Deep Learning Architectures for Transmission of Text Over Noisy Channels

Avoy Datta, Milind Rao, Nariman Farsad, and Andrea Goldsmith
Department of Electrical Engineering, Stanford University

Objectives

We attempt to improve our existing approach of using **joint source-channel coding** to transmit text or other structured data over a noisy channel. To make the coded bits generated by our encoder network more resilient to the impact of erasures, we add a multi-layered, fully-connected residual network on both ends of the channel.

Using a Binary Erasure Channel as a channel model we compare the performance of the new model with the previous model combined with a Reed Solomon code.

Background

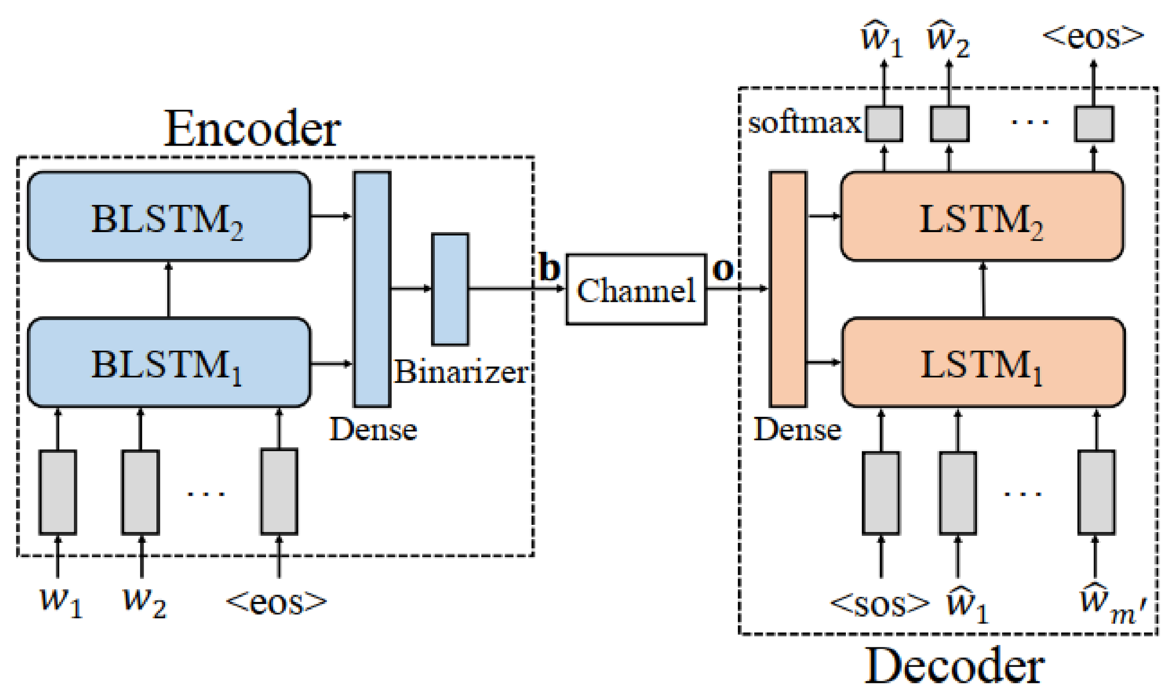

Figure 1: Original Joint Source-Channel Coding architecture

- We previously proposed jointly training an encoder and decoder for joint source-channel coding of text data using sequence to sequence models
- For finite delay constraints or other types of transmission channels, joint source-coding approaches are required for optimal design
- Moreover, what if we are not interested in recovering the structured data precisely at the receiver, but we are interested in correct inference using the structured data?
- **Obstacle:** The original JSC coder was good at mapping from text to bits and back, but was weak at correcting bit errors introduced by the channel. A more robust architecture is required to shield against bit erasures.

