Fashion Recommenders System

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01 | Introduction

Abstract

- Aims to develop three advanced recommendation systems for Twenty Too©, a company specializing in AI-as-a-service solutions for the fashion industry.

- These systems include: a frequently bought together model to suggest complementary products, a product similarity model to recommend visually and contextually similar items, and a personalization model tailored to individual user preferences based on demographics and browsing history.

Introduction

The first system, a frequently bought together model

The second system focuses on product similarity

The third system is a personalization model that tailors recommendations based on individual user demographics and browsing history.

TwentyToo

Welcome To TwentyToo Fashion Recommendation Engine

Discover your perfect style with our curated selection of fashion-forward picks. Whether you're looking for complete looks with our 'Top Picks Together' suggestions, exploring 'Similar Styles' for trending matches, or seeking 'Personalized Picks' tailored just for you, we're here to elevate your wardrobe effortlessly. Start exploring and let your style shine!

Top Picks Together

Similar Styles

Personalized Picks

Screen Recorder is sharing your screen. Stop sharing Hide

27°C غائم جزئيًا Search ENG 9:03 AM 7/20/2024

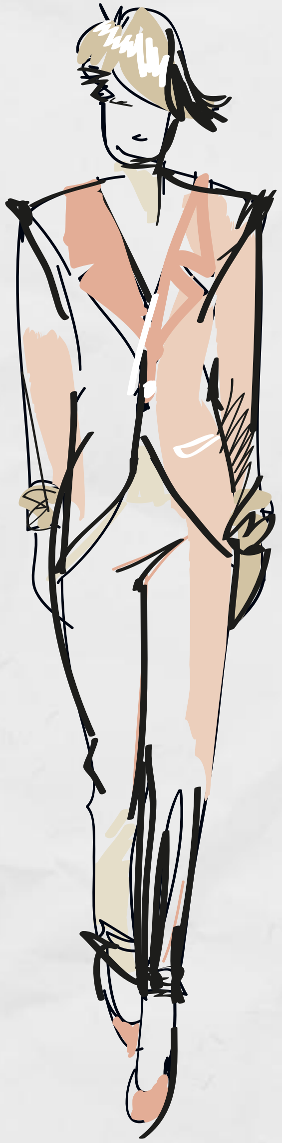
02

Data Preprocessing

Preprocessing 2 datasets

Data1 : users data before 1/6/2023

Data2 : users data after 1/6/2023



First Problem

Extracting Product IDs

Product_Package Before

'{"product_id": "ab27bf375ed51569746345ece5d0dd9e49a39768", "product_brand": "Premoda, "website": "tfk"}'

Product_Package After

ab27bf375ed51569746345ece5d0dd9e49a39768

. Methodology

Regular Expressions:

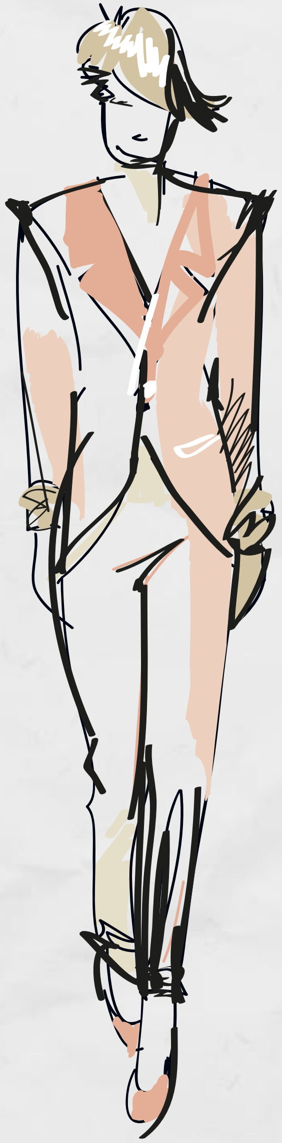
Pattern Used: [a-fA-F0-9]{32,}

Exploding Columns

Data Transformation

Product data

- All Features of Products :
- Id
- Price
- Description
- Prand
- Link of image
- Website
- Etc …



Features Has multi values

- extracts specific price information from the price column which contains lists of dictionaries in string format.

- retrieves attributes such as price value, currency, original status, valid from, and valid to dates, storing them in new columns.

```
'[{'value': 18.0, 'currency': 'USD', 'is_original': True, 'valid_from': '2023/09/13', 'valid_to': False}]'
```

Sample from Other attributes column


```
'{\'_id\': ObjectId(\'663b200a012b93dcf0dee005\'), \'sku\': \'st2205178018028785\', \'Product_URL\': \'https://www.shein.com//GLOWMODE-FeatherFit-Retro-Sport-24-Leggings-p-11096183-ca
t-2190.html?src_identifier=st%3D2%60sc%3Dsports%20legging%60sr%3D0%60ps%3D1&src_module=search&src_tab_page_id=page_goods_detail1672574085241&mallCode=1&scici=Search~~EditSearch~~1~~sp
orts_20legging~~~~0\', \'All_Reviews_Rating\': \'4.93\', \'All_Reviews_Count\': 57.0, \'Clothing-Color\': [\'Russet Orange\'], \'thumbnail\': {\'Type\': \'image\', \'Name\': \'Russet
Orange\', \'Value\': \'thumbnails/f5ba774272a55c90af9e7c388245eeca61835f2e.jpg\'}, \'Images\': \'https://img.ltwebstatic.com/images3_pi/2023/01/11/16734228854574b7a6d68d6d5e091427a5dc
afd2c9.jpg;https://img.ltwebstatic.com/images3_pi/2022/07/25/16587271198da8f58f0a2c820b6c0da28326048a25.jpg;https://img.ltwebstatic.com/images3_pi/2022/07/25/165872712394591 5ff42bfb54
cfbfc446c3cac4698.jpg;https://img.ltwebstatic.com/images3_pi/2022/07/25/16587271215ccbee33cd3204c3edc7ec38041e90e4.jpg;https://img.ltwebstatic.com/images3_pi/2022/07/25/16587271242405
d05f50b56b731ade77aeb05b076b.jpg;https://img.ltwebstatic.com/images3_pi/2022/07/25/1658727118c138e25c7a270770d979acd27ea1ad87.jpg\', \'CM_product_measurements\': \'size:XS;Length:74.8
cm;Inseam:61.5 cm;Waist Size:58 cm;Hip Size:68.5 cm;Thigh:43.8 cm;EU:34 ; size:S;Length:76 cm;Inseam:62 cm;Waist Size:62 cm;Hip Size:72.5 cm;Thigh:46 cm;EU:36 ; size:M;Length:77.2 cm;
Inseam:62.5 cm;Waist Size:66 cm;Hip Size:76.5 cm;Thigh:48.2 cm;EU:38 ; size:L;Length:78.4 cm;Inseam:63 cm;Waist Size:71 cm;Hip Size:81.5 cm;Thigh:51 cm;EU:40/42 ; size:XL;Length:79.6
cm;Inseam:63.5 cm;Waist Size:76 cm;Hip Size:86.5 cm;Thigh:53.8 cm;EU:44 ; size:XXL;Length:80.8 cm;Inseam:64 cm;Waist Size:81 cm;Hip Size:91.5 cm;Thigh:56.6 cm;EU:46\', \'CM_body_measu
rements\': \'\', \'Availability\': True, \'original_thumbnail_url\': \'https://img.ltwebstatic.com/images3_pi/2022/07/25/1658727127bd439737fa3addb6c7f3af46064308a0.jpg\', \'Clothing-D
epartment\': [\'Pants\'], \'preview_image\': \'0001d453006af5200ac06d23a1c8e30b219c4a83_0.jpg\', \'status\': [\'new\'], \'default\': True, \'child_product_ids\': None, \'lang\': \'en
\', \'Length\': \'Cropped\', \'Features\': \'Add TACTEL® Fibre\', \'Sheer\': \'No\', \'Clothing-Pattern\': [\'Plain\'], \'Clothing-Detail\': [\'Contrast Binding\'], \'Clothing-Type\':
[\'Regular\'], \'Clothing-Waistline\': [\'High Waist\'], \'Clothing-Fabric-Elasticity\': [\'High Stretch\'], \'Clothing-Material\': [\'Fabric\'], \'Clothing-Composition\': [\'19% Span
dex\'], \'All-Care\': \'Machine wash, do not dry clean\', \'Original_Description\': \'Color: Russet Orange; Pattern Type: Plain; Details: Contrast Binding; Type: Regular; Waist Line:
High Waist; Length: Cropped; Features: Add TACTEL® Fibre; Fabric: High Stretch; Material: Fabric; Composition: 19% Spandex; Care Instructions: Machine wash, do not dry clean; Sheer: N
o; \', \'s_f\': [\'All_Reviews_Rating\', \'All_Reviews_Count\', \'Clothing-Color\', \'Clothing-Department\', \'All-Price\', \'All-Brand\', \'Clothing-Size\', \'Clothing-Pattern\', \'C
lothing-Detail\', \'Clothing-Type\', \'Clothing-Waistline\', \'Clothing-Fabric-Elasticity\', \'Clothing-Material\', \'Clothing-Composition\', \'All-Care\'], \'is_available\': True,
\'product_description\': \'a pants with color: russet orange _ department: pants _ detail: contrast binding _ material: fabric _ pattern: plain _ type: regular _ waistline: high waist
_ length: cropped _ sheer: no _ target_audience: women _ title: glowmode featherfit™ retro sport 24" leggings\'}<'
```

Other attributes

id	URL	Rating	Count
color	image	product measurements	original description .

Pattern : extract every feature in other attributes to individual columns '([^'])' ?: ?('[^']'|[^,}]+)

ID Before

```
ObjectId('663b200a012b93dcf0dedffe')
```

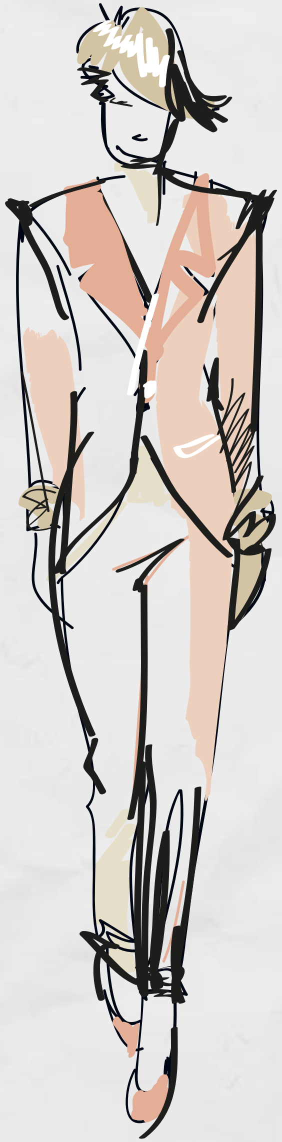
ID After

```
663b200a012b93dcf0dedffe
```

ID Feature

- Extracts the hexadecimal part of the object ID string from the ID column. This is useful for standardizing the ID format.

- *object_id_string.split("(")[1].split(")")[0].strip(""")*



Filtering Data

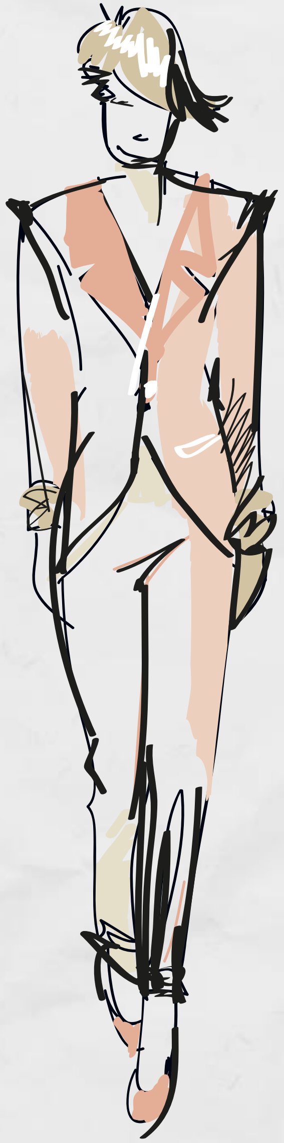
Events of Interest

- Select events that indicate significant user interactions with products

Button Names of Interest

- Include interactions with specific buttons to capture user intent and preferences

- Merge all processed into a single DataFrame.



