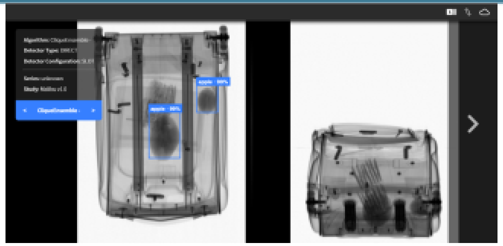
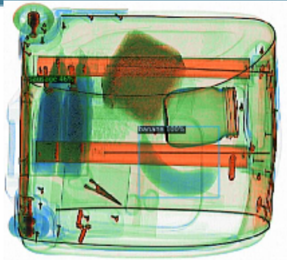
SAND2022-3727C

# Developing a comprehensive, adaptive system for large scale x-ray images





Robert Forrest, Sandia National Labs

SPIE 2022

4 April 2022

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

# Big Picture


Our Task: Aid CBP’s adjudication of data thereby supporting reduction of risk and the rapid and secure flow of commerce into the United States.

# Overview

We run a portfolio of projects using Non-Intrusive Inspection (NII) for Department of Homeland Security / Customs and Border Protection (DHS/CBP).

**This talk will be an overview**: An introduction to the problem and how we think about and engineer adaptive solutions.

Supporting technical details in other talks:

**Resilient adjudication in NII with hierarchical object and anomaly detection**

5 April 2022 • 1:40 PM - 2:00 PM

**Synthetic threat injection using digital twin informed augmentation**

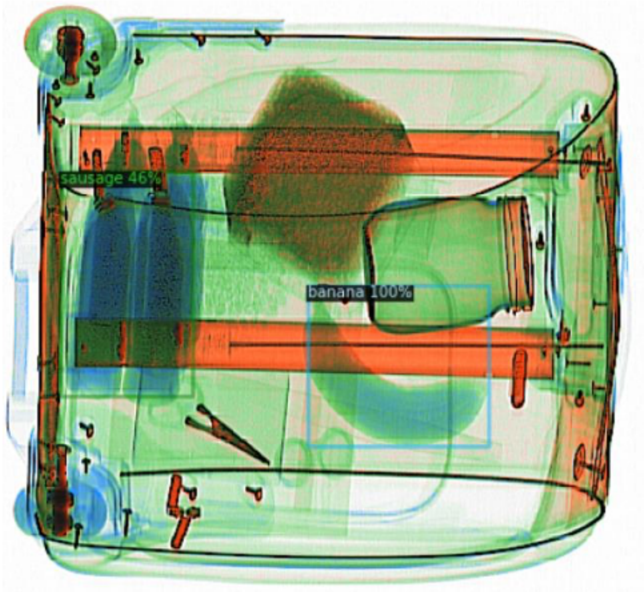
4 April 2022 • 11:40 AM - 12:00 PM

Please connect with us to find out more.

# Experience Gives Perspective

Initial project for DHS: Create an algorithm to find objects in 2D x-rays of packed bags.

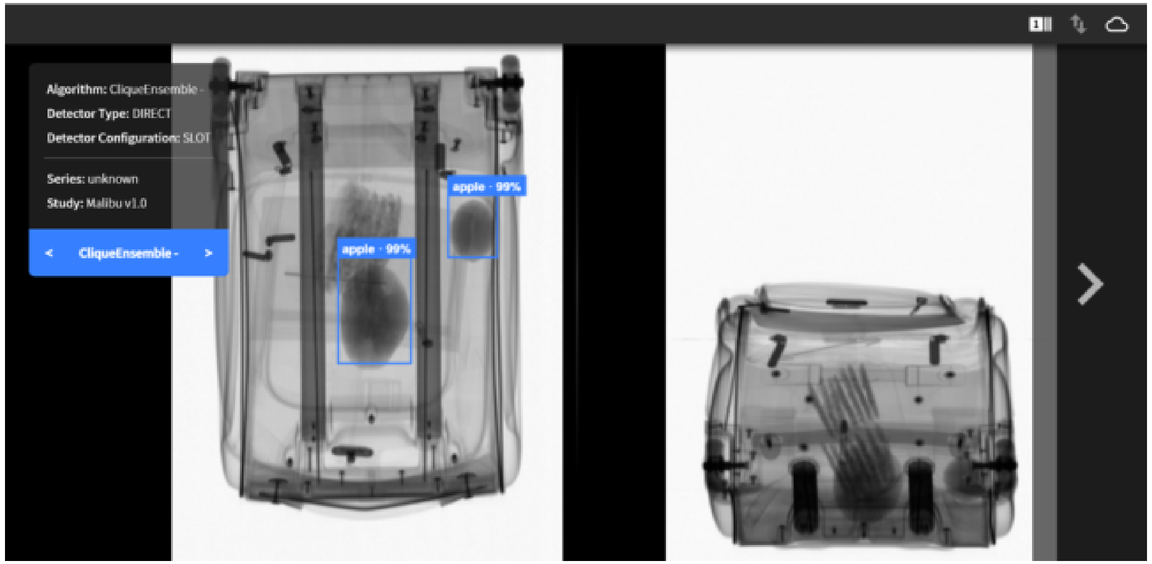
Standard practice: Acquire dataset, use an industry standard NN. Declare success.




