



Can AI-Driven Techniques Revolutionize IEEE 802 Standards?

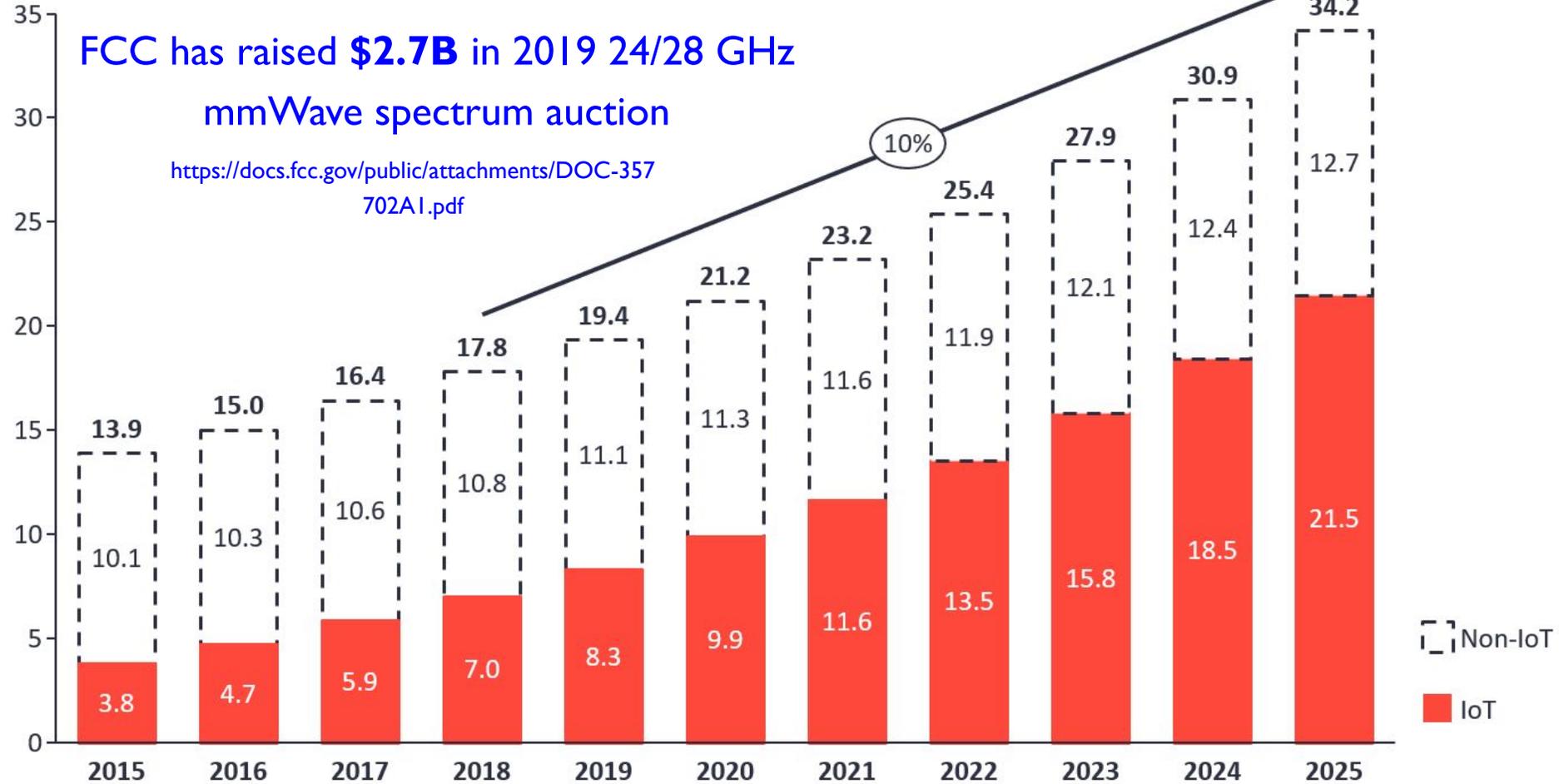
Francesco Restuccia
Assistant Professor
Electrical and Computer Engineering
Associate Faculty, WIOT and Roux Institute
Northeastern University, United States
Email: frestuc@northeastern.edu
Website: <https://restuccialab.org>

- Will focus on wireless protocols (my research focus)
- Similar techniques can be extended to wired 802 standards

The IoT Spectrum is Crowded

> 4x Human Population!

Number of global active Connections (installed base) in Bn



Note: Non-IoT includes all mobile phones, tablets, PCs, laptops, and fixed line phones. IoT includes all consumer and B2B devices connected – see IoT break-down for further details
Source: IoT Analytics Research 2018

The IoT environment changes **unpredictably**
and the **millisecond** level (optimistically)

Static, manual, explicit resource optimization is
likely to **not be the best option**

Security, reconfigurability, adaptability,
resilience must be **embedded** in the IoT
by design

Hold on a second...

