Learning Federated Visual Prompt in Null Space for MRI Reconstruction

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https://github.com/chunmeifeng/FedPR

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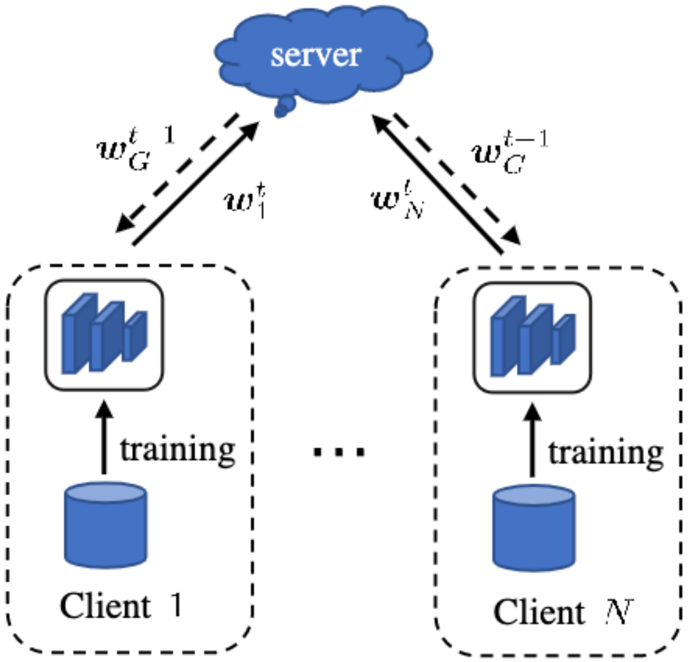
What is the federated learning?



Goals: To facilitate multi-institutional collaborations between data centers. Allowing ***collaborative and decentralized training*** of deep learning-based methods.

A classical FL method, **FedAvg**, **first** receives global model parameters from the server and initializes the client model parameters. **Then**, each client trains model locally on private data and sends the local model to the server. **Finally**, the server aggregates the local updates and further updates the global model by averaging the parameters which will be ***sent back*** to each client ***in the next round***.

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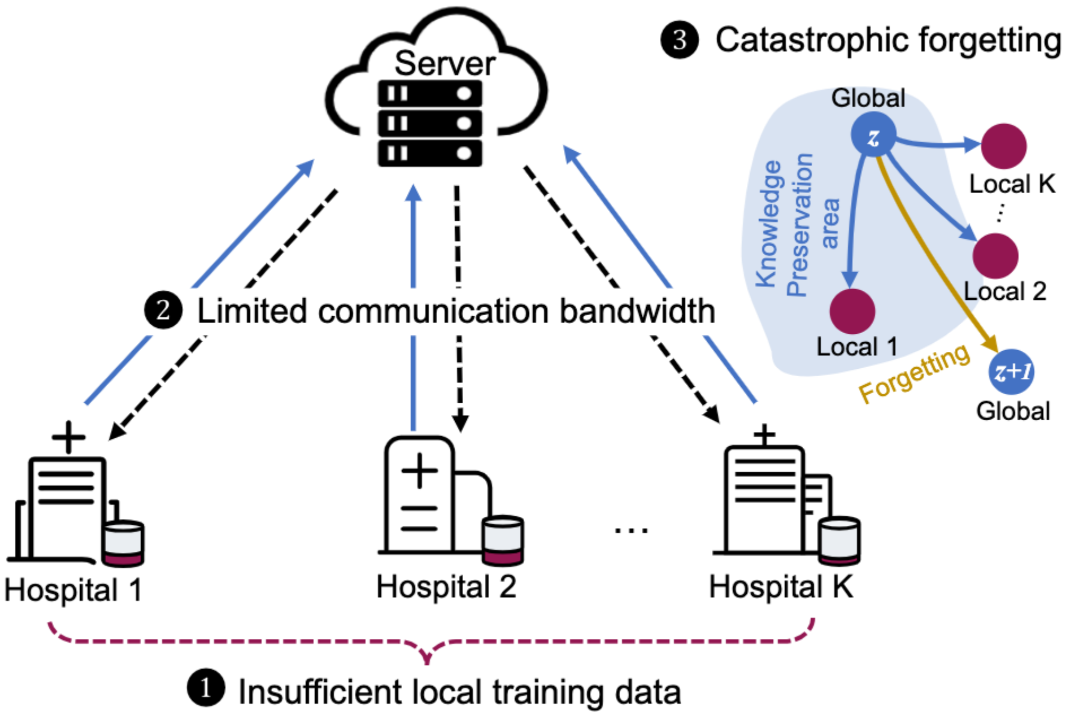

