Active Sensing via Learning

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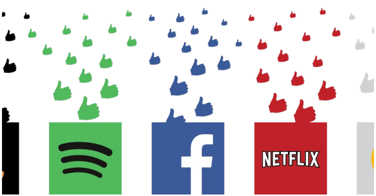
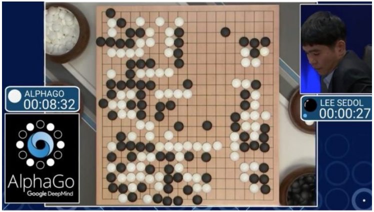




Question: Assume that the variance of the first n natural numbers is 10, and the variance of the first m even natural numbers is 16. Compute $m+n$.

Model output: Let σ^2 be the variance of the first m even natural numbers, and τ^2 be the variance of the first n natural numbers. Then, we have $\tau^2 = \frac{n^2-1}{12}$ and $\sigma^2 = \frac{m^2-1}{3}$. We solve the system of equations:

$$\frac{n^2-1}{12} = 10$$
$$\frac{m^2-1}{3} = 16.$$

This translates into the system

$$n^2 = 121$$
$$m^2 = 48 + 1 = 49.$$

Therefore, $n = \boxed{11}$ and $m = \boxed{7}$, so $n + m = \boxed{18}$.

Question: For every a, b, $b \neq a$ prove that

$$\frac{a^2+b^2}{2} > \left(\frac{a+b}{2}\right)^2.$$

Model output:

$$\tfrac{a^2+b^2}{2} > \left(\tfrac{a+b}{2}\right)^2$$
$$\iff \tfrac{a^2+b^2}{2} > \tfrac{a^2+b^2+2ab}{4}$$
$$\iff a^2+b^2 > \tfrac{a^2+b^2+2ab}{2}$$
$$\iff 2a^2+2b^2 > a^2+b^2+2ab$$
$$\iff a^2+b^2 > 2ab$$
$$\iff a^2+b^2-2ab > 0$$
$$\iff (a-b)^2 > 0$$

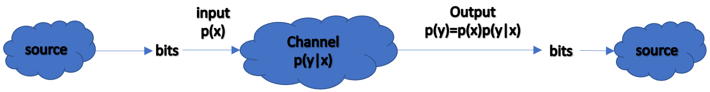
which is true, because the square of a real number is positive.

- Why are neural networks so powerful?
  - Universal functional mapping by pattern matching;
  - Design neural network architectures to explore the problem structure;
  - Incorporating vast amount of data and problem instances;
  - Highly parallel and scalable implementation.
- What are the roles of machine learning for wireless communications?

- The fundamental limits of communications are governed by information theory.
- Channel capacity is the maximum mutual information, which is a function of the channel $p(y|x)$ and the input distribution $p(x)$:

$$C = \max_{p(x)} I(X; Y).$$

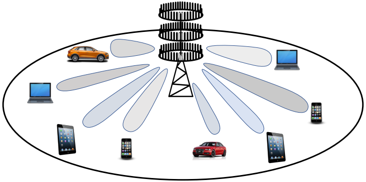
- The overall communication problem can be broken down into the following parts:
  - Use source coding to convert the source into bits.
  - Use pilots to estimate the channel $p(y|x)$.
  - Use adaptive modulation, beamforming, power control for optimizing $p(x)$.
  - Use channel coding to transmit the bits.



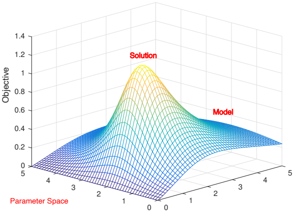
- The traditional communication system design paradigm is *model-based*.

Model-Based Communication System Design

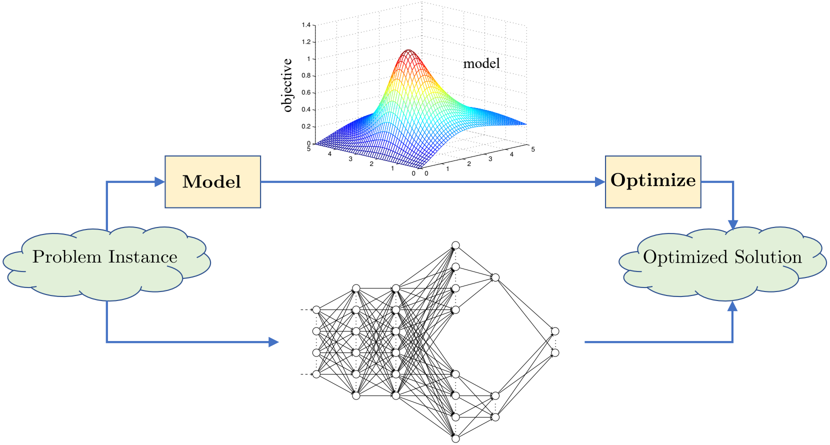
- Channel estimation requires assumption on the model:
  - More parameters make model more accurate, but makes model harder to estimate.
  - Longer pilot makes estimation easier but consumes valuable coherence time/bandwidth.
  - Loss function for channel estimation is typically arbitrary (e.g., square-error).
  - There is no universal theory about which model is the most suitable.
- Mathematical optimization requires precise problem formulation:
  - The same problem can be parameterized in many different ways.
  - The holy grail of optimization is to transform a problem into convex form.
  - There is no universal theory about how to best transform the optimization landscape.



$\Rightarrow$



Role of Machine Learning in Wireless Air Interface



- This Talk: A Data-Driven Approach to Communications and Sensing

Learn to Beamform

- How to obtain channel state information (CSI) for massive MIMO systems?

