Have a Chat with Clustine, Conversational Engine to Query Large Tables

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ABSTRACT

Thanks the recent advances of AI and the stellar popularity of messaging apps (e.g., WhatsApp), chatbots are no longer bound to customer support services and computer museums. Indeed, they provide a mighty, lightweight and accessible way to provide services over the Internet. In this paper, we introduce Clustine, a chatbot to help users query large tables through short messages. The main idea is to combine cluster analysis and text generation to compress query results, describe them with natural language and make recommendations. We present the architecture of our system, demonstrate it with two use cases, and present early validation experiments with 12 real datasets to show that its promises are reachable.

1. INTRODUCTION

According to the Economist, over 2.5 billion people have access to a messaging app such as Facebook Messenger or WhatsApp. This number could reach 3.6 billion within couple of years - half of humanity [1]. As a result, many Internet firms have sought to expand their services to this medium. In most cases, they have done so with *chatbots*, also called *conversational engines*. Recent examples include Facebook's M and Microsoft's Tay. Dozens of smaller businesses have also developed task-specific alternatives, for instance to access bank services, book flights or schedule meetings. In fact, the so-called bot economy has grown so quickly that well-established firms such as Facebook and Russia's Telegram are now dedicating entire marketplaces places to it.

And indeed, chatbots have a number of advantages compared to traditional applications. They rely on natural language, which implies a short - ideally nonexistent - learning phase. Since they live in the user's messaging app, they are lightweight. They require no client installation and no maintenance. Finally, we can easily translate their output to audio thanks with to Text-to-Speech software, an important option for visually impaired users.

HILDA'16, June 26 2016, San Francisco, CA, USA

ISBN 978-1-4503-4207-0/16/06...$15.00

DOI: http://dx.doi.org/10.1145/2939502.2939504

In this paper, we discuss how to engineer a chatbot to help users query large tables. More specifically, we focus on the interface between users and the system. How should the users write their queries? And how should the system answer? Our aim is to develop accessible and efficient techniques to interrogate databases through messaging apps. The challenges we face are twofold. First, our medium imposes draconian restrictions on the quantity of information that we can convey. Users expect short messages, and the support for visuals is close to null - we can send a few pictures at most. Furthermore, we target a casual population, that is, users with a weak knowledge of the database and no programming skills. Typically, we envision distracted managers or hobbyists playing with their mobile phones. In this scenario, SQL is not an option.

Researchers have proposed natural language interfaces to query databases for at least two decades [4, 11]. But those solutions only solve half of the problem. They help users write queries, but they do not help them understand their results. They return tables of data, as traditional database front-ends do. But tables are neither user-friendly nor space efficient. They can quickly saturate screens and overwhelm users - especially on smartphones.

Another shortcoming of natural language interfaces is that they assume that users know what they want, and they know where to find it. But in many cases, the users' requirements are too subjective or fuzzy to be easily cast as a query. For instance, how could we identify the "young customers" in a marketing database or the "happy countries" is a world survey? Ideally, the system should provide guidance. A few interfaces already offer this feature [11], but they focus on the database schema (e.g., which columns and tables to use), not on the parameters of the query.

This paper introduces Clustine, our prototype conversational agent. Clustine offers *bi-directional* support for natural language: it collects queries, but also summarizes their results in plain English - a research direction which has so far received little attention in the literature. Clustine is also *proactive*. Instead of collecting queries passively, it makes suggestions, collects feedback and reacts accordingly.

We summarize our contributions as follows:

- We introduce Clustine, a prototype chatbot based on cluster analysis and interactive query refinement.
- We present an algorithm to describe query results in a compact and informative fashion.
- We showcase Clustine with two scenarios, and validate its suggestions with 12 real-life datasets.

