Sample-Based Cardinality Estimation in Full Outer Join Queries

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Abstract: Efficient query planning is crucial in large smart databases, where the complexity of joining tables can exceed a hundred. This paper addresses the pivotal role of cardinality estimation in generating effective query plans within a Database Management System (DBMS). Over the past decade, various estimation methods have been developed, yet their accuracy tends to decrease as the number of joined tables increases due to specific constraints and prerequisites. This paper introduces EVACAR, a novel cardinality estimation method rooted in the theory of approximate aggregate calculations. Unlike existing methods, EVACAR is designed to alleviate limitations associated with increasing table joins. Our method not only matches but often surpasses the accuracy of machine learning methods, achieving superior results for 75-88% of the evaluated queries (subplans). This advancement signifies a promising step towards optimizing query performance in large-scale smart databases.

1 INTRODUCTION

In the realm of modern Database Management Systems (DBMSs), the query optimizer serves as an indispensable component with the vital task of crafting top-tier SQL query execution plans. Cardinality estimation, known as CardEst, holds a key position in the optimization of queries. CardEst involves the proactive computation of record counts for all subplans within each query, providing the optimizer with the means to make informed choices regarding table join operations. The accuracy and efficiency of CardEst exert a profound influence on the quality of the resultant query plans. Recognizing its central importance in DBMSs, the CardEst problem has received extensive attention from both the academic and industrial communities.

Cardinality Estimation is conventionally characterized as a statistical challenge (Han et al., 2021). Consider a table, denoted as T, with attributes $A = \{A_1, A_2, ..., A_k\}$. Table T can represent either a solitary relational table or a composite of joined tables. Underlying this framework, the assumption prevails that each attribute, A_i, for every $1 \le i \le k$, falls into one of two categories: categorical, wherein values can be mapped to integers, or continuous. The comprehensive set of unique attribute values is signified as D_i. For any search query, Q, executed on table T, a canonical representation emerges: $Q=\{A_1 \in R_1 \wedge A_2 \in R_2 \wedge ... \wedge A_k \in R_k\}$, where $R_i \subseteq D_i$ serves as the specified constraints on attribute A_i (i.e., R_i acts as a filtering predicate). The cardinality, denoted as Card(T, Q), signifies the exact count of records within T that satisfy all the constraints imposed by Q. The fundamental objective of CardEst is to provide an accurate estimation of Card(T, Q) without the need to execute the query Q on the table T.

Within the existing literature, several CardEst methods can be categorized into three distinct classes:

1) Traditional Methods: These methods primarily rely on histograms and samples, finding widespread utilization in Database Management Systems

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(DBMSs). They often hinge on simplified assumptions and heuristic expertise. A range of enhancements has been proposed to bolster their performance, such as: multivariate histogram-based techniques (Gunopoulos et al., 2005), correcting and self-tuning histograms, incorporating query feedback (Khachatryan et al., 2015), approaches for updating statistical summaries within the DBMS (Stillger et al., 2001; Wu et al., 2018), sampling-based solutions including kernel density methods (Heimel et al., 2015; Kiefer et al., 2017), index-based methods (Leis et al., 2017), and random walk-based techniques (Li et al., 2016; Zhao et al., 2018). Some novel methodologies, like the sketch-based approach (Cai et al., 2019), explore innovative directions in CardEst.

2) Query-Based Machine Learning (ML) Methods: These methods strive to train models that can estimate Card(T, Q) directly from a query. Advanced ML techniques have emerged, featuring more complex models like deep neural networks (DNNs) (Kipf et al., 2019) or gradient boosted trees (Dutt et al., 2019).

3) Data-Driven ML Methods: These methods exhibit query-agnostic characteristics by treating each tuple in table T as a point drawn from the joint distribution $P_T(A) = P_T(A_1, A_2, ..., A_k)$. The probability corresponding to a query Q, $P_T(Q)$, can be formulated as $P_T(A_1 \in R_1 \wedge A_2 \in R_2 \wedge ... \wedge A_k \in R_k)$. The cardinality Card(T, Q) can be expressed as the product of $P_T(Q)$ and the size of table T. Consequently, the CardEst problem is reduced to modeling the Probability Density Function (PDF) $P_T(A)$ for the table T. A variety of ML-based models have been introduced for representing $P_T(A)$, including the deep autoregressive model (Yang et al., 2020), trained Probabilistic Graphical Models (PGMs) such as Bayesian Networks (BN) (Wu et al., 2020), a deep probabilistic model over database (RSPN) (Hilprecht et al., 2020), and a novel unsupervised graphical model (FSPN) (Zhu et al., 2021). These methods differ in their estimation approaches. Recent proposals aim to integrate diverse ML methods based on queries and data (Wu et al., 2021).

Currently, prevalent open-source and commercial DBMSs predominantly employ two traditional CardEst methods: PostgreSQL and MS SQL Server utilize histograms, while MySQL and MariaDB make use of sampling.

Nonetheless, existing cardinality assessment methods suffer from various limitations, including:

- Large evaluation times, scaling with the number of subplans in the original query.
- Limiting table joins to attribute equality.
- Joined tables shall form an acyclic graph.
- Simplified assumptions and "magic" numbers for complex table filtering conditions.
- Declining cardinality estimation accuracy as the number of joined tables increases.
- Lacking solid methodological justification, often relying on heuristics.

