"To Learn or not to Learn" - Deep Learning for predicting non-stationary channel

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ABSTRACT

Modern wireless systems are increasingly dense and mobile that makes the channel highly non-stationary, rendering conventional receivers sub-optimal in practice. Predicting non-stationary channels is rare in literature, especially with iterations on channel state feedback from the receiver. This research builds prescience in a transmitter that will make ultra low latency applications reliable by pre-compensating the waveform according to the impending channel impairments. This work explores the apparatus of deep reinforcement learning to understand *when is learning beneficial* and the limits of error performance of non-stationary channels when predicted using sparse, noisy and corrupt channel state information from the receiver.

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1 INRODUCTION

Design and analysis of optimal receivers using conventional communication theory, rely on mathematical and statistical channel models that describe how a signal is corrupted during transmission. In particular, communication techniques such as modulation, coding and detection that mitigate performance degradation due to channel impairments are based on such channel models and, in some cases, instantaneous channel state information about the model. However, there are many propagation environments (such as vehicular networks) where this approach does not work well because the underlying physical channel is highly dimensional, poorly understood, or rapidly time-varying (non-stationary). These channels leads to sub-optimal and sometimes catastrophic performance using conventional receivers. This problem is relatively tractable and has been studied in the literature for linear, stationary channels with normal distribution by employing the gamut of mathematical tools for Bayesian inference that ranges from Autoregressive random walks, Kalman filters and Particle filters.

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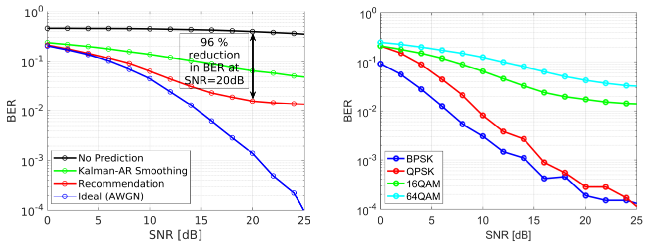
While it is desirable to learn the behavior of the wireless channel, it is a non-trivial problem in practice. Wireless channels are influenced by many external variables that are often correlated, time-dependant or unknown. Therefore, any acquired knowledge about these factors will inevitably be ephemeral, which necessitates long-term learning models that are fast, adaptive and evolve over time. Further, in multicarrier communication systems like OFDM, frequency selective fading can be alleviated if the subcarriers are pre-equalized in accordance to the impending channel response. Therefore, we postulate that in non-stationary channels, the transmitter has to *learn and predict* the most accurate channel response on a per-packet basis such that when the signal is pre-equalized by the *inverse* of the channel it counteracts the effects of wireless channel. For example a Road-Side Unit (RSU) assimilates the Channel State Information (CSI) from vehicles, which is a function of scatterers and vehicle speed to predict future channel states. This temporal knowledge can be obtained using reinforced learning while, decorrelating time-varying, correlated, higher dimensional stochastic variables is one of the strengths of deep neural networks. Therefore, instead of a feed-forward learning model at the receiver, that only learns the past history but is unable to predict future states of the channel, we believe that Deep Reinforcement Learning (DRL) model will make accurate predictions as it involves both the transmitter and the receiver to jointly achieve an optimal performance when communicating over non-stationary wireless channels.

The goal of this work is to achieve the error performance of AWGN channel even when the channel is statistically non-stationary by accurately predicting it at the transmitter. This is realized by using CSIs, obtained as a feedback from the receiver, to decorrelate latent variables using reinforced deep neural networks. Followed by using the predicted channel to pre-equalize the waveform that yields flat-fading across frequency at the receiver, reducing the error rate. This gain in physical layer will also enable novel proactive higher layer protocols for wireless networks.

Example application: Recent explosion in autonomous vehicles has renewed the interest in investigating the properties of the vehicular wireless channel for low-latency, broadband communication. Vehicular networks are unique because the communicating nodes (Vehicle-to-Anything (V2X)) are always moving relative to each other. Consequently, the wireless channel is extremely volatile, which is a combination of many factors like, Doppler shift, shadowing, scattering, etc. More importantly, all of these quantities are time-varying and statistically *non-stationary*. A reliable wireless channel also provides resiliency in higher layer network functions like traffic-aware, low-latency caching of content and coordinated downlink transmission for multiuser communication techniques. Although, V2X is an extreme example of non-stationary channel, the



(a) BER for 16-QAM **(b) BER for different modulations**

Figure 1: Performance of Recommendation system.

proposed research organically applies to other wireless channels with similar properties, like 802.11-(xx), C-V2X and mmWave networks.

