Visual Representation Learning Does Not Generalize Strongly Within the Same Domain

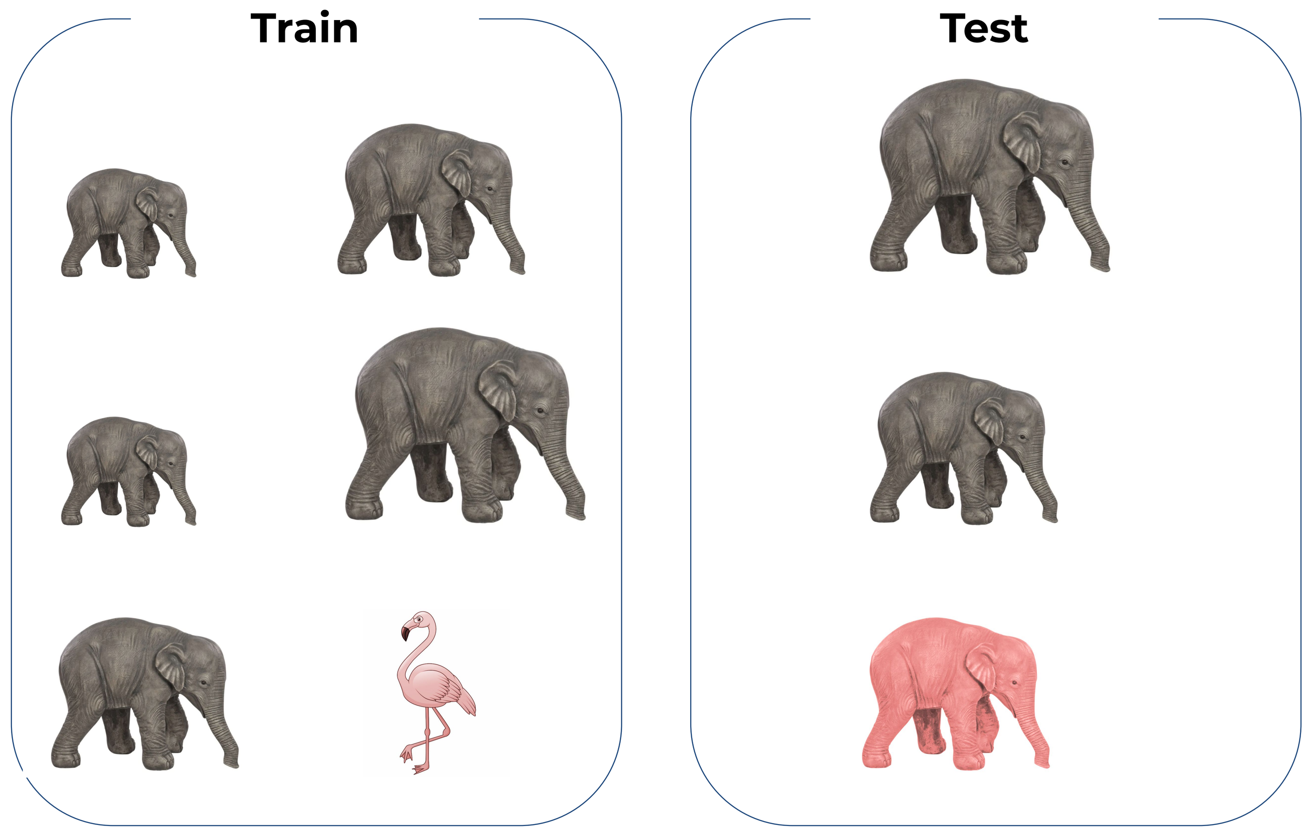
Lukas Schott[1,3], Julius von Kügelgen[2,3,4], Frederik Träuble[2,3], Peter Gehler[3], Chris Russell[3], Matthias Bethge[1,3], Bernhard Schölkopf[2,3], Francesco Locatello[3,‡], Wieland Brendel[1,‡]

(1) University of Tübingen, Germany (2) Max Planck Institute for Intelligent Systems (3) Amazon Web Services (4) University of Cambridge

