U.S. ARMY COMBAT CAPABILITIES DEVELOPMENT COMMAND – AVIATION & MISSILE CENTER

CLARE, TRIP, LUCI, TONY

Name of Presenter

Rank/Title of Presenter

Organization of Presenter

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DD MMM YYYY

AVIATION SYSTEM ASSESSMENT PROGRAM (ASAP)

DEVCOM AVIATION & MISSILE CENTER

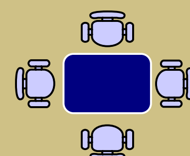
Aircraft Data

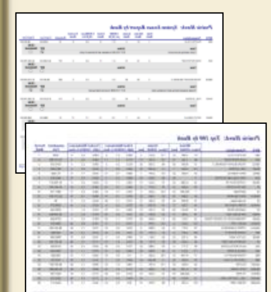
- **Maintenance event data**
- **Corrective Actions**
- **Life limited Items**

ASAP Analysis

Automated Input	Manual Scoring	Automated Output
ASAP Software	Army Maintainer & RAM Engineer	ASAP Software
▪ Stores Data ▪ Converts Raw Data to Usable Format	▪ Attributes Maintenance Action to Hardware ▪ Assign Severity ▪ Correct Mistakes	▪ Tailored Reports ▪ Top drivers ▪ Comparative Analysis

Quality Control Peer Review





Work Unit Code List

Failure Definition and Scoring Criteria

RAM ASAP Team

- 20 Prior Military Team Members
- 304 Years of combined military experience
- 41 Combat Tours

Part / Component RAM Metrics

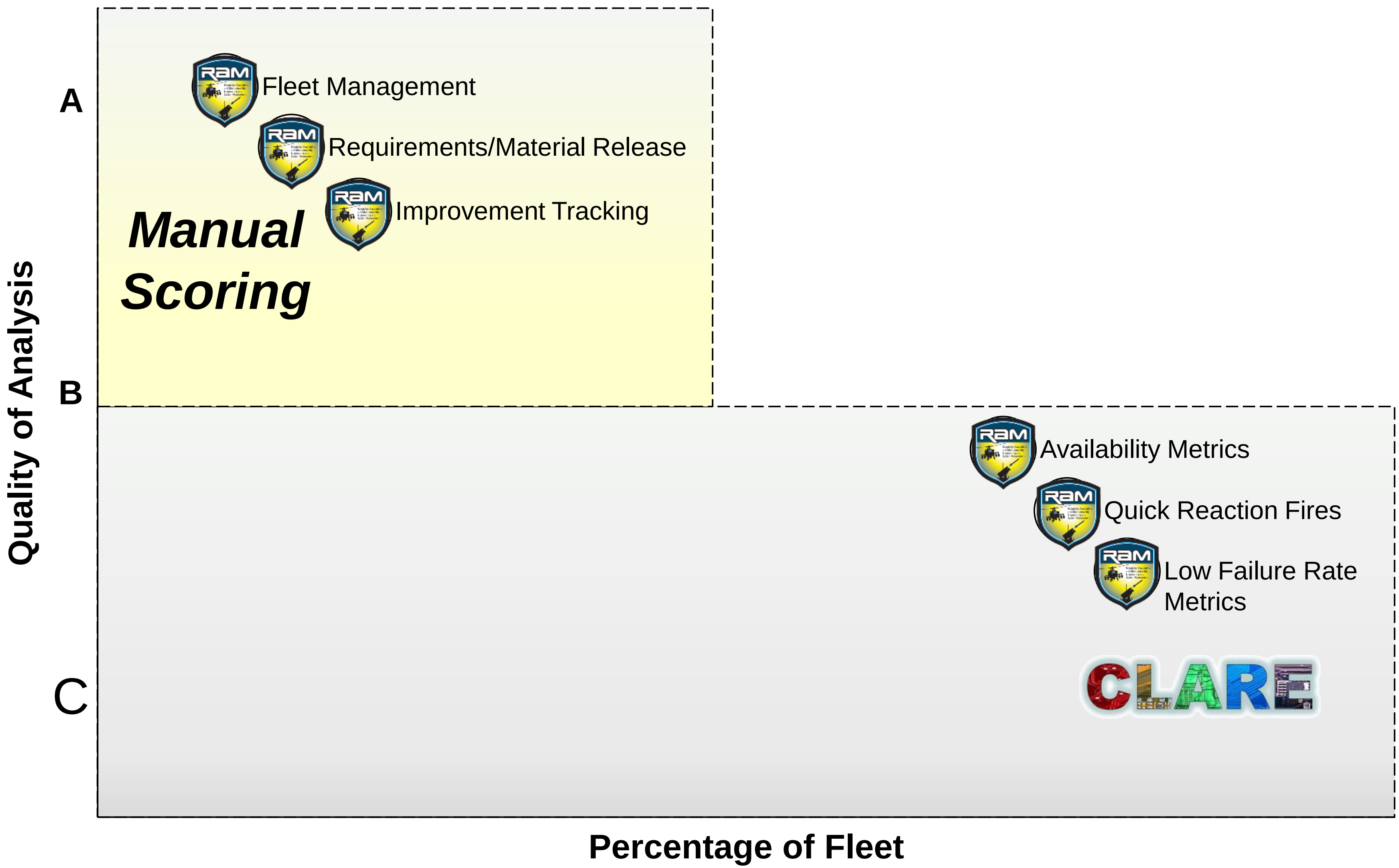
- **Mission Abort Rate**
- **Mission Affecting Failures**
- **Maintenance Man hours**
- **Maintenance Time**
- **System Failures**

Fleet Drivers

- **Operational Tempo**
- **Environmental Factors**
- **Age Related Failures**
- **Trending**
- **Potential Failures**

Fact Based Decision Making

- **Component Upgrades**
- **Maintenance Changes**
- **Resource Allocation**
- **Business Case Analysis**


