

# VISUALIZATION TECHNIQUE FOR THE POWER TRANSIENTS OF A THERMALLY COUPLED SYSTEM

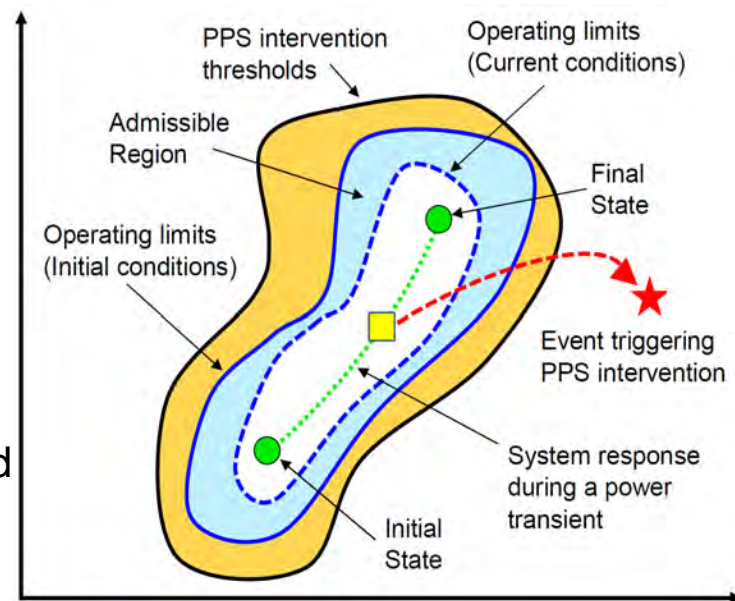


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Nuclear Science and Engineering Division  
Argonne National Laboratory

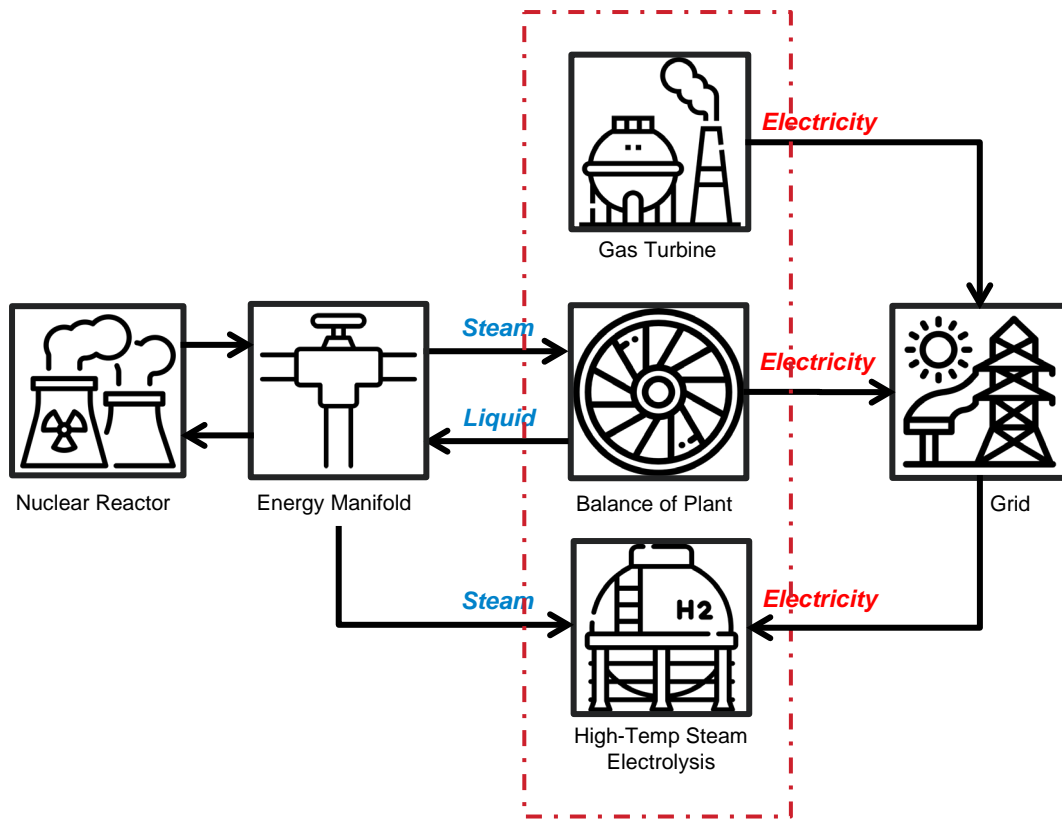
AI & ML Symposium 13.0  
March 28, 2024

# MOTIVATION AND CHALLENGES

- Flexible Operation as a possible solution to cope with the evolving cost structure in U.S. electricity deregulated markets and penetration of renewable energy sources
- Q. What does this entail for Nuclear Power Plants?
  - Electrical power level adjusted on hourly basis
  - Thermo-mechanical load variations might accelerate component wear and tear → Process variables need to be constrained to limit operational and maintenance (O&M) costs.
- Advanced control techniques provide a quantitative estimate of the Normal Operation Region (NOR) and Admissible Region (AR).
- Need for a suitable tool to track and visualize the plant response during transients.



# EXAMPLE TEST CASE



## Three sub-systems:

- Balance of Plant
- High Temp. Steam Electrolysis (HTSE)
- Gas Turbine

## Variables:

- 3 inputs (power set-points);
- 6 monitored process variables.

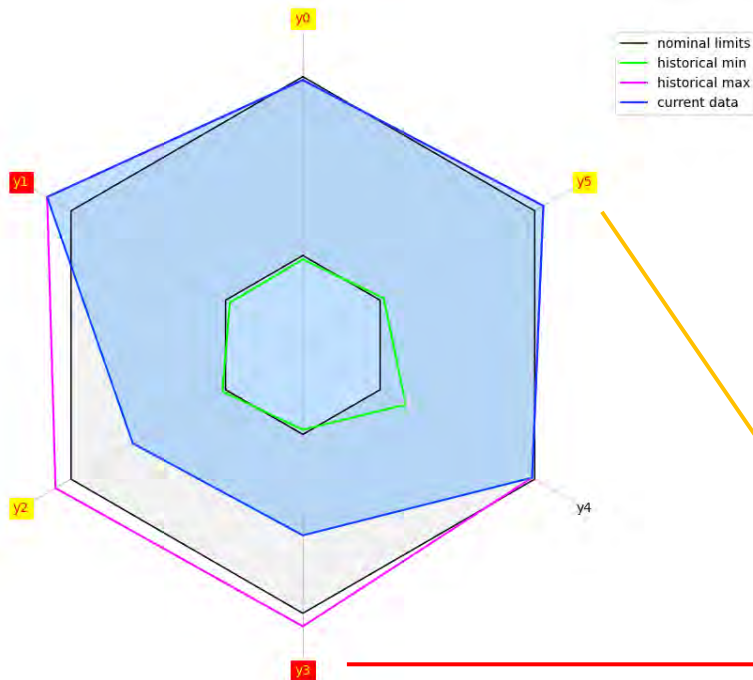
## Examples:

- $y_1$ : Turbine inlet temperature,  $827^\circ\text{C} < y_1 < 1289^\circ\text{C}$  to avoid inefficient combustion and structural degradation
- $y_3$ : HTSE  $\text{H}_2$  Production Rate,  $2.0 \text{ g/s} < y_3 < 10.0 \text{ g/s}$  to avoid cold-start or breakdown of the Solid Oxide Electrolysis Cell

# SOLUTIONS TO NOR VISUALIZATION

## ■ Solution #1: Dynamic Spider Chart for outputs

t: 880.00 second  
y0: 49.44 MW  
y0min: 20.00 MW  
y0max: 50.00 MW  
y1: 1288.55 degC  
y1min: 826.85 degC  
y1max: 1226.85 degC  
y2: 0.80 MW  
y2min: 0.20 MW  
y2max: 1.20 MW  
y3: 6.51 g/s  
y3min: 2.00 g/s  
y3max: 10.00 g/s  
y4: 44.66 MW  
y4min: 25.00 MW  
y4max: 45.00 MW  
y5: 31.56 bar  
y5min: 21.00 bar  
y5max: 31.00 bar



Extension of the well-known spider chart / radar chart for static applications

- 3+ equiangular axes starting from the same point by spokes;
- Length of spokes is proportional to the magnitude;
- Polygon to represent a data point.

Improvement by ANL:

- Animation to track data history;
- Grey ring show bounds;
- Pink / green polygon show historical max / min in each dimension
- Yellow warning indicate historical violations of either the lower or upper bounds
- Red warning indicate historical violations of either lower and upper bounds

# SOLUTIONS TO NOR VISUALIZATION

## ■ Solution #2: 3D Phase Space diagram for outputs

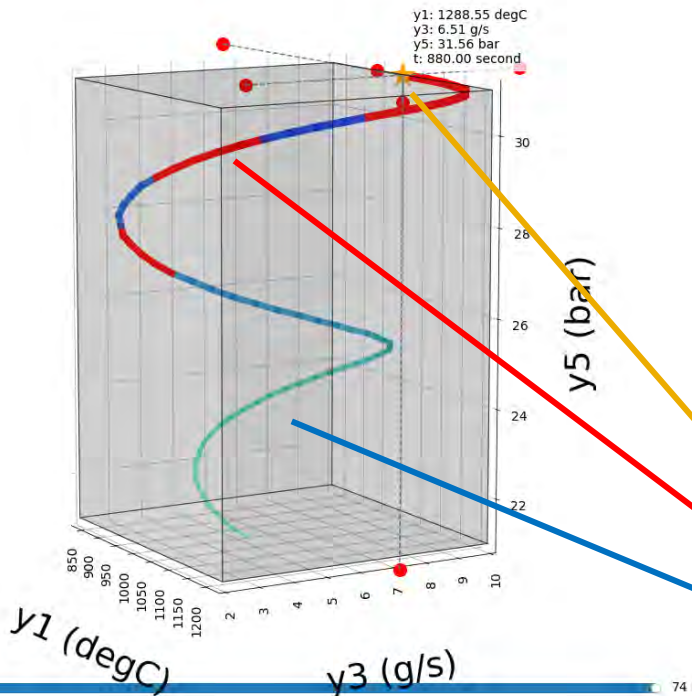
Extension of classic 3D trace plot:

- System response is represented by a 3D trajectory
- Each point represents the values of three selected monitored variables during the transient.

