

Prob & Stats Review

STSCI/INFO/ILRST 3900: Causal Inference

September 4, 2024

Agenda for Today

- Reminders and Announcements
- Probability and Statistics Review
- R/RStudio Intro
- Homework Check-in and Questions

Reminders and Announcements

- HW 1 due Tuesday (September 10) by 5pm
 - Submit a PDF from RMarkdown via Canvas
- Office Hours throughout the week (see Syllabus or website)
 - Filippo: Monday 11am-12pm in Comstock 1187
 - Shira: Wednesday 3-4pm in in Comstock 1187
 - See Ed Discussion for Zoom links/info

Probability and Statistics Review

- Expectation
- Variance
- Conditional Expectation
- Independence
- Bernoulli Random Variables
- Law of Total Expectation
- Confidence Intervals
- Regression (OLS, logistic)

Expectation

(Expected Value, Population Mean, Average)

- Notation: $E(X)$, μ
- The **expected value** of a *finite* random variable

$$\mu = E(X) := \sum_{i=1}^N x_i \cdot P(x_i) \quad \text{where } P(x_i) := \text{Prob}(X = x_i)$$

Expectation

(Expected Value, Population Mean, Average)

- The **expected value** of a *countable* random variable, i.e. the (long run) average

$$E(X) = \sum_{i=1}^{\infty} x_i \cdot P(x_i)$$

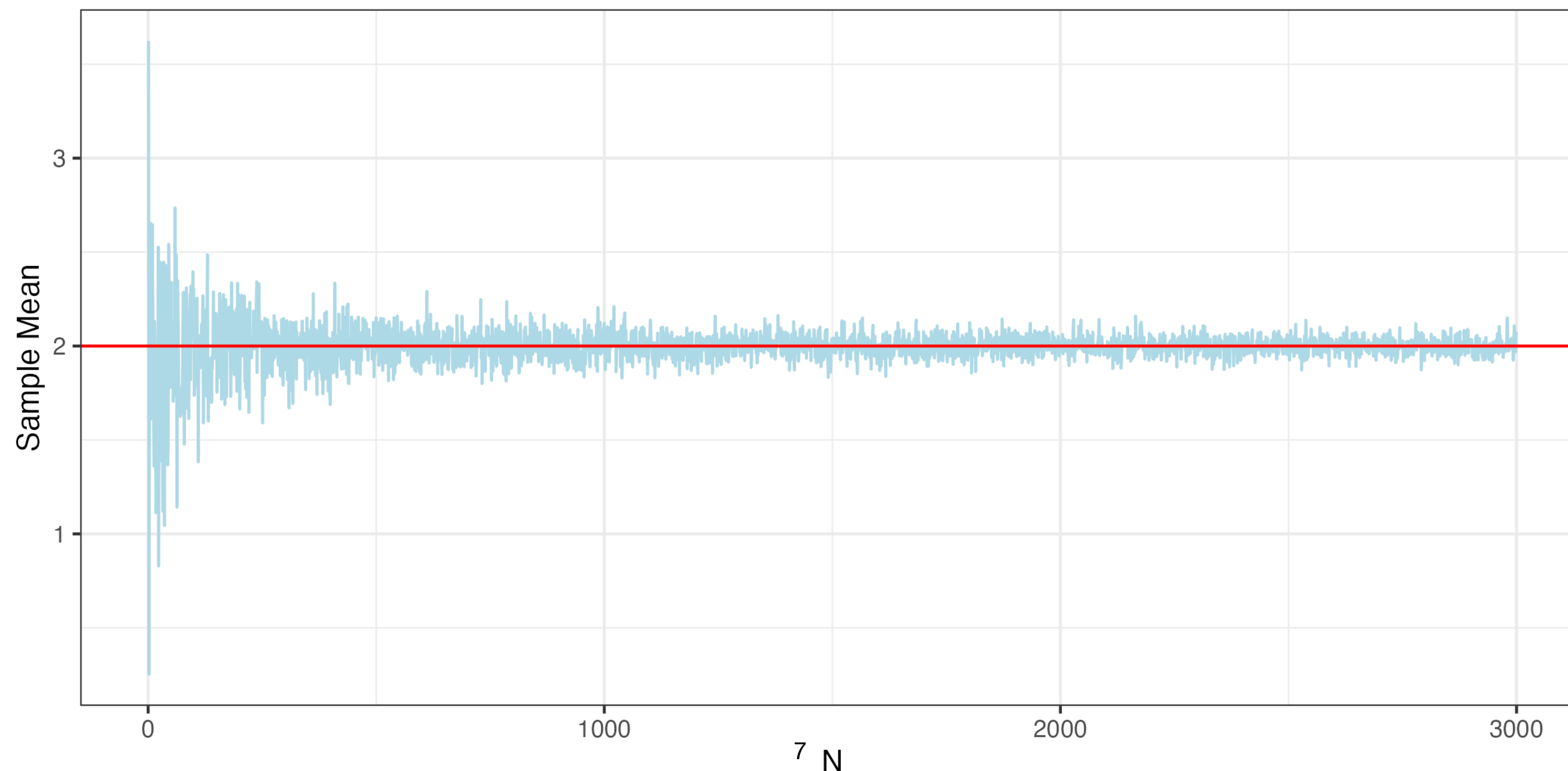
- For n independent and identically distributed (**i.i.d.**) random variables X_1, \dots, X_N

the **sample mean** is $\bar{X} = \frac{1}{N} \sum_{i=1}^N X_i$

- **Law of Large Numbers (LLN)**: the sample mean converges to the expected value (population mean) as $N \rightarrow \infty$
- Example: R (compute the sample mean for larger and larger N)

Expectation

- X_i are random draws from $\sim \mathcal{N}(2, 5)$ (a Normal r.v. with mean 2, variance 5)
- How quickly does the sample mean converge to the population mean?



