CM20315 - Machine Learning

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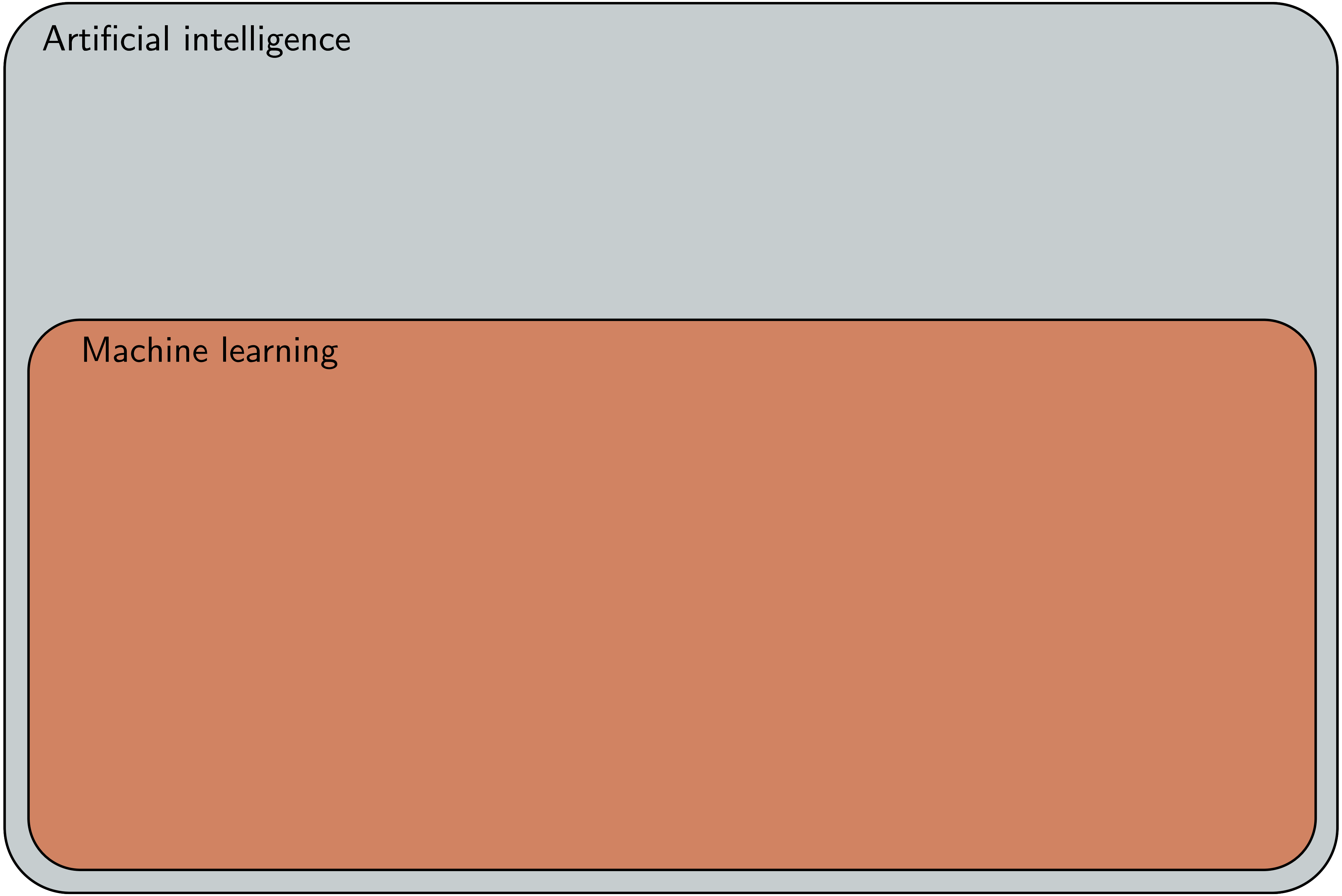
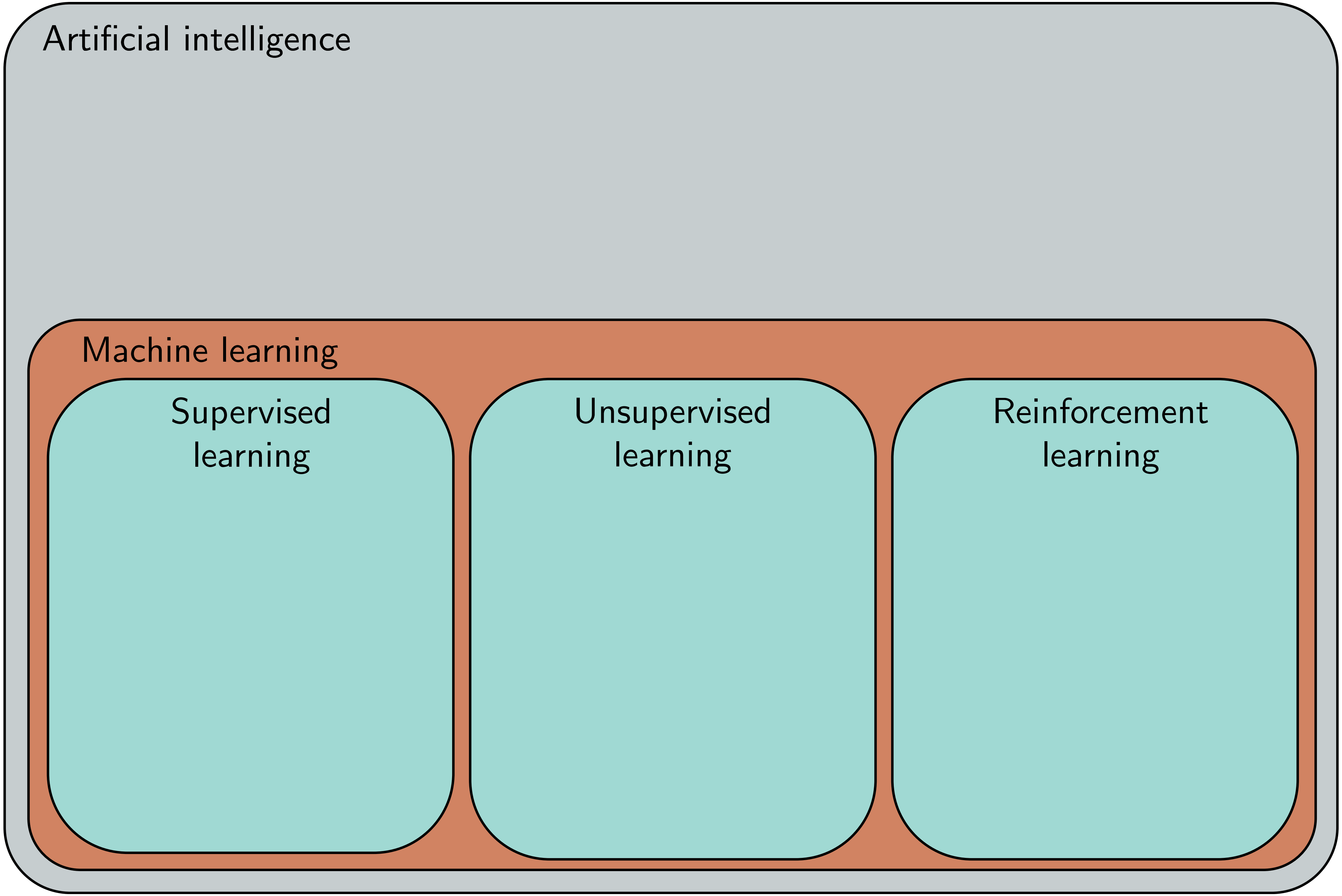
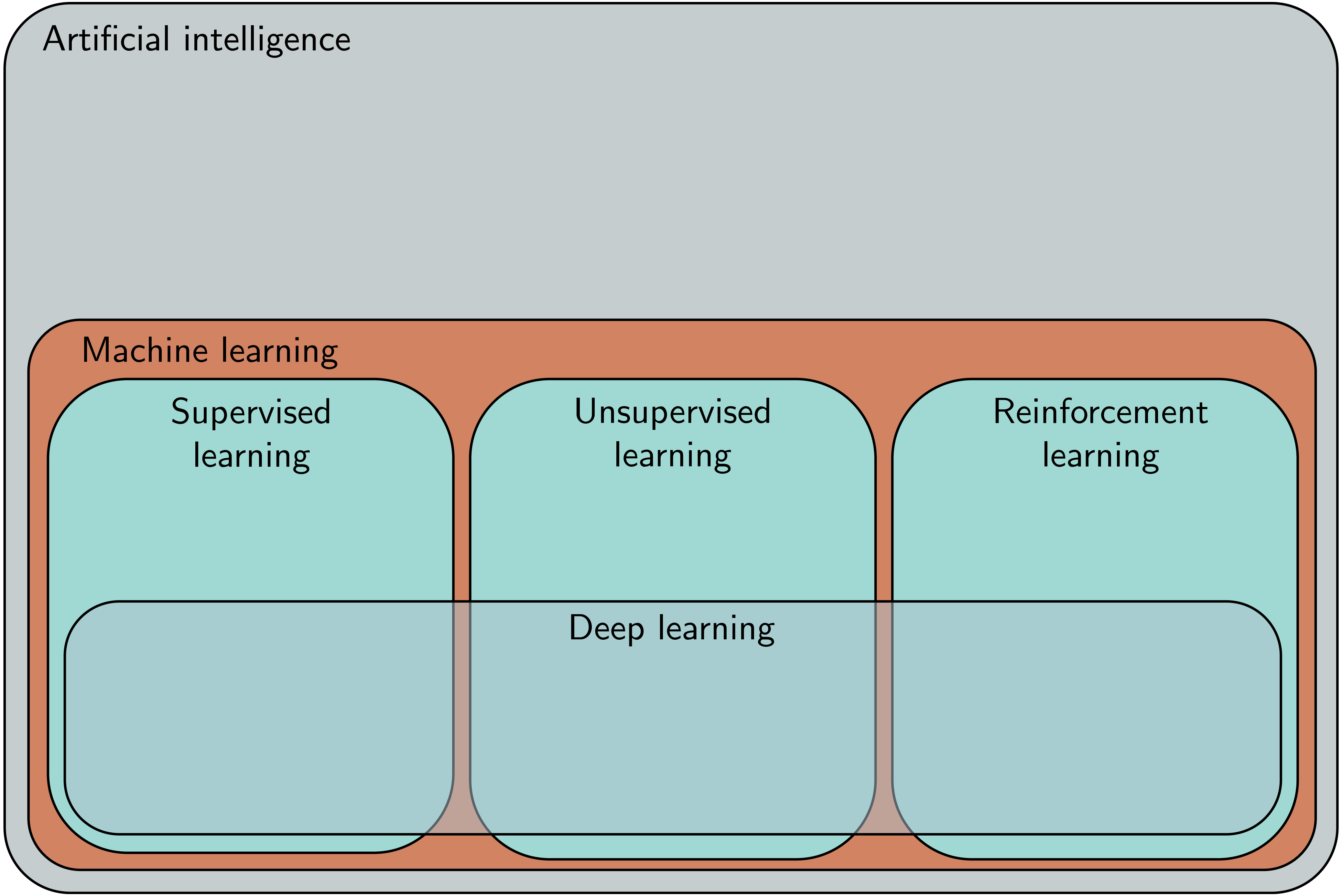
1. Introduction

