

# Advanced Deep Learning

DATA.ML.230

## Introduction

# Artificial intelligence

Machine learning

Supervised  
learning

Unsupervised  
learning

Reinforcement  
learning

Deep learning

Advanced Deep Learning  
DATA.ML.230

Self-supervised  
learning

# Course structure

Week 1	Introduction Loss functions
Week 2	Fitting models and Regularization Residual Neural Networks & processing videos
Week 3	Sequence processing Transformers
Week 4	Contrastive Learning Graph Neural Networks
Week 5	Unsupervised Learning & Generative Adversarial Networks Diffusion models & Variational Autoencoders
Week 6	Self-Supervised Learning Uncertainty estimation of DL models

# Reading material

- Part of the course follows the book:

Simon J. D. Prince, “Understanding Deep Learning”, MIT Press,  
Dec 2023

Book website: <https://udlbook.github.io/udlbook/>

Contains an electronic (pdf) copy of the book. Version used: 29 May 2025

- Other reading material (e.g., papers, tutorials) were used for some parts of the course. References are provided in the slides.

# Practical matters

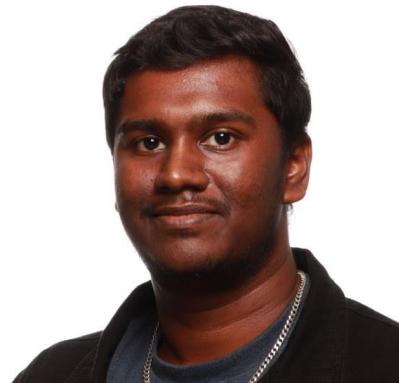
- Lectures and exercise sessions for 6 weeks

Please ask questions in the lectures – put your hand up

- Course's team:



**Lecturer:** Alexandros Iosifidis  
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Vidhi Agrawal  
[vidhi.agrawal@tuni.fi](mailto:vidhi.agrawal@tuni.fi)

# Practical matters

- Lectures and exercise sessions for 6 weeks:
  - 2 lectures per week (Tuesdays and Wednesdays at 14:15-16:00, K1705)
    - We have the same room (K1705) booked for Fridays 12:15-13:00
  - 1 exercise session per week, organized in 6 groups: Pen & paper exercises
    - Group 1: Mondays at 12:15-14:00, TC303
    - Group 2: Mondays at 14:15-16:00, TC303
    - Group 3: Wednesdays at 8:15-10:00, TC315
    - Group 4: Wednesdays at 10:15-12:00, TC315
    - Group 5: Wednesdays at 12:15-14:00, PB212
    - Group 6: Thursdays at 8:15-10:00, PB212

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We will use it **iff** needed –  
depending on the progress on  
a weekly-basis

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- 5 weekly exercises:
  - Programming exercises
  - Deadline: Sunday at 23:55 (a week after the topic's lectures – No extensions!)

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  - 2 lectures per week (Tuesdays and Wednesdays at 14:15-16:00, K1705)
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- 5 weekly exercises:
  - Programming exercises → Pass/Fail
  - Deadline: Sunday at 23:55 (a week after the topic's lectures – No extensions!)
  - **For submissions which are close to be “pass” will receive TA feedback and a resubmission will be allowed with a new deadline (1 week later)**

# Practical matters

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  - 2 lectures per week (Tuesdays and Wednesdays at 14:15-16:00, K1705)
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- 5 weekly exercises:
  - Programming exercises → Pass/Fail
  - Deadline: Sunday at 23:55 (a week after the topic's lectures – No extensions!)
- Exam – closed book, no electronic devices, etc.
- Final grade  $G$ :

$$G = \begin{cases} 0, & \text{if } P < 0 \\ \text{round}[P + (0.25 * W)], & \text{if } P \geq 0 \end{cases}$$

Number of “pass” weekly exercises (max = 6)

↓  
if  $P < 0$

$$P = \max[0, (E - 5)]$$

↑  
Points from exam (max = 10)

Of course,  $G \leftarrow \min(G, 5)$

Need at least 4 “pass” weekly exercises to take the exam

# Artificial intelligence

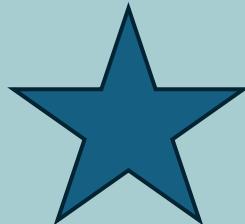
Machine learning

Supervised  
learning

Unsupervised  
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Reinforcement  
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Deep learning



# Supervised learning

- Define a mapping from input to output
- Learn this mapping from paired input/output data examples

# Regression

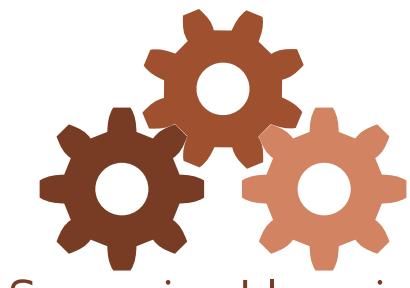
Real world input

6000 square feet,  
4 bedrooms,  
previously sold for  
\$235K in 2005,  
1 parking spot.

