

*Integrated Program in Business Analytics*

# MYNTRA PRODUCTS RECOMMENDATION SYSTEM

IPBA\_B17\_GROUP L

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# Agenda

- I. Business Problem and Objectives
- II. Executive Summary
- III. Data Overview and Key Business Assumptions (if any)
- IV. Data Preparation and Pre-processing
  - Sanity checks, treatment and transformations for analytical dataset preparation
- V. Exploratory Data Analysis
  - Key Business Findings and Insights
- VI. Model Development and Validations
  - Model comparisons on key scoring metrics and model finalization
- VII. Dashboarding (required only when it is in scope of analysis)
- VIII. Business Recommendations and Potential Business Impact
- IX. Next Steps
- X. Appendix

# Business Problem and Objectives

## Overview of Myntra:

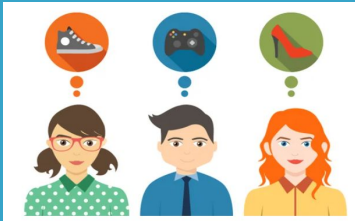
Myntra, founded in 2007, stands as a premier online fashion destination in India, offering a diverse range of apparel, accessories, and lifestyle products. Renowned for its extensive collection of domestic and international brands, Myntra provides customers with access to the latest fashion trends and styles. With innovative technology, personalized recommendations, and convenient shopping features, Myntra delivers a seamless online shopping experience, making it a preferred choice for millions of fashion enthusiasts across the country.

## Business Problem:

- To effectively analyze user data and generate accurate recommendations.
- Consequently, the website experiences lower customer engagement and struggles to increase average order value.

## Objectives:

Personalization



Improved User Experience



Customer Retention



Increased Sales



# Executive Summary

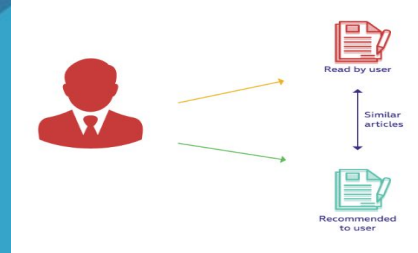
Outlines a high-level overview of the presentation's content, allowing stakeholders to grasp the significance of Myntra's recommendation model and its impact on the company's objectives. The following components constitute the executive summary.

## 1) Recommendation Models used:

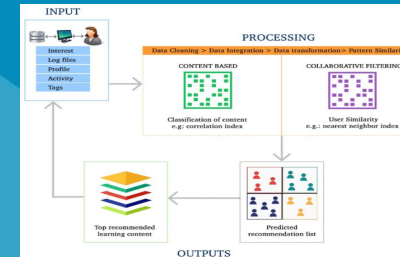
### Popularity based



### Content-based



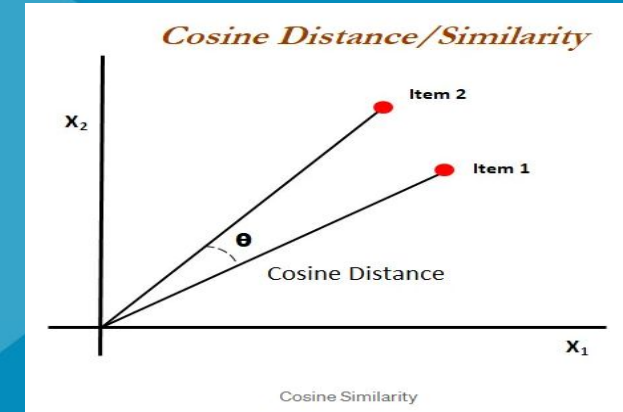
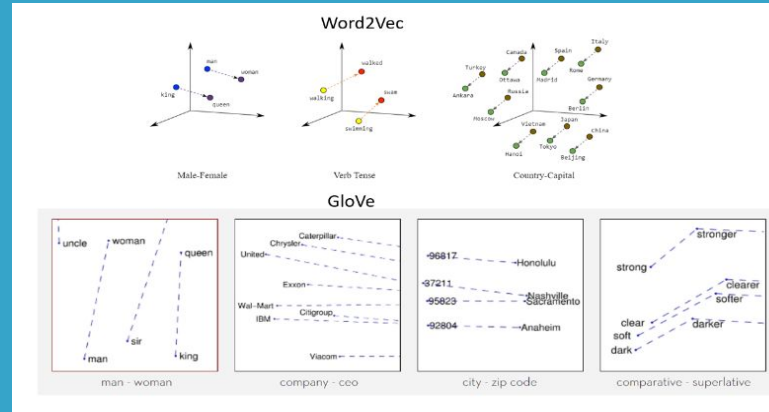
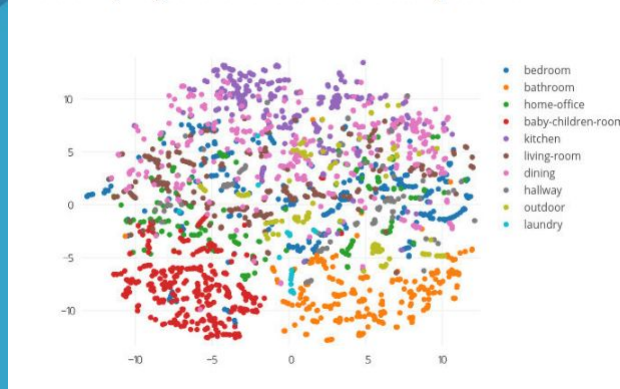
### Hybrid approaches