Improvement by ANL:

- Animation to track data history
- NOR is shown by grey-colored parallelepiped
- Red dots indicate the margin with respect to the NOR bounds
- Thickness of the curve to show the direction of system response;
- **Gold star** shows current value
- **Red trace** -> constraint violation
- **Blue trace** -> constraint compliance.

t: 880.00 second  
y1: 1288.55 degC  
y1min: 826.85 degC  
y1max: 1226.85 degC  
y3: 6.51 g/s  
y3min: 2.00 g/s  
y3max: 10.00 g/s  
y5: 31.56 bar  
y5min: 21.00 bar  
y5max: 31.00 bar

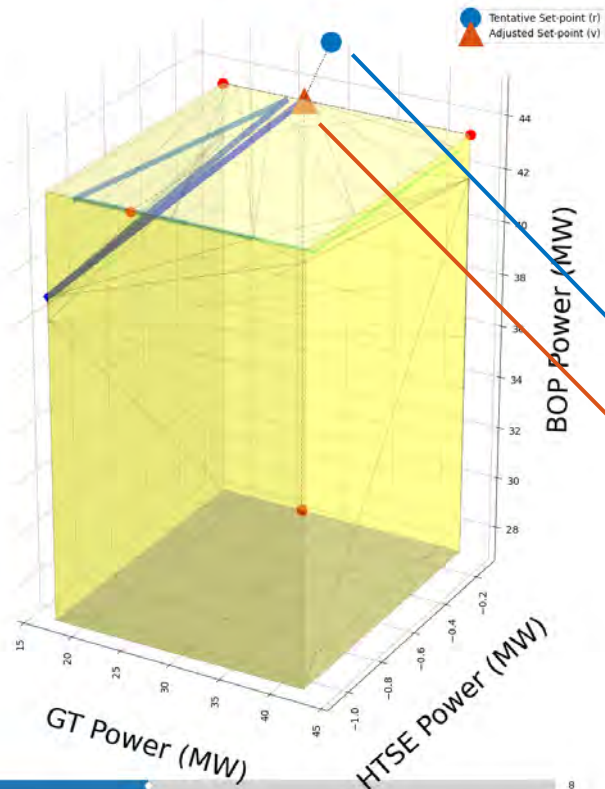


Q. In case of constraint violation, how can the operator modify the input variable?

# SOLUTIONS TO AR VISUALIZATION

## 3D convex polytope for inputs

t: 8.00 hr  
v0: 28.26 MW  
v0min: 20.03 MW  
v0max: 44.55 MW  
v1: -0.25 MW  
v1min: -1.20 MW  
v1max: -0.24 MW  
v2: 43.88 MW  
v2min: 27.78 MW  
v2max: 43.88 MW



If the system dynamics can be described by a state-space representation model:

$$\begin{aligned}\vec{x}(k+1) &= A^d \vec{x}(k) + B^d \vec{v}(k) \\ \vec{y}(k) &= C^d \vec{x}(k) + D^d \vec{v}(k)\end{aligned}$$

The bounds on output can be translated into a admissible region on input:

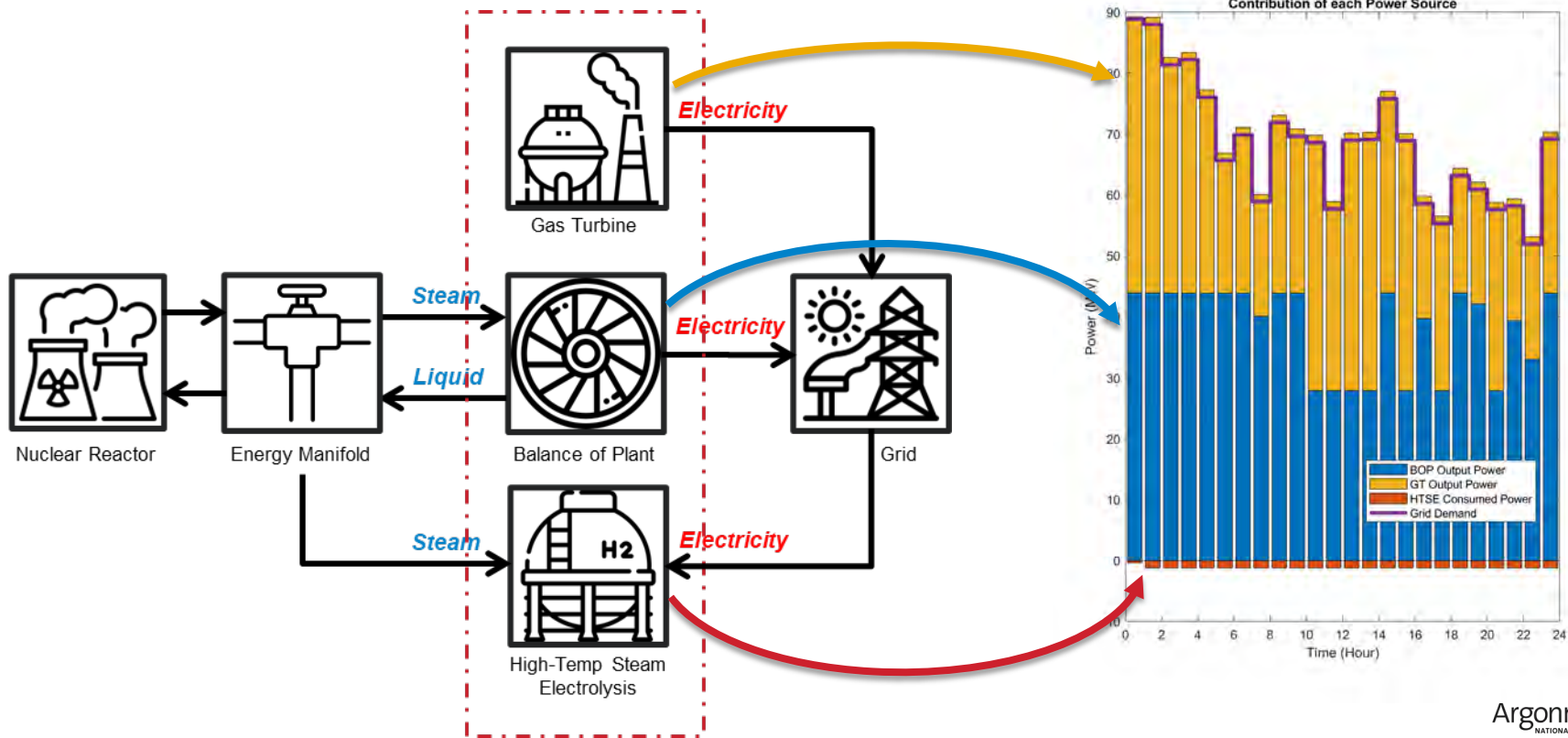
$$H \cdot \vec{v}(k) \leq h$$

And this admissible region is shown by **yellow convex polytope**.

- **Blue Circle** indicates tentative input variable;
- **Orange Triangle** indicates the proposed adjustment as a compromise between (1) performing the desired transient and (2) staying within the Admissible Region.

# DEMONSTRATIONS

- Power transient to be evaluated:

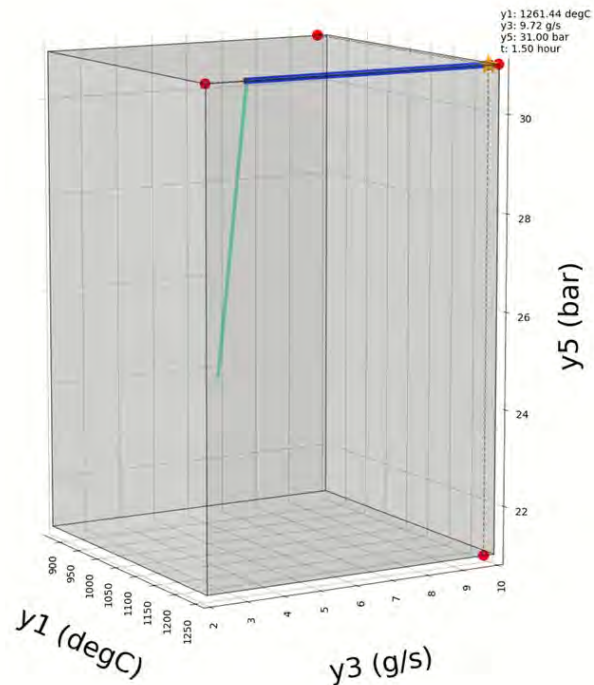
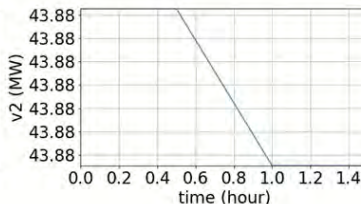
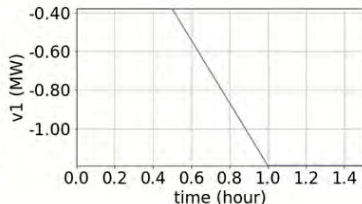
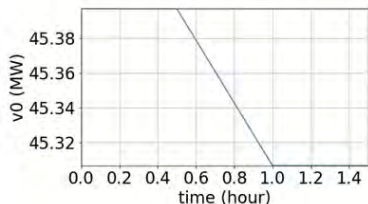
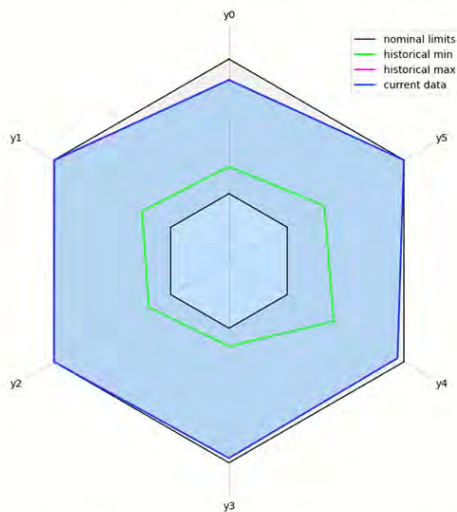


