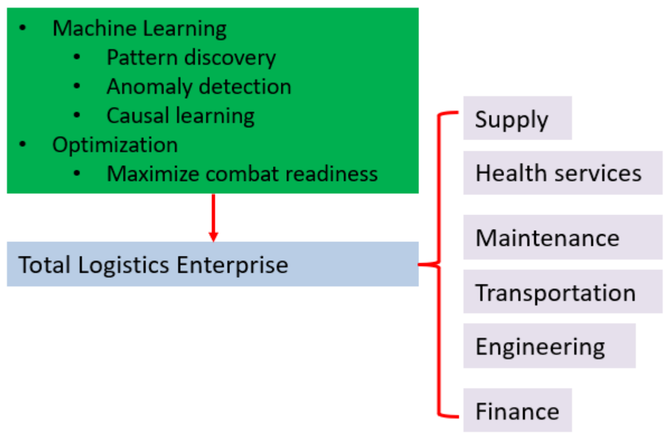
# Leveraging Artificial Intelligence (AI) to Optimize Global Material Distribution

Ying Zhao, Naval Postgraduate School, Monterey, CA, USA, yzhao@nps.edu
10/2019

Naval Postgraduate School

## Big Picture and Challenges




- Naval logisticians often have to manually coordinate material movement across global material distribution processes, often culminating in replenishments at sea (RAS), to achieve optimized delivery of assets to maximize operational availability
- Automation and optimization AI are needed to reduce cognitive burden of logisticians

## Research Data Sets

BLT

(Classic) Battle Load Tool in a Denied Comm Environment

Classic version created for backward compatibility with previous versions of MS Excel)

Compliance: 23MAR019 Version: 04/24/2019 RR

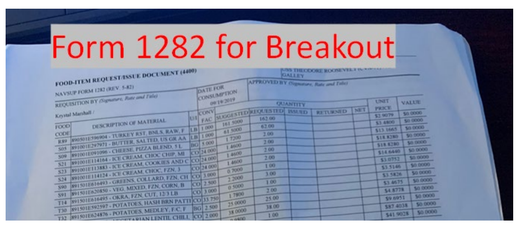
- BLT is used by a CLO representing a ship to place orders, so it should estimate how much to push based on previous RAS info and general statistics from the consumption data.
- BLT can generate a MILSTRIP to place an order to either a SPV or CLF.

Master Consumption

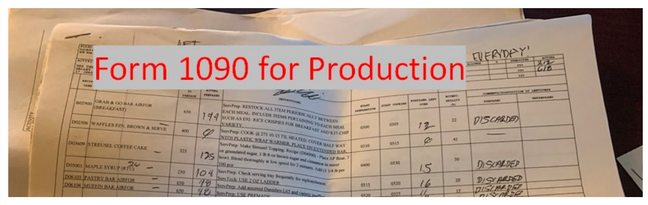
| | | | SUMMER PATROL 18-1 | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | 16-29 | 30-13 | 14-27 | 28-10 | 11-24 JUN 18 | 25-8 JUL 18 | 09-22 JUL 18 | 18-1 TOTAL |
| 890501E198297 | Chicken, Boned, 6/48 oz cn | CN | 44 | 26 | 88 | 82 | 123 | 146 | 122 | 631 |
| 890501E099941 | Fish, Tuna Light, 6/43 oz pg | PG | 118 | 86 | 114 | 162 | 278 | 130 | 150 | 1038 |
| 891001E297682 | Eggs, Scrambled (Dehy) | CO | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 891001E093332 | Soft Serve, Choc, 6/6 lb co | CO | 0 | 0 | 1 | 6 | 60 | 100 | 43 | 210 |
| 891001E093333 | Soft Serve. Van. 6/6 lb co | CO | 0 | 0 | 1 | 6 | 76 | 94 | 92 | 269 |

CARGO & SUSTAINMENT | FLEET FRIEGHT | ENDURANCE | NIS

Form 1282 for Breakout



Form 1090 for Production



Customer Order Trackers (COTs, from the 7th fleet CLOs)
- Current
  - 9M order received
  - Time sent to vendors
  - Goods load date (due date)
  - RAS event date
- Completed
- Canceled

## Research Methods

Identify Current Needs
- In-transit visibility
- In-demand visibility
- Prediction and optimization under uncertainty

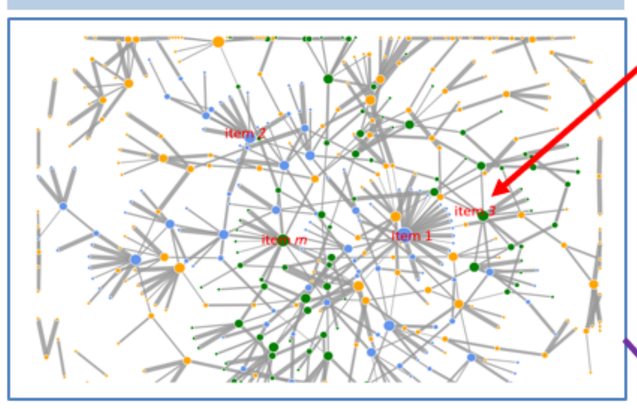
Focus on Specific Areas
- Push logistics
- Food service
- Cascade effects
- Part-maintenance use cases

Selected Algorithms
- Exploratory analysis and visualization
- Pattern discovery
- Anomaly detection
- Lexical link analysis
- Causal learning

## Research Results

- Identified uncertainty factors for BLT
- Designed the item association/graph and cascade computation models for BLT
- Currently in the process of testing these models
- Developed two use cases related to the project