## 2) Technologies Used -> Python

## 3) Word Embeddings-> Count Vectorizer, TF-IDF, Word2Vec, Levenstien and GloVe models.

The following image shows us how a word embedding looks like!



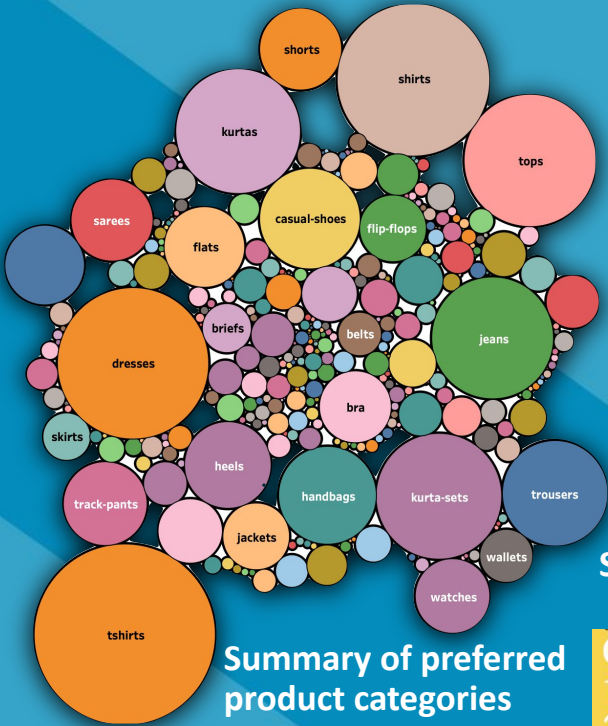


**Data Source:** [Myntra 168k Products \(kaggle.com\)](#)  
**Product Data:** Details about the products available on Myntra,including product name, brand name , rating of product, rating count, prices, sizes, links, and images.

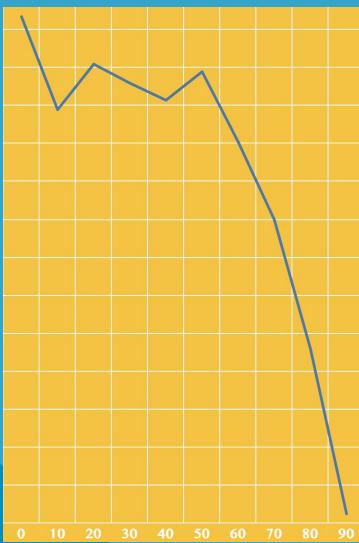
**Ratings Analysis:**  
Mean Rating: 2.26  
Mode Rating: 0

**Price Distribution:**  
Average Discount: 37%, suggesting substantial savings for customers.

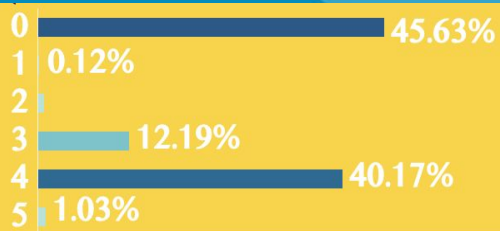
**Spread of Prices:**  
Interquartile Range (IQR): Rs 109, indicating the variability in product prices.



