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# (Invariant) Variational Autoencoders

Sergei V. Kalinin

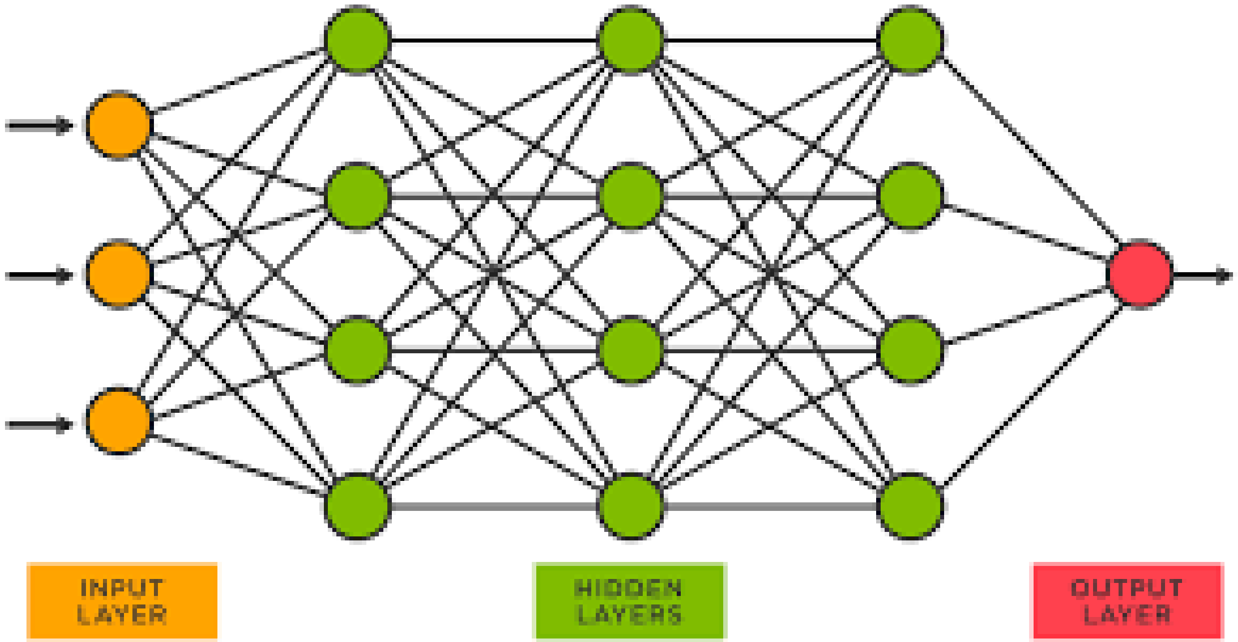
# The VAE Story



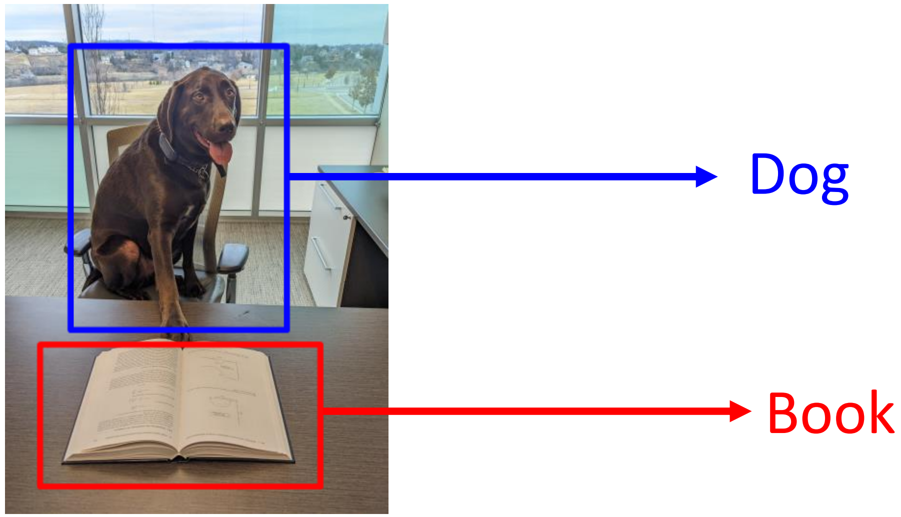
- (Super-brief) introduction into Neural Networks
- What are (Variational) autoencoders?
- Key notions:
  - Encoding and decoding
  - Latent distribution
  - Latent representations
  - Disentanglement of the representations
- Why invariances: rotational, translational, and shear
- Other colors of VAEs:
  - Semi-supervised
  - Conditional
  - Joint
- VAEs for real-world examples
- From VAEs to encoder-decoders (VED)
- Further opportunities:
  - Physics constraints
  - Representation learning
- Active learning: DKL

# What are neural networks?



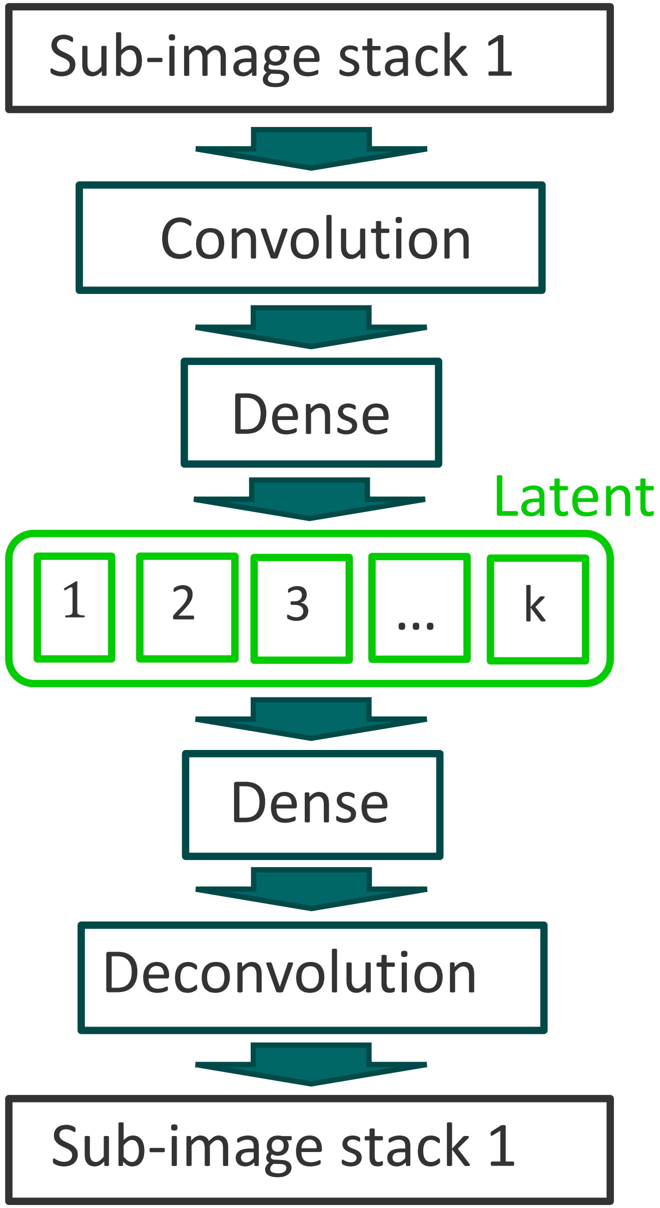



- Supervised machine learning
- Unsupervised machine learning
- Semi-supervised machine learning
- Reinforcement learning

