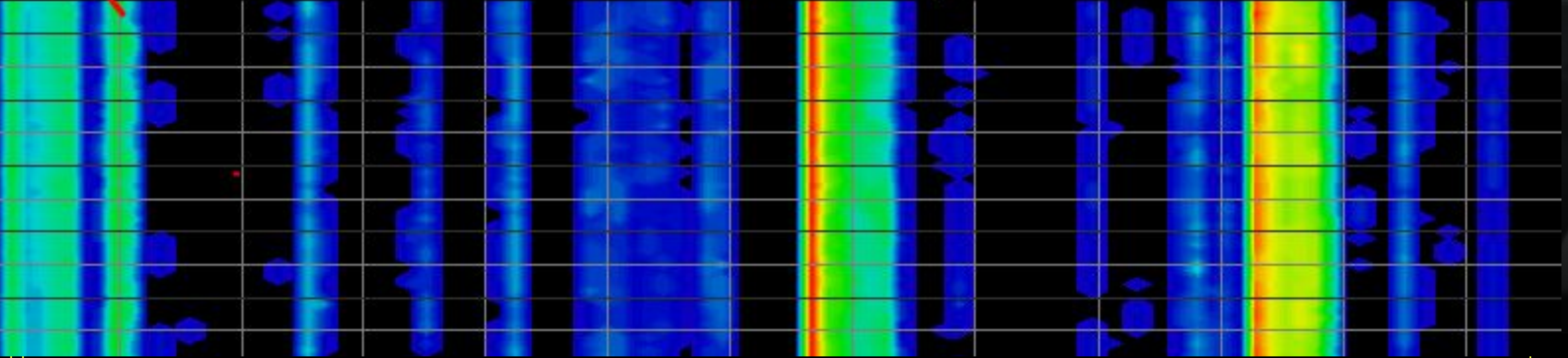

Channel Measurement Campaign

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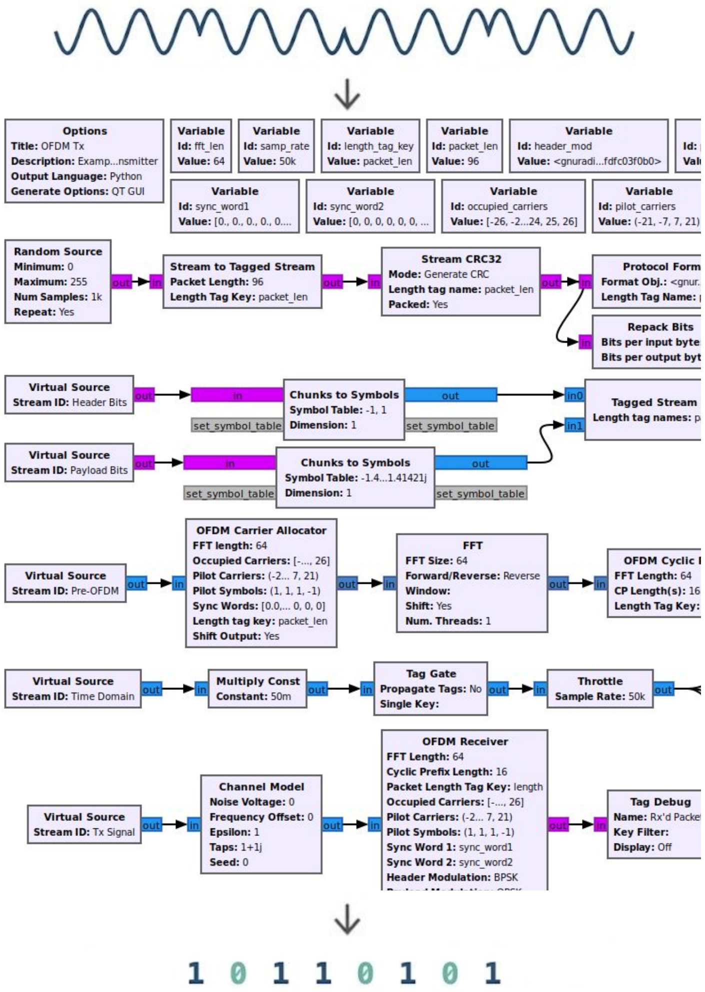
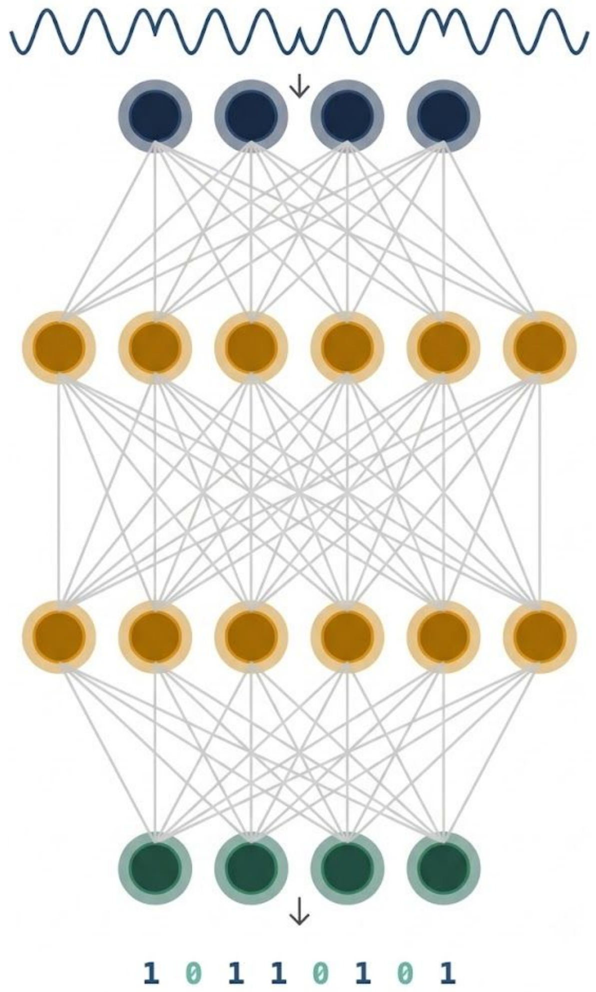
Advisor: Director Ivan Seskar

