Chapter 1: Machine Learning Paradigms

Advanced Topics in Statistical Machine Learning

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Course Overview

Course Team

Lecturers

- Eugenio Clerico — eugenio.clerico@stats.ox.ac.uk (weeks 1-4)
- Desi R Ivanova — desi.ivanova@stats.ox.ac.uk (weeks 5-8)

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Class Tutors

- Eugenio Clerico — eugenio.clerico@stats.ox.ac.uk (sets 1-2)
- Desi R Ivanova — desi.ivanova@stats.ox.ac.uk (sets 1-2)
- Dongqing Li — dongqing.li@kellogg.ox.ac.uk (sets 3-4)
- Kianoosh Ashouritaklimi — kianoosh.ashouritaklimi@jesus.ox.ac.uk (set 5)

Class TAs

- Ruotong Cao — ruotong.cao@jesus.ox.ac.uk (sets 1-2)
- Shiyi Sun — shiyi.sun@spc.ox.ac.uk (set 3)
- Ole Jorgensen — ole.jorgensen@some.ox.ac.uk (set 4)
- Kianoosh Ashouritaklimi — kianoosh.ashouritaklimi@jesus.ox.ac.uk (set 5)

Course Essentials

Who is the course for?

- MMath Part C, OMMS, MSc in Statistical Science, CDT and DPhil students, anyone else who wants to follow along

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Prerequisites

- Only true prerequisite is basic statistics and maths; course should be self–contained
- SB2.2/SM4 Statistical Machine Learning will be very helpful: there is noticeable overlap but because it runs at the same time (for MSc) we will go over everything you need again

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Course resources

- Everything should be available through Canvas `https://canvas.ox.ac.uk/courses/295109`

Course Structure

- Detailed slides provided for each lecture—these should be your primary point of reference
- Also separate set of course notes (~ 100 pages)—designed to supplement lectures, sometimes provides extra details or alternative viewpoints
- 4 problems sheets
- Recorded lectures from previous year available on Canvas site

Assessment

- Written examination (undergrads and masters)
- D.Phil and CDT students wanting to do the course for credit instead will instead write a 12–page literature review on a topic from the course and need to make arrangements for their own marker (see course website for details)

Topics

1. Review of fundamentals

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2. Constrained optimization and SVMs

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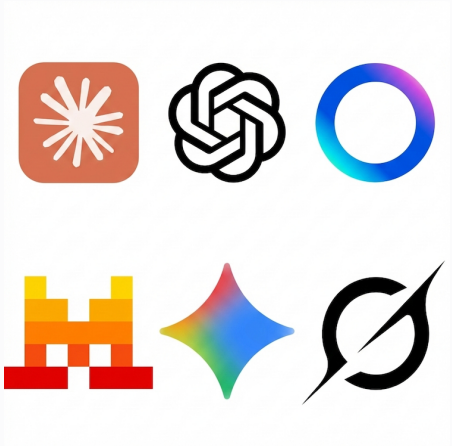
6. Deep learning
7. Variational encoders
8. Large language models

What is Machine Learning?

