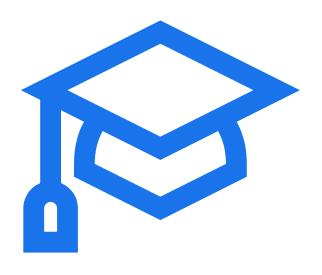


Content



- 1. Hash Function Design
- 2. Table Size & Resizing
- 3. Collision Resolution: Chaining
- 4. Collision Resolution: Open Addressing
- 5. Back-of-the-Envelope Math
- 6. Balanced BSTs
- 7. B-Trees & Treaps
- 8. Tries



Hash Function Design

A hash function is a fast, deterministic mapping $h:U\to\{0,...,2^w-1\}$ that transforms keys into machine-word integers so that, for realistic inputs, the resulting bucket indices are indistinguishable from uniform random. A good hash diffuses small input changes across many output bits (avalanche), exhibits low correlation for nearby keys, and remains consistent with equality (same key \to same hash), while being cheap enough that its cost doesn't dominate table operations

Mix → Mask, not mask raw hashCode.

Keep α low (resize early).

Normalize text; avoid mutable keys.

Seed for untrusted inputs.

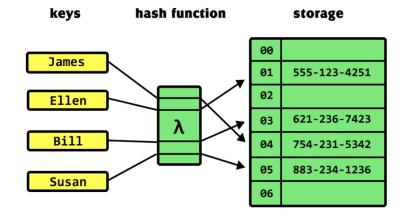




Table Size & Resizing

The table size m is the number of buckets. We choose m and a resize policy to keep the load factor $\alpha = n/m$ near a target so operations stay fast.

Size choice:

- Power-of-two (2^k): index = mix(h) & (m−1)
 - very fast; cheap ×2 growth; good cache locality
 - must mix before masking (raw low bits are biased)
- Prime modulus (p): index = h % p
 - more forgiving for weak hashes
 - o division is slower; awkward growth sequence

Load factor targets:

- Chaining: α≈0.75–2.0 (small-vector buckets help locality)
- Linear/Quadratic probing: α≤0.6–0.7
- Robin Hood: α≤0.85–0.9
- Cuckoo: α≈0.5–0.6

Growth & amortization:

- Trigger when $n > \alpha_{hi} \cdot m$; grow by ×2 (2^k) or ×1.5.
- Optional shrink with hysteresis when $n < \alpha_{lo} \cdot m$.
- Rehash cost is O(m) per resize, but amortized O(1) per insertion across many operations.
- For latency-sensitive systems: incremental rehash (move a few buckets per operation).

Implementation:

- Pre-size: $m \approx [n_{\text{expected}}/\alpha_{\text{target}}]$.
- Open addressing: track tombstones; rebuild if tombstone ratio grows.
- Double hashing: ensure step is coprime with m (odd step for 2^k tables).



Collision Resolution: Chaining

Store each bucket as a container of entries, so multiple keys that hash to the same index live in the same bucket.

Bucket layout options

- Linked list: simple O(1) insert at head; pointer-heavy, poor locality
- Small vector (array) per bucket: better cache locality; scan is branch-light
- Hybrid: small vector (4–8 slots) then spill to list if full

Complexity

- Expected lookup/insert: O(1)
- Successful probe cost ≈ 1 + α/2; unsuccessful ≈ α
- Worst case: O(n) if many collide (defend via better hashing / lower α)

Deletions

O(1) unlink/remove; no tombstones or backward-shifts

Load factor

 Can operate with α > 1 (chains get longer); keep α modest for low p95 latency

Engineering tips

- Pre-store the hash in each entry to avoid recomputation and speed equality checks
- Prefer contiguous storage (small vectors) to reduce cache misses
- Consider resizing earlier or treeifying long buckets in adversarial settings
- Keep bucket scans branch-light (compare hash first, then equals)

Collision Resolution: Open Addressing



Keep all entries in the table itself. On collision, probe alternative slots until an empty one is found.

Core techniques

- Linear probing (LP): i, i+1, i+2, ...
 - cache-friendly, very fast at low α
 - o primary clustering; degrades quickly as α→1
- Quadratic probing (QP): i+1², i+2², ...
 - breaks primary clustering
 - secondary clustering; needs care to guarantee full coverage
- Double hashing (DH): i + k·step(h2) (mod m)
 - better dispersion; avoids both clustering types
 - extra hash cost; step must be coprime with m (odd for 2^k)

Robin Hood hashing

- Idea: equalize probe distances (swap if newcomer is "older").
- Effect: tighter probe-length tail (better p95/p99), supports higher α.
- Note: deletions still use tombstones; bookkeeping of displacement.

Cuckoo hashing (2 choices)

- Each key has 2 possible slots; lookup probes ≤2.
- Inserts may evict and "relocate" a chain; rehash on long cycles.
- Sweet spot: predictable reads, α ≈ 0.5–0.6 (2-way), optional stash for spikes.

