

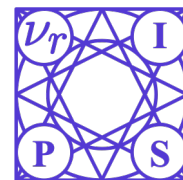


Information Competing Process for Learning Diversified Representations

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Introduction

- ❖ **Representation Learning** aims to make the learned representations more effective on extracting useful information from input for downstream tasks.
- ❖ **Diversified Representations** are learned with different information constraints which encourage representation parts to extract various and useful information from inputs, which results in powerful features to represent the inputs.
- ❖ **Information Competing Process (ICP)** for learning diversified representations.

Method

- ❖ **Unify Supervised and Self-Supervised Objectives.** Let t denote the downstream target (label/input itself), the objective linking the representation r of input x and the target t can be defined as:
$$\max [I(r, t)]$$
- ❖ **Separate and Diversify the Representations.** To explicitly diversify the information, we directly separate the representation r into two parts $[z, y]$ with different constraints:
$$\max [I(r, t) + \alpha I(y, x) - \beta I(z, x)]$$

Method

- ❖ **Competition of Representation Parts.** To prevent any one of the representation parts from dominating the downstream task, we let z and y to accomplish the downstream task t solely. For ensuring the representations catch diversified information through different constraints, we prevent z and y from knowing what each other learned for the downstream task. The objective is:

$$\max [\underbrace{I(r, t)}_{\text{Synergy}} + \underbrace{\alpha I(y, x)}_{\text{Max}} - \underbrace{\beta I(z, x)}_{\text{Min}} + \underbrace{I(z, t) + I(y, t) - \gamma I(z, y)}_{\text{Competition}}]$$

- ❖ **Optimization.** Please kindly refer to our paper.

Experiments

- ❖ **Supervised Setting - Classification Task.**

Table 1: Classification error rates (%) on CIFAR-10 test set.

	VGG16 [34]	GoogLeNet [35]	ResNet20 [12]	DenseNet40 [16]
Baseline	6.67	4.92	7.63	5.83
VIB [1]	6.81 ^{±0.14}	5.09 ^{±0.17}	6.95 ^{±0.68}	5.72 ^{±0.11}
DIM* [14]	6.54 ^{±0.13}	4.65 ^{±0.27}	7.61 ^{±0.02}	6.15 ^{±0.32}
VIB _{x2}	6.86 ^{±0.19}	4.88 ^{±0.04}	6.85 ^{±0.78}	6.36 ^{±0.53}
DIM* _{x2}	7.24 ^{±0.57}	4.95 ^{±0.03}	7.46 ^{±0.17}	5.60 ^{±0.23}
ICP-ALL	6.97 ^{±0.30}	4.76 ^{±0.16}	6.47 ^{±1.16}	6.13 ^{±0.30}
ICP-COM	6.59 ^{±0.08}	4.67 ^{±0.25}	7.33 ^{±0.30}	5.63 ^{±0.20}
ICP	6.10 ^{±0.57}	4.26 ^{±0.66}	6.01 ^{±1.62}	4.99 ^{±0.84}

Experiments

Table 2: Classification error rates (%) on CIFAR-100 test set.

	VGG16 [34]	GoogLeNet [35]	ResNet20 [12]	DenseNet40 [16]
Baseline	26.41	20.68	31.91	27.55
VIB [1]	26.56 ^{±0.15}	20.93 ^{±0.25}	30.84 ^{±1.07}	26.37 ^{±1.18}
DIM* [14]	26.74 ^{±0.33}	20.94 ^{±0.26}	32.62 ^{±0.71}	27.51 ^{±0.04}
VIB _{x2}	26.08 ^{±0.33}	22.09 ^{±1.41}	29.74 ^{±2.17}	29.33 ^{±1.78}
DIM* _{x2}	25.72 ^{±0.69}	21.74 ^{±1.06}	30.16 ^{±1.75}	27.15 ^{±0.40}
ICP-ALL	26.73 ^{±0.32}	20.90 ^{±0.22}	28.35 ^{±3.56}	27.51 ^{±0.04}
ICP-COM	26.37 ^{±0.04}	20.81 ^{±0.13}	32.76 ^{±0.85}	26.85 ^{±0.70}
ICP	24.54 ^{±1.87}	18.55 ^{±2.13}	28.13 ^{±3.78}	24.52 ^{±3.03}

- ❖ **Self-supervised Setting - Disentanglement Task.**

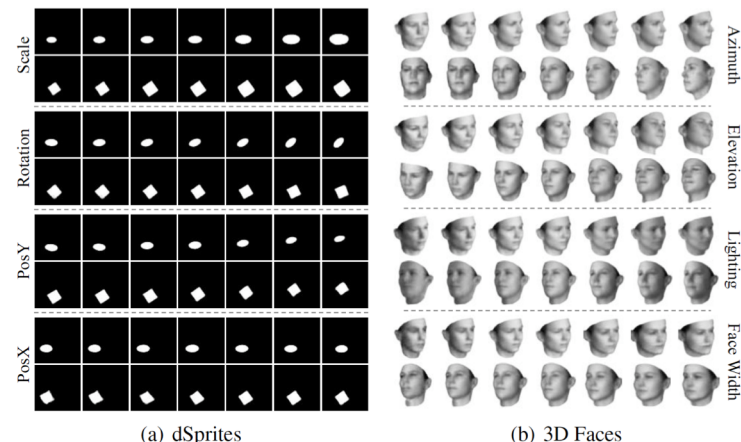


Table 3: MIG score of disentanglement.

	dSprites [24]	3D Faces [27]
β -VAE [13]	0.22	0.54
β -TCVAE [7]	0.38	0.62
ICP-ALL	0.33	0.26
ICP-COM	0.20	0.57
ICP	0.48	0.73

- ❖ **Project Page**

