Foundations of AI and Machine Learning

Alex Olson

Welcome!

- My name is Alex Olson
- Senior Research Associate at CARTE
- Bachelor’s in AI from the University of Edinburgh
- Master’s in AI from UofT in collaboration with the School of Cities
- Published papers in collaboration with a wide array of disciplines
- Work closely with students and faculty on all types of AI

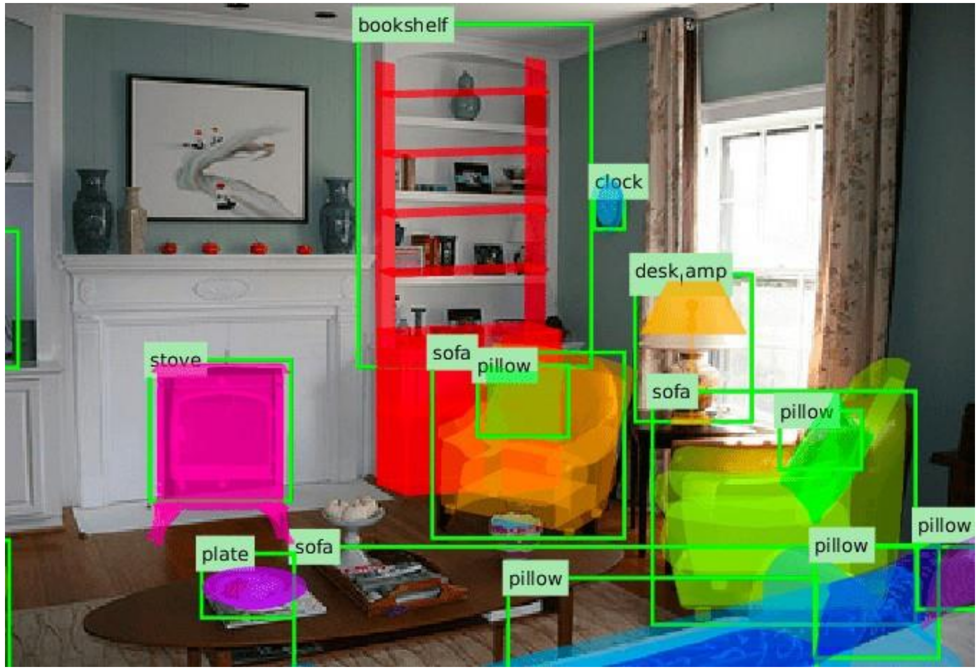
Defining Artificial Intelligence

- Many terms out there with overlapping or confused meanings
  - Artificial Intelligence
  - Machine Learning
  - Deep Learning
  - Data Science
- You will find that in AI, we like to have many terms meaning the same thing!

Artificial Intelligence

- Getting computers to behave intelligently:
  - Perform non-trivial tasks as well as humans do
  - Perform tasks that even humans struggle with

- Many sub-goals:
  - Perception
  - Reasoning
  - Control
  - Planning



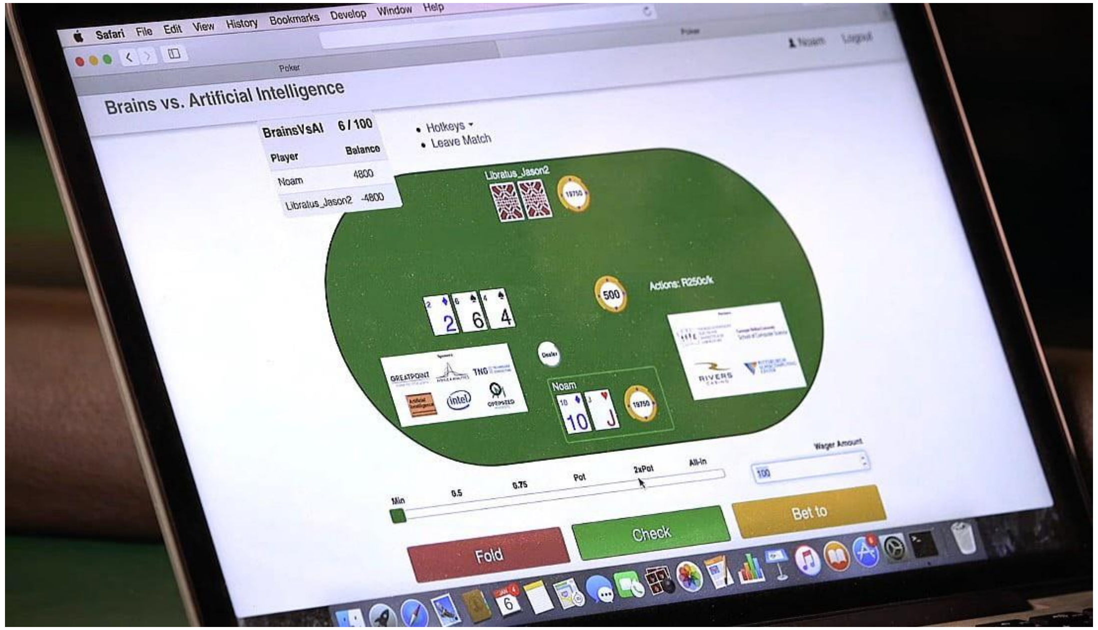
My poker face: AI wins multiplayer game for first time

Pluribus wins 12-day session of Texas hold'em against some of the world's best human players