Modern machine learning

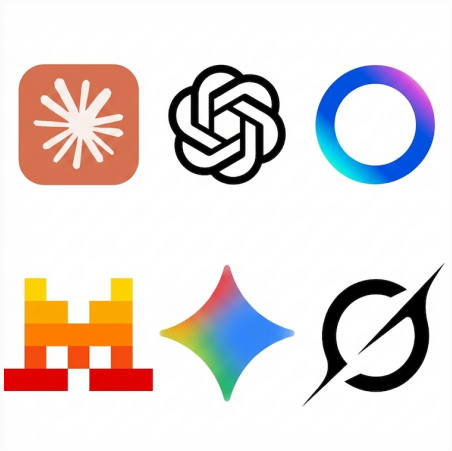


LLMs

diffusion models

self-driving cars

Modern machine learning



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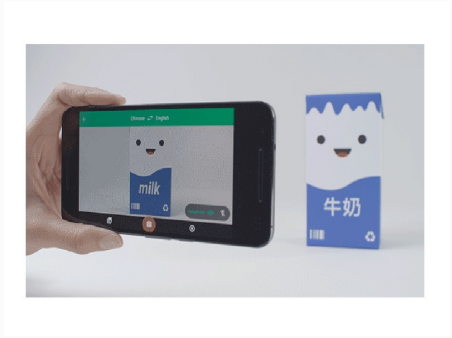
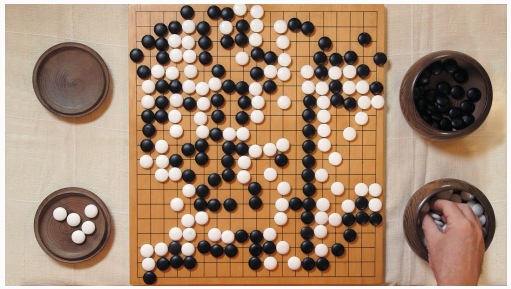


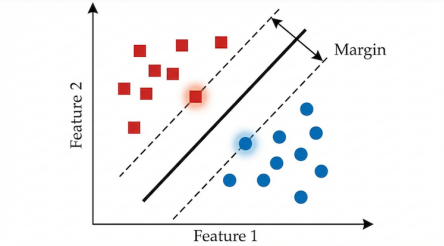
machine translation

image recognition

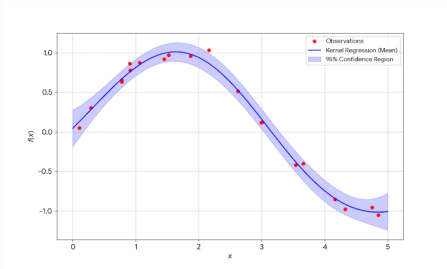


AlphaGo

Classical machine learning



SVMs



kernel regression

recommender systems

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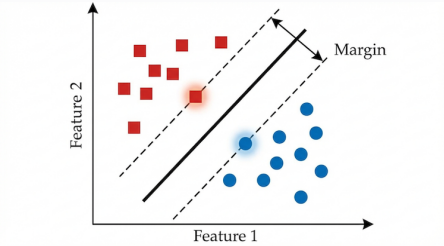

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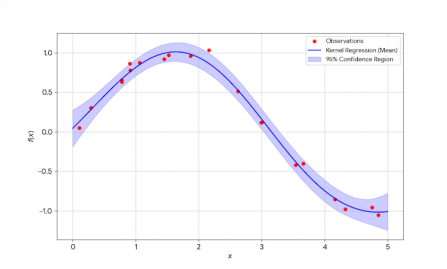

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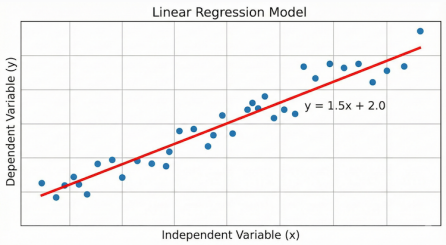
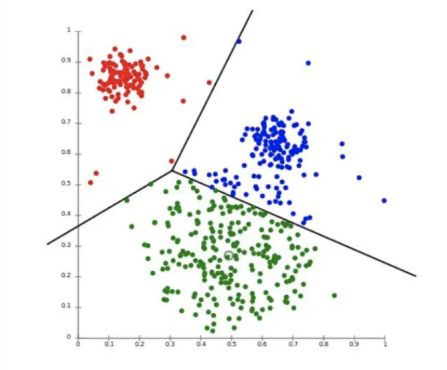
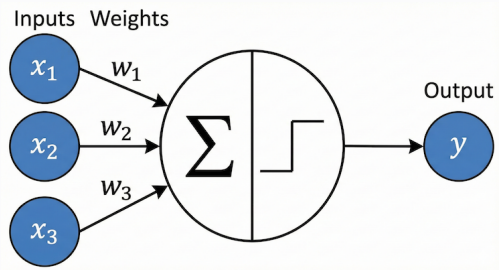


linear regression



k-mean clustering



perceptron

Learning from Data

Kevin Murphy, 2012

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- There is generally a focus on making predictions at unseen datapoints
- Starting point is typically a dataset—we can delineate approaches depending on type of dataset

