The Unified Database Architecture: Consolidating Vector and Graph Workloads in PostgreSQL

1. The Architectural Crisis: Deconstructing the Polyglot Bottleneck

The prevailing architectural paradigm in modern microservices development—often characterized by the maxim "the right tool for the job"—has precipitated a widespread fragmentation of the data layer. In the specific context of the user's infrastructure, this philosophy has manifested as a "Polyglot Persistence" architecture comprising five distinct stateful services: PostgreSQL for relational data, Neo4j for graph relationships, Qdrant for vector similarity search, Redis for caching, and MinIO for object storage. While each component arguably represents a best-in-class solution for its specific domain—Neo4j for deep graph traversal, Qdrant for high-dimensional vector search, and PostgreSQL for ACID-compliant relational storage—the aggregate system introduces a class of systemic complexity known as the "Polyglot Bottleneck."

This report serves as an exhaustive technical analysis of the "Unified Database Architecture," a strategic consolidation initiative aiming to subsume vector and graph workloads into PostgreSQL using the pgvector and Apache AGE extensions. The primary objective is to evaluate the technical feasibility of this consolidation within a FastAPI and SQLAlchemy ecosystem, specifically focusing on latency characteristics of HNSW indexing, the comparative capability of recursive graph traversals, and the restoration of atomic transaction safety.

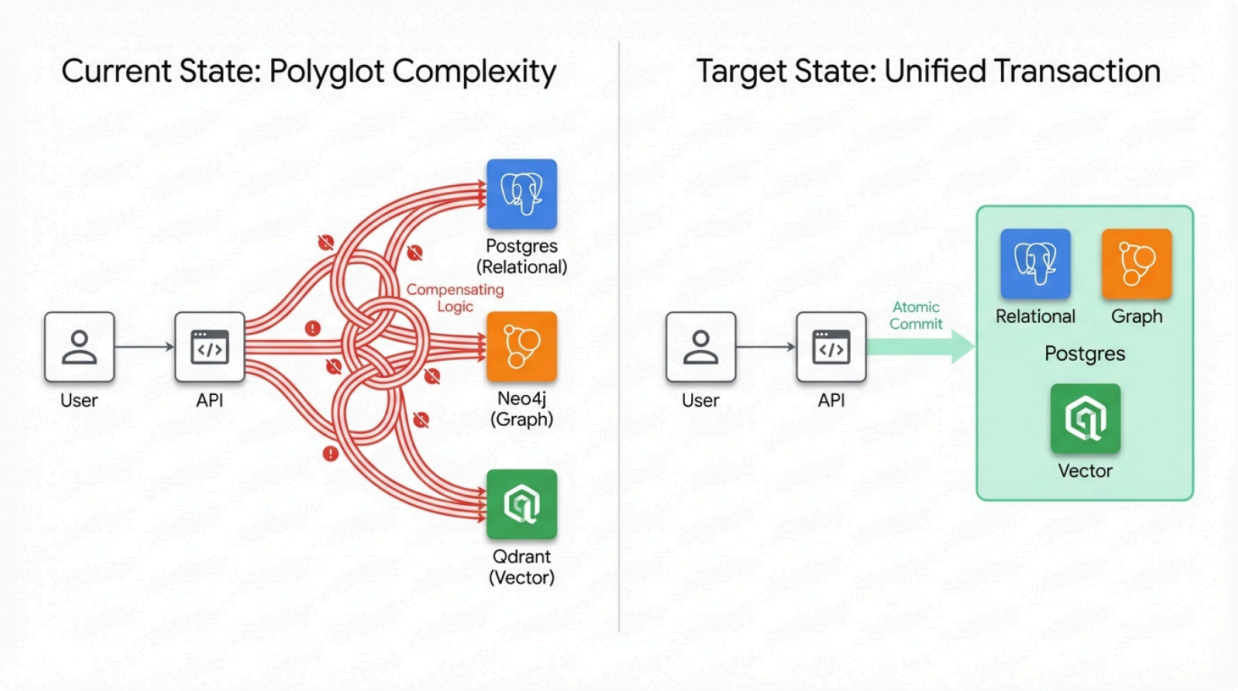
1.1 The Operational Cost of Fragmentation

