

# **PROBLEM STATEMENT**

- → How can we make it easier for customers to find exactly what they're looking for?
- → How can we recommend items that a customer might be interested in?



## WHY IS THIS USEFUL?

- → Quicker and more efficient buying process
- → Reduce returns and transport emissions
- → Increase revenue by increasing the number of purchases per customer



## **DATASETS: PROVIDED BY H&M**

→ TARGET VARIABLE: article\_id

CUSTOMERS: 3 million TRANSACTIONS: 30 million ARTICLES: 100,000







## **EXPLORATION & ANALYSIS**

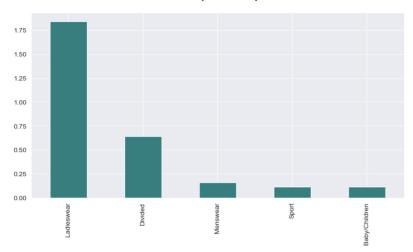
Top customer bought 1346 items

 $\rightarrow$ 

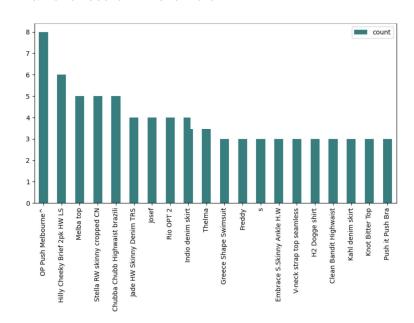
Repurchased top product 8 times



#### TRANSACTIONS BY DEPARTMENT (MILLIONS)



#### **H&M'S TOP CUSTOMER PURCHASES**



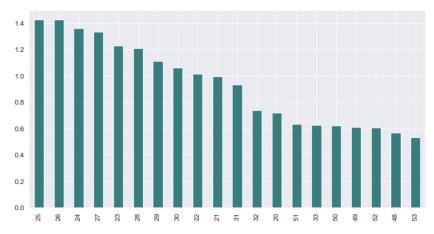
- Ladieswear counts for over 70% of total transactions
- 8 times more ladieswear purchased than menswear

## **EXPLORATION & ANALYSIS**

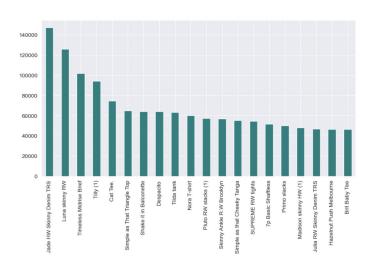
Skinny jeans are H&M's most popular product

Most popular product was a repeated purchase of top customer

#### TRANSACTIONS BY AGE (MILLIONS)



#### **H&M'S TOP PRODUCTS (TRANSACTIONS)**



← Ages 24-26 make the most purchases

## **MODELING**

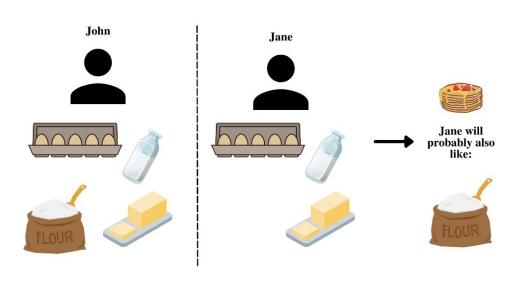
### **BASELINE MODEL:**

- → MOST POPULAR ITEMS
- → RECOMMEND MOST POPULAR ITEM WITHIN A CUSTOMER'S MOST FREQUENTLY PURCHASED PRODUCT TYPE

### **ADVANCED MODELING:**

- → DECISION TREE
- → MARKET BASKET ANALYSIS:
  - ◆ COSINE SIMILARITY
  - PEARSON SIMILARITY

# **COLLABORATIVE FILTERING**



#### **3 INPUT TABLES:**

- → ARTICLE PURCHASE COUNT
- → PURCHASE DUMMY
- → NORMALIZED PURCHASE COUNTS

# **RESULTS**

#### **MOST ACCURATE MODEL?**

→ COSINE SIMILARITY

#### WHICH TABLE?

→ PURCHASE DUMMY

### **ACCURACY METRICS?**

→ RMSE & PRECISION AND RECALL

