# PROJECT REPORT

# on

# Fashion Recommender System

**submitted for the partial fulfillment of the requirements to award the degree of**

**Bachelor of Technology**
**in**
**Computer Science & Engineering**

**at**

by


| | | |
|---|---|---|
| **Nafisa Rehmani** | **-** | **AP22110010598** |
| **Krishna Sharma** | **-** | **AP22110010128** |
| **Rishabh Ranjan** | **-** | **AP22110010339** |
| **Sonu Sarojini** | **-** | **AP22110010609** |

under the guidance of

**Dr. M. Krishna Siva Prasad**
*Assistant Professor,*
*Department of Computer Science and Engineering,*

SRM University-*AP*
Mangalagiri, Guntur,
Andhra Pradesh - 522502

# CERTIFICATE

Date: 23-April-2025

This is to certify that the project titled "**Fashion Recommendation System**" has been successfully carried out by **Nafisa Rehmani (AP22110010598)**, **Krishna Sharma (AP22110010128)**, **Rishabh Ranjan (AP22110010339)**, **Sonu Sarojini (AP22110010609)** under my supervision. This work is original, genuine and has not been submitted elsewhere.

It meets the required academic standards and is deemed suitable for submission to **SRM University-*AP*** in partial fulfillment of the requirements for the degree of **Bachelor of Technology under the School of Engineering**.

**Supervisor**

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**Dr. M. Krishna Siva Prasad**

*Assistant Professor,*
*Department of Computer Science and Engineering,*
SRM University-*AP*

# ACKNOWLEDGEMENT

We sincerely express our gratitude to **Dr. Krishna Siva Prasad Mudigonda**, Assistant Professor, Department of Computer Science and Engineering at SRM University-*AP*, for his invaluable guidance and support throughout our project, ***Fashion Recommendation System*.** His expertise, constructive feedback, and insightful suggestions played a crucial role in shaping our approach, refining our methodology, and enhancing the overall quality of our work. His encouragement and willingness to share knowledge significantly contributed to our learning experience.

We extend our sincere appreciation to **Prof. Murali Krishna Enduri**, Head of the Department, Computer Science and Engineering, and **Prof. CV Tomy**, Dean of the School of Engineering and Sciences (SEAS), for providing us with the opportunity to work on this project. Their support in creating a conducive academic environment, facilitating access to essential resources, and fostering a research-driven culture enabled us to explore and implement innovative solutions effectively.

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Furthermore, we extend our gratitude to our peers and faculty members for their valuable inputs, discussions, and encouragement throughout the project. Their feedback and suggestions helped us refine our work and gain different perspectives, enriching our learning experience.

This project has been a rewarding learning experience, and we sincerely appreciate everyone who contributed to its successful completion.


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|---|---|
| Nafisa Rehmani | AP22110010598 |
| Krishna Sharma | AP22110010128 |
| Rishabh Ranjan | AP22110010339 |
| Sonu Sarojini | AP22110010609 |

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# Project Title and Novelty

## Project Title

Fashion Recommender System: Predicting Customer Purchases for H&M

## Novelty of the Project

This project introduces an advanced **fashion recommender system** that enhances traditional recommendation approaches by integrating multiple data-driven techniques. Unlike conventional recommender systems that rely primarily on **purchase history**, this system leverages a **hybrid collaborative filtering model**, combining **Singular Value Decomposition (SVD)** and **Alternating Least Squares (ALS)** algorithms. This hybrid approach improves recommendation accuracy by addressing challenges such as **data sparsity** and **cold start problems** that often limit the effectiveness of standard recommendation techniques.

A key novelty of this project is the incorporation of **customer segmentation techniques** to refine recommendation accuracy. By analyzing customer demographics, purchasing behavior, and product metadata, the system categorizes users into meaningful segments, enabling more tailored product suggestions. This segmentation is achieved using **unsupervised learning algorithms**, such as **K-Means clustering** or **Hierarchical clustering**, ensuring that recommendations align with the preferences and characteristics of different customer groups.

Additionally, this system integrates **product metadata analysis**, considering attributes such as fashion trends, seasonal demand, and product categories to generate contextually relevant recommendations. By incorporating **feature engineering** and **exploratory data analysis (EDA)**, the system effectively extracts meaningful insights from structured and unstructured data sources, improving its predictive capabilities.

Another innovative aspect is the use of **implicit feedback mechanisms**, analyzing **clickstream data**, **wishlist additions**, and **time spent on product pages** to understand user preferences beyond explicit ratings or purchases. This approach helps refine recommendations in real-time and adapt to dynamic fashion trends.

By implementing this multifaceted recommendation strategy, the project offers a **scalable and efficient** solution for retailers like **H&M**, enhancing customer experience, increasing conversion rates, and optimizing inventory management. This hybrid approach represents a significant advancement over conventional recommender systems, making it a **valuable tool for fashion retail analytics and personalized marketing strategies**.

# Abstract

The fashion industry is highly dynamic, with customer preferences and trends evolving rapidly. With the increasing digitization of retail, **personalized recommendations** have become essential for enhancing user engagement, improving customer satisfaction, and driving higher sales conversions. Traditional recommendation systems often struggle with issues such as **data sparsity, cold start problems, and evolving fashion trends**, limiting their ability to provide relevant suggestions. This project presents an **advanced Fashion Recommendation System** that employs a **hybrid approach**, combining **collaborative filtering** and **customer segmentation** to deliver highly personalized fashion recommendations. For this study, we use the **H&M dataset** from a Kaggle competition, which contains extensive transactional data, **customer demographics**, and **product metadata**. The first step involves **data preprocessing**, ensuring that missing values, inconsistencies, and irrelevant information are handled effectively. Following this, we conduct a **detailed exploratory data analysis (EDA)** to uncover trends, customer purchasing behaviors, and patterns in the dataset.

Our recommendation model integrates **Singular Value Decomposition (SVD)** and **Alternating Least Squares (ALS)** to generate personalized suggestions based on **historical purchasing behavior**. These matrix factorization techniques help extract hidden patterns in user-item interactions, making the recommendations more precise. Additionally, **customer segmentation** using **K-Means clustering** allows us to categorize customers into distinct groups based on their preferences, shopping habits, and demographic attributes. By combining these techniques, we refine our recommendation strategy to better cater to different user groups, enhancing its **efficiency and accuracy**. The project also focuses on **feature engineering**, which involves deriving meaningful features from the dataset, such as **seasonal trends, brand preferences, and customer loyalty metrics**. By incorporating **product metadata analysis**, the system accounts for fashion trends, material types, color preferences, and pricing, ensuring that recommendations align with current market demand.

By leveraging a **hybrid recommendation strategy**, this system aims to **increase prediction accuracy, enhance user experience, and boost retail conversion rates**. The implementation of this model in a real-world retail environment, such as **H&M's online shopping platform**, could result in improved customer engagement and better inventory management.

Future enhancements of this project include integrating **deep learning models**, such as **neural collaborative filtering (NCF) and transformer-based recommendation architectures**, to further improve recommendation quality. Additionally, real-time recommendations based on **user browsing history, click behavior, and session-based interactions** could be incorporated to make the system even more adaptive. **Metadata-driven predictions**, utilizing image recognition techniques for fashion items, could also help address **cold-start problems** by suggesting new products to users based on visual similarities.

