Unsupervised Object Representation Learning using Translation and Rotation Group Equivariant VAE

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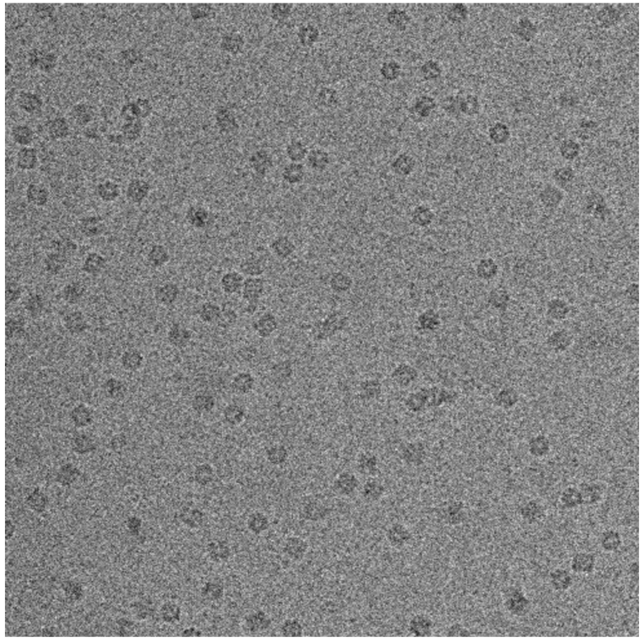
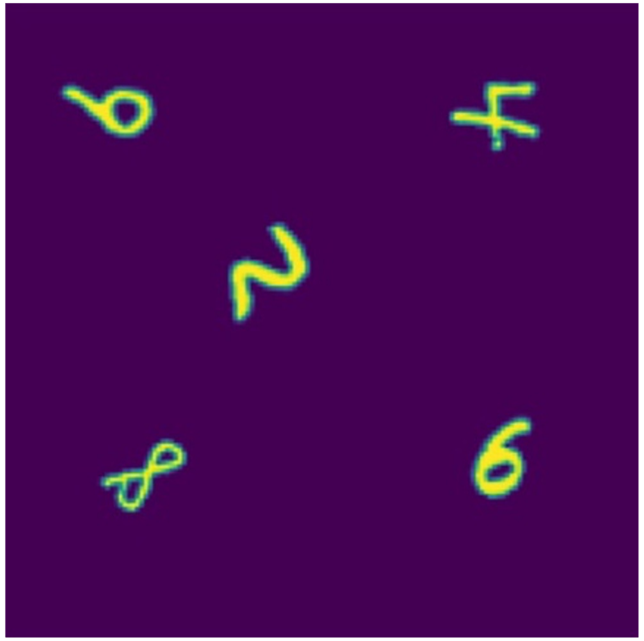
In natural images, objects often have unknown orientations

- The *pose* of an object does not change its nature
- How can we identify different objects independent of their location and pose in an unsupervised manner?

Aerial image
Source: wired.com



Electron-Microscopy Micrograph



Multi-digit hand-written numbers

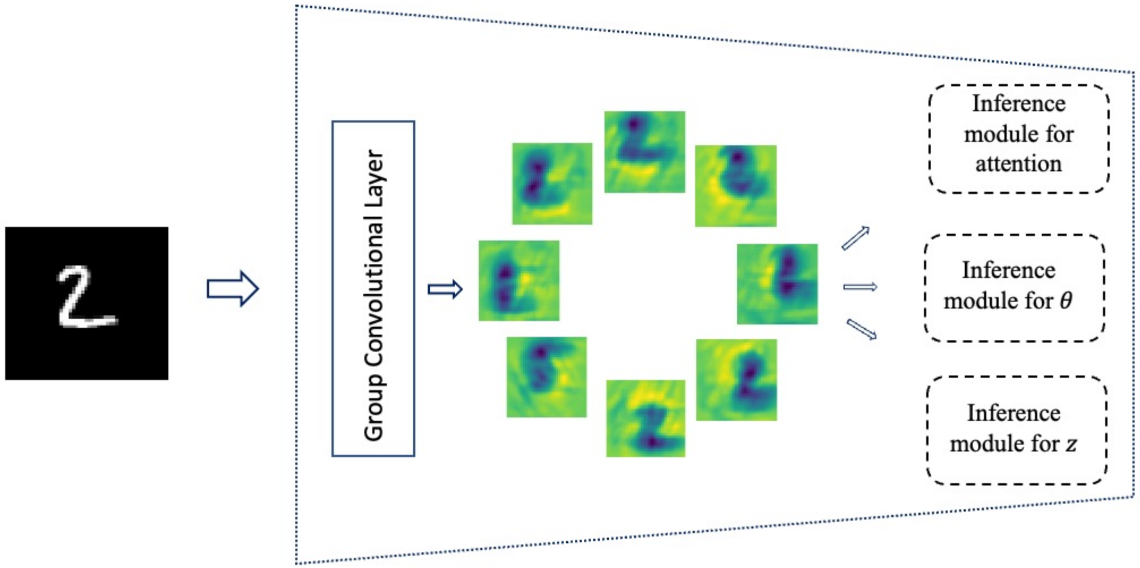
Our Proposed Method

- Goal:
  - Given images of arbitrary objects with unknown pose, learn semantic representations of those objects separately from their rotations and translations with no supervision
  - Perform efficient inference on these variables using a neural network
  - Enable controlled generation of object images from the semantic representations

- Our Proposed method, Translation and Rotation Group Equivariant Variational Auto-Encoder (TARGET-VAE), has three main components:
  1. Translation and rotation group equivariant encoder
  2. Structurally disentangled distributions over rotation, translation, and semantic representation
  3. Spatially equivariant generator

