Exploiting Soft and Hard Correlations in Big Data Query Optimization[*]

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ABSTRACT

Big data infrastructures are increasingly supporting datasets that are relatively structured. These datasets are full of correlations among their attributes, which if managed in systematic ways would enable optimization opportunities that otherwise will be missed. Unlike relational databases in which discovering and exploiting the correlations in query optimization have been extensively studied, in big data infrastructures, such important data properties and their utilization have been mostly abandoned. The key reason is that domain experts may know many correlations but with a degree of *uncertainty* (*fuzziness* or *softness*). Since the data is big, it is very challenging to validate such correlations, judge their worthiness, and put strategies for utilizing them in query optimization. Existing techniques for exploiting soft correlations in RDBMSs, e.g., BHUNT, CORDS, and CM, are heavily tailored towards optimizing factors inherent in relational databases, e.g., predicate selectivity and random I/O accesses of secondary indexes, which are issues not applicable to big data infrastructures, e.g., Hadoop.

In this paper, we propose the *EXORD* system to fill in this gap by exploiting the data's correlations in big data query optimization. EXORD supports two types of correlations; *hard* correlations—which are guaranteed to hold for all data records, and *soft* correlations—which are expected to hold for most, but not all, data records. We introduce a new three-phase approach for (1) Validating and judging the worthiness of soft correlations, (2) Selecting and preparing the soft correlations for deployment by specially handling the violating data records, and (3) Deploying and exploiting the correlations in query optimization. We propose a novel cost-benefit model for adaptively selecting the most beneficial soft correlations w.r.t a given query workload while minimizing the introduced overhead. We show the complexity of this problem (NP-Hard), and propose a heuristic to efficiently solve it in a polynomial time. EXORD can be integrated with various state-of-art big data query optimization techniques, e.g., indexing and partitioning. EXORD prototype is implemented as an extension to the Hive engine on top of Hadoop. The experimental evaluation shows the potential of EXORD in achieving more than 10x speedup while introducing minimal storage overheads.

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1. INTRODUCTION

Most big data applications involve numerous correlations and relationships among their data attributes. These correlations range from *"hard correlations"* that must be satisfied by all data tuples, to *"soft correlations"* that are satisfied by most (but probably not all) data tuples. For example, in transaction log applications, a zip code attribute may imply the location attributes, e.g., city and state (hard correlation), while in online marketing applications, a delivery date can be within 3 to 10 days of the shipping date in most cases (soft correlation). In general, a *"correlation"* from one attribute A_1 to another attribute A_2 means that their values are not independent. Instead, a value in A_1 provides some knowledge about the corresponding value in A_2, e.g., A_1's value may determine a unique value, a possible range, or a set of values for the corresponding A_2 attribute. In traditional database systems, defining these correlations has an immense advantage in both data integrity [10], and query optimization [2, 14, 16, 17].

Unfortunately, in the emerging big data applications and their scalable infrastructures, e.g., Hadoop [22], the data integrity check is usually bypassed for several legitimate reasons including: (1) The data is usually uploaded in the form of large batches of files of GBs or even TBs of records, and thus it is impractical to scan and check them against the integrity constraints, and (2) Given the complexity of big data, it is common that most correlations and semantic constraints are not 100% conformed. And thus, in most cases, domain experts can only provide their "expectations" or "beliefs" on which correlations should hold without guarantees. Because of these reasons, none of the existing big data infrastructures facilitate defining or capturing these correlations. And hence, such important data properties have been abandoned by the state-of-art optimization techniques in big data.

In this paper, we argue that although checking and enforcing the data integrity may not be practical in big data applications, still capturing these correlations can be very beneficial to query optimization. This is especially true because exiting big data infrastructures are increasingly used for structured and/or semi-structured data, where some knowledge about the data is assumed to be known, e.g., Hive [23], Pig [11], and Impala [20]. As mentioned above, a key challenge is that domain experts may only be able to provide their expectations on the possible correlations without guarantees, and there can be many of such candidates with no clear evidence on which ones are truly useful. We will show that the management of these soft correlations although challenging due to their inherent uncertainty, it is very rewarding w.r.t query optimization.

Motivation Scenario 1– Online Marketing and Usage of Data Indexing: *Analytics over transaction logs generated from online marketing is a typical big data application. An example of soft correlations that may exist among the data attributes is that the delivery date in most cases (but not necessarily all cases) is within*

3 to 10 days from the shipping date. Assume the dataset already has an index on the shipping date to efficiently answer queries involving a selection predicate on that attribute, e.g., [4, 6, 8]. However, the crucial limitation of these techniques is that queries involving selection predicates on the delivery date cannot be optimized, and would require a full scan over the data (unless another index is created on the delivery date). Moreover, given the correlation's uncertainty, a query issuer cannot manually translate the predicate to a corresponding one on the shipping date (by going backward 3 to 10 days), and then filtering the results. This blind re-writing may miss some tuples satisfying the original query but not conforming with the soft correlation.

Motivation Scenario 2– Airline Analytics and Usage of Data Partitioning: *Airline analytics companies manage very large data about customer requests, flight status, seat availability, and airport traffics. Most of the major airports worldwide have a unique three-character code, called IATA, which identifies the airport, and hence identifies its city and country. However, many small airports—usually with very limited traffic—do not have IATA code (denoted as "***"), and thus this "***" code neither identifies the city nor the country. Therefore, there is a soft correlation from the airport code to the country, i.e., for most (but not all) records the airport code uniquely determines the country. Assume the data is already partitioned on the country attribute to optimize certain queries [9, 15]. The limitation now is that queries involving predicates on the airport code would require a full scan over the data without making any use of the available partitioning. The challenge is that in the general case, the values violating the correlation may not be known in advance, e.g., each country may assign random code for these small airports of infrequent traffic, and thus manual re-writing to optimize the query is not feasible.*

Clearly, the soft correlations mentioned above open big opportunities for query optimization—especially if we can systematically leverage the special organization that is already present in the data, e.g., indexing [4, 6, 8] or partitioning [9, 15], without the need to create additional ones. This is crucial because building auxiliary structures over big data is a very expensive process w.r.t both time and storage [6, 8, 9], and thus should be kept to minimal whenever possible. Our experimental evaluation also confirms the substantial overheads involved in creating additional partitioning or indexes, which makes it almost impractical to create many of these over a single dataset (Results will be discussed in Figure 6). Therefore, by leveraging the possible correlations among the data attributes, the usage and benefits of the existing techniques (on few targeted attributes) can be extended beyond these attributes without paying these significant costs, and eventually a broader class of queries can be optimized.

Exploiting soft correlations in query optimization is not a new problem and it has been previously studied in the context of relational databases, e.g., [2, 14, 16, 17]. However, most of these techniques have objectives that are specific only to RDBMSs and not applicable to the new emerging Hadoop-like infrastructures. For example, CORDS [14] exploits a correlation between a pair of attributes A_1 and A_2 to provide more accurate selectivity estimation for their conjunctive predicates at query time, and enable generating better query plans. On the other hand, Correlation Maps (CM) [16] and CORADD [17] aim at avoiding the random I/O accesses that may result from a blind usage of secondary indexes on un-clustered attributes, and instead they try to leverage any existing correlation that may link these un-clustered attributes to the clustered attribute on which the relation is sorted.

These issues of predicate selectivity and random vs. sequential access patterns are fundamental in RDBMSs. However, they are not applicable to the highly-distributed big data infrastructures, e.g., Hadoop. First, the physical execution plan in Hadoop is fixed—either map-only job or map-reduce job—and predicate selectivity does not play any role in optimizing this execution plan. Second, with the distributed nature of big data both in storage and retrieval, the data is usually not sorted on a specific attribute, and there is no notion of clustered vs. un-clustered attributes. Third, since the emerging infrastructures are highly distributed, there is no notion of random vs. sequential accesses, instead execution tasks, e.g., map tasks in Hadoop, are assigned to where the data resides, which is called *data locality*. And Fourth since there is no notion of random accesses, it is always safe in Hadoop-like systems to use indexes to answer selection queries regardless of their predicate selectivity. These fundamental differences warrant the need for new correlation exploitation tools that target the new big data distributed infrastructures (More detailed discussion is provided in Section 6).

In this paper, we propose the *"EXORD"* system for Exploiting soft and hard correlations in big data query optimization (Refer to Figure 1). EXORD is distinct from the existing techniques mentioned above in three key aspects, which are:

(1) Infrastructure Type: EXORD is the first correlation exploitation tool targeting the emerging Hadoop-like infrastructures, which are fundamentally different from RDBMSs in their distribution nature, query processing, data retrieval, and index access patterns. Our objective is to avoid full scan plans whenever possible.

(2) Domain Knowledge: All existing techniques are *discovery-based*, where they put the extreme assumption of having no knowledge about the possible correlations that may exist in a given dataset. This assumption puts various restrictions on the correlations that can be captured, e.g., BHUNT [2] is only limited to numerical attributes and the correlations must be in the form of a simple algebraic expression of one operator {+, -, *, or /}. In contrast, EXORD puts the more practical assumption that domain experts have some knowledge on the possible correlations that may exist in the dataset. And hence, they can define *"hard correlations"* (with certainty) and *"soft correlations"* (with fuzziness). Correlations in EXORD can be between any pair of attributes either numerical or categorical, and the relationship logic may range from complex expressions to general look-up functions.

