# IRWA Final Project – Part 1


## Group 23

- Luca Franceschi
- Pau Peirats
- Júlia Othats-Dalès


## 1. Data Preparation

### 1.1 Text Pre-processing

Before performing any analysis on the dataset, we have to clean and standardize the text fields **title** and **description** — to prepare them for indexing and retrieval.

The following preprocessing pipeline was implemented using **NLTK**:

1. **Lowercasing** – Converting everything to lowercase ensures that words sometimes capitalized sometimes not are treated as the same word.
2. **Removing punctuation** – Punctuation marks do not add meaning for most text analysis tasks. Removing them simplifies the data and avoids unnecessary tokens.
3. **Normalization** - This step converts accented or special characters
4. **Tokenization** – splits text into individual tokens using `word_tokenize()`. This is a key step before removing stopwords and applying stemming.
5. **Stopword removal** – Stopwords (like “and”, “the”, “of”) are very common words that usually don't help in understanding the meaning or distinguishing documents. Removing them reduces noise.
6. **Filtering out non-alphabetic tokens** - We removed tokens that contain numbers or symbols, keeping only words made of letters.
7. **Stemming** - We reduced each word to its root form to group similar words tog
8. **Noise reduction** - Words with very few letters (like “a”, “an”, “is”) often have little meaning, so we removed tokens shorter than 3 characters.

Example output fields added to the dataset:

- `title_clean`
- `description_clean`

| pid | title | title_clean |
|---|---|---|
| TKPFCZ9EA7H5FYZH | Solid Women Multicolor Track Pants | solid women multicolor track pant |

These cleaned fields will serve as the **textual representation** of each product in future search and retrieval steps.

### 1.2 Dataset Schema for Future Queries

After cleaning the text fields, the next step is to make sure our dataset includes only the columns that will be useful for the final queries.

The project requires that, for each selected document, the output should contain the following fields when they are available:

- `pid`
- `title`
- `description`
- `brand`
- `category`
- `sub_category`
- `product_details`
- `seller`
- `out_of_stock`
- `selling_price`
- `discount`
- `actual_price`
- `average_rating`
- `url`

All documents in the corpus are now represented using this schema.
The `pid` field is preserved as a unique identifier for evaluation purposes (as required by the validation labels).

### 1.3 Handling of Metadata Fields

**Alternatives Considered**

**Option 1 – Merge into a single text field**

In this option, we would have only one text field with all the metadata, allowing for flexible queries but we lose distinction (brand is not the same thing as category or seller)

**Option 2 – Index as separate fields (Chosen approach)**

In this second option, we treat each as its own field, where each can be preprocessed by lowercasing, removing punctuation, and tokenizing. This way we mantain control for ranking and weighting, don't confuse different concepts and we can make column-specific queries. It can increase the size of the index, and making it a little more complex but it is the best choice for our case because each field has distinct meaning that we want to keep separate and also rank separately.

**Option 3 – Hybrid approach**

We also considered a hybrid approach where we keep separate fields AND create a combined metadata field for general text searches but this option is redundant.

**Other Considerations for metadata Fields**

After choosing to keep separate the fields, we still have to decide how we treat them. Besides the text fields (`title` and `description`), the dataset includes several metadata fields that may also be useful for retrieval:

- `category`
- `sub_category`
- `brand`
- `product_details`
- `seller` We decided to clean `category`, `sub-category` and `product_details` by lowercasing and removing punctuation since they have general descriptions. In the other hand, the `brand` and `seller` fields were kept as they were to preserve the proper nouns. The brands and sellers are identifyers, not descriptions, changing them could result in loss of meaning, and make retrieval less precise, since we could be looking for a specific brand and not find it due to normalization.

**Note:** During preprocessing, we noticed that some brand names appear in multiple slightly different forms. For instance:

- “U.S. Polo Association”
- “US Polo Assn”
- “U. S. POLO ASSN.”
- “u.s polo assn” These inconsistencies clearly reduce the reliability of the data, since the same brand can appear under different variants.
  Ideally, we would want to normalize these brand names so that all of them are treated as a single entity during retrieval. However, after discussing it, we decided*not to perform aggressive normalization at this stage because:
- We might lose meaningful distinctions in the data.
- We don’t currently have a reliable way to unify brand names safely.
- We want to preserve the original text for flexibility in later retrieval or manual correction. Our current approach is therefore a temporary compromise:
  we acknowledge that normalization could improve consistency, but we postponed it until we have a better method to ensure that we don’t lose important brand or seller information in the process.

