# Component Training of Turbo Autoencoders

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Abstract-Isolated training with Gaussian priors (TGP) of the component autoencoders of turbo-autoencoder architectures enables faster, more consistent training and better generalization to arbitrary decoding iterations than training based on deep unfolding. We propose fitting the components via extrinsic information transfer (EXIT) charts to a desired behavior which enables scaling to larger message lengths ( $k \approx 1000$ ) while retaining competitive performance. To the best of our knowledge, this is the first autoencoder that performs close to classical codes in this regime. Although the binary cross-entropy (BCE) loss function optimizes the bit error rate (BER) of the components, the design via EXIT charts enables to focus on the block error rate (BLER). In serially concatenated systems the component-wise TGP approach is well known for inner components with a fixed outer binary interface, e.g., a learned inner code or equalizer, with an outer binary error correcting code. In this paper we extend the component training to structures with an inner and outer autoencoder, where we propose a new 1-bit quantization strategy for the encoder outputs based on the underlying communication problem. Finally, we discuss the model complexity of the learned components during design time (training) and inference and show that the number of weights in the encoder can be reduced by 99.96 %.

### I. INTRODUCTION

Concatenation of blocks, or modularization, is a crucial concept in engineering that breaks down complex systems into smaller, more manageable components to simplify the design process. In communications engineering, iterating between the concatenated blocks of a receiver gives rise to an even more powerful concept: the turbo principle [1]. Here, two or more serially concatenated blocks iteratively exchange extrinsic information. Since its introduction in turbo decoders [2], the principle found application in many different scenarios, such as turbo equalization of multipath channels, multipleinput multiple-output (MIMO) detection, bit-interleaved coded modulation (BICM) and low-density parity-check (LDPC) decoding [1]. These systems show outstanding performance close to the theoretical limits in scenarios closely matching the models assumed in the design, e.g., the channel model. However, in more complex situations or scenarios with hardware impairments or when no suitable channel models is known, machine learning-aided communication systems that are trained to optimize the end-to-end performance can outperform classical systems [3], [4]. Still, the well-understood additive white Gaussian noise (AWGN) scenario serves as

a valuable benchmark and can be seen as the "worst case" scenario for the learning-based systems. Like in conventional communications, the turbo principle has been successfully applied in form of the turbo-autoencoder, called TurboAE, to scale deep-learning based transceivers to more practical block lengths [5]. The TurboAE consists of parallel or serially concatenated convolutional neural networks (CNNs) at the transmitter. At the receiver, information is passed iteratively between another set of two CNNs. It is typically trained in a deep unfolded fashion, i.e., the iterations of the receiver are unrolled into a deep neural network (NN), optimally adapting the constituent NNs to the iterative algorithm. However, this comes at the cost of increased training complexity which scales linearly with the number of iterations. To overcome this issue, component training with Gaussian priors (TGP) has been proposed in [6], [7].

In this paper we consider component-wise autoencoder training for the serial TurboAE. The main contributions of this paper are as follows:

- We apply extrinsic information transfer (EXIT) charts [8] to analyze and optimize the serial TurboAE for block error rate (BLER) or large block lengths by finetuning the inner component to the outer autoencoder [9].
- A Gaussian prior training framework for the serial TurboAE is proposed and demonstrated to drastically reduce the training complexity.
- A new binarization strategy for an encoder output layer (binary phase shift keying (BPSK) modulation) is proposed based on the underlying communication problem.
- The encoder networks are distilled down to just 148 weights by a student-teacher method without performance degradation, enabling practical implementations.

#### **II. PRELIMINARIES**

#### A. Densely Connected Convolutional Layers

Densely connected convolutional neural networks (DCCNNs) [10] allow the training of deeper structures with fewer weights than plain CNNs. A DCCNN consists of blocks of convolutional layers with an increased amount of connections, and transition layers. The input to each densely connected convolutional layer is not only the output from the last layer, but a concatenation of all preceding feature maps within a block. This means the number of feature maps for inputs increases with a growth parameter F, which is the number of output feature maps per layer. Furthermore, each

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Fig. 1: Structure of the CNN-based serial TurboAE communication system consisting of a real-valued encoder, channel, and an iterative decoder.

layer consists of a batch normalization, a rectified linear unit (ReLU) activation and a convolutional layer with kernel size K. Every densely connected block proceeds a transition layer. The output of the transition layer is the only input to the next densely connected block. It interrupts the growth process of the number of feature maps. The transition layer is a  $1 \times 1$  convolutional layer that outputs  $F_0$  feature maps.