Figure 1. **Illustration** of the three **key issues** in federated MRI.

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❶ Insufficient local training data

❷ Limited communication bandwidth

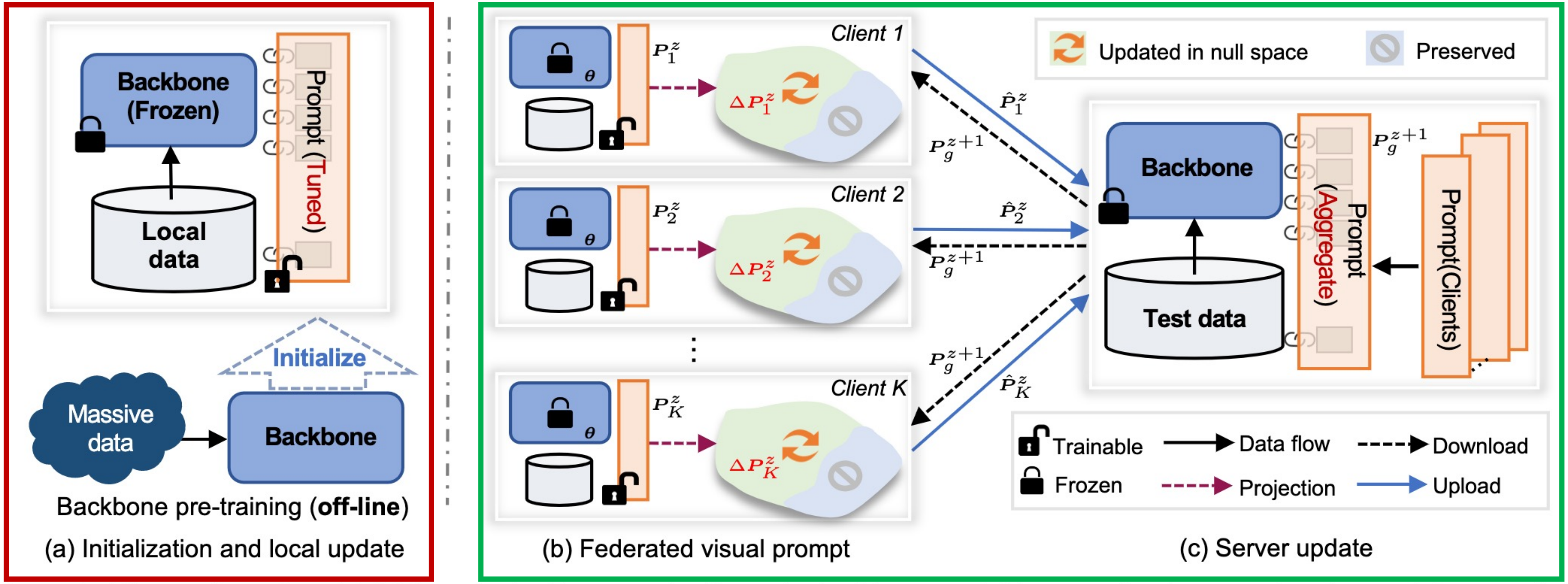

Figure 2. **Illustration** of our **FedPR** method. (a) For each client, the backbone model is pre-trained on massive data and fine-tuned via prompt (see Sec. 3.2). (b) *Federated visual prompt* is executed by updating the local prompt of each client only in the approximate null space of global prompts while preserving the *previously* acquired global knowledge (see Sec. 3.3). (c) Server update by aggregating local prompts.

