Making Structured Data Searchable via Natural Language Generation

with an Application to ESG Data

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Abstract. Relational Databases are used to store structured data, which is typically accessed using report builders based on SQL queries. To search, forms need to be understood and filled out, which demands a high cognitive load. Due to the success of Web search engines, users have become acquainted with the easier mechanism of natural language search for accessing *un*structured data. However, such keyword-based search methods are not easily applicable to *structured* data, especially where structured records contain non-textual content such as numbers.

We present a method to make structured data, including numeric data, searchable with a Web search engine-like keyword search access mechanism. Our method is based on the creation of surrogate text documents using Natural Language Generation (NLG) methods that can then be retrieved by off-the-shelf search methods.

We demonstrate that this method is effective by applying it to two real-life sized databases, a proprietary database comprising corporate Environmental, Social and Governance (ESG) data and a public-domain environmental pollution database, respectively, in a federated scenario. Our evaluation includes speed and index size investigations, and indicates effectiveness ($P@1 = 84\%$, $P@5 = 92\%$) and practicality of the method.

1 Introduction

Keyword-based search offered by modern Web search engines (like Bing or Google) have become pervasive, and terabytes of public, unstructured Web pages available on the Internet are made available for searching that way. However, *structured* data, information stored in relational databases, is not as easily findable using the same mechanism, for various reasons. First, databases are often not exposed on the Web as static HTML pages, for example due to rights violations concerns. Instead, a Web form might give access selectively after filling in a set of fields that comprise a query. The totality of information available that way is known as the *Deep Web* [1]. Second, structured information often comprises

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non-textual information such as numbers, which need to be interpreted in context: for instance, a number like *1970* might either be a date of birth of a person, the annual revenue (in million USD) of a company, or the amount (in tons) of a toxic substance released into the air in an industrial accident. To make sense of numbers in a database, the application using the database together with the database schema provide the appropriate context, and *database report builders* are typically used to search the data. Unfortunately, report builders are often complex and therefore difficult to use.

In this paper, we propose a novel solution to this findability problem for structured data: we address the problem of how to make structured databases searchable *by generating unstructured documents artificially*, which can then be indexed with off-the-shelf inverted index files like any unstructured data and retrieved using e.g. the vector space model. This permits the application of keyword search to a realm it was previously not applicable to. In some sense, we turn the information extraction problem upside down: in information extraction, structured data needs to be extracted from unstructured document collections. Imagine again a value like *1970*: the database schema tells us that it is a numeric entity, but it does not reveal whether it is a year or a monetary amount.[1] We describe a mechanism of generating documents based on simple natural language generation (NLG) rules that permits a non-programmer to write a small set of rules for a database that makes its content findable.

We apply our method to two databases from the environmental domain. The first data set comprises proprietary information about the reported Environmental, Sustainability and Governance (ESG) performance of companies, an area of growing interest in the context of sustainable and ethical investing and good governance [2].[2] ESG databases monitor corporate scandals, environmental issues, ethical concerns such as conflicts of interest, bribery, investment in education or well-being of its workforce (such as training and development program investments in dollars per employee per year), and similar aspects not covered by a company's financial fundamental analysis. In sustainable investment, the hope is that in the longer term, more ethical companies and those that focus not just on quarterly-measured shareholder value will fare better than companies that ignore ethical, social and environmental concerns. Our second data set is a database of toxic spill events in the USA that were reported to meet compliance obligations.

Paper Plan. The remainder of this paper is structured as follows: in Section 2, we discuss previous work in the fields of (structured) database search and text generation, respectively. In Section 3 we present our new method, and Section 4 describes our *E-Mesh* search engine, which implements it. Section 5 describes

[1] Note that even if the database schema contains a column named `PERSON_BIRTHYEAR`, this does not automatically facilitate the search *per se*, as the machine is oblivious to the meaning of these names even if they are mnemonic to humans.

