Deep Learning for Compressive Feedback of Massive MIMO Channel Estimation

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Outline

Background

- What is CSI in MIMO?

CSI Estimation

- Convolutional Neural Networks

Our Work

- Bi-directional Reciprocity
- Spherical Normalization

Why MIMO?

Massive MIMO is a key enabling technology for future wireless communications networks.

- 5G, Ultra-Dense Networks, IoT

S. Marek, “Sprint Spent $1B on Massive MIMO for Its 5G Network in Q2," *SDxCentral*, `https://www.sdxcentral.com/articles/news/sprint-spent-1b-on-massive-mimo-for-its-5g-network-in-q2/2018/06/`. Accessed: Feb 22, 2020.

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The efficacy of MIMO depends on accurate *Channel State Information (CSI)*.

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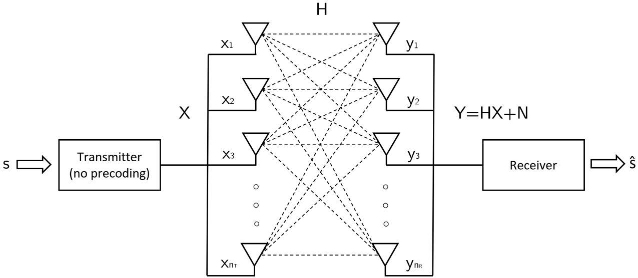
Massive MIMO uses numerous antennas to endow transceivers with spatial diversity.

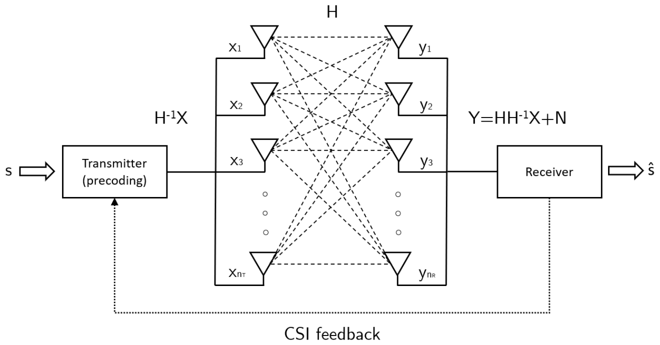


The fading coefficients between each set of Tx/Rx antennas constitute **Channel State Information (CSI)**, **H**. For n_T, n_R antennas,

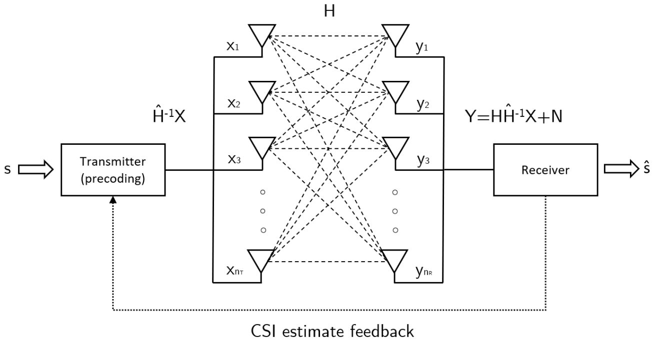
$$\mathbf{H} = \begin{bmatrix} h_{1,1} & h_{1,2} & \dots & h_{1,n_T} \\ h_{2,1} & h_{2,2} & \dots & h_{2,n_T} \\ \vdots & \vdots & \vdots & \vdots \\ h_{n_R,1} & h_{n_R,2} & \dots & h_{n_R,n_T} \end{bmatrix}$$

MIMO and Perfect CSI

Perfect CSI (i.e., exact knowledge of the channel, **H**) allows us to maximize the power of the received symbol by precoding.

