Optimally Summarizing Data by Small Fact Sets for Concise Answers to Voice Queries

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Abstract—Our goal is to find combinations of facts that optimally summarize data sets. We consider this problem in the context of voice query interfaces for simple, exploratory data analysis. Here, the system answers voice queries with a short summary of relevant data. Finding optimal voice data summaries is computationally expensive. Prior work in this domain has exploited sampling and incremental processing. Instead, we rely on a pre-processing stage generating summaries of data subsets in a batch operation. This step reduces run time overheads by orders of magnitude.

We present multiple algorithms for the pre-processing stage, realizing different tradeoffs between optimality and data processing overheads. We analyze our algorithms formally and compare them experimentally with prior methods for generating voice data summaries. We report on multiple user studies with a prototype system implementing our approach. Furthermore, we report on insights gained from a public deployment of our system on the Google Assistant Platform.

Index Terms—voice query, data summary, data vocalization

I. INTRODUCTION

Our goal is to optimally summarize data with a bounded number of facts. This problem arises in the context of voice query interfaces [7], [11], [22], [23], [25] (VQIs). Motivated by the rise of devices such as Google Home or Amazon Alexa, VQIs translate speech input to SQL queries and report the query result via voice output. Voice output must be concise [14], [27], preventing VQIs from transmitting all but the smallest results in detail. Hence, we focus on approximating data as closely as possible, using a length-limited speech summary. We present multiple algorithms to solve this problem efficiently, exploiting pre-processing to reduce run time overheads.

Our optimality criterion is based on the user’s belief about data. We aim to alter the user’s expectations via speech output to bring it as close as possible to the actual data. In that, we follow prior work on data vocalization [25], [28] and visualization (where the goal is to select a plot to reduce deviation between user expectations and data [19], [21]).

The resulting problem is NP-hard (see Section VII) and challenging to solve. Prior work resorted to sampling [25], [27], [28] to generate approximate summaries at run time. We present a new approach that is based on the following hypothesis: typical voice queries are short and simple (as it becomes tedious to formulate long queries without being able to see and edit them). Hence, we can generate answers for all queries up to a certain (small) length in an efficient batch operation. In the following, we present exact and approximate algorithms for this pre-processing step, evaluate their performance, and assess them in user studies.

In summary, our original scientific contributions are threefold. First, we propose several novel algorithms that generate optimized speech summaries of data subsets. Second, we analyze those algorithms formally. Third, we analyze the algorithms experimentally, in terms of computational efficiency and by a user study.

The reminder of this paper is organized as follows. In Section II, we introduce our formal problem model. In Section III, we give an overview of the end-to-end voice querying engine in which the proposed methods are used. Next, we describe an exhaustive algorithm for that problem in Section IV. Then, we present a greedy algorithm to solve the problem in Section V. We show that this algorithm generates guaranteed near-optimal speech summaries. Next, we show in Section VI how to improve efficiency by pruning irrelevant speech fragments early. We analyze complexity of the target problem and of the proposed algorithms in Section VII. In Section VIII, we evaluate all proposed approaches experimentally. Finally, we discuss related work in Section IX before we conclude.

II. PROBLEM MODEL

We introduce our problem model using examples.
Definition 1. We model a Relation as a set $R$ of rows. Each row $r = \langle D_r, v_r \rangle \in R$ is characterized by a pair where $D_r = \{\langle d_i, v_i \rangle \}$ assigns Dimension Columns $d_i$ to values $v_i$ while $v_r$ is a numerical value in the Target Column for $r$.

Example 1. Consider a relation where each row represents delay of a flight. We are interested in how flight delays depend on region and season. Hence, the column containing delays (e.g., in minutes) is our target, we use columns containing season and region as dimensions. Figure 1 illustrates average delays for different data subset in the left plot. We will use this scenario as running example in the following.

For the following definitions, we assume that a relation has been fixed. We consider a simple class of facts that can be easily described via speech output.

Definition 2. A Fact $f = \langle D, v \rangle$ is a pair, consisting of a Scope $D$ and a Typical Value $v$. Scope $D = \{\langle d_i, v_i \rangle \}$ assigns values to a subset of dimension columns while the typical value $v$ averages over the target column. We say that a row $r = \langle D_r, v_r \rangle \in R$ is Within Scope for the fact if $D \subseteq D_r$ (i.e., fact and row values are consistent in the dimension columns). The typical value is the average value in the target column for all rows within scope.

We assume that a speech template is given that allows translating facts of the form above into speech output. This template contains placeholders for the typical value and for (a variable number of) dimension columns.

Definition 3. For our pseudo-code, we model a Speech $F$ as a set of facts. We call its cardinality the Speech Length.

Example 2. The following facts can be derived from the data depicted in Figure 1 assuming the same number of flights for each season and region. The average delay in Summer is 20 minutes (i.e., $F = \langle D, 20 \rangle$ and $D = \{\langle \text{season, Summer} \rangle, \langle \text{region, North} \rangle \}$). The average delay in Winter is 15 minutes ($D = \{\langle \text{season, Winter} \rangle \}$). A speech corresponds to a set of such facts.

We need a criterion to select between alternative fact combinations. We follow prior work on data visualization and vocalization [19, 23] that aims at selecting facts to bring the user’s expectations as close as possible to the actual data. Next, we introduce a user model, modelling how user expectations change after listening to speeches.

Definition 4. We denote by $E(F, r)$ the Expected Value in the target column of row $r = \langle D_r, v_r \rangle$ after listening to facts $F$. Denote by $F_r \subseteq F$ the subset of facts for which $r$ is within scope. If $|F_r| = 1$ then only one fact is relevant to the row and user expectation equals the typical value proposed by that fact. If $|F_r| > 1$ then multiple facts are relevant. Denote by $V_r$ the set of typical values proposed by any fact in $F_r$. We assume that users often have prior knowledge allowing them to determine the most relevant fact among alternatives. Hence, we model user expectations as $\text{arg min}_{v \in V_r} |v - v_r|$ as the value closest to the target. Also, we consider Prior Expectations by the user (before listening) via function $P(r)$.