In addition to these limitations ML-based methods suffer from costly learning and tuning, selection-based methods require dependency on indexes for foreign key joins, while histogram-based methods neglect correlations between selectivity and join attributes.

This paper addresses these limitations by introducing a cardinality estimation method EVACAR grounded in the theory of approximate aggregate calculations (sum, count, etc.) (Zhang et al., 2016; Grigorev et al., 2021; Grigorev et al., 2022), effectively overcoming the shortcomings of existing approaches. EVACAR method was implemented, based on the random selection of small blocks of tables and their subsequent join. It is at least as accurate and efficient as data-based machine learning methods like BayesCard (Wu et al., 2020), DeepDB (Hilprecht et al., 2020), and FLAT (Zhu et al., 2021).

2 DEVELOPMENT OF METHODS FOR ESTIMATING THE CARDINALITY OF TABLE JOINS BASED ON SAMPLING FROM A FULL OUTER JOIN

In the realm of database query optimization, the meticulous estimation of cardinality plays a pivotal role in enhancing the efficiency and accuracy of query execution. In this section, we delve into a novel approach for estimating the cardinality of subqueries, shedding light on a practical methodology to navigate the complexities of large join operations.

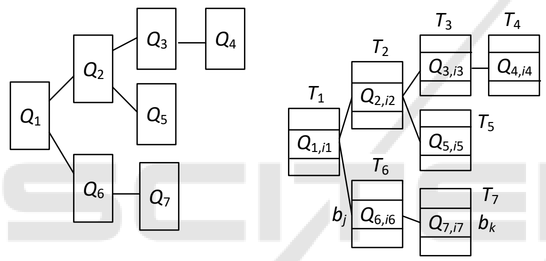
Method. Consider a set of subquery tables, denoted as $Q=(Q_1, Q_2, ..., Q_m)$, which partake in a join operation following the application of filtering conditions dictated by the SELECT statement. These tables are presented in a topological order as:

$$c(Q) = c(Q_1, \dots, Q_m)$$
$$= |Q_1 \bowtie Q_2 \dots \bowtie Q_m| = \sum_{i=1}^{F} \prod_{Q_j} 1_{Q_j,i} \,. \quad (1)$$

Where F represents the number of rows in a full outer join (FOJ), and value $1_{Q_j,i}$ equals 0 if, in the i-th row of FOJ = $(Q_1 ⟗ Q_2 ... ⟗ Q_m)$, the attributes of some Q_j are equivalent to the empty symbol $\emptyset$, signifying no join with the records from Q_j. Otherwise, it is equal to 1. Note: ⊳⊲ is an inner and ⊲⊳ is a full outer join (FOJ).

One of the key advantages of FOJ approach is its ability to be sequentially constructed, traversing through the tree structure of tables, including Q_1, Q_2, ..., Q_m, as indicated in Figure 1a. It achieves this by preserving joins solely between immediately adjacent related tables in structures that share the same tree, without necessitating verification of join conditions from preceding tables. For example, Q1⊲⊳Q2, Q2⊲⊳Q3, Q3⊲⊳Q4, Q2⊲⊳Q5, Q1⊲⊳Q6, and Q6⊲⊳Q7. The execution of expression (1) is achieved through navigation across these structures.

Implementing the FOJ method is inherently time-consuming and generating a uniform sample from the FOJ for approximate cardinality calculation (as in expression (1)) becomes a formidable challenge, especially in scenarios involving a significant number of tables within the join (Zhao et al., 2018).



a) b)

Figure 1: Implementation of a full outer join: a) without breaking up tables of subqueries Q_j into blocks, b) with the breakdown of the original tables T_j into blocks $Q_{j,i}$.

This paper puts forward a distinct approach, emphasizing the partitioning of source tables T_j into logical blocks of records, followed by the selection of those blocks where records meet the filtering conditions. These blocks, represented as $Q_{j,i}$, correspond to the i-th block of the j-th table, where j ranges from 1 to m, $\bigcup_i Q_{j,i} \subseteq T_j; \forall i_1, i_2 (Q_{j,i_1} \cap Q_{j,i_2} = \emptyset | i_1 \neq i_2)$ (Figure 1b demonstrates one block for each table). Subsequently, the cardinality estimate is expressed as:

$$c(Q) = \sum_{i_1,\dots,i_m} c(Q_{1,i_1}, \dots, Q_{m,i_m}) = \sum_{g=(i_1,\dots,i_m)} c_g. \quad (2)$$

In expression (2), the function c(x) adheres to the definition provided in (1). The summation spans across all feasible combinations of blocks $(Q_{1,i_1}, \dots, Q_{m,i_m}) \in R_1 \times R_2 \dots \times R_m$, where $R_j = \{Q_{j,i}\}_i$, set of blocks, $Q_{j,i}$, whose records conform to the filtering conditions.

However, it is important to acknowledge that the number of combinations $(Q_{1,i_1}, \dots, Q_{m,i_m})$ in expression (2) can become exceedingly large. To mitigate the computational burden, we harness the principles of approximate aggregate calculation theory (Zhang et al., 2016; Grigorev et al., 2021; Grigorev et al., 2022) for the summation in expression (2).

