Reversible Networks make 3D Image-to-Image Translation **Memory-Efficient**

Chest CT Super-resolution and Domain-adaptation using Memory-efficient 3D Reversible GANs

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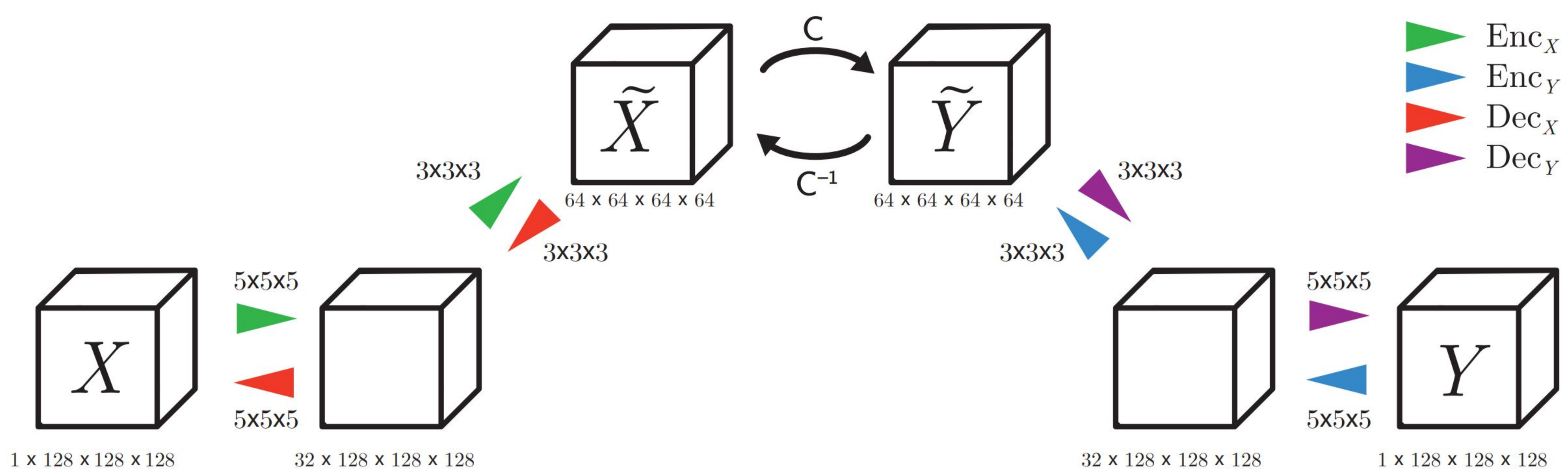
HOW REVGAN WORKS



OBJECTIVE

Image-to-image translation losses from Pix2pix [2] for paired and CycleGAN [3] for unpaired:

$$L_{\text{paired}}(F,G) = L_{\text{GAN}}(G,D_X) + L_{\text{GAN}}(F,D_Y) + \lambda(L_{\text{L1}}(F,X,Y) + L_{\text{L1}}(G,X,Y))$$

$$L_{\text{unpaired}}(F,G) = L_{\text{GAN}}(G,D_X) + L_{\text{GAN}}(F,D_Y)) + \lambda L_{\text{cyc}}(G,F)$$

INTRO

Reversible layers can be effectively used to make image-to-image models more **memory-efficient.**
This allows us to train deep models on memory-intensive **3D medical data.**

PROS

- Equivalent or improved performance
- More memory-efficient
- Works in 3D

CONS

- Trade-off between computation time and memory savings

RESULTS: MEMORY-EFFICIENCY

Depth	Model	Activations (Ours)	Activations (Naive)
0	630.0	+ **2312.4**	(+ 2316.6)
1	644.0	+ **2312.4**	(+ 2719.2)
2	652.0	+ **2312.4**	(+ 3919.3)
4	700.0	+ **2312.4**	(+ 4319.2)
8	748.0	+ **2312.4**	(+ 5519.5)

Table 1: Memory usage (MiB) of 3D-RevGAN (lower is better)

REVERSIBLE LAYERS

For the core we use reversible residual layers using a technique known as *additive coupling* [4, 5]:

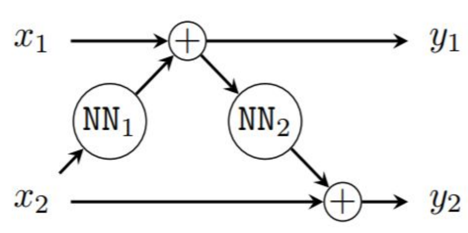


Figure 1a:
Forward additive coupling

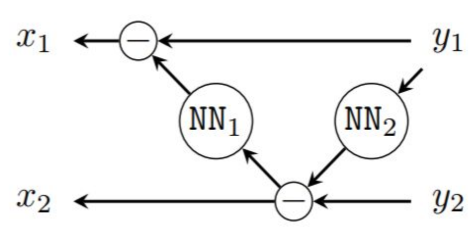


Figure 1b:
Inverse additive coupling

RESULTS: QUANTITATIVE PERFORMANCE

Model	Super-resolution (LR→HR)			Domain-adaptation (B50f→B30f)		
	MAE	PSNR	SSIM	MAE	PSNR	SSIM
Unpaired	0.24 ± 0.007	15.43 ± 0.39	0.44 ± 0.008	0.14 ± 0.003	14.56 ± 0.22	0.28 ± 0.004
Unpaired+2R	$\mathbf{0.23} \pm 0.014$	$\mathbf{16.43} \pm 0.44$	$\mathbf{0.50} \pm 0.024$	$\mathbf{0.13} \pm 0.003$	$\mathbf{17.44} \pm 0.20$	$\mathbf{0.29} \pm 0.003$
Paired	0.18 ± 0.001	15.89 ± 0.16	0.46 ± 0.008	0.14 ± 0.001	18.29 ± 0.15	0.33 ± 0.007
Paired+2R	$\mathbf{0.15} \pm 0.000$	$\mathbf{18.19} \pm 0.08$	$\mathbf{0.48} \pm 0.008$	$\mathbf{0.10} \pm 0.001$	$\mathbf{23.24} \pm 0.16$	$\mathbf{0.46} \pm 0.009$

Table 2: Quantitative results on super-resolution and domain-adaptation tasks

RESULTS: QUALITATIVE PERFORMANCE

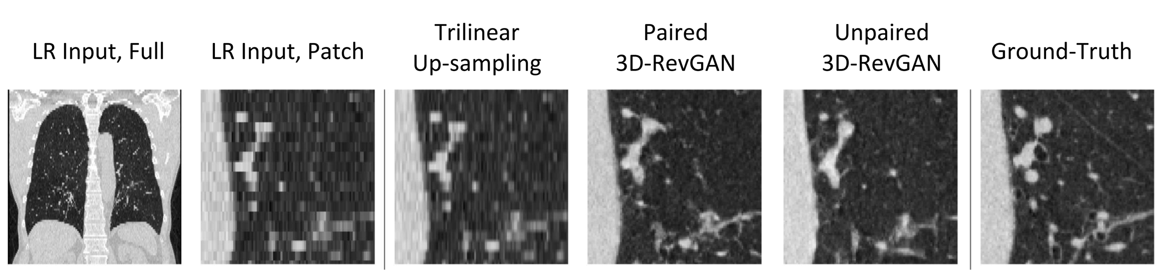


Figure 2: Qualitative results on super-resolution task

SUPER-RESOLUTION DATASET

18 train volumes and 5 test volumes.
Total 671 (±49) slices of size 1024 × 1024.
High-end Canon CT scanner (Aquilion ONE).
Train for 125 epochs on 128×128×128 patches.
Normalized to [-1, 1], uniformly from [-1150, 350] HU.
Down-sampling 4 times in z-dim, 2 times in x-dim and y-dim.

DOMAIN-ADAPTATION DATASET

17 train volumes and 3 test volumes from NLST Dataset.
Siemens scanner in both smooth (B30f) and sharper (B50f) reconstruction kernel.
Each scan contains an average of 169 (±14.7) axial 512×512 slices.
We train for 125 epochs on 64×64×64 patches.
Normalized to [-1, 1], uniformly from [-1150, 350] HU.

PROJECT WEBSITE

The full paper, code and contact information can be found on the project website: https://tychovdo.github.io/RevGAN/midl/

REFERENCES

[1] Tycho F.A. van der Ouderaa, Daniel E. Worrall. "Reversible GANs for Memory-efficient Image-to-Image Translation", in CVPR 2019.
[2] Phillip Isola, et al. "Image-to-Image Translation with Conditional Adversarial Networks", in CVPR 2017.
[3] Jun-Yan Zhu, et al. "Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks" in ICCV 2017.
[4] L. Dinh, D. Krueger, and Y. Bengio. "NICE: Non-linear independent components estimation", 2015.
[5] Aidan N. Gomez, et al. "The Reversible Residual Network: Backpropagation Without Storing Activations", in NIPS 2017.

Take a picture to download paper and code

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