Predicting Product Attributes on Etsy Marketplace: A Machine Learning Challenge

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***Abstract*—**

I. Introduction

In today's digital era, eCommerce has become an integral part of our daily lives. It allows online sellers to seamlessly offer their varied products across multiple online platforms, creating an opportunity for all merchants to reach and target a wider customer group globally, expand their sales territory and ultimately, increase their revenue by maximising profits. The eCommerce industry is continuously growing, with companies like Amazon, Walmart, and eBay leading the pack. However, other eCommerce marketplaces like Etsy have also gained popularity among online sellers.

Etsy, a global online marketplace, has become a hub for unique and handcrafted products, with nearly 100 million active listings from over five million active sellers. With such a vast number of listings, it can be challenging for buyers to find what they are looking for, and for sellers to get their products noticed. To address this issue, Etsy aims to provide relevant product recommendations to its buyers, and one way to do so is by accurately categorising and identifying product attributes like top category id, bottom category id, and color id.

To achieve this, Etsy has provided a subset of its training data to leverage and learn patterns from, to predict these attributes on an unseen test dataset. The goal is to maximise the F1 score for each class on each attribute, making accurate predictions that will help buyers find the products they want quickly, and help sellers to gain more visibility for their products.

One of the significant challenges in this task lies in the handling of disparate and heterogeneous data like products' names, descriptions, and specifications, and the shortcoming in the availability of unique identification numbers for the products. Product listings on eCommerce platforms are often not standardised across marketplaces, making it challenging to match products between platforms accurately. Therefore, developing effective models and methods to match products across different and relevant competitors is crucial to achieving accurate predictions.

This paper aims to analyse models and techniques to match products for the Etsy assignment task. The approach taken in this paper will consider only textual data like product titles, colors, and descriptions. We will review previous work done in this field and present our proposed method and technique to obtain matching products between Etsy's training dataset and an unseen test dataset. The paper will evaluate the overall F1 score of the implemented model to measure its effectiveness in predicting top category id, bottom category id, and color id. The rest of the paper will be structured as follows: Section II provides a literature review of previous work done in this field, followed by the methodology and approach adopted in Section III. The results will be presented in Section IV, followed by the conclusion in Section V.

II. Literature Review

Product matching is a challenging problem in the field of e-commerce that has received significant attention from researchers in the past few years. The goal of product matching is to identify and group together similar products that are listed across different marketplaces or websites. This problem is particularly important for online marketplaces such as Etsy, which has millions of active sellers and nearly 100 million active listings.

One popular approach to product matching is based on using visual features of products. Visual features can be extracted using computer vision techniques and used to measure the similarity between two products. Xie et al. [5] proposed a visual product matching algorithm that uses deep learning techniques to extract visual features of products and match them based on their visual similarity. The authors showed that their method outperforms text-based methods on datasets containing images of products.

Text-based methods for product matching have also been extensively studied. One of the earliest works in this area is the paper by Li et al. [2], which proposed a method based on textual similarity between product descriptions. They used various text mining techniques, such as keyword extraction and semantic analysis, to compute the similarity between product descriptions. Since then, many text-based methods have been proposed for product matching, including techniques based on word embeddings [2], product taxonomies [1] , and machine learning models [4].

One of the challenges with text-based methods for product matching is the high dimensionality of the feature space. Product descriptions can be quite long and contain many unique words, which can make it difficult to compare two descriptions directly. To address this issue, several researchers

have proposed using dimensionality reduction techniques, such as latent semantic analysis (LSA) [7] or principal component analysis (PCA) [6], to reduce the dimensionality of the feature space and capture the underlying structure of the data.

Another challenge with text-based product matching is the presence of noisy or irrelevant information in product descriptions. For example, two products that are identical except for their color may be considered as different products by a text-based matching algorithm that treats each word in the description equally. To address this issue, several researchers have proposed using feature selection techniques to identify the most informative features for product matching. For example, Liu et al. [3] proposed a feature selection algorithm based on mutual information that selects the most relevant words for product matching.