With some probability π_g, we select a combination of blocks $g = (i_1, ..., i_m)$ and build for them $\mathrm{FOJ}_g = \mathrm{FOJ}(Q_{1,i_1}, \dots, Q_{m,i_m})$. For this FOJ_g, we calculate the cardinality $c_g = c(Q_{1,i_1}, \dots, Q_{m,i_m})$ using the formula (1). We repeat samples g n times. Next, we estimate the cardinality using the formula:

$$c(Q,n) = \frac{1}{n} \sum_g \left(\frac{c_g}{\pi_g}\right). \quad (3)$$

As established in prior research (Grigorev et al., 2022), $c(Q,n) \xrightarrow[n\to\infty]{} c(Q)$ and $\forall n (E(c(Q,n)) = c(Q))$, where E is the sign of the mathematical expectation. The estimate (3) is unbiased for any n. Interestingly, these properties are valid for any probability distribution $\{\pi_g\}$ satisfying the conditions $\sum_g \pi_g = 1$ and $c_g > 0 \rightarrow \pi_g > 0$.

For the purpose of establishing confidence intervals around the estimate expressed in formula (3), we draw upon the Student's t-distribution with (n - 1) degrees of freedom:

$$\Delta = \frac{|c(Q) - c(Q,n)|}{c(Q)} \leq t_{n-1,\alpha} \sqrt{\frac{D(n)}{c^2(Q)} \cdot \frac{1}{(n-1)}}, \quad (4)$$

$$D(n) = \left(\sum_g \left(\frac{c_g}{\pi_g} - c(Q,n)\right)^2\right) / n. \quad (5)$$

Here, $c(Q) = E(c(Q,n))$ represents the mathematical expectation of $c(Q,n)$, in essence, the true cardinality value. The coefficient $t_{n-1,\alpha}$ is almost independent of n for n>121, and can be standardized to values 1.645, 1.960, or 2.576 when α assumes values of 0.9, 0.95, or 0.99, respectively.

It is imperative to acknowledge that the accuracy of the estimate $c(Q,n)$ is significantly influenced by the probability distribution $\{\pi_g\}$ (Grigorev et al., 2022).

Independent random sampling of blocks from $R_j = \{Q_{j,i}\}_i, j = 1 \dots m$. For ∀ g we have:

$$\pi_g = \prod_{j=1}^{m} (1/|R_j|). \quad (6)$$

Let us use the results of (Grigorev et al., 2022, formula (10)), and for a sufficiently large n rewrite (4):

$$\Delta \leq t_{n-1,\alpha} \sqrt{\left(\frac{N}{c^2(Q)} \sum_g c_g^2 - 1\right) \cdot \frac{1}{(n-1)}}, \; N = 1/\pi_g. \quad (7)$$

To simplify the analysis of the formula (7), assume that the cardinality value $c(Q)$ is uniformly distributed over K combinations (chains) $g=(i_1, ..., i_m)$. That is, with $c_g = c(Q)/K$, $|\{g\}|=K$. Then we get:

$$\Delta \le t_{n-1,\alpha}\sqrt{(\frac{N}{K}-1)\cdot\frac{1}{(n-1)}}. \quad (8)$$

It follows that the larger K, that is, the number of combinations g with non-empty block joins, the smaller the relative error Δ.

3 ANALYZING METHOD FOR CARDINALITY ESTIMATION IN JOIN OPERATIONS: COMPARATIVE INSIGHTS AND TRADE-OFFS

In this section, we present a cardinality estimation algorithm that can be employed to implement the Method, which was introduced in the preceding section.

Figure 2a illustrates the conventional scheme for constructing a query plan and executing a database management system (DBMS) query. During the plan construction phase, the methods for retrieving records from source tables are determined, and the records themselves are accessed during query execution.

In our Method, during the plan construction phase, we identify the methods for reading records from the source tables, and we read the records at this stage (Figure 2b). This approach enables more accurate estimation of the joined tables cardinality and leads to a more optimized query plan. The cardinality estimation Method implementation is detailed in Algorithm 1.

After executing Algorithm 1, the query optimizer accesses each subplan $S \subseteq Q$ to the card(S) function to evaluate cardinality. The card(S) function calculates the cardinality using the formula (3), where $Q:=S$, $(1/\pi_g) = N = \prod_{j:Q_j \in S} N_j$, $N_j=|R_j|$. c_g value is determined by navigating through the str_g structures, which are prepared by Algorithm 1. The calculation of c_g is carried out in accordance with the expression (1) for the FOJ_g. It can be considered that the query graph is cyclic (see below).

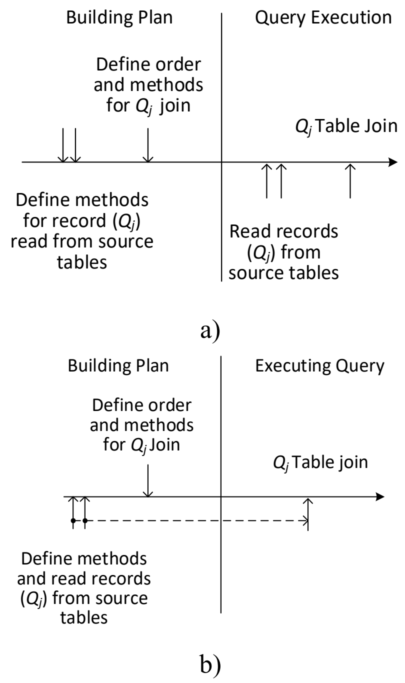


Figure 2: Reading records from source tables: a) query execution stage, b) plan building stage.

Algorithm 1: Independent Random Sampling of Blocks.

