

Computational Methods for Linguists

Ling 471

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04/29/21

Reminders

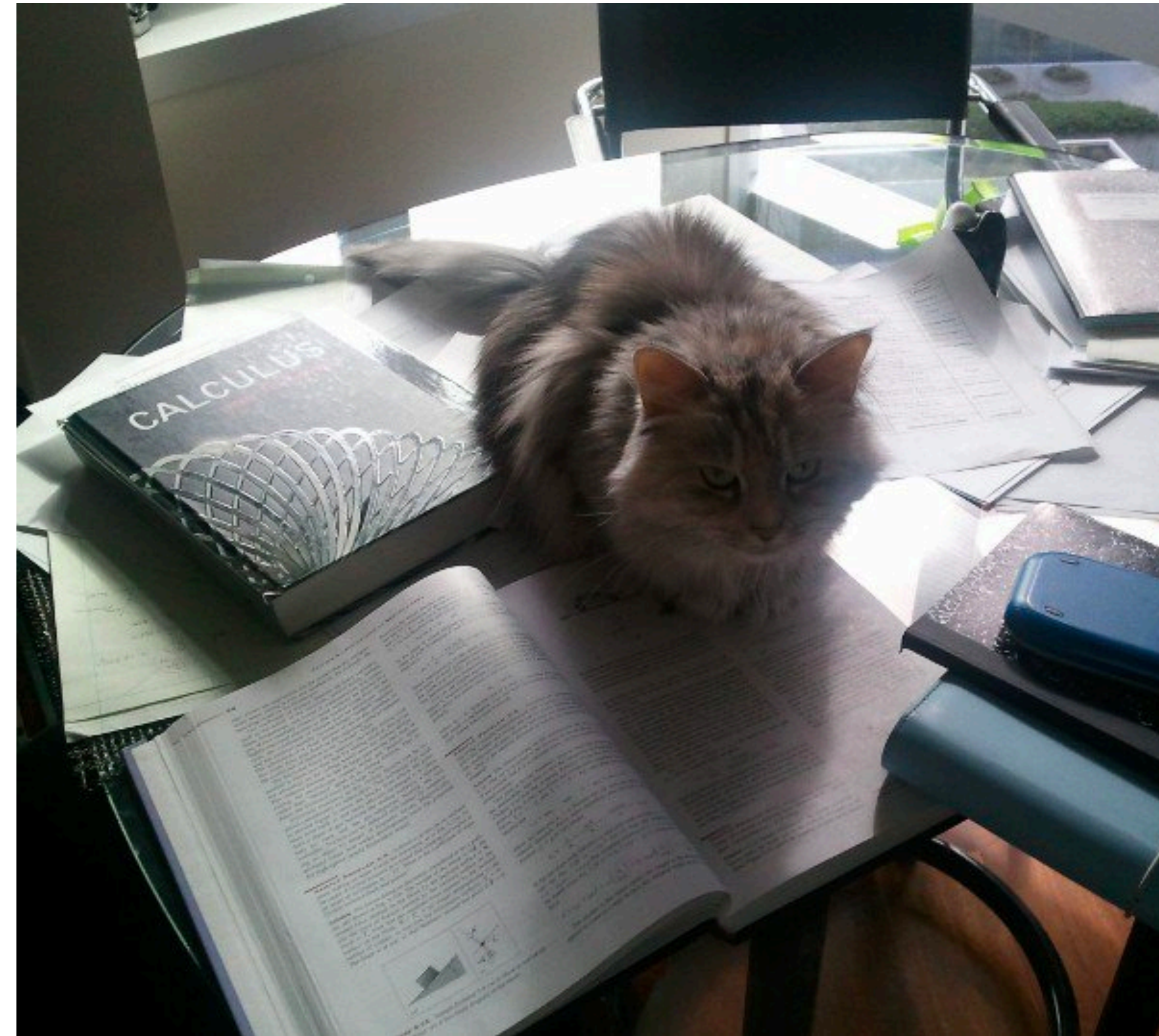
- Make sure to create **private** repository copies for the assignments
 - I was **mistaken** to think forks were private
 - You can **delete** your forked copies if you like
- Can clone and copy manually, or use **import**
- Whichever way you choose, **please do not publish any solutions to the HW anywhere**
- Assignment 3:
 - a “short” description **and** a detailed **walkthrough** available
 - ...is **harder** than Assignment 2
- Please fill out Midterm Course Evaluations!



Questions?

Plan for today

- Data science and probability:
 - what's the **connection**?
- Probability theory **basics**
- Statistics: **distributions** and **estimation**
 - time-permitting
- Some of today's and next week's material may be **dense**
 - Goal: Learn **something** about those things
 - Remember, no exams :)
 - Unlikely to ask you to compute something terrible in HW
 - If this is the **first** time you hear about these things:
 - You will understand them better **next** time you hear about them



Probability and Statistics

Data science and statistics

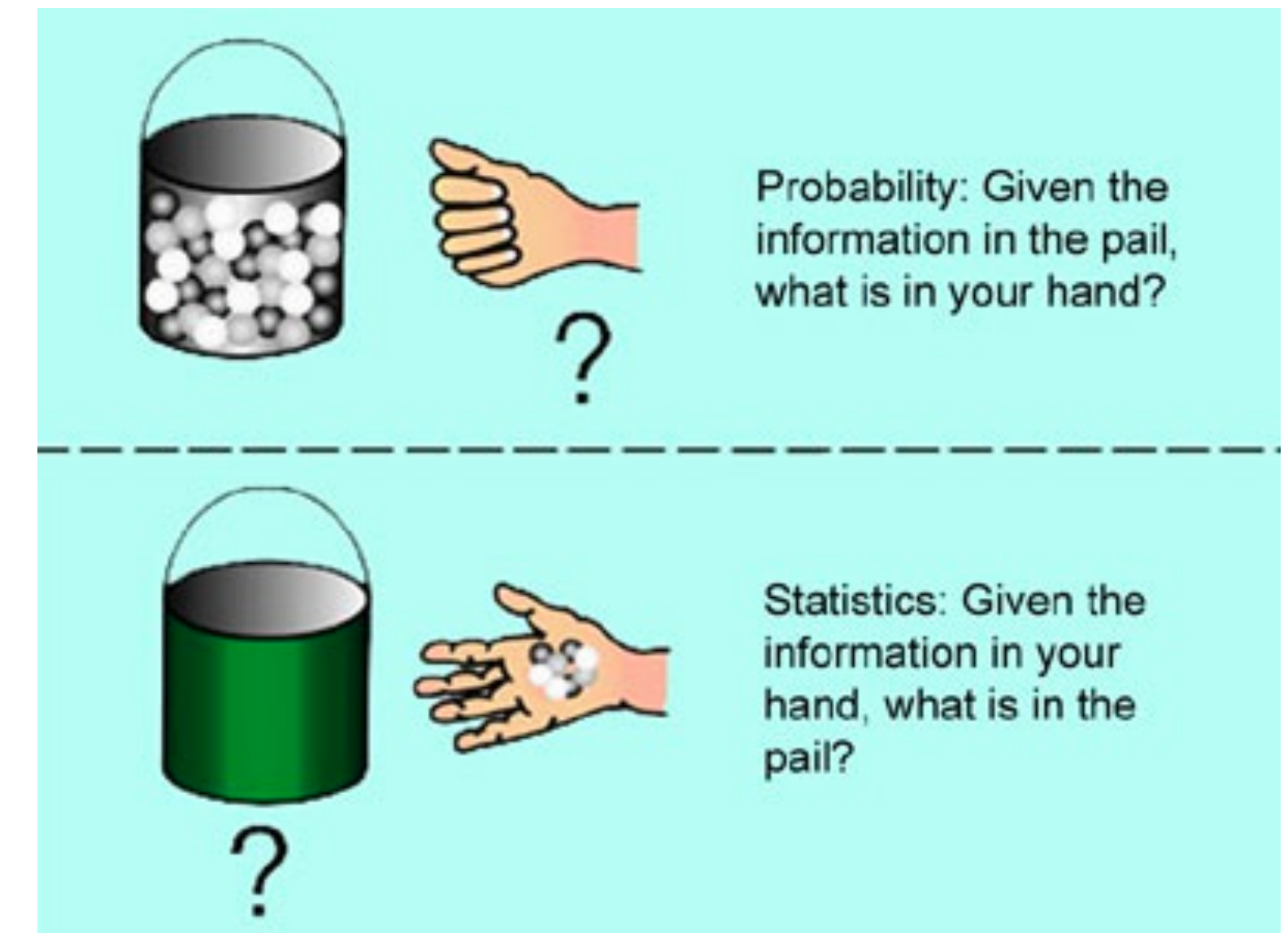
- There is a lot of **randomness** and **uncertainty** in the world
- Many processes in our lives are **data-generating**
 - how many times we click on what
 - how many messages we send/receive, of what kind
 - what places we visit and how often
 - etc., etc., etc.
- Statistics:
 - A **science** of making sense of the world by **sampling** data
 - What is true for the sample, is also true for the population
 - ...if the sample is **random** and sufficiently **large**



<https://www.scribbr.com/methodology/population-vs-sample/>

Statistics and Probability Theory (and Data Science)

