

Fast MRI for All: Bridging Access Gaps by Training without Raw Data

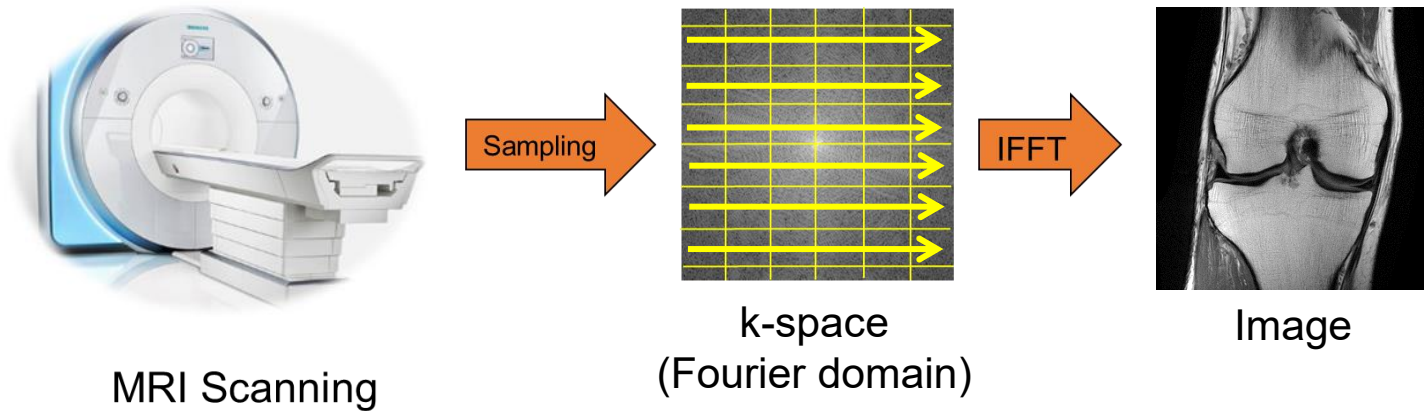
Yaşar Utku Alçalar^{1,2}, Merve Gülle^{1,2} and Mehmet Akçakaya^{1,2}

¹Electrical and Computer Engineering, University of Minnesota, Minneapolis, MN

²Center for Magnetic Resonance Research, University of Minnesota, Minneapolis, MN

MRI Reconstruction Problem

- MRI scanning procedure:



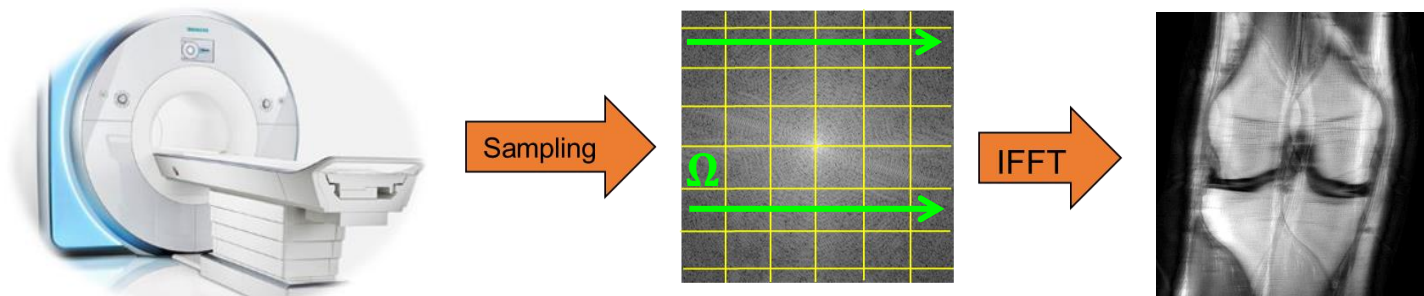
$$\mathbf{y} = \mathbf{E}_{\text{full}} \mathbf{x} + \mathbf{n}$$

acquired measurements (k-space)

encoding matrix

measurement noise

- Accelerated* MRI scanning procedure:



$$\mathbf{y}_{\Omega} = \mathbf{E}_{\Omega} \mathbf{x} + \mathbf{n}$$

$\mathbf{P}_{\Omega} \rightarrow m \times n$ masking operator

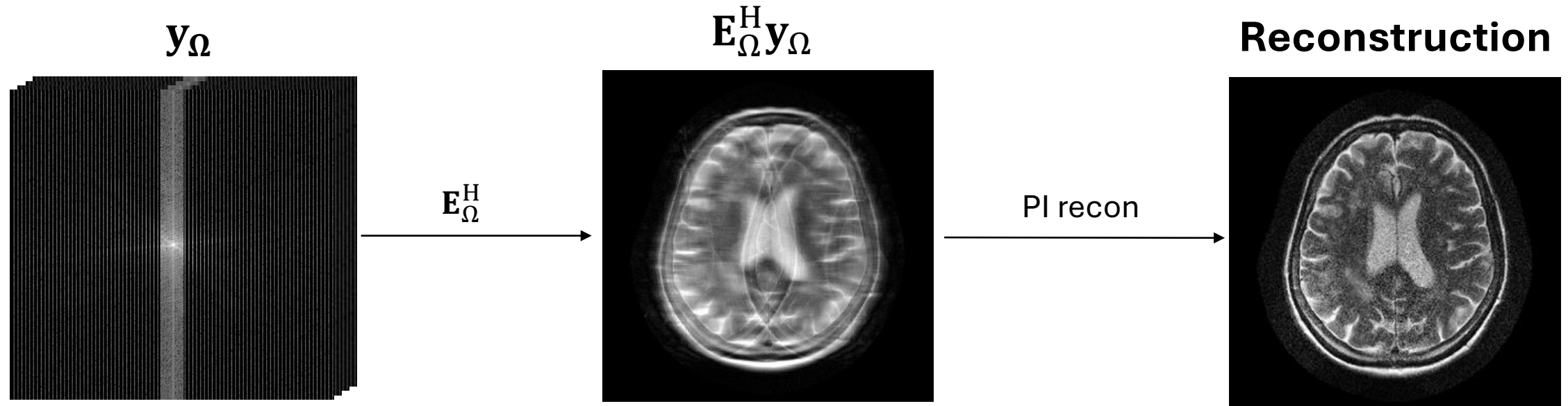
$$\mathbf{E}_{\Omega} = \mathbf{P}_{\Omega} \mathbf{E}_{\text{full}}$$

$$\mathbf{y}_{\Omega}^k \in \mathbb{C}^m, \mathbf{x} \in \mathbb{C}^n \text{ with } m < n$$

Clinical Methods (Parallel Imaging)

- Clinical “parallel imaging” methods use the redundancies among the receiver coils:

$$\mathbf{x}_{\text{PI}} = \arg \min_{\mathbf{x}} \|\mathbf{y}_{\Omega} - \mathbf{E}_{\Omega} \mathbf{x}\|_2^2 = (\mathbf{E}_{\Omega}^H \mathbf{E}_{\Omega})^{-1} \mathbf{E}_{\Omega}^H \mathbf{y}_{\Omega}$$

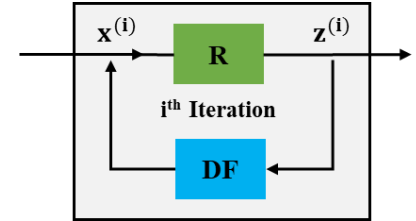


- ✓ They can work in a zero-shot manner without needing raw k-space data
- ✗ Performance degradation begins after $\times 2 - 3$ acceleration

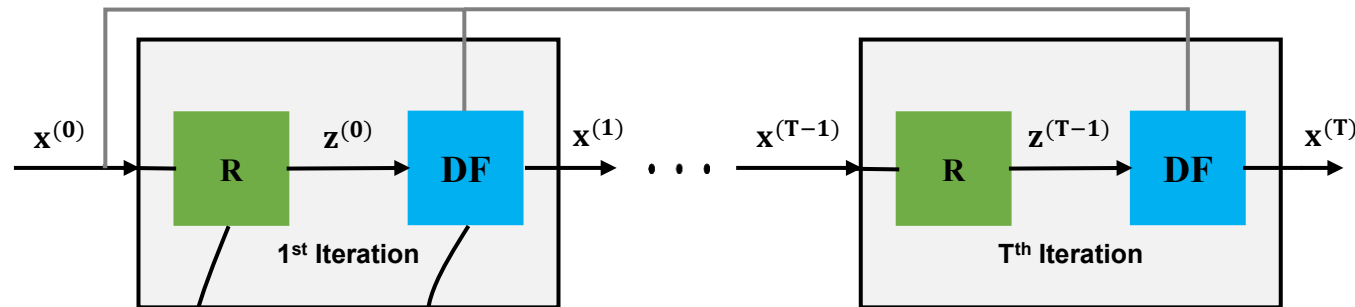
Physics-driven Deep Learning (PD-DL)