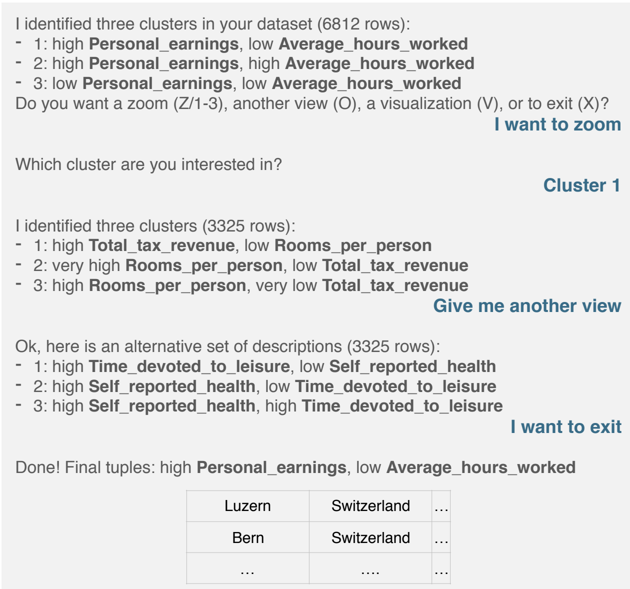


Figure 1: Demonstration of Clustine.

This paper is an early stage report: we present the main ideas behind Clustine and preliminary experiments to show that they are feasible. We will however leave a few questions open for future research.

2. OVERVIEW

Let us define our use case. Our users have access to a large table, containing several dozen columns and 10,000s of tuples. They are interested in a small portion of this table. Our aim is to develop a chat-based service to help them find and consult this interesting portion.

Our solution is based on iterative query refinement. Clustine inspects the dataset, partitions it into a few groups, and asks the user whether they are interested in one of the partitions. If the answer is positive, then Clustine "drills down" into the selection. It splits it into even smaller groups and asks for more feedback. If the answer is negative, then Clustine generates an alternative set of suggestions, and it repeats the cycle. To partition the database, Clustine relies on *cluster analysis*. It forms groups such that similar items are gathered and different items are separated. Thanks to this method, it can provide coherent options: each partition effectively covers one "family" of tuples [13].

Let us illustrate this process with an example. We have access to a database of socio-economic indicators, describing a few thousand regions of the world. Our aim is to find the countries with the "best conditions of life", a purposely ill-defined task. Figure 1 illustrates how to build the query with Clustine. It shows our system's main operations:

- Zoom into one or several partition to refine the selection of tuples.
- Request an alternative description of the partitions, to get another view of the data.
- Request a visualization of the partitions, to be sent as an image (we demonstrate this feature in Section 5).
- Exit: Clustine closes the conversation and returns a sample of the selected tuples.

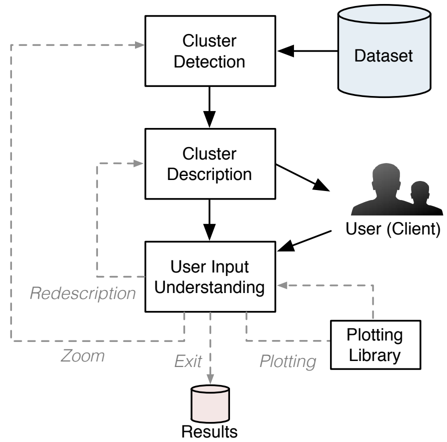


Figure 2: Overview of Clustine's Architecture.

Observe how our method differs from the usual query-result paradigm. Classic database front-ends rely on open questions. The users face a "blank page", and they must build their query from scratch. With Clustine, the system generates a sequence of closed, multiple choice questions. These statements have two roles. First, they summarize the current selection tuples, as they identify and describe its main components. Thus, they offer a text-based alternative to tables and graphics. Second, they provide options for query refinements. They let the users compose complex queries without a writing a single line of SQL.

3. ARCHITECTURE

Figure 2 presents Clustine's architecture. Our system relies on three components. The first component takes a sample of tuples from the database and detects clusters. The second one generates textual synopses of these clusters. The last component collects the users' input and infers what action to carry out next. We implemented the first and last stages with well-known techniques, which we briefly discuss in this section. Designing the second module, which generates text from clusters, was more challenging. We tackled it with an original framework, described in Section 4.

Cluster Detection. In principle, we could implement clustering with any method from the literature. In practice, we opted for the EM algorithm, a generalized variant of k-means [5]. This algorithm can deal with mixed data types and missing values. Furthermore, it returns the mean vector and covariance matrix associated with each cluster. We will exploit this information extensively in the description phase. To determine the number of partitions, we use Bayesian Information Criterion [5], a well established method from the literature. To ensure that the descriptions are compact, we set a low cap on this value (e.g., 3 or 4). This approach causes no loss of generality: the smaller clusters do not disappear, they simply appear later in the exploration.

