The Interactive Join: Recognizing Gestures for Database Queries

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Abstract
Direct, ad-hoc interaction with databases has typically been performed over console-oriented conversational interfaces using query languages such as SQL. With the rise in popularity of gestural user interfaces, users are resorting to gestures as their exclusive mode of interaction. In the absence of keyboard-oriented interaction, database query interfaces require a fundamental rethinking to support gestures. Unlike domain-specific applications, the scope of possible actions is significantly larger if not infinite. Thus, the recognition of gestures and their consequent queries is a challenge. We present a novel gesture recognition system that uses both the interaction and the state of the database to classify gestural input into relational database queries. Preliminary results show that using this approach allows for fast, efficient and interactive gesture-based querying over relational databases.

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Gesture Recognition, Query Interface, Databases, Unsupervised Classification

ACM Classification Keywords
H.5.2 [Information interfaces and presentation: User Interfaces – Graphical user interfaces.]:

Introduction

Gestural user interfaces have become a popular mode of interaction with a wide variety of touch-based, motion-tracking or eye-tracking devices. Given the rising popularity of such devices, domain-specific applications have come up with mappings between standard gestures and actions pertinent to the system. The onus of gesture recognition is on the user interface layer, which identifies the gesture as one of a set of gestures predefined by the operating system. The gesture type, with parameters such as *coordinates* and *pressure* are sent to the application, which then uses them to infer actions. This mapping of gestures to actions can be considered as a **classification problem**, and the bulk of the recognition is performed at the interface layer, independent of the application state.

End-user-friendly interaction with databases is a well-motivated problem [6]. There has been a wide variety of work in open-domain query interfaces, however all current efforts are based on keyboard or mouse-driven interaction, and are hence unsuitable for gestures.

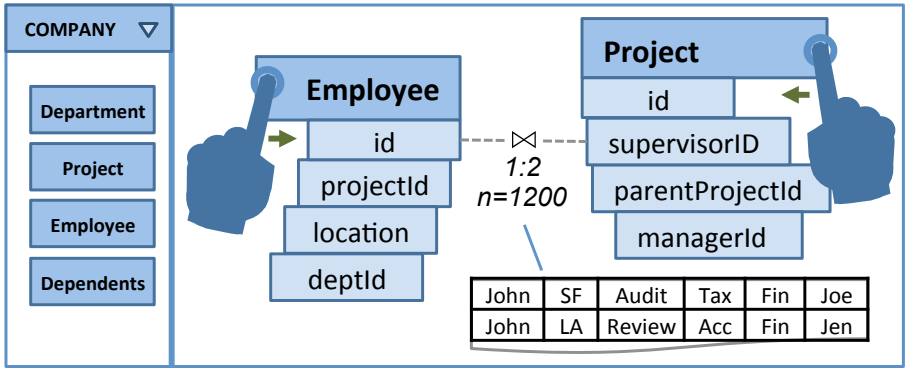

Figure 1: The Interactive Join being performed in the QWiK interface. Tables in a relational database are joined together using multitouch gestures. As two tables are brought close to each other, the attributes are presented in a curve such that they are amenable to be joined. The most likely join is presented as a preview to the user.

In the context of ad-hoc, open-domain querying of relational databases, the use of gestures as the sole mode of interaction faces several challenges. First, the space of possible actions is large[1] – the action depends on the underlying database query language (e.g., SQL), the schema of the database (i.e. the tables and the attributes for each table) and the data contained in it (the unique values for each attribute, and the individual tuples for each table). Thus, the classification problem of mapping a limited set of parameterized gestures to actions becomes a significant challenge – there are simply too many possible actions. Clearly, we need to use more than just the gestural information to perform an adequate classification.

To this end, we develop a novel two-stage classifier that relies on both gestural input and the state of the database to recognize queries. At the first level, the classifier identifies an ordering of candidate query types that are most likely to be associated with the gesture. At the second level, the classifier leverages various metadata stored in the database such as the schema, type information and data distributions for each attribute to narrow down on the exact query being formulated.

