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BeamID: Domain-Adaptive Radio Fingerprinting with MIMO Beamforming Feedback

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The Era of Massive Connectivity

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Today's Digital World Runs on 21+ Billion Connected Devices [1]

Number of the connected devices predicted to reach 39 Billion by 2030

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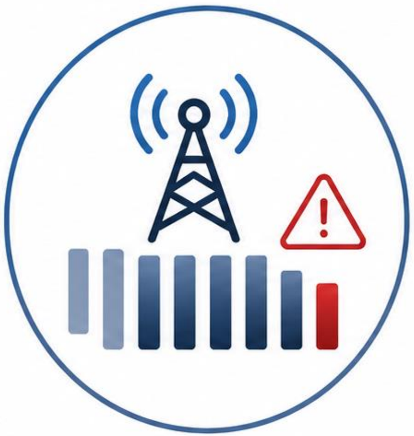
1. State of IoT 2025: Number of connected IoT devices growing 14% to 21.1 billion globally "https://iot-analytics.com/number-connected-iot devices/ "

What are the Implications?



Spectrum Management

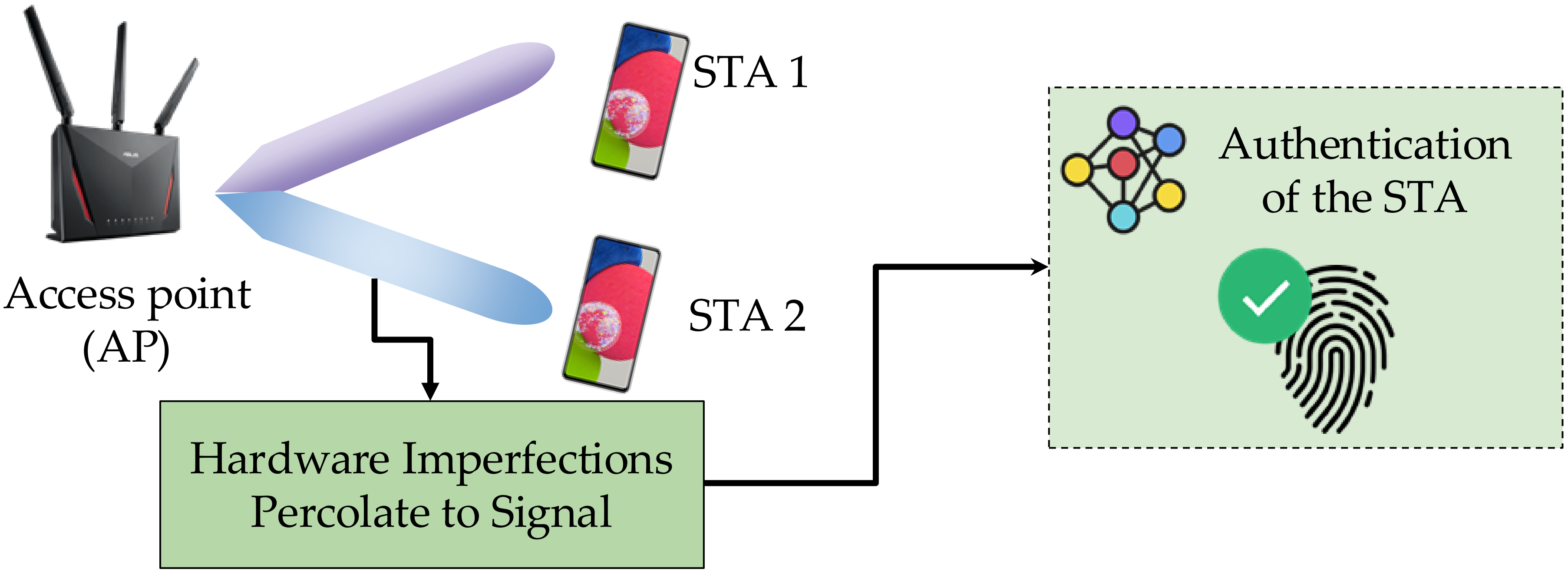
Network Policies

Security Concerns

We need to reliably identify and authenticate devices at the physical layer

Radio Fingerprinting for Authentication

Radio Fingerprinting is a promising alternative to cryptographic authentication



What has been Done so Far ? (1)

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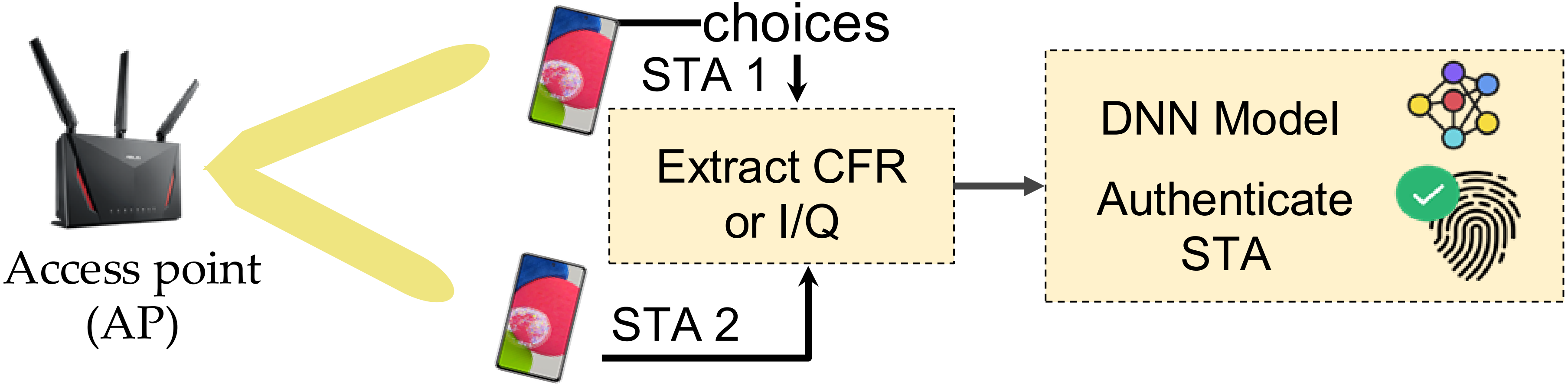
CFR and I/Q based fingerprinting are few of the popular choices

