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A Causal Model of DBMS Suboptimality

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A Causal Model of DBMS Suboptimality

The query optimization phase within a database management system (DBMS) ostensibly finds the fastest query execution plan from a potentially large set of enumerated plans, all of which correctly compute the specified query. Occasionally the cost-based optimizer selects a slower plan, for a variety of reasons. We introduce the notion of *empirical suboptimality* of a query plan chosen by the DBMS, indicated by the existence of a query plan that performs more efficiently than the chosen plan, for the same query. From an engineering perspective, it is of critical importance to understand the prevalence of suboptimality and its causal factors.

We propose a novel structural causal model to explicate the relationship between various factors in query optimization and empirical suboptimality. Our model associates suboptimality with the factors of complexity of the schema, data, query, and optimizer and concomitant interactions among the components of the optimizer. This model induces a number of specific hypotheses that were subsequently tested on multiple DBMSes.

Through a series of experiments that examine the plans for thousands of queries run on one hundred thousand query/cardinality combinations on four popular DBMSes, we observe that the dependent construct of empirical suboptimality prevalence correlates positively with (a) DBMS complexity, (b) schema complex, (c) data complexity, and (d) query complexity, providing empirical support for this model. These nine factors explain in concert over half of the variance of suboptimality, across four disparate DBMSes. Thus, it is the common aspects of these DBMSes that predict suboptimality, *not* the particulars embedded in the inordinate complexity of each of these DBMSes.

An implication of this causal model is that as query evaluation operators are added to a DBMS, the prevalence of slower queries will grow. Through a novel experiment that examines the plans on the aforementioned query/cardinality combinations, we present evidence for a previously-unknown upper bound on the number of operators a DBMS may be able to support before performance suffers. We show that this upper bound may have already been reached by one or more extant DBMSes.

This paper thus provides a new methodology to study mature query optimizers, that of empirical generalization, proposes a novel causal model for empirical query suboptimality, and demonstrates an upper bound that may have already been encountered, with implications for fundamental improvements of those cost-based query optimizers.

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1. INTRODUCTION

Database management systems (DBMSes) underlie information systems and hence optimizing their performance is of critical importance. A relational DBMS's cost-based query optimizer plays an important role, ostensibly finding a fast query execution plan from a potentially large set of possible plans, all of which correctly compute the submitted query, using a cost model that references properties of the underlying relations. But what if the optimizer *doesn't*: what if it selects a slow plan?

This paper provides a thorough investigation into DBMS suboptimality: when the DBMS chooses a slower plan over a faster plan for a given query. We systematically examine the factors influencing the number of suboptimal queries. There could be multiple causes of the suboptimality. One possible cause could be some peculiarity within the tens of thousands of lines of code of that query optimizer. Another possible cause could be the query's complexity. Prior research in other domains shows that increasing complexity negatively influences performance [Campbell 1988; Moody 1998]. A third possible reason could be some fundamental limitation *within the general architecture of cost-based optimization* that will always render a number of queries suboptimal.

To better understand the impact of different factors on suboptimality of query performance and the relationship between operators, especially in a dynamic environment, an experimental approach is needed. Based on existing research and general knowledge of DBMSes, we propose an innovative predictive model of suboptimality in query evaluation. From this point on, by "suboptimality" we mean specifically "empirical suboptimality", indicated by the presence of another plan that can be empirically determined to be faster than the plan that was chosen by the query optimizer. Indeed, as we will elaborate in Section 5.6, where we provide a specific operationalization of this notion, empirical suboptimality is an *ordinal variable*, indicating the degree to which plans across a range of table cardinalities are slower than other (empirically-identified) plans. This contrasts with the conventional notion of query plan suboptimality, which is a binary *categorical variable* associated with a particular cardinality: a plan is either optimal (the best-performing plan) or it is suboptimal.

We employ an experimental methodology on a collection of DBMSes as subjects to test our hypotheses with respect to factors influencing suboptimality, utilizing empirical data collected over a cumulative 16,000 hours (over two years) of query executions. Our research falls within creative development of new evaluation methods and metrics for artifacts, which were identified as important design-science contributions [Hevner et al. 2004].

The key contributions of this paper are as follows.

— We use an innovative *methodology* that treats DBMSes as experimental subjects.
— We find that for a surprisingly large portion of queries, the plan chosen by the query optimizer is not the best plan, for some cardinality of the underlying tables.
— We propose a *predictive model* for DBMSes to better understand the factors causing suboptimality.
— We test the six quite specific hypotheses that arise from that model across a wide range of DBMSes, queries, and data, showing through correlational and regression analyses that four hypotheses are strongly supported, one is weakly in the other direction, and the sixth is partially supported, lending credibility to our particular model.
— Through an innovative analysis, we track the net cumulative benefit of a succession of operators added to the DBMS, and show (a) that there is a *limit* to the number of relational operators that a DBMS can accommodate before slower plans start to dominate and (b) that one or more extant relational DBMSes may have already reached that limit.
— The predictive model and these experimental results suggest several specific engineering directions.
— The model and analyses presented here taken as a whole imply that a new approach to query optimization, fundamentally different from the cost-based approach utilized over the last forty years, may be required to get past the fundamental limitation uncovered in this research.

This paper takes a scientifically rigorous approach to an area previously dominated by the engineering perspective, that of database query optimization. Our goal is to understand cost-based query optimizers as a *general* class of computational artifacts and to come up with insights and ultimately with predictive theories about how such optimizers, again, as a general class, behave. These theories can be used to further improve DBMSes through engineering efforts that benefit from the fundamental understanding that the scientific perspective can provide.

One might ask, shouldn't the task of optimizing queries be left to DBAs? In databases, and especially in data warehouses, the number of users writing and running queries has been growing exponentially. This growth is aided, in part, by the drag and drop query tools provided by the different systems. For example, subject areas allow business users to write queries without knowing anything about the underlying database structure. This, coupled with constantly growing data presents new challenges for tuning. For example, a large data warehouse we are familiar with runs about 30,000 queries on a daily basis. Also, tuning a subject area or tables for one group of queries can negatively impact the performance of other queries. Query optimization experts often take hours to tune and test existing canned queries; the amount expended on this one system for manual query optimization approaches $100K/year. Therefore, we argue that it is important to understand how existing query optimizers can be further improved, and indeed, whether fundamental limitation inherent in these optimizers exist and whether such limitations are indeed already being encountered.

We focus here on the effectiveness of query optimization. The query optimization phase within a DBMS ostensibly finds a fast query execution plan, drawn from a potentially large set of enumerated plans, all of which correctly compute the specified query. (The term “query optimizer” is thus aspirational rather than realistic: the goal of the optimizer isn’t really to find the best plan, but rather to avoid the worst plans.) However, this intermediate goal might not always be realized in practice, for several possible reasons. One is that it may not be practical to enumerate all possible plans, and so the fastest plans, or even the fast plans, may not be considered. Also, because the optimizer chooses a plan based on its estimated query execution time, if that estimate is of, the optimizer may instead choose a different, less efficient plan. From both a scientific perspective and an engineering perspective, it is of critical importance to understand the phenomenon of suboptimality.

We study these aspects across DBMSes to identify the underlying causes. We have developed a predictive causal model that identifies five constructs that may play a role in suboptimality. The ultimate goal is to *understand* a component within a DBMS, its cost-based optimizer, through the articulation and empirical testing of a general scientific theory.

In Section 3 we briefly summarize the vast amount of related work in query optimization to establish the technical basis for our study. The following section introduces the methodology we will follow, that of *empirical generalization* [Cohen 1995]. We present in Sections 4 and 5 a predictive, causal model of suboptimality and state six specific hypotheses derived from that model. We then test these hypotheses across a number of queries, data, and cardinalities, whose results provide strong support for the validity of the proposed model. These are the first scientific results that we are aware of that apply *across* multiple DBMSes, rather than on a single, specific DBMS or on a specific algorithm. In Section 7 presents a follow-on analysis that uncovers a previously-unknown fundamental limit to the number of operators that a cost-based optimizer can support, and shows that this limit may have already been reached by one or more extant DBMSes. We explore in Section 8 implications of the model for research in engineering more efficient DBMSes.

2. MOTIVATION

Consider a simple select-project-join (SPJ) query, with a few attributes in the SELECT clause, a few tables referenced in the FROM clause, and a few equality predicates in the WHERE clause. This query might be an excerpt from a more complex query, with the tables being intermediate results.

```
SELECT t0.id1, t0.id2, t2.id4, t1.id1
FROM ft_HT3 t2, ft_HT2 t1, ft_HT1 t0
WHERE t2.id4=t1.id1 AND t2.id1=t0.id1
```

The optimizer generates different plans for this query as the cardinality of the `ft_HT1` table varies, an experiment that we will elaborate later in depth.

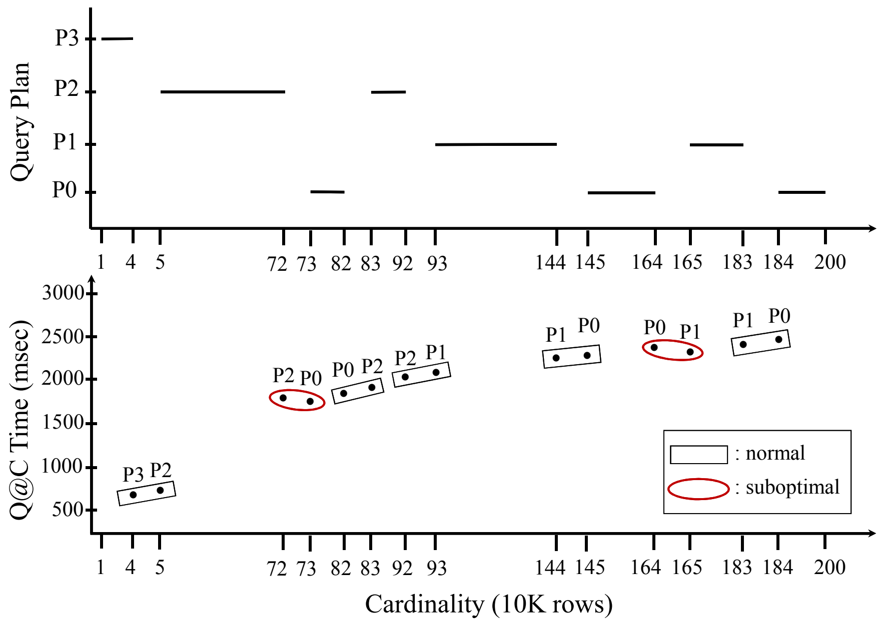


Fig. 1. An Example of Suboptimality and Fluttering

The upper graph in Figure 1 represents the plans chosen by a common DBMS as the cardinality of `FT_HT1` decreases from 2M tuples to 10K tuples in units of 10K tuples. The x-axis depicts the estimated cardinality and the y-axis a plan chosen for an interval of cardinalities. So Plan P0 was chosen for 2M tuples, switching to Plan P1 at 1,830,000 tuples, back to Plan P0 at 1,640,000 tuples, and so on, through the plan sequence P0, P1, P0, P1, P2, P0, P2, and finally P3 at 40,000 tuples.

The lower graph in Figure 1 indicates the query times executed at adjacent cardinalities, termed the "query-at-cardinality" (Q@C) time, when the plan changed. For some transitions, the Q@C time at the larger cardinality was also larger, as expected. But for other transitions, emphasized in red ovals, the Q@C time at the larger cardinality was *smaller*, such as the transition from plan P1 at 1,650,000 to P0 at 1,640,000 tuples: the plan at the higher cardinality actually took *less* time than the plan at the lower cardinality. Such *change pairs*, where the time at the higher cardinality is shorter, identify suboptimal plans. For the change pair at 720,000 tuples, P0 required 2.35sec whereas P1 at a larger cardinality required 2.41sec (as is common, the plan at the higher cardinality takes more time). This query exhibits seven plan change pairs, two of which are suboptimal.

This query also illustrates an interesting phenomenon, in which the optimizer returns to an *earlier* plan. Sometimes the optimizer starts oscillating between two plans, sometimes even switching back and forth when the cardinality estimate changes by a small percentage. The example query showed returning to P0 twice and to P1 and to P2 each once. We call this phenomenon, in which the query optimizer returns to a previous plan, "query optimizer flutter", or simply "flutter".

We have found through our experiments that flutter and suboptimality are all around us: *every* DBMS that we have examined, including two open source DBMSes and two proprietary DBMSes, covering much of the installed base worldwide, exhibit these phenomena, even for very simple queries. In the Confirmatory Experiment de-

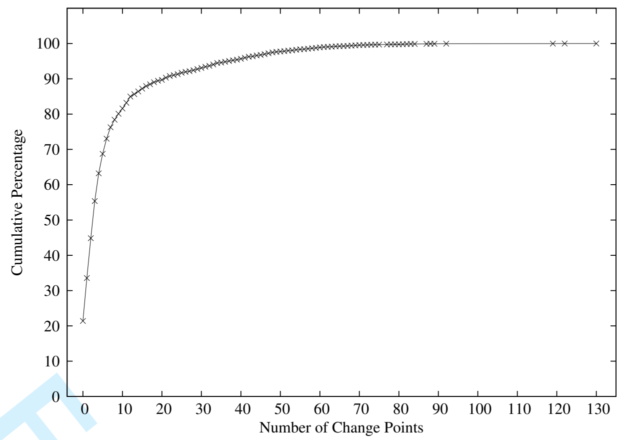


Fig. 2. Cumulative percentage of queries exhibiting the indicated number of plan changes

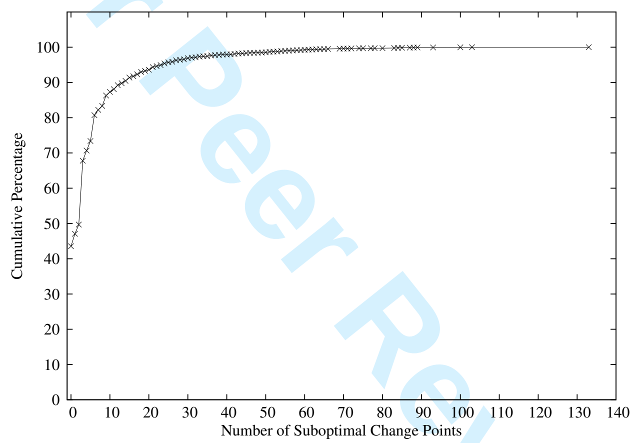


Fig. 3. Cumulative percentage of queries exhibiting the indicated number of changes to a *suboptimal* plan

scribed in detail in Section 6.3, we started with 6,967 query instances (a query run on a specific DBMS) after an extensive query measurement protocol [Currim et al. 2013; Currim et al. 2016] applied its extensive sanity checks. While about 20%, or 1,491, of these query instances contained only one plan, a few of the other query instances switched plans at almost every change in cardinality (we varied the cardinality in increments of 10K tuples, a total of 200 cardinalities): see Figure 2. Slightly over half, or 3,933 query instances, exhibited suboptimality somewhere along those 200 cardinalities; a few had many changes to a plan that was in fact suboptimal, as indicated in Figure 3, across all four DBMSes considered.