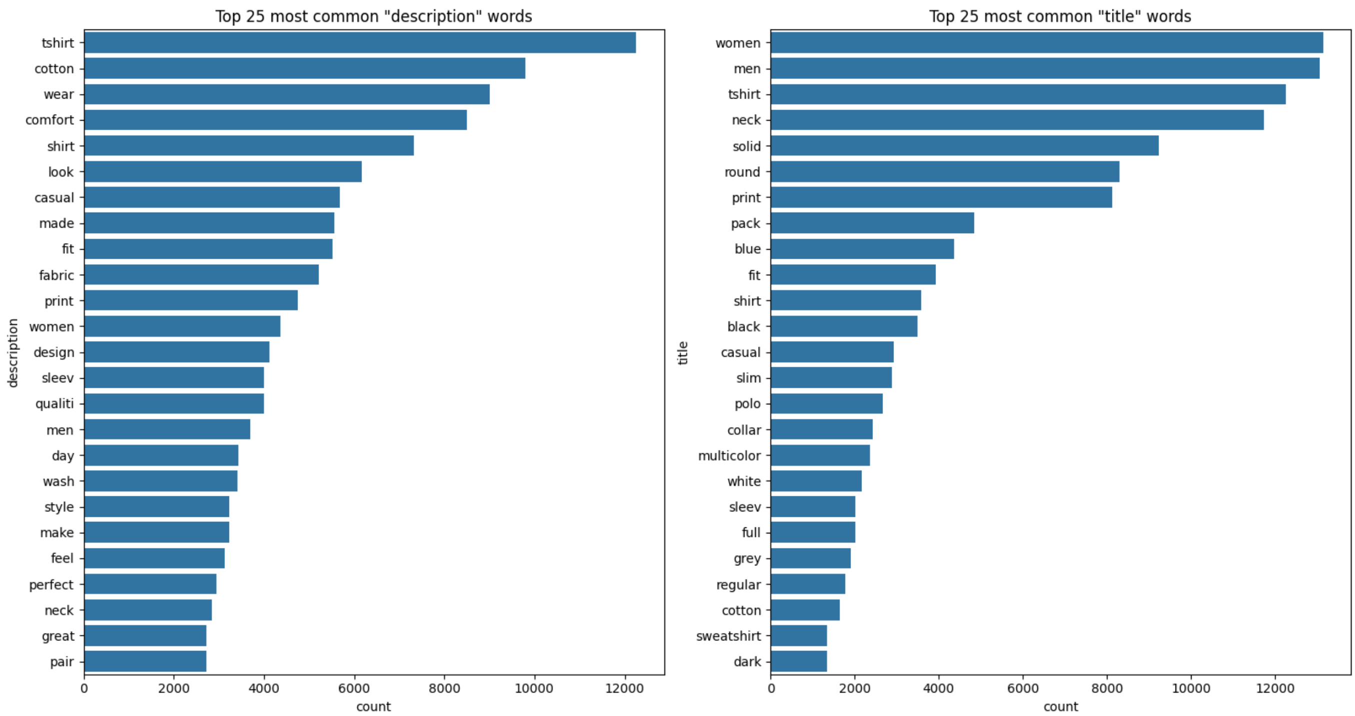
### 1.4 Handling of Numerical and Binary Fields

Some fields in the dataset contain numeric or boolean information. These fields describe quantitative or categorical attributes of the products, which play a different role from textual fields like `title` or `description`.