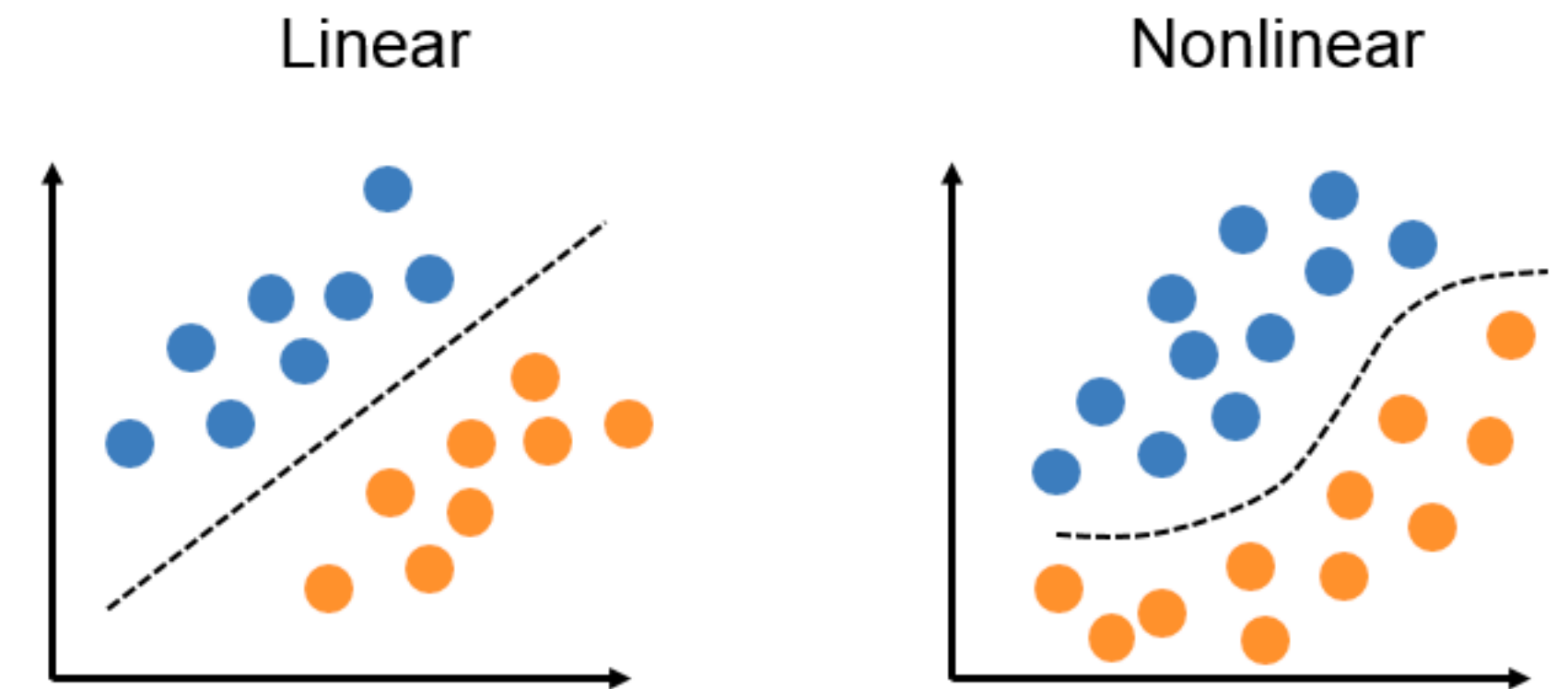
- Probability Theory:
 - Formally estimate how likely an **outcome** is
 - Informally: Oriented at predicting **future** events
 - Given what I know about the population, what sample could I draw?
 - Relies on the notion of probability **distribution**
 - How are probabilities of **all** possible outcomes **distributed**?
- Statistics:
 - Use **probability distributions** to make sense of large data **formally**
 - Informally: Oriented at analyzing **past** events
 - Given the samples which I drew, what can I say about the population?
 - No distribution => no statistics!
- Data Science:
 - Probability + Statistics
 - Analyze past events **and** predict future events, **at scale**, in real world



<https://www.quora.com/What-is-the-difference-between-probability-and-statistics>

Prediction and Probabilities classification problem

- Predictions in data science and ML need to be quantified
- To predict whether a review is POS or NEG:
 - e.g. compute the **probability** of it being POS
 - predict POS if that probability is **high**
 - predict NEG **otherwise**
- **Conditional** probability: $P(Y|X)$
 - where Y is the label and X is the observation
 - e.g. Y = POS and X = "this is a good movie!"
 - **How** to learn $P(Y|X)$?
 - There are mathematical functions which you can use
 - A bit more in our ML-dedicated lectures later...



<https://jtsulliv.github.io/perceptron/>

Probability Theory

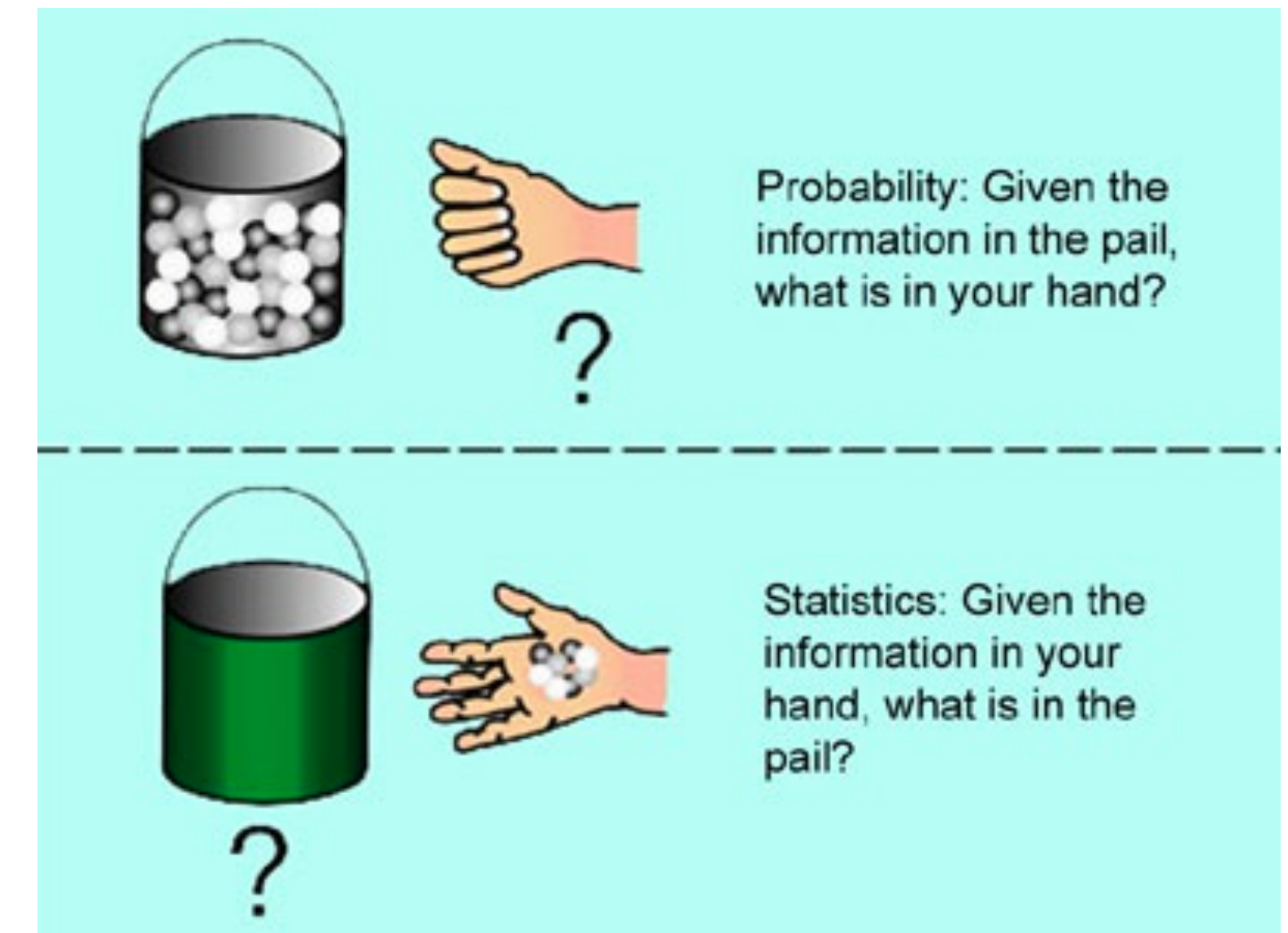
- ...is notoriously unintuitive and hard
- Our **goal**:
 - get familiar with a **subset** of basic concepts
 - not necessarily in the most formal and exhaustive way
 - ...such that we can experiment with some data science models in assignments 4–5



Probability Theory

our goals for this lesson

- Definitions:
 - events, outcomes, sample space, random variable
- Mutually exclusive events
- Sequences and independent events
- Joint probabilities
- Conditional probability
- Marginalizing joint probabilities
- Bonus: Maximum Likelihood Estimation

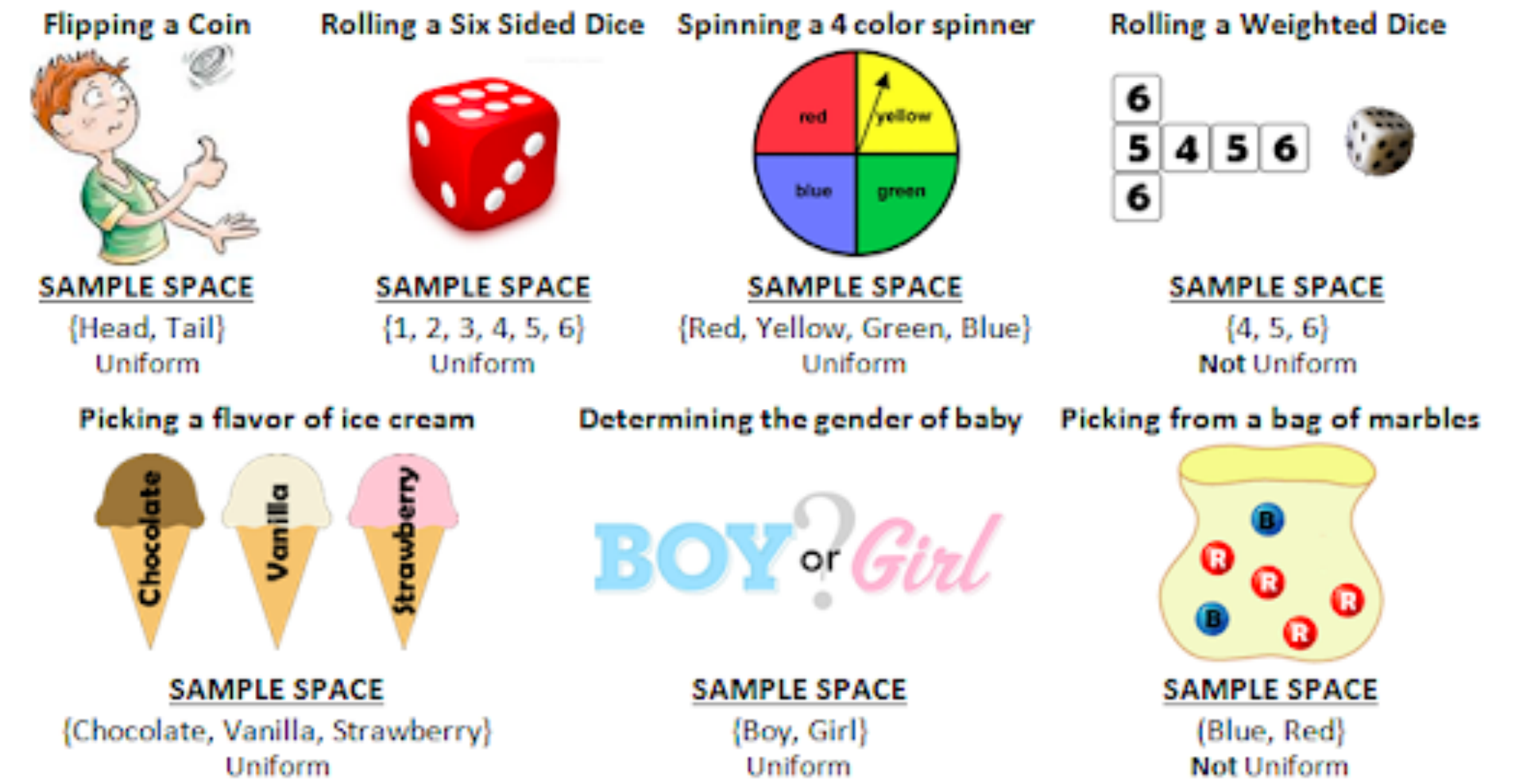


<https://www.quora.com/What-is-the-difference-between-probability-and-statistics>