One oft-stated observation is that the role of query optimization is not to get the *best* plan, but rather to get a plan that is acceptably good. (Thus, the very term "query optimizer" is aspirational rather than accurate.) Figure 4 shows the cumulative distribution of the relative amount of suboptimality (where an x-value of 100 denotes that the query ran 100% slower than the optimal query, that is, twice as long). The good news is that 2,738 query instances, or 67% of the suboptimal queries, exhibited only a small degree of suboptimality: less than 30%. The challenge is that over fifth of all

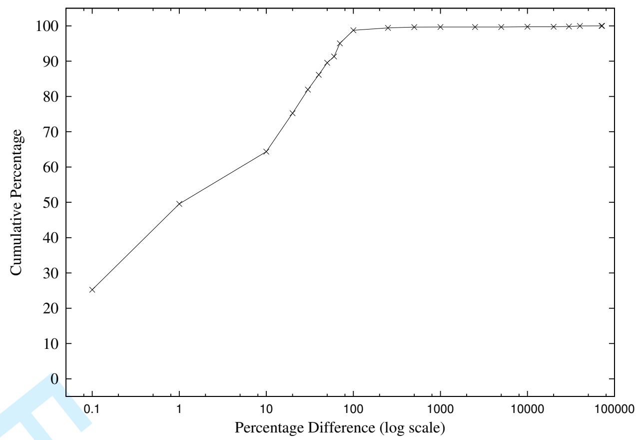


Fig. 4. Cumulative percentage of queries exhibiting the indicated percentage relative suboptimality

queries (1,355) exhibited a significant amount of suboptimality ($\geq 30\%$). The relative slowdown can thus be quite large for some queries.

We started with 7,640 query instances, each of which is a particular query running on a particular DBMS, cf. Experiment 7 of Table I in Section 6.3. After our protocol, we were left with 6,967 query instances, of which 5,475 had at least one change pair, so those are the ones we consider further. Of those, 1,382 had *no* suboptimality, so 4,093 (75%) had some suboptimality.

1,951 (36% of the query instances with a change pair) have the higher cardinality running at least 20% faster than the lower cardinality. That means that 2,142 query instances (slightly over half of the suboptimal queries) were barely suboptimal (<20% slower) and about a third (1,355) were considerably suboptimal (where the higher cardinality ran at least 30% faster than the lower cardinality).

We emphasize four important points.

— First, we used a sophisticated query measurement methodology that reduces the measurement variance, so that the query plans we identify as suboptimal definitely are so.
— Second, these results are over four DBMSes, and thus, such phenomena are not dependent on a particular implementation of cost-based optimization. Rather, they seem to be common to *any* cost-based optimizer, independent of the specific cardinality estimation or plan costing or plan enumeration algorithm or implementation.
— Third, suboptimal plans are *not* the result of poor coding or of inadequate algorithms. We view query optimization in modern DBMSes as an engineering marvel, especially given the complexity of the SQL language and the requirements and expectations of DBMS users, who often demand that important queries simply not get slower with a new release of the DBMS. Rather, the prevalence of suboptimality observed here is a reflection of the complexity of the task of query optimization.
— Fourth, we wanted to understand whether a fundamental limitation exists in the prevalent approach to query optimization utilized by DBMSes generally, and certainly by the four DBMSes that we studies.

This is why we needed a new methodology. We want to understand cost-based optimization deeply. This means that we need to go beyond the examination of a single query optimizer, as is done in almost every paper (with a few important exceptions [Harish et al. 2007; Haritsa 2010; Leis et al. 2015]) over the forty-year history of

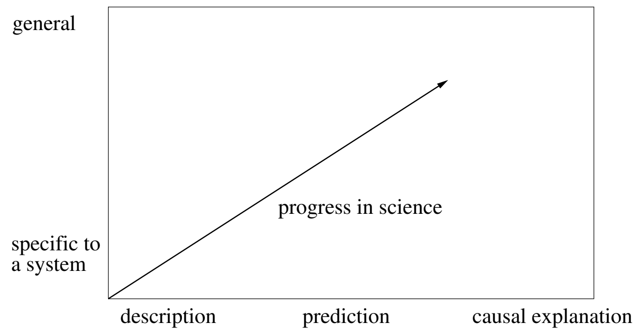


Fig. 5. Empirical Generalization

query optimization research, to study multiple instances of that optimization architecture, in an effort to achieve generalizable results.

Thus, in this paper, we articulate a predictive causal model for how and in what circumstances suboptimality arises and provide compelling evidence via hypothesis testing that this model accurately characterizes the behavior of query optimizers in general. This is what is meant by "empirical generalization" [Cohen 1995] and why it is needed to answer such questions. In the long history of research in database query optimization, or even of databases in general, our model and its hypothesis tests are the first predictive results that we are aware of that apply *across* DBMSes, rather than on a single, specific DBMS or on a specific algorithm. Our goal is to make statements that hold across cost-based optimizers in general, thereby moving up the y-axis of Figure 5. Such a DBMS-agnostic, though paradigmatic, causal model can then provide guidance to the community about where fundamental research is needed and to the DBMS engineers about where to focus their efforts.

3. RELATED WORK

There has been extensive work in query optimization over the last 40 years [Ioannidis 1996; Jarke and Koch 1984], during which a particular quite effective paradigm had taken hold, in both open-source and proprietary DBMSes. In this over-arching paradigm, query optimization and evaluation proceeds in several general steps [Ramakrishnan and Gehrke 2003]. First, the SQL query is translated into alternative query evaluation plans based on the relational algebra via *query enumeration*. The cost of each plan is then estimated and the plan with the lowest estimated cost is chosen. These steps comprise query optimization, specifically *cost-based query optimization* [Selinger et al. 1979]. The selected query plan is then evaluated by the query execution engine which implements a set of physical operators, often several for each logical operator such as join [Graefe 1993].

An influential survey [Chaudhuri 1998] identifies the major themes that have pursued in the hundreds of articles published on this general topic. Chaudhuri reviews the many techniques and approaches that have been developed to represent the query plans, to enumerate equivalent query plans, to handle some of the more complex lexical constructs of SQL, to statistically summarize the base data, and to compute the cost of evaluation plans. He also mentions some of the theoretical work (which is much less prevalent) to understand the computational complexity of these algorithms. Most of this research may be classified as adopting an engineering perspective: how can we architect a query optimizer "where (1) the search space includes plans that have *low cost* (2) the costing technique is *accurate* (3) the enumeration algorithm is *efficient*.

Each of these three tasks is nontrivial and that is why building a good optimizer is an enormous undertaking." [Chaudhuri 1998, page 35]

To determine the best query access plan, the cost model estimates the execution time of each plan. There is a vibrant literature on this subject [Ioannidis 2003; Mannino et al. 1988], including proposals for histograms, sampling, and parametric methods. Again, most of these papers are engineering studies, providing new techniques that improve on the state-of-the-art through increased accuracy or performance. There have also been a few mathematical results, such as "the task of estimating distinct values is *provably* error prone, i.e., for any estimation scheme, there exists a database where the error is significant" [Chaudhuri 1998].

An optimizer for a language like SQL must contend with a huge search space of complex queries. Its first objective must be *correctness*: that the resulting query evaluation plan produce the correct result for the query. This objective must be ensured both by the initial SQL-to-relational algebra translator and by the subsequent query enumerator. A secondary but clearly very important objective is *efficiency*; after all, that is the raison d'être for this phase. As is well known and has been alluded to already, the name for this phase is an exaggeration, as existing optimizers do not produce provably optimal plans. That said, the query optimizers of prominent DBMSes generally do a superb job of producing the best query evaluation plan for most queries. This performance is the result of a fruitful collaboration between the research community and developers.

Early investigation of plan suboptimality resulted in approaches such as dynamic query-reoptimization [Avnur and Hellerstein 2000; Bellamkonda et al. 2013; Kabra and DeWitt 1998; Li et al. 2007], which exploit more accurate runtime statistics that appear while a query is being executed, to steer in-flight plan reoptimization. The very presence of such a radical change to the normal optimize-execute sequence indicates that plan suboptimality was of interest to some researchers.

However, even with great effort over decades, optimizers as a general class are still poorly understood. As has been observed, "query optimization has acquired the dubious reputation of being something of a black art" [Babcock and Chaudhuri 2005]. DeWitt has gone farther, stating that "query optimizers [do] a terrible job of producing reliable, good plans [for complex queries] without a lot of hand tuning" [Winslett 2002, page 59]. And as we will see, suboptimality may occur in sophisticated query optimizers even when considering only simple queries.

While this paper does not provide direct solutions to address suboptimality, we envision that by following up on the implications of our proposed predictive model for suboptimality, engineering practice, such as dynamic reoptimization just mentioned, may benefit. We elaborate on this subject in Sections 6.8 and 8, where we discuss the engineering implications of our causal model.

4. A MODEL OF SUBOPTIMALITY

The purpose of query optimization is to generate optimal plans. So why would suboptimality occur in the first place? Query optimizers are highly complex, comprised of tens or hundreds of thousands of lines of code. There are several reasons for this complexity. First, an optimizer must contend with the richness of the SQL language, whose definition requires about 2000 pages [ISO 2008], with a multiple of linguistic features. Second, an optimizer must contend with the richness of the physical operators available to it. DBMSes have a range of algorithms available to evaluate each of many algebraic operators. Third, the optimizer must contend with an exponential number of query evaluation plans. Kabra and DeWitt [Kabra and DeWitt 1998] identify several other sources of complexity: inaccurate statistics on the underlying tables and insufficient information about the runtime system: "amount of available resources

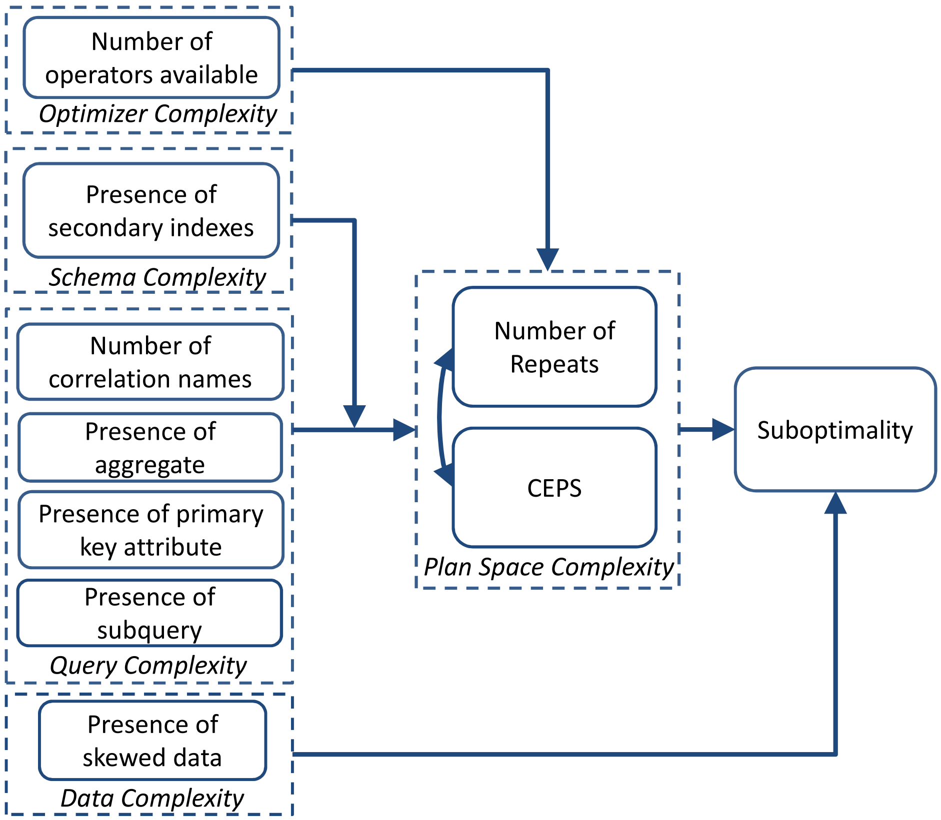


Fig. 6. Predictive Model of Suboptimality

(especially memory), the load on the system, and the values of host language variables.” (page 106). They also mention user-defined data types, methods, and operators allowed by the newer object-relational systems [Melton 2003]. Thus, the task of optimization is very complex, with the result that the optimizers themselves consist of a collection of “components”, that is, the rules or heuristics that it uses during optimization, with each of these components being itself complex.

We wish to understand the causal factors of suboptimality, through a predictive model that explicitly states the relationships between these causal factors. We test this model through experiments over tens of thousand of queries and hundreds of thousands of query executions, showing that there is strong support for this model. We then extract engineering implications from the model, suggestions for the most productive places to look to reduce suboptimality and thus to improve existing query optimizers.

Here we examine the hypothesized influence that each independent variable will have on the one dependent variable, query Suboptimality (with some of the influences mediated by one of the constructs). In the next section we will operationalize these variables, explaining how each is controlled or measured.

4.1. Constructs in the Model

The model concerns five general constructs that we hypothesize will play a role in suboptimality: optimizer complexity, schema complexity, query complexity, data complexity, and plan space complexity. Two constructs include several specific variables that contribute to that construct as a whole. Our model distills many of the widely-held assumptions about query optimization. Our contribution is the specific structure of the model and the specific operationalization of the factors included in the model.

Our theory, which we will investigate in some detail and which is the basis for our predictive model, is that suboptimality is due in part to the complexity of the optimizer and concomitant interactions between the different components used within the optimizer with various sources of complexity in producing a good (hopefully optimal) plan. We argue that with the proliferation of concerns and variability that an optimizer must contend with, it is extremely difficult to ensure that for an arbitrary query that the optimizer will *always* pick the right plan. There are many sources of complexity that may challenge one or more components of the optimizer; our theory implicates specific sources as contributing to observed suboptimal plans.

The model depicted in Figure 6 suggests specific factors that may impact the prevalence of suboptimality. This model has one dependent variable, *Suboptimality* (as noted in Section 1, specifically, *empirical query suboptimality*), on the far right. We observe this dependent variable in our experiments by determining whether each particular query, run on a particular DBMS and using a particular schema, is suboptimal at any cardinality of the input table. In Section 5, we delve into the details of how we operationalize this and the other variables we now examine. The last two sections summarize our contributions and suggest three fundamental directions that are suggested by this study.

4.2. Variables in the Model

The model has several independent variables which influence Suboptimality.

For the construct of *optimizer complexity* we have one independent variable, “Number of operators available (in the DBMS)”. We can manipulate this variable by our choice of DBMS: each DBMS has a set of operators available to its query evaluator and available to the query optimizer to use with in query plans.

We have one variable for the construct of *schema complexity*: “Presence of secondary indexes”. If true, that means that every non-primary-key attribute, for the table for which we vary the cardinality (termed the *variable table*) as well as for the other three tables (termed the *fixed tables*), has a secondary index associated with it. The rationale is that the Presence of secondary indexes expands the number of possible plans: each predicate in the query can often be mapped to one or more operators utilizing that index.

For the construct of *query complexity* we have identified four variables: “Number of correlation names”, “Presence of aggregate”, “Presence of primary key attribute”, and “Presence of subquery”. For each independent variable, we have interventional control in our experiments, in that we can manipulate the values of these variables through the construction of the actual query to be optimized. The first is the number of correlation names defined in the FROM clauses. The second is whether a single aggregate operator (`Sum`) appears in the SELECT clause. The third is whether a primary key attribute appears in at least one predicate in the WHERE clause. The fourth is whether a single subquery appears in the WHERE clause; that subquery evaluates to a single value that is equality-compared with an attribute, in the where clause. The rationale is that each factor may expand the number of plans or otherwise render the search for the optimal plan more complex.

We have one variable for the construct of *data complexity*: that of "Presence of skewed data". Skew is generally defined as how values are distributed with a column of a table. We refine this to "how many duplicate values are present," with zero skew meaning that there are no duplicate values present and 100% skew implies that there is but one value in the entire column. The Presence of skew complicates query time estimation, which in turn complicates the search for the optimal plan.

