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Distributed Messaging System { Kafka }

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Abstract - Nowadays, log processing is very important for internet-based companies. In this paper, we talk about Kafka — a distributed messaging system we created to collect and deliver a large amount of log data with very low delay. Kafka uses some ideas from old log systems and messaging tools, and it works well for both offline and online data reading. While making Kafka, we took some different but useful steps to make it fast and scalable. Our tests showed that Kafka works better than two other famous messaging systems. We are already using Kafka in real-life systems, and it handles hundreds of gigabytes of new data every day.

General Terms : System management, working speed, design choices, and testing.

Keywords : Messaging system, distributed system, log handling, data speed, real-time use.

I. INTRODUCTION

Big internet companies generate a huge amount of log data every day. This data usually includes (1) user activities like logins, page views, clicks, likes, shares, comments, and searches, and (2) system performance data such as service call stacks, latency, errors, and usage of CPU, memory, network, and disk on each machine. This kind of log data has always been important for tracking user behavior and system health.

But in recent times, log handling has become a key part of the production data pipeline. Now, companies use this data for real-time features like:

(1) improving search results,
(2) giving smart recommendations based on user activity,
(3) targeting ads and creating reports,
(4) improving security by blocking spam or fake users, (5) and building newsfeeds that show friends' updates.

These real-time uses need a system that can handle a much higher volume of data than traditional systems. For example, ads and recommendations need to calculate click-through rates not just for the clicked items, but also for many that weren't clicked. Every day, China Mobile collects around 5–8TB of phone call logs [11], and Facebook gathers nearly 6TB of user activity events [12].
Older methods used to scrape log files from servers for later analysis. But now, special tools have been developed for this job. These include Facebook's Scribe [6], Yahoo's Data Highway [4], and Cloudera's Flume [3]. These tools were mainly built to load data into systems like Hadoop [8] for offline analysis.

At LinkedIn, we realized that we also needed to support most of the real-time use cases mentioned above — with a delay of just a few seconds. So we created a new messaging system for log data called Kafka [18].
Kafka combines the features of log aggregators and messaging tools. It is a distributed system with high data speed and can handle log processing in both real-time and offline modes. Kafka has a simple API like a messaging system and is built for scalability and performance. It helps with system management, simplifies our setup, and allows faster working speed with flexible design choices.

Kafka is open-source and has been running in production at LinkedIn for over 6 months. It processes logs of all types and supports both real-time and offline use. It has made our system more efficient by letting us use one tool for everything.
The rest of the paper is organized as follows:
Section 2 covers traditional messaging systems and log aggregators.

Section 3 explains Kafka's architecture and key design choices. Section 4 talks about our deployment of Kafka at LinkedIn. Section 5 shows the testing results and performance. Section 6 ends with future plans and the conclusion.

II. RELATED WORK

Traditional enterprise messaging systems [1][7][15][17] have been around for a long time and are often used to handle asynchronous data flows, acting as event buses. However, these systems aren't always a good fit for log processing. There are a few key reasons for this mismatch.

First, enterprise systems tend to offer more features than needed. For example, IBM Websphere MQ [7] supports transactional features that let you insert messages into multiple queues at once. The JMS [14] specification allows individual messages to be acknowledged after consumption, sometimes out of order. These extra features are often unnecessary when dealing with log data. Losing a few events, like page views, doesn't really matter in the grand scheme of things. These features also make the system management more complex, both in terms of the API and the backend system.

Second, many of these systems don't focus on high throughput. For example, JMS lacks an API that lets producers send messages in bulk. So, each message requires a full TCP/IP roundtrip, which makes it slower and inefficient for our domain's needs. We need systems that can handle a high volume of data with minimal delay.

Third, these systems often lack strong distributed system support. It's not easy to partition and store messages across multiple machines. This makes them less scalable and not suitable for our needs.

Finally, many messaging systems assume that messages will be consumed almost immediately, meaning the queues of unconsumed messages are usually small. However, performance degrades significantly if messages accumulate, as happens with offline consumers like data warehousing applications that process large batches periodically instead of continuous realtime consumption.

