Discrete Mathematics

Combinatorics — Spring 2025

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§1 Combinatorics

Introduction to Combinatorics

Definition 1: Combinatorics is the branch of discrete mathematics that deals with *counting*, *arranging*, and analyzing *discrete structures*.

Three basic problems of Combinatorics:

- **1.** Existence: *Is there at least one arrangement of a particular kind?*
- **2.** Counting: How many arrangements are there?
- **3.** Optimization: Which one is best according to some criteria?

Discrete structures

• Graphs, sets, multisets, sequences, patterns, coverings, partitions...

Enumeration

• Permutations, combinations, inclusion/exclusion, generating functions, recurrence relations...

Algorithms and optimization

• Sorting, eulerian circuits, hamiltonian cycles, planarity testing, graph coloring, spanning trees, shortest paths, network flows, bipartite matchings, chain partitions...

Discrete Structures

We investigate the *building blocks* of combinatorics:

- Sets and multisets
- Sequences and strings
- Arrangements
- Graphs, networks, trees
- Posets and lattices
- Partitions
- Patterns, coverings, designs, configurations
- · Schedules, assignments, distributions

Used in data modeling, logic, cryptography, and the design of data structures.

Enumerative Combinatorics

We learn how to count without explicit listing:

- Permutations and combinations
- Inclusion–Exclusion Principle
- Set partitions, integer partitions, Stirling numbers, Catalan numbers
- Recurrence relations
- Generating functions

Used in probability theory, complexity theory, coding theory, computational biology.

Algorithmic and Optimization Methods

Combinatorics powers *algorithm design* and complexity analysis:

- Sorting
- Searching
- Eulerian paths and Hamiltonian cycles
- Planarity, colorings, cliques, coverings
- Spanning trees
- Shortest paths
- · Network flows
- Bipartite matchings
- Dilworth's theorem, chain and antichain partitions

Used in logistics, scheduling, routing, and complexity optimization.

§2 Basic Counting Principles

Basic Counting Rules

PRODUCT RULE: If something can happen in n_1 ways, and no matter how the first thing happens, a second thing can happen in n_2 ways, then the two things together can happen in $n_1 \cdot n_2$ ways.

SUM RULE: If one event can occur in n_1 ways and a second event in n_2 (different) ways, then there are $n_1 + n_2$ ways in which *either* the first event *or* the second event can occur (*but not both*).

Addition Principle

Definition 2: We say a finite set S is *partitioned* into *parts* $S_1,...,S_k$ if the parts are pairwise disjoint and their union is S. In other words, $S_i \cap S_j = \emptyset$ for $i \neq j$ and $S_1 \cup S_2 \cup ... \cup S_k = S$. In that case:

$$|S| = |S_1| + |S_2| + \ldots + |S_k|$$

Example: Let S be the set of students attending the combinatorics lecture. It can be partitioned into parts S_1 and S_2 where

 $S_1 = \text{set of students that like easy examples.}$

 $S_2 = \text{set of students that don't like easy examples.}$

If $|S_1| = 22$ and $|S_2| = 8$, then we can conclude $|S| = |S_1| + |S_2| = 30$.

Multiplication Principle

Definition 3: If S is a finite set that is the *product* of $S_1, ..., S_k$, that is, $S = S_1 \times ... \times S_k$, then

$$|S| = |S_1| \times \ldots \times |S_k|$$

Example: TODO: example with car plates

Subtraction Principle

Definition 4: Let S be a subset of a finite set T. We define the *complement* of S as $\overline{S} = T \setminus S$. Then

$$\left| \overline{S} \right| = |T| - |S|$$

Example: If T is the set of students studying at KIT and S the set of students studying neither math nor computer science. If we know |T| = 23905 and |S| = 20178, then we can compute the number |S| of students studying either math or computer science:

$$|S| = |T| - |S| = 23905 - 20178 = 3727$$

Bijection Principle

Definition 5: If S and T are sets, then

$$|S| = |T| \iff$$
 there exists a bijection between S and T

Example: Let S be the set of students attending the combinatorics lecture and T the set of homework submissions (unique per student) for the first problem sheet. If the number of students and the number of submissions coincide, then there is a bijection between students and submissions.

Note: The bijection principle works both for *finite* and *infinite* sets.

Pigeonhole Principle

Definition 6: Let $S_1, ..., S_k$ be finite sets that are pairwise disjoint and $|S_1| + |S_2| + ... + |S_k| = n$.

$$\exists i \in \{1,...,k\}: |S_i| \geq \left\lfloor \frac{n}{k} \right\rfloor \quad \text{and} \quad \exists j \in \{1,...,k\}: \left|S_j\right| \leq \left\lceil \frac{n}{k} \right\rceil$$

Example: Assume there are 5 holes in the wall where pigeons nest. Say there is a set S_i of pigeons nesting in hole i. Assume there are n=17 pigeons in total. Then we know:

- There is some hole with at least d = 4 pigeons.
- There is some hole with at most b = 3 pigeons.

Double Counting

If we count the same quantity in *two different ways*, then this gives us a (perhaps non-trivial) identity.

Example ($Handshaking\ Lemma$): Assume there are n people at a party and everybody will shake hands with everybody else. How many handshakes will occur? We count this number in two ways:

- 1. Every person shakes n-1 hands and there are n people. However, two people are involved in a handshake so if we just multiply $n \cdot (n-1)$, then every handshake is counted twice. The total number of handshakes is therefore $\frac{n \cdot (n-1)}{2}$.
- 2. We number the people from 1 to n. To avoid counting a handshake twice, we count for person i only the handshakes with persons of lower numbers. Then the total number of handshakes is:

$$\sum_{i=1}^{n} (i-1) = \sum_{i=0}^{\{n-1\}} i = \sum_{i=1}^{n-1} i$$

The identity we obtain is therefore: $\sum_{i=1}^{n-1} i = \frac{n \cdot (n-1)}{2}$

§3 Arrangements, Permutations, Combinations

Ordered Arrangements

Definition 7: Denote by $[n] = \{1, ..., n\}$ the set of natural numbers from 1 to n.

Hereinafter, let *X* be a finite set.

Definition 8: An *ordered arrangement* of n elements of X is a map $s : [n] \longrightarrow X$.

- Here, [n] is the *domain* of s, and s(i) is the *image* of $i \in [n]$ under s.
- The set $\{x \in X \mid s(i) = x \text{ for some } i \in [n]\}$ is the *range* of s.

Other common names for ordered arrangements are:

- string (or word), e.g. "Banana"
- sequence, e.g. "0815422372"
- tuple, e.g. (3, 5, 2, 5, 8)

Permutations

Definition 9: A permutation of X is a bijective map $\pi : [n] \longrightarrow X$.

Usually, X=[n], and the set of all permutations of [n] is denoted by S_n .

Definition 10: *k-permutation* of X is an ordered arrangement of k *distinct* elements of X, that is, an *injective* map $\pi : [k] \longrightarrow X$.

The set of all k-permutations of X = [n] is denoted by P(n, k). In particular, $S_n = P(n, n)$.

TODO: circular permutations

Counting Permutations

Theorem 1: For any natural numbers $0 \le k \le n$, we have

$$|P(n,k)| = n \cdot (n-1) \cdot \dots \cdot (n-k+1) = \frac{n!}{(n-k)!}$$

This formula is also called the *falling factorial* and denoted $n^{\underline{k}}$ or $(n)_k$.

Proof: A permutation is an injective map $\pi:[k] \longrightarrow [n]$. We count the number of ways to pick such a map, picking the images one after the other. There are n ways to choose $\pi(1)$. Given a value for $\pi(1)$, there are (n-1) ways to choose $\pi(2)$ (since we may not choose $\pi(1)$ again). Continuing like this, there are (n-i+1) ways to pick $\pi(i)$, and the last value we pick is $\pi(k)$ with (n-k+1) possibilities.

Every k-permutation can be constructed like this in *exactly one way*. The total number of k-permutations is therefore given as the product:

$$|P(n,k)| = n \cdot (n-1) \cdot \dots \cdot (n-k+1) = \frac{n!}{(n-k)!}$$

Counting Circular Permutations

Theorem 2: For any natural numbers $0 \le k \le n$, we have

$$|P_c(n,k)| = \frac{n!}{k \cdot (n-k)!}$$

Proof: We doubly count P(n, k):

- **1.** $|P(n,k)| = \frac{n!}{(n-k)!}$ which we proved before.
- 2. $|P(n,k)| = |P_c(n,k)| \cdot k$ because every equivalence class in $P_c(n,k)$ contains k permutations from P(n,k) since there are k ways to rotate a k-permutation.

From this we get
$$\frac{n!}{(n-k)!} = |P_c(n,k)| \cdot k$$
, which implies $|P_c(n,k)| = \frac{n!}{k \cdot (n-k)!}$.

Unordered Arrangements

Definition 11: An unordered arrangement of k elements of X is a multiset $S = \langle X, r \rangle$ of size k.

In a multiset, X is the set of *types*, and for each type $x \in X$, r_x is its *repetition number*.

Example: Let $X = \{ \langle \rangle \rangle, \langle \rangle \rangle, \langle \rangle \rangle, \langle \rangle \rangle$.

- The same multiset could be written as $S = \{2 \setminus 3, 1 \setminus 3, 3 \setminus 1, 0 \mid 1, 1 \mid 1, 1, \dots, 1, 1, \dots, 1, \dots,$

Subsets

The most important special case of unordered arrangements is where all repetitions are 1, that is, $r_x=1$ for all $x\in X$. Then S is simply a *subset* of X, denoted $S\subseteq X$.

Definition 12: A k-combination of X is an unordered arrangement of k distinct elements of X.

Note: The more standard term is *subset*. The term "combination" is only used to emphasize the selection process.

The set of all k-subsets of X is denoted $\binom{X}{k} = \{A \subseteq X \mid |A| = k\}$. If |X| = n, then

$$\binom{n}{k} \coloneqq \left| \binom{X}{k} \right|$$

Example: The set of edges in a simple undirected graph consists of 2-subsets of its vertices: $E \subseteq \binom{V}{2}$.