In the middle of the figure is the construct of *plan space complexity*. Given a particular query, its complexity will impact the total number of candidate plans considered by the optimizer. This variable is not directly observable, again, especially for proprietary systems. However, we *can* measure the number of plans actually generated by the optimizer when presented with different cardinalities of the underlying tables. We term this set of plans the "effective plan space" and term the number of such plans, the cardinality of the effective plan space, or "*CEPS*". Similarly, the variable "Number of repeats" *is* directly measurable as the number of times a plan is reused across the cardinality of the variable table. (We discussed plan reuse and the related phenomenon of *flutter* in Section 2; Figure 1 provided a concrete example in which plan P0 was encountered three separate times across the 200 cardinalities.) For example, if the sequence of plans for a query as the cardinality increases is $A\ B\ B\ B\ C\ C\ A\ B\ B\ B\ C\ B\ C\ C\ C\ B$, then the "Number of repeats" will be six: removing sequential duplicates results in $A\ B\ C\ A\ B\ C\ B\ C\ B$, with the last six distinct plans being duplicates of the first three. Note that CEPS plus the number of repeats gives you the number of plans in the sequence, again, after removing sequential duplicates, nine plans in this particular case. Thus, we associate with the latent construct of plan space complexity two measurable (that is, indirect) variables. Our model stipulates that the construct, and thus the two associated with this construct, intervene between the constructs of optimizer complexity, schema complexity and query complexity and the construct of Suboptimality.

Plan space complexity is an *intervening* construct, in that it is dependent on some of the constructs on its left but is observable and thus exerts influence on the dependent variable on its right. We can observe these variables within experiments and indirectly influence their value but cannot directly intervene to specify their value. For example, we can influence the CEPS through manipulating the values for the independent variables of optimizer and query complexity, but cannot directly set a value for CEPS within an experiment.

4.3. Hypotheses in the Model

Given these six constructs and ten specific variables depicted in Figure 6, let's now examine the causal relationships between these variables, each depicted as a directed arrow between variables (a line originating or ending at a construct is interpreted as originating or ending at all variables in that construct). The causal model predicts specific hypotheses between the the constructs (in particular, between their associated variables).

One causal factor of this model is the optimizer complexity. We hypothesize that optimizer complexity has influence over suboptimality indirectly, via plan space complexity. We hypothesize that an optimizer with a larger number of available operators will generate more plans and hence increase plan space complexity.

Hypothesis 1: Number of operators available will be positively correlated with (a) Number of repeats and (b) CEPS.

We now turn to query complexity, a construct associated with four independent variables. As with the optimizer complexity construct, we include in our model an indirect effect through plan space complexity.

A higher value of each of these specific variables implies a more complex query. We expect a strong relationship between Number of correlation names to CEPS (because it is well-known that the number of potential join combinations is exponential to the number of correlation names) and to Number of repeats (Number of repeats could partially track CEPS).

We also expect a positive relationship between Presence of aggregate (as that will definitely add at least one operator to the query plan), Presence of primary key attribute, and Presence of subquery.

Hypothesis 2: Number of correlation names will be strongly correlated with (a) Number of repeats and (b) CEPS. Presence of aggregate will be positively correlated those those two variables (correlations c–d) and similarly with Presence of primary key attribute (correlations e–f) and Presence of subquery (correlations g–h).

We feel that skewed data (in the "data complexity" construct) will not impact plan space complexity. Rather, our expectation is that it will negatively impact accuracy of plan cost estimation, and thus increase suboptimality directly.

Hypothesis 3: Presence of skewed data will be negatively correlated with Suboptimality.

Let's now turn to the plan space complexity construct. We hypothesize a positive correlation between the two variables associated with this construct. As the Number of plans considered by the optimizer increases, so should CEPS.

The model also predicts a correlation within plan space complexity, between CEPS and Number of repeats. A plan chosen by the optimizer once will be reconsidered at a later cardinality and perhaps chosen, following the past experience of selecting and using that plan among many other plans. Even if many different plans are already used, for the same reason the optimizer may revisit a pool of the previously used plans and choose one of them than to explore other new plans, given the complexity of plan cost estimation. Then the larger CEPS, the more times the optimizer repeats using the same plans. We thus hypothesize that the Number of repeats has a positive correlation with CEPS.

Hypothesis 4: Plan space complexity (CEPS) and Number of repeats will be positively correlated.

The schema complexity construct consists of the variable "Presence of secondary indexes". Such indexes provide opportunities for the optimizer to consider more candidate plans that use these indexes, due to the additional query evaluation operators now applicable. Those additional plans enable the optimizer to possibly do a better job, while also adding complexity to the optimization process. The quality of query optimization "very much depends on how much the query engine relies on [cardinality] estimates and on how complex the physical database design is, i.e., the number of indexes available." [Leis et al. 2015].

We hypothesize that this factor has a more complex role in the model, serving as a *moderator* of two relationships introduced above. We hypothesize that the overall effect of the secondary indexes is to increase the strength of the relationship between query complexity and to plan space complexity. (Note that as the Presence of primary key is required for secondary indexes, we don't include that former independent variable here.)

Hypothesis 5: Presence of secondary indexes will strengthen the correlations between the Query Complexity construct, specifically, the variables Number of correlation names, Presence of aggregate, and Presence of subquery, and the Plan Space

Complexity construct, specifically, variables Number of repeats and CEPS (correlations a–f listed above in Hypothesis 2).

Finally, we hypothesize that queries with a high plan space complexity present challenges to the query optimizer, and thus increase the chance that the query optimizer picks a suboptimal plan. Specifically, for the Number of repeats variable, a query exhibiting a high number of repeats has more opportunities for suboptimality at some cardinality, just because the number of repeats is an indication that the query optimizer is struggling.

Hypothesis 6: Suboptimality will be positively correlated with Plan space complexity, that is, (a) Number of repeats and (b) CEPS.

We have just *described* how suboptimality might arise, through a theory and its elaborated causal model, which implies six specific hypotheses (some with multiple components). We now need to move to *prediction*. How might we test such a model?

The first step to test this model is to *operationalize* each variable. In the next section we describe explicitly how each variable is defined. For the independent variables, we must be able to intervene, that is, set their values before the experimental test commences. For the dependent variables, we need to be able to measure their values during each experiment.

5. VARIABLE OPERATIONALIZATION

In this section we specify how we operationalized each of the seven independent variables in the model. Recall that each independent variable is a property of a DBMS (Number of operators available), of the schema (Presence of secondary indexes), of a query (Number of correlation names, Presence of aggregate, Presence of primary key attribute, and Presence of subquery), of the data (Presence of skewed data), and of the plan space (Number of repeats and CEPS). There is one dependent variable of our model (Suboptimality).

It is important to note that manipulation must be done *outside* the DBMS, as we do not have access to the internal code of proprietary DBMSes. Hence, we do not know (*cannot* know) all the plans that were considered, nor the details of how the plans were selected. But such access is not needed; indeed, to be able to study a phenomenon across many DBMSes, such access is not feasible. But by designing the experiment to examine the plans that each DBMS actually produces, and thus to examine phenomena that can be externally visible, we can obtain valuable insights into general classes of computational artifacts.

5.1. Optimizer Complexity

By "Number of operators available" we mean the number of operators available in the DBMS for selection, projection, join and aggregate functions (that is, potentially relevant for our queries). Our experiments intervene on this variable by selecting a particular DBMS on which to evaluate each query. Across the available DBMSes, as the Number of operators available increases, the complexity of the optimizer increases because it has to choose between more operators.

The `EXPLAIN PLAN` facility specifies the operators(s) employed in that plan. For each DBMS, we collect the unique operators from the plans and count the number of these distinct operators, each used by for at least one query at at least one cardinality by that DBMS. The Number of operators used by a DBMS ranged from 8 to 53 across the queries and data sets used in the Exhaustive, Exhaustive with Keys, and Exploratory Experiments, to be discussed in Section 6.3.

5.2. Schema Complexity

Presence of secondary indexes is easy to operationalize. We generate two databases, one without any secondary indexes and one with a key specified for each table on the non-key (that is, other than the first) attribute.

5.3. Query Complexity

Query complexity is also relatively easy to operationalize. We randomly generate queries, such as the example presented in Section 2. Each query is a select-project-join-aggregate query, with a few attributes in the SELECT clause, a few tables referenced in the FROM clause, a few equality predicates in the WHERE clause, and zero or one aggregate functions in the SELECT clause. As such, some of the complexities mentioned by Kabra and DeWitt [Kabra and DeWitt 1998], such as user-defined data types, methods, and operators, are not considered. Concerning Presence of primary key attribute, if this independent variable was set to 1, we ensured that there was at least one primary key attribute in one of the comparisons in the WHERE condition.

The queries were generated by a simple algorithm. The SELECT clause will contain from one to four attributes, hence, an average of 2.5 attributes. The Number of correlation names in the FROM clause varied from one to four, with duplication of tables allowed (duplicate table names within a FROM clause implies a self-join). In the queries that were generated, from one to four tables were mentioned in the FROM clause. Somewhat fewer tables were mentioned than the Number of correlation names, as the Presence of self-joins reduces the number of unique tables referenced by the queries.

For the query in Section 2, the Number of correlation names is 3, the Presence of aggregate is false (0), the Presence of primary key attribute is false (0), and the Presence of subquery is false (0).

We ensure that Cartesian products are eliminated. We do this by connecting the correlation names that appear in the FROM statement via equi-joins on random attributes. The comparisons are all equality operators. To ensure that the queries are as simple as possible, we do not include any additional predicates in the WHERE clause. This is realized by setting the attributes `maxIsAbsolute` to `true` and `complexUsePercentage` to `100`. Basically, "complex" predicates eliminate the Cartesian product, and by setting complex predicates as "absolute", no additional predicates are included except for those which are necessary for eliminating Cartesian product. Also for simplicity, we include neither disjunctions nor negations.

The value of Presence of subquery was 0 or 1, with 0 indicating no subquery. For each query needing a subquery, we picked a separate generated query and rendered it as a subquery to replace an attribute in the WHERE clause of the original generated query. The following query is an example where this variable had a value of 1.

```
SELECT t0.id2, SUM(t1.id3)
FROM ft_HT2 t0, ft_HT2 t1
WHERE (t0.id2=t1.id1)
GROUP BY t0.id2
```

We then generated another simple select-project (SP) query at random concerning the variable table and simply replaced one side (in this case, the right side) with the generated entire query as a subquery, to produce this final query.

```
SELECT t0.id2, SUM(t1.id3)
FROM ft_HT2 t0, ft_HT2 t1
WHERE (t0.id2 IN (SELECT t2.id3 FROM ft_HT1 t2))
GROUP BY t0.id2
```

We thus have a maximum of only one level of nesting.

5.4. Data Complexity

This independent construct has one variable: Presence of skewed data.

Skew has a very specific definition in statistics, involving elongating the left or right tail of a distribution, thereby moving the mean left or right of the median (in a symmetric distribution the mean = median = mode).

But we start with a distribution without a tail: the uniform distribution: the values from 1 to 2 million (2M). We consider this to be a skew of 0 (no skew). At the other end of the spectrum is one in which all the values are identical, or a skew of 1.0.

We define the skew as "the reciprocal of the Number of distinct values," so $0 < skew \leq 1$. For 2M distinct values, the skew would be $1/2M = 0.000005$, which is practically 0. For exactly one distinct value, the skew would be 1.0. For two distinct values, the skew would be 0.5. For ten distinct values, the skew would be 0.1.

We can generate the table of 2M rows by generating values sequentially from 1 to the Number of distinct values. This creates a "span of values." We repeat this for the second span if necessary, and on and on, until we have 2M values in all.

When varying the cardinality, we remove 10K values from the variable table and then copy those tuples to a new table to ensure that every page is as full as possible (that is, 100% load factor). This gives us a table of 1.99M tuples. (We then get a query plan for this table.) We repeat this removal process until the final cardinality reaches 10K.

The way we effect the 10K removal is as follows. The key idea is to remove individual spans until we've deleted 10K values. Since we don't touch the remaining spans, the Number of distinct values does not change, and so the skew remains constant.

We use two values of skew: $1/2M$ (termed *tiny*) and $1/10K$ (termed *small*). For the former, we generate a single span of 2M values. To shorten the table, it makes no sense to remove this single span in its entirety. But we can remove 10K values from this single span. Note that this changes the skew to 1/1.99M, then eventually to 1/10K, which is still very close to zero (the skew has changed from .0000005 to .00001). For the latter, we generate 2,000 spans each of 10K tuples, and drop a span to reduce to 1.99M tuples, repeating.

5.5. Plan Space Complexity

This explanatory construct includes two variables.

As discussed in Section 4, the "cardinality of the effective plan space" (CEPS) is the number of plans selected as optimal for that query being evaluated on one of the 200 cardinalities for the variable table. It is "effective" because it was chosen, as opposed to the plans that were considered but not chosen. (Recall that for proprietary DBMSes, we do not have access to such plans.) Note that we count only distinct plans. As we saw in Figure 1, fluttering queries return to a previous plan. This particular query has a CEPS of 4.

The Number of repeats is just the number of times a plan associated with a smaller cardinality is repeated, after removing sequential duplicates.

5.6. Empirical Suboptimality

We now consider the one dependent variable at the core of this investigation. How might suboptimality be observed? We have developed a system, DBLAB, that allows us to perform experiments to study this phenomenon of suboptimality. DBLAB submits queries to the DBMS, while varying the cardinality of one of the tables, requesting in each case the evaluation plan chosen by the DBMS. This is done using the `EXPLAIN` SQL facility available in modern DBMSes. (The Picasso system also used this facility to visualize the plan space chosen by a DBMS optimizer [Harish et al. 2007; Haritsa 2010].) We can then compare the performance (execution time) of various plans for the query, to identify those situations when a suboptimal plan was chosen, when in fact there was a different plan that was semantically equivalent to the chosen plan (that is, yielded the identical result) but which ran faster.

We modify the cardinality to produce multiple execution plans for a given query. For one of the DBMSes, we can modify the stored table statistics directly. For the other DBMSes, we had to do so indirectly, by varying the size of the table and running the optimizer on tables of different size. As we vary the cardinality, we collect the plans that the optimizer felt were appropriate for that query at the various cardinalities.

Our definition of suboptimality assumes that actual execution time for any query plan is *monotonically non-decreasing*, that is, unchanged or increasing as the cardinality increases. The intuitive justification is that at the higher cardinality, the plan *has* to do more work, in terms of CPU time and/or I/O time, to process the greater number of tuples. We formalize this property as follows.

Definition: *Strict Monotonicity*: given a query Q and an actual cardinality a,
$\forall p \in \textit{plans}(p)\ \forall c > a\ (\textit{time}(p, c) \geq \textit{time}(p, a))$

where *plans*(p) is the set of plans generated by the optimizer and *time*(p, c) is the execution time of plan p on the data set with the varying table at cardinality c. ■

Note that the comparison is with the same plan p, occurring at higher cardinalities.

To test this assumption, we ran an experiment that we term "Monotonicity". This experiment considered 60 queries, chosen from the pool of queries generated for testing suboptimality, and timed them for cardinalities from 10K to 2M tuples, in steps of 10K tuples (hence, we used 200 cardinalities), for each DBMS (for one DBMS that was very slow, we started with 30K tuples, as will be discussed in Section 6.3). We varied the cardinality of the variable table by starting with the maximum size, running the queries, then deleting 10K tuples and repeating. We performed an "`ANALYZE TABLE`" function to force the DBMS to update the table's statistics to be accurate before actually evaluating the query (we did this for all experiments). We expected that as the cardinality decreased, the run time would also monotonically decrease. However, due to the variance in query time measurement observed even when the cardinality was identical, we encountered spurious violations.

