

# Concept-based Chatbot for Interactive Query Refinement in Product Search

Elizaveta Goncharova<sup>1</sup>[0000-0001-8358-9647], Dmitry Ilvovsky<sup>1</sup>[0000-0002-5484-372X], and Boris Galitsky<sup>2</sup>[0000-0003-0670-8520]

<sup>1</sup> National Research University Higher School of Economics, Moscow, Russia  
{egoncharova, dilvovsky}@hse.ru  
<sup>2</sup> Oracle Inc., Redwood Shores, CA, USA  
boris.galitsky@oracle.com

**Abstract.** Nowadays, retrieval-based dialogue engines witness a significant interest in both industry and academic research. It is an important task to create an automated question-answering engine that may assist a user in the purchasing procedure. In this work, we describe a concept-based chatbot that utilizes a knowledge model to navigate a user to a subset of relevant objects. The knowledge model is built with pattern structures and organized to manipulate with both standard numerical and textual attributes describing the observed products. We provide an experimental evaluation of the introduced chatbot on the Flintkart e-commerce dataset and compare its performance with the faceted search approach.

**Keywords:** Query refinement · Information retrieval · FCA · Pattern structure.

## 1 Introduction

This paper describes ongoing research on creating an information retrieval (IR) chatbot that can assist customers in a search of suitable objects in the e-commerce database. IR chatbots have been an area of intense investigation [21, 24] in many spheres, from web search to electronic libraries. However, conventional search engines are still severely restricted. For example, when a user needs to refine his or her initial general request, a typical systems show either all attributes or the most frequently refined ones which results in the information overload problem and demands many choices to be made until the satisfactory result is found. Besides, such systems are not able to simultaneously operate with different types of data, such as numerical and textual ones.

We base our chatbot on utilizing the knowledge model constructed with the theory of Formal Concept Analysis (FCA) [22] and pattern structures (PS) [7] as its extension, therefore, further in the paper, we will refer to the chatbot as the concept-based one. The usage of the knowledge model allows a system to represent all the objects as hierarchically organized groups (concepts) and the description common for them. Thus, the chatbot can navigate a user through this model and following the specification or the generalization path, introduce only the relevant characteristics of a product.

This paper introduces the main aspects of the designed model, specifically, a method to combine the numerical and textual descriptions which are widely used to describe objects in the e-commerce datasets (Section 3). As for textual descriptions, we also

introduce a new way to define the generalization operation for two textual attributes that provide a better similarity assessment in comparison to the standard strict match of the keywords. We describe the bot architecture in Section 4. Finally, experimental evaluation of the introduced model on the e-commerce dataset is given in Section 5.

## 2 Related Work

The goal of IR is to find relevant objects that satisfy a user’s request and, probably, refine it during a search procedure. Nowadays, the most popular IR systems are based on deep learning (DL) techniques [23, 9, 20]. These models encode the information describing an object with the neural network forming the object embeddings and, then, find the closest vectors to a query embedding. In most cases, this approach is applied to the text data. Lately, there have been some works proposing the neural networks for tabular data as well [6]. Despite the popularity of these methods, they still suffer from insufficient data representation, as we need to represent both a short query that reflects only partial information about the desired object and the whole objects described by many attributes within a vector of the same length.

FCA can serve as a natural mathematical tool for the knowledge-based semantic IR systems with the ability to effectively sustain data as a set of robust and hierarchically connected groups of objects and shared attributes. Traditionally, the studies that apply FCA to IR consider retrieving information from the large collections of unstructured documents, which is reasonable due to the analogy between the binary object-attribute and document-term tables [14]. While the standard IR FCA-based methods have been applied to the binary data which introduce some restrictions for real-life applications [15], PS allowed this type of models to be extended to more complex data such as numbers, graphs, or texts [13, 18, 5].

We claim that introducing a concept model to the e-commerce chatbot is beneficial due to its ability to represent both the numerical and textual attributes of objects. Moreover, the hierarchical organization of similar object groups can help the chatbot to effectively refine insufficient users’ requests. However, first, we should define the rules for computing common descriptions for text attributes. Besides, due to the high computational requirements for building the concept lattice, we need to understand at which step of data exploration the concept model should be constructed.

## 3 Concept Model

A concept model is a principal part of the introduced IR chatbot as it is able to provide a convenient data representation that reflects the relations among the concepts, data, and entities. We build the model using PS, let us briefly recall its main definitions.

Formally, PS is defined as a triple  $(G, (D, \sqcap), \delta)$ , where  $G$  is a set of objects,  $(D, \sqcap)$  is a complete meet-semilattice of descriptions and  $\delta \rightarrow D$  is mapping of an object to its description. The Galois connection between the powerset of objects and the ordered set of descriptions is defined as follows  $A^\square = \sqcap_{g \in A} \delta(g)$ ,  $d^\square = \{g \in G | d \sqsubseteq \delta(g)\}$  for  $A \subseteq G$ , for  $d \in D$ . A pair  $(A, d)$  for which  $A^\square = d$  and  $d^\square = A$  is called a pattern concept.