Radio Fingerprinting

Modulation Recognition

Spectrum Sensing

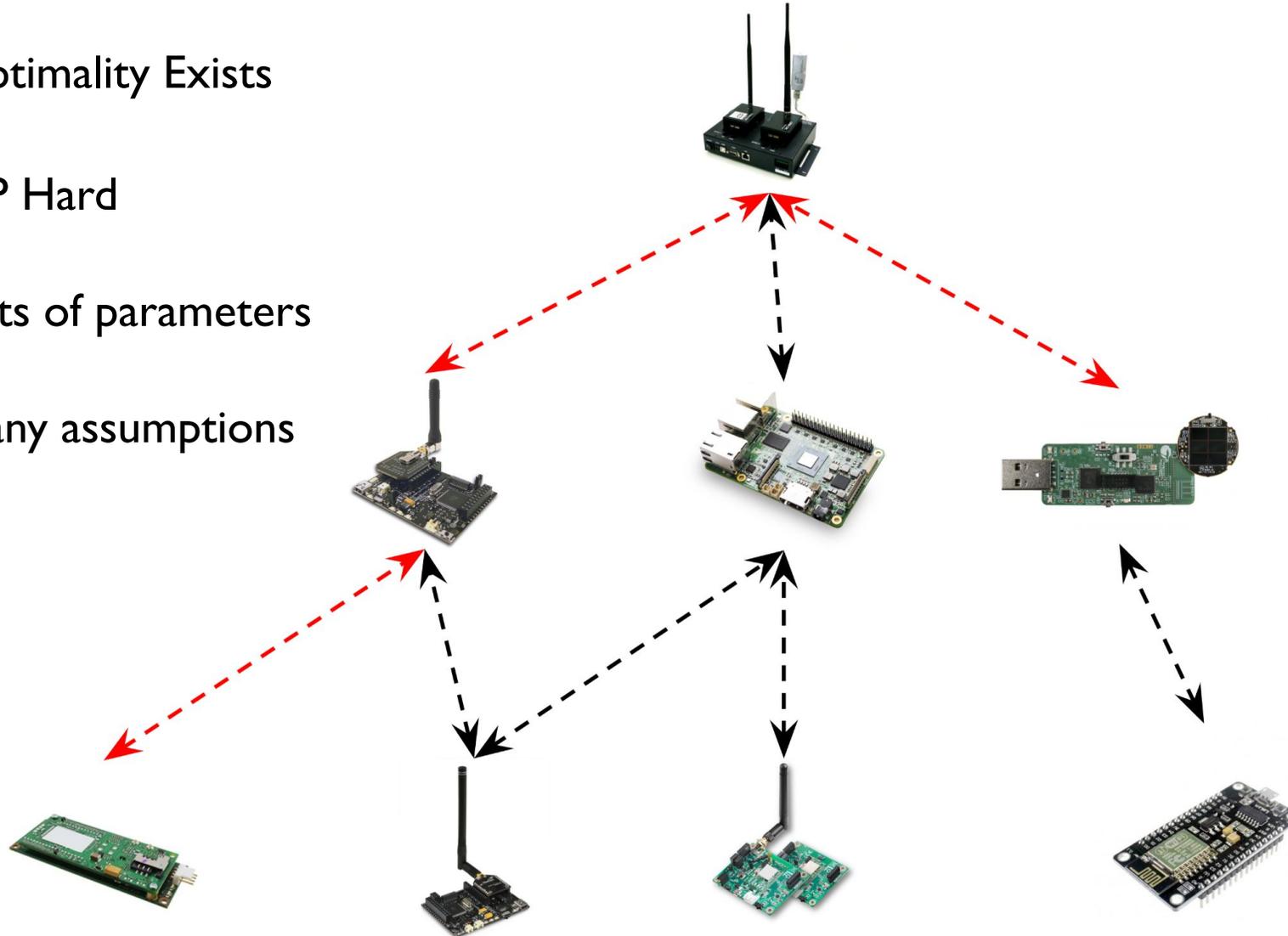
Dynamic Spectrum Access

NOT IN IEEE 802 STANDARDS!

How wireless networks are optimized today

Traditional Approach: Model-Driven

- ✓ Optimality Exists
- ✗ NP Hard
- ✗ Lots of parameters
- ✗ Many assumptions



Model

- Network
- Channel
- Interactions

Constraints

- Physical
- Economical

Solve

- Inner-point
- Gradient descent
- ...