Input: 'm' subqueries (select) of the tables participating in the join; number of records in block L_j for *the* j-th subquery, $j=1...m$. Output: filled structures (str_g) for cardinality estimation.	
1	Opening cursors for all select subqueries.
2	Defining for each subquery Q_j: 1) number of records $\|Q_j\|$,2) number of logical blocks $N_j=\|Q_j\|/L_j= \|R_j\|$.
3	Cycle i=1... n // n - number of samples g
4	Determination of random block numbers $g=(i_1,...,i_m), i_j = N_j \cdot random$ [0,1].
5	Reading blocks $(Q_{1,i1},...,Q_{m,im})$ at offsets $(i_1,...,i_m)$ using cursors. $\|Q_{j,i}\| = L_j$.
6	Navigating the query tree and performing a complete outer join of blocks $Q_{1,i1}$, ..., $Q_{m,im}$ in accordance with the join condition; saving the compressed record numbers of child blocks in str_g structures (the structures are joined in accordance with the query tree, Figure 1b).
7	End of cycle by i
8	Freeing memory allocated for blocks ($Q_{1,i1},..., Q_{m,im}$).

Let us note some important advantages of the Method.

1) The blocks Q_{ji} are small, so their FOJ_g is fast.

2) Algorithm 1 does not access database indexes, so their presence is not required.

3) The condition for joining tables can be arbitrary, that is, it is not necessarily equality of keys.

4) The accuracy of cardinality estimation and the running time of Algorithm 1 are controlled by the number of samples n and the block sizes L_j. It is simple to organize parallel sampling and processing of blocks.

5) There are no problems with assessing the selectivity of the source tables since the records are joined after the subqueries are executed (Figure 2b).

6) The str_g structures are created once for the original query and then used to estimate the cardinality of all subplans $S \subseteq Q$ without additional samples.

But there are also disadvantages of the Method.

The sample size n is limited, since the cardinality assessment time should be short. From (8) follows that if there are many sequences of blocks (i_1, ..., i_m) give an empty join (K is small) and the product of the number of blocks N_j is large (N is large), then the error in cardinality estimation Δ can be large.

This disadvantage can be compensated by increasing the sample size n and parallel computation (3).

Let us highlight two important advantages of the proposed Method.

1) The cardinality of each subplan is estimated from the sample for the original query Q, meaning no additional overhead is required.

Algorithm 1 builds a tree of structures str_g, where the numbers of records of child blocks are stored in a compressed form after constructing the FOJ_g. Any subplan S is a subtree of the original query tree Q. Therefore, any subplan corresponds to a subtree in the tree of joined blocks and structures with record numbers (Figure 3).

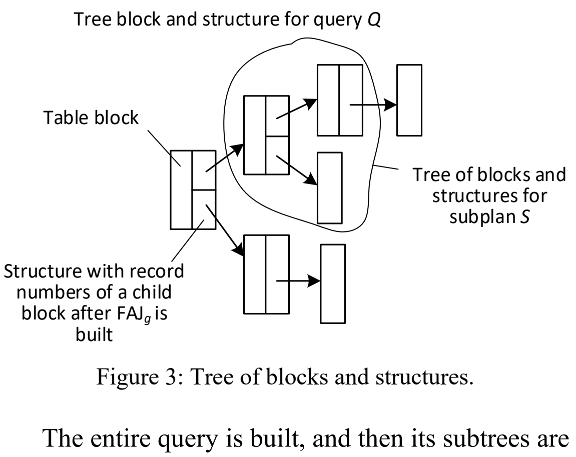


Figure 3: Tree of blocks and structures.

The entire query is built, and then its subtrees are used to evaluate the cardinality of any subplan (see Algorithm 1). Therefore, evaluation of subplans is performed quickly.

2) The join graph of query tables may contain loops.

Existing methods allow one to estimate the cardinality of joins for an acyclic query graph (Figure 1a). But in practice, queries with cyclic graph are used. Let us look at an example of such a request:

```
select * from A,B where A.a1=B.b1
and A.a2>
(select  avg(C.c3)  from  C  where
B.b2=C.c1 and C.c2=A.a3);
```
(9)

It can be noted that the join conditions (A.a1=B.b1) - (B.b2=C.c1) - (C.c2=A.a3) form a cyclic graph A-B-C-A. In addition, attribute a2 is compared with the result of another select query based on the inequality condition.

The main block includes join attributes: table block A - attribute a1, table block B - attributes b1 and b2, table block C - attribute c1 (not shown in Figure 4). Together with the main blocks, we read the attributes a2, a3 (for A) and c2, c31 (for C), which form additional blocks of tables A and C (Figure 4). The values c31 are obtained by grouping the records of block C by c1, c2.

As already mentioned, cardinality c_g in the formula (3) is evaluated with expression (1). An additional condition can be imposed on $1_{Qj,i}=1$. Let there be a join of records (i_A, i_B, i_C) of tables A, B, C. If for rows i_A and i_C of additional blocks of tables A and C an additional filtering condition is met (Figure 4), then only in this case we set $1_{Qj,i}=1$ and add 1 to the cardinality of the query.

