Improving Item Searching On Trading Platform Based On Reinforcement Learning Approach

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Abstract

Item searching on trading platforms is a real challenge nowadays. The number of product offers on the trading platforms is significantly more than real goods. It increases the searching space for a customer and complicates the procedure of a product choosing. Often customers don't know for sure which particular sample of the product they need. They compare specific features among similar products, chose the item, and then compare pricing and shipping. For simplifying the buying process in the e-commerce market we propose to combine similar product offers from different sellers into groups and provide customers with groups of similar items.

We propose an approach, which allows grouping product offers based on the pre-trained core of tags and reinforcement learning technique. The core of tags is built for each group of similar items by processing text descriptions of similar items. The suggested model builds a search query by combining words from the core of tags in order to receive the relevant list of similar items and propose a reference item of the group. As experiments have shown similar products from the e-commerce platform can be easily found if the core of tags for a group is known. The successful results significantly depend on the e-commerce platform, where the core of tags was obtained. It can significantly reduce the search space and alleviate the process of choosing a commodity.

Keywords 1

E-commerce, Item Searching, Item Similarity, Core of Tags, Reinforcement Learning, Experiment

1. Introduction

Lately, we have seen significant growth in online shopping. The quantity of online purchases has been raised significantly. And there are a huge number of offers trying to meet demand. It is quite challenging for a buyer to find the appropriate product and the best proposition.

In this study, we focus on the issue of simplifying the process of product choices for customers. We are working on building a system, which can assist an ordinary customer with choosing the product. In general two options are possible. The first one is when a customer knows exactly what kind of product can satisfy his demands. The task here is to find the best offer among a huge amount of e-market sellers. In that case, the issue is solved by means of information retrieval tools. The second option is when a customer has an unsatisfied demand, but he doesn't know what product with a certain set of attributes can solve a problem. In that case, he faces the obstacle in an overwhelming quantity of propositions. We want to develop an algorithm that can reduce the searching space for a customer. We should simulate human behavior. Observing the real humans behavior we will try to copy it. The system should accept the environment and react respectively.

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For a customer who can't distinctly describe the product, it is important to reduce the offerings on one's searching request. Some sites give an opportunity to limit the offerings. The fewer quantity of offered products the easier for a customer to process them and the more they meet the searching request.

The task of our system is to process product descriptions and to collect the keywords in order to build the core of key attributes. All close products have certain similar words for their presenting. Comparing picture as humans do it is an insuperable point for artificial systems now. Thus we suggest working with product descriptions given by sellers. Receiving offerings we should check whether they meet customer requirements. As a result, a set of keywords that describe product attributes is developed. Then each product description should be estimated on similarity to the core of tags. The most appropriate product is chosen as the standard of comparison. The product descriptions of further offerings on similar searching requests are assessed for proximity to chosen ones as a standard of comparison. Initial request searches for similar groups of products. Then if we specify the searching request with some word it reduces the offering. So we can group similar products and receive significantly reduced offerings.

The aim of the paper is to combine similar product offers from different sellers on the e-commerce website into groups based on the pre-trained core of tags and reinforcement learning technique.

The rest of the paper is organized in the following way. Section 2 substantiates the problem statement and reviews the research in the given field. The proposed approach based on Reinforcement Learning is given in section 3. Results of the experiment are presented in Section 4, and the conclusion is discussed in Sections 5.

2. Related works

E-market sellers are constantly adjusting product descriptions to improve their visibility. It's quite widespread that information given by different sellers to the same product is complementary and even contradictory. E-commerce vendors could give irrelevant information unintentionally or deliberately in order to enhance chances to meet customers' requests. A search engine retrieves the product offers as a user's expectation.

The product matching problem is raised by researchers. The functional similarity of products is assessed by comparing their attributes [1, 4]. There is a drawback in such an approach. It perfectly fits products with a strongly defined set of technical characteristics, but it fails with products, which are described in freestyle. The product classification is set up on regular expressions. Matching relies on the semantic processing of items description [2]. A match function estimates all matches and mismatches in attribute values for products and identifies if the attribute value is missed or mismatched. Product matching is directly regarded as a semantic text matching problem and proposed a pre-trained matching model based on both self- and inter-ensemble [8, 9]. The transformer-based approach for textual product matching and extend it with a CNN for product classification is given [6]. The analysis of existing frameworks for entity matching is provided in [3]. The paper [7] presents the design of a system for mining the Web of HTML-embedded Product Data, Product Matching and Product Classification. The developed system aggregates the results of the various state of the art pre-training models to resolve the identical products. The given system hasn't given product description and price.

For receiving the most complete and relevant data about existing product characteristics and their prices, it is necessary to gather a massive amount of data in a very short time. It can be satisfied only through the parallelization of retrieval tasks. This approach requires hundreds of servers and an Internet connection with exceptionally high broadband. This way is highly expensive. Paper [5] deals with Web data extraction technology applied to online market intelligence Lixto provides OMI services to various clients, especially in the areas of retail. Cloud computing is proposed for peaks instead of the servers, which are idle between successive runs but would require maintenance. For the task solving of big collections construction for product specifications from web pages, the DEXTER is proposed [12]. The techniques to discover, crawl, detect and extract product specifications were proposed. The automatic discovery of new categories built on the navigation structure of the product websites isn't available so far.