Artificial intelligence


Artificial intelligence
Machine learning


Artificial intelligence
Machine learning
Supervised learning
Unsupervised learning
Reinforcement learning



Artificial intelligence
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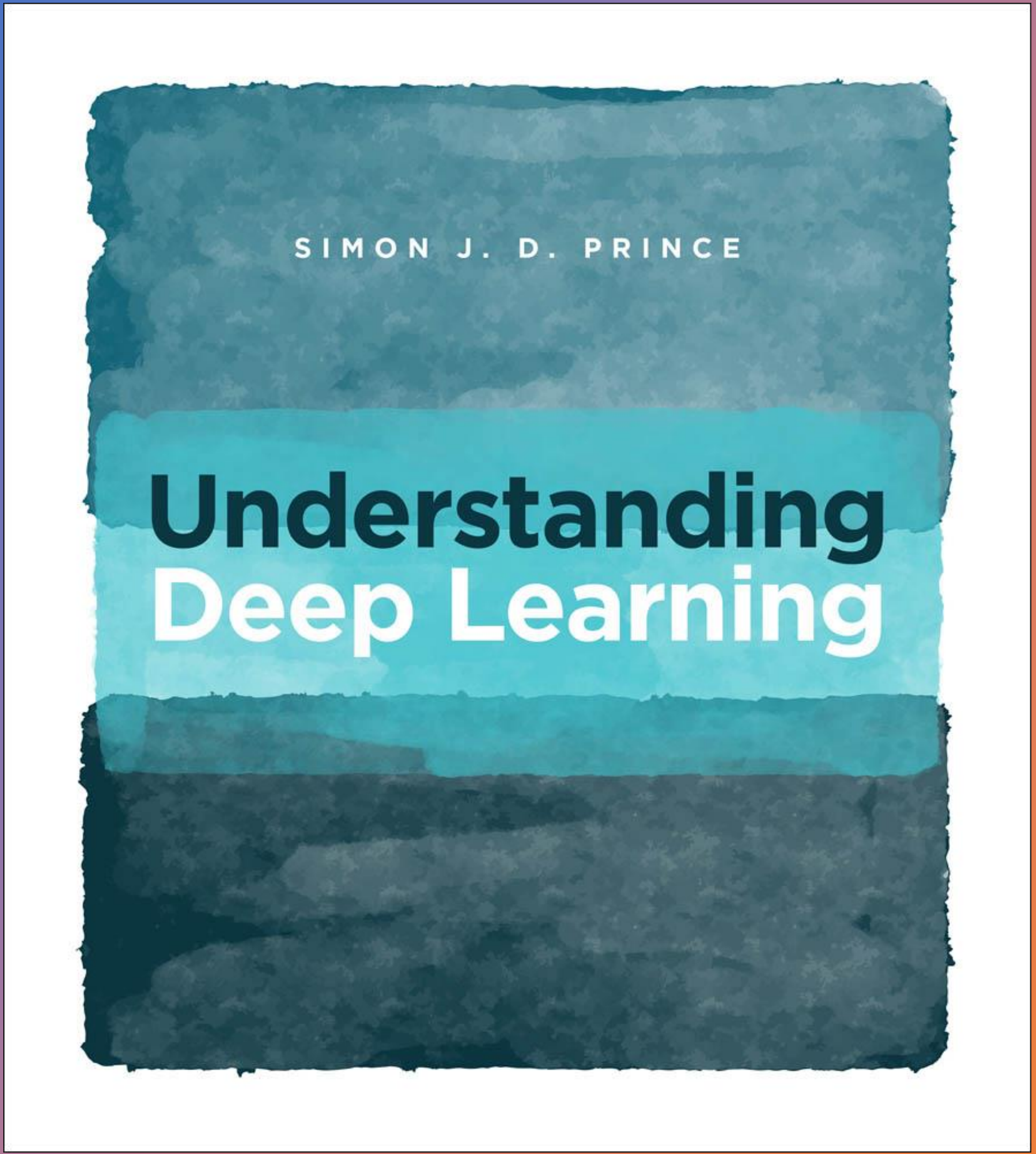
Deep learning



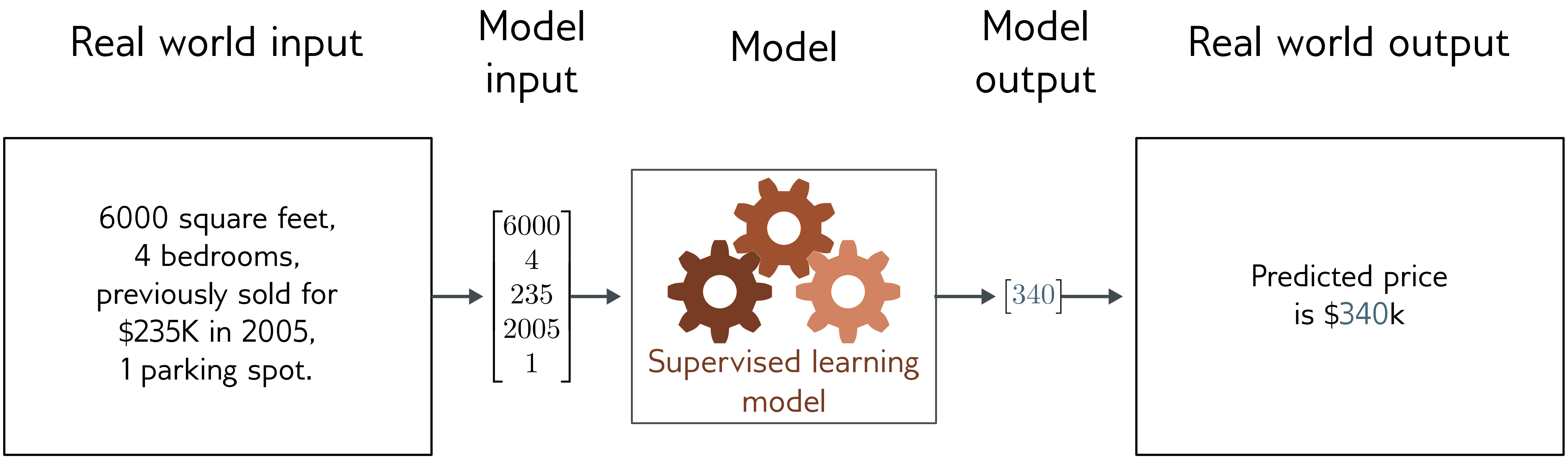
Book

- Examinable unless specified
  - Chapters 1-10,12

Supervised learning

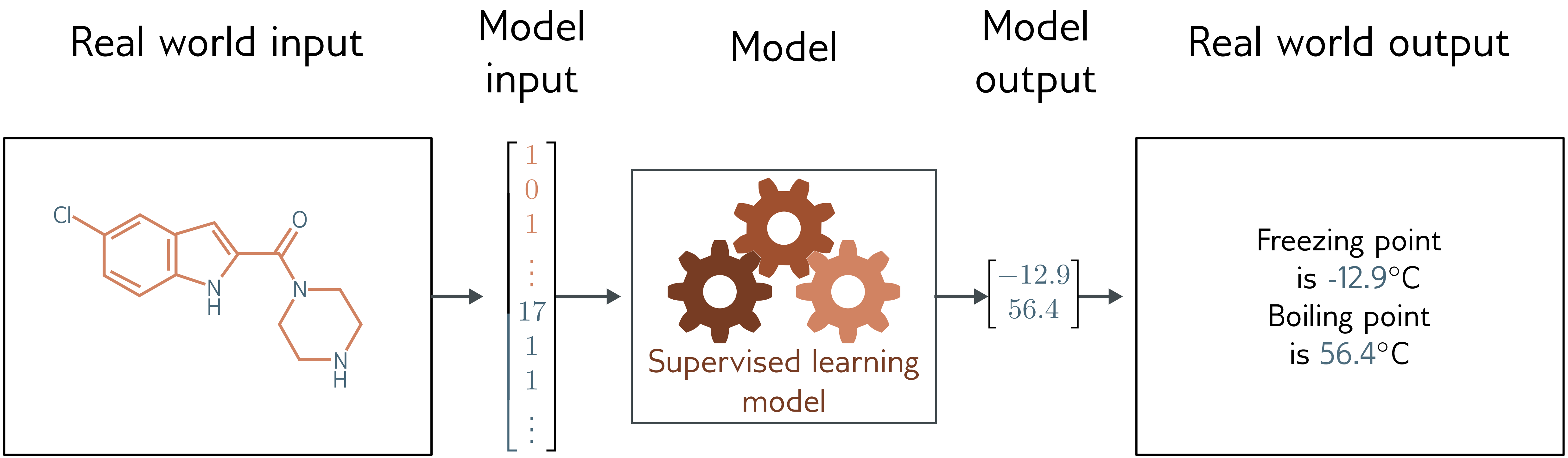
- Define a mapping from input to output
- Learn this mapping from paired input/output data examples

