Leverage Artificial Intelligence to Learn, Optimize, and Win (LAILOW) for the Marine Maintenance and Supply Complex System

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Needs and Challenges

- Capability
- Manpower
- Logistics & Supply
  - Equipment,…,

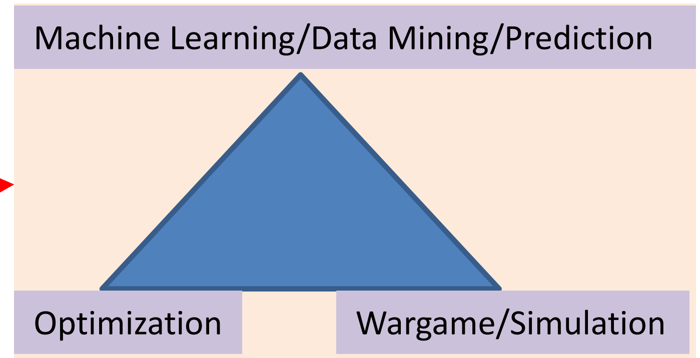
Operation concept e.g., Expeditionary Advanced Base Operations (EABO)

Big data feed from a long chain of readiness components

- Maintenance
- Supply
- Requisition
- Transportation
- Finance processes
- Activities
- Decisions

- USMC requires an agile, flexible, resilient logistics capabilities
- Current status
  - Applies predictive analytics for equipment reliability, spare parts to improve stock performance, synchronizes budget execution, and decreases maintenance cycle time.
  - Optimizes throughput capacity at nodes and arcs of logistical networks and avoid congestion or delays in operations.
- More Needs of deep analytics
  - Ability to analyze big data feed from a long chain maintenance, requisition, transportation, manpower, lesson learned, and finance processes, activities, and decisions.
  - Needs models to predict probability of fail (POF), probability of demand (POD), customer wait time, or adequate spare part inventory.
  - Needs optimization models to achieve desired measures of performance (MOP), e.g., minimizing the downtime of personnel and equipment.
  - Needs simulation tools to handle uncertainty and unknown operational conditions

LAILOW Framework and Methods



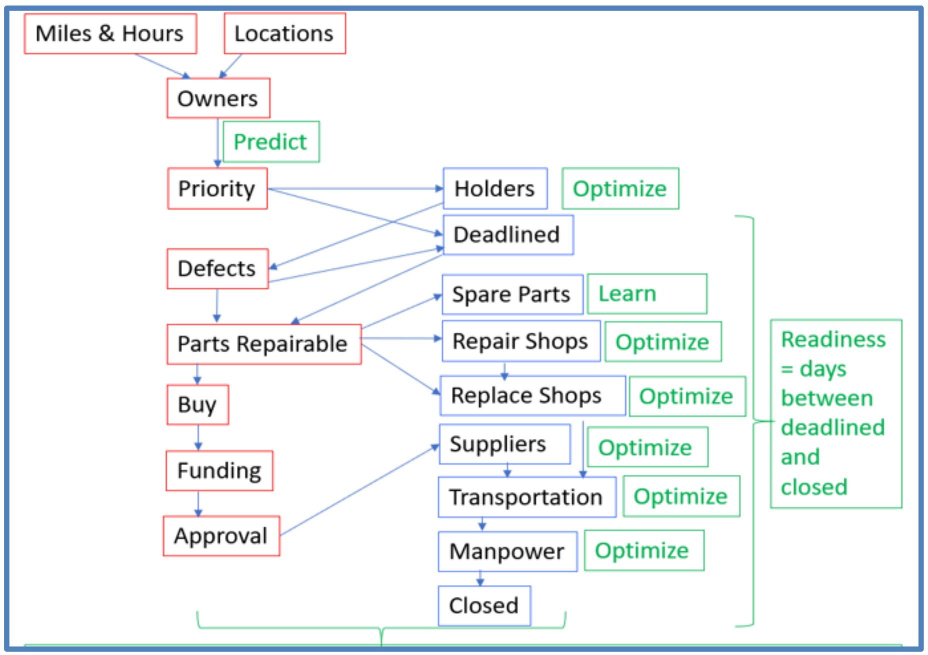
- Databases and data fusion methodologies
- Machine learning, data mining, and prediction algorithms
    - Lexical link analysis
        - Learn associations among parts, identify cascade effect part fail/demand and improve prediction
        - Learn process relations
    - Soar-RL: rule-based reinforcement learning algorithm used to predict readiness
- Optimization and wargame algorithms
    - Coevolutionary algorithms for simulation and optimization

