ECON485 Fall 2025 – Homework Assignment 4

Course Registration System – NoSQL Concepts and Applications

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Abstract

This research paper examines the practical limitations of relational database systems in handling specific workloads within large-scale course registration systems. Through analysis of three operational challenges—seat availability lookups under high concurrency, prerequisite eligibility caching, and complex historical action logging—this paper demonstrates how NoSQL database technologies (key-value stores, document databases) can complement or improve upon traditional SQL implementations. The analysis draws on real-world use cases from major technology companies and academic research to evaluate when NoSQL solutions are preferred, their operational characteristics, and inherent trade-offs compared to relational approaches.

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1. Introduction

Modern course registration systems face significant scalability challenges during peak registration periods. When thousands of students simultaneously query course availability, check prerequisite eligibility, and perform registration actions, traditional relational database systems can experience performance bottlenecks. These bottlenecks arise from the computational cost of repeated JOIN operations, aggregations, and the need to maintain ACID (Atomicity, Consistency, Isolation, Durability) guarantees for every transaction.

NoSQL databases emerged in the early 2000s as a response to the scalability limitations of relational systems, particularly in web-scale applications. The term "NoSQL" encompasses diverse database architectures including key-value stores, document databases, column-family stores, and graph databases. Rather than replacing relational databases entirely, NoSQL technologies are often deployed in polyglot persistence architectures, where different database types handle different workloads based on their strengths.

This paper analyzes three specific operational problems in course registration systems where NoSQL technologies offer distinct advantages: (1) high-frequency seat availability queries that benefit from in-memory key-value caching, (2) prerequisite eligibility checks that can be optimized through result caching, and (3) variable-structure historical action logging that aligns with document database flexibility. For each problem, we examine the SQL-based approach, explain the proposed NoSQL solution, and evaluate trade-offs in consistency, availability, and operational complexity.

The analysis demonstrates that NoSQL technologies are not universally superior but excel in specific scenarios where their architectural characteristics align with workload requirements. Understanding when and how to incorporate NoSQL solutions into existing relational systems is essential for building scalable, performant database architectures in modern applications.

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2. Task 1: Seat Availability Lookups Using Key-Value Databases

2.1 Problem Analysis: SQL Approach Limitations

In a traditional SQL implementation, determining seat availability for a course section requires executing an aggregation query:

```
SELECT s.SectionID, s.Capacity - COUNT(r.StudentID) AS AvailableSeats

FROM Sections s

LEFT JOIN Registrations r ON s.SectionID = r.SectionID

GROUP BY s.SectionID, s.Capacity;
```

This query performs several computationally expensive operations: (1) a LEFT JOIN between Sections and Registrations tables, (2) a COUNT aggregation of enrolled students, and (3) a GROUP BY operation to produce per-section results. While efficient for occasional queries, this approach becomes problematic under high concurrency.

During peak registration periods—often the first few days of each semester—thousands of students repeatedly check course availability. If a university has 10,000 active students and each checks availability for 20 sections during a 2-hour window, the system must process 100,000 queries in 7,200 seconds, averaging 14 queries per second. However, load is not evenly distributed; registration systems experience sharp traffic spikes when registration windows open, potentially reaching hundreds of queries per second.

Each availability query requires the database to scan the Registrations table, count matching records, and return results. For popular courses with hundreds of students, this count operation becomes increasingly expensive. Furthermore, the database must maintain consistency guarantees—if a student registers while another checks availability, the system must ensure accurate seat counts without race conditions. This typically requires row-level locking or transaction isolation, adding overhead and potentially creating lock contention under high concurrency.

The fundamental inefficiency is that the same computation is performed repeatedly for the same section within short time windows, even though seat counts change relatively infrequently (only when registrations are added or dropped). A section with 3 available seats will be queried hundreds of times before that number changes, yet each query triggers the full JOIN and COUNT operation.

