SubDEx: Exploring Ratings in Subjective Databases (Authors' Copy)

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***Abstract*—We demonstrate SubDEx, a dedicated framework for Subjective Data Exploration (SDE). SubDEx enables the joint exploration of items, people, and people's opinions on items, in a guided multi-step process where each step aggregates the most *useful* and *diverse* trends in the form of *rating maps*. Because of the large search space of possible rating maps, we leverage pruning strategies to enable interactive running times. We demonstrate the need for a dedicated SDE framework and the effectiveness and efficiency of our approach, by interacting with the ICDE'21 participants who will act as data analysts.**

I. Introduction

Subjective data is characterized by a mix of facts and opinions. With the proliferation of user-generated content, subjective databases have grown in size [1]. The valuable information they contain is virtually infinite and satisfies various needs. Yet, as of today, dedicated tools for Subjective Data Exploration (SDE) are lacking.

As in general-purpose Exploratory Data Analysis (EDA), SDE requires iterative data filtering and generalization. For instance, a social scientist examining restaurants in Yelp, may benefit from seeing aggregated ratings on a certain cuisine in some neighborhood by reviewers in a certain age range, followed by request to cover additional neighborhoods. Like in EDA, SDE users need guidance as they seldom know precisely what they are looking for and may have only partial knowledge of the underlying data. But, in addition to the common EDA guidance requirements, SDE must additionally satisfy specific needs that occur when exploring a mix of facts and opinions. Let us consider an example.

Mary is a social scientist who would benefit from the ability to extract insights on restaurants in New York City. Figure 1 summarizes a 3-step exploration of those restaurants and their reviewers. In Step I, Mary examines the reviewers' overall ratings and sees no significant difference between age groups (upper histogram). As a young adult, her next operation is to look deeper into that group (Step II). She discovers that they gave the highest ratings for food to restaurants in Williamsburg (upper histogram). She also finds that on average, young female adults have given the lowest ambiance rating (lower histogram). In Step III, Mary dives deeper into the ratings of young female adults and finds that programmers among them provided the lowest overall ratings (upper histogram). She also sees that those reviewers gave the highest service ratings to Japanese restaurants (lower histogram). As illustrated. if chosen properly, in only a few steps, Mary can obtain detailed insights on people's opinions on New York City restaurants.

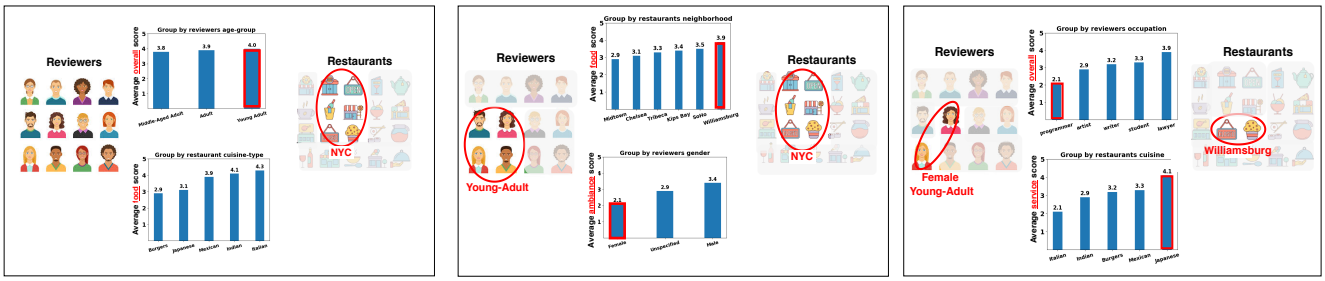
Mary's example illustrates two key needs that characterize SDE: the need to select (simultaneously) subsets and supersets of items and reviewers whose aggregated ratings demonstrate *useful and diverse facets* of reviewers' opinions, and the need to explore *different rating dimensions*, e.g., food vs. service for restaurants. In this work we present SubDEx, a dedicated SDE framework. There are three key challenges in building such a system. First, the system should cater to the above-mentioned needs (challenge **C1**). Namely, it should display to users aggregated ratings that demonstrate useful and diverse facets of the data, while aggregating reviewers and items by different rating dimensions. Second, as in modern EDA tools [2], [3], the system should provide to users some guidance on the next operation to perform, to discover interesting trends in the data (challenge **C2**). Last, the system should enable interactive running times (challenge **C3**).

