

# Bayesian Analysis for the Life Sciences



**Bob O'Hara**

Dept. of Mathematics and Statistics,  
University of Helsinki

[www.rni.helsinki.fi/~boh](http://www.rni.helsinki.fi/~boh)

# Laws of Probability

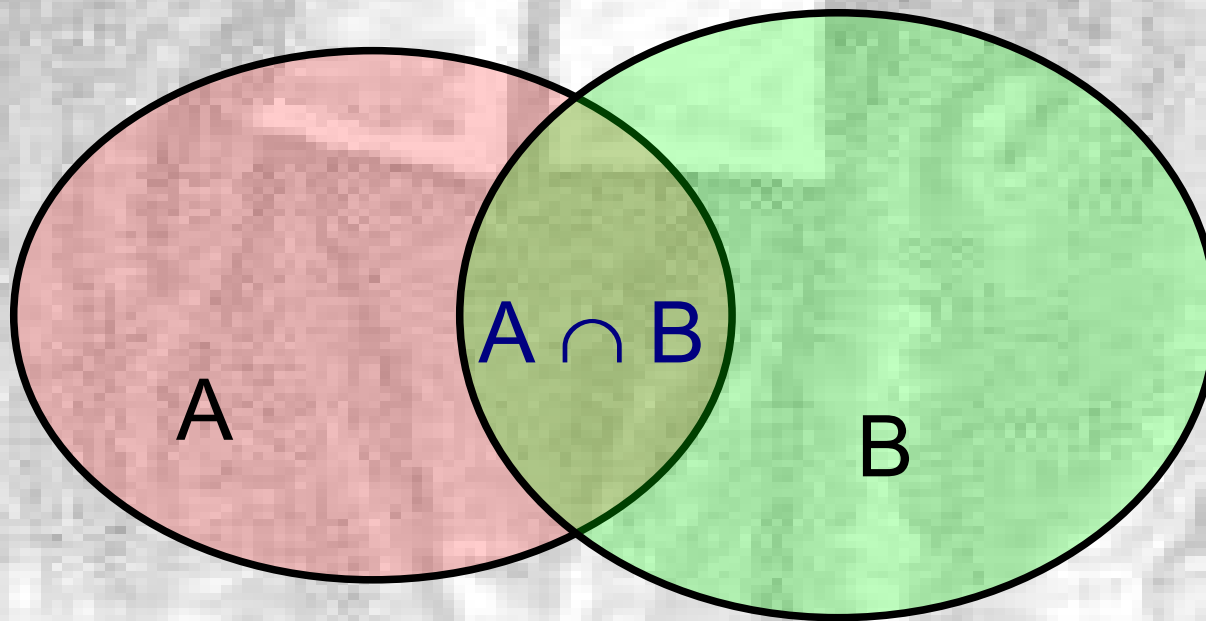
- These are mathematical theorems
- Problem (later): relating these to the real world
- Definitions:
  - A and B are events
  - A – Bus to work is late
  - B – Bus from work is late
  - Sometimes:  $C_i$  – i people waiting for the bus
- Notation:  $A^c$  – not A (i.e. bus not late)

# Basics

- $0 \leq P(A) \leq 1$
- $P(A) + P(A^c) = 1$ 
  - either a bus is late, or is on time
- $\sum P(C) = 1$ 
  - all probabilities add up to 1
- If  $P(A \text{ and } B) = 0$ , then  $P(A \text{ or } B) = P(A) + P(B)$

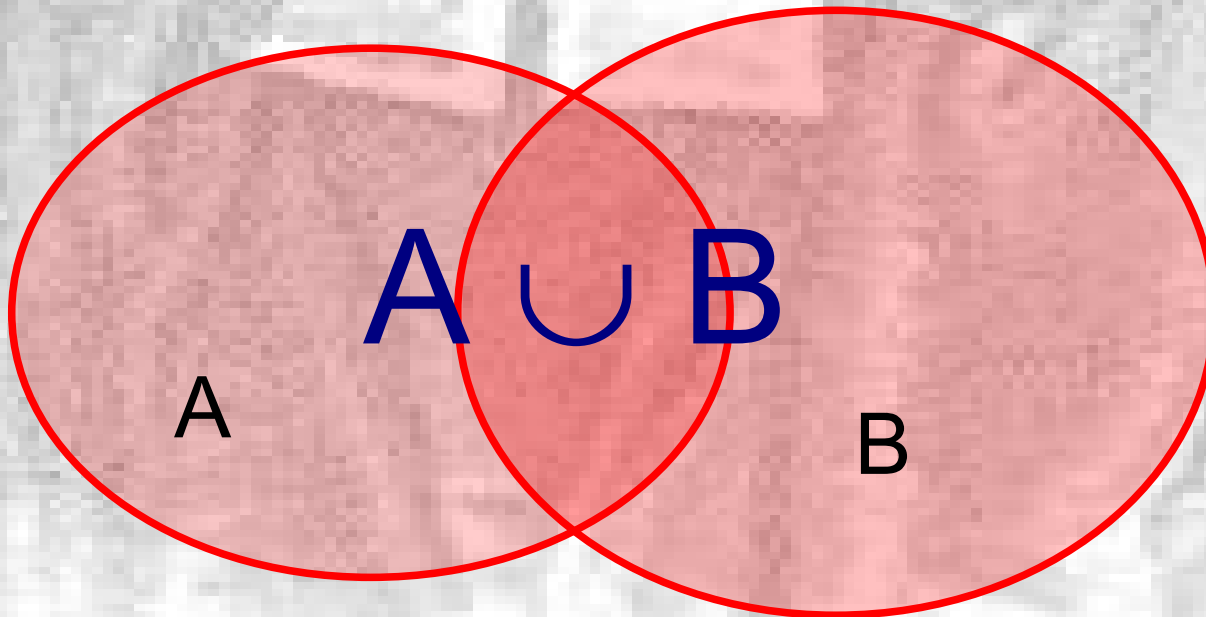
# Intersection: $P(A \cap B)$

- e.g.  $P(A) = 0.4$ ,  $P(B) = 0.2$ ,  $P(A \text{ and } B) = 0.1$
- Question: What is the probability of both buses being late?



# Union: $P(A \cup B)$

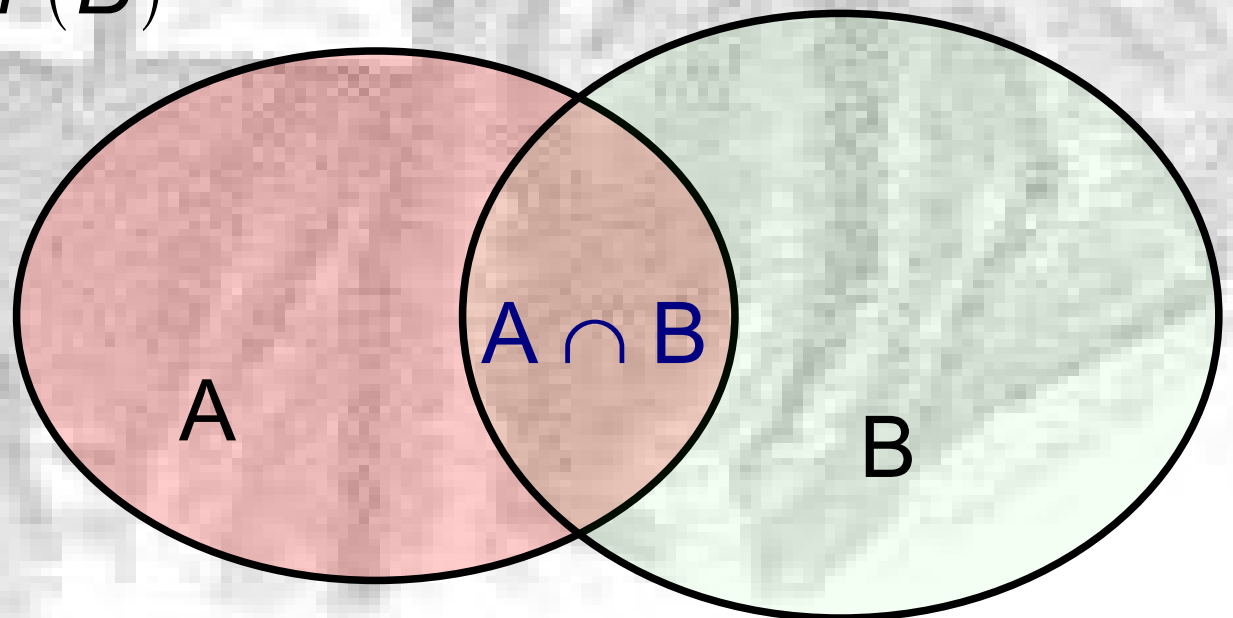
- $P(A \cup B) = P(A) + P(B) - P(A \cap B)$
- What is the probability of at least 1 bus being late?
  - $P(A \text{ and } B) = 0.4 + 0.2 - 0.1 = 0.5$