Model  
input

$$\begin{bmatrix} 6000 \\ 4 \\ 235 \\ 2005 \\ 1 \end{bmatrix}$$

Model



Model  
output

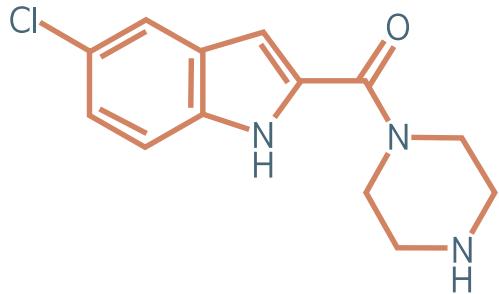
Real world output

Predicted price  
is \$340k

- Univariate regression problem (one output, real value)
- Fully connected network

# Graph regression

Real world input



Model  
input

$$\begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \\ 17 \\ 1 \\ 1 \\ \vdots \end{bmatrix}$$

Model



Model  
output

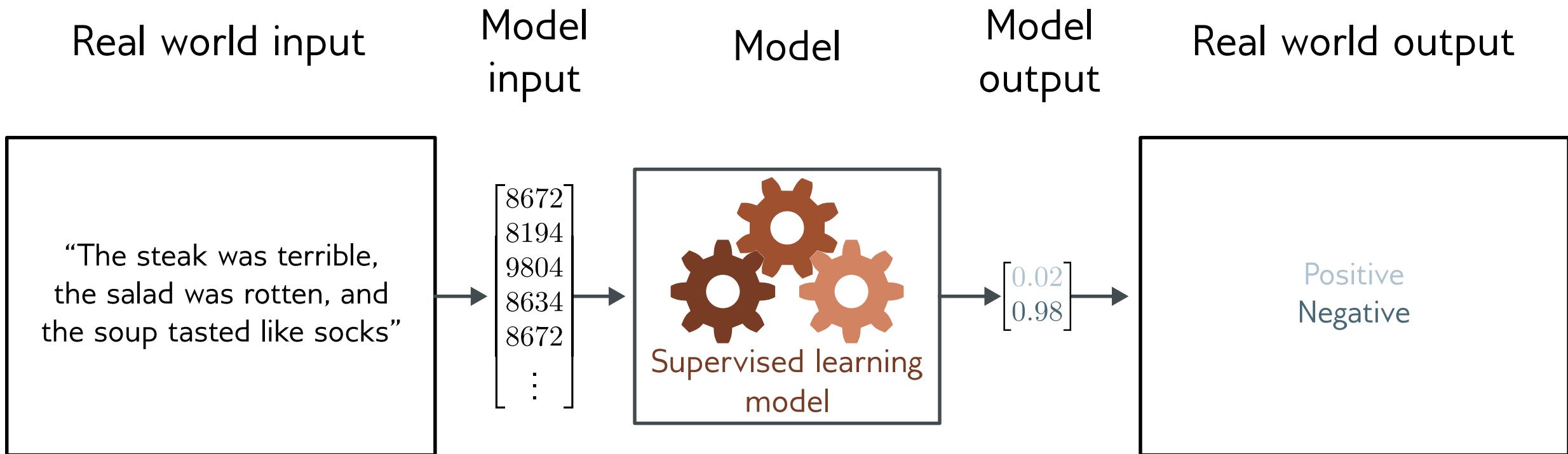
$$\begin{bmatrix} -12.9 \\ 56.4 \end{bmatrix}$$

Real world output

Freezing point  
is  $-12.9^{\circ}\text{C}$   
Boiling point  
is  $56.4^{\circ}\text{C}$

- Multivariate regression problem (>1 output, real value)
- Graph neural network

# Text classification



- Binary classification problem (two discrete classes)
- Transformer network

# Music genre classification

Real world input



Model  
input

$$\begin{bmatrix} 125 \\ 12054 \\ 1253 \\ 6178 \\ 24 \\ 4447 \\ \vdots \end{bmatrix}$$

Model



Model  
output

$$\begin{bmatrix} 0.03 \\ 0.52 \\ 0.18 \\ 0.07 \\ 0.12 \\ 0.08 \\ \vdots \\ 0.01 \end{bmatrix}$$

Real world output

Classical  
Electronica  
Hip Hop  
Jazz  
Pop  
Metal  
Punk

- Multiclass classification problem (discrete classes, >2 possible values)
- Recurrent neural network (RNN)

# Image classification

Real world input



Model  
input

$$\begin{bmatrix} 124 \\ 140 \\ 156 \\ 128 \\ 142 \\ 157 \\ \vdots \end{bmatrix}$$

