



# DEEP ROB

Lecture 21

Unsupervised Learning

University of Michigan | Department of Robotics



# Recall: Videos

The temporal dimension

**Raw video:** Long, high FPS



**Training:** Train model to classify short **clips** with low FPS



**Testing:** Run model on different clips, average predictions





# Supervised Learning

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**Data:**  $(x, y)$

x is data, y is label

**Goal:** Learn a *function* to map  $x \rightarrow y$

```
batch_size = 64
X_batch = data_dict['X_val'][:batch_size]
y_batch = data_dict['y_val'][:batch_size]

# Compute the loss and its gradient at W.
# YOUR_TURN: implement the gradient part of 'svm_loss_naive' function in "linear_classifier.py"
_, grad = svm_loss_naive(W, X_batch, y_batch, reg=0.0)
```



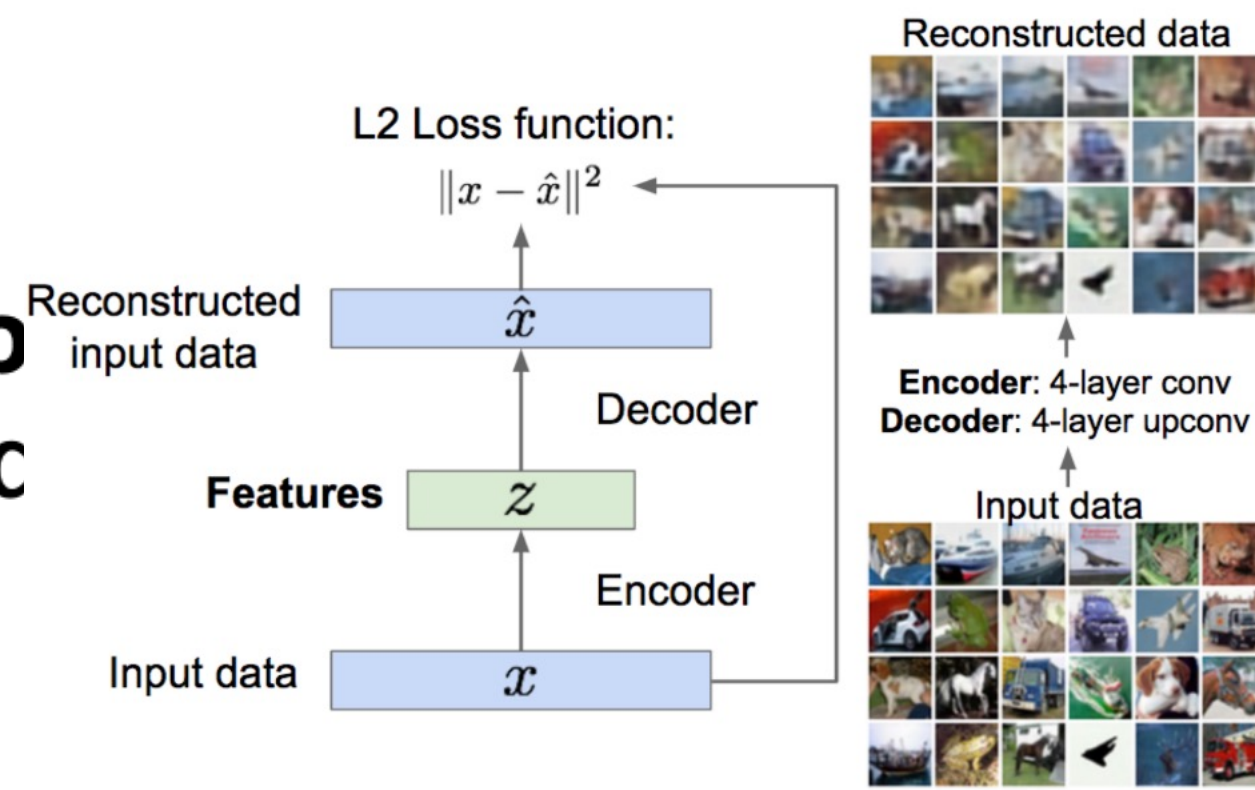
# Unsupervised Learning

## Feature Learning (e.g. autoencoders)

Data:  $x$

Feature Learning (e.g. autoencoders)

Go hic



Reconstructed input data

L2 Loss function:

$$\|x - \hat{x}\|^2$$

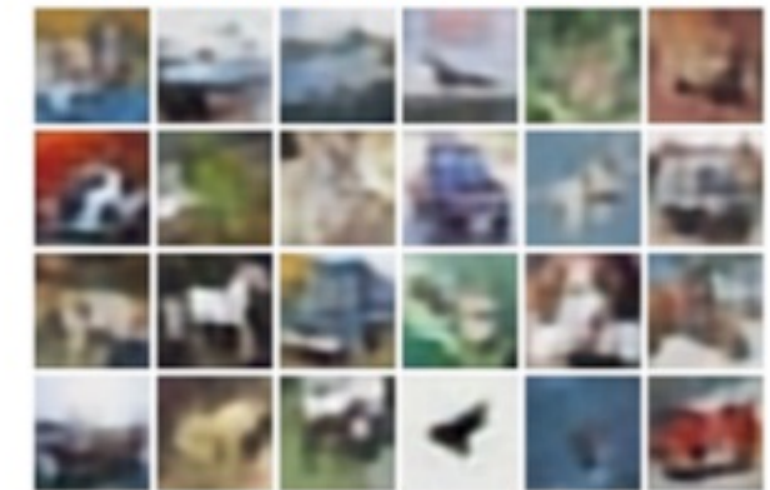
Features  $z$

Decoder

Input data  $x$

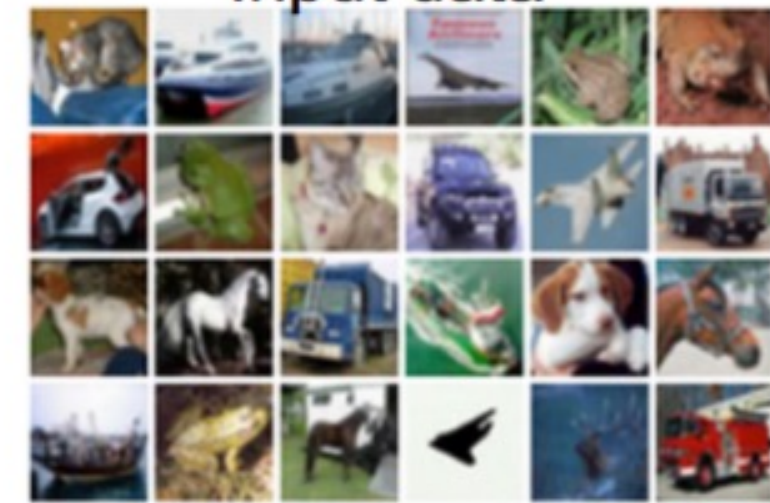
Encoder

Reconstructed data



Encoder: 4-layer conv  
Decoder: 4-layer upconv

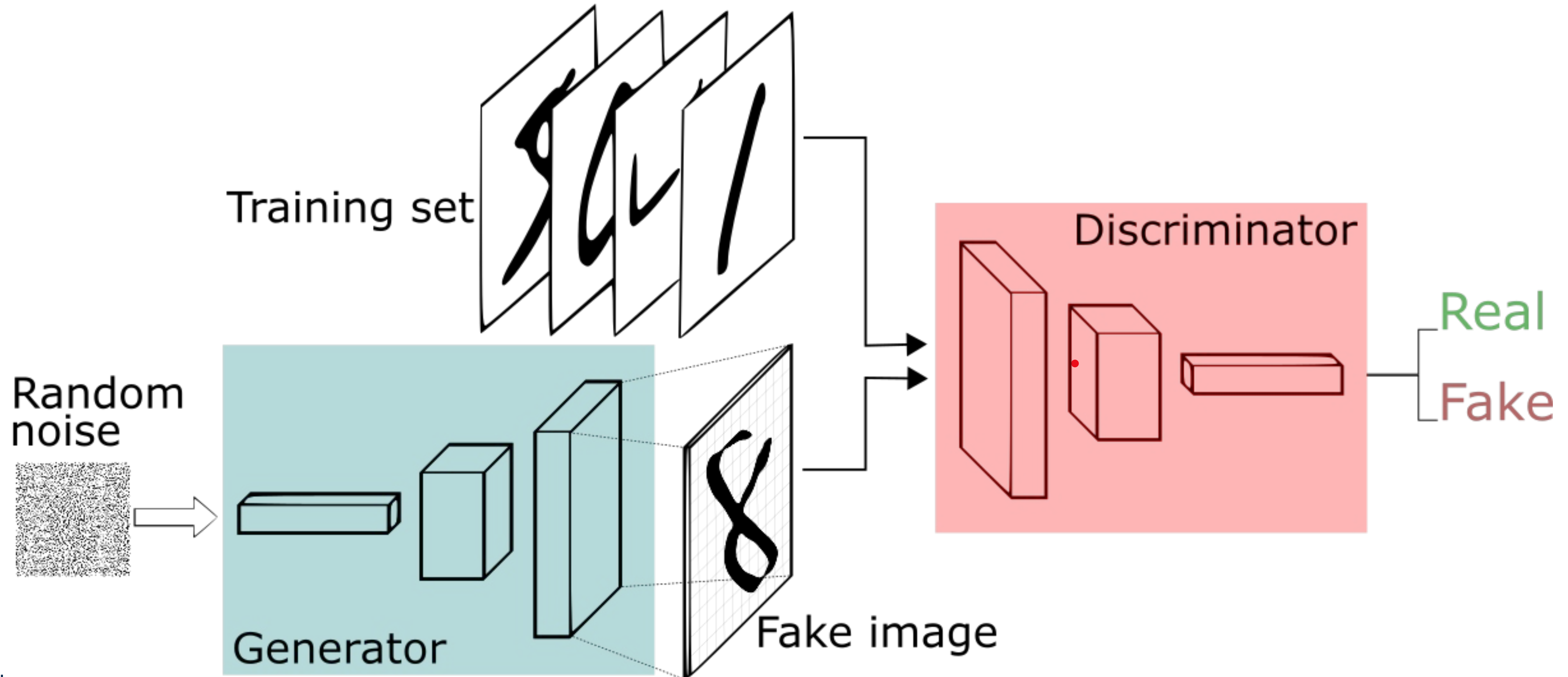
Input data





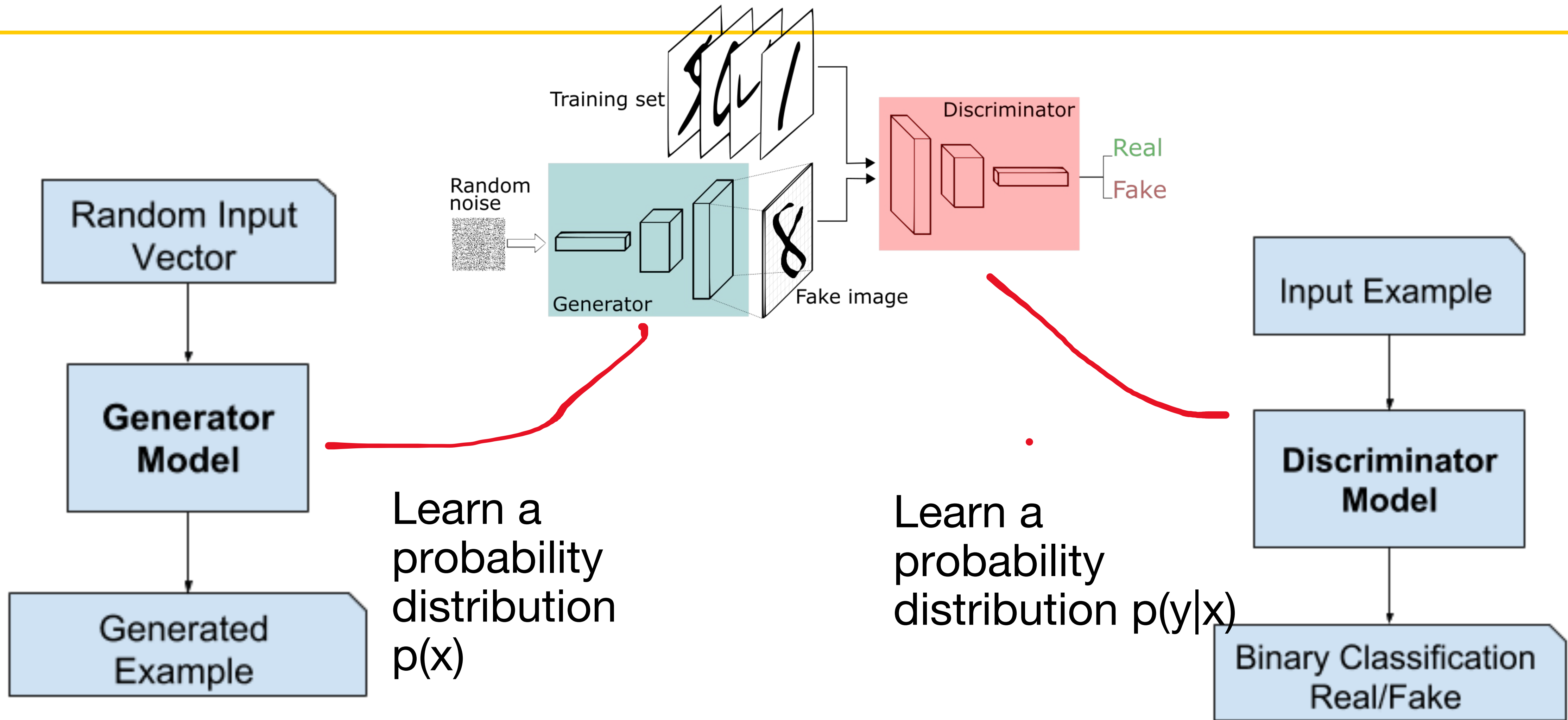
# Discriminative vs Generative

$$\min_G \max_D \left( E_{x \sim p_{data}} [\log D(x)] + E_{z \sim p(z)} [\log (1 - D(G(z)))] \right)$$





# Discriminative vs Generative





# Discriminative vs Generative

**Conditional Generative Model: Learn  $p(x|y)$**

Bayes' rule

$$P(x|y) = \frac{P(y|x) P(x)}{P(y)}$$

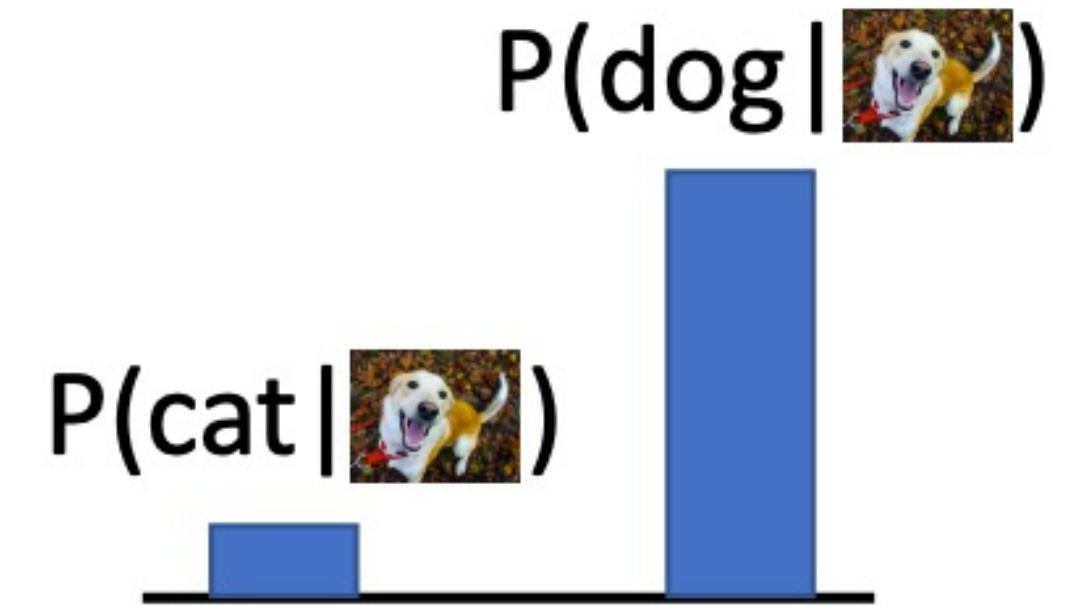
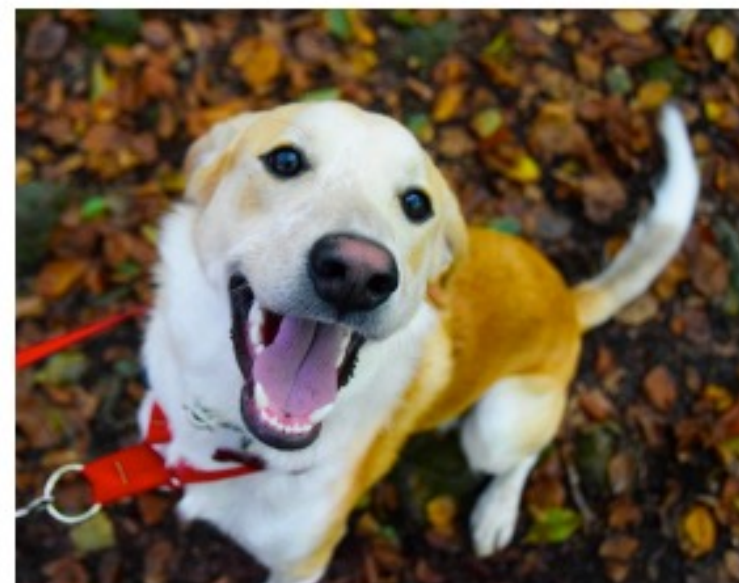
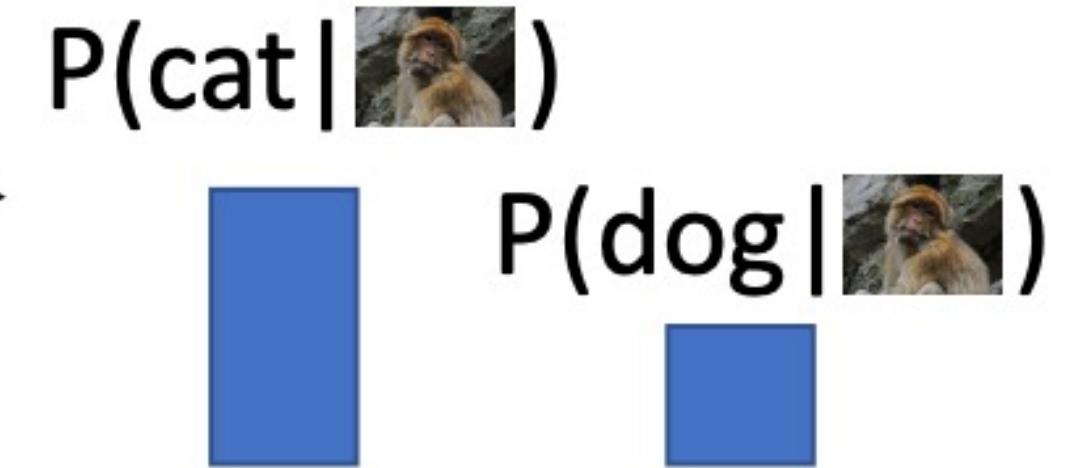
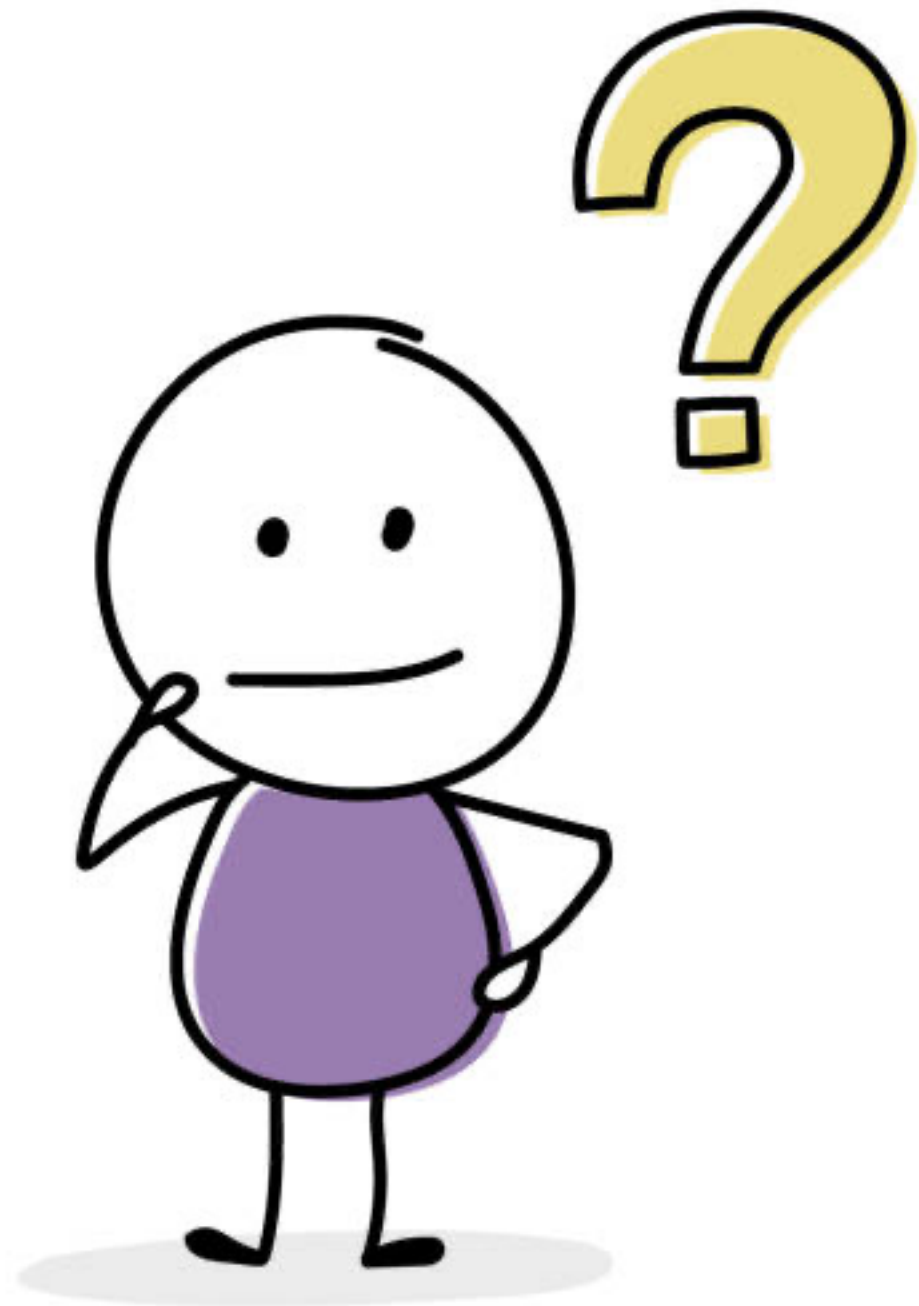
Labels for the equation components:

- $P(x|y)$ : Conditional Generative Model
- $P(y|x)$ : Discriminative Model
- $P(y)$ : Prior over labels
- $P(x)$ : (Unconditional) Generative Model

→ We can build a conditional generative model from other components!