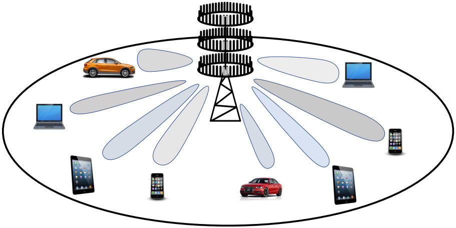


Figure: Cellular base-station with a large-scale antenna array

- **Time-Division Duplex (TDD) Massive MIMO:**
  - Channel reciprocity can be assumed.
  - Uplink pilot transmission followed by CSI estimation at BS and downlink transmission.
- **Frequency-Division Duplex (FDD) Massive MIMO:**
  - Channel reciprocity does not necessarily hold in different frequencies.
  - Downlink pilot transmission followed by CSI estimation and feedback at the users.

Conventional downlink FDD wireless system design involves:

- Independent channel estimation at each UE based on downlink pilot.
- Independent quantization and feedback of each user's channel to the BS.
- Multiuser precoding at the BS based on channel feedback from ALL the users.

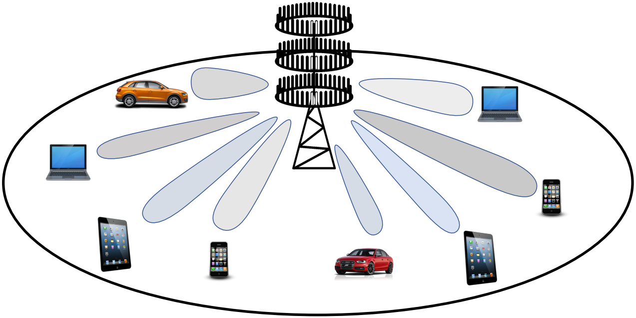
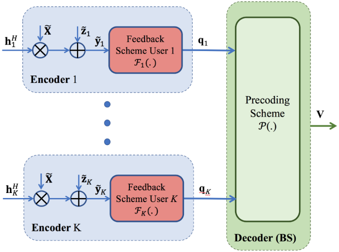
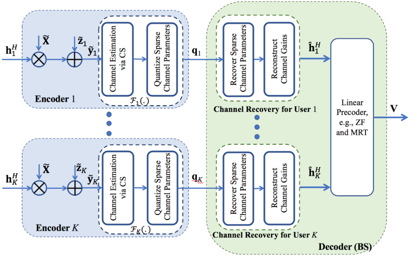


Figure: Cellular base-station with a large-scale antenna array

Single-user channel feedback for multiuser precoding is NOT optimal.

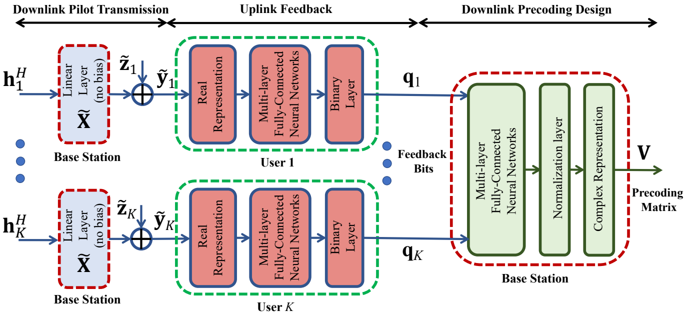


FDD downlink precoding as a DSC problem.



The conventional scheme amounts to a separate source coding strategy.

- The FDD feedback/precoding problem is a distributed source coding (DSC) problem.
- Much more efficient distributed feedback scheme can be designed using machine learning.



- **Downlink Pilot Transmission:** Modelled by a linear neural layer followed by additive noise.
- **Uplink Feedback:** Modelled by an R-layer DNN with B binary activation neurons at the last layer: $\mathbf{q}_k = \operatorname{sgn}\left(\mathbf{W}_R^{(k)}\sigma_{R-1}\left(\cdots\sigma_1\left(\mathbf{W}_1^{(k)}\bar{\mathbf{y}}_k + \mathbf{b}_1^{(k)}\right)\cdots\right) + \mathbf{b}_R^{(k)}\right)$.
- **Downlink Precoding Design:** Modelled by a T-layer DNN with normalization activation function at the last layer: $\mathbf{v} = \widetilde{\sigma}_T\left(\widetilde{\mathbf{W}}_T\widetilde{\sigma}_{T-1}\left(\cdots\widetilde{\sigma}_1\left(\widetilde{\mathbf{W}}_1\mathbf{q} + \widetilde{\mathbf{b}}_1\right) + \cdots\right) + \widetilde{\mathbf{b}}_T\right)$.
- Sum rate maximization can be cast as the following learning problem:

$$\max_{\widetilde{\mathbf{X}},\left\{\Theta_R^{(k)}\right\},\Theta_T} \mathbb{E}_{\mathbf{H},\tilde{\mathbf{z}}}\left[\sum_k \log_2\left(1 + \frac{|\mathbf{h}_k^H\mathbf{v}_k|^2}{\sum_{j\neq k}|\mathbf{h}_k^H\mathbf{v}_j|^2 + \sigma^2}\right)\right], \tag{1}$$

Numerical Results: FDD Massive MIMO System with UE Feedback

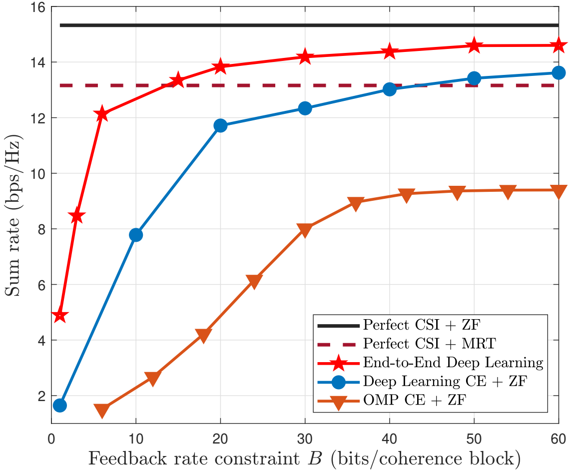


Figure: Sum rate achieved by different methods in a 2-user FDD system with number of BS antennas $M = 64$, Pilot length $L = 8$, number of paths $L_p = 2$, number of users $K = 2$, and SNR $\triangleq 10\log_{10}(\frac{P}{\sigma^2}) = 10$dB.

