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Reverse Ordering Techniques for Attention-Based Channel Prediction

Introduction 1

Objective: predict the channel state information (CSI) in a typical 5G cell in which users move with different velocities

Benefit: enhancing the performance of wireless systems by allowing to adjust the transmission strategies based on the channel prediction

Challenges:

- obtaining precise CSI is difficult because of the fast-changing channel conditions caused by multi-path fading
- linear predictors such as autoregressive (AR) models or Kalman filters (KFs) require
  - the knowledge of the Doppler frequency
  - storing a large number of linear predictors (one for each velocity range)

Contributions 2

- We adapt both the Transformer and the Sequence-to-Sequence with attention (Seq2Seq-attn) model to the channel prediction task
- We introduce novel ordering techniques in these models to make them robust in adapting to CSI sequences of any length
- We do not make any assumptions about the users' velocities

System Model 3

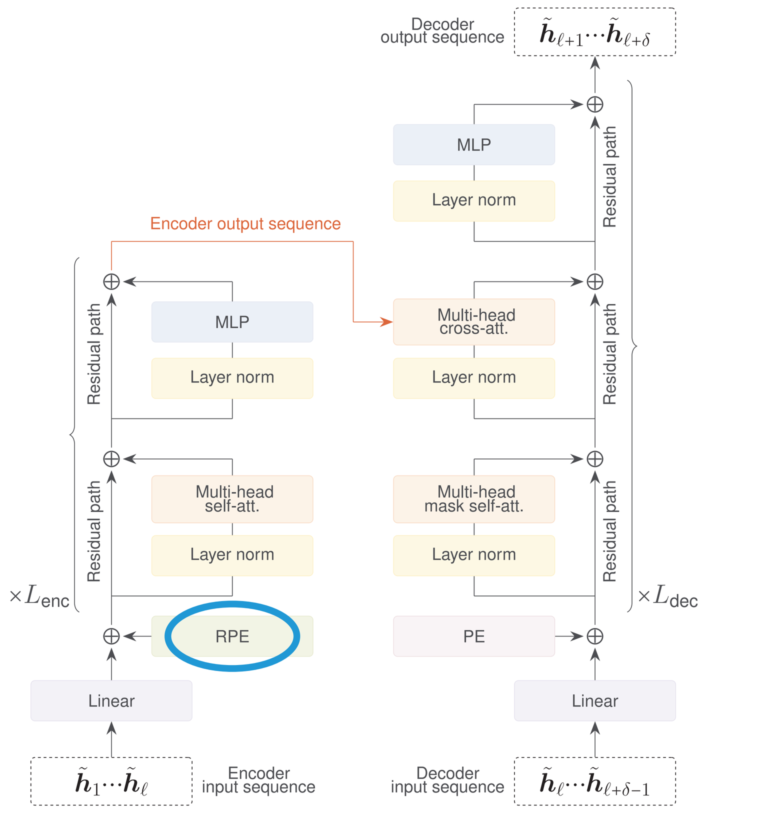
- Base station (BS) with M antennas
- Users with single antenna moving with different velocities
- CSI remains constant for the duration of a slot T_{slot}
- Each frame contains N_{slot} slots
- $\boldsymbol{h}_i \in \mathbb{C}^M$ represents the ith generic slot of the CSI time series

The goal of multi-step CSI prediction is to find the best estimator $f : \mathbb{C}^{M\times\ell} \to \mathbb{C}^{M\times\delta}$ which predicts the CSI vectors $\{\boldsymbol{h}_i\}_{i=\ell+1}^{\ell+\delta}$ based on preceding ℓ observations $\{\boldsymbol{h}_i\}_{i=1}^{\ell}$ with $\ell + \delta \le N_{\text{slot}}$

- Only noisy observations are available for training the models

$$\check{\boldsymbol{h}}_i \leftarrow \boldsymbol{h}_i + \boldsymbol{n}_i \tag{1}$$