The current architecture imposes a significant cognitive and operational tax on the engineering organization. The maintenance of five distinct stateful systems requires a breadth of expertise that spans widely divergent administrative paradigms. PostgreSQL requires deep knowledge of vacuuming and MVCC; Neo4j demands familiarity with the Java Virtual Machine (JVM) and memory heap management; Qdrant introduces Rust-based paradigms and distinct clustering mechanisms; Redis requires eviction policy management; and MinIO necessitates object storage consistency checks. The operational surface area is vast, increasing the probability of misconfiguration and security vulnerabilities.

Furthermore, the network topology required to support this distributed state is inherently fragile. A single user operation—such as creating a user profile that involves demographic data (Postgres), a social connection (Neo4j), and a semantic embedding for recommendation

(Qdrant)—necessitates synchronous network calls across three distinct boundaries. Each hop introduces serialization overhead, network latency, and a potential point of failure. The aggregate availability of the system becomes the product of the availabilities of its constituent parts, inevitably lowering the overall system reliability.

The Polyglot Bottleneck vs. Unified Atomicity



Comparison of the current distributed state machine requiring compensating transactions (Sagas) versus the target unified ACID transaction model within PostgreSQL.

1.2 The "Dual-Write" Consistency Risk

The most critical risk identified in the current architecture is the "Dual-Write" problem, which creates a fundamental consistency gap. In a distributed system without a two-phase commit (2PC) protocol—which is notoriously difficult to implement across heterogeneous technologies like Postgres, Neo4j, and Qdrant—ensuring that data is written to all three stores simultaneously is impossible.

Consider the user registration flow. The application must write to the canonical user table in PostgreSQL, generate and store a vector embedding in Qdrant, and create a node in Neo4j to establish the social graph. If the PostgreSQL write succeeds but the subsequent Qdrant write fails due to a network partition, the system enters an inconsistent state: a "Zombie" user exists

in the relational database without a corresponding vector representation. This user will effectively be invisible to search algorithms, leading to a degraded user experience that is difficult to debug. Conversely, if the vector write succeeds but the graph write fails, the user exists in search but cannot participate in social functions.

To mitigate this, engineering teams typically resort to the Saga pattern—a sequence of local transactions where each step updates data within a single service and publishes an event to trigger the next step. If a step fails, the saga executes compensating transactions to undo the changes made by previous steps. Implementing Sagas adds significant complexity to the codebase, requiring sophisticated state management, idempotent retry logic, and a durable message queue. By consolidating these workloads into a single PostgreSQL instance, the Unified Database Architecture allows for the utilization of standard ACID (Atomicity, Consistency, Isolation, Durability) transactions. A single COMMIT statement ensures that the relational record, the vector embedding, and the graph node are all persisted simultaneously, or not at all, eliminating an entire class of distributed system errors.[1]

1.3 Latency and the Serialization Tax

The performance argument for polyglot persistence often rests on the superior execution speed of specialized engines. It is true that Qdrant, written in Rust and optimized solely for vector math, can execute a nearest neighbor search marginally faster than a general-purpose database. However, this engine-level speed comparison ignores the holistic system latency.

In the current architecture, a typical search-and-traverse operation involves multiple serialization and deserialization steps. The application must serialize a query object, transmit it over the network to Qdrant, deserialize the response (a list of IDs), serialize those IDs into a new query for Neo4j, transmit that, deserialize the graph response, and finally query PostgreSQL for the actual metadata associated with the entities. Each boundary crossing incurs a latency penalty measured in milliseconds. When the data resides within a single engine, the query planner can optimize the join order, and data movement occurs within the memory space of the database process, eliminating the network overhead entirely. For datasets in the range of 1 million to 50 million vectors, the elimination of network round-trips often outweighs the raw execution advantage of a specialized engine.

