Considerations Using Machine Learning in Physical Layer Applications

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Overview

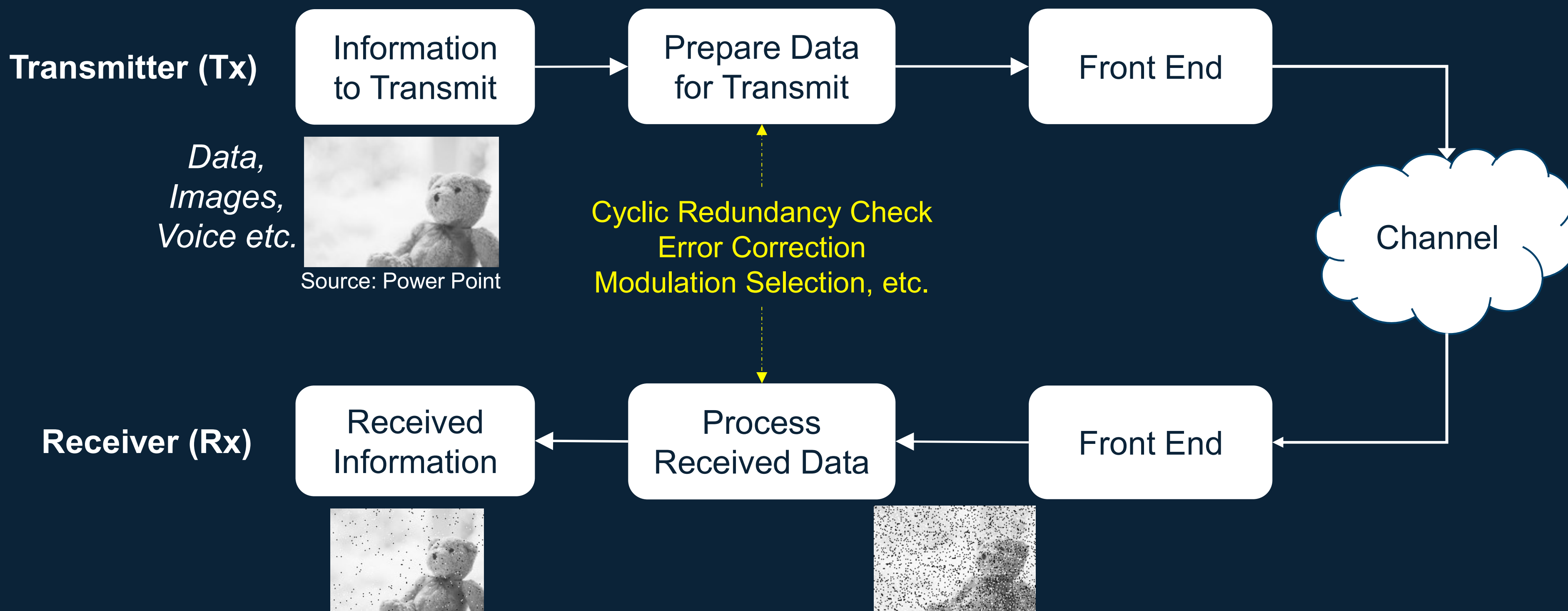
- 6G will attempt to minimize latency while supporting many more devices and with improved data rates compared to 5G