Proposed architecture

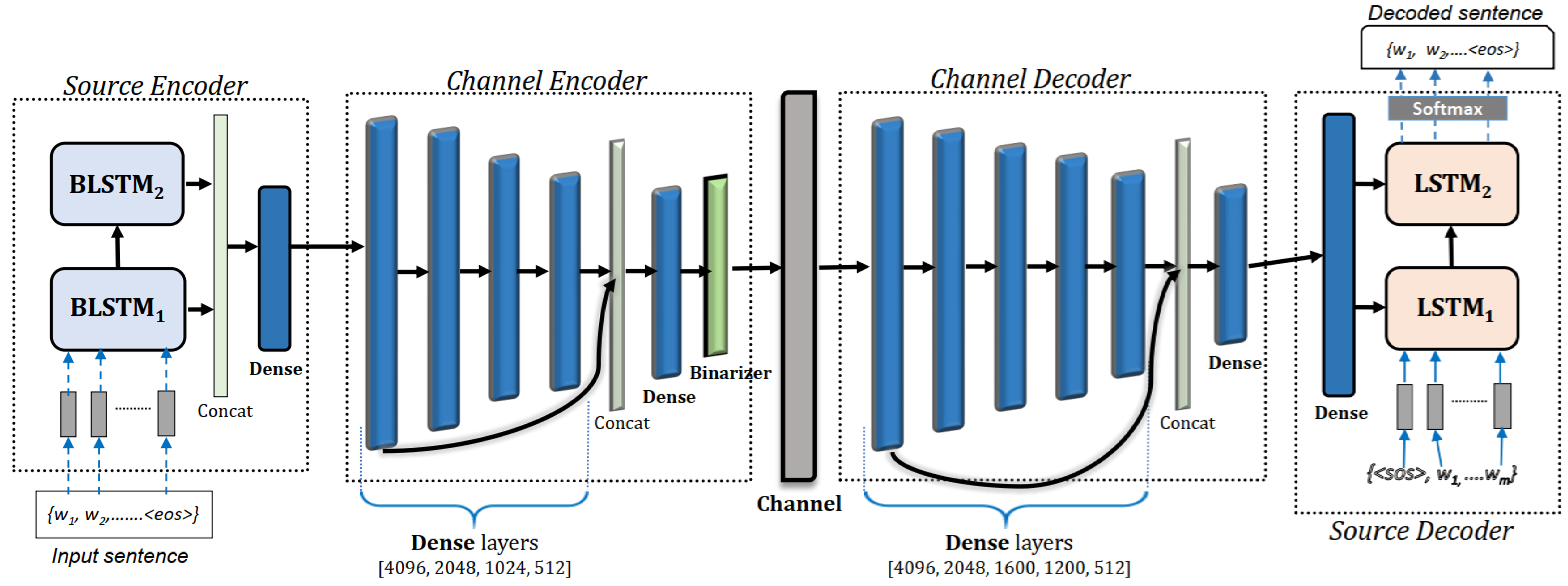

Figure 2: Proposed neural network with attached channel coder

- We introduce a pair of dense residual networks at the junctions between the recurrent nets and the channel. These serve as a *channel encoder* and *decoder* pair. (see Figure 2)
- The channel coder is able to learn features of the channel that enables it to correct bit errors introduced by the Binary Erasure Channel (BEC).
- Skip connections between the first hidden layer and the output layer effectively tackle the problem of *vanishing gradients*. This drastically boosts performance for short bit encodings.
- The source coder and channel coder are trained separately before being jointly trained, since the size of the network poses a barrier to training speed.
- Sentences with similar semantic meaning can be recovered at the decoder.

