Learning to Communicate
From Theory to Practical Over-the-Air Transmission

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NOKIA Bell Labs

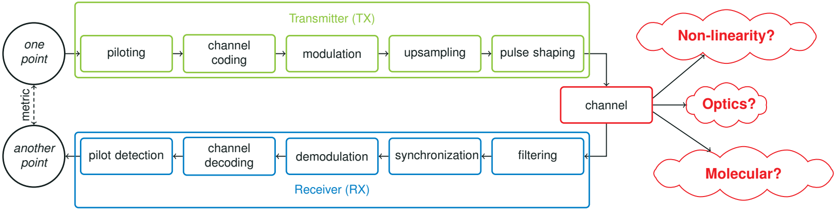
"The fundamental problem of communication is that of reproducing at one point either exactly or approximately a message selected at another point." — Claude E. Shannon, 1948

Outline

Agenda

1. Motivation
2. Learning to Communicate: The Autoencoder
3. From Theory to Practical Over-the-Air Transmission
4. Results for Over-the-air Transmission
5. Conclusion

How it is done today?

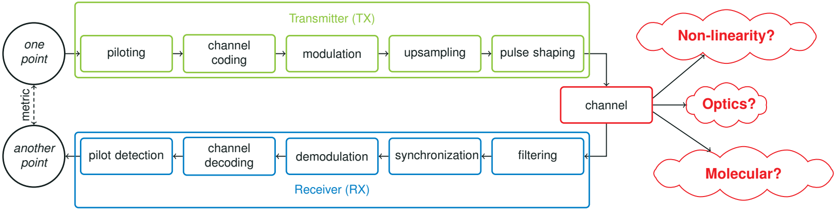


Block-based engineering design

- Independently optimized blocks for specific tasks

→ **Optimality requires many (strong) assumptions!**

How it is done today?



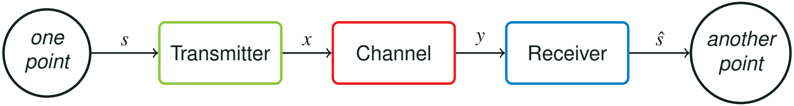
Block-based engineering design

- Independently optimized blocks for specific tasks

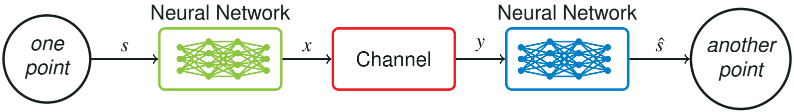
→ **Optimality requires many (strong) assumptions!**

Can we build a system that *learns* to communicate?

The End-to-End Learning Idea



The End-to-End Learning Idea

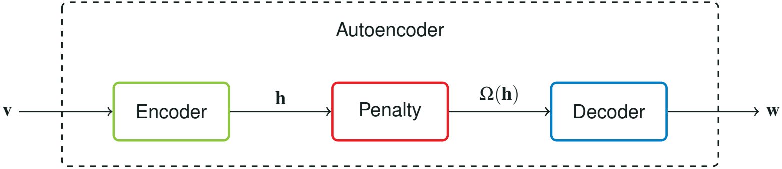


Replace transmitter and receiver by deep neural networks

- No underlying block structure
- All signal processing needs to be learned
- **End-to-end learning**
  - Train to minimize most relevant *end-to-end* metric (e.g., error rate or mutual information)

Agenda

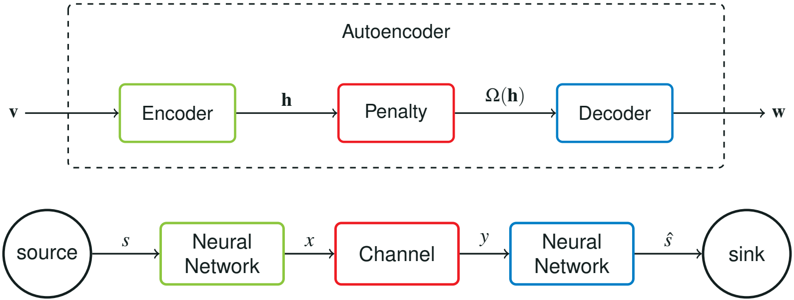
Autoencoder Neural Network



The autoencoder network as communication system

- Perfect fit: channel as penalty layer
- Transmitter is trained to find robust signal x
- Receiver must be able to decode signal y
- System can be trained end-to-end

Autoencoder Neural Network



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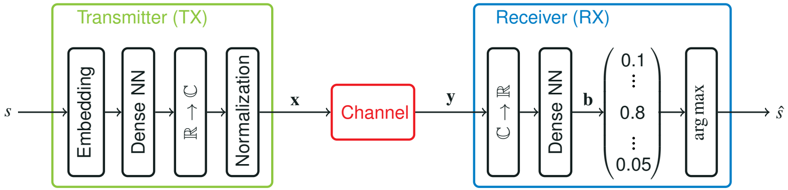
Autoencoder Layer Structure



