Neural Decoding with Log-Ratio Images

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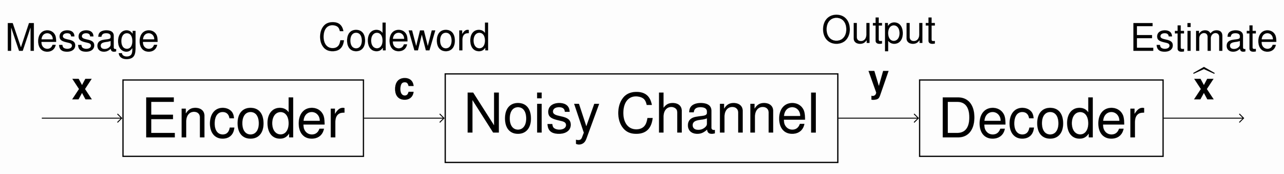
Channel Model



Why Neural Decoding?

	Error Rate	Speed
Classical Decoders [1]	Optimal ✔	Computationally Hard ✖
Neural Decoders	?	Constant once trained ✔

Goal: Reach near-optimal error rate with neural decoders

Current Neural Decoders

- ✖ Naive application of general-purpose networks does not work [3]
- ✖ Mainstream approaches [5][6][7] relying on Tanner Graph have restrictive inductive bias, hurting generalizability [2]
- ✖ Other approaches design special codes/NN [2][4], limiting applicability

Goal:

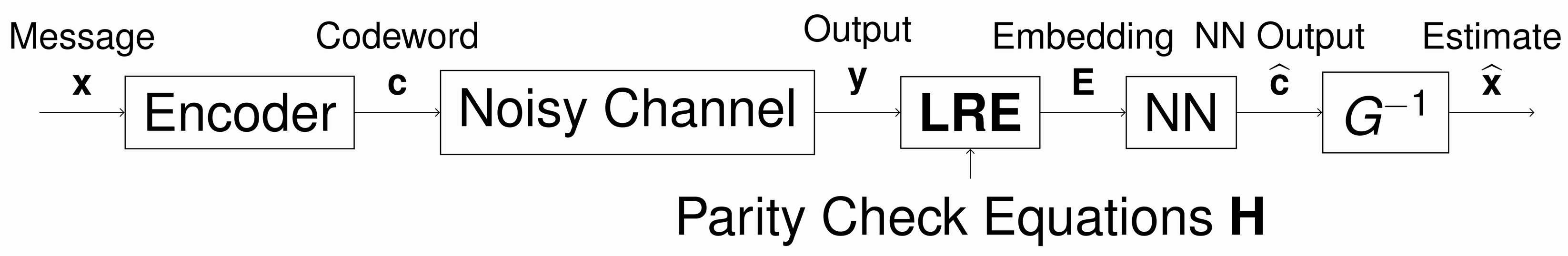
- ▶ Decode with light general-purpose networks
- ▶ Without assumptions on a known algorithm
- ▶ Without requiring special encodings

Challenges of Neural Decoding

- ! Exponential complexity (curse of dimensionality)
  At least $2^{k-2}A_{d_{\min}}$ piecewise affine models are necessary to decode a single bit! 💥
- ! Requirement of extremely high accuracy
  Decoder with 10^{-4} BER $\Rightarrow$ Classifier of 99.99% accuracy!

Single Parity Check Log-Ratio Embedding

Idea: Inject apriori knowledge of the code structure into the channel likelihood



obs(c_j): normalized $P(y_j|c_j)$ assuming $c_j \sim$ Bernoulli(1/2)

$$\text{Extr}_{ij} = \mathbb{P}(c_j = 1 \mid \mathbf{y}, c_j = \sum_{j' \neq j, \mathbf{H}_{i,j'} \neq 0} c_{j'}) = \frac{1 - \prod_{j' \neq j, \mathbf{H}_{i,j'} \neq 0}(1 - 2\,\text{obs}(c_{j'}))}{2}$$

$$\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \xrightarrow{\text{LRE}} \text{logit} \begin{bmatrix} \text{obs}(c_1) & \text{obs}(c_2) & \dots & \text{obs}(c_n) \\ \text{Extr}_{11} & \text{Extr}_{12} & \dots & \text{Extr}_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ \text{Extr}_{m1} & \text{Extr}_{m2} & \dots & \text{Extr}_{mn} \end{bmatrix} = \mathbf{E}$$

