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Encoding Sparse Robot Morphologies with Custom Losses and Variational Autoencoders (VAEs) for Diversity Measurement in an Evolutionary Framework

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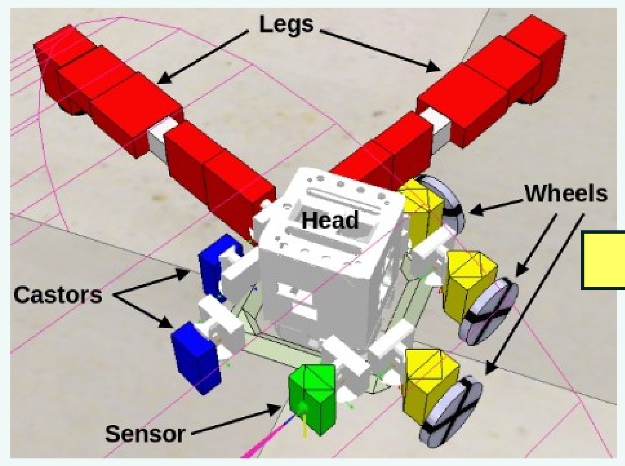
Problem & Objectives

Problem:
- Traditional diversity metrics fail to capture complex underlying relationships in evolved robot morphologies.
- This limits their ability to maintain solution population variation, crucial for avoiding premature convergence during evolution.

Why this approach?:
- VAEs learn directly from data without relying on manually defined metrics.
- They can provide a more flexible & data-driven way to measure morphological diversity - essential for supporting evolutionary exploration and avoiding local optima.

Aim:
Assess whether VAEs can measure morphological diversity by capturing spatial and component features in robotic designs.

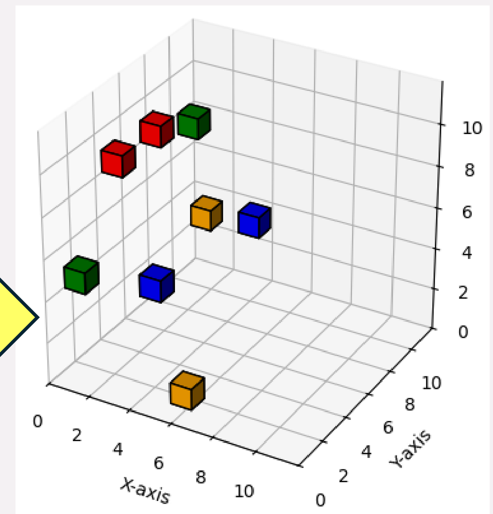
Robot (below)
Example evolved robot that data represents.



Objectives:
- Train a custom VAE on sparse voxel data.
- Evaluate the latent space using dimensionality reduction (PCA and UMAP).
- Compare the VAE to traditional diversity metrics.

Approach & Model Design

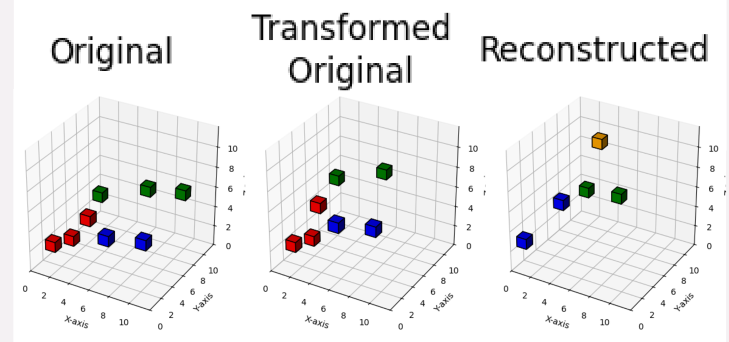
Original Voxel Encoding Format (below)
- Original robots encoded as 11x11x11 grid without skeleton (shown visually).
- Robots had at most 8 components.
- Sparsity caused difficulty for model learning.