Regression



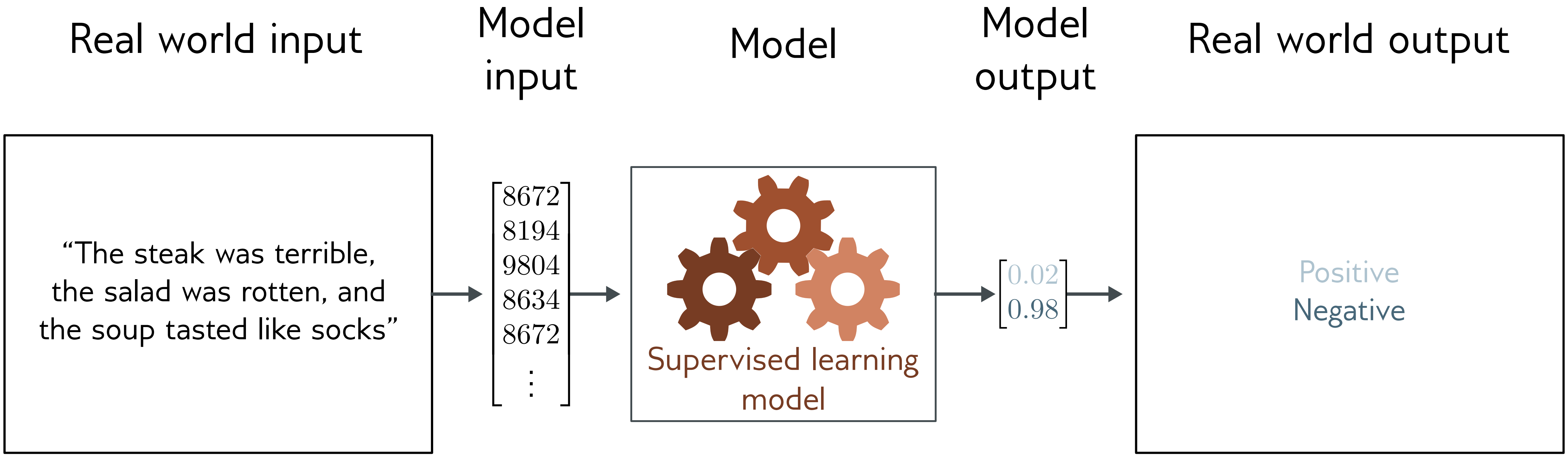
- Univariate regression problem (one output, real value)
- Fully connected network

Graph regression



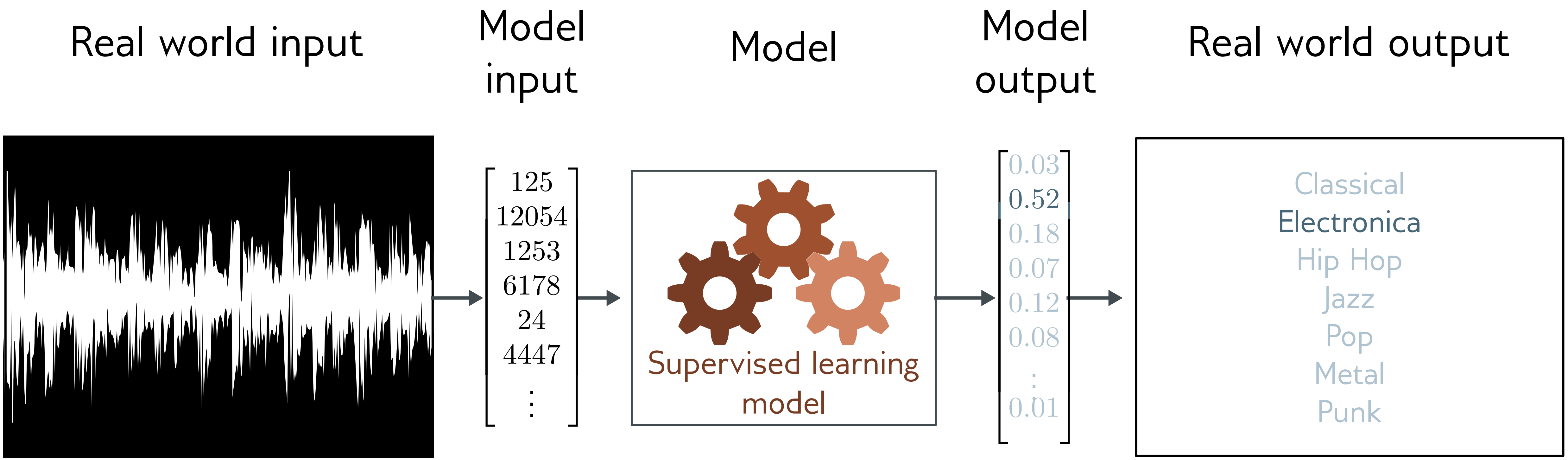
- Multivariate regression problem (>1 output, real value)
- Graph neural network

Text classification



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

Music genre classification

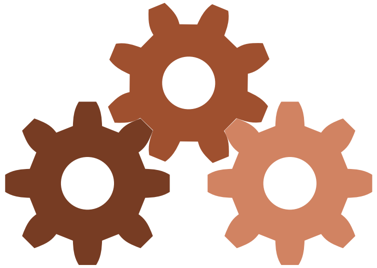


- Multiclass classification problem (discrete classes, >2 possible values)
- Recurrent neural network (RNN)

Image classification

Real world input	Model input	Model	Model output	Real world output

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



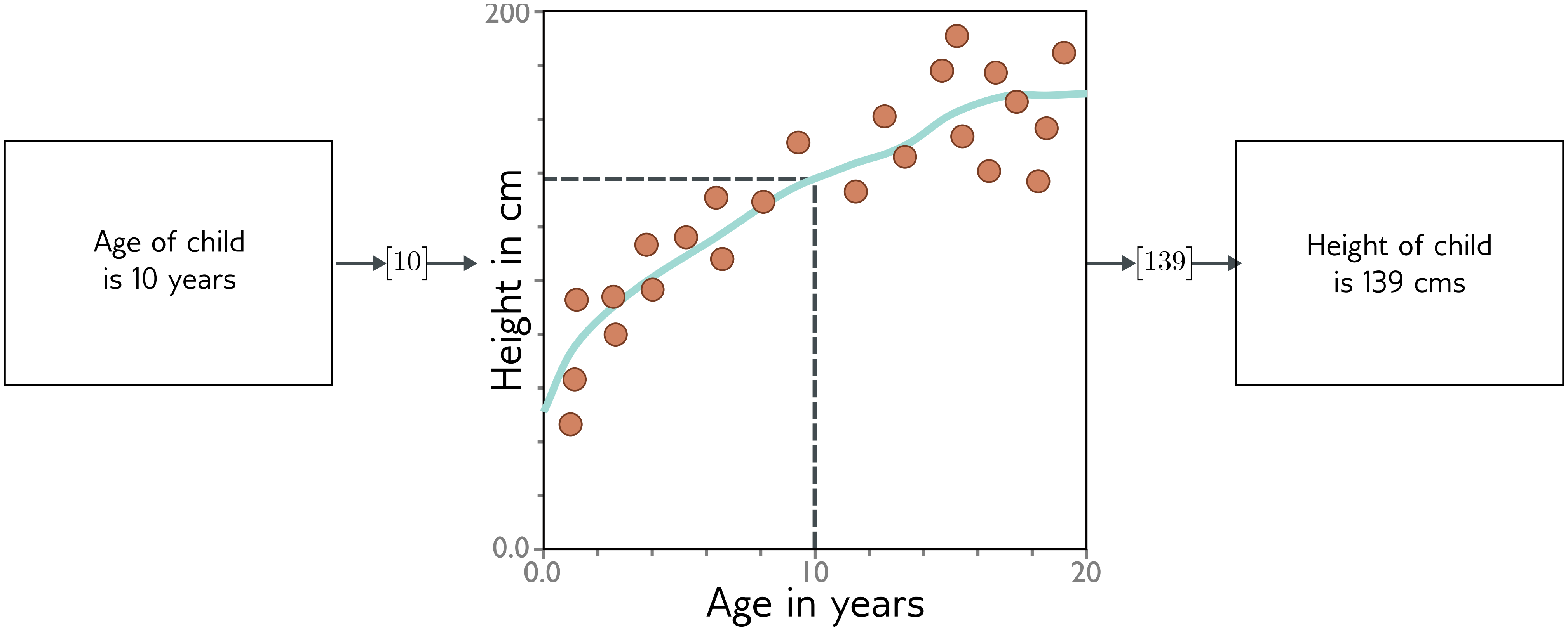
Supervised learning model

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

Aardvark
Apple
Bee
Bicycle
Bridge
Clown
⋮

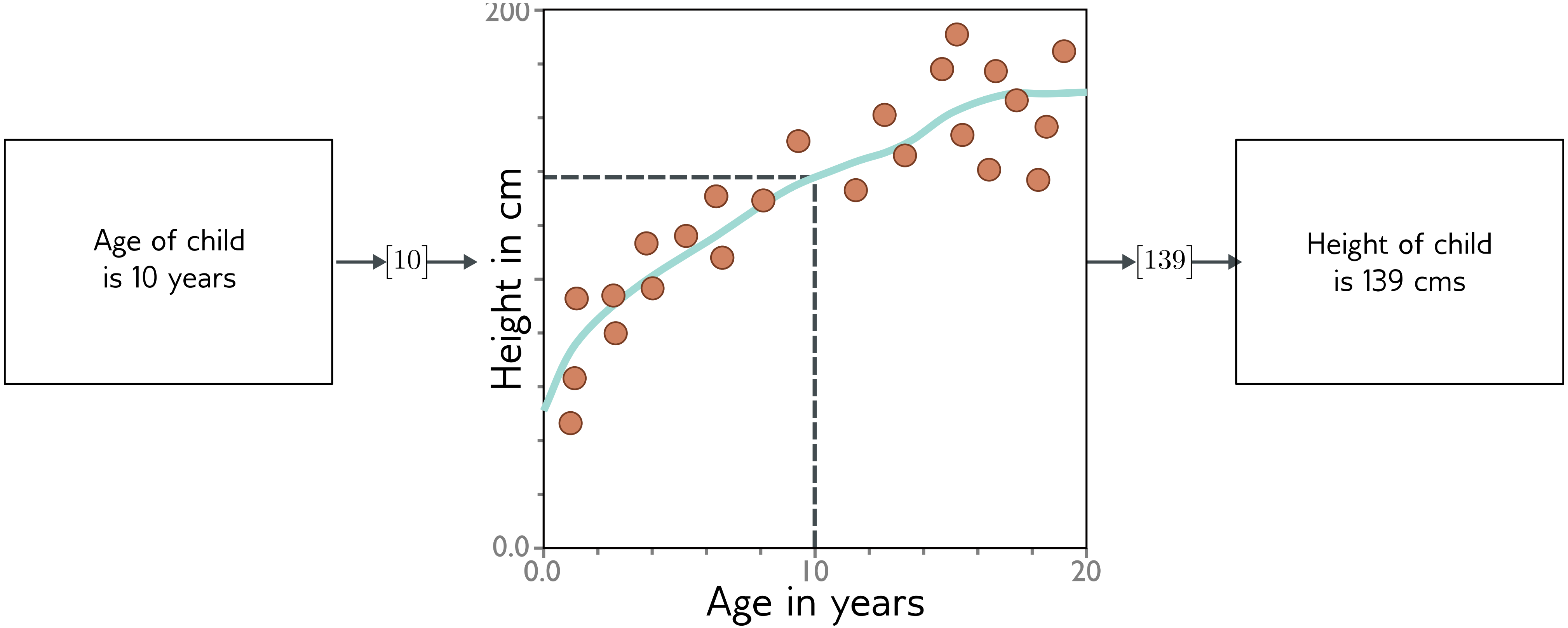
- Multiclass classification problem (discrete classes, >2 possible classes)
- Convolutional network

What is a supervised learning model?