- 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



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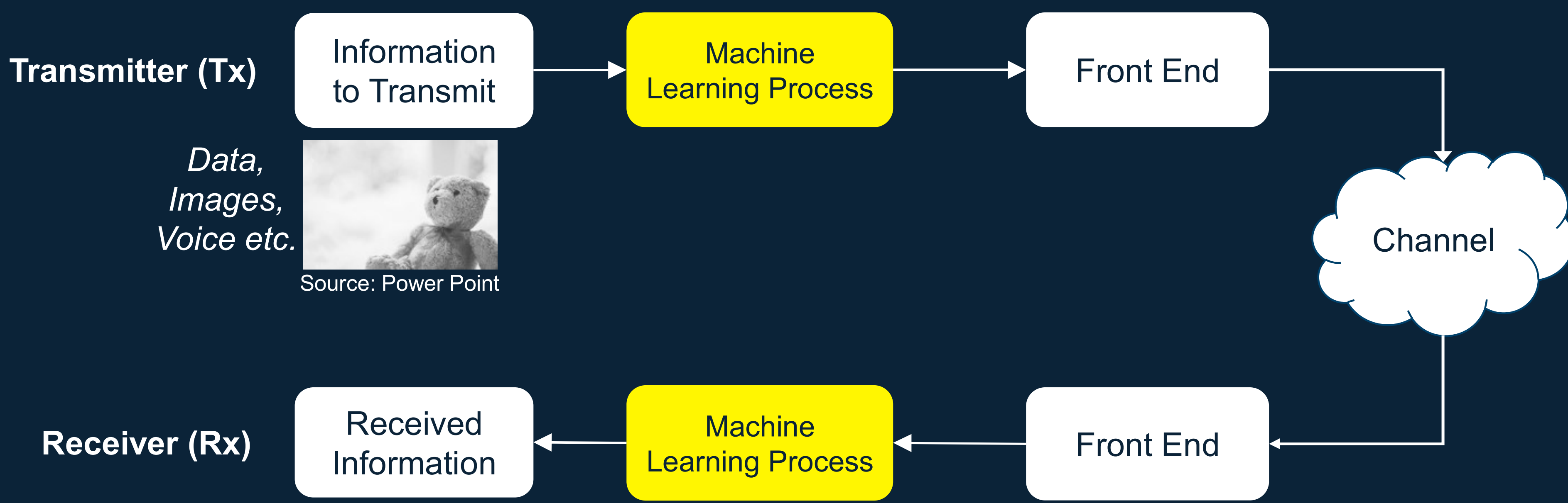
Emerging Technology: Using Machine Learning at the Physical Layer

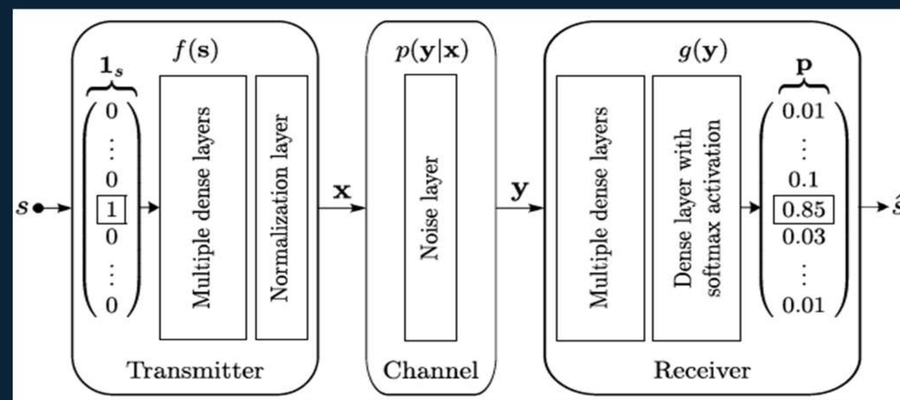
In recent years, Machine Learning (ML) has been explored to prepare data for transmission and processing at the receiver



Physical Layer Design with Machine Learning

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



Source: *An Introduction to Deep Learning for the Physical Layer,* O'Shea and Hoydis, 2017

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?

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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**

Major factors	6G	5G
Peak data rate	> 100Gb/s	10[20] Gb/s
User experience data rate	> 10Gb/s	1Gb/s
Traffic density	> 100Tb/s/km^2	10Tb/s/km^2
Connection density	> 10million/km^2	1million/km^2
Delay	< 1ms	ms level
Mobility	> 1000km/h	350km/h
Spectrum efficiency	> 3x relative to 5G	3~5x relative to 4G
Energy efficiency	> 10x relative to 5G	1000x relative to 4G
Coverage percent	> 99%	About 70%
Reliability	> 99.999%	About 99.9%
Positioning precision	Centimeter level	Meter level
Receiver sensitivity	< −130dBm	About −120dBm

Table from: Chen *et al.*, "Vision, requirements, and technology trend of 6G: How to tackle the challenges of system coverage, capacity, user data-rate and movement speed," IEEE Wireless Communications, vol. 27, no. 2, pp. 218--228, 2020.

