

# Data-Semantics-Aware Recommendation of Diverse Pivot Tables

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## Abstract

Data summarization is essential to discover insights from large datasets. In spreadsheets, *pivot tables* offer a convenient way to summarize tabular data by computing aggregates over some attributes, grouped by others. However, identifying attribute combinations that will result in *useful* pivot tables remains a challenge, especially for high-dimensional datasets. We formalize the problem of automatically recommending *insightful* and *interpretable* pivot tables, eliminating the tedious manual process. A crucial aspect of recommending a set of pivot tables is to *diversify* them. Traditional work inadequately address the table-diversification problem, which leads us to the problem of *pivot table diversification*.

We present SAGE, a data-semantics-aware system for recommending  $k$ -budgeted diverse pivot tables, overcoming the shortcomings of prior work for top- $k$  recommendations that cause redundancy. SAGE ensures that each pivot table is *insightful*, *interpretable*, and *adaptive* to the user's actions and preferences, while also guaranteeing that the set of pivot tables are different from each other, offering a *diverse* recommendation. We make two key technical contributions: (1) a *data-semantics-aware model* to measure the utility of a single pivot table and the diversity of a set of pivot tables, and (2) a *scalable greedy algorithm* that can efficiently select a set of diverse pivot tables of high utility, by leveraging data semantics to significantly reduce the combinatorial search space. Our extensive experiments on four real-world datasets show that SAGE outperforms alternative approaches, and efficiently scales to accommodate high-dimensional datasets. Additionally, through multiple case studies, we demonstrate SAGE's qualitative superiority over existing tools, and through a user study, we validate its practical usefulness and alignment with user preferences.

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## 1 Introduction

Data is at the heart of data-driven decision making. We rely on trends observed in the data to obtain *insights* [22] that help us make informed decisions. However, due to limitations in human

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comprehensibility, data must be *summarized* [29, 37, 64] to enable humans discover insights from the summaries, either directly or via visualizations [68] over the summaries. One of the most common techniques to summarize data is *aggregation*. Simple aggregations involve functions (e.g., SUM) to aggregate all rows. More nuanced aggregations involve multiple groupings of the entities (e.g., GROUP BY GENDER, EDUCATION) and then aggregating each group separately.

While SQL provides functionalities for any custom aggregation query, it is not suitable for novices due to interface-related limitations. Thanks to the ubiquity of spreadsheet software—such as Microsoft Excel [46], Google Sheets [30], Apple Numbers [35], etc.—a substantial portion of businesses (around 60% [21]) and about 2 billion people [49] use spreadsheets for data management and analysis. These users rely on *pivot tables*, a summary of tabular data that computes aggregates over a few data attributes, grouped by other data attributes. Most commercial spreadsheets include a built-in and user-friendly mechanism to construct pivot tables. Spreadsheet pivot tables are particularly suitable for novices, where they can rearrange, group, and aggregate data using intuitive interfaces such as drag-and-drop. Unlike SQL aggregates, spreadsheet pivot tables offer dynamic user interactions, allowing interactive exploration such as drilling down, filtering, sorting, etc.

In an exploratory setting with the goal to discover interesting data trends, a key challenge in constructing insightful pivot tables lies in selecting the right *parameters*, i.e., determining which attributes to use for groupings and aggregations. This task becomes even harder for users who lack knowledge of how the data is represented (especially when the data contains missing or cryptic attribute names), lack domain knowledge, or work with high-dimensional data. In such cases, users must manually explore a vast space of parameter combinations through a tedious trial-and-error process. This involves experimenting with various combinations of (1) grouping attributes, (2) aggregation attributes, and (3) aggregation functions, then manually assessing the *insightfulness* of the resulting pivot tables. We illustrate this challenge with Example 1.1.

**EXAMPLE 1.1.** *Sasha is investigating potential factors affecting salary across various groups in an employee compensation dataset over 21 attributes including ID, Gender, Age, Experience, Degree, Department, Salary, etc. (Figure 1). With an aim to discover salary discrepancies across various group combinations, she starts with the pivot table shown in Figure 2: she puts Gender in the row-groups (A) and Department in the column-groups (B); and chooses Salary as an aggregate attribute (C) and Average as the aggregate function (D).*

*Sasha is interested in Salary discrepancies, so her choice for (C) is fixed. However, she still needs to explore various combinations for (A), (B), and (D). Sasha wishes to put demographic attributes (e.g., Gender, Race, Age, Marital Status, etc.) in the row-groups, as any discrepancy across different rows will indicate discrimination, and all other attributes in the column-groups.*

| ID | Gender | Age | Experience | ... | Degree | Department | Salary    |
|----|--------|-----|------------|-----|--------|------------|-----------|
| 1  | Male   | 48  | 3          | ... | PhD    | IT         | \$50,000  |
| 2  | Female | 32  | 1          | ... | MS     | Sales      | \$20,000  |
| 3  | Male   | 45  | 12         | ... | PhD    | HR         | \$100,000 |

Figure 1: A sample table from an employee compensation dataset.

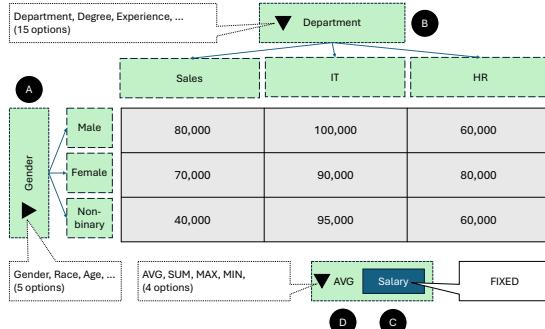


Figure 2: A pivot table requires 4 parameters: (A) row-groups, (B) column-groups, (C) aggregate attributes, and (D) aggregate functions for each aggregate attribute. Users can choose multiple values for each parameter. In Example 1.1, Sasha has fixed (C), but still needs to explore (A) (5 options), (B) (15 options), and (D) (4 options).

Sasha decides to explore 5 demographic and 15 non-demographic attributes, as well as 4 aggregation functions: MAX, MIN, AVERAGE, and SUM. This leaves her  $5 \times 15 \times 4 = 300$  possible combinations,<sup>1</sup> and she must carefully inspect each pivot table to identify salary discrepancies, by manually contrasting the pivot table cells. Assuming each pivot table has 10 cells on average and it takes about 2 minutes to examine each pivot table, Sasha needs  $300 \times 2 = 600$  minutes (10 hours)!

**Recommending Pivot Tables.** Example 1.1 highlights the need for a recommendation system that can automatically suggest the “best” pivot tables. While existing spreadsheet software, such as Microsoft Excel and Google Sheets, are equipped with features for automatic pivot table recommendation, they have several shortcomings, which we show next in Example 1.2.

**EXAMPLE 1.2.** *Frustrated by manual exploration, Sasha tries the pivot table recommendations in Google Sheets (Figure 3), obtaining three recommendations.<sup>2</sup> However, the recommended tables often include too many aggregated attributes beyond her desired Salary, resulting in convoluted and large tables. Sasha also observes that most recommendations are redundant—they default to the groupings by Gender or Department—and lack diversity, causing her to miss out on insights involving other data attributes. While Microsoft Excel provides nine recommendations,<sup>3</sup> it utilizes only 10 out of 21 possible attributes. Additionally, it suggests meaningless aggregations like Sum(Employed Year) and Sum(Age), revealing its shortcoming in grasping the semantics. For both MS Excel and Google Sheets, Sasha failed to specify Salary as her intended aggregate attribute, restricting her ability to steer the recommendations towards her needs. Lastly, Sasha asks ChatGPT for three “insightful” and “diverse” pivot tables, focusing on average Salary. Apparently reasonable at first, she soon*

<sup>1</sup>Sasha chose only one option for each parameter. Multiple options (e.g., Gender and Race for row-groups) will further increase the search space of possible pivot tables.

<sup>2</sup>Test conducted in February 2025.

<sup>3</sup>Tested on Microsoft Excel (Windows) version 2501, February 2025.

| Tool                 | Recommended Pivot Tables                                                                                                                                                                                                                                                                                                                                                                                                                             |
|----------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Google Sheets [30]   | (1) Average of Age, Years of Experience, Annual Bonus, Overtime Hours, Sick Days, Training Hours, Satisfaction Score, #Projects, #Promotions by Gender<br>(2) Average of Performance Rating for each Gender by Department<br>(3) Average of Age, Years of Experience, Performance Rating, Salary, Annual Bonus, Overtime Hours, Sick Days, Training Hours, Satisfaction Score, #Projects, #Promotions by Gender                                      |
| Microsoft Excel [46] | (1) Count of ID by Degree<br>(2) Count of ID by Department<br>(3) Sum of Employed Year by Department<br>(4) Sum of #Promotions by Employed Year and Degree<br>(5) Sum of Age, Children, Performance Rating by Degree<br>(6) Sum of Children, Performance Rating, Salary by Degree<br>(7) Sum of Children, Performance Rating, Salary by Department<br>(8) Sum of Salary by Employed Year and Gender<br>(9) Sum of Employed Year by Gender and Degree |
| ChatGPT [53]         | (1) Average Salary by Years of Experience and Training Hours<br>(2) Average Salary by Department and Children<br>(3) Average Salary by Age and Satisfaction Score                                                                                                                                                                                                                                                                                    |

Figure 3: Google Sheets recommendations are redundant and convoluted; Microsoft Excel includes meaningless recommendations such as SUM(Age); while ChatGPT recommendations look reasonable, they are data-content-unaware as the pivot table values are hallucinated.

realizes that the values of the pivot tables are hallucinated,<sup>4</sup> exposing ChatGPT’s lack of access to the actual data and absence of result validation. Sasha concludes that LLMs are ill-suited for this task, as they do not explicitly enumerate and evaluate all possible options.

Example 1.2 highlights several key limitations of existing tools for automatic recommendation of pivot tables. First, they do not cater to the user needs for a focused and adaptive recommendation of pivot tables. Second, they focus on top-k recommendations [20, 76, 77] and do not consider diversification [24], which may cause the users to miss certain data insights. Finally, existing approaches do not fully leverage the data and its semantics to ensure that the suggested pivot tables are useful, i.e., insightful and interpretable. We propose SAGE, a data-semantics-aware system for recommending k-budgeted diverse pivot tables, which overcomes the shortcomings of the existing approaches. We summarize the limitations of currently available tools and research work in Figure 4 to contrast them against SAGE, and defer a detailed discussion to §8.

**Problem.** The problem we study in this paper is recommending a diverse set of pivot tables, under a size constraint, while ensuring that each recommended pivot table is useful, meaning it is *insightful* and *interpretable*. Furthermore, we want to achieve two usability goals during recommendation: (1) *adaptivity*, which takes into consideration already explored pivot tables by the users, and (2) *customizability*, which enables the users to guide the recommendation process by specifying certain data attributes to prioritize.

**Challenges.** We now highlight three key associated challenges that are associated with the problem:

**Challenge 1: semantic modeling of pivot table utility.** A useful pivot table must be *insightful*, to inform users of meaningful and non-obvious patterns, and *interpretable*, so that users can easily and quickly extract insights from it. Prior work [18, 22, 32, 68] ignore the *semantic aspect*; they use purely statistical measures to model insightfulness, without considering interpretability and semantics of the insight. For instance, the aggregate SUM(Birth\_Year) is

<sup>4</sup>Tested on ChatGPT (GPT-4o), February 2025.

semantically meaningless, even if it indicates strong statistical insight. Furthermore, semantically modeling insightfulness and interpretability of a pivot table in a *multi-group setting* (e.g., group by Gender, Department, Degree) is non-trivial and is not addressed in prior work. In summary, how to model insightfulness and interpretability of a pivot table while remaining aware of the data semantics is a key challenge.

*Challenge 2: modeling table diversity.* Beyond recommending insightful and interpretable pivot tables, our goal is to also *diversify* the set of pivot tables. To the best of our knowledge, the notion of diversity in the context of pivot tables is not defined in prior work. Existing diversification approaches [11, 23–25] do not trivially extend for “table diversification”, where the items under consideration are entire tables rather than individual tuples. Prior work for recommending insightful data summaries [76] or visualizations [68] do not consider diversity. For pivot table diversification, the key challenge is to develop an appropriate distance metric to model both the syntactic (e.g., attribute coverage) and semantic (e.g., provided insights) distances between a pair of pivot tables.

*Challenge 3: developing an efficient system.* Our goal is to recommend highly insightful and interpretable pivot tables, while ensuring diversity among them. Unlike insightfulness and interpretability, which can be measured for each pivot table in isolation, diversity requires considering a *set* of pivot tables. Note that the number of candidate pivot tables grows exponentially with the number of data attributes. Furthermore, finding the best fixed-sized set of pivot tables from these candidates is identical to the minimum set-cover problem, due to the search space growing exponentially with the number of candidates. Consequently, the problem is NP-hard in the number of candidates, which grows exponentially with the number of data attributes. Furthermore, evaluating insightfulness of a pivot table requires its materialization, which adds to the computational complexity. While greedy approaches with approximation guarantees [11, 14, 24, 50, 56] can alleviate the problem of combinatorial search, the requirement of materializing candidate pivot tables remain. Even with approximation algorithms [3, 16, 34, 71] for efficient materialization, without aggressive pruning before materialization, far too many candidates become the bottleneck. Therefore, a key challenge here is to develop mechanisms that can leverage semantic understanding of the data to prune unpromising pivot tables and avoid unnecessary materialization. Another challenge is to discover effective techniques that can “push down” [78] components of the diversity requirements to the search process to further prevent unnecessary pivot table materialization.

**Contributions.** Our main contribution is development of a novel system SAGE, for recommendation of a diverse set of useful pivot tables under a budget (size) constraint. Below, we provide the key contributions we make in this paper:

- We motivate and *formalize the problem* of budgeted recommendation of a diverse set of useful pivot tables, model it as a *constrained optimization problem*, and establish its *desiderata* (§2).
- We provide a formal model to measure the *utility* of a pivot table in terms of insightfulness and interpretability. Unlike prior work, our utility model leverages data semantics (§3).

|                      | Commercial software | Research work | LLMs | This work |
|----------------------|---------------------|---------------|------|-----------|
| Microsoft Excel [46] | ○                   | ○             | ○    | ●         |
| Google Sheets [30]   | ○                   | ○             | ○    | ●         |
| PowerBI [22, 47]     | ●                   | ●             | ●    | ●         |
| Tableau [61]         | ○                   | ●             | ○    | ●         |
| DAISY [76]           | ○                   | ●             | ○    | ●         |
| AutoSuggest [77]     | ○                   | ●             | ●    | ●         |
| ChatGPT [53]         | ○                   | ○             | ●    | ●         |
| Llama3-instruct [44] | ○                   | ○             | ●    | ●         |
| TableGPT [66]        | ○                   | ○             | ●    | ●         |
| SAGE                 |                     |               |      | ●         |

**Figure 4: SAGE satisfies all desirable properties.** While PowerBI, Tableau, DAISY, and AutoSuggest do not directly/always recommend pivot tables, we include them since they recommend summaries. Code for DAISY and AutoSuggest is unavailable, thus we rely on the papers, and mark some things as unknown. LLMs are not designed to directly recommend pivot tables but can be prompted to do so.

- We establish the notion of *pivot-table diversification*, a key component of the problem we study in this paper. Our contribution lies in the formulation of a suitable *distance metric*—which considers both structural and semantic properties of pivot tables—and its application to diversifying a set of pivot tables (§4).
- To ensure SAGE’s efficiency and practicality, we must tackle the NP-hardness of the problem. To reduce the search space, we introduce *aggressive semantic pruning*. To expedite the recommendation process, we leverage offline computation and “push down” diversity requirements to the search process (§5).
- Through an empirical analysis over 4 real-world datasets and case studies, we show that SAGE outperforms prior approaches while staying scalable and efficient (§6).
- We present a user study that validates our utility model and demonstrates SAGE’s superiority over competing baselines based on human perception (§7).

## 2 Recommending a Diverse set of Pivot Tables

In this section, we motivate the need for diversity and adaptivity during recommending pivot tables (§2.1). Then we develop the desiderata for the problem (§2.2) and formalize it (§2.3).