To address **C1**, SubDEx provides the ability to apply, at each step, a filtering or generalization operation on the items and reviewers of interest. It then displays, alongside the resulting rating records, a set of *k rating maps* [4] (see Figure 3(a)). Rating maps are histograms that provide a bird's-eye view of ratings by some reviewers for some items. The rating maps displayed at each step are chosen to be *useful* and *diverse*. Our notion of utility generalizes previous interestingness measures [5], whereas our notion of diversity ensures that different facets of the data are revealed. To ensure that the selected rating maps depict different rating dimensions, we use weighted utility scores where the weights reflect the number of times a rating dimension has been previously shown.

To address **C2**, SubDEx offers two exploration modes: *Recommendation-Powered*, and *Fully-Automated*. In the first mode, the system presents the current k most useful and diverse rating maps at each step, and recommends o next-step operations based on the utility and diversity of the rating maps they generate (see Figure 3). The user can choose one recommendation or perform an operation of her own. This was the case for Mary. The second *Fully-Automated* mode relieves the user from choosing an operation, and generates a fixed-size exploration path, by applying the top-1 operation at each step.

To address **C3**, SubDEx applies pruning optimizations that estimate the weighted utility score for each rating map based on sampling techniques and prune low utility ones. To enable that, we adapted highly efficient sharing and pruning techniques [6] for identifying high-utility rating maps and reduce computational costs.

Due to space limitations, we provide here only a brief



Step I Step II Step III

Fig. 1: **Example of a three-step exploration. The user iteratively examines subsets of the reviewer and item tables. Links between selected reviewer and item groups are aggregated as rating maps, showing "interesting" trends in the data.**

overview of our solution. Full details can be found in [7].

Demonstration Overview: We demonstrate the operation of SubDEx over multiple real-world subjective datasets. Our demonstration illustrates real-life scenarios where a data analyst attempts to identify special data characteristics. The audience will play the role of data analysts, using one (or more) of SubDEx exploration modes. Then, the audience will explore statistics describing the results of other participants, enabling to observe the effect of guidance in SDE. Last, the audience will be allowed to look "under the hood", examining the efficiency of our solution.

Related Work: Subjective data analysis is an emerging research field [1]. Such data is widely used in web applications, online rating systems, and social sciences [5]. SDE can be used for large-scale population studies whose purpose is to extract trends and insights on the users/items, or for extracting recommendations [4]. To the best of our knowledge, SubDEx is the first system dedicated to SDE.

Exploratory Data Analysis (EDA) is an essential task for data scientists, with the goal of extracting insights from datasets. Guiding users in performing EDA is a well-studied task [2], [3]. While general-purpose EDA tools could also be used for SDE, an SDE tool must cater to additional needs that require tailored solutions. Auto-generation of interesting views for a dataset has been studied extensively [8]. A common approach that we follow, is to use heuristic measures of interestingness [5], searching the space of all views, and returning the most interesting ones [6]. Multiple techniques to enable scalable visualization have been proposed [9]. Here we leverage pruning optimizations to identify low-utility rating maps, based on an adaptation of techniques presented in [6].

II. The SubDEx Framework

We begin by providing a short technical background, then present SubDEx's architecture and workflow.

A. Technical Background

Data Model: We consider a special type of database, called a subjective database [1], which includes both objective and subjective attributes. We model our database as a triple $\langle \mathcal{I}, \mathcal{U}, \mathcal{R} \rangle$, representing the sets of items, reviewers, and rating records, resp. Items and reviewers are associated with objective attributes, such as a restaurant address, and a reviewer occupation. An attribute value may be an atomic value or of complex type. For example, the value for the attribute `cuisine` of a restaurant may be multi-valued. The rating records have subjective attributes, reflecting the rating scores assigned by reviewers to items. For instance, a reviewer may rate a restaurant on several dimensions: food, service, and ambiance. Each rating record $r \in \mathcal{R}$ is itself a tuple $\langle i, u, s_1, \ldots, s_t \rangle$, where $i \in \mathcal{I}$, $u \in \mathcal{U}$, and s_j is the rating score that reviewer u assigned to item i for the j-th rating dimension. The rating scores are application-dependent and do not affect our model.

