# Week 15: Primer on probability, likelihood, & Bayesian methods

ANTH 674: Research Design & Analysis in Anthropology

Professor Andrew Du
Andrew.Du2@colostate.edu

Office Hours: Thursdays, 9:00am–12:00pm
In person: GSB 312
Virtual: https://tinyurl.com/F22ANTH674

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## Announcements

- Lecture will span Monday & Wednesday
- Leftover time on Wed. will be for the tutorial
- No homework this week
- Class presentations on **Dec. 5th**
  - Afterwards, will do course surveys (bring laptop)
- No lab on Dec. 7th
- Final paper due on **Dec. 12th at 10pm**

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## Statistics vignette

- How often should 40-year-olds have a mammogram to screen for breast cancer?
- In 2009, US gov't advised 40-year-olds **NOT** to have annual mammograms (caused an uproar)
- **WHY???**

https://www.hopkinsmedicine.org/news/media/releases/despite_new_recommendations_women_in_40s_continue_to_get_routine_mammograms_at_same_rate

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## Some relevant numbers

- Mammograms catch breast cancer in 40-year-olds 80% of the time (true positive rate) (National Cancer Institute)
- False positive rate is 10% (*New England Journal of Medicine*)

What's the probability an asymptomatic person w/ no history of breast cancer has it, given an abnormal mammogram?

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# QUITE low!

- The answer is **3%**
- This is because the background rate of breast cancer is very rare: 0.4% (*Cancer*, *Journal of the American Medical Association*)

https://www.komen.org/breast-cancer/screening/when-to-screen/average-risk-women/
https://www.breastcancer.org/research-news/screening-at-40-instead-of-50-saves-lives

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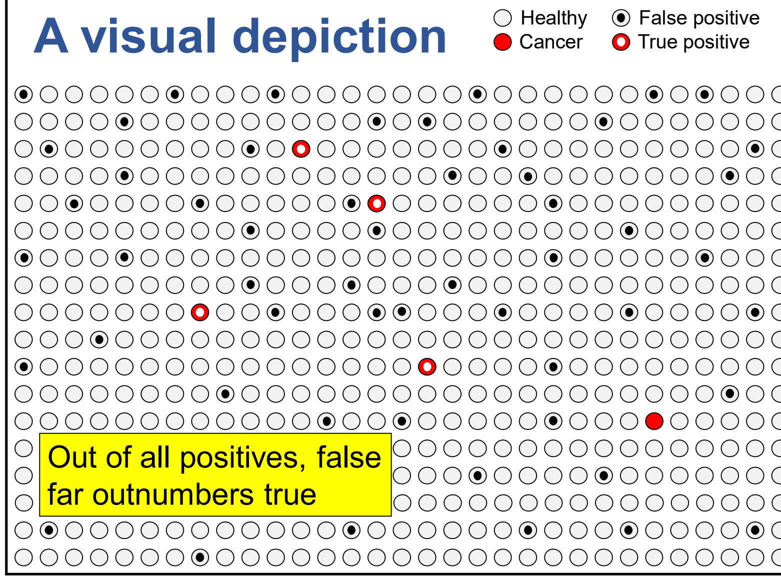
# A visual depiction

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# Or one can use Bayes' theorem

- $P(C|+) = \frac{P(+|C)P(C)}{P(+)}$
- $P(+|C)$ = true positive rate = 0.8
- $P(C)$ = background cancer rate = 0.004
- $P(+)$ = positive mammogram rate = (true positives + false positives) / everyone = 0.1
- $P(C|+) = \frac{0.8 \times 0.004}{0.1} = 0.03$

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# Lecture outline

- Probability theory
  - Fundamentals of probability
  - Probability distributions
- Likelihood
  - Fundamentals of likelihood & maximum likelihood estimation
  - Hypothesis testing & model selection
- Bayesian
  - Subjective probability
  - Prior information & calculating the posterior

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## Foundations of model building

- I covered a **LOT** of methods in this course, so you can pick the best one for your question
- Even better is constructing **your own** method or model, **perfectly** suited for your question
- The topics covered in this lecture are the foundation for building your own models

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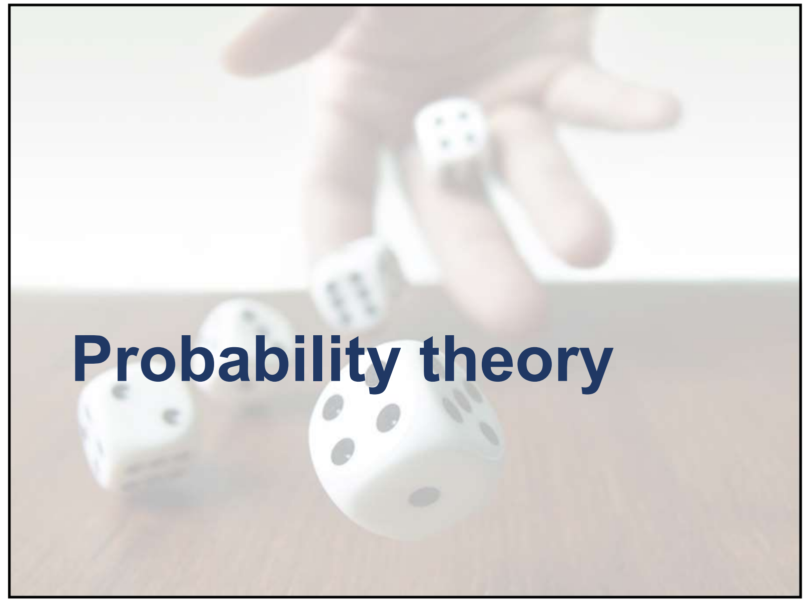

## Probability theory

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## Fundamentals of probability

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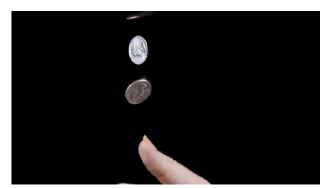
## What is probability?

