“To Learn or not to Learn”: Deep Learning for predicting Non-Stationary channel

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I. Introduction

Communication theory relies on Statistical channel models or Channel State Information (CSI).

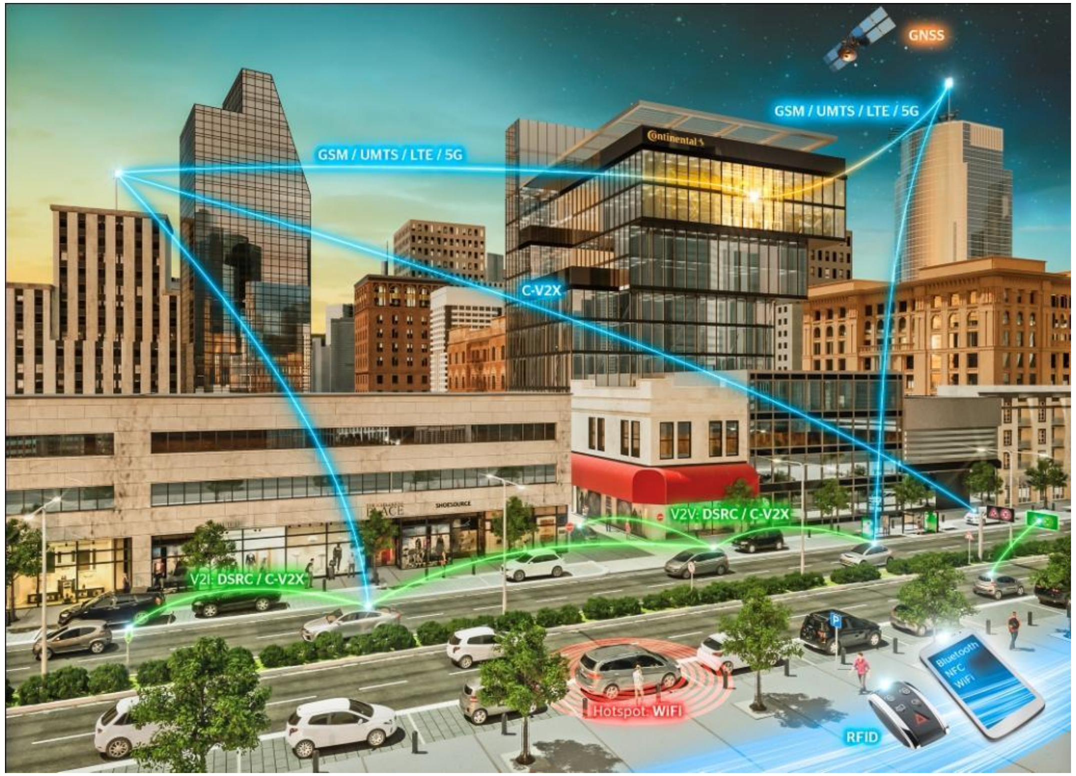
Problem: Modern Channels are highly dimensional, nonlinear, non-stationary → Suboptimal performance using conventional receivers.

Learning not Trivial: Influenced by correlated, temporal, unknown variables.
Acquired knowledge is ephemeral →Long term but Adaptive learning models

Intuition: Tx has to accurately learn and predict channel response → Pre-equalized Signal Counteracts the channel effects.

Non-stationary Wireless Channels

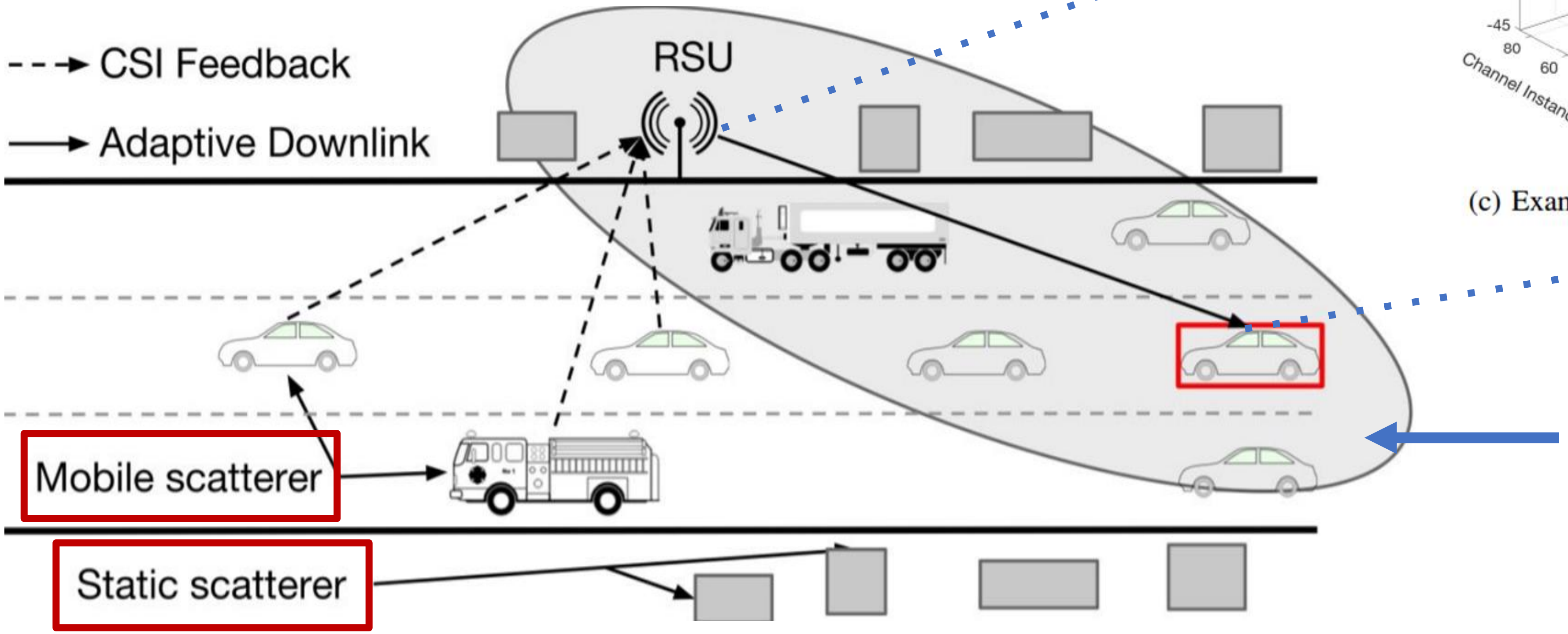
- V2X (Vehicle to Everything) [1]
- HST (High-Speed Train) [2]
- Massive MIMO [3]
- mmWave Networks [4]

