KnowBots: Discovering Relevant Patterns in Chatbot Dialogues

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Abstract. Chatbots have been used in business contexts as a new way of communicating with customers. They use natural language to interact with the customers, whether while offering products and services, or in the support of a specific task. In this context, an important and challenging task is to assess the effectiveness of the machine-to-human interaction, according to business' goals. Although several analytic tools have been proposed to analyze the user interactions with chatbot systems, to the best of our knowledge they do not consider user-defined criteria, focusing on metrics of engagement and retention of the system as a whole. For this reason, we propose the KnowBots tool, which can be used to discover relevant patterns in the dialogues of chatbots, by considering specific business goals. Given the non-trivial structure of dialogues and the possibly large number of conversational records, we combined sequential pattern mining and subgroup discovery techniques to identify patterns of usage. Moreover, a friendly user-interface was developed to present the results and to allow their detailed analysis. Thus, it may serve as an alternative decision support tool for business or any entity that makes use of this type of interactions with their clients.

Keywords: Chatbot analytics · Chatbot analysis · Logs analysis · Sequence mining · Subgroup discovery

1 Introduction

Chatbots have been used in a variety of contexts by providing a natural language interface with an increasingly sophisticated design [14]. Their use in business contexts, as a way of communicating with customers, is becoming more common nowadays [15]. They have been used to address several tasks, like assistance in banking [1], customer service [3], educational tutoring [11,13], language learning [9] and online sales [10], to name a few.

Regarding the development of chatbot systems, the analytics dimension aims to monitor chatbot usage [13]. Developers can create their custom control-panel

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or use a generic analytic tool that tracks the users' interactions and get metrics of them. Thus, analytics tools are valuable instruments for assessing the quality of the chatbot system and, ultimately, users' behavior.

Although many chatbot analytics tools have been developed, they focus on metrics of engagement and retention of the system as a whole. Their use can help chatbot maintainers to understand the behavior of users as well as to discover bottlenecks in the system. However, they cannot be used to explore behaviors in terms of goals, business criteria and unusual patterns, which are the aim of the KnowBots tool.

A category of chatbot systems uses rules to guide the conversation flow. Thus, business criteria can be defined in terms of reaching specific goals described by particular rule(s), whereas unusual patterns are characterized by usage patterns that deviate from the others regarding the attainment of business goals. It is performed by combining sequential pattern mining [6] and subgroup discovery [8] techniques. The former identifies the frequent subsequences and the latter filters the most relevant of them by a quality measure, which is defined according to business' interests. KnowBots also has a friendly user-interface to present the results and to allow their detailed analysis.

The KnowBots is the main contribution of this paper. To the best of our knowledge, the analytics dimension of the chatbots have not been explored scientifically, which is justified for the lack of references on this matter. On the other hand, many commercial tools are available to support the analysis of the chatbot interactions. They explore concepts from data mining, machine learning and information visualization domains.

The remaining sections of the paper are organized as follows: Sect. 2 formally defines the main concepts used in this work. Section 3 summarizes the main analytics tool available currently. Section 4 details the KnowBots tools, presenting their architecture and main features. Section 5 presents the exploratory analysis conducted, describing and discussing the obtained results. The paper ends with Sect. 6, that summarizes the relevant findings and future work directions.

2 Background

This section briefly presents the concepts that this study is based on. It covers chatbot systems, sequential pattern mining and subgroup discovery.

2.1 Chatbot System

Chatbot systems are computer programs designed to use natural language to interact with users, simulating a human conversation [15]. With the popularization of instant messages services and smartphones, chatbot systems started to be explored together with them [13]. Thereby, chatbot has received a lot of attention as a research topic, given the growing number of scientific publications about the subject. Also, it has been used as a business solution, whether in the prospection of new customers [2,10], in the service of these [1,3] or as internal services for employees [16,17].

A chatbot system can be designed using programed script and/or Natural Language Processing (NLP) approach [13]. The former follows a rule-based paradigm, thus it has a limited conversational scope. The latter uses artificial intelligence concepts to simulate a human-based behavior, which supposedly covers a broad conversational scope.