Process:

1. Prepare, generate data with specific demonstration target objects (4 months)
2. Annotate, label all the data. (2 months)
3. Run through industry standard algorithms.
4. Understand performance. Require more data to fill gaps. (Repeat 1.-2.)
5. Pilot System integration, GUI Development (6 months)
6. Present results to customer.

# Successful Demo Of ATR




Customer Response: “What about X?”, “Can you add Y?”, “We are now more concerned with Z.”
“What if it were (my special situation)?”

Lessons Learned:

Require a different approach.

One off solutions are not sufficient, we need continuous development.

Need a strategic method to respond dynamically to threat environment.

# New Systematic Approach – Design Concepts

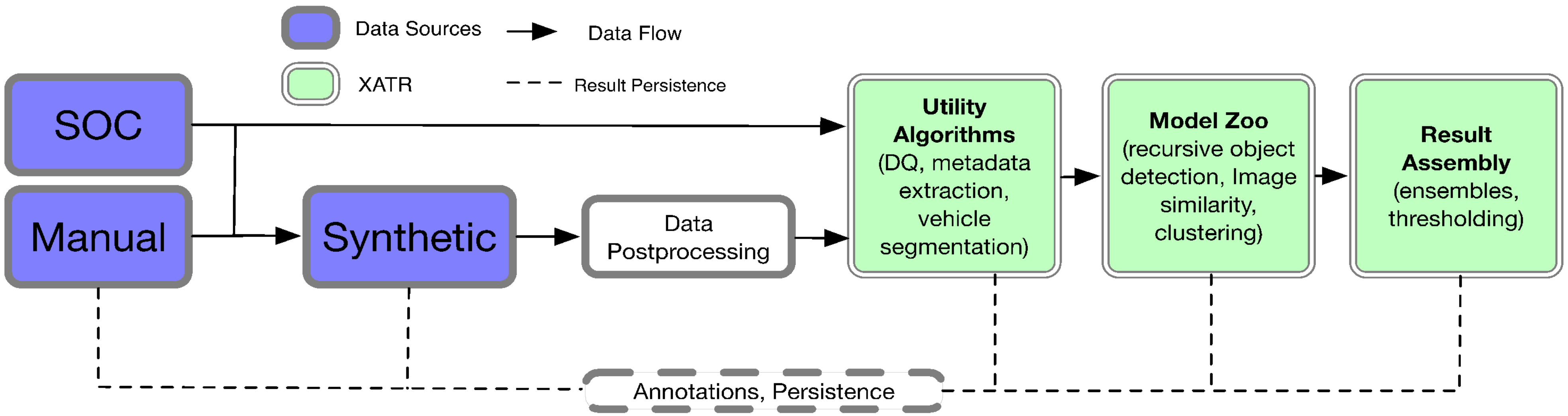
*Expandability*
System should get better over time. Avoid vendor lock in. Use standard APIs. Create a marketplace for ATR 3rd party algorithms.

*Adaptability*
Capability to make configuration changes and algorithm upgrades based on threat environment and mission need. Adaptation to lessons learned, performance and testing results, customer need and the latest techniques and methods.

*Rapid Responsiveness*
Detection of contraband needs to evolve at the speed of the dynamic threat.

