# Capstone_Presentation

## Recommendation for Fashion Product Project

Presented by - Swati Sharma

# Context

**Digitalization of Fashion Retail:**
- Online stores and e-commerce platforms, major channels for discovering and purchasing fashion products.

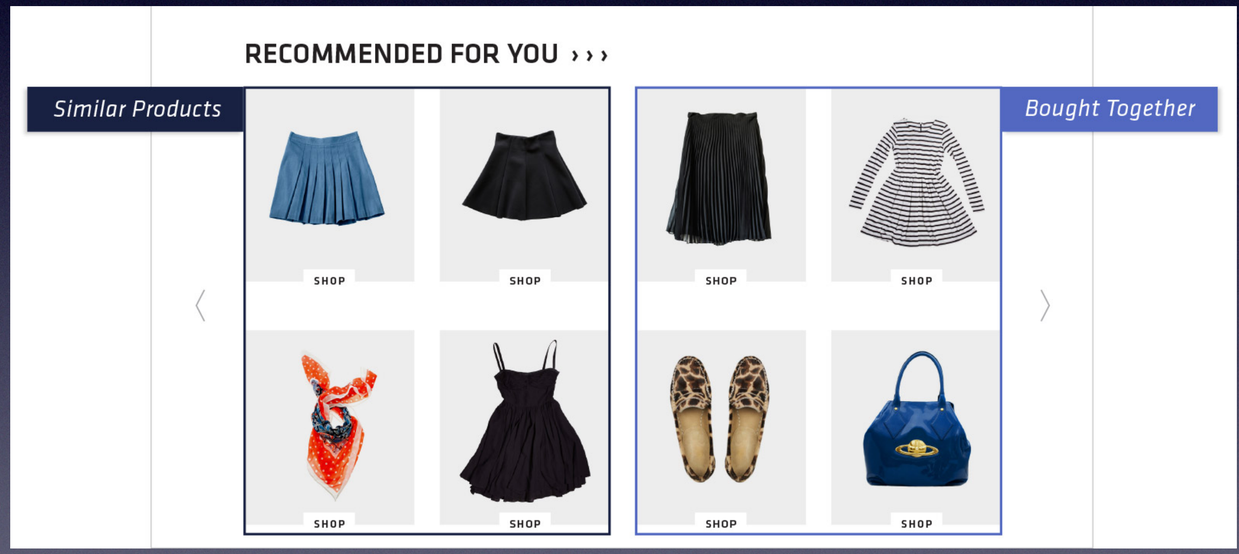
**Challenge of Overwhelming Product Choices:**
- The vast number of available products can overwhelm customers.
- Leads to decision fatigue and abandoned shopping carts.

**Limitations of Traditional Browsing Methods:**
- Sorting by categories or popularity does not fully address individual consumer preferences.
- Results in reduced customer satisfaction and engagement.

# What is the Problem?

What opportunities exist to develop a personalized recommendation system that provide more accurate, diverse and personalized recommendations to users.

- Results in enhancing the shopping experience, reduce user churn, and increase sales on fashion e-commerce platforms.
- Solve the problem of decision fatigue and improve the overall shopping experience.



# Data Collection

**Gather historical data:** Collected raw data as a csv file with columns such as User ID, Product ID, Product name, Brand, Category, Price, Rating, Color, Size.

**Data sources:** Kaggle, an external data source.

| | User ID | Product ID | Product Name | Brand | Category | Price | Rating | Color | Size |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 19 | 1 | Dress | Adidas | Men's Fashion | 40 | 1.043159 | Black | XL |
| **1** | 97 | 2 | Shoes | H&M | Women's Fashion | 82 | 4.026416 | Black | L |
| **2** | 25 | 3 | Dress | Adidas | Women's Fashion | 44 | 3.337938 | Yellow | XL |
| **3** | 57 | 4 | Shoes | Zara | Men's Fashion | 23 | 1.049523 | White | S |
| **4** | 79 | 5 | T-shirt | Adidas | Men's Fashion | 79 | 4.302773 | Black | M |
| **5** | 98 | 6 | Dress | Adidas | Men's Fashion | 47 | 1.379566 | Yellow | L |
| **6** | 16 | 7 | Jeans | Gucci | Men's Fashion | 37 | 1.356750 | White | XL |
| **7** | 63 | 8 | Sweater | Zara | Kids' Fashion | 64 | 4.360303 | Blue | XL |
| **8** | 96 | 9 | Sweater | H&M | Men's Fashion | 53 | 4.466182 | Green | XL |
| **9** | 36 | 10 | T-shirt | Zara | Kids' Fashion | 55 | 4.093234 | White | XL |

Goal: Create valuable insights that drive sales, engagement, and satisfaction
Contains structured data, including user behaviors, product attributes, and transaction details.

# Independent vs Dependent Variables

Independent Variables

Dependent Variable

| User ID | Product ID | Product Name | Brand | Category | Price | Color | Size | Rating |
|---|---|---|---|---|---|---|---|---|
| 19 | 1 | Dress | Adidas | Men's Fashion | 40 | Black | XL | 1.043159 |
| 97 | 2 | Shoes | H&M | Women's Fashion | 82 | Black | L | 4.026416 |
| 25 | 3 | Dress | Adidas | Women's Fashion | 44 | Yellow | XL | 3.337938 |
| 57 | 4 | Shoes | Zara | Men's Fashion | 23 | White | S | 1.049523 |
| 79 | 5 | T-shirt | Adidas | Men's Fashion | 79 | Black | M | 4.302773 |