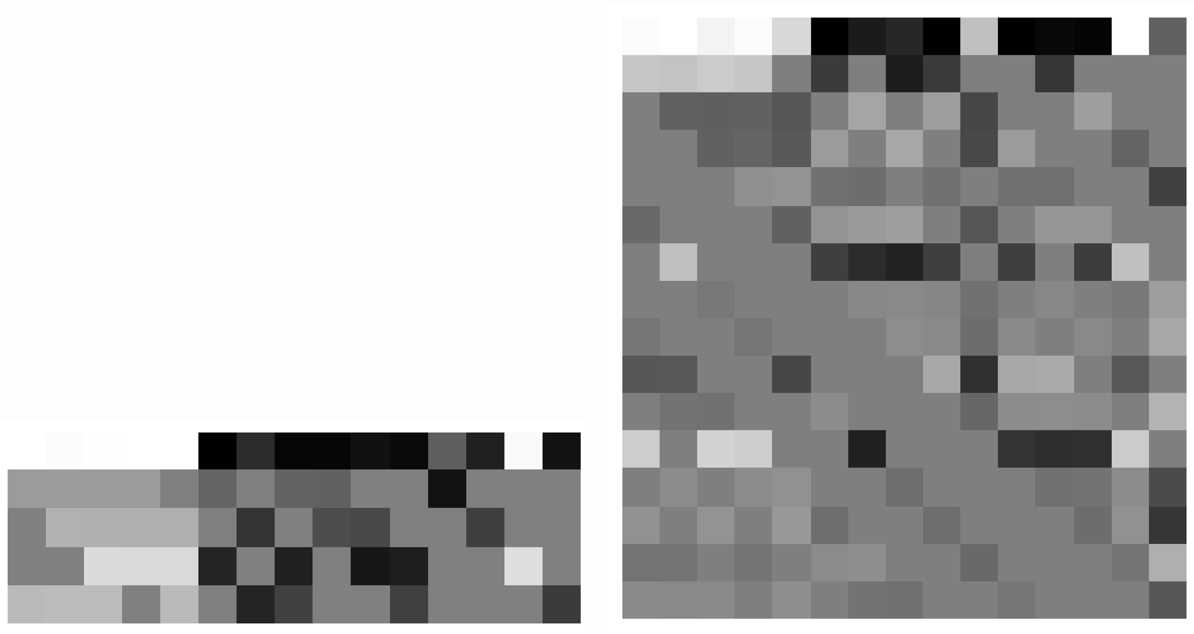


Figure: Examples of BCH[15, 11] SPC-LRE. (a) With Normal Parity-Check Matrix; (b) With Cyclic Parity-Check Matrix

Multiple Parity Check Log-Ratio Embedding

For larger codes, we can group parity check equations to generate likelihoods with stronger knowledge.

