Machine Learning Autoencoder Applied to Communication Channels

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Outline

Context

Communication system context in general - what field will I be treating

- My first point.
- My second point.

- My first point.
- My second point.

Relevance & Challenges

Explain why the work is relevant and explain what are the challenges

- My first point.
- My second point.

Problem Statement

What exactly I will solve in this work

- My first point.
- My second point.

Second Slide Title

- First item.

Second Slide Title

- First item.
- Second item.

Second Slide Title

- First item.
- Second item.
- Third item.

Second Slide Title

- First item.
- Second item.
- Third item.
- Fourth item.

Second Slide Title

- First item.
- Second item.
- Third item.
- Fourth item.
- Fifth item.

Second Slide Title

- First item.
- Second item.
- Third item.
- Fourth item.
- Fifth item. Extra text in the fifth item.

Maximum a Posterior (MAP) Rule

Implementation of a MAP decoder for a linear block code through a BSC.

Algorithm 1 MAP rule for BSC and linear block code.

Input: received block $\mathbf{y}^n \in \{0,1\}^n$, code word set $\mathcal{X}$ and generator matrix $G_{k \times n}$.

Output: message estimation $\hat{\mathbf{u}}^k \in \{0,1\}^k$.

procedure MAP DECODER($y, \mathcal{X}, G$)
  $p \leftarrow$ channel crossover probability
  for i in *range*(2^k) **do**
    distances$[i] \leftarrow d_H(\mathbf{y}, word[i] \in \mathcal{X})$
  $\hat{\mathbf{x}} \leftarrow argmin(\text{distances})$
  $\hat{\mathbf{u}} \leftarrow \hat{\mathbf{x}} G^{-1}$ **return** $\hat{\mathbf{u}}$

Neural Network's Architecture I

Show the architecture used for each case and remarks some important parameters

- Table: DNN array decoder architecture and parameters.

Decoder	Dense: 128, activation: ReLU, input size: n
	Dense: 64, activation: ReLU
	Dense: 32, activation: ReLU
	Dense: k, activation: Sigmoid
Total parameters: 12776	

- Table: DNN one-hot decoder architecture and parameters.

Decoder	Dense: 256, activation: Softmax, input size: n
Total parameters: 4352	

Table: DNN array autoencoder architecture and parameters.

Encoder	Dense: X, activation: ReLU, input size: k Dense: X, activation: ReLU Dense: n, activation: Sigmoid
Channel	Lambda: $Round(\mathbf{x})$, input size: n Lambda: $\mathbf{x} \oplus$ noise
Decoder	Dense: X, input size: n Dense: X, activation: ReLU Dense: k, activation: Sigmoid
Total parameters: XX	

Neural Network's Training

Show the best training parameters for each structure

Table: DNN array decoder training parameters.

Loss func.	Optimizer	N. Epochs	Batch Size
Binary cross-entropy	Adam	2^{16}	256

Table: DNN one-hot decoder training parameters.

Loss func.	Optimizer	N. Epochs	Batch Size
Binary cross-entropy	Adam	2^{14}	256

Table: DNN array autodecoder training parameters.

Loss func.	Optimizer	N. Epochs	Batch Size
Binary cross-entropy	Adam	2^{14}	256

Error Correction and Monte Carlo Simulations

Explain how we could use NN to predict the results with certain confidence.

- My first point.
- My second point.

Blocks

Block Title

You can also highlight sections of your presentation in a block, with it's own title

Theorem

There are separate environments for theorems, examples, definitions and proofs.

Example

Here is an example of an example block.

DNN Array Decoder

Show the results for the array decoder in terms of train p, Mep, Parameters, etc

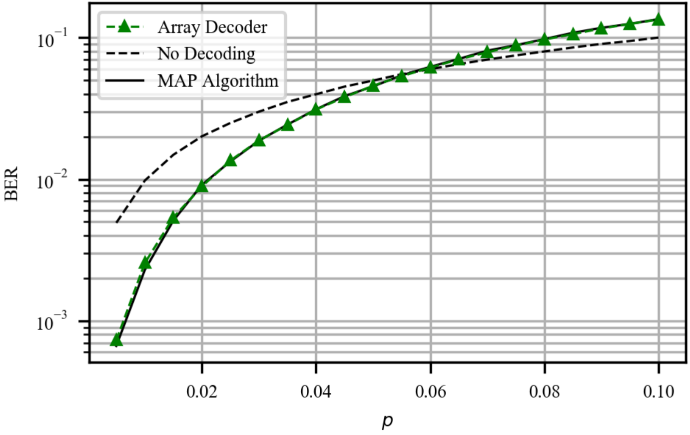

Figure: Array decoding BER performance. NN trained with a channel crossover probability error of $p_t = 0.07$.

