Box Covers and Domain Orderings for Beyond Worst-Case Join Processing

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Abstract

Recent beyond worst-case optimal join algorithms Minesweeper and its generalization Tetris have brought the theory of indexing and join processing together by developing a geometric framework for joins. These algorithms take as input an index \mathcal{B} , referred to as a box cover, that stores output gaps that can be inferred from traditional indexes, such as B+ trees or tries, on the input relations. The performances of these algorithms highly depend on the *certificate* of \mathcal{B} , which is the smallest subset of gaps in \mathcal{B} whose union covers all of the gaps in the output space of a query Q. Different box covers can have different size certificates and the sizes of both the box covers and certificates highly depend on the ordering of the domain values of the attributes in Q. We study how to generate box covers that contain small size certificates to guarantee efficient runtimes for these algorithms. First, given a query Q over a set of relations of size N and a fixed set of domain orderings for the attributes, we give a O(N)-time algorithm called GAMB which generates a box cover for Q that is guaranteed to contain the smallest size certificate across any box cover for Q. Second, we show that finding a domain ordering to minimize the box cover size and certificate is NP-hard through a reduction from the 2 consecutive block minimization problem on boolean matrices. Our third contribution is a O(N)-time approximation algorithm called ADORA to compute domain orderings, under which one can compute a box cover of size $O(K^r)$, where K is the minimum box cover for Q under any domain ordering and r is the maximum arity of any relation. This guarantees certificates of size $O(K^r)$. We combine ADORA and GAMB with Tetris to form a new algorithm we call TetrisReordered, which provides several new beyond worst-case bounds. On infinite families of queries, TetrisReordered's runtimes are unboundedly better than the bounds stated in prior work.

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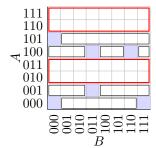
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1 Introduction

Performing the natural join of a set of relational tables is a core operation in relational database management systems. After the celebrated result of Atserias, Grohe and Marx [5] that provided a tight bound on the maximum (or worst-case) size of natural join queries, now known as the AGM bound, a new class of worst-case optimal join algorithms were introduced whose runtimes are asymptotically bounded by the AGM bound. More recently, Ngo et al. and Abo Khamis et al., respectively, introduced the Minesweeper [24] algorithm, and its generalization Tetris [1, 2], which adopt a geometric framework for joins and provide beyond worst-case guarantees that are closer to the highest algorithmic goal of instance optimality. Henceforth, we focus on the Tetris algorithm, the more general of these two algorithms.



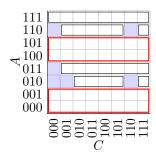


Figure 1 Box cover and certificates of the query $R(A,B) \bowtie S(A,C)$. Red boxes form a box certificate. Red and black boxes together form a box cover.

Let Q be a query over m relations \mathcal{R} and n attributes \mathcal{A} . Let N be the total number of tuples in \mathcal{R} . Throughout this paper, to match the notation of reference [1], we use O-notation to hide polylogarithmic factors in N as well as the query dependent factors m and n. Unlike traditional join algorithms that operate on input tuples, Tetris takes as input a box cover $\mathcal{B} = \bigcup_{R \in \mathcal{R}} \mathcal{B}_R$, where each \mathcal{B}_R is a set of gap boxes (i.e., tuple-free regions) of the relation R whose union covers the complement of R. These boxes imply regions in the output space of queries where output tuples cannot exist. Tetris operates on these gaps by performing qeometric resolutions, which generate new gap boxes. The runtime of Tetris is bounded by $\widetilde{O}((C_{\square}(\mathcal{B}))^{w+1}+Z)^1$ where: (i) $C_{\square}(\mathcal{B})$ is the size of the box certificate for \mathcal{B} , which is the smallest subset of boxes in \mathcal{B} that cover the gaps in the output, i.e., the complement of the output tuples of the join; (ii) w is the treewidth of Q; and (iii) Z is the number of output tuples. Figure 1 shows an example of this geometric framework on query $R(A, B) \bowtie S(A, C)$. Purple unit boxes indicate input tuples, the boxes in the box cover are shown with rectangles, and the boxes in the certificate are drawn as red rectangles. This Tetris result is analogous to Yannakakis's data-optimal algorithm for acyclic queries and its combination with worst-case optimal join algorithms, which yields results of the form $\widetilde{O}(N^{\text{fhtw}} + Z)$, where fltw is the fractional hypertree width [15] and N is the number of tuples in the input. The performance of Tetris's results can be significantly better than Yannakakis-based algorithms, as the certificates are always $\tilde{O}(N)$ and can be o(N), e.g. constant size, on some inputs.

In references [1] and [24], a box cover was assumed to be inferred from the available indexes on the relations. Consider a B+ tree index on a relation R(A, B) with sort order (A, B) and two consecutive tuples (a_1, b_1) and (a_1, b_2) . From these two tuples, a system can infer a gap box $(a_1, [b_1 + 1, b_2 - 1])$ in the output space of any join query that involves R. The boxes in Figure 1 are inferred from B+ tree indexes on R and S with sort orders (A,B) and (A,C), respectively. Using different indexes can result in box covers with vastly different certificate sizes. This motivates the first question we study in this paper: Question 1: How can a system efficiently generate a good box cover for a set of relations?

Given a query Q, let $C_{\square}(Q)$ be the minimum certificate size across all possible box covers for the relations in Q^3 . An ideal goal for a system would be to efficiently generate a box cover whose certificate is of size $C_{\square}(Q)$, ensuring performance as a function of $C_{\square}(Q)$. We refer to this problem as BoxMinC. We present a surprisingly positive result for BoxMinC:

A second upper bound that depends on the number of attributes instead of w is also provided in [1].

This example is borrowed from reference [1].

Note that our use of the notation $C_{\square}(Q)$ is different from reference [1], where \mathcal{B} was assumed to be given, and $C_{\square}(Q)$ was used to indicate the certificate size for \mathcal{B} . Since we drop this assumption, $C_{\square}(\mathcal{B})$ here denotes the certificate size for \mathcal{B} and $C_{\square}(Q)$ denotes the certificate size over all possible box covers.

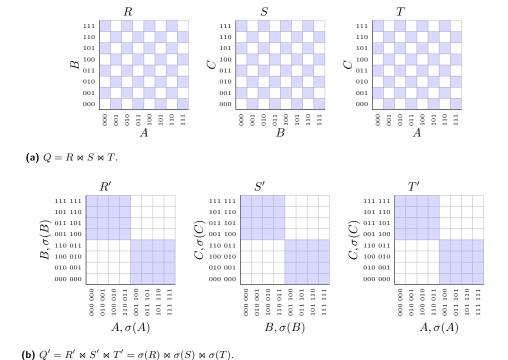


Figure 2 Two equivalent queries (up to attribute reorderings) with different box certificate sizes.

▶ **Theorem 1.** Given a database D, there is a $\widetilde{O}(N)$ -time algorithm that can generate a box cover \mathcal{B} of size at most $\widetilde{O}(N)$ that contains a certificate of size $\widetilde{O}(C_{\square}(Q))$ for any join query Q over any subset of relations in D.

Therefore, in $\widetilde{O}(N)$ time and space, a system can generate a globally good box cover (an index) for all possible join queries over a database.⁴ We achieve this result by observing that the set of all maximal gap boxes in the complements of the relations contains a certificate of size $|C_{\square}(Q)|$ and we provide an $\widetilde{O}(N)$ -time algorithm called GAMB that generates all maximal dyadic gap boxes (and possibly some non-maximal ones) from the relations.

In the second question we study, we consider evaluating a single query Q. There are simple queries which can be geometrically complex and require large box covers and certificates. In many cases, these queries can be modified by reordering each attribute's domain so that smaller covers and certificates are possible. Figure 2 shows an example. In the example, the queries Q and Q' are both triangle queries joining three binary relations. These queries are equivalent up to reordering the domains of each attribute. That is, it is possible to reorder the rows and columns of the grid in Figure 2a to obtain Figure 2b. Let σ be the set of three permutations on the domains of A, B, and C which transforms Q into Q'. Specifically, for each attribute, σ maps the even values to values between 000 and 011, and the odd values to values between 100 and 111. Despite their equivalence up to reorderings, Q requires a box cover of size 96, as each white grid cell in Figure 2a must have a unit gap box covering

⁴ Since any system has to spend $\Omega(N)$ time to index its tuples, this time is within an O(1) factor of any other indexing approach. Appendix B shows that a box cover index can also be maintained efficiently. The Tetris runtimes in reference [1] do not add a O(N) indexing component because it is assumed that indexes are given. In practice, this cost must be paid at some point by the database to answer queries.

it, while Q' only requires a box cover size 6. The same also applies to the certificate sizes, as every gap box in the box cover must also be part of the box certificate in this case. By extending the domains of the attributes, the difference in box cover and certificate sizes can be made arbitrarily large. Therefore, a system could improve the performance of Tetris significantly by reordering the domains of attributes. This motivates our second question: Question 2: How can a system efficiently reorder the domains to obtain a small box cover?

We refer to the problem of finding a domain ordering σ such that the minimum box cover size under σ is minimized as $\mathtt{DomOr}_{\mathtt{BoxMinB}}$. Let \mathcal{B}^* be the minimum size box cover for a query under any domain ordering, $K = |\mathcal{B}^*|$, and σ^* be the ordering under which \mathcal{B}^* is achieved. We first provide a hardness result showing that computing σ^* is NP-hard through a reduction from the 2 consecutive block minimization problem on boolean matrices [17]. We then provide an approximation algorithm, which we refer to as ADORA, for Approximate Domain **Or**dering Algorithm, to obtain the following result:

▶ Theorem 2. Let r be the maximum arity of any relation in the query Q and let K be the minimum box cover size for Q under any domain ordering. There is a $\widetilde{O}(N)$ -time algorithm that computes a domain ordering σ for Q, under which one can compute a box cover of size $\widetilde{O}(K^r)$, guaranteeing a certificate of size $\widetilde{O}(K^r)$.

