

Overlooked Implications of the Reconstruction Loss for VAE Disentanglement

IJCAI 2023 Paper Presentation



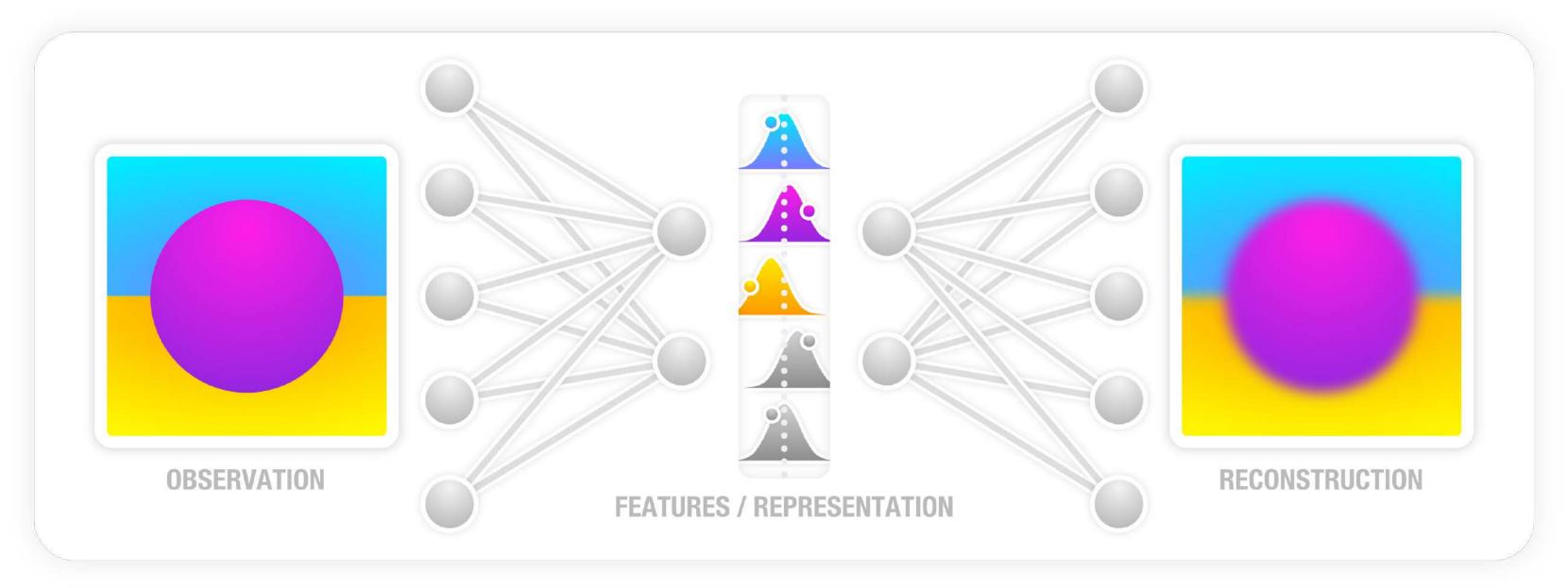




Background

Variational Auto-Encoders

 Variational Auto-Encoders (VAEs) learn to compress data by reconstructing the inputs. • VAEs encode distributions, which are sampled from during training.



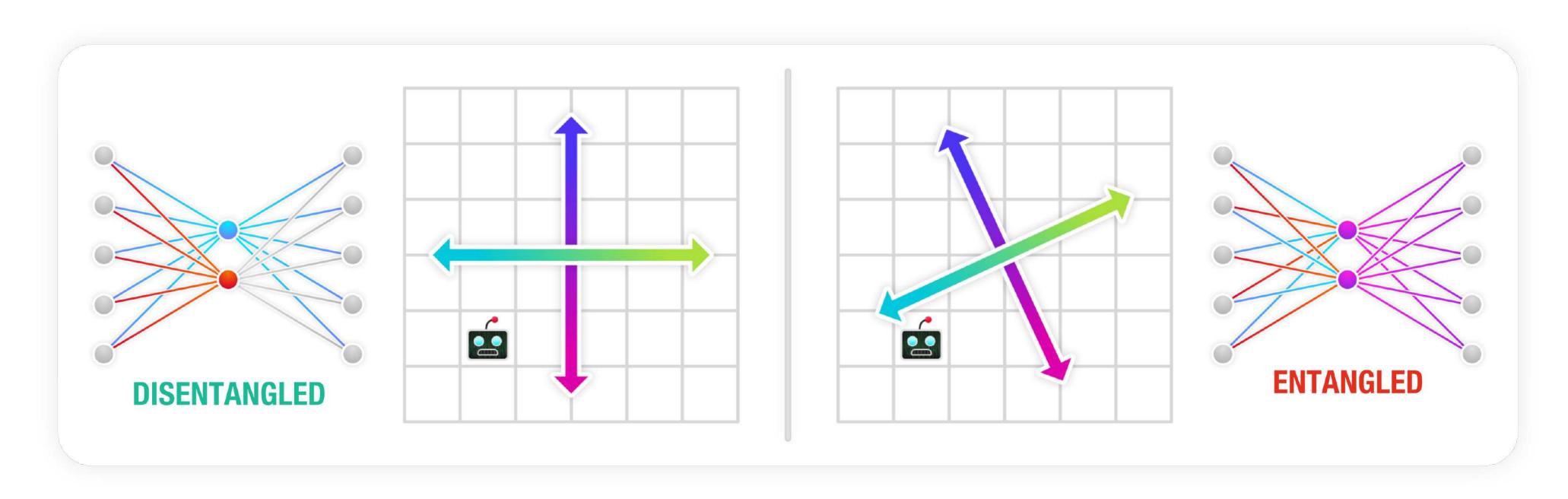
$$L_{\beta {
m VAE}} = L_{
m rec} + L_{
m reg}$$
 Regularisation is usually the focus of disentanglement research