Speech Recognition: Perception + Reasoning

Autonomous Driving: Perception + Reasoning Control + Planning

Game Playing: Reasoning + Planning

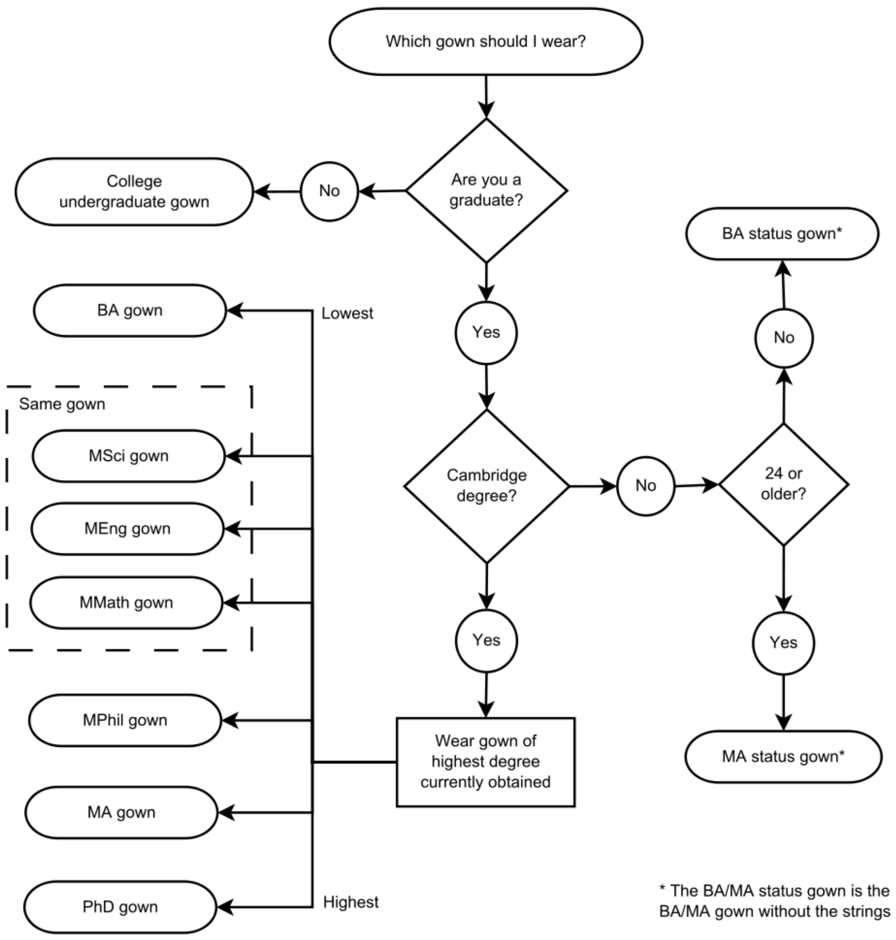


Knowledge-Based AI

Write programs that simulate how people solve the problem

Fundamental limitations:

- Will never get better than a person
- Requires deep domain knowledge
- We don't know how we do some things (e.g., riding a bicycle)



Data-Based AI = Machine Learning

Write programs that learn the task from examples

✅ No need to know how we do it as humans
✅ Performance should improve with more examples

❌ May need many examples!
❌ May not understand how the program works!

Machine Learning

- Study of algorithms that
  - Improve their <u>performance</u> P
  - At some <u>task</u> T
  - With <u>experience</u> E
- Well defined learning task: <P,T,E>

The Machine Learning Process

- Study of algorithms that
  - Improve their performance P
  - At some task T
  - With experience E
- Well defined learning task: <P,T,E>

- Experience
  - Examples of the form
    (input, correct output)
- Task
  - Mapping from input to output
- Performance
  - ”Loss function” that measures error w.r.t. desired outcome

Choices in ML Problem Formulation

- Experience
  - Examples of the form (input, correct output)
- Task
  - Mapping from input to output
- Performance
  - ”Loss function” that measures error w.r.t. desired outcome

Loan Applications

- What historical examples do I have? What is a correct output?
- Predict probability of default? Loan decision? Credit score?
- Do I care more about minimizing False Positives? False negatives?

Classification: Three Elements

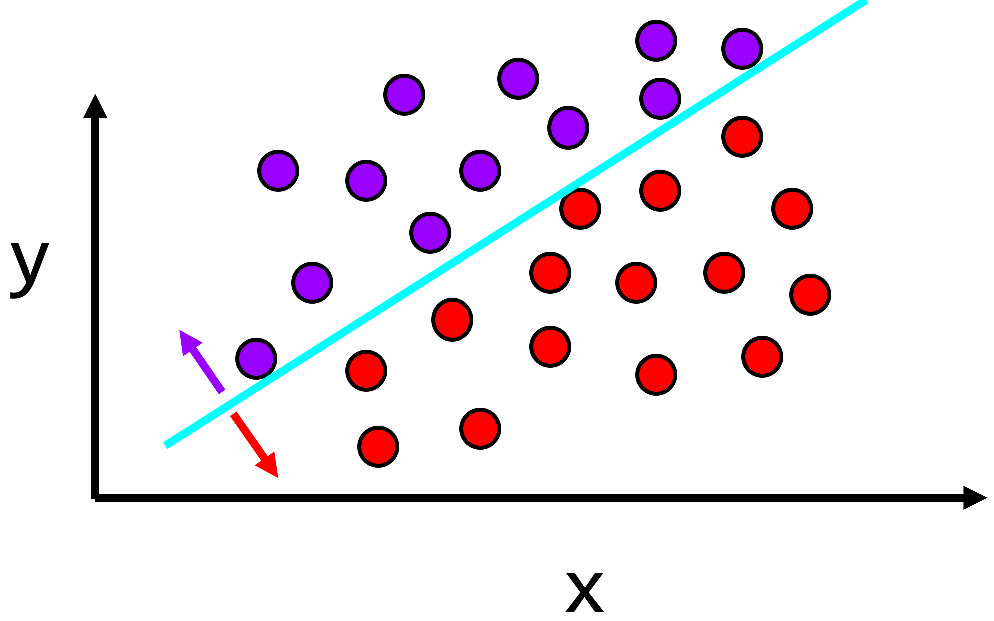
1. Data:
   - x: data example with d attributes
   - y: label of example (what you care about)

2. Classification model: a function $f_{(a,b,c,..}$
   - Maps from X to Y
   - (a,b,c,…) are the parameters

3. Loss function:
   - Penalizes the model's mistakes

Song	Rating
Some nights	⭐⭐⭐⭐⭐
Skyfall	⭐
Comfortably numb	⭐⭐⭐
We are young	⭐⭐⭐⭐
…	…
…	…
Chopin's 5th	???

What is a "model"?



A **useful approximation** of the world

Typically, there are **many reasonable models** for the same data

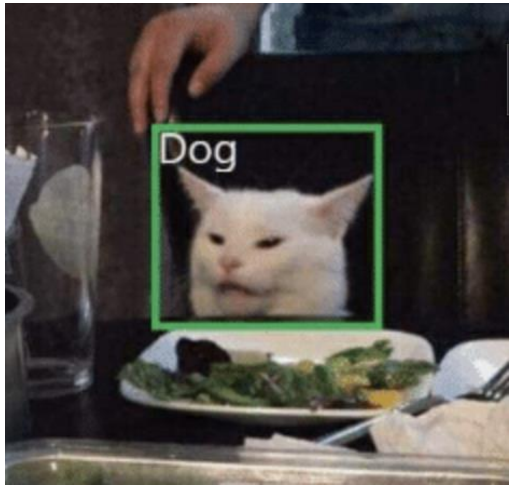
Training a model = finding appropriate values for (a,b,c,...)