(3) Optimized Resource Management: Preparing the soft correlations to be usable by the query optimizer involves a cost for handling the violating records. Therefore, given a set of candidate correlations and limited system resources, deciding on which ones to select and be more beneficial to a given query workload turns out to be a complex NP-Hard optimization problem. EXORD introduces a novel cost-benefit model for soft correlations augmented with a heuristics-based algorithm under which it adaptively and dynamically selects the most beneficial correlations in a practical polynomial time.

As illustrated in Figure 1, the core features of EXORD are infrastructure-independent, and hence they are applicable to big data query optimization in general. As a proof of concept, EXORD prototype is built on top of the Hadoop infrastructure—as one of the most popular big data platforms—and it uses Hive as its high-level query engine. We opt for Hive since it assumes a known structure for the data, which facilitates defining the correlations among the data attributes.

The key contributions of this paper are summarized as follows:

- Proposing "EXORD" as the first system for exploiting the data's correlations in big data query optimization. EXORD realistically put the assumption that domain experts may not guarantee with certainty many of the correlations, and thus EXORD introduces and supports the two types of *hard* and *soft* correlations. (Section 2)

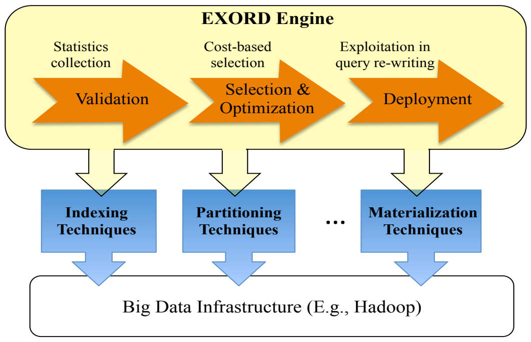


Figure 1: EXORD Utilization and Phases.

- Introducing a new multi-phase approach for managing soft correlations, which consists of a *Validation Phase*, followed by a *Selection & Optimization Phase*, and then a *Deployment & Exploitation Phase*. Throughout these phases EXORD decides whether or not a given soft correlation is worthy of being used, and what is the best strategy to prepare it for deployment. We propose two different strategies, namely *Exclusion*, and *Materialization*, for handling the violation records, each is suited for specific cases. (Section 3)
- Proposing a novel cost-benefit model for soft correlations, and mapping the selection of the most beneficial ones for optimizing a given query workload to the well-known *submodular knapsack* optimization problem. As an NP-Hard problem, we propose a sound heuristic to efficiently solve the selection problem in a practical polynomial time. (Section 3)
- Proposing an algorithm for exploiting the soft and hard correlations in query optimization. We experimentally utilize EXORD on top of two well-known optimization strategies in Hadoop, which are the indexing, and partitioning strategies. EXORD extends the benefits of these strategies beyond their targeted attributes to optimize a broader class of queries. (Section 4)
- Implementing EXORD as an extension to Hive query engine on top of Hadoop. The extensions do not require any changes to Hadoop, and hence they are easily portable across versions. The system's empirical evaluation shows that EXORD enables optimization opportunities that the state-of-art techniques fail to discover. These optimizations lead to up to 12x speedup compared to the naive full-scan evaluation plans. (Section 5)

2. PRELIMINARIES

In this section, we define the target queries to be optimized by EXORD, and formally introduce our definition of correlations.

DEFINITION 2.1 (TARGET QUERIES). *A target query Q in EXORD is a query involving an equality predicate on an attribute A_1 that has no associated access methods—other than a full scan—to check its predicate. The primary objective of EXORD is to leverage any available correlations related to A_1 to re-write Q in terms of other attributes that have more efficient access methods, e.g., indexing or partitioning, to evaluate their predicates.*[1]

DEFINITION 2.2 (CORRELATION). *A correlation C over a given dataset is a directed relationship from one attribute, called "source", to another attribute called "destination". The correlation defines how the source's values can be mapped to the destination's values. C is defined as a five-ary vector $\langle Src, Dest, Type, Granularity, F()\rangle$, where, Src, and Dest, are the source, and destination attributes of the correlation, respectively, Type is the correlation's type as either "Hard" or "Soft", and Granularity is the granularity of mapping from a given source's value to the destination value(s), and it takes either of the values "Singleton" (one-to-one mapping), "Range" (one-to-range mapping), or "List" (one-to-list mapping). Finally, Function F(s) is the mapping function that takes a value $s \in Src$ and returns its corresponding mapping in $Dest$. Depending on the granularity, F(s) returns either of a single value (for "Singleton"), a list of values (for "List"), or a record $\{$lower, upper$\}$ (for "Range").*

[1]The *equality predicates* can be relaxed and extended to *range predicates* but under some restrictions and properties that need to hold for the values being queried. However, for the ease of presentation, we will focus only on equality predicates.

Example 1: *Referring to our motivation scenarios, the correlation in Scenario 1 can be formulated as: $\langle deliveryDate, shippingDate, \text{"}Soft\text{"}, \text{"}Range\text{"}, F()\rangle$, where for a given delivery date d, $F(d).lower = (d$ - 10 days), and $F(d).upper = (d$ - 3 days). In contrast, the correlation in Scenario 2 can be formulated as: $\langle airportCode, country, \text{"}Soft\text{"}, \text{"}Singelton\text{"}, F()\rangle$, where for a given airport code a, Function $F()$ lookups a small table having the list of distinct airport codes and returns the corresponding country (For the special code "***", the function returns Null).*

In general, EXORD treats Function $F()$—which is provided by the system admin—as a black box without the need to know its internal logic. The only requirement is that $F()$ should be a low-cost light-weight function that can be executed with a very little cost per record. This requirement does not limit the applicability of the system since the Src and $Dest$ attributes are not restricted to any specific data type or domain and they can be numerical or categorical. Moreover, $F()$ may range from any mathematical or algebraic expression, to general lookup functions that search some auxiliary structures and perform the mappings—as long as this auxiliary structure is relatively small (few MBs) and can be distributed to the main memory of each machine in the distributed system. Most correlation examples studied in literature, e.g., [2, 16, 17], fall under this scope.

DEFINITION 2.3 (HARD CORRELATION). *A hard correlation C is a correlation having C.Type = "Hard" and it is guaranteed to hold for all records in the dataset D.*

Unlike hard correlations, soft correlations have a degree of uncertainty and not all of them are useful, e.g., the violations for a given correlation can be too many. Therefore, depending on the degree of violations, we categorize soft correlations into *Valid* (useful) and *Invalid* (useless) as follows.

DEFINITION 2.4 (VALID SOFT CORRELATION). *For a soft correlation C of C.Type = "Soft", let $\Phi(C)$ denotes the set of distinct violating values in $C.Src$ (with cardinality $|\Phi(C)|$), and $\Gamma(C)$ denotes the set of violating records in the dataset (with cardinality $|\Gamma(C)|$). Given two user-defined thresholds MaxVioDistinct > 1 and MaxVioRec > 1, C is called a "valid" soft correlation iff either (or both) of the following two conditions is met:*
(1) $|\Phi(C)| \leq$ MaxVioDistinct,
(2) $|\Gamma(C)| \leq$ MaxVioRec

DEFINITION 2.5 (INVALID SOFT CORRELATION). *A soft correlation C of C.Type = "Soft", is called "invalid" iff C is not a valid soft correlation.*

According to Def. 2.4, EXORD considers a soft correlation to be *valid* (useful) under two cases. The first case is where the number of distinct violating values in the correlation's source attribute is less than a given threshold $MaxVioDistinct$ regardless of the number of violating records. This case captures the scenarios where there can be many violating records, but possibly because of few distinct values that are repeating in these records. The second case is where the set of violating records is smaller than a given threshold $MaxVioRec$ even if the number of distinct violating values is large. Typically, $MaxVioDistinct << MaxVioRec$. As we will present in Section 3.2, EXORD offers two different strategies for managing these two cases.

3. EXORD: BASIC FRAMEWORK

We propose a three-phase approach to manage the soft correlations as depicted in Figure 1. In the 1^{st} phase (The *Validation Phase*), EXORD collects few statistics to identify the valid soft correlations. In the 2^{nd} phase (The *Selection & Optimization Phase*), the system selects and prepares a possibly subset of the valid soft correlations that are the most beneficial for a given query workload. This selection is based on a novel cost-benefit that works under limited system resources. The 3^{rd} phase is the *Deployment & Exploitation Phase* in which the correlations are used at runtime for query re-writing and optimization. In the following, we present the first two phases, while the 3^{rd} phase is presented in Section 4.

3.1 Validation Phase

Assume a dataset D and a set of soft correlations in their validation phase $\mathcal{V} = \{C_1, C_2, ..., C_n\}$. Since scanning the dataset can be an expensive operation over big data, EXORD will not perform a dedicated job on D to collect the needed statistics. Instead, the system waits for the first user's job that is going to scan the data anyway, and then piggybacks the statistics collection task over this job. More specifically, the user's map task will be encapsulated within a larger system-created map task, and before the execution of the user's code on an input record r, r is tested against each soft correlation $C_i \in \mathcal{V}$ according to its granularity as follows:

Correlation Granularity	Test Format
Singleton	`Dest = `C_i`.F(Src)`
Range	`Dest ≥ `C_i`.F(Src).lower And Dest ≤ `C_i`.F(Src).upper`
List	`Dest in `C_i`.F(Src)`

For each correlation, each mapper reports two types of statistics: (1) The number of records violating C_i (without reporting the actual records), and (2) Either the distinct violating values ($\Phi(C_i)$) if their number is less $MaxVioDistinct$, or a flag indicating that the number has exceeded the allowed threshold. Notice that the goal is not to enumerate all distinct violating values otherwise it becomes an expensive map-reduce job by itself. Instead, each mapper keeps maintaining the seen-so-far distinct violating values in its memory until the given threshold is exceeded (if happened). And as we will demonstrate in the experiment section, $MaxVioDistinct$ is typically set to few thousands, e.g., $10,000$ or less, and in this case the mapper's consumed memory is very small, e.g., less than 1MB.

