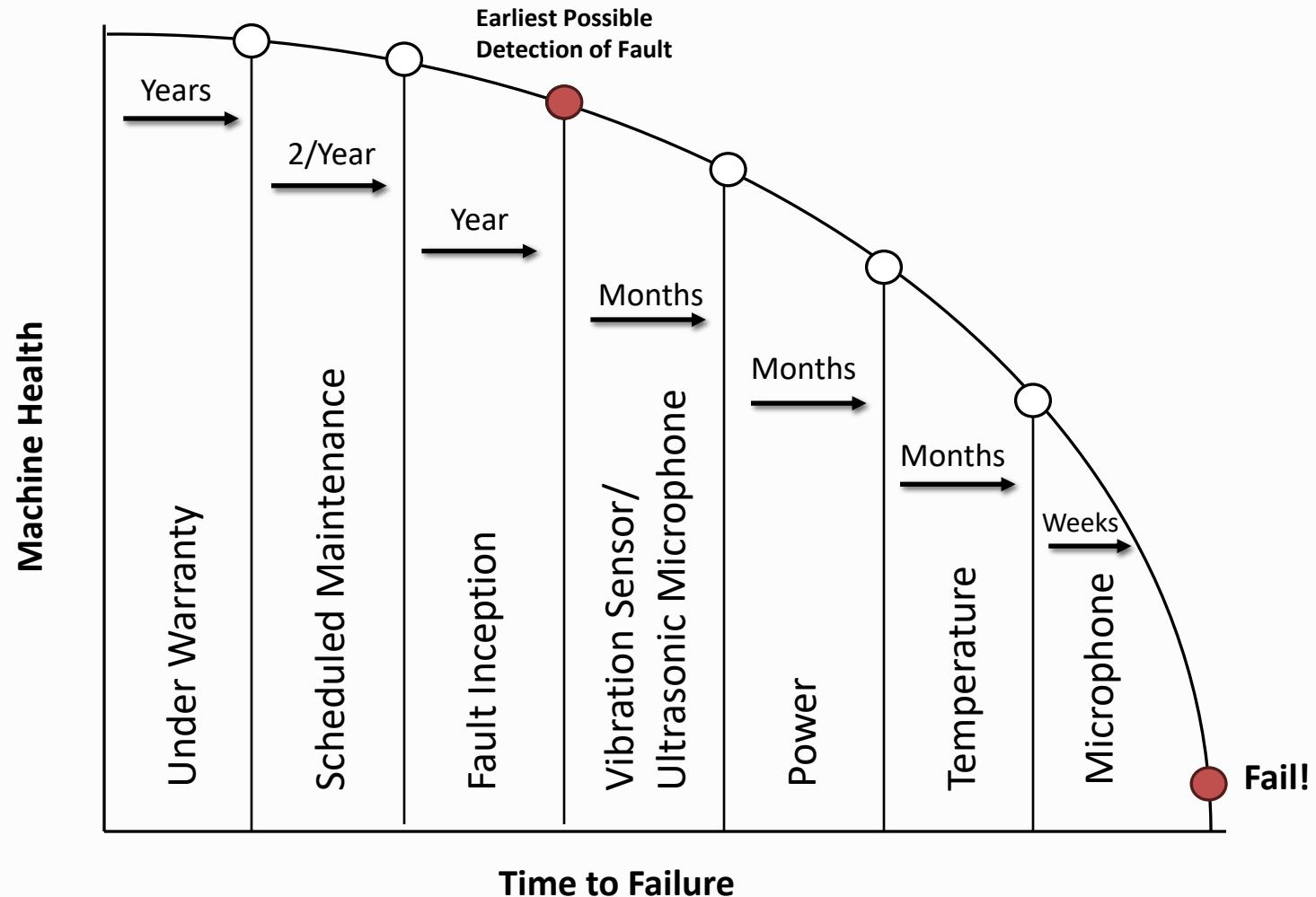


Limitation: early-stage bearing/gear defects: subtle vibrations typically undetectable via amplitude measurements



