

Data Mining

Homework 2

Ashkan Ansarifard

1970082

In this report, I present the implementation and analysis of a Python program designed to scrape and analyze product data from Amazon using web scraping techniques. The objective of this problem is to collect information about products related to the keyword *gpu* from the Amazon.it website, parse the data, and perform an Exploratory Data Analysis. ¹

Web Scraping and Data Collection

The AmazonScraper class has been implemented to do the web scraping and data collection. The scrape_amazon_products method utilizes the Requests library to download web pages and BeautifulSoup for HTML parsing. It iterates through the specified number of pages, extracts relevant information for each product, and stores it in the self.data list.

Tab-Separated Value (TSV) File

The save_to_tsv method converts the collected data into a Pandas DataFrame and saves it to a TSV file using pd.to_csv. Each product's information is stored in a separate line, as written in the requirement of the problem statement.

Delay to Prevent Blocking

To prevent being blocked by Amazon due to excessive requests, a delay of 5 seconds (time.sleep(5)) has been introduced between different web page requests.

Exploratory Data Analysis (EDA)

The analyze_data method has been implemented to perform an EDA on the collected dataset. The analysis includes²:

• **Price Ranges**: Utilizing the Pandas cut function to categorize products into price ranges and visualizing the distribution using a box plot. The dataset has

¹example usage class is problem1_main.py

²The EDA is from analyzing the first 10 pages

been categorized into the following price ranges:

Price Range	Count
500+	72
≤100	33
100-200	11
200-300	4
300-400	0
400-500	0

Table 1: Distribution of Products Across Price Ranges (Console Output)

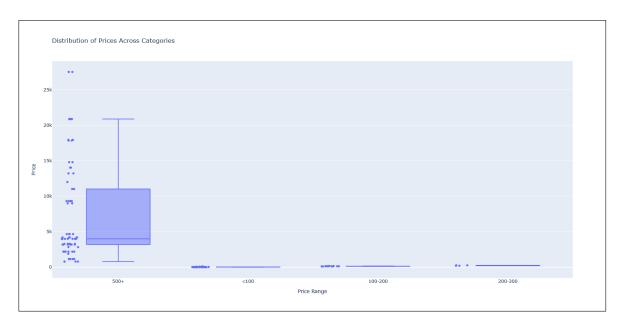


Figure 1: Distribution of prices across different categories

• Customer Reviews: Identifying and printing the top-rated products based on star ratings.



Figure 2: Top Rated Products with Customer Reviews

• **Primeness**: Separating the dataset into Prime and Non-Prime products and providing summary statistics for each category.

	Price	Stars	Reviews
count	31.000000	31.000000	31.000000
mean	3569.806452	1.458065	1409.645161
std	5977.225764	2.148142	2630.628120
min	39.000000	0.000000	0.000000
25%	41.000000	0.000000	1.500000
50%	147.000000	0.000000	5.000000
75%	4195.000000	4.500000	2010.000000
max	20870.000000	4.700000	7114.000000

Table 2: Summary statistics for Prime Products. (Console Output)

	Price	Stars	Reviews
count	89.000000	89.000000	89.000000
mean	3292.707865	1.767416	526.483146
std	11187.100932	2.209112	1671.567141
min	7.000000	0.000000	0.000000
25%	31.000000	0.000000	1.000000
50%	132.000000	0.000000	7.000000
75%	3195.000000	4.400000	62.000000
max	99990.000000	4.700000	7114.000000

Table 3: Summary statistics for Non-Prime Products. (Console Output)

• Top 10 Products by Rating and Price: Plotting the top 10 products based on

both star rating and price using Plotly Express bar charts.



Figure 3: Top 10 Products by Price



Figure 4: Top 10 Products by Star Rating

• Scatter Plot of Price vs. Star Rating: Creating a scatter plot to visualize the relationship between product price and star rating, with marker size indicating the number of reviews.