Fuse Data From the MDR/GCSS-MC Databases

- Data Fusion
  - Master Data Repository (MDR)
  - Global Combat Support System-Marine Corps (GCSS-MC)
    - GCSS-MC provides a deployable, single point of entry for all logistics requirements.
    - GCSS-MC also introduces cutting edge enabling technology in support of logistics operations and modernization
- Digital Twin

Current Data from GCSS-MC

- Land Armored Vehicle (LAV) (1/2013 to 1/2020), E0949 GCSS-MC Maintenance Data Pull-analysis



Time Series of Maintenance Tickets of LAV

SR_NUMB	TAMCN	SERVICE_REQUEST_TYPE	JOB_STATUS_CODE	DEFECT_CODE	OPERATIONAL_STATUS	PROBLEM_SUMMARY	DATE_RECEIVED_IN_SHOP	ECHELON_OF_MAIN	NSN_IN_MAINTENANCE	SERIAL_NUMBER	QUANTITY	UNIT_ISSUE_CODE	DEADLINED_DATE
10168458	E09497M	Maintenance - CM	CLOSED	ELEC.UNK	Operational - Minor	INSTALL IPC	24-FEB-14	2	2355015393578	572440	1	EA	
10168458	E09497M	Maintenance - CM	CLOSED	ELEC.UNK	Operational - Minor	INSTALL IPC	24-FEB-14	2	2355015393578	572440	1	EA	
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10168458	E09497M	Maintenance - CM	CLOSED	ELEC.UNK	Operational - Minor	INSTALL IPC	24-FEB-14	2	2355015393578	572440	1	EA	
10168842	E09497M	Maintenance - CM	CLOSED	HYDR.HYDR	Operational - Degraded	THE SRUTS WHERE BENT	24-FEB-14	2	2355015393578	572453	1	EA	
10170034	E09497M	Maintenance - CM	CLOSED	SUSP.CBB	Deadlined	Front Struts are bent	24-FEB-14	2	2355015393578	572453	1	EA	06-MAR-14
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10170034	E09497M	Maintenance - CM	CLOSED	SUSP.CBB	Deadlined	Front Struts are bent	24-FEB-14	2	2355015393578	572453	1	EA	06-MAR-14

Pre-process Data for Predictive Models

- Aggregate all service tickets

SR_NUMBER	TAMCN	SERVICE_REQUEST_TYPE	DEFECT_CODE	OPERATIONAL_STATUS	ECHELON	MASTER_PRIORITY_CODE	OWNER_UNIT	DATE_CLOSED	OPENED_DATE
11280122	E09497M	Maintenance - CM	PWRT.MDRV	Operational - Degraded	2	06 B-Urgent	M11700	06-SEP-19	10-MAR-14
11280122	E09497M	Maintenance - CM	PWRT.MDRV	Operational - Degraded	2	06 B-Urgent	M11700	06-SEP-19	10-MAR-14
11280122	E09497M	Maintenance - CM	PWRT.MDRV	Operational - Degraded	2	06 B-Urgent	M11700	06-SEP-19	10-MAR-14
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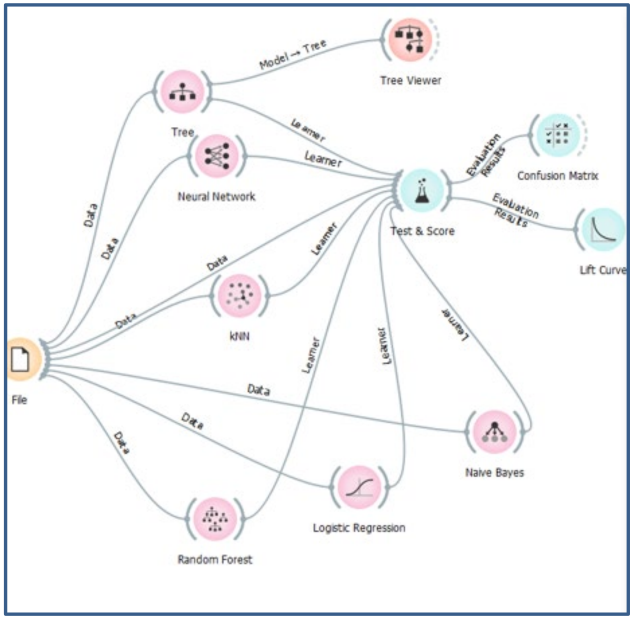
11280122	E09497M	Maintenance - CM	PWRT.MDRV	Operational - Degraded	2	06 B-Urgent	M11700	06-SEP-19	10-MAR-14

- Maintenance history: unique number of service request types, unique number of defect codes, unique number of operational status, unique number of echelon of maintenance, unique number of master priority code, count of job status dates, count of service cross-references, unique number of service parts, count of service activities, count of task numbers.
- Requisition data: maximum of part charge, count of document numbers, count of parts update dates, count of requirement numbers, count of unit issue, count of item types, count of supply route locations.
- Equipment usage data: owner unit address code, equipment operation time code, and meter reading.