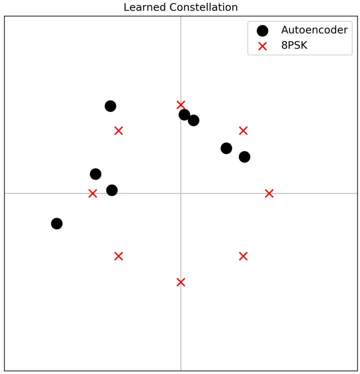
Transmitter Neural Network

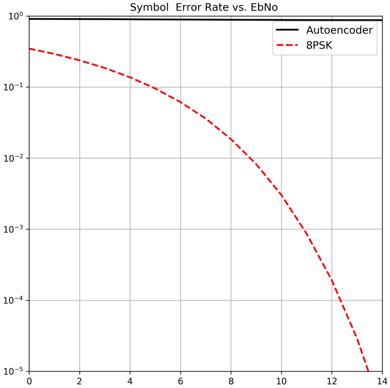
- Input: message $s \in \mathbb{M} = \{1, 2, \ldots, M\}$
- Output: normalized complex symbol sequence $\mathbf{x}$

Receiver Neural Network

- Input: complex sample sequence $\mathbf{y}$
- Output: message $\hat{s} \in \mathbb{M} = \{1, 2, \ldots, M\}$

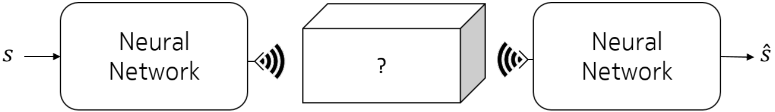
Learning 8-PSK





Agenda

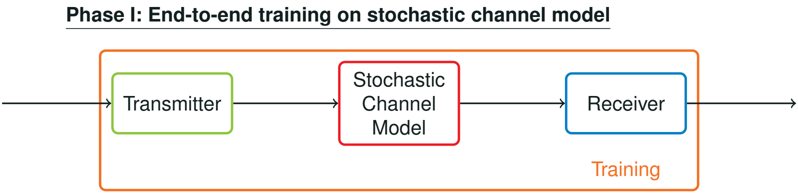
The Gap Between Theory and Practice



- For any real system, the channel is a black box
- Unknown transfer function $\rightarrow$ Gradient backpropagation impossible

$\rightarrow$ ***How can we apply the concept to a real system?***

Solution 1: Two-phase Training Strategy

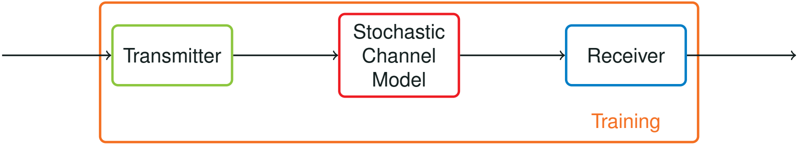


Using a stochastic channel model

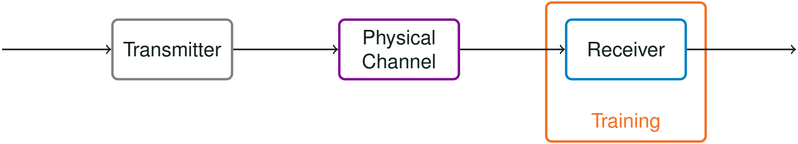
- Described by computable analytic functions
- Must be close to physical channel
- Simple LOS model: phase offset, CFO, SFO and AWGN
- Can be extended (e.g., channel tabs, hardware imperfections)

Solution 1: Two-phase Training Strategy

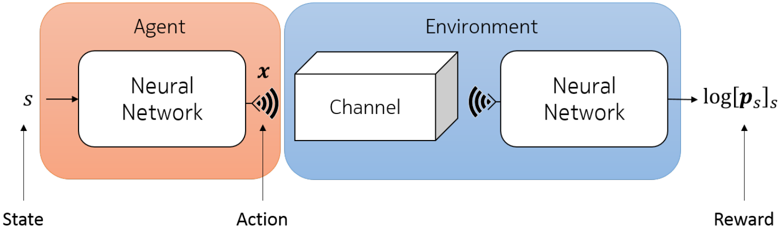
Phase I: End-to-end training on stochastic channel model



Phase II: Receiver finetuning on physical channel



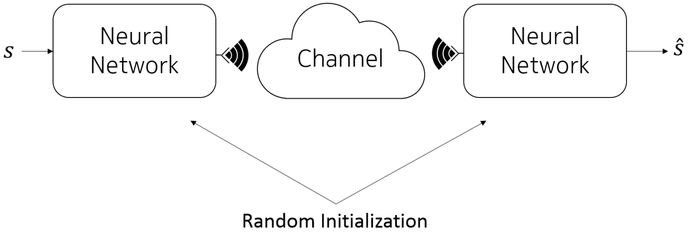
Solution 2: Reinforcement Learning[1]



