

Latent Space Topology of Several Machine Learning Algorithms

CSIC 5011 – Topological and Geometric Data Reduction and Visualisation

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Low Dimensional Representation

- How many dimensions are required to store important information?
- Low-dimensional representation of...
 - **Raw** data.
 - Data after Robust PCA (**RPCA**).
 - Latent space of Variational Autoencoder (**VAE**)
 - Latent space of Bi-directional Generative Adversarial Network (**BiGAN**)



MNIST Fashion Dataset

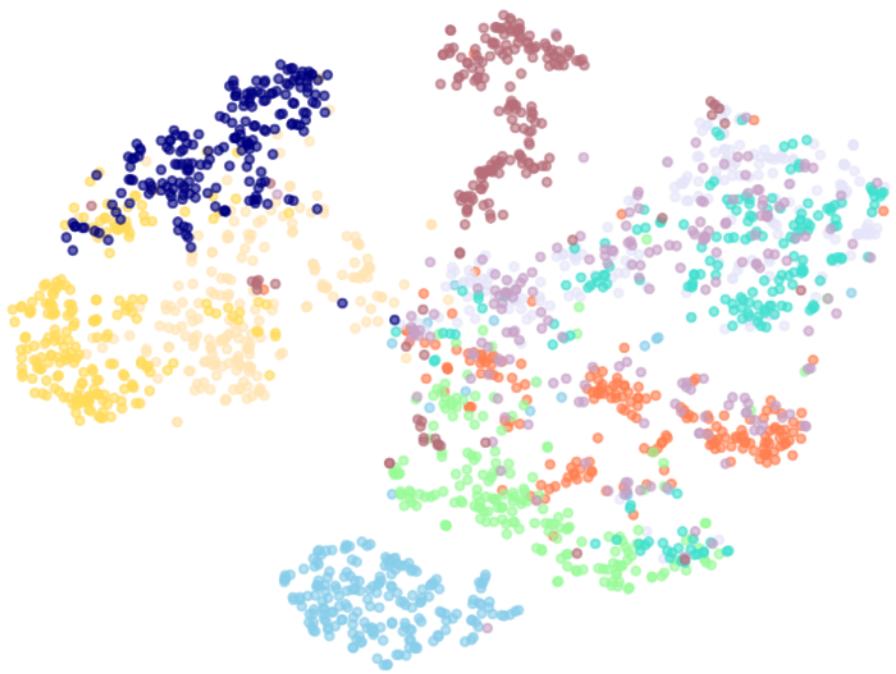
- Images of fashionables
- Training set of 60,000 samples
- Test set of 10,000 samples
- 28x28 grayscale images
- 10 labels
- Reshaped into 784*60000

2D Representation

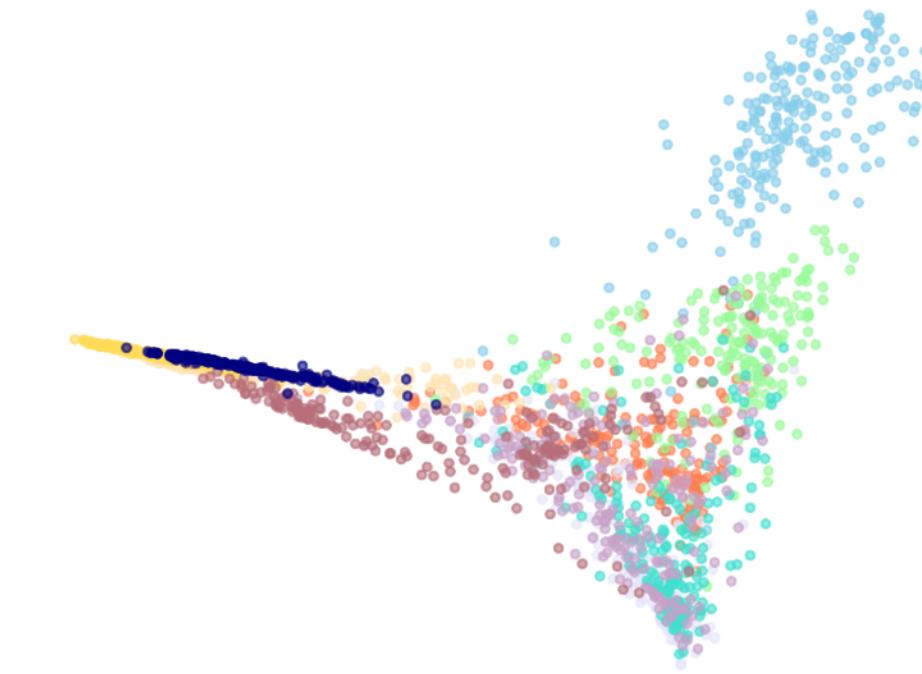
- Linear Discriminant Analysis and t-SNE perform the best
- Trouser and dress categories are most distinct
- Shirt and coat categories are difficult to distinguish.

Best Performance

t-SNE embedding (time 2.573s)



Standard LLE embedding (time 0.891s)



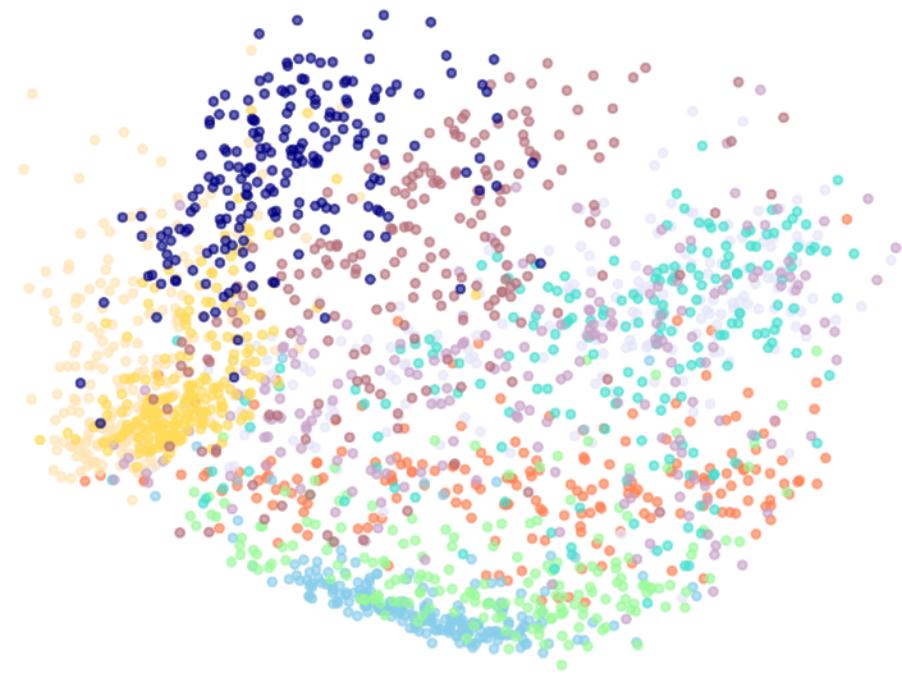
Random projection embedding (time 0.009s)



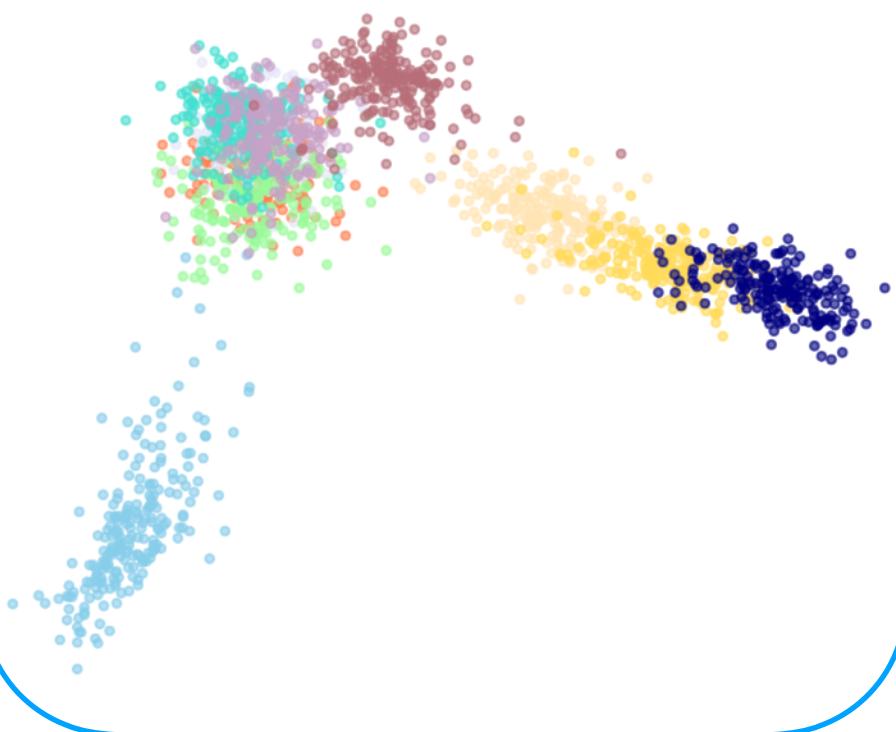
MDS embedding (time 7.271s)



