**ABSTRACT**

This paper develops a query-time missing value imputation framework, entitled QUIP, that minimizes the joint costs of imputation and query execution. QUIP achieves this by modifying how relational operators are processed. It adds a cost-based decision function in each operator that checks whether the operator should invoke imputation prior to execution or to defer the imputations for downstream operators to resolve. QUIP implements a new approach to evaluating outer join that preserve missing values during query processing, and a bloom filter based index structure to optimize the space and running overhead. We have implemented QUIP using ImputeDB - a specialized database engine for data cleaning. Extensive experiments on both real and synthetic data sets demonstrate the effectiveness and efficiency of QUIP, which outperforms the state-of-the-art ImputeDB by 2 to 10 times on different query sets and data sets, and achieves the order-of-magnitudes improvement over offline approach.

**1 INTRODUCTION**

**1.1 Background**

A large number of real-world datasets contain missing values. Reasons include human/machine errors in data entry, unmatched columns in data integration [29], etc. Failure to clean the missing data may result in the poor quality of answers to queries that may, in turn, negatively influence tasks such as machine learning [30], data analytics, summarization [22, 24], etc. built on top of data.

Missing value imputation has been extensively studied in the literature, especially from the perspective of ensuring accuracy [16, 31, 39, 44]. Traditional Extract, Transform and Load (ETL) data processing pipeline treats missing value imputation as part of an offline data preparation process that cleans all the data prior to making it available for analysis. Such an data preparation step is often costly if data is large and if cost per imputation is high.

**1.2 QUIP**

This paper develops QUIP, a QUery-time approach for missing value imPutation that exploits query semantics to reduce the cleaning overhead. Specifically, given as input an SQL query and a corresponding query plan generated by any commercial relational query optimizer (e.g., such as PostgreSQL) or a specialized optimizer designed to reduce imputation costs (e.g., such as ImputeDB [17]), QUIP develops an execution strategy that minimizes the overall (joint) cost of imputing missing data and executing the query based on the query plan.

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1 Such a problem is complementary to the lazy cleaning approach at query time and should not be confused with query-time approaches.
We illustrate the key insights behind QUIP by using a motivating example. Consider a real data set, Wi-Fi location data, collected by sensor data management system TIPPERS [36] in UCI. In Tables 1-3, we select a subset of WiFi location data, Trajectories, Space and User. Trajectories collects the room locations of devices with the corresponding time stamps, Space stores the metadata for room, floor and building where this room is located, and User records the user information that contains the name, email of the user and mac address of the device owned by this user. There are totally 9 missing values in Table 1, 2 and 3 (represented as NULL values, from \( N_1 \) to \( N_9 \), and the blue colored values in brackets are real values that would result were we impute the missing values ), and we treat the imputation method to repair such missing values as black box.

Now consider a commonly used SPJ query in our scenario, in Figure 1, that computes the trajectories (i.e., time and room location) for all registered users (i.e., users in User table) in the locations of interest (e.g., specific rooms in Donald Bren Hall (DBH) building). To reduce number of unnecessary imputations, query execution could delay imputing a missing value until the tuple (with the missing value) encounters an operator that cannot be evaluated without imputation. Such an approach prevents cleaning data that is not necessary to answer the query, and has been used in systems such as [10] and in ImputeDB [17] in the context of missing value imputation. While delaying imputation (until an operators that require data to be cleaned is encountered) reduces the overhead, nonetheless, as we will show, much further improvement could be possible by modifying operator implementations to preserve tuples with missing values thereby enabling the possibility to further delay imputation to later in the query execution. Such a delay could prevent imputation if the tuple containing the missing value is discarded by downstream operators based on different predicates whose evaluation does not require missing value to be imputed. Let us see such a possibility of saving imputations using an example.

Consider first the strategy that cleans data as soon as it encounters an operator that requires it to be cleaned (as in ImputeDB). The total imputation cost will depend upon the query plan chosen to execute the query. For the query in Figure 1, several different query plans are possible. Consider, for instance, a plan where selections (on both tables \( T \) and \( S \)) are pushed before the join. Irrespective of the join order, all missing values for attributes, i.e., \( T.\text{room\_location}, S.\text{Building} \), and those under join attributes, i.e., \( U.\text{mac\_address} \), will be imputed resulting in a total of 8 imputations. An alternate plan might be to delay selections after the joins with the cost of potential high query processing overhead. If, for instance, \( T.\text{room\_location}=S.\text{Room} \) executes first, 3 imputations will be invoked to impute the missing values for the \( T.\text{room\_location} \) \( (N_1, N_2, N_3) \). It will result in 3 matched tuples (with room location as 2206, 3119, 2214).

Next \( N_4, N_5 \) will need to be imputed to execute \( T \bowtie U \), which returns further 3 matches (with mac address as 4ep, fff1 and 9aa4). Now it requires 2 further imputations \( (N_6, N_7) \) to evaluate selection predicate \( S.\text{Building} = 'DBH' \). Thus, such a plan would result in 7 imputations. We note that a plan where \( T.\text{Room\_location}=S.\text{room} \) is executed first also needs 5 imputations. Finally, if we only delay one of the two selections, and clean as soon as an operator encounters missing value, we need 5 (or 6) imputations depending on which selection predicate is pushed down/pulled up.

In contrast, let us now consider a strategy that has the capability to delay imputations and preserve missing values in query processing. Such a strategy could delay imputing prior to selection operations, i.e., \( S.\text{Building} = 'DBH' \) and \( T.\text{Room\_location} \) \( = [2065, 2011, 2082, 2035, 2206] \), and join operation \( T.\text{Room\_location} = S.\text{Room} \) and impute missing values \( U.\text{mac\_address} \) (2 missing values), when executing the join operation \( T.\text{mac\_address} = U.\text{mac\_address} \). This will result in 2 matches (mac address = 4ep) and the other tuples will be eliminated. Then such a strategy will impute \( N_8 \) which is equal to 2082, leading to no match in Space table and thus computing the query above with just 3 imputations.

While this is a toy example with modest savings of a few imputations, in real data set, where cardinality of Trajectories and User table are large (e.g., over 40 million trajectories tuples and 60k+ devices (users) tuples in 10 months UCI-WiFi data set), such an approach can provide an order of magnitude reduction in the number of imputations. With the imputation being expensive such savings can be very significant. Such savings in imputations, as will become clear later in the paper, do come with the increased overhead of preserving tuples with missing values in operators. The key is to design a solution that minimizes the overhead paid by operators to preserve such tuples, and to design a cost-based approach to judiciously decide whether to preserve tuples (and hence potentially reduce imputation costs) or to impute right away so as not to incur overhead of preserving tuples.

This paper develops QUIP, a lazy approach to imputing missing values during query processing, that decouples the need to impute data from the logic of operator implementation. QUIP makes two main modifications to existing query processing. First, it modifies current implementations of the relational operators to be aware that the data may contain missing values and extends the operator implementations to preserve such tuples. For example, consider the selection condition \( S.\text{building} = 'DBH' \) in the query shown in Figure 1. If the selection operator sees a missing value \( v \), it decides on whether to impute \( v \) and evaluate the predicate precisely, or to defer imputation (and correspondingly selection condition evaluation) to downstream operators to handle. The benefit of delaying arises if the downstream operator eliminates the object (due to
its other associated predicate) thus preventing the need to impute the missing values $v$. QUIP develops efficient ways to implement preserving tuples with missing values without the overhead of quadratic increase in size as would be the case if join conditions were naively extended to preserve missing values. Instead, QUIP uses a carefully designed outer join for this purpose.

With operators extended to preserve tuples, QUIP successfully decouples imputation from operator implementation allowing for missing value imputations to be incorporated anywhere in the query tree. Such a capability allows QUIP to reduce the number of imputations in the example above. QUIP can delay imputing prior to selection operations, i.e., $S$.Building = 'DBH' and $T$.Room_location = \{2065, 2011, 2082, 2035, 2206\}, and join operation $T$.Room_location = $S$.Room and, instead, impute missing values $U$.mac_address (2 missing values), when executing the join operation $T$.mac_address = $U$.mac_address. This will result in 2 matches (mac_address = 46op) and the other tuples will be eliminated. QUIP, then, imputes $N_2$ which is equal to 2082, leading to no match in Space table. Thus, QUIP can process the query with the (minimal) number of imputations - viz., 3 in this case.

Note that, QUIP’s goal is not just to minimize imputations. Instead, it minimizes the joint cost of imputing and querying processing. If the imputation is cheap, QUIP will tend to first impute missing values instead of delaying them to reduce query execution overhead. To achieve such a goal, the second modification QUIP makes is to use a cost-based approach to automatically guide each operator on whether to impute or delay missing values by considering both imputation and query processing overheads.

**Contribution:** The paper introduces QUIP framework to answer SQL queries over data that may contain missing values. QUIP judiciously delays imputations to minimize the combined cost of imputing and query processing simultaneously. The key to QUIP is a time and space-efficient outer-join based mechanism to preserve missing values as well as several efficient data structures to wisely remove unnecessary missing values in query processing. QUIP outperforms the state-of-the-art solutions by 2 to 10 times on different query sets and data sets, and achieves the order-of-magnitudes improvement over offline approach. In the rest of the paper, in Section 2 and 3, we described the preliminaries and overview of the approach. Section 4 introduces data structures used in QUIP. Section 5 to 6 describe QUIP algorithm. Section 7 evaluates QUIP, and Section 8 concludes the paper.