Model



Model  
output

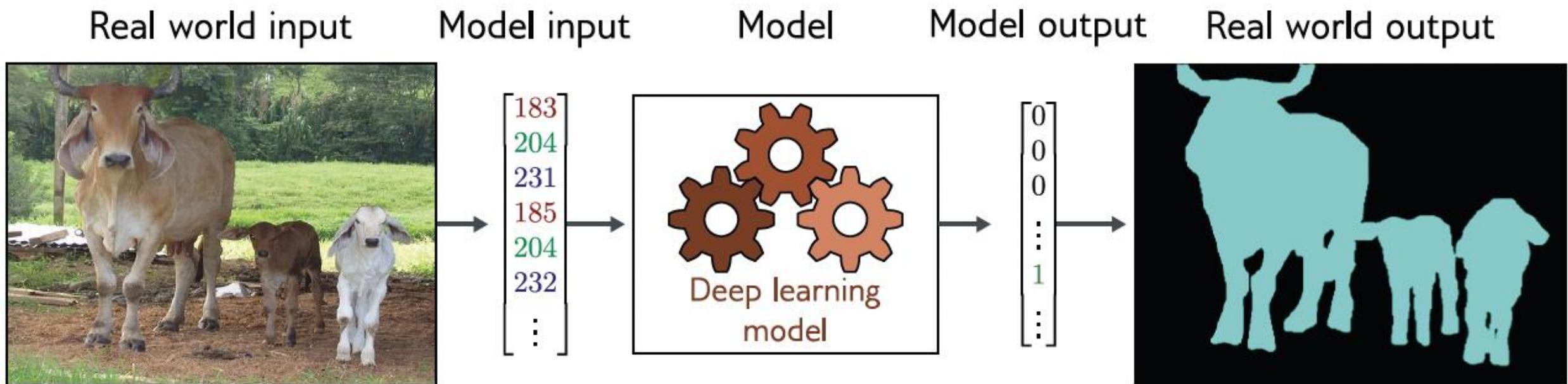
$$\begin{bmatrix} 0.00 \\ 0.00 \\ 0.01 \\ 0.89 \\ 0.05 \\ 0.00 \\ \vdots \\ 0.01 \end{bmatrix}$$

Real world output

Aardvark  
Apple  
Bee  
Bicycle  
Bridge  
Clown  
⋮

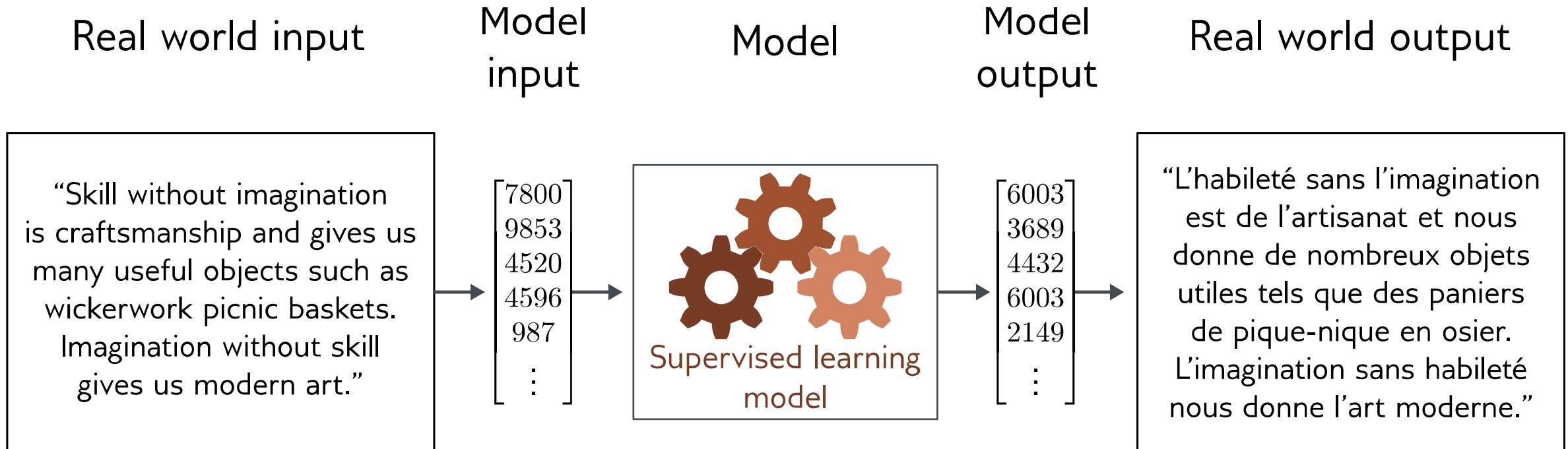
- Multiclass classification problem (discrete classes, >2 possible classes)
- Convolutional network