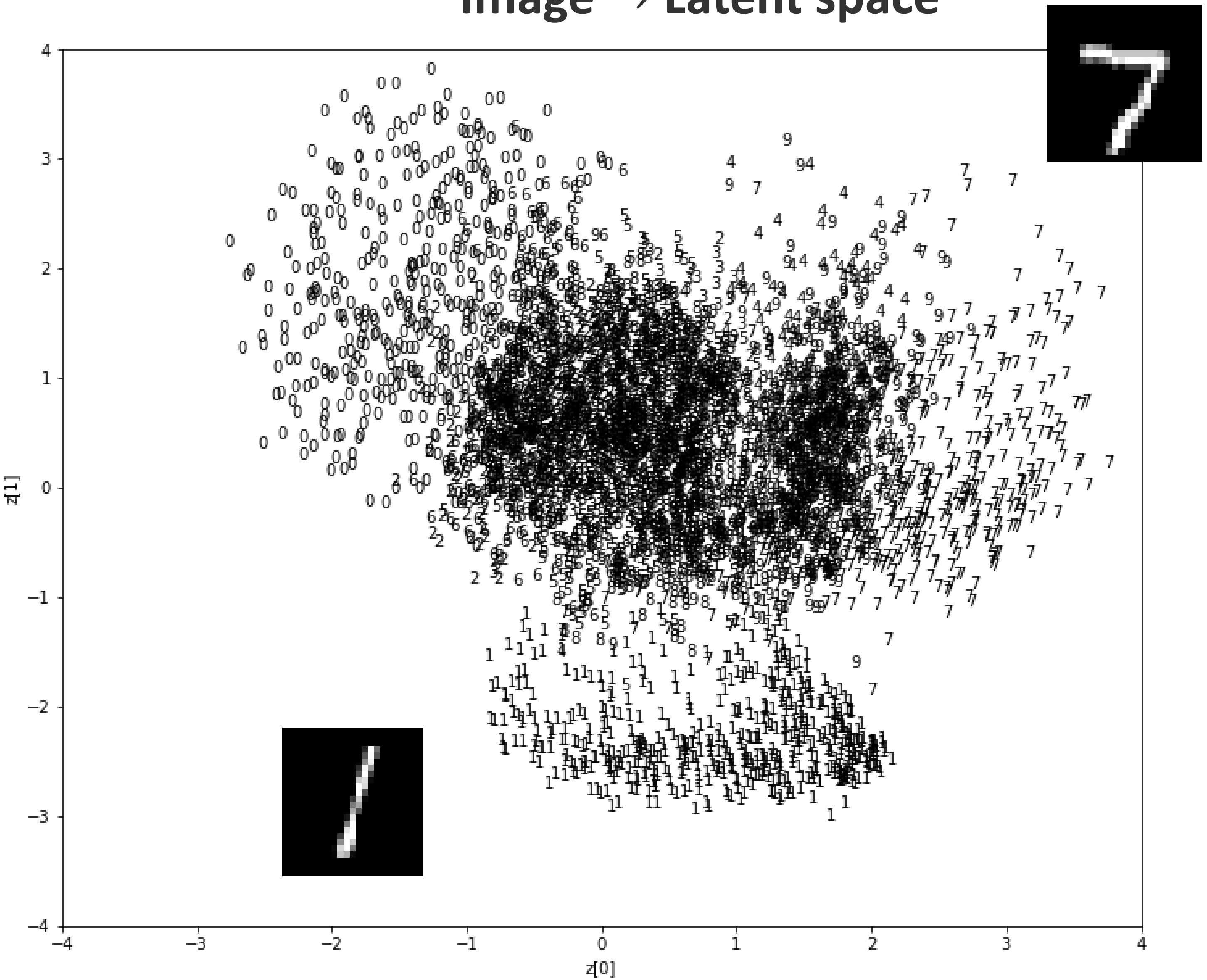


# Autoencoders: Encoding





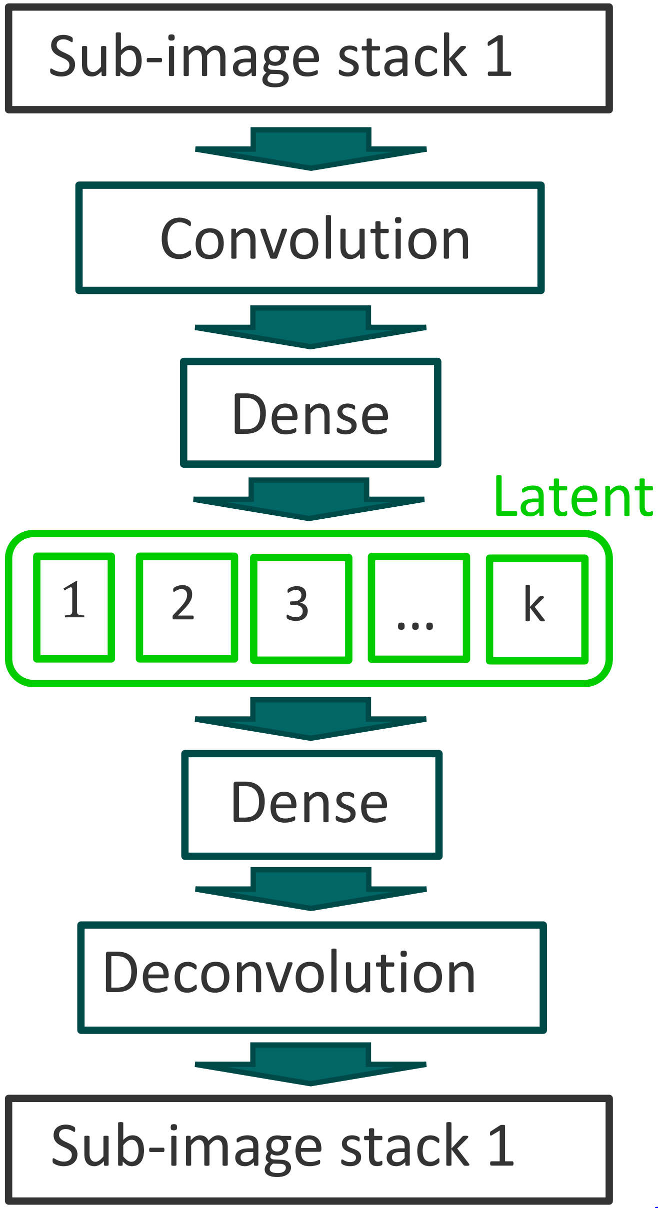

## Image → Latent space



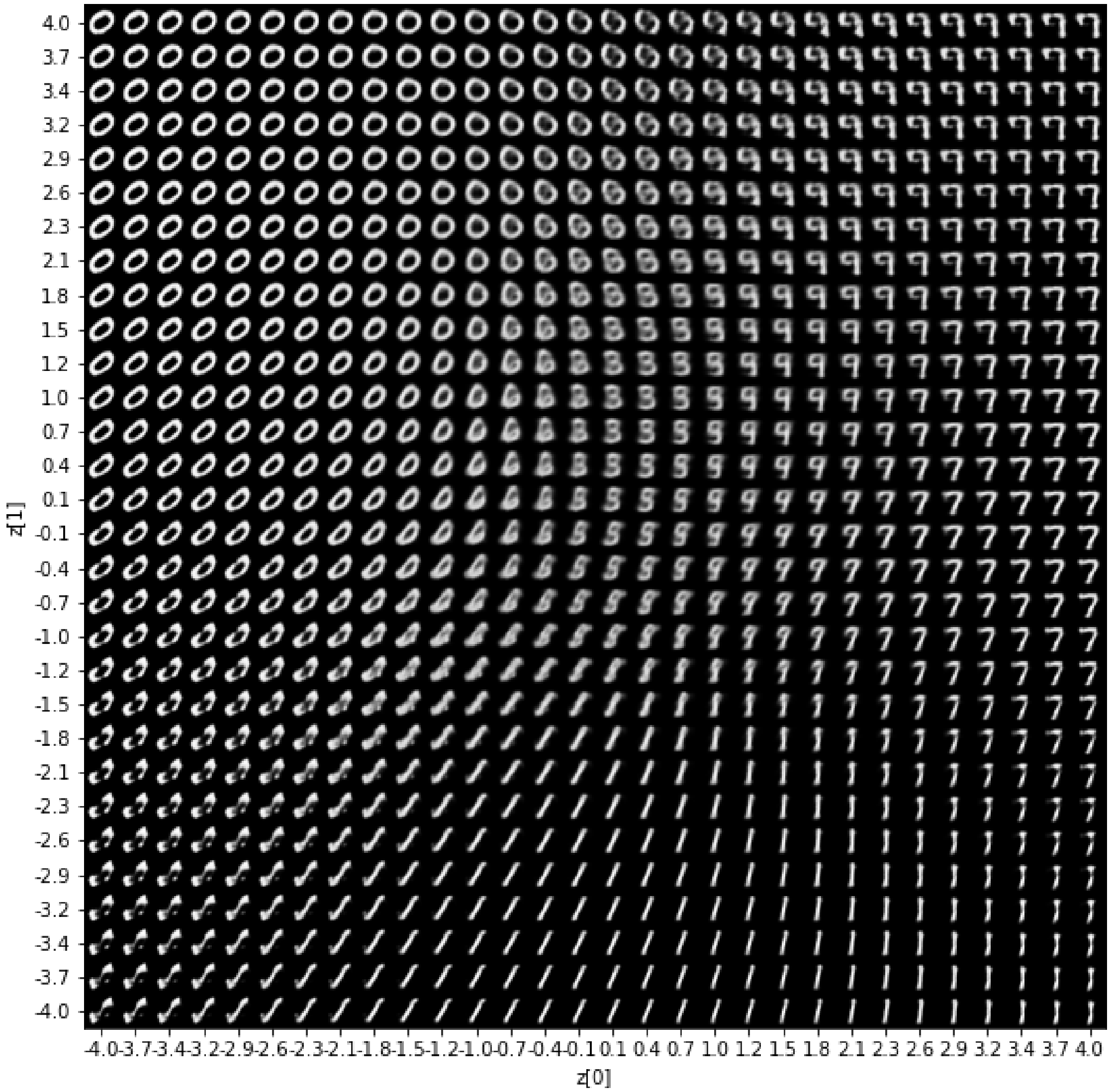

**Latent distribution:** Encoding the data via low dimensional vector

# Autoencoders: Decoding






## Latent space → Image




**Latent representation:** Decoding images from uniform grid in latent space

# AE and Variational AE (VAE)

Geoffrey Hinton

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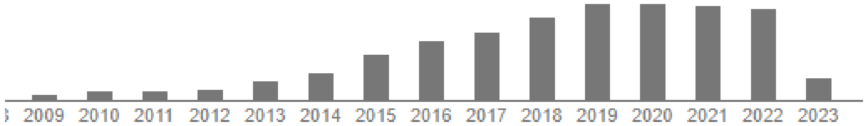
Emeritus Prof. Comp Sci, U.Toronto & Engineering Fellow, Google
Verified email at cs.toronto.edu - Homepage

machine learning   psychology   artificial intelligence   cognitive science   computer science

| TITLE | CITED BY | YEAR |
| --- | --- | --- |
| Imagenet classification with deep convolutional neural networks<br>A Krizhevsky, I Sutskever, GE Hinton<br>Communications of the ACM 60 (6), 84-90 | 130318 | 2017 |
| Deep learning<br>Y LeCun, Y Bengio, G Hinton<br>Nature 521 (7553), 436-44 | 62790 | 2015 |
| Dropout: a simple way to prevent neural networks from overfitting<br>N Srivastava, G Hinton, A Krizhevsky, I Sutskever, R Salakhutdinov<br>The journal of machine learning research 15 (1), 1929-1958 | 42078 | 2014 |
| Visualizing data using t-SNE<br>L van der Maaten, G Hinton<br>Journal of Machine Learning Research 9 (Nov), 2579-2605 | 35035 | 2008 |
| Learning representations by back-propagating errors<br>DE Rumelhart, GE Hinton, RJ Williams<br>Nature 323 (6088), 533-536 | 32239 | 1986 |
| Learning internal representations by error-propagation<br>DE Rumelhart, GE Hinton, RJ Williams<br>Parallel Distributed Processing: Explorations in the Microstructure of ... | 30711 | 1986 |
| Schemata and sequential thought processes in PDP models.<br>D Rumelhart, P Smolenksy, J McClelland, G Hinton<br>Parallel distributed processing: Explorations in the microstructure of ... | 28073 * | 1986 |
| Learning multiple layers of features from tiny images<br>A Krizhevsky, G Hinton | 21876 | 2009 |
| Rectified linear units improve restricted boltzmann machines<br>V Nair, GE Hinton<br>Proceedings of the 27th international conference on machine learning (ICML ... | 21050 | 2010 |
| Reducing the dimensionality of data with neural networks<br>GE Hinton, RR Salakhutdinov<br>Science 313 (5786), 504-507 | 19930 | 2006 |

## Reducing the dimensionality of data with neural networks

| | |
| --- | --- |
| Authors | Geoffrey E Hinton, Ruslan R Salakhutdinov |
| Publication date | 2006/7/28 |
| Journal | Science |
| Volume | 313 |
| Issue | 5786 |
| Pages | 504-507 |
| Publisher | American Association for the Advancement of Science |
| Description | High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such “autoencoder” networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data. |
| Total citations | Cited by 19930 |



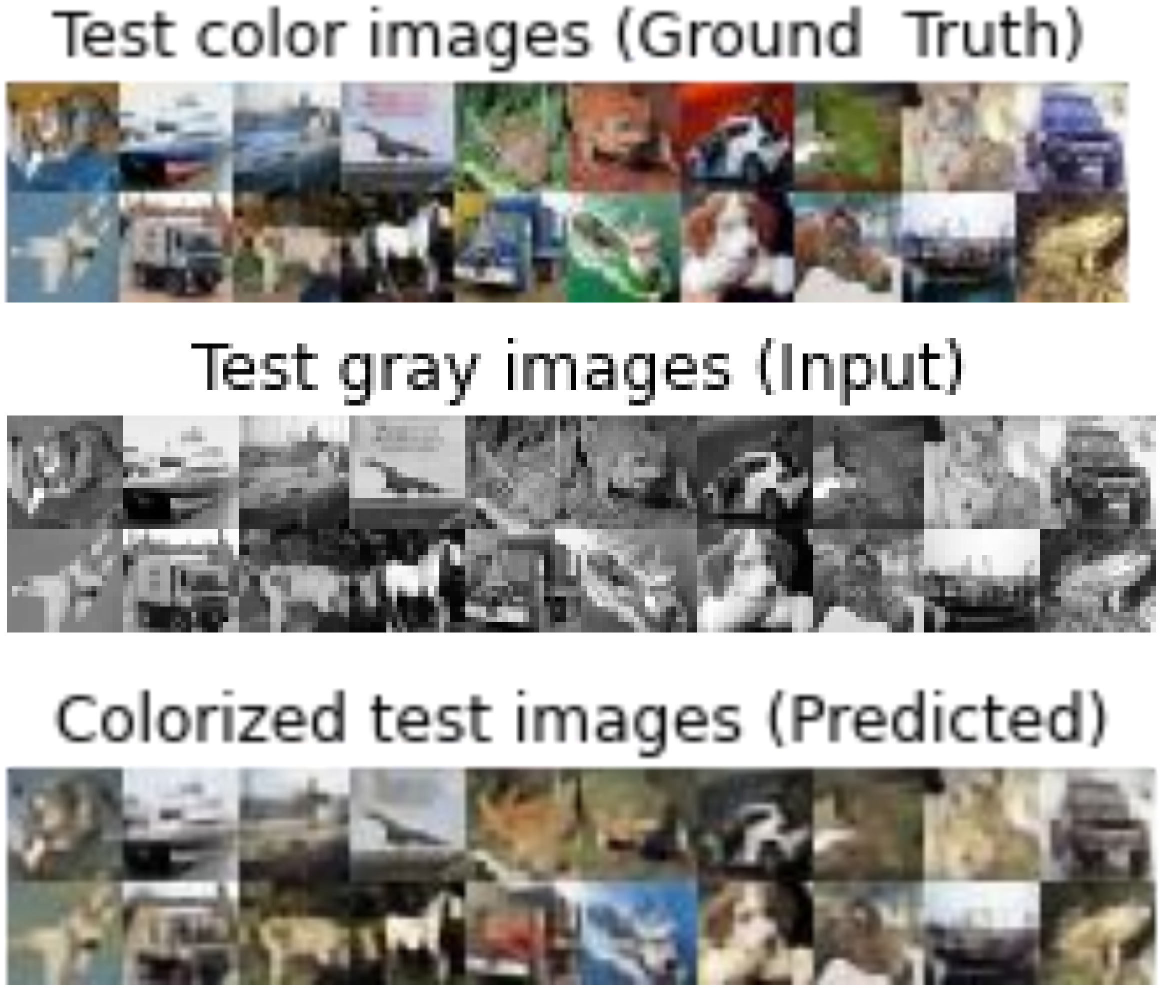
# Denoising



- **Training:** pairs of the high-noise and low-noise images
- **Application:** new high noise images (from the same distribution)
- **Concern:** has to be from the same distribution

# Restoration






- **Training:** pairs of the grayscale and color images
- **Application:** new grayscale images (from the same distribution)
- **Concern:** has to be from the same distribution

# AE and Variational AE (VAE)

## Diederik P. Kingma

Other names ▸

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Research Scientist, Google Brain
Verified email at google.com - Homepage

Machine Learning · Deep Learning · Neural Networks · Generative Models · Variational Inference

| TITLE | CITED BY | YEAR |
|---|---|---|
| Adam: A Method for Stochastic Optimization<br>DP Kingma, J Ba<br>Proceedings of the 3rd International Conference on Learning Representations ... | 141306 | 2014 |
| Auto-Encoding Variational Bayes<br>DP Kingma, M Welling<br>arXiv preprint arXiv:1312.6114 | 26540 | 2013 |
| Semi-Supervised Learning with Deep Generative Models<br>DP Kingma, S Mohamed, DJ Rezende, M Welling<br>Advances in Neural Information Processing Systems, 3581-3589 | 2946 | 2014 |

- Variational Autoencoder (VAE): uses “reparameterization trick” to sample from the latent space
- Can be used for same tasks as AE
- Have a much better-behaved latent space: disentanglement of the representations