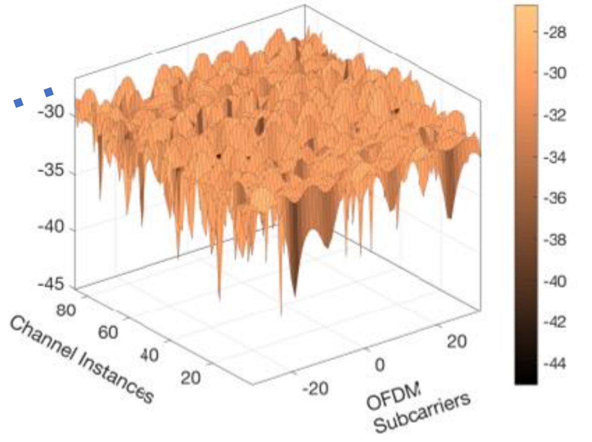


[1] M. Boban, J. Barros, and O. K. Tonguz, "Geometry-Based Vehicle-to-Vehicle Channel Modeling for Large-Scale Simulation,"
[2] Y. Liu, C. Wang, J. Huang, J. Sun, and W. Zhang, "Novel 3-D nonstationary mmwave massive mimo channel models for 5g high-speed train wireless communications,"
[3] J.-q. Chen, Z. Zhang, T. Tang, and Y.-z. Huang, "A non-stationary channel model for 5g massive mimo systems"
[4] S. Wu, C. Wang, e. M. Aggoune, M. M. Alwakeel, and X. You, "A general 3-D non-stationary 5G wireless channel model,"
[5] Qualcomm, "C-V2X"

Non-Stationary Channel Prediction

RSU: Road Side Unit



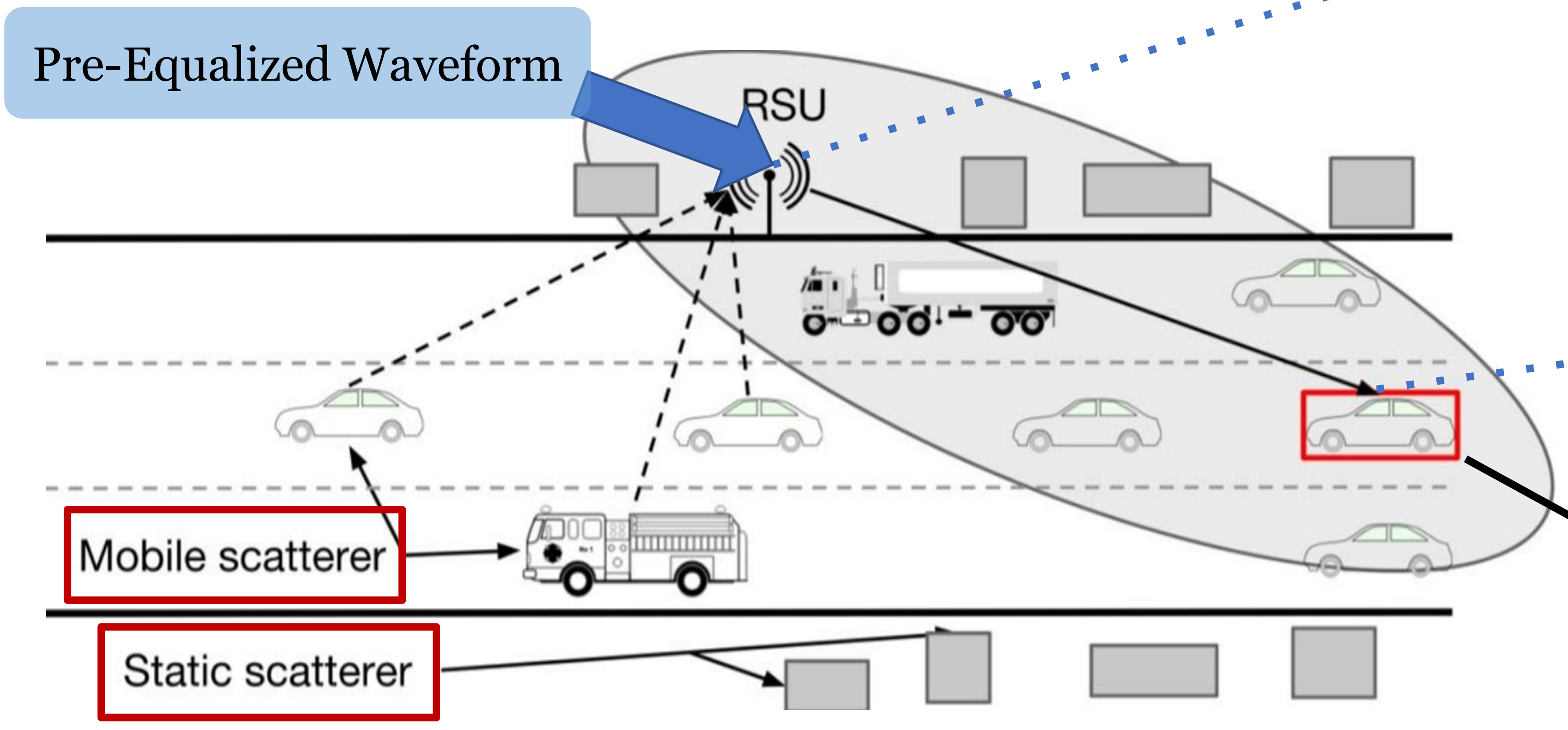


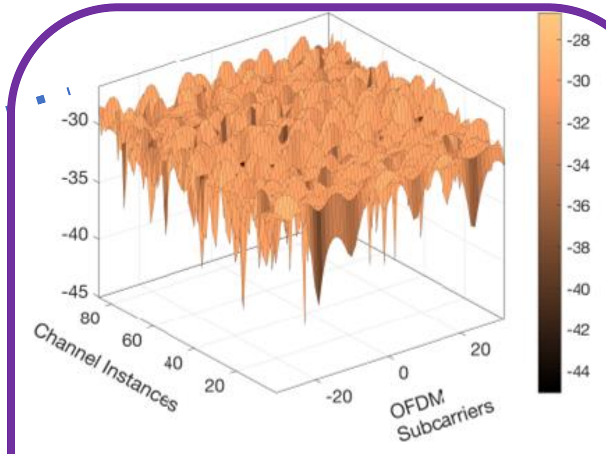
(c) Example channel profile $N_{scat}^{(i)} = 13$

