

# Supervised vs unsupervised learning

## Supervised Learning

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

$x$  is data,  $y$  is label

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

**Examples:** Classification, regression, object detection, semantic segmentation, etc.

## Unsupervised Learning

**Data:**  $x$

$x$  is data, no labels!

**Goal:** Learn some *hidden* or *underlying structure* of the data

**Examples:** Clustering, feature or dimensionality reduction, etc.

# Supervised vs unsupervised learning

## Supervised Learning

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## Unsupervised Learning

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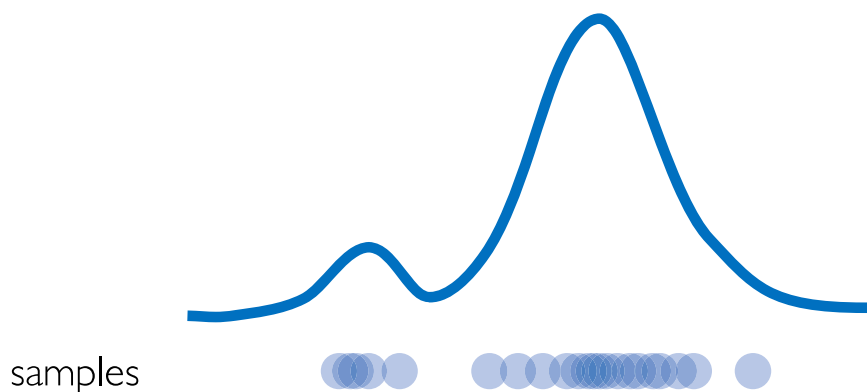
**Goal:** Learn some *hidden* or *underlying structure* of the data

**Examples:** Clustering, feature or dimensionality reduction, etc.

# Generative modeling

**Goal:** Take as input training samples from some distribution and learn a model that represents that distribution

## Density Estimation



## Sample Generation



Input samples

Training data  $\sim P_{data}(x)$



Generated samples

Generated  $\sim P_{model}(x)$

How can we learn  $P_{model}(x)$  similar to  $P_{data}(x)$ ?

# Why generative models? Debiasing

Capable of uncovering **underlying latent variables** in a dataset



Homogeneous skin color, pose

VS



Diverse skin color, pose, illumination

How can we use latent distributions to create fair and representative datasets?

# Why generative models? Outlier detection

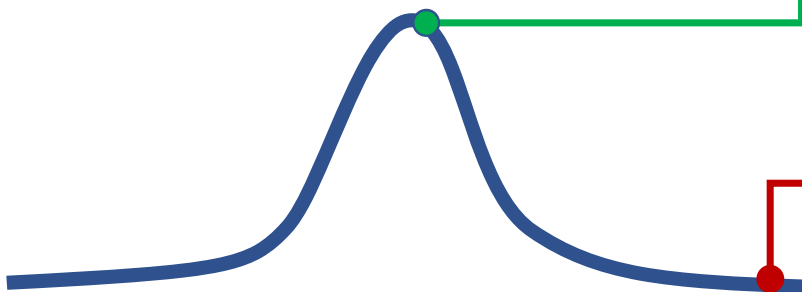
- **Problem:** How can we detect when we encounter something new or rare?
- **Strategy:** Leverage generative models, detect outliers in the distribution
- Use outliers during training to improve even more!

## 95% of Driving Data:

(1) sunny, (2) highway, (3) straight road



Detect outliers to avoid unpredictable behavior when training



Edge Cases



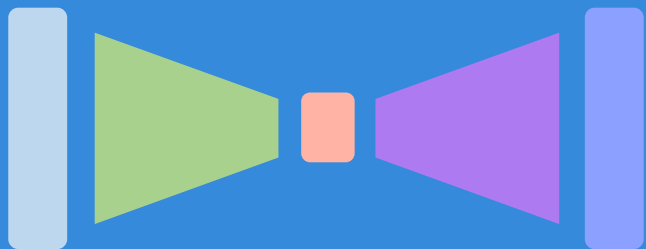
Harsh Weather



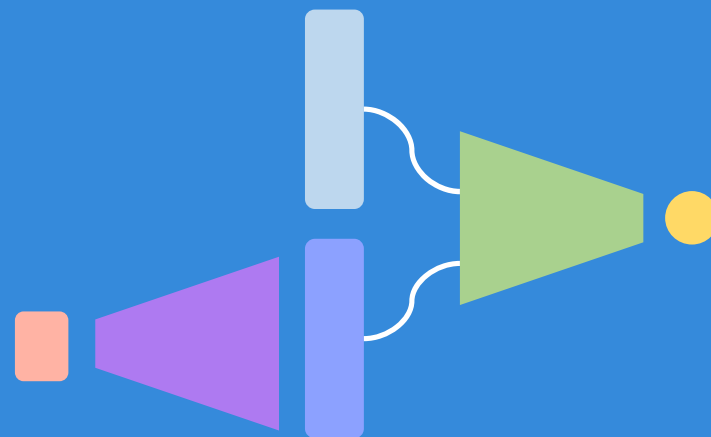
Pedestrians

# Latent variable models

Autoencoders and Variational  
Autoencoders (VAEs)



