

Caching in System Design - HLD Interview Guide

Table of Contents

1. [What is Caching?](#)
 2. [Why Caching Matters](#)
 3. [Cache Hierarchy & Layers](#)
 4. [Caching Strategies](#)
 5. [Cache Eviction Policies](#)
 6. [Cache Consistency & Invalidation](#)
 7. [Distributed Caching](#)
 8. [When to Use Caching in HLD Interviews](#)
 9. [Common Caching Patterns](#)
 10. [Cache Technologies Comparison](#)
 11. [Design Trade-offs](#)
 12. [Real-World Examples](#)
-

What is Caching?

Definition

Caching is storing copies of frequently accessed data in a faster storage layer to reduce access time and computational overhead.

Core Concept

Without Cache:

Request → Database (slow, ~50–100ms)

With Cache:

Request → Cache (fast, ~1ms) ✓

↓ (cache miss)

Database (slow, ~50–100ms)

Key Principles

1. Locality of Reference

Temporal Locality:

Recently accessed items likely accessed again

Example: User views profile multiple times in session

Spatial Locality:

Items near recently accessed items likely accessed
Example: If user reads post #100, likely to read #101, #102

2. The 80/20 Rule (Pareto Principle)

80% of requests hit 20% of data
→ Cache that 20% for massive gains

Example:

Total products: 1M
Popular products: 200K (20%)
If cached: 80% requests served from cache

3. Cost vs. Benefit

Cost:

- └─ Memory (cache storage)
- └─ Complexity (invalidation logic)
- └─ Stale data risk

Benefit:

- └─ 10-100x faster response times
- └─ Reduced database load
- └─ Lower operational costs
- └─ Better user experience

Why Caching Matters

Performance Impact

E-commerce Product Page Example:

Without Cache:

- └─ Database query: 50ms
- └─ Image processing: 100ms
- └─ Recommendations: 200ms
- └─ Total: 350ms
- └─ Cost: \$0.01 per request

With Cache:

- └─ Cached HTML: 1ms
- └─ Cached images: 1ms (CDN)
- └─ Cached recommendations: 1ms

- └ Total: 3ms (117x faster!)
- └ Cost: \$0.0001 per request

Scalability Impact

Database Without Cache:

- └ Max throughput: 1,000 QPS
- └ Need 10 servers for 10,000 QPS
- └ Cost: \$10,000/month

With Cache (95% hit rate):

- └ Cache handles: 9,500 QPS
- └ Database handles: 500 QPS
- └ Need 1 server for 10,000 QPS
- └ Cost: \$1,500/month (85% savings!)

When NOT to Cache

- ✗ Frequently changing data (< 1 second lifespan)
- ✗ Large datasets with low hit rate (<10%)
- ✗ Strict consistency required (financial data)
- ✗ Highly personalized, no reuse
- ✗ Cheaper to compute than store

Cache Hierarchy & Layers

Complete Cache Stack

Layer 1: CLIENT-SIDE CACHE
Browser cache, Mobile app cache
Latency: 0ms (local)
Hit Rate: 30–50%

↓ (miss)

Layer 2: CDN / EDGE CACHE
CloudFront, Cloudflare, Akamai
Latency: 10–50ms (edge location)
Hit Rate: 70–90% (static content)

↓ (miss)

Layer 3: APPLICATION CACHE (In-Memory)

Caffeine, Guava, Local cache
Latency: 0.1–1ms
Hit Rate: 40–60%

↓ (miss)

Layer 4: DISTRIBUTED CACHE
Redis, Memcached
Latency: 1–5ms (network call)
Hit Rate: 80–95%

↓ (miss)

Layer 5: DATABASE CACHE
Query cache, Buffer pool (MySQL InnoDB)
Latency: 5–20ms
Hit Rate: 60–80%

↓ (miss)

Layer 6: DISK STORAGE
Latency: 50–100ms (SSD), 5–15ms (NVMe)

Layer Details

1. Client-Side Cache (Browser/Mobile)

Browser Cache Types:
— HTTP Cache (Cache-Control headers)
— Service Workers (offline support)
— LocalStorage (5–10MB persistent)
— SessionStorage (tab-specific)