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❸ Catastrophic forgetting

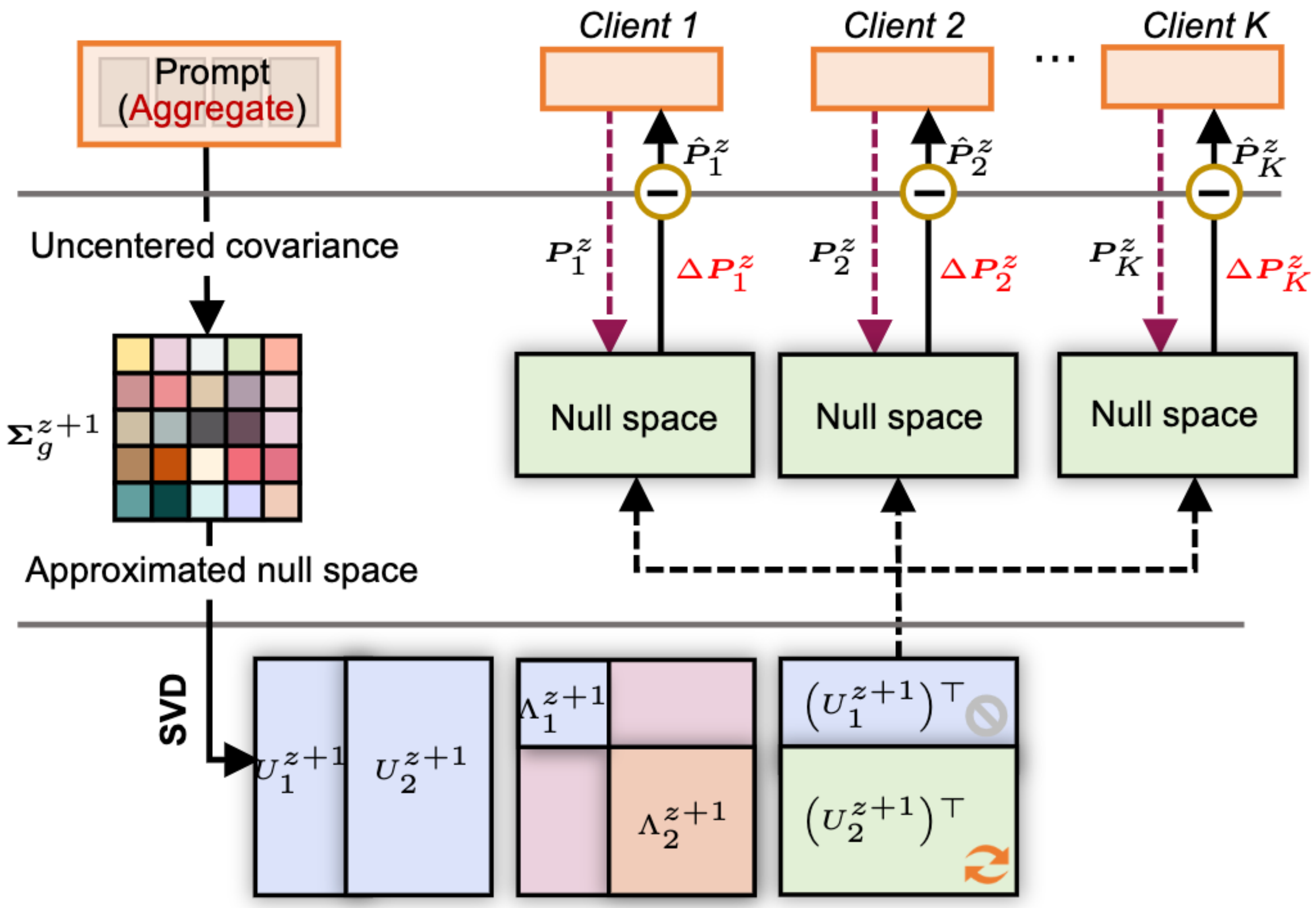

Figure 3. **Illustration** of **federated visual prompt** for updating local prompts in the null space of global prompts.

