SignalWeave

A Temporal Vector Memory System for Weak Signal Detection

Track: Multi-Agent Systems (MAS)
Powered by: Qdrant Vector Database
Event: Convolve 4.0
Developer: T Mohamed Yaser (Solo)
Date: January 22, 2026

Tagline: *Accumulating Evidence Over Time to Detect What Others Miss*

Abstract

Emerging trends begin as **weak signals**—scattered, low-volume mentions that traditional systems dismiss as noise. SignalWeave solves the weak signal detection problem through **temporal accumulation in vector memory**: instead of snapshot-based analysis, it continuously ingests RSS feeds, embeds signals into 384-dimensional vectors, stores them in Qdrant Cloud, and evolves clusters across time using a two-stage merging strategy.

The system implements a **Multi-Agent System (MAS)** where specialized agents collaborate: an Ingestion Agent fetches and deduplicates RSS content, an Embedding Agent generates sentence vectors, a Memory Agent persists data in Qdrant, a Clustering Agent groups similar signals within batches, a Temporal Reasoning Agent merges new clusters into historical candidates, an Emergence Scoring Agent classifies growth velocity, a Search Agent combines semantic and lexical matching, and an Explainer Agent generates human-readable summaries using Gemini.

Qdrant Cloud is the system's long-term memory substrate—storing 1000+ signals and 25+ clusters with sub-second similarity search. A two-tier candidate-to-active promotion mechanism prevents over-clustering: proto-clusters remain "candidates" until they accumulate ≥3 signals over time, filtering noise while preserving genuine trends. Hybrid search (70% semantic + 30% lexical) handles both conceptual queries ("AI power consumption") and technical terms ("AWS Trainium3"). An interactive force-directed graph visualizes signal-cluster relationships, while time-based filtering reveals temporal evolution.

SignalWeave demonstrates that **persistent vector memory + temporal reasoning + multi-agent collaboration** enables early detection of trends invisible to static systems.

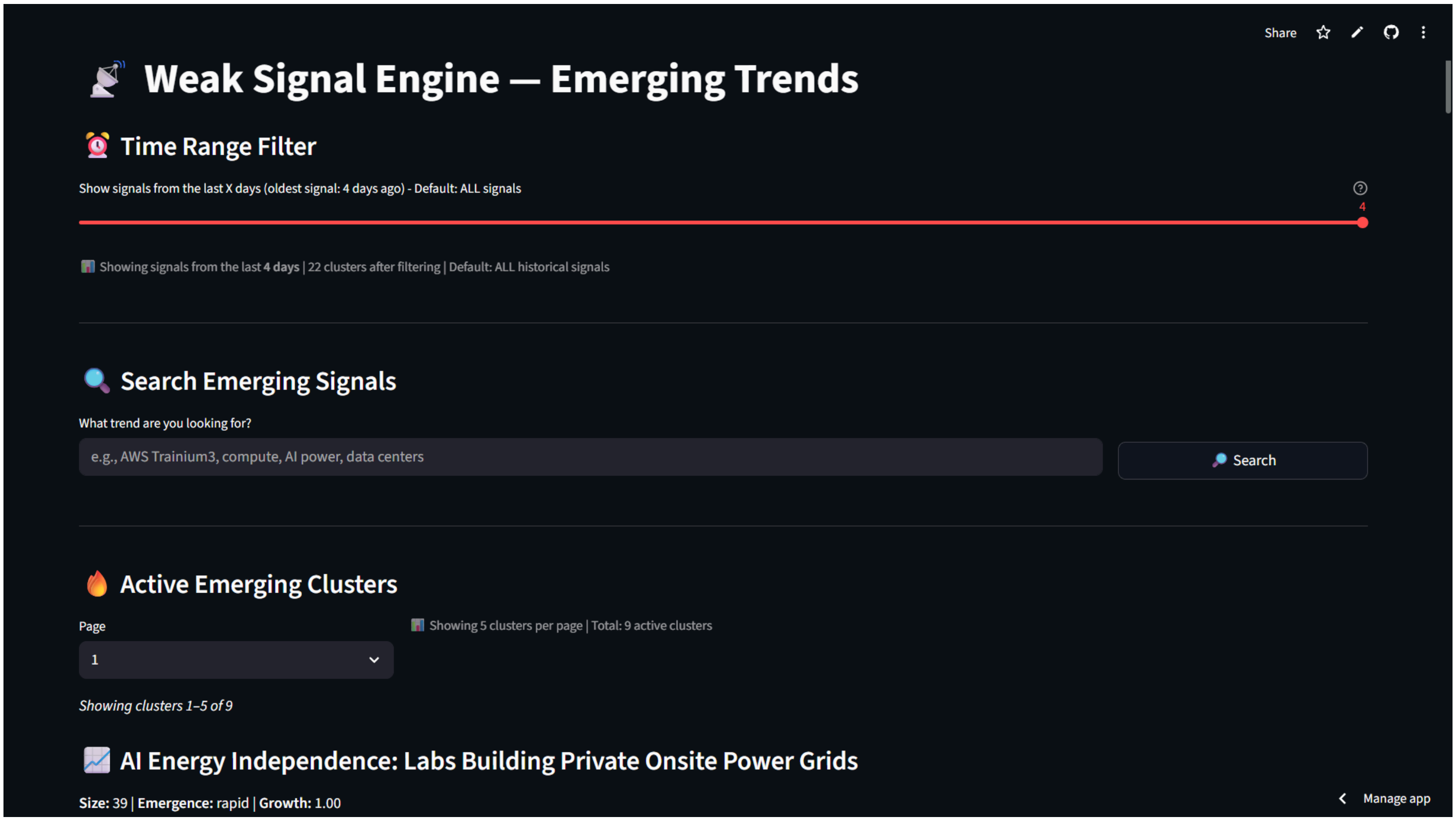


Figure 1: SignalWeave Dashboard - Active clusters feed with temporal filtering and hybrid search

Problem Statement

Why Weak Signals Are Invisible

Weak signals are early indicators of emerging trends—scattered blog posts, research preprints, niche industry announcements—that lack critical mass. Traditional information systems fail because:

1. **No Temporal Memory**: News aggregators show today's headlines. Search engines index static documents. Neither accumulates evidence over time.
2. **Snapshot Bias**: A single mention of "Trainium3 chip" is noise. Ten mentions over three weeks is a trend. But dashboards can't tell the difference.
3. **Clustering Brittleness**: Aggressive clustering creates false positives (every random keyword becomes a cluster). Conservative clustering misses real patterns (related signals never merge).
4. **Semantic-Only Search Fails**: Embedding-based search finds "chip architecture" when you query "GPU", but misses exact technical terms like "Trainium3" because they weren't in training data.