Supervised vs Unsupervised Machine Learning

Supervised Learning

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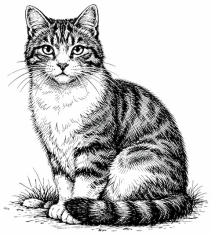
- Most common examples are classification and regression

Supervised Learning—Classification



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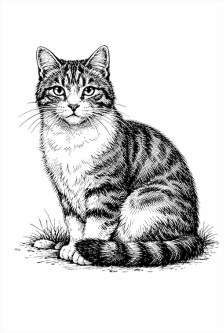
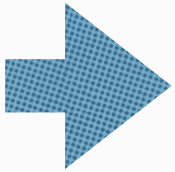
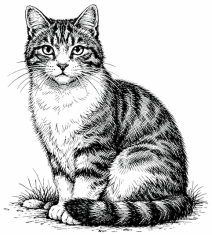




Cat

Supervised Learning—Classification



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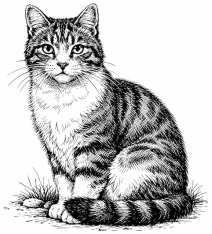

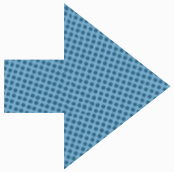

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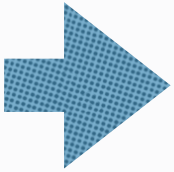

Dog

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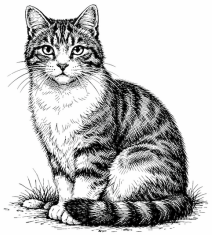

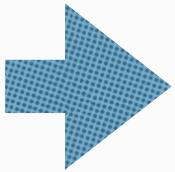

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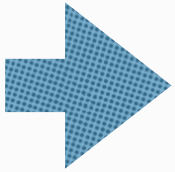

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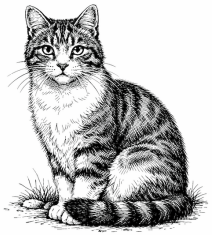

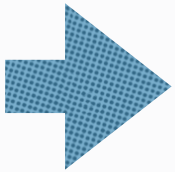

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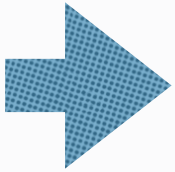

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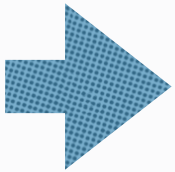

Okapi

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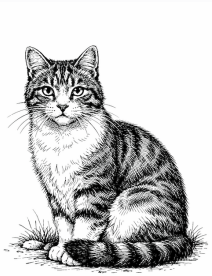
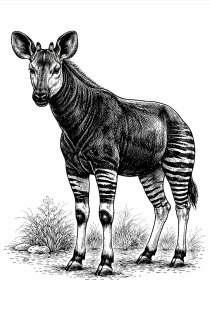




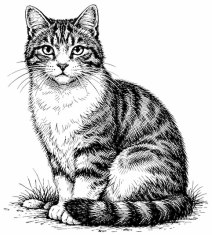
Input x

Cat

Dog

Okapi

Supervised Learning—Classification



Cat

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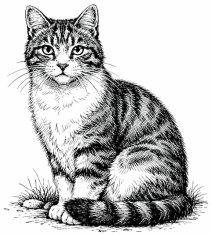
Input x

