

LEARN Codes: Inventing Low-Latency Codes via Recurrent Neural Networks

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Abstract—Designing channel codes under low-latency constraints is one of the most demanding requirements in 5G standards. However, a sharp characterization of the performance of traditional codes is available only in the large block-length limit. Guided by such asymptotic analysis, code designs require large block lengths as well as latency to achieve the desired error rate. Tail-biting convolutional codes and other recent state-of-the-art short block codes, while promising reduced latency, are neither robust to channel-mismatch nor adaptive to varying channel conditions. When the codes designed for one channel (e.g., Additive White Gaussian Noise (AWGN) channel) are used for another (e.g., non-AWGN channels), heuristics are necessary to achieve non-trivial performance.

In this paper, we first propose an end-to-end learned neural code, obtained by jointly designing a Recurrent Neural Network (RNN) based encoder and decoder. This code outperforms canonical convolutional code under block settings. We then leverage this experience to propose a new class of codes under low-latency constraints, which we call *Low-latency Efficient Adaptive Robust Neural (LEARN) codes*. These codes outperform state-of-the-art low-latency codes and exhibit robustness and adaptivity properties. LEARN codes show the potential to design new versatile and universal codes for future communications via tools of modern deep learning coupled with communication engineering insights.

Index Terms—Channel Coding, Low Latency, Communications, Deep Learning, Robustness, Adaptivity.

I. INTRODUCTION

Reliable channel codes have had a huge impact on communications in the modern information age. Since its inception in [1] that was powered by the mathematical insights of information theory and principles of modern

engineering, several capacity-achieving codes such as Polar, Turbo and LDPC codes [2][3][4] have come close to the Shannon limit when operated at large block lengths under Additive White Gaussian Noise (AWGN) channels. These codes were successfully adopted and applied in LTE and 5G data planes [5]. Since 5G is under intensive development, designing codes that have features such as *low latency*, *robustness*, and *adaptivity* has become increasingly important.

A. Motivation

Ultra-Reliable Low Latency Communication (URLLC) code [6] requires minimal delay constraints, thereby enabling scenarios such as vehicular communication, virtual reality, and remote surgery. When considering low-latency requirements, it is instructive to observe the interplay of three different types of delays: *processing delays*, *propagation delays*, and *structural delays*. Processing and propagation delays are affected mostly by computing resources and varying environments [7]. Low-latency channel coding, the focus of this paper, aims to improve the structural delay caused by the encoder and/or decoder. Encoder structural delay refers to the delay between the encoder's receiving the information bit and sending it out. Decoder structural delay refers to the delay between the decoder's receiving and decoding bits from the channel. Traditional AWGN capacity-achieving codes, such as LDPC and Turbo codes with small block lengths, show poor performance for URLLC requirements [7], [11]. There has also been recent interest in establishing theoretical limits and bounds on the reliability of codes at small to medium block lengths [12].

We note that latency translates directly to block length when using a block code; the decoder waits until it receives the entire (noisy) codeword to start the decoding. On the other hand, when using a convolutional code, latency is given by the decoding window length. Thus, there is an inherent difference between block codes and convolutional codes when considering latency. Since the latter incorporates locality in encoding, they can also be locally decoded. While convolutional codes with small constraint lengths are not capacity achieving,

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they can possibly be optimal under the low-latency constraint. Indeed, this possibility was raised by [7] and observed in [8], [9], [10]. Convolutional codes that allows run-length coding beyond block coding schemes [7] perform better than a known converse bound on the performance of block codes. In this work, we advance this hypothesis by showing that we can invent codes similar to convolutional codes that outperform handcrafted codes in the low-latency regime. While convolutional codes are the state-of-the-art in this regime, in the moderate latency regime, Extended Bose-Chaudhuri-Hocquenghem codes (eBCH) also perform well [13].

In addition, low-latency constraint channel coding must take channel effects into account under non-AWGN settings because pilot bits used for accurate channel estimation increase latency [7]. This calls for incorporating both robustness and adaptivity as desired features for URLLC codes. *Robustness* refers to the ability to perform with acceptable degradation without retraining when model mismatches occur; *adaptivity* refers to the ability to learn to adapt to different channel models with retraining. Current traditional channel coding systems require heuristics to compensate for channel effects, which leads to sub-optimality for model mismatches [14]. In general, channels without clean mathematical analysis lack the theory of an optimal communication algorithm and thus rely on sub-optimal heuristics [15]. In short, current channel coding schemes fail to deliver under the challenges of low latency, robustness, and adaptivity.

B. Channel Coding Inspired by Deep Learning: Prior Art

On the past decade, advances in *deep learning* (DL) have greatly benefited engineering fields such as computer vision, natural language processing, and gaming technology [16]. This has generated recent excitement about applying DL methods to communication system design [19][20]. These methods have typically been successful in settings where there is a significant *model-deficiency*, i.e., the observed data cannot be well described by a clean mathematical model. Thus, many initial proposals applying DL to communication systems have also focused on problems where there is model uncertainty due to the lack of, say, channel knowledge [21], [22]. In developing codes for the AWGN channel under low-latency constraints, there is no model deficiency since the channel is well-defined mathematically and simple to describe. However, the main challenge is that optimal codes and decoding algorithms are not known; we refer to this as *algorithm deficiency*.

For *algorithm-deficit* problems, the following two categories of work apply deep learning to communication

systems: (1) designing a neural network decoder (aka neural decoder) for a given canonical encoder such as LDPC or Turbo codes, and (2) jointly designing both the neural network encoder and decoder, referred to as a Channel Autoencoder (aka Channel AE) [19] (as illustrated in Figure 1).

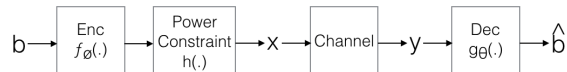


Fig. 1. Channel AE block diagram.

Neural decoders show promising performance by mimicking and modifying existing optimal decoding algorithms. Learnable Belief Propagation (BP) decoders for BCH and High-Density Parity-Check (HDPC) code have been proposed in [24] and [25]. Polar decoding via neural BP is proposed in [26] and [27]. Since mimicking learnable Tanner graphs requires a fully connected neural network, generalizing to longer block lengths is prohibitive. Capacity-achieving performance for Turbo code under an AWGN channel is achieved via Recurrent Neural Networks (RNNs) for arbitrary block lengths [28]. The joint design of neural code (encoders) and decoders via a Channel AE, relevant to the problem under consideration in this paper, has witnessed scant progress. Deep autoencoders have been successfully applied for various problems, such as dimensionality reduction, representation learning, and graph generation [18]. However, Channel AE significantly differs from typical deep autoencoder models in the following two aspects, making its design and training highly challenging:

- 1) The number of possible message bits b grows exponentially with respect to the block length. Hence, Channel AE must generalize to unseen messages with capacity-restricted encoders and decoders [26].
- 2) Channel models add noise between the encoder and decoder, and the encoder needs to satisfy power constraints, thus requiring high robustness in the code.

For Channel AE training, [19] and [20] introduce learning tricks emphasizing both channel coding and modulations. Learning Channel AE without a channel gradient is shown in [32]. Modulation gain is reported in [33]. Beyond AWGN and fading channels, [34] extended RNN to design a code for the feedback channel, which outperforms existing state-of-the-art codes [29], [30]. Extending Channel AE to MIMO settings is reported in [23]. Despite the successes, existing research on Channel AE under canonical channels is currently restricted to very short block lengths (for example, achieving the same performance as a rate 4/7 Hamming code with 4

information bits). Furthermore, existing works do not focus on the low-latency, robustness, and adaptivity requirements.

With this backdrop, this paper poses the following fundamental question: *Can we improve the Channel AE design to construct new codes that comply with low-latency requirements?*

We answer this in affirmative, as described next.

C. Our Contribution

Our primary goal is to design a low-latency code under extremely low-structural-latency requirements. As noted, convolutional codes outperform block codes given low structural latency [7] [8] [9] [10]. An RNN is a constrained neural structure with a natural connection to convolutional codes since the encoded symbol has a locality of memory and is most strongly influenced by the recent past of the input bits. Furthermore, RNN-based codes have shown a natural generalization across different block lengths in prior work [28][26]. With a carefully designed learnable structure that uses Bidirectional RNN (Bi-RNN) for both encoder and decoder, as well as a novel training methodology developed specifically for the Channel AE model, we demonstrate that our Bi-RNN-based neural code outperforms convolutional code.