After all mappers are completed, a centralized task aggregates the results to compute $|\Gamma(C_i)|$, and the final duplicate-free set of $\Phi(C_i)$ (or a flag indicating that its size exceeded $MaxVioDistinct$). Based on these statistics and according to Def. 2.4, each correlation is marked as either *Valid* (and advances to subsequent phases) or *Invalid* (and get eliminated from any further consideration). The statistics and the status of each correlation are maintained in the system's Metadata Repository, which will be highlighted in Section 5.1.

3.2 Selection & Optimization Phase

Unlike hard correlations that are ready for exploitation by the query optimizer, the valid soft correlations need to be first prepared by specially handling the violations and putting strategies for guaranteeing correct query execution. This handling involves a storage cost, which may vary significantly from one correlation to another. Moreover, not all correlations have the same usefulness degree w.r.t query optimization. For example, the system may pay the cost of preparing many valid soft correlations while they are of little or no actual benefit to the current query workload, which may lead to a significant waste in system resources.

In this section, we propose a novel cost-benefit model to automatically and adaptively select the correlations based on their costs and benefits w.r.t to a given query workload and under limited system resources. We show that this optimization problem is very complex, and can be formulated as a submodular knapsack problem, which is known to be an NP-Hard problem [21]. And then, we propose a heuristic to efficiently solve it in polynomial time.

3.2.1 Correlations Cost Model

EXORD offers two different strategies—each comes with an associated cost—for preparing a valid soft correlation, namely *"Exclusion"* and *"Materialization"*. Each strategy is applicable to a given soft correlation according to the following definitions:

DEFINITION 3.1 (EXCLUSION STRATEGY). *For a given valid soft correlation C, the "Exclusion Strategy" is applicable to C iff Condition (1) in Def. 2.4 is True, and it involves copying the $\Phi(C)$ set to EXORD's Metadata Repository.*

DEFINITION 3.2 (MATERIALIZATION STRATEGY). *For a given valid soft correlation C, the "Materialization Strategy" is applicable to C iff Condition (2) in Def. 2.4 is True, and it involves copying the $\Gamma(C)$ set to a separate file, called exception bucket, in the file system.*

As will be discussed in detail in Section 4, the *Exclusion* strategy relies on logically excluding the violating values from being re-written or optimized for during the compilation and optimization time. And since the decision of such exclusion needs to be taken very fast (typically in few milli-seconds), the distinct violating values are not intended to be written to (and read from) the slow-storage of the main file system, e.g., HDFS. Instead, they are kept in EXORD's Metadata Repository—which is a light-weight relational DBMS. The *Exclusion* strategy is well suited for the cases where the number of distinct violating values is small even if the violating records are many (As in Motivation Scenario 2). On the other hand, the *Materialization* strategy relies on physically copying the violating records into separate files (referred to as *"exception buckets"*)—recall that in HDFS, the deletion or update of the original files is not a possible operation. These exception buckets can be relatively large in size, and thus kept in the file system, e.g., HDFS. Nevertheless, their access will be only required during query execution not query optimization.

Given that the storage resources are not infinite, the maximum resources allotted to EXORD, which are referred to as the *Resource Pool*, are defined as follows:

DEFINITION 3.3 (RESOURCE POOL). *The Resource Pool is the maximum allowed storage that valid soft correlations can compete for and consume. It is denoted as $RPool$ = ¡M_{Pool}, H_{Pool}¿, where M_{Pool}, and H_{Pool} are the maximum sizes in the Metadata Repository, and the file system (HDFS), respectively.*

Recall that M_{Pool} is the storage space to be used in the case of the *Exclusion* strategy, whereas the H_{Pool} is the storage space to be used in the case of the *Materialization* strategy.

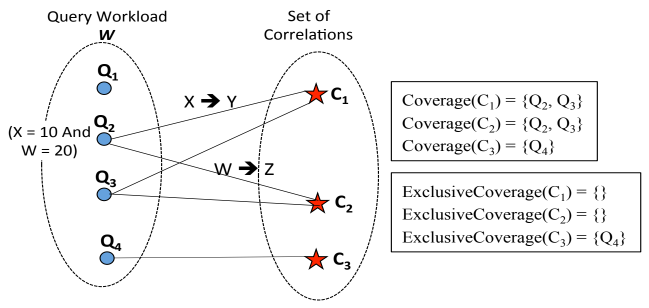


Figure 2: Benefit Factors of Soft Correlations.

Now, the formal cost model of soft correlations is defined as follows (Hard correlations always has zero deployment cost).

DEFINITION 3.4 (CORRELATION COST). *The deployment cost of a valid soft correlation C to be ready for the query optimizer is defined as follows:*

$$Cost(C) = \begin{cases} < \Phi(C).size,\ \infty >, & \text{if only Def. 2.4.(1) = True} \\ < \infty,\ \Gamma(C).size >, & \text{if only Def. 2.4.(2) = True} \\ < \Phi(C).size, \Gamma(C).size >, & Otherwise \end{cases}$$

According to Def. 3.4, if only Condition (1) in Def. 2.4 is True, then the correlation is allowed to compete only for a space in M_{Pool}, whereas if only Condition (2) is True, then it is allowed to compete only for a space in H_{Pool}. And if both conditions are True, then the correlation is allowed to compete for both resources (although a higher priority is given to M_{Pool}) as will be presented in Section 3.2.3. Notice that in the cost model, $\Phi(C).size$ can be exactly computed since the $\Phi(C)$ set is already available, whereas $\Gamma(C).size$ can be only estimated depending on the known $|\Gamma(C)|$ and its percentage w.r.t to base dataset.

3.2.2 Correlations Benefit Model

Given a workload of n queries $W = \{Q_1, Q_2, Q_3, ..., Q_n\}$, the benefit (reward) metric of a valid soft correlation C_i depends on several factors including: (1) The percentage of queries in W for which C_i is applicable, i.e., the queries that involve an equality predicate on $C_i.Src$ column. We refer to these queries as the $Coverage(C_i)$. (2) The percentage of queries in W for which only C_i is applicable, i.e., if C_i is not selected for deployment, then these queries will have no other correlations to optimize them. We refer to these queries as the $ExclusiveCoverage(C_i)$. (3) The actual execution savings, e.g., the wall clock time, achieved by C_i from executing a re-written optimized query Q compared to executing Q without re-writing. And (4) In addition to these factors, maximizing the coverage of W while minimizing the overall cost is also a desirable objective.

As an illustrative example, we present in Figure 2 a set of correlations C_1, C_2, and C_3, and a query workload consisting of four queries. An edge between a correlation C_i and a query Q_j indicates that C_i is applicable to Q_j and can be used to re-write and optimize this query. The edge labels, e.g., *"$X \rightarrow Y$"*, indicate that the correlation can be used to re-write a predicate on its source column X in terms of a predicate on its destination column Y (and Y is assumed to have an associated efficient access method, e.g., an index). In the figure, we include the $Coverage()$ and $ExclusiveCoverage()$ sets of each correlation.

Referring to Figure 2, it is evident that correlations may have different priorities w.r.t each of the four factors mentioned above. For example, if we consider the 1^{st} factor (based on coverage), then C_1 and C_2 will have higher (and equal) priorities over C_3, whereas, if we consider the 2^{nd} factor (based on exclusive coverage), then C_3 gets higher priority. Moreover, according to the 4^{th} factor (W's coverage with minimal cost), if C_1 is selected by the system, then C_2's priority should be significantly lowered since it does not cover any new queries beyond those covered by C_1.

Clearly, including all four factors into the benefit metric makes it very complicated especially because estimating the execution savings (The 3^{rd} factor) requires execution statistics, which may not be available for all correlation-query pairs. To simplify the metric, we make a reasonable and practical assumption that no matter how a query is optimized, e.g., through indexing or partitioning, the savings from executing an optimized version will be significant compared to executing the un-optimized version (full scan). This implies that, it does not matter which of the two correlations C_1 or C_2 to use for optimizing Q_2, what matters is to have Q_2 covered. It also implies that EXORD always favors the use of these special structures over a full scan regardless of the query selectivity. This is a valid assumption in Hadoop-like infrastructures because under the way the indexes are built [6, 8] and the data blocks are accessed in a distributed manner, there is no notion of secondary indexes that may lead to random data accesses and higher overheads compared simple sequential scans (this is unlike the case in RDBMSs). As confirmed by our experiments, even under the worst case where selectivity is close to 100%, both partition-based and index-based techniques are safe to choose as they would perform very similar to a full scan.