Features/ Independent Variables

Variables that is changed

Target Variables/ Label/ Dependent Variables

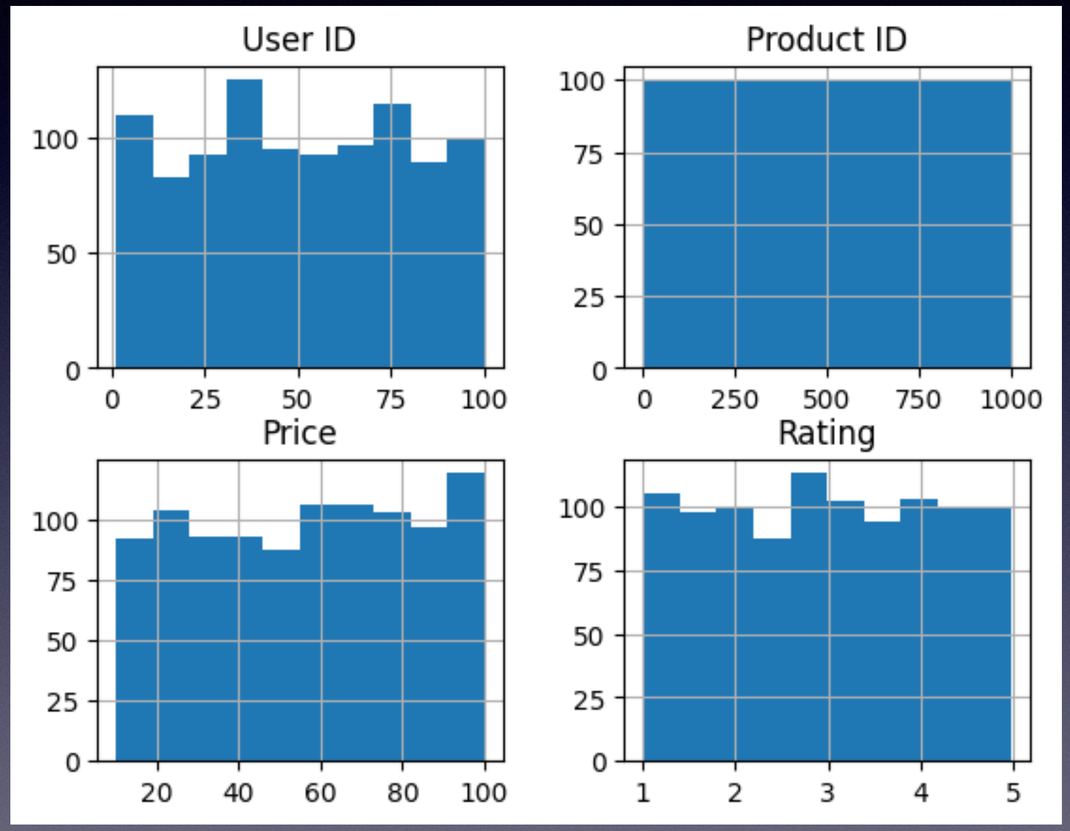
Variables affected by the change

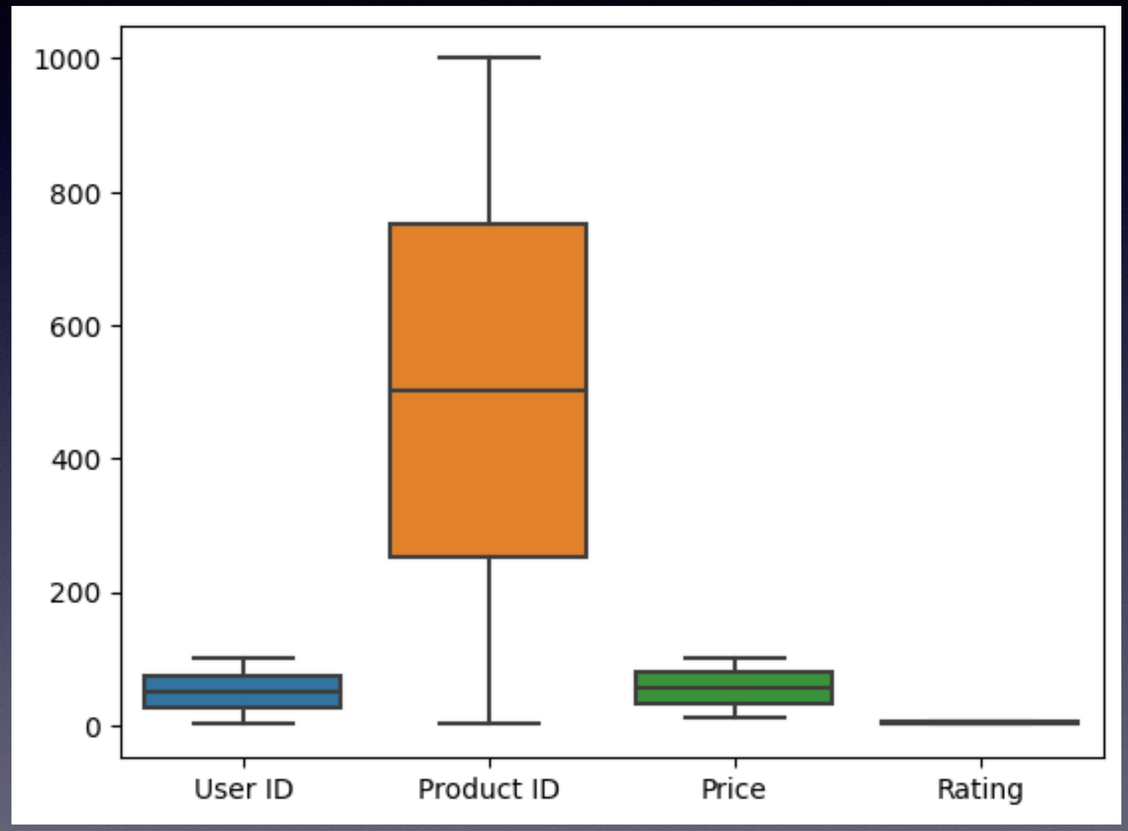
# Data Wrangling / Data Cleaning

Performed a series of processes to explore, transform, and validate raw dataset retrieved into a high-quality and reliable data for analysis. This step include checking out following items:

- **Missing values -** No missing value has been detected
- **Outliers** = No outliers detected in all numeric columns including User ID, Product ID, Price, Rating

