# Example-Driven User Intent Discovery: Empowering Users to Cross the SQL Barrier Through Query by Example

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Traditional data systems require specialized technical skills where users need to understand the data organization and write precise queries to access data. Therefore, novice users who lack technical expertise face hurdles in perusing and analyzing data. Existing tools assist in formulating queries through keyword search, query recommendation, and query auto-completion, but still require some technical expertise. An alternative method for accessing data is Query by Example (QBE), where users express their data exploration intent simply by providing examples of their intended data. We study a state-of-the-art QBE system called SQUID, and contrast it with traditional SQL querying. Our comparative user studies demonstrate that users with varying expertise are significantly more effective and efficient with SQUID than SQL. We find that SQUID eliminates the barriers in studying the database schema, formalizing task semantics, and writing syntactically correct SQL queries, and thus, substantially alleviates the need for technical expertise in data exploration.

CCS Concepts: • **Software and its engineering** → **Programming by example**; Software usability; • **Information systems** → *Structured Query Language*; • **Human-centered computing** → **User studies**; *Usability testing*.

Additional Key Words and Phrases: query by example

## 1 INTRODUCTION

The proliferation of computational resources and data sharing platforms has reached an ever-growing base of users without technical computing expertise, who wish to peruse, analyze, and understand data. From astronomers and scientists who need to analyze data to validate their hypotheses, all the way to computational journalists who need to peruse datasets to validate claims and support their reporting, the broad availability of data has the potential to fundamentally impact the way domain experts conduct their work. Unfortunately, while data is broadly available, data access is seldom unfettered. Existing systems typically cater to users with sound technical computing and programming skills, posing significant hurdles to technical novices, who do not have strong technical background. *Democratization* of computational systems demands equal access to people of different skills and backgrounds [25, 51, 53].

*User Scenario (Adapted from [58]).* Consider a sales executive who needs to prepare a sales report over the last week consisting of sales records indicating which customers bought which products. Most enterprise databases are large and sales records are not stored in a flat format (e.g., spreadsheet). Instead, such large-scale sales information is usually split into multiple tables to achieve database normalization, and stored within a database management system such as PostgreSQL. Furthermore, the table contents are often encoded for compression and reference purposes (e.g., product ID



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instead of product name). Therefore, to generate the sales report, the sales executive will have to (1) familiarize themselves with the data organization (schema) to locate relevant tables and understand the name encoding schemes, and (2) pose a query in the SQL language that is both syntactically and semantically correct to obtain the desired sales records in the correct format (e.g., customer names and product names). These steps are challenging for the sales executive who lacks a technical background, and thus, they would prefer to bypass such complexities. However, an enterprise information worker, such as this sales executive, is often aware of a few *examples* that should be present in the report. They might remember that `John Smith` bought an `iPad` and `Nora Shankar` bought a `Samsung smartphone` last week. Certainly, they might not remember all sales records, but can an *example-based* interaction mechanism effectively assist this sales executive in their task here, with just these examples? Furthermore, for users with some technical skills, would such an interaction model still be useful?

Example-based interactions have been explored as a method to bridge the usability gap of computational systems that typically require precise programs from users, such as in our user scenario above. Under the *programming by example* (PBE) paradigm (also known as *programming by demonstration*), instead of writing a precise program to specify their intent, users only need to provide a few examples of the mechanism or result they desire [7, 24, 43, 56]. Prior work conducted user studies to contrast PBE tools against traditional alternatives [11, 41, 47, 55]. However, none of them considered PBE tools that are specifically designed for data exploration over relational databases. We argue that *query by example* (QBE), a facet of PBE focused on access and exploration of relational data, has unique characteristics and poses distinct challenges compared to general PBE methods. The focus of our work in this paper is to study the effectiveness and usability of state-of-the-art QBE against the traditional relational data access methods that rely on SQL programs, through comparative user studies. We proceed to provide some background on PBE and QBE systems, highlight the unique aspects of QBE that have not been addressed by prior work and call for a targeted study, and summarize our method and the contributions we make in this paper.

**Programming by example (PBE): background and applications.** The PBE paradigm is based on the intuitive premise that users who may lack or have low technical skills, but have expertise in a particular domain, can more easily express their computational desire by providing examples than by writing programs under strict language specifications. This is in contrast with traditional program synthesis [26, 33, 54], which requires a high-level formal specification (e.g., first-order logic) of the desired program. Example-driven program synthesis has been effectively used for a variety of tasks, such as code synthesis for data scientists [11]; data wrangling [23], integration [31], extraction [5, 39], transformation [22, 28], and filtering [67]; data structure transformation [18]; text processing [70], normalization [38], and summarization [15]; querying relational databases [58], and so on.

**Query by example (QBE): the need for a new study.** Example-driven interactions have also been explored in the context of retrieving and exploring relational data, which led to the development of *query by example* (QBE) systems [8, 16, 17, 52, 58]. In QBE systems, a user is expected to provide examples of the data records they would like to retrieve, in place of providing a well-formed query in the SQL language. The QBE system then infers the query the user likely intended, and uses it to retrieve additional records from the database. QBE is a special category of PBE that brings forth unique aspects and challenges. We proceed to describe three significant distinctions that motivate our comparative study evaluation of QBE systems.

First, the traditional mechanism for retrieving relational data requires not only strong technical skills over the SQL language, but also familiarity with the structural organization of the data, called a schema. Schemas can be very complex, may contain domain-specific abstractions, differ from one database to the next, and could also get modified over time.

As a result, even expert users with prior SQL experience can struggle to familiarize themselves with the schema of a previously unseen dataset, leading to difficulties in data exploration. Therefore, QBE needs to be studied from the perspective of users with varied levels of expertise, and the study needs to investigate the pain points specific to relational data access and exploration.

Second, the operational mechanisms in QBE systems fundamentally differ from those in general PBE systems. Traditional PBE approaches often rely on demonstration, where the mechanism to solve the intended task is demonstrated by the user. In contrast, in QBE, the user gives examples of the intended output and not the querying mechanism. Other PBE approaches rely on complete input-output specifications: the user needs to provide, typically small, sample inputs and outputs and the system infers their intended program. This mechanism is also not possible in a data exploration setting, where the input data is predetermined and typically large, and the user can only provide a small set of examples of their intended query output. Since the set of examples in the QBE setting is naturally incomplete, there is typically a much larger number of queries (programs) that could be compatible with them, compared to the general PBE setting; thus, the effectiveness of QBE systems needs to be explored with a targeted study.

Third, the setting of data exploration has two characteristics that can have significant impact in the performance of a QBE system: (1) Since the user needs to provide example records from the dataset at hand, domain expertise can have a bigger impact in the user experience than in the general PBE setting. (2) Data exploration tasks can be vague and subjective, where a strict specification is often hard or even impossible to derive even by experts; this is a perspective not relevant to general PBE and not explored by prior studies.

**Our scope and method.** In this paper, we present findings from our comparative user studies over a QBE tool and the traditional SQL-based mechanism. For our study, we picked SQUID [16, 17] as the QBE tool, since it offers the state-of-the-art QBE mechanism for exploring relational databases. SQUID is built on top of PostgreSQL, which is an open-source relational database management system. Given a few examples of the desired data, SQUID discovers a SQL query by exploiting the semantic similarities observed in the examples. Under the hood, SQUID uses a probabilistic model, which infers a query as the most likely explanation of the provided examples. SQUID and other QBE systems have broad applications in data exploration [30], query reverse engineering [64], and recommendation systems [46].

We conducted two comparative user studies: (1) a controlled experiment study involving 35 participants, and (2) an interview study involving 7 interviewees to gain a richer understanding of users' issues and preferences. All participants and interviewees had varying levels of SQL expertise and experience, but were required to have at least basic SQL skills. Our studies focused on the task of data exploration and explored how SQUID compares against the traditional SQL querying mechanism, over a variety of objective and subjective data exploration tasks. Specifically, our study aimed to identify the most critical issues users face when interacting with the traditional SQL querying mechanism, to what extent a QBE system like SQUID can alleviate these challenges, how effective SQUID is over a variety of data exploration tasks, and what are the possible pain-points of SQUID.

**Contributions.** We summarize our contributions below:

- Through an analysis of the SQL queries issued by the controlled experiment study participants and quantitative analysis of the data collected from the study, we found that participants were significantly more *effective* (achieved more accurate results) and *efficient* (required less time and fewer attempts) over a diverse set of subjective and objective tasks using SQUID compared to manual SQL programming.
- From observations made from the behavior of the interviewees during our interview study, and their qualitative feedback, we identified three key challenges that SQL poses to the users: familiarizing oneself with the database

schema, formally expressing the semantics of the task, and writing syntactically correct queries. From the qualitative feedback of the interviewees, we confirmed that SQUID removes these SQL challenges altogether and assists the users in effective data exploration. Notably, even some of the SQL experts reported that certain subjective queries were extremely hard to encode in SQL and that they would prefer SQUID over SQL in those circumstances.

