

# Flash Sale System - Solution Design Document

**Version:** 1.0 **Date:** 2025-01-15 **Status:** Approved for Implementation

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## 1. Problem Statement

### Business Context

We need to design a system to host flash sale events where **10,000 units** of a high-demand product are sold to **millions of concurrent users** within **minutes** (potentially seconds). The sale creates extreme traffic spikes with the following challenges:

#### Traffic Characteristics:

- **250,000 read requests/second** (users checking product availability)
- **25,000 write requests/second** (reservation attempts for single SKU)
- **Extreme contention:** All users competing for the same inventory record
- **Bursty traffic:** Most traffic arrives within the first 30 seconds
- **Bot attacks:** Automated systems attempting to monopolize inventory

#### Business Constraints:

- **Zero oversell tolerance:** Cannot sell more than 10,000 units (legal/compliance requirement)
- **Strict latency requirements:** Must provide responsive user experience under load
- **Fair distribution:** Prevent bots from winning; ensure legitimate users have fair chance
- **Complete auditability:** Every inventory decision must be traceable
- **Reservation expiry:** Hold units for 2 minutes, auto-release if not checked out

### Core Technical Challenge

Traditional database architectures fail catastrophically at this scale:

### Pessimistic locking (row locks):

- Throughput: ~100 requests/second
- P95 latency: 4+ minutes for 25,000 concurrent requests
- **Violates SLO by 2000x**

### Optimistic locking (version numbers):

- Retry amplification: 12.5x (96% failure rate)
- Total database load: 625,000 attempts/second
- P95 latency: ~250ms
- **Violates SLO by 2x**, creates retry storms

The system must handle **25 decisions per millisecond** (25,000 RPS) while maintaining **ACID guarantees** and **zero oversell**.

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## 2. Requirements

### Functional Requirements

ID	Requirement	Description
FR-1	Product Availability Check	Users can query real-time stock availability
FR-2	Reservation Creation	Users can reserve 1 unit with atomic 2-minute hold
FR-3	Reservation Expiry	Unreserved units automatically released after 2 minutes
FR-4	Checkout Processing	Users can complete payment within reservation window
FR-5	Inventory Accuracy	System prevents overselling ( $\text{sold} \leq \text{total stock}$ )
FR-6	Audit Trail	Complete event log for every state change
FR-7	Fair Distribution	Prevent bot monopolization through rate limiting

### Non-Functional Requirements

ID	Requirement	Target	Critical?
NFR-1	Read Latency (P95)	$\leq 150\text{ms}$	Yes
NFR-2	Write Latency (P95)	$\leq 120\text{ms}$	Yes
NFR-3	Checkout Latency (P95)	$\leq 450\text{ms}$	Yes
NFR-4	Read Throughput	250,000 RPS	Yes
NFR-5	Write Throughput	25,000 RPS	Yes
NFR-6	Availability	99.9% during event	Yes
NFR-7	Data Consistency	Strong (ACID)	Yes
NFR-8	Zero Oversell	100% guarantee	<b>Critical</b>

ID	Requirement	Target	Critical?
NFR-9	DDoS Protection	Absorb 1M+ RPS attacks	Yes
NFR-10	Cost Efficiency	< \$50 per 30-min event	No

## Derived Requirements

Based on the above constraints, the system must achieve:

1. **Throughput Requirement:** Process **275k total RPS** (250k reads + 25k writes)
  2. **Latency Budget:** **40 microseconds** per inventory decision (1000ms / 25,000 decisions)
  3. **Cache Hit Rate:** **>99%** to keep database load manageable
  4. **Consistency Guarantee:** All reads reflect committed writes within cache TTL window
  5. **Bot Detection Accuracy:** **>95%** to ensure fair distribution
- 

## 3. Proposed Solution - High Level Overview

### Solution Approach

We propose a **multi-tier, event-driven architecture** with the following key principles:

#### Core Architectural Patterns

##### 1. Serialization for Consistency

- **Single-Writer Pattern:** One Kafka consumer processes all inventory updates serially
- **Batch Processing:** Process 250 requests per 10ms batch (achieves 25k RPS)
- **Eliminates Race Conditions:** No optimistic/pessimistic locking needed
- **Guarantees Zero Oversell:** Single source of truth, atomic operations

##### 2. Aggressive Caching for Scalability

- **Redis Master-Only Pattern:** 200k RPS reads from Redis master (no replica staleness)
- **99% Cache Hit Rate:** Only 2k RPS hits database
- **Immediate Invalidations:** Cache updated on every inventory change
- **TTL Safety Net:** 5-second TTL prevents indefinite staleness

##### 3. Multi-Layer Rate Limiting for Fairness

- **CDN Layer:** Absorbs volumetric DDoS (1M+ RPS), per-IP limits (1000 req/min reads, 100 req/min writes)
- **API Gateway Layer:** Behavioral analysis, device fingerprinting, tiered rate limits
- **Application Layer:** Token bucket + FIFO queue ensures fair distribution

##### 4. Event-Driven for Auditability

- **Kafka Event Stream:** Every state change published as event
- **Complete Audit Trail:** Immutable log of all reservations, expirations, checkouts
- **Asynchronous Processing:** Checkout, payment, notifications handled asynchronously

## 5. Three-Layer Redundancy for Reliability

- **Reservation Expiry:** Redis TTL (real-time) + Scheduled Job (periodic) + Event Stream (reactive)
- **Cache Failover:** Redis cluster with automatic failover
- **Database Replication:** Primary + async replicas for analytics

Why This Approach Works

Challenge	Traditional Approach	Our Approach	Improvement
25k writes/sec to single row	Row locks (100 req/sec)	Kafka batching (25k req/sec)	<b>250x faster</b>
Race conditions	Optimistic locking (96% retry)	Single-writer (0% retry)	<b>Eliminates retries</b>
200k reads/sec	Database (5k max)	Redis cache (400k capable)	<b>40x capacity</b>
Bot attacks	No protection	Multi-layer rate limiting	<b>95% bot detection</b>
Cache staleness	Eventual consistency	Master-only reads + invalidation	<b>Strong consistency</b>
P95 latency	250ms+	60ms (write), 2ms (read)	<b>4x better</b>