- ~489 independent variables
- Dependent variable = measure of performance (MOP) = the days between opened and closed date more than 65 days (65 days is the mean of the days between the opened and closed dates)
- 2065 service numbers/tickets and 599 (29%) of 2065 have for MOP = 1

Orange Tool as Predictive Models

Workflow

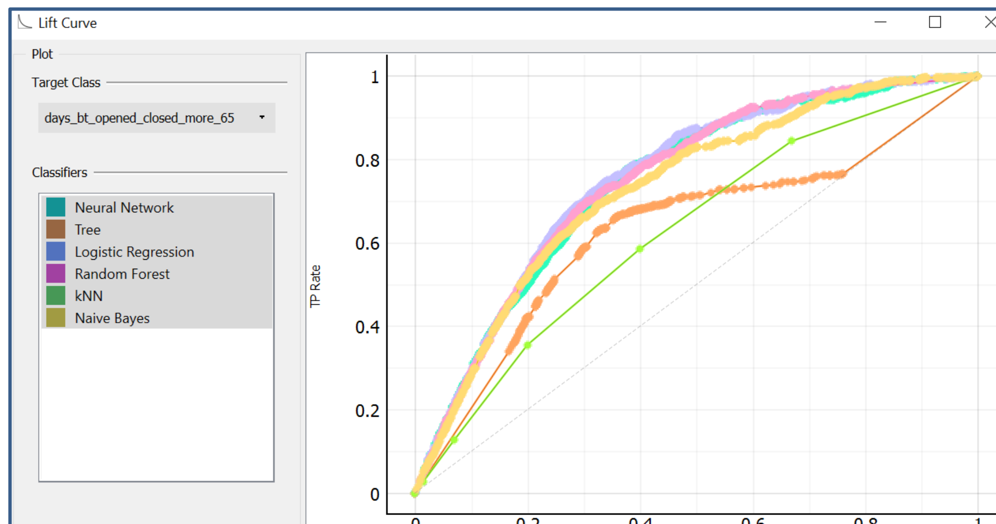


Method	AUC	CA	F1	Precision	Recall
kNN	0.679	0.716	0.421	0.516	0.356
Tree	0.683	0.760	0.554	0.600	0.514
Random Forest	0.849	0.815	0.658	0.711	0.613
Neural Network	0.848	0.802	0.634	0.683	0.593
Naive Bayes	0.828	0.713	0.618	0.503	0.800
Logistic Regression	0.859	0.822	0.651	0.756	0.573

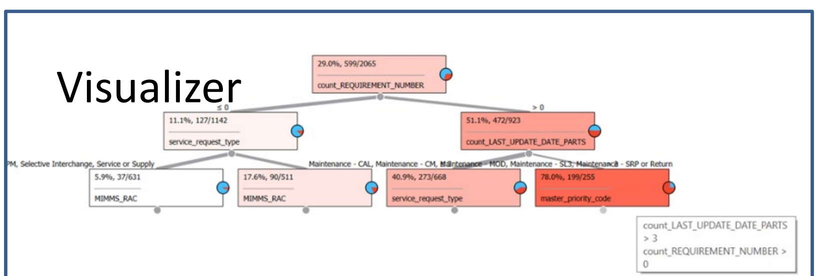
Added Soar-RL Outside Orange

Performance

Lift curve



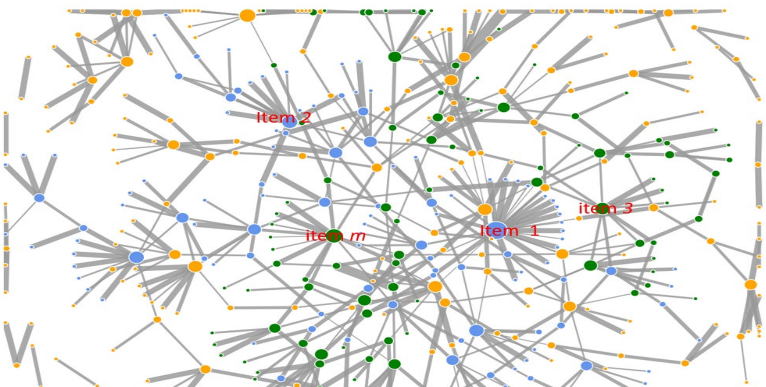
Visualizer



Lexical Link Analysis (LLA): to address the needs to handle the uncertainty, perturbation of a complex Enterprise)