Class label y

Supervised Learning—Classification



Cat

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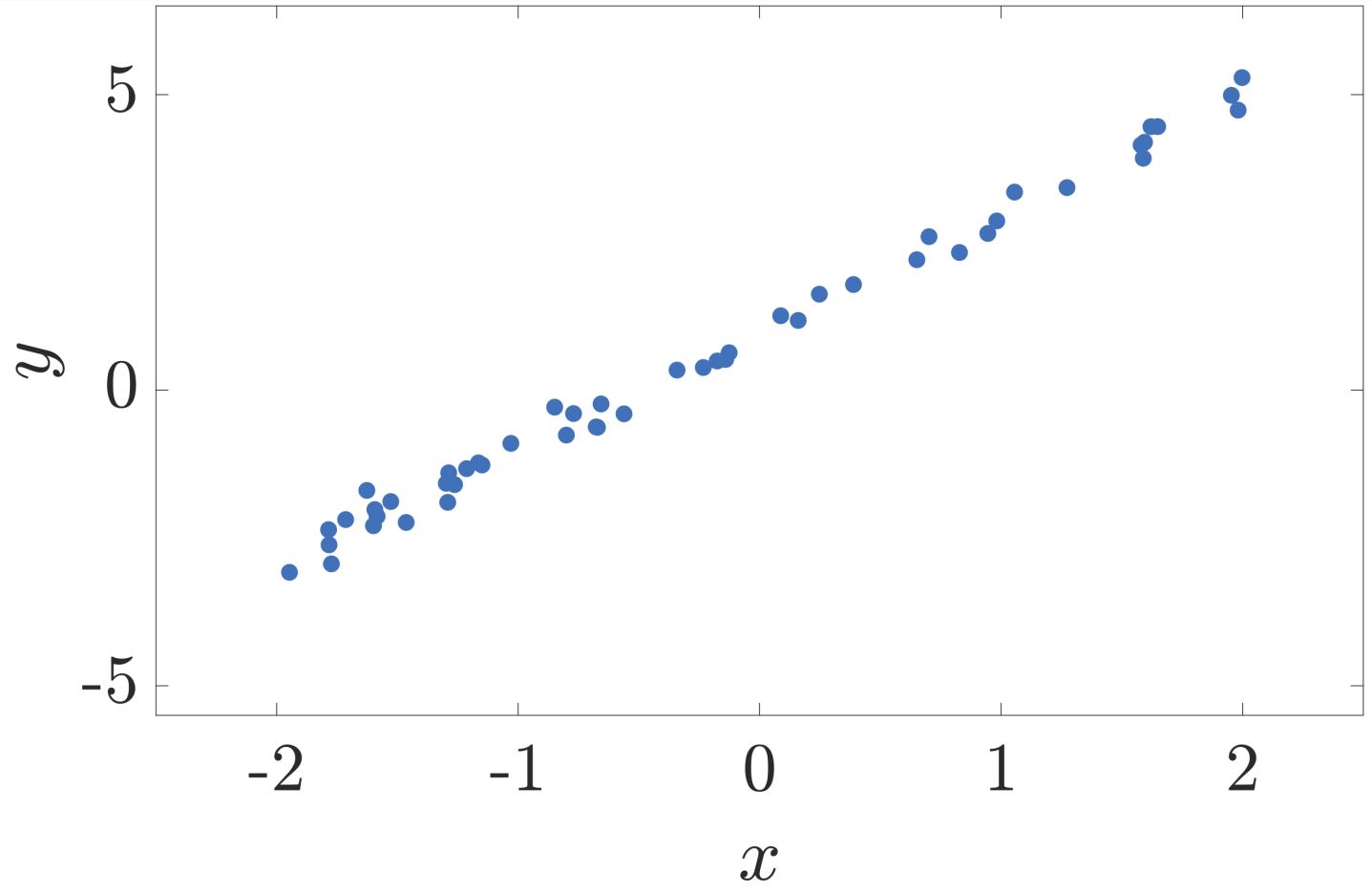
Input x

