Neural Compress-and-Forward for the Relay Channel

NYU WIRELESS | NYU TANDON SCHOOL OF ENGINEERING

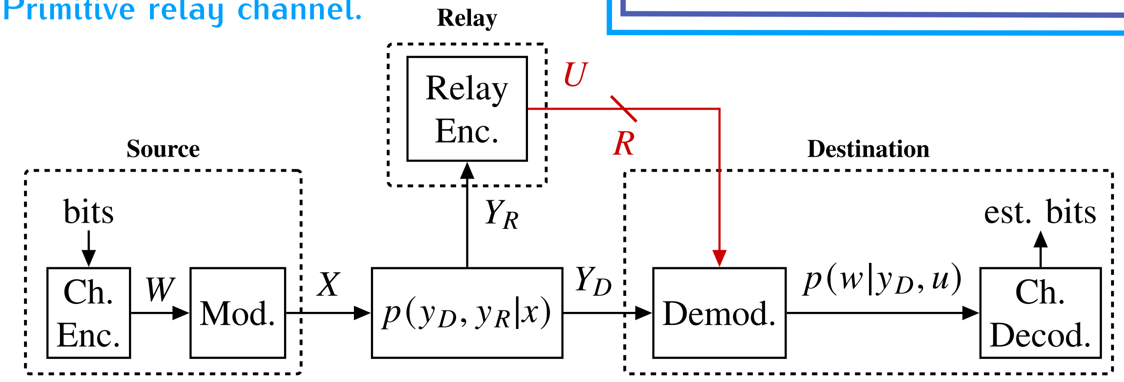
Ezgi Ozyilkan*, Fabrizio Carpi*, Siddharth Garg, Elza Erkip {ezgi.ozyilkan,fabrizio.carpi}@nyu.edu

Overview

Summary: First **proof-of-concept** for a practical neural compress-and-forward relaying scheme, recovering ***binning*** (grouping) of the quantized indices as in the optimal relaying strategy.

- **Relay channel:** a fundamental component of "cooperative" communications.
- **Unknown capacity:** the capacity of the general relay channel is unknown!
- **Compress-and-Forward (CF):** In CF, the relay sends a quantized version of its received signal to the destination.
- **Signal correlation**: Relay and destination signals are correlated, enabling distributed compression.

Primitive relay channel.



- **Primitive relay channel (PRC):** Simplest channel coding problem with a source coding constraint.
- **CF strategy:** Optimal for PRC with *oblivious relaying* (relay unaware of the source codebook) $\Longrightarrow$ esp. suitable for learning!!
- **Task-aware compression:** Relay compresses Y_R to help destination in decoding Y_D and recovering W.

- For a general PRC $p(y_D, y_R|x)$, without time sharing, it's been shown that the following rate is achievable by CF strategy:

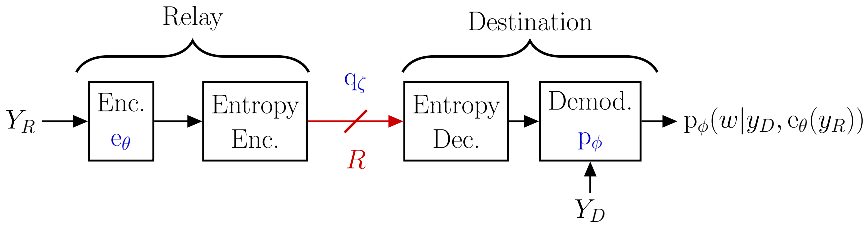
$$C = \max \, \mathrm{I}(X; Y_D, U),$$
$$\text{s.t. } R \geq \mathrm{I}(Y_R; U \mid Y_D),$$

where maximization is with respect to $p(x)p(u \mid y_R)$.

