




# Bayesian Statistics and Hierarchical Bayesian Modeling for Psychological Science

## Lecture 03

Lei Zhang

Social, Cognitive and Affective Neuroscience Unit (SCAN-Unit)  
Department of Basic Psychological Research and Research Methods

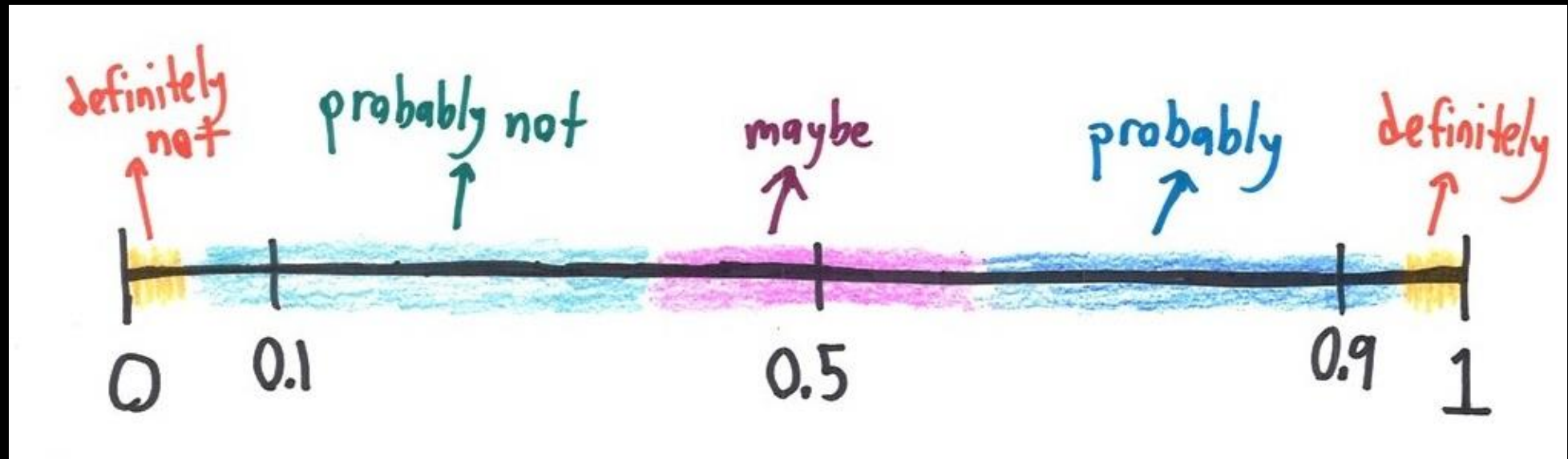
[https://github.com/lei-zhang/BayesCog\\_Wien](https://github.com/lei-zhang/BayesCog_Wien)