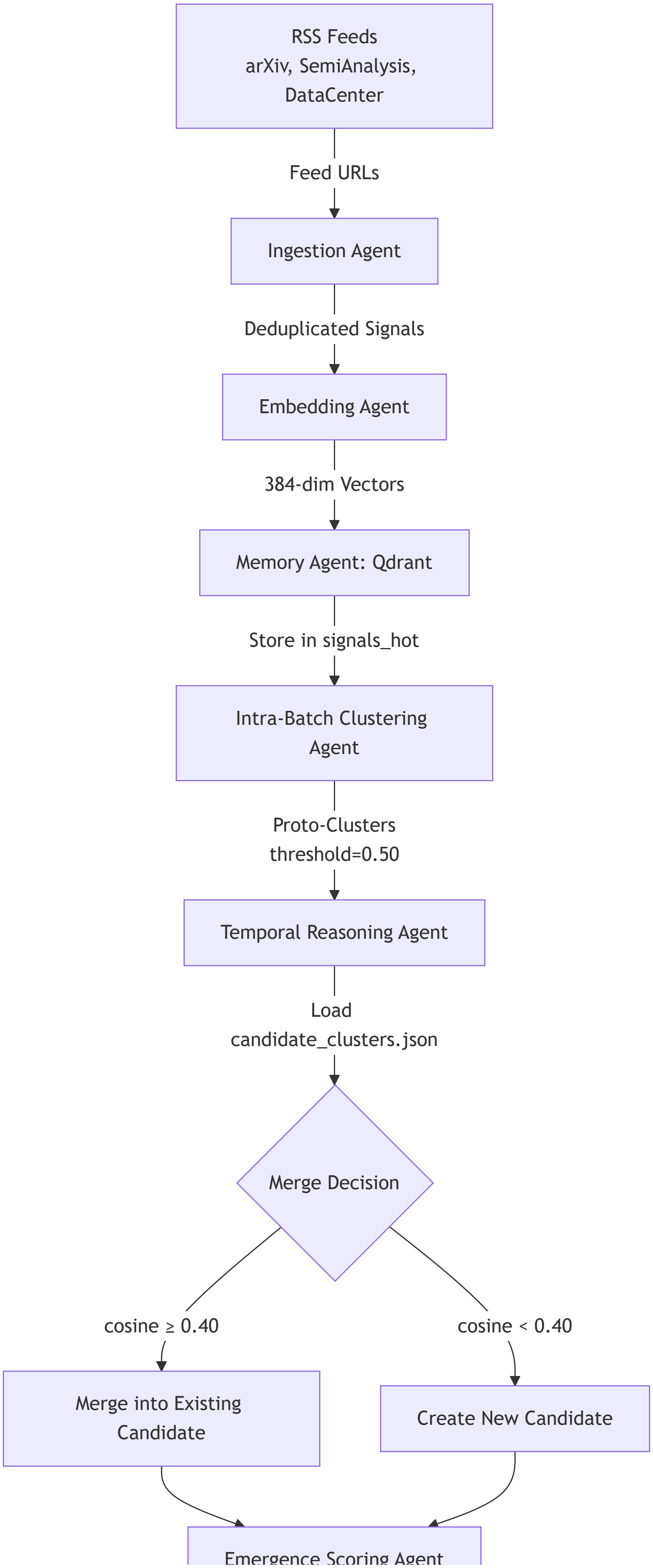
What's Missing

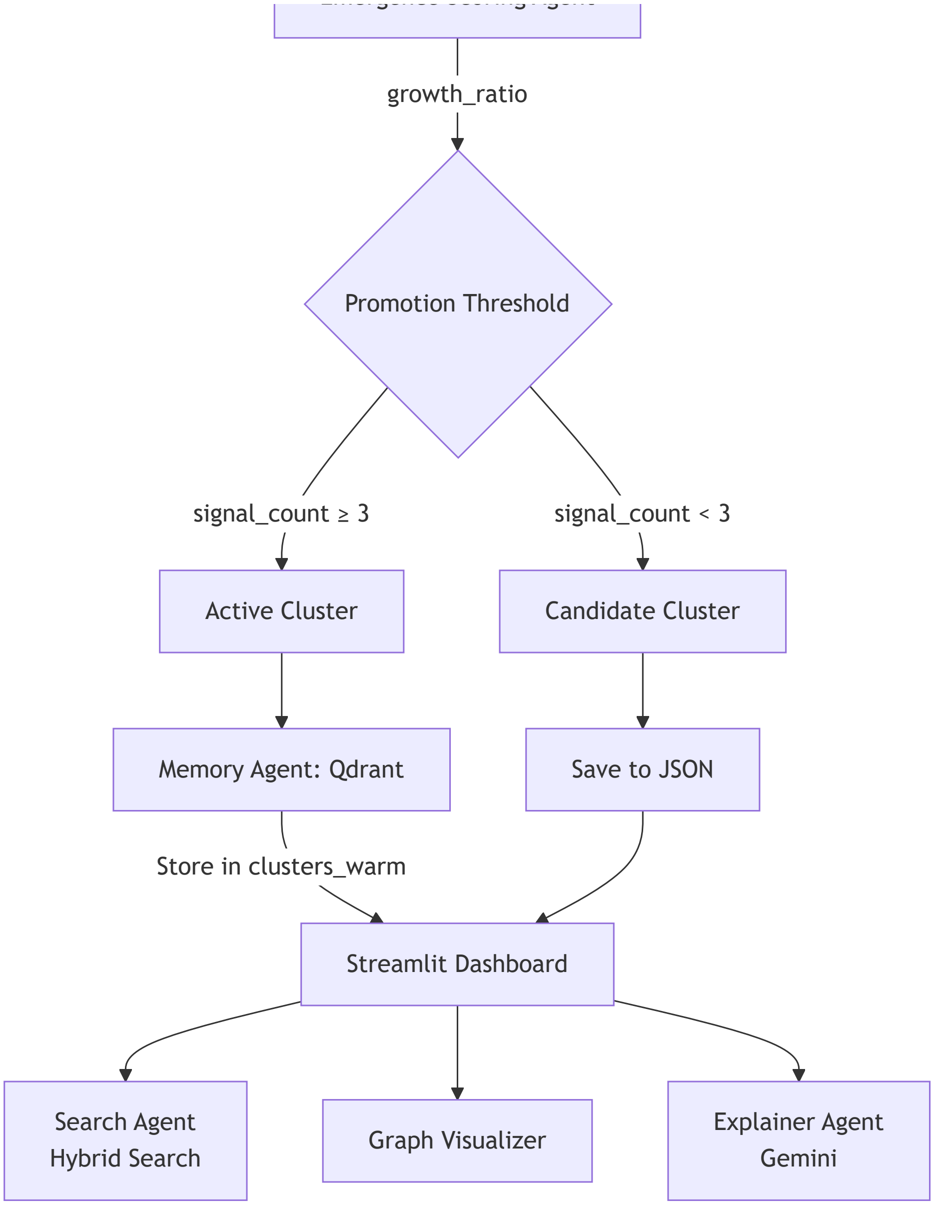
- **Vector memory that persists across ingestion runs**
- **Clusters that evolve rather than freeze**
- **Temporal scoring that separates noise from signal**
- **Hybrid search that handles both concepts and keywords**