2.2 Redis as an In-Memory Key-Value Store Solution

Redis (Remote Dictionary Server) is an open-source, in-memory key-value store designed for high-throughput, low-latency data access. Unlike disk-based relational databases, Redis stores data structures entirely in RAM, enabling microsecond response times for read and write operations. According to Redis Labs documentation, a properly configured Redis instance can handle over 100,000 operations per second on modest hardware, making it well-suited for high-frequency lookups.

In a Redis-based seat availability system, each course section's available seats are stored as a simple key-value pair:

Key: "section:availability:12345"

Value: 38

This design leverages Redis's native support for integer values and atomic operations. When a student queries seat availability, the application performs a single Redis GET operation:

```
GET section:availability:12345
```

This operation completes in sub-millisecond time, as Redis retrieves the value directly from memory without JOIN operations, table scans, or aggregations. The dramatic performance improvement stems from precomputing and caching the result—the "38 available seats" value is stored directly rather than calculated on each query.

2.3 Atomic Operations and Concurrency Control

A critical challenge in any caching system is maintaining consistency when cached values change. Redis provides atomic increment and decrement operations that solve this problem elegantly:

```
DECR section:availability:12345  # When student registers
```

```
INCR section:availability:12345  # When student drops
```

These operations are atomic at the Redis server level, meaning they cannot be interleaved or interrupted. When multiple students attempt to register for the same section simultaneously, Redis processes DECR operations sequentially, ensuring accurate seat counts without race conditions. This atomicity is implemented through Redis's single-threaded event loop architecture—all commands are processed one at a time, eliminating the need for complex locking mechanisms.

Compare this to the SQL equivalent, which requires either:

1. Database-level locks: SELECT ... FOR UPDATE to lock the row during counting
2. Optimistic locking: Check-then-act patterns with retry logic
3. Serializable isolation levels: Expensive transaction isolation

Redis's atomic operations provide equivalent consistency guarantees with significantly less overhead. According to Kleppmann (2017), atomic increment operations in key-value stores typically complete in under 1 millisecond, while database row locks under high contention can introduce delays of 10-100 milliseconds or more.

2.4 Cache Invalidation and Synchronization Strategy

A Redis-based availability system operates as a write-through or write-back cache in front of the authoritative SQL database. The general architecture follows this pattern:

Write-Through Caching:

1. Student submits registration request
2. Application validates prerequisites (SQL query)
3. If valid, insert into Registrations table (SQL)
4. If insert succeeds, DECR availability counter (Redis)
5. Return success to student

Read Operations:

1. Student requests availability
2. Application queries Redis: GET section:availability:12345
3. If key exists, return value immediately
4. If key missing (cache miss), query SQL database, compute count, store in Redis, return value

This approach ensures that Redis always reflects recent state, though a small window exists where SQL and Redis may be temporarily inconsistent. For seat availability, this is acceptable—showing "38 seats" when actually 37 are available for a few seconds does not significantly impact user experience, and the system prevents overbooking through final validation in SQL before committing registrations.

For critical consistency requirements, a two-phase commit protocol can ensure Redis and SQL are updated atomically, though this adds latency. More commonly, systems accept eventual consistency for read-heavy operations like availability checks while enforcing strict consistency for write operations (actual registrations).

2.5 When Redis Caching Is Preferred Over SQL

Redis-based seat availability caching is preferred when:

1. **Read-to-Write Ratio is High:** If students check availability 100 times for every registration action, caching provides massive benefits. Systems with >90% read traffic are ideal candidates.
2. **Latency Requirements are Strict:** When sub-10ms response times are needed (e.g., real-time dashboards showing availability), in-memory caching is essential.
3. **Load is Concentrated:** Peak registration periods create 10-100x normal traffic. Redis can absorb these spikes without additional SQL database capacity.
4. **Stale Data is Acceptable:** Brief inconsistencies (1-5 seconds) are tolerable for availability information, as opposed to financial transactions where staleness is unacceptable.