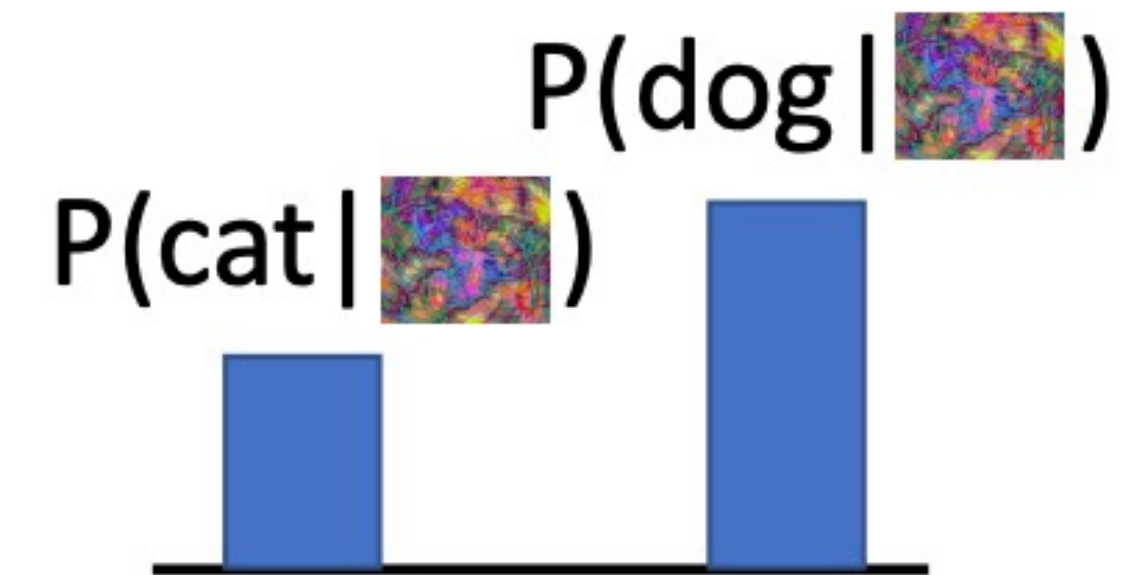
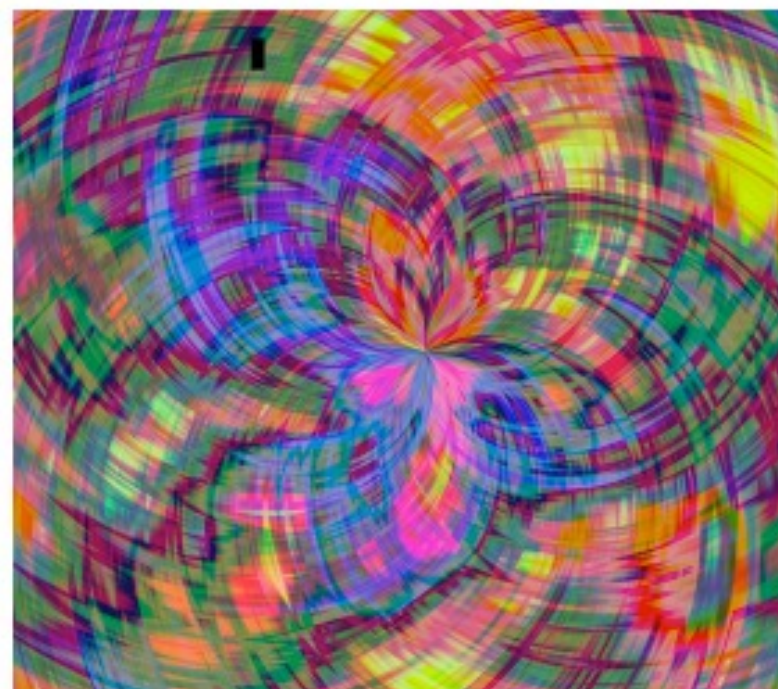
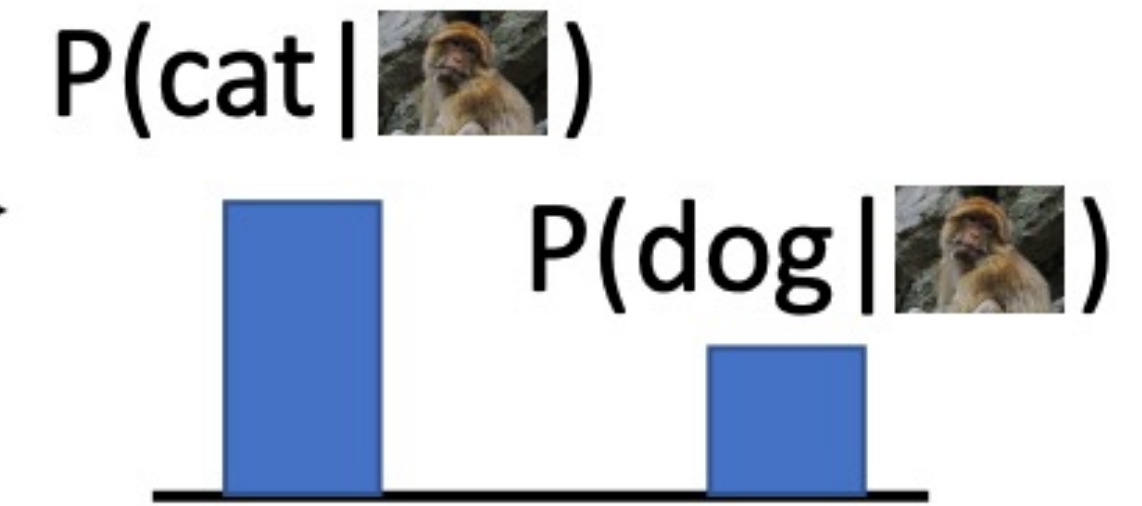
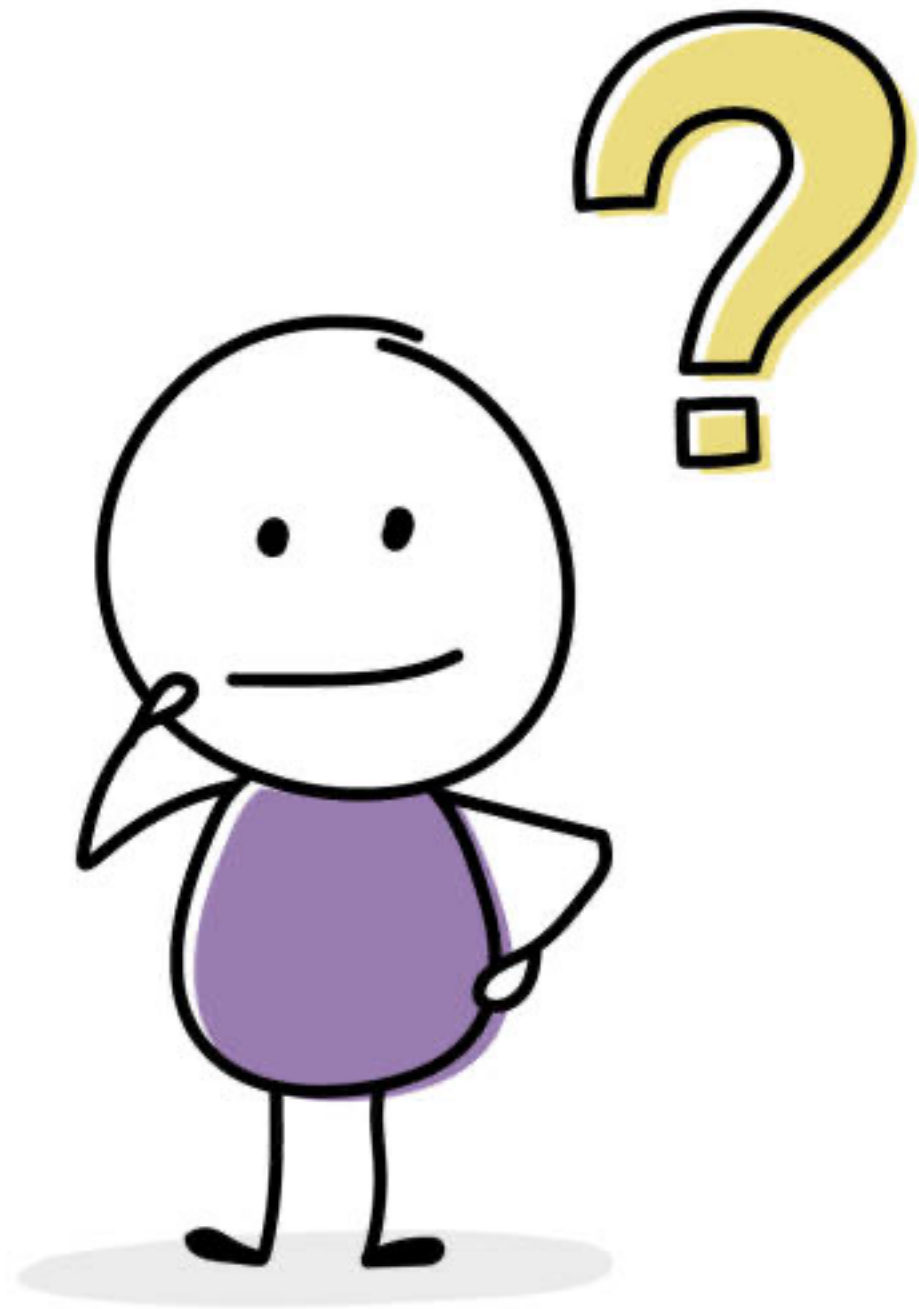
# Discriminative or Generative?