Our system has two additional constraints – the classifier needs to be either unsupervised or trained *offline* to avoid custom training on a per-user level. Second, the system must work at *interactive* speeds, such that the user is guided through the space of queries during the articulation of the gesture itself. This allows the user to gain insight into the database, and at the same time disambiguate the gesture, improving gesture recognition.

[1] When considering n-ary joins, this space is infinite.

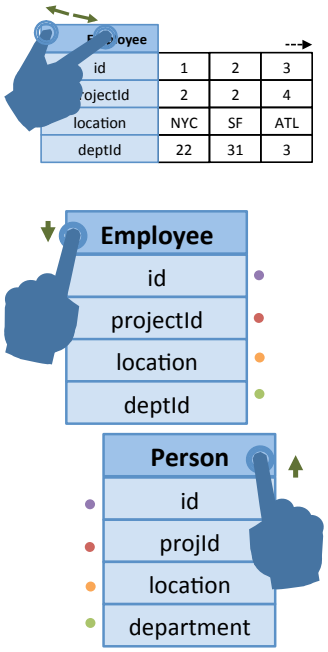

Figure 2: The `PREVIEW` and `UNION` actions.

A Gesture-driven Database Query Interface

As depicted in Figure 1, the database query interface allows users to directly manipulate results by interacting with them in a sequence of gestures. Tables are dragged to the workspace from the database tray. Each table in the workspace represents a *view* of the table, i.e. cloned representation of the data, and can be directly manipulated. Each *gesture* denotes a single manipulation *action* and impacts only the cloned instance – not the original database. There are a finite number of intuitive gestures that the user can learn, each of which when performed on the workspace can correspond to an action. Users can undo each action to return to the previous workspace state. Since actions directly correspond to SQL queries, all actions manipulate the target SQL view to another SQL view. Thus, actions are stackable and can be performed in sequence, manipulating tables in the workspace till the desired result is achieved.

A Gesture Vocabulary

While the size of our gesture vocabulary (and the set of corresponding types of actions) is quite large, we present only three actions for the sake of conciseness and clarity. The three actions, `UNION`, `JOIN` and `PREVIEW` allow the user to view, compose and combine information from the database. The gestures associated with these actions are shown in Figures 1 and 2. At the same time, this condensed vocabulary allows us to motivate and demonstrate various aspects of the gesture recognition problem.

`PREVIEW`**:** This action works on a single table. When dragged from the database tray, each table is represented by the name of the table and its attributes. By making the *pinch-out* gesture on the table in the workspace, the `PREVIEW` action is issued on the target table. This is issued to the database as the SQL query `SELECT * FROM TARGET_TABLE LIMIT 10;`, presenting the first ten rows of the table on screen[2].

`JOIN`**:** Two tables can be composed together by moving them close to each other. The `JOIN` action represents the *inner equijoin* SQL query, representing combinations of rows that have the same value for the attributes that are being joined upon. Upon bringing tables close to each other, the attribute list curves such that users can articulate the intended pair of attributes.

`UNION`**:** Two tables can be unified into a single table if their attributes are compatible; i.e. they have the same number of attributes, and each pair of attributes is of the same data type. To unify tables, the user drags one table onto another from the top, in a stacking gesture. A preview of the unified rows representing both originating tables is depicted.

Gesture Recognition as Classification

We assume the input to our classifier similar to what is available on current multitouch mobile platforms. The UI layer will supply the classifier with a list of (x,y) coordinates and an ordinal identifier indicating which finger it is associated with. These identifiers are assigned arbitrarily when a gesture is initiated, but are consistent over the course of the gesture. Given this input, the classifier makes a decision based on the most recent coordinate for each identifier.

A gesture is classified as a particular query according to the **proximity** and **compatibility** of the tables involved. Proximity encompasses all of the spatial information about the UI elements, including size, shape, position, and

[2]We skip more complex variants of preview for conciseness and to focus on the gesture recognition challenges.