- **How likely an outcome is**
  - E.g., What is the probability a coin flip is heads?
- Can never predict outcome w/ 100% certainty because of variation in process of interest
- Probability lies at the foundation of all statistics



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## The frequentist perspective

- *P = # outcomes / # trials* (<u>range</u>: 0–1)
- Specifically, the relative frequency of some outcome as # trials → infinity
- E.g., how would you infer probability of rolling a 1?


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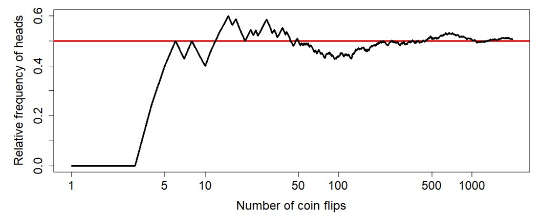
## The frequentist perspective

- <u>SUPER</u> empirical! Requires that a trial can be repeated many, many times (at least in principle)
- Infinity trials not feasible, so this is considered theoretically or need representative sample
  - E.g., statistician John Kerrich flipped coin 2,000 times while imprisoned by Nazis in WW2

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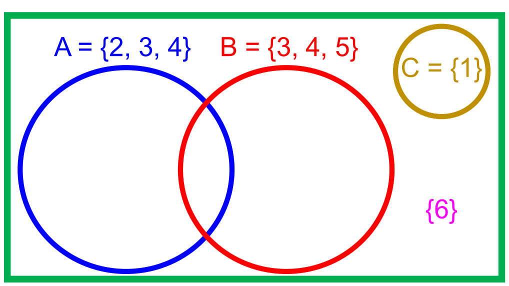
## Probability definitions

- <u>**Sample space**</u>: set of all possible outcomes
- <u>**Event**</u>: any subset of the sample space
  - E.g., P(A) = probability of <u>event</u> A happening

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## First axiom of probability

- <u>**The sum of all probabilities of outcomes within sample space = 1.0**</u>
  1. Events must be <u>**mutually exclusive**</u>: no elements in common, e.g., {1, 2} and {3, 4}
  2. Events must be <u>**exhaustive**</u>: covers all possible outcomes, e.g., {1, 2, 3} and {4, 5, 6}

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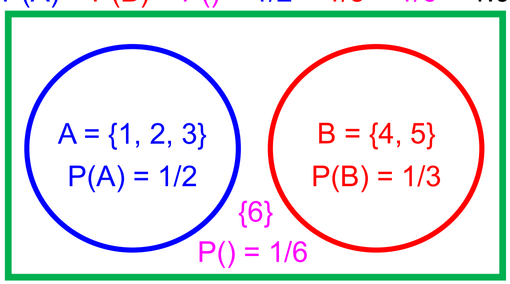
## First axiom of probability

- Outcomes are mutually exclusive (no overlap) & exhaustive (together, comprise entire sample space: {1, 2, 3, 4, 5, 6})

P(A) + P(B) + P() = 1/2 + 1/3 + 1/6 = 1.0

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## Complements

- Can use 1st axiom to calculate probability of the **complement** of an event, i.e., the probability an event *doesn't* happen in sample space
- Complements are represented with a ′ or $^c$
  - $P(A') = P(A^c) = 1 - P(A)$
  - E.g., $P(\{1\}^c) = 1 - P(\{1\}) = 1 - 1/6 = 5/6$
- Works because complements are *always* mutually exclusive and exhaustive

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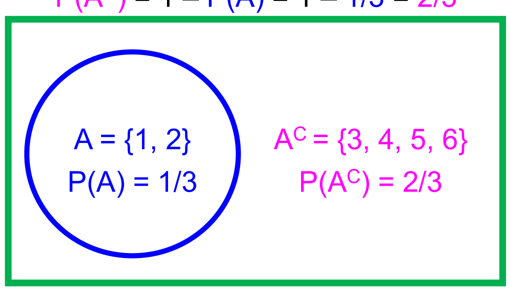
## Complements

- By definition, are mutually exclusive (no overlap) & exhaustive (together, comprise entire sample space)

$P(A^C)$ = 1 – P(A) = 1 – 1/3 = 2/3

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## Intersections

- The common outcomes between two (or more) events
- Intersections are represented with ∩
- "AND" statement in logic; & in R
- E.g., {1, 2, 3} ∩ {3, 4, 5} = {3}
- P({1, 2, 3} ∩ {3, 4, 5}) = P({3}) = 1/6

