



2023 NSRP All Panel Meeting

The Center for Naval Shipbuilding and Advanced Manufacturing Presents the Navy ManTech Project

S2959 – Machine Learning and Schedule Optimization

(A collaboration effort between ONR, NSAM, NNS, and Ingalls)

POP December 2021 – December 2023

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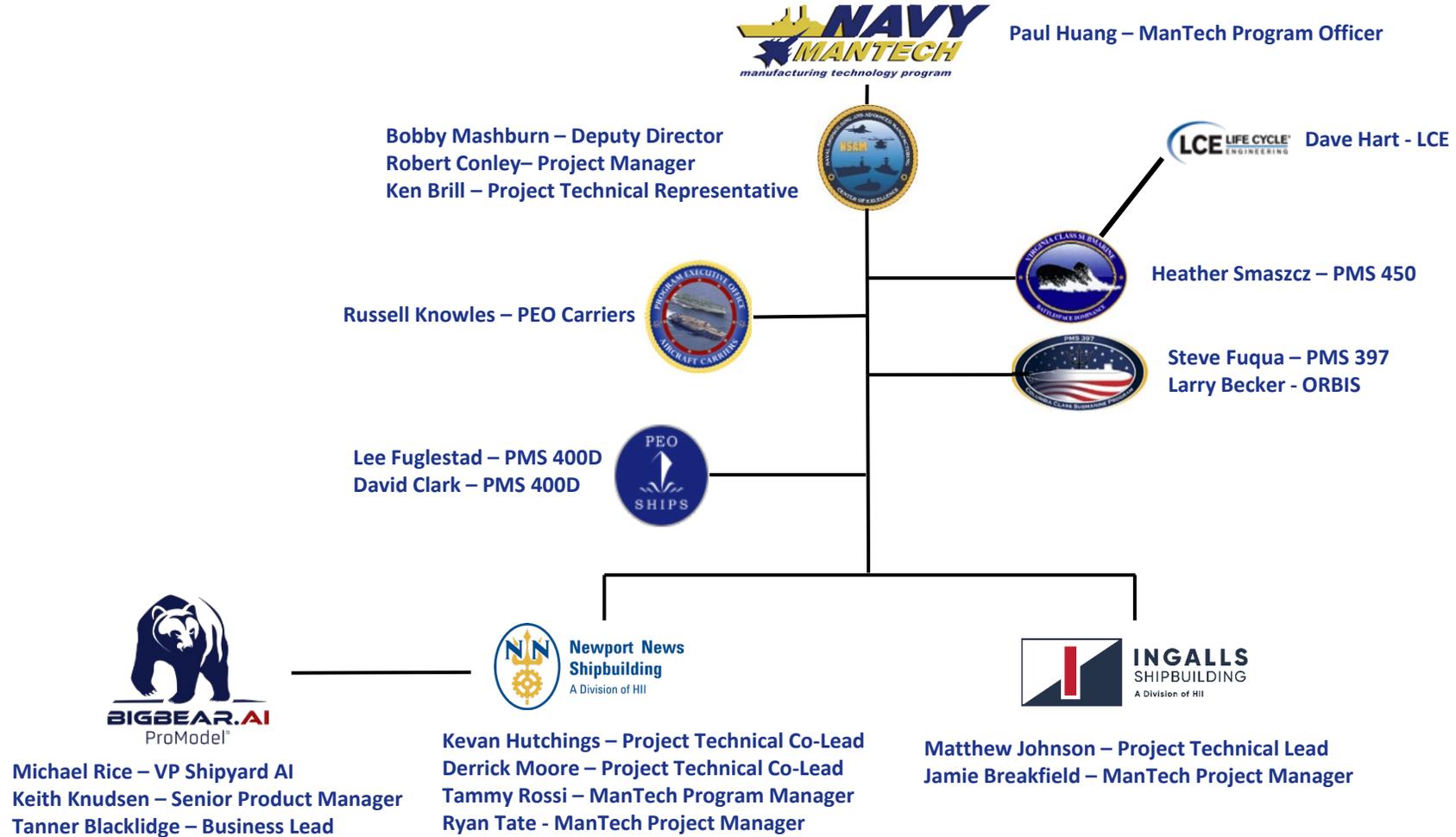
Agenda

