Inventing Communication Algorithms via Deep Learning

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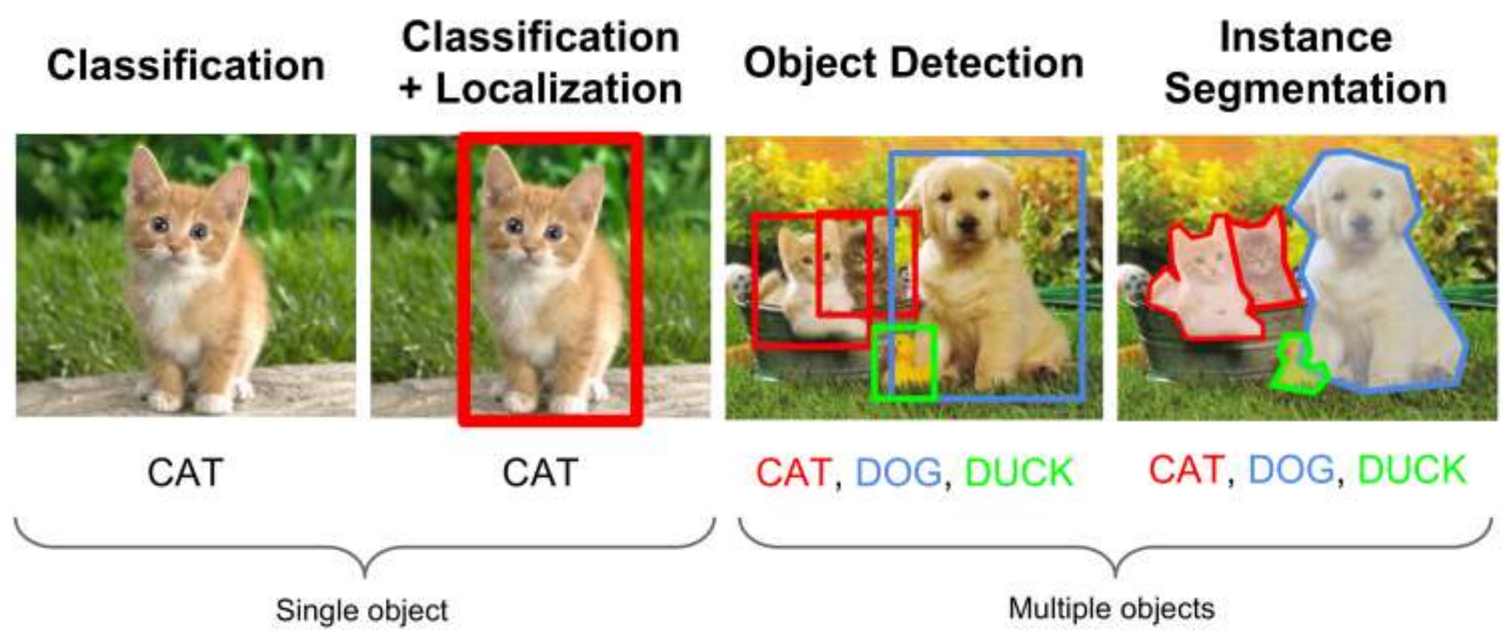
Deep Learning is part of daily life.

Machine Translation (e.g. ``Hello world!'' in Chinese?)



Computer Vision

natural language processing

Model Complexity

- Models are complicated
  - for both NLP and CV
- Data is hard to model
  - Inference problems hard to model
- Deep learning learns efficient models
  - inherently empirical and human-validated

Algorithmic Complexity

- In many problems models are simple
  - unlimited training data
  - mathematical performance metrics

- Challenge: space of algorithms very large

- Success of Deep learning: AlphaZero
  - Chess, Go, Protein Folding

Communication Algorithms

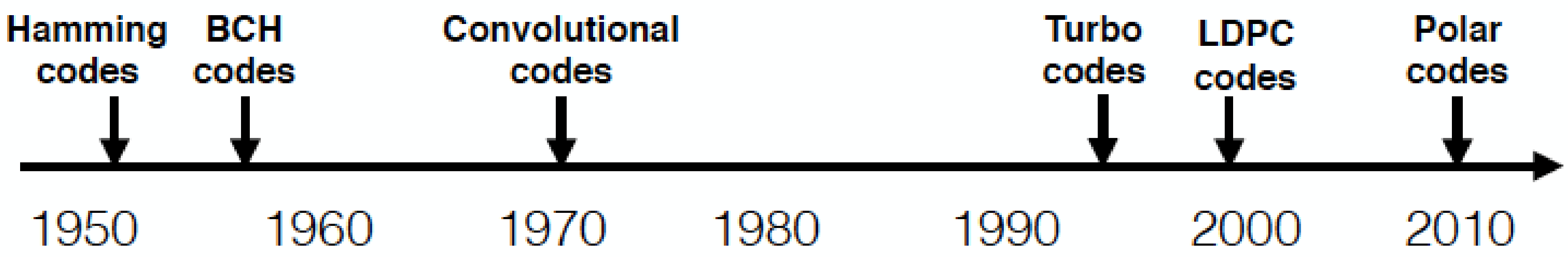
- Simple models: AWGN channel
  - unlimited training data
  - precise performance metrics

- Challenge: space of algorithms very large

- Information Theory, Communication Theory, Coding Theory

AWGN Channel

- Sporadic Progress:
  - individual human ingenuity



- Huge practical impact

Vision

- Discovery of codes
  - human eureka moments

- Automate Progress:
  - use deep learning to search for codes

Two Goals

- New (deep learning) tools for classical problems
  - New state of the art
  - Inherent practical value

- Insight into deep learning methods
  - No overfitting
  - Interpretability

One Lens

- Scalability

- Train on small settings

- Test on much larger (100x) settings

Codes

- Encoders and Decoders
  - end-to-end training
  - gradients have to pass through decoder

- Structure is essential
  - traditional: linearity
  - neural networks are nonlinear

Two Deep Learning Components

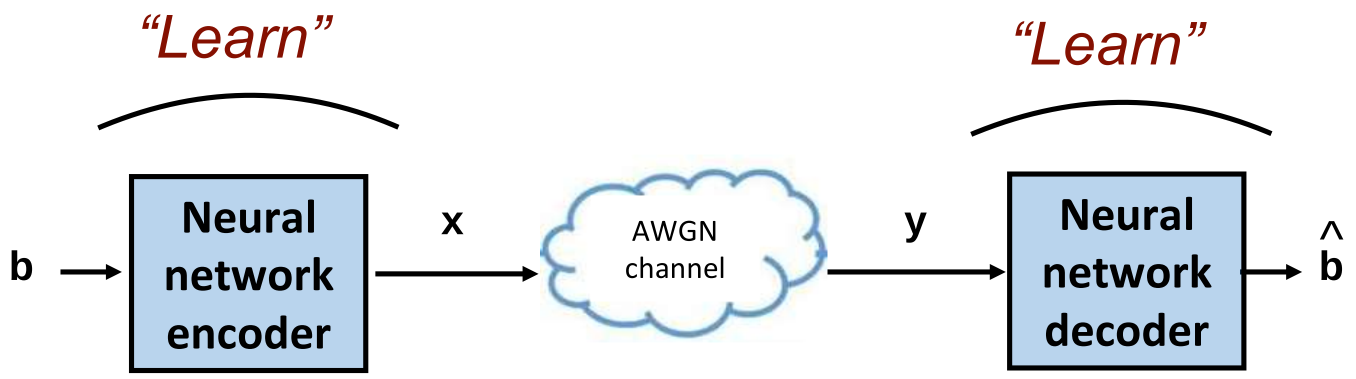
- Recurrent Neural Networks
  - in-built recursion capability

- Gated recurrent units
  - GRU, LSTM, Attention

Inventing Codes

- **AWGN channel**
  - Very well studied; high bar
  - Already close to information theoretic limits
  - **New codes**
  - IP protection
  - robust/adaptive data driven decoders
  - Scientific curiosity

Learning Approach



Code Structure

- **Linear codes**
  - Coding+modulation

- **Neural Networks**
  - Directly map bits to real valued outputs
  - nonlinear
  - Still need a structure

Reed Muller Codes

- **Classical**
- Muller, 1954
- Efficient decoder by Reed, 1954

- **Recent Interest**
  - Polar codes
  - RM codes are capacity achieving (proved for BEC)

RM Codes: Algebraic Construction

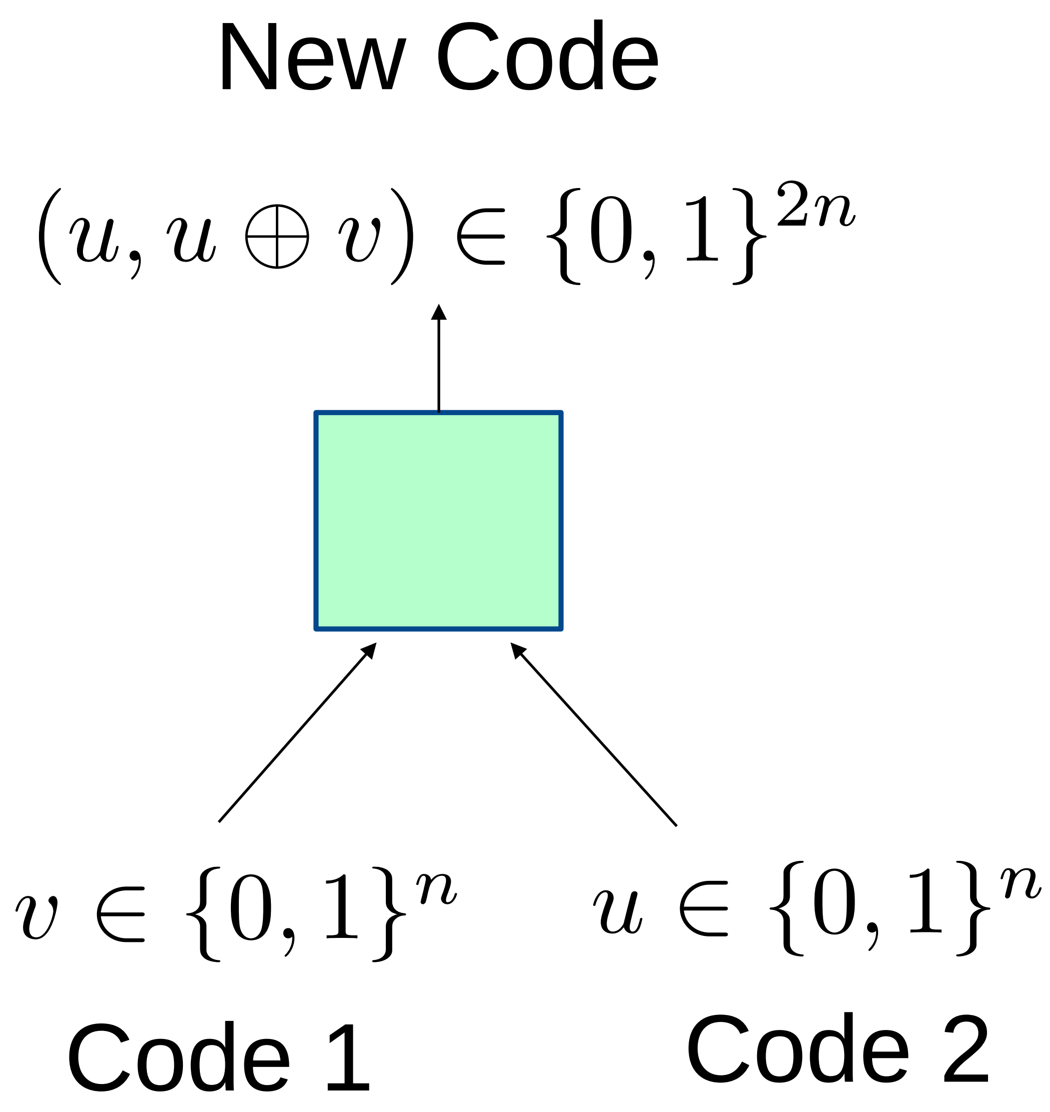
- RM (m,r)

- Codeword is the evaluation of a polynomial of degree utmost r on the vertices of m-dimensional binary hypercube