There are a lot of researches devoted to the problem of categorizing a large number of objects. Existing applications for solving this problem, including image classification and product categorization, are unreliable. An approximation algorithm was developed [13], and Experiments proved on a real crowdsourcing platform demonstrate the effectiveness of the method.

We have already worked on a problem of reduction searching space for customer of e-commrce trading platform. The issues of product matching and clusterization were considered. For improving the process of product searching we have built a core from the tags of the items that have been acclaimed as similar by the experts based on images comparison [9]. The method proposed was proved to be suitable for constructing the core for sneakers. The combining analysis of both item description and item image in order to construct groups of similar items is suggested. If humans can define whether two products are similar or not taking a look at two images and a product description, so it was formed a set of similar products based on customers' judgments and core of keywords was built. Studying available propositions it is learned, that they have disadvantages and don't offer the cross functional approach to solve the studied task.

We have worked on a data set, which could be tagged according to customer estimations [10]. We suggest using crowdsourcing for tagging item images. The mobile application is developed for multiplying sampling. The simplicity of mobile application allows using it by a diverse people population. The application can be used just for fun and bring social benefits. An increasing amount of tagged pictures permits to investigate customer perception, which also depends on age and sex.

In order to reduce searching space we suggest an approach, which combines grouping product offers based on the pre-trained core of tags and reinforcement learning technique. Deep Reinforcement Learning has lately broadly used in a range of domains within physics and engineering, with multiple remarkable achievements. The research [14, 17] has shown that an artificial neural network trained through Deep Reinforcement Learning is able to generate optimal shapes on its own, without any prior knowledge and in a constrained time. To solve the algorithmic trading problem to ensure the optimal trading position at each time point during a trading activity an innovative approach based on deep reinforcement learning is used. The training of the resulting reinforcement learning agent is entirely based on the generation of artificial trajectories from a limited set of market historical data [15]. Reinforcement learning is employed to optimize the model for the purpose of maximizing long-term recommendation accuracy [16].

Therefore, in this paper, the task of improving item searching is investigated under research how response information from e-commerce websites could clarify the item query and increase the accuracy of proposed items.

3. Methods and materials

Nowadays Reinforcement Learning has seen many successful applications in wide areas. This approach gives such benefits as a safe simulated environment for experimenting, infinite numbers of iterations to learn an optimal behavior, and implementation of experience to solve tasks successfully.

Reinforcement learning is one of the methods of machine learning, during which an agent learns by interacting with some environment. We can say that, from the point of view of cybernetics, reinforcement learning is a type of cybernetic experiment. Reinforcement signals are the response of the environment to the decisions made, therefore, such learning is a special case of teaching with a teacher, but the teacher is the external environment or its model. The agent acts on the environment, and the environment acts on the agent. Such a system is said to have feedback. Such a system should be considered as a whole, and therefore the dividing line between the environment and the agent is rather arbitrary.

In our task, the agent interacts with the marketplace by sending a search request. The response of the environment, the site of the marketplace, is a list of items that match the search query. The agent's goal is to get the most complete and accurate list of items that can be combined into one product group but differ in the characteristics of the offers (price, size, color, shipping, etc.). By interacting with the site of the marketplace, the agent can change the content of his search query. This allows him to get different versions of item lists. These lists can contain from a few items to tens of thousands, which complicates their processing. Therefore, the agent's goal is also to reduce the size of the list of items responded to a search query.

Let's define K as a set of groups of items. Let's define I_k as a set of attributes, which describe the k-th group of items. So, every j_k-th item can be presented as a tuple of attributes

$$A_{jk} = \langle a_{jk1}, a_{jk2}, \dots, a_{jkn} \rangle,$$

where $a_{jki}, j \in J_k, i \in I_k, k \in K$, is a linguistic variable whose value corresponds to i-th attribute of k-th group. Notice that a_{jki} is a word or phrase, as well as it can have the null value. We consider the case when the item is described by its title. Let's imagine that we have an ideal item represented by the tuple A_k^*. We need to compare the ideal item to every item from the website and find the group of similar items. The main challenge is how to estimate the similarity of items from the website. We suggest to model the searching as a reinforcement learning procedure. Let's define the initial state as a state where the ideal item is represented by the core of tags. The core of tags can be predefined, for example, according to algorithm from [9]. Therefore we have the ideal item which is presented as $A_k^* = \langle t_1, \dots, t_s \rangle$, where t_q is a tag. From the other side we have the set of items from the website. Every item corresponds to its representation A_{jk}. The similarity metric is not define, but we have a chance to receive the website response to our query. We apply the set of tags from the core to complete the query. The response reflects the similar items from the website point of view and performs the unknown estimation function.