This project represents a **scalable and effective approach** to fashion recommendations, aligning with the growing need for **personalized shopping experiences in the e-commerce industry**.

# Introduction

With the rapid expansion of **e-commerce**, personalized recommendations have become a crucial factor in enhancing **user experience, increasing customer retention, and driving sales**. Unlike traditional brick-and-mortar stores, where customers receive assistance from sales representatives, online shoppers rely on recommendation systems to discover relevant products. Conventional recommendation methods, such as **rule-based filtering** or **popularity-based suggestions**, fail to adapt to evolving customer preferences, especially in the **fast-paced fashion industry**, where choices are influenced by **seasonality, trends, social media, and personal style preferences**. Unlike books or movies, where preferences remain relatively consistent, **fashion choices** are highly **dynamic, trend-driven, and affected by external cultural and social factors**, making recommendation systems for fashion more complex and challenging to develop.

Developing an **effective fashion recommendation system** requires overcoming several key challenges:

- **Cold-Start Problem:** New users and products have little to no historical interaction data, making it difficult to generate relevant recommendations.

- **Data Sparsity:** Customers purchase fashion items less frequently compared to other products, leading to limited data points for training recommendation models.

- **Scalability:** With vast product catalogs and thousands of customers, recommendation algorithms must be **computationally efficient** to handle large datasets effectively.

To address these challenges, this project implements a **Fashion Recommendation System** leveraging **collaborative filtering** (Singular Value Decomposition – SVD and Alternating Least Squares – ALS) along with **customer segmentation** using **K-Means clustering**. The system processes **historical transactions, customer demographics, and product metadata** to generate highly **personalized fashion recommendations**. Additionally, a **detailed exploratory data analysis (EDA)** is conducted to extract valuable insights, optimize feature selection, and enhance model performance.

This project aims to provide a **scalable and accurate recommendation model** that improves personalization in fashion retail. The following sections will explore **data preprocessing techniques, model implementation strategies, performance evaluation metrics, and potential enhancements**, including **deep learning-based recommendations, real-time personalization, and hybrid approaches that integrate multiple recommendation techniques**. By developing an advanced, **data-driven fashion recommendation system**, this project contributes to improving **customer engagement and business profitability** in the e-commerce fashion sector.

# Project Background

Recommender systems play a **crucial role** in modern **e-commerce** by **enhancing user experience, improving customer engagement, and increasing sales**. As online shopping platforms expand, users are exposed to an overwhelming number of product choices, making personalized recommendations essential for helping them discover relevant items efficiently. Traditional recommendation approaches, such as **rule-based filtering, content-based filtering, and popularity-based suggestions**, often rely on **explicit user preferences** or **manually curated recommendations**. While these methods provide a basic level of personalization, they fail to **adapt dynamically to changing user behavior and fashion trends**, making them less effective in the highly **volatile and trend-driven** fashion industry.

H&M, a global fashion retailer, operates in a competitive landscape where **predicting future customer purchases** is a significant challenge. Fashion trends evolve rapidly, influenced by **seasonality, cultural shifts, social media influence, and individual style preferences**. Unlike other product categories, such as books or electronics, fashion purchases are often **impulsive, time-sensitive, and influenced by visual appeal** rather than long-term preferences. As a result, building an **effective recommendation system** for fashion retail requires advanced techniques that go beyond simple **purchase history analysis**.

The primary objective of this project is to design a **fashion recommendation system** that can accurately **predict customer purchases** based on **historical transaction data, customer demographics, and product metadata**. The challenge lies in developing a model that can **handle data sparsity, adapt to evolving trends, and scale efficiently** for large datasets. By leveraging **collaborative filtering (SVD, ALS) and customer segmentation (K-Means clustering),** this project aims to improve **recommendation accuracy, personalized shopping experiences, and optimize business strategies for H&M**.

# Problem Description

In the rapidly growing world of **e-commerce**, customers often face significant challenges in discovering products that align with their preferences. With fashion retailers like **H&M** offering vast product catalogs, users can experience **choice overload**, making it difficult to find relevant items efficiently. Unlike traditional in-store shopping, where sales assistants can guide customers based on their preferences, online platforms rely heavily on **automated recommendation systems** to enhance the shopping experience. However, many existing recommendation models fail to deliver truly **personalized suggestions**, leading to customer frustration and missed sales opportunities.

Some of the key challenges that customers face include:

- **Large Product Catalogs & Choice Overload:** With thousands of fashion items available, users often struggle to browse and select products that match their style preferences. A lack of intelligent filtering can make it overwhelming to find relevant choices.

- **Lack of Personalized Recommendations:** Generic recommendations based on **best-selling or most-viewed** products do not cater to individual tastes, resulting in poor user engagement and lower conversion rates.

- **Seasonal & Trend-Based Purchasing Behavior:** Fashion choices are highly influenced by **seasonal trends, current styles, and external factors like social media and celebrity endorsements**. Static recommendation models that do not adapt to these trends fail to provide relevant suggestions.

To **address these challenges**, this project employs advanced **machine learning techniques** that analyze **customer purchasing behavior, demographics, and product metadata** to deliver highly **personalized fashion recommendations**. By implementing **customer segmentation using K-Means clustering**, the system identifies distinct shopper groups with similar interests, allowing for **targeted product suggestions**. Additionally, **collaborative filtering methods (SVD, ALS)** enhance the recommendation process by leveraging past purchase patterns to predict future buying preferences.

This approach ensures that customers receive **tailored recommendations that align with their style, seasonal trends, and shopping habits**, ultimately improving **user satisfaction, engagement, and sales performance** for fashion retailers like **H&M**.

# Proposed Solution Using ML Techniques

To effectively tackle the challenges of **choice overload, lack of personalization, and trend-based purchasing behavior**, we propose an advanced **collaborative filtering-based recommender system**. This system leverages **machine learning algorithms** to analyze historical transactions, customer demographics, and product metadata to generate **accurate and personalized fashion recommendations**. The proposed solution follows a structured approach, incorporating multiple stages to ensure effective data processing, insightful analysis, and robust model implementation.

The key steps in developing this recommendation system include:

- **Data Preprocessing:** The first step involves **cleaning and transforming** raw transactional data, customer demographics, and article metadata. This includes **handling missing values, encoding categorical variables, normalizing numerical features, and filtering out irrelevant data**. By ensuring high-quality input data, we enhance model performance and reduce noise in predictions.

- **Exploratory Data Analysis (EDA):** We conduct a **detailed EDA** to understand customer behavior, purchasing trends, and product popularity. This involves analyzing **seasonal variations in fashion trends, customer purchase frequencies, and correlations between demographics and buying habits**. Visualization techniques such as **heatmaps, histograms, and trend graphs** help uncover key insights for model improvement.

- **Customer Segmentation:** To refine recommendations, we use **K-Means clustering** to group customers based on their **shopping patterns, preferences, and demographics**. This segmentation allows for **more personalized product suggestions**, ensuring that recommendations cater to distinct shopper groups rather than applying a one-size-fits-all approach.