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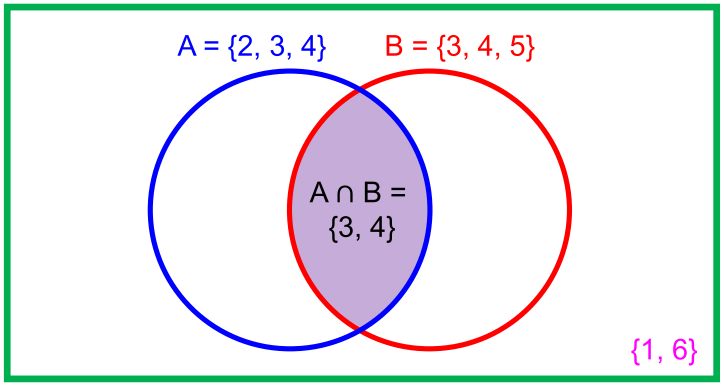
## Intersections



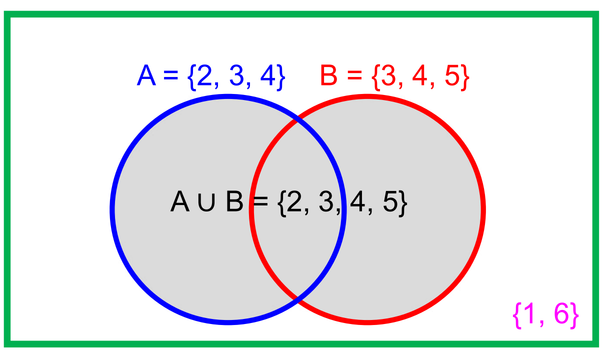



## Unions

- The union of two (or more) events is the set of all outcomes that are in either or both events
- Unions are represented with a ∪
- “OR” statement in logic; | in R
- E.g., {1, 2, 3} ∪ {3, 4, 5} = {1, 2, 3, 4, 5}
- P({1, 2, 3} ∪ {3, 4, 5}) = P({1, 2, 3, 4, 5}) = 5/6



## Unions



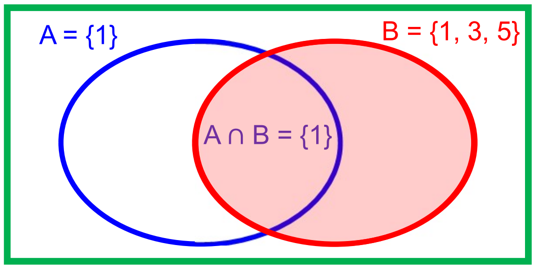



## Conditional probability

- Probability of an event, given prior occurrence of another event
- P(A | B) is probability that A happens, given that B has happened
  - “Probability of A given B” or “probability of A conditional on B”
- E.g., probability of rolling a one, given that you rolled an odd number

## Conditional probability

- P(A | B), e.g., P({1} | {1, 3, 5})
- B becomes new sample space
- W/in B, calculate probability of A also happening




$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P(\{1\}|\{1,3,5\}) = \frac{1/6}{1/2} = 1/3$$

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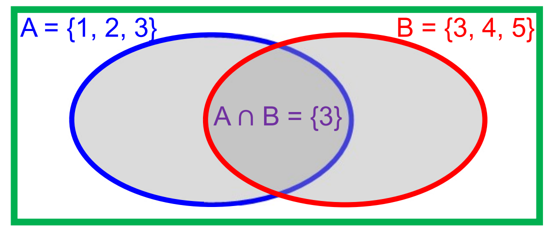
## The addition rule

- Associated with unions, e.g., {1, 2, 3} ∪ {3, 4, 5}
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
- $P(A \cup B) = P(A) + P(B)$ **IF** A and B are mutually exclusive, i.e., $P(A \cap B) = 0$




$$P(A \cup B) = \frac{1}{2} + \frac{1}{2} - \frac{1}{6} = \frac{5}{6}$$

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## The multiplication rule

- Associated with intersections
- $P(A \cap B) = P(A) \times P(B|A) = P(B) \times P(A|B)$
  - Just a rearrangement of conditional probability formula
- If A happening does not affect P(B) and vice versa, A and B are **independent** events
  - $P(B|A) = P(B)$ and $P(A|B) = P(A)$
- **IF** A & B are independ., $P(A \cap B) = P(A) \times P(B)$
  - E.g., if relative frequency of dominant allele in population is $p$, relative frequency of homozygous dominant genotype is $p^2$

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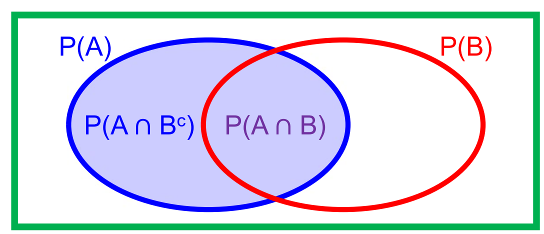
## Law of total probability

- Transforms conditional and/or intersection probabilities into **marginal probability** AKA **unconditional probability** (e.g., P(A), P(B))
- $P(A) = P(A \cap B) + P(A \cap B^C)$
- Also $P(A) = P(B) \times P(A | B) + P(B^C) \times P(A | B^C)$

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## Questions?

