paper code

Unsupervised Learning of Equivariant Structure from Sequences

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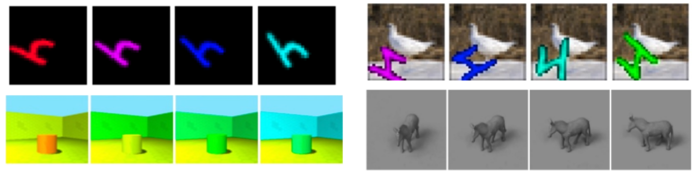
Background

Group structure is a type of compositional structure that can be achieved through **equivariance** relation, which is used in neural networks such as convolution, graphNNs, etc to introduce an informative inductive bias regarding the nature of compositional symmetry underlying the dataset. **But can we learn such a structure in an unsupervised way?** Our work shows that if time-sequential dataset with a certain stationary property, we can learn the underlying symmetries in an unsupervised manner by simply training an auto-encoder to be able to predict the future with linear transition in the latent space.

What is equivariance relation?

Actions: {translation, rotation, color change, view changes etc…}

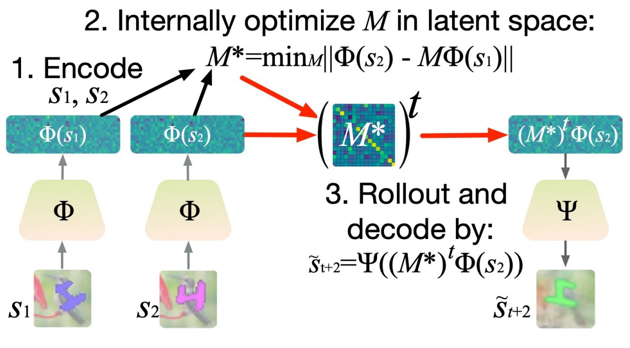


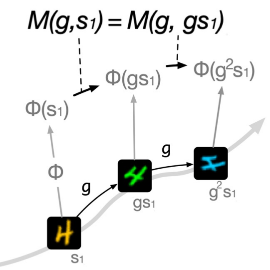
The encoder Φ: $\mathcal{X} \to \mathcal{Z}$ is said to be equivariant if the following diagram commutes with respect to *the action of all* $g \in G$:

$$\begin{array}{ccc} \mathcal{Z} & \xrightarrow{g} & \mathcal{Z} \\ \Phi\uparrow & & \uparrow\Phi \\ \mathcal{X} & \xrightarrow{g} & \mathcal{X} \end{array}$$

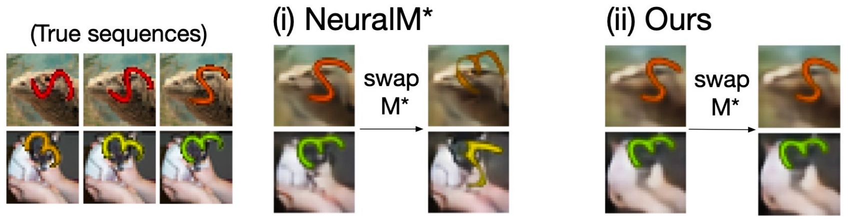
And this relation must hold **for all input $x \in X$ and action $g \in G$**

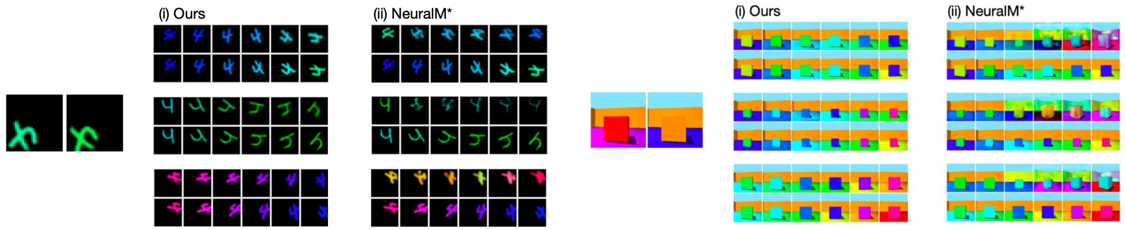
Method: Meta-sequential prediction (MSP)



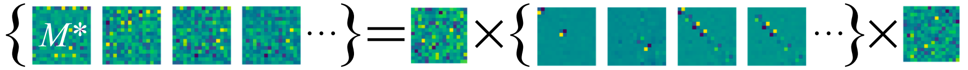


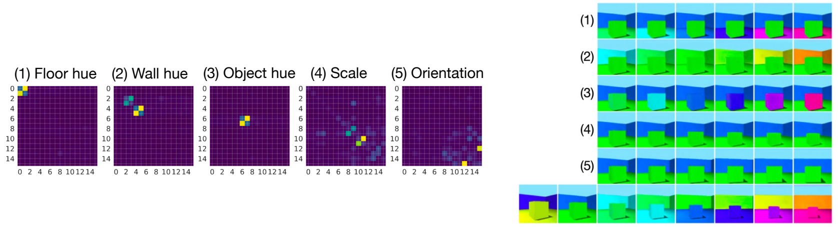
MSP successfully learns equivariance relation without supervision

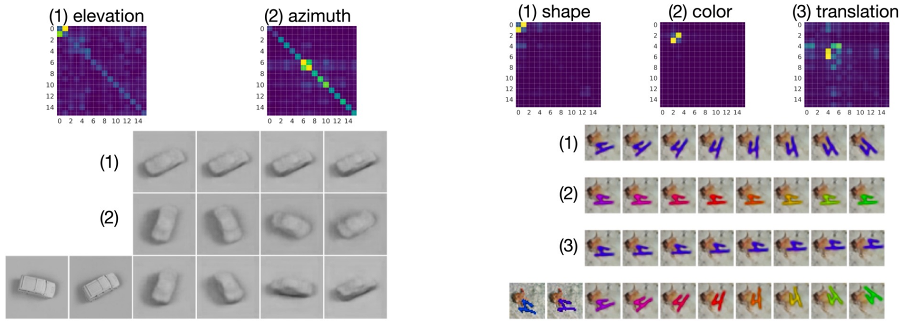




Disentanglement emerges as a byproduct of equivariance



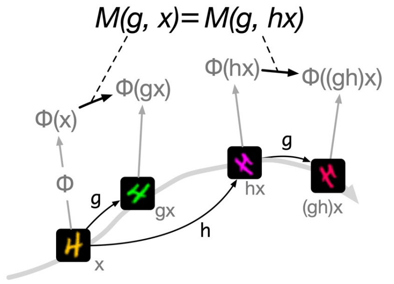




Theoretical guarantees

MSP learning mechanism **provably guarantees** that the trained model captures the components of equivariance relation:

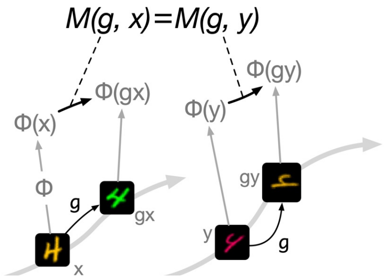
1. In-Orbit Equivariance is always satisfied by the MSP model if the group is commutative, compact and connected



2. Across-Orbit Equivariance is **almost** satisfied by the MSP model if Intra orbital homogeneity is satisfied: that is,

$$\mathbf{M(g,x) = P_{xy}\, M(g,y) P_{xy}^{-1}}$$

is always satisfied



Empirically however, MSP learns the "Full equivariance" with $P_{xy} = I$ on various dataset with differing nonlinearity, suggesting a still yet unproven property of the algorithm encouraging the unsupervised learning of equivariance relation!