### 2.1 The Need for Diversity and Adaptivity

A key limitation of top-k recommendation is that it may provide redundant information, causing the users to miss out on relatively less useful, but complementary data insights. Such lack of *diversity* may even mislead the users to believe in partial insights that are “half-true”. Another shortcoming of existing approaches is that they are not *adaptive* to user actions, i.e., when the user acknowledges a recommendation, it should be excluded from the subsequent iterations. However, commercial pivot table recommendation features

| Gender | Degree |      |       |
|--------|--------|------|-------|
|        | BS     | MS   | PhD   |
| Male   | 200K   | 300K | 1000K |
| Female | 100K   | 200K | 300K  |

(a) Avg. Salary by Gender and Degree

| Gender | Department |       |
|--------|------------|-------|
|        | IT         | Sales |
| Male   | 1000K      | 500K  |
| Female | 400K       | 200K  |

(b) Avg. Salary by Gender and Dept.

Figure 5: Four pivot tables over the dataset of Figure 1. While (a) and (b) indicate gender-based salary gap, (c) and (d) add additional context.

are not adaptive (Figure 4). We proceed to provide an example to highlight the need for *diverse* recommendation to help the users get a broader picture of the dataset, and *adaptive* [41, 63] recommendation to enable the user guide the recommendation process.

**EXAMPLE 2.1.** Recall from Example 1.1 that *Sasha* is interested in salary discrepancies. She initially finds two pivot tables (Figure 5 (a) & (b)) suggesting gender-based pay gap. However, a deeper pattern emerges when she expands her analysis using other aggregate functions (e.g., COUNT) and discovers the pivot tables shown in Figure 5 (c) & (d), which provide her an additional context that the discrepancy stems from the hiring process: employee counts are uneven across degrees and departments. *Sasha* also notes that IT employees earn more than those in Sales, and PhDs earn more than others. This indicates degree- and department-based discrepancies, which are expected and acceptable. *Sasha* concludes that males earn more on average not due to gender bias, but largely because more male PhDs work at IT.<sup>5</sup>

Furthermore, in an incremental setting where *Sasha* iteratively requests for recommendations of a few pivot tables at a time, she expects the system to adapt to her actions. For instance, after she accepts or rejects the suggestions of Figure 5 (a) and (b), the system should avoid recommending redundant pivot tables that reiterate the same concept (gender-based salary gap) across other aspects (e.g., marital status).<sup>6</sup>

## 2.2 Desiderata

We now list key desiderata for a pivot-table recommender:

- D1. Each recommended pivot table must provide *insightful* [18, 68] and *semantically interesting* information. For instance, a significant gap in average salary across genders provides insight into gender-based pay gap.
- D2. Each pivot table must be *interpretable*, ensuring ease of comprehension by humans. For instance, a concise table with 10 cells is more interpretable than one with 1000 cells.
- D3. While insightfulness and interpretability model the goodness of a single pivot table, a desirable property for a set of pivot tables is *diversity*. Thus, the recommended set of pivot tables must minimize redundancy, covering various data aspects.
- D4. The system for pivot table recommendation must allow (I) *customizability*—allowing users to specify the desired size of the recommendation set, degree of diversity, data scope, etc.—and (II) *adaptiveness* to user actions.
- D5. Finally, the system must be *efficient* and *scalable*—to ensure handling large and high-dimensional data effectively—and *accessible*—in terms of cost and availability.

<sup>5</sup>This phenomenon is known as Simpson's paradox [9, 10]. While our focus is not to expose Simpson's paradox, we show this as a motivating use-case.

<sup>6</sup>This example does not dispute any existing fact regarding the relationship between marital status and gender-based salary gaps.

| Gender | Degree, Department |       |    |       |     |       |
|--------|--------------------|-------|----|-------|-----|-------|
|        | BS                 |       | MS |       | PhD |       |
| Gender | IT                 | Sales | IT | Sales | IT  | Sales |
| Male   | 4                  | 1     | 8  | 1     | 10  | 1     |
| Female | 2                  | 8     | 2  | 3     | 1   | 2     |

(c) Count ID by Gender, Degree, and Dept.

| Degree | Department |       |
|--------|------------|-------|
|        | IT         | Sales |
| BS     | 200K       | 100K  |
| MS     | 300K       | 200K  |
| PhD    | 900K       | 400K  |

(d) Avg. Salary by Degree and Dept.

## 2.3 Problem Formulation

We now formalize our problem for a single-relation database instance (dataset)  $D$  by defining a pivot table.

**Definition 2.1 (Pivot Table).** Given a dataset  $D$  over a set of attributes  $A$  and the domain of aggregate functions  $\mathcal{F} = \{\text{COUNT}, \text{SUM}, \text{AVG}, \text{MIN}, \text{MAX}\}$ , a pivot table  $T(\mathbf{F}(V), G)$  takes the following form:

```
SELECT F(V) FROM D GROUP BY G
```

where,  $G=\{G_1, G_2, \dots\} \subseteq A$  is a subset of attributes for grouping;  $V=\{V_1, V_2, \dots\} \subseteq A$  is a subset of attributes for computing aggregates over;  $G \cap V = \emptyset$  ensures that no attribute is used for both grouping and aggregation;  $\mathbf{F}=\{F_1, F_2, \dots\}$  is a set of aggregate functions where  $F_i \in \mathcal{F}$  and  $|\mathbf{F}|=|V|$ ; and with slight abuse of notation,  $\mathbf{F}(V)$  denotes  $F_1(V_1), F_2(V_2), F_3(V_3) \dots$

**Tabular representation of a pivot table.** For  $T(\mathbf{F}(V), G)$ , with  $|G| \geq 2$ , we fix as row-groups and column-groups (Figure 2) two non-empty sets  $R, C \subset G$ , respectively, where  $R \cup C = G, R \cap C = \emptyset$ .

**EXAMPLE 2.2.** Figure 5(c) represents a possible tabular representation for the pivot table: `SELECT COUNT(ID) FROM D GROUP BY Gender, Degree, Department`. Here,  $R=\{\text{Gender}\}$  and  $C=\{\text{Degree, Dept.}\}$

**Pivot table canonicalization.** The above mechanism allows structurally different tabular representations of semantically equivalent tables. However, we only care about the semantics of a table, not its tabular orientation. Thus, we canonicalize a pivot table  $T(\mathbf{F}(V), G)$  by lexicographically sorting  $\mathbf{F}(V)$  and  $G$  to obtain  $\mathbf{F}(V)_{\leq}$  and  $G_{\leq}$ , respectively, and derive the canonical pivot table  $T(\mathbf{F}(V)_{\leq}, G_{\leq})$ . Furthermore, we obtain a *canonical tabular representation* of a pivot table  $T(\mathbf{F}(V), G)$  by assigning to the row-groups ( $R_{\leq}$ ) the first  $\lceil \frac{|G|}{2} \rceil$  elements of  $G_{\leq}$  and the remaining elements to the column-groups ( $C_{\leq}$ ). This process ensures that pivot tables remain *organization-invariant* (e.g., transpose-invariant), i.e.,  $T(\mathbf{F}(V), G)$  and all its variants derived from different permutations of  $\mathbf{F}(V)$  and  $G$  result in an identical canonical tabular representation.

**EXAMPLE 2.3.** The canonical pivot table for Figure 5(c) is: `SELECT COUNT(ID) FROM D GROUP BY Degree, Department, Gender`. The canonical tabular representation is obtained by setting  $R_{\leq}=\{\text{Degree, Dept.}\}$  and  $C_{\leq}=\{\text{Gender}\}$ , which is simply the transpose of Figure 5(c).

Based on the desiderata of §2.2, we set our goal to find a bounded sized (D4-I) set of pivot tables such that the overall utility (D1 & D2) of the pivot tables are maximized while the set of pivot tables meet the minimum diversity requirement (D3).

**PROBLEM 2.1 (RECOMMENDING A SET OF PIVOT TABLES).** Given (i) a set of possible pivot tables  $\mathcal{T}_A$  over a dataset  $D$  with attributes  $A$ , (ii) a function  $\text{Utility} : \mathcal{T}_A \mapsto [0, 1]$  that returns the utility of a pivot table  $T \in \mathcal{T}_A$ , (iii) a function  $\text{Diversity} : 2^{\mathcal{T}_A} \mapsto [0, 1]$  that returns

| Symbol              | Description                                                            |
|---------------------|------------------------------------------------------------------------|
| $D, A, D[A]$        | Database, attributes, possible unique value combinations               |
| $G, R, C$           | Grouping attributes, row-groups, column-groups; $R \cup C = G$         |
| $F, V$              | Aggregation function and attribute                                     |
| $T(F(V), G)$ or $T$ | A pivot table for the query <code>SELECT F(V) FROM D GROUP BY G</code> |
| $T_{r_i}/T^{c_j}$   | The row/column of $T$ with row/column header $r_i/c_j$                 |
| $T_{r_i}^{c_i}$     | The pivot table cell with row header $r_i$ and column header $c_i$     |
| $n, m$              | The cardinality of $D[R], D[C]$                                        |

Figure 6: Table of notations. We use bold letters to denote sets.

the diversity of a set of pivot tables  $\mathbf{T} \subseteq \mathcal{T}_A$ , (iv) a budget  $k \in \mathbb{N}^+$ , and (v) a threshold  $\theta \in [0, 1]$ , find a set of pivot tables  $\mathbf{T}^* \subseteq \mathcal{T}_A$  s.t:

$$\begin{aligned} \text{(objective)} \quad & \mathbf{T}^* = \arg \max_{\mathbf{T} \subseteq \mathcal{T}_A} \sum_{T \in \mathbf{T}} \text{Utility}(T), \\ \text{(size constraint)} \quad & |\mathbf{T}^*| \leq k, \text{ and} \\ \text{(diversity constraint)} \quad & \text{Diversity}(\mathbf{T}^*) \geq \theta \end{aligned}$$

Problem 2.1 balances utility and diversity by maximizing utility while putting a constraint on diversity. Other variants of this problem are possible such as maximizing a linear combination of the objective and the diversity constraint. More details are in §5.

*Adaptive Recommendation of a set of Pivot Tables.* In the adaptive version (D4-II), we discard the already explored pivot tables by the user  $T_u$  from the set  $\mathcal{T}_A$  to obtain  $\mathcal{T}_A - T_u$ . When the user highlights a data scope (D4-I) by specifying a subset of attributes  $A_u \subseteq A$  they want to focus on, we set the possible pivot tables to  $\mathcal{T}_{A_u}$ .

*Considerations.* Multiple aggregates within a pivot table is essentially equivalent to concatenating the corresponding single-aggregate pivot tables, i.e.,  $T(F(V), G) \equiv \bigcup_{F, V \in F, V} T(F(V), G)$ . Therefore, for simplicity and to promote interpretability, we limit each pivot table to have exactly one aggregate. We use  $F$  and  $V$  to denote the aggregation function and attribute, respectively. We summarize the notations used in the rest of this paper in Figure 6.

*A Note on Generalizability.* While our work focuses on recommending pivot tables in spreadsheet environments, the techniques can be generalized to recommend aggregate queries in relational databases. Pivot tables can be represented by SQL aggregate queries involving Group-by, allowing SAGE’s adaptation in RDBMS.

### 3 Utility of a Pivot Table

Based on the desiderata of §2.2, a pivot table has high utility if it offers *insights* (D1) while being easily *interpretable* by humans (D2). Thus, we use insightfulness (§3.1) and interpretability (§3.2) as the two building blocks to model utility of a pivot table.

#### 3.1 Insightfulness

Intuitively, an insightful pivot table must involve attributes that are *significant*, i.e., inherently interesting and relevant (§3.1.1). Furthermore, it should satisfy at least one of the following criteria: (1) provide high *informativeness* (§3.1.2), (2) highlight meaningful *trends* (§3.1.3), or (3) reveal *surprising* [15, 36, 64] findings (§3.1.4). We build on prior work [15, 18, 22, 32, 36, 68] that model insightfulness based on only statistical properties, but significantly extend it by taking a *semantics-aware* approach, enabled by LLMs [44].

*3.1.1 Attribute significance.* Typically, not all data attributes are of interest by humans. E.g., grouping data by Name is typically much less insightful than by Gender. However, semantic understanding

is required to figure out attribute significance. To this end, we consult an LLM [44] to determine the significance for an attribute  $A$ . When attribute name is missing or semantically meaningless (e.g., “Column 1”), we first query an LLM to suggest appropriate names for attributes by providing it with a small sample of the data. LLM’s semantic-reasoning capability allows us to achieve this without any domain-specific pre-configuration. To avoid noise, we employ multiple paraphrased prompts while querying the LLM. In this work, we condition the LLM to return a simple binary answer (yes  $\rightarrow 1$ /no  $\rightarrow 0$ ). However, this component can be replaced by a domain-aware model that can return the likelihood of an attribute being significant for a specific context. We compute attribute significance of a pivot table  $T$ ,  $S_{\text{sig}} : \mathcal{T}_A \mapsto [0, 1]$  as follows:

$$S_{\text{sig}}(T) = \prod_{A \in \{V\} \cup G} \text{Significance}(A) \quad (1)$$

Here,  $\text{Significance} : A \mapsto [0, 1]$  denotes the probability that an attribute  $A \in A$  is a significant attribute w.r.t human interest.

**EXAMPLE 3.1.** For Figure 5(d), Degree, Department, and Salary, all are significant attributes. Thus,  $S_{\text{sig}}(T) = 1 \times 1 \times 1 = 1$ .

**3.1.2 Informativeness.** A statistical way to measure informativeness within data is to measure spread of the values. Intuitively, if values in a pivot table deviate from each other significantly, the “entropy” is high, and so is the informativeness. In this work, we use *deviation* across different groups to model informativeness. Unlike prior work [18, 32, 68] that only consider a two-group setting (Male vs Female), we consider a multi-group setting.

Given a database  $D$  and a pivot table  $T$  with row-groups  $R$  and column-groups  $C$ , let  $D[R]$  and  $D[C]$  be the set of row and column headers for  $T$ , respectively. E.g., for Figure 5(c), the row headers are {Male, Female} and the column headers are {(BS, IT), (BS, Sales), (MS, IT), (MS, Sales), (PhD, IT), (PhD, Sales)}. We use  $T_{r_i}(T^{c_j})$  to denote the row (column) of  $T$  with row (column) header  $r_i$  ( $c_j$ ). We use  $n$  and  $m$  to denote the number of rows  $|D[R]|$  and columns  $|D[C]|$  in  $T$ , respectively. We compute the row-wise and column-wise informativeness scores  $S_{\text{inf}}^{\text{row}}$  and  $S_{\text{inf}}^{\text{col}}$  as follows:

$$\begin{aligned} S_{\text{inf}}^{\text{row}}(T) &= \frac{1}{\binom{n}{2}} \sum_{r_i, r_j \in D[R] \text{ s.t. } i < j} \frac{\|T_{r_i}, T_{r_j}\|_2}{\gamma \cdot m} \\ S_{\text{inf}}^{\text{col}}(T) &= \frac{1}{\binom{m}{2}} \sum_{c_i, c_j \in D[C] \text{ s.t. } i < j} \frac{\|T^{c_i}, T^{c_j}\|_2}{\gamma \cdot n} \end{aligned}$$

Here,  $\gamma$  is a normalization parameter, set to  $\max(T) - \min(T)$ , ensuring that  $S_{\text{inf}}^{\text{row}}$  and  $S_{\text{inf}}^{\text{col}}$  are bounded between 0 and 1. Also note that while we use Euclidean distance ( $L_2$  distance), any other distance function such as  $L_1$  distance can be used here. We compute the informativeness score  $S_{\text{inf}} : \mathcal{T}_A \mapsto [0, 1]$  by taking the maximum of the row-wise and column-wise informativeness scores:

$$S_{\text{inf}}(T) = \max(S_{\text{inf}}^{\text{row}}(T), S_{\text{inf}}^{\text{col}}(T)) \quad (2)$$

**EXAMPLE 3.2.** We first compute the pairwise distances along the rows of Figure 5(d):  $\|T_{BS}, T_{MS}\|_2 = 141.4K$ ,  $\|T_{BS}, T_{PhD}\|_2 = 761.6K$ , and  $\|T_{MS}, T_{PhD}\|_2 = 632.5K$ . We normalize using  $\gamma = 900K - 100K = 800K$  and  $m = 2$ , resulting in normalized distances of [0.088, 0.476, 0.395]. Taking an average gives us  $S_{\text{inf}}^{\text{row}}(T) = 0.32$ . We similarly compute  $S_{\text{inf}}^{\text{col}}(T) = 0.22$  and obtain  $S_{\text{inf}}(T) = \max(0.32, 0.22) = 0.32$ .