lei.zhang@univie.ac.at  
lei-zhang.net  
 @lei\_zhang\_lz



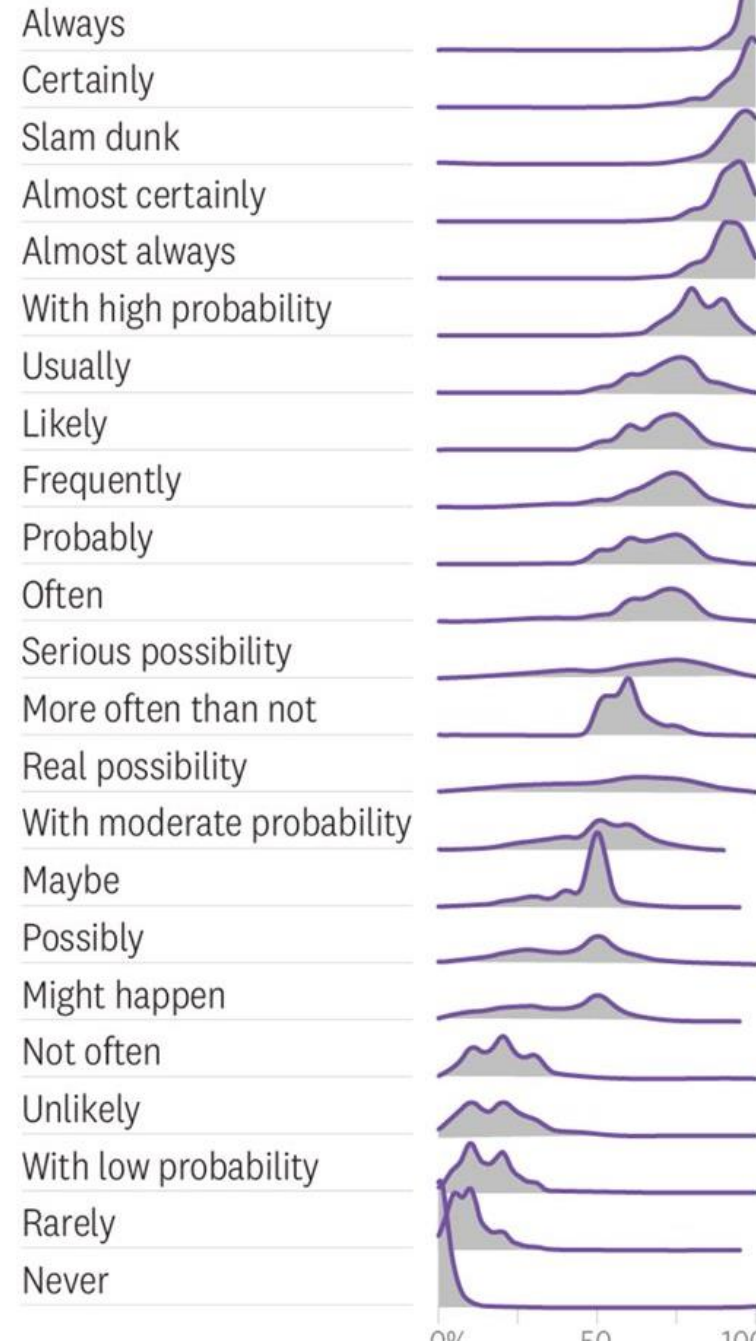
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# BASICS OF PROBABILITY



# to respondents' estimate of likelihood

## Word or phrase



# Probability

cognitive model

statistics

computing

...assigning numbers to a set of possibilities

Properties (Kolmogorov, 1956)

- $p \in [0,1]$
- $\sum p = 1$

Probability are used to express **uncertainty**.