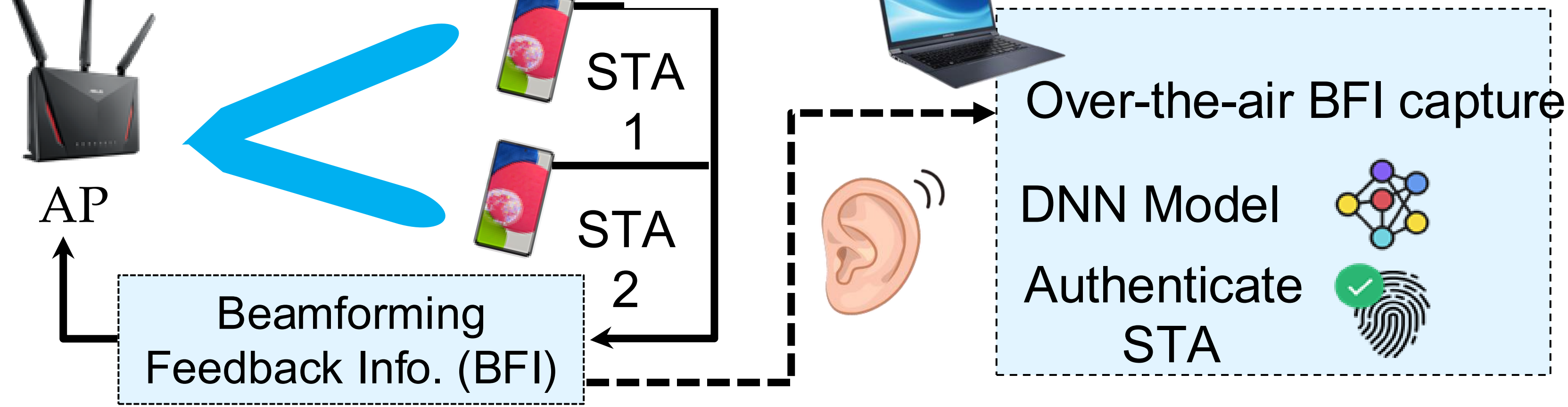


Requires specialized hardware / firmware support

- Kong, R. and Chen, H., 2024. DeepCRF: Deep learning-enhanced CSI-based RF fingerprinting for channel-resilient WiFi device identification. IEEE Transactions on Information Forensics and Security, 20, pp.264-278.
- Kong, R. and Chen, H., 2024. CSI-RFF: Leveraging micro-signals on CSI for RF fingerprinting of commodity WiFi. IEEE Transactions on Information Forensics and Security, 19, pp.5301-5315.
- Restuccia, F., D'Oro, S., Al-Shawabka, A., Belgiovine, M., Angioloni, L., Ioannidis, S., Chowdhury, K. and Melodia, T., 2019, July. DeepRadioID: Real-time channel-resilient optimization of deep learning-based radio fingerprinting algorithms. In Proceedings of the twentieth ACM international symposium on mobile ad hoc networking and computing (pp. 51-60).

What has been Done so Far ? (2)

BFI based fingerprinting doesn’t need specialized firmware / hardware



Cannot generalize to unseen domains

- Meneghello, F., Rossi, M. and Restuccia, F., 2022, July. DeepCSI: Rethinking Wi-Fi radio fingerprinting through MU-MIMO CSI feedback deep learning. In 2022 IEEE 42nd International Conference on Distributed Computing Systems (ICDCS) (pp. 1062-1072). IEEE.
- Meneghello, F., Haque, K.F. and Restuccia, F., 2025, May. Radio Fingerprinting of Wi-Fi Devices Through MIMO Compressed Channel Feedback. In IEEE INFOCOM 2025-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS) (pp. 1-6). IEEE.

Preli. Analysis on Domain Generalization

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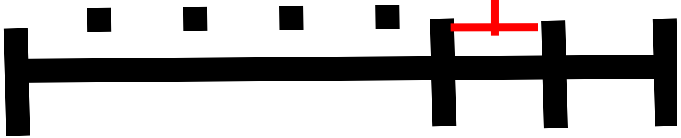
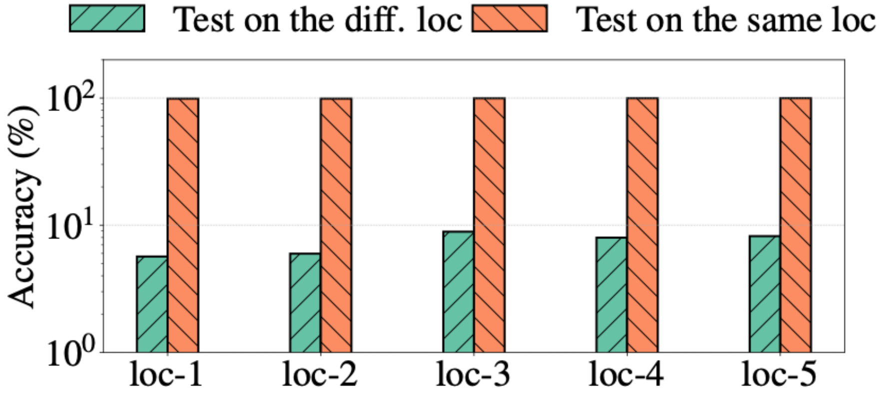
AP

Spacing of 4 inch between two diff. NIC loc.



