Interactively Discovering and Ranking Desired Tuples without Writing SQL Queries

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ABSTRACT

The very first step of many data analytics is to find and (possibly) rank desired tuples, typically through writing SQL queries – this is feasible only for *data experts* who can write SQL queries and *know* the data very well. Unfortunately, in practice, the queries might be complicated (for example, "*find and rank good off-road cars based on a combination of Price, Make, Model, Age, Mileage, and so on*" is complicated because it contains many *if-then-else*, *and*, *or* and *not* logic) such that even data experts cannot precisely specify SQL queries; and the data might be unknown, which is common in data discovery that one tries to discover desired data from a data lake. Naturally, a system that can help users to discover and rank desired tuples without writing SQL queries is needed. We propose to demonstrate such as a system, namely DExPlorer. To use DExPlorer for data exploration, the user only needs to interactively perform two *simple* operations over a set of system provided tuples: (1) annotate which tuples are desired (*i.e., true* labels) or not (*i.e., false* labels), and (2) annotate whether a tuple is more preferred than another one (*i.e.,* partial orders or ranked lists). We will show that DExPlorer can find user's desired tuples and rank them in a few interactions, even for complicated queries.

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1 INTRODUCTION

This paper aims to help user discover a set of desired and ranked tuples through interactive exploration, when precise SQL queries are hard to specify. Informally speaking, given a relational table T, the user wants to find the answer $R = Q(T)$ of an *unknown* SQL query Q, where the term "unknown" either means that the query is too hard to specify, or the data is unknown to the user. Let's illustrate through an example why specifying such SQL queries is hard.

Example 1.1. Suppose a user wants a new manual petrol car that is produced after year 2010, not provided by commercial sellers, and its brand can be either BMW with price $\leq$ 10000, *or Volkswagen with price* $\leq$ 8000. *Moreover, assume that she wants all cars to be ranked by a weighted sum function:* $-0.018 \times price + 0.982 \times powerPS$ *(note: she does not know this function). That is, the ground truth query can be expressed as* Q_1 *below:*

```
SELECT *
FROM Car
WHERE seller != "commercial" AND year ≥ 2010
AND gearbox="manually" AND fuelType="petrol"
AND ((brand = "bmw" AND price ≤ 10000) OR
(brand = "volkswagen" AND price ≤ 8000))
ORDER BY -0.018 * price + 0.982 * powerPS DESC;
```
Q_1

Clearly, Q_1 is hard to specify, because: (i) there are complicated predicates in the WHERE clause, including *and, or, not* and range selection; and (ii) it is hard to provide the weighted sum function in the ORDER BY clause.

Prior Art. (1) *Keyword search* [5] allows the user to retrieve some desired tuples by providing some keywords. However, it is hard to capture complex SQL queries which may contain *if-then-else*, *and*, *or* and *not* logic by under-specified keywords. (2) *Query-by-example* [1] aims to infer user's desired tuples by user provided examples, either desired or not desired. (3) *Partial orders for tuple ranking* [10] ranks tuples based on user provided partial orders for tuple pairs.

(1) and (2) only discover desired tuples (denoted by **decision problem**), and (3) focuses on ranking all tuples (denoted by **ranking problem**). There are also methods that

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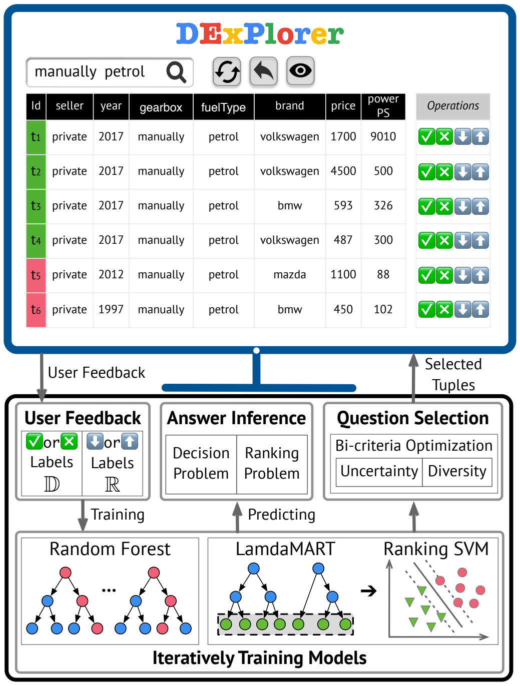

