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DOI
10.1109/ISIE51358.2023.10228152

Publication date
2023

Document Version
Final published version

Published in
2023 IEEE 32nd International Symposium on Industrial Electronics (ISIE)

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Link to publication

Citation for published version (APA):

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A Performance-Adaptive and Time-Monitored Autonomous Ticket Booking Service in Cloud

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Abstract—With the increasing demand for autonomous ticket booking services for all kinds of events, user numbers and service performance requirements increase dramatically. Platforms such as BASH, Ticketmaster, Eventbrite, and SeatGeek, often outsource such services to third parties, but the operation cost is often high. Therefore the performance for time-critical requirements is without monitoring. Furthermore, the cloud platform is becoming a popular solution for event organizing platforms due to its mighty computation power. In order to address these issues, this study presents a cloud-based, performance-adaptive, and time-monitored autonomous ticket booking system, utilizing a paradigm for booking as a service that can be readily included into cloud platforms. Together with the implementation itself, we also provide a variety of flexible service settings that may serve a specified number of concurrent users while consuming the least amount of resources. We carry out thorough implementations to verify our methodology.

Index Terms—time-monitored, cloud platform, autonomous ticket booking, performance-adaptive

I. INTRODUCTION

With the popularity and convenience of the online ticket booking service [7], there have been increasing numbers of platforms which are in need of adaptive autonomous ticket booking solutions. Third-party providers like Ticketmaster, Eventbrite, and SeatGeek are pricey proprietary solutions. These services hold client data while they are operating, jeopardizing privacy and data control. Because a platform depends on those services to provide economic value, any potential failure of those third-party services might have a direct impact on the user experience of its users. The consequent performance degradation harms time-critical requests, and the corresponding solution can be costly. Using an unlimited percentage-based pricing system is a frequent approach; nevertheless, this has substantial costs [13] [9] [2]. Moreover, because all of these services are provided by other companies, users are transferred from the platform to another setting to purchase tickets. Consequently, ticket booking as a time-critical service experiences performance degradation. To that end, this effort attempts to build a solution that can immediately adapt to the current services of a platform, allowing the platform total control, and provide an autonomous Booking-as-a-Service system for platforms that handle these issues. Furthermore, this work aims to support a large concurrent user number and solve these problems. The best practice nowadays for handling high user volumes is to dynamically scale the service’s resources in accordance with the data on the actual workload. Regarding the demands of high computational power and scalability, a cloud-based platform becomes an ideal solution. In this work, we investigate the ideal integration and adaptive configuration for a cloud-based ticket booking platform and conduct a comprehensive analysis.

A. Challenges

There are certain challenges for an autonomous ticket booking platform: 1). Large user number; 2). The conflicts control between tickets availability and purchasing behavior; 3). Faulty purchases; 3). Service availability: for tickets booking service, the service up-time needs to reach 99%.

B. Contributions

The contribution of this work is as follows:

1) We propose an autonomous ticket booking service system that can be directly integrated with a ticket selling platform.

2) We propose a performance-adaptive ticket booking system which offers ticket booking service to numerous users, meeting the time-critical requirement in the meantime.

3) We conduct comprehensive implementation and analysis of the adaptive configurations based on our proposed system. The final solution and configurations are validated by BASH∗†.

II. RELATED WORK

There have been a lot of work done in terms of ticket booking services [10] [3] [8] [11], some work addressing time-critical tasks [6] [5]. The book [10] helps us get a deeper comprehension of the tools and resources that enable the development of scalable and time-critical applications. These studies look into how to assess the cost and quality of a ticket-booking service. [3] analyzes the effectiveness and prices of various cloud services offered by well-known cloud

∗BASH is a tech startup building a platform where people can easily organize and attend events.
companies. The same methodology may now choose a cloud provider and the appropriate services based on the desired performance and cost balance. Sidra Aslam et al. [1] [4] provide further insight into the role of run-time load balancing in distributed, quality service-dependent systems. The current state of availability in cloud technology is investigated and summarized by Mina Nabi in their article [8]. The article explores the popular mechanisms used by cloud providers for error recovery and evaluates their performance in ensuring availability. To predict the workload of a cloud application and dynamically scale resources as needed, Nilabja Roy et al. [11] have developed a system. In terms of load balancing mechanisms, Kubernetes is supported by several cloud providers, including Google Cloud Platform [12]. Kubernetes is a container orchestration system that implements both load balancing and error recovery.

After reviewing the aforementioned works, it becomes clear that there is a significant focus on performance adaptability, including load balancing, scalability, and assessing the quality of service and booking costs. However, the study [3] that evaluates the cost-to-performance ratio of specific cloud services is outdated and doesn't consider newer technologies like cloud functions or even Kubernetes. This work aims to build up a performance-adaptive autonomous booking system and implement comprehensive implementation to demonstrate its performance.