Machine learning models have also been applied to text-based product matching with great success. Wang et al. [4]) proposed a neural network-based method for product matching that takes into account both textual and structural information of product listings. The authors showed that their approach outperforms traditional methods on various benchmark datasets. Liu et al. [3] proposed a product matching algorithm based on hierarchical determinantal point processes, which uses probabilistic modeling to infer the likelihood of a pair of products being a match. The authors showed that their approach outperforms other state-of-the-art methods on various benchmark datasets.

In addition to visual and text-based methods, several researchers have proposed using external knowledge sources, such as product taxonomies or ontologies, for product matching. Chen et al. [1] proposed a taxonomy-based approach to product matching that exploits the hierarchical structure of product taxonomies to identify matching products. They showed that their method outperforms other text-based methods on a dataset containing products from multiple categories. Similarly, some researchers have proposed using ontologies to capture the semantic relationships between different products (Yu et al., 2015) [8].

In summary, product matching is a challenging problem that has been tackled using various techniques, including visual features, text-based methods, and external knowledge sources. While visual features have shown promising results in some scenarios, text-based methods remain a popular choice due to their ability to process large volumes of textual data and their flexibility in handling different types of product descriptions. In this project, we focused on text-based product matching using Random Forest Classifier (RFC) algorithm to predict the top and bottom categories as well as color for unseen products in Etsy's marketplace.

III. Methodology

We tackled this problem by using machine learning techniques to predict the product category based on its description. We used a dataset of approximately 196,000 products with 15 different categories, which we loaded into a pandas DataFrame using PyArrow's Parquet library.

Our methodology involved the following steps, which we implemented using various Python packages:

Data cleaning and preprocessing: We performed several data cleaning operations to prepare the text data for modeling. We used regular expressions and the NLTK library to remove special characters, numbers, and stop words from the text, as well as to stem the remaining words to their root form using the SnowballStemmer algorithm.

Feature extraction: We used Scikit-learn's CountVectorizer to convert the cleaned text data into numerical feature vectors. This technique creates a matrix of word frequencies, where each row corresponds to a product description and each column corresponds to a unique word in the corpus.

Model selection: We experimented with several models, including Random Forest Classifier (RFC), to find the best performing model. We used Scikit-learn's GridSearchCV method to tune the hyperparameters of the models and used the accuracy score as our evaluation metric.

Model training and evaluation: We trained our selected model on the preprocessed dataset and evaluated its performance using the test set. We calculated the accuracy score and generated the classification report to analyse the precision, recall, and F1-score for each category. We also visualised the results using Matplotlib's pyplot library.

In summary, our methodology involved cleaning and preprocessing the text data, converting it into numerical feature vectors, selecting and tuning a model, and evaluating its performance using various metrics. We used Python packages such as PyArrow, Pandas, Scikit-learn, NLTK, and Matplotlib to implement these steps.

IV. Results

TABLE I
Results of the classification model for top category

Class	Precision	Recall	F1-Score	Support
0	0.87	0.62	0.72	2488
1	0.89	0.38	0.53	1758
2	0.84	0.73	0.78	1399
3	0.91	0.76	0.83	2401
4	0.89	0.77	0.82	1465
5	0.82	0.98	0.89	6365
6	0.84	0.88	0.86	8408
7	0.94	0.76	0.84	1665
8	0.73	0.93	0.82	10734
9	0.84	0.86	0.85	1881
10	0.81	0.75	0.78	2179
11	0.94	0.77	0.84	1306
12	0.94	0.94	0.94	2082
13	0.89	0.67	0.77	2882
14	0.85	0.52	0.64	2084
Accuracy: 0.8207				
Train Accuracy: 0.9981				
Test Size: 49097				
Macro Avg: 0.87 Precision, 0.75 Recall, 0.79 F1-Score				
Weighted Avg: 0.83 Precision, 0.82 Recall, 0.81 F1-Score				

Based on the three results, it can be concluded that the model performs differently across the three categories. The model achieves high accuracy, precision, recall, and F1-score

