CSE 446/546: Machine Learning

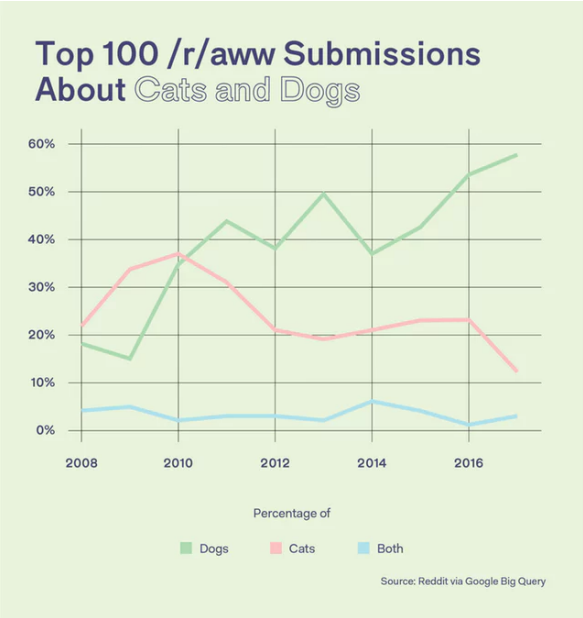
Kevin Jamieson

UNIVERSITY of WASHINGTON

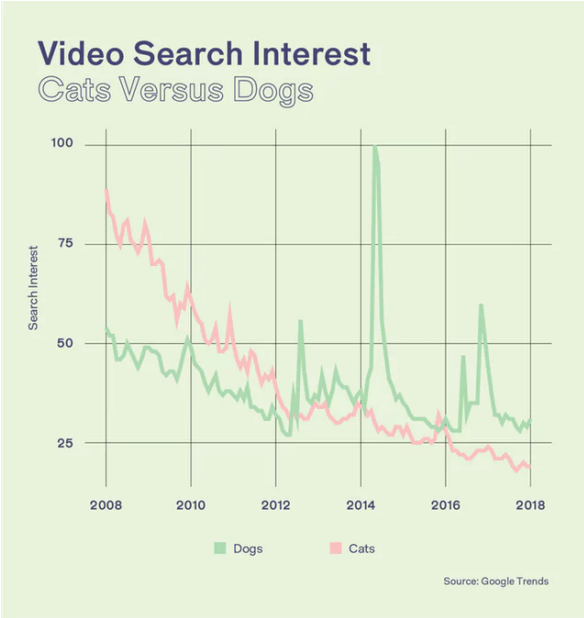
Traditional algorithms

Social media mentions of Cats vs. Dogs

Reddit



Google



Twitter?

Graphics courtesy of https://theoutline.com/post/3128/dogs-cats-internet-popularity?zd=1

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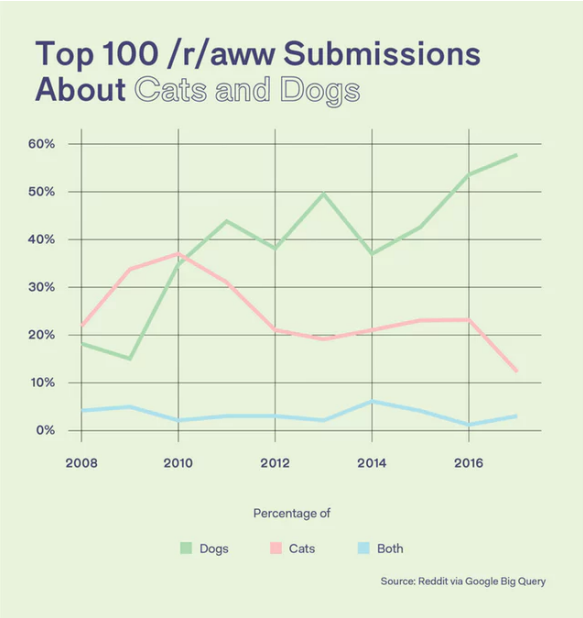

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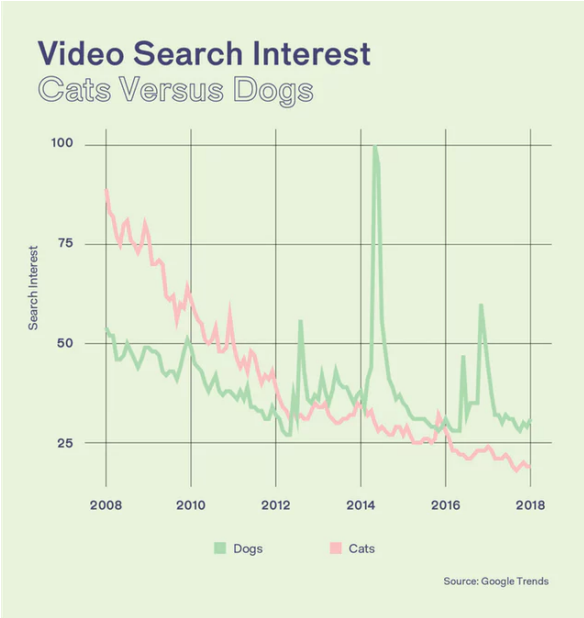

Twitter?

Write a program that sorts tweets into those containing "**cat**", "**dog**", or ***other***

Graphics courtesy of https://theoutline.com/post/3128/dogs-cats-internet-popularity?zd=1

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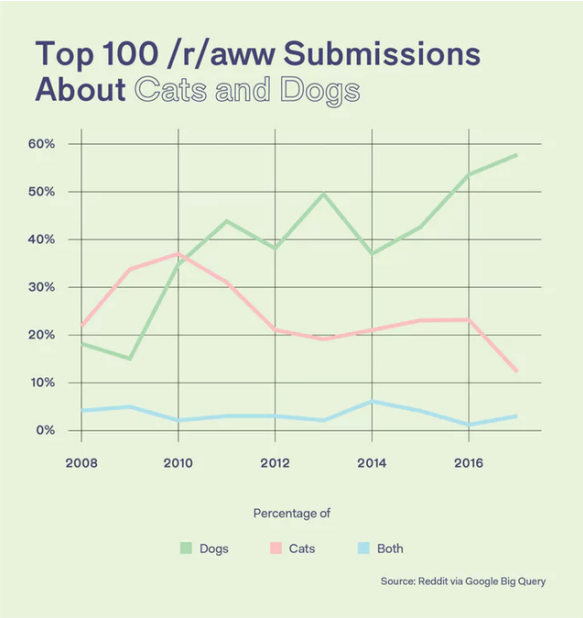

