Iterative Querying in Web-Based Database Applications

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Abstract

Web applications are increasingly relying on databases. The traditional method offered by most web sites of submitting a query across the Internet and getting a response from a server packed in a Hyper Text Markup Language page is no longer satisfying [1][3][4][5]. This is due to the result set: it is often too large or empty. This forces the user to try and guess which constraints should be relaxed or tightened in order to obtain the desired result set. And so, the user goes through several submit/response cycles. Web applications that require this sort of interactive exploration of databases need to use a model that is different from the submit/respond model described above. In this work, we propose an iterative querying model that integrates querying with result browsing.

Keywords: Browsing, iterative querying, result set, and web-based database applications.

1. Introduction

In traditional databases, queries are rigid in that they are intended for asking very specific questions [2]. The results are interesting no matter what the result set is. The individual query itself is the goal. On the other hand, when we are interested in exploration the goal is locating particular records of interest. To do this, we need to provide the user with a combination of result browsing and searching so that he/she can see the query and its results simultaneously. As the user changes the query constraints, the impact on the result set should be immediate.

The aim of this work is to provide how the overall design of such a system might be with some stress on the user interface, which is a key element in the exploration process. The rest of the paper is organized as follows: section 2 presents the user interface. Section 3 details the overall system design. Section 4 concludes the paper.

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2. User Interface

The user interface plays a key role in enhancing the experience of the user. Records are displayed in a scrollable list format with a separate column for each numeric and categorical attribute as shown in Figure 1. At the top of each column is a title bar showing the name of the attribute. The names of the attributes are obtained from the database catalog. Beneath each of these titles is an "attribute control" used for specifying attribute restrictions. Categorical attributes are represented by select lists that allow users to (de) select (un) desired values. Numeric attributes are represented by vertical sliders, which may be resized and dragged to specify desired ranges. Initially, these attribute controls are maximized to include the full value-range of each attribute. Immediately, a user can see how many records are available, the value range of each attribute, and actual matching records. At any stage, the user can scroll through the list of records in the result set and can instantaneously change the sort order of the record list by clicking on the title bar of any column.

Contrast this iterative querying model with the conventional form-based approach [3]. The user would be entering
requirements into a static query page and would not know the result of the actions until the query is submitted and the response is received. If the query was restrictive, the user would most likely be presented with a short message indicating that no records matched the criteria, and that the user should try again. If the query was too loose, the user would probably be shown a single large listing of all matching records, or more likely, a series of linked pages containing twenty or so matching records per page. In both cases, no information is given as to how the query is to be relaxed or tightened, forcing the user to repeat this submit/response cycle as the user adjusts the requirements unaided. Each such cycle requires the attention of the web and database servers, not to forget a round-trip through the network. In the case of iterative querying, empty result sets can be easily avoided or backed out because the user can actually see the result set change as the query is tightened or relaxed.

2.1 Exploration Based on Example Records

Since query results are always visible, this allows a Query-By-Example [6] capability not available in most search interfaces. Rather than explicitly specifying a desired range of attribute values, a user can select example records to direct the exploration. This type of querying can be very useful in situations where the user may not be too knowledgeable about the domain, but knows of some sample records of interest. For example, a user who does not know about horsepower or what a "fast" 0-100-kph time is can still search for sporty cars by selecting several known examples. These records implicitly define a query region comprising the smallest hypercube that contains all the selected data points.

2.2 Exploration Based on Similarity

In addition to querying by example, we can allow sorting by example as well. This is essentially similarity search, except that instead of treating similarity as a separate stand-alone query like some search engines do for web pages (e.g., Excite) [7], it is integrated into the existing view. After selecting one or more sample records, the user can click a button and sort all the records by how "near" they are to the selected examples. Nearness is based on some similarity model. The similarity scores are then displayed in a new column labeled "Rank" which appears after the rank button is pressed.

3. System Design

We now describe the details of how we implement iterative querying. In order to obtain interactive response times, we exploit several key observations. First we must cache data records in the local client. There is little chance of interactive response times unless the interaction between the user and data is moved off of the server and out of the network. While this does place a memory requirement on the client, it offers an advantage beyond that of just faster access - the cache can be tailored to the user and the particular task of data exploration. An initial query representing the set of data to be explored is used to transfer data from the server-side database. This data is then cached using special data structures for further exploration.