Results

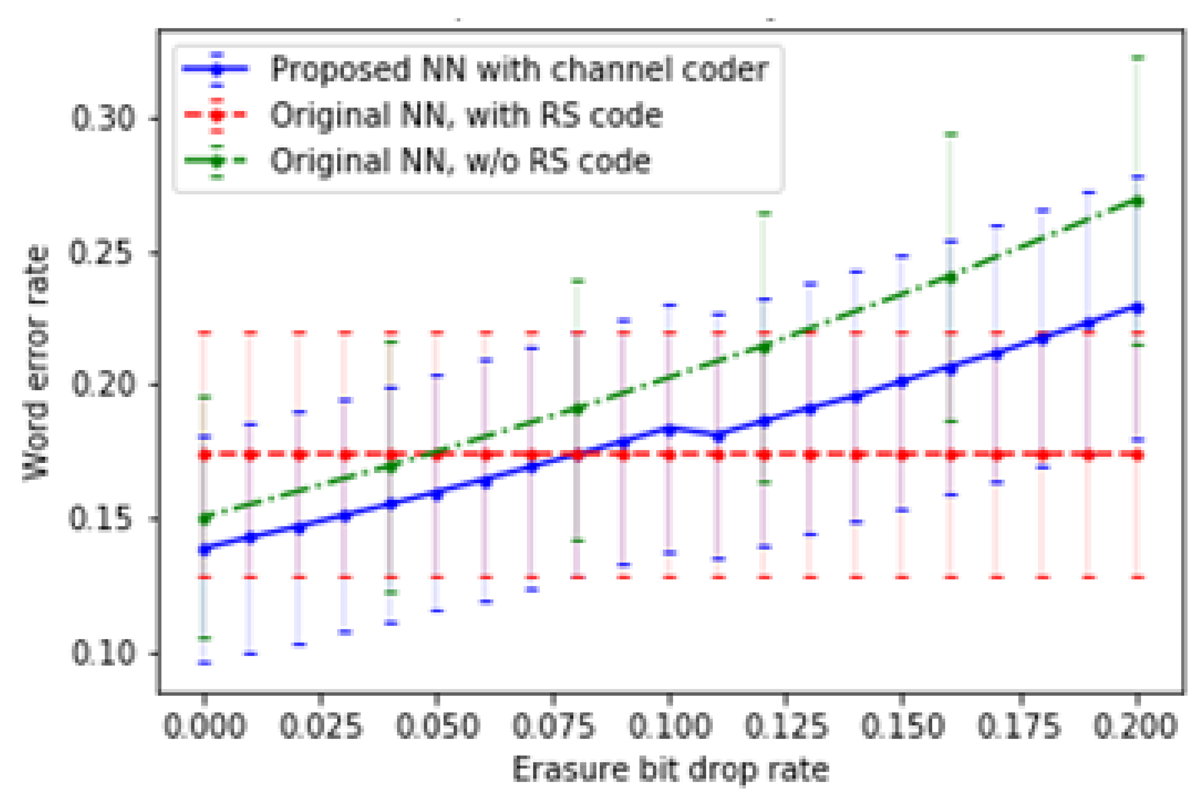

Figure 3: Error rates as a function of channel drop rate

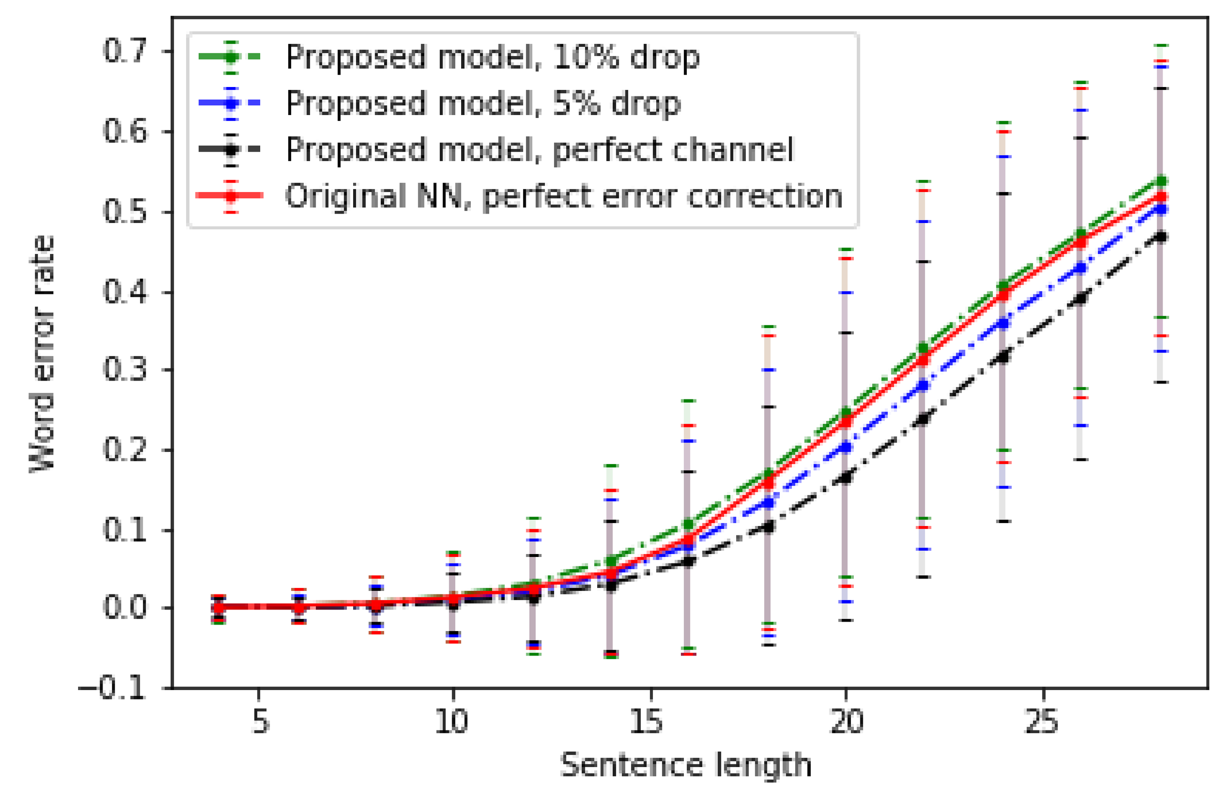

Figure 4: Variation in error with sentence length

Analysis

Punctuation error	**TX:** pitt was 0 of 2 on fourth down and 6 of 13 on third down . **RX (#1):** pitt was 0 . 2 on fourth down and 6 13 of on third down . **RX(#2):** pitt was 0 of 2 on fourth down and 6 to hit on 13 down
Rephrasing	**TX:** lee said the request was denied by the government , a statement seoul confirmed wednesday. **RX(#1):** lee said the request was denied by the government , a statement published confirmed wednesday . **RX(#2):** lee said the request was denied by the government , a statement confirmed wednesday last week.
Long sentence	**TX:** the palestinian economy has amazing potential in the context of independence , with major private sector investment possibilities . **RX(#1):** the palestinian economy has been developed in the context of independence , with major private sector , sectors . **RX(#2):** the palestinian economy has amazing potential in the context of independence , with private broadband sector investment possibilities

{TX: Transmitted sentence; RX(#1): Previous model, perfect channel error correction; RX(#2): Proposed model (5% drop)}

Figure 5: Sample sentences generated by the different models

- Word error rates are independent of mode of error correction
- Proposed *source+channel* coder outperforms *source+RS* for channel **drop rates below 7.5 %**, as well as for longer sentences.

Future Research

- Extend channel coder to variable-length sentence encodings. **Challenge:** Adjust network dimensions for hidden layers without drastically increasing number of model parameters (slows down convergence).
- Research into more robust metrics for measuring semantic similarity between input and output sentences.
- Use emerging developments in NLP to further improve channel coder – try to improve performance for high drop rates.

References

[1] N. Farsad, M. Rao, and A. Goldsmith. Deep learning for joint source-channel coding of text. ICASSP, 2018.

[2] Zhibiao Wu and Martha Palmer. Verbs semantics and lexical selection. In *Proceedings of the 32Nd Annual Meeting on Association for Computational Linguistics*, Stroudsburg, PA, USA. Association for Computational Linguistics.