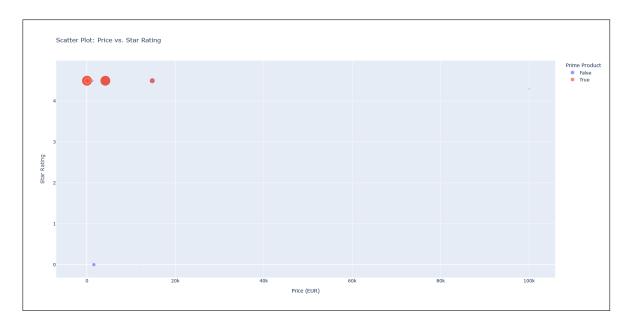


Figure 5: Scatter Plot Price vs. Star Rating

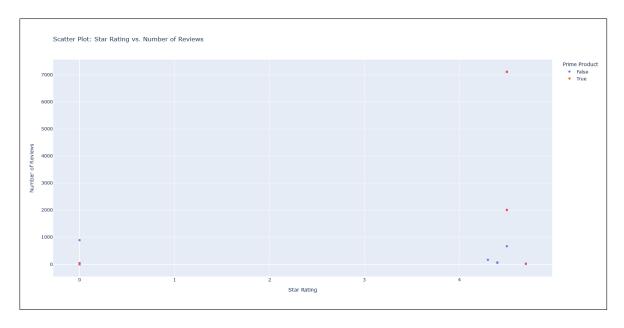


Figure 6: Scatter Plot Star Rating vs. Number of Reviews

In this section, I present the implementation of a search engine extension for the AmazonScraper class. The search engine focuses on evaluating queries based on the product's description, returning the top 10 most related products along with their information.³

Class Implementation: AmazonScraperWithSearchEngine

The AmazonScraperWithSearchEngine class extends the AmazonScraper class to incorporate search engine functionalities. Below, I detail how each requirement in the problem statement has been fulfilled.

Inverted Index and Cosine Similarity

The evaluate_query method has been overridden to include vectorization and cosine similarity calculation. This method takes a user query, transforms it into a TF-IDF vector, and computes cosine similarities with the TF-IDF matrix of product descriptions. The related product indices are then sorted based on cosine similarities, and the top products are returned.

Build Inverted Index

The build_inverted_index method initializes a TF-IDF vectorizer and computes the TF-IDF matrix based on the product descriptions. This serves as the inverted index for the search engine. It checks for the availability of data and prompts the user to run scrape_amazon_products if no data is present.

Usage and Example

To use the search engine, first, instantiate the AmazonScraperWithSearchEngine class with a keyword and the number of pages to scrape. Run scrape_amazon_products

³example usage class is problem2_main.py

to collect data, and then execute build_inverted_index to build the inverted index. Once the inverted index is available, queries can be evaluated using evaluate_query.

Example Usage

To demonstrate the usage of the AmazonScraperWithSearchEngine class, consider the following example which can be found also in problem2_main.py:

1. Instantiate the Search Engine:

```
search_engine = AmazonScraperWithSearchEngine(keyword='gpu
num_pages=5)
```

2. Scrape Amazon Products:

```
search_engine.scrape_amazon_products()
```

3. Build the Inverted Index:

```
search_engine.build_inverted_index(search_engine.df['Descri
```

4. Evaluate a Query:

```
user_query = "high-performance graphics card"
query_result = search_engine.evaluate_query(user_query,
top_N=5)
print("Query Result:")
print(query_result)
```

This example demonstrates the workflow of using the *AmazonScraperWithSearchEngine* class. It begins by instantiating the class with a specified keyword and the number of pages to scrape. The class is then used to scrape Amazon products, build the inverted index based on product descriptions, and finally, evaluate a sample query using the cosine similarity measure. The resulting query result includes the top-related products along with their information.