- The uncertainty, disruption, and perturbation that can impact the logistics
- plans as a whole.
    - Environment and events in wide geographic areas, weather change or mission change from a peace time to a conflict time,
    - a sudden event can cause a perturbation, disruption, and cascade effects for previous logistics and supply plans

- Call for integration of data fusion, data mining, machine learning, optimization, game theory, and complex system theory to address the challenges

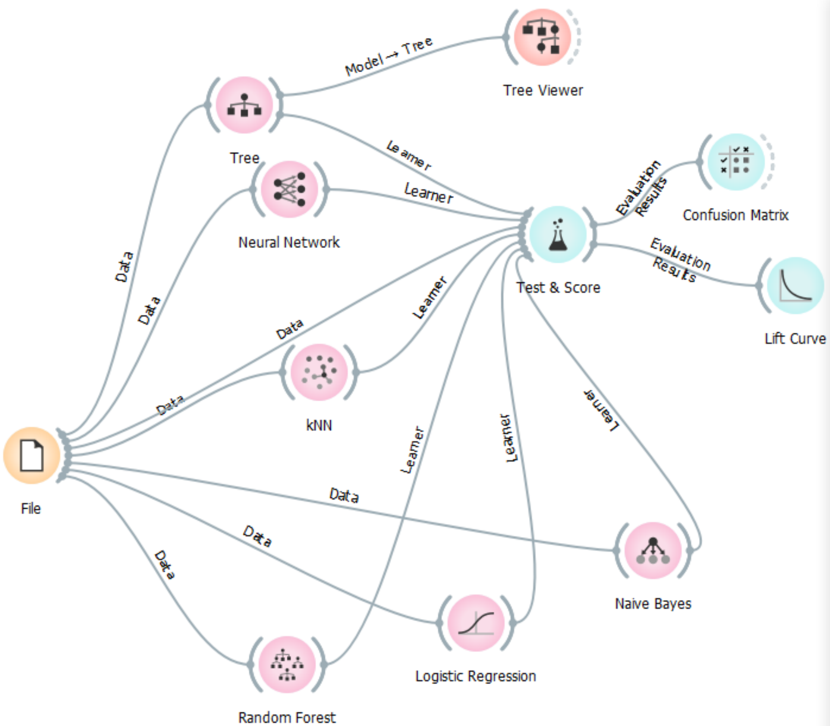


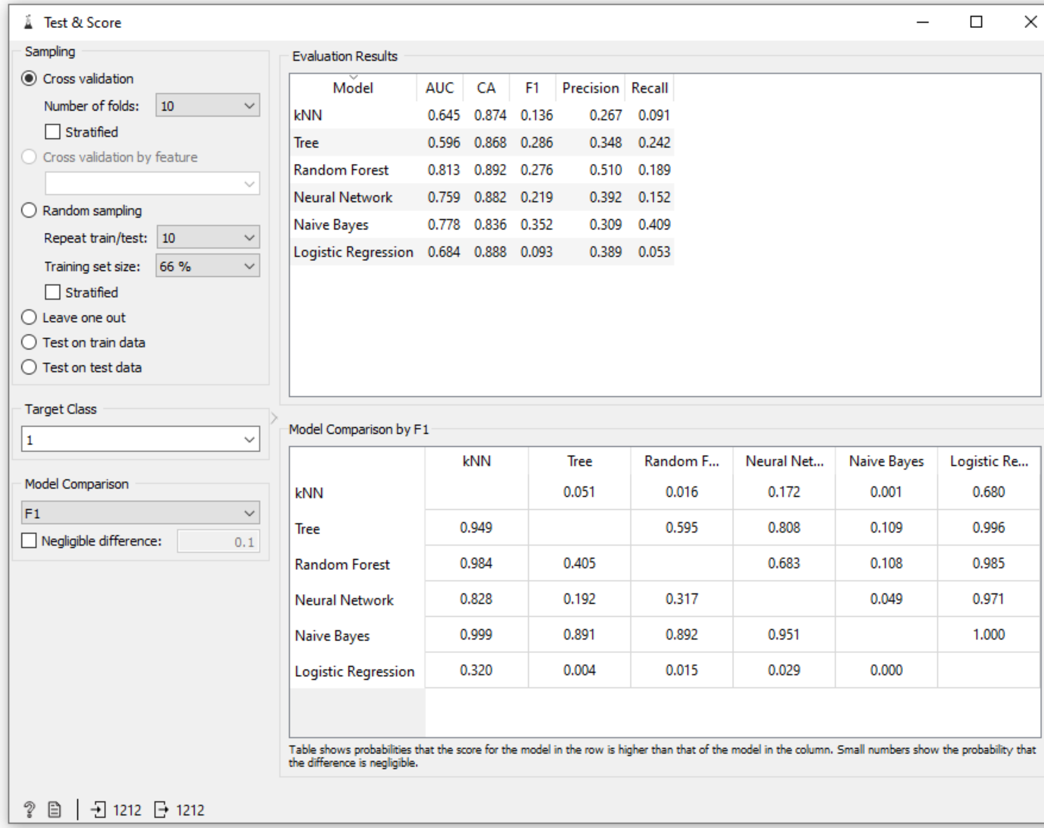
Probability of Failure/Demand

Lexical Link Analysis: Cluster items and compute centrality of items

Individual item predictive models

Predict Deadlined to Closed with and without Part Associations, LLA Improves





Test & Score

Sampling
- (•) Cross validation
  - Number of folds: 10
  - [ ] Stratified
- ( ) Cross validation by feature