Variance

Describes the spread of the data

- Notation: $V(X)$, $Var(X)$, σ^2
- Variance is the average of the squared differences from the mean
- For a random variable X with expected value $\mu := E(X)$, the variance is

$$\sigma^2 = Var(X) := E[(X - \mu)^2] = E[X^2] - \mu^2$$

More explicitly, $Var(X) = \sum_{i=1}^n P(x_i) \cdot (x_i - \mu)^2$ where $P(x_i) := \text{Prob}(X = x_i)$

Sample (Empirical) Variance

For a finite dataset or finite sample

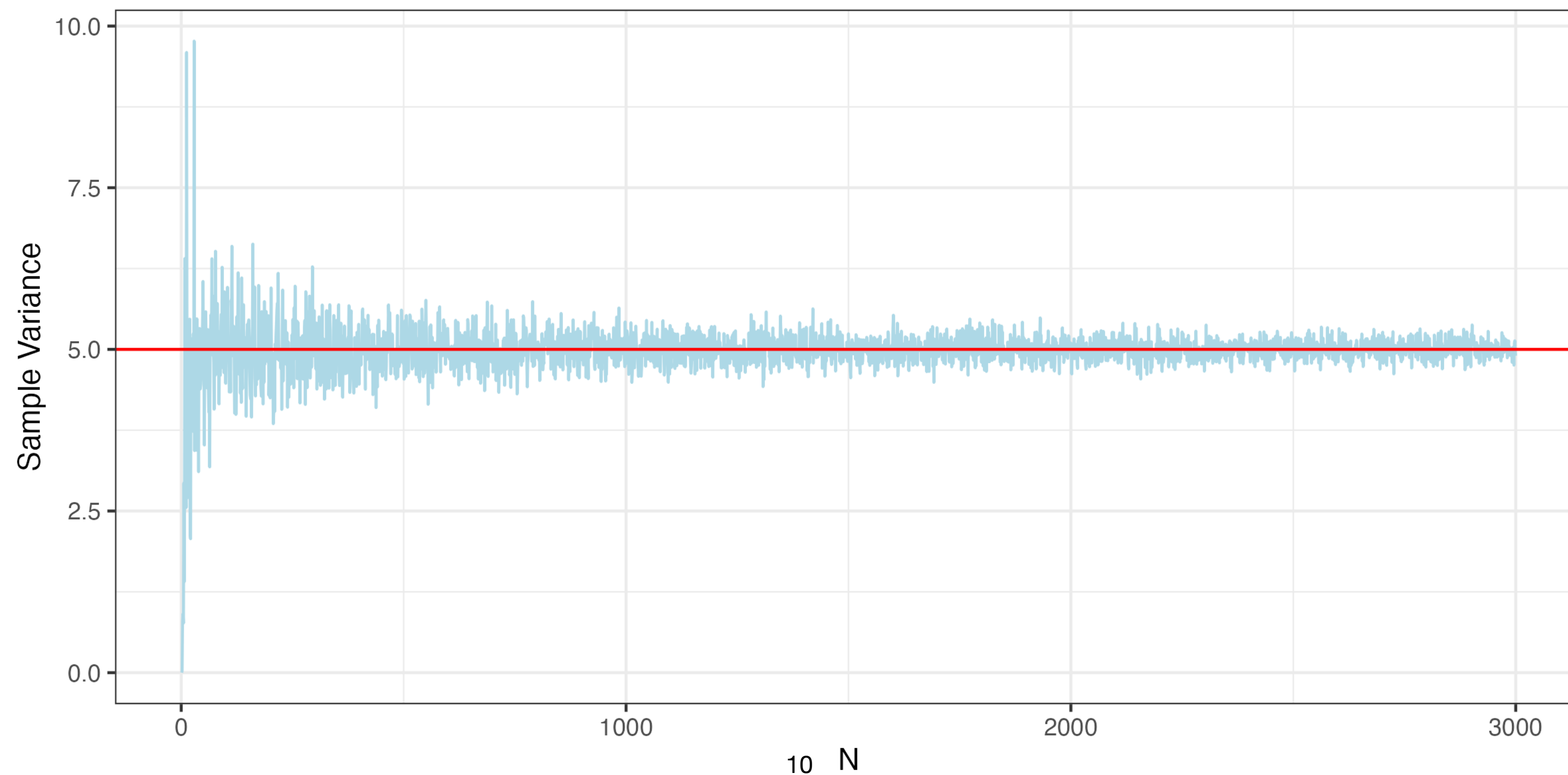
- In practice, you can compute the variance of a finite dataset as

$$\sigma^2 = \left(\frac{1}{N} \sum_{i=1}^N x_i^2 \right) - \bar{X}^2 \quad \text{where} \quad \bar{X} := \frac{1}{N} \sum_{i=1}^N x_i$$

- You don't need to have the formula memorized, just be aware of it
- Likely you'll never have to explicitly compute it this way, just use an R function

Sample Variance

- X_i are random draws from $\sim \mathcal{N}(2, 5)$ (a Normal r.v. with mean 2, variance 5)
- How quickly does the sample variance converge to the population variance?