**3.1.3 Trend.** Trends observed in a pivot table provide insights. However, the degree of insightfulness hinges on two key factors: the *magnitude* of the trend metric and how *atypical* or rare it is. For instance, a positive correlation between income and years of service is generally expected—employees with longer tenures typically earn more. In contrast, a trend showing that new hires earn more on average than long-serving employees contradicts this expectation and thus is particularly insightful.

We use two metrics to quantify the magnitude of a trend: *correlation* and *ratio*. Furthermore, to assess the degree of a trend's rarity, we query an LLM, which is aware of a broader semantic context. Thus, our definition of the *trend score* for a pivot table combines (1) purely statistical insights, reflected in high correlation and consistent ratio across pivot table values and (2) semantic insights, captured through the LLM's assessment of the trend's atypicality. *Correlation.* We use  $\rho_{i,j}$  to denote the Pearson correlation coefficient between the rows  $T_{r_i}$  and  $T_{r_j}$ . Since consulting LLMs is costly, we only consider significant correlations and require the magnitude to be at least  $\tau_\rho$ , a customizable threshold parameter, with a default value of 50%. The indicator function  $[\lvert \lvert \rho_{i,j} \rvert \geq \tau_\rho \rvert]$  denotes if the correlation between the rows  $T_{r_i}$  and  $T_{r_j}$  is significant. We compute the row-wise correlation-trend score  $S_{\text{cor}}^{\text{row}} : \mathcal{T}_A \mapsto [0, 1]$  as follows:

$$S_{\text{cor}}^{\text{row}}(T) = \frac{1}{\binom{n}{2}} \sum_{r_i, r_j \in D[\mathbf{R}] \text{ s.t. } i < j} |\rho_{i,j}| \cdot [\lvert \lvert \rho_{i,j} \rvert \geq \tau_\rho \rvert] \cdot \widetilde{Pr}_{\text{cor}}(r_i, r_j)$$

Here,  $\widetilde{Pr}_{\text{cor}}(r_i, r_j)$  is the likelihood of *not* observing a high correlation between the groups  $r_i$  and  $r_j$  determined by an LLM. We prompt an LLM “In a five-point scale from *very likely* to *very unlikely*, how likely is it that the  $\langle F(V) \rangle$  for  $\langle r_i \rangle$  and  $\langle r_j \rangle$  are  $\langle$ positively/negatively $\rangle$  correlated across  $\langle D[\mathbf{C}] \rangle$ ?”, where each part within  $\langle \rangle$  is replaced with actual values such as “Average Salary” for  $\langle F(V) \rangle$ . We then map the LLM-provided likelihood to a numerical value using the mappings: *very likely*  $\rightarrow$  20%, *likely*  $\rightarrow$  40%, *neutral*  $\rightarrow$  60%, *unlikely*  $\rightarrow$  80%, and *very unlikely*  $\rightarrow$  100%. The intuition behind this *inverse mapping* is that the more unlikely it is to observe a trend, the more insightful it is. We compute  $S_{\text{cor}}^{\text{col}}(T)$  similarly and set the correlation-trend score  $S_{\text{cor}}(T) = \max(S_{\text{cor}}^{\text{row}}(T), S_{\text{cor}}^{\text{col}}(T))$ .

**EXAMPLE 3.3.** In Figure 5(d),  $T_{BS}$  and  $T_{\text{PhD}}$  exhibit a positive correlation of 98%, which is likely (from LLM consultation), leading  $\widetilde{Pr}_{\text{cor}}(BS, \text{PhD})$  to be 40%. The correlation between  $T_{BS}$  and  $T_{MS}$  is 100% (very likely); and  $T_{MS}$  and  $T_{\text{PhD}}$  is 100% (likely). Since all correlations meet the threshold 50%, we compute  $S_{\text{cor}}^{\text{row}}(T) = (0.98 \times 0.4 + 1.0 \times 0.2 + 1.0 \times 0.4) / 3 = 0.33$ . The column-wise correlation-trend score  $S_{\text{cor}}^{\text{col}}(T) = (0.98 \times 0.4) / 1 = 0.39$ . Thus,  $S_{\text{cor}}(T) = \max(0.33, 0.39) = 0.39$ .

**Ratio.** Since correlation fails to capture the relative *magnitude*, we use *ratio trends* based on *persistent* ratios between two groups, e.g.,  $T_{\text{PhD}}$  earning at least 5× more than  $T_{BS}$  across all departments. Like correlation, LLMs inform us the rarity of ratio trends. We compute the row-wise ratio-trend score  $S_{\text{ratio}}^{\text{row}} : \mathcal{T}_A \mapsto [0, 1]$  as follows:

$$S_{\text{ratio}}^{\text{row}}(T) = \frac{1}{\binom{n}{2}} \sum_{r_i, r_j \in D[\mathbf{R}]} (1 - \frac{1}{\pi_{i,j}}) \cdot [\lvert \lvert \pi_{i,j} \geq \tau_\pi \rvert] \cdot \widetilde{Pr}_{\text{ratio}}(r_i, r_j)$$

Here,  $\pi_{i,j}$  denotes the minimum element-wise ratio between  $T_{r_i}$  and  $T_{r_j}$ , i.e., the smallest factor by which any value in  $T_{r_i}$  exceeds its corresponding value in  $T_{r_j}$ . To reduce LLM consultation cost, we use a threshold  $\tau_\pi$  and require  $\pi_{i,j}$  to be at least  $\tau_\pi$  before consulting

an LLM. While we set  $\tau_\pi=2.0$ , it is a customizable parameter (but must be  $\geq 1$ ).  $\widetilde{Pr}_{\text{ratio}}(r_i, r_j)$  denotes the LLM-provided likelihood of *not* observing the ratio trend between  $T_{r_i}$  and  $T_{r_j}$ . Note that for any  $i$  and  $j$ , at most one of  $\pi_{i,j}$  or  $\pi_{j,i}$  can contribute to this score, hence we fix the scaling factor to  $\binom{n}{2}$ . We normalize the trend magnitude by subtracting the inverse of  $\pi_{i,j}$  from 1, so that larger ratios yield higher scores. We compute the column-wise ratio-trend score  $S_{\text{ratio}}^{\text{col}}(T)$  similarly and set the ratio-trend score  $S_{\text{ratio}}(T) = \max(S_{\text{ratio}}^{\text{row}}(T), S_{\text{ratio}}^{\text{col}}(T))$ .

**EXAMPLE 3.4.** In Figure 5(d), the minimum ratio between  $T_{MS}$  and  $T_{BS}$  is 1.5; between  $T_{\text{PhD}}$  and  $T_{BS}$  is 4.0; and between  $T_{\text{PhD}}$  and  $T_{MS}$  is 2.0. After applying the threshold  $\tau_\pi = 2.0$ , the ratio trends for  $(T_{\text{PhD}}, T_{MS})$  and  $(T_{\text{PhD}}, T_{BS})$  are retained. The LLM returns the likelihoods: [Very Unlikely, Unlikely]  $\rightarrow [1.0, 0.8]$  for these two trends. This gives us the row-wise ratio-trend score  $S_{\text{ratio}}^{\text{row}}(T) = (3/4 \times 1.0 + 1/2 \times 0.8) / 3 = 0.37$ . For the column-wise ratio-trend score, no pair satisfies the threshold requirement and thus the score is 0.0. Therefore, the ratio-trend score  $S_{\text{ratio}}(T) = \max(0.37, 0.0) = 0.37$ .

Finally, we compute the trend score by taking the maximum of the correlation-trend and ratio-trend scores:

$$S_{\text{trend}}(T) = \max(S_{\text{cor}}(T), S_{\text{ratio}}(T)) \quad (3)$$

**EXAMPLE 3.5.** For the pivot table of Figure 5(d), we computed the correlation-trend score as 0.39 in Example 3.3 and the ratio-trend score as 0.37 in Example 3.4. Thus,  $S_{\text{trend}}(T) = \max(0.39, 0.37) = 0.39$ .

**3.1.4 Surprise.** Surprising values or *outliers* often indicate insights. E.g., in Figure 5(d),  $T_{\text{PhD}}^{\text{IT}}$  is exceptionally high (900K) in its column. While such outliers can be insightful, not all are. Some, like this one, are expected: IT is high-paying, and PhDs earn more. In contrast, an unusually high  $T_{BS}^{\text{Sales}}$  would be surprising, and thus insightful. Beyond simply identifying outliers, we incorporate the unexpectedness of observing outliers using LLM's semantic knowledge. We compute the row-wise surprise score  $S_{\text{sur}}^{\text{row}} : \mathcal{T}_A \mapsto [0, 1]$  as follows:

$$S_{\text{sur}}^{\text{row}}(T) = \frac{1}{n} \sum_{r_i \in D[\mathbf{R}]} \text{OutlierScore}(T_{r_i})$$

where,  $\text{OutlierScore}(T_{r_i}) = \begin{cases} 1 - \frac{\sum_{c \in O_{r_i}} \widetilde{Pr}_{\text{outlier}}(r_i, c, T_{r_i}^c)}{|O_{r_i}| + 1}, & \text{if } |O_{r_i}| > 0 \\ 0, & \text{otherwise} \end{cases}$

$$O_{r_i} = \{c_j \in D[\mathbf{C}] \text{ s.t. } |T_{r_i}^{c_j} - \mu(T_{r_i})| \geq \tau_O \cdot \sigma(T_{r_i})\}$$

$O_{r_i}$  is the set of column headers for each outlier in  $T_{r_i}$ . E.g.,  $O_{\text{PhD}} = \{\text{IT}\}$ , if 900K is an outlier for the row  $T_{\text{PhD}}$ . We ensure that the score increases with the number of outliers by subtracting the inverse of their count from 1. Since even a single outlier matters, we add 1 to the denominator to ensure that even one outlier results in a score multiplier of 0.5. The threshold  $\tau_O$  is set to 4, since, assuming normal distribution, 99.99% of the population is expected to lie within 4 standard deviations from the mean [27]<sup>7</sup>; and anything outside this range is an outlier.  $\widetilde{Pr}_{\text{outlier}}(r_i, c, T_{r_i}^c)$  denotes the LLM-obtained likelihood of  $T_{r_i}^c$  *not* being an outlier w.r.t  $T_{r_i}$ . We compute  $S_{\text{sur}}^{\text{col}}(T)$  similarly and compute the surprise score:

$$S_{\text{sur}}(T) = \max(S_{\text{sur}}^{\text{row}}(T), S_{\text{sur}}^{\text{col}}(T)) \quad (4)$$

<sup>7</sup>Data in pivot tables may not be normally distributed. We use this heuristic for simplicity and the user can replace this with other methods.

**Computing Insightfulness.** A pivot table is insightful if it exhibits any of the characteristics: informativeness, trend, or surprise. Thus, we take the *maximum* of  $S_{\text{inf}}$ ,  $S_{\text{trend}}$ , and  $S_{\text{sur}}$  (Equations 2, 3, and 4) to compute  $\text{Insightfulness} : \mathcal{T}_A \mapsto [0, 1]$ . To prioritize pivot tables involving significant attributes, we scale this score by  $S_{\text{sig}}$ .

$$\text{Insightfulness}(T) = S_{\text{sig}}(T) \cdot \max(S_{\text{inf}}(T), S_{\text{trend}}(T), S_{\text{sur}}(T)) \quad (5)$$

EXAMPLE 3.6. For the pivot table of Figure 5(d), the attribute significance score  $S_{\text{sig}}(T)=1$  (Example 3.1). The informativeness score  $S_{\text{inf}}(T)=0.32$  (Example 3.2), the trend score  $S_{\text{trend}}(T)=0.32$  (Example 3.5), and since there is no outlier in the pivot table, the surprise score  $S_{\text{sur}}(T)=0.0$ . Thus  $\text{Insightfulness}(T)=1 \times \max(0.32, 0.39, 0.0)=0.39$ .

**Remark 1.** Presence of outliers can inflate the normalization factor  $\gamma$  (§3.1.2), causing  $S_{\text{inf}}$  to shrink significantly due to the compression of the value range of non-outliers. However, such cases typically yield a high  $S_{\text{sur}}$ , complementing the low  $S_{\text{inf}}$ .

**Remark 2.** The Max operator used in Equation 5 may favor the component with the highest mean, without considering their distributions. This a common challenge in multi-criteria decision making [52]. However, standardizing all components to the same mean can distort their relative importance. For example, if all pivot tables have uniformly low informativeness (with low variance) but uniformly high trend (with low variance), normalization would artificially inflate informativeness and suppress trend, leading to incorrect selections. The Max operator retains the strongest signal without distorting component distributions through forced standardization. An alternative is using a weighted linear combination of components, with weights learned from labeled datasets via machine learning, which is orthogonal to our research. Nevertheless, SAGE is agnostic to the choice of the formula to compute *Insightfulness* and any linear formula would work.

## 3.2 Interpretability

A key measure of a pivot table's utility is *interpretability*, which takes into account the cognitive constraints of humans. Consider the aggregate SUM(AGE), row group Degree (3 values), and column groups Employed\_Year (14 values) and Department (2 values), which results in an 84-cell pivot table. Its interpretability suffers due to three reasons: (1) High sparsity resulting from many value combinations yielding empty sets—e.g., no MS hire in 2011 for the IT department (§3.2.1), (2) Semantically invalid aggregate SUM(AGE) (§3.2.2), and (3) Excessive #columns ( $14 \times 2 = 28$ ) from fine-grained yearly grouping, compromising conciseness (§3.2.3). We proceed to describe three desirable interpretability properties.

**3.2.1 Density.** Since each pivot table cell maps to a data subset under a specific value combination (e.g., MS hires in IT in 2011), empty subsets can occur. When aggregated, these empty subsets produce *null* values. However, excessive nulls hinder interpretability [1], as humans struggle to draw insights from sparse tables. This motivates a key interpretability criterion: high *density*. We compute the *density score*  $S_{\text{den}} : \mathcal{T}_A \mapsto [0, 1]$  as follows:

$$S_{\text{den}}(T) = \frac{\sum_{(r_i, c_j) \in D[R] \times D[C]} [\lceil T_{r_i}^{c_j} \neq \text{null} \rceil]}{n \cdot m} \quad (6)$$

EXAMPLE 3.7. The pivot table of Figure 5(d) has 3 rows and 2 columns (total 6 cells) and no null values. Hence,  $S_{\text{den}}(T) = \frac{6}{2 \times 3} = 1.0$ .

**3.2.2 Semantic validity.** Row and column headers in a pivot table represent unique values of the grouping attributes in  $G$ . For interpretability, these headers must be semantically meaningful [8]. E.g., Degree with values {MS, BS, PhD} is interpretable, while a functionally equivalent Degree\_ID with values {1, 2, 3} is not, due to the lack of direct semantic meaning [17]. Similarly, the aggregate function  $F$  must be semantically valid w.r.t  $V$ : AVG is semantically valid for AGE, but SUM is not [40]. Though intuitive for humans, such judgments require domain knowledge. Thus, we leverage an LLM to mimic human reasoning and assess aggregation semantics. We define the *semantic validity score* of  $T(F(V), G)$  based on two criteria: (1) whether the data types of attributes in  $G$  are textual, and (2) the extent to which  $F$  is semantically valid w.r.t  $V$ .

