Self-Driving Radios

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Radio a.k.a wireless physical layer
5G is coming and it is going to be diverse
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The same standard has to support all three devices
What does this mean for the radio?

Radio

- Channel code
  - Coded bits
- Modulation
  - Symbols
- Shaping
  - Tx pulse
- Time-freq mapping
  - Signal over-the-air
Radios offer several control knobs

Radio

- Raw bits
- Coded bits
- Symbols
- Tx pulse
- Signal over-the-air

Channel code
- Coding rate
- Sending rate

Modulation
- Pulse shaping
- Subcarrier spacing
- Cyclic prefix length
- Pilot density

Shaping
- Transmit power

Time-freq mapping
Radios offer several control knobs

This is a huge combinatorial optimization problem

- **Coding rate**: 1/3, 1/2, 2/3 etc.
- **Sending rate**: 2, 4, 6 Mbps
- **Pulse shaping**: Rectangular or Raised cosine or ...
- **Subcarrier spacing**: $15 \text{ kHz} \times 2^n$ ($n = 0, 1, 2, \ldots$)
- **Cyclic prefix length**: Normal or Extended
- **Pilot density**: 1 in 2-12 subcarriers x 2-14 OFDM symbols
- **Transmit power**: 10, 20, 30 dBm
Simple example

- Same home scenario
- Two simple control knobs
  - Sending rate
  - Transmit power

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<th>Low transmit power</th>
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Simple example to illustrate a radio’s dilemma

- Same home scenario
- Two simple control knobs
  - Sending rate
  - Transmit power

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Simple example: formalizing the problem

● 3 values each for both the knobs
  ○ Sending rate: 2, 4, 6 Mbps
  ○ Transmit power: 10, 20, 30 dBm (=10 mW, 100 mW, 1000 mW)

● Same link conditions
● Same goal
  ○ Send 40 kb within 10 ms

● Focus on tradeoff between data rate and energy for the three devices
● Objective of each device is to maximize $\sqrt{\text{data rate} - \alpha \times \text{energy spent}}$
  ○ Backhaul (fixed wireless), $\alpha = 0.01$
  ○ Mobile phone, $\alpha = 0.1$
  ○ IoT sensor, $\alpha = 1$
Optimal choices differ a lot
Optimal choices differ a lot
This problem is challenging

1. Impossible to write heuristics for all possible wireless link conditions
   ○ Need to learn from experience, and be able to generalize to unseen conditions

2. Inherent time dependence
   ○ Actions that the radio takes now affects its future state

3. Large combinatorial state space
   ○ Grows exponentially with more and more control knobs

Insight: This is a sequential control problem, similar to game-playing
Deep Reinforcement Learning (Deep RL)

- Proven for similar scenarios with large state spaces
- Can easily generate the training data through simulations
One-slide RL primer

1. State
2. Agent
3. Environment
4. Action
5. Reward
One-slide (Deep) RL primer
RL Primer in our context

Goal: Send 40 kilobits within 10 ms

Action: Transmit power and sending rate for the next ms

Environment: Wireless channel simulator

Reward: $\sqrt{\text{data rate}} - \alpha \times \text{energy spent}$, with $\alpha$ depending on the device (three agents for the devices)

State: [Past 4 channel qualities, NACK rate, bits remaining, time remaining]
Agent details

- Deep Q-Learning with an LSTM+fully connected network
- Training on 17600 simulated channel traces with Rayleigh fading
Performance of our self-driving radio
What has the agent learnt?

Sensitivity analysis of the trained agent
The backhaul agent is aggressive, using higher sending rate and transmit power
The IoT agent is conservative, using the lowest transmit power necessary
The backhaul agent does not hesitate to use higher powers and sending rates. The IoT agent uses higher power only when absolutely needed.
Power of data and AI-driven control; near-optimal behavior

Infeasible to mimic with heuristics
Performance across traces

CDF of rewards for agent trained for mobile

- Offline optimal
- Self Driving Radio
- LTE heuristic with perfect predictions

CDF

Reward in an episode

-300 -200 -100 0 100 200 300 400 500 600 700
What does this mean?

● AI-driven radio design promises to be flexible and near-optimal

● 5G networks will involve much more
  ○ use-cases...
    ■ Live VR: high throughput, low latency
    ■ Autonomous cars: low latency, high reliability
  ○ control knobs...
    ■ Subcarrier spacing, pilot density, OFDM cyclic prefix length, and so on
  ○ And there could be hundreds of such diverse devices connected

● Today’s radio design based on human heuristics is not scalable
● AI-based *self-driving radios* is a very promising approach
Our Vision for Self-Driving Radios

- So far we have shown that it is possible to “learn” the wireless control plane
  - i.e., it is possible to “learn” how to configure the control knobs exposed by the data plane

- Eventually we can “learn” the wireless data plane itself
  - i.e., we can directly “learn” how to construct signal from bits based on high-level specifications of application and device requirements and constraints

- A world with minimal wireless standards

**Current approach:** handcraft radio protocol for every scenario (NFC, Zigbee, Bluetooth, WiFi, LTE etc.)

**SDR approach:** specify high-level requirements and objectives, ML+AI learns the best radio protocol
Thank You!

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