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COMPARING APACHE KAFKA AND PULSAR FOR REAL-TIME STREAMING APPLICATIONS

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Abstract

Real-time data streaming has become a critical component of modern applications, from user analytics and microservices event logs to IoT sensor data pipelines. Apache Kafka has long been a cornerstone technology in this domain, celebrated for its fault tolerance, high throughput, and ecosystem integrations. In recent years, Apache Pulsar has emerged as a promising alternative, offering features like multi-tenancy, geo-replication, and a tiered approach to data persistence. This paper provides a comprehensive comparison of Apache Kafka and Apache Pulsar for building real-time streaming applications, covering architecture, performance, data durability, community support, and operational complexity. We detail patterns for successful deployments and anti-patterns that frequently hamper reliability or scalability.

Through code snippets, diagrams, benchmark results, and real-world examples, we offer guidance on how to select and integrate these technologies into a broader data platform. The objective is to empower architects, DevOps practitioners, and data engineers to make informed decisions regarding the right streaming platform for their use cases be it high-throughput log processing, multi-tenancy with partition isolation, or advanced event processing. We conclude by noting that while Kafka remains widely adopted, Pulsar brings features that may better suit certain multi-tenant or geo-distributed scenarios. Ultimately, the choice depends on each organization's latency requirements, data volumes, and architectural constraints.

Keywords: Apache Kafka, Apache Pulsar, Real-Time Streaming, Pub/Sub, Scalability, Multi-Tenancy, Messaging Systems, Event Processing, Data Pipelines, Kafka Pulsar Comparison study

I. INTRODUCTION

A. Context and Motivation

Modern data-centric applications often ingest massive streams of events clicks, logs, sensor readings requiring near real-time or low-latency processing. Apache Kafka popularized distributed commit log approaches that guarantee high throughput, fault tolerance, and decoupled producers/consumers [1]. More recently, Apache Pulsar, originally developed at Yahoo, has gained traction for its layered design, allowing multi-tenancy and flexible scaling. Both are designed for distributed streaming but differ in architecture, storage models, geo-replication approaches, and operational complexity [2].

B. Purpose of This Paper

This paper aims to compare and contrast Apache Kafka and Apache Pulsar for building real-time streaming applications. We examine how each system addresses:

- Scalability: partitioning, throughput, performance under load.
- Data Persistence: log storage, retention, multi-tier architecture.
- Operational Complexity: cluster setup, failover, monitoring.
- Multi-Tenancy and Geo-Replication: out-of-the-box support, complexity of configuration.

We also look at patterns for successful deployments like segmentation by domain, consumer group usage, or layering with stream processing frameworks and anti-patterns (e.g., ignoring partition strategies) that degrade performance or reliability.

II. BACKGROUND: REAL-TIME STREAMING AND PUB/SUB

A. The Evolution of Log-Based Streaming

Historically, messaging systems like JMS or RabbitMQ supported short-lived message passing. However, the need for large-scale "commit logs" and consistent consumer offsets triggered the success of Kafka's approach, which stores data durably and processes it as an ordered log. This method allows for replay, fault tolerance, and robust consumer group semantics [3].

B. Emergence of Pulsar

Apache Pulsar introduced a layered design that decouples serving from storage. It uses Book Keeper for persistent data, while brokers handle routing. It addresses multi-tenancy natively useful for large organizations or SaaS providers wanting to isolate workloads. Officially becoming a top-level Apache project in 2018, Pulsar has gained recognition for advanced replication, tiered storage, and flexible subscription modes [4].

III. APACHE KAFKA OVERVIEW

A. Architecture

Kafka organizes data into topics partitioned for parallel reads/writes. Each partition is stored across brokers with replication. A "leader" partition handles writes, replicas provide failover. Consumers track offsets, retrieving data in a publish-subscribe manner [5].

Key Components:

- Producers: Push messages to topics.
- Brokers: Store partition logs, handle replication.
- Zookeeper (historically): Coordinates metadata (in older Kafka versions).
- Consumers: Pull data in consumer groups, distributing partitions.