## 2 PRELIMINARIES

### 2.1 Imputation Operation

As in [17], we view imputation approaches as **blocking** or **non-blocking** in terms of query processing. A blocking strategy reads the whole data to learn a model for imputation (before it imputes any missing value), while a non-blocking strategy can impute missing values independently reading only a (subset of related) tuples. Imputation approaches can roughly be characterized as statistics based, rule based, master data based, time-series based, or learning based approaches [31]. Of these, other than the learning based approaches, many techniques could be used in a non-blocking setting. For instance, ImputeDB [17] used a non-blocking statistics-based mean-value method that replaces a missing value with the mean of the available values in the same column using histograms. Since

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**Figure 2:** Training and Inference time for different MLs.

Histograms are often maintained for query optimization and approximate processing [26, 41] such a technique is non-blocking. Strategies that use master data [19, 38, 42, 43] are also non-blocking since they look up a knowledge base and crowd source the imputations one tuple (or a set of tuples) at a time. Imputation strategies in time series data [14, 28, 32] are often performed by learning patterns over historical data to forecast current missing values or using the correlation across the time series. An example is LOCATER [32] that imputes each missing location of a user at one time stamp by learning user’s pattern from historical data. Such methods also clean one tuple at a time and are, hence, non-blocking. Rule based imputation methods based on differential dependency [39] or editing rules [20] often impute missing values by replacing them with corresponding value of similar objects.

In non-blocking strategies the overall cost of imputation is proportional to the number of tuples imputed and hence, QUIP, which is designed to exploit query semantics to reduce number of imputations performed, can bring significant improvements.

In contrast to the above, learning-based approaches are often blocking. Such techniques, as in [37], may use models such as generative adversarial network (GAN) [12] that can take over hours to train. Such techniques are, hence, not suitable for being called from within online analysis queries due to long latency due to training prior to imputation. Given such a limitation, several prior works have explored reducing the training time of learning-based methods. Miao et al [37] select a small representative sample (about 5%) to speed training by about 4x while maintaining imputation accuracy guarantees. Two widely used learning approaches, XGBoost [18] and LightGBM [27] use histograms to speed up training. (Their APIs are available in standard python packages [5]) Using histograms can reduce training time dramatically - e.g., Xgboost [5] using histograms takes 69.8s on a one-million size table with 10 attributes using 700k training samples and achieves accuracy of 0.985, while it takes only 1s while training on the 20k samples picked by Miao’s approach [37] to achieve 0.971 accuracy. Sampling and histogram methods make learning-based methods amenable to online processing by dramatically reducing learning costs. If learning-costs can be brought down to make blocking strategies practical in online settings, QUIP can bring further improvements by reducing redundant imputations. This is specially the case when the models learnt are relatively complex with non-negligible inference times. Figure 2 lists several machine learning approaches widely used for missing value imputation\(^2\). The figure shows the training time versus total

\(^2\)All of these methods have standard Python packages (sklearn or xgboost).
inference time by varying the percentage of missing values (called missing ratio (MR) for a table with 1M rows, 10 attributes where 1 column have missing values. For approaches with expensive inference, such as SVM and KNN (sklearn.impute.KNNImputer), QUIP achieve 5x to 15x speed-up over ImputeDB in real data by reducing the number of tuples imputed in experiment in Section 7.

In summary, QUIP is useful for non-blocking imputation approaches and also for blocking approaches when learning time is reduced (via sampling, histograms, etc.) so as not to dominate the total inference time, or when imputation of individual missing value itself is expensive (e.g., rule-based approaches).

2.2 Analysis-aware Data Cleaning

The work most relevant to us is ImputeDB [17] that we have already discussed. As mentioned earlier, while ImputeDB and QUIP overlap in their goals, they offer complementary solutions: while ImputeDB develops a novel optimizer that generates a query plan to minimize joint cost of imputation and query processing, QUIP takes a query plan, (e.g., the one generated by ImputeDB), and executes in a way so as to eliminate imputations as much as possible while executing the plan. Our experiments show that by steering the cleaning in the context of the ImputeDB query plan QUIP gets 2 to 10 times of improvement. Our work is also related to query-time cleaning approaches as in [10, 11, 21]. [21] explores repair of denial constraint violations on-demand to integrate data cleaning into the analysis by relaxing query results. QDA [10, 11] develops a lazy strategy for entity resolution to reduce entity resolution overhead during query processing. The method uses a sketch based approach as a filter to eliminate non-matching tuples to reduce cost of ER during queries. The approach developed is specific to ER setting with blocks and there is no effective way to use it for missing value imputation. A naive approach to use the strategy of [11] in our setting (as we will show in Section 7) leads to very high overhead.

3 QUIP OVERVIEW

This section provides an overview of QUIP that executes lazy evaluation of mixed imputation and query processing. The overall strategy is illustrated in Figure 3.

The goal of QUIP is to allow as much laziness as one needs to optimize the joint cost of imputations and query processing, essentially, ensuring lazy but correct execution, where correct execution means that the answers returned by QUIP for a query Q is identical to what would be returned had we imputed all the missing values prior to the query execution. Consider a query Q (as in Figure 1). QUIP uses a third-party optimizer, (e.g., a standard commercial system such as PostgreSQL or a specialized optimizer such as that supported by ImputeDB), to first generate a query plan (plan A in

Figure 3: QUIP Architecture.

Figure 4: Modified Operators in QUIP.
In Figure 6-g) is the answer set of query whenever a missing value is imputed, it must satisfy the predicate in Section 5. The bit is modified during query processing to indicate when one operator in the given query plan tree. For each operator we verify set carries all predicates in the upstream operators.

Filter set, on the other hand, maintains information to enable the filter operation (in Figure 4) to test if a tuple t that is input to the (relational) operator o can be filtered away or not. Let Ao be the attributes associated with o. Filter set is created for each operator in the given query plan tree. For each operator o, we first find all the predicates associated with its downstream operators that are applicable to the attributes of t other than Ao. As an example, consider selection operator \( o = \sigma_{S.Building=DBH}^{\text{in plan tree in Figure 6-a}} \) and \( A_o = \{S.Building\} \), we first add the predicate \( S.Room = T.room\_location \) into its filter set because it is from downstream operators of o and it is applicable in relation S other than S.Building. Then we extend filter set by finding the TRANSITIVE CLOSURE of current filter set. In this example, predicate \( S.Room = T.room\_location \) will be added. We next associate with each join predicate in the filter set a bit (to denote its status) which is initialized to 0. The bit is modified during query processing to indicate when one of the attributes in the join has no remaining missing values. In such a case, the join condition can be used for pruning imputations. We will later develop an efficient mechanism in Section 5.3 to use it for filtering. To illustrate how filter operation works, consider the filter set for the above selection operator \( \sigma_{S.Building=DBH}^{\text{in plan tree in Figure 6-a}} \). Let \( A_o = \{S.Building\} \), we can use the selection predicate \( S.Room = T.room\_location \) right away for each tuple received by \( \sigma_{S.Building=DBH}^{\text{in plan tree in Figure 6-a}} \) to check if this tuple can be filtered first before imputing missing values.

**Bloom Filter:** QUIP maintains a bloom filter [6] to store attribute values for equi-join operators. Let \( BF(a) \) be the bloom filter built for attribute a. In a pipeline implementation, when a tuple rises to the join operator (from either of the two operands), the associated value of the join attribute is inserted into the corresponding bloom filter, if it is not missing. Also, whenever a missing value for a join attribute is imputed (either as part of the join or a further downstream operator), it will be first verified and added into the corresponding bloom filter if it passes the verification.

We next define a concept of bloom Filter completeness with respect to a query Q. Intuitively, a bloom filter of an attribute a, \( BF(a) \), is complete wrt \( Q \) if \( BF(a) \) contains all the values of a that could result in tuples in the answer set of \( Q \). Note that tuples that are filtered away by the selection/join operators will not appear in the query answer, and hence may not be in the bloom filter. Formally, we define the completeness of a bloom filter wrt \( Q \) as follows. Let \( \alpha \) be the set of tuples that satisfies all predicates of \( Q \). Note that if \( Q \) contains a final projection, some of the tuples in \( \alpha \) might not appear in the final answer to \( Q \). However, for the bloom filter \( BF(a) \) for attribute a to be complete, values of a in tuples that satisfy all predicates of \( Q \) must be in \( BF(a) \) even though the tuple is eliminated in the final answer. Tuple \( (\alpha) \) in Figure 6-g) is the answer set of query \( Q \) in Figure 1. Consider attribute S.room and 2206 is its only one attribute value in query answer. The bloom filter of S.room in Figure 6 is complete because it contains 2206. Note that a complete bloom filter may contain the values that are not query answer, but it must not miss a value that will be part of query answer.

Let \( BF(a) \) be the event that causes the bloom filter \( BF(a) \) to be complete. Such an event depends upon the specific implementation of the join algorithm. Consider a join \( L.a \bowtie R.b \), if this join is implemented using nested loop, for inner relation R, bloom filter \( BF(R.b) \) contains all values in R.b (i.e., \( BF(R.b) \) is reached) when the first pass of relation R is processed. For outer relation L, such a condition becomes true only when all tuples have been processed through the join operator. Prior to that we cannot be sure that all of L.values that could result in output from the join are in the bloom filter \( BF(L.a) \). For hash joins, similar to nested loop, the bloom filter contains all values as soon as the hash table based on inner (build) relation has been built and for outer relation such a condition is reached when all tuples have been processed. For sort merge, or multi-pass hash join, the bloom filters for both relations L and R contain all values as soon as the sort or hash table build is finished. Note that a complete bloom filter \( BF(a) \) can only be reached after all the missing values under attribute a have either been imputed or eliminated.

Besides VF list and bloom filter, we also maintain an array, called missing counter, that records the number of missing values for each attribute. Such array could be easily initialized using the metadata or statistics in database. Whenever a missing value is imputed or dropped, we will update its corresponding entry in array.