‡ shared senior authorship

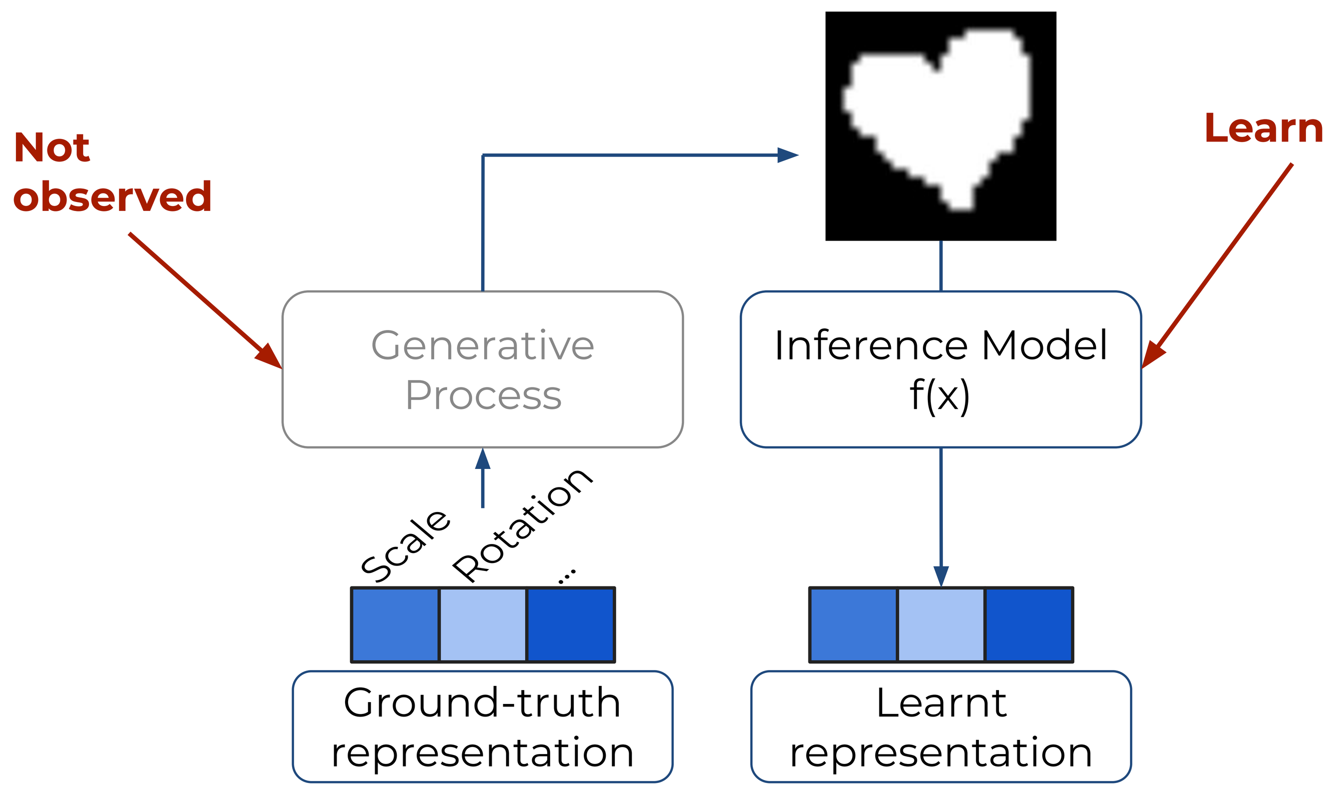
Motivation

Question: Can neural networks generalize factors of variation?
Do neural networks learn underlying mechanisms?