Quality of Analysis
A
B
C
Fleet Management
Requirements/Material Release
Improvement Tracking
Manual Scoring
Availability Metrics
Quick Reaction Fires
Low Failure Rate Metrics
CLARE
Percentage of Fleet

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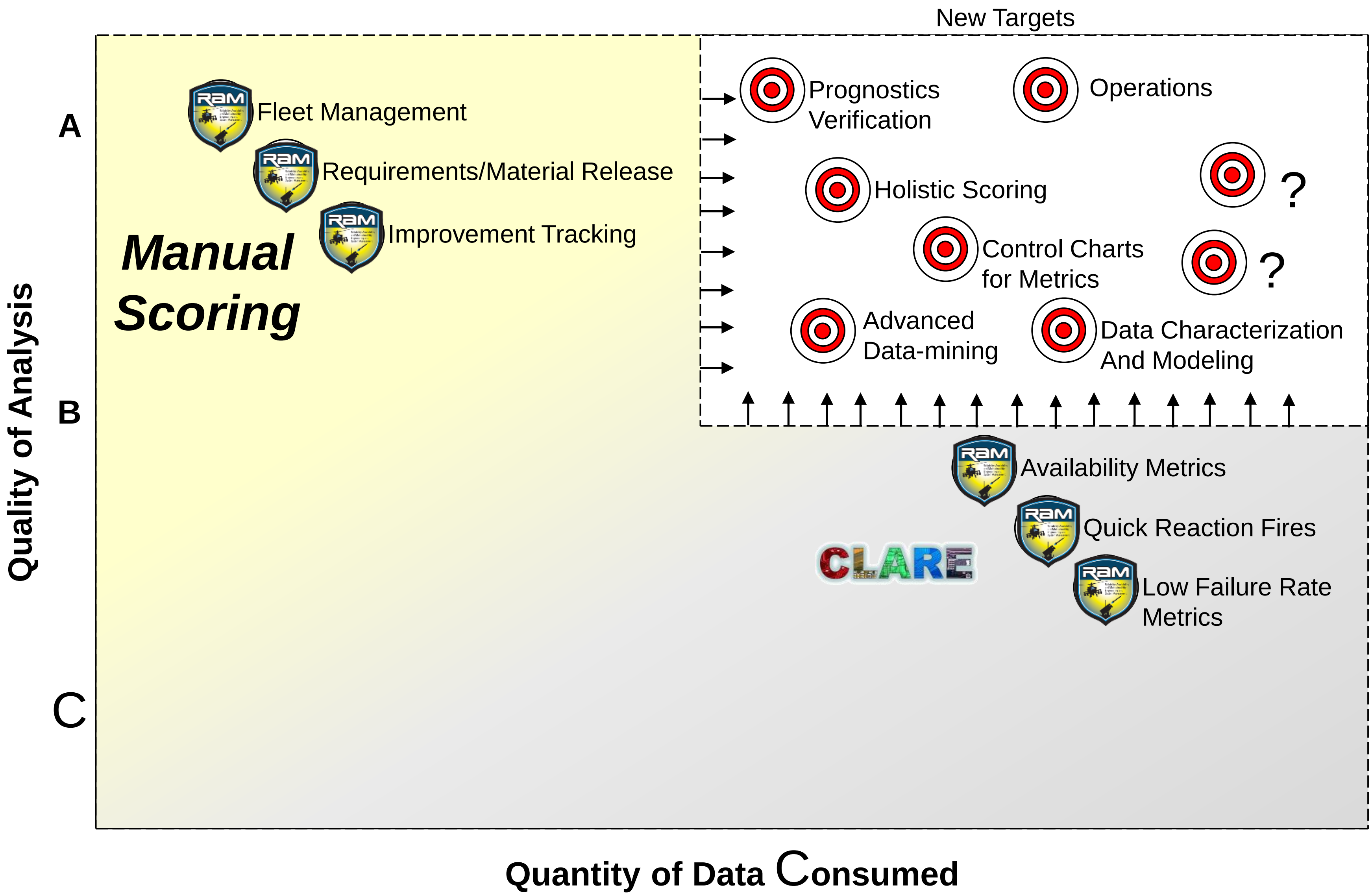


Assumptions

1. The workload on the ASAP tool in FY18 will be the same as FY17.

The demand for ASAP as a tool will not go up or down.

2. The inquiry subject will be in proportion to the failure rate.

The more a part fails, the more analyst will ask the ASAP tool about that part.