In recent years, several specialized log aggregators have been developed. For example, Facebook uses Scribe, where each frontend machine sends log data to a set of Scribe machines. These machines aggregate the logs and dump them periodically to HDFS [9] or NFS devices. Yahoo's Data Highway does something similar, with machines aggregating events and adding them to HDFS in "minute" files. Cloudera's Flume is another log aggregator that supports flexible streaming with extensible "pipes" and "sinks" and offers better distributed support. However, most of these systems are designed for offline consumption and expose unnecessary implementation details to consumers (e.g., the use of "minute files").

Additionally, most of these tools use a "push" model, where the broker sends data to consumers. At LinkedIn, we find the pull model more useful because it allows each consumer to pull messages at its own speed, preventing it from being overwhelmed by faster producers. The pull model also makes it easier to rewind

and reprocess messages, which we discuss more in Section 3.2.
More recently, Yahoo! Research developed a distributed system called HedWig [13], which is highly scalable and durable. However, it is mainly designed for storing commit logs for data stores, rather than handling general log processing.

III. KAFKA ARCHITECTURE AND DESIGN PRINCIPLES

Because existing systems had limitations, we developed a new messaging system for log processing called Kafka. Let's first look at the basic concepts in Kafka. A stream of messages with a specific type is defined by a topic. A producer sends messages to a topic. These messages are stored on servers known as brokers. A consumer subscribes to one or more topics from the brokers and pulls the messages for processing.

Messaging itself is simple, and we tried to make the Kafka API just as simple. Instead of giving you the full API, we'll show you some sample code to demonstrate how it works. Here's an example of how a producer works. A message simply contains a payload of bytes, and users can choose their preferred way of encoding these messages. To make it more efficient, the producer can send multiple messages in a single request.

Sample producer code:

```
producer = new Producer(…);
message = new Message("test message str".getBytes());
set = new MessageSet(message);
producer.send("topic1", set);
```

To subscribe to a topic, a consumer first creates one or more message streams for that topic. The messages published to the topic are split across these streams. The details of how Kafka distributes messages will be discussed in Section 3.2. Each message stream works like an iterator, where the consumer processes each message in the stream. If there are no new messages, the iterator waits until new messages are available.
Kafka supports both a point-to-point delivery model (where multiple consumers share a single copy of the messages) and a publish/subscribe model (where each consumer gets its own copy of the messages).

Sample consumer code:

```
streams[] = Consumer.createMessageStreams("topic1", 1);
for (message : streams[0]) {
    bytes = message.payload();
    // process the bytes
}
```

Kafka's architecture is distributed, so a Kafka cluster is made up of multiple brokers. To balance the load, a topic is divided into several partitions, and each broker stores one or more partitions. This allows multiple producers and consumers to send and retrieve messages simultaneously. In Section 3.1, we'll talk about how each partition is stored and accessed efficiently. In Section 3.2, we'll explain how producers and consumers interact with multiple brokers in a distributed system. Section 3.3 will discuss the delivery guarantees that Kafka offers.

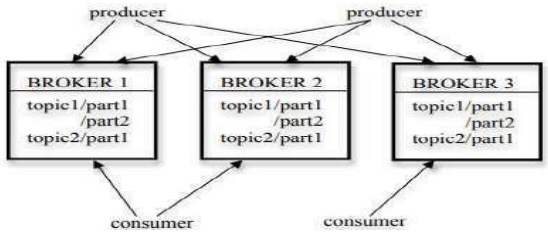

Figure 1. Kafka Architecture

3.1. Efficiency on a Single Partition

In Kafka, we made several design choices to ensure efficiency. One of the key decisions is our simple storage approach. Each partition of a topic is treated as a logical log. In practice, a log is stored as a series of segment files, each roughly the same size (e.g., 1GB).

Whenever a producer sends a message to a partition, the broker simply appends that message to the last segment file. This design

choice helps keep things straightforward and efficient.

To improve performance, we don't immediately flush these segment files to disk after each message. Instead, we wait until a certain number of messages are published or a specific amount of time has passed. A message becomes visible to consumers only after it is flushed to disk. This approach reduces the time spent on disk operations and helps maintain high **working speed** during log processing.