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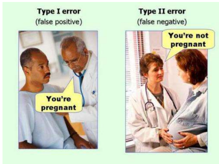
## E.g., Type I error




- What is the probability of getting **at least** one false positive, given 100 tests and $\alpha = 0.05$?
- This is the complement of getting **no** false positives for all 100 tests
    1. P(false pos.) = 0.05
    2. P(false pos.$^c$) = 1 – 0.05 = 0.95
    3. $[\text{P(false pos.}^c)]^{100} = 0.95^{100} \approx 0.006$
        - Assumes tests are independent
    4. $1 - [\text{P(false pos.}^c)]^{100} \approx 1 - 0.006 \approx$ **0.994**
    5. $\mathbf{1 - (1 - \alpha)^n}$

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# Probability distributions

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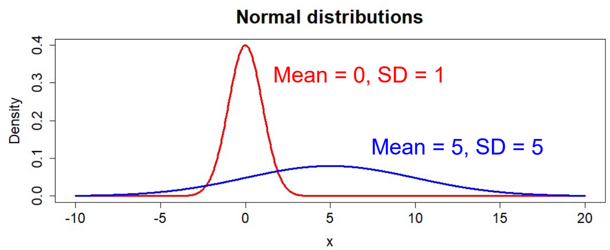
## What is a probability distribution?

- A function that describes how likely certain values are in a **random variable**, i.e., where outcomes are not 100% predictable
- Shape is described by **parameters**

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# Two types of distributions

1. **Discrete probability distributions**
   - Describes random variables whose outcomes are finite or countable (e.g., integers)
   - AKA probability **mass** function (PMF)
   - E.g., binomial distribution, Poisson distribution
2. **Continuous probability distributions**
   - Describes random variables whose outcomes can take on any value within a smooth interval
   - AKA probability **density** function (PDF)
   - E.g., normal distribution, lognormal distribution

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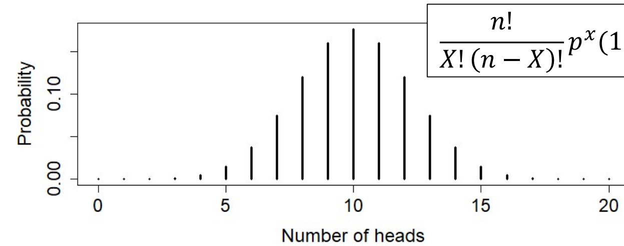
*parameters in red

# Discrete: binomial PMF

- Describes probability of getting $X$ successes in $n$ trials, given a probability of success, $p$
- E.g., probability of flipping $X$ heads in 20 flips, given probability of heads is 0.5

$$\frac{n!}{X!\,(n-X)!}p^x(1-p)^{n-X}$$

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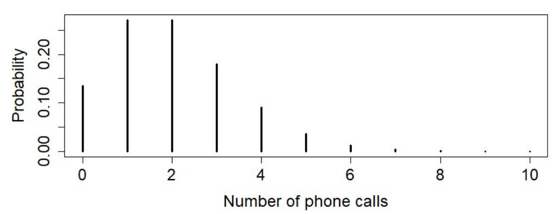
*parameters in red

# Discrete: Poisson PMF

- Describes probability of getting $X$ occurrences of an event in a fixed area or time period, given an average # occurrences in area/time ($\lambda$)
- E.g., probability of getting $X$ phone calls in an hour, given average calls/hour is 2

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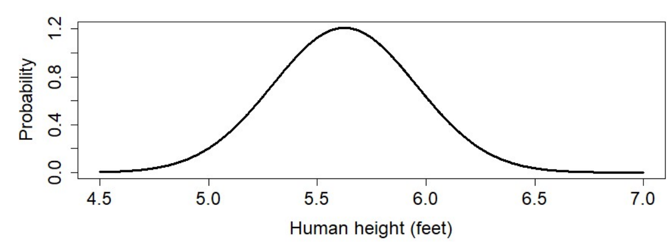
*parameters in red

# Continuous: normal PDF

- Describes how likely a value of $X$ is, given the mean ($\mu$) and SD ($\sigma$)
- $X$ is outcome of additive processes
- E.g., human heights in a population

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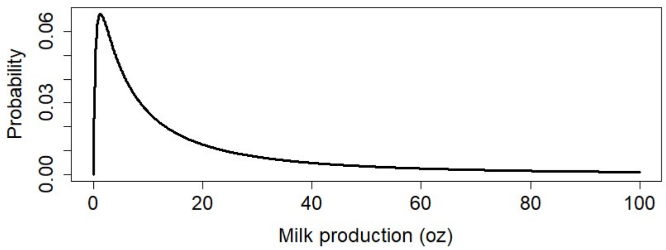
*parameters in red

# Continuous: lognormal PDF

- Describes how likely a value of $X$ is, given the mean ($\mu$) and SD ($\sigma$) in log space
- $X$ is product of multiplicative processes
- E.g., milk production by cows

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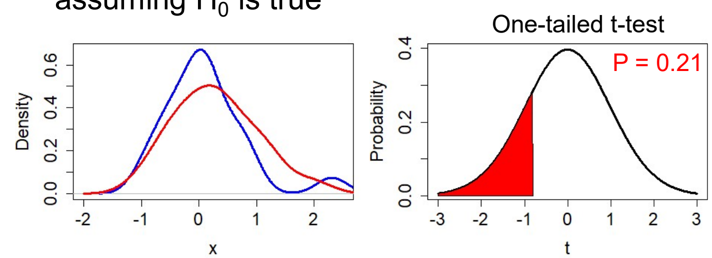
# Cumulative distribution function (CDF)

- Calculates probability that $X$ is ≤ some value for **any** distribution
- E.g., P-values: probability of getting null statistic more extreme than observed statistic, assuming $H_0$ is true

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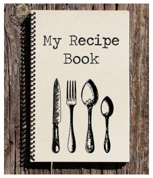
# Simplified modeling recipe

1. Figure out the P(A) that addresses your research question & how to derive P(A) from other probabilities, e.g., P(A | B), P(B)
2. Figure out how to represent each probability with a distribution
3. Carry out the math to get your probability model

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# Questions?