- The transmitter observes the state $s \in \mathcal{M} = [1, \ldots, M]$,
- ...takes the action $\mathbf{x} = f_{\theta_t}(s)$,
- ...and observes the reward $\log\left[\mathbf{p}_s\right]_s \triangleq -l$
- Problem: $\text{argmax}_{\theta_t} \mathbb{E}\left[\log\left[\mathbf{p}_s\right]_s\right] = \text{argmin}_{\theta_t} \ \mathbb{E}\left[l\right]$

[1]F. Aoudia, J. Hoydis. "Model-free Training of End-to-end Communication Systems." arXiv preprint, 2018

Solution 2: Reinforcement Learning[2]



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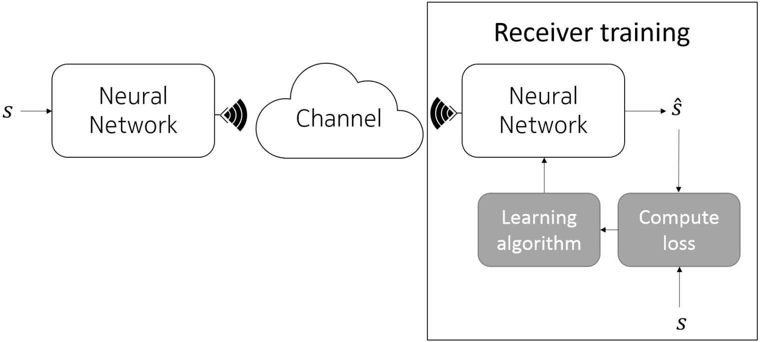

[2] F. Aoudia, J. Hoydis. "Model-free Training of End-to-end Communication Systems." arXiv preprint, 2018

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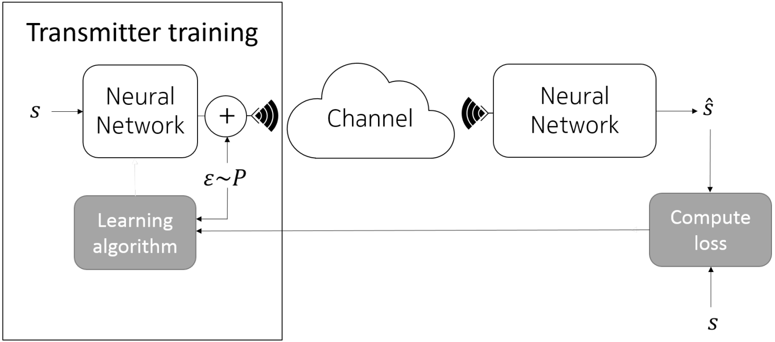

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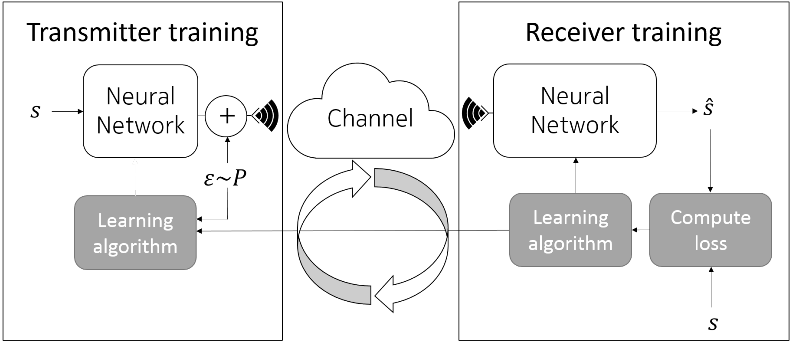

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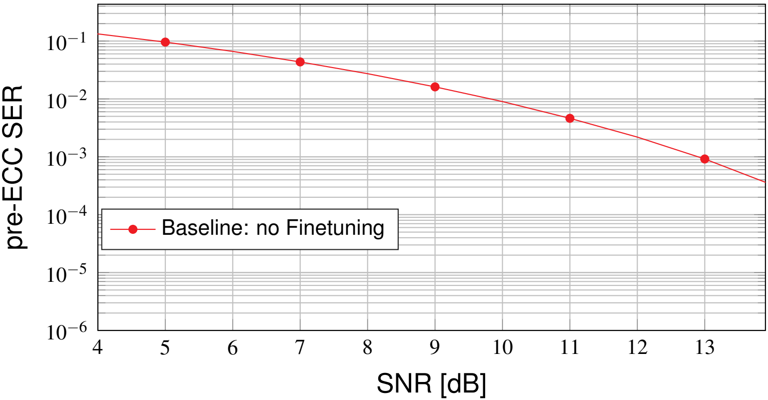
Adaptivity - How to Acquire Training Data?



