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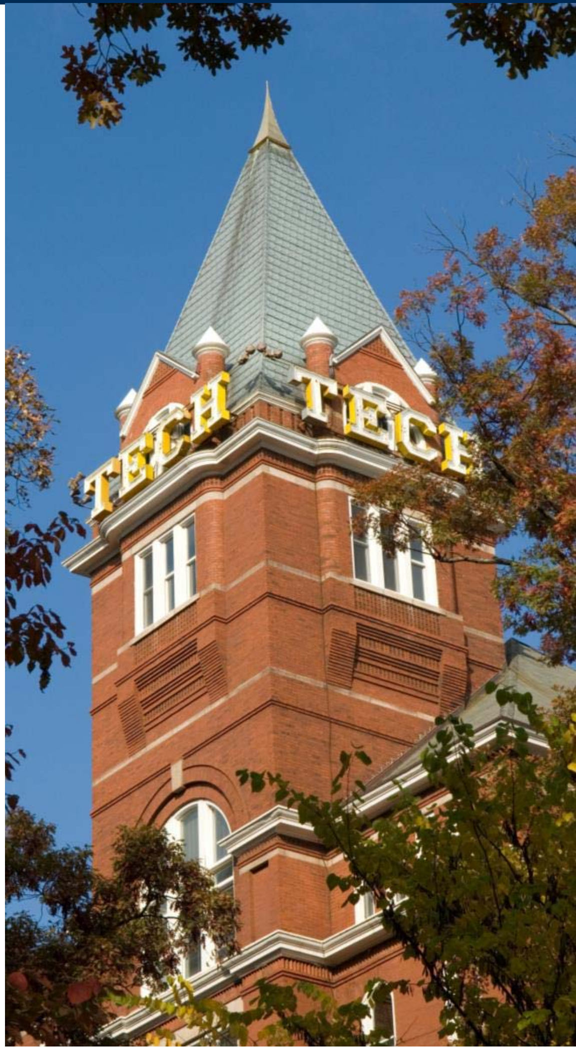
Problem. Solved.



Adaptive and Intelligent Electronic Warfare Support

October 24th, 2019

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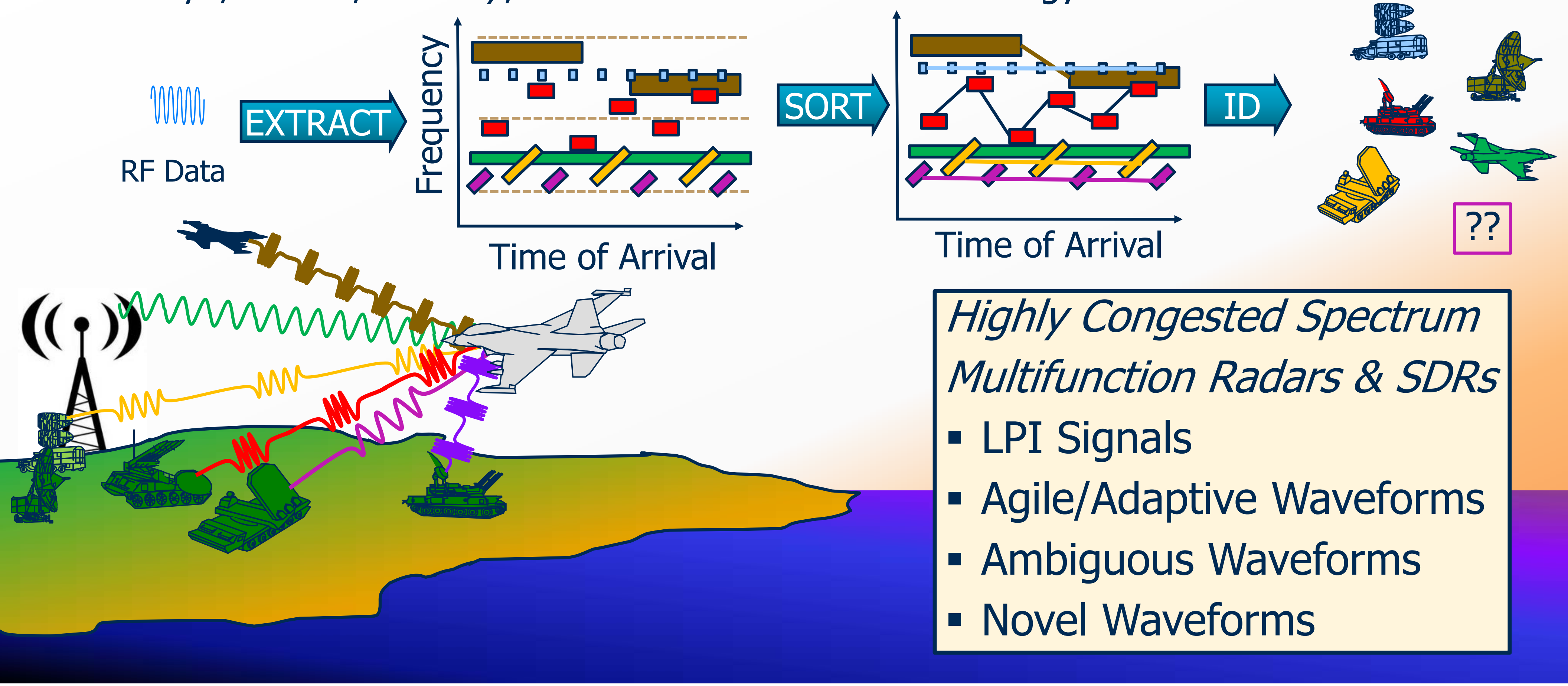
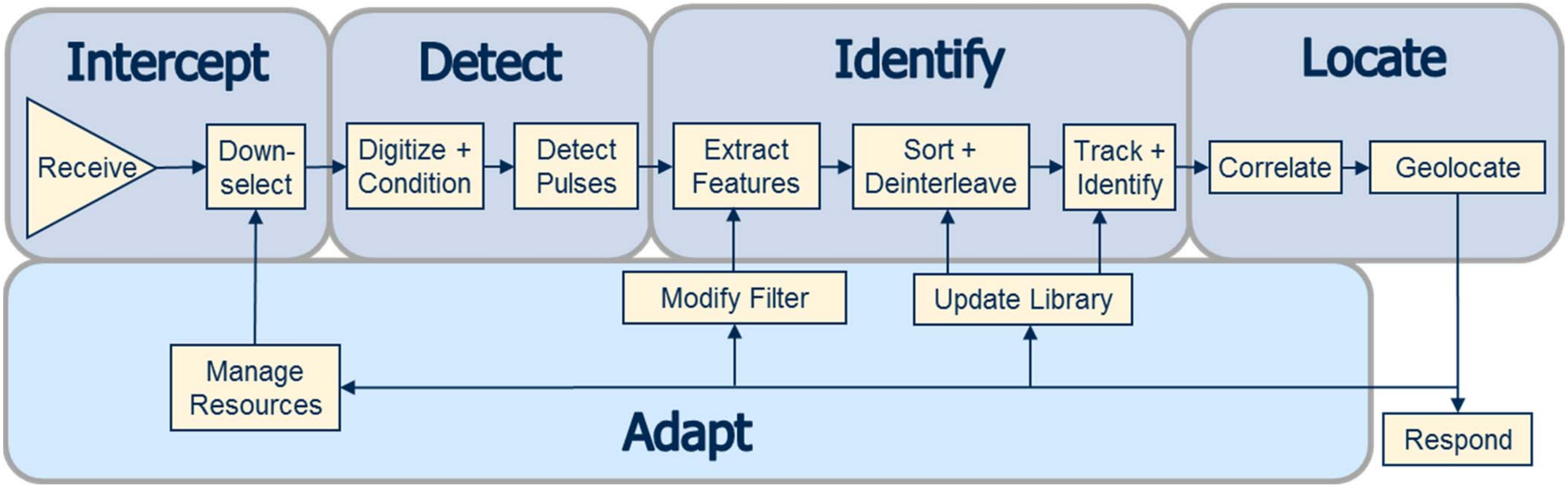
This presentation has been modified from the original version for public release.