The KnowBots supports the analysis of the rule-based chatbot interaction, which can be defined as a set of state machines. For this work's purpose, a chatbot system is a triple $(S,\ r_1,\ \delta)$ where $S = \{r_1,\ \ldots,\ r_n\}$ is a set of n rules r_i; r_1 is the starting point of the chat; and, $\delta = \{(r_1,\ r_2),\ \ldots,\ (r_i, r_j) \mid r_i, r_j \in S\}$ is a set of connected pairs of rules, which define the paths of conversation. Figure 1 illustrates the representation of a simple chatbot rules, they define the input, output and decision points. In this example, $S = \{r_1, \ldots, r_9\}$ and $\delta = \{(r_1, r_2),$ $(r_2, r_3),\ (r_3, r_4),\ (r_4, r_5),\ (r_5, r_6),\ (r_5, r_8),\ (r_6, r_7),\ (r_8, r_9),\ (r_9, r_7)\}$. Business' goals may be defined by the nodes r_3, r_4 and r_9, for instance.

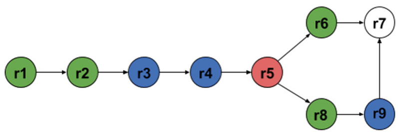

Fig. 1. Illustrative representation of chatbot rules.

2.2 Sequential Pattern Mining

Sequential pattern mining is a data mining field that aims to analyze frequent subsequences in a database of sequences [12]. A sequence $\alpha = \langle \alpha_1 \rightarrow \alpha_2 \ldots \rightarrow \alpha_q \rangle$ is an ordered set of events, where each event α_i is a non-empty and non-sorted collection of items $(i_1,\ \ldots,\ i_d)$. A subsequence of α is a sequence $\beta = \langle \beta_1 \rightarrow \beta_2 \ldots \rightarrow \beta_k \rangle$, such that there are integers $i_1 < i_2 < \ldots < i_k$ in which $\beta_1 \subseteq \alpha_{i_1}, \beta_2 \subseteq \alpha_{i_2}, \ldots, \beta_k \subseteq \alpha_{i_k}$. A subsequence observed repeatedly in the set of sequences with a minimum support threshold is a frequent subsequence, here named pattern.

The representation of a chatbot session, a conversation between a user and the bot, can be defined in terms of the rules triggered during the chat. Without loss of generality, an event is a single rule $\alpha_i \in S$ and a sequence is a chain of rules. For instance, $\alpha = \langle r_1 \rightarrow r_2 \rightarrow r_3 \rightarrow r_4 \rangle$ is a valid sequence for the chatbot system that uses the rules defined in Fig. 1. In this case, the user left the conversation without completing the interaction with the bot, considering that the rule r_7 defines the endpoint of the system.

Over the years, many sequential pattern mining algorithms have been developed. They produce the same outputs but differ in terms of search strategy and data representation, which impact their computational performance [5]. Thus, we arbitrarily choose the CM-SPAN algorithm [6] that is able to customize the minimum and maximum length of the subsequences; mandatory items; and, the size limit of the gap between events.

2.3 Subgroup Discovery

Subgroup discovery algorithms extract interesting relationships between objects considering a particular property or variable [8]. Patterns represent subgroups of the population that have some characteristics in common but differ from the rest when the distribution of a target of interest is observed [4].

For such, it uses quality measures to extract and evaluate the patterns. They can capture the complexity, generality, precision and interest of the subgroups [8]. Specific quality measures can be used to explore particular characteristics of the task, like the chatbot sequences associated with the business criteria, for instance. In this context, business criteria can be defined in terms of the achievement of some rules during the conversation. For instance, hypothetically assuming that in Fig. 1 the rule r_9 collects the user's e-mail. By achieving this rule during the conversation, a user meets a business goal.