Counting *k***-Combinations**

Theorem 3: For $0 \le k \le n$, we have

$$\binom{n}{k} = \frac{n!}{k! \cdot (n-k)!}$$

Proof:
$$|P(n,k)| = \frac{n!}{(n-k)!} = \binom{n}{k} \cdot k!$$

§4 Multisets

Multiset

Definition 13: A *multiset* is a modification of the concept of a set that allows for *repetitions* of its elements. Formally, it is denoted as a pair $M = \langle X, r \rangle$, where X is the *groundset* (the set of *types*) and $r: X \longrightarrow \mathbb{N}_0$ is the *multiplicity function*.

Example: When the multiset is defined by enumeration, it is advisable to use the notation with the star:

$$M = \{a, b, a, a, b\}^* = \{3 \cdot a, 2 \cdot b\} \quad X = \{a, b\} \quad r_a = 3, r_b = 2$$

Example: Prime factorization of a natural number n is a multiset, e.g. $120 = 2^3 \cdot 3^1 \cdot 5^1$.

k-Combinations of a Multiset

Definition 14: Let X be a finite set of types, and let $M=\langle X,r\rangle$ be a finite multiset with repetition numbers $r_1,...,r_{|X|}$. A k-combination of M is a multiset $S=\langle X,s\rangle$ with types in X and repetition numbers $s_1,...,s_{|X|}$ such that $s_i\leq r_i$ for all $1\leq i\leq |X|$, and $\sum_{i=1}^{|X|}s_i=k$.

Example: Consider $M = \{2 \)$, $1 \$, $3 \)$, $1 \$ }.

- $T = \{1 \}$, 2 } is a 3-combination of M.
- $T' = \{3 \ \ \}$ is not.

Counting k-combinations of a multiset is not as simple as it might seem...

k-Permutations of a Multiset

Definition 15: Let M be a finite multiset with set of types X. A k-permutation of M is an ordered arrangement of k elements of M where different orderings of elements of the same type are not distinguished. This is an ordered multiset with types in X and repetition numbers $s_1, ..., s_{|X|}$ such that $s_i \leq r_i$ for all $1 \leq i \leq |X|$, and $\sum_{i=1}^{|X|} s_i = k$.

Note: There might be several elements of the same type compared to a permutation of a set (where each repetition number equals 1).

Example: Let $M = \{2 \}$, 1, 3, 3, 4, then T = (?,), , ,) is a 4-permutation of multiset M.

Binomial Theorem

Theorem 4: The expansion of any non-negative integer power n of the binomial (x + y) is a sum

$$(x+y)^n = \sum_{k=0}^n \binom{n}{k} \cdot x^k \cdot y^{n-k}$$

where each $\binom{n}{k}$ is a positive integer known as a *binomial coefficient*, defined as

$$\binom{n}{k} = \frac{n!}{k! \cdot (n-k)!} = \frac{n \cdot (n-1) \cdot (n-2) \cdot \ldots \cdot (n-k+1)}{k \cdot (k-1) \cdot (k-2) \cdot \ldots \cdot 2 \cdot 1}$$

Multinomial Theorem

Theorem 5: The generalization of the binomial theorem:

$$(x_1 + \ldots + x_r)^n = \sum_{\substack{0 \leq k_1, \ldots, k_r \leq n \\ k_1 + \ldots + k_r = n}}^n \binom{n}{k_1, \ldots, k_r} \cdot x_1^{k_1} \cdot \ldots \cdot x_r^{k_r}$$

Multinomial coefficients are defined as

$$\binom{n}{k_1,\dots,k_r} = \frac{n!}{k_1!\cdot\dots\cdot k_r!}$$

Note: Binomial coefficients are special cases of multinomial coefficients (r = 2):

$$\binom{n}{k} = \binom{n}{k_1, k_2} = \binom{n}{k, n-k} = \frac{n!}{k! \cdot (n-k)!}$$

Proof: TODO

Permutations of a Multiset

Theorem 6: Let S be a finite multiset with k different types and repetition numbers $r_1, ..., r_k$. Let the size of S be $n = r_1 + ... + r_k$. Then the number of n-permutations of S equals

$$\binom{n}{r_1,...,r_k}$$

Proof: In an n-permutation there are n positions that need to be assigned a type.

First, choose the r_1 positions for the first type, there are $\binom{n}{r_1}$ ways to do so. Then, assign r_2 positions for the second type, out of the $(n-r_1)$ positions that are still available, there are $\binom{n-r_1}{r_2}$ ways to do so. Continue for all k types. The total number of choices will be:

$$\binom{n}{r_1} \cdot \binom{n-r_1}{r_2} \cdot \ldots \cdot \binom{n-r_1-r_2-\ldots-r_{k-1}}{r_k} = \binom{n}{r_1,\ldots,r_k}$$

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k-Combinations of an *Infinite* Multiset

Example: Suppose you have a *sufficiently large* amount of each type of fruit (\searrow , \swarrow) in the supermarket, and you want to buy *two* fruits. How many choices do you have?

There are exactly *six* combinations: $\{ \searrow, , \searrow \}, \{ \searrow, , \stackrel{\checkmark}{ } \}, \{ \swarrow, , \stackrel{\checkmark}{ } \}.$

Note that your selection is *not ordered*, so $\{ \triangle, \circlearrowleft \}$ and $\{ \circlearrowleft, \vartriangle \}$ are considered the *same* choice.

k-Combinations of an *Infinite* Multiset [2]

Theorem 7: Let $k, s \in \mathbb{N}$ and let S be a multiset with s types and large repetition numbers (each $r_1, ..., r_s$ is at least k), then the number of k-combinations of S equals

$$\binom{k+s-1}{k} = \binom{k+s-1}{s-1}$$

Proof: Let $S = \langle X, r_{\infty} \rangle = \{ \infty_{\nearrow}, \infty_{\nearrow}, \infty_{\nearrow} \}$ with $r_x = \infty$ and |X| = s = 3.

- Let k = 5 (as an example). Consider a 5-combination of $S: \{ \searrow, , , \searrow, , \searrow, , \searrow \}$.
- Convert to *dots* and *bars*: •• | | |
- Represent as a 2-type multiset: $M = \{ k \cdot \bullet, (s-1) \cdot | \}$
- Observe: each *permutation* of k dots and (s-1) bars corresponds *uniquely* to a k-combination of S.
- Permute the 2-type multiset: $\binom{k+s-1}{k,s-1}$ ways, by <u>Theorem 5</u>.

This method is also known as *Stars and Bars*.

§5 Compositions

Weak Compositions

Definition 16: A weak composition of a non-negative integer $k \ge 0$ into s parts is a solution to the equation $b_1 + ... + b_s = k$, where each $b_i \ge 0$.

Example: Let k=5, s=3. Possible non-negative integer solutions for $b_1+b_2+b_3=5$ are:

- $\bullet \ (b_1,b_2,b_3)=(1,1,3)$
- $\bullet \ (b_1,b_2,b_3) = (1,3,1)$
- $(b_1, b_2, b_3) = (2, 0, 3)$
- $(b_1, b_2, b_3) = (0, 5, 0)$
- ... (total 21 solutions)

Note: If M is a multiset over groundset $\{1, ..., s\}$ with all multiplicities infinite $(r_i = \infty)$, then for $k \ge 0$, the number of sub-multisets of M of size k is exactly the number of weak compositions of k into s parts.

Counting Weak Compositions

Theorem 8: There are $\binom{k+s-1}{k,s-1}$ weak compositions of k > 0 into s parts.

Proof: Observe that
$$k = \underbrace{\underbrace{1+1}_{b_1} + \underbrace{\dots}_{i} + \underbrace{1+1}_{b_s}}_{k \text{ ones}}.$$

Use the *stars-and-bars* method to count the number of s groups composed of k "ones".

Example: Let k=3. There are $\binom{3+3-1}{3,3-1}=\binom{5}{3}=\binom{5}{2}=10$ ways to decompose k=3 into s=3 parts:

$$k = 3 =$$

$$= 0 + 1 + 2 = 0 + 2 + 1$$

$$= 1 + 0 + 2 = 1 + 2 + 0 = 1 + 1 + 1$$

$$= 2 + 0 + 1 = 2 + 1 + 0$$

$$= 3 + 0 + 0 = 0 + 3 + 0 = 0 + 0 + 3$$

Compositions

Definition 17: A *composition* of a positive integer $k \ge 1$ into *s positive* parts is a *solution* to the equation $b_1 + ... + b_s = k$, where each $b_i > 0$.

Theorem 9: There are $\binom{k-1}{s-1}$ compositions of k>0 into s positive parts.

Theorem 10: The total number of compositions of k > 0 into *some* number of positive parts is

$$\sum_{s=1}^{k} {k-1 \choose s-1} = 2^{k-1}$$

Parallel Summation Identity

Q: How many integer solutions are there to the *inequality* $b_1 + ... + b_s \le k$, where each $b_i \ge 0$?

Theorem 11:
$$\sum_{m=0}^{k} {m+s-1 \choose m} = {k+s \choose k}$$

Proof (hint): Introduce a "dummy" variable b_{s+1} to take up the slack between $b_1 + ... + b_s$ and k. Construct a bijection with the solutions to $b_1 + ... + b_s + b_{s+1} = k$, where $b_i \ge 0$.

§6 Set Partitions

Set Partitions

Definition 18: A *partition* of a set X is a set of non-empty subsets of X such that every element of X belongs to exactly one of these subsets.

Equivalently, a family of sets P is a partition of X iff:

- **1.** The family P does not contain the empty set: $\emptyset \notin P$.
- **2.** The union of *P* is *X*, that is, $\bigcup_{A \in P} A = X$. The sets in *P* are said to *cover X*.
- **3.** The intersection of any two distinct sets in P is empty: $\forall A, B \in P$. $(A \neq B) \rightarrow (A \cap B = \emptyset)$. The sets in P are said to be *pairwise disjoint* or *mutually exclusive*.