After σ is obtained with ADORA, a system can run GAMB, which has the same asymptotic runtime, to obtain a box cover that guarantees certificates of size $\widetilde{O}(K^r)$. ADORA is based on an intuitive and powerful heuristic that groups the domain values in an attribute that have identical value combinations in the remaining attributes across the relations and makes the values in each group consecutive. Our approximation ratio does not depend on any other parameters of the query, such as different notions of width or the number of relations. Once an ordering is obtained, Tetris can be executed on the reordered query and the results converted back to the original domain. This technique is formalized in our algorithm TetrisReordered. We construct families of queries for which Tetris on a default ordering has a polynomial runtime with an arbitrarily high degree, but for which TetrisReordered runs in $\widetilde{O}(N)$ time.

2 Notation and Preliminaries

Throughout this paper, we work with a fixed database D. A query Q is an equi-join over a set of m fixed relations \mathcal{R} and a set of n attributes \mathcal{A} from D. We do not differentiate between a query and a query instance, so Q refers to the instance of Q in D. As in reference [1], for ease of presentation we assume the domains of each attribute $A \in \mathcal{A}$ consist of all d bit integers but our results only require domain values to be discrete and ordered. For $R \in \mathcal{R}$ and $A \in \mathcal{A}$, the attribute set of R is denoted attr(R) and the domain of A is denoted dom(A).

Tetris takes as input a box cover \mathcal{B} that contains dyadic gap boxes, which are boxes whose span over each attribute is encoded as a binary prefix. Let $R \in \mathcal{R}$ contain n_R attributes. Formally, a dyadic gap box in \mathcal{B}_R is an n_R -tuple $b = \langle s_1, s_2, \ldots, s_{n_R} \rangle$ where each s_i is a binary string of length at most d. We use * to denote the empty string. We sometimes use b.A to denote the prefix in b corresponding to attribute A. For example, if d is 3, the dyadic box $\langle 01, 1 \rangle$ for $R(A_1, A_2)$ is the box whose A_1 and A_2 dimensions include all values with prefix 01 and 1, respectively, i.e., it is the rectangle with sides $\langle [010 - 011], [100 - 111] \rangle$. Using dyadic boxes allows Tetris to perform geometric resolutions (explained momentarily) efficiently, which is needed to prove the runtime bounds of Tetris.

Although the details of how Tetris works are not necessary to understand our techniques and contributions, we give a brief overview as background and refer the reader to reference [1] for details. Assume each box in \mathcal{B} , say those coming from \mathcal{B}_R , are extended, with prefix *,

to every attribute not in attr(R). This allows us to think of \mathcal{B} as a single gap box index over the output space. The core of Tetris is a recursive subroutine that determines whether the set of boxes in \mathcal{B} covers the entire n-dimensional output space $\langle *, *, \ldots, * \rangle$ and returns either YES or NO with an output tuple o as a witness. The witnesses are inserted into \mathcal{B} . During the execution, this subroutine performs geometric resolutions that take two boxes that are adjacent in one dimension and construct a new box that consists of the union of the intervals in this dimension (and the intersection in all others). When boxes are dyadic, geometric resolution can be done in $\widetilde{O}(1)$ time. This recursive subroutine is called as many times as there are output tuples until it finally returns YES. Two variants of Tetris, called Tetris-Preloaded and Tetris-LoadBalanced run in time $\widetilde{O}(C_{\square}(\mathcal{B})^{w+1} + Z)$ and $\widetilde{O}(C_{\square}(\mathcal{B})^{n/2} + Z)$, respectively (see Theorems 4.9 and 4.11 in reference [1]). $C_{\square}(\mathcal{B})$ in Tetris's runtime is the box certificate size of \mathcal{B} , which is the size of the smallest subset \mathcal{B}' of \mathcal{B} , such that the union of boxes in \mathcal{B} and the union of boxes in \mathcal{B} cover exactly the same space. Equivalently, $C_{\square}(\mathcal{B})$ is the size of the smallest subset \mathcal{B}' of \mathcal{B} whose extended boxes (with *'s as described above) cover all of the gaps in the output space.

We end this section with a note on dyadic vs. general boxes. The notions of certificate, box cover, and the problems we study can be defined in terms of dyadic or general boxes. Except in Section 4, the term box refers to general boxes, and our optimization problems are defined over general box covers and certificates. For both certificates and box covers, the minimum size obtained with dyadic boxes and general boxes are within $\widetilde{O}(1)$ of each other. This is because a dyadic box is a general box by definition and any general box can be partitioned into $\widetilde{O}(1)$ dyadic boxes (Proposition B.14 in reference [1]). Our approximation results for general boxes imply approximation results for dyadic boxes up to $\widetilde{O}(1)$ factors. However, a hardness result for one version does not imply hardness of the other. Our hardness results apply only to general boxes. However, we use dyadic boxes extensively because they are a powerful analytical tool which the results of this paper and reference [1] rely on.

3 Related Work

3.1 Box Cover Problems

The complement of a relation R with k attributes can be represented geometrically as a set of axis-aligned, rectilinear polytopes in k-dimensional space, which may have holes (the tuples in R form the exteriors of the polytopes). The number of vertices in these polytopes is bounded (up to a constant factor) by the number of tuples in the relation. Therefore our work is closely related to covering rectilinear polytopes with a minimum number of rectangles in geometry. This problem has been previously studied in the 2-dimensional setting, i.e., for polygons. The problem is known to be NP-complete, even when the polygon is hole-free [10] and MaxSNP-hard for polygons with holes [6]. There are several approximation algorithms for the problem. Franzblau [12] designed an algorithm that approximates the optimal solution to a factor of $O(\log n)$, where n is the number of vertices in the polygon. If the polygon is hole-free, the approximation factor improves to 2. Anil Kumar and Ramesh [20] showed a tighter approximation ratio of $O(\sqrt{\log n})$ for the same algorithm on polygons with holes. Franzblau et al. [13] also showed the problem is solvable in polynomial time in the special case when polygons are vertically convex. All of these results are limited to 2D and little is known about the problem in higher dimensions.

The approximation algorithms above can be used to generate box covers for the complement of a binary relation R. This is a special case of BoxMinC, where the input is a trivial query with a single binary relation R. Outside of this limited setting, the connection

of covering axis-aligned and rectilinear polygons to BoxMinC breaks. This is because the certificate of a query in this case is the smallest number of boxes that cover the complement of the output, using boxes from the relations. In this case, because the output is not yet computed, it is not known a priori which polytopes should be covered.

There are variants of covering polygons that are less directly related to our problems. Reference [16] studies the more general problem of covering polygons with only obtuse interior angles, and provides approximation algorithms. Reference [21] studies covering the input polygon with squares instead of rectangles. For a survey of geometric covering and packing problems, including shapes beyond polytopes, we refer the reader to references [9] and [28].

3.2 Orderings in Matrices

There are several problems related to ordering the rows and columns of boolean matrices to achieve different optimization goals. The closest to our work is the consecutive block minimization problem (CBMP) [19]. Our hardness results are based on a variant of CBMP, called 2 consecutive block minimization [17], which we review in Section 5.1. There are two other ordering problems for boolean matrices, which are less related to our work: (i) the consecutive ones property test determines whether there is a column ordering such that each row has only one consecutive block of ones [8]; (ii) the doubly lexical ordering problem finds a row and column ordering such that both rows and columns are in lexicographic order [22]. Both problems have polynomial time solutions.

3.3 Worst-Case and Beyond Worst-Case Join Algorithms

A join algorithm is said to be worst-case optimal if it runs in time $\widetilde{O}(\mathrm{AGM}(Q))$, where the AGM bound [5] is the worst-case upper bound on the number of output tuples for a query based on its shape and the number of input tuples. Examples of worst-case optimal join algorithms are Leapfrog Triejoin [29], NPRR [25], and Generic Join [26]. A survey on worst-case optimal join algorithms can be found in reference [23]. There are several results that consider other properties of the query and provide worst-case upper bounds on the size of query outputs that are better than the AGM bound. Olteanu and Závodný [27] show that worst-case sizes of queries in factorized representations can be asymptotically smaller than the AGM bound and provide algorithms that meet these factorized bounds. Joglekar and Ré [18] developed an algorithm which provides degree-based worst-case results that assume knowledge of degree information for the values in the query. Similarly, references [3] and [14] provide worst-case bounds based on information theoretical bounds that take into account, respectively, more general degree constraints and functional dependencies.