Electronic Support - Modern Challenges

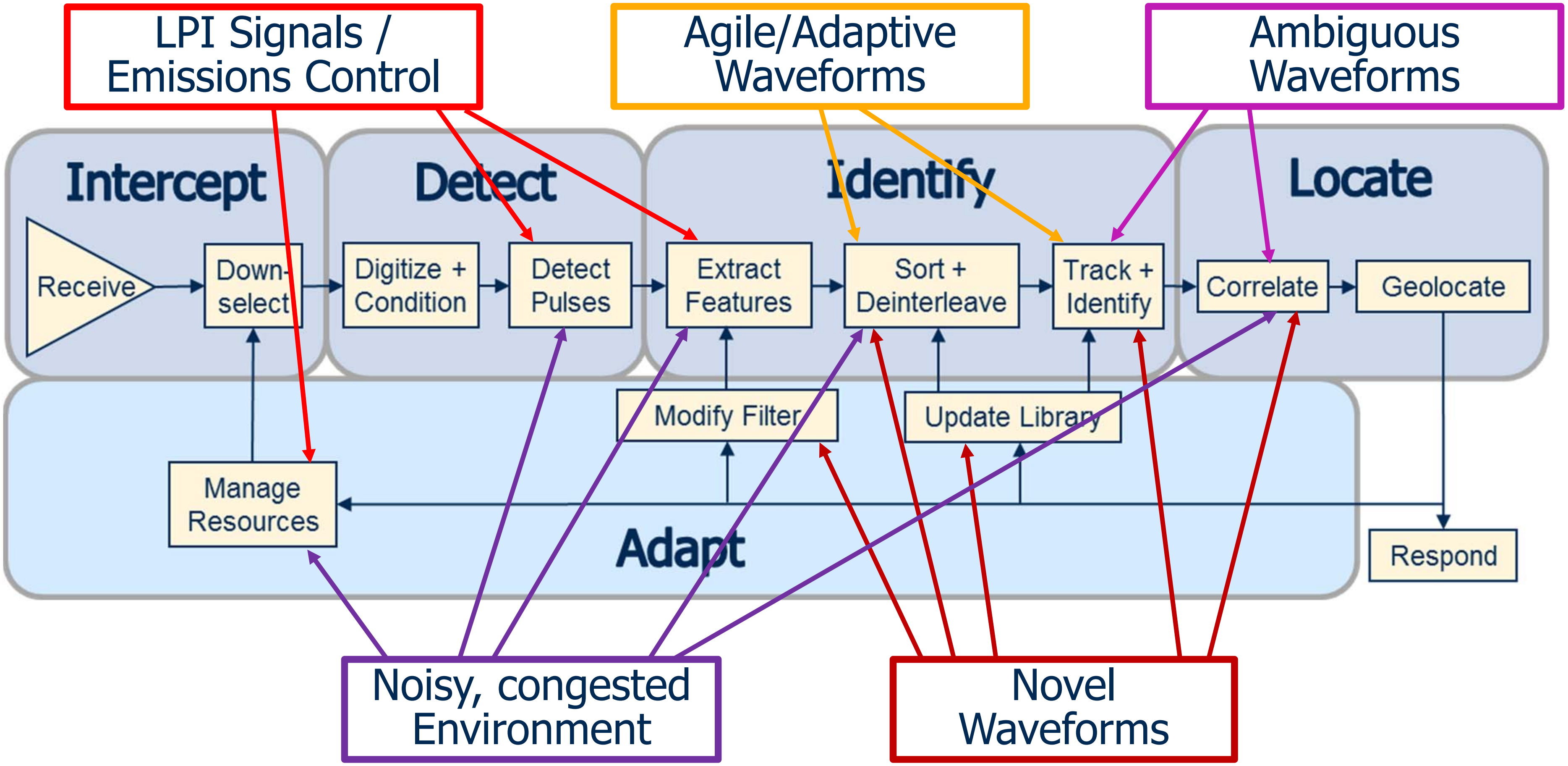
Intercept, *Detect*, *Identify*, and *Locate* sources of RF Energy



Components of a Digital, Cognitive ES System



Specific Challenges of a Digital, Cognitive ES System



What do we want out of an "Intelligent" EW system?

Fidelity

The system makes the best possible decisions or inferences against known inputs.

Flexibility

The system responds to novel inputs with a reasonable guess or decision.

Explainability

The reasoning for each of the system's decisions can be understood by a human or external system.