#### B. Serial Turbo Autoencoder

The serial TurboAE [7] is based on the structure of serially concatenated codes with an iterative (turbo) decoding architecture. However, the encoders and decoders are implemented as CNNs. The system model is shown in Fig. 1. The encoder consists of an outer encoder, an interleaver and an inner encoder. The corresponding decoder is based on a CNN for decoding the inner code and a CNN for decoding the outer code. Again, both are connected by an interleaver and a deinterleaver. For training, the iterations of the decoder are unfolded, yielding a deep neural decoder with intermediate (de-)interleaver layers. The difference to the straight-forward training with stochastic gradient descent (SGD) is the alternating training schedule for the encoder ( $T_{\rm TX}$  updates) and the decoder ( $T_{\rm RX}$  updates). For further details, the reader is referred to [5].

## C. Training with Gaussian Priors

TGP [6], [7] is a method to reduce complexity during training for systems with concatenated components in contrast to unfolding the decoder. The idea is to train each component individually and isolated with a single decoding iteration. Only during inference the components are concatenated as in the desired system. The alignment of the components can be done with EXIT charts. For training, the a priori information from the other component has to be generated artificially. The generation process is well known under two conditions. First, the information, in form of log-likelihood ratios (LLRs), is Gaussian distributed. Second, the variable for which we generate the a priori LLRs consists of bits. The a priori LLR distribution  $L_u^A$  for a bit u and a set a priori information  $I_A$ is then given by

$$L_u^{\mathcal{A}} \sim \mathcal{N}\left((2u-1) \cdot \mu(I_{\mathcal{A}}), 2\mu(I_{\mathcal{A}})\right) \tag{1}$$

where  $\mu(I_A) \approx \frac{1}{2} \left( -\frac{1}{H_1} \log_2 \left( 1 - I_A^{\frac{1}{H_3}} \right) \right)^{\frac{1}{H_2}}$  with constants  $H_1 = 0.3073, H_2 = 0.8935$  and  $H_3 = 1.1064$  [11].



Fig. 2: Block diagrams of the (non-iterative) autoencoders.

## D. EXIT Charts

EXIT charts [8] are a design tool for iterative, component based systems. The key idea is to calculate the input/output behavior of each component and predict the decoding trajectory of the concatenated system. The behavior is displayed by the produced extrinsic information from a certain a priori information. The a priori LLRs can be generated according to (1) and the information between LLRs L and bits u can be approximated [1] by

$$I(\mathbf{L}, \mathbf{u}) \approx 1 - \sum_{i} \log_2 \left( 1 + \exp(-(2u_i - 1) \cdot L_i) \right).$$
 (2)

The chart shows these two curves where one is flipped along the first bisector. This means that the x-axis shows the a priori information of one component and the extrinsic information from the other component and vice versa for the y-axis. The decoding trajectory can be estimated by iterating "pingpong"-wise between the two curves. The intersection of the curves indicates the maximum reachable mutual information by iterating between the components. However, the estimated trajectory is only accurate if the exchanged information is uncorrelated between the components. This does not hold for short block lengths, as cycles in the decoding graph lead to correlated information exchange. A more appropriate design tool for short block lengths are scattered EXIT charts [12]. Here, the chart consists of many trajectories displayed as a scatter plot.