Input Understanding. We implemented this module with a Naive Bayes classifier [5], trained on a manually generated corpus to recognize which action the user is asking for. We encode the data with bags of words, after lower casing and stemming. When the users request zooms, we extract the cluster numbers with regular expressions.

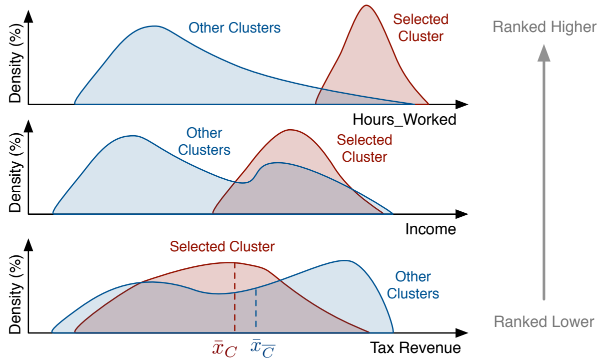


Figure 3: Clustine seeks variables on which the cluster are well separated.

4. DESCRIBING CLUSTERS

We now turn to an important challenge in our study: how to describe a set of partitions with natural language? The EM algorithm defines each cluster by its center (i.e., vector of means) and its covariance matrix. But this information is difficult to interpret. For a start, it involves all the columns in the database. When the data contains dozens or hundreds of variables, mentioning them all clutters the screen and overwhelms the users. Furthermore, novice users may not be comfortable with raw data. They may prefer high level magnitude judgments (e.g., "Your data has high values for Income") rather than literal numbers (e.g., "The average value for Income is 42.5 and the variance of 0.4"). This section discusses Clustine's editorial choices, that is, which columns it uses to describe the clusters, and how it conveys the values of the subsequent tuples.

Ranking Variables. To describe the clusters, Clustine uses few columns only. More specifically, it identifies "high contrast" variables, that is, variables on which the tuples in the cluster are different from those in the rest of the data. We illustrate this idea with Figure 3.

To quantify the contrast associated with each variable, our system uses Cohen's d, from the classic statistics literature [6]. Consider a cluster C. Let $\bar{x}_C$ (resp. $\bar{x}_{\overline{C}}$) describe the mean of the variable x for the tuples inside (resp. outside) the cluster. The variable s is the pooled standard deviation of the two sets. We define Cohen's d as the scaled difference between the means. Formally:

$$d = \frac{\bar{x}_C - \bar{x}_{\overline{C}}}{s}$$

Admittedly, Cohen'd is not the most versatile measure of statistical dissimilarity. More sensitive alternatives exist, such as the Kullback-Leibler divergence [5]. But this indicator is practical. It is based on means and variances, which we obtain "for free" from the EM algorithm. Also, its sign and magnitude are directly interpretable. A positive value implies that the tuples in the cluster have a higher value than those in the rest of the database, while a negative value indicates that the tuples have a low value on the chosen variable. A high magnitude indicates a large deviation, while a low magnitude describes small variations. Thus, we can exploit Cohen's d directly to generate textual descriptions.

Cluster description pipeline. Figure 4 presents Clustine's description pipeline. During the first step, our system computes the contrast associated with each variable.

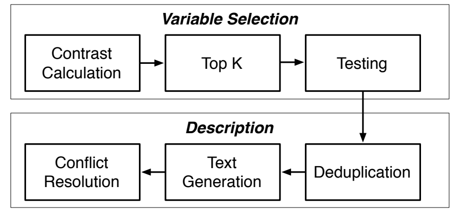


Figure 4: Workflow of Clustine's cluster description module.

It ranks them and selects the top K, for some arbitrary K. Then it checks if the results are statistically significant, that is, how likely it is that they were caused by chance. By default, it uses t-tests, the counterpart of Cohen's d in the hypothesis testing literature [6]. It discards the variables associated with a low confidence. Once this process is completed, Clustine produces the textual explanations. It first deduplicates the variables, as explained in the following paragraph. It then generates text, using handcrafted rules and regular expressions. Finally, it resolves conflicts. The aim of this phase is to detect and hierarchize the clusters that have with the same description. For instance, if two partitions have the label "High income", Clustine detects which one covers the highest values and renames it to "Very high income".