- Finally, we discuss how SQUID and traditional SQL mechanisms complement each other, under what circumstances the users prefer one over the other, and how the QBE tools should be expanded to achieve more user acceptance. While our results validate some findings of prior studies over other PBE approaches [55], we contribute new empirical insights gained from our studies that indicate that even a limited level of domain expertise (knowledge of a small subset of the desired data) can substantially help overcome the lack of technical expertise (knowledge of SQL and schema) in data exploration.

**Organization.** The rest of the paper is organized as follows: We discuss the related work in Section 2. Section 3 gives an overview of the dataset and the two systems used in our studies: SQL[1] and SQUID. In Section 4, we describe the design choices and methods of our comparative user studies. Section 5 and 6 describe the quantitative findings and the qualitative feedback found from the user studies, respectively. We discuss the key take-aways from the user study and provide guidelines to improve QBE tools with additional features in Section 7. Finally, we conclude in Section 8.

## 2 RELATED WORK

In this section, we provide an overview of the existing PBE and QBE approaches, discuss alternative mechanisms that also aid users in data exploration, and discuss prior literature on comparative user studies over other PBE approaches.

### Programming-by-example (PBE) approaches

Many PBE approaches have been developed in the literature to aid novices or semi-experts in a variety of data management tasks. The focus of PBE is to not only solve the task, but also provide the *mechanism* that can solve the task. To this end, all PBE tools learn from the user examples and synthesize programs that can produce the desired results. To help data scientists write complex data-wrangling and data-transformation codes, WREX [11] proposes an example-driven program synthesis approach. To enable integration of web data with spreadsheets, WebRelate [31] facilitates joining semi-structured web data with relational data in spreadsheets using input-output examples. FlashRelate [5] and FlashExtract [39] enable extraction of relational data from semi-structured spreadsheets, text files, and web pages, using examples. Data-transformation-by-example approaches [22, 28] led to the development of the FlashFill [19] feature in Microsoft Excel, which can learn the user's data transformation intent only from a few examples. Beyond data management tasks, recently, PBE has been used for text processing [70], text normalization [38], and personalized text summarization [15]. Live programming [57] helps novice programmers to understand their codes, where they can manipulate the input by directly editing the codes and manipulate the output by providing examples of the desired output. Beyond computational tasks, PBE tools also support creative tasks such as music creation by example [20], where a software takes a song as an example and allows the user to interactively mix the AI-generated music.

### Query by example (QBE), query reverse engineering (QRE), and similar approaches

Some QBE systems [52, 58] focus on identifying relevant relations and joins to compensate the user's lack of schema understanding, but are limited to project-join queries. These systems only exploit the structural similarities of the examples

[1] SQL is a language that is the querying mechanism standard of relational data management systems, but we often, for ease of reference, refer to it as a system within the context of our user studies.

and ignore the semantic similarities. QPlain [8] requires provenance of the examples from the users to better learn the join paths. However, this requires understanding of the schema, content, and domain of the data, which novice users often lack.

Unlike QBE approaches that can work only with partial output (example), query reverse engineering (QRE) approaches require the entire output with respect to the original database. With this complete output specification, QRE can target more expressive queries [65, 73], but only works for very small databases and fails to scale to large databases. Some QRE approaches require the user to specify a small input database and the corresponding output, and constants in the query [65]. However, this requires complete schema knowledge and precise domain knowledge. QRE [4, 36, 50, 61–63, 68, 72] is less challenging than QBE, because it is aware of the entire output, while typically only a small fraction of the output is available for QBE. Thus, QRE systems can build data classification models on denormalized tables [63], assuming the user-provided examples as positive and the rest as negative. However, due to lack of sufficient annotated data, similar techniques do not apply for QBE.

A problem similar to QBE in relational databases is set expansion in knowledge bases [66, 69, 74]. SPARQLByE [9] allows querying datasets in resource description framework (RDF) by annotated (positive/negative) examples. In semantic knowledge graphs, systems exist to address the entity set expansion problem using maximal-aspect-based entity model, semantic-feature-based graph query, entity co-occurrence information, etc. [27, 32, 44, 49]. Although not applicable in the relational domain, these approaches also exploit the semantic context of the examples; however, they cannot learn new semantic properties that are not explicit in the knowledge base.

### Aiding novice users explore relational data

Beyond by-example methods, alternative approaches exist to aid novice users explore relational databases. Keyword-based search [2, 29, 71] allows accessing relational data without knowledge of the schema and SQL syntax, but does not facilitate search by examples. Other notable systems that aim to assist novice users in data exploration and complex query formulation are: QueRIE, a query recommendation based on collaborative filtering [13], SnipSuggest, a context-aware SQL autocompletion system [37], SQL-Sugg, a keyword-based query suggestion system [14], YmalDB, a "you-may-also-like"-style data exploration system [12], and SnapToQuery, an exploratory query specification assistance tool [34]. These approaches focus on assisting users in query formulation, but assume that the users have sufficient knowledge about the schema and the data. VIDA [40], ShapeSearch [60], and Zenvisage [59] are visual query systems that allow visual data exploration, but they require the user to be aware of the trend within the output. Some approaches exploit user interaction to assist users in query formulation and result delivery [1, 6, 10, 21, 42]. There, the user has to provide relevance feedback on system-generated tuples. However, such highly-interactive approaches are not suitable for data exploration as users often lack knowledge about the system-provided tuples, and thus, fail to provide correct feedback reflecting their query intent. Moreover, such systems often require a large number of user interactions.

### User study of PBE approaches

Drosos et al. [11] present a comparative user study contrasting WREX against manual programming. The study results indicate that data scientists are more effective and efficient at data wrangling with WREX over manual programming. Mayer et al. [47] presents comparative study between two user interaction models—program navigation and conversational clarification—that can help resolve the ambiguities in the examples in by-example interaction models. Lee et al. [41] presents an online user study on how PBE systems help the users solve complex tasks. They identify seven types of mistakes commonly made by the users while using PBE systems, and also suggest an actionable feedback mechanism based on unsuccessful examples. Santolucito et al. [55] studied the impact of PBE on real-world users over a tool for shell scripting by example. Their study results indicate that while the users are quicker to solve the task using the PBE tool, they trust the traditional approach more. However, none of these studies focus on QBE in particular, which is a PBE system tailored towards data exploration over relational databases. The performance of a QBE tool is affected by additional factors, such as the subjectivity of the data exploration task and the domain knowledge of the user. Moreover, traditional data access and exploration methods pose hurdles not only to novices, but to expert users as well. These factors indicate the need for a new study that targets QBE systems in particular.

## 3 OVERVIEW OF THE DATASET AND SYSTEMS

In our comparative user studies, we studied how users perceive a state-of-the-art QBE system, SQuID, compared to the traditional SQL querying mechanism, over a variety of subjective and objective data exploration tasks. In this section, we provide an overview of the dataset we used in our studies, along with brief description of both systems.

### 3.1 Dataset

For our comparative user studies, our goal was to emulate data exploration tasks in a controlled experiment setting. Generally, people explore data they are interested in and within a domain they are somewhat familiar with. Moreover, data exploration with QBE expects some basic domain familiarity, as users need to be able to provide examples. Therefore, our goal in selecting a dataset was to identify a domain of general interest, where most study participants can be expected to have a basic level of domain familiarity. Furthermore, the dataset needs to be sufficiently large to emulate the practical challenges that users face during data exploration. We selected the Internet Movie Database (IMDb)[2], which satisfies these goals. The IMDb website is well-known source of movie and entertainment facts, has over 83 million registered users and about 927 million yearly page visits.[3] The database contains information regarding over 10 million personalities along with their demographic information; and about 6 million movies and TV series, along with their genre, language, country, certificate, production company, cast and crew, etc.

### 3.2 Structured query language (SQL)

The traditional way to query a relational database is to write a query in structured query language (SQL). SQL is one of the most widely-used programming languages (54.7% developers use SQL [45]) for handling structured data, is specifically designed to query relational databases, and has been used for over 50 years. SQL is a declarative query language and is primarily based on relational algebra. The SQL language consists of several elements such as clauses, expressions, predicates, statements, integrity constraints, etc. SQL has been implemented by different developers—such as Oracle, Microsoft SQL, MySQL, PostgreSQL, etc.—slightly differently, however, fundamentally, they all work the same way. For our comparative user studies, we picked PostgreSQL, which is a free and open-source relational database management system.

