Conference Article

Implementation of Recommendation System for Campaign Management Based on Digital Wallet Usage Habits

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Abstract

This study seeks to develop an innovative infrastructure for digital wallets that addresses the diverse requirements of both corporate and individual users. The main focus is on real-time monitoring of users' interactions on digital asset management software and generating instant actions through the analysis of this data. In this context, the main objectives of the wallet include providing local solutions as an alternative to high transaction fees, ensuring that assets are securely stored on local cloud systems with digital wallets, and developing applications that will meet the needs of Financial Technology companies and its business partners. Thus, it is aimed to increase the security, efficiency, and cost-effectiveness of digital asset transactions and to improve the user experience in digital wallet use in general. As a result, this study aims to provide a comprehensive solution that aims to offer significant advantages such as security, usability, and cost-effectiveness in the field of digital asset management and storage. It is expected that this study will contribute significantly to the expansion of the digital wallet ecosystem and to users' experiences in digital asset management.

Keywords: Digital wallet, e-Money, complex event processing, big data, smart campaign suggestion, financial solutions

1. Introduction

The change in shopping trends in the market after Covid-19 affects the speed of sales of products and services through digital channels. The provision of diversified financial instruments increases the participation of individuals in the economic system through digital wallets. The rise in end-user expectations in the financial ecosystem is making the use of digital wallets more widespread every day. These wallets allow individuals to manage their disposable income more effectively thanks to smart financial guidance. Considering that the number of smartphone users worldwide has reached 7.2 billion and that 3.7 billion people are expected to use mobile payments for cashless transactions by 2024, the importance of digital wallets is increasing even more [1] [2] [3].

The digital wallet product developed prior to this study offers users the opportunity to manage all their financial balances in different channels on a single platform. Users can easily access their savings, quickly collect third-party receivables, and perform banking transactions on this platform.

In this study, a structure was developed that analyzes the uploads or expenditures made by users to their digital wallets with Apache Flink algorithms within the scope of campaign programs and recommends the most suitable campaigns for them. Here, the data is first created in the Oracle database and transmitted to the Mongo database with an ETL. Afterwards, Apache Flink algorithms process the data here according to the determined rules and produce some campaign outputs.

This article consists of 5 main headings. In the first heading, some statistics that are used as a basis, namely the usage of digital wallets and mobile payments worldwide and the need for which the project was prepared, are explained. In the second section, the materials and methods used in the project are explained. In the third section, the developments made together with the purpose of the project are summarized. The fourth section is devoted to the acknowledgment section. In the last section, some reference articles and books used in the study are included.

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2. Materials and Methods

2.1. Click Stream Data For Complex Event Processing

Apache Flink is an advanced, open-source platform for processing large-scale data streams in real time. It supports continuous data analysis, providing insights while enabling both batch and streaming data processing. The image as given in Fig. 1fE shows a simplified data flow with basic components such as “Source”, “Map” and “Sink” representing the stages for data input, transformation and output.

In the parallelized view, each operator is broken down into subtasks with specific levels of parallelism, determining how many tasks can run simultaneously. For example, the Source and map operators have a parallelism of 2, allowing them to handle more data concurrently, while the Sink has a parallelism of 1. This parallelism flexibility helps achieve high processing speeds.

Flink also includes windowed computations, allowing it to segment data streams based on time windows. The "keyBy," "window," and "apply" operations handle partitioning, time-based processing, and function application, enabling timely analytics on streaming data. Additionally, Flink regularly saves the state of each task as checkpoints, which act as snapshots of data as it flows through the system, providing fault tolerance. State management allows Flink to keep track of information across events—essential for operations that need to maintain context, such as aggregating data over time or across different parts of a data stream.

Flink also includes a Complex Event Processing (CEP) module, which allows users to define custom patterns for detecting complex event sequences. These patterns can specify conditions like event contiguity and maximum allowed time gaps, making it highly versatile. For example, a pattern could be configured to trigger an alert if a sequence of two high-amount expense is detected within a 10-second window. The CEP librarys’ ‘select’ method lets users specify actions to take when these patterns are matched, such as generating alerts or warnings. The module can handle complex event scenarios by supporting nested patterns and conditional branching, making it adaptable for more sophisticated analyses.