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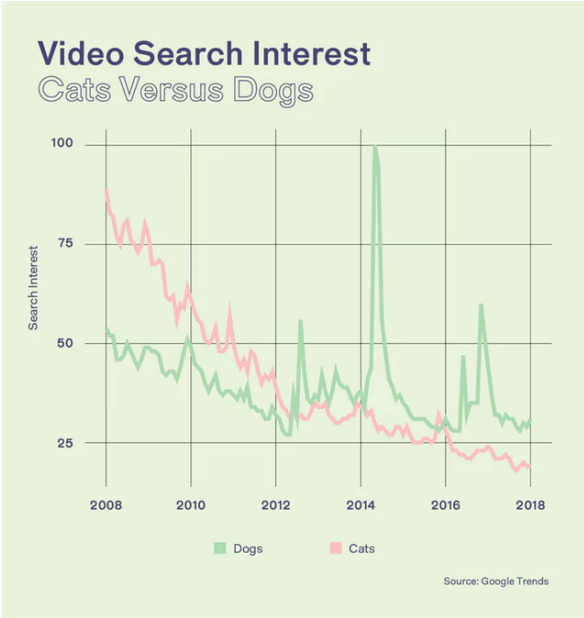


Twitter?

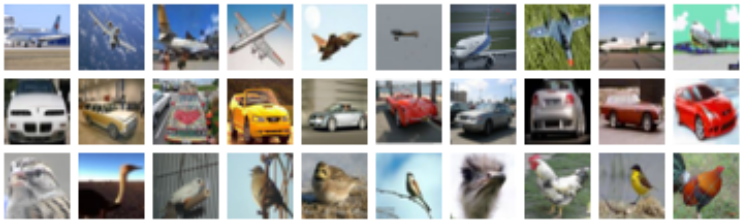
```
cats = []
dogs = []
other = []
for tweet in tweets:
    if "cat" in tweet:
        cats.append(tweet)
    elseif "dog" in tweet:
        dogs.append(tweet)
    else:
        other.append(tweet)
return cats, dogs, other
```

Write a program that sorts tweets into those containing "**cat**", "**dog**", or ***other***

Graphics courtesy of https://theoutline.com/post/3128/dogs-cats-internet-popularity?zd=1

Machine learning algorithms

Write a program that sorts images into those containing "**birds**", "**airplanes**", or ***other.***



airplane

other

bird

Machine learning algorithms

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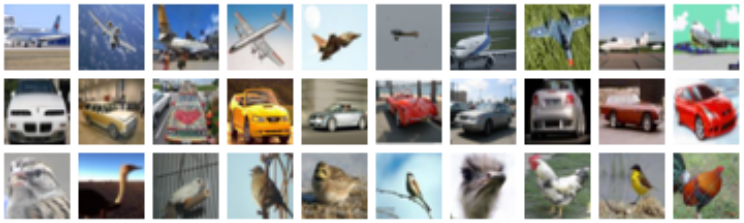

airplane

other

bird

```
birds = []
planes = []
other = []
for image in images:
    if bird in image:
        birds.append(image)
    elseif plane in image:
        planes.append(image)
    else:
        other.append(tweet)
return birds, planes, other
```

Machine learning algorithms

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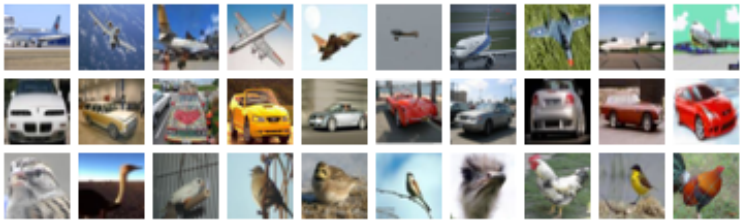
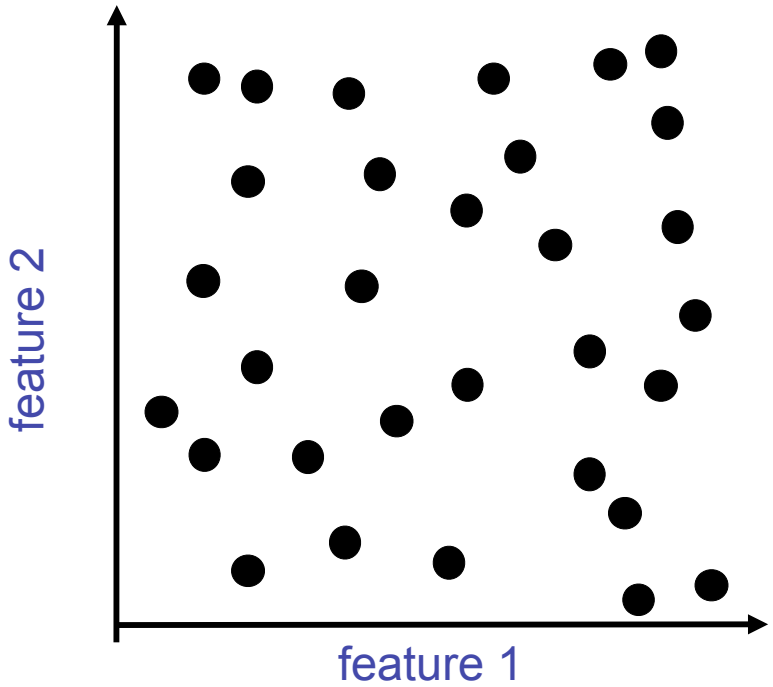


airplane

other

bird

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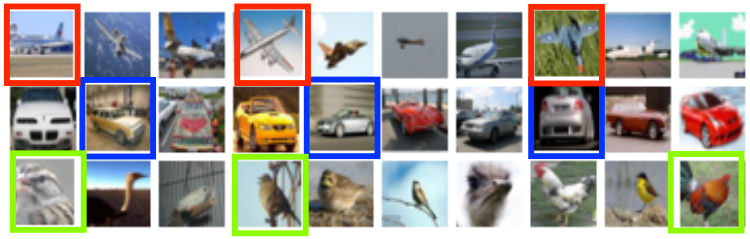

