Semi-supervised Learning Approach to Generate Neuroimaging Modalities with Adversarial Training

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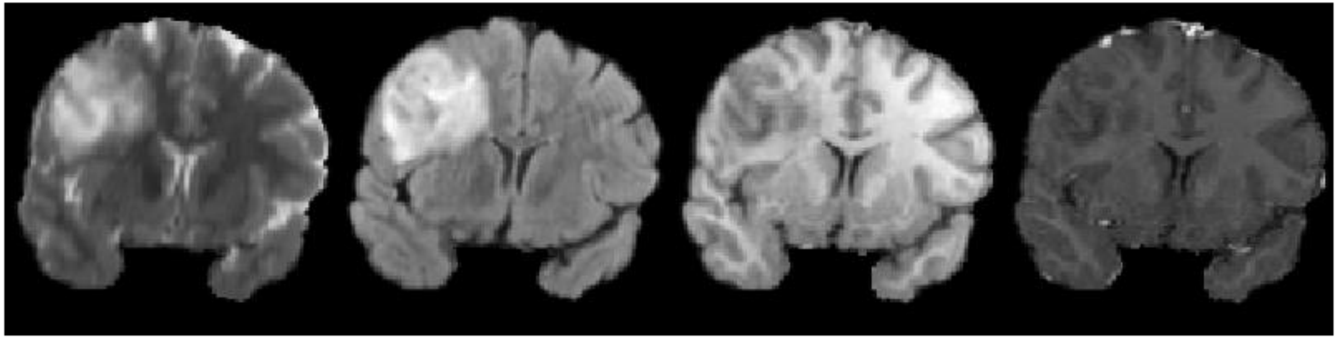
Motivation

- Brain MRI scans come in multiple modalities
- Current state-of-the-art models require multiple modalities
- Expensive, time consuming and sometimes missing



Motivation

– Neuroimaging datasets contain a combination of ***unpaired*** and ***paired***

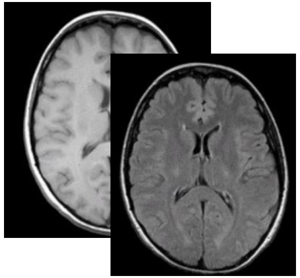
– Limits effectiveness of data driven models

– Usually number of *unpaired* > *paired*

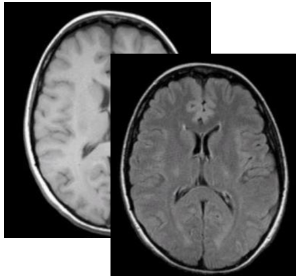
– Our model leverages both unpaired and paired data to impute missing data