Unlike typical messaging systems, Kafka doesn't assign an explicit message ID to each message. Instead, messages are identified by their logical offset in the log. This design avoids the overhead of maintaining extra, seek-intensive random-access index structures that map message IDs to their actual locations. While the message IDs in Kafka are increasing, they are not consecutive. To find the ID of the next message, you simply add the length of the current message to its ID. From this point onward, we'll refer to both message IDs and offsets interchangeably.

A consumer always consumes messages from a specific partition in a sequential manner. If a consumer acknowledges a certain message offset, it means the consumer has already received all the messages prior to that offset in the partition. Behind the scenes, the consumer sends asynchronous pull requests to the broker to have a buffer of data ready for consumption. Each pull request specifies the offset from which to start reading and how many bytes of data to fetch.

Each broker maintains an in-memory sorted list of offsets, which includes the offset for the first message in every segment file. When a consumer sends a pull request, the broker uses this list to find the segment file where the requested message is located and sends the relevant data back to the consumer.

Once a consumer receives a message, it calculates the offset of the next message and uses that offset in its subsequent pull request. The layout of the Kafka log and the in-memory index is shown in Figure 2, where each box represents the offset of a message.

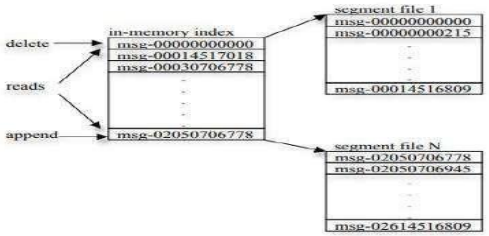

Figure 2. Kafka log

We are highly focused on optimizing the data transfer in and out of Kafka. As previously discussed, the producer can send a batch of messages in a single request. Although the consumer API processes messages one at a time, under the hood, each pull request from the consumer retrieves multiple messages, up to a predefined size—typically in the range of hundreds of kilobytes.

One of the unconventional design choices we made is the decision not to explicitly cache messages in memory within Kafka. Instead, Kafka leverages the underlying file system page cache, which offers a major benefit: it avoids double buffering. This means messages are only cached in the page cache, which retains a warm cache even when a broker process is restarted. Since Kafka doesn't perform memory caching at all, there is minimal overhead in garbage collection, making it feasible to implement Kafka in a VM-based language efficiently.

Another key aspect of Kafka's design is its sequential access to segment files by both producers and consumers. Given that the consumer typically lags slightly behind the producer, standard operating system caching heuristics, such as write-through caching and readahead, work effectively to maintain working speed. The result is that both production and consumption exhibit consistent performance, scalable linearly with the data size, even when handling terabytes of data.

In terms of network access, Kafka optimizes for multi-subscriber systems. A single message can be consumed by multiple consumer

applications. Typically, transferring bytes from a local file to a remote socket involves several steps: (1) reading data into the page cache, (2) copying data to an application buffer, (3) copying the application buffer to a kernel buffer, and (4) sending the kernel buffer to the socket. This process involves 4 data copies and 2 system calls.

On Linux and other Unix-based systems, the sendfile API [5] allows for a more efficient transfer, directly sending bytes from a file channel to a socket channel, avoiding two of the copies and one of the system calls. Kafka uses this API to efficiently deliver log segment bytes from a broker to a consumer, improving the network throughput significantly.

In contrast to many other messaging systems, Kafka does not track the consumption progress of each consumer. Instead, the consumer maintains its own offset, simplifying the broker's architecture and reducing its overhead. However, this introduces a challenge for message deletion: since the broker doesn't know which messages have been consumed by all subscribers, a time-based retention policy is used. If a message has been retained beyond a certain period—typically 7 days—it is automatically deleted.

This approach works effectively in practice, as most consumers, including offline ones, complete consumption on a daily, hourly, or real-time basis. The performance of Kafka remains consistent even with large data sizes, making long-term retention feasible.

A key benefit of this design is that a consumer can rewind and re-consume messages from an old offset. This is not typical in a queue system but is crucial for many use cases. For instance, when an application logic error occurs, it can re-process certain messages after fixing the issue. This is especially useful for ETL data loads into systems like Hadoop or data warehouses. In the event of a consumer crash, data that hasn't been flushed to a persistent store can be reconsumed from the last checkpointed offset, minimizing data loss.