Generative Adversarial  
Networks (GANs)





# What is a latent variable?



*Myth of the Cave*

# What is a latent variable?



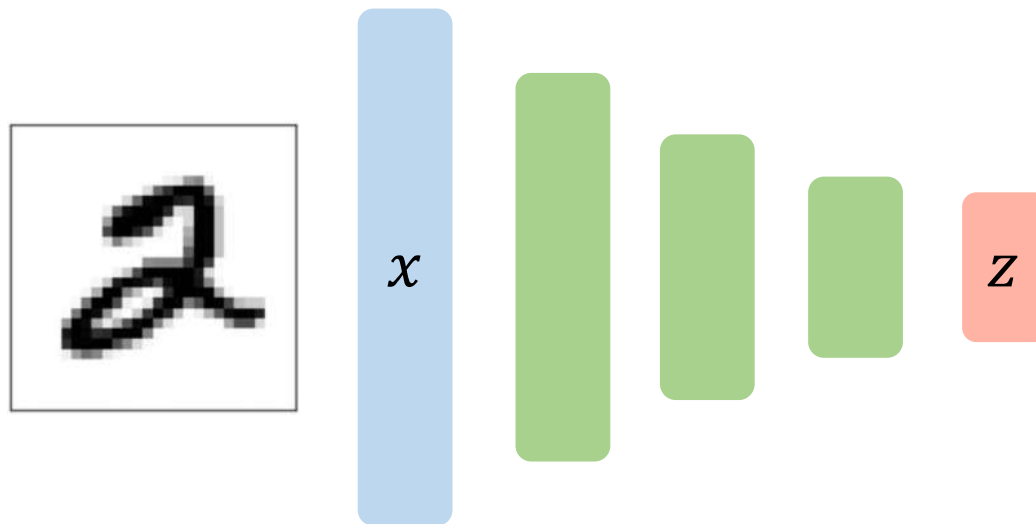
Can we learn the **true explanatory factors**, e.g. latent variables, from only observed data?



# Autoencoders

# Autoencoders: background

Unsupervised approach for learning a **lower-dimensional** feature representation from unlabeled training data



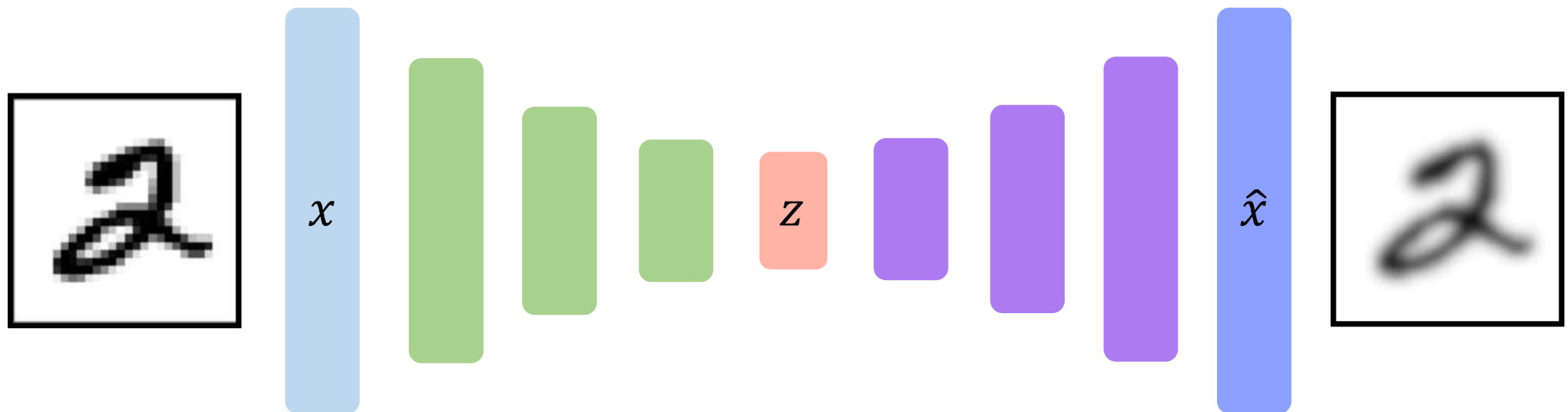
Why do we care about a low-dimensional  $z$ ? 🤔

“Encoder” learns mapping from the data,  $x$ , to a low-dimensional latent space,  $z$

# Autoencoders: background

How can we learn this latent space?