Motivation

Paired examples

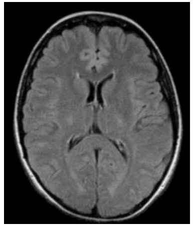


x_1

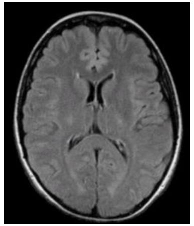


x_2

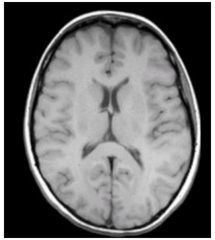
Unpaired examples



x_3



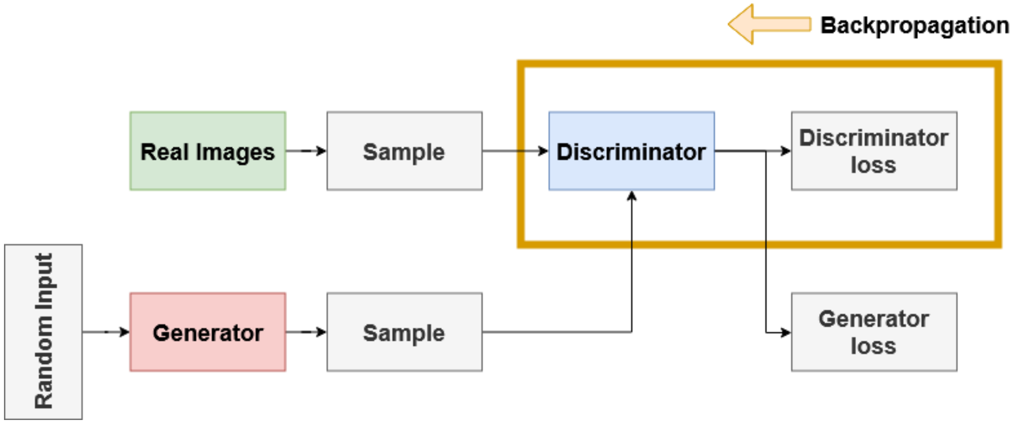
x_4



x_5

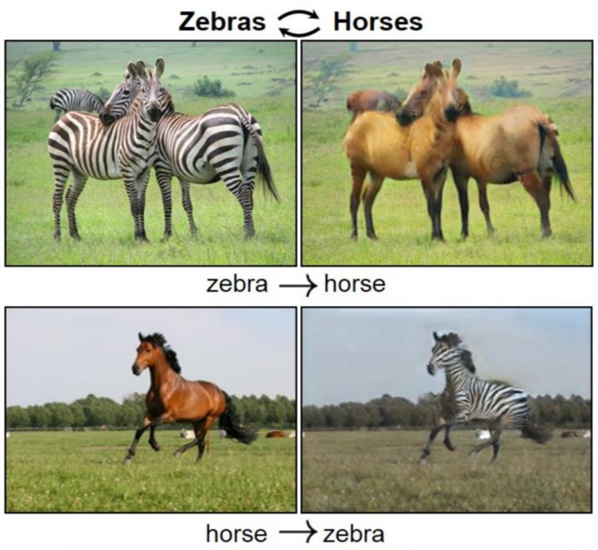
Previous work- GANS[1]

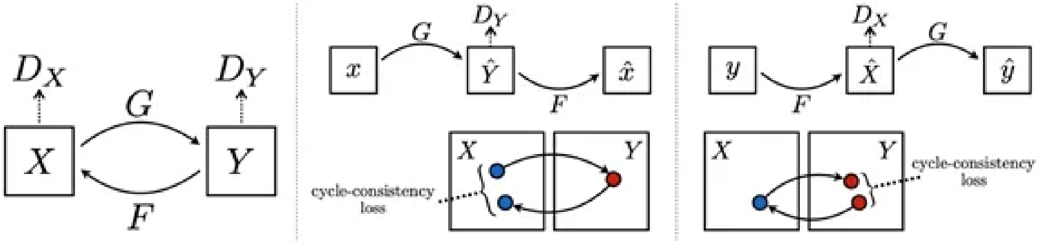
- Aim to generate samples from a given distribution
- Two networks:
  - Generator: Produces images to fool discriminator
  - Discriminator: Distinguishes between “real” examples and “fake” examples created by Generator