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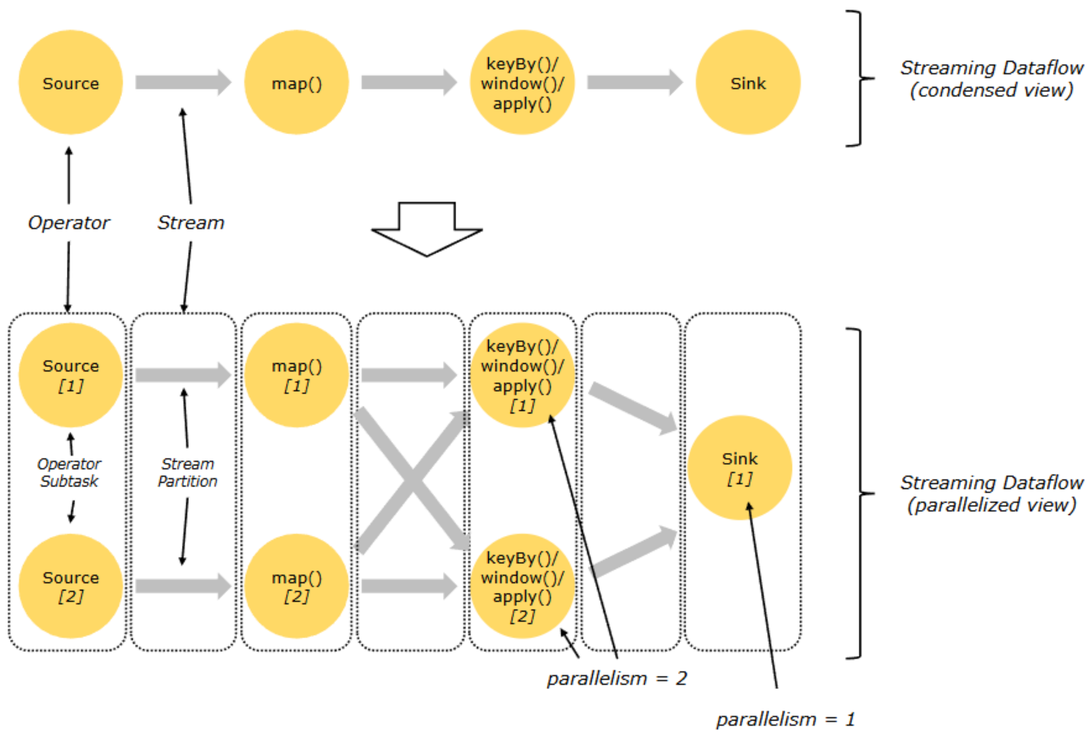

Figure 1: Flink Algorithm Example

2.2. Overall Architecture

The ETL (Extract, Transform, Load) process between Oracle and MongoDB is designed to transfer and synchronize customer and transactional data with near real-time precision, leveraging Quartz for scheduling and automation. By using Quartz, we ensure that data extraction, transformation, and loading occur at regular intervals and without manual intervention. This automated process not only maintains the freshness of data but also keeps the system responsive to new information, allowing for the timely generation of campaign suggestions based on live data. The rules governing the ETL process emphasize data integrity and accuracy. Data moves from Oracle, where initial customer and transaction records are created, through a transformation step tailored to MongoDB's document structure, and finally into MongoDB for high-performance, flexible storage. Data formats for this process are structured primarily in BSON: customer data includes attributes like customer_id, name, and loyalty_tier; transaction data holds transaction_id, timestamp, and amount; and campaign data encompasses campaign_id, start and end dates, and eligibility criteria. With this setup, MongoDB becomes a rich source of real-time data, ready for advanced analytics and campaign targeting. For customer loyalty, K-Means Clustering is our chosen algorithm. It classifies customers into loyalty segments based on behavioral data -specifically transaction frequency, average transaction value, and recency of transactions. With each processing interval, Quartz schedules the clustering algorithm to analyze and group customers anew, enabling the system to dynamically adapt as customer behaviors evolve. Each cluster represents a different level of customer engagement, such as Bronze, Silver, Gold, or Platinum, where each tier reflects varying levels of loyalty. Customers in the Bronze segment might engage sporadically, while Silver and Gold users show more consistency in activity, and Platinum represents the most engaged, loyal customers who are prime candidates for premium campaigns. By regularly recalculating these clusters, the system remains aligned with the latest data, delivering accurate and timely loyalty insights. The segmentation and tiering of customers are essential for crafting effective campaigns. Using click stream data -captured through interactions on the platform and processed in real-time- we gain visibility into each customer's behavioural patterns, allowing for finer segmentation.