Figure 1: An overview of DExPlorer

find and rank tuples, such as SQLSynthesizer [11], but can only support simple ranking functions. That is, *no existing work* can support the complicated case in Example 1.1.

Challenges. Building a system for inferring complicated query intent faces several design choices and research challenges. **(C1)** [User Interface.] What operations shall we provide to the users? **(C2)** [SQL Queries vs. Machine Learning Models.] For the back-end inference, based on the user feedback, shall we reason about SQL queries or train ML models? **(C3)** [Question Selection.] One key challenge is to reduce human cost, such that the back-end engine can quickly converge, which requires algorithms to proactively select the most beneficial tuples for user feedback.

Outline. Section 2 overviews our proposed system, mainly to address **(C1)**, from a design perspective. Section 3 demonstrates DExPlorer using real-world datasets with two main goals: **(G1)** *Easy-to-use*: any user can operate on DExPlorer with simple (click-based) operations; and **(G2)** *Effectiveness*: DExPlorer can return good results in a few user interactions. Section 4 gives details of the back-end, mainly for **(C2)** and **(C3)**, and compares with state-of-the-art solutions.

2 AN OVERVIEW OF DEXPLORER

Figure 1 gives an overview of DExPlorer.

Front-end. It will interact with the user in multiple iterations until user budget is used up or the answer cannot be improved. At each iteration, the system provides a *question* $\mathbb{I}$ with k tuples, on which two operations are permissible: (1) "*click*" to annotate a tuple to be either *true* or *false*; and (2) "*drag*" to annotate that one is ranked higher than another. The answers annotated by the user are then transformed to a set $\mathbb{D}$ of *true*/*false* labels of tuples in $\mathbb{I}$, and a set $\mathbb{R}$ of partial orders between pairs of tuples in $\mathbb{I}$.

Moreover, in order to address the cold-start problem, we allow users to pose a few keyword queries to quickly get some desired tuples.

Back-end. In the i-th iteration, the user will provide a set $\mathbb{D}_i$ of *true*/*false* labels and a set $\mathbb{R}_i$ of partial orders, the back-end of DExPlorer needs to address two problems: answer inference and question selection.

Answer Inference. Given the user feedback from all i iterations, *i.e.,* $\{\mathbb{D}_1, \mathbb{D}_2, \ldots, \mathbb{D}_i\}$ and $\{\mathbb{R}_1, \mathbb{R}_2, \ldots, \mathbb{R}_i\}$, it is to infer the (ranked) result R.

Question Selection. It is to select a set $\mathbb{I}_i$ with k tuples for the user to annotate in the i-th iteration.

Termination. The entire process will terminate, when the user budget is used up, or the back-end inference will converge.

3 SYSTEM DEMONSTRATION

In this section, we demonstrate how DExPlorer works (taking Q_1 as a running example) on the car dataset (https://www.kaggle.com/orgesleka/used-cars-database).

(1) Keyword Search. To bootstrap DExPlorer, user can first input keywords to help DExPlorer find her desired tuples. For example, user can type "manually petrol" in the input box in Figure 2(a) for Q_1, then DExPlorer can select only manually petrol cars for her to label.

(2) Labeling Tuples. When user inputs keywords, DExPlorer selects tuples which are relevant to these keywords for her to label; otherwise DExPlorer selects tuples by the question selection algorithm in Section 4.2. The selected tuples are shown to user as in Figure 2(a), then user can click the second column to annotate a tuple to be either *true* or *false*, and drag the first column of a tuple to adjust its rank. After labeling tuples as shown in Figure 2(a), the user can click the "Recommend" button, then DExPlorer infers user's desired tuples and ranks them by ML models in Section 4.1, and shows the desired ranked tuples to user as in Figure 2(b).