When the set of rules is complex enough to have many paths of conversation, some paths can be more deterministic to the achievement of the goal than others. An uncommon pattern is a set of events (in this case, a conversation path), whose probability of achieving the goals is notably distinct from the other patterns. Given that, the users' answers determine the path of conversation and the chatbot design may influence the answers, the uncommon patterns are valuable information to the development team. The uncommon patterns can reveal users' behaviors that were not expected when the system was developed, for instance.

3 Chatbot Analytic Tools

The scientific literature concerning chatbot analytics is still incipient. A systematic research was conducted using four academic digital libraries: ACM Digital Library, IEEE Explore, Science Direct and Scopus; the query was constructed using the keywords: *chatbot + analytics*, *chatbot + "log analysis"*, *chatbot + "log visualization"*; only a few and unrelated studies were obtained.

On the other hand, there are commercial tools that provide support for the analysis of chatbots dialogues. Table 1 presents such tools and summarizes their main features. The features include the ability to reproduce past dialogues (C); a dashboard with usage metrics (D); analysis of the flow and dropout (FD); text analysis with natural language processing (NLP); sentiment analysis (SA); and, filtering and query functionalities (Q).

The most common feature is the conversation, which is present in all tools, followed by the dashboard. The flow/dropout and query features are present in three of them. In specific, only the *Chatbase* and *Dashbot* tools use NLP to identify the users' "intent" in the dialogues. Also, only *Dashbot* and *Jani* are able to map the input dialogues in sentiments, offering a qualitative and sensitive information for developers and maintainers.

From the features presented in Table 1, the KnowBots support only the FD analysis. However, by exploring the concept of uncommon pattern for a given user-criteria, it explores a new paradigm when compared with the other analytic tools.

Table 1. List of chatbot analytics tools

Name	Main features	URL
BotAnalytics	C-D-FD-Q	http://botanalytics.co
Botlytics	C-Q	http://www.botlytics.co
BotMetrics	C-D	http://bot-metrics.com
Chatbase	C-D-FD-NLP	http://chatbase.com
Dashbot	C-D-FD-NLP-SA-Q	http://www.dashbot.io
Janis	C-D-SA	http://www.janis.ai

Features: C - Conversation; D - Dashboard; FD - Flow/Dropout; NLP - Natural Language Processing; SA - Sentiment Analysis; Q - Query.

4 KnowBots

KnowBots provides an easy analysis of the usage logs given user-defined criteria. It allows a simple identification of patterns in conversations that increase or decrease the likelihood of achieving specific goals. Thereby, allowing chatbot maintainers to make decisions about the chatbots rules and oversee the resulting effects.

4.1 System Architecture

KnowBots is composed of two components: a batch system and a web interface. The former finds frequent patterns and sorts them by a score of relevance, according to user-defined criteria. The latter presents the results with an interactive user interface to handle the findings. Figure 2 illustrates KnowBots pipeline.

The batch system can be triggered interactively or in a background mode. With regards to the chatbot system, currently only rule-based technologies are supported, however, using the concept of intent and NLP algorithms, the KnowBots can be extended to support other types of chatbot systems.

As the KnowBots is a standalone application, it does not require a web server or additional environment customization. However, the web module is only a layer of presentation, which restricts the possibilities of interaction with the user. In future versions, by integrating the tool with a web server, it can be extended with new features like supporting multiple chatbot versions simultaneously, dashboards, query and filters dynamically. Nevertheless, we emphasize that the innovative aspect of the KnowBots tool is the discovery of uncommon patterns considering business criteria.

Next subsections detail both components: the batch system and the web interface.

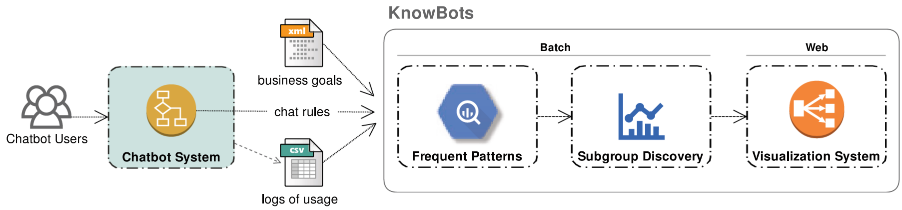

Fig. 2. KnowBots pipeline.