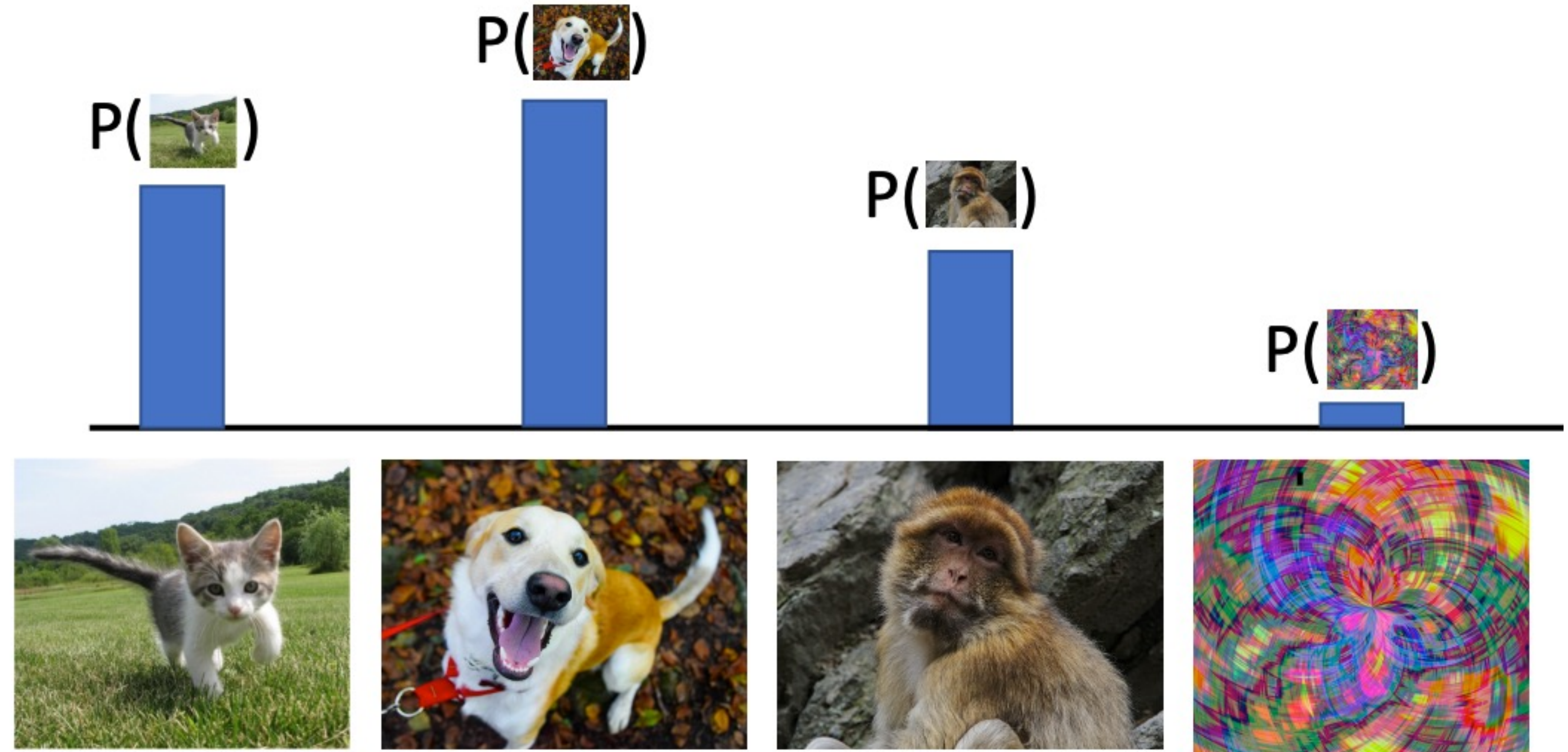
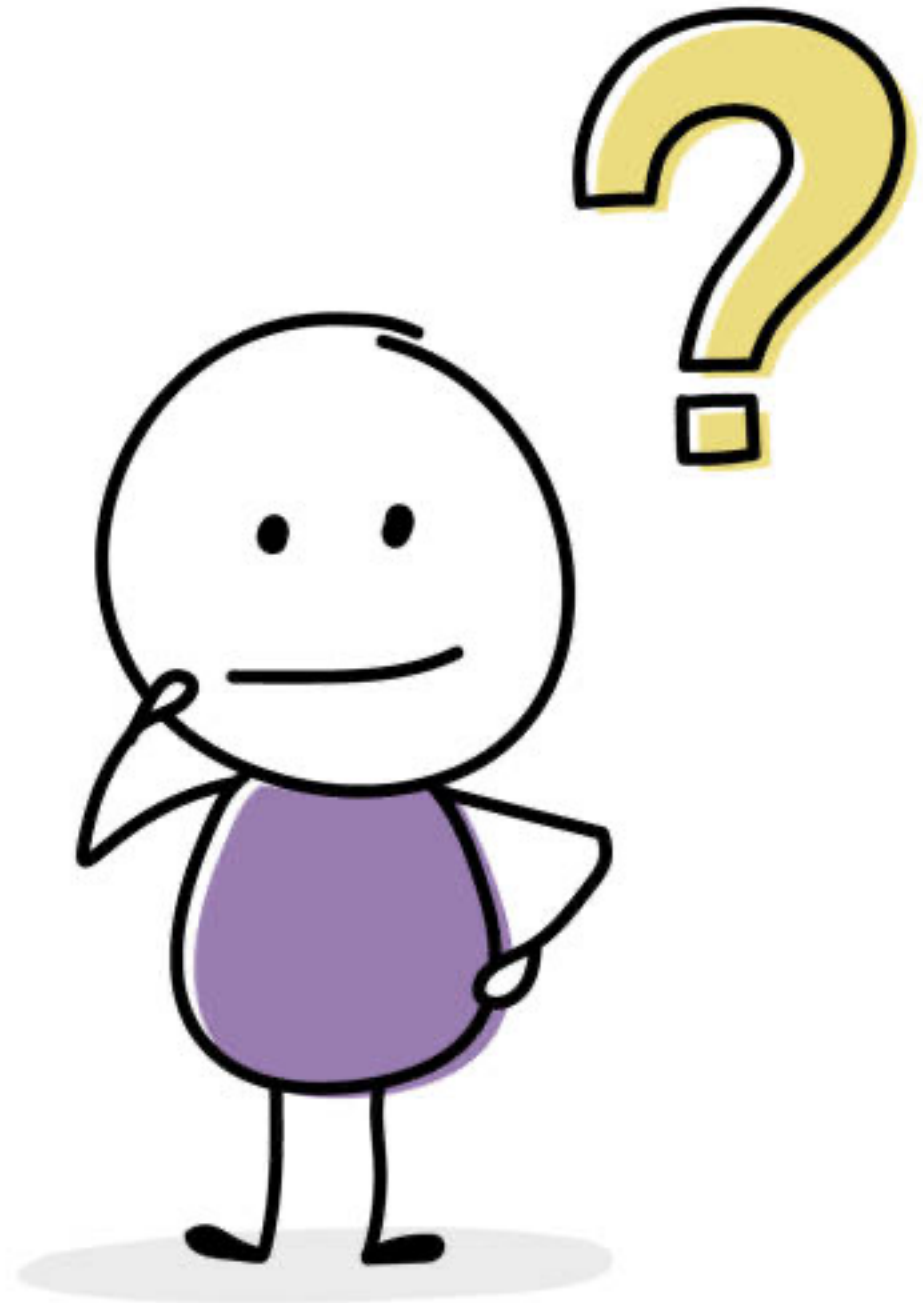