Assuming a normal distribution for our time measurements, 95% of the distribution falls within two σ of the mean. Therefore, to statistically infer with a 95% confidence interval that a violation occurred, we relaxed our definition of monotonicity to the following.

Definition: *Non-Strict Monotonicity*: given a query Q, an actual cardinality C, and the standard deviation of the query executions for cardinality C as σ, Q is non-strict monotonic if $\forall p \in \textit{plans}(p)\ \forall c' > C((\textit{time}(p, c') + \sigma_{c'}) \geq (\textit{time}(p, C) - \sigma_C))$. ■

That said, the suspicious monotonicity violations raised the fundamental question of whether we were using a sufficiently reliable timing method. The answer was *no*, as the experiment used a (popular but) naive measurement technique based on end-to-end timing of which the results are typically perturbed by system noise potentially incurred during the measurement. We realized that the accuracy of this timing data was insufficient for this monotonicity test. We then switched to a new protocol, TTPv1 [Currim et al. 2013], and later TTPv2 [Currim et al. 2016], which fortunately is able to obtain quite accurate and precise timing.

Specifically, as we will see in Section 6.3, using the protocol we observed only 3,347 violations (0.74%) of non-strict monotonicity, for the largest experiment (Experiment 7: Confirmatory) across all the DBMSes we studied. Hence, this result justified our conclusion that the DBMSes under study are indeed monotonic.

We can now turn to empirical suboptimality. Recall that the monotonicity test examines two adjacent Q@Cs for which the *same plan* is observed. To detect suboptimality, we look for adjacent Q@Cs with *different plans*, the "change pairs" mentioned earlier. We look for such change pairs where the computed query time at the *upper* cardinality is *smaller* than the computed query time at the *lower* cardinality. Say the lower cardinality used Plan A and the upper cardinality exhibited Plan B. Had the DBMS query optimizer selected Plan B for the lower cardinality, the query time would have been smaller than that for Plan A, which follows directly from the monotonicity assumption. The conclusion is that for the lower cardinality, the optimizer picked the less efficient plan, and thus, this query exhibits suboptimality. Note that since this approach cannot consider plans that were never chosen, it very likely misses some suboptimal plans (for which there was a better plan not seen), and thus produces a conservative estimate of suboptimality.

Our definition of suboptimality compares the computed run times and standard deviations at the cardinality just before the change pair (designated as $n-1$) and at the change pair (that is, n).

The query is said to be suboptimal if $\mathit{time}_{n-1} - 0.5 \cdot \mathit{stddev}_{n-1} \geq \mathit{time}_n + 0.5 \cdot \mathit{stddev}_n$. In requiring at least one standard deviation of difference, versus just saying a Q@C pair is suboptimal if the time at higher cardinality is faster than the the time of plan at lower cardinality, we minimize spurious or minor differences in plan times. For each Q@C pair, Suboptimality is coded as four levels (0–3), based on the distance in standard deviations, up to three standard deviations. We chose this cutoff because 99.7% of Q@C pairs are less than or equal to three standard deviations. We then sum this value over the Q@C pairs with different plans (the change pairs) to arrive at a single integer for the query instance, thus determining the *empirical suboptimality of that query instance*.

Note that while DBLAB examines the plan at every cardinality, it only has to actually execute the query at change pairs. Since many fewer Q@Cs were involved, we could try many more queries than the Exhaustive Experiment. In the Exploratory Experiment to be described in Section 6.3, the value of Suboptimality ranged from 0 (no suboptimality) to 133, with the majority between 0 and 9. A full 56% of the queries were suboptimal. Because the occurrence of large values of this measure was so rare, we did a log transformation: $\log_{10}(1 + \mathit{subopt})$ in the confirmatory analysis.

6. TESTING THE CAUSAL MODEL

In this section we elaborate on how to test our model and discuss the test results. Specifically, we describe in detail the environmental configurations, data sets, and various experiments that we utilized. We then provide descriptive statistics of the experiments and present the results of correlational and regression analyses.

6.1. Experimental Setup

The measurements were collected using Tucson Timing Protocol Version 1 (TTPv1) [Currim et al. 2013] and Version 2 (TTPv2) [Currim et al. 2016] on a suite of five machines, each an Intel Core i7-870 Lynnfield 2.93GHz quad-core processor on a LGA 1156 95W motherboard with 4GB of DDR3 1333 dual-channel memory and Western Digital Caviar Black 1TB 7200rpm SATA hard drive, running Red Hat Enterprise Linux Server release 5.8 (Tikanga) for TTPv1 and release 6.4 (Santiago) for TTPv2, with a kernel of 2.6.32-358.18.1. The protocol provided calculated query evaluation time, including computation and I/O time, in msec. Both protocols were utilized exactly as specified.

No run violated the experiment-wide sanity checks. For the largest experiment, the Confirmatory Experiment (number 7) discussed below, approximately 10.5% of the query executions (QEs) and 5.1% of the queries-at-cardinality (Q@Cs) were dropped due to query execution and Q@C sanity checks. As a result, excessive variation in calculated query time was observed in only 0.003% of the Q@Cs. A total of 0.43% of Q@C adjacent pairs violated relaxed monotonicity and 0.74% of the Q@Cs violated strict monotonicity, which is acceptable.

We thank the developers of this protocol and of the software that enabled the running of many, many queries for providing us this software.

In these experiments, we installed each disk directly on the machine that also runs the DBMS, ensured a cold cache (disk drive, disk controller, O/S, and DBMS buffer), and discarded any sequence of query executions that appear to be the result of query result caching. We also ensured within-run plan repeatability.

In the following, we describe in detail the data used by our experiments and the experimental scenarios we defined. More details on both can be found in Appendix A.

6.2. Data sets

We generate our experiment data set randomly in each of the experiments. However, we use seeds to control the random data generator so that it can produce repeatable data as required.

Our experiment data set consists of relational tables. There are two types of tables. The first is a “fixed table” that, once created and populated, will never be modified in the future. In contrast, the second type is a “variable table”. We alter the cardinality, physically, of such tables as the experiments are being performed. We generated four configurations for the data sets. The first configuration is a small data set with four tables, each with four integer-typed attributes. The fixed tables were populated with one million rows and the variable table with two million rows (sixty thousand rows for one DBMS). Thus, the size of the tables is roughly 16–32Mbytes, with tiny skew (cf. Section 5.4). We also produced versions of the data set with (i) small skew, (ii) primary keys (of the first attribute), and (iii) primary keys and secondary indexes, for all tables, as detailed in Appendix A.1.

6.3. The Experiments

We are interested in predicting the suboptimal behavior of DBMSes through our model. We selected four relational DBMSes, some open source and some proprietary, that are representative of the relational DBMS market. Each was used in its stock configuration.

In each experiment, we varied the cardinality from 2M (maximum) to 10K (minimum), in increments of 10K. For the one DBMS that was slower than the others and was timing out for the majority of the queries when run between 10K and 2M, we reduced the size of the tables and varied the cardinality from 60K (maximum) to 300 (minimum), in increments of 300.

Utilizing JDBC to manipulate independent variables from outside the DBMS allows us to empirically generalize by moving up the y axis of Figure 5, from one system to several systems and then to a general theory. We don’t reveal the identity of the DBMSes we studied, for two reasons. First, commercial DBMSes include in their user agreements requirements not to release performance data. This is detrimental to science, but we have no choice but to live with that restriction. However, in some sense the specific DBMS doesn’t matter, as we are studying phenomena about cost-based op-

Table I. Experiments 1–7: Detailed Run Statistics

	Experiment	*Protocol*	*Cumulative Hours*	*Number of Query Instances*	*Number of Q@Cs*	*Number of QEs*	*Number of Retained QEs*
1	Monotonicity	—	38	60	12,000	12,000	12,000
2	Exhaustive	TTPv1	1,672	160	32,000	320,000	244,787
3	Exhaustive with Keys	—	28	200	40,000	—	—
4	Initial Exploratory	TTPv1	560	780	8,842	88,420	68,891
5	Refined Exhaustive	TTPv2	1,544	160	32,000	320,000	319,980
6	Exploratory	TTPv2	1,663	1,200	12,560	125,600	114,377
7	Confirmatory	TTPv2	11,375	7,640	99,558	995,580	890,631
	Total		16,880	10,200	236,960	1,861,600	1,650,666

timizers *in general*, and so are interested in making statements that apply across the experimental subjects in our study.

We performed seven separate experiments, each looking at a different aspect. Table I exhibits the statistics of running a number of queries in our experiments. All but the last column list the number of query instances, etc., gathered by the protocol for each experiment. The last column gives the number of query executions retained by the protocol. One of the primary goals of TTPv2 was (i) to reduce the number of query executions discarded due to phantom processes that were indirectly detected and (ii) to collect relevant measures directly associated with I/O, such as BlockIO Delay time [Currim et al. 2016]. Experiments 5, 6, and 7 benefited from that protocol. Other details about the experiments can be found in Appendix A.2.

The queries came from 16 query sets, summarized below with more details in Appendix A.3. It is important to emphasize that while the *queries* all came from the same query pool and while the data sets were also shared by the experiments (see the Appendix for details), the *query executions* for the six experiments, except Experiment 3 with no timing and hence no QEs, are disjoint. As a side comment, we mention that for all four DBMSes, the query plans generated by a DBMS for a particular Q@C of a particular query varied between the experiments, but not between the QEs of that Q@C, by virtue of the way the measurement protocol was designed.

The first experiment, termed "Monotonicity", was described in Section 5.6. This experiment ran quickly, as it only involved 12,000 QEs. That experiment helped us realize that we needed to be much more sophisticated in our approach to timing queries.

When TTPv1 became available, we performed our second experiment, termed "Exhaustive", which more accurately tested the monotonicity assumption. This experiment involved 160 query instances, 32,000 Q@Cs (thus the name: we timed each query ten times at *all* cardinalities, generating 200 Q@Cs for each query instance), and thus 320,000 QEs (ten QEs for each Q@C), requiring 1,672 cumulative hours. The (very small: 1.6%) percentage of strict monotonicity violations observed was consistent with the remaining variance of the query time measurement, concluding that none of the DBMSes violated monotonicity. This also provides a validation of our definition of suboptimality, which requires monotonicity.

We also ran an experiment (termed "Exhaustive with Keys") on the Exhaustive query set but using the data set with primary keys.

The fourth experiment was an "Initial Exploratory" analysis of a prior version of the causal model. That earlier model had fewer independent variables yet also had more complex relationships. Specifically, the model did not include the independent query complexity variables of Presence of secondary indexes, Presence of subquery, nor the schema complexity independent variable of Presence of secondary indexes, nor the plan space complexity independent variable of Number of repeats. The prior model also had Presence of primary key attribute in the schema complexity construct rather than the query complexity construct. In reformulating that independent variable, we were able to remove a complex mediating moderator between the plan space complexity and suboptimality constructs.

In the experiment we ran a representative sample of queries and data sets: (a) 600 queries of one DBMS, (b) 120 queries of another DBMS, (c) 10 queries from each other two DBMSes, all without primary keys defined, and (d) 10 queries from each of the four DBMSes on the primary key data set, for exploration across all combinations, a total of 780 query instances. (Again, consult Appendix A.3 for details on these query sets.) We ran the DBMSes only on the change pairs, unlike the Exhaustive experiments. The protocol retained about 78% of the QEs.

As a large number of QEs (roughly a quarter) were discarded by TTPv1 in these experiments, and as these discarded QEs were correlated with query time (and thus perhaps with suboptimality), we switched to a better measurement protocol that had recently become available: TTPv2 [Currim et al. 2016]. The fifth experiment then was to rerun the Exhaustive experiment (we term this simply “Refined Exhaustive”) using that protocol. The main purpose of this experiment was to reexamine monotonicity within in the enhanced protocol.

We observed that the monotonicity violation rate decreased from 1.54% to 1.02% for strict monotonicity and from 0.61% to 0.60% for non-strict monotonicity, thereby reaffirming our monotonicity assumption (the first benefit). Moreover, the number of retained QEs went up significantly (compare 244K to 320K retained QEs, a second and the primary benefit of TTPv2), while the number of hours required actually went down somewhat (a third benefit). These benefits reassured us of the quality of data for subsequent experiments via the improved protocol.

We subsequently reran the exploratory analysis using TTPv2, this time on a larger sample of queries and data sets: (a) 200 queries of four DBMSes without primary keys defined and (b) 100 queries from each of the four DBMSes on the primary key data set, for exploration across all combinations, a total of 1,200 query instances. We termed this sixth experiment “Exploratory”. This experiment retained 12,100 Q@Cs (3.7% were dropped), concerning 1,123 query instances (6.4% were dropped). Only 443 strict monotonicity violations (0.78%) and 301 relaxed violation (0.54%) were observed. This exploratory analysis allowed us to refine the operationalizations.

The seventh and final experiment was used for confirmatory analysis of the model and thus was called “Confirmatory”. This was the most time-consuming of the experiments. Here we used (a) 800 queries on the data set without primary keys defined and (b) 510 of those queries that had joins on the primary key attributes, on the data set with primary keys, (c) 100 queries on the data set with tiny skew and primary keys, (d) 100 queries with a subquery on the data set without primary keys, (e) 100 queries on the data set with primary keys and secondary indexes defined, (f) 100 queries with a subquery on the data set with primary keys defined, (e) 100 queries with a subquery on the data set with primary keys and secondary indexes defined, and (g) 100 queries on the data set with primary keys and secondary indexes defined, for a total of 1,910 queries and a total of 7,640 query instances (over the four DBMSes). (Again, see Appendix A.3 for details.) We ran the DBMSes at the 99,558 Q@Cs that were observed, roughly 13 per query. The protocol accurately timed both sides of adjacent Q@Cs (53,547 change pairs in all).

In this Confirmatory Experiment, we observed 3,347 strict monotonicity violations (0.74%), and 1,966 relaxed monotonicity violations (0.43%) (out of a total of 452,684 Q@C pairs having identical plans and query instance), which provides further confidence that monotonicity also applies to operators found in queries over data in various contexts (as described above) and that our operationalization of Suboptimality is a valid one.

Table II. Testing Hypotheses 1–7: Correlations on the Confirmatory Study

Variable	*Suboptimality*	*Repeats*	*CEPS*
Operators in DBMS	—	**H1a:** 0.35	**H1b:** 0.27
Correlation names	—	**H2a:** 0.17	**H2b:** 0.46
Presence of aggregate	—	**H2c:** 0.04	**H2d:** 0.10
Presence of primary key attribute	—	**H2e:** *NS*	**H2f:** 0.15
Presence of subquery	—	**H2g:** *NS*	**H2h:** 0.26
Presence of skewed data	**H3:** *-0.05*	—	—
Number of repeats	**H6a:** 0.62	—	—
CEPS	**H6b:** 0.61	**H4b:** 0.45	—

In the remainder of this section, we focus using the measured independent and dependent variables in the Confirmatory experiment to test the predictions that arise out of our causal model in Figure 6.

6.4. Descriptive Statistics

Several initial conclusions can be drawn from this confirmatory experiment, which was the culmination of several years of programming effort and about 30 months of experimental runs, summarized in Table I.

To illustrate the descriptive statistics with the Confirmatory experiment, we started with 7,640 query instances. These resulted in 99,558 Q@Cs, each with ten query executions (QEs). Some of these QEs violated one or more of the (many) sanity checks specified within the TTPv2 protocol, leaving a remaining 890,631 retained QEs. A few of the query instances then violated one or more of the Q@C sanity checks in the protocols (657 in all), with 6,983 query instances retained. Additionally, 16 query instances were dropped *after* the protocol because they were missing data for the only change pair in the query.