Configuration Example:

```
Cache-Control: max-age=3600, public  
ETag: "33a64df551425fcc55e"
```

Use Cases:

- ✓ Static assets (CSS, JS, images)
- ✓ API responses (short TTL)
- ✓ User preferences
- ✓ Form data (temporary)

2. CDN / Edge Cache

How CDN Works:

User in Tokyo requests: example.com/logo.png

↓

DNS resolves to nearest edge (Tokyo)

↓

Edge cache checks:

- └ HIT: Return image (10ms)
- └ MISS: Fetch from origin (200ms), cache it

Next Tokyo user: Served in 10ms

Characteristics:

- └ 200+ global edge locations
- └ Automatic geographic routing
- └ 85–95% hit rate for static content
- └ Massive bandwidth savings

CDN Cache Configuration

Cache Behaviors by Path:

- └ /static/* → Cache 1 year (immutable)
- └ /api/* → Cache 5 minutes (dynamic)
- └ /images/* → Cache 1 day
- └ / → Cache 1 hour (HTML)

Cache Key Components:

- └ URL path
- └ Query strings
- └ Headers (Accept-Language)
- └ Cookies (personalization)

3. Application Cache (In-Memory)

Configuration:

- └ Max size: 10,000 entries
- └ TTL: 10 minutes
- └ Eviction: LRU policy
- └ Statistics: Hit/miss rates

Characteristics:

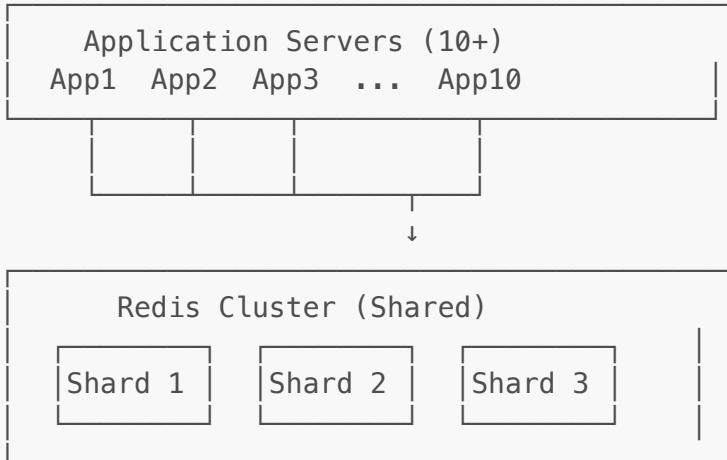
- └ Fastest (no network)
- └ Limited to single server
- └ Lost on restart
- └ Perfect for: Config, sessions

Use Cases:

- ✓ Application configuration
- ✓ User sessions (small scale)
- ✓ Frequently accessed objects
- ✓ Computed results
- ✓ Rate limiting counters

4. Distributed Cache (Redis/Memcached)

Architecture:



Benefits:

- ✓ Shared across all servers
- ✓ Survives server restarts
- ✓ Horizontal scaling
- ✓ Sub-millisecond latency

Redis Data Structures

1. String: Simple key-value
user:123 → {"name": "John", "age": 30}
2. Hash: Structured data
user:123 → {name: "John", age: 30}
3. List: Ordered collections
recent_views:user123 → [prod1, prod2, prod3]
4. Set: Unique items
user:123:friends → {user456, user789}
5. Sorted Set: Rankings/leaderboards
leaderboard → {user123: 1500, user456: 1200}

5. Database Cache

Query Result Cache (MySQL 8.0 deprecated):

Problems:

- ✗ Invalidates entire cache on ANY write
- ✗ Not suitable for write-heavy workloads

Buffer Pool (InnoDB):

- ✓ Automatic caching of data pages
- ✓ Recommended: 70–80% of RAM
- ✓ LRU eviction
- ✓ Transparent to application

Configuration:

`buffer_pool_size = 8GB`

Significantly faster repeated queries

Caching Strategies

1. Cache-Aside (Lazy Loading) ★ Most Common

Read Flow:

1. Application checks cache
2. Cache HIT → Return data (1ms)
3. Cache MISS:
 - Query database (50ms)
 - Store in cache with TTL
 - Return data

Write Flow:

1. Update database
2. Invalidate cache
3. Next read repopulates cache

When to Use

- ✓ Read-heavy (10:1 read:write)
- ✓ Data changes infrequently
- ✓ Can tolerate cache misses
- ✓ Fine-grained control needed

Examples:

- User profiles
- Product catalogs
- Blog posts
- Configuration

Pros & Cons

Pros:

- ✓ Only caches requested data
- ✓ Cache failure doesn't break system
- ✓ Simple to implement
- ✓ Good for read-heavy loads

Cons:

- ✗ Cache miss penalty (3 network calls)
- ✗ Stale data risk
- ✗ Cache stampede vulnerability

2. Read-Through Cache

Read Flow:

1. Application queries cache
2. Cache checks data:
 - HIT: Return data
 - MISS: Cache loads from DB → stores → returns

Key Difference: Cache manages DB loading, not application

When to Use:

- ✓ Want simpler application logic
- ✓ Consistent caching behavior
- ✓ Cache library available

3. Write-Through Cache

Write Flow:

1. Application writes to cache
2. Cache synchronously writes to database
3. Both updated before response

Read Flow:

1. Read from cache (always present)

Result: Cache and database always synchronized

When to Use:

- ✓ Need strong consistency
- ✓ Read-after-write pattern
- ✓ Can tolerate higher write latency

Examples:

- User preferences
- Shopping cart
- Session data

4. Write-Back (Write-Behind) Cache

Write Flow:

1. Application writes to cache (1ms) ✓
2. Cache acknowledges immediately
3. Cache queues async database write
4. Background worker persists to DB

Read Flow:

1. Read from cache (has latest, including pending writes)

When to Use:

- ✓ Write-heavy workload
- ✓ Can tolerate eventual consistency
- ✓ Write performance critical

⚠ Risk: Data loss if cache crashes before DB write

Examples:

- Analytics events
- Logging
- Metrics

✗ NOT for: Financial data, critical transactions

5. Write-Around Cache

Write Flow:

1. Write directly to database (bypass cache)
2. Invalidate cache if exists
3. Cache repopulated on next read

When to Use:

- ✓ Write-once, read-rarely data
- ✓ Avoid cache pollution
- ✓ Write performance critical

Examples:

- Log files
- Archive data
- Batch uploads

6. Refresh-Ahead Cache

Mechanism:

1. Monitor cached items approaching expiry
2. At 75% of TTL: Trigger async refresh
3. Update cache before actual expiry
4. Users always get cache hits

Example Timeline:

T=0s: Item cached (TTL=60s)
T=45s: Async refresh triggered
T=46s: Cache updated
T=50s: User request → HIT (fast!)

When to Use:

- ✓ Latency-sensitive APIs
- ✓ Predictable access patterns
- ✓ Cache misses unacceptable

Examples:

- Home page content
- Top products
- Trending topics

Cache Eviction Policies

Why Eviction Matters

Problem: Limited memory

Cache: 1GB
Total Data: 100GB
Must decide: Which 1% to keep?

Bad eviction → Low hit rate → Poor performance
Good eviction → High hit rate → Fast system

1. LRU (Least Recently Used) ★ Recommended

Algorithm: Evict least recently accessed item

Structure: Doubly Linked List + HashMap

MRU (Most Recently Used)

```
↓  
[Item E] ↔ [Item C] ↔ [Item A]  
↓  
LRU (Least Recently Used) ← EVICT
```

Operations:

- Access: Move to front (MRU)
- Add: Insert at front
- Evict: Remove from back (LRU)
- All $O(1)$ time complexity

Characteristics:

- ✓ Simple and intuitive
- ✓ Good for temporal locality
- ✓ $O(1)$ operations
- ✓ Most widely used

Best For:

- General purpose caching
- Web applications
- Database query cache

Example Scenario

Cache: [A, B, C] (capacity=3)

Access A: [A, B, C] (A moves to front)
Access D: [D, A, B] (C evicted)
Access B: [B, D, A] (B moves to front)
Access E: [E, B, D] (A evicted)

Limitation: Recent ≠ Frequent
If A accessed 1000x, then B, C, D once
A still gets evicted!