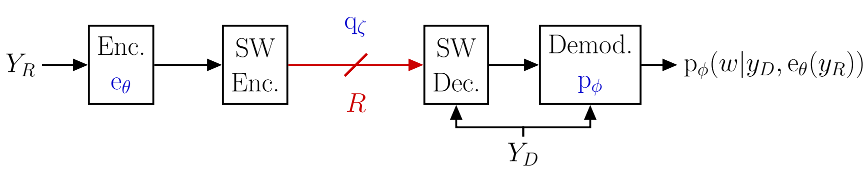
Framework

Main idea: Integrate our recent neural distributed (Wyner–Ziv) compressors into the relay-to-destination link.

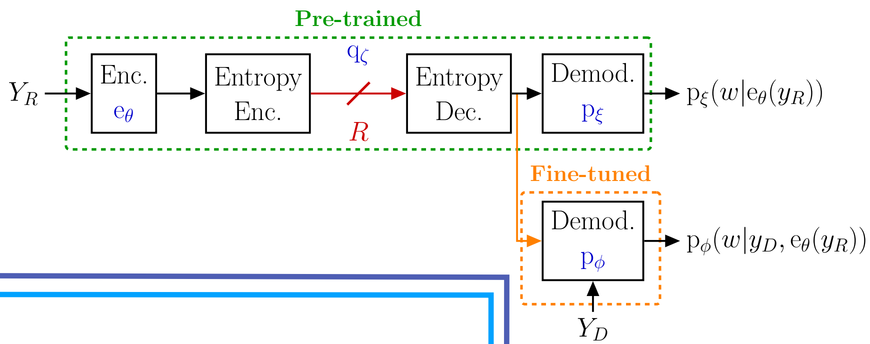
I. Marginal formulation, adapted from (Ozyilkan et al., 2023):



II. Conditional formulation, adapted from (Ozyilkan et al., 2023):



III. Point-to-point (no side information) formulation:



The goal is to **optimize** operational trade-off between relay-to-destination **compression rate** (R) **and** source-to-destination **communication rate** (C).

- Building onto compression rate R, we have an upper bound:

$$\mathrm{I}(Y_R; U \mid Y_D) \leq H(U \mid Y_D),$$
$$\leq \mathbb{E}\left[-\log_2 q_\zeta(e_\theta y_R))\right]$$
$$\triangleq \tilde{R}.$$

- Similarly, based on communication rate C, we have a lower bound:

$$\mathrm{I}(X; Y_D, U) = H(W) - H(W \mid Y_D, U),$$
$$\geq \log(|\mathcal{X}|) - \tilde{D},$$

where $\tilde{D} \triangleq \mathbb{E}\left[-\log(p_\phi(x|y_D, e_\theta(y_R)))\right]$.

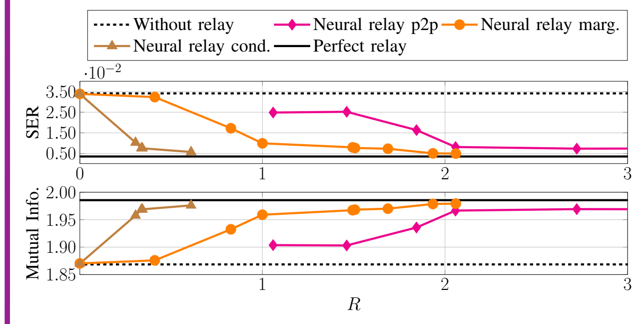
- The **operational training objective** for all schemes can be described by the loss function:

$$L(\theta, \phi, \zeta) = \tilde{R} + \lambda \cdot \tilde{D},$$

where $\lambda > 0$ controls the trade-off and $\{\theta, \phi, \zeta\}$ are learned parameters.