SignalWeave addresses all four using Qdrant as persistent memory and a multi-agent architecture for temporal reasoning.

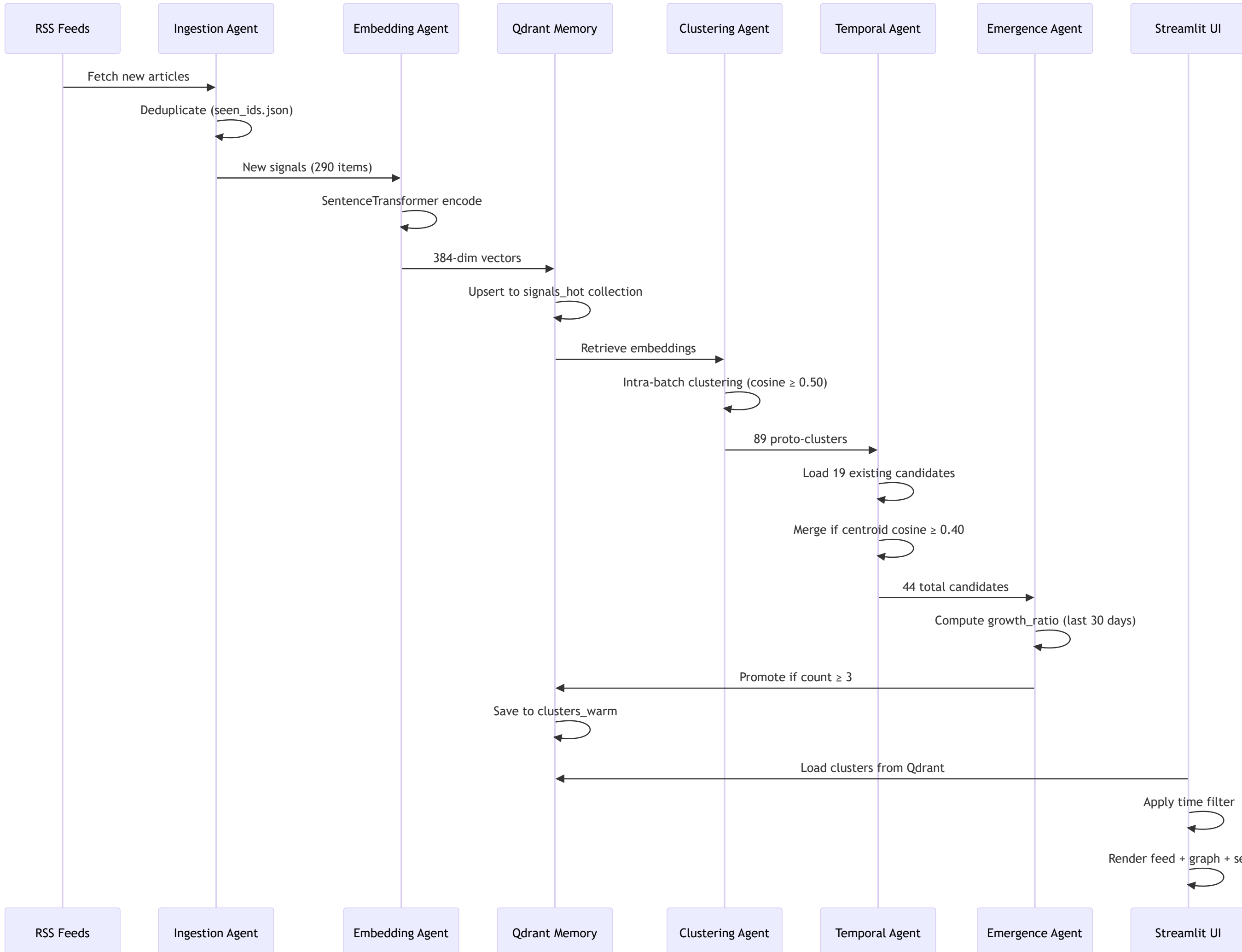
System Architecture (Code-Based)