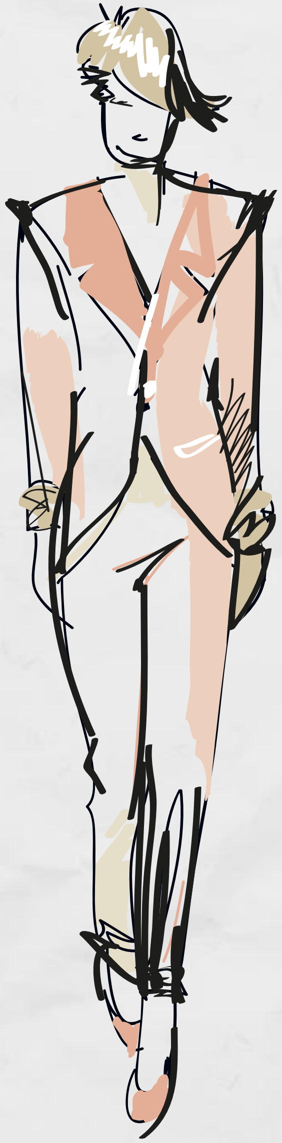
Extract Age from 'Answer' Column

Extract Age from 'Answer' Column

Objective: Derive the age of users from their responses in the 'Answer' column.

- **Method:**
- Use regular expressions to parse birthdates from the 'Answer' column:

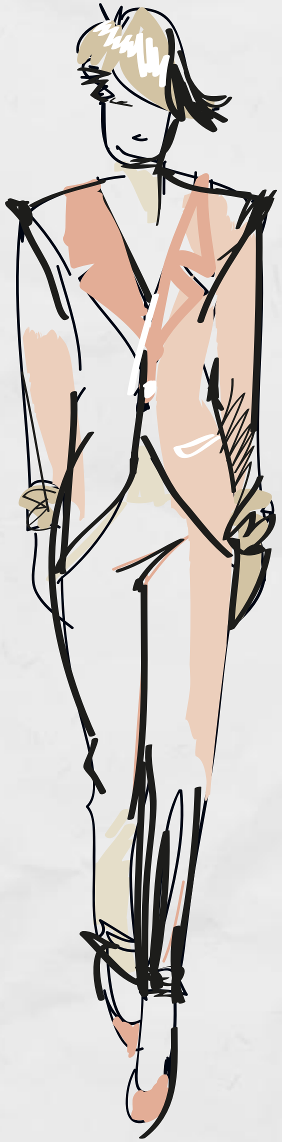
  Pattern: '\b\d{2}-\d{2}-\d{4}\b'
- Calculate age based on the extracted birthdate.



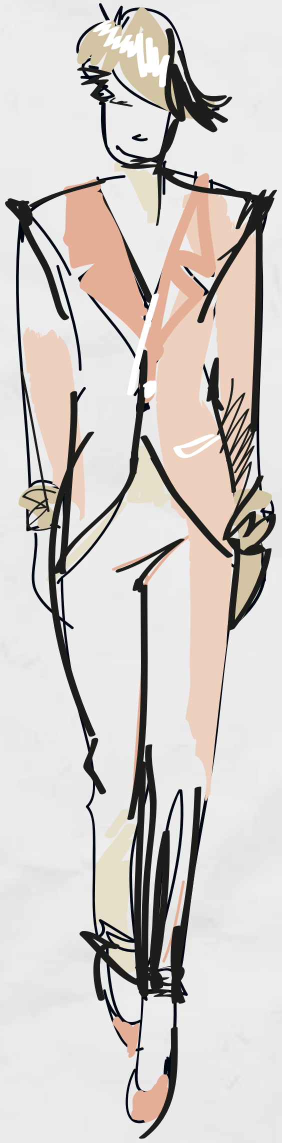
Add Age and Age Group

Add Age and Age Group

Add Age and Age Group	Fill Missing Ages
• Categorize users into age groups based on their extracted ages.	• Group 'User_ID' and apply forward and backward filling. • Use linear regression to predict missing ages based on other features



Filter Data & Apply Interaction Mapping



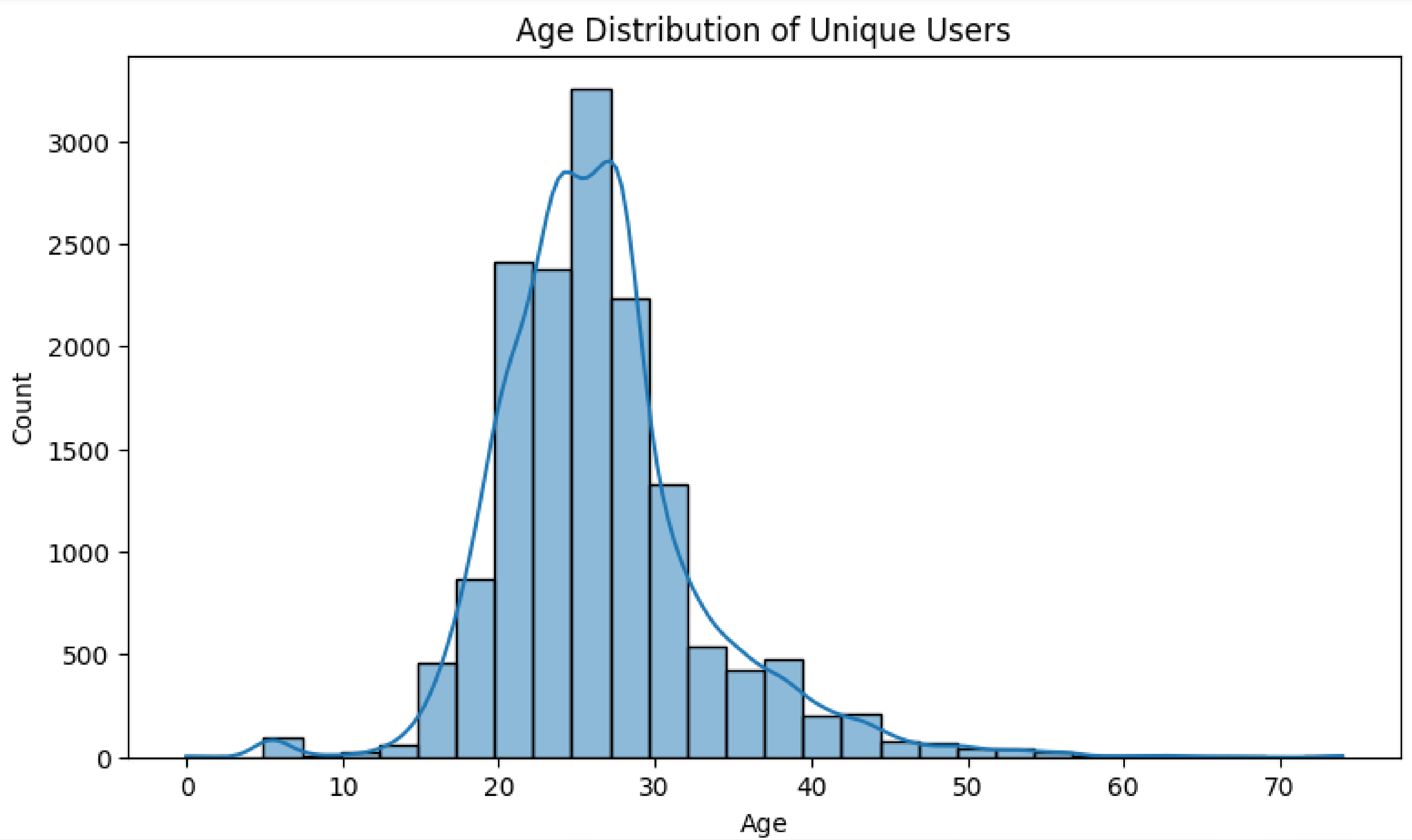
Handle Missing Values in 'City' and 'Region'

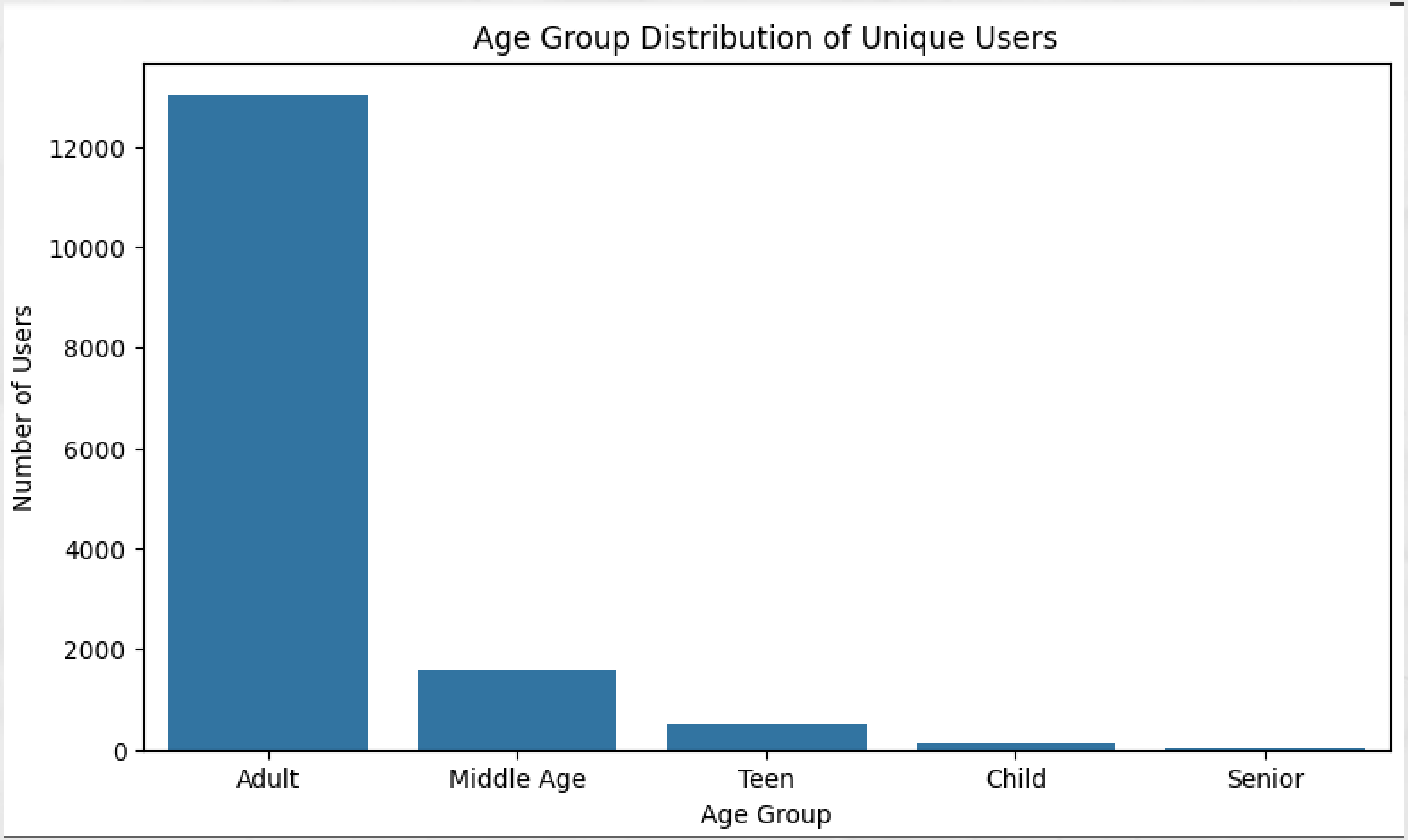
Handle Missing Values in 'City' and 'Region'