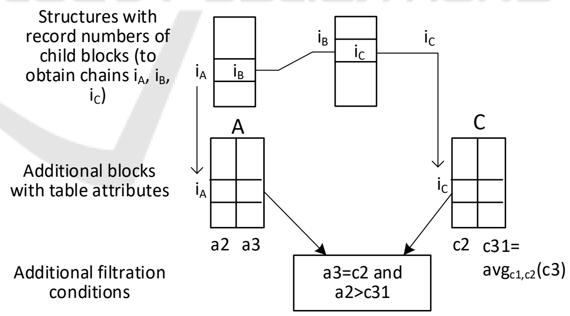


Figure 4: Scheme of additional filtering of record joins for example (9).

4 EXPERIMENTAL EVALUATION

In this chapter, we delve into the experimental results obtained from the implementation of the Method for estimating the cardinality of query subplans, ,which we refer to as EVACAR. The experiments were conducted on a virtual machine (VM) with Ubuntu

18.04.5 OS, powered by Intel Core i5 CPU, 4GB of RAM, and a 20GB disk. The EVACAR program was developed using the C language and compiled with the GCC compiler, resulting in a program size of 40 KB.

The primary dataset used for testing the Method was the STATS dataset (Han et al., 2021), specifically designed for evaluating Cardinality Estimation (CardEst) methods. This dataset exhibits intricate characteristics, including a high number of attributes, substantial distributed skewness, strong attribute correlation, and complex table join structures. Notably, some table key values can be linked to zero or one record in one table, while hundreds of records are associated with another table. We deployed the STATS database within the PostgreSQL 15 Database Management System (DBMS) and employed the libpq library to interface with the EVACAR prototype (Matthew et al., 2005).

One of the most challenging queries in the STATS dataset is Query Q57 (Han et al., 2021), involving six table joins and several filtering conditions (we will call them subqueries). The query, represented below, served as a focal point for our assessments.

```
SELECT COUNT(*) // Q57
FROM posts as p, postLinks as pl,
postHistory as ph, votes as v,
badges as b, users as u
WHERE p.Id = pl. RelatedPostId AND
u.Id = p. OwnerUserId AND u.Id = b.
UserId AND u.Id = ph. UserId AND
u.Id = v.UserId
AND p.CommentCount>=0 AND
p.CommentCount<=13
AND ph.PostHistoryTypeId=5 AND
ph.CreationDate<='2014-08-13
09:20:10'::timestamp
AND v.CreationDate>='2010-07-19
00:00:00'::timestamp
AND b.Date<='2014-09-09
10:24:35'::timestamp
AND u.Views>=0 AND u.DownVotes>=0
AND u.CreationDate>='2010-08-04
16:59:53'::timestamp AND
u.CreationDate<='2014-07-22 15:15
:22'::timestamp;
```

(10)

Running Query Q57 on the virtual machine within the PostgreSQL environment took approximately 17 minutes (measured considering interruptions by the host machine). In terms of pure virtual machine time, the query execution ran roughly 7 minutes, ultimately yielding 17,849,233,970 records.

Table 1 below presents the characteristics of the tables involved in Query Q57.

In the assessments, the 'users' table (No. 1 in Table 1) was designated as the root table for evaluating the cardinality of query (10) and its subplans using the Method, as defined in Algorithm 1 (Section 3). Across all experiments, the product of the number of blocks was maintained at $N = \Pi_{j=1\ldots6} N_j = 10^5$ (as indicated in Table 1), and the number of samples (g) was set at n = 10. The experiments aimed to investigate the impact of the number of blocks (1, 2, 4) in the root subquery on the accuracy and time required for cardinality estimation, as denoted by options 1, 2, and 3 in Table 1.

To evaluate accuracy, we employed the q-error estimate, as defined in (Leis et al., 2015):

$$q - error = \begin{cases} \frac{c_{estimate}}{c_{true}}, IF c_{estimate} \geq c_{true}, \\ -\frac{c_{true}}{c_{estimate}}, IF c_{true} > c_{estimate}, \end{cases} \quad (11)$$

where c_{true} represents the true cardinality value, and c_{estimate} signifies the estimated cardinality value.

Table 2 outlines the results of the experiments and presents confidence intervals for the q-errors of the EVACAR method. In Table 2, the second column signifies the subplan tables, each denoted by their respective numbers as presented in Table 1. For instance, subplan {1,5} represents a join of subqueries from the 'users' and 'posts' tables, while subplan {1,2,3,4,5,6} comprises all subqueries of the original query (10). The third column provides the actual cardinality values of these subplans. Columns 4 to 6 depict the q-errors, representing the discrepancies between the true and estimated cardinality values when using the BayesCard (Wu et al., 2020), DeepDB (Hilprecht et al., 2020), and FLAT (Zhu et al., 2021) methods.

Columns 7 to 12 present the medians (M) and the boundaries of the 95% confidence intervals for q-errors across the examined options 1, 2, and 3. These boundaries are derived from the results of 50 runs of Algorithm 1 (see the Method in Section 2) for each option. A specific notation system is employed for these options, formatted as "n10-uX-vY," where n = 10 signifies the number of samples g, while X and Y represent the number of blocks associated with the 'users' and 'votes' subquery tables, respectively.

An intriguing observation in Table 2 is that the lengths of the confidence intervals tend to increase with the number of blocks in the root subquery, ranging from 1 to 4.

This phenomenon can be attributed to the substantial distributed skewness within the STATS dataset. This is explained by the fact that due to the strong distributed asymmetry of the STATS data set, the number of combinations g with non-empty block joins decreases, the N/K ratio in (8) increases, and the error Δ also increases.

Table 1: Characteristics of Query Tables.