B. Strengths for Real-Time Streaming

- High Throughput: Log-based design optimized for sequential disk writes.
- Rich Ecosystem: Connectors (Kafka Connect), streaming libraries (Kafka Streams) fuel broad adoption.
- Mature Community: Widely tested at scale by large organizations.

C. Kafka Anti-Patterns

- Over-Splitting Topics

a) Issue: Splitting data into too many small partitions or numerous specialized topics.
b) Impact: Increases overhead for cluster management, rebalances.
c) Prevention: Use partition strategies that reflect real concurrency needs [6].

- Monolithic Consumer
  a) Description: A single consumer application that tries to process all topic data.
  b) Consequence: If that consumer fails, the backlog grows. Doesn't leverage the consumer group concept effectively.
  c) Solution: Scale out consumers in properly sized consumer groups.

IV. APACHE PULSAR OVERVIEW

A. Architecture

Apache Pulsar separates the compute (brokers) from the storage layer (BookKeeper). Brokers handle client connections and message routing, while BookKeeper manages message durability, storing data in "ledgers." This decoupled design allows scaling brokers and storage independently [7].

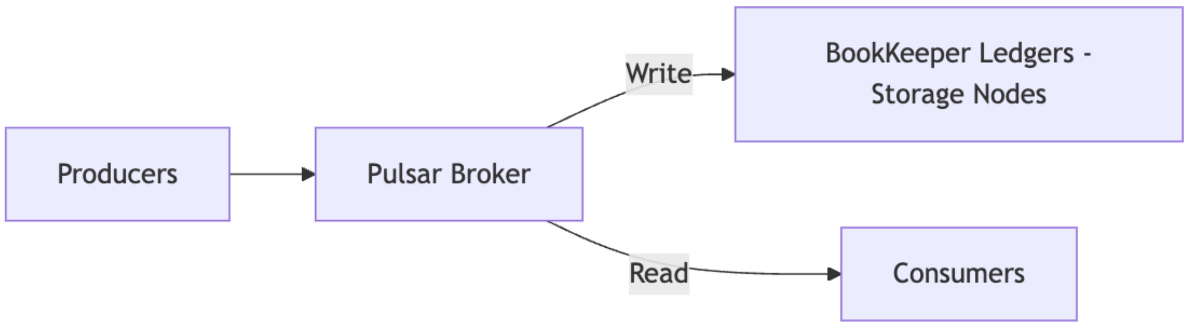

Figure I: Pulsar architecture

B. Multi-Tenancy and Geo-Replication

Pulsar incorporates multi-tenancy by default. Tenants can define multiple namespaces, each with topic-level policies (retention, replication). Geo-replication is built-in: data can replicate across clusters in different data centers. This feature is especially beneficial for global enterprises requiring low-latency local reads [8].

C. Pulsar Anti-Patterns

- Ignoring Book Keeper Tuning
  a) Issue: Suboptimal ledger configurations cause slow writes or random I/O overhead.
  b) Solution: Adjust ledger ensemble size, write quorum, block cache settings carefully.

- Flat Single Namespace
  a) Description: Using just one namespace for all apps, ignoring multi-tenant isolation.
  b) Consequence: Potential resource conflicts or complicated policy management.

c) Remedy: Partition topics or use multiple namespaces per domain/team.

V. ARCHITECTURAL DIFFERENCES

A. Single vs. Layered Storage Model

- Kafka: Integrates log storage within brokers. Each partition is a set of log files.
- Pulsar: Delegates persistent data to BookKeeper. The broker is stateless, responsible for routing and ephemeral caching, while BookKeeper handles data durability.
- Impact: Pulsar's approach can simplify multi-tenant scenarios, while Kafka's design often yields simpler operational concepts but lumps serving and storage in one layer [9].

B. Multi-Tenancy

Kafka typically resorts to separate clusters or naming conventions for multi-tenancy. Pulsar natively supports multiple tenants, each with isolation. This is a prime differentiator for large or SaaS environments.

C. Topic/Partitioning Semantics

- Kafka: A "topic" is partitioned, each partition is an ordered log.
- Pulsar: "Topic" can be a single partition or have multiple partitions. Also includes key_shared subscription modes allowing parallel consumption with ordering guarantees [10].