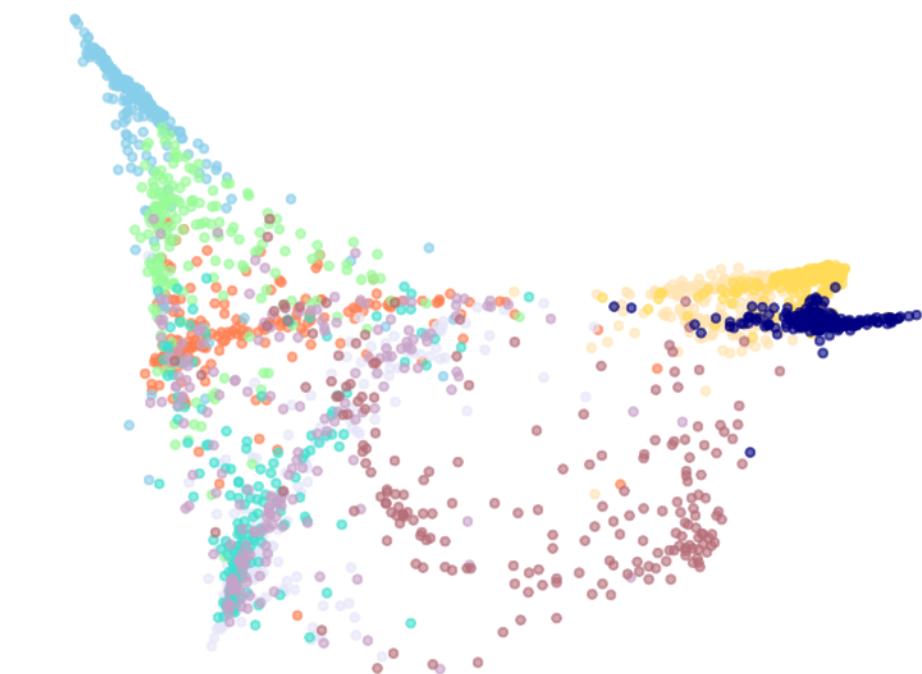
NCA embedding (time 2.113s)



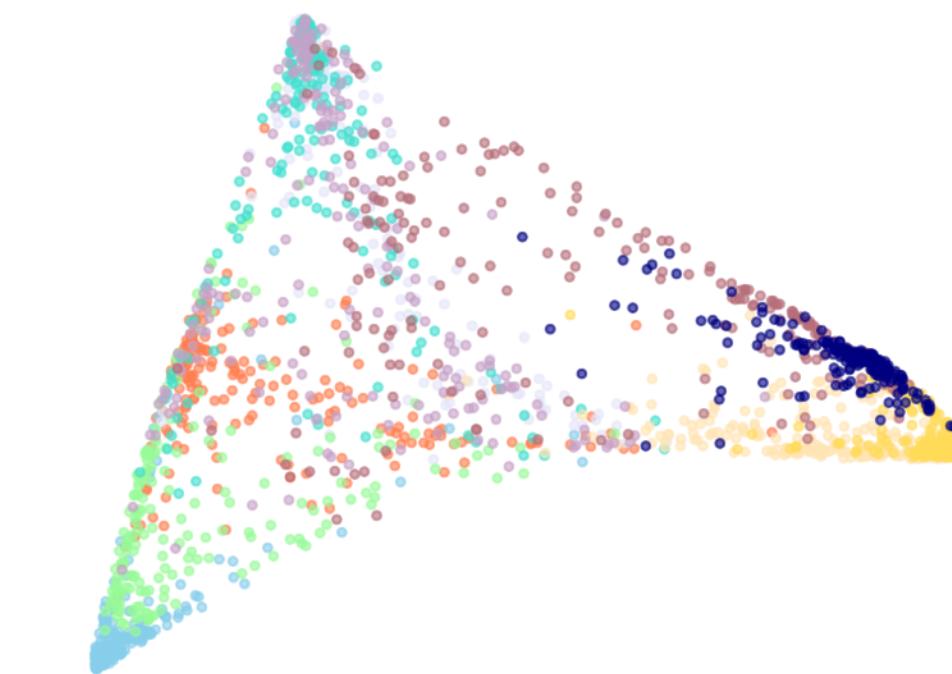
Linear Discriminant Analysis embedding (time 0.394s)



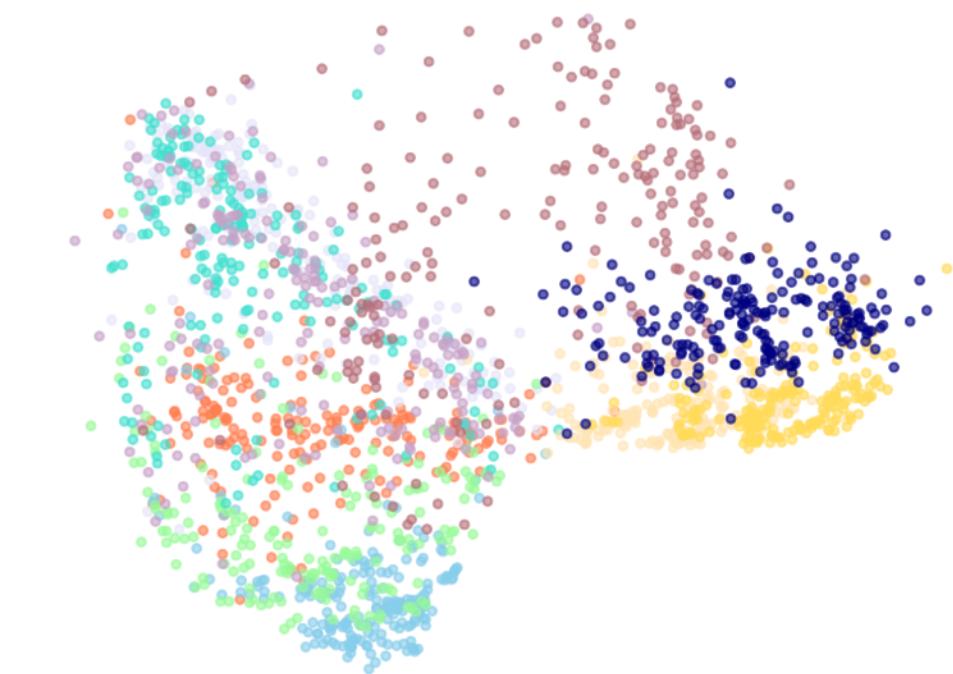
Modified LLE embedding (time 1.519s)



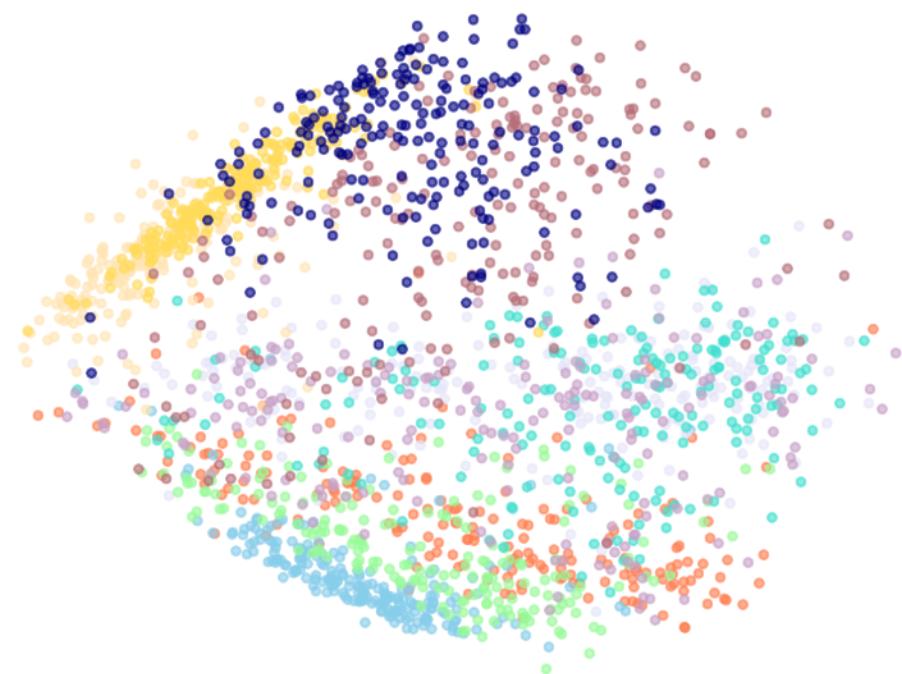
Spectral embedding (time 0.886s)