Adaptability

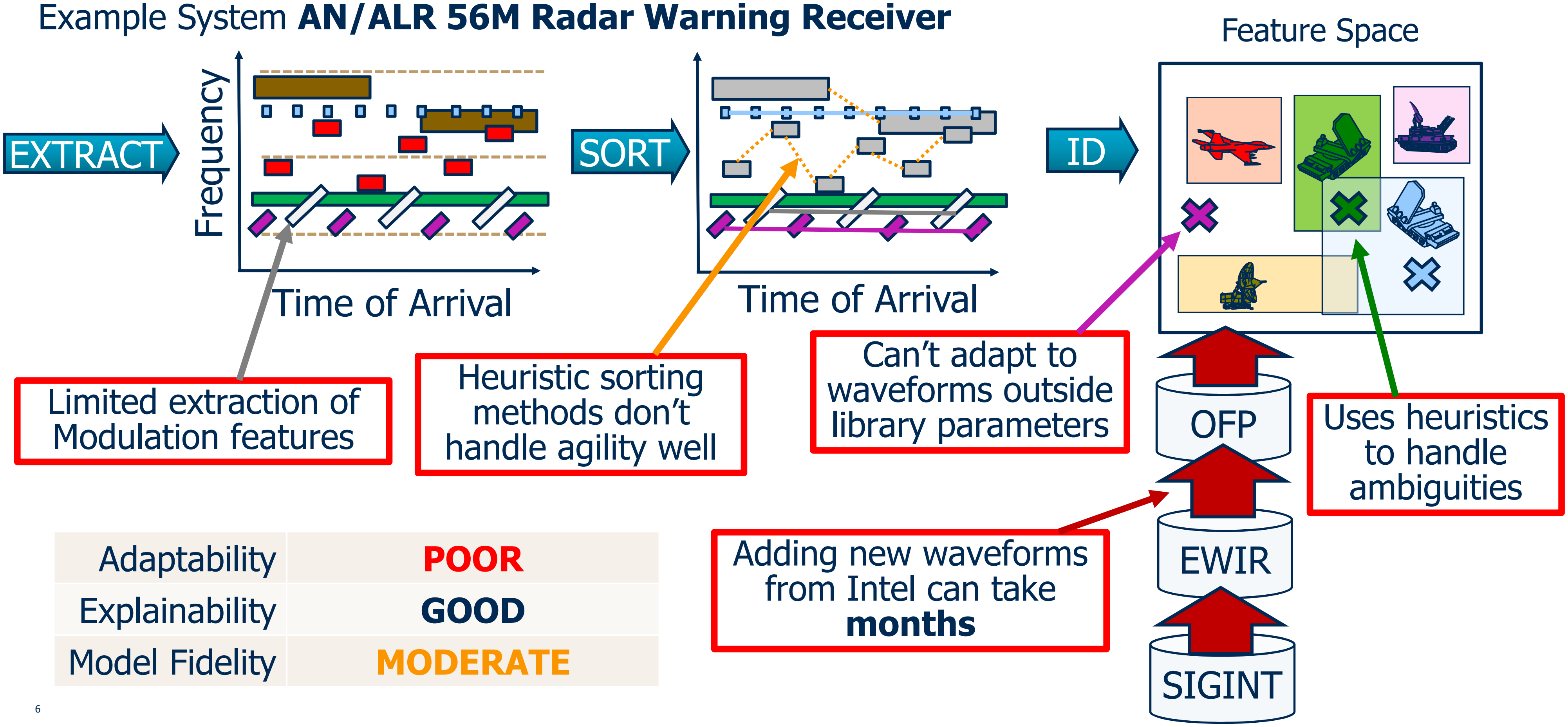
The system can learn from and change after making mistakes or receiving novel inputs, possibly with external/operator assistance.

Timeliness

The system can process known or novel inputs fast enough to respond effectively.

Traditional RF Waveform Recognition

Example System **AN/ALR 56M Radar Warning Receiver**

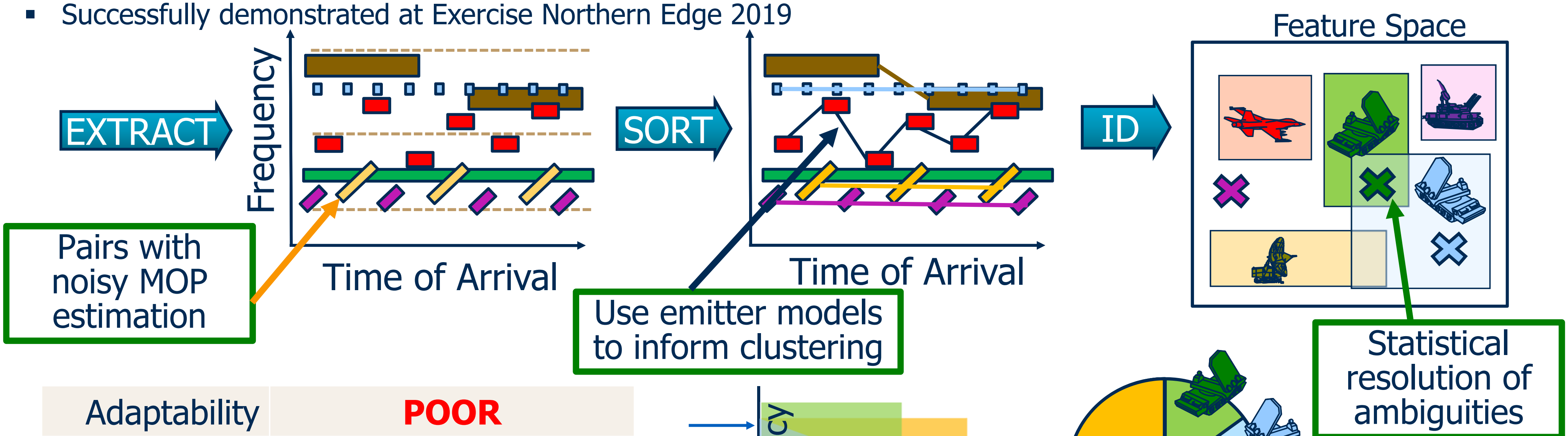


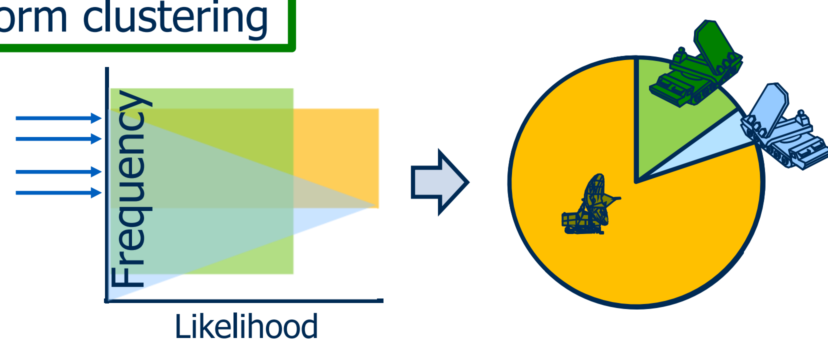
Adaptability	**POOR**
Explainability	**GOOD**
Model Fidelity	**MODERATE**

Bayesian RF Waveform Recognition

Example System ***Bayes Enhanced Electronic Support Tracker*** **(BEEST)**

- Developmed by GTRI and Matrix Technology under AFRL's ESCE program (through FY2019)
- Uses a Multiple Hypothesis Tracker to compute probability of each likely emitter and waveform
- Successfully demonstrated at Exercise Northern Edge 2019