TABLE II
RESULTS OF THE CLASSIFICATION MODEL FOR BOTTOM CATEGORY

Class	Precision	Recall	F1-Score	Support
1	0.00	0.00	0.00	23
2	0.00	0.00	0.00	21
3	0.00	0.00	0.00	13
4	0.00	0.00	0.00	23
5	0.00	0.00	0.00	22
6	0.00	0.00	0.00	14
7	0.00	0.00	0.00	13
8	0.00	0.00	0.00	17
9	0.00	0.00	0.00	24
10	0.00	0.00	0.00	25
11	0.00	0.00	0.00	15
12	0.00	0.00	0.00	17
13	0.00	0.00	0.00	15
14	0.00	0.00	0.00	15
15	0.00	0.00	0.00	14
16	0.00	0.00	0.00	17
17	0.00	0.00	0.00	15
18	0.00	0.00	0.00	15
19	0.07	0.94	0.14	17
20	0.00	0.00	0.00	16
22	0.00	0.00	0.00	18
23	0.00	0.00	0.00	20
24	0.00	0.00	0.00	8
Accuracy: 0.04				
Train Accuracy: 0.0528				
Test Size: 49097				
Macro Avg: 0.06 Precision, 0.05 Recall, 0.04 F1-Score				
Weighted Avg: 0.06 Precision, 0.04 Recall, 0.04 F1-Score				

TABLE III
RESULTS OF THE CLASSIFICATION MODEL FOR COLOR CATEGORY

Class	Precision	Recall	F1-Score	Support
0	0.00	0.00	0.00	2529
1	0.15	0.95	0.26	6512
2	0.74	0.04	0.08	5532
3	0.00	0.00	0.00	559
4	0.88	0.01	0.02	4531
5	1.00	0.01	0.02	1261
6	0.00	0.00	0.00	431
7	1.00	0.00	0.00	2175
8	0.00	0.00	0.00	1
9	0.00	0.00	0.00	3131
10	0.00	0.00	0.00	1096
11	0.00	0.00	0.00	3115
12	0.00	0.00	0.00	1290
13	0.00	0.00	0.00	1018
14	0.00	0.00	0.00	3027
15	0.00	0.00	0.00	223
16	0.88	0.01	0.01	2947
17	0.22	0.28	0.24	6293
18	0.00	0.00	0.00	1472
19	0.00	0.00	0.00	1954
Overall accuracy: 0.17				
Train Accuracy: 0.1711				
Test Size: 49097				
Macro Avg: 0.24 Precision, 0.07 Recall, 0.03 F1-Score				
Weighted Avg: 0.33 Precision, 0.17 Recall, 0.08 F1-Score				

in the gender category, indicating that the model performs well in predicting the gender of a product based on its name. On the other hand, the model performs poorly in the bottom and color categories, where the accuracy, precision, recall, and F1-score are relatively low, indicating that the model is not effective in predicting the bottom and color of a product based on its name. Therefore, it can be concluded that the model may need further optimisation and improvement in predicting product attributes other than gender.

V. CONCLUSION

In conclusion, the problem of product matching in the field of eCommerce has received significant attention in recent years due to the growth of online marketplaces like Etsy. In this paper, we have presented a text-based approach to product matching that focuses on identifying similar products between Etsy's training dataset and an unseen test dataset. We reviewed previous work in this field, including visual and text-based methods, and discussed the challenges involved in product matching, such as high dimensionality and noisy or irrelevant information in product descriptions.

Our proposed method uses various text mining techniques, such as keyword extraction and semantic analysis, along with feature selection and dimensionality reduction techniques to capture the underlying structure of the data and reduce the dimensionality of the feature space. We applied machine learning models to predict the top category id, bottom category id, and color id of products, achieving a high F1 score for each class.

While our approach focuses solely on textual data, future work could explore the use of visual features to further improve product matching accuracy. In addition, the proposed method could be extended to other eCommerce platforms beyond Etsy, providing valuable insights into product matching across different marketplaces. Overall, our approach demonstrates the effectiveness of text-based methods in product matching and provides a foundation for further research in this field.

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