5 - Autoencoders

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Summary

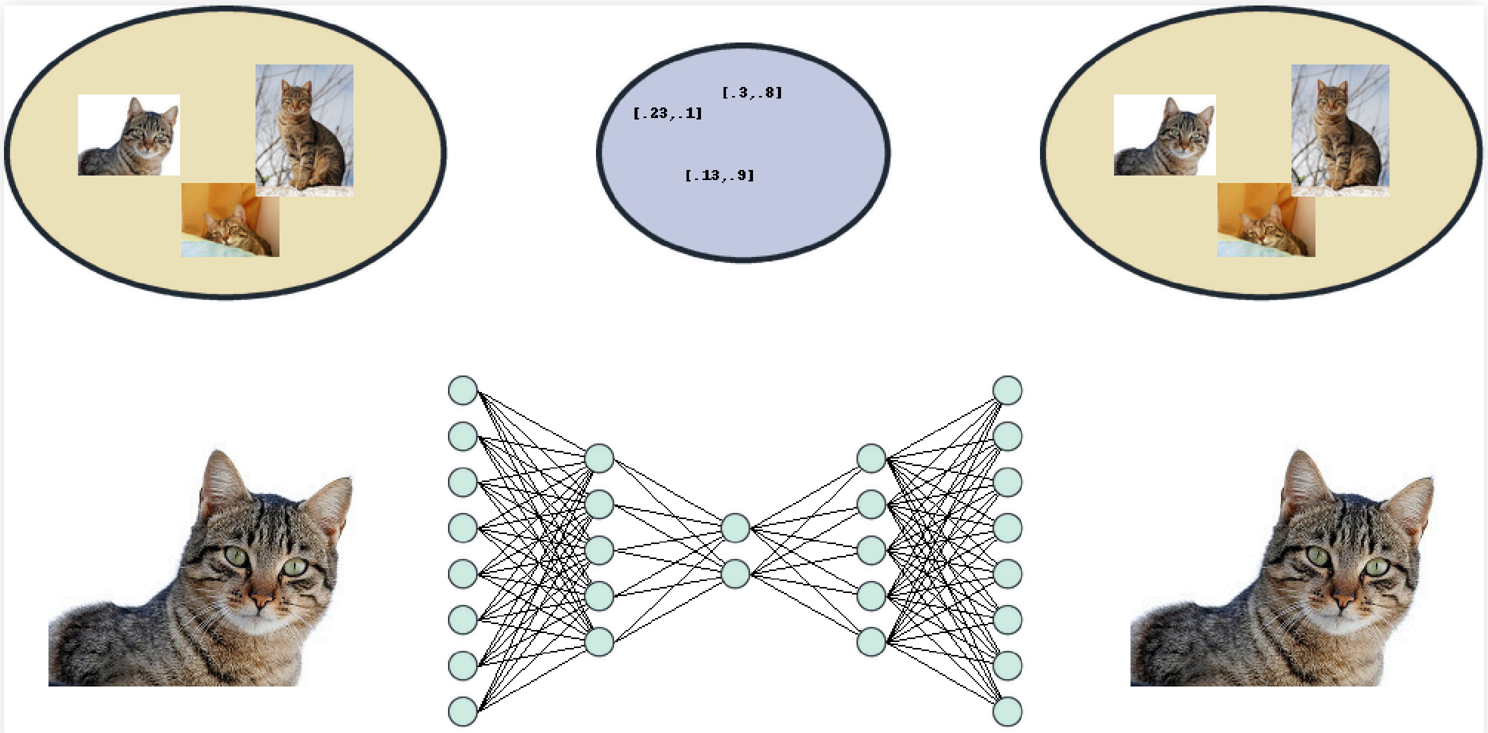
- What are Autoencoders?
- Different restrictions on encoding
  - Undercompleteness
  - Regularization
  - Sparsity
  - Noise reconstruction
- Applications

What are autoencoders?

What are autoencoders?

Network trained to output the input (unsupervised)

- In the hidden layers, one layer learns a **code** describing the input

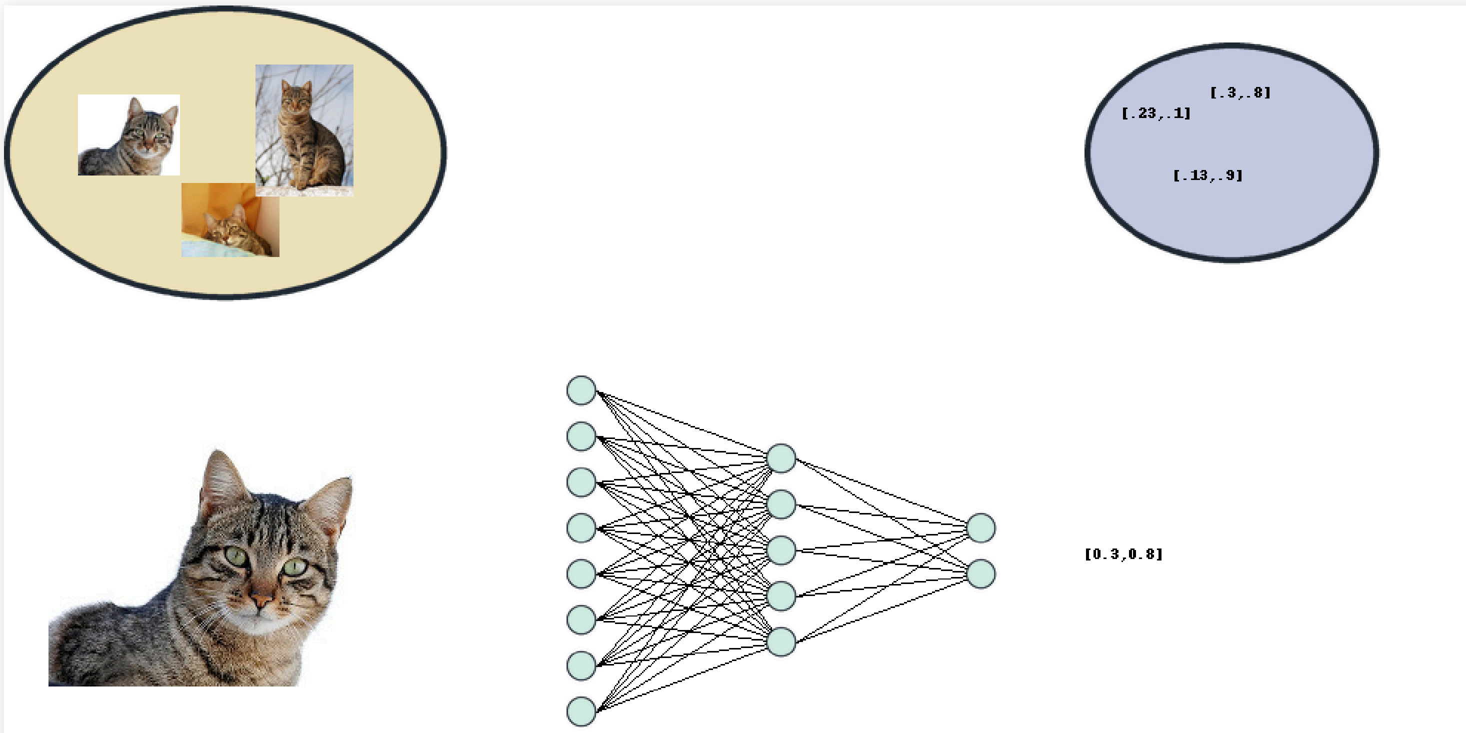


Cat images: Joaquim Alves Gaspar CC-SA

What are autoencoders?

Network trained to output the input (unsupervised)

- The encoder maps from input to **latent space**



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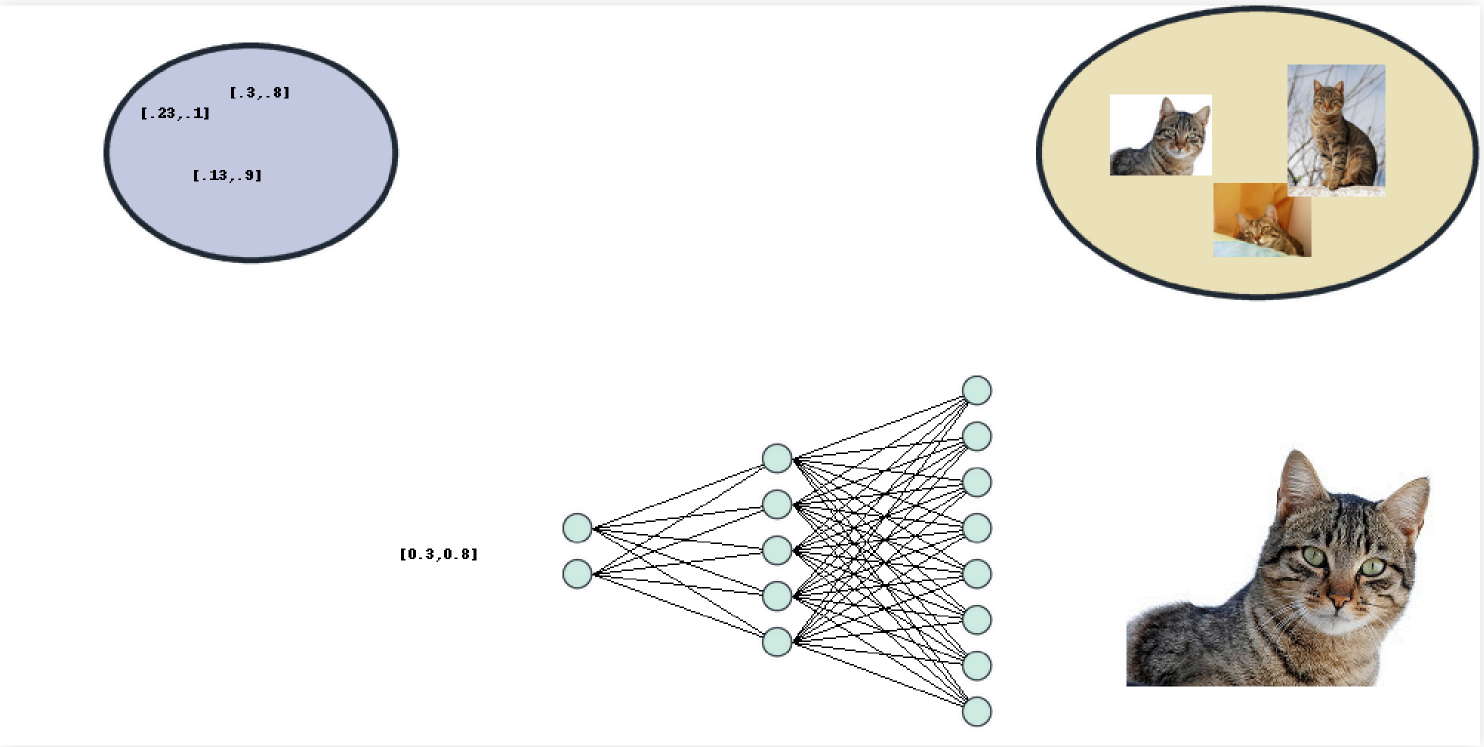
What are autoencoders?

Network trained to output the input (unsupervised)

- The decoder maps from **latent space** back to input space



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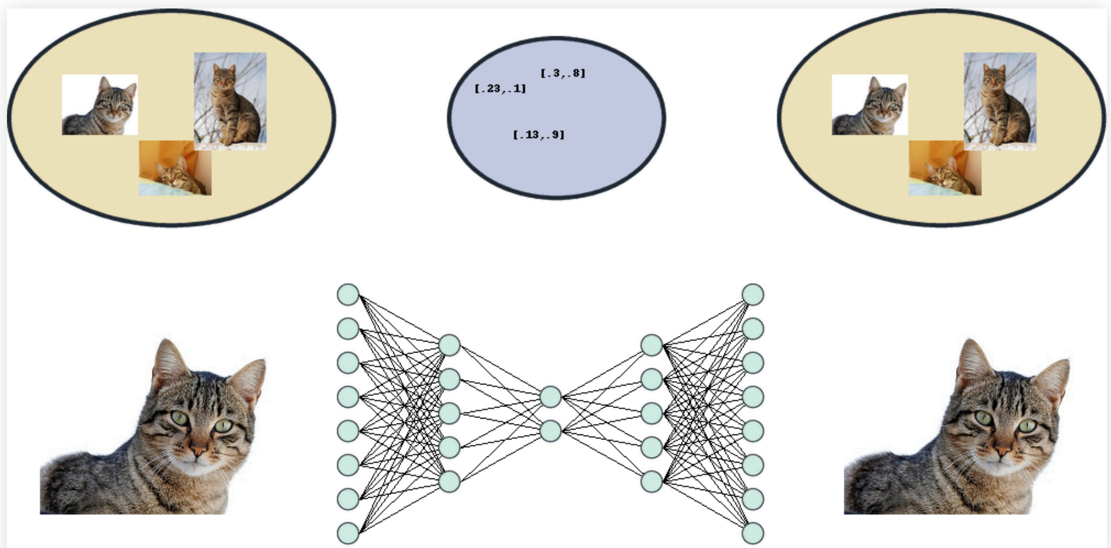
What are autoencoders?