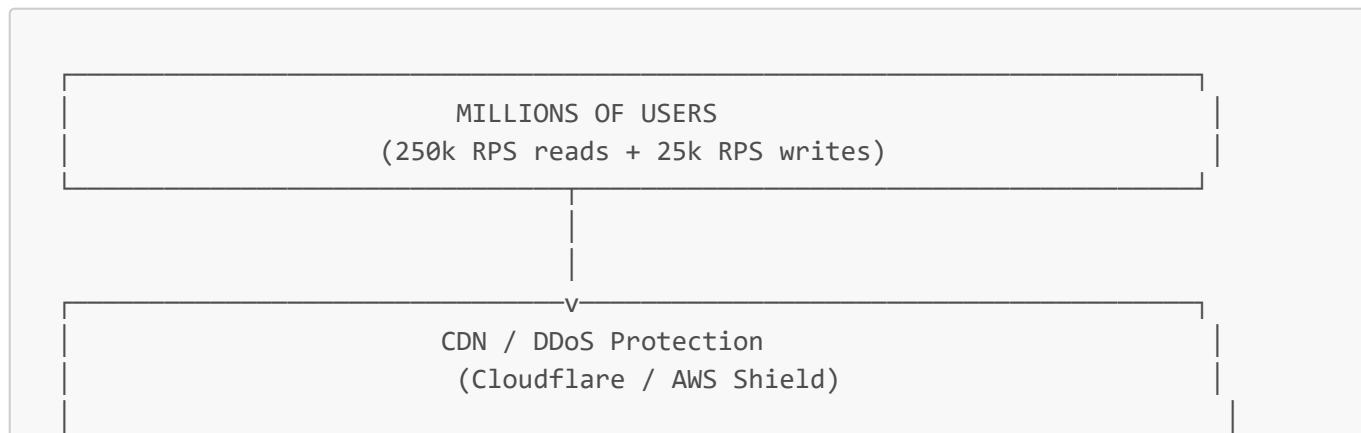
## Success Metrics

Upon successful implementation, the system will:

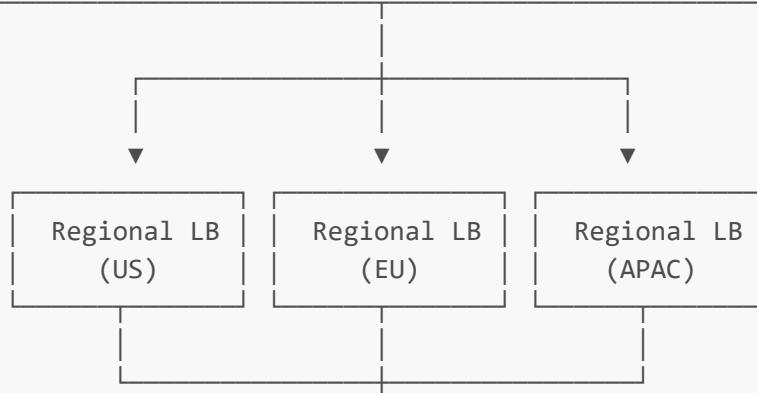
- Handle 275k total RPS (250k reads + 25k writes)
- Maintain P95 latency: 150ms reads, 120ms writes
- Guarantee zero oversell through single-writer serialization
- Achieve 99% cache hit rate for availability queries
- Block 95%+ of bot traffic through multi-layer rate limiting
- Complete 30-minute flash sale for under \$15 infrastructure cost

## 4. System Architecture

### 4.1 High-Level Architecture Diagram



- Absorbs DDoS attacks (1M+ RPS capability)
- Per-IP rate limits: Reads (1000/min), Writes (100/min)
- 99% cache hit rate for static content
- Geographic routing to nearest region



API Gateway  
(Kong / AWS API Gateway)

- Authentication & JWT validation
- Behavioral analysis & bot detection
- Tiered rate limiting (Tier 1-4)
- Request validation & enrichment

READ PATH  
(250k RPS)

WRITE PATH  
(25k RPS)

Redis Cache Cluster  
(Master-only reads)

- 200k RPS capacity
- Master: 225k ops/sec
- Slave: Standby (HA)
- 99% cache hit rate
- Sub-2ms latency