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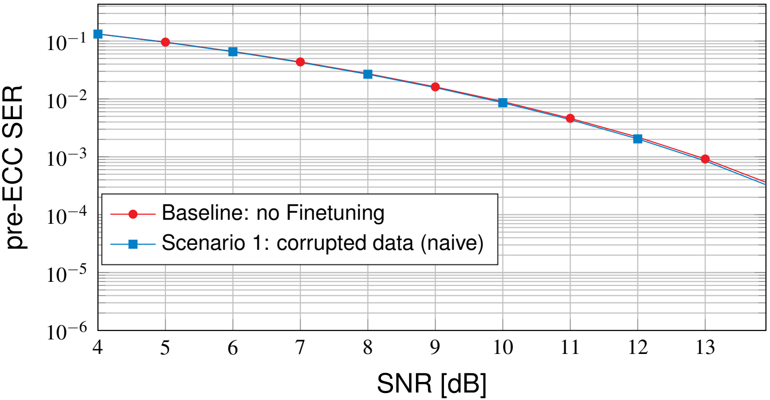

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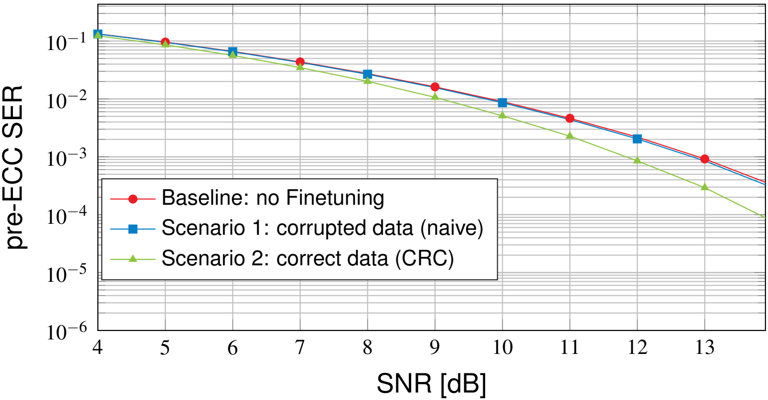

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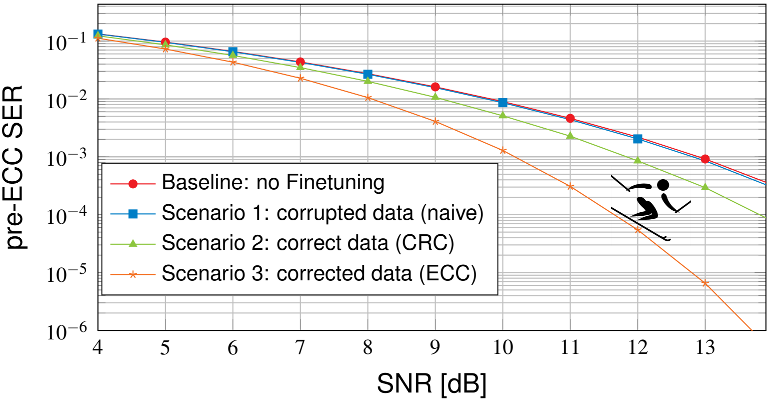
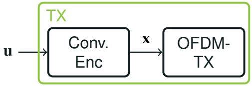


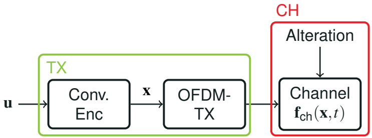
→ ***From errors one learns***

Label Recovery[3]



[3] S. Schibisch et al. "Online Label Recovery for Deep Learning-based Communication through error correcting codes", ISWCS, 2018

Label Recovery[3]



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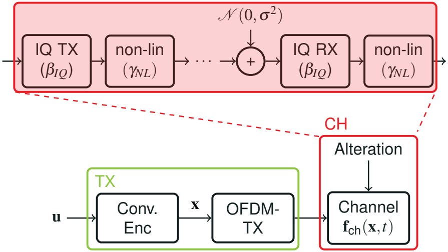

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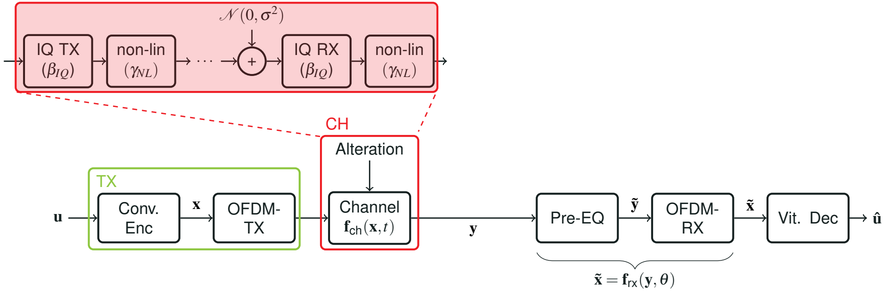