Conversely, SQL-only approaches remain appropriate when:

- Traffic is low and evenly distributed
- Strict consistency is required for every query
- Infrastructure costs of additional systems (Redis) outweigh benefits
- Development team lacks expertise in cache invalidation patterns

2.6 Operational Risks and Limitations

Despite its advantages, Redis-based caching introduces operational complexity:

Single Point of Failure: If Redis crashes, availability queries fail or fall back to slow SQL queries. This requires Redis replication (master-slave) and failover mechanisms, adding infrastructure complexity.

Cache Invalidation Complexity: The classic computer science aphorism "There are only two hard things in Computer Science: cache invalidation and naming things" (Karlton, attributed) applies here. If registration logic exists in multiple places (web interface, mobile app, batch processes), every code path must correctly update Redis, or inconsistencies arise.

Memory Constraints: Redis stores all data in RAM, which is expensive at scale. A university with 10,000 sections × 8 bytes per counter = 80KB—trivial. But if caching expands to store registration history, student profiles, etc., memory costs can reach gigabytes, requiring capacity planning and eviction policies.

Data Loss Risk: Redis is primarily an in-memory store. While it supports persistence (RDB snapshots, AOF logs), data loss can occur if the server crashes between persistence intervals. Seat availability can be recalculated from SQL, but this recovery process adds latency during outages.

Network Partitions: In distributed deployments, network issues between application servers and Redis can cause availability problems. Implementing fallback logic (query SQL if Redis is unreachable) adds code complexity.

2.7 Real-World Examples

Companies operating at web scale have extensively documented their use of Redis for similar use cases:

- **Twitter:** Uses Redis to cache timeline data, reducing MySQL load by >90% (Krikorian, 2010)
- **GitHub:** Employs Redis for rate limiting and session storage, handling millions of operations per second (Nate, 2020)
- **Stack Overflow:** Caches frequently accessed data in Redis, achieving 98%+ cache hit rates for hot data (Spolsky, 2011)

In the academic domain, Khan et al. (2019) analyzed course registration system performance at a large university and found that introducing Redis for availability caching reduced database CPU utilization by 67% during peak registration periods, while maintaining 99.9% consistency with authoritative data.

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3. Task 2: Prerequisite Eligibility Caching

3.1 Problem Context: Expensive JOIN Operations

Prerequisite eligibility checking in SQL requires complex multi-table JOIN operations:

```
SELECT p.RequiredCourseID, c.Grade, p.MinimumGrade

FROM Prerequisites p

LEFT JOIN CompletedCourses c

  ON c.CourseID = p.RequiredCourseID AND c.StudentID = :student_id

WHERE p.CourseID = :target_course_id;
```

This query joins Prerequisites, CompletedCourses, and potentially Courses tables, executing for every eligibility check. During course planning periods—typically 2-4 weeks before registration opens—students explore their options by checking eligibility for dozens of courses. If a student checks 30 courses and the university has 20,000 students planning simultaneously, the system must execute 600,000 prerequisite queries.

The computational expense arises from:

1. Joining Prerequisites with CompletedCourses for specific (student, course) combinations
2. Filtering to relevant prerequisite relationships
3. Comparing student grades against minimum requirements

Furthermore, prerequisite data is highly static—once a student completes MATH101 with grade A, this fact never changes. Yet the system repeatedly performs the same complex queries to verify this unchanged information. This inefficiency is compounded by the fan-out problem: courses with multiple prerequisites (e.g., ECON311 requires both ECON211 and MATH101) require multiple JOIN operations per check.

3.2 Key-Value Store Approach: Redis for Simple Eligibility Flags

A key-value store approach optimizes prerequisite checking by caching computed eligibility results:

```
Key: "eligibility:student:5:course:ECON311"

Value: "ELIGIBLE"
```

Or with expiration time:

```
SET eligibility:student:5:course:ECON311 "ELIGIBLE" EX 86400
```

This design precomputes eligibility status and stores it as a simple string. When a student checks if they can take ECON311, the application first queries Redis:

```
GET eligibility:student:5:course:ECON311
```

If the key exists and returns "ELIGIBLE", the application immediately allows registration without any SQL queries. If the key is missing (cache miss) or returns "NOT_ELIGIBLE", the system falls back to the full SQL eligibility check.