In cases where users may wish to explore data outside the current cache, techniques such as semantic data caching can be used [8].

Fortunately, while the total size of the underlying database can be huge, the scope of the data over which a user performs interactive exploration for some task is often limited enough that corresponding records are able to fit in a reasonably sized cache. For example, in web-based product exploration applications, a user will explore options within one product category at a time and not across product categories. The active set thus typically consists of records in thousands and not millions.

We also take advantage of the fact that there is always a notion of a current state. This state is represented by the current settings of the attribute controls (i.e., the "query") and the corresponding set of matching records. Every adjustment of these controls represents a minor change to an existing query. Rather than execute the new query entirely from scratch, we only need to update the current results to reflect the change. This can be made extremely efficient because of another observation: there is only one mouse. The user can adjust the restrictions of only one attribute at any given instance.

By taking advantage of these observations, we are able to exhibit extremely fast response times, even with datasets containing hundreds of attributes and hundreds of thousands of records.

3.1 Architecture

Figure 2 gives a high-level overview of the proposed architecture. The DataColumn objects represent the data cache with each DataColumn representing one column of attribute data. DataGroup maintains this cache. Observe that with this design, data for different attributes can be loaded and processed asynchronously. Thus, during data loading, the user can see column data appear progressively, rather than having to wait for the entire dataset. Furthermore, once a column of input data has been loaded and its DataColumn object created, the user may immediately begin to restrict or sort on that column, even as other columns are still being loaded.

ListRenderer represents the Graphical User Interface (GUI). It is responsible for rendering the current set of matching records, as well as passing user changes in attribute restrictions to the core engine. This interaction is handled by events and explicit Application Programming Interface (API) calls.

The final piece labeled Core encompasses the entire design. In a Java implementation, this is the hosting applet that must deal with menus, graphical layout and other details. It is also responsible for determining what data source to use and what attributes to select. This is handled through user interaction. The Core component is also responsible for retrieving the data from the data source. It can do so through a standard API we call the DataPump. This design allows us to support various data sources by simply plugging in a different implementation of the DataPump API. In the particular instance shown in Figure 2,
DataPump communicates via HTTP to a Java Servlet running on a web server. This Servlet uses JDBC to communicate with the database. When Core requests data via the DataPump API, the DataPump object passes the request to the Servlet, which in turn issues a query to the database. Data is returned to Core from the DataPump in column-order rather than row-order. This allows each column to be converted into DataColumn objects independently and asynchronously. How data is transferred between the server and the DataPump (row-order vs. column-order, synchronous vs. asynchronous) is entirely up to the DataPump implementation.

For concreteness, we will be describing the design using the example dataset shown in Figure 3. This dataset represents car listings and contains attribute data for the Make of each car and the Distance in miles between the user and seller locations.

Note that this example demonstrates how the data received and cached by the system can be tailored for a particular user - Distance is a derived attribute that depends upon the user and would not exist in the server's database. Each record in this dataset is uniquely identified by an integer in the range [0, n-1], called a record identifier, or RID. These RIDs are not part of the dataset and do not correspond to any database or server-side identifiers. They are simply internal IDs used in the cache, assigned sequentially as records are loaded from the server.

<table>
<thead>
<tr>
<th>RID</th>
<th>Make</th>
<th>Distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>Ford</td>
<td>25</td>
</tr>
<tr>
<td>1</td>
<td>Honda</td>
<td>3</td>
</tr>
<tr>
<td>2</td>
<td>Ford</td>
<td>537</td>
</tr>
<tr>
<td>3</td>
<td>Chrysler</td>
<td>117</td>
</tr>
<tr>
<td>4</td>
<td>Honda</td>
<td>64</td>
</tr>
<tr>
<td>5</td>
<td>Honda</td>
<td>8</td>
</tr>
</tbody>
</table>

Figure 3. A Dataset Example.

### 3.1.1 DataTypes

Each DataColumn is responsible for caching and indexing one attribute's worth of data. DataTypes consist of two basic components: an array of data values indexed by record identifier, and a RID-list. The RID-list contains RIDs sorted by their corresponding attribute value. RID-lists are required for performing fast attribute restrictions, but offer the additional benefit of pre-computed sorts. The DataColumn objects differ for numeric and categorical data types.

