

REVISION LETTER FOR PAPER 179: “NOCAP: NEAR-OPTIMAL CORRELATION-AWARE PARTITIONING JOINS”

We thank the reviewers for the revision opportunity and their clear and constructive reviews. We have made a major revision of the paper, where [the changes in the paper are marked as blue](#). In this document, we provide our responses to all reviewer items and we outline the changes we did to the paper.

Meta-review

“Please address all issues raised in Q14 of each review. Of greatest importance is greater emphasis on the practical algorithm, and significant broadening of experiments to real data set(s) as well as larger data sizes for synthetic data sets. The reviewers have listed several other issues or suggestions (besides those in Q14). Please address as many of those as possible. It is ok to reduce details of the optimal algorithm (Section 3) as needed to ensure that the practical algorithm is explained adequately and experiments are strengthened.”

Response: Overall, we made the following major revisions following the requests prioritized by the meta-review and the key requirements from the reviewers.

- (1) We reconstructed **Sections 3 and 4** by reducing theoretical proofs and adding more details of NOCAP.
- (2) We added scalability experiments by employing larger (SF=50) and different datasets, like JCC-H and JOB (**Fig. 12 in the revised manuscript**).
- (3) We added a discussion on Histojoin and also compared it as a baseline in the experiments (**Fig. 8, 10, and 11 in the revised manuscript**).
- (4) We added an experiment with running NOCAP with Noisy CT (**Fig. 11 in the revised manuscript**).
- (5) We added a microbenchmark to compare NOCAP against DHH with varying thresholds (**Fig. 9 in the revised manuscript**).

Review-1

- (R1-O1) *“The authors should make it more clear from the beginning that they start with a purely theoretical “thought experiment” where they compute optimal partitioning based on integer programming and dynamic programming, both having cost in the number of tuples (i.e. thousands of billions in the big data era that we live in)”*

Response: Thanks for this great suggestion. We have edited our **Introduction** and **Fig. 1** to reflect this. Further, our edits throughout **Sections 3 and 4** clarify this.

- (R1-O2) *“Somehow, the authors assume that partitioning is never done recursively to obtain memory-sized chunks. They assume a multi-phase block nested loops join after the initial partitioning instead. Please motivate.”*

Response: In fact, Recursive Partitioning (RP) is supported by NOCAP. In our implementation, we employ a light optimizer that chooses the cheapest join algorithm according to the cost model in **Table 1** to execute partition-wise joins. Using this cost model, recursive partitioning hardly occurs because it is only triggered when the number of chunks of the smaller relation is larger than 3 (we can compare the cost model between NBJ and GHJ in table 1 and assume $\mu \geq 1$).

- (R1-O3) *“Scale factors 1 and 4 for TPC-H are really very tiny. They do not challenge any serious DBMS at all. Please provide big data experiments as well.”*

Response: Thanks for your feedback. We added new experiments with increased scale factors (10 and 50) in the TPC-H and JCC-H experiments. We also added new experiments using two tables from JOB benchmark. Overall, the same observations hold. See **Section 5.2**.

- (R1-O4) *“The heavy hitter treatment could be compared to the flow-join approach for distributed join processing from Oracle (Roediger et.al., ICDE 2016)”*

Response: Thanks for this remark. The streaming sketch proposed by the flow-join approach can help obtaining the approximate distribution but it is not applicable when we partition R before partitioning S . Note that this is required by any hybrid join in order to cache records with high-frequency keys in memory. The approximated distribution estimation can only be obtained when partitioning S but partitioning R needs to use frequency information to decide how to cache high-frequency keys. As a result, flow-join cannot fully replace the calculation (or estimation) of CT values. We added a discussion in **Section 6** to explain why flow-join may not be suitable in our case.

- (R1-O5) *“The authors should elaborate on their proposed heuristics to compute the correlation vector CT. What happens if it imprecise if, e.g., it is derived from sampling.”*

Response: We found that MCVs naturally exhibits robustness to noise, because we target values that are substantially more common than others, hence, the sampling noise does not typically affect the identified values. As a result, adding noise does not lead to different results. To demonstrate this, we added a new experiment to examine the performance of NOCAP by adding Gaussian noise to CT values, as shown in **Fig. 11**.

Review-2

- (R2-O1) *“The scope of the work is very narrow, too narrow in my opinion. The authors should also discuss non PK-FK join, impact in the case of multiple joins. Also, the authors should discuss what happens if the MCVs are not known in advance.”*

Response: The proposed approach can be extended to general joins (non PK-FK), and already works with noise in the CT information as newly added experiments show. When it comes to general (non PK-FK) joins that are essentially many-to-many joins, we will have

two CT lists which store the frequency per key in each relation, and thus the cost function will need to be amended to use both lists. We leave the extension of the optimization problem as future work, however, our current approach can already provide a reasonable solution. It cannot guarantee a close-to-optimal partitioning solution, but it needs negligible time to find a more suitable partitioning than fixed-threshold DHH. We further discuss this in [Section 6](#). Further, we added a new experiment that shows that NOCAP is robust to noise in the CT values, which is presented in [Fig. 11](#).

- (R2-O2) “While it is instructive to learn how OCAP finds an optimal partitioning in Chapter 3, it is unclear why the optimizations in Sections 3.1.3., 3.1.4, and 3.2 are discussed in the context. The paper would benefit from limiting these discussion to the context of the practical algorithm NOCAP in Chapter 4. This way, the paper gets quicker to its main contribution NOCAP and all aspects contributing to its practicality are discussed in one place. Most of the theorems, optimizations, and proof could well be moved to an optional appendix and the assumptions and limitations should be summarized in a separate discussion (currently this is scattered across Sections 3 and 4). In the limitations, the range of applicability should be discussed, e.g., if the memory buffers for the join are 256KB or 4MB as in the case of MySQL or PostgreSQL, realistic scale factors of TPC-H do not fit into the buffer space discussed in the paper.”

Response: Thanks for your suggestion. We reconstructed both [Sections 3 and 4](#) by merging all the theorems, reducing proofs in [Section 3](#), and adding more detailed discussion of NOCAP in [Section 4](#). While we largely followed the suggested restructuring, we first introduced OCAP in Section 3 for clarity, so we can build on it to propose our core practical algorithm NOCAP in Section 4.

- (R2-O3) “The paper proposes and evaluates a join algorithm that should perform better under join attribute correlation skew. For the evaluation the authors employ a synthetic benchmark of an isolated PK-FK equi-join between two tables with varying correlation skew. The authors also conduct experiments with modified TPC-H data (to introduce correlation skew) and a modified query 12. A major opportunity for improvement is to build the experiments on broader workloads. For example, it would be interesting to see results from realistic/real-world workloads as the JOB benchmark [2]. It would be easier to understand and compare the results of the experiments if they were based on established/existing TPC-H variants with skewed data, e.g. [2] or [3]. Further, for storage-based joins it would be interesting to see results of larger-scale experiments than in the MB-scale. More suggestions for the experimental section in the minor remarks.”

Response: We added new experiments with increased scale factor (10 and 50 for TPC-H) as well as new experiments with JCC-H and JOB data in [Section 5.2](#), where we also observed that DHH with a fixed threshold could not adapt to different workloads. The core observations hold.

- (R2-O4) “The authors argue that their NOCAP join algorithm can better exploit data skew than Dynamic Hybrid Hash Join (DHH), because of DHH’s low and fixed memory budget for high-frequency keys. The authors should add a naive DHH variant with higher threshold(s) and compare that against NOCAP. In doing so, one could see how far DHH can be extended to accommodate the medium-skew scenarios.”

Response: We added one experiment that varies the thresholds of DHH under a certain workload and a memory budget, as shown in [Fig. 9](#), as part of [Section 5.1](#). We observe that the best thresholds of DHH are not the default DHH configurations in both experiments and they also differ when the available buffer changes.

- (R2-O5) “The authors should compare to and differentiate from HistoJoin.”

Response: The implementation of Histojoin in Postgres is actually a specific version of state-of-the-art DHH by setting the memory threshold as 0.02 and the frequency threshold as 0.0. We added the discussion of Histojoin when first mentioning DHH in [Section 2.2](#). We also compared it as a baseline in the experiments using a synthetic dataset ([Fig. 8 and 10](#)). As it has nearly the same performance as DHH, we omit it in the remainder of the experiments.