Relational databases usually organize data in a *normalized* form, to avoid redundancy. This is in contrast with the flat data format where all attributes of an entity are stored together within the same row. For example, the detailed schema of the IMDb database, split in 15 relational tables, is shown in Figure 1. Here, the relation `movie` contains only three attributes about movies: a numerical record `id` (called *primary key*), a text attribute specifying the `title` of the movie, and the `production year` of the movie. However, information about associated genres of a movie is not present in the `movie` table. To figure out the genres of a movie, one would need to write a SQL query to `JOIN` the tables `movie`, `movietogenre`, and `genre`. The query would also need to specify the *logic* behind this join, i.e., which rows in the

[2] IMDb: www.imdb.com/
[3] IMDb.com Analytics: www.similarweb.com/website/imdb.com/

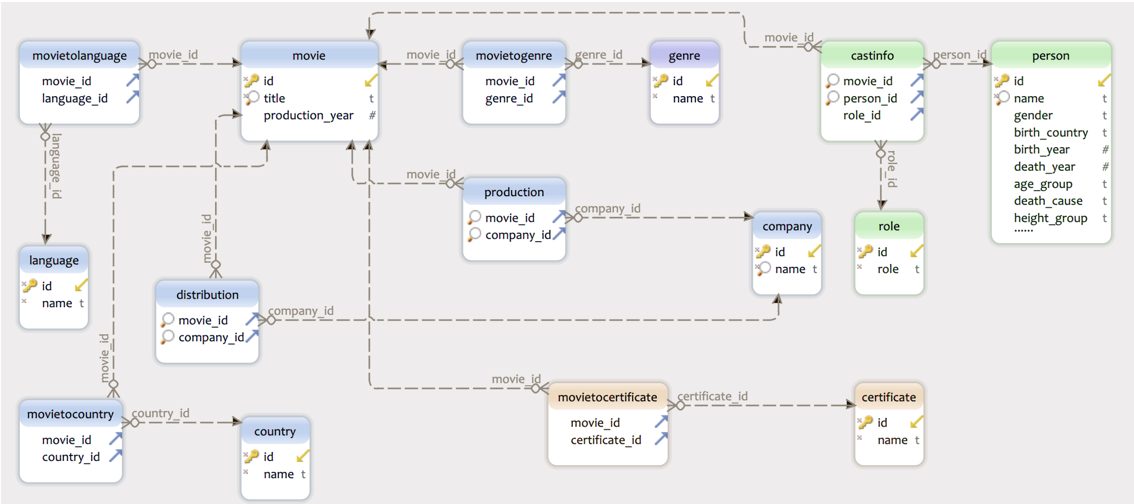



Fig. 1. Complete schema of the IMDb database with 8 main relations: `movie`, `person`, `genre`, `language`, `country`, `company`, `role`, and `certificate`; and 7 connecting relations that associate the main relations: `castinfo`, `movietogenre`, `movietolanguage`, `distribution`, `movietocountry`, `movietocertificate`, and `production`.

`genre` table are relevant to a particular movie in the `movie` table. SQL is a relatively simple language with a limited set of operators (e.g., `SELECT`, `PROJECT`, `JOIN`, etc.). While this simplicity enables the users to learn quickly how to express easy intents using SQL (e.g., the SQL query `SELECT title FROM movie` would retrieve all movie titles), it comes at the cost that complex intents are hard to express in SQL. Specifically, the restrictions in the data organization (normalized schema) and the simplicity of the SQL operators make complex tasks harder to translate in SQL: it requires the users to specify the entire data-retrieval logic. Overall, writing a successful SQL query for a data exploration tasks requires several skills: (1) familiarity with the database schema, (2) understanding of the table semantics, (3) understanding of the SQL operators, (4) knowledge of the SQL syntax, and (5) expertise in translating task intents to SQL.

### 3.3 SQuID

SQUID [16, 17] is an end-to-end system that automatically formulates complex SQL queries over commonly used operators and functions—such as `SELECT`, `FROM`, `WHERE`, `JOIN`, `GROUP BY`, `INTERSECT`, `HAVING`, `COUNT`, etc.—based on a few user-provided examples. SQUID does not require the users to have any knowledge of the database schema or the query language. The key mechanism of SQUID is to extract the *semantic similarity* of the example tuples (e.g, all example entities are Male actors), express them in terms of *selection predicates* (e.g., `Gender = Male`), and then construct a SQL query that includes an appropriate subset of those selection predicates. To figure out the appropriate subset of selection predicates, SQUID distinguishes *coincidental* properties from the intended ones. Intuitively, if a property observed in the example entities is very common over the entities of the database, then it is unlikely to be intended and more likely to be coincidental. For example, if 90% of the people in a database have black hair and the user provides 3 examples where all of them have black hair as well, SQUID assumes that this is just a coincidence and not a genuine intent. In contrast, if a property observed in the example entities is rarely observed over the entities in the database, then it is more likely to be intended. For example, if only 5% of the people in a database have green eyes and all the user examples also have green eyes, SQUID interprets it as a genuine user intent.

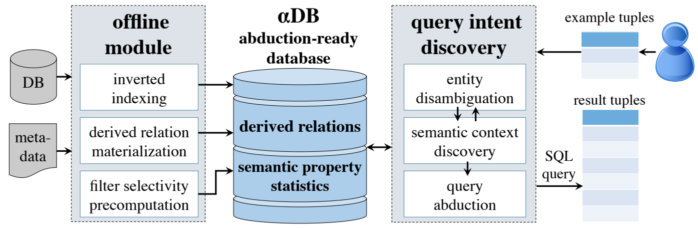



Fig. 2. (Adapted from [16]) SQuID's offline module constructs an abduction-ready database that stores derived relations and semantic property statistics. The query intent discovery module serves the user: it takes the user-provided examples, consults the abduction-ready database, discovers the most likely query, executes it, and returns the results to the user.

SQuID expresses the problem of query intent discovery using a *probabilistic model* that infers the most likely query, given the examples. To mathematically derive the intended query, SQuID applies *abduction* [35, 48], an inference method that aims to find the most likely explanation (query intent) from an incomplete observation (examples). Unlike deduction, the premises do not guarantee the conclusion in abduction. A deductive approach would report all queries whose results contain the examples. While it guarantees that the user's intended query definitely resides within the reported queries, such an approach is of no practical use when the number of reported queries is large. In contrast, thanks to abduction, SQuID finds the most likely query intent, given the examples. Formally, given a database $D$ and a set of examples $E$, SQuID returns the query $Q = \mathrm{argmax}_q\, Pr(q \mid E)$ such that $E \subseteq Q(D)$, where $Q(D)$ denotes the set of tuples in the result of $Q$ over $D$, and $Pr(q \mid E)$ is the probability of $q$ to be the intended query, given the example set $E$.

Figure 2 depicts SQuID's system architecture. To achieve real-time performance, SQuID relies on an offline precomputation strategy that stores semantic properties of all entities of the database and the corresponding statistics of those semantic properties (e.g., how frequently a semantic property is observed in the database) in an *abduction-ready* database. During the online query intent discovery phase, SQuID consults the abduction-ready database to derive relevant semantic properties based on the provided examples, and applies abduction to select the optimal set of properties towards constructing the most likely query. Finally, SQuID executes the inferred query and presents the results to the user.

*Example User Scenario (Adapted from [16]).* A user provides the example set {`Robin Williams`, `Jim Carrey`, `Eddie Murphy`} to query the IMDb database using SQuID in search for "funny" actors (Figure 3). SQuID discovers the following semantic similarities among the examples: (1) all are `Male`, (2) all are `North American`, and (3) all appeared in more than 40 `Comedy` movies. Among these, `Male` and `North American` are very common in the database. In contrast, a very small fraction of actors in the database are associated with such a high number of `Comedy` movies; this means that it is unlikely for this similarity to be coincidental, as opposed to the other two. Based on abduction, SQuID selects the third similarity as the best explanation of the observed example tuples, and produces the following SQL query:

```
SELECT person.name
FROM person, castinfo, movietogenre, genre
WHERE person.id = castinfo.person_id
  AND castinfo.movie_id = movietogenre.movie_id
  AND movietogenre.genre_id = genre.id
  AND genre.name = 'Comedy'
GROUP BY person.id
HAVING COUNT(*) >= 40
```

SQuID then executes this query and presents the results containing two well-known funny actors—`Adam Sandler` and `Ben Stiller`—among others (Figure 3).