Network trained to output the input (unsupervised)

- Encoder, $h = f(x)$, and decoder, $x = g(h)$
- No need for labels, since the target is the input
- Why learn $x = g\left(f\left(x\right)\right)$?



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What are autoencoders?

Network trained to output the input (unsupervised)

- Encoder, $h = f(x)$, and decoder, $x = g(h)$
- Why learn $x = g\left(f\left(x\right)\right)$?
- Latent representation can have advantages
  - Lower dimension
  - Capture structure in the data
  - Data generation

What are autoencoders?

Network trained to output the input (unsupervised)

- Encoder, $h = f(x)$, and decoder, $x = g(h)$
- Autoencoders are (usually) feedfoward networks
  - Can be trained with the same algorithms, such as backpropagation
- But since the target is x, they are unsupervised learners
- Need some "bottleneck" to force a useful representation
  - Otherwise just copies values

Different types of autoencoders

Undercomplete Autoencoders

Autoencoder is undercomplete if h is smaller than x

- Forces the network to learn reduced representation of input
- Trained by minimizing a loss function

$$L(x, g(f(x)))$$

  that penalizes the difference between x and $g(f(x))$
- If linear it is similar to PCA (without orthogonality constraint)
- With nonlinear transformations, an undercomplete autoencoder can learn more powerful representations
- However, we cannot overdo it

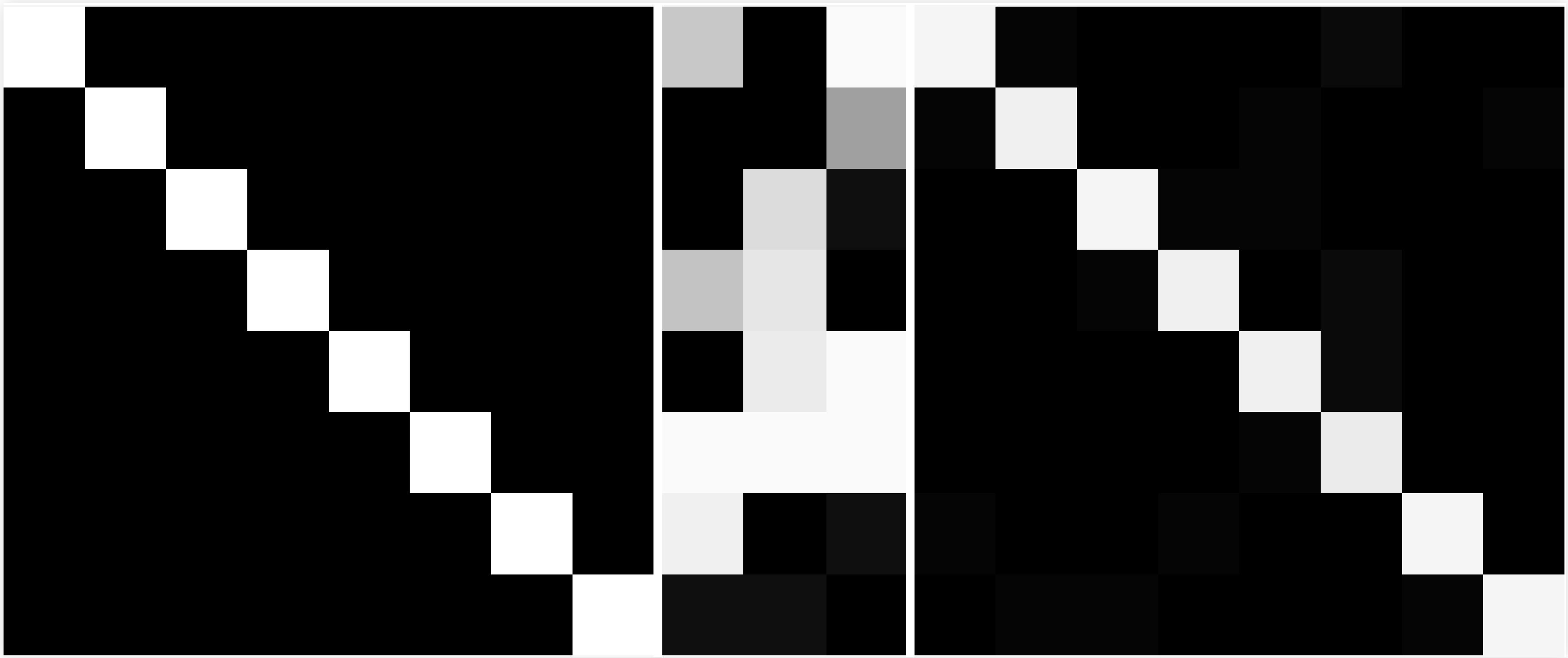
• With too much power, autoencoder can just index each training example and learn nothing useful:

$$f(x_i) = i, \quad g(i) = x_i$$

Undercomplete Autoencoders

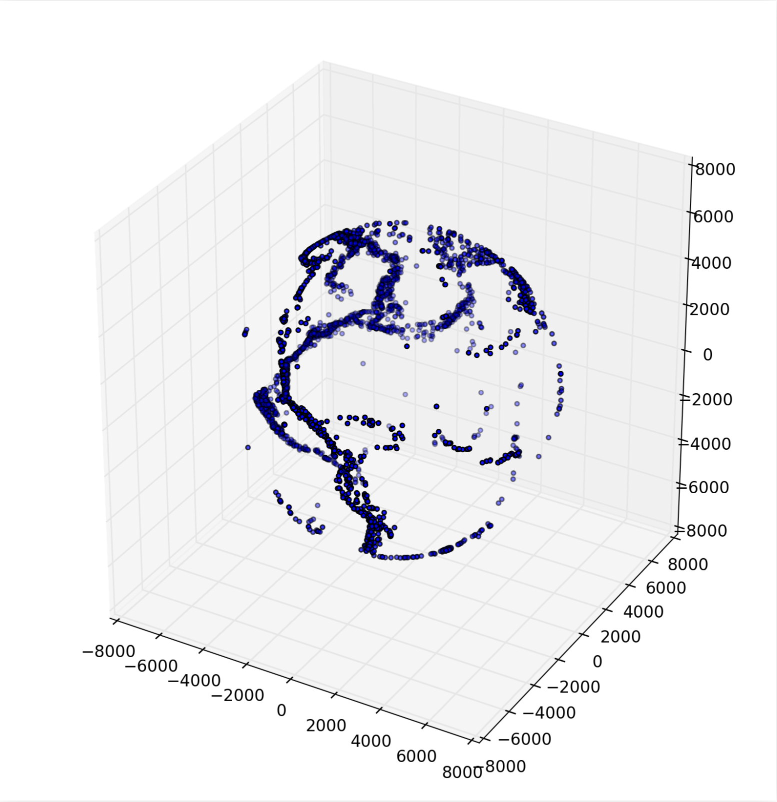
Autoencoder is undercomplete if h is smaller than x

- Mitchell's autoencoder, hidden layer of 3 neurons



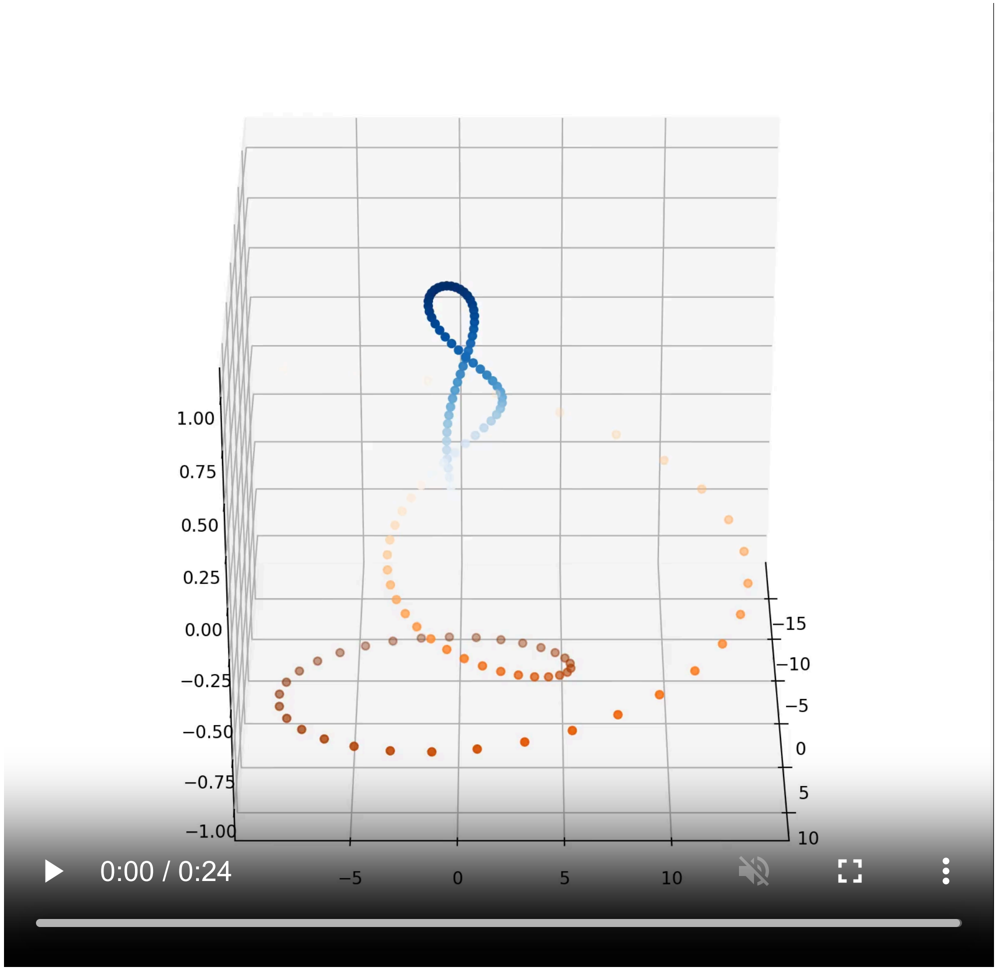
Manifold

- A set of points such that the neighbourhood of each is homeomorphic to a euclidean space
  - Example: the surface of a sphere



