Self-supervised representation learning from random data projectors

Yi Sui, Tongzi Wu, Jesse C. Cresswell, Ga Wu,
George Stein, Xiao Shi Huang, Xiaochen Zhang, Maksims Volkovs

Spotlight talk TRL@NeurIPS 2023
arXiv: 2310.07756
Code: github.com/layer6ai-labs/LFR

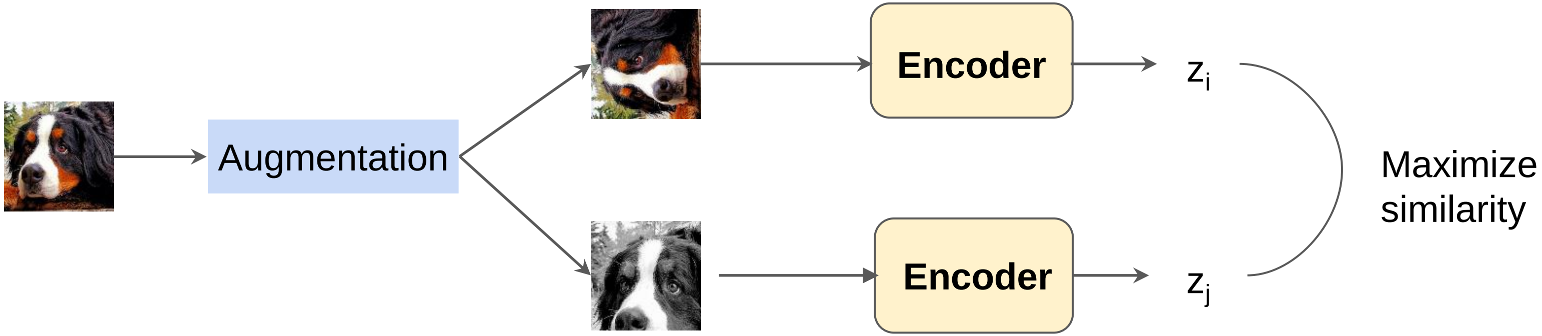
NEURAL INFORMATION PROCESSING SYSTEMS

DALHOUSIE UNIVERSITY
FACULTY OF COMPUTER SCIENCE

layer 6

Self-supervised representation learning

Learn representations from unlabelled data



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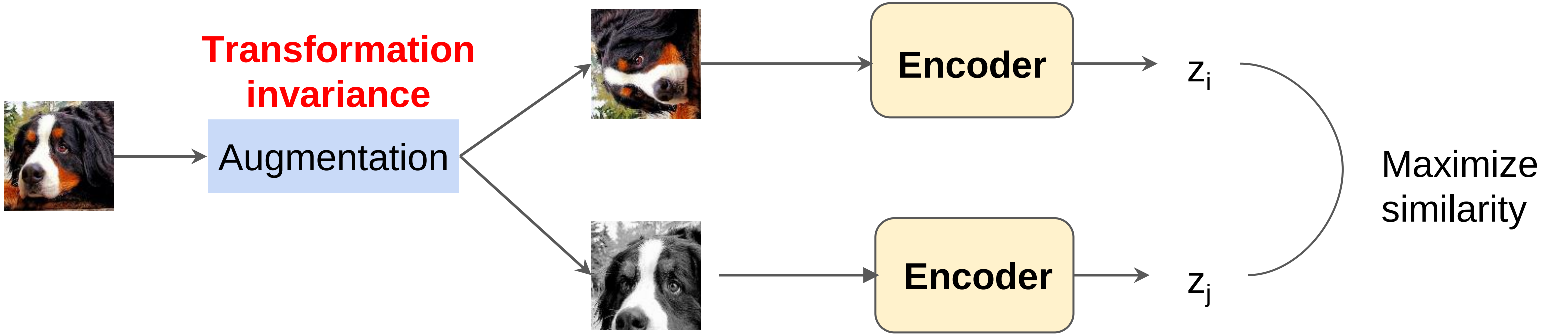

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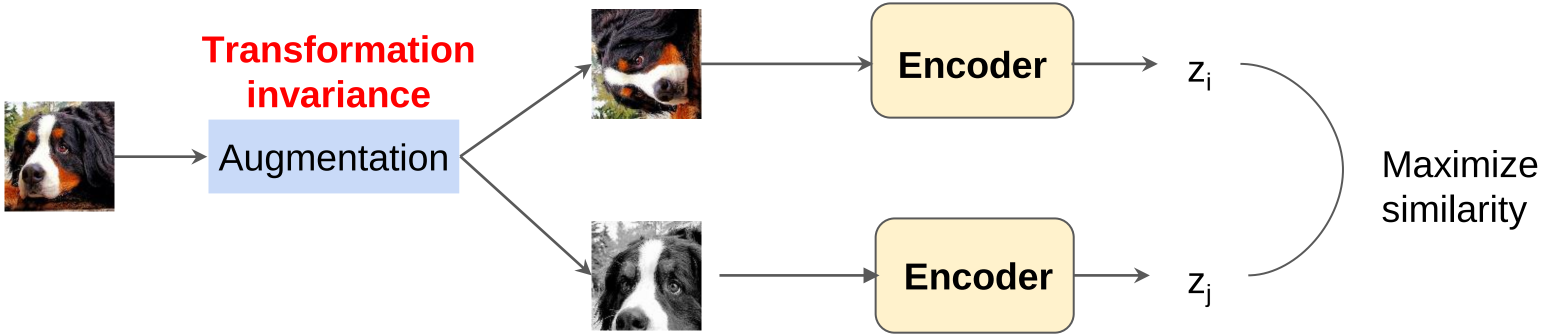
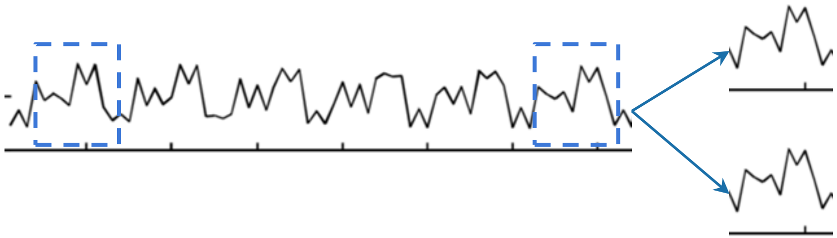