# Image segmentation

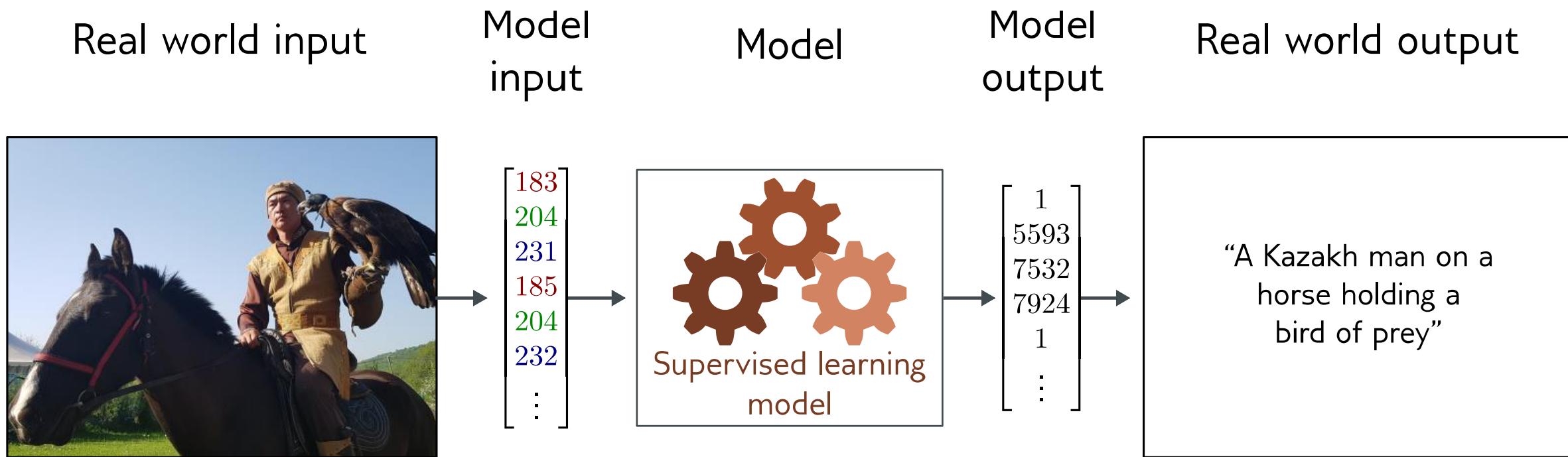


- Multivariate binary classification problem (many outputs, two discrete classes)
- Convolutional encoder-decoder network

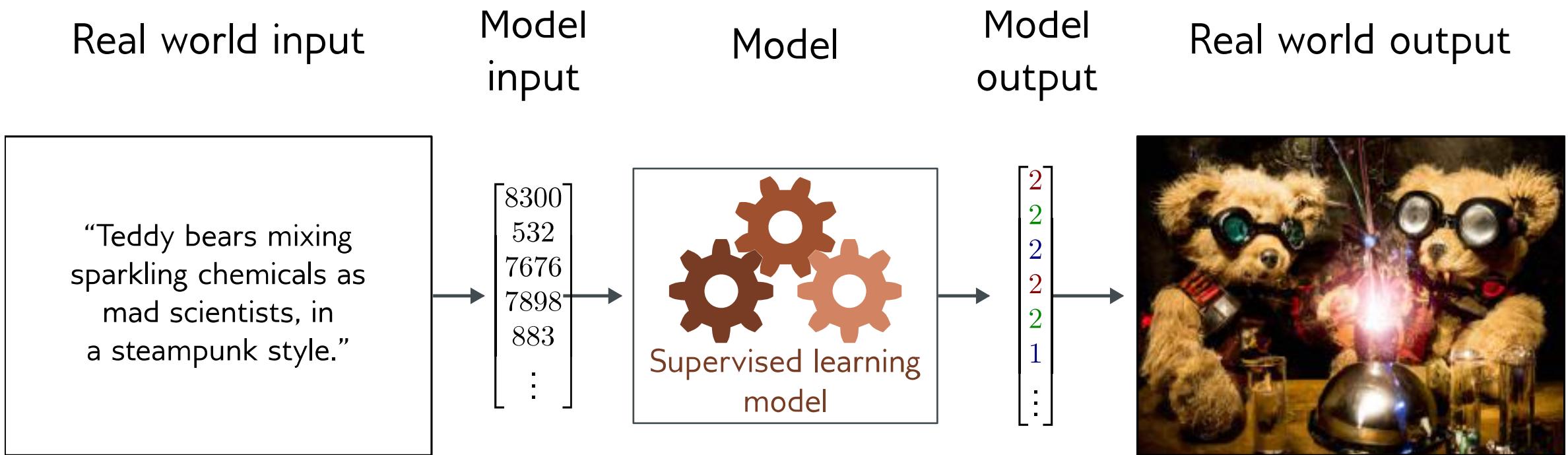
# Translation



# Image captioning



# Image generation from text



# What do these examples have in common?

- Very complex relationship between input and output
- Sometimes may be many possible valid answers
- But outputs (and sometimes inputs) obey rules

“A Kazakh man on a horse holding a bird of prey”

Language obeys grammatical rules



Natural images also have “rules”

# Idea

- Learn the “grammar” of the data from unlabeled examples
- Can use a gargantuan amount of data to do this (as unlabeled)
- Make the supervised learning task easier by having a lot of knowledge of possible outputs

