How Fast Can We Insert? A Performance Study of Apache Kafka

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Abstract—Message brokers see widespread adoption in modern IT landscapes. These systems are comparatively easy to use and configure and thus, present a flexible solution for various data storage scenarios. Their ability to scale horizontally enables users to adapt to growing data volumes and changing environments. However, one of the main challenges concerning message brokers is the danger of them becoming a bottleneck within an IT architecture. To prevent this, the amount of data a given message broker can handle with a specific configuration needs to be known. In this paper, we propose a monitoring architecture for message brokers and similar systems. We present a comprehensive performance analysis of Apache Kafka, a popular message broker implementation, using our approach. As part of the benchmark, we study selected data producer settings and their impact on the achievable data ingestion rate.

Index Terms—Survey, Apache Kafka, big data, performance

I. INTRODUCTION

These days, where data masses keep growing and applications move to the cloud, horizontal scalability becomes increasingly important. Message brokers play a central role in modern IT systems as they allow us to adapt to data sources that face rises in volume or velocity. Moreover, they can be used to decouple disparate data sources from applications using this data. Usage scenarios where message brokers are employed are manifold and reach from e.g., machine learning to stream processing architectures.

When using a certain system within an IT architecture, it is crucial to know if the functional and non-functional requirements for scenarios it is supposed to be used for are met. If non-functional requirements related to performance are not satisfied, the system might become a bottleneck. This situation does not necessarily mean that the system is unfit for a given use case, but might indicate a suboptimal system configuration. It is, therefore, a challenge for users to know about or be able to evaluate the capabilities of a system in certain environments and with distinct configurations. This knowledge is a prerequisite for making informed decisions about whether a system is suitable for the existing use cases. Additionally, it is also crucial for finding well-fitting system configurations. The contributions within this experience paper are as follows:

• We propose an easy-to-use and extensible monitoring architecture. This tooling assortment forms a framework that allows analyzing message brokers.

• Next to the monitoring architecture, we present a performance study of Apache Kafka. This analysis highlights the capabilities of Apache Kafka regarding the manageable rate of incoming records per time unit.

• Furthermore, we allow reproducing the presented results by making all needed artifacts available online.

II. APACHE KAFKA

Apache Kafka is a distributed open-source message broker or messaging system originally developed at LinkedIn in 2010. The core of this publish-subscribe system is a distributed commit log, although it has extended its scope through extensions that were built around or on top of Apache Kafka. An example is Kafka Streams, a client library for developing stream processing applications.

The high-level architecture of an exemplary Apache Kafka cluster is visualized in Figure 1. A cluster consists of multiple brokers, which are numbered and store data assigned to topics. Data producers send data to a certain topic stored in the cluster. Consumers subscribe to a topic and are forwarded new values sent to this topic as soon as they arrive.

Topics are divided into partitions. The number of topic partitions can be configured at the time of topic creation. Partitions of a single topic can be distributed across different brokers of a cluster. Additionally, it is possible to define a replication factor - one being the minimum - for each topic and for each partition. Using this approach data loss in the case of a single broker failure can be prevented. In the context of replication, Apache Kafka defines a so-called leader and follower(s) for each partition. The leader handles all reads and writes for the corresponding topic partition, whereas the follower(s) copy or replicate the inserted data. In Figure 1 the leader partitions are shown in bold type. topic1 has two partitions and a replication factor of one, while topic2 has only one partition and a replication factor of two.

Figure 2 visualizes the structure of an Apache Kafka topic, specifically of a topic with two partitions. Each of these partitions is an ordered and immutable record sequence where new values are appended. A sequential number is assigned to each record within a partition, which is referred to as an offset in the context of Apache Kafka.

1. [http://hpi.de/fileadmin/user_upload/fachgebiete/plattner/publications/papers/gh/kafka2020.zip]
III. BENCHMARK SETUP

A. Monitoring Architecture

The architecture of the monitoring system is shown in Figure 3. Grafana [9], an open-source tool, is the interface to the user. It allows creating dashboards and offers CSV export functionality. For evaluation, version 5.4.5 of Grafana’s docker image is employed. OS-level virtualization through docker is used for ease of installation and replicability of results. The OS base image used in this image allows a simple time zone configuration via an environment variable. That is important for time synchronization among all systems. Later versions of the image contain a different OS, specifically Alpine Linux [10], which does not support this feature anymore.