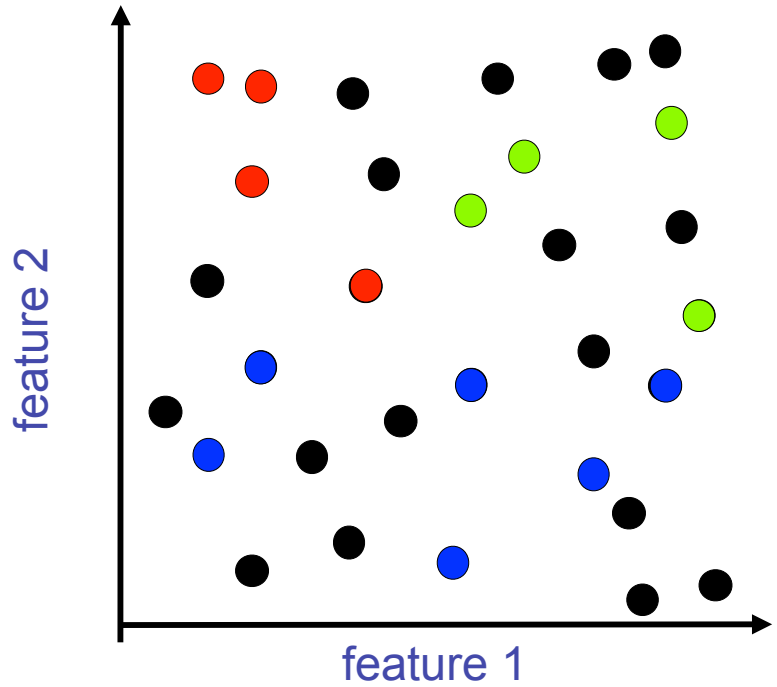


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Machine learning algorithms

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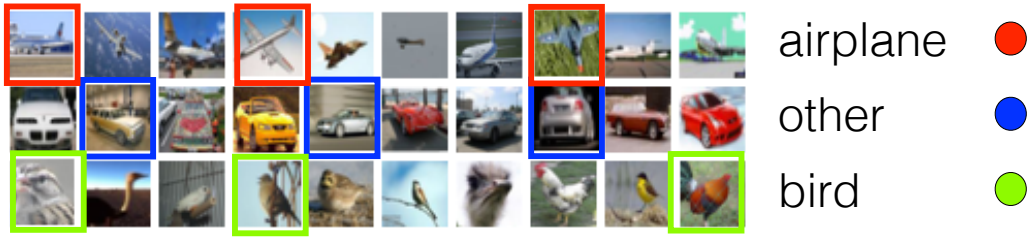

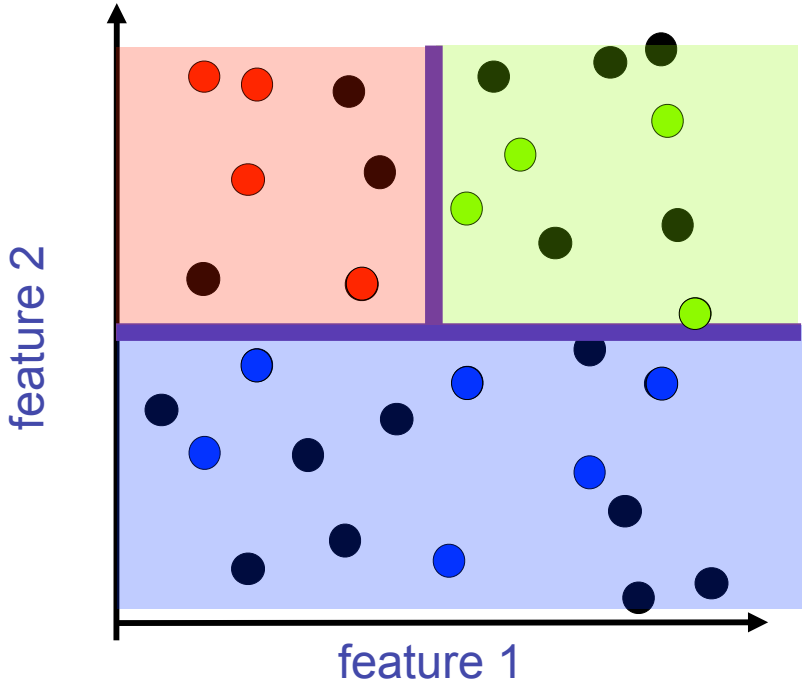


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Machine learning algorithms

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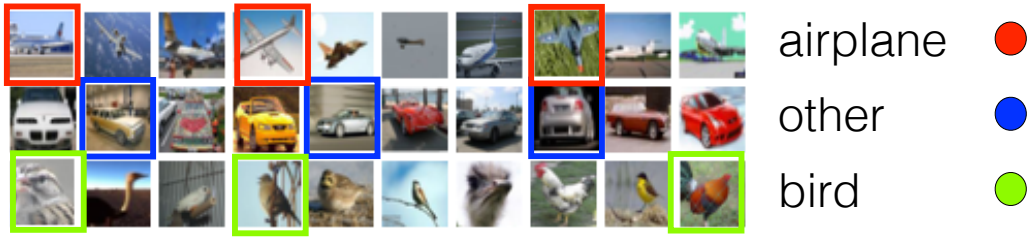

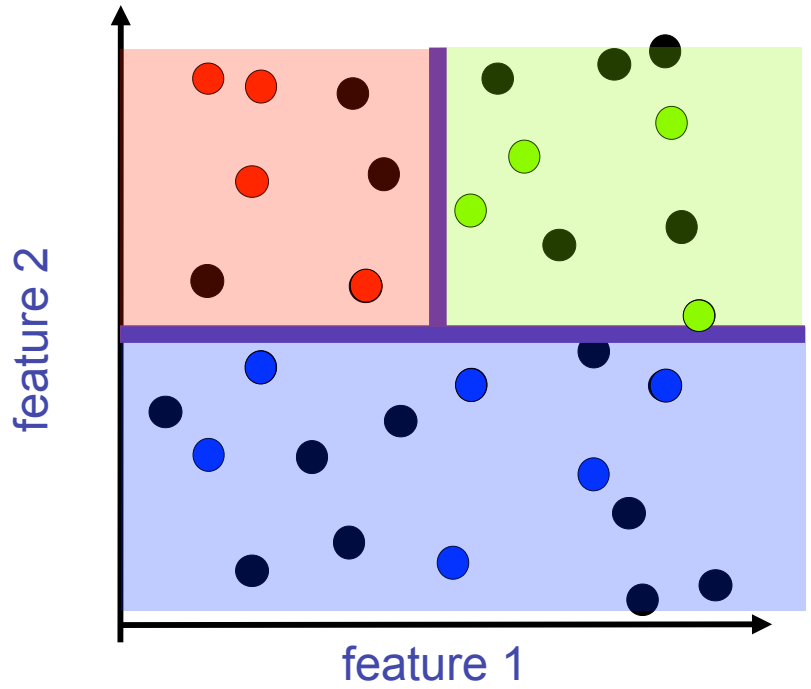


```
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planes = []
other = []
for image in images:
    if bird in image:
        birds.append(image)
    elseif plane in image:
        planes.append(image)
    else:
        other.append(tweet)
return birds, planes, other
```
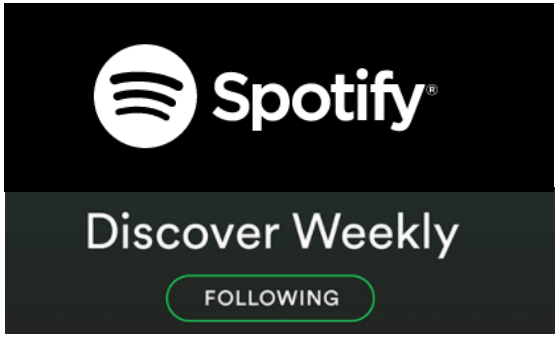