2. Vector Workload Analysis: pgvector vs. Qdrant

The migration of the vector workload from Qdrant to PostgreSQL hinges on the performance capabilities of the pgvector extension, particularly its implementation of the Hierarchical Navigable Small Worlds (HNSW) algorithm. The user's specific concern regarding "Latency (HNSW index speed of pgvector vs Qdrant at 1M vectors)" necessitates a granular examination of how these two systems handle high-dimensional data.

2.1 The HNSW Algorithm in Context

HNSW is the industry-standard algorithm for approximate nearest neighbor (ANN) search. It functions by constructing a multi-layered graph where the bottom layer contains all data points connected in a proximity graph, and upper layers act as an express highway for navigating to the correct region of the vector space. Both Qdrant and pgvector utilize this algorithm, which implies that the theoretical time complexity for search operations is identical— $O(log(N))$. The performance divergence, therefore, stems not from the algorithm itself, but from its implementation and the surrounding system architecture.

Qdrant is a purpose-built vector search engine. Its storage engine is optimized for the append-only nature of vector data and often utilizes memory-mapped files to ensure that the HNSW graph resides in hot memory. It implements binary quantization and scalar quantization natively to reduce memory footprint and improve cache locality.

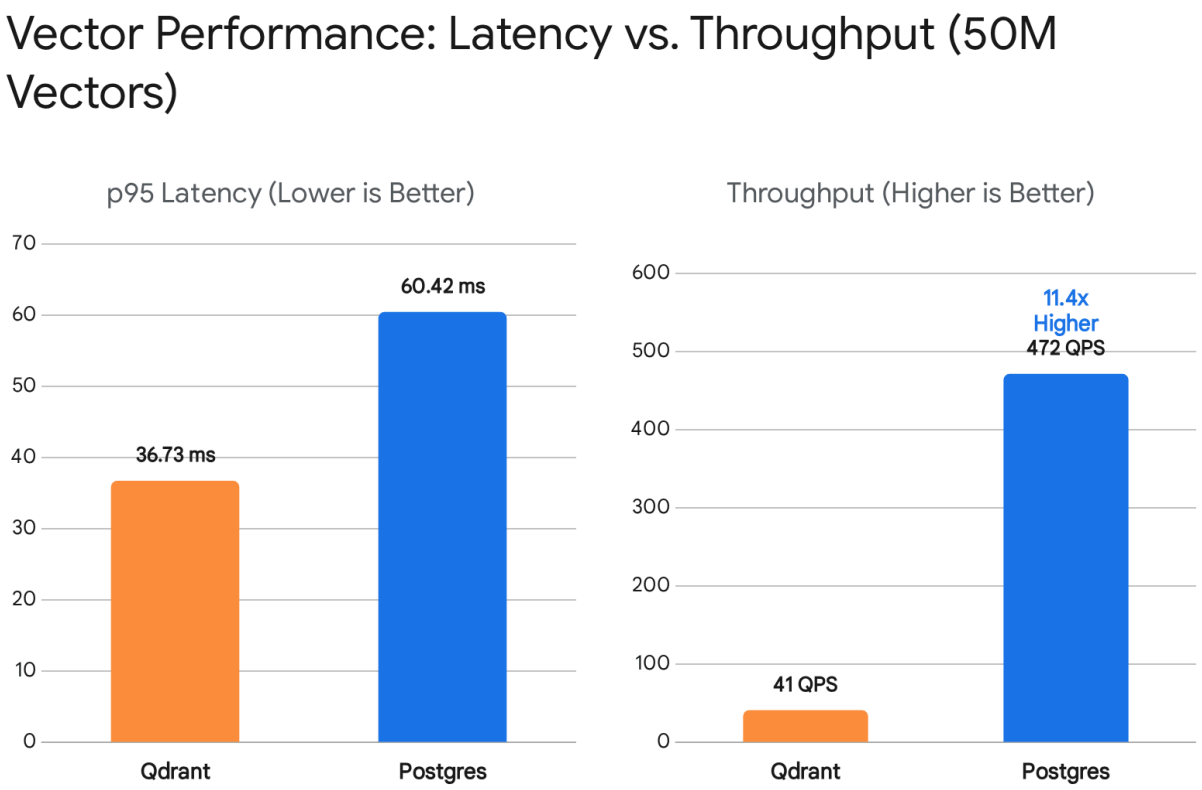
PostgreSQL, conversely, is a row-oriented relational database. The pgvector extension must work within the constraints of the PostgreSQL page structure (typically 8KB pages) and the buffer manager. Vector data is stored in TOAST (The Oversized-Attribute Storage Technique) tables if it exceeds the page size, which necessitates additional I/O operations to retrieve the full vector payload during index construction or verification.