(3) Look up Recommended Results. User can browse the desired ranked tuples recommended by DExPlorer.

(4) Iterate the above Process. If user is not satisfied with current recommended tuples, she can click the "Continue Tagging" button, and DExPlorer will select new tuples for her to label by the question selection algorithm in Section 4.2. Or she can input new keywords (*e.g.,* "bmw") to refine the SQL query. That is, she can iterate the above process until she is satisfied with the recommended results. Then she can download data for down-streaming applications, such as data visualization [6–8].

manually petrol | Search

		seller	offerType	price	abtest	vehicleType	year	gearbox	powerPS	model	kilometer	fuelType	brand	notRepairedDamage	postalCode
≡	✓	private	offer	7800	control	limousine	2010	manually	102	golf	125000	petrol	volkswagen	no	37339
≡	✓	private	offer	9000	test	limousine	2010	manually	122	1er	80000	petrol	bmw	no	12309
≡	✓	private	offer	6250	control	small	2010	manually	60	polo	100000	petrol	volkswagen	yes	95119
≡	✓	private	offer	7390	test	small	2011	manually	69	polo	60000	petrol	volkswagen	no	80935
≡	✓	private	offer	6899	control	small	2012	manually	60	up	80000	petrol	volkswagen	no	32257
≡	✓	private	offer	7150	control	small	2012	manually	60	up	30000	petrol	volkswagen	no	59227
≡	✗	commercial	offer	1100	test	small	2006	manually	38	matiz	150000	petrol	chevrolet	no	07973
≡	✗	private	offer	4500	test	coupe	1973	manually	68	andere	5000	petrol	volkswagen	no	26831
≡	✗	private	offer	15550	test	small	2013	manually	122	a1	20000	petrol	audi	no	54295
≡	✗	private	offer	18800	test	bus	2014	manually	116	5_reihe	20000	petrol	mazda	no	87663

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(a) User Operations

Recommend

seller	offerType	price	abtest	vehicleType	year	gearbox	powerPS	model	kilometer	fuelType	brand	notRepairedDamage	postalCode
private	offer	6299	control	small	2012	manually	6062	up	50000	petrol	volkswagen	no	58511
private	offer	593	test	coupe	2014	manually	326	andere	30000	petrol	bmw	no	90427
private	offer	487	test	limousine	2015	manually	300	golf	20000	petrol	volkswagen	no	66851
private	offer	1	test	coupe	2015	manually	180	scirocco	10000	petrol	volkswagen	no	75203
private	offer	4500	test	limousine	2013	manually	245	3er	20000	petrol	bmw	yes	10115
private	offer	270	test	suv	2014	manually	150	x_reihe	20000	petrol	bmw	no	47228
private	offer	199	control	limousine	2015	manually	136	1er	20000	petrol	bmw	no	25335
private	offer	253	test	limousine	2015	manually	136	1er	20000	petrol	bmw	no	70176
private	offer	301	control	small	2015	manually	136	1er	30000	petrol	bmw	no	73728
private	offer	301	control	small	2015	manually	136	1er	30000	petrol	bmw	no	73728

Page Size 10 First Prev 1 2 3 4 5 Next Last

(b) Recommended Results

Continue Tagging | Download Data as CSV

Figure 2: Front-end of DExPlorer

Result Analysis. Figure 2(b) shows the top-10 recommended ranked desired tuples on Q_1 for user after 3 iterations (*i.e.,* 3 questions are answered, each question contains 10 tuples), where the top-10 tuples all satisfy her hidden decision intent and are well ranked by her ranking intent (*i.e.,* Q_1). The *accuracy* of correctly ranked tuple pairs is higher than 0.8, and the *precision@50* is 0.72 after 3 iterations, meaning that 36 of real top-50 desired tuples are found in the predicted top-50 tuples, which proves that DExPlorer can efficiently find and rank the desired tuples in a few interactions.