# Conditional Probability

- If my bus to work is late, what is the probability my bus home is late too?

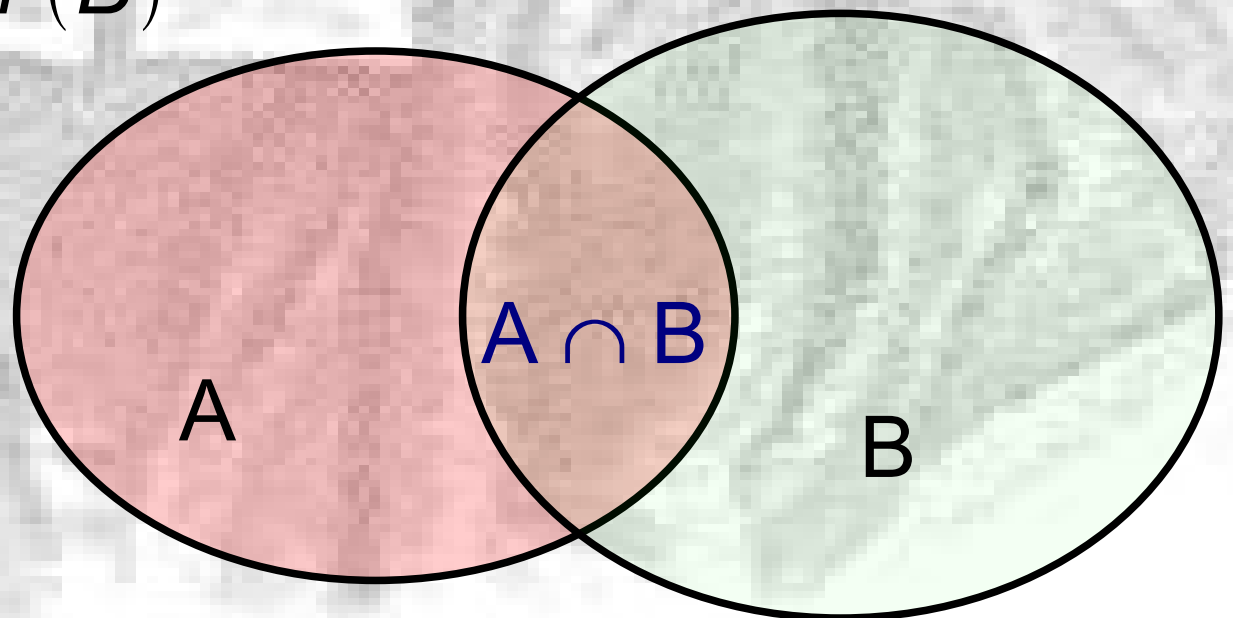
$$Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}$$



# Conditional Probability

- $P(\text{Bus late in evening} \mid \text{late in morning})$
- $= 0.1/0.4$
- $= 0.25$

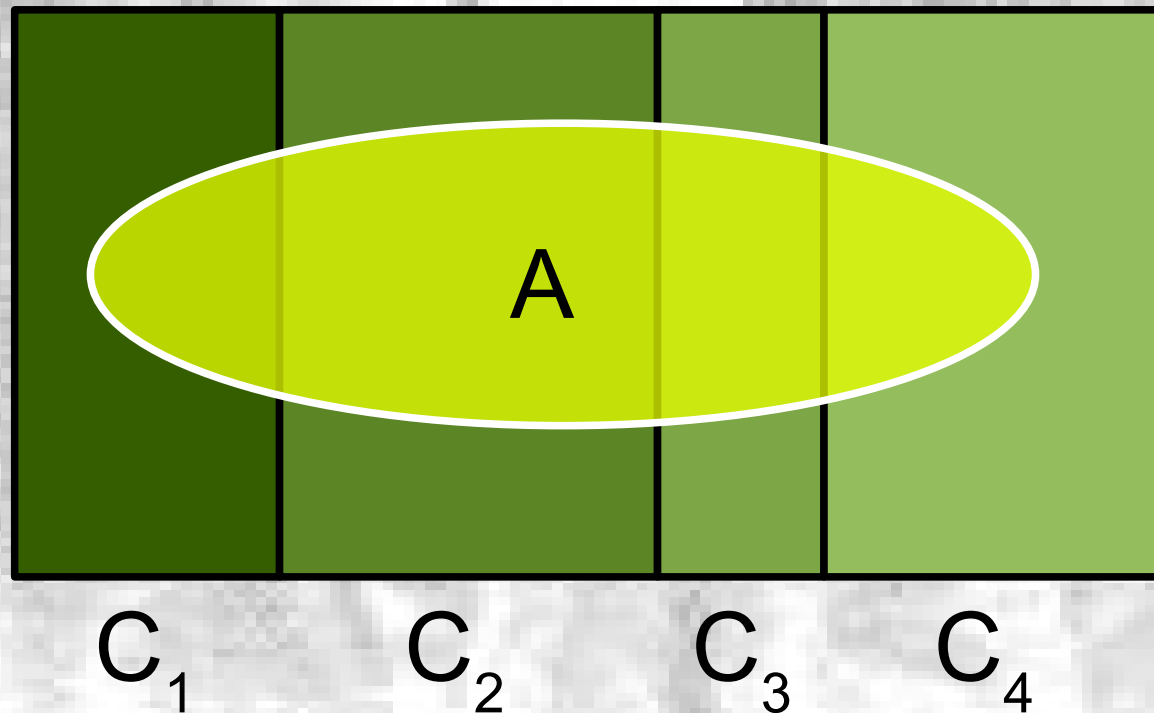
$$Pr(A|B) = \frac{Pr(A \cap B)}{Pr(B)}$$



# Law of Total Probability

- Everything adds up!

$$Pr(A) = \sum_{i=1}^{\infty} Pr(A|C_i) P(C_i)$$



# Independence

- Definition: A and B are independent if

$$Pr(A \cap B) = Pr(A)Pr(B)$$

- The point:

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

- i.e. if the probability of the my bus home being late is independent of probability of the my bus to work being late, then knowing one says nothing about the other

# Late buses

- Bus late in morning:  $P(A) = 0.4$
- Bus late in evening:  $P(B) = 0.2$
- Both buses late:  $P(A \cap B) = 0.1$
- $P(A) \cdot P(B) = 0.4 \times 0.2 = 0.08$ 
  - So A and B not independent
- $P(B|A) = 0.25$ 
  - if my bus is late in the morning, it is more likely to be late in the evening