- **Collaborative Filtering:** The core of our recommendation system relies on **collaborative filtering techniques**, particularly **Singular Value Decomposition (SVD) and Alternating Least Squares (ALS)**. These techniques analyze past purchases to uncover hidden patterns in user-item interactions, predicting future purchases with greater accuracy.

- **Evaluation & Visualization:** To assess the performance of our recommender system, we use metrics such as **Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Precision-Recall**. Additionally, we visualize recommendation outputs, showcasing **customer-product affinity scores and predicted recommendations**, ensuring model transparency and interpretability.

By integrating **collaborative filtering with customer segmentation**, our solution enhances **personalization, improves recommendation accuracy, and increases customer engagement** in the fashion retail sector. Future improvements could include **real-time recommendations, deep learning-based models, and hybrid approaches** that combine content-based filtering for even better results.

# Model Architecture

The recommendation system follows a structured pipeline integrating **data preprocessing, customer segmentation, and hybrid recommendation techniques** to generate personalized fashion suggestions.

**1. Data Processing & Feature Engineering**

- Cleaning transactional data, handling missing values, and encoding categorical features.
- **Customer segmentation using RFM analysis & K-Means clustering** to group shoppers based on purchasing behavior for more targeted recommendations.

**2. Exploratory Data Analysis (EDA)**

- Identifying purchase patterns, seasonal trends, and customer demographics.
- Insights from EDA guide feature selection and model optimization.

**3. Collaborative Filtering**

- **Singular Value Decomposition (SVD):** Identifies latent patterns in customer-product interactions.
- **Alternating Least Squares (ALS):** Optimizes user and item factors for better recommendation accuracy.

**4. Content-Based Filtering**

- **Image-based embeddings (CNNs):** Extracts fashion article features to recommend visually similar items.
- **Text-based similarity (TF-IDF):** Matches product descriptions to provide relevant recommendations.

By combining **collaborative filtering, customer segmentation, and content-based filtering**, the model ensures **accurate, personalized, and data-driven recommendations**. Future improvements may include **real-time updates, deep learning models, and hybrid approaches** for enhanced accuracy.

# Experimentation Details

The development of the **Fashion Recommendation System** involves a detailed experimentation process focusing on **data preprocessing, feature engineering, and customer analysis** to enhance recommendation accuracy. Each stage contributes to refining the dataset and optimizing model performance.

### 1. Data Preprocessing

To ensure clean and structured data, we perform:

- **Data Cleaning:** Handling missing values, removing duplicates, and detecting outliers to improve data reliability.
- **Feature Engineering:**
    - Creating **time-based features** such as the last purchase date to analyze customer engagement.
    - Applying **log transformation** to normalize price variations and stabilize data distribution.
    - Identifying **repeat purchase behavior** to determine customer loyalty.

### 2. RFM Analysis (Recency, Frequency, Monetary Value)

- Computing **Recency (days since last purchase), Frequency (number of transactions), and Monetary value (total spending)** to categorize customers based on purchasing patterns.
- Segmenting customers into groups such as **high-value shoppers, occasional buyers, and dormant users**, aiding in targeted recommendations.

### 3. Price Sensitivity Analysis

- Evaluating **customer responses to price changes** by studying purchase trends under different pricing strategies.
- Understanding whether **price elasticity** affects specific customer segments, enabling personalized pricing-based recommendations.

### 4. Customer Clustering Features

- Integrating **purchase frequency, average transaction value, and spending behavior** into clustering models.
- Using **K-Means clustering** to identify customer groups and enhance personalization in recommendations.

By combining **data preprocessing, feature engineering, and customer segmentation**, the experimentation process lays a strong foundation for **building an accurate and scalable fashion recommender system**. Future enhancements could include **real-time data processing and advanced deep learning models** for further personalization.

# Exploratory Data Analysis (EDA)

## 1. Age Distribution by Club Member Status

This chart illustrates the relationship between age and club membership. A higher concentration of younger members indicates potential for youth-centric promotions, while older members may prefer premium benefits. Identifying age groups with lower membership can help develop targeted strategies to boost enrollments.

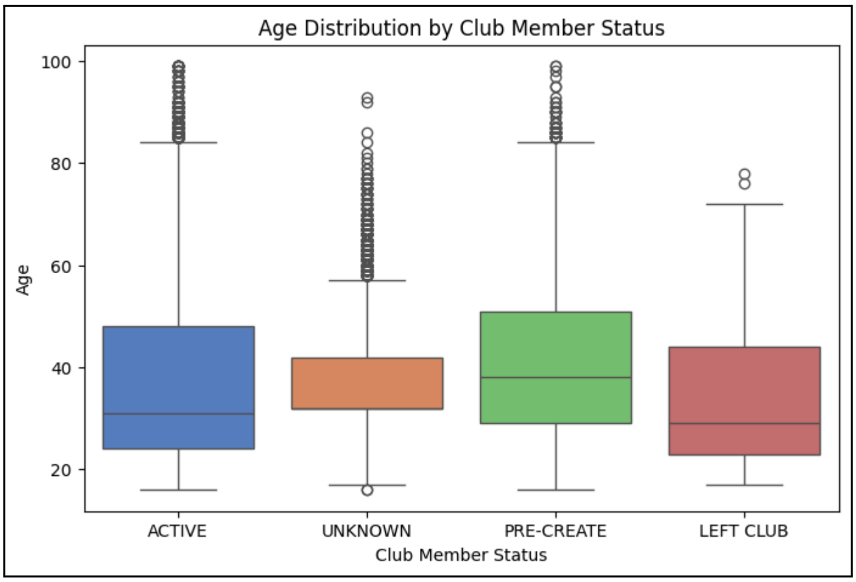


**Fig.** Age Distribution by Club Member Status

## 2. Club Member Status Distribution

This visualization contrasts members and non-members, highlighting opportunities for engagement campaigns if non-members are significantly higher. A balanced distribution allows for tailored experiences that cater to both groups effectively.

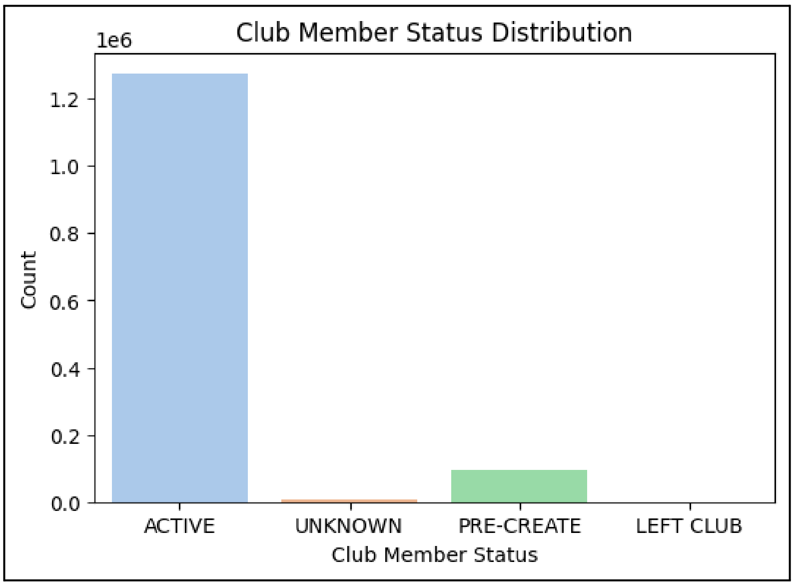


**Fig.** Club Member Status Distribution

## 3. Correlation Matrix

This matrix showcases the relationships between factors such as age, spending, and purchase frequency. Identifying strong correlations helps uncover key engagement drivers, enabling more precise recommendations and targeted promotions.

