Learning to Beamform and to Reflect Without Explicit Channel Estimation

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Optimization of Communication Systems

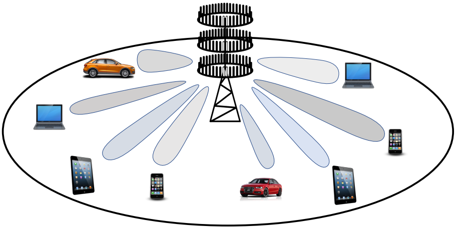
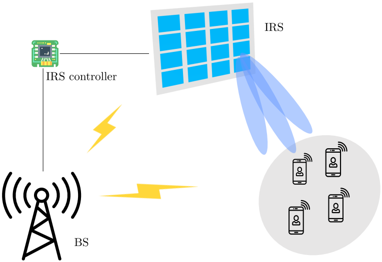


Figure: Cellular base-station with a large-scale antenna array

- **Key Technology for 5G:** mmWave massive MIMO for enhanced mobile broadband.
- Conventional Communication systems are always designed in a **two-step** process:
  - Channel estimation by sending pilot signals.
  - System optimization based on estimated channels.
- **Problem:**
  - Channel estimation for massive MIMO is challenging due to large number of antennas/users
- Can we bypass channel estimation and directly optimize the system?

Optimization of Intelligent Reflecting Surface (IRS) Environment

- IRS is a reflective surface comprised of large number of "intelligent" scatterers.
- Incoming electromagnetic wave is re-radiated with adjustable phase shifts.



- **IRS is ideally suited for passive beamforming**
  - Enhancing the wireless propagation environment.
- **Applications:**
  - Improving network coverage, boosting wireless spectral efficiency;
  - Reducing power consumption, enhancing security, etc.

Machine Learning for IRS System Design

Conventional Communication systems are always designed in a two-step process:

- **Channel estimation** by sending orthogonal pilot signals.
- **System optimization** based on estimated channels.

Channel estimation for IRS is **challenging**:

- The IRS cannot perform active signal transmission and reception.
- Large number of passive elements: Too many channel coefficients to estimate.

System optimization for IRS is also **challenging**:

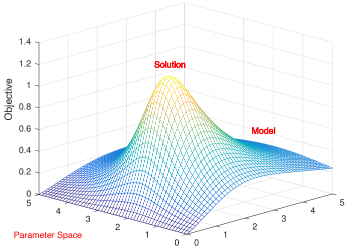
- Large number of phase shifts means a high-dimensional nonconvex optimization problem.

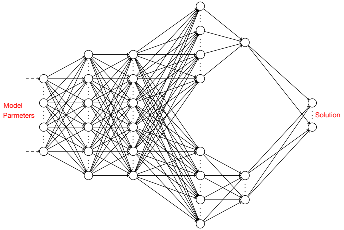
This Talk:

- Optimize system objective based on received pilots without explicit channel estimation.
- Bypass channel estimation by taking a machine learning approach.

Machine Learning vs. Mathematical Programming

- Mathematical optimization requires highly structured models over well defined problems.
- Finding solution efficiently relies on specific and often convex optimization landscape.





- Traditional approach for communication engineering is to model-then-optimize.
- Machine learning approach allows us to be data driven thereby skipping models altogether!
  - Universal function mapping – either by supervised or reinforcement learning
  - No longer need to parameterize the problem for the algorithm
  - Incorporating vast amount of data over poorly defined problems
  - Highly parallel implementation architecture

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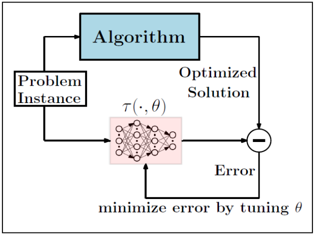
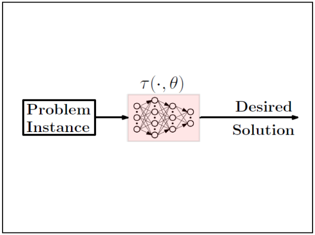


(a) Training Stage



(b) Testing Stage

- Traditional approach for communication engineering is to model-then-optimize.
- Machine learning approach allows us to be data driven thereby skipping models altogether!
  - Universal function mapping – either by supervised or reinforcement learning
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  - Incorporating vast amount of data over poorly defined problems
  - Highly parallel implementation architecture

