Machine Learning Techniques for Radar Automatic Target Recognition (ATR)

Chapter 8: Deep Learning RF Signal Classification

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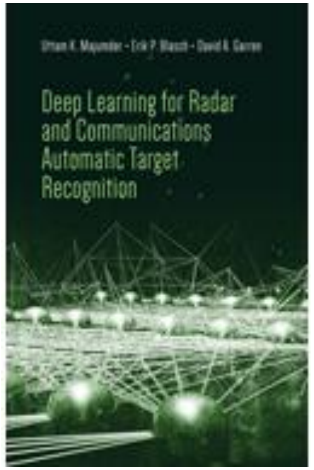
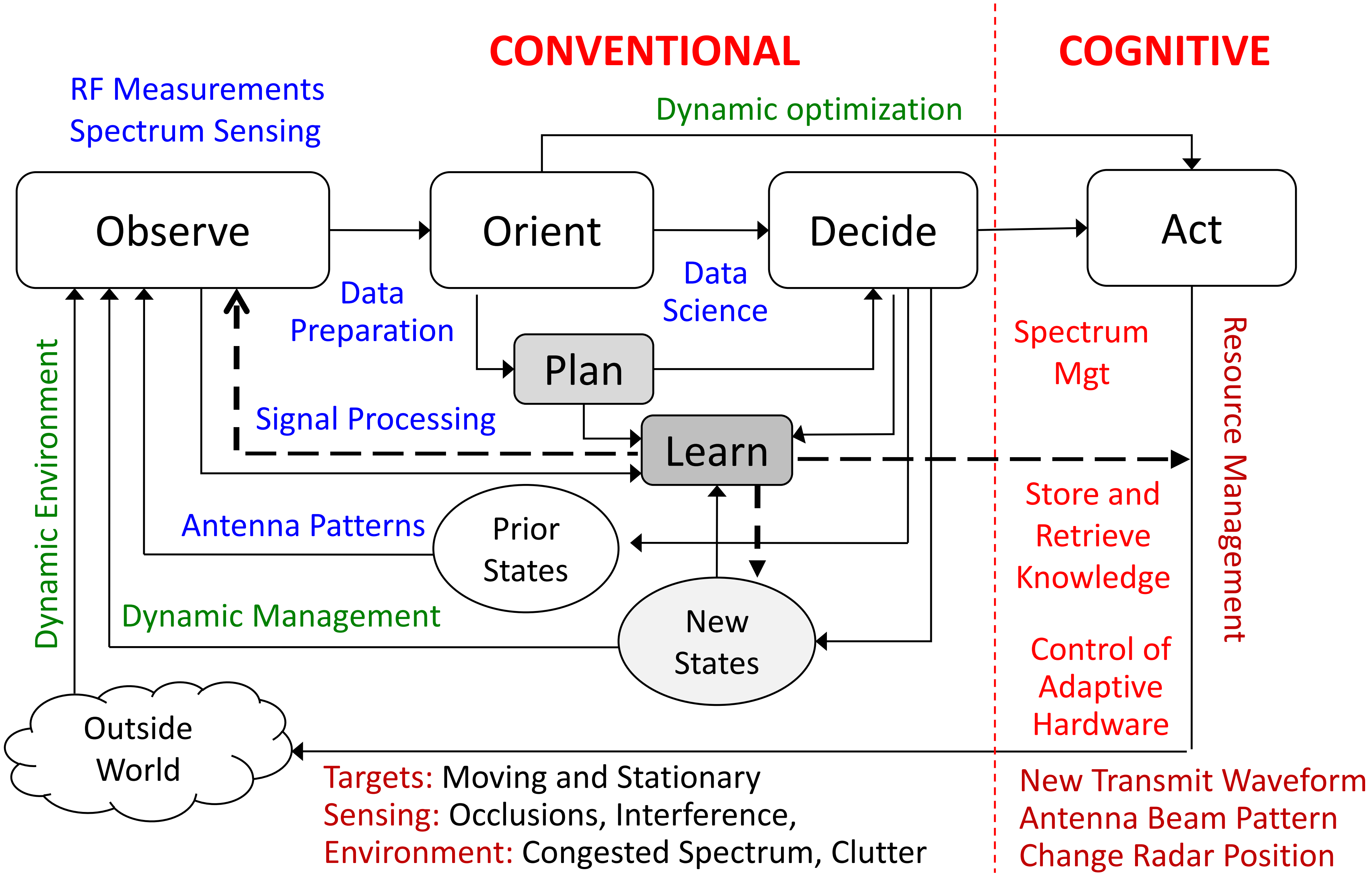
Deep Learning for Radio Frequency Automatic Target Recognition (ATR)

Lecture Outline

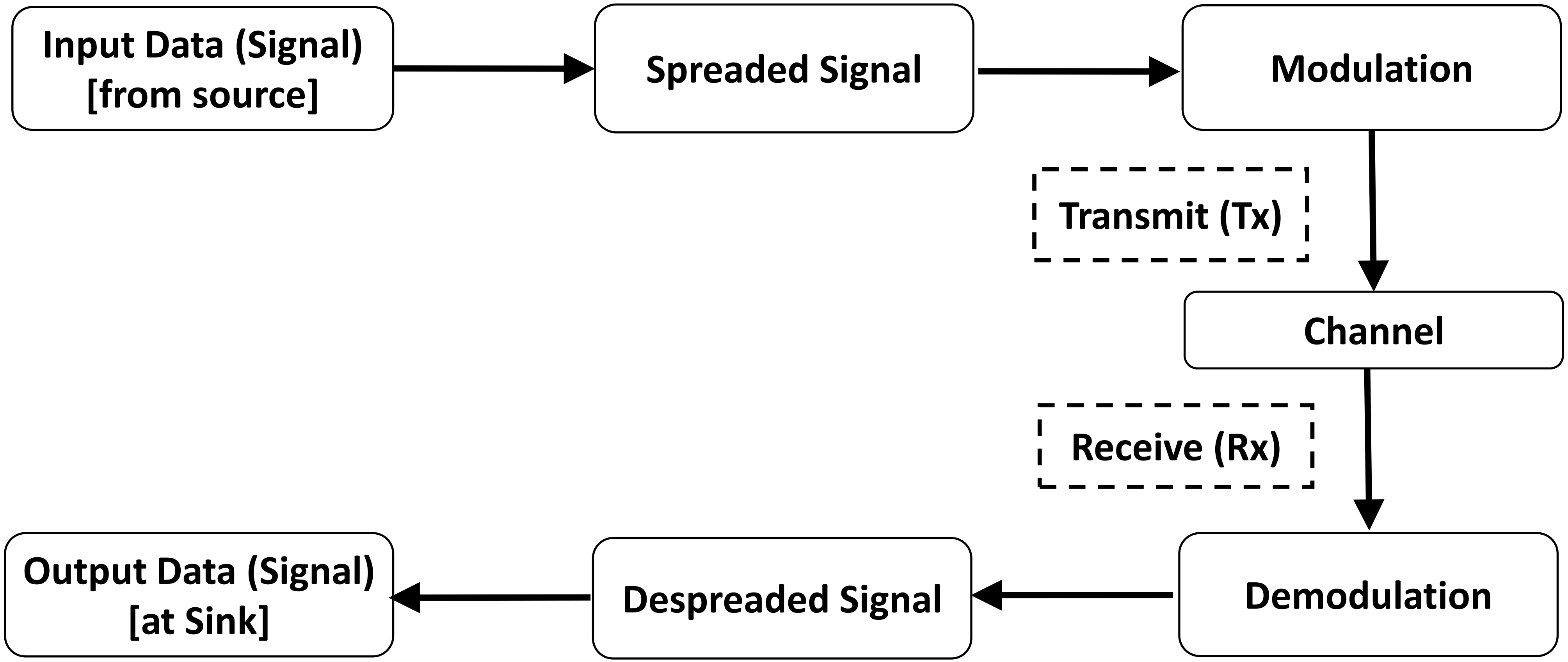
1. Radio Frequency ATR: Past, Present, and Future:
   20 min
2. Mathematics for Machine Learning / Deep Learning:
   20 min
3. Review of ML Algorithms: 25 min
4. Deep Learning Algorithms: 30 min
5. RF Data for ML Research: 15 min
6. DL for Single Target Classification: 30 min
7. DL for Many Targets Classification: 15 min
8. **RF Signals Classification: 15 min**
9. RF ATR Performance Evaluation: 25 min
10. Emerging ML Algorithms for RF ATR: 35 min



