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

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ABSTRACT

Given the recent advances of AI and the stellar popularity of messaging apps (e.g., WhatsApp), conversational engines are no longer seen as quirky artifacts of customer support services and computer science museums. Chatbots provide a mighty, lightweight and accessible way to propose services over the Internet. In this paper, we introduce Clustine, a system designed to help users query large tables through short messages. The main idea is to combine cluster analysis and text generation to compress the query results, describe then with natural language and make recommendations. We detail the architecture of our system, demonstrate it with two use cases, and present early experiments with 10 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. It is therefore no surprise that Internet giants have developed commercial services for this canal. Most of those take the form of *chatbots*, that is, conversational engines. Among those, Facebook's M and Microsoft's Tay have attracted lots of attention recently. Also, dozens of smaller businesses have also proposed 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 market places to it. And indeed, chatbots have a number of advantages compared to traditional applications and Web services. They rely on natural language, which implies a short - ideally inexistent - learning phase. Since they live in the user's messaging app, they are lightweight. They require no client installation, no maintenance and they are possibly more power efficient. Finally, we can easily translate them to audio with to Text-to-Speech software, an important option for visually impaired users.

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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 a database through a messaging app. The challenges we face are twofolds. To begin with, our medium imposes draconian restrictions on the quantity of information that we can convey. Our users expect short messages, and the support for visuals is close to null - we can send a few pictures in the best case. Furthermore, we target a "casual" population, that is, users with a weak knowledge of the database and no programming skills. Typically, we envision managers searching for quick answers on their mobile phones. In this scenario, SQL is not an option.

Database researchers have proposed natural language interfaces to databases for at least two decades [3]. 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 the screen and overwhelm users - especially on a smart phone.

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 [10], 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 - 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 describe two use cases and an early experimental evaluation based on 10 real datasets.

This paper is an early-stage report: we present the main

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

Cluster 1

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

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

Give me another view

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

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

I want to exit

We are done. Final tuples:

Luzern	Switzerland	...
Bern	Switzerland	...
...	....	...

Figure 1: Demonstration of Clustine.

ideas behind Clustine and preliminary experiments to show that they are feasible. Nevertheless, we will omit a few details and leave questions open for future publications.

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 of tuples.

Our solution is based on iterative query refinement. Clustine inspects the dataset, partitions it into a few groups, and ask the user whether they are interested in one of the partitions. If the answer is positive, then Clustine "drills" into the corresponding partition. It splits it into even smaller groups and asks for more feedback. If the answer is negative, then Clustine finds an alternative way to partition the data. It presents the new results to the user, and repeats the cycle. To partition the database, Clustine relies on *cluster analysis*. It forms groups such that similar items are grouped and different items are separated. Thanks to this method, it can provide coherent options: each partition effectively covers one "family" of tuple.

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 in 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.

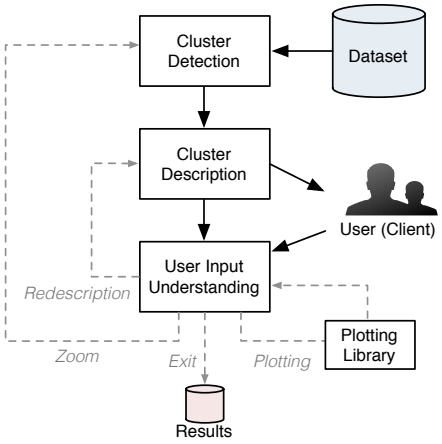


Figure 2: Overview of Clustine's Architecture.

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", which they fill as they see fit. In our case, the system probes the users through 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. They offer a text-based alternative to tables and graphics. Second, they provide options for query refinements. Thanks to this mechanism, the users can 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 [4]. 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 [4], 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 [4], trained 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 relevant cluster numbers with regular expressions.