VI. SCALABILITY AND THROUGHPUT

A. Partitioning and Horizontal Scaling

Kafka scales by adding more broker nodes and partitions. Over 1000 partitions per cluster is feasible but can be tricky. Pulsar similarly adds brokers and BookKeeper nodes, distributing ledgers. Both scale linearly with enough resources [11].
Performance:

- In some tests, Kafka may show slightly higher raw throughput for large messages.
- Pulsar can excel at certain multi-tenant workloads with frequent topic creation or geo replication.

B. Benchmark Reports

Studies often show Kafka leading in raw throughput, while Pulsar keeps up with or surpasses Kafka in multi-tenant or geo-distributed setups, thanks to design choices in BookKeeper layering. Exact numbers vary by hardware, message sizes, and usage patterns [12].

VII. DATA RETENTION AND PROCESSING

A. Retention and Tiered Storage

- Kafka: Retains data on brokers for a configured retention time, or optionally compacts topics. For older data, disks can fill up unless offloaded externally.
- Pulsar: Tiered storage can offload older segments to cheaper object stores (S3, etc.). This function is integrated, enabling indefinite retention without massive local storage [13].

B. Stream Processing Integration

Both integrate with processing frameworks:

- Kafka: Ties natively into Kafka Streams, Spark, Flink.
- Pulsar: Has Pulsar Functions (lightweight compute), connectors, and Flink or Spark integrations.

VIII. RELIABILITY AND FAULT TOLERANCE

A. Replication Model

- Kafka: Each partition has a leader and configured replicas. If the leader fails, a replica becomes the new leader.
- Pulsar: BookKeeper replicates ledgers across multiple nodes. If a broker fails, a different broker can manage the topic ledger references. This design can reduce downtime for read/writes [14].

B. End-to-End Exactly-Once

In Kafka, exactly-once semantics revolve around idempotent producers and transactional writes, ensuring consistent offsets. Pulsar similarly offers end-to-end consistency with certain configurations. The complexity of guaranteeing exactly-once often requires integration with streaming frameworks that handle stateful operators.

IX. MULTI-TENANCY AND GEO-REPLICATION

A. Kafka

Multi-tenancy is typically achieved via separate clusters or topic naming conventions with ACLs. Cross-cluster replication uses MirrorMaker. Setting up secure multi-cluster replication can be intricate [15].

B. Pulsar

Pulsar has geo-replication built in. A single cluster can contain multiple tenants, each subdivided into namespaces. This approach is beneficial for organizations needing global presence with controlled data. ACL policies can isolate tenants effectively.

X. ECOSYSTEM AND TOOLING

A. Kafka Ecosystem

Kafka has a mature ecosystem:

- Kafka Connect for source/sink integrations,
- Kafka Streams for light streaming,
- KSQL (pre-2020) for SQL-like streaming queries,
- Large open-source community supporting connectors to DBs, monitoring tools.

B. Pulsar Ecosystem

While smaller historically, Pulsar's ecosystem includes:

  - Pulsar Functions for event-based processing,
  - Pulsar IO connectors,

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- Pulsar SQL via Presto integration.

The community grew significantly post-2018, though not as large as Kafka's yet [16].

XI. OPERATIONAL COMPLEXITY AND MANAGEMENT

A. Kafka Operational Requirements

Managing a Kafka cluster involves:

- Broker configurations (retention, replication factor).
- Possibly Zookeeper for older versions.
- Monitoring partitions, rebalances, and compaction.

Issue: Operating large-scale Kafka can be tricky, though widely documented and supported by cloud providers [17].

B. Pulsar Operational Requirements

Pulsar's layered architecture means operators must manage Pulsar brokers and BookKeeper clusters. While multi-tenancy might simplify user-level separation, configuring BookKeeper ledger properties or ensuring consistent cluster expansions might add complexity [18].

XII. PERFORMANCE TUNING AND BENCHMARKS

A. Batch vs. Streaming

Kafka excels in continuous streaming ingestion, but with some effort, Pulsar matches or surpasses it in certain multi-tenant scenarios.