2. LFU (Least Frequently Used)

Algorithm: Evict item with lowest access count

Structure: Frequency Buckets

```
Freq 5: [Item A]  
Freq 3: [Item B] [Item C]  
Freq 1: [Item D] [Item E] ← EVICT
```

Characteristics:

- ✓ Keeps truly popular items
- ✓ Resistant to scans
- ✗ Complex implementation
- ✗ New items disadvantaged

Best For:

- Long-running caches
- Stable access patterns
- Content recommendation

3. FIFO (First-In-First-Out)

Algorithm: Evict oldest inserted item

Simple queue structure

Characteristics:

- ✓ Very simple
- ✗ Ignores access patterns
- ✗ Poor performance

Generally NOT recommended

Comparison

Policy	Hit Rate	Complexity	Use Case
LRU	High	$O(1)$	General
LFU	Higher	$O(\log N)$	Stable
FIFO	Low	$O(1)$	Simple
Random	Lowest	$O(1)$	Testing

Recommendation: Start with LRU

Cache Consistency & Invalidation

The Challenge

Scenario:

- T0: Update profile in database
T1: Cache still has old data

T2: User reads from cache → sees stale data

Duration: Until cache expires (TTL) or invalidated

Invalidation Strategies

1. Time-Based (TTL)

Mechanism:

- Set expiry time on cached data
- Automatic eviction after TTL
- Simple and predictable

Pros:

- ✓ Simple to implement
- ✓ Automatic cleanup
- ✓ Predictable

Cons:

- ✗ Data stale until expiry
- ✗ Doesn't reflect immediate updates

TTL Selection Guide

Data Type	TTL	Reasoning
Static content	1 year	Rarely changes
Product catalog	1 hour	Infrequent updates
User profiles	5–15 min	Moderate updates
Session data	Session	Active usage
Real-time data	5–30 sec	Frequent changes
Auth tokens	Validity	Security critical

2. Event-Based Invalidation

Mechanism:

- On data update → explicitly invalidate cache
- Can delete or update cache entry

Workflow:

1. Update database
2. Delete/update cache entry
3. Next read sees fresh data

Pros:

- ✓ No stale data
 - ✓ Immediate consistency
 - ✓ Better UX

Cons:

- x Code coordination needed
 - x Risk of missing invalidations
 - x More complex

3. Message Queue Based

Architecture:

Service A → Database → Publish Event → Kafka
↓
Services B, C, D (invalidate cache)

Workflow:

1. Service updates database
 2. Publishes invalidation event
 3. All services receive event
 4. Each service invalidates own cache

Pros:

- ✓ Decoupled services
 - ✓ Scalable
 - ✓ Reliable delivery

Cons:

- x Eventual consistency
 - x Additional infrastructure
 - x Complexity

Cache Stampede Problem

The Problem

Popular item expires from cache

- T0: Item expires
- T1: 10,000 concurrent requests arrive
- T2: All 10,000 miss cache
- T3: All 10,000 query database simultaneously
- T4: Database overwhelmed → CRASHES

Called: "Cache Stampede" or "Thundering Herd"

Solution 1: Lock-Based

Mechanism:

- Use distributed lock per cache key
- First request acquires lock, queries DB
- Others wait, then read from cache

Result:

- ✓ Only 1 database query
- ✓ 9,999 requests served from cache
- ✓ ~500ms total (including wait)

Tools:

- Redis SETNX for locks
- ZooKeeper lock recipes

Solution 2: Probabilistic Early Expiration

Mechanism:

- Refresh cache BEFORE actual expiry
- Probability increases as expiry approaches
- Spreads refreshes over time

Timeline (TTL=60s):

T=45s: 25% chance to refresh
T=50s: 50% chance to refresh
T=55s: 90% chance to refresh

Result:

- ✓ No simultaneous expirations
- ✓ Gradual database load
- ✓ No stampede

Solution 3: Serve Stale Data

Mechanism:

- Keep expired data temporarily
- Serve stale while refreshing async

Workflow:

1. Cache expires
2. First request: Return stale + trigger refresh
3. Others: Get stale data (fast!)
4. After refresh: Fresh data available

Result:

- ✓ Zero user wait time
- ✓ Only 1 DB query
- ✓ Acceptable staleness (seconds)

Distributed Caching

Why Distribute?