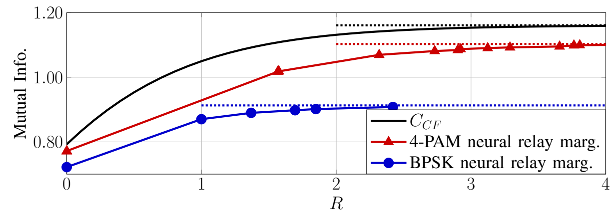
Results

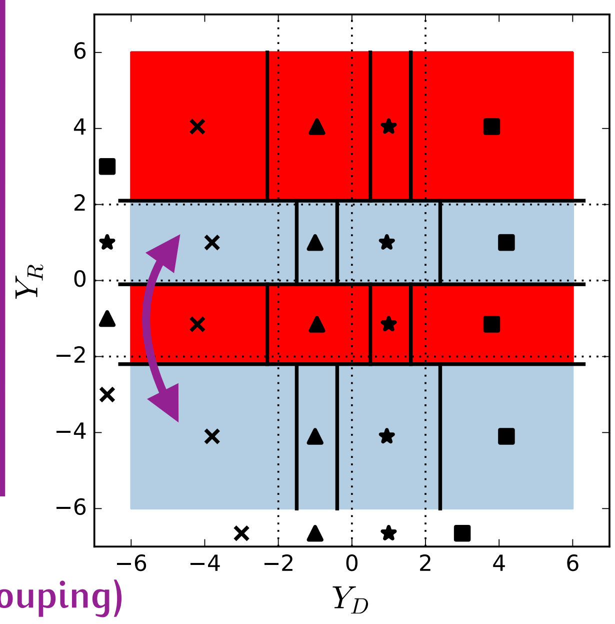
Assume fixed modulation scheme (do not optimize $p(x)$) : BPSK, 4-PAM, 4-QAM.



(Up) 4-PAM results for SNR = 13 dB.

(Down) Mutual information results wrt. upper bound C_{CF} for **marginal model** with SNR = 3 dB.



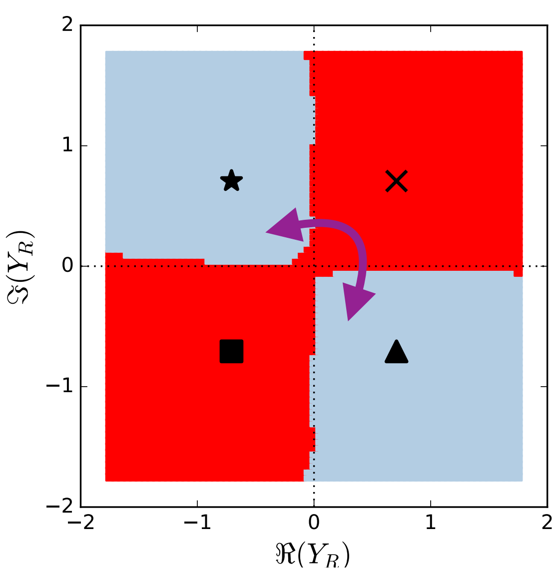


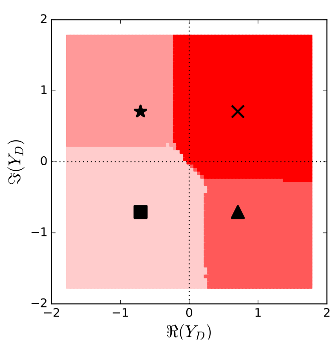
same color $\Longrightarrow$ **binning (grouping)**

Marginal model for **4-PAM** with SNR = 13 dB (up) and for **4-QAM** with SNR = 7 dB (down), both scoring $R \approx 1$.

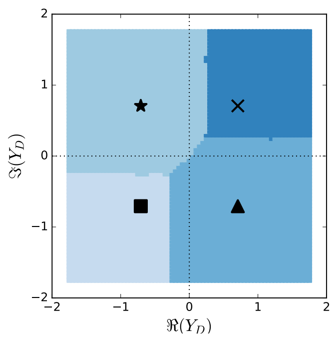
Horizontal lines mark the quantization boundaries on Y_R ; colors show the transmitted index $e_\theta(Y_R)$.

Hard decision boundaries are shifted to favor symbols most likely to be received at the relay $\Longrightarrow$ *interpretable learned CF relaying scheme!!*





Decision boundaries of red (up) and blue (down) indices.



Scan for SPAWC'24 paper, extended version and more:

Conclusion:

- We revisit CF relaying with interpretable neural compressors.
- The learned CF scheme mimics optimal strategy, including binning, and operates near capacity.