

# Neural Network Based Automatic Modulation Classification with Online Training

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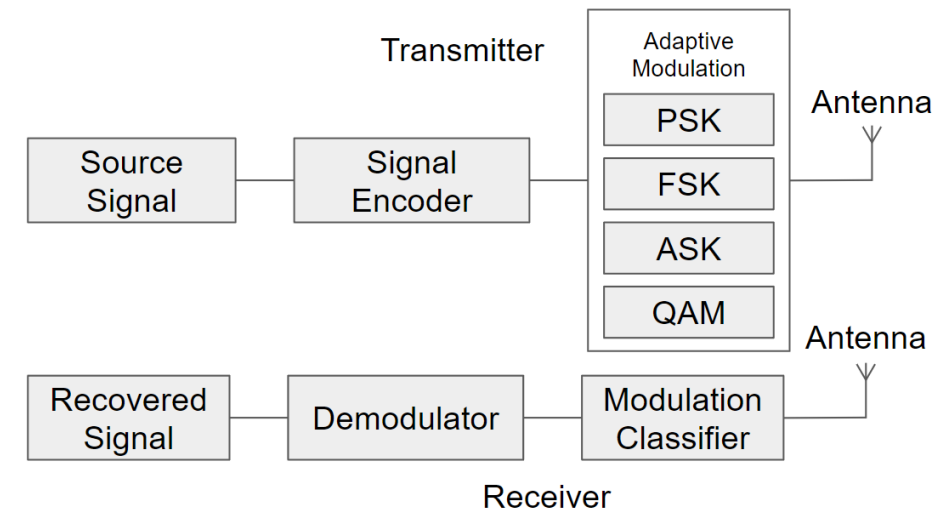
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# Problem

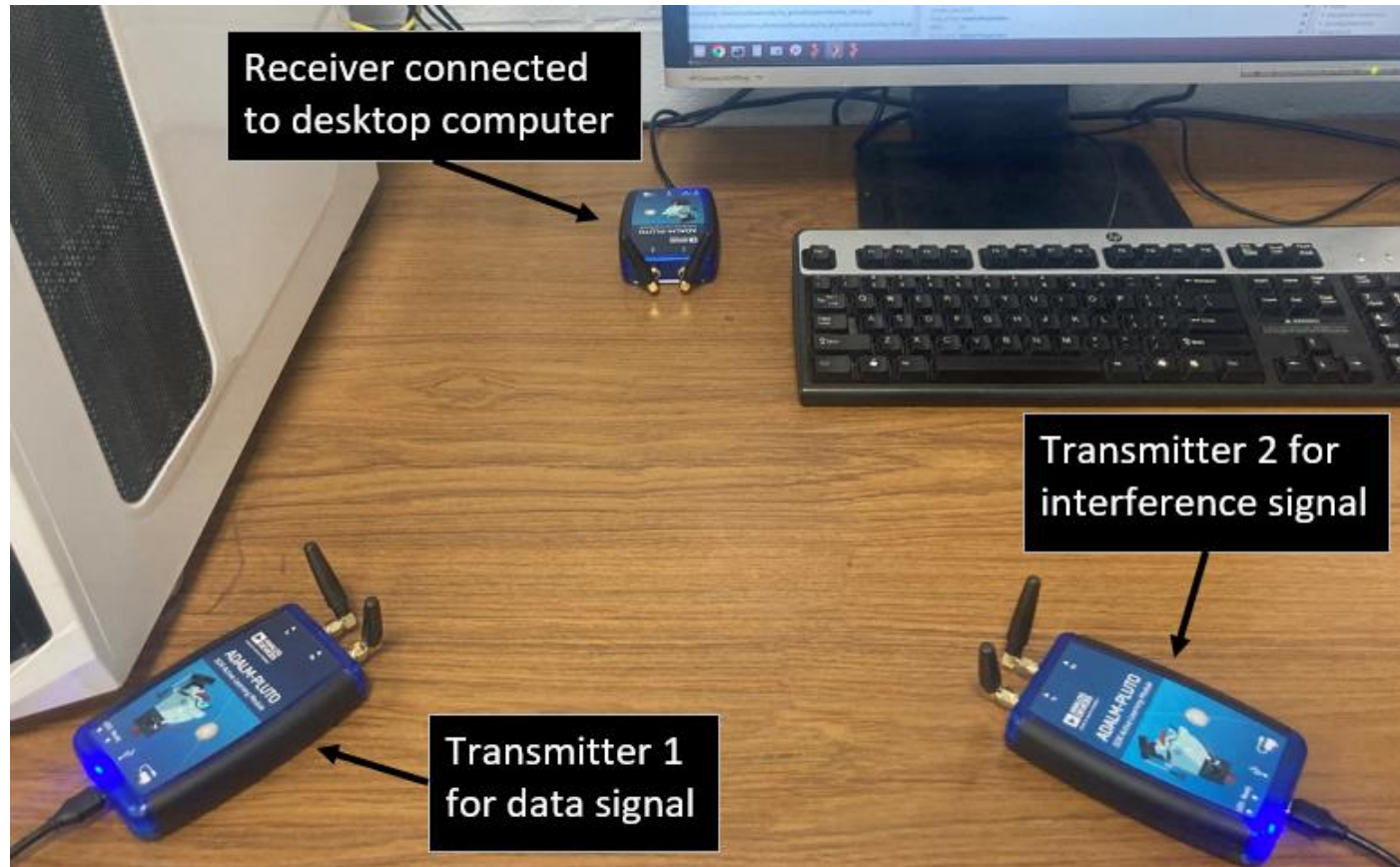
- Radio transmitter can hop between different signal modulations which is called link adaptation (LA).
- Deep learning is used at the receiver to recognize which modulation is being used. At present, the deep learning networks are pretrained.
- In new environments, signal characteristics can be different than what the deep learning networks were trained for. Thus, the existing deep learning networks can sometimes fail in recognizing the signal modulations received.