*Integrability*
Detector exists in a larger system of abundant data, other detectors, and bodies of knowledge. Must provide generic interfaces for interoperability and a means by which many sources can integrate into a larger system.

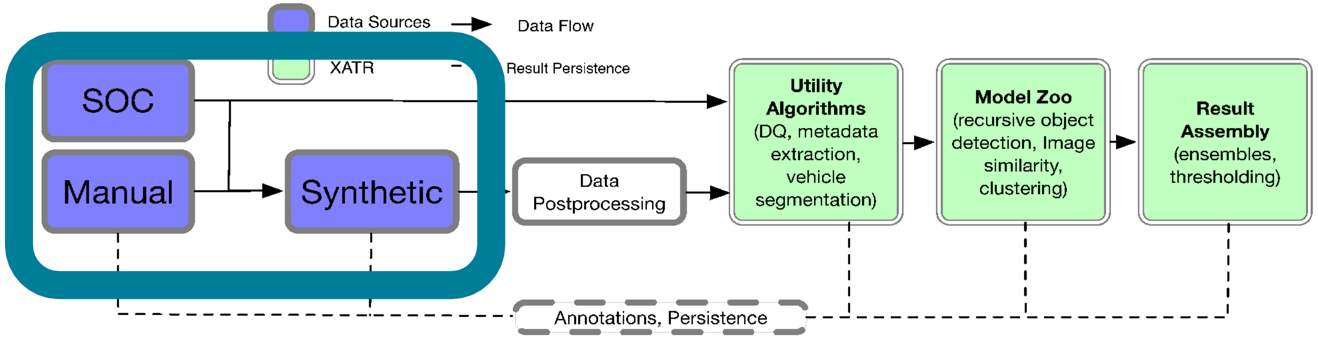
# System Design




Component Overview:

- Metadata: Universal Ontology, Labeling (Manual and Automatic)
- Data: Manually generated, Stream of Commerce (SOC), Synthetic.
- Algorithms: Utility, Model Zoo and Ensemebling
- Inference engine: Recursive, persistent.

# Data




Data is always key.

Reality: normally, no perfect dataset exists – Need to triangulate based on available data.

Three Types:

**SOC** – Plentiful, unlabeled.

Used for: semi-supervised methods and for synthetic data.

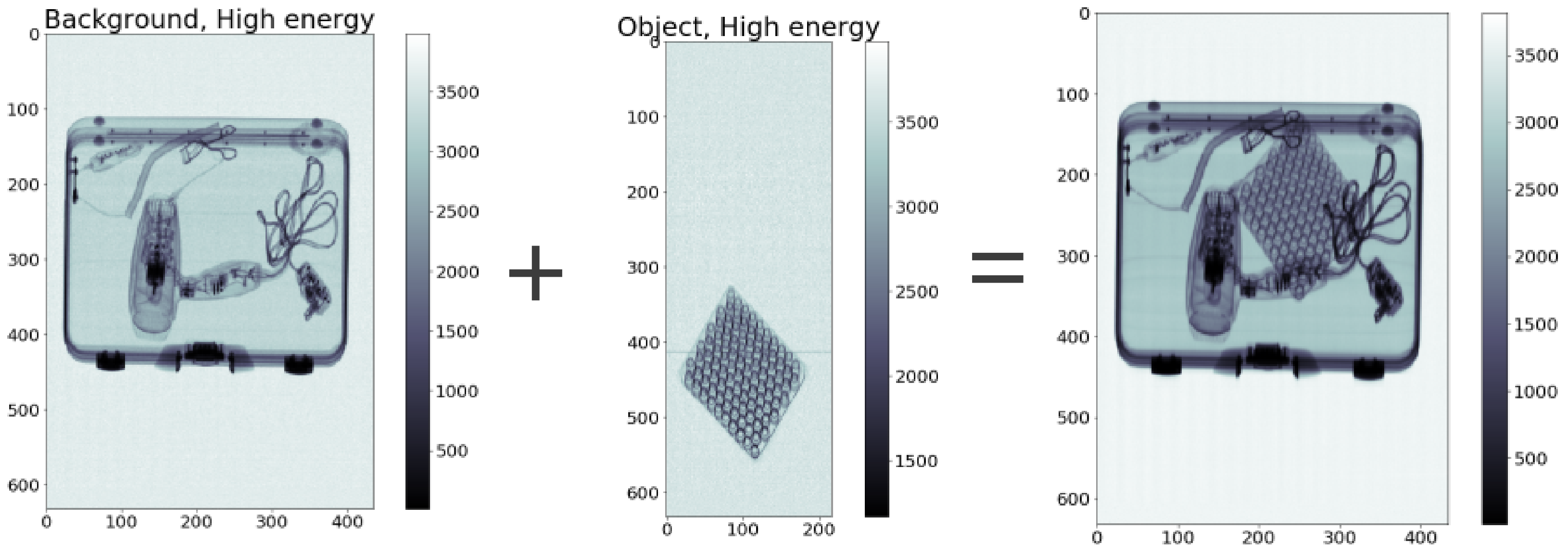
**Manually Generated** – Laborious, labeled, only ground truth available.