Background

Disentanglement (with unsupervised VAEs)

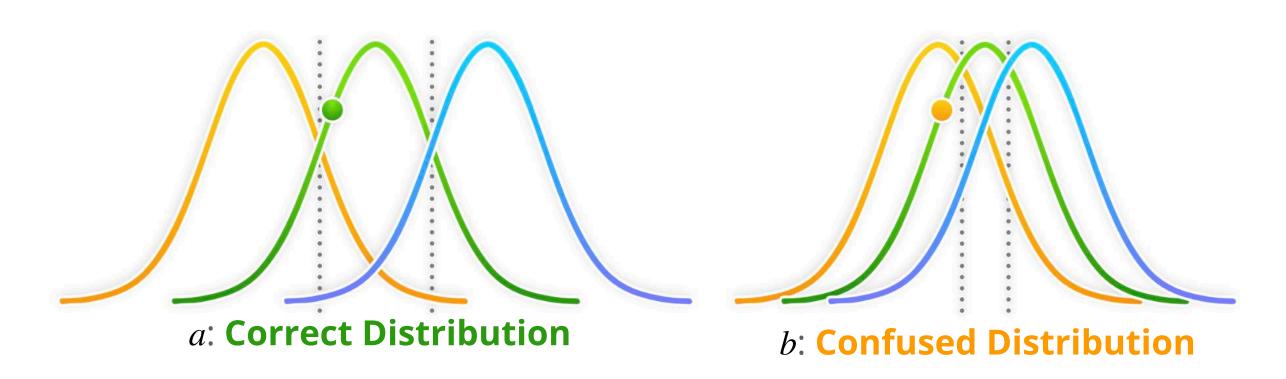
 VAEs are known to produce human interpretable or disentangled representations from data.

- VAEs may fail and produce **entangled** representations.
- Why?



Background

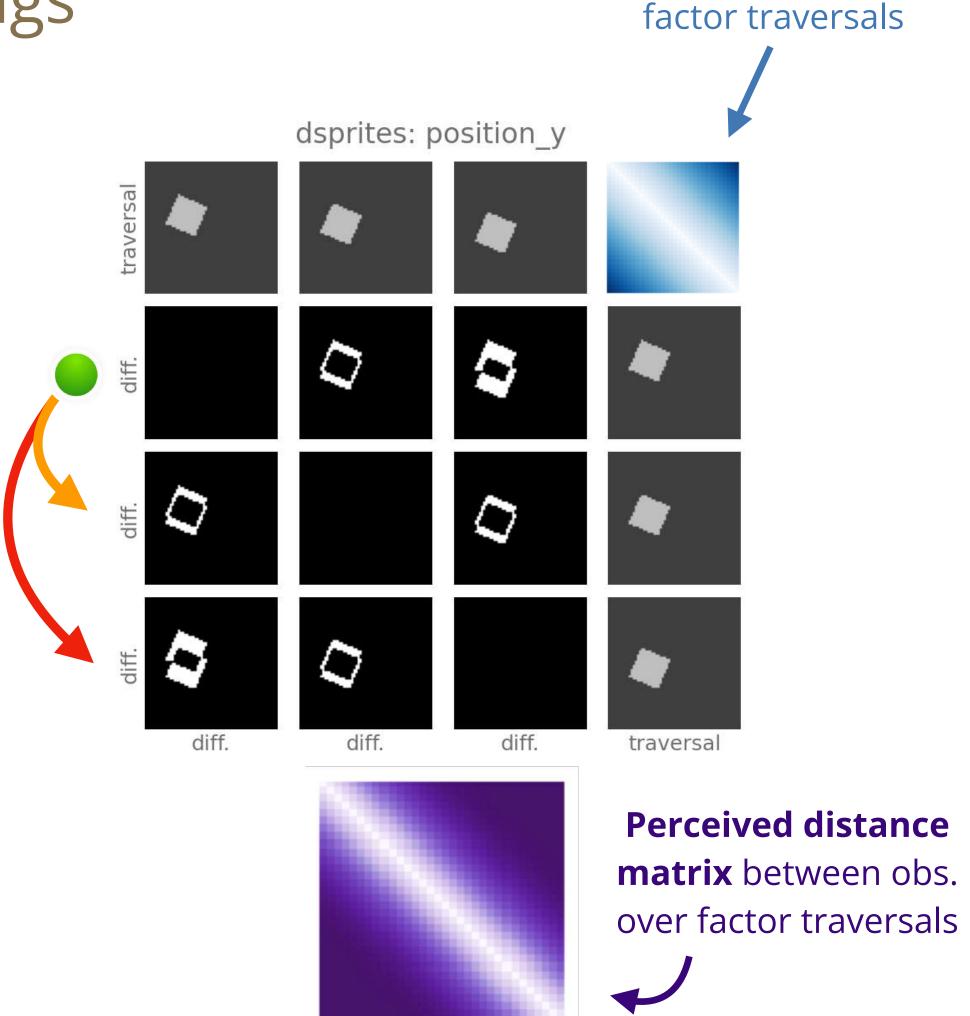
Random sampling reorganises VAE embeddings