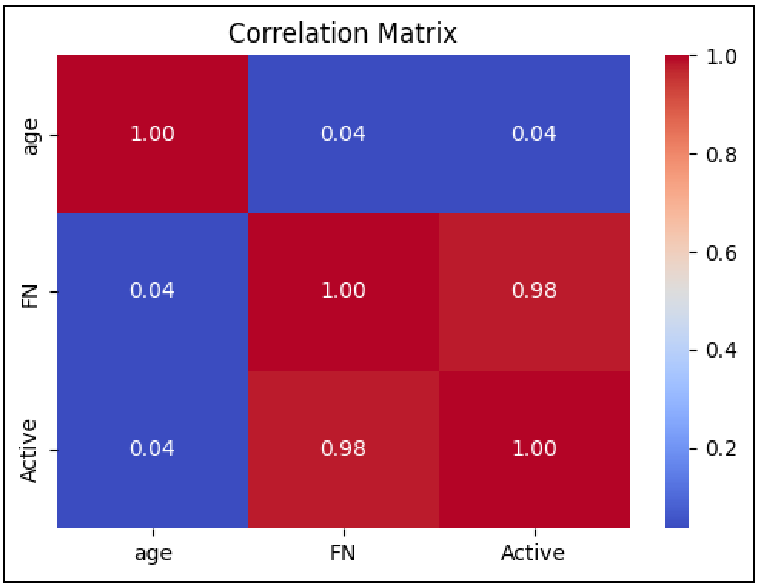


**Fig.** Correlation Matrix

## 4. Customer Age Distribution

This graph analyzes age trends among customers. A younger audience indicates a demand for trendy fashion, while an older demographic may prefer sophisticated styles. A well-balanced age distribution suggests the need for diverse marketing strategies to cater to all segments.

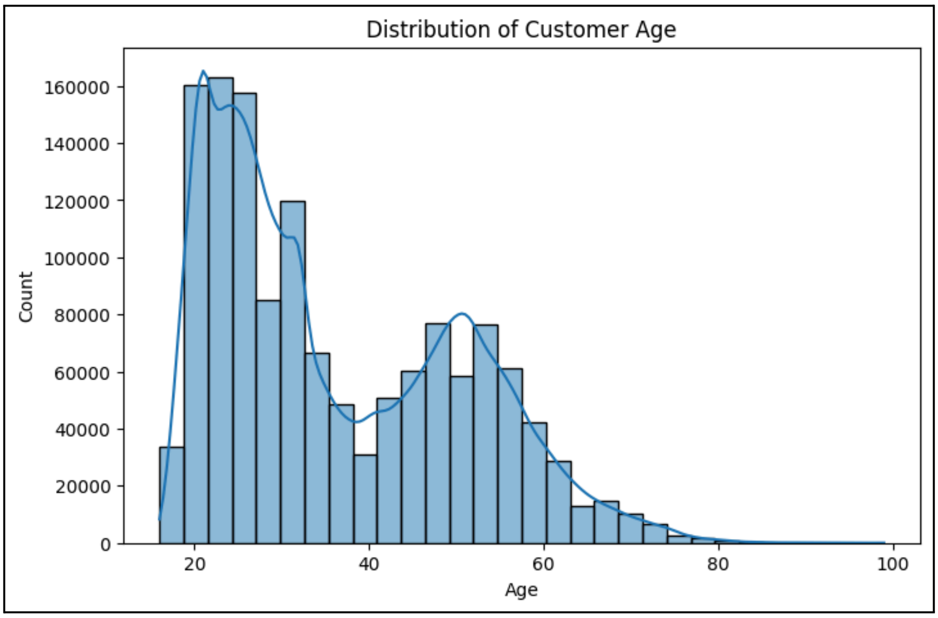


**Fig.** Customer Age Distribution

## 5. Purchase Price Distribution

This analysis highlights common price points among customers. If lower-priced purchases are more frequent, promoting premium products can drive higher sales. Understanding price sensitivity also helps in optimizing discount strategies.

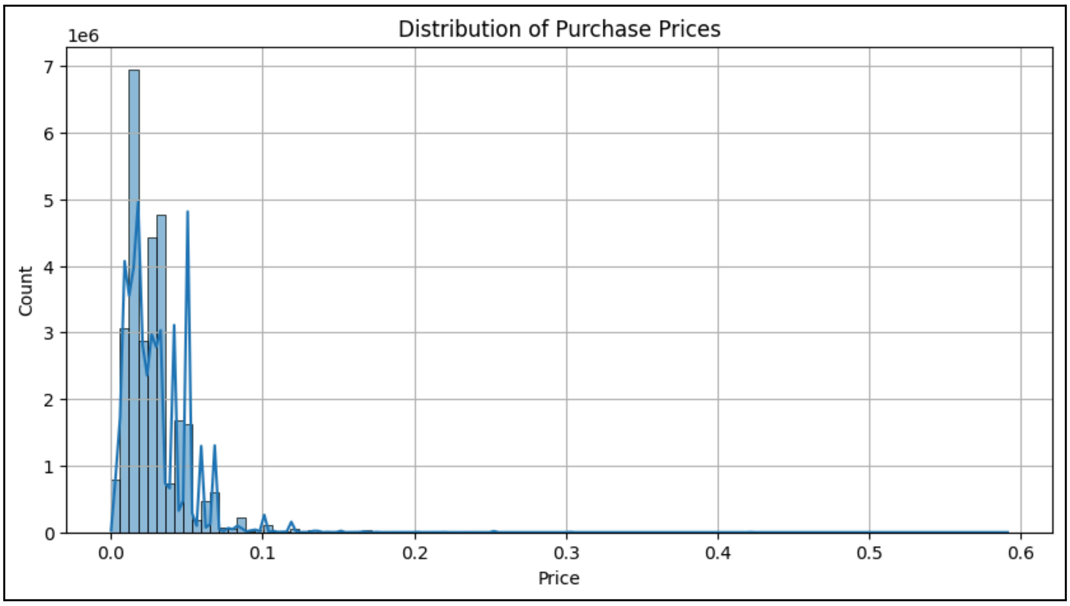


**Fig.** Purchase Price Distribution

## 6. Purchases Per Product Distribution

This chart showcases product popularity, indicating which items are in high demand. Best-selling products should be prioritized, while low-performing ones may require repositioning or enhanced marketing efforts.