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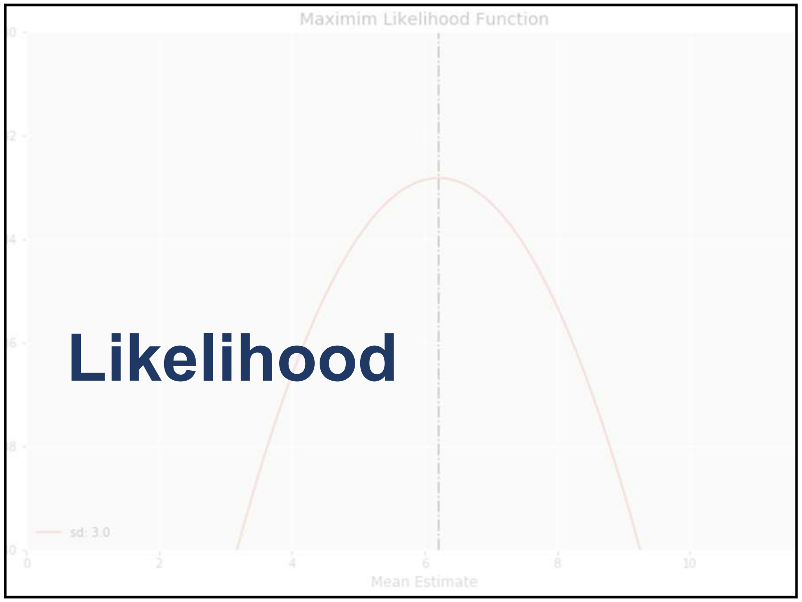


# Likelihood

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# Fundamentals of likelihood & maximum likelihood estimation

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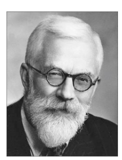
## What is likelihood?

- A principled **frequentist** framework for statistical inference and modeling
  1. Parameter estimation
  2. Hypothesis testing
  3. Model selection
- A lot of methods can be derived, and thus unified, with likelihood (e.g., t-tests, OLS)
- First developed by R.A. Fisher



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## Defining likelihood

- Traditional frequentist tests calculate P(Data | Model), e.g., P-value
- Likelihood inverts the conditional probability to get L(Model | Data)
- E.g., probability asks what is the probability of getting 4 heads out of 10 coin flips (data), given that $p$ = 0.5 (assumed model parameter)
- Likelihood asks how likely is $p$ = 0.5 (model parameter), given that you get 4 heads out of 10 coin flips (data)

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## Another example

Weather (parameter)

| Attire (data) | Cold | Warm |
|---|---|---|
| Jacket | 0.8 | 0.1 |
| T-shirt | 0.2 | 0.9 |
| Total | 1.0 | 1.0 |

- P(attire | cold)
- L(weather | jacket)
- Likelihoods don't have to sum to one (not true probabilities)
- P(jacket | cold) = L(cold | jacket)

- Probability is a statement about observed data
- Likelihood is a statement about the parameter(s)

From Wang (2010)

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## Maximum likelihood estimate (MLE)

- Likelihood provides a framework for estimating unknown parameter(s) in a system
- MLE is the parameter value(s) that makes the observed data most probable (i.e., has the highest likelihood)
  - E.g., on previous slide, MLE is "cold"
  - Given the person wore a jacket, "cold" has a higher likelihood (0.8) than "warm" (0.1)

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## E.g., lion stalking success

- In Ngorongoro Crater (Tanzania), Elliott et al. (1977) found that lions had 34 out 157 successful stalks of wildebeest and zebra
- **Of the entire (partially sampled) population of lions, what is the rate of successful stalks at Ngorongoro?**

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## MLE of stalking success rate

$X$: number of successful stalks (34)

$n$: number of total stalks (157)

$p$: stalking success rate

- Assuming stalks are independent, can model rate ($p$) with binomial distribution
- A good naïve guess of $p$ is 34 / 157 ≈ 0.22 (cf. frequentist definition of probability)

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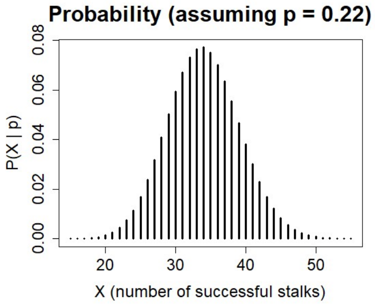
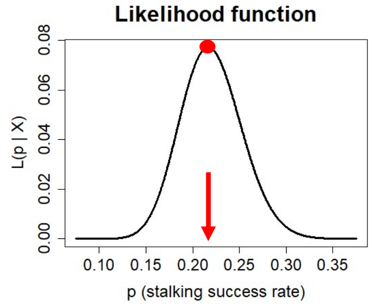
# MLE of stalking success rate




- **Likelihood function** – likelihoods values as fxn. of parameter values (numerically equal to P($X$ | $p$))
- MLE = value of $p$ that gives the highest likelihood

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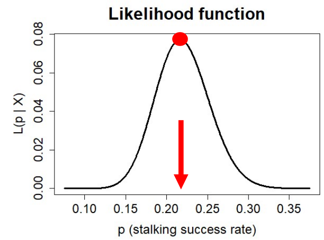
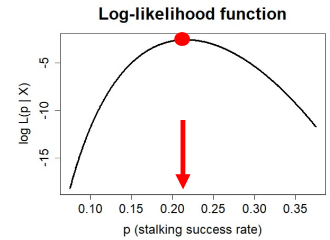
# MLE of stalking success rate