WINLAB



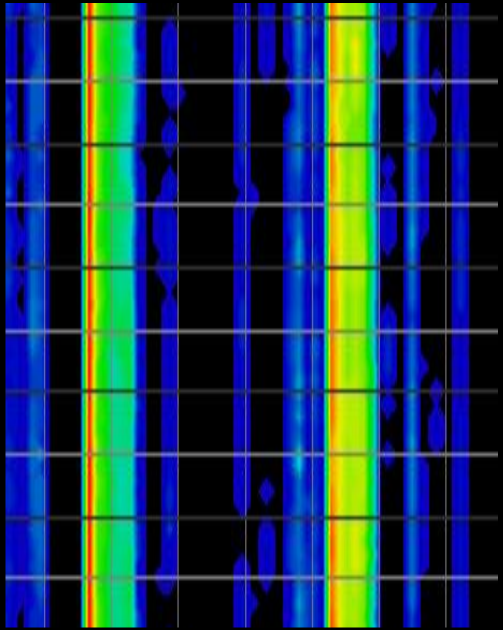
Radio Today

- Radios follow a chain of hard-coded rules made by engineers
- Those rules assume the world behaves a certain way — it often doesn't
- When something unexpected happens, the radio breaks



In the Future

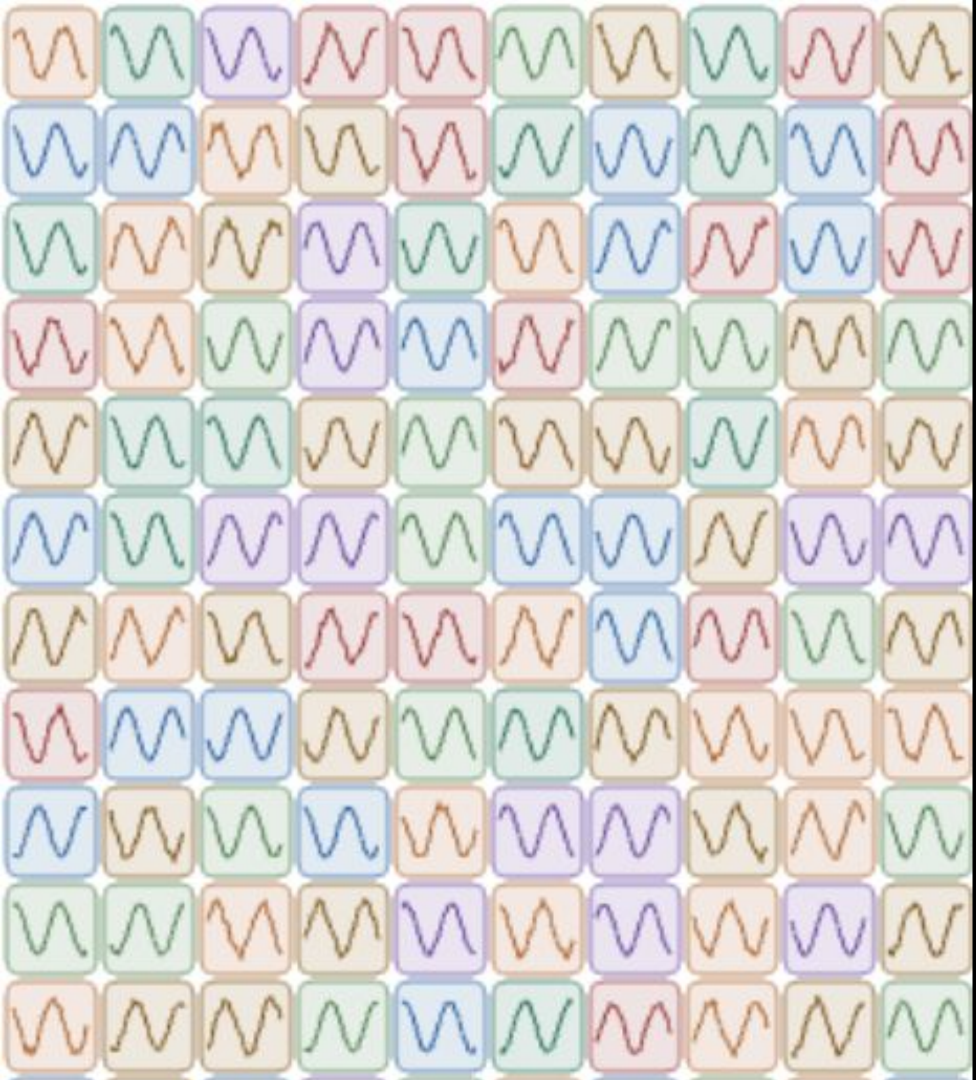
- One AI model handles everything
- Feed it the raw signal, get decoded data out
- It learns from real examples, so it can handle more situations