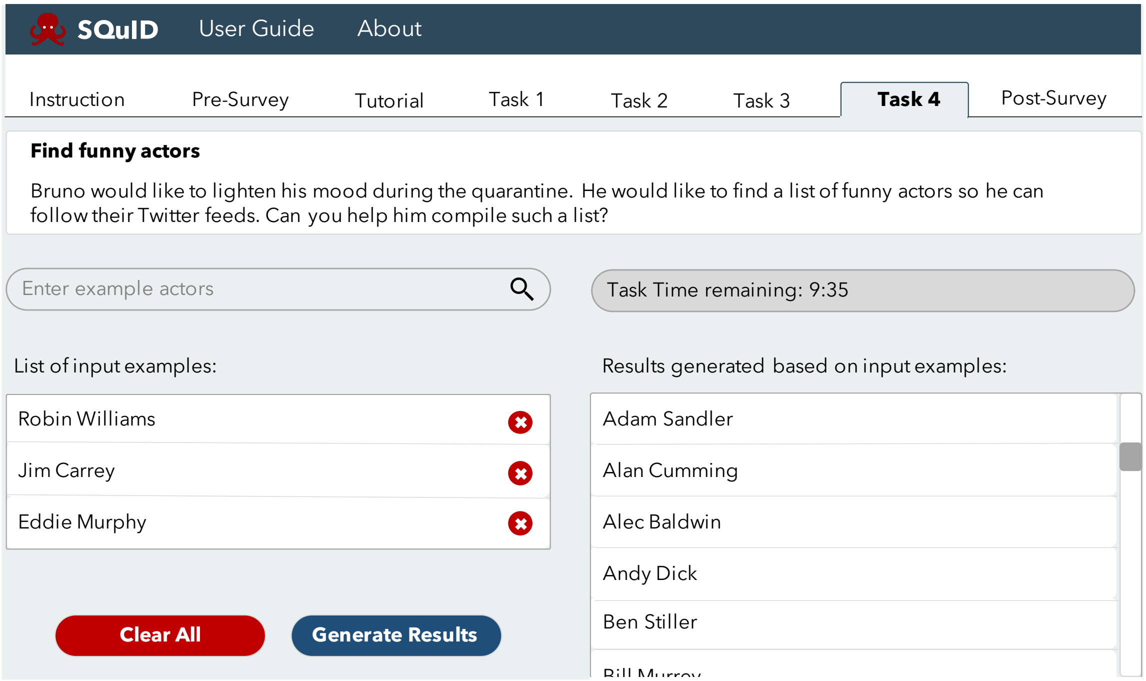



Fig. 3. The graphical user interface of SQUID used in our user study. The task description is at the top. The left panel allows the users to provide examples with an auto-completion feature. SQUID infers the user's intended query from the examples, executes it, and shows the results in the right panel. The result set contains more actors, but we only show the first five (alphabetically) here.

## 4 EVALUATION: COMPARATIVE USER STUDY

In our user studies, our goal was to quantitatively compare the efficacy and efficiency of SQUID and SQL over a variety of data exploration tasks, while also gathering qualitative feedback from users regarding their experiences with the systems. To this end, we opted for two separate comparative user studies: (1) a controlled experiment study, with a fixed set of tasks, over a group of participants of sufficient size to support quantitative evaluation; (2) an interview study, with a flexible set of tasks, over a small group to gather qualitative user feedback. Due to the situation caused by the current COVID-19 pandemic, both studies were conducted online: the controlled experiment was conducted through a website, hosted on our university servers, and the interview study was conducted over Zoom.

For both studies, we provided the database schema (Figure 1) and a graphical user interface with a text box, where the participants could write SQL queries to interact with a PostgreSQL database. For SQUID, we provided a graphical user interface to allow the participants to interact with the system (Figure 3). We now proceed to describe the settings, design choices, and methods of our comparative user studies. We first describe our controlled experiment study over a user group of 35 participants, followed by our interview study with a smaller group of 7 interviewees.

### 4.1 Study 1: controlled experiment study

*Participants.* For our controlled experiment study, we recruited students who were enrolled in an undergraduate computer science course on Data Management Systems at our university during the Spring 2020 semester. The course offers an introduction to data management systems and the SQL language. This ensured that our study participants would have basic familiarity with SQL, which is required to compare the two systems: SQUID and SQL. We invited all 89 students enrolled in this course to take part in the study and 35 of them agreed to participate. We offered extra credit for study participation; students who opted to not participate were given alternative opportunities for extra credit. We labeled these participants P1–P35. The average grade the participants achieved in the course was 86.3 (out of 100), with a minimum grade of 45, and a maximum grade of 100; the standard deviation of the grades was 9.87. This indicates a broad range in our participants' SQL skills, which was one of our goals. While all of them had prior experience and exposure, some had only very basic skills (and failed the class) and some achieved advanced skills.

*Tasks.* We designed 4 data exploration tasks over the IMDb database. Our goal was to observe what challenges a set of diverse tasks poses to the participants and how the challenges vary based on the subjectivity of the tasks and the mechanism (SQUID or SQL) used to solve the tasks. To this end, we designed two objective tasks: (1) to find *Disney* movies and (2) to find *Marvel* movies; and two subjective tasks: (1) to find *funny* actors and (2) to find *strong* and muscular actors. We provided a detailed description for each task to the study participants. (Details are in our supplementary materials.)

*Task-assignment mechanism.* Each participant was assigned all of the four tasks in the sequence: Disney, Marvel, funny, and strong. This order was enforced to ensure that they perform objective tasks first, which are easier, and then move to more complex and subjective tasks. We randomized task-system pairings to make sure that for each task, about half of the participants use SQUID while the other half use SQL. The task-assignment mechanism was as follows: for each user, we randomized which system (SQUID or SQL) they are allowed to use for each task. Everyone did the tasks—Disney, Marvel, funny, strong—in that order, but there were two possible system assignment orders: (a) SQuID, SQL, SQuID, SQL, or (b) SQL, SQuID, SQL, SQuID. Each participant was randomly given one of these assignments. This resulted in randomized task-system pairings, with the constraint that each participant must solve one objective and one subjective task using SQL and the remaining two tasks (also one objective and one subjective) using SQUID. This mechanism also eliminated any potential order bias with respect to the treatment system as half of the participants interacted with SQUID before SQL, while the other half interacted with SQL before SQUID. Within each task (e.g., Disney), each participant used either SQUID or SQL to solve each task, but not both.

*Study procedure.* This study was conducted online and the participants took the study over the Internet on a specific website, hosted on our university servers. We sent out the URL of the website during recruitment. At the beginning of the study, participants were asked a series of questions about their familiarity with SQL. The questions asked the participants to provide answers using a 5-point Likert-scale ranging from "Not familiar (1)" to "Very familiar (5)". Next, there was a question asking them at what frequency they watch movies, followed by a questions about overall movie and actor familiarity where participants could select multiple options. After this survey, participants were given an interactive tutorial, which was divided into two sections, walking them through the steps to obtain results with both SQUID and SQL. The tutorial took about 2–5 minutes to complete. After the tutorial, the participants started the tasks. They had 10 minutes for each task, but could finish before the time was up if they chose to. Participants were asked to avoid using Internet search, but if they did, they were encouraged to report it. After each task, the participants were asked to answer a post-task survey with two questions: the first one was about the difficulty of the task where the participants had to provide answers using a 5-point Likert-scale ranging from "Very difficult (1)" to "Very easy (5)"; and the second one was about their satisfaction with the results where the participants had to provide answers using a 5-point Likert-scale ranging from "Very unsatisfied (1)" to "Very satisfied (5)". After completing all four tasks, the participants were asked to answer four survey questions:

| Interviewee ID | Gender | Country of origin | Program level | SQL expertise | Area of specialization |
|---|---|---|---|---|---|
| I1 | Female | Greece | 2nd year PhD | Medium | Data management |
| I2 | Male | India | 3rd year PhD | Low | Natural language processing |
| I3 | Male | Hong Kong | 2nd year MS | High | Systems |
| I4 | Female | China | 5th year PhD | High | Data privacy |
| I5 | Male | India | 4th year PhD | High | Theory and data management |
| I6 | Female | Japan | 2nd year PhD | Medium | Data privacy |
| I7 | Male | USA | 4th year PhD | High | Data privacy |

Fig. 4. Demographic and experience details of the interviewees who participated in our interview study.

the first one was regarding their preferences between SQUID and SQL where the participants had to provide answers using a 5-point Likert-scale ranging from "Definitely SQL (1)" to "Definitely SQUID (5)"; the second one was about usability comparison between SQL and SQUID where the participants had to provide answers using a 5-point Likert-scale ranging from "SQL was a lot easier (1)" to "SQUID was a lot easier (5)"; the third one was about satisfaction with results obtained using SQUID where the participants had to provide answers using a 5-point Likert-scale ranging from "very unsatisfied (1)" to "very satisfied (5)"; and the fourth one was about accuracy of the results obtained using SQL where the participants had to provide answers using a 5-point Likert-scale ranging from "very inaccurate (1)" to "very accurate (5)".

*Data collection.* During the study, we collected all survey responses and all inputs the participants provided to the systems. Specifically, for SQL, we collected all their queries, including any intermediate queries that they used to reach their final query; for SQUID, we collected all the examples they provided, along with the revision history (addition or removal of examples). We stored all this information in JSON format.

*Data analysis.* During our data analysis, we extracted the JSON data programmatically through Python scripts and implemented custom functions to programmatically analyze the data. To quantitatively evaluate the tasks performed by the participants, we compared their results against the ground-truth results. We collected the ground-truth data from publicly available lists on the IMDb website. For the objective tasks (Marvel and Disney), we determined the ground truth by selecting one list for each. For the subjective tasks (funny and strong), we compiled a list by combining seven different lists for each. We selected lists that meet the following criteria: (1) they have a number of entries that is representative of the task (e.g., there are more than five Marvel movies, thus the list should contain more than five entries), (2) they are frequently-viewed, and (3) they contain entries that match the task objectives. For instance, we collected a list of 300 funny actors, which was compiled from 7 shorter lists of funny actors. One of these lists, titled "Funny Actors", has over 400,000 views, and includes 60 well-known comedians including Jim Carrey, Robin Williams, Eddie Murphy, Mel Brooks, and Will Ferrell.[4] We provide all the lists we used in our supplementary materials.