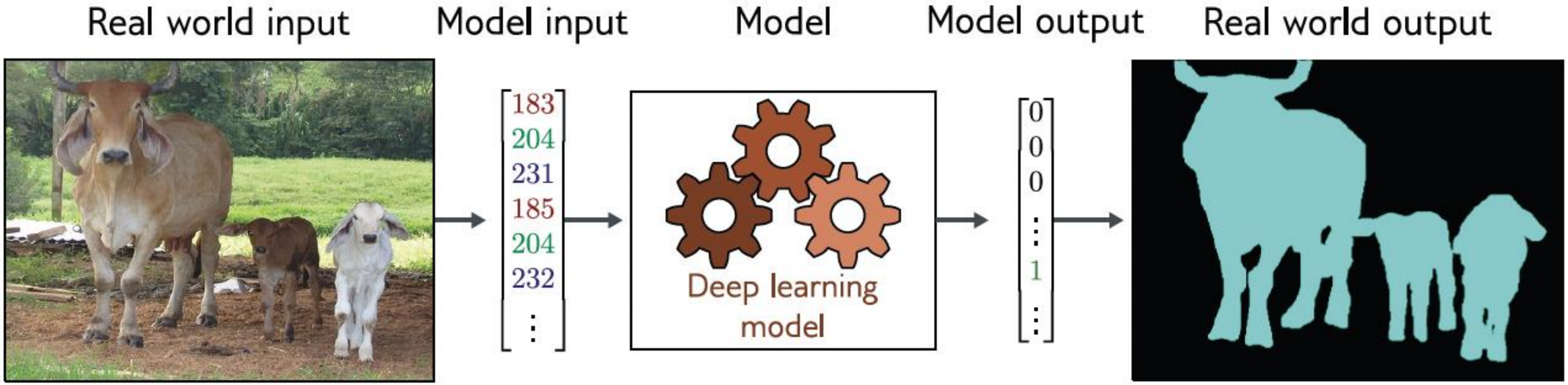
- An equation relating input (age) to output (height)
- Search through family of possible equations to find one that fits training data well

What is a supervised learning model?



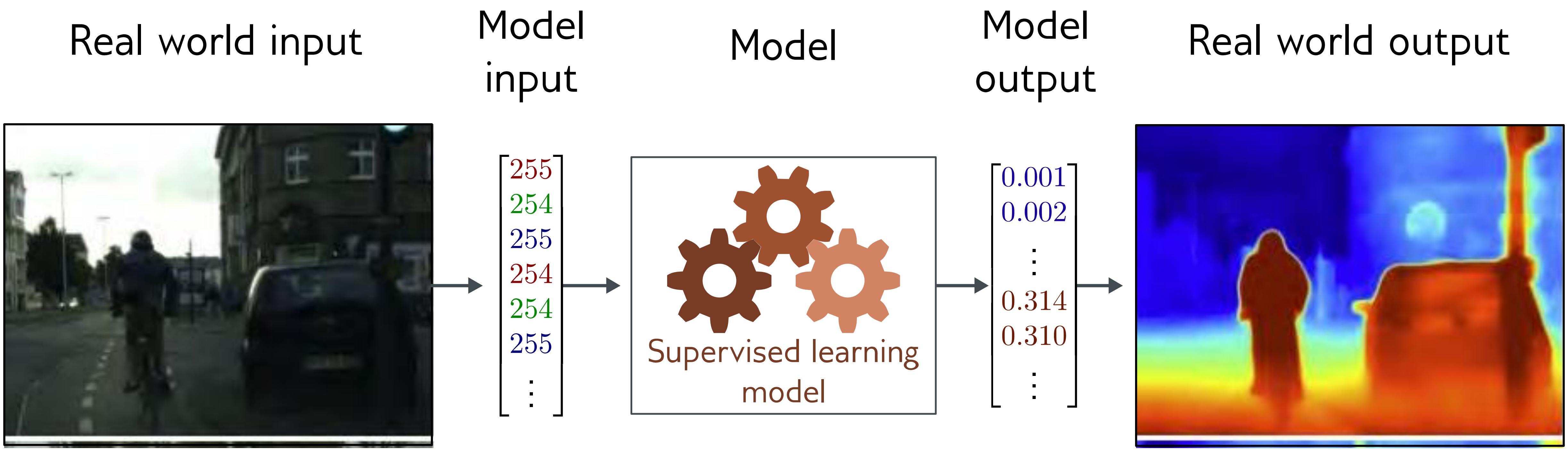
- Deep neural networks are just a very flexible family of equations
- Fitting deep neural networks = "Deep Learning"

Image segmentation



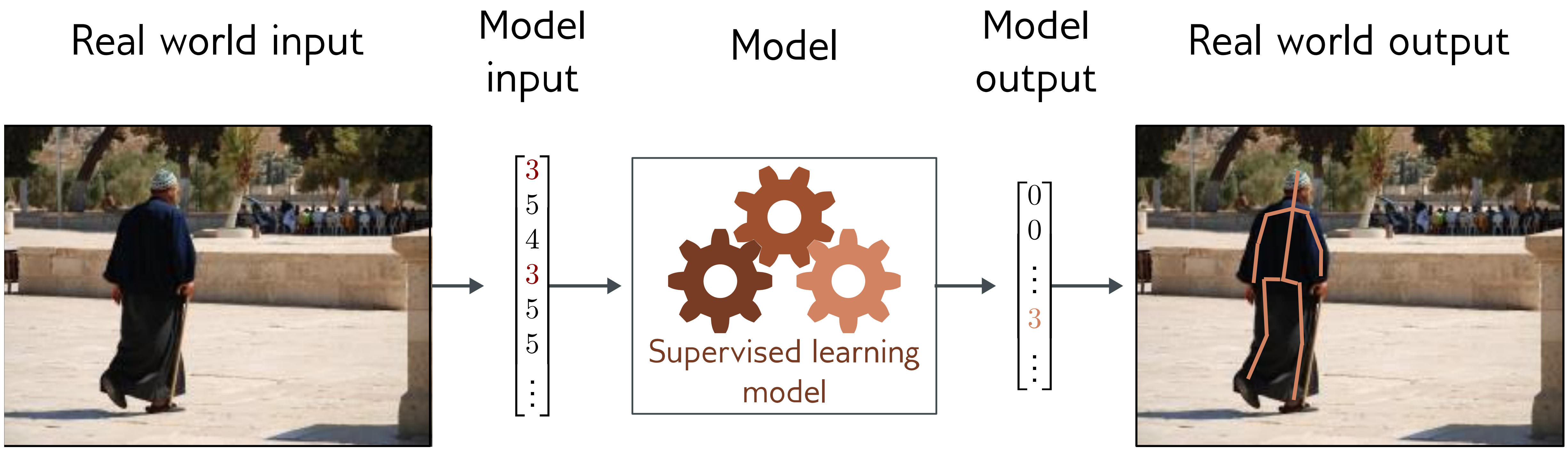
- Multivariate binary classification problem (many outputs, two discrete classes)
- Convolutional encoder-decoder network

Depth estimation



- Multivariate regression problem (many outputs, continuous)
- Convolutional encoder-decoder network

Pose estimation



- Multivariate regression problem (many outputs, continuous)
- Convolutional encoder-decoder network

Terms

- Regression = continuous numbers as output
- Classification = discrete classes as output
- Two class and multiclass classification treated differently
- Univariate = one output
- Multivariate = more than one output

Translation

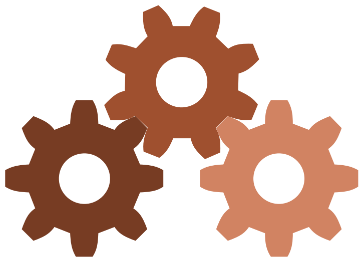
Real world input	Model input	Model	Model output	Real world output
"Skill without imagination is craftsmanship and gives us many useful objects such as wickerwork picnic baskets. Imagination without skill gives us modern art."	$\begin{bmatrix} 7800 \\ 9853 \\ 4520 \\ 4596 \\ 987 \\ \vdots \end{bmatrix}$	 Supervised learning model	$\begin{bmatrix} 6003 \\ 3689 \\ 4432 \\ 6003 \\ 2149 \\ \vdots \end{bmatrix}$	"L'habileté sans l'imagination est de l'artisanat et nous donne de nombreux objets utiles tels que des paniers de pique-nique en osier. L'imagination sans habileté nous donne l'art moderne."