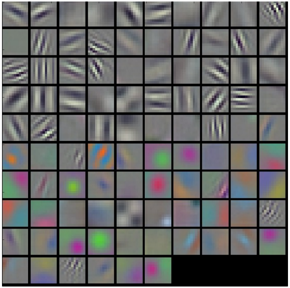


However, $\mathbf{H}$ is not known a priori. Instead, we must generate **CSI Estimates**, $\hat{\mathbf{H}}$.



Goal: Find a low-dimensional representation, feed back to transmitter for recovery of $\hat{\mathbf{H}}$.

- CNNs = state-of-the art performance in image processing applications
- Capable of extracting features from 2D, grid-like data



A. Karpathy, “Visualizing What ConvNets Learn," http://cs231n.github.io/understanding-cnn/. Accessed: Feb 24, 2020.

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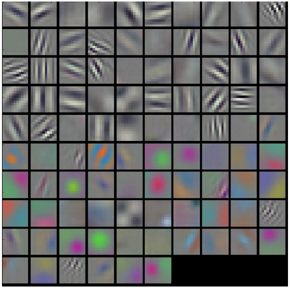

- **Recently, CNNs applied to CSI estimation**

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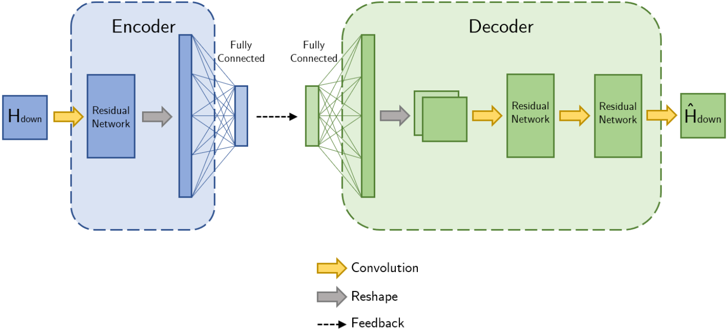
- CNN-based autoencoder for learned CSI compression and feedback [1]



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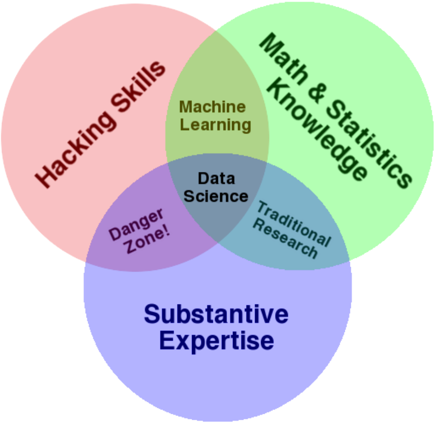

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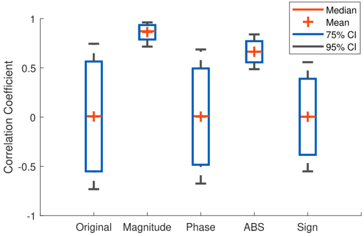
Bi-directional Reciprocity

- Goal = estimate downlink CSI
- In conventional CSI estimation for FDD, uplink is typically not used to estimate downlink
- With CNNs, can leverage correlation between uplink/downlink [3]



Z. Liu, L. Zhang, and Z. Ding, "Exploiting Bi-Directional Channel Reciprocity in Deep Learning for Low Rate Massive MIMO CSI Feedback," *IEEE Wireless Communications Letters*, vol. 8, no. 3, pp. 889–892, 2019