# Artificial intelligence

Machine learning

Supervised  
learning

Unsupervised  
learning

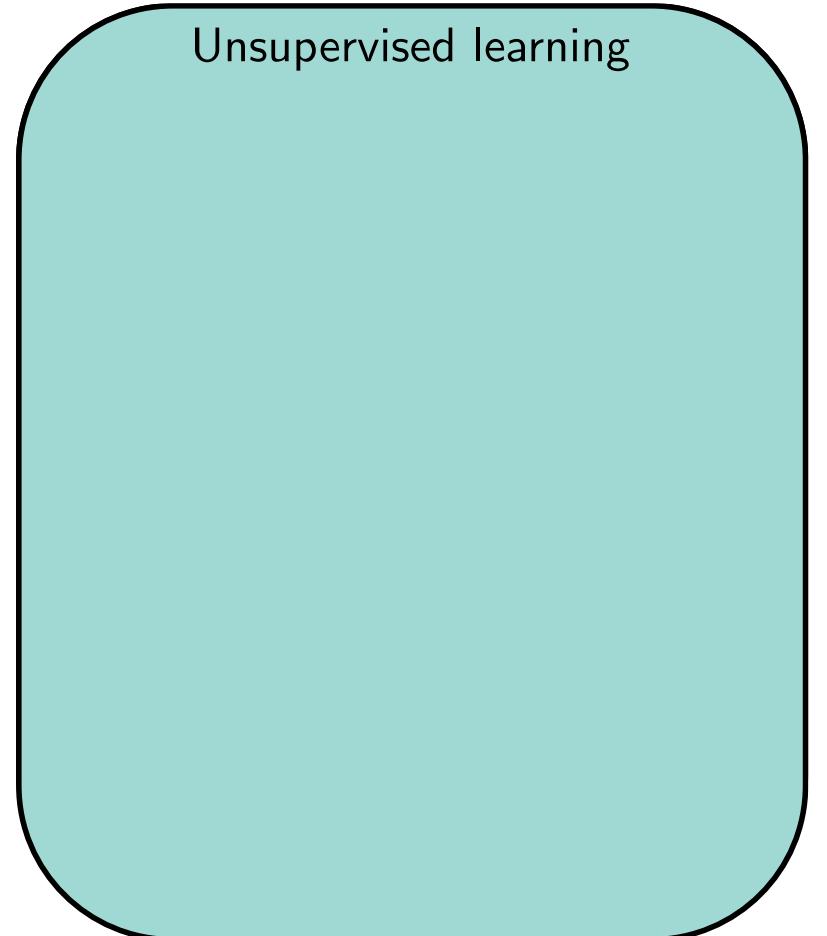
Reinforcement  
learning

Deep learning



# Unsupervised Learning

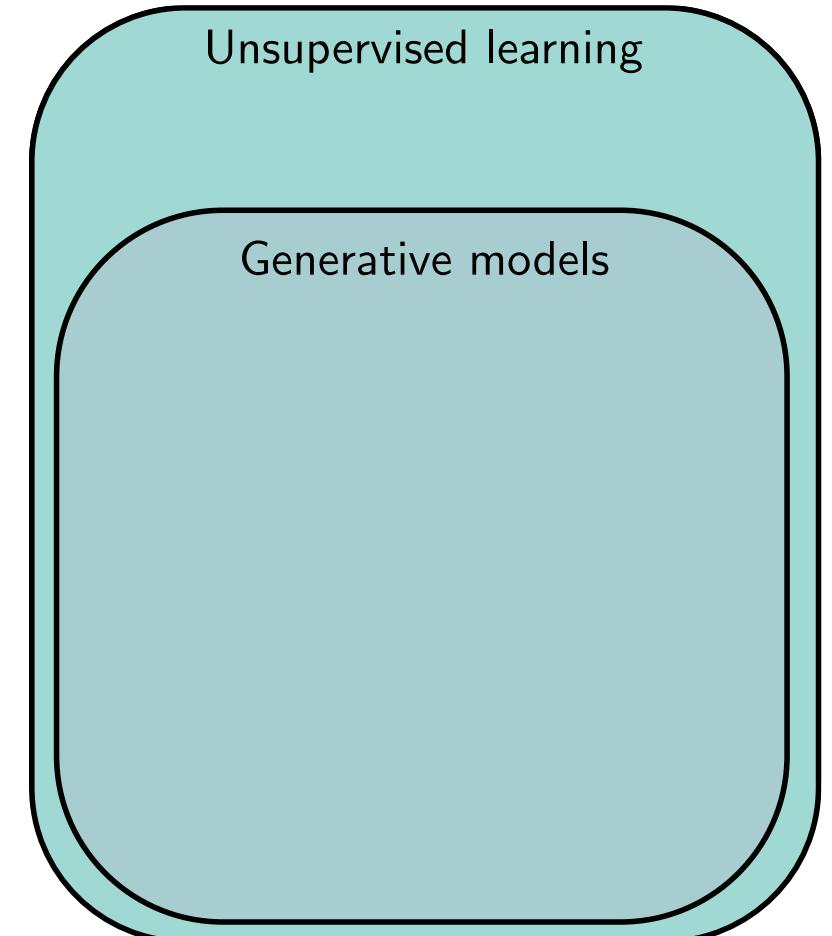
- Learning about a dataset without labels
  - Clustering
  - Finding outliers
  - Generating new examples
  - Filling in missing data