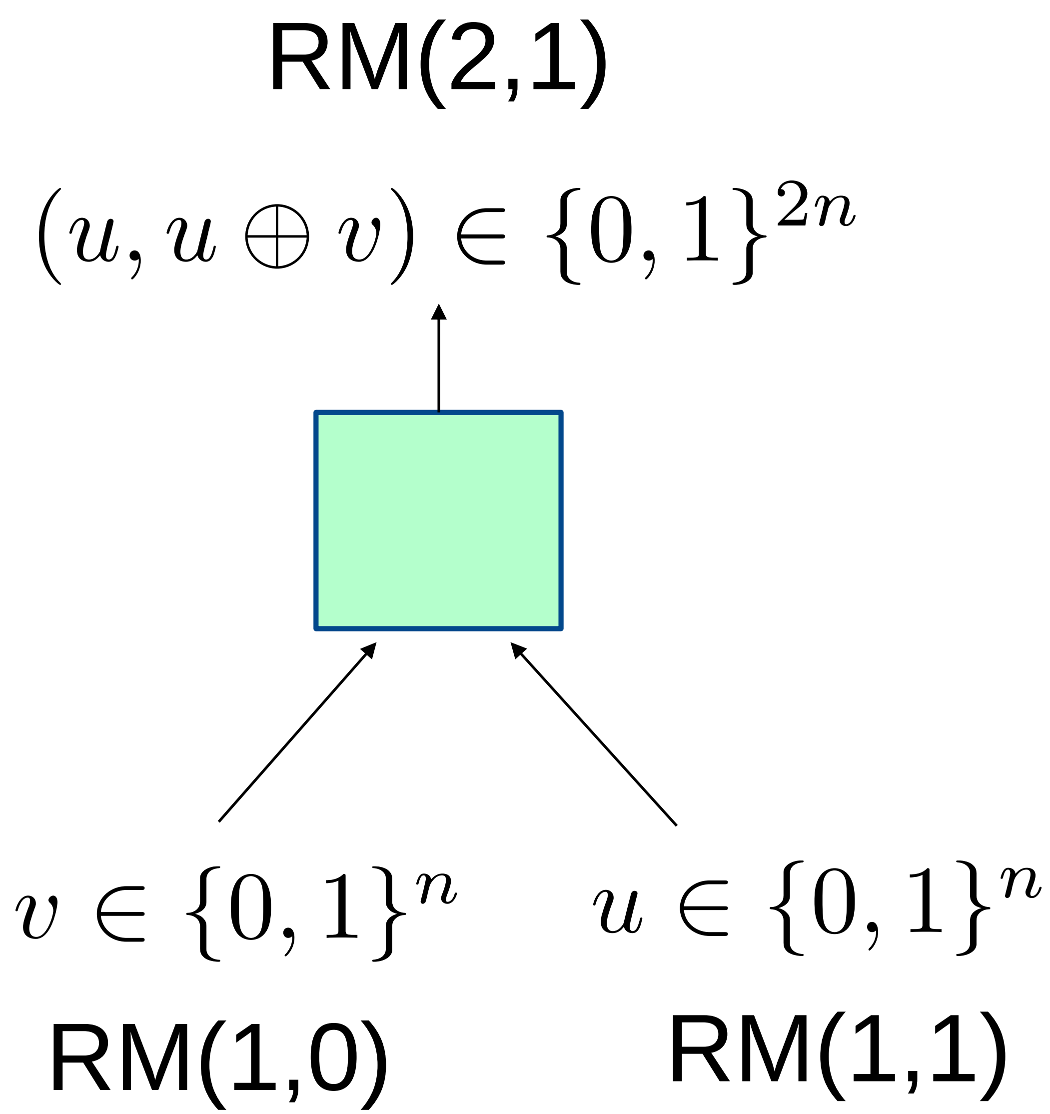
- RM(m,0) is simply the repetition code

- 2^m dimensional codeword

Plotkin construction



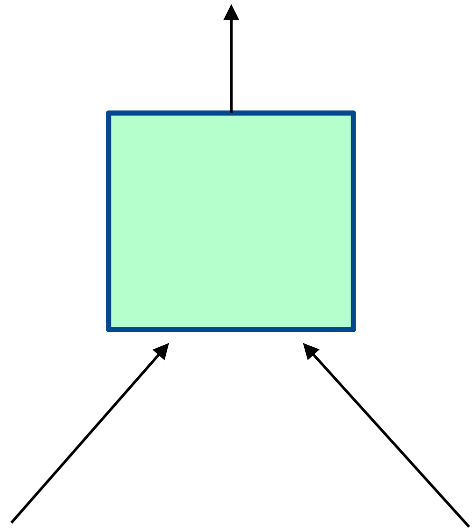
RM Codes via Plotkin construction



Neural Plotkin Construction

New Code

$$(u, g(u, v, u \oplus v)) \in \{0,1\}^{2n}$$

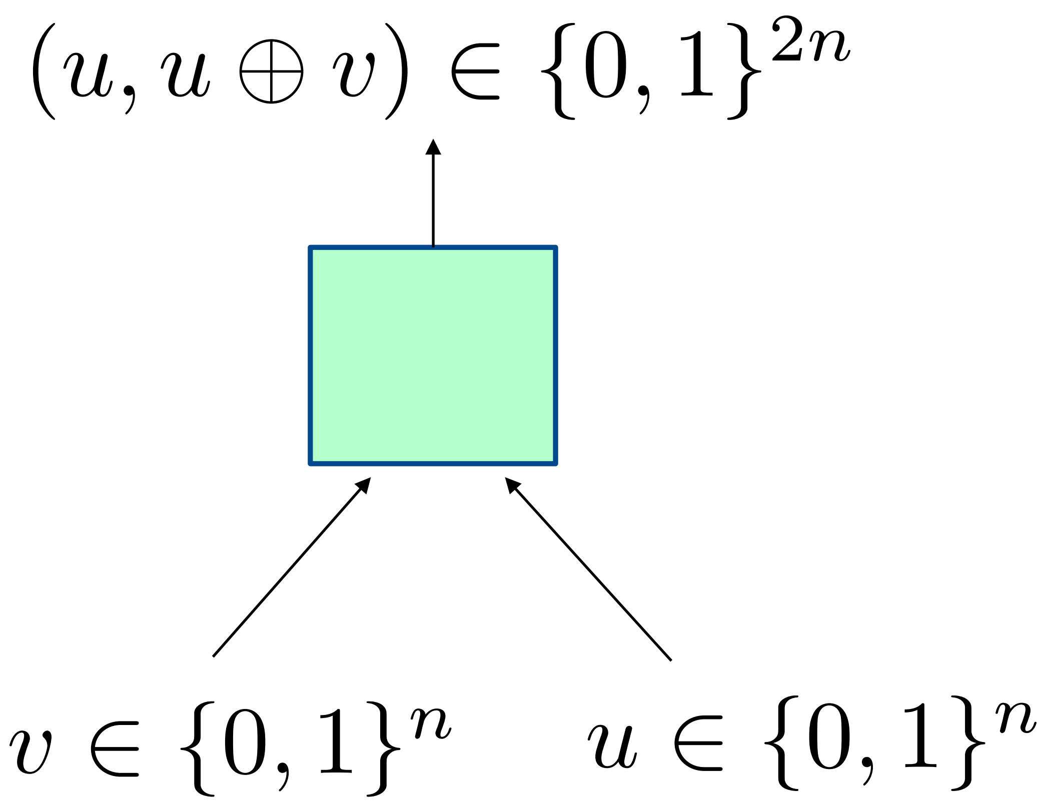


g: **neural network**

$v \in \{0,1\}^n$ $u \in \{0,1\}^n$

Code 1 Code 2

Dumer Decoding



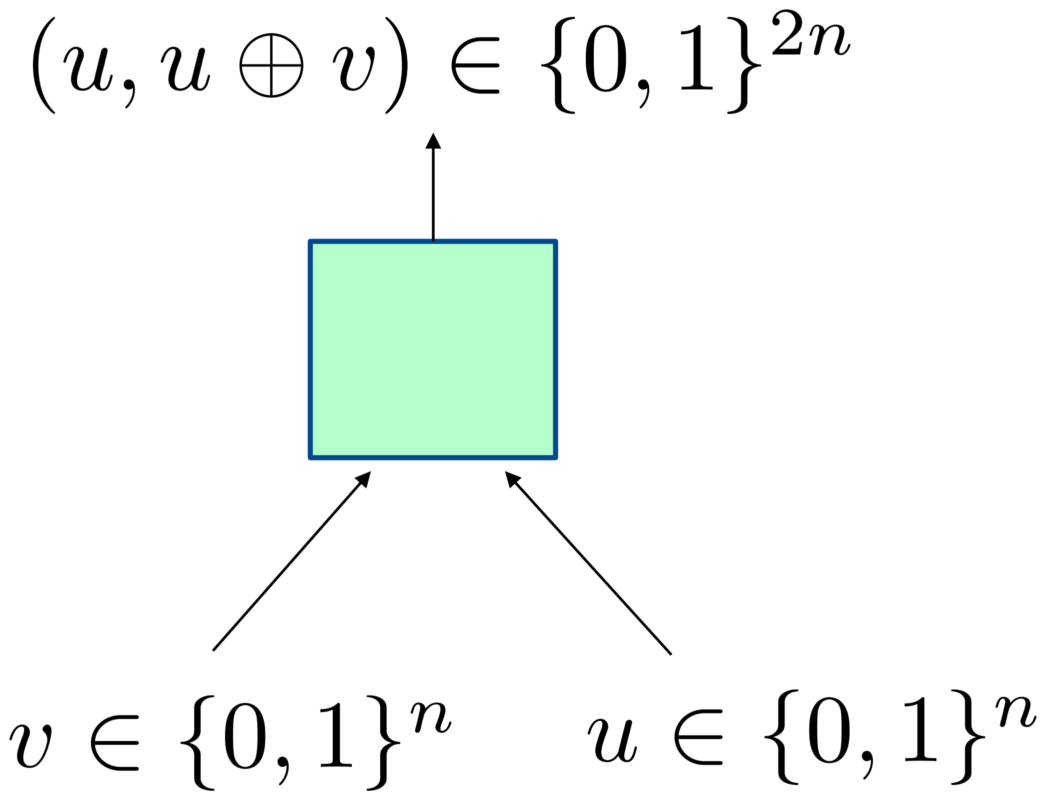
First Decode v