# Probability Functions

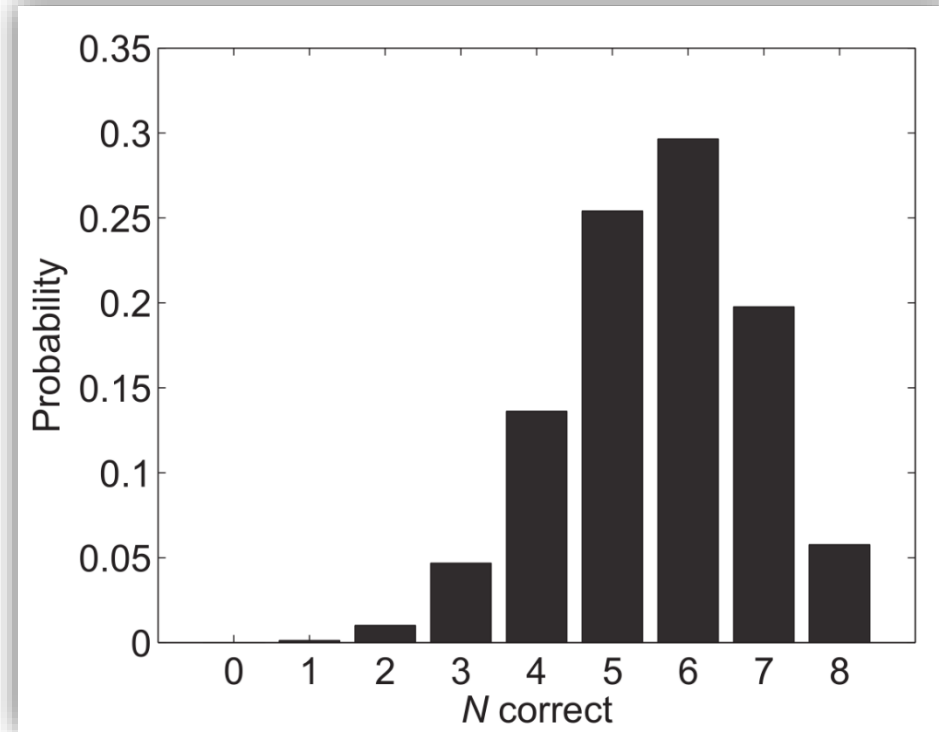
cognitive model

statistics

computing

discrete events – we talk about **mass**

Run a test and  
record each  
student's correct  
responses



# Probability Functions

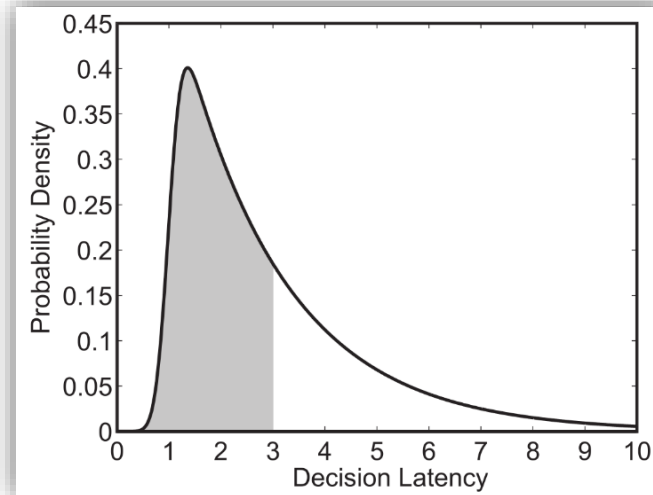
cognitive model

statistics

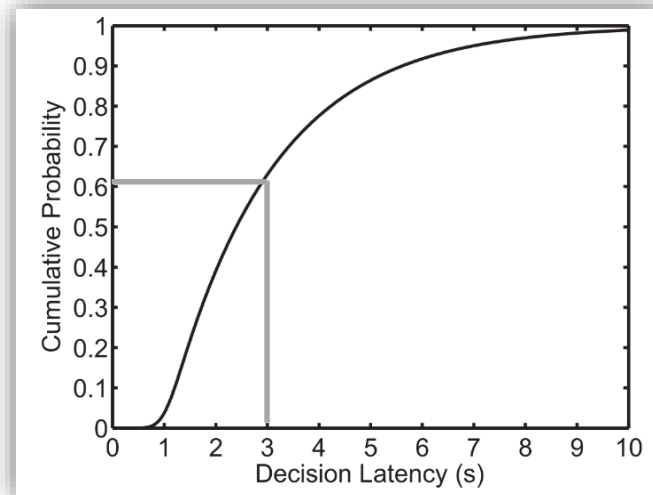
computing

continuous events – we talk about **density**

probability density function  
(PDF)

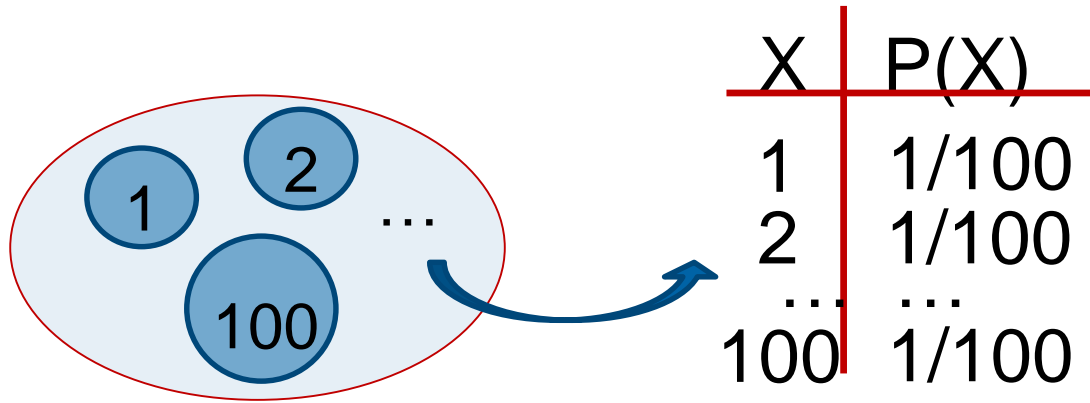


cumulative distribution function  
(CDF)