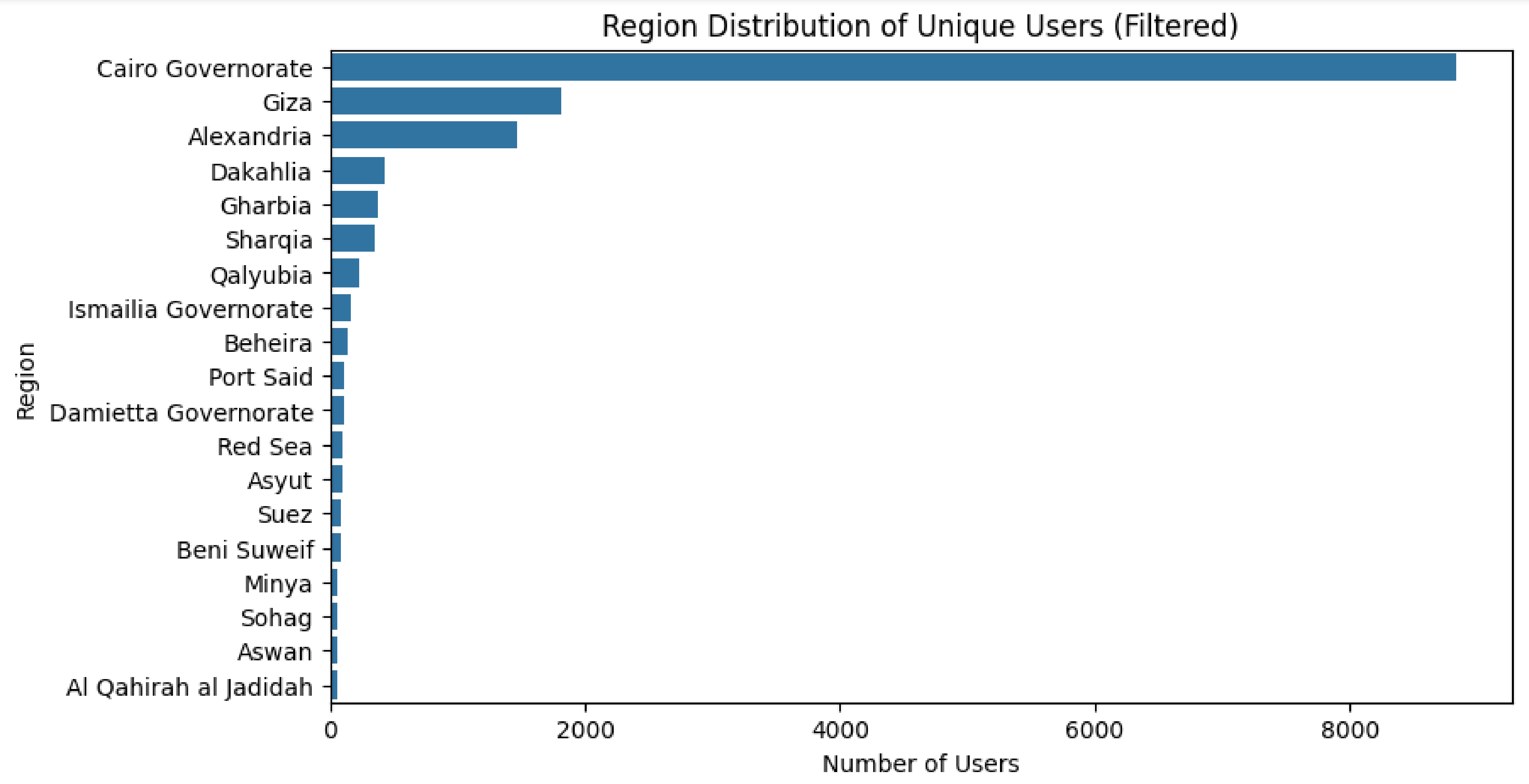
Fill missing 'region' values with corresponding 'city' values and vice versa.

Apply forward and backward filling within user groups.

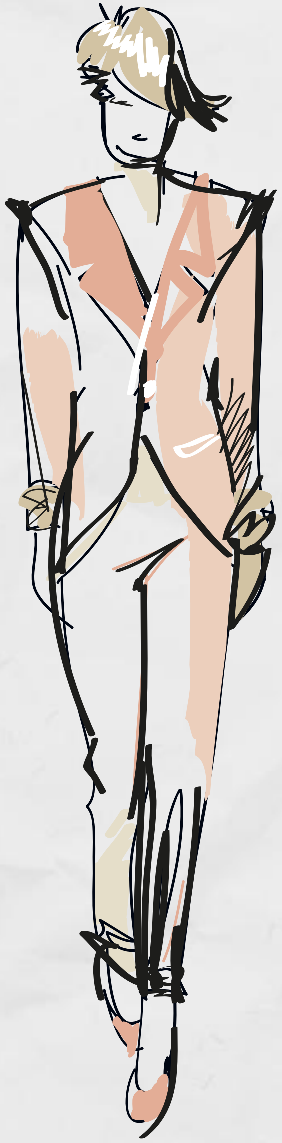
Exploratory Data Analysis


Age Distribution of Unique Users
Count
Age
0
500
1000
1500
2000
2500
3000
0
10
20
30
40
50
60
70


Age Group Distribution of Unique Users
Number of Users
0
2000
4000
6000
8000
10000
12000
Adult
Middle Age
Teen
Child
Senior
Age Group

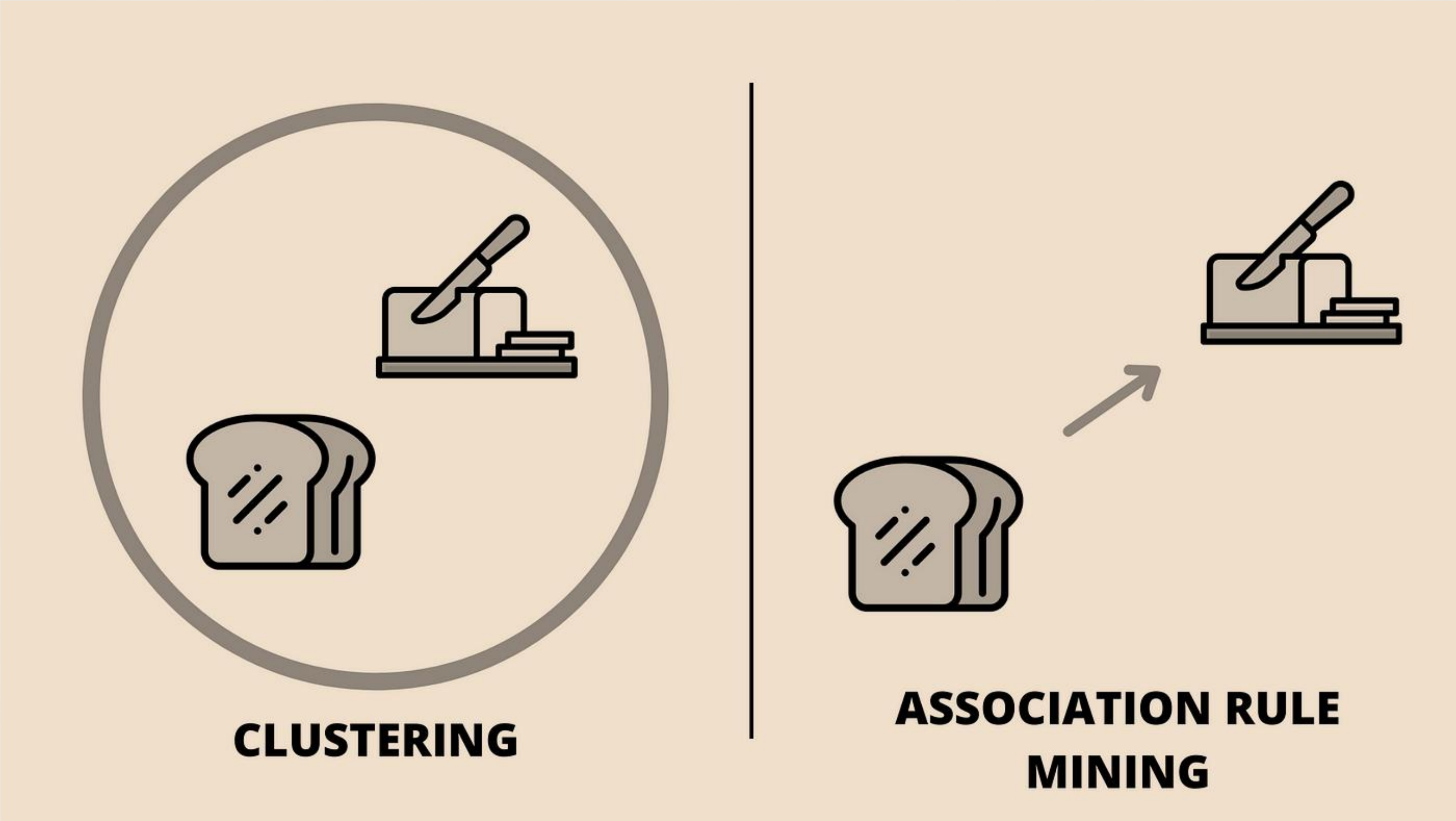

Region Distribution of Unique Users (Filtered)
Cairo Governorate
Giza
Alexandria
Dakahlia
Gharbia
Sharqia
Qalyubia
Ismailia Governorate
Beheira
Port Said
Damietta Governorate
Red Sea
Asyut
Suez
Beni Suweif
Minya
Sohag
Aswan
Al Qahirah al Jadidah
Region
0
2000
4000
6000
8000
Number of Users

03 | I Models



Frequently Bought Together

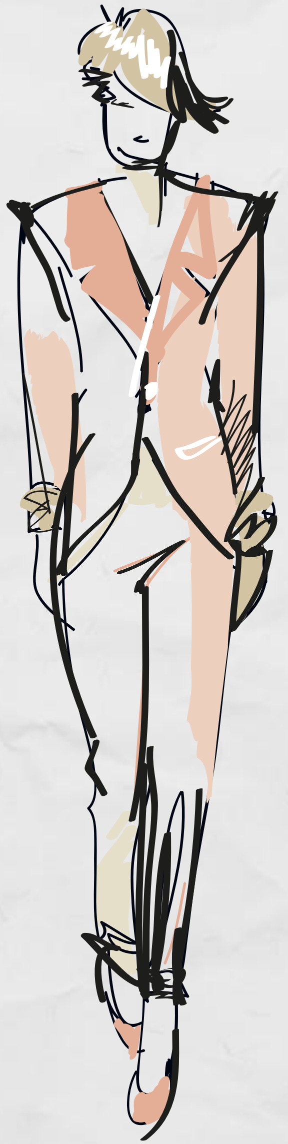
Association Rule Mining



Association Rule Mining

- Data mining technique that aims to discover interesting relationships, patterns, and correlations within large datasets.

- It consists of an antecedent (if part) and a consequent (then part). The dataset contains an antecedent, and we derive a consequent by using the antecedent.