# DEMONSTRATIONS

## Output variables and NOR:



t: 1.50 hour  
y0: 45.30 MW  
y0min: 20.00 MW  
y0max: 50.00 MW  
y1: 1261.44 degC  
y1min: 862.85 degC  
y1max: 1262.85 degC  
y2: 1.20 MW  
y2min: 0.20 MW  
y2max: 1.20 MW  
y3: 9.72 g/s  
y3min: 2.00 g/s  
y3max: 10.00 g/s  
y4: 43.90 MW  
y4min: 25.00 MW  
y4max: 45.00 MW  
y5: 31.00 bar  
y5min: 21.00 bar  
y5max: 31.00 bar  
v0: 45.31 MW  
v1: -1.19 MW  
v2: 43.88 MW

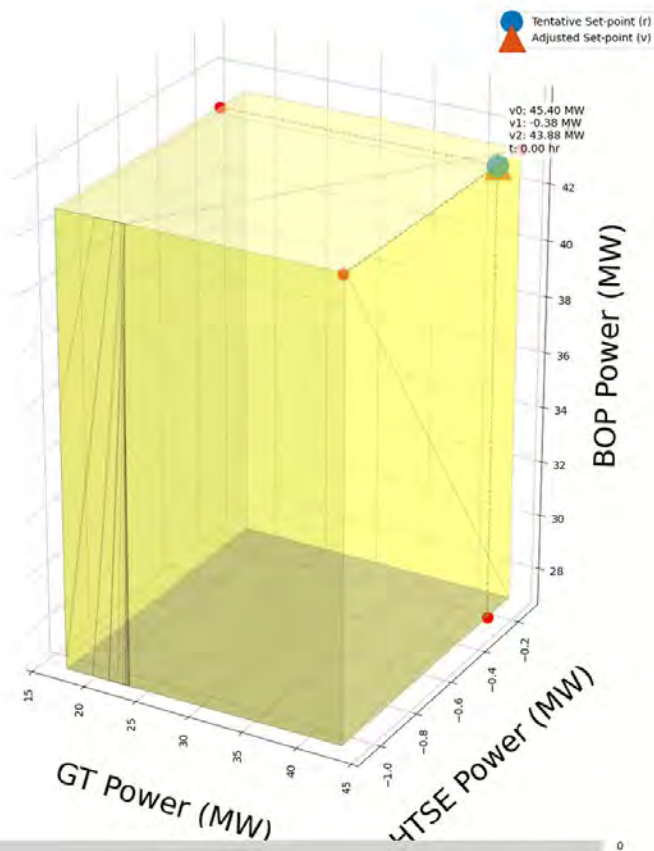




# DEMONSTRATIONS

- Input variables and AR:

t: 0.00 hr  
v0: 45.40 MW  
v0min: 20.00 MW  
v0max: 45.40 MW  
v1: -0.38 MW  
v1min: -1.20 MW  
v1max: -0.24 MW  
v2: 43.88 MW  
v2min: 27.78 MW  
v2max: 43.88 MW



# CONCLUSION

- A visualization technique to evaluate the power transients of a thermally couple system was developed and demonstrated.
- The multi-dimensional admissible region for input variables (system actuators) and the evolution history of key monitored process variables are visible to the operator.
- Any violation of operational constraints will be directly shown and brought to the user's attention. Suggestions on input variable adjustment is also provided.
- This method would strengthen the user trust when planning and evaluating power transients.

## References

- H. Wang, Quantitative Estimation and Visualization of the Normal Operation Region for Power Transient Planning, Invited Talk, 13th Nuclear Plant Instrumentation, Control & Human-Machine Interface Technologies (NPIC&HMIT 2023), Knoxville, TN, July 15-20, 2023
- H. Wang, R. Ponciroli, A.J. Dave, R.B. Vilim, "Control system for multi-system coordination via a single reference governor", ANL/NSE-22/26, Argonne National Laboratory, Lemont, Illinois (2022).

**THANK YOU**

**Rajiv Khadka**

Visualization Researcher

Applied Visualization Laboratory

# Next-Generation Context-Aware Adaptive User Interface: Challenges and Opportunities

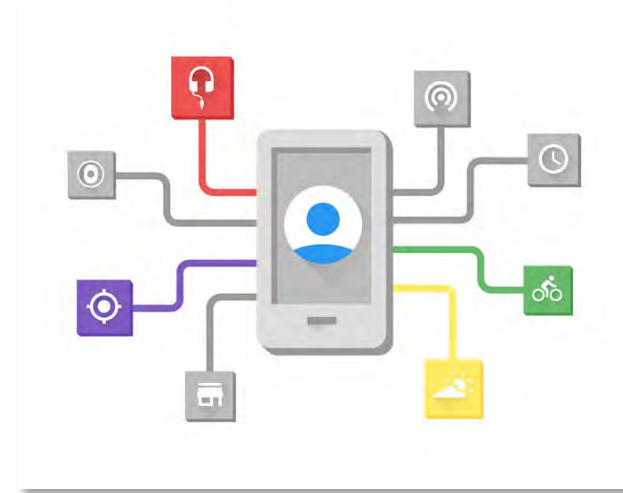
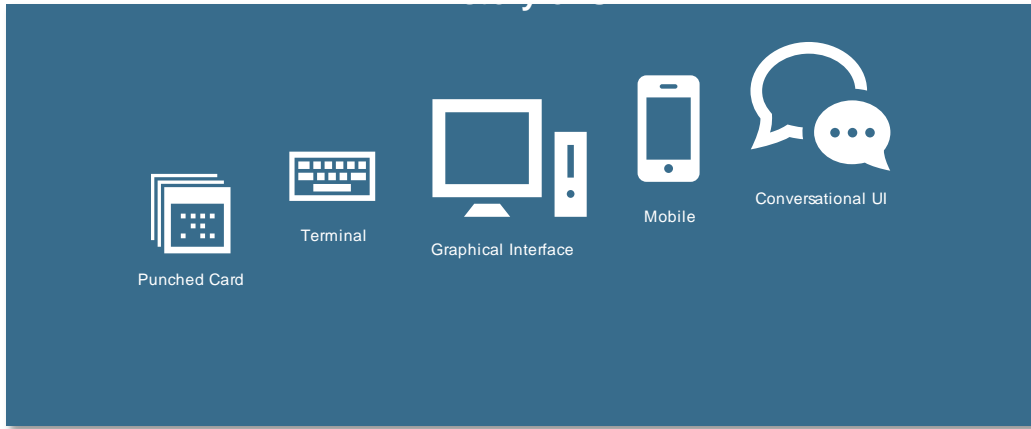
Navigating the future of User Interaction

Battelle Energy Alliance manages INL for the  
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# EVOLUTION OF USER INTERFACES



# CONTEXT-AWARENESS

- *“any information that can be used to characterize the situation of an entity. An entity is a person, place or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves”*. [Dey, 2001]
- Involves gathering and analyzing contextual data like user location, history, device sensors, activity, etc.
- Tailor services and interactions, providing users with personalized and timely experiences

# KEY COMPONENTS OF CONTEXT-AWARENESS

- Sensors and Data Sources
- Context Inference and Interpretation
- Adaptive Behavior and Response Mechanisms
- User Feedback Loop
- Multimodal Interaction Support



# WHY CONTEXT-AWARE USER INTERFACES?

- Personalization and Customization
- Enhanced User Experience
- Contextual Decision Support
- Efficiency and Productivity
- Adaptation to Dynamic Environments
- Anticipation of User Intentions





# CHALLENGES

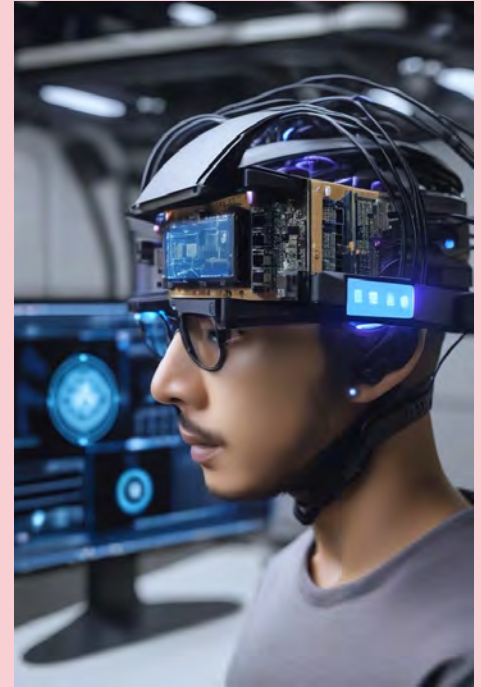
- Data Privacy and Security Concerns
- Accuracy and Reliability of Context Inference
- Scalability Across Devices and Environments
- Technical Complexity
- User Acceptance and Adoption Challenges

# OPPORTUNITIES

- Enhanced Personalization and User Experience
- Contextual Collaboration
- Efficient and Improved Decision Support
- Seamless Integration Across Devices and Platforms
- Increased Efficiency and Productivity
- Potential for New Interaction Paradigms (e.g., AR/VR)

# FUTURE TRENDS

- Continued Integration of AI and Machine Learning
- Advancements in Sensor Technologies
- Convergence with Internet of Things (IoT)
- Emergence of Brain-Computer Interfaces (BCI)



THANK YOU!!  
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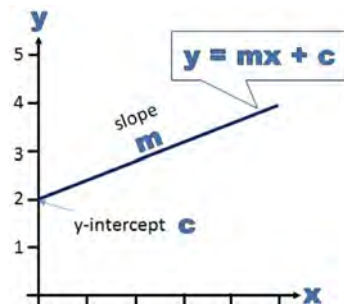
Cody Walker, PhD

March 28, 2024

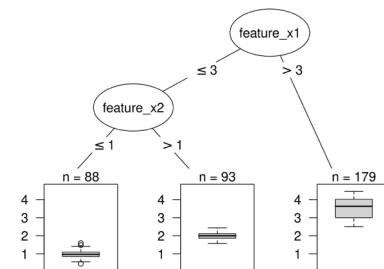
# Improving Machine Learning Explainability with a Graphical User Interface

# Explainability comes in different forms depending on which model you use.

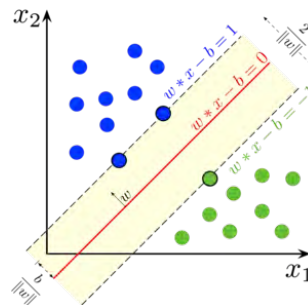
- How do we explain these models to the user?
- How much would you have to explain to go from an input to an output?