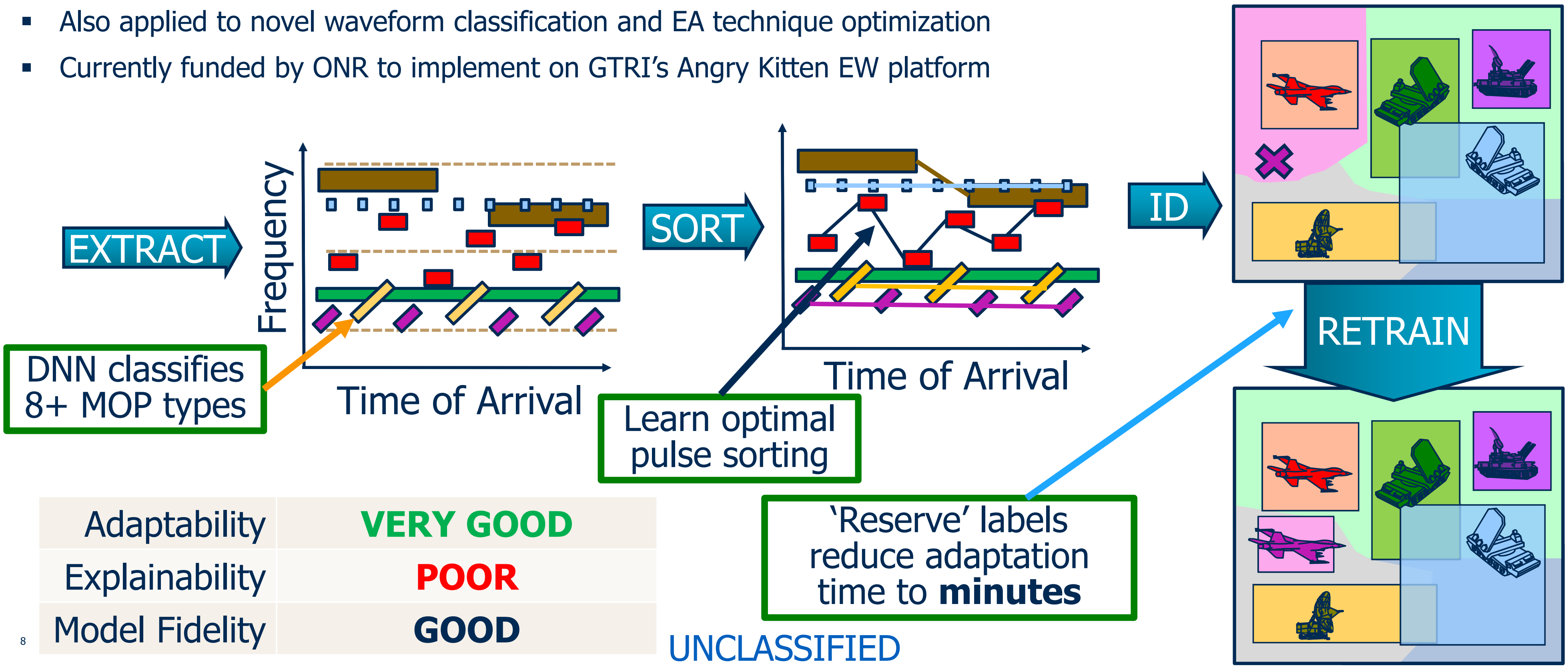


Adaptability	**POOR**
Explainability	**GOOD**
Model Fidelity	**VERY GOOD**

Machine Learning RF Waveform Recognition

Example System ***Neural Arrays for Autonomous Electronic Support***

- DNNs for characterizing RF modulation, and classifying waveforms
- Also applied to novel waveform classification and EA technique optimization
- Currently funded by ONR to implement on GTRI's Angry Kitten EW platform

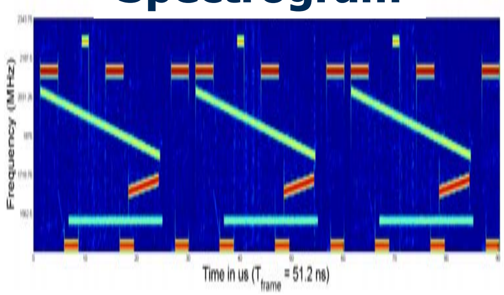


Adaptability	**VERY GOOD**
Explainability	**POOR**
Model Fidelity	**GOOD**

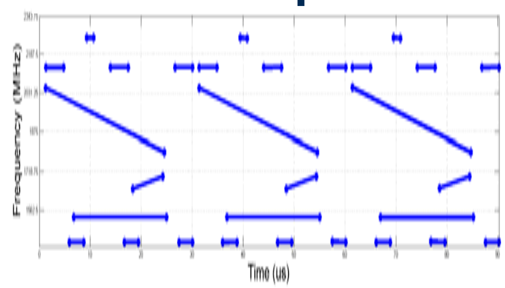
Pulse Detection and Feature Extraction

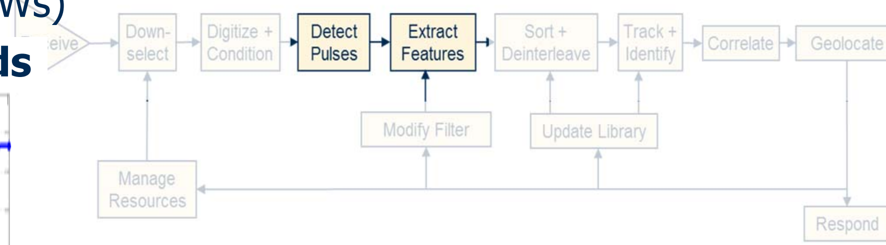
Conversion of raw signal data into Pulse Descriptor Words (PDWs)

Spectrogram



Pulse Descriptor Words



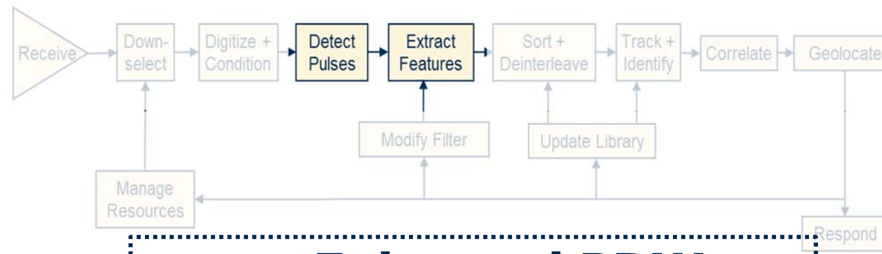


Legacy Approach

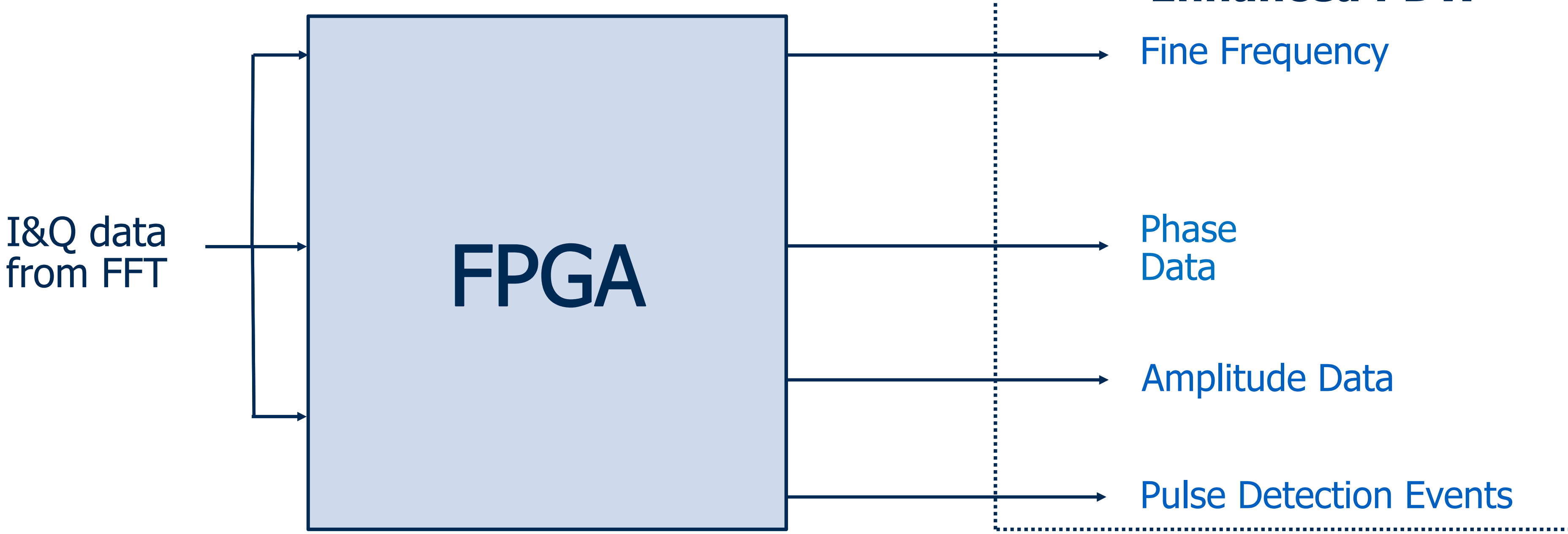
- Specialized analog and digital hardware
- Dedicated circuit for each feature, so only a few are used
  - Time of Arrival (TOA)
  - Amplitude
  - Frequency (sometimes)
  - Angle of Arrival (sometimes)
  - Pulse Width (sometimes)
- Low feature count makes downstream sorting and identification more difficult