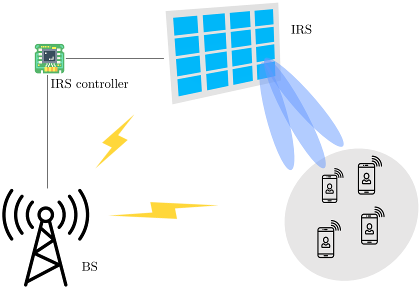
Haoran Sun, Xiangyi Chen, Qingjiang Shi, Mingyi Hong, Xiao Fu, Nicholas D. Sidiropoulos, "Learning to Optimize: Training Deep Neural Networks for Wireless Resource Management", IEEE Transactions on Signal Processing, vol. 66, no. 20, pp. 5438-5453, October 15, 2018. (Figure credit)

Role of Machine Learning for Communication System Design

- Traditionally, communication engineers have invested heavily on channel models.
  - However, models are inherently only an approximation of the reality;
  - Moreover, model parameters need to be estimated – with inherent estimation error.
- Machine learning approach allows us to skip channel modeling altogether!
  - End-to-end communication system design
- Advantages:
  - Direct system optimization without the intermediary step of channel estimation;
  - Implicitly accounting for channel estimation error;
  - Easy to incorporate additional side information such as location;
  - Reduce the required pilot length.
- Challenges:
  - Design framework tailored to different system architectures and objectives;
  - Generalizability to different system parameters;
  - Interpretability of the obtained solution;
  - Large amount of training data.
- This talk provides an example of high-dimensional optimization for communication systems
  - Multiuser beamforming and reflective coefficent design for IRS system
  - Similar approach is also applicable to multiuser channel estimation for massive MIMO systems

Intelligent Reflecting Surface (IRS)

- IRS is a reflective surface comprised of large number of “intelligent” scatterers.



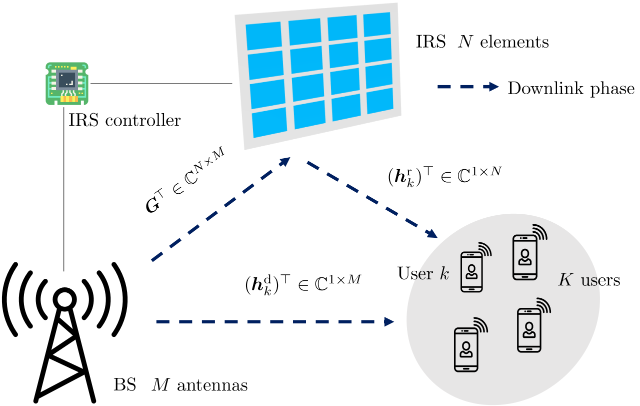
Channel estimation for IRS is **challenging**:

- The IRS cannot perform active signal transmission and reception.
- Due to the large number of passive elements, there are many channel coefficients to estimate.

System Optimization for IRS is also **challenging**:

- Large number of phase shifts means a high-dimensional nonconvex optimization problem.

Channel Model for the IRS System



IRS assisted downlink data transmission:

- Data symbol for the user k: $s^k \in \mathbb{C}$.
- Phase shifts at the IRS: $\boldsymbol{v} = [e^{j\theta_1}, \cdots, e^{j\theta_N}]$ with $\theta_i \in [0, 2\pi)$.
- Beamforming vector for the user k at the BS: $\boldsymbol{w}_k \in \mathbb{C}^M$.

Channel Model for the IRS System

IRS assisted downlink data transmission:

- Received signal at the user k:

$$r_k = \sum_{j=1}^{K} (\boldsymbol{h}_k^d + \boldsymbol{G}\,\mathrm{diag}(\boldsymbol{v})\boldsymbol{h}_k^r)^\top \boldsymbol{w}_j s_j + n_k = \sum_{j=1}^{K} (\boldsymbol{h}_k^d + \boldsymbol{A}_k \boldsymbol{v})^\top \boldsymbol{w}_j s_j + n_k$$

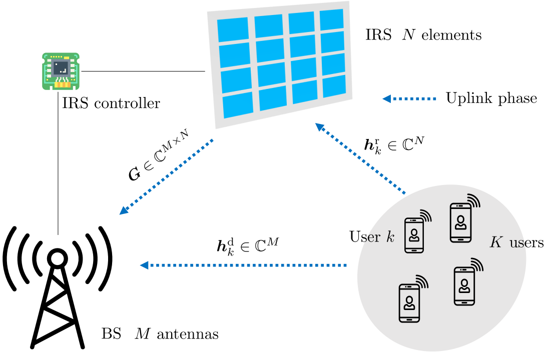
  where $\boldsymbol{A}_k = \boldsymbol{G}\,\mathrm{diag}(\boldsymbol{h}_k^r) \in \mathbb{C}^{M \times N}$ is the cascaded channel

- The achievable rate R_k of user k can be computed as

$$R_k = \log\left(1 + \frac{|(\boldsymbol{h}_k^d + \boldsymbol{A}_k \boldsymbol{v})^\top \boldsymbol{w}_k|^2}{\sum_{i=1, i\neq k}^{K} |(\boldsymbol{h}_k^d + \boldsymbol{A}_k \boldsymbol{v})^\top \boldsymbol{w}_i|^2 + \sigma_0^2}\right)$$

To design beamformers at the BS and reflective coefficients at the IRS:

- Traditional approach: First estimate $\boldsymbol{A}_k$'s and $\boldsymbol{h}_k^d$'s, then design $\boldsymbol{w}_k$ and $\boldsymbol{v}$.
- Machine Learning: Directly optimize without explicitly channel estimation.
- In either case, we rely on a pilot transmission phase.