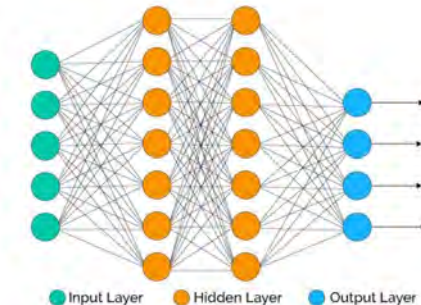
2 [m, c]



2 [2 splits]



Support vectors, kernel trick and hyperplane.



Number of weights, biases, & connections.

Data

Hyperparameter  
s  
& Optimization

Model

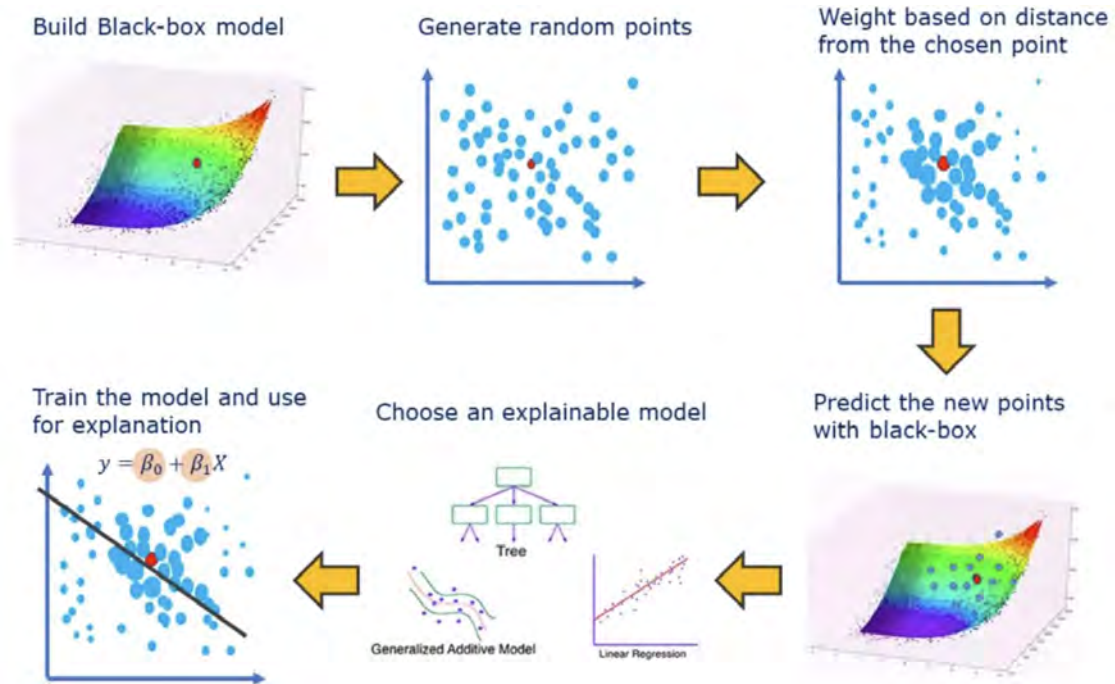
Effects model performance and explainability

Post  
hoc

Explainability

# LIME is a post-hoc method for black-box models.

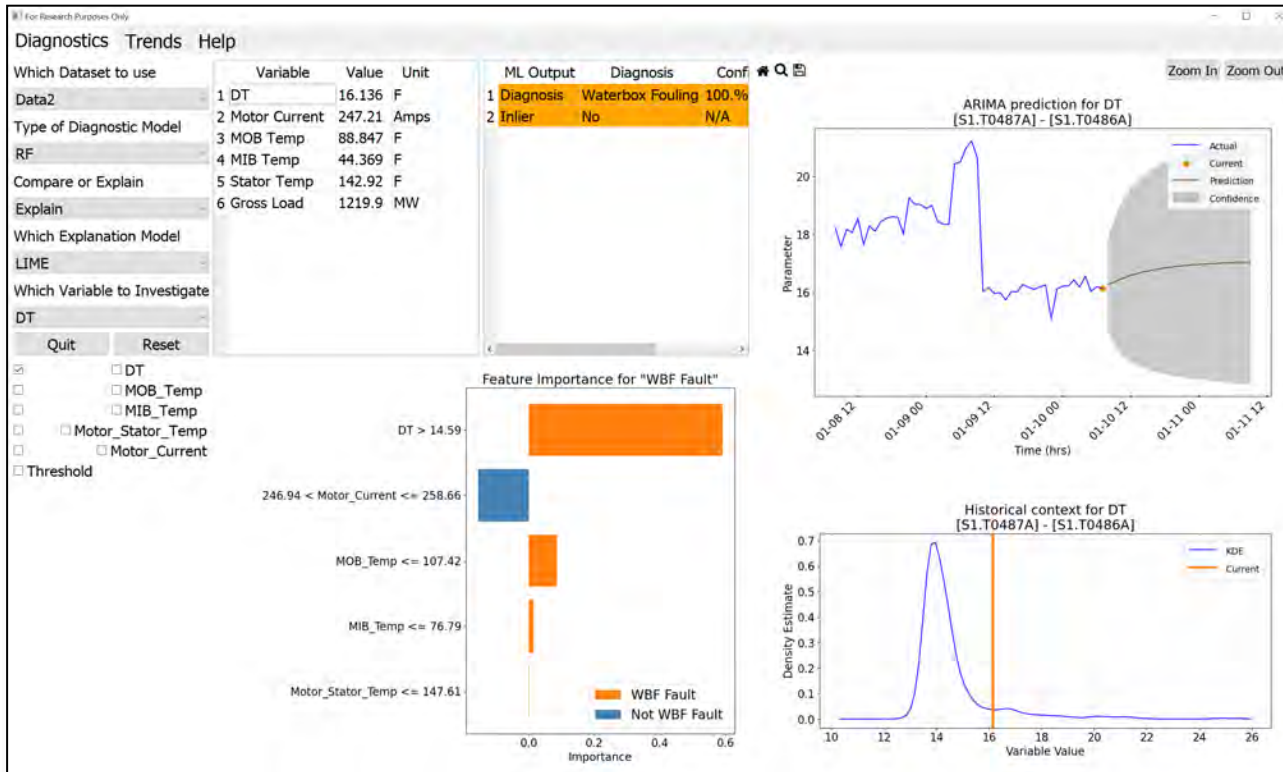
- Local interpretable model-agnostic explanations (LIME) can be used for any model.
- LIME is only valid **locally**.
- SHAP (Shapley Additive Explanations) are another common post-hoc method used to increase explainability.



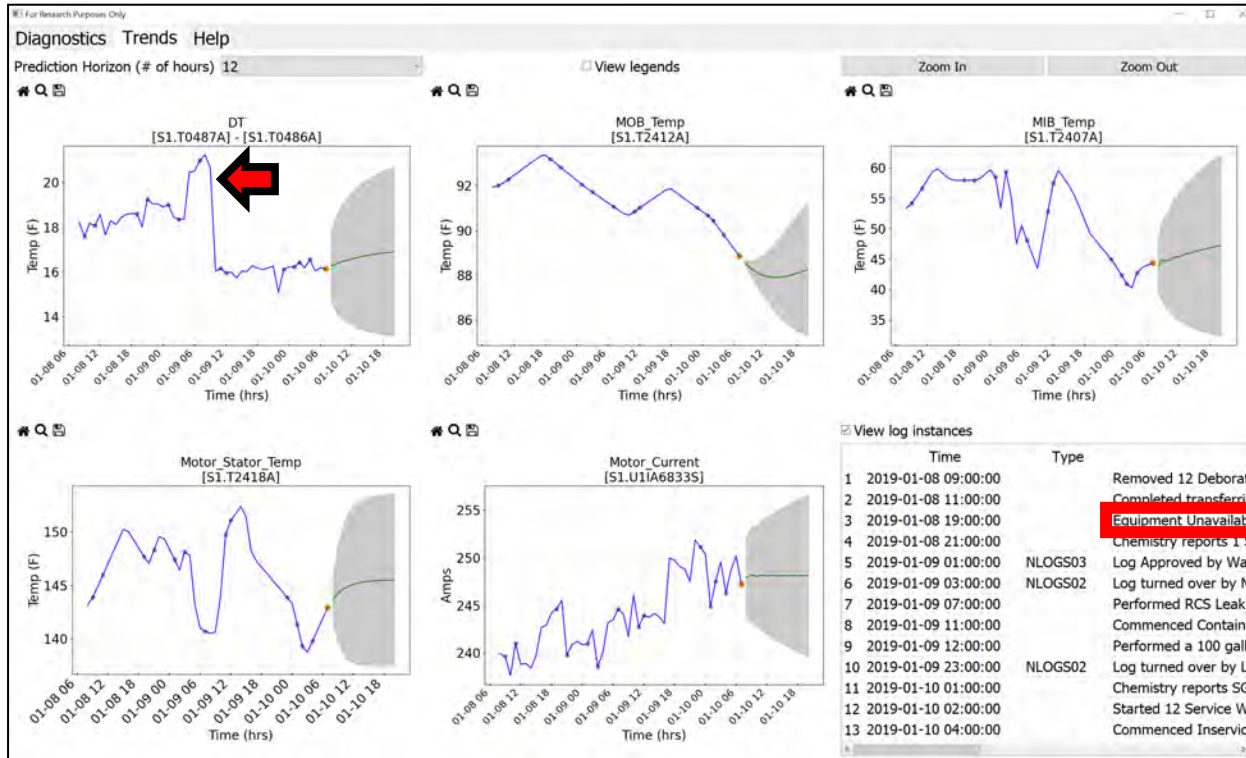
Giorgio Visani, 2020 "LIME: explain Machine Learning predictions." Accessed 2024.  
<https://towardsdatascience.com/lime-explain-machine-learning-predictions-a8f181895b6>



# Model confidence, prognostics, explainability, and historical context all provide evidence for the conclusion.



# Adding context to the data can further improve understanding.





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March 28, 2023



# You-only-look-once (YOLO) and Radio Frequency Signal Analysis

Randall Reese  
Idaho National Lab

# Premise

- Radio Frequency (RF) Signal analysis and Computer Vision.
- How might we identify signals of interest in the RF spectrum?
- All of this is done in the context of a tool called WiFIRE.