- (R2-O6) “The implementation of the approach is carried out in isolation and not integrated into a database system. Integrating the join algorithm into a full system would allow to investigate implicit effects on the entire join execution. It would also allow to directly compare the resulting end-to-end performance against other state-of-the-art systems. The additional comparisons and branches needed in the approach might outweigh the benefits in reduced I/O.”

Response: We agree that integrating NOCAP into a DBMS (e.g., PostgreSQL) is a key next step, and we leave it as future work. We motivate the usefulness of our approach via the I/O analysis, using which we can support that NOCAP outperforms state-of-the-art DHH in an end-to-end manner to. Corroborating the review point, we also observed that CPU-intensive queries (e.g., aggregations) may lower the benefit of reducing #I/Os, as we point out in TPC-H experiments ([Section 5.2](#)).

- (R2-M1) “It is unclear what the initial plot is showing. Which data set, which correlation, etc. How much does the I/O saving translate into actual performance benefit? It seems this is a hypothetical graph, it is treated in the text as a experimental ground truth.”

Response: [Fig. 1](#) is a conceptual graph that is based on execution with synthetic data. We clarified this in the caption of the initial plot.

- (R2-M2) “Fudge factor is never explained. There are many different uses of the term, so the authors should clearly explain what they mean in the paper.”

Response: We use the term fudge factor as defined in the textbook [47], i.e., as the space amplification factor of a hash table. We clarify this at the end of [Section 2.1](#).

- (R2-M3) “The authors assume that the smaller relation is always the primary key relation and the larger the foreign key relation. This need not be the case and then if the join order is switched the optimizations are not applicable anymore.”

Response: Thank you for this remark! Indeed, we build our algorithm with this assumption for clarity, however, the approach can easily work when the larger relation holds the primary key. The core idea is that we can minimize an objective function that is the upper bound of the exact join cost with bounded error. We added a paragraph in [Section 6](#) to discuss how much the bounded error is and how to change our algorithm when the smaller relation is the foreign key relation.

- (R2-M4) *"In the experimental setup, the RAM and SSD are underspecified. It would be informative to know how much RAM the machine has and what the size of the SSD is."*
 - In Section 5.1 we believe that "We verify this by re-running the experiments with disabling sync I/O." should be "We verify this by re-running the experiments with *enabling* sync I/O."
 - In Section 5.1 we cannot fully follow the argument that more garbage collection irons out the latency spike for GHJ. To be clarified by the authors: Is this because garbage collection happens more consistently throughout the measurement series?

Response: We added the specifications in the experimental setup paragraph of **Section 5.1**. We also dug into the reason for the latency spike, and we found that it occurs because of insufficient page pre-allocation when building partitions. Thus, we enabled pre-allocation of a modest number of disk pages prior to writing any pages at partition time, which helped us to alleviate the latency spike. The re-executed experiment without any latency spike is shown in **Fig. 8**.
- (R2-M5) *"The formal definitions are somewhat hard to follow, because the definitions are scattered across the sections."*

Response: We summarize frequently-used notations in **Table 2**.
- (R2-M6) *"Page sizes are not given in the paper, I am assuming 4KB, but this is never explained."*

Response: The page size is 4KB, which is added in the experimental methodology paragraph in **Section 5.1**.
- (R2-M7) *"Missing related work: Histojoin [1]. This work also features a (brief) theoretical discussion of the performance improvements possible in skewed data sets. There is also an interesting thread on the PostgreSQL mailing list about the authors' effort to contribute their solution to the PostgreSQL codebase, which discusses some of the tradeoffs that need to be considered in case of these optimizations: <https://www.postgresql.org/message-id/flat/6EEA43D22289484890D119821101B1DF2C180E40exchange20.mercury.ad.ubc.ca>"*

Response: The implementation of Histojoin is essentially a specific instance of DHH. We added the discussion of Histojoin when introducing DHH. Further, we treat Histojoin as a specific case of DHH. We also compared NOCAP with Histojoin in **Fig. 8** using a synthetic dataset.
- (R2-M8) *"Typos:"*

Response: We have corrected all typos.
- (Others) *"Move and merge the optimizations from Sections 3.1.3 and 3.1.4 into the respective sections (Rounded Hash and Skew Optimization) in Chapter 4. Discuss caching from Section 3.2 in Chapter 4. This may result in a briefer overall discussion in these two chapters. The current experimental evaluation may appear narrow and constructed. The evaluation would greatly benefit from broadening the workloads. If possible add experiments with realistic workloads (e.g., JOB benchmark which is referred to in the introduction). Otherwise consider running larger scale factors of JCC-H and also a broader query set."*

Response: We refined the proof and theorems in **Section 3** and added more discussion to explain NOCAP in **Section 4**. As OCAP, presented in **Section 3**, is used to build our practical algorithm, NOCAP, in **Section 4**, we kept enough level of detail to explain the core ideas of NOCAP. Further, regarding experiments, in **Section 5.2**, we added experiments on TPC-H, JCC-H with larger scale factors and run another experiment using JOB dataset.

Review-3

- (R3-O1) *"I would suggest defining what is meant by correlation and skew in this context, ideally using an example (already in the introduction). Skew in the join attributes means that not every PK has the same number of FKs. But what do the authors mean by correlation? It's a bit ambiguous in my opinion. For example, in related work on estimating join cardinalities, correlation often refers to the correlation of base table predicates (e.g., French actors are more likely to act in French movies)."*

Response: Thanks for this remark that allows us to clarify the use of some terminology. We use "join attribute correlation" to refer to the distribution function that indicates the number of matches a PK has with the FK relation. In turn, the join attribute correlation can be uniform (all PKs have the same number of FK matches) or skewed (some PKs have more matches than others). We clarified this in the **Introduction** of the paper.
- (R3-O2) *"That brings me to my next point: With R and S, the authors probably refer to the two join inputs after base table predicates have already been applied, which means that the correlation table can only be built after that."*

Response: MCVs (CT values) are built before the predicates. NOCAP can be adjusted based on predicates' selectivity assuming independence. In fact, this is what we do in the TPC-H experiments. MCVs are not fully accurate, but NOCAP still outperforms DHH. We also added another experiment to examine the robustness of NOCAP by adding some noise into MCVs, as shown in **Fig. 11**.
- (R3-O3) *"I would suggest dedicating more space in the paper to the practical algorithm. First, it would be good to elaborate more on how far the different approximations/assumptions can be off from the ground truth and what the consequences are."*

Response: Thanks for your suggestion. We refined proofs and theorems in **Section 3** and added more discussion in **Section 4** to elaborate NOCAP.
- (R3-O4) *"For the practical algorithm, they assume that we only know the top-k most frequent keys (and their frequencies). However, what if we could sample the join input? How would that affect the algorithm?"*

Response: Thanks for pointing out this. In our approach, selection with predicates is performed on-the-fly during partitioning, which avoids reading and writing the qualified data to the disk. In order to do this, we assume independence between the selection and the partitioning attribute (that leads to adding some noise in practice, which as we discussed does not hurt our approach). On the contrary,

sampling the join input has to separate the filtering and partitioning process because partitioning relies on the sampled statistics. As such, we would need to do an extra pass to obtain the statistics. We discuss this in [Section 6](#), where we added a paragraph discussing the feasibility of applying sampling to our algorithm.

- (R3-O5) *“The authors state that computing the approximate partitioning scheme takes less than one second for $k = 50K$ and omit its runtime discussion. However, it would still be interesting to learn how that algorithm scales. Modern data warehouses can store PBs of data, with often very large joins. Hence, it would be interesting if their approach is applicable in such a setting as well (where one might want to use $k = 1M$ or so to represent a sufficiently large fraction of the join). With 4B hash values, 1M entries would amount to less than 4MiB in size (8MiB including frequencies).”*

Response: The average time to execute OCAP is less than 2 seconds in all the experiments in [Fig. 8](#). For the larger TPC-H experiments, the runtime of the approximate partitioning was less than one second. Overall, while the runtime of the algorithm will unavoidably increase for larger datasets (with some subtle variations in some cases due to the efficacy of different pruning techniques), the increased data size will also lead to much more I/O cost, thus keeping the calculation of the partitioning a tiny fraction of the overall runtime. Further, note that NOCAP runs on MCVs which is 5% of the data, so even for a dataset with 1B entries, NOCAP problem size is in the order of 50M.