Key Concepts

Support : the proportion of transactions in the dataset that contain a specific itemset

$$Support = \frac{Frequency\ (X,Y)}{N}$$

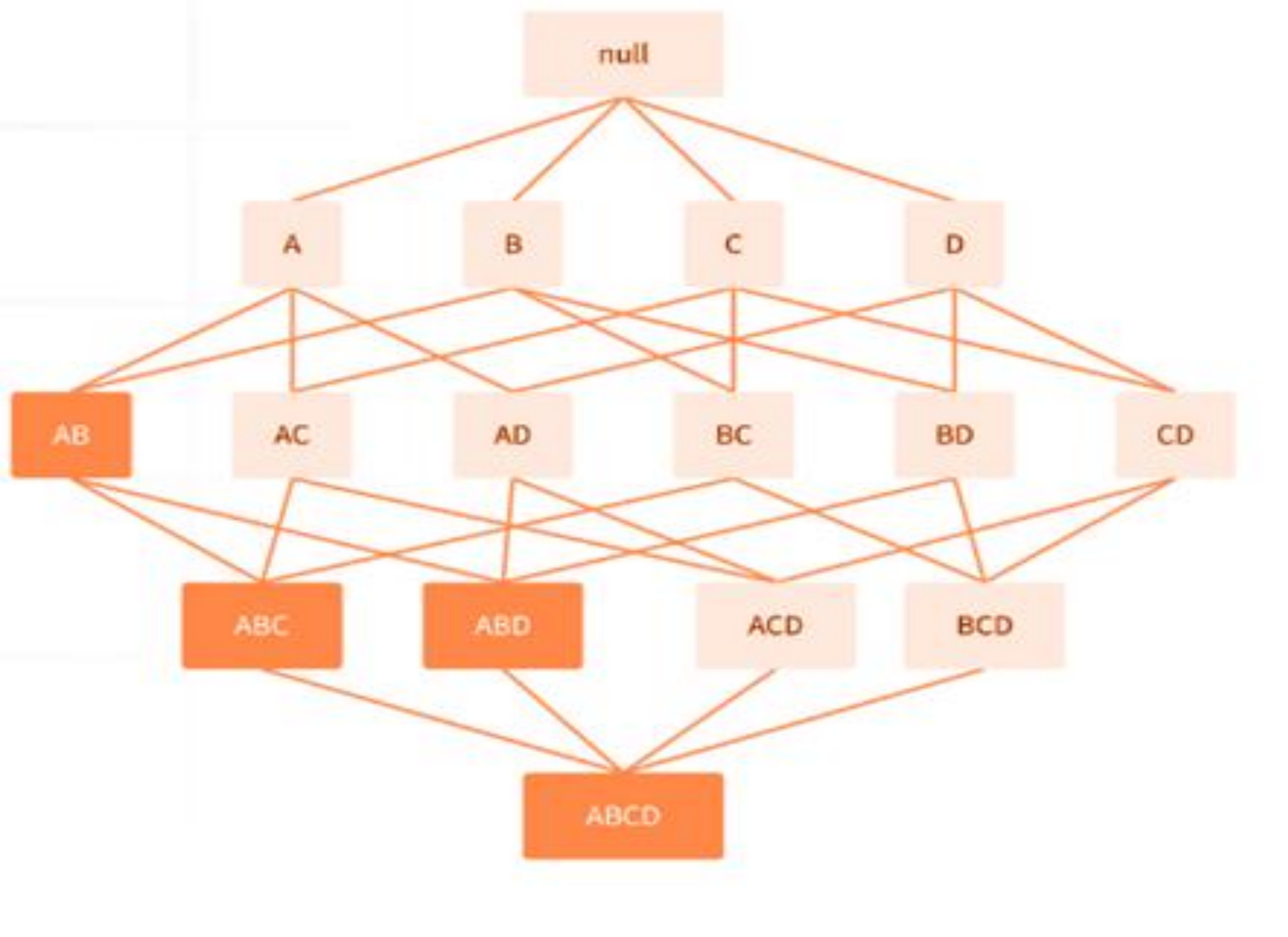
Confidence: the ratio of the number of transactions containing both the antecedent and the consequent to the number of transactions containing only the antecedent.

$$Confidence = \frac{Frequency\ (X,Y)}{Frequency(X)}$$

Lift: quantifies how likely the consequent is to occur when the antecedent is present compared to when the two events are independent.

$$Lift = \frac{Support}{Support(X)*Support(Y)}$$

Apriori algorithm



Apriori algorithm

- Set Min Support Threshold
- Identify Frequent Items
- Generate Candidate Itemsets (Size 2)
- Prune Infrequent Itemsets
- Generate Larger Itemsets
- Repeat Pruning
- Iterate
- Generate Association Rules

Apriori Limitations

- Computational complexity
- Time & space overhead
- Higher memory usage.
- The two primary drawbacks :
  - At each step, candidate sets have to be built.
  - To build the candidate sets, the algorithm has to repeatedly scan the database.

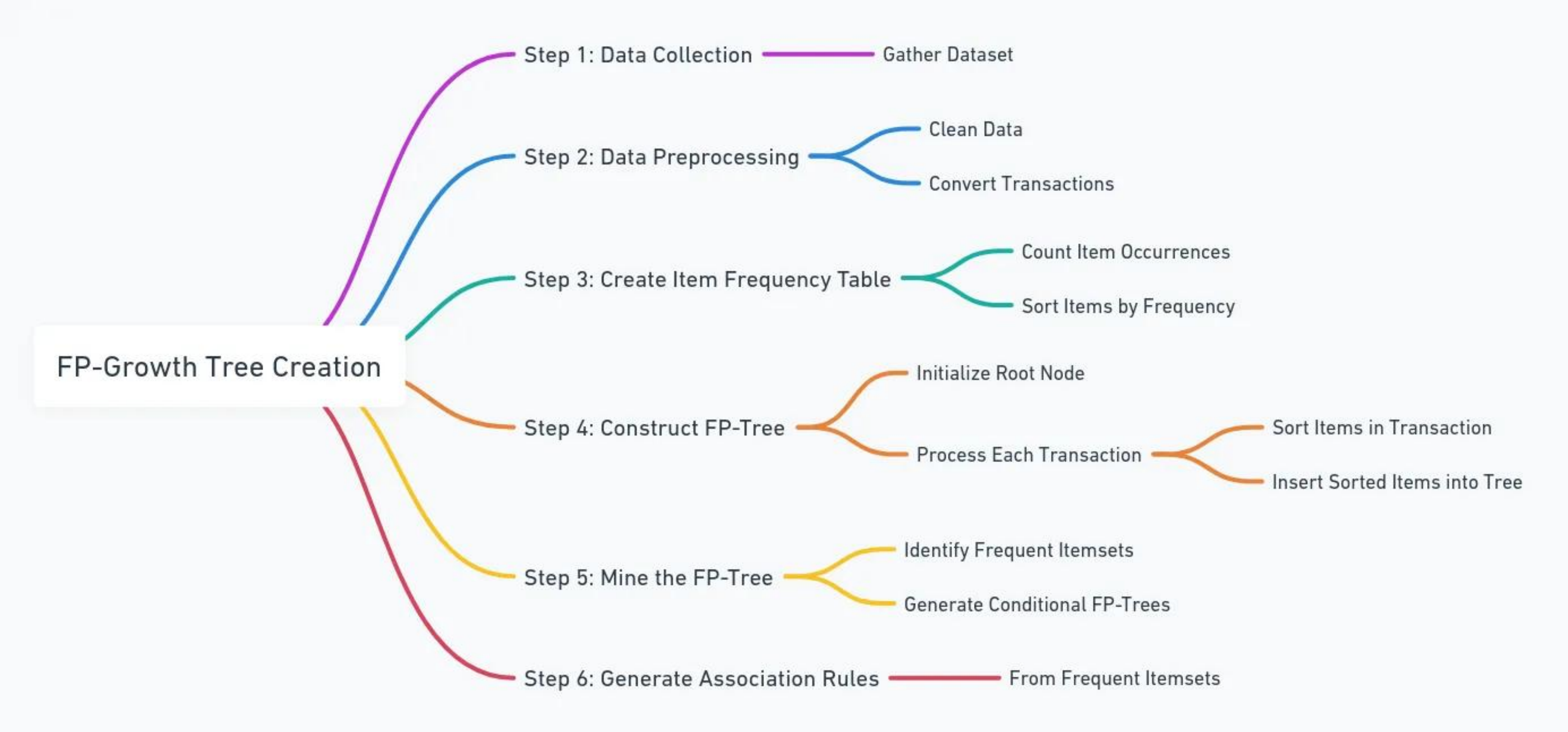
FP-Growth Algorithm

This method is used to mine frequent itemsets within a database without generating candidate sets explicitly.

It uses a compact data structure called the FP-tree (Frequent Pattern Tree) to encode transactions and discover frequent itemsets efficiently.

Transaction ID	Items Purchased
T1	T-shirt, Jeans
T2	Dress, T-shirt
T3	Jeans, Jacket, Sneakers
T4	T-shirt, Jeans, Jacket