Image captioning

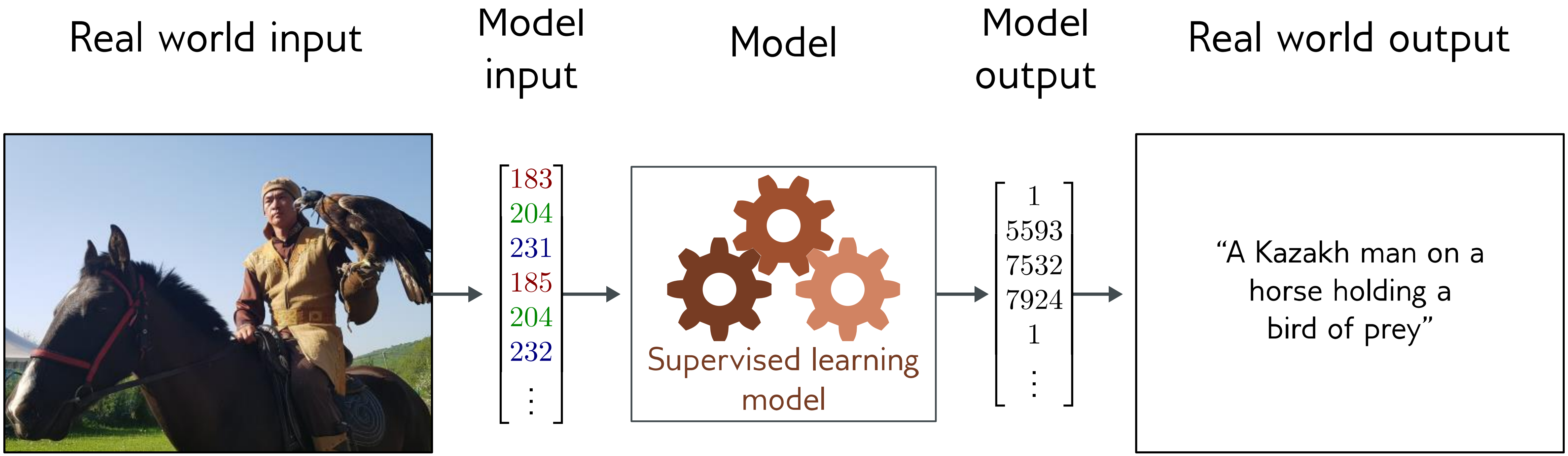
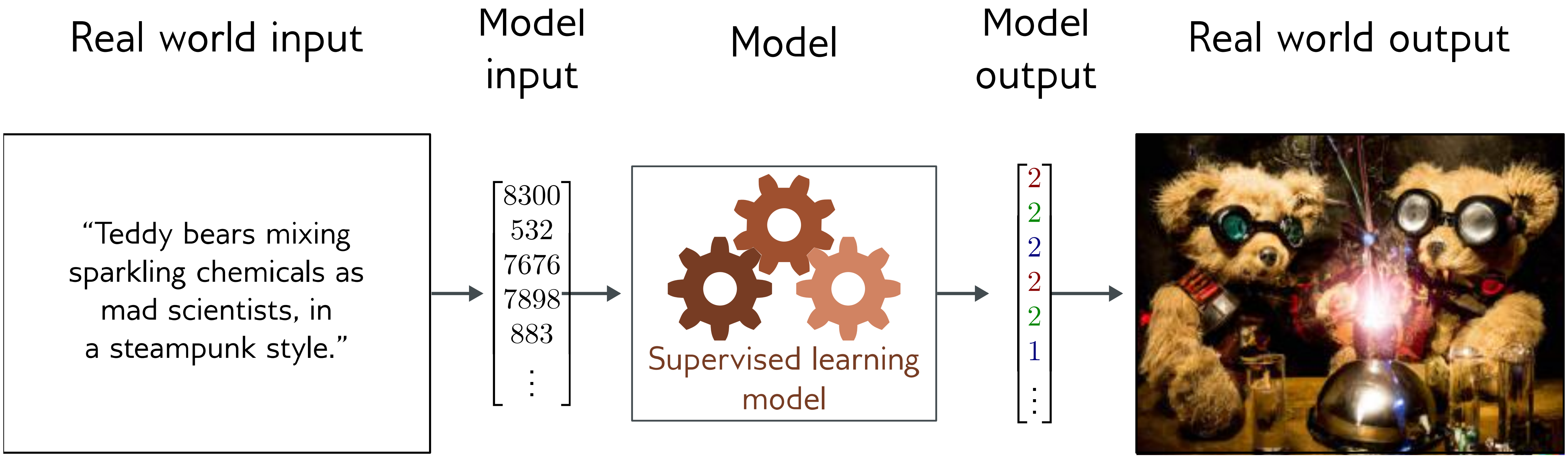


Image generation from text



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

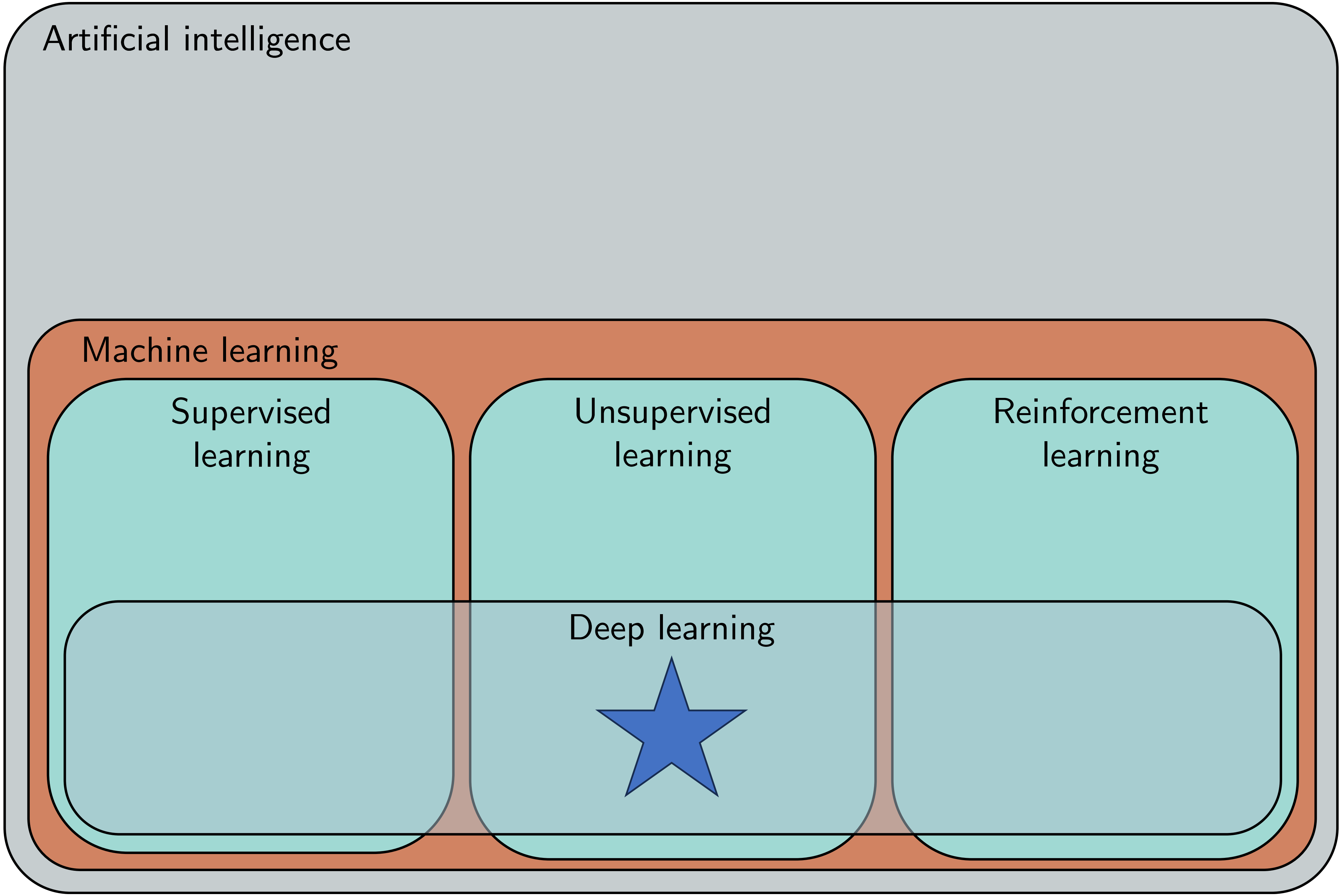
"A Kazakh man on a horse holding a bird of prey"

Language obeys grammatical rules

Natural images also have "rules"

Idea

- Learn the “grammar” of the data from unlabeled examples
  - Ex: Learning certain pixels in an image often appear together (like edges in an image or sentence structure in text)
- Can use a huge amount of data to do this (as unlabeled)
  - Since collecting **labeled** data is expensive, learning from **unlabeled** data allows using a much larger dataset.
- Make the supervised learning task earlier by having a lot of knowledge of possible outputs
  - When **supervised learning** (with labels) is later applied, the model already knows useful patterns, so it **needs less labeled data** and performs better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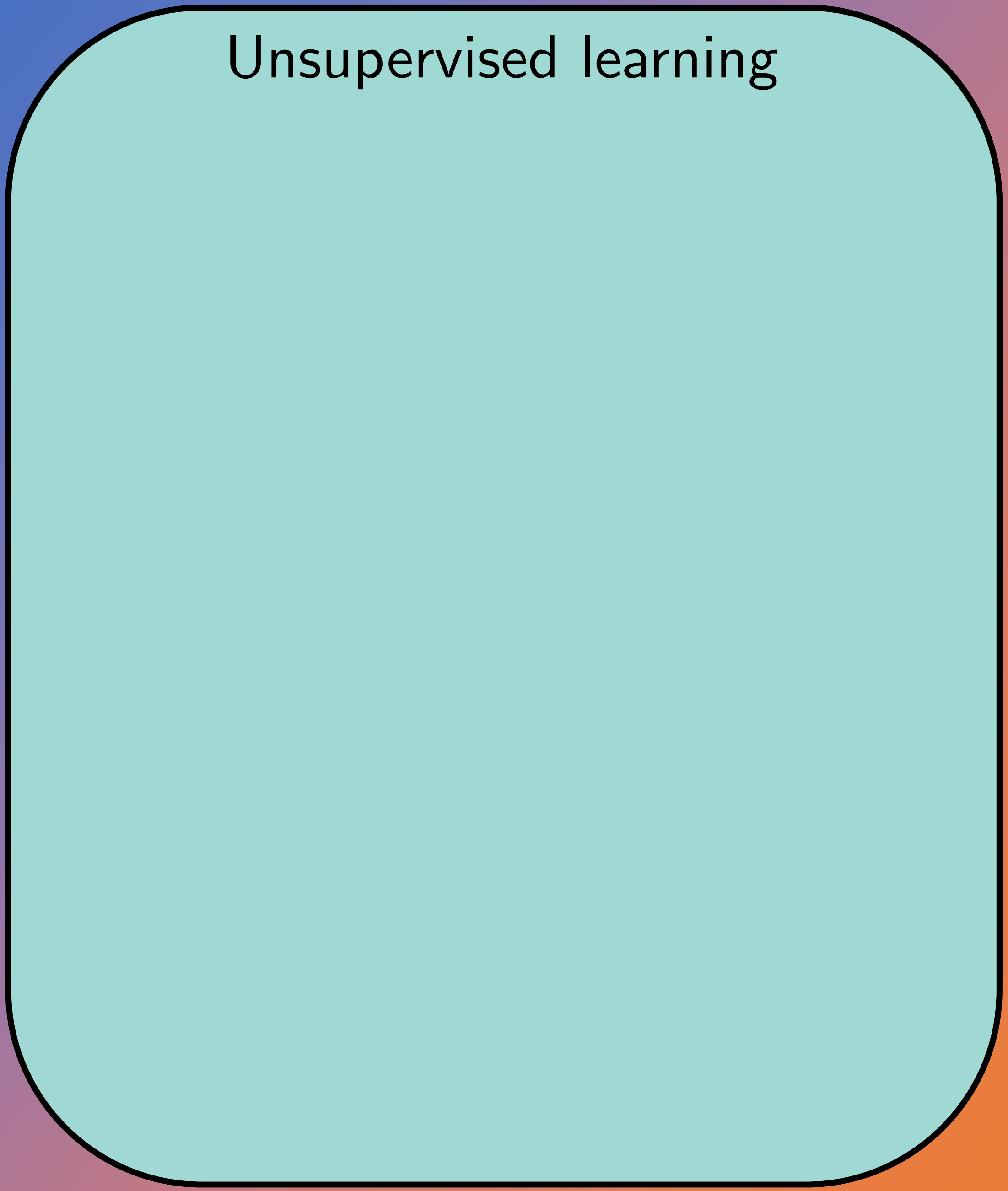
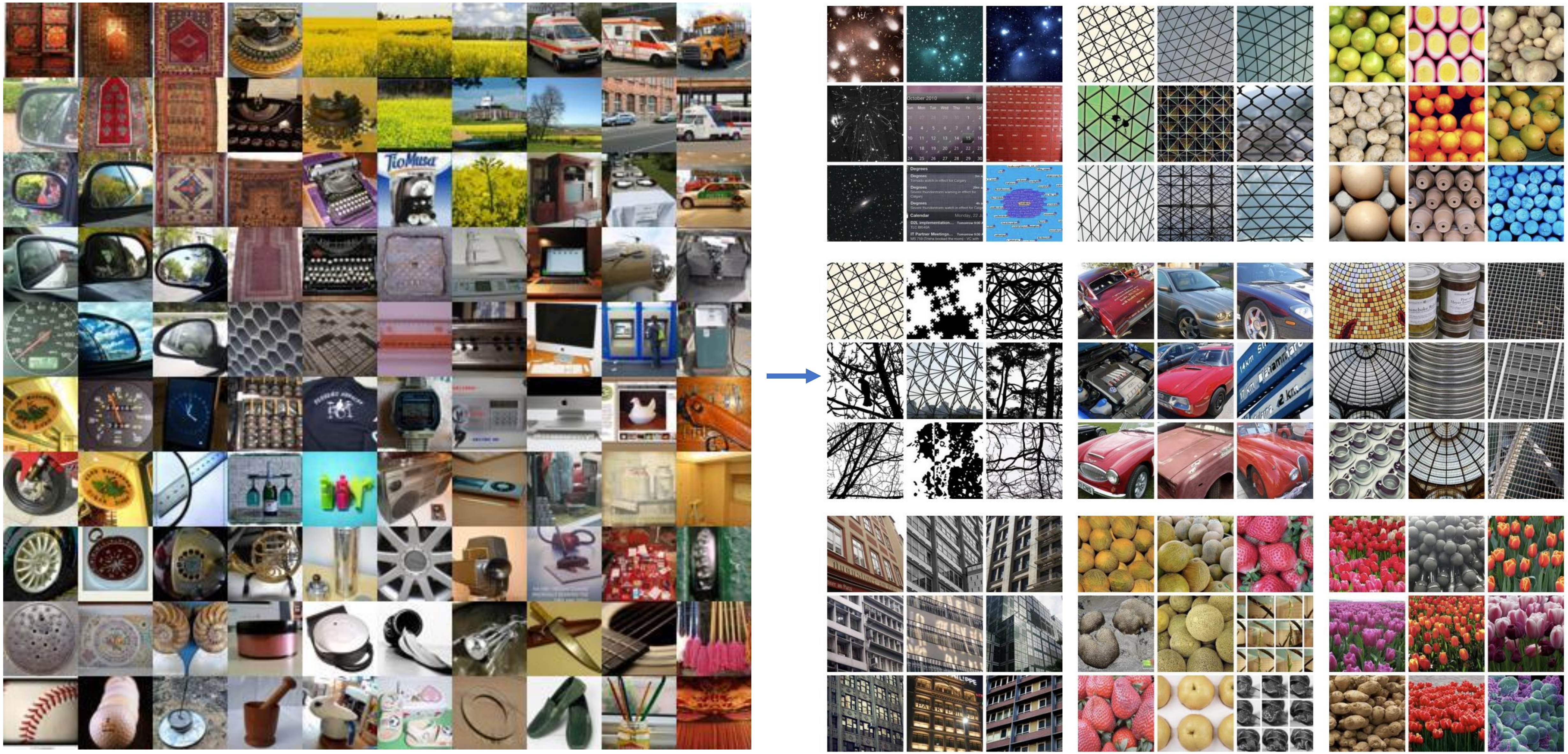