Main Components of TARGET-VAE

1. Translation and rotation group-equivariant encoder



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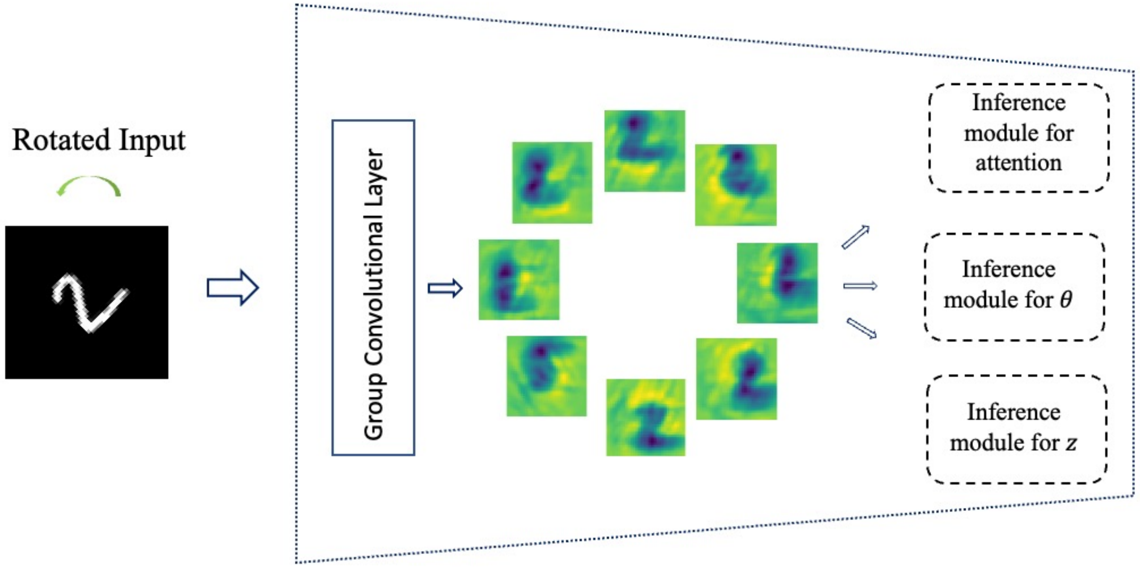

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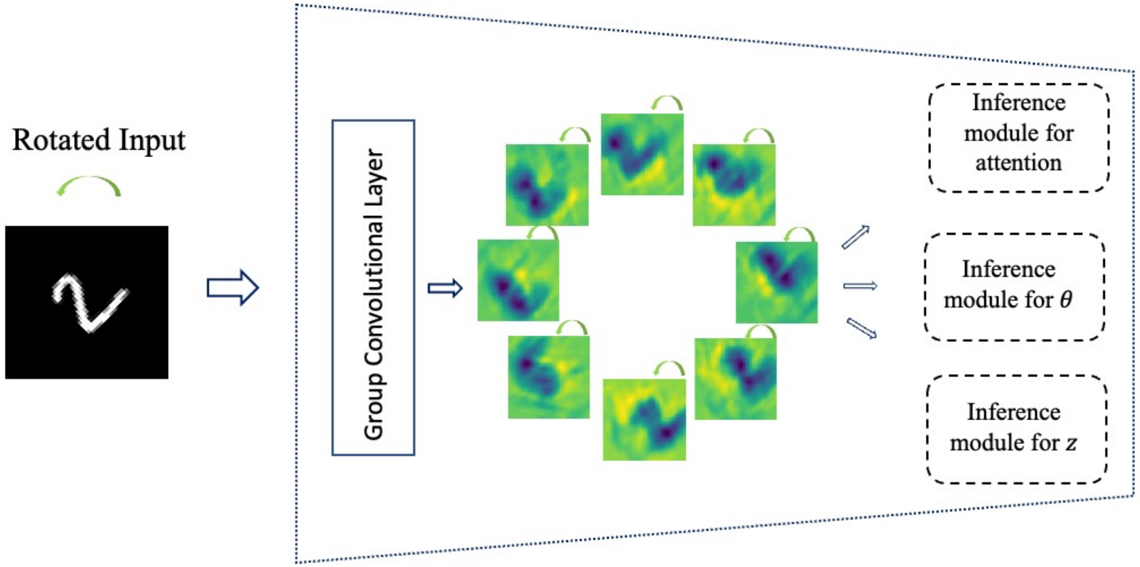