# Bayes' Rule: “The Law of Inverse Probability”

- If I know  $P(A|B)$ , can I find  $P(B|A)$ ?

$$Pr(A \cap B) = Pr(A|B)Pr(B)$$

$$Pr(A \cap B) = Pr(B|A)Pr(A)$$

so

$$Pr(A|B)Pr(B) = Pr(B|A)Pr(A)$$

$$Pr(A|B) = \frac{Pr(B|A)Pr(A)}{Pr(B)}$$

# Bayes' Rule

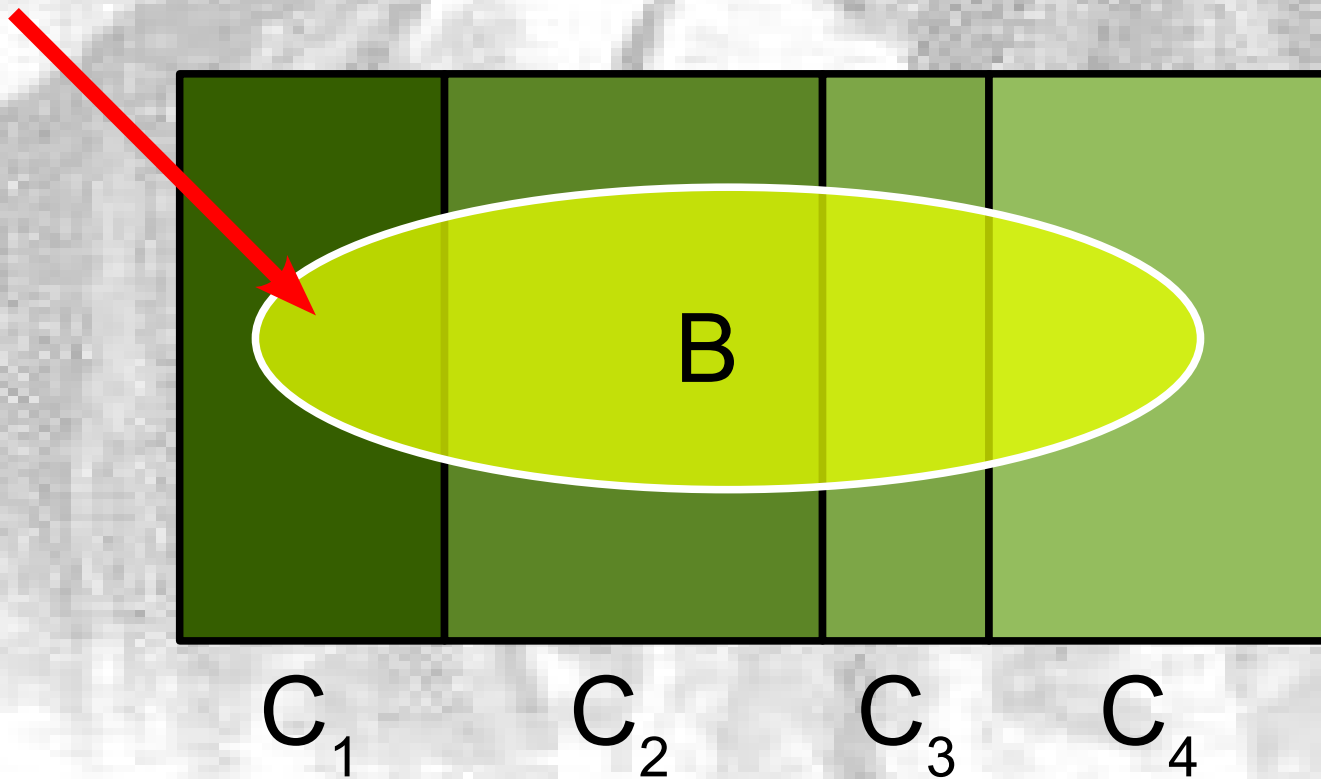
$$Pr(A|B) = \frac{Pr(B|A)Pr(A)}{Pr(B)}$$

- as  $Pr(B) = \sum_{i=1}^{\infty} Pr(B|C_i)Pr(C_i)$

$$Pr(C_1|B) = \frac{Pr(B|C_1)Pr(C_1)}{\sum_i Pr(B|C_i)Pr(C_i)}$$

$$Pr(C_1|B) = \frac{Pr(B|C_1)Pr(C_1)}{\sum_i Pr(B|C_i)Pr(C_i)}$$

$Pr(C_1|B)$



# Will my bus be late in the morning?

$$P(B|A)=0.25 \quad P(A) = 0.4 \quad P(B) = 0.2$$

$$P(A|B) = 0.25 \times 0.4 / 0.2$$
$$= 0.5$$

# Probability Distributions

- Not everything random is just measured as TRUE/FALSE
  - e.g. number of people waiting for a bus
- describe these as a *probability distribution*
  - e.g. probability that  $n$  people are waiting for a bus
- Describes mathematically these probabilities

# How many buses to work will be late?

- 5 working days per week, on how many of them will my bus be late?
- Probability of one bus being late is  $p$
- Assume constant and independent
- Define  $N$  is the *random variable* “number of late buses”
- Then  $\Pr(N=5) = p^5$

# The Binomial Distribution

- $\Pr(N=4)$ 
  - one bus on time. Could be on Monday, Tuesday, Wednesday etc.
  - 5 ways of this happening, with probabilities
    - On time on Monday:  $p(1-p)^4$
    - On time on Tuesday:  $(1-p)p(1-p)^3$
    - On time on Wednesday:  $(1-p)^2p(1-p)^2$
    - On time on Thursday:  $(1-p)^3p(1-p)$
    - On time on Friday:  $(1-p)^4p$
  - Total probability:  $5p(1-p)^4$

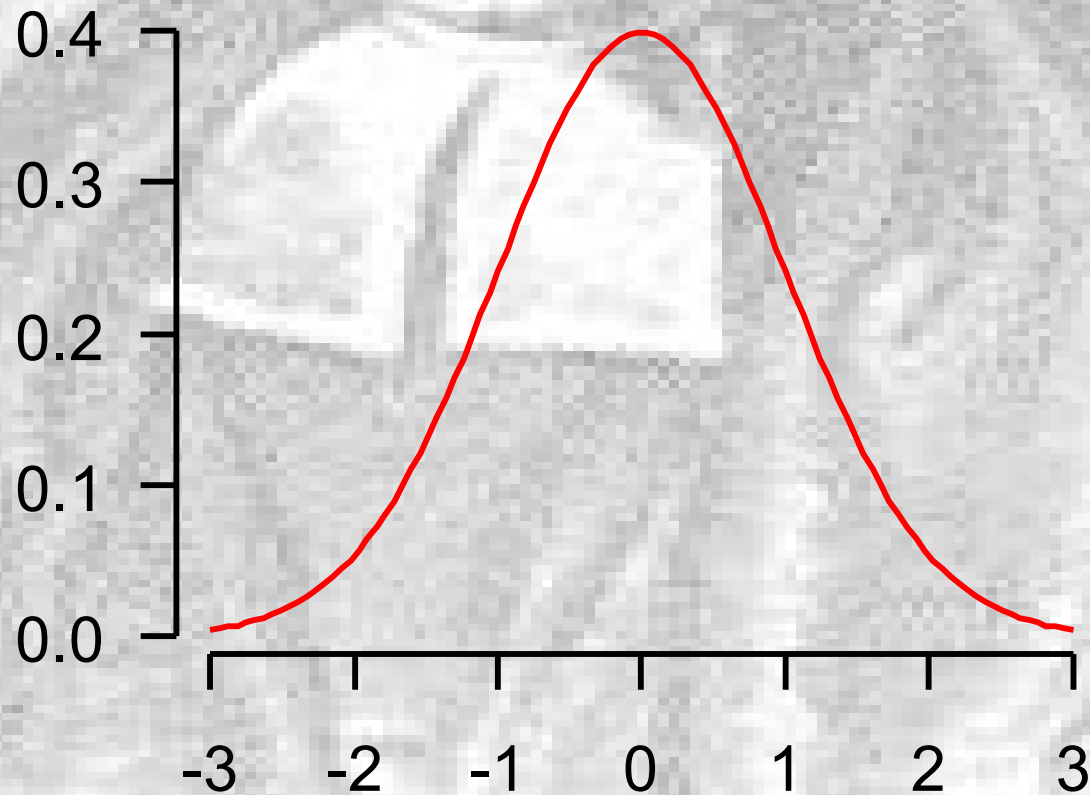
# The Binomial Distribution

- $\Pr(N=3)$ : several ways of happening
  - each one with probability  $p^3(1-p)^2$
- To work out how many ways each  $N$  can happen, use combinatorics
- End up with