A pattern concept is a pair, where the first element is a set of objects (called *pattern extent*) and the second element is the common description (called *pattern intent*) of the objects from the set. As in standard FCA, the sub-concept relation is given by the containment of extents. By defining the specific  $\sqcap$  for different types of attributes, we can apply PS to processing complex heterogeneous data. For the introduced chatbot we have two main types of attributes: the numerical and textual ones.

**Numerical Attributes** We start building the knowledge model by distinguishing a subset of homogeneous objects  $A_h \subseteq G$ , i.e., the set of objects described by the high rate of similar attributes and construct PS. A semilattice operation  $\sqcap$  is defined attribute-wise. The values of numerical attributes are given by intervals. Let  $v_1, v_2 \subseteq R$  be the values of a numerical attribute for two different products. Then,  $[v_1, v_1]$  and  $[v_2, v_2]$  are their interval representations. The meet of these intervals is defined as  $[v_1, v_1] \sqcap [v_2, v_2] = [\min(v_1, v_2), \max(v_1, v_2)]$ . For nominal attributes, the operation  $\sqcap$  is defined as  $x \sqcap y = x$  if  $x = y$  and  $x \sqcap y = *$  otherwise, where  $*$  means “any value”. The navigation model is constructed in the form of *pattern concept lattice* that the chatbot can traverse during communication with a user. The example of this model for the numerical attributes can be found in [github](#)<sup>3</sup>.

**input** :  $\tau\{a_{1t_1}\}, \tau\{a_{2t_1}\}$  — textual descriptions (a set of key words) of  $t_1$  attribute for two objects  $a_1$  and  $a_2$ .

**output**:  $\tau(\{a_{1t_1}\}, \{a_{2t_1}\})$  — a common description of  $t_1$  attribute for two objects  $a_1$  and  $a_2$ .

```

1 foreach key term  $kt_{a_1}$  of the key terms set  $\tau(\{a_{1t_1}\})$  do
2   foreach key term  $kt_{a_2}$  of the key terms set  $\tau(\{a_{2t_1}\})$  do
3     if  $kt_{a_1} == kt_{a_2}$  then
4        $\tau(\{a_{1t_1}\}, \{a_{2t_1}\}).add(kt_{a_1})$ ;
5     else
6       if  $similarity(emb(kt_{a_1}), emb(kt_{a_2})) > threshold$  then
7          $\tau(\{a_{1t_1}\}, \{a_{2t_1}\}).add(kt_{a_1})$ ;
8       end
9     end
10  end
11 end
12 return  $\tau(\{a_{1t_1}\}, \{a_{2t_1}\})$ ;

```

**Algorithm 1:** Computing the intersection of two textual attributes

**Textual Attributes** To process text data we, first, need to define its description, in our case we use simple keywords. Their usage is motivated by the specificity of the data we analyze. Textual attributes in e-commerce datasets are usually defined by a phrase or a sentence. Therefore, it is not necessary to utilize more complex descriptors,

<sup>3</sup> <https://github.com/lizagonch/Chatbot.git>

such as parse trees [19] or parse thickets [4] for such small texts. To calculate common description for two textual attributes (represented as the set of keywords), we define the  $\square$  operation as either a strict match between the keywords or by finding the synonyms in these keywords sets. The synonymity is assessed via pre-trained word embeddings (word2Vec [16] in our case). The algorithm 1 presents the procedure to calculate the intersection for two textual attribute descriptions.

## 4 Chatbot Overview

The idea of the introduced model is as follows, a user starts a search with an imprecise request, the search engine interactively refines a user’s request by moving him or her down or up the lattice (concept model). The concept lattice is built using Close-By-One algorithm [1]. The overall system architecture is shown in Figure 1. At each turn of the dialogue, the user’s utterance written in natural language goes through the NLP pipeline where sentence pre-processing is performed. This module is also responsible for identifying numerical attributes a user wants to refine and textual restrictions imposed on the product. Thus, at the output, we get the user’s query description  $d_q$ . Let us consider each component in more detail.

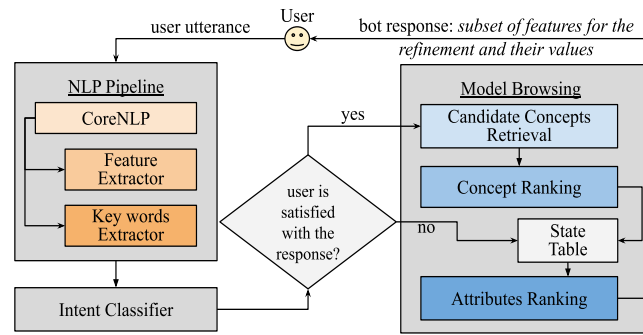


Fig. 1. System architecture

### 4.1 NLP Pipeline

We use Stanford CoreNLP toolkit [12] to perform sentence splitting, tokenization, and lemmatization. Then, the system reveals the restrictions on the numerical attributes. This part is performed with a predefined set of rules that determine attributes names and the values required by the user. Having retrieved these restrictions, we run the keyBERT model to return the set of keywords representing the user’s request.