Pulse Detection and Feature Extraction

Modern Approach



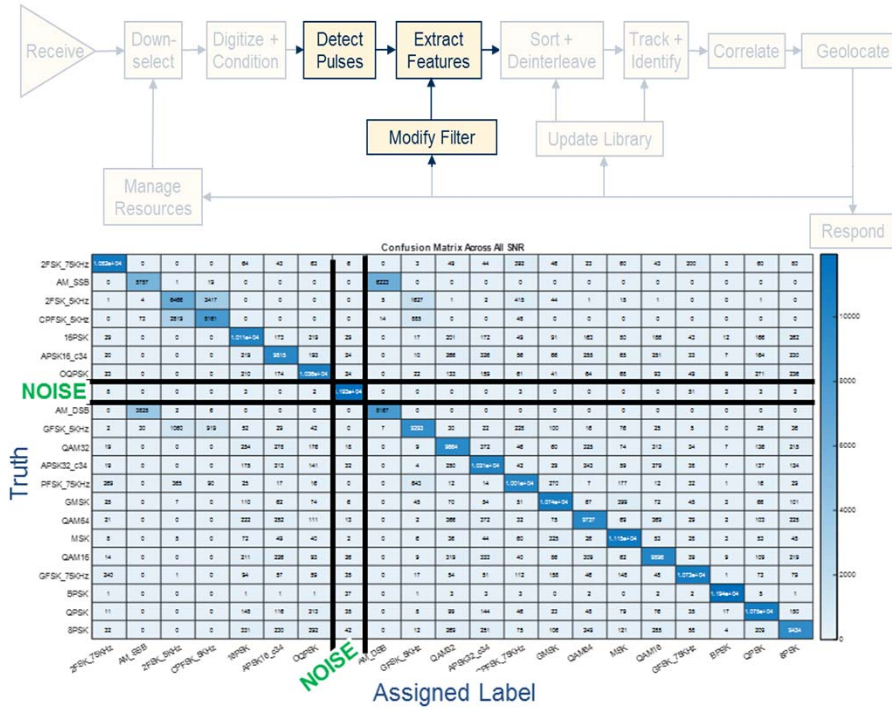
- COTS Field Programmable Gate Arrays (FPGAs) allow easy modification of firmware
- New features still requires significant human engineering
- Example system: B1 'Bone' Kitten Digital Receiver



Pulse Detection and Feature Extraction

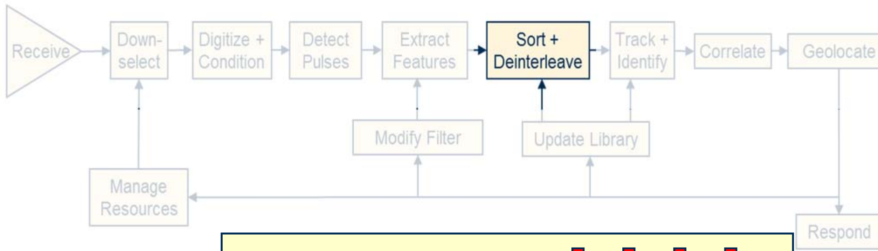
Applying Machine Learning

- New generation of chips allow low SWAP implementation of Deep Neural Networks (DNNs)
- Algorithms can learn an arbitrary number of features, and can be easily retrained
- Key limitation is quality of training data
- Example: Modulation classification for Army Signal Classification Challenge
  - Classified 24 different modulation types from raw signal data
  - Black box architecture uses 22+ million operations – but they are all very simple.



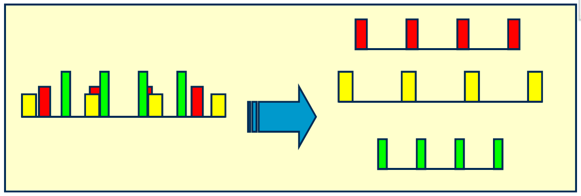
Pulse Sorting

Grouping PDWs by common source and assembling a Waveform Descriptor Word (WDW)



Two Legacy Approaches

- Time Sequence Deinterleaving
  - Look for common pulse repetition interval (PRIs)
  - Challenging in congested environments
  - Fails against agile PRI waveforms
- Pulse feature clustering
  - Group together pulses by their features
  - Fails when waveforms have agile pulse features
  - Legacy systems sometimes have few features to begin with

