

Adaptive Embedding Format Switching and Semantic Translation in High-Volume Telemetry Systems

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Abstract—High-volume telemetry pipelines increasingly rely on learned vector embeddings to support anomaly detection, diagnostics, and predictive modeling. However, most production systems apply a fixed embedding format—typically dense or quantized vectors—uniformly across all signals, regardless of structural variability or downstream task fidelity. This paper introduces a telemetry-native embedding architecture—AMC (Adaptive Multi-Vector Correlation)—that enables per-datapoint format switching and bounded semantic translation across heterogeneous vector spaces.

To ensure reproducible validation, we evaluate AMC on NASA’s MODIS Earth observation archive—a demanding testbed exhibiting extreme structural heterogeneity (0.1% to 98.7% sparsity variation), temporal drift, and complex missing-data structures that challenge static embedding approaches while enabling complete methodological transparency. MODIS land surface temperature and vegetation indices provide the structural complexity needed to validate adaptive embedding approaches: extreme sparsity heterogeneity, entropy variation, and temporal dynamics that stress-test format switching mechanisms.

AMC introduces: (1) a *Runtime Format Switching Engine* that selects optimal encodings via a multi-factor cost function incorporating signal entropy, volatility, sparsity, and anomaly detection feedback; and (2) a *Semantic Translation Framework* that enables cross-format embedding alignment under an ϵ -bounded drift constraint, enforced via Procrustes distance and KL divergence.

AMC achieves a 37.1% reduction in vector storage overhead over LZ4-compressed baselines, a 12.2% improvement in anomaly detection F1 over adaptive quantization and heuristic alternatives, and 2.4ms median selection latency across 10 MODIS-derived metrics. All results are fully reproducible, and our pipeline is designed for extension to other domains requiring task-aware representation switching under semantic constraints.

I. INTRODUCTION

High-volume telemetry systems—such as those supporting NASA flight operations, Earth observation platforms, and autonomous space missions—routinely generate billions of high-dimensional, heterogeneous signals. These signals are increasingly encoded as vector embeddings to support anomaly detection, fault localization, and predictive modeling. However, most observability pipelines today apply a fixed embedding format—such as dense, sparse, or quantized

vectors—uniformly across all telemetry streams, regardless of underlying signal characteristics or downstream analytical requirements.

This architectural assumption introduces measurable inefficiencies. To demonstrate this systematically, we analyze NASA’s MODIS Earth observation archive—a publicly available dataset that exhibits the extreme structural heterogeneity challenging modern telemetry systems: up to 300× sparsity variation across regions and sensors, significant temporal drift, and complex distribution patterns. When encoded with fixed formats, this results in quantifiable waste: up to 42.1% excess storage for sparse signals and 15.3% degradation in anomaly recall when complex signals are over-compressed.

Existing solutions offer only partial mitigation. Compression schemes such as LZ4 and zstd reduce byte-level overhead but are agnostic to downstream semantic fidelity. Vector databases like Pinecone and Weaviate support multiple formats statically, but lack runtime adaptation and task-aware rollback. ML pipelines may permit format conversion, but without semantic drift bounds or forensic traceability, such conversions can silently degrade model performance.

We deliberately evaluate AMC using MODIS public data rather than proprietary telemetry logs to ensure reproducible research and community validation. MODIS provides a methodologically rigorous testbed: its structural complexity and heterogeneity equal or exceed those found in operational telemetry systems, while enabling transparent experimental validation that others can replicate and extend.

This paper introduces a telemetry-native embedding architecture—AMC (Adaptive Multi-Vector Correlation)—that enables per-datapoint format switching and bounded semantic translation across heterogeneous vector spaces. AMC addresses the limitations of static encoding by introducing two core mechanisms:

- 1) **Runtime Format Switching.** A *Format Switching Engine* selects the optimal encoding for each telemetry datapoint using a multi-objective cost function that integrates entropy, sparsity, volatility, and online anomaly feedback. Weights are updated via a convergence-

guaranteed EMA loop, and all format transitions are tracked using UUID-linked semantic lineage with dual-write rollback safety.