We were then left with 6,967 queries, of which we make three general observations. First, perhaps surprisingly, more than half (3,933 queries out of those that emerged) exhibited suboptimality somewhere in the range of cardinality of the varying table. *Every* DBMS exhibits suboptimality.

Secondly, most (3,370) of those suboptimal queries (86%) had the maximum value of Suboptimality (i.e., level 3) for at least one change pair. The phenomenon of query suboptimality that we observed is likely to be a fundamental aspect of either the algorithm (cost-based optimization) or the creator of the algorithm (human information processing). Our model includes both effects.

Third, concerning the causal factors of Suboptimality in our model,

— the cardinality of the effective plan space (CEPS) ranged from 1 to 24 plans across the cardinality range, and
— the Number of repeats ranged from 0 to 108, with the mean being 4.99.

6.5. Correlational Analysis

We tested Hypotheses 1–6 using the strength and significance of correlations of variables involved. These hypotheses predict 14 main effects and 6 moderating effects. Table II lists the hypotheses followed by the correlation observed when testing each hypothesis. ("NS" denotes not significant at the $p < 0.05$ level, the accepted standard for significance. For each dependent variable, we used the Bonferroni correction to control the familywise error rate. "—" denotes no prediction arising from the model.) As can be seen, most of the main effects (17) arising from the causal model are supported and significant. The three exceptions are Hypotheses 2e, 2g, and 3, highlighted in italics in the table.

Table III. Testing Hypothesis 5: Interaction Strength on the Confirmatory Study

Variable	*Repeats*		*CEPS*	
	Not SI	SI	Not SI	SI
Correlation names	0.17	0.15	0.49	0.39
Presence of aggregate	0.04	*NS*	0.12	*NS*
Presence of subquery	0.03	*NS*	0.18	0.17

Hypothesis 3 was not supported because the correlation between Presence of skewed data (recall from Section 5.4 that absence of skew is operationalized as *tiny* skew and presence of skew is operationalized as *small* skew) and Suboptimality was in the opposite direction. Specifically, we observed a negative correlation, indicating that as the skew increases from tiny to small, Suboptimality decreases, though only slightly: -0.05.

In Table III, we examine the interaction strength of Hypothesis 5, between the Query Complexity and Plan Complexity constructs, when the moderator (Presence of secondary indexes) has a value of absent ("Not SI") and when it has a value of present ("SI"). As before, "*NS*" denotes no significant at the $p < 0.05$ level; three of these interactions become not significant when secondary indexes are added. (Recall that it is not possible to compute the interaction strength for Presence of primary key attribute in the presence of secondary indexes.)

This table shows that the strength of all six applicable and significant interactions goes *down* just a little (on average by 0.04), which is opposite to our prediction. Hence, this negative moderation seems small but robust. One possibility is that rather than the added schema complexity of indexes increasing suboptimality, secondary indexes may have *reduced* the complexity of query optimization, since the role of secondary indexes within query optimization is well understood, thereby reducing suboptimality.

In summary, most (12 out of 14) of the main effect hypotheses were significant at the $p < 0.05$ level. One of those hypotheses was (weakly) in the opposite direction. The hypothesized moderation (Hypothesis 5) of Presence of secondary indexes was small but in the opposite direction. Thus, most of the hypotheses in our model were strongly supported.

6.6. Regression Analysis

One use of regression is as a further test of Hypothesis 5, which predicts a (positive) moderation in the presence of query complexity, specifically the Number of correlation names, Presence of aggregate, and Presence of subquery independent variables. Thus our causal model predicts that the interaction strength should increase when secondary indexes appear in the relational schema. (The *direction* of moderation, whether positive or negative, is not involved in this test; rather, an increase in interaction strength only supports that there is a moderating effect, in either direction.) When secondary indexes were not specified, our model explains 7.23% of the variance of Number of repeats and 40.9% of the variance of CEPS. When secondary indexes were defined on the underlying tables, our model explains 7.23% of the variance of Number of repeats and 41.1% of the variance of CEPS. These findings are all consistent with our hypothesis predicting a moderation effect of secondary indexes.

A second use of regression is to compute the amount of variance explained for the intervening and dependent variables, to indicate how much of the underlying phenomena are explained holistically by the model. So we also ran a regression over the independent variables of the model that predict suboptimality over the data from the Confirmatory experiment.

Note that our experiment was over four highly complex DBMSes, each with hundreds of thousands to millions of lines of source code, none shared. Thus, one might expect the amount of variance explained to be low, with a considerable amount of variance to be *within* the DBMS. What we are getting at with our causal model is the impact of *shared* aspects that arise from supporting (a) a common data language (the relational model), (b) a common language (SQL), (c) a common query evaluation approach (operators in the relational algebra), and (d) a common query rewriting approach (cost-based query optimization). Given these basic commonalities, each DBMS supports a certain number of operators, each is impacted by certain characteristics of the schema, query, and data, and each generates a certain number of candidate plans.

Our model explained 52.2% of the variance of the Suboptimality dependent variable. That means that over half of the variance of Suboptimality is explained by our operationalizations of Optimizer Complexity, Schema Complexity, Query Complexity, Data Complexity, and Plan Space Complexity.

To state this a different way, all other possible causes for Suboptimality will in concert have less predictive power than the constructs and specific variables included in the causal model introduced here.

And somewhat extraordinarily, it is the common aspects listed above that predict Suboptimality, *not* the particulars embedded in the inordinate complexity of each of these DBMSes.

6.7. Summary of Model Testing

In our experimental design, we started with a structural causal model that encapsulates our theory for how cost-based query optimizers might select a suboptimal plan for a query at a cardinality. This model implies the six specific hypotheses listed in Section 4. We then performed a series of experiments,

— to refine our operationalizations: specifically Number of operators available, via the Exhaustive with Keys Experiment,
— to test fundamental assumptions, specifically monotonicity, via the Monotonicity and Refined Exhaustive Experiments, and
— to test and make minor refinements to our model: the Initial Exploratory and Exploratory Experiments.

During this exploration, when the TTPv2 protocol became available, we reran experiments to avail ourselves of the increased precision due to a much higher percentage of retained QEs and thus Q@Cs and query instances.

Throughout these six experiments, we were cognizant of the possibility of Type 1 errors: false positives that lead one to believe a relationship exists when it doesn't. To control for such errors, we then performed the final Confirmatory Experiment on a completely different data set consisting of many more query instances, 7,640 in all, running on four DBMSes that each utilize cost-based query optimization, to test our refined model. Statistical inference is only possible in confirmatory analysis, where the model and hypotheses are selected a priori.

Now that the causal model has been found to be supported by the confirmatory analysis, we turn to possible implications of this model.

6.8. Identifying Root Causes of Suboptimality

Our goal in this paper has been to understand cost-based query optimizers as a *general* class of computational artifacts and to articulate and test a predictive model characterizing how such optimizers, again, as a general class, behave. This model can be used to further improve DBMSes through engineering efforts that benefit from the fundamental understanding that the scientific perspective can provide.

Our model includes a number of causal factors of suboptimality. Of these factors, the regression coefficient that was highest was for Number of repeats (0.46, normalized). The next highest regression factor was CEPS (0.27, normalized). These two observations imply that the number of plans being considered is a major determinate of suboptimality, indicating that choosing among many plans is hard, despite many decades of research and development.

The next most influential factor is Presence of skewed data (-0.057, normalized), a small effect that has the salutary effect of decreasing suboptimality.

These factors implicate two broad root causes of suboptimality across DBMSes: (i) the plan search process. and (ii) the cost model.

7. DIMINISHING RETURNS?

One oft-used way to increase DBMS query performance is for the developer to add to the DBMS source code another physical operator that can be then used in query evaluation plans [Graefe 1993].

For example, nested loop join was probably the first implementation of the relational join algebraic operator. B-tree index join was only possible when such indexes were added (quite early in the history of modern DBMSes). Adding hashing to a DBMS enables a hash join operator; adding hash indexes enables (perhaps several physical variants of) hash-index join.

Each subsequent generation of the DBMS thus supports an ever-expanding collection of physical operators, with the current incarnation the most recent within a series of DBMS *generations*. (The study discussed in this paper above was over a recent generation of each DBMS.)

With this new physical operator available, the set of possible plans is expanded, and for certain combinations of query and data, there could be a plan that uses that new operator that is faster than any plan that can be expressed without that operator. In any case, the performance of the best plan for each query/data combination won't get slower, because all prior plans are still available. That is why the number of physical operators grows over the releases of a DBMS.

However, this ideal behavior might not always be seen in practice, for several possible reasons. One is that it may not be practical to enumerate all possible plans, and so the fastest plan may not even be considered. Indeed, query optimization is NP-complete, even when using only one physical join operator [Ibaraki and Kameda 1984]. Also, because the optimizer is choosing a plan based on its estimated query execution time, the optimizer ight not choose the plan with the fastest actual execution time. Thus, if the new plan, with that additional operator, is estimated to be faster than the current chosen plan, the new plan may be chosen even though its actual execution time may be slower than another candidate plan.

This raises a central question: *does an additional operator made available in a release of a DBMS to speed up some queries actually help or hurt the overall performance of that DBMS?*

7.1. A Gedanken Experiment

Consider a Gedanken experiment over DBMS generations. The experiment considers the plan selected for each query at each possible cardinality, that is, each Q@C, for each DBMS generation that adds an operator. In early generations, there will be few plan changes for a given query as the cardinality varies, simply because there are few operators available. For later generations, some Q@Cs will be associated with different plans enabled by the new operators that were added.

In many (hopefully most) cases, a new plan selected by a generation is more efficient than the plan selected by the immediate previous generation. After all, that is the very reason the new operator was added to that subsequent generation. However, sometimes that DBMS generation's query optimizer selects a slower plan. Indeed, the query optimizer also evolves and improves with each new generation, in part to minimize the chance of selecting a slower plan.

Our predictive model in Figure 6 suggests that Suboptimality is causally impacted by the Plan Space Complexity construct, specifically, the constituent variables of CEPS (cardinality of effective plan space) and Number of repeats. This Plan Space Complexity construct is naturally connected to the Number of operators available. Specifically, our Confirmatory Experiment showed that the one variable of Number of operators available accounted for 9.21% of the variance of Suboptimality.

A possible implication of our validated causal model is that as the evolution of generations of the DBMS adds more and more operators, suboptimality will increase.

It is important to emphasize that our causal analysis to this point has been across multiple DBMSes, each with a different set of operators and even number of operators. Let's reprise from Section 1 on page 1: our goal thus far has been "to understand cost-based query optimizers as a *general* class of computational artifacts and to come up with insights and ultimately with predictive theories about how such optimizers, again, as a general class, behave."

The present discussion has a quite different focus. Here we're talking about the query optimizer across multiple DBMS generations, each generation adding one or more operators. (That said, as we'll show shortly, we can still study this phenomenon of increasing suboptimality across DBMSes; this remains a scientific question.)

As a refinement, let's assume each subsequent generation adds a single operator. Starting with a fixed set of queries, for each DBMS, we run each generation on each Q@C and then sum up the query times to compute a *per-generation (total) time* for that DBMS. We can also sum over the four DBMSes, to see how this *overall per-generation time* (a single number for each generation number) varies with generation.

The underlying question then becomes, does an additional operator made available in a subsequent generation of the DBMS actually help or hurt? More fully, is the predicted increase in suboptimality originating from that added operator, a causal effect discovered and validated by the process of *science*, specifically the application of empirical generalization illustrated in Figure 5, compensated for by the increased performance afforded by that operator, a benefit realized by the application of *engineering*, the articulation, elaboration, and implementation of new storage structures and query evaluation algorithms?

Fortunately, the engineering has already been done: current DBMSes have at their disposal multiple query operators, which have been perfected over the decades. Adopting the engineering perspective would predict that the overall per-generation time would monotonically decrease as the generations add query evaluation operators.

Interestingly, adopting the scientific perspective reaches a different conclusion. Our causal model in Figure 6 predicts that as the number of operators increases, the intervening measures of plan space complexity increase, which therefore also increase empirical suboptimality. As the generations of the DBMS contain successively greater numbers of operators, suboptimality will also increase with generation number. Given that each new operator will improve a *shrinking* subset of Q@Cs for any given query, while slower plans can emerge over an *expanding* subset of Q@Cs, our causal model implies that performance will improve with each successive generation, but then start to level off as optimizer missteps become more prevalent. The causal model predicts a point where the increase in execution time due to further missteps obviate the decrease enabled by the new operator. This seems to be a fundamental limitation inherent in cost-based query optimization, due to the inherent inaccuracy of the cost model and the difficulty of enumerating all plans for queries over many table.

Put in simpler terms, engineering considerations alone imply that DBMSes can continue to improve, whereas also adopting the scientific perspective predicts that eventually each DBMS will hit a wall, beyond which improvement is not possible.

Does such a limit exist, and if so, how close are modern DBMSes to that limit?

7.2. Simulating DBMS Generations

While we do not have access to prior generations of our DBMSes (which is why the previous discussion was in the form of a Gedanken experiment), we can use the data already collected on the current version available for each DBMS, to *simulate* the prior generations, each successively having one additional operator, and thus a larger set of realizable query plans. (Note that we use the most recent query optimizer in all of the simulated generations; only the available operators will vary across generations.)

In the next section, we will explain how we characterize the generations of each DBMS. For now assume that each DBMS is associated with a series of generations, with each generation having one more operator. So generation 1 of the DBMS has just one operator, generation 2 has two operators, etc.

Our data consists of the 8,840 query instances and their 112,118 Q@Cs from the exploratory and confirmatory experiments (Experiments 6 and 7) of the previous study. Specifically, we focus on the adjacent (that is, separated by the minimum cardinality, either 10,000 or 300 rows) Q@Cs within change pairs (let's refer to these as the *lower* Q@C and the *upper* Q@C, and thus we also have a *lower plan* and an *upper plan*) for the same query at the *lower* and *upper* cardinalities, each with an actual execution time. All Q@Cs for that query and for that DBMS having cardinalities between the upper Q@C of one change pair and the lower Q@C of the next (higher) change pair are associated with that same plan, guaranteed by the process in which we chose those Q@Cs for actually timing (recall from Section 2 that we start from the highest cardinality, that of 2M tuples, looking for changes in the plan).

For this generational experiment, we associate with each Q@C a generation (a positive integer) that is the earliest generation of the DBMS that contains all the operators in the plan associated with that Q@C. We also only consider change pairs where the lower plan has a generation distinct from that of the upper plan. Say the upper generation is earlier than that of the lower plan, as illustrated in Figure 7. In this figure, as we scan from right to left in decreasing cardinality, we first encounter Plan A from generation 2 at the highest cardinality of 2M rows, then later at 1320K rows (this is the measured Q@C that has Plan A that is closest to the measurement at 910K rows), then a change pair with Plan A at 910K rows and Plan B at the adjacent 900K rows, then later Plan A again at 30K rows. (We show only a few Q@Cs in this example; there are other change pairs that are not relevant to our discussion.)

In this case, the thinking goes that, had we been in the DBMS generation 2, the optimizer would have selected Plan A throughout, because Plan B simply wasn't possible (as it involves an operator not present in generation 2). Then when generation 3 was created by adding an operator, the optimizer chose Plan B for 900K. The reason Plan B was chosen is that it was faster than Plan A at that cardinality, shown in the figure by extrapolating the run time down from 910K to 900K (we will revisit this extrapolation shortly).