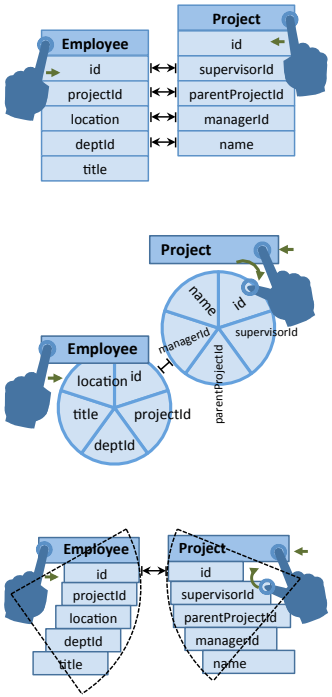

Figure 3: Choices of Table Layout: Tabular, Radial and Arc. The responsive arc layout allows all queries to be expressed unambiguously while still achieving readability.

orientation of table and field graphical representations along with their velocity and acceleration.

Classification based solely on proximity is the currently prevalent UI paradigm. By adding compatibility, we are able to increase the likelihood of selecting semantically meaningful queries. Compatibility criteria include schema information like field type, and data distributions, like histograms, extreme values, intersection in random samples, or total intersection.

We use a maximum entropy classifier in which we define many "features" of queries, including proximity and compatibility features conditioned on each type of query, and combine them linearly in the argument of an exponential. Mathematically, the goodness $g(q)$ of a potential query q with feature values $f_i(q)$ is

$$g(q) = \exp(\sum_i \lambda_i f_i(q)). \quad (1)$$

Features can be binary or real-valued, with 0 being the value of an uninformative feature. Parameters of the classifier, λ_i, can be learned across a collection of recorded training gestures to tune the quality of the classifier. For preliminary experiments in Section , these parameters are set manually, and tuning using training data is scope for further improvement in quality. New queries can be defined by adding new feature functions $f_i(q)$ and adding new potential queries q to the set of queries.

At each classification request, each query type (`JOIN`, `UNION`, `PREVIEW`) independently selects a specific query with the highest goodness and the query with the highest overall goodness is selected. Each query type first considers whether the current gesture could represent a query of its type, i.e., it involves the correct number of tables and the tables are compatible with each other and with the query type. If so, it proceeds to find the best specific query of its type, checking the proximity and compatibility of the fields and tables involved, if necessary.

Design Considerations: Join Layout

While the `PREVIEW` and `UNION` interactions are straightforward, laying out attributes during the `JOIN` interaction faces several challenges. First, due to the textual nature of the information, it needs to be presented such that readability is preserved. Second, the interface should allow the user to express all possible queries. In the case of a pair of tables such that all the attributes are of the same type, there are $m \times n$ possible joins, where m and n are the number of attributes in the two tables.

We consider multiple layout options to represent the `JOIN` operation, as shown in Figure 3. The first option is to present each list of attributes as a simple vertical list. The problem with such a layout is that for any given position of two vertical lists, there may be more than one pair of attributes that are the closest, thus leaving the `JOIN` intent ambiguous. For example, a pair of attributes that are both at the top of the list for their respective tables, aligning the two will always result in aligning the second attributes at the same distance, thereby resulting in an ambiguous gesture.

A second option is to consider a radial layout where each table is represented as a radial menu. Geometrically, two circles can be closest at exactly one location, uniquely specifying a pair of attributes. However, radial menus are hard to read, don't scale to a large number of attributes, and will need to be rotated for all $m \times n$ possible attribute pairs.