We then propose *Low-Latency Efficient Adaptive Robust Neural (LEARN) code*, which applies learnable RNN structures to both the encoder and decoder with an additional low-latency constraint. LEARN improves performance under extremely low-latency constraints. Ours is the first work we know of that creates an end-to-end design for a neural code that improves performance on the AWGN channel (in any regime). In summary, the contributions of this paper include:

1. *Outperforming convolutional codes.* We propose a bi-directional RNN network structure and a tailored learning methodology for Channel AE that outperform canonical convolutional codes. The proposed training methodology results in smoother training dynamics and better generalization. (Section II)
2. *Improving performance in low-latency settings.* We design **LEARN code** for low-latency requirements with specific network designs. LEARN code improves performance in extremely low-latency settings. (Section III).
3. *Showing robustness and adaptivity.* When channel conditions are varying, LEARN codes demonstrate robustness (ability to work well under unseen channels) and adaptivity (ability to adapt to a new channel with few training symbols), showing an order of magnitude improvement in reliability compared to existing state-of-the-art codes. (Section III)
4. *Providing interpretations.* We provide interpretations to aid in the fundamental understanding of why the jointly trained code works better than canonical codes, instrumental in aiding future research. (Section IV)

II. DESIGNING NEURAL CODES THAT OUTPERFORM CONVOLUTIONAL CODES

The reliability of neural-network-based codes relies heavily on two factors: (1) a network structure design, and (2) a training methodology. In this section, we provide guidelines for these two factors and demonstrate that neural codes designed and trained using our guidelines have superior reliability compared to convolutional codes in a block coding setting.

A. Network Structure Design

Canonical channel codes perform better given longer block lengths, which is referred to as *coding gain*. Recent research on the Channel AE model does not show coding gain for even moderate block lengths [19][26] with fully connected neural networks, even with nearly unlimited training examples. We argue that a Recurrent Neural Network (RNN) architecture is a more suitable DL structure for Channel AE. For a brief introduction to RNN and its variants – such as Bidirectional RNN (Bi-RNN), Gated Recurrent Unit (GRU), or Long Short Term Memory (LSTM) – please refer to Appendix A. In this paper, we use the terms GRU and RNN interchangeably.

RNN-based Encoder and Decoder Design

Our empirical results comparing different Channel AE structures (Figure 2) show that for a longer block length, RNN outperforms a Fully Connected Neural Network (FCNN) for Channel AE. The FCNN curve in Figure 2 refers to using FCNN for both encoder and decoder. RNN in Figure 2 refers to using Bi-RNN for both encoder and decoder. The training steps are kept the same for a fair comparison. The repetition code and extended Hamming code performances are shown as a reference for both short and long block lengths.

Figure 2 (left) shows that for short block lengths (4), the performance of FCNN and RNN are close to each other since enumerating all possible code is not prohibitive. On the other hand, for a longer block length (100), Figure 2 (right) shows that in using FCNN, the Bit Error Rate (BER) is even worse than repetition codes, which shows a failure in generalization; RNN outperforms FCNN due to its generalization via parameter sharing and adaptive learnable dependency length. Hence, in this paper, we model the encoder and decoder as RNNs in order to gain generalization across block lengths. Figure 2 also shows that RNNs with tailored training methodologies outperform simply applying RNN

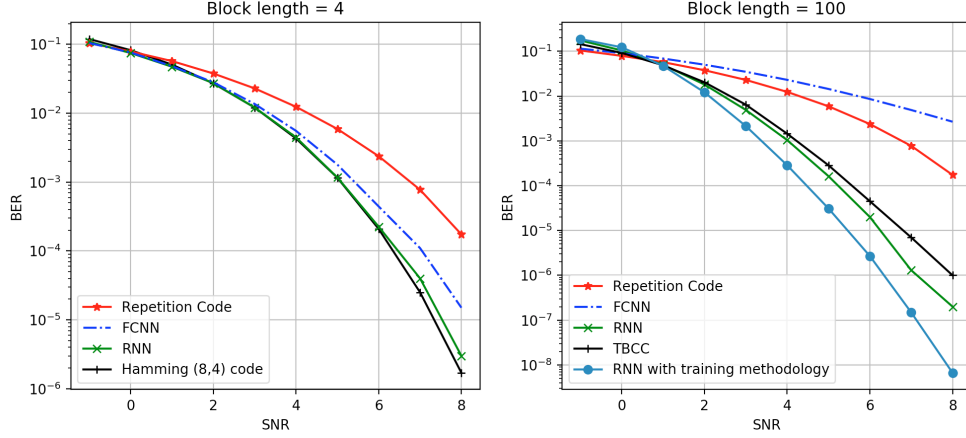


Fig. 2. Channel AE performance on code rate 1/2, where block length (number of information bits) is 4 (left) and 100 (right). TBCC shown on the right is $m=2$, with $g_{11} = 5$, $g_{12} = 7$ with feedback 7.

or FCNN for Channel AE; we illustrate this training methodology in Section II.B.

Power Constraint Module

The output of the RNN encoder can take arbitrary values and does not necessarily satisfy the power constraint. To impose the power constraint, we use a power constraint layer after the RNN encoding layer, as shown in Figure 1. Power normalization enforces that the output code has unit power by normalizing the output as $E[x^2] = 1$. More detail is in the Appendix.

B. Training Methodology

The following training methods result in a faster learning trajectory and better generalization with the learnable structure discussed above.

- Training with a large batch size
- Using Binary Crossentropy (BCE) loss
- Training encoder and decoder separately
- Adding a minimum distance regularizer on encoder.
- Using the Adam optimizer
- Adding more capacity (parameters) to the decoder than the encoder

Some of the training methods are not common in deep learning due to the unique structure of Channel AE. Appendix C shows the empirical evidence, where we reason about the better performance of the above training methods.

C. Performance of RNN-Based Channel AE: AWGN Setting

Applying the network architecture guidelines and the training methodology improvements thus far proposed, we design neural code with Bi-GRU for both encoder and decoder, as shown in Figure 3. The hyperparameters are shown in Figure 4.

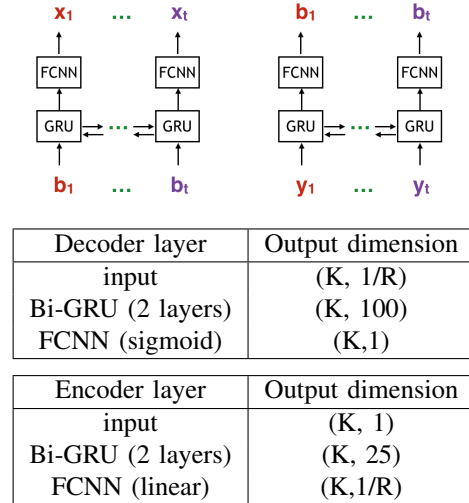


Fig. 3. RNN-based Channel AE encoder (top left), decoder (top right), and network structures (bottom).

Tail-biting Convolutional Code (TBCC) has proven to be the state of the art under a short block length regime [7], [8], [9], [10]. We compare the performance of TBCC with RNN-based channel code on block code settings. The BER performance in the AWGN channel under various code rates is shown in Figure 5. The TBCC BER curve is generated by convolutional code with constraint length up to $m = 7$ by the best generator function from Figure 7, with traceback length equals $5(m + 1)$; we measure the BERs for all TBCCs in Figure 7 empirically using CommPy simulator [52] and plot the best one. Figure 5 shows that RNN-based Channel AE outperforms all convolutional codes up to constrained length 7. RNN-based Channel AE empirically shows the advantage of jointly optimizing encoder and decoder over the AWGN

Encoder	2-layer Bi-GRU w/ 25 units
Decoder	2-layer Bi-GRU w/ 100 units
Power constraint	bit-wise normalization
Batch size	1000
Learning rate	$0.001, \times 1/10$ when saturate
Num epoch	250
Block length	100
Batch per epoch	100
Optimizer	Adam
Loss	Binary Cross Entropy (BCE)
Min Dist Regularizer	0.0
Train SNR at rate 1/2	mixture of 0 to 8dB
Train SNR at rate 1/3	mixture of -1 to 2dB
Train SNR at rate 1/4	mixture of -2 to 2dB
Train method	train ENC once DEC 5 times
Min Distance Regularizer	0.001 ($s = 10$)

Fig. 4. RNN-based Channel AE hyperparameters.

channel.

