

Quantifying and Learning Linear Symmetry-Based Disentanglement

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* Equal Contribution

- Disentanglement is **important**, but there is no agreed-upon definition
- Higgins et al. (2018) provide a formal definition:
Linear Symmetry-Based Disentanglement (LSBD)
- Based on modelling **symmetries** of the real world, using group theory

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- Observations from real world -> data



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Linear Symmetry-Based Disentanglement (LSBD)

- Based on modelling **symmetries** of the real world, using group theory
- Observations from real world -> data
- Transformations in real world -> variation in data



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 - Crucial for evaluation of LSBDD methods, benchmarks

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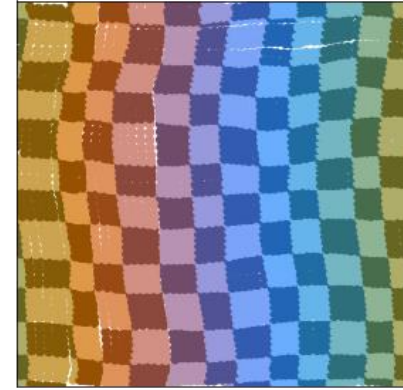
- Crucial for evaluation of LSBDD methods, benchmarks

2. The LSBDD definition defines no **method** to obtain LSBDD representations

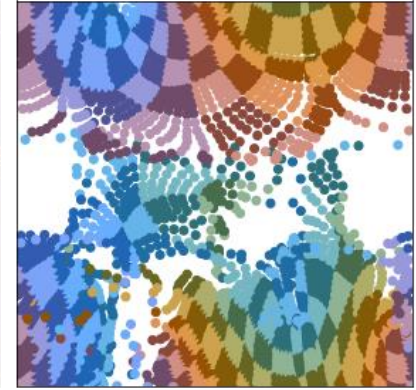
- Some methods exist, but lack formal evaluation due to missing metric

1. \mathcal{D}_{LSBD} : a general metric that quantifies LSBD
 - Follows the formal LSBD definition
 - Works for any encoding and group structure (in theory)
 - Practical implementation for common subgroup: $SO(2)$