Single Server Limits:

- └─ Memory: ~128GB max
- └─ Single point of failure
- └─ No horizontal scaling
- └─ Data lost on restart

Distributed Benefits:

- └─ Terabytes of memory
- └─ High availability
- └─ Fault tolerance
- └─ Better performance

Redis Cluster Architecture

Redis Cluster (16,384 slots)

Master 1: Slots 0–5460

 ↓ (replication)

 Replica 1

Master 2: Slots 5461–10922

 ↓ (replication)

 Replica 2

Master 3: Slots 10923–16383

 ↓ (replication)

 Replica 3

Routing:

 slot = CRC16(key) % 16384

 Example: "user:123" → slot 5265 → Master 1

Consistent Hashing

Problem with Traditional Hashing

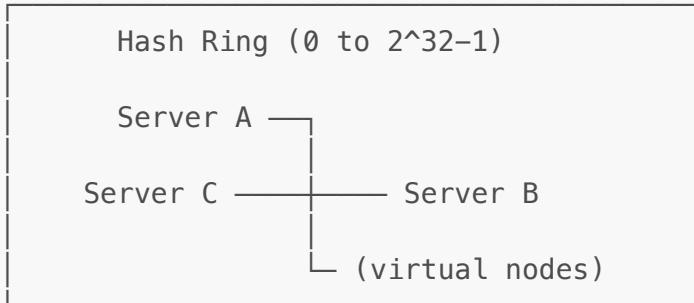
```
server = hash(key) % num_servers
```

With 3 servers:
"user:123" → $12345 \% 3 = 0$ → Server 0

Add 4th server:
"user:123" → $12345 \% 4 = 1$ → Server 1

Result: Different server! Cache miss!
Impact: 75% of 1M cached items remapped!

Consistent Hashing Solution



Key placement: Clockwise to next server
user:123 (hash=150) → Server B
user:456 (hash=250) → Server C

Add Server D:
user:123 → Still Server B ✓
user:456 → Now Server D

Only ~25% keys remapped (much better!)

Replication Strategy

Master-Slave (Recommended):
Master (Write) → Slave 1, 2, 3 (Read)

- ✓ Fast writes
- ✓ Read scalability
- ✗ Replication lag (1–5ms)
- ✗ Possible data loss

Master-Master:
Master A ↔ Master B

- ✓ No single point of failure
- ✗ Conflict resolution needed
- ✗ More complex

When to Use Caching in HLD Interviews

Decision Framework

Strong Signals to Recommend Caching

1. Read-Heavy Workload (>10:1 ratio)

Indicators:

- "Profile viewed 1000x more than updated"
- "Product pages get millions of views"
- "Search results queried repeatedly"

Tell Interviewer:

"This is a read-heavy workload with 100:1 ratio.
Caching can reduce 90% of database load and improve
latency from 50ms to 1ms."

2. Expensive Operations

Indicators:

- "Requires 5 table joins"
- "ML recommendation takes 200ms"
- "Image transformation needed"
- "Complex aggregation query"

Tell Interviewer:

"These operations are expensive. By caching results,
we reduce computation from 200ms to 1ms and save
99% of processing costs."

3. Hot Data (80/20 Rule)

Indicators:

- "Top 20% of products → 80% of traffic"
- "Celebrity posts viewed millions of times"
- "Popular searches repeated frequently"

Tell Interviewer:

"Following the 80/20 principle, caching the top 20%
of data will serve 80% of requests. With 1GB cache,
we can achieve 90%+ hit rate."

4. Repeated Access

Indicators:

- "Users check feed multiple times per hour"
- "Same data requested within minutes"
- "Session data accessed repeatedly"

Tell Interviewer:

"Users exhibit temporal locality. Caching recent accesses for 5 minutes will capture 85% of requests."

