Streamlined Website Insights: Leveraging Kafka, Redis, MongoDB, Flink, Elasticsearch, and Kibana

Group 2:
- Vidushi
- Kamakshi
- Akanksha
- Spandana

Motivation & Impact

Motivation:
- [illegible]

Impact:
- [illegible]

Project Overview

- [illegible]

Introduction

- The landscape of e-commerce analytics is rapidly evolving, driven by advancements in real-time data processing and machine learning technologies.
- This project outlines our novel approach to capturing and analyzing data from a simulated furniture e-commerce website, where user interactions are synthesized to reflect realistic browsing, shopping, and purchasing behaviors.
- Our goal is to deliver a dual-layered view into user engagement and product performance by utilizing a hybrid model that combines the analytical depth of offline machine learning approaches with the immediacy of real-time stream processing.
- This project is an example that illustrates how transformative the hybrid approach of real-time analysis with offline analysis can be in e-commerce.

Explainable AI + Differential Privacy

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Stream Processing

Integration with Flink - Elastic Search- Kibana

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Bloom Filter & Hyperlog log

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Batch Processing

MongoDB- LSH

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Key Learnings:
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Motivation & Impact

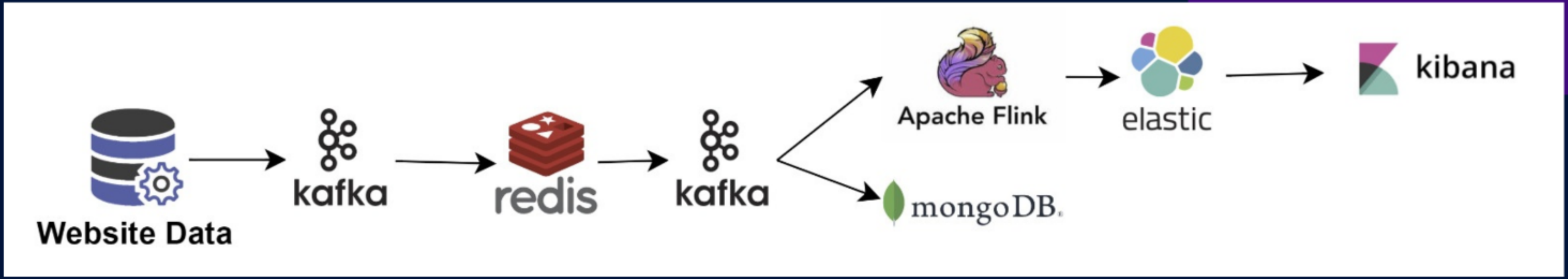
Motivation:

- In the rapidly evolving landscape of e-commerce, businesses are increasingly reliant on technology to understand consumer behavior, anticipate needs, and enhance user satisfaction.
- However, the challenge often lies in balancing the need for immediate response with the requirement for deep, strategic insight.
- Our motivation stems from the need to bridge this gap—integrating real-time responsiveness with comprehensive analytical depth.

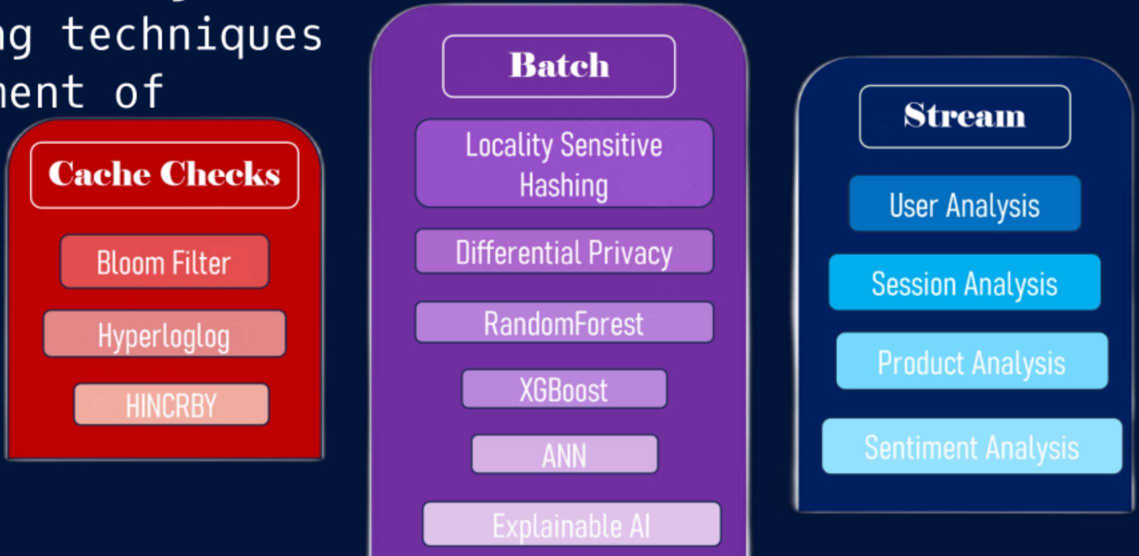
Impact:

- The implementation of our hybrid analytical framework stands to transform e-commerce platforms by providing a more holistic view of the customer journey.
- The dual benefits include enhanced user experiences through personalized interactions and improved business outcomes through optimized product offerings and marketing strategies.
- This approach not only satisfies the immediate expectations of today's online shoppers but also looks ahead, predicting future trends. This sets a new benchmark for responsiveness and understanding in the e-commerce world.