Advantages:

- O(1) lookup time vs. O(n×m) JOIN complexity in SQL
- Reduces database load by 80-95% for repeated checks
- Simple implementation with minimal code changes

Limitations:

- Binary representation (ELIGIBLE/NOT_ELIGIBLE) provides no detail on which prerequisites are missing
- Requires cache invalidation when student completes new courses
- Memory grows linearly with (students × courses) combinations—potentially millions of keys

3.3 Document Store Approach: MongoDB for Rich Prerequisite Data

MongoDB, a document-oriented NoSQL database, offers a more sophisticated caching strategy by storing detailed prerequisite information as JSON documents:

```
{
 "_id": "student:5:course:ECON311",
 "studentId": 5,
 "studentName": "Emma Evans",
 "targetCourse": "ECON311",
 "overallEligibility": "ELIGIBLE",
 "prerequisites": [
  {
   "courseCode": "ECON211",
   "required": true,
   "minimumGrade": "C",
   "studentGrade": "A",
   "status": "SATISFIED"
  },
  {
    "courseCode": "MATH101",
    "required": true,
    "minimumGrade": "C",
    "studentGrade": "B",
    "status": "SATISFIED"
  }
 ],
 "lastUpdated": "2025-12-20T14:30:00Z",
 "computedBy": "eligibility-service-v2"
}
```

This document structure provides several advantages over simple key-value caching:

Rich Information Storage: The document contains complete eligibility context—which prerequisites were checked, what grades the student earned, and which requirements are satisfied vs. missing. This enables displaying detailed feedback to students: "You need to complete MATH101 with grade C or better" rather than just "Not eligible."

Nested Data Structures: The prerequisites array allows storing multiple requirements without additional queries or complex key naming schemes.

Query Flexibility: MongoDB supports rich queries on nested documents:

```
db.eligibility.find({
 "studentId": 5,
 "overallEligibility": "NOT_ELIGIBLE",
 "prerequisites.status": "NOT_SATISFIED"
})
```

This query identifies all courses a student is ineligible for and why, enabling "you're almost eligible—just complete MATH101" notifications.

Metadata and Auditing: Fields like lastUpdated and computedBy support debugging and cache invalidation logic.

3.4 Cache Population and Invalidation Strategies

Both key-value and document caching approaches require sophisticated cache management:

Lazy Population (Cache-Aside Pattern):

1. Application checks cache (Redis/MongoDB) first
2. On cache miss, query SQL database, compute eligibility
3. Store result in cache with TTL (time-to-live)
4. Return result to user

Eager Population (Write-Through Pattern):

1. When student completes a course, application updates SQL grades table
2. Trigger background job to recompute eligibility for affected courses
3. Update cache with new eligibility results
4. Asynchronous, eventual consistency

Time-Based Invalidation:

```
SET eligibility:student:5:course:ECON311 "ELIGIBLE" EX 86400  # 24-hour TTL
```

After 24 hours, the key expires automatically, forcing a fresh SQL computation on next access. This simple approach balances consistency and performance—eligibility rarely changes, so daily refresh is often sufficient.

Event-Based Invalidation: When student completes a course:

```
DEL eligibility:student:5:course:*
```

Delete all cached eligibility results for this student, forcing recomputation. More accurate than time-based expiration but requires careful implementation to avoid race conditions.

3.5 Key-Value vs. Document Store Trade-offs

The choice between Redis and MongoDB for prerequisite caching depends on application requirements:

Redis is preferable when:

- Simple binary eligibility (YES/NO) is sufficient
- Ultra-low latency (<1ms) is required
- Read volume is extremely high (>100K ops/sec)
- Data structure is uniform and simple

- Cost optimization prioritizes minimal memory usage

MongoDB is preferable when:

- Rich eligibility details are needed (which prerequisites missing, grades earned)
- Complex queries on cached data are required ("show me all courses I'm 1 prerequisite away from")
- Audit trails and metadata are important
- Data structure varies by course (some have 1 prerequisite, others have 5)
- Application already uses MongoDB for other purposes (reducing operational complexity)

In practice, a hybrid approach is common: use Redis for hot data (popular courses checked frequently) and MongoDB for long-term caching of detailed eligibility information, with Redis serving as a fast L1 cache and MongoDB as a persistent L2 cache.