Isomap embedding (time 2.815s)



Truncated SVD embedding (time 0.041s)



• T-shirt/top	• Coat	• Sneaker
• Trouser	• Sandal	• Bag
• Pullover	• Shirt	• Ankle boot
• Dress		

Robust PCA

- RPCA to compute minimum rank and separate image
- Dimension reduction on the low-rank matrix
- Low rank image = background, high rank image = decoration

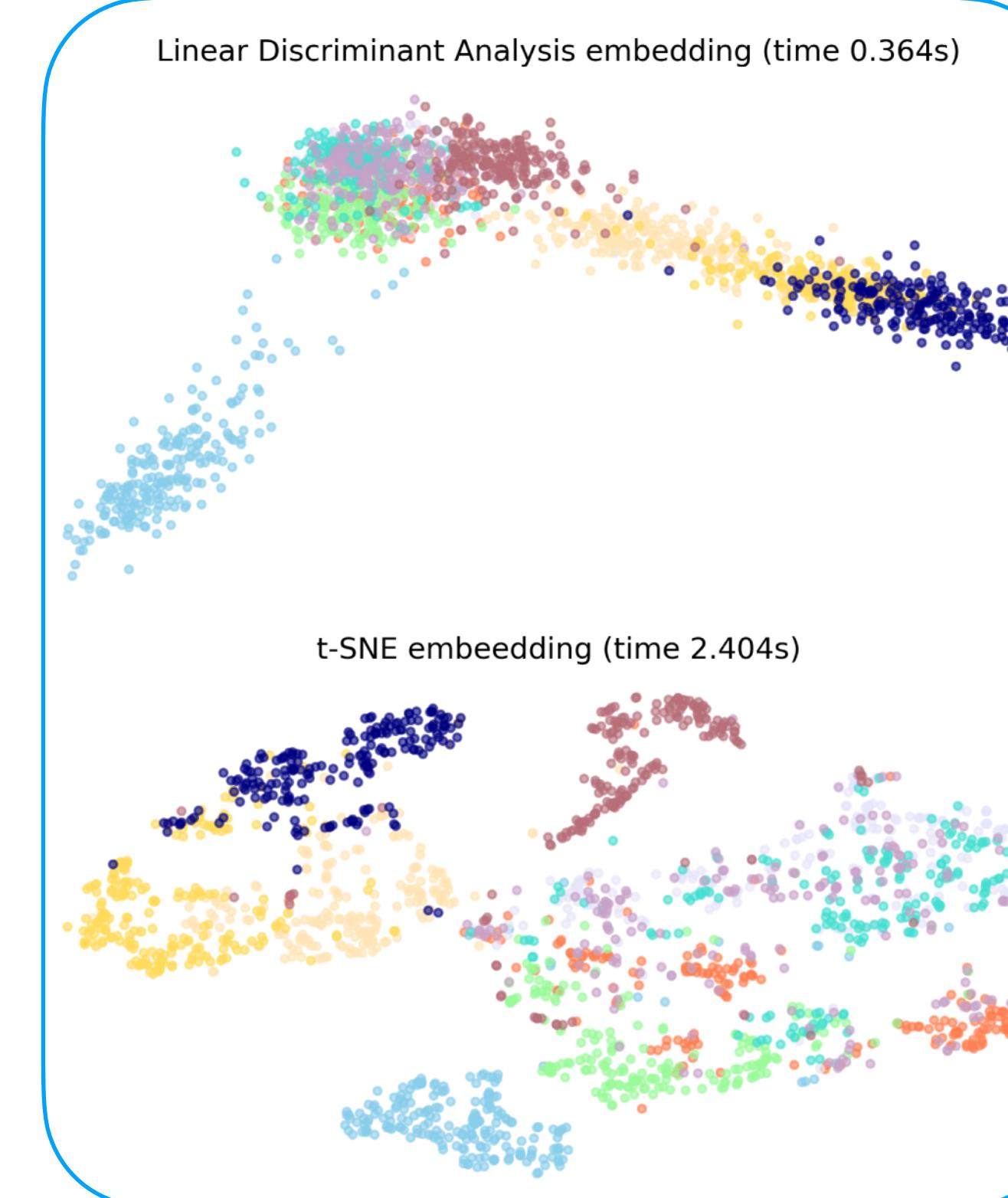
Computed rank = 432



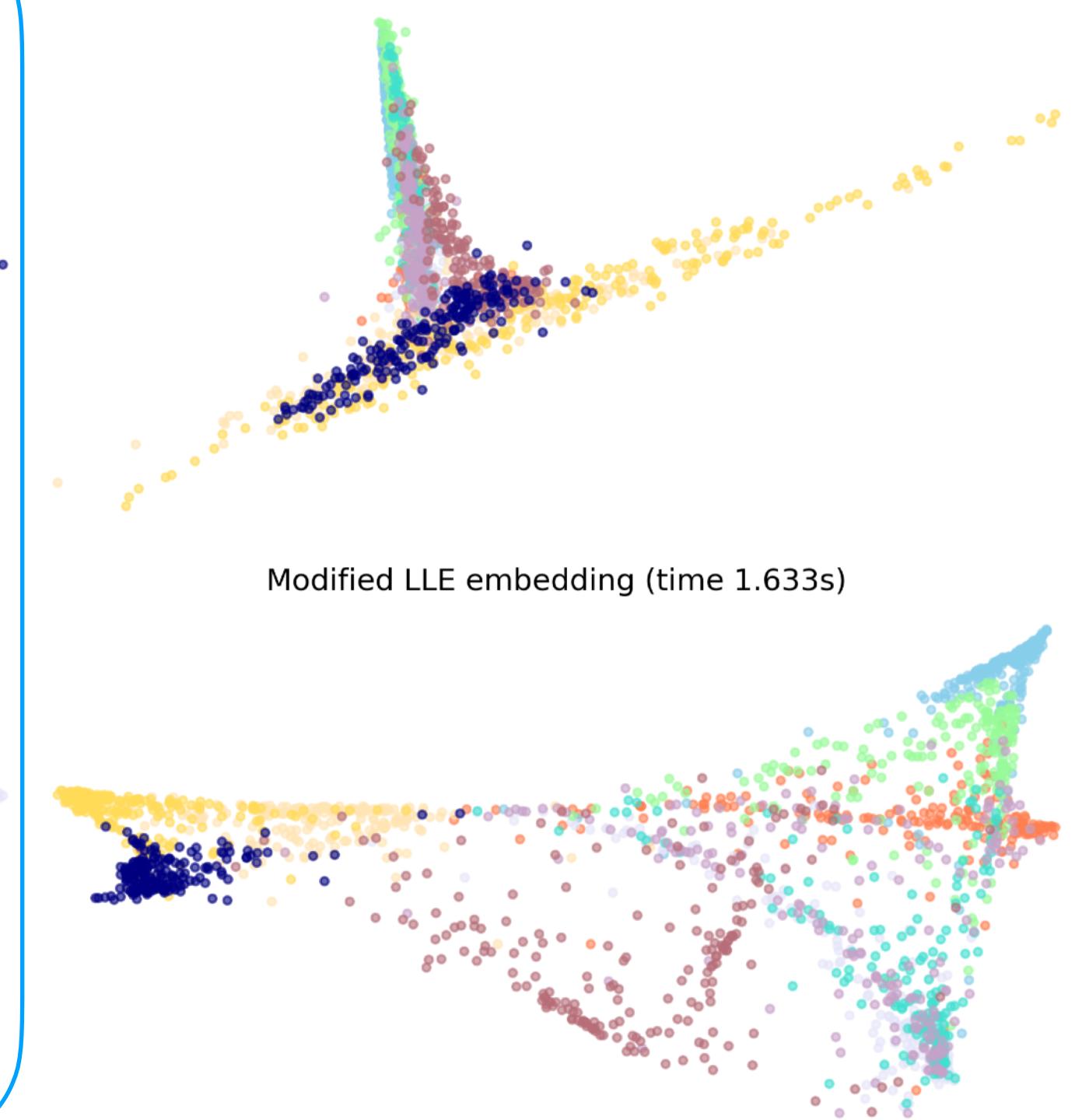
Low Rank

High Rank

Best Performance

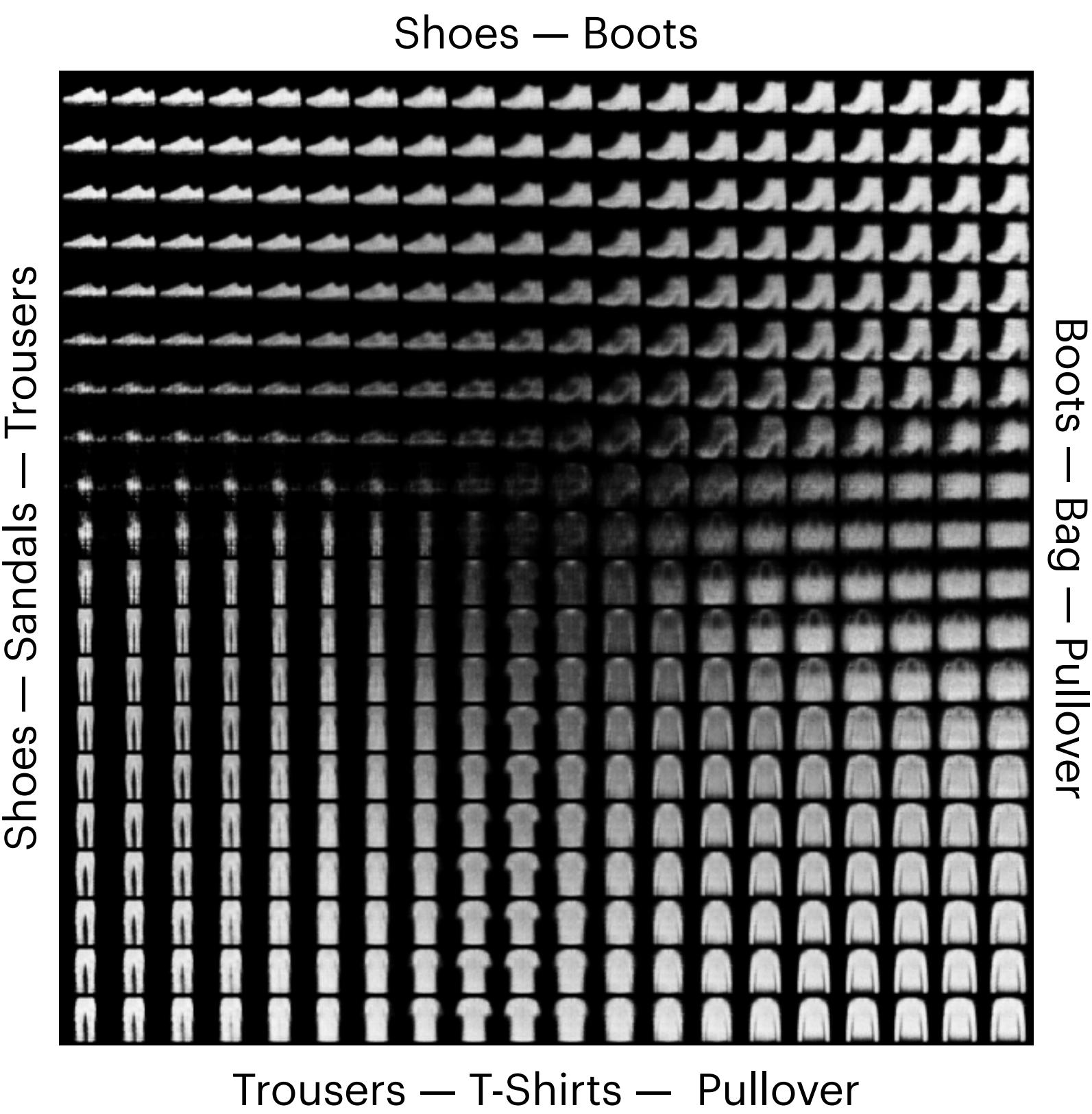
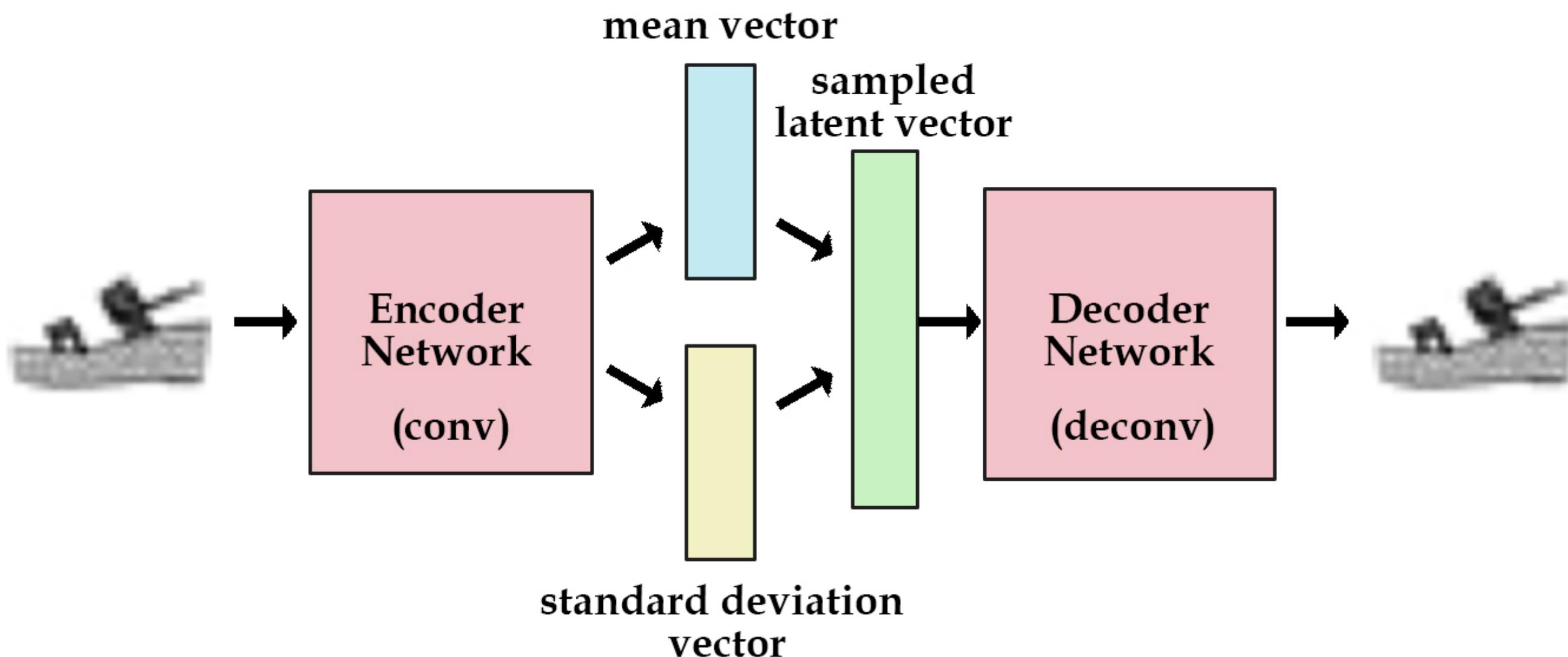


Standard LLE embedding (time 0.885s)



Variational Autoencoder (VAE)

- Use VAE to encode image into latent space
- Dimension reduction on the latent space