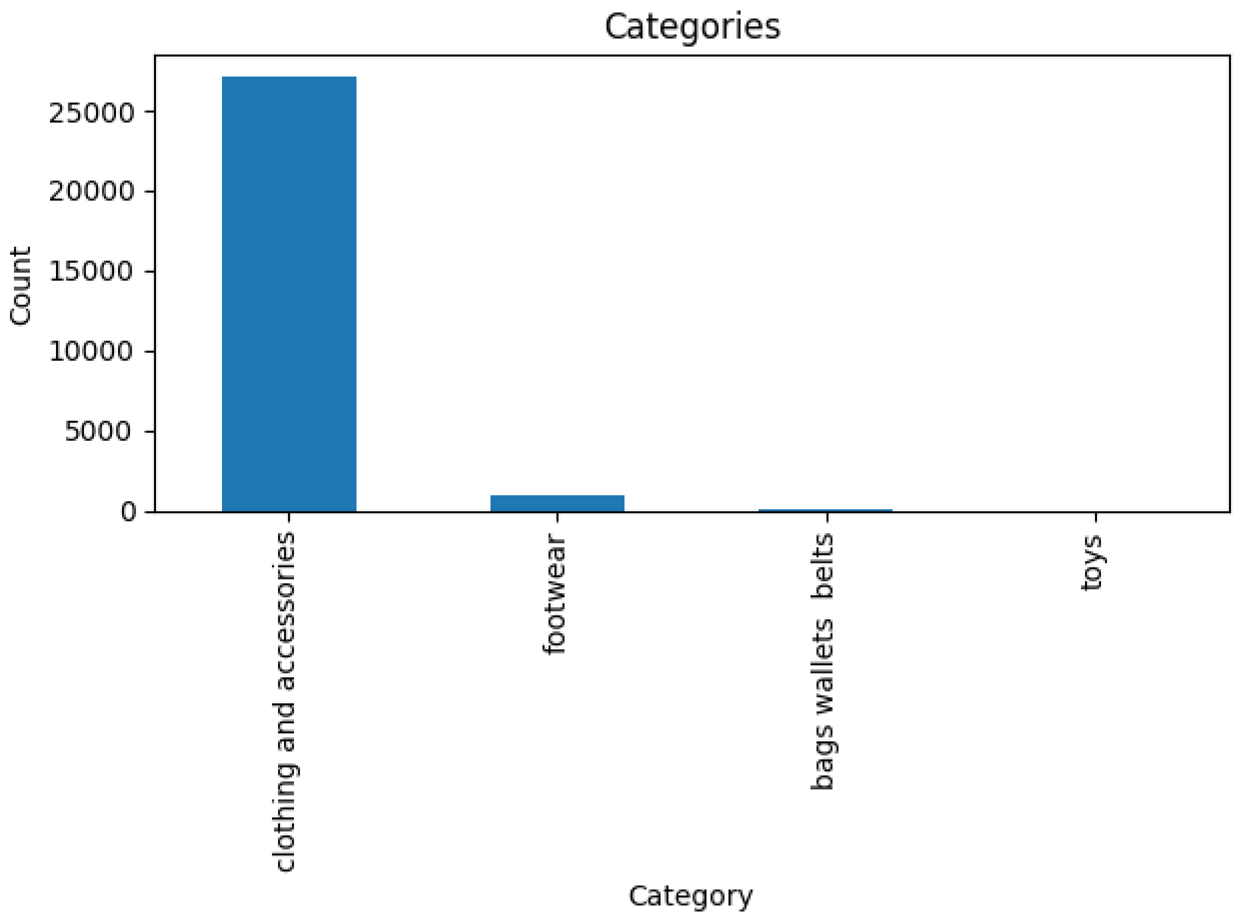
- `out_of_stock`
- `selling_price`
- `discount`
- `actual_price`
- `average_rating` Instead of being indexed as words, they are more useful as filters, sorting criteria, or ranking signals in search and retrieval tasks.

To clean them, we first mapped the True and False labels for the `out_of_stock` field to 1 and 0 respectively. Then, for the `actual_price` and `selling_price` we realized that numbers bigger than a thousand have this format (1,000) so we removed the comma to then convert them to numerical with the `to_numeric+` function on. 'The `average_rating` was easy to directly convert to numeric. Finally, for `discount` we removed "% off" from the string and kept only the percentage as a number.