III. ARCHITECTURE

A. Requirements

1) Functional level: The booking service must offer the expected functionality. At the very least, it should have HTTP endpoints that enable users to: 1) purchase tickets, 2) view purchased tickets, 3) create and sell tickets, and 4) check the number of available tickets.

2) Performance level: From the end-user’s perspective, the following properties are crucial: Minimal latency: High latency can negatively impact user experience and lead to inaccurate purchases. Service availability: The service must be accessible at all times, with minimal downtime. Consistency: Customer purchase behavior must align with ticket availability, which should be continuously updated. Distributed: To provide low-latency access to users worldwide, multiple instances of the service should run concurrently across different continents. Scalable/elastic: The instances should be capable of horizontal and vertical scaling to handle increased concurrent user traffic. High fault tolerance: The service should remain operational in the event of errors or failures, ensuring minimal downtime.

IV. SYSTEM DESIGN

The architecture for our service customization component is presented in Figure 1. By indicating the required number of concurrent users the service should handle, the user communicates with the component. With this data, the Service Customization Tool creates a deployment description that supports the desired user count while minimizing expenses. The service deployment tool receives the created description from the tool and distributes the service automatically in accordance with the description.

Figure 2 illustrates an architecture example of the service developed by the customization component to meet the specifications listed earlier. The service starts at the load balancer, which the user may access by using a front-end to make HTTP requests to our service. The load balancer then splits up the requests amongst the service instances, and the load monitoring component keeps track of the workload and relays that information to the scaling component. In accordance with pre-established configuration limitations and taking into account the workload of the instances, the scaling component modifies the number of service instances. The service will be able to scale to fulfill the demands for availability and low latency. Last but not least, the service instances establish a connection to our database, which stores and retrieves data on tickets, users, and orders. Figure 3 illustrates the information flow within the system, using the example of a user buying a ticket.
is our preferred Object-Relational Mapping (ORM) package, Gin is used to manage HTTP requests and URL matching.

2) Cloud functions: In contrast to the containerized version, the cloud function implementation of the service is not self-contained. Unlike the Kubernetes-based method, services like Google Cloud Functions simply need customers to deliver the code for a single function that complies with the cloud functions service’s HTTP framework criteria. In our particular situation, Google Cloud Functions anticipates a Go function with the arguments “http.ResponseWriter, http.Request” since it makes use of Go’s built-in HTTP framework base.

While function instances can be reused, a different init function is used each time a new instance is generated to establish the database connection. It is not feasible to include a connection pooling mechanism within the functions themselves due to the total isolation of cloud function instances. A service, such PgBouncer, must be hosted and linked to the database in order to solve this problem. Then, rather than directly connecting to the database, cloud functions would link to the PgBouncer instance.

C. Functionality

Both implementations must provide the same functionality and make use of the same logic in order for tests conducted between them to be reliable. The following HTTP endpoints are exposed by both implementations:

- /tickets (GET, POST, DELETE): Find, create or delete tickets. You can also retrieve a single ticket using the ‘id’ query parameter.
- /tickets-buy (POST): Buy a ticket and decrease the available number of that ticket. This returns an order object which can later be retrieved again by the user in a different call.
- /users (GET, POST): Find or create a user/users.
- /users-tickets (GET): Find the tickets bought by a specific user, using the ‘id’ query parameter to select a user.

The vast majority of these functions use simple SQL queries to communicate with the database and produce desired results. Contrarily, the tickets-buy endpoint is considerably more complicated and may be used to introduce erroneous purchases or racial circumstances. By assuring the availability of sufficient tickets and changing the number of available tickets inside the same Postgres transaction, we try to allay both of these worries. This method ensures that the ticket count remains constant while we validate it and alter it appropriately because Postgres transactions are atomic. We then create a new order and provide it to the ticket buyer if there are still enough tickets available and the count has been effectively dropped.

VI. EXPERIMENTS

We carry out a number of trials with various setups of our booking service in an effort to strike the ideal balance between performance and cost. We can ascertain the precise effect of each component on the overall performance and cost of the service by methodically adjusting the configuration of individual components. We then integrate the outcomes of
these tests to produce a variety of configurations that satisfy our specifications. These configurations range in price and performance, with some providing better performance at a higher price and others doing so at a lesser price. This gives the platform utilizing the service freedom by letting them select a configuration that suits their needs, preventing excessive spending on inefficient resources.

VII. METHODOLOGY

We run a workload simulation that simulates concurrent customers submitting requests in an identical way to actual users in order to assess the performance of the service for each configuration. These tests entail exponentially raising the number of virtual users in order to determine the service’s failure threshold. When 99% of requests’ maximum request time reaches 2 seconds, the test is considered to be complete. In order to emulate users, we employ the k6 framework, as illustrated in Figure 4. Each user initially waits for a random period between 1 and 10 seconds, and then queries the remaining number of tickets for a specific ticket using an HTTP GET request to /tickets?id=ticket-id. By waiting for a random duration, we ensure that users do not send requests simultaneously. After an additional waiting period of 10 to 60 seconds, the user purchases a ticket by sending an HTTP POST request to /tickets-buy. Once a ticket is purchased, the user restarts and acts as a new user, repeating the aforementioned sequence of actions until the completion of the test.