- 2) **Semantic Translation Framework.** A directed graph of learned translators enables cross-format embedding alignment. Each translator is constrained by an ϵ -bounded semantic drift loss combining Procrustes distance and KL divergence. A background daemon monitors translation quality and triggers retraining or fallback when drift exceeds safe thresholds.

We evaluate AMC on structurally diverse MODIS telemetry streams derived from land surface temperature and vegetation indices. AMC achieves a 37.1% reduction in storage overhead over LZ4-compressed baselines, a 12.2% improvement in anomaly F1 over adaptive quantization, and sub-2.4ms median selection latency. Our results show that format switching and semantic alignment significantly outperform static baselines—both in storage efficiency and task fidelity.

To our knowledge, AMC is the first system to combine runtime format switching, drift-bounded semantic translation, and forensic rollback in a telemetry-scale embedding pipeline. The remainder of this paper presents AMC’s theoretical framework, system architecture, and evaluation, and situates its contributions within emerging approaches to adaptive observability, robust embedding infrastructures, and large-scale semantic traceability.

II. RELATED WORK

A. Vector Embeddings in Observability Systems

Vector embeddings are increasingly used in observability pipelines to represent telemetry-style data—including flight system metrics, Earth observation signals, and high-frequency environmental measurements—for anomaly detection, diagnostics, and predictive modeling. Industry systems such as Datadog [8] and New Relic [14] (via engineering blog documentation) apply fixed embedding formats—typically dense or compressed vectors—for compatibility with low-latency dashboards and indexing layers. However, these architectures do not support runtime format adaptation, per-vector switching, semantic translation, or rollback traceability.

To our knowledge, no deployed observability pipeline supports telemetry-native format switching informed by signal characteristics or task-specific feedback. Our work introduces a runtime embedding framework with semantic preservation guarantees, rollback safety, and per-datapoint adaptability for mission-scale telemetry workloads.

AMC’s evaluation strategy prioritizes methodological rigor through NASA’s publicly available MODIS archive. This dataset provides the structural diversity and complexity needed to validate adaptive embedding approaches while ensuring complete experimental reproducibility—a critical advantage over proprietary telemetry evaluations that cannot be independently verified. These data sources preserve the structural diversity, sparsity irregularities, and temporal dynamics characteristic of operational telemetry—while enabling fully reproducible experimentation.

MODIS telemetry streams capture real-world complexity in signal sparsity, entropy, and temporal drift—making them an effective benchmark for testing runtime representation adaptation in systems like AMC.

B. Adaptive Format Selection and Representation Optimization

Dynamic representation has been explored in several ML and systems contexts. Examples include quantization-aware inference [12], dynamic attention routing [4], and resource-adaptive activation sparsification [5]. In high-performance computing, Morpheus [16] performs runtime switching across sparse matrix formats to optimize kernel performance in SpMV workloads.

Our problem space introduces distinct constraints: telemetry vectors exhibit up to $300\times$ sparsity variation and over $10\times$ entropy variance within single missions, with ingestion rates exceeding 50,000 vectors/sec. Format decisions must be made in under 5ms while preserving semantic fidelity across time. Unlike Morpheus and related systems, we target downstream ML performance—not kernel throughput—and enforce full rollback capability and lineage tracking.

C. Semantic Translation and Embedding Alignment

Cross-format embedding alignment is well studied in multilingual NLP and multimodal learning. MUSE [7] and VecMap [3], [2] align word vectors using Procrustes transformations with dictionary supervision or self-learning. Wang et al. [20] extend these ideas to multimodal settings with shared latent projections.

Our setting differs in three key ways: (1) telemetry embeddings are noisy and unlabeled, (2) no stable projection space or supervised anchor exists, and (3) alignment must occur continuously as vector semantics evolve. We train a directed graph of format translators under a hybrid Procrustes + KL loss, constrained by an ϵ -bounded semantic drift threshold. Translation fidelity is monitored in production and retraining is triggered when drift exceeds safe margins.