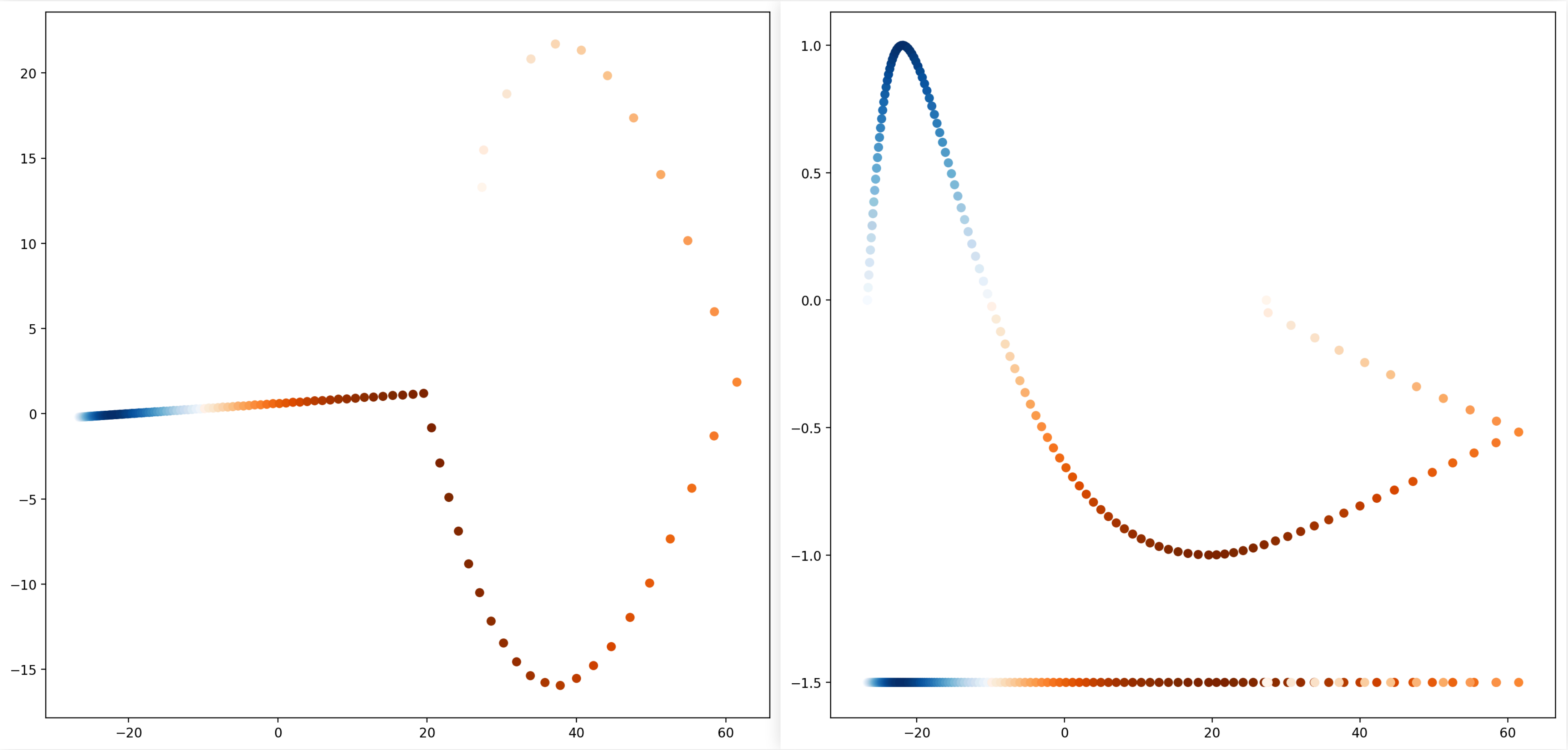
Manifold Learning

- Data may cover a lower dimension manifold of the space



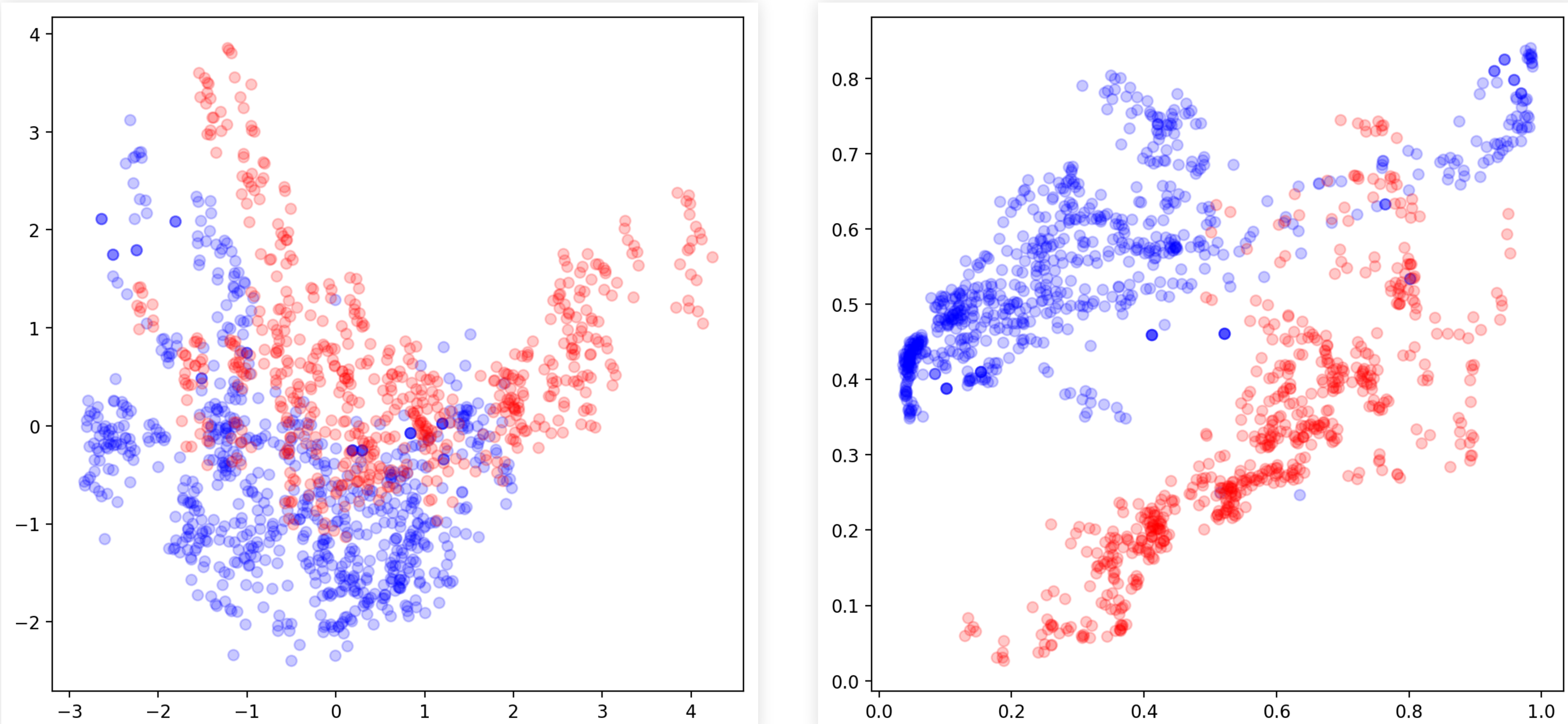
Manifold Learning

- Learn lower dimension embeddings of data manifold



Undercomplete Autoencoders

- Nonlinearity makes dimensionality reduction adapt to manifold
  - PCA vs autoencoder 6,4,2,4,6, UCI banknote dataset (4 features)



Manifold learning with autoencoders

- This works because we force the network in two opposite ways:
  - We demand the ability to reconstruct the input
  - But we also constrain how the network can encode the examples
- Undercompleteness is just one way of doing this

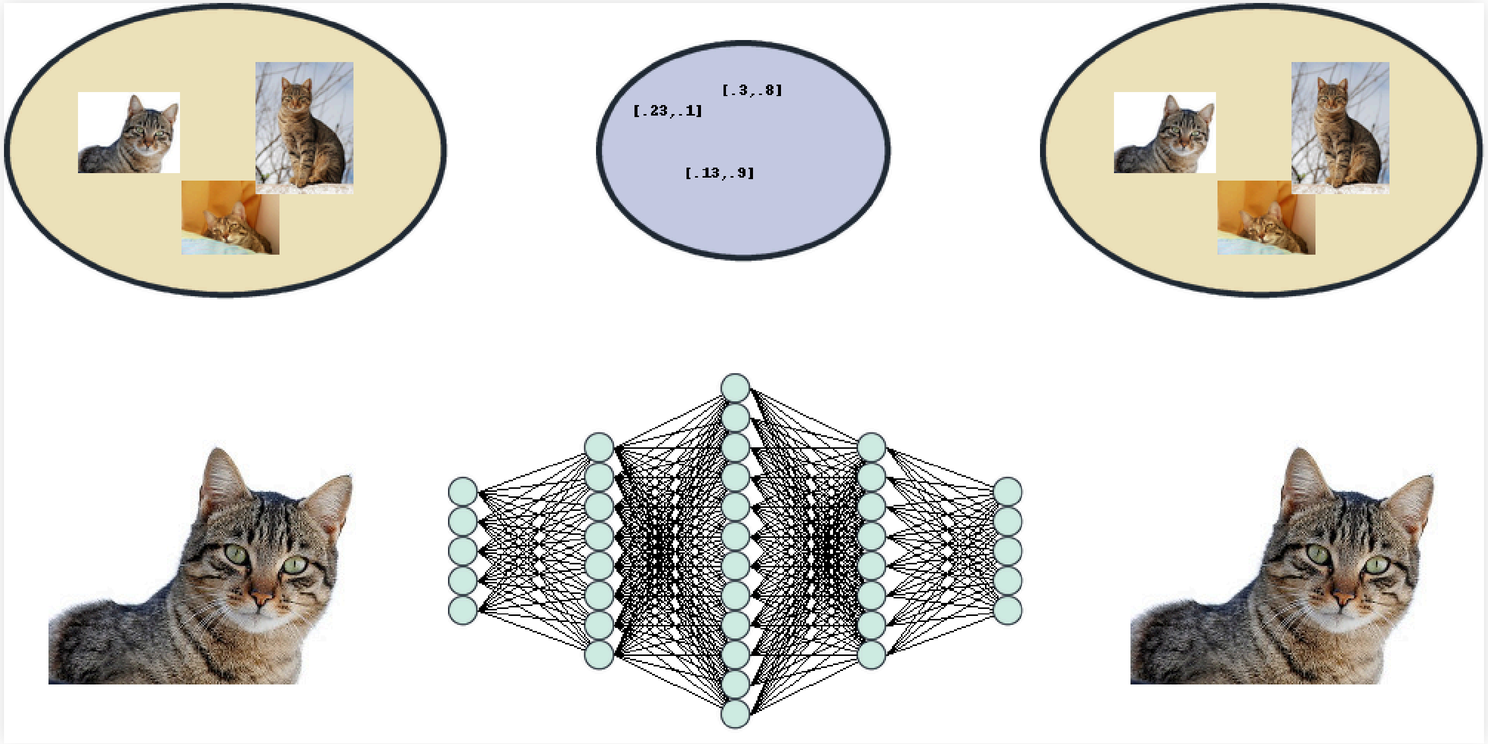
Beware of overfitting.

- If the autoencoder is sufficiently powerful, it can reconstruct the training data accurately but lose generalization power
- In the extreme, all information about reconstructing the training set may be in the weights and the latent representation becomes useless

Regularized Autoencoders

An overcomplete autoencoder has h larger than x

- This, by itself, is a bad idea as h will not represent anything useful



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Regularized Autoencoders

An overcomplete autoencoder has h larger than x

- But we can restrict h with regularization
- This way the autoencoder also learns how restricted h should be

Sparse Autoencoder

- Force h to have few activations
- Example: we want the probability of h_i firing

$$\hat{p}_i = \frac{1}{m}\sum_{j=1}^{m} h_i(x_j)$$

to be equal to p (the sparseness parameter)

Regularized Autoencoders

Sparse Autoencoder

- Include in the loss function a penalization term
- Use the Kullback-Leibler divergence between Bernoulli variables as a regularization penalty

$$L(x, g(f(x))) + \lambda \sum_i \left(p \log \frac{p}{\hat{p}_i} + (1-p) \log \frac{1-p}{1-\hat{p}_i} \right)$$

- Other options include L1 regularization applied to the activation of the neurons, L2, etc.