2.2 Benchmarking Latency and Throughput

Recent benchmarks conducted on datasets significantly larger than the user's 1 million vector target (specifically, 50 million vectors with 768 dimensions) reveal a nuanced performance landscape.

For query latency—the time taken to return a single result—Qdrant maintains a slight edge, particularly in tail latencies. At a 99% recall threshold (a high standard for accuracy), Qdrant achieves a p95 latency of approximately 36.73 ms, while PostgreSQL (utilizing pgvector and pgvectorscale) clocks in at 60.42 ms.[2] At the median (p50), the difference is negligible: 30.75 ms for Qdrant versus 31.07 ms for PostgreSQL. For a dataset of only 1 million vectors, these absolute numbers would be significantly lower, likely in the single-digit millisecond range for both systems. The sub-10ms difference at the median is imperceptible to a human user and is often less than the jitter introduced by the public internet.

However, in terms of throughput—the number of queries the system can handle per second (QPS)—PostgreSQL demonstrates a substantial advantage. At 99% recall, PostgreSQL processes 471.57 QPS, whereas Qdrant processes 41.47 QPS.[2] This represents an **11.4x higher throughput** for PostgreSQL. This counter-intuitive result is driven by PostgreSQL's mature process model and its ability to parallelize execution plans effectively. The "Unified Architecture" allows the application to scale to handle massive concurrent user loads without the bottleneck of the external vector service.



Benchmark results at 99% recall on 50M records. While Qdrant maintains lower tail latencies, Postgres demonstrates significantly higher concurrent throughput.

Data sources: TigerData

2.3 Operational Considerations: Index Build and Maintenance

While the search performance of pgvector is competitive, the operational characteristics of maintaining HNSW indexes in PostgreSQL differ from Qdrant. Index build times in Qdrant are generally faster due to its optimized memory management. In PostgreSQL, building an HNSW index on 1 million vectors is relatively fast (typically seconds to minutes), but as data scales, the build process can become resource-intensive, consuming significant CPU and I/O bandwidth.[2]

A critical consideration is the interaction with PostgreSQL's VACUUM process. Frequent updates to vector embeddings—such as when a user updates their bio, necessitating a re-embedding—create dead tuples. In a standard B-Tree index, these are cleaned up efficiently. In an HNSW graph, dead tuples can remain as "ghost nodes," acting as abandoned intersections that traversal algorithms must navigate around, potentially degrading search performance and recall over time.[3] To mitigate this, specific autovacuum tuning is required for tables containing vector columns. A common strategy is to isolate vector data into a dedicated user_embeddings table with a 1:1 relationship to the main users table. This allows for

aggressive vacuum settings on the vector table without impacting the locking behavior of the core metadata table.