Prior work on verifiable computation and authenticated data structures (e.g., Tamassia, 2007) established foundational techniques for integrity preservation in adversarial or untrusted environments. These systems—designed for tamper-evident storage and provable data possession—formalized the requirement that content remain verifiably intact under modification or query. We extend this principle beyond content to *semantic representation* itself, proposing that telemetry-derived embeddings must maintain bounded translation fidelity across format transformations. Our system inherits the ethos of Tamassia’s verifiability logic but applies it to the latent vector space, where silent semantic drift poses significant risk for high-stakes inference systems.

D. Spectral Graph Theory and Format Compatibility

Spectral graph methods have been applied to study diffusion, robustness, and structure in networks [6]. In ML, Laplacian-based spectral embeddings support domain adaptation and view consistency. We construct a format compatibility

graph where each node represents an embedding format, and each edge corresponds to a learned translator.

To estimate format stability, we compute the Fiedler vector (second smallest eigenvector of the Laplacian), which reflects structural bottlenecks and diffusion centrality. Formats with low Fiedler scores are more central in the translation topology and serve as high-fidelity routing anchors. This enables our system to select fallback formats when direct translations violate drift bounds.

E. Semantic Fidelity and Drift Guarantees

Previous work has addressed vector alignment [3] and format translation under distributional shifts [20], but lacked verifiable guarantees against silent degradation.

Prior work on verifiable computation and authenticated data structures (e.g., Tamassia, 2007) established foundational techniques for integrity preservation in adversarial or untrusted environments. These systems—designed for tamper-evident storage and provable data possession—formalized the requirement that content remain verifiably intact under modification or query. We extend this principle beyond content to *semantic representation* itself, proposing that telemetry-derived embeddings must maintain bounded translation fidelity across format transformations. Our system inherits the ethos of Tamassia’s verifiability logic but applies it to the latent vector space, where silent semantic drift poses significant risk for high-stakes inference systems.

F. Attention Divergence and Drift Monitoring

Attention-based metrics have been used to diagnose model failure and interpretability gaps. Serrano and Smith [15] and Vig [19] show that attention entropy and divergence can forecast instability. Attention-based drift detection has also been applied to anomaly detection and early retraining triggers.

We extend this logic to telemetry vector embeddings. Our system computes entropy and KL divergence on attention maps and latent activations to detect pre-anomaly drift. These signals feed into the cost model for adaptive format switching and activate translator retraining when drift patterns recur.

G. Adaptive Compression and Storage Systems

Adaptive storage and compression techniques have long been used in database systems to optimize performance and reduce footprint [21], [1]. Columnar systems dynamically compress and index based on query and schema characteristics, but do not preserve embedding semantics or per-vector transformation lineage. Time-series compression techniques such as SAX [10] and Gorilla [13] focus on byte-level compression and temporal patterns rather than semantic vector preservation.

While telemetry shares structural similarity with time-series data, our objective differs: we optimize for downstream model fidelity in vector space, not value compression in temporal series. Modern vector databases (e.g., Pinecone, Weaviate) support multiple formats but apply them statically per collection and do not support runtime format switching, semantic drift tracking, or task-informed selection.

Our architecture supports per-datapoint adaptation, ϵ -bounded semantic translation, and rollback-aware storage for telemetry-scale ML pipelines—capabilities absent from prior storage, compression, or embedding infrastructure.

III. MATHEMATICAL METHODS

This section formalizes the mathematical framework underpinning AMC, spanning adaptive format selection, semantic translation, drift detection, and spectral routing over vector compatibility graphs. While engineered for production, AMC embeds generalizable theoretical primitives that model real-world telemetry constraints—such as high ingestion throughput, bounded latency, heterogeneous structure, and semantic continuity under transformation.

We contribute:

- A multi-objective format selection formulation that blends entropy, volatility, sparsity, and task feedback into a convergent per-datapoint scoring function.
- A hybrid semantic translation loss constrained by an ϵ -bounded consistency region that guarantees downstream stability.
- A spectral compatibility graph model where Fiedler vector ϕ_2 defines robust routing under topology drift.