Train the model to use these features to **reconstruct the original data**

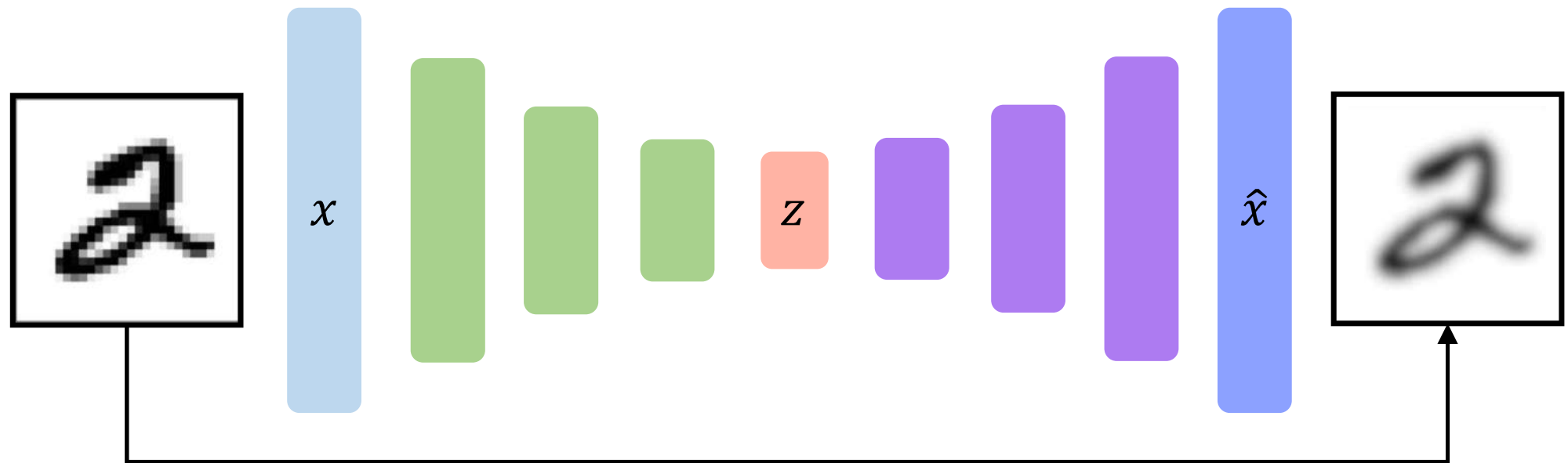


“Decoder” learns mapping back from latent,  $z$ , to a reconstructed observation,  $\hat{x}$

# Autoencoders: background

How can we learn this latent space?

Train the model to use these features to **reconstruct the original data**



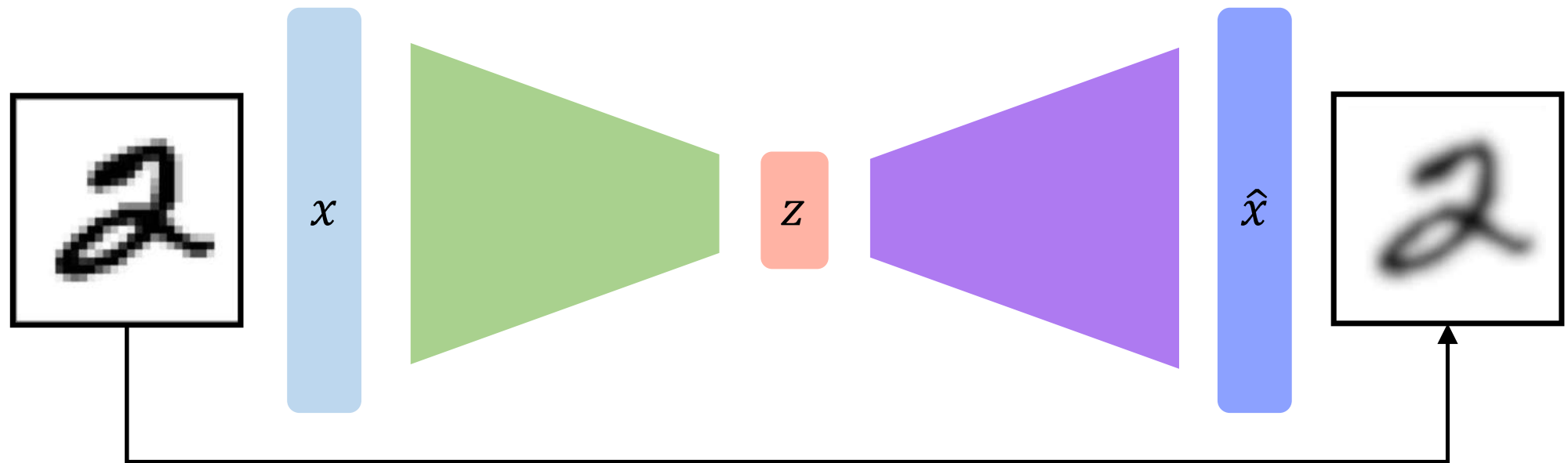
$$\mathcal{L}(x, \hat{x}) = \|x - \hat{x}\|^2$$

Loss function doesn't use any labels!!

# Autoencoders: background

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# Dimensionality of latent space → reconstruction quality

Autoencoding is a form of compression!  
Smaller latent space will force a larger training bottleneck

2D latent space



5D latent space



Ground Truth



# Autoencoders for representation learning

**Bottleneck hidden layer** forces network to learn a compressed latent representation

**Reconstruction loss** forces the latent representation to capture (or encode) as much “information” about the data as possible

**Autoencoding** = **Auto** automatically **encoding** data