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

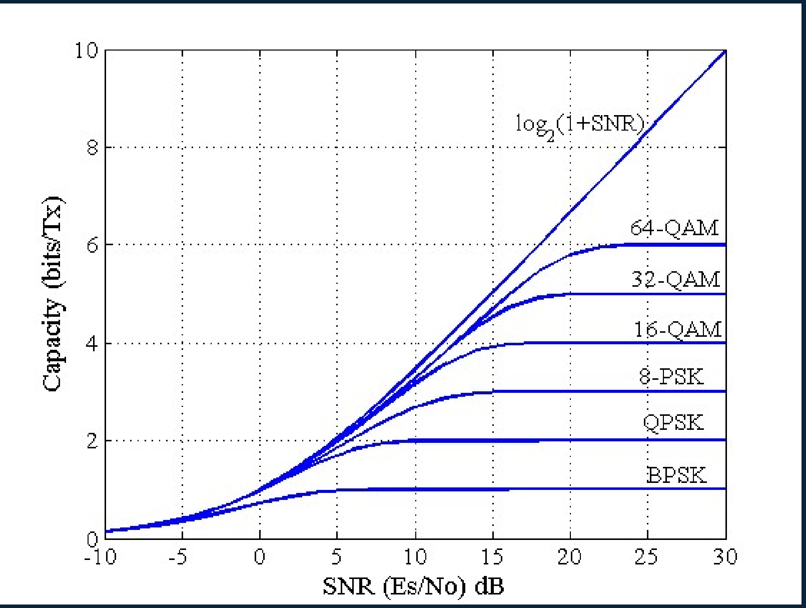
High-Level Findings

- 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?

Capacity limits for an AWGN Channel for different modulations



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

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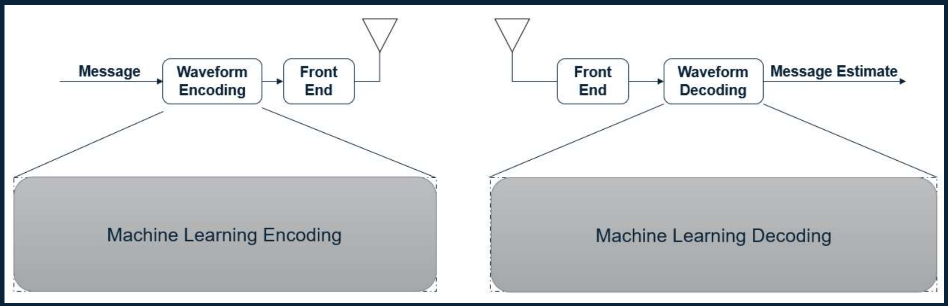
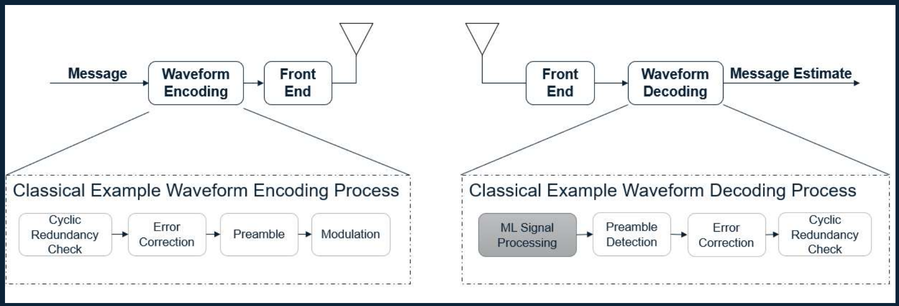
Three Applications of Interest