In Section V we match this model against expectations of actual users in a user study.

Example 3. Assume users expect no delays by default (the prior). After a speech conveying average delays in the South in Summer and in the East in Winter, the resulting expectations by users for flights in specific regions and seasons are depicted in Figure 1 (middle). If conveying average delays in Winter and average delays in the North (i.e., two facts), the resulting expectations are illustrated in the rightmost plot.

Definition 5. We denote by $D(F, r)$ for facts $F$ and row $r = \langle D_r, v_r \rangle$ the Deviation between user expectations and actual value, i.e. $D(F, r) = |E(F, r) - v_r|$. We denote by $D(F) = \sum_{r \in R} D(F, r)$ the accumulated deviation (also “Error”) over all rows of the relation.

Definition 6. We denote by $U(F)$ the Utility of facts $F$ in bringing the user’s expectations closer to actual values. More precisely, it is $U(F) = D(\emptyset) - D(F)$. This definition relies on having a prior defining user expectations in the absence of relevant facts. We use the term Single-Fact Utility for the utility of a singleton fact set.

Example 4. Consider expectations induced by Speech 1 and Speech 2 of our running example (see Figure 1). As outlined before, users expect no delays by default, leading to an accumulated error of $4 \cdot 20 + 4 \cdot 10 = 120$ (assuming one relation row per combination of season and region). After listening to Speech 1, error reduces to 80 (the delta of 40 is the utility of Speech 1). On the other hand, Speech 2 reduces error to $7 \cdot 5 = 35$ and is therefore more useful.

Our goal is to find the combinations of facts with limited cardinality that is most useful.

Definition 7. An instance of the Speech Summarization Problem is defined by a triple $\langle R, F, m \rangle$ where $R$ is a relation to summarize, $F$ a set of available facts, and $m$ the maximal number of facts to use. The goal is to find up to $m$ facts $F^*$ for speech output maximizing utility, i.e. $\text{arg max}_{F^* \subseteq F, |F^*| = m} U(F^*)$.

III. SYSTEM OVERVIEW

The algorithms presented in this paper are executed in the Speech Summarizer component of the system illustrated in
Figure 2: This system answers simple voice queries via voice output, based on the speeches generated during pre-processing. A video, showing a recent demonstration [26], is available [2].

The goal of pre-processing is to pro-actively generate speech answers for all possible queries, up to a certain length. This may not seem practical for written queries. However, we hypothesized that voice input would motivate users to formulate relatively short and simple queries, making pre-processing a viable option. We found that this hypothesis to be largely justified (e.g., see Figure 2(a)). The queries to consider are described in a Configuration file. Based on that, the Problem Generator generates a series of speech summarization problems. Those problems are solved by the Speech Summarizer, using a relational database engine and the algorithms described later.

Currently, we consider queries requesting information on values in a target column for a data subset, defined by a conjunction of equality predicates (the answer of the system may reference columns that do not appear in the query). We found this to be the most common type of voice query in user studies (see Section VII-D). Query length is measured by the number of equality predicates. The Configuration file references a table in a relational database. It specifies the maximal query length to consider, the columns on which to allow predicates (we call them “Dimensions”), and a set of target columns. The Problem Generator creates one query for each combination of a target column and a subset of equality predicates, considering all possible combinations of equality predicates up to the query length. For each such query, we generate a speech summarizing values in the target column for the data subset defined by the query predicates. The facts considered for summarization report average values in the target column for data subsets. We consider one fact for each data subset defined by a conjunction of equality predicates and, by default, up to two additional equality predicates on the dimensions (considering equality predicates for all value combinations that appear in the data set). After selecting a (near)-optimal fact combination, our research focus, the speech is generated according to a simple text template. The summarization methods, presented in this paper, are not specific to the type of queries currently supported, nor specific to our current method of selecting facts.

At run time, the system maps voice queries to the most related speech summary, generated during pre-processing. Each voice query is mapped to one target column and a set of equality predicates. To map text to queries, we train an extractor with a few samples to extract names of target column and predicates on other columns (we currently consider equality predicates only) from input text (this functionality is provided by the Google Assistant framework on which our application is based upon [3]). If a summary was generated for the extracted target column and for the data subset defined by the extracted predicates, the corresponding speech is vocalized. Otherwise, among all speeches referencing the queried target column, the speech describing the most specific data subset that contains the one referenced in the query is used. More precisely, considering predicates \( Q \) extracted from the query, we select a speech summarizing a data subset defined by predicates \( S \) such that \( S \subseteq Q \) and \( |S \cap Q| \) is maximal. Speeches are prefixed with a description of the summarized data subset (an enumeration of restricted columns and their values). Hence, users are aware of the semantics of the description.

Example 5. We made a data set on flight cancellations publicly available via voice queries (see Section VIII-D). Here, we specified one target column (cancellation probability) and six dimensions (e.g., airline and start airport state), enabling queries with up to two predicates. Based on that configuration, we generated 8,500 speeches during pre-processing. In the logs, we found for instance the voice query “cancellations in Winter?”. After receiving this query, the system will extract the target column (cancellation) and the predicate (season = Winter) of the query, then search for matching, pre-generated speeches. Here, as the query has one predicate, a speech has been pre-generated for that precise query. This speech is transmitted via voice output. It describes three facts (the general cancellation probability, a significant increase in February, and a reduced probability for the West) that together provide the best possible approximation of the data.

IV. EXACT ALGORITHM

The exact algorithm finds guaranteed optimal speech summaries. We give an overview in Section IV-A, discuss pruning in Section IV-B, and prove optimality in Section IV-C.

A. Algorithm Overview

The exact algorithm is iterative. Starting from single facts, it expands speeches in each iteration until speeches reach maximum length. While doing so, it prunes speeches that provably cannot expand into an optimal speech. For pruning, it exploits a lower bound on the utility of the optimal speech (generated by a cheaper heuristic). Furthermore, the algorithm avoids enumerating redundant permutations of fact sets.