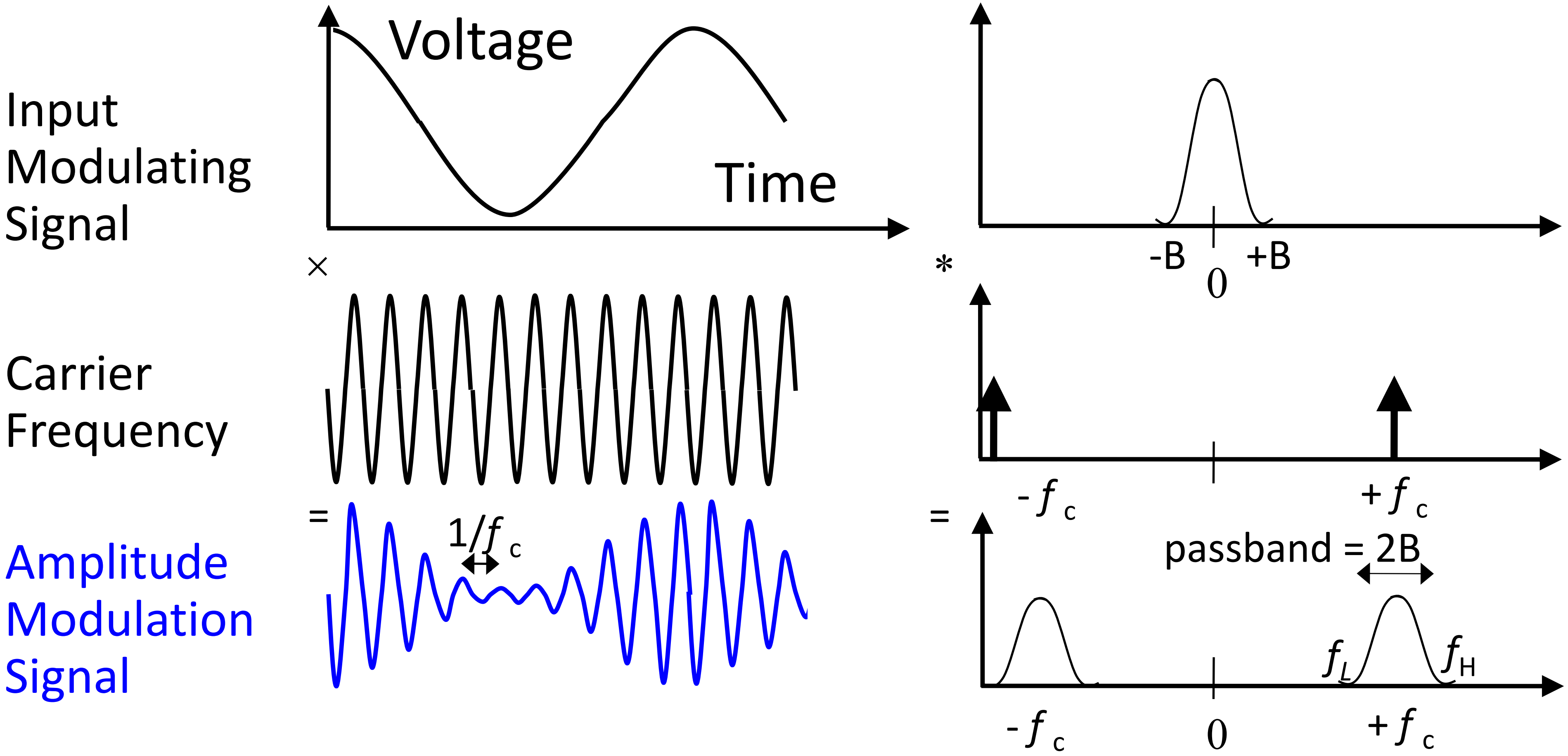
Cognitive RF System



RF Signals: Spread Spectrum Communication



Passband Signal



Signal Modulation

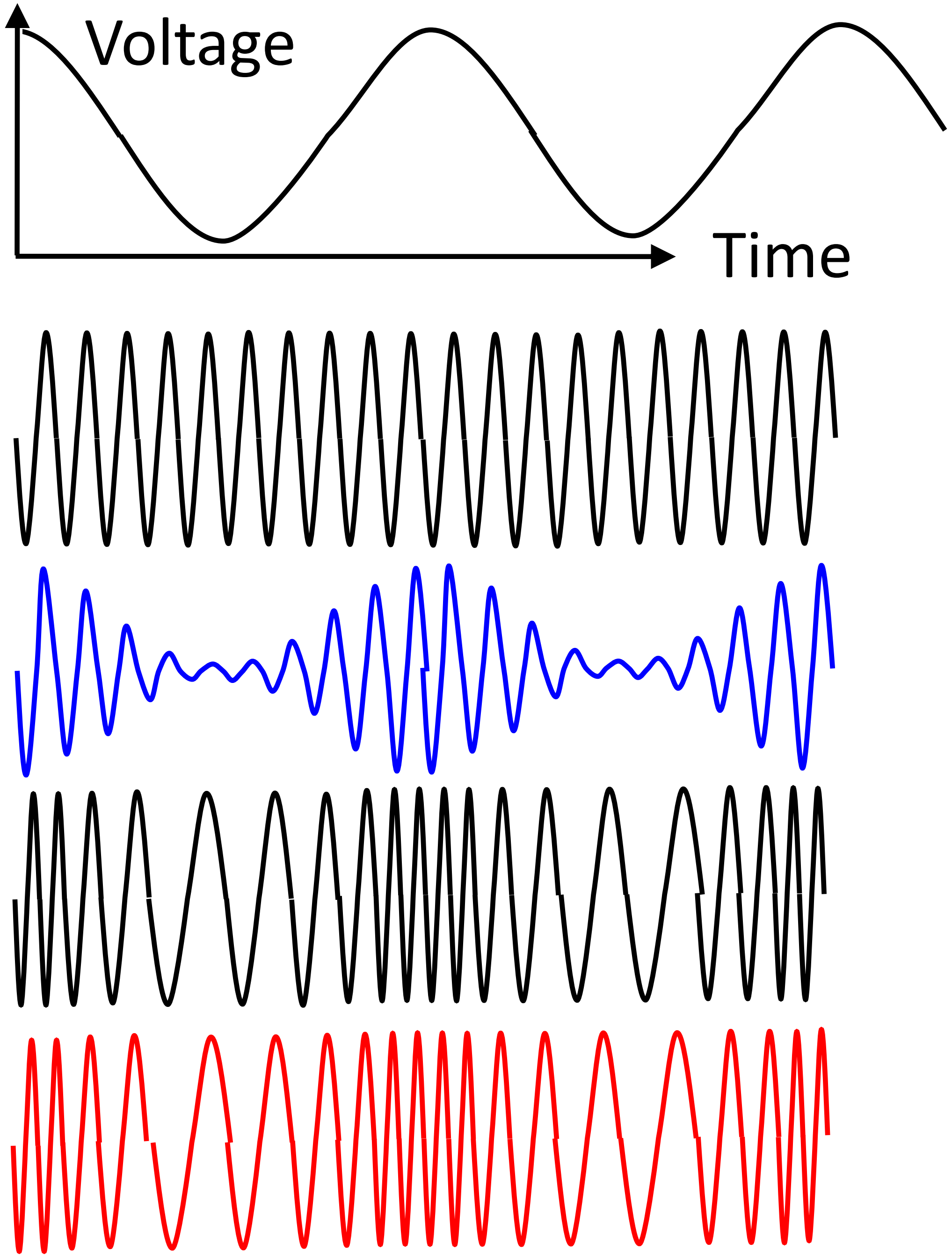
Input Modulating Signal

Carrier Frequency

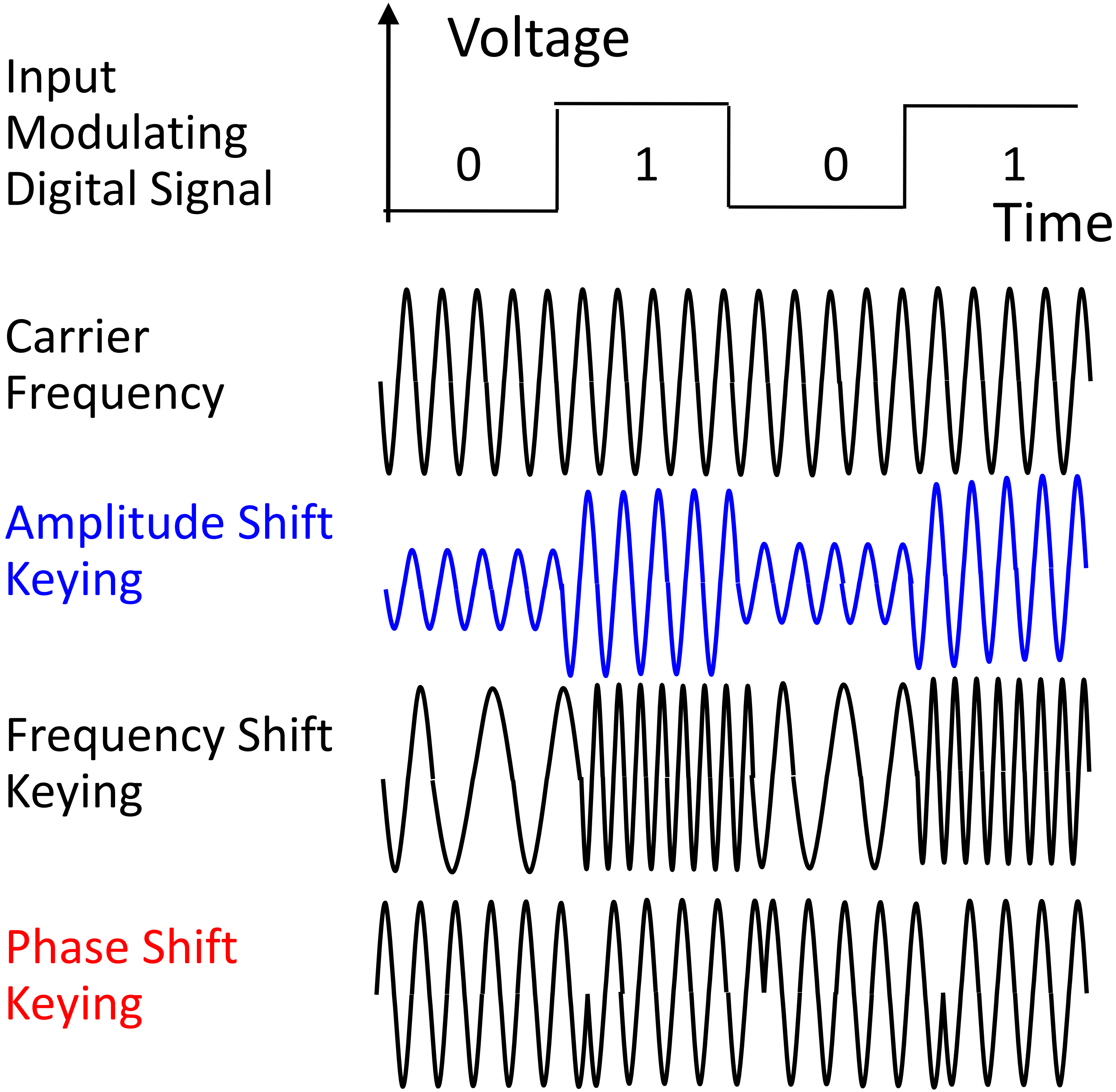
Amplitude Modulation Signal

Frequency Modulation Signal

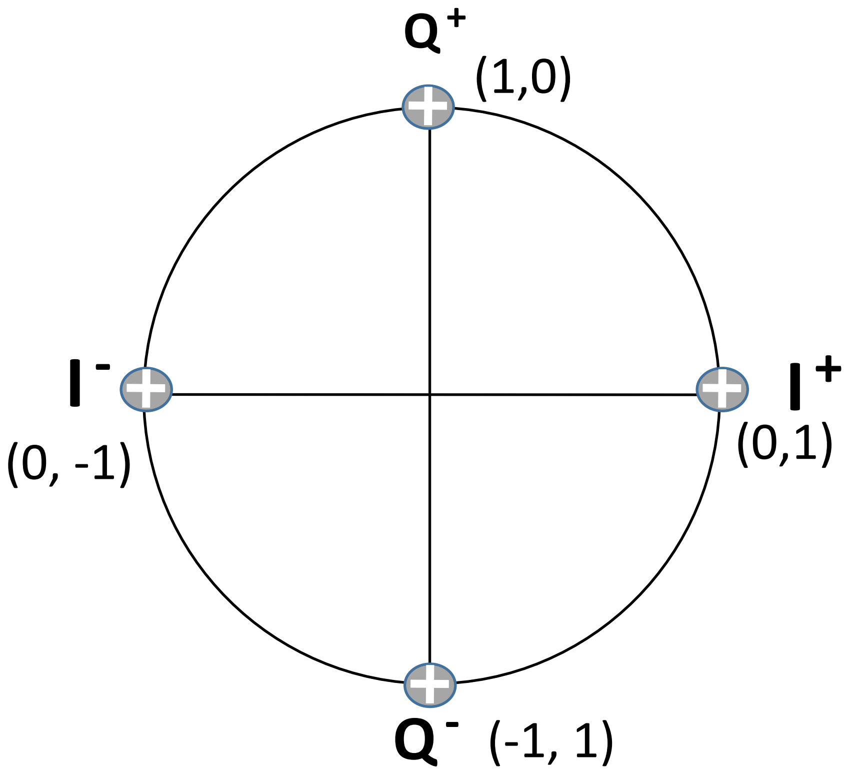
Phase Modulation Signal



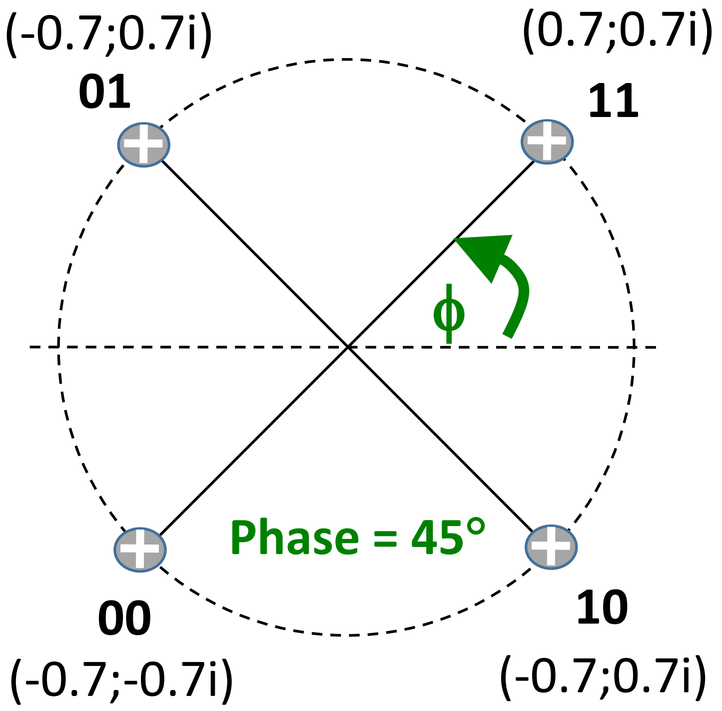
Signal Modulation



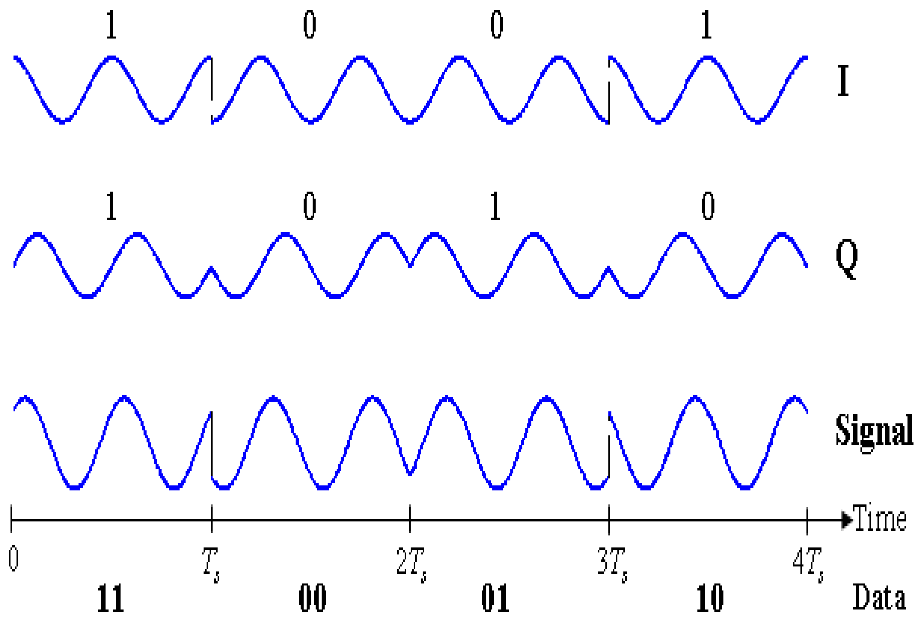
PSK and QAM Signals



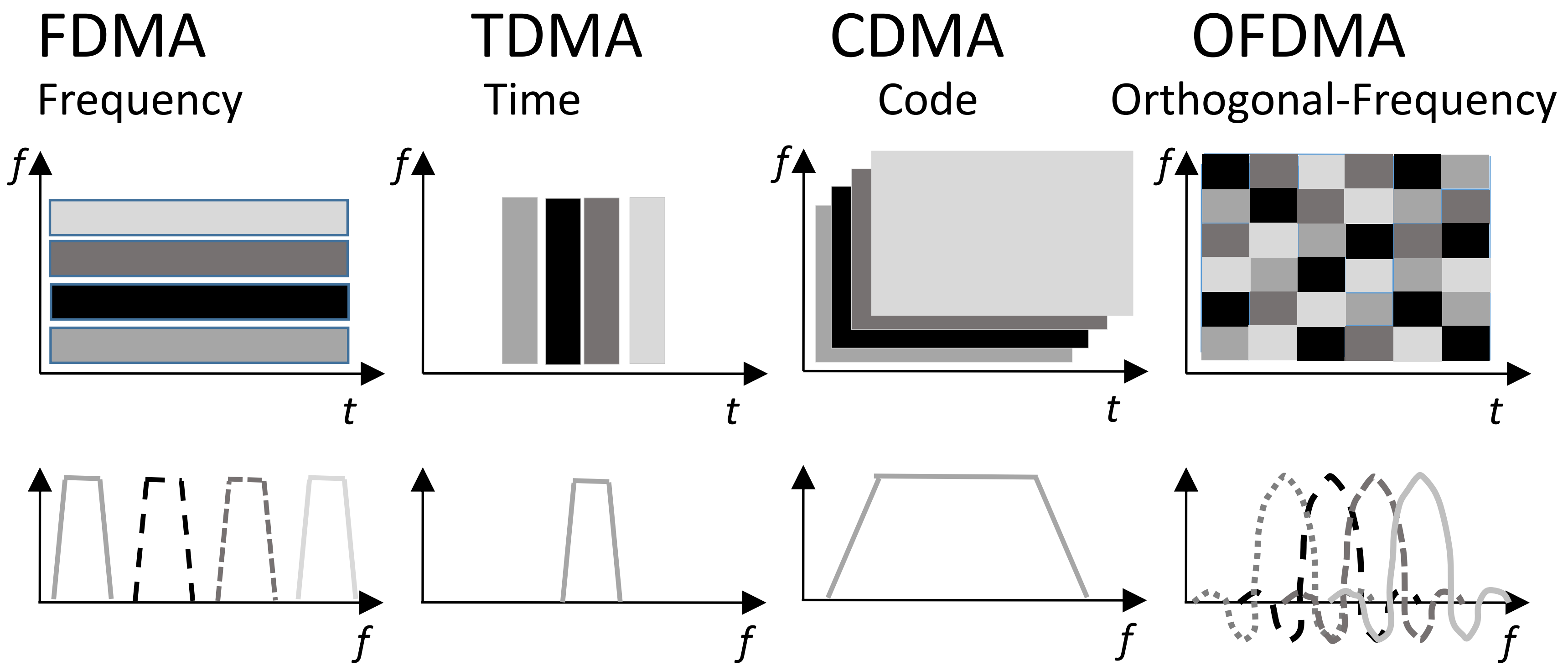
4-PSK



4-QPSK, (also, 4-QAM)



Multiple Access Method



RF Signal Classification Problems

- **DARPA Radio Frequency Machine Learning Systems (RFMLS)** program presented various RF signals Classification problems that can be solved efficiently by Machine Learning techniques.