# Visualize Numerical Data Distribution

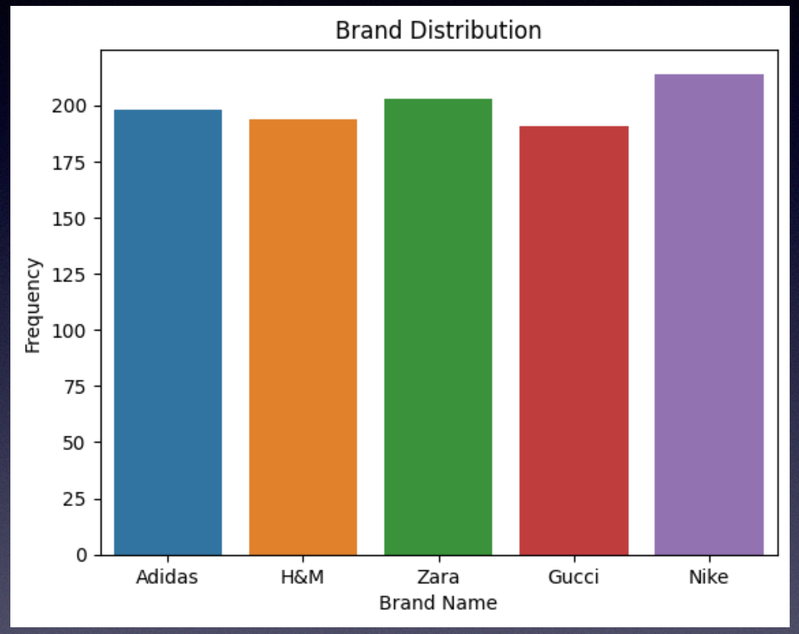


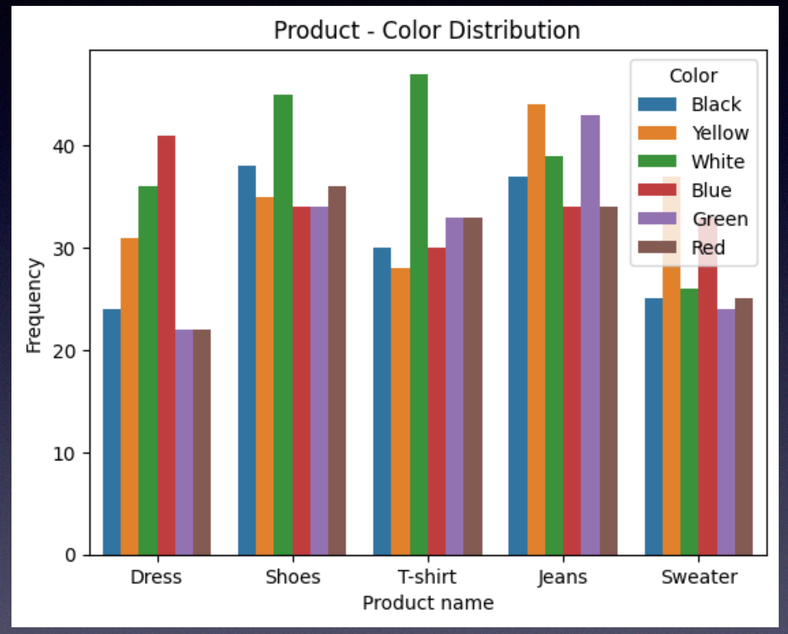



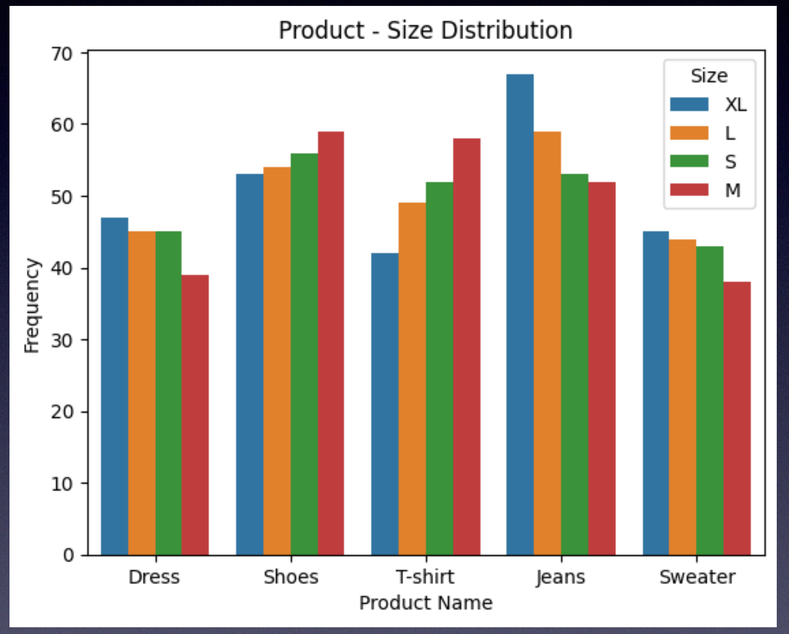

Data Distribution is **multi-modal** with multiple peaks.

**SeaBorn BoxPlot Result**: No outliers detected in any of the numeric columns including User ID, Product ID, Price, Rating.