- An **optimization** problem
- "appropriate" = **minimizes the Loss (cost)** function
- We will focus on a common training algorithm later on

Classification Loss Function

- How unhappy are you with the answer that the model gave?

- $\mathbf{L_{0\text{-}1}(y, f(x))} = 1$ if: $\mathbf{y \neq f(x)}$
  0 otherwise



- **0-1 loss** function: intuitive but hard to optimize = train

- In practice, we use **approximations** of the 0-1 loss – getting warmer or getting colder

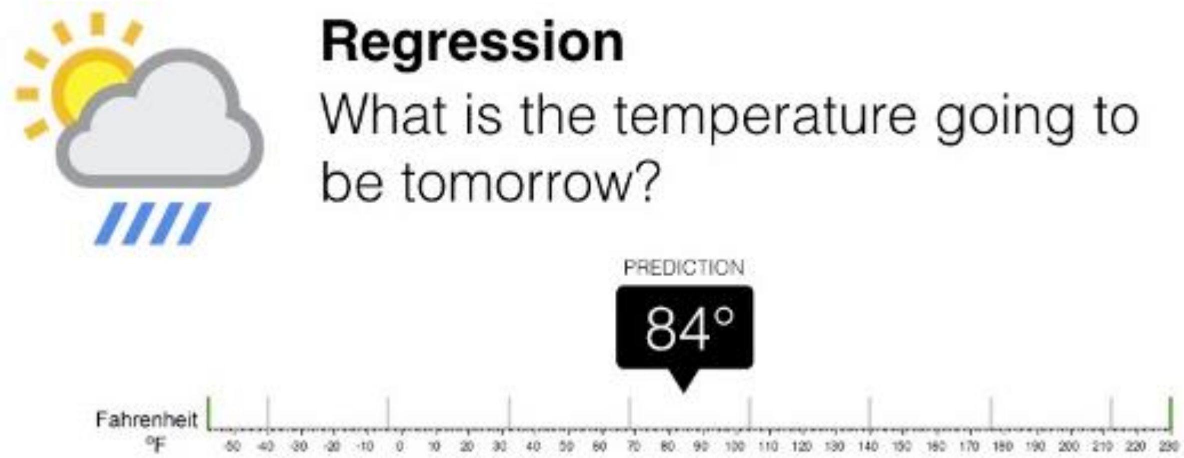
Regression

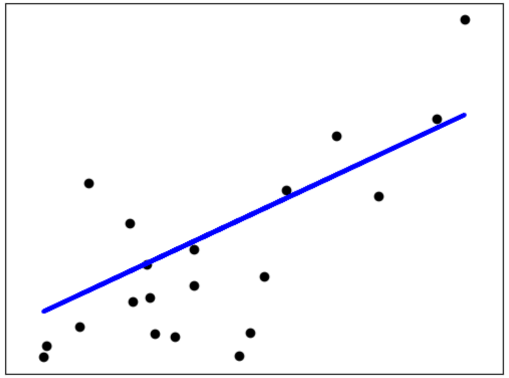
Examples:

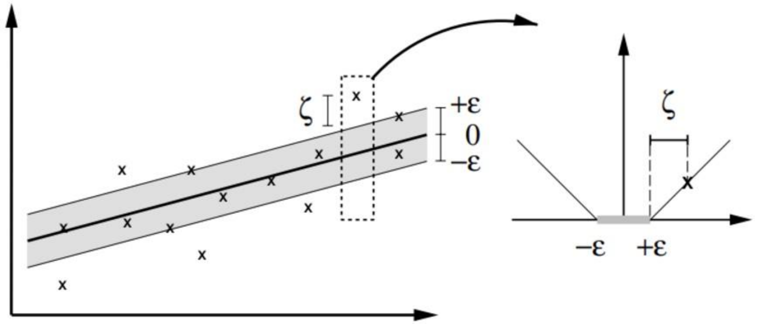
- Stock price prediction
- Forecasting epidemics
- Weather prediction

We will look at:

- Linear Regression
- Ridge Regression
- LASSO







Linear Regression

Data: $S = \{(x_1, y_1), (x_2, y_2), \ldots, (x_i, y_i)\}$

x_i: data example with d attributes

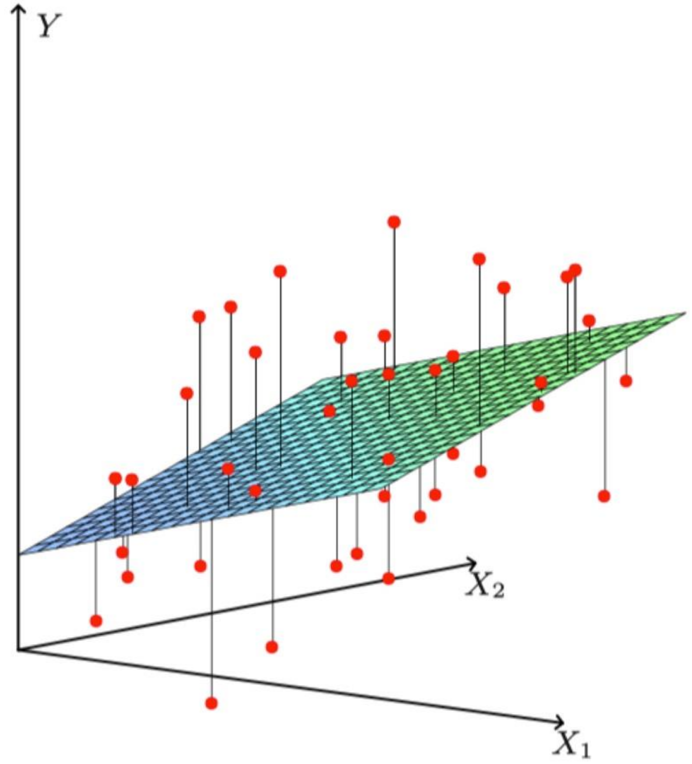
y_i: target of example (what you care about)

Model:

$$f(x;\boldsymbol{\beta}) = \beta_0 + \beta_1 x_1 + \cdots + \beta_d x_d$$

Loss function: Residual Sum of Squares

$$RSS(\boldsymbol{\beta}) = \sum_{i=1}^{n} \left(y_i - f(x_i;\boldsymbol{\beta})\right)^2$$



Ridge Regression

- Linear Regression uses all features; model may be complicated
- **Ridge Regression** penalizes large parameter values

