A Learning Approach to Cooperative Communication System Design

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Outline

1. Background and Motivation
2. Relay-Assisted Cooperative Communication System
3. Learning the Cooperative System
4. Simulation Results
5. Conclusion

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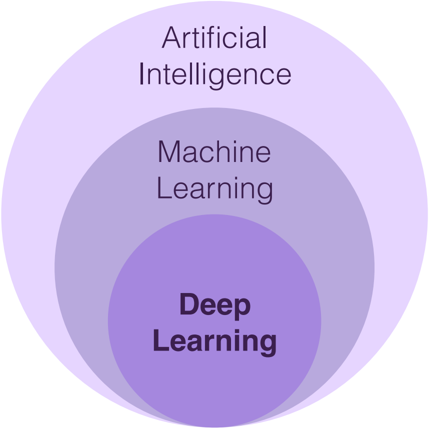
Deep Learning



- Deep learning (DL) is a branch of machine learning ⇒ Learn to make own decisions
- Structures algorithms in **layers** ⇒ Create an "artificial neural network"

Deep Learning in Communication

- Conventional communication system is optimized in a **block-wise** manner:
  source/channel coding, modulation, demodulation, source/channel decoding, equalization

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- Deep learning techniques have been applied to replace certain blocks: channel coding/estimation

Individualized component-wise approach might not optimize the overall system function!

Deep Learning in Communication

Can we optimize the communication system in a holistic manner?

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- Joint design of the transmitter and receiver over the channel
- Expand the optimization space
- ...

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- Joint design of the transmitter and receiver over the channel
- Expand the optimization space
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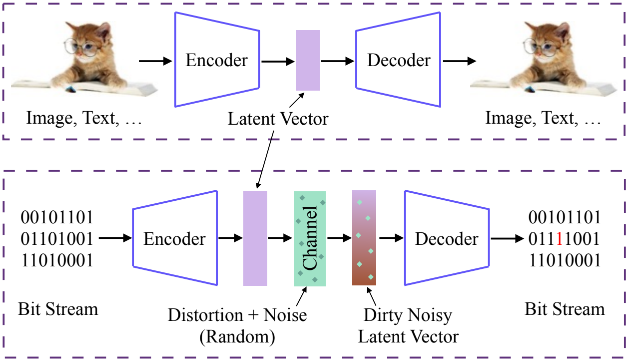
Yes. Communication **Autoencoder**!

- Transmitter and receiver are represented by neural networks (NNs)
- Promising results have been obtained

Autoencoder

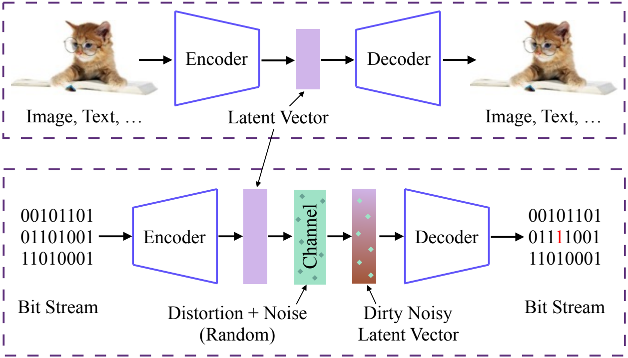
- General autoencoder (AE) learns data structure to compress (top)



General autoencoder (top) v.s. Communication autoencoder. Figure Credit: Zhao, Vuran, Guo and Scott

Autoencoder

- General autoencoder (AE) learns data structure to compress (top)



General autoencoder (top) v.s. Communication autoencoder. Figure Credit: Zhao, Vuran, Guo and Scott

- Communication AE learns the channel behavior to improve transmission accuracy

Autoencoder

Most existing applications are for point-to-point communications

More Complicated Scenarios

Can we design an AE to optimize more complicated communication scenarios?

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Our focus: **Relay-assisted cooperative communication system**

Existing Works for AE+Relay

Constellation design for two-way relay networks[1]

⇒ Focused on constellation optimization. **No detection algorithm** was addressed

[1] T.Matsumine, T.Koike-Akino, and Y.Wang, "Deep learning-based constellation optimization for physical network coding in two-way relay networks," *arXiv preprint arXiv:1903.03713*, Mar. 2019.