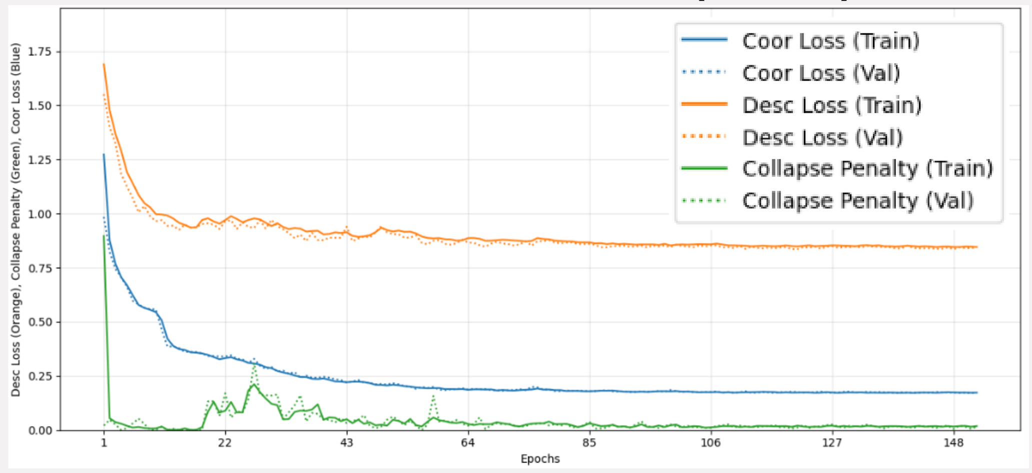
Voxel Rows

Normalised Coordinate Values			One-Hot Encoded Descriptor Values				
X_1	Y_1	Z_1	0_1	1_1	2_1	3_1	4_1
X_2	Y_2	Z_2	0_2	1_2	2_2	3_2	4_2
X_3	Y_3	Z_3	0_3	1_3	2_3	3_3	4_3
X_4	Y_4	Z_4	0_4	1_4	2_4	3_4	4_4
X_5	Y_5	Z_5	0_5	1_5	2_5	3_5	4_5
X_6	Y_6	Z_6	0_6	1_6	2_6	3_6	4_6
X_7	Y_7	Z_7	0_7	1_7	2_7	3_7	4_7
X_8	Y_8	Z_8	0_8	1_8	2_8	3_8	4_8

