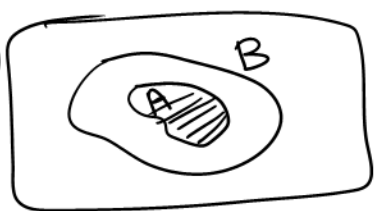


©  $A \subset B \Rightarrow P(A) \leq P(B)$   
 $B = A \cup (B \cap A^c) \Rightarrow P(B) = P(A) + P(B \cap A^c) \geq 0$

**Introduction to Probability**

Properties of probability functions (cont'd)



$P(B) \geq P(A)$

Bonferroni's Inequality:

$$P(A \cap B) \geq P(A) + P(B) - 1 \quad \text{I}$$

Proof:  $P(A \cap B) = P(A) + P(B) - P(A \cup B)$   
 $\geq P(A) + P(B) - 1$

$$P(A \cup B) \leq 1$$

$$-P(A \cup B) \geq -1$$

II

**Theorem 1.2.11.** If  $P$  is a probability function, then

(a)  $P(A) = \sum_{i=1}^{\infty} P(A \cap C_i)$  for any partition  $C_1, C_2, \dots \in \mathcal{B}$  (i.e., disjoint  $C_i$ 's &  $\bigcup_{i=1}^{\infty} C_i = S$ )

(b)  $P(\bigcup_{i=1}^{\infty} A_i) \leq \sum_{i=1}^{\infty} P(A_i)$  for any sets  $A_1, A_2, \dots \in \mathcal{B}$

*Proof of (b)*

Define  $A_1^* = A_1, A_2^* = A_2 \setminus A_1, A_3^* = A_3 \setminus (A_1 \cup A_2)$   
 $\dots, A_k^* = A_k \setminus (\bigcup_{i=1}^{k-1} A_i)$

$$P(\bigcup_{i=1}^{\infty} A_i) = P(\bigcup_{i=1}^{\infty} A_i^*) = \sum_{i=1}^{\infty} P(A_i^*)$$

$A_i^* \subseteq A_i$

$$\sum_{i=1}^{\infty} P(A_i^*) \leq \sum_{i=1}^{\infty} P(A_i)$$

part a:

$$A = A \cap S$$

$$= A \cap (\bigcup_{i=1}^{\infty} C_i)$$

$$= \bigcup_{i=1}^{\infty} (A \cap C_i)$$

disjoint

$$\Rightarrow P(\bigcup_{i=1}^{\infty} (A \cap C_i)) = \sum_{i=1}^{\infty} P(A \cap C_i)$$

**Principle of Inclusion-Exclusion:** For any sets  $A_1, \dots, A_n$ ,

$$P\left(\bigcup_{i=1}^n A_i\right) = \sum_{k=1}^n (-1)^{k-1} \left( \sum_{1 \leq i_1 < \dots < i_k \leq n} P(A_{i_1} \cap \dots \cap A_{i_k}) \right)$$

$$= \sum_{i=1}^n P(A_i) - \sum_{1 \leq i < j \leq n} P(A_i \cap A_j) + \dots + (-1)^{n-1} P\left(\bigcap_{i=1}^n A_i\right)$$

This generalizes  $P(A \cup B) = P(A) + P(B) - P(A \cap B)$  and is proven by induction.

# Introduction to Probability

Probability: the equally likely outcome case

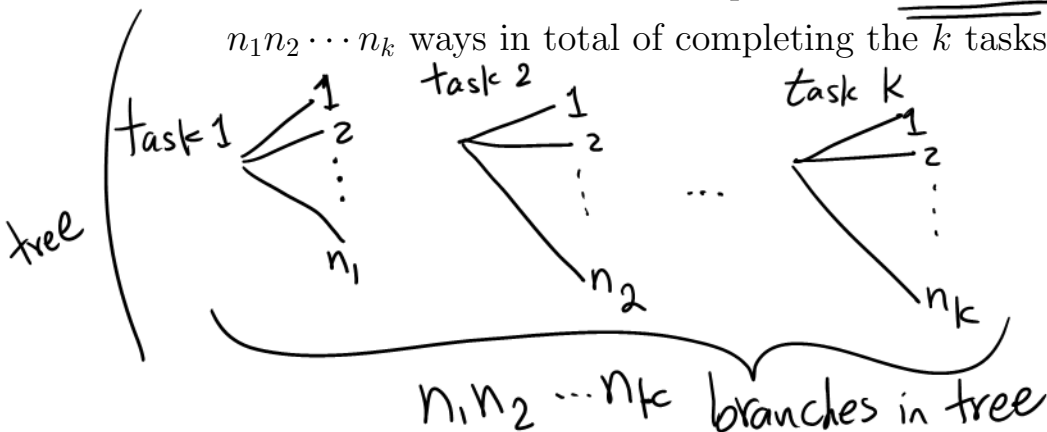
- Sample space is *finite*  $S = \{s_1, \dots, s_N\}$  and all outcomes are equally likely  
e.g., coin toss, die toss, random sampling