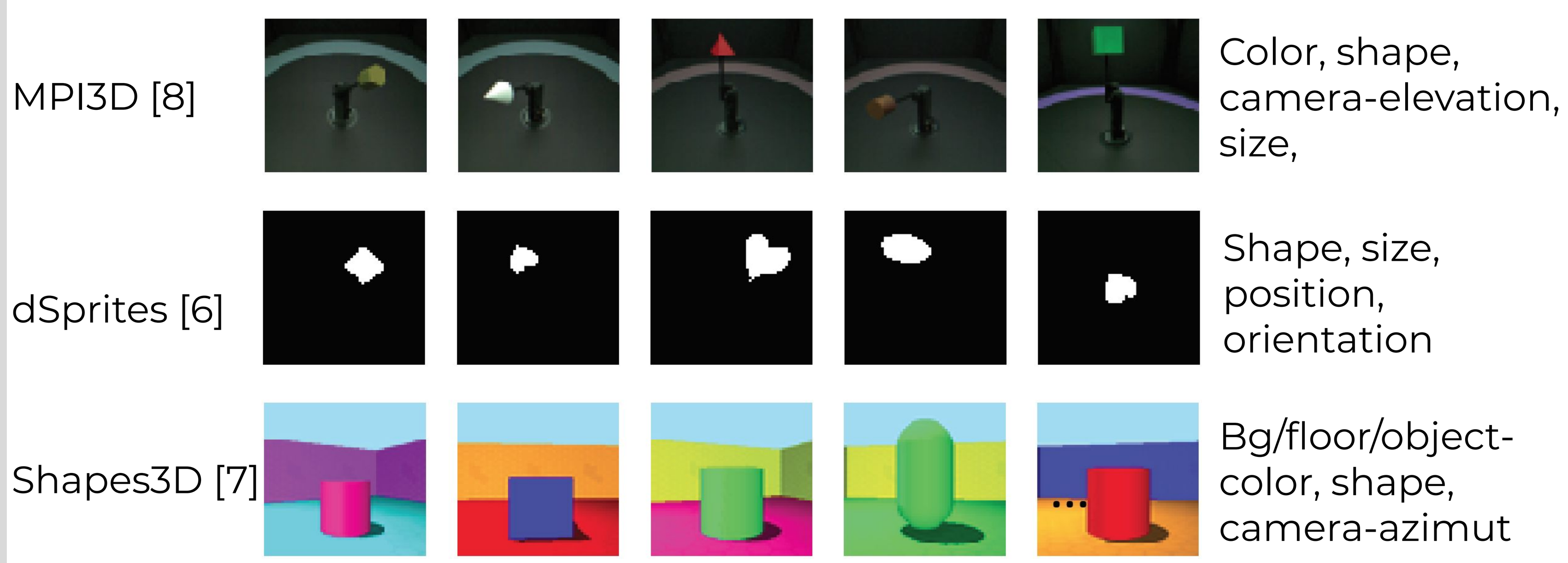


Goal: Test whether models learn the underlying mechanisms of a scene.

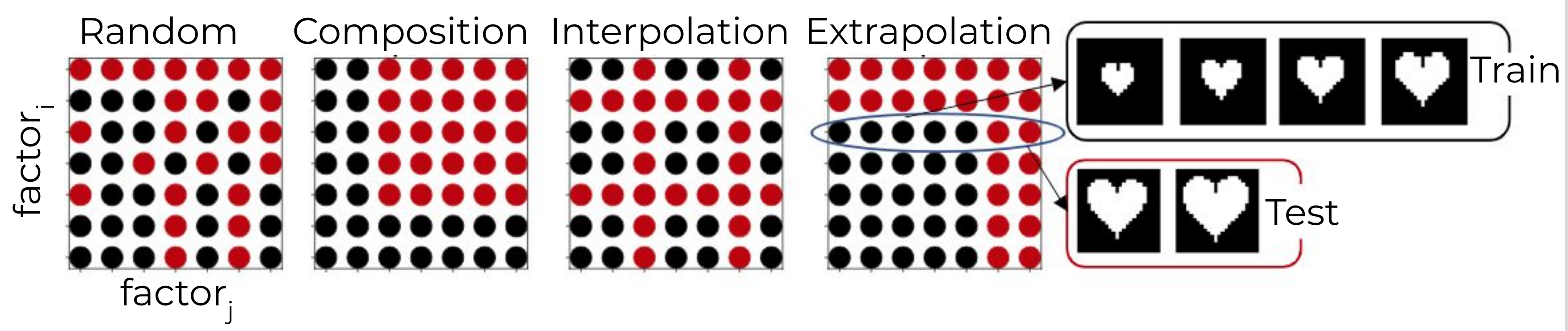
Problem Setting



Datasets



Setup



Factors of variation: Size, color, ...