Uplink pilots training assuming channel reciprocity:

- Pilot symbol of user k: $x_k(\ell)$, $\ell = 1, \cdots, L$.
- The received signal $\boldsymbol{y}(\ell)$ at the BS can be expressed as

$$\boldsymbol{y}(\ell) = \sum_{k=1}^{K} (\boldsymbol{h}_k^d + \boldsymbol{A}_k \boldsymbol{v}(\ell)) x_k(\ell) + \boldsymbol{n}(\ell), \ \ell = 1, \cdots, L.$$

- $\boldsymbol{v}(\ell)$ is the phase shifts of IRS at time slot ℓ.

Overall Problem Formulation

- **Goal:** Design the optimal beamformers $\boldsymbol{W}$ and the reflecting phase shifts $\boldsymbol{v}$ based on the received pilots $\boldsymbol{Y}$ to maximize a network utility $U(\cdot)$.

$$
\begin{aligned}
\underset{(\boldsymbol{W},\boldsymbol{v})=g(\boldsymbol{Y})}{\text{maximize}} \quad & \mathbb{E}\left[U(R_1(\boldsymbol{v},\boldsymbol{W}),\ldots,R_K(\boldsymbol{v},\boldsymbol{W}))\right] \\
\text{subject to} \quad & \sum_k \|\boldsymbol{w}_k\|^2 \le P_d, \\
& |v_i| = 1, i = 1, 2, \cdots, N,
\end{aligned}
$$

  where
  - Beamforming matrix at the BS: $\boldsymbol{W} = [\boldsymbol{w}_1, \cdots, \boldsymbol{w}_k]$.
  - Reflective coefficients at the IRS: $\boldsymbol{v}$.
  - Received pilots in L symbol durations: $\boldsymbol{Y} = [\boldsymbol{y}(1), \boldsymbol{y}(2), \cdots, \boldsymbol{y}(L)]$.

- **Conventional Approach:** First estimate the channels, then optimize $\boldsymbol{v}$ and $\boldsymbol{W}$.
- **Machine Learning Approach:** Parameterizing the mapping function $g(\cdot)$ by a deep neural network and learning the parameters from data.

Conventional Model-then-Optimize Approach:

- Use the received pilots to estimate the channels.
- Optimize the network utility based on the estimated channels.

Uplink Pilot Transmission for Channel Estimation:

- Pilots and uplink phase shifts
  - Total training slots L is divided into τ sub-frames: $L = \tau L_0$.
  - In each sub-frame, use orthogonal pilot sequence $\boldsymbol{x}_k \in \mathbb{C}^{L_0}$.
  - IRS uses different random phase shifts in different sub-frames.
- In the sub-frame t, the overall received pilots:

$$\bar{\boldsymbol{Y}}(t) = \sum_{k=1}^{K} (\boldsymbol{h}_k^{\mathrm{d}} + \boldsymbol{A}_k \bar{\boldsymbol{v}}(t)) \boldsymbol{x}_k^{\mathrm{H}} + \bar{\boldsymbol{N}}(t), \quad t = 1, \cdots, \tau.$$

Beamformer and Reflective Coefficent Design:

- Use optimization techniques, e.g., block coordinate descent (BCD) for sum rate maximization [Guo, et al. '20], minimum rate maximization [Alwazani, et al. '20].

Channel Estimation Strategy

- By the orthogonality of the pilots, the contribution from user k:

$$\bar{\boldsymbol{y}}_k(t) = \frac{1}{L_0}\bar{\boldsymbol{Y}}(t)\boldsymbol{x}_k = \boldsymbol{h}_k^{\mathrm{d}} + \boldsymbol{A}_k\bar{\boldsymbol{v}}(t) + \bar{\boldsymbol{n}}(t)$$
$$\triangleq \boldsymbol{F}_k\boldsymbol{q}(t) + \bar{\boldsymbol{n}}(t),$$