Existing Works for AE+Relay

Constellation design for two-way relay networks[1]

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Our focus: **Joint optimization of the constellation and detection algorithm**

Start with a one-way relay network

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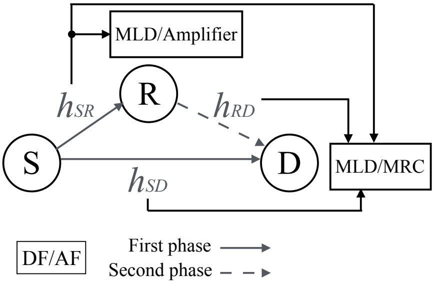
System Model



System model of a 3-node relay network.
Source (S), Relay (R), Destination (D)

- R: half-duplex
- Source message: $m_S \in \{1, 2, \cdots, 2^k\}$, encoded as $\mathbf{x}_S$ of length n
- k/n bits/independent channel uses

System Model

- First Phase:

$$\mathbf{y}_{SJ} = \sqrt{E_S}\mathbf{h}_{SJ}\mathbf{x}_S + \mathbf{n}_{SJ},\ J \in \{R, D\}, \tag{1}$$

E_S: average source transmit energy
$\mathbf{h}_{SJ}$: channel coefficient
$\mathbf{n}_{SJ}$: Gaussian noise vector $\mathcal{CN}(0, 2\sigma^2_{SJ}\mathbf{I})$

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- Second Phase:

$$\mathbf{y}_{RD} = \sqrt{E_R}\mathbf{h}_{RD}\mathbf{x}_R + \mathbf{n}_{RD}, \tag{2}$$

E_R: average relay transmit energy
$\mathbf{h}_{RD}$: channel coefficient
$\mathbf{n}_{RD}$: Gaussian noise vector $\mathcal{CN}(0, 2\sigma^2_{RD}\mathbf{I})$

AF Relaying

- AF relay node:
  - Symbol-wise amplifying operation $x_R = \frac{y_{SR}}{\sqrt{P_S |h_{SR}|^2 + 2\sigma_{SR}^2}}$, $x_R \in \mathbf{x}_R$, $y_{SR} \in \mathbf{y}_{SR}$, $h_{SR} \in \mathbf{h}_{SR}$
  - Drawback: noise amplification $\Leftarrow \mathbf{y}_{SR} = \sqrt{E_S}\mathbf{h}_{SR}\mathbf{x}_S + \mathbf{n}_{SR}$

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  - Drawback: noise amplification $\Leftarrow \mathbf{y}_{SR} = \sqrt{E_S}\mathbf{h}_{SR}\mathbf{x}_S + \mathbf{n}_{SR}$
- Destination:
  - Maximal-ratio combining (MRC)
  - Optimal in the context of AF
  - High complexity: $\mathcal{O}(n \cdot 2^k)$ per block

DF Relaying

- DF relay node:
  - Maximum-likelihood decoding (MLD) $\mathbf{x}_R = \arg\min_{\mathbf{x}\in\mathcal{C}} \|\mathbf{y}_{SR} - \mathbf{h}_{SR}\sqrt{E_S}\mathbf{x}\|^2$, where $\mathcal{C}$ is code book, $|\mathcal{C}| = 2^k$.
  - Drawback: hard decision $\Rightarrow$ information loss

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  - Drawback: hard decision $\Rightarrow$ information loss
- Destination:
  - Near-optimal decoder (NOD)
    $\arg\max_{\mathbf{x}_S\in\mathcal{C}} \Pr(\mathbf{y}_{SD}|\mathbf{x}_S) \sum_{\mathbf{x}_R\in\mathcal{C}} \Pr(\mathbf{x}_S \to \mathbf{x}_R) \Pr(\mathbf{y}_{RD}|\mathbf{x}_R)$
  - Near-optimal in the context of DF
  - High complexity: $\mathcal{O}(n \cdot 2^k \cdot 2^k)$ per block

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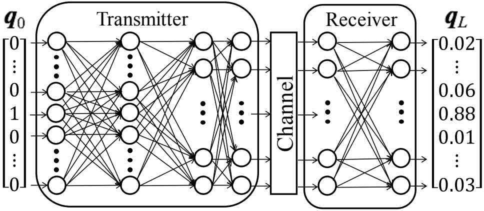
A typical AE



A typical AE for a point-to-point communication system

- Input: one-hot encoding, e.g., $\{00, 01, 11, 10\} \mapsto \{1000, 0100, 0010, 0001\}$

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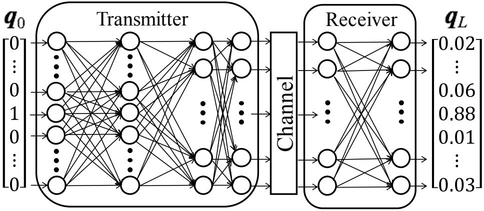