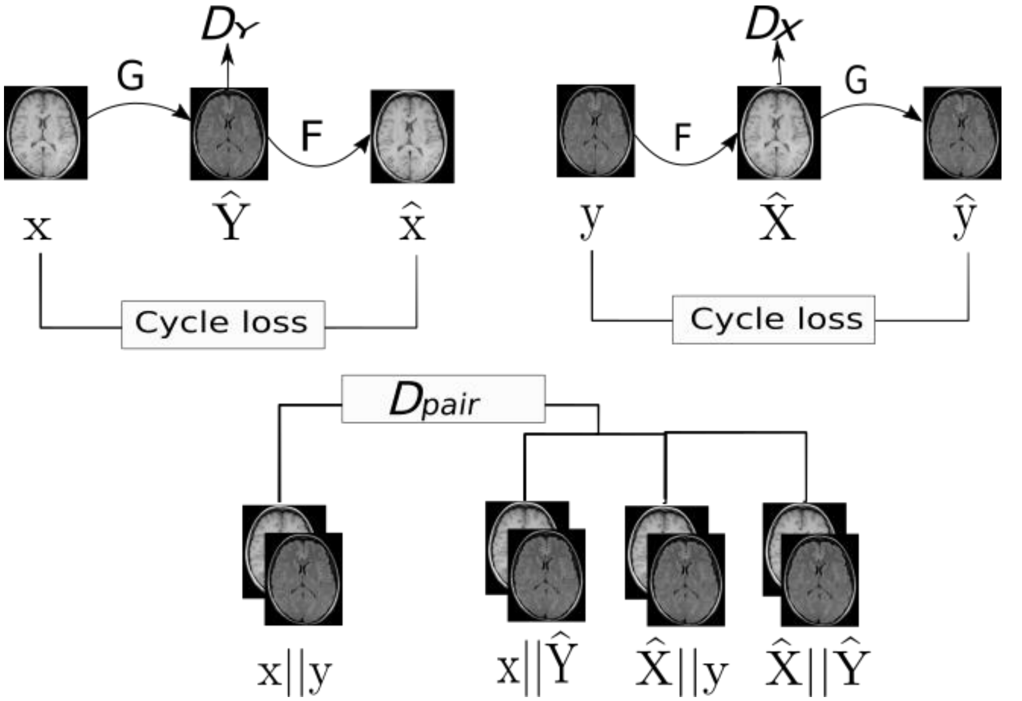
Previous work- CycleGAN

– CycleGAN[2] performs domain adaptation for unpaired datasets





Semi Supervised Adversarial CycleGAN (SSA-CGAN)



$$\mathcal{L}_{F_{Semi}} = \mathcal{L}_{F_{adv}} + \lambda \mathcal{L}_{cyc} + \alpha \mathcal{L}_{pair}$$

Previous work- CWRG

– Cycle Wasserstein Regression GAN (CWRG)[3] works with unpaired and paired data

– Generated samples of timeseries data from post and pre intervention of ICU patients and transcriptomics data for measuring gene expression