# Visualize Categorical Data Distribution



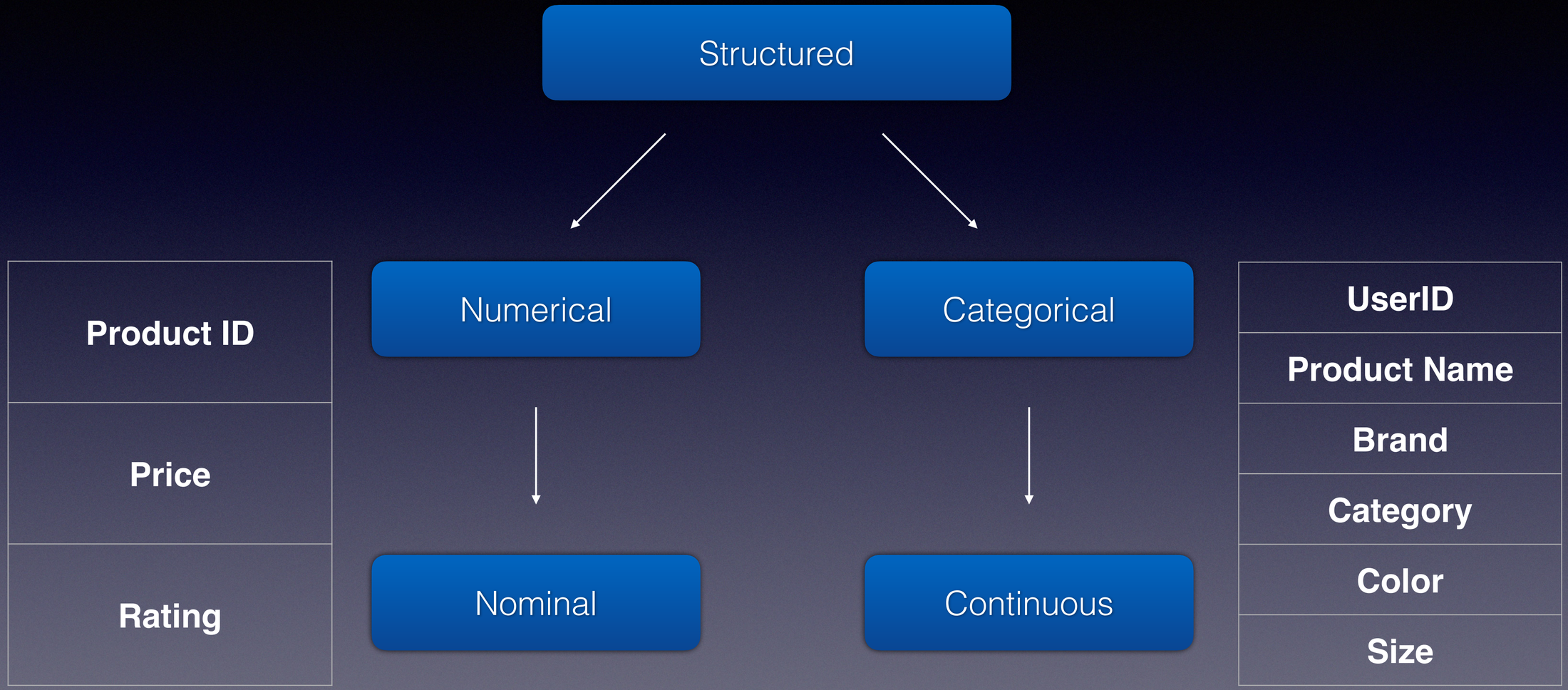




**Summary**:

Frequency of Kid's fashion is slightly higher than the men's and women's fashion.
Count of Nike products are slightly higher than any other brands.
Products such as Jeans, shoes and t-shirts are more popular in this dataset.
In product type jeans, XL seems most popular. M size tops the list in two product categories, shoes and t-shirts.
Color White seems extremely popular in shoes and t-shirt categories.