#### **III. COMPONENT TRAINING FOR SERIAL ARCHITECTURES**

## A. Identifying Component Interfaces

The serial TurboAE can be interpreted as an inner autoencoder, and an outer autoencoder with BPSK modulation and an virtual channel in between. This virtual channel consists of the inner autoencoder and the actual channel, but can be abstracted to an AWGN channel with an certain signal-to-noise-ratio (SNR). The concept is shown in Fig. 2. The goal of the component training is to optimize each autoencoder isolated. Thus, we first identify the components and their interfaces. For a serial TurboAE with rate  $R = \frac{k}{n} = R_{\rm O} \cdot R_{\rm I} = 1/2$  we choose the outer and inner autoencoder to have rate  $R_{\rm O} = 1/2$ and  $R_{\rm I} = 1$ , respectively. [13] showed that this allocation of the rate is optimal for asymptotic block lengths and [14]



Fig. 3: Influence of clipping on the learned modulation.

observed it empirically. The inner autoencoder is shown in Fig. 2a. The input to the inner decoder are the real-valued channel observations y and the available a priori information in form of LLRs  $\mathbf{L}^{A}_{\mathbf{c}}$  from the (artificial) outer decoder. The output are the extrinsic LLRs  $\mathbf{L}_{\mathbf{c}}^{\mathrm{E}} = \mathbf{L}_{\mathbf{c}}^{\mathrm{T}} - \mathbf{L}_{\mathbf{c}}^{\mathrm{A}}$ , where the total LLRs  $\mathbf{L}_{\mathbf{c}}^{\mathrm{T}}$  are the direct output of the NN. As loss, we choose a binary cross-entropy (BCE) loss between c and  $L_c^T$ . To generate artificial a priori LLRs for the inner autoencoder, the outer autoencoder must use BPSK symbols. The outer autoencoder is shown in Fig. 2b. The input to the outer decoder are the a priori LLRs of the coded bits  $\mathbf{L}^{\mathrm{A}}_{\mathbf{c}}$ . The outputs are not only the uncoded bit estimates  $\mathbf{L}_{\mathbf{u}}^{\mathrm{T}}$ , but also the refined extrinsic LLRs  $\mathbf{L}_{\mathbf{c}}^{\mathrm{E}} = \mathbf{L}_{\mathbf{c}}^{\mathrm{T}} - \mathbf{L}_{\mathbf{c}}^{\mathrm{A}}$ , where  $\mathbf{L}_{\mathbf{c}}^{\mathrm{T}}$  is the direct output of the NN. The outputs can be trained with a BCE loss between  $\mathbf{u}$  and  $\mathbf{L}_{\mathbf{u}}^{\mathrm{T}}$ , and  $\mathbf{c}$  and  $\mathbf{L}_{\mathbf{c}}^{\mathrm{T}}$ , respectively. The losses are added without a weighting factor, as they are in the same order of magnitude.

## B. Autoencoder with Binary Modulation

Forcing a BPSK modulation can be seen as a 1 bit quantization of the encoder output layer. The authors of [5] propose to first train the output layer with real valued outputs and apply binarization with a straight-through estimator (STE) for gradient computation afterwards. This procedure outperforms training a model from scratch with binarization and a STE for gradient computation. Here, we propose a new quantization strategy based on the underlying communication problem. Similar to [5], we first train with a real valued output layer and only start the quantization process once the system is trained. For the latter, we propose to clip  $\mathbf{x}$  with a threshold  $x_{\text{clip}}$ , which is gradually decreased from 1.5 to 1.0 in steps of 0.1 every 10 epochs. The key idea is that the clipping is applied after normalization of x, i.e., reducing the energy of the transmission. Consequently, the encoder tries to compensate for this energy loss by increasing the probability of symbols with larger magnitude and decreasing the probability of symbols with smaller magnitudes. Once  $x_{\rm clip} \approx 1$ , the encoder must converge to a BPSK modulation to transmit with the maximum possible energy. For inference we use a binarizer. The advantage of this approach is that no STE is used, thus, no gradient mismatch between forward and backward path during training. The concept and intuition is visualized in Fig. 3.