$$\mathcal{D}_{LSBD} = 0.013$$



$$\mathcal{D}_{LSBD} = 1.179$$

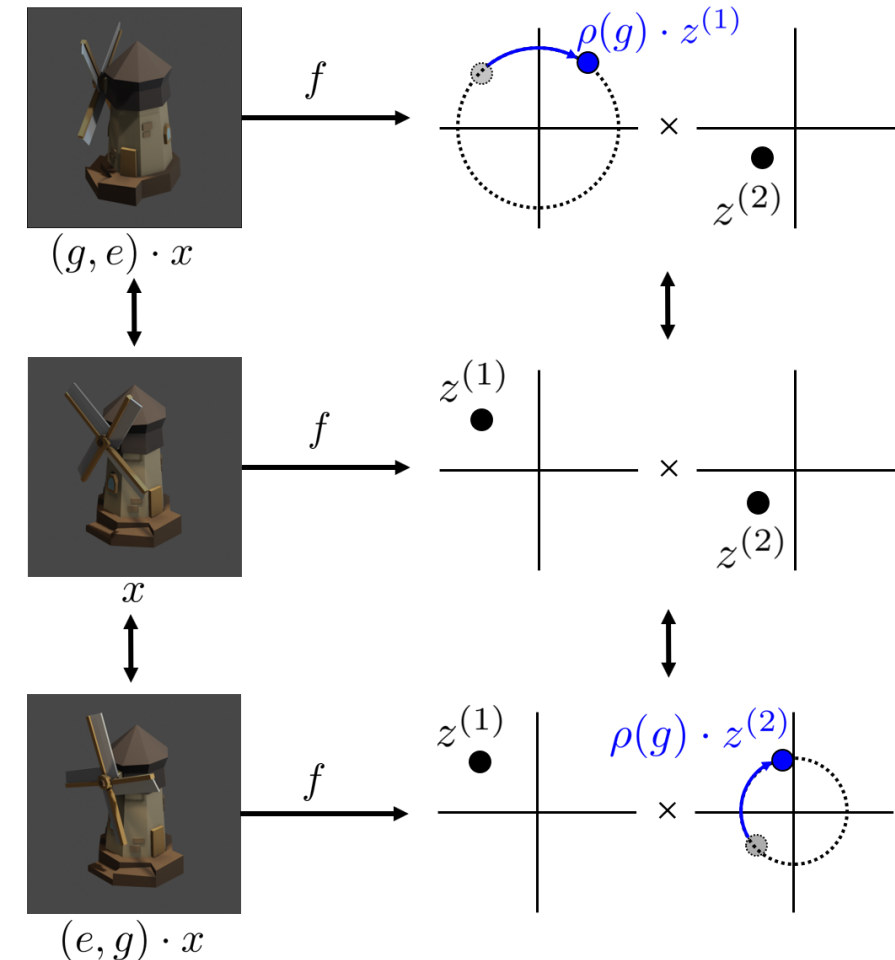


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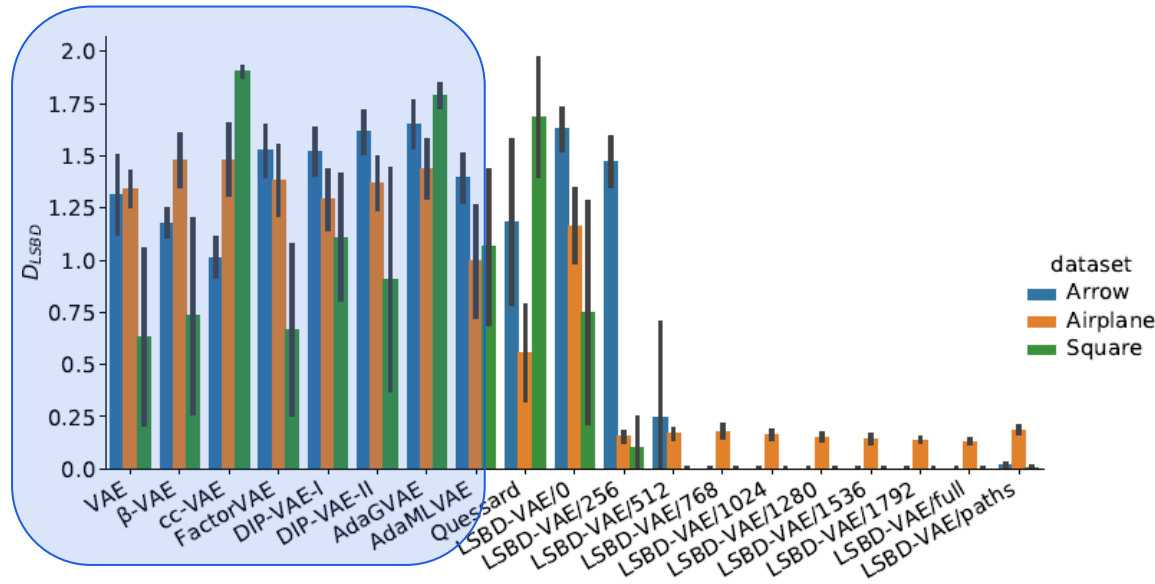
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2. LSBD-VAE: a method to learn LSBD representations

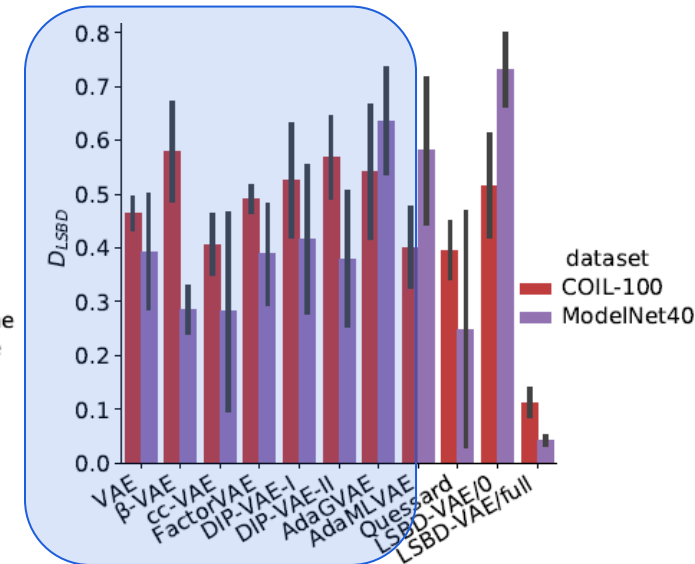
- Idea: use \mathcal{D}_{LSBD} as additional loss component in ΔVAE ,
 - (ΔVAE = VAE with suitable latent topology)
- Requires some assumptions (expert knowledge) to ensure computability