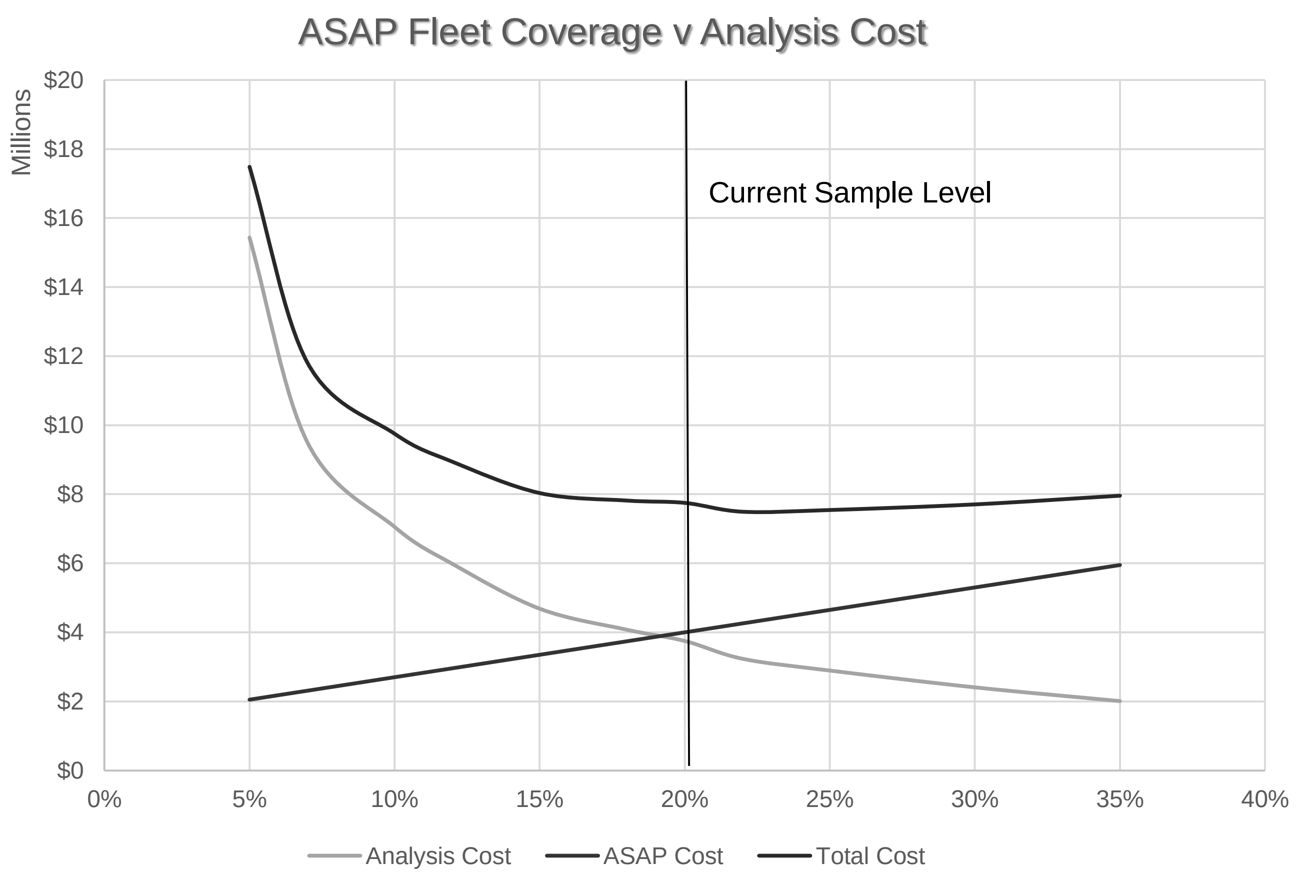
3. ASAP is used by about 25 Man-years worth of analyst labor.

There 12-15 full-time analysts doing RAM work and 140 part time users.
(Users query ASAP ~4000 time a month)

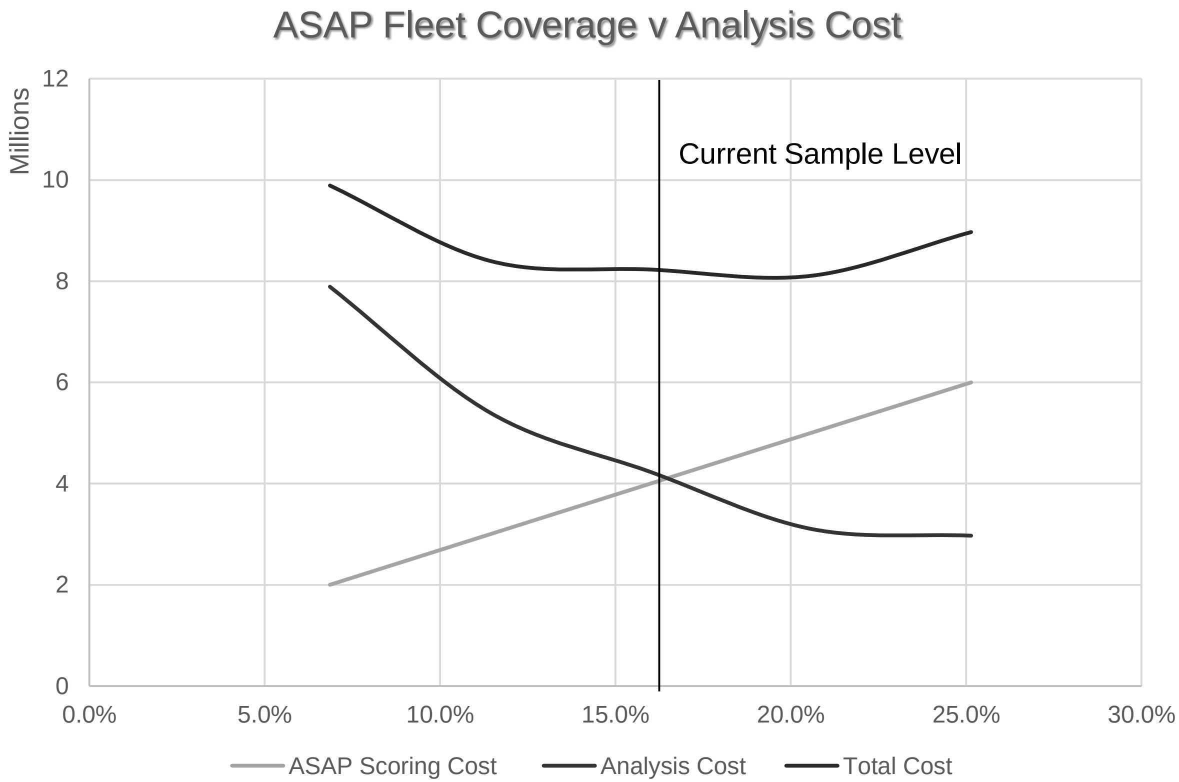
4. The more ASAP has already gathered information and analyzed a Part or Failure, the more help it will be.