In this particular case, as just mentioned, Plan B is more appropriate (faster) than Plan A, but that is not the only possibility. Sometimes the later generation with more operators available chooses a plan that is slower than the plan chosen by the earlier generation, due to the suboptimality we've observed. (We'll examine an example shortly.)

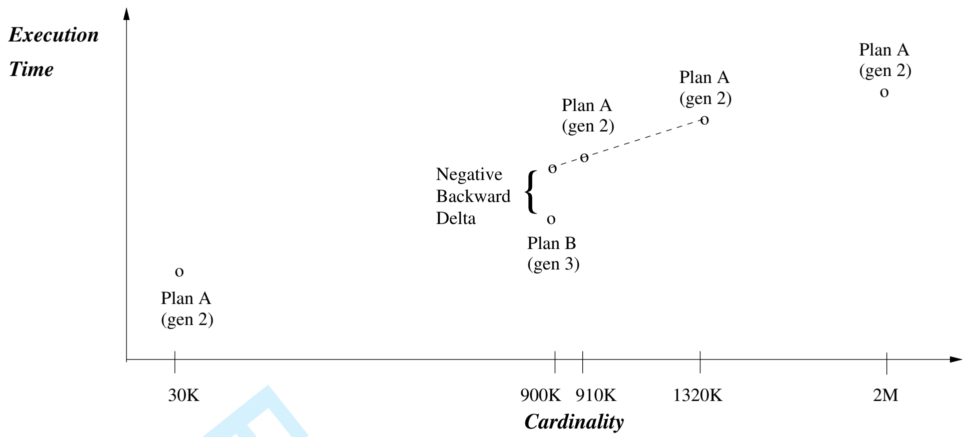


Fig. 7. An Example of a Negative Backward Delta

The question then becomes, does a plan change by a subsequent generation (enabled by the additional operator in that generation) represent a win (runs faster) or a loss (runs slower)? More broadly, do the Q@Cs in the aggregate enabled by each successive generation continue to overcome the increasing burden of suboptimality?

7.3. Characterizing DBMS Generations

To which generation do we assign each DBMS operator?

Note that we don't actually know the specific order in which the operators were added to each DBMS. But even if we did, that order was somewhat arbitrary, with a host of considerations going into those decisions over the years. Given that we are using the same optimizer for each such defined generation, we'll adopt a more systematic ordering of the operators. We start by gathering all single-operator plans, all two-operator plans, and so forth, and order the generation by the prevalence of their appearance in these query plans.

Specifically, for each DBMS we designate the first generation to contain the single operator that maximizes the number of plans at change pairs, that is, maximizing the number of Q@Cs, containing just that operator. So for example, all the plans generated by one DBMS that have exactly one operator involve just the Full Table Scan operator. So no choice was needed: we designate the first generation as just having that one operator. Any plan with just that operator can be constructed by generation 1, as well as by any subsequent generation (as each generation includes that initial operator).

We then examine the plans containing exactly two operators. Using DBMS A again, there are two such: one with the Full Table Scan and Full Table Scan with Join operators (888 Q@Cs) and one with the Full Table Scan and Ref operators (112 Q@Cs). Full Table Scan with Join is thus the operator added by Generation 2, given its prevalence of Q@Cs. Each subsequent generation adds that operator that maximizes the number of plans that operator will eventual enable. So Generation 3 adds the Eq_Ref operator, as that operator enables 633 plans eventually. Generation 4 adds the Ref operator and Generation 5 adds the Index operator.

The generations thus can be characterized from the Q@Cs we encountered: five distinct combinations of two operators, covering 1086 Q@Cs, six combinations of three operators (1126 Q@Cs), two combinations of four operators (104 Q@Cs), and exactly one combination of all five operators (6 Q@Cs). For the four DBMSes in our study, the number of generations ranged from five to thirteen.

7.4. Number of Change Pairs Per Generation

As an illustrative example of how we can look at DBMS query optimizer performance through the lens of change pairs, let's consider the *maximum number of change pairs per query*, or *maximum CPQ*, from the perspective of DBMS generations.

For each query, we count the number of Q@Cs at each generation, so for instance a query might have five Q@Cs at generation 1, seven Q@Cs at generation 2, and 17 Q@Cs at generation 5. We then then take the maximum CPQ over the queries (so perhaps 17 is the maximum for generation 5 over all queries). Our hypothesis is that as the generation increases, the maximum query flutter will increase, which then influences the maximum CPQ. The results are shown in Table IV.

Table IV. Max Change Pairs Per Query, Per Generation

Generation	*Maximum Change Pairs Per Query*
1	1
2	66
3	115
4	136
5	132
6	141
7	42
8	172
9	2
10	12
11	55
12	29
13	1
Cumulative	172

What we notice is that the maximum CPQ does increase with generation, up through generation 8, after which it falls off dramatically. In retrospect, this fall-off makes sense. There can be only 200 Q@Cs for a query, because we look for query plan changes only every 10,000 (300 in one DBMS) tuples down from a maximum of 2M (60,000) tuples. As the generation increases, there is less "room" for more plans (as some fraction of the previously generated plans will still be quite good or even optimal), and so less opportunity for flutter which will show up as a large maximum CPQ. And indeed, at generation 8, there is a query that has an astonishingly high number of change pairs, 172, all waffling between plans within that generation. This analysis indicates that there is something concerning change pairs that seems to get critical around generation 8. We'll return to this in Section 7.8.

7.5. Using Change Pairs

We now consider how change pairs can be used to evaluate the effectiveness of different generations of a DBMS.

Define $ops(p)$ for a given plan p to be the set of operators present in that plan, with some operators perhaps repeated in that plan. A plan p is *applicable* to a DBMS generation g (denoted by a set of operators) if $ops(p) \subseteq g$. By definition, if a generation is applicable to a given plan, it is applicable to all subsequent generations, with one being the *earliest applicable generation*, or *mingen*. For each change pair, containing adjacent Q@Cs, we have either one or two generations to consider. We focus on change pairs with two generations, and start with those for which $mingen(lower) > mingen(upper)$. An example is shown in Figure 8. In this case, the set of operators in Plan A for the

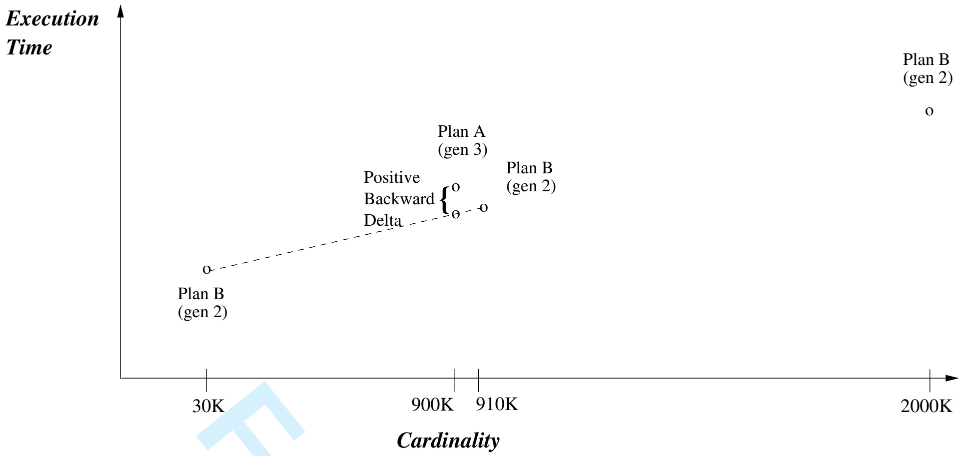


Fig. 8. An Example of a Positive Backward Delta

Q@C at cardinality 900K requires at least generation 3, whereas the set of operators for Plan B for the Q@C at cardinality 910K requires generation 2. (Note that the generations in this example are consecutive, but that is not required. Sometimes the generations within a change pair are quite different, such as generation 2 at the lower plan of a pair but generation 5 at the upper plan.)

To examine the wisdom of picking Plan A for 900K (whose run time was measured as the higher point pair shown, the one above the dashed line), we find the closest Q@C also having Plan A. There are two illustrated here, at cardinalities 30K and 2000K, respectively, with the closer one at 30K. (If there is no such Q@C, we can't do the extrapolation, and simply remove that change pair from further consideration.)

We then extrapolate the measured time for the closest plan of the lower generation to the cardinality of the adjacent higher generation. In this particular case, we use the measured query time of Plan B at cardinalities 30K and 910K to extrapolate an estimated query time at 900K. This realizes an estimate of how fast the query using Plan B would have run on the database having the variable table with a cardinality of 900K. In this particular case, Plan B looks like it would have run *faster* (in fact, was faster even at 910K in this particular example).

Note that for some operators, such as external merge sort, as the cardinality increases, an additonal pass may at some point be needed, but the query time will be roughly linear for a set number of passes. Returning to the situation in Figure 8, the presence of a change in the number of passes, say between 30K and 910K, will have the effect of flattening the slope slightly for Plan B, such that this extrapolation will slightly underestimate the run time of that plan at 900K, and thus overestimate the penalty of going with Plan A rather than Plan B. That said, given that we are extrapolating from the actual run time at a very close cardinality, our extrapolated estimate should be similarly close.

We term this situation a *backward extrapolation*, because we are extrapolating backward from a cardinality of 910K to one of 900K, within the change pair.

With this extrapolation, we can compute, for each change pair, the *relative delta*, defined as the measured time of Plan A (the chosen one) at the lower cardinality (here, 900K) minus the extrapolated time of Plan B at that same cardinality, divided by the larger of the measured and extrapolated time of the plan at the higher generation (here, Plan A). The relative delta is thus scaled by original measured time at that granularity, and thus has a maximum possible value of 1.

In this case, the relative delta is positive (the measured time for the plan associated with the higher generation is greater than the extrapolated time), which indicates that the optimizer chose a slower plan: here, Plan B should have been chosen.

On the other hand, a *negative* relative delta (where the measured time for the plan associated with the higher generation is lower than the extrapolated time, such as that illustrated in Figure 7) implies that the additional operator(s) available to the minimally applicable generation of the upper plan were indeed beneficial, in that that plan was faster. (In such cases, we again divide by the larger value, so the minimum possible value is -1.)

Summarizing, this analysis computes, for a *change pair* (a pair of adjacent Q@Cs for a specific query running on a specific DBMS), a *relative delta* for the earliest applicable generation. A positive relative delta (extrapolated in either the forward or backward direction) reflects that a slower plan was chosen by the DBMS generation, perhaps due to the greater number of operators available. A negative relative delta (forward or backward) reflects that the chosen plan was faster at that cardinality than the one chosen at the adjacent cardinality.

There are ten orthogonal possibilities for each change pair (that is, a pair of adjacent Q@Cs), a total of 66,792 change pairs from the Exploratory and Confirmatory Experiments. (There is also the case of a query instance containing a lone Q@C, meaning that only one plan was chosen across all 200 Q@Cs. This occurred for 2126 out of the 8840 query instances, which we don't consider further.)

(1) The pair of Q@Cs share the same generation: $mingen(lower) = mingen(upper)$ (62,903 change pairs, or 94.2% of the total), which we don't consider further.
(2) The extrapolation yielded a computed query time that was negative, which we also drop (10 change pairs, 0.01%).
(3) The extrapolation was from above and indicated no suboptimality, termed a *negative backward relative delta*, as exemplified in Figure 7, examined earlier (583 change pairs, 0.9%).
(4) The extrapolation, termed a *positive backward relative delta* and exemplified in Figure 8, indicated a suboptimal plan (492 change pairs, 0.7%).
(5) The extrapolation was a *negative forward relative delta*, indicating no suboptimality (795 change pairs, 1.2%).
(6) A extrapolation was from below (consider Figure 7 but with Plan A from generation 5; we would then need to extrapolate from the closest Plan B, which is *at a smaller cardinality*), in a *forward direction*, to compute a *positive forward relative delta*, indicating a suboptimal plan (1218 change pairs, 1.8%).
(7) The pair had an upper plan that was newer but no forward extrapolation was possible (554 change pairs, 0.8%).
(8) The pair had a lower plan that was newer but no backward extrapolation was possible (224 change pairs, 0.3%).
(9) The pair had a relative delta of -1 (2 change pairs, 0.002%).
(10) The pair had a relative delta of 1 (11 change pairs, 0.01%).

From these ten possibilities, we thus retain (3) and (5), which indicate a faster plan at the later generation (1378 pairs: not suboptimal), and (4) and (6), which indicate a slower plan at the later generation (1710 pairs: suboptimal).

7.6. Realizing the Gedanken Experiment

We now have the components in place for performing an experiment that parallels the Gedanken experiment described in Section 7.1.

The analysis in the previous section is for *a single pair of adjacent Q@Cs for a single query running on a specific DBMS*, providing a *relative delta* for the minimally applicable generation. A positive relative delta indicates that the later generation chose a suboptimal plan; a negative relative delta indicates the later generation did not. The relative delta is a percentage difference, and so is not affected by the absolute magnitude of the run time nor by the cardinality in question. Indeed, because it is a percentage difference, the relative delta is not affected by the query nor even which DBMS is involved. (DBMSes vary greatly in the estimated time of individual queries; using the actual query time would artificially give more weight to change pairs from the slowest DBMS.) We associate this relative delta with the later generation, for it is that generation which had the choice between the two plans for that query.

Consider how the *average* relative delta, computed across queries and DBMSes, of query plans associated with that individual generation, might behave across successive generations. The average relative delta for an individual generation is a characterization of the aggregate impact of the query plans associated with that generation, providing a quantitative estimate of the benefit of adding that operator. (We use average so that each point is not impacted by the number of change pairs over which that point is computed. Note that this approach weights the queries equally. This makes sense for our queries, summarized in Section 6.3; those queries are quite similar.)

What does our causal model in Figure 6, supported by the correlational and regression analyses of the Confirmatory Experiment in Sections 6.5 and 6.6, say about this? That causal model asserts that as the number of operators increases in subsequent generations, the intervening measures in plan space complexity increase, which therefore impacts suboptimality, also in a positive direction.

Our Gedanken experiment in Section 7.1 takes this behavior and predicts that as the generations contain successively greater numbers of operators, optimizer missteps will increase and possibly dominate. What is the correspondence with the realizable experiment we are now considering?

If we plot the performance of the DBMS on the y-axis for a workload consisting of a set of queries over a prescribed data set, for a sequence of DBMS generations arranged on the x-axis, the average relative delta is in some way a characterization of the *slope* of this relationship. A negative average relative delta implies that the indicated generation is doing a good job, with less suboptimality, and so the total workload execution time will go down and performance will go up; a positive average relative delta implies that the suboptimal decisions are dominating, indicated by the total workload execution time going up for that generation, and thus performance going down.

We expect that the average relative delta for the first few generations will reflect new operators that improve some plans, a natural result of the efforts of DBMS developers to increase performance over successive generations of their DBMS.

That said, all is not rosy in this picture. Each new operator is applicable to a successively smaller portion of the queries, and perhaps over a successively smaller portion of the cardinality space. As already noted, our causal model predicts that the prevalence of suboptimality will increase as operators are added. It seems that even with DBMS implementers doing smart things, these two considerations predict that the average relative delta will increase, as suboptimality (a positive relative delta) becomes more prevalent. This analysis suggests then that the performance curve will level off and then start dropping off.