- (R3-O6) *“It would be interesting to study the effect of sideways information passing (SIP). In SIP, a Bloom filter is built over the build side and pushed into the probe-side scan. This is similar to the existence map in the optimal algorithm. How would SIP affect the results?”*

Response: Thanks for the suggestion. SIP is typically useful when there are some predicates in the partitioned relation. For example, in our TPC-H experiments, adding Bloom Filter (BF) when scanning the probe-side relation actually makes the input data closer to the estimated CT in the NOCAP algorithm, and thus SIP brings a positive effect to NOCAP. However, maintaining BFs also requires some memory, which introduces new trade-offs between BF accuracy and space for frequent entries. We added a SIP-related discussion in [Section 6](#).

- (R3-O7) *“While I like controlled experiments, I would appreciate experiments on real-world data, like the Join Order Benchmark (JOB). It is hard to tell whether the skew present in the datasets studied is found in real-world data as well or is more of artificial nature.”*

Response: Thanks for your suggestion. We added the experiments using the JOB dataset, where we see queries with significant benefits (up to 25%), as shown in [Section 5.2](#).

NOCAP: Near-Optimal Correlation-Aware Partitioning Joins

ABSTRACT

Storage-based joins are still commonly used today because the memory budget does not always scale with the data size. One of the many join algorithms developed that has been widely deployed and proven to be efficient is the Hybrid Hash Join (HHJ), which is designed to exploit any available memory to maximize the data that is joined directly in memory. However, HHJ cannot fully exploit detailed knowledge of the join attribute correlation distribution.

In this paper, we show that given a correlation skew in the join attributes, HHJ partitions data in a suboptimal way. To do that, we derive the optimal partitioning using a new cost-based analysis of partitioning-based joins that is tailored for primary key - foreign key (PK-FK) joins, one of the most common join types. This optimal partitioning strategy has a high memory cost, thus, we further derive an approximate algorithm that has tunable memory cost and leads to near-optimal results. Our algorithm, termed NOCAP (Near-Optimal Correlation-Aware Partitioning) join, outperforms the state-of-the-art for skewed correlations by up to 30%, and the textbook Grace Hash Join by up to 4 \times . Further, for a limited memory budget, NOCAP outperforms HHJ by up to 10%, even for uniform correlation. Overall, NOCAP dominates state-of-the-art algorithms and mimics the best algorithm for a memory budget varying from below $\sqrt{\|relation\|}$ to more than $\|relation\|$.

1 INTRODUCTION

Joins are ubiquitous in database management systems (DBMS). Further, *primary key - foreign key* (PK-FK) equi-joins are the most common type of joins. For example, all the queries of industry-grade benchmarks like TPC-H [53] and most of Join Order Benchmark (JOB) [31] are PK-FK equi-joins. Recent research has focused on optimizing in-memory equi-joins [5–7, 10, 12, 34, 50, 55], however, as the memory prices scale slower than storage [36], the available memory might not always be sufficient to store both tables simultaneously, thus requiring a classical storage-based join [47]. This is common in a shared resource setting, like multiple colocated databases or virtual database instances deployed on the same physical cloud server [9, 14, 27]. Besides, in edge computing, memory is also limited, which is further exacerbated when other memory-demanding services are running [24]. In several other data-intensive use cases like Internet-of-things, 5G communications, and autonomous vehicles [16, 21], memory might also be constrained. Finally, there are two main reasons a workload might need to use storage-based joins: (1) workloads consisting of queries with multiple joins, and (2) workloads with a high number of concurrent queries. In both cases, the available memory and computing resources must be shared among all concurrently executed join operators.

Storage-based Joins. When executing a join, storage-based join algorithms are used when the available memory is not enough to hold the hash table for the smaller relation. Traditional storage-based join algorithms include Nested Block Join (NBJ), Sort Merge Join (SMJ), Grace Hash Join (GHJ), Simple Hash Join (SMJ), and Hybrid Hash Join (HHJ). Overall, HHJ, which acts as a blend of

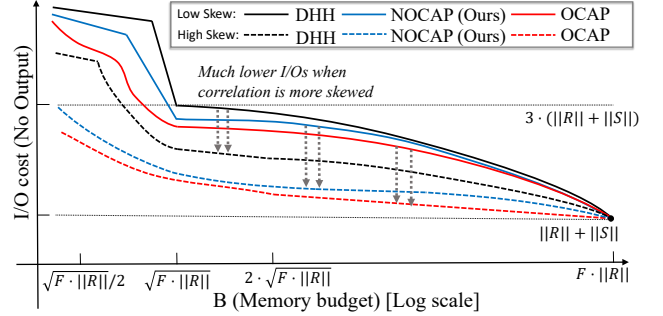


Figure 1: A conceptual graph on the I/O cost of the state-of-the-art DHH, OCAP and NOCAP, assuming $\|R\| \leq \|S\|$. F is the fudge factor indicating the space amplification factor between the in-memory hash table and the stored raw data).

Simple Hash Join and Grace Hash Join, is considered the state-of-the-art approach [19, 30, 51], and is extensively used in existing database engines (e.g., MySQL [38], PostgreSQL [46], AsterixDB [2]). HHJ **uniformly** distributes records from the two input relations to a number of partitions via hashing the join key and ensures that, when possible, one or more partitions remain in memory and are joined on the fly without writing them to disk. The remaining disk-resident partitions are joined using a classical hash join approach to produce the final result. Unlike GHJ and SMJ, HHJ uses the available memory budget judiciously and thus achieves a lower I/O cost. Existing relational database engines (e.g., PostgreSQL [46] and AsterixDB [2, 28]) often implement a variant of HHJ, Dynamic Hybrid Hash join (DHH) that dynamically decides which partitions should stay in memory during partitioning.

The Challenge: Exploit Skew. Although there are many skew **optimizations** for joins [20, 25, 29, 33, 39], a potential detailed knowledge of the join attribute correlation and its skew¹ is not fully exploited since existing techniques use heuristic rules to design the caching and partitioning strategy. In turn, while these heuristics may work well in some scenarios, in general, they lead to suboptimal I/O cost under an arbitrary join correlation. For example, HHJ can be optimized by prioritizing entries with high-frequency keys when building the in-memory hash table [44]. However, practical deployments use limited information about the join attribute correlation and typically employ a fixed threshold for building an in-memory hash table for keys with high skew (e.g., 2% of available memory). As a result, prior work does not systematically quantify the benefit of such approaches, nor does it offer a detailed analysis of how close to optimal they might be. In fact, due to the exponential search space, there is no previous literature that accurately reveals the relationship between the optimal I/O cost and the join correlation, thus leaving a large unexplored space for studying the caching and partitioning strategy.

Key Idea: Optimal Correlation-Aware Partitioning. To study the optimality of different partitioning-based join algorithms, we

¹Note that by “join attribute correlation” (or simply “correlation”) we refer to the distribution function that indicates the number of matches a PK has with the FK relation. In turn, the join attribute correlation can be uniform (same # of FK matches for all PKs) or skewed (some PKs have more matched than others).

model a general partitioning strategy that allows for arbitrary partitioning schemes (not necessarily based on a specific hash function). We assume that the relations we join have a PK-FK relationship, and we develop an algorithm for *Optimal Correlation-Aware Partitioning* (OCAP) that allows us to compare any partitioning strategy with the optimal partitioning, given the join correlation. Our analysis reveals that the state of the art is suboptimal in the entire spectrum of available memory budget (varied from $\sqrt{\|\text{relation}\|}$ to $\|\text{relation}\|$), leading up to 60% more I/Os than strictly needed as shown in Figure 1, where the black lines are the state of the art, and the red lines are the optimal number of I/Os. The OCAP is constructed by modeling the PK-FK join cost as an optimization problem and then proving the *consecutive theorem* which establishes the basis of finding the optimal cost within polynomial time complexity. We propose a dynamic programming algorithm that finds the optimal solution in quadratic time complexity, $O(n^2 \cdot m^2)$, and a set of pruning techniques that further reduce this cost to $O((n^2 \cdot \log m)/m)$ (where n is the number of records of the smaller relation and m is the memory budget in pages). OCAP has a large memory footprint as it assumes that the detailed information of the join attributes correlation is readily available and, thus, can be only applied for offline analysis. Further, note that OCAP models the cost using the number of records as a proxy to I/Os, and is used as a building block of a practical algorithm that we discuss next. We rely on OCAP to identify the headroom for improvement from the state of the art.