Unsupervised Learning

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

DeepCluster: Deep Clustering for Unsupervised Learning of Visual Features (Caron et al., 2018)



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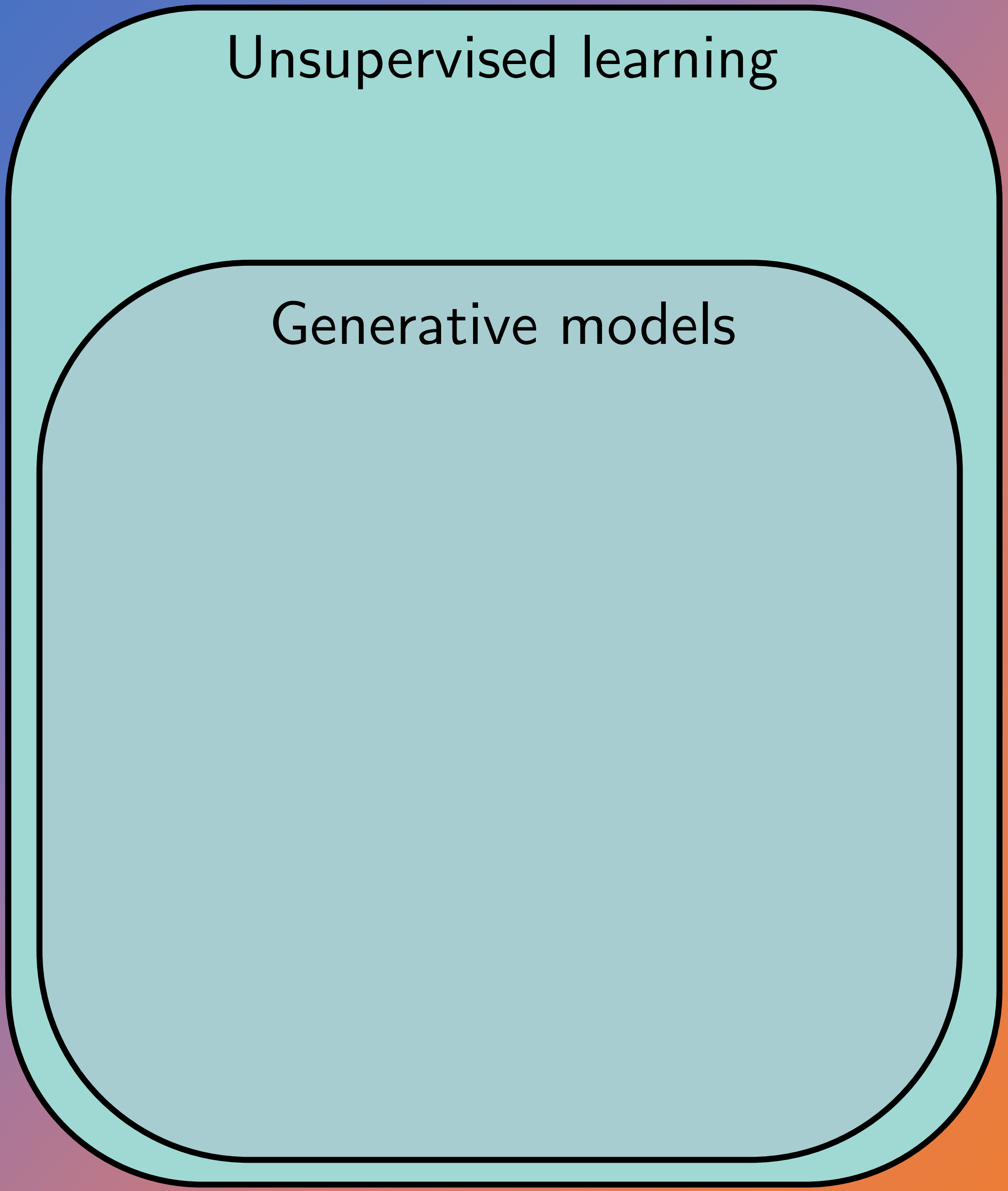
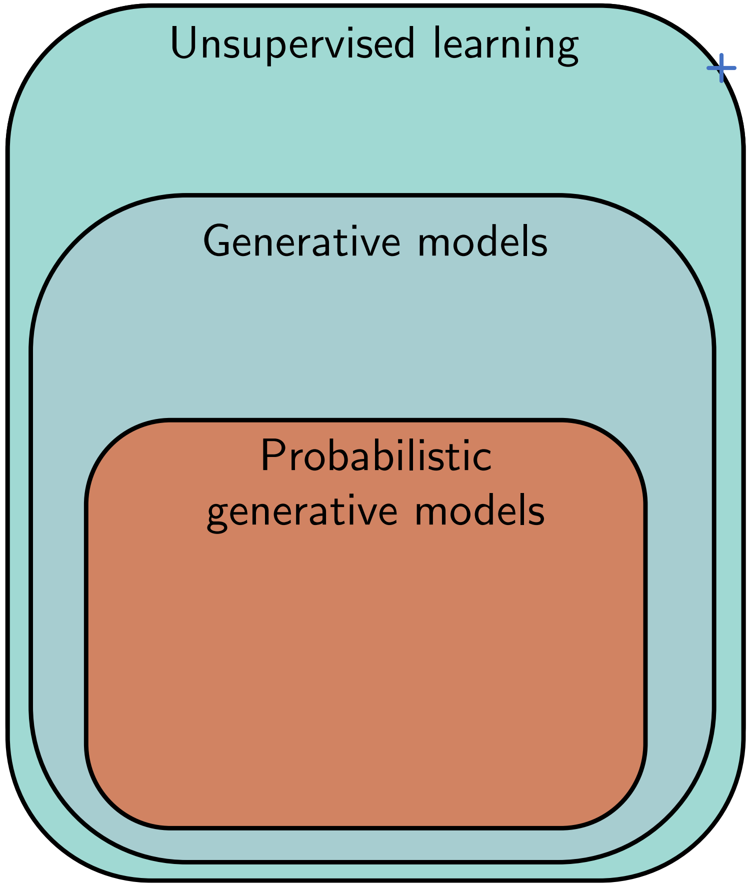