Main Components of TARGET-VAE

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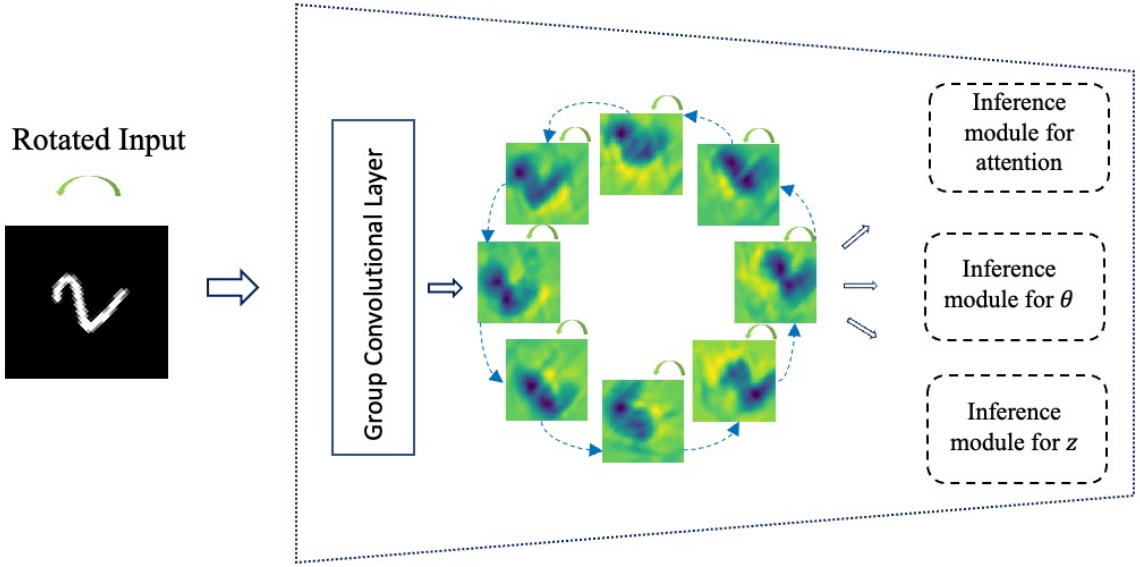
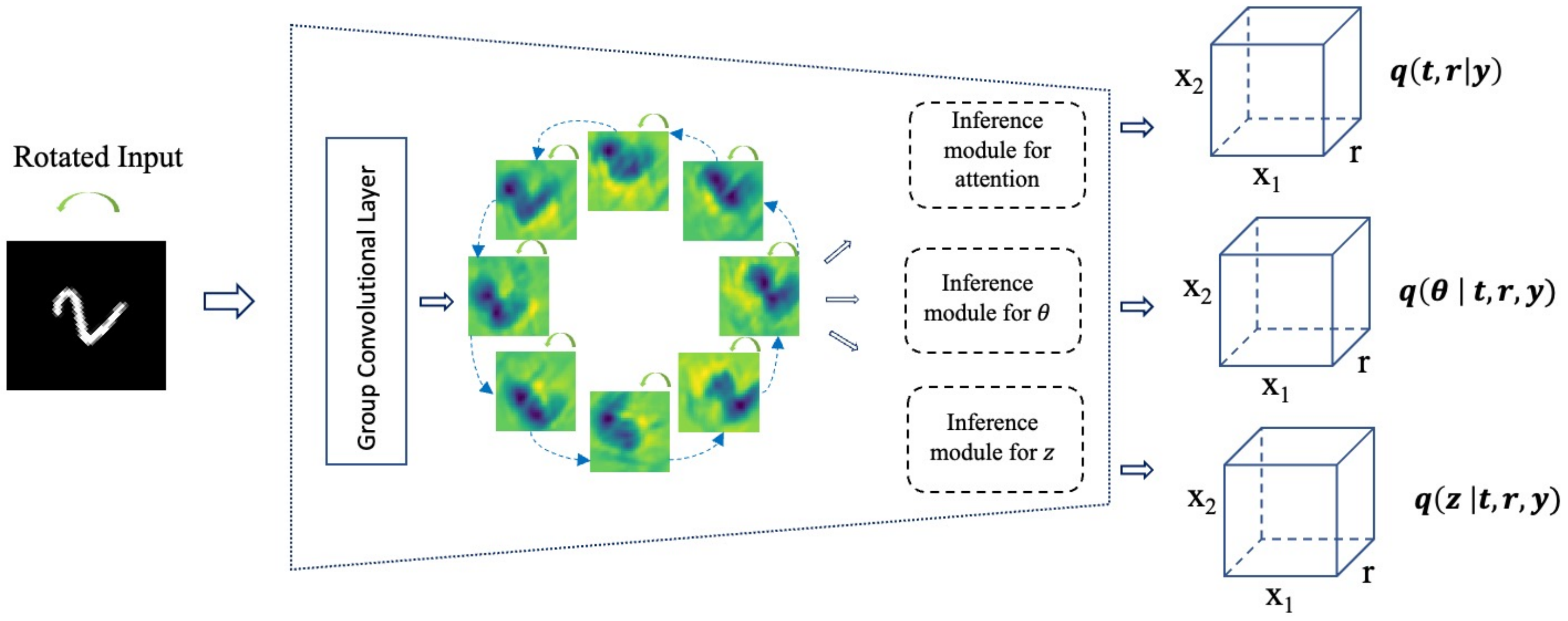