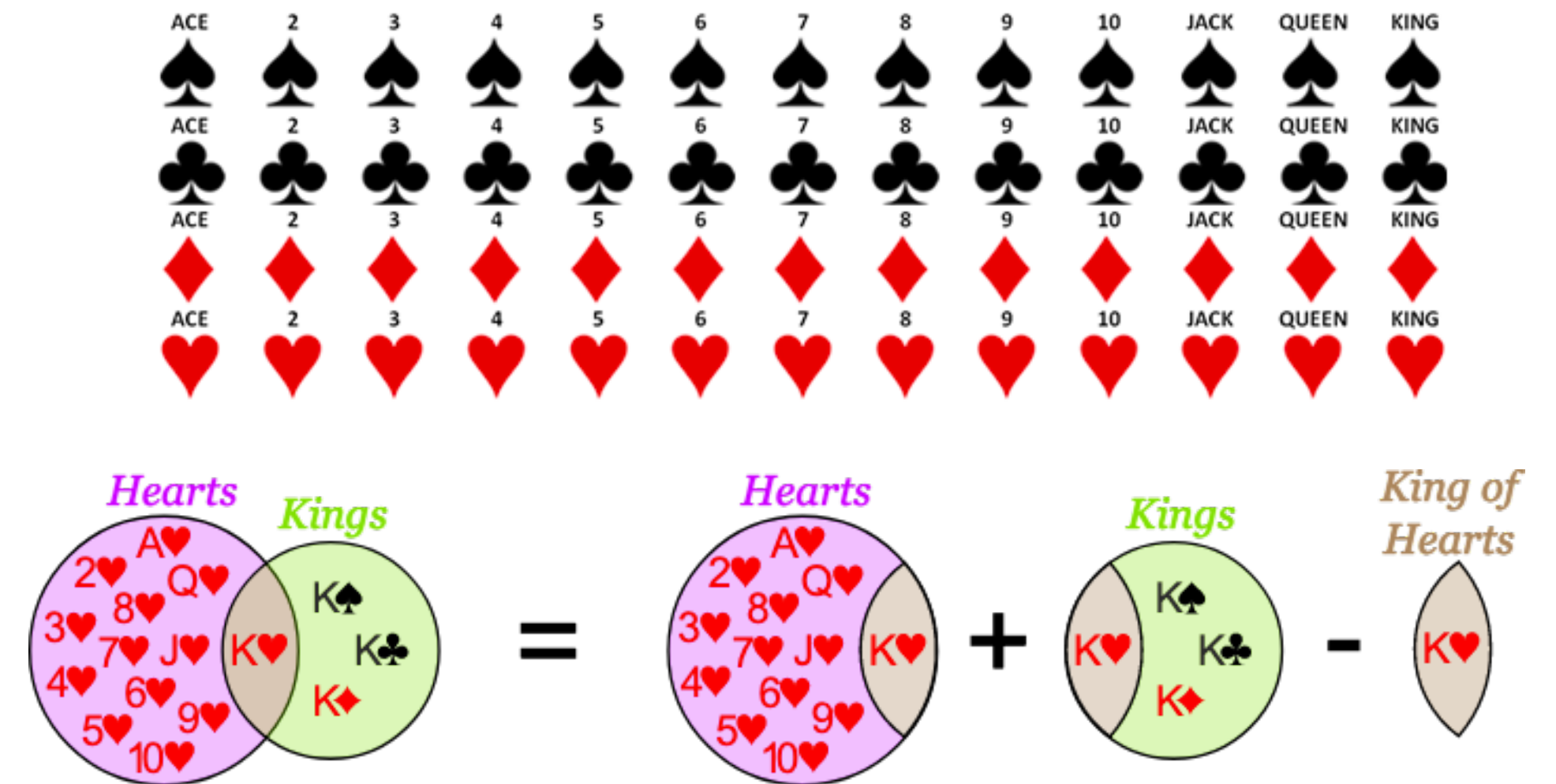
Probability

basic intuitions

- How likely is something to happen?
 - Well, we don't know!
 - But, we can **estimate**
 - based on **prior observations** or base on what we **assume** about the situation
- **Out of n** experiments (the "sample space"), **how many** resulted in a **specific** outcome?
 - this ratio is the **probability** of that specific outcome
 - turns out, you can show formally that it **is** the ratio (MLE)
 - Understanding what the "sample space" is **exactly** is **crucial**
 - The probability will be different based on what the sample space actually is
 - Often times, need to subtract things from what intuitively seems like it's the sample space
 - particularly **conditional** probabilities
 - That's the main reason why probability is often unintuitive



<http://www.geometrycommoncore.com/content/unit6/gcp1/studentsnotes1.html>





<https://www.mathsisfun.com/data/probability-events-mutually-exclusive.html>


Coin toss


the classic probability example


- Sample space
- Experiment
- Outcome


Flipping a Coin

SAMPLE SPACE
{Head, Tail}
Uniform


Rolling a Six Sided Dice

SAMPLE SPACE
{1, 2, 3, 4, 5, 6}
Uniform

Spinning a 4 color spinner

SAMPLE SPACE
{Red, Yellow, Green, Blue}
Uniform

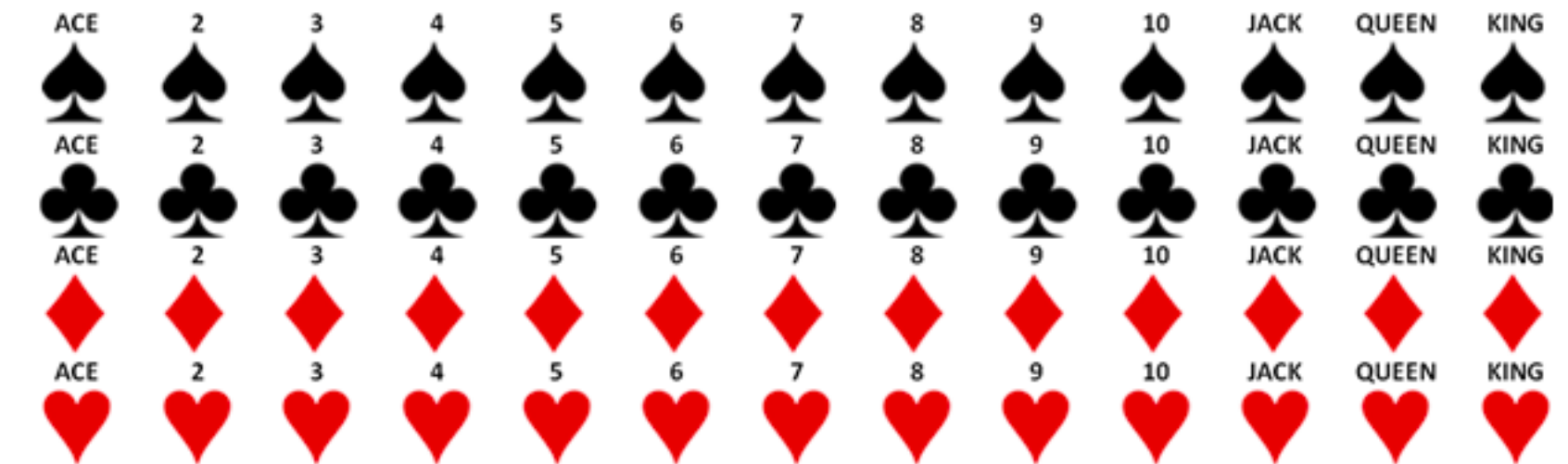
Rolling a Weighted Dice

SAMPLE SPACE
{4, 5, 6}
Not Uniform

Picking a flavor of ice cream

SAMPLE SPACE
{Chocolate, Vanilla, Strawberry}
Uniform

Determining the gender of baby

SAMPLE SPACE
{Boy, Girl}
Uniform

Picking from a bag of marbles

SAMPLE SPACE
{Blue, Red}
Not Uniform

<http://www.geometrycommoncore.com/content/unit6/gcp1/studentsnotes1.html>



Coin toss

the classic probability example

- Sample space
 - {T,H}
- Experiment
 - **one** toss
- Outcome
 - **either H or T**

The image displays seven probability scenarios arranged in two rows. Each scenario includes an illustration, a title, a sample space, and a note on uniformity.