- Hence,  $P(\{s_i\}) = \underbrace{1/N}$  for each  $i = 1, \dots, N$  and

$$P(A) = \sum_{s_i \in A} P(\{s_i\}) = \sum_{s_i \in A} \frac{1}{N} = \frac{\# \text{ elements in } A}{\# \text{ elements in } S}$$

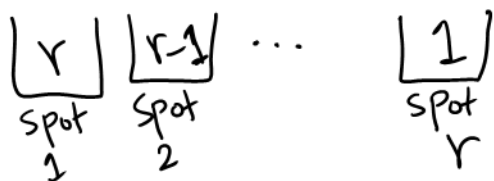
- Application of this probability model sometimes requires *enumerating* or counting the number of possible outcomes of an experiment (each equally likely)
- There are basically 4 counting techniques (combinatorics)

1. **Fundamental Theorem of Counting:** If there are separate  $k$  tasks, where the  $i$ th task can be completed in  $n_i$  different ways, then there are  $n_1 n_2 \dots n_k$  ways in total of completing the  $k$  tasks.



2. **Permutations/ordered arrangements I:**

$r$  objects can be placed in  $r! = r(r-1)(r-2) \dots (1)$  ordered arrangements



# Introduction to Probability

Probability: the equally likely outcome case (cont'd)

3. **Permutations/ordered arrangements II:** When selecting  $r$  objects from  $n$  objects (without replacement), then the number of ordered arrangements possible is

$$n(n-1) \cdots (n-r+1) = \frac{n!}{(n-r)!}$$

$$\boxed{n} \boxed{n-1} \cdots \boxed{n-r+1}$$
  
 spot 1 spot 2 spot  $r$

$$n(n-1) \cdots (n-r+1)$$

$$\boxed{n} \boxed{n} \cdots \boxed{n} = n^r$$
  
 1 2  $r$

Note: # of ordered arrangements with replacement

4. **Combinations/unordered selections:** The number of ways to choose  $r$  objects from  $n$  objects (without replacement), where the ordering doesn't matter, is

$$\binom{n}{r} \equiv \frac{n!}{r! \cdot (n-r)!}$$

Why? Choose ordered arrangements

$$\boxed{n} \boxed{n-1} \cdots \boxed{n-r+1} \Rightarrow \frac{n!}{(n-r)!}$$
  
 1 2  $r$

$$\text{divide out \# ways to arrange } r \text{ objects } (r!)$$
  
 So 
$$\frac{n!}{r! (n-r)!}$$

- Table listing the number of ways to select  $r$  objects from a group of  $n$

	objects chosen without replacement	objects chosen with replacement
→ ordered	$\frac{n!}{(n-r)!}$	$n^r$
→ unordered	$\binom{n}{r} = \frac{n!}{r! \cdot (n-r)!}$	$\binom{n+r-1}{r}$

# Introduction to Probability

Example: the equally likely outcome case

- lotto games often require a player to pick  $r$  from among the first  $n$  integers
- e.g., Minnesota Lottery "Gopher 5": pick  $r = 5$  numbers from  $n = 47$
- Number of possibilities

- if the order matters and no repetition is allowed

$$(47)(46)(45)(44)(43) = 184,072,680$$

$$\frac{n!}{(n-r)!}$$

- if the order matters and repetition is allowed

$$n=47$$

$$r=5$$

$$(47)(47)(47)(47)(47) = 47^5 = 229,345,007$$

$$n^r$$

- if the order doesn't matter and no repetition is allowed

$$\frac{(47)(46)(45)(44)(43)}{(5)(4)(3)(2)(1)} = \binom{47}{5} = 1,533,939$$

$$\binom{n}{r}$$

- In the true Gopher 5 lotto (case 3 above), what is the probability that one lotto ticket matches 4 out of the 5 lottery numbers drawn?