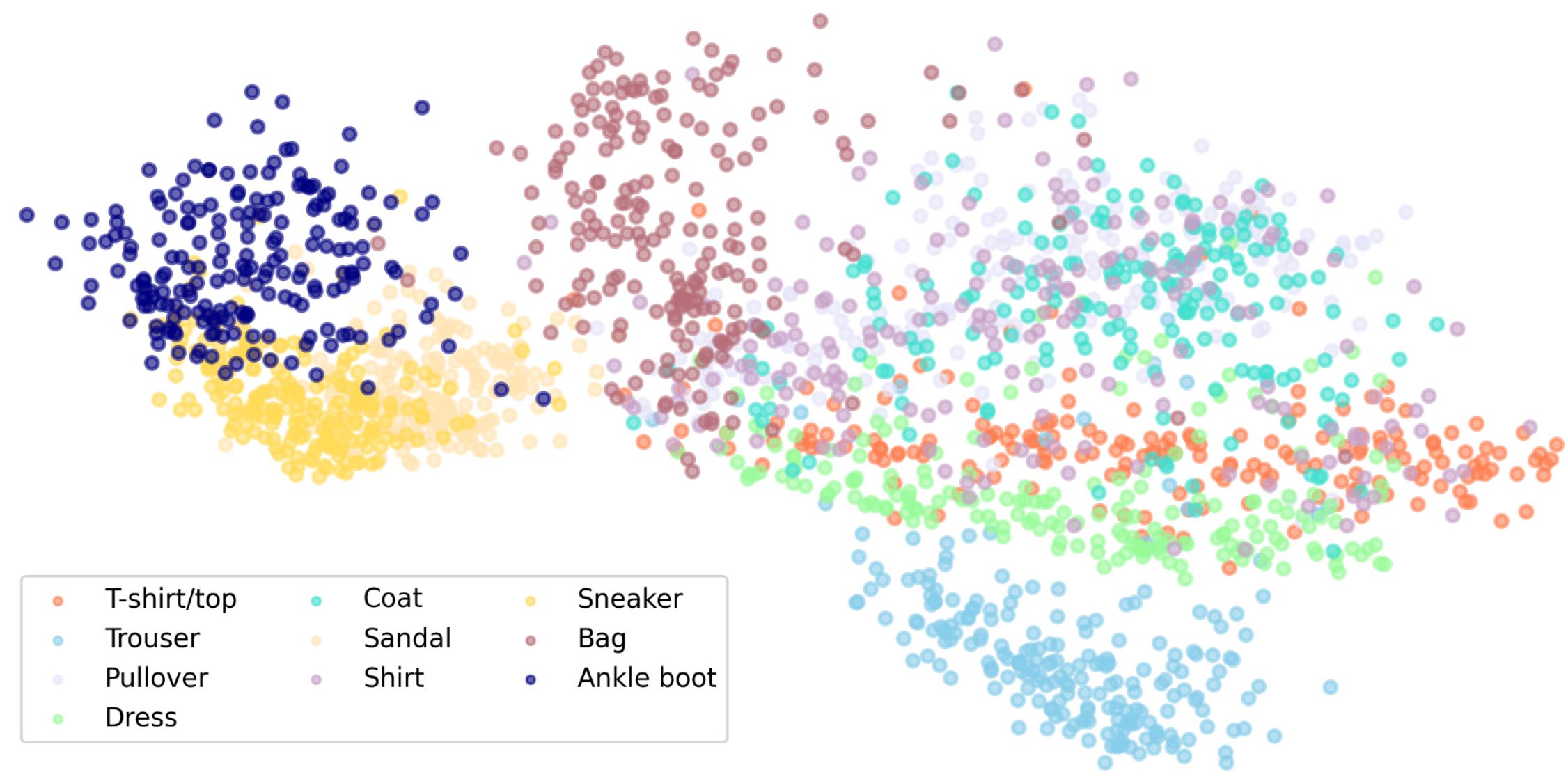


Smooth transitions from one obj into another

Variational Autoencoder (VAE)