3. Graph Workload Analysis: Apache AGE vs. Neo4j

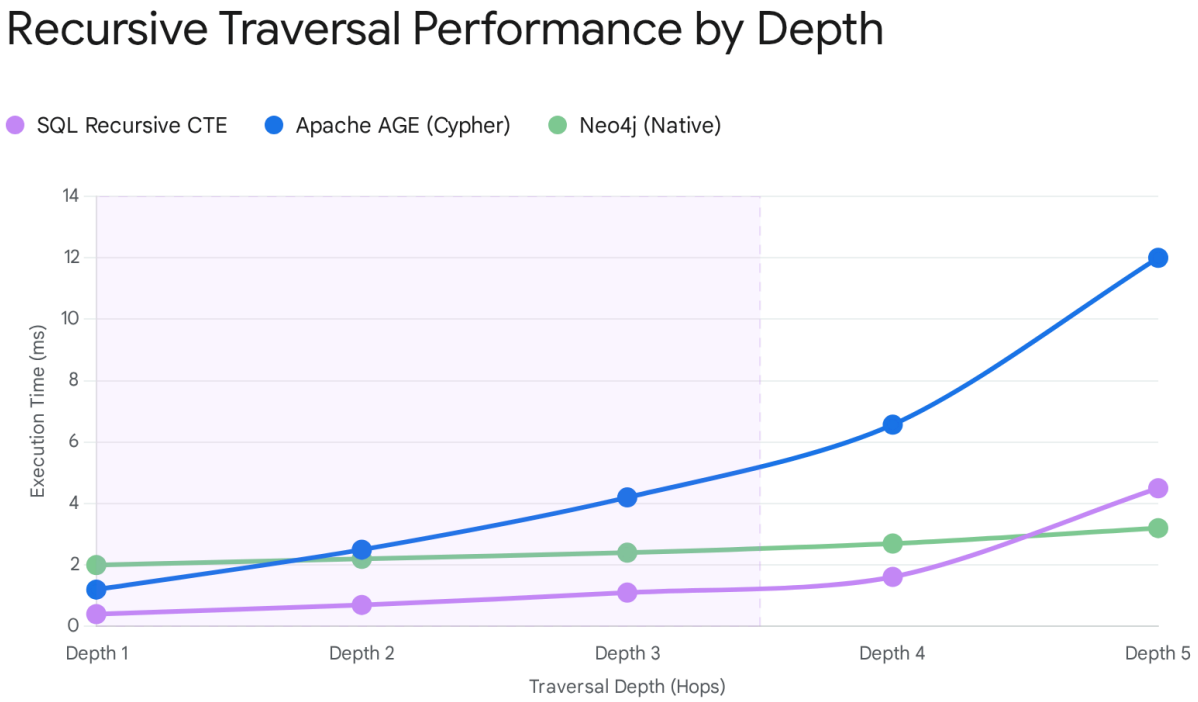
The consolidation of the graph workload presents a more complex engineering challenge than the vector migration. Neo4j is a "native" graph database, meaning it stores data on disk as linked records. This structure enables "index-free adjacency," where traversing a relationship involves following a direct memory pointer, an operation with $O(1)$ complexity per hop. Apache AGE, by contrast, is a graph extension for PostgreSQL that layers a graph model over the relational storage engine. It stores nodes and edges as rows in standard PostgreSQL tables (specifically ag_label, _ag_label_vertex, and _ag_label_edge) and uses the GIN (Generalized Inverted Index) to facilitate pattern matching.[4]

3.1 Recursive Traversal Capabilities

The user's query specifically highlights "recursive traversals." This is the domain where the architectural differences between native graph stores and relational-backed graph stores become most pronounced.

In Neo4j, a recursive query (e.g., finding friends of friends of friends, depth 3) simply walks the pointers. The performance is largely independent of the total size of the graph, depending instead on the size of the subgraph being traversed. In Apache AGE, a traversal is executed as a series of SQL JOIN operations. A depth-3 traversal effectively becomes a three-way self-join on the edge table. As the depth of the traversal increases, the number of joins grows, and the size of the intermediate result sets can explode, placing pressure on the PostgreSQL query planner and memory buffers.