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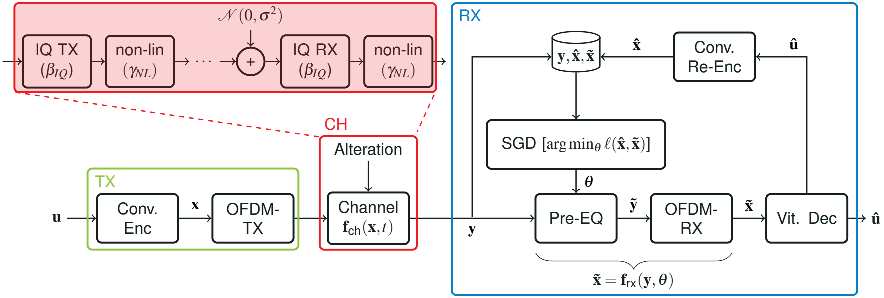

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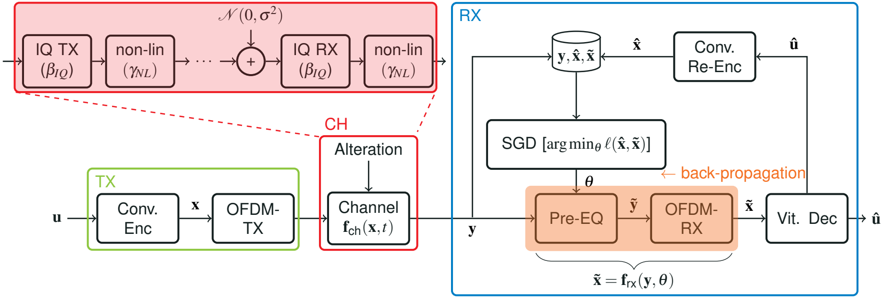

- Physical channel has no gradient (!)
  - → Only receiver can be finetuned

[3] S. Schibisch et al. "Online Label Recovery for Deep Learning-based Communication through error correcting codes", ISWCS, 2018

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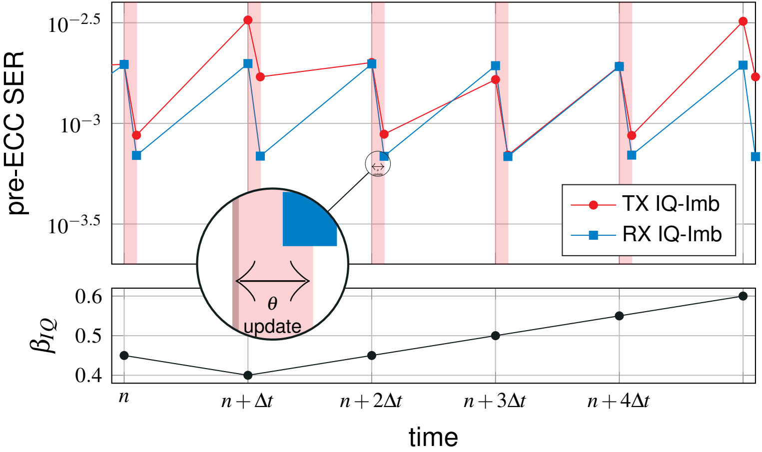
Adaptivity - IQ Imbalance

- SGD-based training is performed on-the-fly:
  - $N_{\Delta t} = 5{,}000$ OFDM symbols per time step Δt



Synchronization Problems [4]

Problem: SFO between Transmitter and Receiver:

- Problem for block-based system $\rightarrow$ messages skipped or repeated $\rightarrow$ insertion and deletion channel
- How to synchronize an AE symbol stream?

[4] S. Dörner et al. "Deep Learning-based Communication Over the Air", IEEE J-STSP, 2018

Synchronization Problems [4]

Problem: SFO between Transmitter and Receiver:

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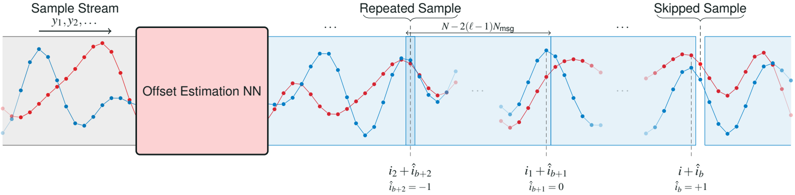
Solution 1: Assisting Offset Estimation Neural Network

- Additional NN can skip or repeat samples



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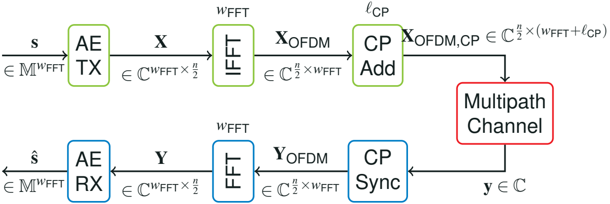
Solution 2: OFDM with cyclic prefix (CP)

- CP allows easy synchronization

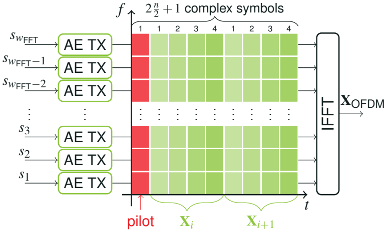


[4] S. Dörner et al. "Deep Learning-based Communication Over the Air", IEEE J-STSP, 2018