Active Sensing via Learning

Active Beam Alignment for TDD mmWave System

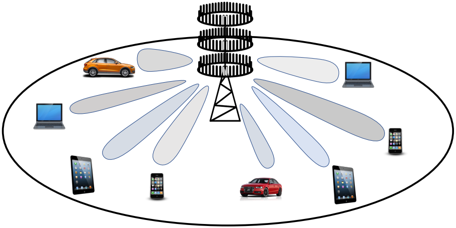
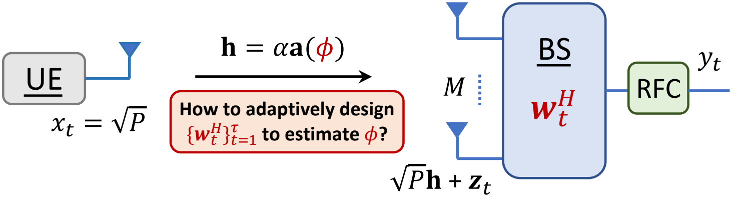


Figure: Cellular base-station with a large-scale antenna array.

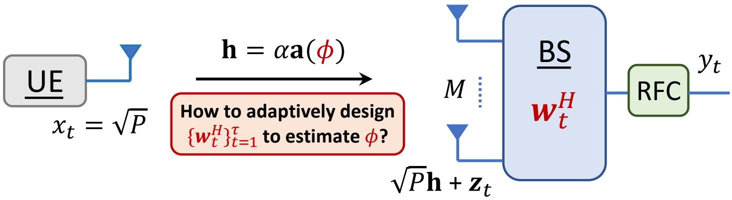
- Motivation: mmWave massive MIMO for enhanced mobile broadband.
- Estimating high-dimensional channel from low-dimensional observations is challenging:
  - Fully digital beamforming: Requires one high-resolution RF chain per antenna element.
  - Hybrid beamforming: Analog beamformer with low-dimensional digital beamforming.
- Initial Beam Alignment: How to find channel direction in an RF chain limited system?

Sensing Architecture with Hybrid Beamforming



- A BS with M antennas and a single RF chain serves a single-antenna user
- The user transmits pilot; the BS tries to estimate the channel.

Sensing Architecture with Hybrid Beamforming

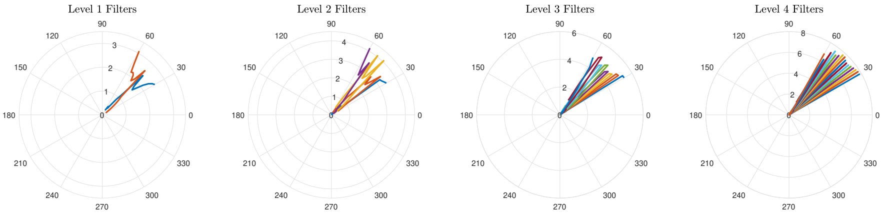


- A BS with M antennas and a single RF chain serves a single-antenna user
- The user transmits pilot; the BS tries to estimate the channel.
- Due to the RF chain limitation, the BS must sense the channel through analog combiners:

$$y_t = \mathbf{w}_t^H \mathbf{h} x_t + \mathbf{w}_t^H \mathbf{z}_t = \sqrt{P}\alpha \, \mathbf{w}_t^H \mathbf{a}(\phi) + n_t, \tag{2}$$

  - $\mathbf{w}_t$ is the sensing (combining) vector in time frame t with $\|\mathbf{w}_t\|^2 = 1$
  - $\alpha \sim \mathcal{CN}(0,1)$ is the fading coefficient,
  - $\phi \in [\phi_{\min}, \phi_{\max}]$ is the angle of arrival (AoA),
  - $\mathbf{a}(\phi) = \left[1, e^{j\pi \sin\phi}, \ldots, e^{j(M-1)\pi \sin\phi}\right]^T$ is the array response vector,
  - $n_t \sim \mathcal{CN}(0,1)$ is the effective noise.

- We can select the sensing vector from a pre-designed codebook that minimizes the expected MSE objective, e.g., the codebook contains the following 30 filters bisecting in angle domain.



- Hierarchical beamforming codebook [Alkhateeb, Ayach, Leus, and Heath, 2014].

Traditional Approach: Bisection in Angle Domain

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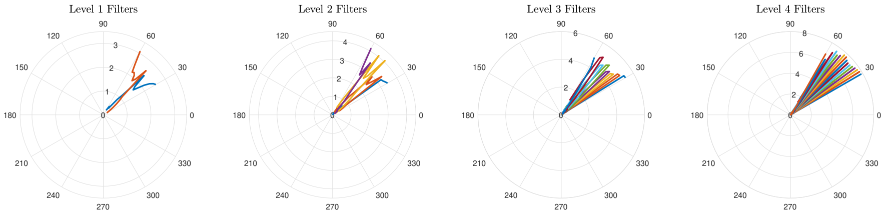
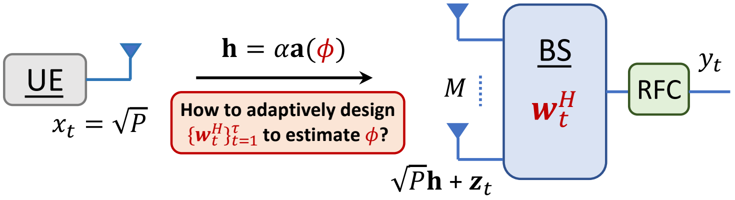


- Hierarchical beamforming codebook [Alkhateeb, Ayach, Leus, and Heath, 2014].