Regularized Autoencoders

Sparse Autoencoder

- Sparse autoencoders make neurons specialize

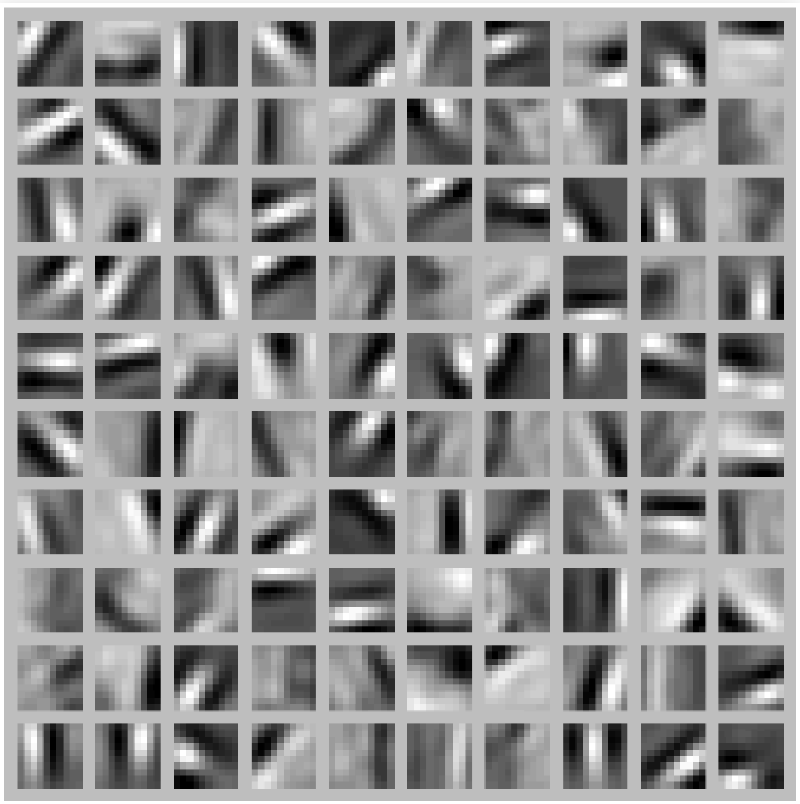
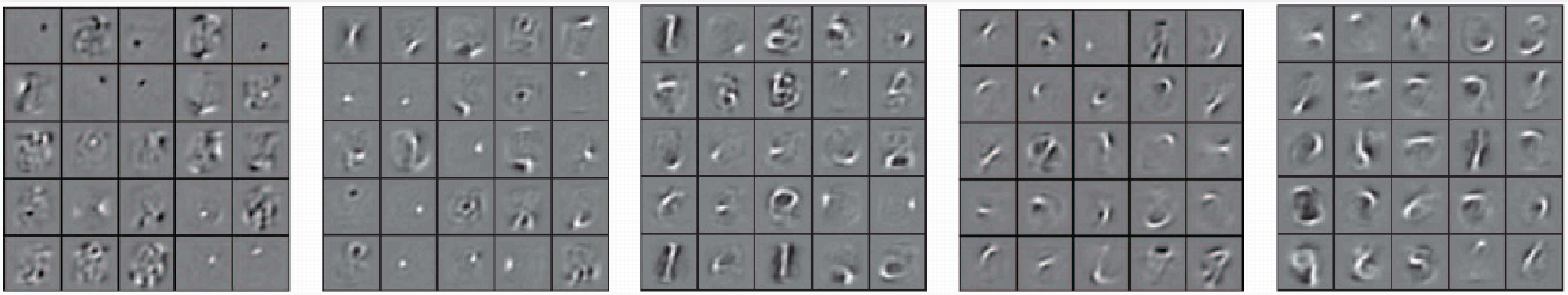


Image: Andrew Ng

- Trained on 10x10 images
- 100 neurons on h
- Images (norm-bounded) that maximize activation

Sparse Autoencoder

- Sparse autoencoders trained on MNIST, different sparsity penalties
- (25 neurons in filter, images correspond to highest activation)



(a) No penalty (b) L1 norm penalty (c) L2 norm penalty (d) Student-t penalty (e) KL-divergence penalty

Niang et. al, Empirical Analysis of Different Sparse Penalties... IJCNN 2015,

Denoising Autoencoders

- We can force h to be learned with noisy inputs
- Output the original x from corrupted $\tilde{x}$: $L(x, g(f(\tilde{x})))$

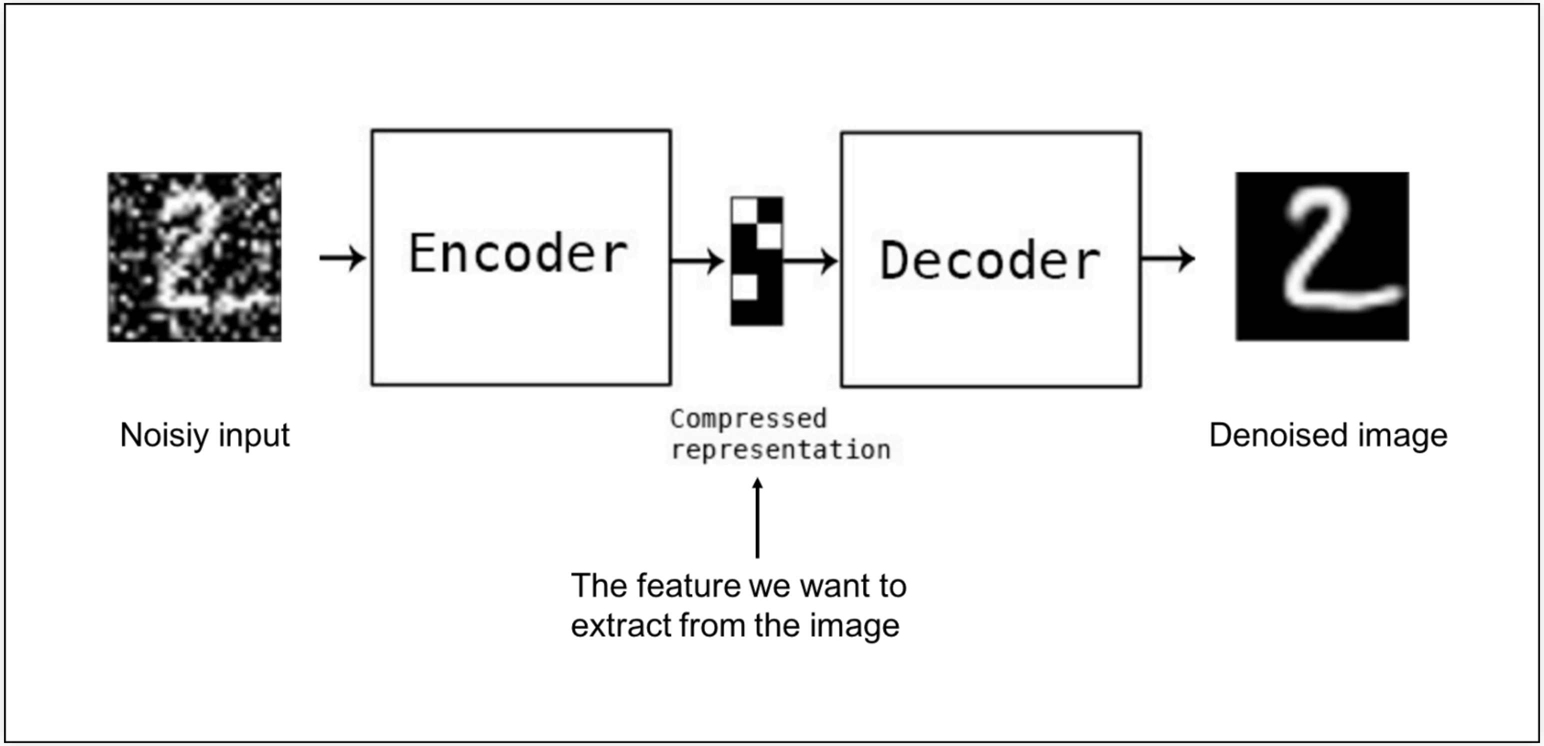


Image: Adil Baaj, Keras Tutorial on DAE

Denoising Autoencoders

- We can force h to be learned with noisy inputs
  - Output the original x from corrupted $\tilde{x}$: $L(x, g(f(\tilde{x})))$
- This forces the autoencoder to remove the noise by learning the underlying distribution of x
- Algorithm:
  - Sample x_i from $\mathcal{X}$
  - Apply corruption $C(\tilde{x}_i \mid x_i)$
  - Train with $(x, \tilde{x})$

Stochastic Autoencoders

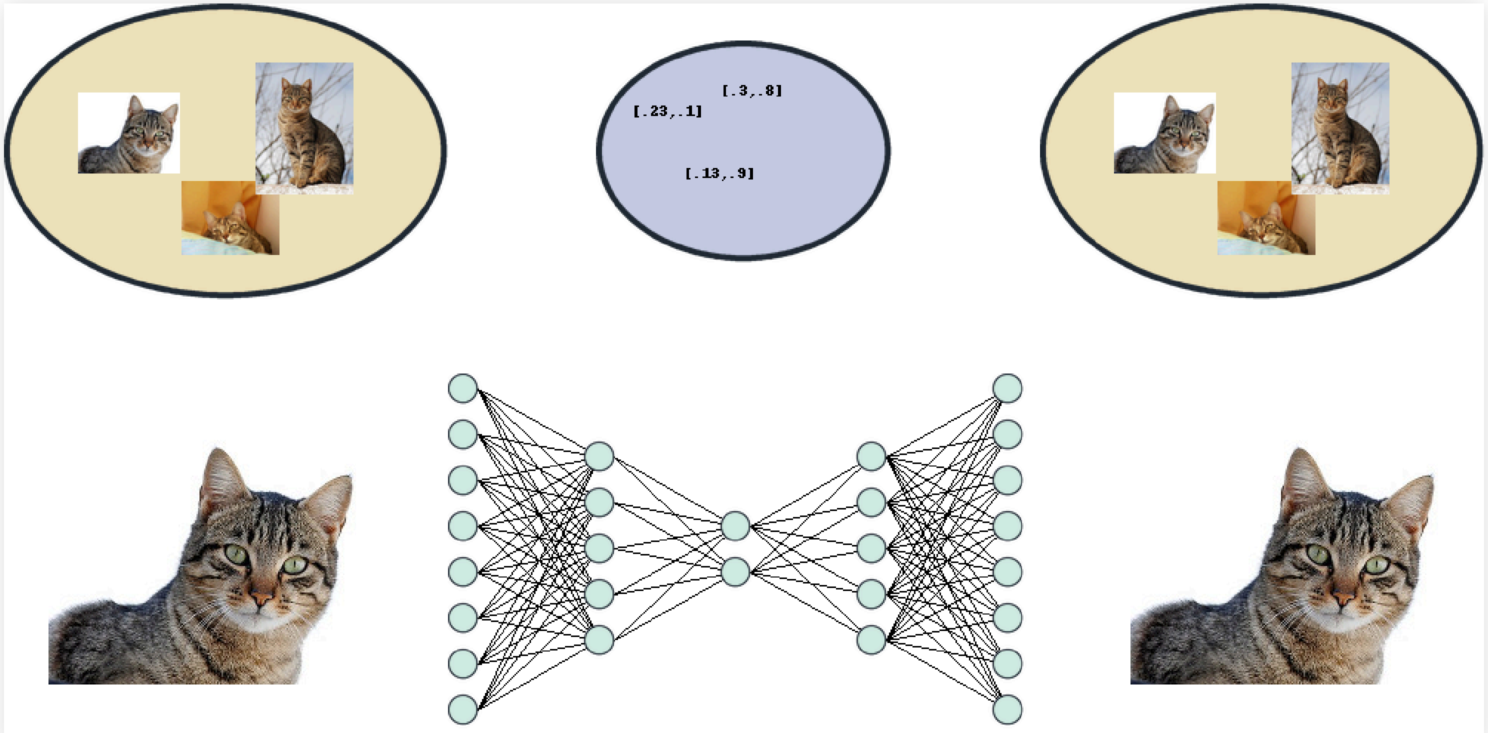
- We can also use autoencoders to learn probabilities
  - Just like with other ANN (e.g. softmax classifier)
- The decoder is modelling a conditional probability $p_{decoder}(x \mid h)$
  - where h is given by the encoder part of the autoencoder
- The decoder output units can be chosen as before:
  - Linear for estimating the mean of Gaussian distributions
  - Sigmoid for Bernoulli (binary)
  - Softmax for discrete categories
- We can think of encoder and decoder as modelling conditional probabilities

$$p_{encoder}(h \mid x) \qquad p_{decoder}(x \mid h)$$

Generating Data

Generating Data

- Can we use autoencoders to generate new examples?