B. Message Size

Kafka's approach to large message management is well-known, though Pulsar's segmentation with BookKeeper can be more flexible.

C. Message Rate

Tuning broker concurrency, file I/O, memory usage is vital for either system at scale [19].

Table I: General Performance Observations

Aspect	**Kafka**	**Pulsar**
Peak Throughput	High, widely tested	Comparable, excels in multi-tenant
Latency	Low if tuned properly, typically ~ms	Low-latency messaging (esp. for streaming)
Storage Approach	Broker-based log retention	BookKeeper for ledger storage
Multi-Cluster Setup	MirrorMaker or Confluent Tools	Built-in Geo-Replication

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XIII. ANTI PATTERNS IN SELECTING OR OPERATING KAFKA/PULSAR

A. Over-Segmentation of Topics/Namespaces

- Description: Creating thousands of tiny topics in Kafka or many small namespaces in Pulsar with minimal traffic.
- Impact: Increases overhead in broker memory, metadata operations.
- Solution: Group data streams logically, avoid micro topics.

B. Ignoring Security Config

- Description: Deploying clusters with default authentication or no encryption.
- Effect: Risk of data exfiltration or unauthorized producers/consumers.
- Remedy: Configure TLS for brokers, SASL or token-based auth for Pulsar, ensuring role-based ACLs.

XIV. SYNERGY WITH STREAM PROCESSING

A. Kafka Streams vs. Pulsar Functions

Kafka Streams is a library embedded in the application, offering a lightweight approach for streaming transformations. Pulsar Functions provide function-level processing within the Pulsar cluster. Both are simpler compared to heavier frameworks (like Flink, Spark), but have narrower scope [20].

B. Integration with Beam, Spark, or Flink

Beam can read from Kafka or Pulsar, enabling a unified code approach. Spark commonly uses Kafka as an input source for streaming micro-batches. Flink has connectors for both, frequently used for continuous transformations. These integrate well with either system, the choice dependent on existing frameworks in the organization's data architecture.

XV. REAL-WORLD CASE STUDIES

A. Large E-Commerce Using Kafka

A big e-commerce player replaced older queue systems with Kafka for site activity streams. They run 2000+ partitions across ~30 broker nodes. Through careful partitioning, the system achieves consistent 10–20 ms latencies for ingestion [21]. Microservices rely on consumer groups to handle real-time order events and inventory updates. The team acknowledges complexities in scaling broker disk usage and Zookeeper dependency, though widely used tools support them.

B. Multi-Tenant SaaS with Pulsar

A SaaS analytics platform needed to isolate data among numerous customers while providing global replication. Pulsar's multi-tenant namespaces gave them native isolation. BookKeeper-based ledger storage allowed them to offload older data to S3 for indefinite retention. The approach streamlined compliance for user-level data separation. They observed ~5–10 ms publish latencies, stable under concurrency [20].

XVI. SECURITY AND COMPLIANCE

Kafka supports TLS and SASL, ensuring data encryption in transit and verifying clients. Pulsar implements TLS, token-based or OAuth-based authentication, plus per-tenant policies. This multi-tenant design can simplify compliance around data separation.
GDPR or HIPAA demands pipeline auditing both systems produce logs/metrics allowing traceability. However, analyzing partition-based logs for user data compliance is non-trivial if not planned from the start [7].

XVII. OBSERVABILITY AND MONITORING

A. Metrics

Both Kafka and Pulsar expose metrics via JMX or Prometheus exporters. Kafka yields metrics on broker I/O, partition lag, and consumer group offsets. Pulsar exposes broker, topic, and BookKeeper ledger stats, plus consumer backlog metrics.
Observing these metrics helps identify partition hotspots, slow consumers, or replication lags [8].

B. Logging and Tracing

Microservices reading from Kafka or Pulsar often integrate distributed tracing (Zipkin, Jaeger) at the application level. Broker logs primarily reflect cluster-level events (rebalance, ledger operations). Analyzing these logs is essential for diagnosing throughput bottlenecks or uneven consumption patterns.