The Solution: Near-Optimal Correlation-Aware Partitioning Join. In order to build a practical join algorithm with a tunable memory budget, we approximate the optimal partitioning provided by OCAP with *Near-Optimal Correlation-Aware Partitioning* (NOCAP) algorithm. NOCAP enforces a strict memory budget and splits the available memory between buffering partitions and caching information regarding skew keys in join correlation. In Figure 1, we construct a conceptual graph to compare our solution and the state-of-the-art storage-based join methods, such as Dynamic Hybrid Hash (DHH). As shown, DHH cannot fully adapt to the correlation and thus results in higher I/O cost than OCAP when the correlation is skewed. Our approximate algorithm, NOCAP, uses the same input from DHH and achieves near-optimal I/O cost compared with OCAP. Further, while DHH is able to exploit the higher skew to reduce its I/O cost, the headroom for improvement for high skew is higher than for low skew, which is largely achieved by our approach. Overall, NOCAP is a practical join algorithm that is mostly beneficial compared to the state of the art, and offers its maximum benefit for a high skew in the join attribute correlation.

Contributions. In summary, our contributions are as follows:

- We build a new cost model for partitioning-based PK-FK join algorithms, and propose optimal correlation-aware partitioning (OCAP) based on dynamic programming (§3.1), assuming that the join attribute correlation is known. OCAP’s time complexity is $O(n^2 \cdot \log m/m)$ and space complexity is $O(n)$, where n is the input size in tuples and m is the memory budget in pages (§3.2).
- We design an approximate correlation-aware partitioning (NOCAP) algorithm based on OCAP. NOCAP uses partial correlation information (the same information used by the state-of-the-art skew optimized join algorithms) and achieves near-optimal performance while respecting memory budget constraints (§4).
- We thoroughly examine the performance of our algorithm by comparing it against GHJ, SMJ, and DHH. We identify that the headroom for improvement is much higher for skewed join correlations by comparing the I/O cost of DHH against the optimal. Further, we show that NOCAP can reach near-optimal I/O cost and thus lower latency under different correlation skew and memory budget, compared to the state of the art (§5). Overall, NOCAP dominates the state-of-the-art and offers performance benefits of up to 30% when compared against DHH and up to 4× when compared against the textbook GHJ.

2 PREVIOUS STORAGE-BASED JOINS

We first review four classical storage-based join methods [19, 23, 26, 47]. (summarized in Table 1), and then present more details of Dynamic Hybrid Hash (DHH), a variant of the state-of-the-art HHJ.

2.1 Classical Storage-based Joins

Nested Block Join (NBJ). NBJ partially loads the smaller relation R (in chunks equal to the available memory) in the form of an in-memory hash table and then scans the larger relation S once *per chunk* to produce the join output for the partial data. This process is repeated multiple times for the smaller relation until the entire relation is scanned. As such, the larger relation is scanned for as many times as the number of chunks in the smaller relation.

Sort Merge Join (SMJ). SMJ works by sorting both input tables by the join attribute using external sorting and applying M -way ($M \leq B - 1$) merge sort to produce the join result. During the external sorting process, if the number of total runs is less than $B - 1$, the last sort phase can be combined together with the multi-way join phase to avoid repetitive reads and writes [47].

Grace Hash Join (GHJ). GHJ uniformly distributes records from the two input relations to a number of partitions (at most $B - 1$) via hashing the join key, and the corresponding partitions are joined then. Specifically, when the smaller partition fits in memory, we simply store it in memory (typically as a hash table) and then scan the larger partition to produce the output.

Hybrid Hash Join (HHJ). HHJ is a variant of GHJ that allows one or more partitions to stay in memory without being spilled to disk, if the space is sufficient. When partitioning the second relation, we can directly probe in-memory partitions and generate the join output for those in-memory partitions. The remaining keys of the second relation are partitioned to disk, and we execute the same probing phase as in GHJ to join the on-disk partitions. When the memory budget is lower than $\sqrt{\|R\|} \cdot F$ (where $\|R\|$ is the size of the smaller relation in pages, and F is the fudge factor that stands for the space amplification factor between the in-memory hash table and the stored raw data), HHJ downgrades into GHJ because it will not be feasible to maintain a partition in memory while having enough buffers for the remaining partitions and the output.

2.2 Dynamic Hybrid Hash Join

Here we review DHH, the state-of-the-art implementation of HHJ, as well as its skew optimization. While there are many different implementations of DHH [26], the core idea is the same across all of them: decide which partitions to stay in memory or on disk.

Table 1: Estimated Cost for NBJ, GHJ, and SMJ for $R \bowtie S$. $\|R\|$ and $\|S\|$ are the number of pages of R and S . Assume $\|R\| \leq \|S\|$. #chunks is the number of passes for scanning S . #pa-runs is the number of times to partition R and S until the smaller partition fits in memory. #s-passes is the number of partially sorted passes of R and S , until the number of the total sorted runs is $\leq B - 1$ (B is the total number of memory available). μ and τ indicate the write/read asymmetry, where RW , SW , and SR denote the latency per I/O for random write, sequential write and sequential read respectively.

Approach	Normalized #I/O	Notation
NBJ(R, S)	$\ R\ + \text{\#chunks} \cdot \ S\ $	None
GHJ(R, S)	$(1 + \text{\#pa-runs} \cdot (1 + \mu)) \cdot (\ R\ + \ S\)$	$\mu \stackrel{\text{def}}{=} RW/SR$
SMJ(R, S)	$(1 + \text{\#s-passes} \cdot (1 + \tau)) \cdot (\ R\ + \ S\)$	$\tau \stackrel{\text{def}}{=} SW/SR$

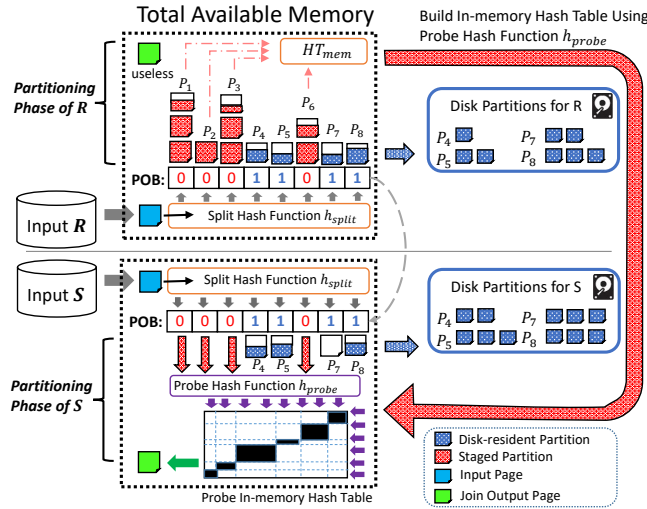


Figure 2: An illustration of partitioning in DHH. Partitions in red are staged in memory when R is being partitioned, while the remaining ones in blue are written to disk.

