The Challenging Neural Decoding With General-Purpose Networks and Its Improvement via Probabilistic Embeddings

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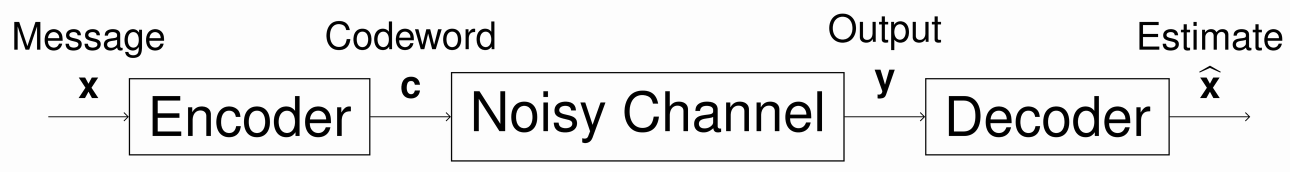
Channel Model



Why Neural Decoding?

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

Goal: Reach near-optimal error rate with neural decoders

Current Neural Decoders

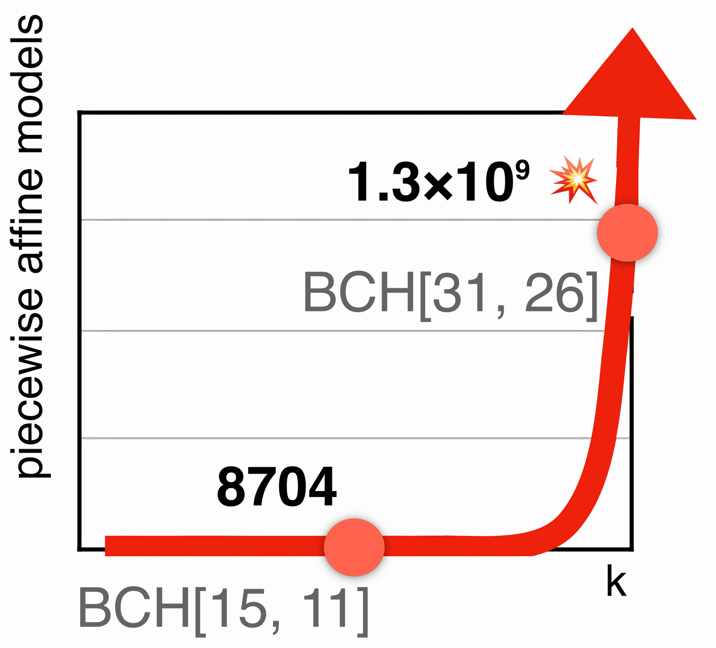
- ✖ Naively applying general-purpose networks does not work [3]
- ✖ Mainstream approaches [5][6][7] relying on Tanner Graph have restrictive inductive bias, hurting generalizability [2]
- ✖ Other approaches design special codes/NN [2][4], limiting applicability

Goal:

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

Challenges of Neural Decoding

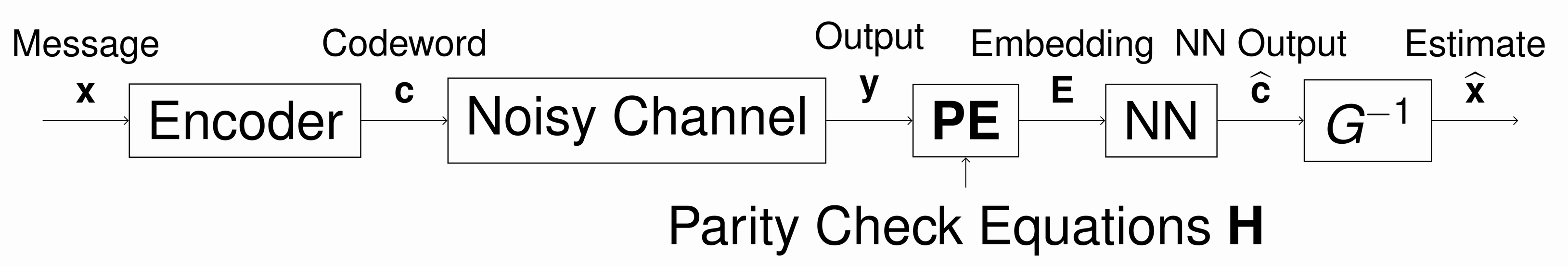
! Exponential complexity
At least $2^{k-2}A_{d_{\min}}$ piecewise affine models are required to fit to decode one bit!



! Requirement of extremely high accuracy
Decoder with 10^{-4} BER ⇒ Classifier of 99.99% accuracy!