# VAE Training



**Latent manifold -> Image space**

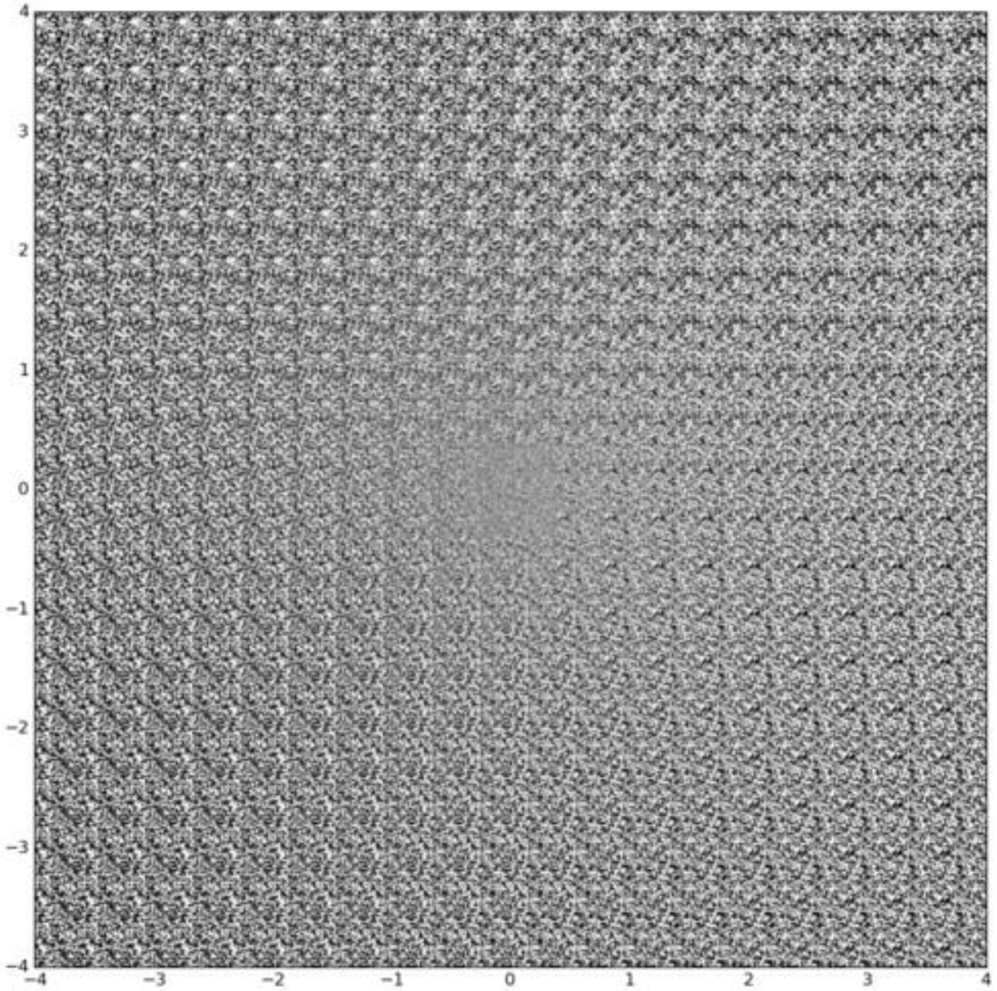
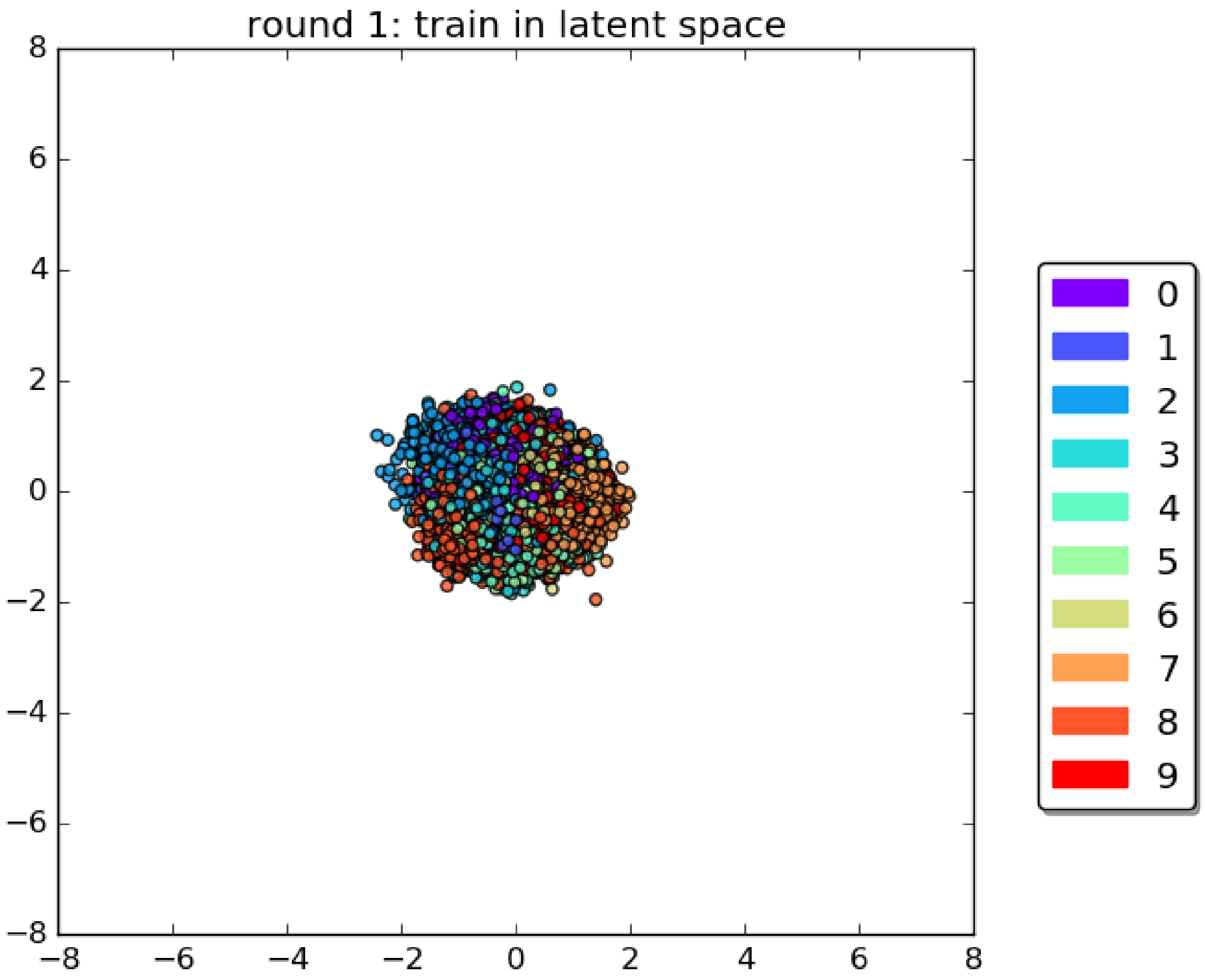
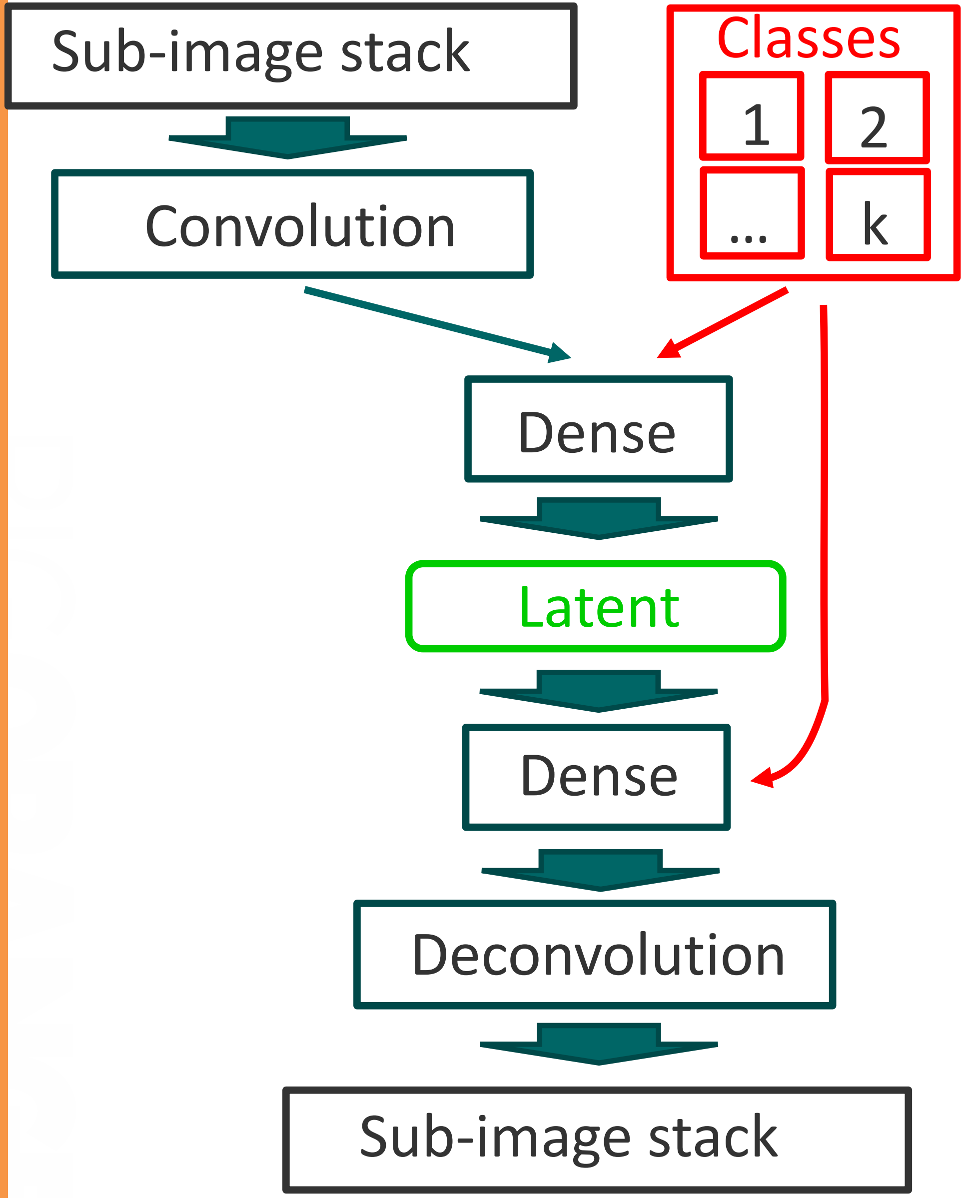


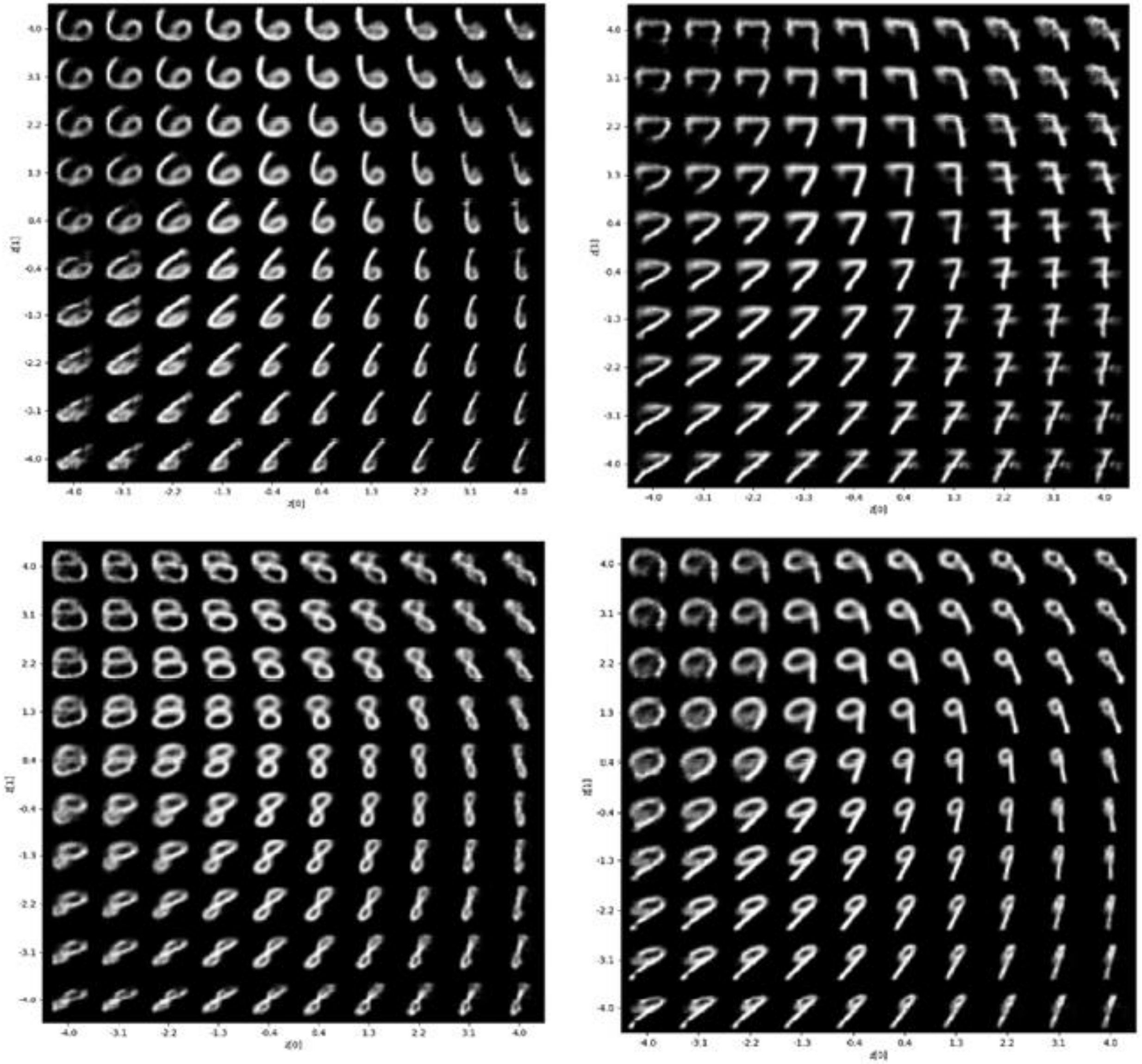

**Image space -> Latent space**



# Conditional VAE





Note the trends in the latent representation for each digit: disentanglement of the representations