- ( ) Random sampling
  - Repeat train/test: 10
  - Training set size: 66 %
  - [ ] Stratified
- ( ) Leave one out
- ( ) Test on train data
- ( ) Test on test data

Target Class: 1

Model Comparison: F1
- [ ] Negligible difference: 0.1

Evaluation Results

Model	AUC	CA	F1	Precision	Recall
kNN	0.645	0.874	0.136	0.267	0.091
Tree	0.596	0.868	0.286	0.348	0.242
Random Forest	0.813	0.892	0.276	0.510	0.189
Neural Network	0.759	0.882	0.219	0.392	0.152
Naive Bayes	0.778	0.836	0.352	0.309	0.409
Logistic Regression	0.684	0.888	0.093	0.389	0.053

Model Comparison by F1

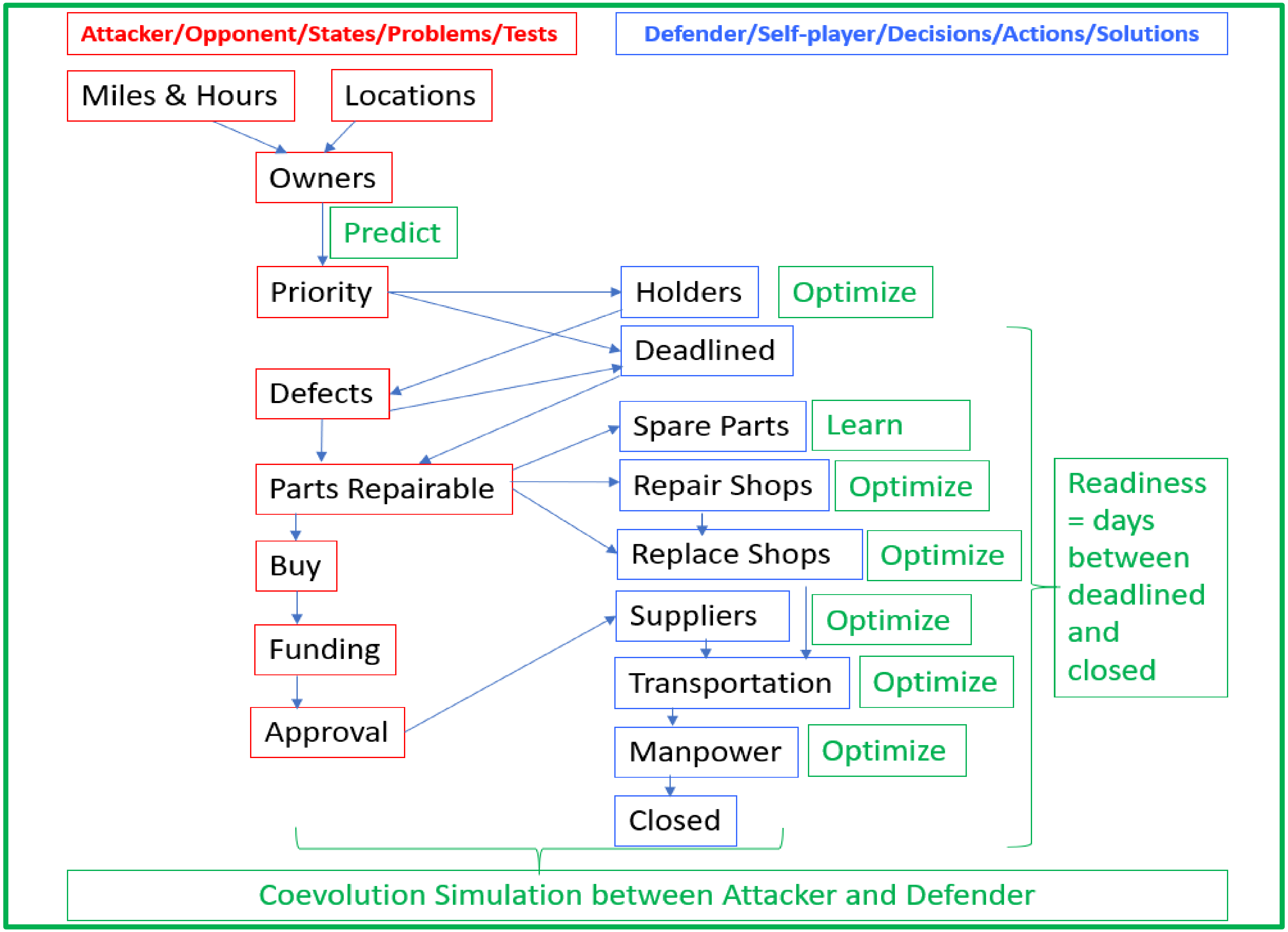
	kNN	Tree	Random F...	Neural Net...	Naive Bayes	Logistic Re...
kNN		0.051	0.016	0.172	0.001	0.680
Tree	0.949		0.595	0.808	0.109	0.996
Random Forest	0.984	0.405		0.683	0.108	0.985
Neural Network	0.828	0.192	0.317		0.049	0.971
Naive Bayes	0.999	0.891	0.892	0.951		1.000
Logistic Regression	0.320	0.004	0.015	0.029	0.000	