The sets in *P* are called *blocks*, *parts*, or *cells*, of the partition.

The block in P containing an element $x \in X$ is denoted by [x].

Examples of Set Partitions

Example: The empty set $X = \emptyset$ has exactly one partition, $P = \emptyset$.

Example: Any singleton set $X = \{x\}$ has exactly one partition, $P = \{\{x\}\}$.

Example: For any non-empty proper subset $A \subset U$, the set A and its complement form a partition of U, namely $P = \{A, U - A\}$.

Example: The set $X = \{1, 2, 3\}$ has five partitions:

- **1.** $\{\{1\}, \{2\}, \{3\}\}$ or $1 \mid 2 \mid 3$
- **2.** $\{\{1\}, \{2,3\}\}$ or $1 \mid 2 \mid 3 \mid$
- 3. $\{\{1,2\},\{3\}\}$ or $12 \mid 3$
- **4.** $\{\{1,3\},\{2\}\}$ or $13 \mid 2$
- 5. $\{\{1,2,3\}\}\$ or 123

Example: The following are *not* partitions of $\{1, 2, 3\}$:

- $\{\{\}, \{1,3\}, \{2\}\}\$, because it contains the empty set.
- $\{\{1,2\},\{2,3\}\}$, because the element 2 is contained in more than one block.
- $\{\{1\}, \{3\}\}\$, because no block contains the element 3.

Counting Set Partitions

Definition 19: The number of partitions of a set X (of size n = |X|) into k non-empty blocks ("unlabeled subsets") is called a *Stirling number of the second kind* and denoted S(n,k) or $\binom{n}{k}$.

Example: Let $X = \{1, 2, 3, 4\}$, k = 2. There are 7 possible partitions:

Theorem 12: Let
$$\begin{Bmatrix} n \\ 0 \end{Bmatrix} = 0$$
 for $n \ge 1$, $\begin{Bmatrix} 0 \\ k \end{Bmatrix} = 0$ for $k \ge 1$, and $\begin{Bmatrix} 0 \\ 0 \end{Bmatrix} = 1$. For $n, k \ge 1$, we have:
$$\begin{Bmatrix} n \\ k \end{Bmatrix} = \begin{Bmatrix} n-1 \\ k-1 \end{Bmatrix} + k \cdot \begin{Bmatrix} n-1 \\ k \end{Bmatrix}$$

Proof (informal): TODO

Bell Numbers

Definition 20: The total number of partitions of a set X of size n = |X| (into an arbitrary number of non-empty blocks) is called a *Bell number* and denoted B_n .

$$B_n = \sum_{k=0}^n \begin{Bmatrix} n \\ k \end{Bmatrix}$$

Note: Consider the special case of n=0. There is exactly *one* partition of \emptyset into non-empty parts: $\emptyset = \bigcup_{A \in \mathcal{O}} A \in \emptyset$. Every $A \in \emptyset$ is non-empty, since no such A exists. Thus, we have $B_0 = S(0,0) = 1$.

Bell Numbers [2]

Theorem 13: For $n \ge 1$, we have the recursive identity for Bell numbers:

$$B_n = \sum_{k=0}^{n-1} \binom{n-1}{k} B_k$$

Proof: Every partition of [n] has one part that contains the number n. In addition to n, this part also contains k other numbers (for some $0 \le k \le n-1$). The remaining n-1-k elements are partitioned arbitrarily. From this correspondence, we obtain the desired identity:

$$B_n = \sum_{k=0}^{n-1} \binom{n-1}{k} B_{n-1-k} = \sum_{k=0}^{n-1} \binom{n-1}{n-1-k} B_{n-1-k} = \sum_{k=0}^{n-1} \binom{n-1}{k} B_k$$

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§7 Integer Partitions

Integer Partitions

Definition 21: An *integer partition* of a positive integer $n \ge 1$ into k positive parts is a *solution* to the equation $n = a_1 + ... + a_k$, where $a_1 \ge a_2 \ge ... \ge a_k \ge 1$.

• The number of integer partitions of n into k positive non-decreasing parts is denoted $p_k(n)$ and defined recursively:

$$p_k(n) = \begin{cases} 0 & \text{if } k > n \\ 0 & \text{if } n \geq 1 \text{ and } k = 0 \\ 1 & \text{if } n = k = 0 \\ p_k(n-k) + p_{k-1}(n-1) & \text{if } 1 \leq k \leq n \end{cases}$$

• The number of partitions of n (into an arbitrary number of parts) is the partition function p(n):

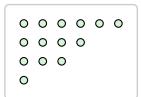
$$p(n) = \sum_{k=0}^n p_k(n)$$

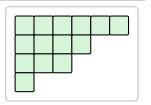
Ferrer Diagrams and Yound Tableaux

Example: Consider an integer partition: 14 = 6 + 4 + 3 + 1.

Ferrer Diagram

Young Tableaux









Norman Ferrer

Alfred Young

§8 Inclusion-Exclusion

The Inclusion-Exclusion Principle

TODO: small example of PIE with 2 or 3 sets

Principle of Inclusion-Exclusion (PIE)

Theorem 14: Let X be a finite set and $P_1, ..., P_m$ properties.

- Define $X_i = \{x \in X \mid x \text{ has } P_i\}$, i.e. the set of all elements from X having a property P_i .
- Define for $S \subseteq [m]$ the set $N(S) = \{x \in X \mid \forall i \in S : x \text{ has } P_i\}$. Observe: $N(S) = \bigcap_{i \in S} X_i$.

The number of elements of X that satisfy *none* of the properties $P_1, ..., P_m$ is given by

$$|X \setminus (X_1 \cup \ldots \cup X_m)| = \sum_{S \subseteq [m]} (-1)^{|S|} |N(S)| \tag{1}$$

Proof: Consider any $x \in X$. If $x \in X$ has none of the properties, then $x \in N(\emptyset)$ and $x \notin N(S)$ for any other $S \neq \emptyset$. Hence x contributes 1 to the sum (1).

If
$$x \in X$$
 has exactly $k \ge 1$ of the properties, call this set $T \in {[m] \choose k}$. Then $x \in N(S)$ iff $S \subseteq T$. The contribution of x to the sum (1) is $\sum_{S \subseteq T} (-1)^{|S|} = \sum_{i=0}^k {k \choose i} (-1)^i = 0$, i.e. zero.

Note: In the last step, we used that for any $y \in \mathbb{R}$ we have $(1-y)^k = \sum_{i=0}^k \binom{k}{i} (-y)^i$ which implies (for y=1) that $0=\sum_{i=0}^k \binom{k}{i} (-1)^i$.

Very Useful Corollary of PIE

Corollary 14.1: 🙀

$$\left| \bigcup_{i \in [m]} X_i \right| = |X| - \sum_{S \subseteq [m]} (-1)^{|S|} |N(S)| = \sum_{\varnothing \; \neq S \subseteq [m]} (-1)^{|S|-1} |N(S)|$$

Applications of PIE

Let's state the principle of inclusion-exclusion using a rigid pattern:

1. Define "bad" properties.

Identify the things to count as the elements of some universe X except for the whose having *at least one* of the "bad" properties $P_1, ..., P_m$. In other words, we want to count $X \setminus (X_1 \cup ... \cup X_m)$.

2. Count N(S).

For each $S \subseteq [m]$, determine N(S), the number of elements of X having *all* bad properties P_i for $i \in S$.

3. Apply PIE.

Use Theorem 14 to obtain a closed formula for $|X \setminus (X_1 \cup ... \cup X_m)|$.

Counting Surjections via PIE

Theorem 15: The number of surjections from [k] to [n] is given by

$$\left| \left\{ f : [k] \underset{\text{surj.}}{\longrightarrow} [n] \right\} \right| = \sum_{i=0}^{n} (-1)^{i} \binom{n}{i} (n-i)^{k}$$

Proof: Let X be the set of all maps from [k] to [n].

1. Define bad properties: Define the "bad" property P_i for $i \in [n]$ as "i is not in the image of f", i.e.

$$f:[k] \longrightarrow [n] \text{ has property } P_i \quad \leftrightarrow \quad \forall j \in [k]: f(j) \neq i$$

The *surjective* functions are exactly those functions that *do not* have any of the "bad" properties.

2. Count N(S): We claim $N(S) = (n - |S|)^k$ for any $S \subseteq [n]$. To see this, observe that f has all properties with indices from S if and only if $f(i) \notin S$ for all $i \in [k]$. In other words, f must be a function from [k] to $[n] \setminus S$, and there are $(n - |S|)^k$ of those.

Counting Surjections via PIE [2]

3. Apply PIE: Using Theorem 14, the number of surjections from [k] to [n] is

$$\begin{split} |X \setminus (X_1 \cup \ldots \cup X_n)| &\stackrel{\mathrm{PIE}}{=} \sum_{S \subseteq [n]} (-1)^{|S|} |N(S)| \\ &= \sum_{S \subseteq [n]} (-1)^{|S|} (n - |S|)^k \\ &= \sum_{i=0}^n (-1)^i {n \choose i} (n-i)^k \end{split}$$

In the last step, we used that $(-1)^{|S|}(n-|S|)^k$ only depends on the size of S, and there are $\binom{n}{i}$ sets $S\subseteq [n]$ of size i.

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More Useful Corollaries

Corollary 15.1: Consider the case n = k. A function from [n] to [n] is a *surjection* iff it is a *bijection*. Since there are n! bijections on [n] (namely, all permutations), we have the following identity:

$$n! = \sum_{i=0}^{n} (-1)^{i} \binom{n}{i} (n-i)^{n}$$

Corollary 15.2: A surjection from [k] to [n] can be seen as a partition of [k] into n non-empty distinguishable (labeled) parts (the map assigns a part to each $i \in [k]$).