Predictor $f(x)$

Class label y

Supervised Learning—Regression



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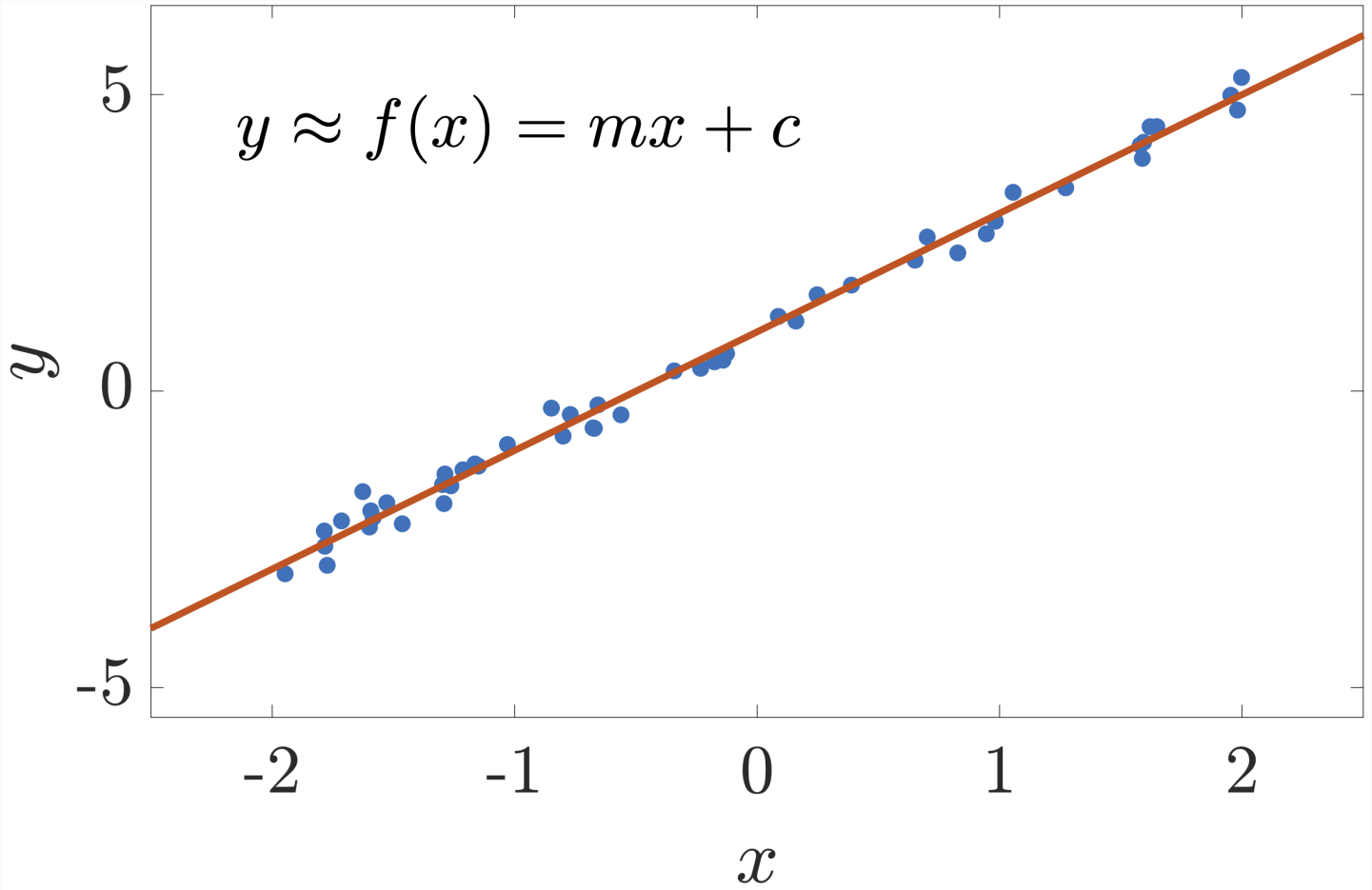

Supervised Learning

Datapoint Index	x_1	x_2	x_3	…	x_M	y
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2	0.56	1.22	0.20	…	1.03	2
3	-3.20	-0.01	0.21	…	0.93	1
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N	2.24	1.76	-0.47	…	1.16	2

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- Use this data to learn a predictive model $f_\theta : \mathcal{X} \to \mathcal{Y}$ (e.g. by optimizing θ)
- Once learned, we can use this to predict outputs for new input points, e.g. $f_\theta([0.48 \;\; 1.18 \;\; 0.34 \;\; \ldots \;\; 1.13]) = 2$