... but bisection can be sensitive to noise.

Initial Alignment as a Sequential Decision Problem



- **Initial Beam Alignment:** The BS can optimize the quality of AoA estimation by designing $\mathbf{w}_t$ at each time frame, possibly sequentially in an adaptive manner, i.e.,

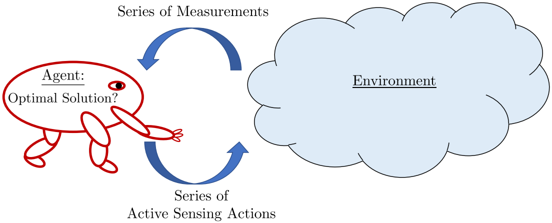
$$\mathbf{w}_{t+1} = \widetilde{\mathcal{G}}_t\left(y_{1:t}, \mathbf{w}_{1:t}\right), \quad \forall t \in \{0, \ldots, T-1\}. \tag{3}$$

- The final AoA estimate is obtained as a function of all past observations as:

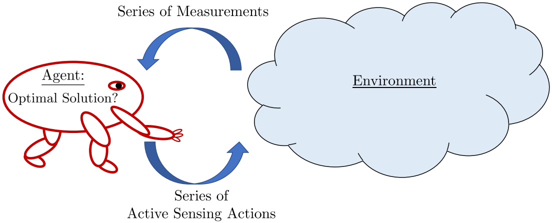
$$\hat{\phi} = \widetilde{\mathcal{F}}\left(y_{1:T}, \mathbf{w}_{1:T}\right). \tag{4}$$

- The goal is to design $\mathbf{w}_{1:T}$ sequentially as function of $y_{1:T}$ so far to minimize $\mathbb{E}\left[\left(\hat{\phi} - \phi\right)^2\right]$.
- This is a high-dimensional sequential decision problem!

Active Sensing Problem



- The active sequential learning problem naturally arises in many inference, sensing, and control settings, e.g., tree-search, sequential design of experiments, the multi-armed bandit.
- Problems involve adaptive estimation/control based on sequential sensing of environment.
- Analytic solutions seem impossible.
- Numerical solutions are computationally complex and in general hard to obtain.



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- Problems involve adaptive estimation/control based on sequential sensing of environment.
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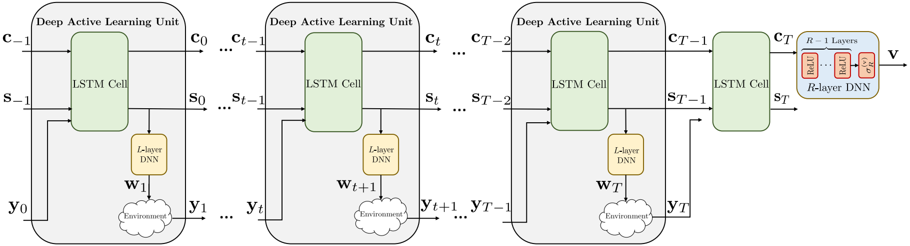
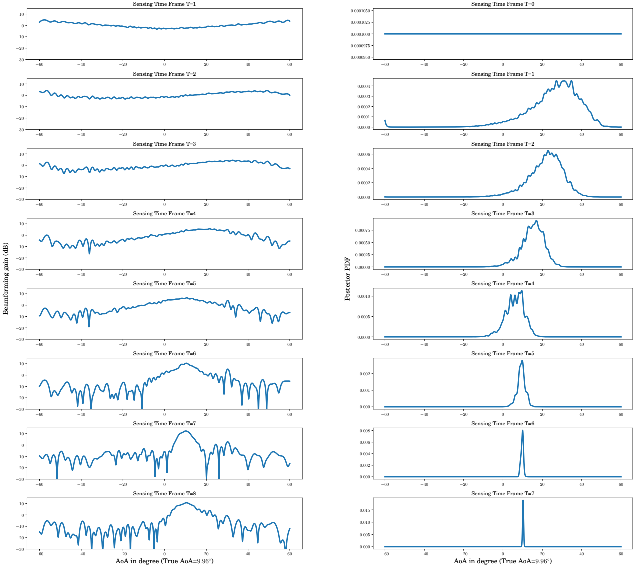
How about using machine learning to find a solution efficiently?

Long Short-Term Memory (LSTM) Architecture for Deep Active Sensing

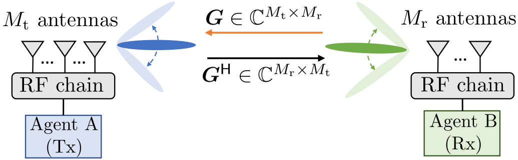


- We use a recurrent neural network with LSTM cells to model the active sensing problem.
- The overall end-to-end sensing architecture is a very deep neural network.
- We train the overall DNN by using stochastic gradient descent to minimize the MSE.

Posterior Distribution of AoA and Optimized Sensing Vectors



Two-Sided Beam Alignment

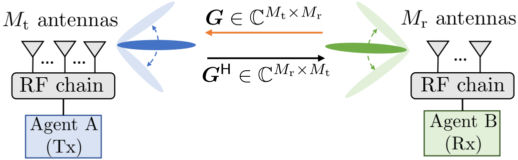


- Received signal at the Rx

$$r = \boldsymbol{w}_\mathrm{r}^\mathsf{H} \boldsymbol{G}^\mathsf{H} \boldsymbol{w}_\mathrm{t} x + n, \tag{5}$$

  - $x \in \mathbb{C}$ is the intended data symbol with $\mathbb{E}[|x|^2] = P$.
  - $\boldsymbol{w}_\mathrm{t} \in \mathbb{C}^{M_\mathrm{t}}$ is the beamforming vectors at the Tx with $\|\boldsymbol{w}_\mathrm{t}\|_2 = 1$.
  - $\boldsymbol{w}_\mathrm{r} \in \mathbb{C}^{M_\mathrm{r}}$ is the beamforming vectors at the Rx with $\|\boldsymbol{w}_\mathrm{r}\|_2 = 1$.
  - $n \sim \mathcal{CN}(0, \sigma_0^2)$ is the additive Gaussian noise.
- **Goal:** Aligning the beams $\{\boldsymbol{w}_\mathrm{t}, \boldsymbol{w}_\mathrm{r}\}$ to maximize the beamforming gain $|\boldsymbol{w}_\mathrm{r}^\mathsf{H} \boldsymbol{G}^\mathsf{H} \boldsymbol{w}_\mathrm{t}|^2$.