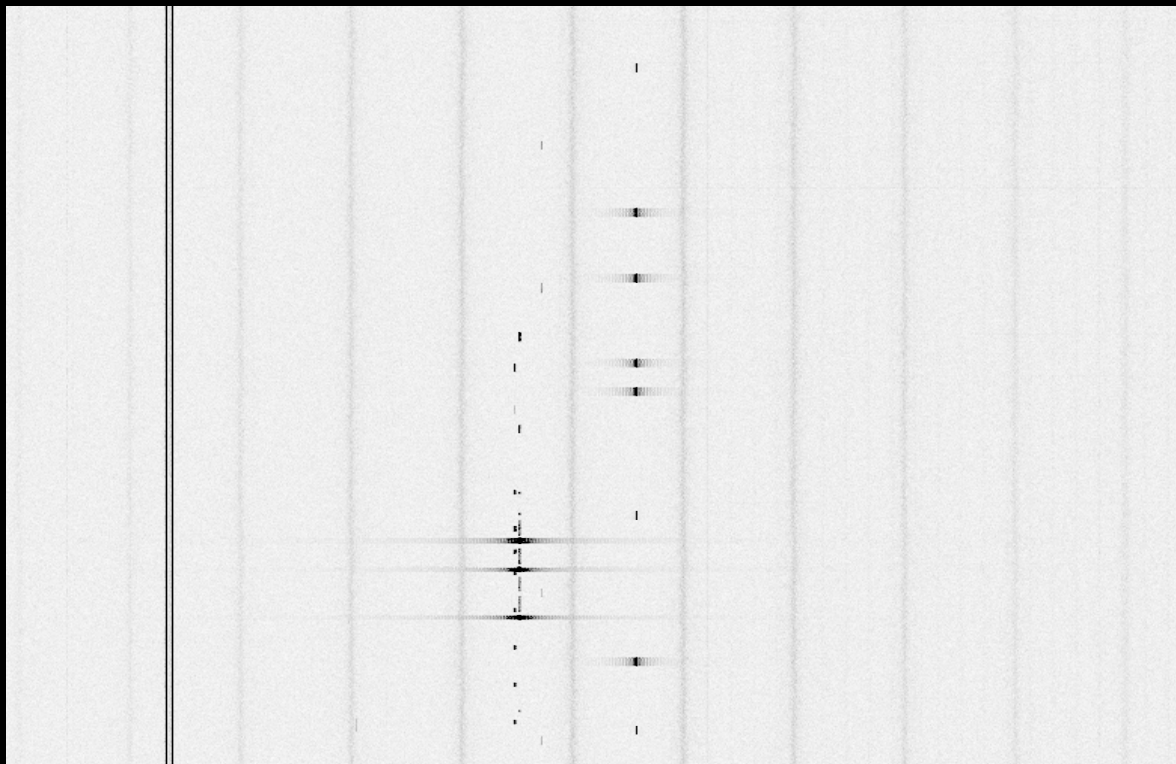
# Premise: Need for Wireless Monitoring

- Signals missing that should be there
  - Equipment failures?
  - Theft?
- Signals that are there that shouldn't be
  - Jamming?
  - Data Exfiltration?
  - Unauthorized User/Device?
- Blackbox analysis
  - Ability to take a device and determine what signals are being emitted
- Signal Compliance Verification
  - Damaged/Low Quality Hardware?
  - Spectrum Misuse?

# Technical Challenges

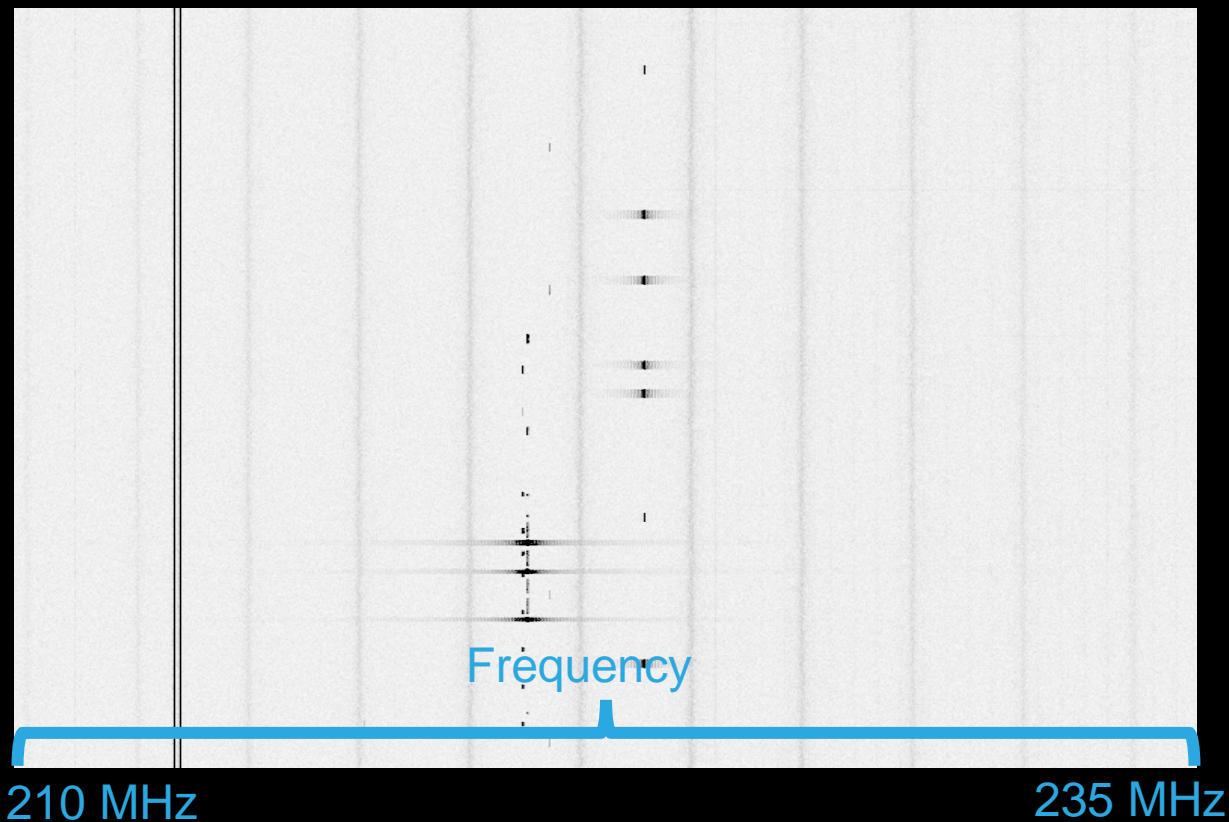
- Large amount of raw wireless data
  - 25 million samples (IQ values) per second
  - IQ value = 16 bits each for I and Q (32 bits / 4bytes total)
  - 5.6 GiB per minute
  - 7.9 TiB per day
- Differentiating signal from noise
- How to keep up with a high sample rate
- Accurate and effective machine learning algorithms for detection and classification of wireless signals