Effective augmentations are not always available



Mass	Velocity	Momentum
2	8	16
…	…	…

LFR (Learning From Randomness)

Domain agnostic representation learning ***without augmentations***

- A good representation should capture useful information that supports various downstream predictive tasks
- Use **random data projections** to simulate arbitrary downstream tasks

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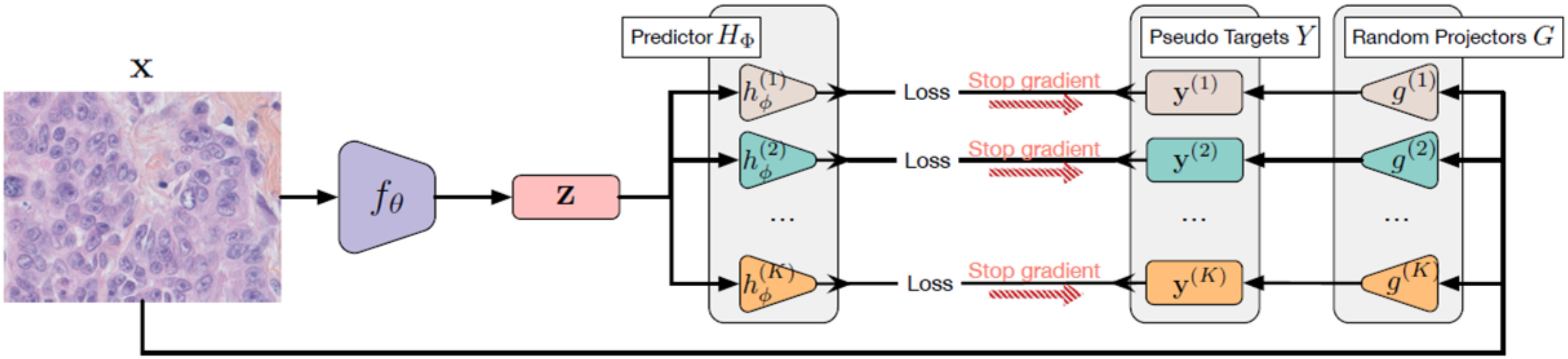

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Diverse projectors focus on different aspects

Similar projectors use redundant features

Linear evaluation performance on downstream tasks

		Time series			Tabular		
		HAR	Epilepsy	MIMIC-III	Income	Theorem	HEPMASS
	Log Reg	57.5 ± N/A	80.9 ± N/A	47.8 ± N/A	84.8 ± N/A	45.3 ± N/A	90.7 ± N/A
	Supervised	96.0 ± 0.6	98.3 ± 0.1	48.8 ± 0.0	81.5 ± 0.2	53.8 ± 0.5	91.5 ± 0.0
	Random Init	80.7 ± 2.3	89.1 ± 0.1	42.4 ± 1.1	83.1 ± 0.2	44.9 ± 0.8	84.3 ± 1.3
Domain-agnostic baselines	Autoencoder	77.2 ± 0.7	90.8 ± 1.3	44.9 ± 0.5	85.0 ± 0.1	50.0 ± 0.4	**90.7 ± 0.0**
	DIET	88.6 ± 1.3	96.8 ± 0.3	33.8 ± 5.2	82.2 ± 0.4	47.1 ± 0.5	-
	DACL	90.7 ± 0.4	97.5 ± 1.5	40.9 ± 0.6	79.8 ± 0.7	47.6 ± 1.0	88.7 ± 0.8
Domain-specific baselines	SimSiam	65.1 ± 0.8	97.4 ± 0.0	41.0 ± 1.9	79.2 ± 1.9	40.9 ± 0.9	85.3 ± 3.1
	SimCLR	87.8 ± 0.4	97.4 ± 0.2	44.1 ± 0.1	-	-	-
	SCARF	-	-	-	84.2 ± 0.1	48.5 ± 1.0	90.1 ± 0.1
	STab	-	-	-	84.2 ± 0.3	50.7 ± 0.7	83.6 ± 1.7
	TS-TCC	91.2 ± 0.8	97.6 ± 0.2	38.5 ± 1.3	-	-	-
	LFR (Ours)	**93.1 ± 0.5**	**97.9 ± 0.2**	**46.6 ± 0.3**	**85.2 ± 0.1**	**51.6 ± 0.7**	90.1 ± 0.2

Results for image modality also available, see preprint on arXiv: 2310.07756