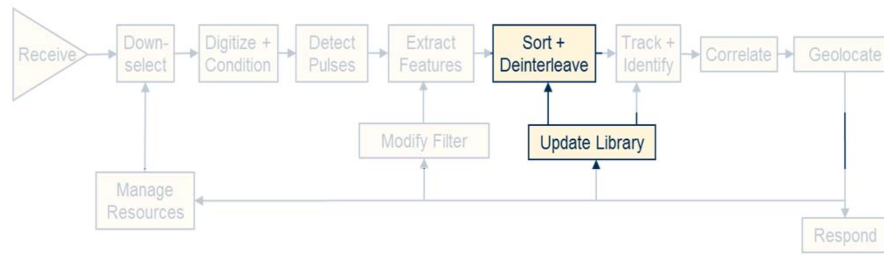


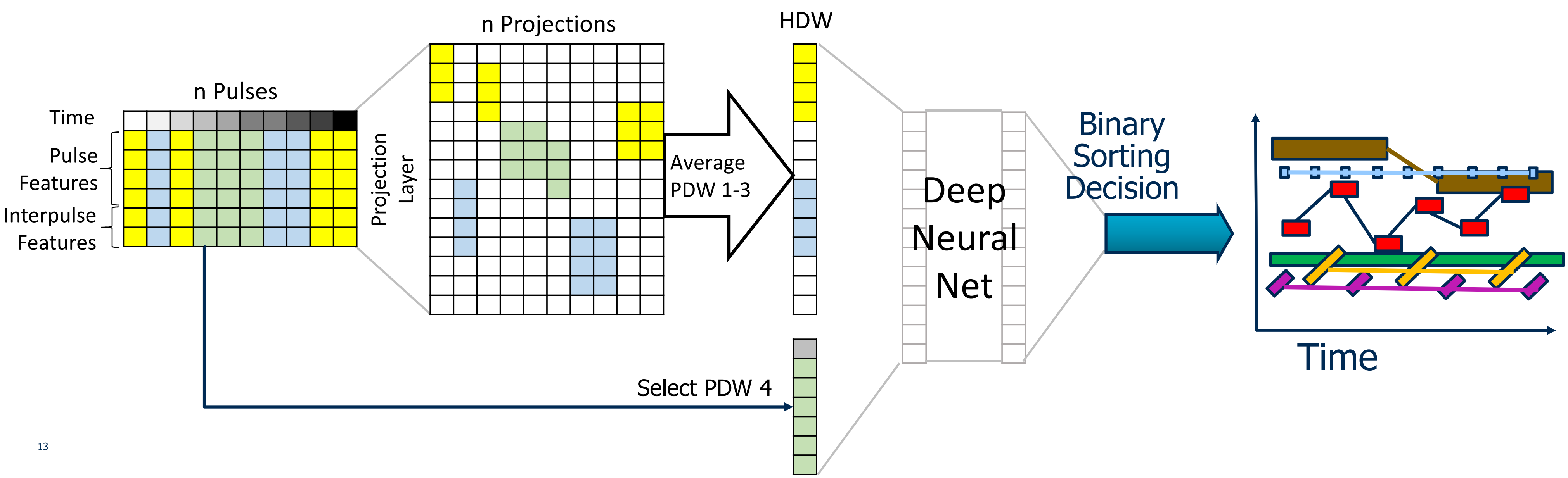
Both methods ultimately require ***hand-coded heuristics*** to counter specific, known agilities

Pulse Sorting

Applying Machine Learning

- A Deep Neural Network can *'learn'* how to cluster
- Easily reconfigured to handle arbitrary feature spaces
- Example: NAAES Pulse Sorting Algorithm





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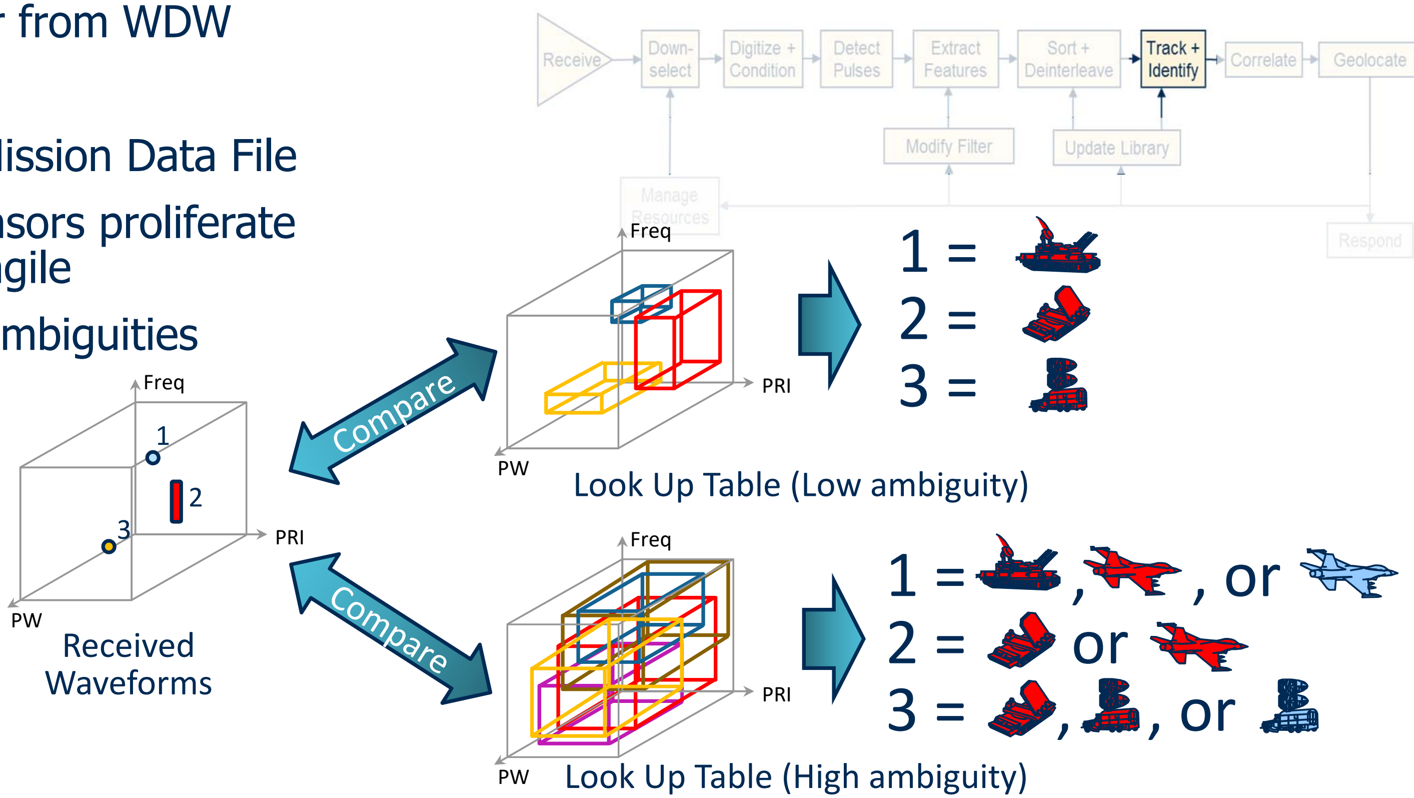
Waveform and Emitter Identification

Determine originating emitter from WDW

Legacy Approach

- Lookup tables defined in Mission Data File
- Ambiguity increases as sensors proliferate and waveforms get more agile
- No innate way to resolve ambiguities

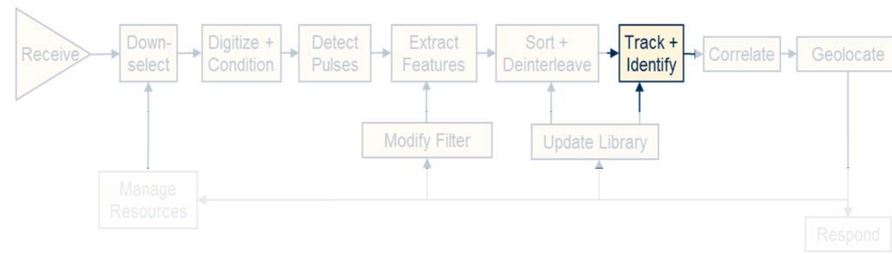


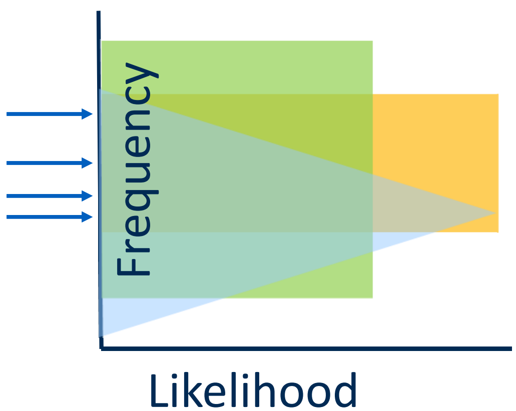
Usually relies on ***hand-coded heuristics*** to counter specific, known ambiguities