Note that the RNN-based Channel AE code is continuous; the performance gain is from both coding gain and high-order modulation gain, as shown in Figure 5 right; the performance gap at a higher SNR is larger. Binarized code leads to a fairer comparison; however, binarizing with the sign function is not differentiable. Bypassing non-differentiability using a straight-through estimator (STE) [50] degrades performance in channel coding [51]. Binarizing code and comparing to high order modulation are deferred to future research.

D. Performance of RNN-Based Channel AE: Non-AWGN Setting

We test the robustness and adaptivity of RNN-based Channel AE on three families of channels:

- 1) AWGN channel: $y = x + z$, where $z \sim N(0, \sigma^2)$.
- 2) Additive T-distribution Noise (ATN) channel: $y = x + z$, where $x \sim T(v, \sigma^2)$, for $v = 3, 5$. This noise is a model for heavy-tailed distributions.
- 3) Radar channel: $y = x + w + z$, where $z \sim N(0, \sigma_1^2)$ and $w \sim N(0, \sigma_2^2)$, w.p. $p = 0.05$. (Assume $\sigma_1 \ll \sigma_2$). This noise model appears when there is bursty interference, for example, when Radar interferes with LTE [39], [15].

Robustness

Robustness implies that when RNN-based Channel AE is trained for the AWGN channel, the test performance with no re-training on a different channel (ATN and Radar) should not degrade significantly. Most existing codes are designed under AWGN since it has a clean mathematical abstraction, and AWGN is the worst case noise under a given power constraint [1]. When both the encoder and decoder are unaware of the non-AWGN channel, the BER performance degrades. Robustness ensures both the encoder and decoder perform well under channel

mismatch, which is a typical use case for the low-latency scheme when channel estimation and compensation are not accurate [5].

Adaptivity

Adaptivity allows RNN-based Channel AE to learn a decoding algorithm from sufficient data (includes retraining) even under no clean mathematical model [28]. We train RNN-based Channel AE under ATN and Radar channels with the same hyperparameters shown in Figure 4 and the same amount of training data to ensure that the RNN-based Channel AE converges. With both learnable encoder and decoder, two cases of adaptivity are tested. First is decoder adaptivity, where the encoder is fixed and the decoder can be further trained. Second is the full adaptivity of both encoder and decoder. In our findings, encoder adaptivity shows no further advantage and is thus omitted.

We now evaluate RNN-based Channel AE for robustness and adaptivity on ATN and Radar channels. The BER performance is shown in Figure 6. Note that under non-AWGN channels, RNN-based Channel AE trained on the AWGN channel outperforms the convolutional code with the Viterbi decoder. It also shows more robust decoding ability for channel mismatching compared to the best convolutional code. As shown in Figure 6, RNN-based Channel AE with decoder-only adaptivity improves over the RNN-based Channel AE robust decoder, while RNN-based Channel AE with full adaptivity with both trainable encoder and decoder shows the best performance.

The fully adapted RNN-based Channel AE outperforms the convolutional code even with CSIR, which utilizes the log-likelihood of T-distribution noise. Thus, designing jointly by utilizing the encoder and decoder further optimizes code under given channels. Even when the underlying mathematical model is far from a cleaner abstraction, RNN-based Channel AE can learn the underlying functional code via self-supervised back-propagation.

RNN-based Channel AE is the first neural code to our knowledge that outperforms existing canonical codes under the AWGN channel coding setting, which opens a new field of constructing efficient neural codes under canonical settings. Furthermore, RNN-based Channel AE can be applied to channels even when mathematical analysis cannot be performed.

III. DESIGNING LOW LATENCY NEURAL CODES: LEARN

Designing codes for low-latency constraints is challenging since many existing block codes require inevitably long block lengths. To address this challenge, we now propose a new RNN-based encoder and decoder architecture that satisfies a low-latency constraint, which we call LEARN. While our encoder and decoder architectures

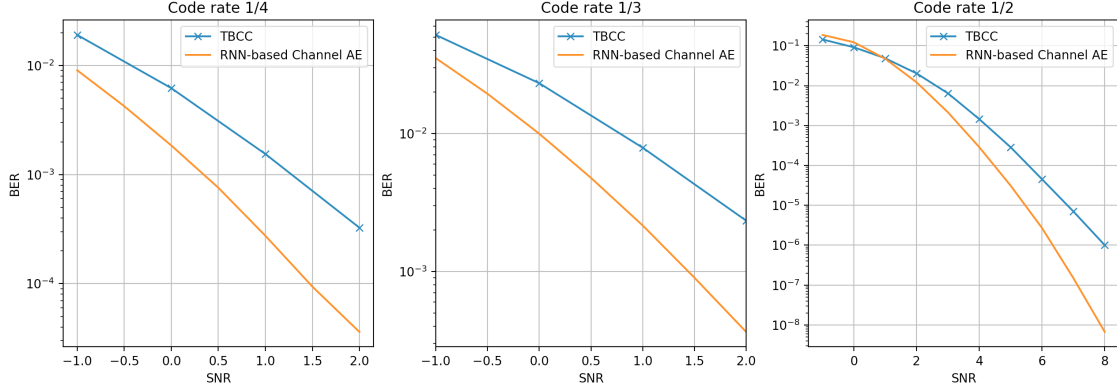


Fig. 5. Comparing RNN-based Channel AE with convolutional code on rate 1/4 (left), 1/3 (middle), 1/2 (right). Block length = 100.

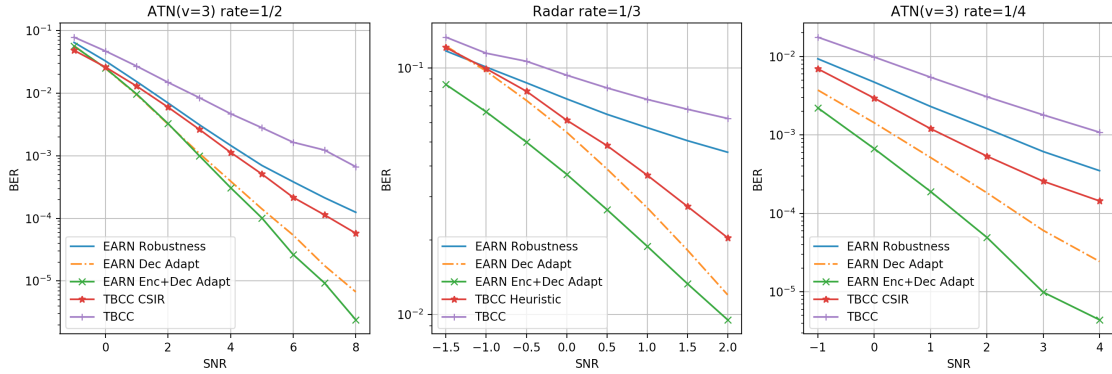


Fig. 6. RNN-based Channel AE vs TBCC, ATN($\nu = 3$) at rate 1/2 (left), Radar ($\sigma_2^2 = 5.0$) at rate 1/3 (middle), ATN($\nu = 3$) at rate 1/4 (right). TBCC is $m=2$, with $g_{11} = 5$, $g_{12} = 7$ with feedback 7

are based on RNNs, we introduce a new block in the decoder architecture so that the decoder can satisfy the extreme low-latency constraint. We show that LEARN code is: (1) significantly more reliable than convolutional codes, which are state-of-the-art under extreme low-latency constraints [7], and (2) more robust and adaptive for various channels beyond AWGN channels. In the following, we first define the latency and review the literature for the low-latency setting.

A. Low-Latency Convolutional Code

Formally, decoder structural delay D is understood in the following setting: to send message b_t at time t , the causal encoder sends code x_t , and the decoder has to decode b_t as soon as it received y_{t+D} . The decoder structural delay D is the number of bits that the decoder can look ahead to decode. The convolutional code has 0 encoder delay due to its causal encoder, and the decoder delay is controlled by the optimal Viterbi decoder [35] with a decoding window of length w , which uses only the last w future branches in the trellis to compute the current output. For code rate $R = \frac{k}{n}$ convolutional code, the structural decoder delay is $D = k - 1 + kw$ [11]. We use

code rate $k = 1$ with $n = 2, 3, 4$; the structural decoder delay is $D = w$. Convolutional code is state-of-the-art code under extreme low latency, where $D \leq 50$ [7].