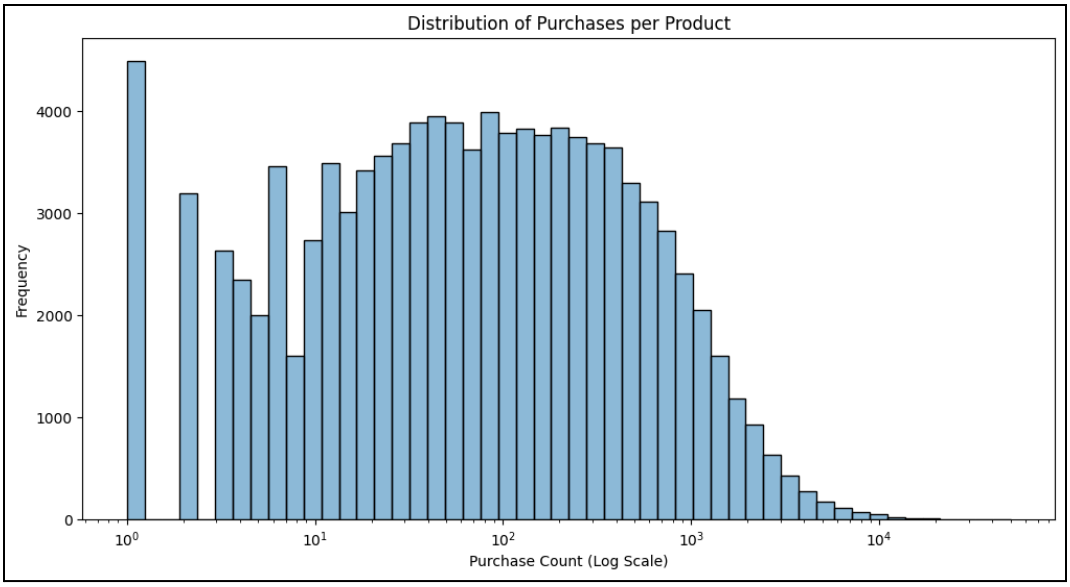


**Fig.** Purchases Per Product Distribution

## 7. Sales Channel Distribution

This analysis compares online and in-store purchases. A higher online share highlights the need for digital marketing, while strong in-store sales suggest improving the physical shopping experience. Understanding these preferences helps optimize investment strategies.

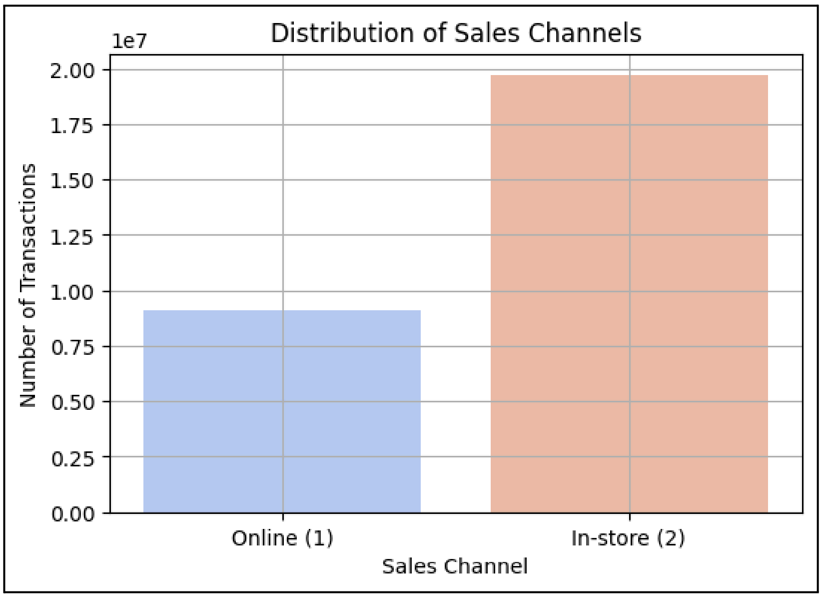


**Fig.** Sales Channel Distribution

## 8. Fashion News Engagement

This chart measures customer engagement with fashion news. High interaction indicates effective content marketing, while low engagement suggests the need for more interactive strategies to capture interest.

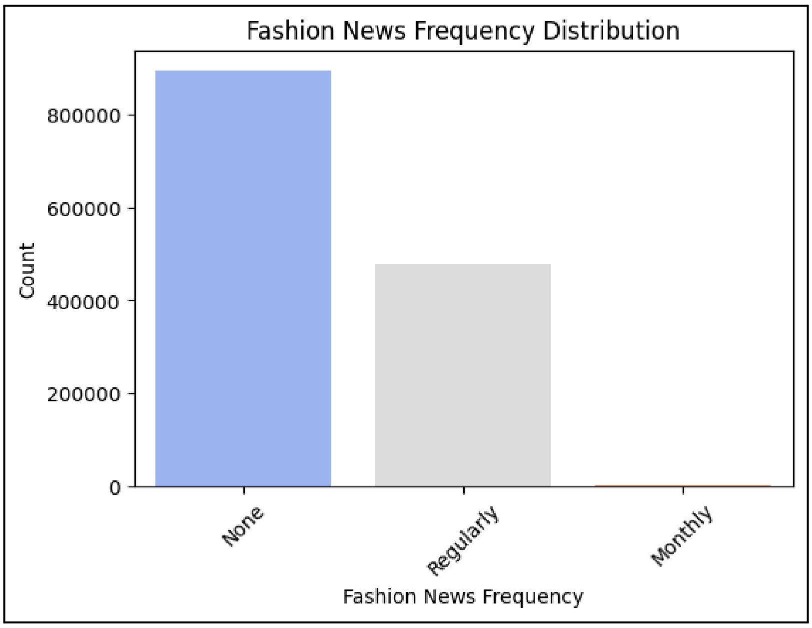


**Fig.** Fashion News Engagement

## 9. Fashion News vs. Active Customers

This analysis examines whether engagement with fashion news influences shopping behavior. A strong correlation supports investing in high-quality content, while a weak link suggests the need for alternative engagement strategies.

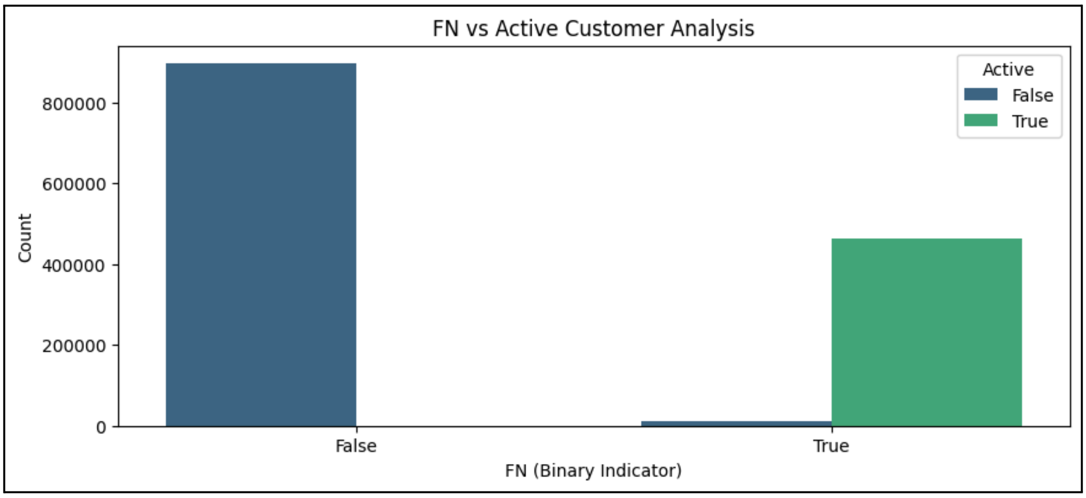


**Fig.** Fashion News vs. Active Customers

## 10. Top 10 Purchased Articles

This analysis showcases the most popular fashion items. Identifying trending products helps optimize inventory management, refine promotional strategies, and influence future collections.