Reviewer, Item and Rating Groups: A reviewer group g_U (resp., item group g_I) is a set of reviewers (resp., items) that share the same values for a set of objective attributes which define its description. For example, consider the groups depicted in Figure 3(a). Here $g_U = \{\langle$`age_group`, `young_adult`$\rangle\}$ contains all young adult reviewers, and $g_I = \{\langle$`state`, `NY`$\rangle$, $\langle$`city`, `NYC`$\rangle\}$ contains all restaurants in New York city. Given reviewer and item groups g_U and g_I, a rating group g_R for g_U and g_I is defined as the group of all rating records $r = \langle u, i, s_1, \ldots, s_t \rangle$ s.t. $u \in g_U$ and $i \in g_I$. A rating group is captured by a set of attribute value pairs shared among reviewers and items, and can thus be interpreted as a predicate on the rating table.

Rating Maps: To provide a bird's eye view of the ratings in a group g_R, we use *rating maps* [4] - histograms that aggregate ratings in g_R using some item/reviewer attributes. Previous work has shown that such histograms are an adequate means of understanding rated datasets [10]. A rating map rm of a rating group g_R for a rating dimension r_i partitions the records in g_R into disjoint subgroups, and assigns to each subgroup $g_j \in g_R$ an aggregated score. W.l.o.g we assume that a rating map rm partitions g_R using solely one reviewer or item attribute. Thus, a rating map can be seen as the result of a GroupBy operation over g_R, followed by an aggregation function (average in this work) to assign a single rating score to each subgroup. For example, consider the upper rating map in Figure 1 step I, obtained by partitioning g_R on age group. It associates to each subgroup its average overall score.

To identify rating maps presenting useful and interesting trends in the data, we next define the utility score of a rating map. We then introduce the refined notion of *dimension-weighted* (DW) utility score of a rating map, which will help SubDEx in presenting different rating dimensions.

To define the utility of a rating map, we generalize common interestingness measures for data exploration [5].
Conciseness. The conciseness score of a rating map rm is a function of the number of subgroups in rm. It favors rating maps containing a small number of subgroups that summarizes a large number of records in g_R. Here we use the compaction gain measure [11]. **Agreement.** The agreement score of a rating map conveys that each subgroup in g_R contains reviewers

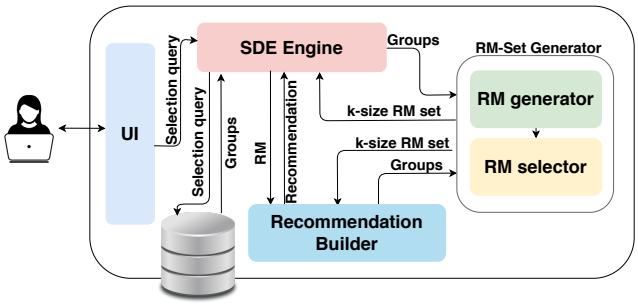


Fig. 2: **SubDEx Architecture.**

who agree among themselves. To measure agreement within a subgroup, here we use *Standard Deviation*, which measures the amount of dispersion of a set of values w.r.t. the mean. The final agreement score is the average score of all subgroups.
Peculiarity This measure ranks a rating map higher if it demonstrates a difference from some reference rating map. We consider two peculiarity scores. One measures the peculiarity of a rating map w.r.t. itself examining the peculiarity of each subgroup within it.The second measures the peculiarity of a rating map w.r.t. previously displayed rating maps (global). It captures the ability of a rating map to show a new facet of the data. To measure the peculiarity, here we use the *total variation distance*, a common deviation measure.

Other measures can be used for each of the above utility criterion, without impacting our solution. The utility score of a rating map is defined as the maximal score, among the four scores mentioned above.

As mentioned, we refine the utility scores to ensure rating maps of different rating dimensions are presented. Intuitively, the Dimension Weighted (DW) utility of a rating map aggregated by dimension r_i is a combination of its utility and a weight reflecting how important it is to promote r_i. Rating dimensions that have been rarely selected would be promoted at the expense of those that have been frequently selected.