Two-Sided Beam Alignment



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- **Goal:** Aligning the beams $\{\boldsymbol{w}_{\mathrm{t}}, \boldsymbol{w}_{\mathrm{r}}\}$ to maximize the beamforming gain $|\boldsymbol{w}_{\mathrm{r}}^{\mathsf{H}} \boldsymbol{G}^{\mathsf{H}} \boldsymbol{w}_{\mathrm{t}}|^2$.
- Given perfect CSI $\boldsymbol{G}$, the optimal beamforming vectors are

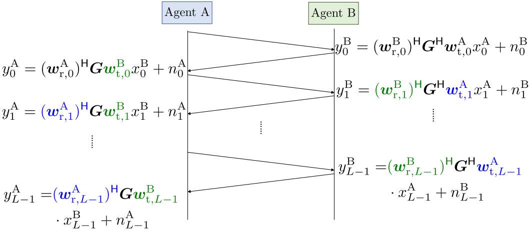
$$\boldsymbol{w}_{\mathrm{t}}^{\star} = \boldsymbol{u}_{\max} / \|\boldsymbol{u}_{\max}\|_2, \tag{6a}$$

$$\boldsymbol{w}_{\mathrm{r}}^{\star} = \boldsymbol{v}_{\max} / \|\boldsymbol{v}_{\max}\|_2, \tag{6b}$$

Here, $\boldsymbol{u}_{\max}$ and $\boldsymbol{v}_{\max}$ are respectively the left and the right singular vectors associated with the largest singular value of the matrix $\boldsymbol{G}$.

Ping-Pong Pilot Protocol

We propose an active learning framework with ping-pong pilot transmission.



In the ℓ-th transmission round:

1. Agent A sends a pilot x_ℓ^{A} to agent B:

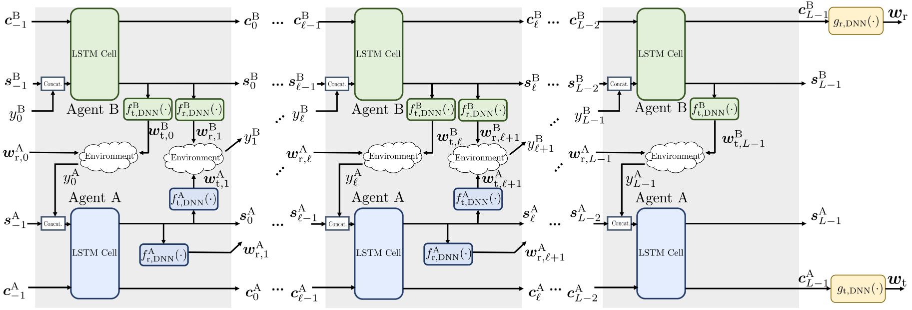
$$y_\ell^{\mathrm{B}} = (\boldsymbol{w}_{\mathrm{r},\ell}^{\mathrm{B}})^{\mathsf{H}} \boldsymbol{G}^{\mathsf{H}} \boldsymbol{w}_{\mathrm{t},\ell}^{\mathrm{A}} x_\ell^{\mathrm{A}} + n_\ell^{\mathrm{B}}, \quad \ell = 0, \cdots, L-1, \tag{7}$$

2. Agent B sends back a pilot x_ℓ^{B} to agent A:

$$y_\ell^{\mathrm{A}} = (\boldsymbol{w}_{\mathrm{r},\ell}^{\mathrm{A}})^{\mathsf{H}} \boldsymbol{G} \boldsymbol{w}_{\mathrm{t},\ell}^{\mathrm{B}} x_\ell^{\mathrm{B}} + n_\ell^{\mathrm{A}}, \quad \ell = 0, \cdots, L-1, \tag{8}$$

After L rounds of pilot transmission, each of the transceivers obtains L measurements of the channel, which can be utilized to design their own data transmission beamforming vectors.

Deep Active Sensing



Agents A and B respectively utilize the historical $\{y_i^{\mathrm{A}}\}_{i=0}^{\ell}$ and $\{y_i^{\mathrm{B}}\}_{i=0}^{\ell}$ to design their transmit/receive sensing beamformers:

$$\boldsymbol{w}^{\mathrm{A}}_{\mathrm{t},\ell+1} = f^{\mathrm{A}}_{\mathrm{t},\ell}\left(\{y_i^{\mathrm{A}}\}_{i=0}^{\ell}\right), \qquad \boldsymbol{w}^{\mathrm{A}}_{\mathrm{r},\ell+1} = f^{\mathrm{A}}_{\mathrm{r},\ell}\left(\{y_i^{\mathrm{A}}\}_{i=0}^{\ell}\right), \tag{9}$$

$$\boldsymbol{w}^{\mathrm{B}}_{\mathrm{t},\ell} = f^{\mathrm{B}}_{\mathrm{t},\ell}\left(\{y_i^{\mathrm{B}}\}_{i=0}^{\ell}\right), \qquad \boldsymbol{w}^{\mathrm{B}}_{\mathrm{r},\ell+1} = f^{\mathrm{B}}_{\mathrm{r},\ell}\left(\{y_i^{\mathrm{B}}\}_{i=0}^{\ell}\right), \tag{10}$$