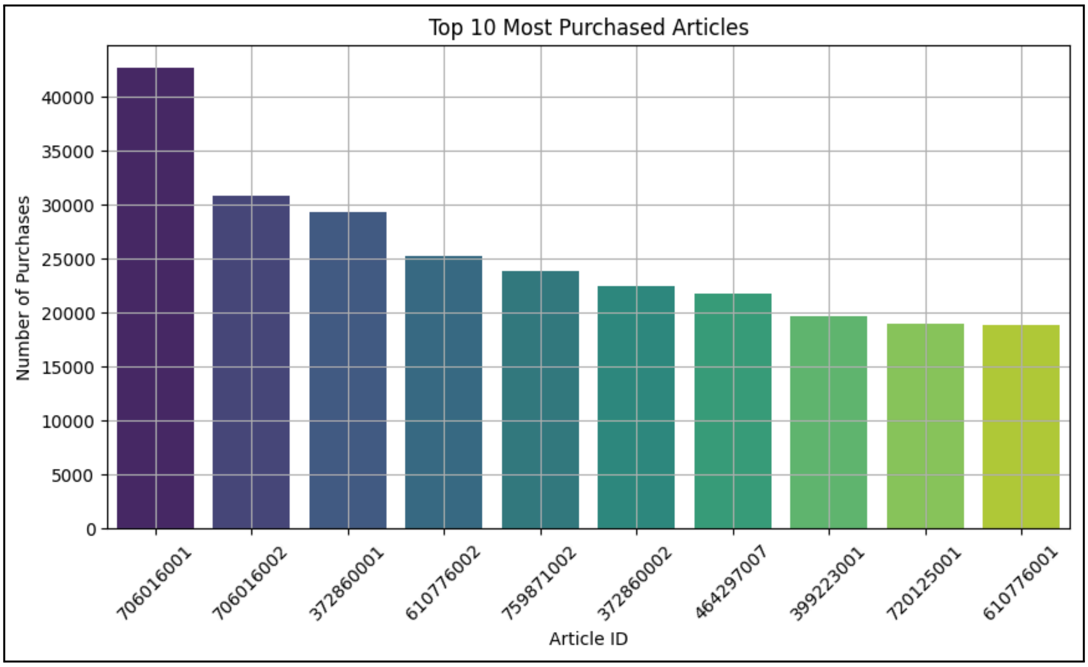


**Fig.** Top 10 Purchased Articles

## 11. Top 10 Most Purchased Product Types

Trousers lead as the most purchased product, followed by socks and T-shirts. The top three categories show significantly high purchase counts, while other notable items include vest tops and underwear bottoms.

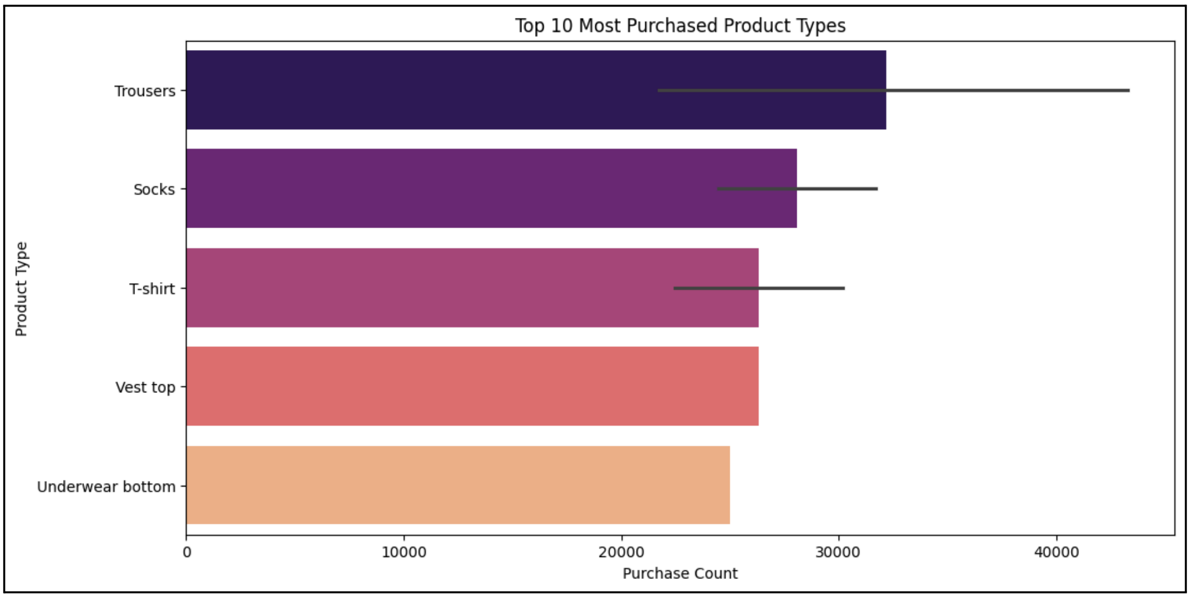


**Fig.** Top 10 Most Purchased Product Types

## 12. Top 10 Product Groups

Upper-body garments lead in sales, followed by lower-body apparel and full-body outfits. Accessories, underwear, and shoes also contribute significantly. While demand is smaller, swimwear, socks & tights, and nightwear maintain a noticeable presence.