### 4.2 Study 2: interview study

We conducted a comparative interview study to gain richer insights on users' behavior, their preferences, and issues they faced while solving the data exploration tasks using both systems.

*Interviewees.* We recruited 7 interviewees for this study by targeting a diverse set of computer science graduate students directly working or collaborating with the data management research lab at our university. Out of the 7 interviewees, 4 were male and 3 were female; 6 of them were international students; and their ages ranged from 25 to 30 years old. All of

[4]Funny Actors: https://www.imdb.com/list/ls000025701

them had experience using SQL for at least one year, however, their expertise varied from moderate to expert. We label the interviewees I1–I7. We provide further details on the interviewees in Figure 4.

*Tasks.* For this study, we asked the interviewees to pick one objective task from the following list: (1) Disney movies, (2) Marvel movies, (3) animation movies, (4) sci-fi movies, (5) action movies, (6) movies by an actor of their own choice, or (7) movies by a country of their own choice. We also asked them to select one subjective task form this list: (1) funny actors, (2) physically strong actors, or (3) serious actors. The variety of tasks allowed interviewees to pick tasks based on their interests and enabled us to observe how the two systems compare over a variety of data exploration tasks. This study was within-subject, i.e., all of the interviewees were required to use both the systems (SQUID and SQL) to solve each task.

*Study procedure.* For each interview, two of our research team members were present, one as primary to lead the interview and ask questions and another as secondary to take notes and ask potential follow-up questions. At the beginning of the study, we provided them the URL of the study website over the chat feature of Zoom. During the study, the interviewees first completed an interactive tutorial and then they were asked to pick two tasks. The interviewees were then asked to solve each task using both SQUID and SQL, so that they can directly contrast the two systems. We asked them to complete each task first using SQUID and then using SQL, so that the examples they would provide while using SQUID would be free from biases due to observing the results from their SQL query outputs. We did not expose through the SQUID interface the query that SQUID generates, thus avoiding biases when the interviewees were completing the SQL tasks. The interviewees followed a think-aloud protocol and shared their screen over Zoom during the study. They were observed by two interviewers who also asked open-ended questions to the interviewees on completion of each of the two tasks using both systems. The questions aimed to gather information on which of the two systems the interviewees prefer, under what circumstances they prefer one over the other, and the justification of why they do so. They were also asked what challenges they faced while using the systems and whether some particular task exacerbated these challenges. Finally, they were asked what type of results they prefer during data exploration: specific or general.

*Data collection.* We recorded all interview sessions. The 7 interviews summed to 467 minutes. On average, each interview lasted about 67 minutes, with the shortest interview lasting 43 minutes and the longest one lasting 77 minutes. Upon completion, we replayed the interview recordings, manually transcribed the responses, and stored them as plain text in a spreadsheet, resulting in 119 responses in total.

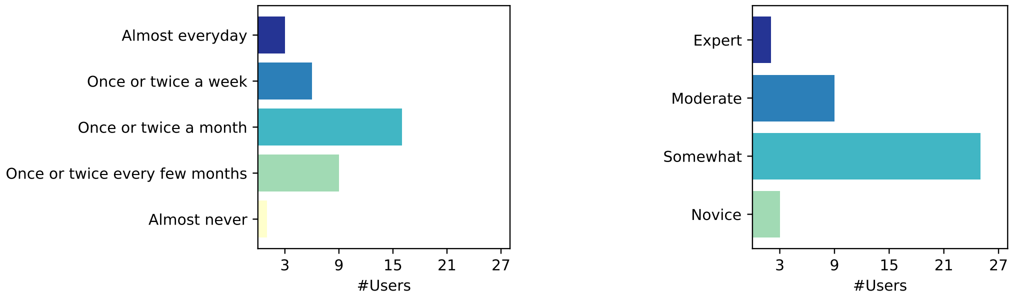
*Data analysis.* We thematically analyzed the responses using our coding software (spreadsheet). Two independent coders from our team independently coded the data. The following six themes emerged after several rounds of analysis: (1) struggle in task understanding, (2) struggle in familiarizing oneself with the schema while using SQL, (3) difficulties with writing syntactically correct SQL queries, (4) struggle with solving vague/subjective tasks using SQL, (5) struggle due to lack of domain familiarity while using SQUID, and (6) preference between precision and recall of the results. Inter-coder reliability was 0.98, calculated using Krippendorff's alpha.

## 5 QUANTITATIVE RESULTS FROM CONTROLLED EXPERIMENT

In this section, we present the quantitative results of the controlled experiment study, summarizing our findings.

### Participants had basic domain knowledge and SQL familiarity

The distribution of self-reported movie-watching frequency among the participants is shown in Figure 5a, with the most common response being 'once or twice a month', followed by 'once or twice every few months'. The responses




(a) Movie-watching frequency.

(b) Overall knowledge of movies and actors.

Fig. 5. Domain knowledge of the participants.

regarding actor and movie familiarity are summarized in Figure 5b: a vast majority of the participants (25 out of 35) reported that they were 'somewhat' familiar with movies and actors. This validates our choice of the IMDb database for conducting the study, as indeed, we observed sufficient domain knowledge among the participants. Regarding SQL expertise, all 35 participants reported being very familiar with easy SQL queries and 34 reported being very familiar with moderately-complex SQL queries. When asked regarding familiarity with complex SQL queries, 27 participants reported being very familiar, 6 were unsure, and 2 were not familiar.

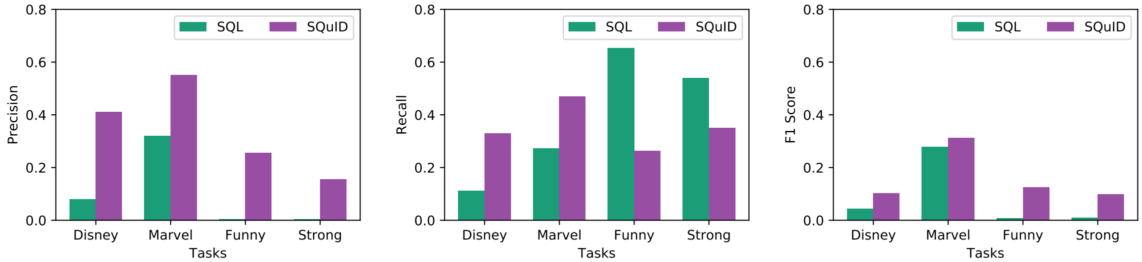
### SQuID is generally more effective than SQL in generating accurate results

To quantitatively measure the quality of the results produced by both SQuID and SQL, we checked them against the ground-truth results (discussed in Section 4.1). We used three widely-used correctness metrics to quantify the result quality: precision, recall, and F1 score. These metrics capture different aspects: precision captures "preciseness", i.e., the fraction of retrieved tuples that are relevant; recall captures "coverage", i.e., the fraction of relevant tuples that are correctly retrieved; and F1 score—which is a harmonic mean of precision and recall—maintains a balance between them.

On average, we found SQuID to be more effective in generating accurate results than SQL (Figure 6). For all four tasks, on average across participants, results obtained with SQuID achieved significantly higher precision than the results obtained with SQL. SQuID achieved higher recall than SQL for the two objective tasks (Disney and Marvel). While SQuID's recall for the subjective tasks (Funny and Strong) was lower than SQL, note that SQL's precision for those tasks was close to 0. This is simply because the SQL queries the participants wrote for those tasks were very imprecise and returned a very large number of results (e.g., all actors in the database). While such general queries can happen to contain a large portion of the correct results (hence the high recall), they contain an extremely large number of irrelevant results making them poorly suited for this retrieval task. In terms of F1 score, SQuID always achieved higher values than SQL implying its effectiveness over SQL for generating more accurate results. The result of t-tests for these findings are shown in Figure 7. Out of the 12 findings, 7 are statistically significant with a p-value less than 0.05.

### Participants were more efficient with SQuID than SQL

SQuID helped the participants solve the tasks more quickly (Figure 8a) and with fewer attempts (Figure 8b) than SQL. On average, the participants were able to solve the tasks using SQuID about 200 seconds faster than when using SQL. Participants were also able to solve the tasks with about 4 fewer attempts while using SQuID compared to SQL. The results of t-test of these findings, shown in Figure 9, signify that most are statistically significant with a p-value less than 0.05.




(a) SQUID achieves higher precision than SQL for all tasks.

(b) SQUID achieves higher recall than SQL in two tasks.

(c) SQUID achieves higher F1 score than SQL for all tasks.