Several results go beyond worst-case bounds and are closer to the notion of instance optimality. The earliest example is Yannakakis' data-optimal algorithm [30] for acyclic queries that runs in time O(N+Z). This was later generalized to an algorithm [11] for arbitrary queries which runs in time $\widetilde{O}(N^{fhtw}+Z)$, where fhtw is the query's fractional hypertree width [15]. The Minesweeper algorithm [24] developed the measure of comparison certificate C_{comp} for comparison-based join algorithms, which captures the minimum number of comparisons needed to prove the output of a join query is correct. Minesweeper runs in time $\widetilde{O}(|C_{comp}|^{w+1}+Z)$, where Z is the number of output tuples and w is the query's treewidth. The Tetris algorithm [1], which motivates our work, generalizes comparison certificates to the geometric notion of a box certificate, reviewed in Section 1. For every comparison certificate C_{comp} , there is a box certificate of size at most $|C_{comp}|$. In this sense, box certificates are

Algorithm 1 GAMB(R): Generates all maximal dyadic gap boxes of R.

```
1: B := \emptyset, \overline{B} := \emptyset

2: for t \in R do

3: for every dyadic box b such that t \in b do

4: \overline{B} := \overline{B} \cup \{b\}

5: for A \in \operatorname{attr}(R) such that b.A \neq * do

6: Let b' be the box when the last bit of b.A is flipped

7: B := B \cup \{b'\}

8: return B \setminus \overline{B}
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stronger than comparison certificates, and Tetris subsumes the certificate-based results of Minesweeper. Our results on finding box covers with small certificates and domain orderings with small box covers improve the bounds provided by Tetris.

4 Generating a Box Cover

Since the runtime of Tetris depends on the certificate size of its input box cover, an important preprocessing step for the algorithm is to generate a box cover with a small certificate. Ideally, a system should generate a box cover that contains a certificate of minimum size, across all box covers. We defined this quantity as $C_{\square}(Q)$ in Section 1. The following lemma states two facts about dyadic boxes that are crucial for our results and the results in reference [1].

▶ Lemma 3. (Propositions B.12 and B.14 [1]) Let b be any dyadic box. Then there are $\widetilde{O}(1)$ dyadic boxes which contain b. Let b' be any (not necessarily dyadic) box. Then b' can be partitioned into a set of $\widetilde{O}(1)$ disjoint dyadic boxes whose union is equal to b'.

Let a dyadic gap box b for a relation R be maximal if b cannot be enlarged in any of its dimensions and still remain a dyadic gap box, i.e., not include an input tuple of R. Generating a box cover with certificate size $\widetilde{O}(C_{\square}(Q))$ can be done by generating the set of all maximal dyadic gap boxes in the input relations. This is because: (1) any general box can be decomposed into $\widetilde{O}(1)$ dyadic boxes by Lemma 3, so decomposing a general box cover into a dyadic one can increase its certificate size by at most a factor of $\widetilde{O}(1)$; and (2) expanding any non-maximal dyadic boxes to make them maximal can only decrease the size of the certificate. We will show that given any query Q with N input tuples, we can generate all maximal dyadic gap boxes over all of the relations in Q in $\widetilde{O}(N)$ time. This also implies that the number of maximal dyadic boxes is $\widetilde{O}(N)$. Interestingly, this is not true for general gap boxes, of which there can be a super-linear number (see Appendix A for an example).

Algorithm 1 shows the pseudocode for our algorithm GAMB that **g**enerates **all maximal** dyadic gap **b**oxes for a relation R in $\widetilde{O}(N)$ time. GAMB loops over each dyadic box b covering each tuple t in R, explores boxes that are adjacent to b (which may or may not be gap boxes) and inserts these into a set B. Then it subtracts the set of all dyadic boxes covering any tuples from B to obtain a set of gap boxes. As we argue, this set contains every maximal dyadic gap box (and possibly some non-maximal ones). To generate all maximal boxes for a query $Q = (\mathcal{R}, \mathcal{A})$, we can simply iterate over each $R \in \mathcal{R}$ and invoke GAMB.

▶ Theorem 4. GAMB generates all maximal dyadic gap boxes of a relation R in $\widetilde{O}(N)$ time.

Proof. Let b' be a maximal dyadic gap box for R. Let A be an attribute of R for which b' specifies at least one bit (so $b'.A \neq *$). Let b be the dyadic box obtained from b' by flipping the last bit of b'.A. Since b' is maximal, b contains at least one tuple $t \in R$. Since b is a

dyadic box containing t, some iteration of the for-loop on line 3 will reach box b. Then the for-loop on line 5 at some iteration will loop over A and generate exactly b' on line 6. Thus b' is added to B and since b' is a gap box, GAMB will not add it to \overline{B} (which only contains non-gap boxes). Therefore b' will be in the output of GAMB. Note that the returned set does not contain any non-gap boxes of R, since every box which contains any tuple of Ris added to \overline{B} . The outer-most for loop has N iterations. The for loop on line 3 has O(1)iterations by Lemma 3. The for-loop on line 5 has n, so O(1), iterations. Finally, the set difference on line 8 can be done by sorting both B and \overline{B} and iterating lockstep through the sorted boxes. Therefore, the total runtime of GAMB is O(N).

By our earlier observation based on Lemma 3, running GAMB as a preprocessing step is sufficient to generate a box cover with a certificate of size $O(C_{\square}(Q))$. Combined with runtime upper bounds of Tetris from reference [1], we can state the following corollary:

▶ Corollary 5. Given a database D of relations with N total tuples, in $\widetilde{O}(N)$ preprocessing time, one can generate a box cover $\mathcal B$ such that running Tetris on $\mathcal B$ yields $\widetilde{O}\big(\big(C_{\square}(Q)\big)^{w+1}+Z\big)$ or $\widetilde{O}((C_{\square}(Q))^{n/2} + Z)$ runtimes for any query Q over D.

One interpretation of this result is that in $\widetilde{O}(N)$ preprocessing time, a system can generate a single global index that will make Tetris efficient on all possible join queries over a database D. In fact, using the bounds from reference [1], these are the best bounds we can obtain up to an $\widetilde{O}(1)$ factor when Q is fixed, since $C_{\square}(Q)$ is the minimum certificate size for any box cover of Q. This is surprisingly achieved with the same index for all queries, so the O(N)preprocessing cost need only be incurred once for a workload of any number of joins. To improve on these bounds, we must modify Q to reduce the box certificate size. We next explore domain orderings as a method to improve these bounds.

5 **Domain Ordering Problems**

We next study the $DomOr_{BoxMinB}$ problem. Given a query Q, our goal is to find the minimum size box cover possible under any domain ordering for Q and to find the domain ordering σ^* that yields this minimum possible box cover size. We begin by defining a domain ordering.

- **Definition 6** (Domain ordering). A domain ordering for a query $Q = (\mathcal{R}, \mathcal{A})$ is a tuple of $|\mathcal{A}|$ permutations $\sigma = (\sigma_A)_{A \in \mathcal{A}}$ where each σ_A is a permutation of dom(A).
- **Example 7.** Let A and B be attributes over 2-bit domains. Let R(A,B) be the following relation presented under the default domain ordering [00, 01, 10, 11] for both A and B:

$$R(A,B) = \{\langle 00,00\rangle, \langle 01,11\rangle, \langle 10,00\rangle, \langle 11,11\rangle \}$$

Consider the domain ordering σ where $\sigma_A = \sigma_B = \{00 \mapsto 00, 01 \mapsto 10, 10 \mapsto 11, 11 \mapsto 01\}$. We write σ as $\sigma_A = \sigma_B = [00, 11, 01, 10]$ to indicate the new "locations" of the previous domain values in the new ordering. Then $\sigma(R)$ denotes the following relation:

$$\sigma(R)(A,B) = \{\langle 00,00 \rangle, \langle 10,01 \rangle, \langle 11,00 \rangle, \langle 01,01 \rangle \}$$

The choice of domain ordering can have a significant effect on box cover sizes and their certificates. We show in Section 5.3 that given a query Q over n attributes, we can construct an infinite family of queries over n attributes which require arbitrarily large box covers and certificates under a default domain ordering, but under another domain ordering, have box covers and certificates of the same size as Q. Our specific problem is this:

▶ Definition 8 (DomOr_{BoxMinB}). Let $K_{\square}(\sigma(Q))$ be the minimum box cover size one can obtain for the query $\sigma(Q)$ obtained from Q by ordering the domains according to σ . Given a query Q, output a domain ordering σ^* such that $K_{\square}(\sigma^*(Q)) = \min_{\sigma} K_{\square}(\sigma(Q))$.

In Section 5.1, we show that DomOr_{BoxMinB} is NP-hard. In Section 5.2, we present ADORA, an approximation algorithm for DomOr_{BoxMinB}. Section 5.3 combines ADORA, GAMB, and Tetris in an algorithm we call *TetrisReordered*, which has new beyond worst-case bounds. In Section 5.3 we also present infinite classes of queries for which TetrisReordered runs unboundedly faster than the versions of Tetris from reference [1].

5.1 DomOr_{BoxMinB} is NP-hard

Our reduction is from the 2 consecutive block minimization problem (2CBMP) on boolean matrices [17].⁵ In a boolean matrix M, a consecutive block is a maximal consecutive run of 1-cells in a single row of M, which is bounded on the left by either the beginning of the row or a 0-cell, and bounded on the right by either the end of the row or a 0-cell. We use cb(M) to denote the total number of consecutive blocks in M over all rows. Let M be a boolean matrix stored as a 2D dense array, each row of which contains at most 2 1-cells. 2CBMP is the problem of finding an ordering σ_c^* on the columns of M such that $cb(\sigma_c^*(M)) = \min_{\sigma_c} cb(\sigma_c(M))$. 2CBMP was shown to be NP-hard in reference [17].

▶ Theorem 9. $DomOr_{BoxMinB}$ is NP-hard.

Proof. We focus on the special case where Q contains a single relation R(A,B) over exactly 2 attributes and show that $\mathsf{DomOr}_{\mathsf{BoxMinB}}$ is NP-hard even in this case. This implies $\mathsf{DomOr}_{\mathsf{BoxMinB}}$ is NP-hard for any number of attributes and relations, since one can duplicate R to another relation S with the same schema, and extend R and S to a third attribute C, taking $R' = R \times \mathsf{dom}(C)$. The ordering that solves $\mathsf{DomOr}_{\mathsf{BoxMinB}}$ on $R' \bowtie S'$ (a trivial intersection query) also minimizes the box cover size for R. For the purposes of the proof, we model R as a boolean matrix M', with a row for each value in $\mathsf{dom}(B)$ and a column for each value in $\mathsf{dom}(A)$. Each cell of the matrix corresponds to a possible tuple in $\mathsf{dom}(A) \times \mathsf{dom}(B)$. The matrix M' contains a 0-cell in column i and row j if the tuple $t = \langle i, j \rangle \in R$, and a 1-cell otherwise. This means that a box cover B for R corresponds directly to a set of rectangles which cover all of the 1-cells of M', and vice-versa. Readers can assume M' is given to $\mathsf{DomOr}_{\mathsf{BoxMinB}}$ as a dense matrix or a list of tuples, i.e., (i, j) indices for the 0 cells.

Let M be an $n \times m$ boolean matrix input to 2CBMP. We construct a $(4n) \times (m+2n)$ matrix M' for input to $\mathsf{DomOr}_{\mathsf{BoxMinB}}$. For each row r_i of M, we create 4 rows in M': $r_{i,1}, r_{i,2}, p_{i,1}$, and $p_{i,2}$. $r_{i,1}$ and $r_{i,2}$ are duplicates of the original row r_i , and $p_{i,1}$ and $p_{i,2}$ are the padding rows of r_i . We also add 2 padding columns that contain 1-cells in the 4 rows of r_i and 2n-2 columns that contain only 0-cells for the 4 rows for of r_i . Let S_i be the set of columns with 1-cells in row r_i of M. Let e_S be the row vector of length m+2n with value 1 on all indices in $S \subseteq [m+2n]$, and 0 everywhere else. The new rows are defined as: (i) $p_{i,1} = e_{\{m+2i-1\}}$; (ii) $r_{i,1} = e_{S_i \cup \{m+2i-1\}}$; (iii) $r_{i,2} = e_{S_i \cup \{m+2i\}}$; and (iv) $p_{i,2} = e_{\{m+2i\}}$. We insert these rows in the (i)-(iv) order, for r_1, \ldots, r_n , and refer to this order as the default row ordering of M'. We refer to the column ordering of M' after this transformation as the default column ordering of M'. An example transformation from M to M' is shown in Figure 3.