Lay the foundation for a large, diverse over-the-air dataset to enable ML-driven wireless communications.

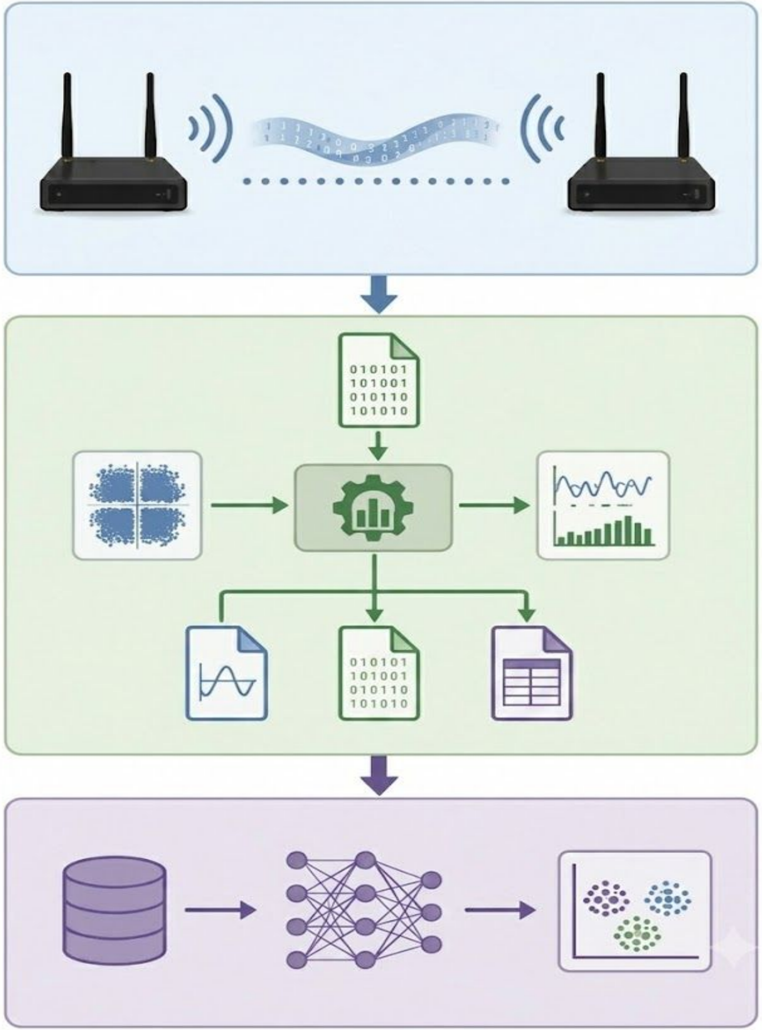
Project

Overview



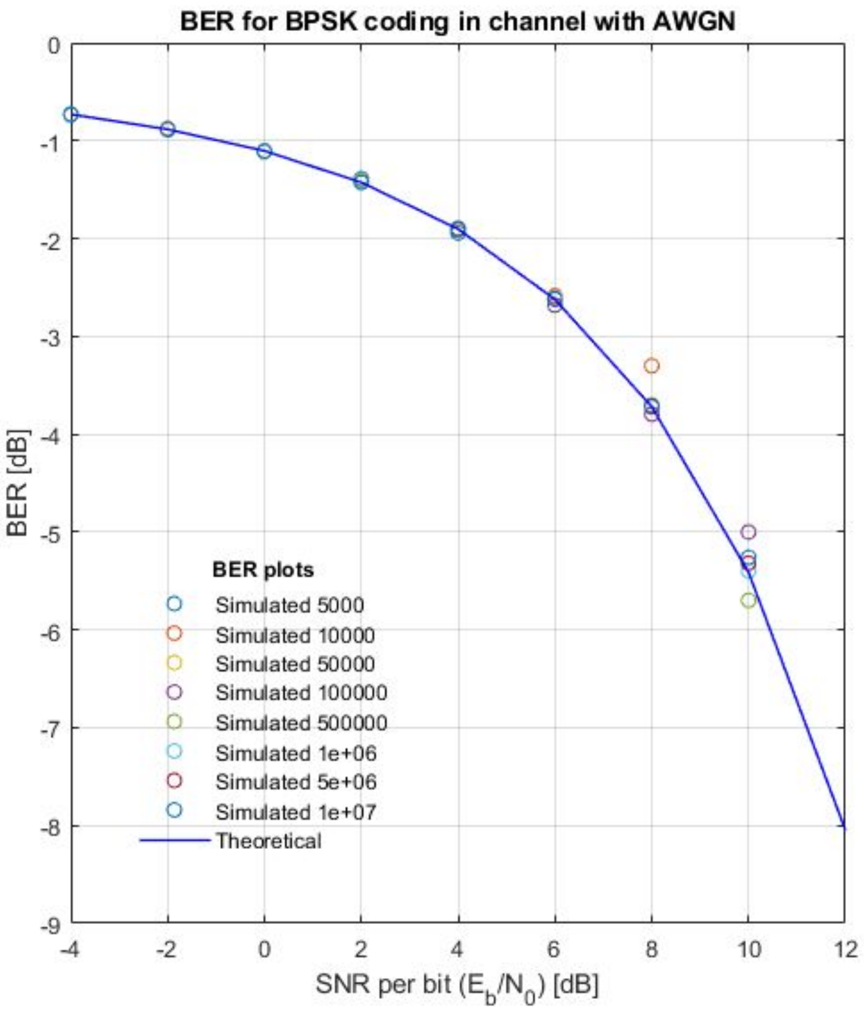
Why Data Matters

- Models learn what they've seen.
- Narrow data = memorization not learning
- Large+Diverse allows for generalizing



What We Built

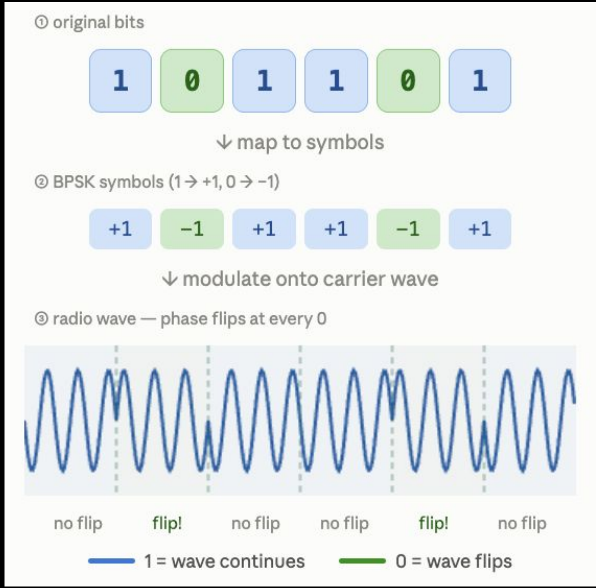