– Uses the l2-norm as a penalty term for the reconstruction of paired data

Experiment 1

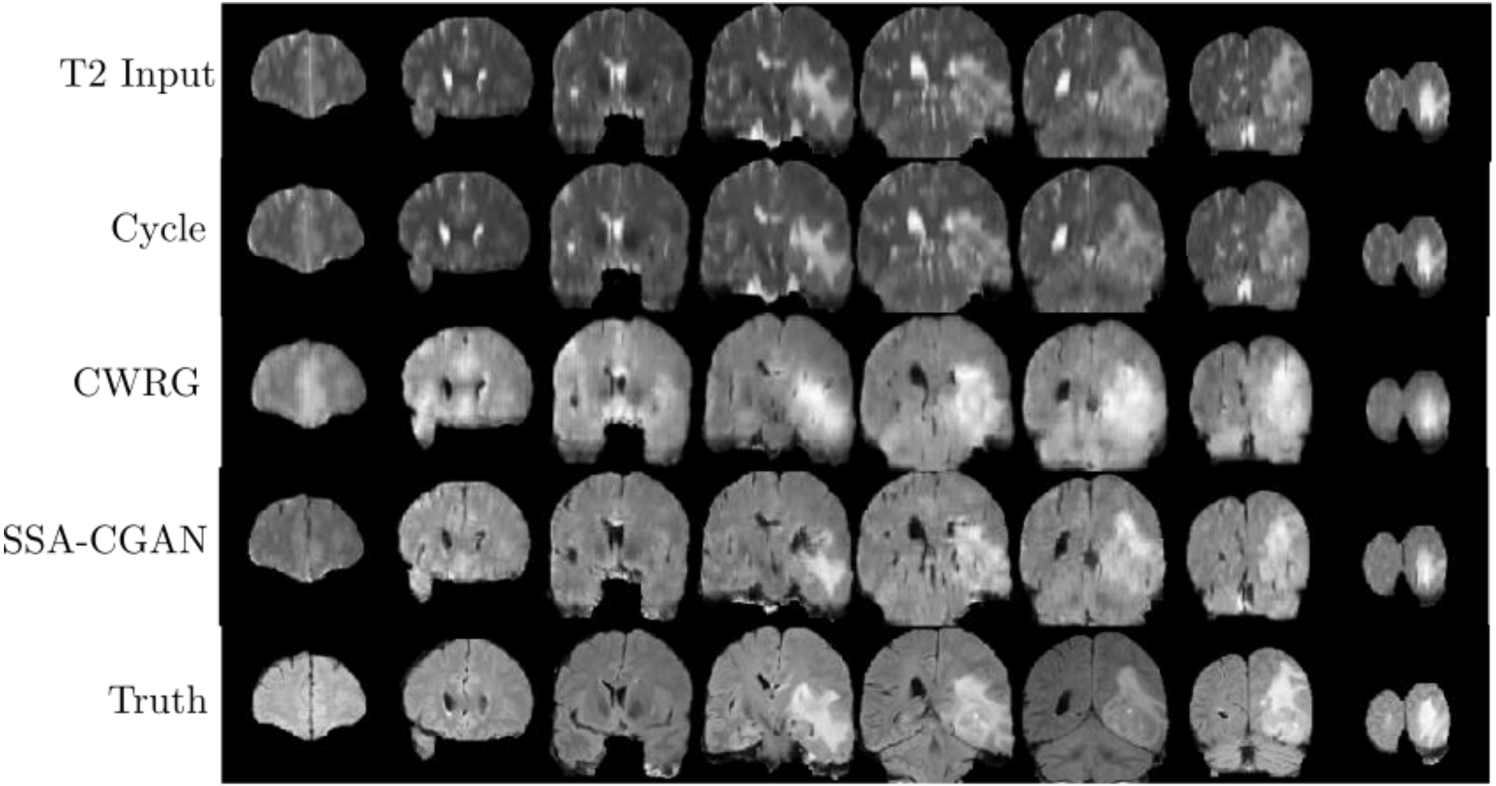
- Evaluate on BraTS (4 modalities) and ISLES (5 modalities) dataset
- MRI scans divided into 2D slices
- Divided X: 30%, Y: 30%, Pair: 10%, Val: 10%, Test: 20%

Dataset	N. modalities	N. examples	Slice type	Avg no. of slices
BraTS	4	285	Coronal	170
ISLES	5	38	Axial	18

Experiment 1

- Evaluate by learning a separate model for transforming from
  - BraTS: T2 $\Longleftrightarrow$ T1, Flair, T1c
  - ISLES: CBF $\Longleftrightarrow$ MTT, CBV, TTP, Tmax
- Compared against CycleGAN, CWRG and our model using only paired data SSA-CGAN-p