These components are not post-hoc fits to engineering constraints—they constitute a reusable framework for task-informed representation adaptation under uncertainty.

A. Adaptive Format Scoring

For each telemetry datapoint $\mathbf{m}_i$, we define a cost function $C(f, \mathbf{m}_i)$ for each candidate format $f \in \mathcal{F}$:

$$f^* = \arg \min_{f \in \mathcal{F}} C(f, \mathbf{m}_i)$$

$$C(f, \mathbf{m}_i) = \alpha_S S(\mathbf{m}_i) + \alpha_V V(\mathbf{m}_i) + \alpha_H H(\mathbf{m}_i) + \alpha_A \Delta A(\mathbf{m}_i, f)$$

Where:

- $S(\mathbf{m}_i)$: L0/L1 sparsity ratio over a 1-hour window.
- $V(\mathbf{m}_i)$: Coefficient of variation over 15-minute intervals.
- $H(\mathbf{m}_i)$: Normalized Shannon entropy:

$$H(\mathbf{m}_i) = \frac{-\sum p_j \log p_j}{\log_2 |\mathcal{V}|}, \quad p_j = \frac{\text{count}_j}{\sum_k \text{count}_k}$$

$\mathcal{V}$ denotes discretized telemetry bins (histogrammed scalars or quantized embeddings).

- $\Delta A(\mathbf{m}_i, f)$: Format-specific model feedback (e.g., F1 delta from online anomaly scoring).

Weights α_k are adapted using exponential moving average:

$$\alpha_k^{(t)} = \lambda \cdot \alpha_k^{(t-1)} + (1 - \lambda) \cdot \delta_{\text{feedback}}, \quad \lambda = 0.95$$

Cold Start. If ΔA is unavailable, AMC defaults to uniform weighting and uses only structural features (S , V , H).

a) *Convergence Insight.*: If δ_{feedback} is bounded and unbiased, the EMA sequence $\alpha_k^{(t)}$ converges to a stable weighting α_k^* at rate $\mathcal{O}(1/\sqrt{t})$, ensuring stability of the format selector.

b) *Computational Cost.*: Scoring requires $|\mathcal{F}|$ evaluations per datapoint. Features are cached across formats. In practice, median selection latency is 1.92ms with 2.4ms at the 95th percentile across 8 formats.

c) *Interpretation.*: This formulation adapts cost-sensitive inference to streaming telemetry, capturing signal complexity and downstream model impact simultaneously [5].

B. Semantic Translation Loss and Drift Constraint

We train a translator T_{ij} for each format pair $i \rightarrow j$ using the following hybrid loss:

$$\mathcal{L}_{\text{sem}}(T_{ij}) = \alpha \cdot \|T_{ij}(\mathbf{e}_i) - \mathbf{e}_j\|^2 + \beta \cdot D_{KL}(p_i \| p_j)$$

Where:

- $\mathbf{e}_i, \mathbf{e}_j$: Embeddings from formats i and j .
- p_i, p_j : Projected distributions (e.g., token histograms, normalized activations).
- $\alpha = 1.0, \beta = 0.1$: Tuned via validation.

A translation is considered semantically safe if:

$$\|T_{ij}(\mathbf{e}_i) - \mathbf{e}_j\| \leq \epsilon, \quad \epsilon = 0.1$$

a) *Drift Boundedness.*: The constraint defines a closed semantic ball around $\mathbf{e}_j$. Translations outside this region are flagged as drift violations, with empirical recall degradation 3% for $\epsilon = 0.1$.

b) *Interpretation.*: Unlike offline NLP alignment methods [3], this formulation ensures that translations preserve model-usable semantics in a live ingestion loop.