Model:

$$f(x;\boldsymbol{\beta}) = \beta_0 + \beta_1 x_1 + \cdots + \beta_d x_d$$

Loss function: Residual Sum of Squares + penalty term

$$RSS(\boldsymbol{\beta}) = \sum_{i=1}^{n} \left(y_i - f(x_i;\boldsymbol{\beta})\right)^2 + \boldsymbol{\lambda} \sum_{j=0}^{d} \beta_j^2$$

Lasso Regression

- **As in Ridge Regression, Lasso** penalizes large parameters
- Penalizes **absolute** instead of squared coefficient values
- **Zeroes out** more coefficients **BUT** optimization is more involved

Model:

$$f(x;\boldsymbol{\beta}) = \beta_0 + \beta_1 x_1 + \cdots + \beta_d x_d$$

Loss function: Residual Sum of Squares + penalty term

$$RSS(\boldsymbol{\beta}) = \sum_{i=1}^{n} \left(y_i - f(x_i;\boldsymbol{\beta})\right)^2 + \lambda \sum_{j=0}^{d} |\beta_j|$$

Example: Prostate Cancer

Stamey et al. (1989)

- x: cancer volume, prostate weight, age, ...
- y: amount of prostate-specific antigen

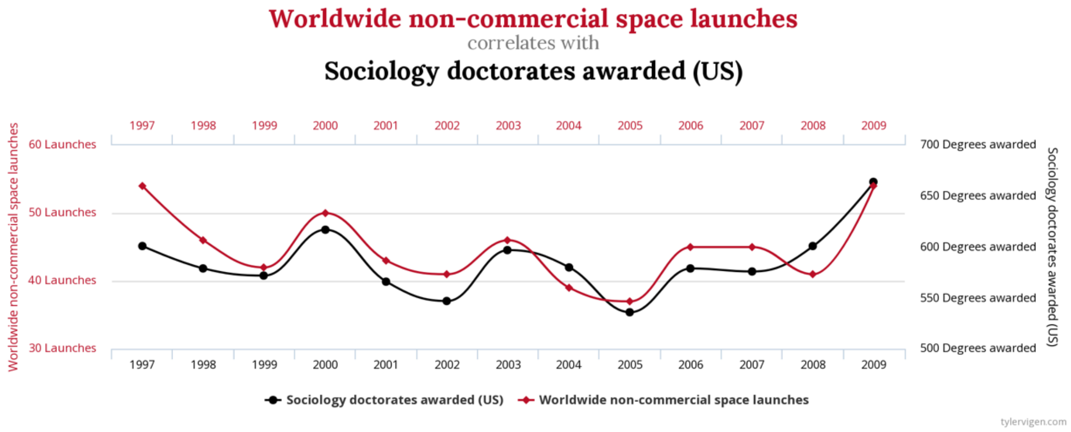
Term	LS	Best Subset	Ridge	Lasso
Intercept	2.465	2.477	2.452	2.468
lcavol	0.680	0.740	0.420	0.533
lweight	0.263	0.316	0.238	0.169
age	−0.141		−0.046	
lbph	0.210		0.162	0.002
svi	0.305		0.227	0.094
lcp	−0.288		0.000	
gleason	−0.021		0.040	
pgg45	0.267		0.133	
Test Error	0.521	0.492	0.492	0.479
Std Error	0.179	0.143	0.165	0.164

Correlation vs. Causation

- Correlation measures the strength and direction of a relationship between two variables
- Causation refers to a cause-and-effect relationship, where one variable directly influences the other
- It's crucial to remember that a strong correlation doesn't necessarily imply causation

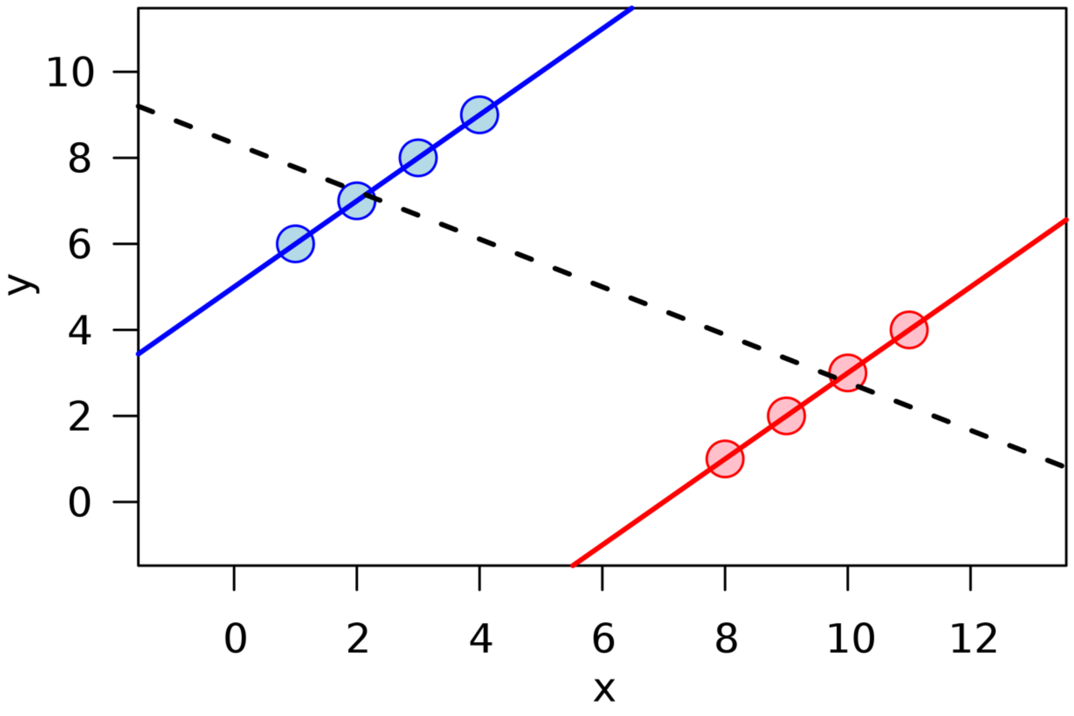
Correlation vs. Causation

- To avoid confusion between correlation and causation:
  - Consider possible confounding variables or third factors
  - Look for evidence of a causal mechanism
  - Test the relationship using controlled experiments or statistical methods



Simpson's Paradox

- A trend or relationship between two factors seems to exist when you look at separate groups but disappears or even reverses when you combine the groups together.
- To avoid Simpson's Paradox:
    - Investigate data at different levels of aggregation
    - Consider the influence of confounding variables
    - Use caution when combining data from different sources or groups