Experiment 1



Experiment 1

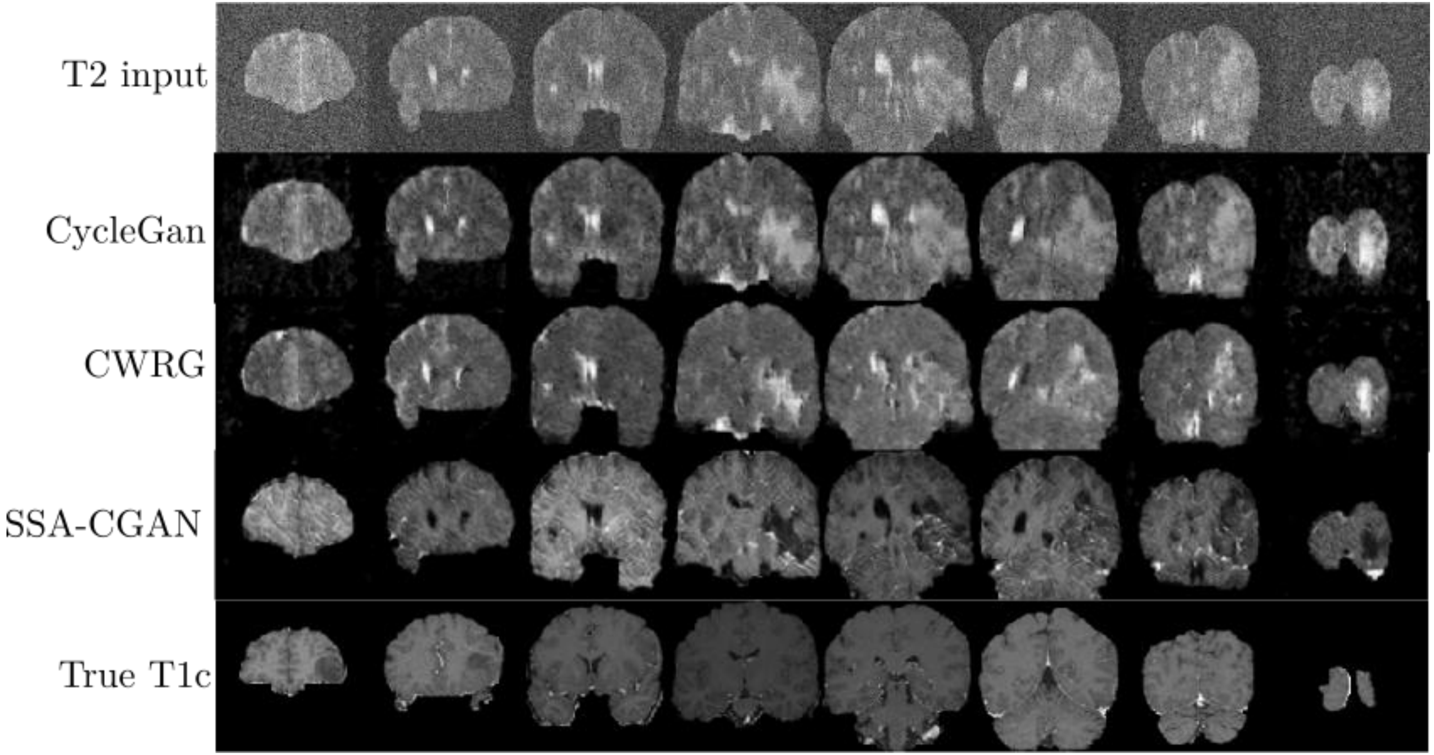
- Average reduction of 33.8%, 46.0% in MAE/MSE across all transformations
- Including unpaired data reduces 18.02 (MAE) and 28.16 (MSE) compared to paired

	Method	T1	T1c	FLAIR	MTT	rCBV	TTP	Tmax
MSE	Cycle	0.0314 ±0.0006	0.5301± 0.4880	0.7072± 0.3956	0.1280± 0.1603	0.2437± 0.3111	0.0616± 0.0017	0.1887± 0.1565
	CWRG	0.7503 ±0.1687	0.4607± 0.3602	0.6145± 0.4279	0.5803± 0.2688	0.6826± 0.2604	0.5785± 0.2945	0.4825± 0.1722
	SSA-CGAN-p	0.0234 ±0.0032	0.0160 ±0.0100	**0.0147± 0.0018**	0.0503± 0.0051	0.0262± 0.0017	0.0443 ±0.0085	0.0348± 0.0021
	SSA-CGAN	**0.0169± 0.0011**	**0.0102± 0.0024**	0.0177± 0.0071	**0.0271± 0.0007**	**0.0202± 0.0014**	**0.0210± 0.0011**	**0.0235± 0.0041**
MAE	Cycle	0.0608 ± 0.0041	0.4924± 0.4146	0.6231± 0.3264	0.2162± 0.1610	0.4236 ± 0.2957	0.1409± 0.0022	0.3048± 0.1939
	CWRG	0.6963± 0.3738	0.4564± 0.3868	0.5603 ±0.5564	0.6819±0.1240	0.7008 ±0.1478	0.5258±0.2860	0.5189±0.2800
	SSA-CGAN-p	0.0508±0.0037	0.0411±0.0118	**0.0390±0.0028**	0.1322±0.0059	0.0834±0.0029	0.1155±0.0118	0.0837±0.0048
	SSA-CGAN	**0.0436± 0.0011**	**0.0338± 0.0046**	0.0426± 0.0089	**0.0947± 0.0018**	**0.0720 ±0.0043**	**0.0754 ± 0.0026**	**0.0613 ±0.006[illegible]**