- These RF Signal Classification Research Includes:

1. <u>RF Fingerprinting:</u> Traditional wireless security relies on a software "identity" for each wireless device, which can often be hacked or otherwise cloned. The RFMLS system will aim to learn to recognize a specific transmitter based on the unique RF fingerprint naturally imparted by hardware imperfections within that transmitter. This task focuses on learning RF features.

https://www.darpa.mil/program/radio-frequency-machine-learning-systems

RF Signal Classification Problems

2. RF Fingerprint Enhancement: To further enhance wireless security, a communication system learns to modify it's transmit waveforms to enhance its natural fingerprint. This task focuses on learning to synthesize waveforms

3. **Spectrum Awareness:** Traditional systems which monitor the RF spectrum use narrow bandwidths and relatively simple strategies (such as the frequency of transmission) to identify the signals occupying the wireless spectrum. Availability of commodity analog-to-digital converters with wide bandwidths combined with proliferation of software defined radios, spectrum sharing, and general wireless technology growth, challenge these approaches. RFMLS systems will learn to understand the difference between important and unimportant signals present in large bandwidths in order to build more useful and accurate spectrum awareness. This task emphasizes goal-driven attention

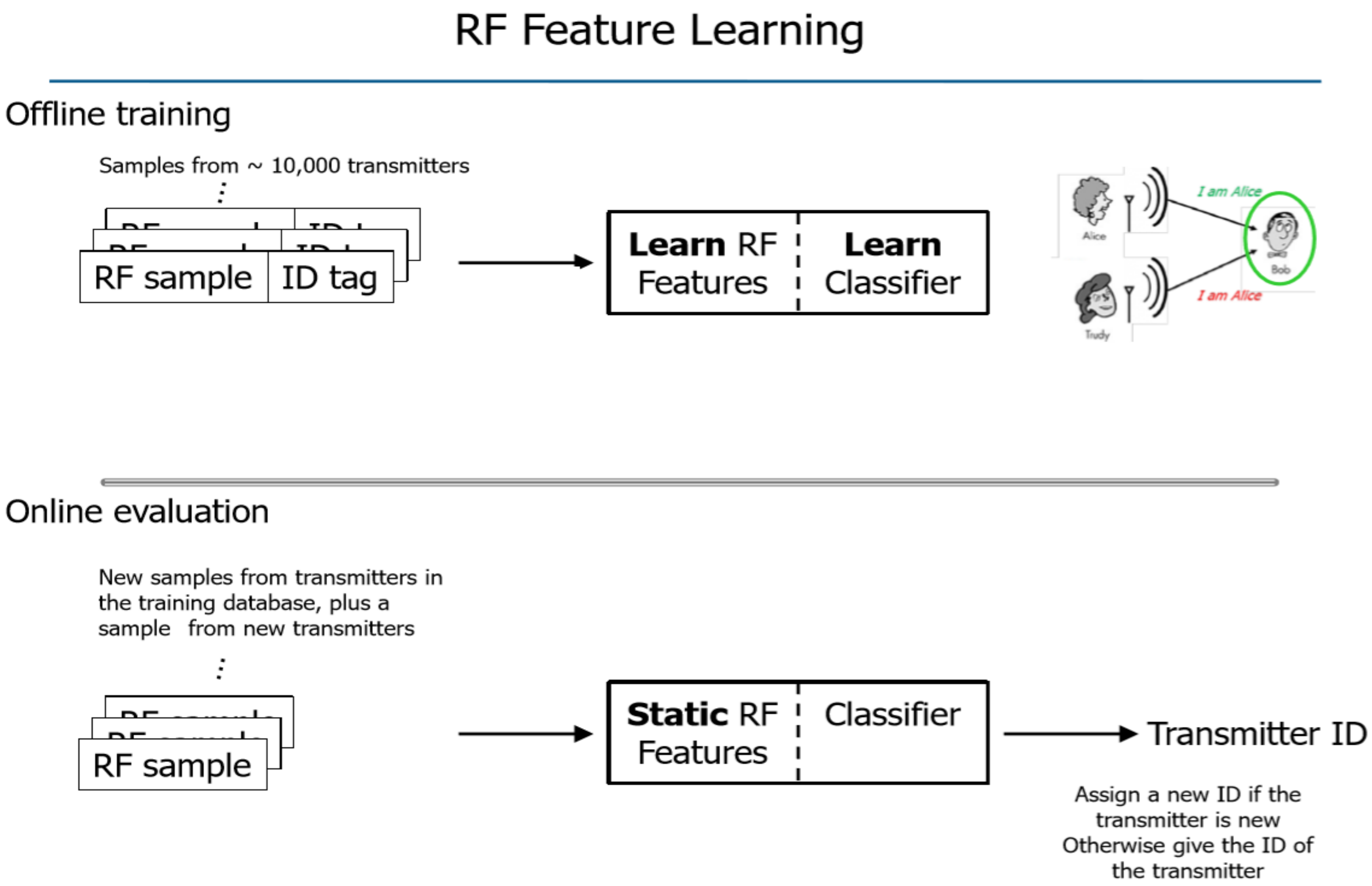
https://www.darpa.mil/program/radio-frequency-machine-learning-systems

RF Signal Classification Problems

<u>4. Autonomous RF System Configuration:</u> To further enhance spectrum awareness performance, a RFMLS system will seek to learn how best to tune and configure its hardware resources in order to maximize the number of important signals discovered in harsh RF environments. This task stresses hardware configuration and control

https://www.darpa.mil/program/radio-frequency-machine-learning-systems

RF Signal Classification Example:



Reference:
DARPA Public Release: RF Machine Learning Systems (RFMLS) Industry Day
https://www.darpa.mil/attachments/RFMLSIndustryDaypublicreleaseapproved.pdf