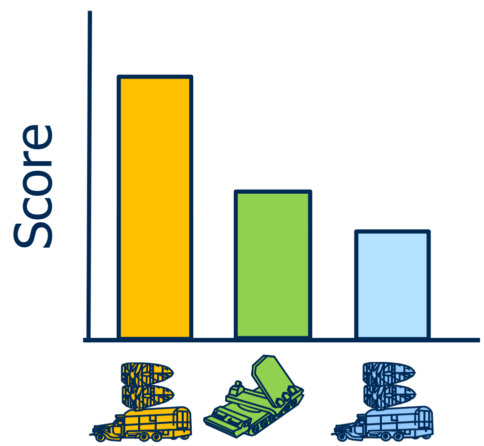
Waveform and Emitter Identification

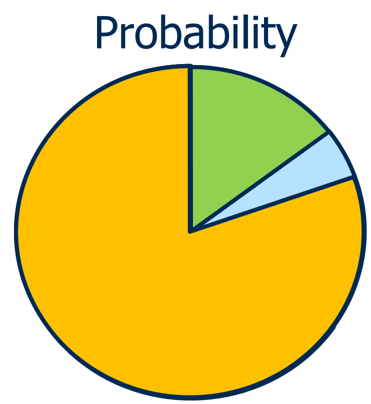
Bayesian/Multiple Hypothesis Approach

- Lookup tables are now probablistic
- Ambiguities generate multiple hypotheses, that are tracked and score independently
- Ambiguity is preserved until resolved by sufficient evidence







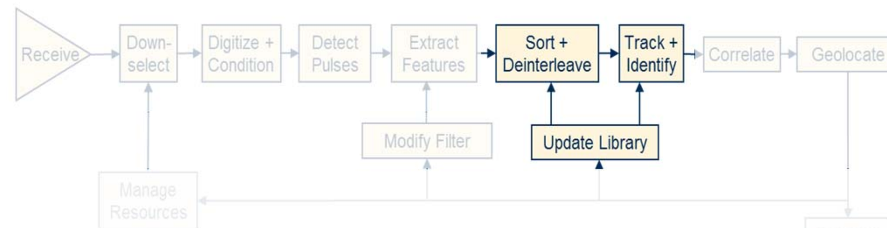


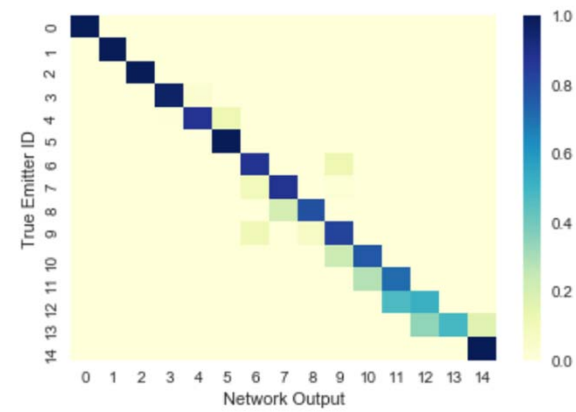
How do we create these probabilistic descriptions in the first place?

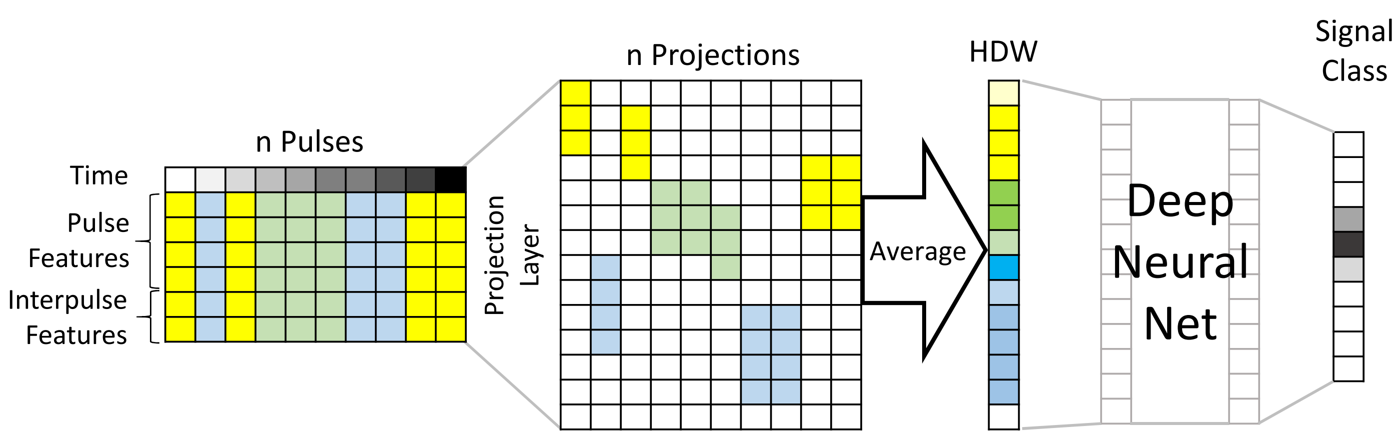
Waveform and Emitter Identification

Machine Learning Approach

- Avoids lookup tables entirely
- Easily combines with sorting logic, since they can share both PDW and WDW representations
- Example: NAAES Pulse Classification Algorithm
- Easily adaptable/retrainable







Emitter Association and Geolocation

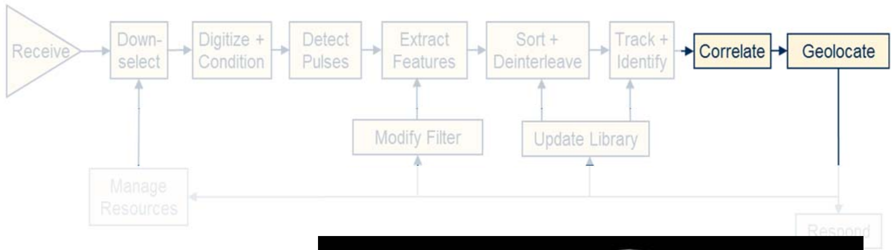
Determine if multiple sensors are observing the same waveforms, and fuse information to locate the emitter