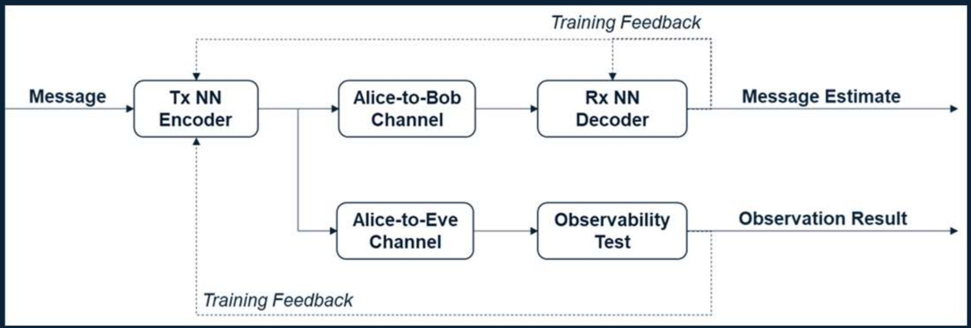
End-to-End System Design



Receiver Processing



Applying Supplemental Constraints



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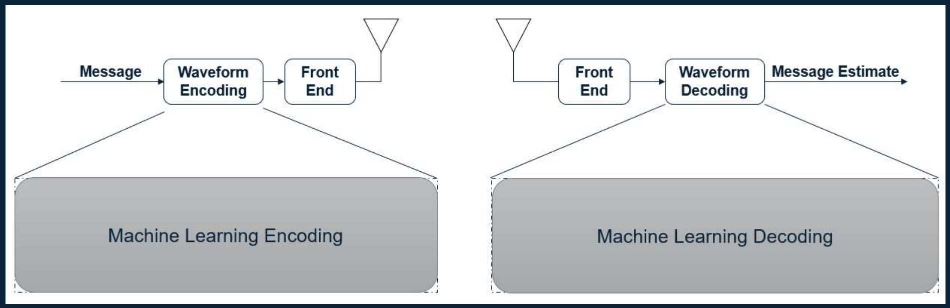

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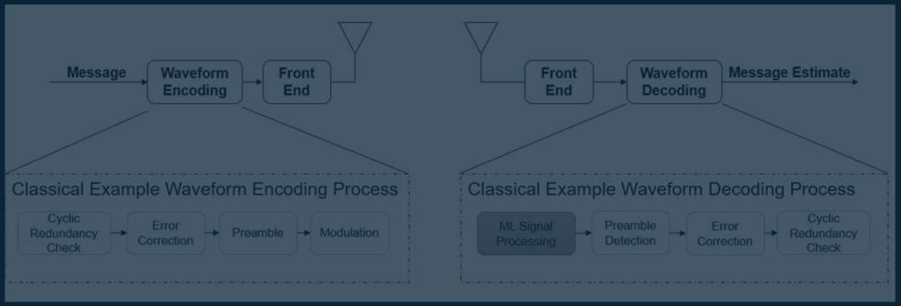

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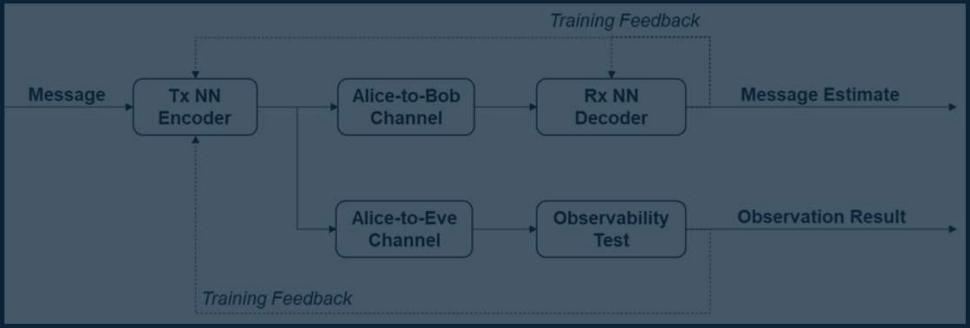