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1. RS = \( \{2065, 2011, 2082, 2035, 2206\} \) in query Figure 1 for short.
5 IMPUTATION AND QUERY PROCESSING

In this section, we describe a general framework for query processing with imputations in QUIP treating the decision function in the modified operator as an oracle. Decision functions will be discussed in the next section. The cost-based design of decision function relies on estimating cost of imputing which relates back to how QUIP imputes missing value and executes query. The strategies to handle blocking or non-blocking imputations in QUIP are controlled by decision function and will also be discussed in Section 6. We focus this section on SPJ (select-join-project) query, discuss extensions to aggregate operator, union, set difference operators and nested queries in Section 9.3. Such extensions are relatively straightforward and not discussed in the paper due to length constraints.

QUIP modifies the original query tree input to it (Figure 6-a) based on an external optimizer replacing each operator by its modified counterpart without changing the structure of tree. Further, it adds a new imputation operator (denoted by \( \rho \)) just above any join and selection operation (Figure 6-b), which will impute all the missing values in the attributes that appear in the predicates of the given query. SPJ operators are modified by changing how data flows through them as shown in Figure 4.

SPJ operators will internally check if a value is missing or not. In QUIP missing values are represented as NULLs. We extend the relational schema with an additional attribute which contains a bit by suitably modifying the tuple \( t \). We denote a modified join operator by \( \sigma \). Consider a selection \( \sigma.p \)\_get\_next() function returns these tuples in Space table (Table 2) with Room value 2214 and 3119 are dropped because they failed to pass the filter set of \( \sigma.S\_building = DBH \) and \( \sigma.S\_building = DBH \), and their get\_next(tuples are shown in Figure 6-c) and Figure 6-d), respectively. Note that the tuples in Space table are imputed. Tuple that passes the filter and verify tests will be returned by \( \sigma.S\_building = DBH \) if \( t.a \) is missing and the decision function decides to impute \( t.a \), then the verify set and predicate will be used to check the imputed value. Note that we can check for \( t.a \) to be missing by adding an appropriate disjunction in the predicate (as shown in example below). If decision function decides to delay imputation or \( t \) passes the verify test and the predicate \( \sigma \) then, \( t \) will be returned by \( \sigma \)\_get\_next(). Otherwise, \( t \) will be discarded and \( \sigma \)\_get\_next() will return the next tuple that satisfies the \( \sigma \).

Example 5.1. Figure 6 illustrates the pipeline implementation of query in Figure 1 in QUIP. In Figure 6-c) to h), the numbered red circle represents the order in which \( \sigma \)\_get\_next() function returns these tuples for each operator. Figure 6-b) states the decisions taken by the decision functions in each operator. In selection operator, such as \( \sigma.S\_building = DBH \), we add another condition \( S\_building = DBH \) to read the missing values from relation \( S \). First, QUIP decides to delay imputations in two selection operator \( \sigma.S\_building = DBH \) and \( \sigma.S\_building = DBH \), and their \( \sigma.S\_building = DBH \) tuples are shown in Figure 6-c) and Figure 6-d), respectively. Note that the tuples in Space table are imputed. Tuple that passes the filter and verify tests will be returned by \( \sigma.S\_building = DBH \). Otherwise, \( \sigma \) will search next satisfied tuple to return until all tuples are consumed.

5.2 Modified Join Operator

We denote a modified join operator by \( \sigma \). Consider a join between relations \( R^L \) and \( R^R \) based on attributes \( a \) and \( b \) respectively (i.e., \( R^L.a \bowtie R^R.b \)), where \( R^L \) and \( R^R \) are the left and right relations respectively, and \( a \) and \( b \) are join attributes. When there is no ambiguity, we will refer to \( R^L \) and \( R^R \) simply as \( L \) and \( R \). Consider join operator \( L.a \bowtie R.b \), and a tuple \( t \) in either \( L \) or \( R \). For each such tuple, QUIP executes a filter, decision function and the verify operations as shown in Figure 4-b). Any tuple that fails to pass the

\[ \text{If } t.a \text{ is missing and the decision function decides to impute } t.a, \text{ then the verify set and predicate will be used to check the imputed value.} \]

\[ \text{Note that we can check for } t.a \text{ to be missing by adding an appropriate disjunction in the predicate (as shown in example below).} \]

\[ \text{If decision function decides to delay imputation or } t \text{ passes the verify test and the predicate } \sigma \text{ then, } t \text{ will be returned by } \sigma \text{\_get\_next(). Otherwise, } t \text{ will be discarded and } \sigma \text{\_get\_next() will return the next tuple that satisfies the } \sigma. \]

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\[ \text{First, QUIP decides to delay imputations in two selection operator } \sigma.S\_building = DBH \text{ and } \sigma.S\_building = DBH, \text{ and their } \sigma.S\_building = DBH \text{ tuples are shown in Figure 6-c) and Figure 6-d), respectively. Note that the tuples in Space table are imputed. Tuple that passes the filter and verify tests will be returned by } \sigma.S\_building = DBH. \text{ Otherwise, } \sigma \text{ will search next satisfied tuple to return until all tuples are consumed.} \]

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\[ \text{\footnote{\text{If index scan is implemented in scan operator, NULL values would be stored in index and be returned. This is supported in most current commercial databases, such as PostgreSQL. [8].}}} \]
filter or verify set will be dropped. We focus our discussions on the modified actions (operation box in Figure 4-b) for those tuples that pass filter and verify tests. We explain the operation in Figure 7-a. Tuples that arrive to operation pass the filter and verify nodes on either left or right side of the input can be classified into two types: 1) Tuples that do not contain missing values in the join attribute. (denoted as L1 or R1 in Figure 7-a)2) Tuples that contain missing values in the join attribute. (denoted as L2 or R2 in Figure 7-a)

Consider join operation \( \text{L.a} \bowtie \text{R.b} \), as shown in Figure 7-a). \( \text{L.a} \bowtie \text{R.b} \) can be rewritten as \( \text{L1} \bowtie \text{R1} \cup \text{L2} \bowtie \text{R2} \cup \text{L2} \bowtie \text{R1} \cup \text{L2} \bowtie \text{R2} \). We next discuss how join is implemented based on whether neither, one or both attributes in the join contain missing values. If there are missing values in both or one side join attribute, then a full/lef(right outer join based modification is implemented for join algorithm as not to lose any missing value. If neither join attributes have missing values, then regular join with one difference that if there are tuples from previous outer-join which contain NULL value in join attribute, we need to pass this tuple above.

Case 1: Both side \( \text{L.a} \) and \( \text{R.b} \) do not contain missing values. \( \text{L2} = \emptyset \) and \( \text{R2} = \emptyset \). In this case, \( \text{L.a} \bowtie \text{R.b} = \text{L1} \bowtie \text{R1} \), and tuples will be joined using the original join implementation in the operator. If these tuples are the outer-join result of previous tuples (they contain NULL values under join attributes), then QUIP simply lets them pass by concatenating NULL values for the attributes corresponding to the other side of the join operation. Such tuples arise if, for instance, a previous join operator had decided not to impute a missing value in its join attribute for this tuple. Otherwise, they will be joined as the original join condition. Consider join operation \( \text{L.a} \bowtie \text{R.b} \) in Figure 6-b), assuming the decision function decides to impute missing values \( N_0 \) and \( N_2 \) in attribute \( \text{U.mac address} \), tuples in \( T \text{ relation in Figure 6-e} \) will join relation \( \text{U} \) in Table 3, which leads to Figure 6-f).

Case 2: Only one side attribute in join operation contains missing values. \( \text{L2} = \emptyset \) or \( \text{R2} = \emptyset \) Without loss of generality, let us consider the case where the left side of join attributes, \( \text{L.a} \), has missing values. In this case, if tuples on the left side are of type 1), they will be joined with right side based on the original join predicate (\( \text{L1} \bowtie \text{R1} \cup \text{L1} \bowtie \text{R2} \)). Else, if the tuple in left side is of type 2), they will be returned as part of outer join by concatenating NULL values in the right columns. Consider join operator \( \text{L.a} \bowtie \text{R.b} \) in Figure 6-e), where only \( T \text{.room_location} \) has missing values. The tuple (1) in Figure 6-e), is a joined tuple from tuple (1) in \( T \text{ relation in Figure 6-c} \) and tuple (1) in \( S \text{ relation in Figure 6-d} \). All the other tuples, i.e., tuples (2) in \( T \text{.room_location} \), are the left join results of \( T \) and \( S \) where the missing values \( N_1, N_2, N_3 \) are preserved with NULLs in columns in \( S \) side. Note that we will not lose the missing value \( N_2 \) in tuple (2) in Figure 6-d although it does not show up in later query processing, because it will be brought back if the \( S\text{.building value in tuple (3), i.e., 2065} \), is matched with any attribute value in \( T \text{.room_location} \) by using the bloom filter \( B(F(T \text{.room_location}) \). In Section 5.3, we will detail how to achieve this using bloom filters.