# (R)VAE on Cards

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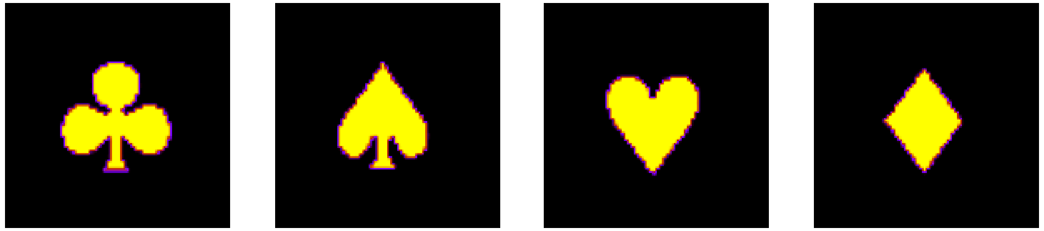
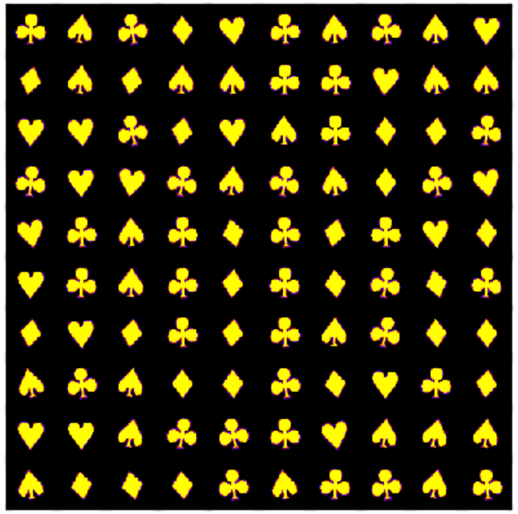
Introduce the **cards** data set:

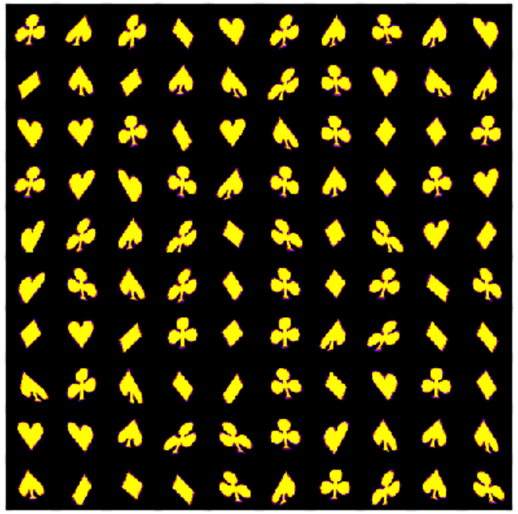
- Classical 4 hands (diamonds, clubs, pikes, hearts)
- Interesting similarities (pikes and hearts)
- And invariances on affine transforms (e.g. diamonds)



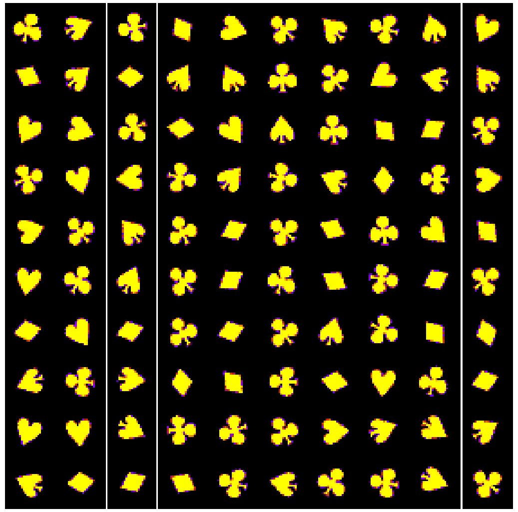
**Cards 1:** Low R (12 deg) and low S (1 deg)



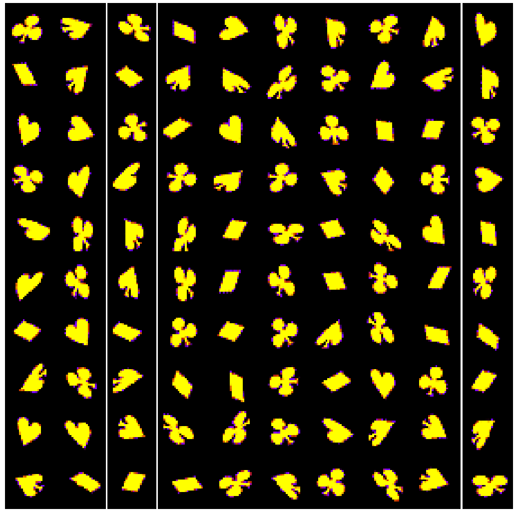
**Cards 2:** Low R (12 deg) and high S (20 deg)



**Cards 3:** High R (120 deg) and Low S (1 deg)



**Cards 4:** High R (120 deg) and high S (20 deg)



- Shear, rotations, and translations are **known** factors of variability (or traits) in data
- Can VAE disentangle representations and discover these factors of variability

# VAE on Cards

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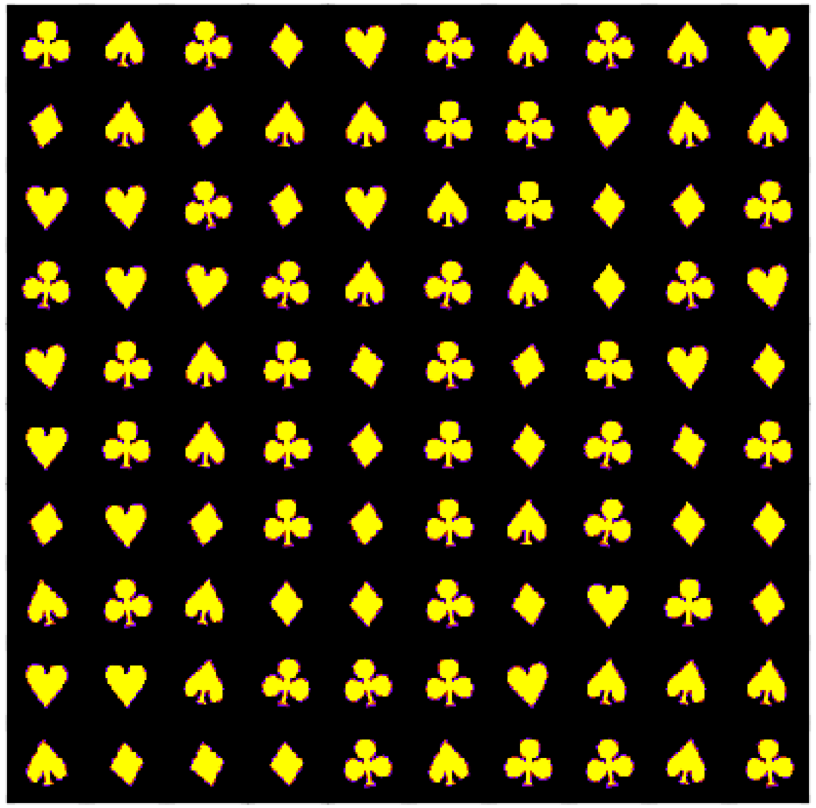
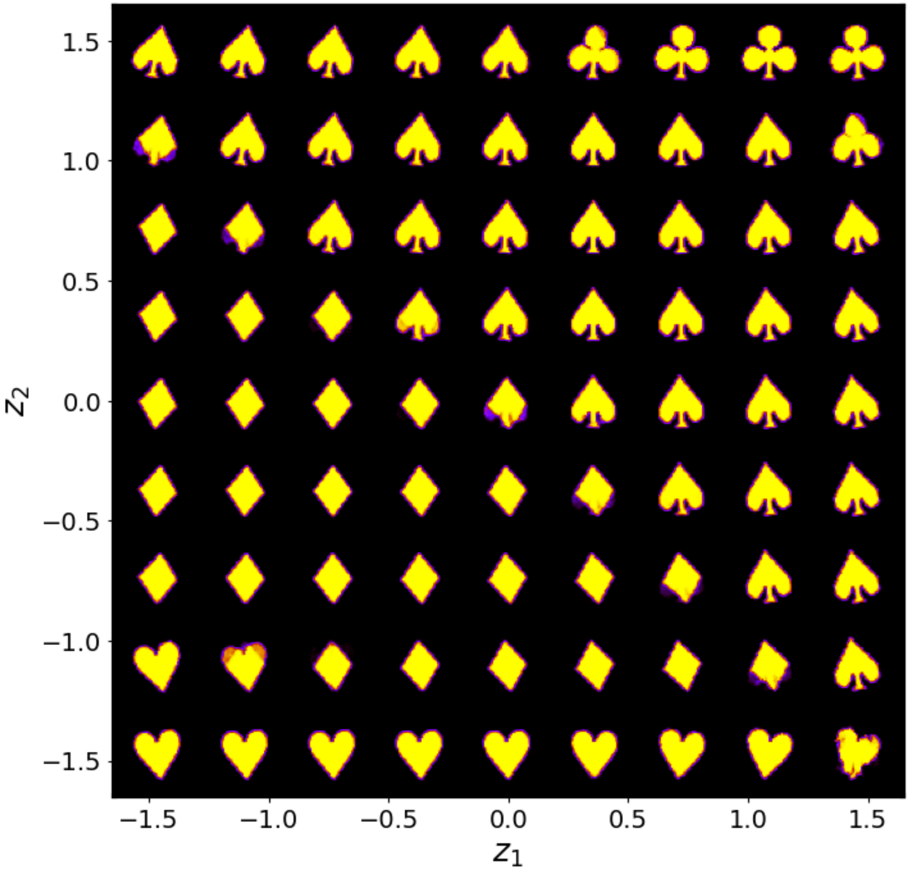
**Example of data**