Scattering Zone

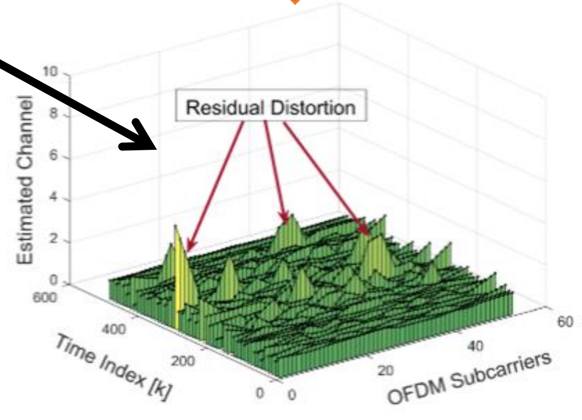
Example of a vehicular Edge network

Intuition





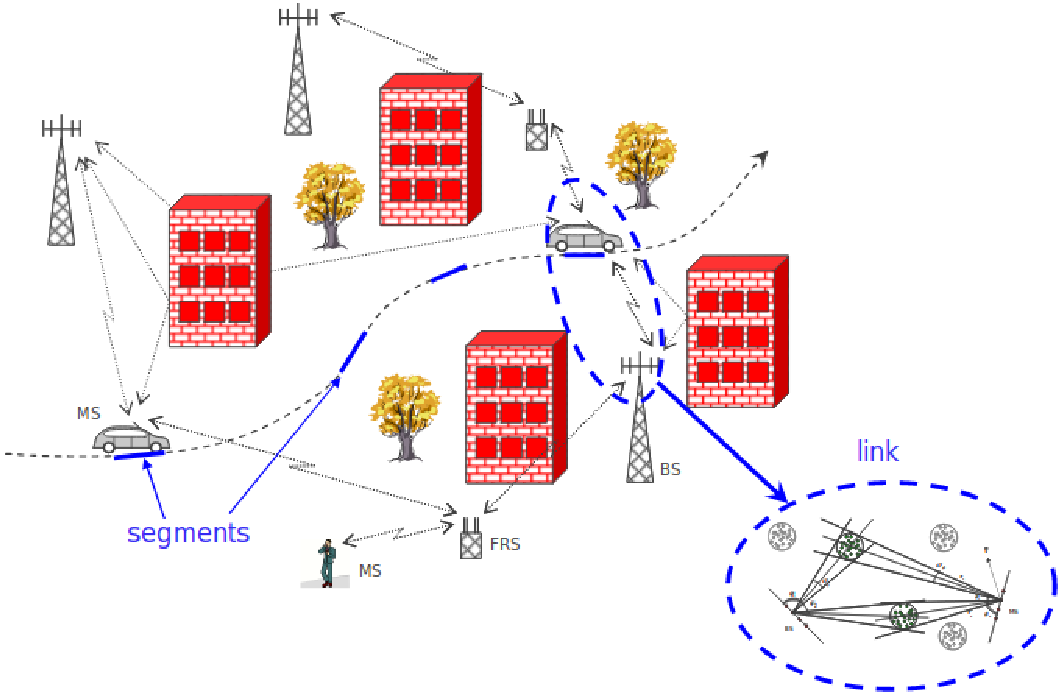
(c) Example channel profile $N_{scat}^{(i)} = 13$

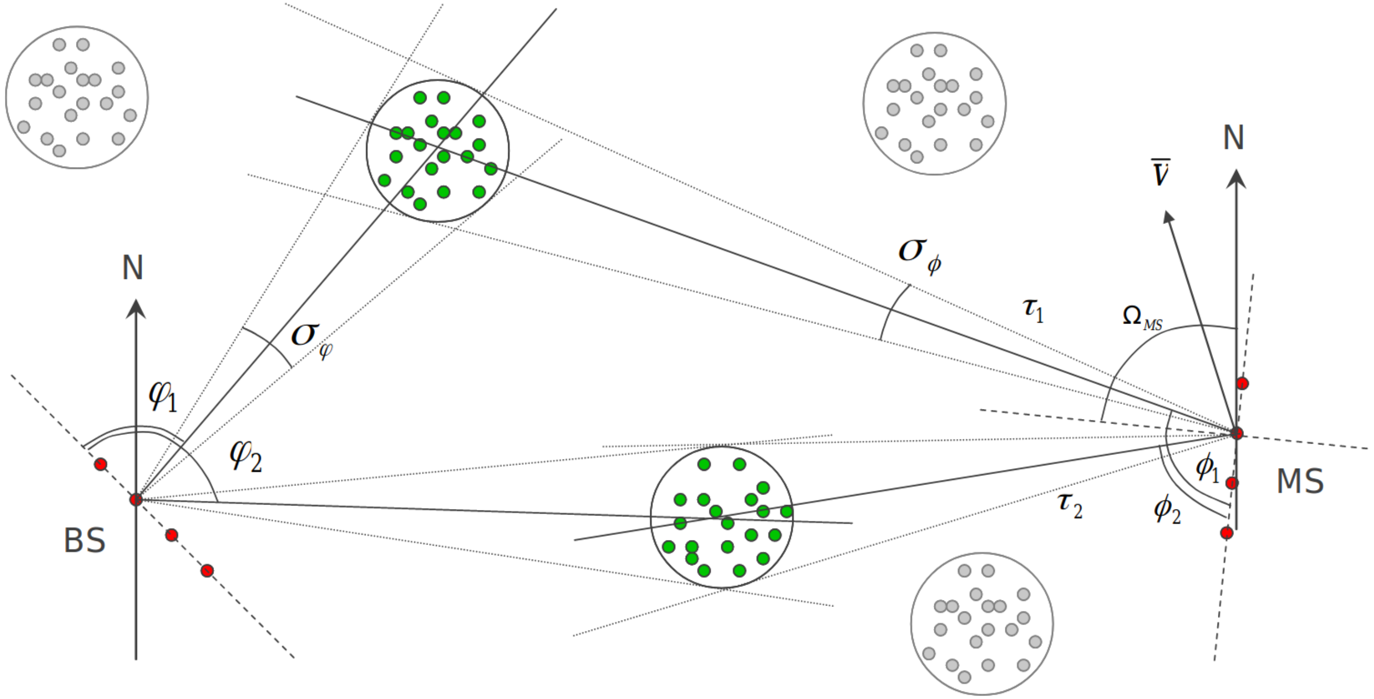


(d) Equalized channel-Receiver

Intuition: Use observable inputs to predict channel & Pre-Equalize → Accurate, Reliable, Low Latency Communications

II. Channel Characterization





Channel Gain **AOD & AOA** **Doppler** **Delay**

$$h(k,n) = \sum_{\ell=1}^{N_s(k)} h(k,n,\ell) \longrightarrow h(k,n,\ell) = \sum_{m=1}^{M_\ell} \alpha_m(k,n) e^{j\varphi_m(k,n)} e^{j2\pi f_{D_m}(k,n)k} \delta(\tau - \tau_m(k,n))\delta(\theta - \theta_m(k,n))\delta(\phi - \phi_m(k,n)$$

[6] Svensson et. al "WINNER II Channel Models".

A typical Non-Stationary Channel Model

Model

$$h(k,n) = \sum_{\ell=1}^{N_s(k)} h(k,n,\ell) \longrightarrow h(k,n,\ell) = \sum_{m=1}^{M_\ell} \alpha_m(k,n) e^{j\varphi_m(k,n)} e^{j2\pi f_{D_m}(k,n)k} \delta(\tau - \tau_m(k,n))\delta(\theta - \theta_m(k,n))\delta(\phi - \phi_m(k,n)$$

Factors

- Scatterering Environment
- Doppler frequency
- Angle of Departures & Arrivals (AoD & AoA)
- Channel gains and path delays, etc…

Measurable

- Number of Scatterers (Ns)
- Locations (S)
- Antenna Configuration

Latent (Uncorrelated) Factors

Measurable (Correlated) Factors

Non-Stationary Channel Prediction

- **Problem Statement**
  - **Prediction and Proactive Transmitter-side Pre-Equalization**

Tx collects CSI & Observable Inputs → Track Temporal behavior → Extract Uncorrelated Latent Structure → Predict Downlink Channel → Pre-Equalize Tx Waveform → Flat-Fading at Receiver

Deep Reinforcement Learning (DRL) **Variational Auto Encoder (VAE)**

III. State-of-the-art Work

A. Classical Approaches

Receiver-Side:

- Estimation & Equalization: Frequency vs Time, Linear vs Nonlinear, Adaptive

Transmitter-Receiver:

- Error Control Coding - Viterbi, LDPC, Rateless Coding

Transmitter Side:

- Precoding - MIMO, Beamforming
- Prediction & Pre-Equalization

Focus on WS Stationary channels, known Distributions using Bayesian inference.