  - Combined channel matrix $\boldsymbol{F}_k := [\boldsymbol{h}_k^d, \boldsymbol{A}_k]$.
  - Combined phase shifts $\boldsymbol{q}(t) := [1, \bar{\boldsymbol{v}}(t)^\top]^\top$.
- Denote $\tilde{Y}_k = [\bar{y}_k(1), \cdots, \bar{y}_k(\tau)]$ as the received pilots of the overall τ sub-frames and $\boldsymbol{Q} = [\boldsymbol{q}(1), \cdots, \boldsymbol{q}(\tau)]$, we have

$$\tilde{\boldsymbol{Y}}_k = \boldsymbol{F}_k\boldsymbol{Q} + \tilde{\boldsymbol{N}},$$

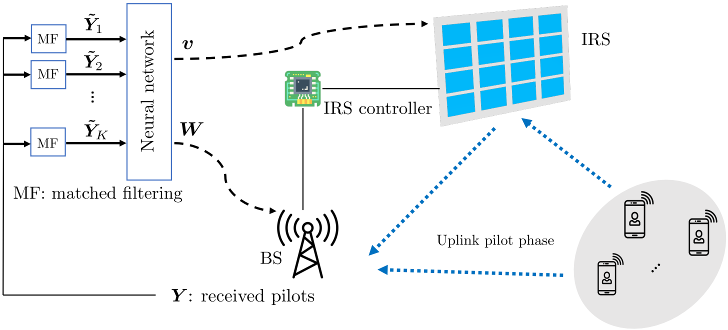
- Channel estimation for the user k:

$$\underset{\hat{\boldsymbol{F}}_k = f(\tilde{\boldsymbol{Y}}_k)}{\text{minimize}} \quad \mathbb{E}\left[\|f(\tilde{\boldsymbol{Y}}_k) - \boldsymbol{F}_k\|_F^2\right].$$

- Linear minimum mean-squared error (LMMSE) estimator:

$$\hat{\boldsymbol{F}}_k = (\tilde{\boldsymbol{Y}}_k - \mathbb{E}[\tilde{\boldsymbol{Y}}_k])\left(\mathbb{E}[(\tilde{\boldsymbol{Y}}_k - \mathbb{E}[\tilde{\boldsymbol{Y}}_k])^{\mathsf{H}}(\tilde{\boldsymbol{Y}}_k - \mathbb{E}[\tilde{\boldsymbol{Y}}_k])]\right)^{-1}$$
$$\mathbb{E}[(\tilde{\boldsymbol{Y}}_k - \mathbb{E}[\tilde{\boldsymbol{Y}}_k])^{\mathsf{H}}(\boldsymbol{F}_k - \mathbb{E}[\boldsymbol{F}_k])] + \mathbb{E}[\boldsymbol{F}_k].$$

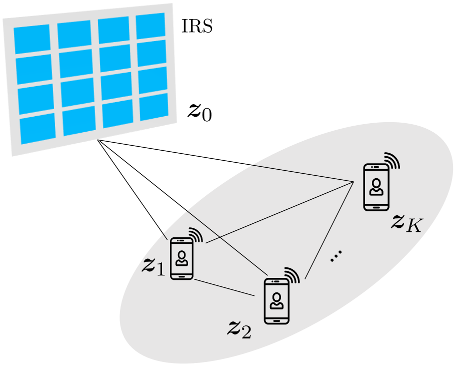
We propose to **bypass channel estimation** and to directly maximize the network utility function based on the received pilots $\tilde{\boldsymbol{Y}}_k$.



- Use a neural network to represent the mapping $(\boldsymbol{v}, \boldsymbol{W}) = g(\boldsymbol{Y})$.
- Adjust the neural network weights to maximize the network utility function.

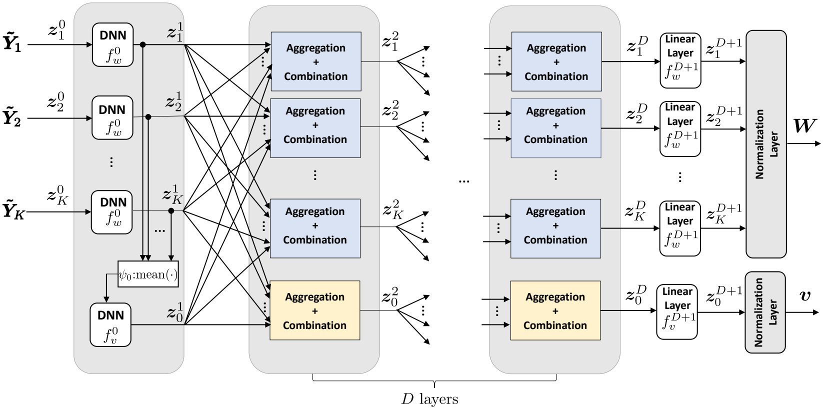
Graph Neural Network Architecture

- Use graph neural network (GNN) to model the interactions between users and IRS.
- The neural network should be **permutation invariant/equivariant** with respect to the users.