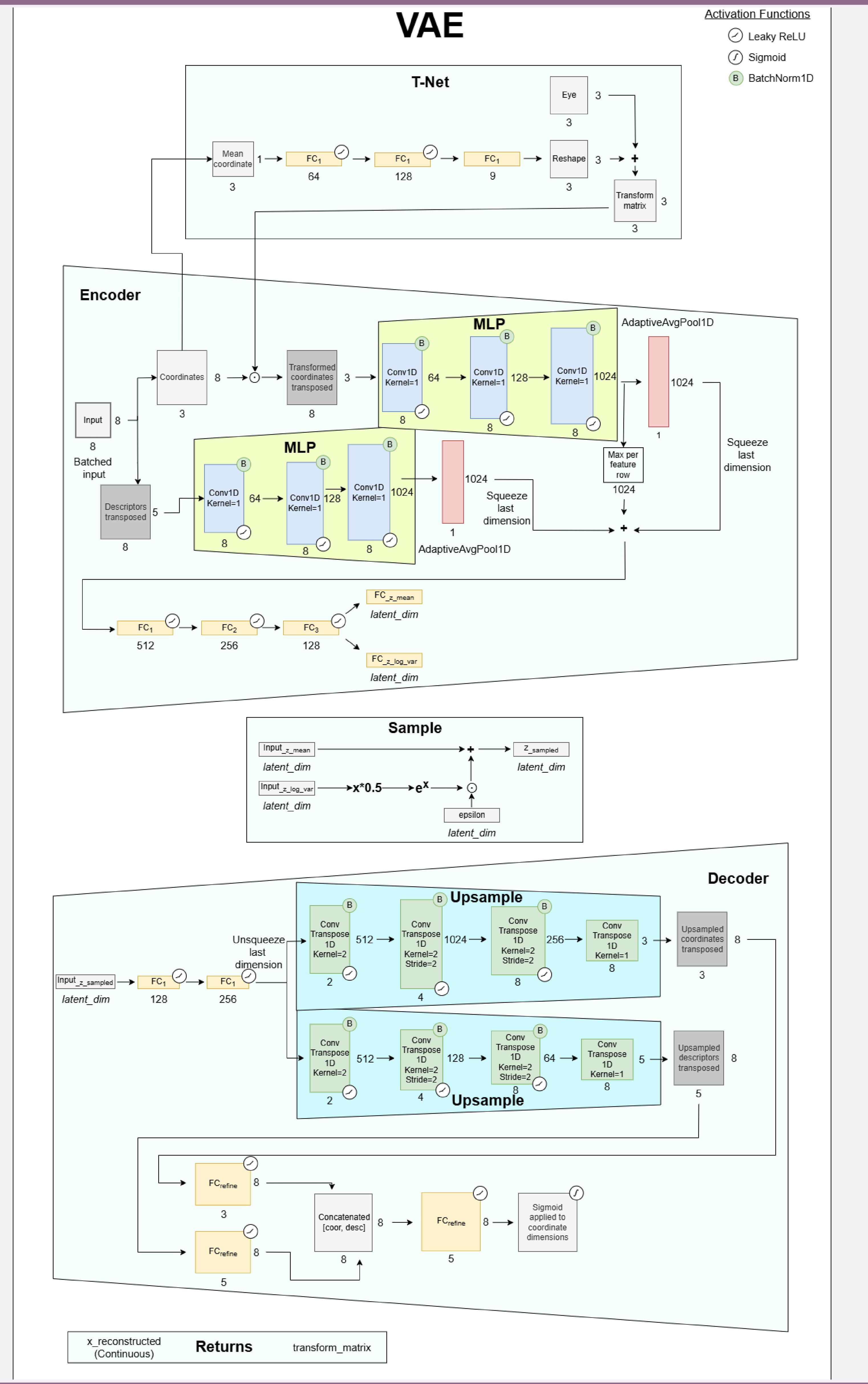
Sparse Voxel Encoding Format (above)
- Represented by 8 voxels, with normalised 3D coordinates & one-hot descriptors.
- Padded voxels added to ensure consistent input size.
- Voxel rows had no inherent order & were shuffled to prevent positional bias, leading to a PointNet inspired architecture & custom entropy-based loss functions.



Iterative Design:
- Adjustments based on reconstruction visuals (above) & loss trends (below).



