

Online Retail Product Recommendation System

Term Project Report

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1 Abstract

This project implements a comprehensive big data analytics system for online retail data processing. The system utilizes Apache Spark for distributed data processing, Apache Kafka for real-time streaming, and MongoDB for data storage. The implementation focuses on building a scalable and efficient pipeline for processing large-scale retail data and generating personalized recommendations.

2 Introduction

2.1 Project Objectives

The primary objectives of this project are:

- To process and analyze large-scale retail transaction data
- To implement real-time data streaming capabilities
- To develop a machine learning-based recommendation system
- To create an interactive web interface for data visualization
- To ensure system scalability and performance

2.2 Project Scope

The project encompasses:

- Data ingestion and processing pipeline
- Real-time streaming implementation
- Recommendation system development
- Web application interface
- Performance optimization

3 System Architecture and Technologies

3.1 Apache Spark Implementation

Apache Spark was chosen as the primary data processing framework for several reasons:

- **Distributed Processing**

- Efficient handling of large-scale retail datasets (3 different CSV files)
- In-memory computing capabilities for faster data processing
- Parallel processing across multiple nodes for better performance
- Optimized data partitioning for efficient data distribution
- **Key Spark Features Used**
 - Spark SQL for structured data processing of retail transactions
 - Spark Streaming for real-time data processing
 - MLlib for implementing ALS-based recommendation system
 - DataFrame API for efficient data manipulation and transformation
- **Implementation Details**
 - Data ingestion from multiple CSV files (online_retail.csv, online_retail_2009-2010.csv, online_retail_2010-2011.csv)
 - Efficient data union operations for combining datasets
 - Schema inference for automatic data type detection
 - Memory optimization through caching of frequently accessed data

3.2 Apache Kafka Integration

Kafka was implemented for real-time data streaming with the following considerations:

- **Purpose and Benefits**
 - Real-time data ingestion from multiple retail data sources
 - Reliable message queuing for data pipeline stability
 - Event streaming for continuous data processing
 - Fault tolerance and data consistency guarantees
- **Implementation Details**
 - Structured streaming pipeline from Spark to Kafka
 - JSON serialization for data transfer
 - Batch processing optimization for better throughput
 - Checkpoint mechanism for fault tolerance
- **Streaming Pipeline Architecture**

- Spark DataFrame to Kafka topic conversion
- Real-time data processing with Spark Structured Streaming
- Fault-tolerant data transfer to MongoDB
- Batch-based processing for better performance

3.3 MongoDB Database

MongoDB was selected for data storage with the following considerations:

- **Database Structure and Design**

- Document-based storage for flexible data schema
- Efficient storage of retail transactions
- Optimized collections for recommendations
- Indexed fields for fast query performance

- **Data Model Implementation**

- Retail transactions collection for storing purchase data
- User recommendations collection for personalized suggestions
- Efficient storage of ALS model recommendations
- Timestamp-based data organization

- **Performance Optimizations**

- Batch operations for efficient data insertion
- Index optimization for fast query execution
- Connection pooling for better resource utilization
- Efficient storage of recommendation results

4 Implementation Details

4.1 Data Processing Pipeline

The data processing pipeline consists of several key components:

4.1.1 Data Ingestion

- Loading multiple retail datasets
- Data validation and schema enforcement
- Initial data cleaning
- Data type conversion

4.1.2 Data Cleaning and Transformation

- Null value handling
- Date format standardization
- Negative value filtering
- Feature engineering
- Data normalization

4.2 Recommendation System

The recommendation system implements collaborative filtering using ALS:

- **ALS Model Implementation**
 - User-item interaction matrix construction
 - Matrix factorization for pattern discovery
 - Cold-start handling for new users/items
 - Efficient model training and prediction
- **Model Parameters and Optimization**
 - maxIter: 10 for balanced training time
 - regParam: 0.01 for regularization
 - alpha: 0.01 for implicit feedback
 - rank: 20 for feature representation
- **Performance Metrics**
 - RMSE evaluation for model accuracy
 - Training time optimization
 - Prediction speed for real-time recommendations
 - Scalability for large user bases

4.3 Web Application

The web interface was implemented using Flask:

- **Features**
 - Interactive recommendation display
 - Real-time data visualization
 - User-friendly interface
 - Efficient data retrieval from MongoDB
- **Implementation Details**
 - Flask-based REST API
 - MongoDB integration for data storage
 - Plotly for data visualization
 - Responsive web design

5 Performance Analysis

5.1 System Performance

- **Processing Performance**
 - Data ingestion speed
 - Processing throughput
 - Memory utilization
 - CPU usage
- **Recommendation System Performance**
 - Model training time
 - Recommendation generation speed
 - Prediction accuracy
 - System scalability

6 Results and Discussion

6.1 Key Achievements

- Successful implementation of distributed processing
- Efficient real-time data streaming
- Accurate recommendation generation
- Scalable system architecture

6.2 Challenges and Solutions

- **Technical Challenges**
 - Data volume handling
 - Real-time processing
 - System scalability
 - Performance optimization
- **Implemented Solutions**
 - Distributed processing with Spark
 - Kafka for real-time streaming
 - MongoDB for efficient storage
 - Optimized system configuration

7 Conclusion

7.1 Project Summary

The project successfully implements a comprehensive big data solution for retail analytics, demonstrating practical application of distributed computing, real-time processing, and machine learning. The system architecture and implementation details are summarized below:

7.1.1 System Architecture Achievements

- **Distributed Processing**
 - Successfully implemented Apache Spark for distributed data processing
 - Achieved efficient handling of large-scale retail datasets

- Optimized memory usage and processing speed
- Implemented effective data partitioning strategies
- **Real-time Processing**
 - Established reliable Kafka-based streaming pipeline
 - Achieved real-time data ingestion and processing
 - Implemented fault-tolerant message queuing
 - Maintained data consistency across the pipeline
- **Data Storage**
 - Implemented efficient MongoDB document storage
 - Optimized database queries and indexing
 - Achieved high data retrieval performance
 - Maintained data integrity and consistency

7.1.2 Technical Implementation Success

- **Data Processing Pipeline**
 - Successfully processed multiple retail datasets
 - Implemented comprehensive data cleaning procedures
 - Achieved efficient data transformation
 - Maintained data quality throughout the pipeline
- **Recommendation System**
 - Implemented ALS-based collaborative filtering
 - Achieved accurate personalized recommendations
 - Optimized model parameters for better performance
 - Successfully handled cold-start problems
- **Web Application**
 - Developed responsive and interactive interface
 - Implemented real-time data visualization
 - Achieved fast recommendation retrieval
 - Ensured smooth user experience

8 References

1. Apache Spark Documentation. (2023). <https://spark.apache.org/docs/latest/>
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4. Spark MLlib Documentation. (2023). <https://spark.apache.org/docs/latest/ml-guide.html>