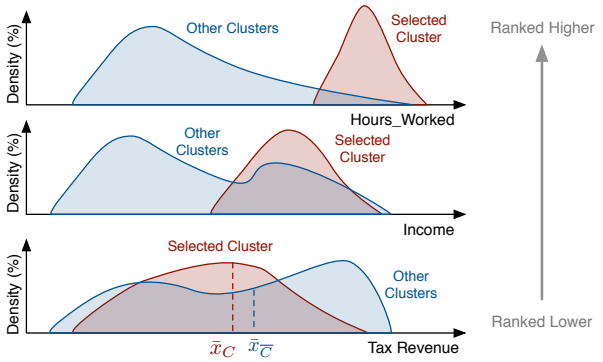


Figure 3: Clustine seeks variables on which the clusters' distributions are well separated.

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 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. Clustine described the clusters with a few columns only. To do so, 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 [5]. 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 follows:

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

Admittedly, Cohen'd is not the most versatile measure of statistical dissimilarity. More sensitive alternatives exist, such as the Kullback-Leibler divergence [4]. 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 value 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. It ranks them and selects the top K, for some arbitrary K.

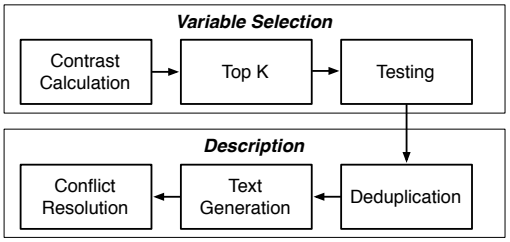


Figure 4: Workflow of Clustine's cluster description module.

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 [5]. It discards the variables associated with low confidences. Once this process has completed, Clustine produces the textual explanations. It first deduplicates the variables (cf. next paragraph). It then generates the 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 will detect which one covers the highest values and rename it to "Very high income".

Deduplication. Our variable ranking scheme may lead to redundancy. This problem may 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 database. It reads this information directly 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 [4]. Finally, it selects one representative column for each cluster. The deduplication step enforces that the results are diverse, but it comes with runtime and accuracy penalties (described in Section 6). Therefore, we leave it as an option, to be chosen by the user.

Redescription. If the users are not satisfied with the selection of columns, 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

We now demonstrate Clustine with two real-life scenarios. We start with the full version of the use case on which we based our running example. Our 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 presents 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

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

I identified three clusters in your dataset (6812 rows):
- Cluster 1: high **Personal_earnings**, low **Average_hours_actually_worked**
- Cluster 2: high **Personal_earnings**, high **Average_hours_actually_worked**
- Cluster 3: low **Personal_earnings**, low **Average_hours_actually_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):
- Cluster 1: high **Total_tax_revenue**, low **Rooms_per_person**
- Cluster 2: very high **Rooms_per_person**, low **Total_tax_revenue**
- Cluster 3: high **Rooms_per_person**, very low **Total_tax_revenue**

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

Give me another view

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

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

Zoom in 3

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

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

Zoom in 1

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

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

I want to exit now

We are done. Final tuples:

Luzern	Switzerland	...
Bern	Switzerland	...
Canberra	Australia	...
Perth	Australia	...
Peace River	Canada	...
...	....	...

Figure 5: Demonstration 1: the OECD dataset.

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

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

Another view

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

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

Other

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

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

Zoom in 1

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

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

Z3

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

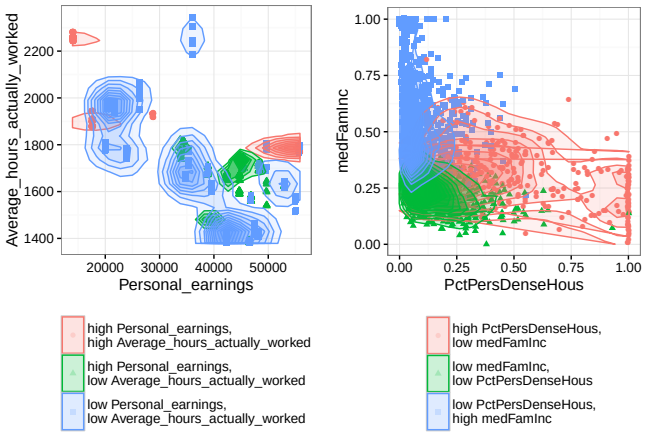
Do you want a zoom (Z/1-3), another view (O), a visualization (V), or to exit (X)?