Table shows probabilities that the score for the model in the row is higher than that of the model in the column. Small numbers show the probability that the difference is negligible.

1212 1212

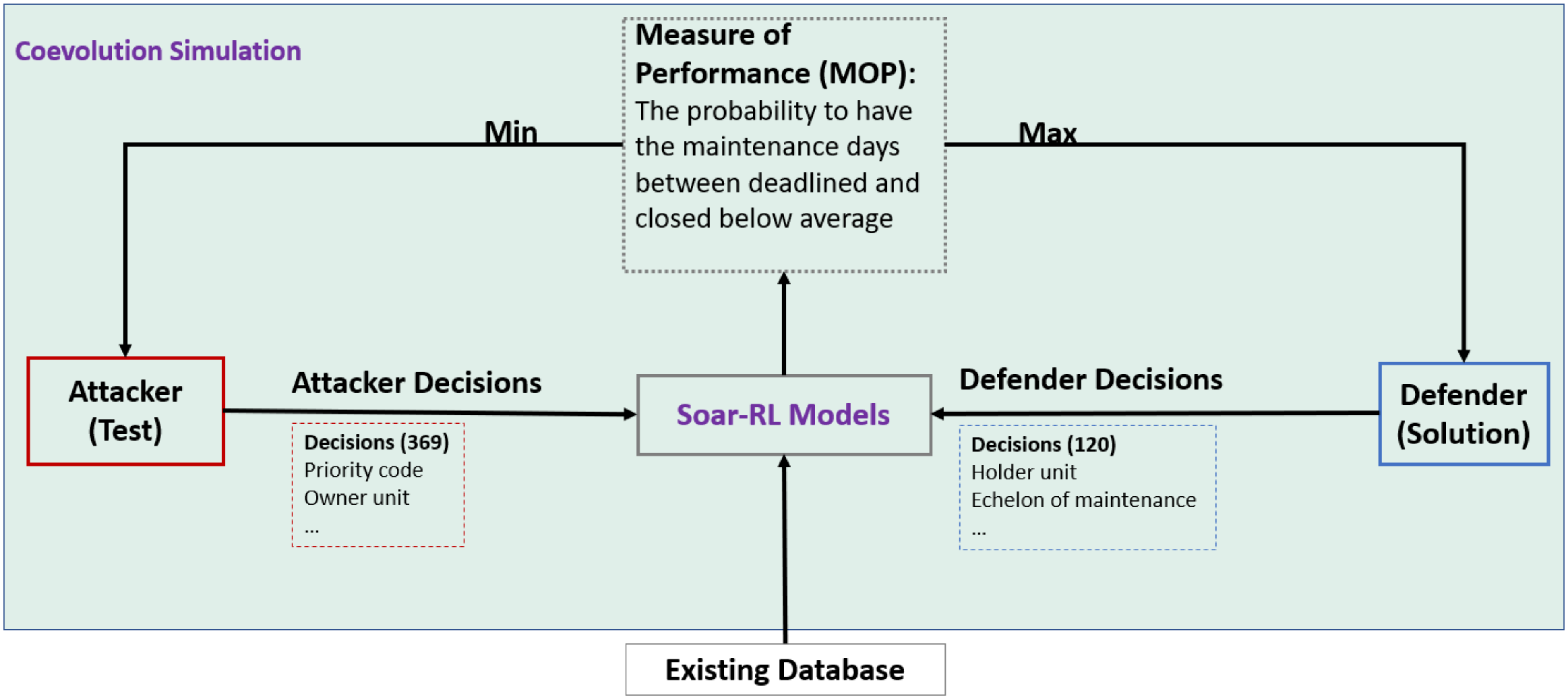
- Aggregate services and filter out zero rnsn (1212, all deadlined service tickets)
- Predict the ones with "deadlined to closed > 32 days" (132, 10.9%) with and without parts associations from LLA