Average analysis (without ASAP) takes 2 weeks.
If ASAP has already scored 5 failures – it becomes a 1 day job.*
If ASAP has already scored 30 failures – it becomes a 1 hour job.*

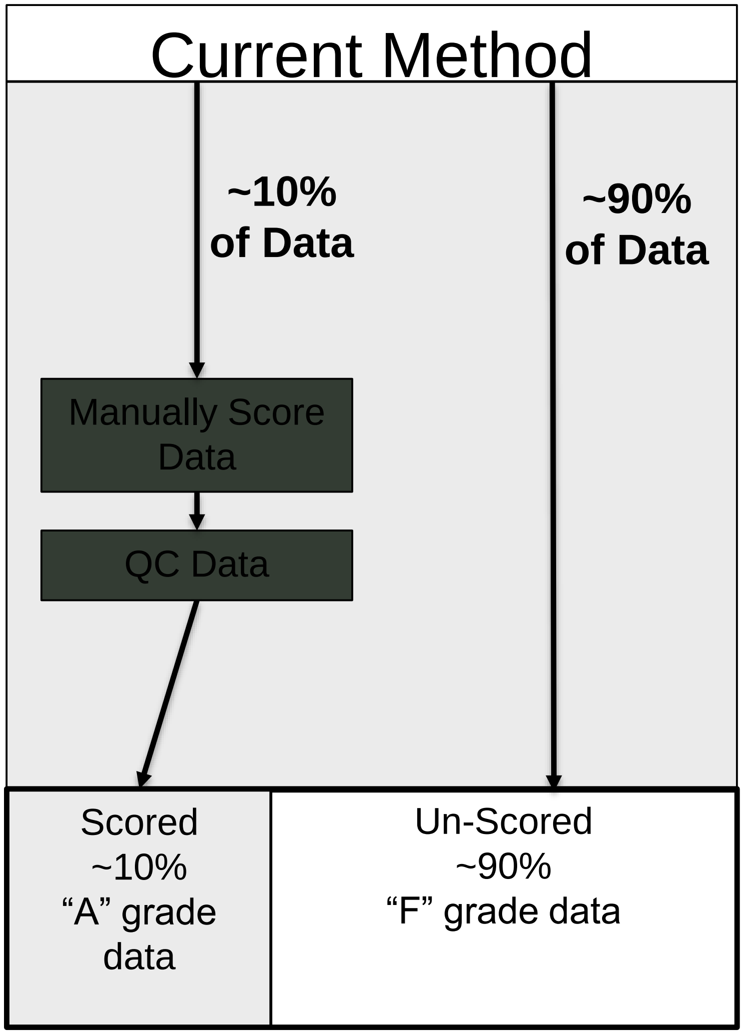
**Over 3 years*

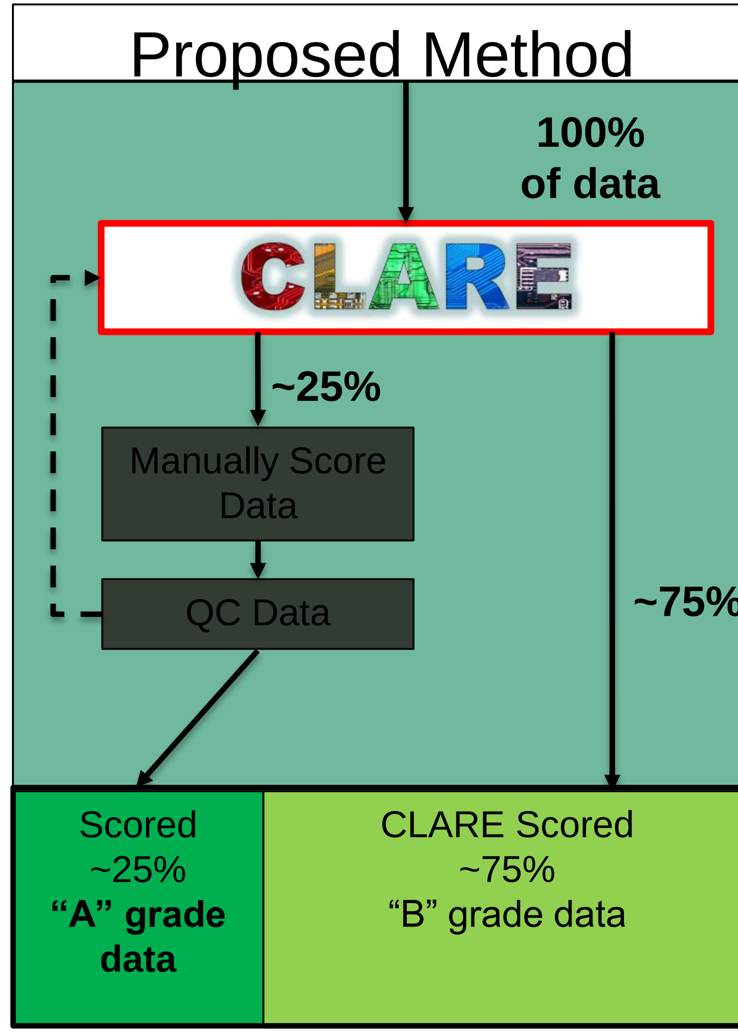

ASAP Fleet Coverage v Analysis Cost
Millions
$20
$18
$16
$14
$12
$10
$8
$6
$4
$2
$0
0%
5%
10%
15%
20%
25%
30%
35%
40%
Current Sample Level
Analysis Cost
ASAP Cost
Total Cost

Analysist Cost



SCORING METHODS





INFORMATION PROVIDED BY CLARE

Raw 2408-13-1

FAULT	ACTION
PMD DUE	COMPLETED
NUMBER 2 SIDE HANDLE BELOW PILOT DOOR BROKEN OFF.	REPLACED HANDLE

Needed information is contained in raw text and requires exact match search to extract data.

CLARE

COMPONENT	FAULT	ACTION	SCD1
‘00	PMD DUE	COMPLETED	S
‘02A02B07	NUMBER 2 SIDE HANDLE BELOW PILOT DOOR BROKEN OFF.	REPLACED HANDLE	U

Contains component codes based on learned features in the raw text.

Contains fault type:

S = Scheduled

U = Unscheduled

(component codes and fault types based on FDSC And scoring methodology from the Aviation System Assessment Program ASAP)

CLARE LANGUAGES AND TOOLS

CLARE's current construction is a composite of SQL actions that are based off of and fed into Deep Learning and Machine Learning algorithms that produce models and engineered features for her to learn from.