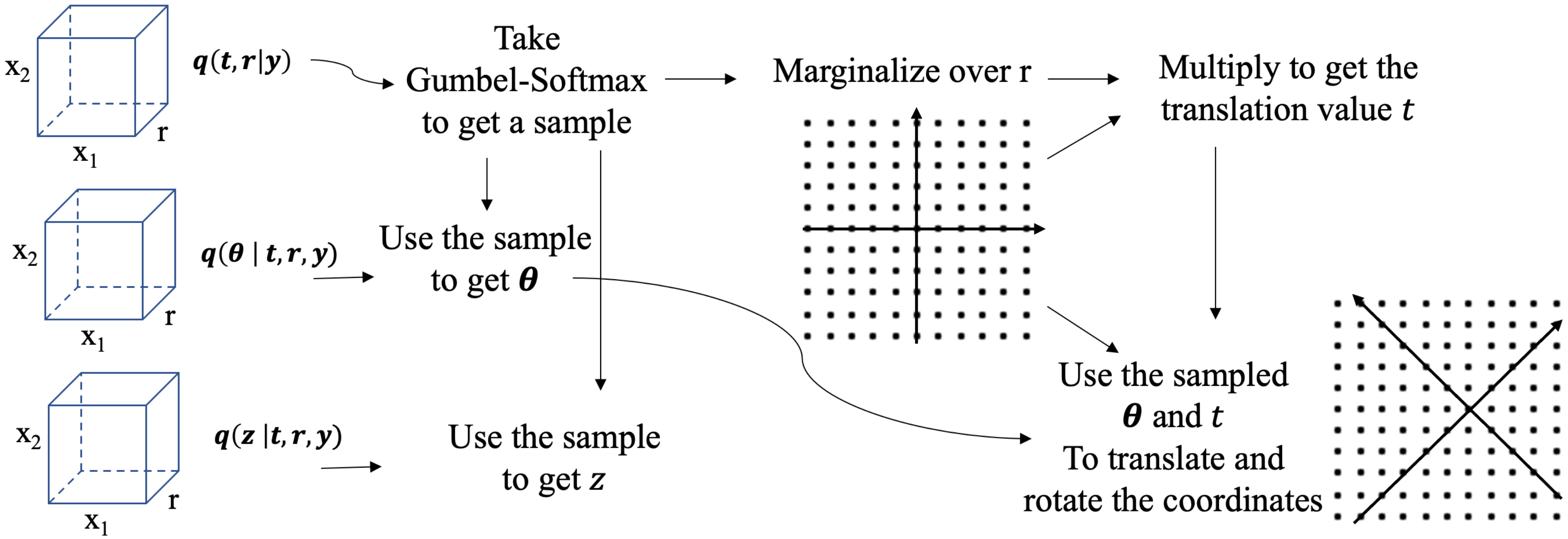
Main Components of TARGET-VAE

1. Translation and rotation group-equivariant encoder



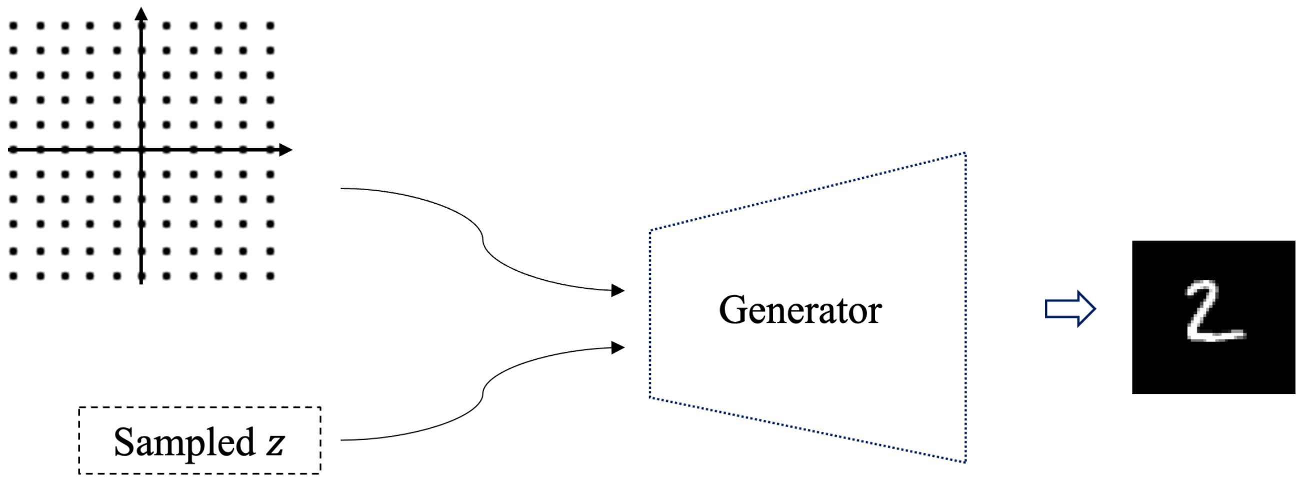
Main Components of TARGET-VAE

2. Structurally disentangled distribution over latent rotation, translation, and a rotation-translation-invariant semantic object representation



Main Components of TARGET-VAE

3. Spatially equivariant generator network



Main Components of TARGET-VAE

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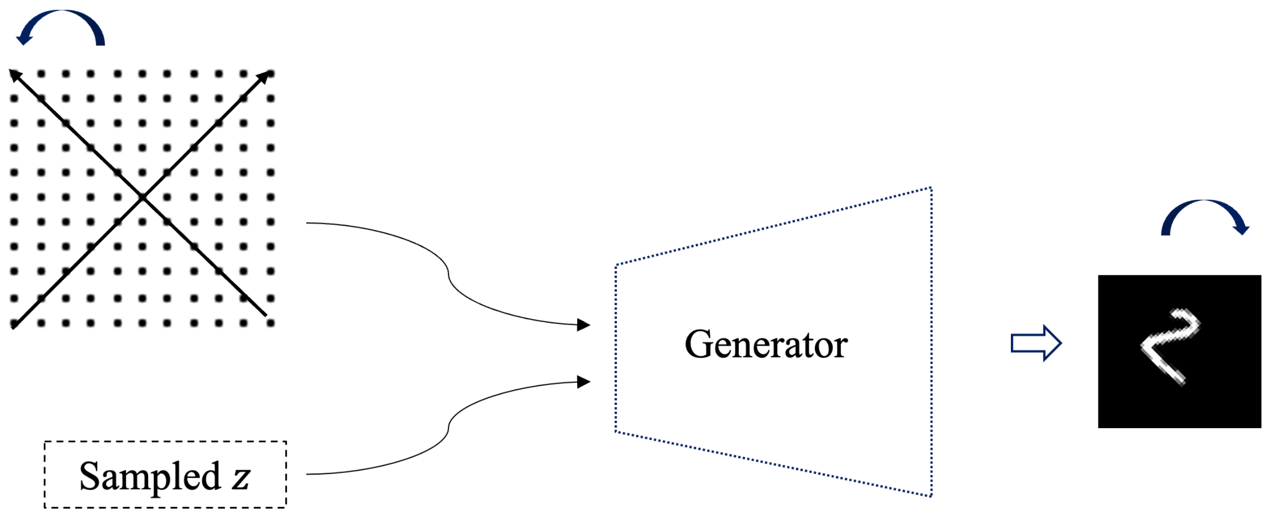