Algorithm [1] shows the associated pseudo-code. Given facts \( F \) and relation \( R \) as input, as well as the maximal speech length \( m \) and a lower utility bound \( b \), the algorithm returns an optimal combination of up to \( m \) facts to summarize \( R \).

The algorithm is executed as a series of relational operators (\( \Gamma \) for grouping and aggregation, \( \sigma \) for filtering, \( \Pi \) for projection, \( \Join \) for joins, and \( \times \) for the Cartesian product). Our implementation executes the algorithm by issuing a series of SQL queries (thereby removing the need for transferring data out of the database system). Initially, Algorithm [1] calculates the associated utility for each fact (Line 6). Utility of a fact (or speech) is calculated by summing up utility over each row (hence, we use sum aggregation while grouping by facts). We require a join as each fact must be matched against all rows that fall within its scope. The corresponding join condition \((M)\) compares values in \( F \) and \( R \) for each dimension \( d \), requiring \( F.d = \text{null} \) or \( F.d = R.d \) for each of them. In each iteration, speeches in \( S \) are expanded by adding one more
1: // Find guaranteed optimal summary for
2: // relation R using m facts from F. Exploit
3: // lower bound b on optimal speech utility.
4: function OPTIMAL SUMMARY(F, R, m, b)
5: // Calculate utility for single fact speeches
6: S ← \( \Gamma_{U,R}(R \not\prec M \cap F) \)
7: // Iteratively combine facts into speeches
8: for i ∈ 2, ..., m do
9: // Expand speech and prune
10: \( S \leftarrow \sigma_{P_i(b,m-i-1)}(\Pi_{U,S,F}(S \times F)) \)
11: end for
12: // Calculate utility of final speeches
13: \( S \leftarrow \Gamma_{U,S,F}(R \not\prec M \cap S) \)
14: // Return speech with maximal utility
15: return arg\( \max_{U}(S) \)
16: end function

Algorithm 1: Exhaustive algorithm for generating guaranteed optimal speech summaries.

Fact (considering all possible facts). Furthermore, speeches are pruned via condition \( \mathcal{P} \), based on several utility-related bounds (represented as \( \mathcal{U} \) in Algorithm 1). Pruning is described in the next subsection. Next, the algorithm calculates the precise utility of each remaining speech by a join between data and speeches (Line 13). Here, \( M \) evaluates to true if the data row falls within the scope of at least one speech fact. Finally, the algorithm returns the speech with maximal utility (Line 15).

B. Pruning Speeches

First, our utility model does not depend on the order in which facts appear in a speech. We prune out redundant fact permutations by enforcing specific order between facts. Specifically, we order facts in decreasing order of single-fact utility via pruning condition \( S \not\cup \mathcal{U}_p \geq F \mathcal{U} \). Here, \( S \mathcal{U}_p \) is the single-fact utility of the last, previously added fact in a speech to expand. \( F \mathcal{U} \) is the single-fact utility of a newly added fact.

Second, we prune speeches that cannot expand into an optimal speech. We compare an upper bound on the utility of all expansions of a candidate speech to a lower bound on optimal utility (input \( b \)). To calculate an upper utility bound for all expansions, we consider the remaining number of expansions \( r \), the constraint that facts are added in decreasing order of single-fact utility, and that single-fact utility is an upper bound for the increase in utility when adding a fact to a non-empty speech. The corresponding pruning condition, \( (b-S \mathcal{U})/r \leq F \mathcal{U} \) (where \( S \mathcal{U} \) is the upper utility bound of the speech to expand, obtained by summing utility of its facts, and \( F \mathcal{U} \) the single-fact utility of a candidate expansion), is justified in detail in the next subsection. Condition \( \mathcal{P} \), used in Line 10 of Algorithm 1 is the conjunction of the two aforementioned pruning conditions. The second pruning formula depends on \( b \) and \( r \), specified as parameters to \( \mathcal{P} \) in Algorithm 1.

Example 6. Reconsider the example depicted in Figure 1. We consider expansions of a speech stating that the average delay in the South in Summer is 20 minutes. Calculating utility under the same assumptions as in Example 4 this fact alone has utility 20. Consider the fact stating that the average delay in Winter is 15 minutes. This fact has single-fact utility 40. We prune the corresponding expansion as it does not order facts by (decreasing) single-fact utility. Now, consider expansion with a fact stating that the average delay in the East in Winter is 20 minutes. Assume we generate speeches with up to two facts. Knowing a speech with utility 85, generated by a heuristic, we can discard the current speech altogether (since \( b = 85, S \mathcal{U} = 20, F \mathcal{U} = 20, r = 1, \) and \( (b-S \mathcal{U})/r > F \mathcal{U} \)).

C. Proof of Optimality

First, we introduce a diminishing returns property.

Definition 8. A set function \( f: S \mapsto \mathbb{R}^+ \) is sub-modular if for all sets \( S_1, S_2 \subseteq S \) where \( S_1 \subseteq S_2 \), the increase by adding a new element \( s \in S \) is higher for \( S_1 \) than for \( S_2 \): \( f(S_1 \cup \{s\}) - f(S_1) \geq f(S_2 \cup \{s\}) - f(S_2) \).

Next, we show that utility, as a function of the set of speech facts, has the aforementioned property.

Theorem 1. Speech utility has diminishing returns.