Conditional Expectation

- Notation: $E(X | Y)$
- The expected value given a set of “conditions”
- Read as “the expectation of X given (or conditioned on) Y ”

$$E(X | Y) = \sum_{i=1}^n x_i \cdot P(X = x_i | Y)$$

$$\text{where } P(X = x_i | Y) = \frac{P(X = x_i \text{ and } Y)}{P(Y)}$$

Conditional Expectation

Example: Roll a fair dice

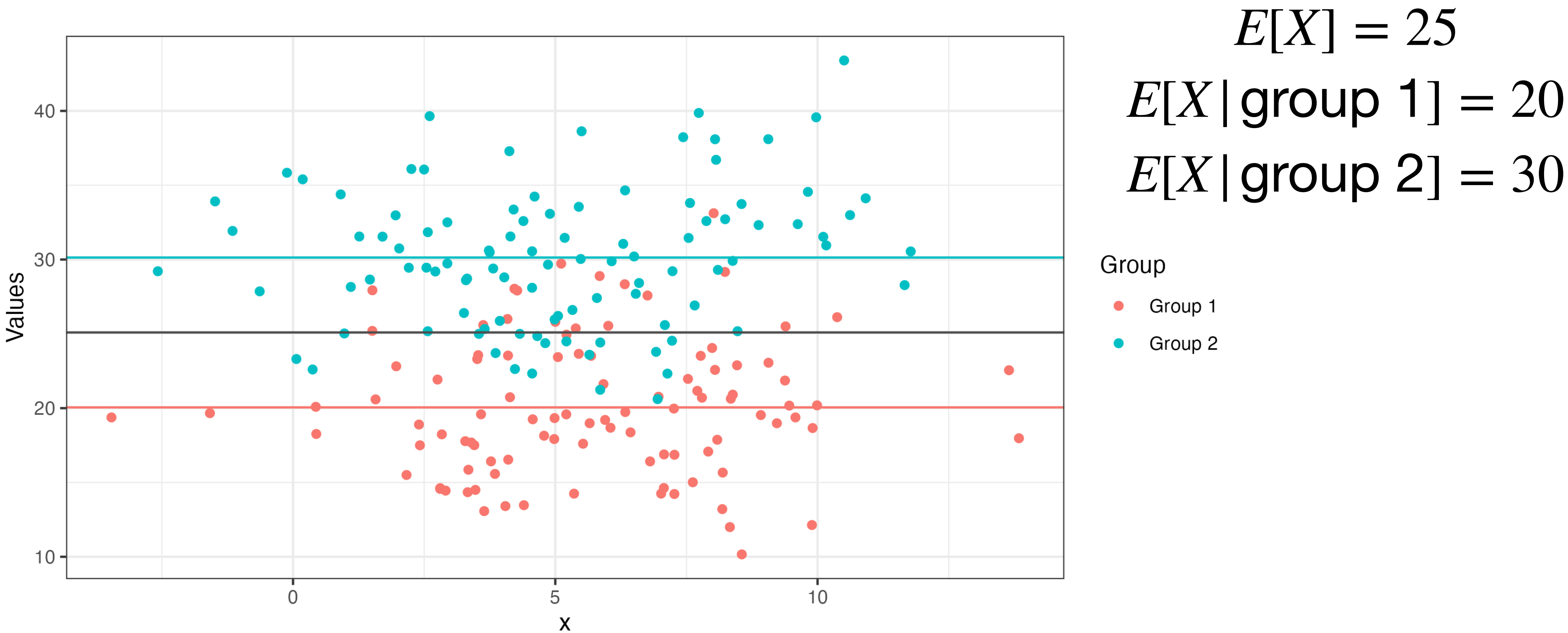
- Let $A = 1$ if you roll an even number, 0 otherwise.
- Let $B = 1$ if you roll a prime number, 0 otherwise. Then,

$$E[A] = \sum_{i=1}^6 a_i \cdot P(a_i) = \frac{0 + 1 + 0 + 1 + 0 + 1}{6} = \frac{1}{2}$$

and the conditional expectation of A given $B = 1$ (i.e. we rolled 2, 3, or 5)

$$E[A \mid B = 1] = \sum_{i=1}^3 a_i \cdot P(a_i \mid B = 1) = \frac{1 + 0 + 0}{3} = \frac{1}{3}$$

Conditional Expectation - Visualized



Independence

- Notation: \perp , $X \perp Y$
- Two random variables are **independent** if the outcome of one does not give any information about the outcome of the other
- Events A and B are independent if $P(A \cap B) = P(A)P(B)$
- Recall: $P(A \cap B) = P(A | B)P(B)$
- If $A \perp B$, then $P(A | B) = P(A)$ and $P(B | A) = P(B)$

Independence

Example: Dice

- Suppose you roll two fair dice. Let A be the value of the first die and let B be the value of the second die.
- If I say that $A = 3$, does that give you any info about what the value of B is?
- We can show that the **events** $\{A = 3\}$ and $\{B = 3\}$ are independent:

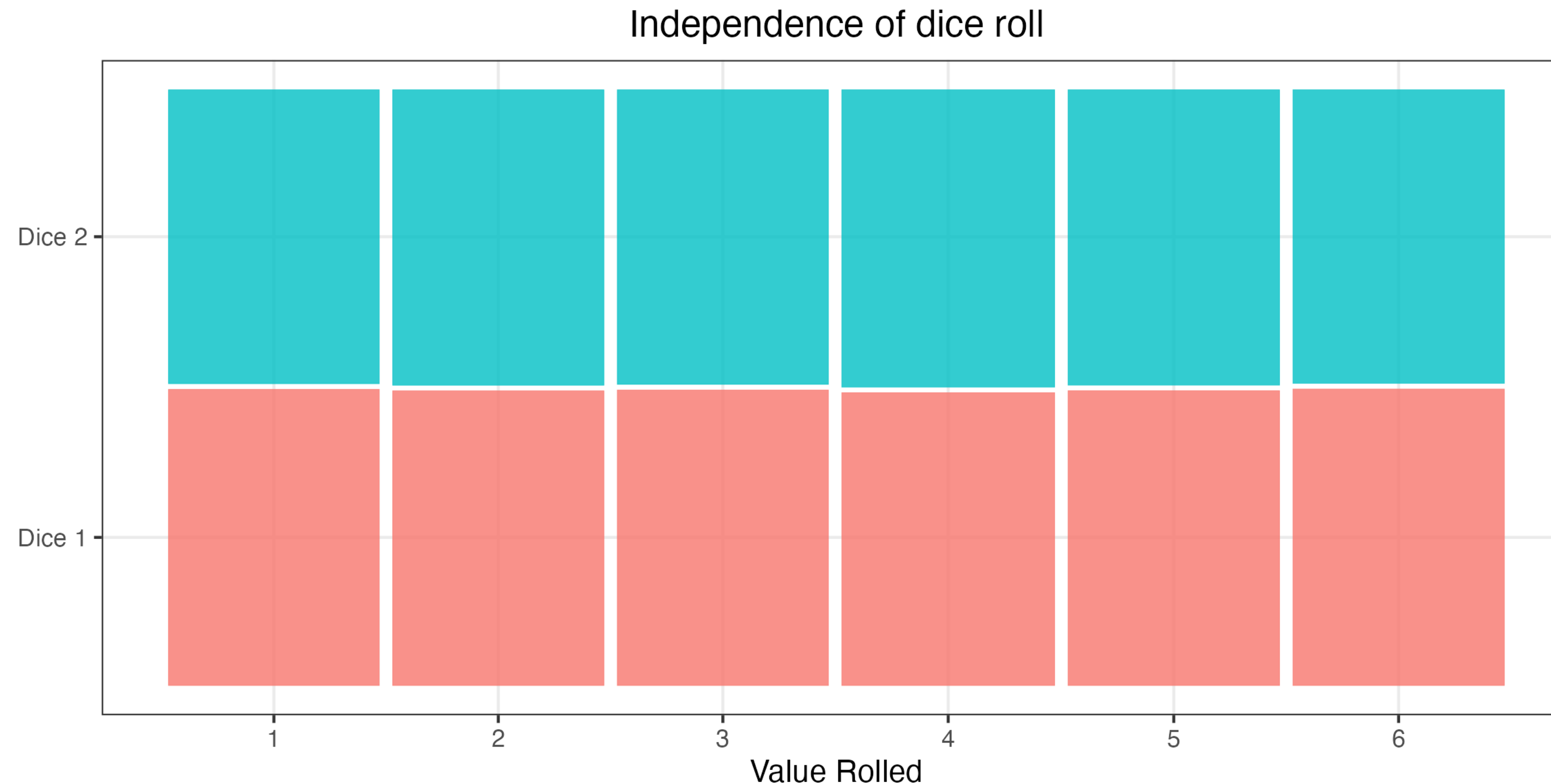
$$\begin{aligned} P(\{A = 3\} \cap \{B = 3\}) &= P(\{A = 3\} \mid \{B = 3\}) \cdot P(\{B = 3\}) \\ &= \frac{1}{6} \cdot \frac{1}{6} \\ &= P(\{A = 3\}) \cdot P(\{B = 3\}) \end{aligned}$$

- To show $A \perp B$, you would show this holds for all values of A and B

Independence

Example: Dice

- If we simulate 100k dice rolls, we see that the joint probability of each combination is equal to the individual probabilities multiplied.



Bernoulli Random Variables

A binary/dichotomous random variable

- Notation: $B(p)$, $\text{Bernoulli}(p)$, $\mathcal{B}(p)$
- Takes the value 1 with probability (w.p.) p , and the value 0 w.p. $q := 1 - p$
- Let $X \sim B(p)$
 - “Let X be a Bernoulli random variable with mean p ”
 - $E(X) = p$ and $\text{Var}(X) = p(1 - p) = pq$
- Cool fact: $E(X) = P(X = 1) = p$

Law of Total Expectation

(i.e. law of iterated expectations, tower rule)

- Useful property (or “trick”) that will be used in class

$$E(X) = E(E(X | Y))$$

- Don’t worry too much about the technical details, just add to your toolbox :)