Case 3: \( \text{L.a} \) and \( \text{R.b} \) both contain missing values in the join attribute. \( \text{L2} \neq \emptyset \) and \( \text{R2} \neq \emptyset \). In this case, tuples of type 1) and 2) can be in both sides of the join column. Tuples of type 1) will be joined using the original join predicate in the operator (\( \text{L1} \bowtie \text{R1} \)). Tuples of type 2), that is, with missing values, will be preserved as in the outer join. That is, if a tuple of \( \text{L.a} \) contains a missing value in \( \text{L.a} \), the modified operator will generate a tuple with values of \( \text{L.a} \) and with NULLs in all the attributes corresponding to \( \text{R.b} \). Likewise, a similar tuple would be created with NULLs for attributes on \( \text{L.a} \) side for all tuples in \( \text{R.b} \) that arrives to the operator with a missing value for \( \text{R.b} \). In this case, QUIP maintains the list of tuple-id, \( L_{temp} \) for tuples in \( \text{L2} \bowtie \text{R2} \) whatever has lesser number of tuples, and use a \( \text{Flag} \) to denote the side of relation to be stored (e.g., \( \text{Flag} = 1 \) denotes tuple-ids for \( \text{L2} \) is stored). The cardinality of \( \text{L2} \bowtie \text{R2} \) is simply the number of missing values in \( \text{L.a} \) and \( \text{R.b} \), which corresponds to their respective missing counters. The reason for maintaining this set will become clear later when we discuss join triggers.

In realizing the implementation of the modified join operation, note that QUIP can exploit the existing join implementation(s) supported by the database in which QUIP is integrated since it only modifies how data flows through the operator and not the operator implementation. For instance, if the database implements a hash join, QUIP continues to use the hash join implementation for tuples with type 1). The only addition it makes is to check if an input tuple to the join has a NULL value in join attribute, in which case, it simply forward this tuple to the next downstream operator by first suitably padding NULLs in the requisite fields like the way an outer-join does.

### 5.3 Join Trigger

Imputation of missing values in the join operation \( \text{L.a} \bowtie \text{R.b} \) may result in QUIP triggering the execution of parts of the join that had not executed prior to the imputation (i.e., \( \text{L1} \bowtie \text{R2}, \text{L2} \bowtie \text{R1}, \) and \( \text{L2} \bowtie \text{R2} \)). QUIP triggers the execution of such partially executed joins as soon as enough imputations have been performed to make such a join possible. Consider a join \( \text{L.a} \bowtie \text{R.b} \), the join that had not executed before, say \( \text{L2} \bowtie \text{R1} \), might be triggered when missing values in \( \text{L2} \) are imputed. To compute such a join, QUIP exploits the previously constructed bloom filter on \( R \) to determine which tuples of \( \text{L2} \) join. Note that since QUIP is based on streaming model, to compute \( \text{L2} \bowtie \text{R1} \), in addition to ensuring that all of the tuples of \( \text{L2} \) are imputed (or eliminated), it is also necessary to ensure that the bloom filter for \( R \) is complete, i.e., \( B(F(R.b)) \) is true, as defined in Section 4.

We describe join trigger of the join operation \( \text{L.a} \bowtie \text{R.b} \) in Algorithm 1 in format of ECA rules [35, 40], i.e., \( \text{when event, if condition, then action} \). For each tuple \( t \in L \) whose \( t.a \) value was missing and
Algorithm 1: Join Trigger of \(L.a \bowtie R.b\).

\[
\text{Input: } L_{\text{temp}}, \text{Flag}
\]

1. When \(t.a\) is imputed:
   2. if \(BFC(R.b)\) is true then
      3. \(B.F_{\text{Join}}(t, B.F(R.b), L_{\text{temp}}, \text{Flag})\)
   4. else
      5. \(L_{R.\text{Ready}} \leftarrow L_{R.\text{Ready}} \cup \{\text{tid of } t\}\)

6. When \(t.b\) is imputed:
   7. if \(BFC(L.a)\) is true then
      8. \(B.F_{\text{Join}}(t, B.F(L.a), L_{\text{temp}}, \text{Flag})\)
   9. else
      10. \(L_{L.\text{Ready}} \leftarrow L_{L.\text{Ready}} \cup \{\text{tid of } t\}\)

11. When \(BFC(L.a)\) is true:
    12. for \(t \in L_{L.\text{Ready}}\)
        13. \(B.F_{\text{Join}}(t, B.F(R.b), L_{\text{temp}}, \text{Flag})\)
    14. \(L_{L.\text{Ready}} \leftarrow \emptyset\)

15. When \(BFC(R.b)\) is true:
    16. for \(t \in L_{R.\text{Ready}}\)
        17. \(B.F_{\text{Join}}(t, B.F(L.a), L_{\text{temp}}, \text{Flag})\)
    18. \(L_{L.\text{Ready}} \leftarrow \emptyset\)

had not been imputed during the execution of \(\tilde{\sigma}_{L.a=R.b}\) when \(t.a\) is imputed, if \(BFC(R.b)\) is true, then QUIP will use \(B.F(R.b)\) for join by calling \(B.F_{\text{Join}}(t, B.F(R.b), L_{\text{temp}}, \text{Flag})\) (Ln.2-3).

In \(B.F_{\text{Join}}(t, B.F(R.b), L_{\text{temp}}, \text{Flag})\) in Algorithm 2, \(t\) will be dropped if \(B.F(R.b)\) returns false. Note that if bloom filter returns false, \(t\) will not be joined with any tuple in relation \(R\). Otherwise, \(B.L(R.b)\) will return matched tuples, called \(T_{\text{matched}}\), in relation \(R\) by executing index look ups. (Ln.4) \(L_{\text{temp}}\) will be removed from \(T_{\text{matched}}\) if \(L_{\text{temp}}\) and \(t\) are in different relations of the triggered join operation. (Ln.6-7) \(7\)

When \(t.a\) is imputed, if \(BFC(R.b)\) is false, then QUIP will insert the tuple id of \(t\) into a list, denoted as \(L_{L.\text{Ready}}\) such that such tuples will be joined later when \(BFC(R.b)\) becomes true. (Ln.4-5 in Algorithm 1) Similarly, when \(t.b\) is imputed, if \(BFC(L.a)\) is true, then QUIP will use the complete bloom filter \(B.F(L.a)\) to join tuple \(t\) with relation \(L\) using \(B.F_{\text{Join}}(t, B.F(L), L_{\text{temp}}, \text{Flag})\) (Ln.7-8). Else, if \(B.F(R.b)\) is false, then QUIP will insert the tuple id of \(t\) into a list, denoted as \(L_{R.\text{Ready}}\) (Ln.9-10).

When \(BFC(R.b)\) (or \(BFC(L.a)\)) becomes true, (Please refer to Section 4 where we describe how to detect when \(BFC()\) is true) QUIP performs join for all tuples in \(L_{L.\text{Ready}}\) (or \(L_{R.\text{Ready}}\)) one by one calling \(B.F_{\text{Join}}(t)\), and \(L_{L.\text{Ready}}\) (or \(L_{R.\text{Ready}}\)) will be set as empty to make sure join is executed only once (Ln.11-18).

**Example 5.2.** Consider join operation \(T_{\text{room location}} = S_{\text{room}}\), which is delayed by degrading imputations in attribute \(T_{\text{room location}}\), and only one side of attribute \(T_{\text{room location}}\) has missing values. Assume hash join is implemented in

\*\*Index is assumed to be built for join attributes, otherwise QUIP can alternatively maintain additional linear pointers from attribute values to their tuples.\*\*

\*\*Simply doing join of \(t \in R2\) using \(B.F(L.a)\) and \(t \in L2\) using \(B.F(R.b)\) will generate duplicated join tuples since the tuples from \(L2 \Rightarrow B2\) will be produced twice. To remove such duplicated results, we use \(L_{\text{temp}}\) the stored tuple-ids in the relation with smaller number of missing values, say \(R2\), to remove joined tuples originated from \(R2\) to implement \(L2 \Rightarrow R1\). On the other hand, tuples \(t \in R2\) is joined using \(B.F(L.a)\), i.e., \(R2 \Rightarrow L\), which makes the join \(L.a \bowtie R.b\) complete.

*This can be determined by looking up their verify set in VF list.*

---

Algorithm 2: \(B.F_{\text{Join}}(t, B.F(a), L_{\text{temp}}, \text{Flag})\)

1. if \(B.F(a) = \emptyset\) then
   2. \(t\) is eliminated;
3. else
   4. \(T_{\text{matched}} \leftarrow \text{Index\_look\_up}(B.F(a))\)
   5. if \((t \in R^2\) and Flag = L) or \((t \in R^1\) and Flag = R) then
   6. \(T_{\text{matched}} \leftarrow T_{\text{matched}} \setminus L_{\text{temp}}\)
7. return \(t \in T_{\text{matched}}\)
6 DECISION NODE

Recall that in QUIP, each modified relational operator includes a decision node to help decide whether a missing attribute value should be imputed prior to the execution of the operator or should imputation be delayed for downstream operators. The strategy used to decide depends upon whether the imputation method is non-blocking or blocking.

We focus on an adaptive cost-based solution for non-blocking imputations, and describe eager and lazy strategies for blocking imputations for short. Eager strategy imputes missing values of the attribute(s) associated with the operator right away prior to evaluation of the operator, while lazy strategy always delays imputing until the tuple with the missing value reaches the imputation operator \( \rho \). These two strategies are discussed and detailed in Section 9.1.

6.1 Obligated Attributes

Non-blocking imputations in QUIP can be placed anywhere in the query tree since QUIP, through operator modification, decouples imputation from the operator implementation. To guide the actions of each operator, we first define a concept of obligated attributes for relations in query \( Q \). Intuitively, an attribute \( a \) in \( R \) is obligated if missing values of \( a \) in \( R \) "must" be imputed in order to answer the query, i.e., for such attributes its values cannot be eliminated as a result of other query conditions or due to imputation of other missing values.

**Definition 6.1. (Obligated Attributes)** Given the set of attributes in predicate set of a query \( Q \) (denoted by \( A_Q \)), an attribute \( a \) in relation \( R \) is said to be obligated if:

- attribute \( a \) appears in a predicate in \( Q \), i.e., \( a \in A_Q \), or \( a \) is one of the attributes listed in a projection operator; and
- all attributes of \( R \) (other than attribute \( a \)) do not appear in any predicate in \( Q \). That is, \( \forall a' \in R - a, a' \notin A_Q \).