No.	Table name	Number of records in the database	Number of records returned by subquery	Block size (number of records) and number of blocks N_j in experimental variants					
				Option 1		Option 2		Option 3	
				Size	N_j	Size	N_j	Size	N_j
1	users	40,325	36,624	37,000	1	18,400	2	9,200	4
2	badges	79,851	79,400	8,000	10	8,000	10	8,000	10
3	postHistory	303,187	66,973	6,700	10	6,700	10	6,700	10
4	votes	328,064	327,982	3,300	100	6,600	50	13,200	25
5	posts	91,976	91,489	9,200	10	9,200	10	9,200	10
6	postLinks	11,102	11,102	11,102	1	11,102	1	11,102	1

Table 2: Experimental Results and Confidence Intervals for q-errors of the EVACAR Method.

#	Subplan queries	Postgresql (c_{true})	q -errors existing methods for assessing cardinality			Median (M) and 95% confidence intervals (n.g. ÷c.g.) q -errors of the new cardinality estimator (EVACAR)					
			bayescard	deepdb	flat	Option 1 Q57-n10-u1-v100		Option 2 Q57-n10-u2-v50		Option 3 Q57-n10-u4-v25	
						M	95%	M	95%	M	95%
1	2	3	4	5	6	7	8	9	10	11	12
1	{1.5}	79,662	1.0	1.5	-1.0	0.1	-1 .1 ÷1.1	1.0	- 2.0 ÷1.5	-1.1	- 2.2 ÷1.9
2	{1,3}	58,416	-1.0	2.4	-1.1	0.1	-1 .1 ÷1.1	1.2	- 2.0 ÷1.4	0.0	- 2.2 ÷1.8
3	{1,4}	31,148	1.1	1.0	-1.1	0.0	-1.4 ÷1.2	1.0	- 2.0 ÷1.5	0.0	- 2.3 ÷1.7
4	{1,2}	71,547	1.0	-1.8	-1.0	0.0	-1.1 ÷1.1	1.0	- 3.4 ÷1.4	-1.1	- 3.5 ÷2.0
5	{1,5,6}	8,909	3.1	**15.3**	**8.6**	-1.1	-1.7 ÷1.4	1.1	- 3.9 ÷1.9	-1.1	- 4.2 ÷2.4
6	{1,5,3}	18,631,047	-1.0	1.0	-1.4	-1.0	-1.8 ÷1.4	1.0	- 3.0 ÷1.6	-1.1	- 4.6 ÷2.0
7	{1,5,4}	2,409,832	-1.2	-1.1	-1.4	0.0	-2.3 ÷1.8	1.1	- 4.1 ÷2.5	-1.1	- 7.2 ÷2.4
8	{1,5,2}	2,954,776	-1.1	1.1	-1.2	-1.0	-1.3 ÷1.4	1.1	- 1.9 ÷2.1	-1.1	- 3.5 ÷2.9
9	{1,3,4}	5,699,168	-1.2	-1.1	-1.6	-1.0	-1.7 ÷1.5	-1.1	- 3.2 ÷2.0	-1.4	- 6.3 ÷3.4
10	{1,3,2}	5,385,663	-1.0	-1.2	-2.2	0.0	-1.4 ÷1.3	1.1	- 4.2 ÷1.8	-1.1	- 6.1 ÷3.2
11	{1,4,2}	858,085	1.0	-2.1	-1.3	-1.1	-2.1 ÷1.5	1.0	- 3.5 ÷1.8	-1.1	- 4.7 ÷2.1
12	{1,5,6,3}	352,054	**18.2**	**19.0**	**38.9**	-1.2	-2.2 ÷1.8	-1.1	- 3.4 ÷3.0	-1.3	- 5.6 ÷2.2
13	{1,5,6,4}	130,192	1.4	**22.2**	**13.2**	-1.0	-3.2 ÷2.3	-1.1	- 3.4 ÷4.7	-1.3	- 9.5 ÷2.3
14	{1,5,6,2}	167,260	1.3	**31.2**	**15.3**	-1.1	-2.1 ÷2.1	1.1	- 4.1 ÷3.3	-1.5	- 8.0 ÷4.0
15	{1,5,3,4}	5,383,224,109	-1.2	-1.2	-1.8	-1.1	-4.5 ÷2.0	-1.1	- 4.6 ÷3.1	-2.0	- 17.7 ÷4.1
16	{1,5,3,2}	4,664,599,508	-2.2	-2.2	-2.4	-1.1	-2.3 ÷1.7	1.1	- 2.3 ÷2.0	-1.4	- 7.2 ÷3.6
17	{1,5,4,2}	488,657,174	-1.4	-1.4	**-8.6**	-1.1	-3.1 ÷2.3	-1.2	- 5.6 ÷2.6	-1.1	- 8.4 ÷5.0
18	{1,3,4,2}	1,389,418,172	-1.2	-1.2	**-8.2**	-1.1	-2.6 ÷1.8	-1.2	- 3.4 ÷2.5	-1.4	- 12.5 ÷4.1
19	{1,5,6,3,4}	67,575,395	**23.1**	**23.1**	**44.2**	-1.2	**-6.9 ÷5.1**	-1.5	**- 8.6** ÷6.0	-2.7	- 28.8 ÷7.7
20	{1,5,6,3,2}	58,582,347	-3.6	-3.6	3.4	-1.2	-4.5 ÷2.3	-1.0	- 6.1 ÷4.1	-1.9	- 8.6 ÷3.3
21	{1,5,6,4,2}	9,726,255	-1.7	-1.9	-1.6	-1.3	-4.8 ÷4.8	-1.1	- 4.8 ÷3.5	-1.5	- 13.4 ÷7.2
22	{1,5,3,4,2}	1,375,709,726,310	-2.8	-2.8	-3.3	-1.1	-5.7 ÷3.4	-1.1	**- 7.0** ÷4.8	-2.0	- 19.1 ÷9.0
23	{5,6}	10,959	1.4	2.2	1.0	-1.0	-1.6 ÷1.5	-1.0	- 2.1 ÷1.4	0.0	- 1.8 ÷1.6
24	{1,2,3,4,5,6}	17,849,233,970	**-7.2**	**-7.2**	2.4	-1.5	**-9.8** ÷4.4	-1.6	**- 14.7 ÷9.8**	-3.4	-62.6 ÷12.7