Traditional Approach: Protocol-Driven

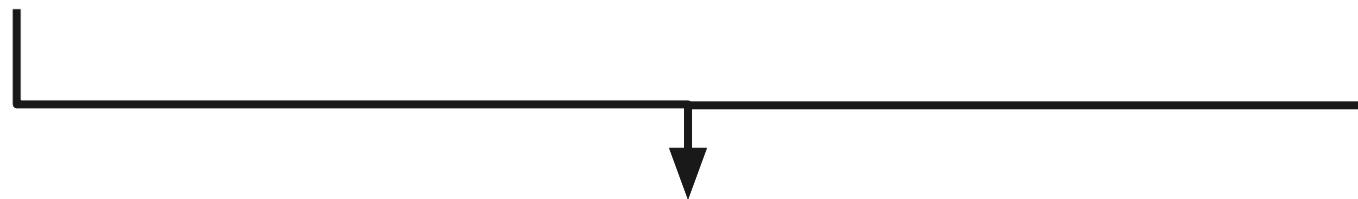
- ✓ Simple, Feasible Approach
- ✗ Not Generalizable
- ✗ Limited Spectrum Agility
- ✗ Heuristic Algorithms



We must rethink how to do network optimization

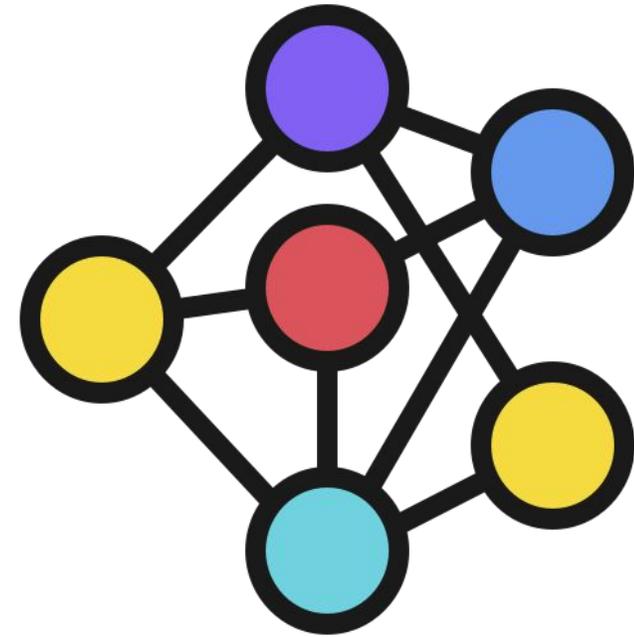
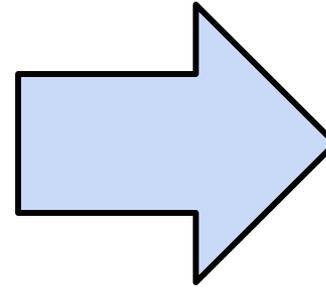
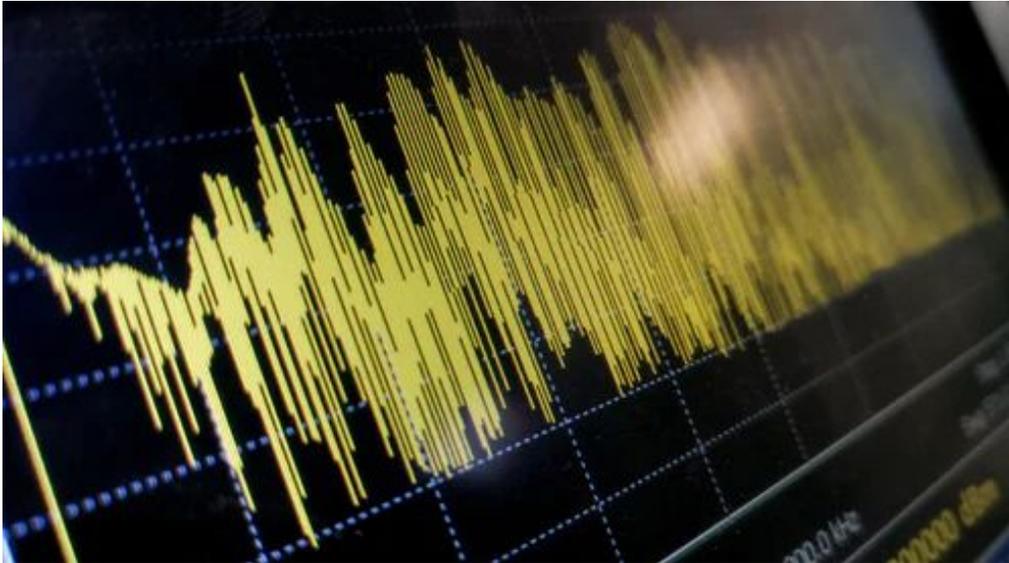
Model-Driven