### C. Fitting Components via EXIT Charts

The outer autoencoder is trained as in [15], where it was found that training in the waterfall region leads to the best overall performance. This means that we train the outer autoencoder to be as good as possible and then fit the inner autoencoder to the resulting outer autoencoder. Moreover, the proposed design via EXIT charts allows to fit autoencoders for large block lengths. We can train the CNN-based autoencoders on short block lengths with a certain EXIT behavior and evaluate the concatenated autoencoders on large block lengths to achieve scaling to large block lengths. Similar to [7] we propose a two step training process. First, we train the inner autoencoder with high a priori information  $I_{\rm A} > 0.8$ . The training process is stopped, once the slope of the EXIT characteristic starts increasing (it starts out flat). Second, set a certain fraction  $\alpha$  of each batch to  $I_{\rm A}=0$  and continue training. As a result, the autoencoder is optimized for high a priori information, which is to be expected from the outer lower rate code, but a reasonably high decoding performance without a priori information to start the iterative decoding. We observed that the fraction  $\alpha$  directly relates to the slope of the EXIT characteristic. A lower  $\alpha$  leads a to steeper slope and vice versa. This is visualized in Fig. 4 for  $\alpha = 0.075$ and  $\alpha = 0.085$  at  $E_{\rm b}/N_0 = 4\,{\rm dB}$ . Further, another inner autoencoder is shown for  $\alpha = 0.08$  at  $E_{\rm b}/N_0 = 2\,{\rm dB}$ . Lastly, two trajectories are shown for an interleaver length of n = 128and n = 2048. We can see that the trajectory for n = 128 does not converge and Fig. 5 reveals that even for  $\alpha = 0.075$  at  $E_{\rm b}/N_0 = 4 \, {\rm dB}$ , the trajectory corridor is quite small. This means the for n = 128 the inner and outer autoencoder are fitted nicely. The other trajectory in Fig. 4 for n = 2048converges to the intersection point which is just shy of 1.0, determining the best possible performance at  $E_{\rm b}/N_0 = 2 \, \rm dB$ even for  $n \to \infty$ .

#### D. Discussion Component vs Unfolded Training

A problem with unfolded training is the computational complexity, as every unfolded iteration runs thorugh a forward and



Fig. 5: Scattered EXIT chart for (k = 64, n = 128). Each point represents an encountered input/output mutual information in a trajectory.

TABLE I: Hyperparameters for architecture and training the serial TurboAE

Parameter	Value	Parameter	Value
CNN Layers	5	Loss	BCE
CNN $F, K$	100, 5	$T_{\mathrm{TX}}, T_{\mathrm{RX}}$	100, 500
DCCNN Blocks	3	Batch size	500 - 2000
Layers per Bl.	3	Learning rate	$10^{-4} - 10^{-6}$
1. DCCNN $F_0, F, K$	16, 12, 5	Encoder SNR	$4.0\mathrm{dB}$
2. DCCNN $F_0, F, K$	16, 16, 5	Enc. $I_A$	0.8 - 1
3. DCCNN $F_0, F, K$	16, 12, 5	Decoder SNR	$0.5 - 4.0\mathrm{dB}$
(k,n)	(64, 128)	Dec. $I_A$	0.6 - 0.9
Padding	Circ. [17]	$\alpha$	0.075

a backward pass. In contrast, TGP is based on a single iteration and, thus, saves computational complexity and time by a factor of the number of iterations  $N_{\rm it}$  in the decoder. While the unfolding increases complexity, it provides the opportunity for the decoder to mitigate short block length effects, i.e., short cycles in the graph and correlated a priori information. As the TGP trained decoder never experiences correlated a priori information during training, it cannot mitigate these effects. An advantage of TGP, in terms of convergence over training epochs, is that the input to the decoders during training is always of good quality, since the a priori LLRs are not output of a previous (potentially untrained) decoder. Therefore, the TGP approach benefits from a fast convergence, especially at the beginning of training. Lastly, TGP does not directly optimize the bit error rate (BER) as unfolded training does [15]. While the decoders optimize the BER in every iteration, the EXIT behavior of the components determine the performance in terms of BER and BLER. We observed that inner components with a steeper slope tend to perform better in terms of BLER and worse in BER than an inner components with a more gentle slope. The steeper slope of the inner component leads to a later intersection with the outer component but a tighter corridor for the trajectory, as shown in Fig. 4. Thus, the outer component can output better bit estimates, if the trajectory converges. However, the trajectory converges less often due to the tighter corridor.