Framework. We visualize one implementation (AsterixDB [2, 28]) of DHH in Figure 2. Compared to HHJ, DHH exhibits higher robustness by dynamically deciding which partitions should be spilled to disk. Specifically, every partition is initially staged in memory, and when needed, a staged partition will be selected to be written to disk, and it will free up its pages for new incoming records. Typically, the largest partition will be selected, however, the victim selection policy may vary in different systems. A bit vector (“Page Out Bits” in Figure 2) is maintained to record which partitions have been written out at the end of the partitioning phase of R . Another hash function is applied to build a large in-memory hash table using all staged partitions. It is worth noting that, when it is insufficient to stage any partition in the memory (i.e., all the partitions are spilled out to disk), DHH naturally downgrades into GHJ. When partitioning the relation S , DHH applies the partitioning hash function first and checks the page-out bit for every record. If it is set, DHH directly probes the in-memory hash table using the probe hash function and generate the join result. Otherwise, DHH moves the joined record to the corresponding output page and flushes

Algorithm 1: DHH-PRIMARY(R, HS_{mem}, B)

```

1  $m_{\text{DHH}} \leftarrow \max \left\{ 20, \left\lceil \frac{\|R\| \cdot F - B}{B - 1} \right\rceil \right\};$ 
2 Initialize a length- $m_{\text{DHH}}$  array POB as  $\{0, 0, \dots, 0\}$ ;
3 Initialize a length- $m_{\text{DHH}}$  partitioning PartPages;
4 foreach  $r \in R$  do
5   PartID  $\leftarrow h_{\text{split}}(r.\text{key})$ ;
6   if POB[PartID] = 0 then
7     if  $\sum_{i=1}^{m_{\text{DHH}}} \text{PartPages}[i].\text{size}() = B - 2 - m_{\text{DHH}}$  then
8       Flush an arbitrary partition  $j$  to disk;
9       POB[ $j$ ] = 1;
10    else append  $r$  to PartPages[PartID];
11  else append  $r$  to the in-disk partition PartID;
12 foreach  $r \in \text{PartPages}$  do add  $r$  to  $HT_{\text{mem}}[h_{\text{probe}}(r.\text{key})]$ ;
13 return  $HT_{\text{mem}}, \text{POB}$ ;

```

Algorithm 2: DHH-FOREIGN($S, HT_{\text{mem}}, \text{POB}$)

```

1 foreach  $s \in S$  do
2   if  $h_{\text{probe}}(s.\text{key}) \in HT_{\text{mem}}$  then
3     if  $s.\text{key}$  is in records  $HT_{\text{mem}}[h_{\text{probe}}(s.\text{key})]$  then
4       join  $s$  with matched records and output;
5   else
6     if POB[ $h_{\text{split}}(s.\text{key})$ ] = 1 then
7       append  $s$  to the in-disk partition PartID;

```

it to the disk if it is full. Finally, DHH performs exactly the same steps as the traditional hash join to probe all the disk-resident partitions. The partitioning and probing of DHH is presented in detail in Algorithms 1 and 2.

Number of Partitions. The number of partitions in DHH (noted by m_{DHH}) is a key parameter that largely determines join performance. A large m_{DHH} requires more output buffer pages reserved for each partition, and, thus, less memory is left for memory-resident partitions. On the other hand, small m_{DHH} renders the size of each partition very large, which makes it harder to stage in memory. No previous work has formally investigated the optimal number of partitions for arbitrary correlation skew, but past work on HHJ employs some heuristic rules. For example, an experimental study [26] recommends that 20 is the minimum number of partitions when we do not have sufficient information about the join correlation. In addition, if we restrict the number of memory-resident partitions to be 1, we can set the number of partitions m_{DHH} as $m_{\text{DHH}} = \left\lceil \frac{\|R\| \cdot F - B}{B - 1} \right\rceil$ [51], where $\|R\|$ is the size of relation R in pages, F is the fudge factor for the hash table, and B is the total given memory budget in pages. Integrating this equation with the above tuning guideline, we configure $m_{\text{DHH}} = \max \left\{ \left\lceil \frac{\|R\| \cdot F - B}{B - 1} \right\rceil, 20 \right\}$.

Heuristic Skew Optimization In Practical Deployments. For ease of notation, we assume that R is the relation that holds the primary key and is smaller in size (dimension table) and that S is

the relation that holds the foreign key and is larger in size (fact table). In PK-FK joins, the join correlation can be non-uniform. [Histojoin \[17\]](#) proposes to cache in memory the Most Common Values (MCVs, maintained by DBMS) to help reducing the I/O cost. Specifically, if the memory budget is enough, Histojoin first partitions the dimension table R and caches entries with high-frequency keys in a small hash table in memory. When it partitions the fact table S , if there are any keys matched in the small hash table, it directly joins them and output. That way, Histojoin avoids writing out many entries with the same key from the fact table and reading them back into memory during the probing phase. However, it is unclear how much frequency should be treated as *high* to qualify for this optimization and how large the hash table for the skewed keys should be within the available memory budget. [In one implementation of Histojoin \[18\]](#), it limits the memory usage to 2% for constructing the hash table specifically for skewed keys. This restriction ensures that the specific hash table fits in memory. Likewise, in PostgreSQL [44], when the skew optimization knob is enabled and MCVs are present in the system cache (thus not occupying the user-specified memory), PostgreSQL follows a similar approach by adding an extra trigger to build the hash table for skewed keys. By default, PostgreSQL also allocates a fixed budget of 2% memory for the hash table dedicated to handling skewed keys, but this allocation only occurs when the total frequency of skewed keys is more than $0.01 \cdot n_S$ (n_S is the number of keys in relation S). In fact, PostgreSQL implements a general version of Histojoin by specifying the frequency threshold. However, existing skew optimizations in both PostgreSQL and Histojoin rely on fixed thresholds (i.e., memory budget for skew keys, and frequency threshold), which apparently cannot be adapted to different memory budget and different join skew. For example, as shown in Figure 1, state-of-the-art DHH are not enough to achieve ideal I/O cost, and they are further away from the optimal for higher skew.

3 OPTIMAL CORRELATION-AWARE PARTITIONING JOIN

We now discuss the theoretical limit of an I/O-optimal partitioning-based join algorithm when the correlation skewness information is known in advance and can be accessed for free. [We assume that \$R\$ is the relation that holds the primary key \(dimension table\) and \$S\$ is the relation that holds the foreign key \(fact table\)](#). More specifically, we model the correlation between two input relations with respect to the join attributes as a *correlation table* CT, [where \$CT\[i\]\$ is the number of records in \$S\$ matching the \$i\$ -th record in \$R\$](#) . Our goal is to find which keys should be cached in memory, and how the rest keys are partitioned on disk that would minimize the total I/Os in the join execution under arbitrary memory budget.

We start with an easy case when no records can be cached during the partition phase (§3.1) and turn to the general case when keys can be cached (§3.2). We note again that the memory used for storing CT as well as the optimal partitioning does not compete with the available memory budget B , which is indeed **unrealistic**. This is why we consider it as a theoretically I/O-optimal algorithm, since it can help us understand the lower bound of any feasible partitioning but cannot be converted into a practical algorithm. [All missing proofs and details are given in our full version \[3\].](#)

Table 2: Summary of our notation.

Notation	Definitions (Explanations)
$\ R\ $ ($\ S\ $)	#pages of relation R (S)
n_R (n_S)	#records from relation R (S)
P_j	the j -th partition ($P_j = R_j$)
$ P_j $	#records in j -th partition
$\ R_j\ $ ($\ S_j\ $)	#pages of a partition R_j (S_j)
\mathbb{P}	a Boolean matrix for partitioning assignment
$f : i \rightarrow j$	returns j for i so that $\mathbb{P}_{i,j} = 1$
$\mathcal{N}_f(i)$	the partition where the i -th records belongs
n	$n = n_R$ in the partitioning context
m	#partitions
B	#pages of the total available buffer
F	the fudge factor of the hash table
CT	the correlation table of keys and their frequency
b_R (b_S)	#records from relation R (S) per page
c_R (c_S)	#records from relation R (S) per chunk in NBJ

3.1 Optimal Partitioning Without Caching

We first build the cost model for partitioning assuming no cached records during the partitioning (§3.1.1), then present the main theorem for characterizing the optimal partitioning (§3.1.2) and find the optimal partitioning efficiently via dynamic programming (§3.1.3).

3.1.1 Partitioning as An Integer Program.

A partitioning \mathbb{P} is an assignment of n records from R to m partitions. As we use at least one page to stream the input relation and the rest of the pages as output buffers for each partition, $m \leq B - 1$. More specific constraints on m will be determined in Section 3.2 and Section 4.1. Once we know how to partition R (the relation with primary key), we can apply the same partition strategy to S .