[2] This data set is commercially available as a data feed, e.g. for research or investment analysis purposes.

our data. Section 6 reports on our evaluation. In Section 7, we summarize and conclude the paper with suggestions for future work.

2 Related Work

We present related work from database and Business Intelligence (BI) search, natural language text generation, and our application area, information systems for environmental and ESG (Environmental, Social and Governance) data.

BI Search. [3] is a general textbook on the state of the art in information retrieval, which form the basis of question answering systems over unstructured data as found in document collections (e.g. [4]). In contrast, [5] surveys traditional natural language database interface techniques. [6] present *SODA*, a system that can search stuctured data across a set of data warehouses in a company. *SODA* does not carry out a natural language analysis of the query, but is capable of recognizing concepts and operators in a free-form text query, from which a query graph is constructed. To implement Soda for a new set of data warehouses, a domain ontology needs to be devised by humans for optimal results. [7] outline a tutorial on keyword search across structured, semistructured and graph data. [8] present a method for making structured data searchable that is based on adding additional tables to any database instance, and by adding a processing layer between Microsoft SQL Server and the ODBC API layer. They index all rows (direct or via foreign key join) such that each row contains all keywords. Unlike ours, their methods does not permit multi-lingual search, nor can it cope with finding numeric content. [9] apply smoothed relevance language models to ranked retrieval of structured data. Their experiments include Wikipedia, IMDB (both more unstructured than structured) and MONDIAL, a small structured data base comprising 9 MB and 17k relational tuples. Again, numeric information and multilinguality are beyond its scope. Traditionally, graph-based algorithms [10–12] have been tried to enable keyword search on relational and other data.

Environmental and ESG Information Systems. "Green" data, i.e. data from the realm of protecting the environment, has recently become available at scale (e.g. [13]). Not surprisingly, data management [14] and search are becoming increasingly important. The United Nations Environment Programme (UNEP) developed UNEP Explorer, a Web-based software for navigating environmental data sets in the public domain [15]. Unlike the method presented in this paper, UNEP Explorer does not have an easy-to-use keyword-based search function that delivers focused results. *ESG*, the Environmental Scenario Generator [16], is an advanced distributed tool to explore environmental data for scenario analysis, particularly around weather situations. It uses maps and a menu-based, i.e. non-textual GUI to solicit input and does not permit keyword search. [17] present *KOIOS*, a keyword search engine for environmental data built on top of the commercial EIS Cadenza (by Dizy GmbH). They take a very different route from the approach presented here: given a structured database, three indices are generated, namely a data index (a graph), a keyword index (which captures unstructured data parts) and a schema index, which represents classes and relationships. All three indices are represented in RDF, and queries are translated into SPARQL. No evaluation regarding retrieval effectiveness, query processing efficiency or index size overhead are described.

[18] make the case for so-called ESG data (short for "Environmental, Social and Governance" company data) to contain valuable evidence that can inform trading.

Natural Language Generation. We are not aware of any previous work that attempts to make structured data searchable by applying natural language *generation* techniques. [19] and [20] survey the state of the art in text generation methods, including systems. [21] is one of the few textbooks on NLG.

3 Method

Imagine a database like the toy example in Figure 1. We cannot query easily what is in the database with a Google-style search engine because we do not have an inverted file index – after all keyword search basically responds to a query with a set of ranked pages that contain the query keywords, and for our database no such (natural language) index exists.