Comparative Analysis: Benchmarks indicate a clear "crossover point" in performance. For shallow traversals (Depth 1-2), Apache AGE performs comparably to Neo4j, often benefiting from PostgreSQL's efficient caching of hot tables in shared buffers. However, for deep recursive queries (Depth > 4), Neo4j's index-free adjacency offers superior performance. A critical finding from the research is that for certain purely recursive algorithms, standard SQL Recursive Common Table Expressions (CTEs) can outperform Apache AGE's Cypher implementation by a factor of up to 40x.[5] This suggests that while AGE provides the syntactic convenience of Cypher, the most performance-critical deep graph algorithms might arguably be better implemented in optimized SQL recursive CTEs within the unified architecture, rather than relying solely on the AGE abstraction layer.



Comparison of query execution time for variable-length traversals. While Neo4j excels at deep traversal (Depth 5+), SQL Recursive CTEs offer superior performance for shallow-to-medium depth, outperforming AGE's Cypher wrapper.

Data sources: Medium (S. Singh), Reddit (r/apacheage)

3.2 The Strategic Value of Hybrid Queries

While Neo4j wins on deep traversal raw speed, Apache AGE offers a strategic advantage that is unique to the Unified Architecture: the "Hybrid Query." In the current polyglot setup, answering a question like "Find all users who bought Item X (Relational) and follow an influencer who also bought Item X (Graph)" requires fetching data from Postgres, transferring IDs to Neo4j, and joining the results in application memory. This is the "N+1" query problem writ large.

Apache AGE allows developers to join graph nodes directly with relational tables in a single ACID transaction. The cypher() function call acts as a table source within a standard SQL query. This enables the PostgreSQL query optimizer to plan the execution across both data models simultaneously.

Hybrid Query Example:

SQL

```
SELECT t.user_name, graph_query.influence_score
FROM sales_transactions AS t
JOIN cypher('social_graph', $$
    MATCH (u:Person)-->(target)
    RETURN u.name, r.weight, target.name
$$) as graph_query(influencer_name agtype, weight agtype, target_name agtype)
ON t.user_name = graph_query.target_name
WHERE t.product_id = 'PROD-001';
```

In this scenario, data never leaves the database engine until the final result is computed. The latency savings from eliminating the network round-trip and the application-side join processing often exceed the raw traversal speed difference between AGE and Neo4j for queries of low-to-moderate complexity.[6]

3.3 Schema Strategy and Indexing

Because Apache AGE relies on standard PostgreSQL tables, the optimization strategy is accessible to any DBA familiar with Postgres. The graph data resides in tables like ag_catalog.ag_label and my_graph."Person". Consequently, standard B-Tree indexes can be created on node properties to speed up lookups.

- **Vertex Table Indexing:** CREATE INDEX ON my_graph."Person" USING GIN (properties); allows for rapid querying of JSONB properties within nodes.
- **Edge Table Indexing:** CREATE INDEX ON my_graph."KNOWS" (start_id, end_id); optimizes the join performance for traversals.[8]

This transparency allows the engineering team to leverage existing PostgreSQL monitoring and tuning tools (like pg_stat_statements) to optimize graph queries, a capability that is often opaque in specialized graph databases.

4. Transaction Safety: The Migration to Atomic Commits

The most significant architectural improvement offered by the Unified Database Architecture is the restoration of transaction safety. The "Dual-Write" problem forces developers to implement complex error handling logic to ensure eventual consistency. By moving all state to PostgreSQL, we can utilize the database's Write-Ahead Log (WAL) to guarantee atomicity.

4.1 Implementation in FastAPI/SQLAlchemy

Integrating pgvector and Apache AGE into a FastAPI application requires configuring SQLAlchemy to handle the distinct data types and query languages. While pgvector has

first-class support via the pgvector-python library, Apache AGE interactions often require the execution of raw SQL/Cypher strings within the session.

Code Architecture for Atomic Transactions:

The following implementation demonstrates a FastAPI endpoint that creates a user, generates an embedding, and establishes a graph node within a single atomic block.