Based on this simplifying assumption, the 3^{rd} factor concerning the actual execution savings can be ignored because all applicable correlations are now assumed to bring "enough" and "acceptable" benefit. Now, for the remaining three factors, the correlation's benefit can be formally defined as follows:

DEFINITION 3.5 (STATIC CORRELATION BENEFIT). *For a given workload W of size n queries, and a soft correlation C_i, the static benefit of C_i is computed as the percentage of queries for which C_i is either applicable or exclusively applicable. That is:*

$$SBenefit(C_i, W) = \frac{|Coverage(C_i)| + |ExclusiveCoverage(C_i)|}{n}.$$

DEFINITION 3.6 (DYNAMIC CORRELATION BENEFIT). *For a given workload W, and a soft correlation C_i, the dynamic benefit of C_i is re-computed after the selection of any other correlation as follows:*

Initial State:

$DBenefit(C_i, W) = SBenefit(C_i, W), \ \ \forall C_i,$

Next State after the selection (and removal) of correlation C_j:

$W = W - Coverage(C_j)$

$DBenefit(C_i, W) = SBenefit(C_i, W), \ \ \forall C_i.$

The static correlation benefit (Def. 3.5) basically takes into account the 1^{st} and 2^{nd} factors, while ignoring the 4^{th} factor. Yet, its computations are easier since the benefits do not depend on the previous decisions taken by the system. In contrast, the dynamic correlation benefit (Def. 3.6) takes the 4^{th} factor into account, and thus whenever a specific correlation is selected, the benefits of the remaining correlations need to be re-calculated.

3.2.3 The Optimization Problem

The optimization problem is now to select a subset of valid soft correlations $\mathcal{C}$ with the objective of maximizing the total benefit

Dominance Type	Cost(C_i) ≤ Cost(C_j) IFF
$C_i \mapsto_{\Phi\Gamma} C_j$	$(\Phi(C_i).size \le \Phi(C_j).size)$ And $(\Gamma(C_i).size \le \Gamma(C_j).size)$
$C_i \mapsto_{\Phi} C_j$	$(\Phi(C_i).size \le \Phi(C_j).size)$
$C_i \mapsto_{\Gamma} C_j$	$(\Gamma(C_i).size \le \Gamma(C_j).size)$

Table 1: Dominance Notations w.r.t Cost() Comparison.

($\sum_{\forall C_i \in \mathcal{C}} Benefit(C_i)$) subject to not exceeding the allowed resources ($\sum_{\forall C_i \in \mathcal{C}} Cost(C_i) \le RPool$).

Clearly, if the benefit function follows Def. 3.5 (Static benefit), then the optimization problem maps to the classic "0/1 knapsack" problem, which is NP-complete, but efficient approximation algorithms exist with computable error bound [13]. On the other hand, if the benefit function follows Def. 3.6 (Dynamic benefit), which is semantically stronger, then the optimization problem maps to the "submodular knapsack" problem, which is even harder to solve or approximate than "0/1 knapsack" [21].

Because of that, we propose an algorithm that combines and retains the pros of both definitions. This is achieved by combining the static definition of the correlations' benefit (Def. 3.5) with a heuristic that captures the essence of the dynamic definition. More specifically, the heuristic will prevent selecting correlations that adds no (or minimal) value to the already selected ones. The heuristic relies on the following definition of correlations' dominance.

DEFINITION 3.7 (CORRELATIONS DOMINANCE). *A correlation C_i (soft or hard) is said to dominate another correlation C_j (soft), denoted as $C_i \mapsto C_j$, iff $Cost(C_i) \le Cost(C_j)$, $ExclusiveCoverage(C_j) = \phi$, and $\frac{|Coverage(C_j) - Coverage(C_i)|}{|Coverage(C_j)|} \le \epsilon$, where ϵ is a small threshold value $\in [0, 1)$.*

The heuristic relies on that before solving the optimization problem, we apply a filtering step that eliminates correlations that are dominated (or nearly dominated) by other correlations. In other words, instead of aiming for the optimal solution according to Def. 3.6 (which is very expensive), we aim for avoiding the worst-case scenario that Def. 3.5 may generate. According to Def. 3.7, a soft correlation can be dominated by either a soft or a hard correlation (but not vise versa). Moreover, a correlation that has a non-empty $ExclusiveCoverage()$ set cannot be dominated by other correlations. It is worth highlighting that if the ϵ threshold is set to zero, then the dominance becomes a *"complete dominance"*. However, the heuristic allows for a *"near dominance"* to be more effective in filtering out correlations that add little contributions. For example, if $\epsilon = 0.15$ and one correlation C_1 covers 10 queries, while another correlation C_2 covers seven of these queries plus one additional new query, then $\frac{|Coverage(C_2) - Coverage(C_1)|}{|Coverage(C_2)|} = 0.14$, and thus $C_1 \mapsto C_2$, and C_2 can be eliminated (if the other conditions are met).

In Figure 3, we sketch the heuristic-based algorithm for solving the correlation-selection optimization problem. The algorithm takes as input a set of n valid soft correlations $\mathcal{P}$, and an observed query workload W. The outcome is a subset of selected correlations $\mathcal{O}$ to deploy along with the deployment strategy assigned to each one. The algorithm is divided into three main phases: *Phase 0* eliminates correlations that are dominated by others, *Phase 1* solves the optimization problem for resource $RPool.M_{Pool}$, i.e., correlations will compete for the available metadata repository storage, and *Phase 2* solves the optimization problem for resource $RPool.H_{Pool}$, i.e., the remaining correlations will compete for the available HDFS storage. Given the computational complexity

```
                Workload-Driven Correlation Selection
Inputs:
        - Set of valid soft correlations $\mathcal{P} = \{C_1, C_2, \ldots, C_n\}$
        - Query workload $W$
Output:
        - subset of correlations to deploy $\mathcal{O}$ (initially empty)
          along with the deployment strategy for each one.

Phase 0: Heuristic-Based Filtering considering both cost components
- For (each soft correlation $C_j$ in $\mathcal{P}$ ) Loop
        - If ( $\exists C_i \mapsto_{\Phi\Gamma} C_j$) Then   Delete $C_j$ from $\mathcal{P}$
- End For

Phase 1: 0/1 knapsack optimization for resource $RPool.M_{pool}$
//Heuristic-Based Filtering considering only $\Phi(C_j).size$ component
- For (each soft correlation $C_j$ in $\mathcal{P}$ ) Loop
        - If ( $\exists C_i \mapsto_{\Phi} C_j$) Then
                - Add $C_j$ to TempList
                - Delete $C_j$ from $\mathcal{P}$
        - End If
- End For
- Result = Solve the optimization problem [17]
- Delete Result from $\mathcal{P}$
- $\mathcal{O} \leftarrow$ (Result with assigned "Exclusion" strategy)

Phase 2: 0/1 knapsack optimization for resource $RPool.H_{pool}$
//Check correlations in TempList and may return some back
- For (each correlation $C_j$ in TempList) Loop
        - If ( none of $C_j$'s dominating correlations is in $\mathcal{O}$) & ($\Gamma(C_j).size \neq \infty$)
            Then Admit back $C_j$ to $\mathcal{P}$
- End For

//Heuristic-Based Filtering considering only $\Gamma(C_j).size$ component
- For (each soft correlation $C_j$ in $\mathcal{P}$ ) Loop
        - If ( $\exists C_i \mapsto_{\Gamma} C_j$) Then   Delete $C_j$ from $\mathcal{P}$
- End For
- Result = Solve the optimization problem [17]
- $\mathcal{O} \leftarrow \mathcal{O}$ + (Result with assign "Materialization" strategy)
```

Figure 3: Workload-Driven Selection for Correlations.

of [13], which is *O(n log n)*, the proposed heuristic-based algorithm also has computational complexity of *O(n log n)*, where n is the number of correlations in $\mathcal{P}$.

In *Phase 0*, we permanently eliminate any correlation C_j that is dominated by another correlation C_i, where the cost function comparison takes both components ($\Phi().size$ and $\Gamma().size$) into account as summarized in Table 1. This means that C_j cannot compete against C_i for either of $RPool.M_{Pool}$ or $RPool.H_{Pool}$ (denoted as $C_i \mapsto_{\Phi\Gamma} C_j$), and thus it is permanently eliminated.

In *Phase 1*, the remaining correlations will compete for the $RPool.M_{Pool}$ resource, i.e., compete for the *"Exclusion Strategy"*. For that purpose the cost function comparison will take only the $\Phi().size$ component into account. The dominance heuristic will be applied again to *"temporarily"* eliminate any dominated correlations given this new cost function comparisons denoted as $C_i \mapsto_{\Phi} C_j$ (Refer to Table 1). After that, the optimization problem is solved approximately using the "FPTAS" technique in [13]. The selected correlations will be added to the output set $\mathcal{O}$, and will be assigned the *"Exclusion"* strategy.

Phase 2 has the same idea of *Phase 1* but with two differences. First, Phase 2 needs to re-examine each correlation, say C_j, that is dominated by others in *Phase 1* (and hence skipped from the competition), and checks whether or not any of C_j's dominating correlations is actually in the output set $\mathcal{O}$. If not, then C_j is admitted back to the candidate pool $\mathcal{P}$, and is given a second chance to compete for $RPool.H_{Pool}$ only if $\Gamma(C_j).size \neq \infty$. Second, correlations in Phase 2 will now compete for the $RPool.H_{Pool}$ resource, i.e., compete for the *"Materialization"* strategy. Therefore, the cost function comparison for the dominance relationship will now rely only on the $\Gamma().size$ component, and the dominance is denoted as $C_i \mapsto_\Gamma C_j$ (Refer to Table 1). Finally, the selected correlations are added to the output set $\mathcal{O}$ and assigned the *"Materialization"* strategy.

• **Execution of the Selected Strategy:** For a given correlation C, if the assigned strategy is *Exclusion*, then no further preparation is needed since the $\Phi(C)$ set is already collected during the *Validation* phase, and the correlation advances to the deployment phase. However, if the assigned strategy is *Materialization*, then still an entire scan over the dataset D is needed to report the violating records and materialize them into an exception bucket file. In this case, the scan is deferred and piggybacked over the next user-submitted job (and only then C advances to the deployment phase), and the created exception bucket is distinct for each D and C pair, and named $D\text{-}C\text{-}ExpBucket$.