Proof: Let \( F_1 \) and \( F_2 \) be two speeches (sets of facts) describing the same data such that \( F_1 \subseteq F_2 \). Denote by \( f \) a relevant fact that neither appears in \( F_1 \) nor \( F_2 \). For a fixed row \( r \) with dimension values \( D_r \) and target value \( v_r \), it is \( D(F_1,r) = \min_{(D,v)\in F_1:D \subseteq D_r} |v - v_r| \geq \min_{(D,v)\in F_2:D \subseteq D_r} |v-v_r| = D(F_2,r) \) since \( F_1 \subseteq F_2 \). Denote by \( \Delta U(F, f) = D(F, r) - D(F \cup \{f\}, r) \) the utility of adding fact \( f \). We distinguish two cases: either the new fact \( f \) provides a better approximation than any fact in \( F_2 \) (case 1) or not (case 2). In case 1, \( f \) provides a better approximation than any fact in \( F_1 \) as well (since \( F_1 \subseteq F_2 \)). Hence, \( D(F_1 \cup \{f\}, r) = D(F_2 \cup \{s\}, r) \) and \( \Delta U(F_1, f) \geq \Delta U(F_2, f) \) (i.e., utility is sub-modular) since \( D(F_1, r) \geq D(F_2, r) \). In case 2, we have \( \Delta U(F_2, f) = 0 \) and therefore \( \Delta U(F_1, f) \geq \Delta U(F_2, f) \) (as the utility delta is non-negative). Utility is aggregated as the sum over multiple rows. The sum of sub-modular functions (with positive weights) is sub-modular [8].

Next, we upper-bound utility of speech expansions.

Lemma 1. For a speech ordering \( m \) facts by decreasing single-fact utility, \( u_i \) is single-fact utility of the \( i \)-th fact and \( U_i \) aggregate utility of the first \( i \) facts, aggregate speech utility is upper-bounded by \( U_i + (m-i) \cdot u_i \) for any \( i \).

Proof. Utility has diminishing returns according to Theorem 1. Hence, single-fact utility is an upper bound for the increase in speech utility after adding the \( i \)-th fact (i.e., \( U_i - U_{i-1} \leq u_i \)). As well, as facts are ordered, we have \( u_k \leq u_k \) for \( k \in i, \ldots, m \) and with \( U_m = U_i + \sum_{k=i+1}^{m}(U_k - U_{k-1}) \leq U_i + \sum_{k=i+1}^{m} u_k \), we obtain \( U_m \leq U_i + u_i \cdot (m-i) \).

Lemma 2. Algorithm 1 maintains an upper bound on the utility of speeches in \( S \mathcal{U} \).

Proof. Algorithm 1 initializes \( \mathcal{U} \) via the single-fact utility (Line 6). In this case, \( \mathcal{U} \) represents exact utility of speeches in
Algorithm 2: Greedily add most useful facts to obtain guaranteed near-optimal speech summaries.

1. Algorithm 1 updates $U$ by adding single-fact utility of new facts after each expansion. Due to diminishing returns (see Theorem 1), single-fact utility upper-bounds utility increase when adding a fact.

**Theorem 2.** Pruning preserves an optimal speech.

*Proof.* A speech is pruned only if one of the two atoms of macro $P(b, r)$ evaluates to false. Assume the first atom $(S\cdot U \geq F\cdot U)$ evaluates to false. This means that a fact with higher single-fact utility follows one with lower single-fact utility. By re-ordering facts, we obtain a speech that satisfies the first atom without changing utility. Assume now that the second atom $((b - S\cdot U)/r \leq F\cdot U)$ evaluates to false. According to Lemma 1, $S\cdot U + r \cdot F\cdot U$ is an upper bound on utility of the completed speech since $r = m - i - 1$ (see Algorithm 1 Line 10). $F\cdot U$ is the single-fact utility of the $i$-th fact ($u_i$ in Lemma 1), and $S\cdot U$ is an upper bound on the aggregate utility of the first $i - 1$ facts (using Lemma 2). As $b$ is a lower bound on the optimal utility, having $S\cdot U + r \cdot F\cdot U < b$ indicates a fragment that cannot be extended into an optimal speech.

This immediately implies our main result.

**Corollary 1.** Algorithm 1 generates an optimal speech.

*Proof.* The algorithm considers all possible speeches that are not pruned out. Due to Theorem 2 pruning preserves optimal speeches. The algorithm calculates exact utility of each remaining speech and therefore identifies an optimum.

**V. GREEDY ALGORITHM**

The greedy algorithm finds guaranteed near-optimal speech summaries efficiently. We describe the algorithm in Section V-A and prove its properties in Section V-B.

A. Algorithm

The greedy algorithm generates speeches by iteratively adding facts, starting from an empty speech. In each iteration, it greedily adds the fact that increases utility by the highest amount. This algorithm is more efficient than exhaustive search as it avoids considering fact combinations for speech expansions. Also, this seemingly simple strategy guarantees speeches within a factor of $(1 - 1/e)$ of the optimal utility.

Algorithm 2 shows the associated pseudo-code. It uses the same basic operators as Algorithm 1. Given a relation $R$ to summarize with up to $m$ facts from $F$, the algorithm returns a near-optimal combination of facts. In each iteration (Line 7), the algorithm calculates utility gain of each fact (i.e., added utility when expanding the current speech by that fact). This is realized by a join, pairing facts with data rows within their scope (join condition $M$), followed by aggregating utility gain for each fact over all rows. After identifying the fact with maximal added utility (Line 9), the algorithm recalculates user expectations based on the expanded speech (Line 11). Here, $E$ represents an SQL expression that calculates the value, expected by users after listening to the current speech, according to our model (see Section II). The resulting values are stored as a column of the updated relation $R$ (and initialized with the prior). They are used for calculating utility gain of facts in Line 7. Finally, the combination of locally optimal facts is returned.

**Example 7.** We consider our running example, illustrated in Figure 1. We calculate utility under the same assumptions as in Example 4. We consider all facts on average delay describing flights within a specific region or season or both. Considering those facts, the greedy algorithm selects either the fact referencing flights in Winter or the one referencing flights in the North (both tied with a maximal utility of 40). In the second iteration, it will select the other one of the two aforementioned facts (now with a maximal utility gain of 25). Other facts, e.g. referencing flights in the South in Summer, with utility 20, are dominated.

B. Proof of Near-Optimality

We prove that Algorithm 2 produces near-optimal speeches.

**Theorem 3.** Algorithm 2 produces speeches with utility within factor $(1 - 1/e)$ of the optimum.

*Proof.* Utility is non-negative, monotone, and sub-modular (according to Theorem 1). Algorithm 2 greedily selects a bounded number of facts for each scope. Doing so guarantees the postulated optimality factor $[15]$. 