2 PRELIMINARY RESEARCH AND RESULTS

Predicting the wireless channel is a three-step process: The first step is accumulation of the CSI from the receivers along with any and all measurable parameters that might affect channel states. Secondly, a carefully orchestrated mathematical treatment (algebraic, Bayesian, neural networks, etc.) to analyze the correlation among the variables that constitute the measured CSI. Non-stationary V2X channel contains many immeasurable and hidden variables that collectively contribute to a particular CSI value. However, these hidden variables may be correlated with other observable parameters like the number of scatterers, vehicle speed and road-side features. In our preliminary work ([1]), we have been successful in employing Tensor Factorization (TF) to address this problem. The third and final step is to utilize the information from the previous two steps to obtain an accurate representation of the channel based on the impending (future) states of the observable variables and pre-compensate the waveform at the transmitter to combat the channel.

Latent variables are responsible for hidden correlations that cannot be ascertained a priori. As an example, in [1], tensors are used to record the multivariate V2X channel to analyze the impact of latent variables on the CSI. In [1], we evaluated the performance of the TF approach using the WINNER model. Vehicles are simulated at a speed of V=20m/s (45mph). The number of fixed scatterers is set to be different in each segment (between 1 to 5) and variable scatterers are chosen uniformly between 0 and 9. The road length is 200m, divided into 20 segments. Figure 1a shows the BER in comparison to the AWGN case (blue) and that without any prediction (black). These results show that the channel prediction system yields >90% improvement in BER for 16-QAM constellation but considerably worse compared to the AWGN channel. It also outperforms other iterative methods like Kalman filter (green). Closing this gap for higher order modulations is the goal of this research. Figure 1b shows the BER for differenet modulations.

3 DRL FRAMEWORK

Channel prediction using TF captures the latent variables of the channel when combined with the observable variables (CSI, scatteres and location). However, there are several factors that limit the performance and practicality of this method. For example, TF assumes a multi-linear decomposition, and computes latent variables that adhere to this constraint. As such the computed latent variables might not be disentangled as desired and also capture the noise in the tensor. In contrast, reinforcement learning captures the temporal variation of the channel while disentangling the latent variables using the β-VAE network, leading to better predictions. Also, deep neural networks serves as complicated function approximators, making the underlying computations generic and tractable. DRL enables an agent to learn and predict in an interactive environment (involving both transmitter and receiver) using feedback from its own actions (predictions) and experiences (flatness of estimated channel at receiver). It leverages deep neural networks to approximate the policy of reinforcement learning to make it tractable for online predictions. Hence, DRL serves as the ideal form of online learning where rewards (function of CSI) are based on past predictions can be used to improve future actions.

The flow of information from transmitter to the receiver is as follows: At the transmitter, the bits that are to be transmitted are modulated to generate the I/Q vectors. These I/Q vectors are pre-equalized with the most accurate prediction of the impending channel profile produced by the Agent (β-VAE). The pre-equalized I/Q vectors are converted to time-domain waveform and transmitted over the non-stationary downlink channel. At the receiver, the baseband signal is estimated using conventional pilot based estimation, equalized, demodulated and decoded to extract information bits. In parallel, the agent works as follows: The CSI is piggy-backed on a low-rate uplink packet and is used to compute a *reward* proportional to the flatness of the estimated channel at the receiver, for the reinforcement learning using a VAE. The *VAE update* stage involves using a N-way tensor to store the CSI and other measurable parameters. This tensor is sparse, as all entries may not have been observed as well as noisy due to correlated latent variables and serves as the input to the β-VAE. The β-VAE computes the disentangled latent representation and generates the output tensor, which is complete and less noisy and contains future states of the channel for impending values of the measurable parameter set. This is obtained in the *VAE query* stage. The generative β-VAE is guided by the reinforcement framework, which determines the optimal value of β based on the cumulative reward. Over time, with more reinforcements, the input tensor gets less sparse improving the predicted channel states.

4 AUTHOR BIOGRAPHY

Maqsood Abdul Careem received the bachelor's degree in electrical and electronic engineering from the University of Peradeniya, Sri Lanka, in 2014. He is currently pursuing the Ph.D. degree under the supervision of Prof. Aveek Dutta from the Department of Electrical and Computer Engineering, University at Albany, Albany, NY, USA. He is a member of the Mobile Emerging Systems and Applications (MESA) lab at University at Albany. His primary research is in learning based optimization of wireless communication. Other research interests include Enforcement in Spectrum Sharing, Emerging heterogeneous wireless networks and Vehicular communications. The expected date of dissertation submission is May 2021.

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