Solution: potential frequency-based accelerometers + acoustic sensors

Machine Health



Adapted from: Chris Murphy, 2020, [link](#)

MEMS (Micro-Electro-Mechanical Systems) Ultrasonic Microphones



Capability: monitors non-audible frequencies



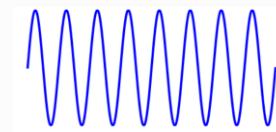
Benefits: directive ultrasonic signals with precise fault localization in bearings and housings

MEMS: Micro-Electro-Mechanic Systems

Equipment



20-100kHz



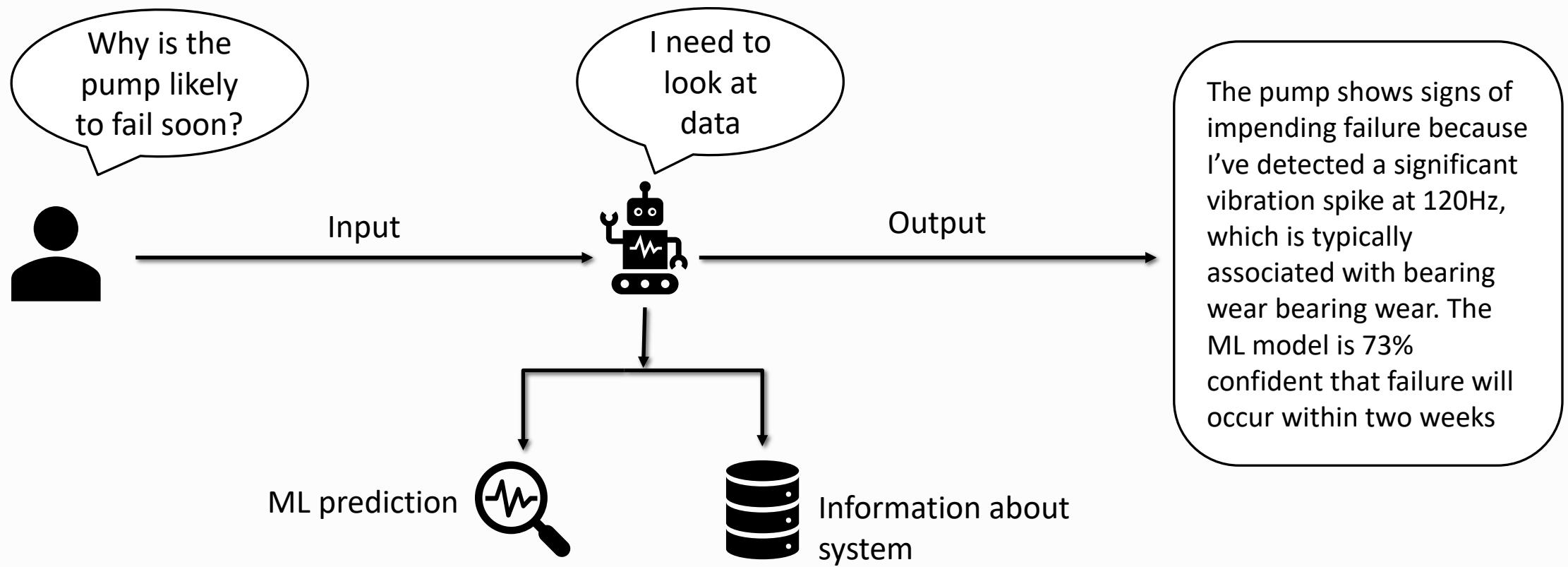
MEMS
Receiver



Alternative sensor: acoustic emission sensor

Explainable AI for future

- Example of interaction with the GenAI



Acknowledgements

- Langley Transformation Initiative
- Office of STEM Internships
- LaRC Center Operations Directorate
- Mentor: Charles Liles
- Braxton VanGundy
- Amentum Center Maintenance, Operations, and Engineering
 - Sarah Ritchey



Questions