If an attribute \( a \in R \) is neither in the projection list nor in \( A_Q \), imputing its missing values will not be required to answer \( Q \) and hence \( a \) would not be obligated. Likewise, if a predicate in \( A_Q \) contains an attribute \( b \) which is also in \( R \), it is possible that such a predicate may result in the tuple of \( R \) to be eliminated thereby making imputation of the corresponding \( a \) value (in case it was missing) unnecessary. Thus, again, such a possibility would prevent \( a \) from being classified as obligated. As an example in Table 3, U.mac_address is a obligated attribute because other attributes U.name and U.email are not in any predicate of query \( Q \) and U.mac_address is in join predicate U.mac_address=T.mac_address.

Since missing values of obligated attributes must always be imputed, there is no benefit in delaying their imputations. In contrast, imputing could potentially reduce number of tuples during query processing. As a result, decision function in the QUIP operators never delay such imputations. For the remaining attributes, QUIP performs a cost-benefit analysis to decide whether to impute.

6.2 Decision function

For each operator \( o \) in query tree, QUIP associates a decision function \( df(a, o) \) for all attribute \( a \) that appears in the predicate associated with \( o \). Decision to delay/impute missing values has implications on both imputation and query processing costs.

Consider a tuple \( t \) in relation \( R = (a, b, c, d) \) and a query tree in Figure 8-a). Say \( t_1 = (N_1, 1, 2, 3) \) (\( N \) represents missing value), if we delay imputing \( t_1.a, t_1.b \) does not join with any tuples in the other relation, we can avoid imputing \( t_1.a \). On the other hand, imputing \( t_2.a \) for \( t_2 = (N_1, N_2, 2, 3) \), could prevent imputation of \( t_2.b \), if the imputed value of \( t_2.a \) is filtered in the selection operator. Imputing \( t_2.a \) may also reduce query processing time since it does not require the operator on attribute \( b \) to be executed.

Since decisions on whether to impute/delay are made per tuple containing missing values locally by the operator, the decision function must not incur significant overhead. In making a decision for operator \( o_3 \) over attribute value \( t.a \) of a tuple \( t \), QUIP assumes if \( t \) contains other missing values in attributes, say \( t.b \) (on which predicates are defined in downstream operators), say \( o_2 \), those operators will decide to impute \( t.b \) if (and when) the tuple \( t \) reaches those operators. For instance, in query tree in Figure 8-a), in making a decision for imputing/delaying \( t.a \), i.e., \( N_1 \), in developing a cost model we assume that the missing value \( N_1 (t.c) \) will be imputed right away. This prevents, QUIP to have to recursively consider a larger search space that enumerates (potentially exponential number of other possibilities wherein downstream operators may delay/impute.)

We build a cost model below to estimate impact of delay/impute decision on both the imputation cost and the query processing cost based on which the operators make decisions in QUIP. To compute the imputation and query processing costs associated of the decision for an operator, QUIP maintains the following statistics:

- \( \text{impute}(a) \): Cost of imputing a missing value of attribute \( a \), computed as a running average over all imputations performed so far for missing values of \( a \).
- \( \text{selectivity}(o_i) \). \( S_i = \frac{|T_c|}{|T_o|} \), where \( T_c \) (\( T_o \)) are tuples that are processed (satisfy) the predicate associated with \( i \).
- \( \text{selectivity}(o_j) \) join operator between relation \( L \) and \( R \) computed as \( S_j = \frac{|T_L|}{|T_o|} \), where \( T_L \) (\( T_o \)) are tuples in relation \( L \) (\( R \) and \( T_o \) are tuples that satisfy \( o_j \)).
- \( TT \text{Join}_o \), the average time taken to join two tuples in (join) operator \( o \);\(^9\)
- \( T_o \): the average number of evaluation tests to perform per tuple in operator \( o \) for tuples without missing values in the attribute to be evaluate in \( o \).\(^{10}\) If \( o \) is join operator, evaluation tests refer to join tests. Else, if \( o \) is selection operator, we set \( T_o = 1 \).

To bootstrap the process of statistics collection, QUIP initially delays all imputations forcing tuples to rise up to the top of the tree (or be dropped if they fail some predicates en-route). During this process, QUIP collects imputed tuple samples to compute \( \text{impute}(a) \) and to determine other statistics such as \( T(o) \), join cost \( TT \text{Join}_o \) and selectivity \( S_o \). These statistics are then adaptively updated during query processing.

**Cost Model for Imputations.** We illustrate how to estimate the imputation cost using an example, and include the mathematical model for imputations and query processing (below) in Section 9.2. Consider a query tree in Figure 8-a), and a tuple \( t = (N_1, 1, N_2, N_3) \).\(^{11}\)

\(^9\) We exclude those tuples containing missing values from \( T_L \) and \( T_o \).

\(^{10}\) We also use the notation \( TT \text{Join}_o \) for selection operator, in this case, \( TT \text{Join}_o = 0 \).

\(^{11}\) A tuple with missing value in the attribute that passes through \( o \) will be simply preserved to the above operator without evaluation immediately, and thus \( T_o \) for such tuple is set to be 1.
To decide whether to impute or delay missing value \( t.a \) (\( N_1 \)), QUIP estimates the total imputation cost in case it chooses to impute or to delay imputing \( t.a \). The set of possible executions that may result for either of the decisions are illustrated in the decision tree shown in Figure 8-b). Each path of the tree corresponds to a possible outcome based on the decision to impute/delay imputing \( t.a \). For instance, in path \( p_2 \), \( t.a \) is imputed but fails the predicate in \( o_1 \), while in path \( p_3 \), \( t.a \) is delayed and \( t \) passes the predicates associated with \( o_2 \) and \( o_3 \), and reaches the imputation operator \( p \), where \( t.a \) is imputed and evaluated in \( p \) using predicate associate with \( o_3 \). The estimated imputation cost in the case of imputing (delaying) \( t.a \), is the summation of the expected imputation cost of all the paths in the left (right) side of tree, i.e., \( p_1, p_2, p_3, p_3, p_3, p_3, p_3, p_3, p_3 \). The expected costs of various paths (shown in Figure 8-c) are computed as a weighted sum of imputations along the path, where the weight corresponds to the probability of execution of that imputation. For instance, for path \( p_1 \), we impute \( t.a \) with the probability of \( 1 \), and, subsequently impute \( t.c \) with the probability of \( S_0, S_0 \). Thus, the cost of path \( p_1 \) is \( impute(a) + S_0, S_0, impute(c) \).

**Cost Model for Query Processing.** Since join costs dominate query execution, QUIP estimates query processing costs by the corresponding join costs. Consider the same decision tree in Figure 8-b). The expected query processing cost if we impute (delay) \( t.a \) is the sum of the expected query processing costs for all the paths in the left (right) side of the tree. Figure 8-d) lists the probability of each path, and also, its query processing cost. The probability is estimated based on selectivity of the predicates along the path, and the cost is estimated by summing execution cost of execution of operators along the path incurred in processing tuple(s) that are generated as a result of processing \( t \). Take \( p_0 \) as an example. Its corresponding probability is \( S_0 \) \((1 - S_0)\) since \( t \) passes \( o_1 \) but fails \( o_2 \). The estimated cost for processing \( t \) (shown in Figure 8-a) in operator \( o_1 \), denoted by \( QP(o_1) \), is \( T_{o_1} + TTJoin_{a_1} \), which is 0 in this example since \( o_1 \) is a selection operator for which \( T_{o_1} \) is 1 and \( TTJoin_{a_1} = 0 \). The cost \( QP(o_2) = T_{o_1} T_{o_2} + TTJoin_{o_2} \) since \( o_2 \) is a join operator and \( T_{o_1}, T_{o_2} \) is the estimated number of join tests to perform in \( o_2 \).

7 EVALUATION

In this section, we evaluate QUIP over two real data sets and one synthetic data set. Similar to ImputeDB, we implemented QUIP on top of SimpleDB [3], a teaching database used at MIT, University of Washington, and Northwestern University, among others. We did so, so that we can directly measure further improvements due to QUIP on ImputeDB query plans. We run our evaluations in a single-node machine with 16GB memory, Apple M1 Pro chip and 1TB flash storage.

7.1 Data sets

**UCI WiFi.** The first data set, UCI-Wifi, is collected from real WiFi connectivity data in UCI campus by Tippers [36], a sensor data management system. UCI-WiFi has three tables, users, wifi and occupancy with 4018, 240, 065 and 194, 172 number of tuples, and totally 383, 676 missing values respectively. WiFi records the continuous connectivity data of devices - that is, which device is at which location in which time interval. occupancy has the occupancy (i.e., the number of people) of locations as a function of time.

**CDC NHANES.** We use the subset of 2013–2014 National Health and Nutrition Examination Survey (NHANES) data collected by U.S. Centers for Disease Control and Prevention (CDC) [1]. CDC data set has three tables, demo, exams and labs, which are extracted from a larger complete CDC data set. demo, exams and labs have 10175, 9813, 9813 tuples, respectively, and all of them have 10 attributes. Among them, there are totally 24 attributes that contain missing values, whose missing rate ranges from 0.04% to 97.67%, with total 81, 714 missing values.