$$\Pr(N=n) = \frac{n!}{N!(N-n)!} p^n (1-p)^{N-n}$$

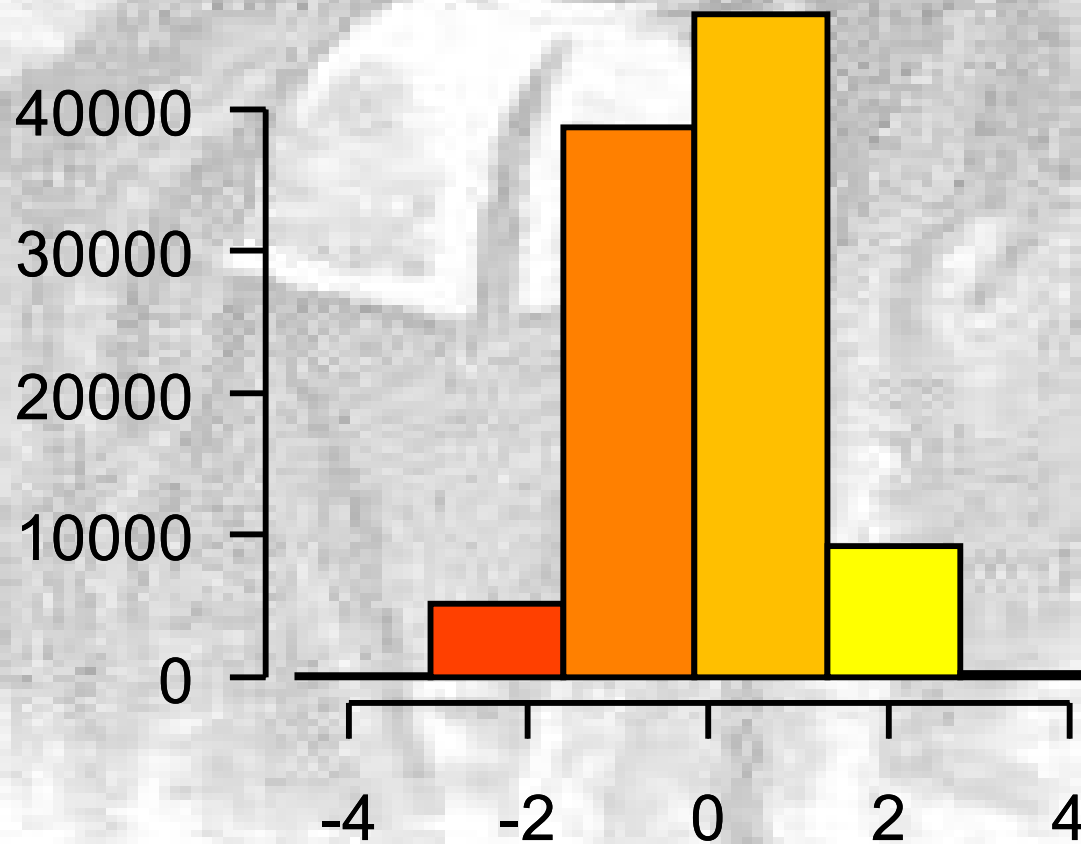
# Discrete to Continuous

- So far, all probabilities have been discrete
- For continuous distributions – use densities