Used For: Synthetic data isolated target items; validation. Experimentation on detector response.

**Synthetic Data** – Key enabling capability. Many uses, not ‘real’.

Used For: Many uses…

# Synthetic Data – Key Capability




Generation of synthetic data from background 'scene' data and isolated 'target' items.

Allows generation of plentiful, labeled, relevant data.

Rapid Response to emerging threats – Train algorithms quickly

Less dependence on fielded detectors.

Many other potential uses.

Important to understand pitfalls.

# Synthetic Data Generation

Method:

In attenuation space, crop target.

Choose background image, logical/strategic placement location.

Combine two images with Beer–Lambert law.

Filter noise to match scene image, avoiding double noise problem. Other histogram inspired adjustments.

GAN refinement.

Note: Can manually generate (target + background) to understand (target) + (background).

Additional improvements, see:

**Synthetic threat injection using digital twin informed augmentation**

4 April 2022 • 11:40 AM - 12:00 PM

# Synthetic Data Usage

Training algorithms generally. Basic Question: Does it help?

Quick Check Analysis

- Defined a Test Set of about 1000 images from 2D x-ray packed bags
- Overall Process:
  - Select % of Original, Synthetic Images, train simple model.
  - Evaluated trained model on Test Set

| | 100% Syn / 0% Original | 0% Syn / 100% Original | 100% Syn / 100% Original |
|---|---|---|---|
| **Accuracy (%)** | 61.0 | 72.2 | 77.4 |

Other Uses:

More training data in difficult to construct configurations.

Provide understanding of algorithm capabilities. Probe edge cases.

Rapid training on new threats using few target images. (Threat library)

Additional results from large scale synthetic data usage in associated talk.

# Conceptual idea: Threat Library

Rapid training on new threats using few target images. Idea: Threat library of images used for object detection.

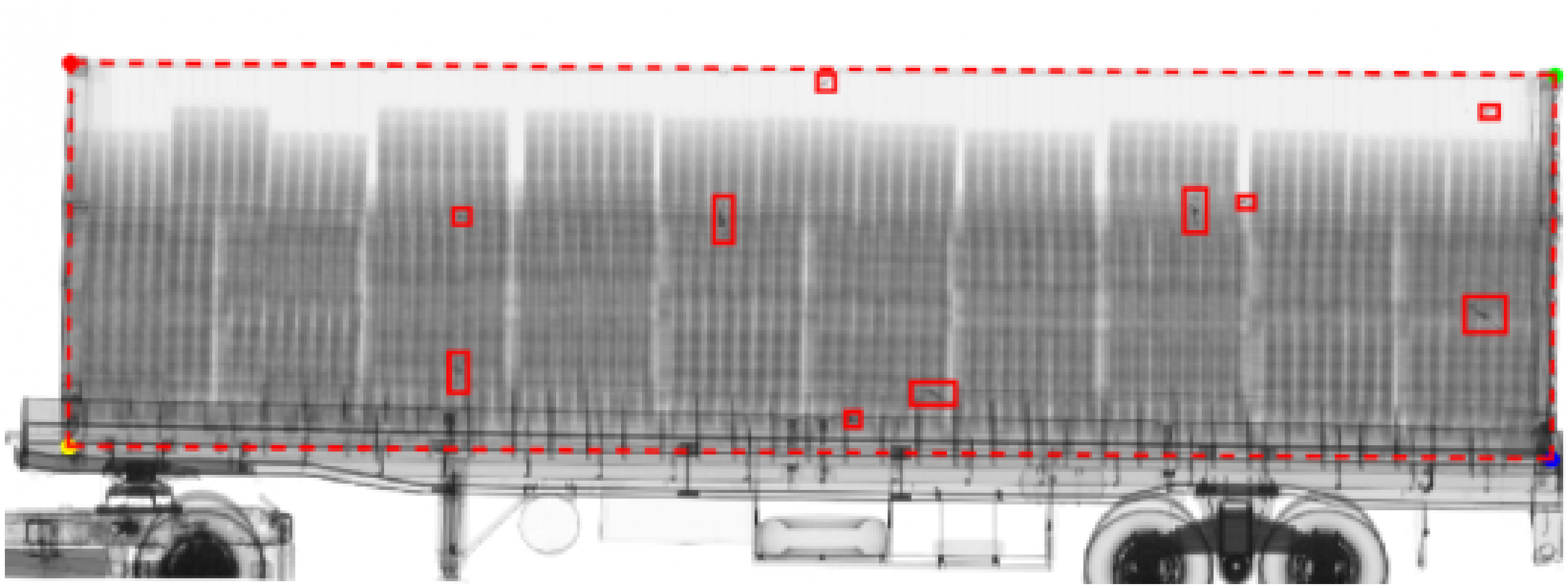
Synthetic data generated with threat images. Models trained and deployed.