⁵ In this section, we use the informal convention of discussing the NP-hardness of minimization problems. Since NP-hardness is defined for decision problems, when we state that a minimization problem like 2CBMP is NP-hard, we are implicitly referring to the decision problem which takes as input an additional positive integer k and accepts if and only if the minimum value of the objective function is at most k.

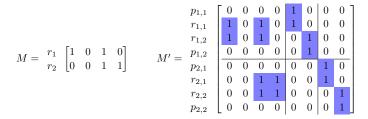


Figure 3 An example of the 2CBMP input matrix M and its corresponding M' matrix.

To prove this theorem, it suffices to prove that there exists an ordering σ_c on the columns of M such that $cb(\sigma_c(M)) \leq k$ if and only if there exist orderings $\sigma' = (\sigma'_r, \sigma'_c)$ on the rows and columns of M' such that $\sigma'(M')$ admits a box cover of size $\leq k+2n$. Proving one direction of this claim is simple. If there exists an ordering σ_c on the columns of M such that $cb(\sigma_c(M)) \leq k$, then set σ'_r equal to the default row ordering of M'. Also, set the last 2n columns in σ'_c equal to the default column ordering of the last 2n columns of M'. Then, set the first m columns in σ'_c equal to σ_c . Then, the 1-cells in the first m columns of $\sigma'(M')$ can be covered by at most k boxes, and the 1-cells in the last 2n columns can be covered by 2n boxes, for a total box cover size of at most k + 2n.

Proving the converse is significantly more involved. Let $\sigma' = (\sigma'_r, \sigma'_c)$ be an ordering on the rows and columns of M' such that $\sigma'(M')$ admits a box cover B of size $\leq k+2n$. We start with two definitions. Two rows $r_{i,j}$ and $r_{k,\ell}$ in M' $(i,k \in [n] \text{ and } j,\ell \in \{1,2\})$ are equivalent if r_i and r_k are equal rows in M (ie. r_i and r_k have 1-cells in the same columns in M). A run of equivalent rows is a sequence E of one or more $r_{i,j}$ rows which are consecutive in σ'_r such that all rows in E are equivalent to one another. We show a sequence of 6 steps that transform σ' to match the default row ordering and except in the first m columns also the default column ordering. For each step, we prove that we can reorder σ' without increasing the number of boxes such that a claim is true of the reordered $\sigma'(M')$, assuming that all of the previous claims hold. The proofs of these claims are provided in Appendices C.1-C.6.

- 1. Every $r_{i,j}$ row can be made adjacent to some equivalent $r_{k,\ell}$ row. (App. C.1)
- 2. Every run of equivalent $r_{i,j}$ rows can be made to have even length. (App. C.2)
- 3. Every run of equivalent $r_{i,j}$ rows can be made to have length 2. (App. C.3)
- 4. The padding rows $p_{i,j}$ can be made adjacent to their matching $r_{i,j}$ rows. (App. C.4)
- 5. The row order σ'_r can be made to exactly match the default row order of M'. (App. C.5)
- **6.** The column order σ'_c can be made to exactly match the default column order of M' on the last 2n columns. (App. C.6)

Two 1-cells c_1 , c_2 are independent in $\sigma'(M')$ if there is no box containing c_1 , c_2 that contains only 1-cells. An independent set is a set of pairwise independent 1-cells. An independent set in $\sigma'(M')$ of size S implies that the minimum box cover size of $\sigma'(M')$ is at least S. We will proceed by constructing a sufficiently large independent set in $\sigma'(M')$. After the above 6 steps, M' and $\sigma'(M')$ differ only by the ordering of the first m columns. In $\sigma'(M')$, the last 2n columns contain an independent set of size 2n, by taking the single 1-cell from each of the $p_{i,j}$ rows. These 2n 1-cells are independent from all 1-cells in the first m columns of σ'_c . Let σ_c be the ordering of the first m columns in σ'_c . We claim the first m columns contain an independent set of size $cb(\sigma_c(M))$. First, any two 1-cells in separate 4-row units are independent from one another, because the padding rows between them contain only 0-cells on the first m columns. If a row of $\sigma_c(M)$ has only one consecutive block, add a 1-cell from the corresponding 4-row unit to the independent set. If a row of $\sigma_c(M)$ has two consecutive blocks, there are two 1-cells in the first m columns of the corresponding 4-row unit which are

independent from one another. Add both to the independent set. Combining the independent sets from the first m columns and the last 2n columns, we get an independent set of size $\operatorname{cb}(\sigma_c(M)) + 2n$. Therefore any box cover of $\sigma'(M')$ has at least $\operatorname{cb}(\sigma_c(M)) + 2n$ boxes. We assumed $\sigma'(M')$ has a box cover of size $\leq k + 2n$, which implies $\operatorname{cb}(\sigma_c(M)) + 2n \leq k + 2n$, so $\operatorname{cb}(\sigma_c(M)) \leq k$, completing the reduction.

5.2 Approximating DomOr_{BoxMinB}

In this section, we provide a $\widetilde{O}(N)$ -time approximation algorithm for $\mathtt{DomOr_{BoxMinB}}$. Section 5.2.1 develops some machinery necessary to prove our approximation ratio, and Section 5.2.2 presents our approximation algorithm, ADORA. Section 5.3 combines ADORA, GAMB, and Tetris to state new beyond worst-case bounds for join processing.

5.2.1 Dividing Relations into Hyperplanes

In the simplest case, suppose the best domain ordering σ^* for Q yields a minimum box cover of size 1. Then there is a single gap box b in some relation $\sigma^*(R)$ such that $\mathcal{B} = \{b\}$ forms a box cover for $\sigma^*(Q)$. Fix an arbitrary attribute $A \in \operatorname{attr}(R)$. We can partition $\operatorname{dom}(A)$ into two sets: values which are in the A-range spanned by b, and values which are not. Consider the domain ordering σ_A obtained by placing all the domain values spanned by b first (in any order), followed by all other values. Doing this for each $A \in \mathcal{A}$ yields a domain ordering σ which recovers the box b to attain a box cover of size 1. Intuitively, any domain values for A which lie in the span of the same set of boxes in the minimum box cover should be placed next to one another. This can be generalized to an approximation algorithm for any minimum box cover size. We begin with definitions needed to formalize this approach.

▶ **Definition 10** (A-hyperplane). Let $R \in \mathcal{R}$ be over a set of attributes attr(R). Let $A \in attr(R)$ and $a \in dom(A)$. The A-hyperplane of R defined by a is the relation $H(R,A,a) = \pi_{attr(R)\setminus\{A\}}(\sigma_{A=a}(R))$ if |attr(R)| > 1 and $H(R,A,a) = \{|\sigma_{A=a}(R)|\}$ if |attr(R)| = 1.

Let $n_R = |\text{attr}(R)|$. The A-hyperplane defined by a in R can be thought of as the "slice" of the n_R -dimensional space occupied by R containing only the (n_R-1) -dimensional subspace where the attribute A is fixed to the value a. This is a natural generalization of "rows" and "columns" which were useful for discussing 2-dimensional relations in Section 5.1.

▶ **Definition 11** (Equivalent domain values). Let $Q = (\mathcal{R}, \mathcal{A})$ be a query, let $A \in \mathcal{A}$, and let $a_1, a_2 \in dom(A)$. a_1 and a_2 are equivalent in Q if for all $R \in \mathcal{R}$ we have $H(R, A, a_1) = H(R, A, a_2)$. In this case, we write $a_1 \sim a_2$.

For $a \in \text{dom}(A)$, the subset of domain values $\text{Eq}(a) = \{a' \in \text{dom}(A) : a \sim a'\} \subseteq \text{dom}(A)$ is called the *equivalence class* of a. The equivalence classes for all of the values in dom(A) form a partition of dom(A). The next lemma bounds the number of these equivalence classes as a function of the minimum box cover size of any domain ordering σ .

▶ **Lemma 12.** Let σ be a domain ordering for $Q = (\mathcal{R}, \mathcal{A})$. Let A be an attribute in \mathcal{A} and h be the number of equivalence classes of the values in dom(A). Then $h \leq 2 \cdot K_{\square}(\sigma(Q)) + 1$.

Proof. Let $A \in \mathcal{A}$ and let $a_1, a_2 \in \text{dom}(A)$ be such that a_1 directly precedes a_2 in σ_A and $a_1 \not\sim a_2$. We refer to the a_1, a_2 boundary as a "switch" along A. Observe that there are at least h-1 switches along A. This minimum is attained when the values in each equivalence class are placed in a single consecutive run in σ_A . Since $a_1 \not\sim a_2$, there is some

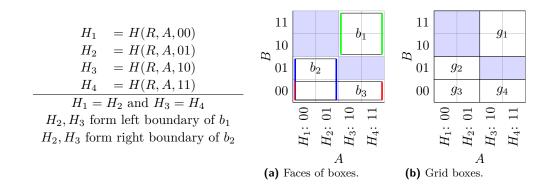


Figure 4 An illustration of how A-hyperplane switches form the boundaries of the gap boxes of R (left) and how dividing R into grid cells defined by hyperplane switches induces a box cover (right).

relation $R \in \mathcal{R}$ such that $H_1 = H(R, A, a_1) \neq H(R, A, a_2) = H_2$. Then there is some tuple t which is in H_1 but not H_2 or vice versa. Assume w.l.o.g. that $t \in H_1$ and $t \notin H_2$. Let $t_1 = \langle a_1, t \rangle$ and $t_2 = \langle a_2, t \rangle$ be the tuples that extend t to attribute A with values a_1 and a_2 , respectively. This means that $t_1 \in R$ and $t_2 \notin R$. Let \mathcal{B} be a box cover for $\sigma(Q)$ with $K_{\square}(\sigma(Q))$ boxes. Let \mathcal{B}_R be the set of boxes in \mathcal{B} that are from R and cover the complement of R (so $|\mathcal{B}_R| \leq K_{\square}(\sigma(Q))$). Let $b \in \mathcal{B}_R$ be a box covering t_2 (and not t_1 since b is a gap box). In this context, a face of b along the A axis is one of the two distinct portions of the boundary of b contained in a hyperplane orthogonal to the A axis that does not contain any interior points of b. Since a_1 and a_2 are adjacent in σ_A , one face of b along the A axis is the (a_1, a_2) switch, i.e. one face of b lies on the boundary between H_1 and H_2 . Every box b has exactly two faces along A, so there are $\leq 2K_{\square}(\sigma(Q))$ faces of boxes in B along the A axis. Two different switches cannot correspond to the same face of the same box. As an example, Figure 4a shows the switches in attribute A and the faces of gap boxes that these switches correspond to, which are highlighted in colour. This completes the argument that each $(a_1,$ a_2) switch corresponds to a distinct face of some box along the A axis. There are at least h-1 switches and at most $2K_{\square}(\sigma(Q))$ box faces, so $h \leq 2K_{\square}(\sigma(Q))+1$.

5.2.2 ADORA

Lemma 12 inspires an approximation algorithm for $DomOr_{BoxMinB}$. Let σ^* be the optimal domain ordering for $DomOr_{BoxMinB}$ on Q. Let $K = K_{\square}(\sigma^*(Q))$ throughout this section. Algorithm 2 presents the pseudocode for our Approximate Domain Ordering Algorithm (ADORA). ADORA uses Algorithm 3 as a subroutine to produce an ordering σ_A for dom(A) that contains each equivalence class in dom(A) as a consecutive run.

▶ Theorem 13. Let $Q = (\mathcal{R}, \mathcal{A})$ be a query and σ^* be an optimal domain ordering for $\mathsf{DomOr}_{\mathsf{BoxMinB}}$ on Q. Let $K = K_{\square}(\sigma^*(Q))$. Then ADORA produces a domain ordering σ in $\widetilde{O}(N)$ time such that $K_{\square}(\sigma(Q)) = \widetilde{O}(K^r)$, where r is the maximum arity of a relation in \mathcal{R} .

Proof. We defer the runtime analysis of ADORA to Appendix D and prove the approximation ratio here. We begin by arguing that given an attribute A, the ordering returned by Algorithm 3 places every equivalence class of dom(A) in one consecutive run. The for-loop on line 5 iterates over each $a \in dom(A)$ that appears in Q and constructs an array $\mathcal{T}[a]$. $\mathcal{T}[a]$ is the result of appending the A-hyperplanes H(R,A,a) for each $R \in \mathcal{S}$ in a fixed order. Line 4 sorts each relation lexicographically starting with A (notice that the order ϕ is

Algorithm 2 ADORA($Q = (\mathcal{R}, \mathcal{A})$): Computes a domain ordering.