Proposed Method of **Probabilistic Embedding**

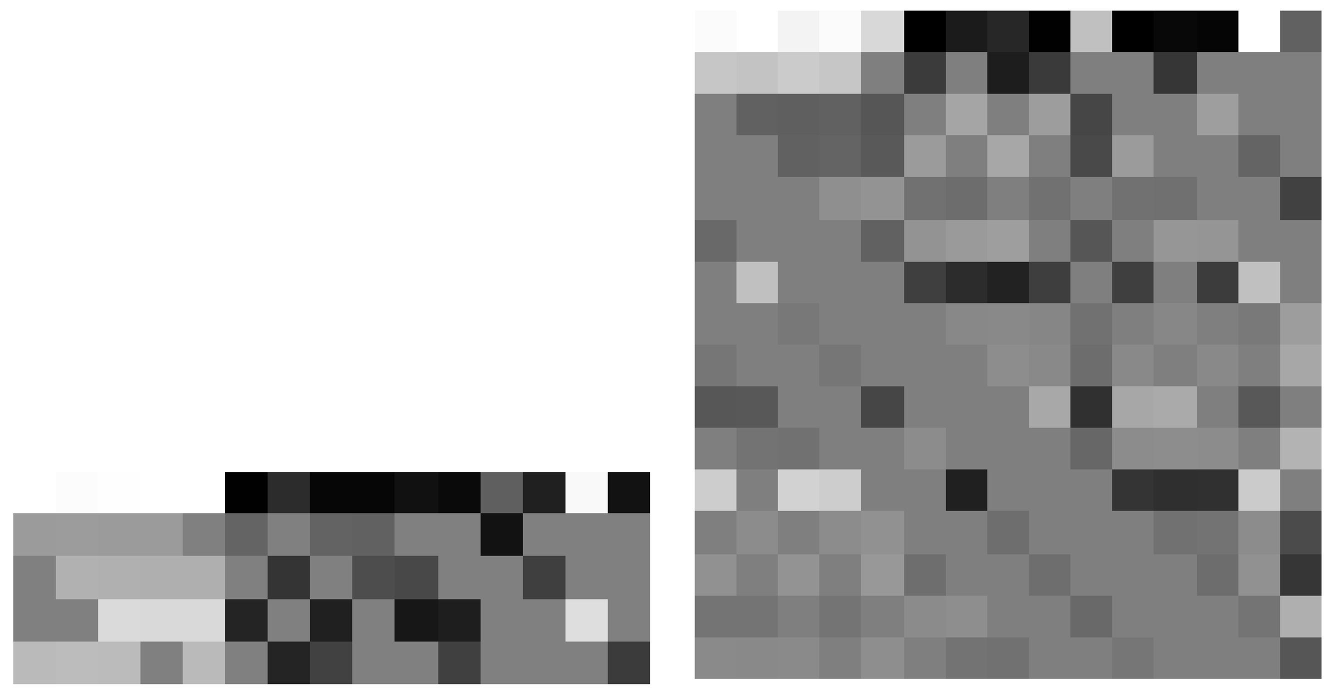
Idea: Inject apriori knowledge of the code structure into the channel likelihood



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

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

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



(a) Normal Parity-Check Matrix

(b) Extended Parity-Check Matrix with Cyclic Rotation

Figure: Examples of BCH[15, 11] Probabilistic Embedding.

Experiments

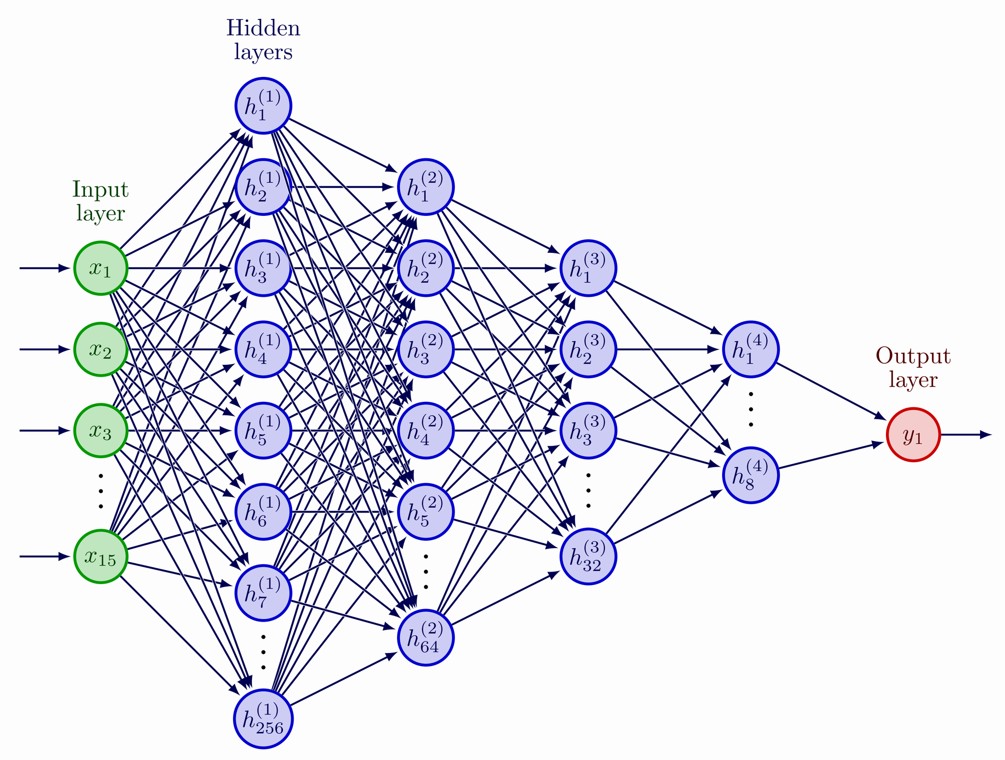


Figure: Feed-forward network of four hidden layers with 256, 64, 32, and 8 hyperbolic tangent activated neurons; Output layer with sigmoid activation.