#### Numeric DataTypes

For numeric attributes, we allocate an integer or float array and copy incoming data values into it. At the same time, we allocate an integer array for the RID-list and store the RID values in order (from 0 to n-1, where n is the total number of records). The RID-list is then sorted by the corresponding attribute values, resulting in a final DataColumn object like the one shown in Figure 4. Observe that Data [RID-list [i]] gives the value of the i-th item in the sorted list of data values.

#### Categorical DataTypes

Categorical DataTypes are somewhat more involved than numeric ones. In addition to a data array and a RID-list, categorical DataTypes also require a hash table and specialized objects called RIDSets. This is due to the fact that users need to be able to add and drop arbitrary categorical values to and from the query. A RIDSet object consists of three components: a categorical string value, an integer count value, and an integer index.

<table>
<thead>
<tr>
<th>RID-list</th>
<th>Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>23</td>
</tr>
<tr>
<td>5</td>
<td>3</td>
</tr>
<tr>
<td>0</td>
<td>537</td>
</tr>
<tr>
<td>8</td>
<td>117</td>
</tr>
<tr>
<td>4</td>
<td>64</td>
</tr>
<tr>
<td>9</td>
<td>8</td>
</tr>
<tr>
<td>3</td>
<td>363</td>
</tr>
<tr>
<td>7</td>
<td>192</td>
</tr>
<tr>
<td>10</td>
<td>41</td>
</tr>
<tr>
<td>6</td>
<td>89</td>
</tr>
<tr>
<td>2</td>
<td>207</td>
</tr>
</tbody>
</table>

Figure 4. RID-list and Data.

We first describe the creation of the categorical data array. Instead of allocating an array of strings to store the data values, an array of RIDSet references is allocated. Also allocated is an empty hash table. As the incoming categorical attribute data is
scanned, the hash table with each string value is probed first. If the probe fails (meaning this is the first time this categorical value is seen), a new RIDSet object is allocated. The string value is stored in the new RIDSet (RIDSet.value) and the RIDSet count (RIDSet.count) is set to one. RIDSet.count will eventually indicate the number of records that share this categorival value. The new RIDSet is then stored in the hash table, indexed by the string value. If the initial probe of the hash table does not fail, we will get back an existing RIDSet whose string value is the same as the current record. In this case, the RIDSet.count is simply incremented by one. In either situation, the current record's corresponding entry in the data array is set to point to this new RIDSet. Once the scan of the input data is finished, we will have exactly one RIDSet object per unique categorical value, and a fully initialized data array consisting of pointers to these RIDSets. At this point, the original categorical data can be discarded. Figure 5 shows this state for a categorical DataColumn constructed from the Make attribute of our example dataset. Observe that if the data array is scanned in order and the string value of each referenced RIDSet is examined, the values seen will correspond exactly with the original input data.

![Figure 5. Make DataColumn (after input scan).](image)

Now a sorted RID-list for this DataColumn must be built. As a performance optimization, rather than sort an entire RID-list as is done for numeric DataColumns, each unique string value (or key) is collected and then sorted in a separate array. The number of keys should be smaller than the total number of records. This improves the sort cost. These keys can be retrieved from the RIDSets, the hash table, or collected during the data-scanning phase. In our running example, an array of 4 keys would be sorted. Next, a temporary variable called index is allocated and its value is set to zero. We then step through the sorted array of keys and for each key, the corresponding RIDSet object is retrieved from the hash table and RIDSet.index is set to be equal to the index. The index is then incremented by RIDSet.count and RIDSet.count is set to be equal to zero. Once this scan is completed, the index value of each RIDSet will indicate where in the RID-list we store the RIDs of those records that share RIDSet.value. At this point, the sorted list of keys can be discarded.

The RID-list is now allocated and a scan of the DataColumn's data array is initiated. For each RIDSet encountered, the corresponding record's RID is stored in the RID-list at the position: RIDSetSet.index + RIDSet.count. RIDSet.count is then incremented by one. Figure 6 shows the completed DataColumn after this scan has finished, along with the temporary sorted array of key values. Note that the RID-list is now in sorted order and all the RIDSet.counts have been restored to their original value.