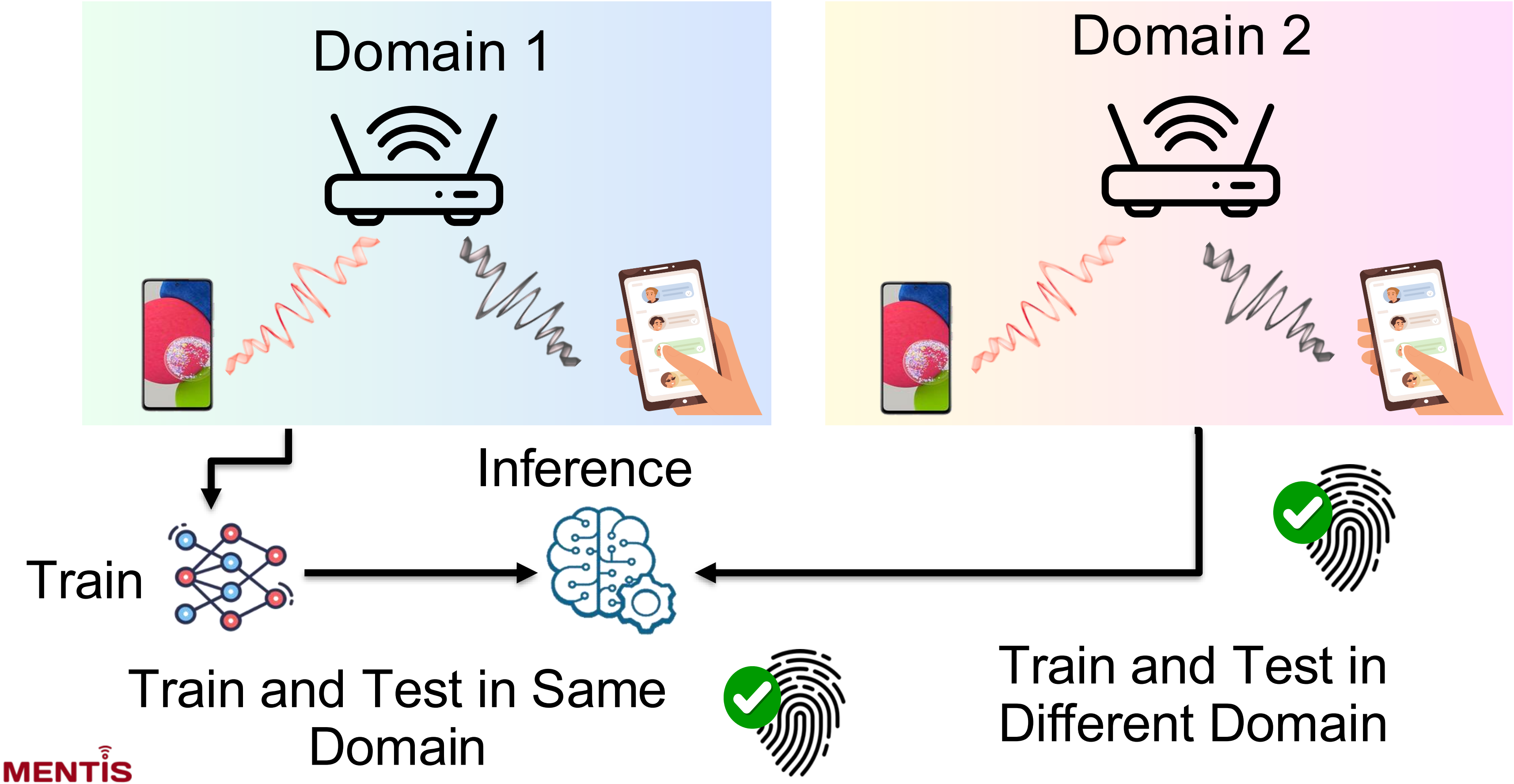
5 diff. location for each NIC

Performed fingerprinting to identify 15 different
NICs with BFI using VGG based model



Domain shift is a fundamental challenge
in radio fingerprinting

BeamID: Domain-Adaptive RFP with BFI



Train and Test in Same Domain

Train and Test in Different Domain

Summary of Contributions

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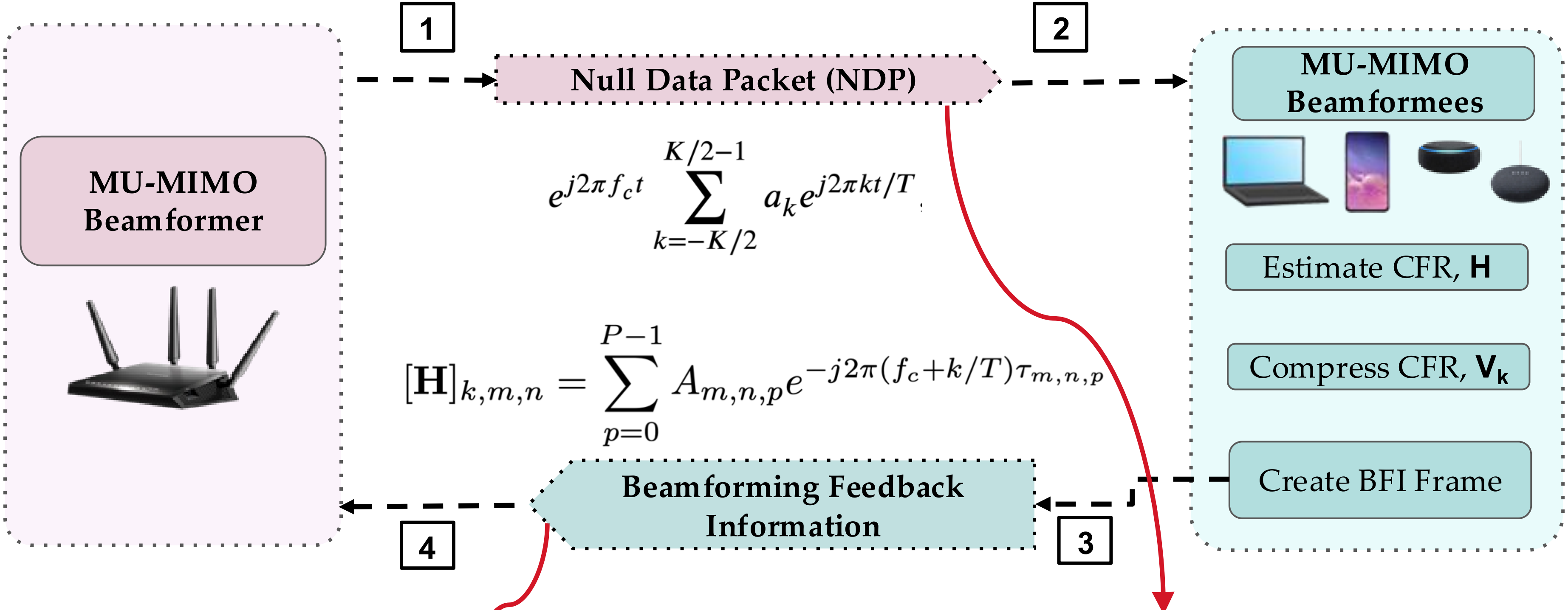
- We propose BeamID, a domain-adaptive RFP framework that exploits MIMO beamforming feedback
- We introduce an embedding-based few-shot adaptation strategy built upon supervised contrastive learning to support domain adaptation
- We validate BeamID with extensive experiments with a Wi-Fi testbed, with 15 different NICs at each of 9 distinct locations
- BeamID takes only 5 target-domain (unseen) samples per client, achieving up to 99% accuracy while requiring only 2.3 seconds of adaptation time