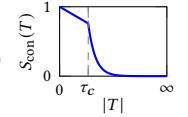
$$S_{\text{sem}}(T) = \frac{|\{A \in G \text{ s.t. } \text{DataType}(A) \text{ is Text}\}|}{|G|} \cdot \text{Pr}_{\text{agg}}(F, V) \quad (7)$$

We compute  $\text{Pr}_{\text{agg}}(F, V)$  from an LLM-generated ranking of  $F \in \mathcal{F}$  based on its semantic validity w.r.t  $V$ . We score the best function 1.0, the next 0.8, and so on, which ensures that  $S_{\text{sem}}(T) \in [0, 1]$ .

EXAMPLE 3.8. The pivot table of Figure 5(d), contains only textual headers. LLM responds to our prompt “Rank the functions COUNT, AVG, SUM, MIN, and MAX, based on their appropriateness for analyzing Salary” with {AVG, ...}. Thus,  $S_{\text{sem}}(T) = \frac{2}{2} \times 1.0 = 1.0$ .

**3.2.3 Conciseness.** While multiple grouping attributes may enhance insightfulness, too many cells reduce comprehensibility [55], and, thus, interpretability. To model this, we define conciseness score  $S_{\text{con}} : \mathcal{T}_A \mapsto [0, 1]$  using a piecewise function [19]:

$$S_{\text{con}}(T) = \begin{cases} 1 - z|T|, & \text{if } |T| \leq \tau_c \\ (1 - z\tau_c)e^{-\lambda(|T| - \tau_c)}, & \text{if } |T| > \tau_c \end{cases} \quad (8)$$



Here,  $|T|$  denotes the number of cells in  $T$ . This formula captures the intuition that interpretability declines gradually at first, but drops sharply once  $|T|$  exceeds a threshold  $\tau_c$ , set to 16. We apply a 3% linear decrease ( $z = 0.03$ ) until  $|T|$  exceeds  $\tau_c$ , and an exponential decay at a rate of 50% ( $\lambda = 0.5$ ) beyond that. This is grounded in cognitive load theory [7, 48], which states that performance declines sharply when cognitive demand exceeds working-memory capacity.

EXAMPLE 3.9. The pivot table of Figure 5(d) has 6 cells. Since  $6 < 16$ , we compute the linear part:  $1 - 0.03 \times 6 = 0.82$ . Thus,  $S_{\text{con}}(T) = 0.82$ .

**Computing Interpretability.** Unlike insightfulness, where a strong signal from *any* single type of insight is sufficient, interpretability demands that *all* criteria be met simultaneously. Therefore, we compute *Interpretability* :  $\mathcal{T}_A \mapsto [0, 1]$  as the average of the three scores:  $S_{\text{den}}$ ,  $S_{\text{sem}}$ , and  $S_{\text{con}}$  (Equations 6, 7, and 8):

$$\text{Interpretability}(T) = \frac{S_{\text{den}}(T) + S_{\text{sem}}(T) + S_{\text{con}}(T)}{3} \quad (9)$$

EXAMPLE 3.10. For Figure 5(d), we obtained values for  $S_{\text{den}}(T)$ ,  $S_{\text{sem}}(T)$ , and  $S_{\text{con}}(T)$  to be 1.0, 1.0, and 0.82, respectively, in the previous examples. Thus,  $\text{Interpretability}(T) = (1.0 + 1.0 + 0.82)/3 = 0.94$ .

## 3.3 Computing Utility

We now define *Utility* :  $\mathcal{T}_A \mapsto [0, 1]$  of a pivot table  $T$  by combining *Insightfulness* (Eq. 5) and *Interpretability* (Eq. 9). To balance their contributions, we introduce a tunable parameter  $\alpha$ , set to 0.5 by

default to give equal weight to both components. However,  $\alpha$  can be adjusted to reflect application-specific preferences.

$$\text{Utility}(T) = \alpha \cdot \text{Insightfulness}(T) + (1 - \alpha) \cdot \text{Interpretability}(T)$$

**EXAMPLE 3.11.** For Figure 5(d), the *Insightfulness* and *Interpretability* scores are 0.39 and 0.94, respectively. Thus,  $\text{Utility}(T) = 0.5 \times 0.39 + 0.5 \times 0.94 = 0.67$ .

*Need for a new Utility Model.* Our *Utility* model significantly extends prior work that address related problems [13, 18, 22, 32, 68, 74]. **First**, prior work ignore the *semantic validity* of the summary *structure*, which directly affects interpretability (e.g., `SUM(Birth_Year)` or `AVG(Zip_Code)` are invalid; `{Val_1, Val_2}` is less interpretable than `{Large, Small}`; and `Gender` is a more interesting grouping attribute than `Employee_ID`). **Second**, prior work rely solely on statistical signals. For example, SeeDB [68] uses an EMD-based deviation metric, which is just one of the seven components of our *Utility* model, while others [22, 74] use value-proportion and statistical-significance tests. Moreover, they do not support multi-group reasoning, required in our setting involving pivot tables. But most importantly, they lack *semantic awareness* to validate an apparent data insight. For instance, “a significant deviation in average height between toddlers and adults” will incur a high score based on their metrics. However, such deviation is trivially expected. In contrast, even a moderate “deviation in average height across socio-economic groups” indicates an interesting insight. **Third**, these methods ignore quality factors, such as `NULL` values in some groups in the data summary (which yields empty bars for visualization). In general, most prior work do not incorporate various aspects of interpretability in their utility models. The above shortcomings of the prior work motivates a *semantics-aware* and *interpretability-focused* Utility model, like ours, that identifies insights that are meaningful in real-world contexts, not merely statistically distinct.

## 4 Diversity in a Set of Pivot Tables

While utility quantifies the goodness of a single pivot table in isolation, *diversity* captures how well a *set* of pivot tables, *collectively*, provide complementary and unique perspectives on the data (D3). High diversity in a set of pivot tables is achieved when the pivot tables are distant from each other with respect to data coverage and the insights they provide.

*Diversity.* Following Max-Min diversification [2], we define diversity of a set of pivot tables  $T = \{T_1, T_2, \dots\}$  by the smallest pairwise distance between  $T$ 's elements. More formally, given a symmetric distance function  $\text{dist} : \mathcal{T}_A \times \mathcal{T}_A \mapsto [0, 1]$ , we define  $\text{diversity} : 2^{\mathcal{T}_A} \mapsto [0, 1]$  of a set of pivot tables  $T \subseteq \mathcal{T}_A$  as follows:

$$\text{Diversity}(T) = \min_{T_i, T_j \in T \text{ s.t. } i < j} \text{dist}(T_i, T_j)$$

*Distance between pivot tables.* A simple heuristic to model  $\text{dist}$  is the degree of disjointness between the attributes that define the pivot-table queries—if two pivot tables operate on the same set of attributes, the distance is 0; for completely disjoint set of attributes, the distance is 1. However, this heuristic fails to account for the *structural semantics* of the pivot-table queries and the *content semantics* of the data in the pivot tables. To this end, we employ a semantics-preserving embedding function  $E : \mathcal{T}_A \mapsto [-1, 1]^p$ ,

which maps a pivot table  $T \in \mathcal{T}_A$  to a  $p$ -dimensional vector. Then, we compute distances between pivot tables in this embedding space:

$$\text{dist}(T_1, T_2) = \frac{1 - \text{cosine\_similarity}(E(T_1), E(T_2))}{2}$$

Here,  $\text{cosine\_similarity} : \mathbb{R}^p \times \mathbb{R}^p \rightarrow [-1, 1]$  is a widely used measure for comparing embeddings [5, 58]. We divide by 2 to achieve normalization s.t  $\text{dist}(T_1, T_2) \in [0, 1]$ .

*Pivot-table embedding.* Pivot-table embedding should capture both the syntactic and semantic characteristics of the pivot table. To this end, we combine the query embedding  $E_Q$  and the content embedding  $E_C$  through concatenation, i.e.,  $E(T) = [E_Q(T); E_C(T)]$ . Concatenating embeddings is a widely used technique in machine learning, natural language processing, and multi-modal learning [82].

*Query embedding.* Queries define the structural intent of a pivot table. While they reference data attributes and are aware of the schema, they are agnostic to the pivot table's content. Thus, the same pivot-table query over different database instances with an identical schema should yield the same query embedding. Effective query embeddings must also capture the semantics of the attribute names and reflect the query semantics. E.g., `GROUP BY Income` and `GROUP BY Salary` are semantically similar and should therefore be close in the query-embedding space. To this end, we use T5 [57], a natural-language encoder fine-tuned over a Text-to-SQL dataset [80], to obtain the query embedding  $E_Q : \mathcal{T}_A \mapsto [-1, 1]^{1024}$ .

*Content embedding.* The content embedding must capture both the statistical and distributional properties of the pivot-table data and structural relationships among its attributes and tuples. In this work, we leverage TAPEX [42], a pre-trained encoder trained on sentence-table pairs, which is designed to understand both the structure and content of tabular data. This results in a content embedding  $E_C : \mathcal{T}_A \mapsto [-1, 1]^{1024}$ .

## 5 The SAGE Algorithm

We now present a solution to Problem 2.1, which is to recommend a  $k$ -budgeted set of pivot tables with maximum utility under a diversity constraint. This is an instance of the NP-hard Maximum Weight Independent Set (MWIS) problem [60] with complexity  $O(|\mathcal{T}_A|^k)$  in the size of the search space ( $\mathcal{T}_A$  in our case). Furthermore,  $\mathcal{T}_A$  grows combinatorially with  $|A|$  (the number of data attributes), leading to an exponential growth. Approximation techniques exist for special cases of MWIS and related problems [12, 39, 51, 60] and alternative formulations are possible such as incorporating diversity into the objective or solving the dual version that maximizes diversity [2] under a utility constraint. However, in SAGE, we adopt a simple greedy approach (§5.2) for two key reasons: (1) Interactive response time is desirable for our problem settings and greedy approach achieves linear time complexity of  $O(|\mathcal{T}_A|)$ . (2) As we demonstrate in §6, our greedy approach works remarkably well in practice over real-world datasets, almost always matching the exact solution.

### 5.1 Optimizations

The linear-time complexity of the greedy approach is still prohibitive for practical use for two reasons: (1) Computing the *Utility* of

candidate pivot tables requires their materialization, which is computationally expensive—especially since  $\mathcal{T}_A$  grows exponentially with  $|A|$ . (2) Some components of *Utility* relies on the LLM, whose inference latency is a bottleneck [67, 69]. To address these efficiency challenges (D5), we introduce two offline optimizations: (1) *Candidate pruning*: based on the query structure of the pivot tables, we eliminate potentially low-utility ones before materialization, thereby significantly reducing the search space and avoiding many materializations (§5.1.1). (2) A lightweight *proxy model*: tailored to the dataset, it approximates LLM inferences efficiently (§5.1.2).

**5.1.1 Pruning.** To prune pivot tables likely to yield low utility without materialization, we leverage three components of *Utility* (§3.3): C-I: *attribute significance* (§3.1.1) used in *Insightfulness* (Eq 5), C-II: *semantic validity* (§3.2.2), and C-III: *conciseness* (§3.2.3) used in *Interpretability* (Eq 9). These choices are motivated by computational efficiency, as these components require knowledge of only the pivot-table query, which defines the structure of the pivot table—such as which attributes are used, number of cells, etc.—and do not require a full materialization over the dataset.

While *Insightfulness* selects only the maximum among multiple components, *Interpretability* averages out three components—two of which are C-II and C-III above. This enables effective pruning of pivot tables that already show low scores for C-II and/or C-III. Furthermore, since C-I interacts in a multiplicative way with other components of *Insightfulness* (Eq 5), a low value will inevitably result in low *Insightfulness*, making it an ideal choice. Our pruning algorithm works as follows: we evaluate scores for the above three components and over-approximate *Utility* (§3.3) by assigning maximum possible values for all other components whose values are unknown. Through this conservative estimate, we discard candidates with a score below a threshold (a system parameter set to 0.5).

**5.1.2 LLM-proxy.** Recall that the computation of pivot-table utility requires LLM inferences (§3), and querying LLMs is time-consuming in practice. Even if we cache the LLM responses, any change in the underlying data or user-specified parameters (D4) would require LLM re-consultation. To expedite this process, we train a cheap but significantly faster decision-tree classifier to mimic LLM behavior, serving as an “LLM-proxy” during the online phase of SAGE (Algorithm 1). We train the classifier over 10,000 LLM prompt-response pairs, where we generate potential LLM-queries based on the dataset. The proxy model is a simple predictive model to answer the fixed-template questions discussed in §3. No re-training of this proxy model is required as long as the data distribution and overall trends in the dataset remain unchanged. While training with additional prompt-response pairs or employing more complex classifiers can further improve the accuracy of this proxy model, we show empirically in Section 6.1 that 10,000 prompt-response pairs already provide reasonable accuracy for practical applications.

## 5.2 SAGE: Greedy Algorithm

Algorithm 1 shows the SAGE workflow. Line 1 denotes the offline pruning step and lines 2–4 show the steps for LLM-proxy training. The online phase is shown in lines 5–14. The pivot tables that survive the pruning step are materialized in line 6, we then compute their *Utility* scores (line 7) and sort the pruned candidate set of

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### Algorithm 1: SAGE algorithm

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```

Input : Database  $D$ ,  

        Unmaterialized candidate pivot table set  $\mathcal{T}_A$ ,  

        Diversity threshold  $\theta$ ,  

        The desired number of pivot tables  $k$   

Output : A high-utility set  $T \subseteq \mathcal{T}_A$  s.t.  $|T| \leq k$  and  $Diversity(T) \geq \theta$   

/* Offline phase: executed once for each dataset. Re-executed if the schema changes or major change happens in the data distribution. */  

/* Prune candidate set based on pivot-table structure (§5.1.1) */  

1  $\mathcal{T}_A^{Pr} \leftarrow Prune(\mathcal{T}_A)$   

/* Building LLM-Proxy (§5.1.2) */  

2  $Q \leftarrow$  list of questions about  $D$  /* Generate prompts for the LLM */  

3  $R \leftarrow$  LLM-Response( $Q$ ) /* Get responses from the LLM */  

4  $LLM\text{-Proxy} \leftarrow Train(Q, R)$  /* Train a proxy prediction model */  

/* Online phase: executed whenever the data changes. */  

/* Materialize and compute utility based on pivot-table contents */  

5 foreach  $T \in \mathcal{T}_A^{Pr}$  do  

6   Materialize  $T$  over  $D$   

7   Compute Utility( $T$ ) /* §3.3 */  

8  $\mathcal{T}_A^{Pr} = sorted(\mathcal{T}_A^{Pr})$  /* Sort by the descending order of Utility */  