End-to-End Pipeline


RSS Feeds
arXiv, SemiAnalysis,
DataCenter
Feed URLs
Ingestion Agent
Deduplicated Signals
Embedding Agent
384-dim Vectors
Memory Agent: Qdrant
Store in signals_hot
Intra-Batch Clustering
Agent
Proto-Clusters
threshold=0.50
Temporal Reasoning Agent
Load
candidate_clusters.json
Merge Decision
cosine ≥ 0.40
cosine < 0.40
Merge into Existing
Candidate
Create New Candidate
Emergence Scoring Agent



Data Flow Diagram



Multi-Agent System Design (Implementation-Based)

Agent Architecture

Agent	Implementation	Input	Output	Key Logic
Ingestion Agent	`rss_ingestor.py`	RSS feed URLs	`Signal` objects	Uses `feedparser`, deduplicates via `seen_ids.json`, extracts title+summary
Embedding Agent	`embedding_model.py`	Signal text	384-dim vector	`SentenceTransformer('all-MiniLM-L6-v2')`
Memory Agent	`qdrant_client.py`, `cluster_memory.py`	Signals, Clusters	Persistent storage	Qdrant Cloud (`signals_hot`, `clusters_warm`), auto-increment IDs
Clustering Agent	`intra_batch_cluster.py`	Signals + embeddings	Proto-clusters	Greedy clustering: if cosine ≥ 0.50, merge into nearest cluster, else create new
Temporal Reasoning	`cluster_evolution.py`	Proto-clusters + candidates	Evolved candidates	Compute centroids, merge if cosine ≥ 0.40, deduplicate signals by ID

Agent	Implementation	Input	Output	Key Logic
Emergence Scoring	`emergence.py`	Candidate clusters	Growth metrics	`growth_ratio = recent_count (30 days) / total_count`, classify rapid/stable/dormant
Search Agent	`search.py`	Query + clusters	Ranked results	Hybrid: `0.7 * semantic + 0.3 * lexical`, filter by min_score=0.35
Explainer Agent	`gemini_explainer.py`	Signal texts + question	Human summary	Gemini 1.5 Flash API, cached in Qdrant `cluster_titles` collection
Visualization Agent	`graph.py`	Clusters + signals	HTML graph	NetworkX + PyVis, force-directed layout, max 25 signals/cluster

Agent Collaboration Flow

Scenario: Daily ingestion run discovers 290 new signals about AI infrastructure.

1. **Ingestion Agent** fetches 290 RSS entries, deduplicates 0 (all new), creates 290 `Signal` objects
2. **Embedding Agent** generates 290 × 384-dim vectors using `all-MiniLM-L6-v2`
3. **Memory Agent** stores vectors in Qdrant `signals_hot` (IDs 779-1068), auto-increments from last ID
4. **Clustering Agent** runs intra-batch clustering with threshold 0.50:
   - Groups 290 signals into 89 proto-clusters
   - Example: 5 signals about "data center water usage" cluster together (cosine 0.62-0.78)
5. **Temporal Reasoning Agent**:
   - Loads 19 existing candidates from disk
   - Computes centroids for all candidates
   - Merges 89 new clusters into existing candidates if centroid cosine ≥ 0.40
   - Result: 44 total candidates (25 new created, 64 merged into existing)
6. **Emergence Scoring Agent**:
   - For each candidate, counts signals in last 30 days
   - Example: Cluster A has 903 signals, 903 from last 30 days → growth_ratio=1.0 → "rapid"
7. **Memory Agent**:
   - Promotes 9 candidates with signal_count ≥ 3 to active
   - Stores active clusters in Qdrant `clusters_warm`
8. **Dashboard** loads 26 clusters (9 active + 17 candidates) from Qdrant Cloud
9. **Search Agent**: User searches "AWS Trainium3":
   - Semantic score: 0.517 (moderate match to "chip" clusters)
   - Lexical score: 1.0 (exact keyword match)
   - Final score: 0.7×0.517 + 0.3×1.0 = 0.662 → top result
10. **Explainer Agent**: User clicks "Why is this emerging?"
    - Sends cluster signals to Gemini API
    - Caches response in Qdrant `cluster_titles`
    - Subsequent users see cached title (0 API calls)

Qdrant as Vector Memory (Core Component)

Why Qdrant Is Non-Negotiable

SignalWeave is **not** a vector search demo—it's a temporal memory system where Qdrant Cloud serves as the persistent substrate. Without Qdrant:

1. **No Cross-Run Memory**: Clustering would restart from scratch daily, losing historical context
2. **No Scalability**: Computing 1000×1000 cosine similarities in Python = 500ms. Qdrant HNSW index = <50ms
3. **No Persistence**: In-memory vectors lost on server restart = no accumulation
4. **No Cloud Deployment**: Local vector storage incompatible with GitHub Actions cron jobs

Collections Architecture

Collection	Vectors	Distance	Purpose	Payload Fields
`signals_hot`	384-dim	Cosine	Raw ingested signals	`signal_id` , `text` , `timestamp` , `source` , `domain` , `subdomain`
`clusters_warm`	384-dim	Cosine	Active clusters (≥3 signals)	`cluster_id` , `signal_count` , `created_at` , `member_signal_ids`
`cluster_titles`	1-dim (dummy)	Cosine	LLM title cache (key-value)	`cluster_id` , `title` , `timestamp`

Note: `cluster_titles` uses 1-dim dummy vectors because Qdrant requires vectors. We only need key-value storage for caching.