On the next step, we can evaluate item matching. Some simple steps should be done. Firstly, we parse item titles from the response. Secondly, we measure the similarity of attributes. Thirdly, we evaluate accuracy of item matching. The reward function defines the dependency between an accuracy and values the attributes of ideal item. In addition, we need take into consideration the amount of items in the response. Actually, we do not know how many items, which similar to the ideal item are on the website.

The optimal amount of items responded by the website, which is denoted N, can be find by experimenting with queries. Note that the ideal item description should be change in order to reduce or increase the value N. Therefore, to obtain the appropriate item group we need to change the values of the ideal item attributes in order to meet the optimal amount of the group N, as well as high accuracy of item matching. To achieve the goal we need to interact with website. The general scheme of proposed approach is presented in the Fig. 1.

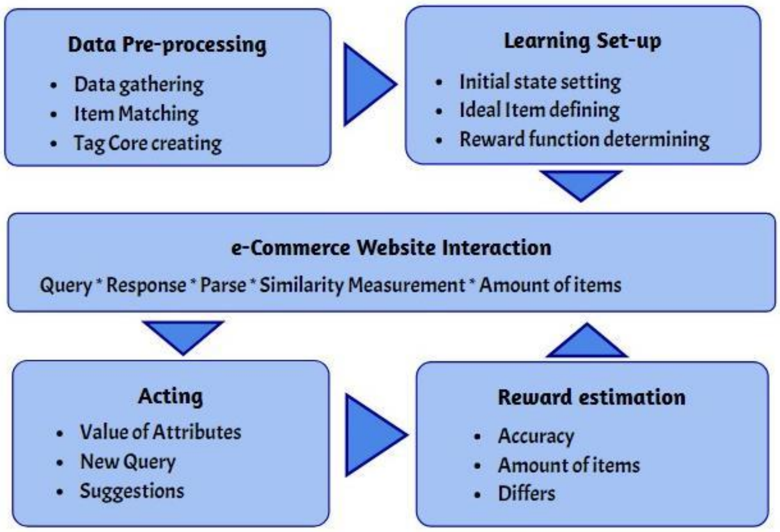

Figure 1: The pipeline of e-commerce website interaction

Therefore, we suggest using the agent which can build the set of attributes, push the query to the website, receive the response, evaluate the item matching and amount of items, and change the initial attribute values. In order to estimate the way suggested we do the experiments with three websites (eBay, Amazon, and AliExpress) and apply the core of tags from [9] as the initial state. The next section describes the experiments and results.

4. Experiments and results

We have core words for items, which have been identified as similar. List of these words and two examples of similar items (photos and description) are shown in Figures 2-4 respectively.

All tags	>0.70	>0.75
adidas casual leather white apply men	leather	leather
comfort unworn new brand unused top	white	white
standard breathable low shoes training	comfort	comfort
sneakers year full article lacing	breathable	low
rubberband lace fabric originals	low	shoes
running athletic slip anti smith stan	shoes	fitness
fitness studio rubber jogging unisex	fabric	summer
textile solid cushioned leisure core	athletic	trainers
superstar summer eur continental black	fitness	toe
spring limited fall edition ftwwht	summer	sports
lightweight light lifestyle classic	lightweight	basketball
weight boost tennis medium barricade	trainers	school
trainers retro toe gym indonesia walking	toe	outsole
campus winter foam performance upper	sports	skate
blue motion support sports control	basketball	
suede	plaid	
trainer cloud basketball grey clear	school	
vietnam cross plaid round sneaker arch	outsole	
scarlet rainbow collegiate green samba	skate	
athletics whtin pattern adv coated	bodybuilding	
twinstrike adjustable jeans one	yamamoto	