Datasets for RF Fingerprinting

- Northeastern University Published a RF Signal dataset to classify

Wi-Fi devices

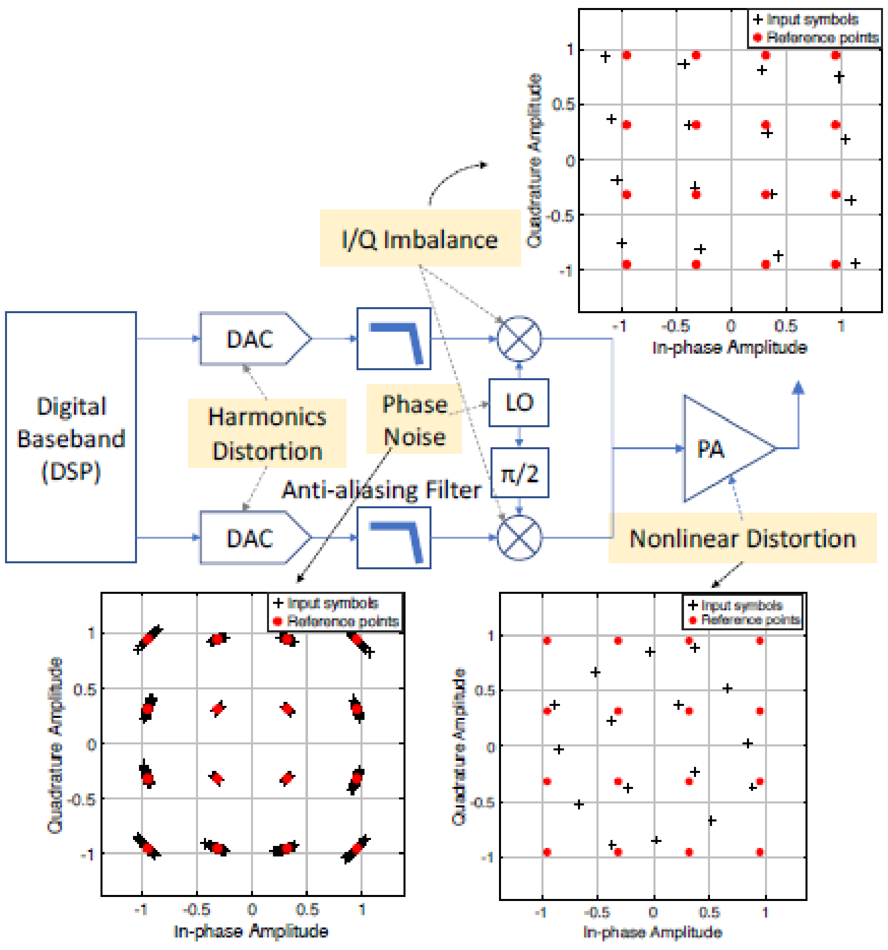
- Their Website can be used to download the data and the paper that describes the data.
- Their Website:

https://genesys-lab.org/oracle

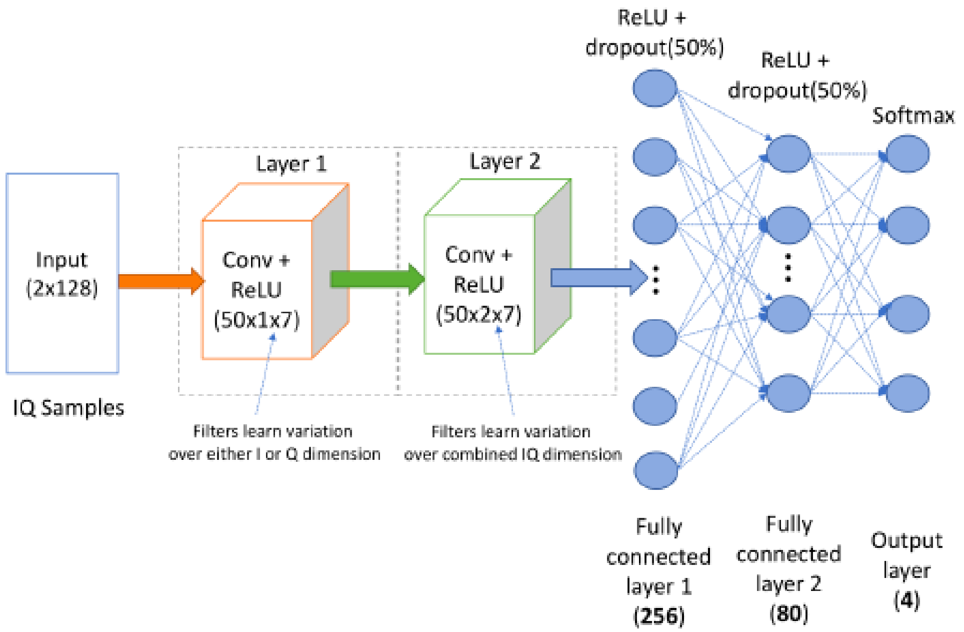
- Their Paper:

K. Sankhe, M. Belgiovine,F. Zhou, S. Riyaz, S. Ioannidis, and K. R. Chowdhury, "ORACLE: Optimized Radio clAssification through Convolutional neuraL nEtworks," IEEE INFOCOM 2019, Paris, France, May. 2019

Background on "ORACLE" NEU RF Signal data



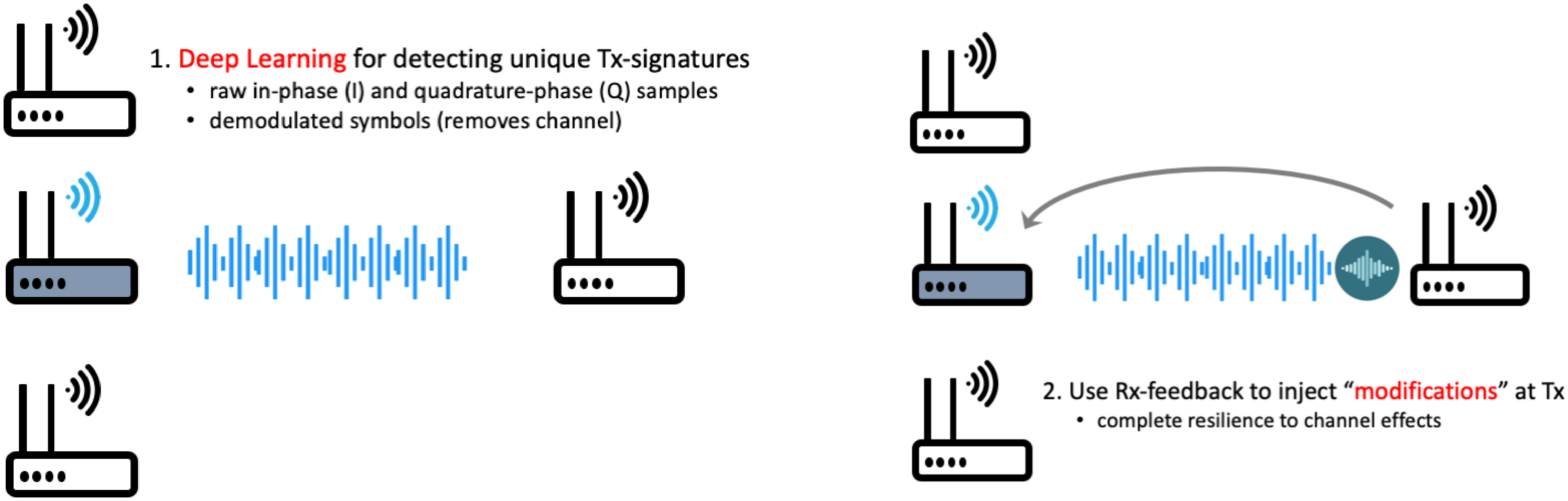
- Northeastern University (NEU) published a paper on 2019
- Central Idea: Use Convolutional Neural Networks to perform "RF Fingerprinting".
- High quality radios don't exhibit as much variation in tolerances. So they also learn signal modifications that allow these high-quality radios to still be identified



