A Pragmatic Memory System for AI Agents: Design & Implementation

Authors: System Architecture Team
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Executive Summary

This white paper presents a production-ready memory system for AI agents based on vector databases, cognitive science principles, and modern async Python patterns. The system implements **RFM (Recency-Frequency-Importance) scoring** derived from Ebbinghaus' forgetting curve [1] [2] [3], **hybrid search** combining dense and sparse embeddings [4] [5] [6], and **cross-encoder reranking** [7] [8] [^41] for precision retrieval.

The architecture prioritizes **pragmatic functionality** over theoretical exploration, addressing the critical gaps identified in the audit: incomplete retrieval logic, embedding abstraction leaks, and missing error handling. This document explains design decisions grounded in science and engineering best practices, then provides the complete working implementation.

1. Theoretical Foundation

1.1 Memory Prioritization: RFM Scoring

Human memory follows predictable decay patterns described by Hermann Ebbinghaus' forgetting curve: $R = e^{-t/S}$, where R is retention, t is time elapsed, and S is memory strength [1] [2]. This exponential decay is steepest in the first 24 hours after learning, then levels off [3].

We adapt this to AI memory systems using **RFM scoring**—a method from marketing analytics that ranks customers by Recency, Frequency, and Monetary value [9] [10] [11]. In our context:

- **Recency (R)**: Time since memory creation, scored via exponential decay $R = e^{-\lambda t}$ where $\lambda = \frac{\ln(2)}{\text{half-life}}$ [1] [12]
- **Frequency (F)**: Access count, scored logarithmically $F = \frac{\log(n+1)}{\log(N+1)}$ to model diminishing returns [9] [11]
- **Importance (I)**: User-assigned score (0.0–1.0) reflecting semantic significance

Aggregation Formula:

$$\text{Priority} = 0.3R + 0.2F + 0.5I$$

This weighting prioritizes **importance over frequency over recency**, aligning with human working memory where relevance trumps temporal proximity [9] [13].

1.2 Hybrid Search: Dense + Sparse Embeddings

Dense embeddings (e.g., Gemini, Cohere) excel at semantic similarity but fail on exact keyword matches [4] [6] [14]. Sparse embeddings (e.g., SPLADE, BM25) provide keyword-level precision but miss conceptual relationships [5] [15].

Hybrid search fuses both via Reciprocal Rank Fusion (RRF) or weighted normalization [4] [5] [15]:

$$\text{Score}_{\text{hybrid}} = \alpha \cdot \text{Score}_{\text{dense}} + (1 - \alpha) \cdot \text{Score}_{\text{sparse}}$$

Qdrant natively supports multi-vector queries using `Prefetch` to run parallel dense/sparse searches, then merges results before reranking [5] [^50].

1.3 Reranking with Cross-Encoders

Bi-encoders (used in initial retrieval) encode queries and documents independently, limiting contextual understanding [7] [^41]. Cross-encoders jointly encode (query, document) pairs, producing fine-grained relevance scores at the cost of speed [8] [[44][47].

Two-Stage Pipeline:

1. **Stage 1 (Retrieval)**: Fast bi-encoder search retrieves top-K candidates (K=50–100)
2. **Stage 2 (Reranking)**: Slow cross-encoder rescores candidates, returning top-N (N=10–20) [7] [[41][53]

FastEmbed's `TextCrossEncoder` with models like `jinaai/jina-reranker-v2-base-multilingual` provides multilingual reranking with 1K context length[[44][47].

2. System Architecture

2.1 Layer Design

The system follows a **5-layer architecture** separating concerns:

1. **Application Layer**: Agent orchestration, FastMCP server
2. **Memory Layer**: QdrantMemory interface, RFMCalculator, Pydantic models
3. **Embedding Layer**: Pluggable embedder factory (Google, Mistral, FastEmbed)
4. **Storage Layer**: QdrantClientManager, collection management
5. **Infrastructure Layer**: Qdrant VM, config manager

2.2 Data Structures

Core Models (Pydantic):

```
class MemoryMetadata(BaseModel):
    recency_score: float = Field(ge=0.0, le=1.0)
    frequency_score: float = Field(ge=0.0, le=1.0)
    importance_score: float = Field(ge=0.0, le=1.0)
```

```
    access_count: int = Field(ge=0)

    @property
    def priority_score(self) -&gt; float:
        return 0.3*self.recency_score + 0.2*self.frequency_score + 0.5*self.importance_sc

class Memory(BaseModel):
    id: str
    text_content: str
    memory_type: MemoryType  # EPISODIC | SEMANTIC | WORKING
    metadata: MemoryMetadata
    created_at: datetime
    agent_id: str
```

Vector Storage:

- **Dense vector**: 768–3072 dimensions (Gemini, Cohere)
- **Sparse vector**: Variable-length key-value pairs (FastEmbed)
- **Payload**: JSON with `text_content`, `priority_score`, `created_at`, `metadata`

2.3 Operational Flows

Memory Storage Flow:

1. Agent calls `add_memory(text, memory_type, importance)`
2. Embedder generates dense + sparse vectors in parallel
3. RFMCalculator initializes scores (R=1.0, F=0.0, I=user_value)
4. Qdrant upserts point with vectors + payload
5. Return memory UUID

Memory Retrieval Flow:

1. Agent calls `retrieve_context(query, limit=20)`
2. Embedder encodes query (task_type="RETRIEVAL_QUERY" for Gemini)[attached_file:1]
3. Execute parallel Qdrant queries:
    - Time buckets (hourly, daily, weekly) with weighted fusion
    - Knowledge bank collection (if configured)
4. Merge top-K candidates (K=50) using RRF
5. Rerank with cross-encoder, filter by threshold (>0.5)
6. Update access counts and priority scores
7. Format context string with temporal citations
8. Return assembled context

Priority Update Flow (on access):

1. Fetch current `access_count`, `created_at`

2. Increment `access_count += 1`
3. Recompute `recency_score = exp(-λ × Δt)`
4. Recompute `frequency_score = log(n+1)/log(100+1)`
5. Aggregate `priority_score`
6. Update Qdrant payload

3. Design Decisions

3.1 Embedder Interface Refactor

Problem: Original design leaked `task_type` into method signatures, breaking abstraction when switching providers[file:3][file:6].

Solution: Move `task_type` to initialization:

```
class Embedder(ABC):
    @abstractmethod
    def embed(self, text: str) -&gt; list[float]: ...

    @abstractmethod
    def embed_batch(self, texts: list[str]) -&gt; list[list[float]]: ...

class GoogleEmbedder(Embedder):
    def __init__(self, config: dict, task_type: str = "RETRIEVAL_DOCUMENT"):
        self.task_type = task_type  # Instance attribute
        self.model = config.get("model", "gemini-embedding-001")
```

This allows `QdrantMemory` to instantiate embedders with correct task types without leaking implementation details[attached_file:1].

3.2 Gemini Integration Corrections

Issues in Original Code:

- Model name: `"models/embedding-001"` → should be `"gemini-embedding-001"`[attached_file:1]
- Missing batch API for high-throughput ingestion[attached_file:1]
- No Matryoshka Representation Learning (MRL) support for dimension truncation[attached_file:1]

Corrections:

- Use `genai.batch_embed_content()` for bulk operations
- Support MRL: `output_dimensionality` ∈ {768, 1536, 3072}[attached_file:1]
- Normalize embeddings when dimensions < 3072[attached_file:1]

3.3 Async Error Handling

Pattern: Wrap all Qdrant calls in try-except with exponential backoff[16] [^42]:

```
from tenacity import retry, stop_after_attempt, wait_exponential

@retry(
    stop=stop_after_attempt(3),
    wait=wait_exponential(multiplier=1, min=2, max=10)
)
async def _query_qdrant_with_retry(...):
    try:
        return await self.client.query_points(...)
    except httpx.TimeoutException as e:
        logger.warning(f"Qdrant timeout: {e}")
        raise
    except Exception as e:
        logger.error(f"Qdrant error: {e}")
        raise
```

3.4 Config Validation

Pattern: Use Pydantic for schema validation[17] [18] [^43]:

```
class MemoryConfig(BaseSettings):
    qdrant_url: str = Field(default="http://localhost:6333")
    collection_name: str = Field(min_length=1)
    embedding_provider: str = Field(pattern="^(google|mistral|fastembed)$")
    embedding_size: int = Field(ge=384, le=3072)

    class Config:
        env_file = ".env"
        extra = "ignore"
```

This fails fast at startup if config is invalid, preventing runtime crashes[18] [^43].

3.5 Reranking Integration

Implementation using FastEmbed[44][47]:

```
from fastembed.rerank.cross_encoder import TextCrossEncoder

reranker = TextCrossEncoder("jinaai/jina-reranker-v2-base-multilingual")

def rerank_results(query: str, candidates: list[dict]) -&gt; list[dict]:
    pairs = [[query, c["text_content"]] for c in candidates]
    scores = reranker.compute_score(pairs, normalize=True)

    for candidate, score in zip(candidates, scores):
        candidate["rerank_score"] = score
```

```
    # Filter low scores, sort descending
    return [c for c in sorted(candidates, key=lambda x: x["rerank_score"], reverse=True)
```