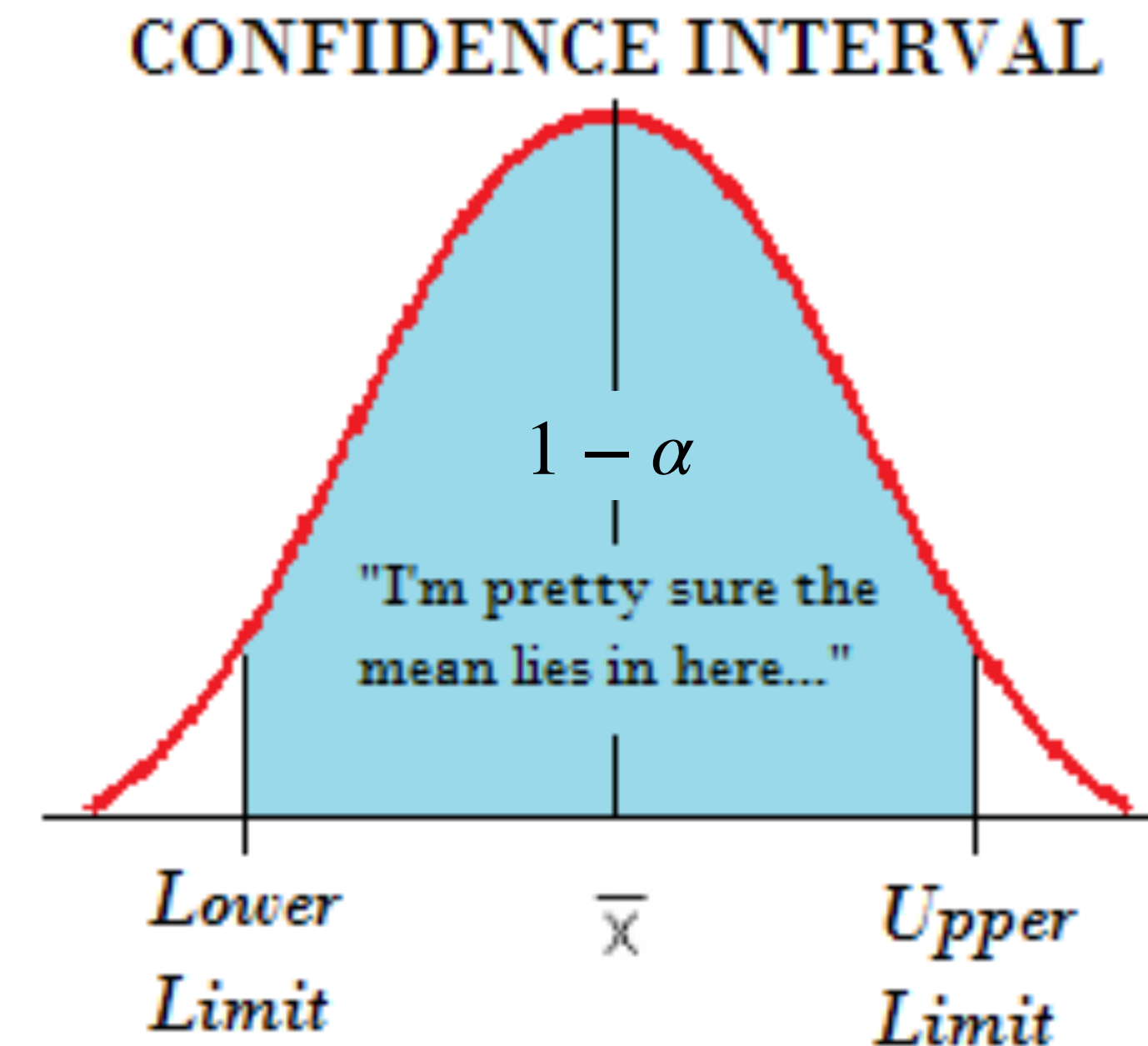
Confidence Intervals

- A set of values that contains the real parameter with probability $1 - \alpha$
- Define $CI = [L, U]$ then $P(L \leq \mu \leq U) = 1 - \alpha$
- Usually $1 - \alpha$ is 95 % or 99 %
- *Example:* X_i are random draws from $\sim \mathcal{N}(2, 5)$
- Estimating expectation of a random variable using sample mean:

$$\hat{E}(X) = \hat{\mu} = \bar{X} = \frac{1}{N} \sum_{i=1}^N X_i$$

Confidence Intervals

- \bar{X} is an estimate for μ with some uncertainty
- $P(\mu \leq \bar{X} - c) = P(\mu \geq \bar{X} + c) = \frac{\alpha}{2}$
- $P\left(\frac{\bar{X} - \mu}{\sigma/\sqrt{N}} \leq \frac{\mu - c - \mu}{\sigma/\sqrt{N}}\right) \Rightarrow -c = Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{N}}$
- $Z_{\frac{\alpha}{2}}$ is the critical value of the Normal distribution (For example in R: `qnorm(0.025)`)
- $CI = \bar{X} \pm Z_{\frac{\alpha}{2}} \frac{\sigma}{\sqrt{N}}$