Figure 2: List of words in the core of tags

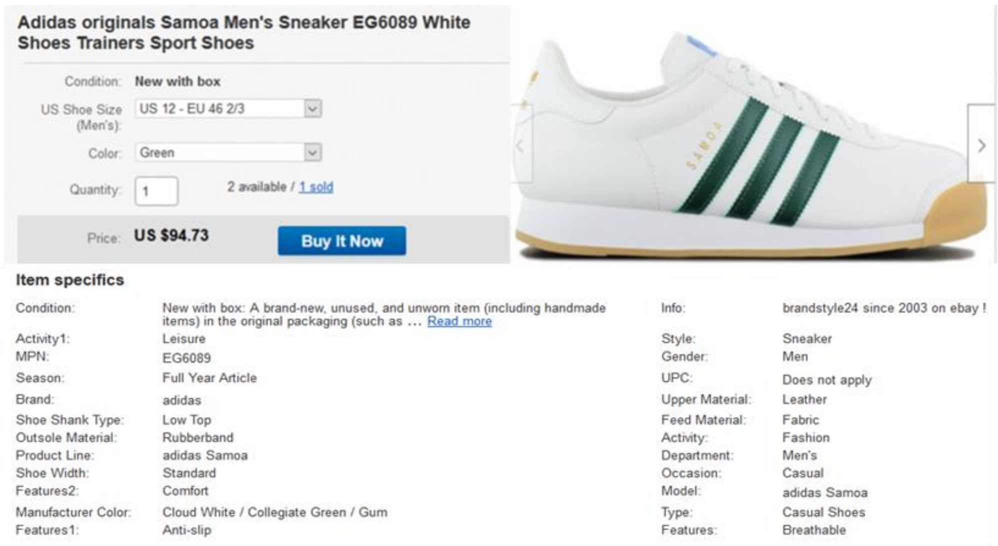

Figure 3: Example of product #1

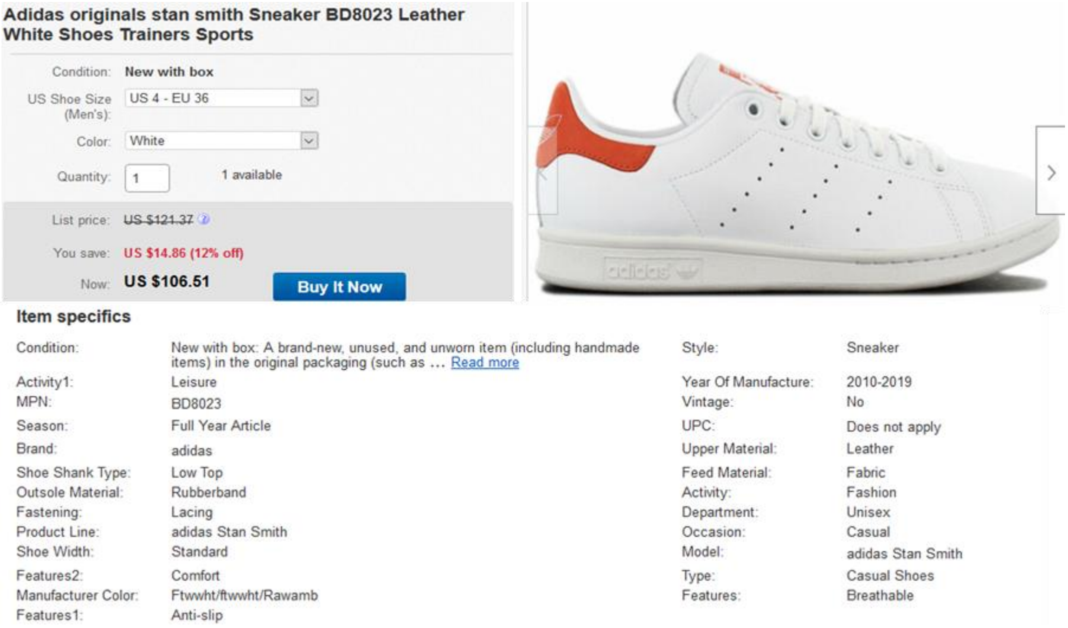

Figure 4: Example of product #2

We have decided to fulfill several experiments to estimate usage of core words for searching similar items on three online platforms such as EBay, Amazon and Aliexpress. Searching is done for all categories items on these platforms herewith in each experiment we use different core words set (quantity, order). The conditions of manual searching are shown in Table 1.

Table 1
Core words usage

Experiment number	Core words sets	EBay	Amazon	Aliexpress
1	leather white comfort low shoes fitness summer trainers toe sports basketball school outsole skate	0	0	-
2	shoes fitness trainers leather white comfort low sports basketball school summer toe outsole skate	0	0	-
3	leather white comfort low shoes fitness	43981	286	107
4	leather white shoes fitness summer	82731	724	429
5	leather white trainers toe sports basketball	2171	504	16
6	leather white shoes school outsole skate	69	183	0
7	white comfort low shoes fitness summer trainers	82	154	13
8	leather shoes fitness basketball outsole skate	50	17	0
9	shoes fitness trainers leather white comfort	62	618	72
10	shoes trainers sports comfort white leather	190	2000	60
11	shoes low comfort trainers leather white	193	2000	30
12	shoes leather fitness trainers sports basketball	19	86	35
13	fitness comfort white leather summer toe	2	112	4
14	sports toe trainers summer shoes white leather	7	843	2

We have faced restrictions for the number of words in the search line on Aliexpress while performing experiment 1 and experiment 2. The length of the search line is only 50 symbols it is about seven core words. So experiment 1 and experiment 2 are not enabled to fulfill on Aliexpress. This restriction influenced using sets from 5-7 core words in other experiments.

During experiment 1 and experiment 2 we use all core words to search similar words on eBay and Amazon, only in experiment 2 we change the core words' order. In all cases, we obtain negative results - "no matching". However, results are different for these online platforms. On eBay, we obtain 0 "exact matching results" for all core words but it proposes some results for matching fewer words and these results of searching are some shoes. The results of experiment on eBay platform are shown in Figure 5.

