Overview

• 6G will attempt to minimize latency while supporting many more devices and with improved data rates compared to 5G

• Machine Learning (ML) techniques have been proposed to address these challenges, including at the physical layer

• This work presents a survey of opportunities and metrics for considering ML use at the physical layer
Current Waveform Design Approach

Engineers select **components** given channel and application constraints such as time of receipt or expected signal power at receiver to design the waveform.

**Transmitter (Tx)**
- Information to Transmit
  - Data, Images, Voice etc.
  - Source: Power Point

**Prepare Data for Transmit**
- Cyclic Redundancy Check
- Error Correction
- Modulation Selection, etc.

**Front End**

**Receiver (Rx)**
- Received Information

**Process Received Data**

**Front End**

**Channel**
Emerging Technology: Using Machine Learning at the Physical Layer

In recent years, Machine Learning (ML) has been explored to prepare data for transmission and processing at the receiver.

Transmitter (Tx)
- Information to Transmit
- Machine Learning Process
- Front End

Receiver (Rx)
- Received Information
- Machine Learning Process
- Front End

Source: Power Point
O'Shea and Hoydis (2017) demonstrate that transmitter, channel, and receiver can be trained as one neural network (NN) and trained as an autoencoder.

- $s$: Represents data to transmit
- $x$: Transmitted signal, inherently includes processing such as modulation and error correction
- $y$: Represents received signal at the receiver
- $\hat{s}$: Estimated data

**Interesting Results**
- Autoencoder produced constellation mapping dependent on constraints
- Error correction inherent in NN process

**Possible Extensions**
- Is it possible to extend this approach to complex channel models?
- Can the joint optimization be leveraged?
6G Specific Challenges

- Channels with higher mobility (e.g. Transportation Systems)
- More interference (e.g. Non-Orthogonal modulation schemes, more devices)
- Time-Varying channels
- Operating at a range of frequencies (e.g. mmWave, THz)
- There is an interest to consider ML at every layer of the communication process, including the physical layer

# Objective and High-Level Findings

## Objectives

- Perform review of current techniques that combine Physical Layer + Machine Learning
- Develop recommendations for future work exploring the field

## High-Level Findings

- ML algorithms should be treated as an additional tool and designers must use full knowledge of system to determine feasibility
- Further research is needed to fully understand how robust ML algorithms are in certain applications. For example:
  - To say a signal is hard to detect, it should be tested against common detection algorithms
  - Algorithms should be tested against typical hardware impairments like offsets
Tradeoffs

- **Performance:**
  Theoretical limits to transmit information over channels

- **Convergence and Explainability:**
  How well can we explain results of ML or reproduce results?

- **Separability of Components:**
  Which components are embedded in ML process or done externally?

- **Hardware and Software Considerations:**
  How feasible is it to build ML processing into radios?

Source: *mathworks.com*, There are fundamental bounds on how much information can be communicated based on physical limitations.
Three Applications of Interest

End-to-End System Design

- Message → Waveform Encoding → Front End
- Waveform Decoding → Message Estimate
- Machine Learning Encoding
- Machine Learning Decoding

Receiver Processing

- Message → Waveform Encoding → Front End
- Waveform Decoding → Message Estimate
- Classical Example Waveform Encoding Process: Cyclic Redundancy Check, Error Correction, Preamble, Modulation
- Classical Example Waveform Decoding Process: ML Signal Processing, Preamble Detection, Error Correction, Cyclic Redundancy Check

Applying Supplemental Constraints

- Message → Tx NN Encoder → Alice-to-Bob Channel → Rx NN Decoder → Message Estimate
- Alice-to-Eve Channel → Observability Test → Observation Result
- Training Feedback
Three Applications of Interest

End-to-End System Design

Receiver Processing

Applying Supplemental Constraints
End-to-End Learning

- **Joint Optimization**
  - Autoencoder combines modulation, interleaving, error correction, etc.
  - Maps data bits to symbols or chips
  - Optimization results dependent on training channel

- **Training**
  - Can be done with simulated channel model (multiple papers) or over-the-air (OTA) channel (Schmitz, 2019)
  - Loss function based on cross entropy between input to the transmitter and the estimated message at the receiver

Source: *Machine Learning Based Featureless Signaling*, Ismail Shakeel, 2018
Example Modulations Produced using Autoencoders

Modulation constellations designed using machine learning, (a) and (b) designed with energy constraints, while (c) is designed with a power constraint (O’Shea, 2017).