```
    for A ∈ A do
    σ<sub>A</sub> := ORDERATTR(Q, A)
    return σ = {σ<sub>A</sub>}<sub>A∈A</sub>
```

defined to place A first). These two facts ensure that after the for-loop on line 5 has finished, $\mathcal{T}[a_1] = \mathcal{T}[a_2]$ if and only if $a_1 \sim a_2$. The final sort of D on line 9 sorts values of $\mathrm{dom}(A)$, say a_i and a_j , according to the lexicographic order of $T[a_i]$ and $T[a_j]$, so the lists are compared item by item from start to end, with each item compared using attribute ordering ϕ . This ensures all A values in the same equivalence class will be in one consecutive run in σ_A .

The output of ADORA is a domain ordering σ , which orders each attribute $A \in \mathcal{A}$ according to the σ_A returned by Algorithm 3. We next prove there exists a box cover for $\sigma(Q)$ of size $\widetilde{O}(K^r)$. Let $R \in \mathcal{R}$. Suppose $|\operatorname{attr}(R)| = n_R$ and note that $n_R \leq r$. Let $A \in \operatorname{attr}(R)$. Lemma 12 states that $\operatorname{dom}(A)$ contains at most 2K+1 equivalence classes, which we proved are placed consecutively in σ_A . By definition, if $a_1 \sim a_2$, then $H(R,A,a_1) = H(R,A,a_2)$. Therefore σ_A consists of a sequence of at most 2K+1 consecutive runs of A-values where the values in each run have identical A-hyperplanes in R. This holds for all $A \in \operatorname{attr}(R)$. The runs of identical hyperplanes partition the n_R -dimensional space of $\sigma(R)$ into at most $(2K+1)^{n_R}$ many n_R -dimensional grid boxes. Each dimension of a grid box is formed by one of the (at most) 2K+1 runs from one attribute. By construction, these grid boxes form a partition of the n_R -dimensional space as each grid box is a distinct combination of equivalence classes for the attributes and the orderings returned by Algorithm 3 cover all the values in $\operatorname{dom}(A)$. Figure 4b demonstrates the grid boxes implied by the equivalence classes in the orderings of a relation. In the figure, there are two equivalence classes for attribute A and three for B, dividing the relation into 6 grid boxes.

We argue that each grid box is completely full of either gaps or tuples. Let $t \in R$, let g be the grid box containing t, and let t' be another point in g. Two points t_1 , t_2 are adjacent if for some attribute A, $t_1.A$ and $t_2.A$ are adjacent in σ_A . Consider moving from t to t' through any sequence of adjacent points in g. When we pass through a point we are moving from one A-hyperplane to an identical A-hyperplane for some attribute A. Thus every point along this path must also be a tuple in R. A similar argument for gaps implies that every point in a grid box that contains one gap must also be a gap. Since the grid boxes partition the domain of R, constructing one box for each gap grid box results in a box cover \mathcal{B}_R for R. Since there are at most $(2K+1)^{n_R}$ grid boxes, $|\mathcal{B}_R| \leq (2K+1)^{n_R}$. We can construct such a box cover for each $R \in \mathcal{R}$ to obtain a box cover for $\sigma(Q)$ of size $\sum_{R \in \mathcal{R}} (2K+1)^{n_R} \leq m(2K+1)^r = \widetilde{O}(K^r)$, completing the proof of ADORA's approximation ratio.

Appendix E shows that our analysis of ADORA's approximation factor is asymptotically tight by defining a family of queries over binary relations which have orderings with box covers of size K, whereas the orderings that ADORA returns require $\Omega(K^2)$ boxes.

5.3 TetrisReordered

We next combine ADORA, GAMB, and Tetris in a new join algorithm we call *TetrisReordered* to obtain new beyond worst-case optimal results for join queries. Algorithm 4 presents the pseudocode of TetrisReordered. Corollary 14 immediately follows from Theorems 4 and 13 from this paper, and Theorems 4.9 and 4.11 from reference [1].

Algorithm 3 OrderAttr(Q, A): Groups equivalence classes for A into consecutive runs.