Protocol-Driven

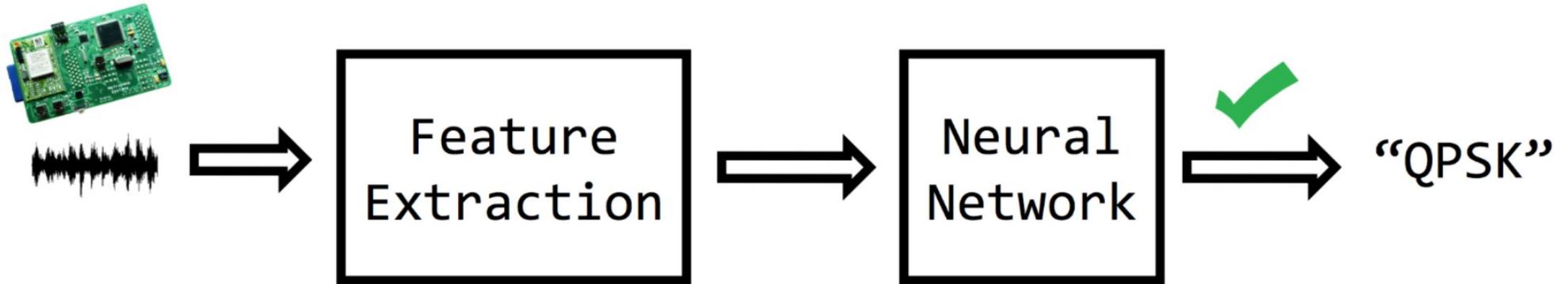


Effective AND Real-Time

Our Approach: Data-Driven Optimization

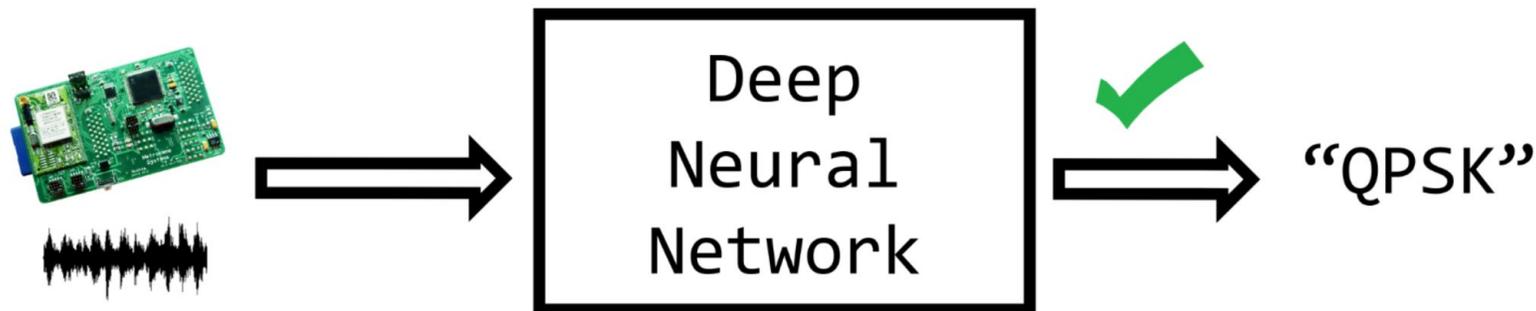


Advantages of Deep Spectrum Learning

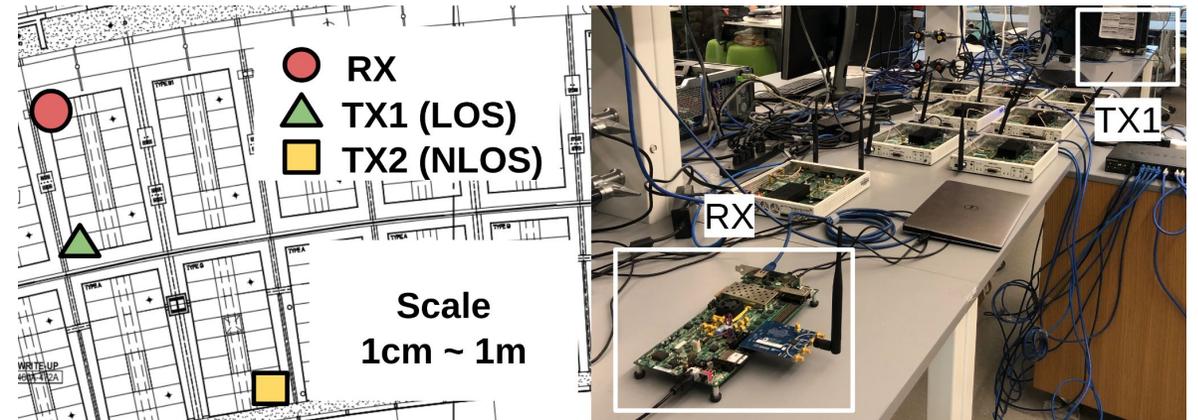
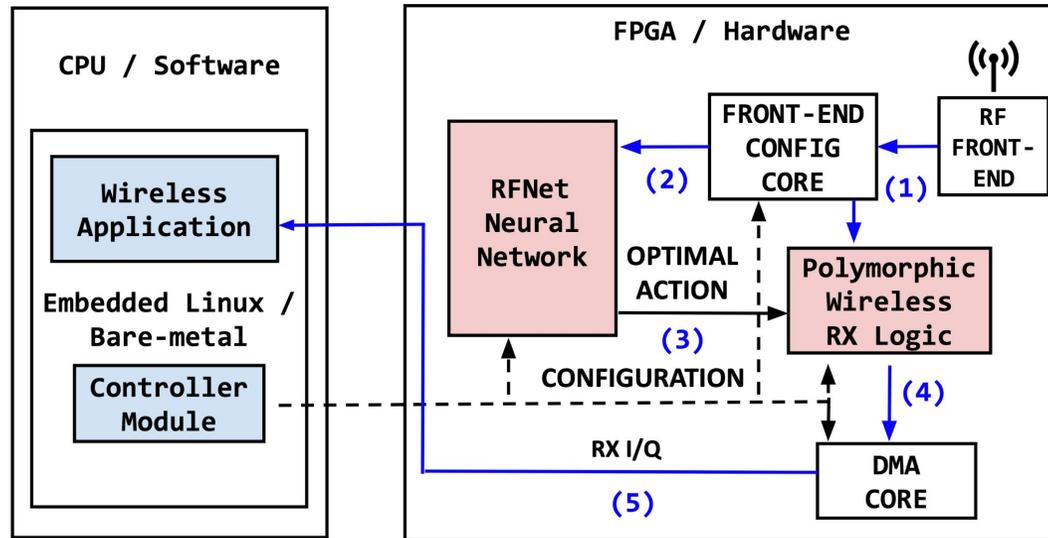