So the question comes down to this: *Is there an empirically-determined point where the decrease due to suboptimality obviates the increase enabled by the new operator: a DBMS generation where the performance actually drops, as predicted? How close might modern DBMSes be to that limit?*

Table V. Beneficial Change Pairs

Generation	*Number of Change Pairs*	*Average Relative Delta*	*Cumulative Relative Delta*
1	—	—	0.00
2	—	—	0.00
3	—	—	0.00
4	24	-0.28	-0.28
5	282	-0.118	-0.130
6	309	-0.274	-0.203
7	336	-0.317	-0.243
8	43	-0.20	-0.241
9	4	-0.1	-0.241
10	17	-0.29	-0.241
11	357	-0.178	-0.225
12	6	-0.2	-0.225
13	0	—	-0.225
Cumulative	1378	—	-0.225

Table VI. Deleterious Change Pairs

Generation	*Number of Change Pairs*	*Average Relative Delta*	*Cumulative Relative Delta*
1	—	—	—
2	—	—	—
3	—	—	—
4	2	0.2	0.2
5	211	0.076	0.077
6	86	0.16	0.102
7	263	0.303	0.196
8	273	0.303	0.231
9	3	0.04	0.230
10	168	0.319	0.245
11	639	0.237	0.242
12	53	0.35	0.245
13	12	0.40	0.246
Cumulative	1710	—	0.246

7.7. Trends Across DBMS Generations

We partition the relevant four sets of change pairs discussed in the Section 7.5 into two groups. The first group consists of those change pairs with a *positive* relative delta (either forward or backward), indicating that the query optimizer selected a slower plan at the later generation (corresponding to a higher generation number), thereby denoting an (empirically) *suboptimal decision* by the query optimizer at that later generation. The second group consists of those change pairs with a *negative* relative delta (either forward or backward) relative delta, indicating that the query optimizer selected a faster plan at the later generation, which was thus an (empirically) *non-suboptimal decision* at that later generation. Note that we can't state unequivocally that the plan will a negative relative delta is optimal (in the original, absolute, sense of that term) because there may be a yet another plan involving the operators within that generation that is even faster. That said, in the other case, a positive relative delta reliably asserts that the plan at this Q@C is demonstrably *empirically suboptimal*, and thus also is suboptimal in the absolute case.

We first examine those change pairs for which the query optimizer made a good decision: the non-suboptimal change pairs, summarized in Table V and designated as *beneficial*. This data aggregates the results over the four DBMSes, which had generations ranging from five to thirteen. Overall, only a small number of change pairs, 1378, or about 2% of the total, satisfied the requirements listed in Section 7.5, including having a different generation number for the lower and upper plans. In fact, there were no such change pairs for the first three generations nor for the last generation. The second column states the number of change pairs added by that generation and the third column the average relative delta across just those change pairs. The last column states the *cumulative relative delta* for that generation, defined as the sum of the average relative delta for those change pairs associated with plans having only operators in its generation, divided by the number of such change pairs. It thus includes the change pairs associated with all previous generations, again, as those plans all include operators made available by that generation.

The averages jump around quite a bit, especially for the first few generations. (One of the reasons is that the number of change pairs associated with an individual generation varies a lot.) Focusing on the last column, we see that the cumulative relative delta starts off at a low of -0.28 (recall that a negative value is good, as it indicates the additional operator was effective at lowering the query time) and slowly increases to -0.225, or more negative numbers trending to less negative numbers, indicating decreasing benefits of optimization.

This general behavior matches our prediction arising from the structural causal model: it gets harder for the DBMS query optimizer to squeeze out performance gains as operators are added to the DBMS over successive generations.

We now examine those change pairs for which the query optimizer made a poor decision, in that we can conclude that there was a better plan (the one right next to it in the change pair), designated as *deleterious*. Table VI provides the same information across the DBMS generations for the suboptimal change pairs: those for which the relative deltas are positive, indicating a decision that increased the query time. While there are still only a small number of such change pairs, there are more deleterious than beneficial pairs, with a relatively greater number showing up at more recent generations. (Half of the beneficial change pairs occurred before generation 8, but half of the deleterious change pairs showed up only in generation 10 or higher.) More strikingly, the cumulative relative delta has the opposite behavior to the non-suboptimal change pairs (which showed decreasing benefits): it *increases* over the generations (indicating greater suboptimality), starting at 0.077 and ending at 0.246, a value *higher* than that of the non-suboptimal change pairs. Both trends were as predicted.

7.8. Have Modern DBMSes Hit The Wall?

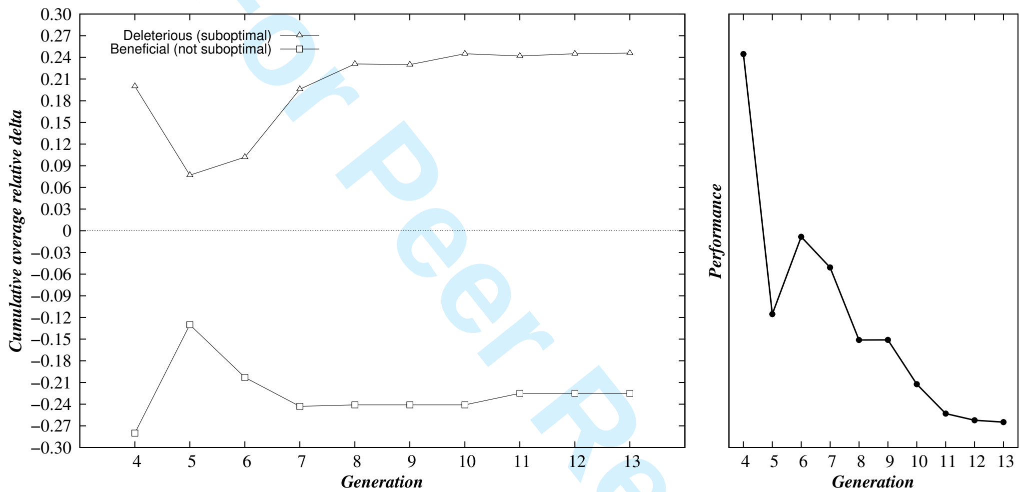
Table VII brings the beneficial and deleterious change pairs together, stating the total number of change pairs associated with each generation and the *average net relative delta*, again, just for change pairs associated with that generation. Note that in the third column, the average net relative delta (per generation), the values transition from negative (indicating better performance), to quite positive (worse performance); recall that the relative delta is bounded by -1 and 1.

The final column in Table VII provides the cumulative net relative delta. This column thus reflects all the change pairs with plans that would have been generated by that DBMS generation (hence, including change pairs at that generation along with those at previous generations). This value provides an indicator of how the four DBMSes together would have performed (say, in total execution time) on the workload of the Exploratory and Confirmatory Experiments, or rather on the 3088 change pairs selected by the criteria in Section 7.5. (We emphasize that our experiment estimates with empirical results just the first derivative of the performance graph, the cumulative net relative delta, and then only for a small number of Q@Cs, and then only as a relative measure, between -1 and 1. It is thus only very roughly indicative of the *shape* of the performance graph.)

We see that the cumulative net relative delta starts out at -0.24, indicating that the new operators are *increasing* the performance (by *decreasing* the query time) for the

Table VII. Assembled Change Pairs and Relative "Performance"

Generation	*Number of Change Pairs*	*Average Net Relative Delta*	*Cumulative Net Relative Delta*
1	—	—	—
2	—	—	—
3	—	—	—
4	26	-0.24	-0.24
5	493	-0.035	-0.045
6	395	-0.179	-0.103
7	599	-0.045	-0.0800
8	316	0.235	-0.0256
9	7	-0.04	-0.0257
10	185	0.263	0.00750
11	996	0.088	0.0296
12	59	0.29	0.0346
13	12	0.40	0.0360
Cumulative	3088	—	0.0360



(a) Cumulative Relative Deltas (b) Performance over Generations

Fig. 9. Trend of Relative Performance over Generations

workload. This happy situation unfortunately starts to deteriorate: after generation 6, with each successive generation, the performance deteriorates. This is as predicted: the optimizer is struggling with both more options (plans over the available operators) to select from and a diminished opportunity to make a significant improvement.

Figure 9 tells the story graphically. Figure 9(a) plots the last column of Table V as the bottom line (beneficial: non-suboptimal cumulative relative delta) and the last column of Table VI as the top line (deleterious: suboptimal cumulative relative delta). Figure 9(b) plots the "Relative Performance", that is, the negation of the cumulative net relative delta (as a positive relative delta denotes a slower query, reflecting decreased performance) appearing as the last column of Table VI, as this characterizes the relative performance across generations. This line has a least squares slope of -0.024.

7.9. Summary

The engineering perspective in Section 7.1 predicts that the overall per-generation run time would "monotonically decrease as the generations add query evaluation operators." The scientific perspective, applying our validated causal model, reaches the opposite conclusion: there will be a point where "the increase in execution time due to suboptimality obviates the decrease enabled by the new operator." The results of this study clearly support the latter (cf. Figure 9(b)).

This highly aggregated result, extracting 3000-odd change pairs having the specified properties of interest stated in Section 7.5 and drawn from over 100,000 Q@Cs implies that these four particular DBMSes, taken together, might be close to or have already hit the wall, where adding an operator actually slows down the average query. And recall the analysis in Section 7.4 in which a related problem cropped up around generation 8. This is the first study we are aware of that compares the generational trends of DBMSes over quite disparate code bases, thus getting at fundamental trends.

It is important to emphasize that we can't say from this one study whether any of these DBMSes have actually transitioned to where, for this class of queries, the cost of the suboptimal change pairs overwhelm the benefits of the non-suboptimal change pairs. Presumably, the DBMS vendors have done extensive tests to ensure that the operator added to each generation did in fact effect a speedup on the representative workloads that they use in evaluating their optimizer enhancements. However, we *can* say that (a) the trends observed strongly point to a decreasing benefit and an increasing cost, as predicted by the simple arguments made above, and (b) if current DBMSes haven't yet reached the point of diminishing returns, that possibility looms in the future.

We reiterate the provisos mentioned earlier. In all of these experiments, we are looking at quite simple queries, over a quite limited range of data, with only a small percentage (3%) of change pairs identified in our experiments. On the other hand, simpler queries are thought to be easier to generate good plans than more complex queries (as Hypothesis 2 in Section 4.3 states). Also, relational data is generally much less uniform in its (i) data types (we used only integer data), (ii) values (the values in our tables are quite evenly distributed), (ii) schemas (the schemas of our tables are identical and quite simple), and (iii) range of table cardinalities (our smallest table is $1/200^{th}$ of the largest table). The simplicity of queries, schemas, and tables in this study should independently, and certainly in concert, minimize the suboptimality observed. Thus, more complex workloads may present an even higher degree of empirical suboptimality.

8. ENGINEERING IMPLICATIONS

We studied a particular phenomenon, suboptimality, when the optimizer selecting a slower plan. This phenomenon is indicated by the existence of a query plan that performs more efficiently than the DBMS's chosen plan, for the same query. From the engineering perspective, it is of critical importance to understand the prevalence of Suboptimality and its causal factors. The genesis of our predictive model was a sense that Suboptimality is caused in part by the inherent complexity of these systems and the concomitant interactions between various rules in the optimizer.

Through a series of experiments managed by our laboratory instrument management system, DBLAB, carried out across several years, we uncovered several surprising results that provide systematic clues as to where current optimizers come up short and how they can be further improved.

— For many queries, a majority of the ones we considered, the optimizer picked a slower plan for at least one cardinality, even when the cardinality estimates were completely accurate and even for our quite simple queries.
— A quarter of the queries exhibited significant suboptimality ($\geq 20\%$ of the run time) at some cardinality.

These two results indicate that there is still research needed on this topic. Fortunately, the causal model can suggest specifically where that research should be focused.

— Many queries exhibited *query fluttering*, in which the query optimizer returned to a previous plan at a higher cardinality.
— Some queries exhibited significant *query thrashing*, with a plan change at almost every cardinality. While this phenomenon was first visualized by Haritsa et al. [Harish et al. 2007; Haritsa 2010] on some complex queries, we have shown that it is present even in a surprising percentage of simple queries.
— Furthermore, some queries exhibited many changes *to a suboptimal plan* as the cardinality was varied.

These particular queries, as well as those of the right-hand side of Figure 4 exhibiting a large degree of suboptimality, can be a starting point for identifying the root cause(s) of query thrashing. The phenomenon can be investigated initially on a per-DBMS basis. Our methodology could then be used to test proposed causal mechanisms of query thrashing across DBMSes, to ascertain the generality of any proposed solutions.

— It may well be useful to explicitly take *cardinality estimate uncertainty* into account. (Leis et al. came to the same conclusion: “The results ... demonstrate that the state-of-the-art in cardinality estimation is far from perfect.” [Leis et al. 2015]).
— This research indicates that aggregates are less of a problem, so that aspect of query optimization is in reasonable shape.

Concerning the plan search process, which was another identified root cause of sub-optimality, in cases where the DBMS is not as sure about the cardinalities of the underlying relations or the speed of the disk (e.g., if such relations migrated frequently to a different disk drive [Reiss and Kanungo 2003]), perhaps the optimizer should explicitly take uncertainty into account. Indeed, others have started to argue that uncertainties in the query planning process should be acknowledged and exploited [Babcock and Chaudhuri 2005].

We mentioned dynamic query optimization in Section 3 earlier. Dynamic query-reoptimization normally requires a significant amount of information to be recorded during query execution, which can incur non-negligible overhead on the overall query performance [Avnur and Hellerstein 2000; Kabra and DeWitt 1998]. We envision that by utilizing the proposed predictive model for suboptimality, it may be possible to enhance reoptimization techniques such that given a particular query, a particular data distribution, and a specific plan operator, just the important statistics that affect the operator’s performance can be identified and should be recorded, thereby reducing the overhead of bookkeeping irrelevant information.

Hence, the methodology introduced in this paper suggests fairly specifically where additional engineering is needed (accommodating cardinality estimate uncertainty) and is not needed (costing of aggregation).

The generational study in Section 7 though implies that the challenge in daunting. That study validates the implications of the causal model in Figure 6, which correctly predicts the almost inexorable rise in per-generation assembled relative delta, which implies that the optimizer will eventually hit the wall where it is no longer improving.

We emphasize that this section of this paper, considering engineering implications of the underlying causal model, contrasts with the rest of the paper, whose focus is on the science and on understanding these complex systems at a fundamental level. Good engineering should be built on solid scientific results. This paper focuses on the latter.

9. SUMMARY

This paper studies an important component of a DBMS, the query optimizer. This component is an amazingly sophisticated piece of code, but is still not well understood after decades of research and development.

While there has been a wealth of research over the last forty years on engineering approaches and refinements to improve the performance of query optimization, this is the first paper to the authors' knowledge to take a scientific approach (in the sense of *empirical generalization*), towards the important phenomenon of *suboptimality*.

This paper makes the following contributions in an attempt to gain new understanding of this component.