The output of these models is a singular learned model that propagates the scored information.

python™

TensorFlow

H_2O.ai

Deep Water

H_2O.ai Caffe mxnet TensorFlow

Microsoft® SQL Server®

```sql
UPDATE ED_SANDBOX.DBO.SCORING_TEMP --UNSCHEDULED RFG
SET U_ID = (SELECT TOP 1 UNSCHEDULED_AH64E.ID FROM ED_SANDBOX.DBO.UNSCHEDULED_AH64E
    WHERE SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD1 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD2 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD3 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD4 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD5 + '%'
    ORDER BY UNSCHEDULED_AH64E.TP/(UNSCHEDULED_AH64E.FP+1) DESC, ID ASC)
FROM ED_SANDBOX.DBO.UNSCHEDULED_AH64E
WHERE U_ID IS NULL

UPDATE ED_SANDBOX.DBO.SCORING_TEMP --UNSCHEDULED RFG
SET U_ID = (SELECT TOP 1 UNSCHEDULED_AH64E.ID FROM ED_SANDBOX.DBO.UNSCHEDULED_AH64E
    WHERE SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD1 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD2 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD3 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD4 + '%'
    ORDER BY UNSCHEDULED_AH64E.TP/(UNSCHEDULED_AH64E.FP+1) DESC, ID ASC)
FROM ED_SANDBOX.DBO.UNSCHEDULED_AH64E
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    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD2 + '%'
    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD3 + '%'
    ORDER BY UNSCHEDULED_AH64E.TP/(UNSCHEDULED_AH64E.FP+1) DESC, ID ASC)
FROM ED_SANDBOX.DBO.UNSCHEDULED_AH64E
WHERE U_ID IS NULL

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    AND SCORING_TEMP.NARR LIKE '%' + UNSCHEDULED_AH64E.WORD2 + '%'
    ORDER BY UNSCHEDULED_AH64E.TP/(UNSCHEDULED_AH64E.FP+1) DESC, ID ASC)
FROM ED_SANDBOX.DBO.UNSCHEDULED_AH64E
WHERE U_ID IS NULL
```

CLARE OVERVIEW (NATURAL LANGUAGE PROCESSING)

Natural language processing (NLP) is a subfield of computer science, information engineering, and artificial intelligence concerned with the interactions between computers and human (natural) languages, in particular how to program computers to process and analyze large amounts of natural language data.

Challenges in natural language processing frequently involve speech recognition, natural language understanding, and natural language generation.

CLARE

- Enables ground truth ingestion
- Record correction
- Faster more accurate search capabilities

- Enhanced manual labeling processes
- Increased data analysis efficiency

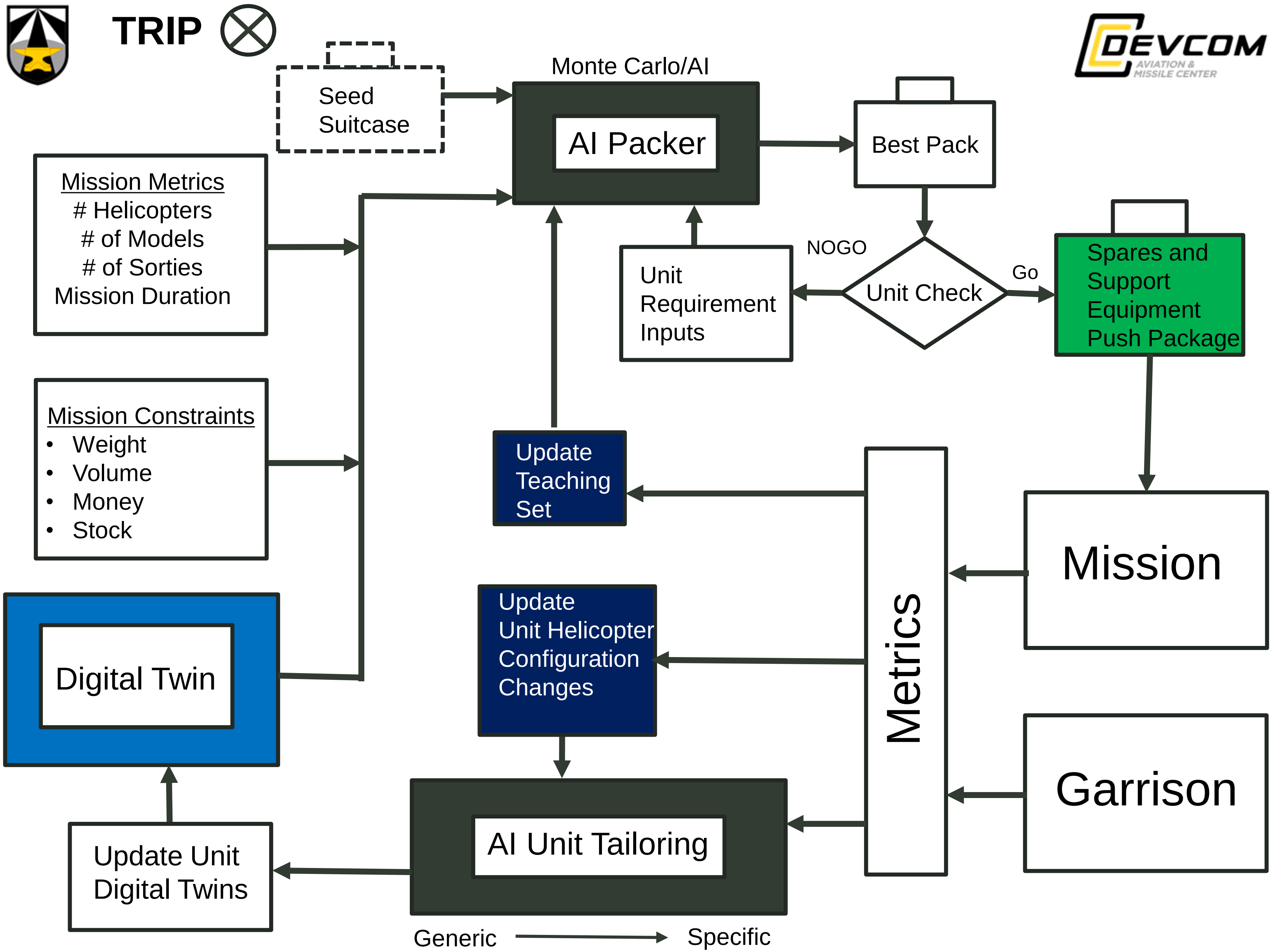
Labeled Maintenance Data

TRIP ⊗

Objective: Develop a Model/AI to do the following:

1. Develop custom Unit Tail Number Digital Twins for field actionable fleet predictions.
2. In conjunction with the digital twins, develop a dynamic spares/support equipment push package estimator based upon specific real-time constraints (weight, volume, stock, money) for remote forward deployments and purchases.