- Automated real over-the-air signal capture experiments
- Swept across multiple signal strength levels automatically
- Every Machine readable
- Trained AI to decode raw signals into bits
- Benchmarked AI vs. classical radio receiver



The Baseline

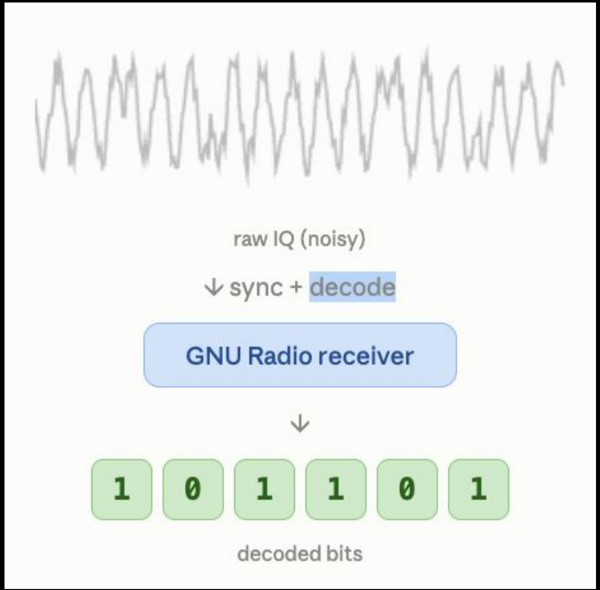
- Baseline = The Truth
- Baseline validates radio chain if it matches theory.
- BPSK = Encoding bits in phase
- Chosen because it's the simplest

