## Information Retrieval and Web Analytics

# Final Project PART 1 Text Processing and Exploratory Data Analysis

Laura Naranjo & Laura Penalver & Aurora Pujols
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TAG: IRWA-2025-part-1 GitHub: https://github.com/aurorapujols/irwa-search-engine

We separate this part 1 of the project in two parts:

- a. Data Preparation (1) in which we load the corpus (product's articles) and pre-process the data.
- b. Exploratory Data Analysis (2): in which we study our data with statistics to understand the dataset.

## 1 PART 1: Data Preparation

In this section we explain how we decided to treat the data and pre-process it.

#### AI use

FIELDS: It gave us ideas on how to treat different types of fields. Mainly that some of them can be used for filtering and others for the index terms.

INDEX: In this part, we used ChatGPT to give us an explanation on what fields "indexed as separate fields in the inverted index" means. It showed us different ways of how the inverted index would look like and we chose a mix of the two best options we found (considering code efficiency and understanding, and for its future usage in the ranking).

CODE: All the code for this part is exclusively made by us, with the help of the code we already did in Practice Session 1. With exception of dataframe processing and plotting.

DEBUGGING: We also used AI tools for debugging, specially when dealing with compilation errors and JSON formatting.

We created a file named data\_prep.py in which we defined all the functions related to the data preparation. The functions are used and tested in the next part (2) when doing the Exploratory Data Analysis.

The first step before processing the data is to load the corpus (1), and we used the function load\_corpus (provided in the repository) in the function load\_corpus\_from\_json. Then, we compute the inverted index (2) and store it in index (with some additional variables, info\_index, and metadata). And, finally, we store the index in a JSON document (3) because the index computation takes a few minutes and it is of easy and faster access to store it and upload it from a JSON.

## 1.1 Document Preprocessing

To preprocess the text (in title, and description), we created a function named join\_build\_terms that given one or more strings, it concatenates them, and then process them by doing the following steps:

- a. Lowercasing all the text
- b. Tokenizing the text
- c. Removing punctuation marks

- d. Removing stop words
- e. Stemming

The function that performs the operations on the text is called build\_terms (based on the Practice Session 1 code). It is important to notice how we added the concatenation of two strings before the pre-processing. We did it because in the following items, we will see that it is interesting to join different fields' texts. For instance, if we treat the title and description as in the Practice Session 1, we can concatenate them and then build the terms (see in Figure 1).

```
title  

"Basic black shirt"

("basic", "black", "shirt", "basic", "black", "t", "shirt", "make", "cotton"]
```

Figure 1: The result of "join build terms" function (not accurate regarding the text processing result).

The function build\_terms is further explained in the README file in the repository.

## 1.2 Queries output

To take into account that for each retrieved document we need to show the information: pid, title, description, brand, category, sub\_category, product\_details, seller, out\_of\_stock, selling\_price, discount, actual\_price, average\_rating, url; we decided to create two dictionaries from the pid of a document to the different data. As we will see in the following items, we are interested in keeping separate the categorical fields from the numerical fields, so we store in two dictionaries info\_index and metadata as shown in Figure 2.

```
info_index[pid] = {
                                                    metadata[pid] = {
      "title": doc.title,
                                                          "out_of_stock": doc.out_of_stock,
      "description": doc.description,
                                                          "selling_price": doc.selling_price,
      "brand": doc.brand,
                                                          "discount": doc.discount,
      "category": doc.category,
                                                          "actual_price": doc.actual_price,
      "sub_category": doc.sub_category,
                                                          "average_rating": doc.average_rating,
                                                         "url": doc.url
      "product_details": doc.product_details,
      "seller": doc.seller
                                                         }
```

Figure 2: The format of the two info dictionaries. "doc" is the JSON Document for a single product's article.