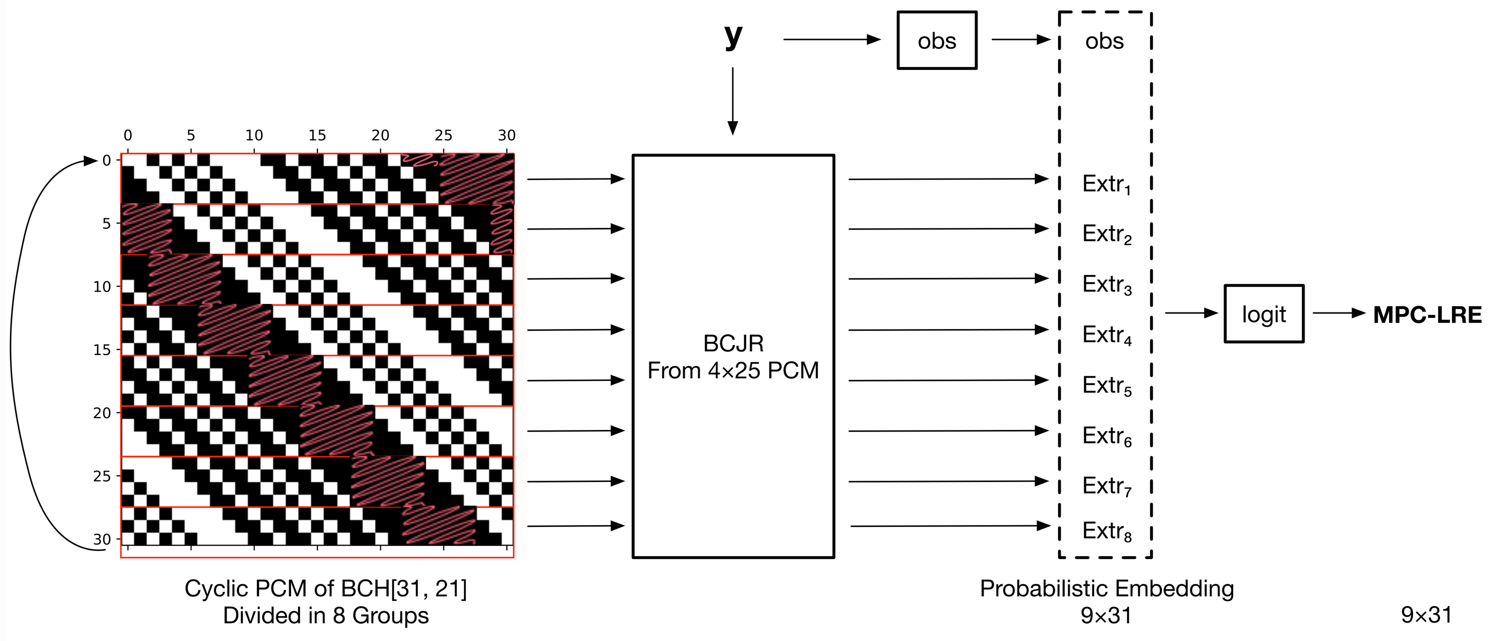


Figure: Iterative Log-Ratio Embedding for BCH[31, 21]

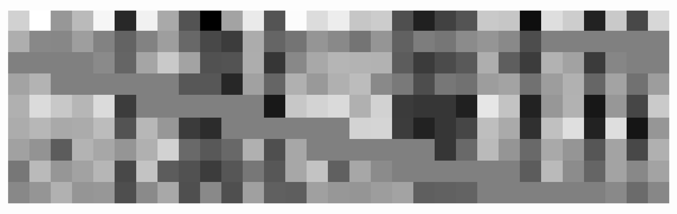


Figure: Example of BCH[31, 21] MPC-LRE

Experiments

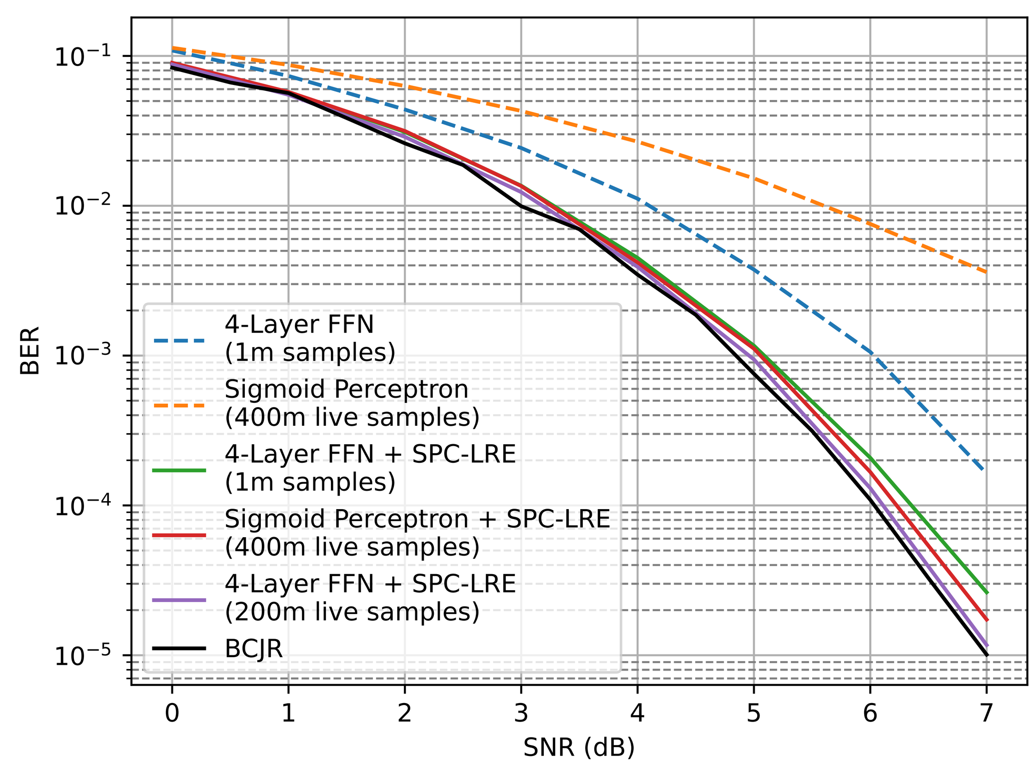


Figure: Decoding BCH[15, 11] through AWGN channel with/without SPC-LRE and by the optimal decoder [1].