Working with vendors and the field to accumulate images.

Versions of synthetic data generated to train models.

# Datasets

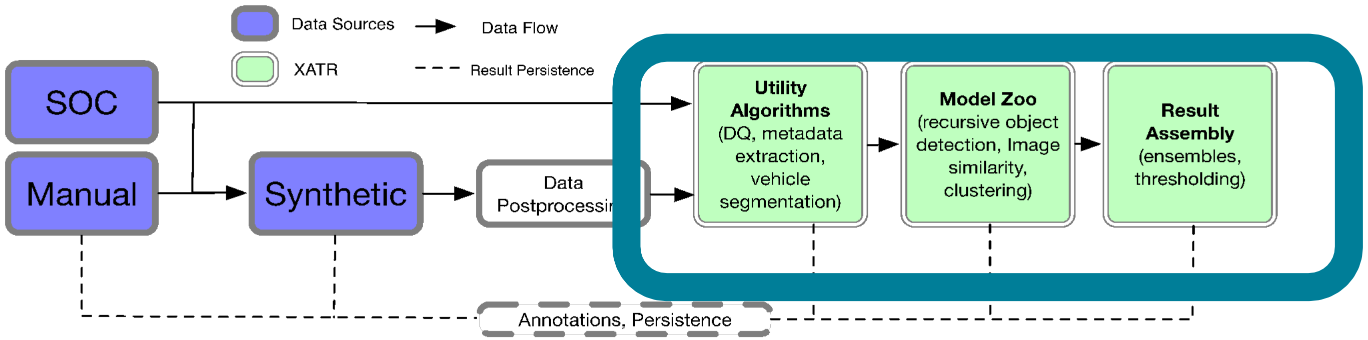
Moving from examining small scale, packed bag x-ray images to large scale NII:



Notes on large scale NII:

- The same techniques as small scale work well.
- However: Material discrimination is more crude on large scale.
- Segmenting and breaking down the image become important…
- Generally more sensitive datasets, difficult to share results.

# Inference Pipeline




Large scale data makes braking down the ‘scene’ important.

Need a modular, configurable, and flexible inference pipeline.