The decision rule of
`if "cat" in tweet:`
is **hard coded by expert.**

The decision rule of
`if bird in image:`
is **LEARNED using DATA**

Machine Learning Ingredients

- **Data**: past observations
- **Hypotheses/Models**: devised to capture the patterns in data
- **Prediction**: apply model to forecast future observations



You may also like…

ML uses past data to make personalized predictions

Mix of statistics (conceptual) and algorithms (programming)

CSE 546: Machine Learning
446

Instructor: Kevin Jamieson

Contact: cse446-staff@cs.washington.edu

Website: https://courses.cs.washington.edu/courses/cse446/23au/

What this class is:

- **Fundamentals of ML:** bias/variance tradeoff, overfitting, optimization and computational tradeoffs, supervised learning (e.g., linear, boosting, deep learning), unsupervised models (e.g. k-means, EM, PCA)
- **Preparation for further learning:** the field is fast-moving, you will learn the foundations of ML to understand the latest results

What this class is not:

- **Survey course:** laundry list of algorithms, how to win Kaggle
- **An easy course:** familiarity with intro linear algebra and probability are assumed, homework will be time-consuming

Prerequisites

- Familiarity with:
  - Linear algebra
    - linear dependence, rank, linear equations
  - Multivariate calculus
  - Probability and statistics
    - Distributions, densities, marginalization, moments
  - Algorithms
    - Basic data structures, complexity
- Use HW0 to judge skills
- **See assigned reading and website for additional review materials!**

Grading

- 5 homeworks
  - Each contains both theoretical questions and will have programming
  - Collaboration okay. You must write, submit, and understand your answers and code (which we may run)
  - Do not Google for answers or ask chatGPT to do it.
  - **READ COLLABORATION POLICY ON WEBSITE**
- Midterm and Final

Grading: Your grade will be based on 5 homework assignments:
HW0 (8%), HW1 (13%), HW2 (13%), HW3 (13%), HW4 (13%).
There will be one midterm worth 20% and a final worth another 20%.
However, depending on whether you are enrolled in 446 or 546, the way the assignments are graded or curved varies (see below).

Communication Channels

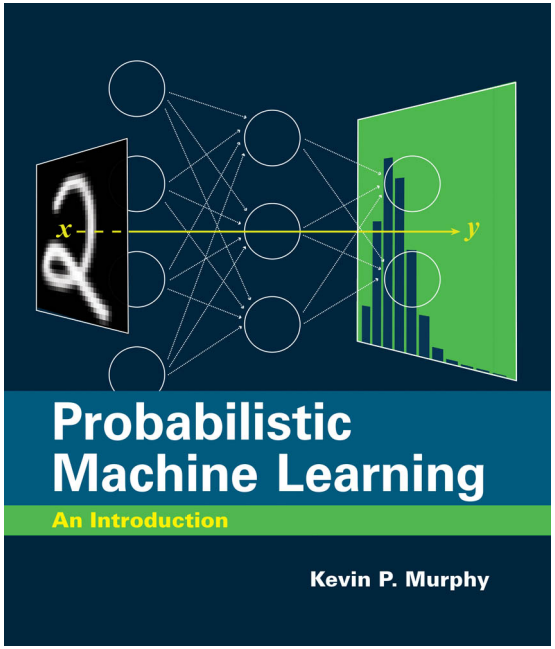
- **Announcements, questions about class, homework help**
  - EdStem (https://edstem.org/)
  - “I think there is a typo in the homework?”
  - “What does this notation mean?”
  - “Is this an accurate description of how this works?
- **Personal concerns (**cse446-staff@cs.washington.edu)
  - “Was in hospital…”, “laptop was stolen…”, etc.
- **Office hours**
  - “How do I get started on problem 2?”
  - “Am I on the right track?”
  - “I have this problem at work—can you point me in the right direction?”
- **Regrade requests**
  - Directly submit on Gradescope
- **Anonymous feedback** (https://feedback.cs.washington.edu/)
  - “Your real-world example X lacked nuance. I would like you to…”

Textbooks

- **Free PDF** Textbook I will assign most reading from:

Probabilistic Machine Learning: An Introduction

Kevin Murphy



  - PDF linked to on website, also in print

- So many more resources on the website!
- I may occasionally point you to other (free) readings

Homeworks

- HW 0 is out (**Due next Wednesday Midnight**)
  - Should be review (but being rusty is expected)
  - Work individually, treat as guide for what to brush up on
- HW 1,2,3,4
  - They are not easy or short. Start early.
- Submit to Gradescope
- Regrade requests on Gradescope
- **Late days: 5 days <u>total</u> over the quarter**
- Assignments due at midnight, submit early and often (do <u>not</u> email me at 12:05)

1. All code must be written in Python
2. All written work must be typeset (e.g., LaTeX)

See course website for tutorials and references.

CSE 446 vs 546

Lecture	Lecture	Section	Homework	Grading
446	CSE2 G20 (Amazon Auditorium) MW 9:00 -- 10:20am	Attend the section you are registered.	**A** problems only. No credit will be rewarded for completing **B** problems.	You will be graded (e.g., curved) against your peers in 446 only (on a 4.0 scale). For example, if you you recieved a (curved) score of 0.9 on the **A** problems, then your full grade on your transcript will be (4.0)*(0.9) = 3.6. Any attempt of the **B** problems will not influence your grade in any way.
546	CSE2 G20 (Amazon Auditorium) MW 9:00 -- 10:20am	None	**A** and **B** problems.	You will be graded (e.g., curved) against your peers in 546 only. Your grade on the **A** and **B** problems will be curved seperately, and then summed. For example, if you you recieved a (curved) score of 0.9 on the **A** problems, and a (curved) score of 0.8 on the **B** problems, then your full grade on your transcript will be (3.8)*(0.9) + (0.2)*(0.8) = 3.58, rounded to 3.6. If only the **A** problems on the homework are attempted, the highest score attainable is a 3.8. If only the **B** problems are attempted, the highest score attainable is a 0.2.