This "rewind" feature is easier to implement in a pull-based model than a push-based one, which further highlights the flexibility Kafka offers for real-time use.

3.2. Distributed Coordination

In this section, we describe how producers and consumers behave in a distributed system. A producer can publish a message to either a randomly selected partition or to a partition determined by a partitioning key and corresponding partitioning function. We focus on how the consumers interact with the brokers in the system.

Kafka introduces the concept of consumer groups. Each consumer group consists of one or more consumers that work together to consume a set of subscribed topics. In this model, each message is delivered to only one consumer within the group. Different consumer groups consume the full set of messages independently, and no coordination is necessary between groups. The consumers within the same group can be in different processes or run on separate machines. The goal is to divide the messages stored on the brokers evenly among the consumers, while minimizing coordination overhead.

To achieve efficient load balancing, we make the partition within a topic the smallest unit of parallelism. This means that all messages from one partition are consumed by a single consumer within a given consumer group. Had we allowed multiple consumers to consume from a single partition simultaneously, coordination would be necessary to manage which consumer processes which messages. This would introduce locking mechanisms and state maintenance, which would incur significant overhead. In contrast, our design minimizes such overhead by allowing consumers to only coordinate during rebalance events, which are infrequent.

To ensure the load is balanced, we require more partitions than consumers in the group. Achieving this is straightforward by over-partitioning the topic.

Another significant design choice is the decision to avoid using a central master node. Instead, consumers coordinate among themselves in a decentralized fashion. Introducing a master node could add complexity, particularly due to the potential for master failures. To facilitate this coordination, Kafka employs Zookeeper, a highly available consensus service.
Zookeeper offers a simple, file system-like API, allowing users to create, set, read, and delete paths. It also provides advanced features: (a) clients can register watchers to be notified when a path or its value changes, (b) paths can be ephemeral (i.e., automatically deleted if the creating client disappears), and (c) Zookeeper replicates data across multiple servers, ensuring high availability.

Kafka uses Zookeeper for several purposes:

1. Detecting the addition and removal of brokers and consumers.
2. Triggering a rebalance process for consumers when brokers or consumers change.
3. Maintaining the consumption relationship and tracking the consumed offsets for each partition.

When a broker or consumer starts, it stores its information in Zookeeper's broker registry or consumer registry. The broker registry includes the broker's host name, port, and the set of topics and partitions it manages. The consumer registry contains information about the consumer group and the set of topics it subscribes to. Each consumer group is associated with an ownership registry and an offset registry in Zookeeper.

Algorithm 1:

```
rebalance process for consumer Ci in group G
For
  each topic T that Ci subscribes to {

   remove partitions owned by Ci from the
  ownership registry
 read the broker and
  the consumer
  registries from
  Zookeeper
  compute PT =
  partitions available
  in all brokers under
  topic T

 compute CT = all consumers in G that
 subscribe to topic T
sort PT
and CT
let j be
the
index
position
of Ci in
CT and
let N =
|PT|/|CT|

  assign partitions from j*N to (j+1)*N - 1 in PT
to consumer Ci  for
  each assigned partition p {

   set the owner of p to Ci in the ownership
  registry
 let Op = the
  offset of
  partition p
  stored in the
  offset registry
  invoke a
  thread to pull
  data in
  partition p
  from offset Op
   }
  }
```

The ownership registry tracks which consumer owns which partition by creating a path for each subscribed partition and storing the consumer's ID at that path. The offset registry stores the offset of the last consumed message for each partition.

When a consumer starts or is notified about changes in brokers or other consumers, it triggers a rebalance. During the rebalance, the consumer computes the set of available partitions for each subscribed topic and the set of consumers subscribing to that topic. These partitions are then range-partitioned into chunks, and each consumer deterministically selects a chunk to consume. The consumer then updates the ownership registry to reflect that it owns the selected partitions.

As messages are consumed, the consumer periodically updates its offset in the offset registry.
When multiple consumers are involved, each will be notified of broker or consumer changes, but at slightly different times. As a result, one consumer may attempt to take ownership of a partition that another consumer still owns. In this case, the first consumer releases its owned partitions, waits briefly, and retries the rebalance process. In practice, this often stabilizes after only a few retries.