Since the partition of [k] into n non-empty indistinguishable parts is denoted $s_n^{\mathrm{II}}(k)$, and there are n! ways to assign labels to n parts, we obtain that the number of surjections is equal to $n!s_n^{\mathrm{II}}(k)$:

$$n!s_n^{\mathrm{II}}(k) = \sum_{i=0}^n (-1)^i \binom{n}{i} (n-i)^k$$

Derangements

Theorem 16: The *derangements* D_n on n elements are permutations of [n] without fixed points.

The number of derangements is given by

$$|D_n| = \sum_{i=0}^n (-1)^i \binom{n}{i} (n-i)!$$

Proof: Let X be the set of all permutations of [n].

1. Define the "bad" property P_i to mean " π has a fixpoint i" ($i \in [n]$):

$$\pi \in X$$
 has property $P_i \leftrightarrow \pi(i) = i$

2. We claim N(S) = (n - |S|)! for any $S \subseteq [n]$.

Indeed, $\pi \in X$ has all properties with indices from S if and only if all $i \in S$ are fixed points of π . On the other elements, i.e. on $[n] \setminus S$, π may be an arbitrary bijection, so there are (n - |S|)! choices for π .

Derangements [2]

3. Using Theorem 14, the number of derangements is given by

$$\begin{split} |X \setminus (X_1 \cup \ldots \cup X_n)| &\stackrel{\mathrm{PIE}}{=} \sum_{S \subseteq [n]} (-1)^{|S|} |N(S)| \\ &= \sum_{S \subseteq [n]} (-1)^{|S|} (n - |S|)! \\ &= \sum_{i=0}^n (-1)^i \binom{n}{i} (n-i)! \end{split}$$

In the last step, we used that $(-1)^{|S|}(n-|S|)!$ only depends on the size of S, and there are $\binom{n}{i}$ sets $S \subseteq [n]$ of size i.

§9 Generating Functions

Generating Functions

A generating function is a device somewhat similar to a bag. Instead of carrying many little objects detachedly, which could be embarrassing, we put them all in a bag, and then we have only one object to carry, the bag.

George Pólya, Mathematics and Plausible Reasoning [1]

A generating function is a clothesline on which we hang up a sequence of numbers for display.

- Herbert Wilf, generatingfunctionology [2]



Abraham de Moivre



George Pólya



Herbert Wilf

Ordinary Generating Functions

Definition 22: An ordinary generating function (OGF) of a sequence a_n is a power series

$$G(a_n;x) = \sum_{n=0}^{\infty} a_n x^n$$

Example: The sequence $a_n=(a_0,a_1,a_2,...)$ is generated by the OGF $G(x)=a_0+a_1x+a_2x^2+...$

Example: $G(x) = 3 + 8x^2 + x^3 + \frac{1}{7}x^5 + 100x^6 + \dots$ generates the sequence $\left(3, 0, 8, 1, 0, \frac{1}{7}, 100, 0, \dots\right)$

Example: Consider a long division of 1 by (1-x), the result is an infinite power series

$$\frac{1}{1-x} = 1 + x^1 + x^2 + x^3 + \dots = \sum_{n=0}^{\infty} x^n$$

Note that all coefficients are 1. Thus, the generating function of (1,1,1,...) is $G(x)=\sum_{n=0}^{\infty}x^n=\frac{1}{1-x}$.

The Core Generating Function

Another proof that (1, 1, 1, ...) is generated by $G(x) = 1 + x + x^2 + x^3 + ... = \sum_{n=0}^{\infty} x^n = \frac{1}{1-x} = S$:

$$S = 1 + x + x^{2} + x^{3} + \dots$$

$$\frac{x \cdot S}{S - x \cdot S} = \frac{x + x^{2} + x^{3} + \dots}{S - x \cdot S} = 1$$

Thus,
$$S = \frac{1}{1-x}$$
.

The generating function $G(x) = 1 + x + x^2 + \dots$ is also known as the *Maclaurin series* of $\frac{1}{1-x}$.

More Examples of Generating Functions

Formula	Power series	Sequence	Description
$\frac{1}{1-x}$	$\sum_{n=0}^{\infty} x^n = 1 + x + x^2 + x^3 + \dots$	(1, 1, 1,)	constant 1
$\frac{2}{1-x}$	$\sum_{n=0}^{\infty} 2x^n = 2 + 2x + 2x^2 + 2x^3 + \dots$	$(2,2,2,\ldots)$	constant 2
$\frac{x}{1-x}$	$\sum_{n=1}^{\infty} x^n = 0 + x + x^2 + x^3 + \dots$	(0, 1, 1, 1,)	right shift
$\frac{1}{1+x}$	$\sum_{n=0}^{\infty} (-1)^n x^n = 0 + 1 - x + x^2 - x^3 + \dots$	$(1, -1, 1, \ldots)$	sign-alternating 1's
$\frac{1}{1-3x}$	$\sum_{n=0}^{\infty} 3^n x^n = 1 + 3x + 9x^2 + 27x^3 + \dots$	$(1,3,9,\ldots)$	powers of 3

More Examples of Generating Functions [2]

Formula	Power series	Sequence	Description
$\frac{1}{1-x^2}$	$\sum_{n=0}^{\infty} x^{2n} = 1 + x^2 + x^4 + x^6 + \dots$	(1,0,1,0,)	regular gaps
$\frac{1}{(1-x)^2}$	$\sum_{n=0}^{\infty} (n+1)x^n = 1 + 2x + 3x^2 + 4x^3 + \dots$	$(1, 2, 3, 4, \ldots)$	natural numbers
	$\frac{1-x^{n+1}}{1-x} = \frac{1}{1-x} - \frac{x^{n+1}}{1-x} =$ $\stackrel{\triangle}{=} (1,1,1,\ldots) - (\underbrace{0,0,\ldots,0}_{n+1 \text{ zeros}},1,1,\ldots) =$ $= (\underbrace{1,1,\ldots,1}_{n+1 \text{ ones}},0,0,\ldots) =$		

Exercises

Example: Find GF for odd numbers: (1, 3, 5, ...).

Example: Find GF for (1,3,7,15,31,63), which satisfies $a_n=3a_{n-1}-2a_{n-2}$ with $a_0=1,\,a_1=3$.

Solving Combinatorial Problems via Generating Functions

Example: Find the number of integer solutions to $y_1 + y_2 + y_3 = 12$ with $0 \le x_i \le 6$.

- Possible values for y_1 are $0 \le y_1 \le 6$.
 - ▶ There is a *single* way to select $y_1 = 0$. The same for other values among 1, ..., 6.
 - There are *no* ways to select any value of y_1 higher than 6.
 - ▶ The number of ways to select y_1 to be equal to n forms a sequence (1, 1, 1, 1, 1, 1, 1, 1, 1, 0, ...).
 - Write this sequence as a polynomial $x^0 + x^1 + ... + x^6$.
 - ▶ Do the same for y_2 and y_3 (in isolation!).
- Since all combinations of y_1 , y_2 and y_3 are valid non-conflicting solutions, we can multiply those polynomials and obtain the *generating function* $G(x) = (1 + x + x^2 + ... + x^6)^3$.
 - For each n, the coefficient of x^n in G(x) is the number of integer solutions to $x_1 + x_2 + x_3 = n$.
 - In particular, we are interested in the coefficient of x^{12} in G(x), denoted $[x^{12}]G(x)$.
 - Use pen and paper Wolfram Alpha to expand G(x):

$$G(x) = x^{18} + 3x^{17} + 6x^{16} + \dots + 28x^{12} + \dots + 6x^{2} + 3x + 1$$

• The *answer* is $[x^{12}]G(x) = 28$ solutions.

Slightly More Complex Combinatorial Problem

Example: Suppose we have marbles of three different colors (, , , , and we want to *count* the number of ways to select 20 marbles, such that:

- There are at least $12 : x^{12} + x^{13} + ... + x^{20}$.
- There are at most 5 \bigcirc : $1 + x + x^2 + x^3 + x^4 + x^5$.

Multiply polynomials and find $[x^{20}]G(x)$:

$$\begin{split} & \big[x^{20} \big] \big(1 + x^2 + x^4 + \ldots + x^{20} \big) \big(x^{12} + x^{13} + \ldots + x^{20} \big) \big(1 + x + x^2 + x^3 + x^4 + x^5 \big) = \\ & = \big[x^{20} \big] \Big(x^{45} + 2x^{44} + \ldots + \underbrace{21x^{20}}_{} + \ldots + 2x^{13} + x^{12} \Big) \\ & = 21 \end{split}$$

Using Power Series in Combinatorial Problems

Example: Find the number of integer solutions to $a_1 + a_2 + a_3 = 12$ with $a_1 \ge 2, 3 \le a_2 \le 6, 0 \le a_3 \le 9$.

• Compose the generating function:

$$G(x) = (x^2 + x^3 + \dots) \cdot (x^3 + x^4 + x^5 + x^6) \cdot (1 + x + x^2 + \dots + x^9)$$

• Substitute the power series with the corresponding simple forms:

$$G(x) = \left(x^2 \cdot \frac{1}{1-x}\right) \cdot \left(x^3 \cdot \frac{1-x^4}{1-x}\right) \cdot \left(\frac{1-x^{10}}{1-x}\right)$$

• Expand the series:

$$G(x) = x^5 + 3x^6 + 6x^7 + 10x^8 + 14x^9 + 18x^{10} + 22x^{11} + 26x^{12} + 30x^{13} + 34x^{14} + 37x^{15} + 39x^{16} + 40x^{17} + \dots + 40x^n + \dots$$

- Sequence: $(g_n) = (0, 0, 0, 0, 0, 1, 3, 6, 10, 14, 18, 22, 26, 30, 34, 37, 39, \overline{40}, ...)$
- Answer for n = 12 is $[x^{12}]G(x) = 26$.

Operations on Generating Functions

Let $F(x) = \sum_{n=0}^{\infty} a_n x^n$ and $G(x) = \sum_{n=0}^{\infty} b_n x^n$ be ordinaty generating functions.