Unsupervised Learning

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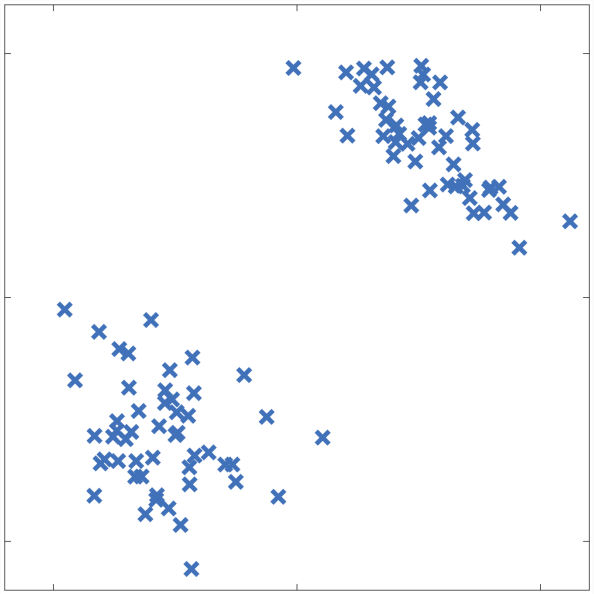
- Examples: clustering, feature extraction, density estimation, representation learning, data visualization, data compression

Unsupervised Learning—Clustering



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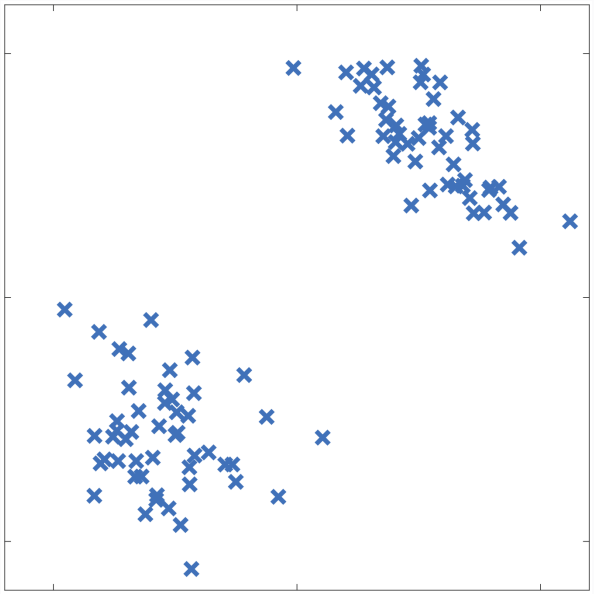

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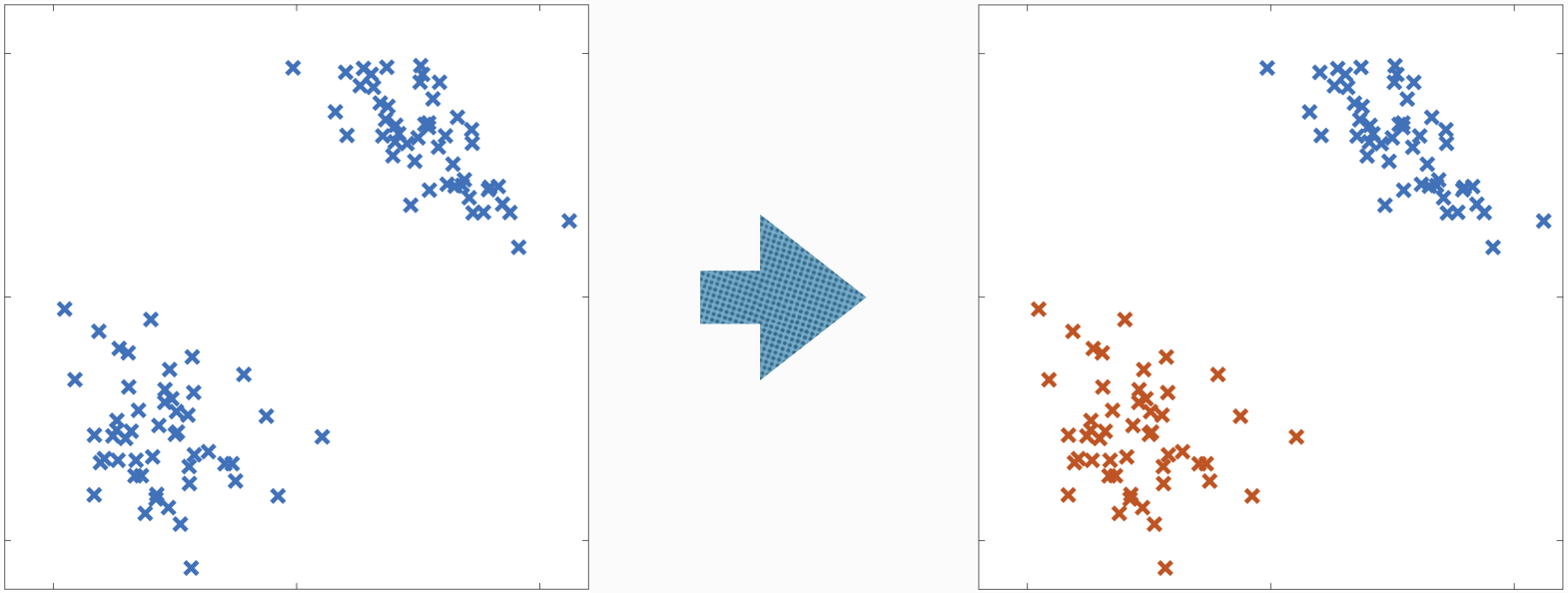