OFDM-Extensions [5]

Several advantages:

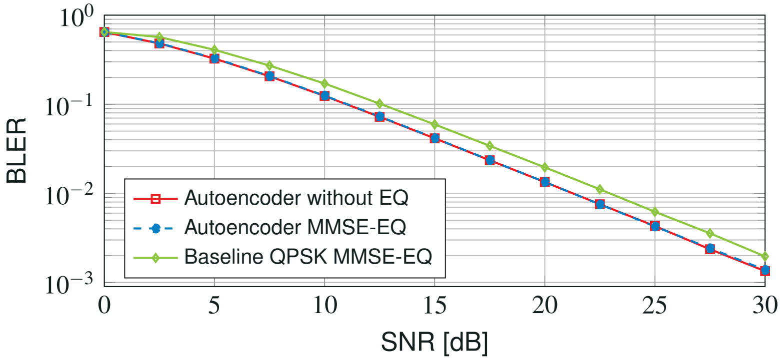
- Robustness against sampling synchronization errors
- Single-tap equalization
- Moderate training complexity (independent sub-carrier modulation)
- Can be embedded in exiting AE setup
- Full compatibility with existing schemes



[5] A. Felix et al. "OFDM-Autoencoder for End-to-End Learning of Communications Systems", SPAWC, 2018

Agenda

Simulated Performance

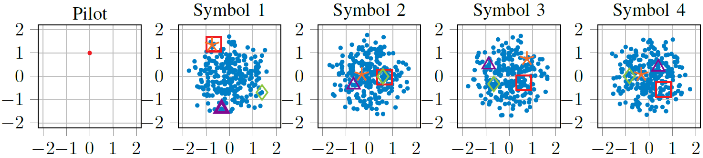


Transmission over 5-tap multi-path channel

- 1 pilot symbol per 8 OFDM symbols
- Autoencoder outperforms QPSK baseline
- Autoencoder *learns* MMSE equalization

Learned IQ-Symbol Constellations

Average Power Normalization (with explicit pilot):



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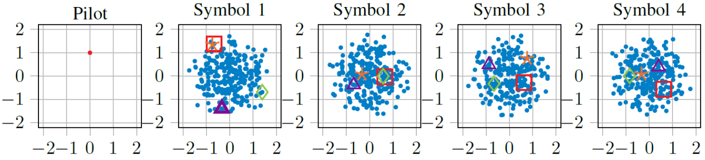
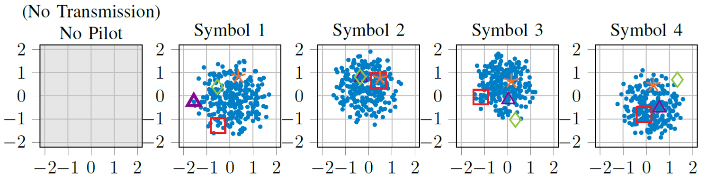
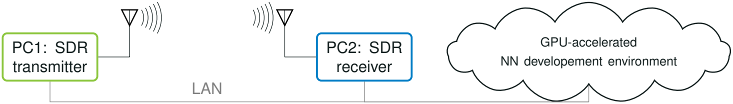


Average Power Normalization (without explicit pilot):



- $\rightarrow$ superimposed pilot

Measurement Setup



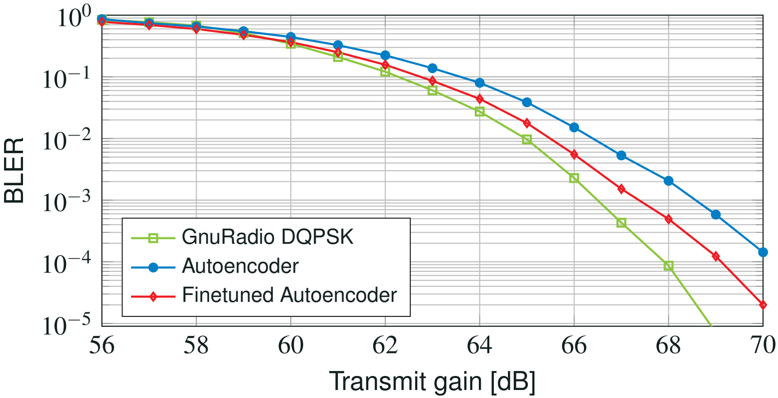
Transmitter and Receiver PCs

- Using USRP software defined radios with GnuRadio
- Connected via LAN to development server