What are the “**right**” features?

What if I want to **change** classification problem?



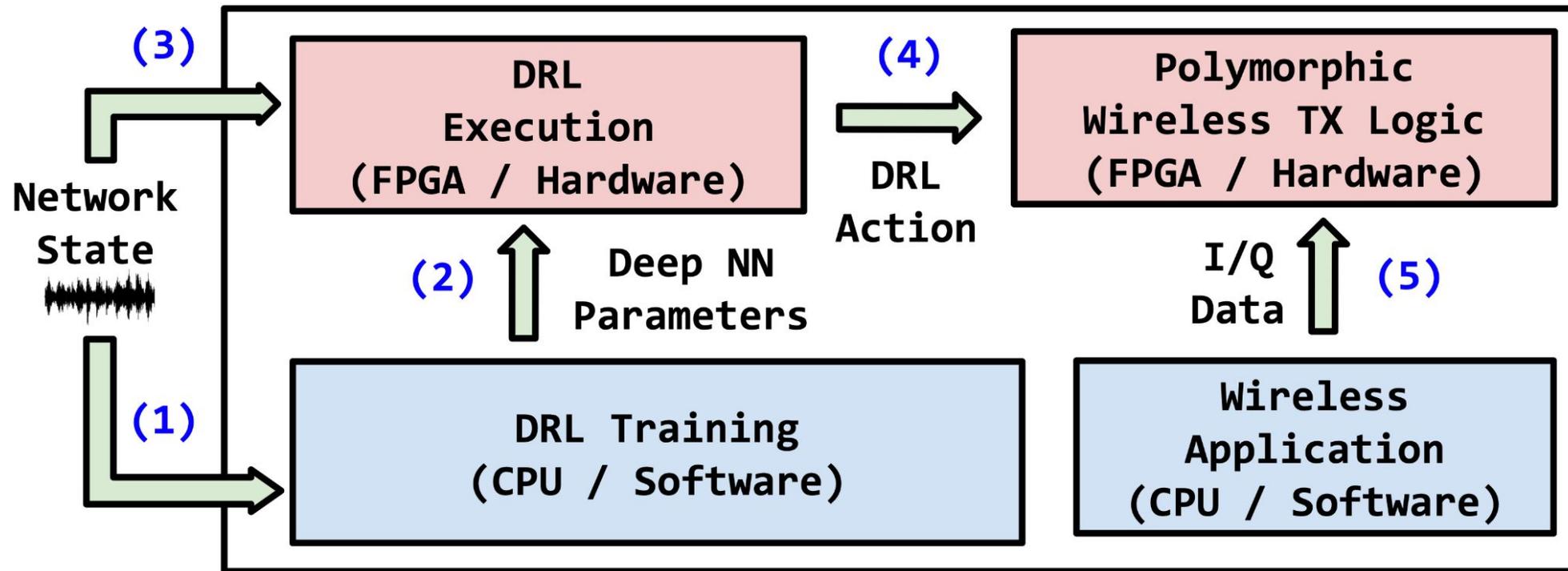
Self-Adaptive Spectrum-Aware Receivers



F. Restuccia and T. Melodia, "Big Data Goes Small: Real-Time Spectrum-Driven Embedded Wireless Networking Through Deep Learning in the RF Loop," **IEEE INFOCOM 2019**