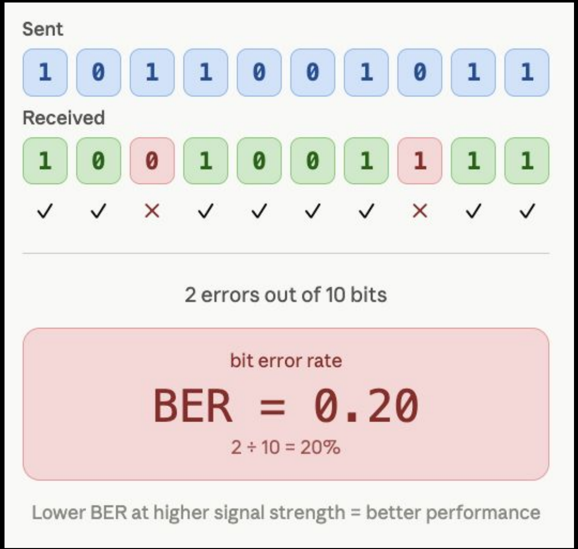
BPSK Pipeline



1 Modulation

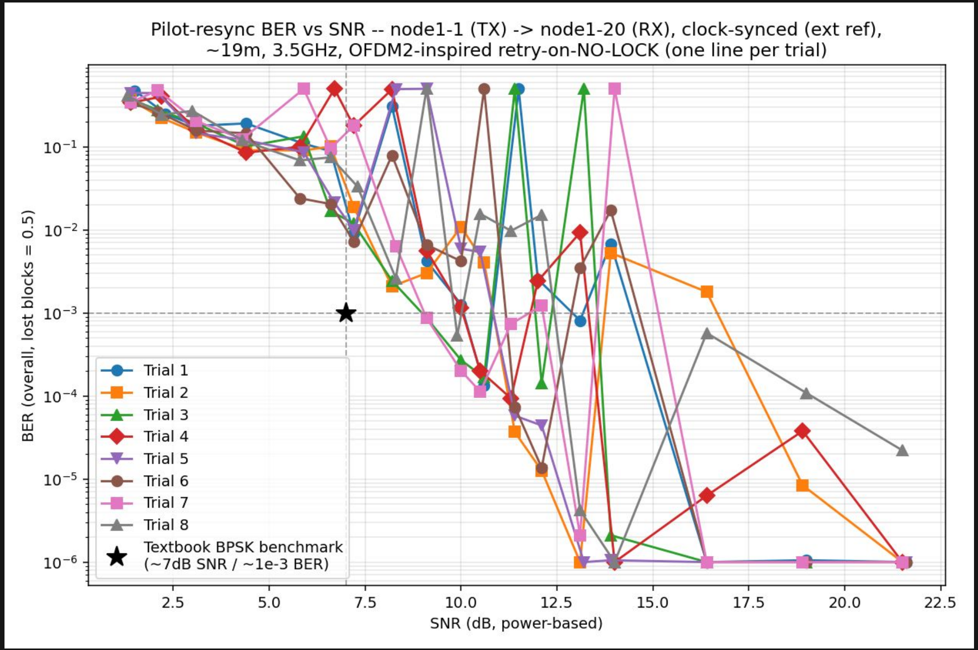
2 Demodulation

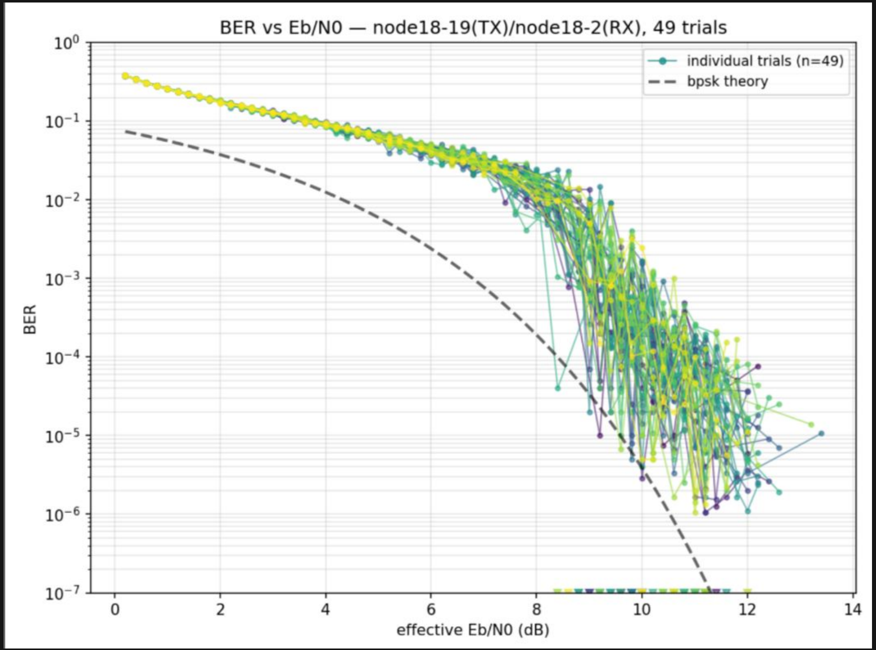




3 Processing

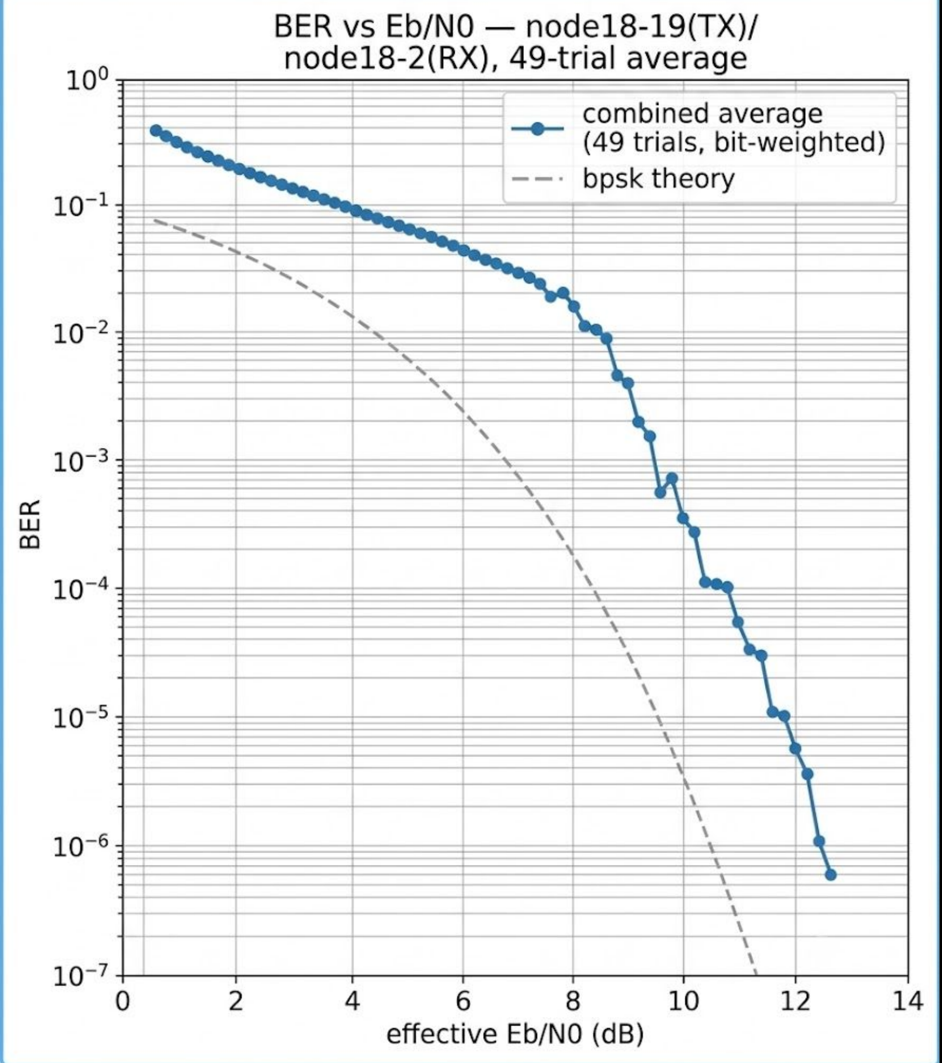
Baseline Progress





- Restarted synchronization for every trial
- Often failed to lock correctly especially at Mid SNR