**Modular Design**:

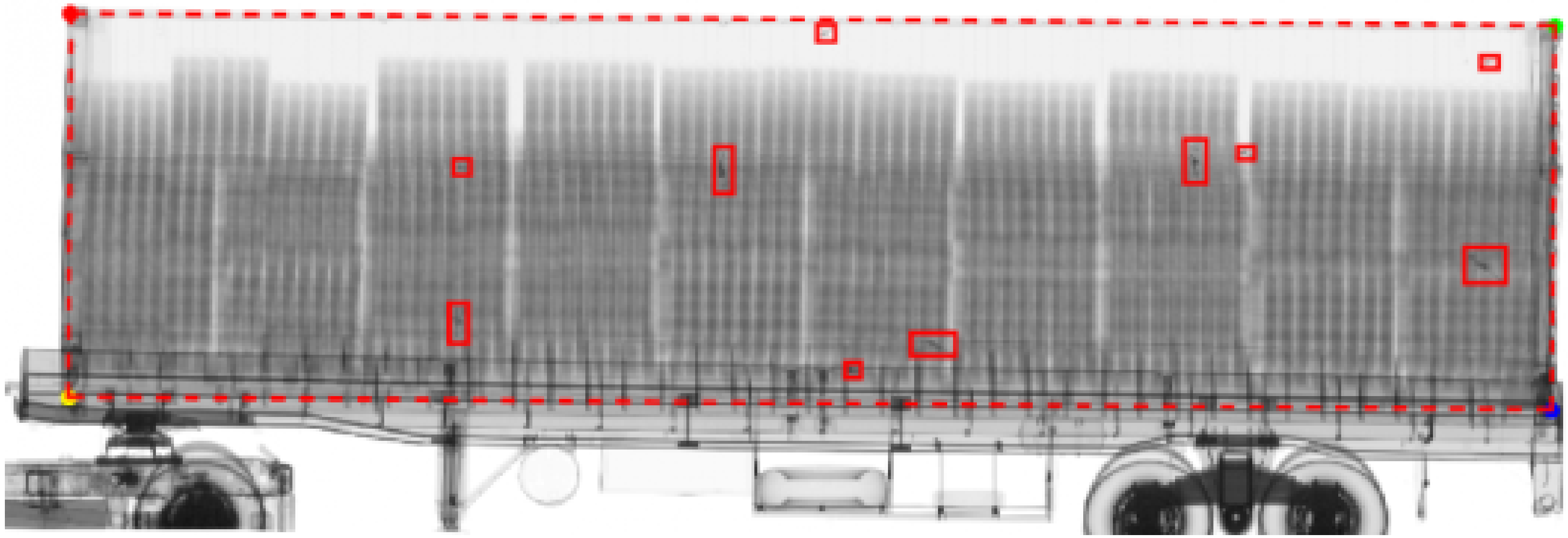
Individual modules perform a specific task, may operate on a sub-section of the image.

Modules provided with all upstream data about image, return products used by downstream modules. All historical knowledge about all images provided.

Modules intended to be easily configured into pipelines.

Pipeline performance measured against standard test sets.

# Notional Pipeline Example



Burden → Image Classification → Image Segmentation → Object Detection → Ensemebling

Image Segmentation → Object Similarity → Ensemebling

Image Classification:

Tractor-Trailer
Good DQ
Detector Type X
Detector Location

Image Segmentation:

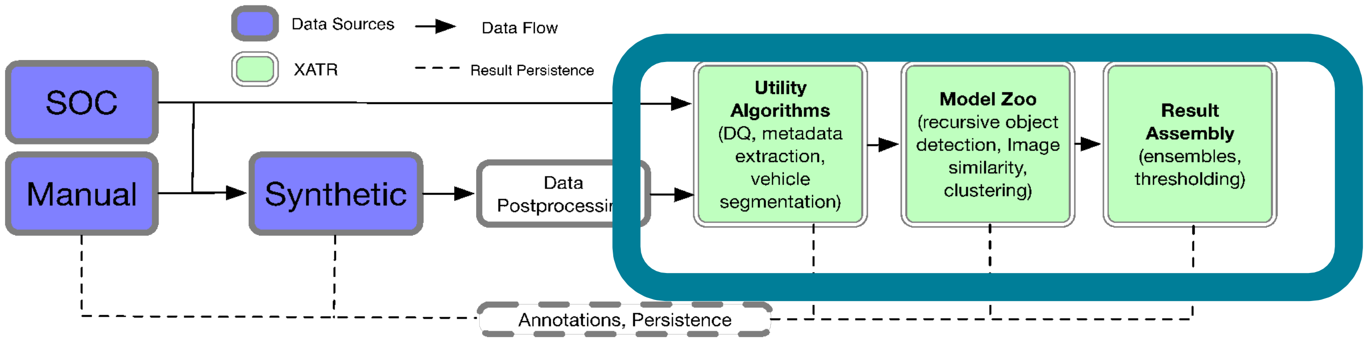
Wheels
Trailer
Cab
ISO container

Ensemebling:

Clique ensemble
Non-Max Suppression
Threshold adjustment

Example: ISO container segmented, generic intermodal OD or Manifest Verification algorithms can be applied in pipeline.