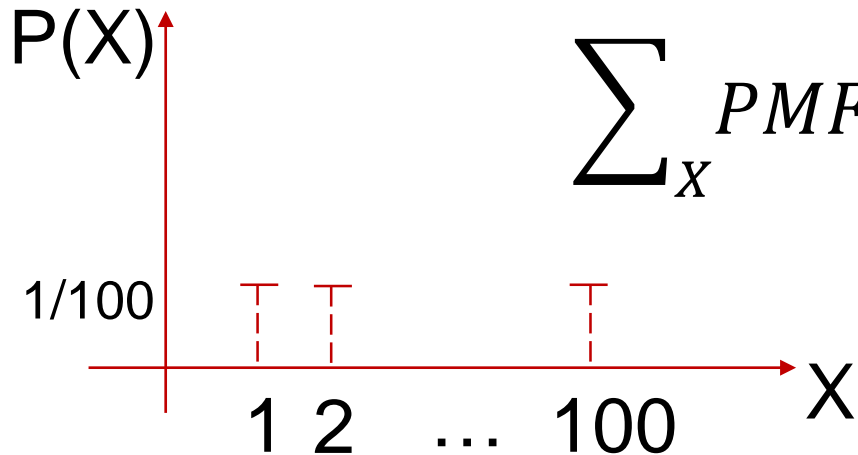


# Another example

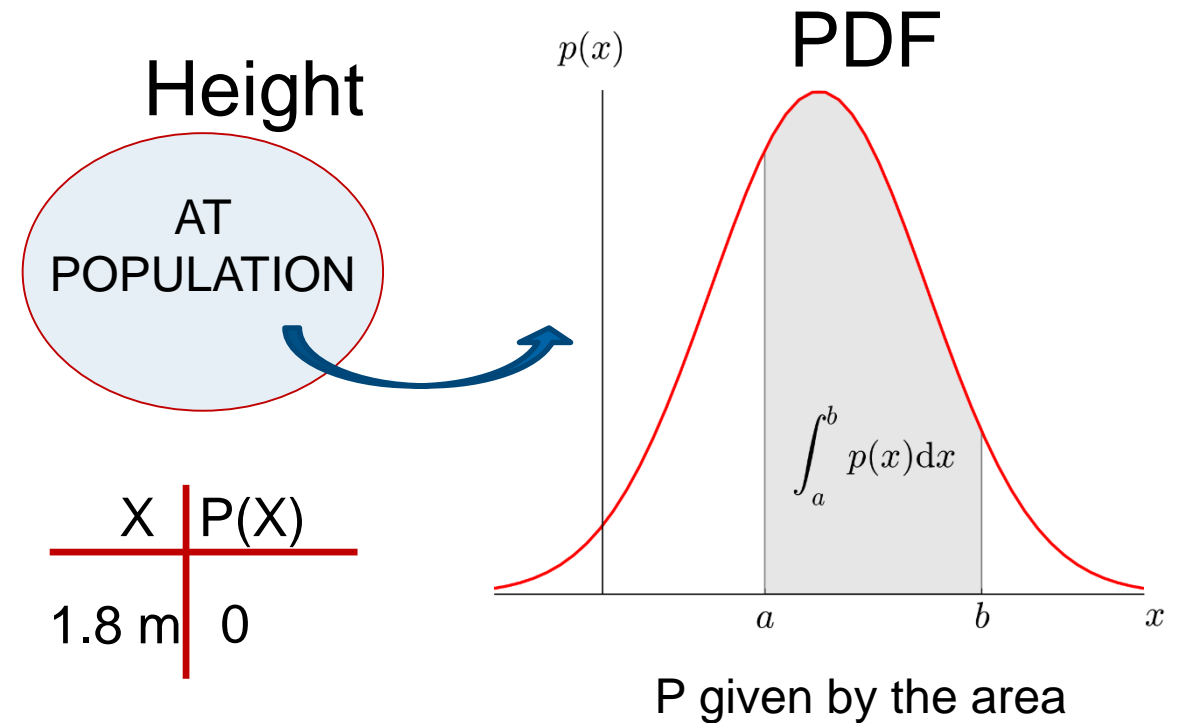
Discrete



$$\sum_X PMF(X) = 1$$



Continuous



$$1.75 \leq X \leq 1.85$$

# Playing with Probability Functions in R

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statistics

computing