# Our Approach

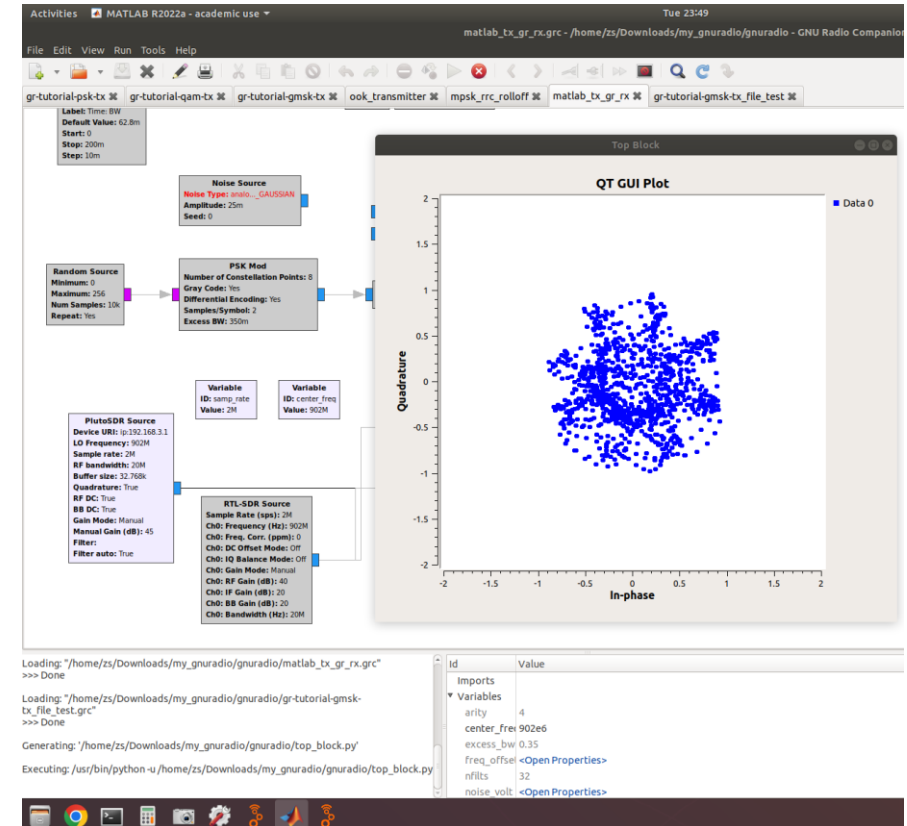
- We periodically transmitted a dictionary of all signal modulations (this will be preceded by a distinct signal pattern that can be easily recognized).
- On the receivers, we collected this dictionary and trained a deep network to learn the signal characteristics. This will make a custom deep network for each radio receiver to allow better performance.
- Accuracy of online training approach (94%) vs pretrained model (11%) under interference signal.

# Overview



# Transmission Setup

- Over-the-air transmission.
- Analog Devices ADALM-PLUTO transmitter/receiver radios.
- MATLAB was used to generate the modulated radio signals.
- GNU Radio was used to receive the I/Q sequence.
- Center frequency: 902 MHz
- Samples per symbol: 8