Unsupervised learning

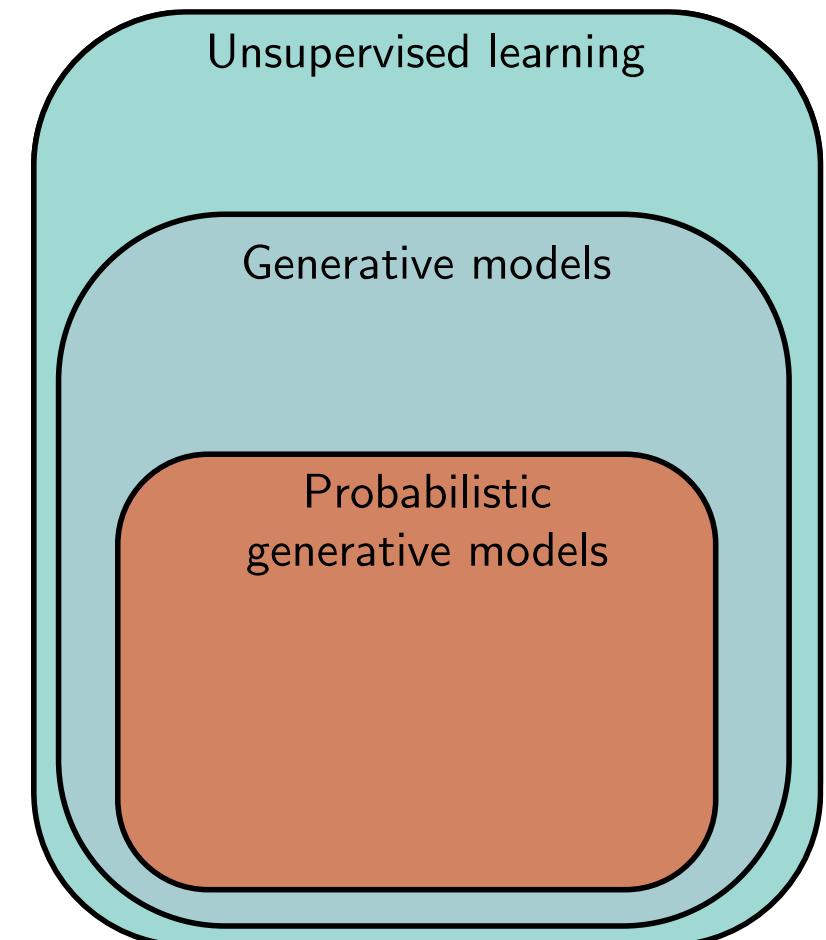
# Unsupervised Learning

- Learning about a dataset without labels
  - e.g., clustering
- Generative models can create examples
  - e.g., generative adversarial networks



# Unsupervised Learning

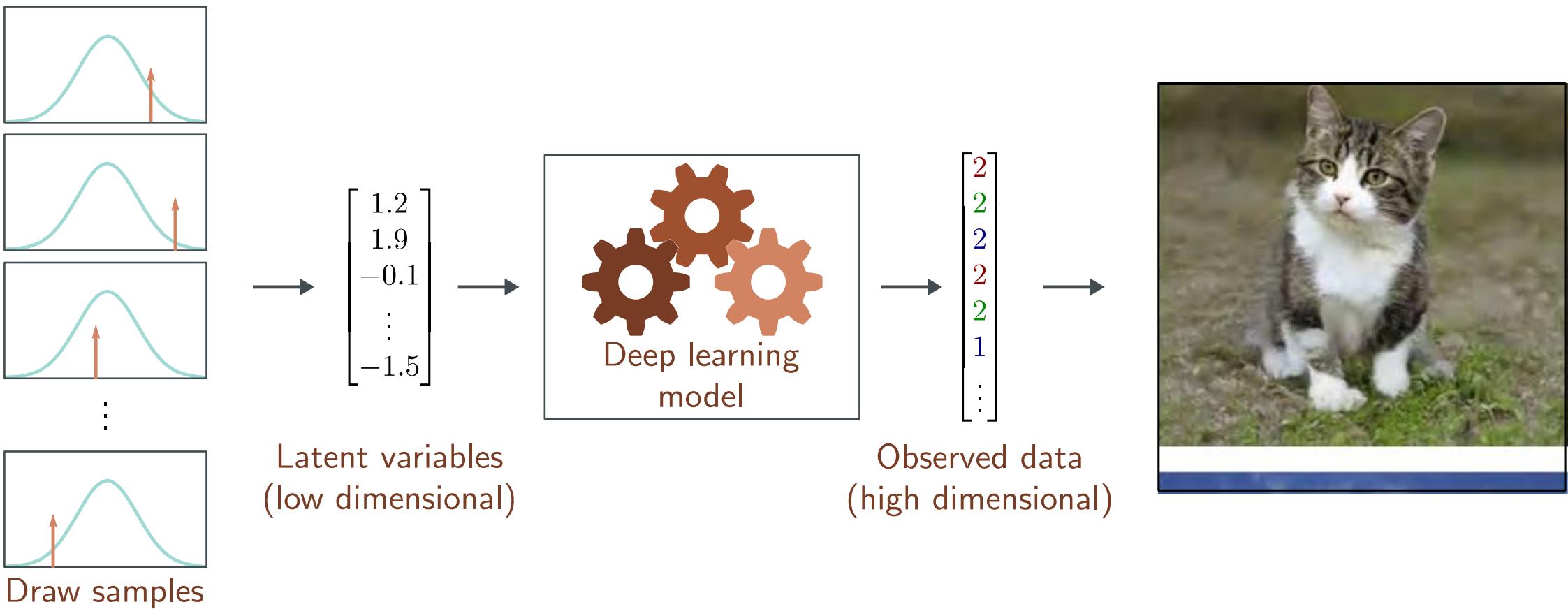
- Learning about a dataset without labels
  - e.g., clustering
- Generative models can create examples
  - e.g., generative adversarial networks
- PGMs learn distribution over data
  - e.g., variational autoencoders,
  - e.g., diffusion models