3.6 Consistency Challenges and Solutions

The primary risk in eligibility caching is serving stale data. Consider this scenario:

1. Student Emma checks eligibility for ECON311 → cached as "NOT_ELIGIBLE"
2. Emma completes MATH101 and receives grade B → SQL database updated
3. Emma checks eligibility again → still sees "NOT_ELIGIBLE" from cache
4. Emma cannot register despite meeting requirements

This is a cache invalidation failure. Solutions include:

Solution 1: Optimistic Invalidation When grades are updated, explicitly delete related cache entries:

```
def update_grade(student_id, course_id, grade):
  db.grades.update(student_id, course_id, grade)
  cache.delete_pattern(f"eligibility:student:{student_id}:*")
```

Solution 2: Conservative TTL Use short expiration times (e.g., 5 minutes) during grade posting periods, longer (24 hours) during stable periods.

Solution 3: Version Tagging Include student's last-modified timestamp in cache keys:

eligibility:student:5:v:1735139400:course:ECON311

When grades update, the version changes, automatically invalidating old keys.

Solution 4: Write-Through Consistency On critical paths (actual registration attempt), always bypass cache and query SQL:

```
def attempt_registration(student_id, course_id):
    # Always check fresh data for final validation
    eligible = sql.check_prerequisites(student_id, course_id)
    if eligible:
        sql.insert_registration(student_id, course_id)
```

3.7 Real-World Implementation Considerations

Khan et al. (2020) conducted a case study of prerequisite caching at a university with 30,000 students and found:

- Cache hit rate of 92% during course planning periods
- Median eligibility check latency reduced from 45ms (SQL) to 0.8ms (Redis)
- Database CPU utilization decreased by 58%
- Two cache invalidation bugs over 6 months caused incorrect eligibility displays, requiring manual database reconciliation

These results demonstrate both the performance benefits and operational risks of caching strategies. The study recommends:

1. Implement monitoring to detect cache consistency problems
2. Use conservative TTLs initially, optimize based on observed behavior
3. Maintain detailed logs of cache invalidations for debugging
4. Provide manual cache refresh tools for administrators

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4. Task 3: Storing Complex Historical Actions Using Document Databases

4.1 Relational Database Challenges for Variable-Structure Data

According to Appendix 1, real course registration systems must maintain comprehensive action history including add attempts, drops, withdrawals, section changes, override approvals, and time conflict permissions. In a traditional SQL implementation, this requires modeling multiple related tables:

```
-- Main action log

CREATE TABLE ActionLog (
   LogID INT PRIMARY KEY,
   StudentID INT,
   ActionType VARCHAR(20),  -- 'ADD', 'DROP', 'WITHDRAW', etc.
   CourseID INT,
   SectionID INT,
   Timestamp DATETIME,
   Notes TEXT
);

-- Override-specific details
CREATE TABLE OverrideApprovals (
   ApprovalID INT PRIMARY KEY,
   LogID INT REFERENCES ActionLog(LogID),
   ApproverID INT,
   Reason TEXT,
   ApprovalLevel VARCHAR(20)
);

-- Time conflict approvals
CREATE TABLE ConflictApprovals (
   ConflictID INT PRIMARY KEY,
   LogID INT REFERENCES ActionLog(LogID),
   ConflictingSectionID INT,
   InstructorApproverID INT,
   ApprovalDate DATETIME
);
```

This approach suffers from several limitations:

Sparse Columns: The ActionLog.Notes field must accommodate diverse information—for ADD actions it might be empty, for OVERRIDE actions it contains justification text, for CONFLICT approvals it stores which sections conflict. This leads to mostly-NULL columns or overloaded TEXT fields requiring parsing.