**VI. PRUNING FACTS**

We show how to prune facts early for greedy speech construction. Section VI-A gives an overview. Section VI-B describes the pruning mechanics in detail. Sections VI-C and VI-D provide details on the cost-based optimizer.

A. Overview

The greedy algorithm must select the fact with maximal utility gain in each iteration (otherwise, the formal guarantees on finding near-optimal speeches do not apply). A naive method calculates utility gain for each fact to determine the maximum. Doing so requires pairing up data rows with facts
(i.e., a join in Algorithm 2), an expensive operation. In some cases, we can conclude more efficiently that fact groups do not yield maximal utility. To do so, we compare an upper bound on utility gain of facts (calculated without a join) against utility of other facts. This creates overheads for calculating bounds and for comparisons. Those overheads only pay off if they remove facts from further considerations. Hence, we use cost-based planning to decide if and how to try excluding facts for minimal processing costs. The following example illustrates the high-level principle.

**Example 8.** We consider our running example from Figure 1 calculating utility as in Example 4. Assume the greedy algorithm selected the fact stating average delays in Winter (15 minutes) in the first iteration. In the second iteration, our goal is to efficiently identify a fact with maximal utility gain. By summing up absolute differences between expected and actual delays for a specific season (expectation is influenced by priors and the first fact), we obtain upper bounds on utility gain of any fact referencing that season. Similarly, we obtain upper bounds for facts referencing specific regions. For instance, facts referencing Fall have an upper bound of 10 and facts referencing the East cannot increase utility by more than five (deviation between actual and expected delay in the East in Winter). Assume we calculate utility gain of the fact stating average delays in the North (15 minutes) first. Based on its utility gain (25) and the upper bounds, we can exclude all other facts from further consideration. Calculating utility of other facts first is less effective for pruning.

**B. Pruning Method**

Algorithm 3 describes the pruning mechanism (it replaces Line 7 in Algorithm 2). We prune facts at the granularity of fact groups, characterized by the set of restricted dimension columns (denoted as \( R.Dims \) in Algorithm 3). For instance, in the context of Example 8, we consider all facts referencing specific regions (but no specific seasons) as one group. Algorithm 3 first determines the set of fact groups (Line 5) and an optimal pruning strategy (Line 7), as discussed in the following subsections. A pruning strategy consists of a source \( S \) and a target \( T \) (\( F(S) \) and \( F(T) \) denote facts associated with the corresponding groups). The pruning source is a set of fact groups whose utility is calculated first. Then, the maximal utility gain of any source fact (denoted as \( m \) in Algorithm 3) is used to prune target facts, based on their upper utility bounds. Upper bounds are calculated by summing up absolute deviation between expectation and correct values (denoted as \( D \) over all data rows (15), grouping by values in dimension columns for a fixed fact group. Clearly, adding a fact can at most decrease error to zero in the data region the fact refers to. This implies the upper bound on utility gain. If the target group is dominated (check in Line 17), we prune not only the target group but also its specializations. The specialization of a target group restricts a strict superset of dimension columns. Specializing a fact reduces its scope to a data subset. Hence, upper utility bounds (obtained by summing deviation over all rows within the scope of a fact) apply to fact specializations as well. Finally, utility is calculated for all remaining fact groups.

**C. Cost Model**

We introduce a cost model for pruning choices. This model estimates processing cost given pruning source and target. For facts in a group \( g \), we denote by \( C_U(g) \) the estimated cost of calculating utility of each fact (this requires a join between facts and data rows). By \( C_D(g) \), we denote estimated cost for calculating deviation between expected and actual values for row groups (this requires a group-by query without joins). Both estimates can be obtained via the query optimizer cost model. Denoting by \( P_g \) the event that group \( g \) is pruned, we can estimate data processing cost of Algorithm 3 as

\[
\sum_{s \in S} (C_U(s)) + \sum_{t \in T} (C_D(t)) + \sum_{g \in G \setminus S} (Pr(\neg P_g) \cdot C_U(g))
\]

. The first term represents cost for calculating bounds based on pruning sources. The second term represents cost of calculating bounds for the pruning targets (we simplify by assuming that all target groups are treated). The last term represents cost of calculating utility for facts that remain after pruning. It depends on the probability \( Pr(\neg P_g) \) that a group \( g \) is not pruned.

A fact group may be pruned if it was a pruning target or if it specializes a pruning target. The following formula covers
both possibilities: \( \Pr(\neg P_g) = \Pr(\exists t \in T : t \subseteq g \land P_t) \). It can be expanded into \( \Pr(\exists s \in S, t \in T : t \subseteq g \land P_{s \rightarrow t}) \), denoting by \( P_{s \rightarrow t} \) the event that the upper utility bound for facts \( t \) is below the lower bound for facts in \( s \). We simplify by assuming independence between different pruning outcomes, obtaining \( \Pr(\neg P_g) = \prod_{s \in S} \prod_{t \in T : t \subseteq g}(1 - \Pr(P_{s \rightarrow t})) \). Finally, we estimate probability for \( P_{s \rightarrow t} \). Modeling utility bounds per fact as a sum over i.i.d. random variables representing utility per row, it approaches a normal distribution as the number of rows grows (due to the Central Limit Theorem).

We assume that per-row utility follows the same distribution, independently of the fact group and of the type of bound calculated. Hence, the per-fact utility distribution only depends on the number of rows within its scope. We simplify by assuming a uniform distribution of rows over dimension values.

Then, the number of rows that are within the scope of a fact is inversely proportional to the number of facts in the fact group. We can estimate the number of facts in groups \( s \) and \( t \), denoted by \( M(s) \) and \( M(t) \) in the following, by referring to query optimizer statistics. The number of facts simply equals the number of distinct value combinations in the dimension columns they restrict. Finally, we assume that the variance of the per-fact utility distribution is fixed and given by \( \sigma^2 \).