Deduplication. Our variable ranking scheme can lead to redundancy. For instance, this problem can occur when several columns contain the same data under different names or encodings (e.g., "Income", "IncomeCode" and "IncomeCategory"). To solve it, Clustine deduplicates the columns. It does so in three steps. First, it obtains the correlation between every pair of variables from the output of the EM algorithm. Second, it detects clusters of correlated columns, using a distance-based clustering algorithm, such as hierarchical clustering or PAM [5]. Finally, it selects one representative column for each cluster.

The deduplication step enforces that the results are diverse, but it can yield losses of accuracy, described in Section 6. We leave it as an option, to be chosen by the user.

Redescription. If the users are not satisfied with the description of the clusters, they can request an alternative one. Then, Clustine inserts the current selection of variables in an exclusion list and reruns the whole pipeline described in Figure 4. To save time, it reuses intermediate results from the previous iterations, such as the contrast scores.

5. USE CASES

Let us demonstrate Clustine with two real-life scenarios. We start with the full version of our running example. The database comes from the OECD, an international economic organization[1]. It describes economic, social and well-being indicators for 2,180 regions in 31 countries, across three years. In total it contains 6,823 rows and 519 columns. Our aim is the find the countries with the "best living conditions", a purposely vague and subjective task.

Figure 5 shows our interaction with Clustine. We exploited three of its five suggestions. First, we selected the regions with the highest salaries and the lowest number of hours worked. We then refined our selection with attributes related to leisure time, health, then unemployment. Observe

[1]http://stats.oecd.org/

I identified three clusters in your dataset (6812 rows):
- 1: high **Personal_earnings**, low **Average_hours_worked**
- 2: high **Personal_earnings**, high **Average_hours_worked**
- 3: low **Personal_earnings**, low **Average_hours_worked**

Do you want a zoom (Z/1-3), another view (O), a visualization (V), or to exit (X)?

I want to zoom

Which cluster are you interested in?

1

I identified three clusters (3325 rows):
- 1: high **Total_tax_revenue**, low **Rooms_per_person**
- 2: very high **Rooms_per_person**, low **Total_tax_revenue**
- 3: high **Rooms_per_person**, very low **Total_tax_revenue**

Give me another view

Ok, here is an alternative set of descriptions (3325 rows):
- 1: high **Time_devoted_to_leisure**, low **Self_reported_health**
- 2: high **Self_reported_health**, low **Time_devoted_to_leisure**
- 3: high **Self_reported_health**, high **Time_devoted_to_leisure**

Zoom in 3

I identified two clusters (1133 rows):
- 1: high **Time_devoted_to_leisure**, high **Self_reported_health**
- 2: low **Self_reported_health**, low **Time_devoted_to_leisure**

Zoom in 1

I identified three clusters (661 rows):
- 1: low **Self_reported_health**, high **Long_term_unemployment**
- 2: low **Long_term_unemployment**, low **Self_reported_health**
- 3: high **Self_reported_health**, low **Long_term_unemployment**

I want to exit now

Done! Final tuples: high **Personal_earnings**, low **Average_hours_worked,** very high **Self_reported_health**, very high **Time_devoted_to_leisure**

Luzern	Switzerland	...
Bern	Switzerland	...
Canberra	Australia	...
Perth	Australia	...
Darwin	Australia	
Peace River	Canada	...
Fort Smith	Canada	
Hauts-de-Seine	France	
...	....	...

Figure 5: Demonstration 1: the OECD dataset.

I identified three clusters in your dataset (1994 rows):
- 1: high **PctPersDenseHous**, low **medFamInc**
- 2: low **medFamInc**, low **PctPersDenseHous**
- 3: low **PctPersDenseHous**, high **medFamInc**

Do you want a zoom (Z/1-3), another view (O), a visualization (V), or to exit (X)?