Best Performance Among 11 Methods

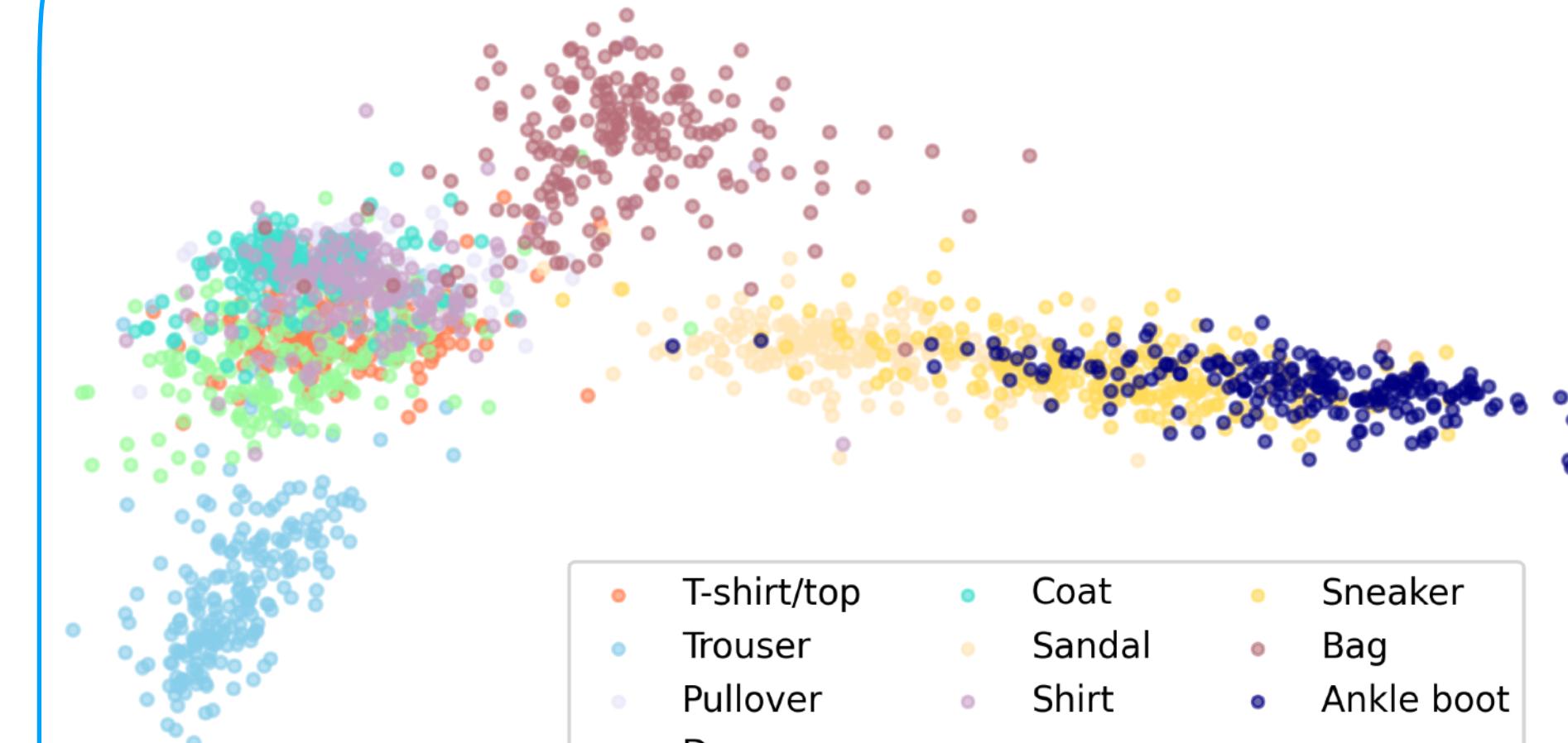
VAE with a latent space of 2 dimensions



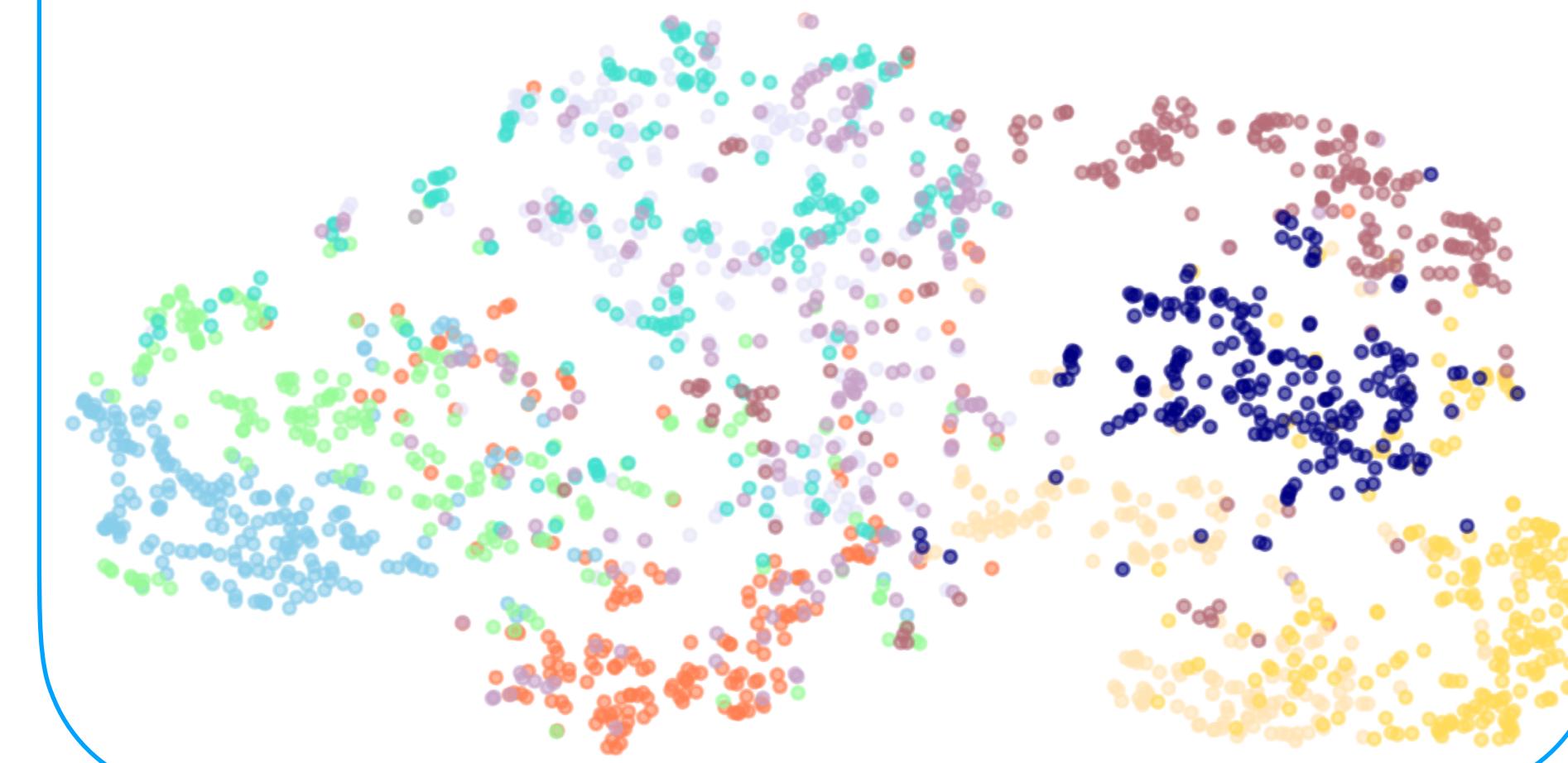
Observations

- VAE itself can encode high-dimensional data into low dimensions