- Design GNN based on graph representation of beamformers and phase shifts.

GNN Architecture



Permutation invariance and equivariance property:

- When the indices of the users permute, the resulting beamformers also permute.
- The DNNs for the users are permutation equivariant with respect to each other.
- The DNN for the IRS is permutation invariant with respect to the users.

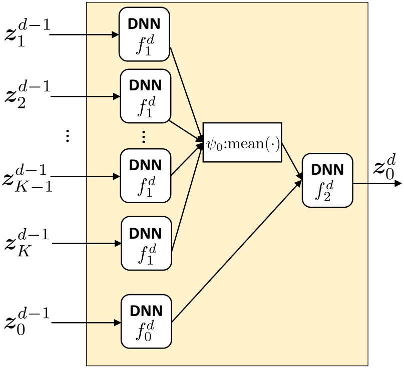


Figure: The IRS node.

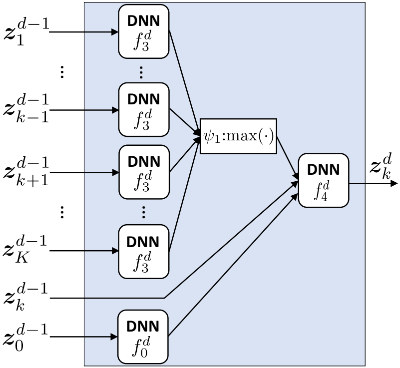
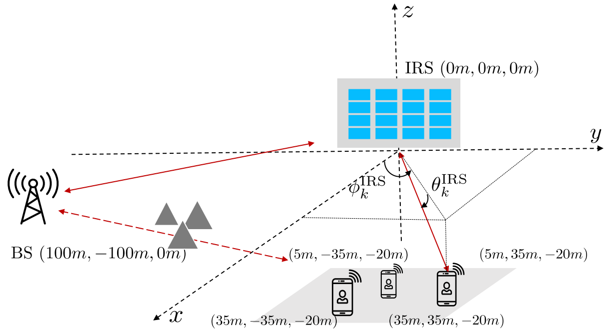


Figure: The k-th user node.

- The aggregation and combination operations are also permutation invariant/equivariant.
- The DNN parameters are tied across the users to make the GNN generalizable to scenarios with different number of users.



- Setting: $M = 8$ antennas at BS, $N = 100$ elements at IRS, $K = 3$ users.
- Direct link channel $\boldsymbol{h}_k^{\mathrm{d}}$ follows Rayleigh fading.
- BS-IRS and IRS-users channels follow Rician fading:

$$\boldsymbol{h}_k^{\mathrm{r}} = \beta_{1,k}\left(\sqrt{\frac{\varepsilon}{1+\varepsilon}}\boldsymbol{h}_k^{\mathrm{r,LOS}} + \sqrt{\frac{1}{1+\varepsilon}}\boldsymbol{h}_k^{\mathrm{r,NLOS}}\right),$$

$$\boldsymbol{G} = \beta_2\left(\sqrt{\frac{\varepsilon}{1+\varepsilon}}\boldsymbol{G}^{\mathrm{LOS}} + \sqrt{\frac{1}{1+\varepsilon}}\boldsymbol{G}^{\mathrm{NLOS}}\right).$$

Simulation Settings

Training configuration

- GNN parameters:

Name	Size	Activation Function
f_w^0	$2M\tau \times 1024 \times 512$	relu
f_v^0	$512 \times 1024 \times 512$	relu
$f_0^1, f_1^1, f_2^1, f_3^1, f_4^1$	$512 \times 512 \times 512$	relu
$f_0^2, f_1^2, f_2^2, f_3^2, f_4^2$	$512 \times 512 \times 512$	relu

- At each epoch, iterate 100 times to update the GNN parameters.
- In each iteration, use 1024 training samples to compute the gradients.

Benchmarks:

- Perfect CSI with BCD.
- LMMSE channel estimation with BCD.
- Deep learning based channel estimation with BCD.
  - Use the same GNN architecture for utility maximization, but with a different loss function $\frac{1}{K}\sum_k \mathbb{E}[\|\hat{\boldsymbol{F}}_k - \boldsymbol{F}_k\|_F^2]$ to estimate channels.