3.1.2 DataGroup

DataGroup manages the DataColumn objects and is the mechanism through which the ListRenderer interacts with the data cache. It also manages two other crucial items - the Restrictions array and the ResultSet counter. The Restrictions array is an array of integers, indexed by RID that keeps track of the number of restrictions against each record. If a record's restriction count is zero, then that record is unrestricted and belongs to the current result set; otherwise it does not. The ResultSet counter indicates the number of unrestricted records (i.e., the size of the current result set).

![Figure 6. Categorical DataColumn for Make (completed).](image)

Initially, all the restriction counts are set to zero and ResultSet is set to the total number of records. When a record is restricted along some attribute, its corresponding restriction count is incremented (even if that record is already restricted along some other attribute). Likewise, whenever a record is unrestricted along some attribute, its restriction count is decremented. Additionally, whenever a record moves out of or into the result set (i.e., its restriction count is incremented from zero or decremented to zero), the ResultSet counter is decremented or incremented accordingly.

3.2 Performance Restrictions

We now discuss how the system uses the data structures just described to realize instantaneous response time for doing interactive exploration. As mentioned earlier, every change to an
attribute control in the GUI represents a change in state. A state change is always a tightening or relaxation of the restriction bounds on one attribute. The ListRenderer passes down state changes to the DataGroup object, which in turn passes the state change down to the appropriate DataColumn object for building the cache.

Numerical Restrictions

While the attribute controls in the GUI represent the current query state for the user, internally the current state is represented differently. The current state for numeric DataColumn is represented by two values, LowerIndex and UpperIndex. These values identify a sub range in the DataColumn's RID-list. Since the RID-list is sorted by attribute value, a sub range in the RID-list corresponds to a sub range in attribute value. Initially, LowerIndex is set to 0 and UpperIndex is set to n-1. A state change on a numeric attribute always means that either the LowerIndex or the UpperIndex may have to change.

Suppose in our car example, all attributes are currently unrestricted, meaning that LowerIndex and UpperIndex for the Distance DataColumn are currently set to 0 and n-1 respectively. The state change Distance < 100 now arrives indicating that the UpperIndex must be changed. Initiating a scan backwards through the RID-list from the current UpperIndex position does this. For each RID encountered, we lookup its corresponding attribute value in the data array and compare it to the new upper bound of 100. If the value lies outside the new boundary, we update the restriction information in the DataGroup and continue the scan. We stop once we reach a value that lies within the new boundary. The current scan position in the RID-list becomes the new value for UpperIndex.

Categorical Restrictions

For categorical attributes, state changes always involve a single categorical value being either restricted or unrestricted. For ease of exposition, assume that each RIDSet in a DataColumn has an additional Boolean flag that indicates whether or not that value is currently restricted. Together, these Boolean flags represent the current state for this attribute. When a state change arrives (e.g., Make = {Ford}, i.e., Ford is excluded), we retrieve the corresponding RIDSet from the hash table. We then scan the portion of the RID-list marked by RIDSet.index and RIDSet.count and update the DataGroup statistics accordingly. We also set the Boolean flag in the RIDSet to indicate the new state. Note that the RIDSet structures allow us to examine only those RIDs that are relevant to the restriction.

The processes described above are essentially identical when relaxing restrictions. The primary difference is in how the DataGroup statistics are updated and, for numeric DataColumns, in what direction the RID-list is scanned. It should be emphasized that when performing restrictions, we need only look at the data of the attribute involved. Additionally, we only examine data for those records actually affected by the restriction change. If a restriction change only affects 50 records, then we only examine those 50 records in one DataColumn, regardless of the total number of records or attributes.

4. Conclusion

We presented a model of a database exploration engine that implements iterative querying in web-based database applications. It has fast response time even when exploring hundreds of thousands of records containing hundreds of attributes. Query borders in our proposal can also be made non-strict such that records that lie just outside the query region can still be included in the result set.

The speed at which query changes are processed is enhanced by processing changes immediately rather than waiting for the user to hit a submit button. This not only results in small query changes that can be effected quickly, but also offers the additional advantage of immediate feedback for the user.

References


Biography

Ramzi A. Haraty is an Assistant Professor of Computer Science at the Lebanese American University in Beirut, Lebanon. He received his B.S. and M.S. degrees in Computer Science from Minnesota State University - Mankato, Minnesota, and his Ph.D. in Computer Science from North Dakota State University - Fargo, North Dakota. His research interests include database
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