$\mathrm{LLR}_u, \mathrm{LLR}_{u \oplus v}$

Next Decode u

Dumer, 2004-06

Neural Dumer Decoding



First Decode v

$\mathrm{LLR}_u, \mathrm{LLR}_{u \oplus v}$

Neural network

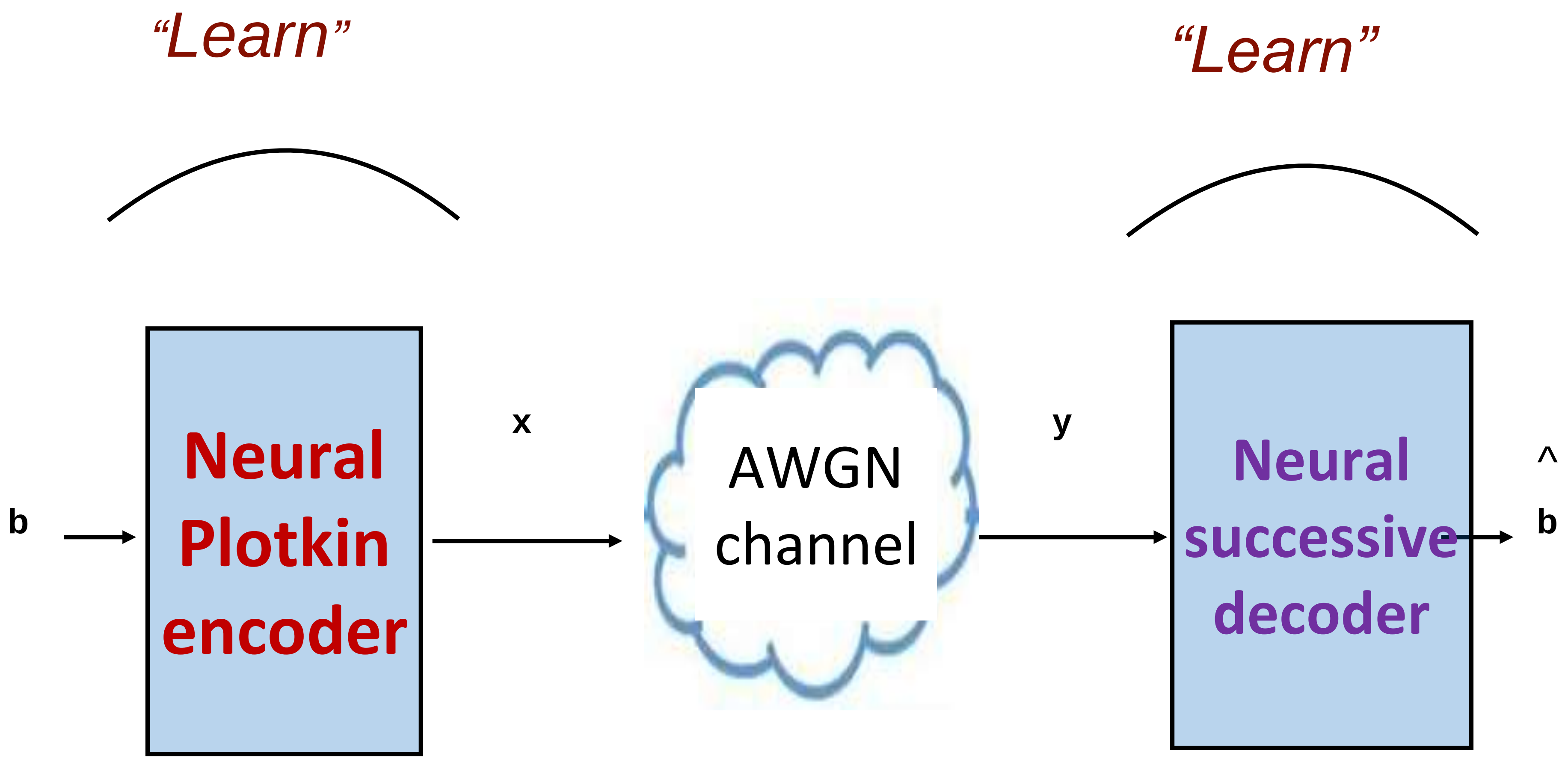
Next Decode u

Dumer, 2004-06

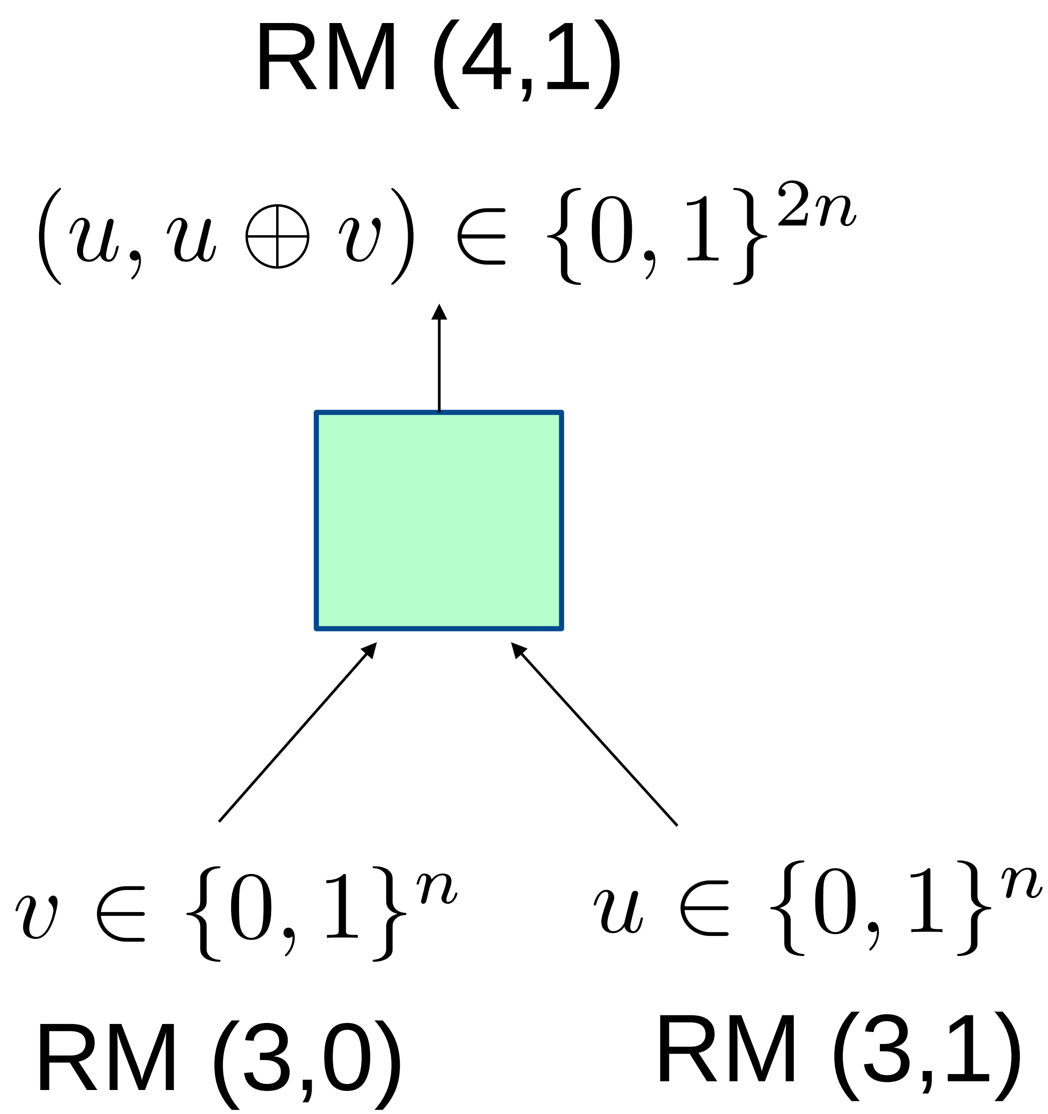
Neural Plotkin-Dumer Codes

- Generalize Plotkin construction via neural networks
- Generalize Dumer decoding via neural networks

Neural Plotkin-Dumer Codes



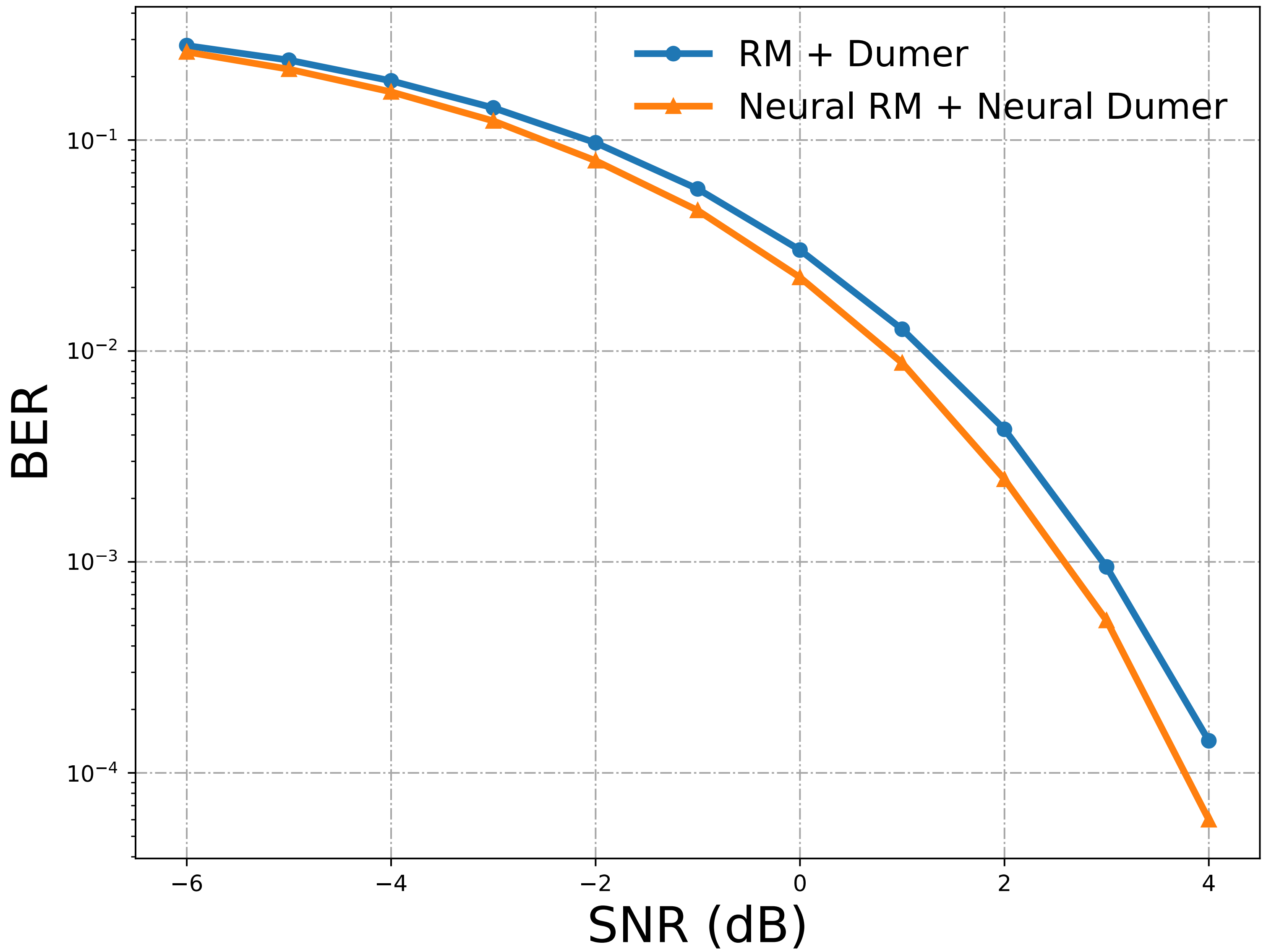
RM Codes (4,1)