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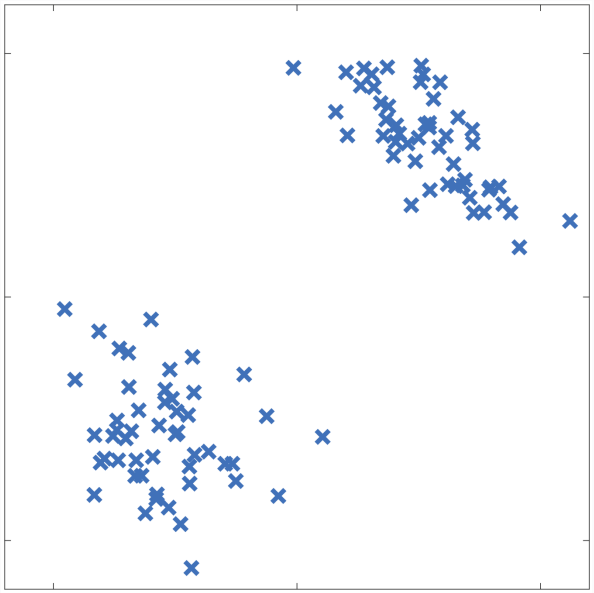
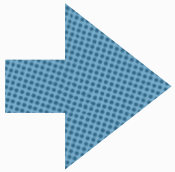
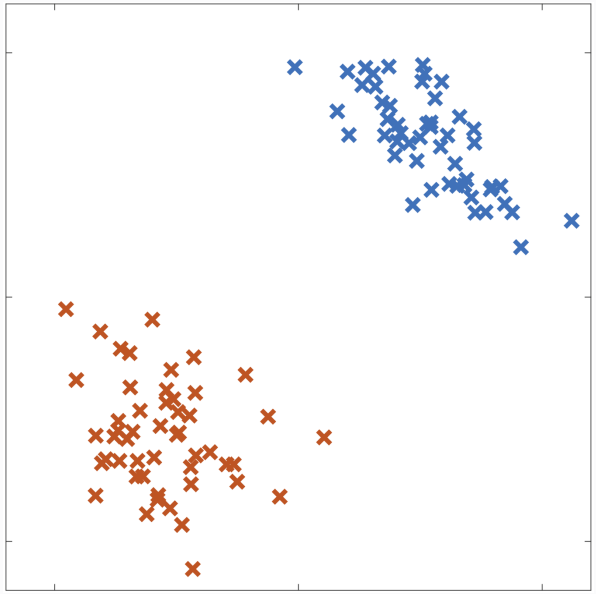


Unlabeled Data





Group into Clusters

Unsupervised Learning—Generative Models

Learn powerful models for generating new datapoints

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These are not real faces: they are samples from a learned model!