Operation	Result
Differentiate $F(x)$ term-wise	$F'(x)=\sum_{n=0}^{\infty}(n+1)a_{n+1}x^n$
Multiply $F(x)$ by a scalar $\lambda \in \mathbb{R}$ term-wise	$\lambda F(x) = \sum_{n=0}^{\infty} \lambda a_n x^n$
$\operatorname{Add} F(x) \text{ and } G(x) \text{ term-wise}$	$F(x)+G(x)=\sum_{n=0}^{\infty}(a_n+b_n)x^n$
Multiply $F(x)$ and $G(x)$ term-wise (Cauchy product, or convolution)	$F(x)\cdot G(x) = \sum_{n=0}^{\infty}\Biggl(\sum_{k=0}^{n}a_kb_{n-k}\Biggr)x^n$

Well-Formed Paranthesis Expressions

Example: Find the number of *well-formed parenthesis expressions* with n pairs of parenthesis.

For example, "(()()))" is a well-formed parenthesis expression with 4 pairs of parenthesis.

Formally, a permutation of the multiset $\{n \cdot "(", n \cdot ")"\}$ is *well-formed* if reading it from left to right and counting "+1" for every opening parenthesis "(" and "-1" for every closing parenthesis ")" never yields a negative number at any time.

Every well-formed expression with $n \ge 1$ pairs of paranthesis starts with "(" and there is a unique matching ")" such that the sequence in between and the sequence after are well-formed. For example:

In other words, a well-formed expression with n pairs of parenthesis is obtained by putting a well-formed expression with k pairs in between "(" and ")" and then appending a well-formed expression with n-k-1 pairs of parenthesis. This gives the equation:

$$a_n = \sum_{k=0}^{n-1} a_k a_{n-k-1}$$

Well-Formed Paranthesis Expressions [2]

$$a_n = \sum_{k=0}^{n-1} a_k a_{n-k-1}$$

Let F(x) be a generating function for a_n , then we know:

$$F(x) = \sum_{n=0}^{\infty} a_n x^n = 1 + \sum_{n=1}^{\infty} \left(\sum_{k=0}^{n-1} a_k a_{n-k-1} \right) x^n = 1 + \sum_{n=0}^{\infty} \left(\sum_{k=0}^{n} a_k a_{n-k} \right) x^{n+1}$$

$$= 1 + x \cdot \sum_{n=0}^{\infty} \left(\sum_{k=0}^{n} a_k a_{n-k} \right) x^n = 1 + x \cdot F(x)^2$$

Newton's Binomial Theorem

Let's revisit the binomial theorem:

$$(1+x)^n = \sum_{k=0}^n \binom{n}{k} x^k = \sum_{k=0}^\infty \binom{n}{k} x^k \quad \forall n \in \mathbb{N}$$

where $\binom{n}{k} = 0$ for k > n.

Note: This shows that $(1+x)^n$ is the generating function for the series $(a_k)_{k\in\mathbb{N}}$ with $a_k=\binom{n}{k}$.

We can extend this result from natural numbers $n \in \mathbb{N}$ to any *real* number $n \in \mathbb{R}$.

Binomial Coefficients for Real Numbers

Definition 23: Let $p(n,k) = n \cdot (n-1) \cdot ... \cdot (n-k+1)$, also called the *falling factorial* $n^{\underline{k}}$.

Extend the definition of binomial coefficients for real numbers $n, k \in \mathbb{R}$:

$$\binom{n}{k} = \frac{p(n,k)}{k!}$$

Note: This definition aligns with the definition of binomial coefficients for natural numbers:

$$\binom{n}{k} = \frac{n!}{k! \cdot (n-k)!} = \frac{n \cdot (n-1) \cdot \dots \cdot (n-k+1)}{k!}$$

Example: Consider the number "-7/2 choose 5":

$$\binom{-7/2}{5} = \frac{-\frac{7}{2} \cdot -\frac{9}{2} \cdot -\frac{11}{2} \cdot -\frac{13}{2} \cdot -\frac{15}{2}}{5!} = -\frac{9009}{256}$$

Note: p(n,0) = 1 and for $k \ge 1$, we have $p(n,k) = (n-k+1) \cdot p(n,k-1) = n \cdot p(n-1,k-1)$. (\star)

Extended Newton's Binomial Theorem

Theorem 17: For all non-zero $n \in \mathbb{R}$, we have:

$$(1+x)^n = \sum_{k=0}^{\infty} \binom{n}{k} x^k$$

Example: Let n = 1/2, then we have an identity for $\sqrt{1+x}$:

$$\sqrt{1+x} = \sum_{k=0}^{\infty} \binom{1/2}{k} x^k$$

To actually *use* this fact, we need some *lemma*...

Lemma 18: For any integer $n \ge 1$, we have:

$$\binom{1/2}{n} = (-1)^{n+1} \cdot \binom{2n-2}{n-1} \cdot \frac{1}{2^{2n-1}} \cdot \frac{1}{n}$$

Extended Newton's Binomial Theorem [2]

Proof: By induction on n.

Base:
$$n=1$$
.

$$\binom{1/2}{1} = \frac{1/2}{1!} = \frac{1}{2} = 1 \cdot 1 \cdot \frac{1}{2} \cdot 1 = \underbrace{(-1)^2}_{1} \cdot \underbrace{\binom{2-2}{1-1}}_{1} \cdot \underbrace{\frac{1}{2^{2-1}}}_{1} \cdot \underbrace{\frac{1}{1}}_{1}$$

Induction step: n to n+1 for n>1. We use the recusion (\star) $p(n,k)=n\cdot p(n-1,k-1)$:

$$\begin{pmatrix} 1/2 \\ n+1 \end{pmatrix} = \frac{p(1/2,n+1)}{(n+1)!} = \frac{(1/2 - (n+1)+1) \cdot p(1/2,n)}{(n+1) \cdot n!} = -\frac{n-1/2}{n+1} {1/2 \choose n}$$

$$\stackrel{\text{III}}{=} -\frac{n-1/2}{n+1} (-1)^{n+1} \cdot {2n-2 \choose n-1} \cdot \frac{1}{2^{2n-1}} \cdot \frac{1}{n}$$

$$= \frac{2n}{2n} \cdot \frac{2n-1}{2n} \cdot (-1)^{n+2} \cdot {2n-2 \choose n-1} \cdot \frac{1}{2^{2n-1}} \cdot \frac{1}{n+1}$$

$$= (-1)^{n+2} \cdot \underbrace{\frac{(2n-2)! \cdot (2n-1) \cdot (2n)}{(n-1)! \cdot (n-1) \cdot n \cdot n}}_{n} \cdot \frac{1}{2^{2n+1}} \cdot \frac{1}{n+1}$$

Catalan Numbers

Proposition 19: Now we can expand $\sqrt{1+n}$ into the following series:

$$\sqrt{1+n} = \sum_{n=0}^{\infty} \binom{1/2}{n} x^n = 1 + \sum_{n=1}^{\infty} -2 \cdot \binom{2n-2}{n-1} \cdot (-1)^n \cdot \frac{1}{2^{2n}} \cdot \frac{1}{n} \cdot x^n$$

Example: Going back to the example with the number of well-formed paranthesis expressions, we get:

$$F(x) = \frac{1 - \sqrt{1 - 4x}}{2x} = \frac{1}{2x} \sum_{n=1}^{\infty} 2 \cdot \binom{2n - 2}{n - 1} \cdot (-1)^n \cdot \frac{1}{2^{2n}} \cdot \frac{1}{n} \cdot (-4x)^n$$

$$= \frac{1}{x} \sum_{n=1}^{\infty} \binom{2n - 2}{n - 1} \frac{1}{n} x^n = \sum_{n=0}^{\infty} \binom{2n}{n} \frac{1}{n + 1} x^n$$

The numbers $C_n := \binom{2n}{n} \frac{1}{n+1}$ are called *Catalan numbers*.

§10 Recurrence Relations

Recurrence Relations

Example:

• Recurrent relation defining a sequence (a_n) :

$$a_n = \begin{cases} a_0 = \text{const if } n = 0\\ a_{n-1} + d & \text{if } n > 0 \end{cases}$$

• *Solving* it results in a non-recursive *closed* formula:

$$a_n = a_0 + n \cdot d$$

• *Checking* it confirms that the formula is correct:

$$a_n = a_{n-1} + d = a_0 + (n-1)d + d = a_0 + n \cdot d$$

Linear Homogeneous Recurrence Relations

Definition 24: A *linear homogeneous* recurrence relation *of degree* k with constant coefficients is a recurrence relation of the form

$$a_n = c_1 a_{n-1} + c_2 a_{n-2} + \dots + c_k a_{n-k},$$

where $c_1, c_2, ..., c_k$ are constants (real or complex numbers), and $c_k \neq 0$.

Examples:

- $b_n = 2.71 b_{n-1}$ is a linear homogeneous recurrence relation of degree 1.
- $F_n = F_{n-1} + F_{n-2}$ is a linear homogeneous recurrence relation of degree 2.
- $g_n = 2g_{n-5}$ is a linear homogeneous recurrence relation of degree 5.
- The recurrence relation $a_n = a_{n-1} + a_{n-2}^2$ is not linear.
- The recurrence relation $H_n = 2H_{n-1} + 1$ is not homogeneous.
- The recurrence relation $B_n = nB_{n-1}$ does *not* have *constant* coefficients.

Characteristic Equations

Hereinafter, (*) denotes a linear homogeneous recurrence relation $a_n = c_1 a_{n-1} + c_2 a_{n-2} + ... + c_k a_{n-k}$.

Theorem 20: $a_n = r^n$ is a solution to (*) if and only if $r^n = c_1 r^{n-1} + c_2 r^{n-2} + ... + c_k r^{n-k}$.

Definition 25: A *characteristic equation* for (*) is the algebraic equation in r defined as:

$$r^k - c_1 r^{k-1} - c_2 r^{k-2} - \ldots - c_k = 0$$

The sequence (a_n) with $a_n = r^n$ (with $r_n \neq 0$) is a solution if and only if r is a solution of the characteristic equation. Such solutions are called *characteristic roots* of (*).

