E-Commerce Product Listing Reviewer

Aditya Nangia
2020168
CSAI

Saksham Bhupal
2020573
CSAI

Akshat Saini
2020019
CSE

Nakul Thureja
2020
CSE

Jayan Pahuja
2020
CSE

***Abstract*—The e-commerce landscape has become fiercely competitive, with numerous sellers offering similar products. This necessitates a multifaceted approach for sellers to succeed. Current methods of manual competitor analysis, customer review monitoring, and product listing optimization are not only time-consuming and error-prone but also fail to capitalize on the vast amount of data available.**

This research proposes an integrated solution that leverages Information Retrieval (IR) techniques, Deep Learning (DL) models, and Large Language Models (LLMs) to address these challenges within a unified interface. The system automates data collection and analysis, empowering sellers with actionable insights to make data-driven decisions. This not only enhances product competitiveness but also allows sellers to thrive in the dynamic e-commerce environment.

Our motivation stems from a desire to bridge the gap in seller-centric IR solutions. By equipping sellers with the necessary tools to navigate the complexities of the online marketplace, this research aims to empower them to optimize listings, effectively respond to customer sentiment, and achieve lasting success. The system's effectiveness was assessed using multiple metrics: sentiment analysis accuracy, similarity matching precision, and listing strength prediction metrics (precision, recall, F1-score).

I. Prroblem Statement

The burgeoning presence of numerous sellers offering identical or similar products on e-commerce platforms has intensified competition, demanding a multifaceted approach. Sellers require a system that automates competitor analysis, streamlines customer review monitoring, and facilitates product listing optimization. This research proposes an integrated solution leveraging Information Retrieval (IR) techniques, Deep Learning (DL) models, and Large Language Models (LLMs) to address these challenges within a unified interface. By harnessing the power of automation and advanced data analysis, this system empowers sellers to make data-driven decisions, enhance product competitiveness, and ultimately thrive in the dynamic e-commerce landscape.

II. Motivation

The booming world of e-commerce has witnessed a dramatic shift, with a multitude of sellers vying for customer attention by offering similar or identical products. This fierce competition has created a critical need for sellers to gain a deeper understanding of the market landscape. While consumers benefit from a vast array of choices, sellers struggle to keep pace. The current landscape demands a more sophisticated approach, one that goes beyond simply listing products and hoping for the best.

Github Link: Github Link

Our motivation for this project stems from a desire to empower sellers and level the playing field. Currently, sellers face a three-pronged challenge: effectively analyzing competitor strategies, staying on top of customer reviews, and constantly optimizing their product listings for maximum impact. Manually tackling these tasks across diverse platforms like Amazon and Flipkart is not only a herculean effort but also prone to inaccuracies. Furthermore, the sheer volume of data available on these platforms can be overwhelming, burying valuable insights beneath a mountain of information.

This project is driven by a fundamental belief: sellers deserve tools that can help them navigate the complexities of the online marketplace. They need a system that automates tedious tasks, unlocks valuable competitor and customer insights, and ultimately empowers them to make data-driven decisions. By bridging the gap in seller-centric information retrieval (IR) solutions, we aim to equip sellers with the knowledge and tools necessary to optimize their listings, effectively respond to customer sentiment, and ultimately achieve lasting success in the ever-evolving world of e-commerce.

III. Literature Review

1) Increased information retrieval capabilities on e-commerce websites using scraping techniques [1]. This study employs web crawling across three e-commerce websites, consolidating data into a database for streamlined retrieval. By scraping HTML tags and storing data systematically, the process ensures efficiency with a 100
2) A Review on Web Scrapping and its Applications [2] This review dives into web scraping, exploring its applications and the technology behind it. It examines the reasons why web scraping is valuable, discusses its advantages and limitations, and explores the tools and libraries commonly used for scraping tasks. Additionally, the review highlights the various applications of web scraping across different fields.
3) Opinion mining and sentiment analysis on online customer review [3]. Opinion mining, crucial in e-commerce, sees rising importance with the surge in online transactions and user-generated content. Reviews on platforms like Amazon express customer sentiments, offering valuable insights. This study focuses on mining Amazon reviews, utilizing algorithms like Naïve Bayes, Logistic Regression, and SentiWordNet for sentiment analysis. The goal is to automate sentiment recognition and enhance understanding of user emotions.