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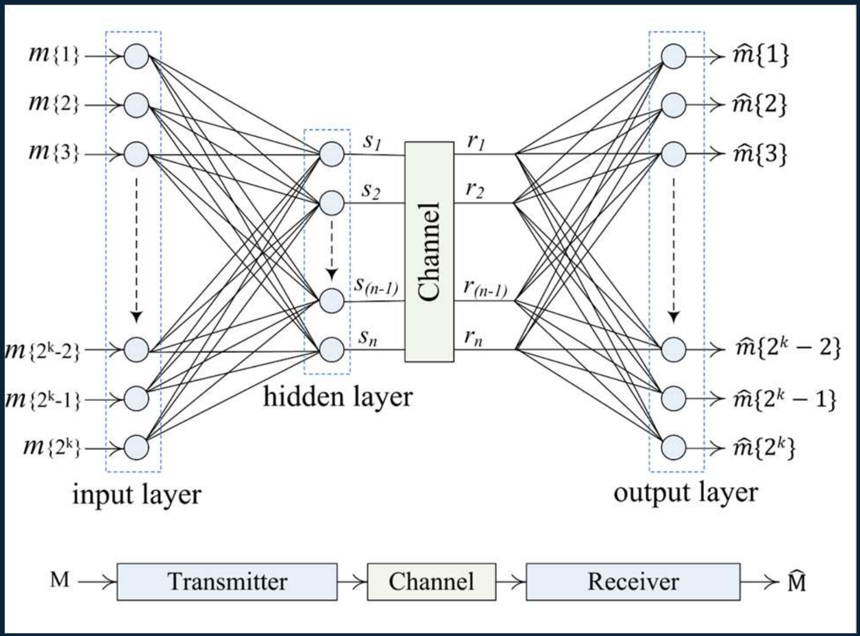
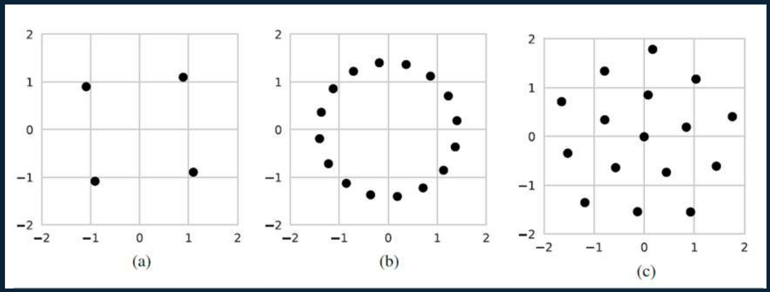
End-to-End Learning

- **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

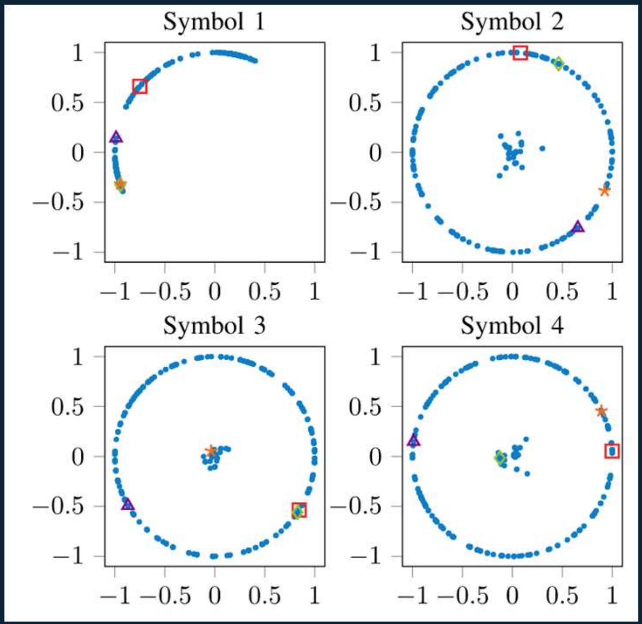


Source: *Machine Learning Based Featureless Signaling,* Ismail Shakeel, 2018

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).



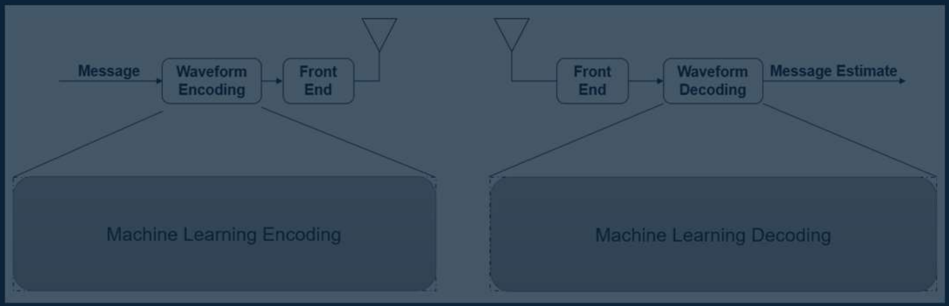
ML design: 4 sequential time slots to transmit 4 symbols. Each 8-bit message maps to a unique sequence of 4 symbols. Markers show the symbols selected for 4 sample messages. 256 total possible sequences. (Dorner, 2018)