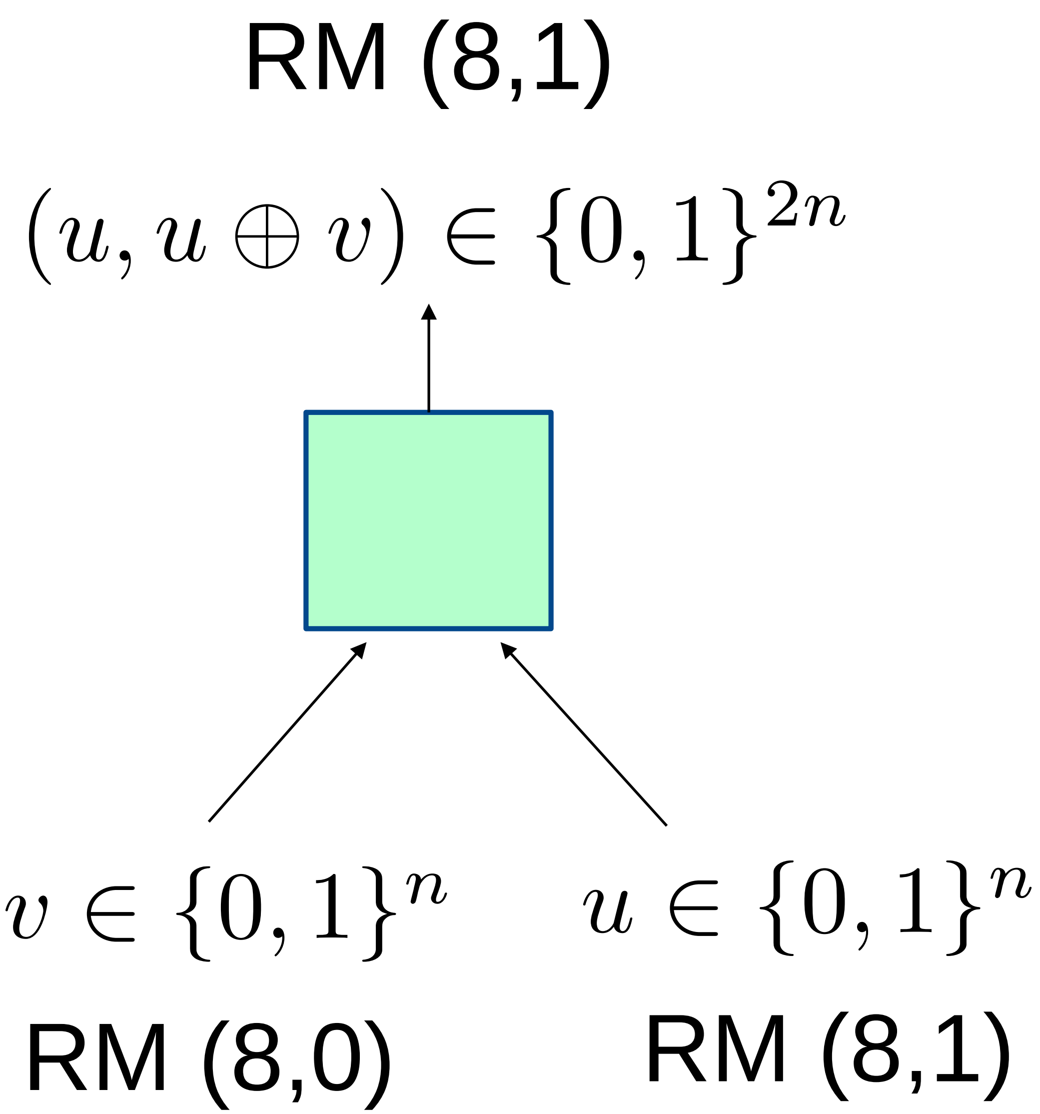
Information Symbols = 5

Coded Symbols = 16

RM vs Neural Plotkin-Dumer Codes



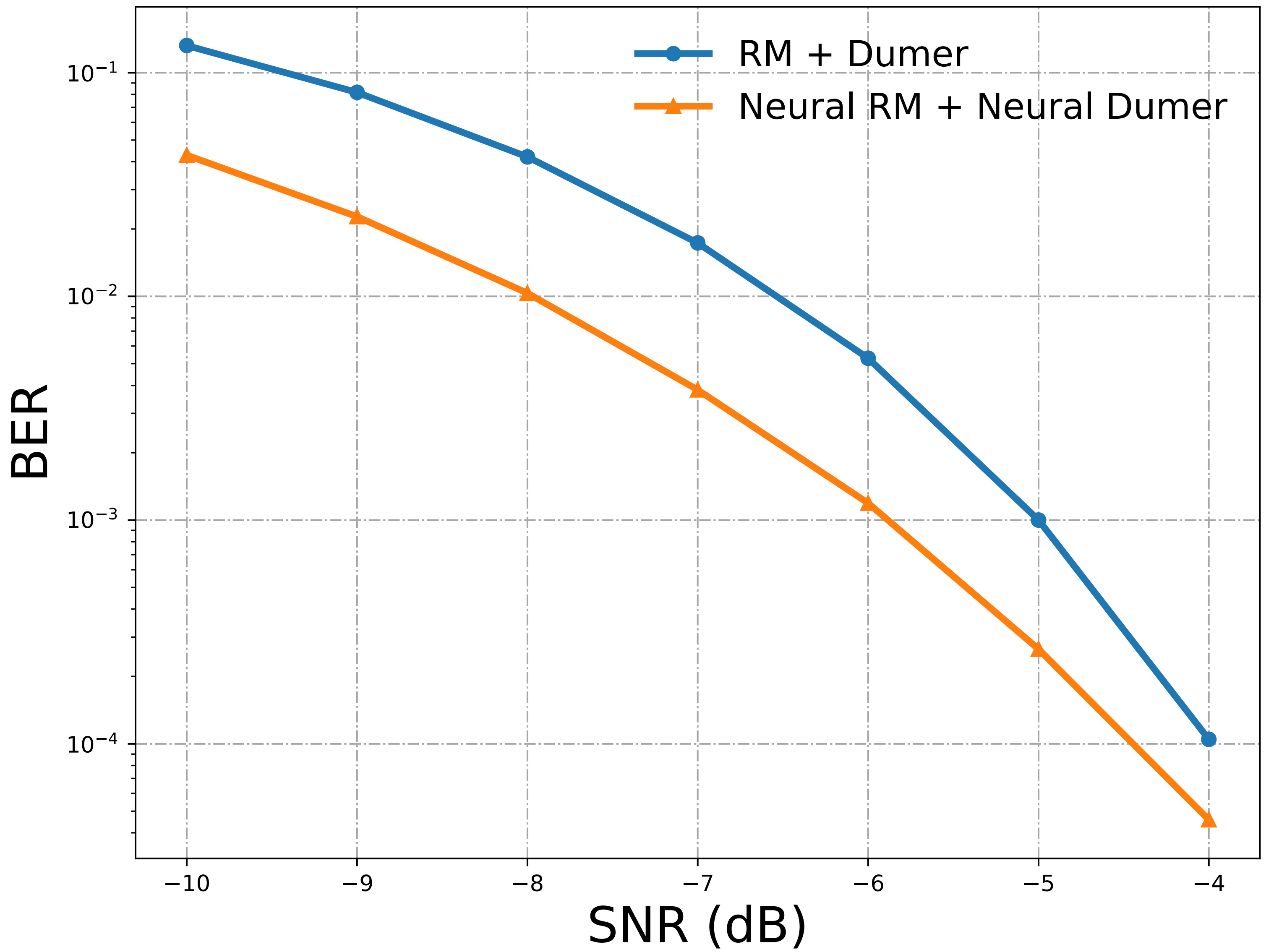
RM Codes (8,1)