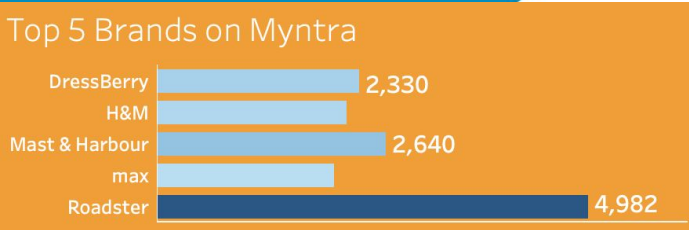
Summary of preferred product categories



Summary of discounts on products



Ratings summary of the data



Summary of most preferred brands

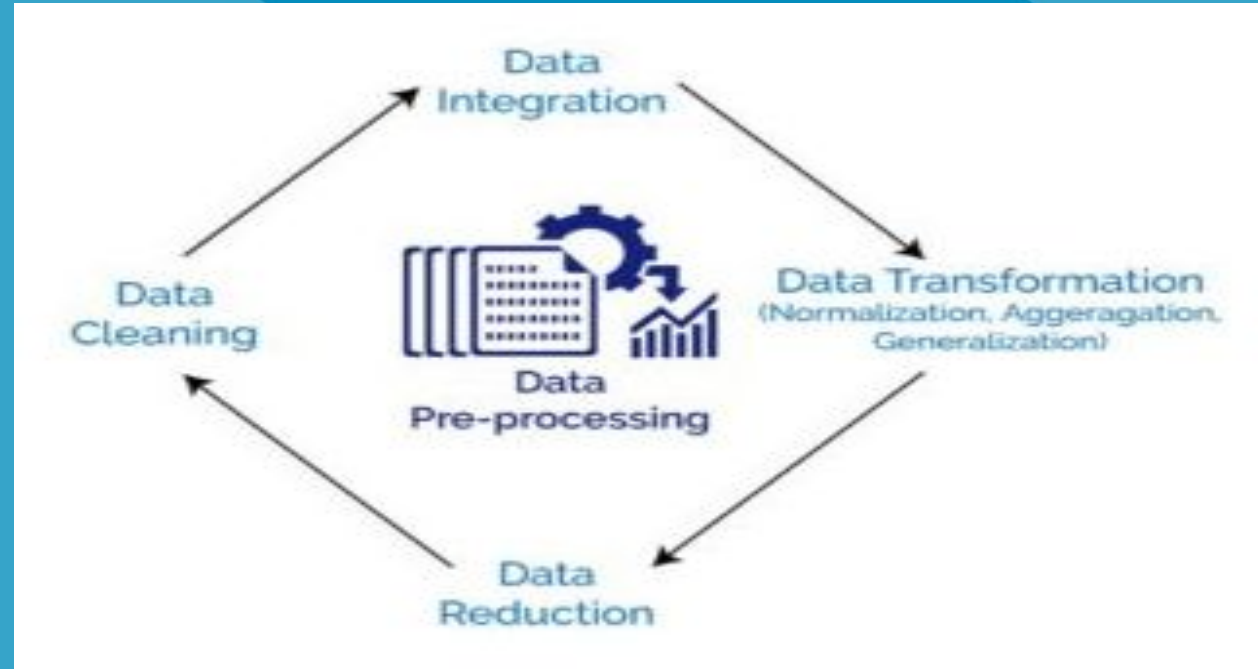
### Key Business Assumptions:

- 1.Handling Data Sparsity:** To manage data scarcity by excluding zero ratings and leveraging implicit feedback effectively.
- 2.Considering Price Sensitivity:** Discounts (average 37%) have significant impact on purchase decisions, so the recommendation should consider the price fluctuations to prompt purchase decisions.
- 3.Accommodating Brand Preferences:** By considering brand popularity and user inclinations.
- 4.Incorporating Size Preferences:** taking into account size availability to suggest products in relevant sizes optimally.
- 5.Focusing on Popular Categories:** Myntra caters heavily to clothing, so the model should prioritise recommendations within this category while considering user preferences for other categories as well.