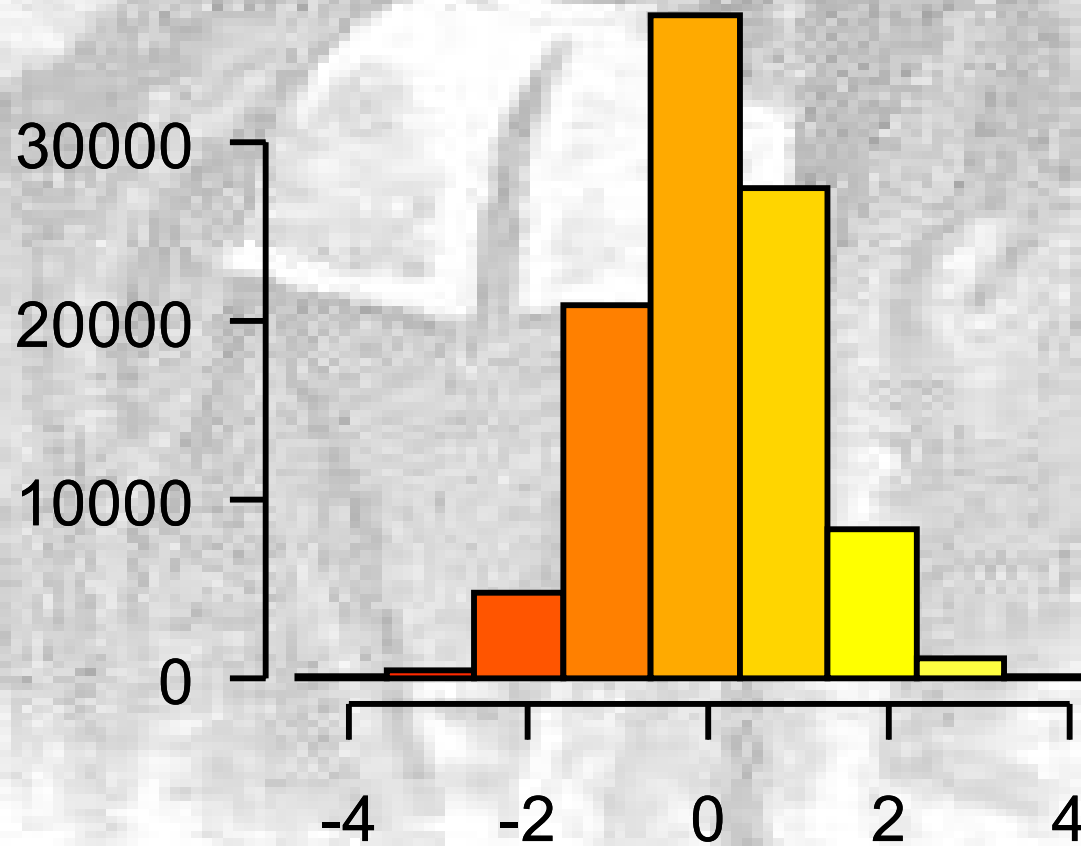
# For example

- Split into classes
- count number in each class



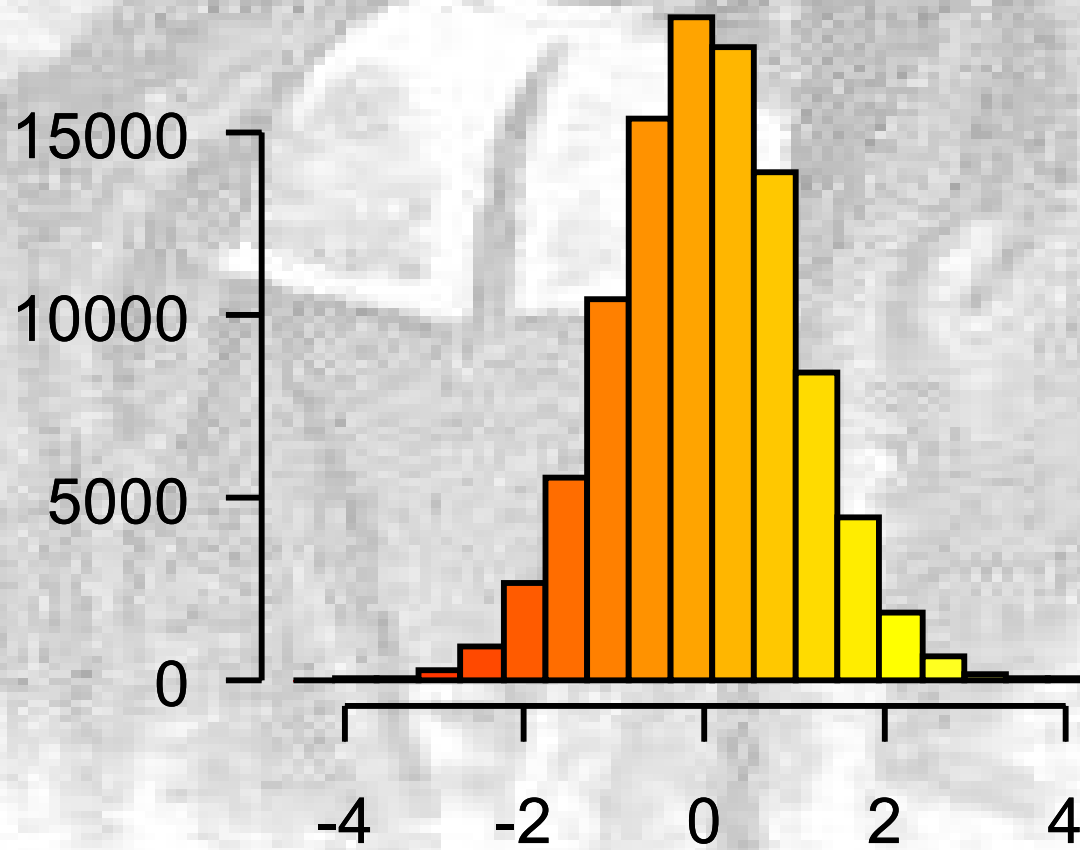
# For example

- Now make class widths smaller



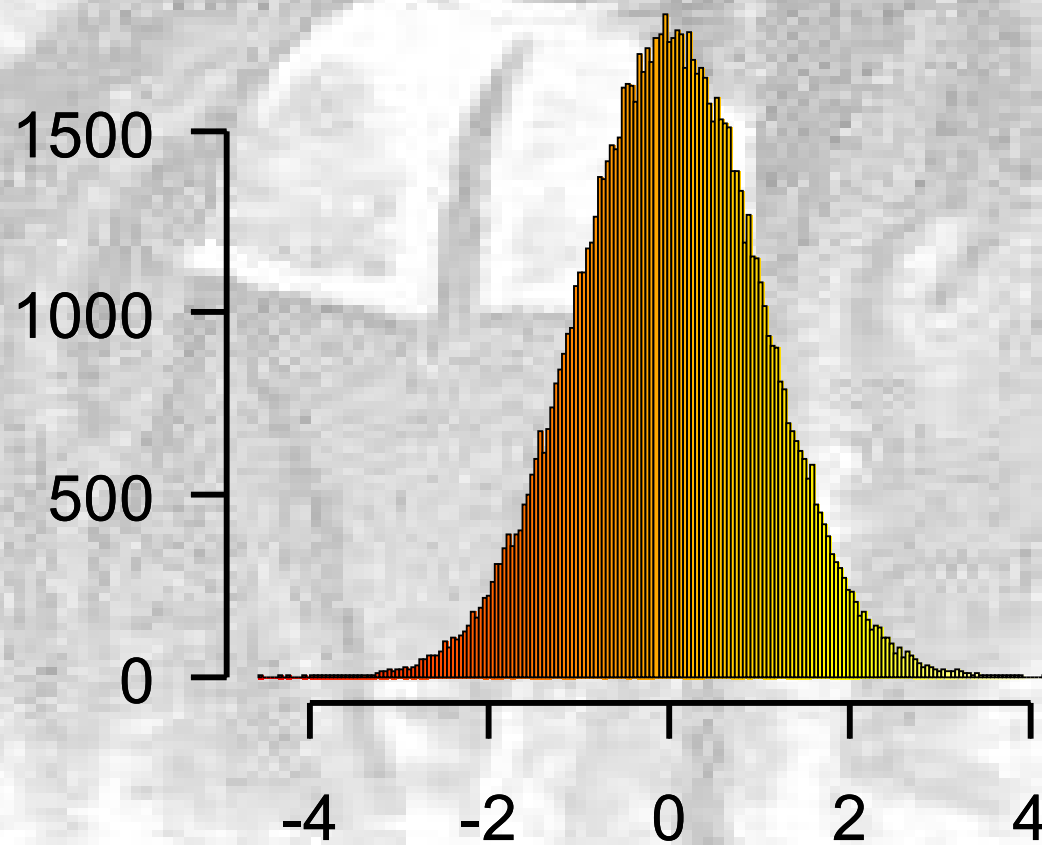
# For example

- ... and smaller



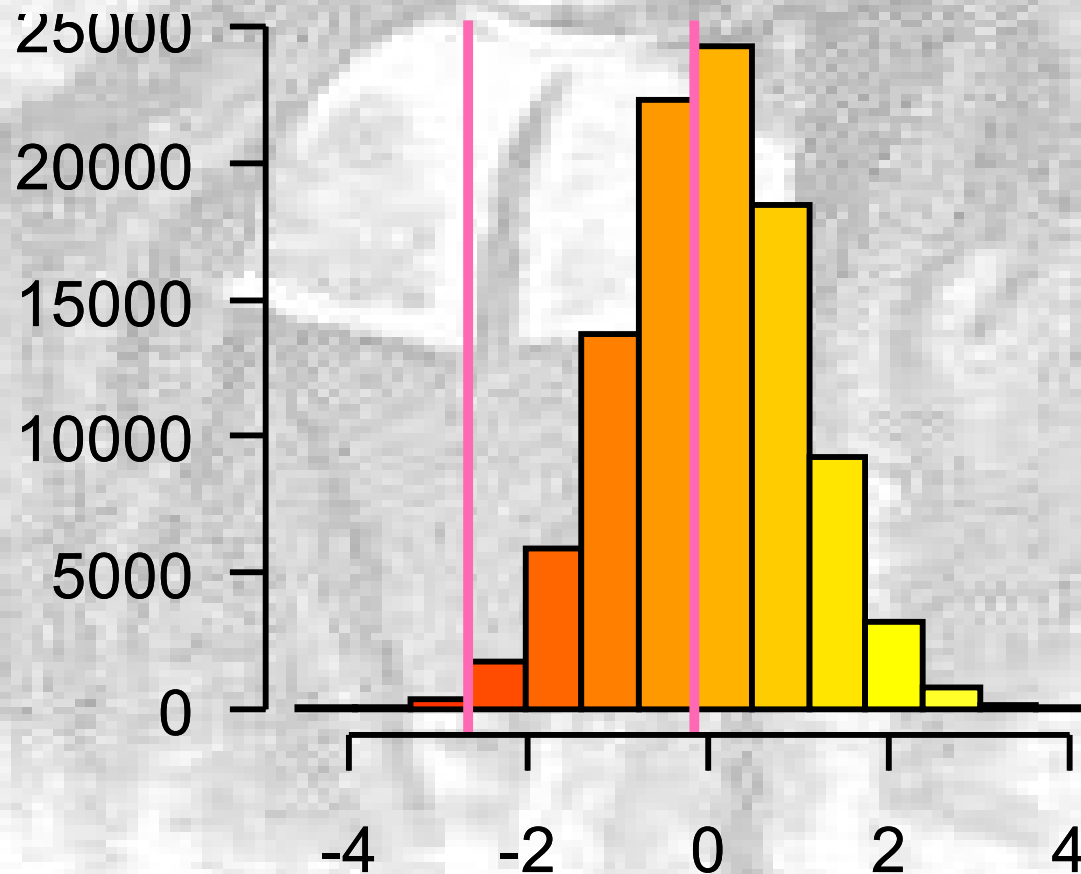
# For example

- Eventually look continuous