Key Takeaways:

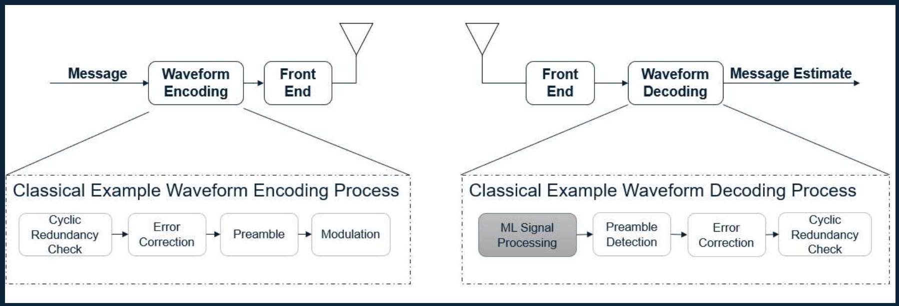
- End-to-End learning may outperform conventional waveform design
- Some papers consider offsets but reliability testing needed
- Designers must be aware of practical limitations to extend simulations to real-time implementations

Three Applications of Interest

End-to-End System Design



Receiver Processing



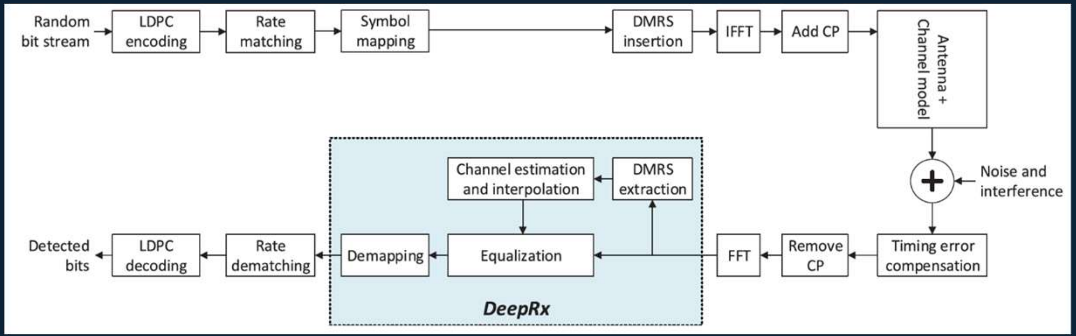
Applying Supplemental Constraints

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

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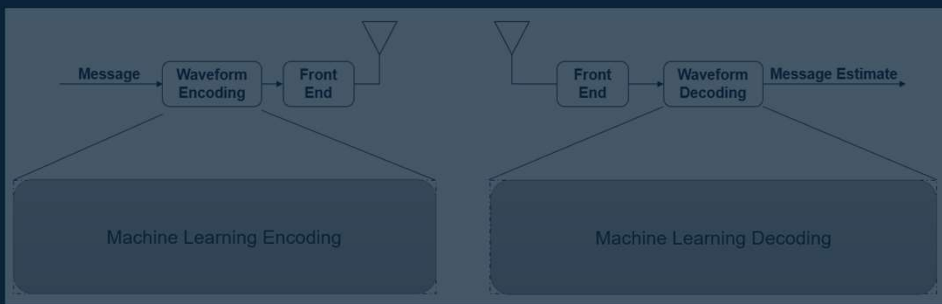