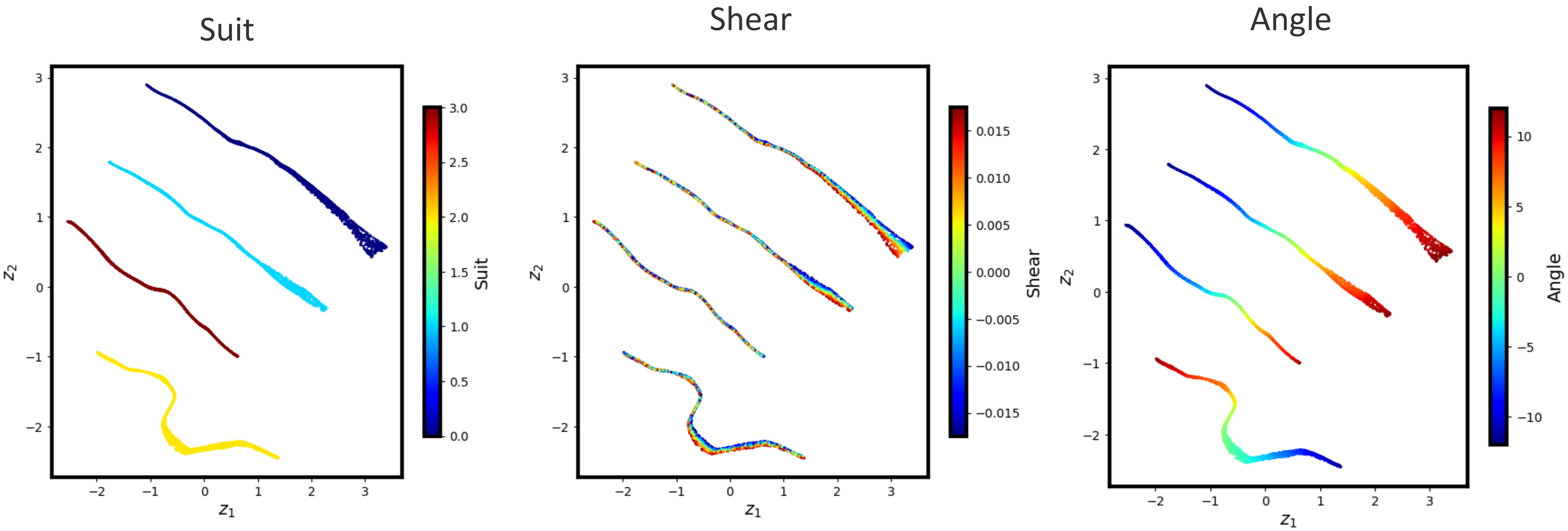
**Latent representation**




**Cards 1:** Low rotation (12 deg) and low shear (1 deg)

# VAE on Cards



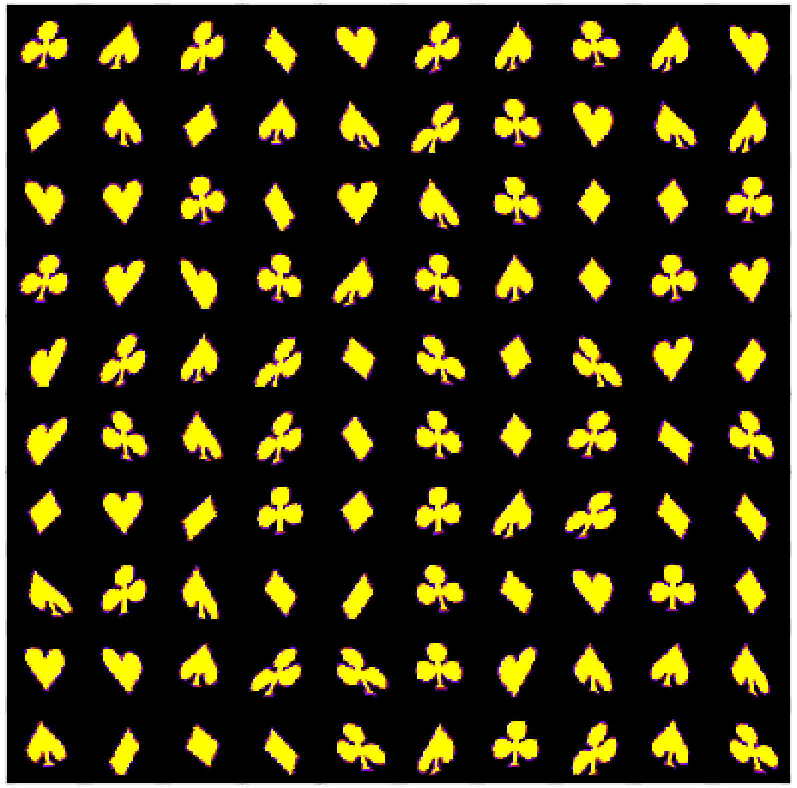



**Cards 1:** Low rotation (12 deg) and low shear (1 deg)

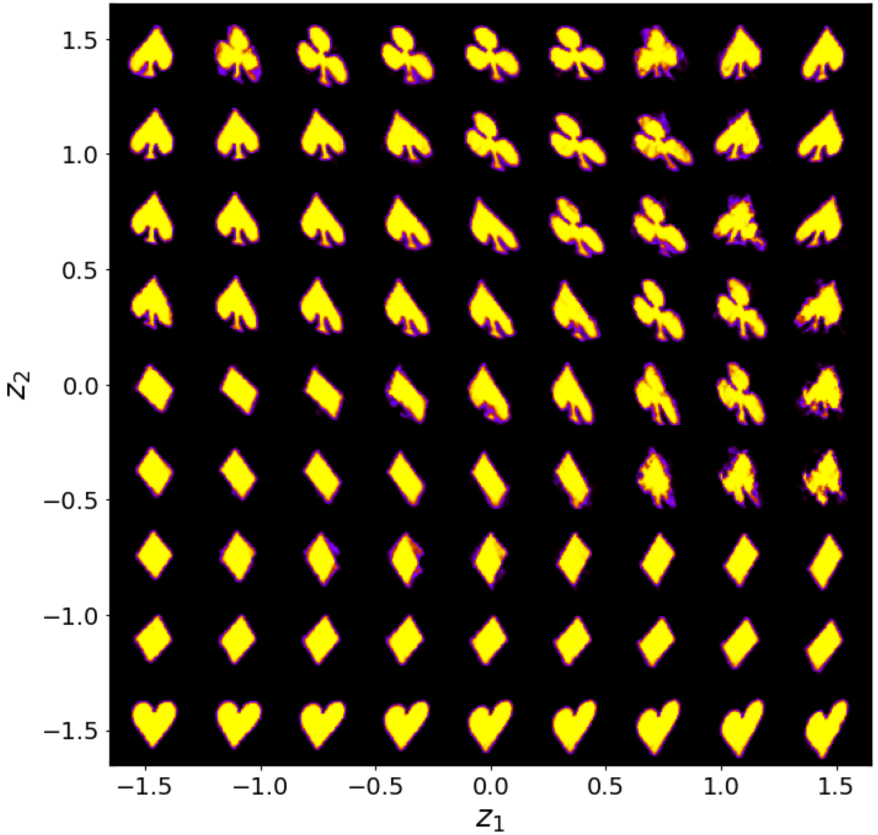
# VAE on Cards



**Example of data**



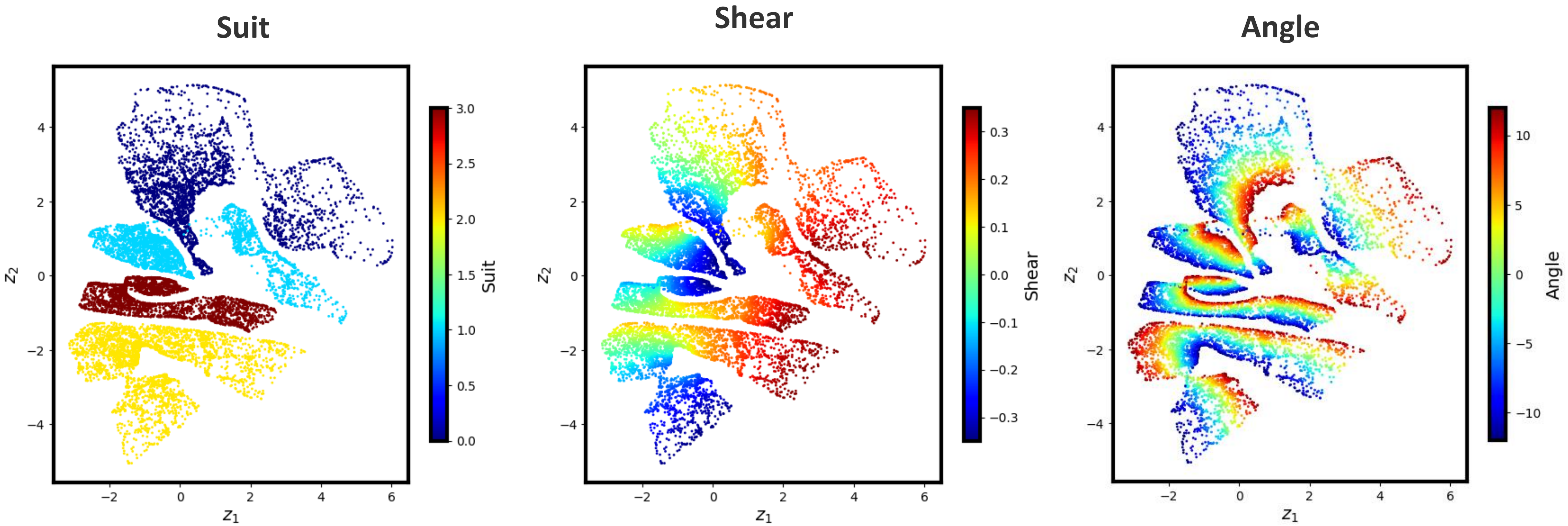
**Latent representation**




**Cards 2:** Low rotation (12 deg) and high shear (20 deg)

# VAE on Cards



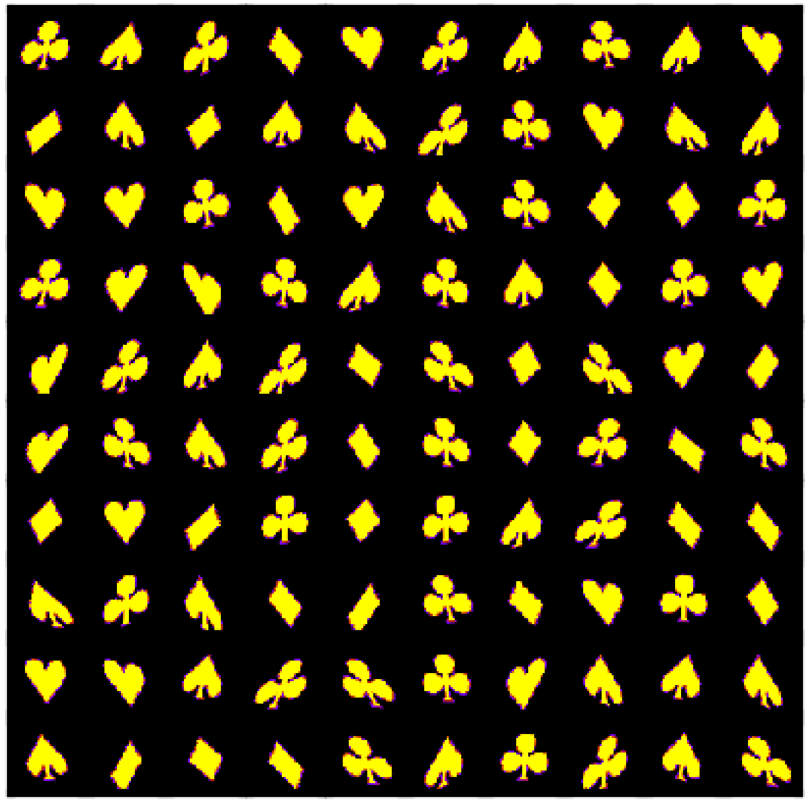