4) Sentiment analysis: A literature review [4] This paper offers a survey of recent advancements in sentiment analysis, a technique that extracts emotional tones from text data. Due to the surge of subjective content online, particularly in reviews, sentiment analysis has become a hot research area. The paper delves into the core methods used in sentiment analysis research, including framework and lexicon development, feature extraction, and polarity classification (positive, negative, or neutral). It highlights the current methodologies, explores existing limitations, and provides an in-depth look at applications in business and blog analysis. Finally, the paper discusses potential future directions for sentiment analysis research.
5) Search engine optimization (SEO) for websites. [5] As the internet expands, search engines play a critical role in indexing and presenting relevant web content. However, many websites overlook the need for visibility, focusing solely on user experience and technical aspects. To address this, a web application is developed to analyze web pages and enhance their search engine friendliness. By providing actionable insights and recommendations, this application aims to improve website rankings and attract more visitors through Search Engine Optimization (SEO).
6) Classification of Customer Reviews based on Sentiment Analysis [6] The paper proposes a system that performs the classification of customer reviews of hotels by means of a sentiment analysis. They extract a domain-specific lexicon of semantically relevant words based on a given corpus, which backs the sentiment analysis for generating a classification of the reviews. The evaluation of the classification on test data shows that the proposed system performs better compared to a predefined baseline.
7) On Application of Learning to Rank for E-Commerce Search E-commerce search is a burgeoning application of information retrieval, with Learning to Rank (LETOR) emerging as a pivotal strategy. While LETOR is extensively studied for web searches, its application to e-commerce searches remains unexplored. This paper addresses practical challenges in implementing LETOR for e-commerce search, including feature representation, obtaining reliable relevance judgments, and leveraging multiple user feedback signals. Experiments on industry datasets reveal insights: popularity-based features enhance relevance-based ones, reducing query attribute sparsity is beneficial, and order rate proves the most robust training objective, followed by click rate, while add-to-cart ratio is less reliable.

IV. Data

A. Input

Seller's product listing. This means it can be a product which the seller is selling on different platforms such as iPhone 15, Laptop Stands, etc. Product URL

B. Output

Insights and recommendations for optimal pricing strategies based on competitor pricing trends and customer price sensitivity. Analysis of customer feedback and sentiment to identify areas for product listing optimization Actionable insights to help sellers enhance their competitiveness in the e-commerce market A review bot which helps in providing suggestive improvements to the listings.

V. Methodology

1) Web Scraping with Ethical Considerations:
   a) Technology: Leverages libraries like Beautiful Soup to extract data from product pages on e-commerce websites.
   b) Challenge Addressed: Automates data collection, eliminating manual work and ensuring access to the latest competitor information.
   c) Ethical Considerations:
      i) Respect robots.txt files that instruct web crawlers on restricted areas.
      ii) Adhere to website terms of service to avoid copyright infringement.
      iii) Be mindful of scraping frequency to avoid overloading website servers.
2) Feature Extraction for Detailed Competitor Comparison:
   a) Technology:
      i) Image Features: Uses a pre-trained deep learning model like ResNet to extract visual features from competitor product images (e.g., color, shape, texture).
      ii) Text Features: Employs TF-IDF (Term Frequency-Inverse Document Frequency) to analyse product descriptions and identify keywords that highlight product features and benefits.
   b) Challenge Addressed: Enables a more nuanced comparison than just product titles. This allows sellers to identify similar products even with slight variations in names or descriptions
3) Identifying Key Competitors Through Feature Matching:
   a) Technology: Utilizes a similarity metric (e.g., cosine similarity) based on the extracted image and text features from the seller's product and competitor's products.
   b) Challenge Addressed: Provides a targeted set of the most relevant competitors for analysis rather than an overwhelming list from the entire marketplace. This allows sellers to focus their energy on the most impactful competition.
4) Sentiment Analysis of Customer Reviews:
   a) Technology: Employs Natural Language Processing (NLP) tools such as VADER Sentiment Analysis, NLTK, and Beautiful Soup to analyse customer reviews for the seller's product and identify positive, negative, or neutral sentiment.