Multiple Hypothesis Approach

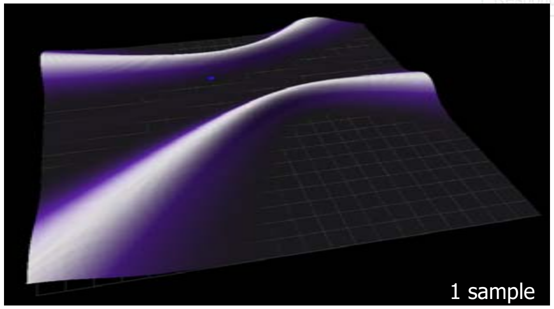
Hypothesis A – Waveforms belong to different emitters

Hypothesis B – Waveforms belong to same emitter

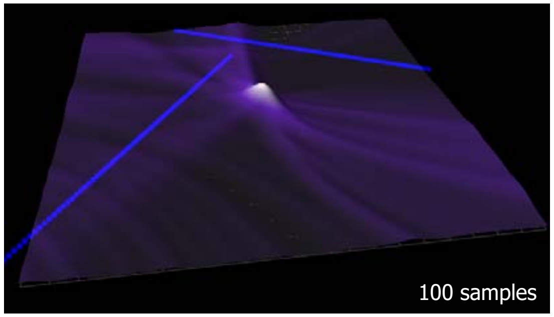
- Collect evidence until sure
- Several methods to locate an emitter once the waveforms are correlated
    - Triangulation from measured angles of arrival
    - Time difference of arrival
    - Frequency difference of arrival
- Geolocation methods themselves often leave ambiguity that is resolved over time



Initial location uncertainty

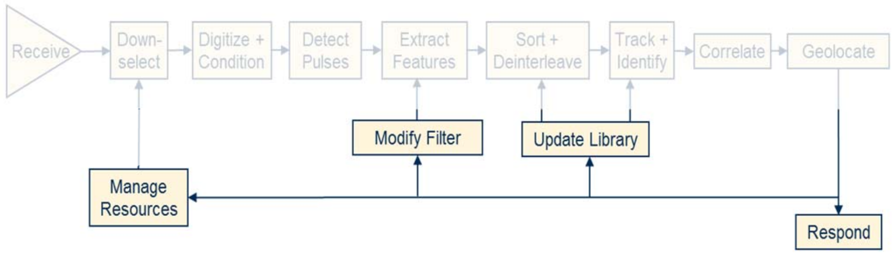


After tracking



Adaptive Electronic Support

- Update mission data at an operational tempo
- Minimize need for human intervention



Legacy Approach to Novel Conditions

- Send it back to the SME
- Could take months

Machine Learning Approach

- Retrain the Deep Neural Network
- Takes a few minutes (10000x faster!)
- Black box - almost impossible to validate

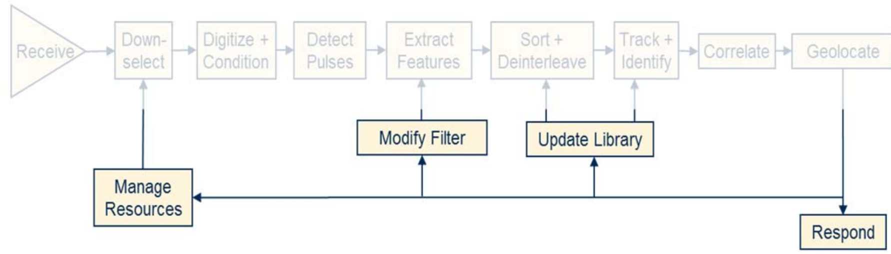
Any other options?

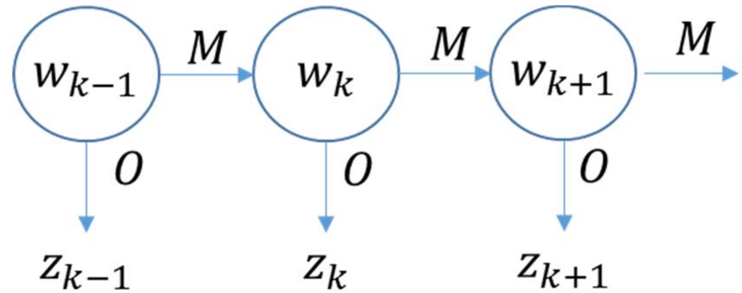
Adaptive Electronic Support

Markov Processes

Model emitters as having a randomly varying state, from which we get noisy observations

- Can use 'gradient descent' (the same calculus trick as Neural Networks) to rapidly update the model
- Computation cost scales poorly as the number of states increases
- May not be practical for modern, agile radars



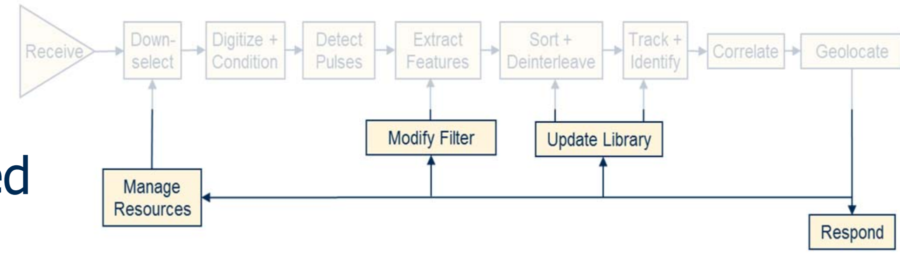


Produces robust probabilistic models, but scales poorly

Adaptive Electronic Support

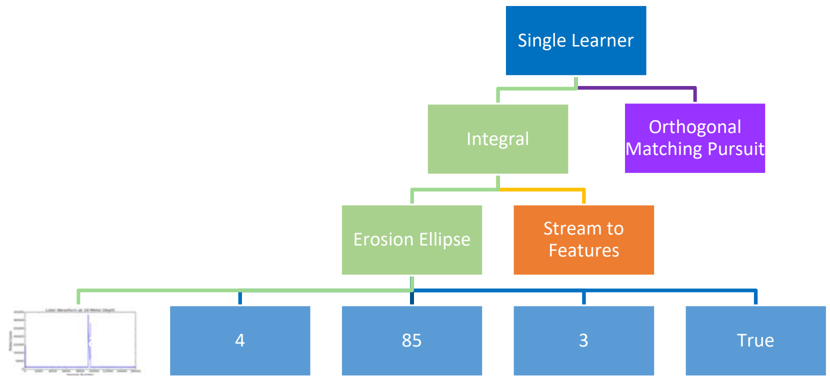
Evolutionary Algorithms

- Example: GTRI's EMADE python environment



Produce multiple solutions, which can be switched out easily as conditions change

1. Randomly tweak the components of an algorithm
   - Tuning parameters
   - Swap out sub-functions
   - Order of sub-functions
2. Test against the new environment
3. Keep only the subset that perform well
4. Iterate until solutions stop improving



Visualization of algorithm decompostion

Great for updating heuristics, but doesn't produce probabilistic results

Conclusion

- ES Mission is to *Intercept*, *Detect*, *Identify*, and *Locate* RF threats
- Legacy implementations highly stressed by software definable radars
- Need *flexibility* and *adaptability* to handle novel waveforms in a timely manner
- Algorithms must be *explainable* to gain warfighter's trust
- No magic bullet – a Cognitive ES system will have to combine various technologies to meet requirements, and may vary based on specific mission