Measurement Process

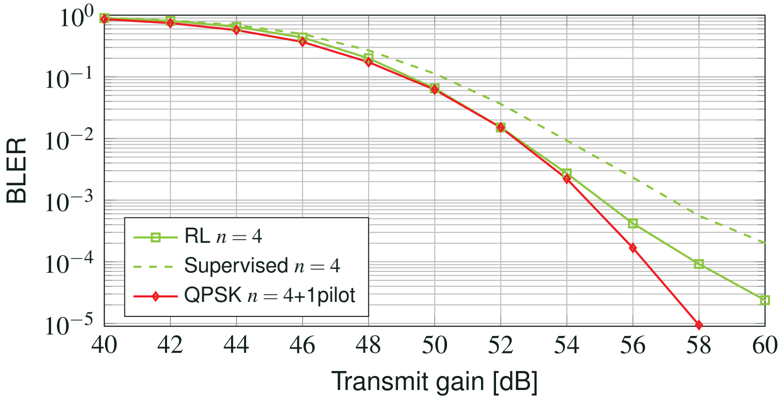
- Transmission of long message sequence by transmitter
- Recording of whole sequence by receiver
- Offline decoding by GPU-accelerated server

Over-the-Air Measurement Results



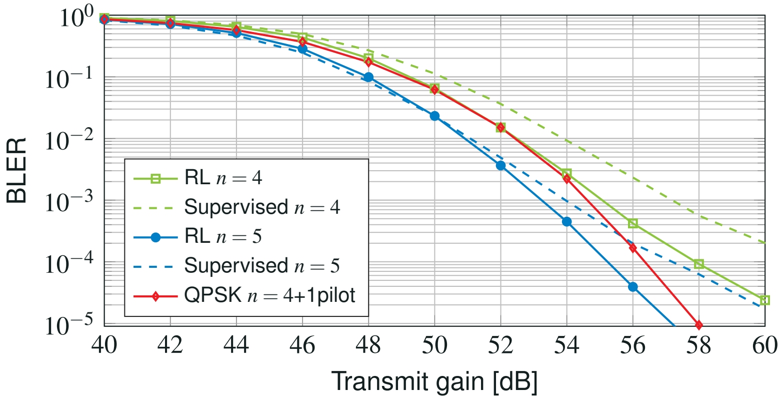
- 46m LOS channel, same information rate and same conditions for GnuRadio DQPSK and AE system
- The setup uses a single-carrier system (no OFDM)

Reinforcement Learning Over-the-Air



- 5m LOS channel, same information rate and same conditions for QPSK and AE system
- OFDM-based system

Reinforcement Learning Over-the-Air



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Conclusion

- World's first over-the-air communication system where signal processing is solely based on neural networks
- Proof of concept as SDR implementation
- Major challenges:
  - Unknown channel gradient → RX finetuning or RL training
  - Training complexity: enhanced network structure
  - How to synchronize? → OFDM-extensions
- Future steps:
  - Theoretical analysis: how *good* is the system really? Spectral efficiency?

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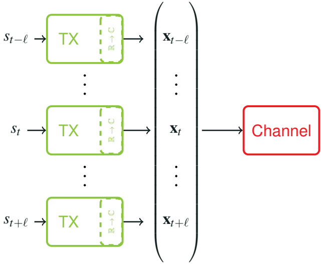
Thank you for your attention!

For details:

- S. Dörner, S. Cammerer, J. Hoydis, S. ten Brink, "Deep Learning-based Communication Over the Air", arXiv:1707.03384, 2017
- Google Colab Notebook - Autoencoders - Learning to communicate

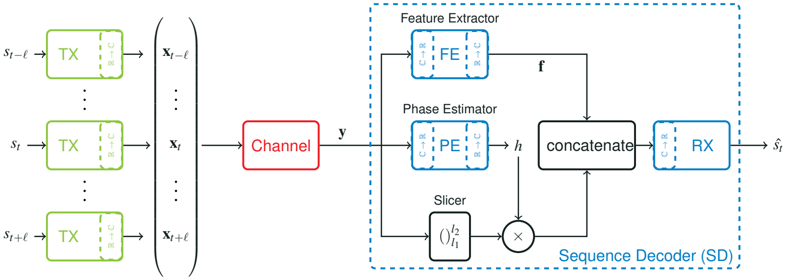
Upgrade to Sequence Autoencoder



Temporal Extension

- Problem: temporal dependencies (message s_t influenced by messages s_{t-1} and s_{t+1})
- Solution: multiple transmitter outputs concatenated

Upgrade to Sequence Autoencoder



Receiver Extension

- FE: extract features on sequence including multiple messages
- PE: estimate phase on sequence including multiple messages
- expert knowledge: complex phase shift by estimated phase h
- $\rightarrow$ same concept but more *sophisticated* receiver-NN

Dealing with Sample Frequency Offset

Problem: SFO between Transmitter and Receiver:

- more or less samples recorded than transmitted
- problem for block-based system → messages skipped or repeated → insertion and deletion channel