FP-Growth Algorithm Steps



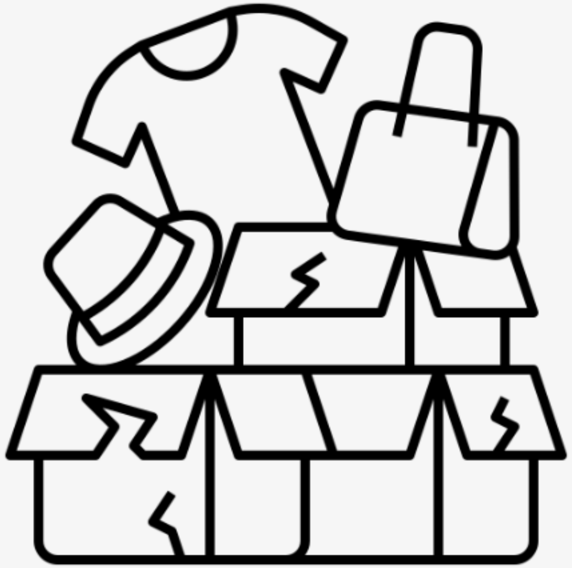
TwentyToo

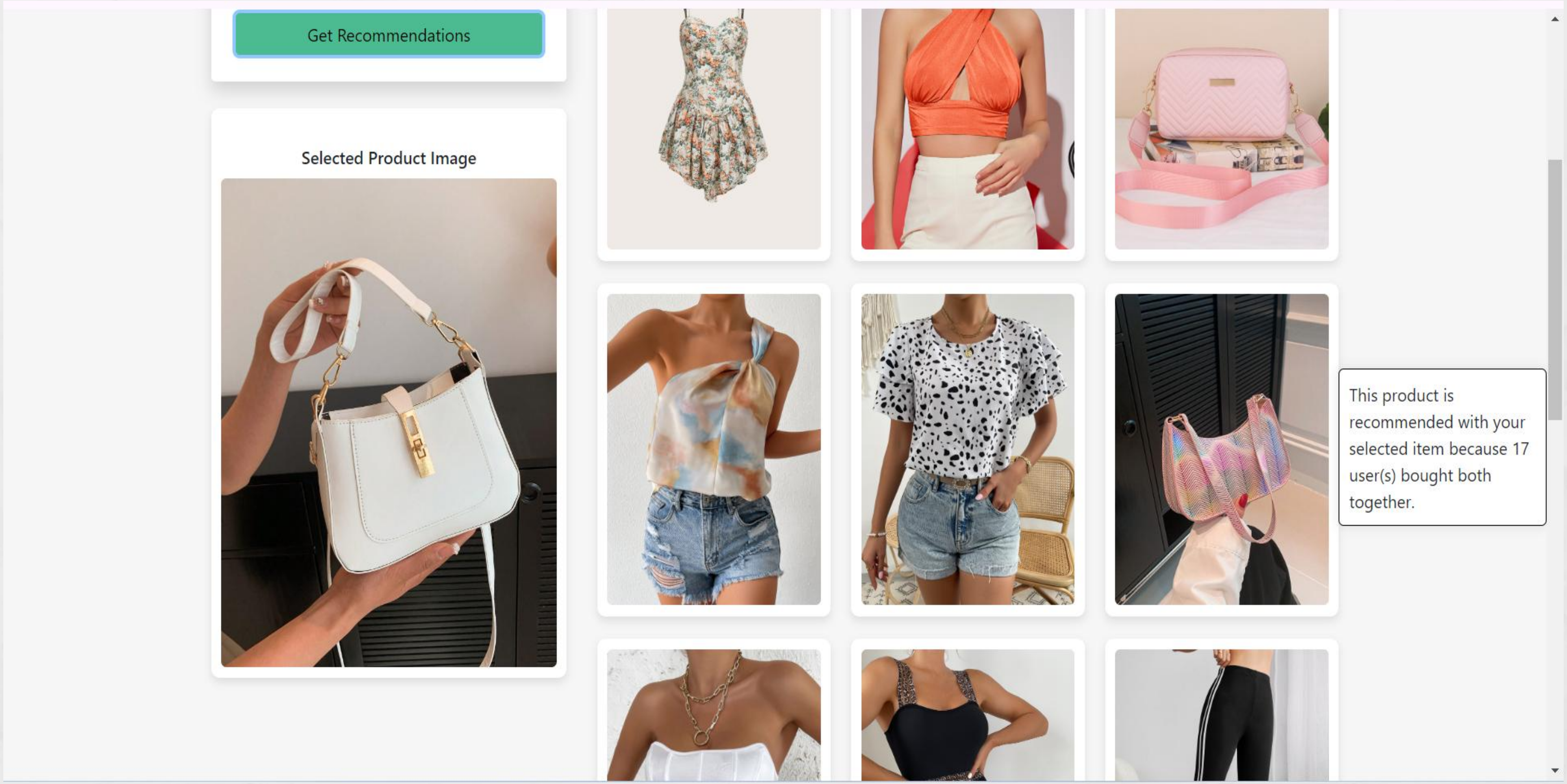
Top Picks Together

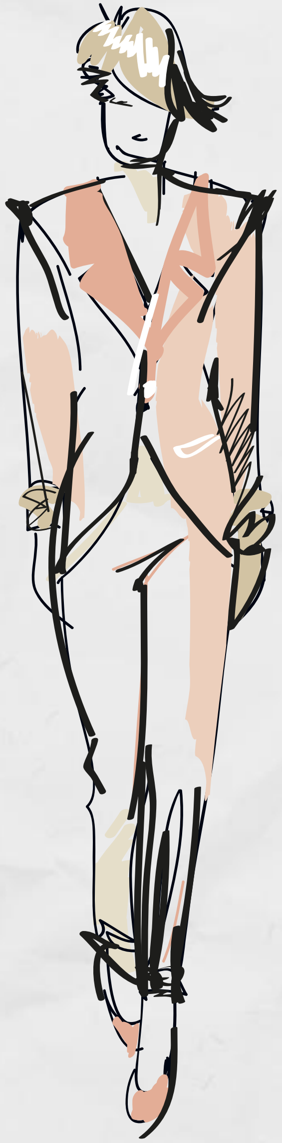
Select Product Title:

minimalist hobo bag mini twist ...

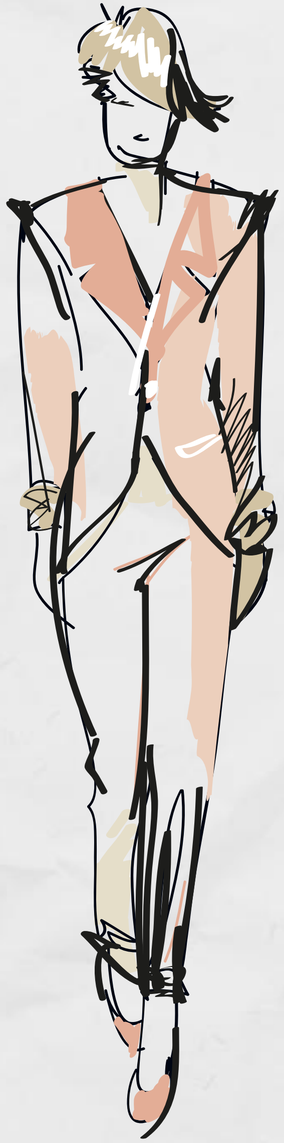
Get Recommendations




Get Recommendations
Selected Product Image
This product is recommended with your selected item because 17 user(s) bought both together.



Similarity Model



Content based

Content type

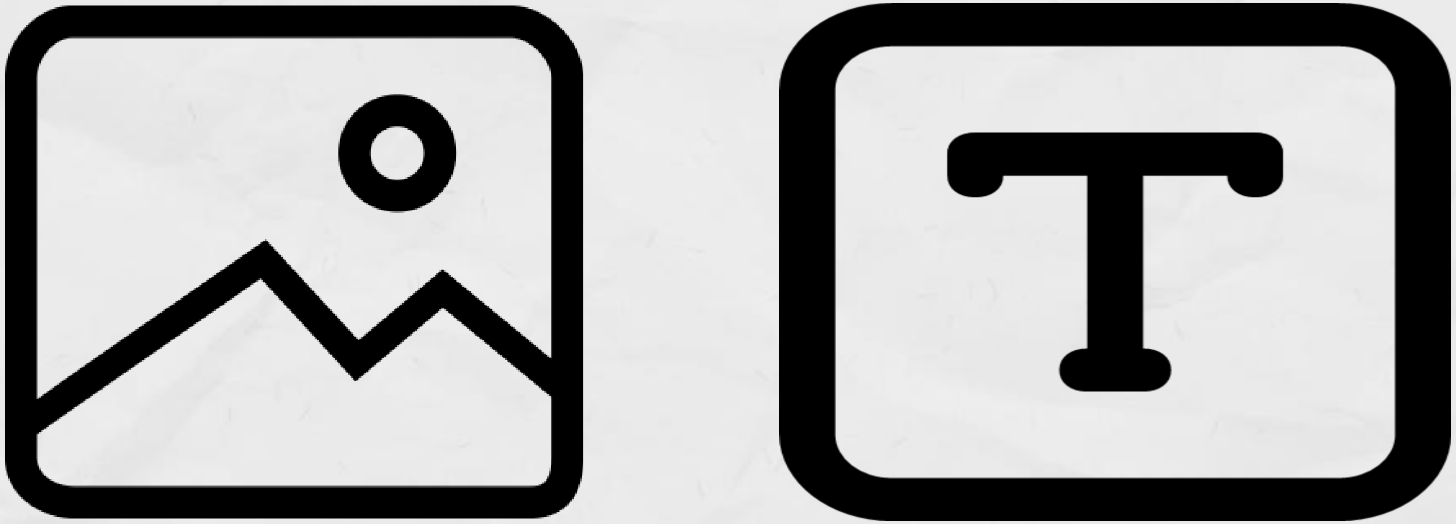
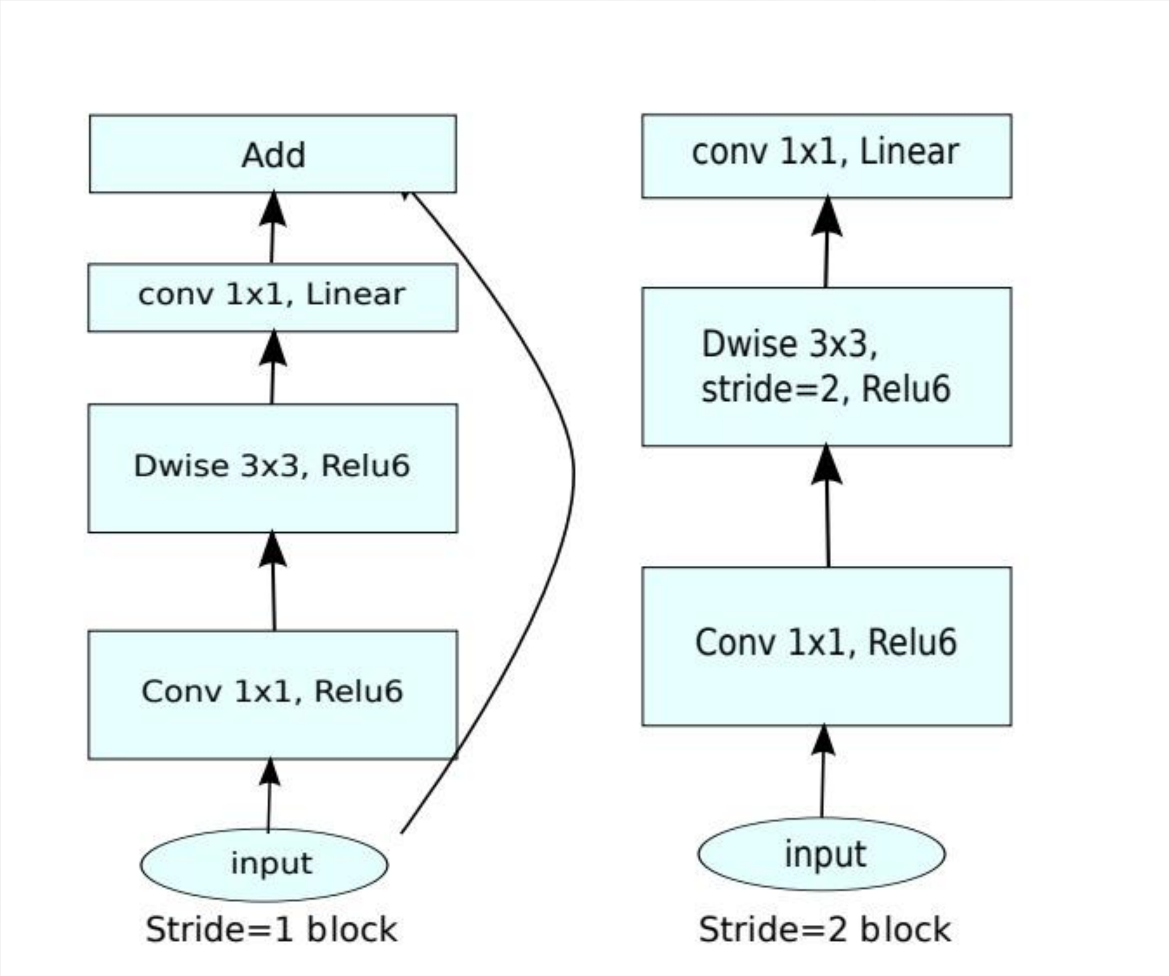