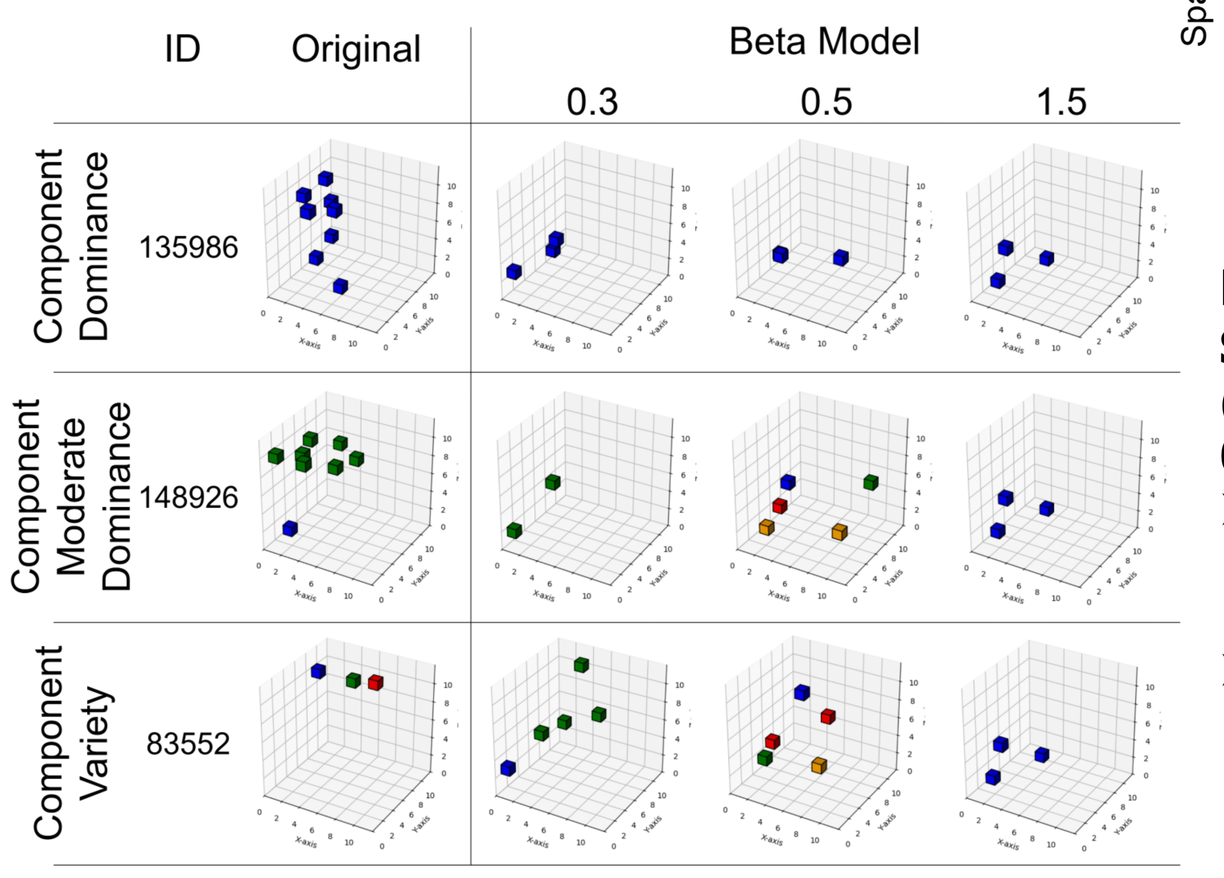
Final VAE Architecture (right)
- T-Net module ensures invariance to input transformations such as rotation.
- Shared MLP layers for efficient learning.
- Parallel branches support joint encoding of coordinates & descriptors.