Other Types of Machine Learning

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Discriminative vs Generative Machine Learning

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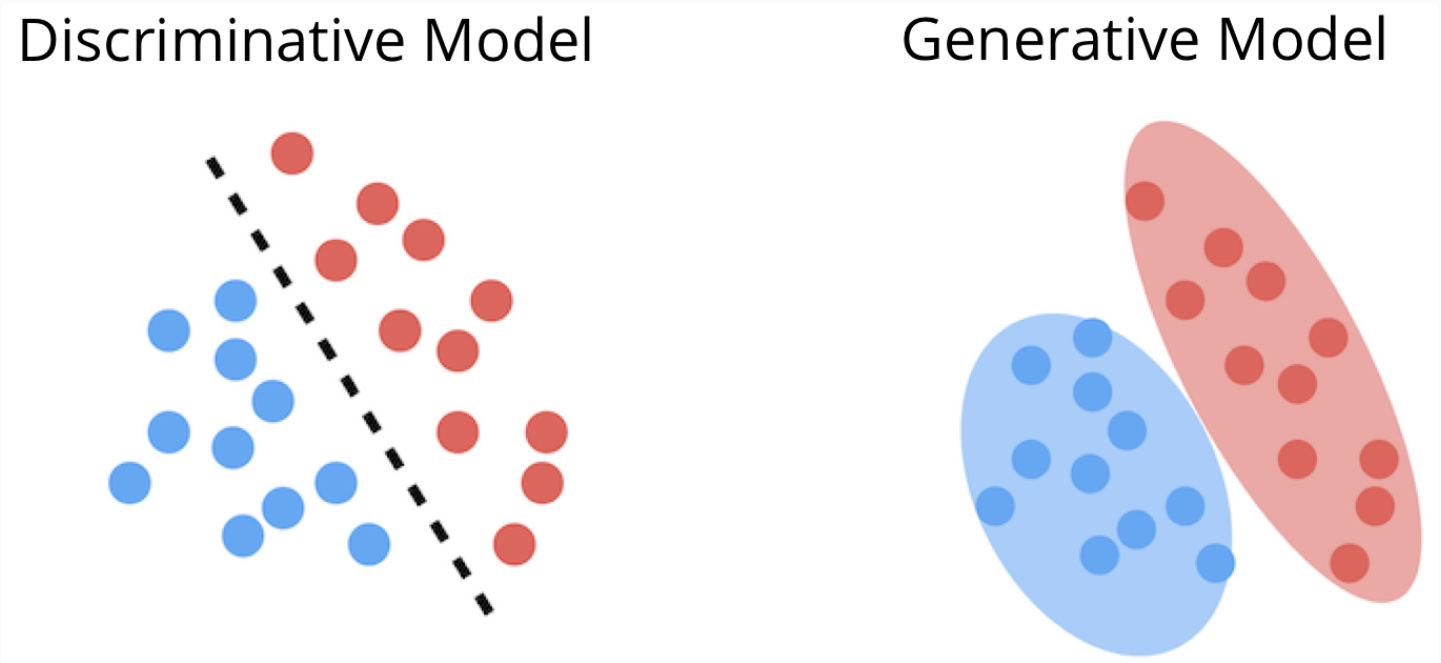

Image credit: Jason Martuscello, medium.com

Discriminative Machine Learning

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Common approaches: neural networks, support vector machines, random forests, linear/logistic regression, k–nearest neighbors

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    - This is the foundation for Bayesian machine learning

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- Tend to require more problem–specific expertise

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- Supervised learning has access to **outputs**, unsupervised learning does not
- Discriminative methods try and **directly** make predictions, generative methods try to explain **how** the data is generated

Further Reading

- Look at the course notes!
- Chapter 1 of K P Murphy. **Machine learning: a probabilistic perspective.** 2012.

  `https://www.cs.ubc.ca/~murphyk/MLbook/pml-intro-22may12.pdf`.
- L Breiman. **"Statistical modeling: The two cultures".** In: **Statistical science** (2001)