- Not enough bits/ trials: To measure fewer errors, you need to send more data

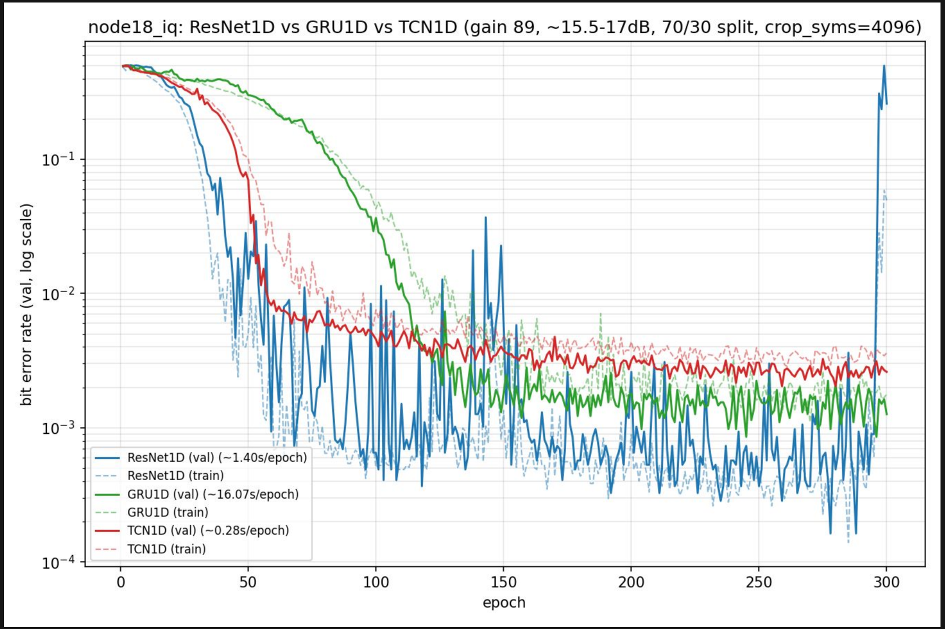
- Remained synchronized by locking at high gain during the power sweep and stayed locked
- More bits transmitted at higher SNR's — so we can measure the error rate accurately when errors are rare.