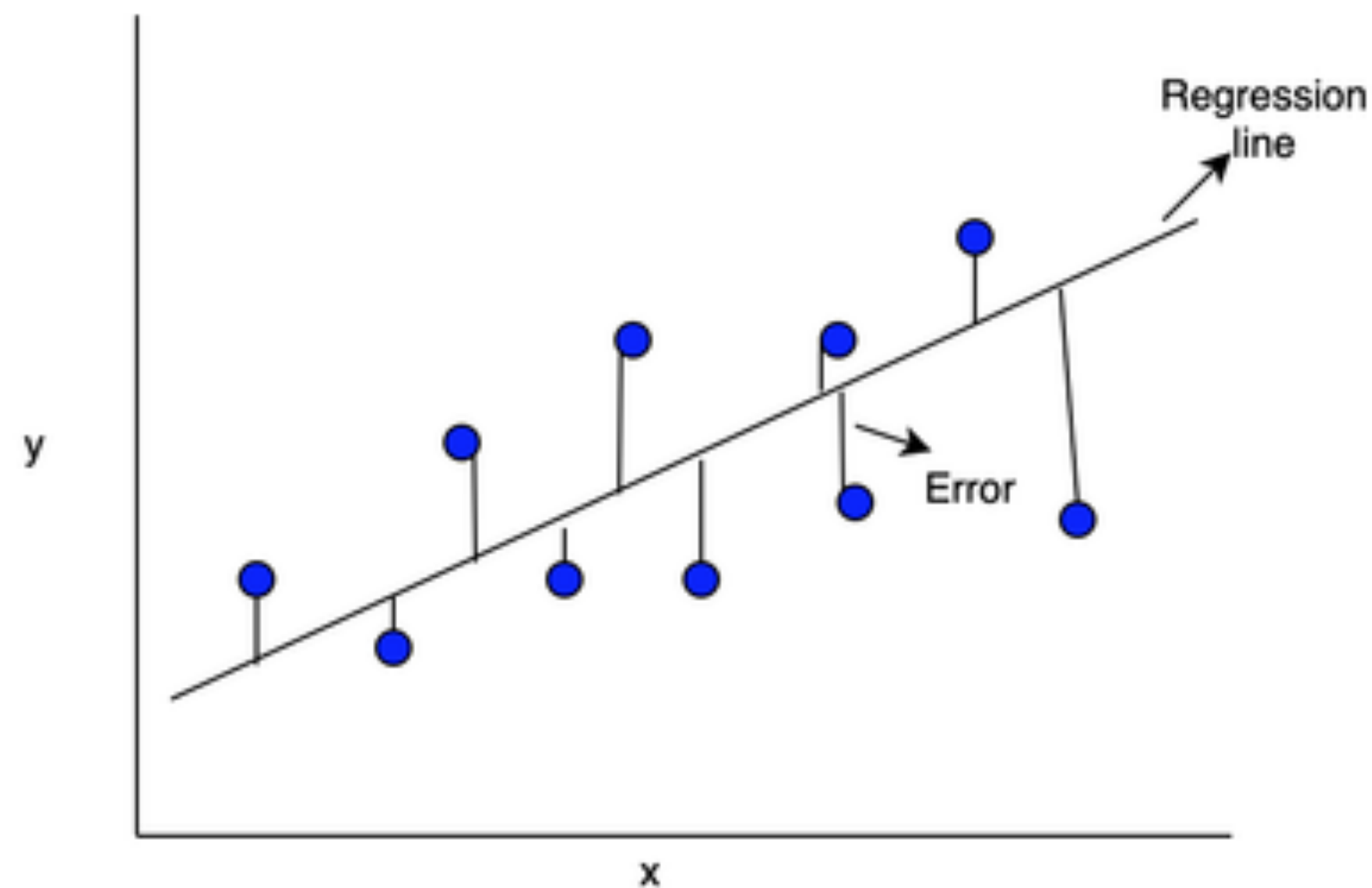
Regression

- Estimates the relationships between X and Y where
- Y - the dependent variable, outcome/response
- X - independent variable, regressor/explanatory
- Main types of regression: Linear and Logistic

Regression

Linear Regression

- Assume data was generated: $Y_i = \alpha + \beta X_i + \varepsilon_i$ for $i = 1, \dots, N$
- α, β are the coefficients where α is the intercept and β the slope



Regression

Linear Regression

- Using ordinary least squares (OLS) to estimate $\hat{Y}_i = \hat{\alpha} + \hat{\beta}X_i$
- Minimizes sum of squared errors: $(\hat{\alpha}, \hat{\beta}) = \operatorname{argmin}_{a,b} \sum_{i=1}^N (Y_i - (a + bX_i))^2$
- $\frac{\partial}{\partial a} SSE = \sum_{i=1}^N -2(Y_i - a - bX_i) \quad \Rightarrow \quad \hat{\alpha} = \bar{Y} - \hat{\beta}\bar{X}$
- $\frac{\partial}{\partial b} SSE = \sum_{i=1}^N -2(Y_i - (\bar{Y} - b\bar{X}) - bX_i)X_i = \sum_{i=1}^N -2[(Y_i - \bar{Y})X_i - b(X_i - \bar{X})X_i]$
 $\Rightarrow \hat{\beta} = \frac{\sum_{i=1}^N (Y_i - \bar{Y})(X_i - \bar{X})}{\sum_{i=1}^N (X_i - \bar{X})^2}$

Regression

Logistic Regression

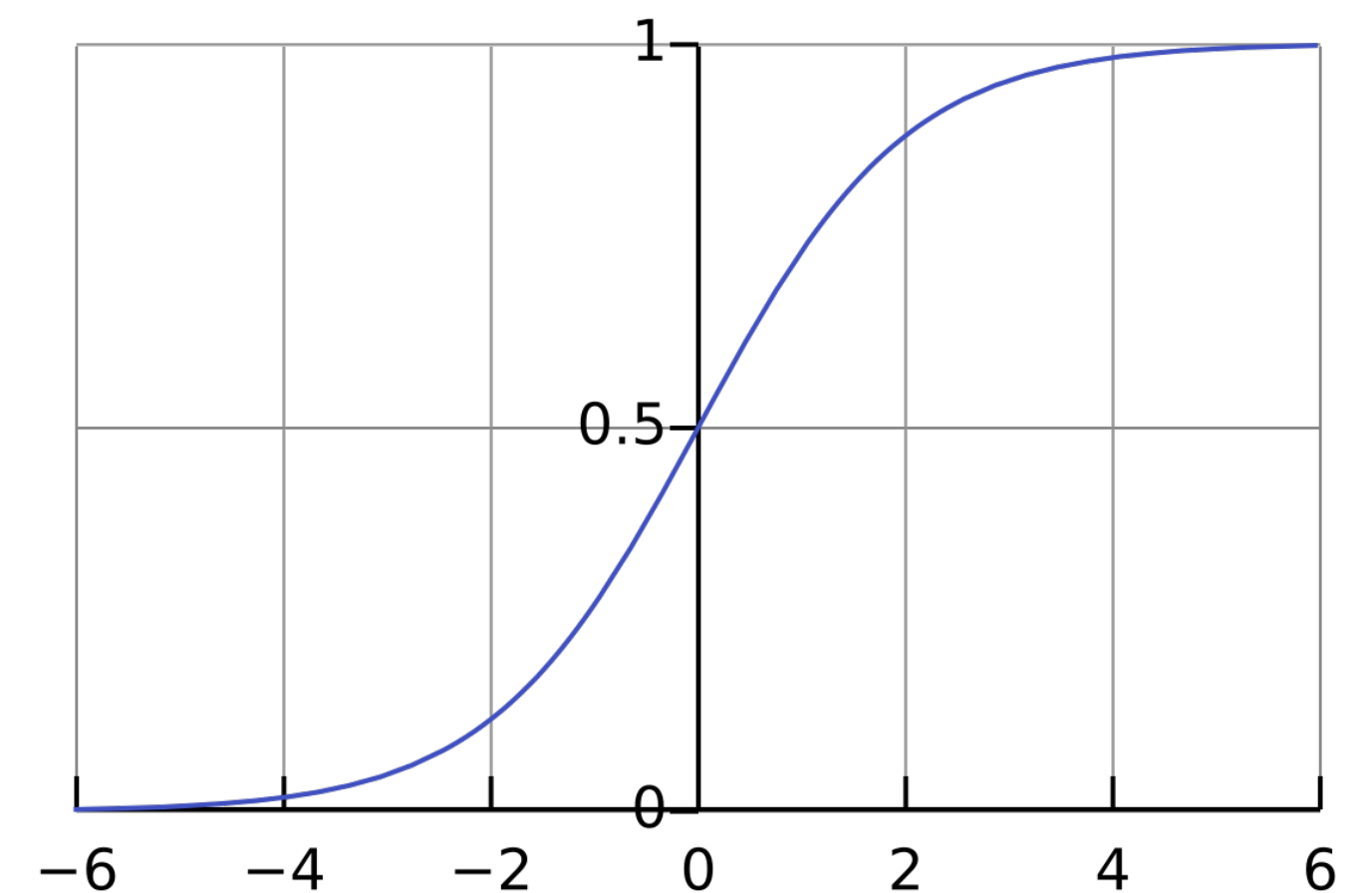
- Y_i - the outcome variable is binary for $i = 1, \dots, N$
- Use a link function to estimate $P(Y_i = 1) := p_i$ that satisfies $\mathbb{R} \rightarrow (0,1)$