# Discriminative or Generative?



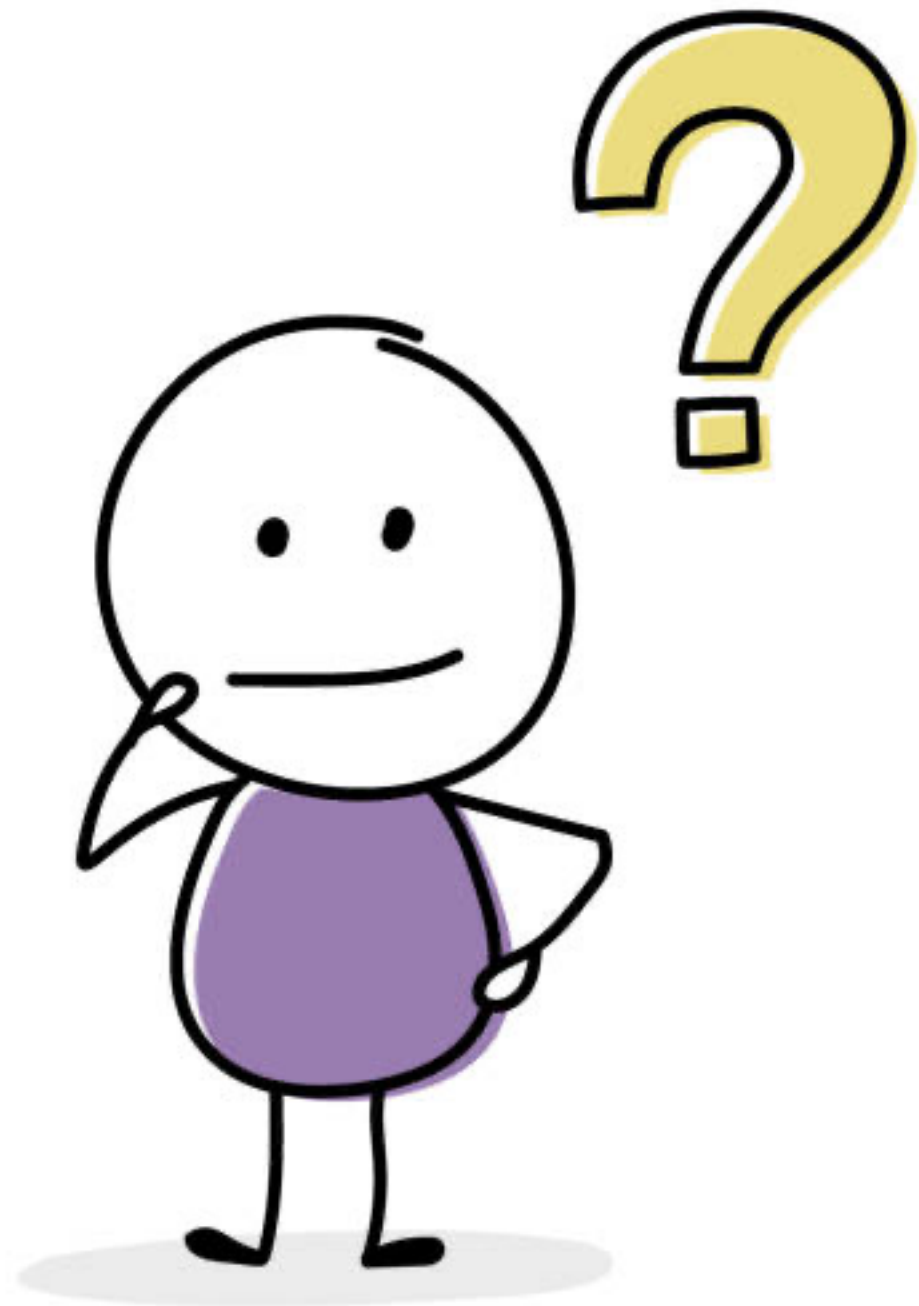


# Discriminative or Generative?





# Discriminative or Generative?



$P(\text{cat image} | \text{cat})$



$P(\text{dog image} | \text{cat})$



$P(\text{monkey image} | \text{cat})$



$P(\text{noise image} | \text{cat})$



$P(\text{cat image} | \text{dog})$



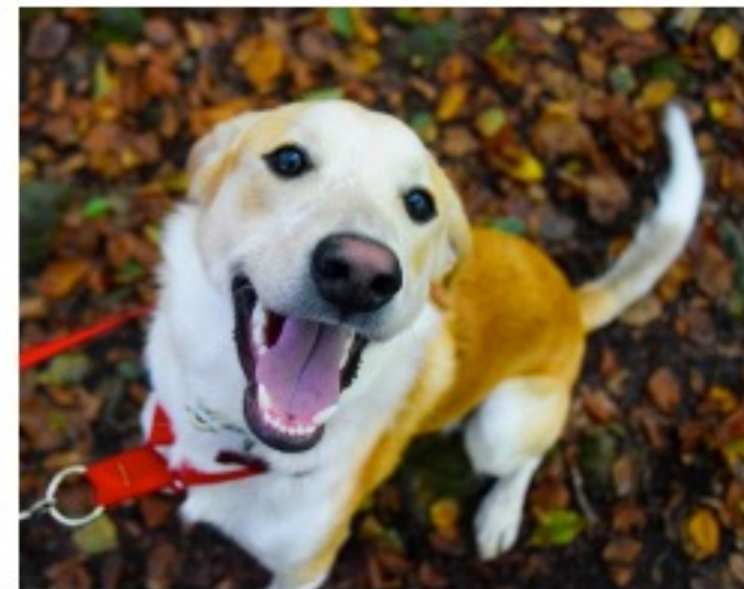
$P(\text{dog image} | \text{dog})$



$P(\text{monkey image} | \text{dog})$



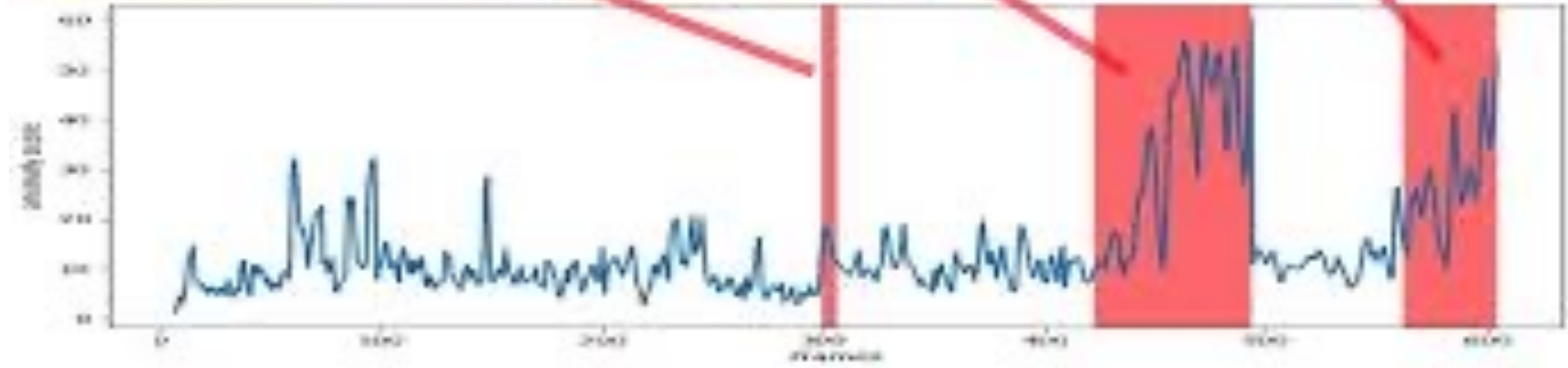
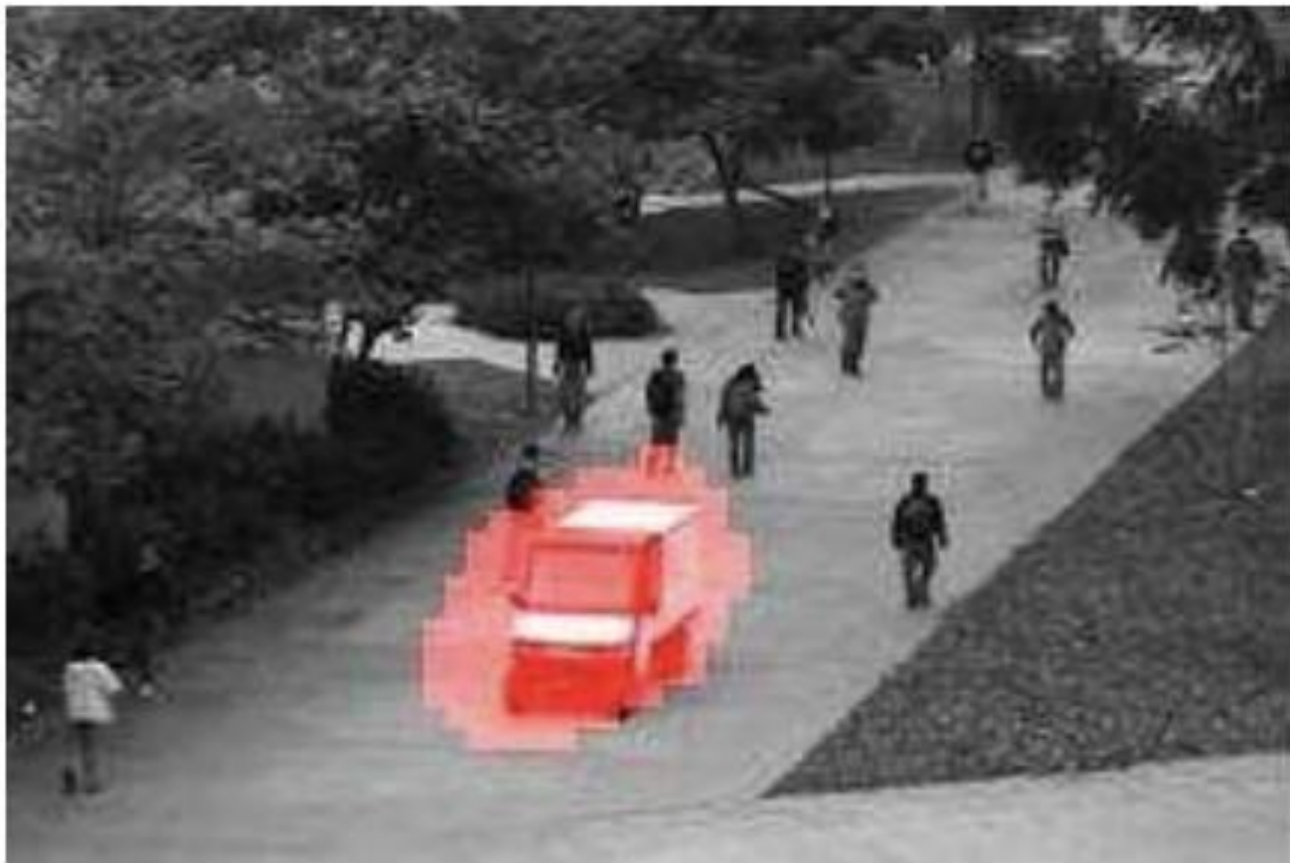
$P(\text{noise image} | \text{dog})$