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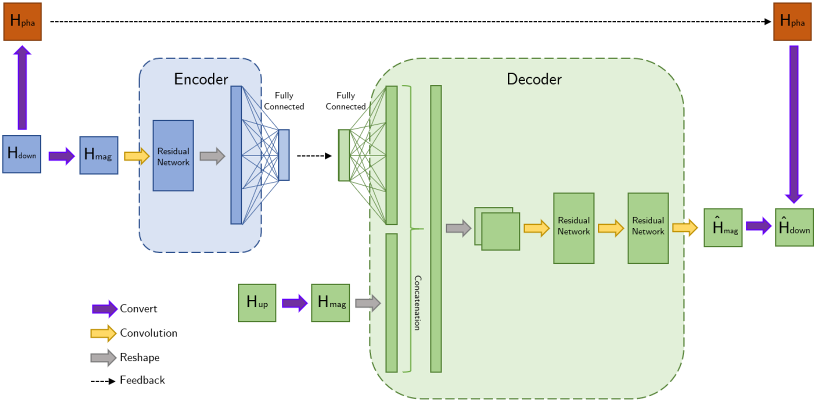
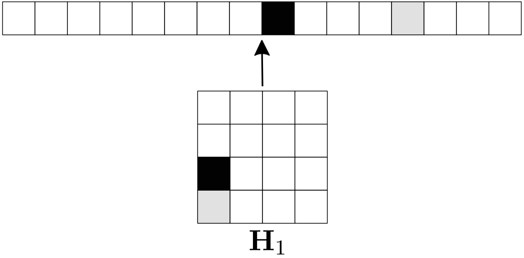


CSI matrices are sparse in 2D frequency domain.



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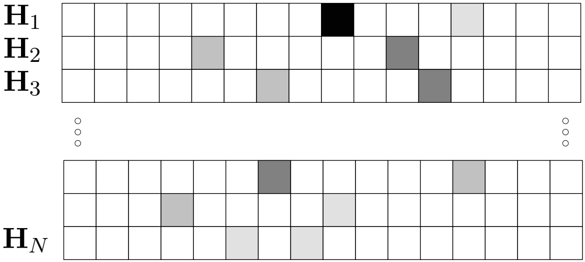
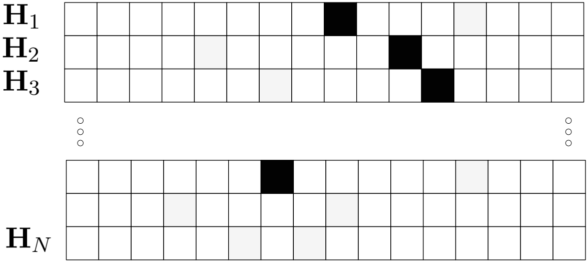


Naive normalization of dataset, $\mathbf{H}$: cast all values to range [0,1] by scaling all entries by $\max(\mathbf{H}) - \min(\mathbf{H})$.



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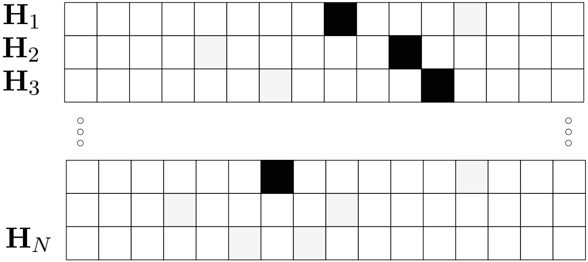
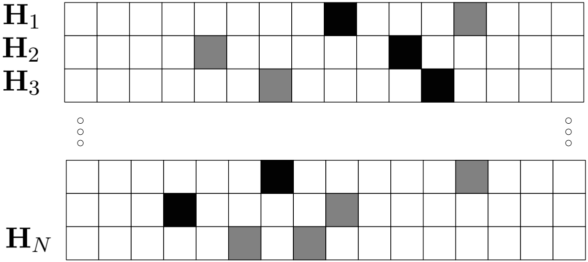


- Low-magnitude entries have less influence in updates during training.

Solution: Spherical normalization. Scale each entry by sample power, $||\mathbf{H}_k||$.