- Most common- logistic function: $\sigma(t) = \frac{1}{1 + e^{-t}}$

- In a linear model we estimate $\hat{Y}_i = \hat{\alpha} + \hat{\beta}X_i$

- In logistic model we estimate $\hat{p}_i = \frac{1}{1 + e^{-(\hat{\alpha} + \hat{\beta}X_i)}}$

- $\alpha + \beta X_i = \ln \left(\frac{p_i}{1 - p_i} \right)$



Regression

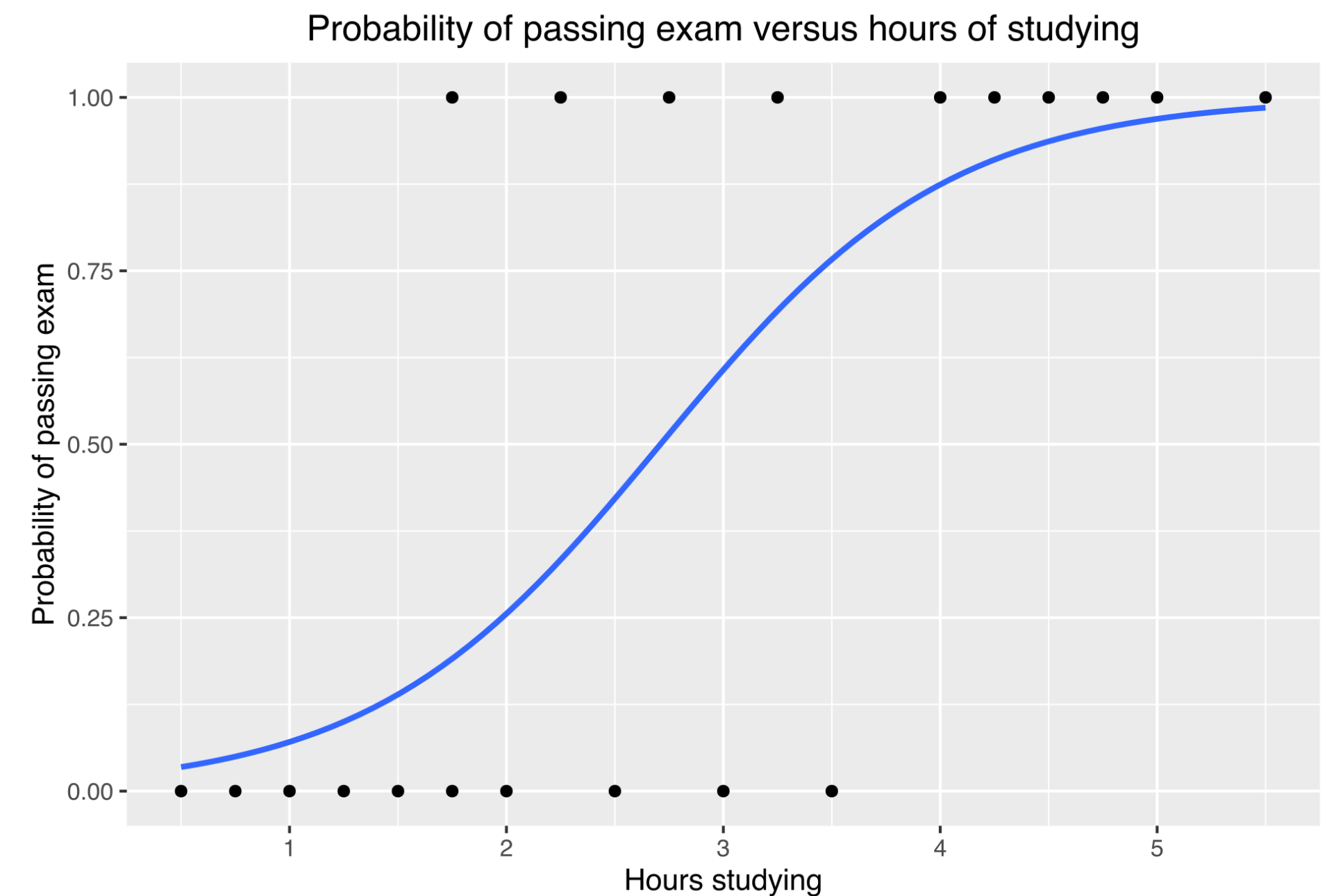
Logistic Regression

- Odds ratio: $\frac{p_i}{1 - p_i} = \frac{P(Y_i = 1)}{P(Y_i = 0)}$
 - For example: $\frac{P(\text{Passing exam})}{P(\text{Not passing})} = \frac{3/4}{1/4}$ the odds ratio is 3 : 1
- To estimate $\hat{\alpha}, \hat{\beta}$ we use maximum likelihood estimates (MLE)
- Likelihood function: $L(a, b; y) = \prod_{i=1}^N P(Y_i = y_i) = \prod_{i=1}^N p_i^{y_i} (1 - p_i)^{(1-y_i)}$
- Log likelihood: $l(a, b; y) = \sum_{i=1}^N y_i \ln(p_i) + (1 - y_i) \ln(1 - p_i) = \sum_{i=1}^N \ln(1 - p_i) + y_i \ln \left(\frac{p_i}{1 - p_i} \right)$