# Data Preparation and Pre-processing (Sanity checks, treatment and transformations for analytical dataset preparation)

Data preparation and pre-processing for a Myntra recommendation model involve several steps to ensure that the data is clean, structured, and suitable for analysis. Here's an overview of the process:

- 1) **Data Collection:**
- 2) **Data Cleaning:**
- 3) **Data Integration:**
- 4) **Feature Engineering:**
- 5) **Text Pre-processing (if applicable):**
- 6) **Data Transformation:**

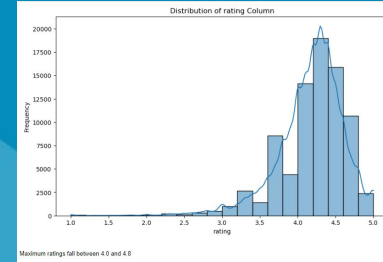
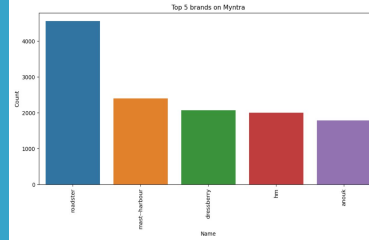
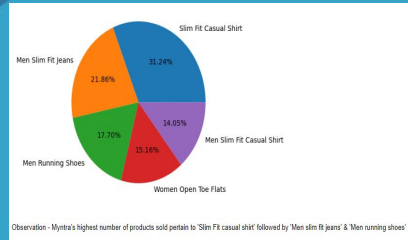
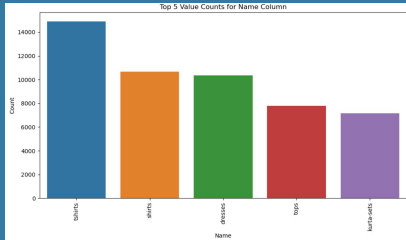


# Exploratory Data Analysis (EDA)

In the exploratory data analysis (EDA) for the Myntra recommendation model, we aim to gain insights into the characteristics of the dataset, identify patterns, and understand the relationships between variables. Here's an outline of the EDA process for the Myntra recommendation model:

**Dataset Overview:** Myntra dataset with 168029 rows & 13 columns

**Product Analysis:** Popularity based RM. Top products sold on Myntra. Logarithmic transformation .



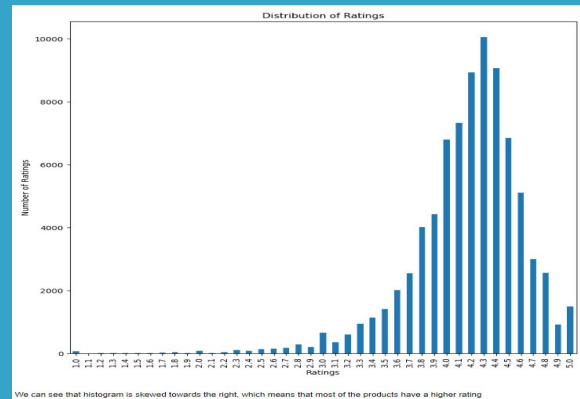
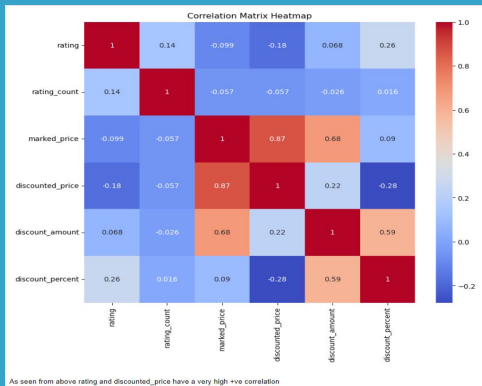
```
myntra.columns
Index(['product_name', 'brand_name', 'rating', 'rating_count', 'marked_price',
      'discounted_price', 'sizes', 'product_link', 'img_link', 'product_tag',
      'brand_tag', 'discount_amount', 'discount_percent'],
      dtype='object')

myntra.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 168029 entries, 0 to 168028
Data columns (total 13 columns):
#   Column              Non-Null Count  Dtype
---  --
0   product_name        168029 non-null object
1   brand_name          168029 non-null object
2   rating              168029 non-null float64
3   rating_count        168029 non-null int64
4   marked_price        168029 non-null int64
5   discounted_price    168029 non-null int64
6   sizes               168029 non-null object
7   product_link       168029 non-null object
8   img_link            168029 non-null object
9   product_tag        168029 non-null object
10  brand_tag           168029 non-null object
11  discount_amount     168029 non-null int64
12  discount_percent    168029 non-null int64
dtypes: float64(1), int64(5), object(7)
memory usage: 16.7+ MB
```