WF need: Garrison Medium, Deployment/remote operations High
ROI: High (Very High for spare buys)
Use Case: Same as ASAP and CLARE
MU1.0: Low fidelity digital twin needed for use in fleet management and requirement development. Any tool beats status quo.
SUX.0: Each drop bring a set of tools needed but not available.
C-Growth: Complexity, spiral tool drops, Monte Carlo/AI integration.
FUNDED


TRIP
Seed Suitcase
Monte Carlo/AI
AI Packer
Best Pack
Mission Metrics
Helicopters
of Models
# of Sorties
Mission Duration
NOGO
Unit Requirement Inputs
Unit Check
Go
Spares and Support Equipment Push Package
Mission Constraints
Weight
Volume
Money
Stock
Update Teaching Set
Metrics
Mission
Digital Twin
Update Unit Helicopter Configuration Changes
Garrison
AI Unit Tailoring
Update Unit Digital Twins
Generic
Specific

LUCI

Objective: Develop a Natural/QASAS AI tool to convert unstructured free text to structured failure codes.

- Improved stockpile management.
- Improved shelf life determination
- Improved failure trend/prediction

WF need: High

ROI: High

Use Case: 25k backlog (unlabeled), 5k per year

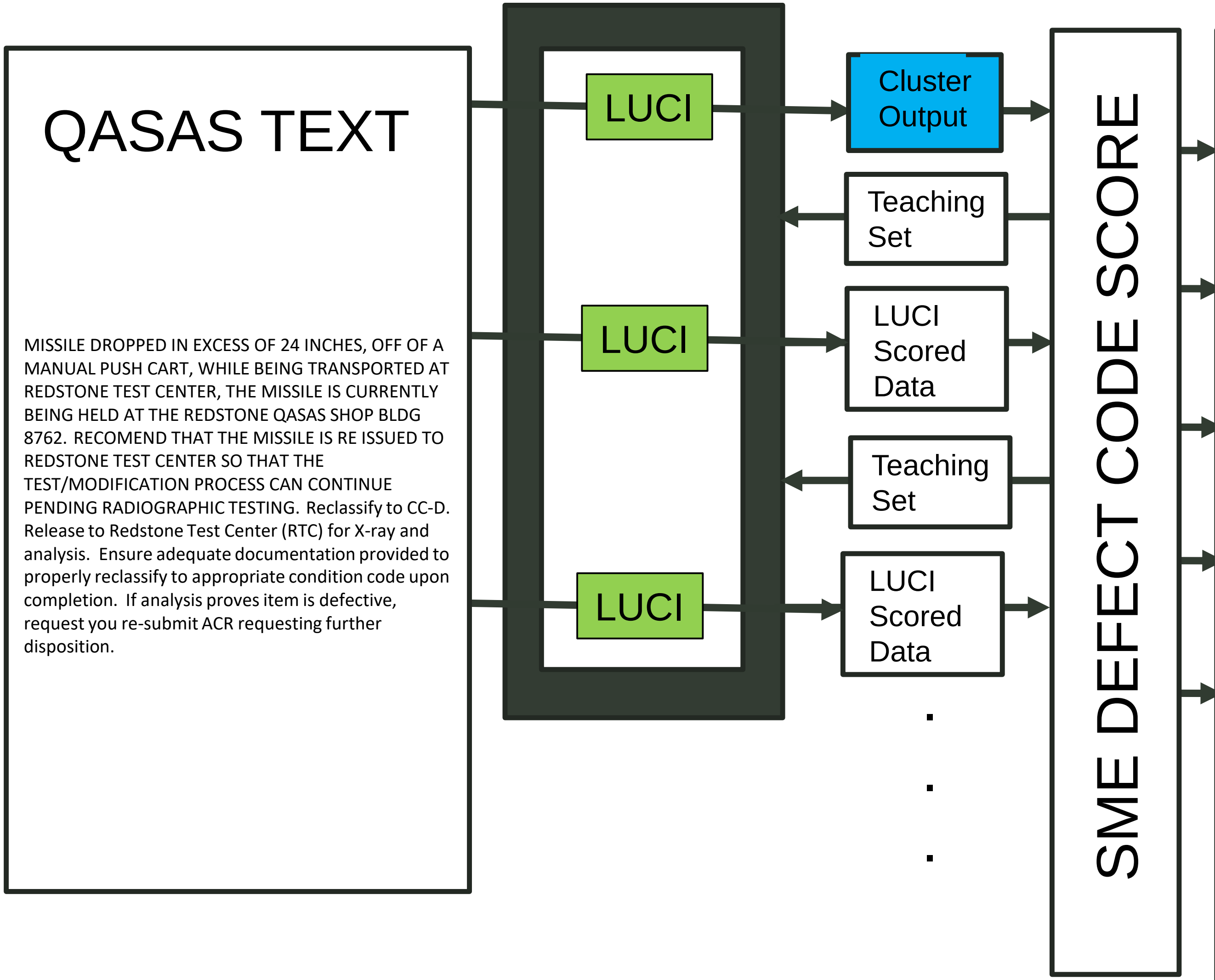
MU1.0: Utilization of significant information to analysts.