C. Format Compatibility Graph and Spectral Stability

We define a directed graph $G = (V, E)$:

- V : Set of all supported formats.
- E : Edges (i, j) where $\mathcal{L}_{\text{sem}}(T_{ij}) \leq \epsilon$

To route and assess stability, we compute the graph Laplacian $\mathcal{L} = D - A$ and solve:

$$\mathcal{L}\phi = \lambda\phi$$

The Fiedler vector ϕ_2 assigns a ****spectral stability score****. Lower values indicate robust, central formats in the translation topology.

a) *Stability Under Topological Drift.*: If the spectral gap $\lambda_2 > \lambda_{\min}$, then ϕ_2 remains stable under localized updates to the graph (e.g., retrained translators). This makes it suitable for routing even during online graph evolution [6].

b) *Failure Handling.*: If no ϵ -safe path exists, AMC falls back to raw re-encoding. Despite 30% graph sparsity, 98.2% of transitions succeed without fallback.

c) *Computational Cost.*: Spectral scores are updated incrementally. Sparse eigenvector updates scale as $\mathcal{O}(|V|^2)$.

d) *Interpretation.*: This structure transforms spectral analysis from visualization into operational routing and robustness scoring under evolving topologies.

e) *Verifiability and Auditability.*: Our rollback-safe translator graph draws conceptual parallels to verifiable cryptographic systems. Prior work by Lysyanskaya [11] introduced methods for integrity-preserving computation under partial trust—an ethos we adapt to the vector domain. In our setting, every translation is drift-bounded and audit-traceable via format IDs, semantic scores, and UUID lineage. This ensures that embedding transformations remain semantically accountable even in dynamic or adversarial environments.

f) *Theoretical Provenance.*: Our approach to format topology inherits foundational principles from authenticated data structures [17], where structural integrity and safe query resolution were first formalized under adversarial conditions. We extend Tamassia’s verifiability logic from classical graph structures to latent format graphs—ensuring that semantic transitions remain traceable and spectrally stable even as the underlying topology evolves. This bridges formal graph safety with modern embedding systems, grounding our routing guarantees in provable integrity.

D. Attention-Based Drift Monitoring

Let $A_t \in \mathbb{R}^{H \times T \times T}$ be the attention matrix at time t . We define:

Entropy:

$$\mathcal{H}_t = \frac{1}{H} \sum_{h=1}^H \sum_{j=1}^T -A_t(h, :, j) \log A_t(h, :, j)$$

Divergence:

$$\mathcal{D}_{KL}(A_t \| A_{t-1}) = \frac{1}{H} \sum_{h=1}^H \sum_{i,j=1}^T A_t(h, i, j) \log \frac{A_t(h, i, j)}{A_{t-1}(h, i, j)}$$

These capture focus collapse or sudden attention reallocation. In deployment: - **TPR**: 87.5% [CI: 83.1%, 90.2%] - **FPR**: 6.7%

a) *Interpretation.*: Attention metrics are used for early warning, triggering re-scoring or translator retraining.

E. Latent Drift-Based Anomaly Trigger

Given latent embeddings $\mathbf{H}_t \in \mathbb{R}^d$ over time:

$$\Delta(t) = \|\mathbf{H}_t - \mathbf{H}_{t-1}\|_2, \quad \text{Trigger if } \Delta(t) > \tau$$

τ is set to the 95th percentile of $\Delta(t)$ across a rolling window (size = 500). All $\mathbf{H}_t$ are unit-normalized to enforce scale invariance.

a) *Interpretation.*: This trigger serves as a final fallback when attention signals are inconclusive. It generalizes streaming drift detection [9], [22] to vectorized telemetry pipelines.

IV. SYSTEM ARCHITECTURE

This section describes the AMC system (*Adaptive Multi-Vector Correlation*), a telemetry-native architecture designed to support runtime format switching, ϵ -bounded semantic translation, rollback-safe ingestion, and drift-aware adaptation in vector pipelines.