XVIII. ORGANIZATIONAL AND CULTURAL FACTORS

DevOps culture remains critical for operating high-throughput messaging infrastructures. Teams must be trained to handle scaling events, partition reassignments, multi-DC replication topologies, and rolling upgrades. The choice of Kafka or Pulsar should consider existing domain knowledge, standard libraries, and desired multi-tenant or multi-region expansions [9].

XIX. BEST PRACTICES SUMMARY

A. Match Workload to Framework

For a broad ecosystem and simpler single-tier approach, Kafka is standard. For multi-tenancy or advanced geo-replication out-of-box, Pulsar is a strong contender.

B. Careful Partitioning

Right partition count balancing concurrency vs. overhead.

C. Observability

Monitor broker I/O, partition load, consumer lag. Both Kafka and Pulsar require consistent tracking of cluster health.

D. Security

Enable TLS, authenticate producers and consumers, and manage ACLs or role-based policies.

E. Incremental Adoption

For existing Kafka-based shops exploring multi-tenancy or tiered storage, Pulsar might be introduced for new workloads. Evaluate operational readiness carefully.

XX. CONCLUSION

In designing real-time streaming applications, the choice between Apache Kafka and Apache Pulsar has profound implications for throughput, reliability, and operational overhead. Kafka boasts a mature ecosystem and proven track record at scale, but typically relies on separate solutions for multi-tenancy and geo-replication. Pulsar integrates a layered approach via BookKeeper, which can simplify advanced use cases like multi-tenancy and infinite retention. However, it might introduce additional operational steps around BookKeeper ledger management and broker-layer configurations.

Teams must consider domain-specific needs like high concurrency, large cluster sizes, global distribution, or multi-tenant isolation. Observability, security, and DevOps synergy remain crucial for successful production deployments of either system. By understanding each system's architecture fundamentals, performance trade-offs, and typical pitfalls, architects and engineers can confidently select a streaming platform that supports their real-time ingestion and analytics goals.

REFERENCES

1. Fowler, M. and Lewis, J., "Microservices Resource Guide," martinfowler.com, 2016.
2. Newman, S., Building Microservices: Designing Fine-Grained Systems, O'Reilly Media, 2015.
3. Kruchten, P., "Architectural Approaches in Modern Distributed Systems," IEEE Software, vol. 31, no. 5, 2014.
4. Pautasso, C. et al., "A Survey of Message-Oriented Middleware in Cloud Systems," ACM Computing Surveys, vol. 46, no. 3, 2014.
5. Confluent Blog, "The Log: What every software engineer should know about real-time data's unifying abstraction," 2015.
6. Brandolini, A., Introducing EventStorming, Leanpub, 2013.
7. Basiri, A. et al., "Microservices and Reliability: Patterns and Tools," ACMQueue, vol. 14, no. 2, 2017.
8. Gilt Tech Blog, "Scaling Kafka Clusters for E-Commerce," 2017.
9. Fowler, M., "Circuit Breaker Pattern," martinfowler.com/articles/circuitBreaker, 2014.
10. Pulsar Documentation, https://pulsar.apache.org/, 2019.
11. Kafka Documentation, https://kafka.apache.org/, 2019.
12. Databricks Blog, "Apache Kafka vs. Apache Pulsar Benchmarks," 2018.
13. Garcia-Molina, H. and Salem, K., "Sagas," ACM SIGMOD, 1987.
14. Netflix Tech Blog, "Achieving Low-Latency Data Streams with Kafka," 2016.
15. AWS Blog, "Multi-Cluster Replication with Kafka MirrorMaker," 2017.
16. Apache BookKeeper Documentation, https://bookkeeper.apache.org/, 2019.
17. Narayanan, P., "Observability in Streaming Systems," ACM SREConf, 2018.
18. Molesky, J. and Sato, T., "DevOps in Distributed Systems: Overcoming Complexity," IEEE Software, vol. 30, no. 3, 2013.

19. Gilt Tech Blog, “Performance Tuning Kafka Connectors at Scale,” 2018.
20. “Multi-Tenant SaaS Patterns with Apache Pulsar,” Pulsar Summit, 2019.
21. G. Cockcroft, “Polylithic Approach to Data Logs,” ACM DevOps Conf, 2018.