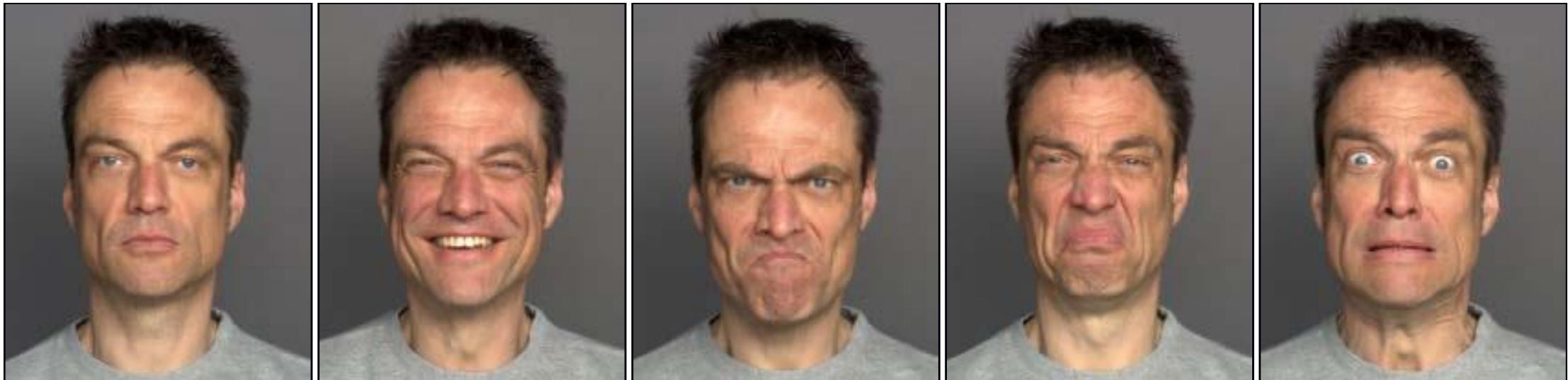
# Generative models



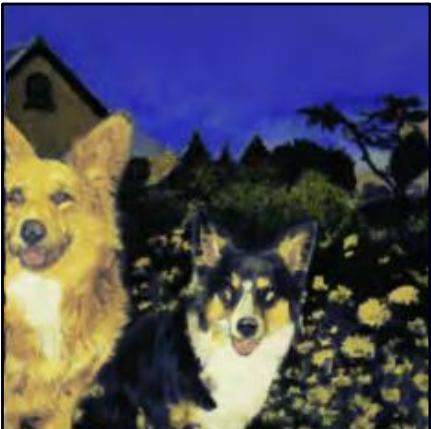
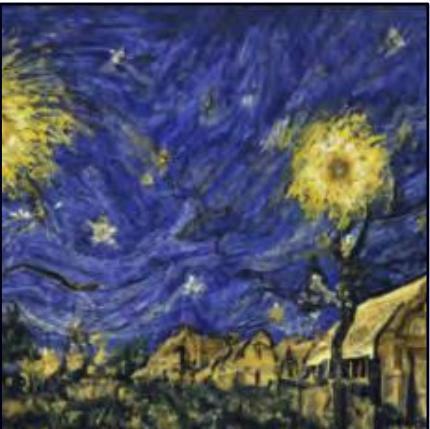
# Latent variables



# Why should this work?



# Interpolation



# Conditional synthesis



I was a little nervous before my first lecture at the University of Bath. It seemed like there were hundreds of students and they looked intimidating. I stepped up to the lectern and was about to speak, when something bizarre happened.

Suddenly, the room was filled with a deafening noise, like a giant roar. It was so loud that I couldn't hear anything else and I had to cover my ears. I could see the students looking around, confused and frightened. Then, as quickly as it had started, the noise stopped and the room was silent again.

I stood there for a few moments, trying to make sense of what had just happened. Then I realized that the students were all staring at me, waiting for me to say something. I tried to think of something witty or clever to say, but my mind was blank. So I just said, "Well, that was strange," and then I started my lecture.

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I was a little nervous before my first lecture at the University of Bath. It seemed like there were hundreds of students and they looked intimidating. I stepped up to the lectern and was about to speak, when something bizarre happened.

Suddenly, a giant rabbit ran into the lecture hall! The students started screaming and running around in panic. I was so shocked that I couldn't move. The rabbit ran up to me and hopped onto the lectern. Then, in a booming voice, it said:

"I am the Easter Bunny! I have come to give you all a special gift!"

The students were so surprised that they stopped screaming and listened to the Easter Bunny. Then, the Easter Bunny started handing out chocolate eggs to everyone in the lecture hall. The students were so happy that they started cheering and clapping. I was so relieved that the Easter Bunny had saved my lecture! After that, I was able to continue and the students paid attention for the rest of the hour. It was a great success!