- How to find MLE of $p$ (tip of bell curve)?
- Take derivative of function, set it to zero (maxima of function), and solve for $p$
- Easier to do this with **log-likelihood** function




Maximum at same value of $p$

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# Getting MLE of $p$

1. $L(p|X) = \frac{n!}{X!(n-X)!} p^X (1-p)^{n-X}$ (binomial dist.)
2. $\log L(P|X) = \log\left(\frac{n!}{X!(n-X)!}\right) + X\log(p) + (n-X)\log(1-p)$
3. $\frac{d}{dp}\log L(p) = 0 + \frac{X}{p} - \frac{n-X}{1-p}$
4. $\frac{X}{\hat{p}} - \frac{n-X}{1-\hat{p}} = 0$ (the hat indicates an estimated parameter)
5. $\boldsymbol{\hat{p} = \frac{X}{n}}$
6. $\mathrm{se}(\hat{p}) = \sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$ (derived using log-likelihood function)

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# MLE of stalking success rate

- So $\hat{p} = \frac{X}{n} = \frac{34}{157} \approx 0.22$
- This matches our naïve estimate, but we derived it formally
- MLE has good statistical properties: as $n \to \infty$,
  - Estimate is unbiased
  - Has the smallest possible variance among all unbiased estimators
  - Sampling distribution is normal

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# Questions?



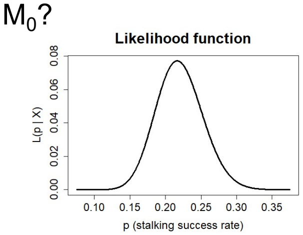
# Hypothesis testing

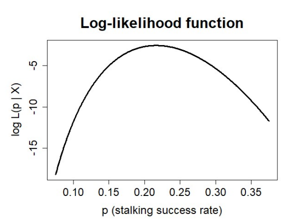
- Let's say the literature says lion stalking success rates should be 0.1 ($H_0 \rightarrow M_0$)
- We can test if the underlying parameter generating our observed data (i.e., MLE; $M_1$) is significantly different from 0.1
- **$M_0$**: P(success. stalk) = $p$ = 0.1
  - zero free parameters
- **$M_1$**: $p$ is free to vary (i.e., is estimated)
  - one free parameter
- Which model fits the data better?



# Hypothesis testing

- $L(M_0 \mid X) = 7.7e\text{-}6$;  $\log L(M_0 \mid X) = -11.8$
- $L(M_1 \mid X) = 0.08$;  $\log L(M_1 \mid X) = -2.6$
- More complex models (more free parameters) always fit the data better
- How to know if $M_1$ fits data significantly better than $M_0$?






# Likelihood ratio tests (LRT)

- If models are nested (complex model has ≥1 extra parameter), can use LRT to test if more complex model ($M_1$) is sig. better than simpler one ($M_0$)

$$LR = -2(\log L[M_0] - \log L[M_1])$$

- If $M_0$ is supported by the data, the two likelihoods should not differ by more than sampling error
- LR follows $\chi^2$ dist. w/ degrees of freedom = difference in # free parameters between models
- For our example, $LR = -2(-11.8 - [-2.6]) = 18.4$
  - P = 1.8e-5

## Model selection

Hirotugu Akaike

- Formalized way of competing hypotheses (models) against each other on equal footing
- The Akaike Information Criterion (AIC) balances goodness of fit (logL) and model complexity ($K$ = # free parameters)

$$\mathrm{AIC} = -2\log L + 2K$$

- AIC measures amount of information lost in approximating reality w/ model (lower AIC is better)
- Can transform into weights (sum to one across models, w/ larger weights → more support)

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## Our lion stalking example

| Model | Descrip. | logL | K | AIC* | AIC weight |
|---|---|---|---|---|---|
| $M_0$ | $p$ = 0.1 | -11.8 | 0 | 23.55 | 2.7e-4 |
| $M_1$ | $p$ free to vary | -2.6 | 1 | 7.13 | 0.9997 |

*General rule: >2 difference in AIC → good support

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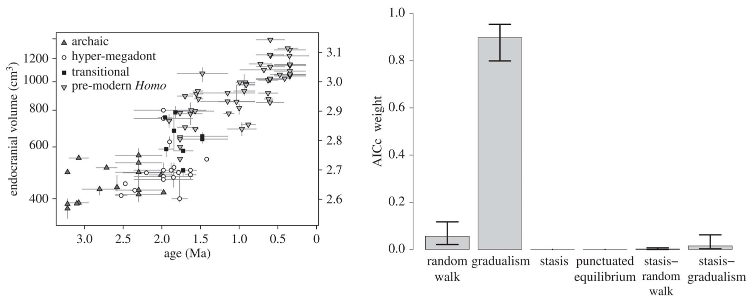
## Another example

- How did hominin brain size increase over time?




Du et al. 2018

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## Questions?

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$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

# Bayesian paradigm

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## Bayesian paradigm

- There are two main differences compared to the frequentist paradigm:

1. A different definition of probability (i.e., **<u>subjective probability</u>**)
2. The incorporation of **<u>prior information</u>** in models

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## Probability: a test

- Are you a frequentist or Bayesian?
- I flip a coin and then cover it with my hand


- What is the probability that the coin is heads?