Basic segments, for instance, consist of users with minimal activity, identified through lower transaction frequencies and smaller purchase amounts. Mid-tier segments capture customers with moderate but steady engagement, while high-tier segments target those with frequent transactions and higher average spending. The premium segment, derived from click stream analysis, includes customers who interact heavily with the platform and exhibit the highest engagement. These tiers are designed to guide campaign allocation: Bronze-level customers may receive introductory offers, while Gold and Platinum members enjoy personalized, high-value campaigns tailored to maximize engagement and brand loyalty.

A dedicated campaign management module, built in Java, enables admin users to create, configure, and deploy campaigns tailored to each customer segment. Through Quartz scheduling, the module supports timed campaign rollouts and automated updates, ensuring that each customer receives campaign messages and notifications at optimal times. Within this module, admins define campaign parameters like eligibility criteria, start and end dates, and relevant promotional content. Once a campaign is active, customer data -updated in real time through click stream interactions- guides automated campaign assignment based on loyalty tiers.

The module also integrates with a notification system, allowing for in-app messages, e-mails or SMS notifications to alert customers of relevant campaigns, keeping them

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informed and engaged without manual intervention. This integrated platform -with its automated ETL, real-time clustering, click stream analytics, and seamless campaign management- creates a responsive environment for customer loyalty and engagement. Each component, from data processing to campaign delivery, is designed to work in harmony, maximizing the relevance of interactions and reinforcing customer relationships through intelligent segmentation and automated, personalized engagement strategies.

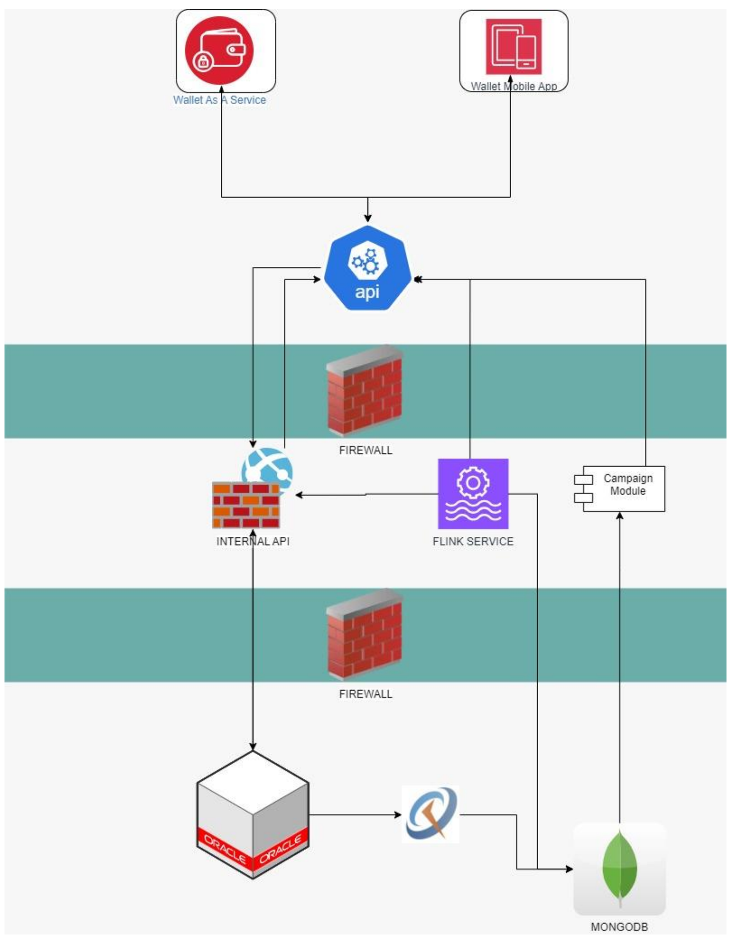

Figure 1: Modular Service-Based Architecture

3. Result

This study aims to develop an innovative infrastructure for digital wallets. It is aimed to develop a solution that meets the needs of both corporate and individual users. The main focus is on real-time monitoring of users' digital wallet data and generating instant actions through the analysis of this data.

This study, the data is first created in the Oracle database and transmitted to the Mongo database with an ETL. Afterwards, Apache Flink algorithms process the data here according to the determined rules and produce some campaign outputs.

As a result, this project provides a comprehensive solution that aims to offer significant advantages such as security, usability, and cost-effectiveness in the field of digital asset management and storage. It is expected that this study will significantly contribute to the expansion of the digital wallet ecosystem and users' experiences in digital asset management.

4. Acknowledgment

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