B. Deep Learning (DL) Approaches

Benefits of DL for PHY

1. For unknown channel models

2. May improve BER for Heuristics

3. Potential for Online learning - flexibility & reconfigurability

4. High parallelism

Drawbacks of DL PHY

Classical approach good enough
— PHY has solid math foundation
— Very good codes (LDPC, polar)
— PHY is sensitive to latency

DL State-of-the Art: Similar performance as classical, but high HW overhead

DL for PHY Channel

Rx Side:

Decoder, Detector, Estimator

Tx-Rx Side:

Popular for Channel Coding

End-to-End Learning [DeepSig]

Tx Side:

LSTMs for prediction

Similar performance as classical, but high HW overhead

Learning will be Beneficial for Non-Stationary Channels

IV. Proposed Methodology

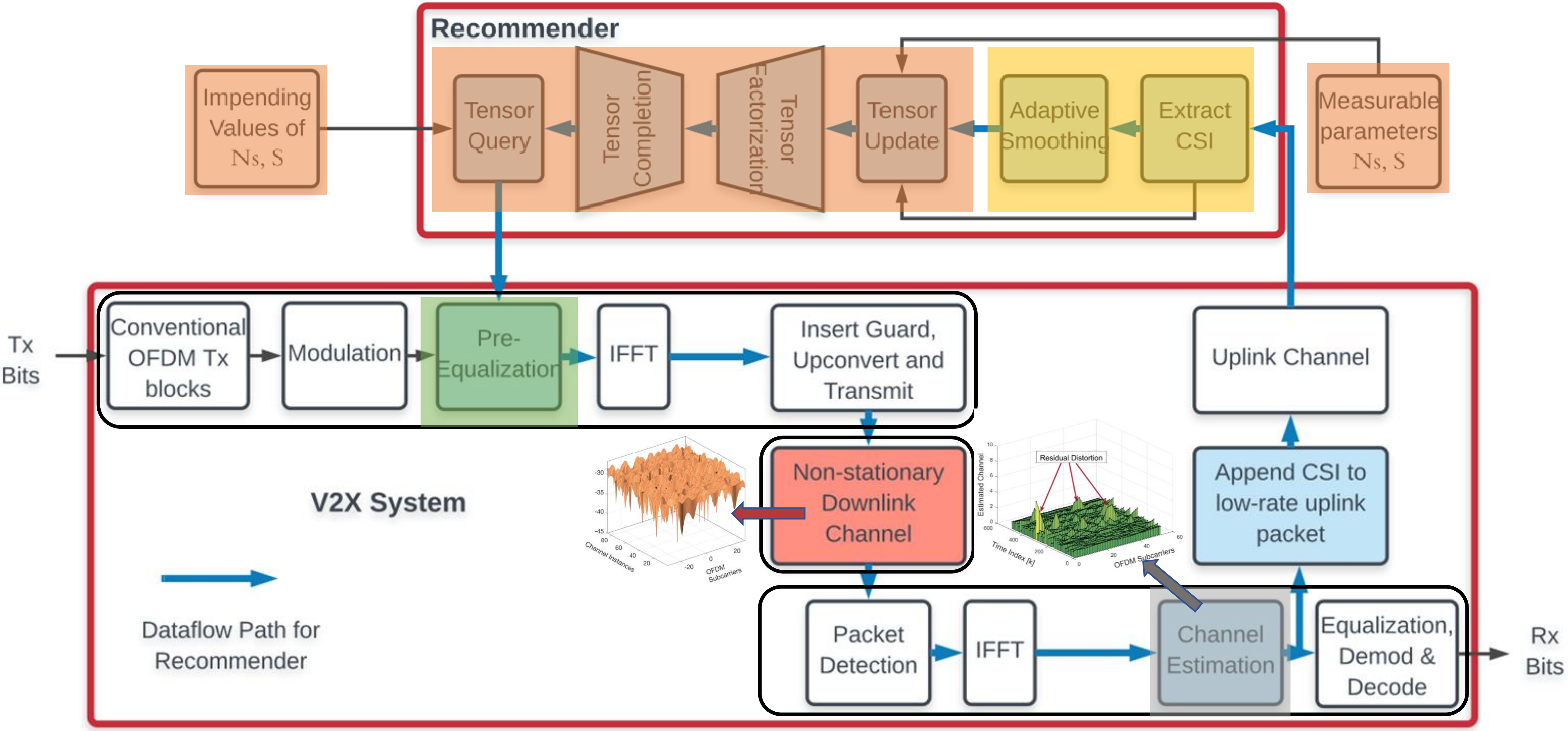
Preliminary Research & Publications:

[1] **Maqsood Careem** and A. Dutta, “Real-time Prediction of Non-stationary Wireless Channel,” IEEE TWC (Under Review).

[2] **Maqsood Careem** and A. Dutta, “Spatio-temporal recommender for v2x channels,” in 2018 IEEE 88th Vehicular Technology Conference (VTC-Fall), Aug 2018, pp. 1–7.

[3] **Maqsood Careem** and A. Dutta, "Channel Analytics for V2X Communication," 2018 IEEE 5G World Forum (5GWF), Silicon Valley, CA, 2018, pp. 433-436.

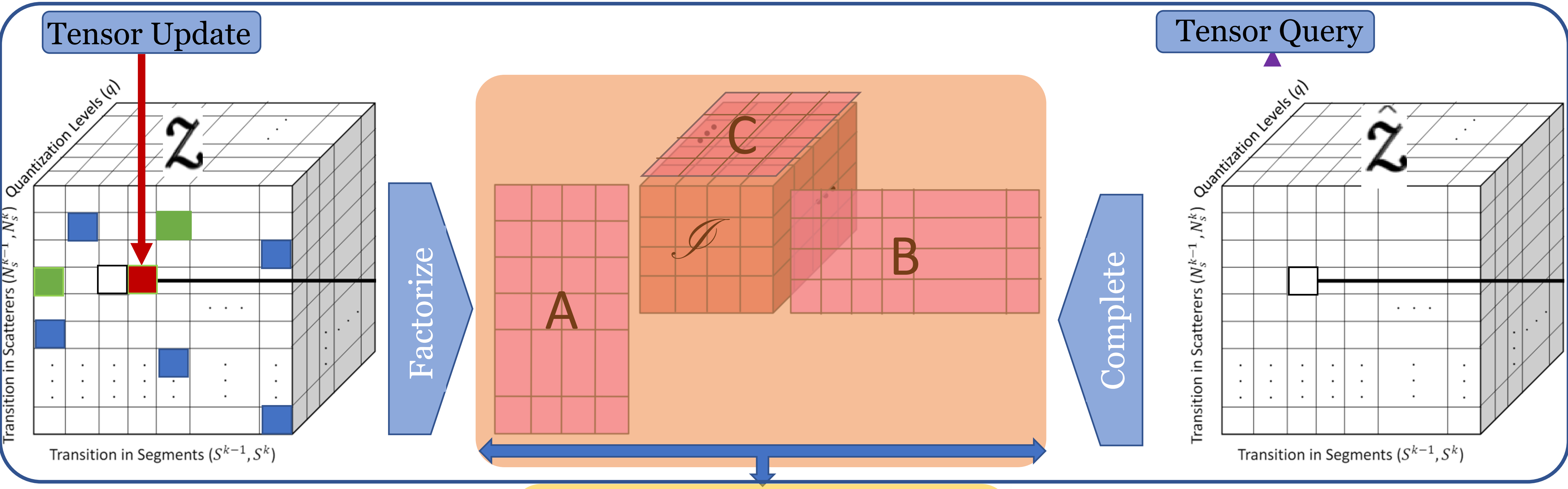
Non-Stationary Channel Prediction System