- In computational MRI, additional regularization is often incorporated:

$$\arg \min_{\mathbf{x}} \underbrace{\|\mathbf{y}_{\Omega} - \mathbf{E}_{\Omega} \mathbf{x}\|_2^2}_{\text{Data Fidelity (DF)}} + \underbrace{\mathcal{R}(\mathbf{x})}_{\text{Regularizer (R)}}$$



- PD-DL methods learn the proximal operator of a regularizer
- One common PD-DL approach: Unrolled networks
 - Fix the number of iterations and “unroll” the optimization process

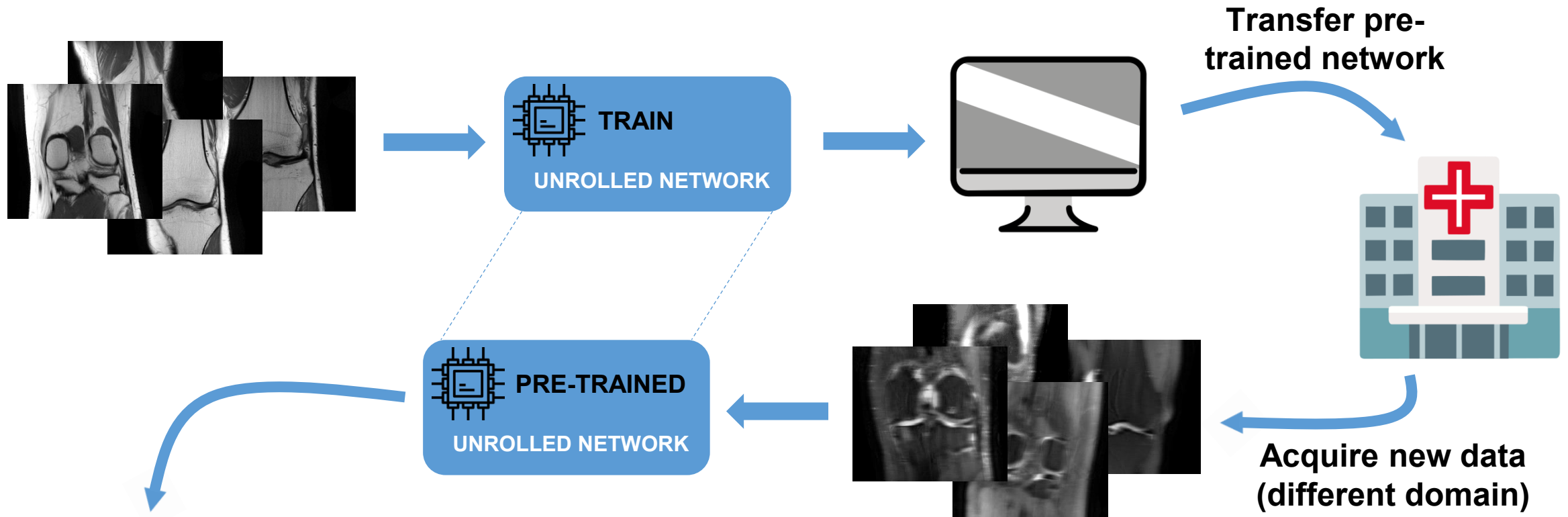


Data Fidelity → Solved via physics knowledge

Regularization (~denoising) → Solved implicitly with NNs

Need for Training without Raw Data

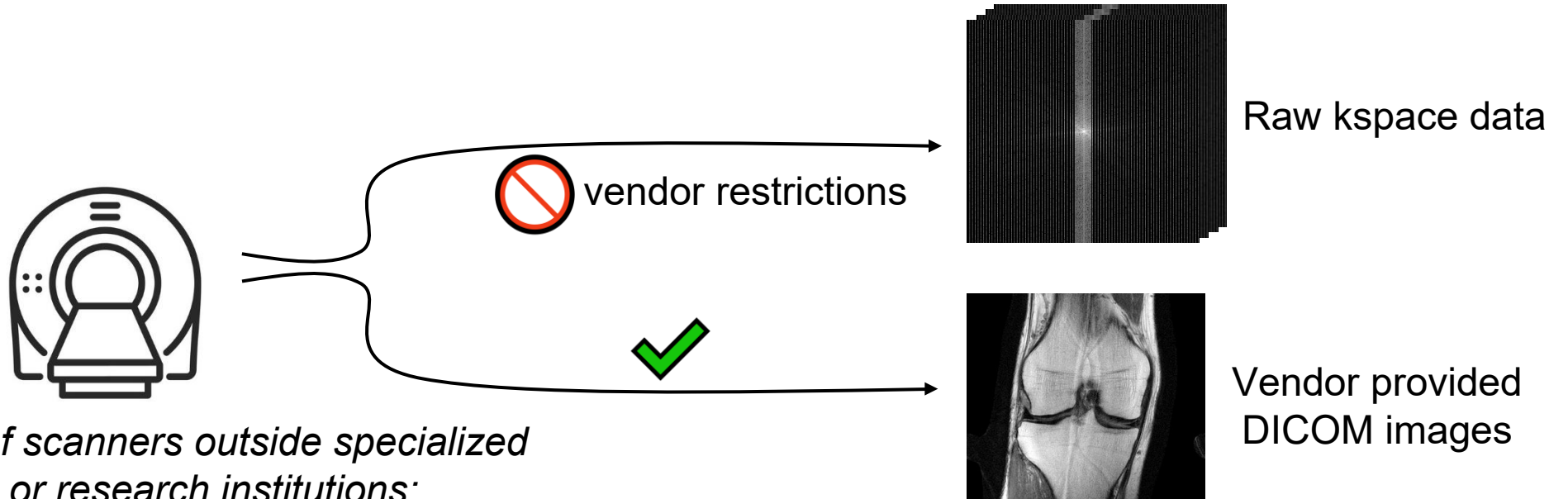
- Despite emerging AI methods, parallel imaging continues to define everyday MRI practice
- The main reason for this is the issue of **generalizability**



Models trained on specific scanners or populations fail under distribution shifts

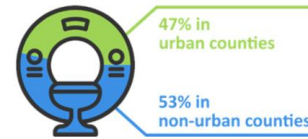
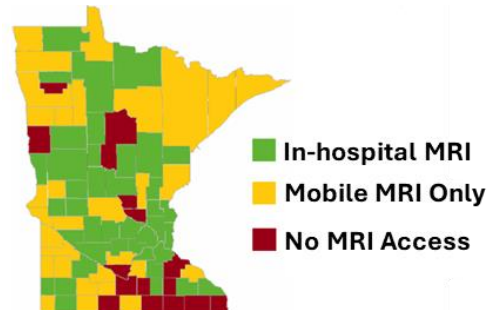
Need for Training without Raw Data

- Fine-tuning models for specific domains is necessary to optimize performance
- **Caveat:** This fine-tuning requires access to raw k-space data



Majority of scanners outside specialized academic or research institutions:

- Local hospitals
- Mobile MRI units

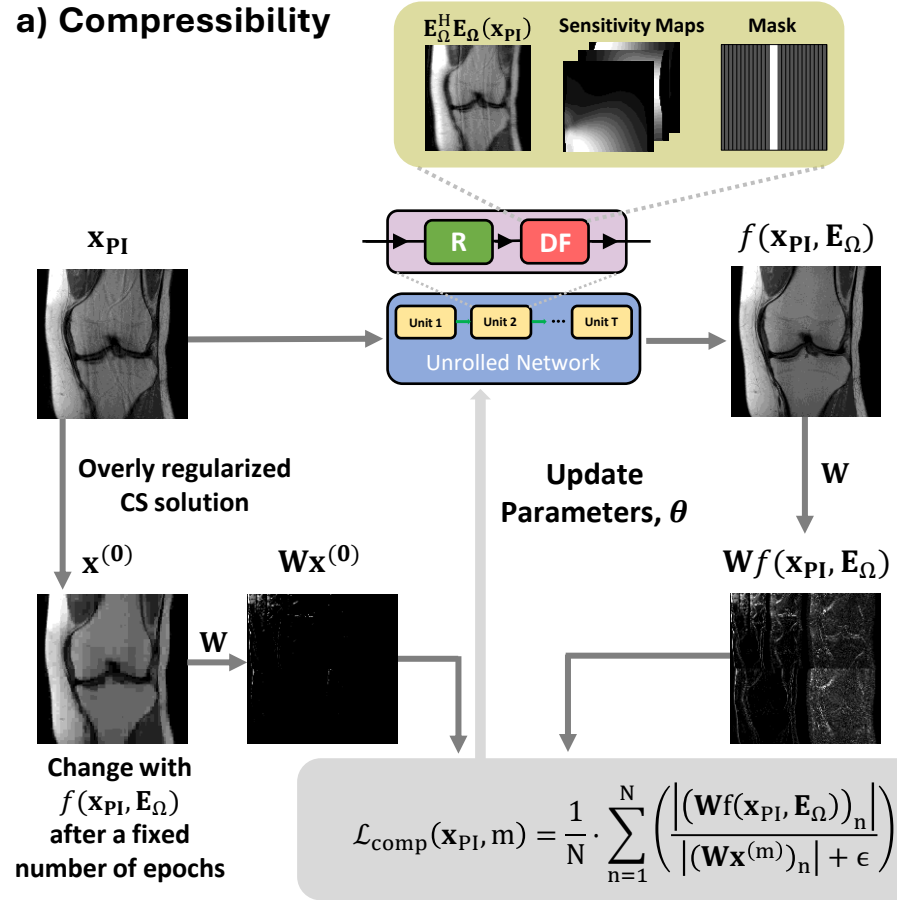


- Non-urban MRI scanners do not enjoy the specialized expertise in academic medical centers
- No vendor research agreements, needed for raw data access
- Cannot use or fine-tune fast MRI methods that require raw data

We need a training pipeline that does not require raw kspace data!