Simpson's Paradox

- In 1973, UC Berkeley found that men applying were more likely to be admitted than women

	All	Men	Women
Applicants Admitted	41%	44%	35%

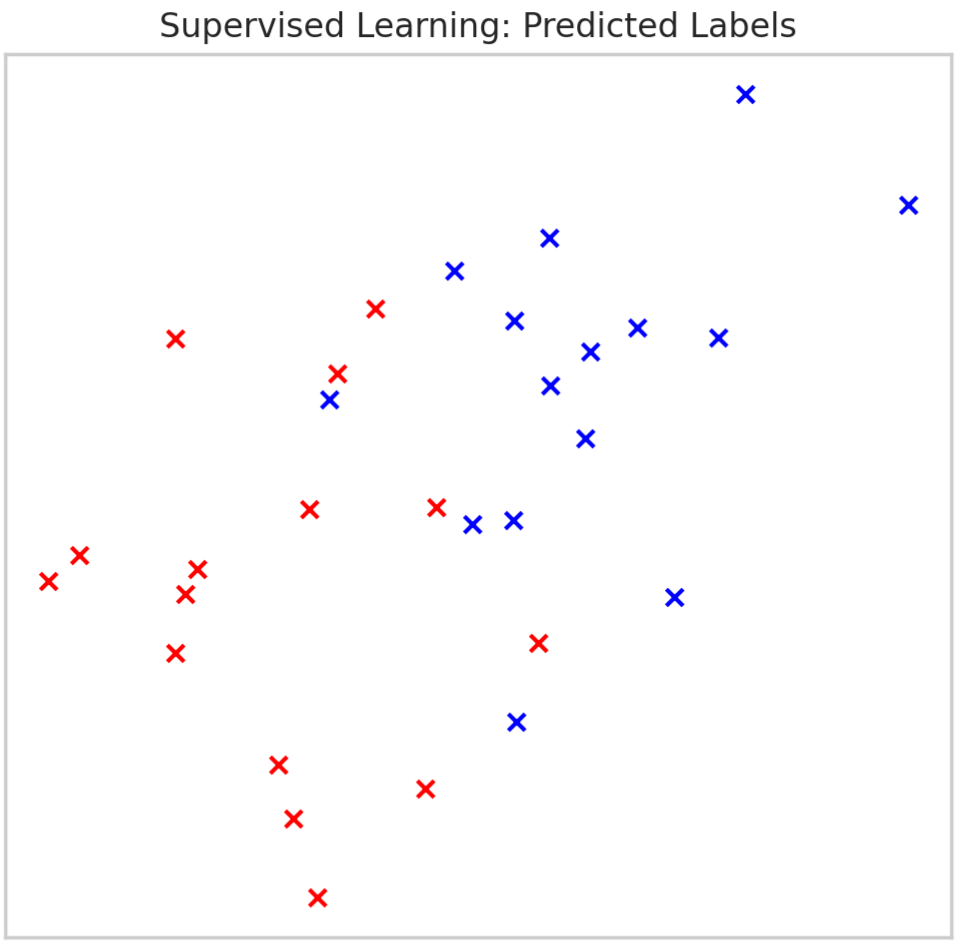
Simpson’s Paradox

- In 1973, UC Berkeley found that men applying were more likely to be admitted than women
- But when analyzed at a department level, they found only a small subset of departments with a lot of applicants were biased
- Solving the problem required a targeted approach, not a general one

Department	All	Men	Women
A	64%	62%	82%
B	63%	63%	68%
C	35%	37%	34%
D	34%	33%	35%
E	25%	28%	24%
F	6%	6%	7%
Applicants Admitted	**39%**	**45%**	**30%**

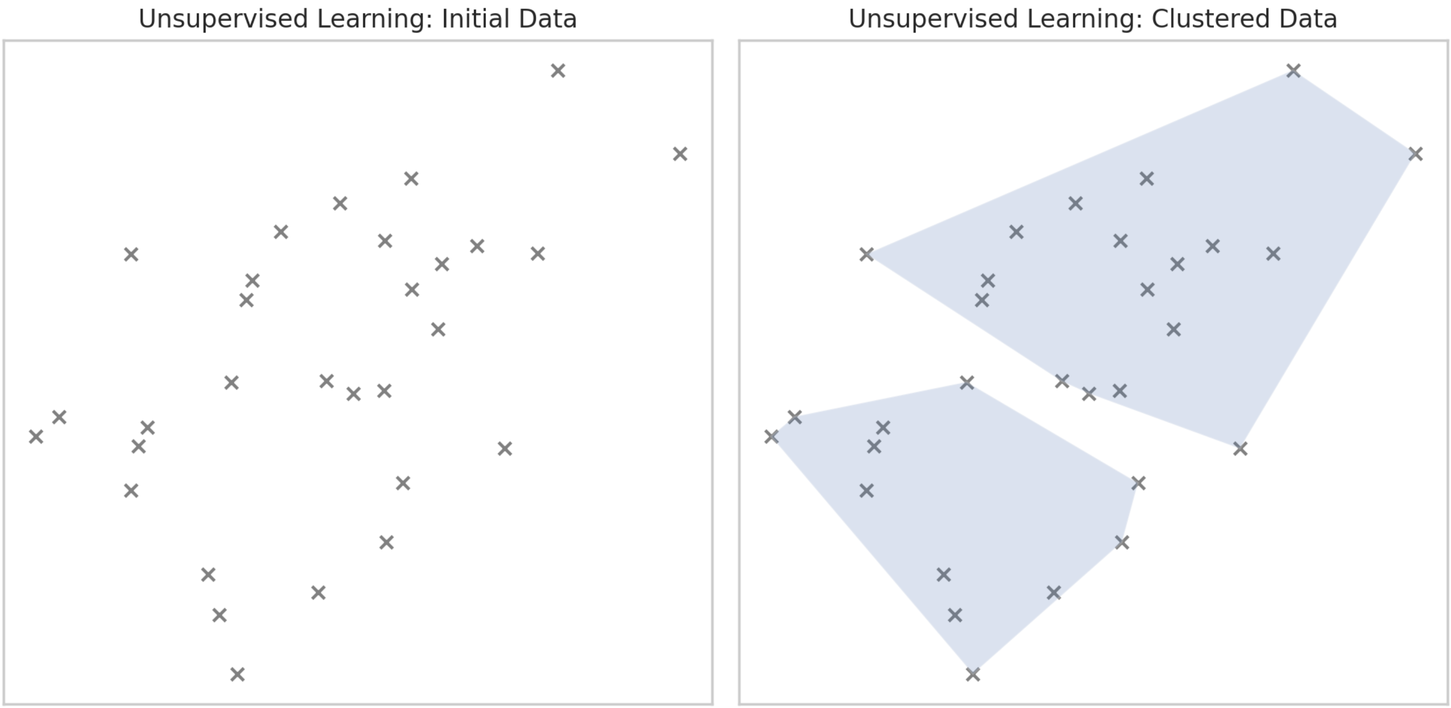
Supervised vs Unsupervised

- So far we have looked at two types of <u>supervised</u> learning
- In both our classification and regression examples, we have examples where we "know the answer"
- With supervised learning, we have a strong definition of the model's performance