In this paper, we confine our scope to investigating extreme low latency with no encoder delay under extremely low structural decoder delay $D = 1$ to $D = 10$ with code rates 1/2, 1/3, and 1/4. The benchmark we are using is convolutional code with variable memory length. Under an unbounded block length setting, longer memory improves performance; however, under a low-latency constraint, longer memory may not necessarily mean better performance since the decoding window is shorter [7]. Hence, we test for all memory lengths under 7 to get the state-of-the-art performance of the Recursive Systematic Convolutional (RSC) code, whose generating functions are shown in Figure 7 (top), with the convolutional code encoder shown in Figure 7 (bottom). The decoder is Viterbi with a decoding window $w = D$.

B. LEARN Network Structure

Using the network design proposed in the previous section, we propose a novel RNN-based neural network architecture for LEARN (both encoder and decoder) that

m	R=1/2			R=1/3			R=1/4				Feedback
	g11	g12		g11	g12	g13	g11	g12	g13	g14	
1	2	3	1	3	3	3	1	3	3	3	3
2	5	7	5	7	7	7	5	7	7	7	7
3	15	17	13	15	17	13	15	17	15	17	17
4	23	35	25	33	37	25	27	33	37	37	37
5	53	75	47	53	75	53	67	71	75	75	75
6	133	171	133	145	175	135	135	147	163	163	163
7	247	371	225	331	367	237	275	313	357	357	357

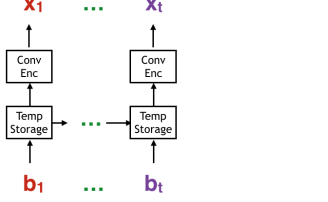
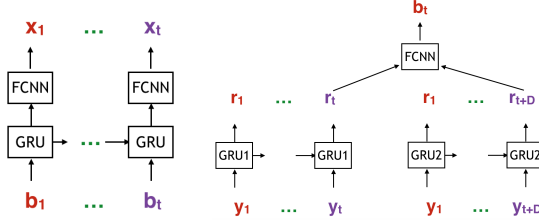


Fig. 7. Convolutional code generator matrix in octal representation (top) [7] and encoder (bottom).

satisfies the low-latency constraint. Our proposed LEARN encoder is illustrated in Figure 8 (top left). The causal neural encoder is a causal RNN with two layers of GRU added to a Fully Connected Neural Network (FCNN). The neural structure ensures that the optimal temporal storage can be learned and extended to a non-linear regime. The power constraint module is bit-wise normalization, as described in the previous section.



Decoder layer	Output dimension
Input	(K, 1/R)
GRU1 (2 layers)	(K, 100)
GRU2 (2 layers)	(K, 100)
FCNN (sigmoid)	(K,1)

Encoder layer	Output dimension
Input	(K, 1)
GRU (2 layers)	(K, 25)
FCNN (linear)	(K,1/R)

Fig. 8. LEARN encoder (top left), LEARN decoder (top right), and network structures (bottom).

Applying the Bi-RNN decoder for low-latency code requires the computation of lookahead instances for each received information bit, which is computationally expensive in both time and memory. To improve efficiency, the LEARN decoder uses two GRU structures instead of Bi-RNN structures. It has two GRUs: one GRU runs till the current time slot, and another GRU runs further for D steps; the outputs of the two GRUs are then summarized by a FCNN. The LEARN decoder

ensures that all the information bits satisfying the delay constraint can be utilized with the forward pass only. When decoding a received signal, each GRU needs to process only one step ahead, which results in decoding computation complexity $O(1)$. Viterbi and BCJR low-latency decoders need to go through the trellis and backtrack to the desired position, which requires going forward one step and backward with delay constraints steps, resulting in $O(D)$ computation for decoding each bit. Although GRU has a large computational constant due to the complexity of the neural network, the computation time is expected to diminish [38] with emerging AI chips. The hyperparameters of LEARN differ from block code settings. To summarize the differences: (1) the encoder and decoder use GRU instead of Bi-GRU, (2) the number of training epochs is reduced to 120, and (3) we do not use a partial minimum distance regularizer.

C. Performance of LEARN: AWGN Setting

Figure 9 shows the BER of a LEARN code and state-of-the-art RSC codes with varying memory lengths as illustrated in Figure 7 (top) for rates 1/2, 1/3, and 1/4 as a function of SNR under latency constraints $D = 1$ and $D = 10$. As the figure shows, for rates 1/3 and 1/4 under the AWGN channel, LEARN code under extreme delay ($D = 1$ to $D = 10$) shows better performance in Bit Error Rate (BER) compared to the state-of-the-art RSC codes from varying memory lengths in Figure 7 (top). LEARN outperforms all RSC codes listed in Figure 7 (top) with $D \leq 10$ with code rates 1/3 and 1/4, demonstrating a promising application of neural code under the low-latency constraint.

For higher code rates (such as $R = \frac{1}{2}$ and $D \geq 5$), LEARN shows comparable performance to convolutional codes but degrades at a high SNR. We expect further improvements can be made via improved structure design and hyperparameter optimization, especially at higher rates.

D. Robustness and Adaptivity

The performance of LEARN with reference to robustness and adaptivity is shown in Figure 10 for three different settings: (1) delay $D = 10$, code rate $R = 1/2$, with ATN ($\nu = 3$) channel; (2) delay $D = 2$, code rate $R = 1/3$, with ATN ($\nu = 3$) channel; and (3) delay $D = 10$, code rate $R = 1/2$, with the Radar ($p = 0.05$, $\sigma_2 = 5.0$) channel. As shown in Figure 10 (left), with ATN ($\nu = 3$), which has a heavy-tail noise, LEARN with robustness outperforms convolutional code. Adaptivity with both encoder and decoder performs best and is better than when only the decoder is adaptive. By utilizing the degree of freedom in designing an encoder and decoder, neural designed coding schemes can match canonical

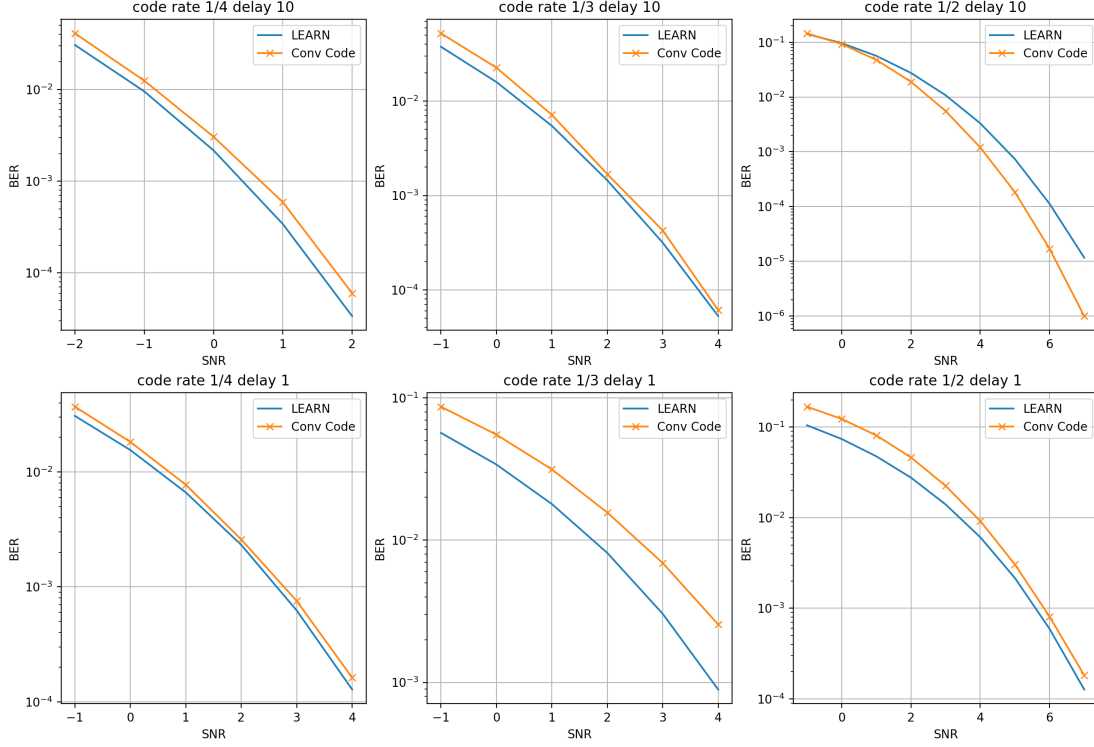


Fig. 9. BER curves comparing low-latency convolutional code vs LEARN under the AWGN channel with rate 1/4, 1/3, and 1/2.

convolutional codes with Channel State Information at Receiver (CSIR) at a low code rate ($R = 1/2$) and outperform convolutional codes with CSIR at a high code rate ($R = 1/3$).