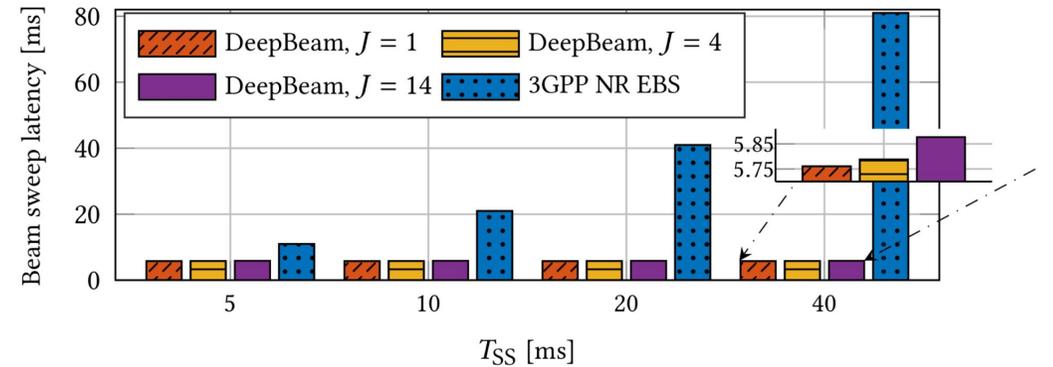
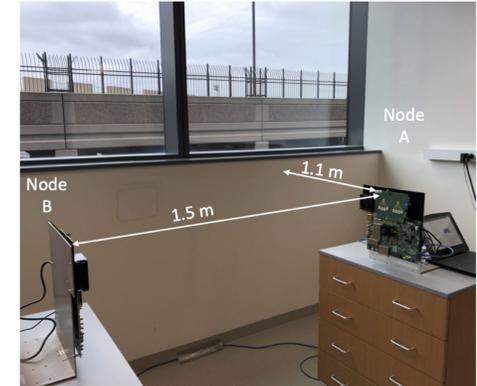
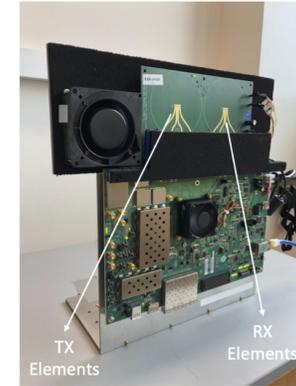
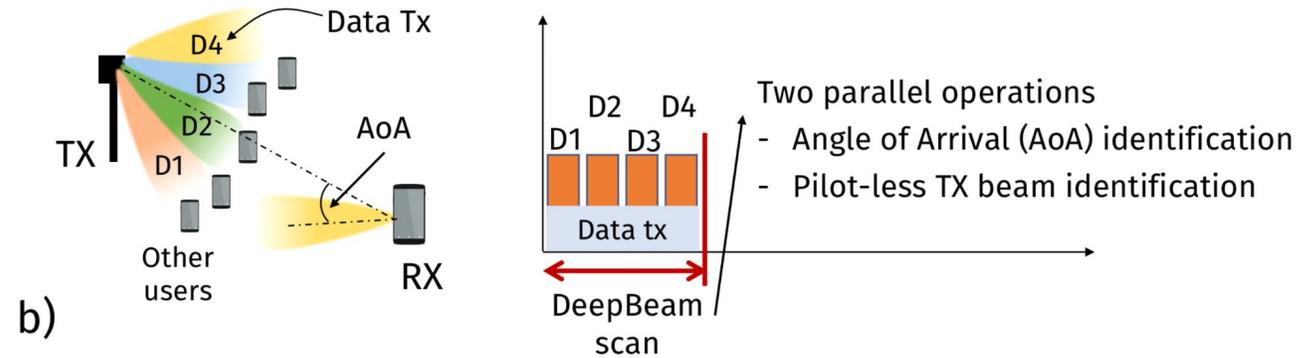
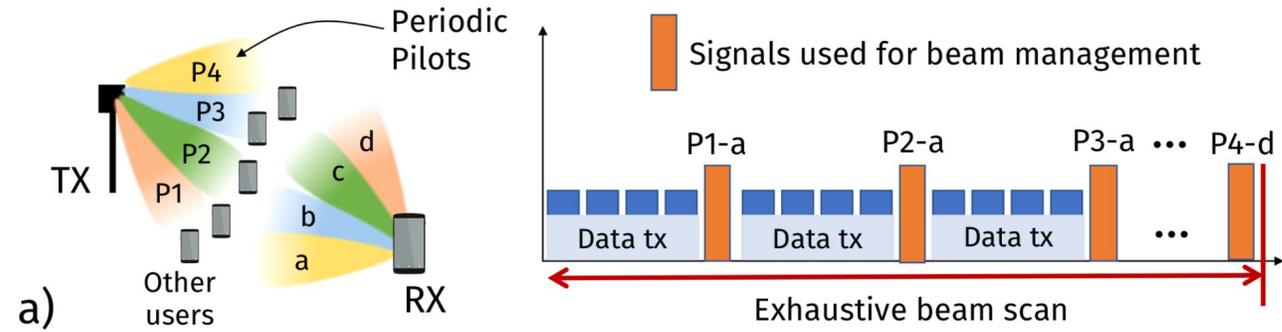
F. Restuccia and T. Melodia, "PolymoRF: Polymorphic Wireless Receivers Through Physical-Layer Deep Learning," **ACM MobiHoc 2020, SIGMOBILE Research Highlights 2020, Communications of the ACM Research Highlight.**