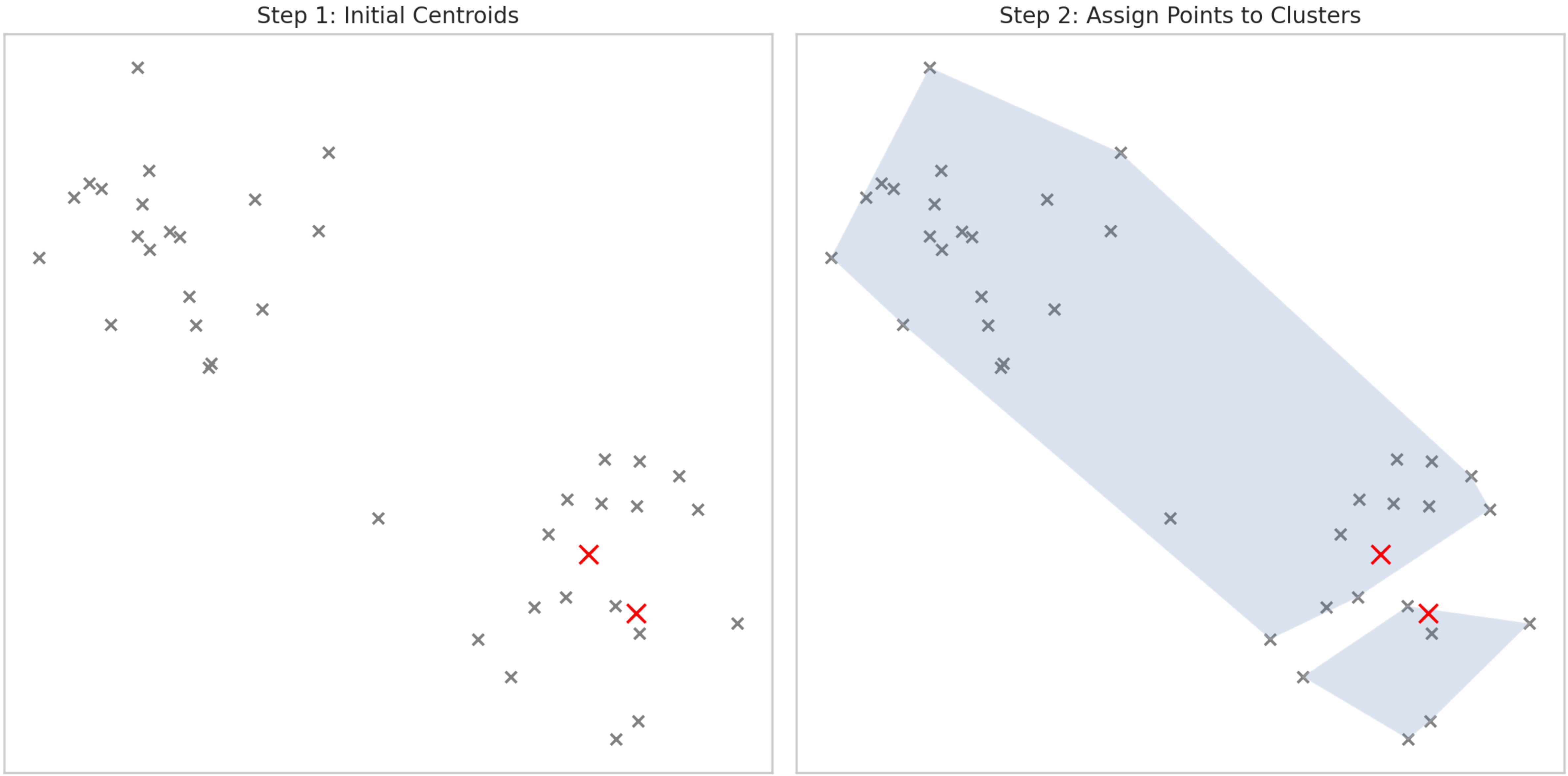
Supervised vs Unsupervised

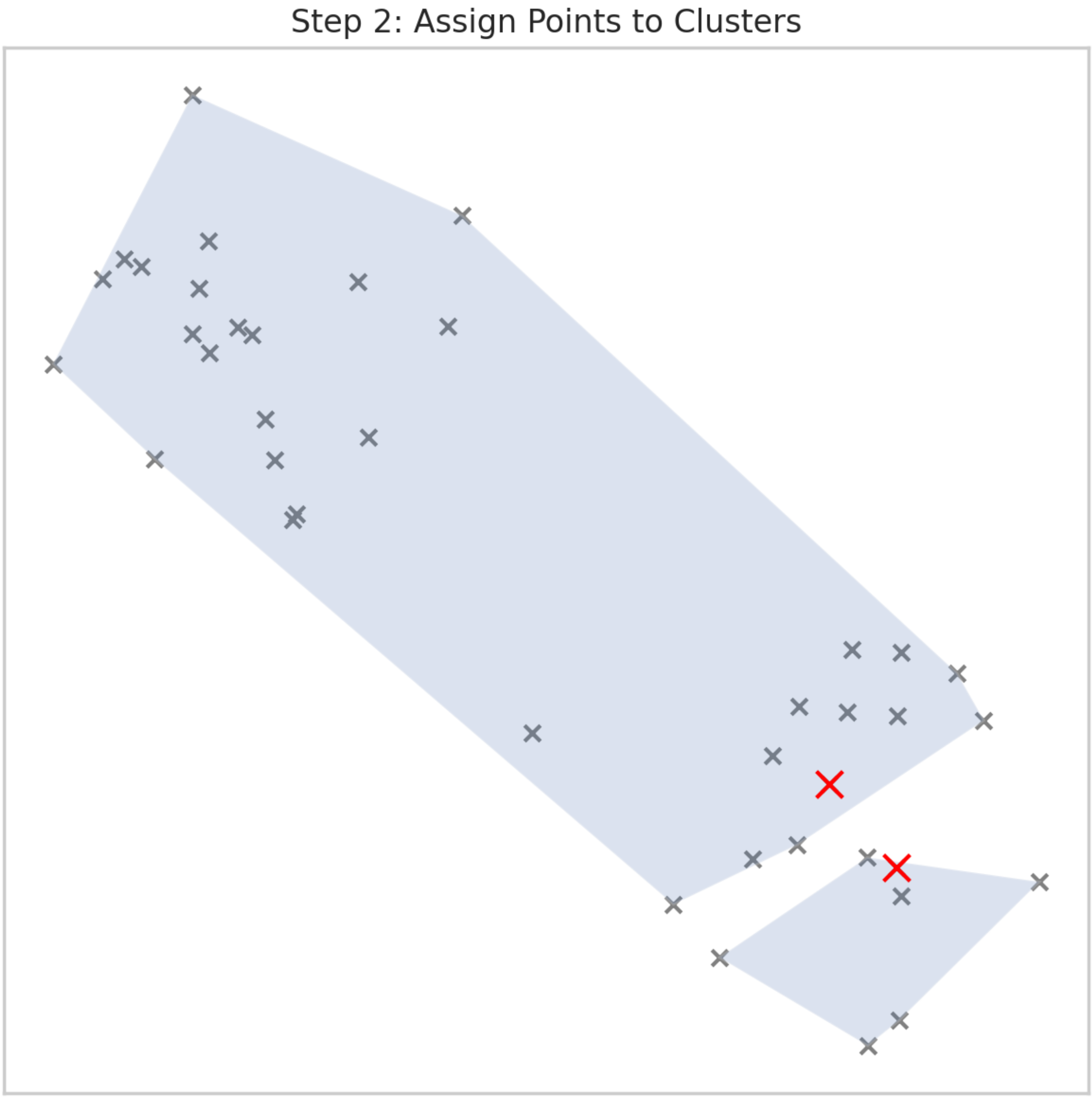
- In <u>unsupervised</u> learning, we don't know what the answer is – collecting this data may be costly, or impossible
- Unsupervised approaches attempt to uncover patterns in the data without relying on a pre-defined label