In this way, for any document given by pid we can retrieve the information we want easily and efficiently. The function that gets this information and constructs the dictionaries is get\_articles\_info. To test it, in data\_prep.py we have loaded the corpus, got the dictionaries from this function, and printed them in JSON files to see their content (with names metadata\_dict.json and info\_index\_dict.json in the root folder).

## 1.3 Categorical fields

To handle the categorical fields (category, sub\_category, brand, product\_details, and seller), we considered the following:

- We might be interested in keeping some of the terms separate when creating the index by indexing with different fields. This will make it possible to consider different weights when adding to the tf-idf of a document. If, for instance, we consider a word in the query appearing in the category field more relevant than it appearing in the description, then the documents can be ranked accordingly.
- We might not keep all fields separate due to computation restrictions. Maybe less important fields like product\_details and seller could be processed as a single new field in the index.

This is why we decided to consider the structure in Figure 3 for the index.

Figure 3: Index with fields as subindex. "termX" is the terms in the pre-processed fields and "fieldX" are the fields of each document considered in the index ("title"+"document", "bran", "category", "sub\_category", "product details"+"seller").

For title and description, we will consider them of the same weight if a term appears on them, so we treat it as a single field for the index. The same happens for product\_details and seller. But for the other three categorical fields (brand, category, and sub\_category) we will take each of them as a term in the index because we consider them of relatively high and different importance.

In table 1 we can see what pros and cons this implementation has.

Pros	Cons
Helps give more importance to certain fields	Makes the indexing and searching process more
when ranking the documents.	complicated.
Lets us treat important fields (e.g. brand, cate-	Takes more time and resources to build the index
gory) differently than others we might consider	and ranking.
less important (e.g. seller).	
Allows more control over how search results are	Needs extra care to balance the weights between
sorted.	fields (maybe we use weights of important fields
	that make user preference worse).

Table 1: Caption

## 1.4 Numerical fields

To handle the numerical fields (out\_of\_stock, selling\_price, discount, actual\_price, and average\_rating), we decided to use them as parameters for filtering. For example:

- Use out\_of\_stock as a filter for ranking out of all products that either are in stock or not.
- Use the discount as a variable to filter if the products need to have a discount or not.
- Use the selling\_price and actual\_price for sorting the final rankings (optional if the user wants to) or even filter out some products.
- Use average\_rating also for filtering and/or sorting.

But all these terms are not gonna be used in the index, as it does not make sense to include numbers as text (they loose their meaning). And we only store them in the previously mentioned dictionary called metadata.

# 2 PART 2: Exploratory Data Analysis

In this section we provide an exploratory data analysis to describe the dataset.

#### AI use

EDA: We used ChatGPT to help us code the plots and with debugging.

STREAMLIT: We took the code we made in the jupyter notebook (test.ipynb) and asked it to adapt it to a Streamlit web interface. We asked for some further modifications to make it more efficient and understandable.

The first thing we did was take a look at the loaded dataframe (table of data) of the corpus (see in Figure 4.

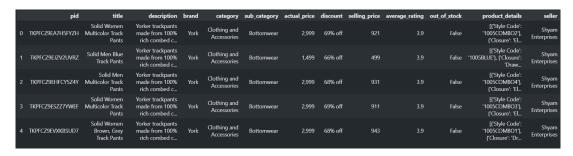


Figure 4: Dataframe with the fields of a document. First 5 articles.

From the dataframe, we can see how the numerical fields need to be pre-processed before doing an EDA with them, because they can't be converted to floats with ",", and the discounts are not in percentage (0.XX) format. But we will se more of that later.

In the report, we will now see what we observe in the data through different fields of the dataframe.

**NOTE:** we did the EDA with the help of a Jupyter notebook (test.ipynb), and visualized it better through a streamlit web interface (shown how to visualize it in the README file).

## 2.1 Word Count Distribution

For the fields title and description, we can count how many words they have and plot their distribution (see Figure 5.