Downlink Sum Rate vs. Uplink Pilot Length

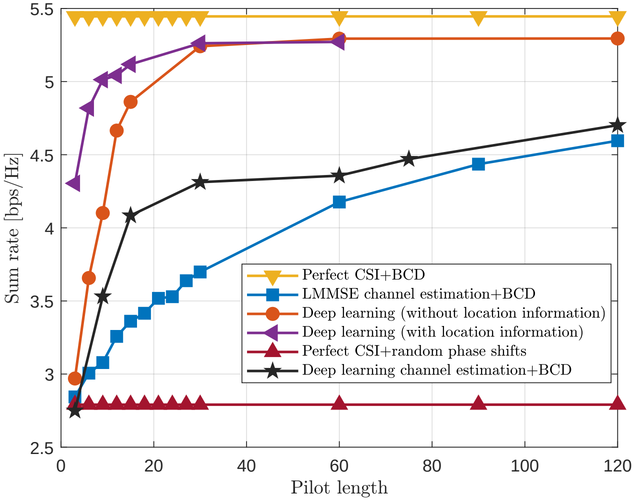


Figure: $M = 8$, $N = 100$, $K = 3$, $P_d = 20$dBm, and $P_u = 15$dBm.

Testing Sum Rate vs. Training epochs.

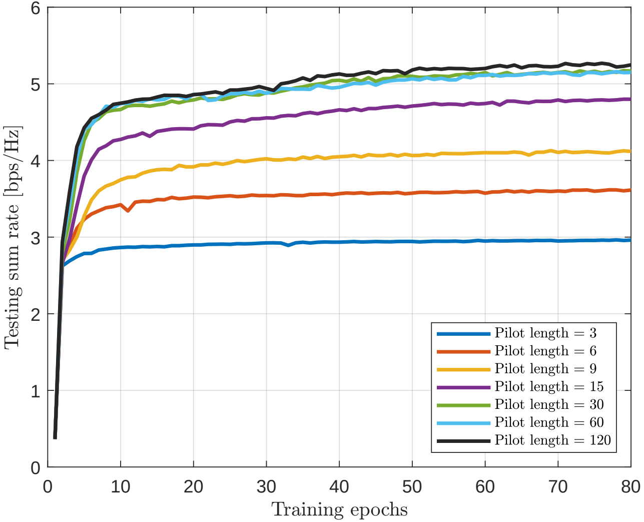


Figure: 100×1024 training samples at each epoch.

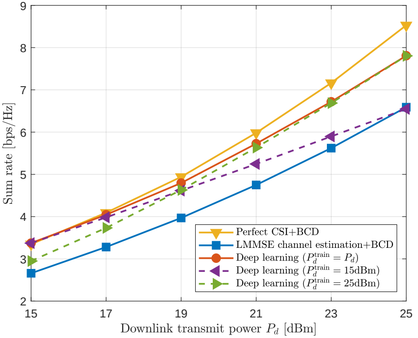


Figure: Generalizability in downlink transmit power with $P_u = 15$dBm, $M = 8$, $N = 100$ and $L = 75$.

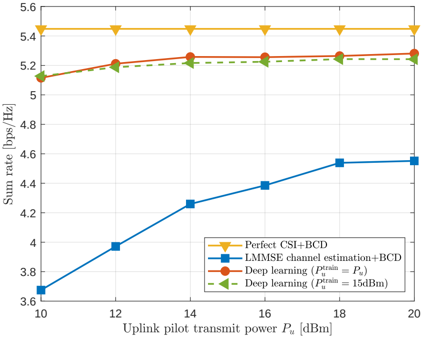


Figure: Generalizability in pilot transmit power with $P_d = 20$dBm, $M = 8$, $N = 100$ and $L = 75$.

Generalizability in Number of Users

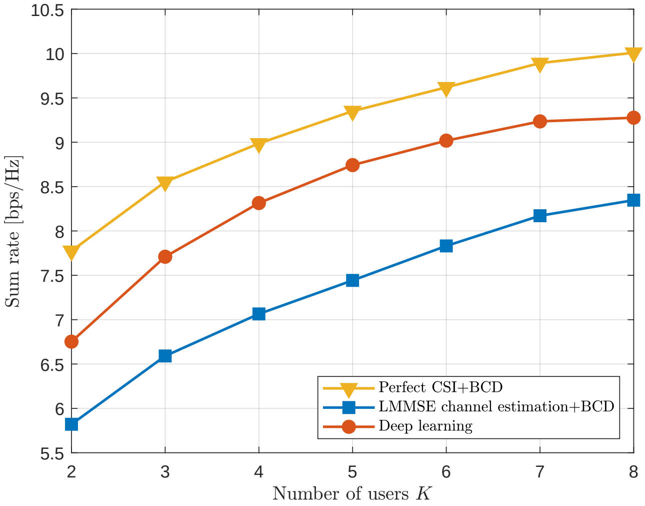


Figure: $M = 8$, $N = 100$, $L = 25K$, $P_u = 15$dBm and $P_d = 25$dBm. GNN is trained for $K = 6$.