Table 1. A Sample Toy Database Table `T_PERSON`

ID	Name	Weight	Age
1	John	80	35
2	Anna	60	33

To address this, we generate English prose documents, one per table row, using a set of template generation rules as shown in Table 2. Each rule comprises a `pattern` section containing a template with canned text that may contain slots that may be filled with values bound to variables (e.g. $P). We say the template gets *instantiated* and we call the resulting document *surrogate document*, as its main purpose is to make the data in the database row *findable*. There is no need to physically store surrogate documents in a file system, as their only purpose is to feed an indexing process, and they can be stored memory-efficiently together with the index itself in compressed form. The `keyword` section of the generation rule adds terms to the surrogate document to increase recall, but marks them as "not for rendering", as the keywords listed here are not part of any system response to the user. In particular, we aim for the pattern to be linguistically well-formed, whereas the `keyword` section is just a bag of terms and phrases that may be useful for retrieval. The `datapoint` section finally provides a binding between rows in the database row under consideration and the parameter variables in the `pattern` section. Database rows get processed one by one, so in the first iteration $P gets bound to `John` (i.e. `T_PERSON.NAME`), in the second iteration $P gets bound to `Anna`, and so on. Field names from the schema are added to the `keyword` section automatically, thus potentially supplementing any human-written generation rules. Table 2 shows a toy rule for explanation purposes; Appendix A lists a real generation rule in XML format as used by our system.

Table 2. A Natural Language Generation Rule That Generates Table 3 From the First Row in Table 1

pattern:	\$P weighs \$W kilograms and is \$A years old.
keywords:	kg age
datapoint:	`T_PERSON.NAME|T_PERSON.Weight|T_PERSON.AGE`

Table 3. Generated Two-Part Surrogate Document

John weighs 80 kilograms and is 35 years old.
kg age

Default rules control the output for non-existing data-points. All text generation rules are defined per language, as they have an ISO-639 language attribute; a separate index is automatically generated for each language that has at least one generation rule. Thus our method can generate a set of search engines in various languages from a single XML specification file.

The number of generation rules that need to be authored for a database table with $|T|$ tables and $|R|$ rows each is at most $|T| \times |R|$; in practice, one rule can generate surrogates covering multiple columns (Table 2 used a single rule for all four columns).

Ease of Customization. A key benefit of our method is that there are no software changes necessary to deal with a change of the database schema or with the addition of a new database: the only modification/extension required is the adaptation or extension of the text generation rules in a single XML file.

4 System

We implemented the method described in the previous section in Java. The architecture of our system *E-Mesh* is shown in Figure 1. A data reader component based on the Apache Hibernate framework [22] iterates over all database rows for each database tables; we will henceforth call each row *data points*. A text generator component (based on the Apache Velocity template engine) reads a set of NLG rules and instantiates them by binding data points mentioned in rules to variable parameters. Generation rules like the one in Table 2 were represented in XML. Variable values are inserted where they occur inside of generation templates that comprise the core part of rules, thus instantiating *surrogate documents*. An indexer component (based on the Apache Lucene search library) indexes these documents on the fly, creating one index per language for which generation rules exist. This completes the offline processing. The actual search engine provides online access to the indexed documents and makes them available to a GUI (again based on Lucene and the Glassfish servlet container). Figure 2 shows the *E-Mesh* search engine's user interface.