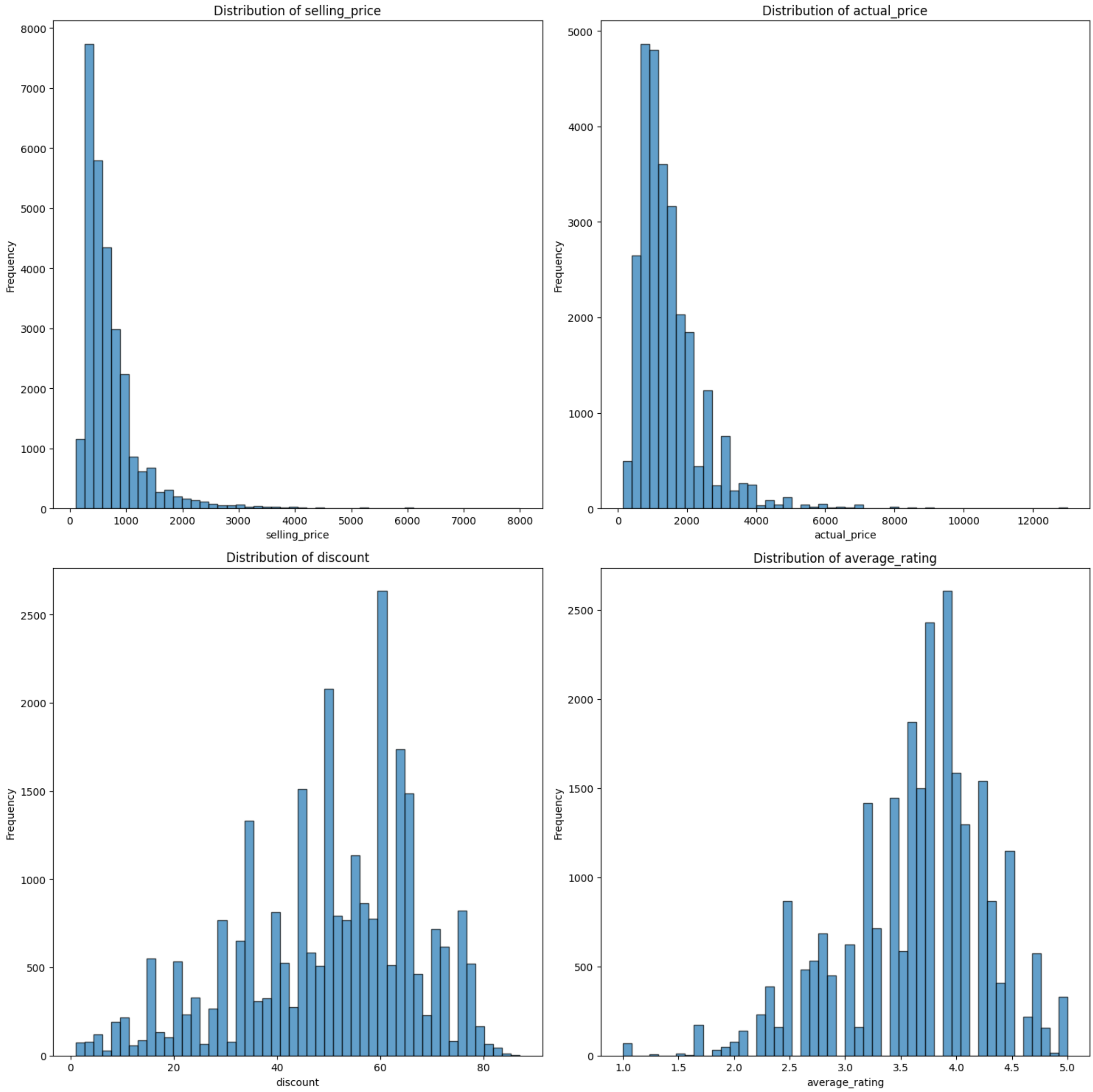
## 2. Exploratory Data Analysis