I want a zoom in 3

I identified three clusters (836 rows):
- 1: high **PctForeignBorn**, high **PersPerOwnOccHous**
- 2: low **PctForeignBorn**, low **PersPerOwnOccHous**
- 3: high **PctForeignBorn**, low **PersPerOwnOccHous**

Another view

Ok, here is an alternative set of descriptions (836 rows):
- 1: high **PctFam2Par**, high **PctRecImmig10**
- 2: low **PctRecImmig10**, low **PctFam2Par**
- 3: high **PctRecImmig10**, low **PctFam2Par**

Other

I identified three clusters (836 rows):
- 1: high **medIncome**, low **PctOccupManu**, low **NumUnderPov**
- 2: low **medIncome**, high **PctOccupManu**, low **NumUnderPov**
- 3: low **medIncome**, high **NumUnderPov**, low **PctOccupManu**

Zoom in 1

I identified three clusters (201 rows):
- 1: low **medFamInc**, low **PersPerFam**, high **NumUnderPov**
- 2: high **NumUnderPov**, high **medFamInc**, low **PersPerFam**
- 3: high **medFamInc**, low **NumUnderPov**, high **PersPerFam**

Z3

I identified three clusters (77 rows):
- 1: high **medIncome**, low **PctPersDenseHous**
- 2: high **PctPersDenseHous**, low **medIncome**
- 3: low **medIncome**, low **PctPersDenseHous**

Exit

Done! Final tuples: low **PctPersDenseHous**, very high **medFamInc,** high **medIncome**, low **PctOccupManu**, very low **NumUnderPov,** high **PersPerFam**

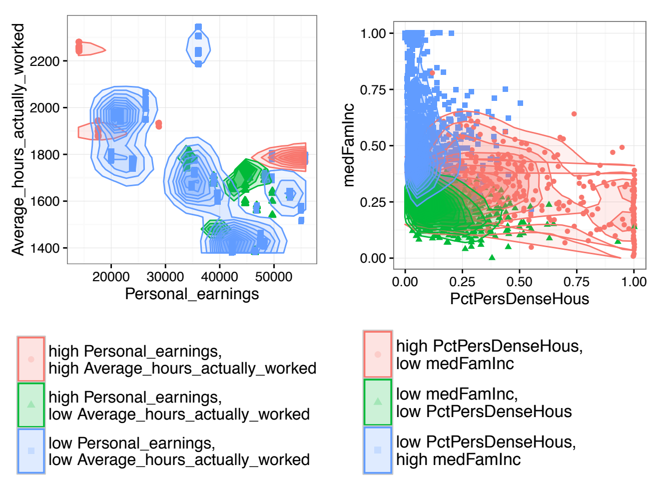
New Berlin	WI	...
Sunrise City	FL	...
East Provid.	RI	...
Newark City	NJ	...
Jackson Town	NJ	...
...	....	...

Figure 6: Demonstration 2: cities, crime and wealth in the US.

that Clustine's second suggestion was irrelevant to us. We simply discarded it by requesting a new view.

Our second scenario is based on the Crime and Communities dataset, from the UCI repository[2]. The data contains 128 crime and socio-economic indicators for 1,994 US cities. Our aim is to find the richest communities. Figure 6 represents the system's output and our answers. We narrowed our selection down to 77 rows using columns related to housing, incomes and family structure. A few of the variables were obvious to us, such as `medIncome`. But we discovered a few others through Clustine's suggestions. Examples of those are `PctOccupManu`, which describes the proportion of people employed in manufacturing, or `PctPersDenseHousing`, which reports the number of houses with more than 1 person per room.

After each suggestion, Clustine gives the option to visualize how it partitions the data. The aim is to let users perform "sanity checks" and obtain more details. Figure 7 presents two of those visualization. In both cases, we observe that the labels of the clusters match their position in the attribute space, as expected.



(a) OECD dataset, first view. (b) Crime dataset, first view.

Figure 7: Two-dimension views of Clustine's suggestions.