`dnorm()` – PDF

`pnorm()` – CDF

`qnorm()` – quantile, inverse cdf

`rnorm()` – random number generator



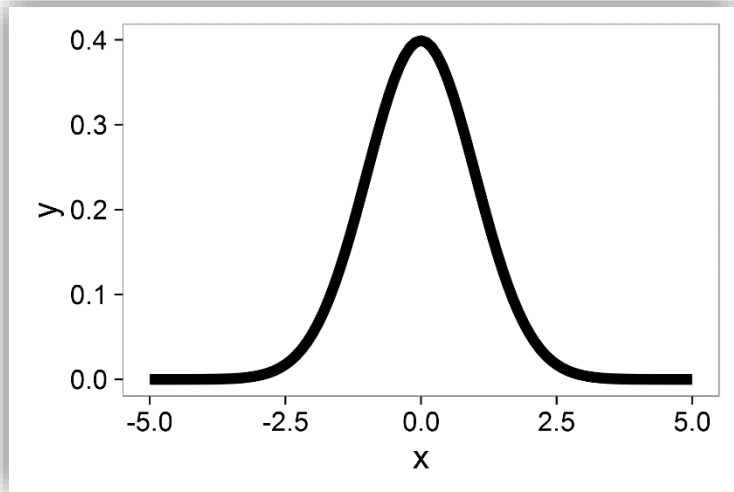
# Example: Normal(0,1)

cognitive model

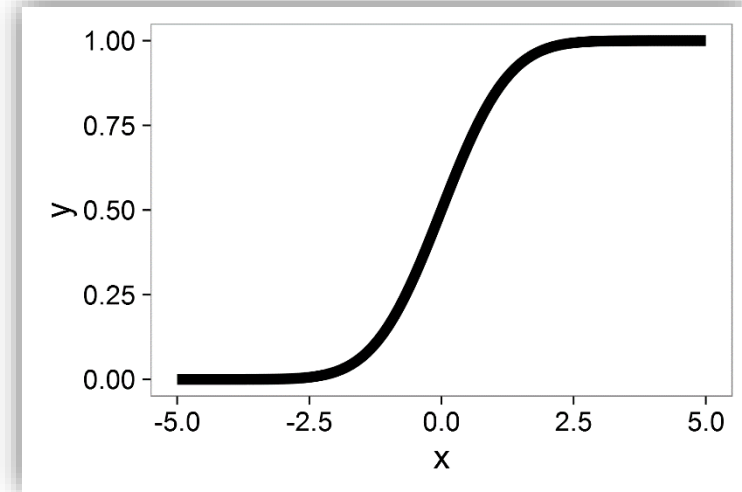
statistics

computing

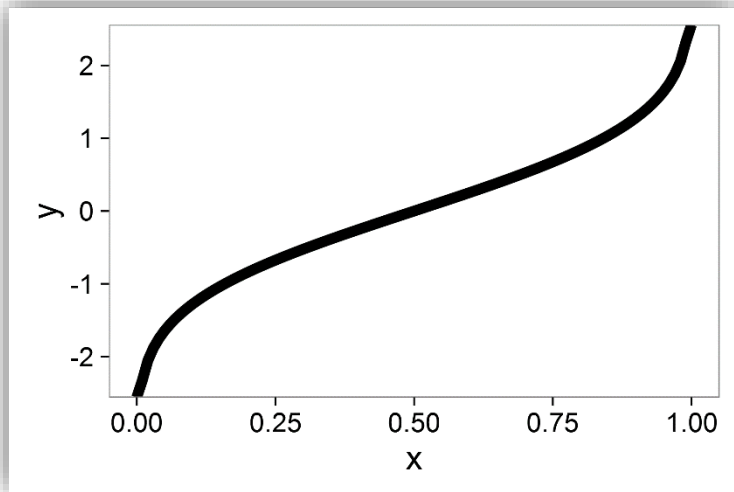
**d**norm()