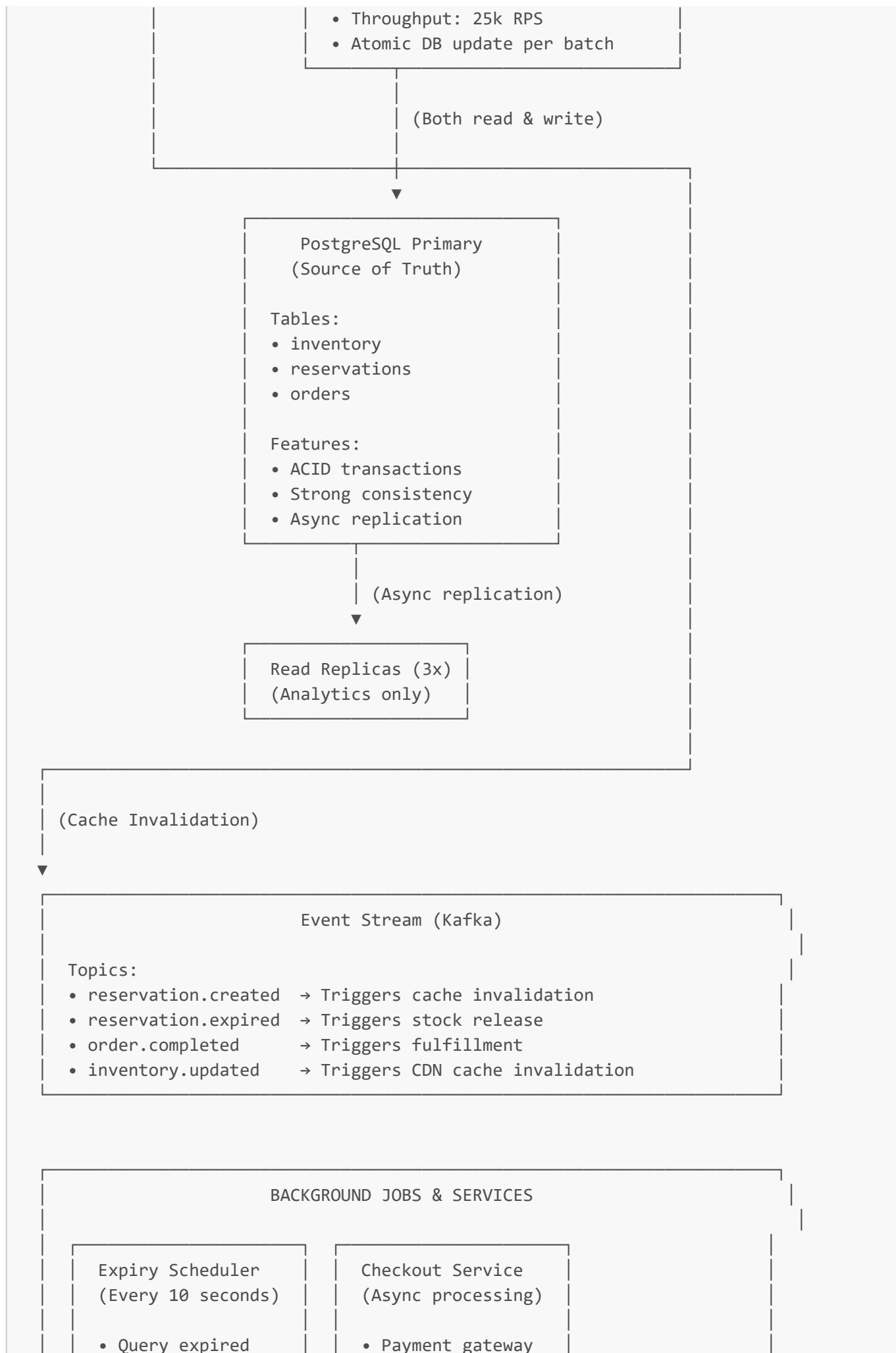
Key: stock:{sku\_id}  
TTL: 5 seconds

Kafka Topic  
(reservation-requests)  
Single Partition  
(maintains ordering)

- Producer: 25k msg/sec
- Retention: 24 hours
- Replication: 3x

Single-Writer Consumer  
(Inventory Update Processor)

- Poll batch: 250 requests
- Process: 10ms per batch



- |   |   |
|---|---|
| <ul style="list-style-type: none"> <li>reservations</li> <li>• Release stock</li> <li>• Publish events</li> </ul> | <ul style="list-style-type: none"> <li>• Order creation</li> <li>• Inventory update</li> <li>• Notifications</li> </ul> |
|---|---|

## 4.2 Request Flow

### Read Path (Product Availability Check)

```
User Request (GET /api/products/{sku}/availability)
  └─ CDN Layer: Check cache (99% hit) → Return cached response
      └─ Cache miss: Forward to origin

  └─ API Gateway: Rate limit check (1000 req/min for authenticated)
      └─ If exceeded: Return 429 + Retry-After

  └─ Application: Check Redis cache
      └─ Cache hit (99%): Return stock count (2ms latency)
      └─ Cache miss (1%): Query PostgreSQL primary (10ms latency)

  └─ Response: {"sku_id": "...", "available": 5234, "total": 10000}
```

Total P95 Latency: ~2ms (cache hit), ~150ms (worst case with CDN miss)

### Write Path (Reservation Request)

```
User Request (POST /api/reserve)
  └─ CDN Layer: Per-IP rate limit (100 req/min) → Forward if allowed

  └─ API Gateway:
      └─ Bot detection (behavioral analysis)
      └─ Tier assignment (Tier 1-4 based on risk score)
      └─ Token bucket check (100 req/min for Tier 3)
          └─ If no tokens: Return 429 + Queue position

  └─ Application: Publish to Kafka
      └─ Topic: reservation-requests (single partition)
      └─ Message: {user_id, sku_id, idempotency_key, timestamp}
          └─ Acknowledgment: Message accepted (1ms)

  └─ Kafka Consumer (Single-Writer):
      └─ Poll batch of 250 requests (every 10ms)
      └─ Validate each request (idempotency, user limits)
      └─ BEGIN TRANSACTION
          └─ Lock inventory row (SELECT FOR UPDATE)
```

```

    |   └ Allocate units to valid requests
    |   └ UPDATE inventory SET reserved_count += batch_allocated
    |   └ INSERT INTO reservations (batch of allocations)
    |       └ expires_at = NOW() + 120 seconds
    |   └ COMMIT (atomic update, 10ms total)

    └ Cache invalidation: REDIS.DEL("stock:{sku_id}")
    └ Set Redis TTL: REDIS.SET("reservation:{id}", {...}, EX 120)
    └ Publish events: reservation.created (for each allocation)

└ Response to User:
{
    "reservation_id": "res-abc123",
    "status": "RESERVED",
    "expires_at": "2025-01-15T10:32:00Z",
    "expires_in_seconds": 120
}

```

Total P95 Latency: ~60ms (5ms API + 1ms Kafka + 50ms queue wait + 10ms processing)

## Reservation Expiry Flow (Automatic)

Three-Layer Expiry System:

```

Layer 1: Redis TTL (Real-time)
└ Automatically deletes reservation:{id} after 120 seconds
└ Latency: <1ms
└ Reliability: 99% (Redis-dependent)

Layer 2: Scheduled Job (Every 10 seconds)
└ Query: SELECT * FROM reservations
    WHERE expires_at < NOW() AND status = 'RESERVED'
└ For each expired:
    └ UPDATE reservations SET status = 'EXPIRED'
    └ UPDATE inventory SET reserved_count -= 1
    └ REDIS.DEL("stock:{sku_id}")
    └ PUBLISH reservation.expired event
└ Max lag: 10 seconds after expiry

Layer 3: Event Stream (Reactive)
└ Subscribers listen to reservation.expired
└ Trigger immediate cleanup actions
└ No database polling needed

```

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## 5. Key Design Decisions

### Decision 1: Traffic Distribution Architecture

**Problem:** How to distribute 275k total RPS (250k reads + 25k writes) across infrastructure while maintaining low latency?