Exit

We are done. Final tuples:

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.



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

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

related to leisure time, health, then unemployment. Observe 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 and safest communities. Figure 6 represents Clustine's suggestions and our answers. The descriptions correspond to what we could expect. For instance, partitioning the US cities according to their income and their housing situation seems natural to us. But this use case also highlights one limit of Clustine: it assumes that the database's column names are self-explanatory. Unfortunately, this assumption does not always hold. We leave this problem open for future work.

After each suggestion, Clustine gives the option to visualize the underlying data. The aim is to let users perform "sanity checks" and obtain more details. Figure 7 presents two of these visualizations - one for each dataset. In both cases, we observe that the labels of the clusters match their position in the attribute space.

6. VALIDATION OF THE DESCRIPTIONS

We now present our experimental results. To be efficient, Clustine must detect meaningful clusters, describe them accurately and do so with a low latency. The first aspect depends entirely on our choice of clustering algorithm. Because we used EM, a well known algorithm [4], we will not

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

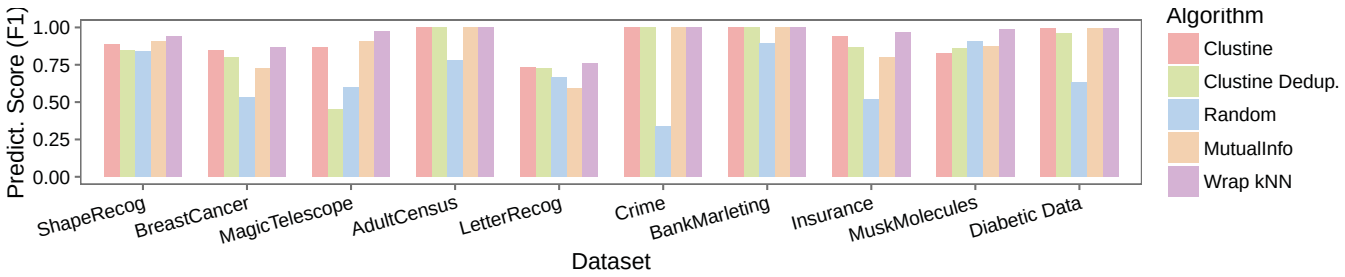


Figure 8: Accuracy of the variable selection algorithms. Higher is better.

Figure 9: Execution time of the variable selection algorithms. Lower is better. The cross indicates that the experiment exceeded 1 second.

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

Table 1: Characteristics of the datasets.

discuss it further in this paper. We will instead focus on Clustine's column selection engine, described in Section 4. We will evaluate its accuracy, then its runtime.

All the experiments that follow are based on 10 datasets from the UCI repository. We present their characteristics in Table 1. Our experimental system is a MacBook Pro with an 2.6 GHz Intel Core i5 processor and 8 GB main memory. We write 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).

6.1 Accuracy of the Column Selection

In this section, we evaluate the quality of Clustine's column selection algorithm. Our aim is to test whether the columns it choses are indeed "instructive". To do so, 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 confront Clustine's column selection method to two standard feature selection algorithm. The first algorithm `Wrap-kNN` is a *wrapper* from the statistics literature [7]. It builds sets of columns greedily. It adds the variables one after other, keeping at each stop those that yield the best classification score. It stops once is has obtained a view with K dimensions. We expect it to be slow but accurate, since it optimizes exactly our metric. The algorithm `MutualInfo` computes the Mutual Information (i.e., statistical dependency) between each variable and the vector of cluster labels, and it retains the top K variables. We expect to be fast, but less accurate than `Wrap-kNN`. We also added 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.

We present two variants of Clustine: with and without deduplication, resepectively denoted `Clustine` and `Clustine Dedup`. Since Clustine targets real-time interaction we target speed. We aim to be as fast as possible, while maintaining competitive accuracy scores.

