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HIGH INTEGRITY SYSTEMS

Master Thesis

AN EVALUATION OF DIFFERENT OPEN SOURCE ESP PLATFORMS TOWARDS CONSTRUCTING A FEATURE MATRIX

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Official Declaration

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Abstract

Contents

1 Introduction

Nowadays, the explosion of the number of digital devices and online services comes along with an immense amount of data that is auto generated or collected from the interactions of users. For instance, from 2016, the Netflix company already gathered around 1.3 PB of log data on a daily basis [1]. With this unprecedented scale of input data, companies and organizations have tremendous opportunities to utilize them to create business values. Many trending technologies such as Big Data, Internet of Things, Machine Learning and Artificial Intelligent all involves handling data in great volume. However, this also brings about a challenge to collect these data fast and reliably.

Once the data is ingested into the organization, it needs to be transformed and processed to extract insights and generate values. In the context of enterprise applications, as the systems grows over time with more services, the need for an effective data backbone to serve these huge amount of data to these services and to integrate them together while maintaining a good level of decoupling becomes inevitable.

Moreover, all these steps of collecting, processing and transferring data must be done in real-time fashion. One of the prominent methods is event stream processing which treats data as a continuous flow of events and use this as the 'central nervous system' of the software systems with event-driven architecture.

1.1 Motivation

To develop a system evolving around streams of events, the primary basis is a central event store which can ingest data from multiple sources and serve this data to any interested consumer. Usually a Event Stream Processing platform will be used as it is designed orienting to the concept of streaming. However, in order to choose the suitable platform, user will usually be burdened by a plethora of questions which need to be answered. The concerns include how well is the performance and reliability of the platform, does the platform provide necessary functionalities, will it deliver messages with accuracy that meets the requirements, can the platform integrate with the existing stream processing framework in the infrastructure, to name but a few.

As there are many platforms now available on the market both open-source and commercial with each having different pros and cons, it could be challenging and time consuming to go through all of them to choose the most suitable option that matches the requirements. It would be greatly convenient to have a single standardized evaluation of these platforms which can be used as a guideline during the decision making process. Therefore, the goal of this thesis is to derive a feature matrix to help systematically determine the right open-source Event Stream Processing platform based on varying priority in different use cases.

1.2 Related Work

There are a number of articles and studies which compare and weigh different platforms and technologies. Many of them focus on evaluating the performance between platforms. There are comparisons of time and resource behavior of Apache Kafka and Apache Pulsar [2] [3], time efficiency between Apache Kafka and NATS Streaming [4].

Some other surveys cover more platforms and a wider range of evaluating aspects such as the comparisons of Apache Kafka, Apache Pulsar and RabbitMQ from Confluent [5] [6]. However, these assessments are conducted only briefly on the conceptual level. Apart from these studies, most of the scientific researches only concentrate on comparing different stream processing frameworks such as Apache Spark, Apache Flink and Apache Storm [7] [8] [9]. Therefore, in general, there is still lack of in-depth investigation into the differences of Event Stream Processing platforms and their conformability with event-driven use cases and this is where the thesis will fill in.

1.3 Contribution

In this thesis, three open source Event Stream Processing platforms, namely, Apache Kafka, Apache Pulsar and NATS Streaming are selected for evaluation based on preliminary measures and reasoning. Each platform is assessed against a set of criteria covering all important quality factors. The results are summarized in the form of a feature matrix with adjustable weighting factors of quality categories and features. Therefore, the matrix can be tailored to the need of user and adapted to individual use case to determine the most suitable platform for that case according to its priorities.

In the evaluation, sample implementations and code snippets are presented to illustrate the features of the platforms. Moreover, best practices for each platform in different use cases are also drawn out. These can be used as a reference for actual implementation of applications on top of these platforms.

1.4 Organization of this Thesis

The thesis is organized as follows. Chapter 2 gives theoretical background of the topics stream processing and Event Stream Processing (ESP) platforms. Chapter 3 enumerates prominent open-source ESP platforms currently available and furthermore derives criteria to choose the top three platforms which are considered in this thesis. Moreover, it also includes the elaboration of comparison metrics and the form of the feature matrix. After that, chapter 4 presents the evaluation of each platform against the comparison scheme and gives a discussion on the resulted feature matrix. Finally, the conclusion summarizes and proposes future improvement for the matrix.

2 Background

In order to conduct the comparison effectively, it is necessary to first lay a good theoretical basis of event-driven architecture, event stream processing and the concrete roles of an Event Stream Processing platform. Based on that, a comprehensive set of evaluation metrics can be determined.

2.1 Event Driven Architecture

In distributed systems comprised of multiple services, these services need to have a mechanism to coordinate and work together to achieve end results.

