Self-supervised representation learning from random data projectors

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arXiv: 2310.07756
Code: github.com/layer6ai-labs/LFR

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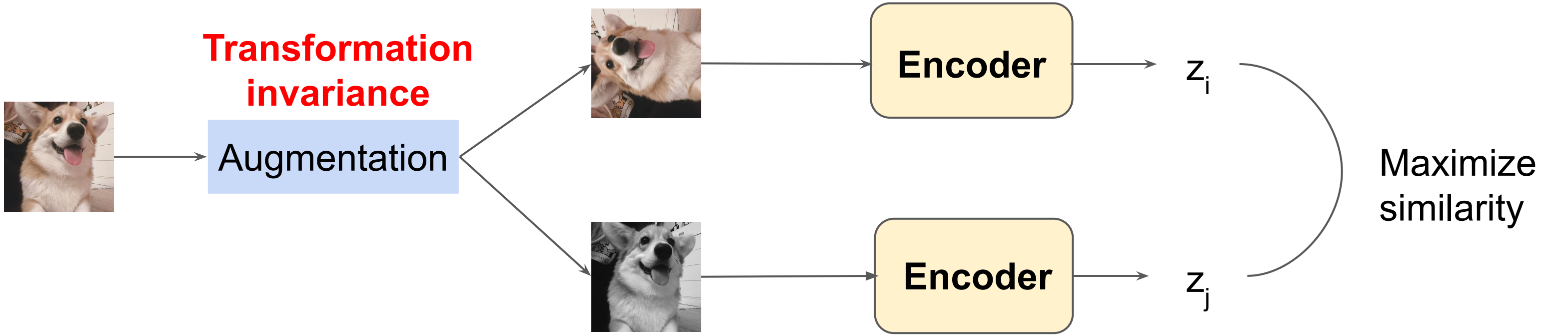
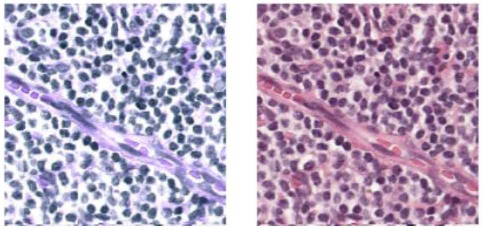
layer 6

Self-supervised representation learning

Learn representations from unlabelled data



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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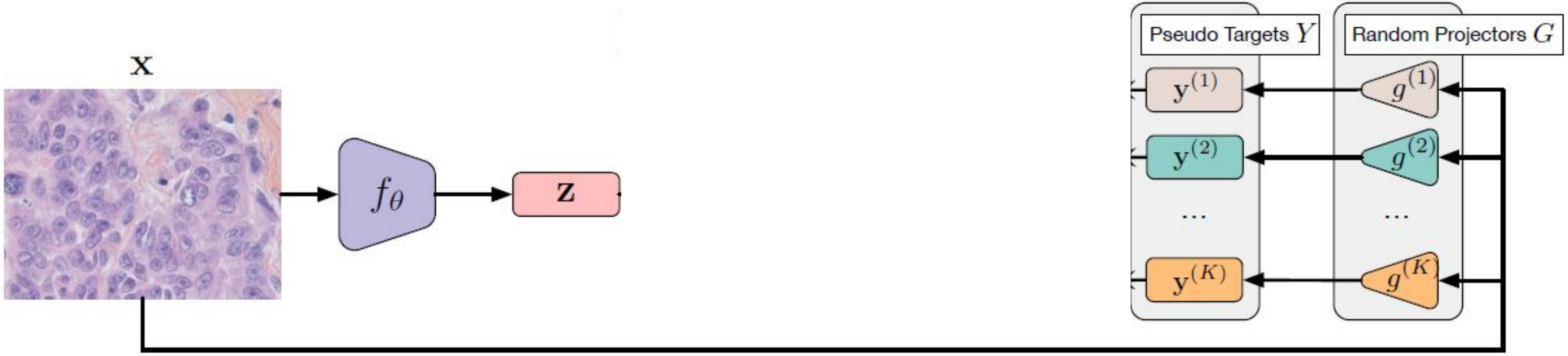