Figure 8 presents the accuracy of our algorithms for each dataset. We observe that `Wrap-kNN` dominates the scores in all cases. It is then followed by `Clustine` and `MutualInfo`, with a weak advantage for the former (`Clustine`'s score is equivalent or better in 7 cases out of 10). The algorithm `Clustine Dedup.` comes next, and `Random` comes last. In conclusion, `Clustine` is competitive: it is at least good as a well established feature selection algorithm. However, the deduplication does incur a loss accuracy, as it eliminates all

variables which appear as redundant. This effect is strongest with `MAGICTelescope`, where it discards 2 variables out of 3.

6.2 Runtime of the Column Selection

We present the results of our runtime experiments in Figure 9. In all cases, `Clustine` 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 appears 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 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 in practice (that is, everything except the calculation of the means and variances, including the deduplication). We observe that they are almost negligible. In conclusion, 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 trans-disciplinary: it involves the database researchers [8] as well as the visualization community [13]. Among others, existing solutions exploit sampling [1], visualizations [13], interactive query refinement [6], relevance feedback [2] or modern interface devices such as touch screens [9]. But to the best of our knowledge, no one has ever attempted to develop a chatbot to support this task. Our work is very close to Blaeu [12], which also uses cluster analysis to help users build queries. But Blaeu is relies exclusively on visuals, it provides no mechanism to summarize its findings. Clustine is also close to SeeDB [14], 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 [3]. Li and Jagadish's system is probably one of the most successful example of this effort [10]. 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 is also close to ABCD [11], a natural language-based machine learning engine. But this system focuses exclusively on regression models, while are 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 aksing 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

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10. REFERENCES

[1] S. Agarwal, A. P. Iyer, A. Panda, S. Madden, B. Mozafari, and I. Stoica. Blink and it's done: interactive queries on very large data. *PVLDB*, pages 1902–1905, 2012.

[2] J. Akbarnejad, G. Chatzopoulou, M. Eirinaki, S. Koshy, S. Mittal, D. On, N. Polyzotis, and J. S. V. Varman. Sql querie recommendations. *Proc. VLDB*, pages 1597–1600, 2010.

[3] I. Androutsopoulos, G. D. Ritchie, and P. Thanisch. Natural language interfaces to databases–an introduction. *Natural language engineering*, pages 29–81, 1995.

[4] C. Bishop. *Bishop Pattern Recognition and Machine Learning*. Springer, New York, 2001.

[5] J. Cohen. *Statistical power analysis for the behavioral sciences*. Lawrence Erlbaum Associates, 1977.

[6] K. Dimitriadou, O. Papaemmanouil, and Y. Diao. Explore-by-example: An automatic query steering framework for interactive data exploration. In *Proc. SIGMOD*, pages 517–528, 2014.

[7] I. Guyon and A. Elisseeff. An introduction to variable and feature selection. *The Journal of Machine Learning Research*, pages 1157–1182, 2003.

[8] S. Idreos, O. Papaemmanouil, and S. Chaudhuri. Overview of data exploration techniques. In *Proc. SIGMOD*, pages 277–281, 2015.

[9] L. Jiang and A. Nandi. Snaptoquery: providing interactive feedback during exploratory query specification. *Proc. VLDB*, pages 1250–1261, 2015.

[10] F. Li and H. Jagadish. Constructing an interactive natural language interface for relational databases. In *Proc. VLDB*, pages 73–84, 2014.

[11] J. R. Lloyd, D. Duvenaud, R. Grosse, J. B. Tenenbaum, and Z. Ghahramani. Automatic construction and Natural-Language description of nonparametric regression models. In *AAAI*, 2014.

[12] T. Sellam and M. Kersten. Cluster-driven navigation of the query space. *IEEE TKDE*, PP(99):1–1, 2016.

[13] C. Stolte, D. Tang, and P. Hanrahan. Polaris: a system for query, analysis, and visualization of multidimensional relational databases. *TVCG*, 2002.

[14] M. Vartak, S. Rahman, S. Madden, A. Parameswaran, and N. Polyzotis. Seedb: Efficient data-driven visualization recommendations to support visual analytics. *Proc. VLDB*, pages 2182–2193, 2015.