SUX.0: Field application to improve QASAS effectiveness.

C-Growth: Clustering, AI to Missiles

FUNDED Hellfire Pilot, many users after successful pilot. Leverage much of CLARE work

LUCI



Defect Name	Defect Code	Defect Code Classification
Shelf Life Expired	CAA12B	Major
Palletization In		or
Pallet Broken		or
Pallet Missing		or
Pallet wood nc		or
Presence of tw properly applie opening withou applied to prev without breakir		jor
Identification marking incorrect, incomplete, or illegible. Color code incorrect or missing Color code incorrect or missing	VOP15F	Major
Color code incorrect or missing	VOP15B	Major
Markings or color code are incomplete, faded, partially illegible or incorrect but the material can be identified.	VOP29F	Minor
Bar Code Labels missing, faded, or damaged and not readable with a scanner	VBL35J	Incidental
Paint Coverage: Bare spots (that when combined) that exceed 5% of surface area.	COP261	Minor
Damage or conditions that could result in container not being sealed, i.e., holes, dents, cracks, gouges, bent frames or distortions.	ROP160	Major

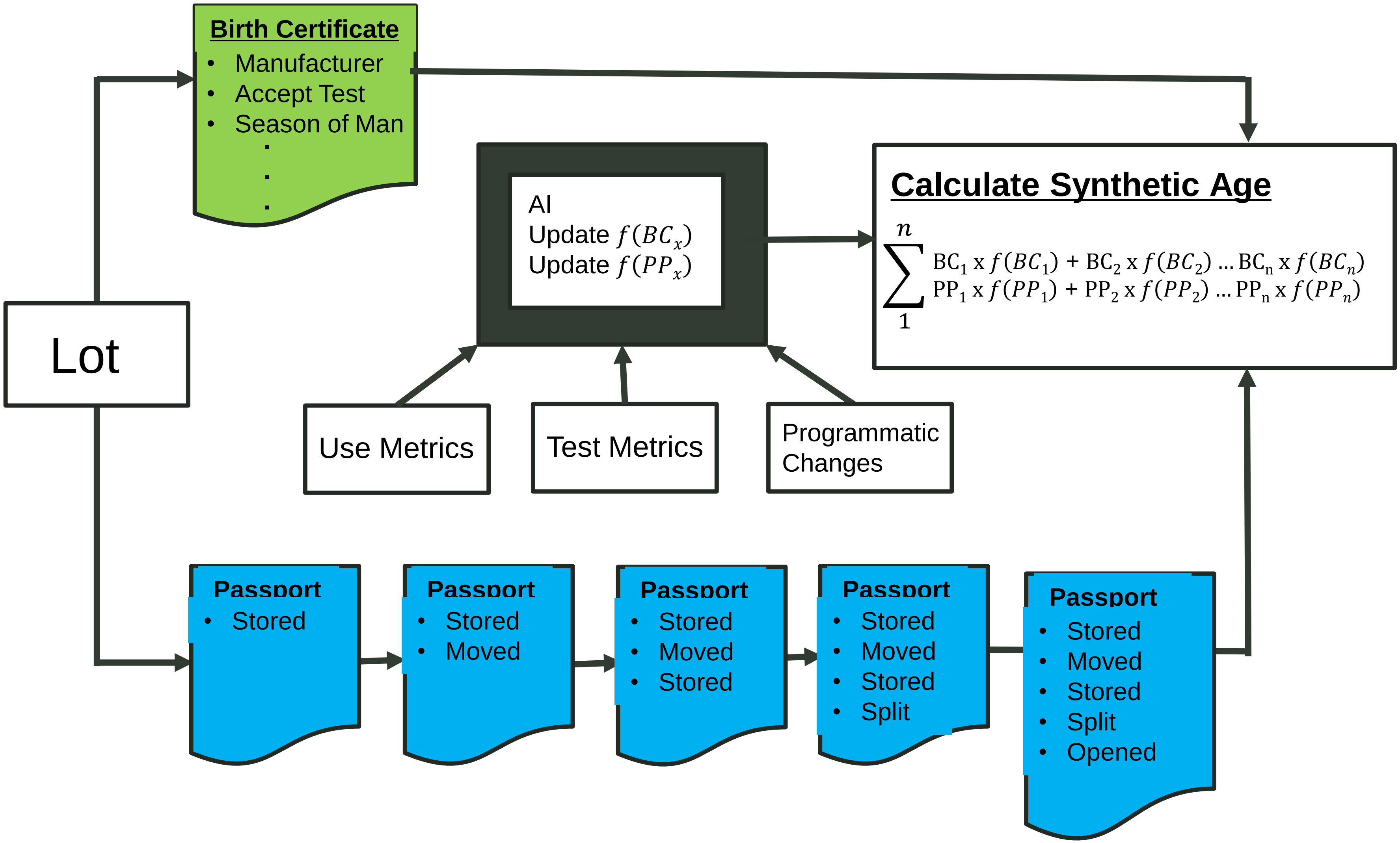
TONY Really AQDT (Tony Working Huntsville Title)

Objective: Develop a AI (Deep Learning) tool to track Remaining in A munition inventory.