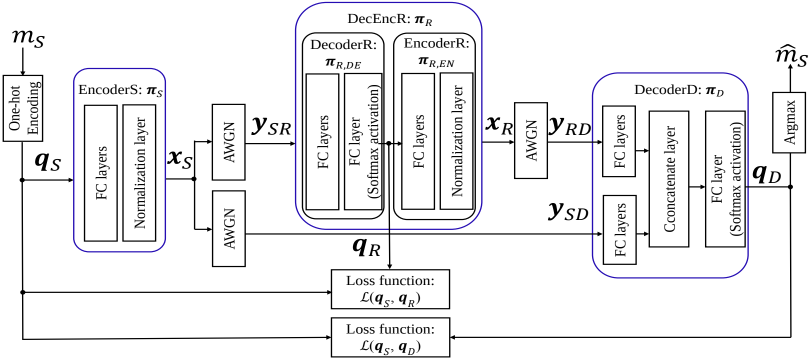
A typical AE for a point-to-point communication system

- Input: one-hot encoding, e.g., $\{00, 01, 11, 10\} \mapsto \{1000, 0100, 0010, 0001\}$
- Output: softmax, i.e., $\phi(\mathbf{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{k} e^{z_j}}$, $i = 1, 2, \ldots, k$ and $\mathbf{z} = [z_1, z_2, \ldots, z_k] \in \mathbb{R}^k$

Proposed AE Structure

$\mathbf{q}_R$: soft probability

Advantage: eliminate noise amplification and hard decision



Block diagram of the proposed AE for the cooperative communication system

End-to-End Loss

- Expected loss (a large number of data sets)

$$L_{SD}(\boldsymbol{\pi}_S, \boldsymbol{\pi}_R, \boldsymbol{\pi}_D) = \mathbb{E}_{\mathbf{q}_S}[\mathcal{L}(\mathbf{q}_S, \mathbf{q}_D)] \tag{3}$$

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- Estimated through sampling

$$L_{SD}(\boldsymbol{\pi}_S, \boldsymbol{\pi}_R, \boldsymbol{\pi}_D) \triangleq \frac{1}{B}\sum_{i=1}^{B} \mathcal{L}(\mathbf{q}_{S,i}, \mathbf{q}_{D,i}) \tag{4}$$

B: batch size
$\{\mathbf{q}_{S,i}, \mathbf{q}_{D,i}\}$: the i-th input output pair of training sample

Objective

$$\textbf{(P1)} \quad \min_{\boldsymbol{\pi}_S, \boldsymbol{\pi}_R, \boldsymbol{\pi}_D} \quad L_{SD}(\boldsymbol{\pi}_S, \boldsymbol{\pi}_R, \boldsymbol{\pi}_D)$$

Proposed AE

How to design the training algorithm?

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A desirable way: directly train the whole model to minimize L_{SD}

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Experimental results **Do Not** demonstrate a favorable performance

Proposed AE

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A desirable way: directly train the whole model to minimize L_{SD}

Experimental results **Do Not** demonstrate a favorable performance

A novel training algorithm is required!

A Two-Stage Training Scheme

$$\{\boldsymbol{\pi}_S, \boldsymbol{\pi}_R, \boldsymbol{\pi}_D\} \Rightarrow \{\boldsymbol{\pi}_S, \boldsymbol{\pi}_{R,DE}, \boldsymbol{\pi}_{R,EN}, \boldsymbol{\pi}_D\} \tag{5}$$

A Two-Stage Training Scheme

$$\{\boldsymbol{\pi}_S, \boldsymbol{\pi}_R, \boldsymbol{\pi}_D\} \Rightarrow \{\boldsymbol{\pi}_S, \boldsymbol{\pi}_{R,DE}, \boldsymbol{\pi}_{R,EN}, \boldsymbol{\pi}_D\} \tag{5}$$

(P2) First stage: $\min_{\boldsymbol{\pi}_S, \boldsymbol{\pi}_{R,DE}} \quad L_{SR}(\boldsymbol{\pi}_S, \boldsymbol{\pi}_{R,DE})$

Second stage: $\min_{\boldsymbol{\pi}_{R,EN}, \boldsymbol{\pi}_D} \quad L_{SD}(\boldsymbol{\pi}_{R,EN}, \boldsymbol{\pi}_D)$

Training SNR

- Fixed SNR: γ
- Mixed SNR: $\gamma \in \{\gamma_l, \gamma_l + \Delta, \cdots, \gamma_u - \Delta, \gamma_u\}$

Training Algorithm

Algorithm 1 Two-stage training of the proposed AE model

Input Number of channel uses n, number of information bits (per message) k; SNR parameters Δ, γ_l and γ_u

FIRST STAGE: TRAINING OF THE SOURCE-RELAY LINK

Construct a partial model for the source-relay link;
Randomly generate $\gamma_{SR} \in \{\gamma_l, \gamma_l + \Delta, \cdots, \gamma_u - \Delta, \gamma_u\}$;
Train this partial model to minimize $L_{SR}(\boldsymbol{\pi}_S, \boldsymbol{\pi}_{R,DE})$;
Save EncoderS and DecoderR;

SECOND STAGE: TRAINING OF THE ENTIRE NETWORK

Load EncoderS and DecoderR;
Incorporate the loaded components to construct the complete AE model;
Randomly generate $\gamma_{IJ} \in \{\gamma_l, \gamma_l + \Delta, \cdots, \gamma_u - \Delta, \gamma_u\}$ for $(I, J) \in \{(S, R), (R, D), (S, D)\}$;
Train the proposed AE model to minimize $L_{SD}(\boldsymbol{\pi}_{R,EN}, \boldsymbol{\pi}_D)$;
Obtain EncoderR and DecoderD.