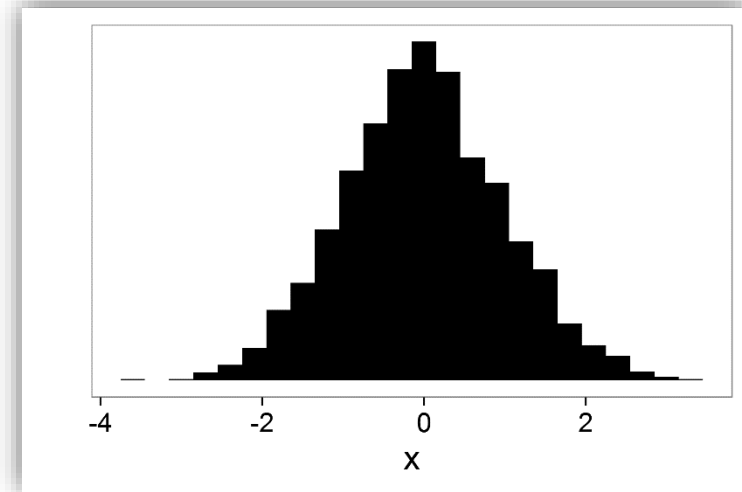
**p**norm()



**q**norm()



**r**norm()



# Joint Probability and Conditional Probability

cognitive model

statistics

computing

## Joint Probability

$$p(A, B) = p(B, A)$$

- e.g.,  $p(\text{raining, cold})$ :  $p(\text{raining})$  AND  $p(\text{cold})$

## Conditional Probability

$p(A|B)$  – ‘p of A given B’ – event B is fixed, not uncertainty

$$p(A, B) = p(A|B)p(B)$$

- e.g.,  $p(\text{raining, cold}) = p(\text{raining}|\text{cold})p(\text{cold})$



# BAYES' THEOREM

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

# Bayes' theorem

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statistics

computing

$$p(A, B) = p(B, A)$$

$$p(A, B) = p(A|B)p(B)$$

$$p(B, A) = p(B|A)p(A)$$

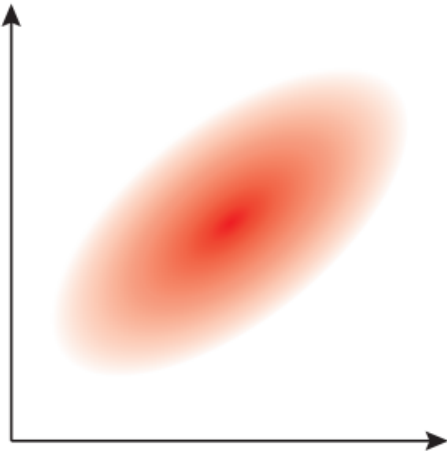
$$p(A|B)p(B) = p(B|A)p(A)$$

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

$$p(A | B) = \frac{p(B | A) p(A)}{\sum_{A^*} p(B | A^*) p(A^*)}$$

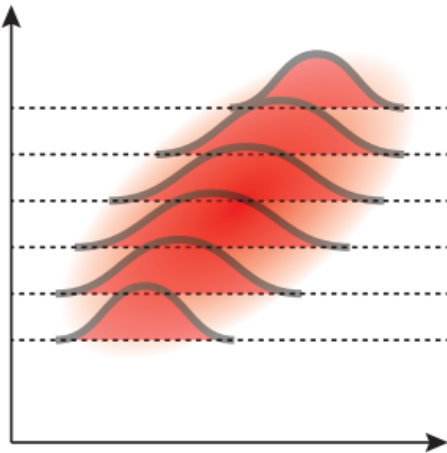
$A^*$  is a variable that takes on all possible values

joint distribution



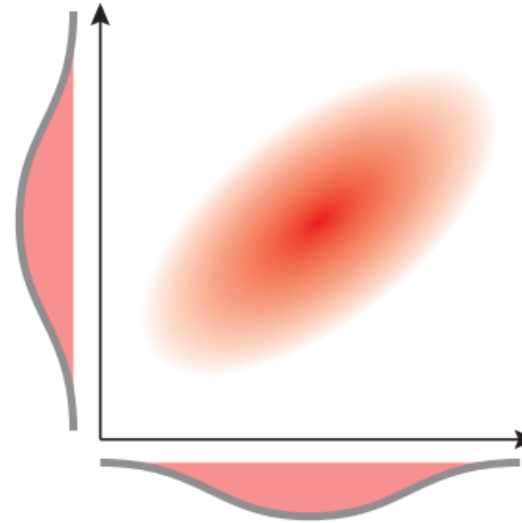
The "co-distribution" of  $x$  and  $y$ .

conditional distribution



The probability distribution of  $x$ ,  
given that we know the value of  $y$ .

marginal distribution



The density of  $x$ - (or  $y$ -) values,  
without knowing the other's value.