B. System Architecture And Workflow

An SDE process starts when a user loads a dataset to an analysis UI. She then executes a series of filtering/generalization operations. In each exploration step, the user examines a rating group g_R, defined by a reviewer group g_U and an item group g_I, and a set of rating maps relevant for g_R. To move to the next step, the user performs an operation on g_U, on g_I, or on both, where each operation can be seen as a selection query over g_U and g_I.

The architecture of SubDEx is depicted in Figure 2. Given a user selection query (that is either recommended by SubDEx or manually specified by the user), the *SDE engine* first extracts from the database the corresponding reviewer, item and rating groups. It then sends those groups to the *RM-Set generator* which returns a k-size set of *diverse* rating maps describing the *most interesting* trends in the current rating group. Each rating map *rm*, is then passed to the *Recommendation Builder* which returns the top-o most interesting next-step operations associated with *rm*. The *SDE Engine* then selects the overall top-o operations with the highest utility (among all generated $k \times o$ operations), and displays the selected rating maps and recommendations to the user. To speed-up computation, the *SDE Engine* calls the *Recommendation Builder* several times in parallel, each time with a different rating map.

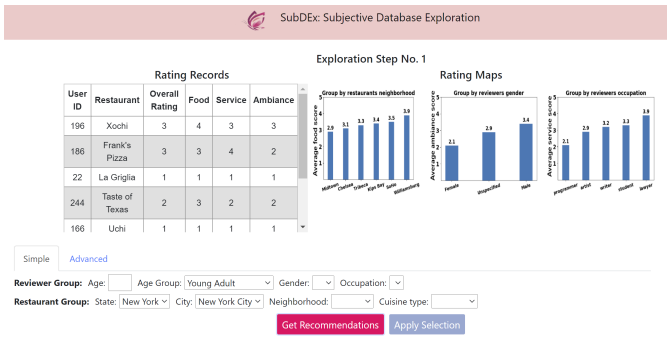
System UI: The user interacts with the system using a dedicated UI (see Figure 3). The user investigates a rating group, by specifying the attribute-value pairs of interest defining the reviewer and item groups. The selection is done using a simple drop-down menu, or, for advanced users, by providing SQL predicates using the advanced screen (see Figure 3(a)). When the user investigates a rating group she can decide whether she wants to perform a recommended operation, or to provide an operation of her own. By clicking on "Apply Selection", the corresponding rating group is displayed alongside a set of rating maps. By clicking on "Get Recommendation", a pop-up window depicting next-step recommendations appears (Figure 3 (b)). To select one recommended operation, the user may click on "Apply Selection" associated with it.

We next briefly describe the operation of the *RM-Set Generator* and the *Recommendation Builder* modules. Full details can be found in [7].

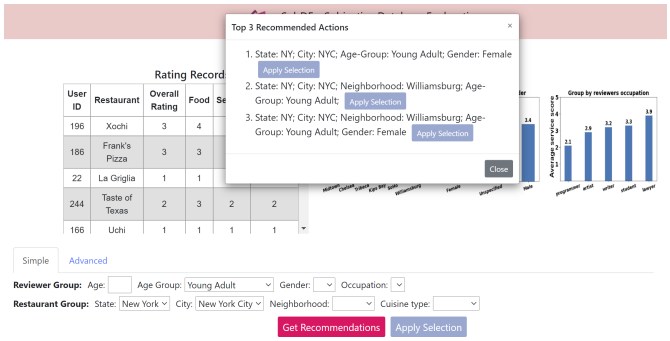
RM-Set Generator: The *RM-Set Generator* is composed of two modules: *(1) RM-Generator* that outputs, w.h.p., the top $l \times k$ rating maps with the highest DW utilities; *(2) RM-Selector* that selects the most diverse k-size set of rating maps. We next briefly describe these modules.
RM-Generator. This module prunes low-utility rating maps, generating only the top $l \times k$ maps with the highest utilities, where l is a constant ≥ 1. To this end, we adapted the sharing and pruning techniques of [6] for identifying high-utility rating maps and reduce computational costs. A main difference is that in our setting, (and unlike in [6] where the utility of a rating map is defined by a single score), the utility of a rating map is the maximum of 4 criteria. Thus, the key challenge here is to adapt these optimizations to our context.
RM-Selector. Our goal is to select the most diverse k-size set of rating maps, among the rating maps returned by the RM-Generator. We define the diversity of a set of rating maps to be the minimum distance between two selected maps. Here we use the Earth Mover's Distance (EMD) to measure the distance between rating maps, a measure that was shown to be well-adapted for comparing rating maps [4], [6]. EMD ensures that rating maps having different shapes are selected. Our experimental results over real-life data show that this also increases the probability of choosing rating maps aggregated by different attributes, thereby exposing different data facets. This module employs the simple and efficient GMM algorithm [12] to identify a diverse k-size set of rating maps, which achieves a 2-approximation factor.

