

## Purpose

- Magnetic resonance imaging (MRI) scan times are relatively slow, especially for dynamic acquisitions like in the heart
- Scan time can be accelerated by compressed sensing<sup>1</sup> (CS) schemes that exploit data redundancy to reconstruct undersampled MR images
- However, CS-based reconstruction times are long because they employ iterative algorithms to solve optimization problems
- Critical time between patient exam and diagnosis is extended by hours – making MRI infeasible for urgent clinical situations

Goal: Use convolutional neural networks to efficiently and accurately reconstruct *highly* undersampled dynamic MRI data

## Background

- CS-based image reconstruction<sup>1</sup> is based on iteratively solving non-linear inverse problems of the form:

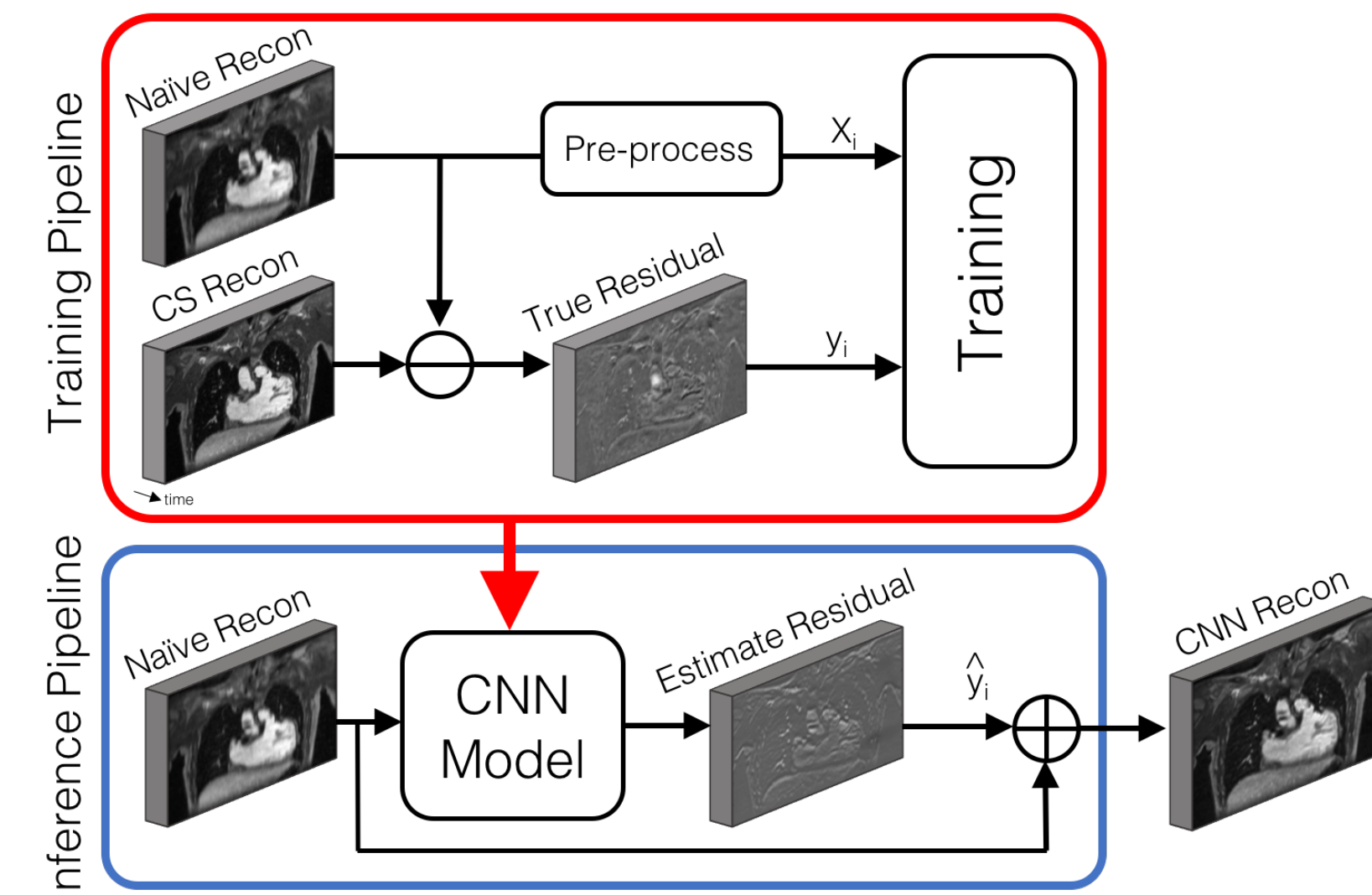
$$\text{minimize}_x \|\mathcal{F}_s x - y\|_2^2 + \lambda \|\phi(x)\|_1$$

- CNNs are well-suited for modelling this task<sup>2</sup> and have previously been used to learn CT<sup>3</sup> and MRI<sup>4</sup> static CS recon pipelines

- Still many questions: Similar performance for dynamic data? Best loss function to train on? Upper limit for undersampling? How to evaluate CNN reconstructions?