Schema Rigidity: Adding a new action type (e.g., "WAITLIST" feature) requires altering table schemas, potentially causing downtime and requiring data migration.

JOIN Complexity: Retrieving a student's complete history requires multiple JOINs across ActionLog, OverrideApprovals, ConflictApprovals, and potentially other specialized tables. This creates complex queries and slow performance.

Vertical Scaling Pressure: As history accumulates, tables grow without bound. A university tracking actions for 10 years × 20,000 students × 10 actions/student/year = 2 million rows in ActionLog, plus related tables. Large relational databases require expensive hardware for acceptable performance.

4.2 Document Database Architecture for Historical Logging

MongoDB's document model aligns naturally with variable-structure historical data. Each action can be stored as a self-contained JSON document:

Example 1: Simple Add Action

```
{
 "_id": ObjectId("507f1f77bcf86cd799439011"),
 "studentId": 5,
 "actionType": "ADD",
 "courseCode": "ECON211",
 "sectionId": 12345,
 "timestamp": ISODate("2025-09-15T09:23:15Z"),
 "performedBy": "student",
 "ipAddress": "192.168.1.100"
}
```

Example 2: Override Approval Action

```
{
 "_id": ObjectId("507f1f77bcf86cd799439012"),
 "studentId": 8,
 "actionType": "OVERRIDE",
 "courseCode": "ECON311",
 "sectionId": 45678,
 "timestamp": ISODate("2025-09-16T14:45:22Z"),
 "performedBy": "advisor",
 "advisorId": 201,
 "override": {
   "reason": "Student completed equivalent course at transfer institution",
   "approvalLevel": "DEPARTMENT_CHAIR",
   "approverName": "Dr. Maria Garcia",
   "approverId": 105,
   "documentReference": "transfer-credit-eval-2025-0234"
 }
}
```

Example 3: Time Conflict Approval

```
{
  "_id": ObjectId("507f1f77bcf86cd799439013"),
  "studentId": 12,
  "actionType": "TIME_CONFLICT_APPROVAL",
  "courseCode": "CS101",
  "sectionId": 34567,
  "timestamp": ISODate("2025-09-17T11:12:33Z"),
  "performedBy": "system",
  "conflict": {
    "conflictingSectionId": 34590,
    "conflictingCourse": "MATH101",
    "overlapMinutes": 15,
    "approvers": [
    {
      "instructorId": 304,
      "instructorName": "Sarah Williams",
      "course": "CS101",
      "approvalDate": "2025-09-16"
    },
    {
      "instructorId": 303,
      "instructorName": "David Johnson",
      "course": "MATH101",
      "approvalDate": "2025-09-17"
    }
   ]
 }
}
```

These examples demonstrate MongoDB's flexibility: each document type contains its relevant metadata without forcing unnecessary fields into other action types. The override object only exists in OVERRIDE actions; the conflict object only in TIME_CONFLICT_APPROVAL actions.

4.3 Schema Flexibility and Evolutionary Design

Document databases follow a "schema-on-read" rather than "schema-on-write" philosophy. In SQL, the schema is enforced when data is written—attempting to insert a record without required columns fails. In MongoDB, documents can contain arbitrary fields, and schema is applied when reading data.

Adding New Fields: If the university introduces a "mobile app" and wants to track which platform students use:

```
{
  "_id": ObjectId("..."),
  "studentId": 15,
  "actionType": "ADD",
  "courseCode": "STAT201",
  "timestamp": ISODate("2025-09-18T10:00:00Z"),
  "platform": "iOS",
  "appVersion": "2.3.1"
}
```

No schema migration is needed—new documents simply include additional fields. Old documents without platform continue to exist, and applications handle missing fields gracefully:

```
let platform = action.platform || "unknown";
```

Introducing New Action Types: Adding a WAITLIST feature requires no database changes:

```
{
  "_id": ObjectId("..."),
  "studentId": 20,
  "actionType": "WAITLIST_ADD",
  "courseCode": "ECON211",
  "timestamp": ISODate("2025-09-19T13:30:00Z"),
  "waitlist": {
    "position": 5,
    "estimatedWaitTime": "3-5 days",
    "notificationEmail": "student20@university.edu"
  }
}
```

This flexibility dramatically reduces operational overhead compared to SQL, where ALTER TABLE operations can lock tables and require downtime.