Project Overview



- Initially, website data encapsulating user interactions is collected and streamed in real-time using Apache Kafka.
- This stream is then interfaced with Redis, where Bloom Filter & Hyperlog log are implemented and then valid user data is again loaded into another kafka topic.
- Following this, the valid users data is stored in MongoDB for advanced offline batch processing, including techniques such as Locality Sensitive Hashing and development of models.
- Parallelly, the data is channeled into Apache Flink and Elasticsearch, to generate real time insights and the visual representations are crafted using Kibana.



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Batch Processing

MongoDB- LSH

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- It works by hashing similar input items into the same "buckets" with high probability, allowing for the identification of items that are similar to a query item quickly.
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Explainable AI + Differential Privacy

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Explainble AI + Differential Privacy

- Developed two machine learning models and one deep learning model aimed at predicting customer purchasing behavior.
- These models are meticulously crafted to analyze various customer data points and predict whether a customer is likely to make a purchase.
- In our model, we use differential privacy to add 'noise' to the data in a controlled way. This is done by the Laplace mechanism that we applied to the numerical features in our dataset.
- Differential Privacy is crucial when working with user data because it helps to protect individual privacy without sacrificing the utility of the dataset as a whole.
- In our project, we used SHAP (SHapley Additive exPlanations), which is an approach to explain the output of machine learning models.
- We apply SHAP to interpret the predictions of our models, helping us to understand which features are most influential in predicting whether a user will make a purchase.

Stream Processing

Integration with Flink - Elastic Search- Kibana

- Consumes user session data from the valid_customer_session Kafka topic.
- Flink processes streaming data from Kafka, handling user session data as it flows in real-time.
- By using Flink, Converts each message into a session summary, identifying key user activities and product interactions.
- Analyzes sentiments in product reviews classifying them into Elasticsearch's product_sentiment index.
- Elasticsearch allows for the efficient indexing and storage of large volumes of data processed by Flink enabling real-time insights and visualization through Kibana.

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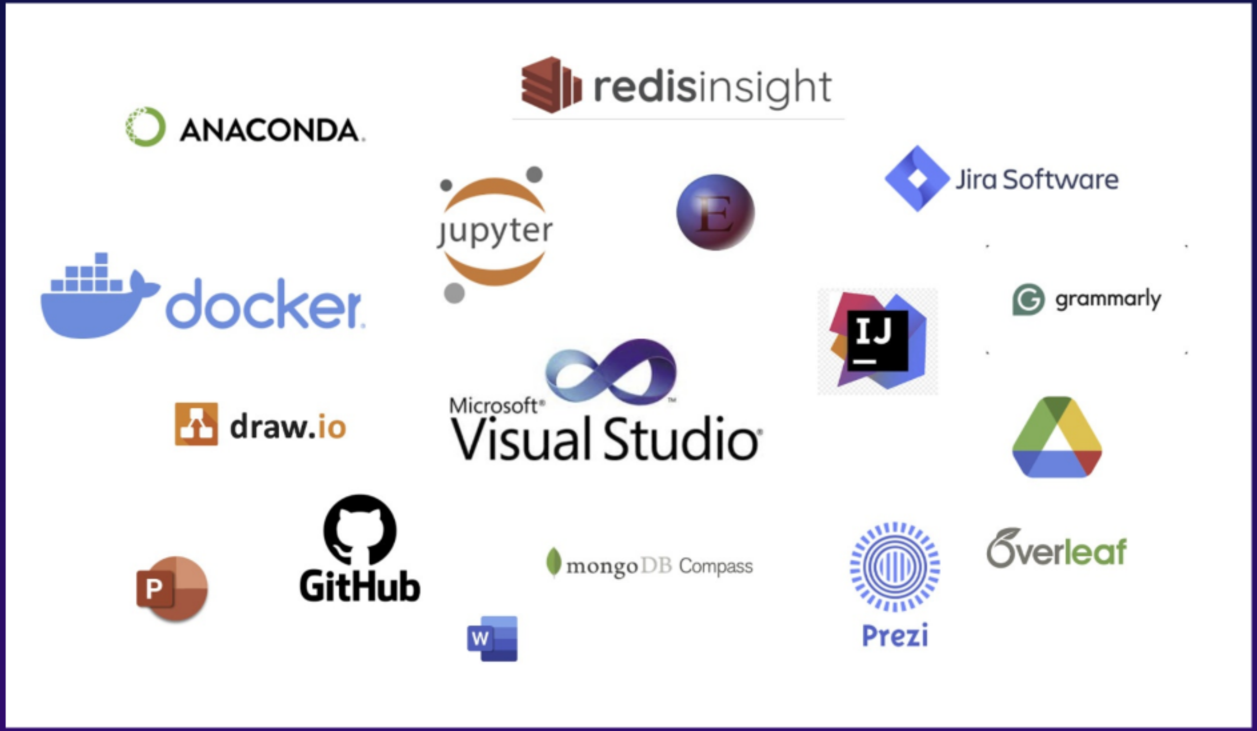
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