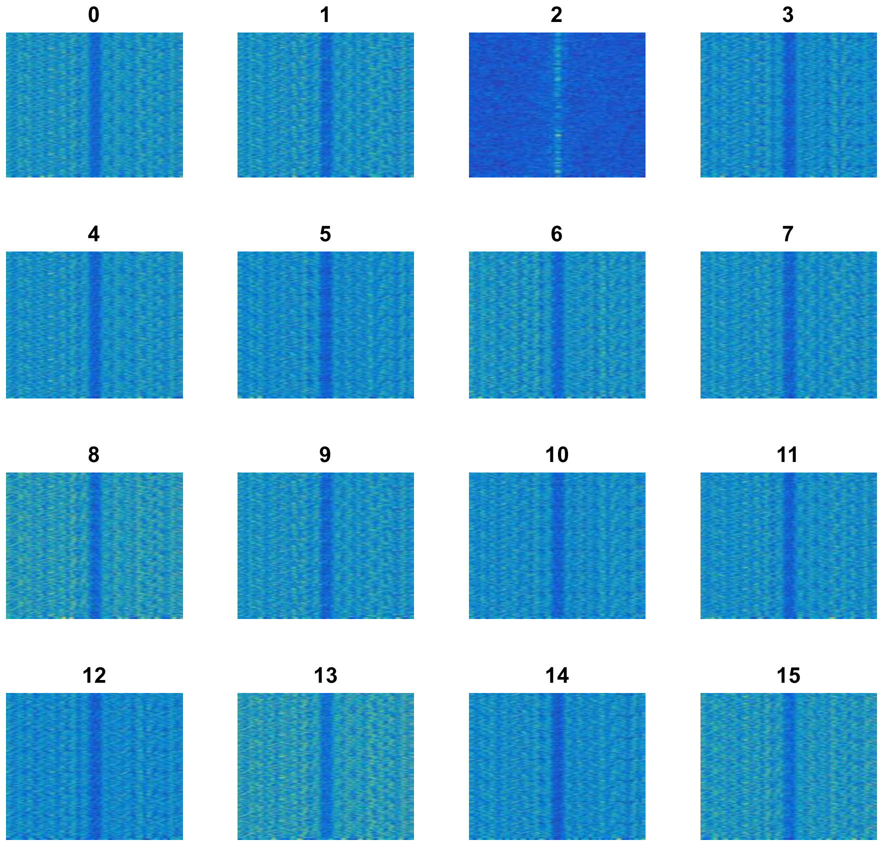
NEU RF Signal Dataset:

Dataset #1 : It consists of recordings of collected raw IQ samples from 16, high-end X310 USRP SDRs with the same B210 radio as a receiver.

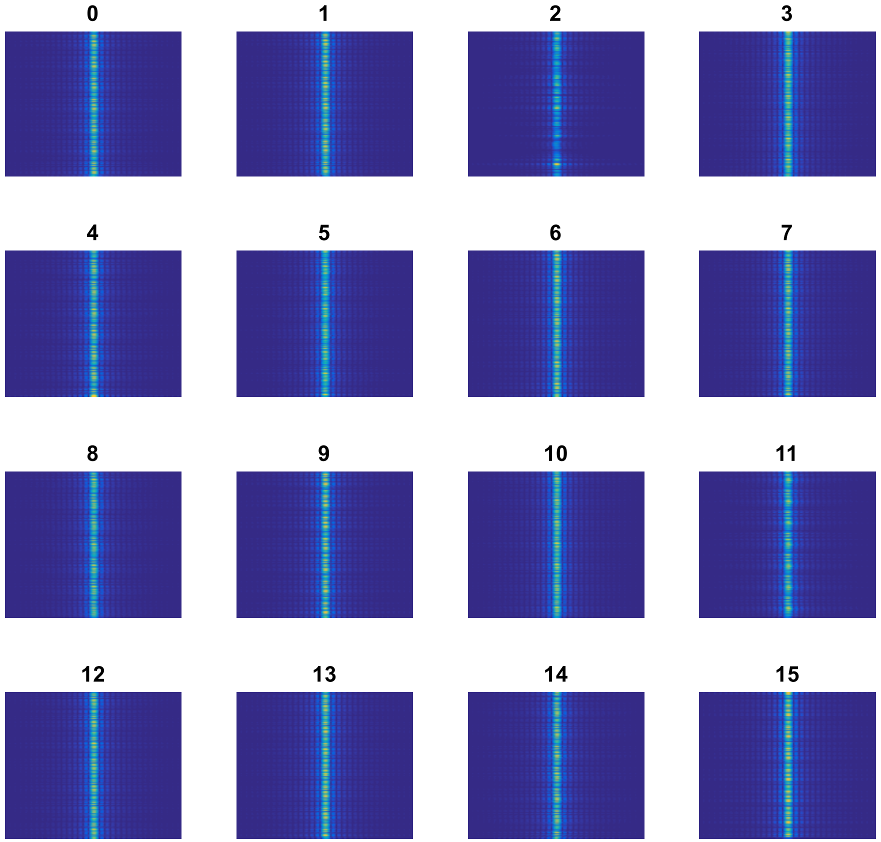
Dataset #2: It consists of recordings of demodulated IQ symbols obtained after equalizing over-the-cable transmission from X310 USRP SDR transmitter and B210 radio as a receiver