- Project Team / Acknowledgements
- Background
- Objectives / Potential Benefits
- Technical Approach
- Status / Next Steps





Project Team / Acknowledgements





Background

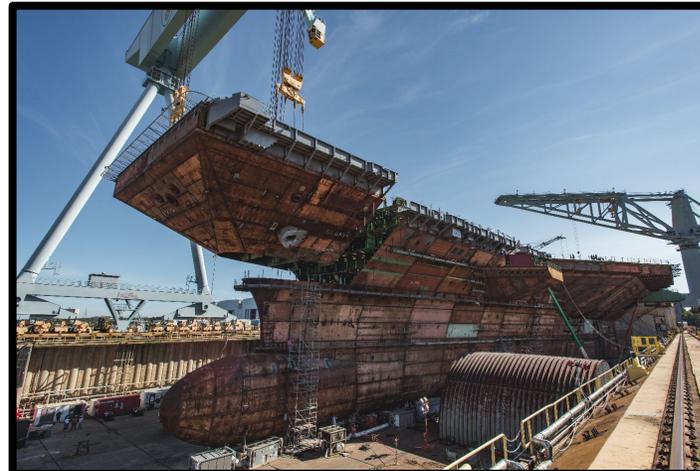
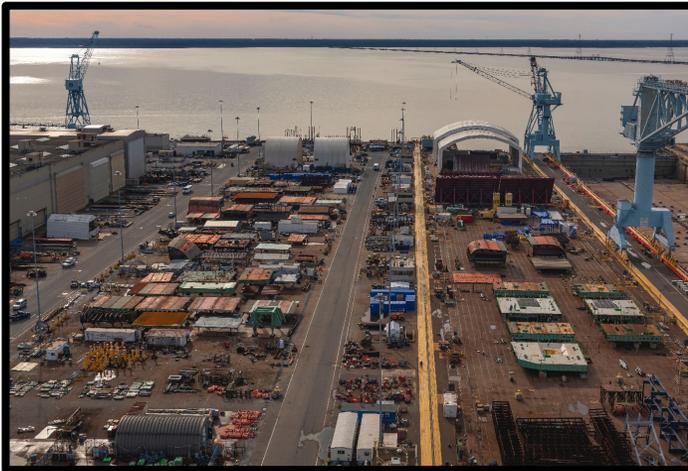
- At Newport News Shipbuilding (NNS) and Ingalls Shipbuilding (Ingalls), a single ship is erected from hundreds of modules. Multiple chains of dependencies exist during construction, and may be disrupted at any point, introducing risk to the construction schedule.
- Current planning systems account for these risks in many ways such as using redundancies, buffers, and alternative plans to form the basis of robust risk mitigation plans.
- Shipyards cannot significantly grow their footprint, leaving them extremely space constrained, often producing units outside an optimal schedule incurring both cost and schedule penalties.
- Current scheduling practices require integration of multiple departments, tribal knowledge sources, and multiple trial runs to reduce overall timelines while not overloading limited capacities throughout the yard and supply chain.





Background (Continued)

- Ingalls and NNS are using BigBear.ai's (ProModel) Shipyard AI program to track the current location, resource requirements, and progress of thousands of modules.
- Automated schedule optimization can enable additional timeline compression, plan adherence, cost savings, and more efficient footprint utilization with no increase in manpower.
- Application of machine learning algorithms can allow the scheduling systems to learn from historical and simulated production runs and apply lessons learned to current and future vessels.

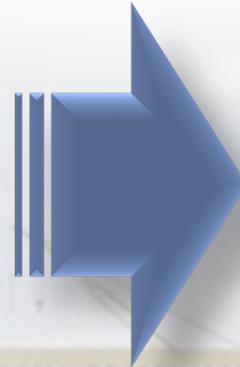




Objectives / Potential Benefits

Objectives

- Enhance Shipyard AI
- Utilize ML techniques to 'learn' business rules based on historical data
- Identify common features, create classifications
- Make placement recommendations based on ship unit attributes



Benefits/Impact

- Reduced vessel construction time
- Enhanced communication to internal supply chain
- Reduce time required to generate a viable and executable capacity plan
- Optimize capacity plans with respect to Safety, Quality, Cost, and Schedule

Estimated NNS/Ingalls Combined ROI = 5.0





Technical Approach

Phase I Approach:

- Conduct Organizational Needs Workshops at NNS and Ingalls
- Gather Use Cases and Functional Requirements for NNS and Ingalls
- Incorporate Use Cases and Functional Requirements into System Design
- Develop Initial Proof of Concept and installed at both yards
- Conduct Initial Proof of Concept testing

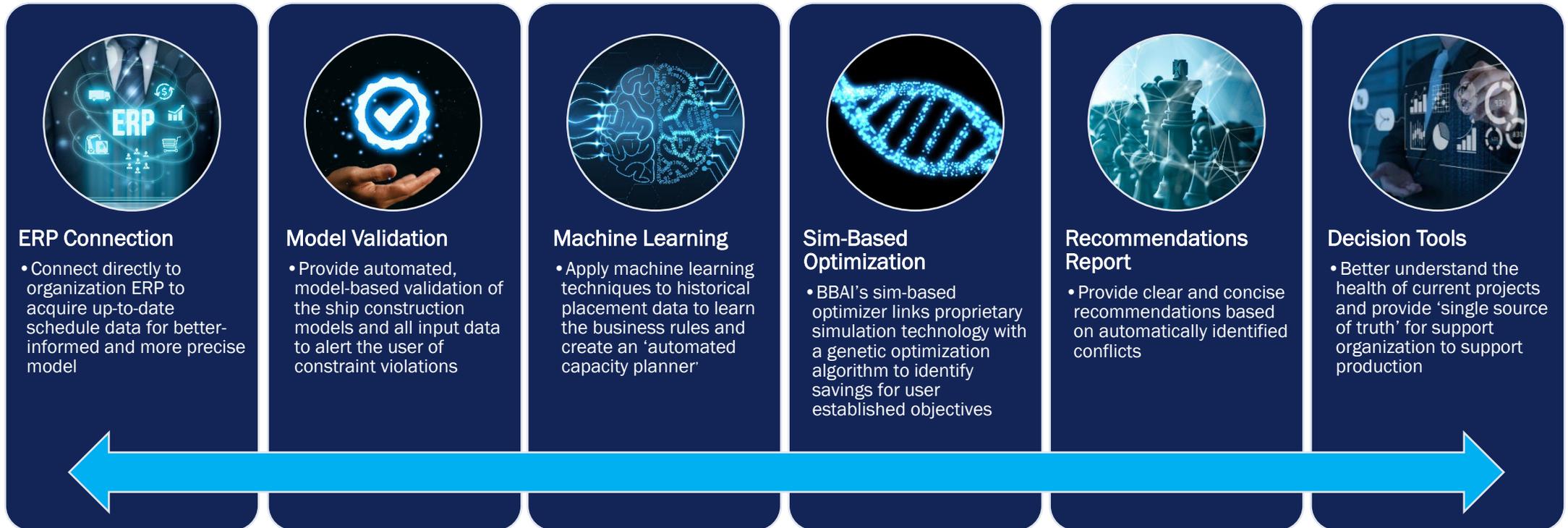
Task No.	Description	As of Jan 2023
1	Project Initiation	Complete
2	Envision the Machine Learning and Schedule Optimization Capability	Complete
3	Develop Initial Proof of Concept (POC) and Conduct Initial Testing	Complete
4	Phase I Reporting	In process
5	Update Functional Requirements and Test Plan	Not started
6	Final System Development	Not started
7	Final System Testing and Review	Not started
8	Develop Implementation Plan	Not started
9	Final Reporting	Not started





Technical Approach

Components of Initial Solution (Proof of Concept)