Grafana gets data from Graphite [11], an open-source monitoring tool. It consists of three components: Carbon, Whisper, and Graphite-web. Carbon is a service that retrieves time-series data, which gets stored in Whisper, a library for persisting such data. Graphite-web comprises an interface that also allows designing dashboards. However, these dashboards are not as appealing and functionally comprehensive as Grafana’s components, which is why Grafana is employed. For the installation of Graphite, the official docker image in version 1.1.4 is used, again for time zone configuration reasons.

Graphite receives its input from two sources: collectd [12] and jmxtrans [13]. The former one is a daemon collecting system and application performance metrics that runs on the broker’s machines in the described setup. It offers plugins that can be used to gather a multitude of OS-level measurements. Memory usage, system load, and interface information, as well as received or transmitted packages, are examples for metrics that were captured within the conducted studies.

Jmxtrans, the other data source for Graphite, is a tool for collecting Java Virtual Machine (JVM) runtime metrics. These metrics are provided via Java Management Extensions (JMX) [14]. Making use of jmxtrans allows tracking various information. As part of the studies of this paper, we tracked, e.g., JVM memory usage, the number of incoming bytes, and the number of messages entering Apache Kafka per time unit.

Apache Kafka is the system under test (SUT) in the evaluation presented within this paper. However, it can be exchanged by other systems running in a JVM. The proposed architecture is not limited to Apache Kafka or message brokers in general.

The gathered information is summarized in a Grafana dashboard. Exports of the collected Grafana data enable detailed analysis. Within the presented study, the measured system is installed on three virtual machines that all have the same hardware setups and configurations, which are shown in Table I.

B. Benchmark Execution

Each analysis run lasts ten minutes. The main characteristic studied is the number of incoming or ingested messages, particularly, the one-minute rate of this key performance indicator (KPI), i.e., the number of incoming messages during the last minute. If not stated otherwise, the data sender is executed on the broker server where the topic is stored.

To reduce the number of manual steps needed, Ansible [15] is used for automation. Starting the Ansible script triggers building the project, the topic creation, and the assignment of the created topic to the first of our three Apache Kafka brokers. For all measurements, we use topics with a single partition and a replication factor of one. After these three steps are done, the data sender is started. Subsequently, a rise in the number of incoming messages of Apache Kafka is one change that can be recognized on the Grafana dashboard. Once the configured period of sending is over, the Ansible script stops and the dashboard charts adapt correspondingly.

| Characteristic       | Value                                      |
|----------------------|--------------------------------------------|
| Operating system     | Ubuntu 18.04.2 LTS                         |
| CPU                  | Intel(R) Xeon(R) CPU E5-2697 v3 @ 2.60GHz, 8 cores |
| RAM                  | 32GB                                       |
| Network              | 10Gbit via Fujitsu PRIMERGY BX900 S1       |
| Disk                 | min. 13 Seagate ST320004CLAR2000 in RAID 6, access via Fibre Channel with 8Gbit/s |
| Hypervisor           | VMware ESXi 6.7.0                          |
| Kafka version        | 2.3.0                                      |
| Java version         | OpenJDK 1.8.0_222                         |

TABLE I

SYSTEM CHARACTERISTICS OF THE APACHE KAFKA BROKER NODES
time when the data is exported as CSV from the dashboards. The timeframe of these exports is configurable in Grafana.

The data set from the Grand Challenge published 2012 at the conference Distributed and Event-Based Systems (DEBS) [16] is used as input. It contains data captured from multiple sensors that is combined to single records by an embedded PC within the manufacturing equipment. One record comprises 66 columns with numerical and Boolean values. If the end of the file is reached, the data sender starts again from the beginning.

### C. Data Sender Configuration

Table [II] shows the properties that we applied to the Apache Kafka producer unless otherwise stated. A producer batches messages to lower the number of requests to increase the throughput. The batch size limits the size of these message packages. The used default value is the official one of 16,384 bytes, as defined in the Apache Kafka documentation [8].