Scenario	Sample Space	Uniformity
Flipping a Coin	{Head, Tail}	Uniform
Rolling a Six Sided Dice	{1, 2, 3, 4, 5, 6}	Uniform
Spinning a 4 color spinner	{Red, Yellow, Green, Blue}	Uniform
Rolling a Weighted Dice	{4, 5, 6}	Not Uniform
Picking a flavor of ice cream	{Chocolate, Vanilla, Strawberry}	Uniform
Determining the gender of baby	{Boy, Girl}	Uniform
Picking from a bag of marbles	{Blue, Red}	Not Uniform

<http://www.geometrycommoncore.com/content/unit6/gcp1/studentsnotes1.html>

Coin toss series

the classic probability example



<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- Sample space
 - **depends** on the number of tosses
 - for **2**: {HH, HT, TH, TT}
- Experiment
 - A number of tosses
- Outcome
 - A **sequence** of Hs and Ts
- Statistically, the $P(H)$ is estimated by a large number of experiments
 - toss the coin a billion times
 - compute **how many H** you got (**N**)
 - **N/billion** is the statistical/empirical estimate of **P(H)**
 - and you can actually **prove it formally**
 - Maximum Likelihood Estimation (MLE)

A Fair Coin



<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- A **fair** coin is a coin such that **$P(H) = 1/2$**
- In other words, you can toss it a billion times and expect H to come up ~500 mln times
 - what if I actually did it and got 500,000,001 Heads?
 - $500,000,001/1,000,000,000 = 0.500000001$
 - for all practical purposes, that's **still $1/2$** :)

Probability and Frequency



<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- How probable is some outcome?
 - e.g. H or T
- How frequent is some outcome?
 - e.g. H or T
- What's the difference?
 - Frequency is observed
 - Probability is estimated

Probability of sequence in NLP

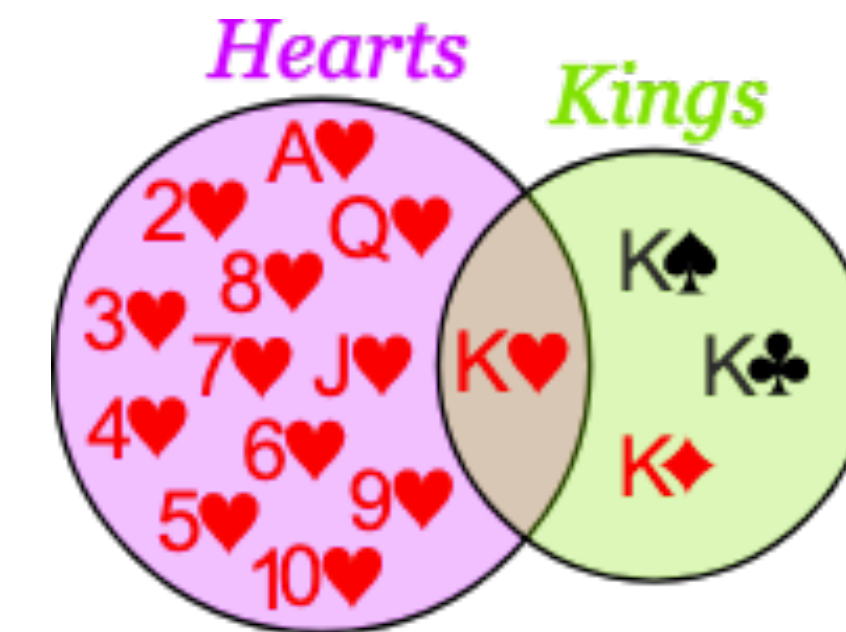
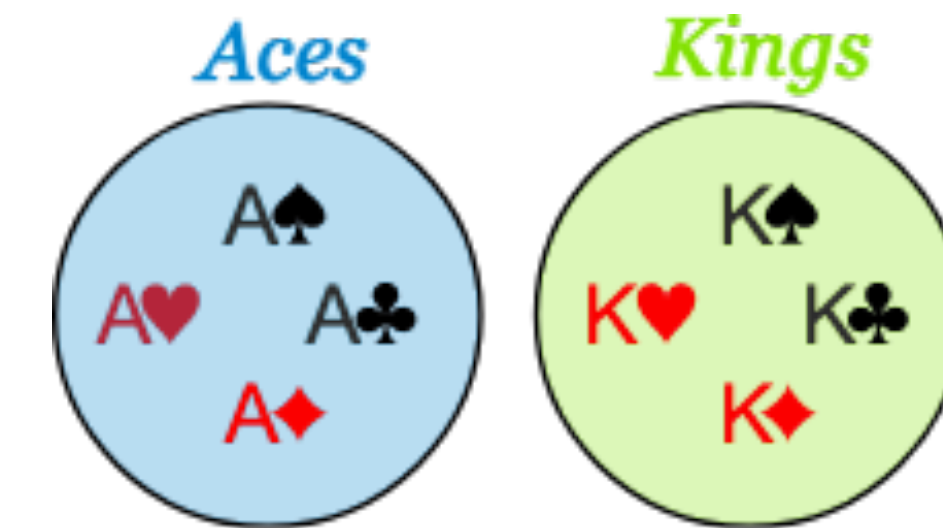


<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- Very important in data science and NLP!
 - ...because, we usually deal with **many** events
 - ...because, **texts** are **sequences** :)
 - ...of words, characters, syllables, sentences, paragraphs...
 - **language modeling:**
 - estimating probabilities of textual sequences
 - given what we've seen before, what is the **most likely** continuation?

“Probabilities sum to 1” ...for mutually exclusive events

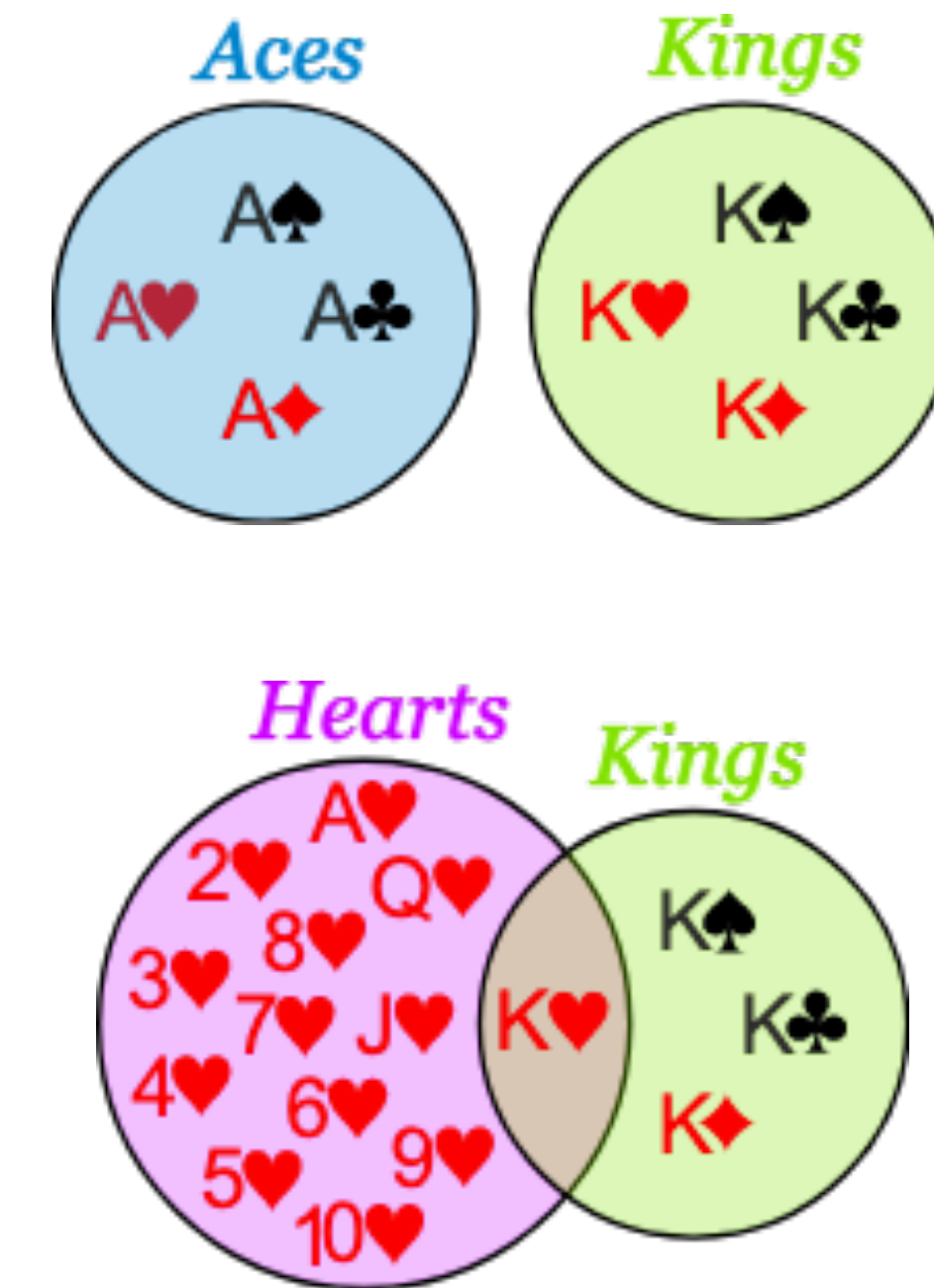
- Why? What does that mean?
 - This refers not to any set of probabilities but only to those which account for **all possible outcomes** in a specific setting
 - Just a convention/definition
 - $1 = 100\%$
 - Consider all possible outcomes in the **coin toss** setting
 - e.g. {H,T}
 - when you toss a coin, it **must** result in H or T
 - ...There is a 100% probability that ONE of the possible outcomes will be observed
 - Notation: $P(H) + P(T) = 1$



<https://www.mathsisfun.com/data/probability-events-mutually-exclusive.html>

Mutually exclusive events

- e.g. H and T in a coin toss
 - $P(H \text{ and } T) = 0$
 - for one coin toss
- e.g. $P(\text{King and Ace}) = 0$
 - if drawing **one** card
- but: $P(\text{King and Hearts}) > 0$