Partitioning. We encode a partitioning \mathbb{P} as a Boolean matrix of size $n \times m$, where $\mathbb{P}_{i,j} = 1$ indicates that the i -th record belongs to the j -th partition. If the i -th record from R does not have a match in S , i.e., $CT[i] = 0$, we will not assign it to any partition. We can preprocess the input to filter out these records so that each of remaining records belongs to exactly one partition, [although it is unrealistic in practice](#). In this way, a partitioning \mathbb{P} can be compressed as a mapping function $f : [n] \rightarrow [m]$ from the index of record to the index of partition in \mathbb{P} , such that i -th record from relation R is assigned to $f(i)$ -th partition in \mathbb{P} . Let $P_j = \{i \in [n] : f(i) = j\}$ be the set of indexes of records from R assigned to the j -th partition in \mathbb{P} . We can then derive the number of pages for R_j and S_j as $\|R_j\| = \lceil |P_j|/b_R \rceil$, $\|S_j\| = \lceil \sum_{i \in P_j} CT[i]/b_S \rceil$, where b_R (resp. b_S) is the number of records per page for R (resp. S). Moreover, we use $\mathcal{N}_f(i) = \{i' \in [n] : f(i') = f(i)\}$ to denote the records from S that fall into the same partition with the i -th record in R . [We summarize frequently-used notations in Table 2.](#)

Cost Function. Given a partitioning \mathbb{P} , it remains to join partitions in a pair-wise manner. Reusing the cost model in Table 1, the cost of computing the join results for a pair of partitions (R_j, S_j) is $\min\{NBj(R_j, S_j), SMj(R_j, S_j), GHj(R_j, S_j)\}$, by picking the cheapest one among NBj, SMj, and GHj. We omit DHH here for simplicity, which does not lead to major changes of the optimal partitioning,

since in most cases NBJ is the most efficient one when taking read/write asymmetry into consideration (write is generally much slower than read in modern SSDs [41, 42]). For ease of illustration, we assume only NBJ is always applied in the pair-wise join, i.e., the *join cost* induced by partitioning \mathbb{P} is $\text{Join}(\mathbb{P}, m) = \sum_{j=1}^m \text{NBJ}(R_j, S_j)$. It can be proved that most of the following results still apply when all of NBJ, SMJ, and GHJ can be used for the partition-wise joins as long as we always pick the one with minimum cost.

Recall the cost function of NBJ in Table 1. For simplicity, we assume $\|R_j\| \leq \|S_j\|$ for each $j \in [m]$. The general case when $\|R_j\| \geq \|S_j\|$ exists for some $j \in [m]$ will be discussed in Section 6. By setting $\# \text{chunks} = \lceil \|R_j\| / ((B-2)/F) \rceil$, $\|R_j\| = |P_j|/b_R$ and $\|S_j\| = \lceil \sum_{i \in P_j} \text{CT}[i] / b_S \rceil$, we obtain the cost function as follows:

$$\begin{aligned} \text{Join}(\mathbb{P}, m) &= \|R\| + \sum_{j=1}^m \left\lceil \frac{|P_j|}{c_R} \right\rceil \cdot \left\lceil \sum_{i \in P_j} \frac{\text{CT}[i]}{b_S} \right\rceil \\ &\leq \|R\| + m + \frac{n_R}{c_R} + \sum_{j=1}^m \left\lceil \frac{|P_j|}{c_R} \right\rceil \cdot \sum_{i \in P_j} \frac{\text{CT}[i]}{b_S} \\ &= \|R\| + m + \frac{n_R}{c_R} + \frac{1}{b_S} \cdot \sum_{i=1}^n \text{CT}[i] \cdot \left\lceil \frac{|\mathcal{N}_f(i)|}{c_R} \right\rceil \end{aligned}$$

where $c_R = \lfloor b_R \cdot (B-2)/F \rfloor$ is a constant that denotes the number of records per chunk in relation R , and \mathbb{I} is the indicator function. Note that the I/O cost of read and write both relations is the same for all partitioning strategies.

Integer Program. Given the number of partitions m , finding a partitioning \mathbb{P} for R (containing the primary key) of n records with minimum cost can be captured by the following integer program:

$$\begin{aligned} \min_{\mathbb{P}} \quad & \text{Join}(\mathbb{P}, m) \\ \text{subject to} \quad & \sum_{j=1}^m \mathbb{P}_{i,j} = 1, \forall i \in [n] \\ & m+1 \leq B \\ & \mathbb{P}_{i,j} \in \{0, 1\}, \forall i \in [n], \forall j \in [m] \end{aligned}$$

However, solving such an integer program takes exponentially large time by exhaustively searching all possible partitionings. We next characterize the optimal partitioning with some nice properties.

3.1.2 Main Theorem.

For simplicity, we assume that CT is sorted in ascending order, i.e., if $i_1 \leq i_2$, then $\text{CT}[i_1] \leq \text{CT}[i_2]$. With sorted CT, we present our main theorem for characterizing the optimal partitioning \mathbb{P} with three critical properties. Firstly, each partition of \mathbb{P} contains consecutive records lying on the sorted CT array. Then, we can define a partial ordering on the partition in \mathbb{P} . Secondly, the sizes of all partitions are in a weakly descending order. At last, the size of each partition except the first one (or the largest one) is divisible by c_R .

THEOREM 3.1 (MAIN THEOREM). *Given an arbitrary sorted CT array, there is an optimal partitioning $\mathbb{P} = \langle P_1, P_2, \dots, P_m \rangle$ such that*

- **(consecutive property)** for any $i_1 \leq i_2$, if $i_1 \in P_j$ and $i_2 \in P_j$, then $i \in P_j$ holds for any $i \in [i_1, i_2]$;
- **(weakly-ordered property)** $\left\lceil \frac{|P_1|}{c_R} \right\rceil \geq \left\lceil \frac{|P_2|}{c_R} \right\rceil \geq \dots \geq \left\lceil \frac{|P_m|}{c_R} \right\rceil$;

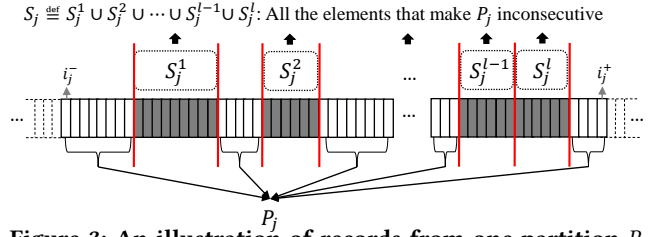


Figure 3: An illustration of records from one partition P_j lying in a non-consecutive way in the sorted CT.

- **(divisible property)** for any $2 \leq i \leq m$, $|P_i|$ is divisible by c_R , where P_j be the set of indexes at which records are assigned to the j -th partition of \mathbb{P} , i.e., $P_j = \{i \in [n] : f(i) = j\}$.

LEMMA 3.2 (SWAP LEMMA). *For a partitioning \mathbb{P} , if there exists a pair of indexes i_1, i_2 with $\text{CT}[i_1] > \text{CT}[i_2]$ and $|\mathcal{N}_f(i_1)| \geq |\mathcal{N}_f(i_2)|$, it is feasible to find a new partitioning \mathbb{P}' by swapping records at i_1 and i_2 , such that $\text{Join}(\mathbb{P}) \geq \text{Join}(\mathbb{P}')$.*

To prove the main theorem, the high-level idea is to transform an arbitrary partitioning \mathbb{P} into \mathbb{P}' with desired properties, while keeping the join cost of \mathbb{P}' always smaller (or at least no larger) than that of \mathbb{P} . The essence is a *swap* procedure, as described by Lemma 3.2, which can reassign records in a way such records with larger CT values always appear with fewer records in a partition. Its proof directly follows the definition of join cost. Next, we will show how to transform an arbitrary partitioning \mathbb{P} step by step.

Consecutive Property. Given an arbitrary partitioning \mathbb{P} , we first show how to transform it into \mathbb{P}' such that \mathbb{P}' satisfies the consecutive property while $\text{Join}(\mathbb{P}') \leq \text{Join}(\mathbb{P})$. As described in Algorithm 3, we always identify a partition whose records are not consecutive on the sorted CT, say P_j , and apply the swap procedure to it. Let i_j^- and i_j^+ be the minimum and maximum index of records from P_j lying on CT. Let $S_j^1, S_j^2, \dots, S_j^\ell$ be the longest consecutive records whose indexes fall into $[i_j^-, i_j^+]$ in CT, and belong to the same partition $P_{j'}$ for some $j' \neq j$ ($S_j^{i_1}$ and $S_j^{i_2}$ may belong to different partitions). We denote $S_j = S_j^1 \cup S_j^2 \cup \dots \cup S_j^\ell$ as the set of all records that make P_j non-consecutive with respect to the sorted CT (Figure 3).