Solution: Assisting Offset Estimation Neural Network

- can skip or repeat samples

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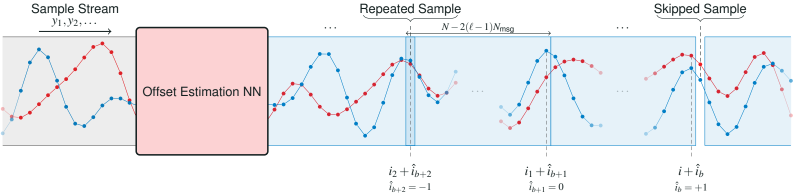

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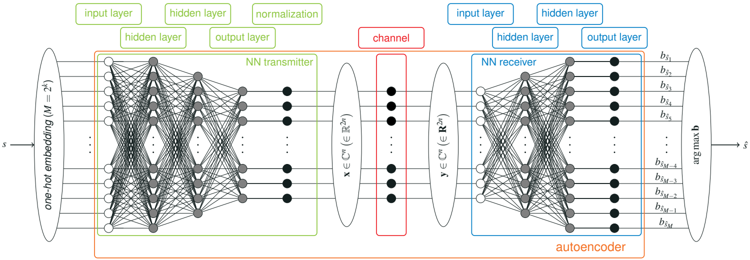
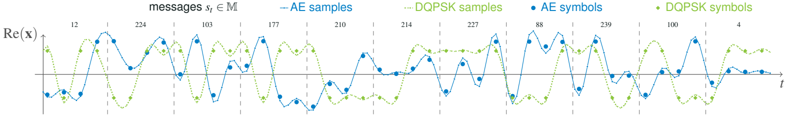
Autoencoder NN Layer Structure

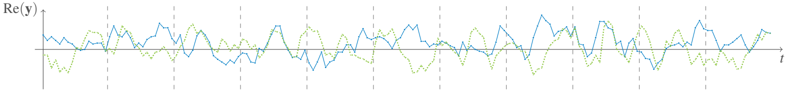


Physical Layer Signals

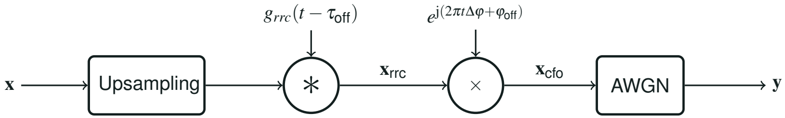
Sent Sample Sequence:



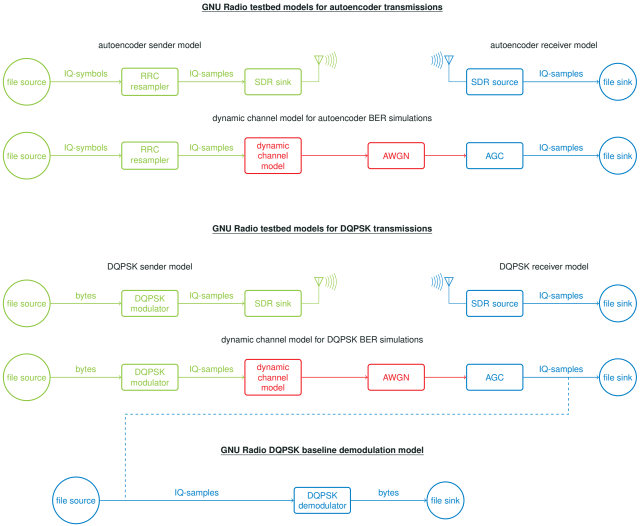
Received Sample Sequence:



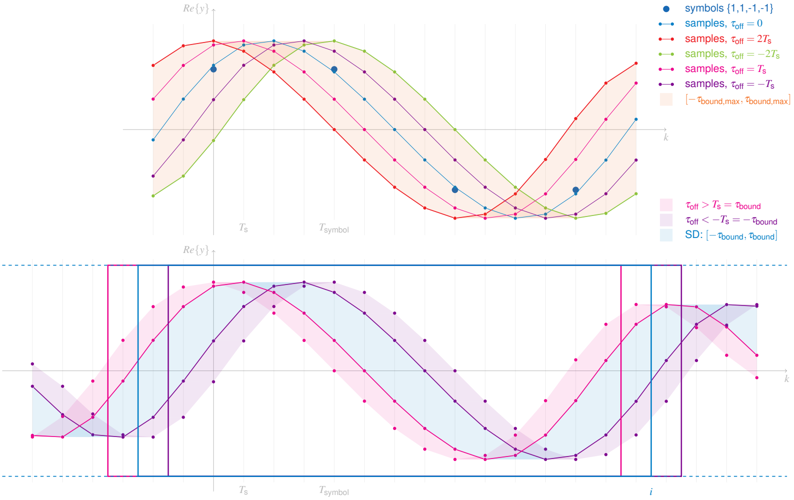
Synthetic LOS Channel Model



GnuRadio Measurement Setup



Sample Frequency Offset Impact



OE's decision impact to an exemplary window slice of length $N_{\text{seq}} = 17$:

skip offset $\hat{i} = 1$ | **no offset** $\hat{i} = 0$ | **repeat sample** $\hat{i} = -1$

Development Server Setup