A VAE prefers to minimise sampling errors by placing **embeddings** close together that it also perceives as **close in the data space**

We use this idea to measure the similarity of observations directly using the reconstruction loss "Perceived distances"

$$\mathrm{d}_{\mathrm{pcv}}(ledowndowndown,ledowndowndown) = \lim_{\hat{oldsymbol{x}} o oldsymbol{x}} \mathcal{L}_{\mathrm{rec}}(ledowndowndowndown,ledowndowndown)$$

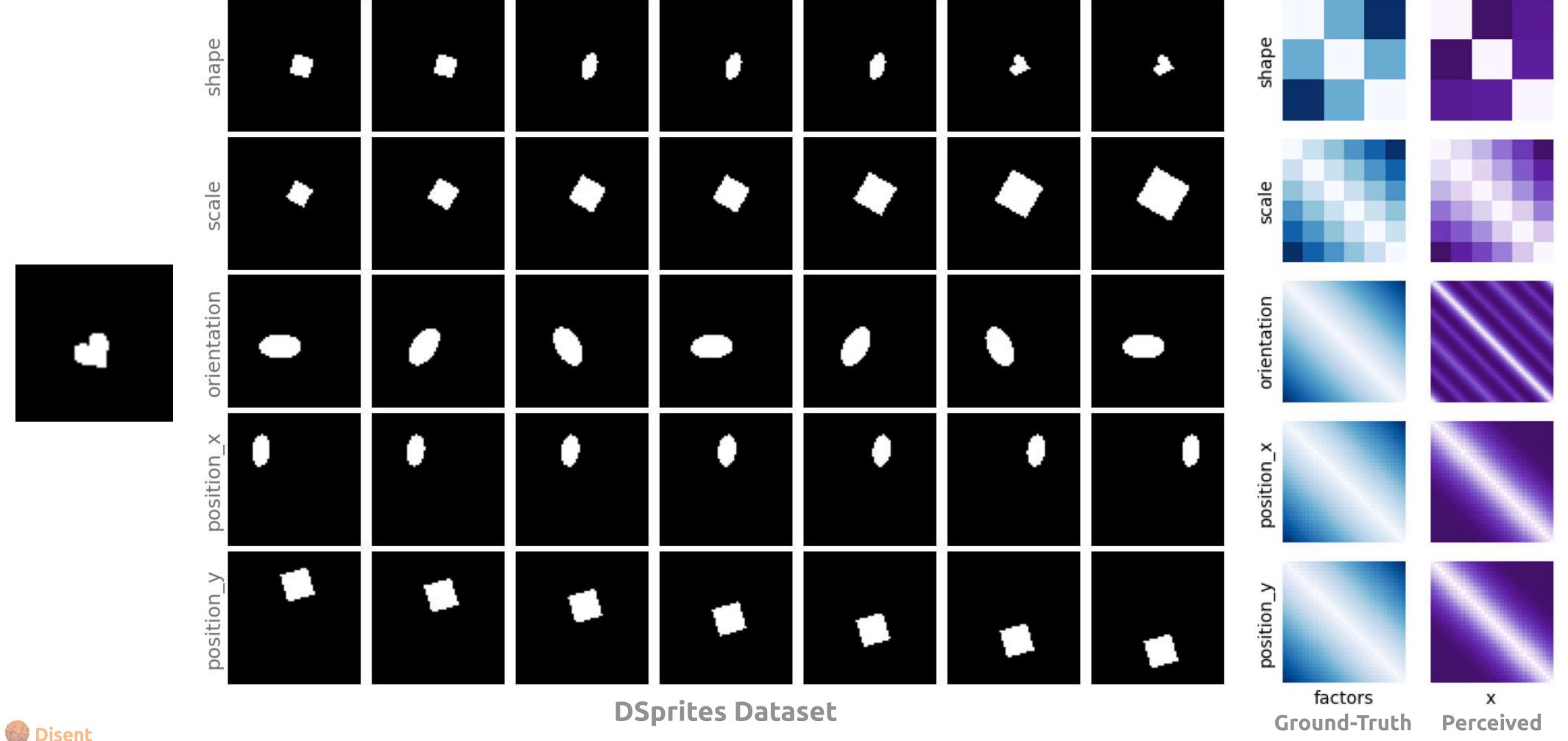


Ground-truth