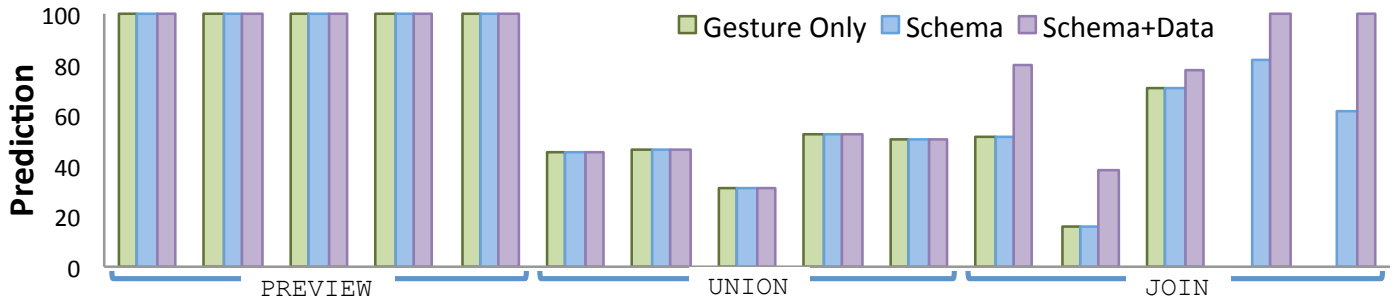

Figure 4: Prediction scores for a workload of 15 queries, where 100% represents correct classification at the start of the gesture articulation, and 0% represents an incorrect classification even after completion of the gesture. Information from the schema and data in the database allows our classifier to better predict the intended database query for ambiguous gestures.

As a solution to these problems, we use an *arc* layout, such that attributes are vertically stacked ensuring readability, but are placed in an arc connected at the table label. This ensures that joining intent is unambiguous since arcs can be closest at exactly one location. Further, the orientation of the arcs are flexible and user controllable (a multitouch interaction involving four points, two for each table), allowing the user to specify any pair of attributes as the join predicate.

Preliminary Results

We now share some preliminary results on the quality of our gesture recognition system. Experiments were performed by collecting multitouch coordinates (a series of X, Y coordinates per touched finger) from a prototype system implemented using Javascript and HTML on an iPad. Each set of coordinates represents a multitouch gesture on one or more tables, representing a database query. For `JOIN` queries, we test the classifier by not allowing for rotations to the arc, forcing the classifier to resolve ambiguity. In the database, each table contained 4 attributes with varying types and data distributions. Coordinates were collected for 15 different gestures, articulating 5 gestures each for `JOIN`, `UNION` and `PREVIEW` queries.

We identify three key metrics: **Accuracy**, **Prediction** and **Performance**. Accuracy measures the fraction of the queries that our classifier correctly identified from the gestures. Prediction measures how quickly our classifier can correctly map the gesture to the intended query. It is calculated as the fraction of touch coordinates till the query is correctly identified. Performance measures how quickly the system can react to a given input, measured as the number of milliseconds it takes to identify the query at each new touch coordinate.

For performance, we observed that our system performs well within the 10ms range per classification and can thus maintain a fluid touch interaction. As expected, all `PREVIEW` queries are trivial to recognize since both touch points are on the same object. In terms of accuracy, the baseline gestural recognition fails to recognize 2 of the 15 queries tested. Given schema information, our classifier correctly recognizes 100% of the queries (and implicitly, query types). As shown in Figure 4, using the data

distribution information significantly improves *prediction* ability for `JOIN` queries, and has no impact on `UNION` queries, since the `UNION` operator does not leverage the data information for disambiguation.

Related work

Gestural interaction in domain-specific use cases has been studied [13] widely. User-friendly solutions to interacting with databases have ranged from example-driven querying [1], to automated form generation [7] spreadsheet interfaces [2] to autocompletion [8, 9] and query recommendation [3]. Visual analytics systems such as Tableau [12], TaP [5] and SQL Server Kinection [10] map interactions and gestures from the UI layer to a set of database query templates, without considering the contents of the database itself. Probabilistic methods to improving gesture recognition[14] and mapping interaction to actions [4, 11] have been discussed before, however such methods would be too computationally intensive to recognize the space of all possible database queries. In contrast to these systems, our classifier performs a two-stage recognition, mapping gesture coordinates to action types, and then further using an arc layout and database statistics to successfully identify the exact query.

Ongoing Work

We plan to evaluate the usability and learnability of our system over users at multiple levels of proficiency of querying databases and our gestural interface. Gesture coordinates from these user studies will then be used to further tune the parameters of our classifier, which can then be evaluated using k-fold cross tests to measure the benefits (in accuracy and prediction) and generality (across both users and queries) of user training. Finally, we plan to evaluate the impact of providing insights to the user in the form of result previews for the most likely query *while* the user is articulating the gesture itself.

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