- It has same good performance as the two non-ML algorithms
- Latent space of VAE has a clear structure

Linear Discriminant Analysis embedding (time 0.192s)

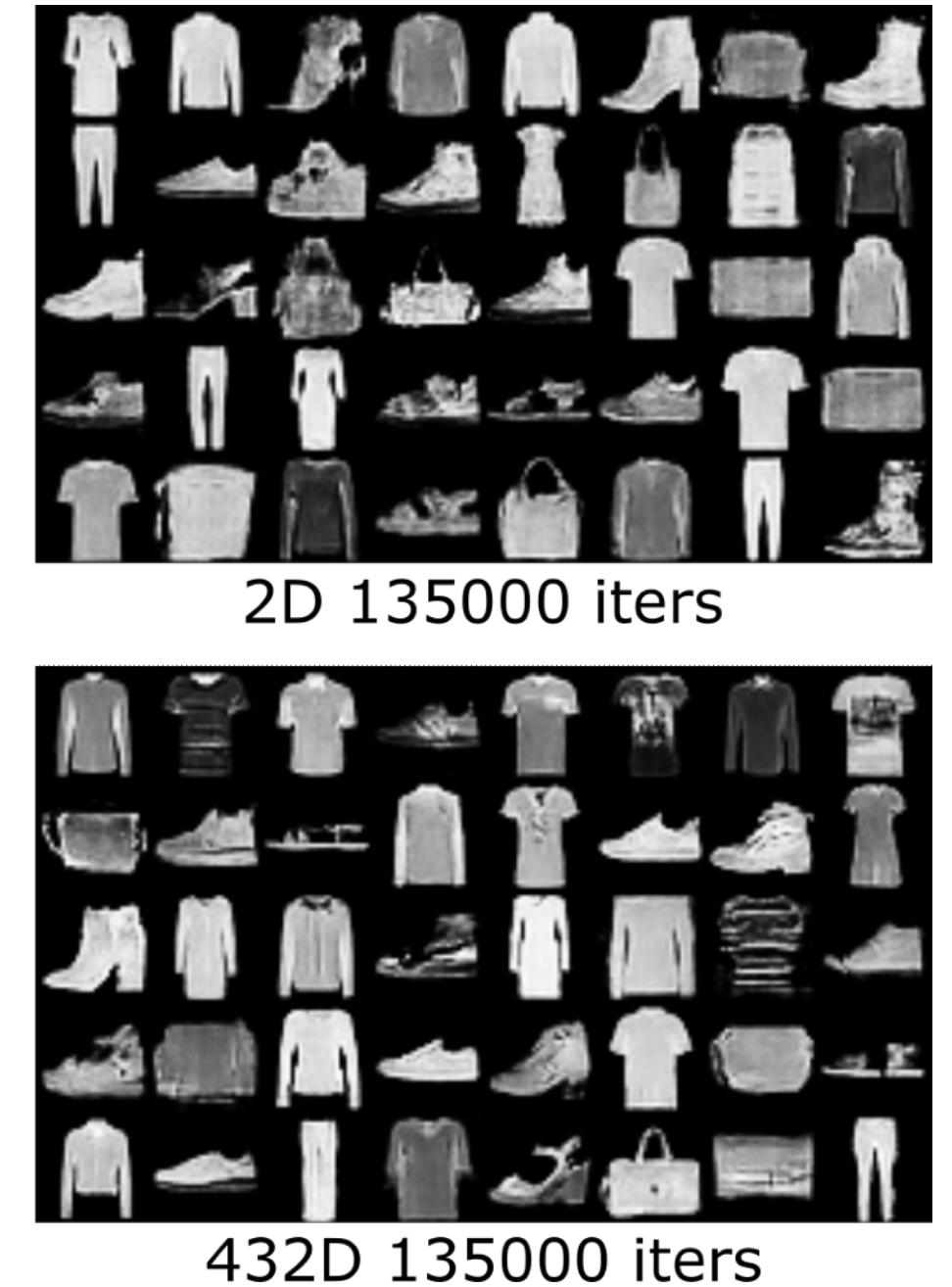
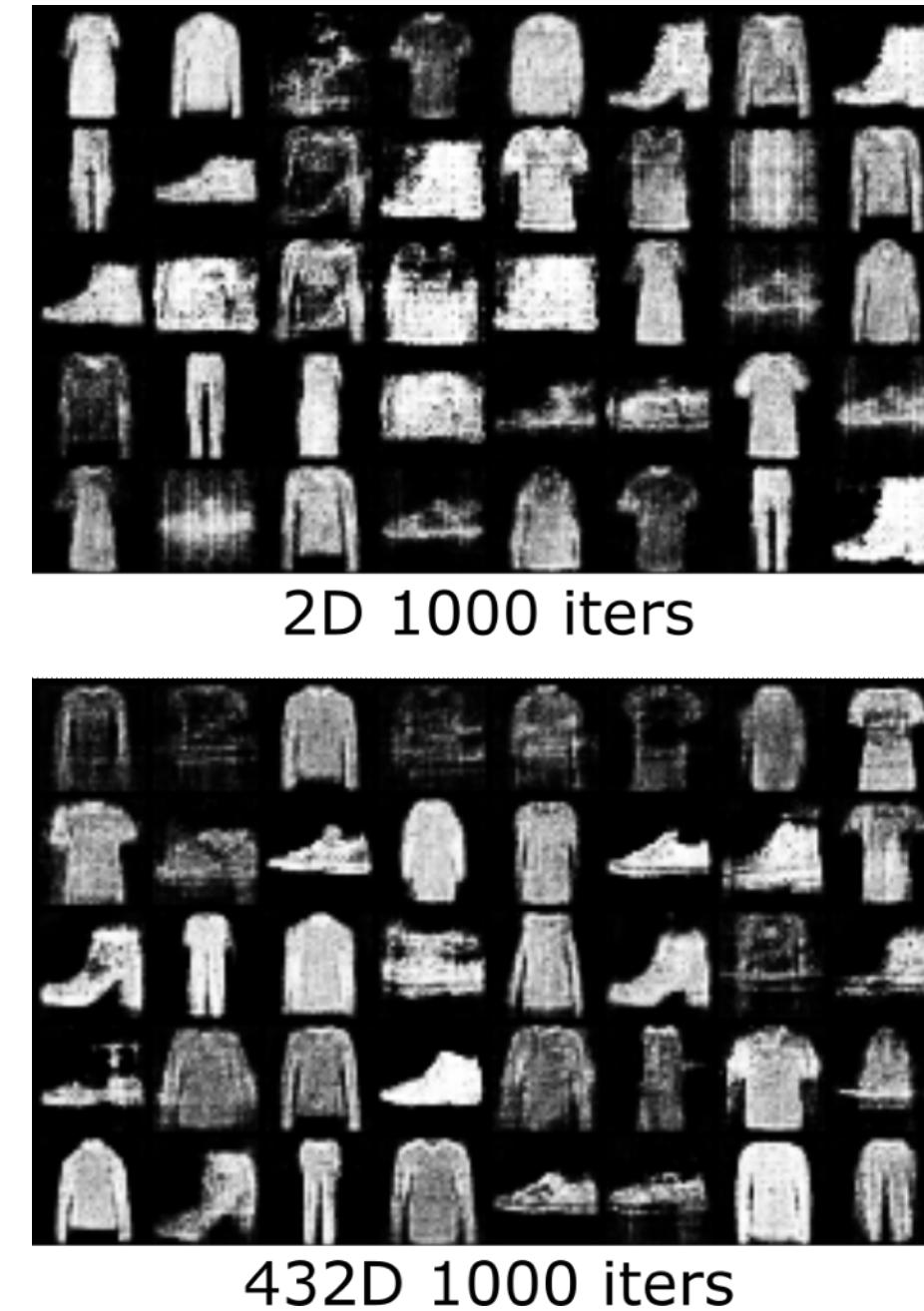
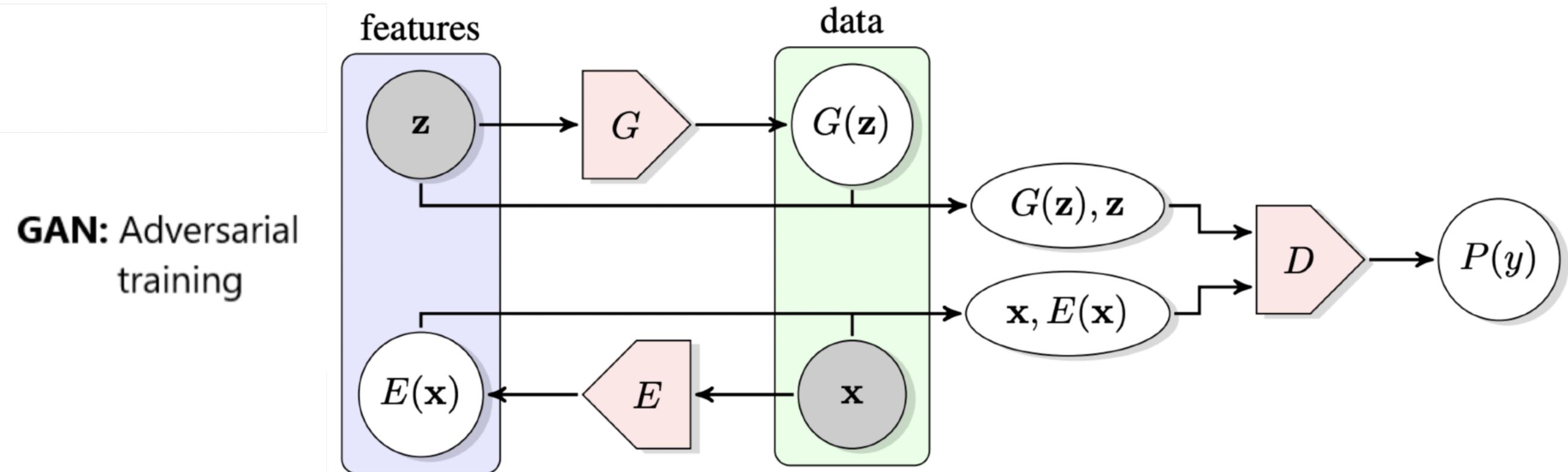