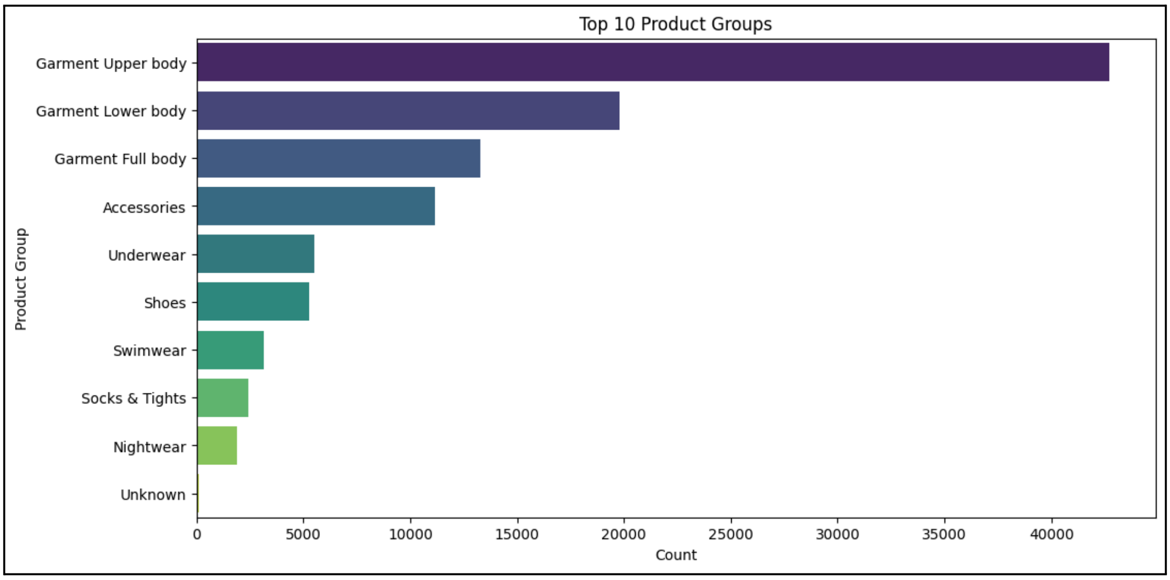


**Fig.** Top 10 Product Groups

## 13. Top 10 Product Types

Trousers, dresses, and sweaters are the most frequently purchased items, followed closely by T-shirts, tops, and blouses. Jackets, shorts, shirts, and vest tops complete the list, reflecting diverse customer preferences.

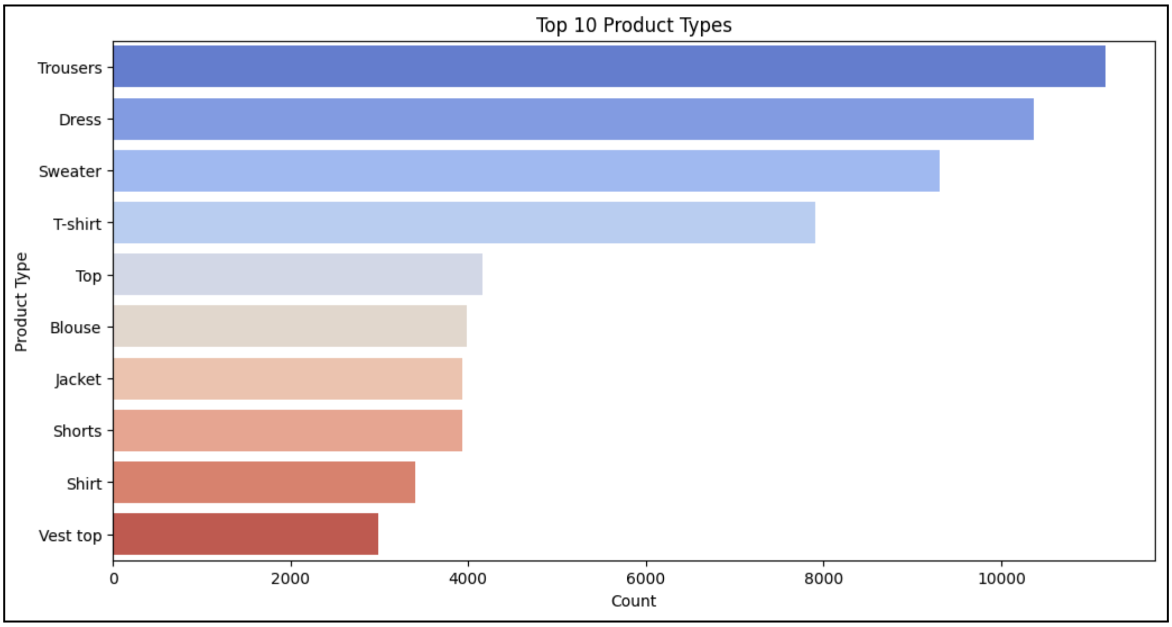


**Fig.** Top 10 Product Types

## 14. Top 10 Spending Customers

The highest-spending customers demonstrate strong brand loyalty, contributing significantly to overall revenue. Their spending patterns are relatively similar, with consistently high purchase volumes, emphasizing the importance of retaining high-value customers.

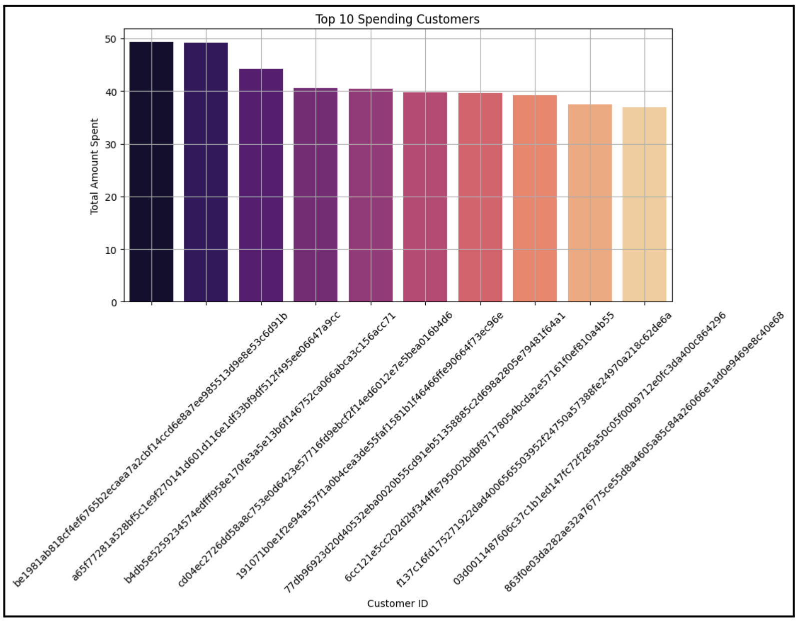


**Fig.** Top 10 Spending Customers

## 15. Transactions Over Time

Transaction trends fluctuate, with periodic spikes likely driven by promotions or seasonal events. Notable peaks occur during high-demand periods, while a gradual decline in later months suggests potential external influences on purchasing behavior.