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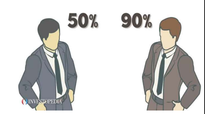
## Subjective probability




- Recall that the frequentist definition of probability is the relative frequency of some outcome as # trials → infinity
- Problematic for unique events
  - E.g., what is the probability that Vermont is larger than New Hampshire?
- Subjective probability quantifies our **<u>uncertainty</u>** or **<u>degree of belief</u>** in some event, whether it is repeatable or not

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# Treatment of parameters

- The frequentist paradigm treats parameters as **fixed** quantities
  - E.g., the average height of *all* humans on Earth
- Randomness is introduced by the sampling process (e.g., each sample of data gives a different mean estimate of height)
- The Bayesian paradigm treats parameters themselves as **random b/c of our uncertainty about them**

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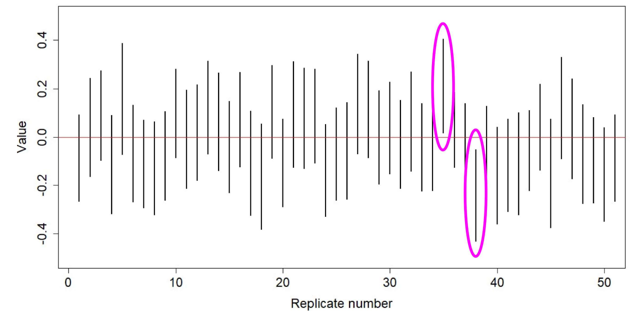
# E.g., 95% CIs

- **Frequentist**: fixed parameter is either inside CI or not (in long run, 5% of CIs exclude parameter)

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# E.g., 95% CIs

- **Frequentist**: fixed parameter is either inside CI or not (in long run, 5% of CIs exclude parameter)
- **Bayesian**: treats parameter as random due to uncertainty, so 95% CI interpreted as a 95% probability parameter is inside CI
  - A Bayesian confidence interval is called a **credible interval**

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# Questions?

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## Prior information

- The main debate: should one incorporate prior knowledge about quantity of interest, external to the dataset?
- E.g., I carry out a presidential approval rating poll in an area and got 41%, even though other organizations got around 55%
- Should I adjust my results upwards (e.g., average 41% and 55%)?
- Unscientific and unethical? Or smart to “stand on the shoulder of giants”?

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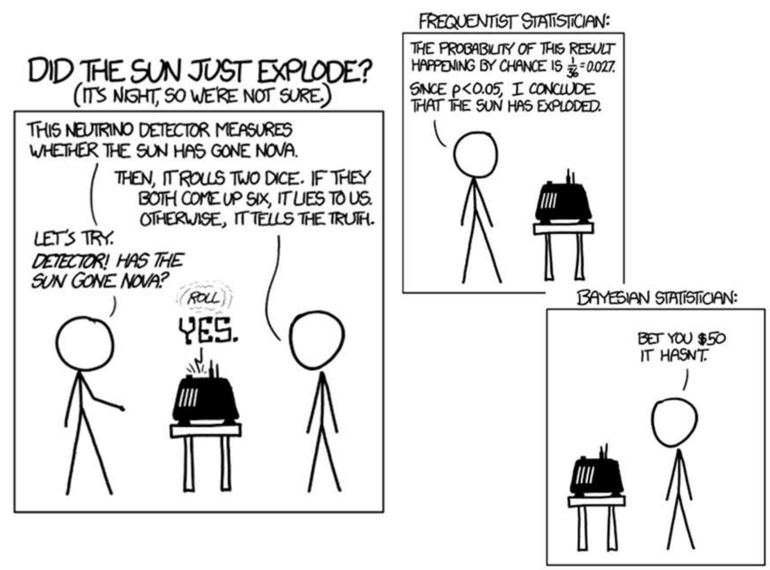


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## Prior information

- It can be argued that **every** researcher incorporates their own biases into their studies
- E.g., researcher finds implausible results and runs experiment for longer
- The Bayesian paradigm enables researchers to incorporate prior information in their models in a principled, formalized manner

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## How to incorporate prior information?


Thomas Bayes

- Bayes’ theorem (or Bayes’ rule):

Prior probability: quantifies prior information

Likelihood: summarizes the data

$$P(H|D) = \frac{P(H)P(D|H)}{P(D)}$$

Posterior probability: probability of hypothesis/model given the data

Scaling factor: Makes area under $P(H|D)$ distribution sum to one

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## Example: lost wallets

- What is the probability ($p$) that police officers will return lost wallets to owners but steal some money?

From Wang (2010)

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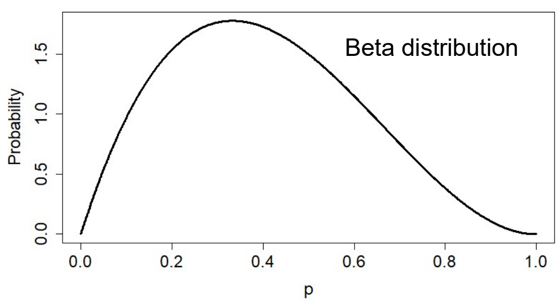
## 1. Formulate the prior, P(H)

- What do **YOU** think the probability is?
- Quantify this with a probability distribution

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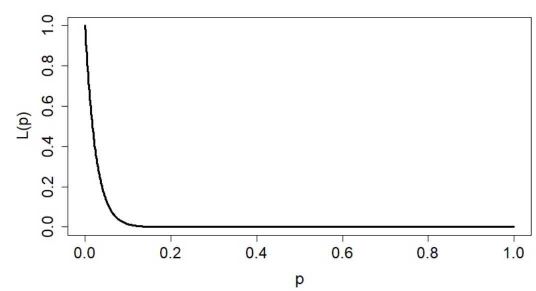
## 2. Collect data & formulate likelihood function, P(D | H)

- In experiment run by *Primetime*, 40 out of 40 officers returned wallets w/ **NO** money missing
- Create likelihood function using binomial dist.