From CFR to BFI



$$e^{j2\pi f_c t}\sum_{k=-K/2}^{K/2-1} a_k e^{j2\pi k t/T},$$

$$[\mathbf{H}]_{k,m,n} = \sum_{p=0}^{P-1} A_{m,n,p}\, e^{-j2\pi(f_c+k/T)\tau_{m,n,p}}$$

52 0.032155 BeijingX_76:65:3e … 1a:e0:65:4e:ea:ca … 802.11 61 VHT/HE NDP Announcement, Sounding Dialog Token=114, Flags=........C

53 0.033717 1a:e0:65:4e:ea:ca BeijingX_76:65:3e 802.11 1011 Action No Ack, SN=28, FN=0, Flags=........C

Beamforming feedback matrices

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```
29… 4.7133… Netgear_63… Netgear_24… 802… 1… Action No Ack, SN=33, FN=7, Flags=........C

> Frame 29814: 1095 bytes on wire (8760 bits), 1095 bytes captured (8760 bits) on interface wlp58s0mon, id 0
> Radiotap Header v0, Length 64
> 802.11 radio information
> IEEE 802.11 Action No Ack, Flags: ........C
v IEEE 802.11 Wireless Management
  v Fixed parameters
      Category code: VHT (21)
      VHT Action: VHT Compressed Beamforming (0)
    > VHT MIMO Control: 0x548c90, Nc Index: 1 Column, Nr Index: 3 Rows, Channel Width: 80 MHz, Grouping (Ng): 1
    v VHT Compressed Beamforming Report [truncated]: 5ee5855a5dd2695e4fbd575a49a1375e437f0f664355e16d472fbf6d4f0
      > Average Signal to Noise Ratio
      v Feedback Matrices
          SCIDX: -122, ϕ11:485, ϕ21:322, ψ21:86, ψ31:46
          SCIDX: -121, ϕ11:466, ϕ21:308, ψ21:87, ψ31:39
          SCIDX: -120, ϕ11:445, ϕ21:299, ψ21:86, ψ31:36
          SCIDX: -119, ϕ11:417, ϕ21:283, ψ21:87, ψ31:33
          SCIDX: -118, ϕ11:383, ϕ21:263, ψ21:89, ψ31:33
          SCIDX: -117, ϕ11:341, ϕ21:240, ψ21:91, ψ31:35
          SCIDX: -116, ϕ11:303, ϕ21:223, ψ21:91, ψ31:39
          SCIDX: -115, ϕ11:271, ϕ21:215, ψ21:86, ψ31:40
```

Transmitted unencrypted