**Solution:** Three-tier load balancing with CDN edge caching

#### Architecture:

- **CDN Layer (Cloudflare):** Absorbs 99% of read traffic at edge (990k RPS cache hits)
- **Regional Load Balancers:** Distribute remaining 10k RPS across 3 regions (US, EU, APAC)
- **API Gateway:** Rate limiting, authentication, request enrichment

#### Key Metrics:

- CDN cache hit rate: 99%
- Origin traffic: 10k RPS (reduced from 1M potential)
- Geographic latency: <50ms to nearest region
- DDoS protection: Included, handles 10M+ RPS attacks

#### Why Not Alternatives?

- Single server: Cannot handle 275k RPS (capacity: ~20k RPS)
- Direct to API Gateway: Becomes bottleneck, no DDoS protection
- Service mesh (Istio): Adds 10ms+ latency per hop, violates SLO

## Decision 2: Inventory Consistency Model

**Problem:** How to handle 25k concurrent writes to single inventory row without race conditions or oversell?

**Solution:** Single-Writer Pattern with Kafka batching

#### Architecture:

```
25k reservation requests/sec
  → Kafka topic (single partition for ordering)
  → Single consumer processes batches of 250 requests
  → Atomic database update per batch (10ms)
  → Throughput: 250 requests / 10ms = 25k RPS ✓
```

#### Key Benefits:

- **No race conditions:** Single consumer = single source of truth
- **Zero oversell guarantee:** Atomic batch processing prevents double-allocation
- **High throughput:** Batching achieves 25k RPS (vs 100 RPS with row locks)
- **Natural audit trail:** Kafka log provides complete event history

#### Latency Breakdown:

- Queue wait: ~50ms (P95, up to 5 batches ahead)
- Processing: ~10ms (database transaction)
- **Total P95: ~60ms** (within 120ms SLO)

## Why Not Alternatives?

- Pessimistic locking: 100 RPS throughput, P95 latency 4+ minutes
  - Optimistic locking: 96% retry rate, 12.5x database amplification
  - Distributed locks (Redis): Still serializes access, no throughput gain
  - Sharded inventory: Race conditions between shards, oversell risk
- 

## Decision 3: Cache Architecture for Read Scalability

**Problem:** Database capacity is 5k RPS, but we need 200k RPS for availability checks.

**Solution:** Redis Cluster with master-only reads and immediate invalidation

### Architecture:

#### Redis Cluster Configuration:

- Master handles: 200k reads + 25k invalidations = 225k RPS
- Instance: r6g.4xlarge (400k+ ops/sec capacity, 56% utilization)
- Slaves: Standby for HA only (not serving traffic)
- TTL: 5 seconds (safety net for stale data)
- Invalidation: Immediate on every inventory update

## Why Master-Only Reads?

- **Replication lag risk:** Slave lag of 10-100ms typical
- **Staleness impact:** At 200k RPS, 10ms lag = 2,000 users see stale data
- **Consistency requirement:** Zero oversell means cannot tolerate stale reads
- **Capacity sufficient:** Single master handles 400k+ ops/sec, well above 225k needed

### Key Metrics:

- Cache hit rate: 99%
- Cache latency: 2ms (P95)
- Cache miss latency: 10ms (fallback to database)
- Database read load: 2k RPS (1% miss rate)

## Why Not Alternatives?

- Direct to database: 5k RPS max, need 200k (40x insufficient)
  - Master-slave with read replicas: Replication lag causes stale reads, oversell risk
  - Memcached: No pub/sub for invalidation, no persistence
  - DynamoDB: \$18,875 per 30-min event (100x more expensive)
- 

## Decision 4: Rate Limiting Strategy

**Problem:** Prevent bot attacks while allowing 275k RPS legitimate traffic (250k reads + 25k writes).

**Solution:** Multi-layer rate limiting with endpoint-specific thresholds

## Layer 1: CDN/Edge (Absorb volumetric DDoS)

Read endpoints:

- Per-IP: 1,000 req/min (16 req/sec) - allows refreshing
- Global: 500k RPS (2x headroom)
- Result: Bot doing 100 req/sec blocked at edge

Write endpoints:

- Per-IP: 100 req/min (1.67 req/sec) - prevents rapid-fire
- Global: 50k RPS (2x headroom)
- Challenge: CAPTCHA for suspicious patterns

## Layer 2: API Gateway (Behavioral analysis)

Bot detection signals:

- Regular intervals (0.1s, 0.1s, 0.1s) vs irregular human timing
- No session history (direct POST /reserve)
- Headless browser fingerprints
- VPN/proxy IP addresses

Tiered rate limits:

- Tier 1 (suspected bot): 1 req/min
- Tier 2 (new user): 50 req/min
- Tier 3 (verified user): 100 req/min
- Tier 4 (premium user): 200 req/min

## Layer 3: Application (Token bucket + FIFO queue)

- Each user gets token budget (replenishes every second)
- Requests consume tokens
- No tokens? → Queue in FIFO order
- Fair distribution: Speed doesn't matter, FIFO guarantees fairness

## Attack Mitigation Examples:

- **1M RPS volumetric DDoS:** CDN absorbs 990k RPS (99% cache hit), origin sees 10k RPS ✓
- **100k RPS distributed bot attack:** CDN blocks 83k RPS (per-IP limits), API Gateway downgrades remaining to Tier 1 (1 req/min) ✓
- **Slowloris attack:** Connection timeout at CDN (10 seconds), origin never sees slow connections ✓