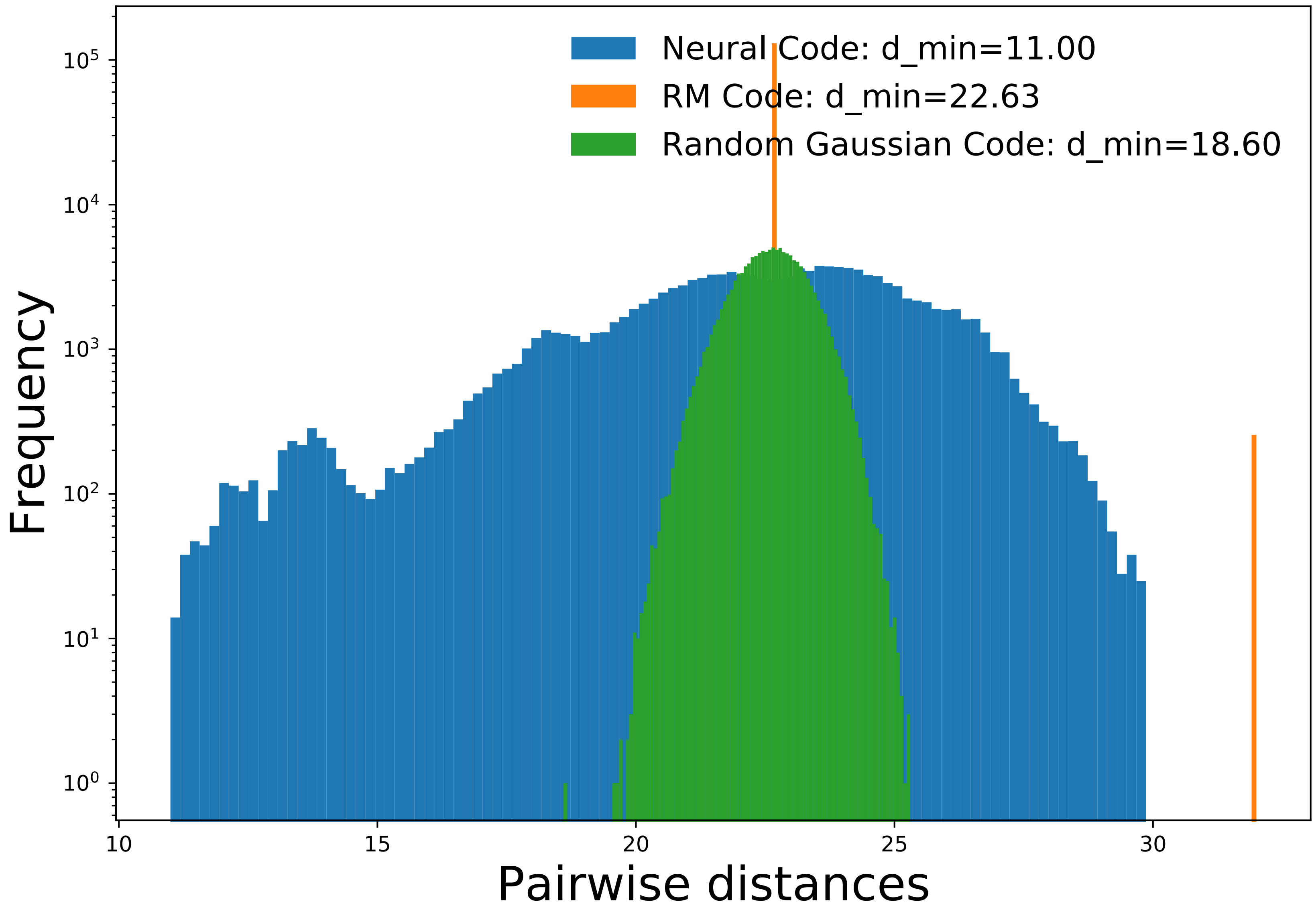
Information Symbols = 9

Coded Symbols = 256

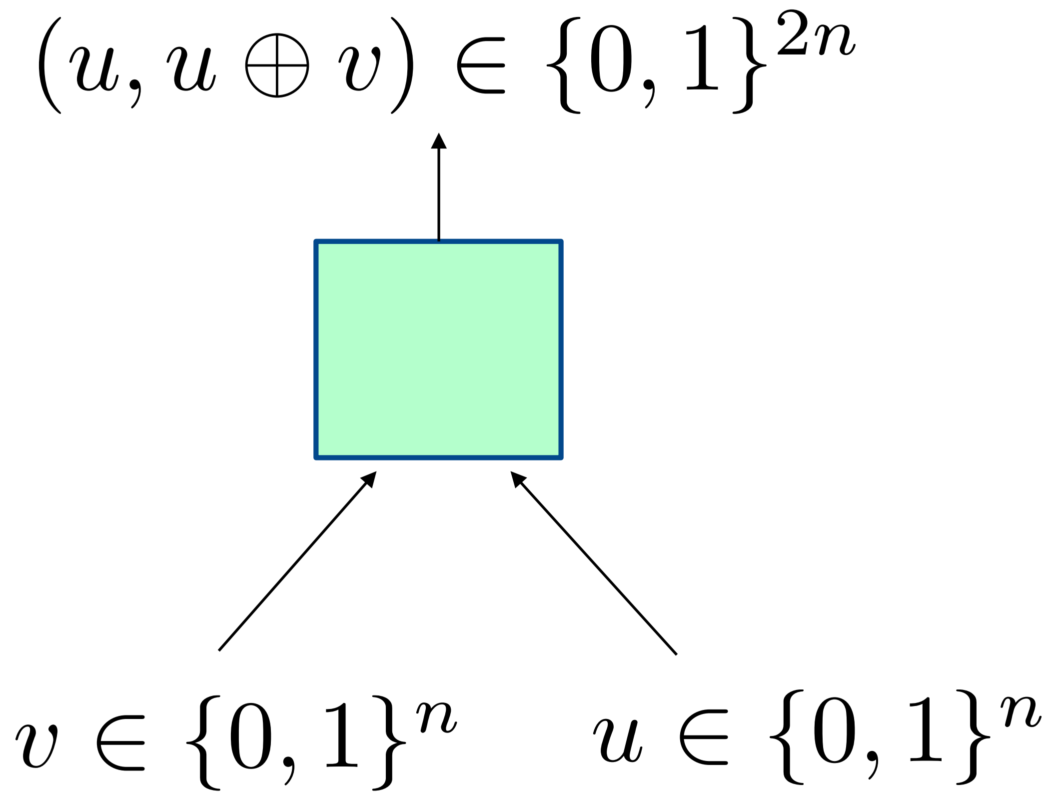
RM vs Neural Plotkin-Dumer Codes



Pairwise Codeword Distances



Reed (ML) Decoding

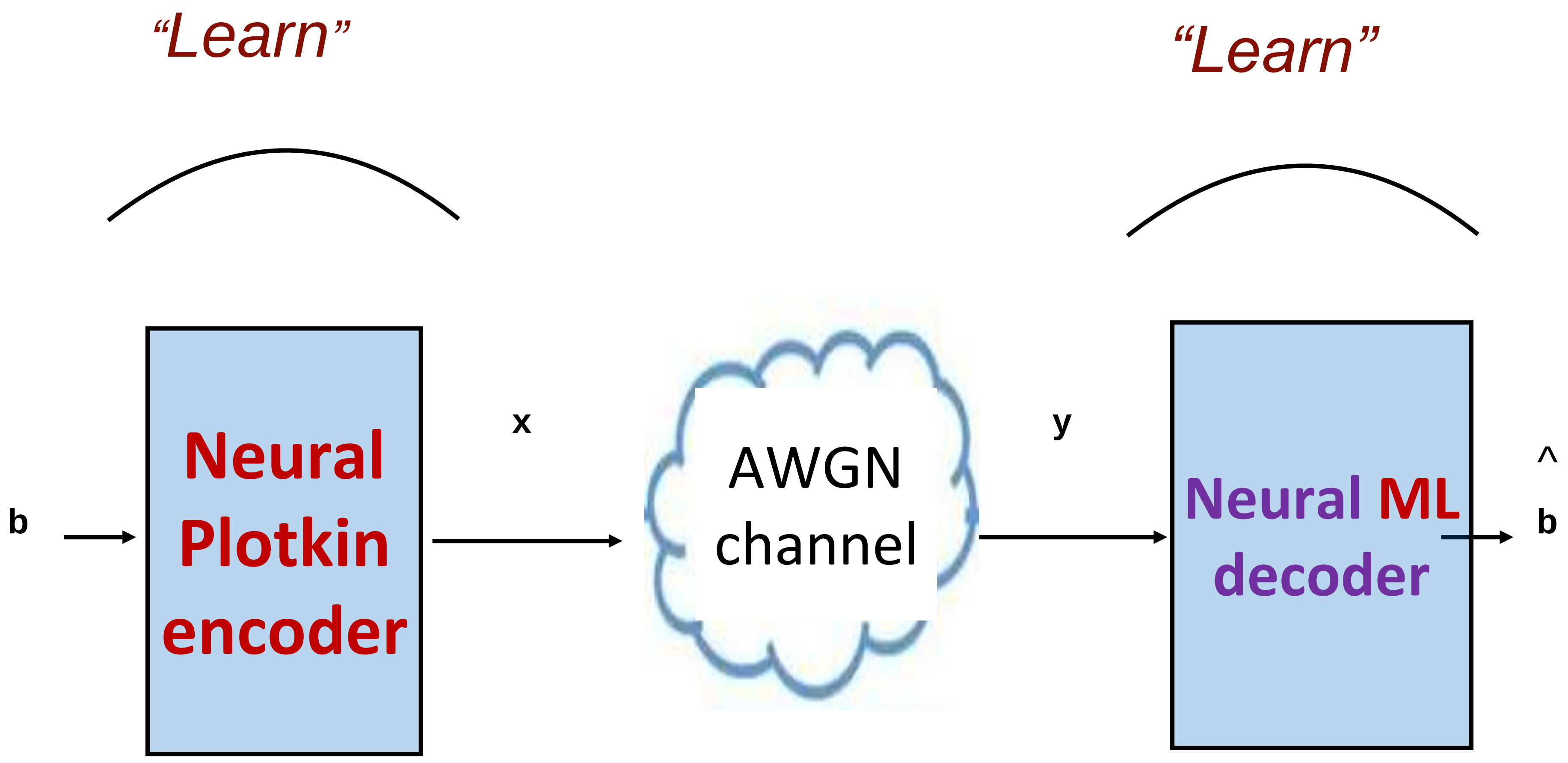


Fast Hadamard Transform

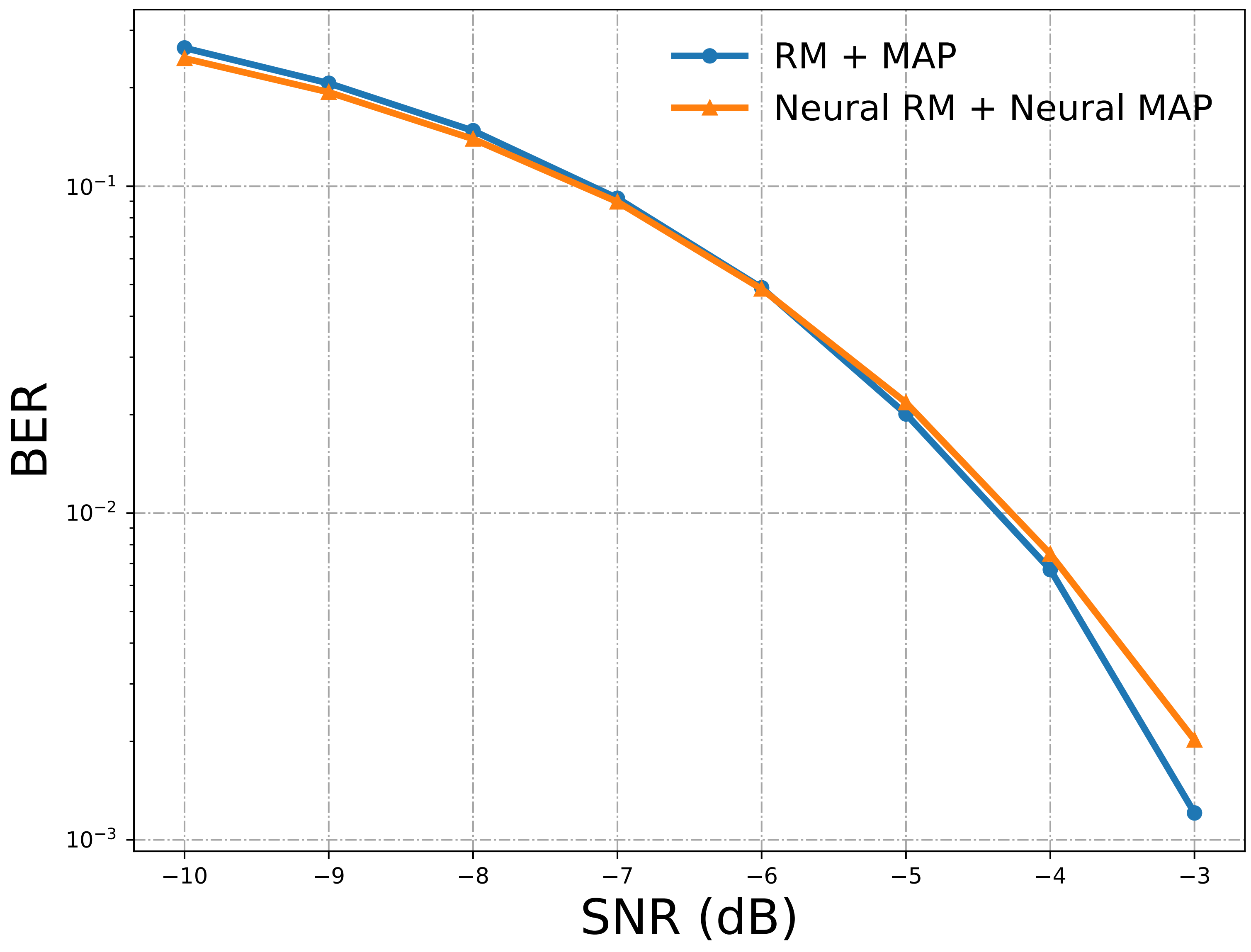
Efficient, first order RM codes

Reed, 1954

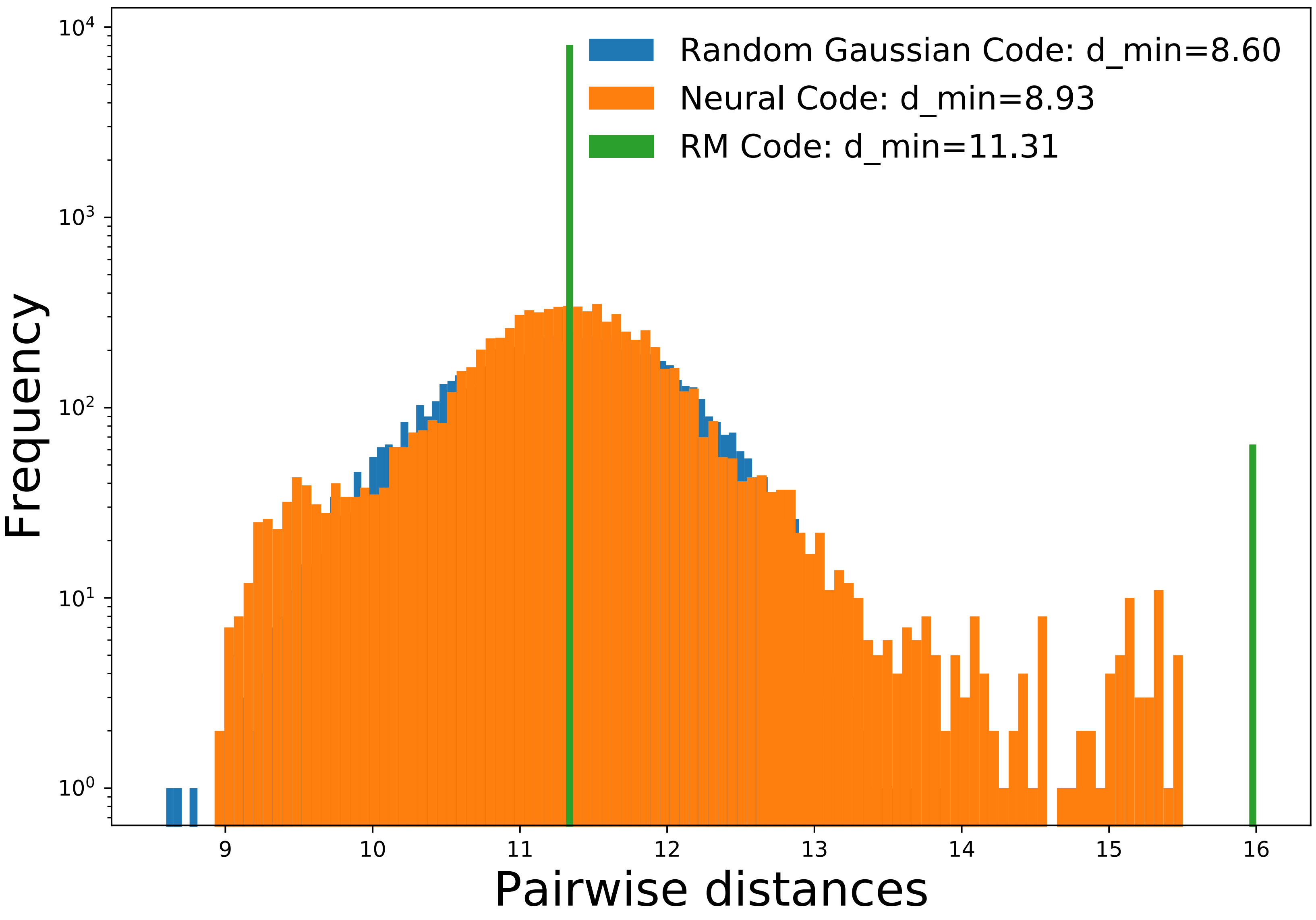
Neural Plotkin Codes



RM (6,1) vs Neural Plotkin Codes



Pairwise Codeword Distances



Ongoing Work

- **Extension to longer block lengths**
- **Higher order RM codes**
  - Decoding gets complex
  - Long conjectured to be efficient
  - Abbe-Ye RPA decoding

- **Neural Polar codes**
  - Soft polarization

Long Block lengths: Learning to Decode

- Fix encoding
  - convolutional codes
- Deep Learning decoders
  - learn Viterbi and BCJR algorithms
  - dynamic programming
- **Learning an Algorithm**: strong generalization
  - across block lengths
  - across SNR

Sequential Encoding

- Fixed encoders
  - convolutional codes

- Optimal decoders
  - Viterbi (block error)
  - BCJR (bit error)
  - dynamic programming

- Formulaic and generalize readily
  - across block lengths
  - across SNR

Deep Sequential Decoding

- Neural network decoders
- Sequential decoders
  - Recurrent neural networks (RNN)
- Representation capability
  - can encode Viterbi/BCJR in principle
- Key question:
  - Can SGD learn the optimal rules?

Setting

- Supervised training:

- Rate 0.5 convolutional code

- Neural Network Architecture
  - Two layer Bi-GRU RNN; sigmoidal output

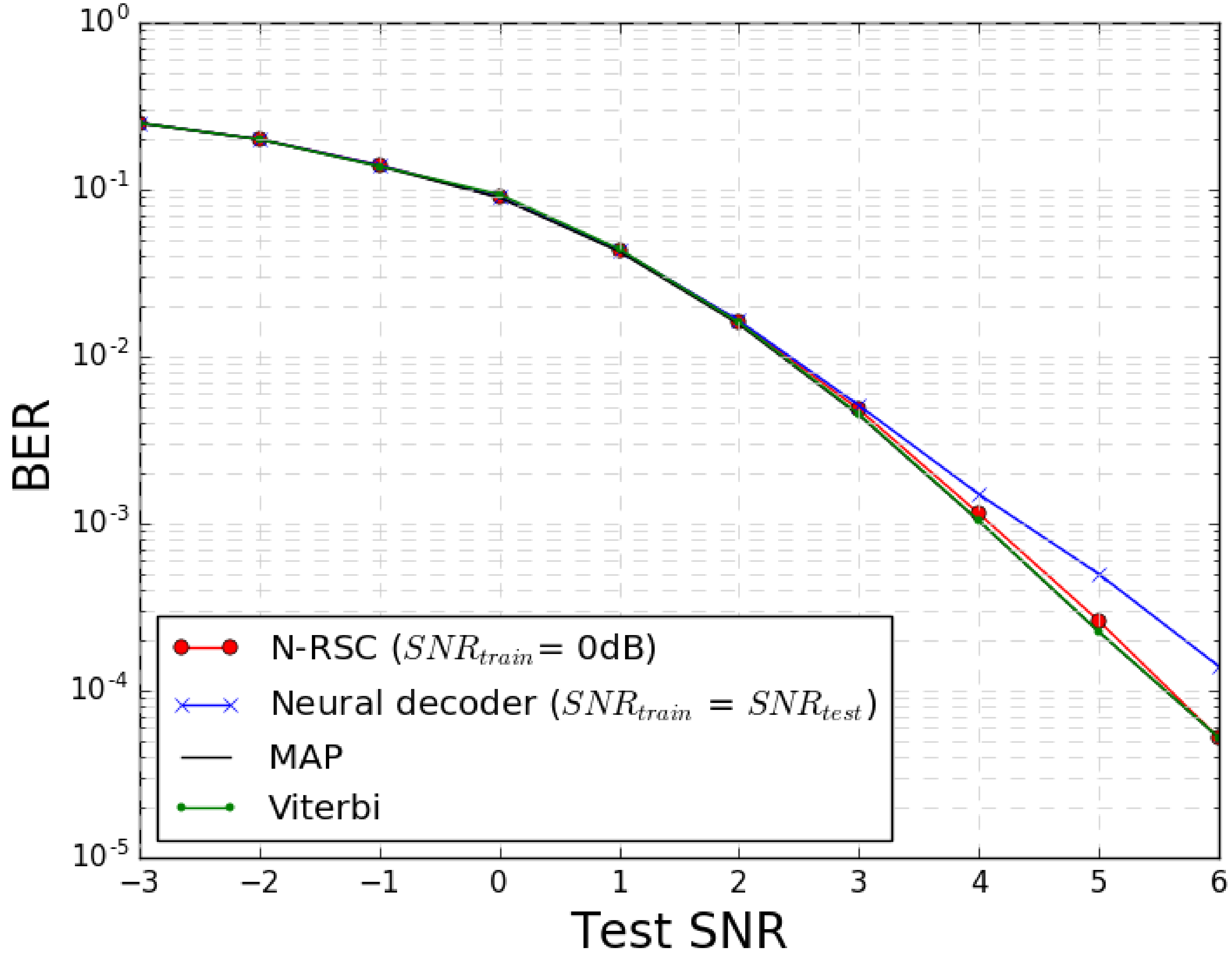
Training: Zoom in

- Training:
  - L2 loss function
  - Block length 100

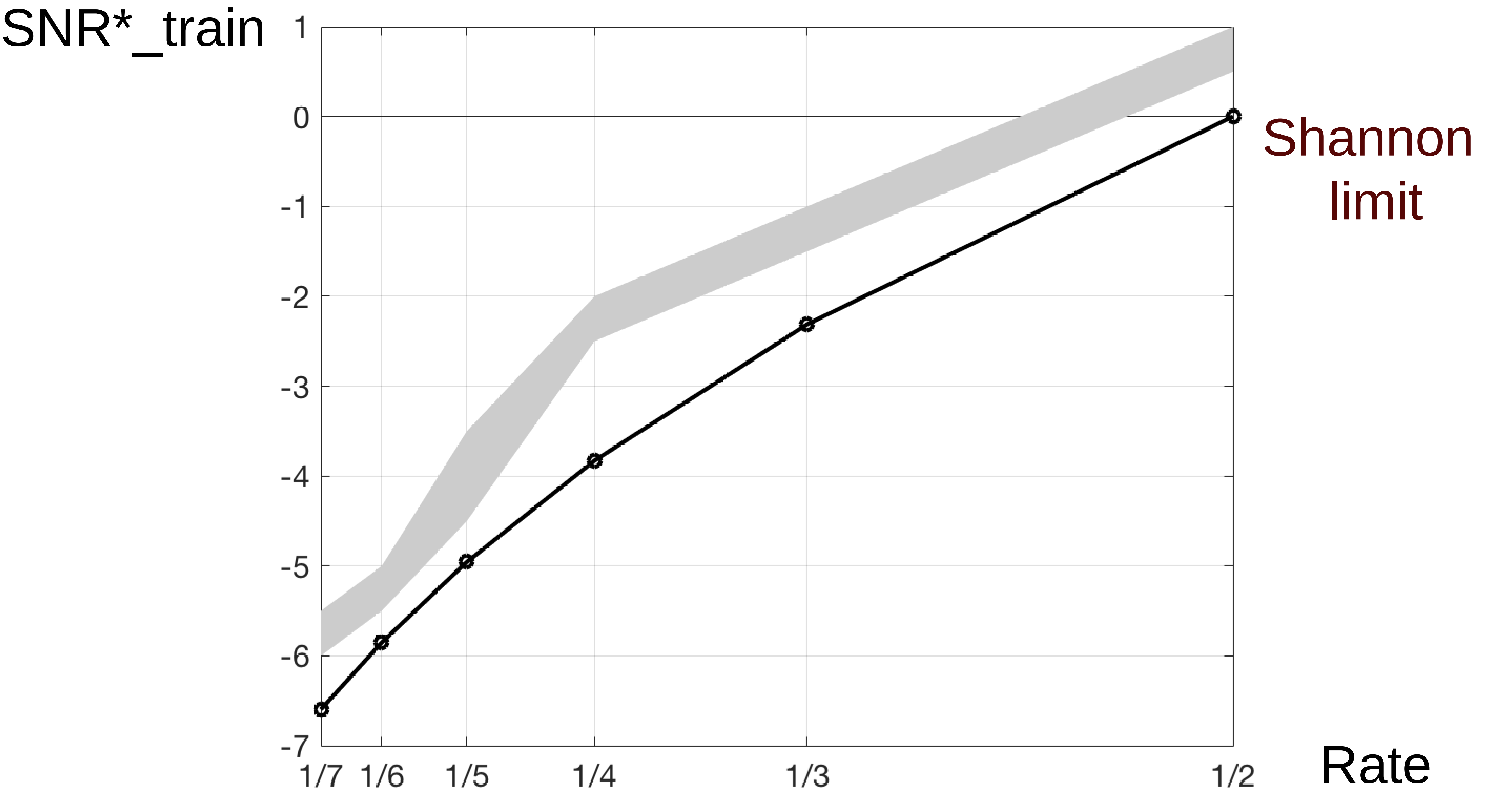
- 10K training examples

- Choice of SNR:
  - training = test SNR?
  - a variety of SNRs during training?

Not Quite There

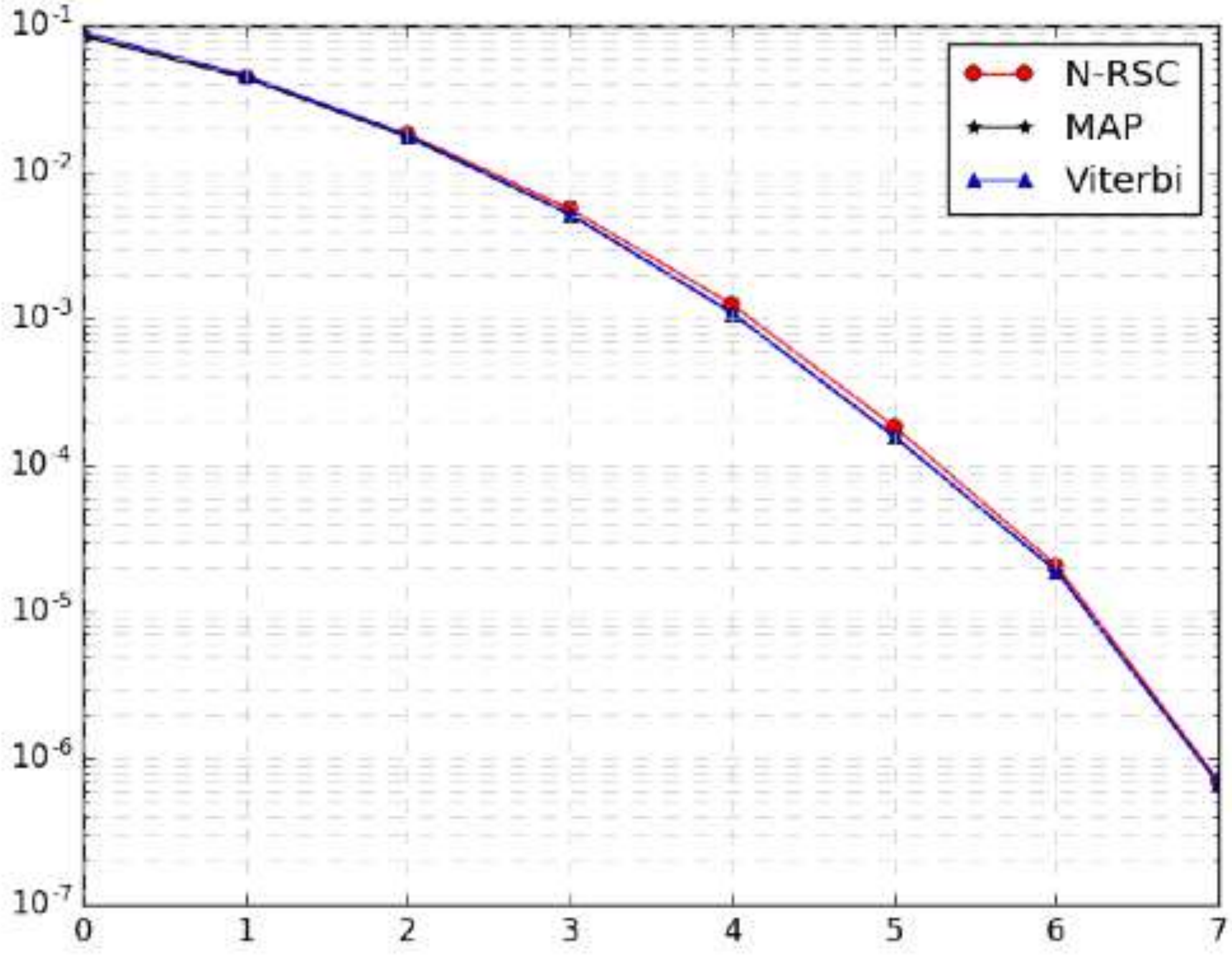


Hardest Training Examples



SGD Learns Viterbi and BCJR

BER



SNR

Train: block length = 100 Test: block length = 100K

Decoding Turbo Codes

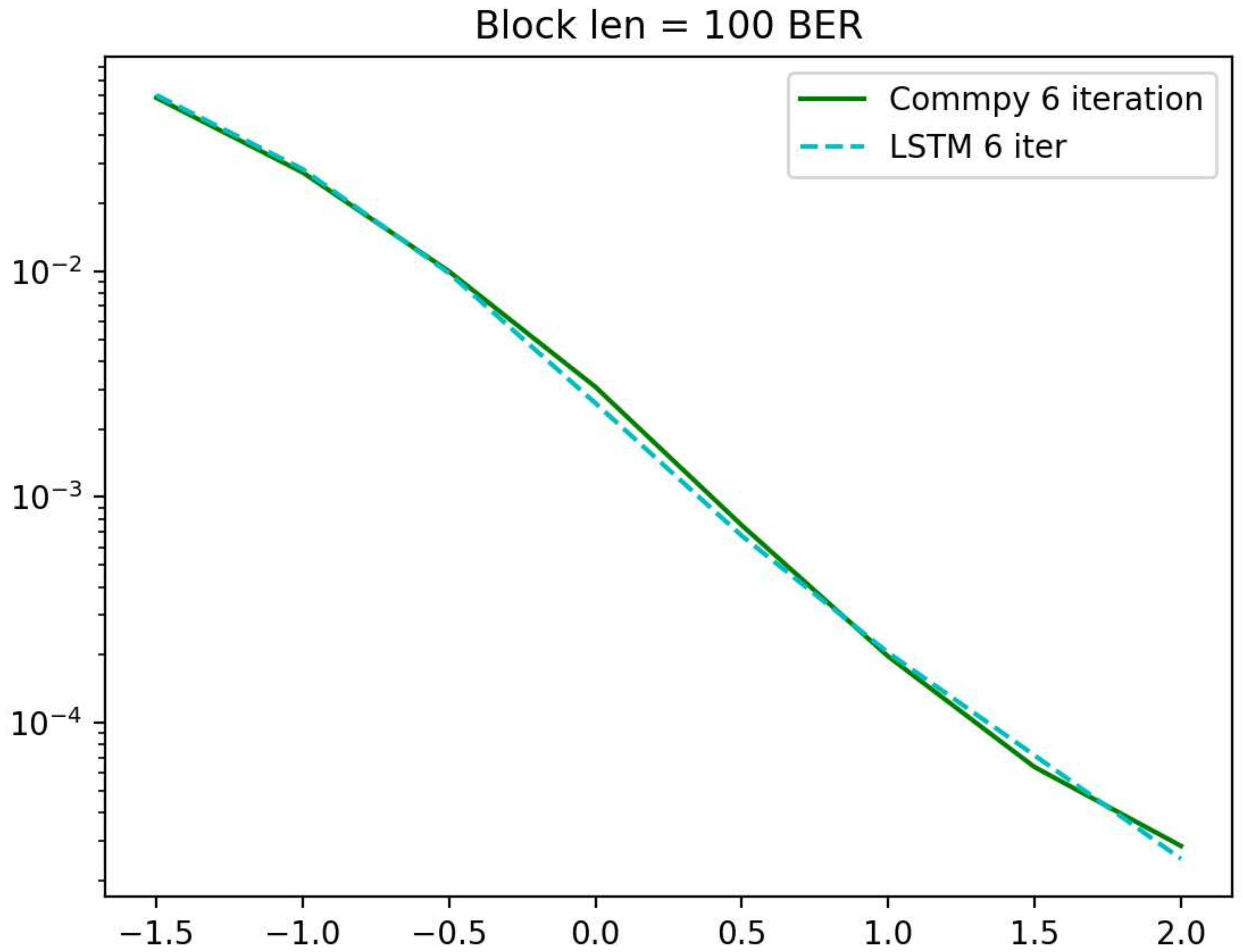
- Training:
  - L2 loss function
  - Block length 100
  - 10K training examples

- Retain iterative decoding structure

- Use neural convolutional decoders as modules

Decoding Turbo Codes

BER



SNR

Train: block length = 1000 Test: block length = 100K

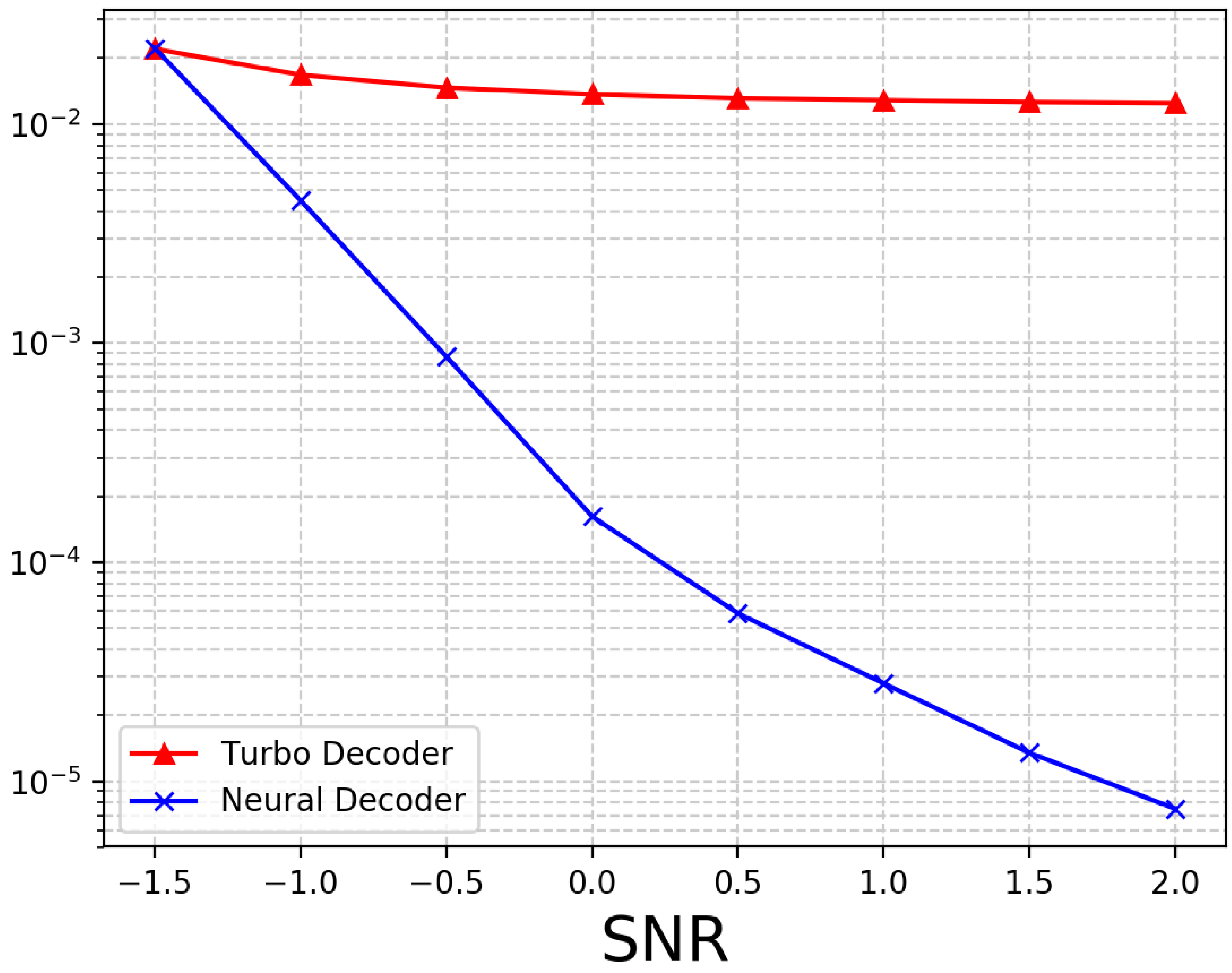
Typical Error Analysis

- Standard Information Theoretic tool
  - nuanced understanding of decoders
  - Statistics of noise that cause most error