5. Static/Slow-Changing Data

Indicators:

- "Product descriptions rarely change"
- "Config updated once per day"
- "Historical data (immutable)"

Tell Interviewer:

"This data is static or slow-changing. We can cache aggressively with long TTL (hours to days) and achieve 95%+ hit rates."

6. Performance Critical

Indicators:

- "Need sub-100ms response"
- "Serving 100K+ requests/second"
- "Real-time user experience"

Tell Interviewer:

"Performance is critical. Caching enables sub-10ms responses and allows us to handle 100K QPS with minimal infrastructure."

✖ Red Flags Against Caching

1. Frequently Changing

- "Stock prices update every second"
- "Real-time bidding"
- "Live sports scores"

Tell Interviewer:

"This data changes too frequently for effective caching. The TTL would be <1 second, making cache hit rate too low to justify the complexity."

2. Write-Heavy

- "More writes than reads"
- "Data written but rarely read"

Tell Interviewer:

"Write-heavy pattern doesn't benefit from caching.
We'd spend more time invalidating than serving from cache."

3. Strong Consistency

- "Financial transactions"
- "Exact inventory counts"
- "Legal/audit data"

Tell Interviewer:

"This requires strong consistency. Caching introduces eventual consistency which is unacceptable here. We'll query database directly for every request."

Top 10 HLD Questions: Where to Use Caching

1. Design Twitter/Instagram Feed

Cache Opportunities:

- ✓ User timelines (expensive joins)
- ✓ Celebrity posts (read millions of times)
- ✓ Trending hashtags
- ✓ User profiles
- ✓ Images/videos (CDN)

What to Tell Interviewer:

"I'd implement caching at multiple layers:

1. CDN Layer:
 - Images/videos cached at edge (1 year TTL)
 - Reduces latency: 200ms → 20ms
 - Saves 80% bandwidth costs

2. Redis Layer (5 min TTL):

- User timelines: Post IDs + metadata
- Profile information
- Follower/following counts

3. Invalidation:

- New post: Invalidate follower timelines
- Fanout-on-write: Regular users (<1K followers)
- Fanout-on-read: Celebrities (millions of followers)

Expected Results:

- Cache hit rate: 85–90%
- Timeline load: 50ms → 5ms
- DB load reduction: 90%
- Can serve 10M users with 10x less infrastructure

2. Design YouTube/Netflix

Cache Opportunities:

- Video metadata (title, views, likes)
- Recommendations
- User watch history
- Video content (CDN)
- Thumbnails

What to Tell Interviewer:

"Caching is fundamental to video streaming:

1. Content Delivery (CDN):

- 90% of video served from edge locations
- User in India: Served from Mumbai edge (20ms)
- Without CDN: From US origin (200ms)
- Cost: ~80% reduction in bandwidth

2. Metadata (Redis, 1 hour TTL):

- Video details rarely change
- Single video: millions of metadata requests
- Database: 1K QPS → Cache: 100K QPS

3. Recommendations (30 min TTL):

- Expensive ML computations (200ms)
- Pre-compute and cache
- Personalized per user segment

4. Performance Impact:

- Page load: 2s → 500ms (4x faster)
- DB queries: 10 per page → 1 per page

3. Design URL Shortener

Cache Opportunities:

- Popular URLs (80/20 applies heavily)
- URL → Original mapping
- Click statistics

What to Tell Interviewer:

"URL shortener is ideal for caching:

1. Extreme Read-Heavy: 100:1 ratio
 - URLs written once, read thousands of times
 - Viral links: millions of clicks
 - Top 20% URLs: 80% of all traffic
2. Simple Data Model:
 - Key-value: short → original
 - Perfect for Redis
 - Sub-millisecond lookups
3. Strategy:
 - Cache popular URLs (LRU eviction)
 - No TTL (URLs immutable)
 - Write-around (avoid cache pollution)
 - 1GB cache = 10M URLs
4. Performance:
 - Without cache: 50ms (DB query)
 - With cache: 1ms (Redis)
 - 50x improvement!
 - Cache hit rate: 95%+

This allows serving 1M QPS with minimal infrastructure."

4. Design Amazon E-commerce

Cache Opportunities:

- Product catalog
- Product images
-