B. Tensor Factorization & Completion

$$f_{\mathcal{W}}(\mathbf{A},\mathbf{B},\mathbf{C}) = \frac{1}{2}||\mathcal{Z} - [\![\mathbf{A},\mathbf{B},\mathbf{C}]\!]||^2_{\mathcal{W}} + \frac{\lambda}{2}(||\mathbf{A}||^2 + ||\mathbf{B}||^2 + ||\mathbf{C}||^2)$$

$$\hat{\mathcal{Z}} = \mathcal{W} * \mathcal{Z} + (1 - \mathcal{W}) * [\![\mathbf{A},\mathbf{B},\mathbf{C}]\!]$$

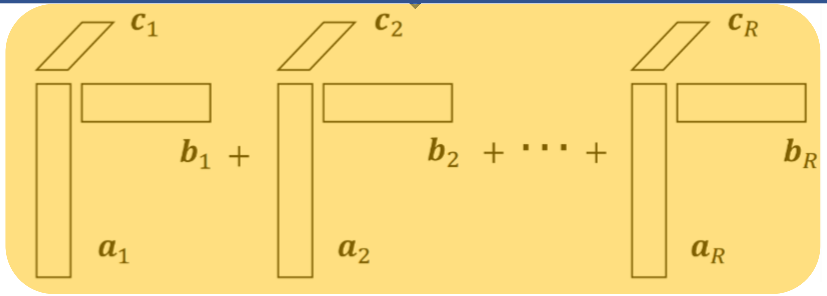


$\mathcal{Z}$ - Channel Tensor

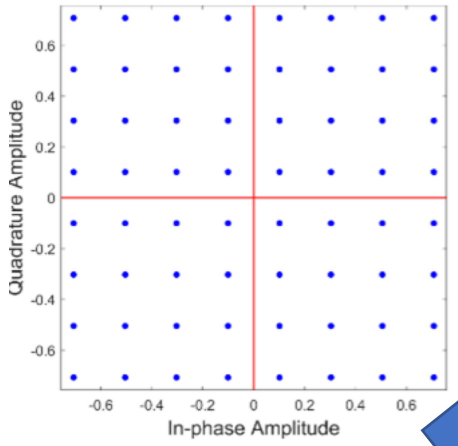
$A = [a_1, \dots, a_R]$ - transition in scatterers (N_s^{k-1}, N_s^k)

$B = [b_1, \dots, b_R]$ - Transition in segment (S^{k-1}, S^k)

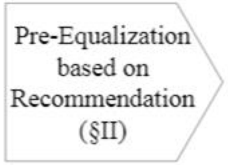
$C = [c_1, \dots, c_R]$ - quantized levels (q)