Test-train-split: split all factors except shape: ~30%(train) : ~70%(test) samples

Training: Sample from the generative process on the training data in any way.

Un-/ weakly supervised: VAE, Ada-GVAE, SlowVAE, PCL
Fully Supervised: MLP, CNN, CoordConv, SetEncoder, Equivariant, ...
Transfer Learning: RN50 on IN-21k, RN101 on IN21-k, DenseNet on IN1-k

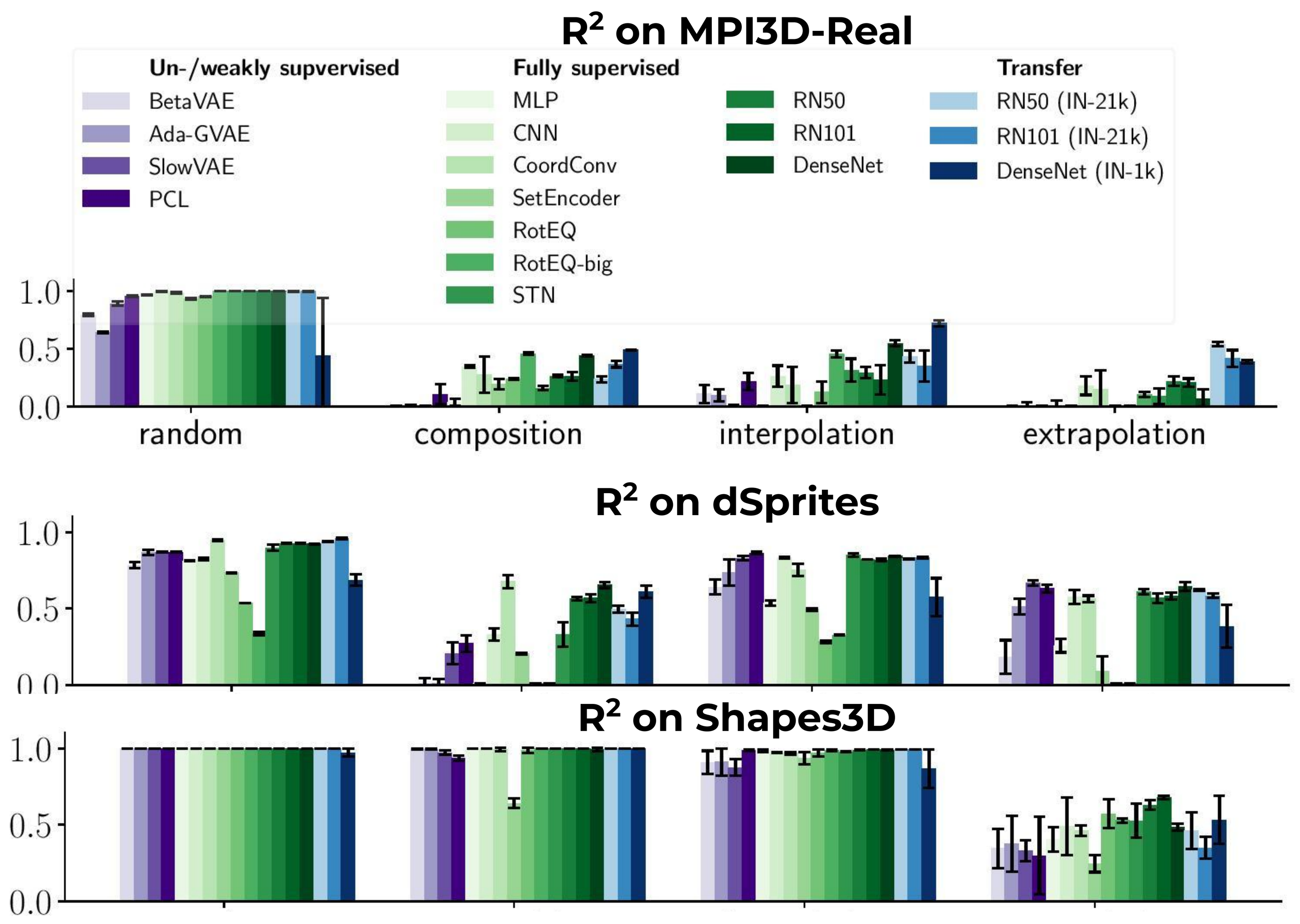
Evaluation

Regression of factors of variation:

$$R_i^2 = 1 - \frac{\text{MSE}_i}{\sigma_i^2} \qquad \text{MSE}_j = \mathbb{E}_{(\mathbf{x},\mathbf{y})\sim p_{te}}\left[(\mathbf{y}_j - f_j(\mathbf{x}))^2\right]$$