Enjoy!

- ML is becoming ubiquitous in science, engineering and beyond
- This class should give you a basic foundation for understanding and applying ML

Probability review

Definitions

- **Random Variable**: A variable that takes on different values determined randomly.
  - Example: The height of a person from the US.

- **Distribution**: The different values a random variable can take on along with the probability of that value.

- We talk about **sampling** from a distribution:
  - “Consider a sample of 100 different heights of people from the US drawn randomly from the distribution of all heights.”

Independence

Let X and Y be **random variables**

Ex. X is the outcome of the first roll of a 6-sided dice, Y is the outcome of the second roll of the dice

(X and Y take values in {1,2,3,4,5,6} each with equal probability)

An **event** is statement about the world that holds or not:

Define events $A = \{X \in \{3,4\}\}$,

$B = \{X = 1\}$,

$C = \{Y \in \{3,4\}\}$

Every event is assigned a **probability**:

$P(A) = P(X \in \{3,4\}) =$ $P(3) + P(4) + P(X \in \{3\} \cap \{4\})$

$= 1/3$

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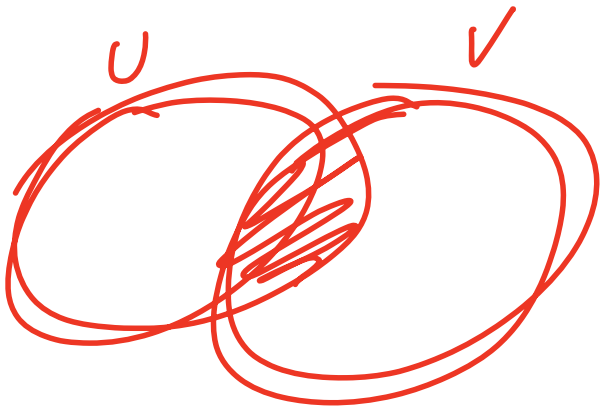

Every event is assigned a **probability**:

$P(A) = P(X \in \{3,4\}) = 1/3$

For any events U, V we have $P(U \cup V) = P(U) + P(V) - P(U \cap V)$

Independence

Let X and Y be **random variables**

Ex. X is the outcome of the first roll of a 6-sided dice, Y is the outcome of the second roll of the dice

(X and Y take values in {1,2,3,4,5,6} each with equal probability)

An **event** is statement about the world that holds or not:

Define events $A = \{X \in \{3,4\}\}$,
$B = \{X = 1\}$,
$C = \{Y \in \{3,4\}\}$

For say events U, V are **independent** if $P(U \cap V) = P(U)P(V)$

Are A, B independent? B,C? A, C?

$P(A \cap B) = P(X \in \{3,4\}, X = 1) = 0$

$P(A) = 1/3 \qquad P(B) = 1/6$

Independence

Let X and Y be **random variables**

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For say events U, V are **independent** if $P(U \cap V) = P(U)P(V)$

Are A, B independent (no)? B,C (yes)? A, C (yes)?

Independence

Let X and Y be **random variables**

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For say events U, V are **independent** if $P(U \cap V) = P(U)P(V)$

We define the **conditional probability** of event U given V as

Bayes rule

$$P(U \mid V) = \frac{P(U \cap V)}{P(V)}$$

What is $P(X \leq 4 \mid X \geq 3)$? $= \frac{P(x \in \{3,4\}) = 1/3}{2/3} = \frac{1}{2}$

Independence

Let X and Y be **random variables**

Ex. X is the outcome of the first roll of a 6-sided dice, Y is the outcome of the second roll of the dice

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We define the **conditional probability** of event U given V as

$$P(U \mid V) = \frac{P(U \cap V)}{P(V)}$$

What is $P(X \leq 4 \mid X \geq 3) = \frac{P(3 \leq X \leq 4)}{P(X \geq 3)} = \frac{1/3}{2/3} = 1/2$

Independence

Let X and Y be **random variables**

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For say events U, V are **independent** if $P(U \cap V) = P(U)P(V)$

We define the **conditional probability** of event U given V as

$$P(U \mid V) = \frac{P(U \cap V)}{P(V)}$$

Observe: if U, V are independent then $P(U \mid V) = P(U)$.

In words: if independent, V tells you nothing about U (and vice versa)

Mean, variance

Mean $\mathbb{E}[X], \mu$

The expected value of X, each value is weighted by the probability of seeing it.

$$\mathbb{E}[X] = \sum_x P(X = x)x$$

Variance $\text{Var}(X), \sigma^2$

The expected squared deviation of X from its mean.

$$\mathbb{E}[(X - \mathbb{E}[X])^2]$$

$$= \mathbb{E}[X^2] - \mathbb{E}[X]^2$$

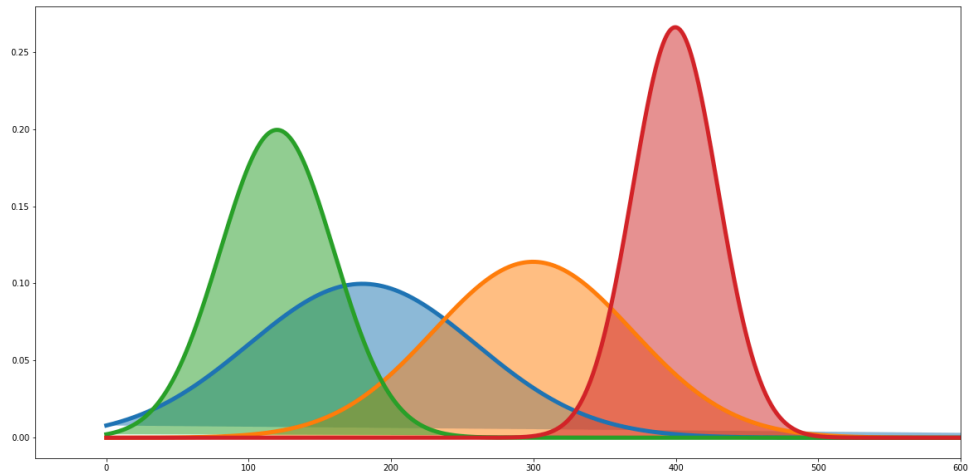
Median M

The value of X that is separating the higher half of it's range from the lower half.

$$P(X \leq M) = .5$$

Mean, variance

The mean is a prediction of the value of the random variable. Answers the question "What do I expect the height of a random person to be?"