4. Implementation Details

4.1 Collection Schema

Qdrant Collection Configuration:

```
vectors_config = {
    "dense": models.VectorParams(
        size=768,  # Gemini embedding-001 with MRL
        distance=models.Distance.COSINE
    )
}

sparse_vectors_config = {
    "sparse": models.SparseVectorParams(
        index=models.SparseIndexParams(on_disk=False)
    )
}

# Payload indices for filtering
payload_schema = {
    "priority_score": models.PayloadSchemaType.FLOAT,
    "created_at": models.PayloadSchemaType.DATETIME,
    "memory_type": models.PayloadSchemaType.KEYWORD,
    "agent_id": models.PayloadSchemaType.KEYWORD
}
```

4.2 Temporal Bucketing

Time-Based Queries for context-aware retrieval:

```
time_buckets = [
    ("hourly", timedelta(hours=1), 0.4),
    ("daily", timedelta(days=1), 0.3),
    ("weekly", timedelta(weeks=1), 0.2),
    ("monthly", timedelta(days=30), 0.1)
]

async def query_time_bucket(bucket_name, delta, weight):
    cutoff = datetime.now(UTC) - delta
    filter_condition = models.Filter(
        must=[
            models.FieldCondition(
                key="created_at",
                range=models.DatetimeRange(gte=cutoff)
            )
        ]
    )
```

```
    results = await client.query_points(
        collection_name="agent_memory",
        query=query_embedding,
        query_filter=filter_condition,
        limit=20
    )

    # Apply temporal weight to scores
    for r in results:
        r.score *= weight

    return results
```

4.3 RFM Score Updates

On Memory Access:

```
async def update_priority_on_access(memory_id: str):
    point = await client.retrieve(
        collection_name="agent_memory",
        ids=[memory_id]
    )[^0]

    metadata = point.payload["metadata"]
    created_at = datetime.fromisoformat(metadata["created_at"])
    access_count = metadata["access_count"] + 1

    # Recompute scores
    recency = rfm_calculator.calculate_recency_score(created_at)
    frequency = rfm_calculator.calculate_frequency_score(access_count)
    importance = metadata["importance_score"]

    priority = 0.3*recency + 0.2*frequency + 0.5*importance

    # Update payload
    await client.set_payload(
        collection_name="agent_memory",
        payload={
            "metadata.access_count": access_count,
            "metadata.recency_score": recency,
            "metadata.frequency_score": frequency,
            "priority_score": priority
        },
        points=[memory_id]
    )
```

5. Production Considerations

5.1 Scalability

Qdrant Cluster Setup[^54]:

- Replication factor ≥ 2 for high availability
- Shard distribution across nodes for load balancing
- gRPC for lower latency vs. REST

Batch Operations:

- Use `batch_embed_content()` for ingestion (50-100 texts/batch)[attached_file:1]
- Use `upsert_batch()` for Qdrant uploads (100-1000 points/batch)[^48]

5.2 Error Recovery

Circuit Breaker Pattern[^42]:

```
class CircuitBreaker:
    def __init__(self, failure_threshold=5, timeout=60):
        self.failure_count = 0
        self.failure_threshold = failure_threshold
        self.timeout = timeout
        self.last_failure_time = None
        self.state = "CLOSED"  # CLOSED | OPEN | HALF_OPEN

    async def call(self, func, *args, **kwargs):
        if self.state == "OPEN":
            if time.time() - self.last_failure_time &gt; self.timeout:
                self.state = "HALF_OPEN"
            else:
                raise Exception("Circuit breaker is OPEN")

        try:
            result = await func(*args, **kwargs)
            if self.state == "HALF_OPEN":
                self.state = "CLOSED"
                self.failure_count = 0
            return result
        except Exception as e:
            self.failure_count += 1
            self.last_failure_time = time.time()
            if self.failure_count &gt;= self.failure_threshold:
                self.state = "OPEN"
            raise
```

5.3 Monitoring

Key Metrics:

- Retrieval latency (p50, p95, p99)
- Embedding generation time
- Reranking time
- Qdrant query time
- Memory storage growth rate
- Priority score distribution

Logging Strategy:

- Structured JSON logs (timestamp, level, component, event, metadata)
- Async logging to avoid blocking main thread
- Separate log streams for errors, warnings, info

6. Conclusion

This memory system implements scientifically-grounded principles (Ebbinghaus forgetting curve, RFM scoring, hybrid search) with pragmatic engineering practices (async/await, error handling, config validation). The design prioritizes **working functionality** over theoretical purity, addressing all critical gaps identified in the audit.

The complete implementation follows in the next section, providing production-ready code that can be deployed immediately with minimal configuration.
[19] [20] [21] [22] [23] [24] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] [39] [40]

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