After L rounds of pilot transmission, the beamformers for data transmission are designed as:

$$\boldsymbol{w}_{\mathrm{t}} = g_{\mathrm{t}}\left(\{y_i^{\mathrm{A}}\}_{i=0}^{L-1}\right), \qquad \boldsymbol{w}_{\mathrm{r}} = g_{\mathrm{r}}\left(\{y_i^{\mathrm{B}}\}_{i=0}^{L-1}\right), \tag{11}$$

The overall objective is to maximize $\mathbb{E}\left[|\boldsymbol{w}_{\mathrm{r}}^{\mathsf{H}}\boldsymbol{G}^{\mathsf{H}}\boldsymbol{w}_{\mathrm{t}}|^2\right]$.

Interpretation of Learned Active Sensing Strategy

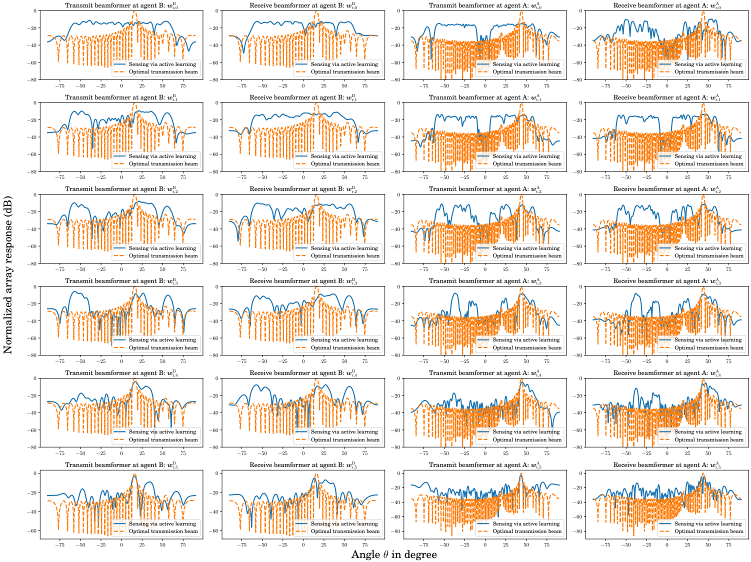
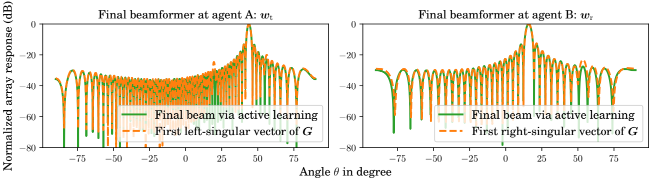
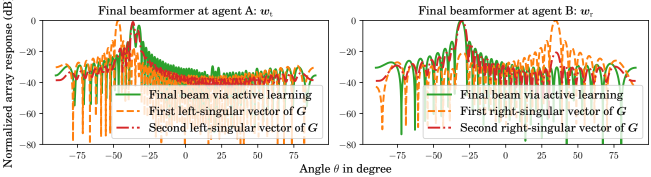


Figure: Learned **sensing** beamforming patterns for a specific mmWave channel realization.

Singular Value Decomposition Over the Air



(a) Example of beamformers matching the strongest singular-vector direction



(b) Example of beamformers matching the second singular-vector direction

Figure: Two examples of learned **data transmission** nbeamforming patterns after 6 ping-pong pilots.

Performance on Ray-Tracing Channel Model

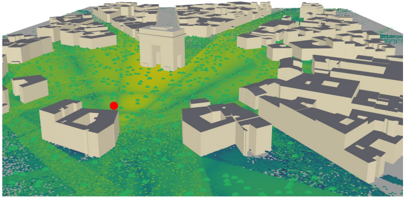


Figure: Ray-tracing model.

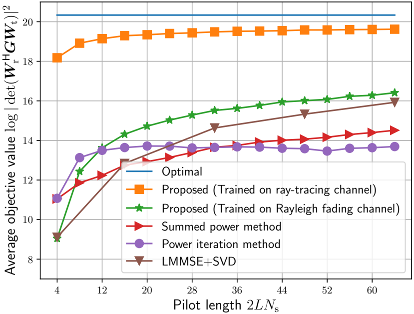


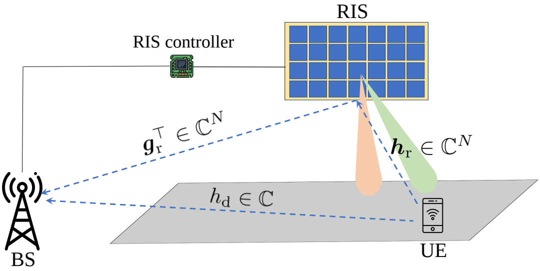
Figure: $M_\mathrm{t} = 64$, $M_\mathrm{r} = 16$ and $N_\mathrm{s} = 2$.

- The model trained with site-specific ray-tracing channel achieves the best performance.
- The model trained with Rayleigh fading channel can generalize to the ray-tracing scenario.
- Here, we assume fully digital system with two data streams, trained using GRU.

Localization and Beam Tracking

RIS-Assisted Active Uplink Localization

- A single user (UE) repeatedly transmits pilot symbols
- The base station (BS) receives the pilots through reflection by the RIS
- The BS determines the location of the user based on the received pilots



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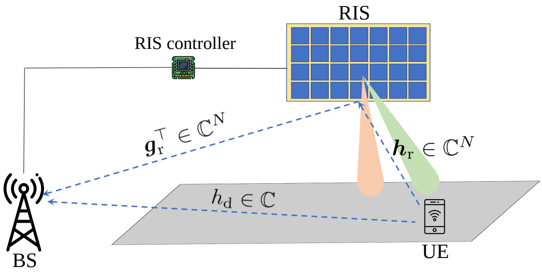


The idea is to adaptively configure the RIS:

- The uplink RIS configurations are sequentially designed by the BS as a function of previous measurements to minimize localization error.
- As a result, the RIS can focus the beam progressively to locate the user over time as more measurements become available.