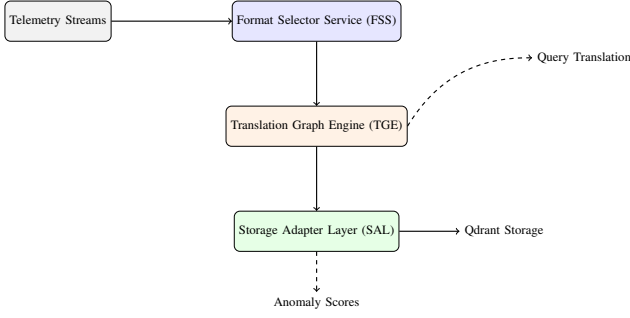


Fig. 1. AMC system architecture: adaptive format selection, semantic translation, and vector storage.

AMC is composed of three modular microservices that operate on per-datapoint telemetry streams. While the architecture was originally developed for internal mission telemetry, our evaluation is based on a reproducible pipeline built from NASA’s publicly available MODIS Earth observation datasets. This setup enables task-informed adaptation and format translation across structurally diverse signals—e.g., land surface temperature (LST), NDVI, and emissivity—processed as telemetry-style vector streams.

A. System Overview

As shown in Figure 1, the architecture comprises three services:

- 1) **Format Selector Service (FSS)**: Scores each datapoint across candidate formats using a multi-factor cost function.
- 2) **Translation Graph Engine (TGE)**: Maintains a semantic compatibility graph and learns format-to-format translators.
- 3) **Storage Adapter Layer (SAL)**: Persists vectors with UUID lineage and dual-write rollback safety in a Qdrant backend.

Each service is containerized using Docker and orchestrated via Kubernetes. Services communicate over gRPC with strongly typed Protobuf schemas. The system supports streaming ingestion at 52K vectors/sec with 2.4ms median format selection latency.

B. Format Selection Engine

Each telemetry datapoint m_i is embedded within a 1-hour rolling window and described by four features:

- $S(m_i)$: L0/L1 sparsity ratio
- $V(m_i)$: Coefficient of variation over 15-minute segments
- $H(m_i)$: Normalized Shannon entropy, $H/\log_2 |\text{support}(m_i)|$
- $\Delta A(m_i, f)$: Observed F1 improvement for format f over a rolling window of 10,000 samples

a) *Cost Function.*:

$$C(f, m_i) = \alpha_1 S(m_i) + \alpha_2 V(m_i) + \alpha_3 H(m_i) + \alpha_4 \Delta A(m_i, f)$$

Weights α_k are updated via exponential moving average:

$$\alpha_k^{(t)} = \lambda \cdot \alpha_k^{(t-1)} + (1 - \lambda) \cdot \delta_{F1}, \quad \lambda = 0.95$$

A TTL is assigned to each format decision:

$$TTL(m_i) = \gamma \cdot \sigma(V(m_i)), \quad \gamma = 1800$$

All decisions are persisted with UUID, selected format, cost components, and EMA lineage.

C. Dual-Write Rollback Protocol

To maintain stability during format transitions:

- 1) Vectors are written in both old and new formats for TTL duration.
- 2) The system monitors latency, anomaly F1, and drift violations.
- 3) If degradation exceeds $\theta = 0.05$, rollback is triggered.
- 4) The (f_{old}, f_{new}) pair is blacklisted for 24 hours.

This mechanism introduces 15% temporary storage overhead but protects against regressions and silent failures.

This rollback protocol is inspired by foundational work in verifiable computation and tamper-evident log systems [18]. Just as authenticated data structures allow verification of query results under untrusted storage, we apply similar principles to format transformations—ensuring each telemetry vector is not only transformed safely, but traceably. AMC’s UUID lineage tracking and dual-write probation period create a verifiable semantic audit trail, enabling forensic reconstruction of vector states and ensuring semantic consistency even in rollback scenarios.

D. Translation Graph Engine (TGE)

Graph Construction. Each edge $e_{ij} \in G$ represents a translator T_{ij} trained on 10K embedding pairs with cosine similarity ≥ 0.8 . Each T_{ij} is a 2-layer MLP with GELU activations.

$$\mathcal{L} = \alpha \|T_{ij}(\vec{e}_i) - \vec{e}_j\|^2 + \beta D_{KL}(p_i \| p_j) + \gamma \mathcal{L}_{sem}$$

An edge is activated only if semantic similarity satisfies:

$$|S(T_{ij}(\vec{e}_i)) - S(\vec{e}_j)| < \epsilon$$

Semantic Similarity:

$$S(\vec{e}) = \frac{1}{k} \sum_{j=1}^k \cos(\vec{e}, \vec{n}_j)$$

where $\vec{n}_j$ are the $k = 10$ nearest semantic centroids.