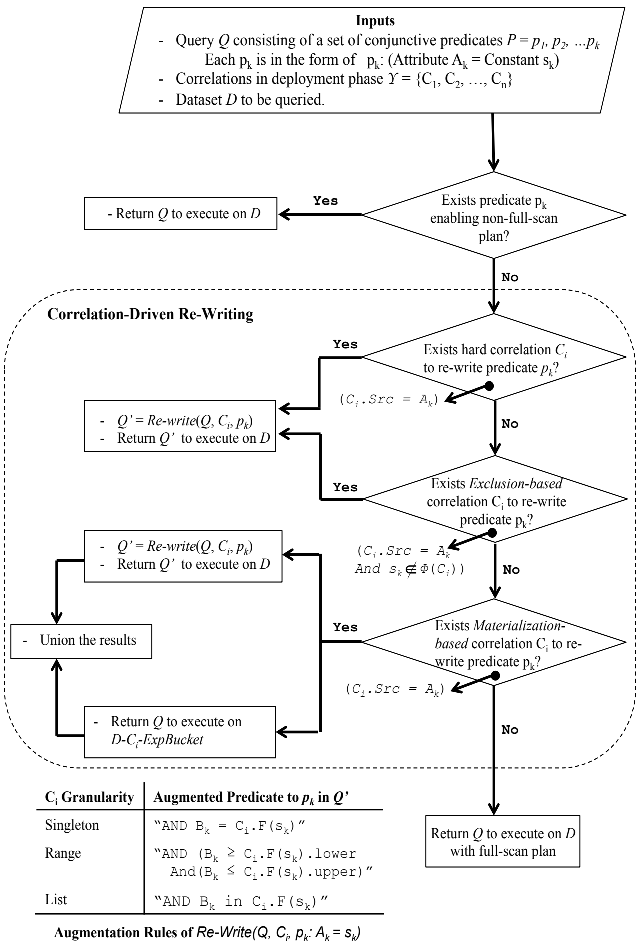
4. DEPLOYMENT & EXPLOITATION PHASE

The ultimate goal of EXORD is to exploit the available correlations to re-write queries and enable more efficient access plans. In Figure 4, we present the flowchart of the exploitation procedure. The procedure takes as input a set of correlations in their deployment phase $\mathcal{Y} = \{C_1, C_2, ..., C_n\}$, a dataset D to be queried, and a target query Q as defined in Def. 2.1 consisting of a set of conjunctive predicates $p_1 \wedge p_2 \wedge ...p_k$. Set $\mathcal{Y}$ includes a mix of hard correlations, and soft correlations along with their deployment strategies as either *Exclusion*, or *Materialization*.

As the first step, the system checks whether any of Q's predicates, say p_k, can enable an access plan other than a full scan, e.g., by leveraging indexing or partitioning strategies. If that is the case, then Q is returned without correlation-driven re-writing. Otherwise, EXORD tries to re-write any of the predicates using the available correlations in $\mathcal{Y}$. While searching $\mathcal{Y}$, the priority is given first to the *hard* correlations, followed by the *Exclusion-based* soft correlations, followed by the *Materialization-based* soft correlations (The 2nd, 3rd, and 4th conditions in the flowchart, respectively). The intuition is that *hard* correlations apply to the entire dataset D without any restrictions or exceptions, and thus they are given the highest priority. On the other hand, the *Exclusion-based* correlations are given higher priority over the *Materialization-based* correlations because, as will be explained next, the processing of queries under the latter strategy involves more overhead due to the need for scanning the corresponding exception bucket.

Assume the selected correlation is $C_i \in \mathcal{Y}$, and it will be used to re-write a specific predicate in Q, say p_k, which is in the form of p_k: $A_k = s_k$, where A_k is one of the data's attributes, and s_k is a constant value. Therefore, $C_i.Src$ = "A_k", and we assume $C_i.Dest$ = "B_k", which is another attribute in D. The re-writing procedure, which generates a new query Q' is the same regardless of the C_i's type. That is, the three different correlation-driven re-writing cases illustrated in Figure 4 (The 2nd, 3rd, and 4th conditions) execute the same $Re\text{-}Write(Q,\ C_i,\ p_k\text{: } A_k = s_k)$ procedure. $Re\text{-}Write$ augments an additional predicate (in a conjunctive form) to p_k, where the format of the new predicate depends on C_i's granularity as illustrated in Figure 4 (bottom table).

After generating the new query Q', the execution plan to generate the correct results depends on the correlation's type and the adopted deployment strategy. That is, in the cases where C_i is a *hard* correlation or an *Exclusion-based* soft correlation, only the new query Q' needs to execute on the original dataset D (The 2nd, and 3rd cases in the flowchart). Whereas, in the case where C_i is a *Materialization-based* correlation, executing Q' on D may not be


Inputs
- Query Q consisting of a set of conjunctive predicates $P = p_1, p_2, ...p_k$ Each p_k is in the form of p_k: (Attribute A_k = Constant s_k)
- Correlations in deployment phase $\Upsilon = \{C_1, C_2, …, C_n\}$
- Dataset D to be queried.
Exists predicate p_k enabling non-full-scan plan?
Yes
- Return Q to execute on D
No
Correlation-Driven Re-Writing
Exists hard correlation C_i to re-write predicate p_k?
Yes
$(C_i.Src = A_k)$
- $Q' = Re\text{-}write(Q, C_i, p_k)$
- Return Q' to execute on D
No
Exists *Exclusion-based* correlation C_i to re-write predicate p_k?
Yes
$(C_i.Src = A_k$ And $s_k \notin \Phi(C_i))$
No
Exists *Materialization-based* correlation C_i to re-write predicate p_k?
Yes
$(C_i.Src = A_k)$
- $Q' = Re\text{-}write(Q, C_i, p_k)$
- Return Q' to execute on D
- Union the results
- Return Q to execute on $D\text{-}C_i\text{-}ExpBucket$
No
Return Q to execute on D with full-scan plan
Augmentation Rules of $Re\text{-}Write(Q, C_i, p_k\text{: } A_k = s_k)$

C_i Granularity	Augmented Predicate to p_k in Q'
Singleton	"AND B_k = C_i.F(s_k)"
Range	"AND ($B_k \geq C_i$.F(s_k).lower And($B_k \leq C_i$.F(s_k).upper)"
List	"AND B_k in C_i.F(s_k)"

Figure 4: Exploitation in Query Optimization Flowchart.

enough as it may miss some data records that satisfy Q but in violation of C_i, i.e., may miss records in $\Gamma(C_i)$. Therefore, the new query Q' executes on D, and also the original query Q executes on the execution bucket file *D-C_i-ExpBucket*, and then the results union together to generate the final correct results. Since the results from the two queries are guaranteed to be disjoint, there is no special processing needed to eliminate duplicates when constructing the final answer.

5. EXPERIMENTS

5.1 Implementation & Setup Details

Implementation Details: EXORD is implemented as an extension to Apache Hive 1.2.0. We used MySQL DBMS as the metadata repository engine. We extended Hive SQL interface and added a new command ``Create Correlation ...'' through which the database admins can define the soft and hard correlations along with their parameters—As introduced in Def. 2.2. The metadata repository stores the defined correlations, their status, the statistics collected from the *validation* phase, and the assigned strategy. In addition, for the Exclusion-based soft correlations, the distinct violating values are stored in the metadata repository.

Cluster Setup: We used Apache Hadoop infrastructure (version 1.1.2). All experiments are conducted on a dedicated local shared-nothing cluster consisting of 20 compute nodes. Each node consists of 32-core AMD 3.0GHz CPUs, 128GB of memory, and

ID	Source Column	Dest Column	Short Desc.	Strategy
C_1	StartAirportIATA	StartCountry	In most cases, the airport code determines the country (Refer to Motivation Scenario 2)	Exclusion
C_2	ConfTimestamp	RequestTimestamp	In most cases, the *ConfTimestamp* is within 1 to 5 mins from the *Requesttimestamp*	Materialization
C_3	TicketPrice	TicketClass	The price givens an indication on the ticket class code.	Materialization

Figure 5: Correlations in the Working Dataset.

DataSet Size	Partitioning (map-reduce Job)		Indexing (map-reduce Job)	
	Storage	Time (sec)	Storage	Time (sec)
500 GBs	1.5 TBs	962	192GBs	2605
1 TB	3 TBs	2173	413GBs	6643
2.3 TBs	~ 7 TBs	4669	1.12TBs	16369

Figure 6: The storage (including 3-way replica) and time overheads of creating an additional data organization (Partitioning or Indexing) for *Current-Auxiliary (Aux)* technique.

2TBs of disk storage, and they are interconnected with 1Gbps Ethernet. We used one server as the Hadoop's master node, while the other 19 servers are slave nodes. Each slave node is configured to run up to 20 mappers and 12 reducers concurrently. The following Hadoop's configuration parameters are used: sort buffer size was set to 512MB, JVM's are reused, speculative execution is turned off, and a maximum of 4GB JVM heap space is used per task. The HDFS block size is set to 128MB with a replication factor of 3.