[2]http://archive.ics.uci.edu/ml/

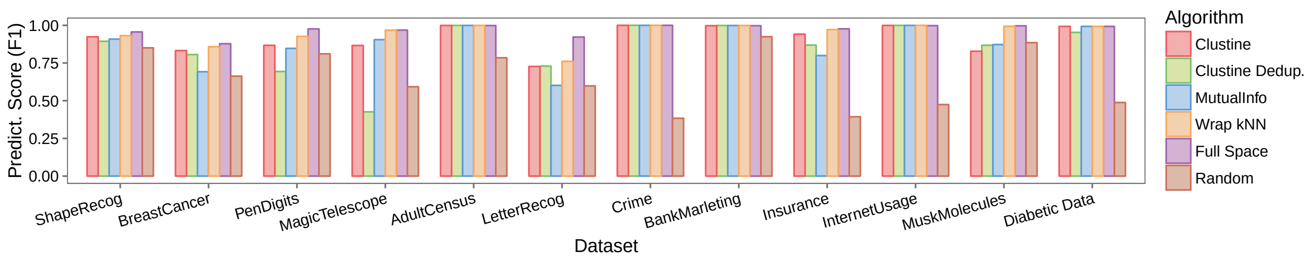


Figure 8: Accuracy of the variable selection algorithms. Higher is better.

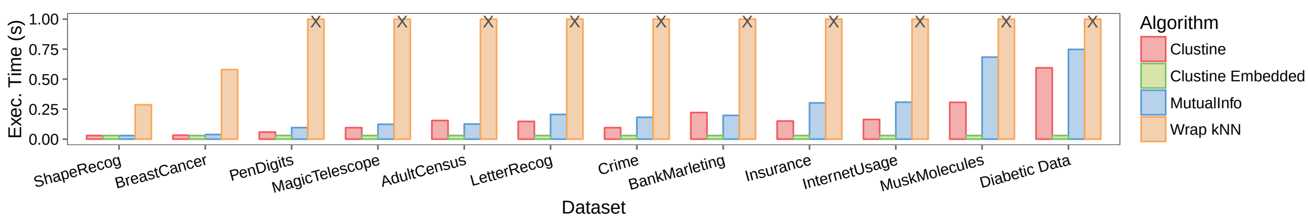


Figure 9: Execution time of the variable selection algorithms. Lower is better.

Dataset	Columns	Rows
ShapeRecog	16	180
BreastCancer	34	234
PenDigits	17	7,496
MAGICTelescope	11	19,022
AdultCensus	14	32,578
LetterRecog	16	20,000
Crime	128	1,996
BankMarketing	17	45,213
Insurance	86	5,900
InternetUsage	70	7,463
MuskMolecules	167	6,600
Diabetic Data	11	101,818

Table 1: Characteristics of the datasets.

6. VALIDATION OF THE DESCRIPTIONS

To be efficient, Clustine must detect meaningful clusters, describe them accurately and do so with a low latency. Achieving the first objective depends entirely on the clustering algorithm. Because we used EM, a well-known method [5], we will not discuss this aspect further in this paper. We will however evaluate how Clustine describes the clusters. More specifically, we will focus its column selection strategy. We will check if the columns used to describe the clusters are indeed "informative", and we will measure how fast Clustine can detect them. All our experiments are based on 12 datasets from the UCI repository, described in Table 1.

Our system is a MacBook Pro with an 2.6 GHz Intel Core i5 processor and 8 GB main memory. We wrote our code in R, exploiting its native C primitives for common operations (e.g., computing covariance matrices) and our own C library for information theoretic operations (used in one of the baselines).

Accuracy of the Column Selection. To evaluate the quality of Clustine's column selection algorithm, we exploit statistical classifiers. We first cluster the whole database with the EM algorithm - as our system does. We obtain one cluster label for each tuple. We then reduce the dataset, by selecting only the columns mentioned by Clustine. We train a classifier to infer the cluster labels from this reduced dataset. If this operation succeeds, then we conclude that the columns are instructive: the projection contains the information necessary to reconstitute the structure of the whole data. Oppositely, if the classifier fails, then the chosen columns probably give a poor view of the data's overall distribution. Technically, we used 5-Nearest Neighbors classifiers. We chose those for their simplicity and efficiency. We measure the prediction accuracy with the F1 score on 5-fold cross validation. Higher is better.

We benchmark two variants of Clustine's column selection algorithm: with and without deduplication, respectively denoted `Clustine` and `Clustine Dedup`. Since we built our system for real-time interaction we target speed. Our objective is to be as fast as possible while maintaining a competitive accuracy. We compare our algorithms to four baselines. The first baseline, `Full Space`, returns all the columns in the data set. The aim is to measure how much information Clustine loses during the column selection process. Our hope is that this loss is as small as possible. The second and third baselines come from the classic feature selection literature [8]. `MutualInfo` computes the Mutual Information (i.e., statistical dependency) between each column and the vector of cluster labels, and it retains the top K variables. We chose this algorithm because it is fast and reasonably accurate. `Wrap kNN` choses columns greedily, picking at each step those that yield the best classification score with a 5-NN classifier. This method is very accurate, but also very slow. Finally, we implemented a random baseline to ensure that the results are worth the effort. By default, we set $K = 3$. We run each experiment five times and average the results.