A. Metrics

We keep track of each HTTP request’s duration in order to assess how well our service is functioning during these testing. We stop the test when the 99th percentile of these times hits 2 seconds, and we keep track of the most virtual users who were reached up to that point.

We gather these metrics at the front-end level, where we time how long it takes from the time a request is sent to our service to the time it is returned, as shown in Figure 5.

B. Testing environment

We carried out the testing on a Google Compute Instance to make sure that our trials could be repeated and that they were consistent. We specifically used the ‘e2-standard-8’ machine type, which has 32 GB of RAM and 8 virtual central processing units (vCPUs).

VIII. EXPERIMENT 1: DATABASE PERFORMANCE

A. Methodology

We progressively increase the number of simulated users until the 99th percentile of HTTP requests sent by these users reach a threshold of 2 seconds in order to find the best configuration for our system. Iteratively increasing the number of vCPUs assigned to the database with each iteration of this operation. The impact of introducing a read replica to the system is examined in a second experiment once the ideal number of vCPUs has been established. The primary instance of the database is offloaded from some read operations by a read replica, which runs as a separate instance of the database and duplicates each update from it.

B. Results

The visualization depicted in figure 6 reveals that enabling access to more CPU cores leads to a substantial increase in the maximum count of simultaneous supported users. Furthermore, introducing a read replica yielded a performance improvement within expected bounds, as demonstrated in figure 7. Notably, during the experiments, approximately 75% of the requests issued by the simulated users were merely of a read nature.
IX. EXPERIMENT 2: SERVICE PERFORMANCE WHEN USING KUBERNETES

A. Methodology

Until the 99th percentile of the HTTP request length hits a specified threshold of 2 seconds, we gradually increase the number of virtual users in our workload to establish the service’s maximum capacity. We do several tests on a handful of chosen machine types to assess the effect of various machine types on the service capacity. We conduct the experiment many times with progressively more nodes running our service on each type of computer.

B. Results

Several settings can be used to attain certain maximum supported concurrent user counts, as illustrated in figure 8. Each node type’s performance improves as the number of nodes rises, as predicted. The fact that the ”e2-highcpu-4” node type could never support more than 30000 virtual users on this graph further demonstrates the networking limitations of our testing gear. Both the ”custom” and “e2-highcpu-4” node types could probably accommodate more than 30,000 virtual users, although better hardware would be needed to confirm this assertion.

X. EXPERIMENT 3: SERVICE PERFORMANCE WHEN USING CLOUD FUNCTIONS

A. Methodology

The allotted RAM and the maximum number of instances for each function are changed for our tests using the Cloud Functions implementation.

B. Results

Figure 9 illustrates how restricting the number of concurrent instances of each cloud function increases the number of concurrent users that our service can accommodate. The greatest results are obtained when the maximum number of instances per function is 20. If we raise the maximum number of open connections, performance suffers similarly, albeit not to the same extent as with the Cloud Functions implementation, as demonstrated in figure 11. The findings in figure 10 demonstrate when memory allocation for individual cloud functions begins to impede the system’s overall throughput. The bottleneck is removed by allocating 1 GiB or more of RAM for each function. Any additional gigabytes appear to have little advantage.
XI. Experiment 4: Service Performance Characteristics of Different Configurations

A. Methodology

Lastly, we suggest a variety of setups that enable growing numbers of concurrent users utilizing the findings from the tests previously presented. We try to minimize the anticipated expenses for each of these setups. We calculate these expenses using Google’s pricing calculator.

B. Results

The six configurations we chose are displayed in Table I. These configurations are in accordance with Table II, which lists the maximum number of concurrent users for each setup along with the associated monthly cost. For the amount of people it serves, each configuration attempts to be as economical as feasible. All four of the configurations—A, B, C, and D—utilize Cloud Functions. Cloud Functions have a zero scaling capability. Two configurations, D and E, are available to accommodate a maximum of 20,000 concurrent users. The 20000 users are supported by Configuration D, which employs a less efficient node type that scales up to two instances. Configuration E is a preferable choice since it never scales down if a platform employing this service needs continual scalability. Two configurations, D and E, are available to accommodate a maximum of 20,000 concurrent users. The 20000 users are supported by Configuration D, which employs a less efficient node type that scales up to two instances. Option D works better if the platform hardly ever uses all of its capacity. Configuration F offers the best value for 30000 concurrent users.

ACKNOWLEDGMENT

This research is funded by China Scholarship Council and the European Union’s Horizon 2020 research and innovation program under grant agreements 825134 (ARTICONF project), 862409 (BlueCloud project) and 824068 (ENVRI-FAIR project). The research is also supported by EU Life-Watch ERIC.

REFERENCES