When a new consumer group is created, no offsets are initially available in the offset registry. In such cases, the consumers begin consuming messages from either the smallest or the largest offset, based on a configuration setting. This is done by using an API provided by the brokers.

3.3. Delivery Guarantees

Kafka, as a messaging system designed for real-time use, guarantees at-least-once delivery. While exactly-once delivery is often sought after in distributed systems, it typically requires two-phase commits, which introduce significant system management complexity and overhead. Instead, Kafka makes a design choice to avoid this costly mechanism, as most applications can tolerate the occasional duplicate message or handle it at the application level.
In normal operation, Kafka often achieves effectively exactly-once delivery within a consumer group, but if a consumer crashes unexpectedly (without a clean shutdown), its assigned partitions are reassigned. The new consumer process may read some messages again—those occurring after the last offset successfully committed to Zookeeper. These duplicates are rare, but handling them efficiently is critical for preserving data speed and correctness.

Applications that are sensitive to duplicates can implement deduplication logic using either:

- The message offset, returned by Kafka.
- A unique key embedded within each message.

This strategy is generally more efficient and scalable than using transaction-based models.
Kafka maintains message ordering within a single partition, which ensures that log handling for individual streams remains deterministic. However, there is no ordering guarantee across partitions. This design simplifies parallel consumption and improves working speed in highthroughput environments.

Kafka ensures data integrity by storing a CRC (cyclic redundancy check) with each message in the log. During message production and consumption, Kafka can verify CRCs to detect and correct I/O or network errors. If a broker detects inconsistent CRCs due to corruption, a recovery process is triggered to discard the corrupted entries. This built-in mechanism serves as part of Kafka's testing and fault-tolerance design.

However, the system currently lacks built-in replication, meaning if a broker storing unconsumed messages goes down permanently (e.g., due to hardware failure), those messages are lost. Kafka acknowledges this limitation and plans to support message replication in future versions. This would enhance system reliability, ensuring that every message is redundantly stored across brokers,

thereby improving fault tolerance and system management robustness.
The rebalance logic that governs partition ownership among consumers (as outlined in Algorithm 1) plays a critical role in maintaining distributed coordination and consistent message consumption across partitions. It ensures a balanced and fault-resilient architecture while minimizing overhead and maximizing data throughput.

IV. KAFKA USAGE AT LINKEDIN

At LinkedIn, Kafka serves as a core messaging system that enables efficient log handling and real-time data flow across the infrastructure. As shown in Figure 3 (simplified), Kafka is deployed in a distributed system configuration, with a dedicated Kafka cluster present in each data center where user-facing services are hosted.

This design choice ensures that log data is captured as close to the source as possible, enhancing data speed and reducing latency. Frontend services—which include user interactions, API calls, and various internal transactions—generate a wide variety of log events. These logs are batched and published directly to the local Kafka cluster. By batching, the system reduces the overhead of frequent small writes, thereby improving working speed and system efficiency.

To support scalability and system management, Kafka brokers are distributed behind a hardware load balancer, which evenly routes incoming publish requests. This avoids bottlenecks on individual brokers and ensures that publishing throughput remains consistent under high load.

Kafka's architecture supports real-time use cases, so online consumers (services that subscribe and react to messages) run within the same data center as the brokers. This local deployment reduces cross-data-center latency and enhances overall system responsiveness.
The LinkedIn deployment of Kafka reflects practical and tested design decisions optimized for high-throughput, low-latency messaging systems. It ensures reliable log capture, maintains consistent data speed, and supports both real-time analytics and downstream batch processing systems—all with minimal operational complexity.

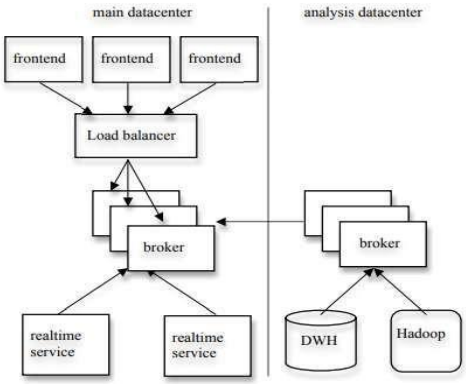

Figure 3. Kafka Deployment

To support large-scale offline analysis, LinkedIn has deployed an additional Kafka cluster in a separate data center, strategically positioned near the Hadoop cluster and data warehouse infrastructure. This instance of Kafka functions as a replica, pulling data from Kafka clusters in the live datacenters through a set of embedded consumers. These consumers ensure efficient log handling across geographically distributed environments.