Algorithm 3: SWAP(\mathbb{P})

```

1 while there exists  $P_j \in \mathbb{P}$  that is non-consecutive do
2   while true do
3     left, right  $\leftarrow \min_{i \in [n]: f(i)=j} i, \max_{i \in [n]: f(i)=j} i$ ;
4      $S_j \leftarrow \{i \in [n] : \text{left} \leq i \leq \text{right}, f(i) \neq j\}$ ;
5     if  $S_j = \emptyset$  then break;
6      $\ell \leftarrow \min_{i \in S_j} i$ ;
7     if  $|\mathcal{N}_f(\ell)| > |P_j|$  then
8       SWAP( $f(\ell), f(\text{left})$ ), left  $\leftarrow \text{left} + 1$ ;
9     else SWAP( $f(\ell), f(\text{right})$ ), right  $\leftarrow \text{right} - 1$ ;
10 return  $\mathbb{P}$ ;
```

Algorithm 3 maintains two pointers left and right to indicate the smallest and largest indexes of records to be swapped. Consider the smallest index $\ell \in S_j$. If $|\mathcal{N}_f(i)| > |P_j|$, we swap ℓ and left by

putting the record at i into $P_{f(\ell)}$ and the record at left into $P_{f(\ell')}$ (By definition, we have $P_{f(\ell)} = \mathcal{N}_{f(\ell)}$). Otherwise, we swap ℓ and right similarly. We repeat the procedure above until all partitions become consecutive on the sorted CT. It is not hard to see that the resulted partitioning from $\text{SWAP}(\mathbb{P})$ is “consecutive”, and the cost does not increase in the process above, thanks to the swap lemma.

Algorithm 4: ORDER(\mathbb{P})

```

1 while there exists  $P_{j'} \preceq P_j \in \mathbb{P}$  s.t.  $\lceil \frac{|P_{j'}|}{c_R} \rceil < \lceil \frac{|P_j|}{c_R} \rceil$  do
2    $\ell, \ell' \leftarrow \min_{i \in P_j} i, \min_{i \in P_{j'}} i$ ;
3   for  $i \leftarrow 0$  to  $|P_{j'}|$  do  $\text{SWAP}(f(\ell + i), f(\ell' + i))$ ;
4    $\mathbb{P} \leftarrow \text{SWAP}(\mathbb{P})$ ;

```

Weakly-Ordered Property. Given a partitioning \mathbb{P} with consecutive property, we next show how to transform it into \mathbb{P}' such that \mathbb{P}' satisfies both consecutive and weakly-ordered properties. As each partition in \mathbb{P} contains consecutive records in the sorted CT, we can define a partial ordering \preceq on the partitions in \mathbb{P} . For simplicity, we assume that $P_1 \preceq P_2 \preceq \dots \preceq P_m$. As described in Algorithm 4, we always identify a pair of partitions that are not “weakly-ordered”, i.e., $P_{j'} \preceq P_j$ but $\lceil |P_{j'}|/c_R \rceil < \lceil |P_j|/c_R \rceil$. In this case, we can apply Lemma 3.2 to swap records between $P_{j'}$ and P_j . This swap would turn P_j into non-consecutive on the sorted CT. If this happens, we further invoke Algorithm 3 to transform P_j into a consecutive one; moreover, $P_{j'}$ will be put after P_j in the sorted CT. We will repeatedly apply the procedure above until no unordered pair of partitions exists in \mathbb{P} . In fact, a strongly-ordered property also holds by replacing $\lceil |P_j|/c_R \rceil$ with $|P_j|$. We keeps the weakly-ordered version here so that it does not conflict with the following divisible property.

Divisible Property. Given a partitioning \mathbb{P} satisfying the consecutive and weakly-ordered property, we next show how to transform it into \mathbb{P}' such that \mathbb{P}' also satisfies divisible property as follows. We start checking the m -th partition P_m . If $|P_m|$ is divisible by c_R , we just skip it. Otherwise, we move records from the previous partition P_{m-1} to P_m until $|P_m|$ is divisible by c_R . After done with P_m , we move to P_{m-1} . We continue this procedure until $|P_m|, |P_{m-1}|, \dots, |P_2|$ are all divisible by c_R . This fine-grained movement between adjacent partitions naturally preserves the consecutive property as well as the join cost.

3.1.3 Dynamic Programming.

With Theorem 3.1, we can now reduce the complexity of finding the optimal partitioning in a brute-force way by resorting to dynamic programming, and searching candidate partitionings with consecutive, weakly-ordered, and divisible properties.

Formulation by Consecutive Property. We define a sub-problem parameterized by (i, j) : finding the optimal partitioning for the first i records in the sorted CT using j partitions. The join cost of this sub-problem parameterized by (i, j) is denoted as $V[i][j]$. Recall that the optimal solution of our integer program in Section 3.1.1 is exactly $V[n][m]$. As described by Algorithm 5, we can compute V in a bottom-up fashion. More specifically, we use $V[i][j].\text{cost}$ to store the cost of an optimal partitioning for the sub-problem parameterized by (i, j) and $V[i][j].\text{LastPar}$ stores the starting position

of the last partition correspondingly. We also define $\text{CalCost}(s, e)$ as the per-partition join $\text{PPJ}(R_{j'}, S_{j'})$ (omitting the term $\|R_{j'}\|$ in $\text{NBJ}(R_{j'}, S_{j'})$ for a pair of partition $R_{j'}$ and $S_{j'}$, if we let $P_{j'} = [s, e]$). This can be easily computed using the pre-computed prefix sum:

$$\text{CalCost}(s, e) = \left(\sum_{i=1}^e \text{CT}[i] - \sum_{i=1}^{s-1} \text{CT}[i] \right) \cdot \left\lceil \frac{e-s+1}{c_R} \right\rceil \quad (1)$$

The essence of Algorithm 5 is the following recurrence formula:

$$V[i][j].\text{cost} = \min_{0 \leq k \leq i-1} \{V[k][j-1].\text{cost} + \text{CalCost}(k+1, i)\}$$

which iteratively search the starting position of the last partition in $[0, i-1]$. Also, we can backtrack the index of the last partition to produce the mapping function f from each index to its associated partition, as described by Algorithm 6.

Algorithm 5: PARTITION(CT, n, m)

```

1 Initialize  $V$  of sizes  $n \times m$ ;
2 for  $i \leftarrow 1$  to  $n$  do
3    $V[i][1].\text{cost} \leftarrow \text{CalCost}(1, i)$ ,  $V[i][1].\text{LastPar} \leftarrow 1$ ;
4 for  $i \leftarrow 2$  to  $n$  do
5   for  $j \leftarrow 2$  to  $\min(m, i)$  do
6      $V[i][j].\text{cost} \leftarrow +\infty$ ;
7     for  $k \leftarrow 0$  to  $i-1$  do
8        $\text{tmp} \leftarrow V[k][j-1].\text{cost} + \text{CalCost}(k+1, i)$ ;
9       if  $\text{tmp} < V[i][j].\text{cost}$  then
10         $V[i][j].\text{cost} \leftarrow \text{tmp}$ ;
11         $V[i][j].\text{LastPar} \leftarrow k+1$ ;
12 return  $V$ ;

```

Algorithm 6: GETCUT(V, n, m)

```

1  $\text{LastPar} \leftarrow n$ ;
2 for  $j \leftarrow 0$  to  $m-1$  do
3   for  $i \leftarrow V[\text{LastPar}][m-j].\text{LastPar}$  to  $\text{LastPar}$  do
4      $f(i) \leftarrow m-j$ ;
5    $\text{LastPar} \leftarrow V[\text{LastPar}][m-j].\text{LastPar} - 1$ ;
6 return  $F$ ;

```

The time complexity of Algorithm 5 is $O(m \cdot n^2)$, which is dominated by the three for-loops, and the space complexity is $O(m \cdot n)$ for storing V . This significantly improves the brute-force enumerating method, whose time complexity is as large as $O(m^n)$.