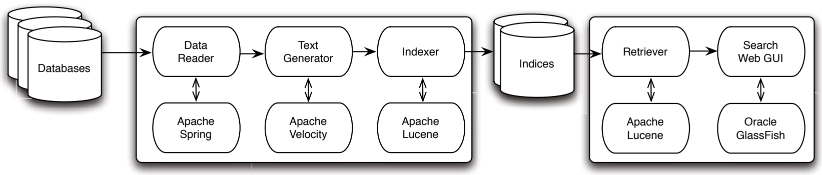

Fig. 1. *E-Mesh* System Architecture

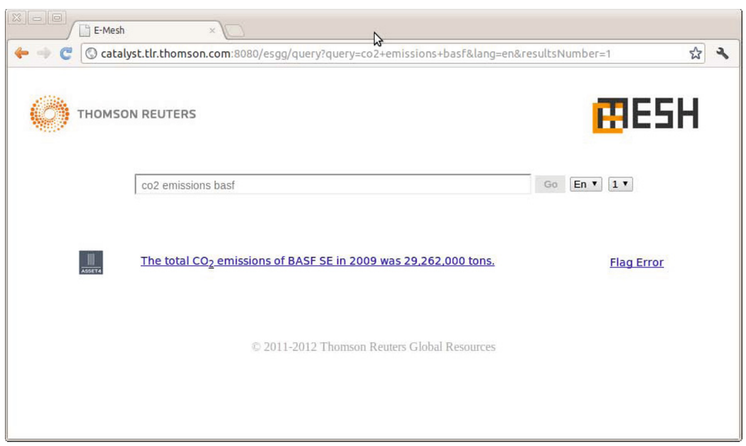

Fig. 2. Screen Capture of *E-Mesh*'s Web GUI

5 Data

We apply the methods described above to two data sets. The first data set is a proprietary database comprising Environmental, Social and Governance (ESG) information such as data points describing a company's environmental performance (e.g. carbon emissions), social/ethical performance (e.g. investments in employee training, ongoing harassment litigation) or governance performance (e.g. reports on insider trading, corruption charges against management). The data set is part of the Datastream product sold by Thomson Reuters, so the method is also applied to a second data set for easier replication of our study. We use a toxic spill database covering environmental pollutions in the U.S., data which was put into the public domain by the U.S. government [23].[3] This data set, henceforth TOXICSPILL for short, contains information about release events, namely time of the event, the name of the company responsible for the spill, the location, and the name of the chemical accidentally released. Table 4 summarizes the size and content of the two data sets and their corresponding generation rules.

Table 4. Data Setup Used in Our Experiments

Database	Size	Tables	Average Columns/Table	Generation Rules
ESG	21,000 MB	111	9.81	28 (EN) / 28 (DE)
TOXICSPILL	401 MB	1	87	2 (EN) / 2 (DE)

6 Evaluation

6.1 Experimental Design

Evaluating natural database interfaces or question answering systems over structured data poses the problem that the user does not know what he or she can ask, as the database schema is not known to them. Knowledge of the schema, on the other hand, would biases the user and hence any evaluation. There is also no standard evaluation database and query corpus available, which is partly due to the fact that many query systems are domain specific and/or database specific. To address these issues, we created two query corpora as follows: we generated a random list of companies, a random list of data point names, and a random list of years. We then asked human subjects not involved in this study to formulate one human natural language search query for each $\langle$company; data point; year$\rangle$ triple. With a probability 1/2, we included a the year from the interval [2008; 2012] into the query (years covered in our snapshop of the databases). The resulting two query corpora (one used as a development set and another one used as a test set) comprise 50 queries each, 25 asking for data from the ESG and the other 25 asking for data from the TOXICSPILL data set. We then ran these two query sub-corpora against the *E-Mesh* system, and evaluated the correctness of the results, measuring precision at ranks one and five, respectively. This methodology ensures independence while generating queries that are as natural as feasible and at the same time the resulting queries are not "unfair" to the system in the sense that the information needs encoded by the queries should in principle be answerable by the data in the databases at hand.

Baseline & Hypothesis. We compare the precision of the implemented method compared to a baseline which applies a TFIDF ranking to a "raw" index of data rows together with their names (taken from the schema), without applying our proposed generation templates. Our hypothesis is that the proposed *offline NLG approach significantly increases retrieval performance*.

[3] The data is publically available from `http://data.gov`

6.2 Empirical Evaluation Results and Discussion

Indexing. The system was subjected to the generation of search engines for English and German based on the data described above. This paper presents some findings for the query corpus, which was only in English (we leave the evaluation for German for future work). A set of rules were authored, which took about 3 hours for ESGG, and 1.5 hours for TOXICSPILL, respectively. One database was completely modeled, the other one partially (but our method ensures to always obtain a functional system). The result is shown in Table 4.

We carried out the indexing on a desktop PC with Intel CoreDuo PC with two x86 cores (model 6,400) at 2.13 GHz with 3 GB RAM. The method's observed offline indexing run time (Figure 3) and the persistent storage space required for the generated inverted file indices (Figure 4) grow linearly with the number of rules and database rows (since the number of templates is constant) in the offline indexing step, and there is no additional runtime overhead for searching the generated index of surrogate documents.