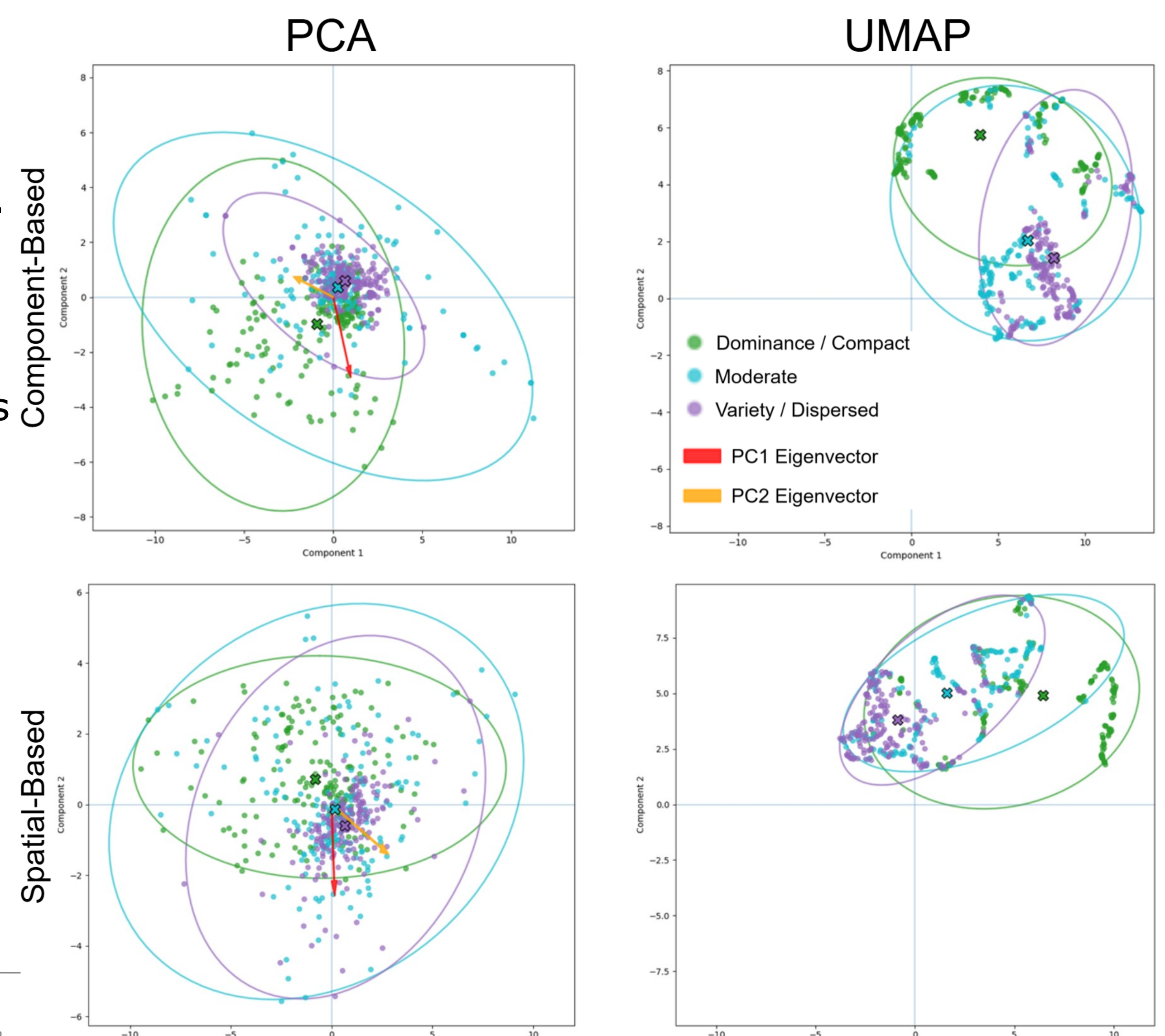


Results & Latent Space Analysis

- Two evaluation dataset categories: component dominance & spatial layout (compact to dispersed).
- Each included three datasets for evaluation.
- These were used for initial unsupervised analysis using PCA and UMAP, revealing latent space separation.
- The β = 0.3 model was selected for deeper analysis based on reconstruction quality, loss trends and metric separation.

Reconstruction Comparison (below)
(Component-based datasets shown)
- Lower β values preserve variation.
- Higher β compresses outputs into identical structures.
- Shows trade-off between reconstruction quality & latent regularity.