The work (Han et al., 2021) highlights that data-driven machine learning methods founded on Probabilistic Graphical Models (PGMs) deliver improved accuracy and performance in testing scenarios. These methods strike an optimal balance between the precision of cardinality estimation and the assumption of parameter independence. Consequently, this study undertook a comparison of such methods, specifically BayesCard, DeepDB, and FLAT. It is important to note that comparing these methods posed a challenge because the source material (Han et al., 2021) only provides random cardinality values for subplans.

To facilitate the comparison, q-errors were computed (as depicted in columns 4-6 of Table 2) and contrasted with the confidence intervals of q-errors pertaining to options 1, 2, and 3. To quantify this comparison, a metric was introduced:

$$d = \frac{max(\,|\mathrm{LL}|,\mathrm{UL}) - |e|}{|e|}. \qquad (12)$$

Within this context, LL (Lower Limit) and UL (Upper Limit) represent the lower and upper bounds of the confidence interval for the q-error during the estimation of subplan cardinality, as delineated in columns 8, 10, and 12 of Table 2. Meanwhile, max(|LL|, UL) signifies the maximum q-error observed for the newly developed EVACAR method at a confidence level of 0.95, referred to as the maximum q-error. Additionally, |e| corresponds to the absolute value of the q-error encountered when estimating subplan cardinality using any of the compared methods.

When assessing the new EVACAR method, the metric 'd' (12) was employed to discern its performance. This metric takes into consideration the relationship between the maximum q-error, observed with EVACAR, and the absolute q-error when using one of the compared methods.

Here is the interpretation of the metric 'd' in different scenarios:

1) $d \le 0$ signifies that the new EVACAR method surpasses the other methods under comparison. This outcome is deduced from the maximum q-error being smaller than the absolute q-error (|e|).
2) $0 < d \le k$, it implies that the maximum q-error of EVACAR is comparable to |e| at a specified level 'k'. In such cases, the deviation from |e| is bounded by $k \cdot |e|$.
3) $d > k$, it indicates that the maximum q-error of EVACAR is not comparable to |e| at a level 'k'. In this scenario, the deviation from |e| is higher than $k \cdot |e|$.

For each of the three options (1, 2, and 3), the metric 'd' was calculated for the BayesCard (b), DeepDB (d), and FLAT (f) methods, in conjunction with the subplans outlined in Table 2. The distribution of the number of subplans categorized by their 'd' values is visually depicted in Figure 5. Utilizing this data, a comparative analysis was performed to evaluate the accuracy of cardinality assessment for the methods under consideration. This comparison is presented in terms of the percentage of subplans, as detailed in Table 3.

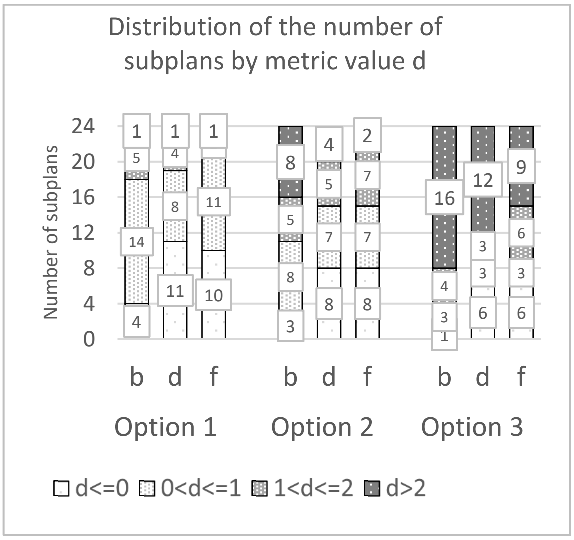


Figure 5: Subplan number by 'd' value distribution.

Table 3: Comparison of methods by accuracy (in % of the number of subplans in Figure 5).

			BayesCard (b)	DeepDB (d)	FLAT (f)
Option 1	more precisely	1	17	46	42
	q - error is comparable at level "1"	2	58	33	46
	q - error is comparable at level "2"	3	21	17	8
Option 2	more precisely	4	13	33	33
	q - error is comparable at level "1"	5	33	29	29
	q - error is comparable at level "2"	6	21	21	29
Option 3	more precisely	7	4	25	25
	q - error is comparable at level "1"	8	13	13	13
	q - error is comparable at level "2"	9	17	13	25

The analysis of Table 3 reveals that for option 1, the EVACAR method consistently outperforms the compared methods in terms of precision. Its maximum q-error is on par with these methods at a confidence level of "1" for a substantial majority of the evaluated subplans, ranging between 75% and 88% (cumulative sum of lines 1 and 2 for Option 1). Furthermore, at a confidence level of "2," the EVACAR method demonstrates superior accuracy, aligning with 96% of the subplans (sum of lines 1, 2, and 3 for Option 1).