Datasets (Application & Synthetic): Most of our experimental evaluation uses an application dataset from the airline analytics domain. In addition, we generate a synthetic dataset to stress test some extreme cases and broader ranges of configuration parameters. The application dataset contains airline traffic logs from 100s of airline companies and consists of customers' ticket reservation records. Each record has more than 80 attributes, however the key ones of interest to us include: `StartCountry, StartCity, StartAirportIATA`, which define the starting point of a flight (and similar attributes exist for the destination point), `RequestTimestamp, ConfTimestamp`, which define the timestamp of a user requesting a reservation, and the timestamp of confirming the reservation, and the `TicketClass, TicketPrice` attributes, which define the seat class and the corresponding price. The total size of the dataset is around 2.3 TBs, and with the 3-way replication the total size is around 7 TBs in HDFS. For experimental purposes, we create three versions of the dataset with different sizes, which are *Small* (500GBs), *Mid* (1.0 TB), and *Large* (2.3 TBs).

The dataset has several interesting soft correlations. In Figure 5, we summarize few correlations that will be our focus. Correlation C_1 is explained in detail in Motivation Scenario 2 in Section 1. Correlation C_2 indicates that in the majority of the cases, the confirmation timestamp is within 1 to 5 mins after the request timestamp, however there can certainly be exceptions to this correlation. Moreover, there is a correlation between the ticket price and the ticket class (Correlation C_3), and we are going to synthetically control such correlation in different ways as will be explained in the experiments.

5.2 Performance Evaluation

5.2.1 Query Execution Gain

We start by studying the gain from using EXORD in query execution. We assume the soft correlations described above are already processed and they are in their deployment phase. As indicated in Figure 5, Correlation C_1 uses the *Exclusion* strategy, while the remaining correlations use the *Materialization* strategy. In the following, we demonstrate the effectiveness of EXORD in the context of both selection and aggregation queries on top of two special access methods, namely partitioning and indexing.

EXORD is compared against two baseline techniques, which are referred to as *"Current"* and *"Current-Auxiliary"* (or *"Aux"* for short). For a given query involving a selection predicate over an attribute A, *Current* would perform a full scan over the data since A—by default—has no special organization associated with it. In contrast, in *Aux*, we manually build an additional special organization over A to efficiently support its queries. In Figure 6, we report the storage and time overheads involved in building such additional organizations. The key observation is that building these additional organizations involves significant overheads that make it almost impractical to build several of them over a single dataset. As the experimental evaluation will show, EXORD can provide very similar performance to *Aux* without paying this huge cost upfront.

Correlation C_1: To study the benefits of using Correlation C_1, we first partition the data on the `StartCountry` attribute. Nevertheless, our equality-based selection query (C_1-*selection*) involves a selection predicate on the `StartAirportIATA` attribute instead. In the query, we experiment with 10 different airport codes (excluding "***") from different countries to have diverse selectivity, and then average their results. The performance of the C_1-*selection* query is presented in Figure 7(a). The current technique [15] (labeled as *"Current"*) have to perform a full scan over the data, EXORD makes use of Correlation C_1 and adds an additional predicate over the `StartCountry` which enables leveraging the existing partitioning, and *"Aux"* makes use of the additional partitioning created based on `StartAirportIATA` attribute. As the results show, both EXORD and *Aux* achieve a factor of 12x speedup, and their performance is identical as they both touch only the same relevant partitions. The key difference between them is that EXORD does not pay the partitioning overhead reported in Figure 6.

In Figure 7(b), we study a more complex variation of Query C_1-*selection*, i.e., C_1-*aggr*, in which the query involves an equality-based selection followed by an aggregation. In this case, the aggregation overhead—more specifically, the shuffling/sorting and the reduce phase overheads—are the same to all techniques including EXORD. Yet, the benefits from EXORD are still significant as it saves around 65% of the job's execution time, which is mostly due to the savings in the map phase. Again, EXORD has identical performance to *Aux*.

Correlation C_2: In Figure 8, we demonstrate the usage of Correlation C_2 under the presence of indexes. In these experiments, we build a local Hadoop++ index over the `RequestTimestamp` attribute in each partition and use a customized InputFormat to access the data as introduced in [6]. Our experimental queries C_2-*selection* and C_2-*aggr* involve a selection predicate on the `ConfTimestamp` attribute instead. Correlation C_2 uses the *Materialization* strategy for storing the violating records in a separate exception bucket. The exception bucket sizes are 273MBs, 695MBs, and 1.17GBs for the datasets of sizes 500GBs, 1TB, and 2.3TBs, respectively. We repeat each experiment with 5 different timestamps, and for each timestamp we execute three experiments with matching granularities of a Second, Minute, and Hour to have different selectivities.

In Figure 8(a), we present the results of the selection query C_2-*selection*. The state-of-art technique [6] (*"Current"*) have to perform a full scan over the data without the use of the index, EXORD triggers two jobs; one over the entire dataset and leverages the index, and another one to scan the exception bucket, and *"Aux"* leverages the additional index built on the `ConfTimestamp` attribute. As the results show, EXORD achieves up to 82% reduction in the

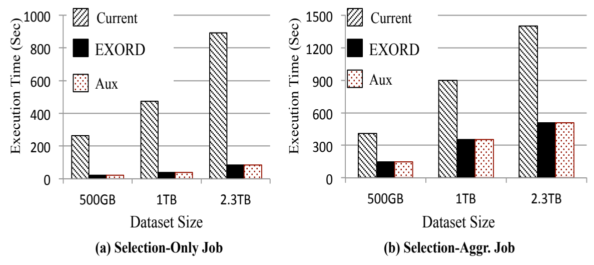


Figure 7: Study of Correlation C_1 (Use of Partitioning).

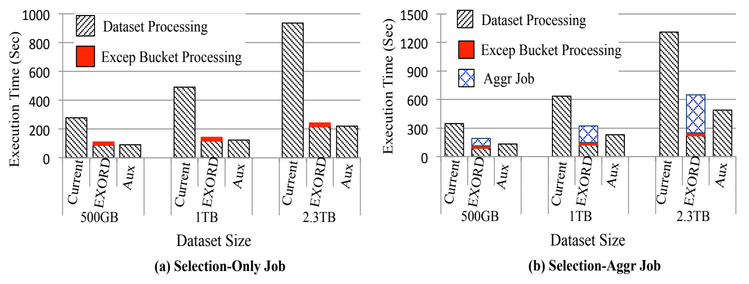


Figure 8: Study of Correlation C_2 (Use of Indexing).

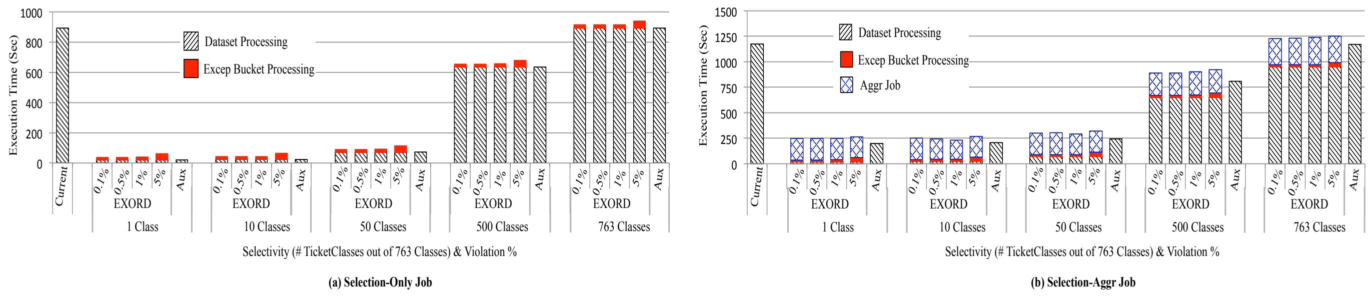


Figure 9: Study of Correlation C_3 (Use of Partitioning over the 2.3TBs Dataset).

query time compared to *Current*, and the only additional overhead compared to *Aux* is the processing of the exception bucket—which is relatively very small compared to the data.

In Figure 8(b), we present the performance of the aggregation Query C_2-*aggr* in which we aggregate over the `StartAirportIATA` attribute and calculate the count of the entries after applying the selection predicate. Both the *Current* and *Aux* techniques execute the query in a single map-reduce job, whereas EXORD executes three jobs (one selection over the entire dataset, one selection over the execution bucket, and then one aggregation on the output of the first two jobs). Again, EXORD achieves around 50% reduction in the query time compared to *Current* and has a slight overhead compared to *Aux*. Yet, this overhead is negligible compared to the pre-processing overhead that *Aux* pays to build the index, which would require around 150 of such C_2-*aggr* queries to just redeem the index-building overhead.

Correlation C_3: For Correlation C_3, we use the largest dataset of size 2.3TBs which contains 763 distinct codes in the `TicketClass` attribute, and we partition the data based on that attribute. We synthetically assign price ranges for the class codes such that some ranges are unique to specific classes, i.e., given a price in that range it maps to a single ticket class, while other ranges map to several (or all) classes. The purpose of such assignment is to have various selectivities as will be described next. In these experiments, we vary the percentage of the records violating the price-class correlation over the values of $\{0.1\%, 0.5\%, 1\%, 5\%\}$, which lead to the exception bucket sizes of $\{1.9\text{GBs}, 11.4\text{GBs}, 22\text{GBs}, 97.3\text{GBs}\}$, respectively.

In Figures 9(a) and 9(b), we illustrate the performance of the selection query (C_3-*selection*), and its extended aggregation query (C_3-*aggr*), respectively. The selection predicate is on the `TicketPrice` attribute. On the x-axis of the figures, we vary the TicketClass selectivity of the price predicate such that the price maps to either 1, 10, 50, 500, or 763 (All) classes. The overall record selectivity from the predicate is kept the same of approximately 10% of the input data. For both experiments, the *Current* technique would perform a single job (either a map-only for C_3-*selection*, or a map-reduce for C_3-*aggr*) that scans the entire dataset. In contrast, EXORD would perform two map-only jobs for C_3-*selection*, and an additional third map-reduce job for C_3-*aggr*. On the other hand, *Aux* makes use of the additional partitioning created on the `TicketPrice` attribute and can answer both queries in a single job as in the *Current* technique.