## Methodology

### Deep Reconstruction Workflow:



## 4-D cardiac MRI datasets:

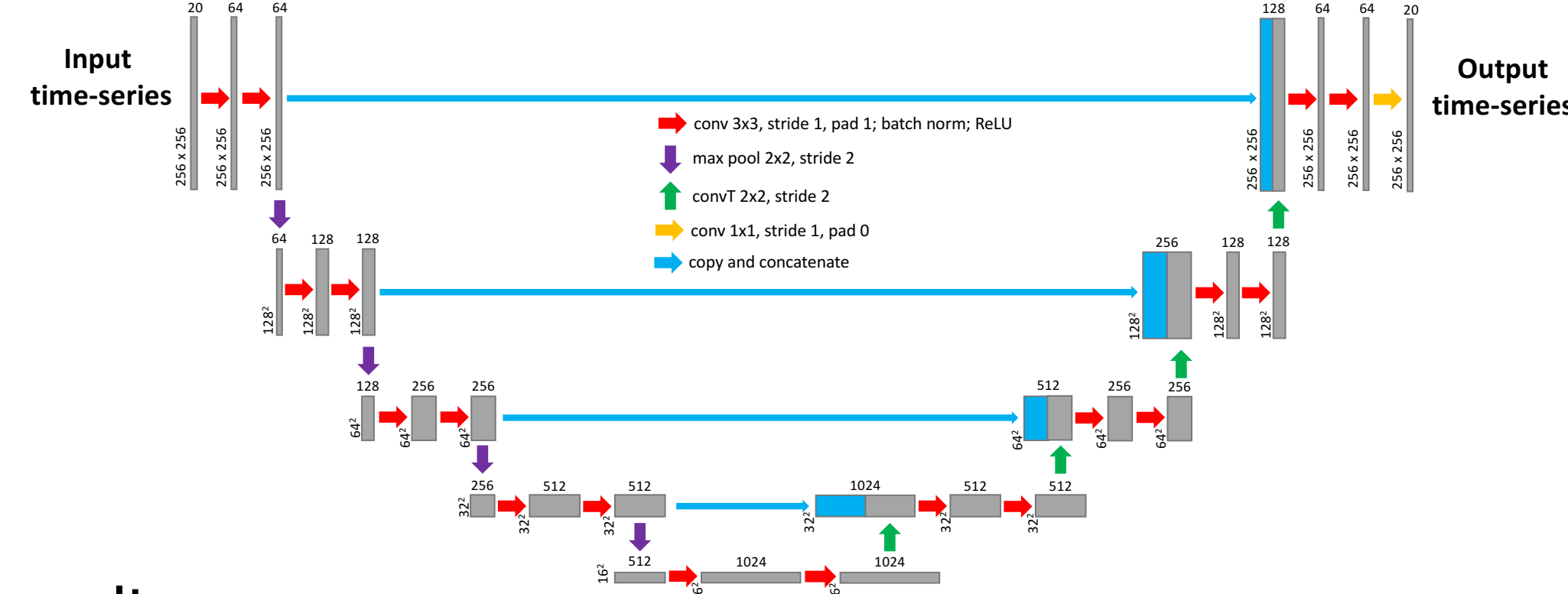
(Courtesy of Dr. Shreyas Vasanawala)



- Each dataset is expanded into  $N=896$  (2D+time) examples
- Each example has 20 time frames (50 ms temporal resolution)
- Datasets are *not* fully sampled, but are diagnostic quality
- Acquisition time: ~15 min, CS reconstruction time: ~2 hours