As for Figure 10 (middle) ATN ($\nu = 3$) channel with code rate $R = 1/3$ and Figure 10 (right) Radar ($\sigma_2 = 5.0$) channel with code rate $R = 1/4$, the same trend holds. Note that under the Radar channel, we apply the heuristic proposed in [15]. We observe that LEARN with full adaptation gives an order-of-magnitude improvement in reliability over the convolutional code heuristic [15]. This experiment shows that by jointly designing both encoder and decoder, LEARN can adapt to a broad family of channels. LEARN offers an end-to-end low-latency coding design method that can be applied to any statistical channels and ensure good performance.

IV. INTERPRETABILITY OF DEEP MODELS

The promising performance of LEARN and the RNN-based Channel AE leads to an inevitable question: how do we interpret what the encoder and decoder have learned? Answering this can inspire future research as well as help us find caveats and limitations. In this section, we present interpretation analysis via local perturbation for LEARN and RNN-based Channel AE encoders and decoders.

A. Encoder Interpretability

The *significant recurrent length* of RNNs is a recurrent capacity indicator that helps to interpret neural encoder and decoders. The RNN encoder's significant recurrent length is defined, at time t , as how long a sequence the input u_t can impact as RNN operates recurrently. Assume two input sequences, $u_1 = u_{1,1}, \dots, u_{1,t}, \dots, u_{1,T}$ and $u_2 = u_{2,1}, \dots, u_{2,t}, \dots, u_{2,T}$, where only $u_{1,t}$ and $u_{2,t}$ differ. Taking a batch of u_1 and u_2 as input for the RNN encoder, we compare the output absolute difference along the whole block between $x_1 = f(u_1)$ and $x_2 = f(u_2)$ to investigate how long the input flip at time t can affect. To investigate LEARN's RNN encoder, we flip only the first bit (position 0) of u_1 and u_2 . The code position refers to the block bit positions, and the y-axis shows the averaged difference between two different sequences. Figure 11 (top left) shows that for an extremely short delay $D = 1$, the encoder's significant recurrent length is short. The effect of the current bit diminishes after 2 bits. As the delay constraint increases, the encoder's significant recurrent length increases, accordingly. The LEARN encoder learns to encode locally to optimize under the low-latency constraint.

For RNN-based Channel AE with Bi-RNN encoder, the block length is 100, and the flip is applied at the middle 50th bit position. Figure 11 (top right) shows the encoder trained under the AWGN and ATN channels. The encoder trained on ATN shows a longer

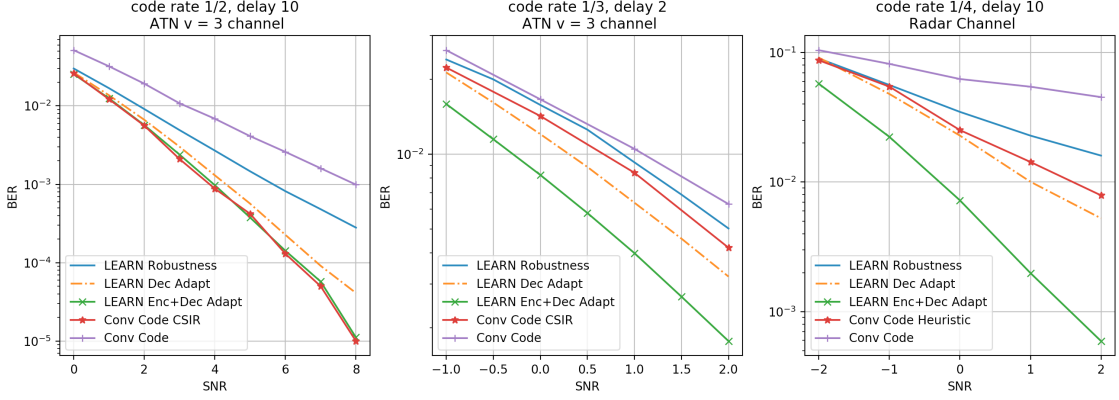


Fig. 10. LEARN robustness and adaptivity in ATN ($\nu = 3$, $R = 1/2$, $D = 10$) (left), ATN ($\nu = 3$, $R = 1/3$, $D = 2$) (middle), and Radar ($p = 0.05$, $\sigma_2 = 5.0$, $R = 1/4$, $D = 10$) (right) channels.

significant dependency length. ATN is a heavy-tail noise distribution to alleviate the effect of extreme value; increasing the dependency of code improves reliability. Note that even the longest significant recurrent length is only backward 10 steps and forward 16 steps; thus, the GRU encoder actually did not learn very long recurrent dependency. AWGN capacity-achieving code has some inbuilt mechanisms to improve long-term dependency, for example, the Turbo encoder uses interleaver to improve the long-term dependency [3]. Improving the significant recurrent length via a more learnable structure design is an interesting future research direction.

B. Decoder Interpretability

The decoder's significant recurrent length can illustrate how it copes with different constraints and channels. Assume two noiseless coded sequences, $y_1 = y_{1,1}, \dots, y_{1,t}, \dots, y_{1,T}$ and $y_2 = y_{2,1}, \dots, y_{2,t}, \dots, y_{2,T}$, y_1 and y_2 equals y_1 other than at time t , where $y_{1,t} = y_{2,t} + p$, where p is the large deterministic pulse noise; $p = 5.0$ for our experiment. We compare the output absolute difference along the whole block between $\hat{u}_1 = g(y_1)$ and $u_2 = g(y_2)$ to investigate how long the pulse noise can affect. For the LEARN decoder, we inject pulse noise at the starting position. Figure 11 (bottom left) shows that for all delay cases, the noise most significantly affected the position equal to the delay constraint. This shows that the LEARN decoder learns to coordinate with the causal LEARN encoder. Since $D = 1$, the maximized decoder difference along the block is at position 1; when $D = 10$, the maximized decoder difference along the block is at position 10. Other code bits have a less significant but non-zero decoder difference.

The LEARN decoder's significant recurrent length implies that it not only learns to utilize the causal encoder's immediate output, but it also utilizes outputs in other time slots to help decoding. Note that the maximized

significant recurrent length is approximately twice the delay constraint; after less than approximately $2D$, the impact diminishes. The LEARN decoder learns to decode locally to optimize under different low-latency constraints. For RNN-based Channel AE with the Bi-RNN encoder,

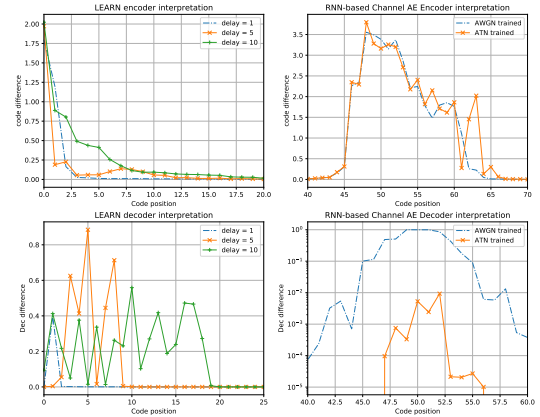


Fig. 11. Encoder interpretation for LEARN (top left) and RNN-based Channel AE (top right). Decoder interpretation for LEARN (bottom left) and RNN-based Channel AE (bottom right).

the perturbation is applied at the middle 50th position, still with block length 100. Figure 11 (bottom right) shows the decoder trained under the AWGN and ATN channels. The AWGN-trained decoder is more sensitive to pulse noise with extreme values than the ATN-trained decoder. By reducing the sensitivity for extreme noise, the ATN-trained decoder learns to alleviate the effect of non-Gaussian noise. The RNN-based Channel AE decoder learns to optimize the utilization of received signals under different channel settings.