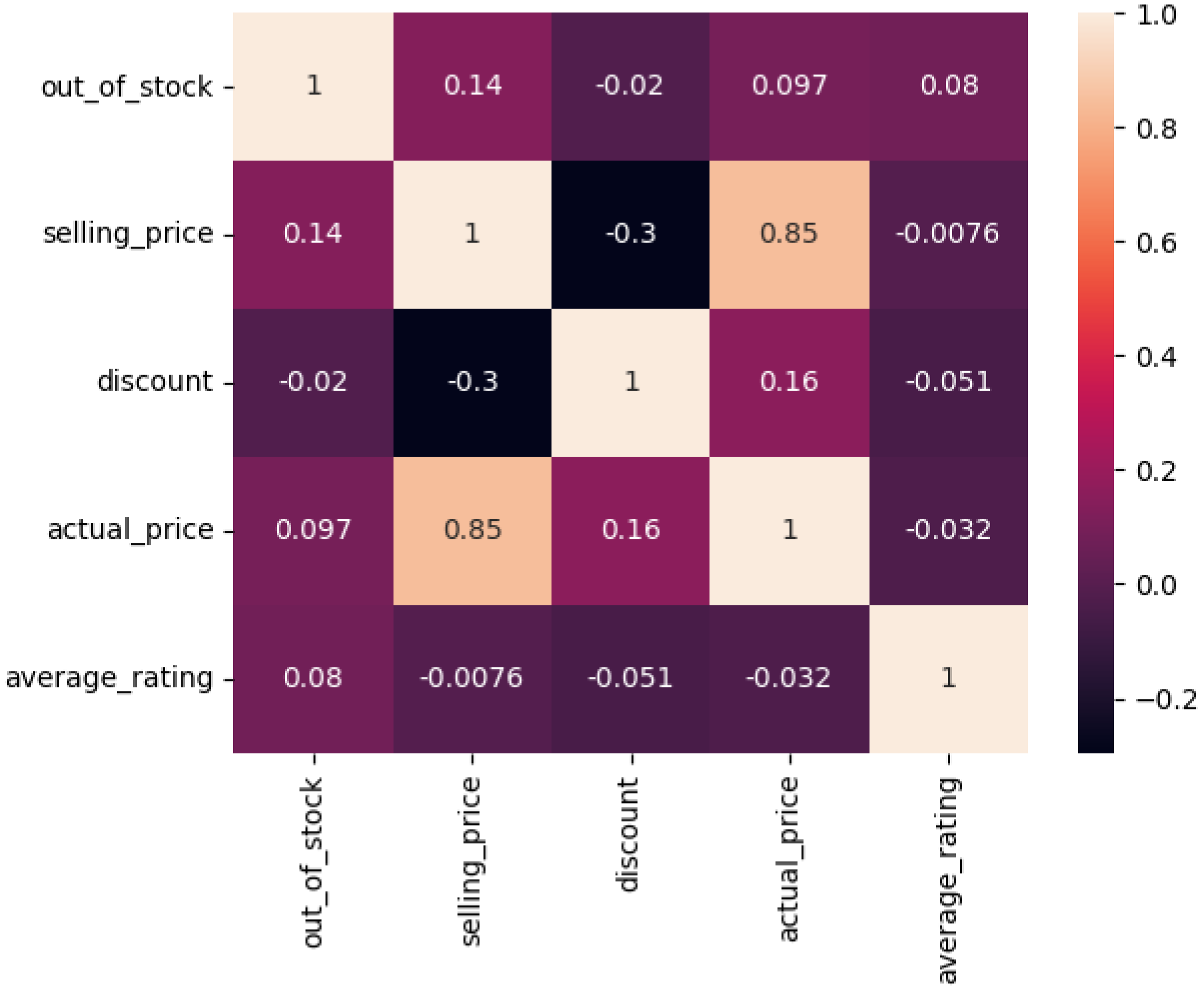

We can see that most common words are related to clothing...