Data load jobs then move the collected logs from this distributed system into Hadoop and the data warehouse, where various analytical processes and reporting jobs are run. This setup not only supports complex analytics but also enables rapid prototyping and ad hoc querying via simple scripts run against the raw event streams. With minimal tuning, the end-to-end latency of this pipeline averages around 10 seconds—meeting LinkedIn's real-time use and analysis needs.

Currently, Kafka processes hundreds of gigabytes of data and nearly a billion messages daily, a figure expected to rise as more legacy systems are transitioned into this robust messaging system. Kafka's system management capabilities, including rebalance processes, automatically redirect traffic when brokers are

taken offline for maintenance, showcasing strong fault tolerance and operational flexibility. To ensure data integrity, LinkedIn implements a comprehensive auditing system. Every message is tagged with a timestamp and origin server name, and each producer emits periodic monitoring events. These are published to Kafka in a dedicated topic, allowing consumers to validate message counts against these monitors and detect any data loss across the pipeline. This end-to-end validation process represents a critical part of system testing.

For integration with Hadoop, LinkedIn uses a custom Kafka input format, enabling MapReduce jobs to directly read Kafka streams. These jobs compress and organize raw data for future batch processing. Kafka's stateless broker architecture and client-side offset tracking allow MapReduce tasks to restart without duplication or message loss, aligning with the design choice of fault-tolerant and scalable ingestion.

For serialization, LinkedIn selected Avro, a compact, fast format that supports schema evolution—crucial for maintaining compatibility as systems evolve. Each message includes a schema ID and serialized payload. A lightweight schema registry enables consumers to decode these messages efficiently, enhancing data speed and consistency without repeated lookups.

Through these architecture choices, LinkedIn has developed a high-performance messaging infrastructure that excels in real-time use, system reliability, and scalability, powering both online services and large-scale analytics with minimal overhead and robust fault handling.

V. EXPERIMENTAL RESULTS

To evaluate Kafka's working speed and efficiency, we conducted a performance comparison against two widely-used messaging systems: Apache ActiveMQ v5.4 and RabbitMQ v2.4. These systems were selected due to their popularity and strong reputation in message queuing and throughput. ActiveMQ was tested with its default persistent message store (KahaDB), and an alternative store showed no significant variation, indicating consistent performance across configurations.

The experiment was run on a simple distributed system setup using two high-spec Linux machines: each equipped with 8 cores (2GHz), 16GB RAM, and a 6-disk RAID 10 configuration, connected via a 1Gbps network. One machine hosted the broker, while the other alternated between running as a producer or a consumer. This setup allowed controlled system testing under comparable hardware conditions.

Producer Test: Evaluating Publish Throughput

We tested each system by publishing 10 million messages, each 200 bytes in size. Kafka producers were configured to send messages in batch sizes of 1 and 50, while ActiveMQ and RabbitMQ did not support user-configured batching and operated effectively at batch size 1.

Kafka significantly outperformed its counterparts, achieving 50,000 messages/sec at batch size

1 and 400,000 messages/sec with a batch size of 50. These rates are orders of magnitude

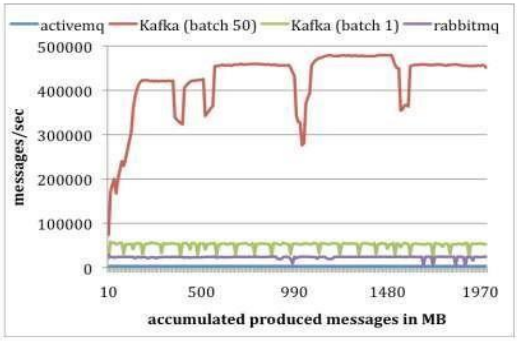

Figure 4. Producer Performance

higher than ActiveMQ and more than double RabbitMQ's throughput. Kafka's high data speed results from several design choices:

1. Asynchronous publishing: Kafka producers do not wait for broker acknowledgments, enabling faster message sending. This strategy fits well in log handling use cases, where real-

time use and speed are prioritized over strict durability.