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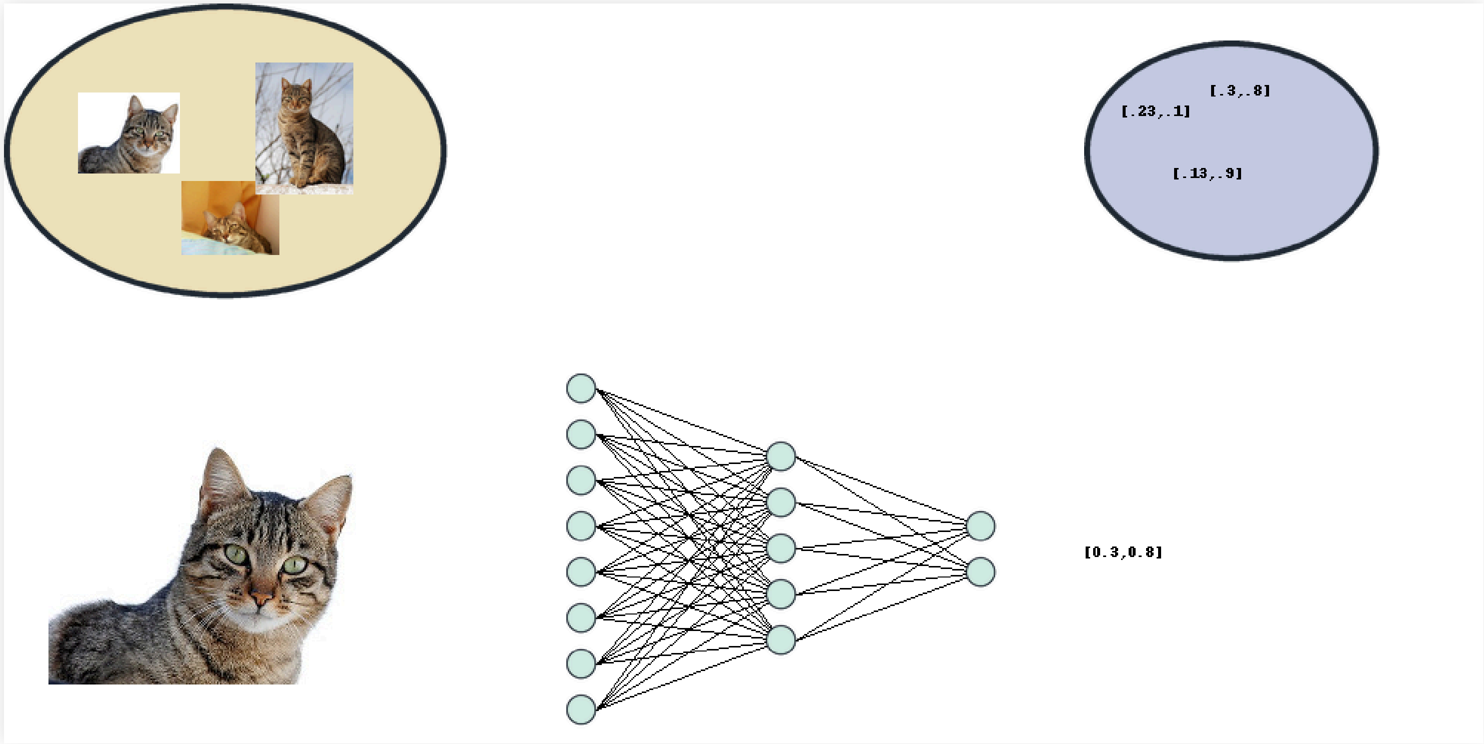
Generating Data

- Autoencoders create a latent representation from the data



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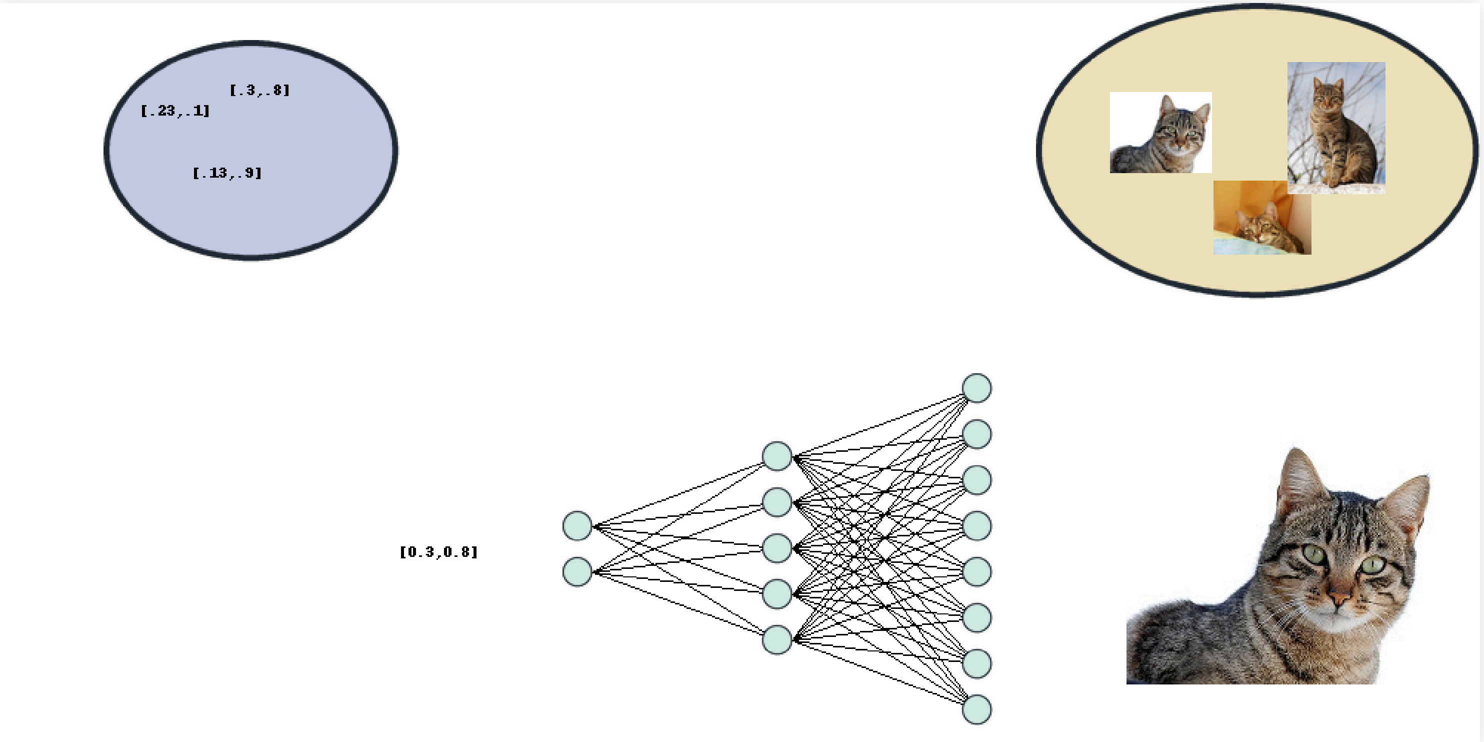
Generating Data

- And then decode to recreate the data from this representation



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Generating Data

- Can we use the decoder to generate new examples?

Discriminative vs Generative

- A discriminative model tries to approximate a function $p(y \mid x)$
  - E.g. Logistic regression or softmax ANN predict the probability of each class given the features
- A generative model approximates $p(x, y)$ and then finds $p(y \mid x)$:

$$p(x, y) = p(y \mid x)p(x)$$

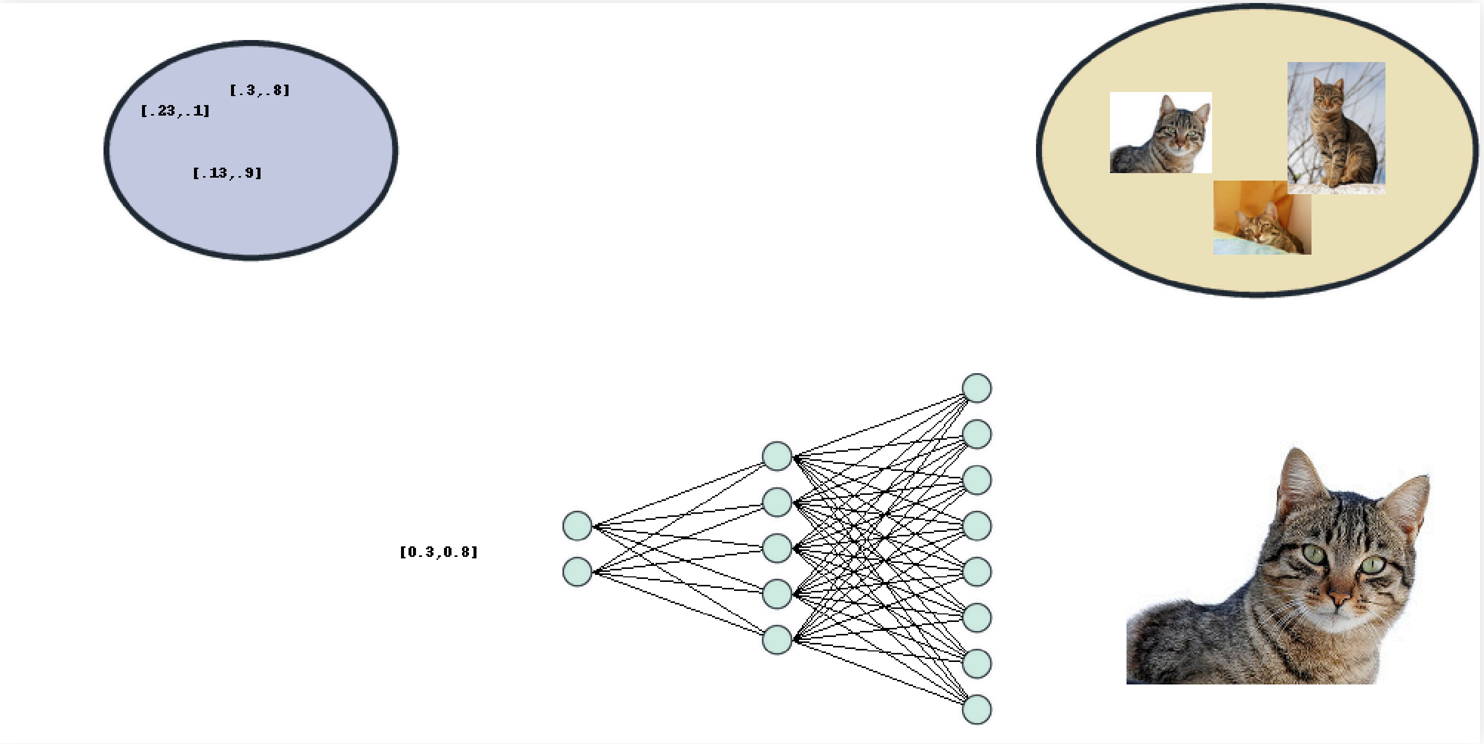
  - This is generative because, knowing $p(x, y)$, we can sample from the distribution

With autoencoders

- We decode from h, so we need to find its distribution in order to generate examples from $p(h, y) = p(y \mid h)p(h)$