- To work out the probability that an observation is between 2 values

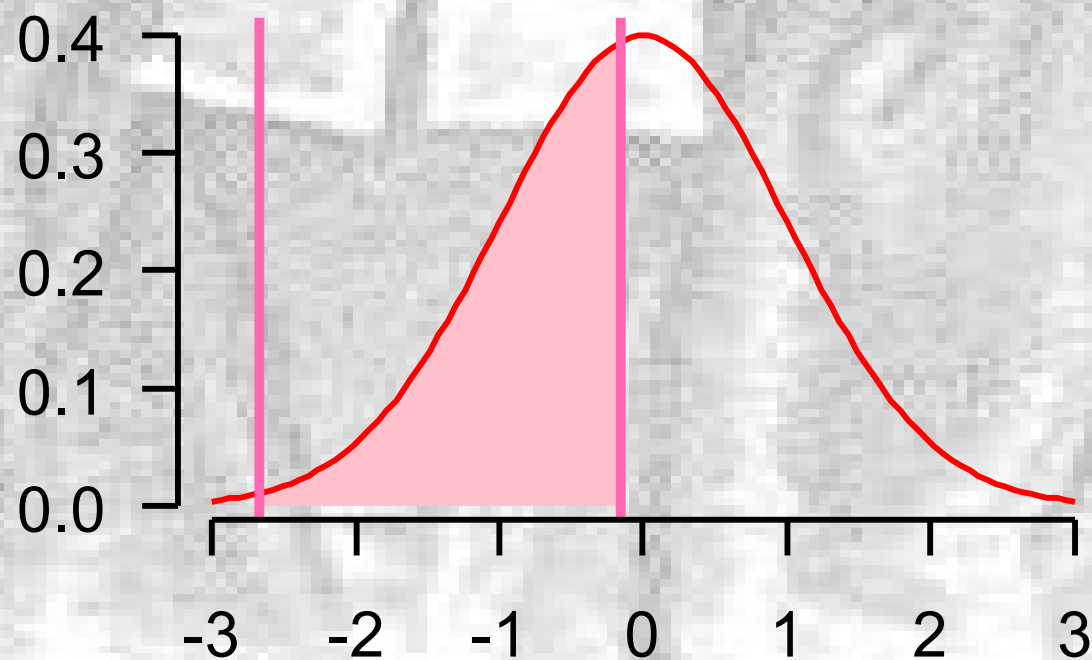
$$Pr(a < x < b) = \sum_a^b Pr(x)$$



- Now make  $x \rightarrow 0$
- Probability becomes an integral

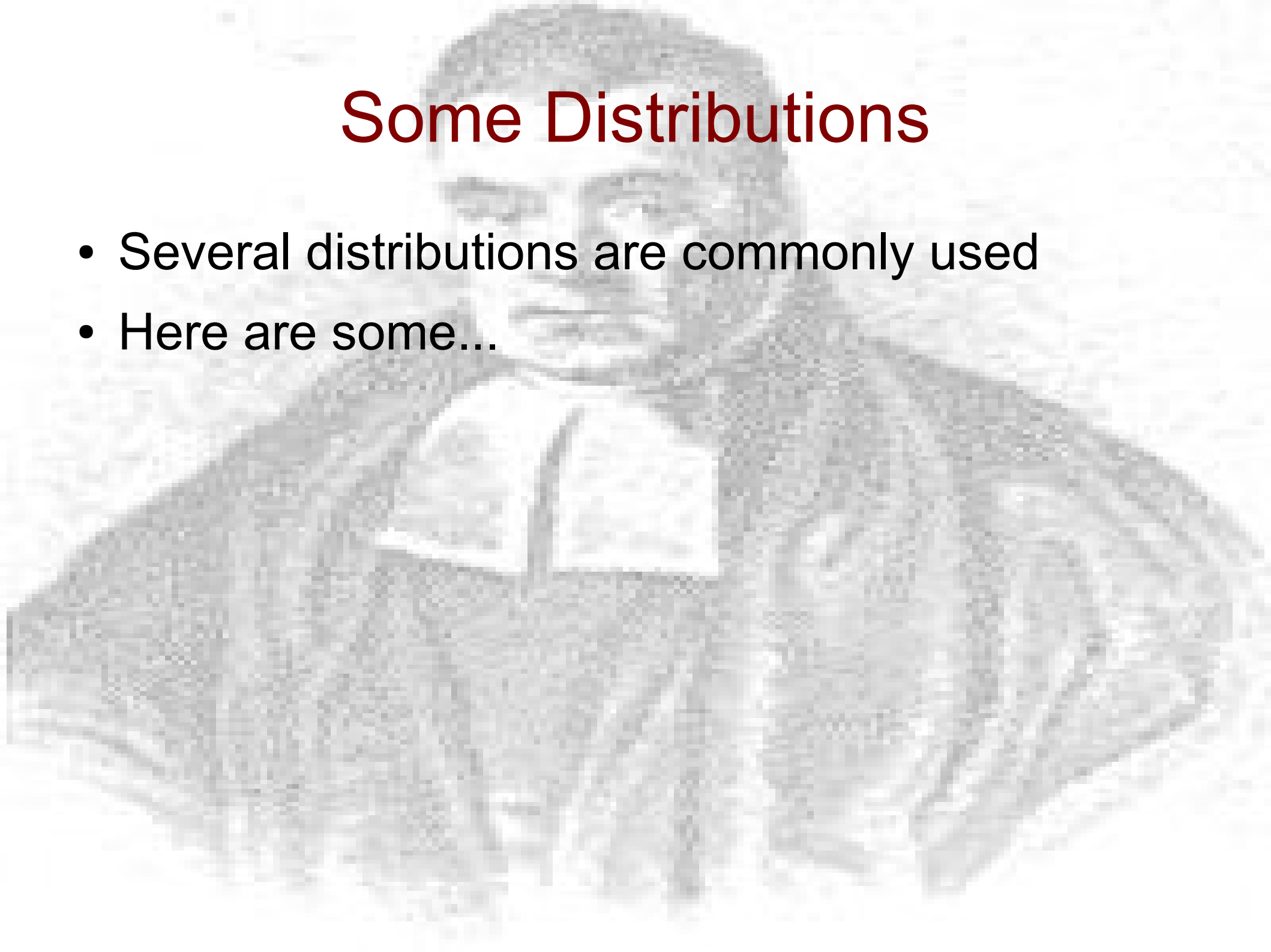
$$Pr(a < x < b) = \int_a^b f(x) dx$$

- $f(x)$  is called a *probability density function*



# Some Distributions

- Several distributions are commonly used
- Here are some...