4 BACK-END ALGORITHMS

4.1 Answer Inference

Decision Answer Inference. The decision problem is a binary classification problem - deciding whether a tuple is desired or not. There are several choices: decision tree (DT), random forests (RF), or support vector machines (SVM). The work [1] uses DT for **decision problem**. However, DT is not ideal to capture complex predicates. Thus we use RF for decision answer inference.

Ranking Answer Inference. DExPlorer assumes user's ranking intent can be expressed by a weighted sum function $f(t) = wt$, which is a common assumption in many data exploration systems [10]. Thus DExPlorer uses Ranking SVM [4] to learn w. Besides, inspired by the GBDT + LR model in many commercial IR systems [3], we develop a hybrid ranking model: LambdaMART [9] + Ranking SVM. The LambdaMART model outputs a transformed feature $\vec{t}''$ for each tuple $\vec{t}'$, and $\vec{t} = \vec{t}' \oplus \vec{t}''$ is fed to Ranking SVM.

4.2 Question Selection

In each user iteration, we need to select a list of k tuples from the table T as one question $\mathbb{I}$. When selecting tuples, we should consider about their uncertainty and diversity.

4.2.1 *Uncertainty and Diversity.*

We should select tuples which the ML models are uncertain about, and these selected tuples should be as diversified as possible. Now, we define the uncertainty and diversity of tuples.

Uncertainty for Decision Questions. We define the uncertainty of a tuple t as the entropy of the predicted results of all decision trees in the random forest.

Uncertainty for Ranking Questions. Given a pair of tuples t_i and t_j, the Ranking SVM model learns a parameter vector $\vec{w}$, and the model is uncertain about the tuple pairs whose $|\vec{w} \cdot \vec{t}_i - \vec{w} \cdot \vec{t}_j|$ are close to 0.

Diversity. Let $\vec{v}'(t)$ be the predicting vector of all trees in RF for tuple t, and let $\vec{v}''(t)$ be the transformed feature of tuple t

output by the LambdaMART model (*i.e.,* $\vec{v}''(t) = \vec{t}''$). We use $\vec{v}(t) = \vec{v}'(t) \oplus \vec{v}''(t)$ to compute the diversity. We define the similarity s of tuple t_i and t_j as: $s(t_i, t_j) = cos(\vec{v}(t_i), \vec{v}(t_j))$.

Definition 4.1 (Question Selection). Given a partially trained RF model and hybrid ranking model, a table T, and a number k, the problem is to select a set of k tuples S^* from T such that the following equation is minimized:

$$S^* = \underset{S \subseteq T, |S|=k}{\arg\min} \sum_{t \in S}(1-u(t)) + \alpha \sum_{t_i, t_j \in S} |\vec{w} \cdot \vec{t}_i - \vec{w} \cdot \vec{t}_j| + \beta \sum_{t_i, t_j \in S} s(t_i, t_j) \tag{1}$$

where $u(t)$ is the normalized uncertainty of tuple t, α is a parameter to trade-off decision and ranking questions, $\vec{w}$ is the weight vector output by the hybrid ranking model, β is a parameter that provides a trade-off between the uncertainty and diversity, and $s(t_i, t_j)$ is the similarity of t_i and t_j.

4.2.2 ***Algorithms.*** Considering both uncertainty and diversity is hard due to it is NP-hard [2]. We thus propose to first solve the question selection by only considering decision and ranking uncertainty (*i.e.,* $\beta = 0$), and then incorporate the diversity into the solution obtained in the first step.