Generating Data

- Intuition: we need to sample the right part of the latent space



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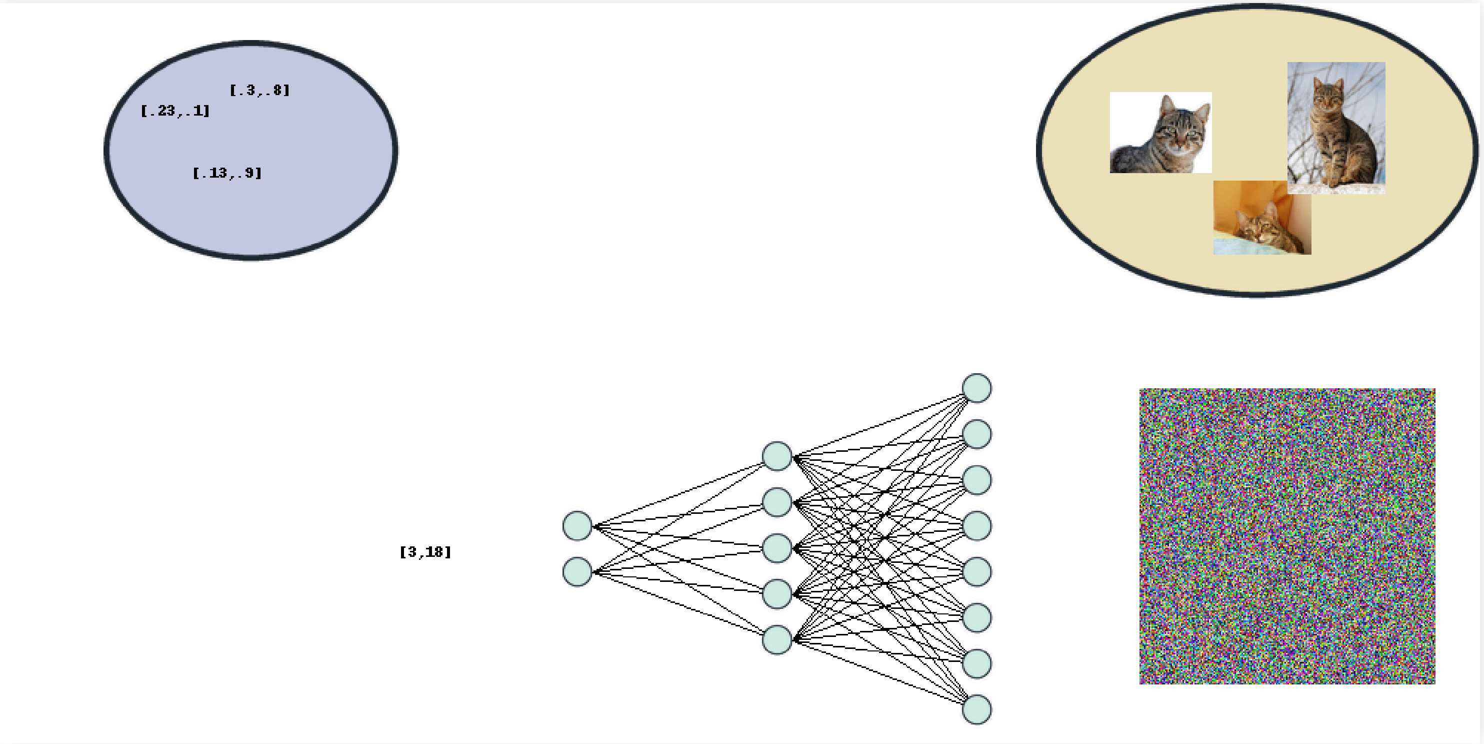
Generating Data

- Intuition: if outside the right region, the result is garbage



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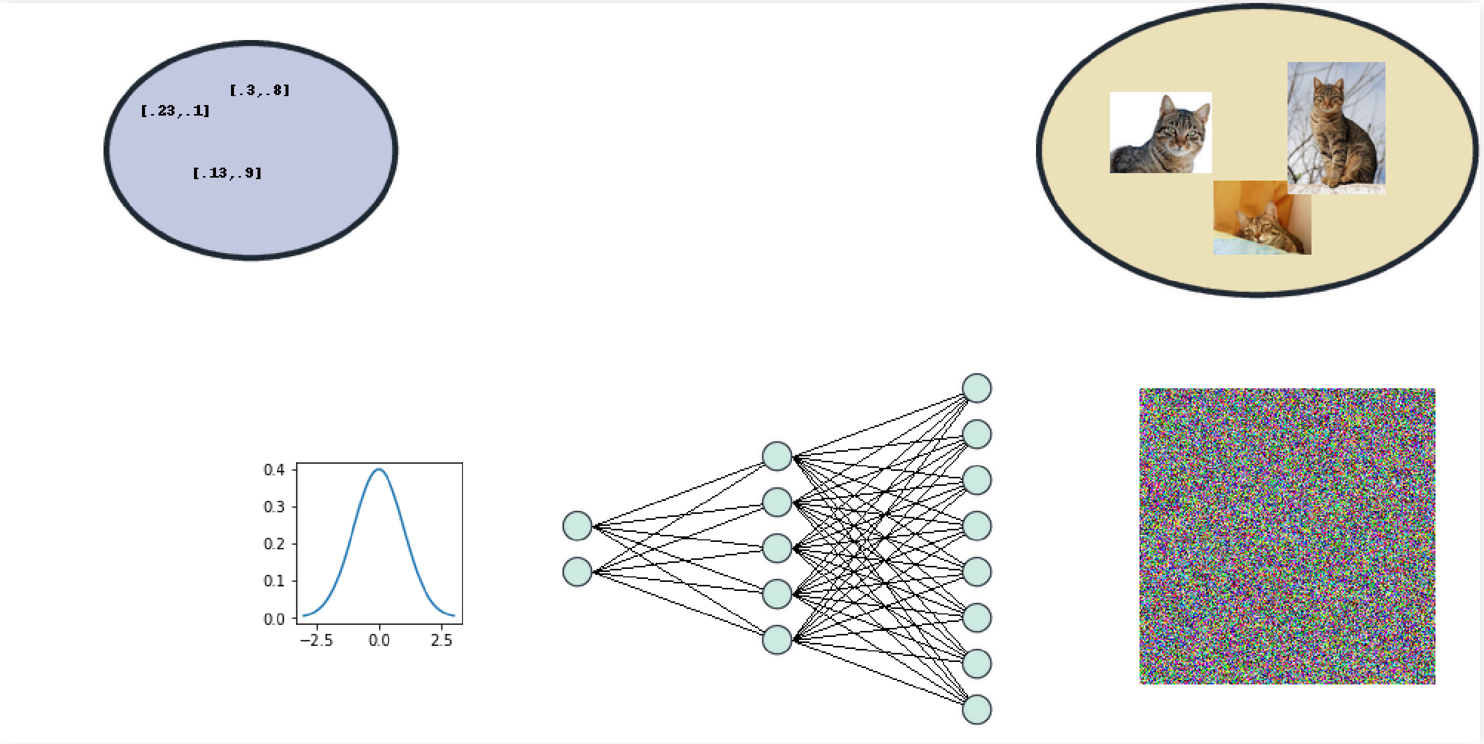
Generating Data

Generative adversarial networks

- Fix the latent space with some distribution

- The result will be garbage because net not trained



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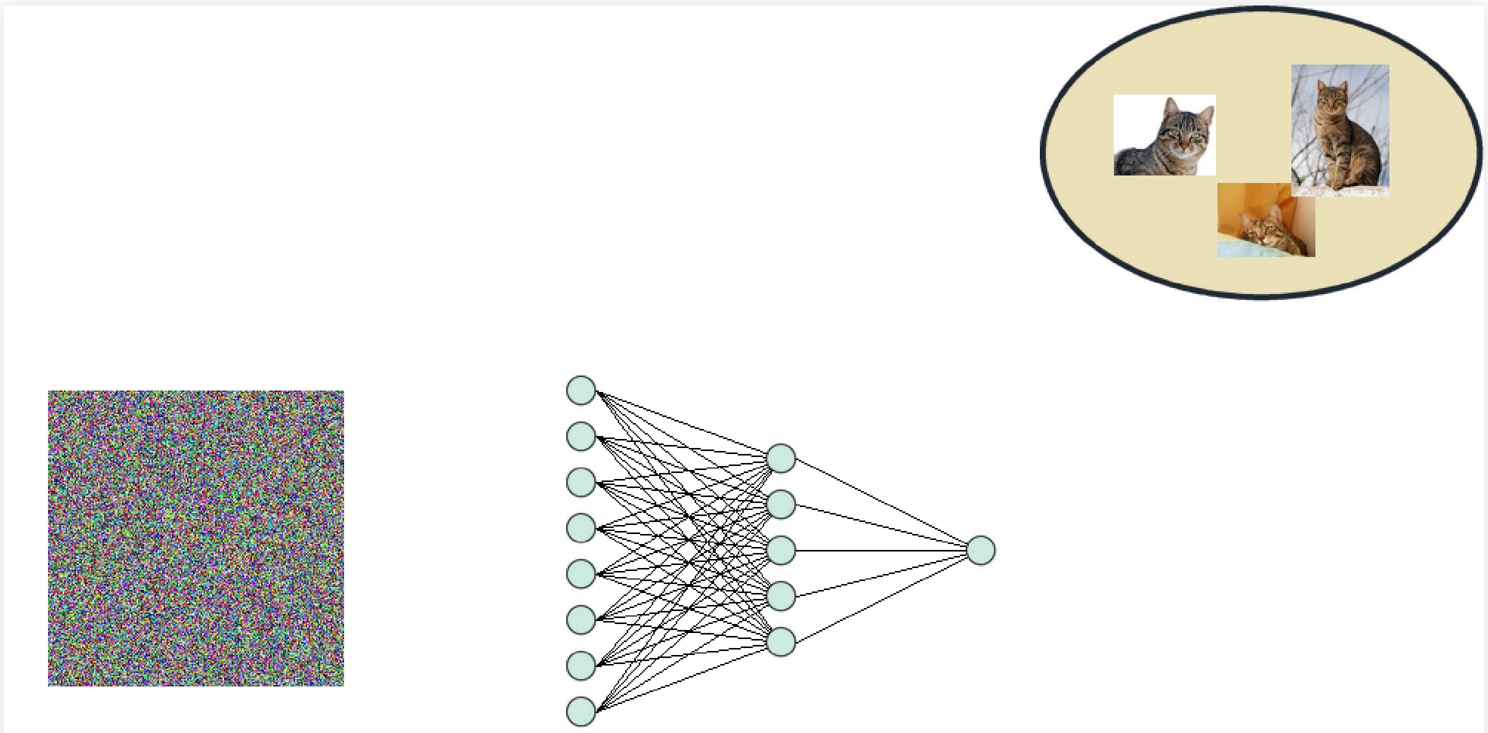
Generative adversarial networks

- Train a network to distinguish the real examples from fakes



Generating Data

Generative adversarial networks

- One network creates examples from given distribution
- The other distinguishes real from fake
- Train both, alternating, so each becomes increasingly better

Ian Goodfellow

Generative adversarial networks

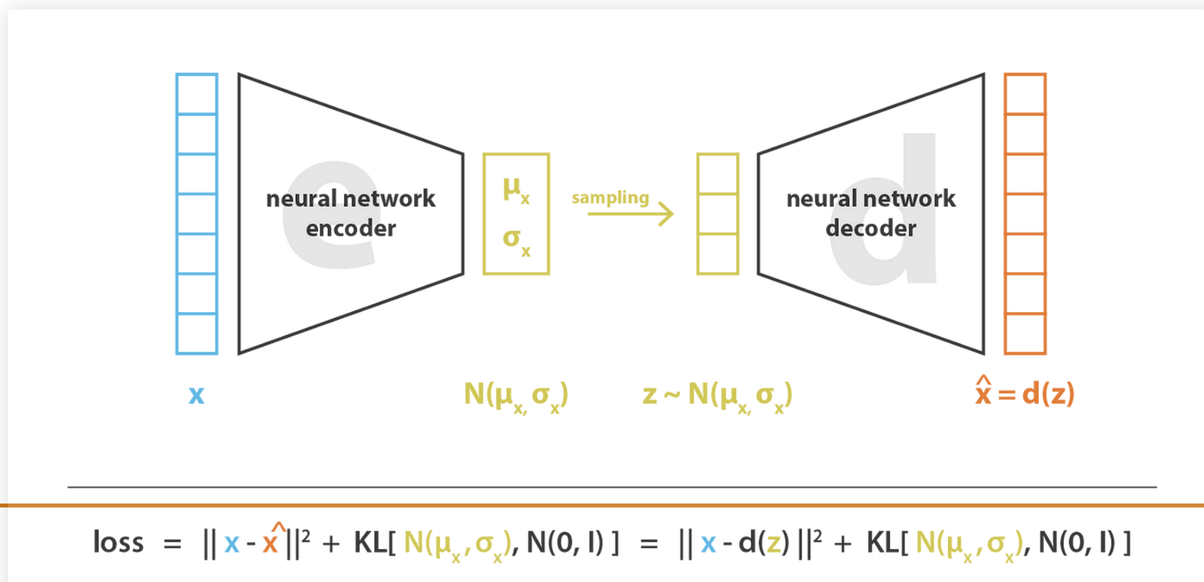
- One network creates examples from given distribution
- The other distinguishes real from fake
- Train both, alternating, so each becomes increasingly better
- As a result, the generator learns to map our fixed initial distribution to the space of our target examples.