# Artificial intelligence

Machine learning

Supervised  
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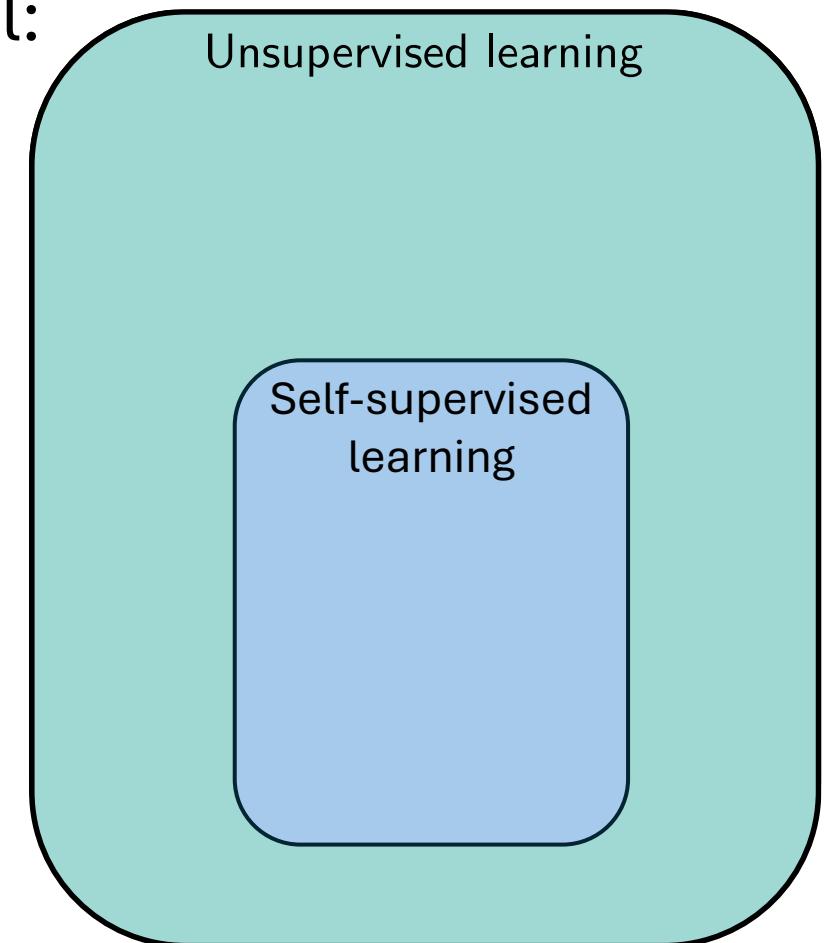
Deep learning

Self-supervised  
learning

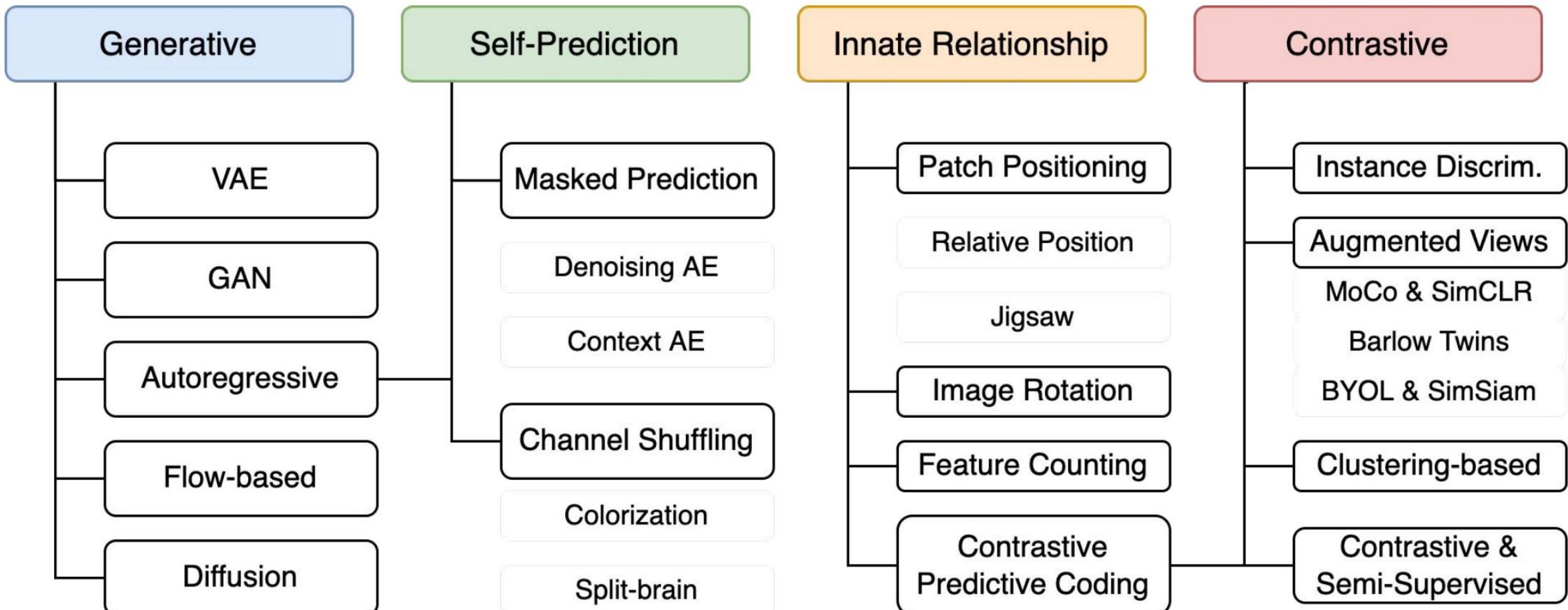


# Self-supervised Learning

- Use an unlabeled dataset to train a model:
  - learning good data representation from unlabeled dataset
  - Construct supervised learning tasks automatically (without human-provided labels)



# Self-supervised Learning



From: Weng, Kim, "Self-Supervised Learning: Self-Prediction & Contrastive Learning", NeurIPS 2021 Tutorial