As the results show, both EXORD and *Aux* are very efficient compared to *Current* and their performance increases relative to the number of relevant partitions that need to be touched. In the worst case, where all partitions need to be touched, *Aux* performs identical to *Current*, and EXORD has a slight overhead due to the processing of the exception bucket (and triggering three jobs instead of one in the case of C_3-*aggr* in Figure 9(b)).

Synthetic Dataset. We generate a synthetic dataset of size 1TB (3 TBs with replication) to stress test the query selectivity and violation percentage parameters. The dataset is generated as follows. Each record consists of four attributes; namely `Id`, `Field1`, `Field2`, and `Tail`. The first three attributes are integers, and the `Tail` attribute is a large text field of size 3KBs. Our focus is on `Field1` (which has an index by default), and `Field2` which has a soft correlation (based on a simple mathematical formula) to `Field1`. `Field1` has the domain range between 1 and 10^6. The tested query is a selection query over `Field2` with a range predicate that varies the record selectivity from 1% to 100% as indicated in Figure 10, and within each selectivity degree, the correlation's violation percentage varies from 0% (Hard correlation) to 40%.

In Figure 10, we compare *Current* (which performs a full scan), *Aux* (which builds and leverages an additional index over `Field2`), and EXORD. The key insights from the figure are that: (1) Allowing large exception buckets may hurt the performance and may diminish the savings from exploit the correlation. Typically is it recommended to only accept correlations, i.e., consider them as valid according to Def. 2.4, only if the violation's percentage is around or below 10% of the base data. A more concrete recommendation is to have the upper bound on the exception bucket size, i.e., *MaxVioRec* in Def. 2.4, equal to the amount of data that can be processed by a single wave (or at most two waves) of mappers. For example, in our cluster setup, we have 400 concurrent mappers and each processes 128MBs of data, which leads to 51GBs that can be processed in a single wave of mappers. In Figure 10, the 1% and 5% violations fit in one wave, while 10% fits in two waves (and it doubles for 20%

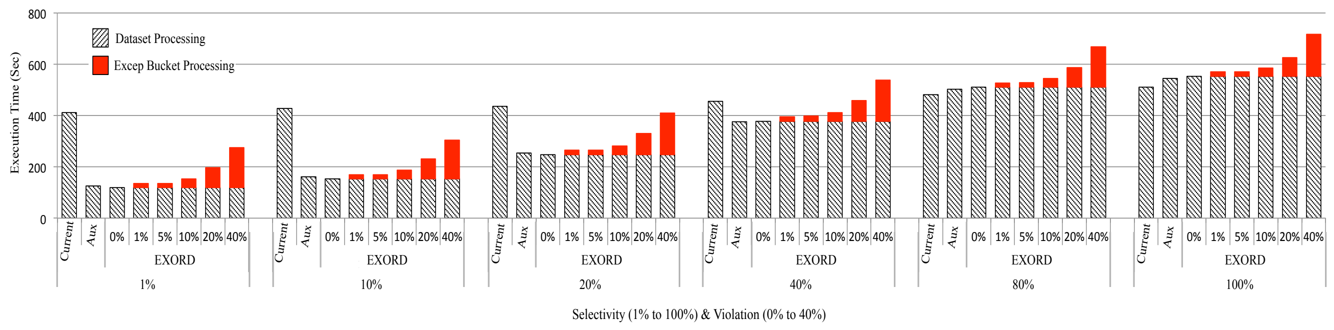


Figure 10: Synthetic datasets under various selectivity and violation percentages.

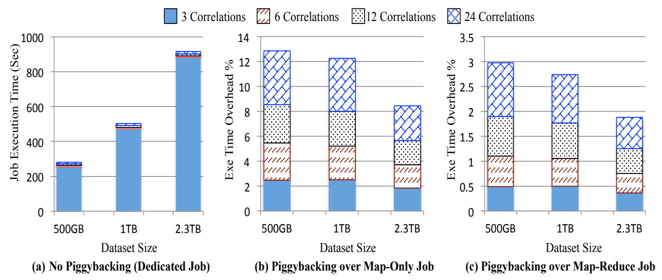
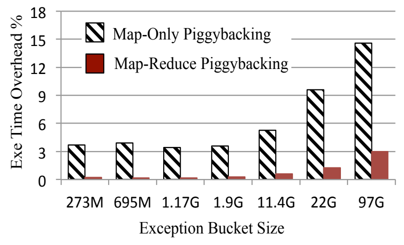


Figure 11: Validation Overhead of Soft Correlations.

# Values	Insertion Time
1	12.6 msec
10	22.9 msec
100	43 msec
1000	0.97 sec
10,000	8.32 sec

(a) Exclusion Strategy: Insertion into SHARC DB Repository



(b) Materialization Strategy: Overhead to create Exception Buckets

Figure 12: Preparation Overhead of Soft Correlations.

and 40%). And (2) Even with bigger selectivity percentage, e.g., 80% and 100%, the overheads from the index processing and the exception bucket are relatively small compared to *Current*—if we exclude the un-recommended settings of 20% and 40% violations. These overheads are between 5% for *Aux* and EXORD-0% violation, and 11% for the EXORD-10% violation. The index overhead is due to increasing the dataset size (by around 10%), and hence increasing the I/O cost.

5.2.2 Validation and Preparation Overheads

We now focus on evaluating the overheads involved in the validation and preparation of soft correlations.

Validation Overheads: In Figure 11(a), we show the validation overhead if it were to be performed as a separate system-triggered map-only job without piggybacking. This experiment verifies the importance of piggybacking to avoid the high encountered overhead. The figure shows the execution time for each of the three dataset sizes while validating the the three correlations C_1, C_2, and C_3. The small stacked bars illustrate the additional time overhead in the cases of having 6, 12, and 24 correlations to be validated instead of just 3 correlations (these correlations are replicas of the 3 correlations with slight variations). The key observation is that a dedicated scan over the data just to validate the correlations can be expensive, especially in the case of large datasets.

In Figures 11(b) and 11(c), we illustrate the piggybacking performance that EXORD applies over a map-only, or map-reduce job, respectively. As expected, if the validation task is piggybacked over a map-reduce job, then the overhead is negligible, and many correlations can be verified at the same time since the additional CPU cost for checking more correlations is almost entirely masked by the job's own execution time. In the case of the map-only job, the additional overhead percentage ranges from 3% to 13% (See Figure 11(b)). It is worth highlighting that as the dataset gets larger, the scanning overhead of reading the data from HDFS and starting more map tasks dominates the overall cost, and thus the additional CPU time becomes less apparent.

Preparation Overheads: For the *Exclusion* strategy, the preparation overhead involves the insertion of the violating values into EXORD's metadata repository, which is a MySQL DB. The overhead of this task is tiny and negligible as it takes few seconds for the values to be inserted into the database. For completeness, we report in Figure 12(a) the time overhead to insert a number of values varying from 1 (which is the case for correlation C_1) to 10,000 into MySQL database. On average, each value is 20 bytes, and the database table has a B+-tree index built before inserting the values.

For the *Materialization* strategy, the preparation overhead involves a piggybacked job to collect the violating records and copy them to an exception bucket. In Figure 12(b), we report this overhead under the two cases of piggybacking the preparation job over a user's map-only job (scanning and reporting 10% of the data) and a map-reduce job (aggregating over the entire dataset). On the x-axis, we consider the creation of the exception buckets corresponding to the Correlations C_2 and C_3 studied in Section 5.2.1, and the y-axis shows the overhead percentage to the user's job. As expected, the overhead depends on the exception bucket's size, and it is clearly much smaller if the user's job is map-reduce job. However, in EXORD, we perform the piggybacking over the first user's job regardless of whether it is a map-only or map-reduce. This is because the savings in query execution are significant and they redeem the paid overhead in just one job.

5.2.3 Optimizations of Correlation Selection

In this section, we evaluate the proposed heuristic-based algorithm for correlation selection under limited resources. We enumerated 16 different correlations that the domain experts believe to exist in our working dataset. For example, in addition to the three correlations presented in Figure 5, other similar correlation include: `StartAirportIATA` $\rightarrow$ `StartCity`, `DestAirportIATA` $\rightarrow$ `DestCountry`, `DestAirportIATA` $\rightarrow$ `DestCity`, and `RequestTimestamp` $\rightarrow$ `ConfTimestamp`. Other interesting correlations include `ToFlightDays` $\rightarrow$ `Purpose`, and `ToFlightDays` $\rightarrow$ `Duration`. Capturing these correlations is not only important w.r.t query optimization, but also important w.r.t the business logic and providing better pricing models. In addition

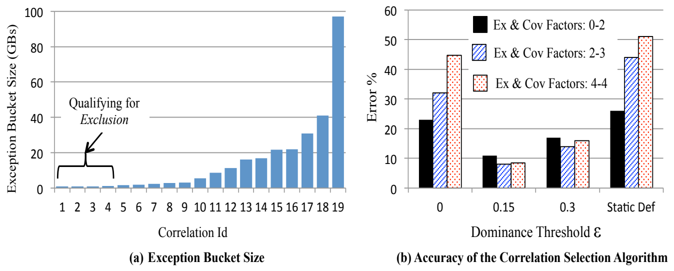


Figure 13: Heuristic-Based Correlation Selection.

to these correlations, we replicated the `TicketPrice` attribute in correlation C_3 three more times, and replicated C_3 along with these new attributes. The purpose of this replication is to have the four violation percentages studied in Figure 9(a) all present in the dataset at once. Therefore, the selection pool has 19 soft correlations.