4.2 Batch System

The batch system receives three input files: a JSON containing the chatbot rules; an XML describing the business goals; and, a CSV containing the usage logs.

The chat rules consist of a directed graph, where the nodes are the interactions and the edges represent the possible paths of the conversation, as presented in Fig. 1. It is defined in a JSON file containing the following structure:

```
{
  "id": "Chatbot example"
  "version" : 1,
  "rules" : [
  {
    "id": "r1",
    "title": "Hello",
    "type": "display",
    "next": [ "r2" ]
  },
  ...
  {
    "id": "r5",
    "type": "decision",
    "next": [ "r6", "r8" ]
  },
  ...]
}
```

A goal can be defined by specific nodes, thus when a user reaches them during a conversation, the respective goal is achieved. Multiple goals can be defined, and each one of them may be associated with a single or multiple nodes. The following structure is used to define the goals:

```xml
<?xml version="1.0" encoding="UTF-8"?>
<goals>
  <goal>
  <id>Email</id>
  <title>User provides an email</title>
  <rules>
    <rule>r9</rule>
  </rules>
  </goal>
  ...
</goals>
```

The usage logs are the collected dialogues of the users with the chatbot system. Unlike the other systems, KnowBots does not use the dialogue content, but the path followed during a conversation. The CSV file with the usage log contains the following columns:

Session: A session identifier. A session begins when a user enters in the chatbot system and ends when the user leaves the chat.
Timestamp: Date and time the event occurred.
Chat_version: The version of the chatbot system.
From: The previous rule identifier.
To: The current rule identifier.

To identify the most frequent patterns, the CM-SPAM algorithm [6] provided by the SPMF tool [7] is used. The usage logs are mapped as sequences of items, as described in Subsect. 2.2. We set the size of the subsequences between 2 and 3, and discarded all the frequent patterns that do not have a decision node as part of the subsequence. It will result in patterns that are the smallest possible, containing a fork, which represents users' decision. Such decisions were taken to reduce the number of patterns found by the CM-SPAM, however other hyperparameters' values could be used instead.

The KnowBots tool uses a quality measure to compute a score of interest for each frequent subsequence identified in the previous step. This approach can capture the users' behavior patterns that deviate from the norm, considering the use of a particular chatbot system and the business criteria. The main advantage of using subgroup discovery is that one can score the sequence patterns based on how unusual the patterns are in terms of a particular target (the goal). As the final result, one should expect to obtain unusual (yet interesting) behaviors from the given usage logs of users. The unusualness is both in terms of increasing the chance of reaching the goal and decreasing it.

Let $p(A)$ be the probability of the users to go through the rule A; $p(A \mid B)$ be the conditional probability of the users to go through the rule A given that they went through the rule B; r_* be the rule of interest in terms of business goals; $\alpha = \langle \alpha_1 \rightarrow \alpha_2 \ldots \rightarrow \alpha_k \rangle$ be a frequent subsequence, where $\alpha_i \in S$ and α_1 is the event of the pattern. The quality measure is defined according to Eq. 1:

$$QM = |c_1| * c_2 * p(\alpha), \tag{1}$$

where $c_1 = p(r_* \mid \alpha) - p(r_* \mid \alpha_1)$ indicates the improvement (or reduction) that following the pattern represent to achieve the goal, and $c_2 = p(\alpha_1 \mid r_*) - p(\alpha \mid r_*)$ captures how unusual the pattern is for the goal. The third criteria is the support of the pattern.

It is worth highlighting that this framework is extensible concerning the frequent patterns and the subgroup discovery steps. In the former, the patterns could explore other kinds of user-information such as gender, geographic region, operational system and web browser, for instance. In the latter, different quality measures could be used, focusing on distinct characteristics of the chatbot rules.