/* Greedy selection (§5.2) */  

9  $T \leftarrow \emptyset$  /* Initialize an empty set */  

10 while  $|T| \leq k$  do  

11   foreach  $T' \in \mathcal{T}_A^{Pr}$  do  

/* No pivot table in T is within  $\theta$  distance away from  $T$  */  

12     if  $\nexists T' \in T$  s.t.  $dist(T, T') < \theta$  then  

13        $T \leftarrow T \cup \{T'\}$   

14 return  $T$ 

```

---

pivot tables by descending order of utility (line 8). The greedy selection phase (lines 9–14) selects pivot tables greedily while ensuring that they satisfy the diversity constraint w.r.t the already selected ones in  $T$ . If a candidate pivot table is at least  $\theta$  away from all the previously selected tables, we include it to  $T$  (lines 12–13). The algorithm terminates when we have selected  $k$  pivot tables or no more candidates satisfy the diversity constraint.

## 5.3 SAGE<sup>+</sup>: A Practical Variant

Even after the two optimizations, SAGE may not ensure interactive speed especially when the dataset has millions of tuples or hundreds of attributes, hurting its practical adoption. To this end, we propose SAGE<sup>+</sup>, a variant of SAGE that incorporates sampling and approximation techniques to ensure practically acceptable runtimes in an interactive setting, which is essential for spreadsheet environments. Specifically, to handle high-cardinality and high-dimensionality, it (i) uses 20% of the data samples when the dataset is large (e.g., contains 1M+ tuples or 100+ attributes) for candidate pivot-table generation, (2) uses 10% subsampling for approximating *Trend* (§3.1.3) and *Surprise* (§3.1.4) scores, and (iii) applies dimensionality reduction using Johnson-Lindenstrauss lemma [38], which preserves pairwise distances up to a distortion factor ratio  $\epsilon = 0.2$ , for approximating the *Informativeness* score (§3.1.2). Furthermore, SAGE<sup>+</sup> uses multiple cores (12 in our experiments) for parallelizing computations. Note that SAGE<sup>+</sup> does not improve the theoretical runtime complexity compared to SAGE; instead, it provides practical enhancements that ensure better suitability for practical use.

## 6 Experimental Results

We now present experimental results to demonstrate the efficacy of SAGE in practical settings to address the following questions:

- (Q1) How do SAGE’s runtime and recommendation quality compare quantitatively with those of existing methods? (§6.2)
- (Q2) What is the effect of the optimization techniques—pruning and LLM-proxy—on SAGE’s runtime performance? (§6.3)
- (Q3) How well does SAGE scale with data growth? (§6.4)
- (Q4) How do key parameters (budget  $k$  and diversity threshold  $\theta$ ) influence the quality of SAGE recommendations? (§6.5)
- (Q5) How do SAGE recommendations qualitatively compare against commercial software and LLMs over real datasets and how does SAGE adapt based on user feedback? (§6.6)

### 6.1 Experimental Setup

**6.1.1 Setup.** All experiments were run on machines with 256 GB RAM running Ubuntu 22.04 LTS with CPU 12 cores and GPU NVIDIA H100 96GB with CUDA 12.8. We implemented our solutions (available publicly [6]) with Python 3.10.3. For embeddings, we utilized TAPEX-large [45] and T5 trained by Spider [28]. We employed Llama-3-7B [43] as the LLM for semantic consultation.

**6.1.2 Offline Phase.** As discussed in §5.1, SAGE relies on two offline optimizations: pruning (§5.1.1) and developing an LLM-Proxy model (§5.1.2). The LLM-Proxy model is composed of a decision tree whose parameters are learned from a training dataset of prompts and their corresponding answers retrieved from Llama-3-7B [43]. We configured the decision tree to have a maximum depth of 15 and used the Gini function as the splitting criterion. We generated 10,000 prompts—for each of Correlation (§3.1.3), Ratio (§3.1.3), and Surprise (§3.1.4)—splitting the resulting datasets 80/20 into training and test sets. On average, across the 4 datasets, the LLM-Proxy model achieved an accuracy of 90%, 89%, and 64% for Correlation, Ratio, and Surprise, respectively. On average, the offline phase took about 92 minutes per dataset, which includes both pruning and LLM-Proxy training.

**6.1.3 Datasets.** We used four real-world datasets with varying domains and sizes to assess SAGE’s generalizability.

- **Marketing** [59] contains 2,240 tuples and 28 attributes (19 categorical and 9 numerical), capturing demographic and behavioral information about customers like marital status & purchase history.
- **Video** [31] comprises video game sales from various countries, platforms, and release years, containing 16,600 tuples across 11 attributes (7 categorical and 4 numerical).
- **House** [4] contains information about property sales, comprising 1,460 tuples and 81 attributes (58 categorical and 23 numerical).
- **Cover Type** [83] is a large dataset with 581,000 tuples and 110 attributes, containing tree observations across a National Forest.

**6.1.4 Baselines.** Below, we list the baselines. To the best of our knowledge, no existing open-source tool or academic work directly addresses our problem setting of recommending a set of diversified pivot tables. Therefore, we include commercially available software as baselines, despite their internal logic not being open-sourced.:

**Brute-Force** considers all possible  $k$ -sized pivot table sets and follows an exhaustive approach to solve Problem 2.1. In the absence of ground truth, its results can be treated as the optimal solution.

**Top-k** ranks candidate pivot tables in descending order of their utility scores and selects the top- $k$ , without accounting for diversity. For fair comparison, we applied our optimizations here.

**LLM** refers to Llama-3-8B-Instruct by Meta [43], a transformer-based large language model. We prompted it with a data sample and asked for interesting and diverse pivot tables in natural language.

**DAISY** [76] is a query recommendation system trained on crowdsourced “interesting” queries. Due to the original model and data not being available, we did our own implementation. We generated insightful pivot tables from Auto-Suggest [77], created negative training data by replacing attributes in the positive tables with random ones, and trained a binary classifier to distinguish them.

**Microsoft Excel** [46] is a widely used commercial spreadsheet software that offers built-in pivot table recommendations. We used the Windows version 2501.

**PowerBI** [22, 47], also by Microsoft, is a business intelligence software that offers “quick insights” in various forms. For comparison, we only considered ones that align with our format of pivot table.

**Google Sheets** [30] is an online spreadsheet software known for easy collaboration, which recommends pivot tables. We used the browser version during February, 2025.

For Excel, PowerBI, and Google Sheets,  $k$  cannot be controlled. Thus, we consider the first- $k$  items. Google Sheets fails to produce more than 3 recommendations, thus, we exclude it when  $k > 3$ .

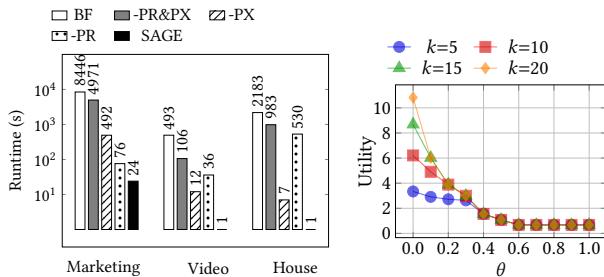
### 6.2 Contrasting against Baselines

Table 1 contrasts SAGE against the baselines across three datasets. Our primary metrics for comparison are *Utility* (Util) and *Diversity* (m-dist). However, since *Insightfulness* and *Interpretability* constitute *Utility* (§3), we report them for additional context. The results show that SAGE effectively balances utility and diversity, outperforming approaches like Top-k, which inherently lack diversity. For Marketing, SAGE achieves a strong overall performance, ranking either best or second-best in both metrics. Notably, when SAGE marginally loses in terms of diversity, that is usually complemented by significantly higher utility. For example, in Marketing,  $k = 10$ , LLM’s diversity (0.20) is more than SAGE’s diversity (0.11). However, LLM’s utility (3.69) is about half of SAGE’s utility (7.44). A similar situation is seen for  $k = 3$  where GSheets yields only 30% of SAGE’s utility. Recall that SAGE’s goal is to just satisfy the diversity constraint, not maximize it.

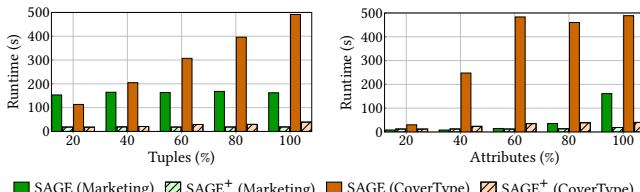
For Video, SAGE outperforms all baselines across all cases in utility and two cases in diversity. SAGE and Top-k’s similar performance can be attributed to the dataset attributes, such as North-America Sales and Europe-Sales, which possess similar value ranges, leading to comparable utility. For House, Top-k marginally outperforms SAGE in utility, but at the cost of very low diversity. SAGE diversity is relatively poor here, because the pruning phase retained only 11 of 81 attributes, where others used all attributes.

While Top-k achieves high utility by design, it fails to diversify. LLM performs well on Marketing but struggles on Video and House, because Marketing has many categorical values, which LLMs are





**Figure 7: (Left)** Effect of optimization techniques. We used  $k=4$  and  $\theta = 0.1$ . **(Right)** Effect of  $\theta$  on Utility on the Video dataset.



**Figure 8:** SAGE and SAGE<sup>+</sup> runtime (s) w.r.t (Left) #tuples, (Right) #attributes. We used  $k = 5$  and  $\theta = 0.10$  for these experiments.

PR/PX = plain greedy), no pruning (No PR), no LLM-proxy (No PX), and SAGE with both optimizations. Notably, we find that greedy achieves exact results in par with Brute Force, validating our choice.

BruteForce shows an infeasible runtime of over 19K seconds (over 5 hours) even for a moderate  $k = 5$ , as the number of candidate pivot table combinations was  $\binom{130}{5} \approx 286M$ , for only 5 data attributes. LLM-proxy causes slight decrease (3%) in utility due to less accurate proxy classifier, however, boosts performance significantly. Pruning does not hurt utility, due to its conservative filtering of unpromising candidates. Figure 7 (left) shows runtime comparison over three datasets (limited to 5 attributes), where both optimizations offer significant performance boost across the board. Pruning is significantly beneficial for high-dimensional datasets, due to the exponential growth of the candidate space w.r.t attributes.

## 6.4 Scalability

Figure 8 shows the runtimes of SAGE and SAGE<sup>+</sup> w.r.t #tuples (left) and #attributes (right), averaged over three executions. For both SAGE and SAGE<sup>+</sup>, runtime increases linearly with data cardinality and quadratically with dimensionality, because increasing dimensions significantly expands the combinatorial search space. SAGE<sup>+</sup> shows only small fluctuations as #tuples or #attributes increases, thanks to its sampling and approximation methods. Remarkably, SAGE<sup>+</sup> processed the CoverType dataset (110 attributes, 581K tuples) in under 50 seconds—demonstrating practical scalability. Despite the substantial runtime reduction, SAGE<sup>+</sup> maintained comparable utility and diversity scores to SAGE (within a 10% variation).

## 6.5 Parameter Sensitivity

Figure 7 (right) depicts the impact of varying the diversity threshold ( $\theta$ ) on the utility score over the Video dataset. We observe that as  $\theta$  increases, the utility score drops for all  $k$ . This is expected because a higher  $\theta$  constrains the selection of candidates more stringently, leading to fewer eligible items. To satisfy this stricter criterion, the

algorithm may be compelled to select items with lower utility to maintain diversity, thus decreasing the total utility. The utility drop becomes particularly significant for high values of  $k$ , as satisfying a high diversity threshold for a larger result set is more challenging.

## 6.6 Case Studies

We now present findings from case studies in which we manually examined the pivot tables for qualitative insights regarding recommendations made by SAGE vs. commercial software and LLMs.

**6.6.1 Diverse and meaningful aggregates.** We found SAGE to consistently recommend diverse and semantically meaningful aggregates. For Video, SAGE's includes COUNT, MAX, MIN, SUM, and MEAN. In contrast, Excel, Google Sheets, and PowerBI typically involve only SUM or COUNT. While LLMs too suggest a variety of aggregates, they often involve hallucinated attributes. E.g., LotLocation is not an attribute of House, which LLM recommends. Despite requesting to use the specified aggregates, LLM still selects out-of-scope aggregates such as median or standard deviation. Excel once suggested SUM(Birth\_Year), a completely meaningless aggregate.

**6.6.2 Diverse and meaningful attributes.** We found SAGE to select diverse and semantically meaningful attributes for aggregation and grouping. In Video, SAGE utilizes Publisher, Sales, and Year for various aggregations, providing comprehensive coverage of the attribute space. This contrasts sharply with Excel and Google Sheets, which make repetitive GROUP BY choices, while LLM consistently focuses only on Sales for aggregation. In House, SAGE identifies attributes such as KitchenAbvGr, HalfBath, and FullBath for aggregations that other baselines ignore. While only SAGE and LLM appropriately use SalesPrice for aggregation, LLM limits itself to aggregate only over this attribute. In contrast, SAGE diversifies selection of attributes, avoiding meaningless choices made by other tools, such as PowerBI's poor recommendation to GROUP BY ID.

**6.6.3 Avoiding unsurprising summaries.** Since SAGE can assess the degree of surprisingness in observed trends, it avoids recommending trivial summaries with low utility. Unlike other tools that consistently recommend common aggregations such as SUM(INCOME), regardless of context, SAGE avoids recommendations that provide obvious insights (e.g., people with low GDP spend less). For the Video dataset, existing baselines typically focused on aggregations such as SUM(SALES). In contrast, SAGE included diverse types of aggregations such as MEAN(NA\_Sales) and MAX(JP\_Sales). Additionally, it discovered more surprising patterns, such as COUNT(YEAR) GROUP BY GENRE, which were not considered by others.

**6.6.4 Adaptive recommendation.** We evaluated SAGE's adaptability to user needs (desiderata D4) through a case study on the Video dataset. Initially, the user indicates Genre as a grouping attribute they are interested in, and requests three recommendations ( $k = 3$ ). In the first round, SAGE suggests pivot tables showing COUNT(Publishers) and AVERAGE(Global Sales) by Genre and Region. After the user indicates disinterest in Publishers, SAGE adapts by recommending COUNT(Years) and AVERAGE(EU Sales) by Genre, which the user accepts. For the third recommendation, SAGE presents SUM and MEAN of EU Sales and Global Sales by Genre, further diversifying the aggregates while maintaining focus

on the user-specified grouping on *Genre*. Unlike existing pivot table recommenders that disallow customizability and lack mechanism for user feedback, SAGE dynamically adapts to user preferences.

## 7 User Study

To validate whether our utility (§3) and diversity (§4) models align with real-world user perception, we conducted a comprehensive user study with 36 participants, 53% of whom use spreadsheets daily or several times per week. The study comprised five sections, each containing 1–4 objective questions followed by an open-ended prompt for participants to explain their choices. Below, we summarize each section’s setup and key findings based on the responses.

**#1 Validating Insightfulness.** We presented four pairs of pivot tables; within each pair, one had a high score and the other a low score for one of the *Insightful* components: (a) Attribute Significance (§3.1.1), (b) Informativeness (§3.1.2), (c) Trend (§3.1.3), and (d) Surprise (§3.1.4). For each pair, participants had to select the more insightful table or indicate a tie. The percentages of participants who chose the high-scoring pivot table (declared a tie) were 88.9% (8.3%), 91.7% (8.3%), 91.7% (8.3%), and 75.0% (16.7%), respectively. These results show that, on average, 86.8% of participants agreed with our notion of pivot-table insightfulness, demonstrating strong alignment between our model and human perception.

**#2 Validating Interpretability.** Setup of this section was identical to the previous one, but to validate three *Interpretability* components: (a) Density (§3.2.1), (b) Semantic validity (§3.2.2), and (c) Conciseness (§3.2.3). The percentages of users who identified the high-scoring pivot table as more interpretable (declared a tie) were 77.8% (8.3%), 91.7% (5.6%), and 91.7% (8.3%), respectively. These results show that, on average, 87.1% of participants agreed with our notion of pivot-table interpretability, demonstrating strong alignment between our model and human perception.

**#3 Validating Utility via Ablation.** This section included two questions, each presenting a pair of pivot tables for participants to choose the one that is overall more useful—i.e., shows strong insights while being easy to interpret—or declare a tie. We found that 86.1% (8.3%) of participants preferred (tied with) the balanced summary over a highly interpretable but low-insight summary, and 69.4% (13.9%) preferred (tied with) the balanced summary over a highly insightful but less interpretable one. These results establish that both components of our utility model are essential.

**#4 Validating Diversity.** We asked participants to compare two sets of pivot tables, one more diverse than the other. A striking 91.7% preferred the diverse set, confirming alignment between our model and user perception.

**#5 Contrasting with Other Baselines.** We asked two questions to compare recommendations by SAGE with four other baselines: Microsoft Excel, Google Sheets, an LLM-based method, and Top-K, with names of the tools anonymized to avoid any bias. Among the participants, 52.8% preferred SAGE over the other tools and 13.9% noted that all recommendations are equally good. This result confirms that SAGE consistently provides more user-aligned recommendations compared to existing baselines.

The free-text justifications helped us understand participants’ reasoning and we found several interesting responses. For instance,

one wrote, “Tool A (SAGE) is [...] the best option, because each table provides useful insights. Tool B has the odd sum of birth year attribute, while Tool C essentially has the same table twice [...].” We provide additional details of the user study in the Appendix.

## 8 Related Work

**Data Summarization.** Below, we discuss three major areas that share the general problem that we address, which is recommending interesting aggregates or views to help users understand data.

**OLAP Cube Exploration.** Prior work in OLAP cube exploration [54, 62–65] aim to identify “surprising” data regions to help users uncover previously unseen and interesting patterns. These approaches define surprise based on user familiarity, and interestingness based on purely statistical methods. However, they lack awareness of the underlying data *semantics*, often resulting in recommendations that are practically uninteresting and hard to interpret. Moreover, they typically suggest a single item or a top- $k$  list, without considering *bundle* suggestions that offer a *set* of diversified items.

**Insight Generation and Visualization.** A number of prior work define informative summaries as tables that exhibit significant statistical disparities among groups [13, 18, 22, 32, 68, 74]. Some measure the significance of insights using null-hypothesis testing [13, 22] while others exploit LLMs [74]. While insight generation and visualization recommendation [13, 74, 75, 79] are related to our work, most prior works in this space do not incorporate the three key dimensions together: insightfulness, interpretability, and diversity. Notably, recommending a  $k$ -budgeted *set* of summaries is a significantly harder problem than simple top- $k$  recommendation.

**View or Exploration-step Recommendation.** View recommendation systems [73, 75, 81] explore a related direction. Voyager [75] ranks visualizations based on perceptual effectiveness to improve interpretability whereas ViewSeeker [81] compares multiple visualizations using various similarity measures. However, these systems are not semantics-aware and do not consider diversity. Smart Drill-Down [37] enables users to discover and summarize interesting groups of tuples described by rules. However, their unit is a rule, while ours is a pivot table. Auto-Suggest [77] and DAISY [76] leverage large-scale user logs, SQL queries, or crowdsourcing to recommend pivot tables based on historical usage patterns. However, they cannot ensure pivot-table informativeness, as they do not validate the content of the generated pivot tables.

In summary, prior work fall short in one of the following aspects. **First**, they do not consider the semantic validity and interpretability aspects of the summary structure. E.g., (a) the aggregates  $\text{SUM}(\text{Birth\_Year})$  and  $\text{AVG}(\text{Zip\_Code})$  are semantically invalid, and (b) an attribute with values  $\{\text{Val\_1}, \text{Val\_2}\}$  is not interpretable whereas  $\{\text{Large}, \text{Small}\}$  is. **Second**, they lack *semantic awareness* to validate an apparent data insight. For instance, they typically determine the degree of insightfulness purely based on statistical properties, such as whether aggregated values between two groups significantly deviate from each other, without factoring in the degree of expectedness of that deviation based on common knowledge (e.g., a significant deviation in average height between toddlers and adults is expected). In contrast, SAGE consults with an LLM—which can mimic a human domain expert who can provide

the likelihood of observing a statistically interesting phenomenon—and effectively prunes statistically insightful, but practically mundane insights. **Third**, beyond simple top-k, they do not focus on the *bundle recommendation problem*—which involves suggesting a set of  $k$  results—with diversity requirements, which is our focus. **Fourth**, while a few works consider diversity in summarization [26, 72, 73, 79], they ignore the semantic aspect of diversity. DAISY [76] models diversity during query collection, not recommendation, while QAGView [73] diversifies at a tuple-level granularity. In contrast, we use a semantics-aware model for the distance metric—using query and contend embedding—to ensure semantic diversity across the recommended pivot tables.