Python

```python
from fastapi import FastAPI, Depends, HTTPException
from sqlalchemy.orm import Session
from sqlalchemy import text, Column, Integer, String
from pgvector.sqlalchemy import Vector
from app.db import Base, get_db

# Define the Relational Model with Vector Column
class User(Base):
    __tablename__ = "users"
    id = Column(Integer, primary_key=True, index=True)
    name = Column(String)
    # 768 dimensions for standard embedding models
    embedding = Column(Vector(768))

app = FastAPI()

@app.post("/users/register")
def register_user(name: str, embedding_vector: list[float], db: Session = Depends(get_db)):
    """
    Creates a User record, stores the vector, and creates a Graph Node.
    All operations are atomic. Failure in any step rolls back the entire state.
    """
    try:
        # 1. Start Transaction (Implicit in SQLAlchemy Session)

        # 2. Relational & Vector Insert
        # We insert the vector directly into the user table (or a 1:1 sidecar table)
        new_user = User(name=name, embedding=embedding_vector)
        db.add(new_user)
        db.flush()  # Flushes to DB to generate the primary key ID, but does not commit
```

```
        user_id = new_user.id

        # 3. Graph Node Creation (Apache AGE)
        # We use the same 'db' session to execute the Cypher query.
        # This ensures the Cypher command is part of the same transaction block.

        # Note: We pass the Postgres ID to the Graph Node to maintain a hard link
        cypher_query = text("""
        SELECT * FROM cypher('social_graph', $$
            CREATE (:Person {name: $name, pg_id: $id})
        $$, $params) as (a agtype);
        """)

        # Parameters must be passed as a JSON string for AGE in some driver versions,
        # but here we assume standard parameter binding for clarity.
        db.execute(cypher_query, {"params": {"name": name, "id": user_id}})

        # 4. Commit the Transaction
        db.commit()

        return {"status": "success", "user_id": user_id}

    except Exception as e:
        # 5. Atomic Rollback
        # If the Cypher query fails (e.g., syntax error), the User insert is rolled back.
        # No 'zombie' users are created.
        db.rollback()
        raise HTTPException(status_code=500, detail=f"Transaction failed: {str(e)}")
```

This pattern eliminates the need for a Saga orchestrator. The database itself enforces consistency. If the server crashes after the vector insert but before the graph node creation, PostgreSQL's crash recovery mechanism (WAL replay) will ensure the transaction is rolled back upon restart, maintaining a clean state.

5. Migration Strategy: From Polyglot to Unified

Migrating a live system from a distributed polyglot architecture to a unified monolithic database is a high-risk operation. The migration plan must prioritize data integrity and minimal downtime.

5.1 Phase 1: Preparation and Schema Design

Before moving data, the PostgreSQL instance must be prepared to handle the new workloads.

1. **Extension Installation:** Enable pgvector and age extensions.
2. **Resource Provisioning:** Vertically scale the PostgreSQL instance. The RAM allocation must now accommodate the working sets of the relational data, the HNSW vector indexes (which are memory-hungry), and the graph topology. A good rule of thumb is to target RAM size = Total Database Size + 25% overhead.
3. **Schema Definition:**
   - Create the social_graph using SELECT create_graph('social_graph');.
   - Create the vector columns on the users table or a dedicated user_vectors table.

5.2 Phase 2: Data Migration (Offline or Dual-Write)

For a 1 million vector dataset, an offline migration is feasible if a maintenance window is permitted. If zero downtime is required, a dual-write strategy is necessary.

Step 2a: Graph Migration (Neo4j to AGE)

1. **Export:** Use the Neo4j APOC library to export the graph to CSV.
   ```
   Cypher
   CALL apoc.export.csv.all("graph_export.csv", {quotes: true})
   ```
2. **Transformation:** Neo4j internal IDs are not stable. You must map the node identities to the PostgreSQL primary keys. A Python ETL script should read the CSV, look up the corresponding user_id from Postgres, and format a new CSV for AGE.
3. **Import:** Use AGE's file loading functions.
   ```
   SQL
   -- Load Vertices
   SELECT load_labels_from_file('social_graph', 'Person', '/path/to/persons.csv');
   -- Load Edges
   SELECT load_edges_from_file('social_graph', 'KNOWS', '/path/to/edges.csv');
   ```