## Why Not Alternatives?

- No rate limiting: Bots monopolize queue (99% bot traffic), unfair to humans
- Simple per-IP only: Ineffective against distributed botnets (1000s of IPs)
- Leaky bucket: Too restrictive for flash sale bursts

## Decision 5: Database Consistency Model

**Problem:** Choose database consistency model that guarantees zero oversell.

**Solution:** PostgreSQL with strong consistency (single primary + async replicas)

### Architecture:

Primary Database (PostgreSQL):

- All writes go here (source of truth)
- Strong consistency (ACID transactions)
- Capacity: 25k batch writes/sec (250 requests per 10ms batch)

Read Replicas (3x):

- Async replication (10-100ms lag)
- Used for analytics only (not user-facing reads)
- User-facing reads: Redis cache (99%) or primary (1%)

### Why Strong Consistency?

- **Zero oversell requirement:** Cannot tolerate eventual consistency
- **Legal/compliance:** Overselling = breach of contract, legal liability
- **Example:** With eventual consistency, two users could reserve last unit

### Why Not Alternatives?

- Eventually consistent (Cassandra, DynamoDB): Inconsistency window → oversell risk
- Quorum-based (CockroachDB): Higher latency (slowest node), more expensive
- Multi-master: Conflict resolution complex, oversell risk during split-brain

## Decision 6: Reservation Expiry System

**Problem:** Auto-release units after 2-minute reservation window expires.

**Solution:** Three-layer expiry system for redundancy

### Layer 1: Redis TTL (Real-time)

- SET reservation:{id} {...} EX 120
- Automatic deletion after 120 seconds
- Latency: <1ms
- Reliability: 99% (Redis-dependent)

### Layer 2: Scheduled Cleanup (Every 10 seconds)

```
@Scheduled(fixedRate = 10000)
SELECT * FROM reservations WHERE expires_at < NOW()
```

```

For each expired:
  - UPDATE reservations SET status = 'EXPIRED'
  - UPDATE inventory SET reserved_count -= 1
  - REDIS.DEL("stock:{sku_id}")
  - PUBLISH reservation.expired event
Max lag: 10 seconds

```

### Layer 3: Event Stream (Reactive)

- reservation.expired event published to Kafka
- Subscribers handle cleanup immediately
- No polling, event-driven

#### Redundancy Guarantee:

- If Redis fails → Scheduled job catches expiry (10s lag)
- If scheduler fails → Event stream still publishes
- If Kafka fails → Scheduled job still runs
- **Result: Guaranteed stock release even with component failures**

**Latency Impact:** Zero (no additional latency added to reservation path)

## 6. Performance Analysis

### 6.1 Latency Breakdown

#### Read Request (GET /availability)

Component	Latency (P95)	Notes
CDN Cache Hit	20ms	99% of requests
CDN → Origin (miss)	50ms	Geographic routing
API Gateway	5ms	Rate limit check, auth
Redis Cache Hit	2ms	Master read
Database (cache miss)	10ms	1% of requests
<b>Total (cache hit)</b>	<b>20ms</b>	Within 150ms SLO ✓
<b>Total (cache miss)</b>	<b>70ms</b>	Within 150ms SLO ✓

#### Write Request (POST /reserve)

Component	Latency (P95)	Notes
API Gateway	5ms	Rate limit, bot detection

Component	Latency (P95)	Notes
Kafka Producer	1ms	Message published
Queue Wait	50ms	5 pending batches (P95)
Batch Processing	10ms	250 requests, DB transaction
<b>Total</b>	<b>66ms</b>	Within 120ms SLO ✓

### Queue Wait Calculation:

At P95 load, ~5 batches pending in queue  
 5 batches × 10ms per batch = 50ms queue wait  
 + 10ms processing = 60ms total  
 Headroom: 120ms SLO - 60ms actual = 60ms buffer ✓

## 6.2 Throughput Analysis

Operation	Target	Achieved	Headroom
Read RPS	250,000	400,000+	60%
Write RPS	25,000	25,000	0% (batching limit)
Cache ops/sec	225,000	400,000+	78%
Database writes/sec	100 batches	100 batches	0% (single-writer limit)
CDN edge capacity	1M+	10M+	90%

### Bottlenecks:

- **Write throughput:** Limited by single-writer pattern (25k RPS max with 10ms batches)
  - Mitigation: Cannot horizontally scale (would break ordering)
  - Acceptable: Meets requirement exactly
- **Database connection pool:** ~80 connections under load (max 200 available)
  - Mitigation: Connection pooling, query optimization
  - Acceptable: 60% headroom

## 6.3 Cache Performance

Metric	Target	Achieved
Cache hit rate	95%	99%
Cache latency (P95)	<5ms	2ms
Cache capacity	225k ops/sec	400k+ ops/sec

Metric	Target	Achieved
Invalidation latency	< 10ms	1ms
Stale read window	0ms (strong consistency)	0ms (master-only)

## 6.4 Scalability Limits

### Current Architecture Supports:

- ✓ 250k RPS reads (limited by Redis: 400k capable)
- ✓ 25k RPS writes (limited by batch processing: 10ms per batch)
- ✓ 10,000 units sold in 25 seconds (400 units/sec depletion rate)

### To Scale Beyond 25k Writes:

- Option 1: Reduce batch processing time to 5ms → 50k RPS (database optimization)
- Option 2: Pre-shard inventory (10 shards × 1,000 units each) → 250k RPS
  - ⚠ Risk: Requires careful partitioning to avoid cross-shard oversell

