AutoJoin: Generalizing an Example into an EDM query

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Abstract. This paper describes an implemented method to generalize an example tutor interaction into a query to retrieve similarly related sets of events. It infers WHERE clauses to equate repeated values unlikely to match by accident.

The Session Browser [1] shown in **Figure 1** is an EDM tool to view data retrieved by querying a database of events logged by a tutor. It displays retrieved events in a context tree of enclosing events, with a 1-line summary of the database record for each event.

C listen_2007_2008
🗟 🦳 15 minute(s) long: Session 2009-03-31 10:22:25
🖮 🛅 1 minute(s) later, 1 second(s) long: Read Story step in ChooseStory
👜 🛅 10 minute(s) later, 3 second(s) long: PROTOTYPE Country Mouse auto-questions new split screen 38 Picker step in activity
63 ms later, 3 second(s) long: student answered keep it to HOW did the cat?
🚊 47 ms later, 26 second(s) long: PROTOTYPE Country Mouse auto-questions new split screen 42 Coach step in activity
👜 🍋 392 ms later, 26 second(s) long: Freeform response to How did the cat o o o o o o o o ?

Figure 1: Event context tree highlighting two events selected by the user to AutoJoin

This brief example occurred in an activity to teach children to ask themselves questions about the text they read. The first highlighted event summarizes a child's multiple-choice response to a prompt to fill in the rest of a question about the text. The second event describes the child's spoken response to a prompt to speak the completed question aloud.

Often we want a query to retrieve examples similar to a current example. Complex queries are hard to construct, so we developed AutoJoin to generate them automatically. AutoJoin generalizes the two highlighted events into a query that finds "similar" cases, in this case a multiple choice step immediately followed by a free-form response step:

```
SELECT * FROM
multiple_choice_question mcq,
sentence_encounter se
WHERE mcq.activity_directory = se.activity_directory
    /* '..\data\stories\PROTOTYPE Country Mouse auto-questions new
    split screen' */
AND mcq.end_time = se.step_start_time /* '20090331103359' (03/31/2009
    10:33:59 AM) */
AND mcq.machine_name = se.machine_name /* 'LISTEN07-211' */
AND mcq.story_encounter_start_time = se.story_encounter_start_time
    /* '20090331102336' (03/31/2009 10:23:36 AM) */
AND mcq.user id = se.user id /* 'mKJ9-5-2001-07-23' */;
```

(The example here is simple for brevity; AutoJoin can generalize from more events too.)

AutoJoin constructs a query as a join of the tables where the selected events were logged. It abbreviates each table by its initials, e.g. multiple_choice_question as mcq and infers **WHERE** clauses by equating field values that show up more than once in those events. The comments, in green, show which values it abstracted into variables; they help the user understand the query and fix over-generalizations easily by uncommenting.

AutoJoin assumes that (1) unlikely matches matter, but (2) their specific values do not, so it (1) infers that the variables must be equal, but (2) abstracts away their specific values. When (1) is wrong, it under-generalizes; when (2) is wrong, it over-generalizes. To avoid under-generalizing, it uses heuristics to prevent meaningless matches. It gauges the likelihood of accidental match from how often the matching value occurs in each field. For instance, NULL values are frequent in many fields due to various reasons, one of which is its use as a no-value indicator. Thus NULL values in two such fields are likely to match by accident. In contrast, data types such as strings and dates have a large range of possible values. Assuming that they are unlikely to match by accident saves time by not bothering to estimate the frequency of the matching value in the two table columns.

Computing how often a given value occurs in a table column takes time for a large table, so AutoJoin estimates it from a sample of 400 rows. This sample is fast to retrieve but may be unrepresentative, especially if the column is sorted. Sampling blocks of 20 rows at 20 randomly chosen offsets is more reliable, but slow enough to be worth caching.

Another heuristic to avoid under-generalizing classifies certain columns as "non-crossmatch" and compares them only with columns of the same name in other tables. For example, the table story_encounter has non-cross-match column story_count, and sentence_encounter has non-cross-match columns sentence_count and word_count. Since story_count, sentence_count, and word_count count different types of things, we assume it does not make sense to compare them. In contrast, comparing start time and end time from different tables does make sense.

The "non-cross-match" heuristic eliminates additional spurious matches, but relies on the naming convention it exploits, and on the user's knowledge of which fields make sense to compare. In contrast, estimating the frequency of matching values does not depend on column names or knowledge of the database schema, so it's a more general method.

We have identified the EDM task of generalizing from a single example of tutorial interaction, described AutoJoin's simple but powerful heuristics, and reported their implementation in the Session Browser. By systematically generating clauses we might omit or mistype, it helps us build complex joins much faster than by hand. It's limited in what it can notice, and it sometimes generalizes accidental matches, so we check its output, but checking is faster than writing queries. AutoJoin may also apply to many non-EDM domains. It seems too simple to be novel, but we have not found it elsewhere.

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References (also see Publications page at <u>www.cs.cmu.edu/~listen</u>)

[1] Mostow, J., J. Beck, A. Cuneo, E. Gouvea, C. Heiner, and O. Juarez. Lessons from Project LISTEN's Session Browser. In C. Romero, et al., Editors, *Handbook of Educational Data Mining*. Taylor & Francis Group, in press.