<https://www.mathsisfun.com/data/probability-events-mutually-exclusive.html>

Probability of sequence of independent events

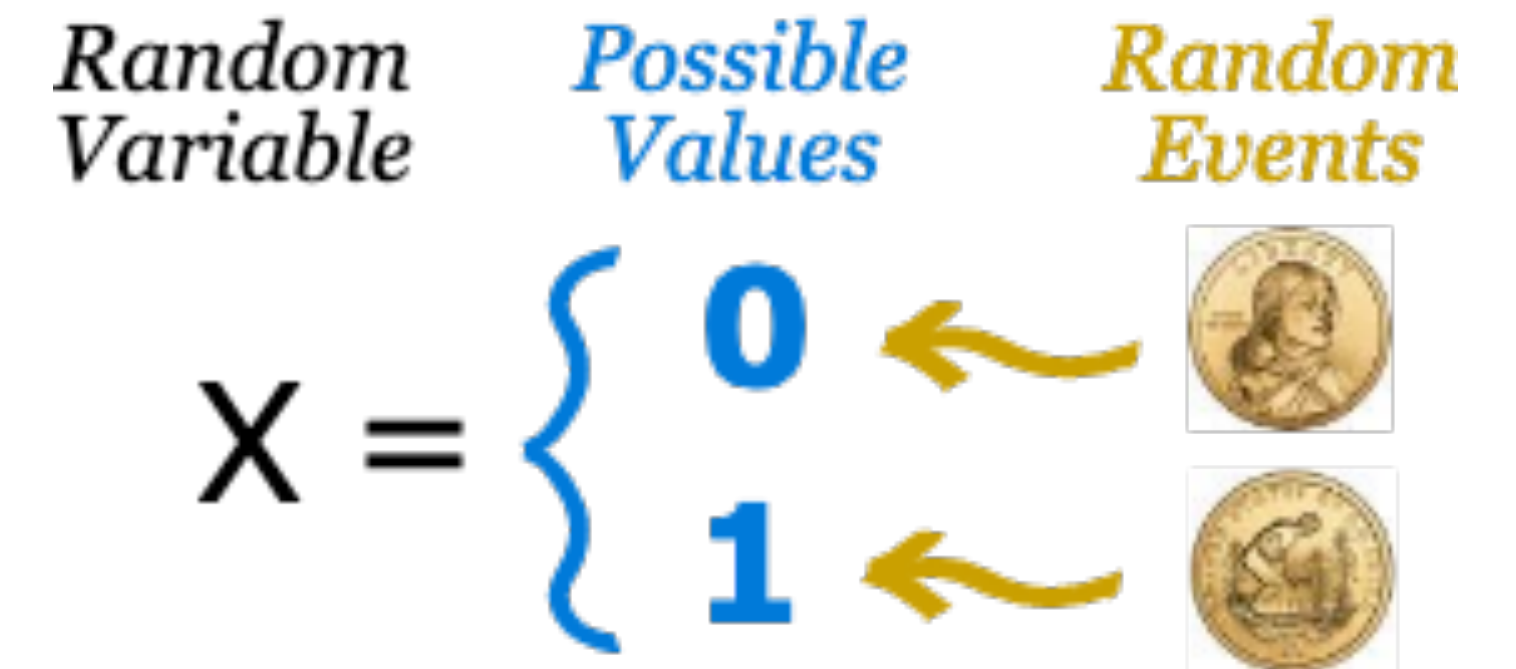


<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- Suppose you toss a fair coin twice
- What's the sample space?
 - {HH, HT, TT, TH}
- What's $P(HH)$?
 - $1/4$
 - observe: this is $P(H) * P(H)$
 - Probability of a sequence is a **product**
- What's $P(HT, \text{ in this order})$?
 - $1/4$
- What's P of getting one H and one T, any order?
 - $1/2$
 - observe: this is $P(HT) + P(TH)$!
 - you want to estimate the P of getting one OR the other!
 - Probability of a disjunction is a **sum**

Random variables

- Set of possible values from a probabilistic experiment
 - e.g. {H, T}
 - we can call H=1 and T=0, or any other arbitrary value!
 - the point is, there is two of them and they are mutually exclusive
- Potentially confusing:
 - What do people mean when saying P(X) or P(A)?
 - it depends, but most often they mean:
 - if A is a random variable and the values are e.g. {1,2,3,4,5,6}
 - then P(A) may refer specifically to P(A=1) or P(A=5)



<https://www.mathsisfun.com/data/random-variables.html>

Independent events



<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- One event does not affect the other
 - e.g. coin toss/die roll etc.
- $P(A \text{ and } B) = P(A) * P(B)$ **only** if A and B are independent

- P(1)?
- P(2)?

Independent events



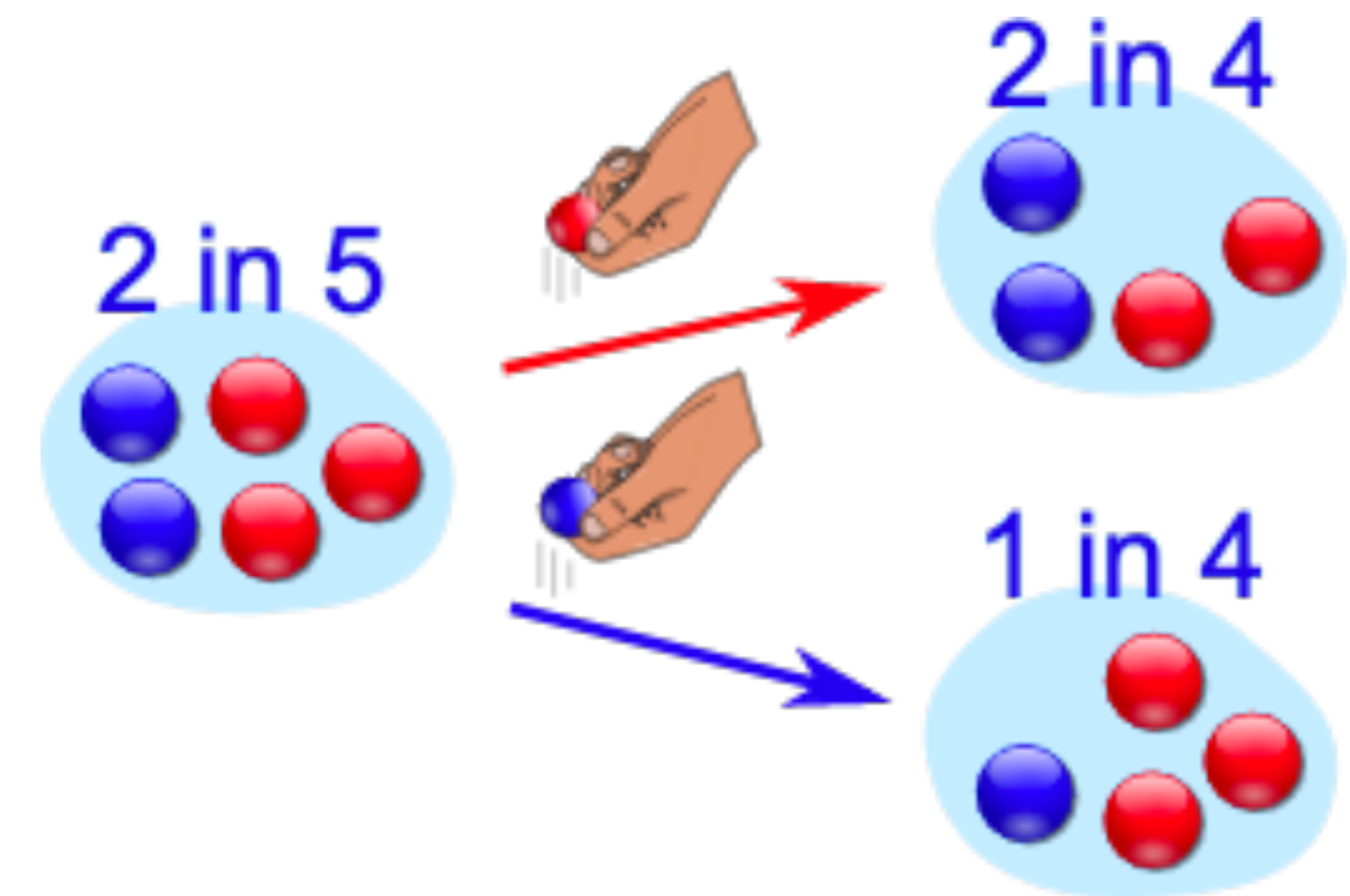
<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- One event does not affect the other
 - e.g. coin toss/die roll etc.
- $P(A \text{ and } B) = P(A) * P(B)$ **only** if A and B are independent

- $P(1) = 1/1024$
- $P(2) = 1/1024$
 - whaaaat?!
- This is unintuitive, because we were not comparing $P(1)$ to $P(2)$
 - we were comparing $P(1)$ with something more like $1 - P(1)$

Conditional probability

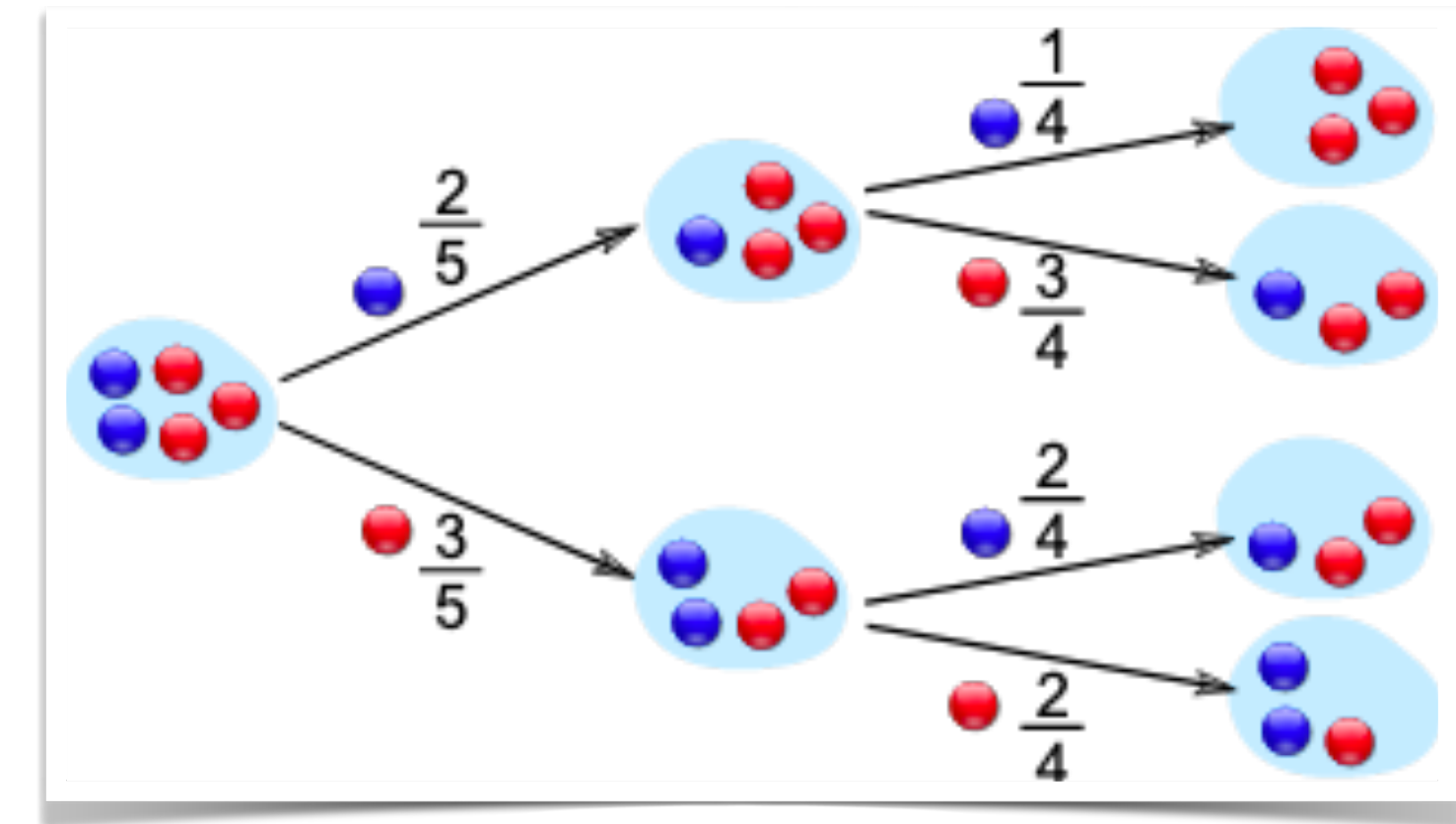
- What's the probability of A **given** B?
 - e.g., if it is very sunny, is it more or less likely that it will rain in 30 minutes?
 - (compared to when it is **not** sunny)
 - e.g. if you see lightning, is it more or less likely that you hear thunder in a few seconds?
 - (compared to when you **don't** see a lightning)
 - Formal example: removing marbles from a bag
 - consider the **sample space**