DNN One-hot Decoder

Show the results for the one-hot decoder in terms of train p, Mep, Parameters, etc

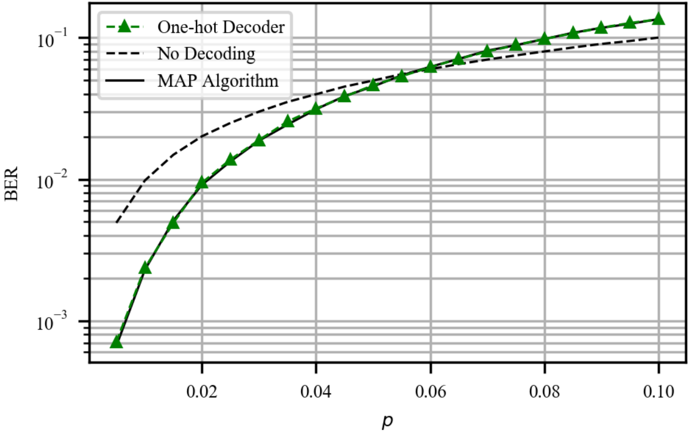

Figure: One hot decoding BER performance. NN decoder trained with a channel crossover probability error of $p_t = 0$.

DNN Autoencoder

Show the results for the autoencoder in terms of train p, Mep, Parameters, etc

- My first point.
- My second point.

Delay Time Analysis

Comparison of decoding time for each method.

Table: Decoding time comparison between the MAP algorithm and the DNN decoders and autoencoders. The data is normalized to the mean MAP algorithm decoding time.

MAP	A. Dec.	One-hot Dec.	A. Auto.	One-hot Auto.
1.00 ± 0.02	0.74 ± 0.03	0.76 ± 0.02	$\pm$	$\pm$

Conclusions

- My first point.
- My second point.

Future Work

- My first point.
- My second point.

Acknowledgment

- My first point.
- My second point.

Bibliography I

[1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]

C. E. Shannon, “A mathematical theory of communication,” *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 5, pp. 3–55, Jan. 2001.

F. D. Calabrese, L. Wang, E. Ghadimi, G. Peters, and P. Soldati, “Learning radio resource management in 5g networks: Framework, opportunities and challenges,” *CoRR*, vol. abs/1611.10253, 2016.

T. J. O’Shea and J. Hoydis, “An introduction to machine learning communications systems,” *CoRR*, vol. abs/1702.00832, 2017.

T. J. O’Shea, K. Karra, and T. C. Clancy, “Learning to Communicate: Channel Auto-encoders, Domain Specific Regularizers, and Attention,” *arXiv e-prints*, Aug. 2016.

Bibliography II

D. Goldin and D. Burshtein, "Performance Bounds of Concatenated Polar Coding Schemes," *arXiv e-prints*, Oct. 2017.

E. Worm, S. Member, P. Hoeher, S. Member, and N. Wehn, "Turbo-decoding without snr estimation," *IEEE Communications Letters*, pp. 193–195, 2000.

A. J. Viterbi, "Error bounds for convolutional codes and an asymptotically optimum decoding algorithm," *IEEE Transactions on Information Theory*, vol. IT-13, pp. 260–269, April 1967.

P. Robertson, P. A. Hoeher, and E. Villebrun, "Optimal and sub-optimal maximum a posteriori algorithms suitable for turbo decoding.," *European Transactions on Telecommunications*, vol. 8, no. 2, pp. 119–125, 1997.

M. Ibnkahla, "Applications of neural networks to digital communications-survey," *Signal Processing*, vol. 80, pp. 1185–1215, 07 2000.

M. A. Nielsen, "Neural networks and deep learning," 2018.

K. P. Murphy, *Machine learning : a probabilistic perspective*. Cambridge, Mass. [u.a.]: MIT Press, 2013.

M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. J. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Józefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. G. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. A. Tucker, V. Vanhoucke, V. Vasudevan, F. B. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and

Bibliography IV

X. Zheng, "Tensorflow: Large-scale machine learning on heterogeneous distributed systems," *CoRR*, vol. abs/1603.04467, 2016.

F. Chollet *et al.*, "Keras." `https://keras.io`, 2015.

G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural Computation*, vol. 18, no. 7, pp. 1527–1554, 2006.
PMID: 16764513.

M. Benammar and P. Piantanida, "Optimal training channel statistics for neural-based decoders," in *52nd Asilomar Conference on Signals, Systems, and Computers, ACSSC 2018, Pacific Grove, CA, USA, October 28-31, 2018* (M. B. Matthews, ed.), pp. 2157–2161, IEEE, 2018.