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## 3. Update prior w/ data, P(H | D)

- Bayes' theorem: $P(H|D) = \frac{P(H)P(D|H)}{P(D)}$
- Oftentimes, we ignore the scaling factor, $P(D)$
  - Probability distribution looks identical; only scale of y-axis changes
  - OK b/c only care about which values of $p$ are more probable relative to each other
- So $P(H|D) \propto P(H)P(D|H)$
  - Prior can be thought of as weighting certain values of $p$ in the likelihood
  - If prior is uninformative (all values of $p$ likely), just doing a likelihood analysis

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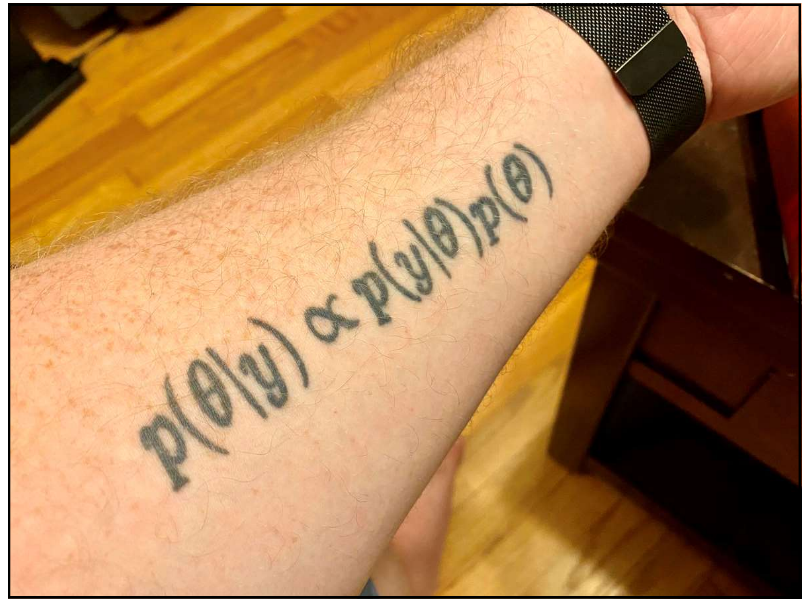


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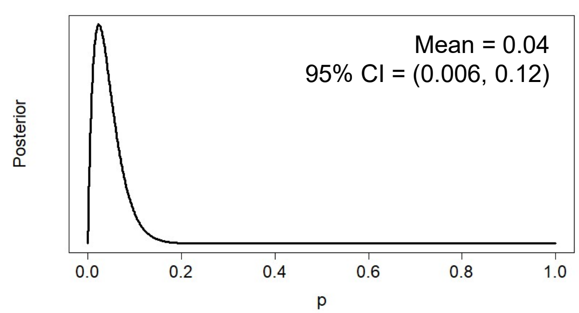
## 3. Update prior w/ data, P(H | D)

- $P(H|D) \propto P(H)P(D|H)$
- Multiply prior by the likelihood

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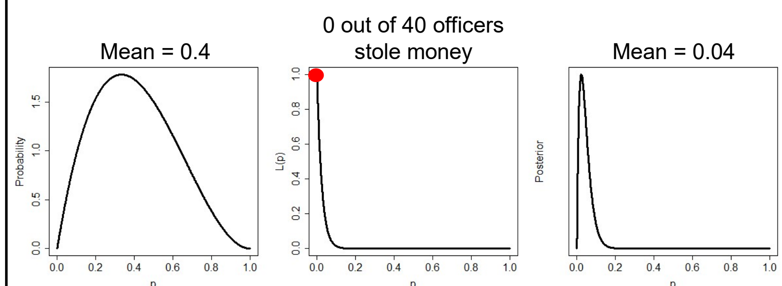
## Prior, likelihood, posterior




- **NB**: w/ zero officers stealing money, MLE of $p$ is zero
- Do we actually expect NO officers to steal money?

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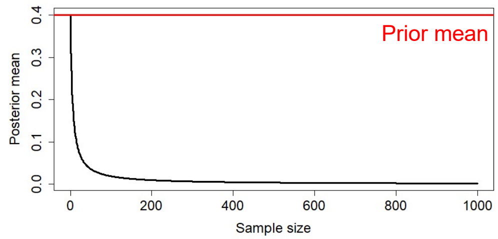
## Influence of dataset size

- Assuming we collect more data and still no officers steal money
- At small $n$, prior dominates
- At larger $n$, MLE dominates ("data speak for themselves")

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## Questions?

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## Summary

- Probability theory quantifies how likely certain events are and how likely certain values in data are
- Likelihood is a principled framework for inferring parameters, testing hypotheses, and comparing models
- Bayesian methods offer a formalized framework for combining prior information w/ the likelihood

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