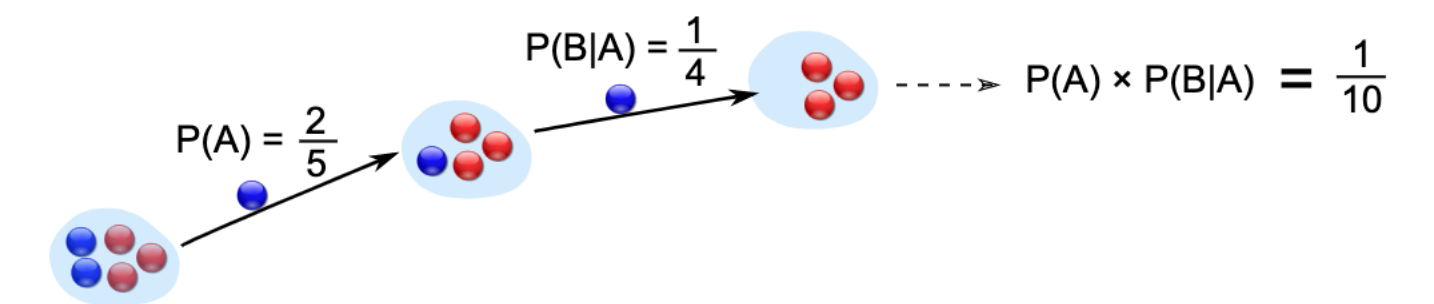
<https://www.mathsisfun.com/data/probability-events-conditional.html>

Conditional probability definition

- $P(\text{thunder} \mid \text{lightning}) = P(\text{L and T})/P(\text{L})$
 - $P(\text{L and T})$:
 - estimated by counting all occurrences when **both** things occurred
 - $P(\text{L})$:
 - estimated by counting all occurrences when **L** occurred
- Conditional prob. is crucial in the **Bayes** Theorem
 - and the Naive Bayes classification algorithm
 - the bread and butter of many data science techniques
- Assignment 4



So the probability of getting **2 blue marbles** is:



And we write it as

$$P(\text{A and B}) = P(\text{A}) \times P(\text{B} \mid \text{A})$$

"Probability Of" points to P(A and B)
"Given" points to P(B | A)
Event A points to A, *Event B* points to B

"Probability of event A and event B equals the probability of event A times the probability of event B given event A"

Marginal probabilities

- Prepresent conditional probabilities in tables
 - the table has joint probabilities in it, of two events
 - to marginalize a probability of A is to compute $P(A)$ by removing any dependencies on other events
 - by summing along row or column
 - e.g. 0.24 is the P of being a Freshman
 - e.g. 0.45 is the P of being Single
 - the marginals should sum up to 1
 - across row and separately along column
 - why?

All values of A

		0	1	2
All values of B	0			Every outcome falls into a bucket
	1		$P(A = 1, B = 1)$	
	2			Remember “,” means “and”

Joint Probability Table				
	Single	In a relationship	It's complicated	Marginal Year
Freshman	0.13	0.09	0.02	0.24
Sophomore	0.16	0.10	0.02	0.28
Junior	0.12	0.10	0.02	0.23
Senior	0.01	0.09	0.00	0.10
5+	0.03	0.12	0.01	0.15
Marginal Status	0.45	0.48	0.07	

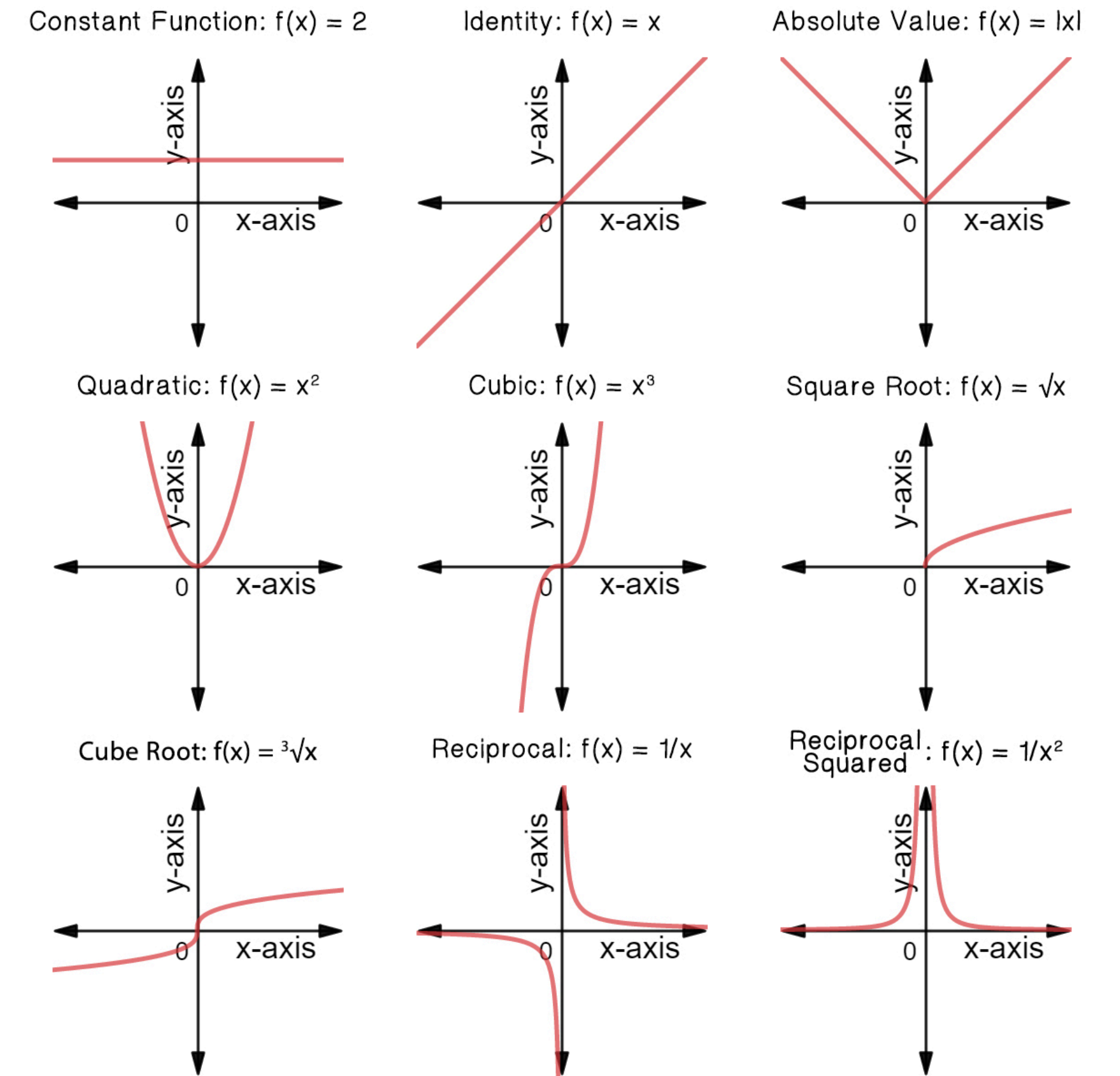
<https://web.stanford.edu/class/archive/cs/cs109/cs109.1176/lectures/12-ContinuousJoint.pdf>

Statistics

**Let's work with probabilities to estimate what
the world looks like!**

Functions review

- Functions are bread and butter of statistics
- Function:
 - input—output
 - given \mathbf{x} , what is the value of \mathbf{y} ?
 - $f(x)$
 - e.g $f(x): y = 2x$
- Function equations can be visualized as lines and curves (in 2D)
- **Probabilities** can be seen as functions
 - what is the **probability** of observing **datapoint** x ?
 - ...need to know how datapoints are **distributed**
 - **probability functions** describe such **distributions**