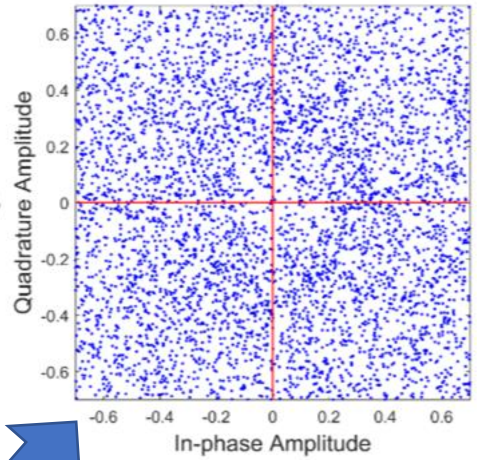


Results: Prediction and Pre-Equalization

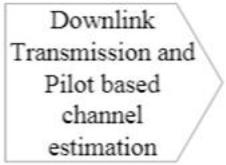


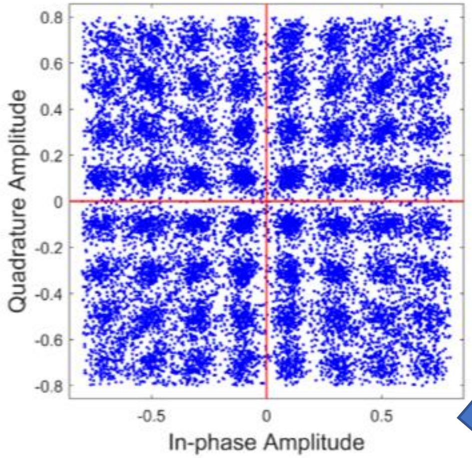
(a) Before compensation



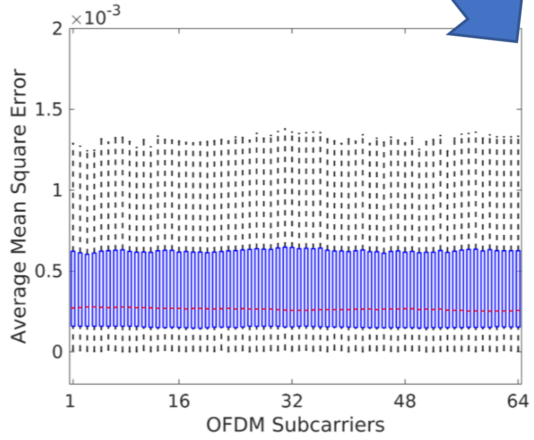


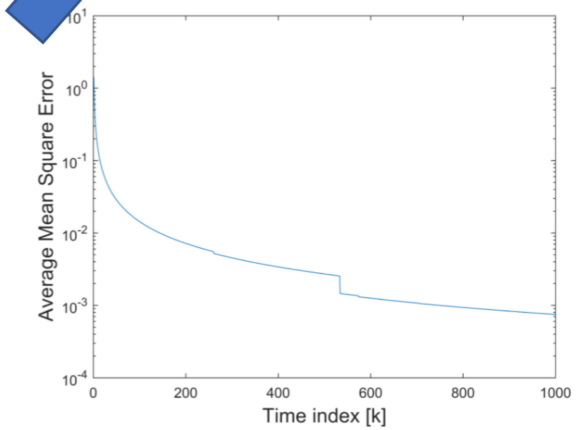
(b) After Pre-equalize



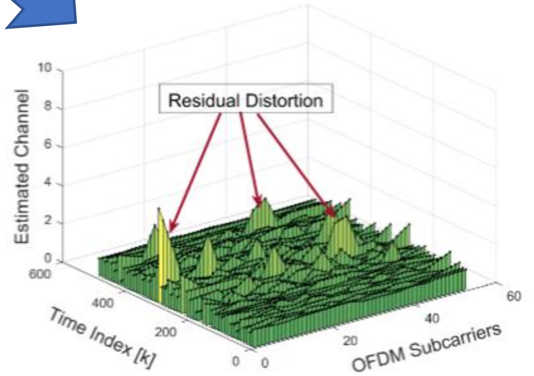


(c) Received constellation



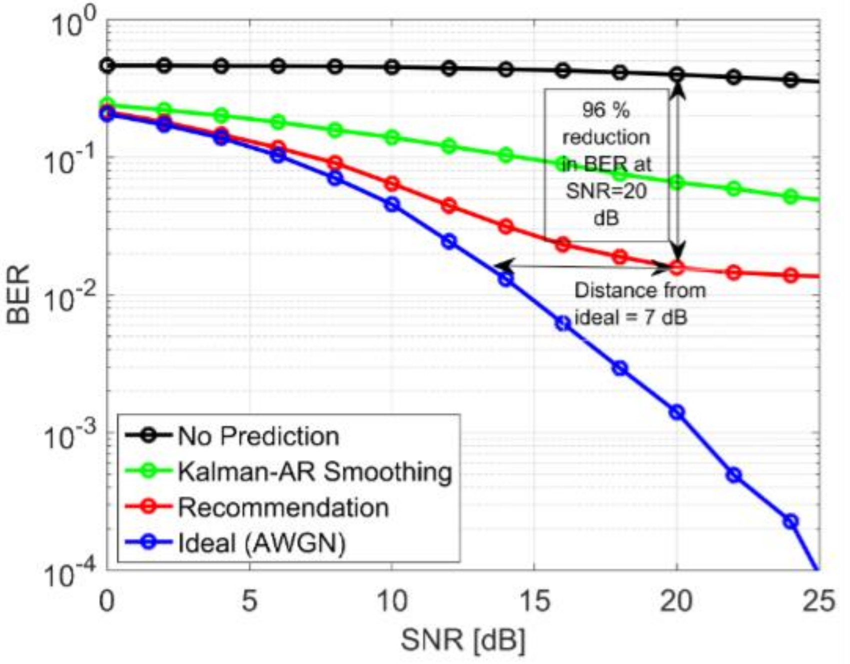


Channel Prediction Accuracy