Distinct Roots Case

Theorem 21: Let c_1 and c_2 be real numbers. Suppose that $r^2-c_1r-c_2=0$ has two *distinct* roots r_1 and r_2 . Then the sequence (a_n) is a solution of the recurrence relation $a_n=c_1a_{n-1}+c_2a_{n-2}$ if and only if $a_n=\alpha_1r_1^n+\alpha_2r_2^n$ for n=0,1,2,..., where α_1 and α_2 are constants.

Proof (sketch): Since r_1 and r_2 are roots, then $r_1^2 = c_1 r_1 + c_2$ and $r_2^2 = c_1 r_2 + c_2$. Next, we can see:

$$\begin{split} c_1 a_{n-1} + c_2 a_{n-2} &= c_1 \big(\alpha_1 r_1^{n-1} + \alpha_2 r_2^{n-1} \big) + c_2 \big(\alpha_1 r_1^{n-2} + \alpha_2 r_2^{n-2} \big) \\ &= \alpha_1 r_1^{n-2} (c_1 r_1 + c_2) + \alpha_2 r_2^{n-2} (c_1 r_2 + c_2) \\ &= \alpha_1 r_1^{n-2} r_1^2 + \alpha_2 r_2^{n-2} r_2^2 \\ &= \alpha_1 r_1^n + \alpha_2 r_2^n \\ &= a_n \end{split}$$

To show that every solution (a_n) of the recurrence relation $a_n=c_1a_{n-1}+c_2a_{n-2}$ has $a_n=\alpha_1r_1^n+\alpha_2r_2^n$ for some constants α_1 and α_2 , suppose that the initial condition are $a_0=C_0$ and $a_1=C_1$, and show that there exist constants α_1 and α_2 such that $a_n=\alpha_1r_1^n+\alpha_2r_2^n$ satisfies the same initial conditions.

Solving Recurrence Relations using Characteristic Equations

Example: Solve $a_n = a_{n-1} + 2a_{n-2}$ with $a_0 = 2$ and $a_1 = 7$.

- The characteristic equation is $r^2 r 2 = 0$.
- It has two distinct roots $r_1 = 2$ and $r_2 = -1$.
- The sequence (a_n) is a solution iff $a_n=\alpha_1r_1^n+\alpha_2r_2^n$ for n=0,1,2,... and some constants α_1 and α_2 .

$$\begin{cases} a_0 = 2 = \alpha_1 + \alpha_2 \\ a_1 = 7 = \alpha_1 \cdot 2 + \alpha_2 \cdot (-1) \end{cases}$$

- Solving these two equations gives $\alpha_1=3$ and $\alpha_2=-1$.
- Hence, the *solution* to the recurrence equation with given initial conditions is the sequence (a_n) with

$$a_n = 3 \cdot 2^n - (-1)^n$$

Fibonacci Numbers

Example: Find the closed formula for Fibonacci numbers.

- The recurrence relation is $F_n = F_{n-1} + F_{n-2}$.
- The characteristic equation is $r^2 r 1 = 0$.
- The roots are $r_1 = (1 + \sqrt{5})/2$ and $r_2 = (1 \sqrt{5})/2$.
- Therefore, the solution is $F_n = \alpha_1(\frac{1+\sqrt{5}}{2})^n + \alpha_2(\frac{1-\sqrt{5}}{2})^n$ for some constants α_1 and α_2 .
- Using the initial conditions $F_0 = 0$ and $F_1 = 1$, we get

$$\begin{cases} F_0=\alpha_1+\alpha_2=0\\ F_1=\alpha_1\cdot(\frac{1+\sqrt{5}}{2})+\alpha_2\cdot(\frac{1-\sqrt{5}}{2})=1 \end{cases}$$

- Solving these two equations gives $\alpha_1=1/\sqrt{5}$ and $\alpha_2=-1/\sqrt{5}$.
- Hence, the *closed formula* (also known as Binet's formula) for Fibonacci numbers is

$$F_n = \frac{1}{\sqrt{5}} \left(\frac{1+\sqrt{5}}{2} \right)^n - \frac{1}{\sqrt{5}} \left(\frac{1-\sqrt{5}}{2} \right)^n = \frac{\varphi^n - \psi^n}{\sqrt{5}}$$

Single Root Case

Theorem 22: Let c_1 and c_2 be real numbers. Suppose that $r^2-c_1r-c_2=0$ has a *single* root r_0 . A sequence (a_n) is a solution of the recurrence relation $a_n=c_1a_{n-1}+c_2a_{n-2}$ if and only if $a_n=\alpha_1r_0^n+\alpha_2nr_0^n$ for n=0,1,2,..., where α_1 and α_2 are constants.

Example: Solve $a_n = 6a_{n-1} - 9a_{n-2}$ with $a_0 = 1$ and $a_1 = 6$.

The characteristic equation is $r^2 - 6r + 9 = 0$ with a single (repeated) root $r_0 = 3$. Hence, the solutions is of the form $a_n = \alpha_1 3^n + \alpha_2 n 3^n$.

$$\begin{cases} a_0 = 1 = \alpha_1 \\ a_1 = 6 = \alpha_1 \cdot 3 + \alpha_2 \cdot 3 \end{cases} \implies \begin{cases} \alpha_1 = 1 \\ \alpha_2 = 1 \end{cases}$$

Thus, the *solution* is $a_n = 3^n + n3^n$.

Generic Case

Theorem 23: Suppose that the characteristic equation for (*) has t roots r_i , each repeated s_i times. A sequence (a_n) is a solution of the recurrence relation (*) if and only if $a_n = \sum_{i=1}^t \left(r_i^n \cdot \sum_{j=0}^{s_i-1} x^j \alpha_{i,j} \right)$ for n=0,1,2,..., where $\alpha_{i,j}$ are constants.

Example: Find generic solution for $a_n = 7a_{n-1} - 16a_{n-2} + 12a_{n-3}$.

The characteristic equation is $r^3 - 7r^2 + 16r - 12 = 0$ with roots $r_0 = 2$ (repeated $s_0 = 2$ times) and $r_1 = 3$ (repeated $s_1 = 1$ time). Hence, the solution is of the form $a_n = (\alpha_1 n + \alpha_2) 2^n + \alpha_3 3^n$.

Linear Non-Homogeneous Recurrence Relations

$$a_n = c_1 a_{n-1} + c_2 a_{n-2} + \ldots + c_k a_{n-k} + F(n)$$

Example: $a_n = 3a_{n-1} + 2n$ is non-homogeneous.

Definition 26: An associated homogeneous recurrence relation is the relation without the term F(n).

Solving Non-Homogeneous Recurrence Relations

Theorem 24: If $(a_n^{(p)})$ is a *particular* solution of the non-homogeneous linear recurrence relation $a_n = c_1 a_{n-1} + c_2 a_{n-2} + \ldots + c_k a_{n-k} + F(n)$, then *every solution* is of the form $(a_n^{(p)} + a_n^{(h)})$, where $(a_n^{(h)})$ is a solution of the associated homogeneous recurrence relation.

Example: Find all solutions of the recurrence relation $a_n = 3a_{n-1} + 2n$. What is the solution with $a_1 = 3$?

- First, solve the associated homogeneous recurrence relation $a_n=3a_{n-1}.$
- It has a general solution $a_n^{(h)} = \alpha 3^n$, where α is a constant.
- To find a particular solution, observe that F(n)=2n is a polynomial in n of degree 1, so a reasonable trial solution is a linear function in n, for example, $p_n=cn+d$, where c and d are constants.
- Thus, the equation $a_n = 3a_{n-1} + 2n$ becomes cn + d = 3(c(n-1) + d) + 2n.
- Simplify and reorder: (2 + 2c)n + (2d 3c) = 0.

$$\begin{cases} 2 + 2c = 0 \\ 2d - 3c = 0 \end{cases} \implies \begin{cases} c = -1 \\ d = -3/2 \end{cases}$$

• Thus, $a_n^{(p)} = -n - 3/2$ is a *particular* solution.

Solving Non-Homogeneous Recurrence Relations [2]

• By Theorem 24, all solutions are of the form

$$a_n = a_n^{(p)} + a_n^{(h)} = -n - 3/2 + \alpha 3^n,$$

where α is a constant.

- To find the solution with $a_1 = 3$, let n = 1 in the formula: $3 = -1 3/2 + 3\alpha$, thus $\alpha = 11/6$.
- The solution is $a_n = -n 3/2 + (11/6)3^n$.

§11 Annihilators

Operators

Definition 27: *Operators* are higher-order functions that transform functions into other functions.

For example, differential and integral operators $\frac{d}{dx}$ and $\int dx$ are core operators in calculus.

In combinatorics, we are interested in the following three operators:

- Sum: (f+g)(n) := f(n) + g(n)
- Scale: $(\alpha \cdot f)(n) := \alpha \cdot f(n)$
- *Shift*: $(\mathbf{E} f)(n) := f(n+1)$

Examples:

- Scale and Shift operators are *linear*: $\mathbf{E}(f-3(g-h)) = \mathbf{E} f + (-3) \mathbf{E} g + 3 \mathbf{E} h$
- Operators are *composable*: $(\mathbf{E} 2)f := \mathbf{E} f + (-2)f$
- $\mathbf{E}^2 f = \mathbf{E}(\mathbf{E} f)$
- $\mathbf{E}^k f(n) = f(n+k)$
- $(\mathbf{E} 2)^2 = (\mathbf{E} 2)(\mathbf{E} 2)$
- $(\mathbf{E} 1)(\mathbf{E} 2) = \mathbf{E}^2 3\mathbf{E} + 2$

Applying Operators

Examples: Below are the results of applying different operators to $f(n) = 2^n$:

$$\begin{split} 2f(n) &= 2 \cdot 2^n = 2^{n+1} \\ 3f(n) &= 3 \cdot 2^n \\ \mathbf{E} \, f(n) &= 2^{n+1} \\ \mathbf{E}^2 \, f(n) &= 2^{n+2} \\ (\mathbf{E} \, -2) f(n) &= \mathbf{E} \, f(n) - 2f(n) = 2^{n+1} - 2^{n+1} = 0 \\ (\mathbf{E}^2 \, -1) f(n) &= \mathbf{E}^2 \, f(n) - f(n) = 2^{n+2} - 2^n = 3 \cdot 2^n \end{split}$$

Compound Operators

The compound operators can be seen as polynomials in "variable" E.