# Inference Input

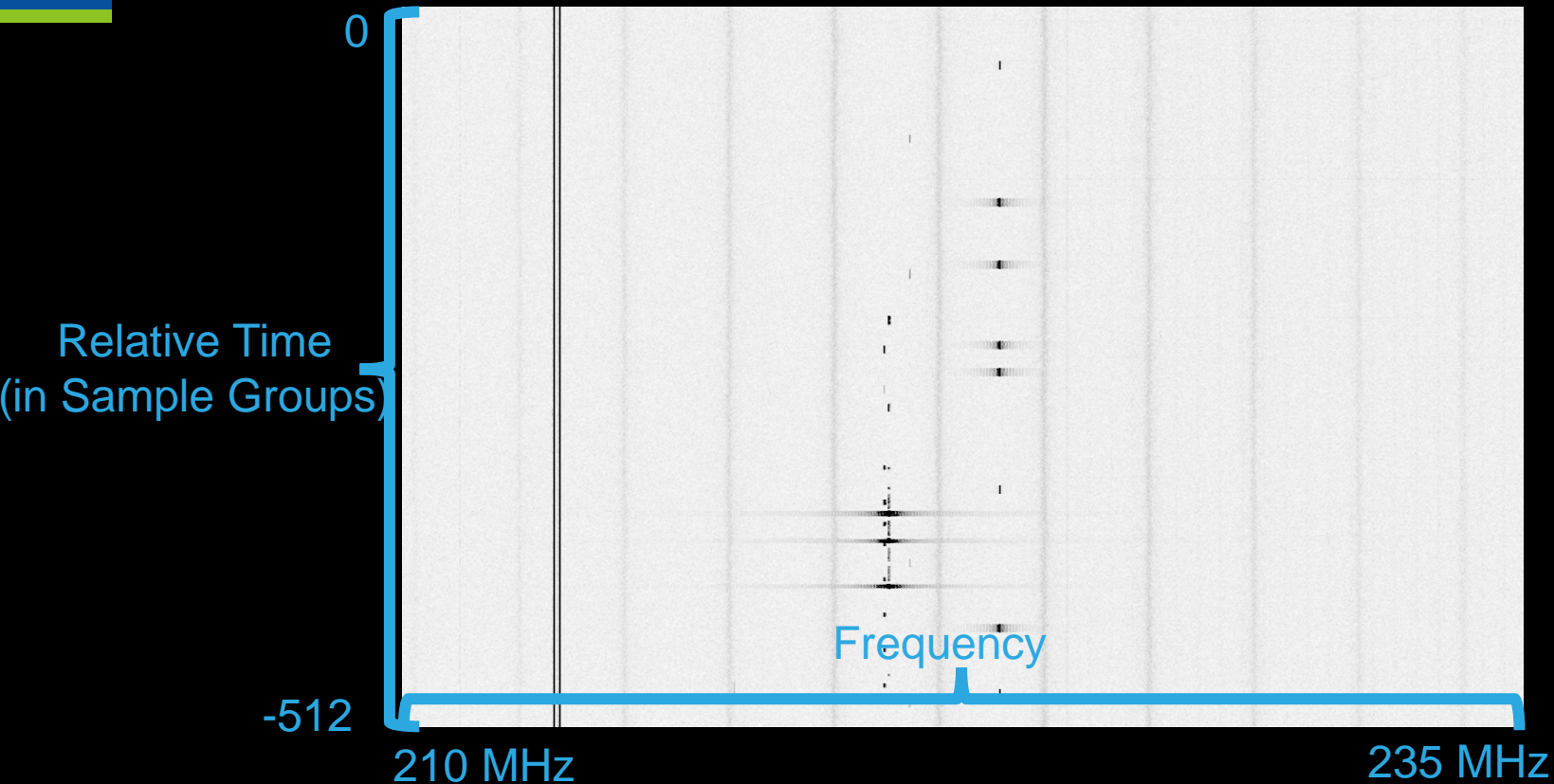




# Inference Input

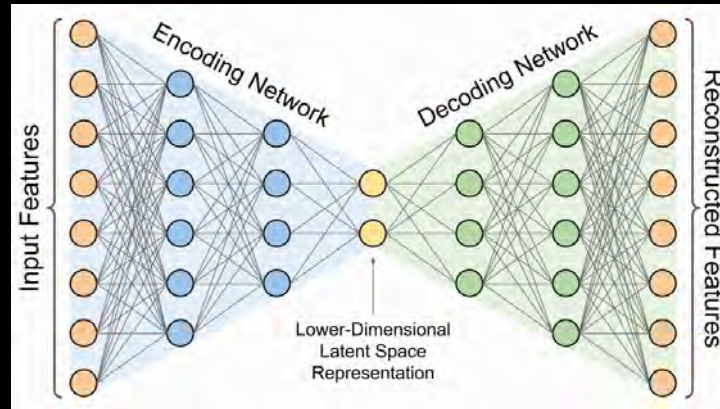


# Inference Input



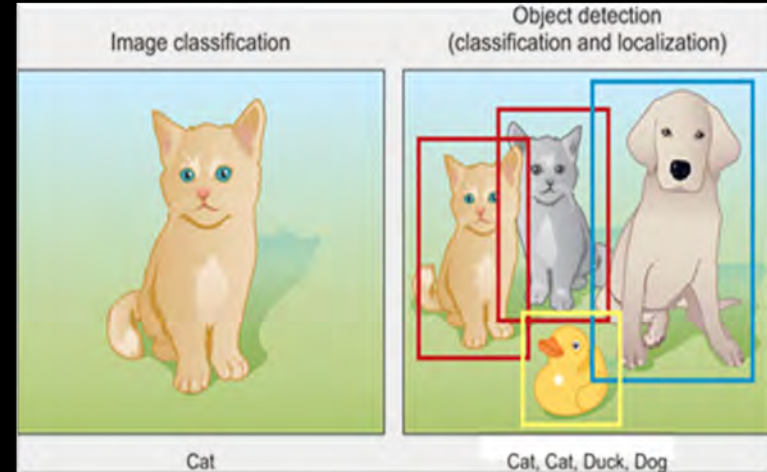
# Aside: Wireless Environment Baseline

- Goal: Identify anomalous signals using an unsupervised approach
- Strategy:
  - Collect data at the target location
  - Train an autoencoder model to compress and restore the collected data – this is the baseline model
  - Apply the baseline model to a new sample and then compare the sample to the reconstructed version
  - Any signal that is reconstructed poorly – beyond a calculated threshold – is considered anomalous



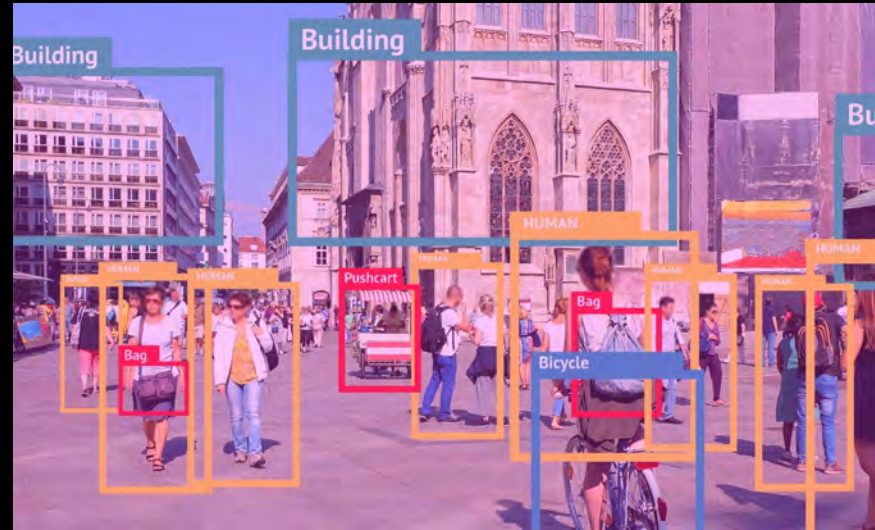
# Our Focus: Signal Classification and Localization

- Goal: Identify known signals of interest. Unlike anomaly detection, this is a supervised ML problem.
- Strategy:
  - Collect data with known signals and manually label the data
  - Train an object detection model using **YOLO(V7)**
  - During inference, the model is used to determine bounding boxes of identified signals
  - System draws the identified bounding boxes from the model
  - Allow for multiple classes of signals to be identified in a single image (Multi-label)



# How does YOLO work?

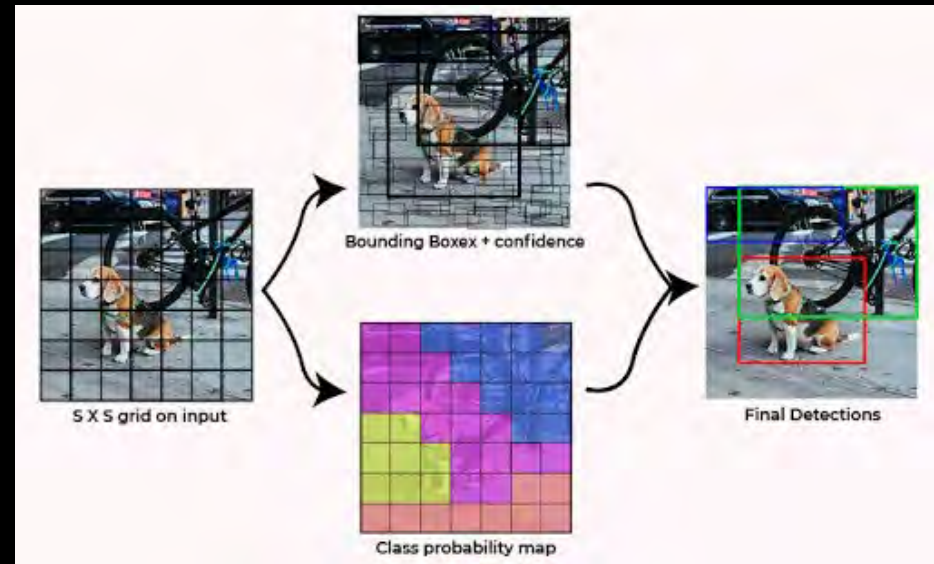
- Single pass (You only look once) as opposed to multi-pass approaches like DPM or R-CNN.
- Uses a single convolutional neural network as opposed to a complex pipeline of sliding windows and classifiers.
- Allows for global awareness within each image.



Redmon, Joseph, Santosh Divvala, Ross Girshick, and Ali Farhadi. "You only look once: Unified, real-time object detection." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 779-788. 2016.

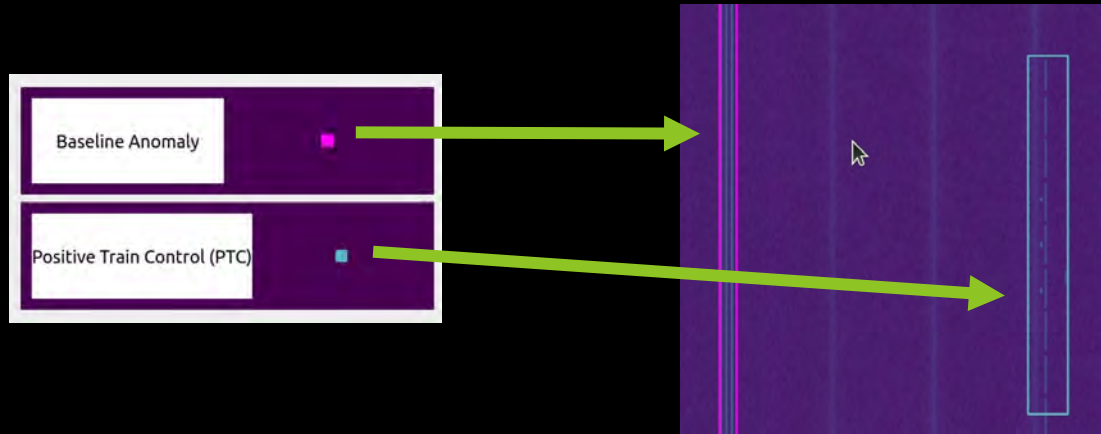
# How does YOLO work? (cont.)

- Divide input image into an  $S \times S$  grid ( $S$  is chosen as a hyperparameter).
- Each grid square predicts up to  $B$  many bounding boxes within that grid square.
- Calculate class probabilities for each grid square as well as confidence levels (IOU).
- Bounding box predictions and class probabilities are combined to create a final predicted set of boxes.
- Boxes with confidence below a certain threshold are dropped.