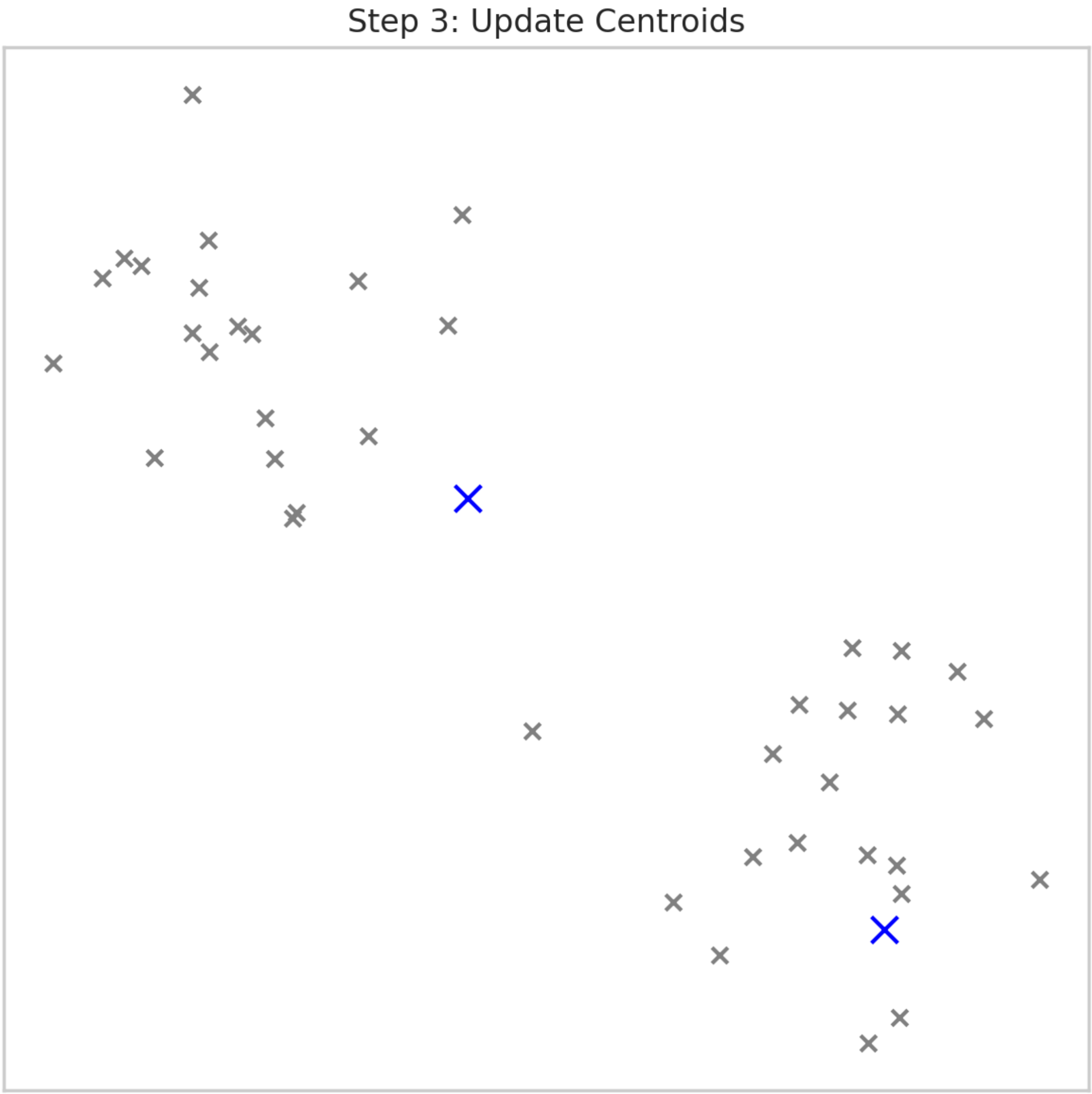


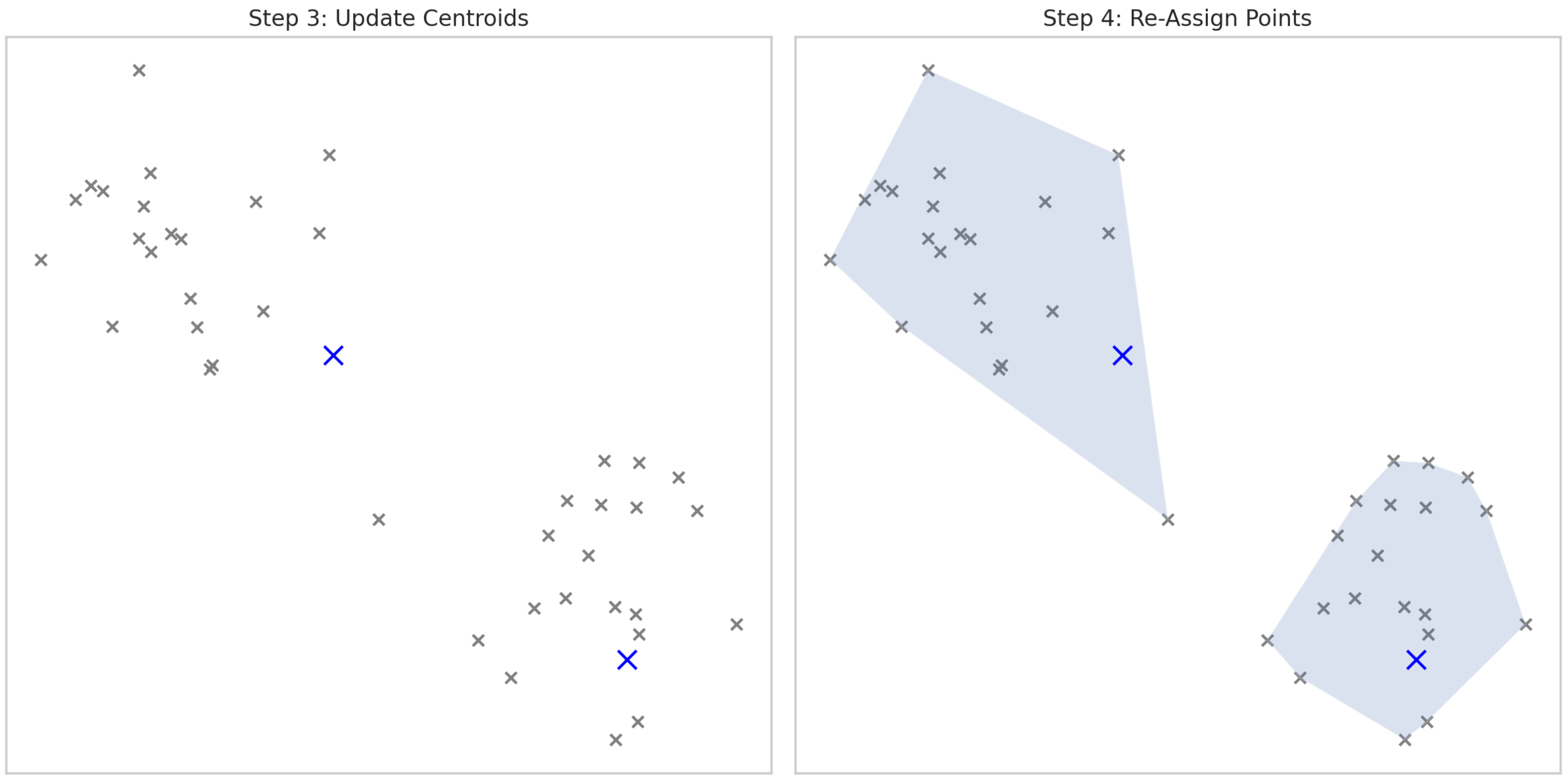
Unsupervised Learning: K-Means Clustering

- Clustering approaches seek to uncover groups within data
- Starting with randomly set groups, we measure the similarity of each point to the possible groups, and re-assign
- This process continues until no points change group


Step 1: Initial Centroids
Step 2: Assign Points to Clusters


Step 2: Assign Points to Clusters


Step 3: Update Centroids



Programming Languages for AI

- Python
  - Dominates AI development due to extensive libraries like TensorFlow, PyTorch, and scikit-learn.
  - Easy syntax, strong community, rich ecosystem for AI research and production.
  - Slower execution compared to lower-level languages, can struggle with very large-scale, performance-critical systems.

Programming Languages for AI

- R
  - Specialized for statistics and data visualization, with packages like caret and ggplot2.
  - Most useful for data preprocessing, statistical modeling, and some ML tasks.
  - Less suited for general-purpose AI development or production-grade systems.

Programming Languages for AI

- C++
  - High performance for real-time applications like gaming or embedded AI. Libraries like dlib and OpenCV excel in computer vision.
  - Core of many Python-based AI tools (e.g., TensorFlow's backend).
  - Steeper learning curve, verbose syntax, slower development time.
- Java
  - Scalability and enterprise use, with frameworks like Weka and Deeplearning4j.
  - Can interact with Python tools via APIs or frameworks like Apache Spark.
  - Verbose and less favored for rapid prototyping.
- Julia
  - High-performance numerical computing, increasingly adopted for AI and optimization.
  - Growing interoperability with Python (e.g., PyCall).