2.2 Event Stream Processing

With the increasing amount of data, the demand about how data is processed and analyzed also evolves over time. In the early day, data is usually collected over a period of time and stored in a big bounded batch in a data warehouse. Some scheduled batch jobs will then go over the entire batch of data to generate insights and reports tying to the needs of the organization. However, this type of data processing gradually cannot keep up with the need of faster analysis allowing companies to response more timely to change. Therefore, the concept of stream processing begins to progress.

Unlike its batch counterpart, stream processing aims at handling unbounded data which is a better form for representing the flow of events in real world given their continuous and boundless nature. By processing this influx of data continuously as they arrives, events and patterns can be detected with low latency making stream processing more suitable for real-time use cases. Moreover, the input data can come from an uncountable number of sources with varying transmission rates. Therefore, data may arrive late and out of order with respect to the time it is generated at the source. In this case, for it sees data in an endless fashion, stream processing gives more tolerance for late data and more flexibility to assemble data into windows and sessions to extract more useful information. It is even suggested that a well-designed stream processing system with guarantee of correctness and the capability to effectively manage the time semantics could surpass batch processing system [10]. Back in the time when using stream processing was a trade-off between accuracy and low-latency, it was a popular idea to run two batch and stream processing pipelines in parallel to achieve both fast and correct results [11]. As stream processing engines grow more mature and accurate, the demand for such system is lessened [12].

Moreover, stream processing is not merely a data processing paradigm to achieve low latency result. Applying the concept of streaming on the architectural level also has the potential to help build more scalable and resilient systems. In simplest scenarios, a monolithic architecture with all components packaged and deployed as a single artifact is a good choice for its simplicity. However, as the application expands, it becomes harder to scale. Therefore, the microservices architecture arises. In general, an application is disassembled into self-contained and loosely-coupled services, each of which maintains its own database and communicates with other only via a mutually agreed contract [13]. This approach proves to help the application scale more freely and speed up the development process. Nevertheless, it only works at its best when services are truly independent from each other which is usually not the case in reality. It is unavoidable that services must maintain a certain level of dependence and sharing of data. When services grow with more functionalities, they need to expand the service contract to expose more data to outside which then contradicts with the philosophy of microservices because of higher coupling. This is known as the dichotomy of data and services [14]. The problem of coupling emerges not only between services of applications but also between data systems in general. A sophisticated software system can comprise of multiple data systems with different functionalities such as relational database, document store, cache, monitoring system, data warehouse. Data needs to be shared and synchronized between these components in an efficient way. This can quickly turns the entire system into a big tangled mesh. As an example, this problem was experienced at LinkedIn as their system became increasingly complex [15].

This problem can be tackled by using stream processing in event-driven systems. In such systems, every operation, state change or any information can be recorded in form of an event. Events from all services are gathered and written orderly to an append-only log called event stream. On the contrary to the previous approach where data is encapsulated in each service, this stream is used as the single source of truth shared by all services. Any data service in the system can consume and process this log of raw events using stream processing to generate the current system state. This approach is usually known as event sourcing [16]. This log-centric design fits seamlessly into a distributed environment with numerous moving components to allow data to be replicated among services with minimal coupling [17]. Moreover, services also have the flexibility to derive different data structures from the raw events to match their specific access pattern. The task of data representation is now done at individual data service instead of in the central data store. This is referred by Martin Kleppmann as turning the database inside out [18]. The result is a more neatly organized system with every services synchronize and communicate via the event streams.

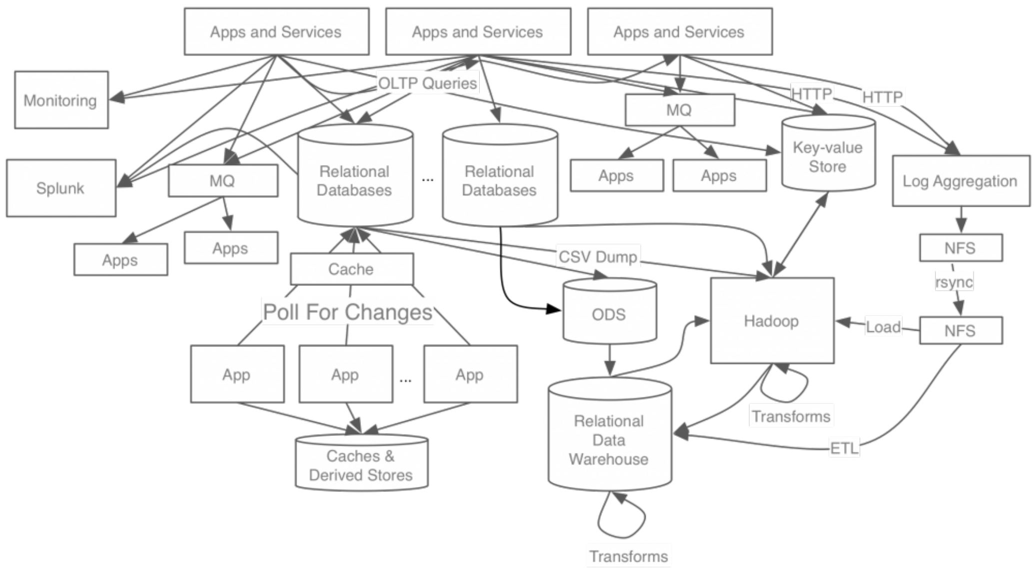

Figure 2.1: The tangled data systems at LinkedIn in the old day [15].