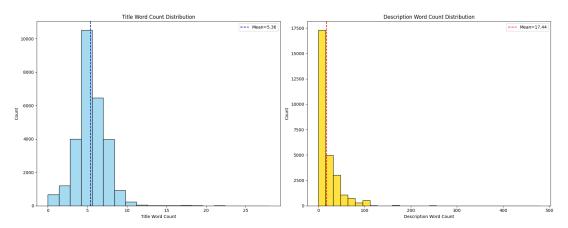


Figure 5: Word count distribution for title (blue) and description (yellow). The dotted line is the mean for the respective distributions.

From the distributions we can see how the title word count has a similar distribution to the Gaussian (with most documents having a title of around 5 words), while the descriptions seem to have between 0 and 100 words but most of them have very limited descriptions (around 0 and 20).

In conclusion, titles seem to have a very consistent titling style. But most products have very short descriptions which means maybe this field is not very significant for most products or they are very general products that are hard to differentiate from the rest.

## 2.2 Average Sentence Length

For the descriptions, we can also look at the average sentence length (see Figure 6).

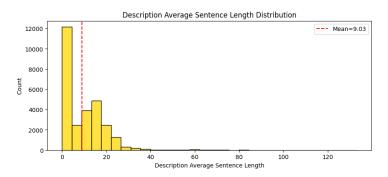


Figure 6: Average sentence length in of the field description.

From the histogram we can see how the sentences in the description are very short and concise. This can mean that the sentences are keyword based and few have detailed descriptions about the product.

## 2.3 Word Dictionary and Word Cloud

Regarding the categorical fields, we can also look at the vocabulary in our corpus. We can try to look at the total number of words in the documents.

It is important to notice that we are talking about the words after filtering all the fields with build\_terms, that is, without the stop words and stemming (reduces the amount of words in the dictionary considerably).

We find that the total number of *unique words* is **16,829**. We know there are 28,080 documents so it means that the vocabulary is very limited and specific to the context we are in (clothes, shopping, accessories, etc.). This makes the few words in a document very relevant for its retrieval when trying to match them with the user query.

From all the words in the corpus (not only taking unique words), we can also build a word cloud to visualize the most common words. In the Jupyter notebook (test.ipynb) we printed the top 20 words and the amount of times they appear throughout the corpus. An interesting one is the number '1'. This number is very much meaningless when taking into consideration the queries of the users (we do not know what it is referring to: âĆň, cm, etc.). Therefore, we thought maybe it would be necessary to take numbers out in the build\_terms function. Latter, we will discuss why we do not do it in the end.

Then, we constructed the word cloud in Figure 7.

From the word cloud we can see predominant themes like: "cloth", "wear", "topwear", "neck", "round", "western", "accessori", etc. Which indicates that the corpus focuses heavily on apparel types, styles, and garment features. Also, terms like "casual", "polo", "regular", "winter wear", "full-sleev", "half-sleeve", reflect how the style, types and seasonal descriptions of clothes are very common. In addition, the materials are also common, for instance, "cotton".

#### 2.4 Out of Stock Distribution

Switching to the numerical variables, that we saw could be interesting for filtering, we can first take a look at the out of stock distribution (Figure 8).

In the distribution, we can see how filtering out the products that are out of stock (is interesting for a user as they cannot buy these products), we would eliminate 5.85% of the documents. When taking into account the processing, this number is not as big, but could increase the computation time in some extreme cases. Most of the products are in stock (94.15%).

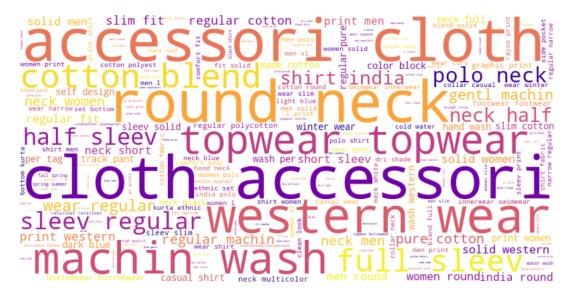
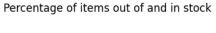


Figure 7: Word cloud from the processed categorical fields in the corpus.