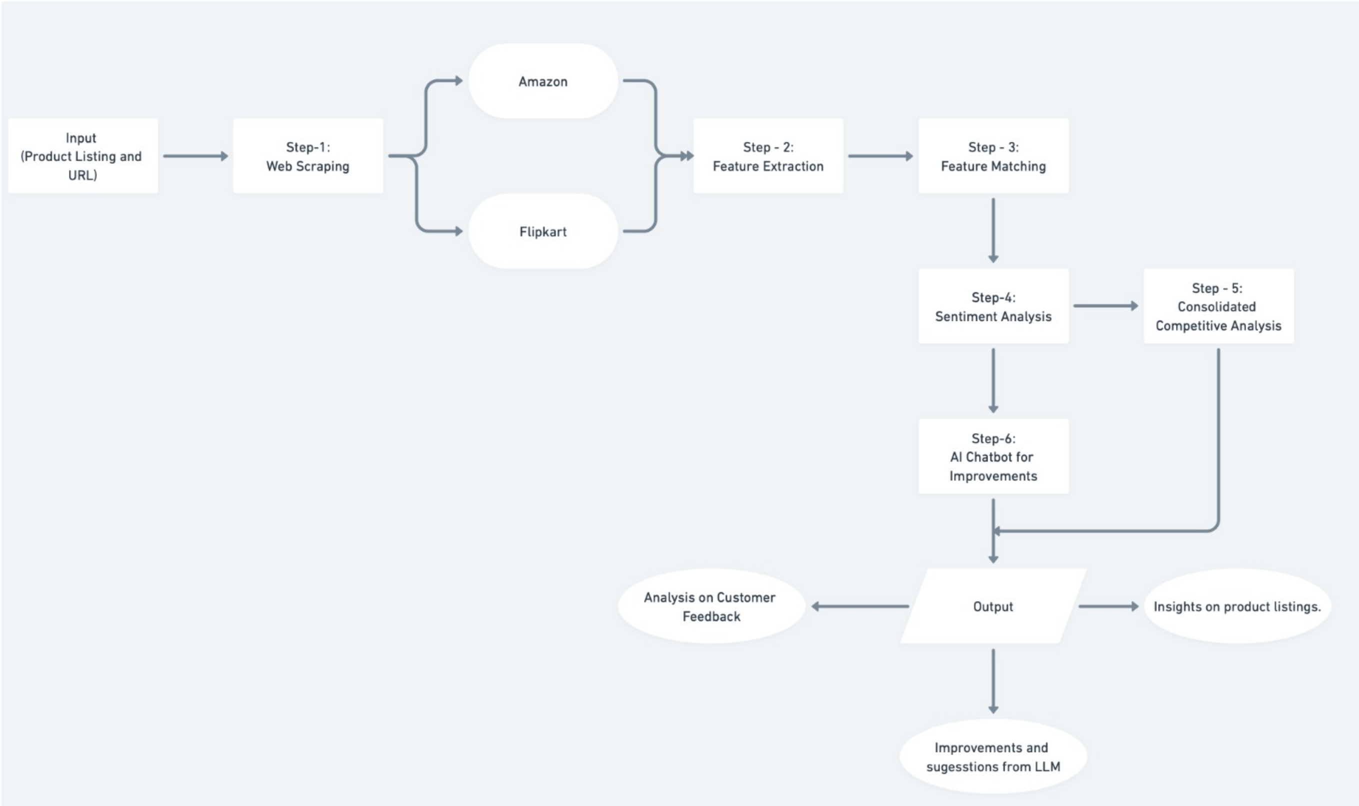

Fig. 1

   b) Challenge Addressed: Provides sellers with insights into customer satisfaction and helps them understand areas for improvement in their own product or listing.