- The goal is to estimate the unknown UE position $\boldsymbol{p}$ based on T observations $\{y_t(\boldsymbol{\theta}_t)\}_{t=0}^{T-1}$.
- The design of RIS configuration is a function of historical measurements.
- The estimated UE position $\hat{\boldsymbol{p}}$ is a function of all T historical observations.

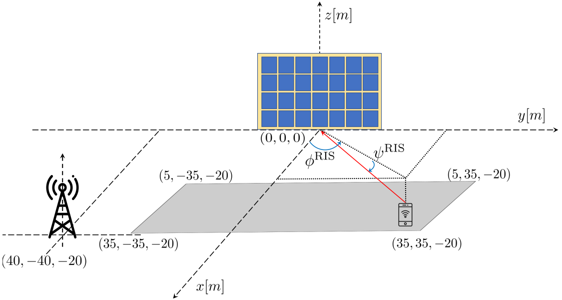
$$\begin{aligned} \underset{\{q_t(\cdot)\}_{t=0}^{T-1},\, f(\cdot)}{\text{minimize}} \quad & \mathbb{E}\left[\|\hat{\boldsymbol{p}} - \boldsymbol{p}\|_2^2\right] \\ \text{subject to} \quad & |[\boldsymbol{\theta}_t]_n| = 1,\ \forall n, t, \\ & \boldsymbol{\theta}_{t+1} = q_t(\{y_\tau\}_{\tau=0}^{t}),\ t = 0, \cdots T-1, \\ & \hat{\boldsymbol{p}} = f(\{y_t\}_{t=0}^{T-1}). \end{aligned}$$

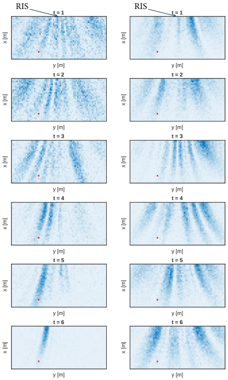
- The problem amounts to optimizing the functions $\{q_t(\cdot)\}_{t=0}^{T-1}$ and $f(\cdot)$.

Proposal:

- To use an LSTM network to automatically construct state vectors from the historical measurements and to extract temporal features and long-term dependencies in these observations to facilitate the design of reflection coefficients.

Single-RIS for Localization

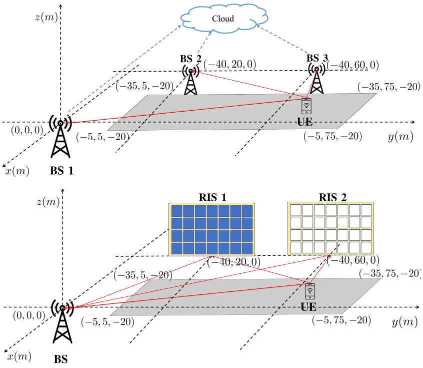


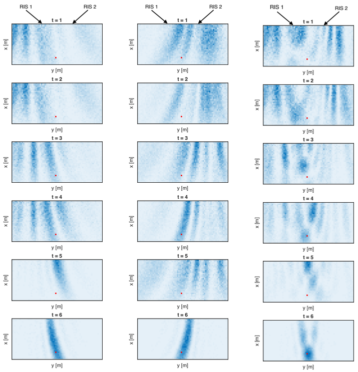


- The BS is located at $\boldsymbol{p}^{\text{BS}} = (40m, -40m, -20m)$
- An 8×8 RIS is located at $\boldsymbol{p}^{\text{RIS}} = (0m, 0m, 0m)$
- The unknown user locations $\boldsymbol{p}$ are uniformly generated within a rectangular area on the x-y plane $(20 \pm 15m, 0 \pm 35m, -20m)$.
- Diagram shows the beamforming patterns of active sensing (left) vs. non-active (right)

Multiple RISs for Triangulation

- Localization becomes more accurate if multiple anchor points are deployed.
- Instead of deploying extra base-stations, a more cost-effective solution is to use RISs.





The RIS reflection patterns of left panel, right panel, and combined patterns are shown.

Active Beam Tracking Using RIS

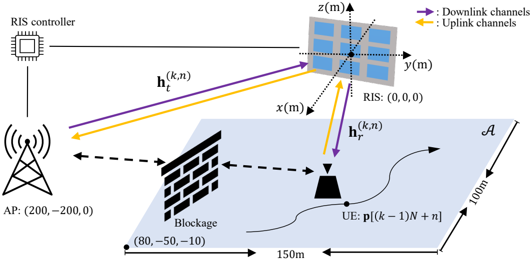


Figure: RIS-assisted mobile communication system

- Goal: Maintaining beam alignment through RIS for enhanced mobile communications.
- Assumption: Time-division duplex (TDD) system with channel reciprocity.
- Active Beam tracking: Adaptively set RIS coefficients to learn to focus on the users:
  - Estimating high-dimensional channels based on the low-dimensional received pilots is challenging
  - Frequently "start-from-scratch" estimation will lead to significant overhead.

