# Probability

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- 1. Basic definitions
  - random process, sample space, events
- 2. Probability laws
  - disjoint events, compliment rule, addition rule, independence, multiplication rule

- Statistical inference, the process of using sample data to reach a conclusion, inherently involves uncertainty
  - Which cases from the population ended up in the sample data?
  - Which cases ended up in the treatment and control groups?
  - Could the data generation process have unfolded differently?

- A random process describes any phenomenon whose outcome cannot be predicted with certainty
- A sample space refers to the collection of possible outcomes of a random process
- An event describes the realization of one (or more) outcomes from a random process

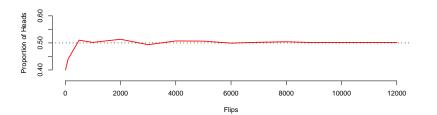
Process	Space	Event
Flipping a Coin	{H,T}	Seeing H
Rolling a 6-sided Die	{1,2,3,4,5,6}	Seeing an odd number
Person takes Vaccine	{Disease, No Disease}	No Disease

# Probabilty

 Probability describes the long-run relative frequency of an event over infinitely many repetitions of a random process

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- Probability describes the long-run relative frequency of an event over infinitely many repetitions of a random process
- The theoretical justification for this definition is the Law of Large Numbers, which states that the proportion of times an outcome is observed will converge to it's probability
  - For example, when flipping a fair coin we'll say P(Heads) = 0.5 because the proportion of heads will converge to 0.5 if the random process is repeated many times



- Two events are **disjoint** or *mutually exclusive* if they cannot both occur simultaneously
  - ▶ If we flip a single coin, "Heads" and "Tails" are disjoint
  - ▶ If we roll a six-sided die, "Odd" and "≥ 4" are *not* disjoint

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  - ▶ If we flip a single coin, "Heads" and "Tails" are disjoint
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- We can express the probability of disjoint events using the notation: P(A<sub>1</sub> ∩ A<sub>2</sub>) = 0
  - In words, the probability of observing both A<sub>1</sub> and A<sub>2</sub> simultaneously is zero



### Probability distributions are used to map disjoint events to probabilities

Here is an example for the sum of two rolls of a six-sided die:

Event	2	3	4	5	6	7	8	9	10	11	12
Probability	1/36	2/36	3/36	4/36	5/36	6/36	5/36	4/36	3/36	2/36	1/36

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Probability	1/36	2/36	3/36	4/36	5/36	6/36	5/36	4/36	3/36	2/36	1/36

- A valid probability distribution must satisfy all of the following:
  - All events must be disjoint
  - Each event must have a probability  $\geq 0$
  - The probability of the entire set of events (sample space) sums to exactly 1



If two events are disjoint, the probability that *either* event occurs is given by:

$$P(A_1\cup A_2)=P(A_1)+P(A_2)$$

For example, for a single coin flip:

 $P(\text{Heads} \cup \text{Tails}) = P(\text{Heads}) + P(\text{Tails}) = 0.5 + 0.5 = 1$ 



If the events are *not* disjoint, the probability that either event occurs is given by:

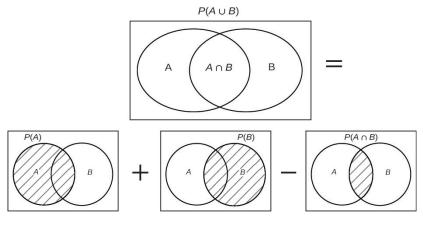
$$P(A_1 \cup A_2) = P(A_1) + P(A_2) - P(A_1 \cap A_2)$$

For example, consider a single roll of a six-sided die:

$$P(>3 \cup Even) = P(>3) + P(Even) = 3/6 + 3/6 - 2/6 = 0.667$$

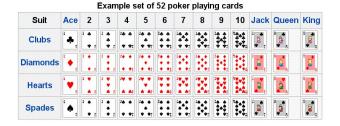


Venn diagrams provide a useful heuristic for understanding the addition rule:





A standard deck of playing cards contains 52 cards that belong to 4 different suits:



For the random process of drawing a single card, find the following probabilities:

- 1)  $P(\text{Heart} \cap \text{Diamond})$
- 2) *P*(Heart ∪ Diamond)
- 3)  $P(\text{Heart} \cup \text{Even Number})$



- 1)  $P(\text{Heart} \cap \text{Diamond}) = 0$
- 2)  $P(\text{Heart} \cup \text{Diamond}) = 13/52 + 13/52 = 0.5$
- 3)  $P(\text{Heart} \cup \text{Even Number}) = \frac{13}{52} + \frac{20}{52} \frac{5}{52} = 0.538$



