Senbazuru: A Prototype Spreadsheet Database Management System

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ABSTRACT

Spreadsheets have become a critical data management tool, but they lack explicit relational metadata, making it difficult to join or integrate data across multiple spreadsheets. Because spreadsheet data are widely available on a huge range of topics, a tool that allows easy spreadsheet integration would be hugely beneficial for a variety of users.

We demonstrate that Senbazuru, a prototype spreadsheet database management system (SSDBMS), is able to extract relational information from spreadsheets. By doing so, it opens up opportunities for integration among spreadsheets and with other relational sources. Senbazuru allows users to search for relevant spreadsheets in a large corpus, probabilistically constructs a relational version of the data, and offers several relational operations over the resulting extracted data (including joins to other spreadsheet data). Our demonstration is available on two clients: a JavaScript-rich Web site and a touch interface on the iPad. During the demo, Senbazuru will allow VLDB participants to search spreadsheets, extract relational data from them, and apply relational operators such as select and join.

1. INTRODUCTION

Spreadsheets are an extremely popular data management tool, allowing users to complete a range of data tasks commonly associated with relational systems: projection, sorting, aggregation, and simple ETL (Extract, Transform and Load) jobs. The sheer number and diversity of spreadsheets is remarkable; our Web crawl using the URLs in the ClueWeb09 corpus [4] found 410,554 spreadsheet files scattered across 51,252 domains. Moreover, the data is often the result of intense human focus and effort. These spreadsheets *should* be prime targets for ad-hoc data integration and analysis. For example,

Policy expert Fred wants to see whether the strength of the connection between smoking and lung cancer is consistent across all U.S. states. Fred does not have the relevant data at hand, but assumes it is "out there" on the Web somewhere.

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In one sense, the user is fortunate: different branches of the government have collected the data relevant to his task and made them available online, likely via two separate downloadable spreadsheets, one for the smoking statistics and one for the lung cancer statistics. Unfortunately, finding such data via current search engines is quite tedious. In our case, Fred would need to issue a text query, then review all the returned documents before finding the relevant spreadsheets. Moreover, because spreadsheets do not have explicit relational schema, the user cannot benefit from society's huge investment in data integration tools that work on relational databases. Instead, Fred will likely have to write custom code to combine the two spreadsheets.

Extracting relational data from spreadsheets would enable traditional database management tools, such as data integration systems, to be applied to spreadsheet data. There is a body of recent work that performs database-style operations inside a spreadsheet interface [6, 8, 11], but these approaches are not useful for spreadsheet datasets that already exist. Other studies have attempted to transform spreadsheet data into the relational model, making further integration among spreadsheets possible. Some extraction systems require explicit sheet-specific user-provided rules [2, 7], which might yield good results for a single spreadsheet but they are not practical in our setting: the corpus is very large and it is impractical for users to manually transform all of them. Abraham and Erwig[1], and Cunha *et al.* [5] automatically infer some spreadsheet structure, but they cannot process the *hierarchical* spreadsheets that constitute much of the most interesting data. Figure 1 shows a hierarchical spreadsheet downloaded from the U.S. Census Bureau.[1] This type of spreadsheets is commonplace in the Web: we have found about 32.5% spreadsheets in the Web are hierarchical, and more than 60% in popular Internet domains [3].

Therefore, to build a useful end-to-end spreadsheet management system, we should be able to extract relational data from a large number of existing spreadsheets, including the hierarchical ones. The main technical challenges are:

- ***Extraction*** – The spreadsheet in Figure 1 shows the smoking rate among different U.S. demographic groups. Each row describes a different smoking rate configuration. For example, 13.7 in the *value region* represents smoking people that are Male, White, and 65 years and over in the *attribute region*, and it yields an annotating *relational tuple* at bottom. To construct such a *relational tuple* is not straightforward: the spreadsheet does not explicitly indicate which cells are attributes,

[1] The U.S. Census Bureau: http://www.census.gov/

which cells are values, or which attributes describe which values. Also, the spreadsheet does not clearly state how to assemble the attributes into coherent sets. For example, the left-hand attributes in rows 26 and 32 belong to the same set (race), but row 25 does not. This grouping information is critical when constructing any relational format of the data. In summary, Figure 1 shows a clean, high-quality spreadsheet, recovering relational data from it requires us to: (1) detect *attributes* and *values*; (2) identify the hierarchical structure of *left* and *top attributes* if any exists; (3) generate *relational tuples*; and (4) assemble the tuples into high-quality *relational tables*.

- ***Repair*** – Extracting metadata is brittle: even a single extraction error can yield wrong tuples that will poison any downstream applications. For example, if the extractor fails to recognize that row 20 annotates row 26, the extracted relational tuples from row 27 to 31 will all be incorrect, as none contains any mention of the attribute Male. Thus, it should always be possible to manually repair any automatic extraction errors.