distance matrix over

Characterising Existing Datasets

Ground-truth distances usually correspond to VAE perceived distances

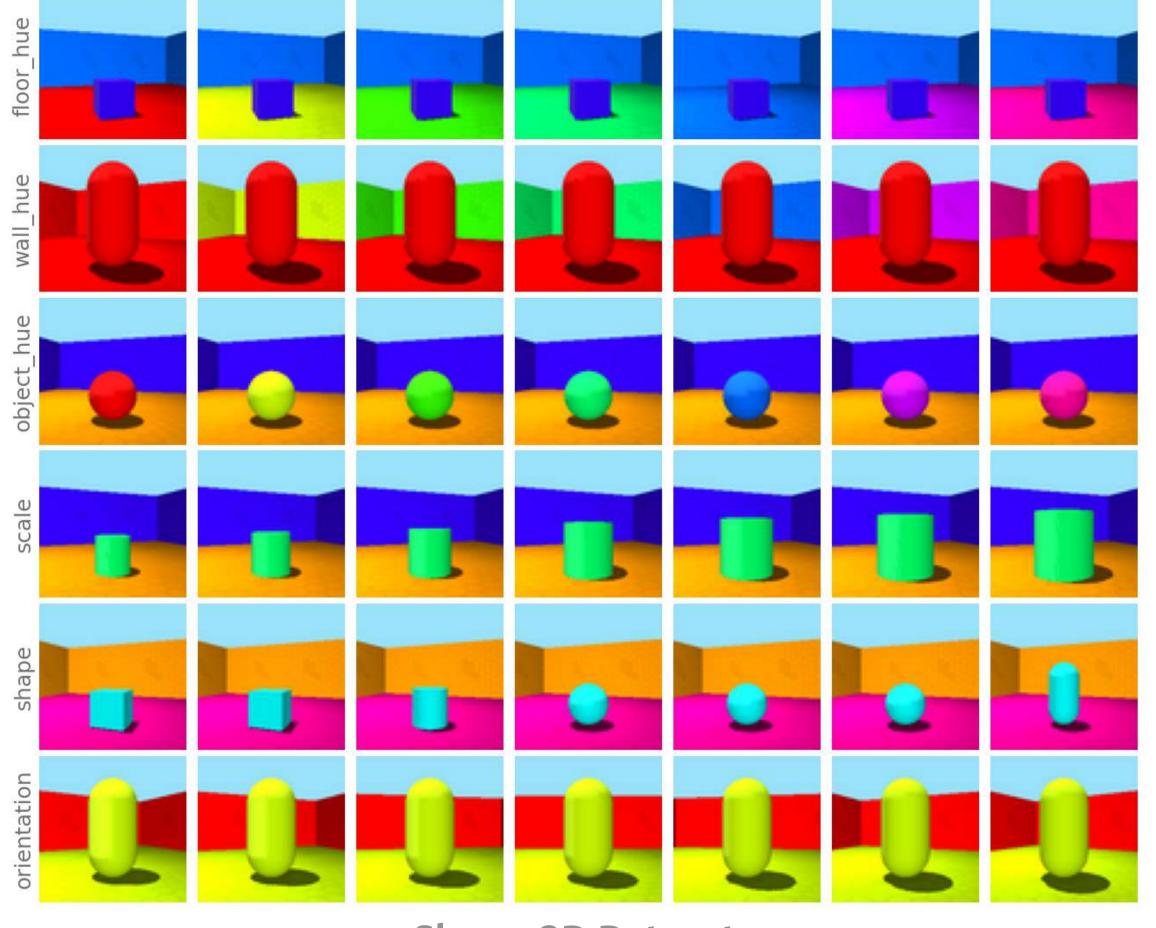




Characterising Existing Datasets

Ground-truth distances usually correspond to VAE perceived distances

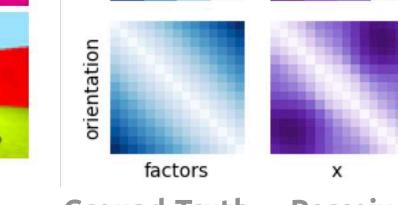






• Colour is circular in nature, can be learnt from any starting point





Ground-Truth

floor_hue

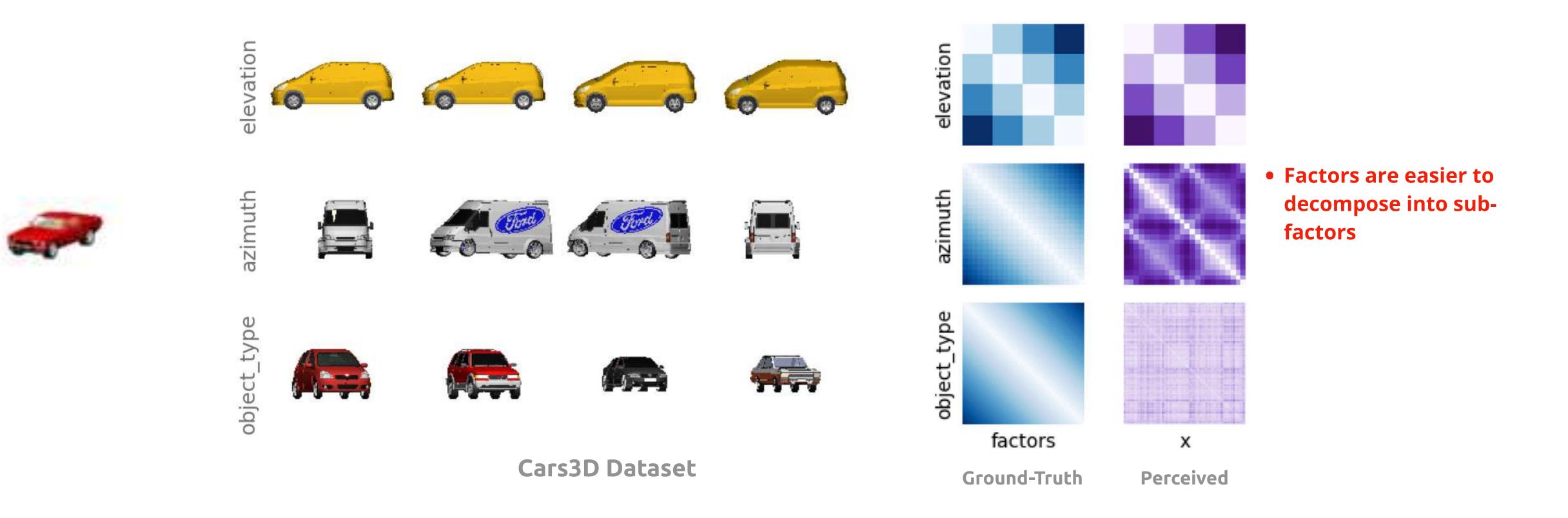
shape