- For any event, A, we define  $A^C$  as the **complement** of A
  - A<sup>C</sup> represents all outcomes in the sample space that *do not* belong to A
  - For example, if A is seeing a 6 when rolling a six-sided die, A<sup>C</sup> is rolling either a 1, 2, 3, 4, or 5

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  - For example, if A is seeing a 6 when rolling a six-sided die, A<sup>C</sup> is rolling either a 1, 2, 3, 4, or 5
- The complement rule states:  $P(A^{C}) = 1 P(A)$

For example, when rolling a six-sided die:

$$P(1 \cup 2 \cup 3 \cup 4 \cup 5) = 1 - P(6) = 1 - 1/6 = 0.1667$$



A standard deck of playing cards contains 52 cards that belong to 4 different suits:

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Suit	Ace		2			3		4	1		5		6		7	8	9		10	Jack	Queen	King
Clubs	*	2	*	ŧ	2	* * *	2	2. <b>4</b>	* *:	2.4	*	24	*	2.4 .4 .4	**		H	2	11	8	8	8
Diamonds	•	2	•	:	2	:	:	*	• •:	2.	•		•	1+ + +	•				à	8	€.	۰ <u>۲</u> ,
Hearts	٠,	3			2	:		*	•			5	*	2.W.	**	**				5	2,	8,
Spades	۴.	2	•		2	***		2	۰ •:	24	*	1	*	14 4 4	**		÷.	2		5	°	8

Example set of 52 poker playing cards

For the random process of drawing a single card, find the following probabilities:



1) 
$$P(\text{Heart}^{C}) = 1 - \frac{13}{52} = 0.75$$
  
2)  $P(\text{Heart}^{C} \cup \text{Even Number}) = P(\text{Heart}^{C}) + P(\text{Even Number}) - P(\text{Heart}^{C} \cap \text{Even Number}) = \frac{39}{52} + \frac{20}{52} - \frac{15}{52} = 0.846$ 

- Two random processes are independent if knowing the outcome of one process provides no insight into the outcome of the other
  - Flipping a fair coin and rolling a six-sided die are *independent* random processes
  - A single student receiving a calculus test score and a physics test score are not



- Two random processes are independent if knowing the outcome of one process provides no insight into the outcome of the other
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- If events A<sub>1</sub> and A<sub>2</sub> arise from independent random processes, the multiplication rule states:

$$P(A_1 \cap A_2) = P(A_1) * P(A_2)$$

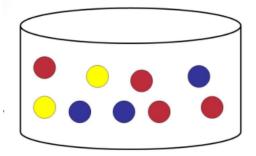


Disjoint events generally are *never* independent (aside from the trivial case where one event has zero probability)
 If A<sub>1</sub> and A<sub>2</sub> are *disjoint*, then P(A<sub>1</sub> ∩ A<sub>2</sub>) = 0
 If A<sub>1</sub> and A<sub>2</sub> are *independent*, then P(A<sub>1</sub> ∩ A<sub>2</sub>) = P(A<sub>1</sub>) \* P(A<sub>2</sub>)



## Dependent events

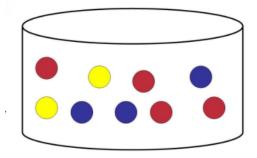
- When probability of an event can be influenced by another event, we must use conditional probability
  - A simple example is sampling from a small population
  - Let A<sub>1</sub> denote the event of randomly drawing a yellow ball, clearly P(A<sub>1</sub>) = 2/9





Now let A<sub>i</sub> represent the i<sup>th</sup> draw (without replacement) from the urn being a yellow ball

- What is  $P(A_1 \text{ and } A_2)$ ?
- What about  $P(A_1 \text{ and } A_2 \text{ and } A_3)$ ?