Image Based

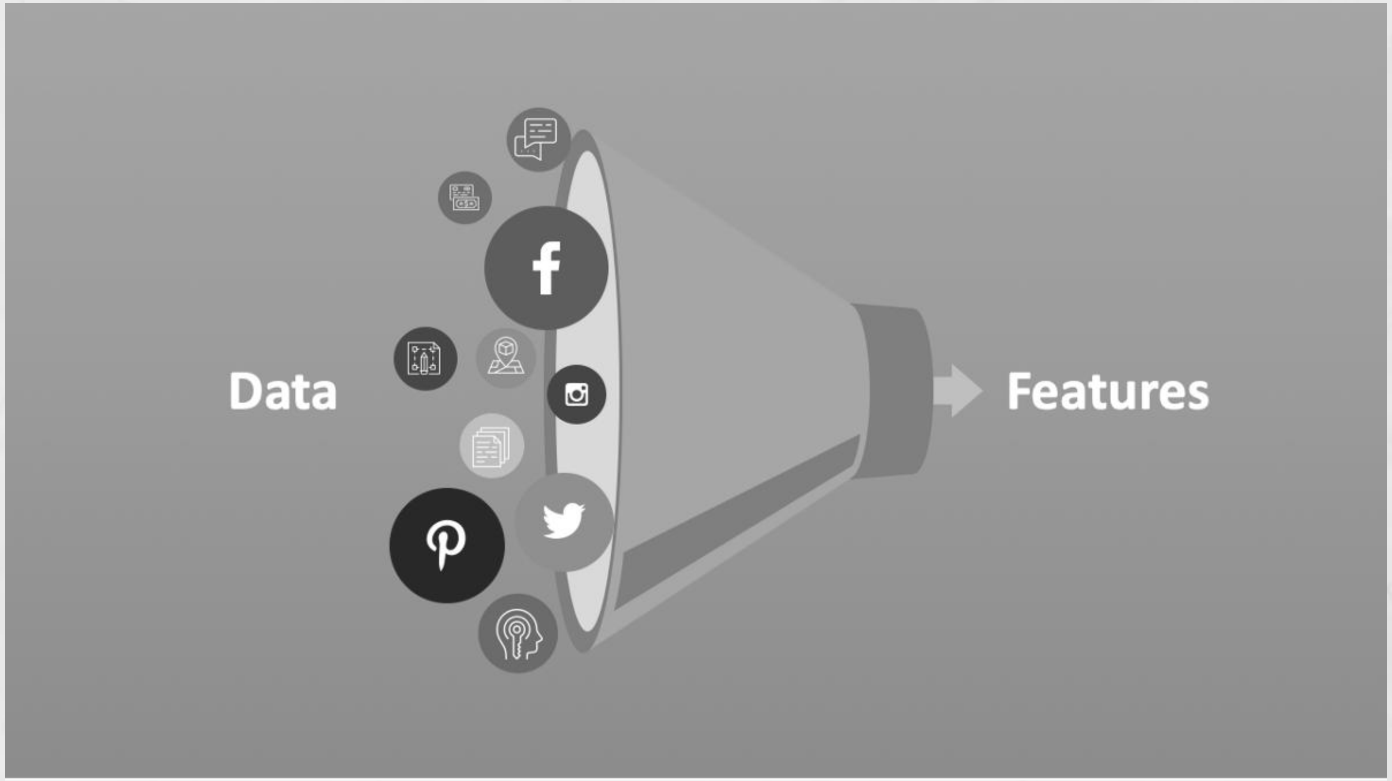
MobileNetV2



Input	Operator	t	c	n	s
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	

Feature Extraction Process

- Image Fetching and Preprocessing
- Feature Extraction using MobileNetV2
- Storing Features



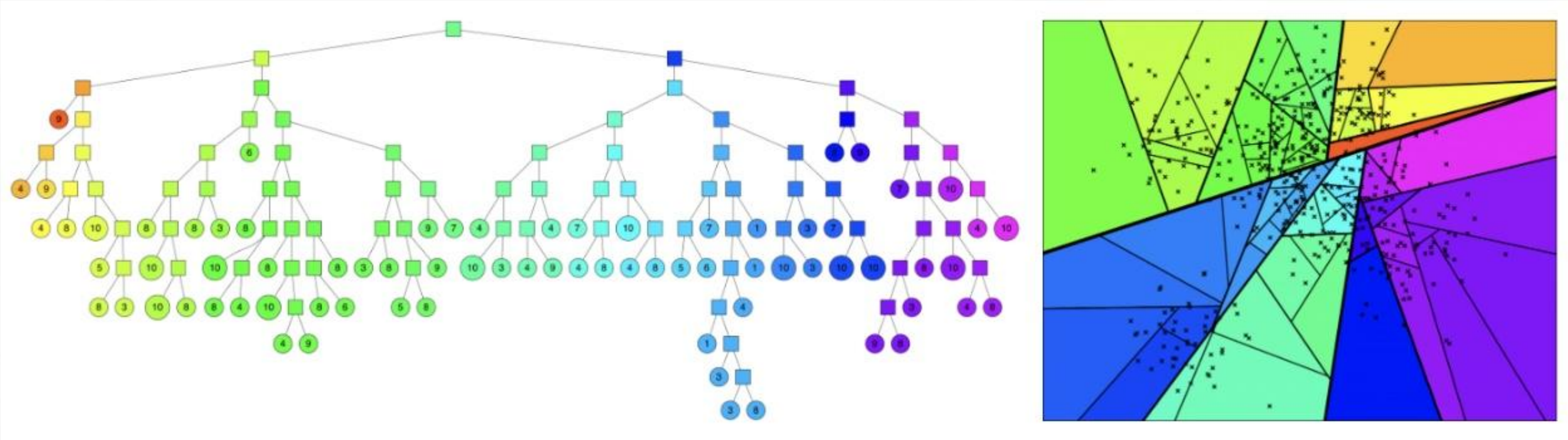
Similarity Computation

- **Cosine Similarity**
- **Top-K Similar Images**
  - **Retrieving Features**
  - **Calculating Similarities**
  - **Sorting and Selecting**

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Text Based

Annoy (Approximate Nearest Neighbors Oh Yeah) Index



Feature Extraction using Tf-Idf Vectorization

- **Combined Important Features (Color, Target Audience, Department, Product Description)**
- **Applied Tf-Idf Vectorization on combined features**

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

TF-IDF

Term x within document y

$tf_{x,y}$ = frequency of x in y

df_x = number of documents containing x

N = total number of documents

Using Annoy Index for Similarity Search

Building the Annoy Index based on the Tf-Idf Matrix

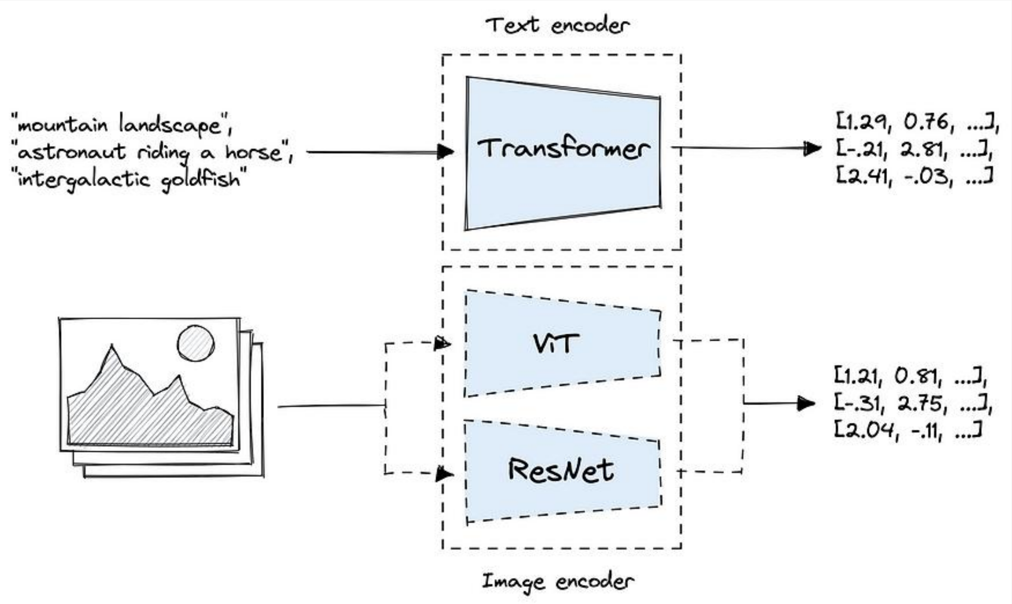
Cosine distance metrics for similarity search