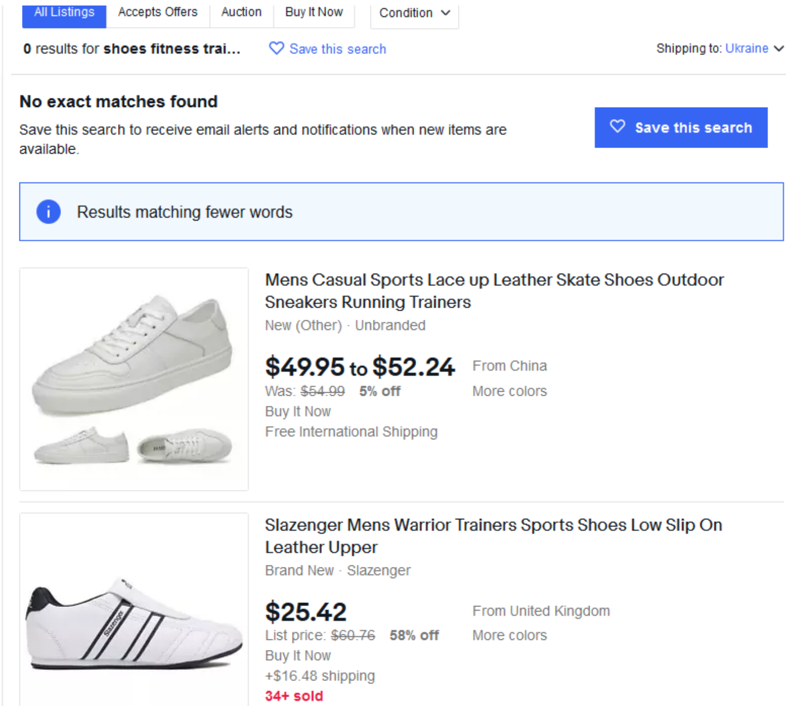

Figure 5: The results of experiment on eBay platform

On Amazon, there is no searching result using all core words and it is recommended to use fewer words - sets of three key words, however, results of these queries are not successful regarding to our aim. There are some results of experiment 1 and experiment 2 on Amazon platform in figure 6.

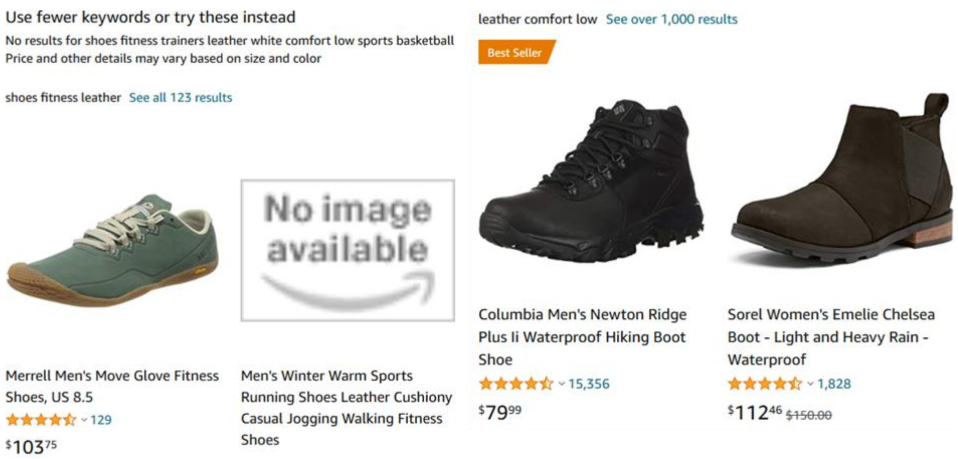

Figure 6: The results of experiment on Amazon platform

We can observe from the Ttable 1 that search results are very different for each platform and different sets of core words (experiments). There is difference not only in numbers of results but also in content of these results.

First of all, we can see that numbers of search results on Aliexpress are less than on eBay and Amazon. Analysing content of these results we face to the fact that, in the most experiments, obtained items do not match with our target item (Figures 7-8).