# XATR: Automated Threat Recognition Execution Engine




Responsible for execution of inference pipeline.

Ability to operate locally (port net restricted) or in the cloud.

Executes in parallel on available modules. Based on modules registered required input/output.

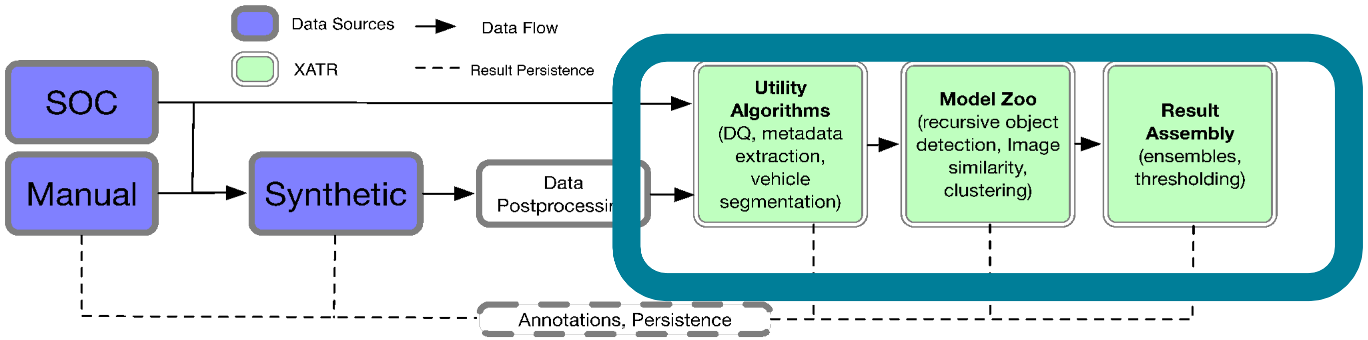
Serves up versioned datasets

Recursion and performance monitoring…

For quantitative results, See:

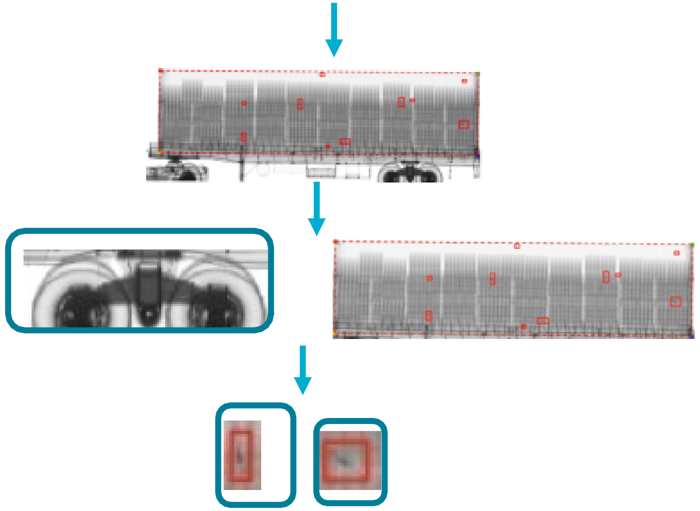
**Resilient adjudication in NII with hierarchical object and anomaly detection**
5 April 2022 • 1:40 PM - 2:00 PM

# XATR: Two Core Capabilities




## Recursion

Full Image



XATR continues hierarchy until all available modules are run.

## Automated Performance Measuring

- Like CI/CD for ML
- Ability to change configs, ML weights, pipelines.
- Versioned test datasets served.
- Result metrics built in.
- Iterative approach to development.

Fundamental Ontology Objects

# Conclusion

Both large and small scale adjudication of NII x-ray data are similar, but require thinking systematically about adjudication. Avoiding one off analysis and vendor lock in.

We designed a system that is expandable, adaptable,  responsive and integrates easily into other systems.

Synthetic data is a key enabling capability that helps inevitable issues with lack of data.

Our modular execution pipeline (XATR) adheres to the above principles, we believe such open, adaptable systems are the future of adjudication for NII.