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Algorithm 1: FedPR

Input: Private datasets from K clients: $\mathcal{D}^1, \mathcal{D}^2, \ldots, \mathcal{D}^K$, local updates T, communication rounds Z, pre-trained model parameters $\boldsymbol{\theta}$, prompt embeddings $\boldsymbol{P}$, learning rate η, hyperparameter γ;

// **ServerExecution:**

Initialize global prompt $\boldsymbol{P}_g$ with parameters $\boldsymbol{\theta}$.

for *each communication round* $z \in \{1, 2, ..., Z\}$ **do**

  for *each client* $k \in \{1, 2, ...K\}$ *in parallel* **do**

    $\boldsymbol{P}_k^z \leftarrow \boldsymbol{P}_g^z$;

    $\hat{\boldsymbol{P}}_k^z \leftarrow \text{LocalUpdate}(k, \boldsymbol{P}_k^z)$;

  end

  $\boldsymbol{P}_g^{z+1} \leftarrow \sum_{k=1}^{K} \frac{|\mathcal{D}^k|}{|\mathcal{D}|} \hat{\boldsymbol{P}}_k^z$;

  Compute the uncentered covariance matrix:

  $\boldsymbol{\Sigma}_g^{z+1} = \left(\boldsymbol{P}_g^{z+1}\right)^\top \boldsymbol{P}_g^{z+1}$;

  Approximate the null space of $\boldsymbol{\Sigma}_g^{z+1}$:

  $\boldsymbol{\Sigma}_g^{z+1} = \boldsymbol{U}^{z+1} \boldsymbol{\Lambda}^{z+1} \left(\boldsymbol{U}^{z+1}\right)^\top$;

  Select the smallest diagonal singular values of $\boldsymbol{\Lambda}_2^{z+1}$ with the ratio of γ;

  Get $\boldsymbol{U}_2^{z+1}$ corresponding to $\boldsymbol{\Lambda}_2^{z+1}$.

end

return $\boldsymbol{P}_g^{z+1}$

// **LocalUpdate** $(k, \boldsymbol{P}_k)$**:**

for *each local epoch* $t \in \{1, 2, ...T\}$ **do**

  Get the updated parameters $\Delta \boldsymbol{P}_k^z$:

  $\Delta \boldsymbol{P}_k^z = \boldsymbol{U}_2^{z+1} \left(\boldsymbol{U}_2^{z+1}\right)^\top \boldsymbol{P}_k^z$;

  $\hat{\boldsymbol{P}}_k^{z,t+1} \leftarrow \boldsymbol{P}_k^{z,t} - \eta_k \Delta \boldsymbol{P}_k^{z,t}$;

end

return $\hat{\boldsymbol{P}}_k^z$

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Table 1. **Quantitative comparison** of state-of-the-art FL methods with regard to `In-Federation` and `Out-of-Federation` scenarios, where **# Com.cost** is the communication cost, Ub indicates the upper-bound of FL algorithms, ↑ and ↓ indicate increments and decrements compared with FedAvg (*w.* FFt). Detailed analyses are provided in Sec. 4.2.