Under those assumptions, we can express pruning probability by comparing two normal distributions:

\[
\Pr(P_{s \rightarrow t}) = \Pr(u_s > u_t | u_s \sim \mathcal{N}(\mu, \sigma^2), u_t \sim \mathcal{N}(\mu + \frac{1}{M(t)} \sigma^2))
\]

. Here, \( \mathcal{N}(\mu, \sigma^2) \) designates the normal distribution with mean \( \mu \) and variance \( \sigma^2 \). This cost model is based on various simplifying assumptions. Nevertheless, we will show experimentally that it is sufficient to avoid bad pruning plans.

### D. Pruning Optimization

We select pruning plans based on the cost model presented in the last subsection. Function \textsc{OptPrune}, used in Algorithm 3, returns the minimum cost plan among a set of candidates. The number of candidate plans grows exponentially in the number of fact groups. To reduce optimization overheads, we use several heuristic to obtain a smaller set of candidate plans, calculated by Algorithm 4.

When selecting pruning sources, Algorithm 4 prioritizes fact groups with few member facts. For such groups, the expected utility is higher as each fact tends to cover more rows. For each possible pruning source, Algorithm 4 considers multiple possible pruning target sets. Pruning targets are selected according to a heuristic function \( H \). Given pruning sources \( S \) and remaining groups \( L \), the value of a pruning target \( t \) is given by \( H(t, S, L) = \Pr(P_t) \cdot |\{l \in L : t \subseteq l\}| \). This function estimates the expected number of fact groups that can be removed after calculating bounds for target \( t \). After selecting the next pruning target, all fact groups specializing the target group are removed from further consideration. If the target group can be successfully pruned, those fact groups would be implicitly pruned as well. Hence, we exclude them from further consideration. Each combination of a source and target set yields a new plan candidate.

**Algorithm 4:** The optimal pruning plan is selected from plan candidates generated by this algorithm.

```
1: // Generate plans for pruning facts \( F \) on relation \( R \).
2: function \textsc{Plans}(\( F, R \))
3: // Initialize set of plan candidates
4: \( P \leftarrow \emptyset \)
5: // Collect available fact groups
6: \( G \leftarrow \textsc{PowerSet}(R, \text{Dims}) \)
7: // Iterate over pruning sources
8: for \( S \subseteq G : \exists s \in S, g \in G \setminus S : M(g) < M(s) \) do
9: // Initialize pruning target set
10: \( T \leftarrow \emptyset \)
11: // Initialize pruning targets left
12: \( L \leftarrow G \setminus S \)
13: // Iterate until no targets left
14: while \( L \neq \emptyset \) do
15: // Select next pruning target
16: \( t \leftarrow \arg \max_{t \in L}(H(t, S, L)) \)
17: // Add to pruning targets
18: \( T \leftarrow T \cup \{t\} \)
19: // Add corresponding plan candidate
20: \( P \leftarrow P \cup \{\langle S, T \rangle\} \)
21: // Discard specialization groups
22: \( L \leftarrow L \setminus \{g \in G | t \subseteq g\} \)
23: end while
24: end for
25: return \( P \)
26: end function
```

### VII. Complexity Analysis

We analyze the complexity class of speech summarization.

**Theorem 4.** Speech summarization is \( NP \)-hard.

**Proof:** We use a reduction from set cover. An instance of set cover is defined by a universe \( U \), a set \( S \) of subsets of \( U \), and an integer \( m \). The decision variant asks whether \( U \) can be covered with \( m \) elements from \( S \). We reduce to speech summarization as follows. We use a relation \( R \) with one row for each element in \( U \). For each subset \( s \in S \) (with \( s \subseteq U \)), we introduce a candidate fact \( F_s \) with value \( 1 \). That fact restricts the dimension columns such that exactly rows \( R_s \subseteq R \) associated with elements from \( s \), fall within its scope. We introduce one relation column \( C_s \), associated with \( s \), such that only rows \( R_s \) are set to a unique value \( v_s \) in \( C_s \) and \( F_s = \{\langle (C_s, v_s)\rangle, 1\} \). We set a uniform prior \( P(r) = 0 \) for all rows, the target value is uniformly set to one. We can achieve a deviation of zero if and only if each row falls within the scope of at least one fact. If the optimal speech with \( m \) facts has deviation zero then \( U \) can be covered with \( m \) sets from \( S \). The reduction has polynomial time complexity.

Next, we analyze time and space complexity of the proposed algorithms. We denote by \( n = |R| \) the number of rows in the
relation to summarize, by \( m \) the maximal number of facts to select, and by \( k = |E| \) the number of fact candidates. We measure time and space complexity by the number of rows (or row combinations) processed or stored.

**Theorem 5.** Algorithm 1 has time complexity \( O(n \cdot \binom{k}{m}) \).

**Proof:** Under worst case assumptions, only the first of the two pruning condition (eliminating redundant fact permutations) is effective. Then, the number of partial speeches grows quickly in the number of iterations. This means that the accumulated cost of prior join operations is negligible, compared to the cost of the final join. Selecting \( m \) facts out of \( k \) candidates yields \( O\left(\binom{k}{m}\right) \) possibilities. The last join pairs potentially optimal speeches with \( n \) data rows. Assuming nested loops joins, its complexity is in \( O(n \cdot \binom{k}{m}) \).

**Theorem 6.** Algorithm 2 has time complexity \( O(m \cdot n \cdot k) \).

**Proof:** The operation with dominant complexity is the join between data rows and facts. A nested loops join has complexity \( O(n \cdot k) \). We perform \( O(m) \) iterations.

**Theorem 7.** Algorithm 1 is in \( O(\binom{k}{m}) \) space.

**Proof:** The relation with dominant space requirements is the one storing candidate speeches. It has \( O(\binom{k}{m}) \) rows (using a similar reasoning as for Theorem 5).

**Theorem 8.** Algorithm 2 is in \( O(n + m + k) \) space.

**Proof:** Besides the input, the algorithm stores a user expectation associated with each row, a utility value for each fact, and one optimal fact for each iteration. Respectively, space consumption is in \( O(n) \), \( O(k) \), and \( O(m) \).