# The multiplication rule seemingly suggests: P(A₁ and A₂) = P(A₁) \* P(A₂) = <sup>2</sup>/<sub>9</sub> \* <sup>2</sup>/<sub>9</sub> ≈ 0.05

•  $P(A_1 \text{ and } A_2 \text{ and } A_3) = P(A_1) * P(A_2) * P(A_3) = (\frac{2}{9})^3 \approx 0.01$ 



### The multiplication rule seemingly suggests:

- $P(A_1 \text{ and } A_2) = P(A_1) * P(A_2) = \frac{2}{9} * \frac{2}{9} \approx 0.05$
- $P(A_1 \text{ and } A_2 \text{ and } A_3) = P(A_1) * P(A_2) * P(A_3) = (\frac{2}{9})^3 \approx 0.01$
- However, observing a yellow ball on the first draw alters the chances of getting a yellow ball on the second or third draw
  - This is most obviously evidenced by the fact that drawing 3 yellow balls is impossible!
  - Clearly the multiplication rule needs to be adjusted to work for dependent events



In our example, it's easy to see P(A<sub>1</sub>) = 2/9 and P(A<sub>2</sub>|A<sub>1</sub>) = 1/8, as well as P(A<sub>3</sub>|A<sub>1</sub>, A<sub>2</sub>) = 0
 These examples illustrate the concept of *conditional probability*, and they lead us to the general multiplication rule:

$$P(A \text{ and } B) = P(A) * P(B|A) = P(A|B) * P(B)$$



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It's often useful to rearrange this equation:

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



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Example set of 52 poker playing cards

For the random process of drawing a single card, find the following probabilities:

1) 
$$P(\text{Heart}|\text{Red})$$
  
2)  $P(\text{Ten}| \ge \text{Seven})$ 



1) 
$$P(\text{Heart}|\text{Red}) = P(\text{Heart} \cap \text{Red})/P(\text{Red}) = \frac{13/52}{26/52} = 0.5$$
  
2)  $P(\text{Ten}| \ge \text{Seven}) = P(\text{Ten} \cap \ge \text{Seven})/P(\ge \text{Seven}) = \frac{4/52}{16/52} = 0.25$ 



# Estimating probabilities from contingency tables

- Recall that contingency tables are a method used to relate two categorical variables
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# Estimating probabilities from contingency tables

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- Since we've defined probability as a long run frequency, it makes sense to use proportions observed in a sample as our best estimate of certain probabilities

	death	not
black	38	142
white	46	152

In the Florida Death Penalty study (the table shown above), we might estimate P(Death|WhiteOffender) = 46/(152 + 46) = 0.232



Contingency tables can help us understand three distinct types of probabilities used in scenarios involving two variables (ie: two random processes)

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1) A marginal probability only considers a single variable, for example: P(Death) = 84/378 = 0.222



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- 1) A marginal probability only considers a single variable, for example: P(Death) = 84/378 = 0.222
- 2) A joint probability simultaneous considers both variables, for example:  $P(\text{Death} \cap \text{WhiteOffender}) = 46/378 = 0.165$



Contingency tables can help us understand three distinct types of probabilities used in scenarios involving two variables (ie: two random processes)

	death	not
black	38	142
white	46	152

- 1) A marginal probability only considers a single variable, for example: P(Death) = 84/378 = 0.222
- 2) A joint probability simultaneous considers both variables, for example:  $P(\text{Death} \cap \text{WhiteOffender}) = 46/378 = 0.165$
- 3) A conditional probability considers one variable, under the assumption that the other has already been observed, for example: P(Death|WhiteOffender) = 46/198 = 0.232



The table below describes survival of residents of Boston, MA in 1721 that were exposed to smallpox. Some of these residents had been inoculated using a controlled strain of smallpox:

	Lived	Died	Total
Inoculated	238	6	244
Not Inoculated	5136	884	6020
Total	5374	890	6264

State whether each of the following is a marginal, joint, or conditional probability, then estimate it using the data presented above:

- 1) That a resident died from their exposure
- 2) That a resident died given they'd been inoculated
- 3) That a resident had been inoculated given they've died
- 4) That a randomly chosen resident was both inoculated and ended up dying



- 1) P(Died) = 890/6264, marginal
- 2) P(Died|Inoculated) = 6/244, conditional
- 3) P(Inoculated|Died) = 6/890, conditional
- 4)  $P(\text{Inoculated} \cap \text{Died}) = 6/6264$ , joint

- We need to understand probability because most of the data we analyze is the consequence of one or more *random processes*:
  - Sampling from a population, randomly assigning treatment and control groups, etc.



- We need to understand probability because most of the data we analyze is the consequence of one or more *random processes*:
  - Sampling from a population, randomly assigning treatment and control groups, etc.
- At its most basic level, probability involves three major rules:
  - ▶ The addition rule:  $P(A \cup B) = P(A) + P(B) P(A \cap B)$
  - The complement rule:  $P(A^{C}) = 1 P(A)$
  - The multiplication rule: P(A and B) = P(A) \* P(B|A) = P(A|B) \* P(B)