Self-Adaptive Spectrum-Aware Transmitters



F. Restuccia and T. Melodia, "DeepWiERL: Bringing Deep Reinforcement Learning to the Internet of Self-Adaptive Things," **IEEE INFOCOM 2020**

Deep Learning for Beam Management



M. Polese, F. Restuccia, and T. Melodia, "DeepBeam: Deep Waveform Learning for Coordination-Free Beam Management in mmWave Networks," **ACM MobiHoc 2021**.

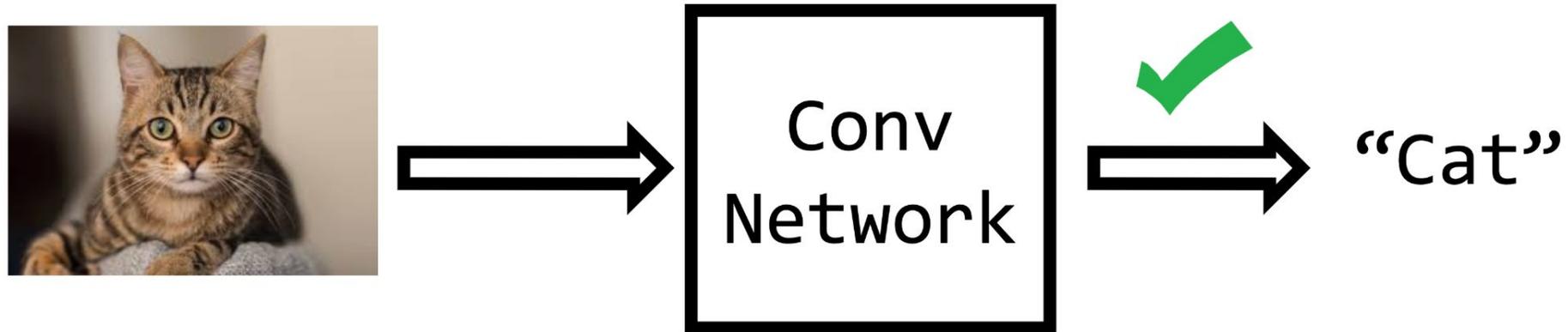
Deep Learning for Radio Fingerprinting

| Task | Description | # of Devices |
|------|--------------------------------------|--------------|
| A1 | Very High Population | 10,000 |
| A2 | High Population | 1000 |
| A3 | Medium Population | 500 |
| A4 | Low Population | 100 |
| B1 | Train One Day Test Another | 50 |
| B2 | Train on a Mix of Days Test on a Mix | 100 |
| B3 | Train and Test on a Single Day | 100 |
| C1 | SNR: Train High Test Medium | 100 |
| C2 | SNR: Train High Test Low | 100 |
| C3 | SNR: Train Medium Test High | 100 |
| C4 | SNR: Train Medium Test Low | 100 |
| C5 | SNR: Train Low Test High | 100 |
| C6 | SNR: Train Low Test Medium | 100 |

| Task | Testing Accuracy Per-Slice / Per-Transmission Accuracy (PSA/PTA) | | | |
|------|---|----------------------|----------------------|---------------|
| | WiFi | | | |
| | Raw I/Q before FFT | | Equalized | |
| | Baseline | ResNet-50-1D | Baseline | ResNet-50-1D |
| A1 | 0.082 / 0.130 | 0.164 / 0.262 | 0.062 / 0.101 | 0.014 / 0.030 |
| A2 | (0.299 / 0.378 | 0.393 / 0.612 | 0.327 / 0.434 | 0.392 / 0.555 |
| A3 | 0.354 / 0.398 | 0.467 / 0.629 | 0.454 / 0.478 | 0.430 / 0.549 |
| A4 | 0.335 / 0.575 | 0.490 / 0.631 | 0.762 / 0.639 | 0.699 / 0.637 |
| B1 | 0.017 / 0.016 | 0.013 / 0.012 | 0.232 / 0.335 | 0.175 / 0.258 |
| B2 | 0.444 / 0.695 | 0.520 / 0.811 | 0.678 / 0.674 | 0.751 / 0.735 |
| B3 | 0.310 / 0.598 | 0.441 / 0.746 | 0.210 / 0.432 | 0.308 / 0.542 |