Unsupervised Learning

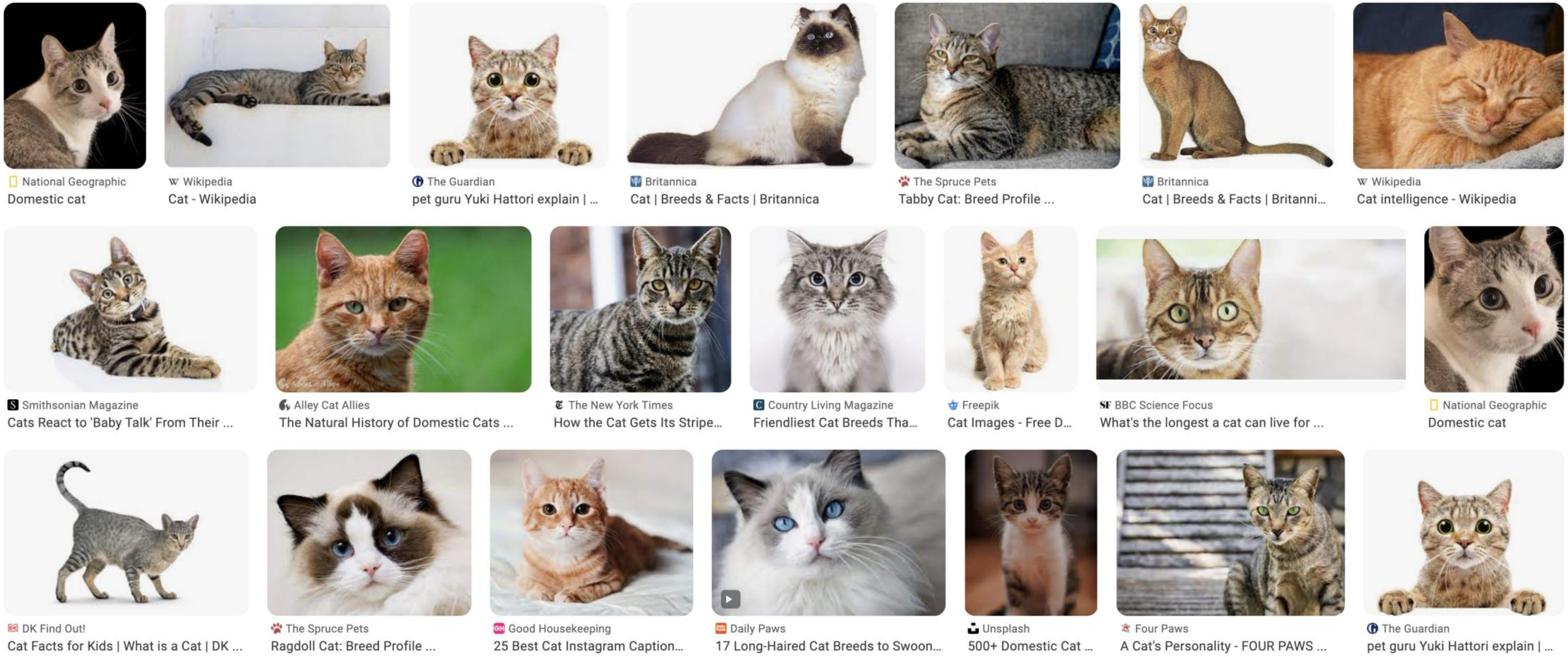
- Learning about a dataset without labels
    - e.g., clustering
- Generative models can create examples
    - e.g., generative adversarial networks

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., normalizing flows,
  - e.g., diffusion models



Generative models



Generative models

Latent Variables

Some generative models exploit the fact that data can be lower in dimension

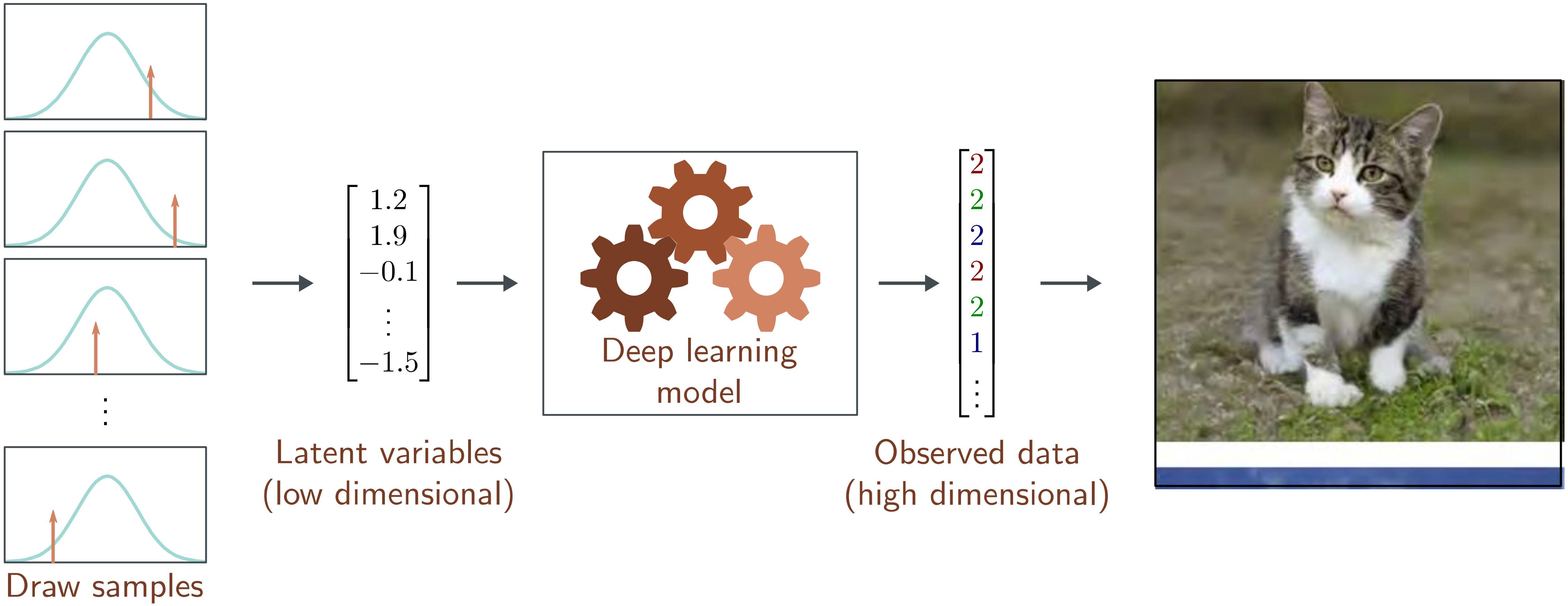
The number of valid English sentences is much smaller than the number of strings created by adding words at random.

Real-world images are a tiny subset of the images that can be created by drawing random red, green, and blue (RGB) values for every pixel.

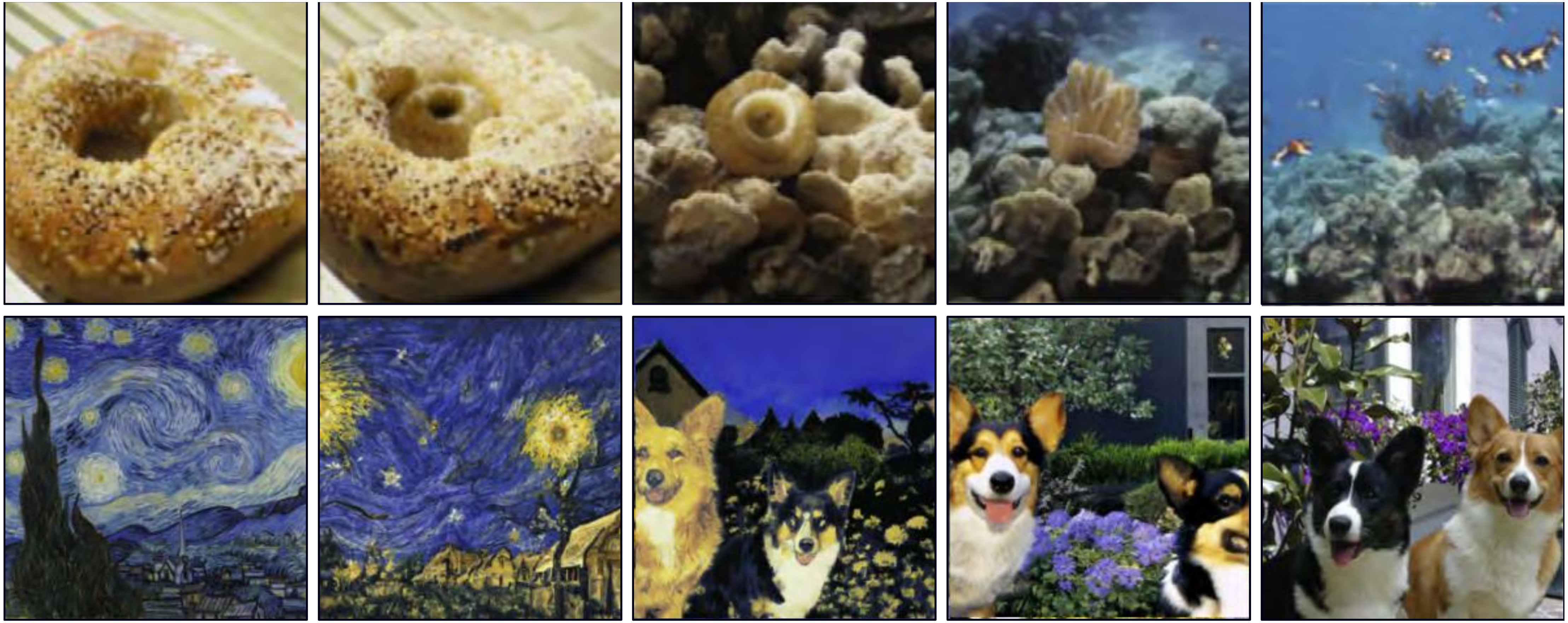
Why should this work?

The human face contains roughly 42
muscles, so it’s possible to describe most of the variation in images of the same person in the same lighting with just 42 numbers.

Latent variables



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.