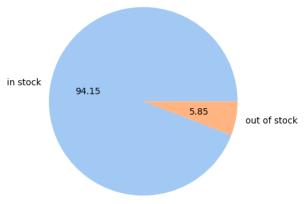


Figure 8: Out of stock distribution.

## 2.5 Rankings

After processing the numerical data, we can start treating the numbers and creating rankings based on average\_rating, prices and discount.

In Figure 9 we can see the rankings based on actual\_price. From Subfigure 9a we see how the products with lowest actual price, it is 0, but actually have a selling price. This can indicate errors in the data. In Subfigure 9b we see that the products with largest prices are either big clothing pieces or they include more than one product. This also shows us that maybe having the numbers in the index can be a good indicator of products that might interest the user (contradicting what we found in the word cloud).

In Figure 10 we can see the rankings based on selling\_price. From these we can see that the ones with lowest prices seem to be accessories (which makes sense), and that the most expensive are of full tracksuits, possibly dresses, coats, and big clothing pieces.

Finally, in Figure 11 we can see the products with the highest discounts (most seem to be T-shirts) and the ones with no discount. And in Figure 12 we can see the top brands and sellers. It is interesting to notice that the top brand and seller do not actually have a value. However, we can still see that the top brand is **ECKO Uni** and the top seller **RetailNet**.

	pid	title	actual_price	discount	selling_price	url
1705	TSHFZ3JEEZC6KTVB	Solid Women Polo Neck Blue T-Shirt	0.0	0.0	1099.0	https://www.flipkart.com/reebok-solid-men-polo
1734	SOCFH2UDUMG6GMSR	Men Striped Ankle Length	0.0	0.0	499.0	https://www.flipkart.com/reebok-men-striped-an
1891	TKPFZ3JRBVZD3AKM	Solid Women Grey Track Pants	0.0	0.0	1499.0	https://www.flipkart.com/reebok-solid-men-grey
1922	SWSFJY5ZBJAVWWJX	Full Sleeve Solid Men Sweatshirt	0.0	0.0	2399.0	https://www.flipkart.com/reebok-full-sleeve-so
1949	TKPFZ3JRYR599GGY	Solid Men Grey Track Pants	0.0	0.0	1499.0	https://www.flipkart.com/reebok-solid-men-grey
1950	TSHFK3W7AZQYSWGF	Solid Men Polo Neck Green T-Shirt	0.0	0.0	1299.0	https://www.flipkart.com/reebok-solid-men-polo
1953	JCKFJY5A7Q7XCMHK	Full Sleeve Solid Men Sports Jacket	0.0	0.0	3699.0	https://www.flipkart.com/reebok-full-sleeve-so
1958	TSHFZ3JDCZQHVU8G	Solid Men Polo Neck Green T-Shirt	0.0	0.0	1599.0	https://www.flipkart.com/reebok-solid-men-polo
1964	SOCFYY5RGZHT3AZF	Original Cotton Half Cushion Women Ankle Lengt	0.0	0.0	399.0	https://www.flipkart.com/reebok-original-cotto
2020	TSHFK3W7JGJUXFUT	Printed Women Round Neck Dark Blue T-Shirt	0.0	0.0	3999.0	https://www.flipkart.com/reebok-printed-men-ro