Technical Approach

Project Challenges & Required Technology

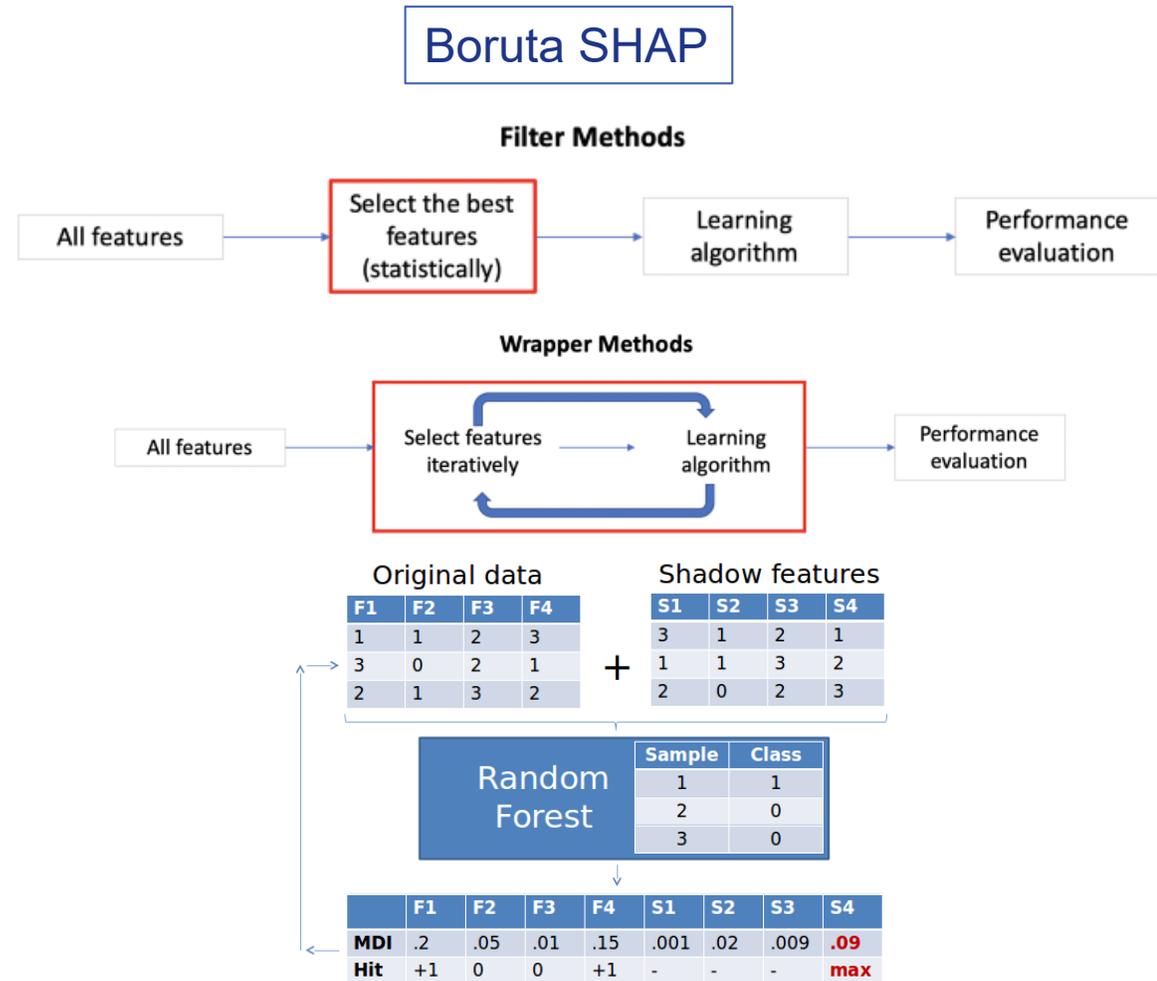
Challenges

- Many features
- Many potential models
- Many Laydown locations

Technologies Required

- HyperOPT for model selection
- Boruta SHAP for feature selection
- Utilized Databricks for scaling

Boruta SHAP





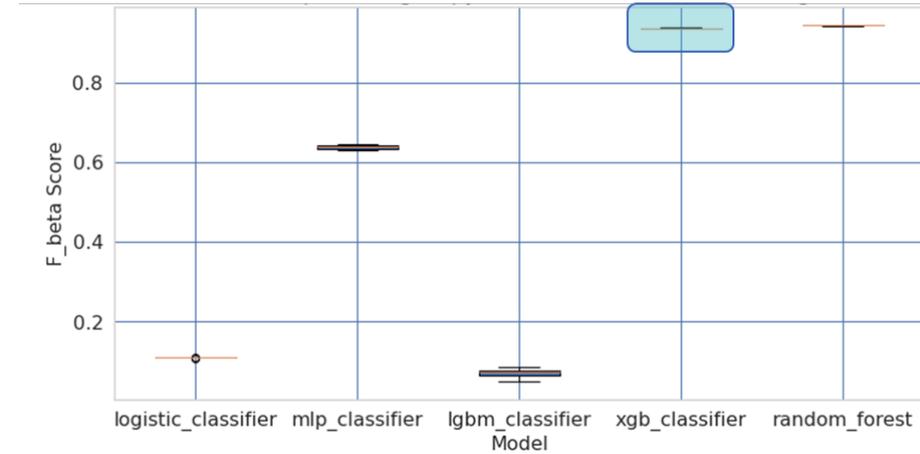
Technical Approach

ML Model Selection Process:

5 Models - Scored using Cross Validation

- MLP, Random forest & XGB were promising
- MLP & XGB classifiers - more generalizing
- Highest predictive accuracy - 45.3%
- XGB accuracy - 77.7% for top 5 locations /unit

Top 5 Model Performance



Model Performance on Test Data

Model	F-beta Score	Top Result	Top 2	Top 3	Top 5
Logistic Classifier	0.118	0.081	-	-	-
MLPClassifier_3L_100N	0.414	0.374	0.526	0.624	0.750
Random Forest300	0.460	0.451	0.493	0.506	0.523
Random Forest500	0.474	0.463	0.598	0.659	0.724
XGB Classifier20	0.474	0.453	0.600	0.676	0.777

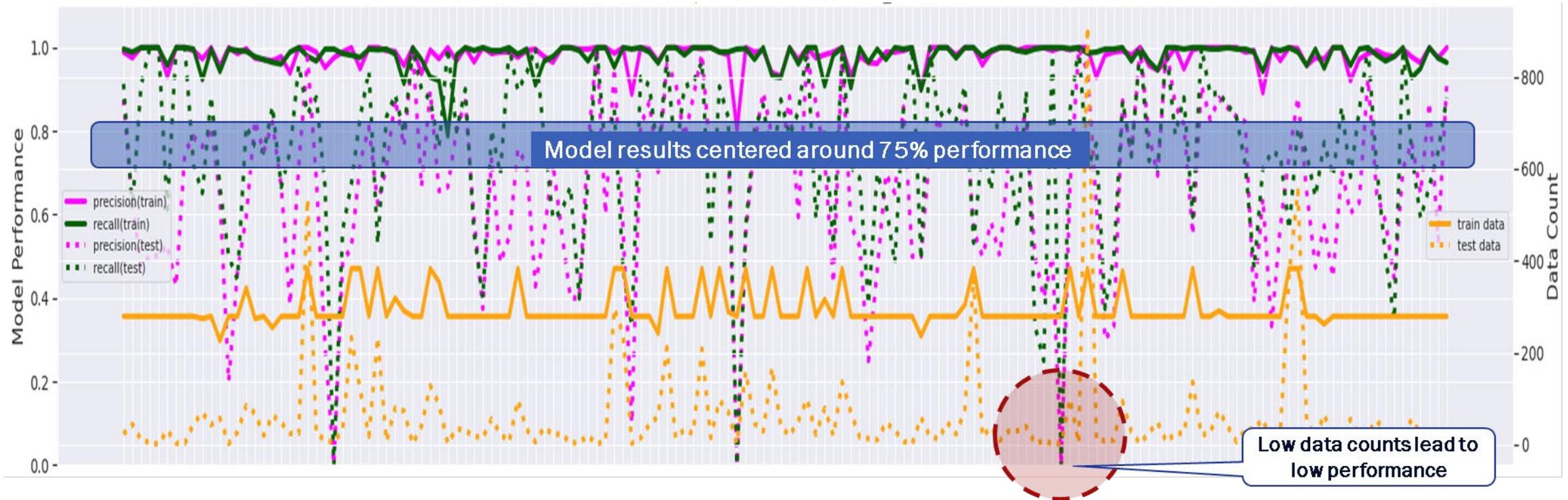


Technical Approach

Machine Learning Results for Shipyard AI

High precision/recall from optimized model

- Model performs well for shipyard locations that have more data
- Model average precision/recall is roughly 75% using test data





Status / Next Steps

Current Status

- Completed POC testing at Ingalls and NNS
- Generating interim Business Case analyses
- Phase I reporting and Go/No-Go recommendation

Phase II Approach

- Update Functional Requirements and Final Test Plan
- Final System Development and Delivery
- Final System Acceptance Testing and Documentation





Questions?





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