Method	# Com.cost	In-Federation			Out-of-Federation		
		PSNR	SSIM	NMSE	PSNR	SSIM	NMSE
SingleSet	18.43 M	28.79(3.35)↓	0.805(0.099)↓	0.021(0.011)↓	28.92(2.15)↓	0.808(0.091)↓	0.032(0.011)↓
Centralized (Ub)	18.43 M	36.71(4.57)↑	0.947(0.044)↑	0.009(0.005)↑	35.73(4.66)↑	0.940(0.041)↑	0.008(0.013)↑
FedAvg (*w.* FFt) [22]	18.43 M	32.14(0.00)	0.903(0.000)	0.010(0.000)	31.07(0.00)	0.899(0.000)	0.021(0.000)
FedBN [18]	18.69 M	28.31(3.83)↓	0.817(0.086)↓	0.044(0.034)↓	25.65(5.42)↓	0.731(0.186)↓	0.080(0.059)↓
FedProx [17]	18.43 M	32.84(0.70)↑	0.901(0.002)↑	0.010(0.000)	31.98(0.91)↑	0.905(0.006)↑	0.018(0.003)↑
SCAFFOLD [12]	18.43 M	33.08(0.94)↑	0.914(0.010)↑	0.009(0.001)↑	32.20(1.13)↑	0.915(0.016)↑	0.018(0.003)↑
MOON [16]	18.43 M	34.06(1.92)↑	0.927(0.023)↑	0.008(0.002)↑	31.16(0.09)↑	0.907(0.008)↑	0.023(0.002)↓
FedReg [35]	18.43 M	33.29(1.15)↑	0.890(0.013)↑	0.009(0.001)↑	32.41(1.34)↑	0.907(0.008)↑	0.017(0.004)↑
FL-MRCM [9]	18.43 M	33.60(1.46)↑	0.922(0.019)↑	0.013(0.003)↓	32.72(1.65)↑	0.911(0.012)↑	0.016(0.005)↑
FedMRI [7]	17.46 M	33.35(1.21)↑	0.923(0.020)↑	0.014(0.004)↓	32.00(0.93)↑	0.914(0.015)↑	0.019(0.002)↑
`Ours` (*w.* Pro)	**0.11** M	35.29(3.15)↑	0.927(0.024)↑	0.009(0.001)↑	34.65(3.58)↑	0.921(0.022)↑	0.010(0.011)↑
`Ours` (Full)	**0.11** M	**36.43**(4.30)↑	**0.945**(0.042)↑	**0.007**(0.003)↑	**35.60**(4.53)↑	**0.939**(0.040)↑	**0.008**(0.013)↑

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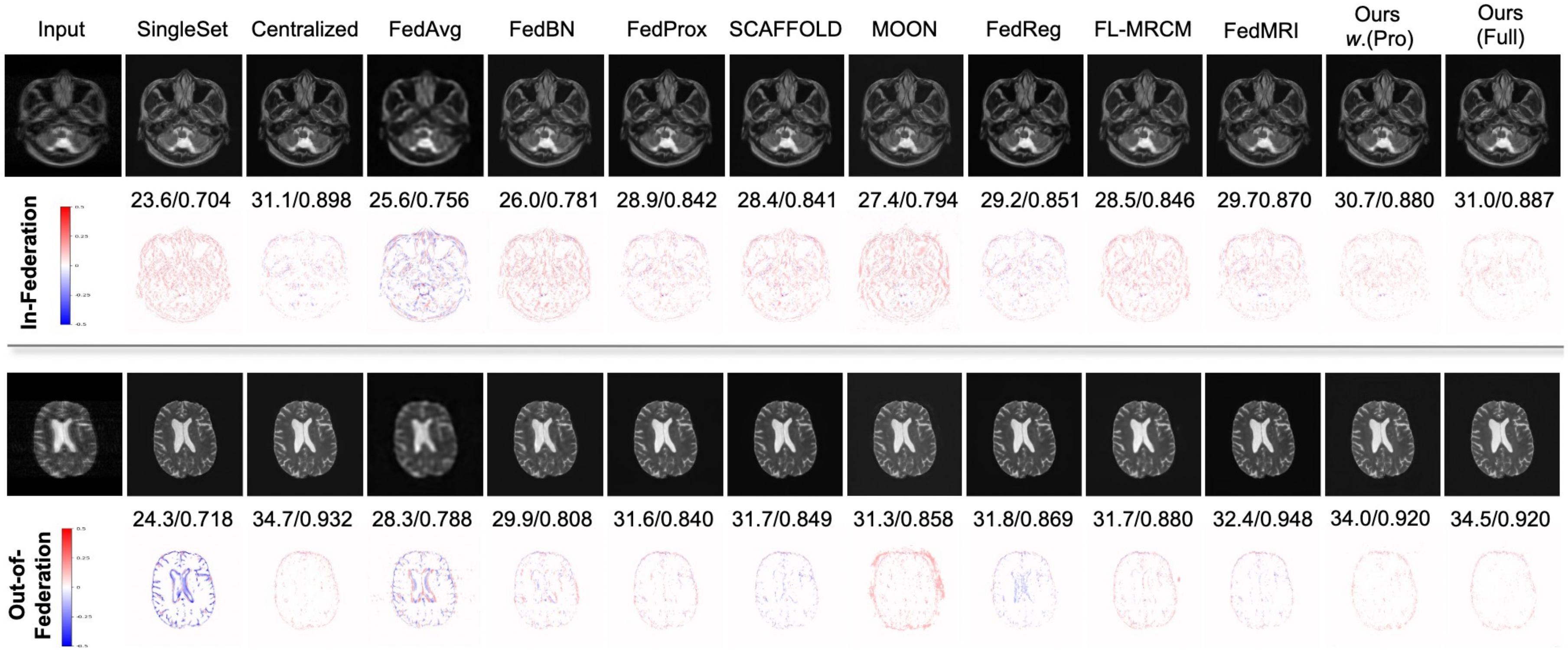