## (a) Actual Price Sorting (ASCENDING).

	pid	title	actual_price	discount	selling_price	url
10272	SUIFNNPF3W8GEHAB	3 Piece Solid Women Suit	12999.0	0.60	5199.0	https://www.flipkart.com/true-blue-3-piece-sol
10287	SUIFPDS2DEZNSKTH	2 Piece Self Design Women Suit	12999.0	0.60	5199.0	https://www.flipkart.com/true-blue-2-piece-sel
10315	SUIFNMK2FQDWYTUZ	2 Piece Solid Men Suit	12999.0	0.60	5199.0	https://www.flipkart.com/true-blue-2-piece-sol
25423	JCKFQF5K72AT2JDC	Full Sleeve Solid Women Casual Jacket	12999.0	0.50	6499.0	https://www.flipkart.com/puma-full-sleeve-soli
25815	JCKFQF5KMJJ349H8	Full Sleeve Solid Women Casual Jacket	12999.0	0.40	7799.0	https://www.flipkart.com/puma-full-sleeve-soli
26089	SWSFUMFGQFKVZGYH	Full Sleeve Printed Men Sweatshirt	12999.0	0.40	7799.0	https://www.flipkart.com/puma-full-sleeve-prin
6895	JEAF8S4GWU5YKQTF	Skinny Men Blue Jeans	12990.0	0.40	7794.0	https://www.flipkart.com/gas-skinny-men-blue-j
25569	JCKFW8EFUXMSBHMZ	Full Sleeve Solid Men Padded Jacket	10999.0	0.45	6049.0	https://www.flipkart.com/puma-full-sleeve-soli
6870	JCKF8SWBNSGY5TPX	Full Sleeve Self Design Women Casual Jacket	10990.0	0.52	5188.0	https://www.flipkart.com/gas-full-sleeve-self
6901	JEAF65G3MZYG3BQM	Maxx Regular Men Black Jeans	10990.0	0.39	6692.0	https://www.flipkart.com/gas-maxx-regular-men

(b) Actual Price Sorting (DESCENDING).

Figure 9: Actual Price Sorted Documents.

	pid	title	actual_price	discount	selling_price	url
19482	SOCFYNKS7XZ3YUKZ	Men Printed Calf Length (Pack of 5)	0.0	0.00	0.0	https://www.flipkart.com/foot-fix-men-printed
27574	TKPFZAGJYK9YGRAA	Striped Men Black Track Pants	0.0	0.00	0.0	https://www.flipkart.com/ravilka-striped-men-b
16485	SOCET7QRNHYG9HHB	Women Mid-Calf/Crew (Pack of 2)	199.0	0.50	99.0	https://www.flipkart.com/welwear-men-mid-calf
20435	BDAFUBD2EJHFCRNC	Men Printed Bandana	199.0	0.50	99.0	https://www.flipkart.com/t10-sports-men-printe
7654	SOCFFGA2FYZQBFXT	Women Color Block Ankle Length (Pack of 3)	499.0	0.76	118.0	https://www.flipkart.com/your-shopping-store-m
24437	SOCFZAGJC3VUFQU9	Women Solid Ankle Length (Pack of 3)	399.0	0.69	120.0	https://www.flipkart.com/ina-group-men-solid-a
24438	SOCFZ7GFAZGYZGR7	Men Solid Ankle Length (Pack of 3)	399.0	0.69	120.0	https://www.flipkart.com/ina-group-men-solid-a
24439	SOCFZ7JX39ZEW8GE	Women Solid Ankle Length (Pack of 3)	399.0	0.69	120.0	https://www.flipkart.com/ina-group-men-solid-a
20253	CAPEX5YHPH3MSGFC	Cotton 5 panel baseball Cap	249.0	0.50	124.0	https://www.flipkart.com/t10-sports-cotton-5-p
16402	SUSECSFFVNKG5VGG	Brand Trunk Y- Back Suspenders for Men (Black)	499.0	0.74	125.0	https://www.flipkart.com/brand-trunk-y-back-su
906	TSHF5FRXKGF6A4FH	Printed Women Round Neck White T-Shirt	998.0	0.87	128.0	https://www.flipkart.com/jack-royal-printed-me
25325	SOCFPR9UF8Q4FCHG	Men Ankle Length (Pack of 3)	499.0	0.73	132.0	https://www.flipkart.com/puma-men-ankle-length