Rules of thumb

- Target load factor: LP/QP ≤ 0.6–0.7, Robin Hood ≤ 0.85–0.9, Cuckoo ≈ 0.5–0.6.
- Deletions: use tombstones; rebuild when tombstones accumulate.
- With 2^k tables: mix → mask, and for DH use an odd step.

Back-of-the-Envelope Math

Simple *uniform hashing*; "probe count" ≈ number of bucket inspections. Using rough, quick calculations to estimate system capacity, storage needs, or performance requirements for hashing-related components like hash tables or distributed hash tables

How it works:

- **Define Parameters:** Start with key requirements like the number of users, the size of data per user, or the expected query rate.
- **Use Rules of Thumb:** Leverage well-known approximations, such as powers of two (10 doublings = ~1 million, 20 doublings = ~1 billion) or common latency figures.
- **Perform Simple Arithmetic:** Apply basic multiplication, division, and unit conversions to arrive at an estimate.
- Simplify Assumptions: Use simplified assumptions, such as multiples of 10 for easier computation.
- **Iterate and Compare:** Compare estimates for different architectural choices to find the most suitable design.

Example:

If you need to estimate the total storage for 200 million user records, each containing a small 5MB hash key and associated data:

Calculation:

200 million users * 5 MB/user = 1 billion MB = 1,000 GB = 1 TB.

Balanced BSTs

Self-balancing binary search trees keep height O(log n) by enforcing invariants and applying rotations after updates.

Invariants & Height Bounds

- AVL: balance factor ∈ {-1,0,+1} at every node → height ≤ 1.44 AVL: read-heavy workloads; best lookup times due to · log₂ n.
- Red-Black (RB): no red-red parent/child; equal black-height on RB: write-heavy / mixed workloads; fewer rebalances, all root-leaf paths \rightarrow height $\leq 2 \cdot \log_2 n$.

Operations & Costs (worst-case)

- Search / Insert / Delete: O(log n)
- Rotations: AVL tends to rotate more (tighter balance); RB rotates less (looser balance).

Best usage in practice:

- Order / range queries, sorted iteration.
- k-th smallest / rank via subtree sizes.
- Good default map/set with predictable worst-case latency.

AVL vs RB:

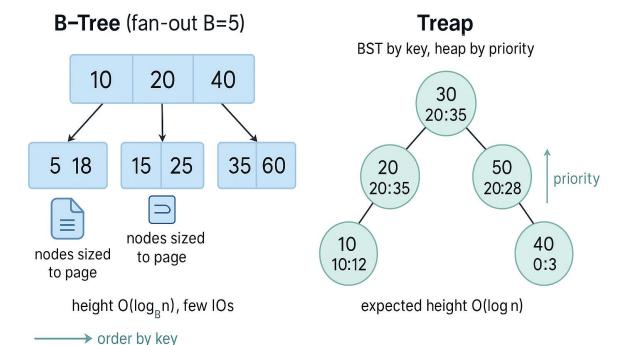
- stricter balance.
- simpler constant factors.

Common augmentations

- Order-statistics tree: store subtree size \rightarrow select(k), rank(x) in O(log n).
- Interval tree: store max(high) in each node → interval stabbing queries in $O(\log n + k)$.
- Also: range sums/min/max with subtree aggregates; 2D variants (range trees).



B-Trees & Treaps



B-Trees

- High fan-out (B children per node) ⇒ height O(log B n).
- Nodes sized to page size (e.g., 4–16 KiB) → few I/Os, great range scans.
- Standard in databases/filesystems; split/merge on updates; bulk-load friendly.

Treaps (simple randomized balancing)

- BST by key + heap by random priority.
- Expected O(log n), tiny code; easy split/merge/concat.
- Great for in-memory sets with order/range and order-stats via subtree_size.
- No strict worst-case bound (probabilistic balance).

B-Trees maximize storage locality/I-O efficiency;

Treaps give lightweight probabilistic balance for in-memory maps/sets.

Tries

A trie, or prefix tree, is a specialized tree-like data structure used to store and retrieve a dynamic set of strings, where the keys are sequences of symbols (e.g., characters or bits). Each node in a trie represents a common prefix of one or more keys, and the path from the root to a node defines that prefix.

Prefix tree keyed by symbols (characters or bits). A key is the path from root; operations depend on key length L, not on set size n.

How tries are structured:

Root node: The trie starts with an empty root node that does not store a character. It acts as the starting point for all search and insertion operations.

Edges: Each edge connecting a parent node to a child node represents a single character or symbol.

Paths: The concatenation of characters along a path from the root to any node forms a unique prefix. A complete key is stored by traversing a path from the root, and the node at the end of the path is often marked as "terminal" to indicate a full word or key.

Shared prefixes: Keys that share a common prefix will also share the same sequence of nodes from the root. This "path sharing" is what makes tries memory-efficient for datasets with many similar keys.