Perceived



Characterising Existing Datasets

Ground-truth distances usually correspond to VAE perceived distances

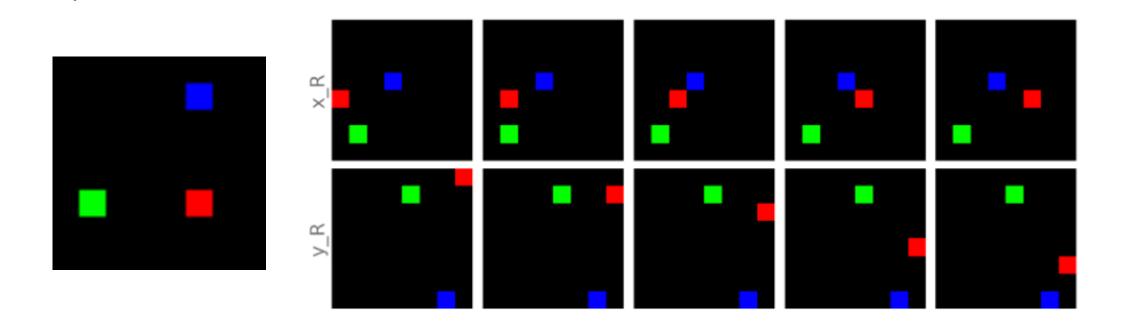


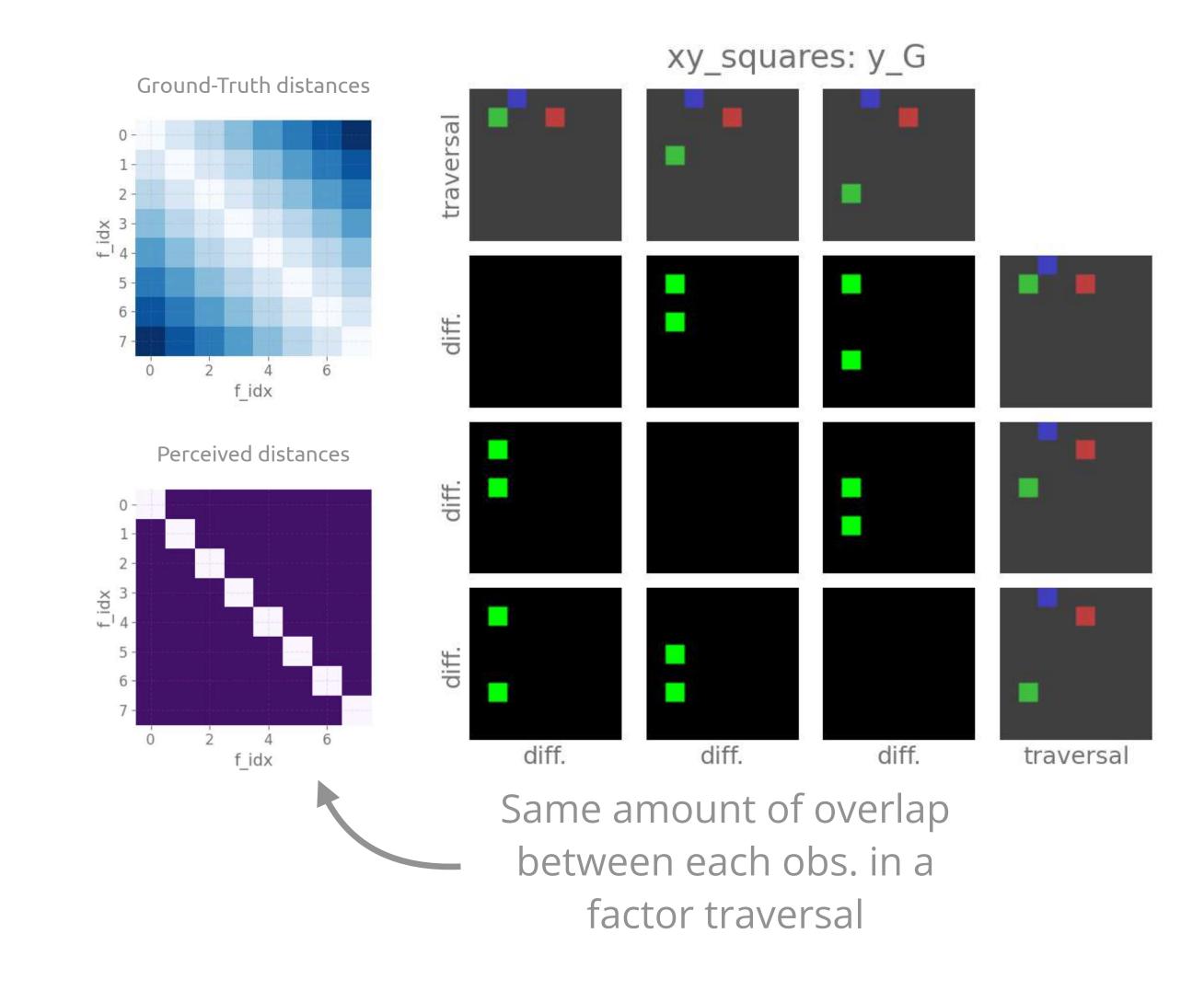


Adversarial Dataset

XYSquares Example - Adversarial for pixel-wise reconstruction losses

- Design example dataset with constant overlap along factor traversals
 - Cannot minimise recon. error due to sampling, no ordering
- 8x8 grid with **x** & **y** positional factors