**Smart Campus.** We used the SmartBench [23] simulator to generate synthetic sensor and semantic data based on seed data collected from a real system at the UCI campus using Tippers [36]. In smart-campus data set, we generate 2 semantic tables, location, occupancy, 4 synthetic sensor tables, WiFi, Bluetooth, Temperature, Camera, as well as a space table and user table. smart-campus data set has totally approximately 2 million (1,892,500) tuples and 1.6 million missing values (1,634,720). The more detailed metadata for the above three data sets are shown in Section 9.4.

7.2 Query Set

We create three query workloads to evaluate QUIP, random (with random selectivity), low-selectivity and high-selectivity. In each query workload, the majority of queries are SPJ-aggregate queries that contains select, project, join, aggregate (group by) operations. SP queries are also included. Each query workload contains 20 queries.

7.3 Imputation Methods

We chose four imputation approaches, two blocking, i.e., Top-k nearest neighbor [7] (Knn) and XGBoost [5, 18], and two non-blocking, i.e., histogram-based mean value imputation [17] and LOCATER [32]. Among them, Knn, XGBoost and mean value imputations are widely used and their implementations are available in standard Python packages, such as sklearn or xgboost. LOCATER, which is an expensive time-series imputation approach, imputes missing location and occupancy in UCI-WiFi and Smart-Campus data set. This technology has already been deployed and running in UCI in several real location-based applications for over one year, such as occupancy [33] and crowd tracing [9]. Thus, we believe LOCATER is good fit for real testing in our live problem settings.

\[ 2 \] We thank ImputeDB [17] for providing this data set whose link can be found in [2, 4].
7.4 Strategies Compared

We evaluated QUIP with two versions, QUIP-lazy and QUIP-adaptive, as defined in Section 6, and compared QUIP with Offline and ImputeDB. Offline approach first imputes all missing values in the data set and then executes query processing. ImputeDB [17] uses a parameter \( \alpha \) between 0 and 1 to trade-off efficiency with quality. In particular, ImputeDB drops tuples with missing values in order to improve efficiency, though dropping tuples can result in reduced quality. It uses \( \alpha \) as a parameter to explore such a trade-off. Higher the value of \( \alpha \), more tuples with missing value will be dropped, leading to reduced quality. Since we are not exploring trade-off between quality and efficiency in this paper (our interest is in reducing the number of imputations without loss of quality), when comparing against ImputeDB we set the value of \( \alpha \) to be 0 so as to prevent tuples with missing values from being dropped by ImputeDB. We note that ImputeDB’s strategy for trading quality with efficiency can also be incorporated in QUIP though we do not explore such a strategy in this paper. We also compare QUIP with QuERy [11], and include the results in Section 9.4.

7.5 Results

Experiment 1: Runtime & Imputations. In Figure 9 and Figure 10 we evaluate the runtime and number of imputations, i.e., the number of missing values that are imputed for Offline, ImputeDB, QUIP-lazy and QUIP-adaptive approaches using the random query set. Among them, QUIP-lazy is applied on blocking imputations, i.e., KNN and XGboost while QUIP-adaptive is applied on non-blocking imputations, i.e., Mean and LOCATER. In CDC data set we only apply Mean imputation since LOCATER is not applicable. We make several observations. First, both lazy and adaptive versions of QUIP achieves big savings in the number of imputation. It requires only 4.7% and and 21% of imputations compared to ImputeDB over UCI UCI-WiFi dataset (in Figure 9) and CDC dataset (in Figure 10) respectively when expensive imputations are used, i.e., KNN, LOCATER and XGboost. Comparing with Offline approach, QUIP only imputes less than 1% of missing values to answer the query. In contrast, when cheap imputations are used such as Mean imputation, QUIP tends to impute data first since doing so will potentially save the query processing time by reducing temporary tuples, and thus has similar imputations as ImputeDB.

Second, QUIP has similar performance with ImputeDB when cheap imputations (Mean) or learning approaches with training and inference phases are used whose training time dominates the imputation costs (e.g., as in XGboost) are used. For such learning approaches, reducing imputation numbers would not make a big improvement if inference cost is negligible comparing with training time. However, it would be expected to make a difference if the learning approach whose inference cost is comparable to training, as in the case of KNN and SVM (see Figure 2).

Third, QUIP outperforms ImputeDB and Offline by around 20x and 1000x in UCI-Wifi, and the improvements are around 4x and 85x in CDC when costly non-blocking imputations (LOCATER) or blocking imputations with expensive inference (KNN) are used.

The above observations demonstrate that QUIP by wisely delaying imputations can potentially achieve significant savings leading to great improvement of query execution time when imputations with expensive inference time are used.

Experiment 2: Quality of Query Answer. QUIP achieves the same answers as the eager strategy (that imputes all missing data prior to executing the query) irrespective of whether the imputation strategy is either blocking and non-blocking. ImputeDB, in contrast, may result in different answers when using a learning-based method. In ImputeDB, depending upon where the imputation operator is placed, the model learnt by the imputation operator may differ based on the subset of data that is input into the imputation operator. As a result, the quality of the answer may vary. To compare QUIP to ImputeDB in terms of quality under KNN imputation (which is blocking) using Symmetric-Mean-Absolute-Percentage-Error (SMAPE) [34]. This is the quality metric used in ImputeDB [17]. We compute SMAPE as tuple-wise absolute percentage deviations for each query. On the CDC and UCI-WiFi data set, SMAPE value for for ImputeDB is 0% to 4% in CDC data set and 0% to 3% in UCI-WiFi data set. In contrast, by design (and also validated experimentally) QUIP achieves a SMAPE of 0 in both data sets.

Experiment 3: Query Selectivity Effects. We first use the following query template to generate low-selectivity and high-selectivity query workloads: SELECT a, AVG(b) FROM R1, ..., Rn WHERE [Pred\(_i\)] [Pred\(_{\leq} \)] GROUP BY a, where Pred\(_\leq i\) refers to the set of join predicates, \( \{ R_i.x = R_j.x \} \) among all relations, and Pred\(_i\) refers to a set of selection predicates, \( \{ R_i.a_i >= x_i \} \) by choosing a random attribute \( a_i \) in every relation. We varies the selectivity of each selection predicate as 0, 0.2, 0.4, 0.6, 0.8, 1 by changing the operands \( x_i \), and the selectivity of join predicate is set to be low and high by...
modifying the matching numbers of joined attribute values. KNN is applied in CDC data set, while in UCI-WiFi and Smart-Campus data set, LOCATER is used to impute location and occupancy, and Mean-value is used to impute other missing values. In CDC and UCI-WiFi data set, we report the effect from selectivity of selection predicates in Figure 11, and the effects from both join and selection selectivity are evaluated in synthetic data set in Figure 12.

With increasing selectivity of selection predicates, both ImputeDB and QUIP have an increase in imputation numbers and running time, and QUIP has a considerably lower imputations and running overhead than ImputeDB at all selectivity levels. In CDC data set where join operations are relatively selective, QUIP tends to delay imputations in selection operators because join predicates will help eliminate lots of temporary tuples and thus reduce the number of imputations in the case where imputation overhead is costly than query processing. In WiFi data set whose join attributes have missing values, instead of imputing all join attributes values before join as ImputeDB does, QUIP delays imputations due to following two reasons. First, imputations in join attributes can be saved if such delayed tuples can be dropped using filter set in VF list. Second, in a temporary tuple \( t \) containing missing values in join attributes, among several join and selection predicates, instead of imputing all missing values in tuple \( t \), it is possible that only a few imputations will eliminate \( t \) because the imputed values failed their predicates stored in verify set in VF list.

In synthetic data set, it is interesting to note that when join selectivity is high, QUIP tends to first impute missing values in selection operators because join predicates would not help eliminate imputations much in this case, and thus QUIP’s performance is closer to ImputeDB when the selection predicates is less selective. When the join operators are highly selective, i.e., selectivity is low, QUIP tends to delay imputing missing values in selection operators because low join selectivity would help eliminate most temporary tuples and thus save most imputations. In Figure 12(a), QUIP outperforms ImputeDB considerably in this case.

**Experiment 4: Bloom Filter Effect.** We evaluate the effect of bloom filter used in QUIP and report the results in Table 4 where SM stands for Smart-Campus. Specifically, let \( \Delta \text{Runtime} \) be the difference of running time between QUIP and QUIP without bloom filter. Similarly, \( \Delta |\text{Temporary Tuples}| \) and \( \Delta \text{Imputations} \) measures the difference of number of temporary tuples and imputations. We observe that using bloom filter would not help reduce imputations but help save the number of temporary tuples and thus reduce the query processing time. Note that it only works when the join attributes have missing values, which exist in UCI-WiFi and Smart-Campus data set. If there are no missing values under join attributes, such as CDC data set, QUIP will not execute outer join and thus bloom filter will not be applied.

**Experiment 5: QUIP with Different Query Plans.** We compare the performance of QUIP that takes different query plans as input in real data sets in Figure 13. In particular, QUIP takes the query plan from ImputeDB and PostgreSQL on random query set. We observe that the performance of the lazy strategy of QUIP is not affected by the query plan it takes when blocking imputations (e.g., KNN) are used. This is because whatever the query tree is, all the missing values will be delayed in selection or join operator and imputed at imputation operator \( \rho \) that is on the top of query tree, and thus lead a stable performance. We also observe that when taking different plans for non-blocking operators, such as LOCATER, the plan generated by ImputeDB is better, which demonstrates the effectiveness of ImputeDB. But taking the plan by PostgreSQL also leads to an acceptable performance, which shows the robustness of QUIP to different underlying query plans.