Another producer property varied throughout the benchmark runs is `acks`, which determines the level of acknowledgments for sent messages. There are three different options:

- **0**: The producer does not wait for any acknowledgment and counts the message as sent as soon as it is added to the socket buffer.
- **1**: The leader will send an acknowledgment to the producer as soon as the message is written to its local log. The leader will not wait until its followers, i.e., other brokers, have written it to their log.
- **all**: The leader waits until all in-sync replicas acknowledge the message before sending an acknowledgment to the producer. By default, the minimum number of in-sync replicas is set to one.

As the benchmark only uses of topics with a replication factor of one, the existing replica is also the in-sync replica.

A configuration parameter defined by the data sender and not by the Apache Kafka producer is `read-in-ram`. This boolean setting determines how inputs are read. If `read-in-ram` is not set, the data source object returns an iterator object of the records. If it is set, the source object first loads the entire data set into memory (by converting it into a list) and then returns an iterator object for the created data structure.

Furthermore, the number of messages sent by the data sender per time unit is configurable. We use `java.util.concurrent.ScheduledThreadPoolExecutor` for achieving that. This class can execute a thread periodically. By making this delay configurable, we can determine how many messages should be sent per time unit. Each execution sends a single message to the broker. A configured delay of, e.g., 10Kns, leads to an input rate of 100K messages/second (MPS).

### IV. Performance Analysis

#### A. Result Summary

Figure [4] visualizes the maximum achieved input rate of Apache Kafka for selected configurations. Particularly, the input rates illustrated in this and the following figures are the one minute rate of incoming MPS, which is a KPI provided by Apache Kafka. For all benchmark scenarios with the maximum configured input of 1 million MPS, we picked the runs that have the most stable input rates over time.

The highest input rate with about 421K MPS was achieved with two distinct data sender processes, which were configured to send 500K MPS each. However, this accounts for less than half of the configured input rate. With a single data sender configured to send 1 million, the input rates were lower. The results for an acks level of one and all are almost similar with an input rate of about 340K MPS. Surprisingly, sending messages without waiting for acknowledgment, i.e., acks set to zero, hurt the achieved input rate. The maximum was at about 294K MPS with increased batch size. In contrast to the other benchmark scenarios, the achievable input rate can be positively influenced by a higher batch size without harming the stability of the input rate.

#### B. Input Rate of 100,000 Messages/Second

Figure [5] shows the one minute rate of incoming MPS for a configured input of 100K MPS. The altered parameters for this benchmark series are the data sender locality, the acks level, and the read-in-ram option. Similarly to all other figures, an increase in the number of incoming messages per second can be seen at the beginning. This is when the data sender is started and the one minute rate slowly adapts. Moreover, a drop at the end of the time dimension is present in all charts, after the data sender has transmitted messages for the configured duration and has shut down. Consequently, the most interesting part for the evaluations is the data presented in the center of plots.

Figure [5] shows that almost all analyzed system settings reach the configured input of 100K MPS. The only exception is the remote; acks=0; read-in-ram=false configuration (shown in blue). In this setting, the data sender was executed remotely, specifically on a 2015 Apple MacBook Pro, which was connected using Ethernet. For the other benchmark runs, the data sender was executed on the broker where the topic is stored. The configured input could be reached for all acks levels and both read-in-ram modes as presented in the chart.

| Property                  | Value                                                                 |
|---------------------------|-----------------------------------------------------------------------|
| key-serializer            | org.apache.kafka.common.serialization.StringSerializer                 |
| value-serializer          | org.apache.kafka.common.serialization.StringSerializer                 |
| batch-size                | 16,384 bytes                                                          |
| buffer-memory-size        | 33,554,432 bytes                                                      |
| acks                      | 0                                                                     |

**TABLE II**

APACHE KAFKA DEFAULT PRODUCER PROPERTIES
D. Input Rate of 1,000,000 Messages/Second with acks=0

The following three figures, Figure 7, Figure 8, and Figure 9, visualize the results for an input rate of 1M MPS. The difference between these three charts is the acks level, whereas Figure 7 shows the results for acks set to zero. Overall, none of the configurations visualized in Figure 7 reach the configured rate. Moreover, it can be seen that, again, the run where read-in-ram is set to false (shown in blue) performs worst with an achieved rate of about 210K MPS. Thus, running the data sender side this way is omitted in the following.