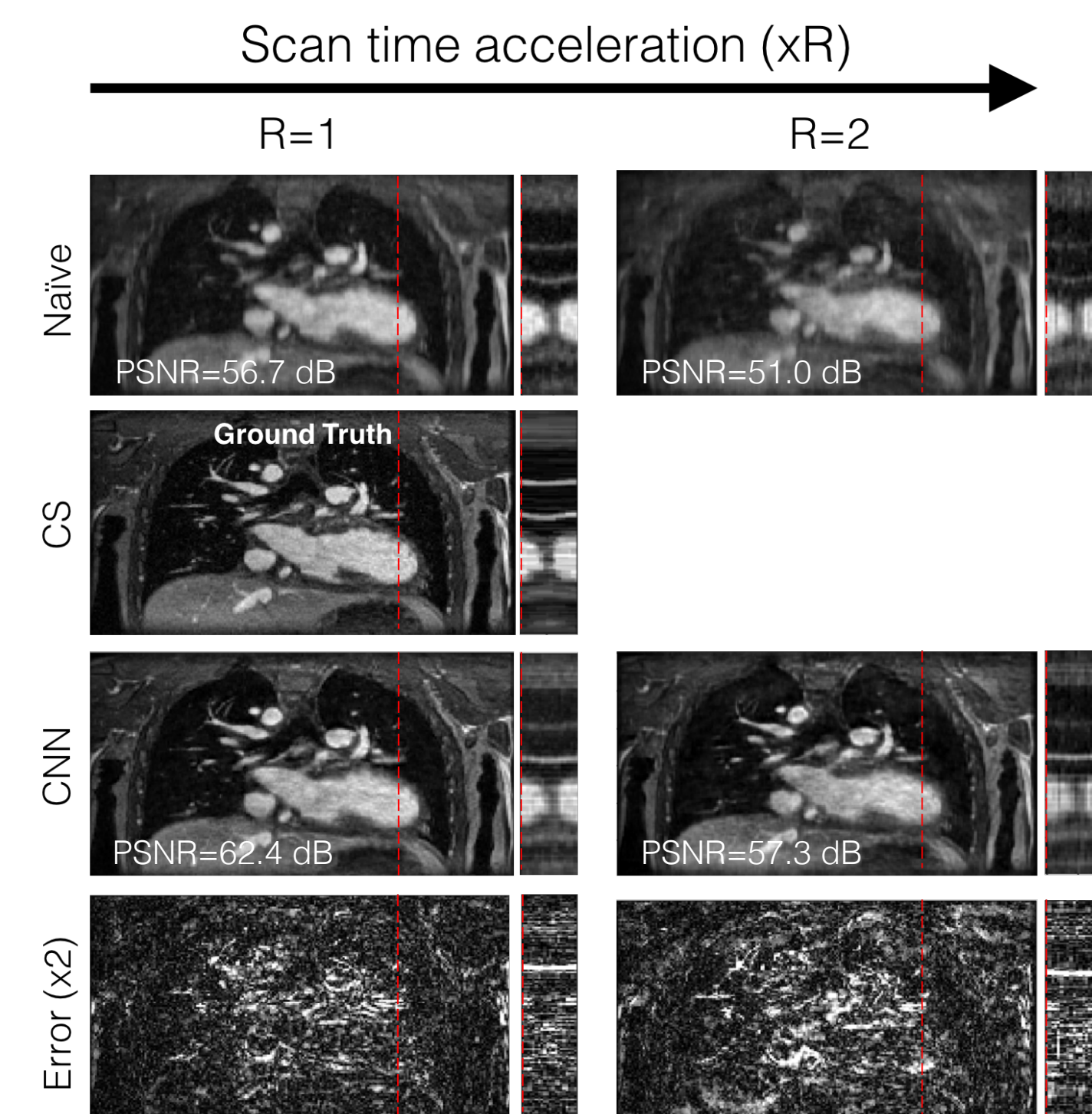
$N_{\text{train}} = 2688$   
 $N_{\text{val}} = 896$   
 $N_{\text{test}} = 896$