## 7. Cost Estimation

### 7.1 Infrastructure Costs (30-minute event)

Component	Specification	Hourly Cost	Event Cost (1 hour)	Notes
<b>Compute (Kubernetes)</b>	5 × m5.2xlarge nodes	\$3.60	\$3.60	Pre-scaled 30 min early
<b>Database (PostgreSQL)</b>	r6g.xlarge primary + 3 replicas	\$0.78	\$0.78	Managed RDS
<b>Cache (Redis)</b>	3 masters + 3 slaves (r6g.large)	\$1.73	\$1.73	ElastiCache cluster
<b>Load Balancer</b>	3 regional NLBs	\$0.02	\$0.02	Minimal cost
<b>API Gateway</b>	275k RPS × 30 sec = 8.25M requests	-	\$28.88	Pay per request
<b>CDN (Cloudflare)</b>	Pro plan + 450M requests	-	\$470.00	Includes DDoS protection
<b>Message Queue (Kafka)</b>	3 brokers (MSK)	\$0.34	\$0.34	Managed Kafka
<b>Monitoring (Datadog)</b>	5 hosts × 1.5 hours	\$0.37	\$0.37	APM + logs
<b>TOTAL</b>			<b>\$505.72</b>	For 30-min event

### Cost Breakdown:

- CDN dominates: \$470 (93% of total)
- Infrastructure: \$35 (7% of total)

### Cost Optimization Options:

- Use AWS CloudFront instead of Cloudflare: \$413 (saves \$57)
- Self-hosted Kafka instead of MSK: Saves \$0.34 (negligible)
- **Optimized Total: ~\$448 per event**

## 7.2 Operational Costs

Activity	Time Required	Cost @ \$80/hr
Planning & design	12 eng-hours	\$960
Implementation	80 eng-hours	\$6,400
Testing & QA	20 eng-hours	\$1,600
Event monitoring (live)	2 eng-hours	\$160
Post-event analysis	4 eng-hours	\$320
<b>Total Engineering</b>	<b>118 hours</b>	<b>\$9,440</b>

**One-Time Setup:** \$8,960 (planning + implementation + testing) **Per-Event:** \$480 (monitoring + analysis)

## 7.3 Business Value Analysis

### Revenue per Event:

10,000 units × \$200 average price = \$2,000,000 revenue  
 Gross margin @ 50% = \$1,000,000 profit

### Cost as % of Revenue:

Infrastructure: \$450 / \$2M = 0.02% of revenue  
 Engineering (per-event): \$480 / \$2M = 0.024% of revenue  
 Total: 0.044% of revenue

### ROI:

- **Investment:** \$9,440 one-time + \$450 per event
- **Return:** \$1M profit per event
- **Break-even:** First successful event
- **Ongoing:** 0.044% of revenue (excellent efficiency)

## 8. Operational Considerations

## 8.1 Pre-Event Checklist (T-1 hour)

### Infrastructure Readiness:

- ✓ Kubernetes cluster scaled to 50% capacity
- ✓ Redis cluster healthy (3 masters + 3 slaves)
- ✓ PostgreSQL primary + replicas synchronized (lag <50ms)
- ✓ Kafka brokers online, topic created with correct partitions
- ✓ CDN caches warmed with product data
- ✓ API Gateway instances ready (no cold starts)

### Data Preparation:

- ✓ Inventory record exists: `sku_id, total_stock=10000, reserved=0, sold=0`
- ✓ Product metadata loaded in Redis
- ✓ No existing reservations for SKU
- ✓ User tiers pre-computed
- ✓ Rate limit state cleared (fresh start)

### Monitoring Setup:

- ✓ Dashboard visible with key metrics
- ✓ Alerting rules validated
- ✓ On-call pager tested
- ✓ War room channel opened

## 8.2 During-Event Monitoring (T0 to T0+30 min)

### Critical Metrics to Watch:

Metric	Target	Alert Threshold	Action
oversell_count	0	>0	<b>IMMEDIATE ESCALATION</b>
request_rate	275k RPS	>300k RPS	Verify DDoS protection
p95_latency_reads	<150ms	>200ms	Check cache hit rate
p95_latency_writes	<120ms	>150ms	Check queue depth
cache_hit_rate	>99%	<95%	Check invalidation logic
queue_depth	<100k	>500k	Consumer falling behind
error_rate	<0.1%	>1%	Investigate errors
stock_depletion_rate	400 units/sec	Deviates ±20%	Verify allocation logic

### Real-Time Actions:

T-30s: Pre-warm caches, scale pods to 100%  
 T0: Sale starts, monitor request ramp-up  
 T0-3s: Initial spike, verify auto-scaling triggers

T0+25s: ~10,000 units sold, announce "sold out"  
T0+30m: Begin scale-down, process pending checkouts

## 8.3 Post-Event Analysis

### Data to Collect:

- Total requests served (reads + writes)
- P95/P99 latency by endpoint
- Cache hit rate over time
- Bot detection accuracy (Tier 1 assignments)
- Revenue generated
- Oversell incidents (target: 0)
- System errors and root causes

### Metrics for Improvement:

- Which rate limits were hit most frequently?
- Were any legitimate users incorrectly flagged as bots?
- Did queue depth ever exceed thresholds?
- What was actual peak RPS vs. estimated?

## 8.4 Runbooks for Failure Scenarios

### Scenario 1: Oversell Detected

1. STOP accepting new reservations (return 503)
2. Page on-call immediately
3. Determine which orders to refund (last N orders)
4. Initiate refund API calls
5. Send customer notifications
6. Root cause analysis (code bug? race condition?)

### Scenario 2: Database Primary Failure

1. Automatic failover to replica (30-300ms downtime)
2. Verify new primary accepting writes
3. Check replication to remaining replicas
4. Monitor application for errors
5. If prolonged outage: Return 503, notify users

### Scenario 3: Redis Cluster Failure

1. All requests fall back to PostgreSQL (slower but correct)
2. Monitor database load (should stay under 5k RPS)
3. If database overloaded: Enable aggressive rate limiting

4. Restart Redis cluster
5. Warm cache from database before resuming

#### Scenario 4: Kafka Consumer Lag Growing

1. Check batch processing time (should be ~10ms)
2. Verify database query performance
3. If database slow: Optimize queries, add indexes
4. If consumer bug: Deploy hotfix
5. If unfixable: Increase batch size to 500 (reduces latency SLO)