Turning the feature read-in-ram on leads to an increase of about 40K MPS to, in total, approximately 250K MPS. In an attempt to increase this number even further, we raised the batch size. The purple line in Figure 4 visualizes the measurements for a doubled default batch size. The brown line represents the results for the quadrupled default batch size of 65.54kB. It can be seen that increasing the batch size has a positive impact on the input rate. While doubling the size leads to an input rate of more than 260K MPS, a batch size of 65.54kB enables to ingest about 290K MPS. So a higher batch size leads to a higher ingestion rate in this setting, which is not a surprising observation. The higher the batch size, the lower the the required number of send actions for the same amount of messages. Thus, the overhead that potentially comes with an invocation of the send method can be lowered.

E. Input Rate of 1,000,000 Messages/Second with acks=all

Figure 8 shows ingestion rates for an acks level of one. Different to before, not all runs reach a steady input rate. The only steady rate of about 340K MPS is achieved with the default batch size. For the altered batch sizes, which are identically altered for the benchmarks with input rates of one million MPS, we observe a spiky trend. After reaching a peak at about 420K MPS at the beginning, input rates decrease, whereas the swings for the 32.77kB run are higher than those for the batch size of 65.54kB. While the purple line never reaches this peak level again, the green line has its overall peak at about 440K MPS at the end. Most of the time though, the input rate of the higher batch sizes is below the one with the default batch size. The peak ingestion rates could not be sustained. Summarizing, increasing the batch size when acks are set to one lead to an increase of the maximum input rate, but also caused a non-steady behavior. Most of the time, this input rate was lower than the one with the default batch size.

This behavior is different from the one observed before in Figure 4, where acks is set to zero. In the previous figure, we can recognize that increasing the batch size leads to a sustainable, i.e., steady, raise in the realizable input rate. Moreover, it is surprising to see that the overall reached input rates for acks level of one are higher compared to those where acks are disabled. While the input rates for the runs without acknowledgments never reach 300K MPS, the benchmark run with the default batch size and acks set to one reaches a steady input rate of about 330K-340K MPS. These runs were repeated multiple times, always with the same unexpected result.

F. Input Rate of 1,000,000 Messages/Second with acks=1

Figure 9 shows a similar result as Figure 8. The only approximately steady input rate is achieved with the default batch size. The runs with doubled and quadrupled batch sizes again show a peak at the beginning and a fall afterward to below the steady input rate realized with a default batch size.
The run with the batch size of 32.77kB performs better most of the time compared to the run with the highest batch size.

Compared to the other acks levels, the configuration with the default batch size reaches about the rate as the corresponding run with acks set to one. The other two configurations have the same peak as the ones with acks set to one, but are overall hard to compare to the results shown in Figure 8 due to the unsteady and spiky trend. However, it is clear that the trends are similar to Figure 8 and thus, different from the runs presented in Figure 7 where acks are set to zero. Concerning the overall realized input rates, the results are again surprisingly better compared to those shown in Figure 7.

G. Summary for Single Data Sender

Summarizing the insights shown so far, the most promising configuration has the default batch size and acks set to one or all if a preferably steady input rate is aimed. A steady rate is usually desired as it makes the system’s behavior predictable.

In all studies, the limiting factor could be the data sender. To check if this is the case, we performed further analyses. Particularly, we not only execute a single data sender, but start two distinct data senders with separate data files. Each of them is configured to send data at an input rate of 250K MPS as we saw in Figure 6 that this is a well-achievable target. The difference among the runs is the level of acknowledgment as well as the locality, i.e., on which server the data senders are executed. Figure 10 visualizes the results.

H. Input Rate of Overall 500K MPS with Two Data Senders

To see if the server resources are a limiting factor, we distributed the data sender. Figure 10 shows the results. The blue and the green line represent the measurements where both data senders run locally, i.e., on the broker node containing the topic partition. The blue line shows the results for acks set to zero and the green line stands for an acks level of one.

Similar to the previous results, the acks set to one overall outperforms acks set to zero. However, neither of both lines have a steady input rate. Both have the highest spike at the beginning, which is a behavior seen before. Nevertheless, the input rates are the highest on average compared to the previous figures with a maximum input rate of about 460K MPS.