Example: The compound operators $\mathbf{E}^2 - 3\mathbf{E} + 2$ and $(\mathbf{E} - 1)(\mathbf{E} - 2)$ are equivalent:

$$\begin{aligned} \text{Let } g(n) &\coloneqq (\mathbf{E} - 2) f(n) = f(n+1) - 2 f(n) \\ \text{Then } (\mathbf{E} - 1) (\mathbf{E} - 2) f(n) &= (\mathbf{E} - 1) g(n) \\ &= g(n+1) - g(n) \\ &= [f(n+2) - 2 f(n-1)] - [f(n+1) - 2 f(n)] \\ &= f(n+2) - 3 f(n+1) + 2 f(n) \\ &= (\mathbf{E}^2 - 3 \, \mathbf{E} + 2) f(n) \quad \checkmark \end{aligned}$$

Operators Summary

Operator	Definition
addition	$(f+g)(n)\coloneqq f(n)+g(n)$
subtraction	$(f-g)(n)\coloneqq f(n)-g(n)$
multiplication	$(\alpha \cdot f)(n) \coloneqq \alpha \cdot f(n)$
shift	$\mathbf{E}f(n)\coloneqq f(n+1)$
k-fold shift	$\mathbf{E}^kf(n)\coloneqq f(n+k)$
composition	$(X+Y)f\coloneqq Xf+Yf$
	$(X-Y)f\coloneqq Xf-Yf$
	$XYf\coloneqq X(Yf)=Y(Xf)$
distribution	X(f+g) = X f + X g

Annihilators

Definition 28: An *annihilator* of a function f is any non-trivial operator that transforms f into zero.

TODO: examples!

Annihilators Summary

Operator	Functions annihilated	
$\mathbf{E} - 1$	α	
$\mathbf{E} - a$	αa^n	
$(\mathbf{E} - a)(\mathbf{E} - b)$	$\alpha a^n + \beta b^n [\text{if } a \neq b]$	
$({\bf E} - a_0)({\bf E} - a_1)({\bf E} - a_k)$	$\sum_{i=0}^k \alpha_i a_i^n$ [if a_i are distinct]	
$({\bf E} - 1)^2$	$\alpha n + \beta$	
$({f E}-a)^2$	$(\alpha n + \beta)a^n$	
$(\mathbf{E}-a)^2(\mathbf{E}-b)$	$(\alpha n + \beta)a^n + \gamma b^n$ [if $a \neq b$]	
$({f E}\!-\!a)^d$	$\left(\sum_{i=0}^{d-1} \alpha_i n^i ight) a^n$	

Properties of Annihilators

Theorem 25: If X annihilates f, then X also annihilates αf for any constant α .

Theorem 26: If X annihilates both f and g, then X also annihilates $f \pm g$.

Theorem 27: If X annihilates f, then X also annihilates $\mathbf{E} f$.

Theorem 28: If X annihilates f and Y annihilates g, then XY annihilates $f \pm g$.

Annihilating Recurrences

- **1.** Write the recurrence in the *operator form*.
- **2.** Find the *annihilator* for the recurrence.
- **3.** *Factor* the annihilator, if necessary.
- **4.** Find the *generic solution* from the annihilator.
- **5.** Solve for coefficients using the *initial conditions*.

Example:
$$r(n) = 5r(n-1)$$
 with $r(0) = 3$.

1.
$$r(n+1) - 5r(n) = 0$$

(E-5) $r(n) = 0$

- **2.** $(\mathbf{E} 5)$ annihilates r(n).
- **3.** $(\mathbf{E} 5)$ is already factored.
- **4.** $r(n) = \alpha 5^n$ is a generic solution.
- 5. $r(0) = \alpha = 3 \implies \alpha = 3$

Thus,
$$r(n) = 3 \cdot 5^n$$
.

Annihilating Recurrences [2]

Example:
$$T(n) = 2T(n-1) + 1$$
 with $T(0) = 0$

- 1. T(n+1) 2T(n) = 1(E-2)T(n) = 1
- **2.** $(\mathbf{E} 2)$ does *not* annihilate T(n): the residue is 1.
 - $(\mathbf{E} 1)$ annihilates the residue 1.
 - Thus, $(\mathbf{E}-1)(\mathbf{E}-2)$ annihilates T(n).
- **3.** $(\mathbf{E} 1)(\mathbf{E} 2)$ is already factored.
- **4.** $T(n) = \alpha 2^n + \beta$ is a generic solution.
- **5.** Find the coefficients α , β using T(0) = 0 and T(1) = 2T(0) + 1 = 1:

$$\begin{array}{l} T(0) = 0 = \alpha \cdot 2^0 + \beta \\ T(1) = 1 = \alpha \cdot 2^1 + \beta \\ \end{array} \implies \begin{array}{l} \left\{ \alpha = 1 \\ \beta = -1 \end{array} \right.$$

Thus,
$$T(n) = 2^n - 1$$
.

Annihilating Recurrences [3]

Example:
$$T(n) = T(n-1) + 2T(n-2) + 2^n - n^2$$

1. Operator form:

$$(\mathbf{E}^2 - \mathbf{E} - 2)T(n) = \mathbf{E}^2 \big(2^n - n^2\big)$$

2. Annihilator:

$$({\bf E}^2-{\bf E}-2)({\bf E}-2)({\bf E}-1)^3$$

3. Factorization:

$$(\mathbf{E}+1)(\mathbf{E}-2)^2(\mathbf{E}-1)^3$$

4. Generic solution:

$$T(n) = \alpha(-1)^n + (\beta n + \gamma)2^n + \delta n^2 + \varepsilon n + \zeta$$

5. There are no initial conditions. We can only provide an asymptotic bound.

Thus,
$$T(n) \in \Theta(n2^n)$$

§12 Asymptotic Analysis

Asymptotics 101

Definition 29 (*Big-O notation*): The notation $f \in O(g)$ means that the function f(n) is *asymptotically bounded from above* by the function g(n), up to a constant factor.

$$f(n) \in O(g(n)) \quad \leftrightarrow \quad \exists c > 0. \, \exists n_0. \, \forall n > n_0: |f(n)| \leq c \cdot g(n)$$

Definition 30 (*Small-o notation*): The notation $f \in o(g)$ means that the function f(n) is asymptotically dominated by g(n), up to a constant factor.

$$f(n) \in o(g(n)) \quad \leftrightarrow \quad \forall c > 0. \ \exists n_0. \ \forall n > n_0: |f(n)| \leq c \cdot g(n)$$

Note: The difference is only in the $\exists c$ and $\forall c$ quantifier.

Note: Flip \leq to \geq in the above definitions to obtain the dual notations: $f \in \Omega(g)$ and $f \in \omega(g)$.

Definition 31 (*Theta notation*): $f \in \Theta(g)$ iff $f \in O(g)$ and $g \in O(f)$.

Limits

Notation	Name	Description	Limit definition
$f \in o(g)$	Small Oh	f is dominated by g	$\lim_{n \to \infty} \frac{f(n)}{g(n)} = 0$
$f\in O(g)$	Big Oh	f is bounded above by g	$\limsup_{n \to \infty} \frac{ f(n) }{g(n)} < \infty$
$f \sim g$	Equivalence	f is asympotically equal to g	$\lim_{n \to \infty} \frac{f(n)}{g(n)} = 1$
$f\in\Omega(g)$	Big Omega	f is bounded below by g	$\liminf_{n \to \infty} \frac{f(n)}{g(n)} > 0$
$f\in\omega(g)$	Small Omega	f dominates g	$\lim_{n \to \infty} \frac{f(n)}{g(n)} = \infty$

Asymptotic Equivalence

Definition 32: The notation $f \sim g$ means that functions f(n) and g(n) are asymptotically equivalent.

$$f \sim g \quad \leftrightarrow \quad \forall \varepsilon > 0. \, \exists n_0. \, \forall n > n_0: \left| \frac{f(n)}{g(n)} - 1 \right| \leq \varepsilon \quad \leftrightarrow \quad \lim_{n \longrightarrow \infty} \frac{f(n)}{g(n)} = 1$$

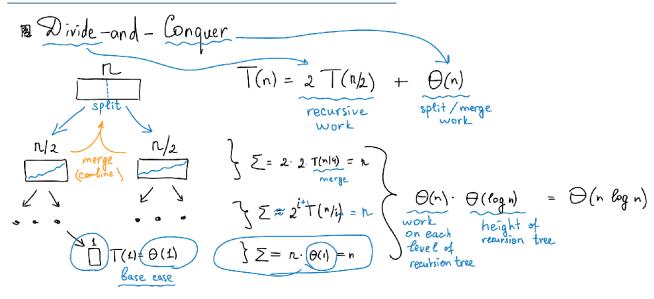
Note: $f \sim g$ and $g \sim f$ are equivalent, since \sim is an equivalence relation.

Note: $f \sim g$ and $f \in \Theta(g)$ are *different* notions!