- Classical result for ML decoder:
  - dominant error due to large noise vector magnitude
  - not true for turbo decoder

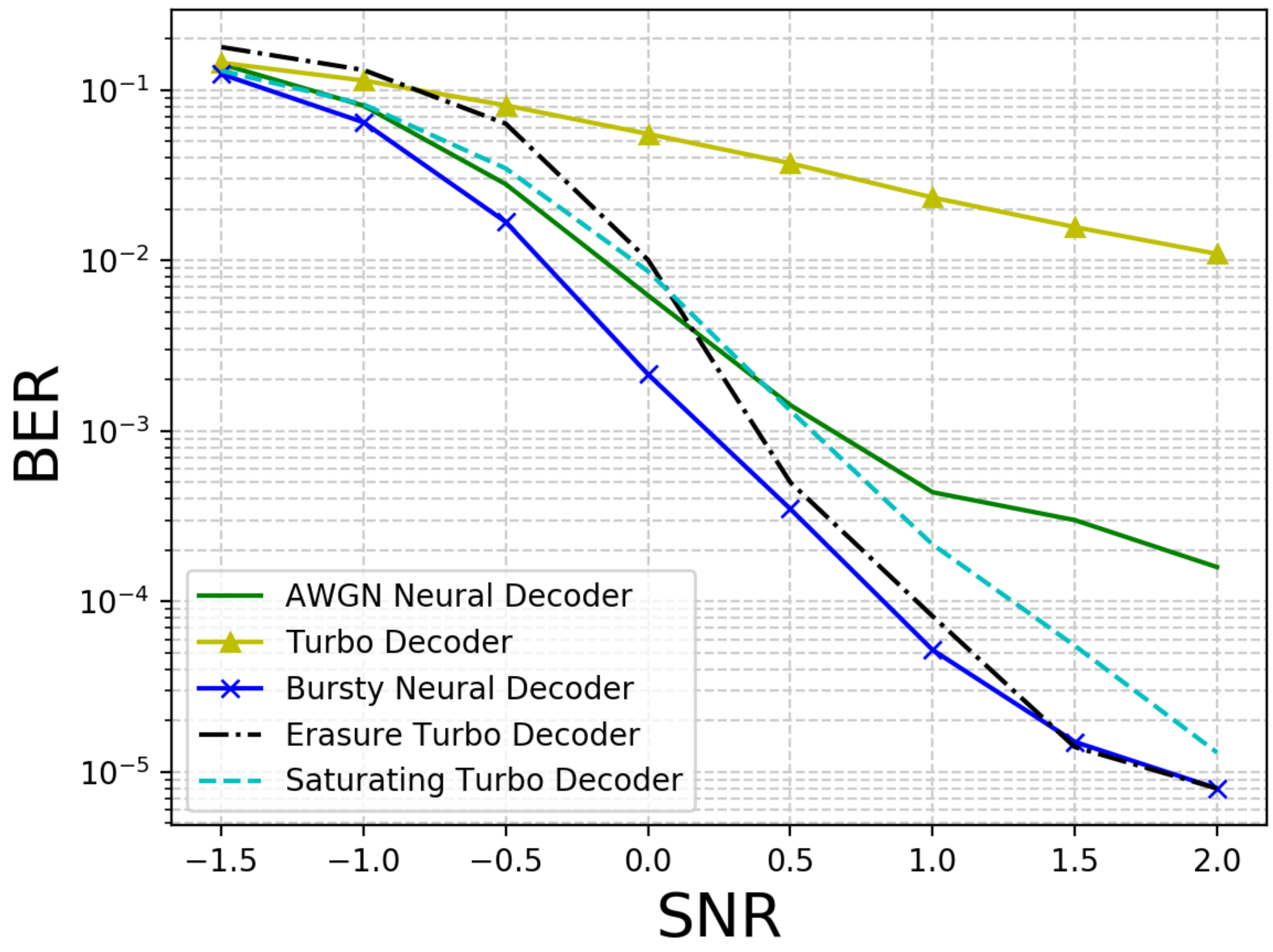
- Finding: neural decoder similar to ML decoder

Robustness



Fixed Decoder; change noise to T-distribution

Adaptivity: Bursty Noise



Retrain decoder with bursty noise

Typical Error Analysis

- Feedback neural encoder/decoder:

  dominant error due to noise amplitude being large

- Robustness to non-Gaussian noise

Inventing Codes

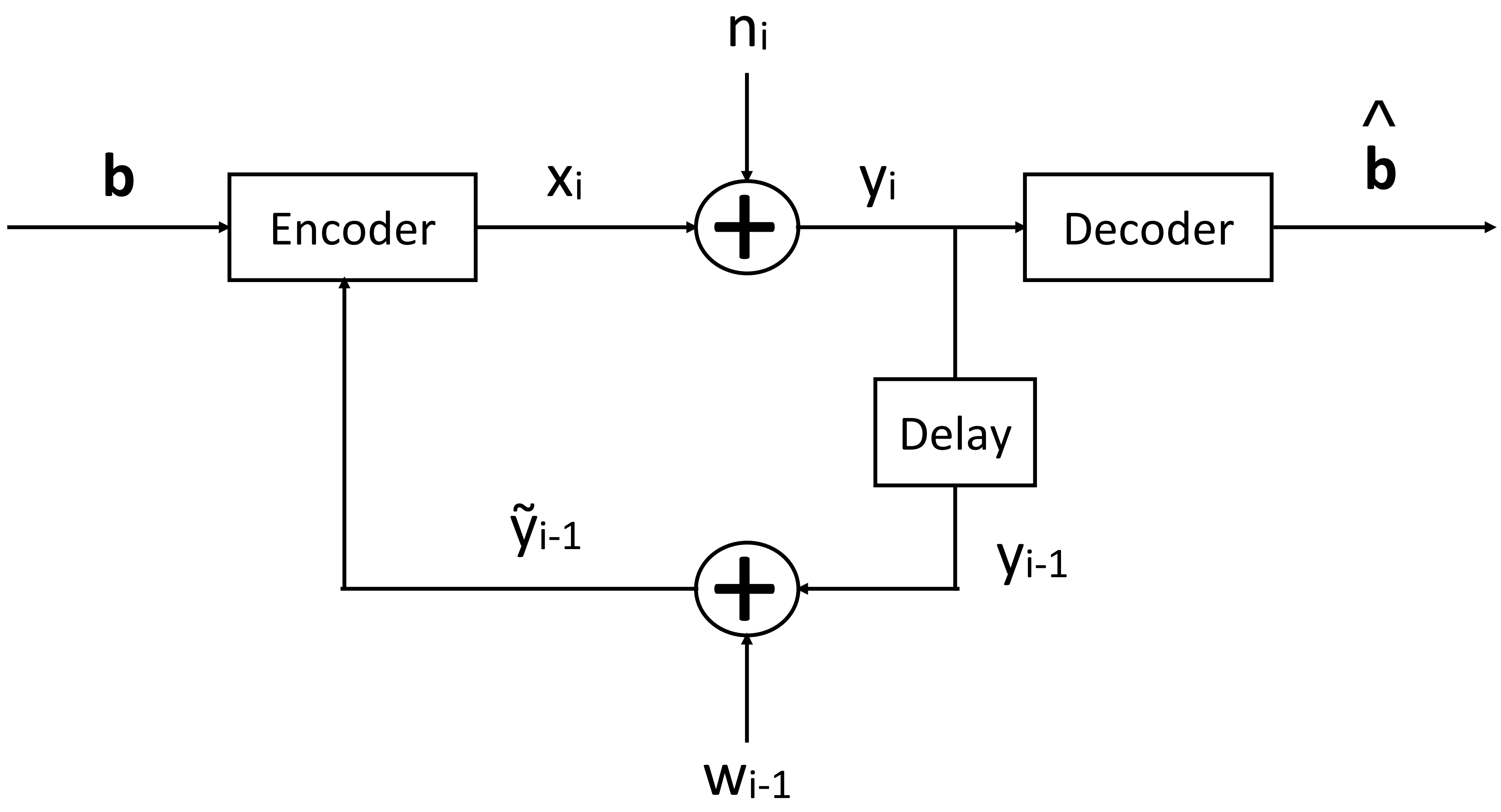
- AWGN channel
  - very well studied; high bar

- **Network Information Theory**
  - AWGN channel with feedback
  - relay channel
  - interference channel

Communication with Feedback

- Joint encoding and decoding
- AWGN channel with feedback
  - noisy feedback
- Deep Learning methods
  - beat Schalkwijk-Kailath scheme
  - even with noiseless feedback
- Robustness to noisy feedback
  - generalization: block lengths; SNR

AWGN Channel with Feedback



Key challenge: how to combine **b** with feedback

Literature

- Noiseless feedback
  - Schalkwijk-Kailath, '66
  - posterior matching
  - improved reliability

- Noisy feedback
  - Kim-Lapidoth-Weissman, ’07
  - Linear codes very bad
  - Negative result

- Opportunity to test deep learning approach

Sequential Neural Architecture

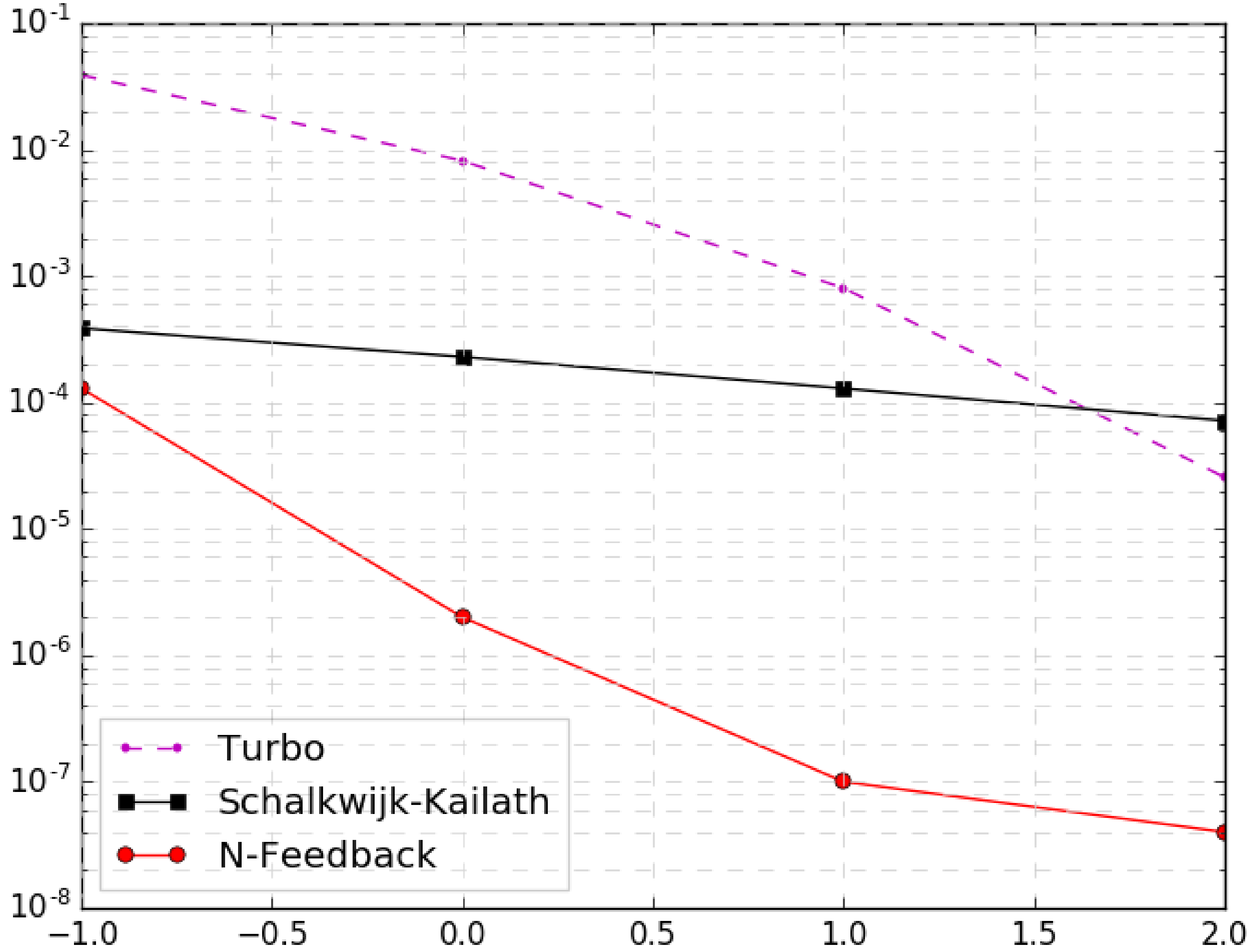
- Encoder and Decoder: RNN

- Several Innovations
  - systematic bits
  - parity bits use feedback
  - power allocation to bits
  - “correct” concatenations