Spectrum of RF Signals Before and After Preprocessing



Before Pre-Processing



After Pre-Processing

Figures show a spectrogram sample from each of the 16 different transmitters

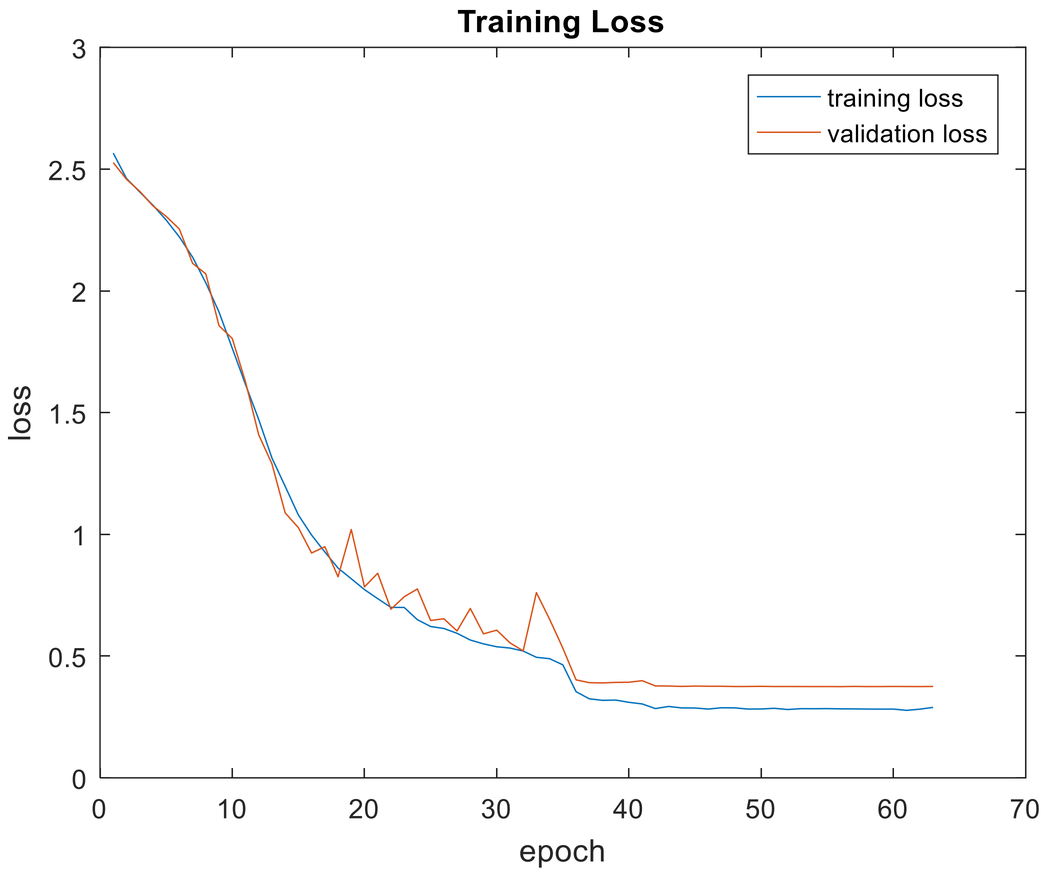
DNN Model Configuration and Training

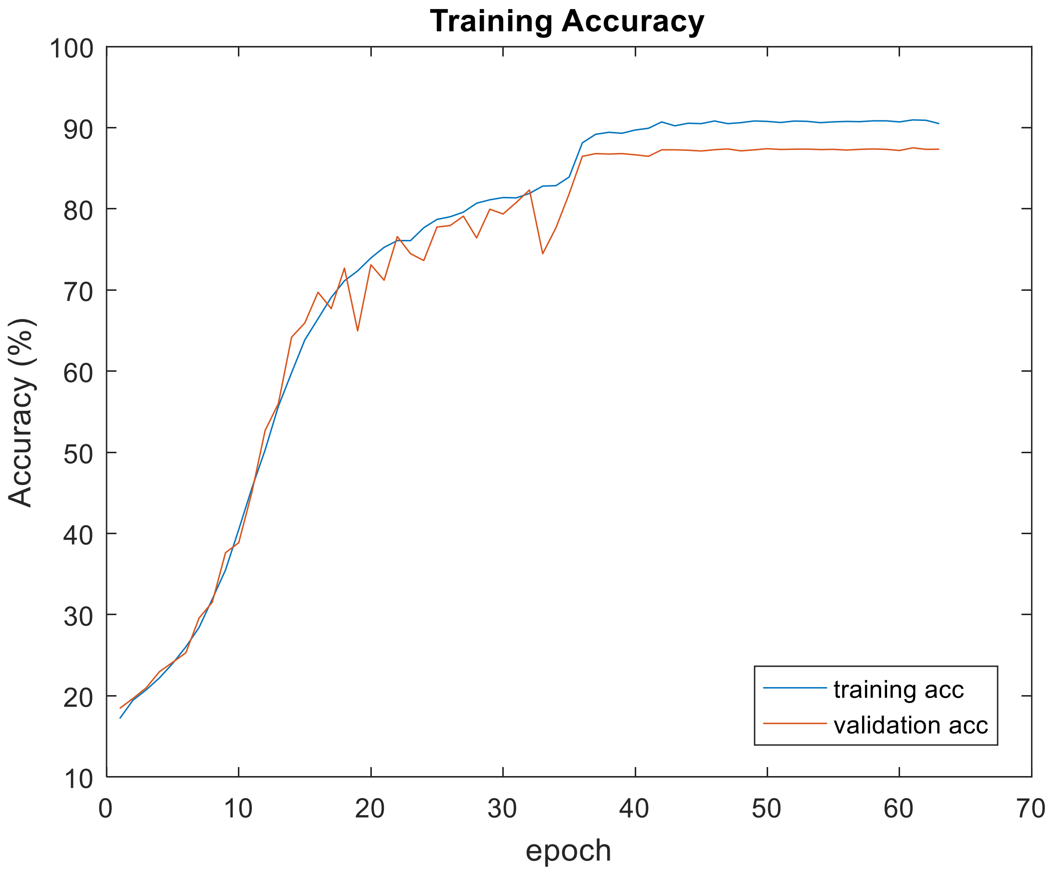
- New model with different kernel/layer arrangement was constructed Following NEU DNN Model:
  - 6 conv layers, followed by ReLU.
  - 3 fully connected layers, using ReLU for hidden layers and softmax for the 16 output neurons.
  - Using batch normalization instead of dropout.
- The model is trained with initial learning rate of 0.0001, batch size of 128
- Early stopping based on validation loss monitoring is used, and the learning rate is reduced on validation loss plateau of 3 steps or more.
- This model/training setup achieved ~90% training and 85-87% validation accuracy in several tests.
- Training generally terminates around 60-70 epochs, taking around 20-30minutes on GPUs

DNN Model Details

Input: Batch Size x (128x2x1) tensor
2D Convolution, 64 count 31x2 kernel, followed by ReLU
2D Convolution, 64 count 15x2 kernel, followed by ReLU and Batch Norm
2D Convolution, 64 count 15x2 kernel, followed by ReLU
2D Convolution, 64 count 7x2 kernel, followed by ReLU and Batch Norm
2D Convolution, 64 count 15x2 kernel, followed by ReLU
2D Convolution, 64 count 7x2 kernel, followed by ReLU and Batch Norm
Fully-Connected layer with 512 neurons, followed by ReLU and Batch Norm
Fully-Connected layer with 128 neurons, followed by ReLU and Batch Norm
Fully-Connected layer with 16 neurons, followed by Softmax

Plot for Training Loss and Accuracy Progression





RF Signals Classification Summary

- We presented Various RF Signals and Modulations
- Discussed RF Signal Classification Problems that can be solved by Machine Learning Algorithms Efficiently
- We Presented Northeastern University (NEU) RF Signals Data
- We illustrated DNN Based Approach to classify NEU Wi-Fi Signals