```
0050  3c 37 86 24 52 63 17 02  15 00 90 8c 54 5e e5 85   <7·$Rc·· ····T^··
0060  5a 5d d2 69 5e 4f bd 57  5a 49 a1 37 5e 43 7f 0f   Z]·i^O·W ZI·7^C··
0070  66 43 55 e1 6d 47 2f bf  6d 4f 0f af 59 51 f7 aa   fCU·mG/· mO··YQ··
0080  39 4f e2 a6 1d 4d d0 a6  fd 4c bf a8 e1 48 ad ae   9O···M·· ·L···H··
0090  c5 3a 9d b0 ad 2a 8b a0  95 26 81 9c 79 24 6f 88   ·:···*·· ·&··y$o·
00a0  61 1c 32 08 51 10 c6 11  4c 16 94 53 67 30 81 19   a·2·Q··· L··Sg0··
00b0  83 32 70 ef aa 3a 5e d1  e2 42 44 b5 16 45 24 8f   ·2p··:^· ·BD··E$·
00c0  3a 45 06 65 4a 43 e3 46  5a 3f c4 26 62 3b b8 0c   :E·eJC·F Z?·&b;··
00d0  6a 3d b7 fa 7d 41 bc ec  95 43 ba e4 b5 47 e9 e4   j=··}A·· ·C···G··
00e0  d1 49 40 eb b9 4b 59 ef  89 49 66 f1 69 45 6d f3   ·I@··KY· ·If·iEm·
```

Packet Bytes

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BeamID Walkthrough

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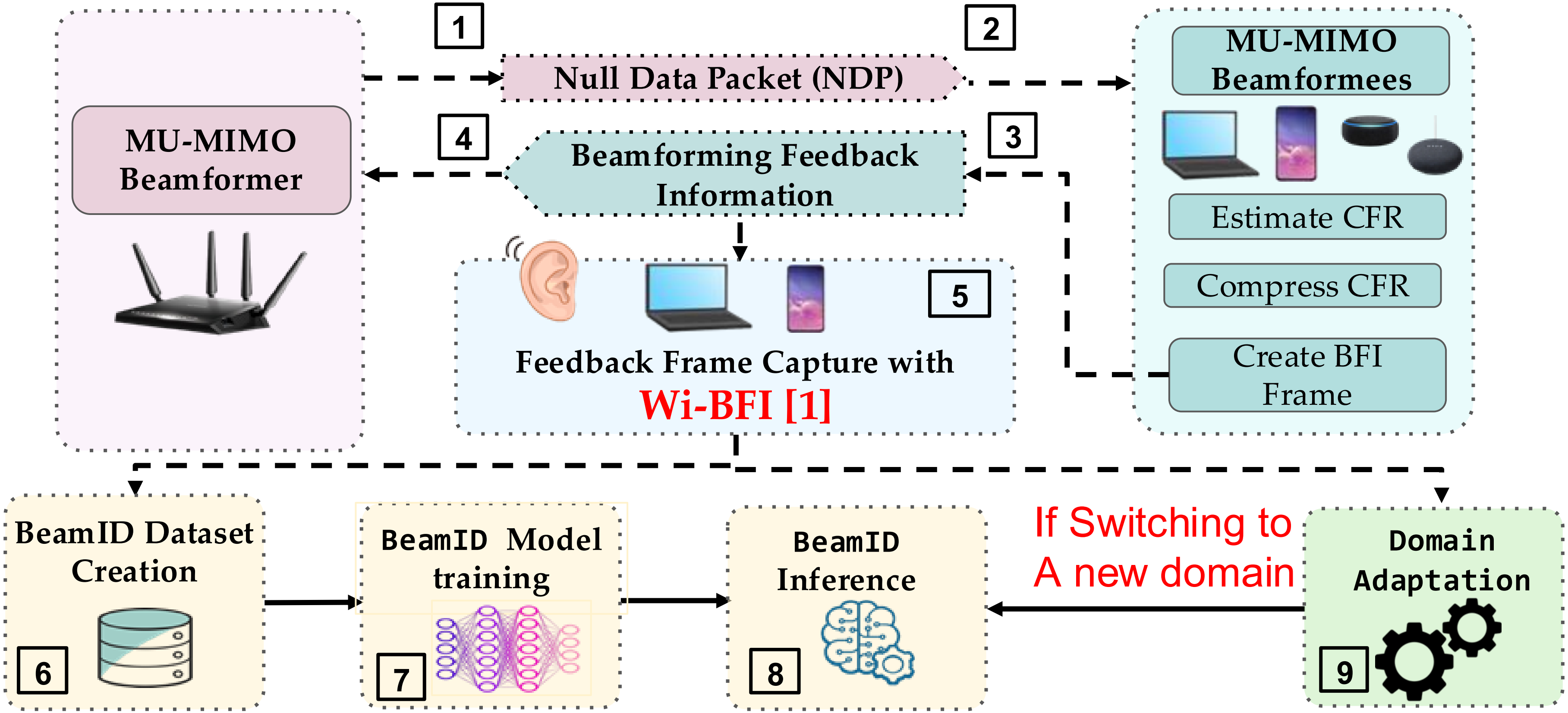

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1. Haque, K.F., Meneghello, F. and Restuccia, F., 2023, October. Wi-BFI: Extracting the IEEE 802.11 beamforming feedback information from commercial Wi-Fi devices. In Proceedings of the 17th ACM Workshop on Wireless Network Testbeds, Experimental evaluation & Characterization (pp. 104-111).

Source-Domain Representation with Embedding