Fig. 6. Comparison of SQUID vs. SQL in terms of average precision, recall, and F1 score.

| | Precision | | Recall | | F1 Score | |
|---|---|---|---|---|---|---|
| Task | p-value | *t* | p-value | *t* | p-value | *t* |
| Disney | **0.004** | 3.0781 | **0.0389** | 2.1457 | 0.151 | 1.468 |
| Marvel | 0.1047 | 1.6669 | 0.0588 | 1.9554 | 0.7195 | 0.3621 |
| Funny | **0.0001** | 4.3845 | **0.0042** | -3.0751 | **0.0** | 8.6225 |
| Strong | **0.011** | 2.6935 | 0.1751 | -1.3859 | **0.0** | 6.4942 |

Fig. 7. *t* test results for precision, recall, and F1 score. Out of 12 findings, 7 are statistically significant. In all cases, df = 33.

### Participants generally found SQUID easier to use and more satisfying, but still preferred SQL

Figures 10a and 10b show self-reported overall satisfaction with the results produced by SQUID and SQL, respectively. Generally, participants found the results produced by SQUID more satisfying than the results produced by SQL. Out of the 35 participants, 23 were somewhat or very satisfied with SQUID. In contrast, 18 reported that the results produced by SQL were somewhat or very accurate. However, we found that the self-reported satisfaction does not correlate with the actual correctness of the results (measured in terms of precision, recall, and F1 score), and in fact, the participants generally did better with SQUID than SQL, although they did not always realize it. Figure 10c shows self-reported overall evaluation comparing SQUID and SQL in terms of ease of use. Out of the 35 participants, 19 reported that SQUID was easier, 6 reported that they had the same level of difficulty, and 10 reported that SQL was easier.

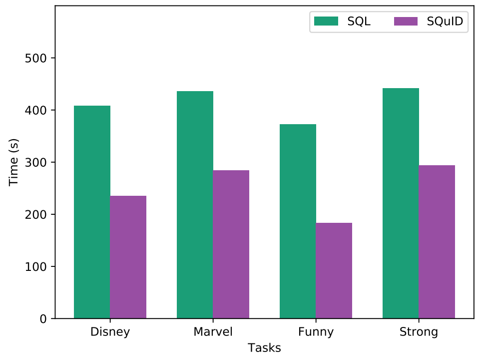
However, despite reporting that SQUID was easier to use and the results were more satisfying, the participants were still leaning towards SQL as a preferred mechanism for data exploration. Figure 10d shows self-reported overall preference between SQUID and SQL, where 11 reported that they would prefer SQUID while 19 reported that they would prefer SQL. Five participants reported no preference.

## 6 QUALITATIVE FEEDBACK FROM INTERVIEW STUDY

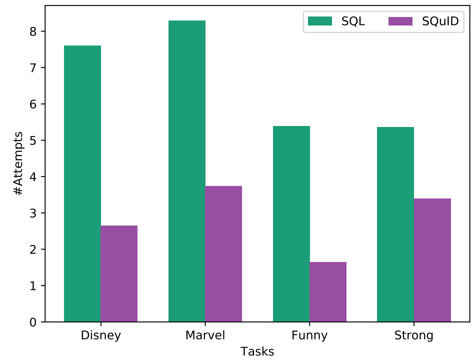
We now report the results of our interview study and describe six main themes that emerged from our qualitative analysis.

### Studying the schema is challenging, even for SQL experts

All seven of our interviewees from the interview study commented that it was difficult to become acquainted with the database schema. “As a user, I have to *explore* the schema”, I1 said. I1 continued, “The query itself was not complicated. It was time consuming to get familiar with the schema itself. Even for experienced users, reading through the schema and




(a) Time required to solve each task.




(b) Number of attempts required to solve each task.

Fig. 8. Comparison of SQL vs. SQuID in terms of effort (average time required and average number of attempts) for solving the same set of tasks.

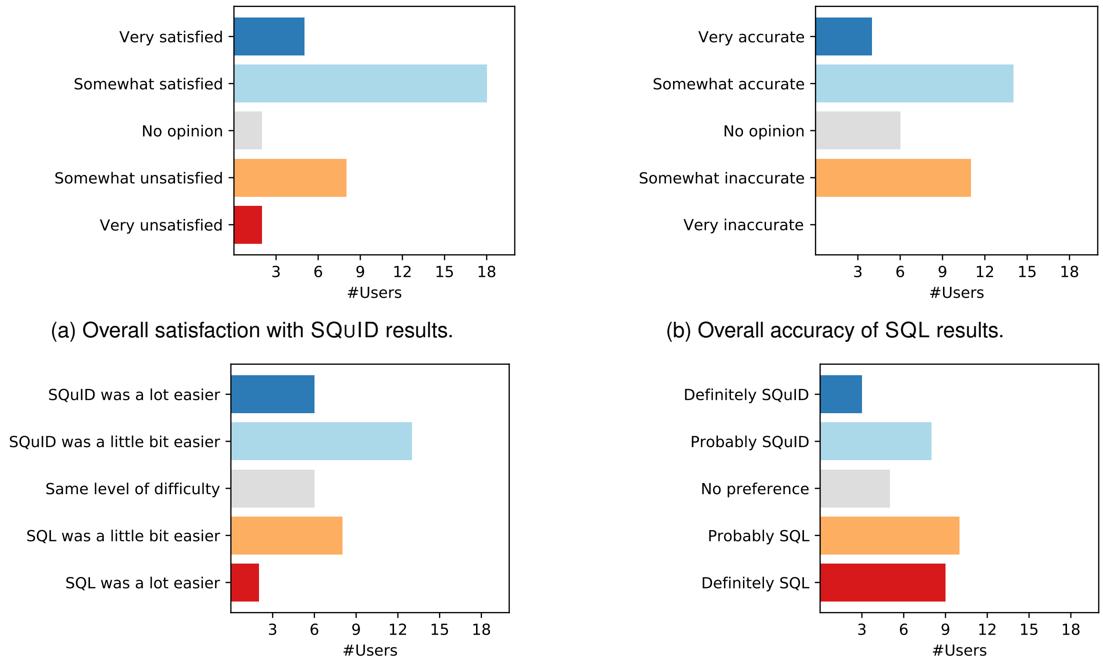
| | Task completion time | | #Attempts | |
|---|---|---|---|---|
| Task | p-value | *t* | p-value | *t* |
| Disney | **0.0014** | -3.5000 | **0.0** | -4.7578 |
| Marvel | **0.0146** | -2.5767 | **0.0008** | -3.6985 |
| Funny | **0.0008** | -3.7105 | **0.0007** | -3.7441 |
| Strong | **0.0132** | -2.6206 | 0.0595 | -1.9518 |

Fig. 9. *t* test results for task completion time and number of attempts. Out of the 8 findings, 7 are statistically significant. In all cases, df = 33.

getting acquainted to [it] . . . takes time." When asked about the comparison in difficulty between writing the SQL query and understanding the schema, I3 said "Looking at the schema diagram was harder. I kept going back and forth trying to understand it." Understanding the schema may be complicated not only because it can be difficult to learn what keys connect the tables, but also because it may be hard to interpret the structure of the individual tables. I5 said, "I think it was pretty hard because I was not sure where to look for comedy based on actors. I was thinking that [the] Role [table] might have the attribute, but it didn't. Then I had to go through joining five tables!"

### SQL requires stricter syntax, which makes writing queries hard

All interviewees struggled to a varying degree to write a SQL query because of different issues; e.g., some of them could not figure out the correct spelling of attributes. For instance, one would query for the genres 'scifi' or 'comedic', neither of which exist in the database. I4 said, "The difficult part was to get the accurate predicate for the query, and I had to [explore the database] for that." SQL requires strict string matching, which can be extremely difficult to overcome for someone who is unfamiliar with the database constants and SQL syntax. While it is possible to query a table and view its content to see how the names are spelled, very few interviewees did this. It appears that the ability to write a SQL query is based on experience and recent exposure to SQL. Interviewees noted that they do not use SQL on a daily basis—some even said they had not used SQL in months—thus, it was difficult to recall specific syntax. For instance, two of the interviewees—who had relatively lower SQL expertise—could not remember the requirements for joining tables. I7 had to use Google to help with this syntax, and I2 did not recall that SQL could join more than two tables. I5 said, "I was




(a) Overall satisfaction with SQUID results.

(b) Overall accuracy of SQL results.

(c) Usability

(d) Preference

Fig. 10. Comparison of SQUID vs. SQL in terms of satisfaction with the results, overall ease of use, and preference (self-reported).

making a lot of mistakes about where to have the underscores, where to not have underscores, and for those things I had to look through the [schema] multiple times." An interesting note, I6 spent the vast majority (over 9 minutes) attempting to find the name 'Japan' in the database, and spent less than 1 minute writing the actual query. SQUID reduces the need to recall exact spelling by providing an auto-completion feature as the user types examples. Although it does not provide an auto-correct if the name is spelled incorrectly, the auto-completion feature allows the users to type what they know and scroll through the suggestions until they find the proper name. We observed several of our interviewees initially spelled a movie name incorrectly, but they were helped by the auto-completion feature. For example, I2 initially typed 'Spiderman' in the search bar, but the title is spelled 'Spider-Man' in the database. I2 was able to correct the spelling when he typed 'Spider' in the search box and autocomplete showed the entire title. The search bar also helped I5 who noted, "If I was missing some spellings, there were some suggestions."