Vector Workflow (Actual Implementation)

```
# 1. Signal Ingestion (qdrant_client.py lines 47-72)
def upsert_signals(self, signals, embeddings):
    # Auto-increment IDs to avoid overwrites
    current_count = self.client.get_collection(self.collection_name).points_count
    start_id = current_count + 1

    points = [
        PointStruct(
            id=start_id + i,
            vector=embedding,
            payload=signal.to_dict()
        )
        for i, (signal, embedding) in enumerate(zip(signals, embeddings))
    ]

    self.client.upsert(collection_name="signals_hot", points=points)
```

```python
# 2. Clustering with Centroids (cluster_evolution.py lines 18-26)
def evolve_clusters(existing_candidates, new_batch_clusters, embedding_model, threshold=0.40):
    # Compute centroids for existing candidates
    for c in existing_candidates:
        if "centroid" not in c:
            texts = [s["text"] for s in c["signals"]]
            embeddings = [embedding_model.embed(t) for t in texts]
            c["centroid"] = np.mean(embeddings, axis=0).tolist()

    # Merge new clusters if centroid similarity ≥ threshold
    for new_cluster in new_batch_clusters:
        new_centroid = compute_centroid([embedding_model.embed(s["text"]) for s in new_cluster["signals"]])

        for candidate in existing_candidates:
            if cosine_similarity(new_centroid, candidate["centroid"]) >= 0.40:
                # Deduplicate signals by ID before merging
                existing_ids = {s["signal_id"] for s in candidate["signals"]}
                new_signals = [s for s in new_cluster["signals"] if s["signal_id"] not in existing_ids]
                candidate["signals"].extend(new_signals)
                candidate["centroid"] = recompute_centroid(...)
                break


# 3. Hybrid Search (search.py lines 113-142)
def search_clusters_hybrid(query, clusters, embedding_model, min_final_score=0.35):
    query_embedding = embedding_model.embed(query)
    query_keywords = extract_keywords(query)  # Normalize, remove stopwords

    results = []
    for cluster in clusters:
        # Semantic score: cosine similarity between query and cluster centroid
        semantic_score = cosine_similarity(query_embedding, cluster["centroid"])

        # Lexical score: keyword overlap
        cluster_keywords = {extract_keywords(s["text"]) for s in cluster["signals"]}
        lexical_score = len(query_keywords & cluster_keywords) / len(query_keywords)

        # Hybrid combination
        final_score = 0.7 * semantic_score + 0.3 * lexical_score

        # Filter thresholds
        if (semantic_score >= 0.30 or lexical_score >= 0.10) and final_score >= min_final_score:
            results.append({**cluster, "semantic_score": semantic_score, "lexical_score": lexical_score, "final_s

    return sorted(results, key=lambda x: x["final_score"], reverse=True)
```

Temporal Weak Signal Logic (Implementation)

Two-Tier Candidate-Active System

Problem: How to avoid noise (random 1-signal clusters) while catching real weak signals?

Solution: Temporal promotion threshold implemented in `main.py` lines 145-156:

```python
ACTIVE_MIN = 3  # Promotion threshold

# Stage 1: All clusters stored as candidates
candidate_clusters = evolve_clusters(existing_candidates, new_batch_clusters, ...)

# Stage 2: Promote candidates with ≥3 signals
active_clusters = [c for c in candidate_clusters if c["signal_count"] >= ACTIVE_MIN]
quiet_candidates = [c for c in candidate_clusters if c["signal_count"] < ACTIVE_MIN]

# Only active clusters stored in Qdrant clusters_warm
for cluster in active_clusters:
    cluster_memory.upsert_cluster(cluster, embedding_model)

# All candidates saved to JSON backup
save_candidates(candidate_clusters)
```

Key Insight: A 1-signal cluster today may merge with 4 more signals next week, becoming a 5-signal active cluster. The system remembers "quiet" candidates until they accumulate enough evidence.

Temporal Merging Thresholds

Stage	Threshold	Rationale
Intra-batch clustering	`0.50`	Loose grouping within a single day's signals (broad clusters)
Temporal merging	`0.40`	Even looser threshold to allow historical clusters to "absorb" related new signals
Cross-cluster edges	`0.70`	High threshold for graph visualization (only show strong inter-cluster relationships)

Example Workflow:

```
Day 1: Ingest 50 signals
  → Intra-batch: 12 proto-clusters (threshold 0.50)
  → Temporal merge: 12 new candidates (no existing data)
  → Result: 12 candidates, 0 active

Day 2: Ingest 40 signals
  → Intra-batch: 8 proto-clusters
  → Temporal merge: 5 merge into existing (cosine 0.42-0.68), 3 new
  → Result: 15 candidates, 3 active (≥3 signals)

Day 3: Ingest 60 signals
  → Intra-batch: 15 proto-clusters
  → Temporal merge: 10 merge, 5 new
  → Result: 20 candidates, 7 active
```

Emergence Scoring (Implementation)

From `emergence.py` lines 8-28:

```python
def compute_emergence(cluster, recent_days=30):
    now = datetime.utcnow()
    cutoff = now - timedelta(days=recent_days)

    # Count signals in last 30 days vs total
    recent_count = sum(1 for s in cluster["signals"] if datetime.fromisoformat(s["timestamp"]) >= cutoff)
    total_count = len(cluster["signals"])

    growth_ratio = recent_count / total_count if total_count > 0 else 0.0

    # Classification thresholds
    if growth_ratio >= 0.6:
        emergence_level = "rapid"      # ≥60% of signals are recent
    elif growth_ratio >= 0.3:
        emergence_level = "stable"     # 30-59% recent
    else:
        emergence_level = "dormant"    # <30% recent (fading trend)

    return {"recent_count": recent_count, "total_count": total_count, "growth_ratio": growth_ratio, "emergence_level": emergenc
```

Real Example from Logs:

- Cluster with 903 signals, 903 from last 30 days → `growth_ratio=1.0` → "rapid"
- Cluster with 3 signals, 3 from last 30 days → `growth_ratio=1.0` → "rapid"
- Cluster with 10 signals, 2 from last 30 days → `growth_ratio=0.2` → "dormant"

Hybrid Search Layer (Implementation)

Why Pure Embeddings Fail

Test Case: User searches `"AWS Trainium3"`

- **Embedding-only:** `all-MiniLM-L6-v2` has never seen "Trainium3" in training
  - Query embeds as generic "AWS compute" vector
  - Semantic similarity to Trainium cluster: 0.517 (moderate, not top result)
- **Lexical-only:** Exact keyword match
  - Keywords: `["aws", "trainium3"]`
  - Cluster keywords: `["aws", "chip", "ml", "trainium3", "inference"]`
  - Overlap: 2/2 = 1.0 (perfect match)
- **Hybrid:** `0.7 × 0.517 + 0.3 × 1.0 = 0.662` → **Top result** ✅