Recommendation Builder: Recall that an operation q is a selection criteria defined over the underlying reviewer and item groups (i.e., g_U and g_I) of g_R. Namely, q is a set of attribute-value pairs, defined as the union of g_U and g_I. Let q' denote the current selection operation over a rating group g_R, and let q denote a next-step operation. Although the space of possible choices for q is very large, it is natural to expect that a user would be interested in a *small adjustment* to the current selection query [13]. Thus, to ensure that operation recommendations are understandable to users and preserve their train of thought, we limit q to be different from q' in at most 2 attribute-values pairs. Namely, q may add a new attribute-value pair to q', and may remove or change one of the existing attribute-value pairs in q'.

For each candidate operation, the essence of the resulting



(a) **An example of exploration step screen with** 3 **rating maps.**



(b) **Top-**3 **next-step recommendations pop-up.**

Fig. 3: **UI of SubDEx.**

rating group is presented to the user in the form or a set of rating maps. Correspondingly, we define the utility of an operation q to reflect the utility scores of the resulting rating maps. Namely, the utility of q is defined as the sum of the DW utilities of rating maps selected after applying q. To compute the utility of an operation q, the *Recommendation Builder* uses the *RM-set Builder*, to find the k-size set of rating maps to be displayed in the next step. We can compute the utility scores of x operations simultaneously, where x is the number of available cores. Finally, given a rating map rm, the *Recommendation Builder* returns the top-o operations associated with rm with the highest utility scores.

III. Demonstration

We demonstrate the operation of SubDEx over three real-world subjective datasets: 12) Movielens[1], which contains reviewers' ratings on movies; (2) Yelp[2], which contains people's reviews of various businesses, including restaurants; (3) Hotel Review[3], which consists of reviewers' reviews on hotels. For the last two datasets, following [1], we extracted from the reviews text the rating scores for multiple rating dimensions (e.g., food, service, and ambiance for restaurants). We evaluate two aspects of SubDEx (i) learnability and usability, showing the ability of users to use the functionalities of SubDEx for different information needs , and (iii) scalability, examining how different parameters affect the performance.

Learnability and usability: We demonstrate the learnability and usability of the system via two scenarios.

Identifying special data characteristics. We simulate a scenario where a data analyst seeks "irregular" groups. An irregular group is described by two or three attribute-values shared by the reviewers (resp., items), whose rating scores for the same rating dimension have all been set to 1. This scenario simulates a common real-life event where the goal is to identify special data characteristics. To examine the benefit of guidance during exploration, we will randomly assign each participant with one of the optional exploration modes, and will ask her to load one of the datasets. The participants would then use the system to find the irregular groups.

Insight extraction. In the second scenario, we will use SubDEx for the task of insight extraction - a common goal of data exploration. For all examined datasets, the Kaggle platform[4] contains several EDA notebooks, manually created by fellow data scientists to demonstrate their EDA process in obtaining insights. From these notebooks, we gathered three lists containing between 5 to 10 insights on each dataset. An example of insight on MovieLens is that the average rating score young adult reviewers gave to thriller movies is significantly higher than that of adult reviewers. Here again, each participant can choose a dataset, and will be randomly assigned with one of the exploration modes.

In both scenarios, the audience can examine statistics describing the aggregated results of other participants. These statistics include the average number of exploration steps, and the average precision and recall. These statistics are obtained by aggregating the results by different exploration modes and by different datasets.

Scalability: Last, the audience will be allowed to look "under the hood", examining the efficiency of our algorithms. For this part of the demonstration, we will use growing fragments of the underlying database, showing the effect of different data and system parameters on performance.

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[1]https://grouplens.org/datasets/movielens/100k/
[2]https://www.yelp.com/dataset
[3]https://www.kaggle.com/datafiniti/hotel-reviews
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