```
1: \phi := any attribute ordering of \mathcal{A} which places A first
 2: S := \{R \in \mathcal{R} : A \in \operatorname{attr}(R)\}, D := \bigcup_{R \in \mathcal{S}} \pi_A(R), \mathcal{T} := \emptyset
 3: for R \in \mathcal{S} do
 4:
         Sort R lexicographically according to \phi
 5: for a \in D do
         \mathcal{T}[a] := []
 6:
         for R \in \mathcal{S} in a fixed order do
 7:
              \mathcal{T}[a].append(H(R, A, a))
 8:
 9: Sort D by ordering a_i and a_j according to the lexicographic order of \mathcal{T}[a_i] and \mathcal{T}[a_j]
10: return \sigma_A = D (append a \notin D to \sigma_A in arbitrary order)
```

▶ Corollary 14. Let $Q = (\mathcal{R}, \mathcal{A})$ be a join query. Let w be the treewidth of Q, $n = |\mathcal{A}|$, and r the maximum arity of a relation in \mathcal{R} . Let σ^* be an optimal solution to $\mathsf{DomOr}_{\mathsf{BoxMinB}}$ on Qand let $K = K_{\square}(\sigma^*(Q))$. TetrisReordered computes Q in $\widetilde{O}(N + K^{r(w+1)} + Z)$ time by using Tetris-Reloaded or in $\widetilde{O}(N + K^{rn/2} + Z)$ time by using Tetris-LoadBalanced as a subroutine.

Algorithm 4 TetrisReordered(Q).

```
1: \sigma := ADORA(Q) (Algorithm 2)
2: for R \in \mathcal{R} do
          \mathcal{B}_R := \text{GAMB}(\sigma(Q)) \text{ (Algorithm 1)}
4: return \sigma^{-1}(\text{Tetris}(\mathcal{B} = \{\mathcal{B}_R\}_{R \in \mathcal{R}}))
```

We next show that there are infinite families of queries for which these bounds are arbitrarily smaller than prior bounds stated for Tetris in reference [1]. In fact, given an arbitrary query Q with any number of output tuples and any certificate size, and a default domain ordering σ , we can generate families of queries for which TetrisReordered is unboundedly faster than Tetris on σ . Our method can be seen as a generalization of the "checkerboard" example in Figure 2.6 Take an arbitrary query $Q = (\mathcal{R}, \mathcal{A})$ with N input tuples and Z output tuples. Recall that the minimum certificate size for Q under its default ordering is denoted $C_{\square}(Q)$. Let σ_{ADR} be the ordering ADORA generates on Q and let U be the corresponding upper bound on $K_{\square}(\sigma_{ADR}(Q))$ provided by Theorem 13. Recall that U depends on r, the maximum arity of a relation in \mathcal{R} , and is an upper bound on the minimum box cover and certificate size for $\sigma_{ADR}(Q)$. We generate a family of queries Q_p from Q for p=1,2,..., whose minimum certificate size (under σ) increases to $2^{rp}C_{\square}(Q)$ but the upper bound provided by ADORA according to Theorem 13 remains at U.

Let \mathcal{A}_p be the attribute set obtained from \mathcal{A} by adding, for each $A \in \mathcal{A}$, an additional p bits as a prefix to the d bits of A. For every relation $R \in \mathcal{R}$, construct a relation R_p with $\operatorname{attr}(R_p) \subseteq \mathcal{A}_p$ corresponding to $\operatorname{attr}(R)$. For each $t \in R$, add the following tuples to R_p :

$$\{\langle p_A t. A \rangle_{A \in \text{attr}(R)} : p_A \in \{0, 1\}^p \ \forall A \in \text{attr}(R)\}$$

The example in Figure 2 is a simplified version of the one used to prove Lemma J.1 in reference [1], which shows that general resolutions, which are logical operations on two DNF clauses, are more powerful than geometric resolutions, which are constrained to contiguous geometric boxes.

The p bits added to each attribute do not affect the structure of the query, since these bits vary over all possible valuations for each tuple from the original query. For each attribute A, these bits effectively create 2^p "copies" of each A-hyperplane. This increases the size of the query's input, output, and box certificate under the default ordering. The query $Q_p = (\mathcal{R}_p, \mathcal{A}_p)$ has input size $2^{rp}N$, output size $2^{np}Z$, and minimum box certificate size $2^{rp}C_{\square}(Q)$, where r is the maximum arity of a relation in \mathcal{R} and $n = |\mathcal{A}|$. However, this construction does not affect the number of equivalence classes on any dimension. Instead, it increases the size of each equivalence class by a factor of 2^p . To see this, consider two values of an attribute $A \in \mathcal{A}$, a_1 and a_2 , that were in the same equivalence class in Q. That is, they had the same A-hyperplanes for every relation $R \in \mathcal{R}$ such that $A \in \text{attr}(R)$. After adding the p bits, there will be 2^p "copies" of a_1 and a_2 , one for each p-bit prefix that was appended to tuples that contained a_1 and a_2 . Each copy will have the same (but larger) A-hyperplane. The number of equivalence classes on each attribute will remain the same, so the bound of Theorem 13 on $K_{\square}(\sigma_{ADR}(Q))$ will remain at U. As p increases, the performance gap between TetrisReordered and prior versions of Tetris becomes arbitrarily large.

6 Open Problems

The problems defined in this paper are ripe for further study. Beyond NP-hardness, we know little about DomOr_{BoxMinC}. Even if the domain ordering is fixed, we do not know of a way to approximate the minimum certificate size that is asymptotically faster than computing the join. Appendix B.3 in reference [1] describes how to use a variant of Minesweeper to compute a certificate. In Appendix G of the online version of this paper [4], we show a variant of Tetris can do the same. These approaches effectively compute the join to compute a certificate. A difficult aspect of this problem is that a certificate is a box cover for the output relation using boxes from the input relations. However, since the output tuples are not known a priori, the exact space that needs to be covered is not known at domain reordering time. It is also not known a priori which input tuples are part of the output and therefore which gap boxes from the input relations are part of the certificate.

Similarly, little is known about the following problems: (1) determining whether a specific gap box is in the minimum-size certificate under a fixed domain ordering; (2) verifying that a given domain ordering induces a box cover or certificate of minimum size; and (3) variants of $\mathsf{DomOr}_{\mathsf{BoxMinB}}$ and $\mathsf{DomOr}_{\mathsf{BoxMinC}}$ under additional assumptions about the structure of the input relations. As an example, Appendix F shows that if the input relations are fully semi-join reduced (a problem known to be hard for cyclic queries [7]), so all input tuples are part of the output and all gap boxes are relevant to the certificate, then the minimum box cover and certificate sizes are within an $\widetilde{O}(1)$ factor of one another. In this special case, ADORA approximates $\mathsf{DomOr}_{\mathsf{BoxMinC}}$.

Each of these open problems can be defined over general or dyadic boxes, creating two related but distinct problems. Sufficiently strong hardness of approximation results for either version of a problem would imply the difference is negligible, since the solutions would be within an $\widetilde{O}(1)$ -factor of one another by Lemma 3. Theorem 9 shows that the general box versions of $DomOr_{BoxMinB}$ and $DomOr_{BoxMinC}$ are NP-hard, but this theorem does not imply a hardness result about the dyadic versions of these problems. Proving a hardness of approximation result is a direction for future study. Until such a result is known, the distinction between general and dyadic boxes is crucial to studying these problems.

Developing an ADORA-like preprocessing algorithm that provides similar results but is query-independent, or has a better approximation ratio, is also a direction for future research.

ADORA runs in $\widetilde{O}(N)$ time, so its query-dependence precludes the possibility of a sub-linear time join algorithm using ADORA. The domain ordering must be computed from scratch for each different query, even if the relations in the database have not changed. Sharing some of this computation between different queries would improve on our results.

7 Conclusions

For queries with fixed domain orderings, we established a $\widetilde{O}(N)$ -time algorithm GAMB to create a single globally good box cover index which is guaranteed to contain a certificate at most a $\widetilde{O}(1)$ factor larger than the minimum size certificate for any box cover. We then studied $\mathtt{DomOr}_{\mathtt{BoxMinB}}$, the problem of finding a domain ordering that yields the smallest possible box cover size for a given query Q. We proved that $\mathtt{DomOr}_{\mathtt{BoxMinB}}$ is NP-hard and presented a $\widetilde{O}(N)$ -time approximation algorithm ADORA that computes an ordering which yields a box cover of size $\widetilde{O}(K^r)$, where K is the minimum box cover size under any ordering and r is the maximum arity of any relation in Q. We combined ADORA, GAMB, and Tetris in an algorithm we call TetrisReordered and stated new beyond worst-case optimal runtimes for join processing in Corollary 14. TetrisReordered can improve the known performance bounds of prior versions of Tetris (on any fixed ordering) on infinite families of queries.

Our work leaves several interesting problems open as discussed in Section 6. Our results are limited to the problems $DomOr_{BoxMinB}$ and $DomOr_{BoxMinC}$, and there are several interesting variants of these problems for which little is known.

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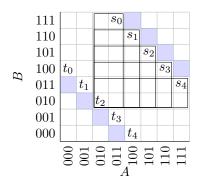
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A Example with $\omega(N)$ Maximal General Gap Boxes

In Section 4, GAMB generates all maximal dyadic gap boxes in $\widetilde{O}(N)$ time. The use of dyadic boxes instead of general boxes in GAMB is necessary, because there are relations for which the number of maximal general gap boxes is asymptotically greater than the number of tuples in the relation. Our construction generalizes the example in Figure 15 in Appendix B.3 of reference [1]. Let N be an even number, A and B be attributes over domains of size N, and R_N be the following relation.

$$R_N(A,B) = \{\langle i,N/2-i-1\rangle: 0 \leq i < N/2\} \cup \{\langle N/2+i,N-i-1\rangle: 0 \leq i < N/2\}$$



- **Figure 5** Example of a relation $R_8(A, B)$ with $\omega(N)$ maximal general gap boxes.
- **Algorithm 5** InsertMDBCI(R, B, t): Update B after t is inserted to R.