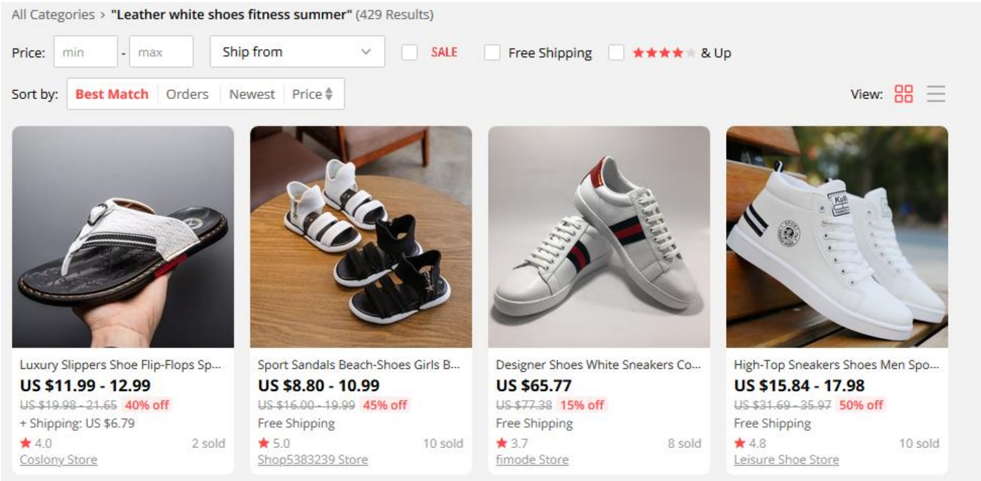

Figure7: Some results of experiment #4

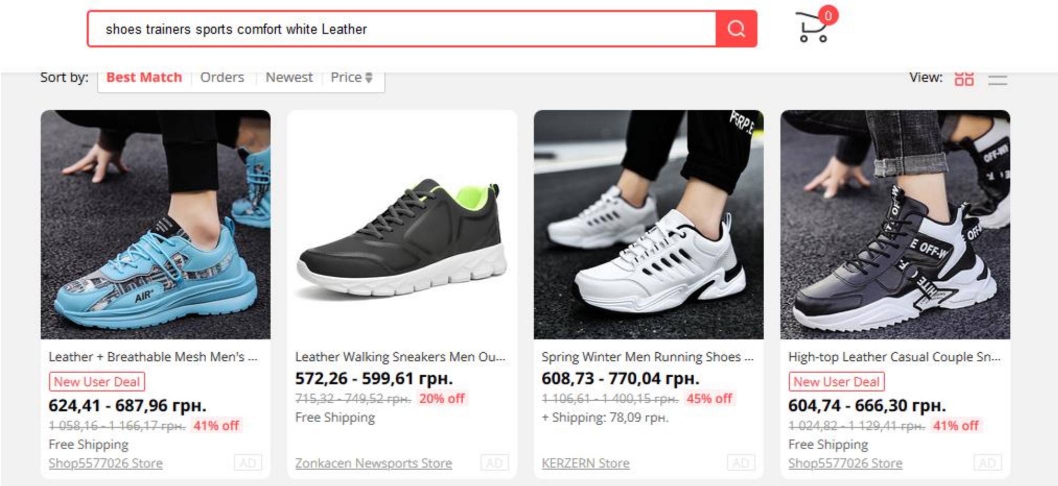

Figure 8: Some results of experiment #10

However, the best result is achieved in experiment #9 (set of core words - "shoes fitness trainers leather white comfort"): from 72 obtained items 33 items match our target item (Figures 9-10).

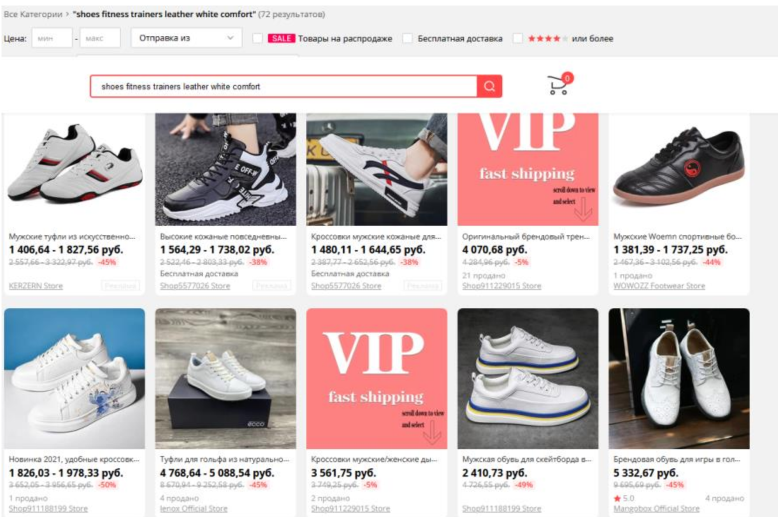

Figure 9: Some results of experiment #9

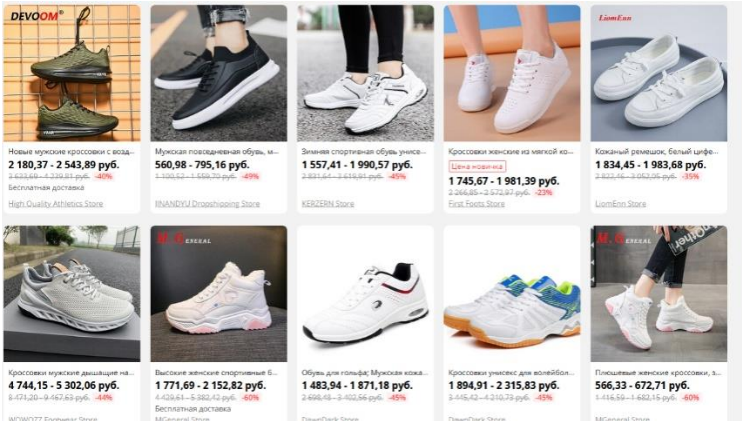

Figure 10: Some results of experiment #10

In these figures we can see photos of some items which are different from our target item, however, in some cases there are several models in different colour including white colour (Figure 11), in another cases there is word "white" in description (Figure 12). In other experiments and on other online platforms we face to parallel instances: there are several models in different colours; there is word "white" in description and it can be mistake or there is white colour in some detail of shoes.