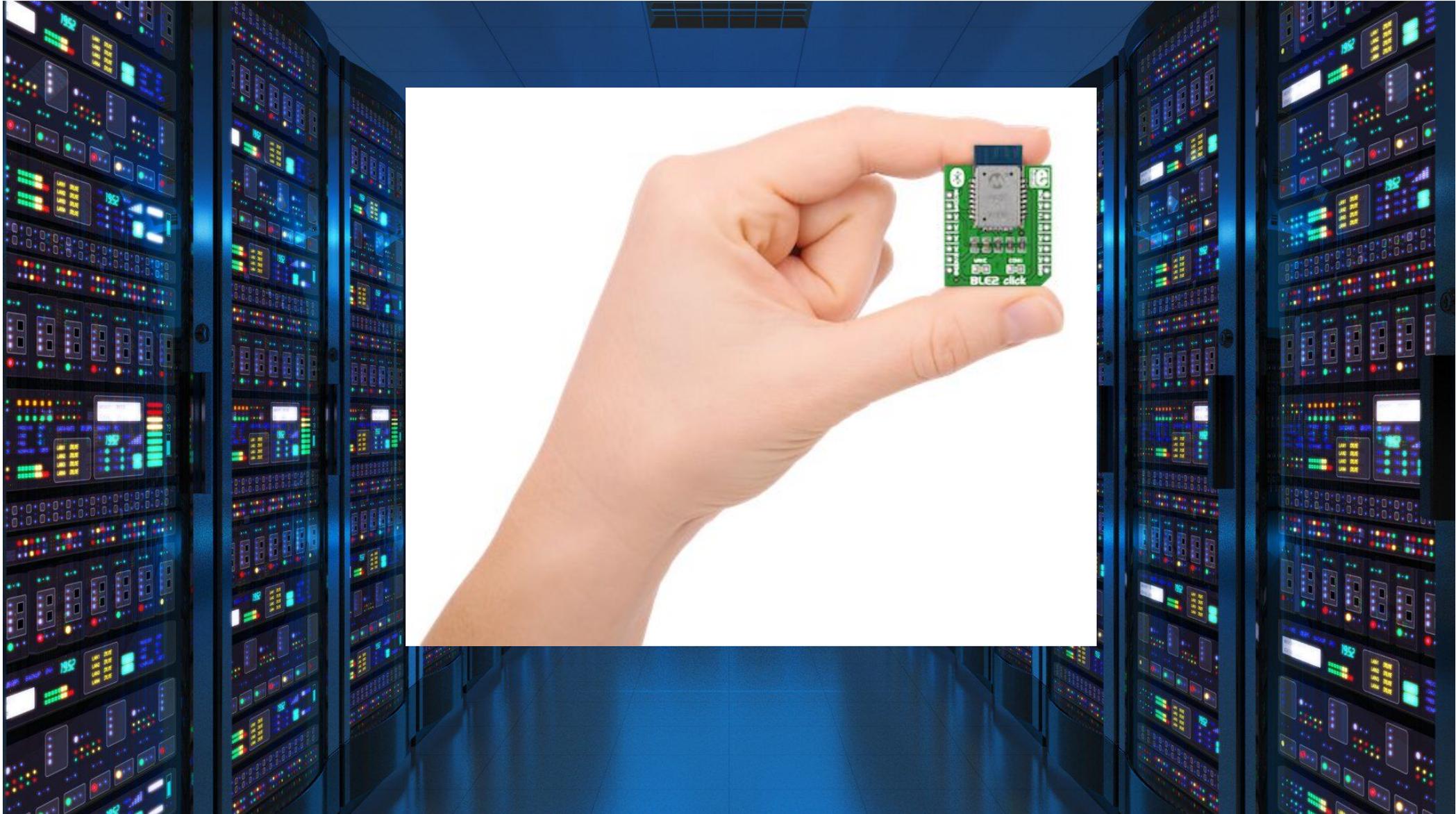
A. Al-Shawabka, F. Restuccia, S. D'Oro, T. Jian, B. Costa Rendon, N. Soltani, J. Dy, K. Chowdhury, S. Ioannidis and T. Melodia, "Exposing the Fingerprint: Dissecting the Impact of the Wireless Channel on Radio Fingerprinting," **IEEE INFOCOM 2020**.

Challenges of Deep Learning in Wireless



F. Restuccia and T. Melodia, "Deep Learning at the Physical Layer: System Challenges and Applications to 5G and Beyond," **IEEE Communications Magazine**, Vol. 58, Is. 10, October 2020.

Also, let's not forget...



- We now understand AI/ML can be a tremendous resource
- Lingering issues:
 - How do we transition from research to 802 standard?
 - Bridge the existing gap b/w academia/standard communities
 - How do we make these models smaller, faster, more accurate?
 - Great research & development opportunities

Thanks!
Questions?