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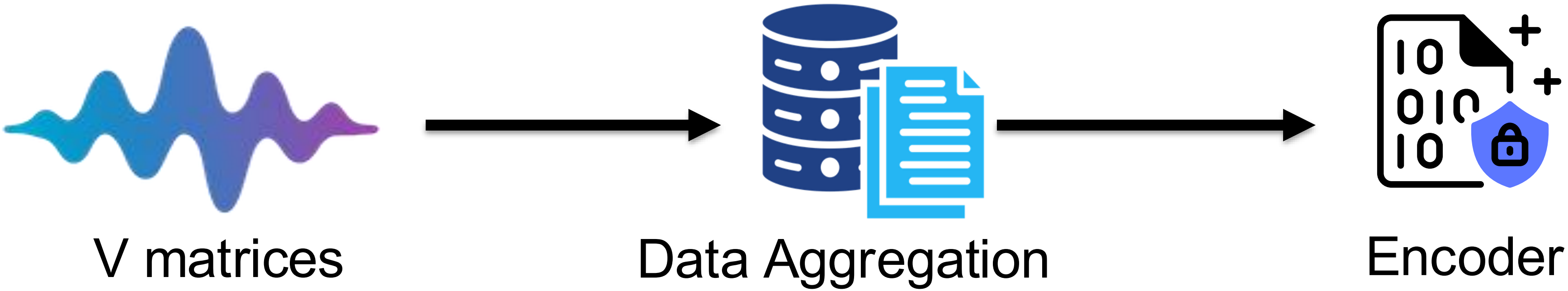

V-matrix Tensor

Shape: (B × 16 × 250)

1D Convolution Block 1

1D Convolution Block 2

1D Convolution Block 3

Conv1D (32),

Batch Normalization,ReLU

Global Average Pooling

AdaptiveAvgPool1D →

(B × 128)

Output Embedding $z \in \mathbb{R}^d$

(d = 128)

Enabling Domain Invariant Features

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We employ Supervised Contrastive loss, which directly enforces intraclass compactness and inter-class separation-properties

$$\mathcal{L}_{\text{sup}}^{(i)} = -\frac{1}{|\mathcal{P}(i)|} \sum_{p \in \mathcal{P}(i)} \log \frac{\exp(\mathbf{z}_i^\top \mathbf{z}_p / \tau)}{\sum_{a \in \mathcal{B} \setminus \{i\}} \exp(\mathbf{z}_i^\top \mathbf{z}_a / \tau)}$$

Numerator pulls same-client embeddings together, whereas, Denominator contrasts against all other embeddings in the batch

To enable device identification during training, the contrastive objective is combined with a standard cross-entropy loss

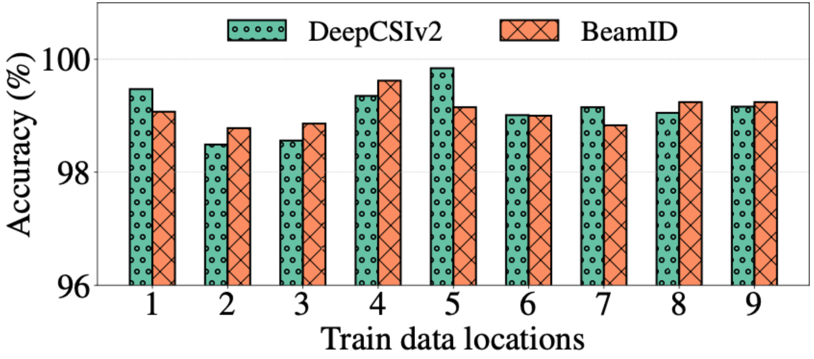
$$\mathcal{L}_{\text{CE}} = -\sum_{i \in \mathcal{B}} \log p(y_i \mid \mathbf{z}_i)$$

The overall training objective

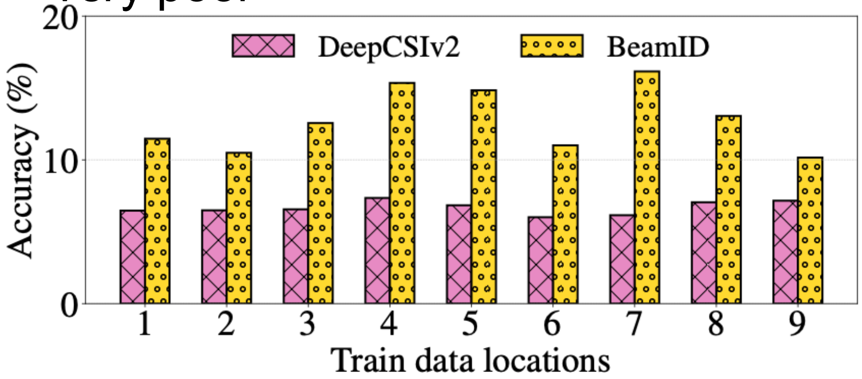
$$\mathcal{L} = \mathcal{L}_{\text{sup}} + \lambda \, \mathcal{L}_{\text{CE}}$$