### SQL requires parameter tuning for subjective tasks; SQUID alleviates this

Some exploration tasks can be subjective and inherently vague, e.g., how does one define a "funny" actor *precisely*? How many comedies, exactly, does an actor have to star in before they are considered funny? These questions have no clear answers, and such parameters can vary from person to person and from day to day. In practice, it may be very difficult, if not impossible, to think of objective measures for a subjective concept, which makes subjective tasks very complicated to specify with SQL. I2 said, "Even if I forget about syntax . . . figuring out how to go about writing the pseudo code query for funny actors [is difficult]". One of the most common blunders of interviewees who used SQL to find "funny" actors was to query all actors who had been in some comedy movie. I3 was the first to acknowledge this. "I had to play around with a lot of smaller queries," he said, "to get the one that I eventually had, which I was still not satisfied with. It seems like I pulled many actors and actresses that happened to be in some comedy." I3 elaborated, "Vague tasks are generally a lot more open to interpretation. Coding up a query that meets someone's vague specifications [is] hard . . . It was very hard to nail down what the correct definition of funny is." I4 also recognized that vague tasks are difficult to define. She even said, "This probably isn't a query that I should write in SQL!" She continued, "strong and muscular are very vague descriptors, and SQL needs clear rules. I have to use genre as a proxy, and that makes the query very nasty."

On the other hand, SQUID can interpret complex parameters without any involvement from the user, sparing them the mental burden of defining and implementing a complex query. I4 also said, "In order to write a SQL query, you need to understand the schema well, know your data well, and know your question well . . . But if the task is exploratory and you only have a vague idea in mind, like 'strong actors' . . . it would be very hard, if not impossible, to write a SQL query." Indicating how SQUID helped in the subjective tasks, I3 said "SQUID is a lot more user-oriented. You could just put in some actor names and it would infer what you really want."

### SQUID produces precise results, which is preferred for data exploration

We asked interviewees whether they would prefer a long list that includes all relevant names, but may also include many irrelevant names (high-recall) or a shorter list that includes exclusively relevant names with very few irrelevant names, but may miss some relevant names (high-precision). Six out of seven interviewees reported that they would prefer having a shorter list with higher precision, while one interviewee had no preference. "I think I'm okay with not having all Marvel movies listed here," I2 said, "but I definitely don't want anything outside of Marvel movies. It's fine that [the results] are missing some Thor movies. I wouldn't have liked it if there were movies from DC [Comics] in here." Comparing the SQL results to the SQUID results, I5 said, "I think the [SQUID ] results were not too few but not too many. It was easily understandable, and I could actually see if these were actors I was looking for . . . The [SQL ] results were just too many, and most of the names I didn't know, so it was not easy to find the names that I was looking for." I6 said, "I prefer a shorter list because if there are too many movies listed, then probably, it would be overwhelming and I could not say if the results are right."

### SQUID's interactivity aids users to enrich examples

Three interviewees mentioned that the results produced by SQUID helped them think of more examples in an iterative process. I6, who struggled to think of examples, was able to think of only three sci-fi movies, but when she saw 'Avatar' in the list of results, many other ideas came to her mind. Even if the intermediate results (the first or second round of results generated) were not all intended, some of them were useful in reminding the interviewees of relevant examples. For instance, I2 said, "SQUID was [nice] because it was slightly interactive. I could look at the results and update my examples." During a task, I7 said, "[The results are] useful because now I can use Guardians of the Galaxy." I7 later added, "I think when I gave the first few examples, it gave me some results and that helped me think of more that I was looking for, and it eventually did complete the task." SQUID's results reminded the interviewees of examples that hadn't been in the forefront of their mind, but were nonetheless relevant. I3 said, "I saw the movie Transformers, and that's something I had in my mind, but it did not occur to me when I was entering the examples. There were a bunch of other movie names [like that]." Since SQUID can provide serendipitous, but helpful, intermediate results, the user's lack of domain familiarity can still be alleviated to some extent.

### Domain familiarity is crucial to evaluate the results, for both SQUID and SQL

SQUID requires a basic familiarity with the domain. For those who struggle to think of even one relevant example, like I6, SQUID presents a unique challenge. All interviewees could easily think of a few examples that fit the task, but they struggled beyond that. I7 said, “It was very easy to come up with two or three, but the more examples I had to give the harder it became”. Two interviewees suggested that SQUID adopt an interactive system where it would ask the user whether or not a particular result was relevant on a case-by-case basis. This could alleviate some of the difficulty of thinking of relevant examples.

Furthermore, users who possess very little knowledge of the domain may be unable to recognize the results, and thus would be incapable of verifying them. But this is true for both SQUID and SQL. It was not uncommon for the interviewees to tell us that they could hardly recognize the names in the results, especially for SQL. I1, for instance, said, “Honestly, I don’t recognize any of the results.” This, apparently, was partly due to the large number of results returned by SQL, where there is a high chance that there will be unfamiliar names. Most people are only familiar with a relatively small subset of actors, rather than the entirety of the IMDb database. This made it difficult for the users to evaluate the results produced by both SQUID and SQL.

## 7 DISCUSSION AND FUTURE WORK

In this section, we summarize significant findings found from the quantitative and qualitative analysis of our comparative user studies and highlight the key take-aways.

### SQUID alleviates SQL pain-points: schema complexity, semantic translation, and syntax

From our interviews, we identified three key pain-points of the traditional SQL querying mechanism, all of which are removed when using SQUID:

*Schema complexity.* One significant difficulty that we observed during the use of SQL was the requirement of schema understanding. To issue a SQL query over a relational database, the user must first familiarize themselves with the database schema [3, 16, 58]. The schema is often complex, such as the IMDb schema shown in Figure 1, and requires significant effort to understand. The user also needs to correctly specify the constant values (e.g., `Comedy` and not `Comedic`), name of the relations (e.g., `movietogenre` and not `movie_to_genre`), and name of the attributes (e.g., `id` and not `movie_id`) in the SQL query. Moreover, some attributes reside in the main relation (e.g., `person.name`) while others reside in a different relation (e.g., names of a movie’s genres reside in the relation `genre` and not in the relation `movie`). From a closer look at some of the user-issued SQL queries, we observed futile efforts to guess keywords, incorrectly trying values such as “comedic”, “superhero comics”, and “funny”, which do not exist in the database and result in syntax or semantic errors. In structured databases, if one does not know the exact keywords, they end up issuing an incorrect SQL query, which returns an empty result. In contrast, SQUID frees the user from this additional overhead as it leverages the database content and schema and associates it automatically with the user-provided examples.

*Semantic translation.* After studying the schema, the next task was to translate the task’s semantics formally to a language (e.g., SQL) that computational systems understand. While this is relatively easy for objective tasks (e.g., finding all movies produced by Disney), the same is not true for subjective tasks (e.g., finding all “funny” actors). As our qualitative feedback indicates, expressing subjective or vague tasks is hard in any formal language and not only in SQL. For example, for the task of finding all “funny” actors, even the SQL experts struggled to encode the concept “funny” in SQL. Many participants wrote a SQL query to retrieve all actors who appeared in at least one movie whose genre is Comedy. However, upon observing the output of such an ill-formed query, they were not satisfied with the results. This is because appearing in only one comedy movie does not necessarily make an actor funny. Usually, actors who appear in "many" comedy movies are considered funny. The key struggle here is to figure out what is the right threshold for "many", i.e., in *how many* comedy movies should an actor appear to be considered "funny". In contrast, SQUID is able to discover these implicit constants from the user-provided examples. For retrieving funny actors, SQUID learns from the user-provided examples what is the usual number of comedy movies all the example actors appeared in, and subsequently, uses that number to define the notion of "many". For instance, in the usage scenario of Section 3.3, SQUID inferred that appearing in 40 comedy movies is sufficient for an actor to be considered funny. This parameter (40) was automatically inferred based on the user-provided examples: SQUID automatically discovered that each example actor appeared in 40 or more comedy movies in the IMDb database.

*Language syntax.* SQL is a programming language with several operators and keywords, and similar to all programming languages, SQL also requires strict syntax. While issuing a SQL query, even a minor syntactic error will result in complete failure and will return no result. Moreover, the syntax error messages that the SQL engine provides are often ambiguous and confusing to novice users. We observed that one of our interviewees could not recall the correct syntax of the JOIN operation. This stringent requirement of syntax poses significant hurdles to novice and even intermediate SQL users. In contrast, SQUID completely bypasses SQL, eliminating this challenge.