Main Components of TARGET-VAE

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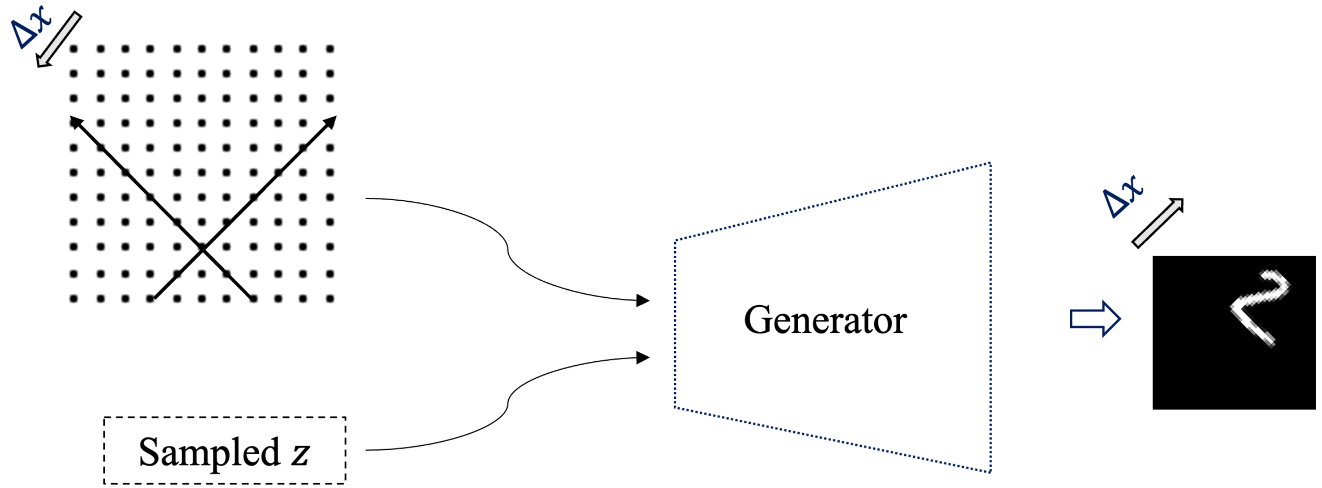
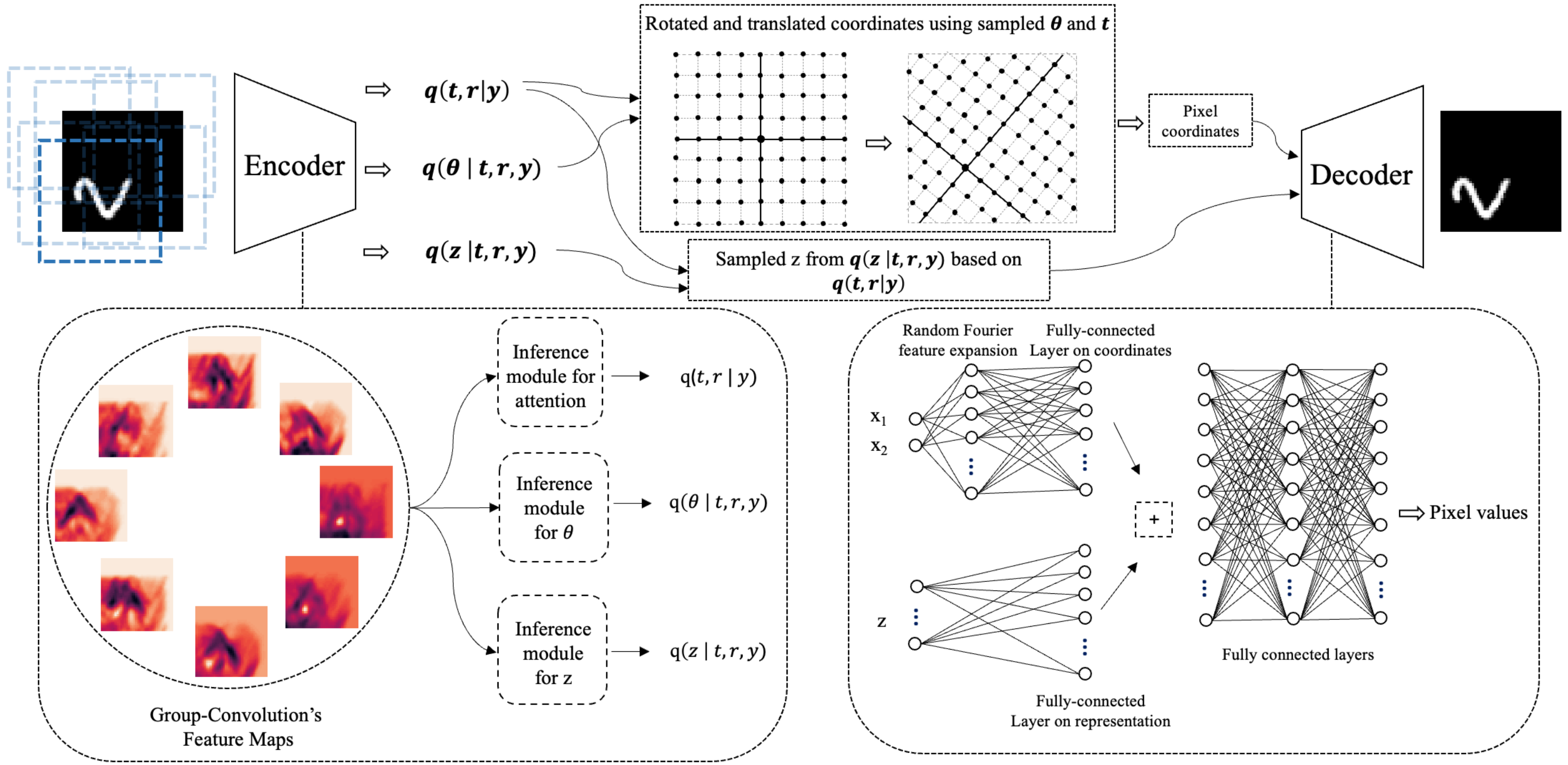
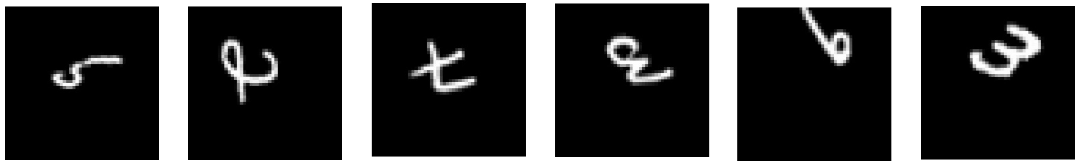