Figure 4. **Qualitative comparison** of different algorithms in terms of reconstruction images and error maps with corresponding quantitative measurements in PSNR/SSIM under `In-Federation` and `Out-of-Federation` scenarios. The less texture in the error map, the better reconstruction quality.

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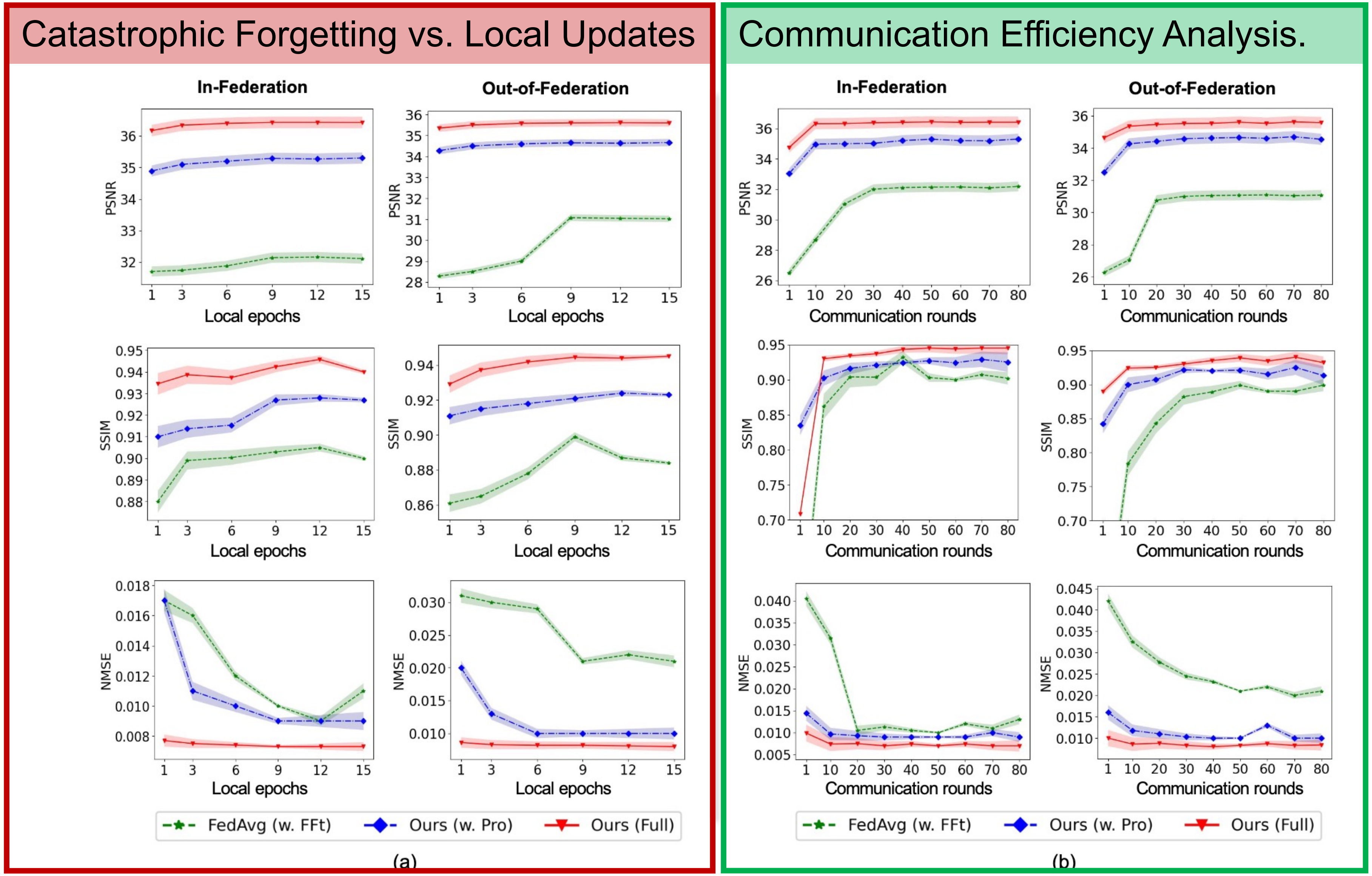