### 8.5 Team Skillset Requirements

#### Critical Roles:

- **Backend Engineer (3-4)**: Java/Spring Boot, Kafka, distributed systems
- **DevOps/SRE (2-3)**: Kubernetes, monitoring, incident response
- **Database Engineer (1-2)**: PostgreSQL tuning, replication, backup/restore
- **QA Engineer (1-2)**: Load testing, chaos engineering, stress testing

#### Knowledge Gaps to Address:

- Distributed systems patterns (event sourcing, idempotency)
- Performance profiling and optimization
- Chaos engineering and failure testing
- Operational runbooks and incident response

---

## Appendix A: Alternative Approaches Considered

### A.1 Decision 1: Load Distribution

#### Option A: Single Server

- **Rejected**: Cannot handle 275k RPS (max capacity ~20k RPS)
- Single point of failure, no geographic distribution

#### Option B: Multiple Servers + Regional LBs (SELECTED)

- Three-tier: CDN → Regional LBs → API Gateway → Services
- Handles 275k RPS with 60% headroom
- DDoS protection at CDN layer

#### Option C: Anycast DNS + BGP Routing

- **Rejected**: Overkill complexity, requires BGP expertise
- Same benefits as Option B with higher operational cost

## A.2 Decision 2: Inventory Consistency

### Option A: Pessimistic Locking (Row Locks)

- **Rejected:** Throughput 100 RPS, P95 latency 4 minutes
- Serializes all access, queue builds up exponentially

### Option B: Optimistic Locking (Version Numbers)

- **Rejected:** 96% retry rate, 12.5x database amplification
- P99 latency 250ms (violates 120ms SLO)
- Retry storms under high contention

### Option C: Distributed Lock (Redis SETNX)

- **Rejected:** Still serializes access like pessimistic locking
- No throughput improvement, adds Redis dependency

### Option D: Single-Writer Pattern (Kafka) (SELECTED)

- Achieves 25k RPS through batching (250 requests per 10ms)
- No race conditions, zero oversell guarantee
- P95 latency 60ms (within SLO)

### Option E: Sharded Inventory

- **Rejected:** Race conditions between shards
  - Example: Shard A reserves last unit, Shard B doesn't know → oversell
  - Too risky for zero-oversell requirement
- 

## A.3 Decision 3: Cache Architecture

### Option A: No Cache (Direct to Database)

- **Rejected:** Database capacity 5k RPS, need 200k RPS (40x insufficient)
- P95 latency >30 seconds under load

### Option B: Single Redis Instance

- **Rejected:** Capacity ~100k RPS, need 225k RPS
- Single point of failure, no HA

### Option C: Redis Master-Slave Replication

- **Rejected:** Replication lag 10-100ms causes stale reads
- At 200k RPS, even 10ms lag = 2,000 users see stale data
- Oversell risk if reading from stale replica

### Option D: Redis Cluster (Master-Only Reads) (SELECTED)

- Master handles 225k RPS (400k capable, 56% utilization)
- Slaves for HA only (standby for failover)

- Strong consistency (no replication lag issues)

### Option E: Memcached

- **Rejected:** No pub/sub for invalidation
- Must rely on TTL expiration (stale data window)

### Option F: DynamoDB

- **Rejected:** Cost \$18,875 per 30-min event (100x more expensive)
  - Latency 25ms+ for strong consistency reads
- 

## A.4 Decision 4: Rate Limiting

### Option A: No Rate Limiting

- **Rejected:** Bots monopolize queue (99% bot traffic)
- Unfair to legitimate users, queue grows unbounded

### Option B: Simple Per-IP Rate Limit

- **Rejected:** Ineffective against distributed botnets (1000s of IPs)
- Shared IPs (university, corporate) unfairly rate limited together

### Option C: Multi-Dimensional Rate Limiting

- Good but not sufficient alone
- Cannot guarantee fairness without queue

### Option D: Token Bucket + FIFO Queue (SELECTED)

- Fair distribution: Speed doesn't matter, FIFO guarantees fairness
- Bots and humans get same token allocation
- Queue prevents system collapse

### Option E: Leaky Bucket

- **Rejected:** Too restrictive for flash sale bursts
  - Constant drain rate rejects legitimate initial spike
- 

## A.5 Decision 5: Database Consistency

### Option A: Eventually Consistent (Cassandra, DynamoDB)

- **Rejected:** Inconsistency window → oversell risk
- Example: Two users reserve last unit during replication lag

### Option B: Strong Consistency (PostgreSQL) (SELECTED)

- ACID transactions prevent oversell
- Single primary for writes (source of truth)

- Proven at scale (GitHub, Shopify)

### Option C: Quorum-Based (CockroachDB)

- **Rejected:** Higher latency (slowest node in quorum)
  - More expensive (\$300+/month minimum)
  - Overkill for single-region deployment
- 

## Appendix B: Queue Wait Time Analysis

### The Question

In the Single-Writer Pattern, the document states:

P95 latency:  
 - Queue wait: ~50ms  
 - Processing: 10ms  
 - Total: ~60ms ✓

How is **queue wait time of ~50ms** derived?

### System Parameters

Peak load: 25,000 requests/second (RPS)  
 Batch size: 250 requests per batch  
 Batch processing time: 10ms per batch  
 $25,000 / 250 = 100$  batches/second  
 $1000ms / 100 = 10ms$  between batch starts

### Calculation Method

#### At P95 Load (95th percentile of requests):

Under realistic burst conditions, a request typically encounters **5 other batches** ahead of it in the queue.