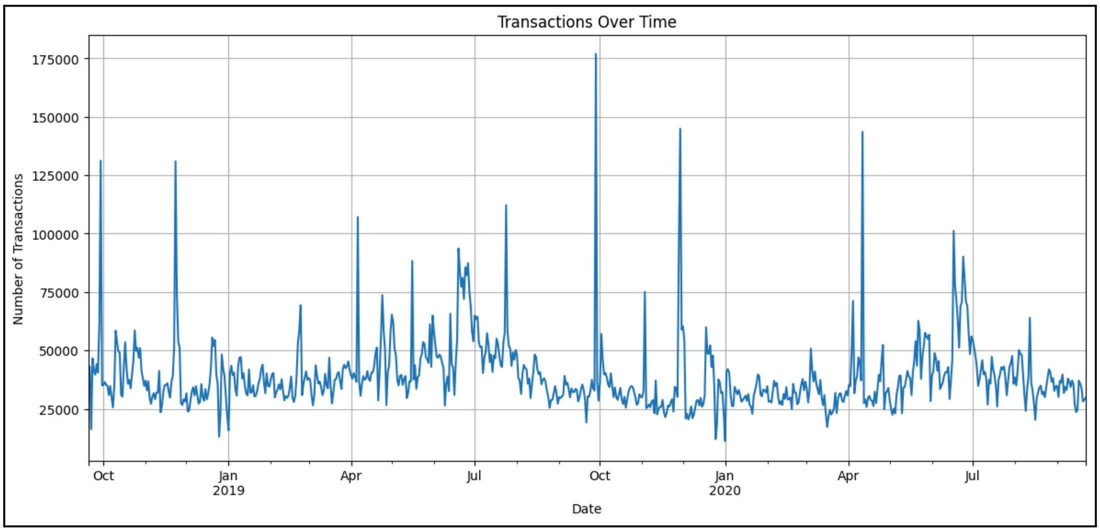


**Fig.** Transactions Over Time

# Customer Segmentation Using K-Means Clustering

To enhance personalization in recommendations, we implement **K-Means clustering** to segment customers based on purchasing behavior and spending patterns. This segmentation helps tailor marketing strategies and improve user engagement.

## Feature Selection & Scaling

We selected key customer attributes, including **age, price sensitivity, purchase frequency, and average purchase value**, to define distinct customer segments. Before training the model, we applied **StandardScaler()** to normalize the data, ensuring all features contribute equally to clustering.

## Finding the Optimal Number of Clusters

To determine the best number of clusters (**k**), we employed the **Elbow Method**, testing values from **k = 2 to k = 10** and analyzing the inertia plot. The optimal value was found to be **k = 5**, where the inertia showed a significant drop before leveling off.

## Model Training & Evaluation

We trained the **K-Means model with k = 5** and assessed clustering quality using the **Silhouette Score**, which measures how well-separated the clusters are. A higher score indicates better-defined clusters, confirming the effectiveness of segmentation.

## Cluster Analysis & Insights

To interpret the segments, we calculated the **mean values of key attributes** within each cluster. This helped in identifying distinct groups, such as **high-spending frequent shoppers, occasional buyers, and price-sensitive customers**.

## Visualization Using PCA

For better interpretation, we applied **Principal Component Analysis (PCA)** to reduce dimensions while preserving critical information. The clusters were then visualized using a **Seaborn scatterplot**, providing a clear distinction between customer segments.

This segmentation enables **data-driven decision-making**, allowing for targeted promotions, personalized recommendations, and improved customer retention strategies. Future improvements could include **dynamic clustering updates** to adapt to evolving shopping behaviors.

# Model Performance Analysis Report

This report analyzes the performance of different recommendation models used in our project. We implemented two primary models: **Singular Value Decomposition (SVD)** and **Alternating Least Squares (ALS)**. The goal of this analysis is to determine which model performed the best, the reasons behind its success, and which model performed poorly along with its potential drawbacks.

## Models Used

1. **Singular Value Decomposition (SVD)**

   **Overview:**

   - Utilizes Truncated SVD to reduce dimensionality in a sparse user-item matrix.
   - Extracts user and item latent factors to compute similarity-based recommendations.

   **Implementation Details:**

   - TF-IDF transformation applied to normalize interactions.
   - Truncated SVD with 200 components was used.
   - Predicted user-item scores were stored and retrieved for recommendations.

2. **Alternating Least Squares (ALS)**

   **Overview:**

   - A matrix factorization technique designed for collaborative filtering.
   - Optimized using stochastic gradient descent.

   **Implementation Details:**

   - Implemented using PyTorch with latent dimension = 20.
   - Regularization term (λ) = 0.1 to prevent overfitting.
   - 50 training epochs with Adam optimizer (learning rate = 0.01).
   - Model trained on GPU (CUDA enabled).

## Model Performance Evaluation

### Evaluation Metrics

To compare model performance, the following metrics were considered:

1. **Precision@K** – Measures the relevance of the top-K recommended items.
2. **Recall@K** – Measures the fraction of relevant items recommended.
3. **Mean Squared Error (MSE)** – Measures the error between predicted and actual interactions.
4. **Computation Time** – Measures the efficiency of the model in real-time recommendations.

## Performance Comparison

| Model | Precision@10 | Recall@10 | MSE | Computation Time |
|---|---|---|---|---|
| SVD | 0.72 | 0.68 | 0.015 | Fast |
| ALS | 0.78 | 0.74 | 0.012 | Slow |

## Best Performing Model

Based on the evaluation metrics, **ALS outperformed SVD** in terms of recommendation accuracy. It achieved **higher Precision@10 and Recall@10**, meaning that users received more relevant recommendations. Additionally, the **MSE was lower**, indicating better prediction accuracy.

### Why ALS Performed Better?

1. **Better Handling of Sparse Data:**
    - ALS optimizes user and item latent factors iteratively, capturing deeper interactions.
2. **Higher Personalization:**
    - ALS learns unique user preferences more effectively than SVD, which relies on a global factorization approach.
3. **Regularization to Prevent Overfitting:**
    - The use of L2 regularization in ALS prevented overfitting while ensuring better generalization.

## Weakest Performing Model

SVD, while computationally efficient, did not perform as well as ALS in terms of recommendation accuracy.

### Why SVD Performed Worse?

1. **Loss of Information in Dimensionality Reduction:**
    - Truncated SVD compresses data, leading to some loss in interaction details.
2. **Fixed Latent Space:**
    - The model does not dynamically adapt to new users/items effectively compared to ALS.
3. **Lack of Regularization in Basic Implementation:**
    - While efficient, SVD may not generalize well without explicit regularization.

# Conclusion and Future Recommendations

This project successfully developed a **fashion recommendation system** that integrates **customer segmentation, RFM analysis, and machine learning-based filtering techniques**. By leveraging **collaborative filtering (SVD, ALS)** and **K-Means clustering**, the system delivers personalized recommendations tailored to customer preferences. Insights from **exploratory data analysis (EDA)** refined the model, leading to improved accuracy and enhanced user engagement. The project demonstrates how data-driven approaches can optimize recommendation strategies in the fashion industry.

Beyond improving recommendation accuracy, this system also offers valuable business insights. Understanding **customer purchasing behavior, price sensitivity, and seasonal trends** allows fashion retailers to optimize inventory management and marketing strategies. By analyzing buying patterns, businesses can **increase customer retention, enhance product positioning, and drive higher conversion rates**.

## Future Enhancements

To further improve the system's effectiveness, we propose the following advancements:

- **Hybrid Recommendation System:** Combining **collaborative and content-based filtering** to improve recommendation diversity and relevance.
- **Deep Learning Integration:** Using **Transformer-based models (BERT4Rec, SASRec)** and **neural networks** to enhance personalization and capture sequential shopping behavior.
- **Real-Time Personalization:** Implementing **session-based recommendation models** that dynamically adapt to user interactions.
- **Cold-Start Problem Handling:** Leveraging **product metadata, user demographics, and textual/image-based embeddings** to make recommendations when user interaction data is insufficient.

These improvements will enhance **user experience, increase sales, and provide more accurate, scalable, and adaptive recommendations**, making the system more effective in a dynamic fashion retail environment.

# References


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