Generating Data

- Can we use autoencoders to generate new examples?
  - Yes, if we know the "shape" of the latent space

Variational Autoencoders

- Train the autoencoder to encode into a given distribution
  - E.g. mixture of independent Gaussians
- This way we learn the distribution for generating examples of each type



Variational Autoencoders

- How do we backpropagate through random sampling?
- Reparametrize: z is deterministic apart from a normally distributed error

$$z = \mu + \sigma \odot \epsilon \qquad \epsilon \sim \mathcal{N}(0, 1)$$

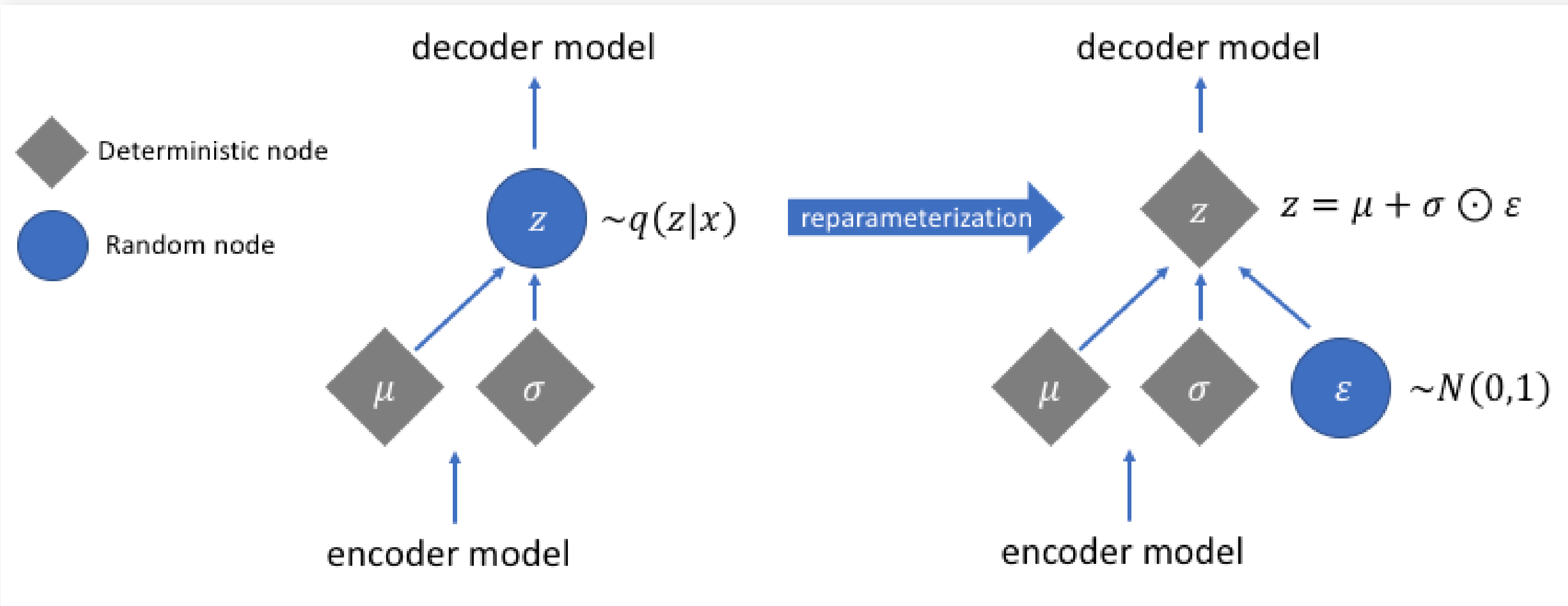


Image: Jeremy Jordan, Variational autoencoders.

Variational Autoencoders

- VAE can learn to disentangle meaningful attributes
  - We can force the independence of the latent variables

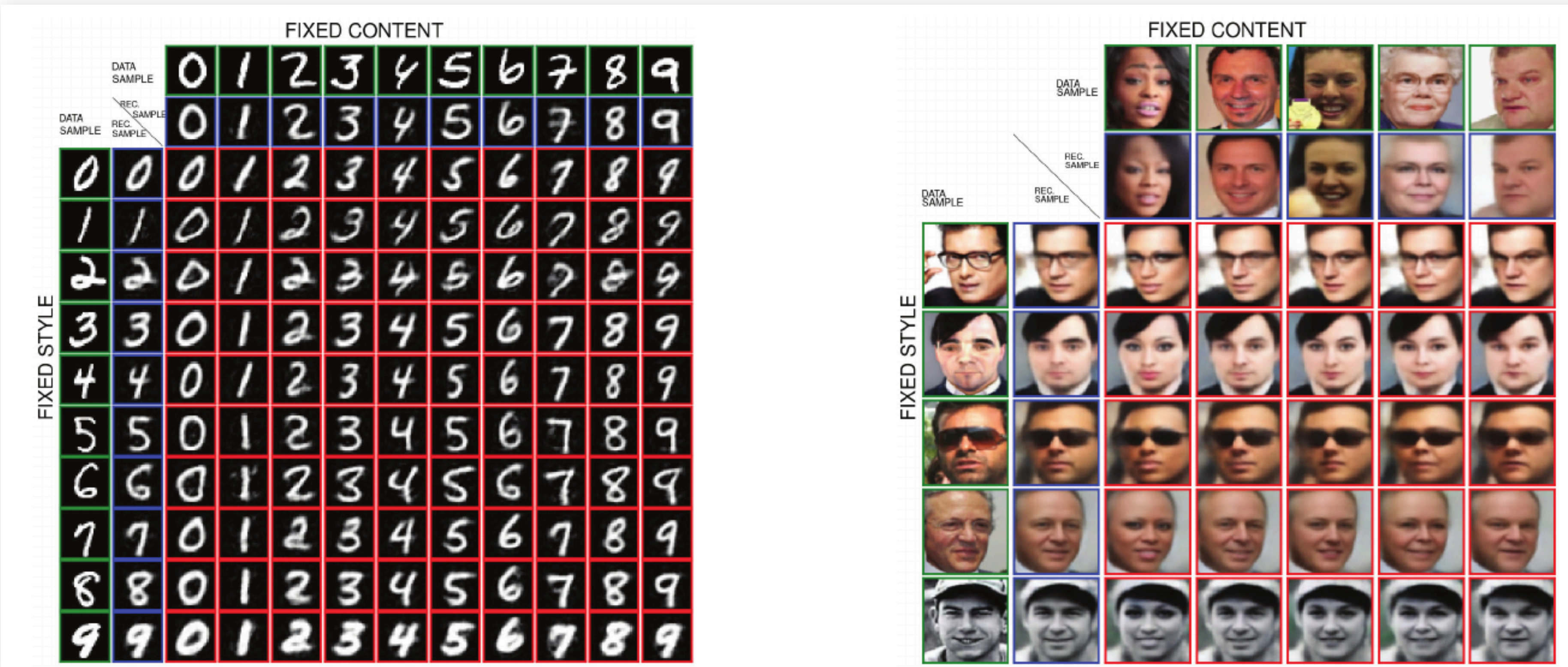


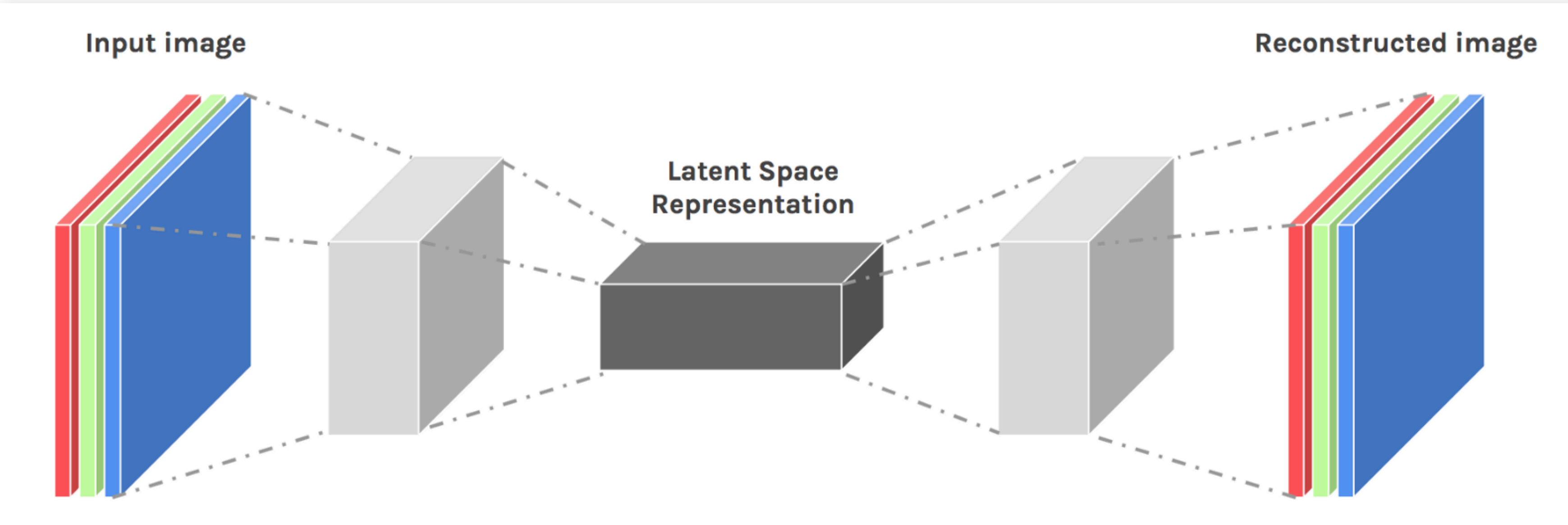
Image: Bouchacourt et. al., Multi-level variational autoencoder, 2018

Convolutional Autoencoders

Convolutional Autoencoders

Use convolutions and upsampling to reconstruct

- Latent space is narrow, need to restore original dimensions

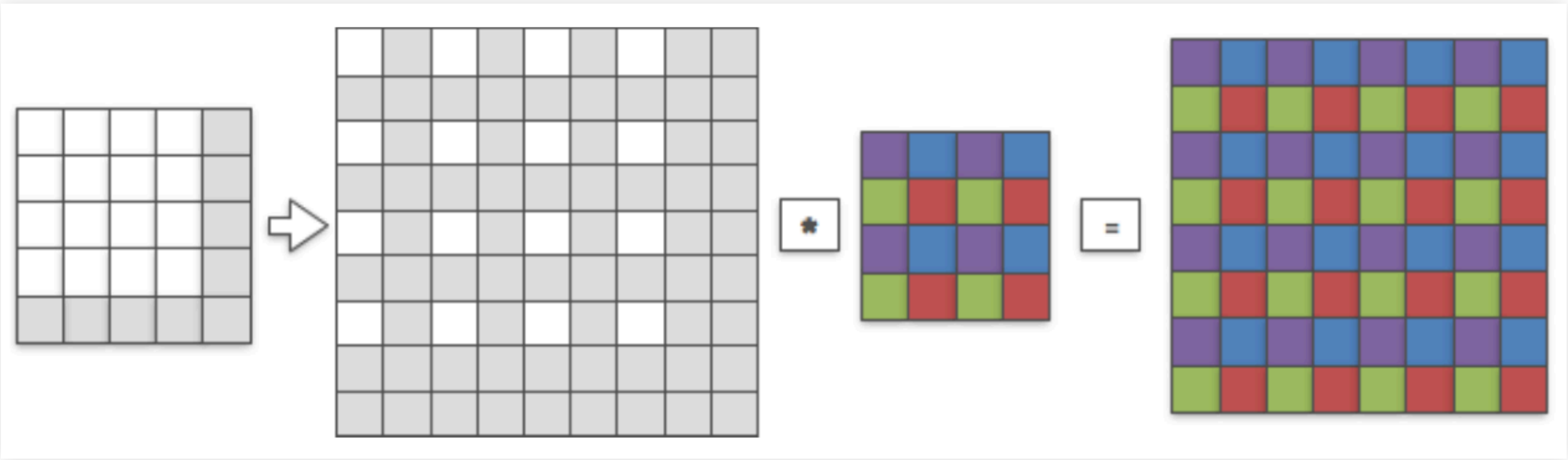


Barna Pásztor, Aligning hand-written digits with Convolutional Autoencoders

Convolutional Autoencoders

- Upsample followed by convolution (in 2D)

```
from tensorflow.keras.layers import UpSampling1D,UpSampling2D
UpSampling1D(size=2)
UpSampling2D(size=(2, 2), data_format=None, interpolation='nearest')
```