## (a) Selling Price Sorting (ASCENDING).

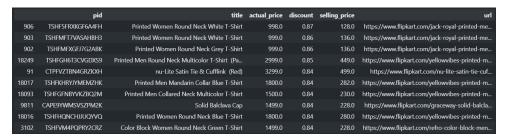
	pid	title	actual_price	discount	selling_price	url
2067	TKTFZ3YGGMMNBYEZ	Solid Women Track Suit	9999.0	0.20	7999.0	https://www.flipkart.com/reebok-solid-men-trac
11010	BZRFVAX2QGTEGHRH	Checkered Single Breasted Party Women Full Sle	7999.0	0.00	7998.0	https://www.flipkart.com/true-blue-checkered-s
25815	JCKFQF5KMJJ349H8	Full Sleeve Solid Women Casual Jacket	12999.0	0.40	7799.0	https://www.flipkart.com/puma-full-sleeve-soli
26089	SWSFUMFGQFKVZGYH	Full Sleeve Printed Men Sweatshirt	12999.0	0.40	7799.0	https://www.flipkart.com/puma-full-sleeve-prin
6895	JEAF8S4GWU5YKQTF	Skinny Men Blue Jeans	12990.0	0.40	7794.0	https://www.flipkart.com/gas-skinny-men-blue-j
11008	BZRFVDGUJHTQHDAX	Self Design Single Breasted Party Women Full S	6999.0	0.00	6998.0	https://www.flipkart.com/true-blue-self-design
6898	JEAF8S4GE8PKH7H3	Regular Fit Men Dark Blue Cotton Blend Trousers	10990.0	0.36	6925.0	https://www.flipkart.com/gas-regular-fit-men-d
6901	JEAF65G3MZYG3BQM	Maxx Regular Men Black Jeans	10990.0	0.39	6692.0	https://www.flipkart.com/gas-maxx-regular-men
25423	JCKFQF5K72AT2JDC	Full Sleeve Solid Women Casual Jacket	12999.0	0.50	6499.0	https://www.flipkart.com/puma-full-sleeve-soli
6855	JEAFEN3WGHH3ZEFY	Skinny Men Blue Jeans	9990.0	0.35	6493.0	https://www.flipkart.com/gas-skinny-men-blue-j
14194	JEAFQFGWXSVSMRWC	Slim Women Dark Blue Jeans	7999.0	0.20	6399.0	https://www.flipkart.com/levis-slim-men-dark-b

(b) Selling Price Sorting (DESCENDING).

Figure 10: Selling Price Sorted Documents.



(a) Discount Sorting (ASCENDING).



(b) Discount Sorting (DESCENDING).

Figure 11: Actual Price Sorted Documents.

	count		count
brand		seller	
	2009		1643
ECKO Unl	951	RetailNet	1411
Free Authori	860	SandSMarketing	887
ARBO	806	BioworldMerchandising	842
REEB	802	ARBOR	783
Pu	798	Keoti	660
True Bl	793	AFFGARMENTS	587
Keo	660	Black Beatle	548
Amp	585	AMALGUS ENTERPRISE	477
Black Beat	548	Tayab Manch Fashions	436
vims rai	503	KAPSONSRETAILPVTLTD	415
yellowvib	492	GRACEWAY	408
PixF	429	T-SHIRT EXPRESS	393
Oka	414	OKANE	386
Gracew	405	WHITE SKY	371
TEE BUD	393	SHOEFLY	358
Shoef	358	ArvindTrueBlue	338
Marca Disa	353	ModaElementi	333
٧	343	Marca Disati	330
CupidSto	338	CupidStoreIN	329

(a) Top brands.

(b) Top sellers.

Figure 12: Distributions of word counts in titles and descriptions.

From the EDA we have gained some information on the corpus, its content and the information we are gonna work with. This will help us understand how we can make an Information Retrieval system that provides the user with relevant products to their queries.