5) Consolidated Competitive Analysis
   a) Technology: Weighted Scoring: Develop a scoring system that assigns weights to data from different websites based on factors like website popularity, relevance to the seller's target audience, or trustworthiness of the source.
   b) Challenges Addressed:
      i) Inconsistent Data Formats: By normalizing features extracted from different websites, the system can handle inconsistencies in data formats and ensure fair comparisons across platforms.
      ii) Varying Website Relevance: The weighted scoring approach addresses the challenge of varying relevance and importance of different e-commerce platforms, allowing the system to prioritize data from more pertinent sources.
6) AI Chatbot for Customer Reviews:
   a) Technology: Answer Generation: Train the chatbot using natural language generation (NLG) models like T5 or GPT-3 to generate clear, concise, and informative answers to user questions using the retrieved information from customer reviews.

VI. Listing Strength Predictor: NOVELTY

In our initial pursuit of a comprehensive "MultiModal Listing Strength Predictor," we aimed to develop a model that could assess a product listing's overall effectiveness in an e-commerce setting. This document details our initial exploration using VisualBERT, a powerful multimodal deep learning architecture.

A. Problem Domain:

Effectively crafted product listings are vital for e-commerce success. This work focuses on predicting key metrics that influence listing performance:

1) Average Review Sentiment: The overall sentiment of customer reviews for a product.
2) Average Rating: The average numerical rating assigned by customers.
3) Average Number of Products Sold: The average quantity of a product sold over a specific period.

B. Proposed Methodology:

This approach utilizes VisualBERT, a state-of-the-art deep learning architecture adept at handling both textual and visual data. Each product listing is characterized by four key features: Title, Description, Price, and Image.

1) Feature PreProcessing: Textual Features (Title, Description, Price): Textual data undergoes preprocessing techniques such as tokenization, stemming, and lemmatization to normalize and clean the data. Then finally all three are concatenated into one string.

Image Feature: The image is preprocessed using computer vision techniques such as resizing, normalization, and feature extraction using a pre-trained image classification model.

2) Text and Image Embedding: A text embedding model, BERT, is employed to create a dense vector representation capturing the semantic meaning of the combined textual features (Title, Description, Price). The preprocessed image is fed through a separate ViT model to generate an image embedding, capturing visual information about the product.

3) Multimodal Fusion and Prediction: The text embedding and image embedding are combined using appropriate fusion techniques to create a unified multimodal representation of the product listing. This multimodal representation is fed into three separate VisualBERT models, each trained for a specific prediction task:

1) Average Review Sentiment Predictor: Outputs a continuous value indicating the expected average sentiment of future reviews (e.g., negative, neutral, positive).
2) Average Rating Predictor: Outputs a continuous value reflecting the anticipated average rating customers will assign to the product.
3) Average Number of Products Sold Predictor: Outputs a continuous value representing the projected average number of units sold over a defined timeframe.

4) Listing Optimization: Thresholds are established for each predicted value (sentiment, rating, number of products sold). Based on these thresholds, the listing can be categorized as ”good” or ”bad” in terms of its predicted performance. Sellers can iteratively modify their listings (e.g., adjusting title, description, price, or image) based on the model’s predictions and reassess the listing’s performance after each change.

C. Initial Exploration and Future Work

While the ”MultiModal Listing Strength Predictor” was an ambitious goal, this exploration served as a valuable first step. Our initial implementation with VisualBERT lays the groundwork for further development. Future work may explore:

1) Training on Average Number of Products Sold since we were unable to capture that data
2) Training on Average Number of Reviews since we were unable to capture that data
3) Reducing the inference time so that the final good or bad prediction can be given immediately as the changes are happening.

VII. Evaluation

We employed two distinct evaluation metrics to assess the effectiveness of our system. The first metric gauges the performance of the sentiment analysis component, specifically its ability to accurately classify sentiment (e.g., positive, negative, neutral) within the data. The second metric evaluates the performance of the implemented similarity matching algorithm, focusing on its precision in identifying similar data points. We have also used ML model evaluation metrics to evaluate our listing strength prediction model.