# First Example

Joint probability :  $P(X = 0, Y = 1) = 0.1$

$$\sum_{x,y} P(X = x, Y = y) = 1$$

Marginal probability :

$$P(Y = 1) = 0.1 + 0.3 = 0.4$$

$$P(X = 0) = 0.1 + 0.5 = 0.6$$

$$P(X = x) = \sum_y P(X = x, Y = y)$$

		disease	
		X	
symptoms	Y	0	1
		0.5	0.1
	1	0.1	0.3

# Second Example

cognitive model

statistics

computing

Row	Column			Marginal
	...	$c$	...	
$\vdots$ $r$ $\vdots$	...	$\vdots$ $p(r, c) = p(r c) p(c)$ $\vdots$	...	$p(r) = \sum_{c^*} p(r c^*) p(c^*)$
Marginal		$p(c)$		

## Second Example

cognitive model

statistics

computing

Eye color	Hair color				Marginal (Eye color)
	Black	Brunette	Red	Blond	
Brown	0.11	0.20	0.04	0.01	0.37
Blue	0.03	0.14	0.03	0.16	0.36
Hazel	0.03	0.09	0.02	0.02	0.16
Green	0.01	0.05	0.02	0.03	0.11
Marginal (hair color)	0.18	0.48	0.12	0.21	1.0

$$p(A | B) = \frac{p(B | A) p(A)}{\sum_{A^*} p(B | A^*) p(A^*)}$$



## Exercise IV

cognitive model

statistics

computing

Suppose that in the general population, the probability of having a rare disease is 1/1000. We denote the true presence or absence of the disease as the value of a parameter,  $\vartheta$ , that can have the value  $\vartheta = \text{☹}$  if disease is present in a person, or the value  $\vartheta = \text{☺}$  if the disease is absent. The base rate of the disease is therefore denoted  $p(\vartheta = \text{☹}) = 0.001$ .

Suppose(1): a test for the disease that has a 99% hit rate:  $p(T = + | \vartheta = \text{☹}) = 0.99$

Suppose(2): the test has a false alarm rate of 5%:  $p(T = + | \vartheta = \text{☺}) = 0.05$

**Q:** Suppose we sample a person at random from the population, administer the test, and it comes up positive. What is the posterior probability that the person has the disease?

## Exercise VI

cognitive model

statistics

computing

Q: What is the posterior probability that the person has the disease?

$$\rightarrow p(\vartheta = \text{☹} \mid T = +)$$

# Exercise VI

cognitive model

statistics

computing

Test result	Disease		Marginal (test result)
	$\theta = \ddot{\smile}$ (present)	$\theta = \smile$ (absent)	
$T = +$	$p(+ \ddot{\smile}) p(\ddot{\smile})$ $= 0.99 \cdot 0.001$	$p(+ \smile) p(\smile)$ $= 0.05 \cdot (1 - 0.001)$	$\sum_{\theta} p(+ \theta) p(\theta)$
$T = -$	$p(- \ddot{\smile}) p(\ddot{\smile})$ $= (1 - 0.99) \cdot 0.001$	$p(- \smile) p(\smile)$ $= (1 - 0.05) \cdot (1 - 0.001)$	$\sum_{\theta} p(- \theta) p(\theta)$
<b>Marginal (disease)</b>	$p(\ddot{\smile}) = 0.001$	$p(\smile) = 1 - 0.001$	1.0

$$\begin{aligned}
 p(\theta = \ddot{\smile} | T = +) &= \frac{p(T = + | \theta = \ddot{\smile}) p(\theta = \ddot{\smile})}{\sum_{\theta} p(T = + | \theta) p(\theta)} \\
 &= \frac{0.99 \cdot 0.001}{0.99 \cdot 0.001 + 0.05 \cdot (1 - 0.001)} \\
 &= 0.019
 \end{aligned}$$