4.3 User Interface

The web interface works as a presentation layer of the results previously computed. By using interactive resources, the chatbot maintainer can explore the relevant patterns as illustrated in Fig. 3. The circle indicates the pattern, while the triangle indicates the node related to the business goal. Text templates and probabilities are used to describe the reasons why each pattern is relevant as illustrated in the *Pattern detail* window.

The tool also has an interface for the analysis of the flow/dropout. It uses a scale of colors to indicate the main paths and the critical dropout points. Additionally, it is possible to visualize the number of session conversations that achieved the goal by going through a specific point.

5 Exploratory Analysis

We illustrate the potential of KnowBots by analyzing the usage logs of a real-world chatbot system that provides advice on technical courses for unemployed people. The chat has 87 rule nodes, where 32 of them are decision ones. A single business goal is considered: *"user provides email address"*, which is obtained at the end of the dialogue. The shortest path of conversation to reach this goal will go through 8 decision points, whereas the longest would have more than 15 of them.

After the summarization of the obtained results, a discussion about them including the strengths and limitations of the tool is conducted.

5.1 Results

Overall, 24 relevant patterns were identified from the 3266 sessions analyzed. Table 2 presents the top 10 of them. The column *Rules* contains the rules id; columns *c1*, *c2* and *Support* are the components defined in Eq. 1; the quality measure result is presented in column *QM*. Particularly in c1 column, the bold values highlight the negative scores, which indicate patterns that decreased the probability of achieving the goal.

The first pattern is illustrated in Fig. 3. It says: *"users who did not provide their home address rightly showed a lower probability in providing their e-mail*

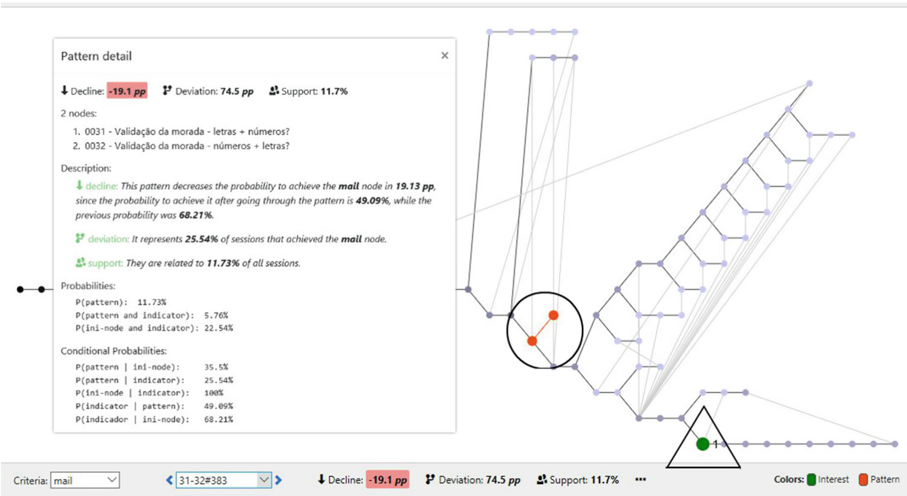

Fig. 3. KnowBots interface with details of a relevant pattern.

Table 2. Top 10 relevant patterns identified for the KnowBots tool.

Ranking	Rules	c1 (pp.)	c2 (pp.)	Support (%)	QM
1	31-32	**−19.1**	74.5	11.7	0.1665
2	74-75	**−26.9**	88.0	4.6	0.1089
3	29-30	**−48.1**	98.2	2.1	0.0992
4	35-36-48	14.6	87.8	3.0	0.0385
5	74-77-78	14.0	13.0	19.6	0.0357
6	38-39-50	12.2	69.4	3.5	0.0296
7	44-45-46	**−23.8**	22.7	4.3	0.0232
8	39-40-47	18.9	70.4	1.5	0.0200
9	41-42-61	15.7	46.7	2.7	0.0198
10	29-31-35	8.9	7.5	27.3	0.0182

than the ones who did". Precisely, the probability of users to give their email decreases in 19.13 pp. when they did not provide their home address correctly. It represents 25.54% of sessions that achieved the goal and it was observed in 11.73% of the sessions. Using this information, the chatbot maintainers can explore alternatives such as the relaxation of the validation rules and/or change the order of the dialogues, for instance.