V. CONCLUSION

In this paper, we demonstrated the power of neural network-based architectures to achieve state-of-the-art performance for simultaneous code and decoder design. We showed that our learned codes significantly outperform convolutional codes in short to medium block lengths. However, in order to outperform state-of-the-art codes such as Turbo or LDPC codes, we require additional mechanisms such as interleaving to introduce long-term dependence. This promises to be a fruitful direction for future exploration.

In the low-latency regime, we achieved state-of-the-art performance with LEARN codes. Furthermore, LEARN codes beat existing codes by an order of magnitude in reliability given channel mismatch. Our present design is restricted to extreme low latency; however, with additional mechanisms for introducing longer term dependence [40], [41], we believe that it is possible to extend these designs to cover a larger range of delays. This is another interesting direction for future work. Finally, we focused only on extreme structural latency. Latency depends on other factors as well (e.g., computational complexity). Optimization of neural decoders to reduce other latency poses an interesting open problem.

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APPENDIX
APPENDIX A
RECURRENT NEURAL NETWORKS : AN
INTRODUCTION

As illustrated in Figure 12 (left), RNN is defined as a general function $f(\cdot)$ such that $(y_t, h_t) = f(x_t, h_{t-1})$ at time t , where x_t is the input, y_t is the output, h_t is the state sent to the next time slot and h_{t-1} is the state from the last time slot. RNN can only emulate causal sequential functions. Indeed, it is known that an RNN can capture a general family of measurable functions from the input time-sequence to the output time-sequence [31]. Illustrated in Figure 12 (right), Bidirectional RNN (Bi-RNN) combines one forward and backward RNN and can infer current state by evaluating through both past and future. Bi-RNN is defined as $(y_t, h_t^f, h_t^b) = f(x_t, h_{t-1}^f, h_{t+1}^b)$, where h_t^f and h_t^b stands for the state at time t for forward and backward RNNs [16].

RNN is a restricted structure which shares parameters between different time slots across the whole block, which makes it naturally generalizable to a longer block length. Moreover, RNN can be considered as an overparameterized non-linear convolutional code for both encoder and decoder, since convolutional code encoder can be represented by causal RNN and BCJR forward-backward algorithm can be emulated by Bi-RNN [28]. There are several parametric functions $f(\cdot)$ for RNN, such as vanilla RNN, Gated Recurrent Unit (GRU), or Long Short Term Memory (LSTM). Vanilla RNN is known to be hard to train due to diminishing gradients. LSTM and GRU are the most widely used RNN variants which utilize gating schemes to alleviate the problem of diminishing gradients [16]. We empirically compare Vanilla RNN with GRU and LSTM under test loss trajectory, which shows the test loss along with the training times. The test loss trajectory is the mean of 5 independent experiments. Figure 12 right depicts the test loss along training time, which shows that vanilla RNN has slower convergence, GRU converges fast, while GRU and LSTM have similar final test performances. Since GRU has less computational complexity, in this paper we use GRU as our primary network structure [36]. In this paper, we use the terms GRU and RNN interchangeably.

APPENDIX B
POWER CONSTRAINT MODULE

The power normalization enforces the output code has unit power by normalizing the output. In the following, we investigate three implementations on the power constraint layer that are differentiable. We let b , \hat{x} , x denote the message bit sequence, output of the encoder, and the normalized codeword, respectively.

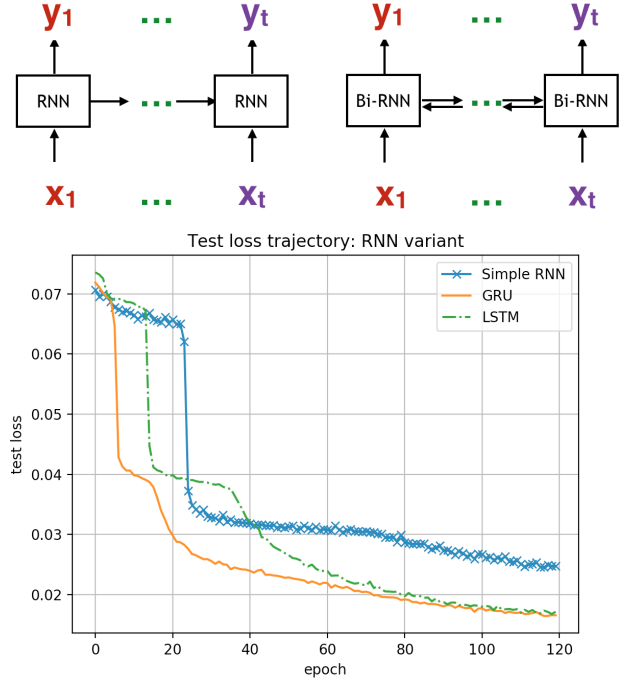


Fig. 12. Basic RNN structure (left), Bi-RNN (middle), and test trajectory for RNN variants selection (right)

1. *hard power constraint*: use hyperbolic tangent function in training ($x = \tanh(\hat{x})$) and threshold to -1 and +1 for testing, which only allows discrete coding schemes.
2. *bit-wise normalization*: $E\|X_i\|_2^2 \leq 1, \forall i$. We have $x_i = \frac{\hat{x}_i - \text{mean}(x_i)}{\text{std}(x_i)} \forall i$. For a given coding bit position, the bit power is normalized.
3. *block-wise normalization*: $E\|X\|_2^2 \leq 1$, We have $x = \frac{\hat{x} - \text{mean}(x)}{\text{std}(x)} \forall i$ which allows us to reallocate power across the code block.

For bit-wise and block-wise normalizations, the behaviors in training and testing are different. During the training phase, bit-wise and block-wise normalizations normalize input mini-batch according to the training mini-batch statistics. During testing phase, the mean and std are precomputed by passing through many samples to ensure that the estimations of mean and std are accurate.

Figure 13 left shows that block-wise normalization does offer better learning test trajectory, while bit-wise normalization shows slightly worse performance. Hard power constraint using \tanh , due to saturating gradients, results in high test error. Since neural code operates on communication systems, reallocating power might be against hardware constraints. To satisfy maximized power constraint, we use bit-wise normalization in this paper.

APPENDIX C TRAINING METHODOLOGY

In this section we give empirical evidence for the best tricks of trade to design superior codes used in this paper.

A. Using Large Batch Size

Deep Learning models typically use mini-batching to improve generalization and reduce the memory usage. Small random mini-batch results in better generalization [43][45], while large batch size requires more training to generalize. However, Figure 13 middle shows that larger batch size results in much better generalization for Channel AE, while small batch size tends to saturate in high test loss. Large batch size is required due to the following reasons:

(1) Large batch offers better power constraint statistics [37]. With a large batch size, the normalization of power constraint module offers a better estimation of mean and standard deviation, which makes the output of the encoder less noisy, thus the decoder can be better trained accordingly.

(2) Large batch size gives a better gradient. Since Channel AE is trained with self-supervision, the improvement of Channel AE originates from error back propagation. As extreme error might result in wrong gradient direction, large batch size can alleviate this issue.

The randomness of training mini-batch results in better generalization [16]. Figure 13 right shows that even with small block length ($L = 10$) when enumeration of all possible codes becomes possible, random mini-batching outperforms fixed full batch which enumerates all possible codes in each batch. Note that training with all possible codewords leads to worse test performance, while training with large random batch (5000) outperforms full batch settings. Thus we conclude that using a large random batch gives a better result. In this paper due to GPU memory limitation, we use batch size 1000.

B. Use Binary Crossentropy Loss

The input $u \in \{0, 1\}^k$ and output $\hat{u} \in \{0, 1\}^k$ are binary digits, which makes training Channel AE a binary self-supervised classification problem [19]. Binary Crossentropy (BCE) is better due to surrogate loss argument [46]. MSE and its variants can be used as the loss function for Channel AE [23][26] as MSE offers implicit regularization on over-confidence of decoding. The comparison of MSE and BCE loss is shown in Figure 14 left.