The variance captures the spread in your data. Also captures the error in the prediction using the mean. "How much do people's heights deviate?"

$$\mathbb{E}[(X - \mathbb{E}[X])^2]$$

Maximum Likelihood Estimation

Your first consulting job

- *Billionaire*: I have special coin, if I flip it, what's the probability it will be heads?
- *You*: Please flip it a few times:

H H T T H

- *You*: The probability is: 3/5

- *Billionaire:* Why?

Coin – Binomial Distribution

- **Data**: sequence *D= (HHTHT…)*, **k heads** out of **n flips**
- **Hypothesis:** P(Heads) = θ, P(Tails) = 1-θ
  - Flips are i.i.d.:
    - Independent events
    - Identically distributed according to Binomial distribution

- $P(\mathcal{D}|\theta) = P(HHTHT|\theta)$

$= P(T|\theta, HHTH)\,P(HHTH|\theta)$

$= (1-\theta)\cdot P(HHTH|\theta) = \theta^k(1-\theta)^{n-k}$

Maximum Likelihood Estimation

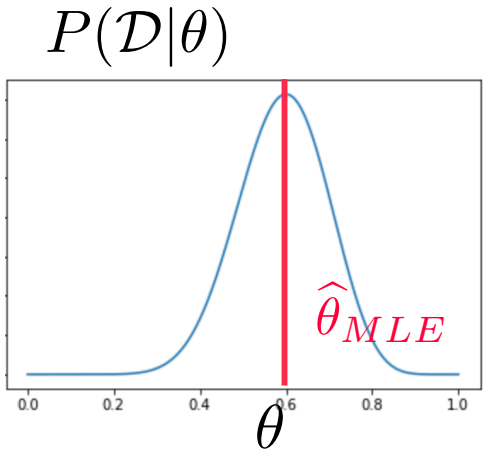
- **Data**: sequence *D= (HHTHT…)*, **k heads** out of **n flips**
- **Hypothesis:** P(Heads) = θ, P(Tails) = 1-θ

$$P(\mathcal{D}|\theta) = \theta^k(1-\theta)^{n-k}$$

- Maximum likelihood estimation (MLE): Choose θ that maximizes the probability of observed data:

$$\widehat{\theta}_{MLE} = \arg\max_{\theta} P(\mathcal{D}|\theta)$$

$$= \arg\max_{\theta} \log P(\mathcal{D}|\theta)$$



Your first learning algorithm

$$\widehat{\theta}_{MLE} = \arg\max_{\theta} \log P(\mathcal{D}|\theta)$$

$$= \arg\max_{\theta} \log\left(\theta^k (1-\theta)^{n-k}\right)$$

$\log(ab) = \log(a) + \log(b)$

$\log(a^b) = b\log(a)$

- Set derivative to zero:

$$\frac{d}{d\theta} \log P(\mathcal{D}|\theta) = 0$$

$$\frac{d}{d\theta} \log\left(\theta^k (1-\theta)^{n-k}\right) = \frac{d}{d\theta}\left(k \log(\theta) + (n-k)\log(1-\theta)\right)$$

$$= \frac{k}{\theta} + \frac{n-k}{1-\theta}\cdot(-1) = 0$$

$$\rightarrow (1-\theta)k - \theta(n-k) = 0 \rightarrow \widehat{\theta} = \frac{k}{n}$$

Maximum Likelihood Estimation

Observe $X_1, X_2, \ldots, X_n$ drawn IID from $f(x;\theta)$ for some "true" $\theta = \theta_*$

Likelihood function $L_n(\theta) = \prod_{i=1}^{n} f(X_i;\theta)$

Log-Likelihood function $l_n(\theta) = \log(L_n(\theta)) = \sum_{i=1}^{n} \log(f(X_i;\theta))$

Maximum Likelihood Estimator (MLE) $\widehat{\theta}_{MLE} = \arg\max_{\theta} L_n(\theta)$

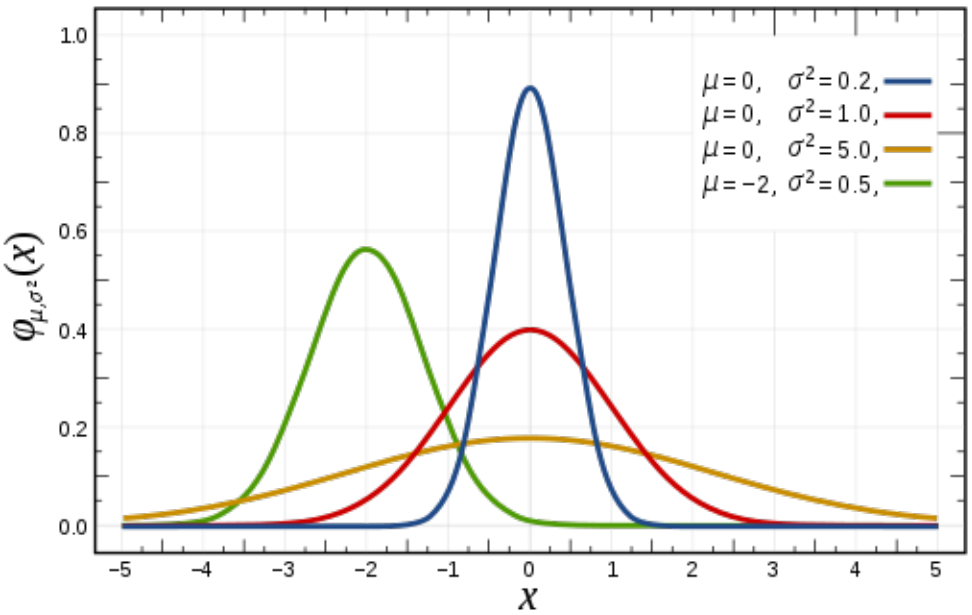
Recap

- Learning is…
  - Collect some data
    - E.g., coin flips
  - Choose a hypothesis class or model
    - E.g., binomial
  - Choose a loss function
    - E.g., data likelihood
  - Choose an optimization procedure
    - E.g., set derivative to zero to obtain MLE

What about continuous variables?