Regression

Logistic Regression

- Log likelihood: $l(a, b; y) = \sum_{i=1}^N \ln(1 - p_i) + y_i \ln \left(\frac{p_i}{1 - p_i} \right) = \sum_{i=1}^N -\ln(1 + e^{a+bX_i}) + y_i(a + bX_i)$
- To find MLE we solve $\frac{\partial}{\partial(a, b)} l(a, b; y) = 0$
- No close form solution
iterative method such as:
gradient descent or Newton–Raphson



R

- R is an open-source programming language
- Used for statistical computing and creating plots
- Download and install R



<https://cran.r-project.org/>

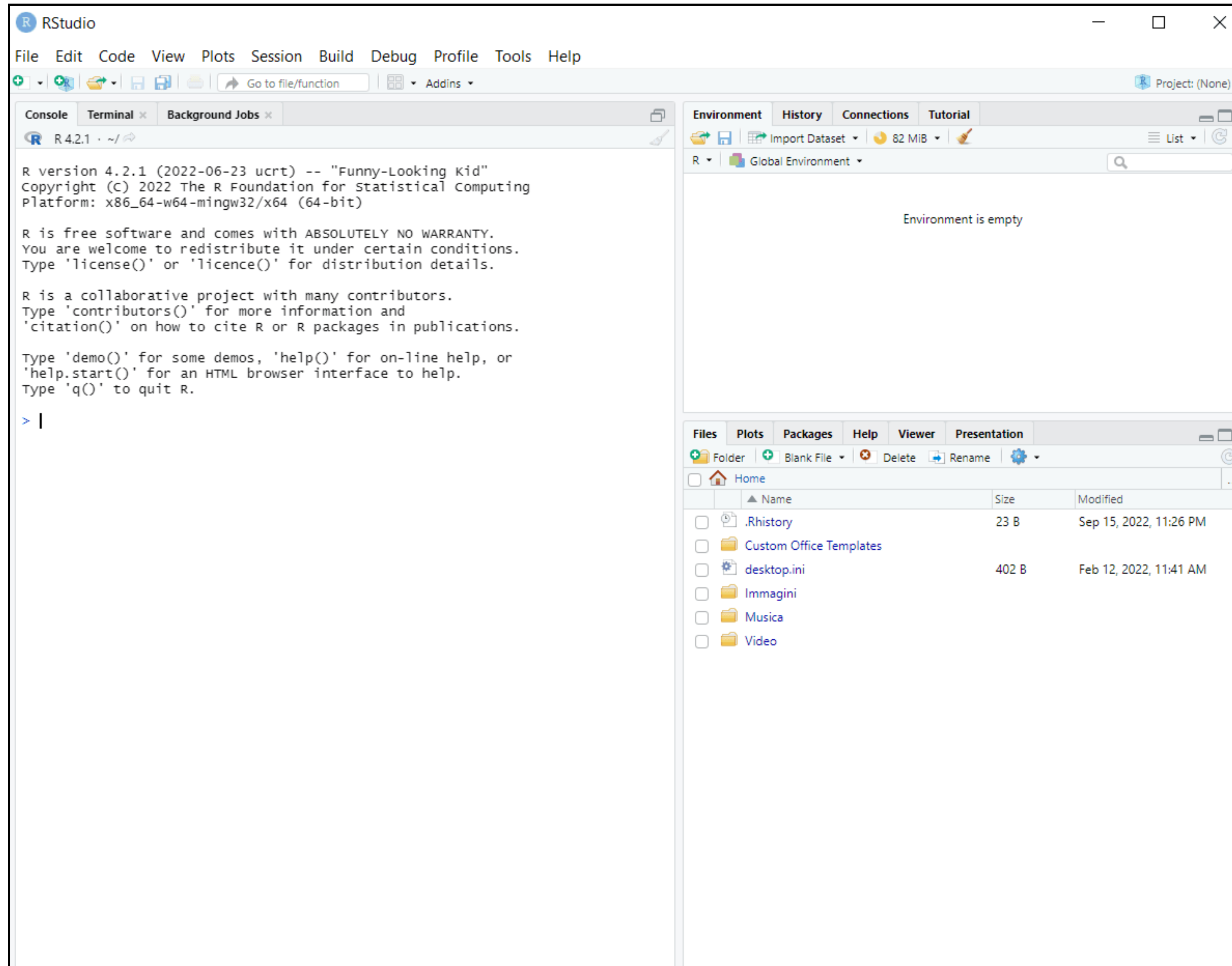
RStudio

- RStudio is an open-source IDE (integrated development environment)
- Download and install RStudio (scroll down for earlier versions)



<https://posit.co/download/rstudio-desktop/>

RStudio



RStudio

Quick Demo

- Console- calculator, create variable
- Environment
- Files
- Plots
- Help
- Script

R Markdown

- `install.packages("rmarkdown")`
- `install.packages("knitr")`
- Download HW 1 and open in RStudio
- R Markdown tutorial



<https://www.rforecology.com/post/how-to-use-rmarkdown-part-one/>

- Subscripts and superscripts: to get Y_i^a inline use `Y_{i}^{a}`

Questions

- Homework Check-in
- R/RStudio