Simulation and Wargame Set Up

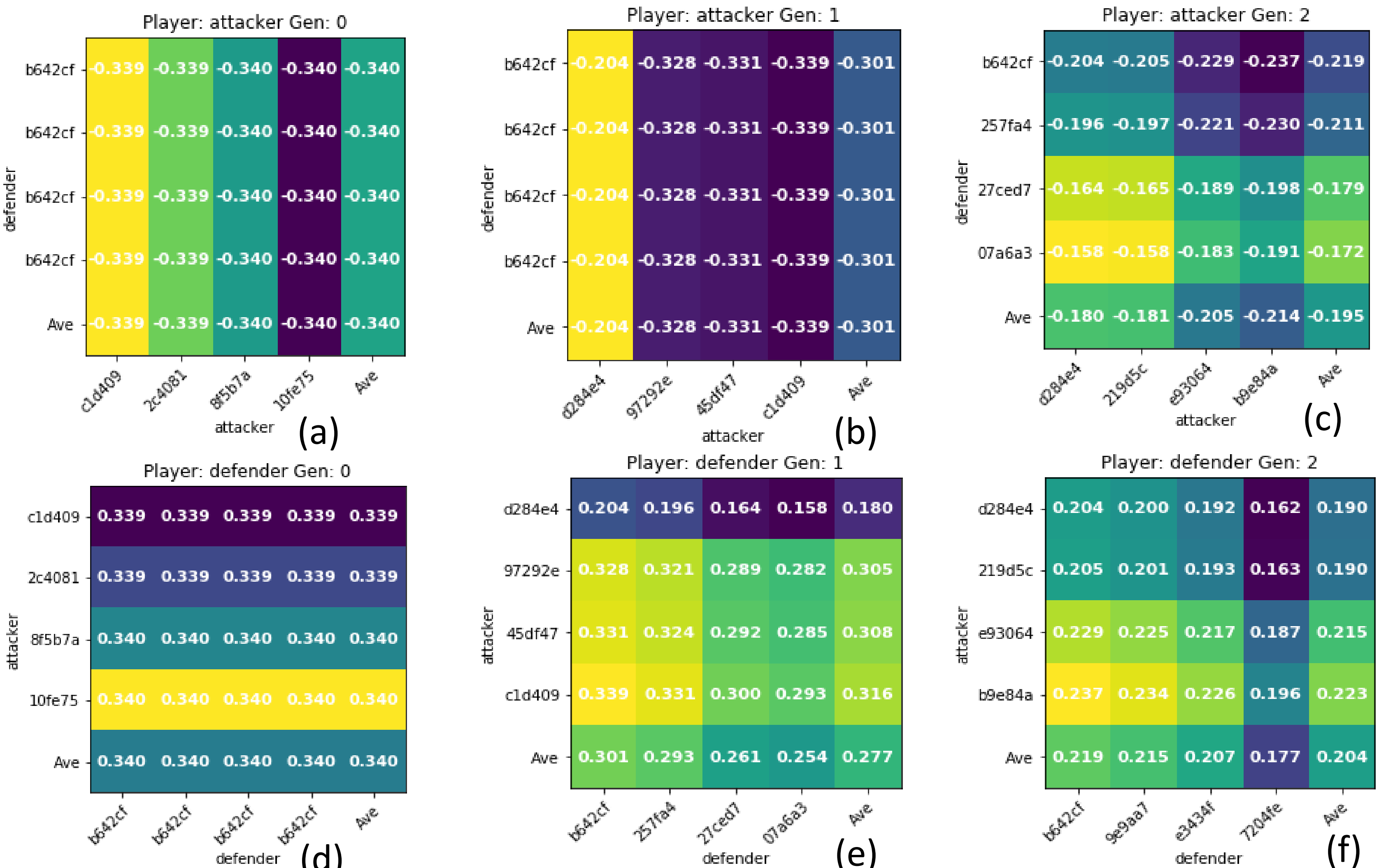


Coevolutionary Algorithms: Simulation and Wargame

Simulated new data/what if analysis



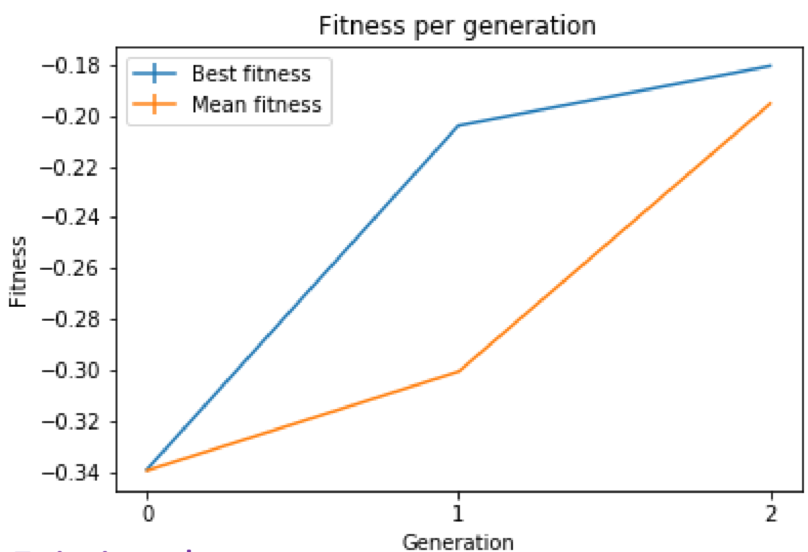
Coevolution Process



Soar-RL and Coevolutionary Algorithms

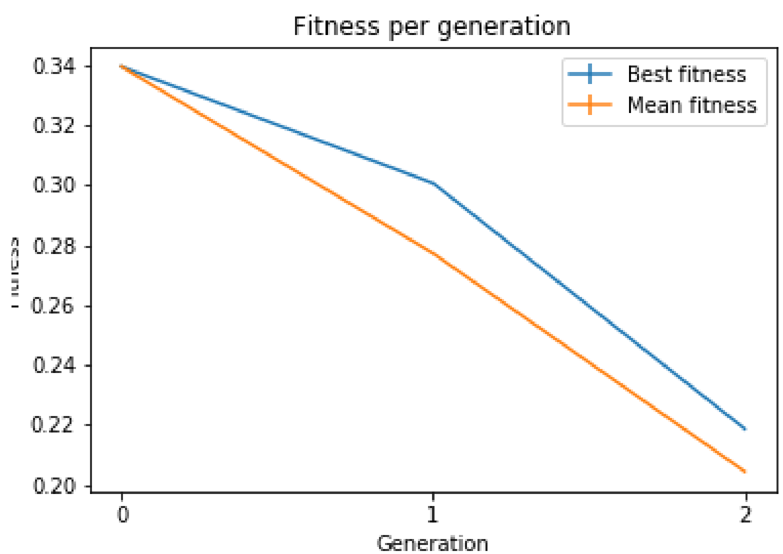
Attackers/Problems

Defender/Solutions



Existing data

(a)



Existing data

(b)

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Conclusions

- Soar-RL results comparable in predictive accuracy for predicting a readiness measure.
- Soar-RL is also rule-based and explainable, integrated with the coevolutionary algorithms for optimization and wargame
- The wargame shows that in terms of the readiness (or fitness) value,
  - The logistics solutions, on average, worsens in evolution, while
  - The opponent, representing logistics tests, on average, improves in evolution.
  - The Soar-RL and Coevolutionary algorithm integration potentially can systematically
    - Simulate and discover possible new tests or “vulnerabilities” of the whole maintenance and supply system, and
    - Evolve solutions or “resiliency” accordingly
- The LAILOW framework provides a holistic predictive and simulation platform to improve total readiness of a resilient and agile USMC logistics enterprise.
- Recommendations: It is imperative for United States Marine Corps (USMC) to adopt more advanced data sciences, including: machine learning/artificial intelligence (ML/AI) techniques to focus on the entire spectrum or end-to-end (E2E) logistic planning for the complex enterprise of maintenance, supply, transportation, health services, general engineering, manpower, lesson learned, and finance.
- Continuous work in this area jointly with the development of Global Combat Support System-Marine Corps (GCSS-MC) is necessary

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