A. Evaluating sentiment analysis

We adopted a lexicon-based approach to evaluate the sentiment analysis algorithm’s performance. Positive (2), neutral (1), and negative (0) labels were assigned as ground truth based on the average product rating on e-commerce websites. A five-point star rating system was employed, with ratings from 0 to 2.5 mapped to the negative label, 2.5 to 3.5 mapped to neutral, and 3.5 to 5 mapped to positive. For the predicted sentiment scores, a similar discretization strategy was implemented. Scores ranging from -1 to -0.25 were assigned the negative label, -0.25 to 0.25 were assigned neutral, and 0.25 to 1 were assigned positive. Subsequently, the performance evaluation mirrored a standard multi-class classification task. We computed precision, recall, F1-score, and accuracy to assess the model’s effectiveness in classifying sentiment.

	precision	recall	f1-score	support
1	0.00	0.00	0.00	0
2	1.00	0.89	0.94	18
accuracy			0.89	18
macro avg	0.50	0.44	0.47	18
weighted avg	1.00	0.89	0.94	18

B. Evaluating similarity matching

The evaluation of the similarity matching algorithm employed two distinct metrics tailored to the data type: ROUGE score for textual similarity and Root Mean Squared Error (RMSE) for image similarity. A combined similarity score was constructed by dividing the ROUGE score by the RMSE. This score served as the basis for retrieving the top 10 most similar products which served as the ground truth. The retrieved product set was then compared against set of top 10 most similar products generated by the algorithm. The number of matching products served as the evaluation metric for the overall effectiveness of the similarity matching process.

```
Number of common values:  7
```

C. Listing strength predictor

The performance of the listing strength prediction model was assessed using established machine learning evaluation metrics, including precision, recall, and F1-score. These metrics were calculated for both the averaging rating predictor and the average sentiment review predictor.

	precision	recall	f1-score	support
3	0.00	0.00	0.00	6
4	0.00	0.00	0.00	60
5	0.40	1.00	0.57	44
accuracy			0.40	110
macro avg	0.13	0.33	0.19	110
weighted avg	0.16	0.40	0.23	110

test Accuracy: 0.4
test Loss: 45.720574378967285

	precision	recall	f1-score	support
2	0.00	0.00	0.00	25
3	0.88	1.00	0.93	288
4	0.00	0.00	0.00	16
accuracy			0.88	329
macro avg	0.29	0.33	0.31	329
weighted avg	0.77	0.88	0.82	329

test Accuracy: 0.8753799392097265
test Loss: 85.35110169649124

References

[1] D. Kurniawati and D. Triawan, "Increased information retrieval capabilities on e-commerce websites using scraping techniques," in *2017 International Conference on Sustainable Information Engineering and Technology (SIET)*, 2017, pp. 226–229.

[2] V. Singrodia, A. Mitra, and S. Paul, "A review on web scrapping and its applications," in *2019 International Conference on Computer Communication and Informatics (ICCCI)*, 2019, pp. 1–6.

[3] K. L. S. Kumar, J. Desai, and J. Majumdar, "Opinion mining and sentiment analysis on online customer review," in *2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, 2016, pp. 1–4.

[4] A. Barbar and A. Ismail, "Search engine optimization (seo) for websites," in *Proceedings of the 2019 5th International Conference on Computer and Technology Applications*, ser. ICCTA '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 51–55. [Online]. Available: https://doi.org/10.1145/3323933.3324072

[5] D. Gräbner, M. Zanker, G. Fliedl, and M. Fuchs, "Classification of customer reviews based on sentiment analysis," in *Information and Communication Technologies in Tourism 2012*, M. Fuchs, F. Ricci, and L. Cantoni, Eds. Vienna: Springer Vienna, 2012, pp. 460–470.

[6] S. K. Karmaker Santu, P. Sondhi, and C. Zhai, "On application of learning to rank for e-commerce search," in *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval*, ser. SIGIR '17. New York, NY, USA: Association for Computing Machinery, 2017, p. 475–484. [Online]. Available: https://doi.org/10.1145/3077136.3080838