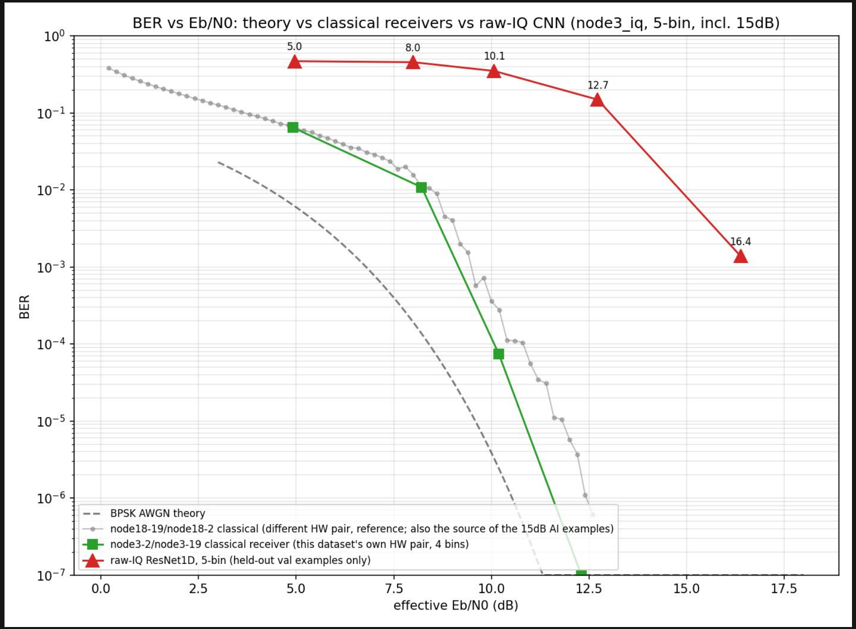


ML Preparations

- Baseline = Ground Truth
- Focus on a single SNR
- Capture Signal
- 40 files 50,000 symbols used in training.
- Random 4000 symbol frames.
- Train a model to translate a Signal into Bits.