Pipeline of CUPID

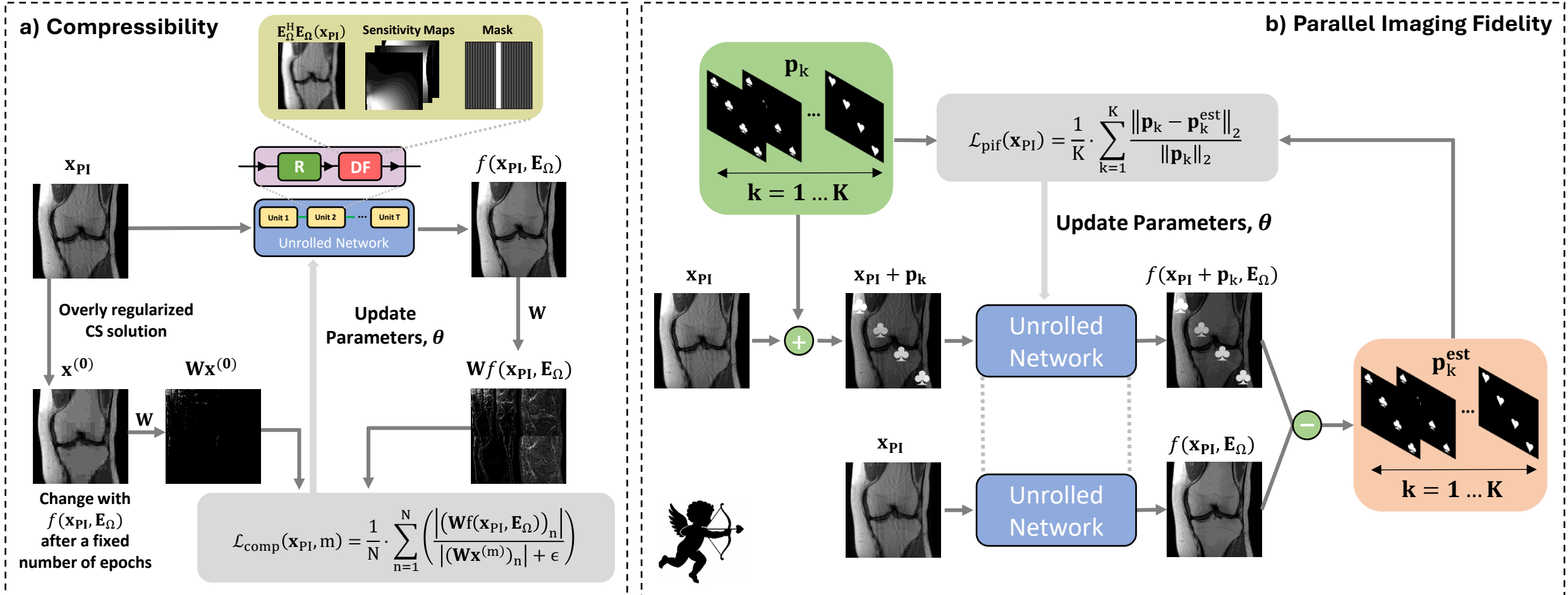
a) Compressibility



b) Parallel Imaging Fidelity

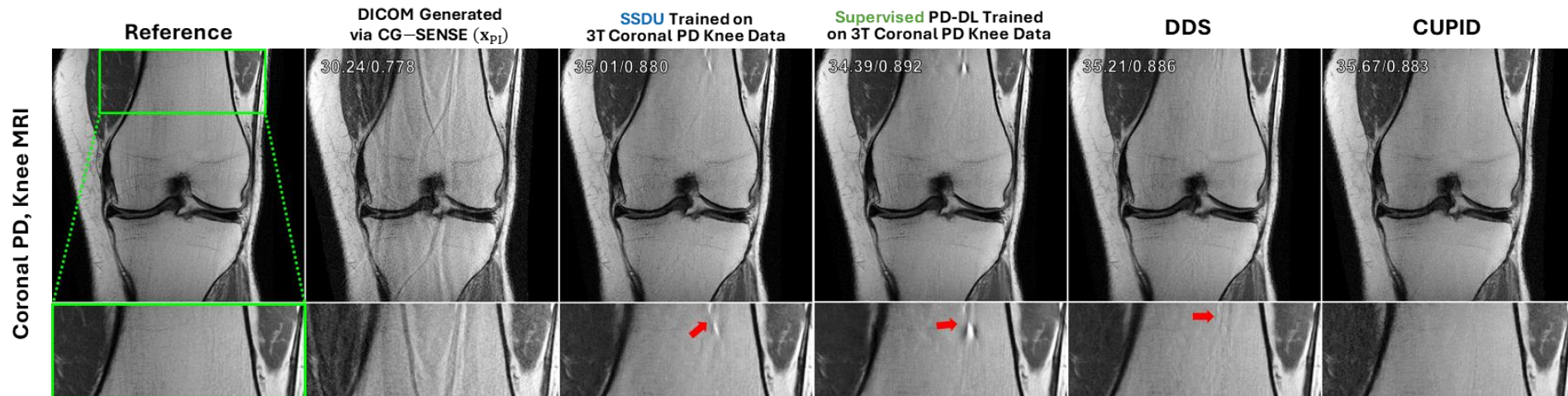
$$\mathcal{L}_{CUPID} = \mathcal{L}_{comp} + \lambda \cdot \mathcal{L}_{pif}$$

Pipeline of CUPID



Contributions & Out-of-Distribution Illustration

- 🔥 **CUPID** is the **first PD-DL framework trainable solely from routine DICOM images acquired at target acceleration rates**
- 🔥 Operates in both **database-level unsupervised** and **zero-shot (subject-specific)**
- 🔥 Achieves **reconstruction quality matching** supervised and self-supervised methods requiring raw k-space data