Question Selection without Diversity. We set $\beta = 0$ in Eq. (1) to ignore diversity:

$$S^* = \underset{S \subseteq T, |S|=k}{\arg\min} \sum_{t \in S}(1 - u(t)) + \alpha \sum_{t_i, t_j \in S} |\vec{w} \cdot \vec{t}_i - \vec{w} \cdot \vec{t}_j| \tag{2}$$

To better illustrate the optimization problem, we first denote $S = [t_1, t_2, ..., t_k]$, where $\vec{w} \cdot \vec{t}_i \leq \vec{w} \cdot \vec{t}_j$ iff $i \leq j$, then we expand the second term of Eq. 2 to Eq. 3. Thus we have:

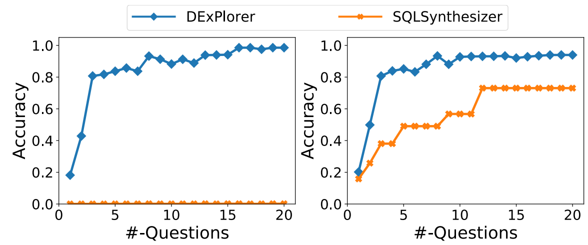
$$\begin{aligned} S^* &= \underset{S \subseteq T, |S|=k}{\arg\min} \sum_{i=1}^{k}(1 - u(t_i)) + \alpha \sum_{i=1}^{k} \Big((i-1)\vec{w} \cdot \vec{t}_i - (k-i)\vec{w} \cdot \vec{t}_i\Big) \\ &= \underset{S \subseteq T, |S|=k}{\arg\min} \sum_{i=1}^{k}(1 - u(t_i)) + \alpha \sum_{i=1}^{k}(2i - k - 1)\vec{w} \cdot \vec{t}_i \end{aligned} \tag{3}$$

We sort T by $\vec{w} \cdot \vec{t}$ in ascending order and obtain a sorted list $T = [t_1, t_2, ..., t_{|T|}]$. We use T_m to denote the prefix of list T with length m, *i.e.,* $T_m = [t_1, t_2, ..., t_m]$. We define $S(m, n) = \underset{S \subseteq T_m, |S|=n}{\arg\min} \sum_{i=1}^{|S|}(1 - u(t_i)) + \alpha \sum_{i=1}^{|S|}(2i - k - 1)\vec{w} \cdot \vec{t}_i$ and $F(m, n)$ denotes the corresponding optimal value. We can see that $S(|T|, k)$ is the optimal solution of Eq. 2 and $F(|T|, k)$ is the corresponding optimal value. Then we have:

$$F(m, n) = \min(F(m-1, n), F(m-1, n-1) + \phi(m, n)) \tag{4}$$

where $\phi(m, n) = (1 - u(t_m)) + \alpha(2n - k - 1)\vec{w}\vec{t}_m$. Thus we devise a dynamic programming algorithm to find the optimal solution for Eq. 2.

Question Selection with Diversity. When considering both uncertainty and diversity, we optimally choose tuples with high uncertainty by the above dynamic programming algorithm, but when adding a tuple t to the result set S, we check whether t has a high similarity with existing selected tuples. If yes, we just drop it; else, we include it to the result.



(a) Q_1 (b) Q_2

Figure 3: Effectiveness

4.2.3 ***Comparison.*** We compare our method with state-of-the-art solution for discovering and ranking desired tuples: SQLSynthesizer [11]. Since SQLSynthesizer can only support simple (hierarchical) ranking function, we also test another SQL query Q_2 by replacing the **ORDER BY** clause in Q_1 with "**ORDER BY** *year, -kilometer, -price, powerPS* **DESC**". The *accuracy* of correctly ranked tuple pairs of Q_1 and Q_2 are shown in Figure 3(a) and Figure 3(b) respectively.

From Figure 3, we can know SQLSynthesizer only supports simple (hierarchical) ranking function (i.e., Q_2), and has a poor performance on complex ranking function (i.e., Q_1), while DExPlorer supports both simple and complex ranking functions well. Also, DExPlorer performs better than SQLSynthesizer on Q_2, which is due to RF can better capture user's complex query intents, and the effectiveness of the question selection algorithm in DExPlorer.

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