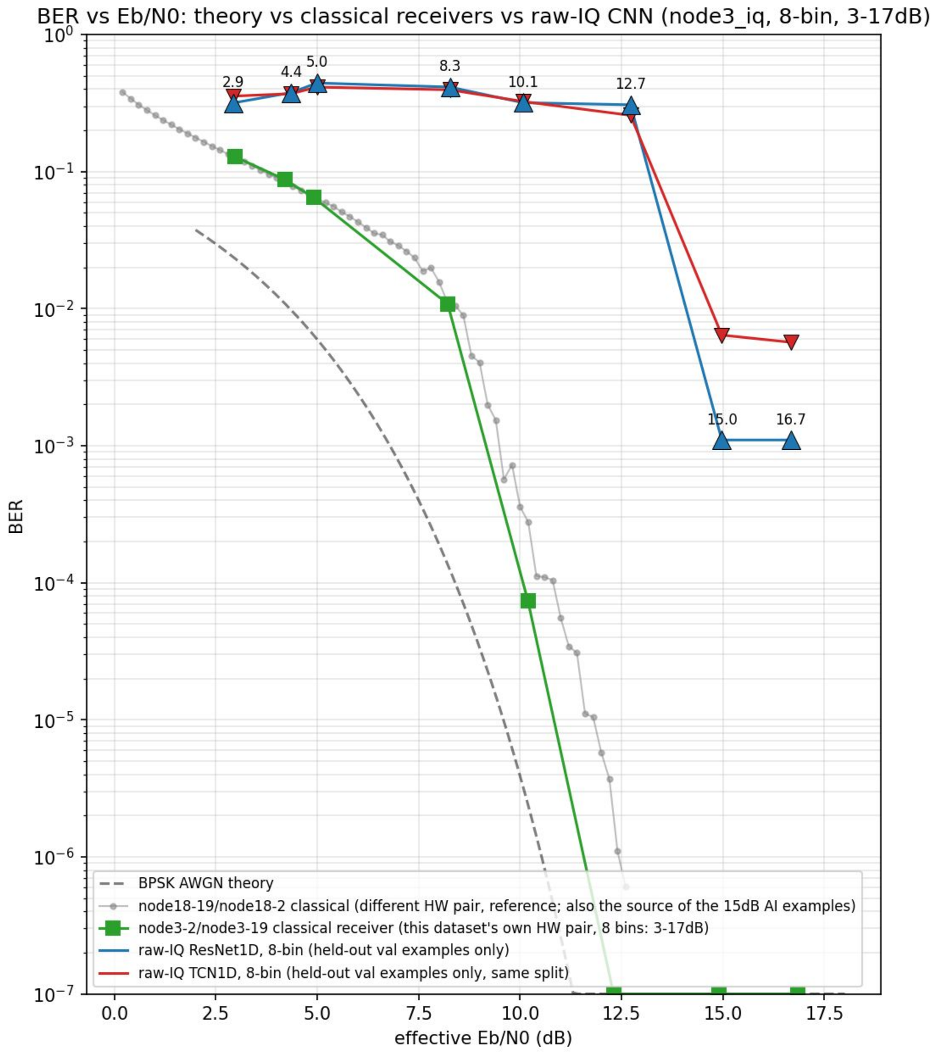
Machine Learning





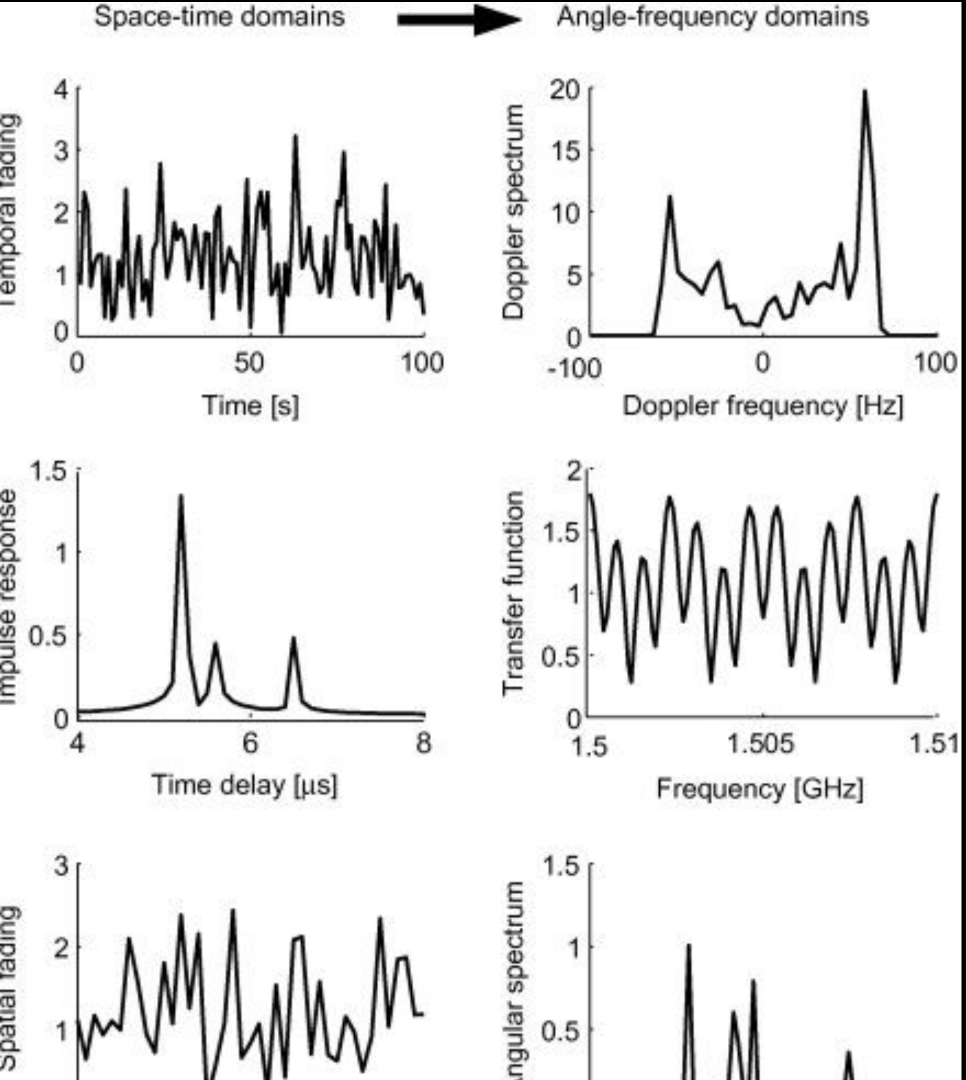
- Tested three different neural networks
- **ResNet**: most accurate but unpredictable late in training
- **TCN**: nearly as accurate, 5x faster to train
- **GRU**: 57x slowest

- Trained ML on real signals
- At stronger signals, the NN starts to perform well & mimicking waterfall shape
- First proof the NN can adapt across conditions



Where we Left off

- Validated end-to-end signal pipeline over real OTA hardware
- Automated multi-SNR data collection pipeline (Ansible + SigMF)
- Trained and compared three neural architectures on real IQ data
- ResNet achieves lowest BER, TCN is 5x faster — both reach ~10^{-3} at high SNR
- Gap vs. classical receiver remains.



What Next

- Scale beyond BPSK to different modulations
- Collect larger, more diverse dataset across more node pairs and environments
- Incorporate more parameters into sweeps; bandwidth, frequency, subcarriers.
- Improve ML demodulation ability to replicate classical SNR curve

Questions?

Channel Measurement Campaign