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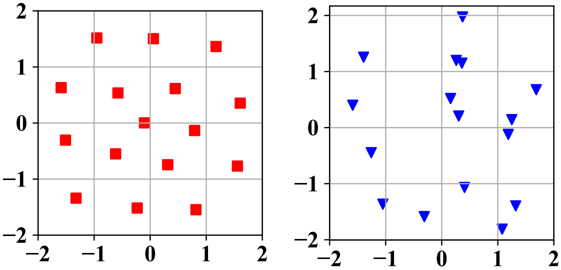
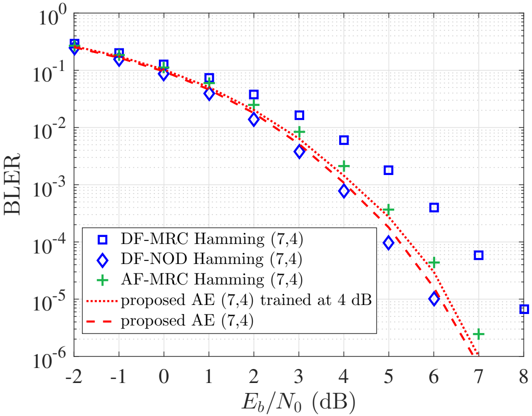
Learned Constellations



Constellations of $\mathbf{x}_S$ (red squares) and $\mathbf{x}_R$ (blue triangles) with an average power constraint for $(n, k) = (2, 4)$

- $\mathbf{x}_S$: APSK-like $\Rightarrow$ Shaping gain
- $\mathbf{x}_R$: Irregular Overlapping Non-conventional

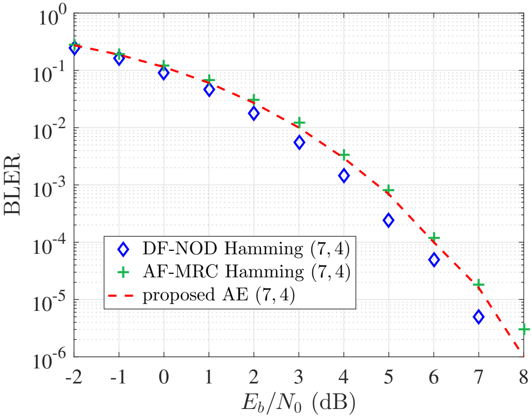
BLER Performance



BLER performance comparison of the proposed AE and the baseline schemes for $(n, k) = (7, 4)$

$\Rightarrow$ Competitive BLER performance

Robustness under Non-Gaussian Channels



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e.g., interference produced by radar signals

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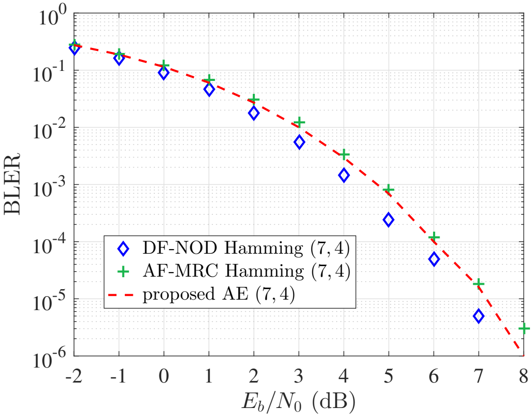

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Scheme	**Noise amplification**	**Hard decision**	**Channel estimation**	**Decoding complexity per block**
DF	No	Yes	Yes	$\mathcal{O}(n \cdot 2^k \cdot 2^k)$
AF	Yes	No	Yes	$\mathcal{O}(n \cdot 2^k)$
AE	No	No	No	$\mathcal{O}(n \cdot 2^k)$

$\Rightarrow$ The proposed AE is a competitive alternative for the conventional relaying techniques DF and AF

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Future works:

A theoretical perspective and performance guarantee need to be provided!

Consider other relay networks, e.g., two-way, full-duplex, ...

Take Away

Carefully designed training algorithm, loss functions, and structure
$\Rightarrow$ AE works

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$\Rightarrow$ AE works

More general scenarios, Theoretical perspective
$\Rightarrow$ a longer journal version of this work :)

Thanks!

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