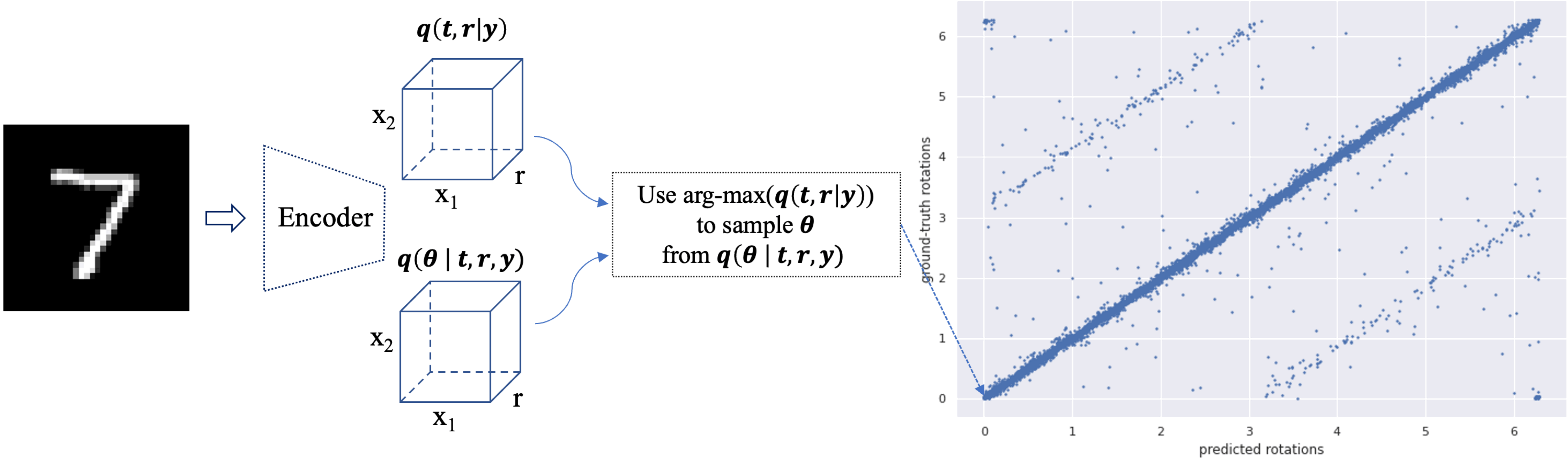
TARGET-VAE: Translation and Rotation Group Equivariant VAE



Results – TARGET-VAE Accurately Predicts Rotation without Supervision

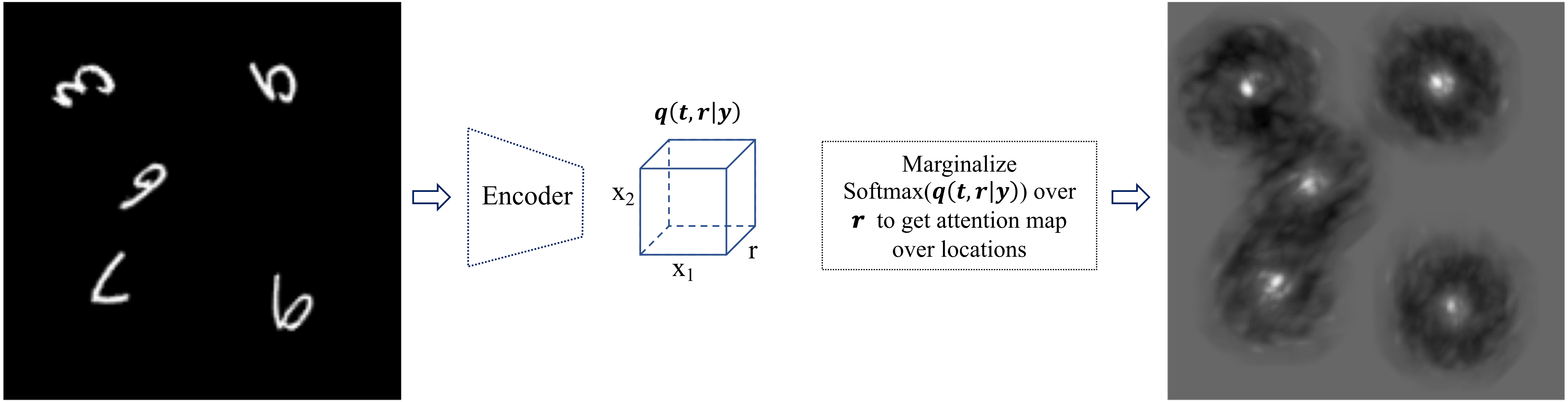
Rotated and Translated Digits:



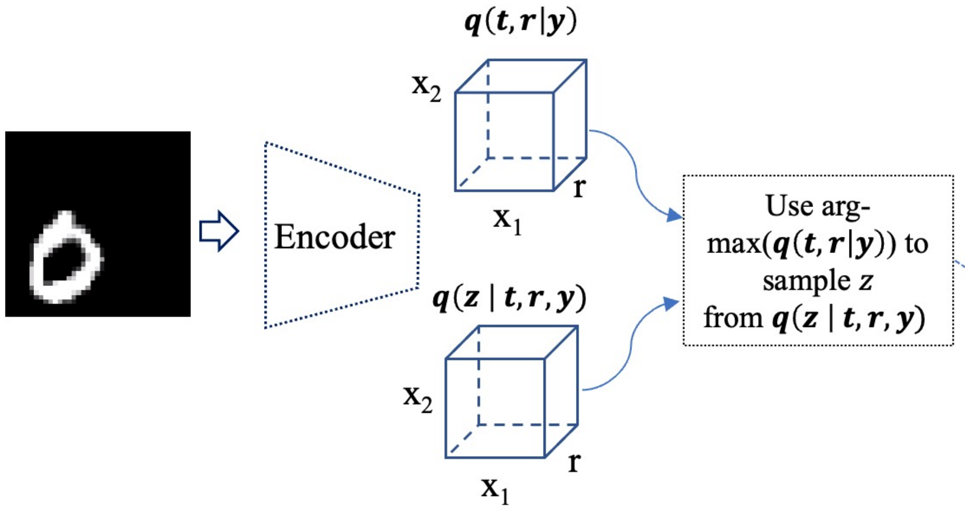


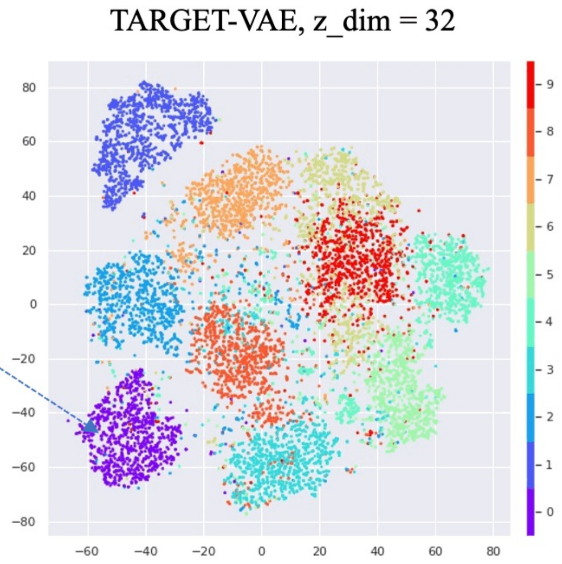
Circular Correlation coefficient = 0.86

Results – TARGET-VAE Accurately Predicts Translation without Supervision



Results – TARGET-VAE Learns Rotation and Translation Invariant Semantic Representation





Clustering Accuracy: 71.6 %

Table 2: Clustering accuracy (%) on MNIST(N) and MNIST(U)

Model	MNIST(N)	MNIST(U)
VAE (z_dim=4) [3]	15.3	12.8
Beta-VAE (z_dim=4) [4]	15.1	18.0
Spatial-VAE (z_dim=2) [6]	37.1	28.2
TARGET-VAE P_4 (z_dim=2)	56.4	56.6
TARGET-VAE P_8 (z_dim=2)	60.1	57.1
TARGET-VAE P_{16} (z_dim=2)	60.1	63.4
TARGET-VAE P_4 (z_dim=32)	65.1	64.3
TARGET-VAE P_8 (z_dim=32)	**77.7**	69.1
TARGET-VAE P_{16} (z_dim=32)	75.2	**71.2**

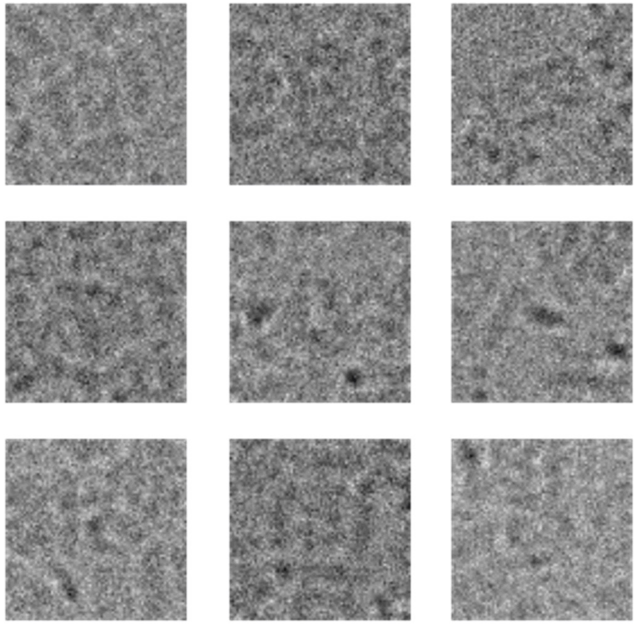
Results – Identifying Protein Heterogeneity on Cryo-EM Particle Stack