Example Usage Results

In the following, result of the search engine for different query lengths are shown. The list of queries are:

1. Gaming GPU

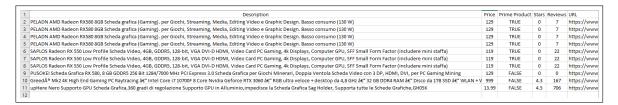


Figure 7: Query result - Gaming GPU

2. GPU for video editing

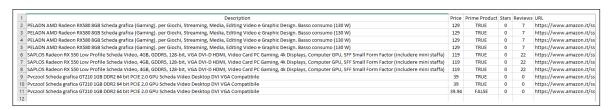


Figure 8: Query result - GPU for video editingd

3. Best budget GPU

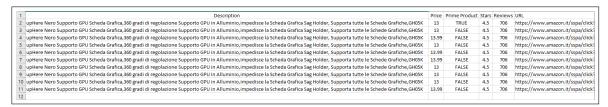


Figure 9: Query result - Best budget GPU

4. NVIDIA GPU



Figure 10: Query result - NVIDIA GPU

5. AMD gaming graphics card



Figure 11: Query result - AMD gaming graphics card

Radeon RX 550 Low Profile Scheda Video, 4GB, GDDR5, 128-bit, VGA DVI-D HDMI, Video Card PC Gaming, 4k Displays, Computer GPU



Figure 12: Query result - Long Query GPU

Part 1: Shingling

The Shingling class generates shingles from a given document. Shingles are created by sliding a window of size k through the document. Each shingle is a substring of length k. The generate_shingles method creates a set of shingles from the input document.

Part 2: Minwise Hashing

The MinwiseHashSignature class is designed for minwise hashing. It generates multiple hash functions using the MD5 algorithm. For each set of elements, the class updates a signature matrix with hash values. The generate_signatures method takes a collection of sets and returns a signature matrix, where each column represents the minwise hash signature of a set.

Part 3: Locality-Sensitive Hashing (LSH)

The LSH class implements the Locality-Sensitive Hashing technique. It uses minwise hash signatures to build hash tables. The index_signatures method populates hash tables based on the signatures of the input sets. The query_signatures method retrieves candidate sets by querying hash tables with the signature of a query set. The find_near_duplicates method uses LSH to find near-duplicates within a collection of shingles.

Part 4: Threshold Intersection Analysis

The class contains a method named s_curve_plot_and_analysis that analyzes the threshold intersection for different values of r and b. It iterates through combinations of r and b, calculates the probability of becoming a candidate using the S-curve formula, and plots the results. The analysis involves checking for step-shaped curves that indicate optimal values for r and b.

Part 5: Choosing Optimal Parameters

The choose_r_b_values method in the LSH class helps in selecting suitable values of r and b based on a given threshold probability. It iterates over possible combinations of r and b, calculates the expected threshold probability, and selects values that closely match the given threshold.

Part 6: Jaccard Similarity Calculation

The ShingleComparison class calculates Jaccard similarity between sets of shingles. The compare_shingle_sets method takes a collection of shingles and descriptions, computes Jaccard similarities, and identifies near-duplicate pairs based on a specified threshold.

Performance Metrics

- The elapsed time for LSH execution is measured using the elapsed_time_lsh attribute.
- The Jaccard similarities between shingle sets are stored in the jaccard_values attribute.
- The near-duplicate pairs and their Jaccard similarities are stored in a DataFrame (df) in the ShingleComparison class.

The provided code implements the Locality-Sensitive Hashing technique using Apache Spark. The steps involve tokenizing product descriptions, creating Word2Vec representations, and using MinHashLSH for approximate similarity joins. Below is an overview of the key components of the Spark implementation:

- 1. **Initialization:** The Spark session is initialized with the name "Amazon-ScraperLSH".
- 2. **DataFrame Conversion:** The Pandas DataFrame obtained from web scraping is converted to a Spark DataFrame (spark_df).
- 3. **Tokenization:** Product descriptions are tokenized using the 'Tokenizer' class.
- 4. **Word2Vec Representation:** Word2Vec representations of product descriptions are created using the 'Word2Vec' model.
- 5. **MinHashLSH:** MinHashLSH is applied to generate hash values for the features, and the DataFrame is divided into two halves for efficient processing.
- 6. **Approximate Similarity Join:** The code performs an approximate similarity join using LSH with a specified Jaccard distance threshold.
- 7. **Result Presentation:** The results are presented in the form of a DataFrame showing near-duplicate pairs along with their Jaccard distances.
- 8. **File Export:** The final near-duplicate information is saved to a CSV file, and the file is made available for download.