#### SQUID is generally more effective than SQL and boosts efficiency

In our controlled experiments, we noted that SQUID is generally more effective than SQL in deriving accurate results. For objective tasks, we found that SQUID outperforms SQL in all three correctness metrics—precision, recall, and F1 score. However, it is important to highlight that our interviewees noted that SQUID is particularly useful and preferable to SQL for *subjective* tasks. This does not contradict our quantitative analysis. While SQL has higher recall than SQUID for subjective tasks, SQUID achieves much higher F1 scores, because SQL's precision for these tasks is close to 0. This is because an extremely general SQL query (e.g., one that returns all the data) may have very high recall, but it will not be of use to the exploration task that expects targeted results. Furthermore, SQUID significantly boosts the user's efficiency in data exploration. This was confirmed by our controlled experiment study where we found that participants achieved their goal much faster (in about 200 fewer seconds) and with less effort (with about 4 fewer attempts) while using SQUID compared to SQL.

Lack of domain knowledge is a handicap for SQUID, as it requires at least a few initial examples for its inference. This is a general issue with all query-by-example mechanisms [16, 22, 58]. However, even when the user lacks domain knowledge, they can use alternative mechanisms—such as keyword search, Internet search, or very basic SQL queries (when the user has some SQL familiarity)—to come up with some initial examples. In contrast, when a user does not know SQL, learning it from scratch takes significant time and effort. While SQUID's by-example paradigm can help both expert and novice users alike, in general, programming-by-example systems are most beneficial when domain knowledge outweighs technical knowledge and experience [55]; otherwise, a hybrid system is more desirable. However, lack of domain knowledge is a problem for SQL as well. Without basic knowledge over the data domain (e.g., what are the entities and what are their properties), understanding the schema can be harder. Furthermore, without sufficient domain knowledge, debugging SQL queries, i.e., validating whether the user-issued SQL queries are correct or not, based on the results, is also challenging.

### SQUID promotes serendipitous discovery, aiding users in data exploration

SQUID is *interactive* in a sense that the users can revise their examples based on the results and even use some of the results as examples in the next iteration. A number of interviewees mentioned that by looking at the results that SQUID generated from their initial examples, they were able to come up with new examples. Moreover, when their examples contained some unintentional bias—e.g., while retrieving Disney movies, they only provided examples of recent movies—they were able to receive implicit feedback of that bias by SQUID as the results SQUID generated reflected the same bias. This feedback mechanism helped them revise their examples accordingly. In contrast, SQL does not offer such interactivity or feedback mechanism. While some interviewees used subqueries of the main query to view some intermediate results, this was just for the purpose of verifying the correctness of the main query. In contrast, SQUID's natural interaction and feedback mechanism offers additional help to the users. This makes SQUID particularly suitable for the task of data exploration. SQUID often promotes *serendipity* in the results—providing a good balance between *exploration* (serendipitous, surprising, and novel discovery) and *exploitation* (similar to the examples)—which is a desired property during data exploration.

### SQUID is particularly useful for solving complex and subjective tasks

The specific properties of SQUID, specifically interactivity, providing feedback, and promoting serendipitous discovery, make it a significantly better choice for solving subjective tasks that are usually ambiguous and vague, and are very hard to solve using SQL. For example, in our studies, we used "strong actors" or "funny actors" as two examples of subjective tasks. Participants of both our controlled experiment study and interview study found thinking of examples easier than expressing their intent using SQL, especially for subjective tasks. Our results indicate that SQUID provides an easier mechanism for data retrieval and helps users overcome the difficulty of writing overly complex SQL queries for subjective tasks. In contrast, for objective tasks, we found both SQUID and SQL equally effective, given the user has basic SQL expertise.

### Trust on a system depends on prior exposure, expertise, type of the tasks, and system explainability

During our controlled experiment, we wanted to measure how much the participants trust the mechanism that produces the results by asking the questions: "how well do you think SQUID did in generating the desired results?" and "how accurate were the SQL results?" While some participants reported that they were more satisfied with the results produced by SQUID than SQL, interestingly, many of them reported that they prefer SQL over SQUID even though they generally did better with SQUID (Figure 10d). This result is in line with prior work that compared a PBE tool against traditional shell-scripting and found that despite performing better using the PBE tool, users tend to trust the traditional shell-scripting more [55]. We validated this by checking against ground-truth results where SQUID groups achieved results with higher precision (more specific) and F1 score (more accurate), as shown in Figure 6.

Since the participants performed better when using SQUID compared to SQL, we interpret their preference for SQL to be due to three possible sources of bias: (1) *Familiarity:* The participants were at the time taking a course on relational databases and SQL, which may have artificially increased their confidence in their SQL skills. They had prior experience with SQL, but were experiencing SQUID for the first time through the study. (2) *Explainability:* SQL exposes the precise mechanism (the code) that produces the results, while we did not provide participants with an explanation of the inner workings of SQUID nor exposed the query it produces. (3) *Domain expertise:* Low domain expertise poses a hurdle in producing examples for SQUID; we posit that the users may consider SQL a more versatile mechanism for such circumstances.

We further investigated the issue of trust during our interview study by asking all our interviewees the question: "Which of these two systems, SQUID or SQL, do you trust more?" We expected SQL experts to trust SQL more, but did not observe any strong trend. Rather, the interviewees mentioned that for objective tasks, they were more confident about the SQL queries they wrote, and hence, they trusted SQL more. In contrast, for the subjective tasks, they reported that they trusted the results produced by SQUID more, as for the subjective tasks, the most common complaint was that SQL produced too many results (less specific) and perhaps retrieved the entire database content. Ultimately, SQUID can also provide explanations, by exposing the SQL query it synthesizes in order to generate the results and the underlying mechanism used to synthesize the query. We shed more light on this in the future work.

### SQUID is easy to learn

A desired property for any system is *learnability*: how easy it is to get used to the system. From our study, we found that it was very easy for the participants to learn how to use SQUID almost instantly. SQUID's interface is intuitive and both novices and experts learned how to use it, just by observing its behavior. In contrast, when participants did not know how to write certain classes of SQL queries, they simply gave up and mentioned that they cannot express their logic in SQL. This is particularly significant considering that all our study participants and interviewees had prior exposure to and experience with SQL, while this was their first experience using SQUID.

### Limitations and future work

Our study results indicate that SQUID effectively helped users with various levels of SQL familiarity perform their tasks faster and more efficiently. However, our work explored only one example of QBE systems and recognizably with a limited number of participants. Additional work is needed to study the impact of QBE systems further. While our goal was to draw a comparison between traditional and QBE systems, additional studies might investigate how complete novices (users with no SQL expertise) use QBE systems. Furthermore, future studies can expand the list of tasks to tease apart better the impact of using QBE systems for various task types. From the interviewees' feedback, we extracted a few directions for future work to improve user experience while using QBE systems:

*Exposing the synthesized SQL query for explainability.* One shortcoming of SQUID is that the user is unaware of the mechanism SQUID uses to generate the results. Under the hood, SQUID synthesizes a SQL query from the user-provided examples, which it uses to produce the results. A possible future work for QBE systems is to expose the SQL query and allow the users to fine tune the query parameters to suit their specific purposes.

*Exposing internal mechanism for further explainability.* In addition to exposing the SQL query, QBE systems can provide further explanation mechanisms by exposing the particular semantic similarities that the system discovers across the examples, and its confidence in each similarity being intended. This can also guide users in revising their examples to emphasize borderline semantic similarities that SQUID missed, or diversify examples to avoid coincidental similarities among the examples.

*Tuple suggestion to enrich examples.* A few interviewees reported that it would be helpful if SQUID could suggest a few tuples that the user may consider adding to the examples. Such a tuple-suggestion mechanism will help the users supply additional examples and diversify the examples, in case the users lack domain knowledge.

*Interaction with the results for feedback.* Another direction of future work is to allow the users to interact with the results produced by QBE system: the user will accept or reject a few result tuples which will act as feedback to the system. This will help QBE system learn the user intent better.

*Extensive user study.* More extensive user studies are needed in the future to evaluate all these additional features and determine whether they contribute positively to the users' trust and satisfaction in QBE systems.

## 8 CONCLUSIONS

Our comparative user studies found that database users, with varied levels of prior SQL expertise, are significantly more effective and efficient at a variety of data exploration tasks with SQUID over the traditional SQL querying mechanism that requires database schema understanding and manual programming. Our results indicate that SQUID eliminates the barriers of familiarizing oneself with the database schema, formally expressing the semantics of an intended task, and writing syntactically correct SQL queries. The key take-away of this work is that in a programming-by-example tool like SQUID, even a limited level of domain expertise (knowledge of a subset of the desired data) can substantially help overcome the lack of technical expertise (knowledge of SQL and schema) in data exploration and retrieval. This indicates that programming by example can lead to the democratization of complex computational systems and make these systems accessible to novice users while aiding expert users as well. Our studies validate some prior results over other PBE approaches but also contribute new empirical insights and suggest future directions for QBE systems to further increase system explainability and user trust.

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