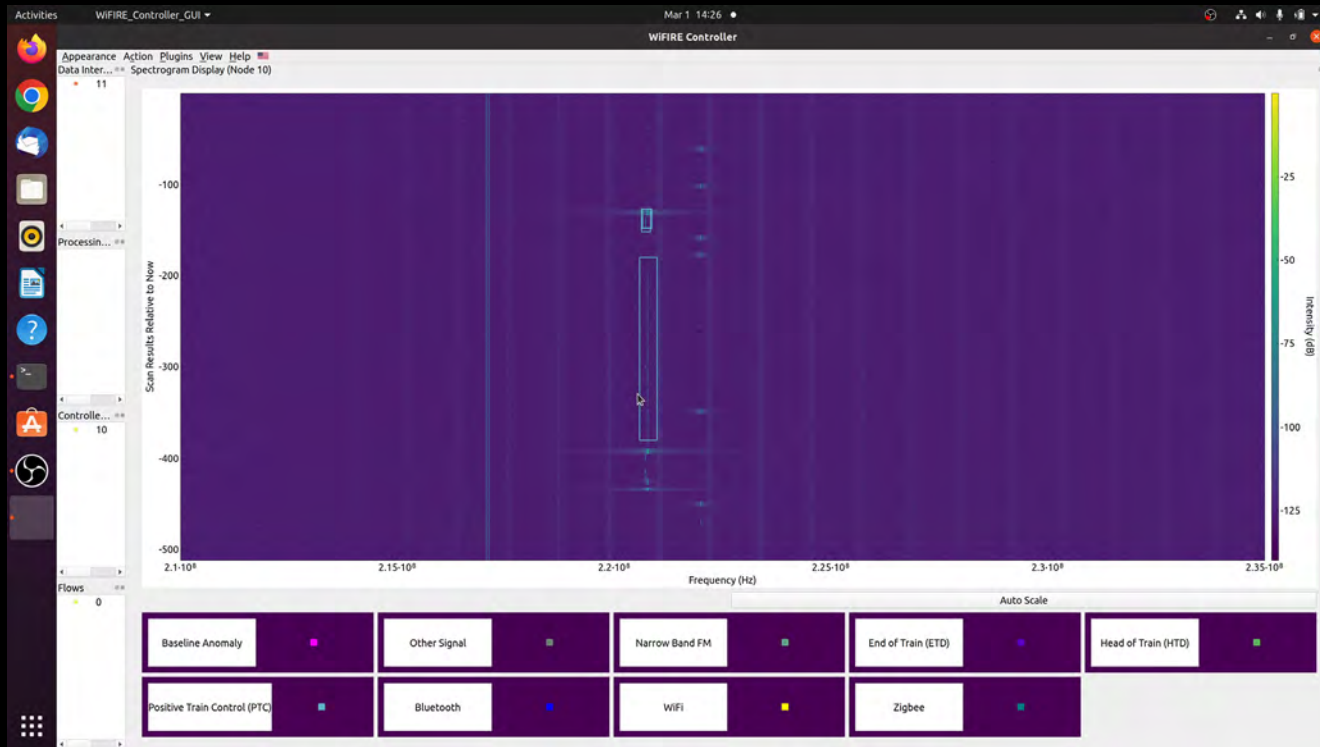


# Results

- Baseline Comparison and Signal Classification inferencing done in parallel
- Inference results are returned as a set of bounding boxes
- These bounding boxes are shown as color-coded overlays on the User Interface