We demonstrate that Senbazuru, a prototype spreadsheet database management system (SSDBMS), is able to extract relational information from a large number of spreadsheets; doing so opens up opportunities for data integration among spreadsheets and with other relational sources. Senbazuru consists of three functional components we view as critical for a useful SSDBMS:

- ***Search*** – Using a textual search-and-rank interface, the *search* component allows a user to quickly locate relevant datasets in a huge Web spreadsheet corpus.
- ***Extract*** – The *extract* component is composed of a background ***extraction pipeline*** that automatically obtains relational data from spreadsheets, and a ***repair interface*** that allows users to manually repair extraction errors. Moreover, this component automatically exploits commonalities among errors to probabilistically reapply one user fix to other similar mistakes, thereby minimizing explicit manual intervention.
- ***Query*** – The *query* component supports basic relational operators, especially selection and join, which the user can apply to spreadsheet-derived relations.

We have a working prototype of Senbazuru, available as a desktop Web application and also as an iPad application. Recall our policy expert Fred, now newly equipped with an SSDBMS. Fred can use Senbazuru's *search* component to rank datasets by relevance to his text query, smoking by state. He then picks the best hit. The *extract* component automatically generates a relational table for the spreadsheet, allowing Fred to fix an extraction error with a single drag-and-drop. Fred can also use the *query* component to select a portion of the data about smoking by states, and join with another dataset about cancer by states. Overall, Senbazuru requires only a few clicks and two text queries, and yields a new dataset that is exactly what Fred wants.

In the rest of this paper, we will give an overview of the backend framework of Senbazuru (Section 2), describe how the end-user can interact with Senbazuru's interface during the demonstration with a walk-through example (Section 3), and conclude with a brief summary of technical problems the system addresses (Section 4).

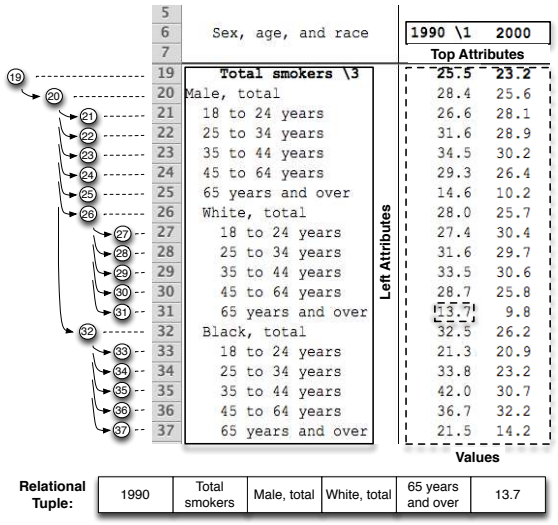


Figure 1: A screenshot of a spreadsheet with implicit hierarchical attributes in its left-hand column. At bottom, the relational tuple corresponds to the highlighted value *13.7*.

2. SYSTEM FRAMEWORK

In this section, we describe the backend software framework that allows Senbazuru to offer the standard SSDBMS services: *search*, *extract*, and *query*, as shown in Figure 2.

Search – The *search* component helps the user to retrieve relevant datasets in a potentially enormous corpus via Web search-style relevance ranking. Currently, Senbazuru has indexed more than 1,800 spreadsheets collected from the U.S. Census Bureau. For each spreadsheet in the corpus, the ***indexer*** uses the Python xlrd package to extract text from each cell, then uses Apache Lucene to index the text. When a query arrives, the ***searcher*** uses the inverted index and TFIDF-style ranking to sort the datasets by relevance. As with a standard Web search, the results of *search* comprise a list of potentially useful objects for the user to examine.

Extract – The *extract* component consists of a sequence of pipeline components that convert the data in each spreadsheet into the relational model. Most of the *extract* takes place when the corpus of spreadsheets is first added to the system, before any query arrives. A small portion of the *extract* is deferred until the user provides manual error repairs.

1. Frame Finder – First, each raw spreadsheet is sent to the *frame finder*. This module identifies *data frame* structures in each spreadsheet. A characteristic *data frame* layout is shown in Figure 1: a rectangular *value region* of numeric values (outlined with the dashed rectangle), with additional rectangular *attribute regions* above (labeled *top attribute* and outlined with a solid rectangle) and to the left (labeled *left attribute*, similarly outlined). We use a conditional random field (CRF) [9] to assign a semantic label to each non-empty row in the spreadsheet, thus finding the *data frame*. The module passes the *data frame* to the next step and discards everything else in the raw spreadsheet.