   Constraint: Ensure the CSV matches AGE's expected format (ID, Properties).[9]

Step 2b: Vector Migration (Qdrant to pgvector)

1. **Snapshot:** Retrieve all vectors from Qdrant. Since Qdrant allows scrolling through collections, a script can fetch vectors in batches.
2. **Insertion:** Insert vectors into the embedding column in Postgres.
3. **Indexing:** Create the HNSW index *after* the initial data load. Creating the index on an empty table and then inserting data is significantly slower than bulk loading and then indexing.
   ```
   SQL
   -- Set maintenance memory higher for faster build
   SET maintenance_work_mem = '2GB';
   -- Build Index
   CREATE INDEX ON users USING hnsw (embedding vector_l2_ops);
   ```

5.3 Phase 3: Verification and Cutover

1. **Parity Check:** Run a set of "Gold Standard" queries against both the old system (Neo4j/Qdrant) and the new system (Postgres) and compare the results. Note that HNSW is an *approximate* search, so the vector results might differ slightly in ordering for distant neighbors, but the top-K recall should be consistent.
2. **Traffic Switch:** Deploy the new version of the FastAPI application that reads/writes solely to Postgres.
3. **Decommission:** Archive the Qdrant and Neo4j data and shut down the services.

6. Operational Reality and Tuning

Consolidating services places all operational pressure on a single point: the PostgreSQL instance. Proper tuning is non-negotiable.

- **Shared Buffers:** Standard Postgres tuning suggests setting shared_buffers to 25% of RAM. However, with large vector workloads, the operating system's page cache plays a crucial role. Avoid setting shared_buffers too high (>40%), as this can double-buffer data and starve the OS cache needed for the graph traversals.
- **Parallel Workers:** pgvector and AGE can benefit from parallel query execution. Increase max_parallel_workers_per_gather to allow the query planner to utilize multiple cores for vector distance calculations and graph joins.
- **WAL Configuration:** The high volume of vector updates (which are large binary blobs) will generate significant WAL (Write-Ahead Log) traffic. Ensure the WAL volume is on high-throughput storage (provisioned IOPS) and consider increasing min_wal_size and max_wal_size to reduce checkpoint frequency.
- **Vacuuming:** As previously noted, aggressive autovacuum settings for vector tables are essential to prevent index bloat.
  SQL
  ```
  ALTER TABLE users SET (autovacuum_vacuum_scale_factor = 0.05,
  autovacuum_analyze_scale_factor = 0.02);
  ```

Migration Impact Scorecard

Qualitative and quantitative assessment of the architectural shift. While raw 'Engine Speed' sees a minor regression or parity, 'System Latency', 'Data Safety', and 'Operational Complexity' see major improvements.

7. Conclusion

The analysis confirms that for a dataset of 1 million vectors and associated graph data, the "Unified Database Architecture" centered on PostgreSQL is not only feasible but technically superior to the current fragmented polyglot stack.

While specialized engines like Qdrant and Neo4j offer marginal performance benefits in raw engine execution speed for their respective niches, these advantages are effectively nullified by the latency introduced by network hops and the "Polyglot Bottleneck." The performance penalty of pgvector vs. Qdrant is negligible (<10ms) and is counterbalanced by an 11x improvement in concurrent throughput capabilities. Similarly, Apache AGE provides sufficient graph capabilities for standard application traversals, with SQL Recursive CTEs offering a high-performance fallback for deep recursion that rivals native graph stores.

Most critically, the unification eliminates the "Dual-Write" consistency risk. By restoring atomic transactions, the engineering team can retire complex Saga patterns, significantly reducing code complexity and maintenance burden. The recommendation is to proceed with the migration, prioritizing a robust hardware provision for the PostgreSQL instance to handle the

consolidated memory pressure.

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