**Cards 2:** Low rotation (12 deg) and high shear (20 deg)

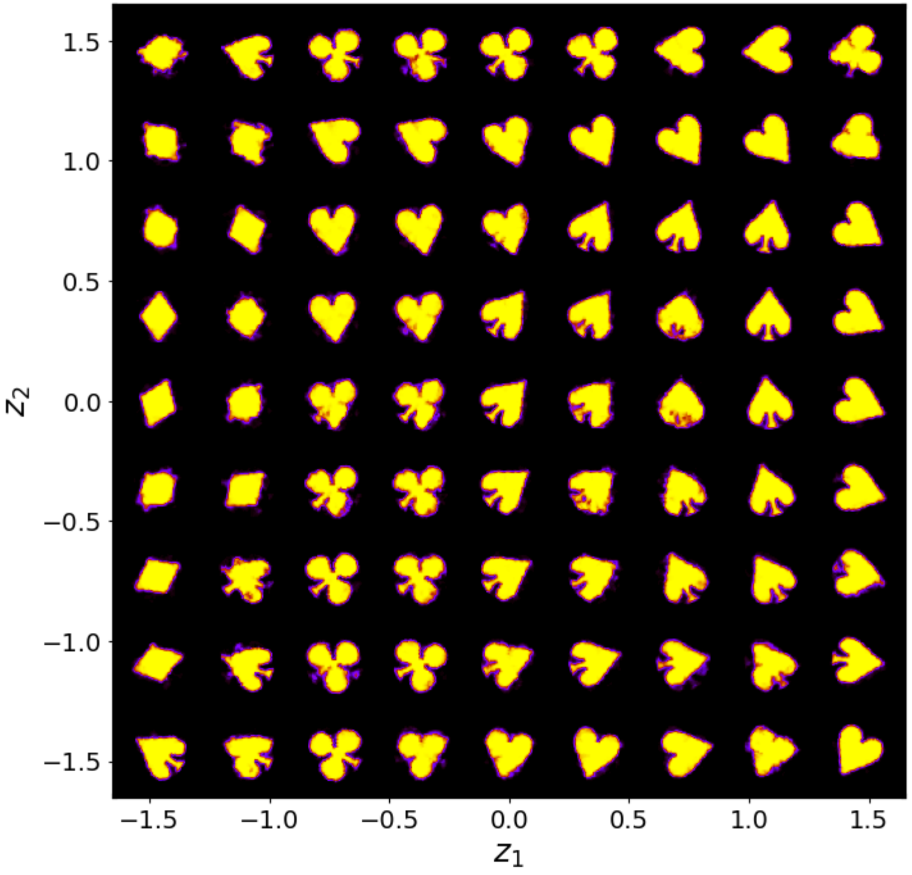
# VAE on Cards



**Example of data**



**Latent representation**




**Cards 3:** High rotation (120 deg) and low shear (1 deg)

# VAE on Cards

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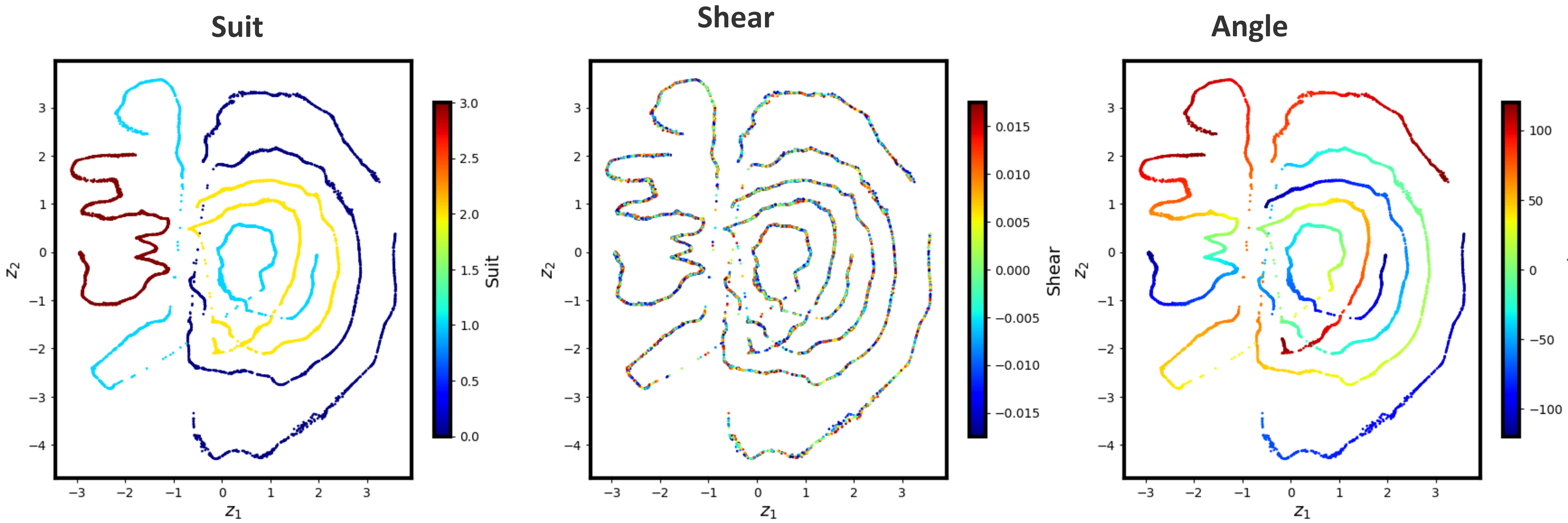


**Cards 3:** High rotation (120 deg) and low shear (1 deg)

# VAE on Cards

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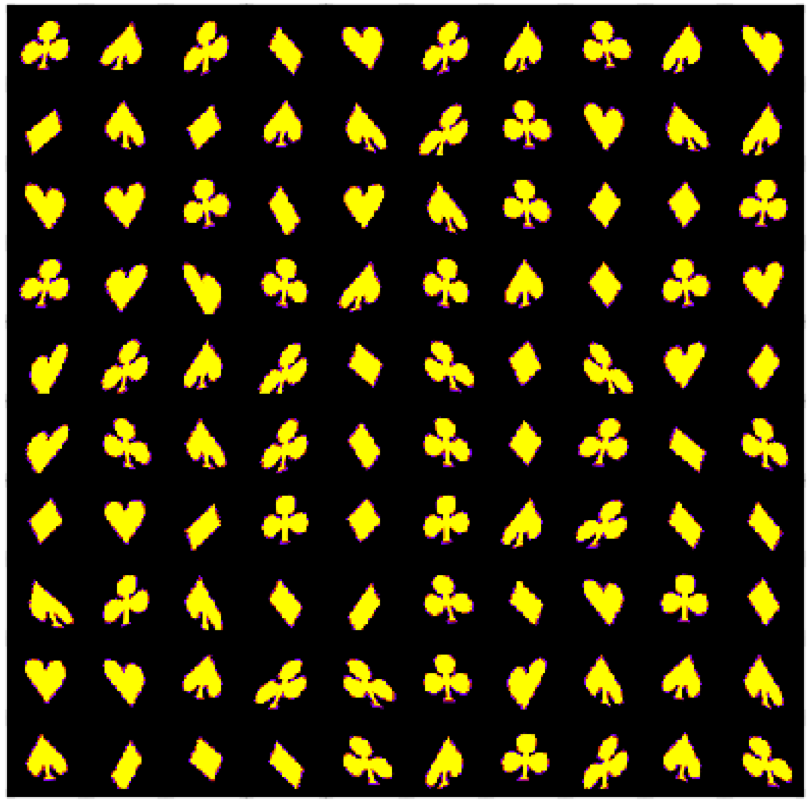
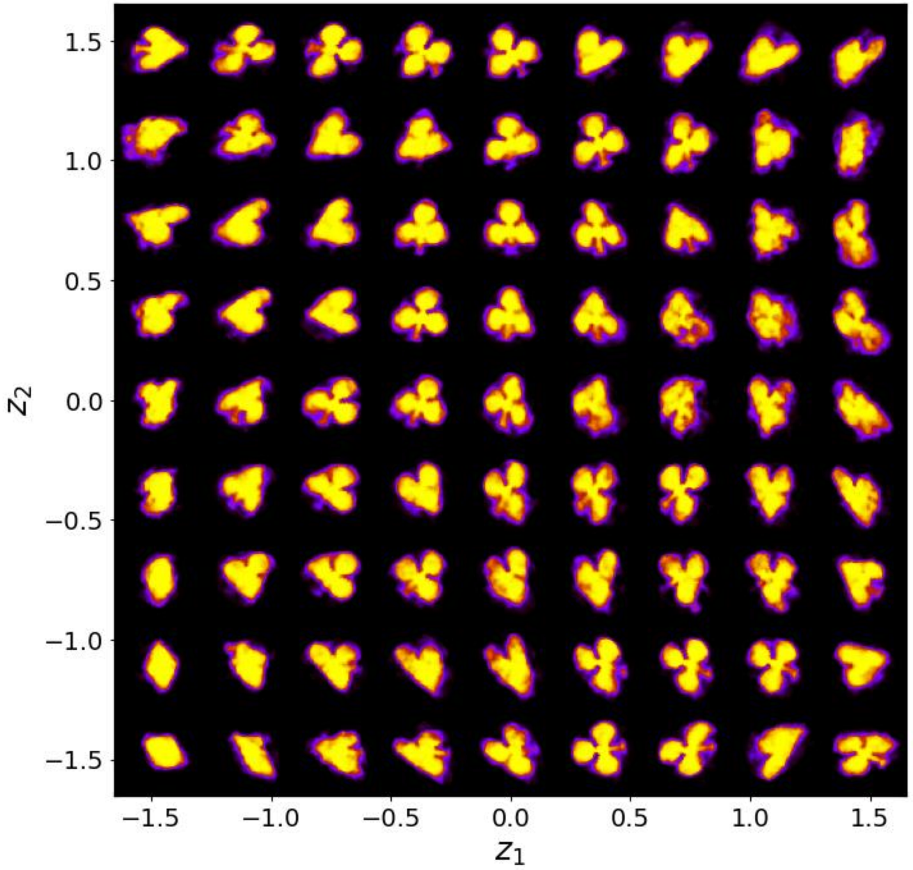
**Example of data**