Maximizing Minimum Rate

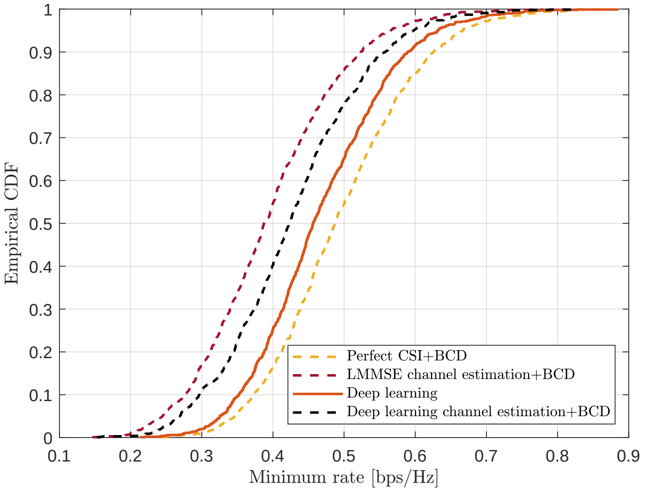


Figure: $M = 4$, $N = 20$, $K = 3$, $L = 75$, $P_d = 20$dBm, and $P_u = 15$dBm.

Generalizability in Number of Users

Table: **Minimum rate** $(\mathrm{bps/Hz})$ at $M = 4$, $N = 20$, $P_d = 20\mathrm{dBm}$, $P_u = 15\mathrm{dBm}$.

L	K	Deep learning	LMMSE+BCD	Perfect CSI+BCD
$L = 5K$	2	0.587	0.529	0.786
	3	0.386	0.335	0.496
	4	0.274	0.240	0.351
$L = 25K$	2	0.726	0.620	0.786
	3	0.466	0.395	0.496
	4	0.315	0.284	0.351

Interpretation of Solutions from GNN

We train the proposed GNN for a single user case, then use **array response** to interpret the resulting beamforming pattern from GNN.

- Array response at the M-antenna BS is:

$$f_b(\phi_1, \theta_1) = |\boldsymbol{a}_{\mathrm{BS}}(\phi_1, \theta_1)^{\mathsf{H}} \boldsymbol{w}|,$$

  where

$$\boldsymbol{a}_{\mathrm{BS}}(\phi_1, \theta_1) = [1, \cdots, e^{j\frac{2\pi(M-1)d^{\mathrm{BS}}}{\lambda_c}\cos(\phi_1)\cos(\theta_1)}].$$

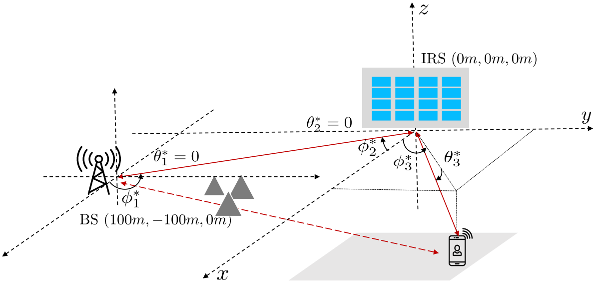
- Array response of an $L \times L$ IRS on yz-plane is:

$$f_i(\phi_2, \theta_2, \phi_3, \theta_3) = |\boldsymbol{a}_{\mathrm{IRS}}(\phi_2, \theta_2)^{\mathsf{H}} \operatorname{diag}(\boldsymbol{v}) \boldsymbol{a}_{\mathrm{IRS}}(\phi_3, \theta_3)|,$$

  where for $i_1(n) = \operatorname{mod}(n-1, L), i_2(n) = \lfloor (n-1)/L \rfloor$

$$[\boldsymbol{a}_{\mathrm{IRS}}(\phi_k, \theta_k)]_n = e^{j\frac{2\pi d^{\mathrm{IRS}}}{\lambda_c}\{i_1(n)\sin(\phi_k)\cos(\theta_k) + i_2(n)\sin(\theta_k)\}}.$$

- ϕ_1/θ_1: the azimuth/elevation angle of arrival from the IRS to the BS.
- ϕ_2/θ_2: the azimuth/elevation angle of departure from the IRS to the BS.
- ϕ_3/θ_3: the azimuth/elevation angle of arrival from the user to the IRS.