```
for each b \in B such that t \in b do
       B := B \setminus \{b\}
2:
       for each b' such that t \in b' \subseteq b do
3:
            for A \in \text{attr}(R) such that |b.A| < d do
4:
                Let b'' be the box when one bit is added to b'.A such that t \notin b''
5:
                B := B \cup \{b''\}
6:
```

Consider the following sets of tuples which are not in R_N .

$$T_N = \{t_i = \langle i, N/2 - i \rangle : 0 \le i \le N/2\}$$

 $S_N = \{s_i = \langle N/2 + i - 1, N - i - 1 \rangle : 0 \le i \le N/2\}$

Figure 5 depicts R_8 , T_8 , and S_8 . In this diagram, a set of 5 maximal general gap boxes with bottom left corners at t_2 is depicted. The top right corners of these boxes are the 5 tuples in S_8 . In fact, for each $0 \le i \le 4$, there are 4 or 5 maximal general gap boxes in R_8 with their bottom left corner at t_i . This property generalizes from R_8 to any value of N. For each $0 \le i \le N/2$, there are at least N/2 maximal general gap boxes in R_N with their bottom left corner at t_i . Since there are N/2+1 tuples in T_N , the total number of maximal general gap boxes in R_N is at least $(N/2+1)(N/2) = \Theta(N^2) = \omega(N)$.

В Incremental Maintenance of a Maximal Box Cover Index

Theorem 4 states that running GAMB on a relation R produces a set of dyadic gap boxes containing all maximal dyadic gap boxes of R. In this section, we refer to such a set as a maximal dyadic box cover index (MDBCI) for R. An MDBCI can be thought of as an index for R that can be computed once and used in any query over R. Traditional database indexes are useful because they are easy to incrementally maintain when tuples are added to or removed from a relation, so the index does not need to be computed from scratch every time the relation is modified. The following results show that efficient incremental maintenance is also possible with MDBCIs. The proofs of Theorems 15, 16, and 17 can be found in Appendix B of the online version of this paper [4].

▶ **Theorem 15.** Suppose that R is a relation with MDBCI B. Let $t \notin R$. Let $R' = R \cup \{t\}$ and let B' be the result of running Algorithm 5 with R', B and t as input. Then B' is an MDBCI for R'.

Algorithm 6 DeleteMDBCI(R, B, t): Update B after t is deleted from R.