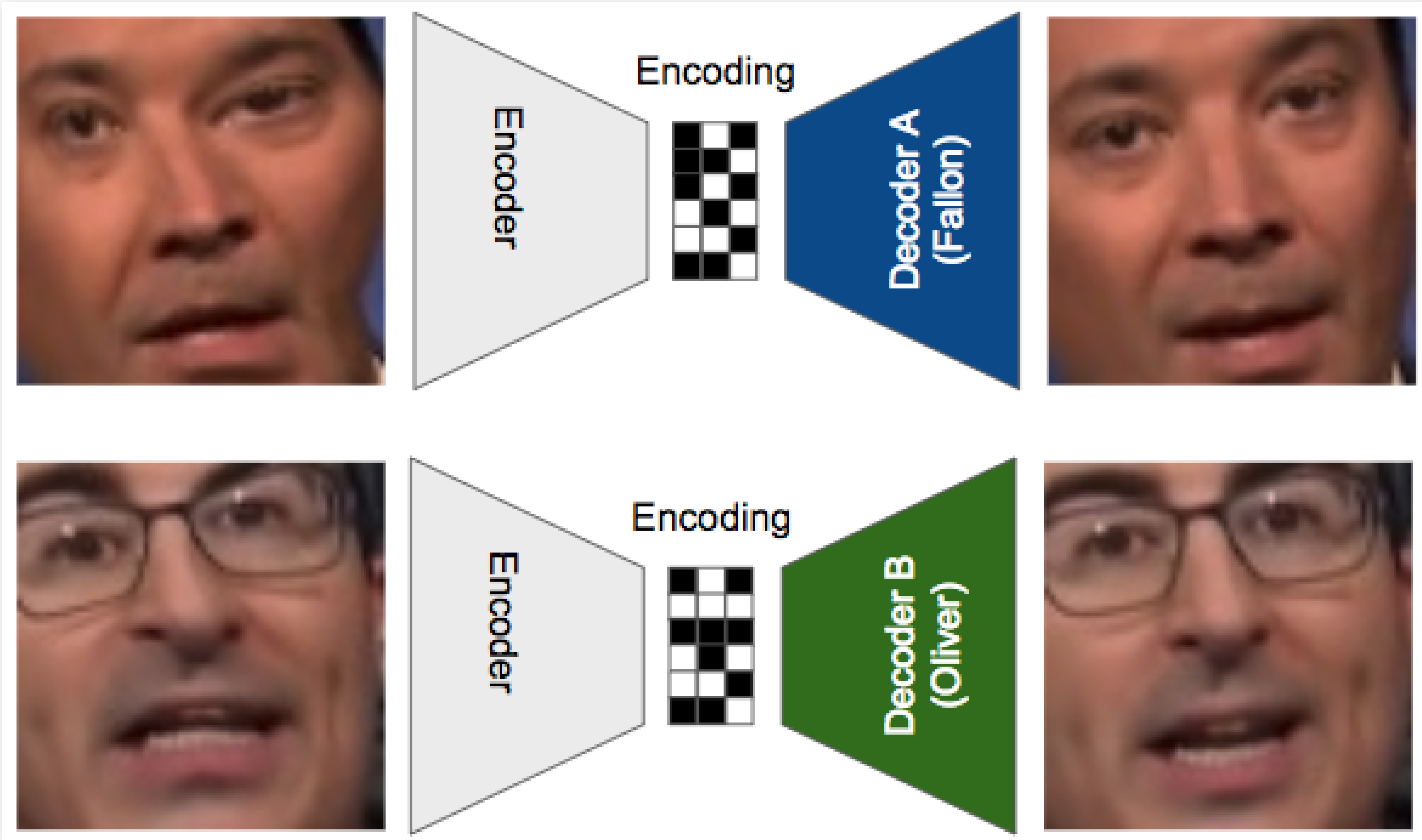


Shi et. al., Is the deconvolution layer the same as a convolutional layer?

Example: deep fakes

- Train the same encoder on different sets of inputs
- But for each set reconstruct with a specific decoder
- With this we can "translate" between sets

Example: deep fakes



Gaurav Oberoi, Exploring DeepFakes, https://goberoi.com/exploring-deepfakes-20c9947c22d9

Applications

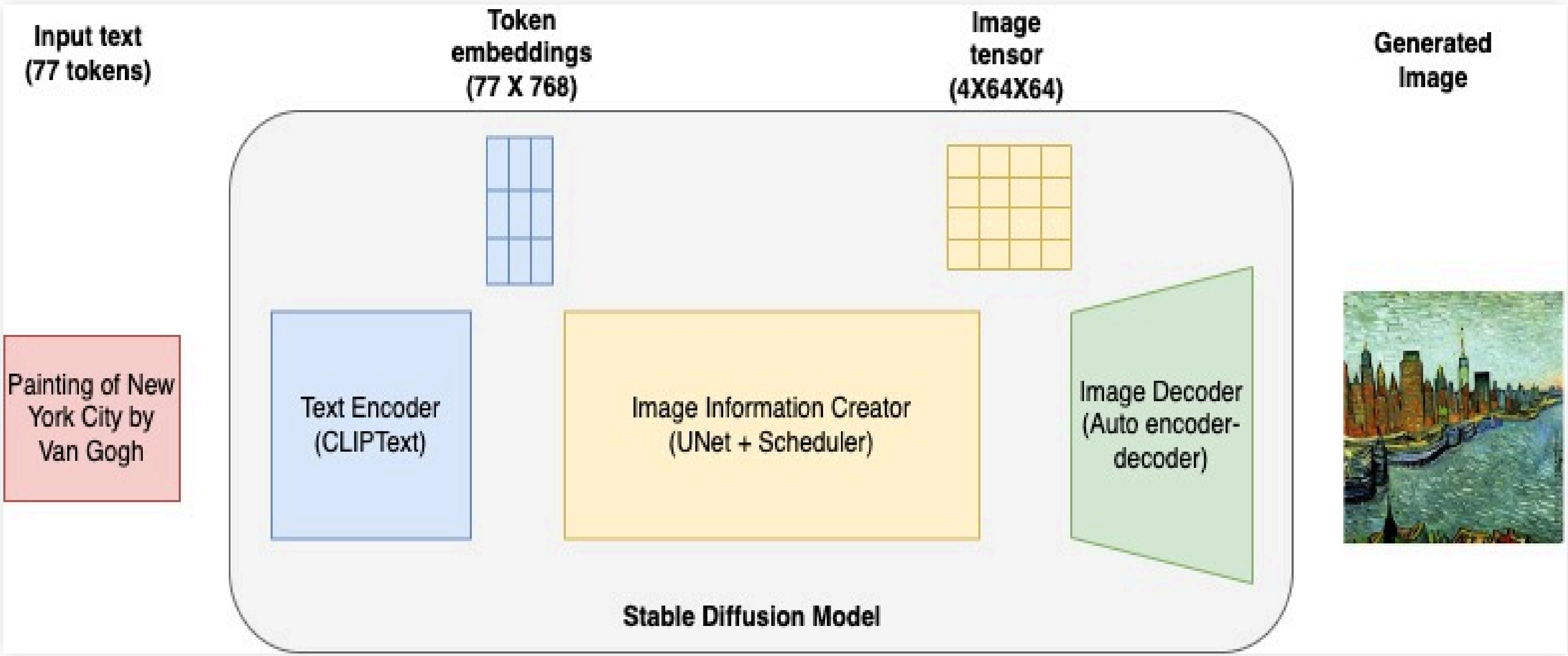
Example: deep fakes

- Train with images from videos
- Process video:
  - Input Fallon to encoder
  - Output Oliver using Oliver decoder

Gaurav Oberoi, Exploring DeepFakes, https://goberoi.com/exploring-deepfakes-20c9947c22d9

Example: Text-to-image

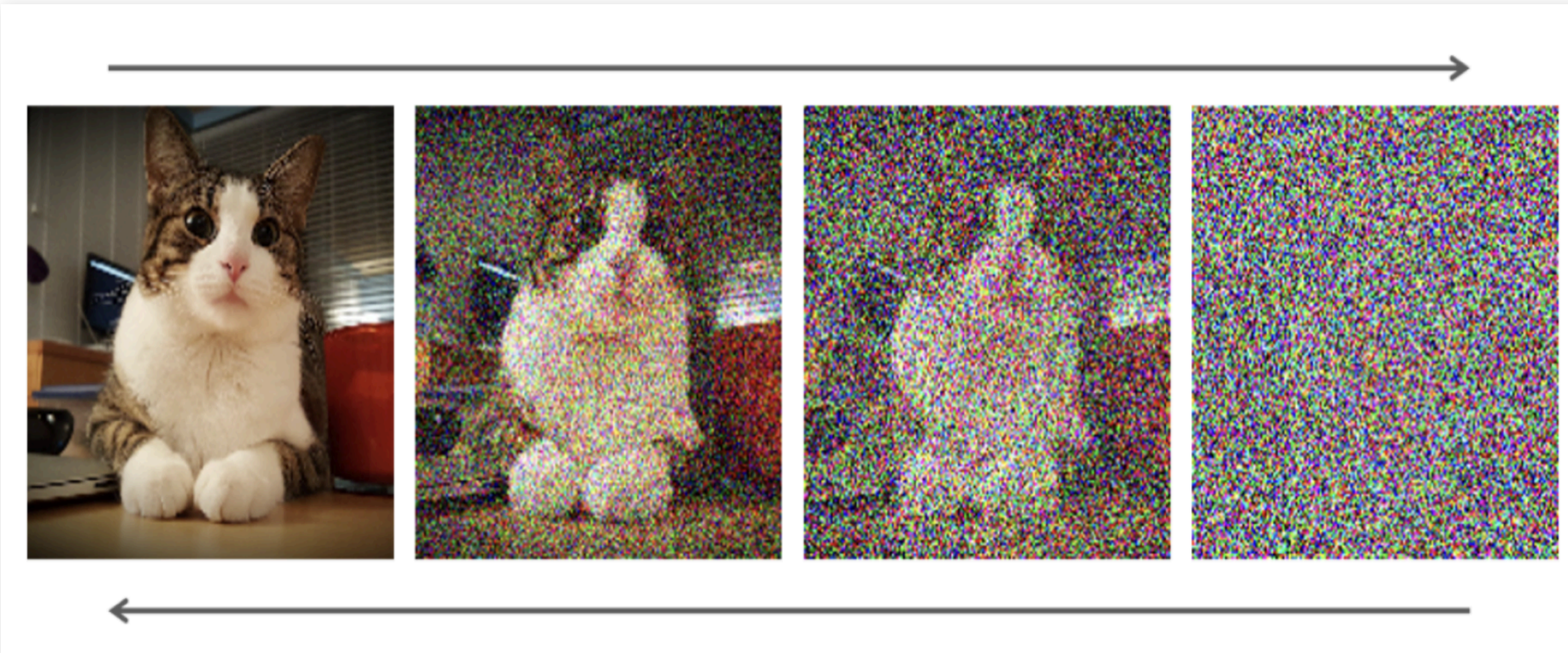
- Stable Diffusion, DALL-e



Amazon Machine Learning Blog, https://aws.amazon.com/blogs/machine-learning/create-high-quality-images-with-stable-diffusion-models-and-deploy-them-cost-efficiently-with-amazon-sagemaker/

Example: Text-to-image

- Based on U-Net model architecture: CNN for image segmentation



Edge AI and vision, https://www.edge-ai-vision.com/2023/01/from-dall%C2%B7e-to-stable-diffusion-how-do-text-to-image-generation-models-work/

Summary

Autoencoders

Summary

- Autoencoders: learn the input in the output
  - Unsupervised learning
  - Using restrictions (dimension, regularization)
  - Or reconstruction (from corrupted inputs)
- Convolutional Autoencoders
- Recent applications

Further reading:

- Goodfellow et.al, Deep learning, Chapter 14