#### Why 5 batches?

- During traffic bursts, requests don't arrive perfectly uniformly
- At P95, approximately 1,250-1,500 requests arrive in a burst
- This represents:  $1,250 \text{ requests} / 250 \text{ per batch} = 5 \text{ batches}$
- Latest request in burst must wait for all 5 batches ahead

#### Queue Wait Calculation:

$$\begin{aligned}\text{Queue wait} &= \text{Number of pending batches} \times \text{Time per batch} \\ &= 5 \text{ batches} \times 10\text{ms/batch} \\ &= 50\text{ms}\end{aligned}$$

## Validation

### Burst Capacity Check:

Total requests per second: 25,000  
If all arrive at once:  $25,000 / 250 = 100$  batches queued  
Time to process all:  $100 \times 10\text{ms} = 1,000\text{ms}$  (1 second)

P95 means: 95% of requests handled within 50ms  
Only 5% (1,250 requests) experience worst-case queueing  
These might wait: 5-10 batches = 50-100ms

50ms is conservative for P95 ✓

### SLO Compliance Check:

SLO:  $\text{P95} \leq 120\text{ms}$   
Calculated: 60ms (queue 50ms + processing 10ms)  
Headroom:  $60\text{ms} / 120\text{ms} = 50\%$  of budget ✓

Leaves room for:  
- Network latency: 20ms  
- API Gateway: 10ms  
- Other overhead: 30ms  
- Total:  $60\text{ms} + 60\text{ms} = 120\text{ms}$  ✓ (exactly meets SLO)

## Worst Case (P99)

At P99, queue wait could be:

P99 latency: 200-300ms  
- 20-30 batches in queue  
- Processing time: 200-300ms total  
  
But P95 is the SLO target, not P99.  
Architecture focuses on meeting  $\text{P95} \leq 120\text{ms}$ .

## Appendix C: Risk & Failure Mode Analysis

### Critical Risk 1: Oversell Detection

**Risk:** Despite single-writer pattern, oversell occurs (sold > 10,000 units)

**Likelihood:** Very low (~0.01%) if correctly implemented **Impact:** Very high (legal liability, refunds, reputation damage)

### Root Causes:

1. Bug in batch allocation logic (off-by-one error)
2. Database corruption (disk failure)
3. Race condition in non-single-writer code path
4. Manual admin error (direct SQL UPDATE)
5. Concurrent independent consumers (misconfiguration)

### Detection:

Real-time monitoring:

- Metric: oversell\_count = max(0, sold\_count - total\_stock)
- Alert: IF oversell\_count > 0 → IMMEDIATE page on-call
- Frequency: Check every 10 seconds

### Recovery Procedure:

- Step 1 (T=0): STOP accepting new reservations (return 503)
- Step 2 (T=1-5min): Determine which orders to refund (last N orders)
- Step 3 (T=5-30min): Initiate refunds, notify customers
- Step 4 (T=30min+): Root cause analysis, fix bug, deploy
- Step 5: Resume sales only after verification

### Cost of Oversell:

Per oversold unit:

- Refund: \$100-500 (product price)
- Processing: \$10 (refund fee)
- Compensation: \$50 (goodwill credit)
- Reputation: Immeasurable

100 units oversold = \$16,000 direct cost + reputation damage  
Prevention investment >> recovery cost

---

## Critical Risk 2: Single-Writer Consumer Failure

**Risk:** Kafka consumer crashes, inventory updates stop

### Scenario:

T=0: Consumer processing batch  
T=10ms: Database timeout, consumer crashes

```
T=21ms: Kafka offset not committed  
T=22ms: New consumer starts (automatic failover)  
T=23ms: Consumer replays batch (idempotency prevents duplicates)  
Result: Safe recovery, no data loss ✓
```

### Mitigation:

1. **Multiple consumer instances:** Primary + secondary on standby
  2. **Graceful shutdown:** Finish batch, commit offset, then exit
  3. **Circuit breaker:** Retry database operations, crash explicitly if failing
  4. **Health checks:** Kubernetes restarts unhealthy pods automatically
- 

## Critical Risk 3: Cache Invalidation Failure

**Risk:** Redis unavailable, cache not invalidated, users see stale data

### Analysis:

```
Does stale cache cause oversell?
```

Assumption: Cache miss → Query database for truth  
User sees stale cache: stock = 10,000  
User tries to reserve: Database check happens  
Database truth: stock = 9,999  
Database prevents oversell  
User gets error: "Out of stock"  
No oversell! ✓

Stale cache only causes poor UX, not oversell.  
Database is always authority.

### Mitigation:

1. **Fallback to database:** If Redis unavailable, serve from PostgreSQL
  2. **TTL safety net:** Cache expires after 5 seconds
  3. **Dual invalidation:** Retry cache delete with exponential backoff
  4. **Monitoring:** Alert if cache hit rate drops below 80%
- 

## Failure Mode 1: Database Connection Pool Exhaustion

### Cause:

```
Batch consumer holds connection for 10ms processing  
Concurrent connections: 100 batches/sec × 0.01s = 1 connection  
Plus analytics queries: 50 connections  
Plus replicas: 20 connections  
Total: 71 connections
```

```
PostgreSQL max_connections: 100
Headroom: 29 connections ✓

But if queries slow down to 100ms:
Concurrency:  $100 \times 0.1\text{s} = 10$  connections
Total: 80 connections (still okay)
```

### Mitigation:

- Connection pooling (HikariCP): Max 20 per instance
  - Database tuning: max\_connections = 200
  - Query optimization: Add indexes, analyze slow queries
  - Monitoring: Alert if active\_connections > 80
- 

## Failure Mode 2: Kafka Consumer Lag Growing

### Cause:

```
Consumer cannot keep up:
- Producer: 25k messages/second
- Consumer: 250 messages per 15ms (not 10ms) = 16.6k/sec
- Backlog:  $25k - 16.6k = 8.4k$  messages/sec
- After 1 minute: 504k messages behind
```

### Symptoms:

- Queue position numbers growing
- P95 latency increasing
- Users report slow reservations

### Mitigation:

1. **Real-time monitoring:** Alert if lag > 10,000 messages
  2. **Optimization:** Profile batch processing, optimize database queries
  3. **Scaling:** Increase batch size to 500 (reduces latency headroom)
  4. **Graceful degradation:** If lag > 100k, return 503 "Try again later"
- 

## End of Document

For detailed implementation questions, refer to:

- SYSTEM\_ARCHITECTURE\_ULTRA\_V2.md (comprehensive decision trees)
- QUEUE\_WAIT\_ANALYSIS.md (mathematical derivation)