**Diversification Algorithms.** Query result diversification [70] methods define diversity across three aspects: (1) content, (2) novelty, and (3) coverage [24, 25]. Max-Sum diversification [14, 24, 56] maximizes the linear combination of diversity and utility scores, while Max-Min diversification maximizes the minimum diversity between selected items. However, existing diversification methods target tuples or documents, not entire tables. Thus, they do not trivially extend to table recommendations, as in our case.

## 9 Conclusions and Future Work

We presented SAGE to recommend diverse set of pivot tables while balancing insightfulness and interpretability. We introduced a utility model for a single pivot table, a diversity metric for pivot-table sets, and a simple greedy algorithm built on two optimization techniques for efficient recommendation. We empirically showed that SAGE outperforms baselines in diversity while maintaining high utility. Our case studies illustrated SAGE’s ability to avoid generic patterns and provide data-semantics-aware suggestions. To the best of our knowledge, this is the first work to combine diversity and data-semantics for data summarization.

SAGE currently does not incorporate contextual information, such as the user’s workflow (e.g., their end goals) or broader ecosystem (e.g., tools in their software stack). Integrating such context could significantly enhance the quality of recommendations. Another promising direction is to support alternative forms of data summaries—such as textual descriptions that highlight key trends—in addition to structured formats like pivot tables.

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## A Appendix

### A.1 User Study

We provide snapshots of the user study responses and questions used to validate each component of our model. Figure A1 presents the user response distributions for all study questions. In each pie chart, a proportion greater than 50% indicates that participants selected SAGE’s result, corresponding to the validation score we report. Figure A3 shows a question evaluating insightfulness by asking participants to select the more surprising outlier. Figure A4 evaluates interpretability by asking users to choose the more interpretable pivot table. Figure A5 evaluates utility via an ablation setting where Summary 2 has reduced interpretability. Figure A6 evaluates diversity by asking users to select the more diverse set of pivot tables. Finally, Figure A7 asks participants to choose their preferred system output across all criteria, allowing comparison against other tools. Table A1 presents the representative rationales provided by participants for the snapshot questions.

**A.1.1 Participants’ Background and Experience.** Additionally, we provide participants’ background and experience regarding data summarization in Figure A2. Most participants use spreadsheets several times a week, yet the majority do not regularly apply data summarization techniques in their work. Furthermore, many participants reported low confidence in interpreting meaningful insights from summarized data. These results highlight the need for effective data summarization tools. We also asked participants to share their experience with automated summarization tools. Some participants noted “*I don’t like when AI assistants often show irrelevant summaries and visualizations, or hallucinates queries.*”, “*AI assistants can be poor at some of these things, but they are proficient at interpreting data and knowing what kind of tables are useful based on data. I love Tableau, but it can be frustrating because it isn’t always the most user-friendly.*” and “*I don’t like when the heatmap overlay ends up providing the same color or very similar for all values, I feel like this doesn’t provide much additional context. I did like how in certain cases it provided very relevant information and important groupings straight to you without having to think about it.*” With these notes, we could know that participants had a clear preference for tools that provide relevant, interpretable summaries and highlight meaningful groupings, and they were frustrated when systems produced irrelevant unhelpful outputs.

Moreover, we also asked participants to describe their ideal tool for summarizing spreadsheet datasets and what features they would like to see. Participants noted, “*I would like to be able to specify which columns to compare/summarize (i.e. a workflow that simplifies tasks that I can perform with Python, SQL, or excel formulas), as well as receive a few potentially insightful suggestions that have not yet been considered by my own analysis.*”, “*Would like it to automatically and efficiently identify hidden trends and correlations and present them in a readable way.*” and “*Sometimes I explore data with a specific goal. For example, I might like to investigate the potential reason of a drop on a metric. It would be great if there is an auto-summarizing tool providing some insights based on the given data and my input questions in natural language.*” In summary, participants want tools that let them specify what to analyze while also suggesting new insights they might not have considered. They prefer systems that

can automatically reveal hidden trends or correlations and present them in a clear and readable way.

### A.2 Scalability

Figure A8 compares the runtime performance of SAGE and SAGE<sup>+</sup> as we vary #tuples (left) and #attributes (right) across four datasets. As expected, runtime grows with dataset size in both dimensions. When increasing the number of tuples, SAGE shows a steady increase in runtime across all datasets, whereas SAGE<sup>+</sup> consistently achieves substantially lower runtime, with improvements particularly pronounced on larger datasets such as Video and CoverType. When increasing the number of attributes, the performance gap becomes even more evident that SAGE’s runtime rises sharply due to the rapidly expanding search space, while SAGE<sup>+</sup> scales more smoothly because it approximates candidate combinations. Notably, on the full CoverType dataset, SAGE<sup>+</sup> completes execution in under 50 seconds, compared to over 8 minutes for SAGE.

### A.3 Tuning the Diversity Threshold $\theta$

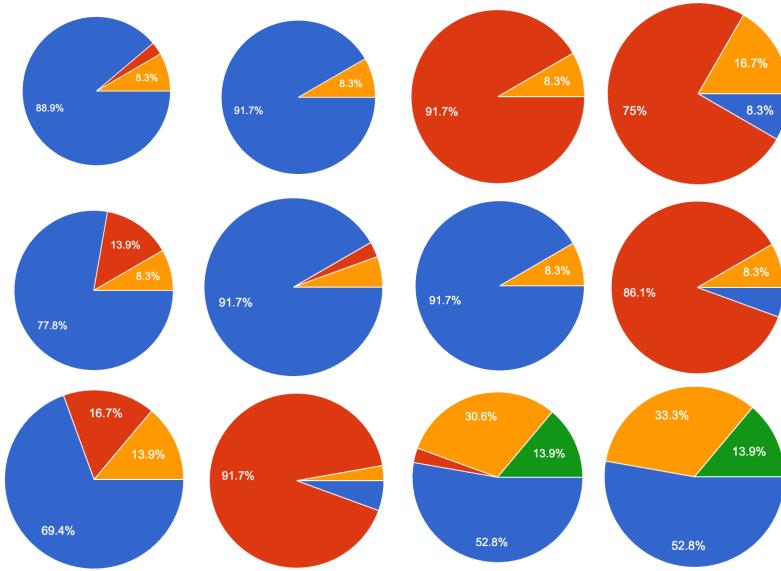
When the user is unable to specify a desired diversity threshold  $\theta$ , either due to unfamiliarity of the dataset or lack of expertise, the desired number of pivot tables  $k$  can be used as a guideline to derive the value of  $\theta$ . In that scenario, a trivial extension to our approach would be to cluster the candidate pivot tables into  $k$  groups, and then apply a greedy strategy to maximize a linear combination of *Utility* (§3) and *Diversity* (§4) as was done in prior work [33].

### A.4 Brute Force

For the brute-force algorithm, we first enumerate all possible pivot table queries, then materialize them and compute their embeddings. Next, we generate all possible sets of size  $k$ , resulting in  $|\mathcal{T}_A|^k$  candidate sets. For each candidate set, we verify whether it satisfies the pairwise distance threshold and compute the sum of utility scores. The set with the highest utility among those meeting the distance constraint is selected as the final result. Algorithm 2 describes this brute-force procedure. Its time complexity is  $O(|P| \cdot (n^2m + nm^2) + 2 \cdot |P| \cdot \text{embedding\_size} + |\mathcal{PT}| \cdot k)$ , where the  $n^2m + nm^2$  term accounts for outlier computation, *embedding\_size* is the size of the embeddings, and the  $|\mathcal{PT}| \cdot k$  term accounts for evaluating all size- $k$  sets over the pivot tables. As the number of distinct pivot tables  $|\mathcal{PT}|$  grows combinatorially with respect to the number of attributes and aggregation choices, where  $|\mathcal{PT}| = |\mathcal{T}_A|^k$ . Therefore, the final time complexity is  $O(|\mathcal{T}_A|^k)$ .

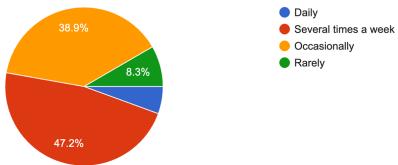
### A.5 Time Complexity of the Greedy Approach

The overall time complexity of the greedy algorithm in Algorithm 1 is  $O(|P_{\text{prun}}| \log |P_{\text{prun}}| + |P_{\text{prun}}| \cdot (n^2m + nm^2 + \text{tree\_depth}) + 2 \cdot |P_{\text{prun}}| \cdot \text{embedding\_size})$ , where  $|P_{\text{prun}}|$  is the number of tables after pruning, *tree\_depth* is the depth of the LLM-proxy cache, and *embedding\_size* is the dimensionality of the embedding vectors. The term  $|P_{\text{prun}}| \log |P_{\text{prun}}|$  corresponds to sorting the utility scores. The term  $n^2m + nm^2$  accounts for outlier computation, as in the brute-force approach. The overall complexity is dominated by the utility score computation—specifically, the pairwise distance calculations—since both *tree\_depth* and *embedding\_size* are constants. Therefore, the dominant term is:  $O(|P_{\text{prun}}| \cdot (n^2m + nm^2))$ .

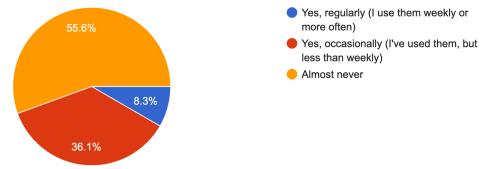


**Figure A1:** Twelve user study pie charts summarizing participant responses. Each chart shows the proportion of participants selecting our SAGE's result, and values above 50% indicate that SAGE was preferred.

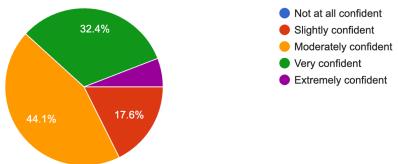
S6.Q1. How frequently do you use spreadsheets (e.g., Excel, Google Sheets) in your work or studies?  
36 responses



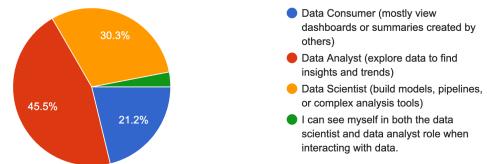
S6.Q2. Have you used tools that automatically generate data summaries (e.g., PowerBI, Tableau, dashboards, AI assistants)?  
36 responses



S6.Q3. How confident are you in interpreting useful insights from data summaries as opposed to raw data?  
34 responses



S6.Q4. Which of the following best describes your primary role when interacting with data?  
33 responses



**Figure A2:** User study response summaries for participants' background and experience.

## A.6 Offline Preprocessing

The offline time for generating prompts and training a LLM-proxy-cache classifier is as follows. We generated 10,000 prompts for correlation, ratio, and surprise detection, and trained separate decision tree classifiers that incorporate prompt variables as described in the likelihood prompt. The total time taken was 2742.70 seconds for surprise and 3171.92 seconds for trend in the marketing dataset, 1404.61 seconds for surprise and 3129.57 seconds for trend in the video dataset, 3599.58 seconds for surprise and 3087.07 seconds

for trend in the house dataset, and 1473.68 seconds for surprise and 3569.50 seconds for trend in the cover type dataset. Table A2 reports the accuracy of our method across the three evaluation metrics for each dataset. The results are consistent across datasets, with the surprise metric showing moderate accuracy, while both the correlation and ratio metrics achieve relatively high accuracy.

The offline pruning step takes 1.57 seconds for the house dataset (780,840 combinations), 0.04 seconds for the video dataset (2,145

**S1.Q4.** Summary 1 and Summary 2 below present the *average income* of employees grouped by *education level* and *marital status* for two different datasets.

Sometimes, an unexpected or surprising pattern gives interesting insights about a dataset, possibly indicating data issues such as wrong unit (e.g., a child having a weight of 300 lbs, where it should have been 300 oz). To help you notice such values, we are overlaying a heat map on the cells. Darker means higher, lighter means lower values.

Examine the two summaries and identify the one you think best shows **interesting insights based on a surprising pattern**.

## Summary 1

AVERAGE of Income GROUP BY Marital Status and Education Level

| Education Level | Marital Status |         |           |        |       |
|-----------------|----------------|---------|-----------|--------|-------|
|                 | Divorced       | Married | Separated | Single | Widow |
| High School     | 422K           | 447K    | 432K      | 404K   | 420K  |
| Some College    | 410K           | 355K    | 437K      | 468K   | 387K  |
| Bachelor        | 425K           | 441K    | 528K      | 291K   | 315K  |
| Master          | 251K           | 310K    | 444K      | 315K   | 449K  |
| PhD             | 305K           | 400K    | 536K      | 514K   | 485K  |

AVERAGE of Income

---

## Summary 2

AVERAGE of Income GROUP BY Marital Status and Education Level

| Education Level | Marital Status |         |           |        |       |
|-----------------|----------------|---------|-----------|--------|-------|
|                 | Divorced       | Married | Separated | Single | Widow |
| High School     | 385K           | 460K    | 503K      | 990K   | 431K  |
| Some College    | 457K           | 384K    | 990K      | 450K   | 431K  |
| Bachelor        | 253K           | 374K    | 316K      | 380K   | 335K  |
| Master          | 417K           | 369K    | 317K      | 307K   | 317K  |
| PhD             | 332K           | 416K    | 311K      | 369K   | 304K  |

AVERAGE of Income

- Summary 1 provides more interesting insights than Summary 2
- Summary 2 provides more interesting insights than Summary 1
- Both summaries provide equally interesting insights

Figure A3: User study question in which participants select the more surprising outlier patterns between two pivot tables.

combinations), 2.73 seconds for the marketing dataset (43,848 combinations), and 16.51 seconds for the cover type dataset (2,785,120 combinations). Although the house dataset contains far more combinations than the marketing dataset, its pruning time is smaller.

This is because the pruning process first computes attribute significance, and only if the attribute is considered interesting does it proceed to compute interpretability. For the house dataset, only a small number of attributes are considered significant, resulting

**S2.Q1.** Summary 1 and Summary 2 below are generated from two different datasets. A NULL value in a data summary doesn't provide any readable value, it may indicate that the values are either unknown or missing. \*

Identify which summary is easier for you to understand based on how readable the values are. In other words, consider which numbers are easiest to interpret and make sense of.

After looking at both the summaries, select the statement you agree with the most.

## Summary 1

Average of Income group by Marital Status and Education

| Average of Income   | Marital Status |          |         |        |          |
|---------------------|----------------|----------|---------|--------|----------|
| Education           | Alone          | Divorced | Married | Single | Together |
| <b>High School</b>  | 50K            | 75K      | 100K    | 125K   | 150K     |
| <b>Some College</b> | 200K           | 162K     | 125K    | 88K    | 50K      |
| <b>Bachelor</b>     | 60K            | 75K      | 90K     | 105K   | 120K     |
| <b>Master</b>       | 50K            | 75K      | 100K    | 125K   | 150K     |
| <b>PhD</b>          | 500K           | 450K     | 400K    | 350K   | 300K     |

## Summary 2

Average of Income group by Marital Status and Education

| Average of Income   | Marital Status |          |         |        |          |
|---------------------|----------------|----------|---------|--------|----------|
| Education           | Alone          | Divorced | Married | Single | Together |
| <b>High School</b>  | Null           | Null     | Null    | Null   | Null     |
| <b>Some College</b> | Null           | Null     | Null    | Null   | Null     |
| <b>Bachelor</b>     | Null           | Null     | Null    | 500K   | Null     |
| <b>Master</b>       | Null           | Null     | Null    | Null   | Null     |
| <b>PhD</b>          | Null           | Null     | Null    | Null   | 530K     |

- Summary 1 is more interpretable than Summary 2
- Summary 2 is more interpretable than Summary 1
- Both summaries are equally interpretable

Figure A4: User study question in which participants selected the more readable pivot table.

in far fewer interpretability computations and therefore a shorter pruning time compared to the marketing dataset.

## A.7 Experiments on a Large Dataset

Table A3 shows the results on the cover type dataset. Although the utility score for SAGE<sup>+</sup> is slightly lower than that of SAGE (upto 18% decrease), the runtime is reduced significantly, decreasing from

\*

**S3.Q2.** Consider Summary 1 and Summary 2 below.

Select the summary that you find **more useful**, that is, it **provides good data insights without making it too hard to interpret**. Then select the statement you agree with the most.

### Summary 1

AVERAGE of Income GROUP BY Marital Status and Education Level

| Education Level | Marital Status |         |           |        |       |
|-----------------|----------------|---------|-----------|--------|-------|
|                 | Divorced       | Married | Separated | Single | Widow |
| High School     | 87K            | 145K    | 123K      | 110K   | 66K   |
| Some College    | 66K            | 56K     | 137K      | 110K   | 121K  |
| Bachelor        | 150K           | 188K    | 225K      | 262K   | 300K  |
| Master          | 52K            | 147K    | 133K      | 71K    | 68K   |
| PhD             | 68K            | 80K     | 102K      | 93K    | 79K   |

AVERAGE of Income

### Summary 2

AVERAGE of Income GROUP BY Birth Year and Marriage Date

| Birth Year | Marriage Date |        |         |         |         |         |         |         |         |         |         |         |         |         |
|------------|---------------|--------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
|            | 1/1/13        | 1/1/14 | 1/10/13 | 1/10/14 | 1/11/13 | 1/11/14 | 1/12/13 | 1/12/14 | 1/13/13 | 1/13/14 | 1/14/13 | 1/14/14 | 1/15/13 | 1/15/14 |
| 1893       | 102K          | 95K    | 100K    | 104K    | 108K    | 117K    | 106K    | 115K    | 119K    | 108K    | 124K    | 115K    | 115K    | 139K    |
| 1899       | 555K          | 562K   | 569K    | 576K    | 584K    | 591K    | 598K    | 605K    | 612K    | 619K    | 626K    | 634K    | 641K    | 648K    |
| 1900       | 100K          | 98K    | 103K    | 103K    | 99K     | 107K    | 92K     | 96K     | 94K     | 101K    | 104K    | 103K    | 116K    | 108K    |
| 1940       | 88K           | 82K    | 95K     | 83K     | 101K    | 98K     | 88K     | 86K     | 103K    | 102K    | 103K    | 105K    | 92K     | 99K     |
| 1941       | 89K           | 86K    | 82K     | 78K     | 83K     | 84K     | 92K     | 91K     | 96K     | 90K     | 84K     | 96K     | 98K     | 95K     |
| 1943       | 78K           | 79K    | 78K     | 72K     | 74K     | 74K     | 84K     | 79K     | 83K     | 90K     | 79K     | 83K     | 89K     | 81K     |
| 1944       | 71K           | 69K    | 81K     | 79K     | 77K     | 81K     | 80K     | 71K     | 82K     | 77K     | 81K     | 82K     | 74K     | 71K     |
| 1945       | 500K          | 507K   | 514K    | 521K    | 529K    | 536K    | 543K    | 550K    | 557K    | 564K    | 571K    | 579K    | 586K    | 593K    |
| 1946       | 72K           | 62K    | 65K     | 62K     | 61K     | 57K     | 64K     | 62K     | 56K     | 59K     | 66K     | 57K     | 56K     | 59K     |
| 1947       | 58K           | 63K    | 63K     | 56K     | 61K     | 56K     | 58K     | 57K     | 55K     | 50K     | 57K     | 51K     | 49K     | 46K     |
| 1948       | 59K           | 51K    | 55K     | 51K     | 54K     | 48K     | 52K     | 48K     | 52K     | 44K     | 44K     | 41K     | 47K     | 46K     |
| 1949       | 55K           | 55K    | 51K     | 49K     | 45K     | 42K     | 48K     | 46K     | 42K     | 39K     | 37K     | 39K     | 38K     | 37K     |
| 1950       | 50K           | 43K    | 42K     | 47K     | 42K     | 36K     | 35K     | 37K     | 31K     | 30K     | 31K     | 30K     | 28K     | 24K     |
| 1951       | 42K           | 41K    | 42K     | 39K     | 38K     | 35K     | 32K     | 27K     | 27K     | 24K     | 22K     | 23K     | 19K     | 18K     |
| 1952       | 42K           | 38K    | 36K     | 33K     | 28K     | 29K     | 24K     | 21K     | 21K     | 17K     | 17K     | 14K     | 12K     | 8K      |

AVERAGE of Income

- Summary 1 is overall more useful than Summary 2
- Summary 2 is overall more useful than Summary 1
- They are equally useful

Figure A5: User study question in which participants select the more useful table from two pivot tables.

489 seconds to only 40 seconds. This demonstrates that SAGE<sup>+</sup> provides a substantial efficiency improvement while still maintaining competitive utility performance.

### A.8 LLM Prompts

Here we present the LLM prompts used for Attribute Significance, Semantic Validity, and Likelihood. The details are shown in Figures A9, A10, and A11. The placeholders {} in each prompt represent variables that should be filled in when generating actual

**S4.Q1.** Consider two summary SETS: **Set 1** and **Set 2**.

You can click on each set to see more details, but it is not really required. You can get a pretty good idea of the summarization aspects from the summary table descriptions.

Then choose the statement you agree with the most.

**Summary Set 1**

1. COUNT of Employee GROUP BY Marital Status and Birth Year
2. COUNT of Employee GROUP BY Marital Status
3. COUNT of Employee GROUP BY Birth Year

**Summary Set 2**

1. COUNT of Employee GROUP BY Marital Status and Education Level
2. AVERAGE Income GROUP BY Birth Decade and Gender
3. MAXIMUM Years of Experience GROUP BY Location and Job Role

- Summary Set 1 is more diverse than Summary Set 2
- Summary Set 2 is more diverse than Summary Set 1
- They are equally diverse

**Figure A6:** User study question in which participants select the more diverse set from two sets of pivot tables.

**Algorithm 2:** Brute-Force Recommendation

---