- *Billionaire*: What if I am measuring a **continuous variable**?
- ***You*: Let me tell you about Gaussians…**

$$P(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$



Some properties of Gaussians

- affine transformation (multiplying by scalar and adding a constant)
  - $X \sim N(\mu,\sigma^2)$
  - $Y = aX + b \quad \rightarrow \quad Y \sim N(a\mu+b,a^2\sigma^2)$

- Sum of Gaussians
  - $X \sim N(\mu_X,\sigma^2_X)$
  - $Y \sim N(\mu_Y,\sigma^2_Y)$
  - $Z = X+Y \quad \rightarrow \quad Z \sim N(\mu_X+\mu_Y, \sigma^2_X+\sigma^2_Y)$

MLE for Gaussian

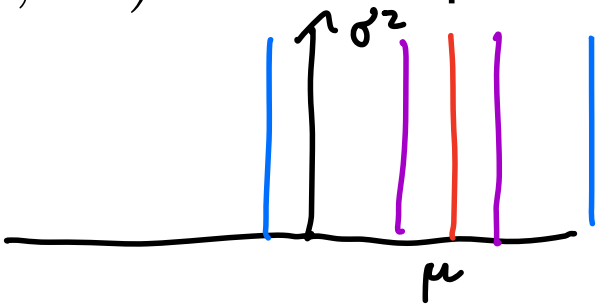
- Prob. of i.i.d. samples $D=\{x_1,\ldots,x_n\}$ (e.g., temperature):

$$P(\mathcal{D}|\mu,\sigma) = P(x_1,\ldots,x_n|\mu,\sigma)$$
$$= \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \prod_{i=1}^{n} e^{-\frac{(x_i-\mu)^2}{2\sigma^2}}$$

- Log-likelihood of data:

$$\log P(\mathcal{D}|\mu,\sigma) = -n\log(\sigma\sqrt{2\pi}) - \sum_{i=1}^{n}\frac{(x_i-\mu)^2}{2\sigma^2}$$

- What is $\widehat{\theta}_{MLE}$ for $\theta=(\mu,\sigma^2)$? Draw a picture!



Your second learning algorithm: MLE for mean of a Gaussian

- What's MLE for mean?

$$\frac{d}{d\mu}\log P(\mathcal{D}|\mu,\sigma) = \frac{d}{d\mu}\left[-n\log(\sigma\sqrt{2\pi}) - \sum_{i=1}^{n}\frac{(x_i-\mu)^2}{2\sigma^2}\right]$$

$$= + \sum_{i=1}^{n}\frac{(x_i-\mu)}{\sigma^2} = 0$$

$$\sum_{i=1}^{n} x_i = \sum_{i=1}^{n}\mu = \mu n$$

$$\hat{\mu}_{MLE} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

MLE for variance

$$\frac{d}{d\sigma}\sigma^{-2} = -2\sigma^{-3}$$

- Again, set derivative to zero:

$$\frac{d}{d\sigma}\log P(\mathcal{D}|\mu,\sigma) = \frac{d}{d\sigma}\left[-n\log(\sigma\sqrt{2\pi}) - \sum_{i=1}^{n}\frac{(x_i-\mu)^2}{2\sigma^2}\right]$$

$$= -n/\sigma + \sum_{i=1}^{n}\frac{(x_i-\mu)^2}{\sigma^3} = 0$$

$$n\sigma^2 = \sum_{i=1}^{n}(x_i-\mu)^2$$

$$\hat{\sigma}^2_{MLE} = \frac{1}{n}\sum_{i=1}^{n}(x_i-\mu)^2 = \frac{1}{n}\sum_{i=1}^{n}(x_i-\hat{\mu}_{MLE})^2$$

Learning Gaussian parameters

- MLE:

$$\widehat{\mu}_{MLE} = \frac{1}{n}\sum_{i=1}^{n} x_i$$

$$\underline{\widehat{\sigma^2}_{MLE}} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \widehat{\mu}_{MLE})^2$$

- MLE for the variance of a Gaussian is **biased**

$$\mathbb{E}[\widehat{\sigma^2}_{MLE}] \neq \sigma^2$$

- Unbiased variance estimator:

$$\widehat{\sigma^2}_{unbiased} = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \widehat{\mu}_{MLE})^2$$

Maximum Likelihood Estimation

Observe $X_1, X_2, \ldots, X_n$ drawn IID from $f(x;\theta)$ for some "true" $\theta = \theta_*$

Likelihood function $L_n(\theta) = \prod_{i=1}^{n} f(X_i;\theta)$

Log-Likelihood function $l_n(\theta) = \log(L_n(\theta)) = \sum_{i=1}^{n} \log(f(X_i;\theta))$

Maximum Likelihood Estimator (MLE) $\widehat{\theta}_{MLE} = \arg\max_{\theta} L_n(\theta)$

Under benign assumptions, as the number of observations $n \to \infty$ we have $\widehat{\theta}_{MLE} \to \theta_*$

The MLE is a "recipe" that begins with a *model* for data $f(x;\theta)$

Applications preview

Maximum Likelihood Estimation

Observe $X_1, X_2, \ldots, X_n$ drawn IID from $f(x;\theta)$ for some "true" $\theta = \theta_*$

Likelihood function $L_n(\theta) = \prod_{i=1}^{n} f(X_i;\theta)$

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Maximum Likelihood Estimator (MLE) $\widehat{\theta}_{MLE} = \arg\max_{\theta} L_n(\theta)$

Under benign assumptions, as the number of observations $n \to \infty$ we have $\widehat{\theta}_{MLE} \to \theta_*$

Why is it useful to recover the "true" parameters θ_* of a probabilistic model?