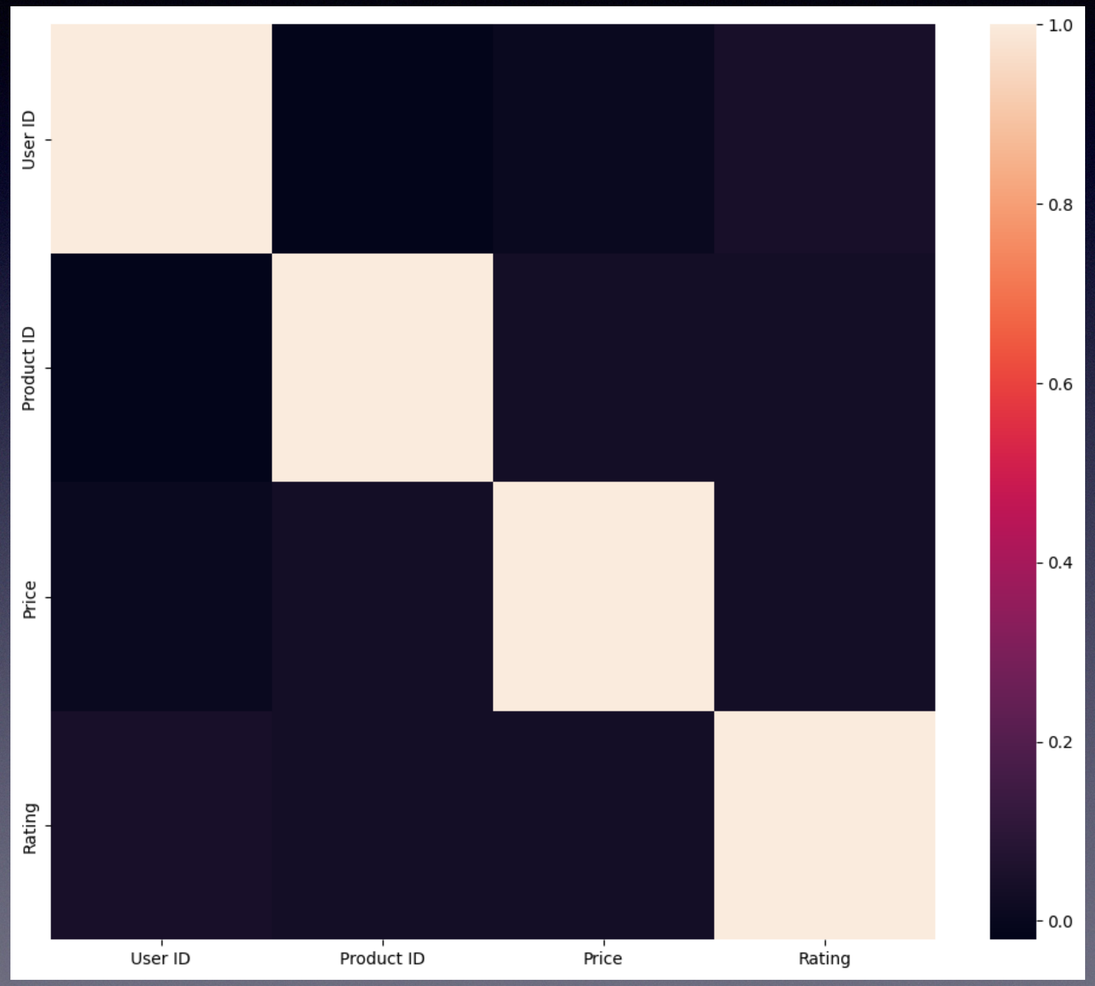
# Type of Dataset



# Exploratory Data Analysis

**Feature correlation heatmap -** Gain a high level view of relationships amongst the features

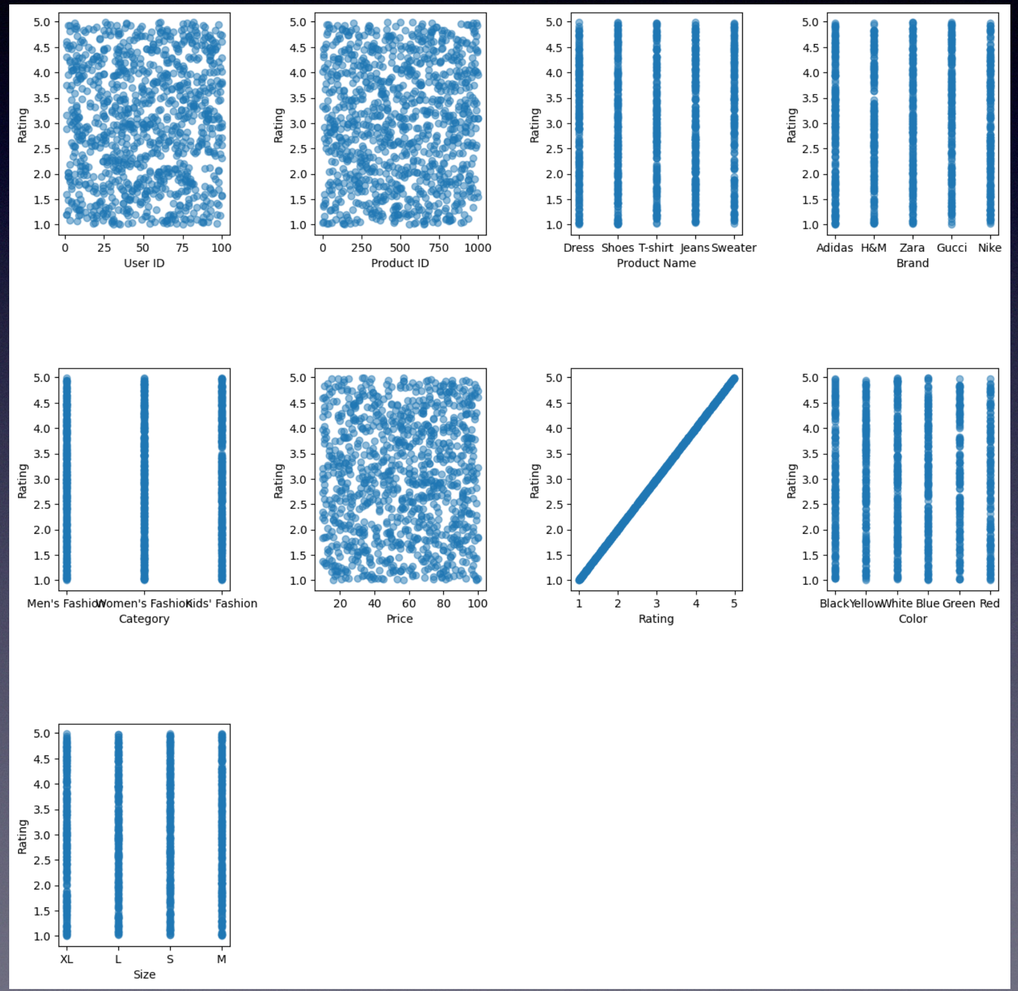
- There is no correlation between any of the features including the target variable “Rating”.
- Suggests non-linear relationships between the features.



# Exploratory Data Analysis - Continue

Created a Scatter plots for visualizing the relationship between a numeric feature against target variable, Rating.

- Further confirms no clear relationship between various features.
- User ID, Product ID and Price seems too concentrated and no meaningful insight can be extracted.
-

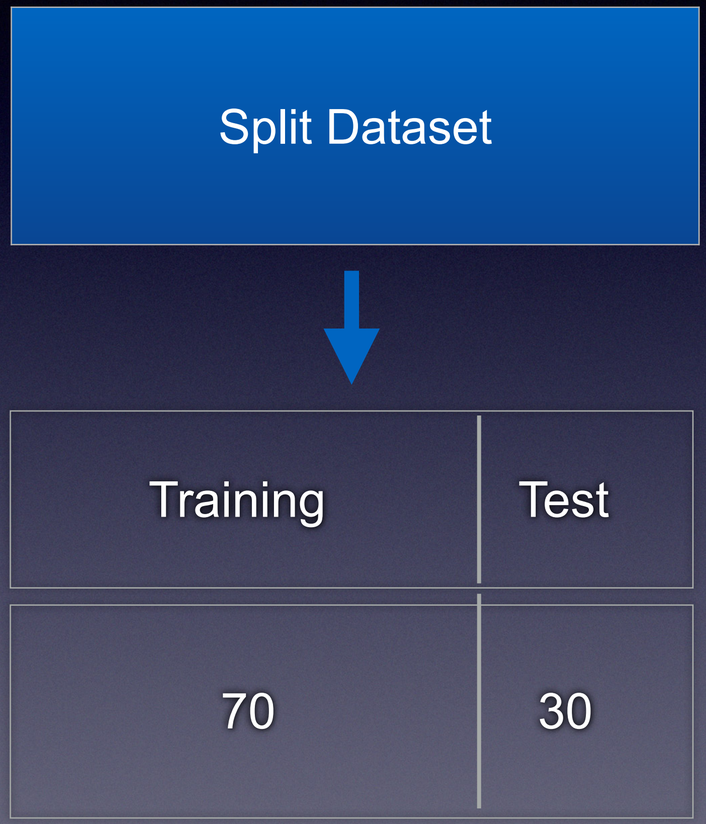


# Pre-processing and Training data

Help us learn the relationship between the input features and the target variable (Rating).