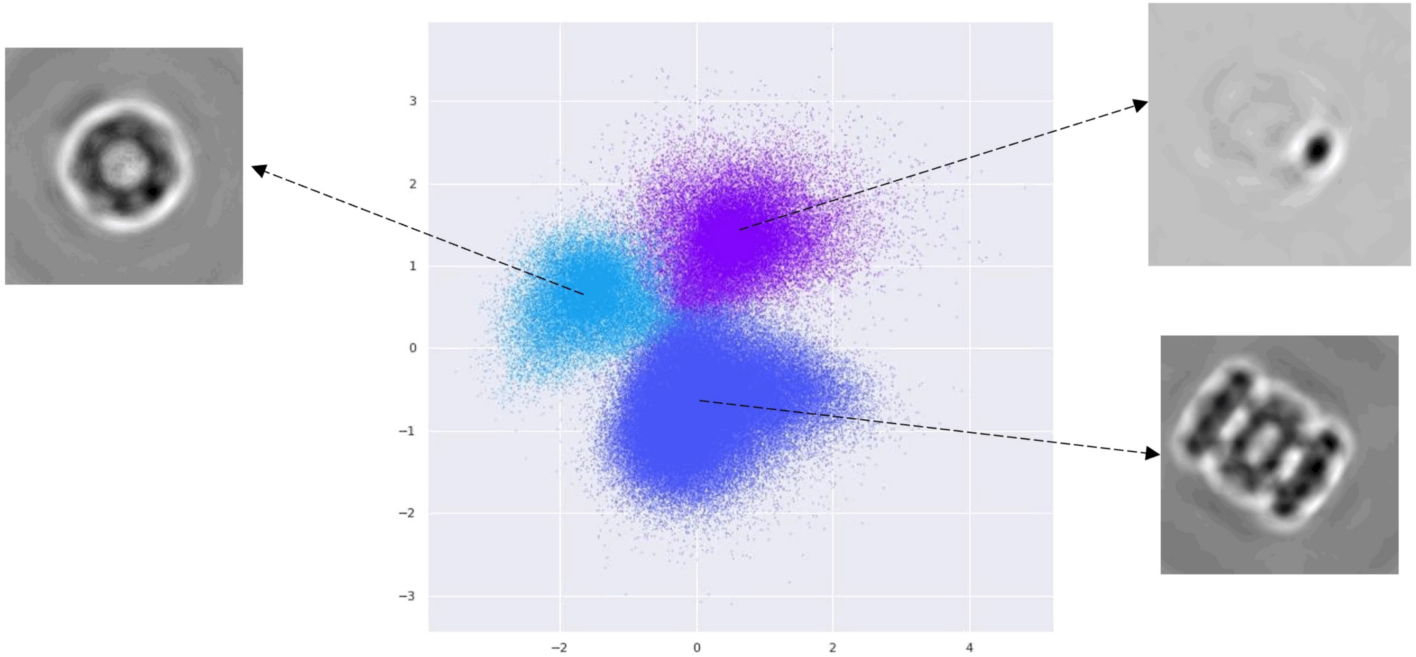
EMPIAR 10025 - T20S Proteasome at 2.8 Å Resolution

Particle stack of 161,292 images 400x400 downsampled to 100x100

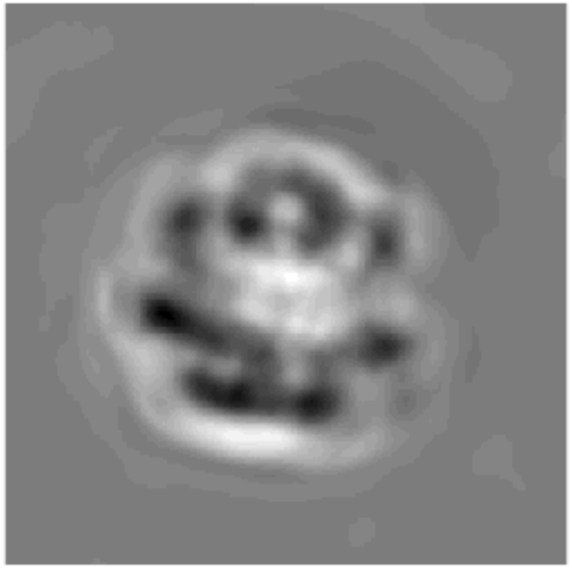
Pixel spacing: (0.66 Å, 0.66 Å)

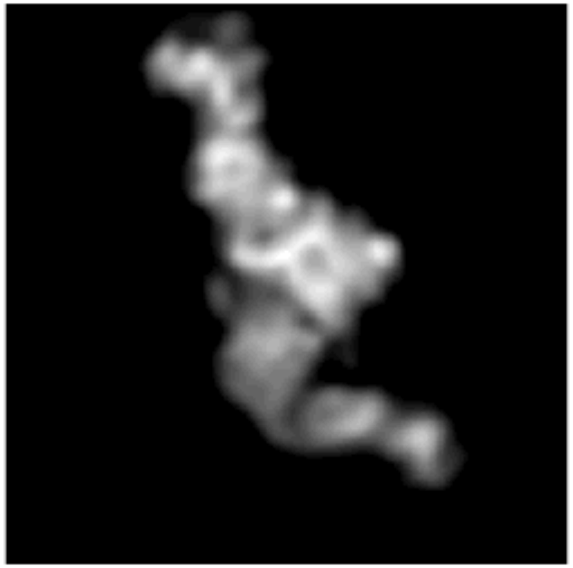
Latent dimension = 2

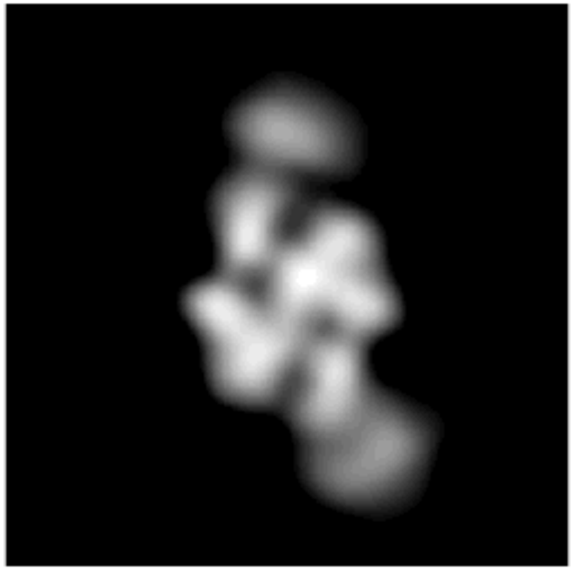




Results – Identifying Protein Heterogeneity on Cryo-EM Data







Conclusions and future work

- By designing models to capture relevant equivariances, we are able to better disentangle content from rotation and translation
- Accurate amortized inference on rotation and translation
- Learn disentangled semantic representations of objects with the ability to generate new images from the object manifold
- In the future
    - Multi object detection and unsupervised object tracking over time
    - Amortized pose inference for 3D reconstruction
    - Fully unsupervised particle picking + 2D classification

Thanks!

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