t-SNE embedding (time 2.650s)



Bi-directional Generative Adversarial Network (BiGAN)

- Use GAN to encode image into latent space
- Dimension reduction on the latent space
- Generate realistic (but fake) images



Bi-directional Generative Adversarial Network (BiGAN)



Generated Images
Iter=135000

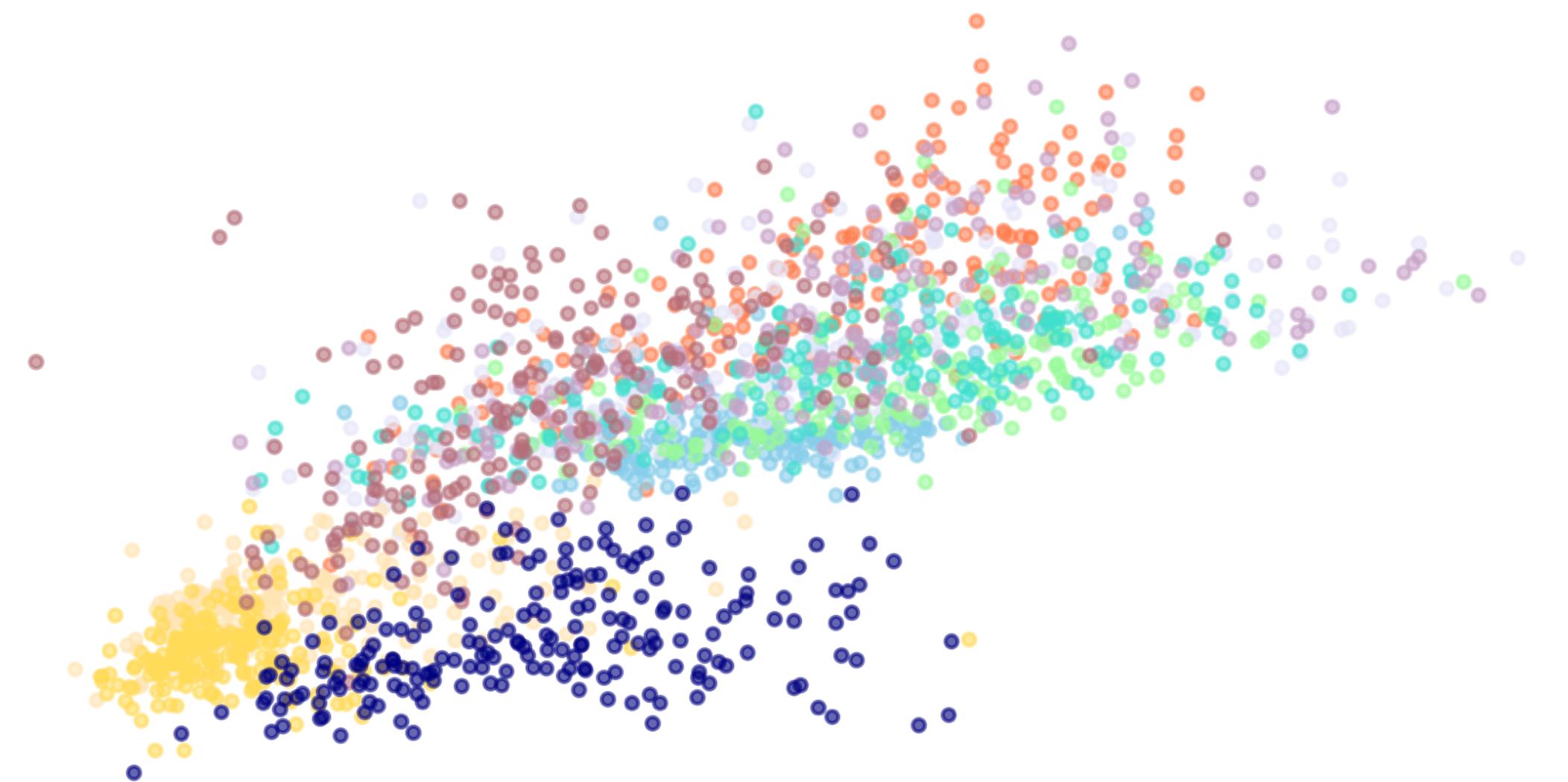


Reconstructed Images
Iter=135000

Bi-directional Generative Adversarial Network (BiGAN)