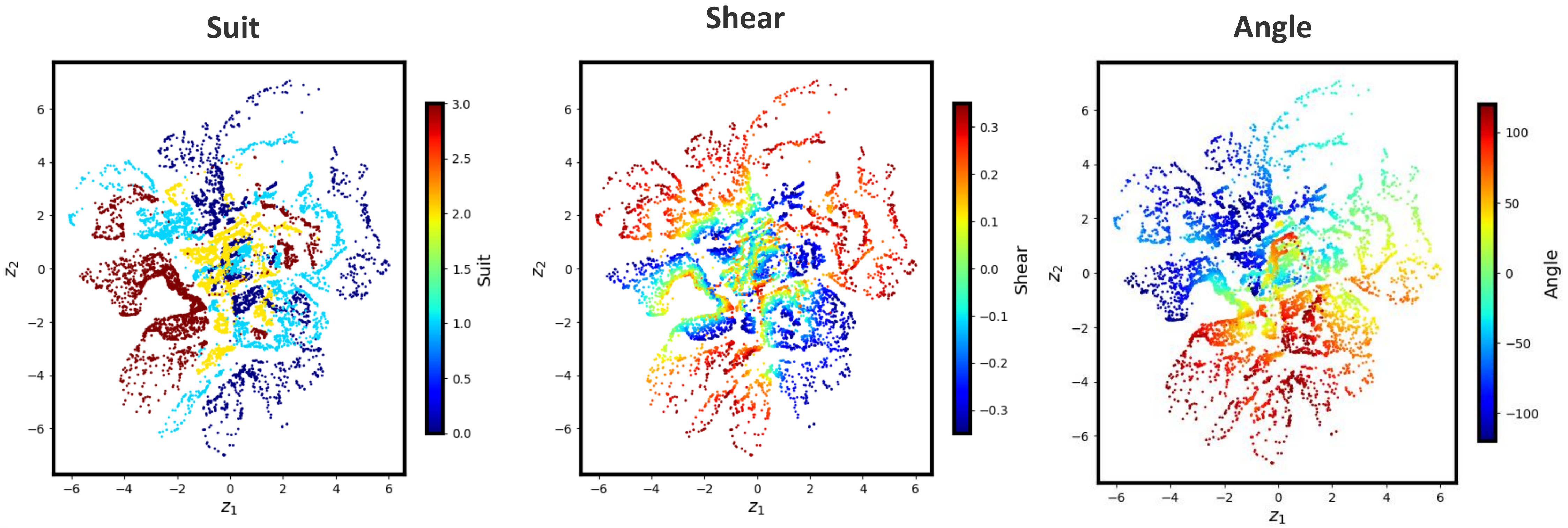
**Latent representation**




**Cards 4:** High rotation (120 deg) and high shear (20 deg)

# VAE on Cards



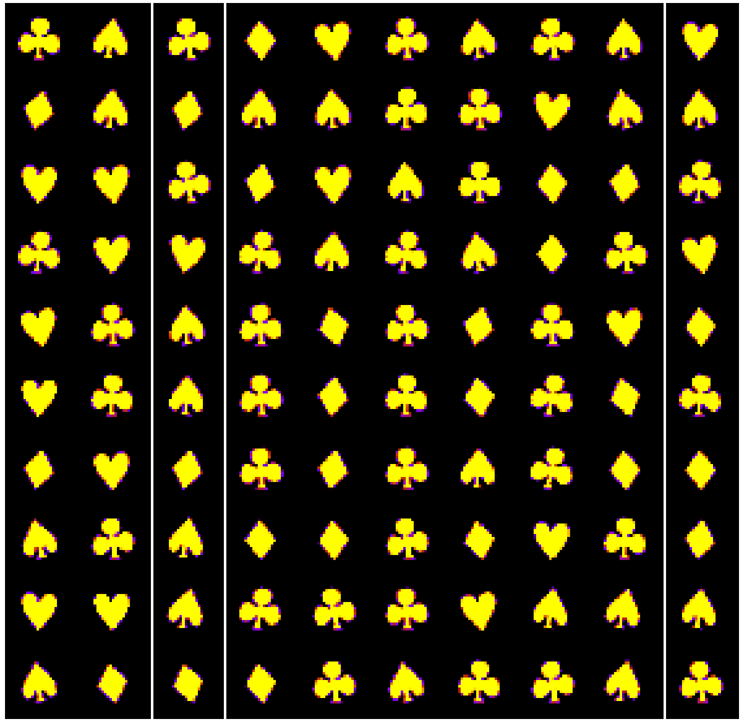



**Cards 4:** High rotation (120 deg) and high shear (20 deg)

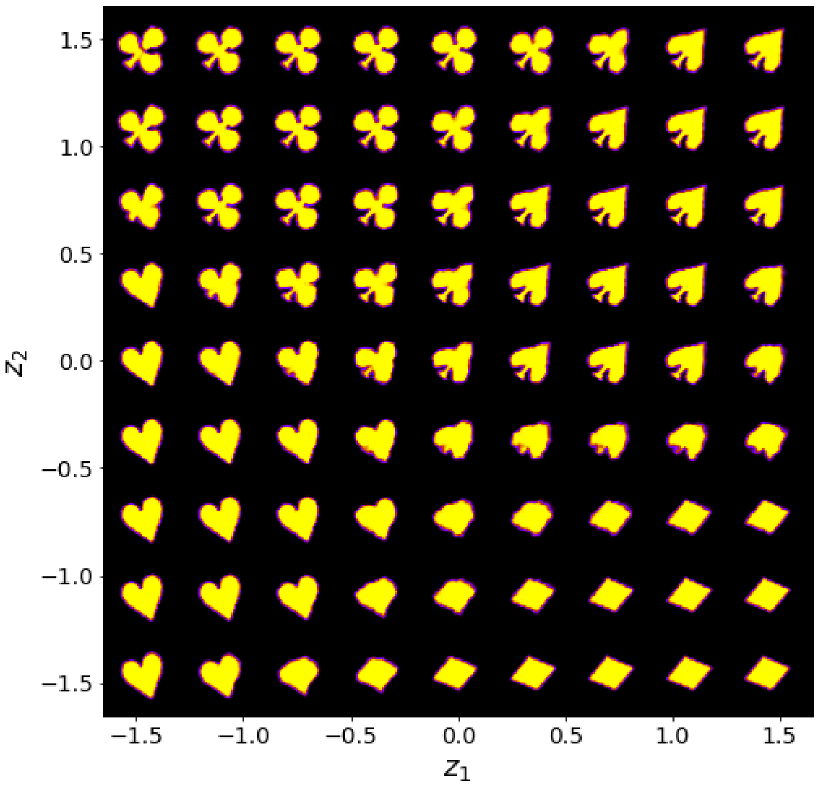
# rVAE on Cards



**Example of data**



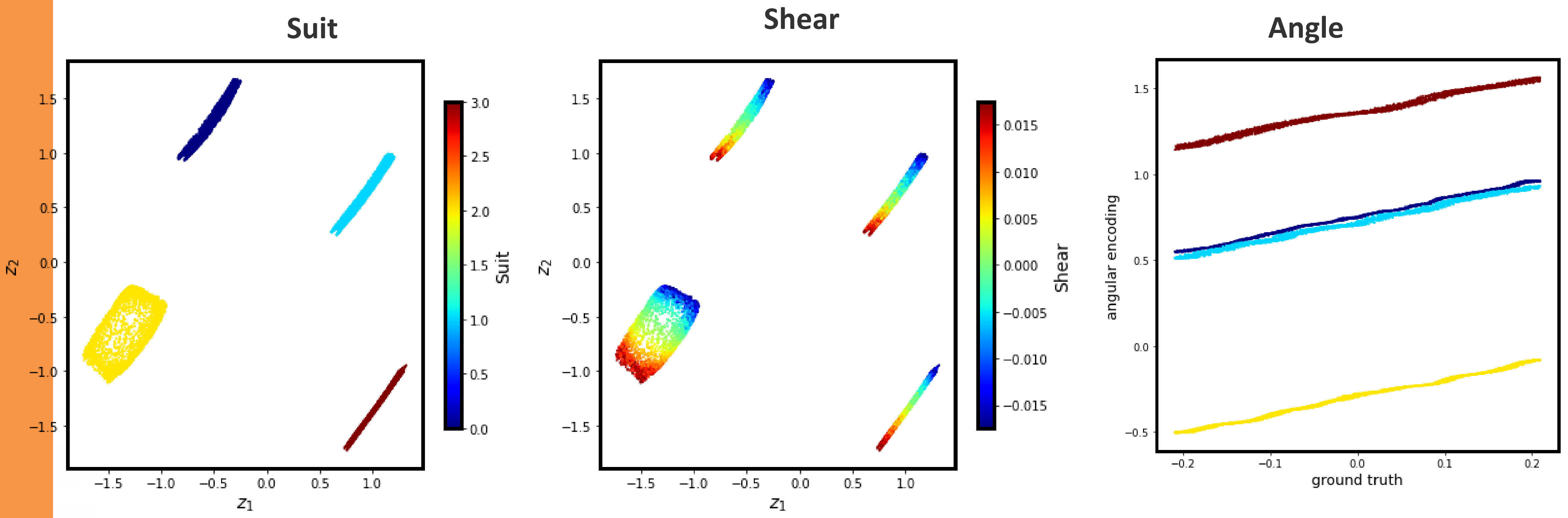
**Latent representation**




**Cards 1:** Low rotation (12 deg) and low shear (1 deg)

# rVAE on Cards






**Cards 1:** Low rotation (12 deg) and low shear (1 deg)

# rVAE on Cards

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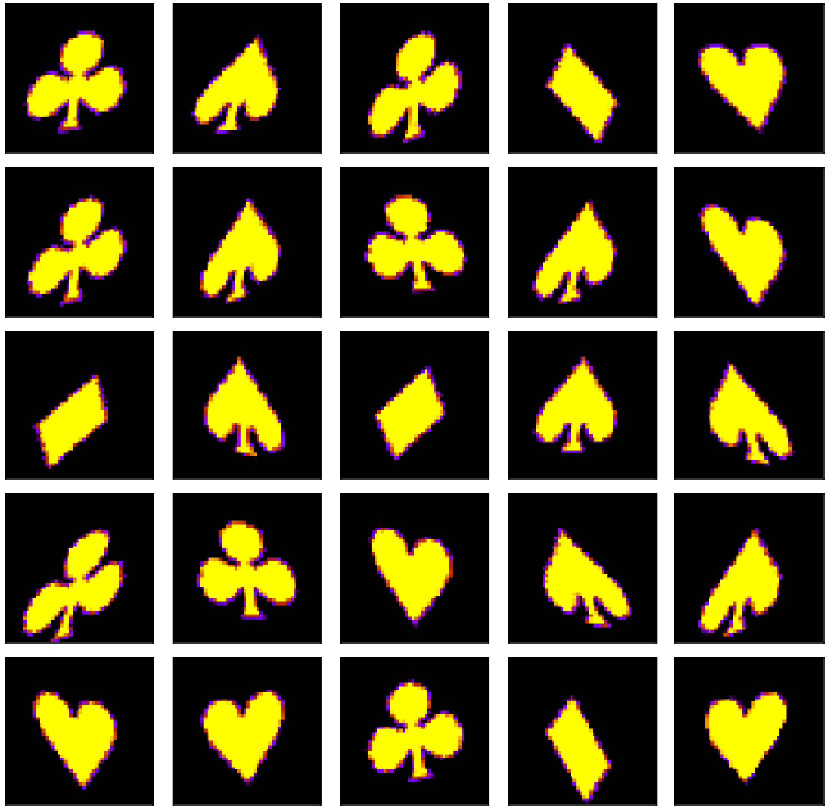
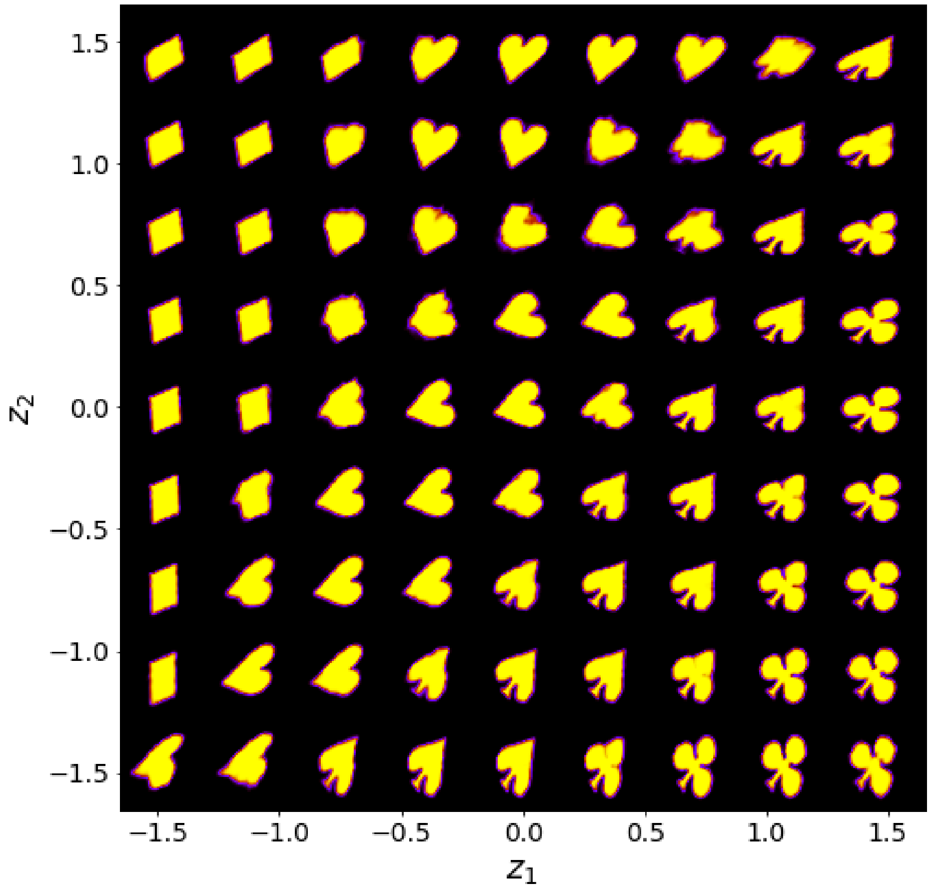
**Example of data**