**Price Analysis:** The maximum discounted products on Myntra

**Rating Analysis:** Average rating given to most of the products is 4.17. Highest rated products on myntra is 5.0. Maximum ratings fall between 4.0 and 4.8. Highest Rated Product - products with the highest rating, considering the 'rating' column as the primary criterion and the 'rating count' column as the secondary criterion in case of a tie

**Correlation Analysis:** Rating and discounted price have a very high positive correlation. We can see that histogram is skewed towards the right, which means that most of the products have a higher rating



# Model Development and Validations

## Algorithmic Approaches

**Popularity based Recommendation Model** by recommending the top N items to the user & category-wise (for each brand name)

**Countvectorizer:** Transforms product text data into numerical vectors by counting the occurrences of words, facilitating analysis of text data in popularity-based model.

**TF-IDF Vectorizer:** Utilized to convert product text data into numerical vectors based on term frequency-inverse document frequency, enabling analysis of textual features' importance for popularity-based models.

**Word Embeddings:** Embedding technique that transforms words into dense vectors, capturing semantic similarities and relationships between product names used in developing content-based model. E.g., Word2Vec, GloVe

**GloVe Embeddings:** Embedding method that generates word representations by leveraging global word co-occurrence statistics, enhancing semantic understanding and context awareness.

**Fuzzy Wuzzy:** Library used for fuzzy string matching, aiding in comparing and identifying similarities between strings, particularly helpful in data preprocessing and deduplication tasks.

**Levenshtein:** Algorithm used for measuring the dissimilarity between two strings by calculating the minimum number of operations required to transform one string into another, useful for tasks such as spell checking and string comparison.



## Conclusion and Model Finalisation

With our final approach of Levenshtein Hybrid model below is working and understanding of the model.

In our recommendation system:

### Model 1 - Cosine Similarity Recommendation:

- Utilizes a GloVe embedding
- Computes cosine similarities
- Captures semantic relationships between products.

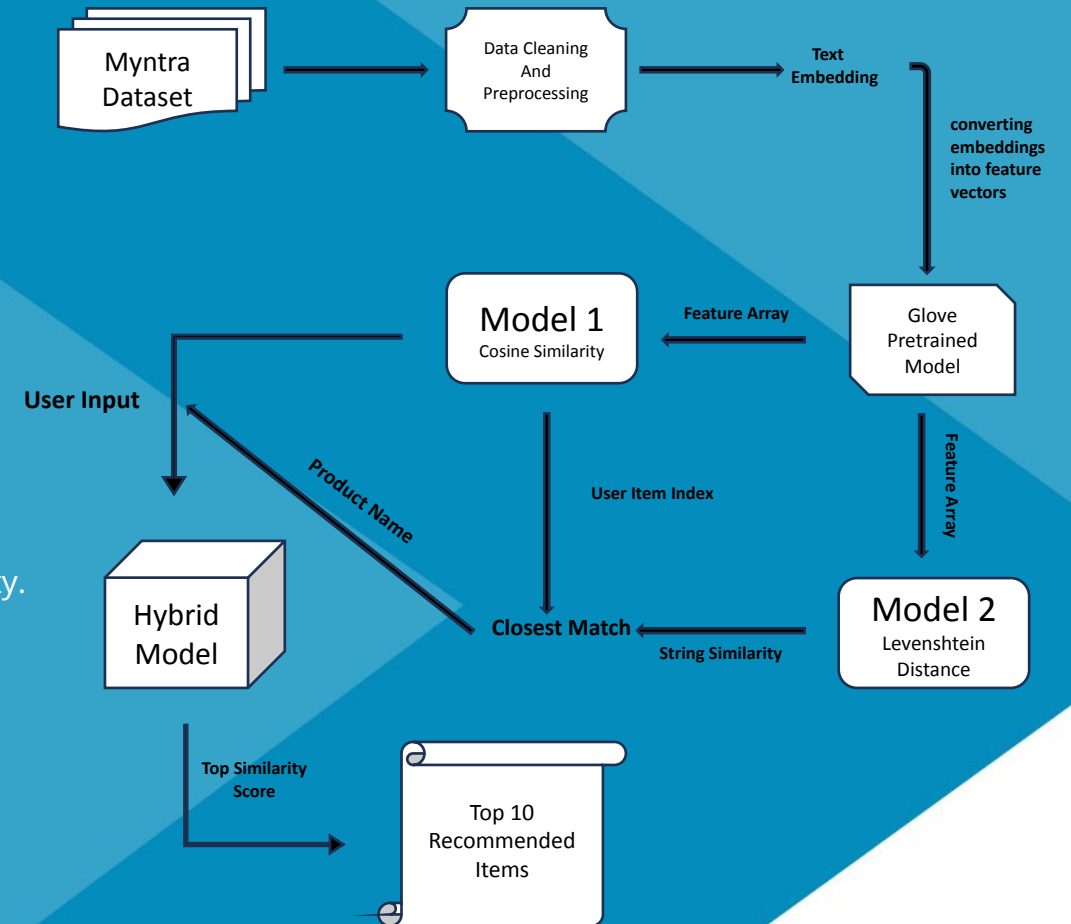
### Model 2 - Levenshtein Distance Matching:

- Utilizes the Levenshtein Distance metric to measure string similarity.
- Directly matches user input to product names in the dataset.
- Facilitates user engagement by offering recommendations based on input similarity.

### Hybrid Recommendation Approach:

- Combines both similarity-based and name-matching methods.
- leverages both GloVe embeddings and Levenshtein distance.
- Provides users with a comprehensive recommendation list tailored to their input.

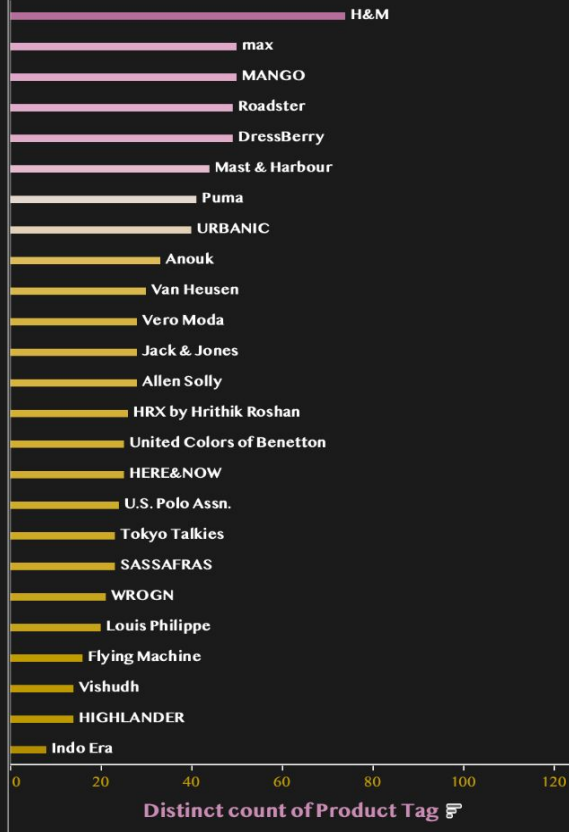
By integrating these models, our recommendation system offers personalized and accurate suggestions, enhancing user satisfaction and engagement.



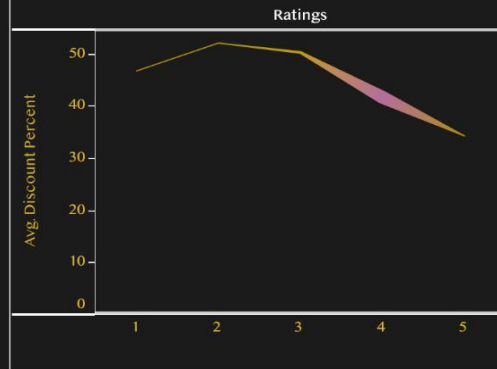
# Dashboarding

Here we are providing a detailed analysis of various brands and their products, showcasing average ratings, maximum discount percentages, marked prices, and rating counts. It covers brand performance and product-specific discount strategies, vital for understanding market trends and customer preferences. This information was possibly analysed using Power BI & Tableau Desktop, indicated by the mention of sharing a Power BI file for reference. The data is essential for insights into business strategies, pricing, and consumer satisfaction.