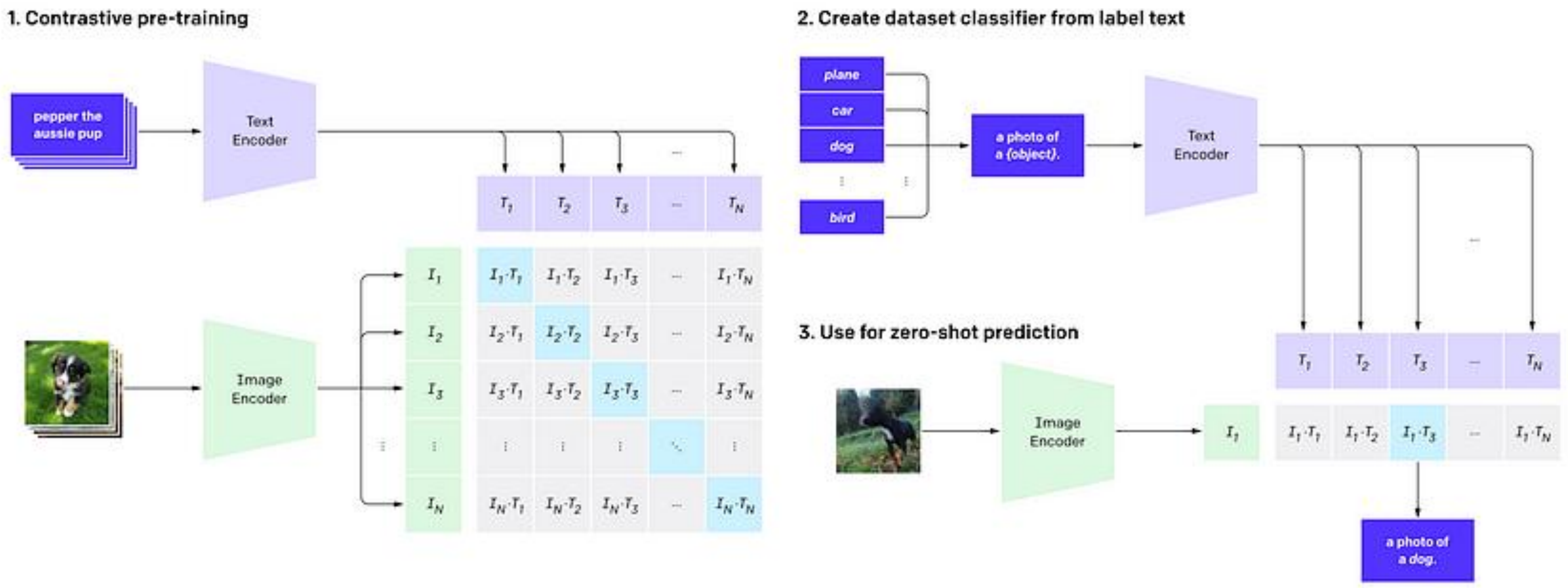
Both
Text & Image

Fashion CLIP

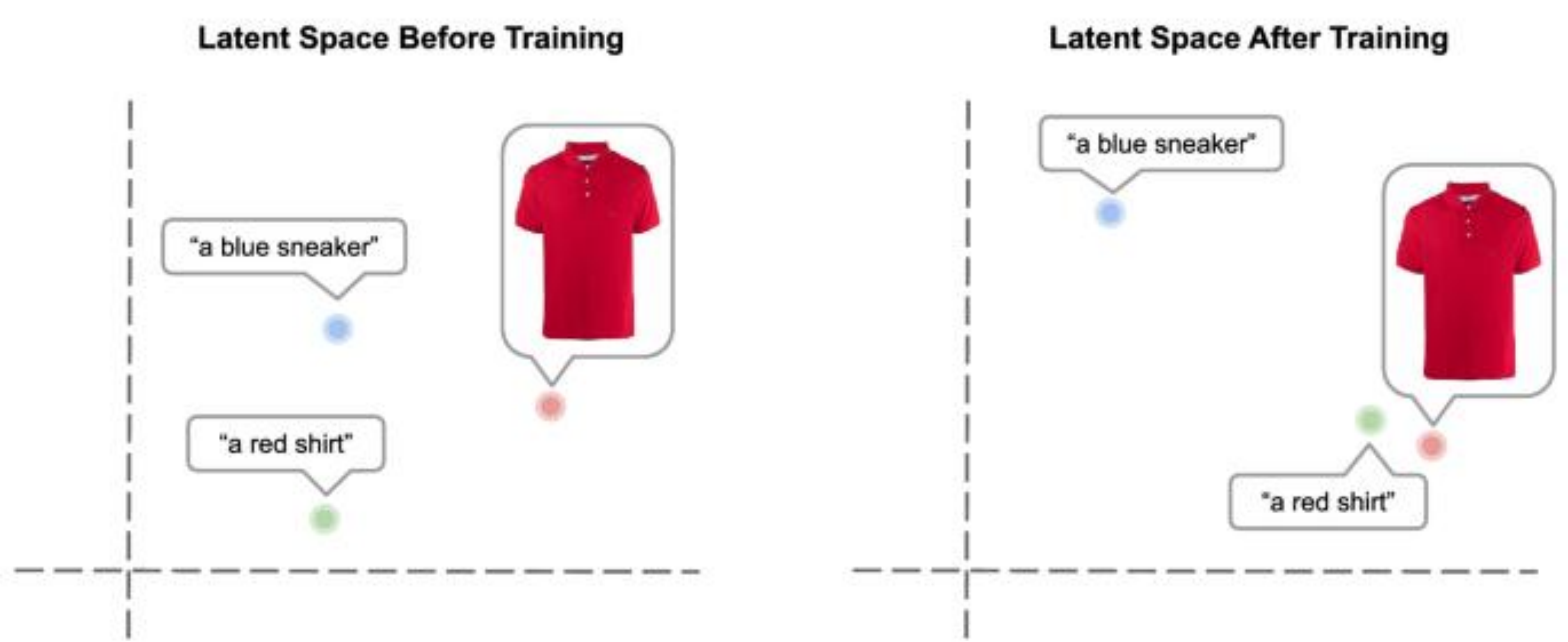
Architecture Overview:

- **Vision Encoder**: Converts images into fixed-size embeddings using a convolutional neural network (Vision Transformer).
- **Text Encoder**: Converts text descriptions into fixed-size embeddings using a transformer-based model (Transformer).





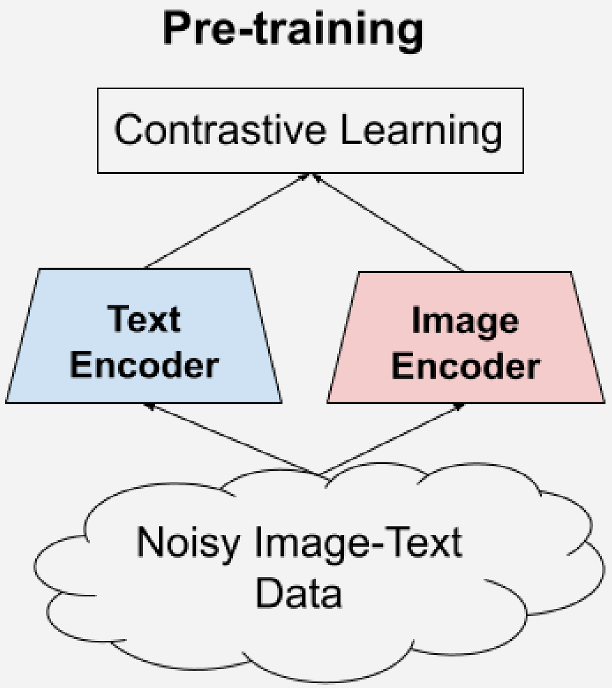
CLIP pre-trains an image encoder and a text encoder to predict which images were paired with which texts in our dataset. We then use this behavior to turn CLIP into a zero-shot classifier. We convert all of a dataset's classes into captions such as "a photo of a dog" and predict the class of the caption CLIP estimates best pairs with a given image.


Latent Space Before Training
"a blue sneaker"
"a red shirt"
Latent Space After Training
"a blue sneaker"
"a red shirt"

ALIGN

Architecture Overview:

- **Dual-Encoder System**: Separate encoders for images and text.
- **Encoders Used**: EfficientNet for images, BERT for text.
- **Contrastive Loss**: Aligns visual and textual representations in a shared latent space.
- **Training Data**: Over one billion noisy image-text pairs, minimally filtered to retain scale.



Evaluating Retrieval

Setting	Model	Flickr30K (1K test set) R@1 image → text	Flickr30K (1K test set) R@1 text → image	MS-COCO (5K test set) R@1 image → text	MS-COCO (5K test set) R@1 text → image
Zero-shot	ImageBERT	70.7	54.3	44.0	32.3
	UNITER	83.6	68.7	-	-
	CLIP	88.0	68.7	58.4	37.8
	ALIGN	***88.6***	***75.7***	***58.6***	***45.6***
Fine-tuned	GPO	88.7	76.1	68.1	52.7
	UNITER	87.3	75.6	65.7	52.9
	ERNIE-ViL	88.1	76.7	-	-
	VILLA	87.9	76.3	-	-
	Oscar	-	-	73.5	57.5
	ALIGN	***95.3***	***84.9***	***77.0***	***59.9***

TwentyToo

Similar Styles

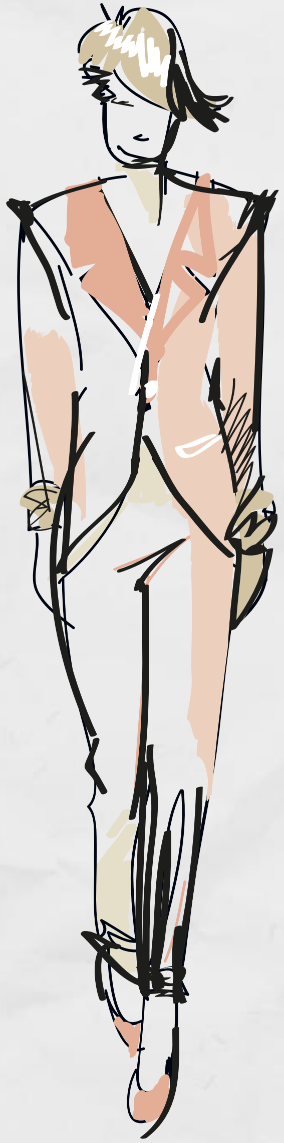
Select Product Title:

minimalist hobo bag mini twist ...

Select Model:

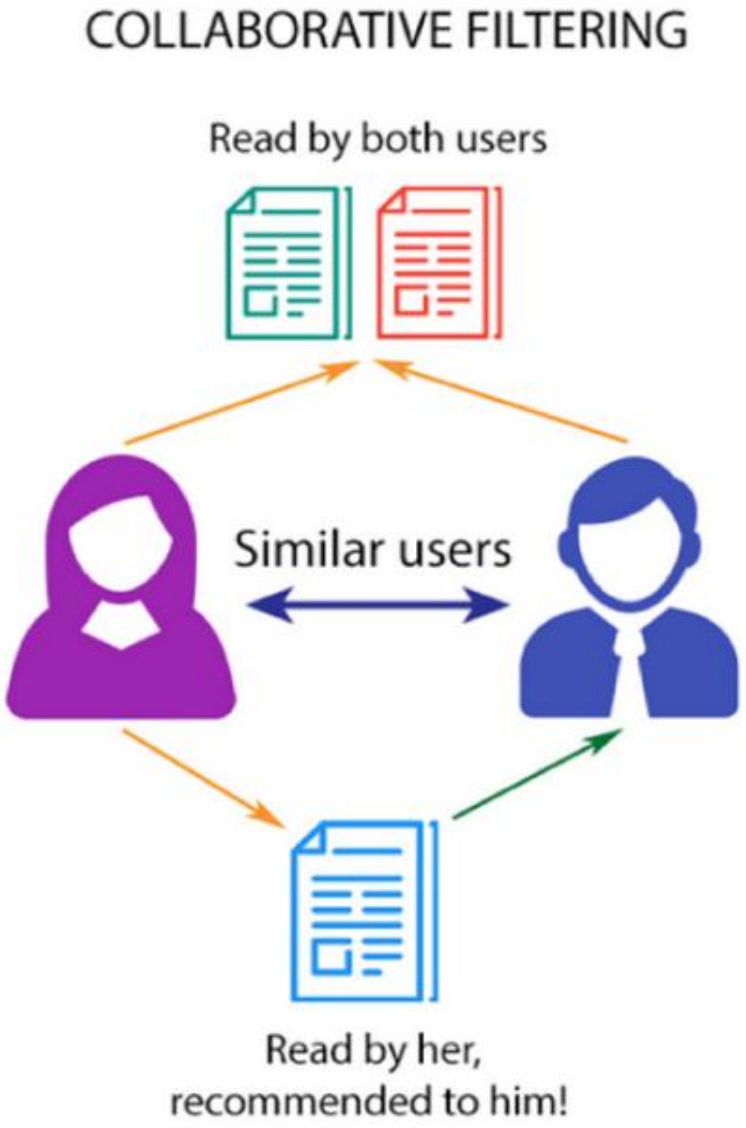
ROBERTA

ROBERTA
F-CLIP



User Based Collaborative Filtering

Collaborative Filtering

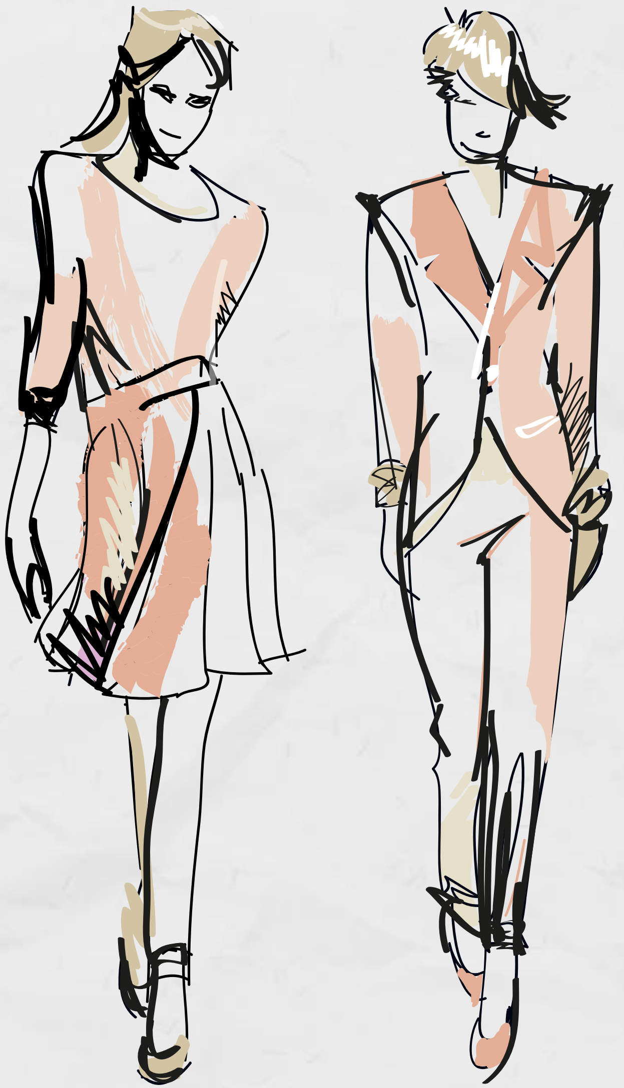


Methods for User Personalization

Similarity Based on interaction

Similarity Based on Embeddings

Two-Tower Model

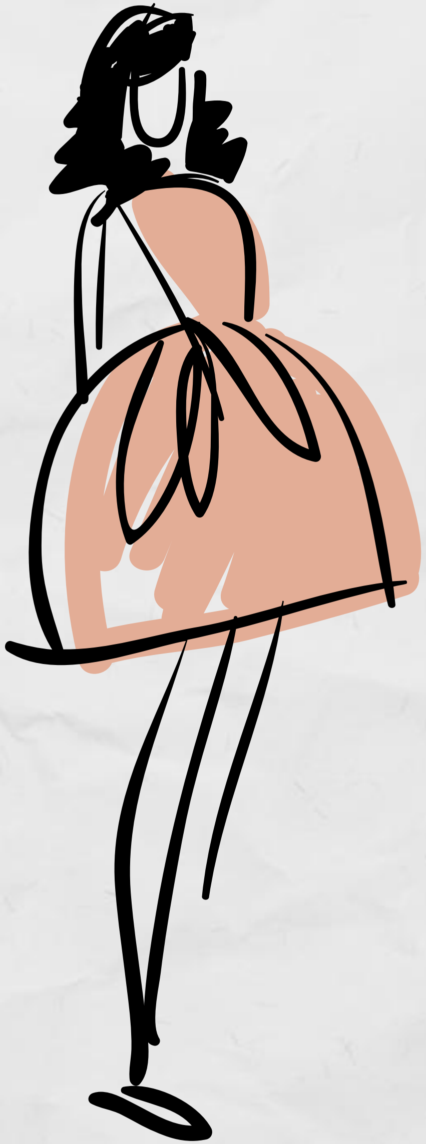


Similarity Based on Interaction

Overview

IDENTIFIES USERS WITH SIMILAR INTERACTION PATTERNS.

USES INTERACTION DATA TO RECOMMEND ITEMS.



Components

INTERACTION DATA

SIMILARITY CALCULATION

RECOMMENDATION GENERATION

Items

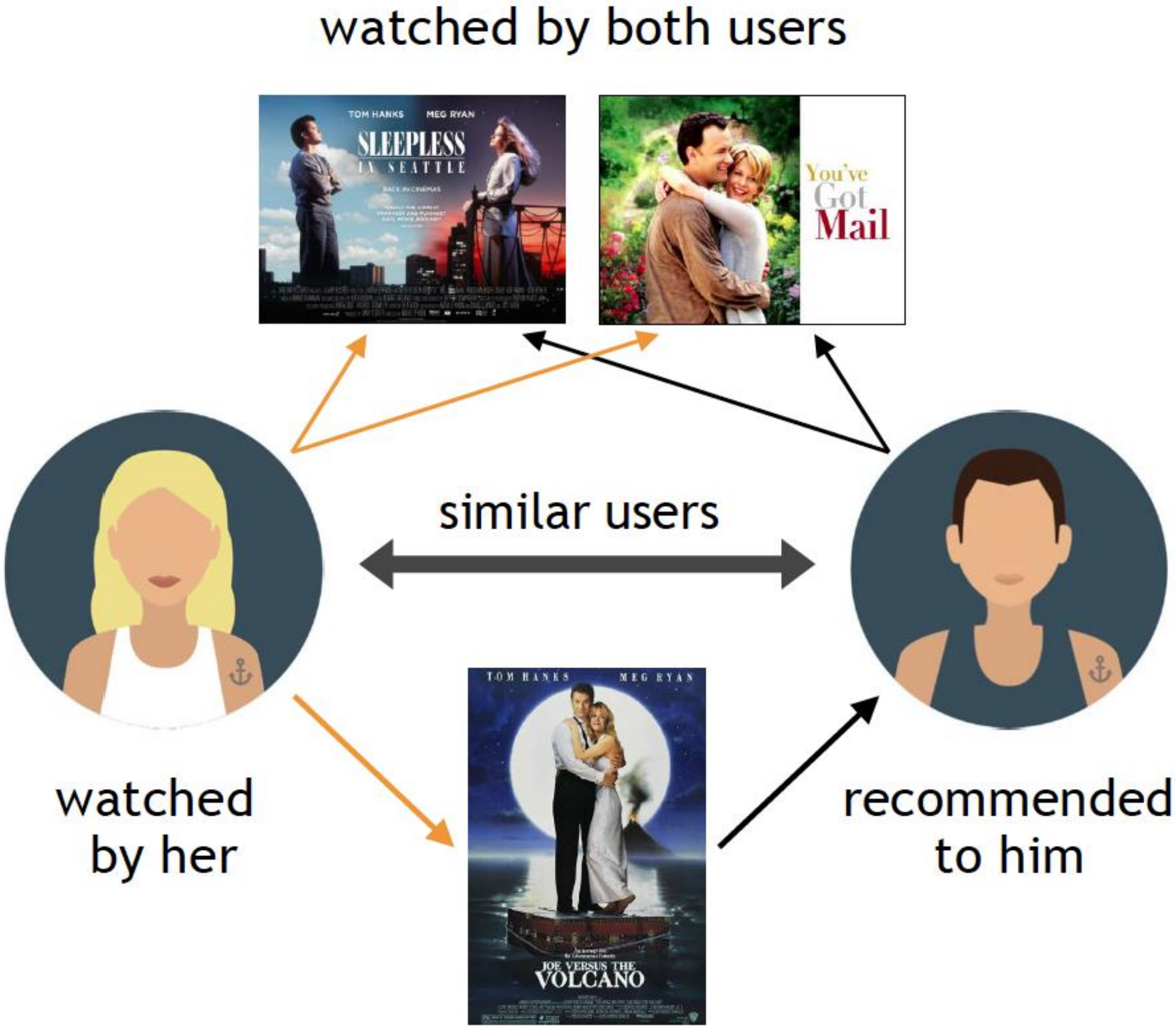
Users

10	-1	8	10	9	4
8	9	10	-1	-1	8
10	5	4	9	-1	-1
9	10	-1	-1	-1	3
6	-1	-1	-1	8	10

User-item Interaction matrix

$$\cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum\limits_{i=1}^{n} A_i B_i}{\sqrt{\sum\limits_{i=1}^{n} A_i^2} \sqrt{\sum\limits_{i=1}^{n} B_i^2}}$$

Collaborative Filtering



Similarity Based on Embeddings

Overview

Uses embeddings to capture relationships in a high-dimensional space.

Computes similarity between user embeddings for recommendations

Components

- Embeddings Generation
- User Embeddings Calculation
- Similarity Calculation
- Recommendation Generation

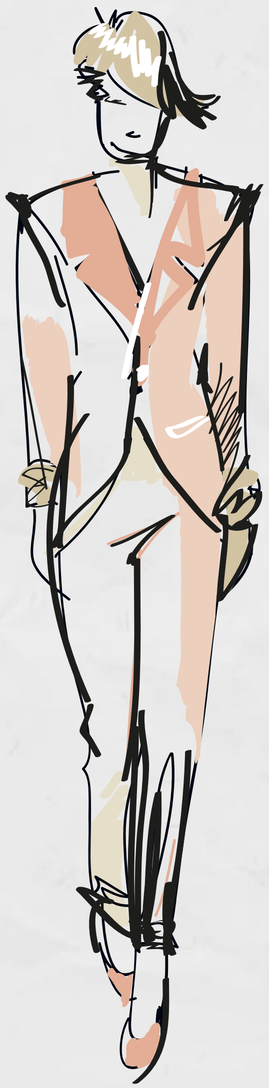
Embdeeing genreation

- CLIP Fashion can be used to generate embeddings for items based on their descriptions or titles

- Compute user embeddings as the average of the embeddings of the items they have interacted with.

Similarities

Recommendation Generation

Tow Tower

Components

USER TOWER

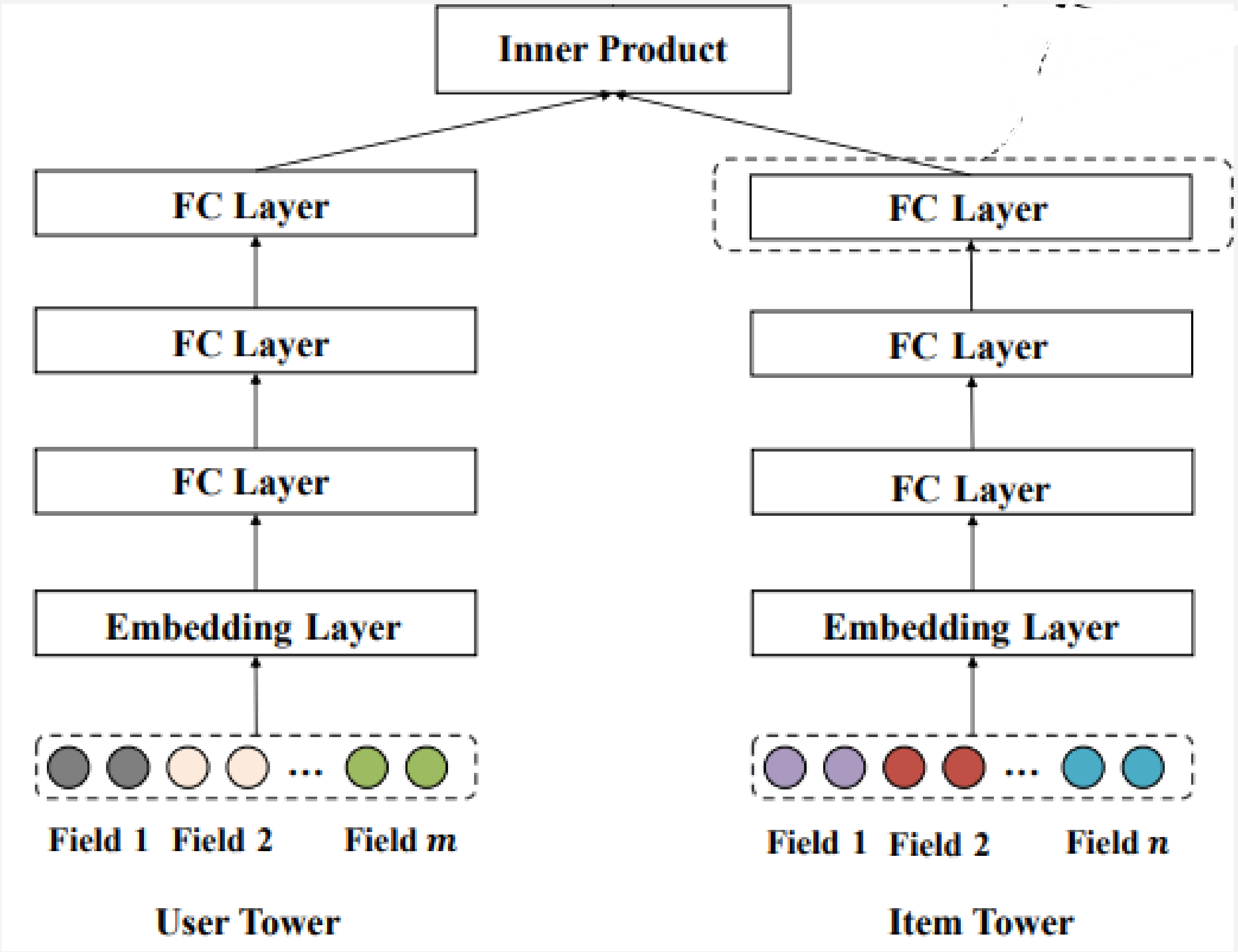
ITEM TOWER

INTERACTION LAYER

TRAINING

RECOMMENDATION GENERATION

Two-Tower Model



Choosing the Right Approach

TwentyToo

Personalized Picks

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Get Recommendations

Documentation

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THANKS