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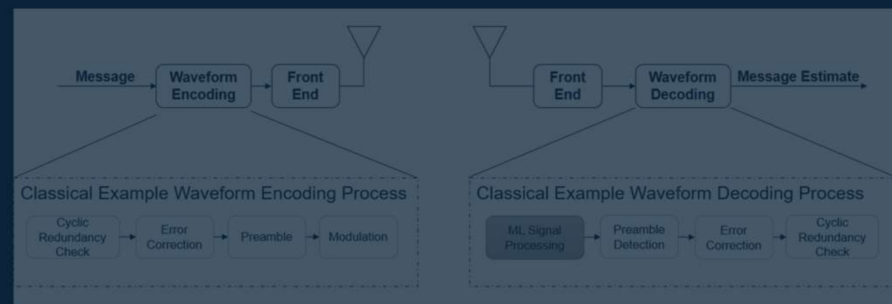
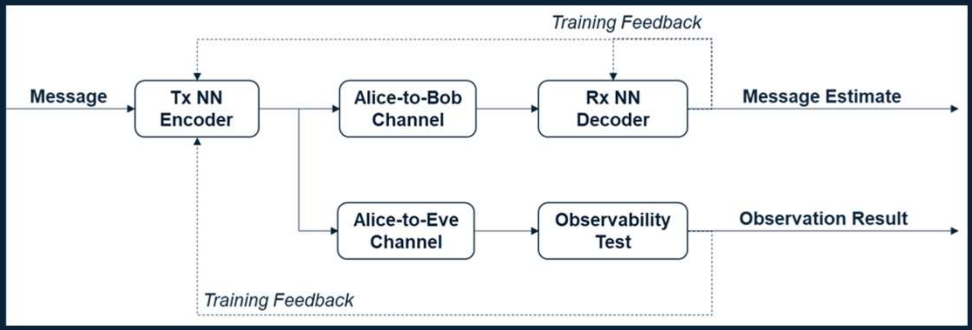


Applying Supplemental Constraints



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

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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

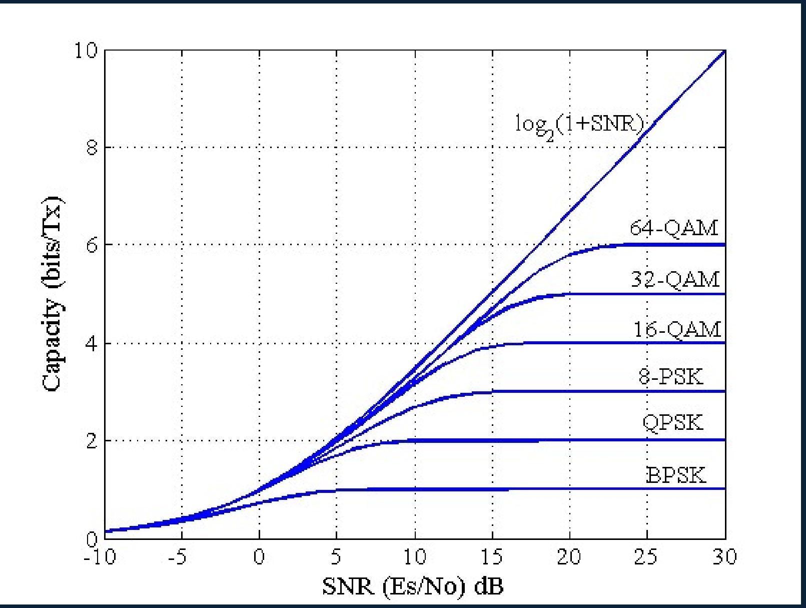
Hurdles

- 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

Capacity limits for an AWGN Channel for different modulations



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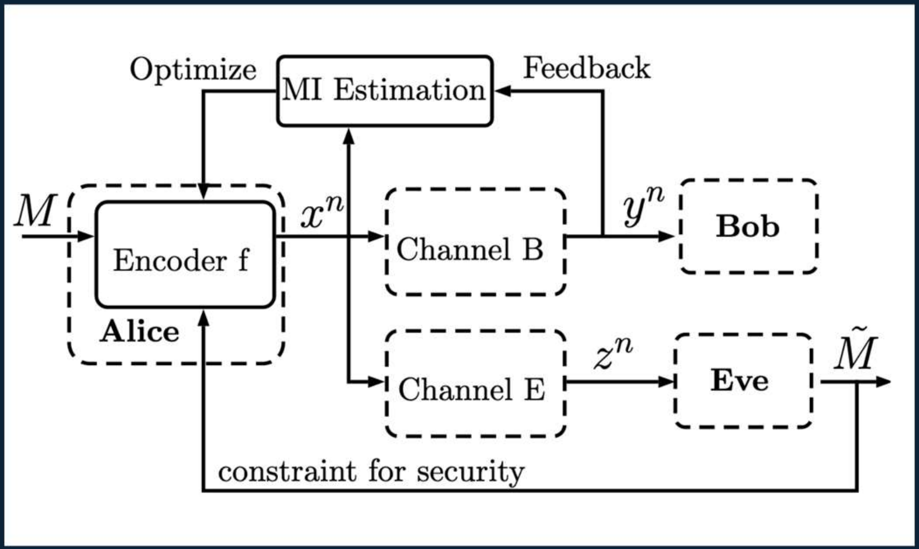
Backups