# IV. RESULTS

For the serial TurboAE the encoders are plain CNNs and the decoder are DCCNNs with hyperparameters for architecture and training as in Tab. I. For all evaluations we use interleavers according to the LTE standard [16].



Fig. 6: BER over an AWGN channel for long codes (R = 0.5), based on short (n = 128) component codes.



Fig. 7: BLER over an AWGN channel (k = 64, n = 128,  $N_{it} = 6$ ).

## A. Decoding Performance for Large Block Lengths

Fig. 6 shows the BER of the serial TurboAE with training with Gaussian priors (TGP) compared to the LTE turbo code for large block lengths  $(k \in \{800, 1024\}, n \in \{1600, 2048\},$ R = 1/2). To the best of our knowledge, this is the first time that a competitive performance of an autoencoder is demonstrated for a message length of  $k \approx 1000$ . The performance for the serial TurboAE is evaluated with the outer autoencoder and inner autoencoder ( $E_{\rm b}/N_0 = 2 \, \mathrm{dB}, \, \alpha = 0.08$ ) shown in Fig. 4. For the evaluation we increased the number of inputs to the CNNs and increased the size of the interleaver. Also the turbo-product framework [18] can be used in case the NNs are not based on CNNs. Note, the components are trained with k = 64, n = 128 and are not trained or finetuned for longer lengths. While the performance is roughly 0.1 dB worse than the LTE turbo code in the low SNR regime, the serial TurboAE shows an error floor for higher SNRs. This error floor behavior is due to the intersection in Fig. 4 being just shy of a mutual information of 1.0.

## B. Comparison of TGP and Unfolded Training

The decoding performance after training is shown in Fig. 7 in terms of BLER for short block lengths (k = 64, n = 128,  $R = \frac{1}{2}$ ). The serial TurboAE with TGP and  $N_{\rm it} = 6$ iterations performs slightly better than the serial TurboAE with unfolded training. Both perform marginally better than the LTE turbo code. Further, the outer code with the proposed gradual



Fig. 8: Convergence speed comparison in terms of BER vs. training epochs (k = 64, n = 128).

clipping outperforms the STE-based proposition from [5]. A more prominent advantage shows the training behavior which is displayed in Fig. 8. The figure compares the valdiation BER of the components with TGP and the unfolded training. Note, the BER of the outer code is without iterative decoding and the inner code is with iterative decoding. Both need significantly fewer epochs for training than the unfolded training. Finally, we observed that component-wise TGP is more robust in a sense that the component autoencoders consistently converged to the same shown performance, while for the unfolded training, the shown results are from the best run out of many.

### V. DISCUSSION ON MODEL COMPLEXITY

A valid criticism of autoencoders for channel coding is the increased computational and memory complexity. The proposed systems [5], [7], [19] consists of a huge amount of weights, see Tab. II. However, the complexity is simply outside the scope of these works. Therefore, these works can be seen as design time systems, where a great exploration space is needed to find good solutions. This exploration space of a NN is usually coupled to the number of trainable weights. However, once a good solution is found, the knowledge can be distilled into smaller NNs [20]. The intuition is that the solution is inside the solution space of the larger and the smaller NN. However, the smaller NN can not converge to the solution, as the needed convergence trajectory is not inside the solution space. A common knowledge distillation approach is the student-teacher approach. Here, the student is influenced by a regression loss with the outputs of the teacher. We applied this approach to the encoder with an mean squared error (MSE) loss. A smaller CNN-based encoder with a total of 148 weights (reduction by 99.96%) for the inner and outer encoder in total was able to represent the solution from the large encoder without any loss in performance.

## VI. CONCLUSION

We introduced the component-wise TGP for the serial TurboAE and demonstrated a faster and more consistent training. By training the components to match a desired EXIT curve, the resulting serial TurboAE shows a competitive BER for message lengths of  $k \approx 1000$ . To the best of our knowledge, this is the first autoencoder that performs close to classical codes in this regime. Furthermore, we proposed a new quantization strategy to force a trainable encoder to a BPSK modulation. Lastly, we demonstrated a reduction of the number of weights by 99.96% in the encoder after training. Future works could include the exploration of different autoencoders as components and complexity reduction in the decoder.

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