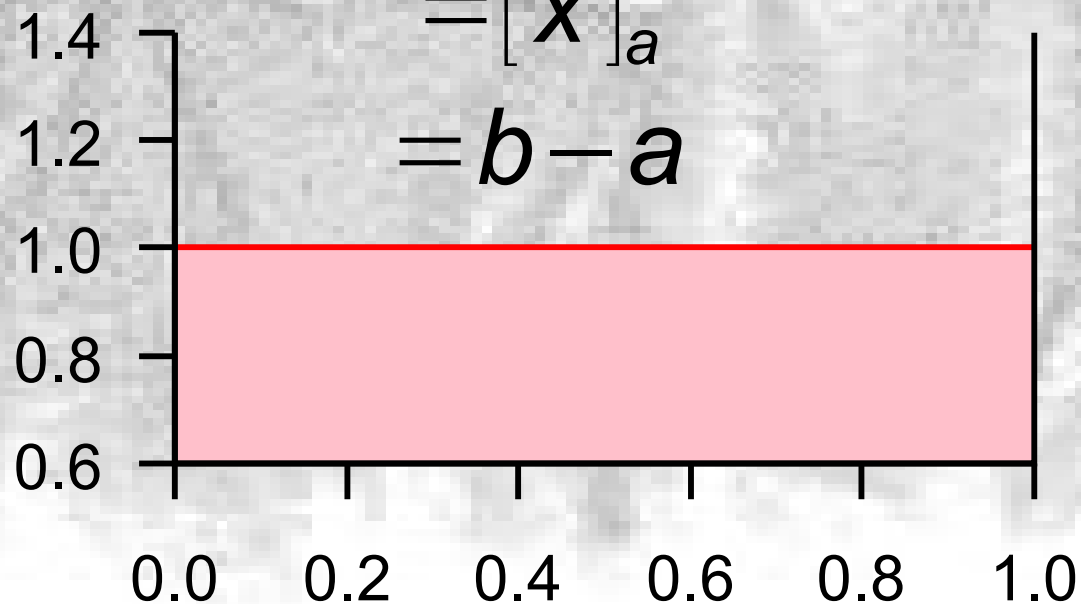


# Uniform Distribution

- Probability density constant  $f(x) = 1$ 
  - usually defined between 0 and 1

$$Pr(a < x < b) = \int_a^b 1 dx$$

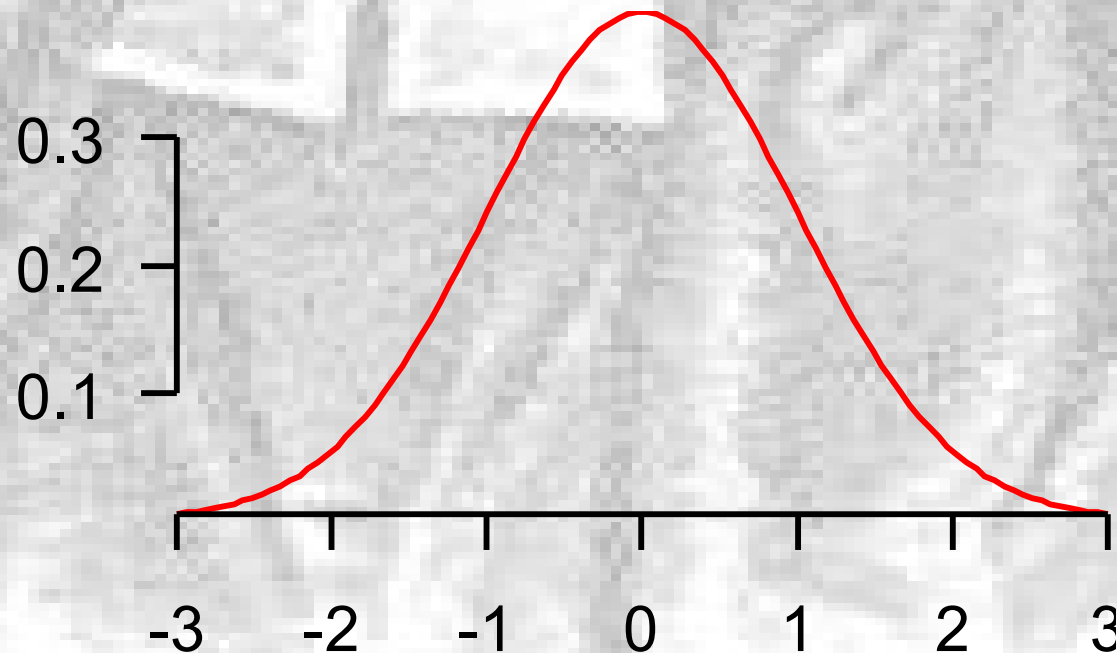
$$= [x]_a^b$$
$$= b - a$$



# Normal Distribution

- Commonly used
- Probability density function

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$



# Expectations

- “Average” values
  - theoretical values
- Definition:

$$E(x) = \int_{-\infty}^{\infty} x f(x) dx$$

- In general:

$$E(g(x)) = \int_{-\infty}^{\infty} g(x) f(x) dx$$

$$E(g(x)) = \sum_{i=-\infty}^{\infty} g(i) Pr(x=i)$$

# Expected Value for a Uniform Distribution

- Simple Example

$$\begin{aligned} E(X) &= \int_0^1 x \cdot 1 \, dx \\ &= \left[ \frac{x^2}{2} \right]_0^1 \\ &= \frac{1}{2} \end{aligned}$$

# Variance

- $\text{Var}(X) = E(X^2) - E^2(X)$
- e.g. Uniform:

$$\begin{aligned}\text{Var}(X) &= \int_0^1 x^2 dx - \left(\frac{1}{2}\right)^2 \\ &= \left[\frac{x^3}{3}\right]_0^1 - \frac{1}{4} \\ &= \frac{1}{12}\end{aligned}$$

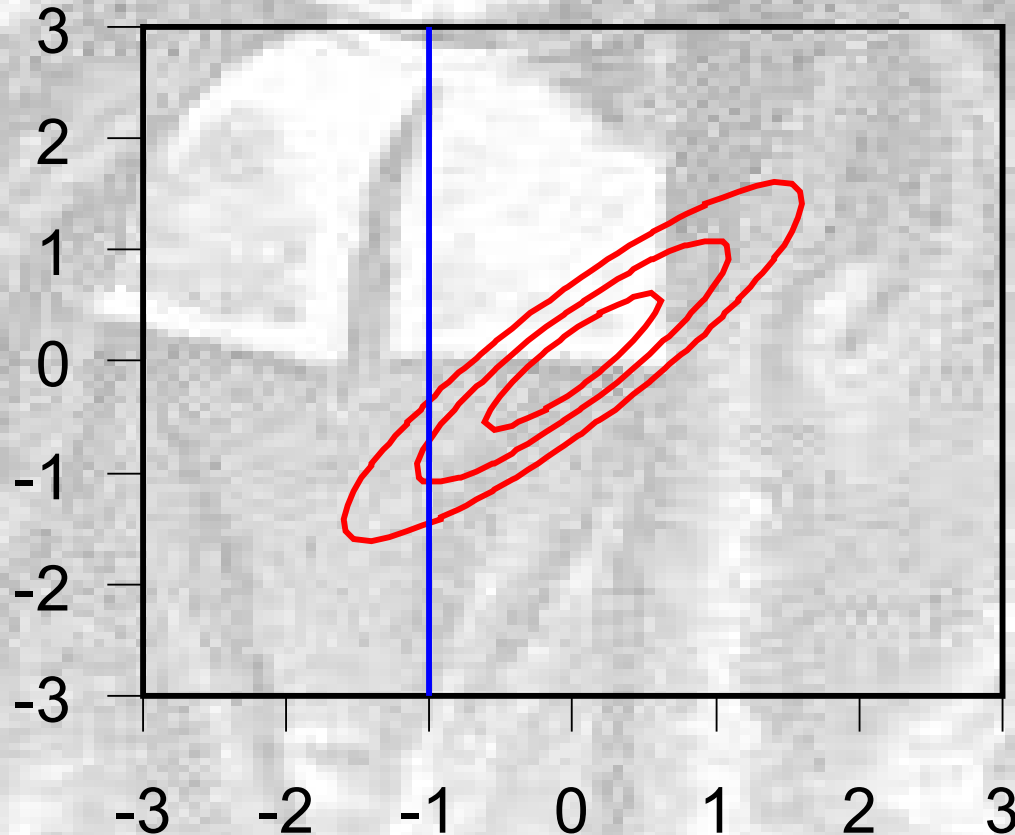
# Conditional and Marginal Distributions