The purple line shows the run where one data sender is invoked on the broker that stores the topic and one data sender at another broker. The brown line draws the results for the run where the data senders are executed on the two brokers that do not store the topic. Our measurements show that both of these settings lead to the same result: a steady input rate of about 420K MPS. These results reveal two main insights.

Firstly, although a single data sender can create an input rate of 250K MPS as shown in Figure 6, two independently executed data senders do not reach the expected input rate of 500K MPS. Hence, the limiting factor seems to be at the broker side for this setting with a single partition. Secondly, Figure 10 shows that it makes a difference where the data senders are invoked. Both executed on the same host seem to overwhelm the server or impede each other.

Figure 11 visualizes what these message input rates mean with respect to data size. The amount of incoming data in MB/s is visualized for the setting where both data senders were local and remote with acks set to one. It can be seen that the maximally achieved input rate of Figure 10 corresponds to an input rate of about 100MB/s. For the constant input rate where both data senders were executed remotely, a size-wise input of close to 92MB/s is reached. Consequently, given the resources described in Section III-A, the input rate is not bound by network or disk as both can handle higher rates.
V. RELATED WORK

Dobbelaere and Esmaili [17] compare Apache Kafka with RabbitMQ [13], which is another open-source message broker. The impact of different acknowledgment levels is also one factor amongst others that are evaluated in the conducted Apache Kafka study. However, their results do not show a clear difference in the achieved throughput between an acks level of one and zero in the analyzed setting.

Noach, Costan, and Boug [19] evaluate the performance of Apache Kafka in combination with stream processing systems. They also study the influence of Apache Kafka characteristics, the producer batch size being one of them. Similarly to this paper’s results, their findings reveal that a higher batch size does not necessarily lead to higher throughput.

Kreps et al. [5] present a performance analysis of three systems: Apache Kafka, RabbitMQ, and Apache ActiveMQ [20]. Similarly to the work presented before, they analyze the influence of the batch size of the Apache Kafka producer. In addition to the producer performance, they study the Apache Kafka consumer behavior and compare it to the other two systems. The achieved throughput for Apache Kafka in [5] is in a similar range as the work presented in this paper.

Apache Pulsar [21] is a message broker originally developed at Yahoo!. It makes use of the distributed storage service Apache BookKeeper [22]. Similarly to Apache Kafka, Apache Pulsar employs the concept of topics to which producers can send messages and to which consumers can subscribe. The blog post [21] presents a brief performance analysis. The throughput that was achieved in their study using an SSD is 1,800K MPS. However, they do not give details about the benchmark setup, making it hard to assess the results.

VI. CONCLUSION AND FUTURE WORK

We propose a monitoring architecture for Apache Kafka and similar systems, especially for applications running in a JVM. Its design goals include the ease of setup and the usage of state-of-the-art technologies, such as Grafana, and collectd. We performed a comprehensive performance study on Apache Kafka using this suggested benchmarking landscape. Moreover, we evaluate and discuss the outcomes for selected Kafka producer configurations. The development and benchmarking artifacts, such as the data sender and the Grafana dashboard, are published to achieve transparency and reproducibility.

In the defined setting with a single topic with one partition and a replication factor of one, we could achieve a maximum steady throughput of about 420K MPS, which corresponds to about 92 MB/s. Furthermore, we identified and quantified the impact of the data producer batch size, acknowledgment level, data sender locality as well as of additional aspects on the input rate performance. A surprising finding is related to the influence of the acknowledgment level. Having acknowledgments enabled resulted in better performance, i.e., a higher message input rate, which was unexpected. A deeper analysis of why this behavior could be observed is part of future research.

Moreover, a comparison to similar systems, such as Apache Pulsar, Amazon SQS, or RabbitMQ, would be of interest to the research community. Further work should also focus on the analysis of data producers employed in data stream processing frameworks, such as Apache Flink or Apache Beam. These systems often provide their own Kafka producer implementations or interfaces. It would be interesting to investigate if these embedded producers perform differently in comparable settings with respect to the achievable input rate.

Furthermore, it is interesting how the input rate behaves when scaling via, e.g., the number of topic partitions. With a growing number of partitions, scaling the number of broker nodes becomes an additional dimension whose influence can be measured. The impact of higher replication factors is another area of interest which can be studied in future research.

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