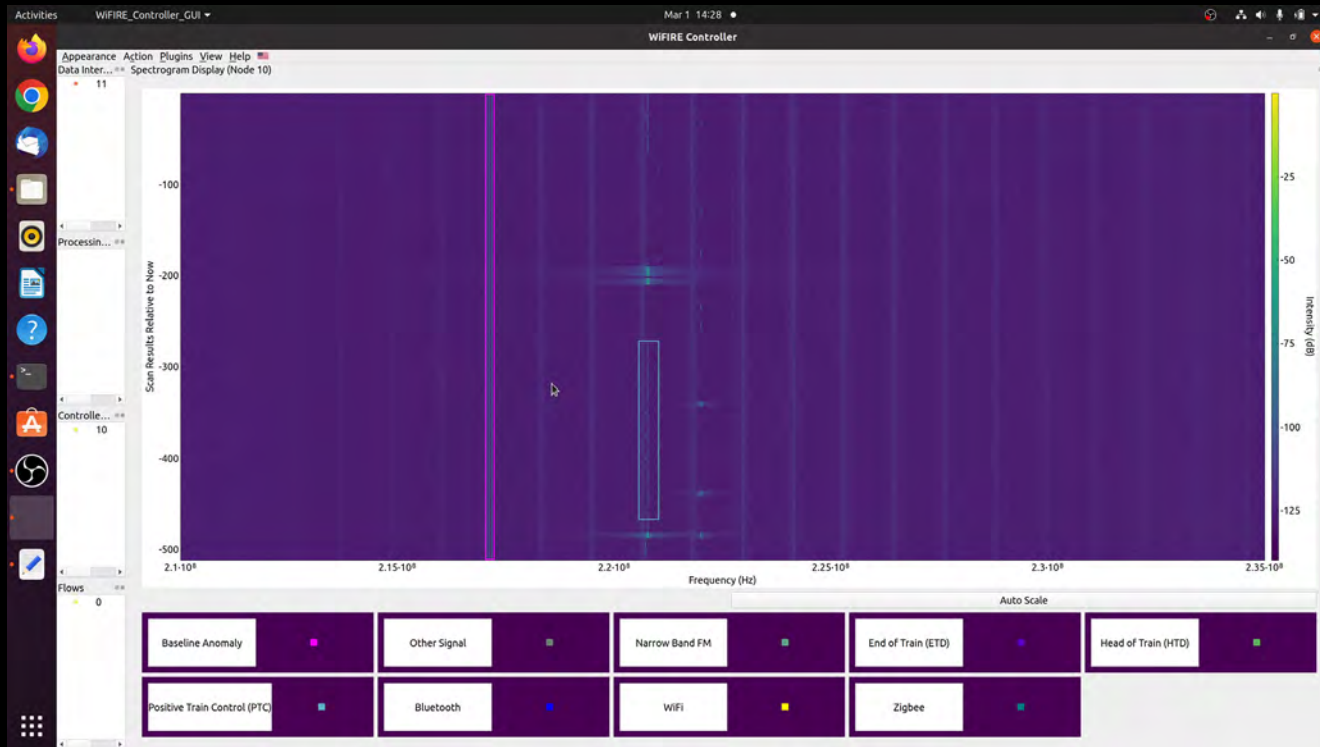


# Results (cont).

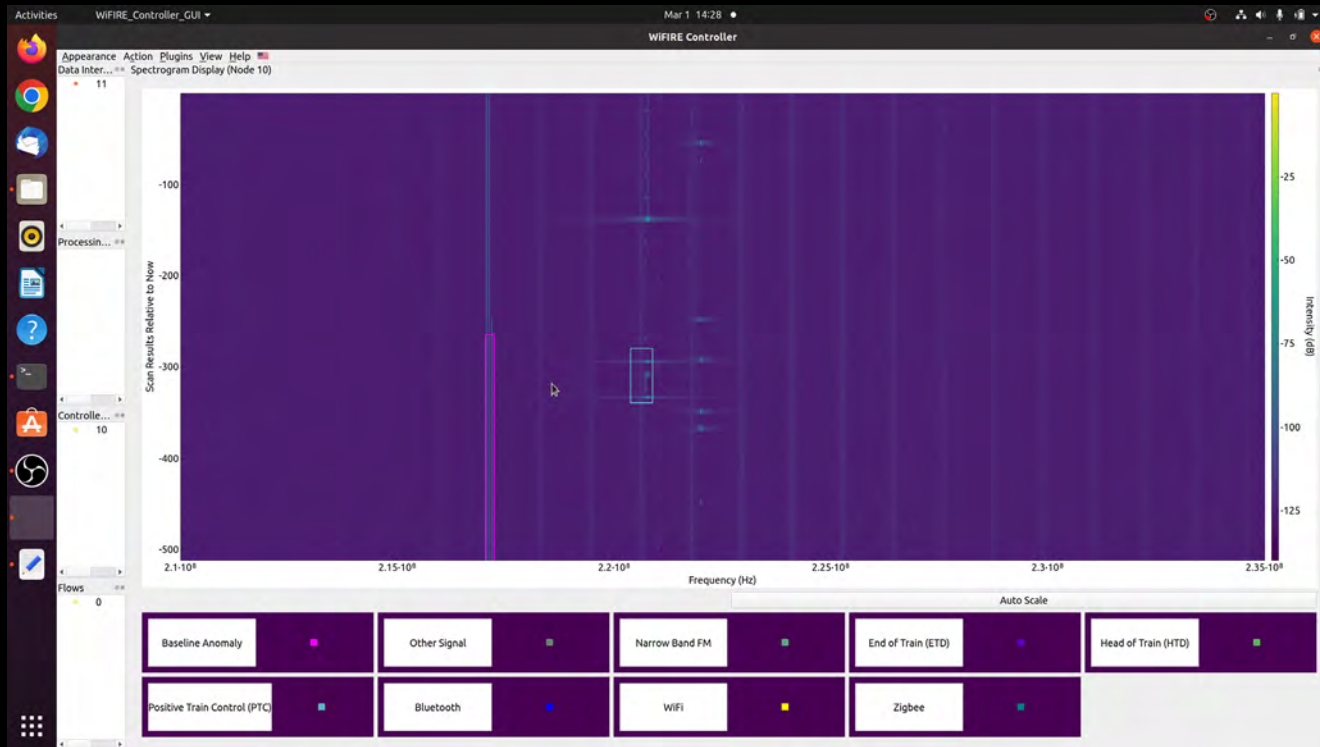




# Results (cont).

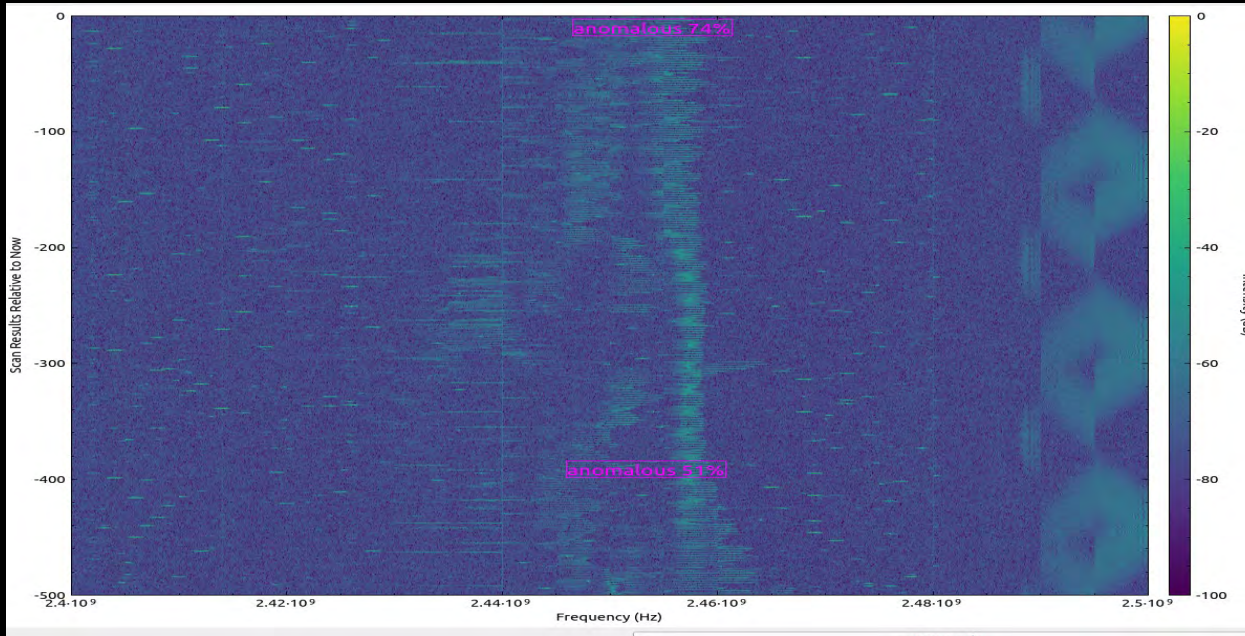


# Results (cont).



# Weird Anomaly Detected at C3

- Below is an anomaly that we detected using these models. It is in the 2.4 Ghz. range.





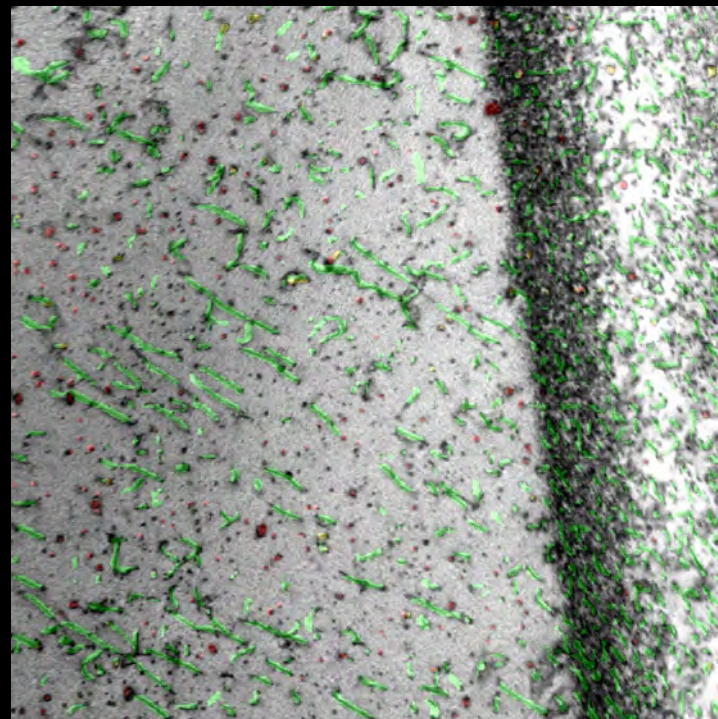
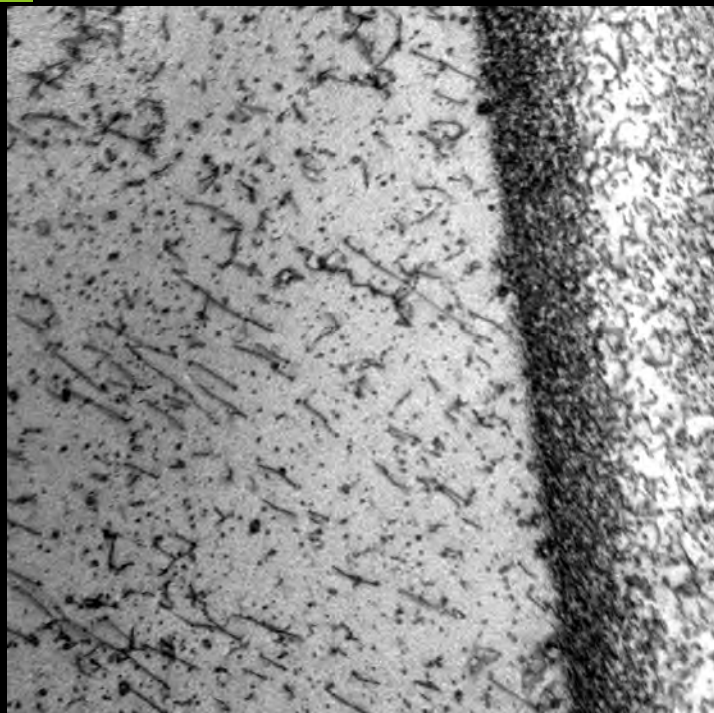
Idaho National Laboratory

28 Mar 2024

# Yolo for Dislocation-Type Defects in PM-HIP Alloys via Transfer Learning

Matthew Anderson, Michael Wu, Jeremy Sharapov

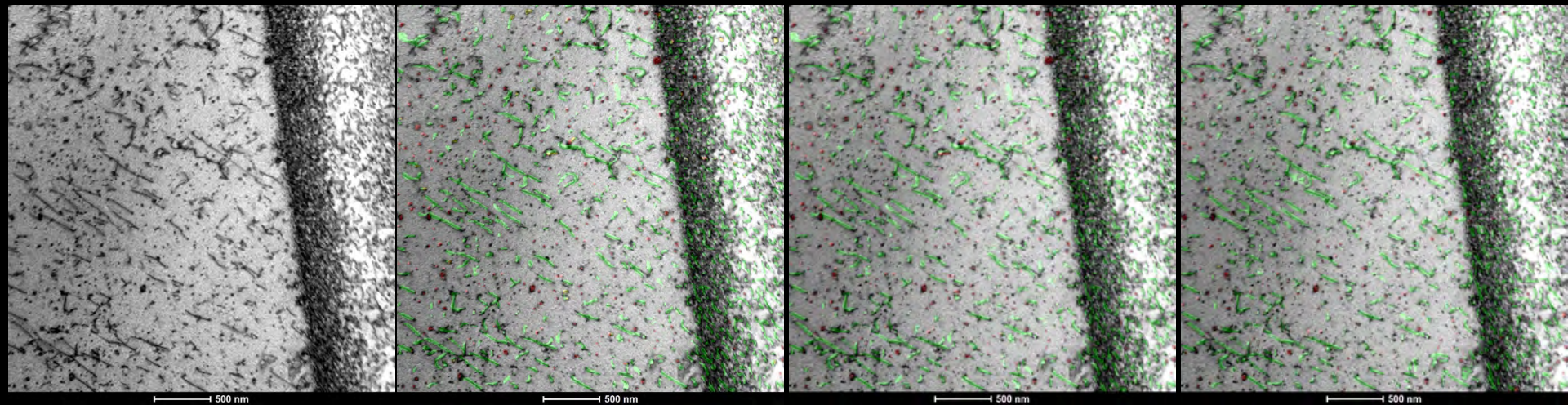
# Yolo for Dislocation-Type Defects via Transfer Learning



## Challenges:

- Experts required to label
- TEM images can be challenging to interpret
- Very small number of images expected to be labelled
- Density and dislocation-type defect identification crucial for material property analysis
- Not a large domain field with large community support

# Solution: Transfer Learning



0.17723

0.33158



# INL High Performance Computing Resources

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A right-sized solution for DOE Nuclear Energy research and development

# Bitterroot

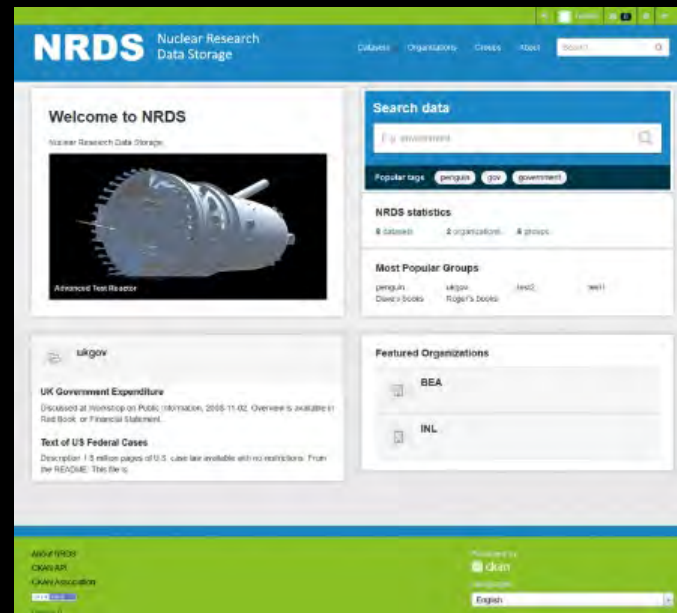
- 384 Nodes
  - Node specs
    - 2 Sapphire Rapids 56 core CPUs
    - 256 GB RAM
  - 48 nodes with HBM
- 41,888 cores
- 200 Gb/s OmniPath network
- Will complement existing systems (Sawtooth, Lemhi, Hoodoo, Viz)
- Delivery 16 March 2024
- Expected commissioning date: 16 April 2024

Commodity Technology Systems-2 (CTS-2)



# NSUF Nuclear Research Data System (NRDS): <https://nrds.inl.gov>

- NRDS:
  -
- Near real time analysis
  -
- Publicly available
  - 
  - 
  - 
  -
- FpAIRe data
  -
- AI analysis
  -
- Active detection





# Questions?