Pilot Transmission Phase

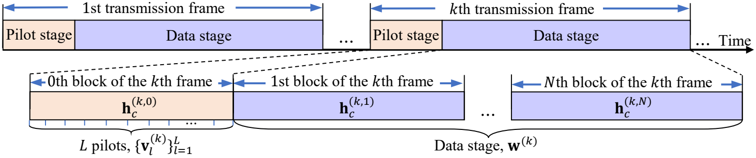


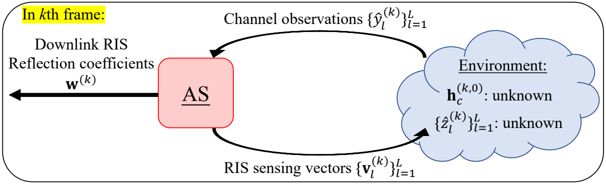
Figure: Frame structure of the proposed transmission protocol.

- The time-varying channels are split into sufficiently small fixed-length blocks:
  - The channels within each block is assumed to remain constant;
  - The channels are **correlated** across the blocks due to the mobility of the UE.
- The ℓth pilot received by the AP in the pilot stage (0th block) of the kth frame:

$$\widehat{y}_\ell^{(k)} = \left(\mathbf{h}_t^{(k,0)}\right)^\top \operatorname{diag}\left(\mathbf{v}_\ell^{(k)}\right)\mathbf{h}_r^{(k,0)} x_\ell^{(k)} + \widehat{z}_\ell^{(k)} = \sqrt{P_u}\left(\mathbf{v}_\ell^{(k)}\right)^\top \mathbf{h}_c^{(k,0)} + \widehat{z}_\ell^{(k)}, \qquad (13)$$

  - The ℓth RIS **sensing vector** for in the kth frame: $\mathbf{v}_\ell^{(k)} = [e^{j\theta_1}, \cdots, e^{j\theta_{N_r}}]^\top$ with $\theta_i \in [0, 2\pi)$.
  - $\mathbf{h}_c^{(k,0)} \triangleq \operatorname{diag}(\mathbf{h}_t^{(k,0)})\mathbf{h}_r^{(k,0)} \in \mathbb{C}^{N_r}$ is the cascaded channel in the 0th block of the kth frame.
- The idea is to exploit the temporal channel correlation by designing the best sensing vector $\mathbf{v}$.

Update the RIS configurations for both sensing and communications in a sequential fashion.



- In the pilot stage of the kth frame, the RIS sensing vectors are designed as:

$$\{\mathbf{v}_\ell^{(k)}\}_{\ell=1}^L = \mathcal{G}^{(k)}\left(\left\{\{\widehat{y}_\ell^{(j)}\}_{\ell=1}^L\right\}_{j=1}^{k-1}, \left\{\{\mathbf{v}_\ell^{(j)}\}_{\ell=1}^L\right\}_{j=1}^{k-1}\right) \tag{14}$$

  - $\mathcal{G}^{(k)}: \mathbb{C}^{L(k-1)} \times \mathbb{C}^{N_r L(k-1)} \to \mathbb{C}^{N_r L}$ is the active sensing scheme in the kth frame.

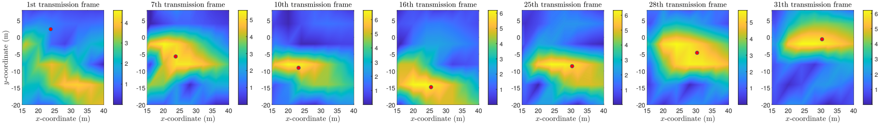
- Using the newly received pilots, design $\mathbf{w}^{(k)}$ for the N blocks in the subsequent data frame:

$$\mathbf{w}^{(k)} = \mathcal{F}^{(k)}\left(\left\{\{\widehat{y}_l^{(j)}\}_{l=1}^L\right\}_{j=1}^{k}, \left\{\{\mathbf{v}_l^{(j)}\}_{l=1}^L\right\}_{j=1}^{k}\right) \tag{15}$$

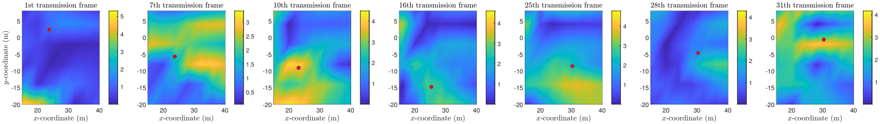
  - $\mathcal{F}^{(k)}: \mathbb{C}^{Lk} \times \mathbb{C}^{N_r Lk} \to \mathbb{C}^{N_r}$ is the downlink alignment scheme in the kth frame.

- Goal: Maximizing the downlink data rate

Visualizing Downlink RIS Reflection Coefficients



(a) Proposed active sensing approach using LSTM

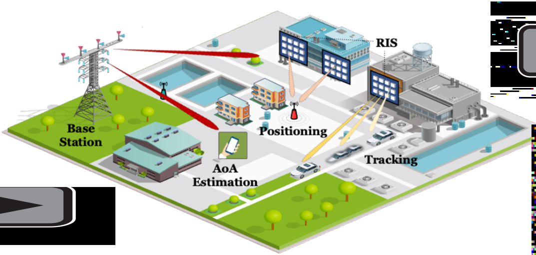


(b) DNN-based benchmark (fixed sensing vector learned from channel statistics)

Figure: Instantaneous downlink rate around the position of the UE obtained in different transmission frames. UE transmits $L = 10$ pilots in each pilot stage, each frame contains $N = 30$ blocks, $P_u = P_d = 15$dBm, $N_r = 64$.

Conclusions

- Machine learning enables a data-driven approach for communications and sensing tasks:
  - Data-driven design of massive MIMO beamformers *without* explicit channel estimation.
  - Data-driven design of active sensing strategies for beam alignment, beam tracking, and localization.
- Designing neural network architecture to fit the problem structure is the key to success.
  - GNN is able to capture the spatial relationship of the BS, the RIS, and the mobile users.
  - LSTM network is able to capture the temporal correlations across multiple sensing stages and to track the time-varying nature of the channel by summarizing the state of the system.



Data-Drive Methods are the Future of Optimization!

Further Information

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