Best Performance Among 11 Methods

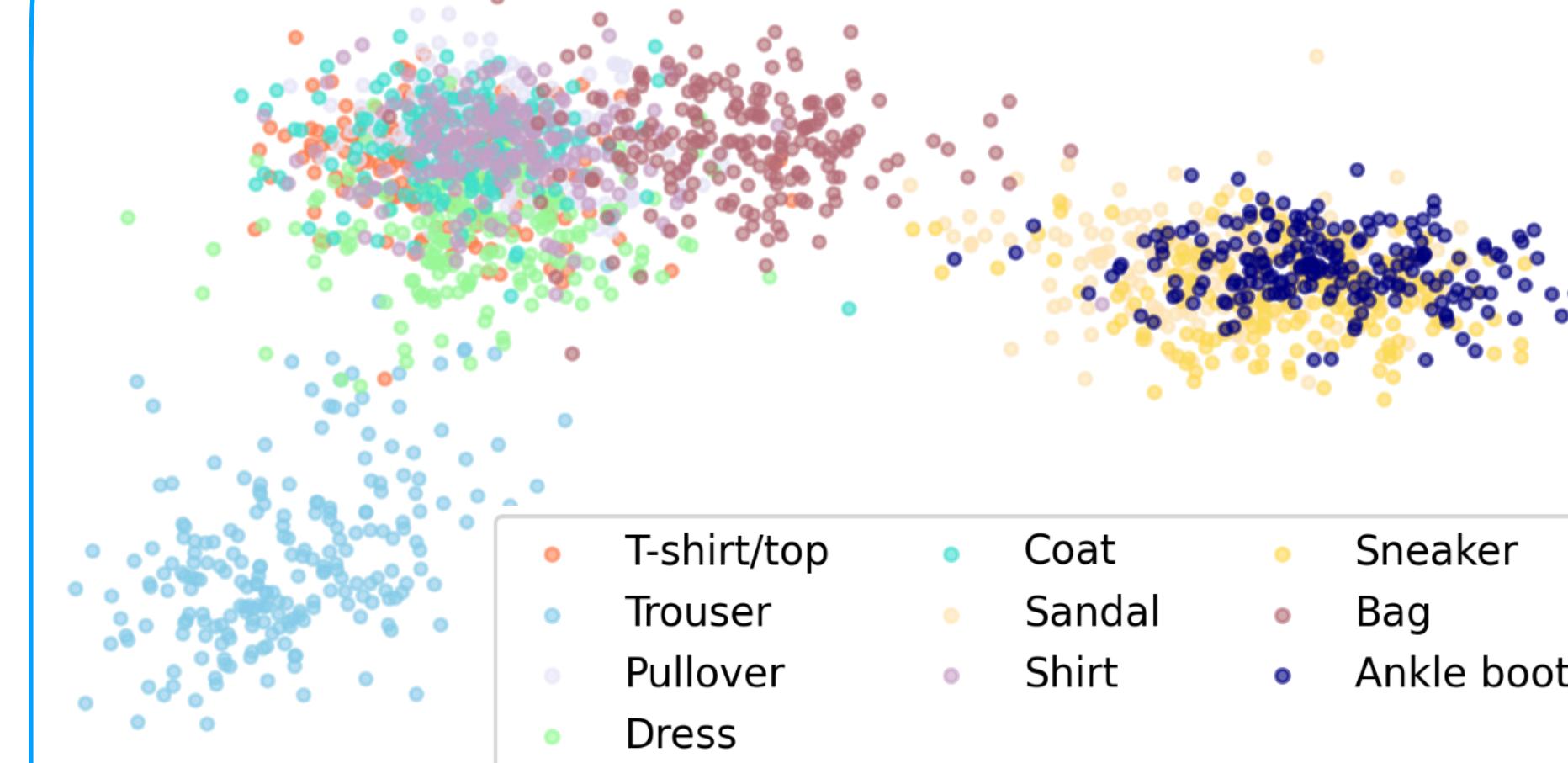
BiGAN with a latent space of 2 dimensions



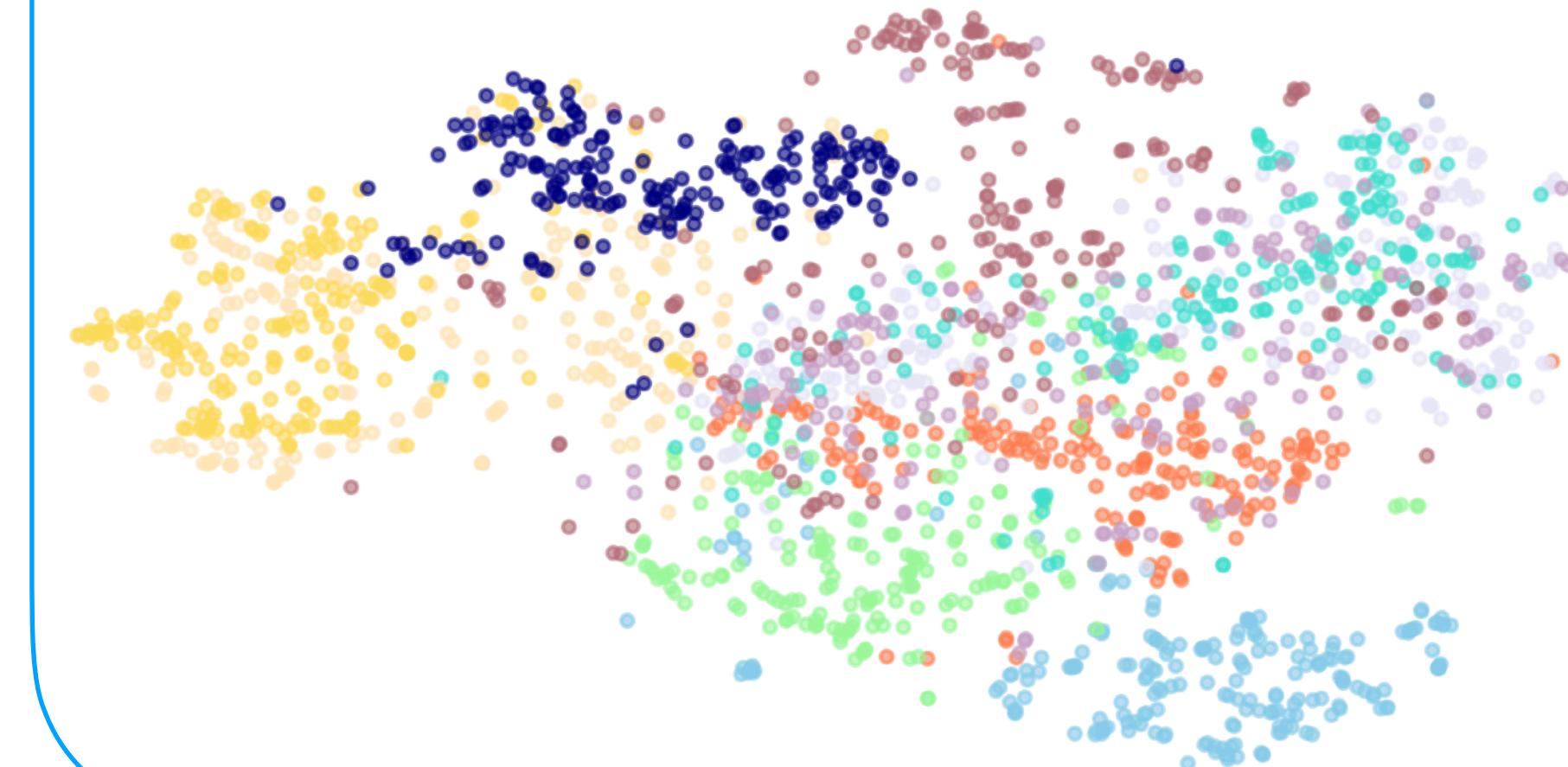
Observations

- GAN demonstrates proficiency in creating high-quality images.
- GAN exhibits limitations in effectively reducing dimensionality
- Latent space of GAN is not well organised

Linear Discriminant Analysis embedding (time 0.201s)



t-SNE embedding (time 2.700s)



Conclusion

- High-dimensional images have distinct features even in 2D
- To our surprise, linear methods perform best in dimension reduction
- RPCA can separate layout and decoration patterns
- VAE (as the name suggests) can encode high-D data into low-D but generated image are not detail-rich
- BiGAN (as the name suggests) on the other hand can generate high quality image but cannot encode information in a structured way