### 4.2 Intent Classifier

The proposed IR bot operates using the compiled hierarchical lattice-based knowledge model. It means that the system can navigate a user up (in case of generalization intent),

or down (refinement intent) the lattice. If a user wants to change the direction of a search, the bot should navigate him or her to another candidate concept at the same level of the concept lattice, where the level is the shortest way from the root concept to the current one. If a user clarifies some features proposed by the chatbot, then the chatbot moves in the right direction. Otherwise, asking to return on the previous step corresponds to generalization intent. We use manually constructed regular expressions to recognize the navigational intent.

### 4.3 Search Procedure

After identification of the intent, the system navigates a user through the knowledge model. Based on the user’s intent, the bot provides various procedures to query processing. (i) If the user wants to *refine* his current position, the bot finds all most specific concepts that satisfy an input query description and updates the *State Table* with new candidate concepts. (ii) In the case of *update* intent the bot returns the user to the parent concept of the current  $(A_i, d_i)$  concept. (iii) *Change of interest* makes the bot return to the stack of promising concepts (*State Table*) and moves to the next candidate concept.

All candidate concepts in the *State Table* are ranked based on the stability measure [2, 8, 11], and each feature in the concept intent is assessed with respect to its diversity. The most stable concepts are introduced to the user first, whereas the most variable characteristics are proposed to the user for further refinement.

## 5 Experiments

We present the preliminary experiments to compare the concept-based chatbot performance with the faceted search<sup>4</sup> technique which is a standard approach for e-commerce IR. The experiments are performed on the publicly available Flipkart dataset<sup>5</sup> that contains information about more than 40000 objects from the e-commerce website. To compare the chatbot with the faceted search, which is not able to process textual data, we have retrieved 100 objects belonging to the category ‘*Computers – Laptops*’ described only by the numerical attributes. To measure the effectiveness of the proposed  $\square$  operation for textual attributes we use the same concept-based bot, but define the generalization operation as the strict match of the keywords corresponding to the textual attributes. For this experiment, we have retrieved 300 objects belonging to the ‘*Clothing – Jeans*’ category. The motivation for choosing these small datasets is that both the faceted search and the IR-chatbot should be launched after a user found the specific category of products that he or she is interested in that usually include up to 500 objects.

To assess the model performance we calculate the average number of iterations (**IN**) a user needs to achieve a satisfactory result. The lower this number is the faster a user finds relevant objects. Average Precision (**AP**) measures how many times during the dialogue a user had a *refinement* navigational intent. We also evaluate the number of cases where a user was not satisfied with the response of the bot and asked it to move in another direction (Unsatisfactory Rate (**UR**)).

<sup>4</sup> <https://apex.oracle.com/en/>

<sup>5</sup> <https://data.world/promptcloud/product-details-on-flipkart-com>

So far, we have not conducted the conversation of the bot with real customers, thus, in a preliminary experiment, we generated 60 random scenarios of possible users’ requests. The scenario takes the form of a few relevant features and a range of their values that the user should sequentially introduce to the system. Table 1 presents the results of the experimental evaluation.

**Table 1.** Comparison of the knowledge-based search with the faceted search.

Model	Laptops ( <i>only numerical attributes</i> )			Jeans (+ <i>textual attributes</i> )		
	AP	UR	IN	AP	UR	IN
Concept-based bot	0.7	0.24	5.6	0.72	0.14	6.6
Faceted search	—	0.31	6.2	—	—	—
Concept-based bot ( <i>key words-strict match</i> )	—	—	—	0.68	0.25	8.6

**AP** and **UR** metrics indicate the ability of the bot to rank the promising pattern concepts and retrieve relevant features for refinement. The obtained results show that in nearly 70% of cases attributes introduced by the chatbot were assessed as significant. While, in almost 25% of cases in the “*Laptops*” category, a user had *change of direction intent*. The main metric evaluating the effectiveness of the search engine is the average number of dialogue turns (or clicks for the faceted search) that a user performed to find the set of items that are needed. In our experiments, this metric is in favor of the chatbot, 5.6 versus 6.2 respectively. For textual data processing, the approach that applies embeddings techniques to  $\square$  operation improves the performance of the model and makes a search procedure more precise (6.6 versus 8.6 dialogue turns).

## 6 Conclusion

In this paper, we have introduced an IR chatbot that utilizes the concept-based knowledge model to help users in finding a particular item in the e-commerce database. In comparison to a standard search engine, this system can operate with both structured data and textual descriptions that can also be obtained from any external resource.

We have compared the performance of the proposed model with that of the faceted search using the small product database retrieved from the online store. In this work in progress, we have not yet compared the performance of the model with the current state-of-the-art IR systems and other promising query enrichment FCA-based techniques [10, 17, 3], however, the obtained results based on the artificially generated scenarios of user-machine interaction has shown that the number of steps required by the proposed model is less than the one required by faceted browsing. In the future, we plan to add more functionality to the model, such as more advanced processing of textual information (e.g., a pre-defined set of syntactic patterns could be exchanged by the DL conversational engine) and more intelligent search of relevant attributes that should be introduced to the user. This can be achieved by encapsulating the history of users’ purchases.

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