Some Properties of Asymptotics

```
\begin{split} f \in O(g) \text{ and } f \in \Omega(g) & \leftrightarrow \quad f \in \Theta(g) \\ f \in O(g) & \leftrightarrow \quad g \in \Omega(f) \\ f \in o(g) & \leftrightarrow \quad g \in \omega(f) \\ f \in o(g) & \rightarrow \quad f \in O(g) \\ f \in \omega(g) & \rightarrow \quad f \in \Omega(g) \\ f \sim g & \rightarrow \quad f \in \Theta(g) \end{split}
```

Divide-and-Conquer Algorithms Analysis



Divide-and-Conquer Recurrence

$$T(n) = a \cdot T\left(\frac{n}{b}\right) + f(n)$$

- T(n) is the *cost* of the recursive algorithm
- *a* is the number of *parts* (*sub-problems*)
- n/b is the *size* of each part
- $T(\frac{n}{b})$ is the cost of each *sub-problem*
- f(n) is the cost of *splitting* and *merging* the solutions of the subproblems

Hereinafter, $c_{\text{crit}} = \log_b a$ is a *critical constant*.

Master Theorem

The master theorem [3] applies to divide-and-conquer recurrences of the form

$$T(n) = a \cdot T\left(\frac{n}{b}\right) + f(n)$$

Case	Description	Condition	Bound
Case I	"merge" ≪ "recursion"	$f(n) \in O(n^c)$	$T(n) \in \Theta(n^{c_{ ext{crit}}})$
		where $c < c_{ m crit}$	
Case II	"merge" ≈ "recursion"	$f(n) \in \Thetaig(n^{c_{ ext{crit}}} \log^k nig)$	$T(n) \in \Thetaig(n^{c_{ ext{crit}}} \log^{k+1} nig)$
		where $k \ge 0$	
Case III	"merge" ≫ "recursion"	$f(n)\in\Omega(n^c)$	$T(n)\in\Theta(f(n))$
		where $c>c_{ m crit}$	

Note: Case III also requires the *regularity condition* to hold: $af(n/b) \le kf(n)$ for some constant k < 1 and all sufficiently large n.

Note: There is an *extended* Case II, with three sub-cases (IIa, IIb, IIc) for other values of k. See <u>wiki</u>.

Examples of Master Theorem Application

Examples: Determine the case of Master Theorem and the bound of T(n) for the following recurrences.

1.
$$T(n) = 3T(n/9) + \sqrt{n}$$

2.
$$T(n) = 2T(n/4) + n^{0.51}$$

3.
$$T(n) = 5T(n/25) + n^{0.49}$$

4.
$$T(n) = T(\lfloor \frac{n}{2} \rfloor) + T(\lceil \frac{n}{2} \rceil)$$

5.
$$T(n) = 3T(n/9) + \frac{\sqrt{n}}{\log n}$$

6.
$$T(n) = 6T(n/36) + \frac{\sqrt{n}}{\log^2 n}$$

7.
$$T(n) = 4T(n/16) + \sqrt{\frac{n}{\log n}}$$

Akra-Bazzi Method

The Akra-Bazzi method [4] is a *generalization* of the master theorem to recurrences of the form

$$T(n) = f(n) + \sum_{i=1}^k a_i T\Biggl(b_i n + \underbrace{h_i(n)}_*\Biggr)$$

- k is a constant
- $a_i > 0$
- $0 < b_i < 1$
- $h_i(n) \in O\left(\frac{n}{\log^2 n}\right)$ is a small perturbation

Bound of T(n) by Akra–Bazzi method:

$$T(n) \in \Theta\left(n^p \cdot \left(1 + \int_1^n \frac{f(x)}{x^{p+1}} dx\right)\right)$$

where p is the solution for the equation $\sum_{i=1}^{k} a_i b_i^p = 1$

Example of Akra-Bazzi Method Application

Example: Suppose the runtime of an algorithm is expressed by the following recurrence relation:

$$T(n) = \begin{cases} 1 \text{ for } 0 \le n \le 3\\ n^2 + \frac{7}{4}T\left(\left\lfloor \frac{1}{2}n \right\rfloor\right) + T\left(\left\lceil \frac{3}{4}n \right\rceil\right) \text{ for } n > 3 \end{cases}$$

- Note that the Master Theorem *is not* applicable here, since there are *two* different recursive terms.
- Let's apply the Akra-Bazzi method. First, solve the equation $\frac{7}{4}(\frac{1}{2})^p + (\frac{3}{4})^p = 1$. This gives us p = 2.
- Next, use the formula from AB-method to obtain the bound:

$$\begin{split} T(x) &\in \Theta\left(x^p \left(1 + \int_1^x \frac{f(u)}{u^{p+1}} du\right)\right) = \\ &= \Theta\left(x^2 \left(1 + \int_1^x \frac{u^2}{u^3} du\right)\right) = \\ &= \Theta(x^2 (1 + \ln x)) = \\ &= \Theta(x^2 \log x) \end{split}$$

§13 Advanced Topics

Gamma Function

Definition 33: *Gamma function* $\Gamma(x)$ is the most common *extension* of the factorial function to real and complex numbers. It is defined for all complex numbers $z \in \mathbb{C}$ (except non-positive integers) as

$$\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt$$

For positive integers z = n, it is defined as

$$\Gamma(n) = (n-1)!$$

Motivation: The factorial is defined for positive integers as $n! = 1 \cdot 2 \cdot ... \cdot n = (n-1)! \cdot n$.

We want to *extend* this definition to *all real numbers* and capture its *recursive* nature.

Overall, we are looking for a *smooth* function $\Gamma(x)$ such that:

- $\Gamma(n+1) = n!$ for all $n \in \mathbb{N}$, matching the factorial.
- $\Gamma(x+1) = x \cdot \Gamma(x)$, satisfying a *recursive* property.
- $\Gamma(x)$ is defined for all *real* numbers x > 0.

Definition of a Gamma Function

The main definition of a gamma function is known as *Euler integral of the second kind*:

$$\Gamma(z) = \int_0^\infty t^{z-1} e^{-t} dt$$

Gauss proposed a function $\Gamma(x)$ defined by the *limit*

$$\Gamma(x) := \lim_{n \to \infty} \frac{n! \cdot n^x}{x \cdot (x+1) \cdot \dots \cdot (x+n)} = \lim_{n \to \infty} \frac{n! \cdot n^x}{\prod_{k=0}^n (x+k)} \quad \text{for } x > 0$$

Integral Definition

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$$

Let's check that the integral definition is indeed a suitable definition of a gamma function.

$$\begin{split} \Gamma(z+1) &= \int_0^\infty t^z e^{-t} dt \\ &= \left[-t^z e^{-t} \right]_0^\infty + \int_0^\infty z t^{z-1} e^{-t} dt \\ &= \lim_{t \to \infty} \left(-t^z e^{-t} \right) - \left(-0^z e^{-0} \right) + z \int_0^\infty t^{z-1} e^{-t} dt \end{split}$$

Note that $-t^z e^{-t} \longrightarrow 0$ as $t \longrightarrow \infty$, so:

$$\Gamma(z+1) = z \int_0^\infty t^{z-1} e^{-t} dt = z \cdot \Gamma(z)$$

Limit Definition

$$\Gamma(x) = \lim_{n \to \infty} \frac{n! \cdot n^x}{\prod_{k=0}^{n} (x+k)}$$

Let's check that the limit definition is indeed a suitable definition of a gamma function.

Step 1. Write $\Gamma(x+1)$.

$$\Gamma(x+1) = \lim_{n \to \infty} \frac{n! \cdot n^{x+1}}{\prod_{k=0}^{n} (x+1+k)} = \lim_{n \to \infty} \frac{n! \cdot n^{x+1}}{\prod_{k=1}^{n+1} (x+k)}$$

Step 2. Multiply both numerator and denominator by x and rearrange:

$$= \lim_{n \to \infty} \frac{n! \cdot n^{x+1}}{(x+1) \cdot \dots \cdot (x+n+1)} = \lim_{n \to \infty} \frac{n! \cdot n^x}{x \cdot (x+1) \cdot \dots \cdot (x+n)} \cdot \frac{n}{x+n+1} \cdot x$$

Step 3. Take the limit. As $n \longrightarrow \infty$, the ratio $\frac{n}{x+n+1}$ approaches 1.

$$\Gamma(x+1) = x \cdot \Gamma(x)$$

Equivalence of Definitions

Let's prove the equivalence of two definitions: integral and limit.

We claim:

$$\int_0^n t^{x-1} \left(1 - \frac{t}{n}\right)^n dt \stackrel{?}{=} \lim_{n \to \infty} \frac{n! \cdot n^x}{x \cdot (x+1) \cdot \dots \cdot (x+n)}$$

Note that as $n \to \infty$, the integrand $\left(1 - \frac{t}{n}\right)^n$ approaches e^{-t} , so this integral approximates $\Gamma(x)$.

Substitute $u = \frac{t}{n}$:

$$\int_0^n t^{x-1} \left(1 - \frac{t}{n}\right)^n dt = n^x \int_0^1 u^{x-1} (1 - u)^n du = n^x \cdot \mathbf{B}(x, n+1)$$

where B(x, n + 1) is the Beta function:

$$\mathbf{B}(x,y) = \int_0^1 t^{x-1} (1-t)^{y-1} dt = \frac{\Gamma(x) \cdot \Gamma(y)}{\Gamma(x+y)}$$

Equivalence of Definitions [2]

Then:

$$I_n = n^x \cdot \mathbf{B}(x,n+1) = n^x \cdot \frac{\Gamma(x) \cdot \Gamma(n+1)}{\Gamma(x+n+1)} = \frac{n! \cdot n^x}{x \cdot (x+1) \cdot \ldots \cdot (x+n)}$$

Take the limit on both sides. Since $\lim_{n\longrightarrow\infty}I_n=\Gamma(x),$ we have:

$$\Gamma(x) = \lim_{n \to \infty} \frac{n! \cdot n^x}{x \cdot (x+1) \cdot \dots \cdot (x+n)}$$

Using the Gamma Function

$$n! = \Gamma(n+1)$$

$$\binom{r}{k} = \frac{\Gamma(r+1)}{\Gamma(k+1) \cdot \Gamma(r-k+1)}$$

$$\Gamma(n+1) \approx \sqrt{2\pi n} \left(\frac{n}{e}\right)^n$$

$$B(x,y) = \frac{\Gamma(x)\Gamma(y)}{\Gamma(x+y)}$$

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