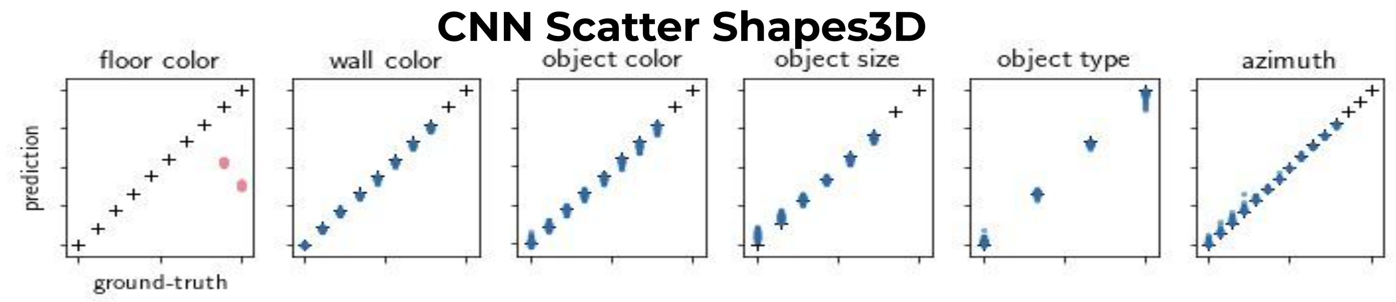
$R^2 = 1$ → perfect regression, 100% variance explained
$R^2 = 0$ → e.g. always predicting the mean
$R^2 < 0$ → worse than predicting the mean

Results - All Models



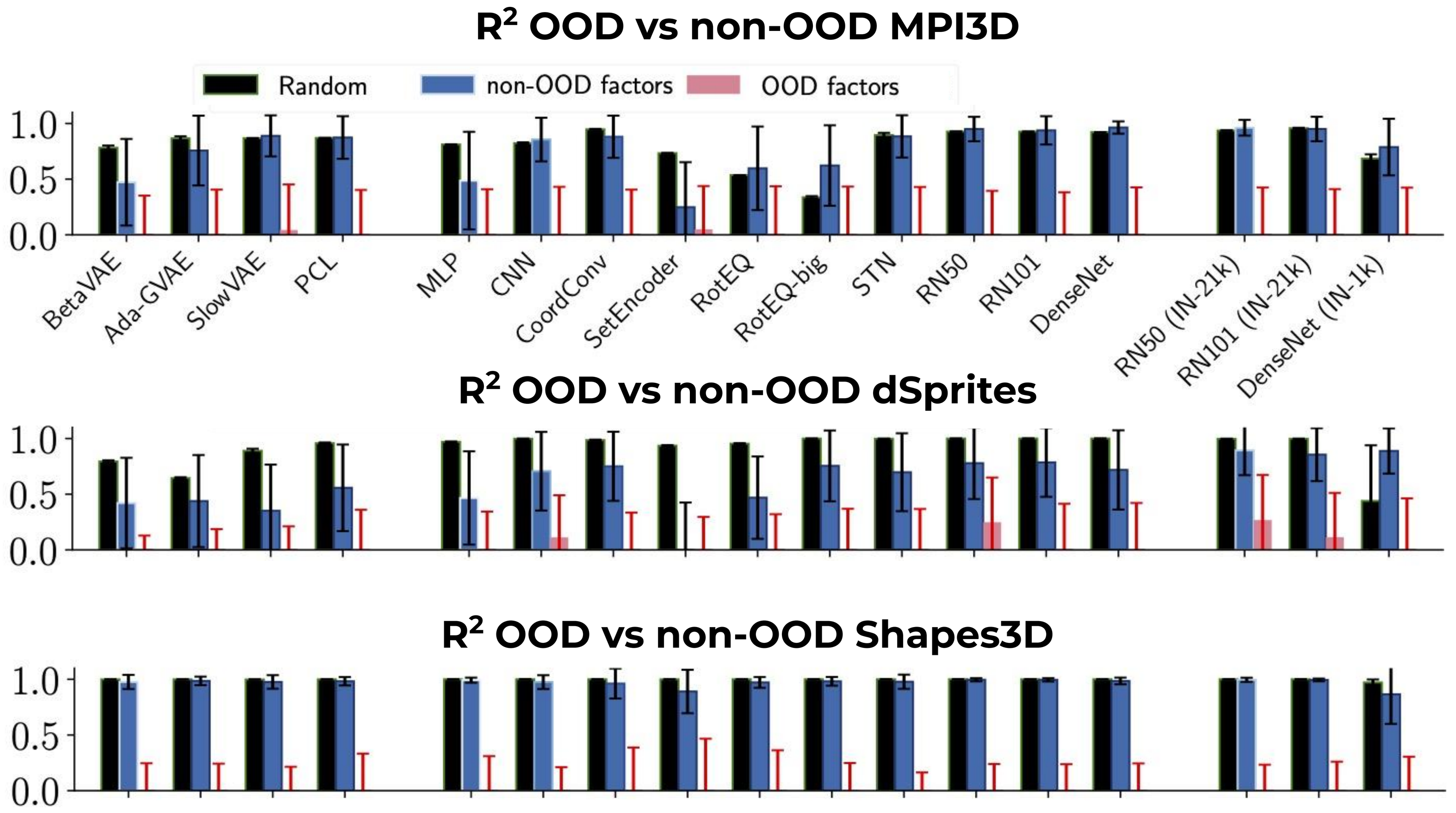
- On realistic dataset (MPI3D): Models do **not** learn underlying mechanism
- Shapes3D color composition/ interpolation works fairly well
- Extrapolation most difficult → investigate further