Learn item associations/graphs and compute cascade effects




Knowledge and rules from human SMEs

Existing predictive models

Perturbations and disruptions
- Δ quantity

Identified uncertainty factors for push logistics:
- Recipe change
- Ingredient change
- Large number of vendors
- Big area,
- Different lead time
- Complex schedules
- RAS uncertainty
- Food production uncertainty
- Data collection uncertainty

Combat readiness of the global material distribution
- Quantities to push of all items
- Cost
- Time

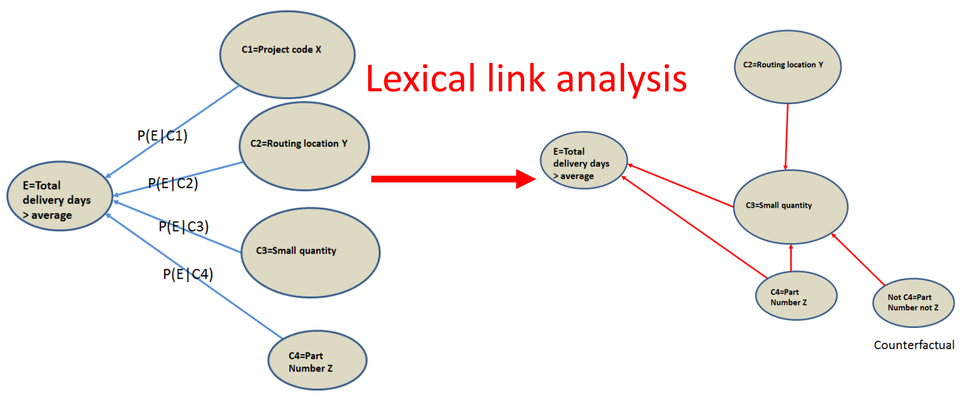
## Research Results: Use Cases and Student Theses

**Use Case 1**:

Jones, J. P. (2018). *MV-22 supply chain agility: A static supply chain supporting a dynamic deployment* (Master's thesis). Naval Postgraduate School, Monterey, CA.

Zhao, Y., MacKinnon, D., & Jones, J. (2019). Causal learning using pair-wise association to discover supply chain vulnerability. *Proceedings of the 11th International Conference on Knowledge Discovery and Information Retrieval (KDIR 2019)*, Vienna, Austria.

**MV-22 Supply Chain Data**
– Part criticality and availability status
– Response time and routing locations
Result: Causal Learning Model

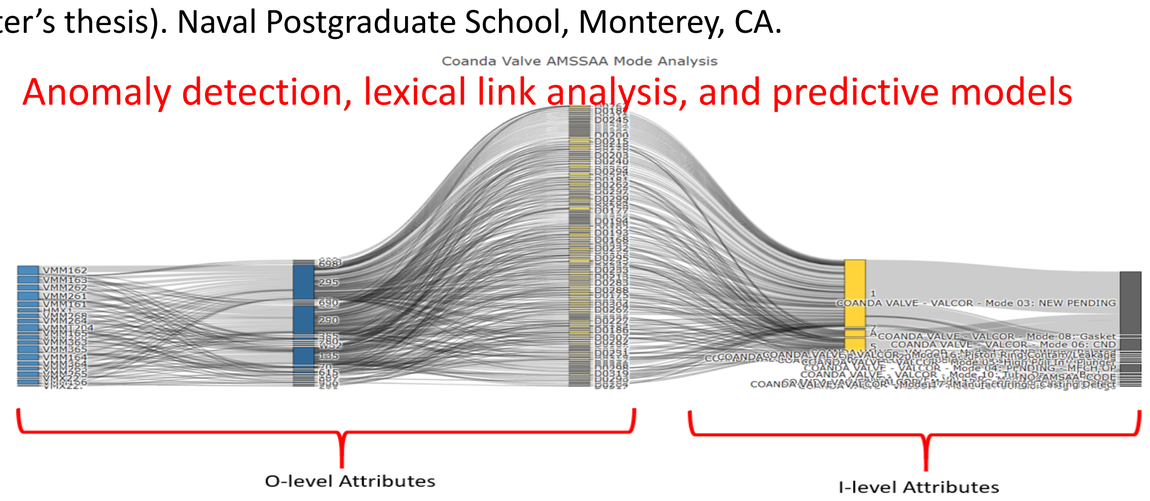



**Use Case 2**:

Deschler, P. (2019). *Applying big data analytics to improve MV-22 component reliability* (Master's thesis). Naval Postgraduate School, Monterey, CA.

Coanda Valve AMSSAA Mode Analysis

Anomaly detection, lexical link analysis, and predictive models




Multi-stage maintenance data from operational level (O-level), intermediate level (I-level), and depot-level (D-level) maintenance data fused together:
- Step 1: O-level, organizational level as well, e.g., the squadron level, to identify what are thrown away or repairable at the I and D-levels.
- Step 2: I-level, to quality and timely material support at the nearest location with the lowest practical resource expenditure.
- Step 3: D-level, to conduct at industrial establishments and original equipment manufacturers (OEMs)

## Conclusions and Future Work

- There are huge potential opportunities to leverage AI for learning, optimizing, and winning (LAILOW) in the complex global material distribution enterprise.
- Future work:
  - Test the designed item association/graph and cascade computation models for BLT; improve BLT for push logistics
  - Generate the models for Marine parts maintenance, supply, and logistics

**Researchers: Dr. Ying Zhao (PI), yzhao@nps.edu**
**Sponsor: Naval Postgraduate School Research Program (NPS-19-N068-B)**
**Topic Sponsor: N4 - Fleet Readiness & Logistics**