Impact of Super Contrastive Learning

- Train and Tested in the same domain
- BeamID and SOTA approach-– both achieves ~99%



- Train and Tested in the different domain
- DeepCSIv2's performance is random
- BeamID is not totally random but still very poor



Few-Shot Domain Adaptation in Embedding Space

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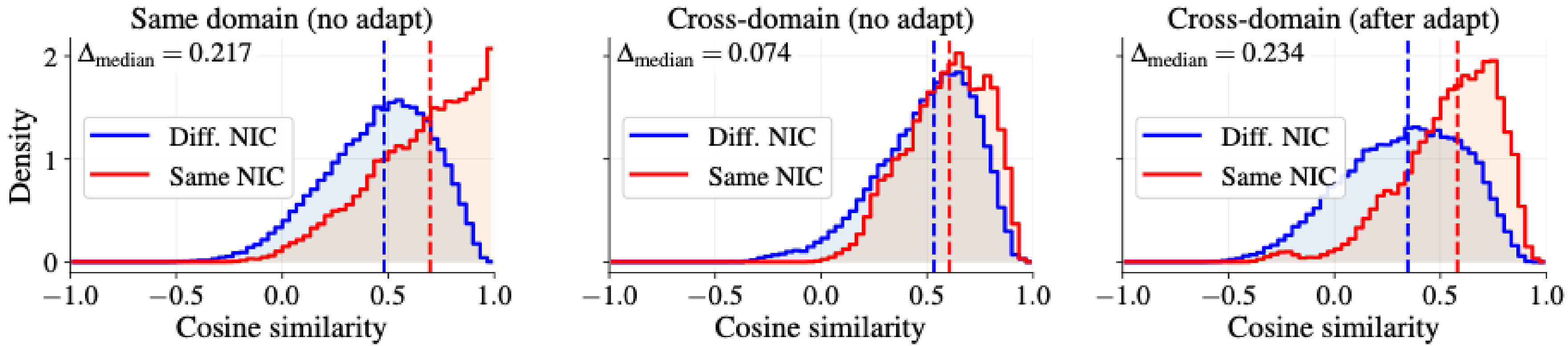
- Collect K-shot labeled target samples
- Fine-tune classifier + last encoder layer
- Align target embeddings with source clusters
- Preserve inter-client separation

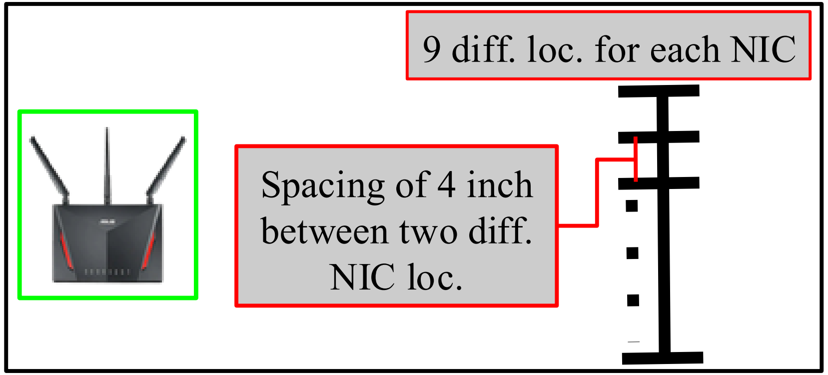
$$D_s \xrightarrow{f_\theta(.)} Z_s$$

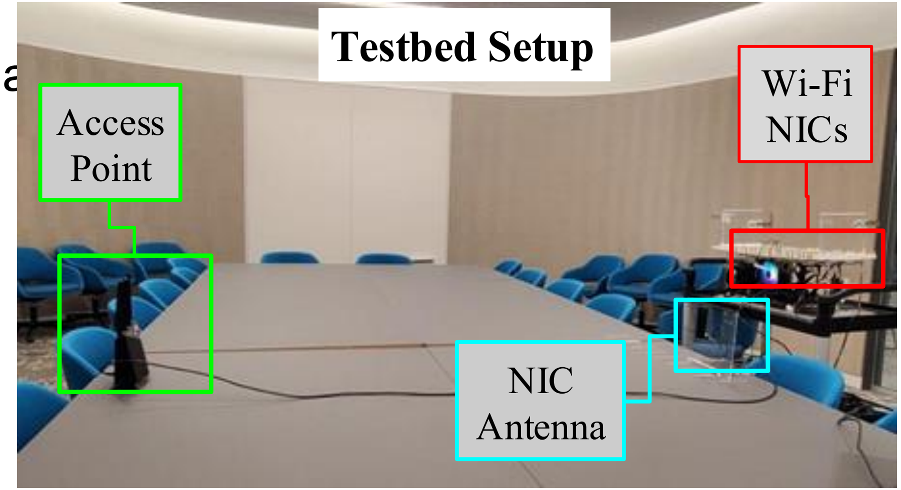
$$D^k_t \xrightarrow{\text{Fine-tune}} Z_t \approx Z_s$$

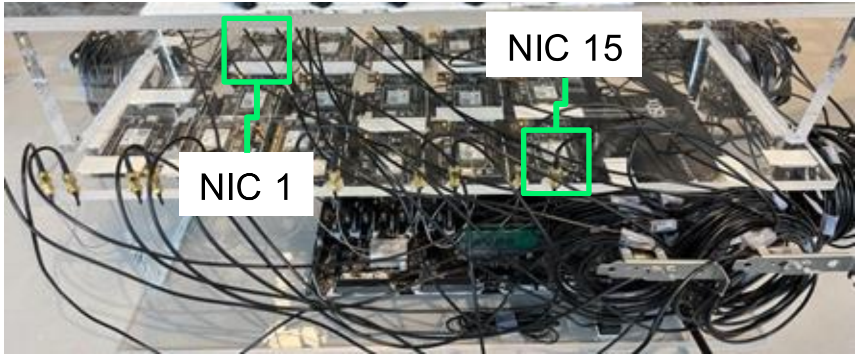


Experimental Evaluation

- Evaluate BeamID with WiSEC testbed, a large-scale multi-NICs platform
- Hosts 15 intel AX210 Wi-Fi NIC implementing IEEE 802.11ax.
- Used ASUS RT-AX86U as AP

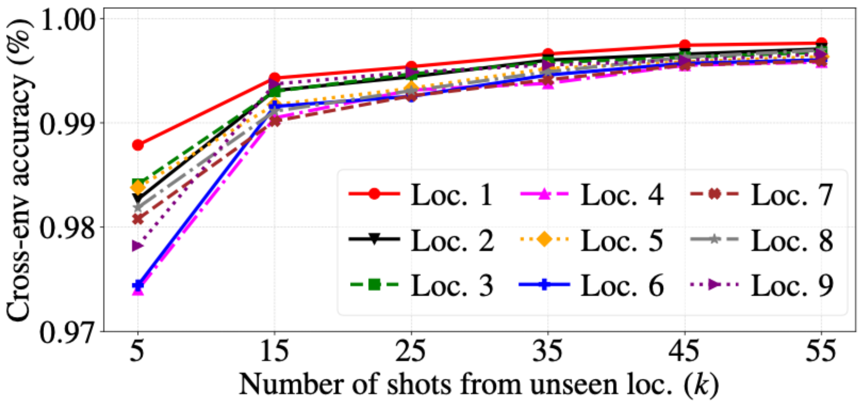


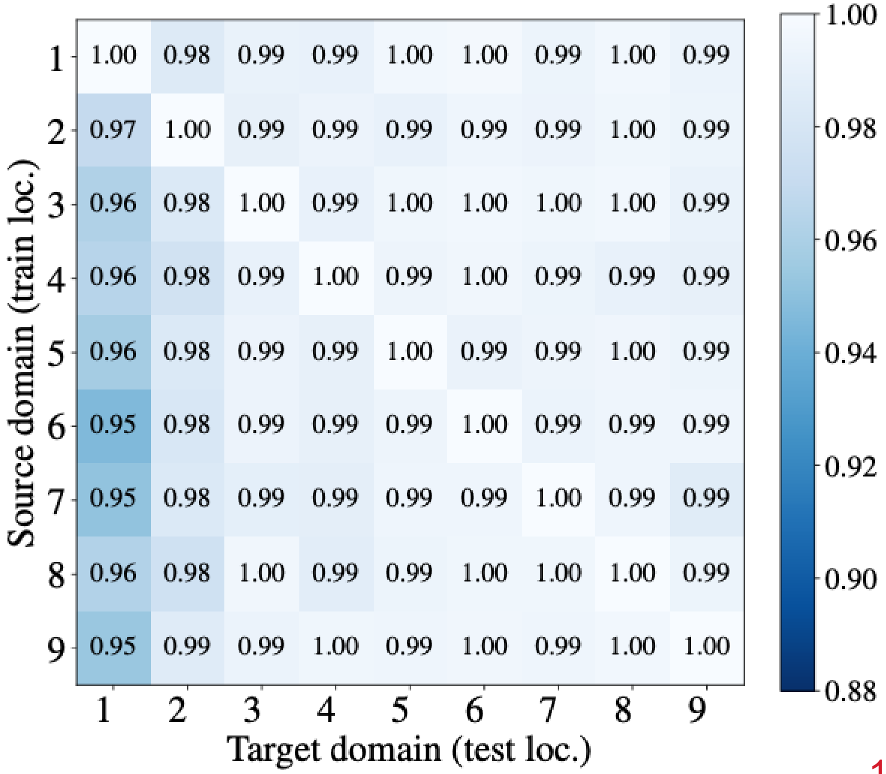




BeamID Performance (1)

Performance with domain adaptation Pairwise cross-domain transfer accuracy at k = 1





- Legends show the training domain
- Tested with rest of the domain

BeamID Performance (2)

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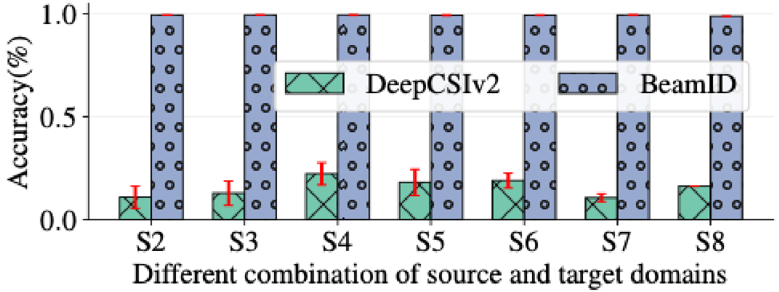