Figure 5. **Reconstruction accuracy** of FedAvg (*w.* FFt), **Ours** (*w.* Pro), and **Ours** (Full) versus **(a)** local epochs and **(b)** communication rounds under `In-Federation` and `Out-of-Federation` scenarios.

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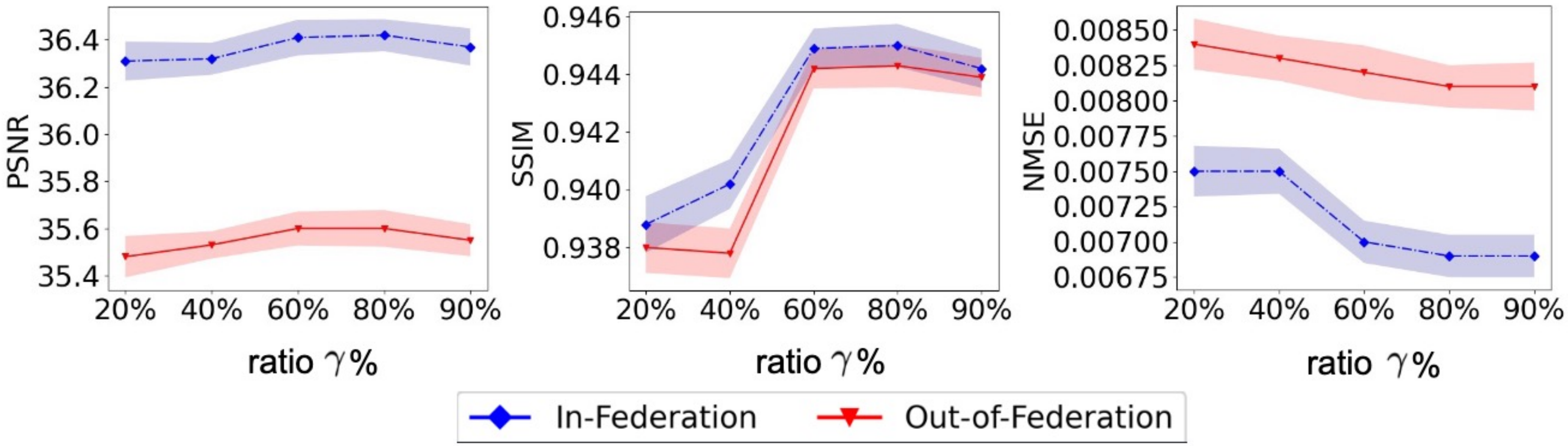

Figure 6. Analysis of the **ratio** γ % of the approximate null space in terms of PSNR, SSIM, and NMSE.

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Thanks!