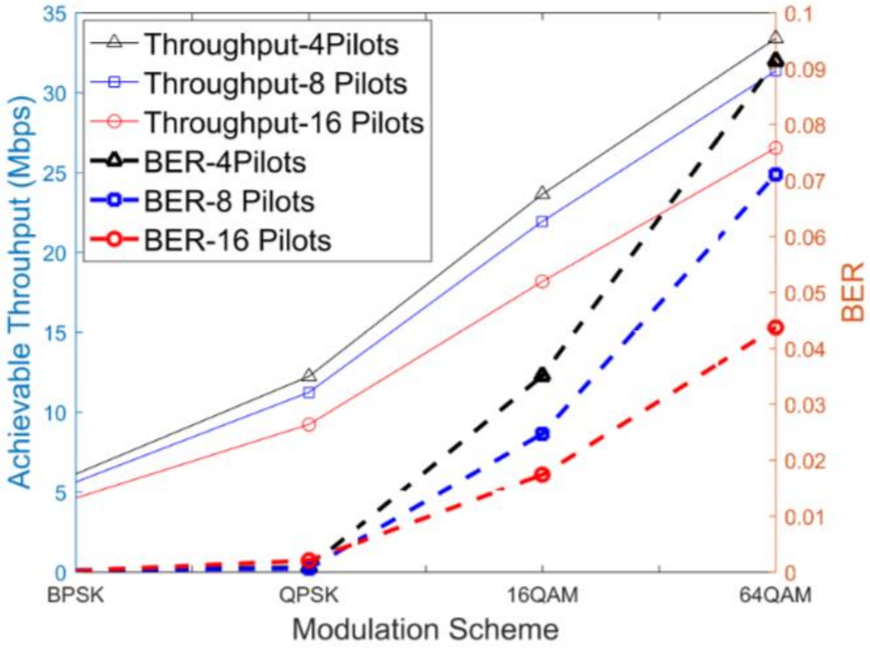


(d) Equalized channel-Receiver

Results: Performance at Receiver



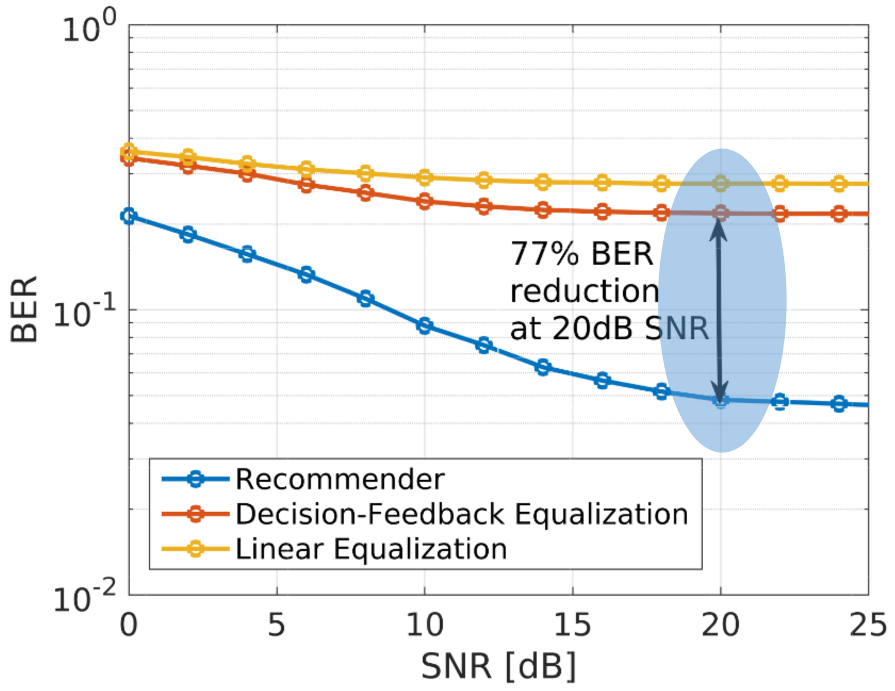
(a) BER for 16-QAM scheme



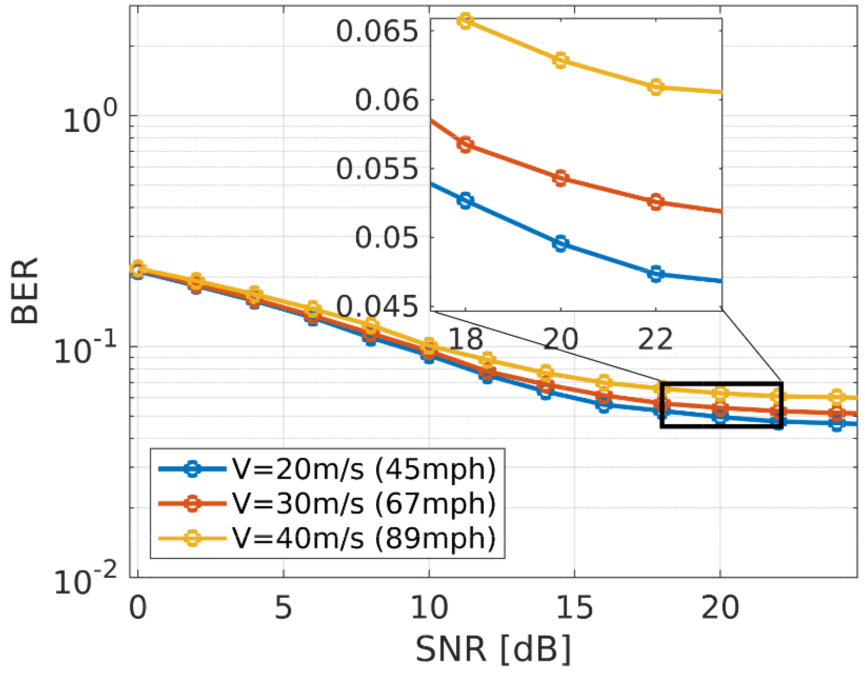
(c) Throughput and BER for different modulations

Higher Data Rates, Lower Latency, But Room for Improvement

Pre-Equalization over Post-Equalization



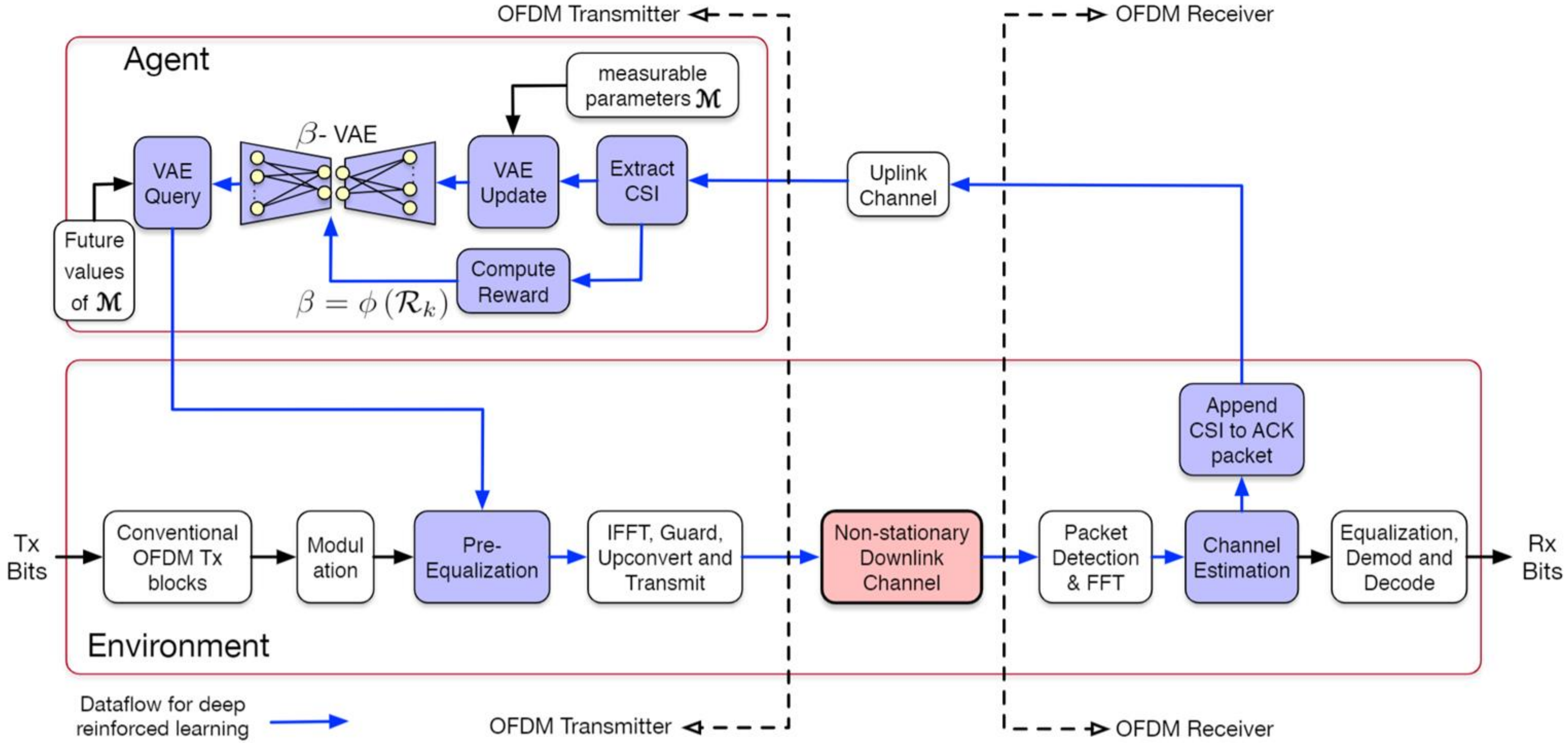
Comparison with state-of-the-art receiver side techniques