We then execute a validation task to collect statistics on these correlations. In Figure 13(a), we illustrate the exception bucket sizes for the 19 correlations (ordered by the size). Only 4 out of the 19 correlations qualify for the *Exclusion* strategy. Therefore, to simplify our experimental setup, we assume that these 4 qualified correlations will all fit in the metadata allowed pool M_{pool} since the total combined sizes of their violating values are less than 1MB. We then focus on the optimization selection problem of the remaining 16 correlations competing for the H_{pool} resource.

To setup the experiment, we vary the available resource pool H_{pool} over the values 100GBs, 150GBs, and 200GBs, and the $\Gamma().size$ costs of the 16 correlations are set according to the results in Figure 13(a). The benefit model of the correlations is created as follows. We build a workload of 50 queries, and distribute these queries over the $ExclusiveCoverage()$, and $Coverage()$ sets according two configuration parameters, namely $ExFactor$, and $CovFactor$. The $ExFactor$, which varies over the values {0, 2, 4}, defines the number of queries that are exclusively assigned to correlations (random assignment). And then, for the remaining correlations, each will be replicated between 2 to $CovFactor$ times over the $Coverage()$ set of some different correlations (random assignment). The $CovFactor$ varies over the values of {2, 3, 4}. For example, if $CovFactor$ is set to 3, then each query is replicated either 2 or 3 times (random selection within this range), and the corresponding correlations are also chosen randomly.

As discussed in Section 3.2.3, the computational complexity of the proposed heuristic-based algorithm for correlation selection is $O(n \log n)$, where n is the number of correlations. In contrast, the optimal brute-force algorithm is exponential as it entails enumerating all permutations of the 16 correlations of all sizes from 1 to 16 (no repetition, but the order matters) and selecting the highest-benefit feasible solution.

We omit the detailed results of the heuristic-based algorithm under each configuration of the three changing variables H_{pool}, $ExFactor$, and $CovFactor$, due to space limitations. In summary, the execution time is in the order of milliseconds ranging from 34 to 52 milliseconds. In these experiments, the dominance threshold ϵ (in Def. 3.7) is set to 0.15. In contrast, the brute-force algorithm is prohibitively expensive and a single execution takes around 7.8 Days (187.2 Hours). We executed the brute-force algorithm under three selected configurations to get their ground-truth optimal solution, which are: {*150GBs, 0, 2*}, {*150GBs, 2, 3*}, and {*150GBs, 4, 4*}, where the numbers correspond to the H_{pool}, $ExFactor$, and $CovFactor$, respectively. Clearly, the brute-force algorithm is not a practical solution.

Regarding the accuracy of the heuristic-based algorithm, we focus on the three configurations for which we obtained the optimal highest-benefit selection, and test the heuristic-based algorithm under three values for the dominance threshold ϵ as depicted in Figure 13(b). In addition, we suppress the heuristic and thus the algorithm now maps to the static definition of the correlations' benefits (Def.3.5). The y-axis of Figure 13(b) shows the error percentage computed as $100 * (opt - approx)/opt$, where opt and $approx$, are the optimal and the approximated values, respectively.

As the results in Figure 13(b) show, the static definition yields a relatively high error rate. This is due to unnecessary selection of correlations having high overlap in their coverage. When ϵ is set to zero, the error rate is also high because in this case the heuristic-based algorithm is filtering out only the correlations that are completely dominated by others, which are very few. The 0.15 and 0.3 threshold values give much better results as they are more flexible in their dominance definition, and they can filter out correlations that offer minor contributions even if they are not completely dominated by others. As a conclusion, the proposed heuristic-based algorithm is a practical algorithm compared to the non-practical brute-force search algorithm. The accuracy of the results is within an acceptable range, especially since the optimization effort is typically a best effort task in the first place.

6. RELATED WORK

Query Optimization in Big Data. Query optimization in big data is a fundamentally important problem, especially because (1) the datasets to be processed are getting very large, (2) the analytical queries are increasing in complexity and may take hours to execute if not carefully optimized, and (3) the pay-as-you-go cost model for cloud computing adds additional urgency for optimized processing. Because of these reasons, various aspects of query optimization have been studied on the emerging highly-scalable infrastructures, e.g., Hadoop [22]. These optimizations include techniques such as indexing [4, 6, 8], pre-partitioning [15], reorganization and colocation [9], materialization and re-usability of intermediate results [3, 7, 19], among many others.

Although the aforementioned optimizations have shown to be very effective in saving system's resources and execution time, they do not come for free. Instead, they usually encompass significant overheads w.r.t time and storage [4, 7, 8, 9] (Refer also to our reported results in Figure 6). The proposed EXORD system is complementary to and can work in conjunction with most of the existing techniques, e.g., indexing either local indexes [4, 6] or global indexes [8], pre-partitioning [9, 15], and materialization [7]. The key advantage is that EXORD would enable optimizing a broader class of queries (beyond those on a single indexed or partitioned attribute) with minimal additional cost. Without EXORD, existing systems either perform a full scan, which is up to 10x slower, or pay the high cost of building more auxiliary structures, and still get almost the same performance as in EXORD.

Data Correlations in Relational DBs. Correlations represent important features of the data, which if effectively captured and leveraged would lead to significant improvement in query processing [2, 14, 16, 17]. That is why discovering and exploiting correlations have been extensively studied in RDBMSs including functional dependencies [12, 18, 24], conditional functional dependencies [1, 10], soft correlations [2, 14, 16, 17], and denial constraints [5]. The closest techniques to EXORD (in sprit) include BHUNT [2], CORDS [14], Correlation Maps (CM) [16], and CORADD [17], which all try to discover and exploit soft correlations in query optimization. However, these techniques are either heavily tailored towards the processing mechanism of relational DB—which is fundamentally different from Hadoop-like infrastructures—and thus they are not applicable in our context [14, 16, 17], or very restricted in their correlation definition compared to EXORD [2].

In more details, CORDS [14] tries to discover only the presence of correlations between pairs of attributes (say A_1 and A_2) and estimate their strength without keeping track of the detailed mappings from one attribute to the other. This is because CORDS objective is not query re-writing but instead providing better estimation for predicate selectivity for queries involving conjunctive predicates, e.g., over A_1 and A_2. This is crucial in RDBMSs because under the typical assumption of independence the estimated selectivity can be way off, which leads to bad query plans and significant un-necessary overheads. However, in Hadoop-like infrastructures there is no notion of conjunctive predicate selectivity or different query plans; it is always a single plan (map-only for certain types of jobs or map-reduce for other types). Even more, predicate selectivity in general is not critical in Hadoop-like systems because as we discussed in Section 1 (and confirmed by the experimental evaluation), it is safe to always leverage an index (or partitioning) if exist instead of a full scan regardless of the selectivity.

The CM [16] and CORADD [17] techniques have the observation that secondary indexes (on un-clustered attributes) usually have poor performance due to the random access of disk pages. However, if such un-clustered attributes are correlated with the clustered attribute (on which the relation is sorted), then by re-writing the query and adding predicates on that clustered attribute a significant performance gain can be achieved. The two systems have focused on capturing such mappings using new compressed data structures, called *Correlation Maps (CMs)*, instead of the traditional secondary indexes [16], and providing better design for the database in the form of materialized views and recommendations for their clustered attributes [17]. Again, these issues although fundamental in RDBMSs, they are not applicable to Hadoop-like infrastructures. First, big datasets typically do not have a *clustered attribute* on which the entire dataset is sorted. Second, as we highlighted in Section 3.2.2, there is no notion of a random vs. sequential accesses in Hadoop-like systems.

On the other hand, BHUNT [2] has the same objective as EXORD, which is capturing the soft correlations and the mapping mechanism from one attribute to another, and then using that for query re-writing and adding additional predicates. However, as an automatic discovery tool, BHUNT puts strong restrictions on the correlations that can be captured. First, the attributes A_1 and A_2 have to be numerical (numbers or dates), and second their mapping has to be an algebraic expression in the form of ($A_1 \oplus A_2$), where $\oplus$ is one of {+, -, *, /}. This significantly limits the applicability of the system in big data applications. In contrast, EXORD is a validation tool, which enables defining correlations on attributes of any data type, and domain experts can provide more complex and broader ranges of mappings, e.g., complex expressions or even look-up functions searching auxiliary metadata information.

7. CONCLUSION

We proposed the *EXORD* system for exploiting the data's correlations in the context of big data query optimization. EXORD supports two types of correlations; the *hard* correlations—which are guaranteed to hold for all data records, and the *soft* correlations—which hold for most of the data records with a degree of uncertainty. We introduced a multi-phase approach for the validation, selection, and deployment of the soft correlations. We proposed a novel cost-benefit model that maps the adaptive selection of the most beneficial soft correlations w.r.t a given query workload to the well-known submodular knapsack optimization problem. And as an NP-Hard problem, we proposed a heuristic-based algorithm to efficiently solve it in a polynomial time. EXORD is an infrastructure-independent system that can be integrated with various big data query optimization techniques, e.g., indexing, partitioning, and materialization. Our prototype is implemented as an extension to the Hive engine on top of the Hadoop infrastructure. The experimental evaluation has shown that, with minimal overheads, EXORD can optimize a broader class of queries and speeds them up by more than 10x compared to the state-of-art techniques.

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