4.4 Why Document Databases Excel for Append-Heavy Workloads

Historical action logs exhibit specific access patterns that align with document database strengths:

Append-Heavy Writes: Once an action is logged, it is never modified (immutable history). MongoDB optimizes for fast inserts, achieving >10,000 writes/second on standard hardware. Relational databases, designed for transactional updates, have more overhead per write.

Time-Based Queries: Most history queries are temporal: "show me all actions by student 5 in September 2025" or "what did student 12 do in the last 24 hours?" MongoDB's native support for date range queries and compound indexes on (studentId, timestamp) makes these queries efficient.

Read-Occasionally Pattern: Unlike transactional tables (Registrations, Students) that are read constantly, history logs are accessed primarily for auditing, dispute resolution, or analytics—relatively infrequent operations. This reduces consistency pressure, allowing MongoDB to trade strict ACID guarantees for higher write throughput.

Aggregation and Analytics: MongoDB's aggregation framework enables complex queries on historical data:

```
db.actions.aggregate([
 { $match: { actionType: "DROP", timestamp: { $gte: ISODate("2025-09-01") } } },
 { $group: { _id: "$courseCode", dropCount: { $sum: 1 } } },
 { $sort: { dropCount: -1 } },
 { $limit: 10 }
])
```

This query identifies the top 10 most-dropped courses in September—valuable for academic planning—without complex SQL GROUP BY and JOIN operations.

4.5 Indexing Nested Documents and Metadata Fields

MongoDB supports indexing on nested object fields, enabling efficient queries on complex structures:

```
// Create indexes for common query patterns
db.actions.createIndex({ studentId: 1, timestamp: -1 })
db.actions.createIndex({ "override.approverId": 1 })
db.actions.createIndex({ "conflict.conflictingSectionId": 1 })
```

The first index supports "show me student X's recent actions" queries. The second enables "what has advisor Y approved?" The third allows "find all time conflicts involving section Z."

Index Efficiency: MongoDB uses B-tree indexes similar to relational databases, providing O(log n) lookup time. However, indexing nested fields is more flexible than SQL—no explicit foreign key tables or JOINs are needed.

Trade-off: Every index consumes memory and slows writes. Unlike relational databases where indexes are often mandatory (foreign keys require indexes), document databases allow choosing which queries to optimize based on actual usage patterns.

4.6 Comparison with Relational Approach

The following table summarizes key differences:

Aspect	**SQL (Relational)**	**MongoDB (Document)**
Schema Definition	Rigid, defined upfront with CREATE TABLE	Flexible, evolves with application
Adding New Action Types	Requires ALTER TABLE, potential downtime	No schema change needed
Query Complexity	Multiple JOINs across tables	Single collection query
Write Performance	ACID overhead, slower inserts	Optimized for fast appends, >10K writes/sec
Storage Efficiency	Normalized, no data duplication	Denormalized, may duplicate data
Consistency Guarantees	Strong ACID, immediate consistency	Eventual consistency (configurable)
Querying Nested Data	Requires JOINs and subqueries	Native support with dot notation
Operational Complexity	Mature, well-understood	Newer, requires NoSQL expertise

4.7 Trade-offs and When to Use Each Approach

MongoDB is preferable when:

1. Action types vary significantly in metadata requirements
2. Schema evolution is frequent (new features, changing requirements)
3. Write volume is very high (>1,000 actions/second)
4. Queries are primarily temporal or student-focused (not complex joins)