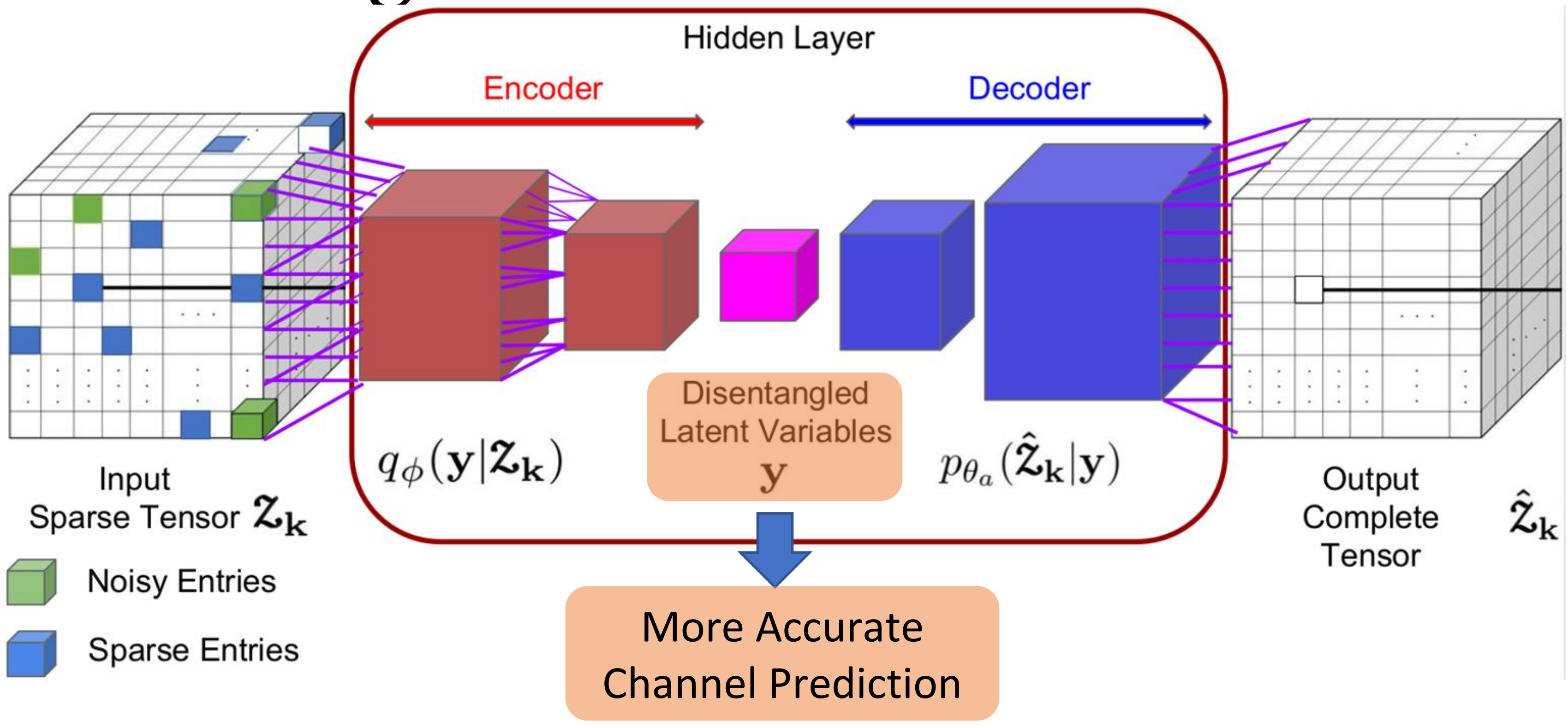
BER varying speeds of the communicating nodes

Significant Improvement over State-of-the-Art Approaches

B. Deep Reinforcement Learning for Non-stationarities

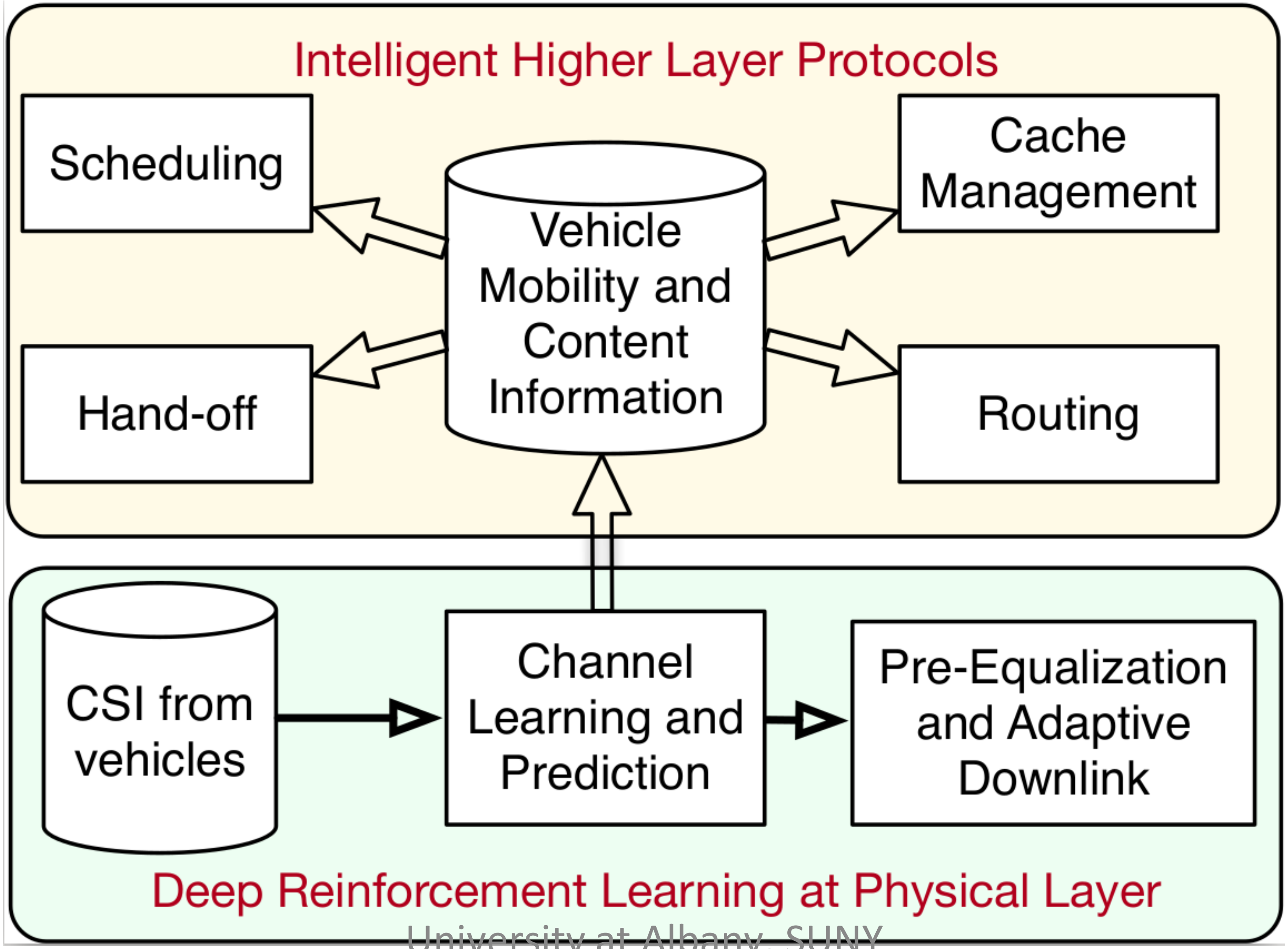


Unique Advantage



VAE Loss Function $\mathcal{L}\left(\theta,\theta_a,\phi;\mathcal{Z}_k,\hat{\mathcal{Z}}_k,\beta\right)=E_{q_\phi(\mathbf{y}|\mathcal{Z}_k)}\left[\log p_{\theta_a}\left(\hat{\mathcal{Z}}_k|\mathbf{y}\right)\right]-\beta D_{\mathrm{KL}}\left(q_\phi(\mathbf{y}|\mathcal{Z}_k)\|p_\theta(\mathbf{y})\right)$

V. Intelligent Higher Layer Functions



VI. Conclusion and Discussion

- Modern channels are non-stationary → conventional receivers sub-optimal.
- Observable Inputs and Latent Factors helps address the Non-stationarity
- Learning will be beneficial over Non-stationary channels

Ongoing Work

- Real time hardware implementation
- Practical Evaluation using Rigorous measurement campaigns
- Investigate Causal Meta Learning strategies to address Non-Stationarity

Thank you

Questions & Feedback