**One-hot Encoding on Categorical Features:**

- User ID
- Product Name
- Brand
- Category
- Color
- Size

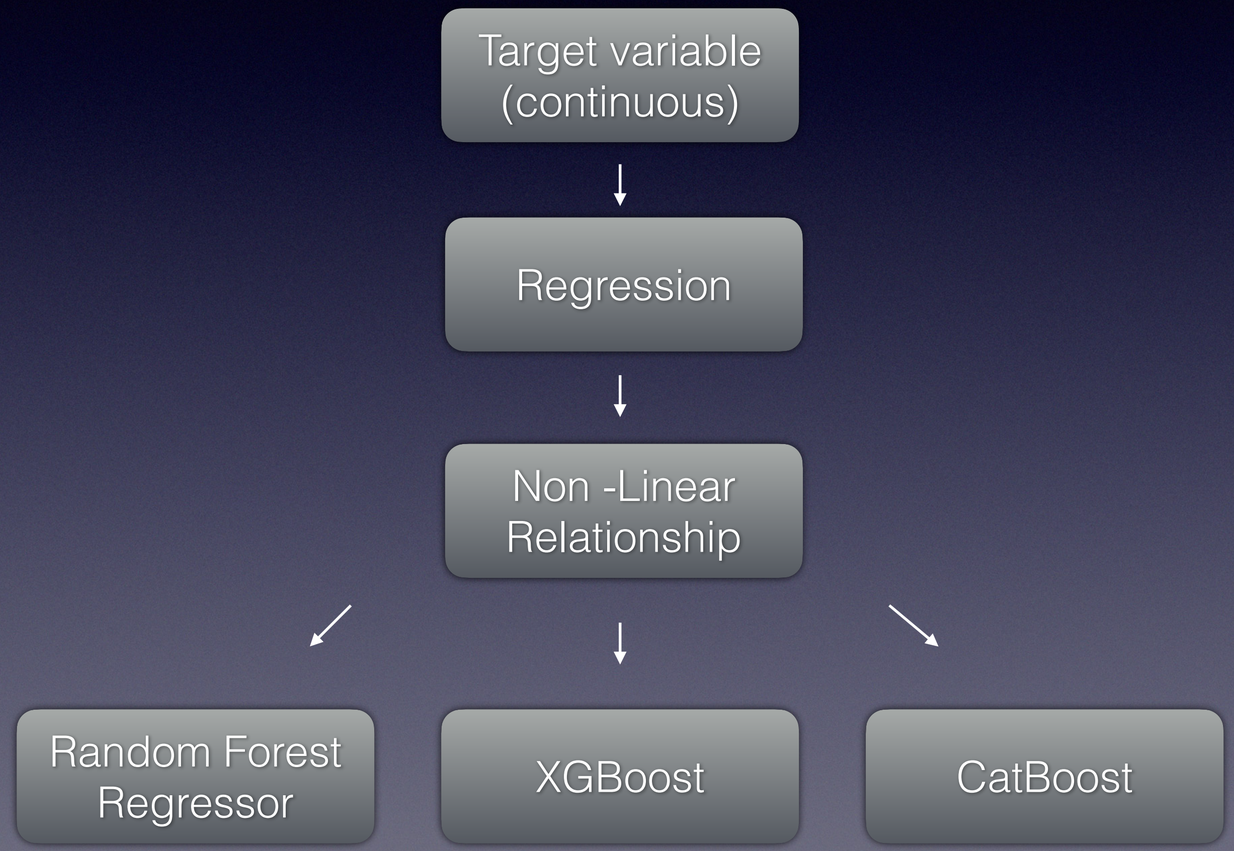


# Machine Learning Algorithms

Choosing the right ML algorithm is crucial.

The choice depends on Problem Type:

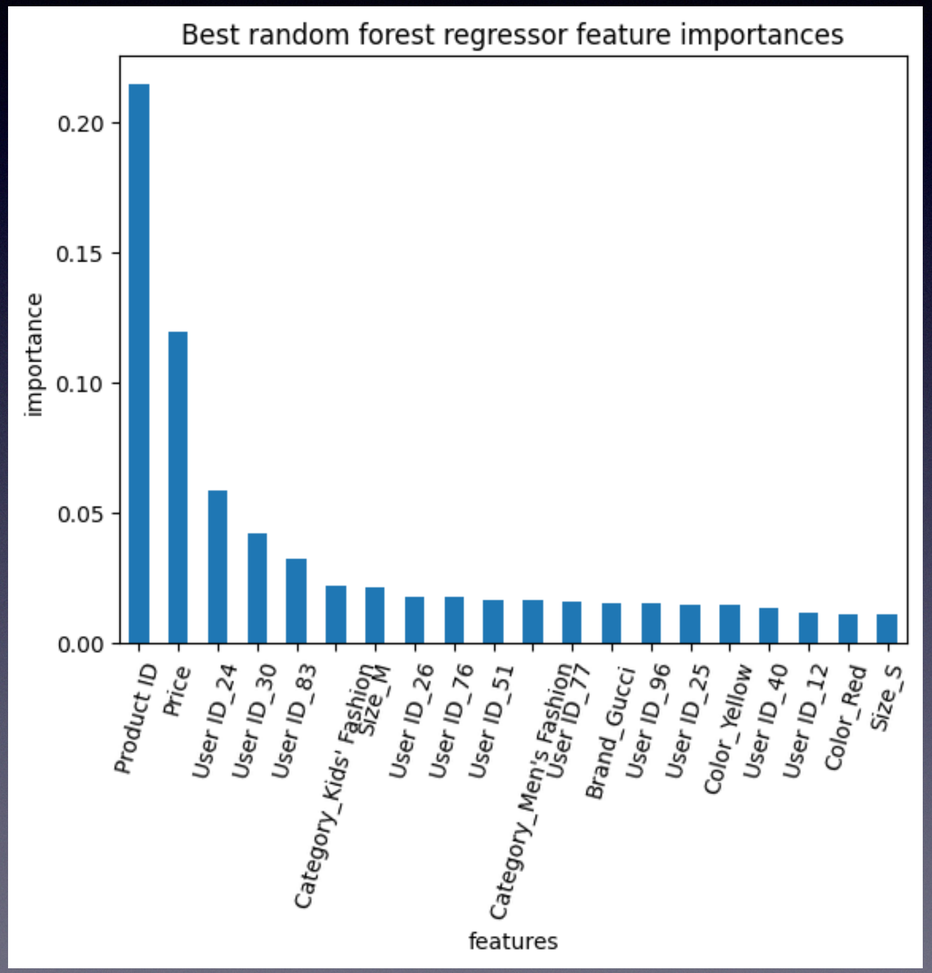
- **Type of problem: Regression Problem** (Target, Rating is continuous)
- **Nature of the data: Supervised learning as Labeled data**
- **Goals of the analysis: Predict a continuous numerical value**
- **Model performance: Mean Squared Error (MSE), R-squared ($R^2$) and RMSE**



# Random Forest Model

Identify the dominant features based on their importance in a Random Forest model are as follows:

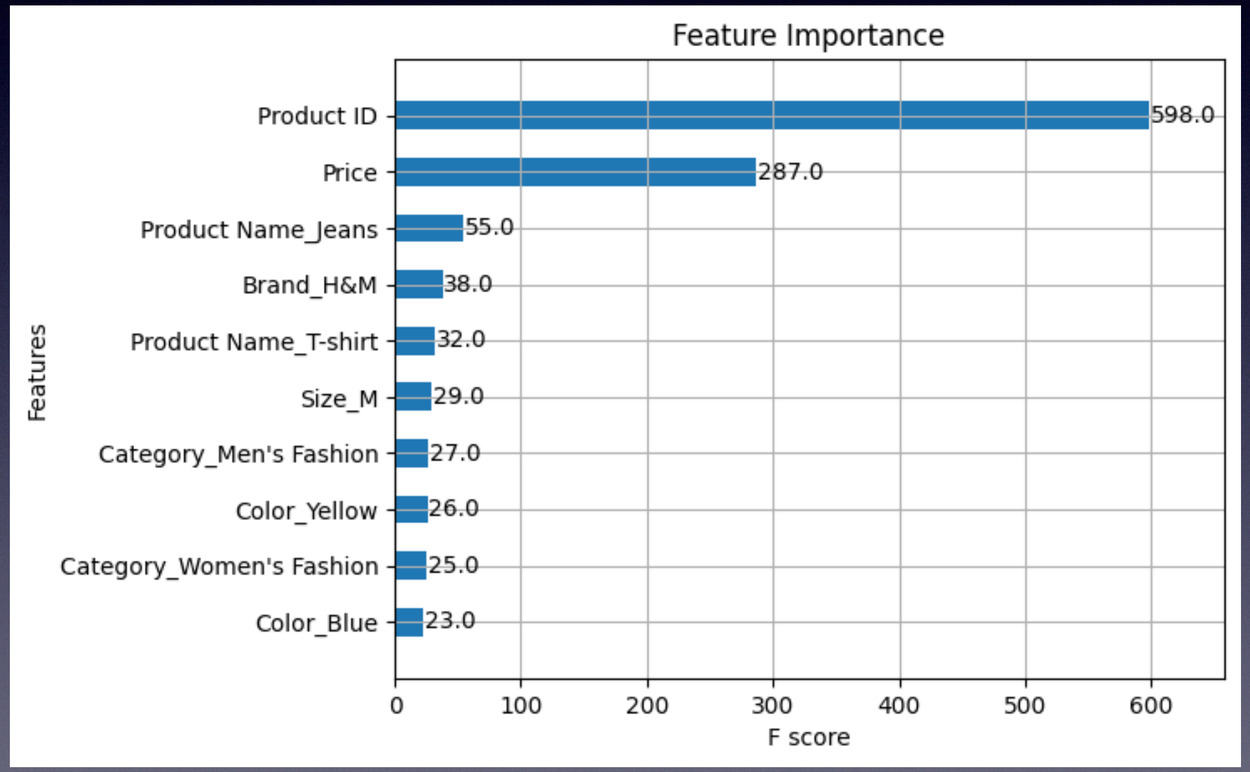
- Product ID
- Price
- User ID_24
- User ID_30
- User ID_83
- Category_Kid’s Fashion
- Size_M
- User ID_26
- User ID_76
- User ID_51