# What can we do with a generative model?

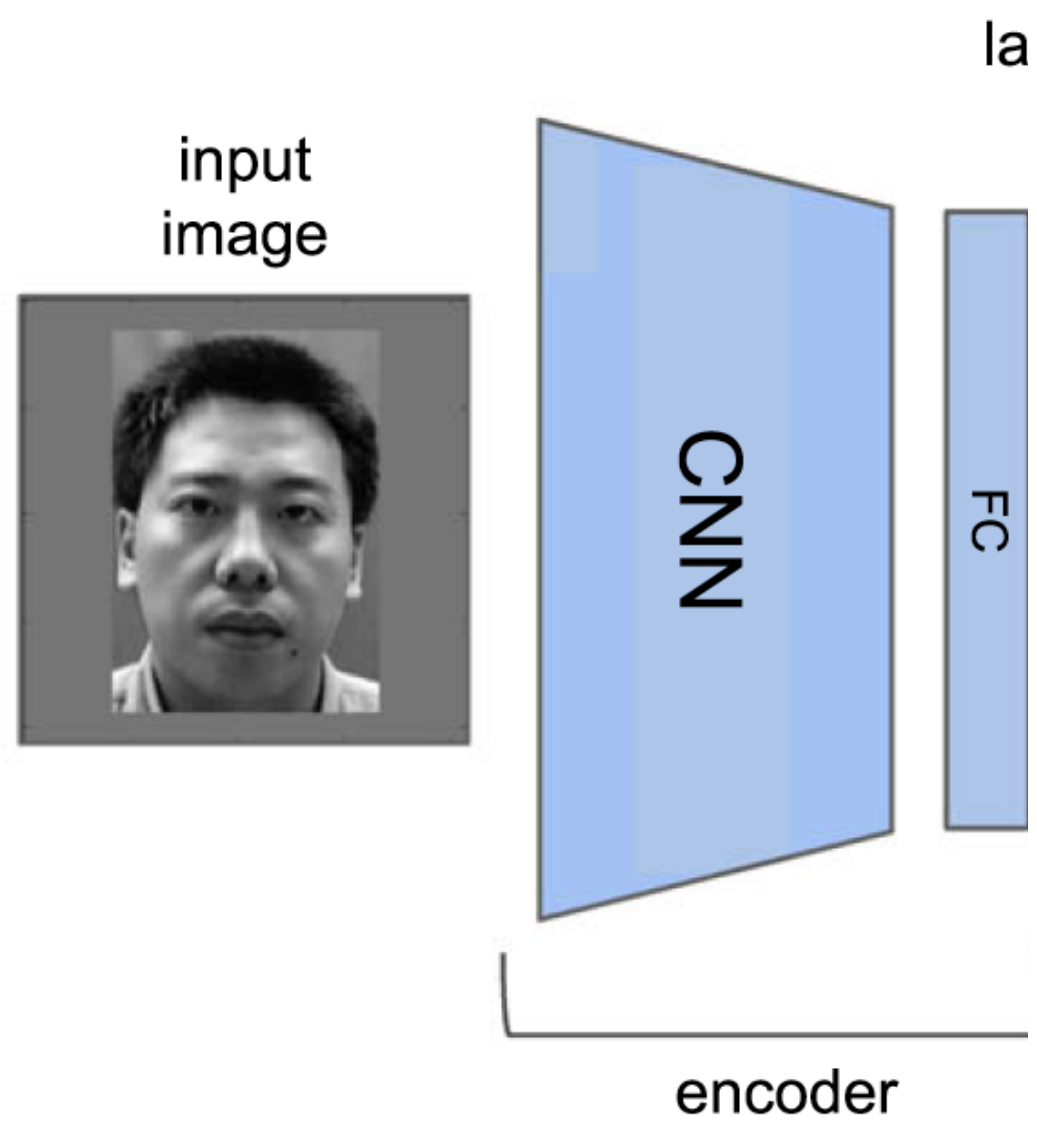
- Detect outliers / Anomaly Detection



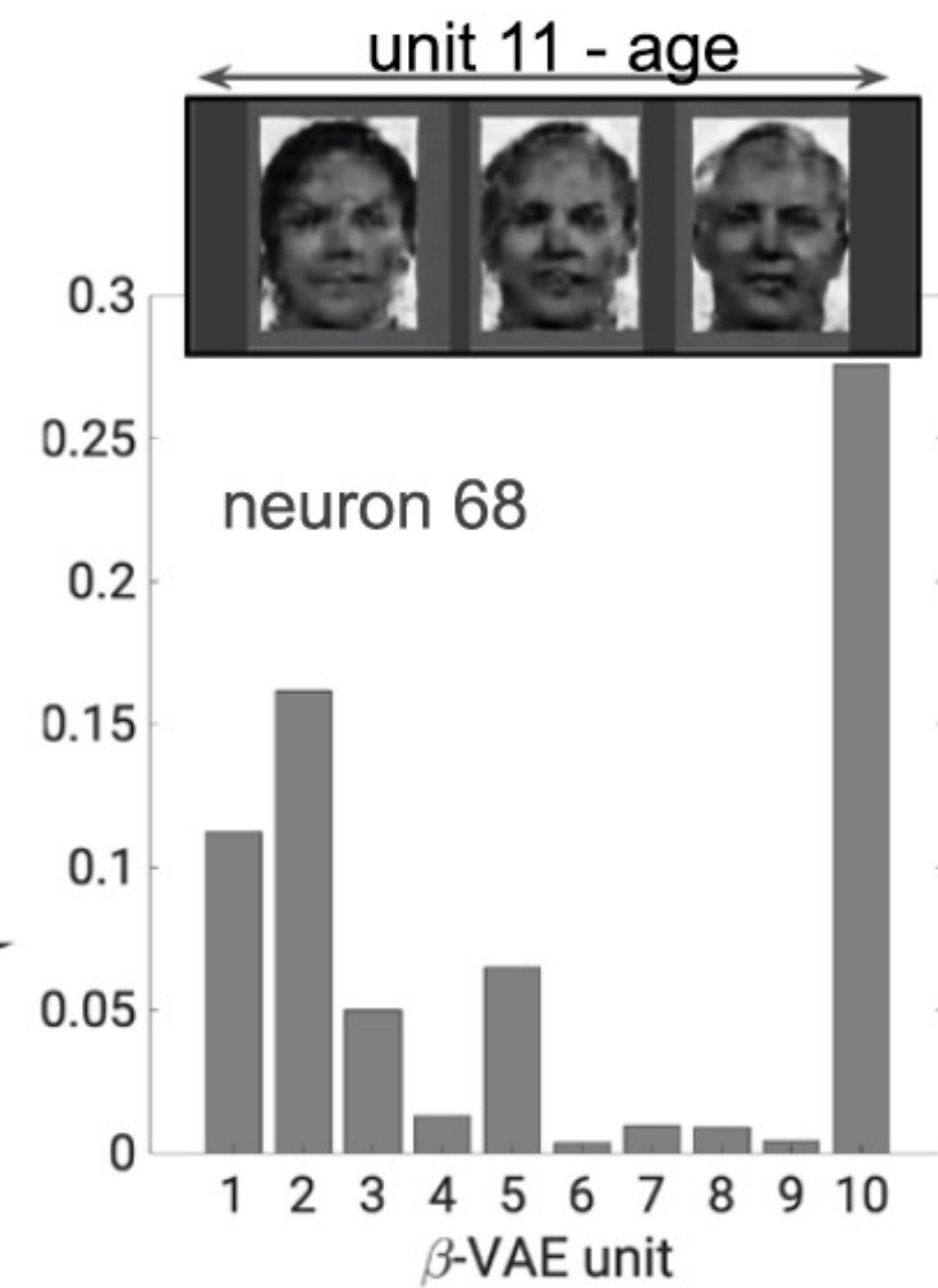