  - Smaller ecosystem and less community support than Python.

Machine Learning Libraries

- PyTorch
  - Intuitive and flexible, with dynamic computation graphs allowing for easier debugging and experimentation.
  - Strong adoption in research, supported by an active community.
  - Less mature deployment tools compared to TensorFlow (though this gap is narrowing).
  - Can be slower in some production scenarios without optimization.

Machine Learning Libraries

- TensorFlow
  - Comprehensive ecosystem with tools for training (TensorFlow), deployment (TensorFlow Serving, TensorFlow Lite), and explainability (What-If Tool).
  - TensorFlow.js and TensorFlow Lite make it suitable for web and mobile development.
  - Strong community and corporate support (Google).
  - Integration with Keras offers a high-level API for beginners.
  - Steeper learning curve compared to PyTorch.
  - Debugging can be less straightforward due to static computation graphs (though this has improved with TensorFlow 2.x).

Machine Learning Libraries

- Scikit-learn
  - Easy-to-use interface for classical machine learning tasks like regression, classification, and clustering.
  - Excellent for preprocessing and feature engineering (e.g., PCA, scalers).
  - Strong documentation and wide adoption in education and small-scale projects.
- XGBoost
  - Extremely efficient and scalable for tabular data tasks.
  - Known for achieving high accuracy with minimal tuning.
  - Distributed training support for large datasets.
- HuggingFace Transformers
  - Simplifies the use of pre-trained transformers for NLP, vision, and multimodal tasks.
  - Strong community and regularly updated with state-of-the-art models.
  - Easy fine-tuning and deployment of large language models (LLMs).