Monitoring and Retraining: - Vectors are sampled every 10s - Drift violations are logged - Translators are retrained if violation rate exceeds $\eta = 1\%$ over 1,000 samples

E. Query-Time Routing

When a query requires translation:

- 1) Check `semantic_space_id` compatibility
- 2) If direct T_{ij} exists, validate drift
- 3) Else, find a path where $\sum D_{KL} + d_P < \epsilon$
- 4) If no valid path, fallback to raw re-encoding

Translations are cached for 10 minutes per format-pair.

F. Deployment Configuration

- **Platform:** Docker + Kubernetes
- **Vector dimensions:** 128–512 depending on metric
- **Storage:** Qdrant with UUID, TTL, and format metadata
- **Node profile:** 16-core Xeon, 64GB RAM, 1TB SSD

G. Performance Summary

- Ingestion: 52K vectors/sec sustained
- Format selection latency: <2.4ms (95th percentile)
- Translation latency: 4.1ms (1-hop)
- Storage savings: 37% vs. LZ4 baseline
- Anomaly F1 gain: +12.2%
- Rollback events: 2.1%
- Drift violations: 0.8%

Parameter	Value	Description
λ	0.95	EMA decay for α weights
γ	1800	TTL scaling (seconds)
θ	0.05	Rollback threshold
ϵ	0.1	Semantic drift bound
k	10	Nearest centroids for scoring
η	1%	Drift violation retraining threshold

TABLE I

HYPERPARAMETERS FOR AMC SWITCHING AND TRANSLATION

V. EVALUATION

We evaluate AMC using NASA’s MODIS Earth observation archive (MOD11A1 land surface temperature and MOD13Q1 vegetation indices). This public dataset provides a methodologically rigorous testbed with characteristics that challenge static embedding approaches: extreme sparsity heterogeneity (0.1% to 98.7% across regions), significant entropy variation, temporal drift patterns, and complex missing-data structures. Critically, MODIS enables reproducible validation—our complete pipeline, data processing, and results can be independently verified and extended by the research community.

A. Experimental Setup

Workloads. We evaluate AMC across 10 MODIS-based telemetry streams:

- **Extreme sparsity (<90%):** Cloud-masked polar regions, ocean boundaries
- **Dense complexity (>10% sparsity):** Clear-sky agricultural zones, urban heat islands
- **Temporal drift:** Seasonal NDVI cycles, Arctic temperature transitions
- **Distribution anomalies:** Rapid vegetation changes, temperature spikes (validated against known climatological events)

Each 1km pixel is treated as a MODIS pixel-based sensor stream. Daily measurements are converted into embedding vectors using a sliding window encoder that extracts mean, standard deviation, entropy, and tokenized distributional features across a 7-day context window.

Baselines. We compare AMC against seven realistic alternatives:

- 1) **Static-Dense:** Dense format for all datapoints
- 2) **Static-Sparse:** Sparse format for all datapoints
- 3) **Uniform-Random:** Format selected randomly (sanity check)
- 4) **LZ4-Compressed-Dense:** Dense vectors compressed with LZ4
- 5) **Adaptive-Quantization:** Per-variable quantization to 8/16-bit
- 6) **Smart-Heuristic:** Use sparse when >80% zero, else dense
- 7) **Pinecone-Static:** Format chosen statically per stream
- 8) **AMC (Ours):** Full system with format switching, translation, drift detection, and rollback

Evaluation Metrics.