```

Input :Database  $D$ 
        Diversity threshold  $\theta$ ,
        Number of pivot tables to select  $k$ 
Output :A diverse, high-utility pivot table subset  $T$  under the size
        budget  $k$  and diversity constraint  $d$ 
1 Generate all possible (unmaterialized) pivot-table queries  $P$ 
2 foreach  $p \in P$  do
3   Materialize  $p$  over  $D$ 
4   Compute embedding  $e(p)$  (query + content)
5   Compute utility score  $u(p)$ 
6  $T^* \leftarrow \emptyset$   $best\_score \leftarrow -\infty$ 
7 Generate all possible sets of  $k$  pivot-table queries PT
8 foreach  $T \in PT$  do
9   foreach  $T' \in T$  do
10    if  $Distance(T, T \setminus \{T'\}) < \theta$  then
11      continue
12    Calculate utility score  $u$  for  $T$  if  $u > best\_score$  then
13       $best\_score \leftarrow u$ 
14       $T^* \leftarrow T$ 
15 return  $T^*$  /* Return final diverse, high-utility pivot table set */

```

---

prompts. For example, in Figure A9, {table} represents the pivot table. Figure A11 shows the ranking of aggregate functions for the

Semantic Validity score. The results of the marketing dataset include the following attributes: ['Education', 'Income', 'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth', 'AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmps', 'Country', 'Response', 'Year\_Birth', 'Marital\_Status', 'NumDealsPurchases', 'Complain'] The results of the video dataset include: ['Genre', 'Year', 'NA\_Sales', 'EU\_Sales', 'JP\_Sales', 'Global\_Sales', 'Publisher'] The results of the house dataset include: ['MSSubClass', 'OverallQual', 'GrLivArea', 'Year-Built', 'YearRemodAdd', 'FullBath', 'SalePrice', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'Id', 'OverallCond']

## A.9 Datasets

**Marketing.** The Marketing dataset [59] comprises demographic and behavioral information about customers, including marital status and purchase history. It consists of 2,240 tuples and 28 attributes, encompassing a diverse set of features: 9 numerical attributes (e.g., Year\_Birth, Income) and 19 categorical attributes (e.g., Education, Marital\_Status, Complaint).

**Video.** The Video dataset [31] comprises video game sales from various countries, platforms, or release years. It contains 16,600 tuples across 11 attributes. Out of these, 7 attributes are categorical (e.g., Platform, Genre, Publisher) and 4 are numerical (e.g., Rank, Year, NA\_Sales, Global\_Sales).

**S5.Q1.** Below you can see **summary sets** generated by Tool A, Tool B, and Tool C over the **same dataset**. Click on each tool to see more details \*

#### Tool A

1. COUNT of ID GROUP BY Marital Status
2. SUM of Income GROUP BY Education Level
3. SUM of Income GROUP BY Marital Status

#### Tool B

1. COUNT of ID GROUP BY Marital Status
2. SUM of Birth Year GROUP BY Marital Status
3. SUM of Income GROUP BY Marital Status

#### Tool C

(This is an LLM-based tool, only generated queries and not the results. The attributes "Age" and "Age Group" were hallucinated. So, we cannot provide the summaries.)

1. AVERAGE of Income, Age and COUNT of Income GROUP BY Education Level and Marital Status
2. AVERAGE of Income GROUP BY Age Group
3. AVERAGE, STANDARD DEVIATION, MINIMUM, and MAXIMUM of Income GROUP BY Education Level

After reviewing them, select the statement you agree with the most.

- Tool A summary set is much better than Tool B and Tool C
- Tool B summary set is much better than Tool A and Tool C.
- Tool C summary set is much better than Tool A and Tool B.
- They are about the same.

**Figure A7: User study question in which participants selected the most diverse and useful set of pivot tables.**

**House.** The House dataset [4] contains information about residential property sales, comprising 1,460 tuples and 81 attributes. Among the attributes, 23 are numerical (e.g., SalePrice, LotArea, OverallQual, GrLivArea) and 58 are categorical (e.g., Street, HouseStyle, RoofStyle, GarageType).

**Cover Type.** The Covertype dataset [83] is a large dataset with 581,000 tuples and 110 attributes, containing tree observations across four areas of the National Forest in Colorado for. We used this large dataset to stress test the scalability of SAGE<sup>+</sup>.

## A.10 Baselines

Below, we list details regarding the baselines:

**Brute-Force.** We employ an exhaustive Brute-Force search, which considers all possible k-sized pivot table sets and follows a naive exhaustive approach to solve Problem 2.1. Note that in the absence of an absolute ground-truth, the results obtained from this technique can be treated as the optimal solution.

**Top-k.** This baseline ranks candidate pivot tables in descending order of their utility scores and selects the top- $k$  as the recommended set, without accounting for the diversity constraint. To ensure a fair comparison, we apply our optimization techniques (pruning and LLM-proxy) prior to the selection phase. This allows it to generate recommendations within a runtime comparable to that of SAGE.

**LLM.** We used Llama-3-8B-Instruct (Meta) [43] as a transformer-based large language model (LLM) as another baseline. While LLMs are increasingly used for tabular data tasks, few tools address our specific problem. We prompted the model with a small data sample and asked for interesting and diversified pivot tables in natural language, according to our problem setup.

**DAISY.** DAISY [76] is a query recommendation algorithm proposed in prior work. It first generates a set of random queries and clusters them based on similarity. From each cluster, representative queries are sampled. Human annotators are then employed to evaluate pairs of queries: if the left query is more interesting, the pair is

| Criterion                           | Participant Rationale                                                                                                                                                                                                                                                                                                                                                                                                                                        | Implication                                                                                                   |
|-------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------|
| #1 Validating Insightfulness        | “Specific values in summary 2 have significantly unexpected patterns, whereas in summary 1 they are less significant.”<br>“There are some interesting outliers that I would find interesting.”                                                                                                                                                                                                                                                               | Participants preferred insights that reveal unexpected patterns.                                              |
| #2 Validating Interpretability      | “No Nulls in summary 1 increases readability and thus easiest to interpret and make sense of.”<br>“With so many null values, it’s harder to understand the data well enough to derive insights.”                                                                                                                                                                                                                                                             | Participants preferred clear tables and it improves user comprehension.                                       |
| #3 Validating Utility via Ablation  | “Summary 2 is not only too large to understand, but the choice of grouping attributes is not really helpful (especially when we are supposed to be summarizing the data) since there are too many combinations of values which are already not very meaningful when used together in a GROUP BY in the first place.”<br>“Although there is a more clear difference in some values of table two, table one has a more reasonable number of rows and columns.” | Participants preferred compact, insightful tables over larger but harder to interpret ones.                   |
| #4 Validating Diversity             | “Summary 2 is more diverse. Summary 1 is just separating out the first summary table into its separate parts while summary 2 provides new information that could be interesting.”<br>“Set 2 offers more variety in what it covers, as opposed to summary 1, which only covers 3 attributes.”                                                                                                                                                                 | Participants preferred tables that provide non-redundant insights rather than variations of the same pattern. |
| #5 Contrasting with Other Baselines | “Tool A is better than Tool B since a sum of birth year is not useful or insightful. Tool C is bad because of the hallucination mentioned.”<br>“A is the best option, as B is not very useful because of the sum of birth year. C could be useful if there were not hallucinated attributes.”                                                                                                                                                                | Participants preferred SAGE for providing insightful, interpretable, and diverse summaries.                   |

Table A1: Representative participant rationales and derived implications.

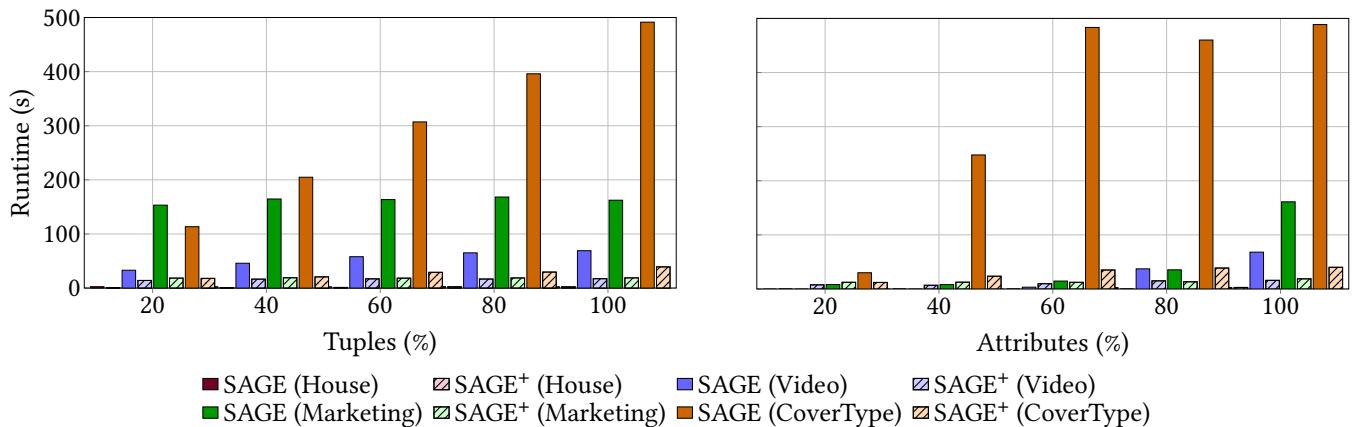
Figure A8: SAGE and SAGE<sup>+</sup> runtime (s) w.r.t (#tuples, #attributes). We used  $k = 5$  and  $\theta = 0.1$  for these experiments.

Table A2: Accuracy comparison across datasets and metrics.

| Dataset   | Surprise | Correlation | Ratio |
|-----------|----------|-------------|-------|
| Marketing | 0.65     | 0.89        | 0.88  |
| Video     | 0.61     | 0.92        | 0.91  |
| House     | 0.63     | 0.88        | 0.87  |
| Covertype | 0.66     | 0.90        | 0.90  |

labeled as 1; if the two are similar, as 0; and if they are too different, as -1. However, the original training data and model used by DAISY are not publicly available. To address this limitation, we developed our own version of the DAISY model. Specifically, we constructed training data using the Auto-Suggest Pivot Table framework [77]. Since DAISY’s training approach resembles contrastive learning—by labeling pairs of queries as more or less interesting—we mimicked this by treating pivot tables crawled from the web as insightful. We then randomly selected columns to replace parts of the original table, generating less-interesting alternatives. Following DAISY’s

**Task: Attribute Significance**

Task: Identify the attributes that are likely to be useful for grouping or aggregating the data in meaningful ways. Please identify at least one relevant attribute. Only return the result in the following JSON format: {"chosen\_columns": "<a list of names for interesting column to be analyzed>"}.