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*)

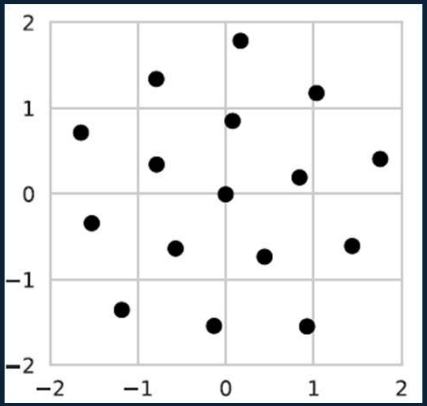


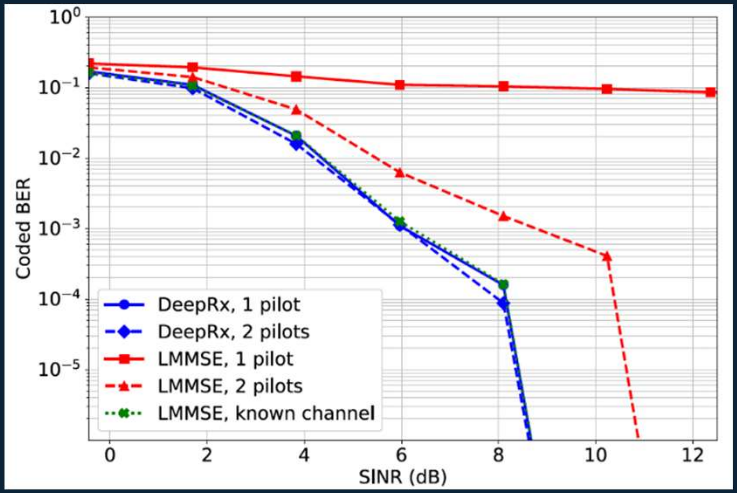
Source: *Deep Learning Based Wiretap Coding via Mutual Information Estimation,* Rick Fritschek *et al.*, 2020

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**


ML-Designed Constellation



BER of an ML-designed Receiver (Blue) vs Traditional

Tradeoffs

- **Performance:**
  Theoretical limits to transmit information over channels
- **Convergence and Explainability:**
  How well can we explain results of ML or reproduce results?
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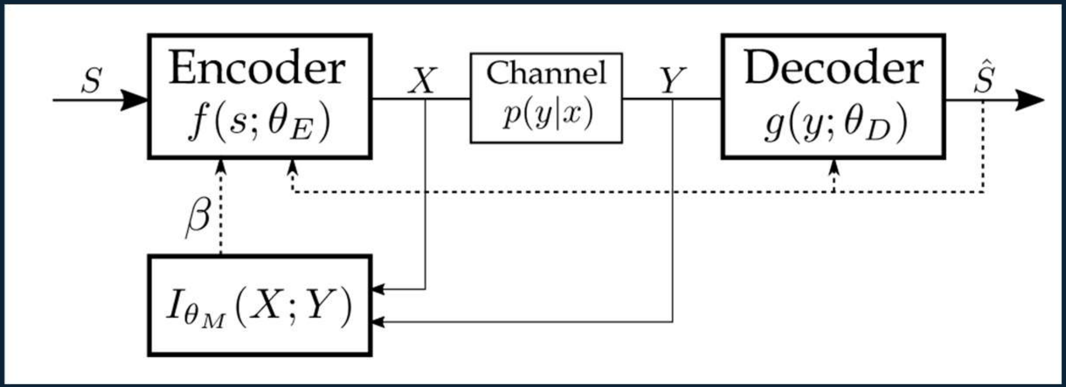

Source: *Capacity-Driven Autoencoders for Communications,* Letizia and Tonello, 2021