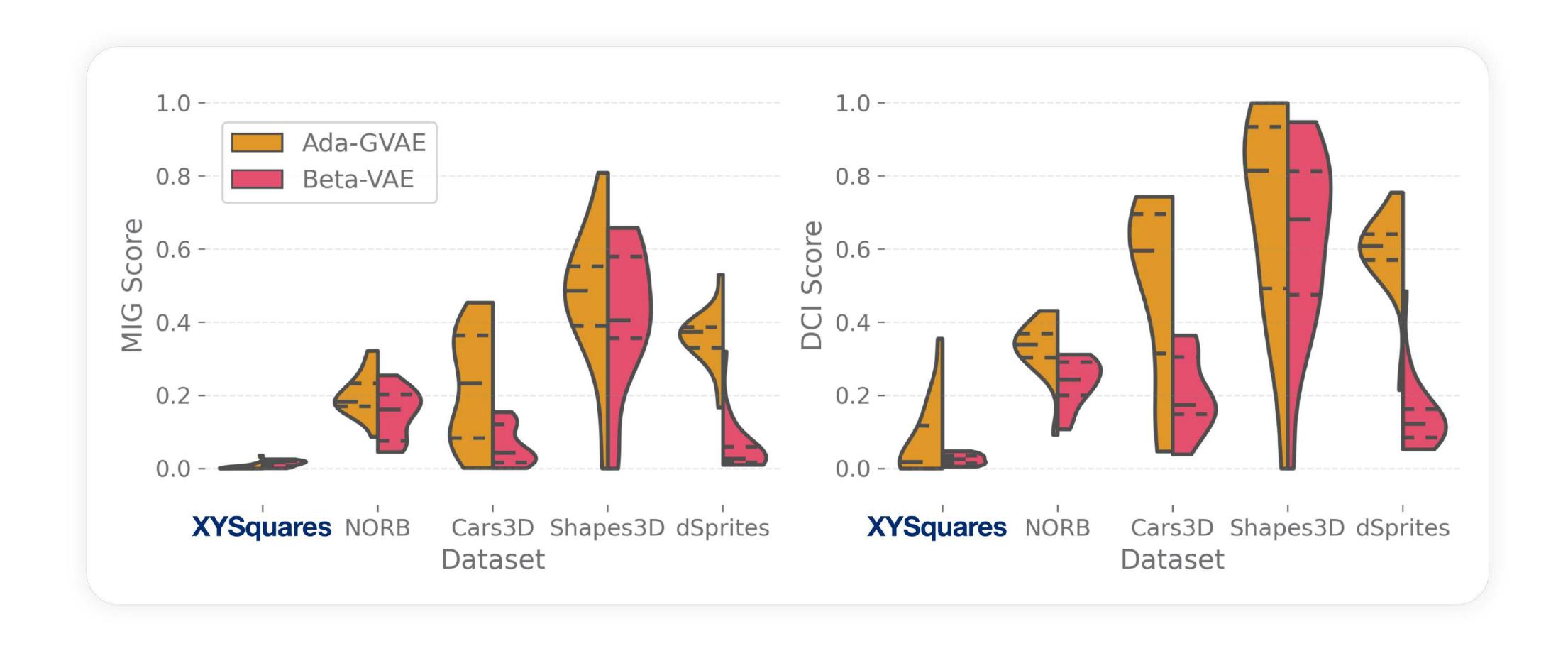






Adversarial Dataset

XYSquares Example - Disentanglement compared to benchmark datasets

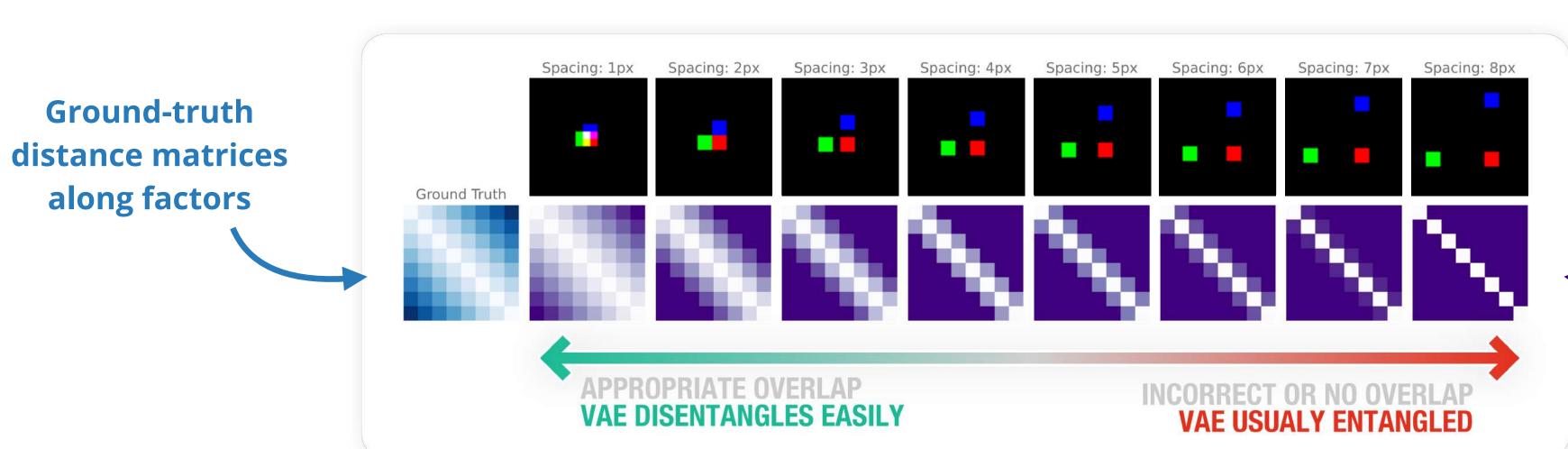


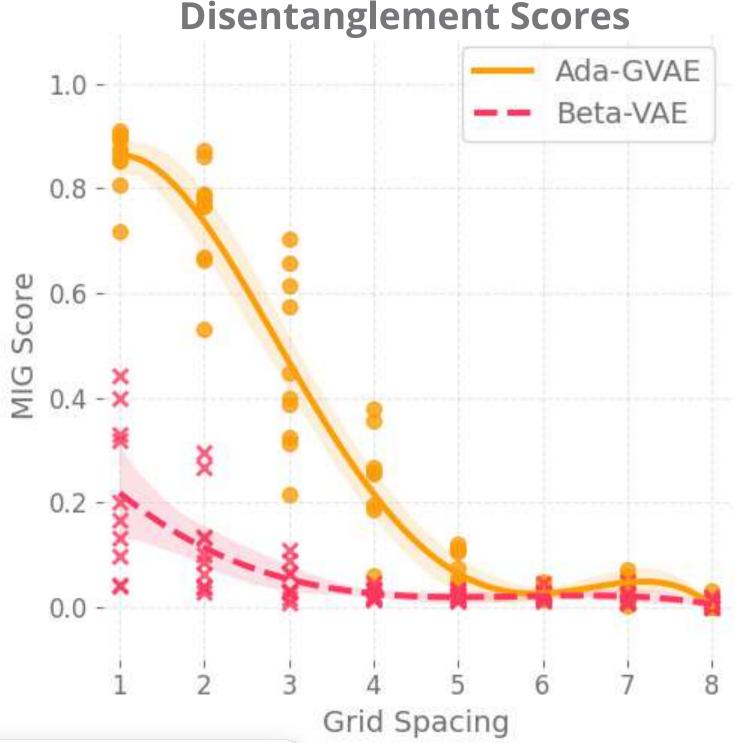


Re-enabling Disentanglement

XYSquares example - Adjusting the data

- Train VAEs over XYSquares data with varying spacing which changes perceived distances.
 - decrease spacing, appropriate overlap, correlated
 distances between observations, better disentanglement
 - increase spacing, no overlap, constant distances between observations, worse disentanglement