**8 CONCLUSION**

This paper studies query-driven missing value imputation and proposes QUIP, a technique to intermix query processing and missing value imputation to minimize query overhead by taking a reasonable good query plan as input. Specifically, QUIP co-optimizes imputation cost and query processing cost, and proposes a new implementation based on outer join to preserve missing values in query processing. Real experiments shows that QUIP outperforms the state-of-the-art technique ImputeDB 2 to 10 times and achieves order of magnitudes improvement over standard offline approach.

| CDC | UCI-WiFi | SM-low | SM-high |
|-----|----------|--------|---------|
| \( \Delta \text{Runtime} \) | 0 | 67ms | 31ms | 73ms |
| \( \Delta |\text{Temporary Tuples}| \) | 0 | 124,711 | 58,311 | 137,826 |
| \( \Delta \text{Imputations} \) | 0 | 0 | 0 | 0 |

**Figure 13: QUIP with Different Query Plans.**
9 APPENDIX

9.1 Decision Functions for Blocking Imputations

In the context of blocking-based imputations, we need to differentiate between learning-based strategies that have a separate learning and inference (imputation) stages versus other strategies that do not have a learning phase.

Let us first consider blocking learning-based strategy with dominant learning part and its imputation cost dominates query processing costs. In this case, QUIP will take an easier strategy, where QUIP will impute missing values of the attribute(s) associated with the operator right away prior to evaluation of the operator. Such a strategy is exactly the one that ImputeDB takes.

For those learning-based imputations where learning cost is not dominant, or other blocking imputations which have high cost (e.g., rule-based approaches [20, 39]), it is advantageous to use a lazy strategy where QUIP always delays imputing until the tuple with the missing value reaches the top of query tree, i.e., imputation is performed inside the imputation operator \( \rho \) in Section 5. Note that in case of learning-based imputations where learning cost is not dominant and inference cost is comparable, the learning phase can be done eagerly and inference part becomes non-blocking, and thus our designed decision functions could be applied on inference. Both strategies can be simulated in QUIP by setting the decision function to always impute (eager) or to always delay (lazy).

9.2 Cost Models in Decision Function

Cost Model for Imputations. For a tuple \( t \) with missing value in attribute \( a \) received by operator \( o \) in query tree, \( df(a,o) \) computes the expected imputation cost in the case of impute or delay by building a decision tree, as shown in Figure 14-b. Consider a tuple \( t = (N_1, 2, N_2, 3) \) received in \( o_1 \), decision tree contains \( o_1 \) and its downstream operators before imputation operator, i.e., \( o_1, o_2, o_3 \). Let each root-to-leaf path in decision tree be \( p = \{dag(a_1, ..., a_j, result)\} \). For simplicity, we denote such a path by \( p = \{a_1, ..., a_j\} \). Each of such path \( p \) corresponds to a possible evaluation result of \( t \). Those paths with result as red colors means tuple \( t \) is eliminated while the green color means \( t \) passes all predicates. Each edge from a operator \( o \) denotes the evaluation result of \( t \), i.e., \( y \) means \( t \) passes \( o \) while \( n \) means \( t \) fails \( o \). For instance, \( p_5 \) corresponds to the case when \( t.a \) is imputed and fails the predicate associated with \( o_1 \), while \( p_3 \) means that the imputation of \( t.a \) is delayed (and thus cannot be evaluated in \( o_1 \)), and \( t \) passed the predicates in \( o_2, o_3 \), then \( t.a \) is forced to be imputed in operator \( o_1 \) and be re-evaluated using \( \sigma_{R,d \geq x} \) associated with \( o_1 \).

Let \( E[\text{IMP}(\text{impute})] \) and \( E[\text{IMP}(\text{delay})] \) be the expected imputation cost of tuple \( t \) based on imputing and delaying \( t.a \).

\[
E[IM(\text{impute})] = E[IM(\text{delay})] = \text{summarizing the expected cost of paths where \( t.a \) is imputed (delayed) in decision tree. For instance, } E[IM(\text{impute})] = E[IM(p_1)] + E[IM(p_2)] + E[IM(p_3)] + E[IM(p_4)]. \] 

\[
E[IM(p_1)] = \sum_{a_i \in \text{pred}, t.a = \text{missing}} \text{impute}(a_i) \ast \text{Prob}(a_i), \] 

where \( a_i \) is the attribute of \( t \) to be evaluated in \( o_1 \) and \( \text{Prob}(a_i) \) is the probability that \( t \) will reach operator. \( \text{Prob}(a_i) = \prod_{a_j \in \text{pred}} t.a = \text{missing} \text{So}_j \) where \( f(a_j) \) is the ancestors of \( a_i \) in decision tree. If \( f(a_i) = \emptyset \), then

\[
\text{Prob}(a_i) = \prod_{a_j \in \text{pred}} t.a = \text{missing} \text{So}_j \] 

Figure 14: Decision Function Example.

\[
\text{Prob}(a_1) = 1. \] 

Figure 14-(c) lists the expected imputation cost of all paths. Taking \( p_3 \) for example, if \( t.a \) is delayed and \( t \) could reach \( o_3 \) with probability \( \text{So}_3 \), the expected imputation cost for \( t.c \text{So}_2 \) is \( \text{So}_3 \ast \text{impute}(c) \). Similarly, if \( t \) reach the imputation operator and \( t.a \) be imputed there with probability \( \text{So}_3 \ast \text{So}_1 \), then the expected imputation cost of \( t.a \) is \( \text{So}_2 \ast \text{So}_1 \ast \text{impute}(a) \).

Query Processing Cost. In SP query, we assume the join cost dominates the overall query processing cost, and thus we use the estimation of join cost to approximate query processing time. Based on the same decision tree built for deciding imputing \( t.a \) or not, let \( E[QP(\text{impute})] \) and \( E[QP(\text{delay})] \) be the expected query processing cost based on imputing or delaying \( t.a \). Similarly, \( E[QP(\text{impute})] \) is summation of the costs of the paths where imputing \( t.a \) is decided, i.e., \( E[QP(\text{impute})] = E[QP(p_1)] + E[QP(p_2)] + E[QP(p_3)] + E[QP(p_4)] \). The expected query processing cost of a path \( p \) is the summation of the expected cost in each operator in this path, i.e., \( E[QP(p)] = \sum_{x \in \text{pred}} \text{QP}(x) \ast \text{Prob}(x) \), where \( \text{QP}(x) = (\prod_{a_i \in \text{pred}} t.a = \text{missing} \text{So}_j \ast \text{TTJoin}_{o_j} + \text{Prob}(a_i) = (\prod_{a_i \in \text{pred}} t.a = \text{missing} \text{So}_j \ast (1 - \text{So}_j \ast \text{Prob}(a_i) + (1 - I(a_j) \ast (1 - \text{So}_j) )) \ast I(a_j) \ast \text{So}_j \) is the indicator function that if \( t \) passes the predicate associated with \( o_j \), then \( I(a_j) = 1 \) otherwise \( I(a_j) = 0 \). Figure 14-(d) lists the expected imputation time cost for all paths in decision tree. Taking \( p_4 \) for example, its probability is \( \text{So}_4 \ast (1 - \text{So}_3) \) since \( t \) passes \( o_1 \) but fails \( o_2 \). The estimated query processing time in \( o_1 \) \( QP(o_1) \), is simply \( T_{o_1} \ast TTJoin_{o_2} \), which is 0 in this example since \( o_1 \) is a selection operator, while \( QP(o_2) = T_{o_2} \ast TTJoin_{o_2} \), since \( o_2 \) is a join operator and \( T_{o_1} T_{o_2} \) is the estimated number of join tests to perform in \( o_2 \). (Note that as we mentioned before, \( T \) is 1 if \( o \) is a selection operator.)

Decision Making. Based on the estimated imputation and query processing cost of impute and delay decisions for missing value \( t.a \), decision function will determine \( t.a \) if \( E(\text{IMP}(\text{impute}) - E(\text{IMP}(\text{delay}))) + E(\text{QP}(\text{impute})) - E(\text{QP}(\text{delay})) < 0 \); otherwise, decision function will delay imputing \( t.a \).

9.3 Extensions to Other Operators

In this section, we extend QUIP to handle aggregate, union, set minus operators and nested query. In addition, QUIP uses an optimization technique to speed up max and min query, and we show in Section 9.4.2 that the proposed optimization can improve MIN/MAX query around 2x to 4x in different query workloads.

Aggregate Operators. QUIP can be easily extended for aggregate operators, max, min, count, sum, avg, group by by adding them
max T.time
FROM Trajectories as T, Space as S, User as U
WHERE T.mac_address = U.mac_address AND T.Room_location = S.room AND S.building = 'DBH'

FIGURE 16: Aggregation Query

in the top of query plan tree. Among them, QUIP specially optimizes for max and min operators, which are two of commonly used operators for data analysis. Consider aggregation query in Figure 16 which seeks to find the latest time stamp of WiFi connectivity events that happens in ‘DBH’ building. The query plan tree is shown in Figure 15-a correspondingly. During query processing, QUIP maintains a temporary maximum time t under T.time it has seen so far, and creates a selection operator \( \sigma_{T.time > t} \). QUIP then pushes this operator to the leaf as shown in Figure 15-b to filter out all the tuples in relation T whose time value is less than or equal to the current max time t. Likewise, for min operation, select min(T.time), QUIP would create a selection operator \( \sigma_{T.time < t} \) where t corresponds to temporary minimum value for T.time. Note that tuples filtered by this selection condition do not affect the query result since they cannot be the part of query answer. To see why this optimization can be powerful, assume that the first temporal maximum value we see happens to be a large number, which is close to the final maximum. In such a case, the selection operator we added \( \sigma_{T.time > t} \) will be very selective which could help filter most tuples in relation T.