1. Traditional disentanglement methods don't learn LSB-D representations

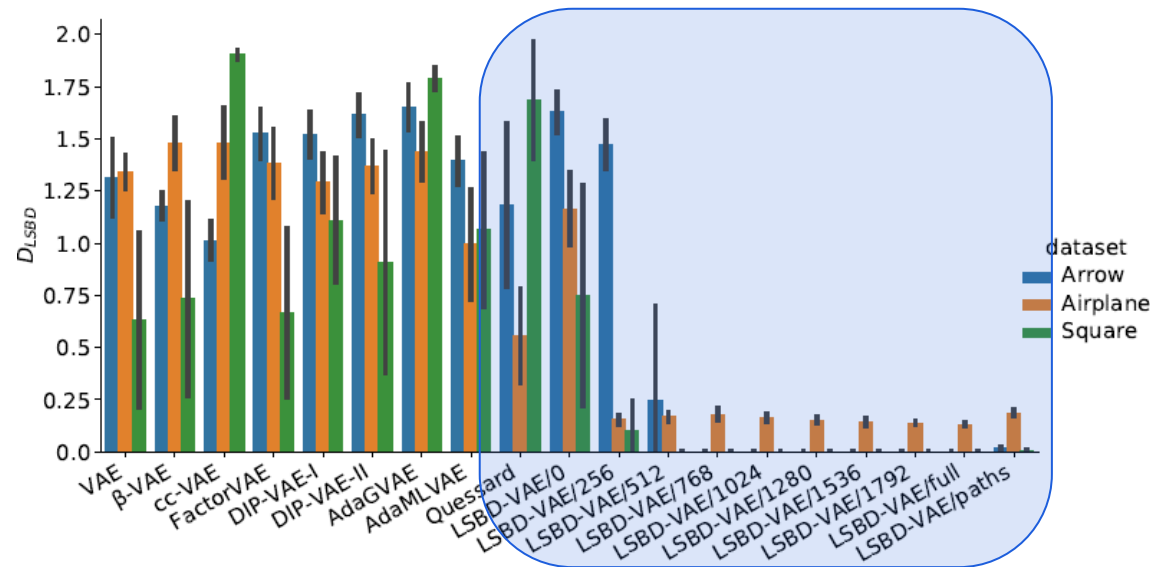


(a) Datasets with $SO(2) \times SO(2)$ symmetries

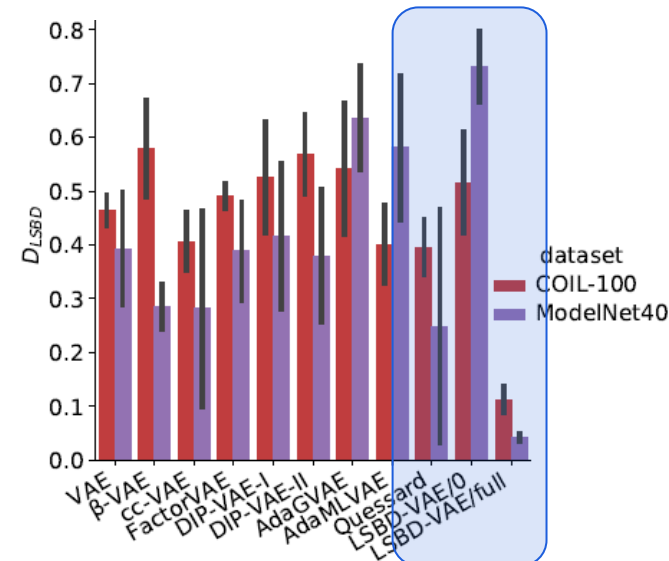


(b) Datasets with $SO(2)$ and non-symmetric variation

1. Traditional disentanglement methods don't learn LSB-D representations
2. Our method and other LSB-D methods can learn LSB-D representations, with limited supervision on transformations