Table 4 and Table 5 present a detailed analysis of the computational and temporal characteristics of the established EVACAR method in comparison to the existing cardinality estimation techniques as outlined in (Han et al., 2021).

Table 4: Space-time characteristics of compared cardinality estimation methods.

	BayesCard	DeepDB	Flat
Average cardinality estimation time per subplan request, ms	5.8	87	175
Model size, MB	5.9	162	310
Training time, min	1.8	108	262
Model update time when inserting 10^6 records into the DB, sec	12	248	360

The experiments featured in (Han et al., 2021) were executed on two distinct Linux servers, each tailored for specific purposes. The first server was equipped with 32 Intel(R) Xeon(R) Platinum 8163 processors, operating at 2.50 GHz, and boasted a Tesla GPU V100 SXM2 alongside 64 GB of RAM, primarily designated for model training. In contrast, the second server relied on 64 Intel(R) Xeon(R) E5-2682 processors with the same clock speed, 2.50 GHz, for the cardinality estimation tasks related to PostgreSQL. It's important to emphasize that the experiments involving the EVACAR method were conducted on a virtual machine (VM) featuring a single Intel CPU Core i5 processor with 4GB of RAM.

When we focus on option 1, the EVACAR method emerges as remarkably time-efficient when compared to the Flat method for individual subplan requests. Specifically, it takes only 92 ms to process a subplan request, whereas the Flat method consumes nearly double the time, clocking in at 175 ms per request. To provide a more granular perspective, EVACAR dedicates a mere 90 ms to assessing the cardinality of 24 subplans out of a total 2,200 ms, with the remainder of the time predominantly allocated to hashing table blocks.

Notably, the EVACAR method exhibits a substantially lower memory consumption in terms of RAM when contrasted with DeepDB and Flat. In the context of the first option, EVACAR utilizes a mere 13.1 MB of memory, significantly less than DeepDB's 162 MB and Flat's 310 MB. It is essential to acknowledge that, by configuring EVACAR to constrain the maximum number of records within a block to 65,536 records (unsigned short), the allocated memory footprint can be further reduced to just 7.1 MB for option 1.

An additional distinguishing feature of the EVACAR method is its independence from the need for model training and updates. Conversely, DeepDB and Flat involve substantial time and computational resources for these training and model updating processes, a distinction highlighted in Table 4.

5 CONCLUSION

This research highlights the potential of employing a randomized selection of small blocks and conducting full outer joins to leverage the theory of approximate aggregate calculations (e.g., sum, count) for estimating the cardinality of all subplans within the original query. To address the limitations and shortcomings of existing approaches, we have developed a cardinality estimation method and an accompanying algorithm.

Table 5: Space-time characteristics of the developed cardinality estimation method EVACAR.

Parameter	Unit	EVACAR Characterisitcs per variant		
		1: Q57-n10-u1-v100	2: Q57-n10-u2-v50	3: Q57-n10-u4-v25
1. Total VM time (gprof)	ms	2,200	3,000	5,800
2. Time for one subplan request (1/24)	ms	2,200/24= 92	3,000/24= 125	5,800/24=242
3. Cardinality calculation per subplan (1/24) of VM time	ms	90 /24=3.8	60/24=2.5	50/24=2.1
4. Memory capacity (valgrind), n =10	MB	1.1(blocks)+1.2*n= 13.1	0.8+ 0.6*10=6.8	0.8+ 0.3*10=3.8
5. Memory (valgrind) (max. block size 65,536 rec. (ushort))	MB	1.1+1.2/2*n =7.1	0.8+ 0.6/2*10=3.8	0.8+ 0.3/2*10=2.3
6. Memory capacity for one request (1/24) and one sample from the FOJ (1/n =1/10)	MB	(1.1+1.2)/ 24= 0.1	(0.8+0.6)/ 24= 0.06	(0.8+0.27)/24= 0.04
7. Memory for one request (1/24) and one sample from the FOJ (1/ n =1/10) (max. block size 65,536 records)	MB	(1.1+1.2/2)/24=0.07	(0.8+0.6/2)/24= 0.05	(0.8+0.3/2)/24= 0.04

The method offers the advantage of block selection after the execution of subqueries from the original query, eliminating the need for a priori analysis of filtering conditions. This method allows for arbitrary conditions when joining tables, without a strict requirement for attribute equality. Consequently, this opens up the possibility of more precise cardinality estimation in scenarios involving a larger number of table joins. This is particularly significant since high-performing data-driven machine learning (ML) methods for CardEst tend to experience diminishing performance and accuracy as the number of joined tables increases. Developed method for cardinality estimation also accommodate the presence of cycles within the query graph.

We implemented an EVACAR method and conducted comparative evaluations with modern ML methods such as BayesCard, DeepDB, and FLAT using STATS test. The experimental results unequivocally affirm the efficacy of the EVACAR method. Our future work is focused on the estimation error (3) reduction by finding a probability distribution for choosing a combination of blocks that is different from the uniform distribution.

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