Although the final both test loss for BCE and MSE tends to converge, MSE leads to slower convergence. This is due to the fact that MSE actually punishes over-confident bits, which makes the learning gradient more

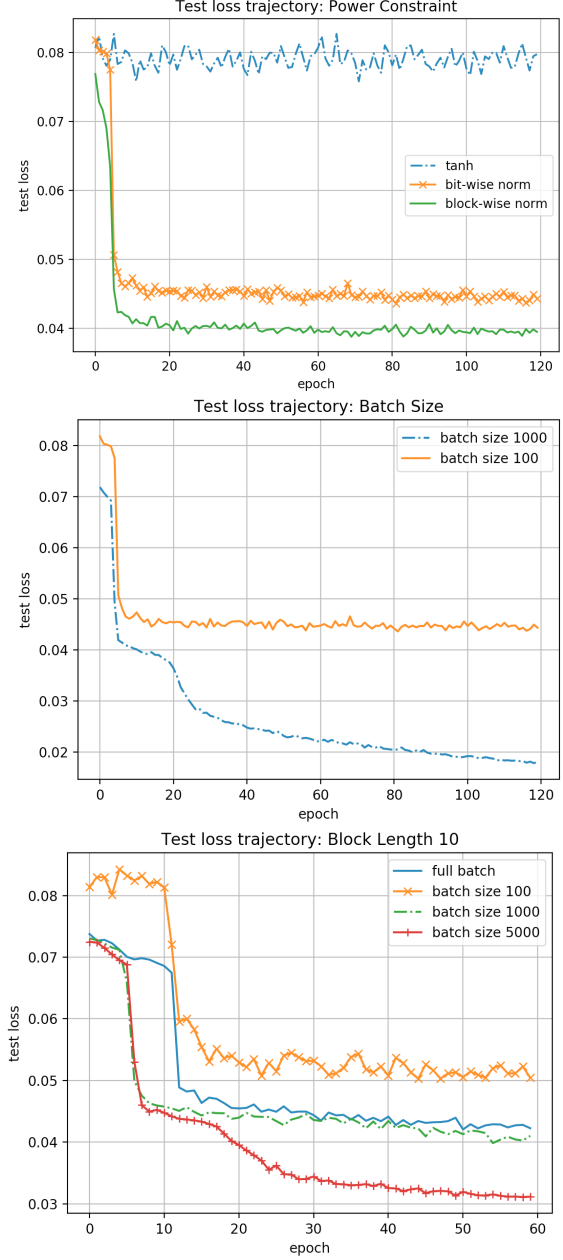


Fig. 13. Test loss trajectory on different power constraint (left), different batch size with block length 100 (middle) and random batch with block length 10 (right)

sparse. As faster convergence and better generalization are always appreciated, BCE is used as a primary loss function.

C. Separately Training Encoder and Decoder

Training encoder and decoder jointly with end-to-end back-propagation leads to saddle points. We argue that training Channel AE entails separately training encoder and decoder [32]. The accurate gradient of the encoder

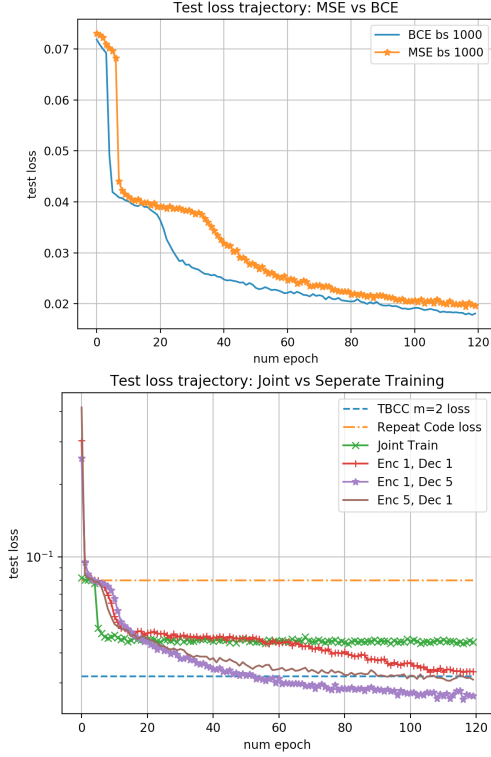


Fig. 14. Test loss trajectory different loss functions (left), Training jointly vs separately (right)

can be computed when the decoder is optimal for a given encoder. Thus after training encoder, training decoder until convergence will make the gradient of encoder more trustable. However, at every step training decoder till convergence is computationally expensive. Empirically we compare different training methods in Figure 14 right. Training encoder and decoder jointly saturates easily. Training encoder once and training decoder 5 times shows the best performance, and is used in this paper.

D. Adding Minimum Distance Regularizer

Naively optimizing Channel AE results in paired local optimum: a bad encoder and a bad decoder can be locked in a saddle-point. Adding regularization to loss is a common method to escape local optima [16]. Coding theory suggests that maximizing minimum distance between all possible input messages[5] improves coding performance. However since the number of all possible messages increases exponentially with respect to code block length, computing loss with maximized minimum distance for long block code becomes prohibitive.

Exploiting the locality inherent to RNN codes, we introduce a different loss term solely for the encoder which we refer to as the partial minimum code distance regularizer. Partial minimum code distance

$d(u_L) = \min_{u_1, u_2 \in R^L, u_1 \neq u_2} \{\|f_\theta(u_1) - f_\theta(u_2)\|_2^2\}$ is the minimum distance among all message with length L . Computing pairwise distance requires $O(\binom{2^L}{2})$ computations. For long block code with block length $L_B \gg L$, RNN encoded portion L has minimum distance M , which guarantees that the block code with block length L_B has minimum distance at least M , while can be as large as $\frac{L_B}{L}M$. Partial minimum code distance is a compromise over computation, which still guarantees large minimum distance under small block length L , while hoping the minimum distance on longer block length would still be large. The loss objective of Channel AE with partial maximized minimum code distance is $L(u) = E_z \|g_\phi(h(f_\theta(u)) + z) - u\|_2^2 + \lambda d(u_L)$. To beat convolutional code via RNN autoencoder, we add minimum distance regularizer for block length 100, with $L = 10$ and $\lambda = 0.001$. The performance is shown in Figure 15, while the left graph shows the test loss trajectory, and the middle graph shows the BER.

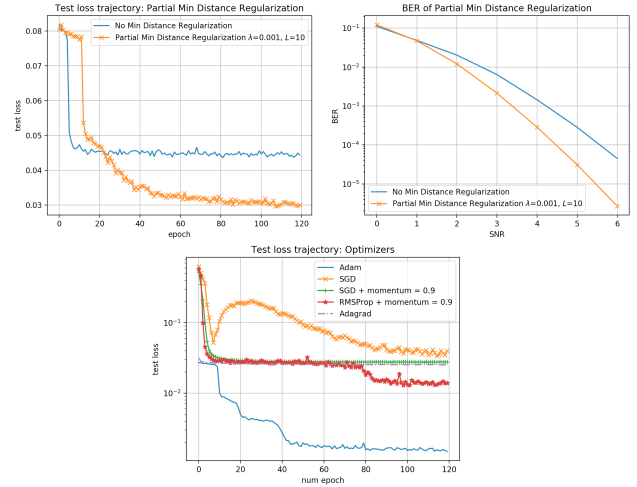


Fig. 15. Effect of Partial Minimum Distance Regularization, Test loss trajectory(left) and BER(middle). Test loss trajectory different optimizers with learning rate 0.001 (right)

E. Using Adam optimizer

The learning rate for encoder and decoder has to be adaptive to compensate the realizations of noise with different magnitude. Also as training loss decreases, it is less likely to experience decoding error, which makes both encoder and decoder gradient sparse. Adam[49] has adaptive learning rate and exponential moving average for sparse and non-stationary gradient, thus in theory is a suitable optimizer. The comparison of different optimizer in Figure 15 right shows that Adam empirically outperforms all other optimizers, with faster convergence and better generalization. SGD fails to converge with learning rate 0.001 with high instability. Thus we use Adam for training Channel AE.