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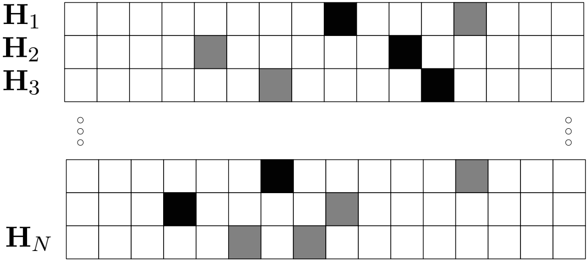

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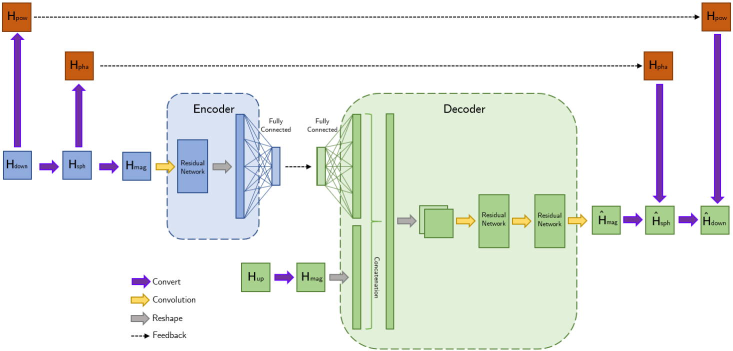
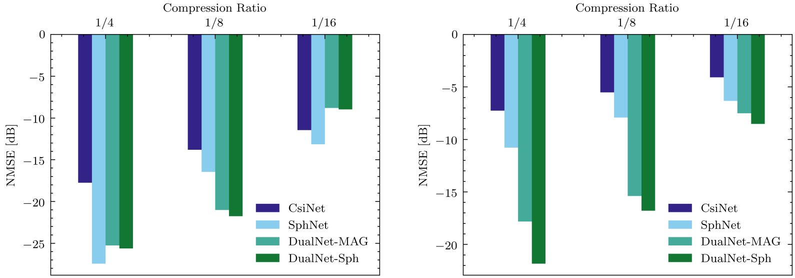
Spherical Normalization



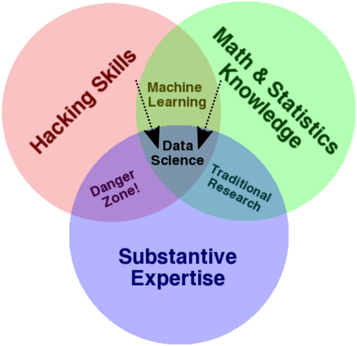


(a) Indoor (b) Outdoor

Figure: NMSE (lower is better) comparison of bidirectional reciprocity and spherical normalization against CsiNet for increasing compression ratio [4]

Z. Liu, M. del Rosario, Z. Liang, L. Zhang, and Z. Ding, “Spherical Normalization for Learned Compressive Feedback in Massive MIMO CSI Acquisition.” Submitted to 2020 IEEE International Conference on Communications Workshops (ICC Workshops)

Incorporating domain knowledge (i.e., bi-directional reciprocity, power-based normalization) improves estimation performance.



Questions?

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[1] C. Wen, W. Shih, and S. Jin, "Deep learning for massive mimo csi feedback," *IEEE Wireless Communications Letters*, vol. 7, pp. 748–751, Oct 2018.

[2] D. Conway, "Data science venn diagram." `http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram`. Accessed: Feb 20, 2020.

[3] Z. Liu, L. Zhang, and Z. Ding, "Exploiting Bi-Directional Channel Reciprocity in Deep Learning for Low Rate Massive MIMO CSI Feedback," *IEEE Wireless Communications Letters*, vol. 8, no. 3, pp. 889–892, 2019.

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Appendix

Two massive MIMO scenarios with single UE using COST 2100 model.

1. **Indoor** environment using 5.3GHz, 0.1 m/s UE mobility, square area of length 20m
2. **Outdoor** environment using 900MHz, 1 m/s UE mobility, square area of length 400m

Dataset: 10^5 channel samples, vary compression ratio from $\frac{1}{4}$ to $\frac{1}{16}$

Hyperparameters: Adam optimizer with learning rate 10^{-3}, batch size 200, 1000 epochs, MSE loss