## Modified U-net<sup>5</sup> architecture:



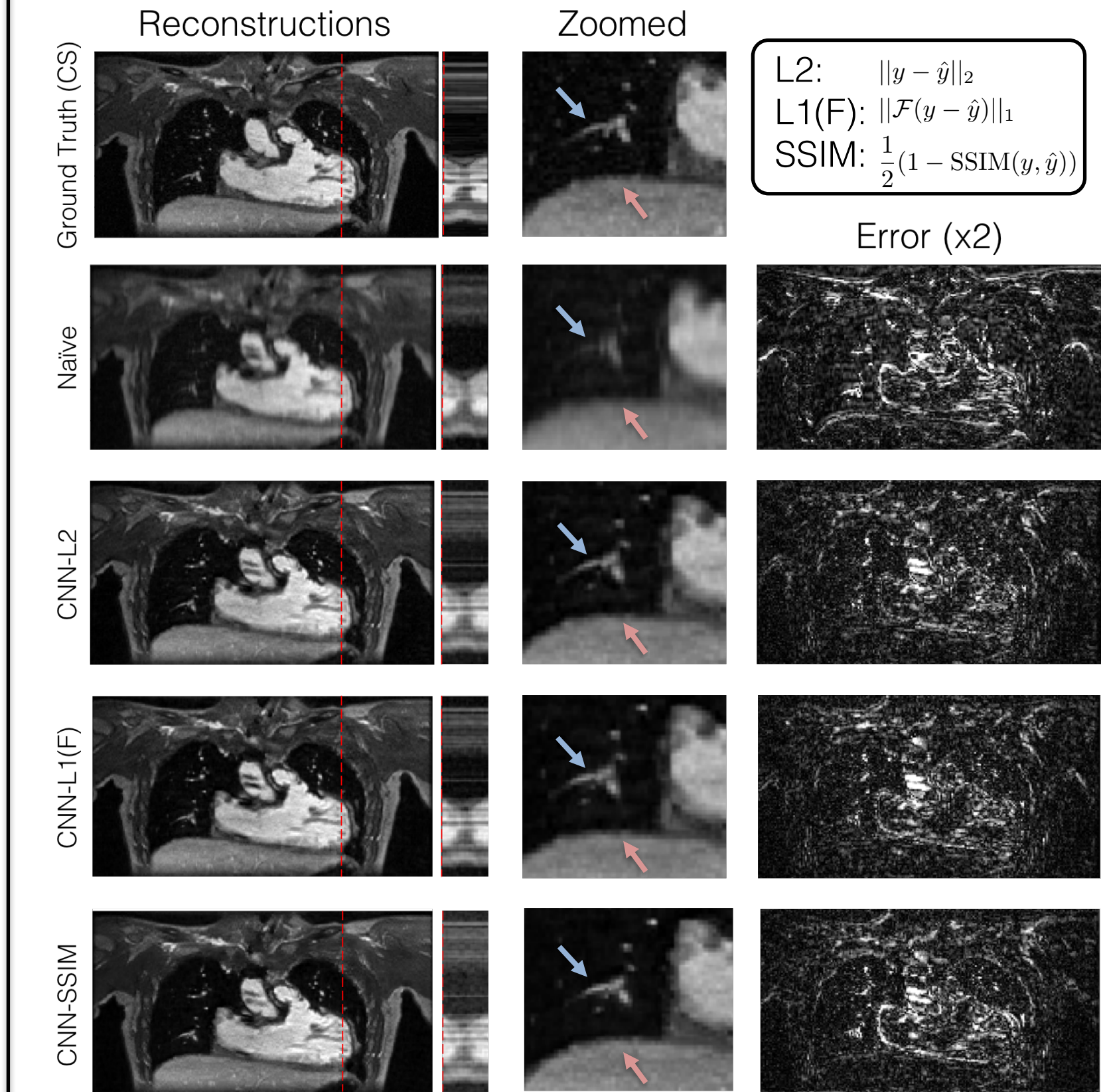
## Results

### Experiment #1: Can CNN reconstruct undersampled data better than CS?



- Used L2 loss
- Ground truth is diagnostic quality CS recon
- CNN outperforms Naïve recon by ~6 dB

## Experiment #2: Does loss function impact image quality?



$$L2: \|y - \hat{y}\|_2$$

$$L1(F): \|\mathcal{F}(y - \hat{y})\|_1$$

$$SSIM: \frac{1}{2}(1 - SSIM(y, \hat{y}))$$

### Performance Statistics:

	PSNR (dB)	SSIM	Speed
CS (Truth)	-	-	2hr19 m
Naïve	57.792	0.629	3s
CNN-L2	<b>62.976</b>	0.734	57s
CNN-L1(F)	62.923	<b>0.743</b>	53s
CNN-SSIM	62.526	0.720	200s

- L1 / L2 similar performance
- SSIM better at preserving structure and edges

## Discussion / Conclusions

- We present a CNN model that can reconstruct dynamic MR images comparable to standard techniques in under one minute (150x faster than CS)
- Potential to *also* accelerate scan time (2x faster than standard)
- Not able to resolve temporal dynamics well – look to RNNs?
- CNNs provide faster scan and recon times – potential to make MRI cheaper and more feasible in urgent clinical situations

## References

[1] M Lustig, et al. "Compressed sensing MRI." IEEE signal processing magazine, 2008. [2] K Gregor, and Y LeCun. "Learning fast approximations of sparse coding." ICML, 2010. [3] KH Jin, et al. "Deep Convolutional Neural Network for Inverse Problems in Imaging." arXiv, 2016. [4] K Hammernik, et al. "Learning a Variational Network for Reconstruction of Accelerated MRI Data." arXiv, 2017. [5] O Ronneberger, et al. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical Image Computing and Computer-Assisted Intervention. 2015