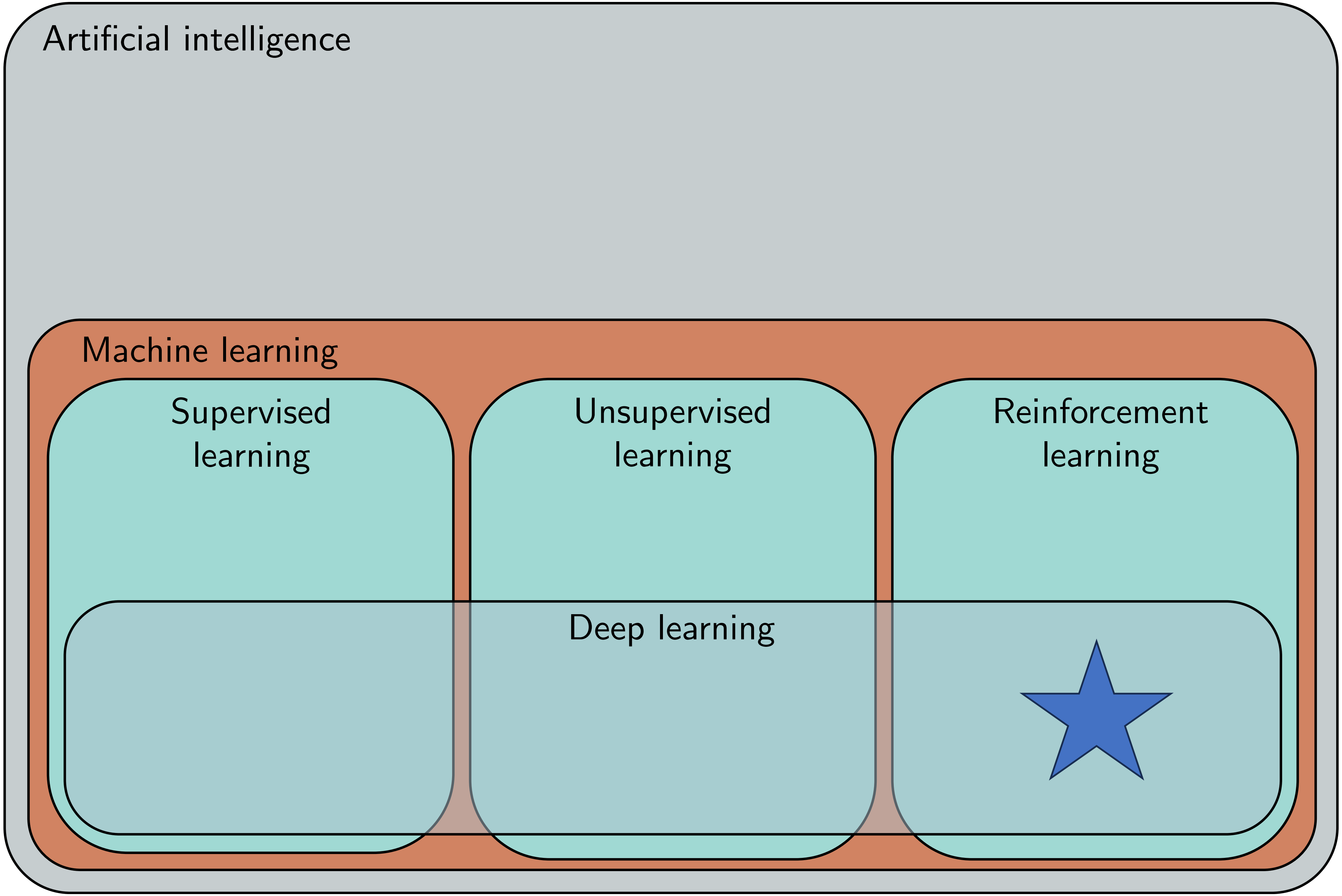
I stood there for a few moments, trying to make sense of what had just happened. Then I realized that the students were all staring at me, waiting for me to say something. I tried to think of something witty or clever to say, but my mind was blank. So I just said, ”Well, that was strange,” and then I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

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!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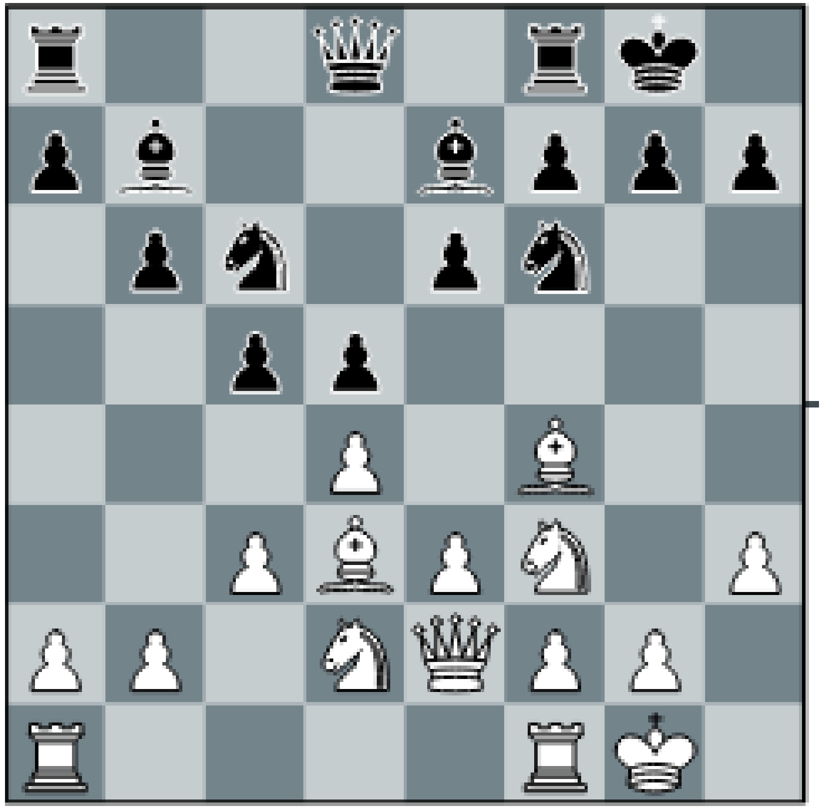
Reinforcement Learning

- An agent that lives in a world and can perform certain actions at each timestep.
- Taking an action can also produce rewards
- The goal is to choose actions that lead to high rewards
- *temporal credit assignment problem:* reward may occur some time after the action is taken
- exploit what it knows or explore other opportunities



Reinforcement learning

- A set of states
- A set of actions
- A set of rewards

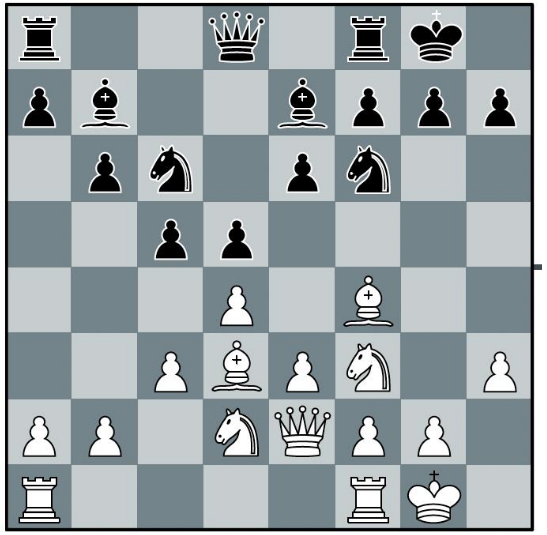
- Goal: take actions to change the state so that you receive rewards

- You don’t receive any data – you have to explore the environment yourself to gather data as you go

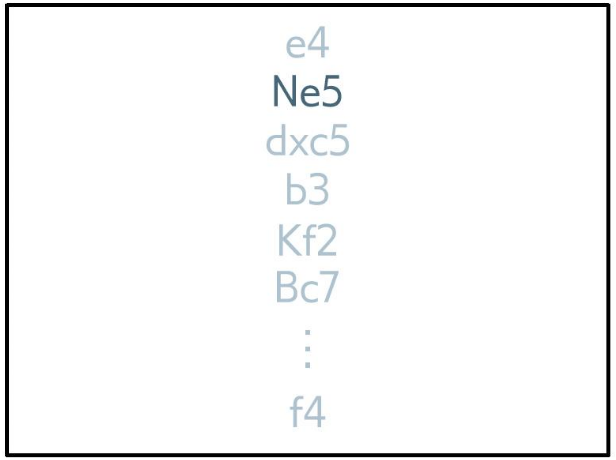
Example: chess

- States are valid states of the chess board
- Actions at a given time are valid possible moves
- Positive rewards for taking pieces, negative rewards for losing them

State



Action



Example: chess

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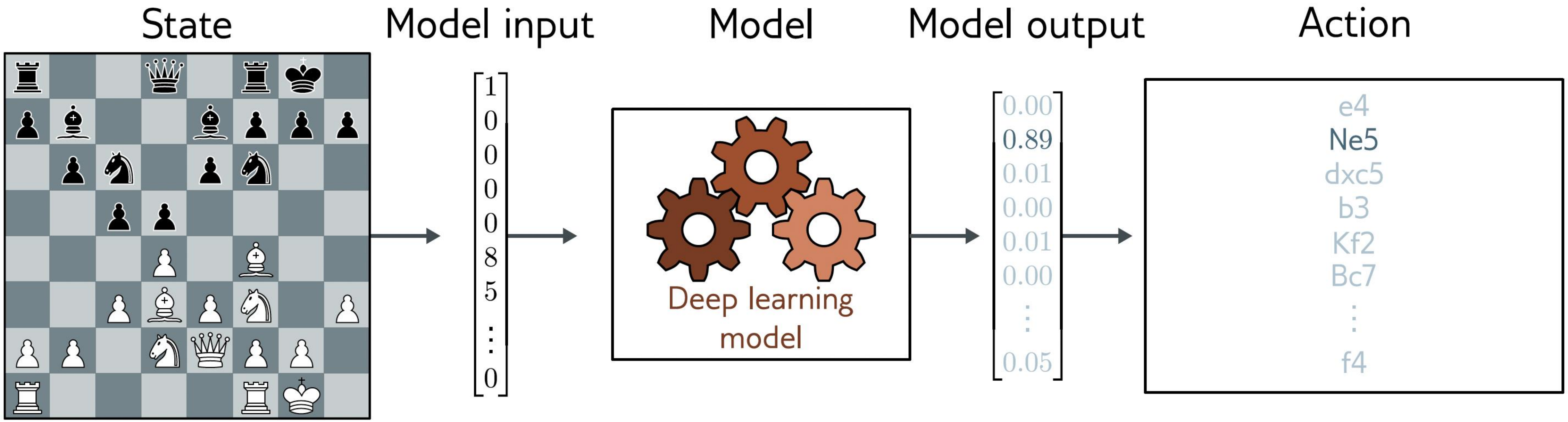

Why is this difficult?

- Stochastic
  - Make the same move twice, the opponent might not do the same thing
  - Rewards also stochastic (opponent does or doesn’t take your piece)
- Temporal credit assignment problem
  - Did we get the reward because of this move? Or because we made good tactical decisions somewhere in the past?
- Exploration-exploitation trade-off
  - If we found a good opening, should we use this?
  - Or should we try other things, hoping for something better?

This course

- Chapter 1 - Introduction
- Chapter 2 - Supervised learning
- Chapter 3 - Shallow neural networks
- Chapter 4 - Deep neural networks
- Chapter 5 - Loss functions
- Chapter 6 - Training models
- Chapter 7 - Gradients and initialization
- Chapter 8 - Measuring performance
- Chapter 9 - Regularization
- Chapter 10 - Convolutional networks
- Chapter 11 - Residual networks
- Chapter 12 - Transformers
- Chapter 13 - Graph neural networks
- Chapter 14 - Unsupervised learning
- Chapter 15 - Generative adversarial networks
- Chapter 16 - Normalizing flows
- Chapter 17 - Variational autoencoders
- Chapter 18 - Diffusion models
- Chapter 19 - Deep reinforcement learning
- Chapter 20 - Why does deep learning work?
- Chapter 21 - Deep learning and ethics

Networks specialized to text
Text generation
Automatic translation
ChatGPT

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Generative learning (unsupervised)
Generating random cats!

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Feedback