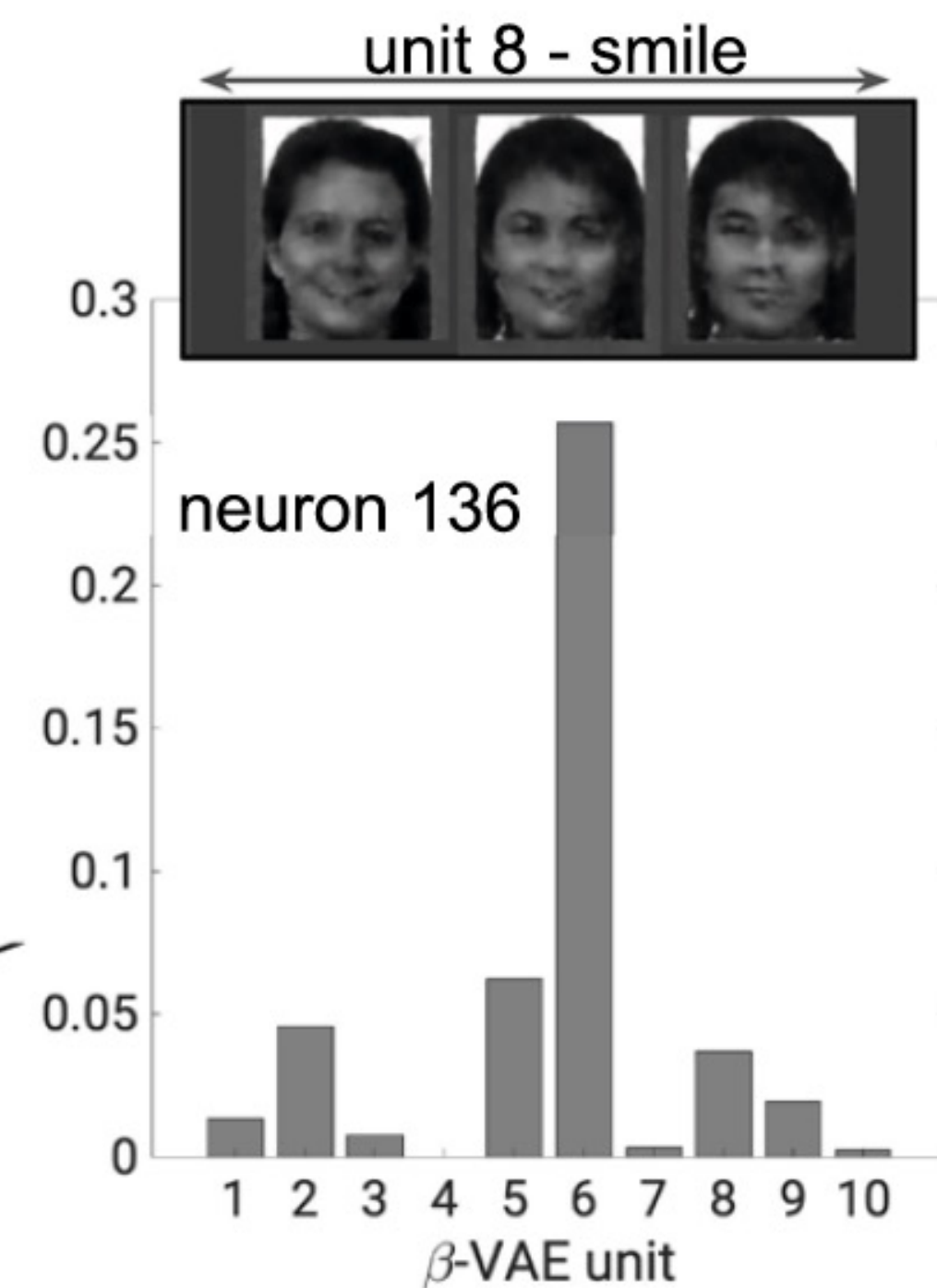
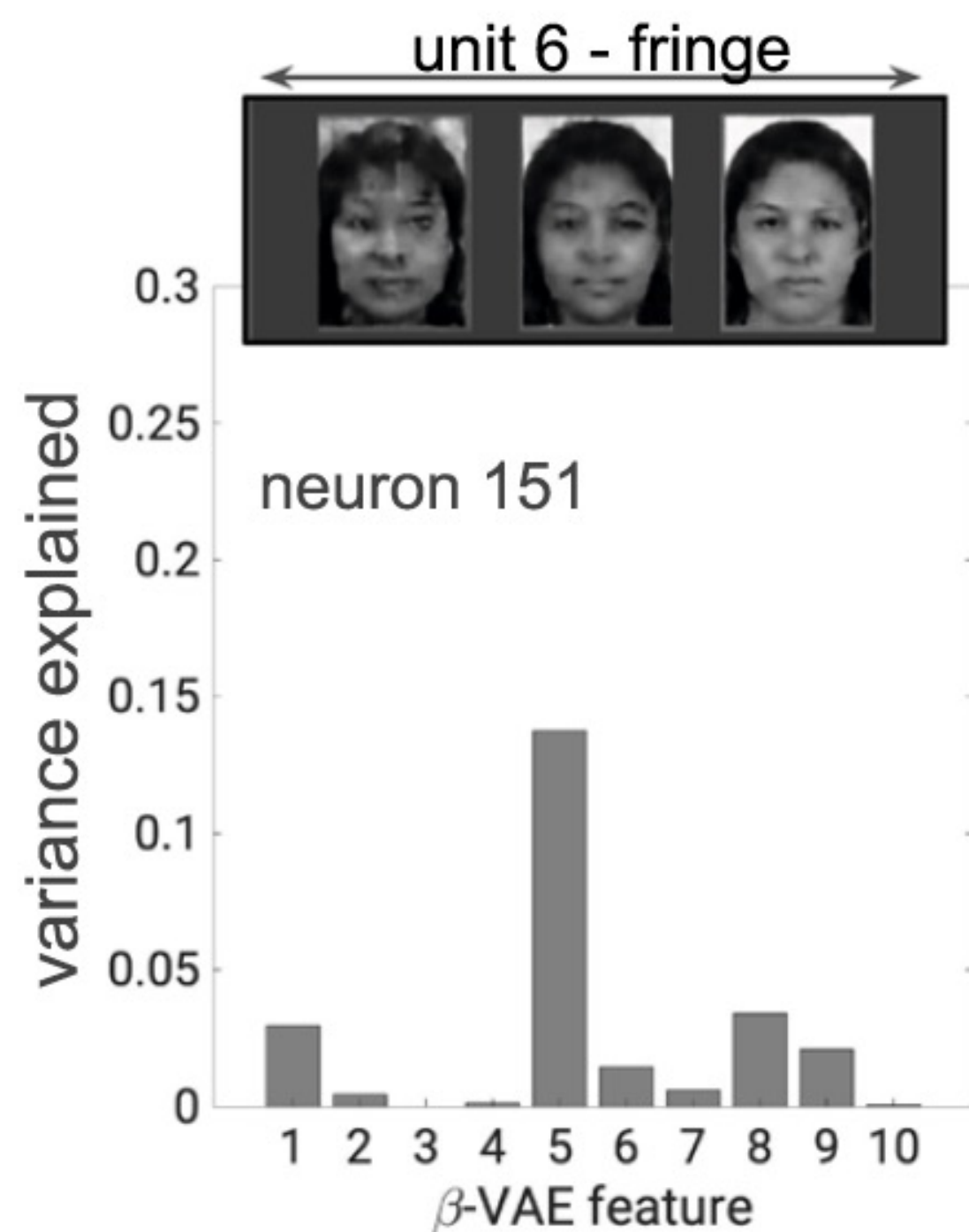
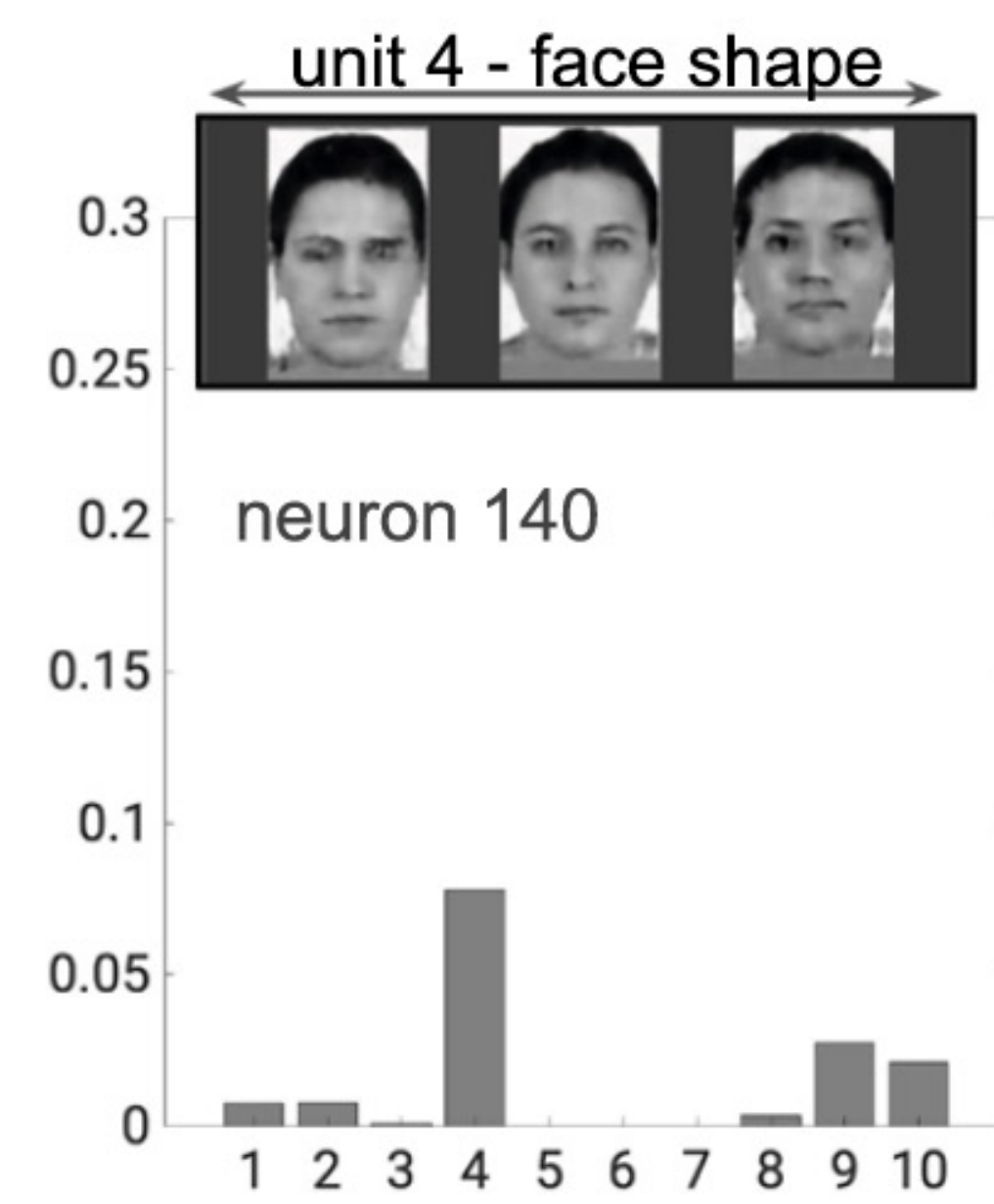
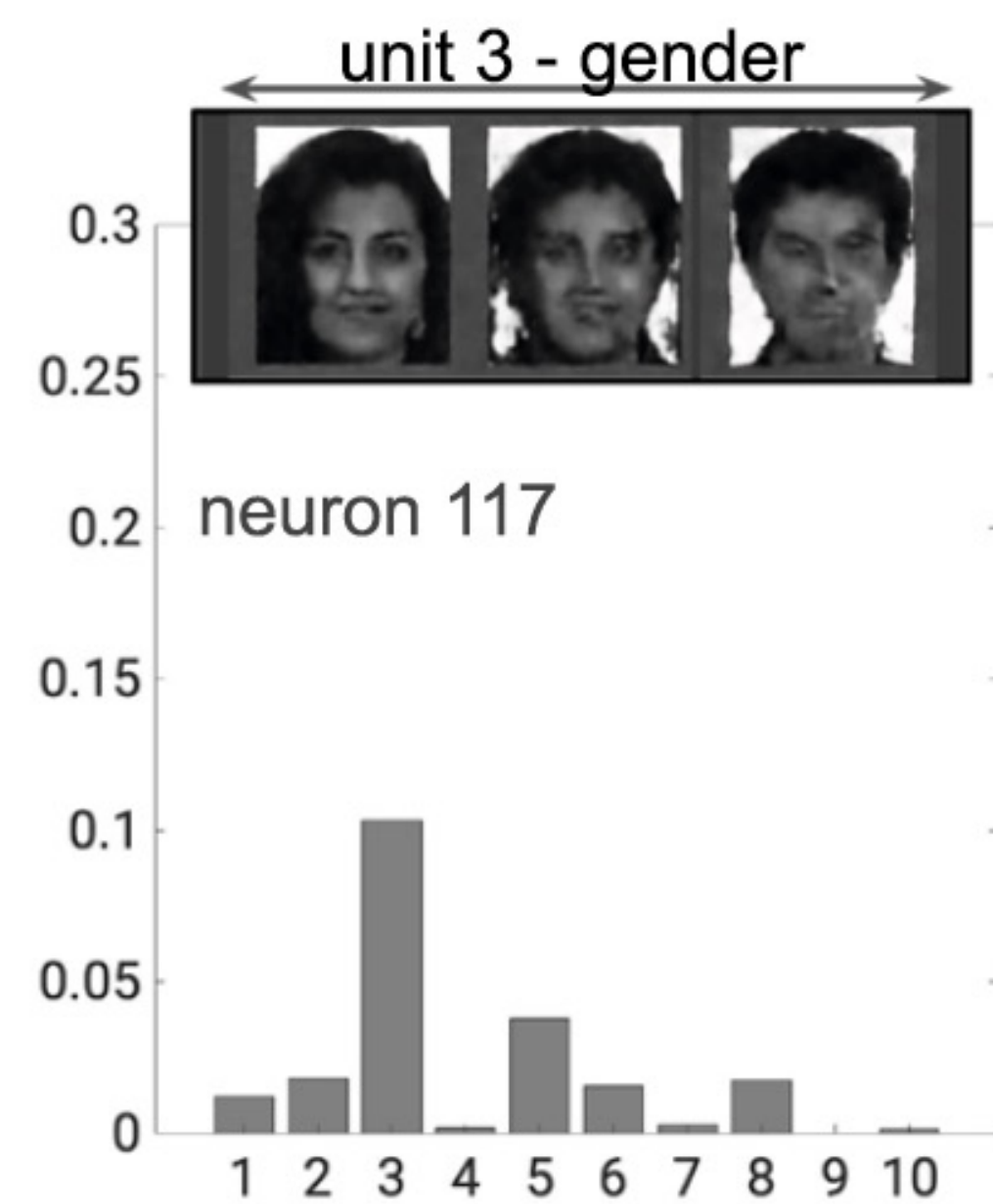
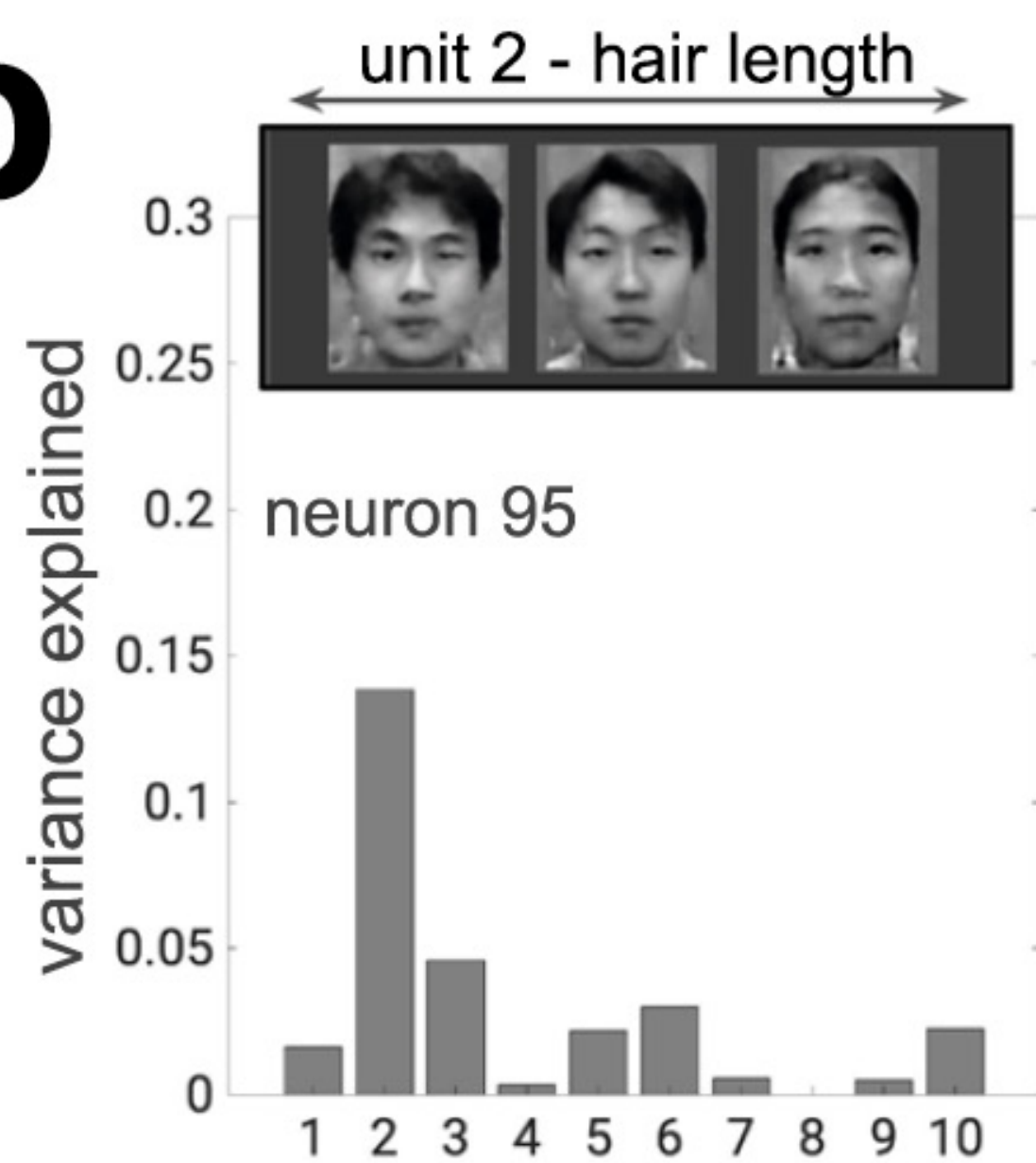