F. Adding more capacity (parameters) to the decoder than the encoder

Channel AE can be considered as an overcomplete autoencoder model with the noise injected in the middle layer. In what follows, we perform the analysis of the introduction of the noise as done in [39] and for simplification consider only Minimum Square Error (MSE) (Binary Cross-entropy (BCE) loss would follow the same procedure). Assume $z \sim N(0, \sigma^2)$ is the added Gaussian noise, u is the input binary bits, f_θ is the encoder, g_ϕ is the decoder, and $h(\cdot)$ is the power constraint module. Applying Taylor expansion (see appendix for more details), the loss of Channel AE can be written as: $L = \|g_\phi(h(f_\theta(u))) - u\|_2^2 + \sigma^2 \|J_{g_\phi}(u)\|_F^2$, where $\|J_{g_\phi}(u)\|_F^2 = \sum_i^k \sum_j^n (\frac{\partial g_\phi(c)_i}{\partial c_j})^2$ is the Jacobian of function g_ϕ . The reconstruction error $\|g_\phi(h(f_\theta(u))) - u\|_2^2$ can be interpreted as the coding error when no noise is added. With smaller $\frac{\partial g_\phi(c)_i}{\partial c_j}$, the decoder results in an invariance and robustness of the representation for small variations of the input [42], thus the Jacobian term $\sigma^2 \sum_i^k \sum_j^n (\frac{\partial g_\phi(c)_i}{\partial c_j})^2$ is the regularizer encouraging the decoder to be locally invariant to noise [44]. The Jacobian term reduces the sensitivity of decoder, which improves the generalization of decoders.

Empirically there exist an optimal training SNR for neural decoders [28] and Channel AE [19]. When training with too large noise σ^2 , the Jacobian term dominates, hence the reconstruction error becomes non-zero, which degrades the performance. When training with too small noise, the decoder is not local invariant, which reduces the generalization ability.

Also as the Jacobian term only applies regularization to the decoder, thus the decoder needs more capacity. Empirically the neural decoder has to be more complicated than encoder. With training for 120 epochs, the encoder/decoder size 25/100 and 100/400 units shows better test loss, comparing to the cases where encoder is less complicated than decoder. As encoder/decoder with 25/100 units works as well as encoder/decoder with size 100/400 units, we take 25 units encoder and 100 units decoder for most of our applications. Further hyper-parameter optimization such as Bayesian Optimization[47] could lead to even better performance.

Encoder and Decoder Hyperparameter Design after 120 epochs		
Enc Unit	Dec Unit	Test Loss
25	100	0.180
25	400	0.640
100	100	0.690
100	400	0.181

APPENDIX D FURTHER EMPIRICAL RESULTS

A. Alternative Minimum Distance Regularizer

As RNN encoder has small dependency length (see section 4), small Hamming distance of messages may cause small minimum code distance. Another method of regularizing is to directly regularize the minimum distance between messages with small Hamming distances. The method starts by enumerating all messages within Hamming distance s to a random message u of length L_B , which contains $\sum_{i=1}^s \binom{L_B}{i} + 1$ messages, then compute the minimum distance among the enumerated messages as a regularization term. However, this method doesn't guarantee any minimum distance property even among short block length, and the computational complexity is high with even small s . Empirically this method doesn't work well.

B. Loss Analysis for Encoder and Decoder Size

This section shows the derivation of loss analysis used in the main text. Using Minimum Square Error (MSE), the loss of Channel AE is $L = E_z \|g_\phi(h(f_\theta(u)) + z) - u\|_2^2$. The output of the encoder is denoted as $c = h(f_\theta(u))$. Using 1st order Taylor expansion following [48], with the assumption that noise z is small and ignoring all higher order components, the decoder is approximated as: $g_\phi(c + z) = g_\phi(c) + \frac{\partial g_\phi(c)}{\partial c} z + O(z)$.

Note that the 1st order Taylor expansion is a local approximation of functions. Hence, the assumption of ignoring higher order components is only valid with small z locally. Then by expanding the MSE loss, we have: $L = \|g_\phi(h(f_\theta(u))) - u\|_2^2 + E_z \text{tr}(z^T \frac{\partial g_\phi(c)}{\partial c}^T \frac{\partial g_\phi(c)}{\partial c} z)$, which yields: $L = \|g_\phi(h(f_\theta(u))) - u\|_2^2 + \sigma^2 \|J_{g_\phi}(u)\|_F^2$.

C. Low Latency Benchmark: Convolutional Code with Different Memory length

The benchmarks of applying convolutional code under extreme low latency constraint are shown in Figure 16. Note that there doesn't exist a uniform best convolutional code under different delay constraints and code rates. Thus the convolutional codes reported in main section are using the best convolutional codes shown in Figure 16.

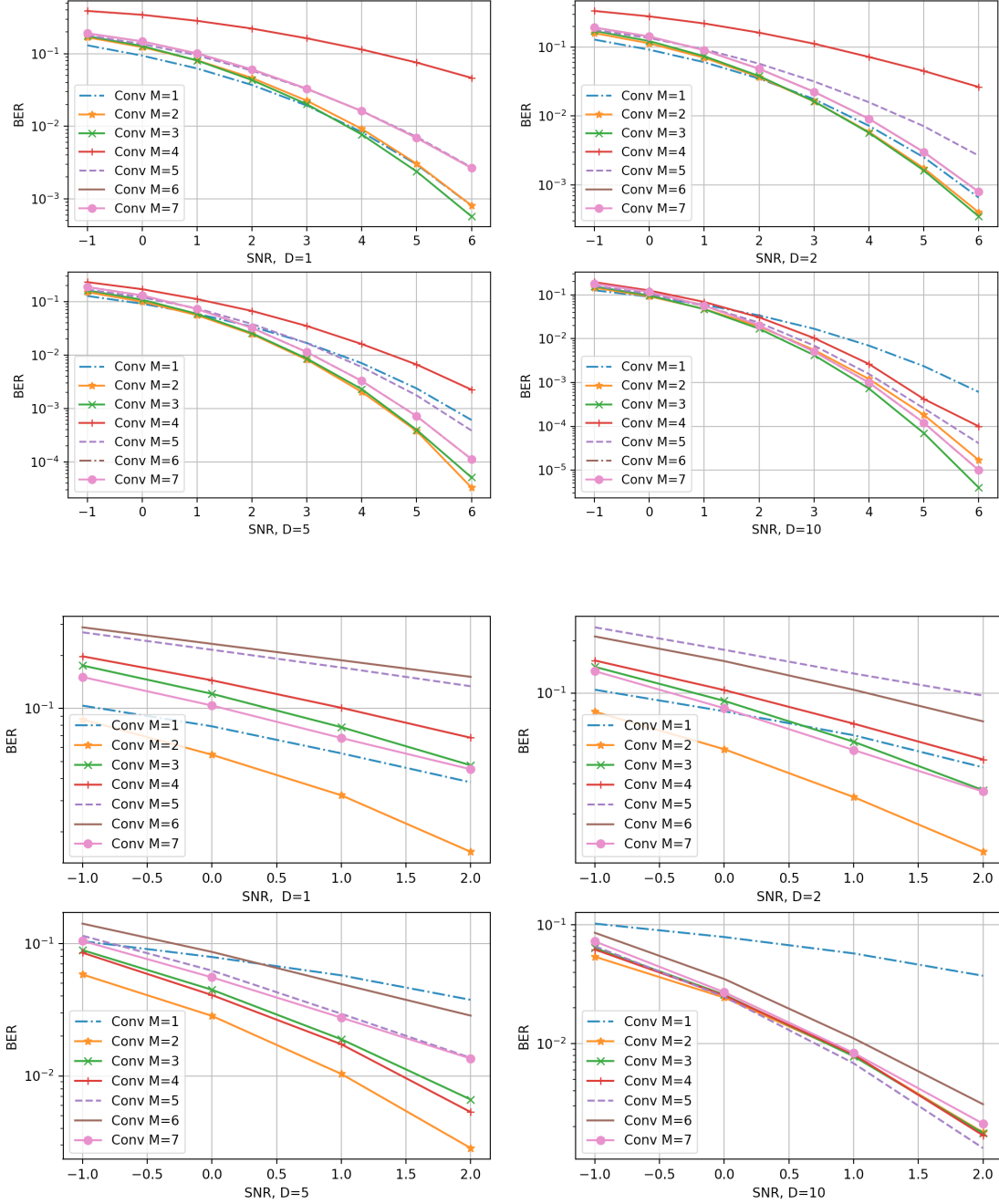


Fig. 16. Convolutional Code with different delay constraint on rate 1/2 (top), rate 1/3 (bottom)