2. Hierarchy Extractor – The next stage is the *hierarchy extractor*, which recovers the attribute hierarchies for the *data frame*'s *attribute regions*. In each *attribute region*, we want to know which attributes describe which other attributes. For example, in Figure 1, the attribute at row 31

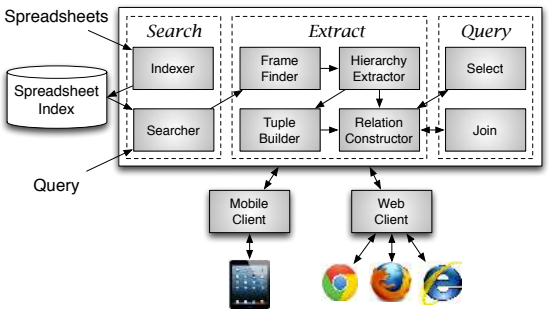


Figure 2: The software framework for Senbazuru.

is annotated by attributes at rows 26, 20, and 19. These annotations are critical in correctly extracting the relational tuples. Our solution is based on a conditional random field (CRF), in which each random variable represents whether an attribute pair is parent-child. For example, consider the hierarchy on the left of Figure 1: a variable representing an attribute pair (20, 26) is true while variables for (20, 31) and (24, 25) are false. We define a set of node and edge potentials to capture human intuitions about which attribute pairs are likely to be parent-child, and also global potentials or constraints to ensure that the resulting variable assignment yields a strict tree structure. Therefore, the output of the CRF extraction is a high-quality attribute hierarchy.

The *hierarchy extractor* includes a small but important step that is deferred until query time when a user interacts with the ***repair interface***. When a user observes the *hierarchy extractor*'s initial output, she has the option to repair the resulting hierarchy by dragging and dropping attributes, as shown in Figure 3. We translate each repair operation to a set of variables with observed assignments. We also add repair potentials to the CRF to ensure the observed assignments can be probabilistically applied to other similar variables. Every single user repair operation will trigger Senbazuru to re-run the CRF. As a result, the *hierarchy extractor* makes a single explicit repair action by the user fix many similar extraction errors at once, yielding refined hierarchies with little user effort.

3. Tuple Builder – The *tuple builder* is algorithmically straightforward, and it generates a relational tuple for each value in the *value region*, annotated with relevant attributes from *attribute regions*. For example, Figure 1 shows the full six-field tuple we want to recover for the outlined value 13.7.

4. Relation Constructor – Finally, the *relation constructor* assembles these relational tuples into relational tables. It clusters attributes in different tuples into consistent columns and recovers a label for each column. For example, this final step recognizes that attributes Male, total and Female, total should go into the same column, and that the column should be called gender. This clustering model exploits information from the recovered hierarchies as well as existing collections of schema such as Freebase and YAGO [10]. Figure 4 (a) shows an example of a recovered relation.

Query – After a user searches for a relevant dataset and repairs extraction errors, the *query* component allows her to apply relational operators on the spreadsheet-derived data. In particular, we have implemented ***select*** and ***join***. We will cover the two relational operators in detail as part of our interface discussion in Section 3.1.

3. DEMONSTRATION

We plan to show an end-to-end demonstration of Senbazuru to *search, extract,* and *query* spreadsheets. Users can choose to interact with Senbazuru using either the Web browser client or the iPad tablet client. In this section, we first describe how to use Senbazuru's interface, then show a walk-through example.

3.1 User Interface

The two client interfaces for Senbazuru are shown in Figure 4. They allow users to *search* for data, to view and edit the *extract* results, and to use *query* operations.

Search – As with other search-and-rank tools, a user types keywords in the search box, and obtains a list of relevant spreadsheets. She can then browse results and select the most relevant one. For example, in Figure 4 (a), a user enters "smoking" as the *search* query. She can examine the top hit's raw spreadsheet by clicking "Spreadsheet" or check other relevant spreadsheets by clicking "Next."

Extract – After selecting the most relevant spreadsheet, a user can use *extract* to transform the spreadsheet data into a relational table. She can review the extracted hierarchical metadata by clicking "Data Tree." Figure 3 shows the interface for viewing the extracted hierarchies. To repair any extraction errors, she can drag and move a node of the tree from one place to another. After observing the user's repair action, Senbazuru will automatically re-run *extract* and display a new tree. For example, as shown on the left of Figure 3, a user performs a repair by clicking and dragging White, total so that it becomes a child of Male, total. Meanwhile, the *extract* component automatically discovers that Black, total should also be moved. Thus, the user's one single repair action can trigger multiple fixes, yielding the hierarchy shown on the right. After repairing extraction errors, the user can review the generated relations by clicking "Relational Table," as shown in Figure 4(a).

Query – Users can perform *query* operations on the extracted relational table. They are not required to write SQL statements and can apply *select* and *join* via the interface:

1. Select – The *select* feature, also called *filter*, is similar to executing a selection query on the recovered relation. Clicking "Filter," a user can use a faceted-search interface to specify the filter conditions. This interface is automatically composed by Senbazuru. For example, Figure 4 (a) shows that the user limits the displayed data to smoking statistics for people who are Female, Black, and 18 to 24 years old.