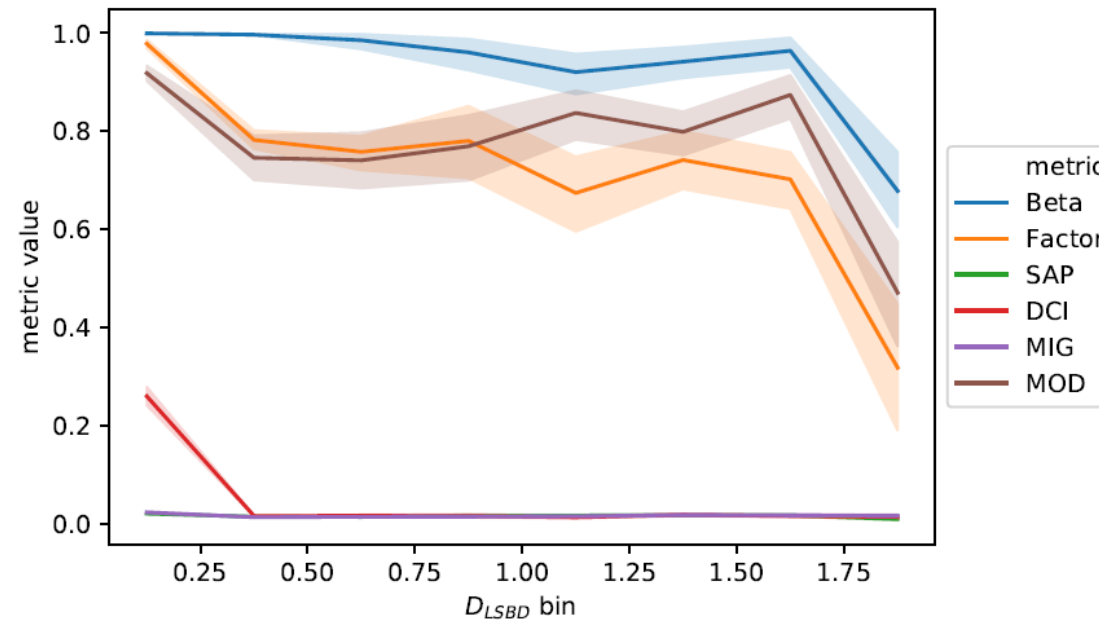


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(b) Datasets with $SO(2)$ and non-symmetric variation

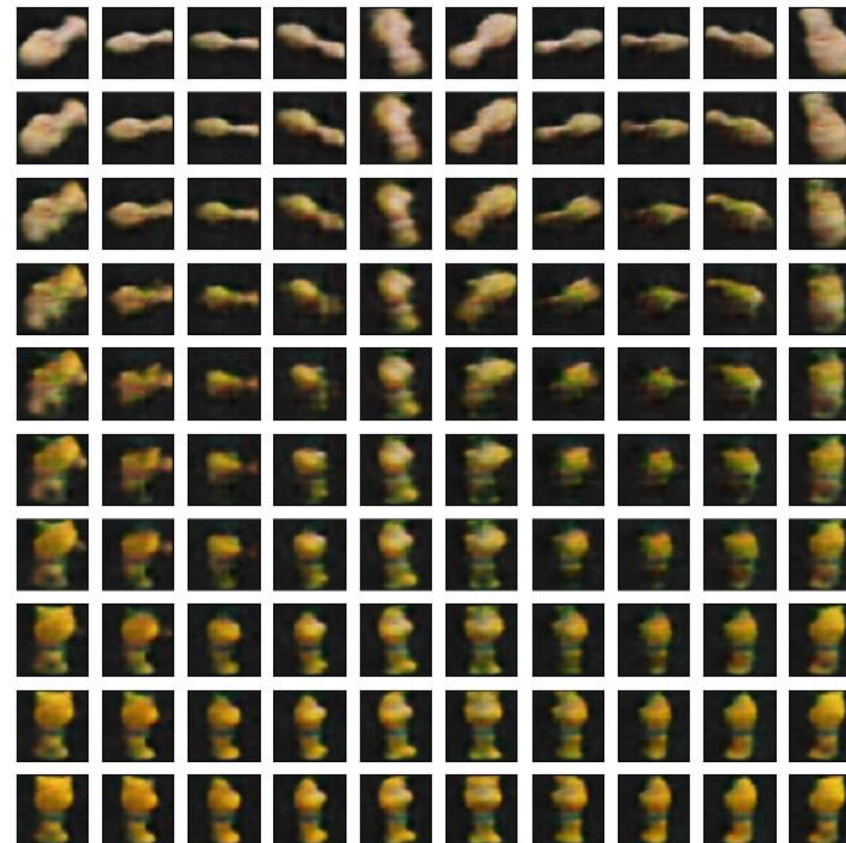
1. Traditional disentanglement methods don't learn LSBD representations
2. LSBD-VAE and other LSBD methods can learn LSBD representations, with limited supervision on transformations
3. LSBD representations also satisfy previous disentanglement notions (but not vice versa)



β -VAE



Ours



- We have devised a metric (\mathcal{D}_{LSBD}) and method (LSBD-VAE)
- We have shown that our method can learn LSBD representations with little supervision
- We have confirmed that traditional disentanglement models do not optimize for LSBD
- We demonstrate that LSBD satisfies previous notions of disentanglement, but also captures other desirable properties.



Thank you!

See you at the poster session!