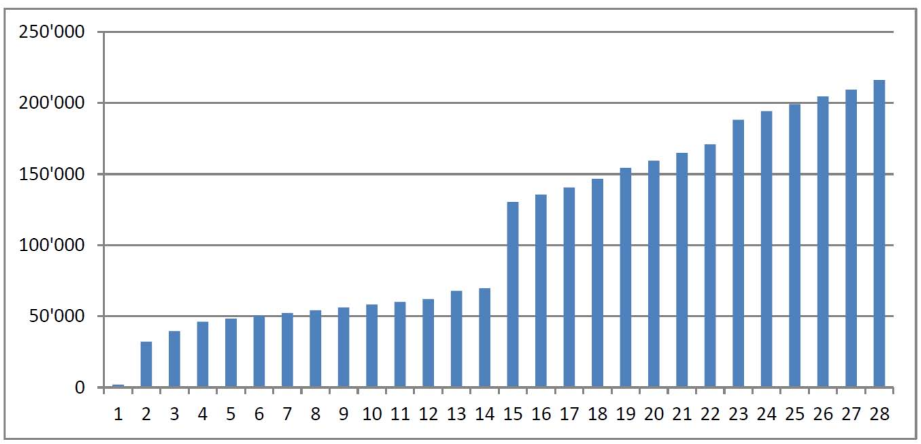

Fig. 3. Scalability of Text Generation Rules: Index Generation Time (in ms) Grows Nearly Linearly With the Number of Rules (ESG database)

Retrieval. The system was tested on the test corpus of 50 test queries[4], half of which ask for information from the ESG database and the other half with information needs from the TOXICSPILL database. The system logs all queries so once the system has been used by real users, more large-scale evaluations can be carried out. We found that the precision at rank one was 80% for the ESG data set and 88% for the the TOXICSPILL data set, amounting to a total of P@1 = 84%. If we look at precision at the top five ranks, precision rises to 92% for both databases. Note that our query corpus is small, so getting

[4] Comprising only English examples; the evaluation of German is left for future work.

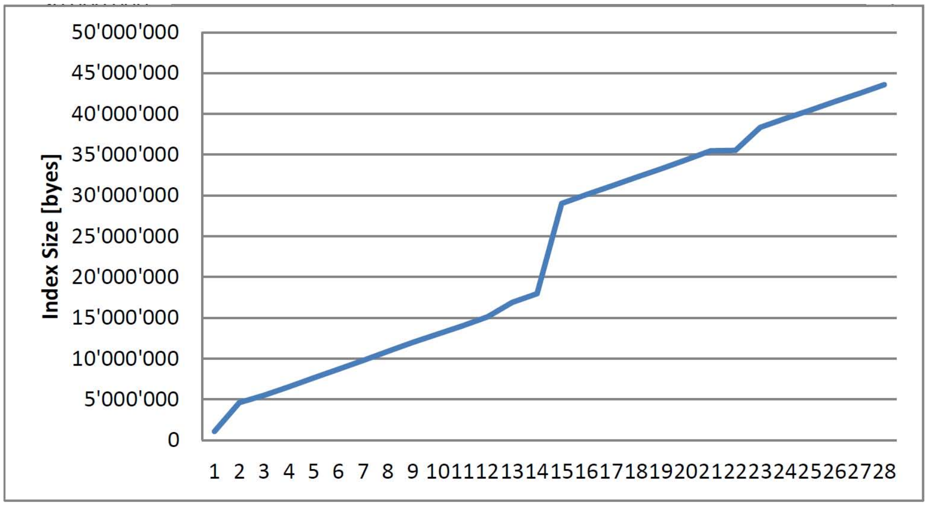

Fig. 4. Scalability of Text Generation Rules: Index Size (in bytes) Grows Nearly Linearly As a Function of the Number of Rules (ESG database)