Finally, we bound the number of facts and queries considered by the system. Let \( d \) be the number of dimension and \( t \) the number of target columns, and \( l \) the number of predicates used in each query and in each fact.

**Theorem 9.** The number of facts is in \( O\left(\binom{d}{l} \cdot n^l\right) \).

**Proof:** A fact is defined by picking \( l \) of \( d \) columns and one of \( O(n) \) possible equality predicates for each column.

**Theorem 10.** The number of queries is in \( O(t \cdot \binom{d}{l} \cdot n^l) \).

**Proof:** A query is defined by picking one of \( t \) target columns, \( l \) of \( d \) columns for placing predicates, and one of \( O(n) \) possible predicates for each column.

### VIII. Experimental Evaluation

We evaluate our algorithms in various experimental settings.

#### A. Experimental Setup

Table I summarizes the data sets used for the following experiments. We consider an extract from the American Community Survey (ACS) focused on disability statistics, results of the 2019 Stack Overflow Developer survey\(^1\) a data set on flight delay\(^4\) (frequently used to evaluate OLAP interfaces \(^2\)),

![https://insights.stackoverflow.com/survey/2019](https://insights.stackoverflow.com/survey/2019)

![https://www.kaggle.com/usdot/flight-delays](https://www.kaggle.com/usdot/flight-delays)

\(^1\)https://www.kaggle.com/usdot/flight-delays

\(^4\)https://data.fivethirtyeight.com/

| Data Set      | Size  | #Dims | #Targets |
|---------------|-------|-------|----------|
| ACS NY        | 2 MB  | 3     | 6        |
| Stack Overflow| 197 MB| 7     | 6        |
| Flights       | 565 MB| 6     | 1        |
| Primaries     | 6 MB  | 5     | 1        |

![Fig. 3: Performance comparison of presented algorithms in three scenarios (the red line marks the timeout).](image)

and a data set on the democratic primaries\(^3\). Table II reports the number of dimensions and the total number of target columns. Unless noted otherwise, we generate speeches with three facts (prior work shows that user retention decreases sharply after three facts [27]), considering all facts restricting up to two dimension columns. For all experiments, we use the average value in the target column as a (constant) prior. We used Postgres 9.5 as relational database, running on a t3.2xlarge EC2 instance with eight virtual cores and 350 GB of EBS volume. The operating system is Ubuntu Linux 18.04.

#### B. Comparing Pre-Processing Methods

We compare four methods for generating speeches. We compare the exact algorithm (see Section V), E in the following plots, against the greedy algorithm G-B in its base version (see Section V), and with two other greedy variants, G-P and G-O, that use different types of fact pruning. Algorithm G-P uses the fact pruning method described in Section VI-B with a simple pruning strategy. It uses all fact groups for pruning in the same order in which they are considered by Algorithm 4. Algorithm G-O uses the pruning optimizer and cost model, introduced in Sections VI-C and VI-D. Figure 3 shows computation time and average utility of generated speeches for three scenarios and several target columns. We consider cancellation and delay for flights (F-C, and F-D), prevalence of hearing loss, visual impairment, and cognitive impairment for the ACS data (A-H, A-V, and A-C), and competence, optimism, and job satisfaction for the Stackoverflow data set (S-C, S-O, and S-S). We set a per-scenario timeout of 48 hours of processing time. We measure speech utility according to the model from

\(^3\)https://data.fivethirtyeight.com/
randomly selecting facts and ranked them according to our flights and ACS data set, we generated 100 speeches by generated using voice “Salli” on TTSMP3.com. First, for the 10 cents per human intelligence task (HIT). Speeches were require a worker acceptance rate of at least 75% and pay the Amazon Mechanical Turk (AMT) platform. W e generally added cost for establishing and comparing utility bounds). The pruning may even increase computational overheads (due to model of user expectations) through a series of experiments on C. User Studies sessions per fact. G-O reduces overheads, compared to G-P .

increasing speech length, compared to the number of dimen-
numbers of dimensions mentioned per single fact. Figure 4 reports corresponding results. Scaling is more graceful when increasing speech length, compared to the number of dimensions per fact. G-O reduces overheads, compared to G-P.

C. User Studies

We validate our model of speech quality (based on our model of user expectations) through a series of experiments on the Amazon Mechanical Turk (AMT) platform. We generally require a worker acceptance rate of at least 75% and pay 10 cents per human intelligence task (HIT). Speeches were generated using voice “Salli” on TTSMP3.com. First, for the flights and ACS data set, we generated 100 speeches by randomly selecting facts and ranked them according to our quality model. For both data sets, we selected three speeches (best ranked, worst ranked, and median) for the next study. We asked 50 crowd workers to compare speeches and to rate each on a scale from one to ten according to the criteria “Precise”, “Good”, “Complete”, and “Informative”. Comparing alternative descriptions of the same data gives crowd workers a base for evaluating the quality of specific speeches. Figure 5 reports average ratings and the number of times, the corresponding speech won a relative comparison. Speech quality, measured according to the model used for optimization, correlates with user preferences.

For the next study, we used the best and worst ranked speech from the ACS scenario, shown in Table III. We asked AMT workers to estimate 15 data points, characterized by a borough of New York City and an age group, according to two speeches. We created 20 HITs per data point and per speech, i.e. 600 HITs in total (599 of them were answered before the deadline). Figure 6 shows how median estimates, speech, i.e. 600 HITs in total (599 of them were answered before the deadline). Figure 6 shows how median estimates, W e asked 50 crowd workers to compare speeches and to rate each on a scale from one to ten according to the criteria “Precise”, “Good”, “Complete”, and “Informative”. Comparing alternative descriptions of the same data gives crowd workers a base for evaluating the quality of specific speeches. Figure 5 reports average ratings and the number of times, the corresponding speech won a relative comparison. Speech quality, measured according to the model used for optimization, correlates with user preferences.