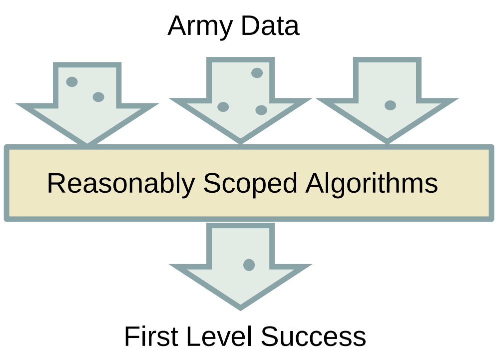
- Improved Ammunition Cost of Ownership
- Improved shelf-life determination
- Decrease disposal/replenishment costs.
- Improved failure trend/prediction

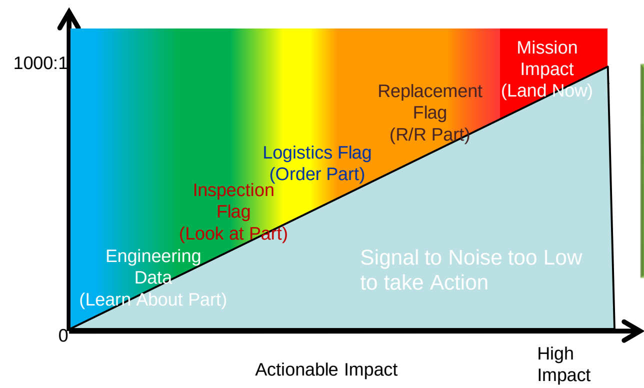
WF need: High
ROI: TBD
Use Case: Massive, but complex
MU1.0: New significant information to analysts.
SUX.0: Cost of Ownership, RAM Prediction, TBD Spiral Projects
C-Growth: Deep Learning, Multiple Layered Charrettes, AI to Ammo.
FUNDED

TONY

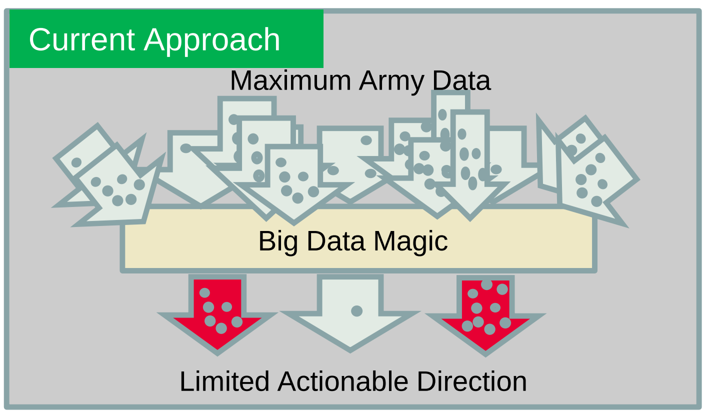

Birth Certificate
Manufacturer
Accept Test
Season of Man
Lot
AI
Update $f(BC_x)$
Update $f(PP_x)$
Calculate Synthetic Age
$\sum_{1}^{n}$ $BC_1 \times f(BC_1) + BC_2 \times f(BC_2) \ldots BC_n \times f(BC_n)$
$PP_1 \times f(PP_1) + PP_2 \times f(PP_2) \ldots PP_n \times f(PP_n)$
Use Metrics
Test Metrics
Programmatic Changes
Passport
Stored
Passport
Stored
Moved
Passport
Stored
Moved
Stored
Passport
Stored
Moved
Stored
Split
Passport
Stored
Moved
Stored
Split
Opened

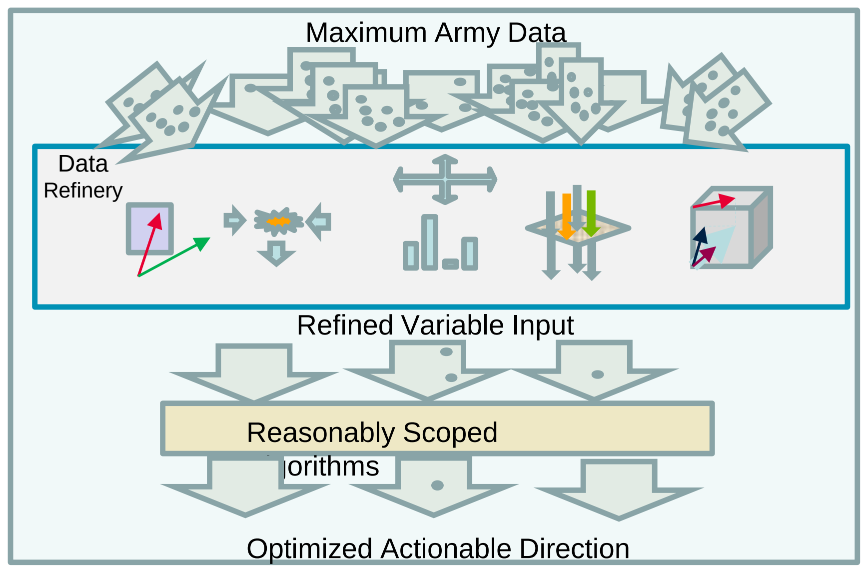
DATA REFINERY





Signal-to-Noise ratio determines the confidence in actionable impact decisions.

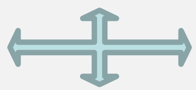




DATA REFINERY

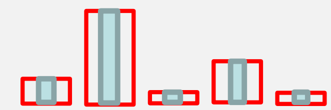
Data Intake Manifold

Data routed through DR and connected to feedback loop in applicable DR customers (algorithms).

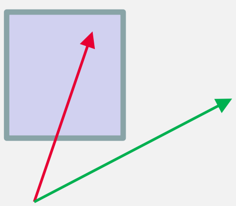


Configuration Tagged Data Pulling

LRUs tagged by significant events. Optimal data pull yields all available relevant data without the confounding noise from superseded LRU designs and maintenance practices.

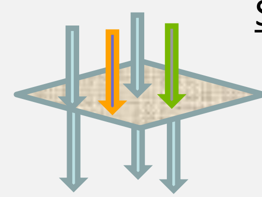


N-Space Noise Traffic Mapping



Direct Physics of Failure measurement (High S/N) may be a bad indicator of impending failure. Oblique measurement (Low S/N) may be better.

SME/AI Data Cleansing



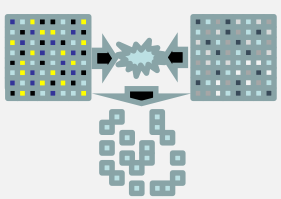
SME Data Scrub Practices

Teaching Sets

Machine Learning

Attestation Distance Mining

Two poor quality data sources may yield useful information if they are very independent (High attestation distance).



Other Data Refining

- Synthetic Variables
- Bayesian Engines
- Etc.