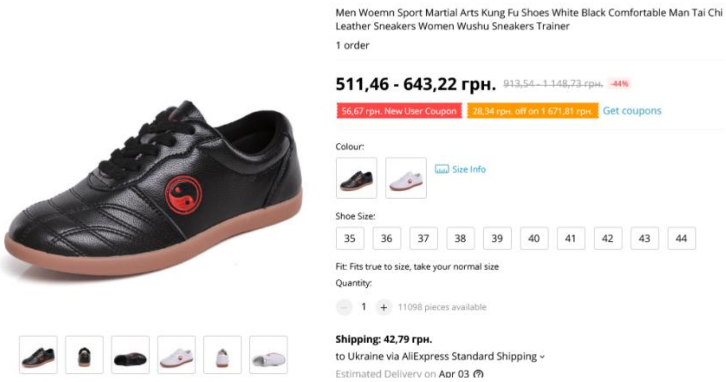

Figure 11: Experiment result (models in different colour including white colour)

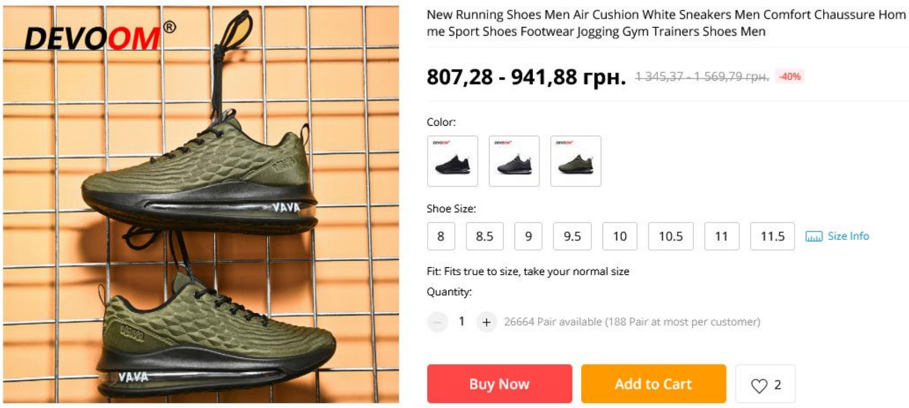

Figure 12: Experiment result (word "white" in description)

The results of searching on Amazon platform much better than on Aliexpress but in this case we face to searching noise. There are a lot of items which are not matched with our target item in each experiment on Amazon platform. We obtained the best result in the experiment #10 (set of core words - shoes trainers sports comfort white leather) and some results are depicted in Figure 13. We obtained 2 000 items: approximately 30% are matched to our goal item and unfortunately though there is a lot of noise in this result like in results of other experiments. Also such huge quantity of found items is not good result because our goal is making easy searching process for customers but when customers using core words obtain many items it will confuse them.