2. Join – The *join* feature allows users to integrate two arbitrary spreadsheet-derived relations. The user starts by

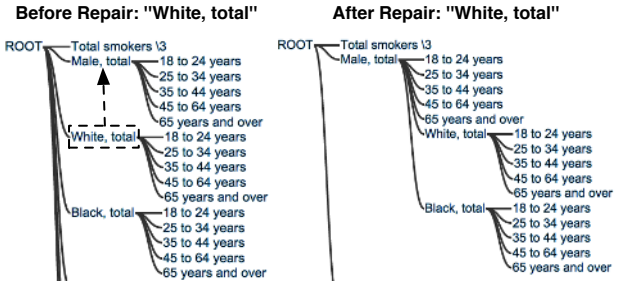
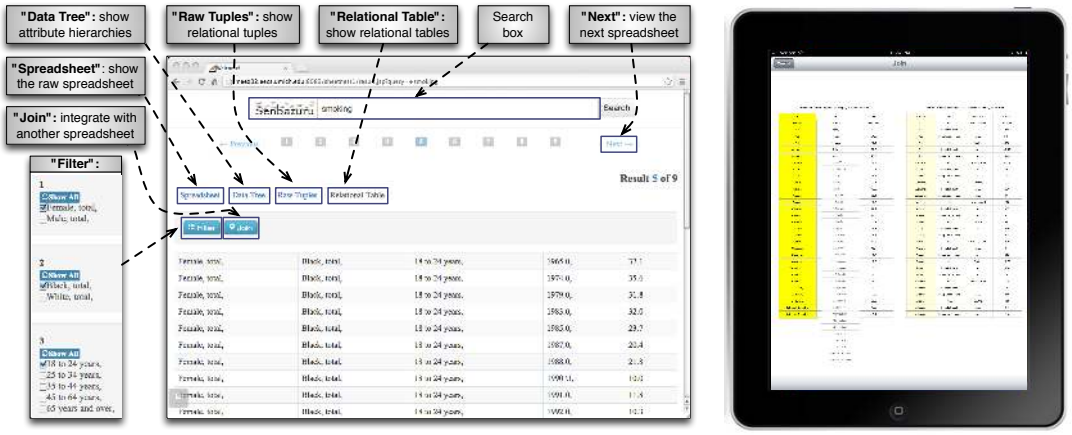


Figure 3: Senbazuru recovers the attribute hierarchy seen in Figure 1, and makes the recovered structure available for manual user repairs.



(a) (b)

Figure 4: Screenshots of two Senbazuru clients, as a desktop application (a) and an iPad application (b).

applying the *search* and *extract* features as described above. Once the user has found a good result, she clicks "Join" and enters a second text query. The query yields a second ranked result list. She chooses a relevant join target from this ranked list and obtains a correctly extracted relation. She indicates which columns from each dataset should be used as an equijoin key.

For example, Figure 4 (b) shows a screenshot of the *join* process on our iPad client. When the user touches a column, Senbazuru highlights it in bright yellow, as shown on the left of the figure. Meanwhile, Senbazuru faintly highlights a column on the right-hand table to indicate a possible join. The user can drag the column, highlighted in bright yellow, from the left-hand relation to the right and release it. This action indicates the join key; Senbazuru executes the appropriate join and shows the user the resulting brand-new relation.

3.2 A Walk-through Example

We will demonstrate Senbazuru's workflow through Fred's example. Recall that our policy expert Fred wants to find the relationship between smoking and lung cancer across the U.S. states. Using Senbazuru, Fred can obtain the requested data through the following steps:

1. Search for "smoking by state."
2. Browse the returned spreadsheets and select the most relevant one.
3. Click "Data Tree" and check the correctness of the extracted attribute hierarchies.
4. Repair the hierarchies if any extraction errors exist.
5. Click "Data Table" to review the extracted relation.
6. Repeat the process from step 1 to get the relational table for the most relevant lung cancer spreadsheet by querying "lung cancer by state."
7. Specify join columns to create a new table.
8. Review the result, using the faceted *select* interface.

In addition to Fred's example, VLDB attendees are welcome to try many other interesting queries, such as "employment statistics 2010" and "Michigan GDP."

4. CONCLUSION

Senbazuru is a prototype spreadsheet management system. It searches a large number of Web crawl spreadsheets, and it automatically transforms spreadsheets into relations while allowing users to fix the extraction errors effectively and efficiently. Finally, it supports selection queries on the resulting relations and join queries to integrate arbitrary spreadsheets. We believe a demo of Senbazuru will be of great interest to the VLDB attendees and the database community as a whole.

5. ACKNOWLEDGMENTS

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