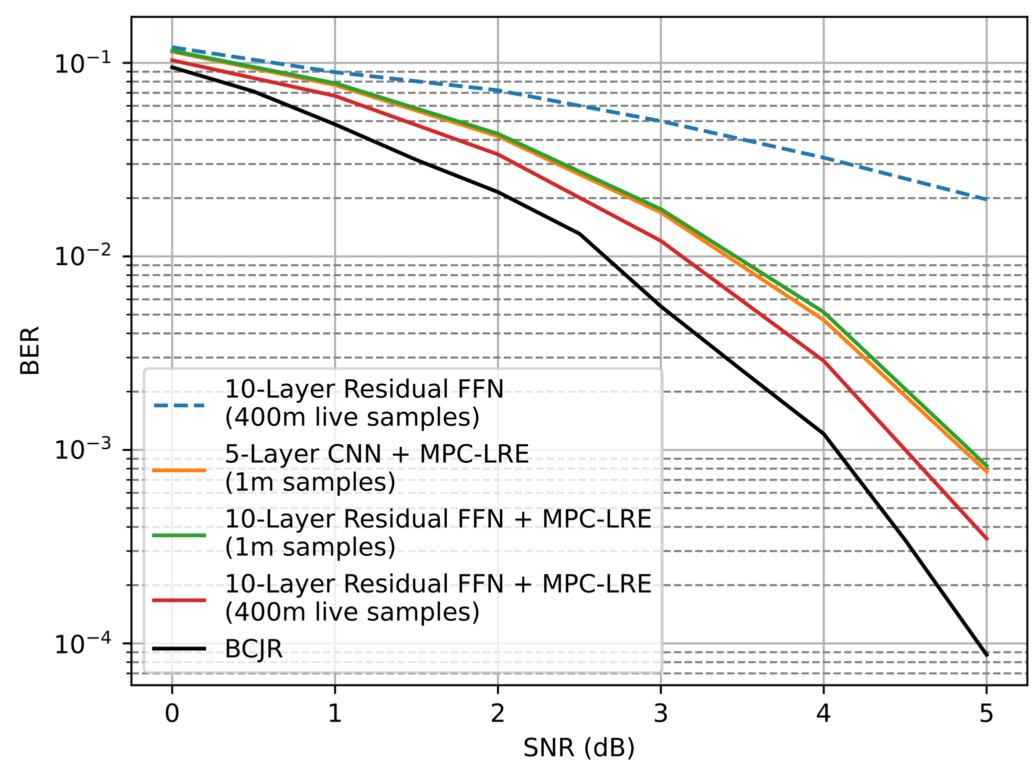


Figure: Decoding BCH[31, 21] through AWGN channel with/without MPC-LRE and by the optimal decoder [1].

References

[1] Bahl, L., Cocke, J., Jelinek, F., Raviv, J.: Optimal decoding of linear codes for minimizing symbol error rate (Corresp.). IEEE Transactions on Information Theory 20(2), 284–287 (Mar 1974)

[2] Choukroun, Y., Wolf, L.: Error Correction Code Transformer. In: Advances in Neural Information Processing Systems. vol. 35, pp. 38695–38705. Curran Associates, Inc. (Dec 2022)

[3] Jiang, Y.: Deep Learning for Channel Coding. Thesis, University of Washington, Seattle, Washington, United States (2021)

[4] Jiang, Y., Kim, H., Asnani, H., Kannan, S., Oh, S., Viswanath, P.: Turbo Autoencoder: Deep learning based channel codes for point-to-point communication channels. In: Advances in Neural Information Processing Systems. vol. 32, pp. 2758–2768. Curran Associates, Inc. (Dec 2019)

[5] Nachmani, E., Marciano, E., Lugosch, L., Gross, W.J., Burshtein, D., Be'ery, Y.: Deep Learning Methods for Improved Decoding of Linear Codes. IEEE Journal of Selected Topics in Signal Processing 12(1), 119–131 (Feb 2018)

[6] Nachmani, E., Wolf, L.: Hyper-Graph-Network Decoders for Block Codes. In: Advances in Neural Information Processing Systems. vol. 32, pp. 2329–2339. Curran Associates, Inc. (Dec 2019)

[7] O'Shea, T., Hoydis, J.: An Introduction to Deep Learning for the Physical Layer. IEEE Transactions on Cognitive Communications and Networking 3(4), 563–575 (Dec 2017)

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