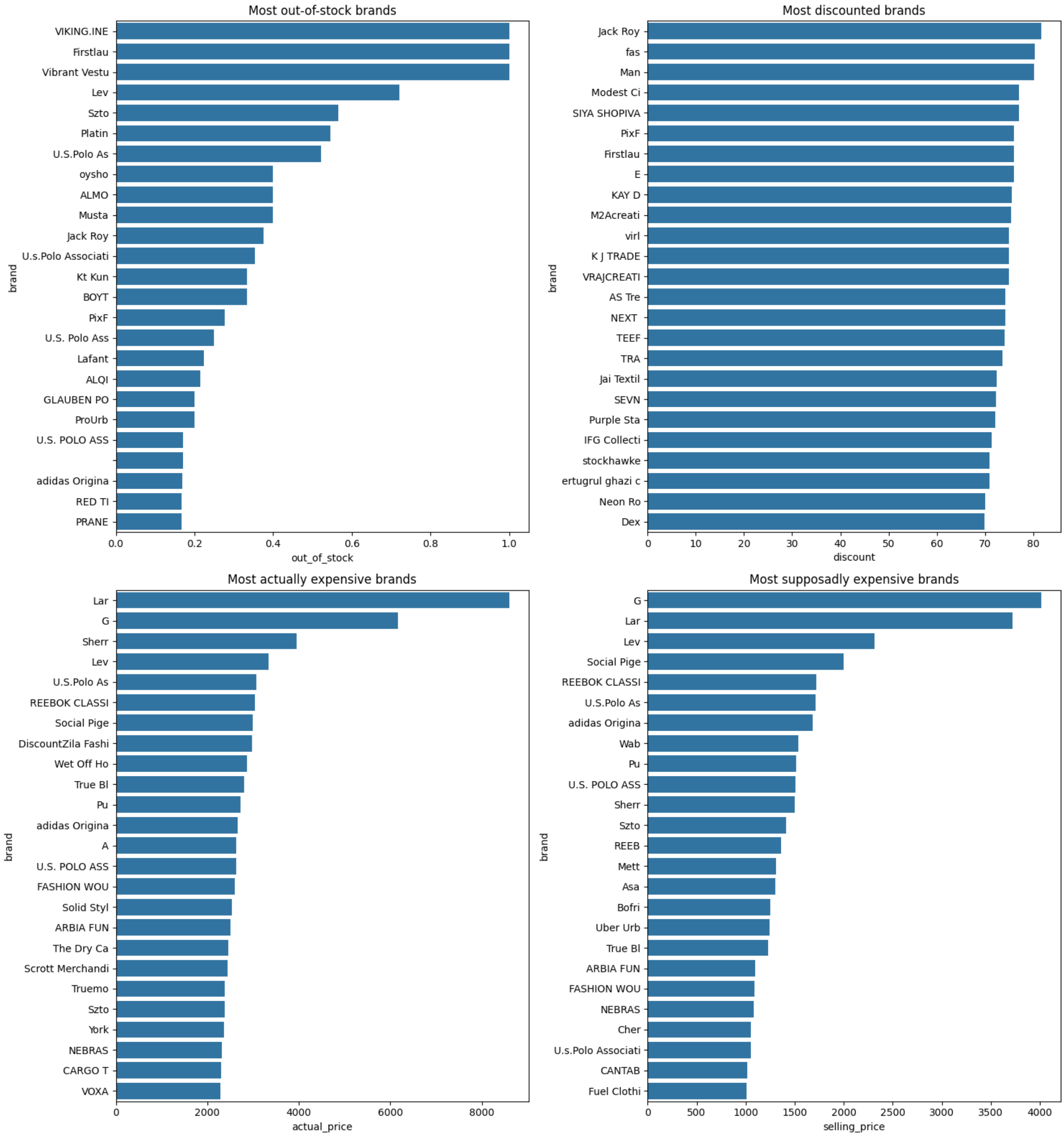

... and that makes tootal sense since most of the products are related to exactly that.




Among all products, we can see that most of them cost actually more than what they are supposed to. Also, ratings seem to be a bit right-skewed (people rate the products good on average).




We can clearly see that the most correlated variables are *actual_price* and *selling_price*, which of course makes sense. We can also see that *discount* and *selling_price* are negatively correlated (about -30%), which also makes sense.




We can see that some of the most out-of-stock brands are also the most expensive ones... the *supply and demand enomic model of price determination in microeconomics* seems to work!