## Unique Product Categories for Top 25 Brands with the Widest Range



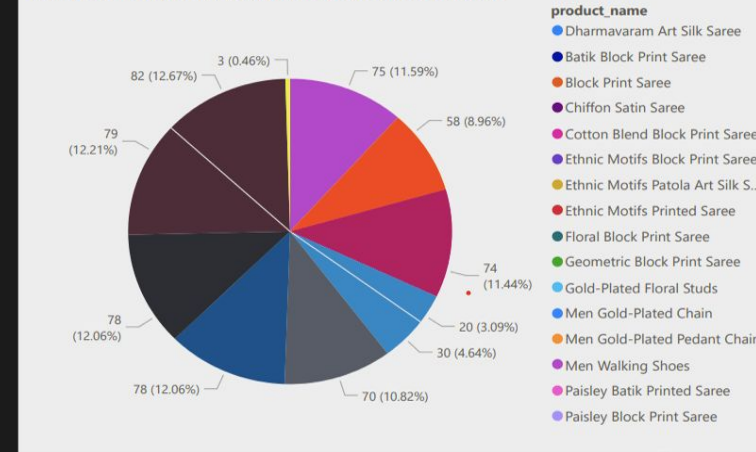
## Ratings Vs Discount %



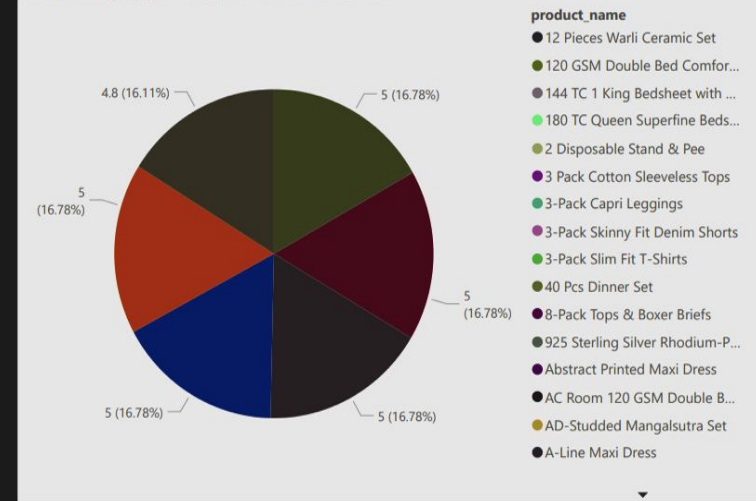
## Top 10 Market Price Products Vs Discount %



## Max of discount\_percent by product\_name and brand\_name



## Max of rating by product\_name and brand\_name



## Business Recommendations and potential business impact

1. Personalized Recommendations:  
Utilize user data for tailored product suggestions.
2. Enhanced User Experience:  
Improve browsing experience with intuitive recommendations.
3. Reduced Cart Abandonment:  
Minimize abandonment rates by recommending complementary products.
4. Improved Inventory Management:  
Optimize inventory based on user preferences and purchase patterns.
5. Customer Loyalty:  
Enhance satisfaction and loyalty through personalized recommendations.
6. Competitive Edge Amplified:  
Propel Myntra ahead with a pioneering, personalized shopping journey.

### Conclusion:

Implementing personalized recommendations on Myntra's platform can revolutionize user engagement, drive sales, and solidify its position as a leader in the e-commerce industry.

## Next Steps

- Use other E-commerce datasets (E.g., AJIO, Amazon, Flipkart)
- Try new approaches viz Neural Network, Deep Learning & AI
- Enhance, evaluate and fine-tune recommendation accuracy
- Deploy the refined recommendation system into production
- Establish monitoring mechanisms to track its performance over time



# Appendix

Title of Appendix

Business Problem and Objectives

Executive Summary

Data Overview and Key business assumptions

Data Preparation and Pre-processing

Exploratory Data Analysis (EDA)

Model Development and Validations

Dashboarding

Business Recommendations and potential business impact

Next Steps

# Thank You