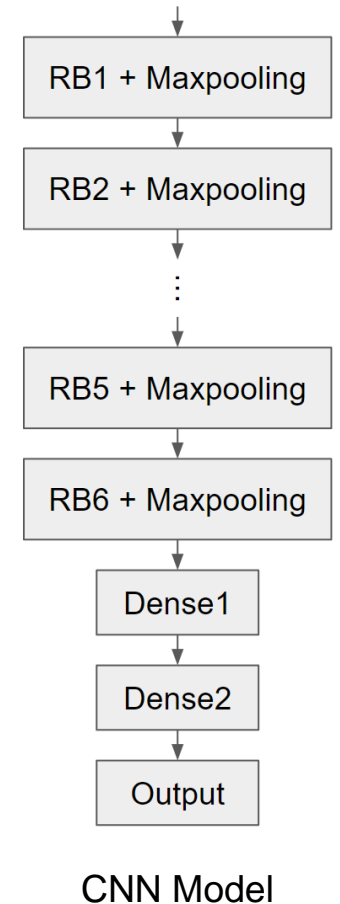
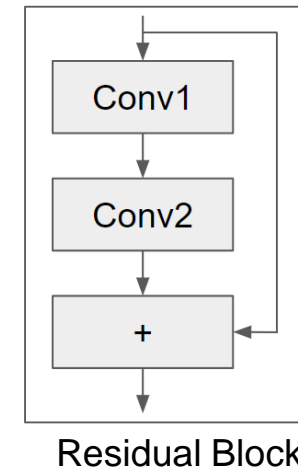
# Dataset

- Two seconds for each modulation class.
- I/Q sequence split into 1024 x 2 vectors.
- Training labels generated based on the transmission order.
- 2500 samples collected for each class.

Modulation Order	Modulation Classes
1	BPSK
2	QPSK
3	8PSK
4	16PSK
5	32PSK
6	DQPSK
7	OQPSK
8	16APSK
9	32APSK
10	64APSK
11	128APSK
12	16QAM
13	64QAM
14	128QAM
15	256QAM
16	FSK
17	GFSK
18	CPFSK
19	PAM4
20	MSK
21	GMSK
22	B-FM
23	DSB-AM-WC
24	DSB-AM-SC
25	SSB-AM

# CNN Model

- CNN with customized residual blocks (RB).
- Each block has two convolutional layers with a skip connection.
- Six residual blocks and six max pooling layers.
- Three dense layers as the classifier.
- Network was trained for 20 epochs, and each took about 8 seconds on the desktop GPU.



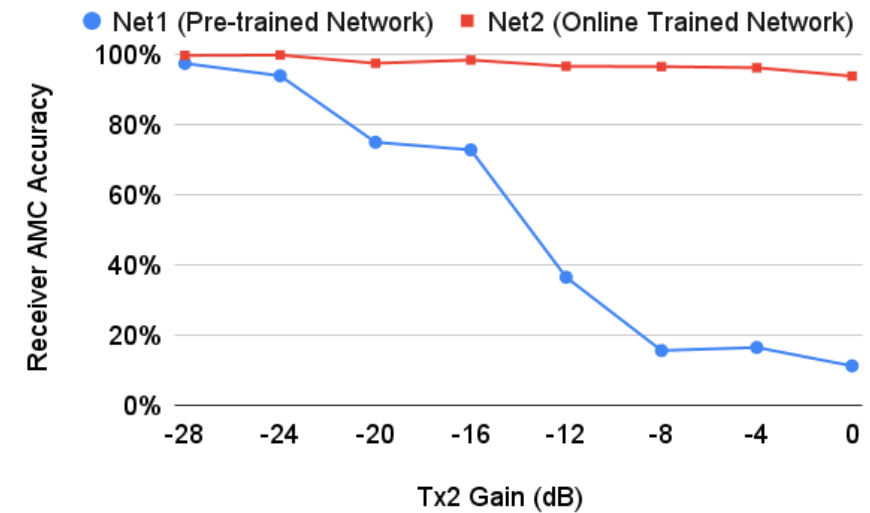
# Experiment Setup

- Tx1: the data signal transmitter.
- Tx2: the interference signal transmitter.
- Interference signal: random data sequence modulated with 128QAM.
- Increase the transmission gain of Tx2 from -28 dB to 0 dB.
- Net1: pre-trained network, only performed inference tasks.
- Net2: trained periodically with the received signals.



# Results

- The classification accuracy of Net1 decreased from 97.46% to 11.22%.
- Net2 was trained periodically with the new dictionary data from Tx1.
- The classification accuracy of Net2 only dropped to 93.82%.





# Conclusion

- We developed an approach to improve the performance of the automatic modulation classification system by having transmitter periodically send a know sequence of modulation signals.
- The received data was used to retrain the AMC system.
- It allows the receiver to adjust to unknown distortions/interference.
- Our approach provides better accuracy against a pre-trained model (94% vs 11%).

# Future Work

- Reason for training on edge (especially for radio signal classification).
  - Privacy Protection and Anomaly Detection.
  - Lower Latency and Higher Energy Efficiency.
  - Establishment of reliable communication channel between edge and cloud.
- Implementation on edge devices.
  - Nvidia Jetson.
  - FPGAs.
- Deep learning for demodulation.
  - Incorporation of demodulation and AMC system.
  - End-to-end radio communication system.
- Dataset release.
  - More data collection.
  - Currently no similar dataset available.

Questions?