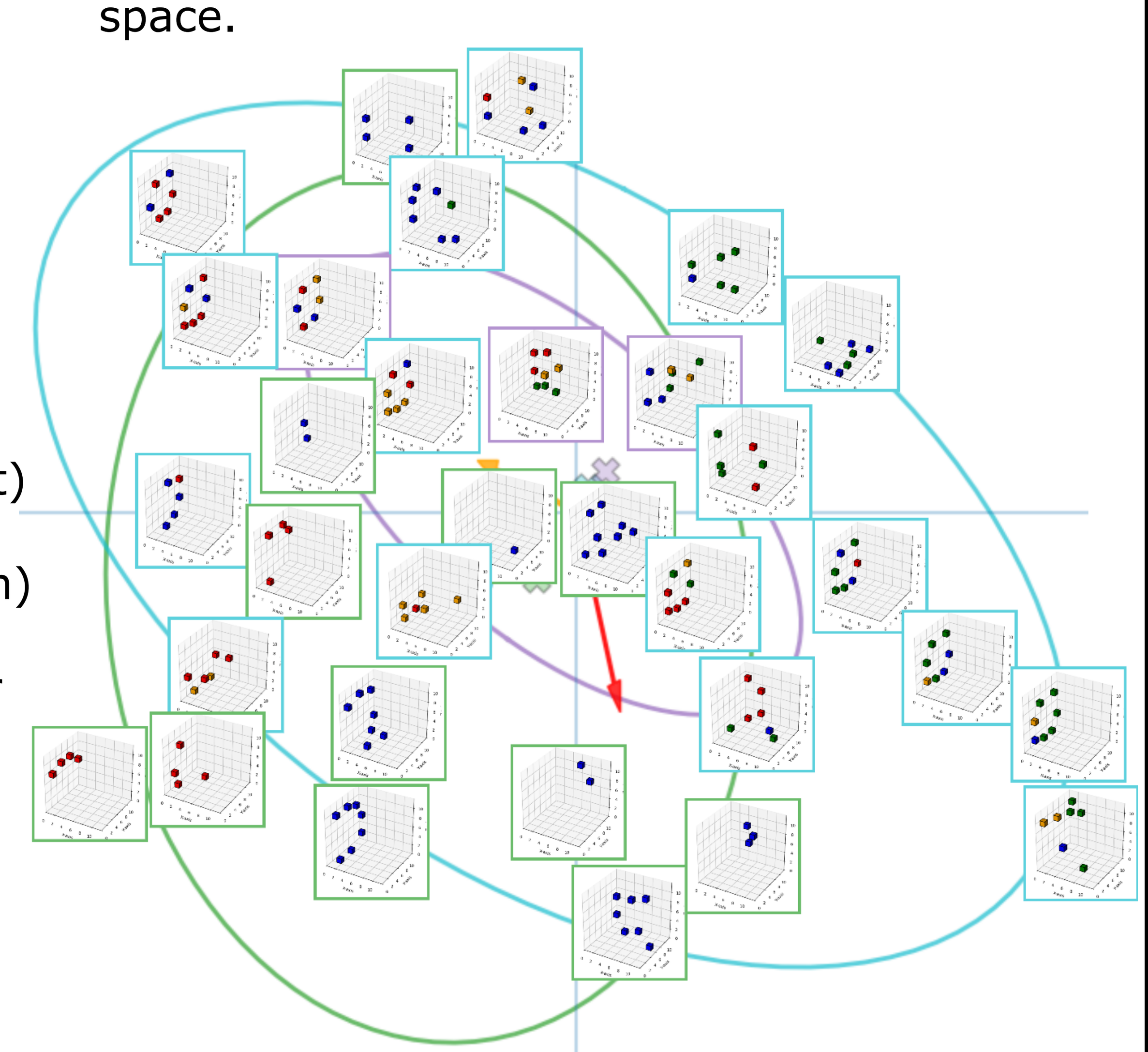
Latent Space Structure (above)
(PCA & UMAP for β = 0.3 model shown)
- Distinct clusters formed & separation by datasets.
- Highlights how model organises diverse morphologies.

Component Dominance: 187 Samples
Component Moderate Dominance: 187 Samples
Component Variety: 187 Samples

Ellipse Areas:	Ellipse Overlap Areas:	Centre of Mass Euclidean Distances:
147.91	130.00 (87.89%)	1.78
205.24	41.95 (87.59%)	2.22
47.89	47.89 (100.00%)	0.46

Metrics (above)
- Centre of mass distance, ellipse area & overlap, measure dataset separation.
- Higher centroid distances & lower overlap indicate clearer morphological difference.
- Supports visual findings of structure in latent space.

Morphology Overlay (right)
(PCA for component-based datasets, β = 0.3 model shown)
- Diagonal trend reveals regular placement of similar designs.
- Symmetrical robots cluster lower left. Spread-out designs appear upper right.
- Suggests latent space captures physical structure.



Conclusion

Key Findings:
- VAEs can measure morphological diversity by learning directly from robot structure without predefined categories.
- Grouped datasets showed clear separation in latent space across both spatial & component variations.
- Patterns such as symmetry, component positioning & variation emerged in overlays & projections.
- The model encoded meaningful morphological relationships suitable for diversity analysis in evolutionary computation (EC).

Future Work

- Exploration with Real-World Data.
- Utilise Latent Space for Novelty Generation.
- Incorporating Diversity Measurement into EC Framework Loop.