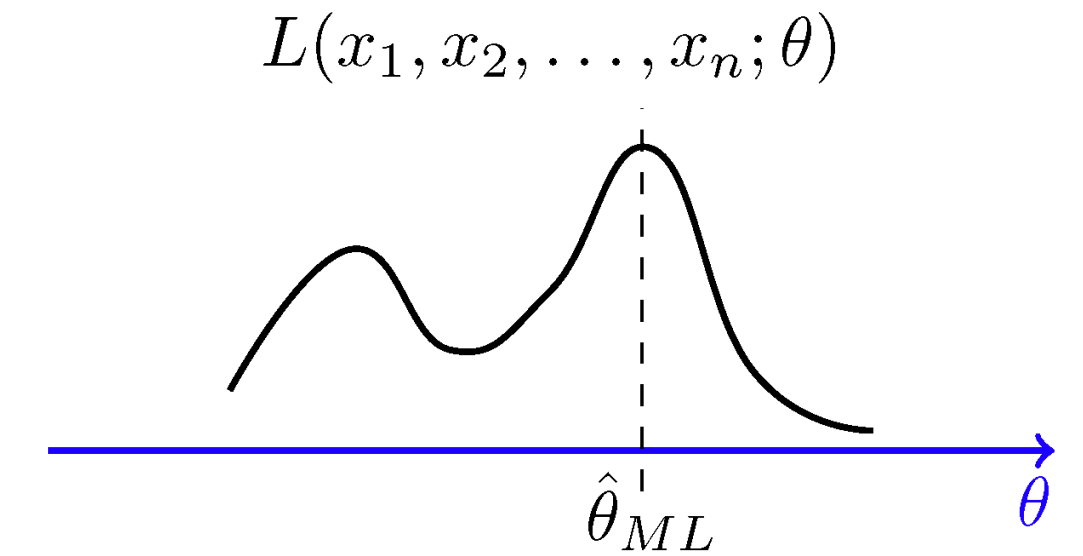
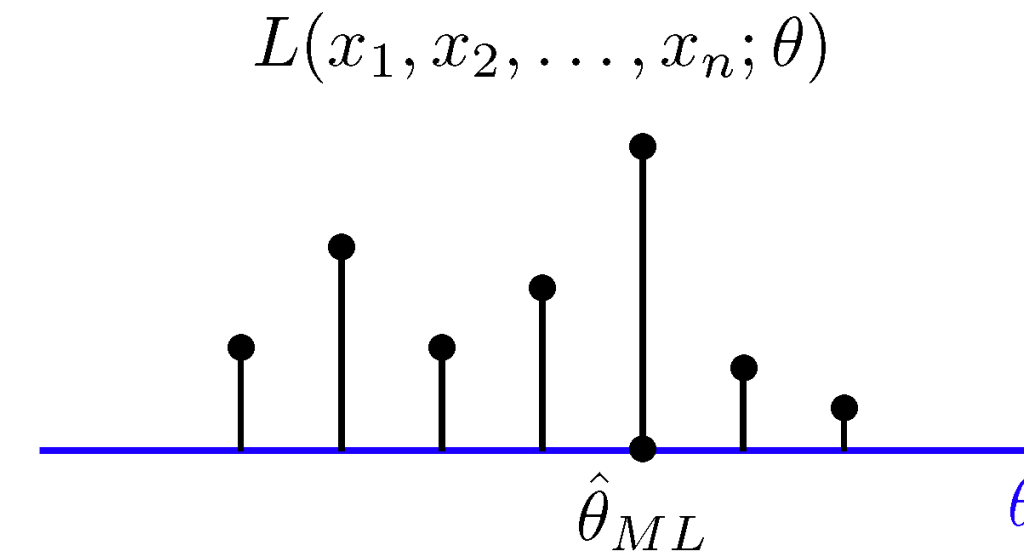


<https://www.expil.com/t/classifying-common-functions-4320>

Maximum (log) Likelihood

Maximum likelihood estimation

- Goal:
 - Represent probabilities **abstractly**, as formulae
 - Prob. of each outcome is a **parameter**
 - Parameters can be **unknown**; we want to **estimate** their values
 - e.g. (weighted, non-fair) coin toss
 - What's the $P(H)$?
 - we don't know, so we will use an abstract parameter
 - θ
 - then $P(T) = 1 - \theta$
 - then $P(HT) = \theta * (1 - \theta)$
 - then $P(HHHTT) = \theta^3 * (1 - \theta)^2$
 - What is θ ?



https://www.probabilitycourse.com/chapter8/8_2_3_max_likelihood_estimation.php

Maximum likelihood



<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- Suppose we tossed a non-fair coin 5 (billion) times:
 - $\text{result}\{H,H,H,T,T\}$
 - what's the $P(H)$?
 - $3/5$
 - This is by definition, which is theoretical
 - Can we get some practical evidence for this?

Maximum likelihood estimation

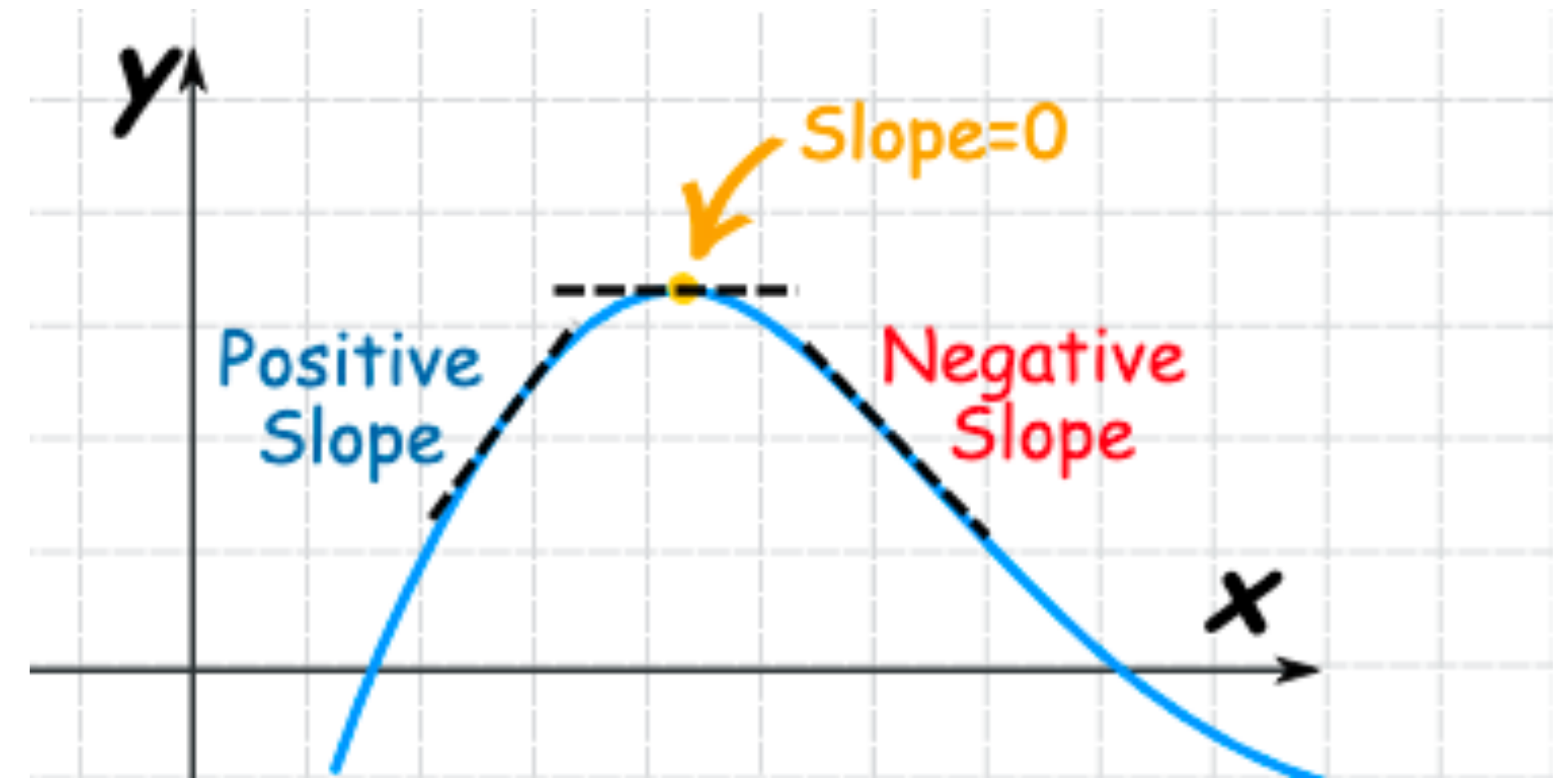


<https://www.air-worldwide.com/blog/posts/2019/3/understanding-probability-are-you-asking-the-right-questions/>

- Yes!
- We know there is some P of getting H:
 - call it θ
- What do we know about $P(T)$?
 - it has to be $1-\theta$
- $D = \{HHHTT\}$
 - What's $P(D)$?
 - $P(D)$ is the **product** of the probabilities

Maximum likelihood estimation

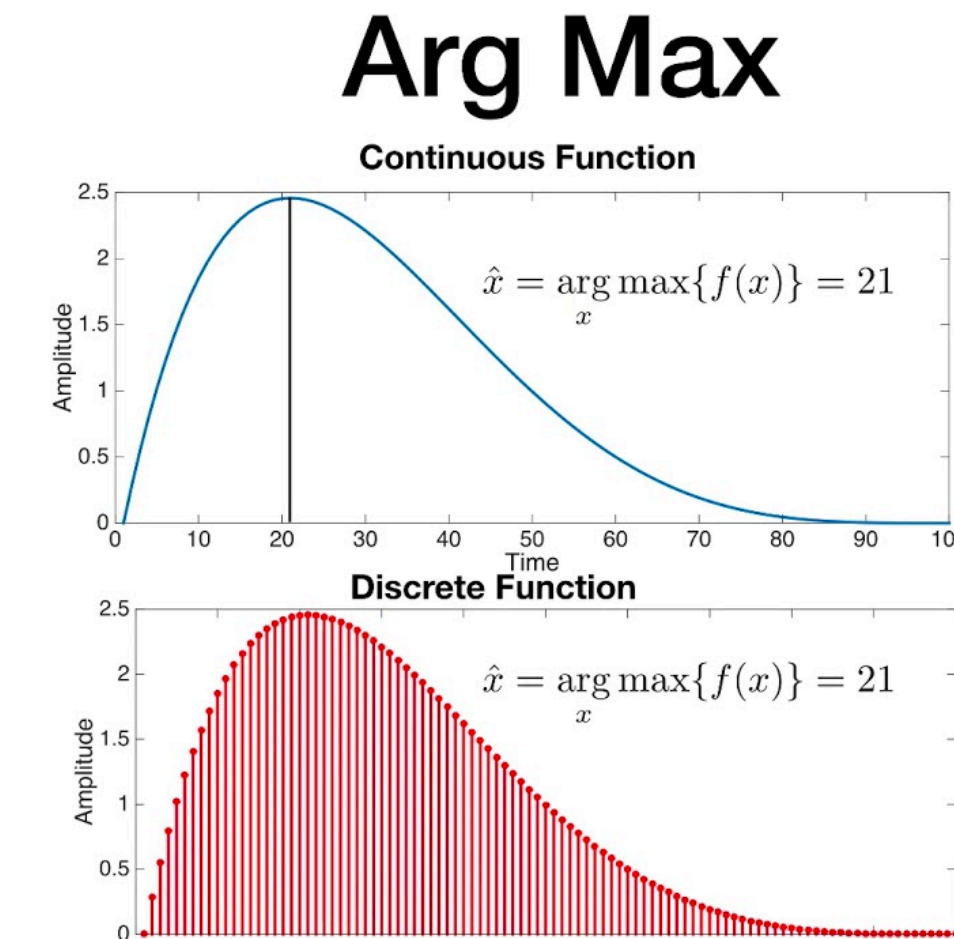
- $D = \{HHHTT\}$
 - $P(D) = \theta^3 * (1 - \theta)^2$
- What are we after here?
 - θ (aka $P(H)$)
- We want a value for θ **such that** $P(D)$ is **max!**
 - how to find the **maximum** point of a function?
 - think of functions as **curves**
 - a curve becomes **flat** at its maximum
 - a curve's **slope** is its **derivative**, and derivative = **0** at the flat point
 - which may be directly **computable** (calculus)
 - we know how to compute derivatives for a range of functions
 - we just **look it up**
 - for functions for which we **can't** compute the derivatives:
 - we estimate by **other means** ("gradient descent")