Figure 8 presents the accuracy of each method. We observe that `Full Space` dominates all the other algorithms. Indeed, selecting columns induces a loss of information, this is the downside of compressing the results. Nevertheless, the loss is neglectable on half of the datasets, and it is less than 5% away from the best competitor in the other cases. In our scenario, this penalty is acceptable. The method `Wrap kNN` comes close second, which shows that detecting small and informative sets of variables is possible. However, this high accuracy comes with a considerable runtime penalty, as we will show in the next section. The methods `Clustine` and `MutualInfo` respectively come third and fourth, with a weak advantage for the former (`Clustine`'s score is equivalent or better in 10 cases out of 12). The algorithm `Clustine Dedup.` comes next, and `Random` comes last. We conclude that `Clustine` is not the most accurate framework, but it is competitive: it is at least good as `MutualInfo`, a well established feature selection algorithm. However, the deduplication incurs a loss accuracy, because it drops potentially predictive variables.

Runtime of the Column Selection. We present the results of our runtime experiments in Figure 9. In all cases, `Clustine` is very fast, as it is comparable to or much faster than `MutualInfo`, an already fast algorithm. Since both algorithms scale linearly with the number of rows and columns, the difference comes from the constant factors. Computing and comparing means and variances is faster than estimating mutual informations (both operations were implemented in C).

To measure Clustine's runtime, we accounted for the time necessary to compute the mean and variance of each column. But this measurement is very pessimistic. In practice, we obtain this information directly from the EM algorithm, and therefore we can perform the column selection without even reading the data. The bars associated with `Clustine Embedded` in Figure 9 show the runtime of the computations that actually occur (that is, everything except the calculation of the means and variances, including the deduplication). We observe that they are almost negligible. Therefore, the cost of describing the partitions is almost entirely shared with the clustering step.

7. RELATED WORK

Data exploration. During the last decade, several papers have described systems and interfaces to support users with no precise requirements, or no preliminary knowledge of the data. The effort is inter-disciplinary: it involves database researchers [9] as well as the visualization community [14]. Among others, existing solutions exploit sampling [2], visualizations [14], interactive query refinement [7], relevance feedback [3] or modern interface devices such as touch screens [10]. But to the best of our knowledge, no one has ever attempted to develop a chatbot to support exploration. Our work was inspired by Blaeu [13], which also uses cluster analysis to help users build queries. But Blaeu relies on visualizations, and it provides no mechanism to summarize its findings. Clustine is also close to SeeDB [15], which recommends database views. But SeeDB helps users visualize the result of their queries, it does not help writing them. Furthermore, it relies almost exclusively on visuals.

Natural language datbase interfaces. Authors have introduced database interface based on natural language for at least two decades [4]. Li and Jagadish's system is probably one of the most successful example of this effort [11]. But these interfaces rely on the classic query-result paradigm. Typically, those system helps users compose SQL statements, using schema information. In contrast, we help them understand their results, using machine learning. Those two approaches are orthogonal. Our work also resembles ABCD [12], a natural language-based machine learning engine. But this system focuses exclusively on regression models, while target database queries and cluster analysis.

8. CONCLUSION

In this paper, we presented Clustine, our prototype chatbot to help users interrogate large tables. Compared to existing natural language interfaces, our system is based on inverted querying: instead of asking the users to write queries from scratch, the software comes up with its own suggestions. Thanks to this paradigm, our users can compose complex queries with only a shallow knowledge of the data, a minimal amount of characters and an end-to-end support for natural language.

Our main priority for the future is to run extensive user studies, in order to further evaluate and improve our system. More generally, little to no work has addressed the problem of describing data with natural language. We are convinced that this research direction has a bright future ahead.

9. ACKNOWLEDGMENTS

This work was supported by the Dutch national program COMMIT

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