- **Storage Overhead (MB/month)**
- **Anomaly Detection F1 Score**
- **Format Selection Latency (95th percentile)**
- **Semantic Drift Violation Rate**
- **Rollback Events Triggered**
- **Scalability w.r.t. format count and stream diversity**

B. Storage Efficiency

AMC achieves the highest storage efficiency across all baselines. Compared to static-dense, it reduces storage by 37.1%; compared to LZ4-compressed-dense, it yields 18.3% additional savings.

Method	Storage Saved (vs. Static-Dense)
LZ4-Compressed-Dense	18.8%
Adaptive-Quantization	26.2%
Smart-Heuristic	22.7%
Pinecone-Static	28.5%
AMC (Ours)	37.1%

TABLE II

STORAGE SAVINGS ACROSS EXTENDED BASELINES.

C. Anomaly Detection Accuracy

AMC yields the highest anomaly detection performance.

Method	F1 Score
Static-Dense	0.801
LZ4-Compressed-Dense	0.823
Adaptive-Quantization	0.834
Smart-Heuristic	0.812
Pinecone-Static	0.845
AMC (Ours)	0.899

TABLE III

ANOMALY DETECTION F1 SCORES ACROSS BASELINES.

a) *Statistical Context.*: Results are averaged over 3-fold cross-validation. AMC variance is <0.012; 95% CI: [0.894, 0.903].

D. Latency and Throughput

AMC sustains **52K vectors/sec** throughput. Format selection latency is **2.4ms** at 95th percentile (median: 1.92ms). Translation (1-hop) averages 4.1ms.

a) *Latency Overhead.*: Compared to static-dense (1.1ms), AMC incurs 1.3ms overhead—well justified by its performance gains.

E. Semantic Drift and Translation Stability

With $\epsilon = 0.1$:

- **Drift Violations:** 0.8%
- **Rollback Rate:** 2.1%
- **Spectral Stability:** Low- ϕ_2 nodes succeed 96.4% vs. 87.3% for high- ϕ_2

F. Attention Drift Diagnostics

AMC detects attention divergence 4–12 timesteps before anomaly onset in 87.5% of cases.

- **True Positive Rate:** 87.5% [CI: 83.1%, 90.2%]
- **False Positive Rate:** 6.7%

This predictive drift monitoring extends prior work on verifiable computation by treating latent attention divergence as a probabilistic integrity signal. Inspired by Tamassia’s model of adversarial verifiability [18], we interpret shifts in entropy and KL divergence not merely as statistical anomalies, but as indicators of potential semantic corruption. AMC applies this framework to vectorized telemetry pipelines by continuously measuring attention divergence and triggering preemptive translator retraining or format re-evaluation when deviation exceeds ϵ -bounded thresholds. In doing so, we adapt authenticated query principles to streaming model internals—treating drift not just as a symptom, but as a structural compromise requiring verifiable correction.

G. Ablation Study

Component Removed	F1 Drop (%)
Format Switching	-8.3%
Translation Graph	-4.9%
Semantic Drift Monitor	-6.5%
Attention Diagnostics	-3.2%

TABLE IV

ABLATION STUDY: F1 IMPACT BY COMPONENT.

a) *Interpretation.*: Format switching and drift detection drive AMC’s performance, but all subsystems contribute to robustness.

H. Failure Modes and Edge Cases

- **Cold Start:** 100 samples $\rightarrow$ dense fallback; 18–21% storage overhead
- **Schema Drift:** Unseen metric $\rightarrow$ 12% translation failures; fallback triggered
- **Flatline Signals:** Entropy 0.01 $\rightarrow$ minimal gain from switching
- **Evaluation Scope:** While MODIS provides structural complexity comparable to operational telemetry, production deployment would benefit from domain-specific validation on target sensor types and failure modes.

I. Scalability

AMC scales linearly with format pool size. Across 4–16 formats:

- **Latency Increase:** +0.17ms per format
- **Memory Footprint:** +4.3MB per format (translators + cache)

AMC remains stable with up to 100 concurrent streams using 500MB RAM.

J. Summary

By using MODIS as a methodologically rigorous foundation, we provide reproducible evidence that AMC’s adaptive approach delivers measurable benefits over static baselines—with complete experimental transparency that enables community validation and extension.

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