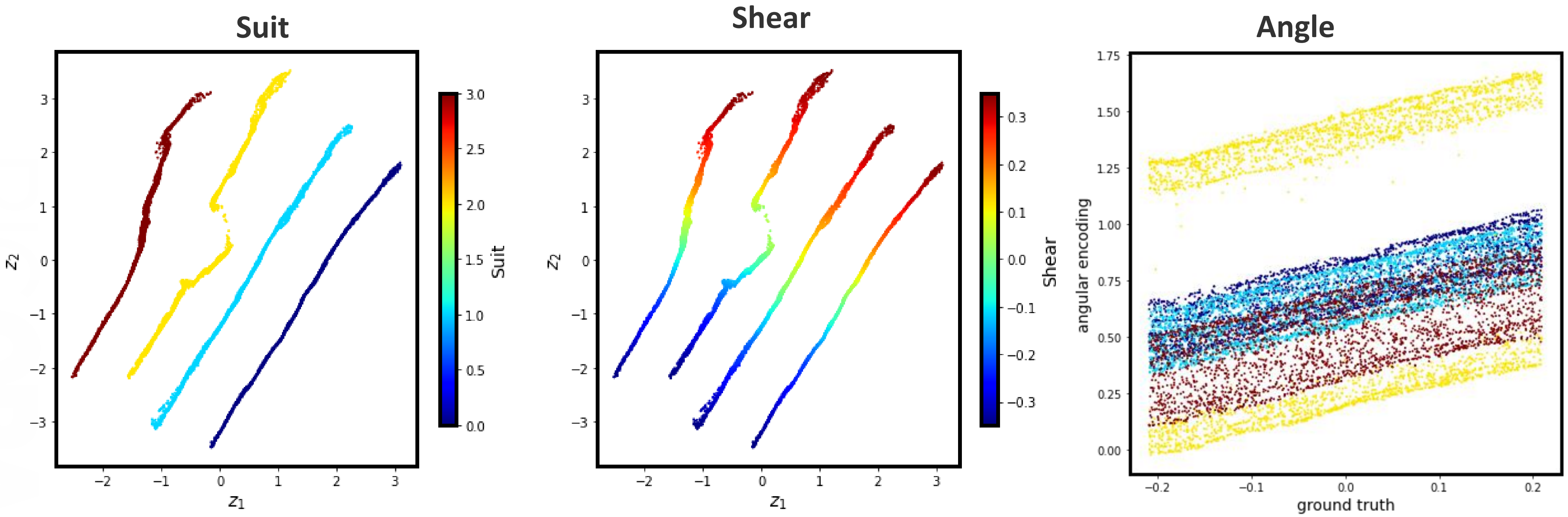
**Latent representation**




**Cards 2:** Low rotation (12 deg) and high shear (20 deg)

# rVAE on Cards



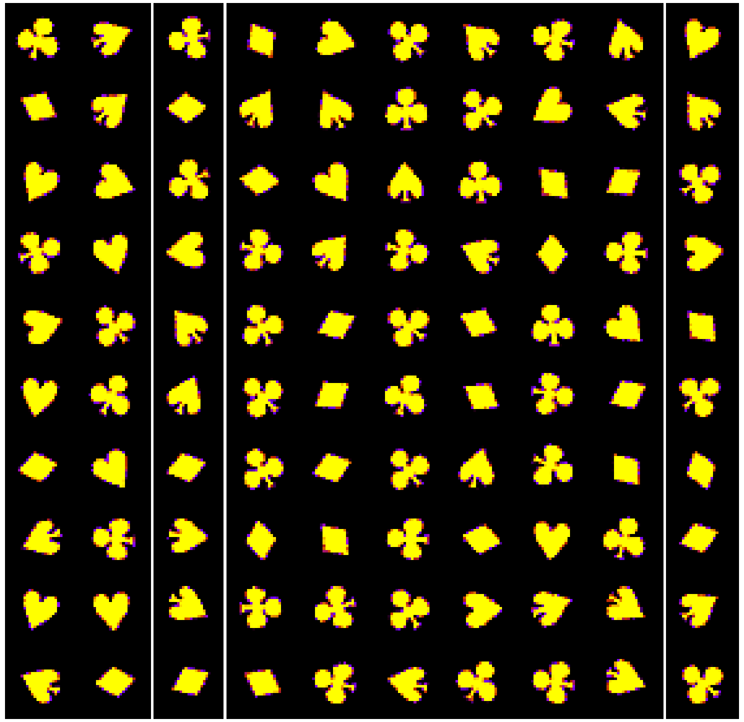



**Cards 2:** Low rotation (12 deg) and high shear (20 deg)

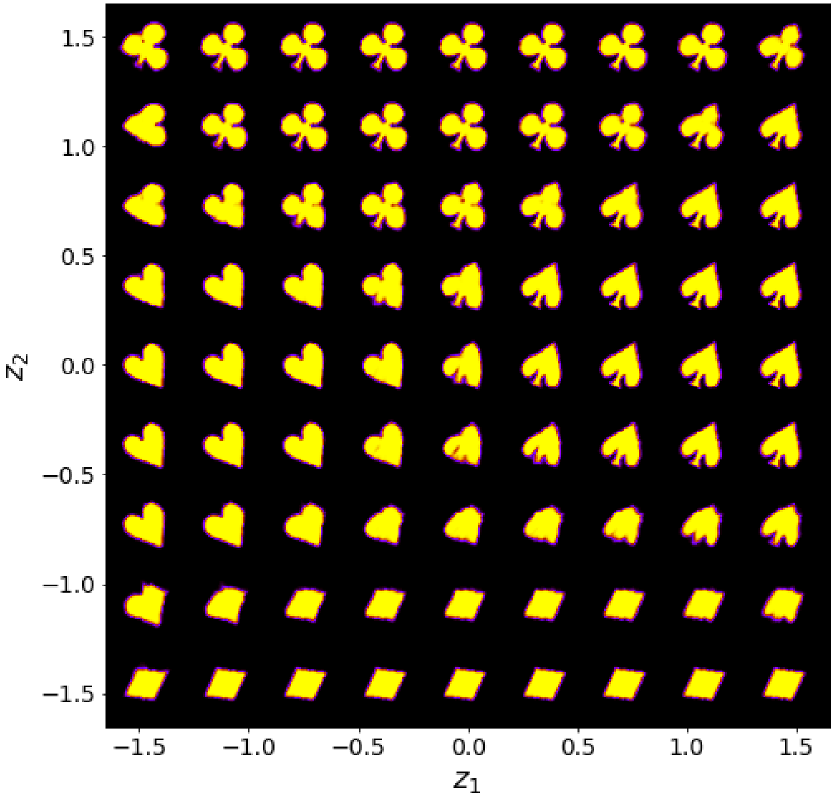
# rVAE on Cards



**Example of data**



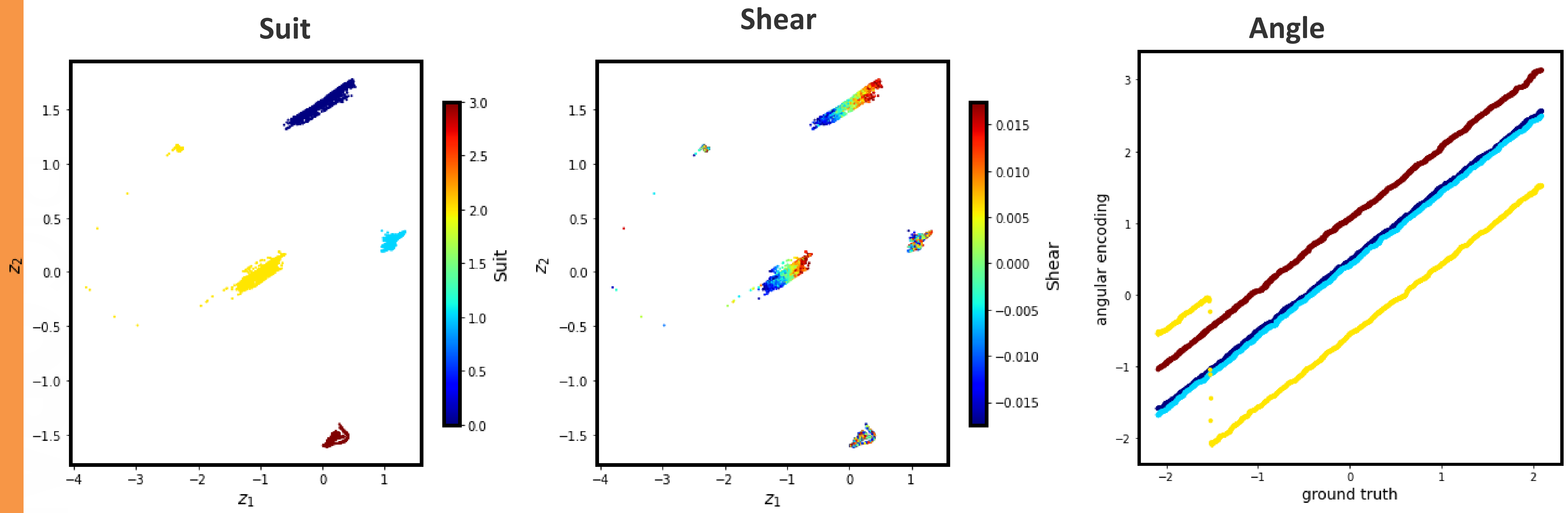
**Latent representation**




**Cards 3:** High rotation (120 deg) and low shear (1 deg)

# rVAE on Cards



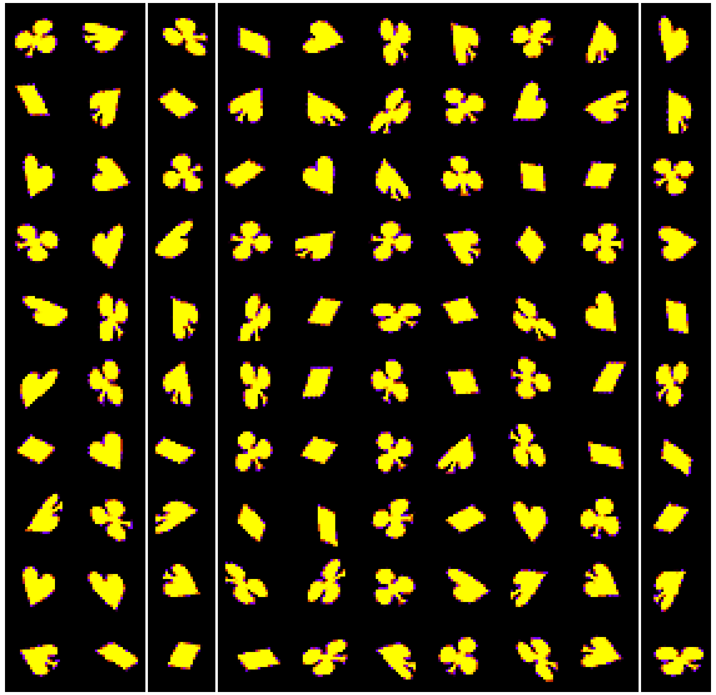



**Cards 3:** High rotation (120 deg) and low shear (1 deg)

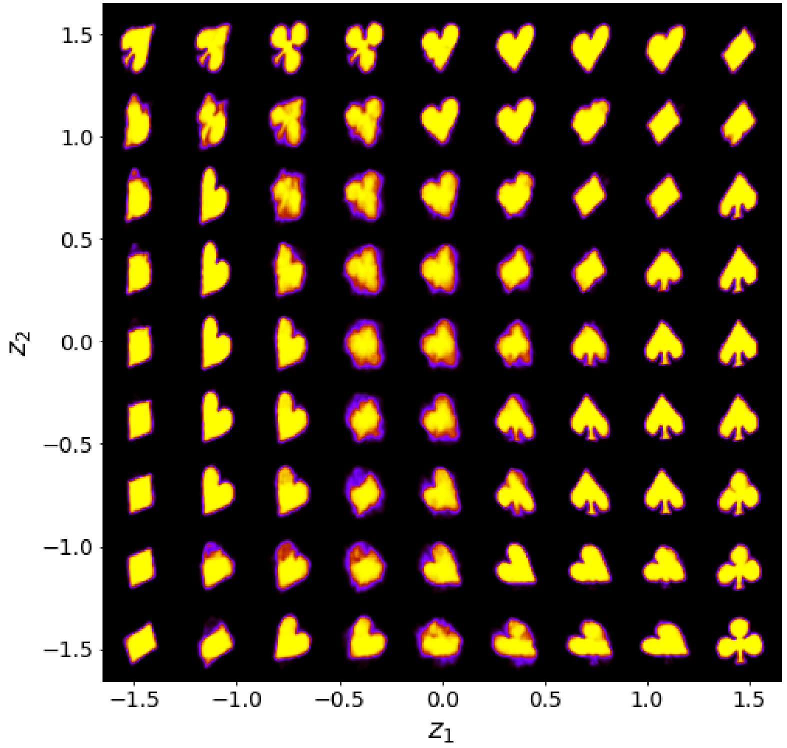
# rVAE on Cards



**Example of data**



**Latent representation**




**Cards 4:** High rotation (120 deg) and high shear (20 deg)

# rVAE on Cards

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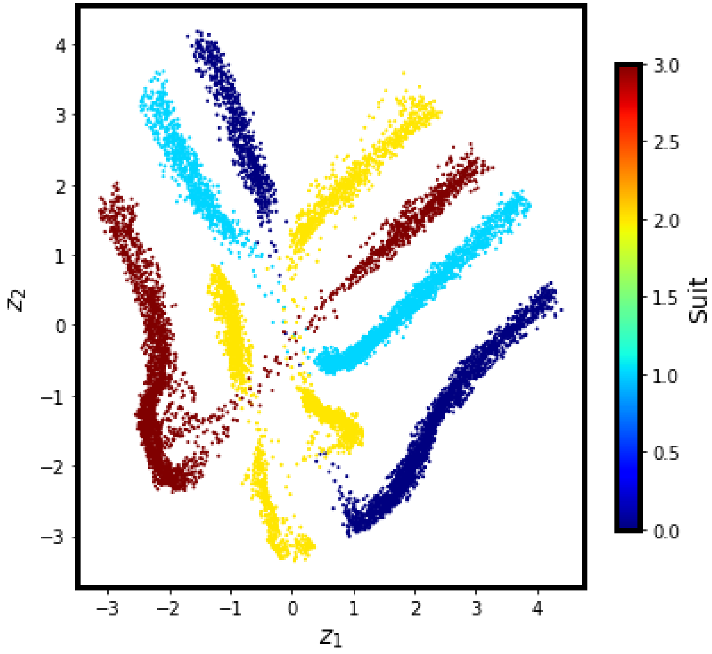
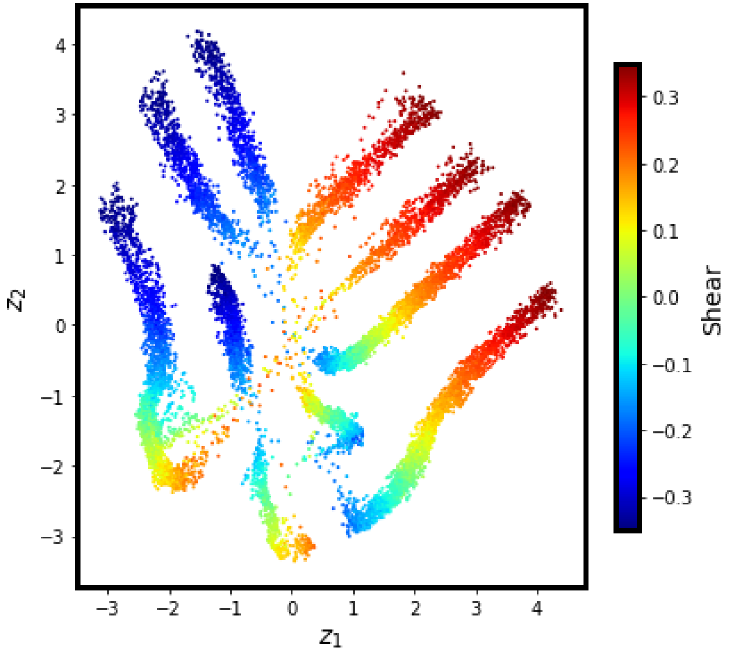
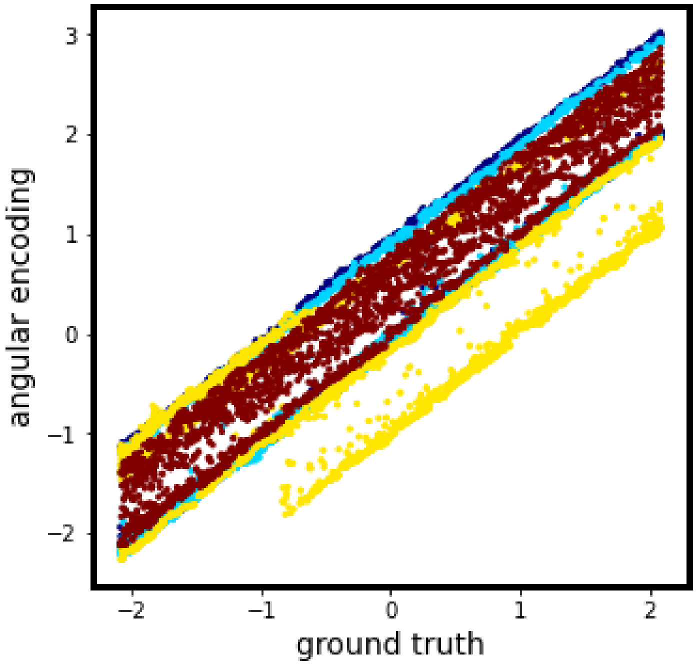
Suit




Shear




Angle




**Cards 4:** High rotation (120 deg) and high shear (20 deg)