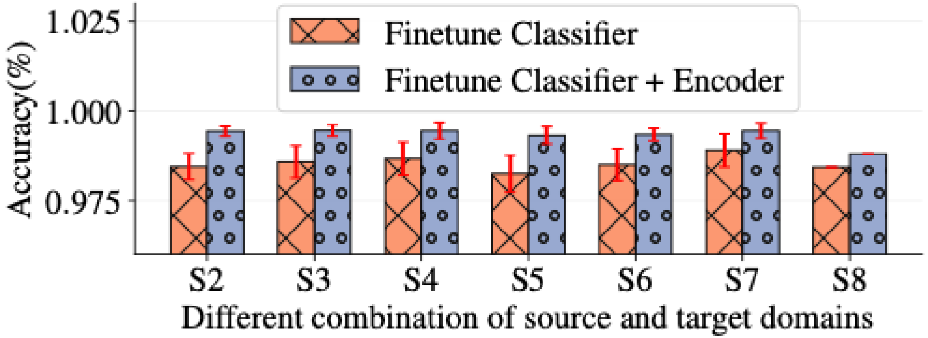
Experimental Scenarios with Training and Testing Locations

Experimental Scenario	Train loc.	Test loc.
S2	1, 2	3, 4, 5, 6, 7, 8, 9
S3	1, 2, 3	4, 5, 6, 7, 8, 9
S4	1, 2, 3, 4	5, 6, 7, 8, 9
S5	1, 2, 3, 4, 5	6, 7, 8, 9
S6	1, 2, 3, 4, 5, 6	7, 8, 9
S7	1, 2, 3, 4, 5, 6, 7	8, 9
S8	1, 2, 3, 4, 5, 6, 7, 8	9

Accuracy vs number of source environments



Impact of fine-tuning the encoder



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Computational Overhead of BeamID

- Executed BeamID in a linux machine with intel core i7-12700K CPU and RTX A4000 GPU with 84 GB RAM
- BeamID takes only 133 ms for inference time whereas it takes up to 2.32 s for adapting to an unseen domain

Fine-tuning Type	Inference (ms)	Adaptation (s)	Peak Memory (MB)
DeepCSIv2	227	–	344.21
BeamID (No adapt)	133	–	26.59
BeamID (Finetune Classifier)	133	2.21	34.96
BeamID (Finetune Class.+Enc.)	133	2.32	35.15

Possible Next Steps?

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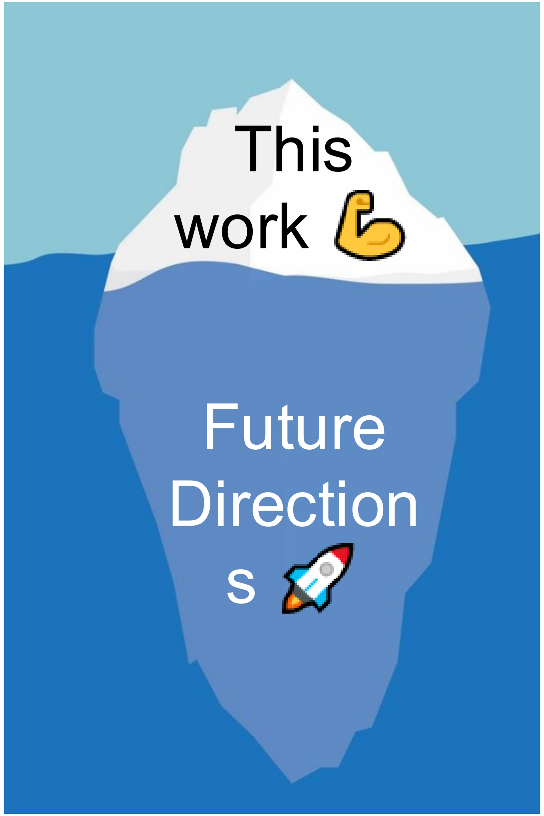

✅ Few-shot cross-domain RFP from standard MIMO beamforming feedback

⚠️ Extend BeamID across heterogeneous AP hardware

⚠️ Generalize BeamID across different frequency bands

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THANK YOU

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