Key Takeaways:
- End-to-End learning may outperform conventional waveform design
- Some papers consider offsets but reliability testing needed
- Designers must be aware of practical limitations to extend simulations to real-time implementations

ML design: 4 sequential time slots to transmit 4 symbols. Each 8-bit message maps to a unique sequence of 4 symbols. Markers show the symbols selected for 4 sample messages. 256 total possible sequences. (Dorner, 2018)
Three Applications of Interest

End-to-End System Design

Receiver Processing

Applying Supplemental Constraints
Receiver Processing

- Individual block processing for channel estimation (He, 2018), equalization (Chang, 2019), or demapping (Shental, 2019)
- Joint optimization of components (learned channel estimation, equalization, and demapping) in one network for 5G signals (Honkala, 2021)
- Joint ML approach outperformed a LMMSE receiver

Key Takeaways:
- Joint ML optimization can outperform individual blocks developed with ML algorithms
- ML can outperform certain conventional techniques

Source: Honkala et al., "DeepRx: Fully convolutional deep learning receiver," 2021. See notes section for full citation
Three Applications of Interest

End-to-End System Design

Applying Supplemental Constraints

Not covered in this presentation but can be considered an extension of an End-to-End System Design
Key Take Aways

**Pros**

- End-to-end learning may outperform conventional waveform design
- Joint ML optimization can outperform individual blocks developed with ML algorithms depending on the design and channel conditions
- ML-based waveforms may provide new tools to develop waveforms based on various constraints

**Hurdles**

- More work needed to validate reliability for future systems
- Operationalizing the training of end-to-end networks is a challenge. Most techniques require a genie/feedback between transmitter and receiver
- Thorough analysis of techniques in comparison to traditional techniques is necessary to “sell” ML-based systems
Summary

- Summary of a literature review, considerations when using ML-based algorithms
- Emerging field that is being actively researched in industry and academia with applications various communication systems including 6G
- Should be treated as an additional tool for waveform and receiver design
- Additional work recommended to understand how techniques compare to conventional designs

Source: mathworks.com, There are fundamental bounds on how much information can be communicated based on physical limitations
Backups
Limiting Observability

- **Low Probability of Intercept**
  - Design of a constellation such that data is unintelligible to an eavesdropper (*Fritschek, 2020*)
  - View eavesdropper as generative adversarial network to encrypt transmissions (*Abadi, 2016*)

- **Low Probability of Detection**
  - Generate featureless noise-like sequences for undetectable chips (*Shakeel, 2018*)

**Key Takeaways:**
- ML-based waveforms can provide new algorithms to evade detection by adversaries
- Further evaluation against various detection algorithms is necessary for deployment
Findings

• **End-to-End Systems**: Further improvements on O’Shea’s autoencoder approach have been made in recent years.

• **Receive Processing**: ML systems built to replace only the receive-side processing have shown gains over traditional receivers.

• **Limiting Observability**: Fritschek (2020) designed LPI signals, and Shakeel (2018) designed LPD signals, both using end-to-end methods.
Tradeoffs

- **Performance**: Theoretical limits to transmit information over channels
- **Convergence and Explainability**: How well can we explain results of ML or reproduce results?
- **Separability of Components**: Which components are embedded in ML process or done externally?
- **Hardware and Software Considerations**: How feasible is it to build ML processing into radios?

Source: *Capacity-Driven Autoencoders for Communications*, Letizia and Tonello, 2021