Extrapolation - Qualitative



→ OOD factors different behavior on non-OOD vs OOD factors
→ OOD factors tend towards the mean

Extrapolation - Error Analysis

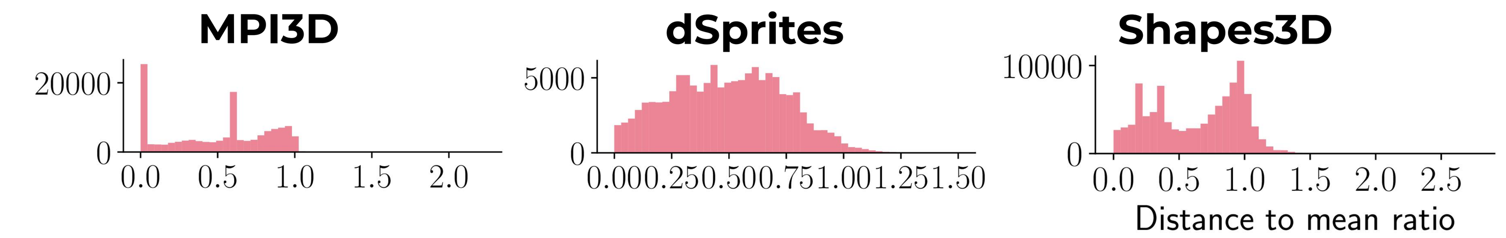


→ OOD factors R^2 low → Models do not extrapolate
→ non-OOD R^2 better → Models are surprisingly modular

Extrapolation Towards the Mean

$$\frac{|f(\mathbf{x}^i)_j - \bar{\mathbf{y}}_j|}{|\mathbf{y}_j^i - \bar{\mathbf{y}}_j|}$$

if in [0, 1] → prediction closer to mean than ground-truth
if > 1 → further away from mean



Values mostly in [0,1]→ Models tend to extrapolate towards the mean

Conclusions

- In more difficult settings, our tested ML models are unable to generalize and do not learn the underlying model.
- Models are surprisingly modular and tend to extrapolate towards the mean.
- On the non-artificial MPI3D we found transfer learning to be most helpful.

References

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lukas.schott@gmail.com