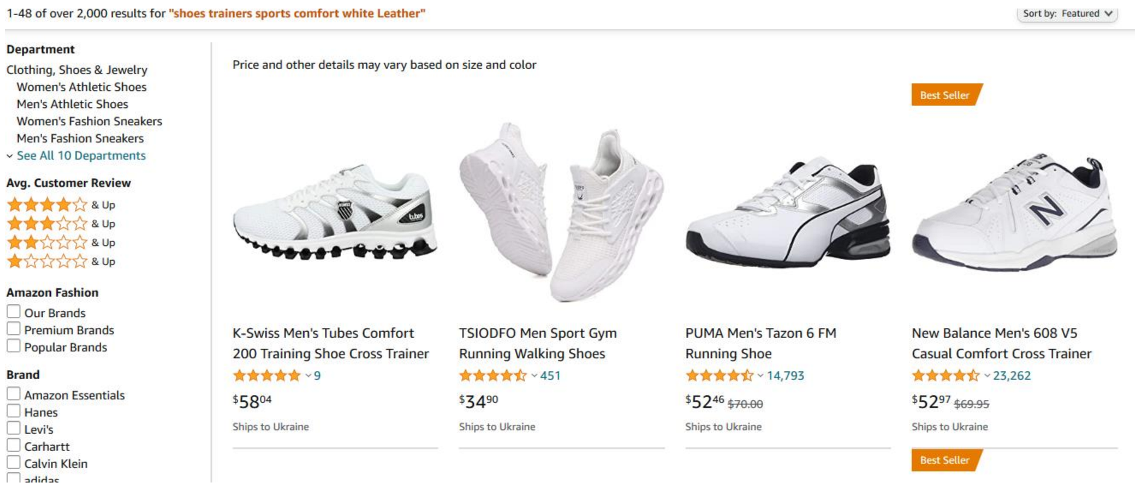

Figure 13: Experiment result on Aliexpress platform

Finally, experiments' results obtained on eBay are characterized by two features. The first one is our results are cleaned from different searching noise - we obtain only shoes using our core words. However, these items are not always matched with our target item. The second one is the bigger numbers of successful experiments in comparison with Amazon and Aliexpress. The best results we got in the experiment #4 (core words - leather white shoes fitness summer) and the experiment #10 (core words - shoes trainers sports comfort white leather). In these experiments, we obtained the bigger number of matched items; however, in the results of the experiment # 4we obtained 82731 items that reduces the value of this experiment. Some results of the experiments #4 and #10 are depicted in Figure 14.

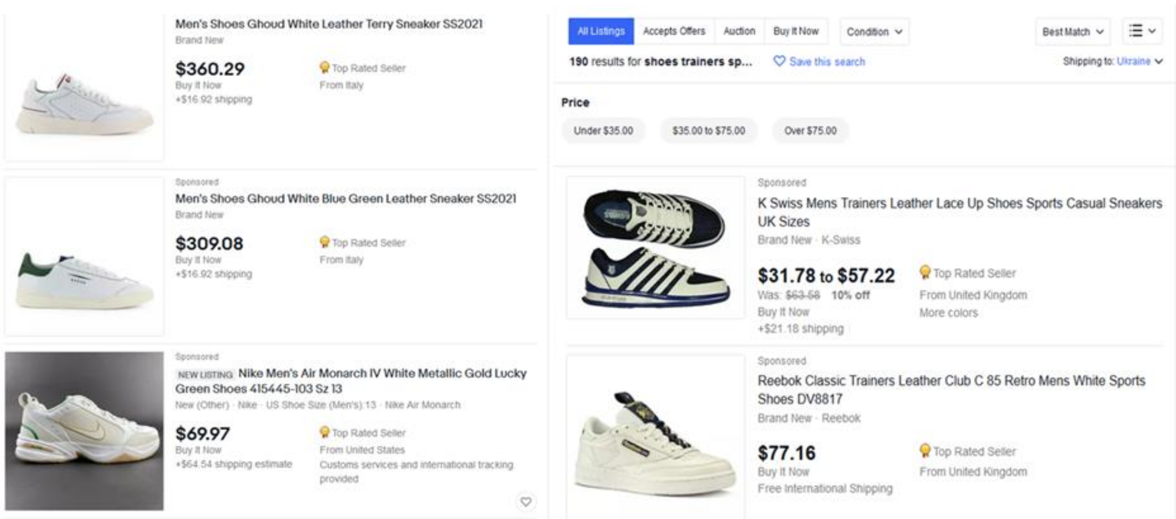

Figure 14: Some results of the experiments #4 and #10

Thus, we can tell that the best result we obtained using core words “shoes trainers sports comfort white leather”. The experiment results also have shown that products from the e-commerce platform can be found if the core of tags for a group is known. The successful results significantly depend on the e-commerce platform, where the core of tags was obtained.

5. Discussion and conclusion

E-Commerce has influenced significantly online product search. There are a lot of scientific works are devoted to simplifying the search for the desired product. Nevertheless, there is still a meaningful gap between the commodity that consumers want to acquire and the relevance of goods that are suggested in response to the search query. In order to define if two proposals relate to the same commodity some approaches suggest extracting a set of item attributes from the web pages and comparing these attributes using a matching function [18]. To discover eventually multiple products present in the response for the search query on e-commerce platform along with their relevant attributes, and leveraging the entire title and description text for this purpose the new idea researches are struggling.

A novel composition of sequence labeling and multi-task learning as an end-to-end trainable deep neural architecture is proposed [19]. For attribute extraction, researchers join together lexical, word embedding, and dictionary features to learn the attribute using joint extraction model. They use the supervised learning technique using CRF algorithm [20]. It is quite difficult to identify equal commodities on multiple e-commerce platforms because the description for a particular product can be different. The neural matching model is also widely used [21, 22] to combine product titles and attributes descriptions. The existing approaches for product searching and matching have some drawbacks: they include offers from a narrow range of trading platforms and thus do not appropriately cover the diversity that is found on the Web. They give a small number of common product attributes and cannot be used to assess if exact product attributes have been properly extracted from textual product descriptions.

Thus, we suggest using the agent approach, which allows developing a set of attributes, push the search query, receive the response, assess the item matching and its number, and vary the initial attribute values. The suggested model builds a search query by merging words from the core of tags, so we can obtain the relevant list of similar products and propose a reference item of the group. The experiments indicated that a group of similar commodities can be generated, but the successful results substantially depend on the e-commerce platform, where the core of tags was made.

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