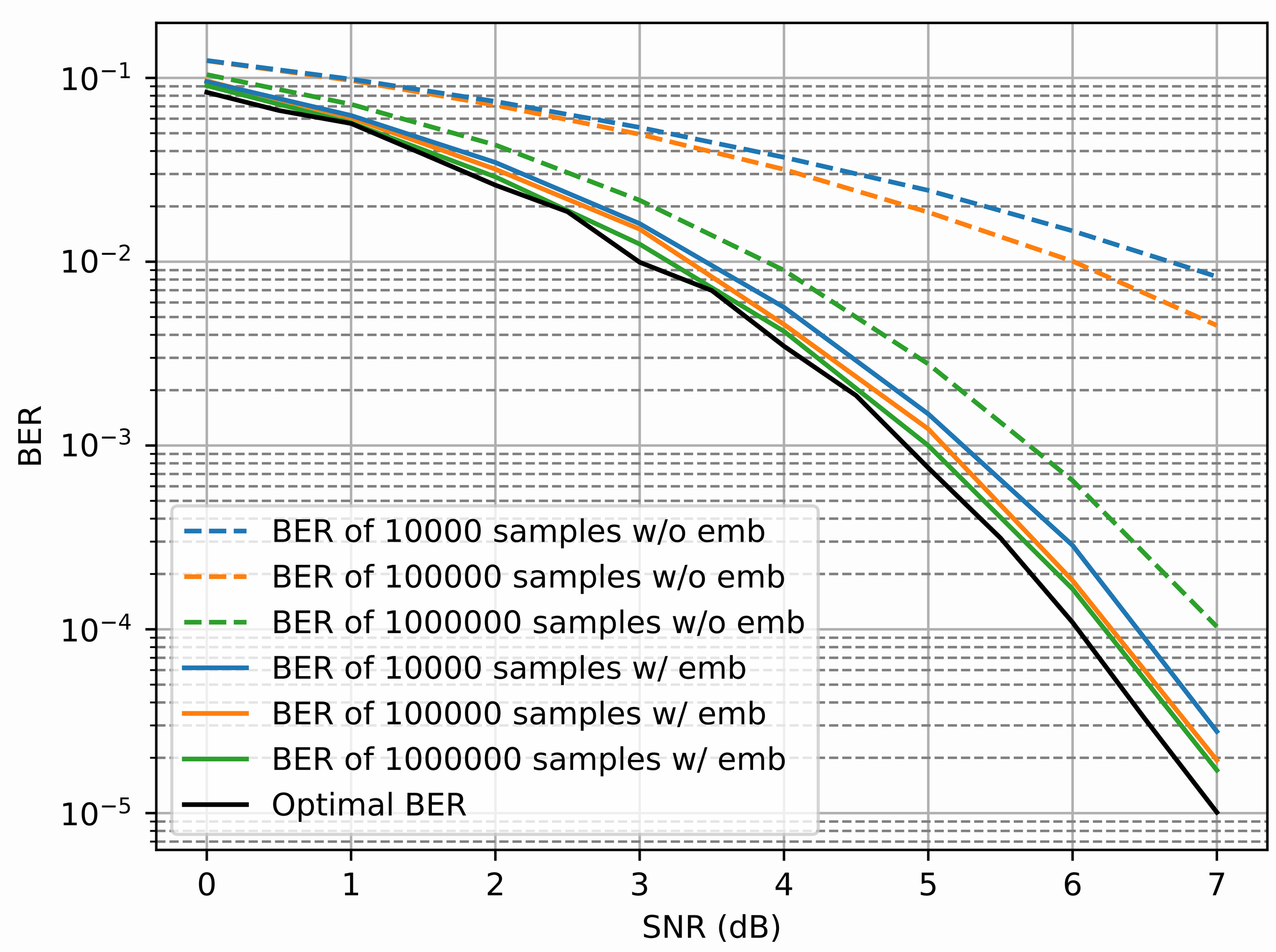


Figure: Decoding BCH[15, 11] through AWGN channel by FFN with/without probabilistic embedding and by the optimal decoder [1]. Averages of 10 trials.

As far as we know, this is the first approach that demonstrates decoding performance close to the theoretical optimality of BCH[15, 11] with an FFN!

References

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