— Shows that even for simple queries, over a simple schema and relatively small range of table sizes, the prevalence of *query suboptimality*, *query flutter*, and *query thrashing*, three problems that have not been systematically investigated across multiple DBMSes, is high, and thus there is still research needed on this mature topic of query optimization.
— Introduces a new *methodological perspective* that treats DBMSes as experimental subjects within empirical generalization.
— Proposes *operationalizations* of several relevant measures that apply even to proprietary DBMSes, as well as an overarching *predictive model* that attempts a causal explanation of suboptimality, encoding some of what is known about query optimization.
— Tests *six hypotheses* deductively derived from the predictive causal model. A correlational analysis and a regression analysis provided *strong support* for our model, across DBMSes, thus confirming what was informally articulated but never coherently tested.
— Uncovers compelling *evidence* (i) that (empirical) suboptimality correlates with four operationalizations of query complexity, (ii) that suboptimality correlates with two operationalizations of plan space complexity, (iii) that the Presence of secondary indexes is a contributor to plan space complexity, (iv) that schema complexity, as operationalized by the Presence of secondary indexes, moderates these two interactions (though weakly and in the opposite direction), and (v) that the Presence of skewed data may diminish Suboptimality slightly.
— Explains a *significant portion* (52.2%) *of the variance of empirical suboptimality* for the kinds of queries we looked at, based on the interactions as well as the factors that we identified in the model: optimizer complexity, query complexity, and plan space complexity. No other factor, as yet unknown, nor combination of factors, will themselves predict as much variance as the factors we studied in this paper. And somewhat extraordinarily, it is these common aspects that predict suboptimality, not the particulars embedded in the inordinate complexity of each of these DBMSes. That said, it is certain that there remain several unknown causal factors; identifying those factors may also have important engineering implications.
— Articulates for the first time a *limit* on the number of operators a DBMS may be able to support, given that the empirical evidence suggests that additional operators speed up a smaller and smaller portion of the query/cardinality space while incurring an increasing chance of suboptimality over the remaining space, which is growing.
— Applies a novel experiment over pairs of adjacent Q@Cs, providing empirical evidence that *this limit exists* and may have already been reached by one or more our subject DBMSes.
— Identifies *specific directions for engineering interventions*.

— Provides a *path toward scientific progress* in the understanding of a key enabling technology. It is important to emphasize that our model doesn't apply to only one implementation of the algorithm or to one DBMS. Rather, it is quite broad, applying to any DBMS with a cost-based optimizer.

This paper thus suggests a framework of casual model elaboration and directed engineering efforts.

10. FUTURE WORK

There are at least three fundamental directions that could be taken in future work: (i) model testing and refinement, (ii) following up on engineering implications drawn from the predictive causal model, and (iii) applying the empirical generalization perspective to other aspects of DBMSes.

The model proposed and tested here, shown in Figure 6, is relatively simple, with six constructs and their relationships. Some of the predicted relationships were not borne out in the confirmatory analysis.

Might further testing support or reject the hypothesized correlation between Number of repeats (in the Plan complexity construct) and Presence of primary key attribute and Presence of subquery (both in the Query complexity construct)? Why did the hypothesized moderation by the Presence of secondary indexes (in the Schema complexity construct) *decrease* the influence of Query complexity on Plan space complexity?

Finally, why did the Presence of skewed data (actually, the increase in skew from tiny to small, in the Data complexity construct) *decrease* Suboptimality? (As others have noted, "cardinality estimates are usually computed based on simplifying assumptions like uniformity and independence. In real-world data sets, these assumptions are *frequently* wrong, which may lead to sub-optimal and sometimes disastrous plans ... the cardinality estimators of the major relational database systems produce bad estimates for many realistic queries, in particular for multi-join queries." [Leis et al. 2015])

Our causal model is extensible, in that we can add other factors, as long as their proper operationalization can be established, and additional causal links. It would be useful to consider

— *schema complexity:* foreign keys and uniqueness and other kinds of constraints,
— *query complexity:* complex predicates, multiple nesting of subqueries and different types of subqueries, query operators such as `EXCEPT` and `UNION`, other SQL clauses such as `ORDER BY` and `GROUP BY`, and user-defined data types, methods, and operators,
— *data complexity:* data that doesn't exhibit uniformity or independence data, and
— *plan space complexity:* the actual space of plans considered by the optimizer (discussed below).

Our Confirmatory experiment used only two values of skew, tiny ($1/2M$) and small ($1/10K$), for the data complexity construct. It would be useful to extend the study to (much) larger values. (This could increase the number of duplicates in joins, which may dramatically increase the query time.) But more to the point, our definition of skew utilizes a uniform distribution of values, albeit across a narrowing range as skew increases. It would be useful to look at other distributions, such as an increasing distribution and a normal distribution, as well as a very spiky distribution, in part to see whether the positive impact of skew on suboptimality continues (our intuition remains that with substantial skew, suboptimality will increase). It would also be useful to run experiments over entirely different benchmarks, including those based on real-world data and queries such as the Join Order Benchmark [Leis et al. 2015], appropriately modified to provide a range of values for the various constructs such as data skew.

Kabra and DeWitt have identified another source of complexity: inaccurate statistics on the underlying tables and insufficient information about the runtime system: "amount of available resources (especially memory), the load on the system, and the values of host language variables." [Kabra and DeWitt 1998, p. 106]. Might there be other unanticipated relations, that are unknown simply because they haven't been looked for?

It may be useful to look into query flutter and thrashing in greater detail, as those phenomena provide concrete indicators of problematic optimizer behavior. One possible methodological approach is to utilize SQL optimizer hints, such as "`+ SEMIJOIN`" in MySQL and "`enable_hashjoin(false)`" in PostgreSQL, to encourage the optimizer to produce more plans at a given cardinality, that can then be timed to make more explicit the entire plan space (recall that CEPS, the cardinality of the effective plan space, is no greater and probably much smaller than the cardinality of the plan space).

Along with adding such factors to the model, one can watch whether these other factors impact (at all, and if so, how much) these initial constructs and relationships. So for example it would be interesting to study how a suboptimal subquery can affect the suboptimality of the containing query. For instance, is it true that if many subqueries are themselves suboptimal, does that causally impact whether the overall query is suboptimal?

It would also be useful to study other relational DBMSes, as the model should apply to any such DBMS using a cost-based optimizer.

All of the above activities are in the tradition of science, specifically empirical generalization (cf. Figure 5).

The second fundamental direction takes the validated model and draws engineering implications. Our model has provided specific directions for implementation interventions: improving buffer allocation algorithms and accommodating cardinality estimate uncertainty. One can further ask, for each causal relationship in the model, relationships that have been validated in empirical studies, what is it about the cost-based query optimizer that that interaction is evidenced? And then one can ask, what changes to that optimizer might ameliorate that relationship?

It may be that that relationship is *baked into the optimizer*. For example, the study in Section 7 was predicated on some basic aspects of adding operators: each successive operator *benefits* a smaller region of query/cardinality (specifically, Q@Cs) and is susceptible to suboptimality on a larger region of Q@Cs (cf. Section 7.1). That seems like a fundamental limitation.

But other relationships may be avoidable, through selection of alternative algorithms. After all, this study generalizes over only four DBMSes.

Engineering also provides alternative methodologies to studying the model variables, which we have examined only from the "outside" of the DBMS. It would be useful to manipulate DBMSes internally (at least for those that are open-source or are available within the DBMS vendor), turning on and off the rules and observing suboptimality. (An example is a study of cardinality estimation, cost model, and plan enumeration [Leis et al. 2015].) And it may be possible to determine whether certain query rewrite techniques are employed within each DBMS, perhaps introducing other "DBMS complexity" factor(s) in our model.

If extant cost-based query optimizers are hitting a wall, it might be necessary to fundamentally revisit query optimization, to come up with an entirely new approach that is less impacted by number of operators and by CEPS and thus avoids the flutter phenomenon.

The identified limit is inherent in cost-based query optimization. Engineering approaches can help ameliorate the effect identified here. One approach might be to time query plans as they run (effectively introducing an empirical cost model) in order to provide more accurate cost estimates, though that is itself time-consuming when there is a large plan space. Another that has been proposed is to replace multiple physical operators of a logical operator (in this case, the join operator, which can have as physical operators nested-loop, sort-merge, hash, and index join) with a single physical operator (in this case, g-join) that performs equally or better that the alternative physical operators, hopefully in all cases [Graefe 2012]. Doing so can reduce optimizer errors when choosing between the previously-available multiple variants. This approach is aligned with our theoretical and empirical results: if adding physical operators gets us close to or beyond the limit of performance improvement, as we have seen, then removing variants should move the DBMS away from that limit. However, the g-join has not yet been demonstrated to be applicable in all situations and for all queries, and in any case, the limit still remains.

Engineering solutions to *eliminate* the identified limit, to allow continued introduction of new operators, thus requires perfecting the cost model and making query plan enumeration deterministic, neither of which seems to be practical, or adopting an entirely new tact that eschews cost-based query optimization entirely, such as a learning-based approach or defining a single physical operator for each logical operator.

A third fundamental direction is to return to science, but examine dependent measures other than suboptimality. This paper demonstrates that by employing an extensible causal model, many complex factors can be studied via a systematic, statistically sound, scientific manner to better understand the causal factors and their relationships. What other areas of the rich field of databases might be amenable to this approach?

The methodology utilized in this paper to introduce a predictive causal model has suggested the scope of the problem of query suboptimality, a number of contributing factors, and a collection of specific engineering efforts that can now be considered. An ultimate goal is a refined causal model that fully explains how query suboptimality arises in cost-based optimizers, thereby enabling engineering solutions that address this important issue.

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Table VIII. Experiments 1–7: Detailed Run Statistics

	Experiment	*Data Sets Used*	*Lab Shelves*	*What was Examined?*	*Was Query Timed?*	*Number of Retained (Raw) Q@Cs*
1	Monotonicity	A	6.0	all cardinalities	yes	12,000 (12,000)
2	Exhaustive	A	5.19 + 6.0	all cardinalities	yes	27,948 (32,000)
3	Exhaustive with Keys	B	6.0	change pairs	no	40,000 (40,000)
4	Initial Exploratory	A + B	5.19 + 5.2 + 6.0	change pairs	yes	8,171 (8,842)
5	Refined Exhaustive	A	7.1	all cardinalities	yes	29,515 (32,000)
6	Exploratory	A + B	7.1	change pairs	yes	12,100 (12,560)
7	Confirmatory	A + B + C +D	7.1	change pairs	yes	94,502 (99,558)
	Total					184,236 (196,960)

A. DETAILS ON THE EXPERIMENTS

Table I in Section 6.3 lists the run statistics of the seven experiments used in this paper. In this appendix we provide more detailed information on the experiments, walking through the columns in succession of Table VIII, given below.

A.1. Data Sets

The third column identifies the data set(s) used in each experiment, that is, the specific tables being queried. There are four data sets, named A, B, C, and D.

We first discuss the features shared between the four data sets. As introduced in Section 2, the queries referenced tables `ft_HT1`, `ft_HT2`, `ft_HT3`, and `ft_HT4`. All four tables contain four columns, each of type integer. The specific values of the rows for all but the first column depend on the Presence of skewed data. Section 5.4 provides the algorithm for generating the values for different values of skew; this algorithm is used in the second to fourth columns, which for any row will have identical values. The first column holds a unique integer starting from 1 and going to 60K or 2M, for use in an optional primary key.

There was one version of the last three tables, for use with MySQL, with cardinality 60K, and one version for the rest of the DBMSes, with cardinality 2M.

We generate 200 versions of `ft_HT1`, termed the *variable table*. For MySQL, these version contain 300, 600, 900, 1200, ..., 59,700, and 60,000 rows; for the rest of the DBMSes, these versions contain 10,000, 20,000, 30,000, ..., 1,970,000, and 2M rows, as introduced in Section 2.

We now identify the four successive data sets, elaborating on the discussion in Sections 6.2–6.3. Data Set C is the simplest to describe: it specifies no primary key, has no duplicate rows, and has no skew (of course, for any of the four tables). Data Set A differs from Data Set C only in that there is skew. As summarized at the end of Section 5.4, we use two values of skew, tiny and small.

Data Set B is similar to Data Set A, adding the specification of the first column as the primary key. And Data Set D is similar to Data Set B, adding the specification that the other three columns should each be associated with a secondary index, only for each (one) column. We see the confirmatory experiment examined a much larger variation of data sets than the exploratory studies.

A.2. Other Details

The next column of Table VIII concerns the *Lab Shelf*. DBLAB utilizes the metaphor of a bookshelf of lab notebooks. Here, each shelf is associated with a version of DBLAB itself. For the experiments in this paper, we used at various times over the last three years lab shelves (that is, program versions) 5.19, 5.2, 6.0, and 7.1. Versions 5.19 and 5.2 were very similar; both implemented TTPv1. Version 6.0 also implemented TTPv1, but collected more query measures that were not relevant for this paper. Version 7.1 implemented TTPv2.

The DBLAB system also includes support for *experiment scenarios*, each of which is a small amount (a few hundred lines) of Java code that actually performs the experiment, such as varying the cardinality and running different queries on the data. The only difference in the scenario code across these experiments was in accommodating the details of the data set (that is, creating secondary indexes and data skew).

The bottom line is that while the lab shelf and experiment scenario varied somewhat, the only important aspect was the *Protocol* column of Table I.

We now turn to the fifth column, "what was examined?" Here there are just two possibilities, all 200 cardinalities or just the cardinalities at which the query plan changed. The sixth column, "what was timed?", indicates that Exhaustive with Keys, described in Section 6.3, just collected query plans, not timing any of them.

The last column states how many Q@Cs the experiments measured (each with 10 QEs), termed *raw*, and how many Q@Cs were retained after the protocol (listed in the third column of Table I) dropped query executions and Q@Cs via its many sanity checks. (Note that we don't list QEs and retained QEs in Table I for Exhaustive with Keys simply because we did not use timing data in that experiment.)

A.3. Query Sets

The following sets of queries were used in the seven experiments.

QSa. 100 queries over the four tables, generated as described in Section 5.3 (on Data Set A)
QSb. 100 queries (on Data Set A)
QSc. 100 queries (on Data Set A)
QSd. 100 queries (on Data Set A)
QSe. 100 queries (on Data Set A)
QSf. 100 queries (on Data Set A)
QSg. 100 queries (on Data Set A)
QSh. 100 queries (on Data Set A)
QSi. 100 queries (on Data Set A)
QSj. 100 queries (on Data Set A)
QSk. A query set consisting of the 390 queries drawn from *QSa*–*QSj* (on Data Set B)
QSl. A query set consisting of 110 new queries (on Data Set B)
QSm. A query set consisting of 100 queries without aggregates (on Data Set C)
QSn. A subquery query set consisting of 100 queries, each with a subquery (on Data Sets A, B, and D)
QSo. A subquery query set consisting of 100 queries, each with a subquery (on Data Set D)
QSp. A query set consisting of 100 queries drawn from *QSk* (on Data Set D)

Experiment 1 (Monotonicity) used the first 50 queries from QSa for one DBMS plus the first six queries from QSa and two queries each from *QSd* and *QSe* for MySQL, for a total of 60 query instances.

Experiment 2 (Exhaustive) used the first 50 queries from *QSa* for the three other DBMSes plus the ten queries for MySQL from Experiment 1, for a total of 160 query instances. Experiment 5 (Refined Exhaustive) used the same 160 queries.

Experiment 3 (Exhaustive with Keys) used the first 50 queries from *QSa* for the four DBMSes, for a total of 200 query instances.

Experiment 5 (Initial Exploratory) used the (100) queries from *QSa*–*QSf* (for one DBMS), the first 20 queries from *QSa*–*QSf* (for another DBMS), the first 10 (primary key) queries from *QSa* (for the four DBMSes), and the first 10 (non-primary key) queries from *QSa* (for the other two DBMSes), for a total of 780 query instances.

Experiment 6 (Exploratory) used QSa and QSb, plus the first 100 (primary key) queries from QSk, for the four DBMSes, for a total of 1200 query instances.

Experiment 7 (Confirmatory) used QSc–QSj, along with QSk except the (first 100) queries included in Experiment 6, QSl for primary key (for two runs, or 220 queries), QSm for no data skew, QSn for primary key and subquery, QSn for subquery, QSn and QSo for primary key and secondary index and subquery, QSp for primary key and secondary index, all across the four DBMSes, for a total of 7,640 query instances.