2.3 Event Stream Processing Platform

An Event Stream Processing platform must facilitate the construction of software systems revolving around streams of events. Therefore, it must have a number of fundamental capabilities. Firstly, it must provide the mechanism for events storage. Optimally, it should also support the option to persist events for an infinite period of time since this will be the single source of truth that the entire system depends on. Accessing interface must be provided for applications to publish and consume events. The platform should also enable the processing on the events streams either by providing a native stream processing tool or integrating with external stream processing framework. Moreover, the platform should come with ready-to-be-used tools to integrate with a wide range of existing data systems effortlessly including also legacy systems.

The order of events must be preserved by the platform throughout their entire life cycle: in storage, transit and under process. All of these capabilities should be in a real-time, high throughput, scalable and highly reliable fashion so that the platform would not become the bottleneck in the system. Finally, the platform must have a rich set of utility tools for monitoring and management.

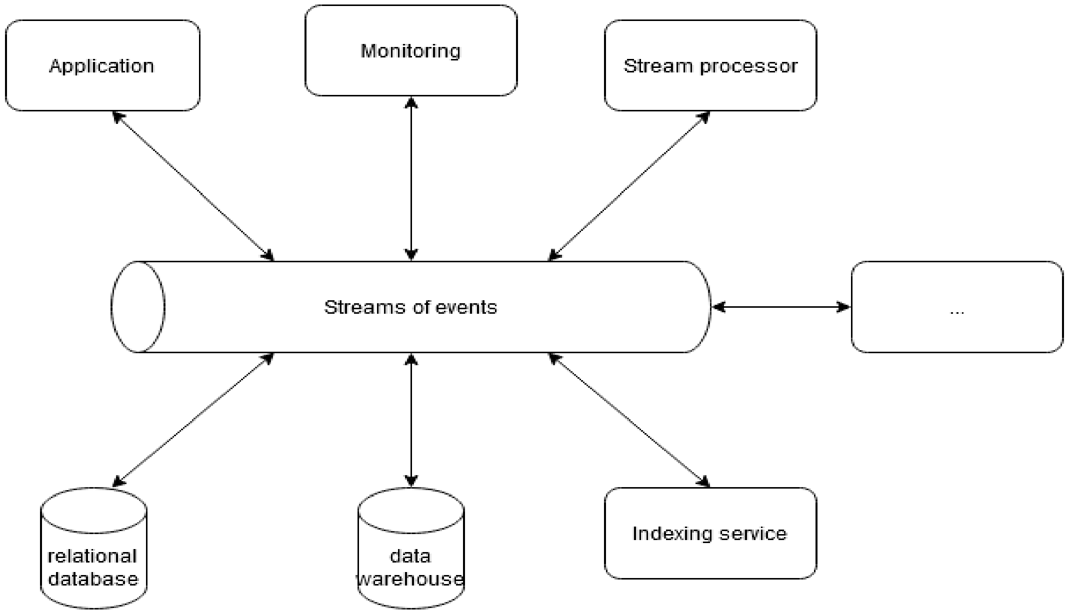

Figure 2.2: System with streams of events as the single source of truth.

3 Evaluation Scheme

3.1 Considered Platforms

As the concept of using event streams as the source of truth gains more attention and becomes more popular, many projects aiming at creating a processing platform based on streams started to take shape.

Numerous companies first started their projects as in-house products and then later open-sourced them to enhance the development pace with the help of community. Kafka, which was first developed at LinkedIn, is the first prominent name in the field. It was later open sourced to the Apache Software Foundation. Yahoo! also created their own stream processing platform named Pulsar and it is now also an Apache project. The company Alibaba joins the trend as well by open sourcing their RocketMQ to Apache Foundation. In addition, there is the NATS streaming server, which is created by Synadia and is currently an incubating project of Cloud Native Computing Foundation. Pravega is also a new name with fast advancement.

Since an adequate evaluation for all these platforms could not be contained within the scope of the thesis, only three platforms will be selected based on a set of criteria indicating the maturity and the size of the active community.

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3.2 Evaluation Metrics

3.3 Structure of Feature Matrix

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