# XG Boost Model

Identify the dominant features based on their importance in a XG Boost model are as follows:

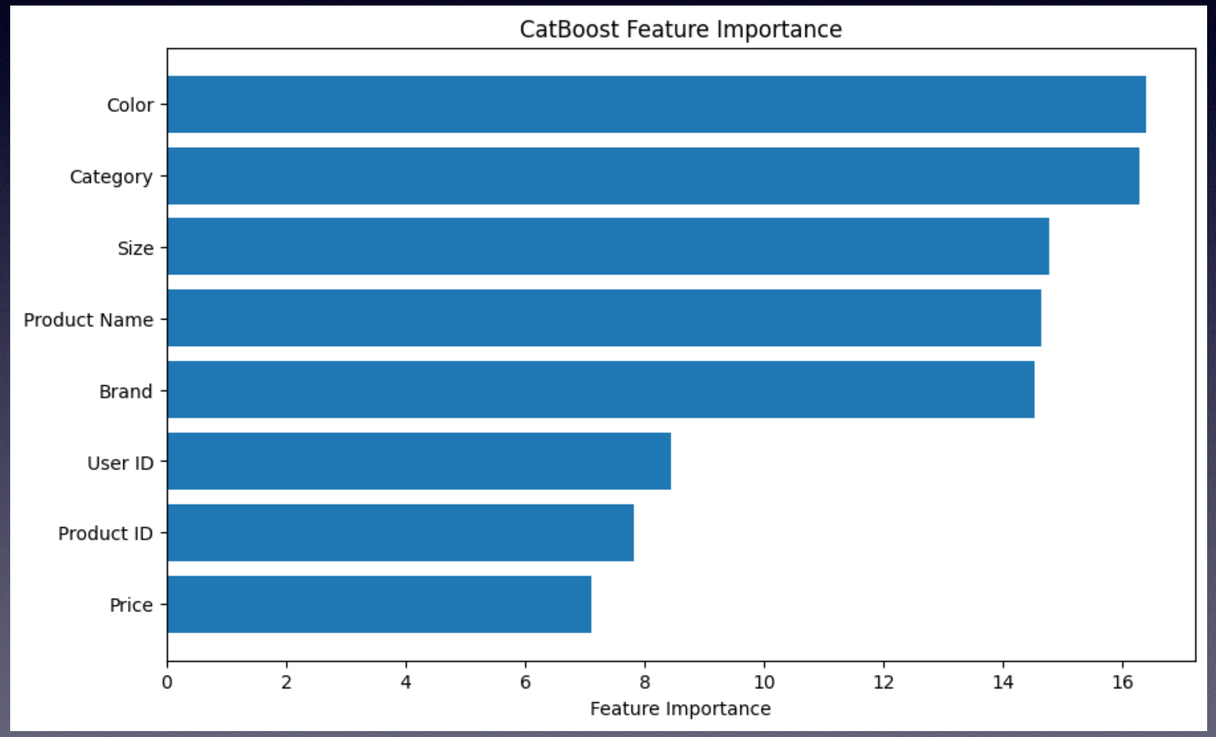
- Product ID
- Price
- Product Name_Jeans
- Brand_H&M
- Product Name T-shirt
- Size_M
- Category_Men’s Fashion
- Color_Yellow
- Category_Women’s Fashion
- Colo_Blue



# CatBoost Model

Identify the top dominant features based on their importance in a Cat Boost model are as follows:

- Color
- Category
- Size
- Product Name
- Brand
- User ID
- Product ID
- Price



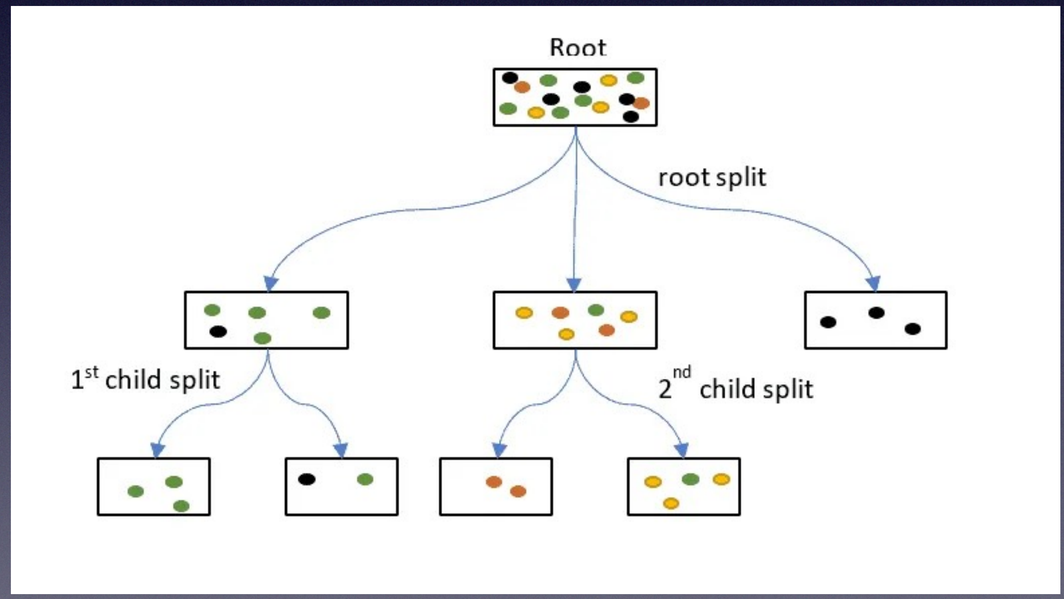
# ML steps

| | Random Forest | XGBoost | Cat Boost |
|---|---|---|---|
| Import libraries | scikit-learn | xgboost | scikit-learn |
| Initialize the model | RandomForestRegressor() | xgb.XGBRegressor() | CatBoostRegressor() |
| Train the model | model.fit(X_train, y_train) | model.fit(X_train, y_train) | model.fit(X_train, y_train) |
| Predict on test data | model.predict(X_test) | model.predict(X_test) | model.predict(X_test) |
| Evaluate the model | Mean Squared error: 1.43<br>RMSE: 1.19 | Mean Squared error: 1.44<br>RMSE: 1.20 | Mean absolute error: 1.53<br>RMSE: 1.23 |
| Hyperparameter Tuning | GridSearchCV | GridSearchCV | GridSearchCV |

# CatBoost Algorithm Overview

**Key Features:**

- An advanced **gradient boosting** algorithm optimized for performance, particularly when handling **categorical data**.
- Dataset include large number of categorical features such as Color, Size, User ID, Category etc.
- Making it an excellent choice for our training dataset
- Its ability to handle categorical variables directly and its **ordered boosting** method provide a significant advantage over other algorithms like **XGBoost** and **Random Forest Model.**



# Singular Value Decomposition (SVD)

**Collaborative-based Filtering**

| User ID | Product ID | Rating |
|---|---|---|
| 56 | 22 | 4.568632 |
| 56 | 177 | 4.567658 |
| 56 | 423 | 4.502435 |
| 56 | 125 | 4.139373 |
| 56 | 194 | 3.792556 |

+

**Content-based Filtering**

| Product ID | Price | Rating |
|---|---|---|
| 323 | 95 | 2.326168 |
| 549 | 96 | 4.283951 |
| 561 | 96 | 3.968456 |
| 567 | 96 | 1.206723 |
| 858 | 96 | 4.451841 |

→

**Hybrid Recommendations**

| Product ID | Price | Rating |
|---|---|---|
| 22 | 89 | 4.568632 |
| 177 | 12 | 4.567658 |
| 423 | 83 | 4.502435 |
| 125 | 56 | 4.139373 |
| 194 | 92 | 3.792556 |
| 43 | 39 | 3.601869 |
| 76 | 39 | 2.974139 |
| 563 | 39 | 4.043087 |
| 658 | 40 | 3.252305 |
| 696 | 39 | 4.592767 |

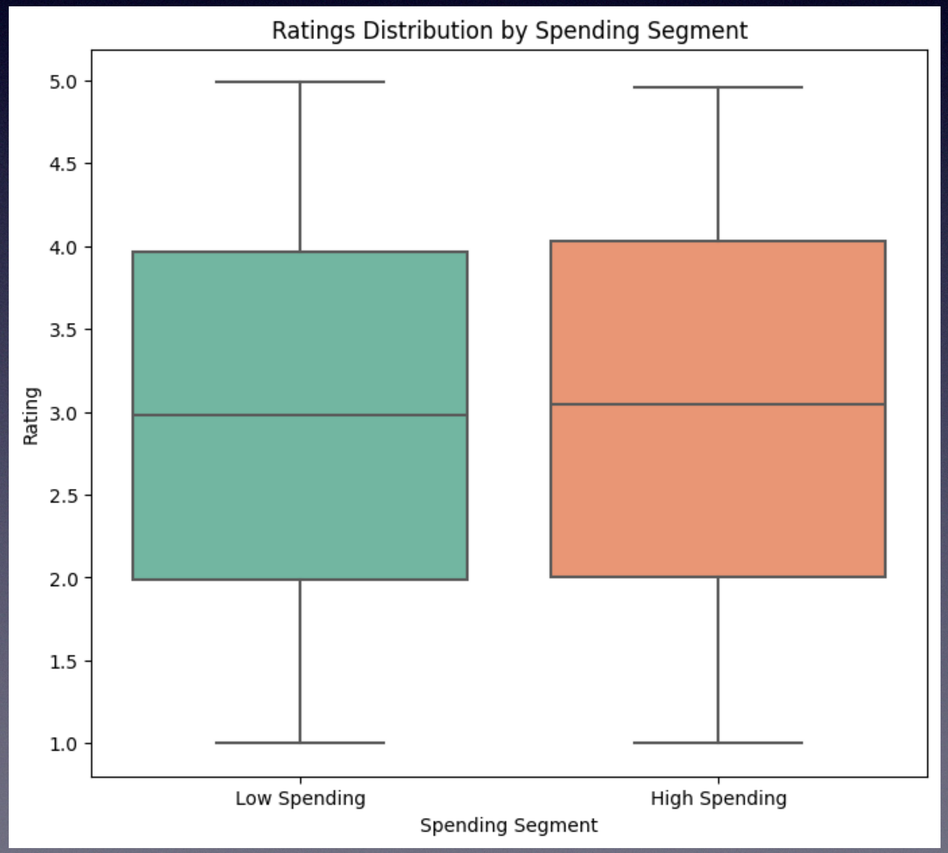
RMSE value of 0.2666 confirms the model performance.

# Visualize the Distribution of Ratings per Segment

- **High-Spending**: Users whose total spending or average purchase amount is above a threshold, 70.
- **Low-Spending**: Users whose total spending or average purchase amount is below a certain threshold, which is 70.

**Computed Average Rating per Spending Segment**

| Spending Segment | Rating |
|---|---|
| High - Spending | 3.04 |
| Low - Spending | 2.97 |



# Recommendation and Key Findings

- Adding more relevant features especially time-based features that track **seasonal preferences** (e.g., winter jackets in cold months).
- Recommend products based on **recent purchases** or **trends**.
- **Time decay**: Give higher weights to more recent interactions or purchases.
- Focus on top feature importances such as Product ID, Price, Size M and Color Yellow, which is consistent among all the models.
- Can include external data sources such as marketing campaigns, competitor actions to stay updated.
- Tuning the model periodically with fresh data to keep it up to date.