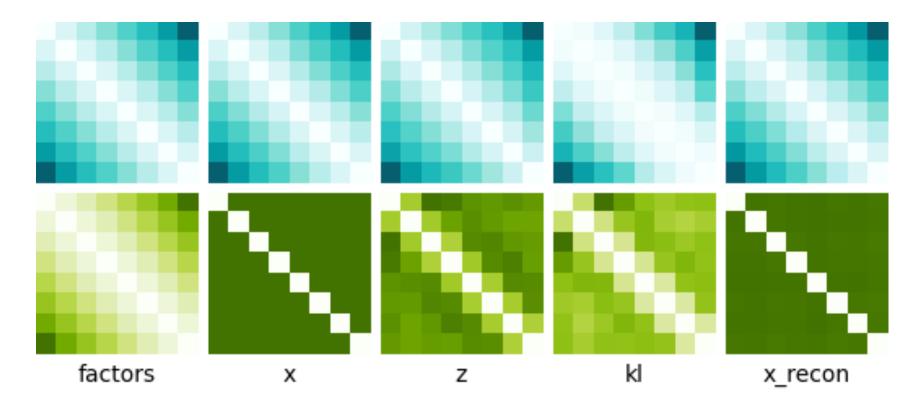
Perceived distance matrices along factors

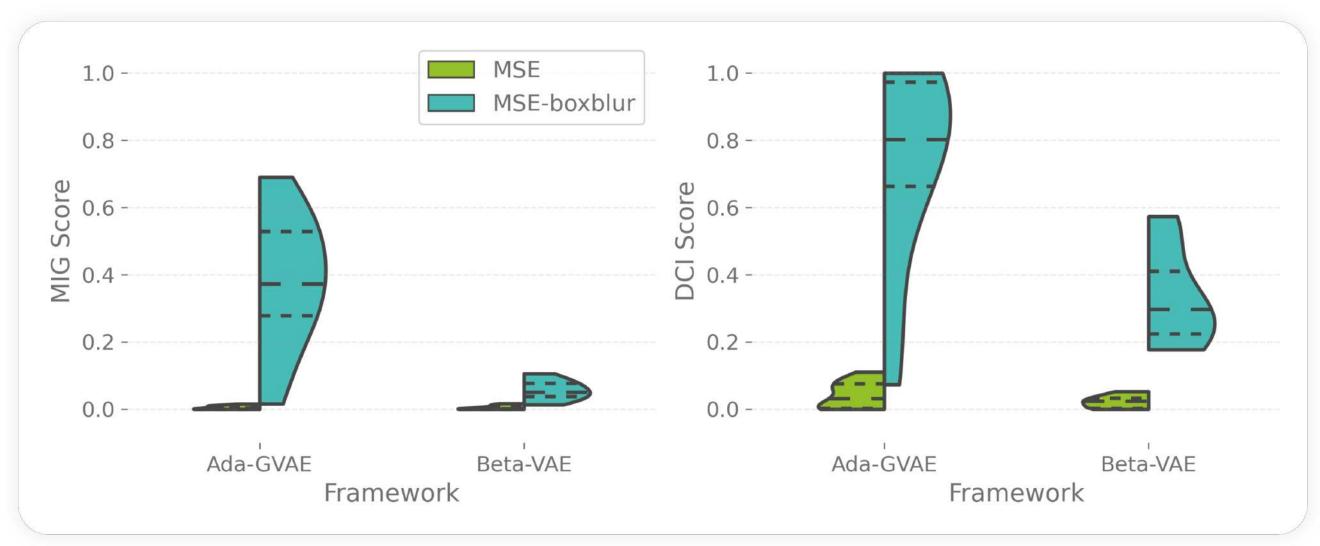


Re-enabling Disentanglement

XYSquares example - Adjusting the loss

- If perceived distances once again correspond to ground-truth distances, disentanglement can occur.
- Adjust the reconstruction loss to re-enable disentanglement. An example that is appropriate for XYSquares is adding a box blur augment to data.







Conclusion

And considerations for unsupervised disentanglement research

- Disentanglement in benchmarks is largely accidental
 - Fundamental characteristics of existing benchmark datasets encourage VAEs to learn disentangled representations.
 - New benchmark datasets are required.
- Disentanglement depends on the data and reconstruction loss too.
 - Unsupervised disentanglement is ultimately not from special regulariser and algorithmic choices.
- Disentanglement is subjective
 - e.g. RGB, HSV or categorical representations for colours, binary or continuous encodings for positions, split or combined factors.
 - There are infinitely many datasets with infinitely many choices of what constitutes their ground-truth factors.
 - Supervision ultimately required



SCAN FOR PAPER & RESOURCES

co. The End