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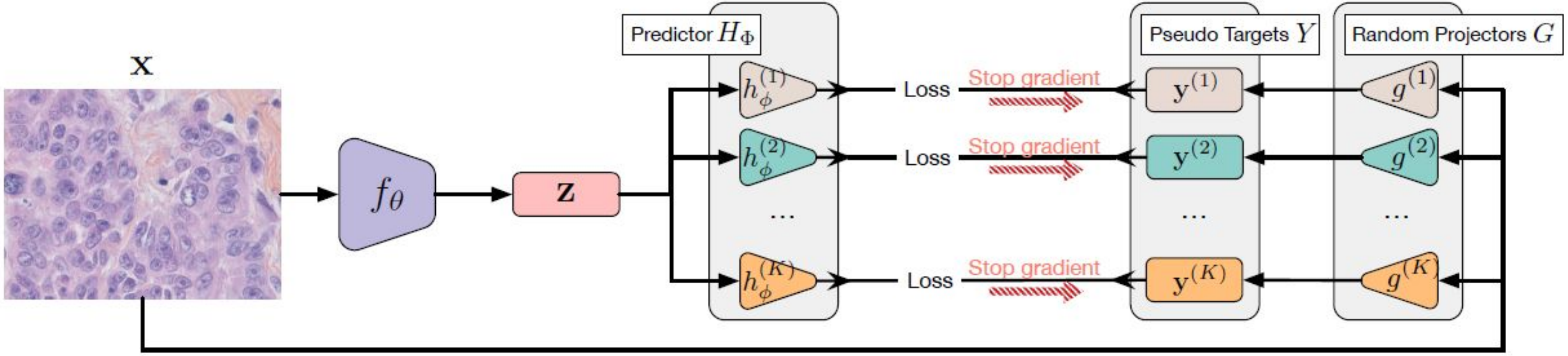

Random data projectors

- **Initialization** | Randomly initialized neural networks
- **Training** | Projectors are fixed during training
  - LFR can train faster than standard methods like SimCLR with only *one* pass through the encoder and no CPU-intensive augmentations
- **Diversity** | Diverse projections benefit the learned representations
  - Use determinantal point process to select diverse projectors from larger candidate pool

Diverse projectors focus on different aspects

Similar projectors use redundant features

Linear evaluation performance on downstream tasks

		Tabular		Time series			Image
		Income	HEPMASS	HAR	Epilepsy	MIMIC-III	Kvasir
	Log Reg	84.8 ± N/A	90.7 ± N/A	57.5 ± N/A	80.9 ± N/A	47.8 ± N/A	-
	Supervised	81.5 ± 0.2	91.5 ± 0.0	96.0 ± 0.6	98.3 ± 0.1	48.8 ± 0.0	83.2 ± 0.2
	Random Init	83.1 ± 0.2	84.3 ± 1.3	80.7 ± 2.3	89.1 ± 0.1	42.4 ± 1.1	28.9 ± 5.7
Domain-agnostic baselines	Autoencoder	85.0 ± 0.1	**90.7 ± 0.0**	77.2 ± 0.7	90.8 ± 1.3	44.9 ± 0.5	72.4 ± 0.6
	DIET	82.2 ± 0.4	-	88.6 ± 1.3	96.8 ± 0.3	33.8 ± 5.2	71.3 ± 0.9
	DACL	79.8 ± 0.7	88.7 ± 0.8	90.7 ± 0.4	97.5 ± 1.5	40.9 ± 0.6	72.1 ± 0.1
Domain-specific baselines	SimSiam	79.2 ± 1.9	85.3 ± 3.1	65.1 ± 0.8	97.4 ± 0.0	41.0 ± 1.9	72.6 ± 1.4
	SimCLR	-	-	87.8 ± 0.4	97.4 ± 0.2	44.1 ± 0.1	72.1 ± 0.3
	SCARF	84.2 ± 0.1	90.1 ± 0.1	-	-	-	-
	STab	84.2 ± 0.3	83.6 ± 1.7	-	-	-	-
	TS-TCC	-	-	91.2 ± 0.8	97.6 ± 0.2	38.5 ± 1.3	-
	LFR (Ours)	**85.2 ± 0.1**	90.1 ± 0.2	**93.1 ± 0.5**	**97.9 ± 0.2**	**46.6 ± 0.3**	**74.9 ± 0.6**

Medical datasets

More results available in the paper