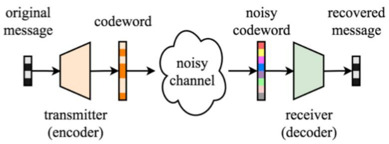
# Deep Learning for Wireless Channel Coding


**Yun Liao (yunliao@stanford.edu)**

**CS230 Deep Learning, Stanford University**


## Introduction

- Communication system:




- Channel coding is the key to reliable transmission in noisy wireless environment.
- The encoder adds parity information to the original messages, and the decoder recovers the messages from the received noisy codewords.
- Conventional channel coding schemes usually assume perfect channel model.
- We aim to use deep learning to find good coding schemes without knowing channel model a priori.

## Dataset

- Messages are randomly generated length-$k$ binary sequences. Channel is random realizations of given classes of channel.
- For AWGN channel, white Gaussian noise is added to the signal.
- For nonlinear channel, signal experiences inter-symbol interference and a nonlinear distortion apart from Gaussian noise.

## Problem Description

Given a code rate $r$, design a pair of mappings from $k$-bit messages to length $k/r$ codewords, and then from noisy codewords back to $k$-bit recovered messages, such that the error of the recovered messages (on bit or sequence level) is minimized.

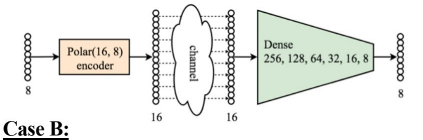
- Case A: (short fix length code) fix $r$=1/2, $k$=8
- Case B: (unconstrained code length) fix $r$=1/2

## Architecture

**Case A:**

Encoder: Conventional polar encoder

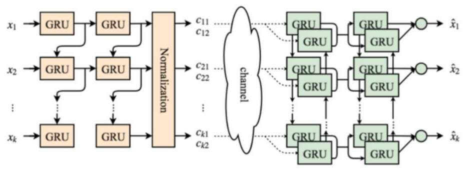
Decoder: 6-layer DNN decoder with 8 output units or 3-layer DNN decoder with $2^8$ output units




**Case B:**

Encoder: 2-layer GRU with 20 hidden units

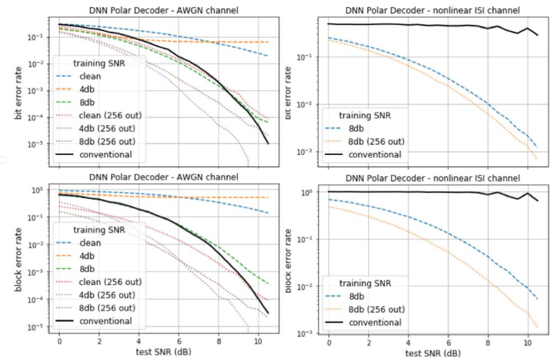
Decoder: 2-layer bidirectional GRU with 100 units




| Case A | Train sets x 8 | Test sets x 44 | Case B | Train set x 1 | Test sets x 26 |
|---|---|---|---|---|---|
| Samples | 2,000,000 | 100,000 | Samples | 1,000,000 | 5,000 |
| k | 8 | 8 | k | 100 | {100, 200} |
| SNR (dB) | {4, 8, 10, ∞} | {0, 0.5…10.5} | SNR (dB) | Uniform(0,5) | {0, 0.5…5} |
| channel | AWGN, Nonlinear | AWGN, Nonlinear | channel | AWGN | AWGN |

## Results and Analysis

**Case A** – comparing (1) conventional polar decoder, (2) DNN decoders learned at different noise level, (3) DNN decoder as a $2^k$-class classifier.



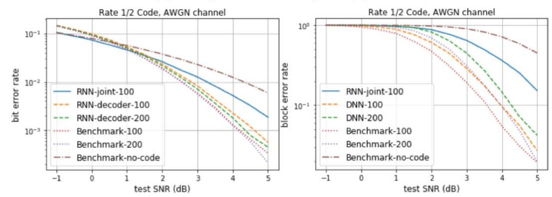

**Key insights:**

(1) Impact of noise level in training: optimal training SNR = 8dB.

(2) error distribution.

(3) DNN decoder significantly outperforms conventional decoder under imperfect channel model.

**Case B** – compared with (1) existing convolutional codes, (2) convolutional encoder + RNN decoder, (3) longer block length, (4) direct transmission wo/ channel coding.




**Key insights:**

(1) Gain of RNN in lower SNR regime.

(2) Directly generalizes to longer block without much loss.

## Conclusions

- Design novel channel coding schemes/decoding algorithms with deep learning.
- For fixed length short code, DNN decoder significantly outperforms conventional ones when channel is not perfectly modeled.
- For long codes with unconstrained length, RNN decoder gets near-optimal performance; jointly learned RNN encoder and decoder achieves lower error rate compared to existing convolutional codes when channel is highly noisy.