just a single query wrong leads to a 0.04 decrease, as it happened with one query where the user gave a short form of a company, in a situation where many other companies with similar names exist: in query #29 from the test set, `Metal Finishing lead 2002` the user is seeking information on lead spills of a company called `Metal Finishing Co. Inc.` in the year 2002. When run against the TOXICSPILL database *E-Mesh*, returns the correct result on rank 3 instead of top rank (wrongly placing `Quality Metal Finishing Co.`'s lead emissions at the top). Overall, looking at the top five results for any query, our method ($P@5 = 92\%$) improves over the baseline (64%).

Discussion. Our hypothesis, namely that the proposed offline NLG approach significantly increases retrieval performance, could be confirmed: it holds individually for the ESG dataset, and it holds overall, although we did not observe an improvement for the TOXICSPILL dataset. In future work, we will investigate whether this is caused by a shortage in generation rules.

We also measured the retrieval speed, and observed a mean processing time of 12 ms per query on average.

Table 5. Evaluation Results

	E-Mesh Dev.		Baseline Test		***E-Mesh* Test**	
	P@1	P@5	P@1	P@5	P@1	P@5
ESG	0.32	0.40	0.20	0.36	0.80 ▲	0.92 ▲
TOXICSPILL	0.92	0.92	0.92	0.92	0.88	0.92
all	0.62	0.66	**0.56**	**0.64**	**0.84 ▲**	**0.92 ▲**

The rather static offline text generation process has two potential issues that we have identified so far. First, the concept of surrogate document generation from rows of data sometimes lacks flexibility; an extension to querying more than one data point at the same time (responding to a single natural language query), i.e. the natural language counterpart of a join, is not straight forward to implement. Second, dynamic computations cannot be handled directly. For example, Table 1 has an "age" row, which is an example of a data field that should be updated regularly. Such changing data needs to trigger an incremental re-indexation process. If the age is computed on the fly from a date of birth stored in the database (a better design), such a mapping also needs to be carried out symmetrically at retrieval time if the user asks for the age. On the flip side, the present method trades space for runtime speed, and it is maximally interoperable with unstructured search of document collections, as it basically transforms structured search into an *un*-structured search.

7 Summary and Conclusion

We presented a novel method that uses natural language generation for making structured data searchable. We described its implementation in our search engine *E-Mesh*, which was evaluated on a set of queries against two databases. The method proved to be both fast and offers high accuracy at a reasonable index overhead.

In future work, the method could be extended to provide more complex text generation capabilities. Another possible extension is the combination of data-points from more than one database in a single surrogate document. Our query corpus is limited in size; once logfiles have been gathered after production deployment, the effectiveness can be more systematically assessed. We also plan to evaluate the system performance for other languages (such as German, which we already implemented).

To the best of our knowledge, this is the first paper to suggest how search engines for structured data including numeric data can be "generated" by harnessing NLG techniques to create an inverted file index offline for a set of structured databases, and we offer a way of doing it that easily supports multiple languages. We measured an improvement in precision of the method when retrieving the top five answers for a corpus of 50 queries from a set of two federated databases (performing at $P@5 = 92\%$ compared to a baseline of $P@5 = 64\%$. In the future, we plan to evaluate languages other than English, notably our German rule set.

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A Sample XML Generation Rule

```
<generate-rule>
  <template lang="en">
    <index>company codes</index>
    <index>CO2</index>
    <render>The total CO&lt;sub&gt;2&lt;/sub&gt; emissions
           of ${Company} in ${Year} was ${CO2} tons.</render>
    <index>carbon dioxide equivalents</index>
    <default>I don't know how large were the total CO&lt;sub&gt;2&lt;/sub&gt;
            emissions of ${Company} in ${Year}.</default>
  </template>
  <datareader database="Asset4">
    <param result="CO2">En_En_ER_DP023</param>
  </datareader>
</generate-rule>
```