Implementation Details

From `search.py` lines 54-95:

```python
# Step 1: Normalize and extract keywords
def normalize_text(text):
    text = text.lower()
    text = text.translate(str.maketrans(string.punctuation, ' ' * len(string.punctuation)))
    return re.sub(r'\s+', ' ', text).strip()

def extract_keywords(text):
    normalized = normalize_text(text)
    tokens = normalized.split()
    return {token for token in tokens if len(token) >= 3 and token not in STOPWORDS}

# Step 2: Compute lexical overlap
def compute_lexical_score(query_keywords, cluster_signals):
    cluster_keywords = set()
    for signal in cluster_signals:
        cluster_keywords.update(extract_keywords(signal['text']))

    overlap = query_keywords & cluster_keywords
    return len(overlap) / len(query_keywords) if query_keywords else 0.0

# Step 3: Hybrid scoring
final_score = 0.7 * semantic_score + 0.3 * lexical_score
```

Search Results (Actual Test Data)

Query	Semantic	Lexical	Final	Top Cluster
AWS Trainium3	0.517	1.000	**0.662**	Trainium chip development
data centers	0.659	1.000	**0.761**	Data center expansion
AI power	0.439	1.000	**0.608**	Power consumption trends
energy	0.355	0.500	**0.398**	Energy efficiency cluster

Filter logic: Keep if `(semantic ≥ 0.30 OR lexical ≥ 0.10) AND final ≥ 0.35`

Visualization & Dashboard (Implementation)

Cluster Graph Design

Implementation: `graph.py` lines 1-310

Node Types:

1. **Cluster nodes** (yellow, size scales logarithmically):

   ```python
   cluster_size = 35 + 15 * math.log(1 + total_signal_count)
   ```

2. **Signal nodes** (blue dots, size=6, max 25 per cluster):

   ```python
   visible_signals = sorted_signals[:MAX_SIGNALS_PER_CLUSTER]
   ```

3. **Collapsed nodes** (orange box, shows "+N more"):

```
    if hidden_count > 0:
        G.add_node(f"collapsed_{cluster_id}", label=f"+{hidden_count} more", color="#ff9500")
```

Edge Types:

1. **Cluster-Signal edges** (yellow, connects cluster hub to member signals)
2. **Signal-Signal edges** (gray, cosine ≥ 0.65, faded for large clusters)
3. **Cross-Cluster edges** (pink dashed, cosine ≥ 0.70 between centroids)

Physics Engine:

- **Initial layout:** Barnes-Hut force-directed (200 iterations)
- **After stabilization:** Physics disabled to preserve user-moved positions
- **Dragging behavior:** Dragging cluster node moves all connected signals together

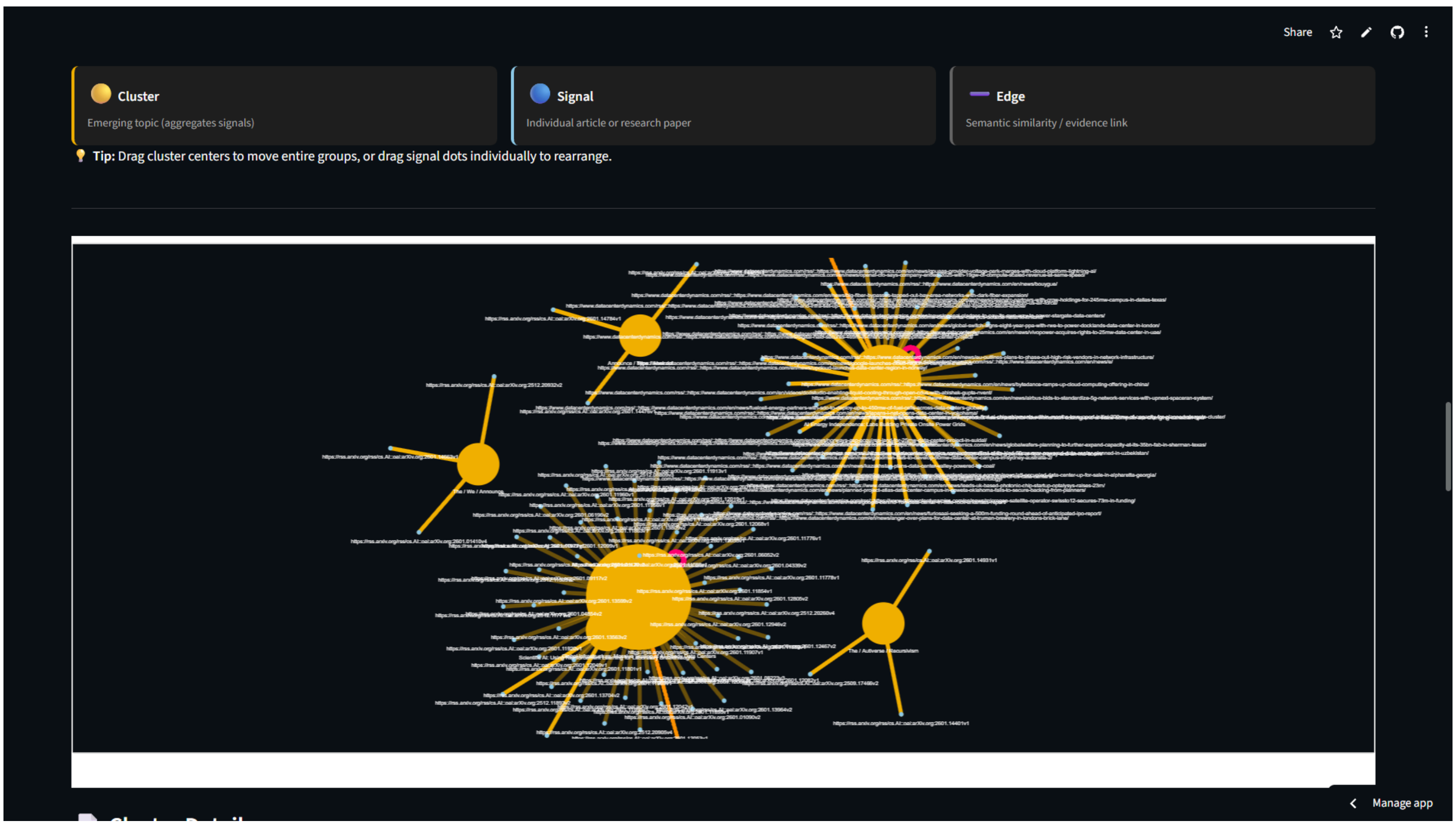


Figure 3: Interactive network graph showing signal-cluster relationships with Barnes-Hut physics