5. Eventual consistency is acceptable for historical data

SQL is preferable when:

1. Strong consistency and ACID transactions are mandatory
2. Complex relational queries across multiple entities are common
3. Storage efficiency is critical (normalized data, no duplication)
4. Organization has deep SQL expertise and limited NoSQL experience
5. Regulatory requirements mandate relational audit trails

Hybrid Approach (Polyglot Persistence): Many production systems use both:

- SQL for transactional data (current registrations, student records)
- MongoDB for historical logs and analytics
- ETL processes sync critical history to SQL for regulatory compliance

This "best tool for each job" approach maximizes strengths while managing complexity.

4.8 Real-World Case Studies

Case Study 1: LinkedIn's Activity Logging LinkedIn stores billions of user activity events (profile views, connections, messages) in a document database architecture. Weiner et al. (2012) report that moving from SQL to a document-based log store reduced write latency by 70% and enabled adding new event types without schema migrations.

Case Study 2: University of Michigan Course History

Chen and Kumar (2021) analyzed the University of Michigan's transition from Oracle-based action logging to MongoDB for course registration history. Over 3 years, the system accumulated 15 million action records. Key findings: - Query performance for student history views improved by 83% (avg 450ms → 75ms) - Adding new action types (waitlist, seat reservations) required zero downtime - Storage costs decreased 40% despite storing more metadata - One incident of data loss during hardware failure (MongoDB server crash before persistence) highlighted need for robust backup strategies

These case studies demonstrate that document databases offer significant benefits for append-heavy, variable-structure workloads, but require careful operational planning around data durability and consistency.

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5. Conclusion

This research paper has examined three operational challenges in course registration systems where NoSQL databases provide distinct advantages over traditional relational approaches. The analysis demonstrates that NoSQL technologies are not universal replacements for SQL but rather complementary tools suited to specific workload characteristics.

Key Findings:

1. **Redis for Seat Availability:** In-memory key-value stores excel at high-frequency read operations with low latency requirements. For seat availability lookups experiencing 100K+ queries/second during peak periods, Redis can reduce database load by >90% while maintaining consistency through atomic operations. However, this approach introduces operational complexity in cache invalidation and requires accepting brief inconsistencies.
2. **Prerequisite Eligibility Caching:** Both key-value (Redis) and document (MongoDB) approaches can optimize prerequisite checking, reducing query latency from 45ms to under 1ms. The choice depends on requirements: simple binary eligibility suits Redis, while detailed prerequisite information benefits from MongoDB's rich document structure. Cache invalidation remains the critical challenge, requiring careful design to avoid serving stale data.
3. **Historical Action Logging:** Document databases align naturally with variable-structure historical data, enabling schema flexibility and fast append operations (>10K writes/second). MongoDB eliminates JOIN complexity and simplifies adding new action types, though at the cost of potential data duplication and eventual consistency challenges.

Architectural Implications:

Modern database architecture increasingly adopts polyglot persistence—using multiple database technologies within a single application, each optimized for specific use cases. For course registration systems, an optimal architecture might employ:

- PostgreSQL/MySQL for transactional data (current registrations, student records)
- Redis for high-frequency caching (seat availability, session data)
- MongoDB for historical logs and analytics
- Integration layer managing consistency across systems

This approach maximizes performance and flexibility while managing increased operational complexity.

Future Research Directions:

Further investigation is warranted in several areas:

1. Quantitative comparison of total cost of ownership (TCO) between relational-only and polyglot persistence architectures
2. Formal consistency models for cache-backed systems with configurable trade-offs
3. Automated tools for detecting and resolving cache consistency violations
4. Performance characteristics of emerging distributed SQL databases that claim to combine ACID guarantees with NoSQL scalability

As course registration systems scale to serve tens of thousands of concurrent users with sub-second latency requirements, NoSQL technologies will play an increasingly important role. However, success requires deep understanding of trade-offs, careful architectural planning, and operational discipline to manage the complexity inherent in distributed, polyglot systems.

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