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TABLE II: Comparing two alternative speech descriptions.

| Speech   | Worst | Best |
|----------|-------|------|
| Speech   | About 30 out of 1000 persons in Manhattan identify as visually impaired. It is 35 for Brooklyn. It is 35 overall. | About 80 out of 1000 elder persons identify as visually impaired. It is 17 for adults. It is 3 for teenagers in Manhattan. |

![Fig. 7: Error when using different models to predict how crowd workers process conflicting facts.](https://www.visualizefree.com/)

Fig. 7: Error when using different models to predict how crowd workers process conflicting facts.

We primarily target use cases where visual interfaces are unavailable, e.g., due to limitations of the device (e.g., smart speakers without screen). Nevertheless, we performed a user study over Zoom in which we compare our voice interface against a public interface for visual data analysis. We recruited 10 undergraduate students (nine of them in computer science) for this study. Participants used their smart phones to access the Stackoverflow data set via the voice interface. Next, we allowed users to freely explore the data to find interesting facts. We asked them to evaluate overall usability of each interface on a scale from one to ten. We show the results on the right-hand side of Figure 8.

D. Public Deployment

Using our greedy approach, we made three data sets publicly available for voice querying via the Google Assistant platform, namely the Stackoverflow developer survey, flight statistics, and data on the democratic primaries. The first two data sets have been available since January 2020, the last one was available over a period of two months during the democratic primary season. We generated speeches using the approach presented in this paper. At the time of writing, we received about 1,500 unique voice queries. We analyzed the last 50 voice queries for each of the three data sets.

First, we classified the 150 queries into help requests, requests for repeating the last output, supported and unsupported (data access) queries (S-Query and U-Query), and other requests. Table III shows the results. Help requests are relatively common and show the importance of corresponding mechanisms (which our application provides). We take the low number of “repeat output” requests as a sign that voice output was mostly understandable.

![Fig. 8: User study comparing visual to voice query interfaces.](https://www.visualizefree.com/)

TABLE III: Classification of last 50 voice requests for three public Cloud deployments.

| Request Type | Primaries | Flights | Developers |
|--------------|-----------|---------|------------|
| Help         | 17        | 9       | 4          |
| Repeat       | 3         | 0       | 0          |
| S-Query      | 16        | 12      | 13         |
| U-Query      | 1         | 5       | 16         |
| Other        | 13        | 24      | 17         |
columns (we had one single voice query with three predicates during one of our user studies). Most queries fall into the category of retrieval queries (supported) while fewer queries ask for extrema or relative comparisons. We did not encounter any voice queries that translate into complex SQL queries using features such as exists condition or predicates on groups (i.e., having clauses). In summary, a relatively large portion of the queries analyzed in the last subsection (the supported data subset) is between 5 and 10%” likely leads to gains for properties like “Precise” and “Informative”.

Finally, we performed a small experiment in which we trained a machine learning (ML) model with pairs of speech fragments and summaries (i.e., a text containing facts considered by our approach and the summary generated). Our goal was to verify whether ML methods can use a small seed set of summaries to generate the remaining ones. We focus on speeches for a common query template (i.e., for queries with predicates on the same combination of dimension columns) which tend to be similar. For the flights data set, we selected the dimension with the largest number of distinct values (start airport region with 52 values) and consider all queries placing one predicate on that dimension. Our implementation is based on the Simpletransformers library.

Internally, it uses a sequence-to-sequence model based on pre-trained language models (an approach known to require orders of magnitude less training samples compared to prior methods [5]). We trained for 10 epochs on a Google CoLab standard GPU. We used 49 training samples (training took 30 seconds) and three samples for testing. ML predictions are fast (24 milliseconds per sample) and generate speeches that use similar syntactic patterns as ours. However, the ML-generated speeches are often redundant (multiple facts in the same speech referencing the same dimension) and tend to focus on overly narrow data subsets (e.g., cancellations in specific months instead of seasons). We created 900 AMT HITs to compare ML-generated speeches to the ones generated by our approach, according to the adjectives shown in Figure 11 and using the same experimental setup. The ML-generated speeches were consistently ranked lower (average rating below 5.92 for any adjective) compared to the proposed approach (average ratings 7https://simpletransformers.ai/)
of more than 7.28 for any adjective). ML-based summarization is showing promise but will likely require specialized variants for satisfactory performance.

IX. RELATED WORK

This work connects to prior work on generating speech summaries (“data vocalization”) [25, 27–29]. While prior work exploits sampling or incremental processing, we generate optimal speeches in a pre-processing step. We compare against a corresponding baseline in Section VIII-E.

Our work connects to work on voice and multi-modal interfaces [11, 22–24]. It differs by our focus on summarizing large data sets via voice output. Prior work on natural language to SQL interfaces [1, 2, 9, 10, 18, 32] addresses challenges in translating text to queries. Instead, our primary focus is on translating query results into concise text.

Our approach connects to prior work optimizing which visualizations or OLAP cubes to show to users [7, 12, 19–21, 30, 31]. Typically, this work optimizes at the granularity of plots, characterized by breakdown attributes and potentially data subsets. The search space in speech generation is larger as each fact can refer to different attributes and different data subsets. At the same time, the amount of information that can be transmitted via speech tends to be lower, motivating higher efforts in picking the right pieces of information to transmit. As opposed to non-speech sonifications [4, 17] (e.g., translating time series into a pitch), we focus on generating speech descriptions instead.

We can state our problem as summarizing [6] a large text, containing various facts, concisely. We try a simple variant in Section VIII-E. Our work relates to prior work on data-to-text generation. Early approaches use domain-specific rules [3, 13]. Recent work [16] exploits machine learning to learn summarizing data for certain domains, based on training samples. Most prior work focuses on generating multi-paragraph summaries that would be too long for voice output. Our problem model, maximizing utility by a bounded number of facts, is motivated by the conciseness constraints particular to voice summaries. Our method uses standard SQL operations and can be executed without moving data out of the database system. Furthermore, our approach can be applied without training samples or hand-crafted summarization rules.

X. CONCLUSION

We generate speech answers to voice queries efficiently via pre-processing. Our approach reduces run time overheads and was validated in a public deployment.

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