Transformer-RPE Model 4

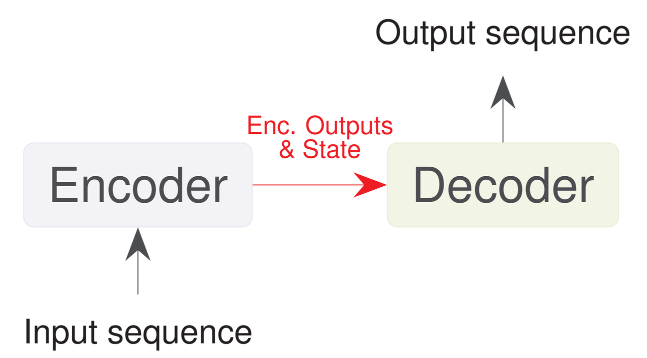


- Differently from the original model, we introduce a novel reverse positional encoding (RPE) in the encoder
- The RPE enhances the robustness of the model to sequences of variable lengths, as the PE linked to the latest known slots remains consistent for shorter or longer sequences
- The RPE can be obtained by first computing the PE

$$\mathrm{PE}(j, 2i) = \sin(j/(10000^{2i/d_{\text{model}}}))$$
$$\mathrm{PE}(j, 2i+1) = \cos(j/(10000^{2i/d_{\text{model}}}))$$

and then by reversing the order with respect to the position index j

Seq2Seq-attn-R Model 5



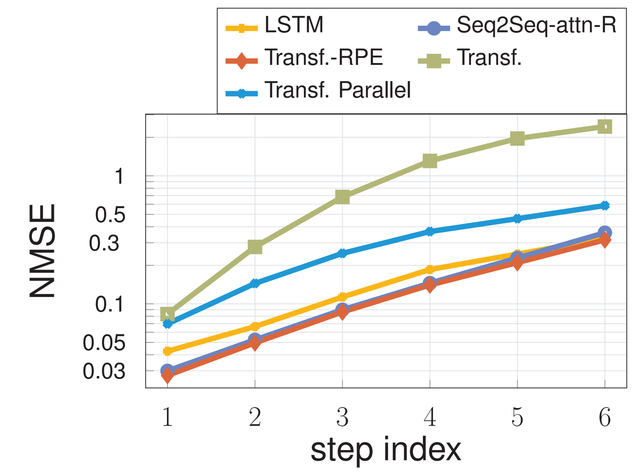
- The Seq2Seq model comprises an encoder and a decoder neural network, which are both recurrent neural networks (RNNs), e.g., gated recurrent units (GRUs)
- The encoder RNN encodes the input sequence to produce a final state which in turn is used as initial state for the decoder RNN
- To encourage the decoder to leverage the important parts of the encoder outputs, an attention mechanism precedes the decoder GRU
- We reverse the encoder outputs to ensure that the attention scores linked to the latest known slots remain consistent for shorter or longer sequences

Simulation Setup 6

- Scenario "BERLIN_UMa_NLOS" from QuadriGa (CSI with 25 paths)
- $N_{\text{samples}} = 150,000$ CSI sequences
- $N_{\text{slot}} = 20$
- $T_{\text{slot}} = 0.5\,$ms
- Center frequency $2.62\,$GHz
- $M = 32$ antennas (8 vertical, 4 horizontal)
- Users randomly distributed over a $120\,\mathrm{deg}$ sector
- Users' velocities between $0\,$km/h and $120\,$km/h

NMSE vs. prediction step 7

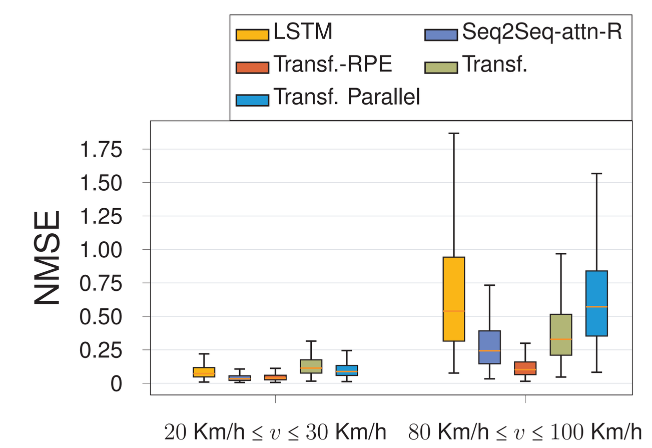
$\ell = 14, \delta = 6$, SNR=15 dB (different from training)



- The prediction error increases with advancing time steps into the future
- The proposed models outperform the others

NMSE vs. velocity 8

$\ell = 8, \delta = 2$, SNR=15 dB (different from training)



- The proposed models exhibit superior performance across various velocity ranges
- All models exhibit a smaller NMSE in the range of [20, 30] Km/h as opposed to the range of [80, 100] Km/h

References 9

1. A. Vaswani *et al.*, "Attention is All you Need," in *Proc. Adv. Neural Inf. Process. Syst.*, 2017.
2. D. Bahdanau, K. Cho, and Y. Bengio, "Neural Machine Translation by Jointly Learning to Align and Translate," in *Proc. Int. Conf. Learn. Represent.*, 2015.