```
# Input:  
**Table:**  
{table}  
Only return the result in the following JSON format: {"chosen_columns": "<a list of names for interesting column to be analyzed>"}.  
# Output:
```

**Figure A9: Prompt for Attribute Significance****Task: Likelihood**

**Task Description:** {groupA}and {groupB}on {aggregate function} {value\_attribute} have a correlation of {magnitude}. Based on this, how likely is it that this correlation is desirable? Choose the appropriate likelihood from following scale. Return the result as JSON in the following format: {"likelihood": "<one likelihood from the scale>"}.

Please return only the JSON output. Do not include explanations, code, or the full table.

```
# Input:  
**Likelihood Scale:**  
Very Likely  
Likely  
Neutral  
Unlikely  
Very Unlikely  
  
Return the result as JSON in the following format: {"likelihood": "<one likelihood from the scale>"}.  
# Output:
```

**Figure A10: Prompt for Likelihood**

|        |                   | #PT | T(s) | Ins  | Int  | Util | Div<br>m-dist | Div<br>heatmap |
|--------|-------------------|-----|------|------|------|------|---------------|----------------|
| $k=3$  | SAGE              | 3   | 489  | 3.00 | 2.23 | 2.62 | 0.30          |                |
|        | SAGE <sup>+</sup> | 3   | 40   | 2.83 | 2.23 | 2.53 | 0.32          |                |
| $k=5$  | SAGE              | 5   | 489  | 5.00 | 3.72 | 4.36 | 0.20          |                |
|        | SAGE <sup>+</sup> | 5   | 40   | 4.98 | 3.72 | 4.35 | 0.21          |                |
| $k=10$ | SAGE              | 10  | 489  | 9.81 | 7.44 | 8.63 | 0.20          |                |
|        | SAGE <sup>+</sup> | 10  | 40   | 6.77 | 7.44 | 7.11 | 0.20          |                |

**Table A3: Utility scores of SAGE and SAGE<sup>+</sup> on the Cover Type dataset for different values of  $k$ . We set  $\theta = 0.3$  for  $k = 3$ ,  $\theta = 0.2$  for  $k = 5$ , and  $\theta = 0.1$  for  $k = 10$ .**

classification framework, we trained a model to distinguish between insightful and less-insightful queries. While our implementation is not identical to the original DAISY model, it captures its core idea.

Our trained model achieved 80% accuracy on a dataset containing 541,599 instances, with 433,279 used for training and 108,320 for testing.

**Microsoft Excel.** Microsoft Excel [46] is a widely used commercial spreadsheet software that offers built-in pivot table recommendations based on the underlying data. We used the Windows version 2501, evaluated during February 2025.

**PowerBI.** Microsoft PowerBI [22, 47] is a business intelligence software that offers “quick insights” [22] in various forms including visualizations. For comparison, we focus only on the recommendations where the underlying query excludes the WHERE clause, which aligns with our settings.

**Google Sheets.** Google Sheets [30] is an online spreadsheet software known for easy collaboration. Google Sheets provide automatic recommendation of pivot tables for a dataset. We used the browser version during the month of February, 2025.

For Excel, PowerBI, and Google Sheets,  $k$  cannot be controlled. Thus, we consider the first- $k$  items when more than  $k$  were returned.

**Task: Semantic validity**

**Task Description:** Given an input column of data and a list of candidate aggregation functions, rank the aggregation functions based on their suitability for summarizing the given column. Return only the ranked list of aggregation functions (from most to least suitable), using only functions from the candidate list. Do not return the entire table or any explanation only the ranked list. Return the result as JSON in the following format: {"ranked\_aggregation\_functions": ["<aggregation function 1>", "<aggregation function 2>", ...]}. Please return only the JSON output.

```
# Input:  
**Column:**  
{column}  
**Candidate aggregation function:**  
MEAN  
SUM  
  
COUNT  
MIN  
MAX  
Return the result as JSON in the following format: {"ranked_aggregation_functions": ["<aggregation function 1>", "<aggregation function 2>", ...]}.  
# Output:
```

**Figure A11: Prompt for Semantic validity**

Also, Google Sheets fail to produce more than 3 recommendations, this we omit it when  $k > 3$ .

logic in prompts. These systems exhibit critical limitations including poor semantic understanding that leads to meaningless aggregations and low-quality recommendations that focus on schema rather than content.

## A.11 Case Studies

Here, we present case study results comparing SAGE to commercial software and LLMs on marketing data A12. As shown in our main paper case study, Excel returns “SUM(Income) GROUP BY (Country)” which produces predictable results since higher GDP countries typically have higher incomes, while LLM suggests “MEAN(Income) GROUP BY (Year\_Birth)” which expectedly shows higher income for mid-age groups. In contrast, SAGE recommends “SUM(Income) GROUP BY (Complain, Education)” which reveals unexpected relationships between complaints and education levels relative to income. Both LLM and PowerBI return meaningless “GROUP BY(ID)” aggregations.

## A.12 Related Work

We detailed the standards from Figure 4 in Table A4. Current commercial software has significant limitations in delivering smart recommendations. Microsoft Excel and Google Sheets provide redundant GROUP BY attributes and prefer numerical over categorical attributes, creating meaningless aggregations like SUM(YEAR). PowerBI identifies statistical trends but lacks diverse selections and suffers from complexity issues. Tableau requires prior user query logs and manual value selection. Large Language Models (LLMs) like ChatGPT present additional challenges: they hallucinate attributes and result tables, lack inherent scoring mechanisms, and fail to exhaustively evaluate candidates without explicit user-defined

| Tool            | Recommended Pivot Tables                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                               |
|-----------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Google Sheets   | (1) SUM(NumDealsPurchases, NumCatalogPurchases, NumStorePurchases) GROUP BY (Country)<br>(2) COUNT(ID) GROUP BY (Country)                                                                                                                                                                                                                                                                                                                                                                                                              |
| Microsoft Excel | (1) SUM(Income) GROUP BY (Country)<br>(2) SUM(MntWines) GROUP BY (Country)<br>(3) SUM(MntFishProducts, MntSweetProducts, MntGoldProds) GROUP BY (Country)<br>(4) SUM(MntFruits, MntMeatProducts, MntFishProducts) GROUP BY (Education)<br>(5) SUM(MntMeatProducts, MntFishProducts, MntSweetProducts) GROUP BY (Marital_Status)<br>(6) SUM(MntWines, Income, Year_Birth) GROUP BY (Marital_Status)<br>(7) SUM(Year_Birth) GROUP BY (Country, Teenhome)                                                                                 |
| PowerBI         | (1) COUNT(Dt_Customer) GROUP BY (ID, NumDealsPurchases)<br>(2) SUM(Teenhome) GROUP BY (Country)<br>(3) SUM(MntFruits) GROUP BY (Education, ID)<br>(4) COUNT(Dt_Customer) GROUP BY (ID, Income)<br>(5) SUM(NumDealsPurchases) GROUP BY (Education)<br>(6) SUM(Kidhome) GROUP BY (Education)<br>(7) COUNT(Year_Birth) GROUP BY (ID, Teenhome)<br>(8) SUM(Teenhome) GROUP BY (Education)<br>(9) COUNT(ID) GROUP BY (Education)                                                                                                            |
| LLM             | (1) MIN(MntMeatProducts) GROUP BY (Recency)<br>(2) MEAN(NumWebPurchases) GROUP BY (Teenhome)<br>(3) SUM(NumStorePurchases) GROUP BY (Complain)<br>(4) MAX(NumDealsPurchases) GROUP BY (Education)<br>(5) MEAN(Income) GROUP BY (Year_Birth)<br>(6) COUNT(MntWines) GROUP BY (Country)<br>(7) MEDIAN(Income) GROUP BY (NumWebVisitsMonth)<br>(8) STD(Income) GROUP BY (AcceptedCmp1)<br>(9) SUM(Income) GROUP BY (Marital_Status)<br>(10) COUNT(Recency) GROUP BY (MntFruits)                                                           |
| SAGE            | (1) COUNT(NumStorePurchases) GROUP BY (Complain)<br>(2) COUNT(AcceptedCmp5) GROUP BY (Complain)<br>(3) COUNT(Year_Birth) GROUP BY (Complain)<br>(4) SUM(AcceptedCmp5) GROUP BY (Complain)<br>(5) MEAN(AcceptedCmp2) GROUP BY (AcceptedCmp4)<br>(6) SUM(Income) GROUP BY (Complain, Education)<br>(7) SUM(Complain) GROUP BY (AcceptedCmp4, AcceptedCmp5)<br>(8) COUNT(Education) GROUP BY (Marital_Status)<br>(9) SUM(NumWebVisitsMonth) GROUP BY (Marital_Status)<br>(10) COUNT(NumStorePurchases) GROUP BY (AcceptedCmp3, Education) |

Figure A12: Results of SAGE, commercial software, and LLM on marketing data.

| Property                         | Standards                                                                                                                                                                                                                                                    | Excel (Mac OS) | Excel (MS OS) | GSheet | Power BI | Tableau | ChatGPT | Llama3-instruct | DAISY | AutoSuggest | TableGPT |
|----------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------|---------------|--------|----------|---------|---------|-----------------|-------|-------------|----------|
| Recommends pivot tables          | If it always recommends pivot tables as their RESULTS, then mark them as ●. If it only recommends queries, then it is marked as ○. If it only recommends other visualizations, then it is marked as ◉. If it never includes pivot tables, then mark it as ○. | ●              | ●             | ●      | ●        | ●       | ●       | ●               | ●     | ●           | ●        |
| Multiple recommendations         |                                                                                                                                                                                                                                                              |                |               |        |          |         |         |                 |       |             |          |
| Budgeted recommendations         | If it includes the functionality of recommending multiple tables, then mark it as ●, if not ○.                                                                                                                                                               | ○              | ○             | ○      | ○        | ○       | ○       | ●               | ●     | ●           | ●        |
| Valid and Useful recommendations | If it has a functionality where users can choose the number of pivot tables, then mark it as ●, if not ○.                                                                                                                                                    | ●              | ●             | ●      | ●        | ●       | ●       | ●               | ●     | ●           | ●        |
| Interpretable Recommendations    | Is there any recommendation including invalid or useless results such as hallucinations or summing IDs? If they explicitly care about this, we say ●. If they trained on user logs or create hallucinations, we say ○. Otherwise, ○.                         | ○              | ○             | ○      | ○        | ○       | ○       | ○               | ●     | ○           | ○        |
| Adaptive recommendations         | Does the software explicitly consider interpretability (e.g., avoiding sparse or large tables)? If not, mark ○. If it requires explicit user input, mark ●. Otherwise, mark ○.                                                                               | ○              | ●             | ○      | ○        | ○       | ○       | ○               | ●     | ●           | ●        |
| Diversity Aware                  | Allows user attribute specifications<br>Can the user specify attributes of interest? If yes, mark ●, otherwise, ○.<br>Does the software allow adaptive recommendations based on user input? If yes, mark ●; otherwise, ○.                                    | ○              | ○             | ○      | ○        | ○       | ○       | ○               | ○     | ○           | ○        |
| Attribute-name semantics aware   | Does the software consider attribute names when generating pivot tables? If different names lead to different recommendations, mark ●; otherwise, ○.                                                                                                         | ○              | ●             | ●      | ●        | ●       | ●       | ●               | ●     | ●           | ●        |
| Attribute-order insensitive      | Is the system insensitive to attribute order? If order changes affect results, mark ○. If the system is robust to ordering, mark ●.<br>Does the system recommend tables based on syntactic data patterns? If yes, mark ●; otherwise, ○.                      | ○              | ○             | ○      | ○        | ○       | ○       | ○               | ○     | ○           | ○        |
| Data syntactic aware             | Does the system recommend tables based on data semantics? If it does so correctly, mark ●. If it attempts but often fails, mark ○. Otherwise, ○.                                                                                                             | ●              | ●             | ●      | ●        | ●       | ●       | ●               | ●     | ●           | ●        |
| Data semantic aware              | Does the system recommend tables with a single action? If yes, mark ●; otherwise, ○.<br>Does the system require additional resources such as GPU or quotas? If only hardware is needed, mark ●. If limited by quotas or data collection, mark ○.             | ●              | ●             | ●      | ●        | ●       | ●       | ●               | ●     | ●           | ●        |
| No additional requirements       | Free (no cost)                                                                                                                                                                                                                                               | ○              | ○             | ○      | ○        | ○       | ○       | ○               | ○     | ○           | ○        |
| Open-source (transparent)        | Is the system's code openly available (e.g., GitHub)? If yes, mark ●; otherwise, ○.                                                                                                                                                                          | ○              | ○             | ○      | ○        | ○       | ○       | ○               | ●     | ●           | ●        |

Table A4: Comparison of Pivot Table Recommendation Systems with Standards Included