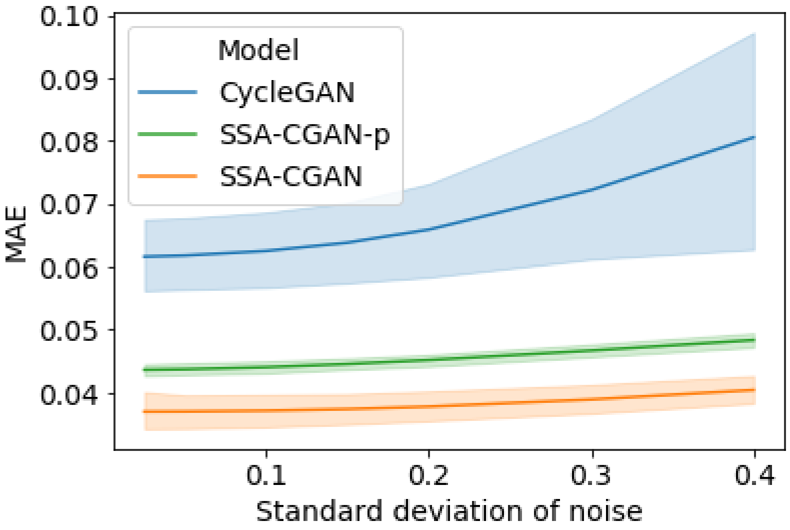
Experiment 2

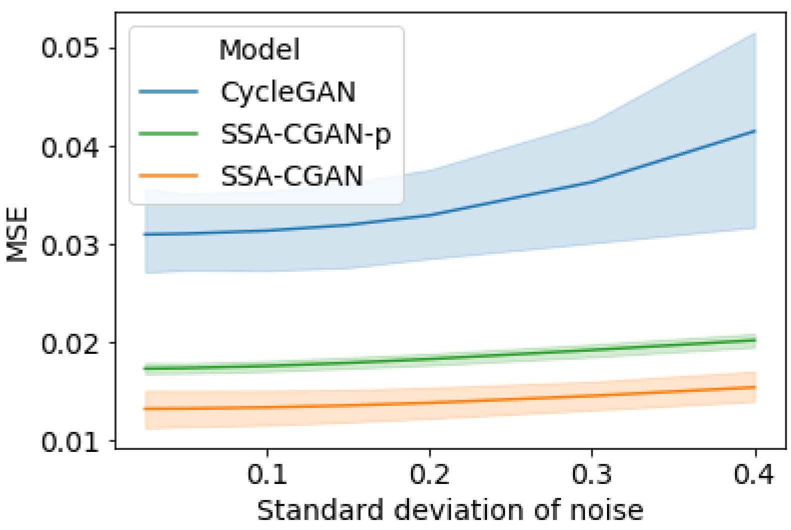
- Inject Gaussian noise to test data of various levels
- Simulate noisy conditions and evaluate robustness of models
- Models were not trained with noisy samples

Experiment 2



Experiment 2





Conclusion

- Neuroimaging data often has missing data
- Reduces effectiveness of data driven models
- SSA-CGAN uses paired and unpaired data to impute missing data
- Improves reconstruction and more robust

References

[1] Goodfellow, Ian, et al. "Generative adversarial nets." *Advances in neural information processing systems*. 2014.

[2] Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." *Proceedings of the IEEE international conference on computer vision*. 2017.

[3] McDermott, M.B., et al. “Semi-supervised biomedical translation with cycle wasserstein regression gans.” *Thirty-Second AAAI Conference on Artificial Intelligence* (2018)