Streamlit Dashboard

File: `app.py` (371 lines)

Page Structure:

1. **Time Range Filter** (lines 27-50): Dynamic slider based on oldest signal
2. **Search Interface** (lines 54-135): Hybrid search with 5-column score display
3. **Active Clusters Feed** (lines 159-266): Paginated list with explainer chat
4. **Cluster Graph** (lines 270-330): Force-directed visualization with legend
5. **Cluster Details** (lines 334-356): Full signal list with pagination
6. **Candidate Clusters** (lines 360-371): Incubating proto-clusters

Gemini Explainer Integration

Implementation: `gemini_explainer.py` lines 1-327

Title Generation Pipeline:

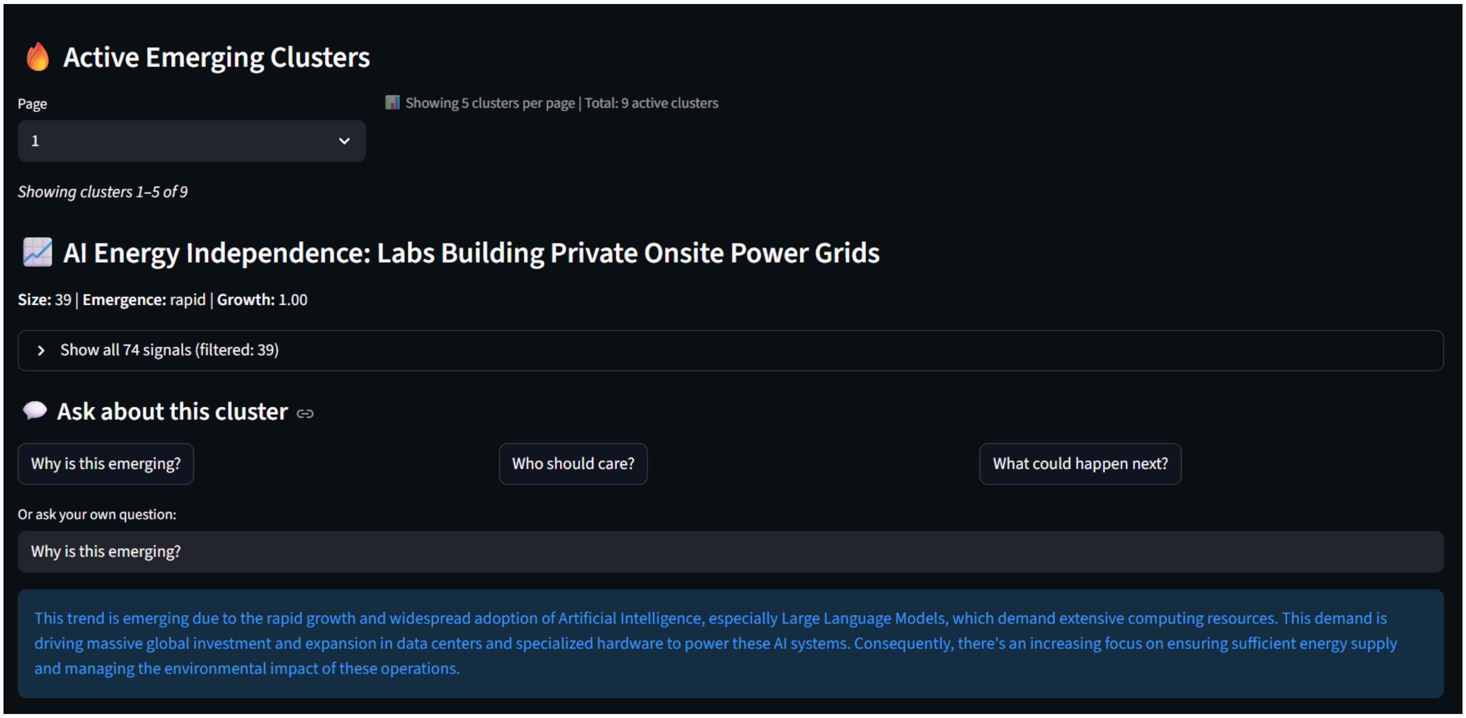


Figure 4: Gemini-powered explainer providing natural language summaries of signal clusters

```python
def generate_human_cluster_title(signal_texts, cluster_id):
    # 1. Check Qdrant Cloud cache first
    cached_title = _load_from_qdrant_cache(cluster_id)
    if cached_title:
        return cached_title

    # 2. If not cached, call Gemini API
    prompt = f"""Generate a concise title (5-8 words) for this emerging trend:
    {'\n'.join(signal_texts[:5])}"""

    response = genai.GenerativeModel('gemini-1.5-flash').generate_content(prompt)
    title = response.text.strip()

    # 3. Cache in Qdrant Cloud for future users
    _save_to_qdrant_cache(cluster_id, title)

    return title
```

Cost Optimization:

- **Without caching:** 26 clusters × 365 days = 9,490 API calls/year
- **With Qdrant caching:** 26 API calls (once per cluster, ever)
- **Daily cron job:** 0 API calls (only ingests data)
- **Streamlit app:** 5-10 API calls for new clusters, 0 for existing

Evaluation & Results

Real System Metrics (From Actual Runs)