	ϕ_1^*	θ_1^*	ϕ_2^*	θ_2^*	ϕ_3^*	θ_3^*
Scenario 1	2.356	0	-0.785	0	0.588	-0.506
Scenario 2	2.356	0	-0.785	0	-0.588	-0.506

Beamforming Pattern for $N = 10 \times 10$, $M = 8$

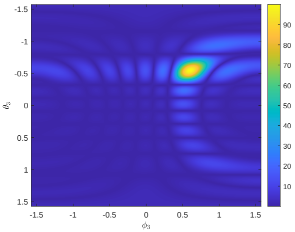


Figure: IRS, $\phi_3^* = 0.588$, $\theta_3^* = -0.506$.

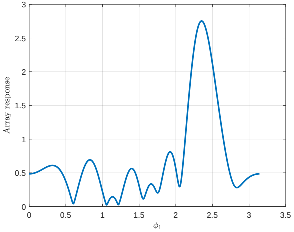


Figure: BS, $\phi_1^* = 2.356$.

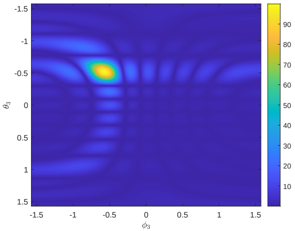


Figure: IRS, $\phi_3^* = -0.588$, $\theta_3^* = -0.506$.

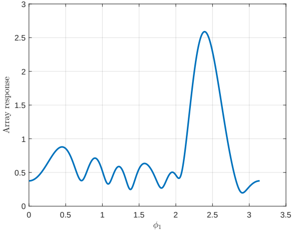
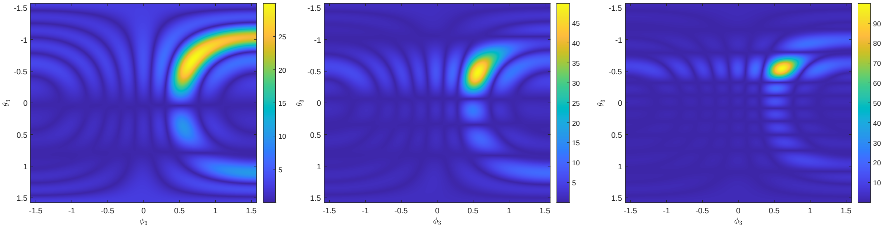


Figure: BS, $\phi_1^* = 2.356$.

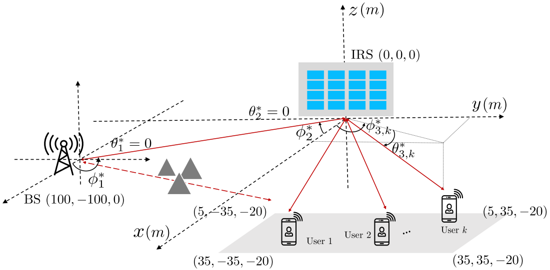
Large IRS array leads to more focused reflective pattern.



(a) $N = 3 \times 10$. (b) $N = 5 \times 10$. (c) $N = 10 \times 10$.

Figure: Array response of the IRS with $\phi_3^* = 0.588$, $\theta_3^* = -0.506$.

Multiuser Beamforming and Reflecting Patterns for Maximizing Min Rate



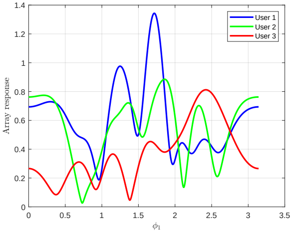


Figure: BS, $\phi_1^* = 2.356$.

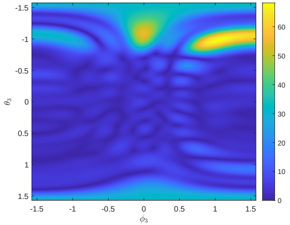


Figure: IRS, $\phi_3^* = -1.176, 0, 1.176$,
$\theta_3^* = -0.994, -0.980, -0.994$.

Summary

- We show that it is possible to bypass explicit channel estimation for optimizing the beamforming and reflective patterns in an IRS assisted communication system.
- This is accomplished by a graph neural network that maps the received pilots directly to the desired IRS configuration and beamforming matrix at the BS.
- The GNN is permutation invariant and equivariant with respect to the users.
- The user locations can be incorporated to further enhance the performance.
- The GNN can learn to solve both sum-rate and min-rate maximization problems.
- The resulting beamforming and reflective patterns are interpretable.
- The proposed approach is much more efficient in term of required pilot length.

Concluding Remarks

- Traditional paradigm for communication system design is to model-then-optimize.
- Machine learning allows a data-driven approach that
  - Perform multiuser beamforming and reflective coefficient design with implicit channel estimation;
  - Perform channel estimation, feedback and precoding without explicit channel model.
- Key advantages are to account for model uncertainty and channel estimation error.
- Key issues are: generalizability, interpretability, neural network architecture.
- How far can we push machine learning? Many open questions...

Thank you!

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