Before we continue: Two additional pieces

arg max

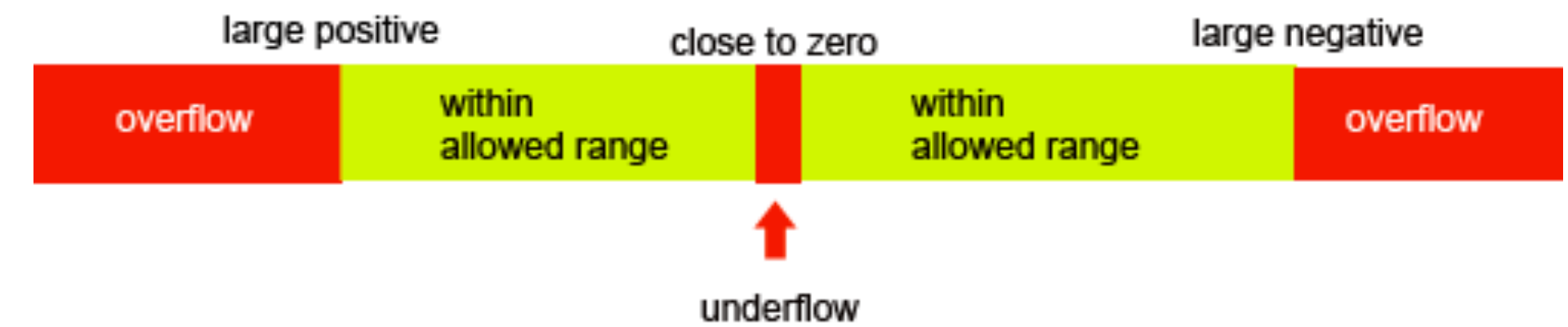
- functions look like **curves** (in 2D)
- Those curves have **maxima** along the **Y-axis**
- The point on the **X-axis** where Y is maximum:
 - is the **arg max**
- Why is this important:
 - We want to find parameters for probability functions given our observations
 - If the function has parameter θ , **which** value for θ results in **maximum** probability for the **observed** sequence/data?



Logarithms and Products

- Probabilities range from **0 to 1**
- Suppose you have a **loooooong** sequence of events
- What happens if you multiply **many-many** numbers **each** ranging between 0 and 1?
 - your number becomes **so small** that the computer **cannot represent** it
 - **logs** to the rescue!

LIMITS OF FLOATING POINT NUMBERS

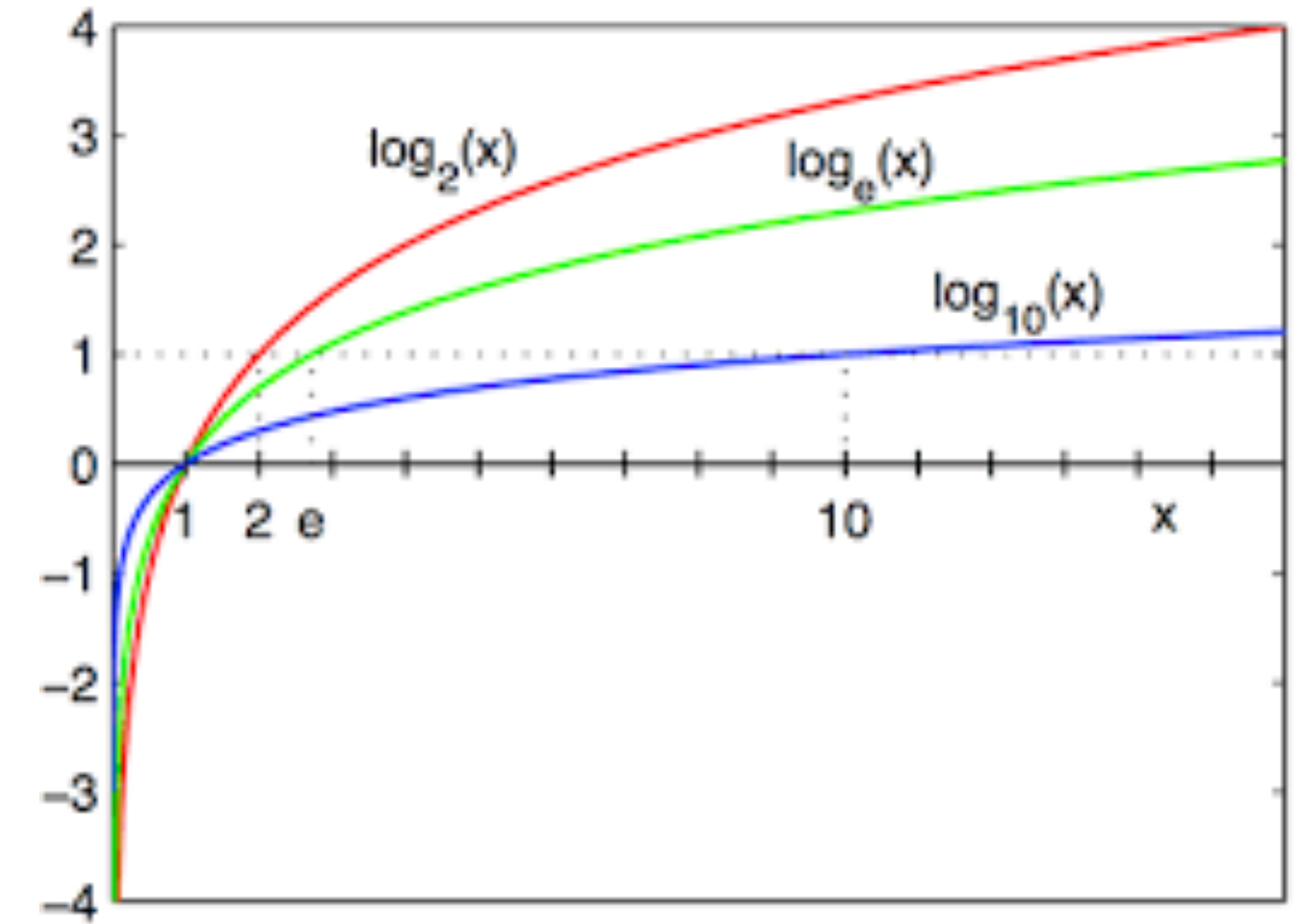


(c)www..teach-ict.com

https://www.teach-ict.com/as_as_computing/ocr/H447/F453/3_3_4/floating_point/miniweb/pg9.htm

Logarithms and Products

- $\log(x*y) = \log(x) + \log(y)$
- Due to certain **properties of the log**:
 - Can use $\log(P(A))$ **in place** of $P(A)$
 - for likelihood estimation
 - $\arg \max$ of $P(D)$ will be where $\arg \max$ for $\log(P(D))$ is!
 - and $\ln(P(D))$
 - \Rightarrow Can use **sum of logs instead** of product



<https://en.wikipedia.org/wiki/Logarithm>

- Reminder:
 - log is inverse function to exponent
 - e.g. $10^2 = 100$
 - $\Rightarrow \log_{10}(100) = 2$
 - \ln is "natural log"; it is "base 2.71828" (e)

Maximum likelihood

for calculus fans

- $D = \{HHHTT\}$

- $P(D) = \theta^3 * (1 - \theta)^2$

- What are we after here?

- θ (aka $P(H)$)

- We want a value for θ such that $P(D)$ is max!

- we know the derivative for natural log of x

- as well as for $\ln(1-x)$

- use θ as x

$$P(D) = \theta^3 (1 - \theta)^2$$

$$\hat{\theta} = \arg \max_{\theta} P(D; \theta) =$$

$$\arg \max_{\theta} \ln(\theta^3 (1 - \theta)^2) =$$

$$\frac{d}{d\theta} \ln(\theta^3 (1 - \theta)^2) = \frac{d}{d\theta} \ln(\theta^3) + \frac{d}{d\theta} \ln((1 - \theta)^2)$$

$$= \frac{d}{d\theta} \ln \theta^3 + \frac{d}{d\theta} \ln (1 - \theta)^2 =$$

$$3 \frac{d}{d\theta} \ln \theta + 2 \frac{d}{d\theta} \ln (1 - \theta)$$

$$3 \cdot \frac{1}{\theta} + 2 \cdot \left(\frac{-1}{1 - \theta} \right)$$

$$\frac{3}{\theta} - \frac{2}{1 - \theta} = 0 \implies \frac{3}{\theta} = \frac{2}{1 - \theta} \implies 3(1 - \theta) = 2\theta \implies 3 - 3\theta = 2\theta \implies 3 = 5\theta \implies \theta = \frac{3}{5}$$

Lecture survey in the chat