Some obvious patterns were also found, which helped the validation of the tool and increased the confidence in the results. For instance, before asking for the email, the bot asks if the user desires to receive a newsletter about new courses. It is reasonable to assume that the users who answer "no" for the newsletter would be more resistant in providing their email in the next step (second pattern in Table 2). The probability of providing the email decreased in almost 27 pp. for those who answered "no" to the newsletter. In this case, the KnowBots quantified the impact of this problem making it measurable.

In summary, 4 out of 10 patterns indicate that attaining them reduces the probability to achieve the goal. They may represent possible issues in the chatbot design. The other 6 patterns indicate that the probability of achieving the goal is increased by following them. A positive example is the 4^{th} pattern, it is related to 3% of the sessions and increases the probability to achieve the goal in almost 15 pp. when compared with other alternatives. Only users with a background in business domain follow this path, however the main hypothesis to explain it is the order in which the different domains are presented to the user. The fact that it is the first option among several domains may be a relevant factor to the observed users' behavior. Alternatively, different versions could use different sequences to compare the alternatives.

In practice, the analysis of these patterns brought new insights to the developers as well as a better understanding of users' behavior. The other feature available in the KnowBots tool is the flow/dropout analysis. Using it, we realized that 7 rules were not achieved by any of the sessions. They are related to the validation of the zip code address and they are close to the first fork in the path of conversation. Furthermore, iteratively the dropout was analyzed and the following results were observed: 2 rules are related to more than 20% of the sessions' dropout; 7 rules are related to more than 5%; and, 16 rules are related to at least 1%. Some of these rules validate the users' input, which shows that when the bot asks for the same input repeatedly, the users leave the conversation.

5.2 Discussion

In this exploratory analysis, the KnowBots was able to identify interesting patterns concerning the business goal investigated. Some results were not expected for the chatbot developers, whereas others were quantified using objective criteria. The analysis of the identified patterns can be used to guide the investigation of the chatbot system, mainly when business goals are taking into account.

The use of language templates to describe the patterns simplified the understanding of the metrics according to the business stakeholders. In comparison with the other tools, they have not employed natural language to present results. Although we did not perform a usability test with the KnowBots users, they were able to use the tool and perform the proposed tasks easily.

Regarding the patterns, other characteristics could be employed to represent the sequences. In addition to the rules, each event can describe details of the user context like operational system and browser; temporal information like the day of week and period of the day; and also, personal information like gender and age, for instance. Such features would increase qualitatively the pattern analysis. Even though they were not used in this study, due to the lack of such information in the available transactional records, the CM-SPAM algorithm supports intrinsically the use of this data. We plan to explore this feature in further studies.

Analogously, the quality measure could also be modified to capture other perspectives of the problem. For instance, the criteria c_2 and the support (Eq. 1) are inversely proportional, such that while one increases, the other decreases, and vice-versa. In practice, they are important because the user can choose not to provide the email. In other scenarios, only one of these criteria could be employed, for instance.

In summary, the proposed approach showed to be able to detect possible chatbot problems. The KnowBots is the result of a real-world demand, given the lack of tools that are able to support business criteria in the usage log analysis. To the best of our knowledge, it is the first chatbot analytics tool to address this problem.

6 Conclusion

This work presented the KnowBots, a tool for mining and visualization of chatbot usage logs analysis. It finds unusual and relevant patterns by combining sequence mining and subgroup discovery techniques. Specifically, the tool provides useful information concerning users behavior in terms of business goals. It is a descriptive machine learning task that aims to minimize the efforts of chatbot maintainers in the analysis of the chatbot systems.

Despite the rapid growth of chatbot-related technologies, the investigation of analytics tools is still subtly addressed in the literature. In further studies, we plan to explore new attributes in the sequences like temporal data, profile information and user context. Additionally, by supporting multiple versions of the same chatbot system, the KnowBots can be a validation and decision-support tool.

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