- Training: end-to-end

Noiseless Feedback

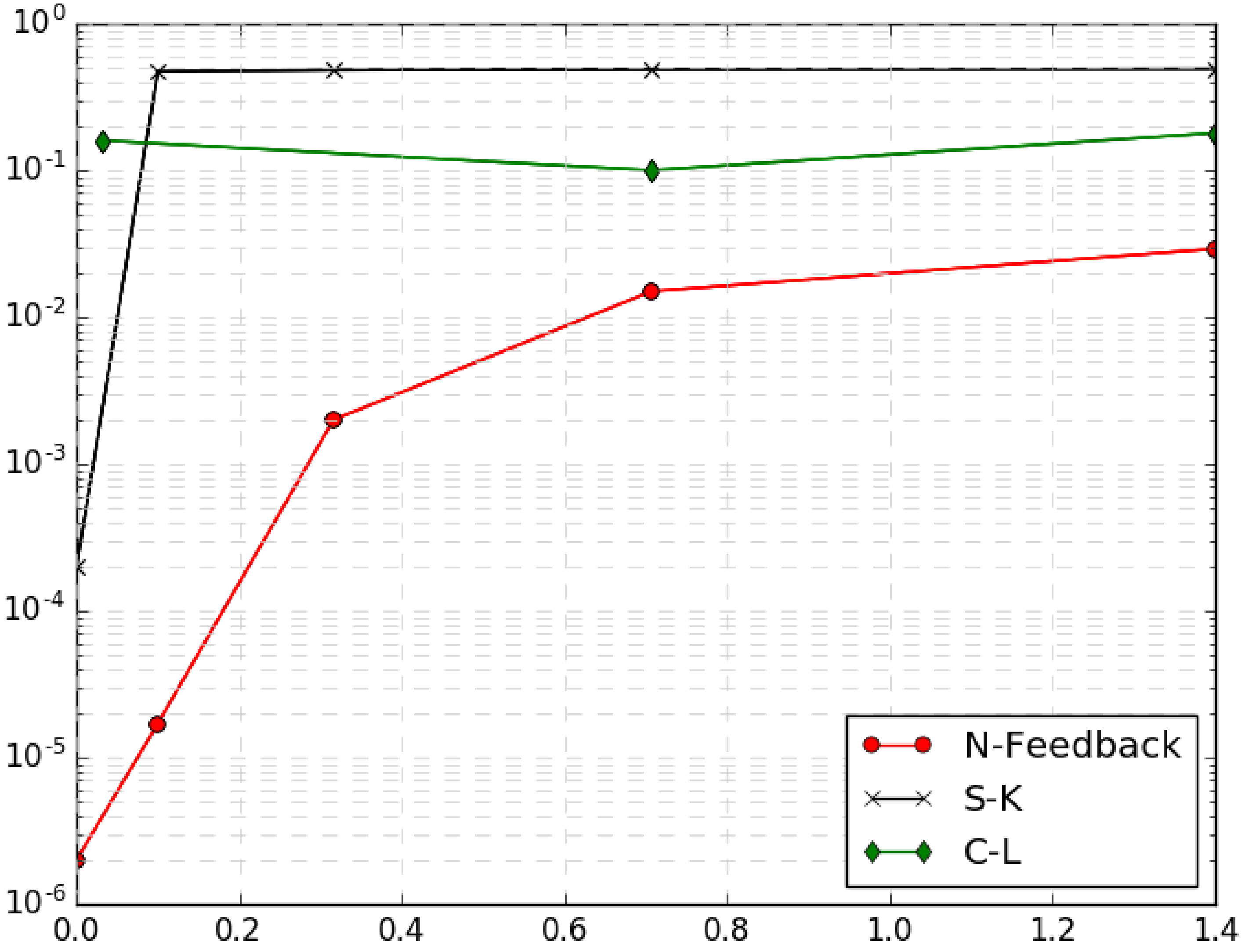
BER



SNR

- Rate 1/3, blocklength = 50

Noisy Feedback

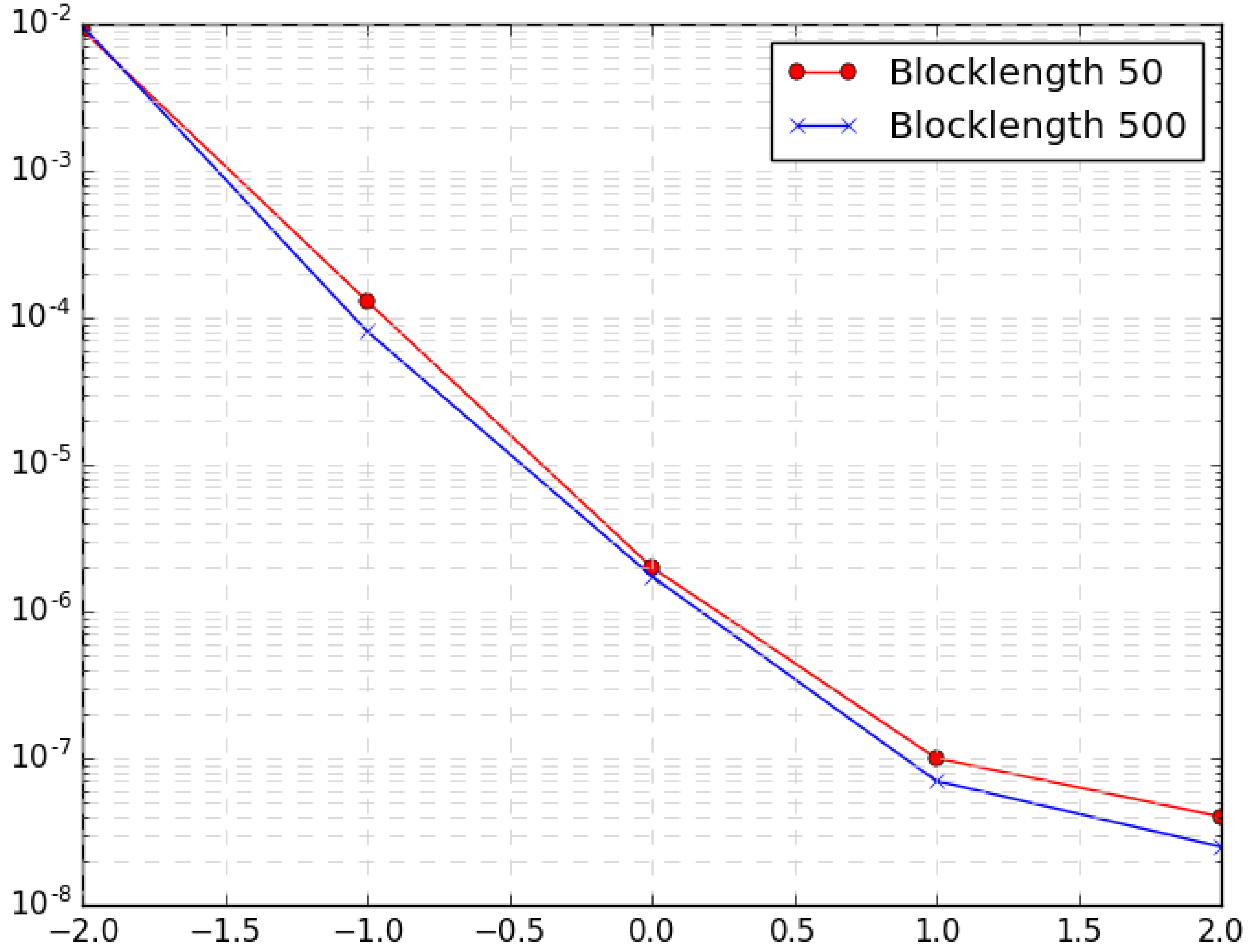


BER

Feedback Noise

Generalization: Blocklength

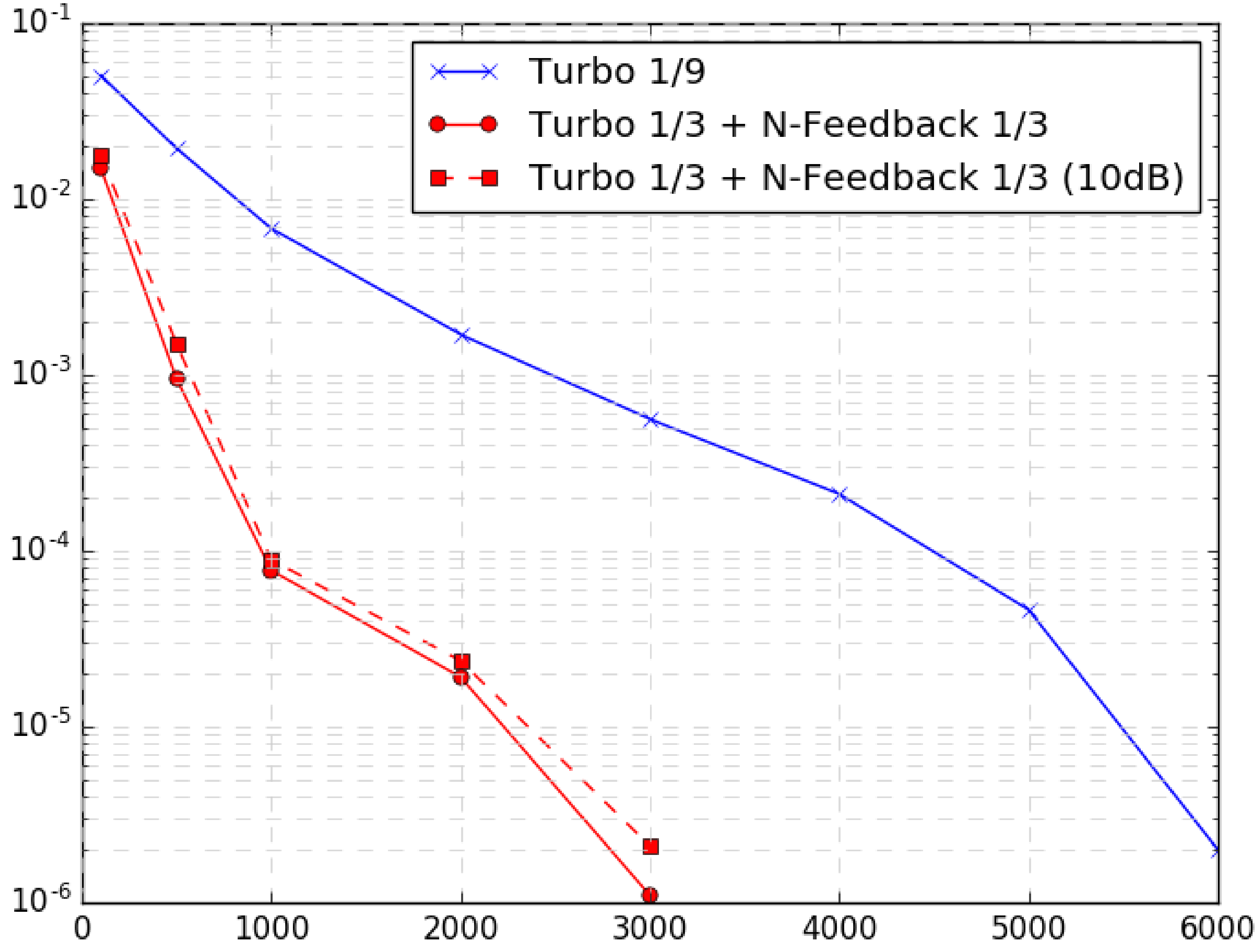
BER



SNR

Improved Error Exponents

BER



Blocklength

Properties of the Feedback Code

- Nonlinear convolutional code
  - Maps information bits directly to real numbers

- Dynamic memory
  - Feedback influences the memory

- Gated RNNs
  - Can capture long term and short term memory

Theoretical Agenda

- **Gated Recurrent Neural Networks**
  - Nonlinear dynamical systems
  - Switched linear systems

- **Learning Theory meets Switched Dynamical Systems**
  - Many open questions (AISTATS ‘19,’20, ICML ‘19)
  - Basic theoretical/mathematical value

Defense Against the Dark Arts

- **deepcomm.github.io**

  - Instructional material
  - Social networking

Collaborators

RM Codes: V. Jamali, X. Liu, A. Makkuva, H. Mahdavifar