2. Efficient message format: Kafka uses a lightweight format with only 9 bytes overhead per message, while ActiveMQ incurs a 144-byte overhead, due to heavy JMS headers and B-Tree indexing. This means Kafka uses 70% less storage space.
3. Effective batching: Kafka's batch size of 50 minimizes RPC overhead and nearly saturates the network link, a significant working speed boost for high-throughput applications.

Consumer Test: Evaluating Read Throughput

In the second part of the study, a single consumer retrieved the same 10 million messages. All systems were configured to prefetch about 1000 messages (~200KB) per pull request, with automatic acknowledgments. Since the messages were cached in memory or buffers, disk I/O was minimized.

Kafka achieved 22,000 messages/sec, over four times faster than ActiveMQ and RabbitMQ. Key factors behind this superior performance include:

- Compact data format, reducing transferred data size.
- Kafka's brokers avoid maintaining delivery states for each message, unlike ActiveMQ and RabbitMQ.
- Kafka leverages the sendfile API, which reduces system call overhead and accelerates transmission.

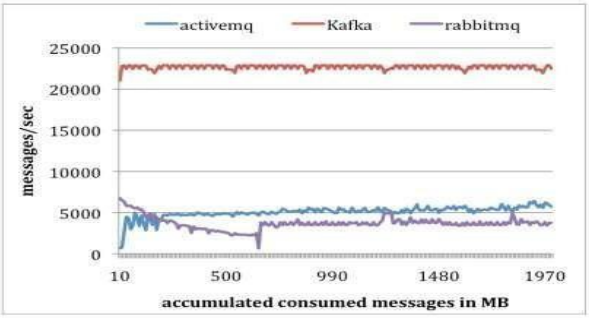

Figure 5. Consumer Performance

Importantly, no disk writes occurred during Kafka's consumer tests, while ActiveMQ continued writing KahaDB pages to disk, indicating higher overhead in state tracking.

This testing highlights the potential performance gains achievable through Kafka's design decisions and optimization for log aggregation and high-throughput messaging systems. While systems like ActiveMQ and RabbitMQ offer a broader feature set, Kafka's specialized architecture provides outstanding system management efficiency, especially for real-time and large-scale data pipelines.

VI. CONCLUSION AND FUTURE WORKS

In this paper, we introduced Kafka, a high-performance messaging system designed specifically for managing large-scale log handling operations. Kafka leverages a pull-based consumption model, allowing client applications to control their own processing rate and revisit previously consumed data, providing significant flexibility and system management benefits.

By focusing on the unique requirements of log processing rather than general-purpose messaging, Kafka achieves far greater data speed and scalability than traditional systems. Its distributed system architecture allows for seamless scaling and has proven effective in both real-time use and offline data processing scenarios at LinkedIn.

Kafka's key design choices, such as batching, simplified message formats, and decentralized offset tracking, have contributed to exceptional working speed and throughput. The system has already been integrated into a variety of production workflows at LinkedIn, supporting services that range from monitoring to analytics.

Future Directions and Enhancements

Looking ahead, we plan to enhance Kafka in the following ways:

1. Replication Support:
   We aim to add native replication across multiple brokers to strengthen data availability and durability. This will protect against hardware failures and

allow the system to maintain integrity even during broker outages. We plan to support both asynchronous and synchronous replication models, enabling a balance between producer latency, throughput, and data guarantees depending on the use case.

2. Stream Processing Capabilities:
   Many real-time applications that consume data from Kafka perform recurring tasks such as windowed aggregation, stream joins, and integration with secondary stores. To address this, we plan to extend Kafka with native stream processing support. This includes: o Semantically partitioning messages by key to ensure related messages are delivered to the same consumer, simplifying operations like joins.
   - o Building a library of stream utilities such as windowing techniques, aggregation operators, and join mechanisms.

These enhancements will help Kafka evolve beyond a messaging system into a more complete platform for real-time distributed stream processing, without compromising on its core strengths in system management, scalability, and data speed.

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