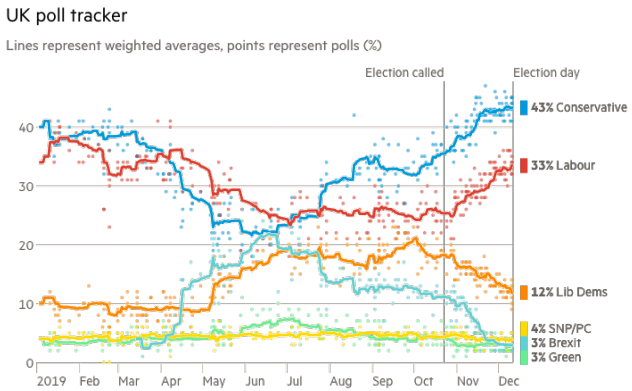
- **Estimation** of the parameters θ_* is the goal
- Help **interpret** or summarize large datasets
- Make **predictions** about future data
- **Generate** new data $X \sim f(\,\cdot\,;\widehat{\theta}_{MLE})$

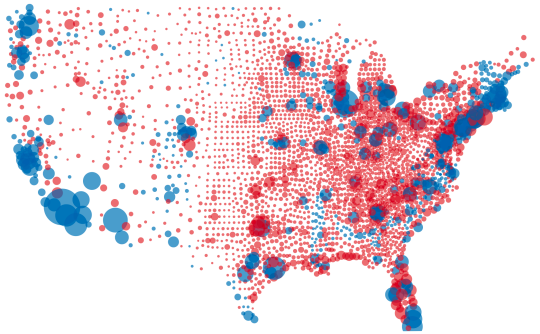
Estimation

Observe $X_1, X_2, \ldots, X_n$ drawn IID from $f(x;\theta)$ for some "true" $\theta = \theta_*$

Opinion polls
How does the greater population feel about an issue?
Correct for over-sampling?

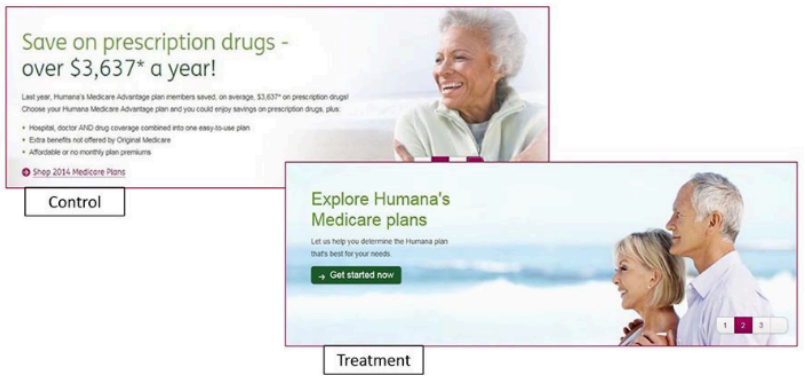
- θ_* is "true" average opinion
- $X_1, X_2, \ldots$ are sample calls





A/B testing
How do we figure out which ad results in more click-through?

- θ_* are the "true" average rates
- $X_1, X_2, \ldots$ are binary "clicks"

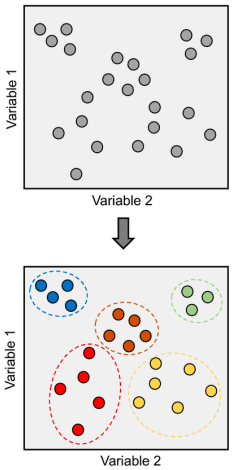


Interpret

Observe $X_1, X_2, \ldots, X_n$ drawn IID from $f(x;\theta)$ for some "true" $\theta = \theta_*$

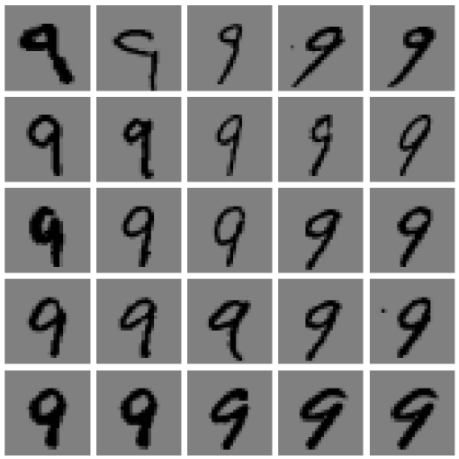
Customer segmentation / clustering
Can we identify distinct groups of customers by their behavior?

- θ_* describes "center" of distinct groups
- $X_1, X_2, \ldots$ are individual customers



Data exploration
What are the degrees of freedom of the dataset?

- θ_* describes the principle directions of variation
- $X_1, X_2, \ldots$ are the individual images

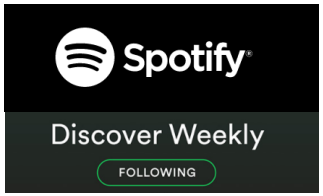


Predict

Observe $X_1, X_2, \ldots, X_n$ drawn IID from $f(x;\theta)$ for some "true" $\theta = \theta_*$

Content recommendation
Can we predict how much someone will like a movie based on past ratings?

- θ_* describes user's preferences
- $X_1, X_2, \ldots$ are (movie, rating) pairs



Object recognition / classification
Identify a flower given just its picture?

- θ_* describes the characteristics of each kind of flower
- $X_1, X_2, \ldots$ are the (image, label) pairs

(a) (b) (c)

Figure 1.1: Three types of Iris flowers: Setosa, Versicolor and Virginica. Used with kind permission of Dennis Kramb and SIGNA.

index	sl	sw	pl	pw	label
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
	...				
50	7.0	3.2	4.7	1.4	Versicolor
	...				
149	5.9	3.0	5.1	1.8	Virginica

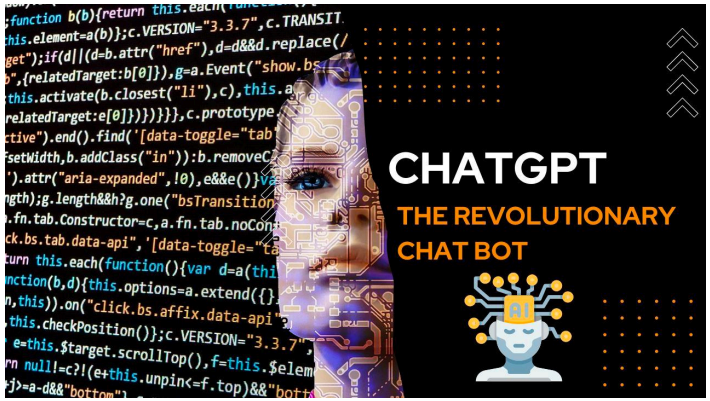
Generate

Observe $X_1, X_2, \ldots, X_n$ drawn IID from $f(x;\theta)$ for some "true" $\theta = \theta_*$

Text generation
Can AI generate text that could have been written like a human?

- θ_* describes language structure
- $X_1, X_2, \ldots$ are text snippets found online

"Kaia the dog wasn't a natural pick to go to mars. No one could have predicted she would..."



https://chat.openai.com/chat

Image to text generation
Can AI generate an image from a prompt?

- θ_* describes the coupled structure of images and text
- $X_1, X_2, \ldots$ are the (image, caption) pairs found online

"dog talking on cell phone under water, oil painting"

https://labs.openai.com/