- Important distinction in practice
- Conditional distribution:  $P(x|y)$
- Marginal distribution:

$$P(x) = \int_{-\infty}^{\infty} P(x|y)P(y)dy$$

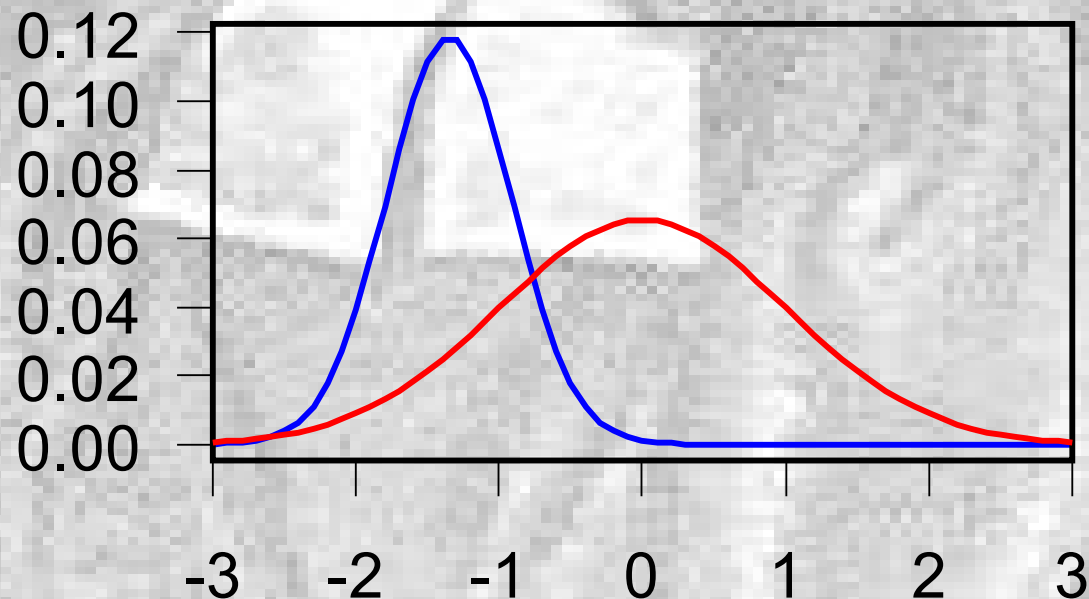
# Example: Bivariate Normal

- $x$  and  $y$  correlated:

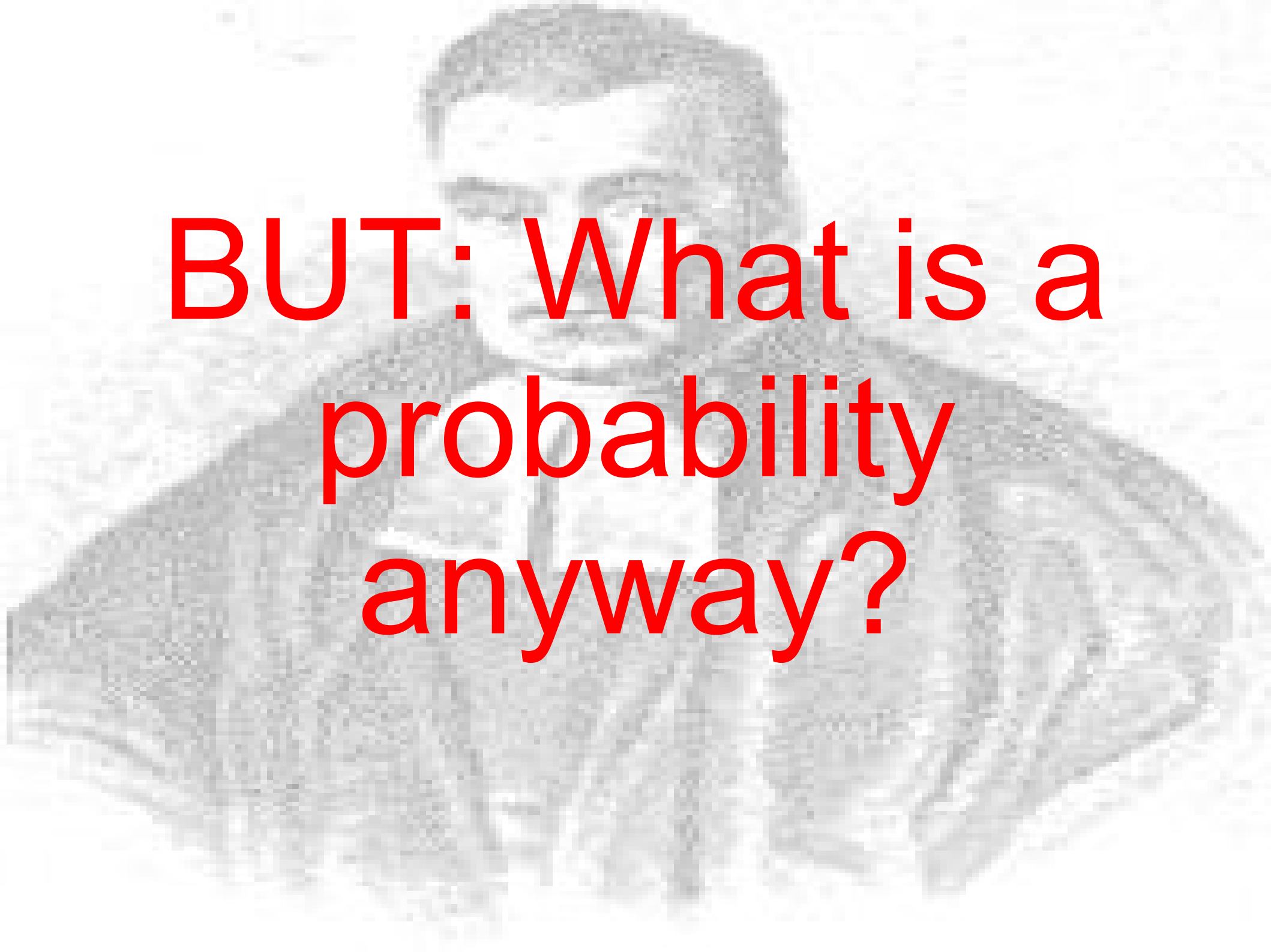


# Example: Bivariate Normal

- $P(y)$  and  $P(y|x=-1)$
- **Marginal** and **Conditional**



- Marginal distribution has a larger variance
  - summed over all values of  $x$



**BUT: What is a  
probability  
anyway?**