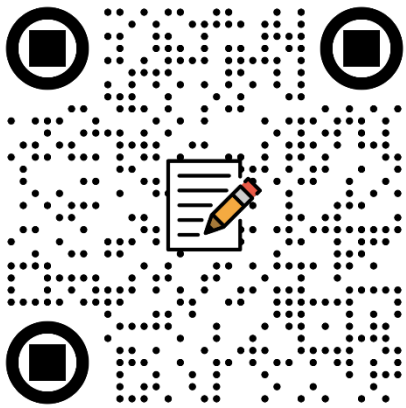


- Supervised and SSDU models trained on 3T data fail to generalize to 1.5T scans
- DDS (trained on both 3T and 1.5T data) does a better job though some performance degradation persists

Links & Contact Information

- For all the results, ablation studies, technical details for perturbations, and radiologist readings please refer to our paper or publicly available code:

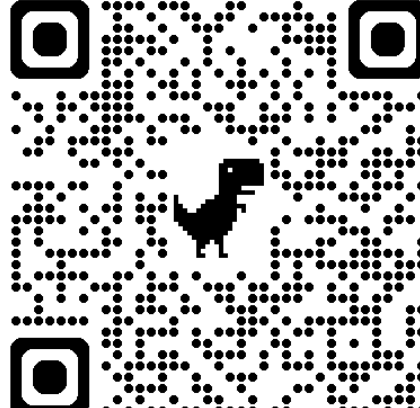
Paper



Code



Utku's Homepage



Spotlight Poster Session:

Date: Fri 5 Dec

Time: 4.30PM – 7.30PM

Place: Exhibit Hall C,D,E (San Diego)