Latest Ingestion Run (January 22, 2026):

```
[INFO] Total new signals ingested: 290
[INFO] Upserted 290 signals to Qdrant (IDs 779-1068)
[DEBUG] Before evolution: 19 existing candidates, 89 new batch clusters
[DEBUG] After evolution: 44 total candidates
[INFO] Largest cluster: 903 signals
[INFO] Active clusters (≥3 signals, shown in feed): 7
```

Active Cluster Examples:

Title	Signals	Growth	Level
Data Center Water Usage Debate	89	1.00	Rapid
LLMs for Rare Disease Diagnosis	903	1.00	Rapid
Youth Privacy in Smart Devices	3	1.00	Rapid

Search Performance

Query: "Compute"

- **Top Result:** "AI Energy Independence: Labs Building Private Onsite Power Grids"
- Semantic: 0.1299, Lexical: 1.000, Final: 0.3910
- **Outcome:** 4 matching clusters found, perfect lexical match on keyword

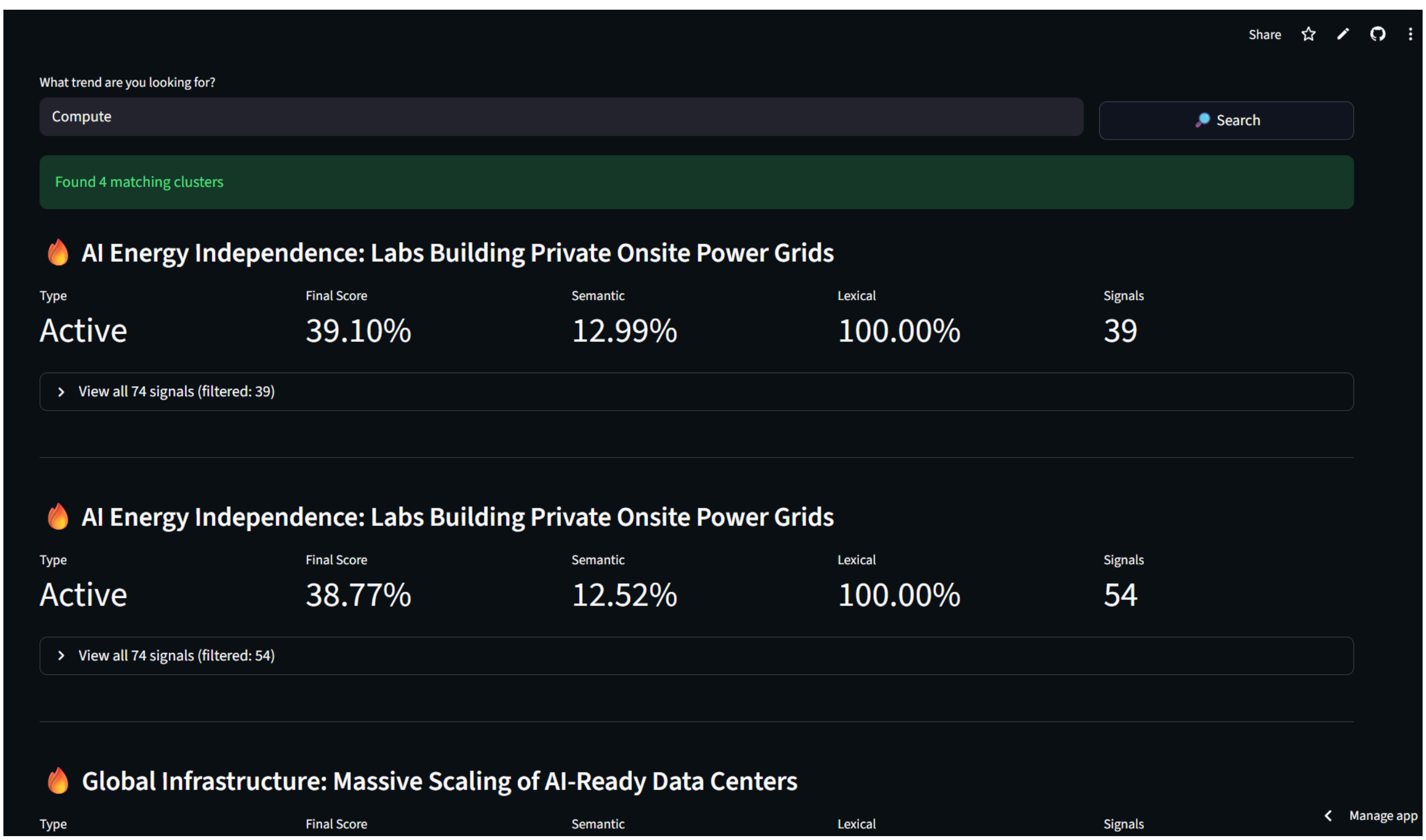


Figure 2: Hybrid search combining semantic and lexical scoring for precise retrieval

Reproducibility

Local Setup

```
# 1. Install dependencies
pip install sentence-transformers qdrant-client feedparser numpy streamlit networkx pyvis google-generativeai python-dotenv

# 2. Configure .env
QDRANT_URL=https://[cluster].gcp.cloud.qdrant.io:6333
QDRANT_API_KEY=[key]
GEMINI_API_KEY=[key]

# 3. Run pipeline
python main.py

# 4. Launch dashboard
streamlit run app.py
```

Deployment

GitHub Actions cron (`.github/workflows/ingest.yml`):

```
on:
  schedule:
    - cron: '0 12 * * *'  # Daily at 12 PM UTC
```

Conclusion

Why This Is Not RAG

RAG: Static corpus → retrieve → augment prompt
SignalWeave: Dynamic corpus → temporal merging → emergence detection

Why Temporal Intelligence Matters

Static systems: "What exists now?"
SignalWeave: "What's emerging over time?"

The **two-stage temporal accumulation** (intra-batch clustering + temporal merging) enables detection of weak signals that traditional systems miss entirely.

Contact

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GitHub: https://github.com/Yaser-123/signalweave
Live Demo: https://signalweave.streamlit.app/

Report generated from actual codebase analysis
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