# What can

- Detect out
- Feature lea



# b



interotemporal face patch neurons



# What can we do with a Generative model?

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- Detect outliers / Anomaly Detection
- Feature learning (without labels)
- **Sample to generate new data**
  - Conditional: generate new data **conditioned** on input labels

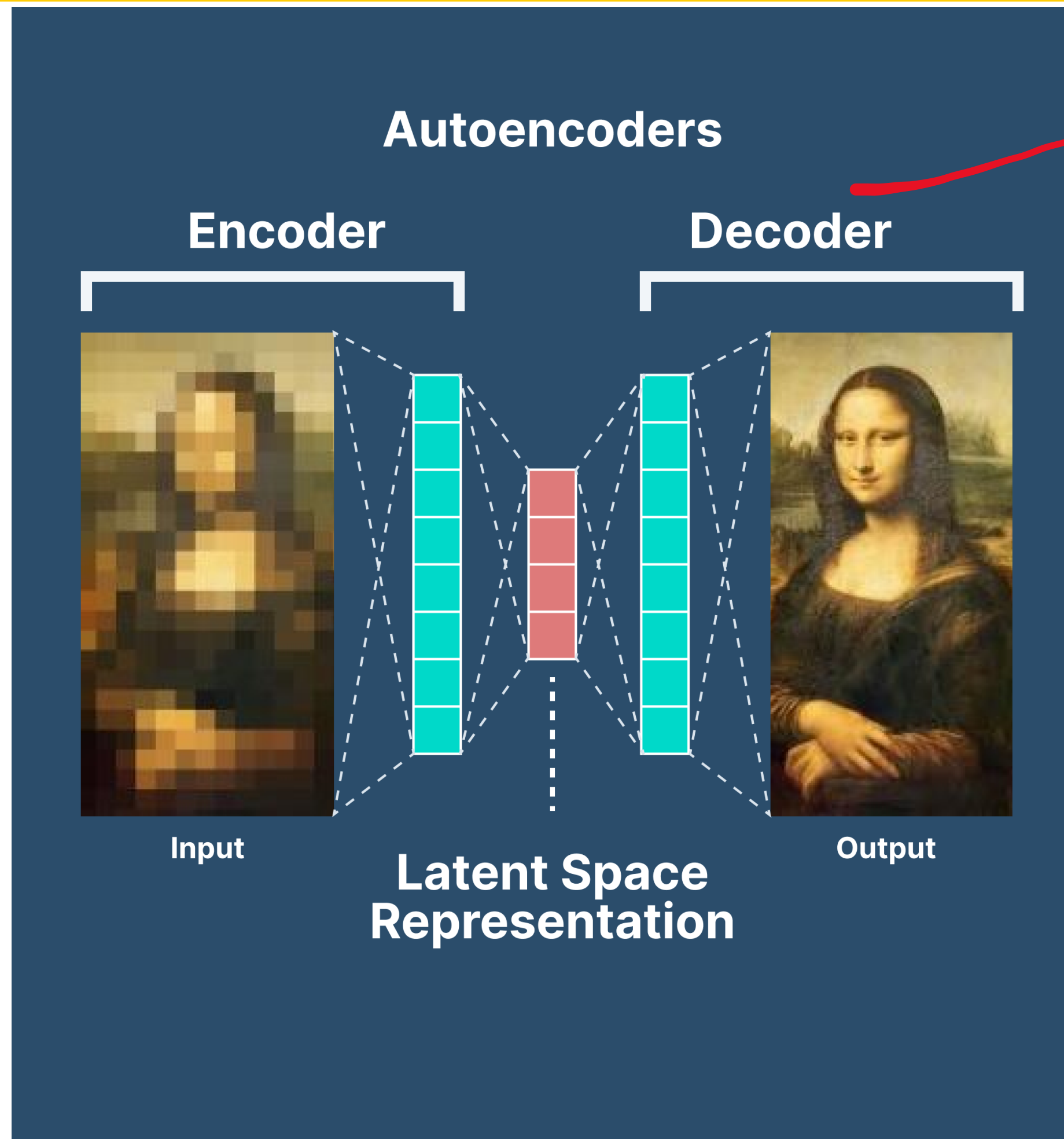
Example: MNIST

<https://colab.research.google.com/github/tensorflow/docs/blob/master/site/en/tutorials/generative/cvae.ipynb>

<https://ijdykeman.github.io/ml/2016/12/21/cvae.html>



# Autoencoder



Decoder: Generative!

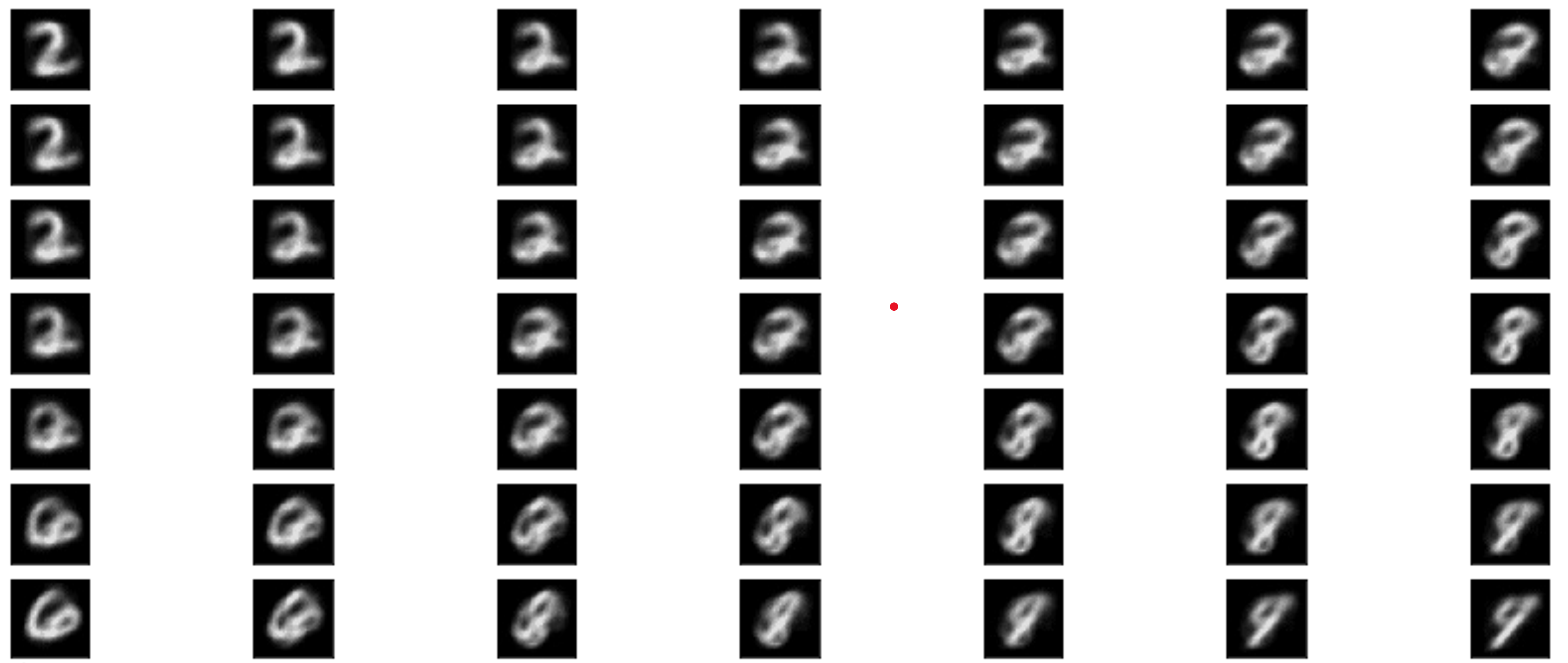
Reconstruction

Minimizing the difference between original input and reconstructed output



# Some problems with Autoencoder

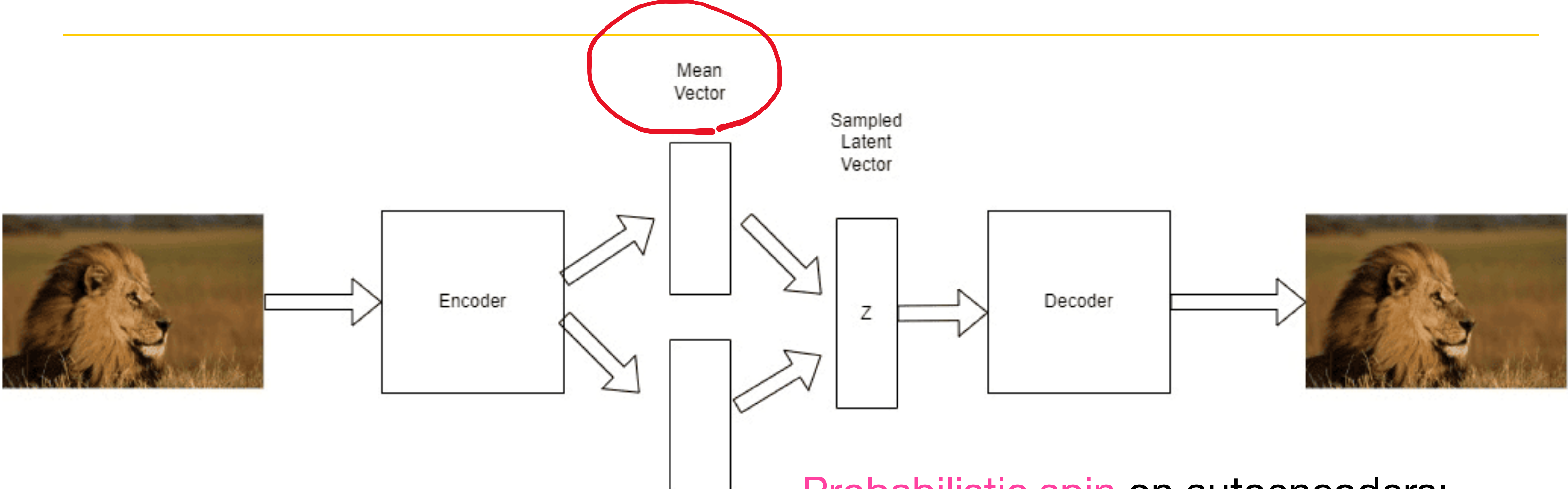
2? 9? Smooth transition **X**







# Variational Autoencoder (VAE)



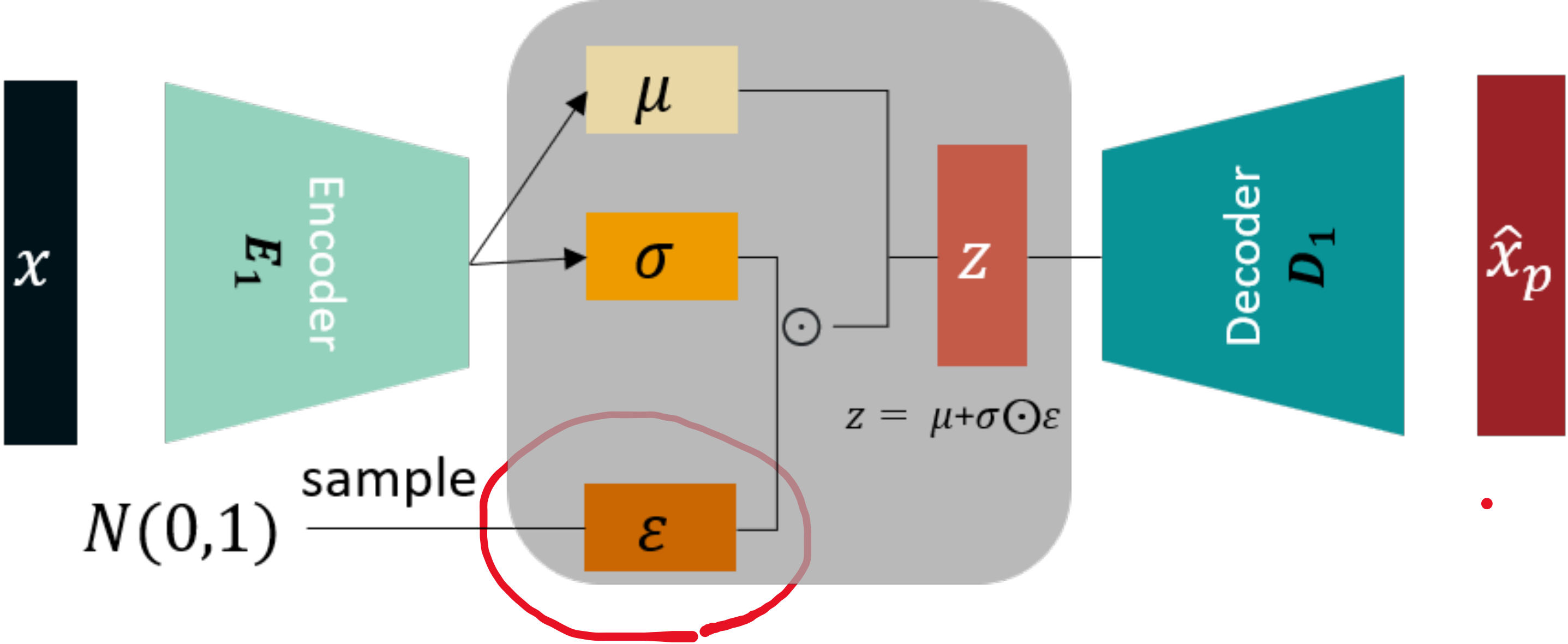
“reparameterization” trick

Probabilistic spin on autoencoders:

- 1. Learn latent features  $z$  from raw data
- 2. Sample from the model to generate new data



# Variational Autoencoder (VAE)



“reparameterization” trick



# What can we do with a Generative model?

## Variational Autoencoders: Generating Data

example:

32x32 CIFAR-10



Labeled Faces in the Wild



Figures from (L) Dirk Kingma et al. 2016; (R) Anders Larsen et al. 2017.



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