To complete this technique, we need to specify when to maintain this temporal value and where to put the introduced selection operator. First, the temporal value QUIP maintains should be valid, which means that it should pass all the selection and join predicates. QUIP maintains this value just above any selection and join operators close to the root. Second, we push down the selection operator introduced similar as many query optimizers do to potentially remove more tuples. Thus generally, QUIP will push down this selection operator to the corresponding leaf node in the tree except in one special case. If the aggregate attribute a is in a relation R which is blocked in query processing, then the introduced selection operator related with a will be placed just above the first join operator associated with R. As an instance, if we want to find the room with maximum room ID, i.e., max(S.room), and a hash joined is implemented in join operator \( \rho_{T.Room\_location=S.room} \). Assume that the right relation S is build relation, which will be used to build a hash table. If we still put the introduced selection operator \( \sigma_{S.room > t} \) at the leaf under this join operator, it will not help eliminate tuples because the first valid tuple in S relation will be popped up only after all tuples in S have been scanned to build a hash table. In this case, QUIP will place \( \sigma_{S.room > t} \) above \( \rho_{T.Room\_location=S.room} \) as shown in Figure 15. Note that as time goes by, the introduced selection operator will become more selective as the maintained temporal value should be closer to real one. We show in our experiments that this simple optimization for max and min query is powerful and will improve the query execution time up to 2x to 4x in our tested query sets.

FIGURE 17: Set Minus Operator.

Union Operator \( \cup \). Consider a union operation L \( \cup \) R. We modify union operator based on the logic in Figure 4-b. For tuples received by union operator L \( \cup \) R in both relations L and R, we first apply filter by using filter set in VF list in Figure 5. Tuples that failed filter test will be dropped, and then for the other tuples, QUIP calls decision function to decide for all attributes, which are in L and R as well as appear in the given query predicates, whether to impute or delay imputations for missing values in the received tuples. For any missing value v in the received tuples, if the decision function decides to impute v, QUIP will call verify operation to evaluate the imputed value. If decision function decides to delay imputation, we just preserve the corresponding missing value in the tuple. A tuple whose all imputed values passed verification test will be forwarded above to next operator in query tree. L \( \cup \) R will simply return all tuples in L and R that passed filter and verify tests.

Set Minus Operator \( \setminus \). Consider a set minus (also known as EXCEPT in PostgreSQL) operation L \( \setminus \) R that returns tuples in relation L but not in R. Set minus operator is a blocking operator for QUIP, and all the tuples returned by set minus operators should be evaluated. In Figure 17, the red curve blocks a sub tree T' (1) in Figure 17) whose root is set minus operator L \( \setminus \) R. For the sub trees in the left and right branch of operator L \( \setminus \) R, i.e., T1 and T2 in Figure 17, we apply QUIP normally on them to execute the query processing and missing value imputation. In addition, in operator L \( \setminus \) R, all missing values in L and R will be imputed to make sure that the tuples in set minus operator L \( \setminus \) R can be evaluated immediately.\(^{13}\) Except tree T', QUIP will normally execute its functionality in other parts of the query tree, as shown in (2) in Figure 17. The reasons to eagerly evaluate L \( \setminus \) R instead of delaying missing values in set minus operator are two-folds. First, if there are missing values in R and we delay imputations, this will cause the tuples in L to be delayed.

\(^{13}\)If there are projection operators in the top of T1 and T2, then all missing values in L and R will normally be imputed.
Table 5: CDC NHANES Data Set.

| Attr                        | Missing |
|-----------------------------|---------|
| age_months                  | 93.39%  |
| age_yrs                     | 0.00%   |
| gender                      | 0.00%   |
| id                          | 0.00%   |
| income                      | 1.31%   |
| is_citizen                  | 0.04%   |
| marital_status              | 43.30%  |
| num_people_household        | 0.00%   |
| time_in_us                  | 81.25%  |
| years_edu_children          | 72.45%  |
| cholesterol                 | 22.31%  |
| creatine                    | 72.59%  |
| hematocrit                  | 12.93%  |
| head_circumference          | 97.67%  |
| height                      | 7.60%   |
| weight                      | 0.92%   |
| white_blood_cell_ct         | 12.93%  |
| vitamin_b12                 | 45.83%  |
| arm_circumference           | 5.22%   |
| bloodPressure_secs          | 46.86%  |
| bloodPressure_systolic      | 26.91%  |
| body_mass_index             | 7.72%   |
| cuff_size                   | 23.14%  |
| head_circumference          | 97.67%  |
| height                      | 7.60%   |
| waist_circumference         | 11.74%  |

Table 6: UCI-WiFi Data Set.

| Attr                        | Missing |
|-----------------------------|---------|
| name                        | 0.00%   |
| mac_addr                    | 19.95%  |
| email                       | 0.00%   |
| group                       | 89.77%  |
| mac_addr                    | 0.00%   |
| start_time                  | 0.00%   |
| end_time                    | 0.00%   |
| lid                         | 0.00%   |
| start_time                  | 0.00%   |
| duration                    | 0.00%   |
| start_time                  | 0.00%   |
| occupancy                   | 71.17%  |
| type                        | 61.50%  |

Table 7: MAX/MIN Optimizations.

| Query     | # of Imputations | Running Time(ms) | |RT| |
|-----------|------------------|------------------|---------|
| CDC-Q6    | 81               | 81               | 102     | 104  | 0   |
| CDC-Q7    | 9                | 882              | 127     | 376  | 9806|
| CDC-Q8    | 241              | 1781             | 197     | 732  | 8823|
| UCI-WiFi-Q5| 983             | 1672             | 3461    | 4971 | 53755|
| UCI-WiFi-Q6| 747             | 3464             | 2873    | 7045 | 34988|

Figure 18: Nested Query

SELECT U.name, T.time, T.room_location
FROM Trajectories as T, User as U
WHERE U.mac_address = T.mac_address AND
T.Room_location is in
{SELECT S.room from Space as S
WHERE S.building = 'DBH'}

Figure 19: Nested Query Tree.

of nested query does not contain missing values in the attributes that the outside operator directly operates on. For example, consider the nested query in Figure 18. Its query tree is shown in Figure 19. For the sub tree \( T' \) that corresponds to the green box in Figure 19, we call QUIP to handle the query processing and missing value imputations there such that there are no missing values in the query answer \( S.room \) returned by this sub query. Note that in this query, the sub tree \( T' \) is blocking since we need to wait all satisfied \( S.room \) are returned and then values in \( T.Room_location \) can be evaluated. For the other part of query tree, QUIP will be executed as normal.

9.4 Evaluation

9.4.1 Data Sets. We report the metadata of two real data sets, CDC and UCI-WiFi, in Table 5 and Table 6, respectively. In particular, we show the schema and size (cardinality) of all relations in these data sets, as well as the percentage of missing values for each attribute.

9.4.2 Optimizations for Min/MAX Queries. In Table 7 we report the effect of MAX/MIN optimizations in Section 9.3 in real data sets using KNN imputations, and we denote QUIP and QUIP- as the QUIP with and without MAX/MIN optimization, and \(|RT|\) as the number of tuples removed by the extra selection operators introduced by this optimization technique. In most cases, the MAX/MIN optimization helps eliminate tuples aggressively and reduce the number of imputations by around 50% to 90%. It thus also speeds up the overall query running time considerably by around 2x to 4x in different queries. This optimization does not work well for CDC-Q6 because we observe that the introduced selection operator is in the rightmost leaf node in the query tree, which is a left deep
tree. In this case, this extra selection operator is too close to the root and thus takes effect in the very end of pipeline processing, which will not improve the performance much.

9.4.3 Comparison with QuERy. We compare QUIP with QuERy [11] in Table 8. We first denote by $T$ the total query execution time, which contains imputation costs and query processing time $T_Q$, and we denote by $\#Imp$ the number of imputations performed. QuERy, that is designed for ER problem, will execute cartesian product when one of the join inputs contains dirty data. (blocks in ER problem or missing values in imputation problem) We consider two versions of QuERy and convert them to apply on the imputation problem. One is an adaptive solution, denoted by QuERy-Adaptive which adaptively cleans the dirty data based on q cost-based solution. We modify it to apply to imputation problem by first converting the imputation problem (one of the join inputs contains dirty data) into a QuERy-Lazy, which always delays cleaning to the very end of query processing. This can be achieved by disabling decision function and making it always return false to implement the lazy imputation strategy. We observe that in the CDC data set, where there are no missing values under join attributes, QuERy-Adaptive performs similar imputations as QUIP, but the costly join approach adds overheads significantly. As for QuERy-Lazy approach, it achieves similar imputations as QUIP, but the costly join approach adds overheads significantly.

| Approach        | CDC | UCI-WiFi | SM-low | SM-high |
|-----------------|-----|----------|--------|---------|
| $T$(ms)         |     |          |        |         |
| QUIP            | 201.6 | 997.7 | 800.2 | 9568.3 |
| QuERy-Adaptive  | 441.4 | 8056.6 | 8713.5 | 17221.4 |
| QuERy-Lazy      | 1 min | 5 min | 43 min | $> 5h$ |
| $T_Q$(ms)       |     |          |        |         |
| QUIP            | 123.1 | 748.6 | 1280.7 | 3247.3 |
| QuERy-Adaptive  | 131.2 | 1149.6 | 1673.5 | 10418.7 |
| QuERy-Lazy      | 1 min | 5 min | 43 min | $> 5h$ |
| $\#Imp$         |     |          |        |         |
| QUIP            | 771 | 3559 | 773 | $1.8 \times 10^5$ |
| QuERy-Adaptive  | 4432 | 98672 | $1.72 \times 10^5$ | $1.8 \times 10^5$ |
| QuERy-Lazy      | 735 | 3219 | 768 | $1.79 \times 10^5$ |

Table 8: Comparing with QuERy.

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