$\square \square \square \square \square$ 
 $\binom{5}{4}$ 
 $\binom{42}{1}$ 
 $\binom{47}{5}$

# of ways to check 1 from the remaining 42 "Wrong" number.

ticket possible

.00014

# Conditional probability and independence

## Defining conditional probability

- So far all probabilities are with respect to  $S$ , i.e.,  $P(A)$  of some event  $A \subset S$



- Knowledge of some kind might affect our opinion concerning  $P(A)$

– Roll two six-sided die (36 equally likely outcomes)

– let event  $A$  = first die is 1

$$P(A) = \frac{6}{36} = \frac{1}{6}$$

– what is  $P(A)$ ?

– let event  $B$  = sum is 3

$$\{(1,2), (2,1)\}$$
$$P(B) = \frac{2}{36} = \frac{1}{18}$$

– we might give a different guess for  $P(A)$  if we know  $B$  has occurred

- $P(A|B)$  denotes the conditional probability of  $A$  given  $B$  occurs

$P(A|B) = \frac{1}{2}$

$$P(\text{"1st roll is 1"} \mid (1,2), (2,1)) = \frac{1}{2}$$

- In conditioning,  $B$  can be thought of as the updated sample space

- Note: In a sense, all probability is conditional.

The notation  $P(A)$  can be interpreted as shorthand for  $P(A|S)$

$$P(A) = P(A|S)$$

# Conditional probability and independence

Formal definition of conditional probability

- *Definition:* If  $A, B$  are events in  $S$  with  $P(B) > 0$  then

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

- In conditioning,  $B$  can be thought of as the updated sample space  
i.e., not all of  $S$  is relevant since we know  $B$  has occurred
- This is actually a “semi”-formal definition (i.e., a more general, but technical, definition of conditional probability exists using Borel fields; see STAT 642)

# Conditional Probability and independence

## Conditional probability function

$P(\cdot|B)$  is a probability function that satisfies the usual axioms and properties

$$P: S \rightarrow [0, 1]$$

Axioms:

- $\underbrace{P(A|B)} \geq 0$  for all events  $A$

- $\underbrace{P(B|B)} = 1$  ( $B$  is the updated sample space)

- If  $A_1, A_2, \dots$  are pairwise disjoint events, then

$$P\left(\bigcup_{i=1}^{\infty} A_i \middle| B\right) = \sum_{i=1}^{\infty} P(A_i|B)$$

Handwritten notes:

- $P(A) \geq 0$
- $P(S) = 1$
- $P\left(\bigcup_{i=1}^{\infty} A_i\right) = \sum_{i=1}^{\infty} P(A_i)$

Some properties:

- $P(A^c|B) = 1 - P(A|B)$

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

# Conditional Probability and independence

## Example of conditional probability

Roll two six-sided die (36 equally likely outcomes) (1<sup>st</sup> roll, 2<sup>nd</sup> roll)

$$S = \left\{ \begin{array}{l} (1,1), (1,2), \dots, (1,6) \\ \vdots \\ (6,1), (6,2) \dots (6,6) \end{array} \right\}$$

Events:  $A$  = first die is 1;  $B$  = sum is 3;  $C$  = sum is 7

Calculations:

$$P(A) = 6/36 = 1/6$$

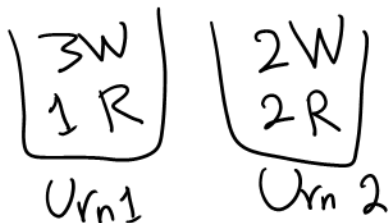
$$P(B) = 2/36$$

$$P(C) = 6/36$$

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{1/36}{2/36} = 1/2$$

$$P(C|B) = \frac{P(C \cap B)}{P(B)} = 0$$

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



Question: Select 1 ball randomly from Urn 1 & place into Urn 2; Then select 1 ball from Urn 2. What is the probability that the ball selected from Urn 2 is red?



$$\begin{aligned}
 P(2^{\text{nd}} R) &= P(\underbrace{1^{\text{st}} W \cap 2^{\text{nd}} \text{Red}} \text{ or } \underbrace{1^{\text{st}} \text{Red} \cap 2^{\text{nd}} \text{Red}}) \\
 &= P(\underbrace{1^{\text{st}} W \cap 2^{\text{nd}} \text{Red}}) + P(\underbrace{1^{\text{st}} \text{Red} \cap 2^{\text{nd}} \text{Red}}) \\
 &= P(2^{\text{nd}} \text{Red} \mid 1^{\text{st}} W) P(1^{\text{st}} W) + P(2^{\text{nd}} \text{Red} \mid 1^{\text{st}} \text{Red}) P(1^{\text{st}} \text{Red}) \\
 &= \left(\frac{3}{4} \cdot \frac{2}{5}\right) + \left(\frac{1}{4} \cdot \frac{3}{5}\right) = \frac{9}{20}
 \end{aligned}$$