```
1: for every dyadic box b such that t \in b do
2: addb := True
3: for each b' such that t \in b' \subset b do
4: for A \in \text{attr}(R) such that b'.A \neq * do
5: Let b'' be the box when the last bit of b'.A is flipped
6: if there is no box in B that contains b'' then addb := False
7: if addb then
8: B := B \cup \{b\}
```

- ▶ **Theorem 16.** Suppose that R is a relation with maximal dyadic box cover index B. Let $t \in R$. Let $R' = R \setminus \{t\}$ and let B' be the result of running Algorithm 6 with R', B and t as input. Then B' is an MDBCI for R'.
- ▶ **Theorem 17.** Algorithms 5 and 6 run in $\widetilde{O}(1)$ time.

C Proof that DomOr_{BoxMinB} is NP-hard

This section contains proofs of the 6 transformation steps we used in the proof of Theorem 9.

C.1 Proof of Step 1

 \triangleright Claim. Every $r_{i,j}$ row can be made adjacent to some equivalent $r_{k,\ell}$ row.

Let $r_1 := r_{i,j}$ be a row which is not adjacent to any equivalent row. Let $r_2 := r_{k,\ell}$ be any row equivalent to r_1 (at least one such row exists because we duplicate each row of Mwhen constructing M'). Since r_1 is not adjacent to any equivalent row and there are an even number of rows equivalent to r_1 , there must be some run E of rows equivalent to r_1 with odd length. If E has length 1, we assume r_2 is the one row in E, and therefore r_2 is not adjacent to any equivalent row. If E has length at least 3, we assume r_2 is the second row in E, and therefore r_2 is not adjacent to $p_{k,\ell}$. Let $p_1 := p_{i,j}$ and let $p_2 := p_{k,\ell}$. Let c_{p_1} be the column where p_1 has a 1-cell, and let c_{p2} be the column where p_2 has a 1-cell. Let c_1 and c_2 be the columns where r_1 and r_2 both have 1-cells. Let $b_1 \in B$ be the box covering the padding column in r_1 with greatest width. Let $b_2 \in B$ be the box covering the padding column in r_2 with greatest width. Let $b_3 \in B$ be the box covering the padding column in p_1 . Let $b_4 \in B$ be the box covering the padding column in p_2 . Our approach will be to remove the rows r_1, r_2, p_1 , and p_2 from M', then insert them in the order (p_1, r_1, r_2, p_2) at the bottom of M'. In this order, the 1-cells of these rows can be covered by 4 boxes, regardless of the column ordering. A box of width 1 and height 2 can be used to cover the two 1-cells in each of the columns in $\{c_1, c_2, c_{p_1}, c_{p_2}\}$. To show that this modification does not increase the number of boxes in B, it suffices to show that there are at least 4 boxes which can be removed from Bwhen we remove these 4 rows from M'. We split our analysis into four cases.

- 1. $b_1 \neq b_3$ and $b_2 \neq b_4$. In this case, all of $\{b_1, b_2, b_3, b_4\}$ are distinct and all 4 of these boxes are removed when we remove the rows r_1, r_2, p_1, p_2 .
- 2. $b_1 \neq b_3$ and $b_2 = b_4$. Since $b_2 = b_4$, r_2 is adjacent to p_2 . By our previous assumptions about r_2 , r_2 is not adjacent to any equivalent row. W.l.o.g., assume that p_2 is directly below r_2 . Let r_3 be the row directly above r_2 . r_3 is not equivalent to r_2 , so there exists

- a box b_5 covering at least one of c_1 or c_2 in r_2 with height 1, since it cannot extend vertically to either p_2 or r_3 . b_5 is not equal to b_2 , because b_2 has height 2. $\{b_1, b_2, b_3, b_5\}$ is a set of 4 distinct boxes which are removed when we remove the rows $\{r_1, r_2, p_1, p_2\}$.
- 3. $b_1 = b_3$ and $b_2 \neq b_4$. Since $b_1 = b_3$, r_1 is adjacent to p_1 . Suppose w.l.o.g. that p_1 is directly above r_1 . Let r_3 be the row directly below r_1 . Since r_1 is not adjacent to any equivalent rows, r_3 is not equivalent to r_1 . Therefore, there is a box $b_6 \in B$ covering at least one of c_1 or c_2 in r_1 which has height 1, since it cannot extend vertically to either p_1 or r_3 . b_6 is not equal to b_1 , since b_1 has height 2. Now the set of boxes $\{b_1, b_2, b_4, b_6\}$ is a set of 4 distinct boxes which are removed when we remove the rows $\{r_1, r_2, p_1, p_2\}$.
- 4. $b_1 = b_3$ and $b_2 = b_4$. This case can be proven by combining the arguments from the previous two cases. Since $b_2 = b_4$, we can define the box b_5 exactly as in case 2. Since $b_1 = b_3$, we can define the box b_6 exactly as in case 3. Then, $\{b_1, b_2, b_5, b_6\}$ is a set of 4 distinct boxes which are removed from B when we remove the rows $\{r_1, r_2, p_1, p_2\}$.

Proof of Step 2 C.2

 \triangleright Claim. Every run of equivalent $r_{i,j}$ rows can be made to have even length.

Let E_1 be a run of equivalent $r_{i,j}$ rows of odd length. By the claim of step 1, E_1 has length ≥ 3 . Let r_1 be the second row in E_1 . Since E_1 has odd length and there are an even number of rows equivalent to r_1 , there exists another run E_2 of rows equivalent to r_1 with odd length. E_2 also has length ≥ 3 . Let c_{p1} be the column which has a 1-cell only in r_1 and its corresponding padding row. Let $b \in B$ be the box which covers c_{p1} in r_1 . Since r_1 is not adjacent to its padding row, b has height 1. If we remove r_1 from M', b can be removed. By inserting r_1 directly below the first row in E_2 , a unit box can be used to cover c_{p1} in r_1 . Let r_2 be the first row in E_2 . Let c_1 and c_2 be the two columns of M' where r_1 and r_2 share 1-cells. To cover these two 1-cells in r_1 , we can extend vertically the boxes covering c_1 and c_2 in r_2 . We may assume these boxes can be extended vertically, because at most two of the rows in E_2 have their c_1 (or c_2) cell covered by a box which stretches horizontally from a padding column. That is, there is some row in E_2 where the box covering the c_1 (or c_2) cell can be extended vertically to cover the c_1 (or c_2) cell of r_1 . Hence, this transformation can be made without increasing the size of B. After this, both E_1 and E_2 have even length. Continue this process until every run of equivalent $r_{i,j}$ rows have even length.

C.3 Proof of Step 3

 \triangleright Claim. Every run of equivalent $r_{i,j}$ rows can be made to have length 2.

Let E be a run of equivalent $r_{i,j}$ rows of even length greater than 2. So E has a length of at least 4. Let r_1 be the second row in E and let r_2 be the third row in E. Since E has length at least 4, neither r_1 nor r_2 are adjacent to their respective padding rows, p_1 and p_2 . We claim the boxes covering the padding columns in r_1 and r_2 have width 1. We split our analysis into two cases. Let c_1 and c_2 be the two columns where r_1 and r_2 both have 1-cells.

- 1. c_1 and c_2 are adjacent. At most 2 of the rows in E have their padding columns adjacent to (c_1, c_2) on either side. This means there is some row r_3 in E where the box b covering c_1 and c_2 does not also cover its padding column. b can be extended vertically to cover c_1 and c_2 in all rows of E. Any boxes covering padding columns for rows in E can be replaced with boxes of width 1, and all of the 1-cells in the rows of E remain covered.
- 2. c_1 and c_2 are not adjacent. At most 2 rows in E have their padding columns adjacent to c_1 on either side. This means there is some row r_3 in E where the box b covering c_1 does

not also cover its padding column. b can be extended vertically to cover c_1 in all rows of E. The same argument applies for c_2 . Any boxes covering padding columns for rows in E can be replaced with boxes of width 1, and all 1-cells in the rows of E remain covered.

Now, removing p_1 and p_2 removes two boxes from B, since unit boxes must be covering the single 1-cells in p_1 and p_2 . Inserting (p_1, p_2) in order in between r_1 and r_2 , we can cover the 1-cells in (c_{p1}, p_1) and (c_{p2}, p_2) by extending vertically the width 1 boxes covering (c_{p1}, r_1) and (c_{p2}, r_2) . This splits any boxes which vertically streched from r_1 to r_2 into two. There were at most two such boxes, so the total number of boxes in B does not increase. Now E is split into two distinct runs of equivalent rows, one of length 2 and one of length |E| - 2. This process can be repeated until all runs have length exactly 2.

C.4 Proof of Step 4

ightharpoonup Claim. The padding rows $p_{i,j}$ can be made adjacent to their matching $r_{i,j}$ rows.

Let $r_1 := r_{i,j}$ be a row which is not adjacent to its padding row $p_1 := p_{i,j}$. By the claim of step 3, we know r_1 is adjacent to exactly one row, r_2 , that is equivalent to r_1 . Let p_2 be the padding row matching r_2 . Let c_1 and c_2 be the columns where r_1 and r_2 share 1-cells. Let c_{p_1} be the column which has 1-cells only in r_1 and p_1 . Let c_{p_2} be the column which has 1-cells only in r_2 and p_2 . Let b_1 be the box which covers the 1-cell in row r_1 and column c_{p_1} of greatest width. Let b_2 be the box which covers the 1-cell in p_1 . Let p_2 be the box which covers the 1-cell in p_2 . We split our analysis into two cases.

- 1. r_2 is adjacent to p_2 . In this case, similar to our argument in step 1, there exists a box $b_5 \in B$ with height 1 which covers c_1 or c_2 (or both) in r_2 . By removing the rows $\{r_1, r_2, p_1, p_2\}$, the 4 distinct boxes $\{b_1, b_2, b_3, b_5\}$ are all removed from B. By inserting the rows (p_1, r_1, r_2, p_2) in order at the bottom of the matrix, we can cover their 1-cells with at most 4 boxes, so the total number of boxes in B does not increase.
- 2. r_2 is not adjacent to p_2 . In this case, r_1 is not adjacent to p_1 and r_2 is not adjacent to p_2 , so $\{b_1, b_2, b_3, b_4\}$ are 4 distinct boxes in B which are removed if we remove rows $\{r_1, r_2, p_1, p_2\}$. By inserting (p_1, r_1, r_2, p_2) in order at the bottom of the matrix, we can cover their 1-cells with at most 4 boxes, so the size of B does not increase.

We can repeat this process until all $r_{i,j}$ rows are adjacent to their matching $p_{i,j}$ rows.

C.5 Proof of Step 5

 \triangleright Claim. The row order σ'_r can be made to exactly match the default row order of M'.

By the claims of steps 3 and 4, all of the rows are now divided into separate 4-row units containing a run of two equivalent $r_{i,j}$ rows surrounded by their two matching padding rows. There are no boxes in B which can stretch vertically across two or more of these separate units, because there are no two $p_{i,j}$ rows which share a 1-cell. Thus, we are free to reorder these units arbitrarily. Order the units so that for all i, the i-th unit contains two $r_{i,j}$ rows which correspond to the i-th row of the original matrix M. The resulting row order σ'_r is then equal to the default row ordering of M', modulo any equivalent rows which are swapped from their default positions. Since equivalent rows are equal up to reordering the columns of M', there exists an ordering on the columns of M' that transforms $\sigma'_r(M')$ back to the original matrix M'. In other words, the row ordering σ'_r is now equivalent to the default row ordering of M' up to a relabelling of the rows. This is sufficient for our purposes, since we can relabel the rows accordingly and move on to modifying the column ordering only.

C.6 Proof of Step 6

The column order σ'_c can be made to exactly match the default column order of M' on the last 2n columns.

For each padding row $p_{i,j}$, the box b covering the single 1-cell in $p_{i,j}$ has width 1. By step 4, each padding row is adjacent to its corresponding $r_{i,j}$ row. This means b extends vertically to also cover the only other 1-cell in its column. Therefore, by moving this column to the right side of the matrix, we do not increase the total number of boxes in B. Once all of these padding columns have been moved to the right, the boxes covering all of their 1-cells all have width 1. Thus, we can reorder them to exactly match the last 2n columns in the default column ordering of M' without modifying any boxes in B.

D **ADORA's Runtime Analysis**

ADORA calls Algorithm 3 n, so O(1), times. In Algorithm 3, the sorting of m relations according to ϕ on line 4 takes O(N) time. The for-loop beginning on line 5 iterates over each domain value $a \in D$ and each $R \in S$ and appends H(R, A, a) to $\mathcal{T}[a]$. Since R was sorted lexicographically according to ϕ , which places A as the first relation, all tuples with the same A-value are now consecutive in R. Therefore, with a single linear pass through R, we can compute all of the hyperplanes H(R, A, a). We do this for each relation, so the runtime is bounded by O(mN) = O(N). For the final sorting of D on line 9 observe that the total size of the array \mathcal{T} , summed over all domain values a, is at most N. Thus, we are sorting an array of arrays where the total amount of data is of size O(N), which can be done in O(N)time (e.g., with a merge-sort algorithm that merges two sorted sub-arrays in O(N) time), completing the proof that ADORA's runtime is O(N) as claimed in Theorem 13.

Ε The ADORA Approximation Bound Is Tight

Theorem 13 proved that ADORA produces a domain ordering σ for Q such that $K_{\square}(\sigma(Q)) =$ $O(K^r)$, where K is the minimum box cover size under any domain ordering and r is the maximum arity of a relation in Q. We will show that this bound is tight by presenting a class of 2D relations R_d for which ADORA returns a domain ordering σ such that $K_{\square}(\sigma(R_d)) = \Omega(K^2)$, where K is the minimum box cover size for R_d under any ordering. For any integer d > 0, let $R_d(A, B)$ be the relation over 2 d-bit attributes A and B given by

$$R_d(A,B) = \{\langle 0a,0b \rangle : a,b \in \{0,1\}^{d-1}, a \neq b\} \cup \{\langle 1a,1b \rangle : a,b \in \{0,1\}^{d-1}, a \neq b\}$$

As an example, R_3 is illustrated in Appendix E of the online version of this paper [4]. The default ordering of R_d has a minimum box cover of size $K = 2^d + 1$. However, there is a bad ordering σ_d such that $\sigma_d(R_d)$ has a minimum box cover size of $\Omega(2^{2d}) = \Omega(K^2)$. The key observation about this example is that no rows or columns in R_d are equal, so ADORA may return σ_d as a solution. Since R_d has arity 2, the bound of Theorem 13 is tight in this case.

Approximating DomOr_{BoxMinC} On Fully Semi-join Reduced Queries

This section serves to illustrate that if the input relations of a query Q are fully semi-join reduced, so we know a priori that all of the input tuples contribute to the query's output, then DomOrboxMinC can be approximated with ADORA. We use the term "dangling" (input) tuple as follows. Assume the domain ordering σ is fixed. Given a query $Q = (\mathcal{R}, \mathcal{A})$ (under

- σ) and a relation $R \in \mathcal{R}$, the tuple $t \in R$ is a dangling tuple if there is no tuple t' in the output of Q such that $\pi_{\operatorname{attr}(R)}(t') = t$. Q is said to be fully semi-join reduced [7] if there are no dangling tuples in any of the relations in \mathcal{R} . The problem of fully semi-join reducing a query by removing all of the dangling tuples is known to be hard for cyclic queries [7]. Proposition 18 (proven in Appendix F of the online version of this paper [4]) shows that an oracle which computes the full semi-join reduction of a query Q would allow us to bridge the gap between minimizing the box cover size and certificate size for Q.
- ▶ Proposition 18. Q be a fully semi-join reduced query under σ . Let $K_{\square}(Q)$ be the size of the minimum box cover for Q under σ . Let $C_{\square}(Q)$ be the size of the minimum certificate of Q under σ . Then $K_{\square}(Q) = \widetilde{\Theta}(C_{\square}(Q))$.