Speedup by Weakly-Ordered Property. Combining the weakly-ordered property in Theorem 3.1 with the pigeonhole principle, for any sub-problem parameterized by (i, j) , there exists an optimal partitioning such that: (i) the “largest” partition contains at least the first $\left\lfloor \frac{i-1}{j} \right\rfloor + 1 - c_R$ records in the sorted CT, and (ii) the “smallest” partition contains at most the last $\left\lfloor \frac{i}{j} \right\rfloor + c_R$ records in the sorted CT. Note that the “largest” (“smallest”) partition is not essentially the largest (smallest) in terms of the actual partition size. It is possible that $P_{j'} \preceq P_{j'+1}$ and $\lceil |P_{j'}|/c_R \rceil = \lceil |P_{j'+1}|/c_R \rceil$ but $|P_{j'}| \leq |P_{j'+1}|$. However, even if $|P_{j'}| \leq |P_{j'+1}|$, the difference cannot be larger

than c_R from the weakly-ordered property. As such, the “largest” partition for the sub-problem parameterized by (i, j) cannot be smaller than $\lfloor \frac{i-1}{j} \rfloor + 1 - c_R$. Similar analysis can be applied to the upper bound of the size of the “smallest” partition. Synthesizing above analysis, we can get two tighter bounds on k in line 8:

- $k \geq \max\{(i - c_R) \cdot (1 - \frac{1}{j}), 0\}$. The partition P_j contains records from $CT[k+1 : i]$, and $|P_j|$ should be no larger than the last (“smallest”) partition in $V[k][j-1]$. The last (“smallest”) partition for the sub-problem parameterized by $(k, j-1)$ is at most $\lfloor \frac{k}{j-1} \rfloor + c_R$. Hence, $i - k \leq \lfloor \frac{k}{j-1} \rfloor + c_R$.
- $k \leq \max\{i - \lfloor \frac{n-i-1}{m-j} \rfloor - 1 + c_R, 1\}$. The partition P_j contains records from $CT[k+1 : i]$, and it should be no smaller than the “largest” partition of remaining records in $CT[i+1 : n]$. Recall that, we still need to put the remaining $n - i$ records into $m - j$ partitions. The largest partition of the sub-problem parameterized by $(n - i, m - j)$ contains at least $\lfloor \frac{n-i-1}{m-j} \rfloor + 1 - c_R$ records. Hence, $i - k \geq \lfloor \frac{n-i-1}{m-j} \rfloor + 1 - c_R$.

After changing the range of the third loop (line 8, Algorithm 5) to $[\max\{(i - c_R) \cdot (1 - \frac{1}{j}), 0\}, \max\{i - \lfloor \frac{n-i-1}{m-j} \rfloor - 1 + c_R, 1\}]$, we can skip the calculation of $V[i][j]$ when $(i - c_R) \cdot (1 - \frac{1}{j}) > i - \lfloor \frac{n-i-1}{m-j} \rfloor - 1 + c_R$. This pruning reduces the time complexity to $O(n^2 \log m)$.

Speedup by Divisible Property. To utilize the divisible property, we initially put the first $(n \bmod c_R)$ records in the first partition, and then change the step size (line 5 and line 8) of Algorithm 5 to c_R . This way, we can shrink the size of V to $(\lceil n/c_R \rceil + 1) \times m$. Recall that m can be as large as $B - 1$, F is a constant larger than 1, and thus $c_R = \lfloor b_R \cdot (B - 2)/F \rfloor \geq m$. Therefore, the time complexity can be reduced to $O\left(\frac{n^2 \log m}{m^2}\right) = O\left(\frac{n^2 \log m}{m^2}\right)$ and the space complexity to $O(n/c_R \cdot m) = O(n)$.

3.2 Optimal Partitioning With Caching

We move to the general case when records can be cached. In this case, some records stay in memory during the partition phase, so as to avoid repetitive reads/writes, while remaining records still go through the partitioning phase as Section 3.1. A natural question arises: which records should stay in memory and which records should go to partition? As we can see in DHH (Figure 2), the hash function h_{split} , together with POB actually categorizes all the join keys by their indexes into two sets, memory-resident keys as $K_{\text{mem}} \subseteq [n]$ and disk-resident keys as $K_{\text{disk}} = [n] - K_{\text{mem}}$. Then, it suffices to find an optimal partitioning (without caching) for K_{disk} , which degenerates to our problem in Section 3.1. Together, we derive a general join cost function $\text{Join}(K_{\text{disk}}, \mathbb{P}, m)$ as:

$$\left[\sum_{i \in K_{\text{disk}}} \frac{CT[i]}{b_S} \cdot \left\lceil \frac{|\mathcal{N}_f(i)|}{c_R} \right\rceil \right] + (1 + \mu) \cdot \left\lceil \frac{|K_{\text{disk}}|}{b_R} \right\rceil + \mu \cdot \sum_{i \in K_{\text{disk}}} \left\lceil \frac{CT[i]}{b_S} \right\rceil$$

where b_R (resp. b_S) represents the number of records per page for relation R (resp. S), and μ is the ratio between random write and sequential read. Compared to the original cost function $\text{Join}(\mathbb{P}, m)$, the new cost function $\text{Join}(K_{\text{disk}}, \mathbb{P}, m)$ involves two additional terms

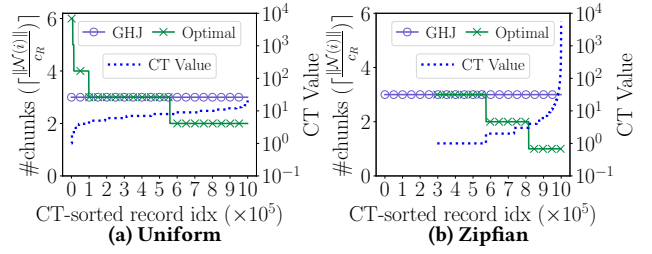


Figure 4: A comparison on the number of passes required for the outer relation S between the partitioning adopted by DHH/GHJ and our optimal partitioning. Assume $B \leq \sqrt{\|R\| \cdot F}$ (DHH without skew optimization downgrades to GHJ). Suppose $n_R = 1M$, $n_S = 8M$, $F = 1.02$ and $B = 320$ pages. Moreover, the record size of R is 1KB, which occupies 250 pages. In (a), random (uniform) partitioning (GHJ), the partition size is around $250K/319 \approx 784$ pages which require $\lceil 783/(318 \times F) \rceil = 3$ passes to scan every partition of S . In contrast, the optimal partitioning allows the number of passes to vary from 2 to 6, which follows a non-monotonically decreasing trend as CT value increases. In (b), a similar pattern can be observed when there is skewed correlation (the optimal partitioning naturally excludes records with $CT[i] = 0$).

Algorithm 7: OCAP(CT, n, B)

```

1 tmp ← +∞, f ← ∅;
2 for k ← 0 to c_R do
3   V ← PARTITION(CT[1 : n - k], n - k, B - 2 - ⌈ $\frac{k \cdot F}{b_R}$ ⌉);
4   c_probe ← ⌈ $\frac{n-k}{b_R}$ ⌉ + V[n - k][B - 2 - ⌈ $\frac{k \cdot F}{b_R}$ ⌉].cost;
5   c_part ← μ · (⌈ $\frac{n-k}{b_R}$ ⌉ + ⌈ $\frac{1}{b_S}$ ⌉ · ∑_{i=1}^{n-k} CT[i]);
6   if tmp < c_probe + c_part then
7     tmp ← c_probe + c_part;
8     f ← GETCUT(V, n - k, B - 2 - ⌈ $\frac{k \cdot F}{b_R}$ ⌉);
9 return f;
```

$-\mu \cdot (\lceil |K_{\text{disk}}|/b_R \rceil + \lceil \sum_{i \in K_{\text{disk}}} CT[i]/b_S \rceil)$ as the cost of partitioning both relations, and $\lceil |K_{\text{disk}}|/b_R \rceil$ as the cost of loading R in the probing phase. Together, we have the following integer program:

$$\begin{aligned} & \min_{K_{\text{disk}}, \mathbb{P}} \text{Join}(K_{\text{disk}}, \mathbb{P}, m) \\ & \text{subject to} \quad \left\lceil \frac{n - |K_{\text{disk}}|}{b_R} \cdot F \right\rceil + m + 2 \leq B, \\ & \quad \sum_{j=1}^m \mathbb{P}_{i,j} = 1, \forall i \in [n] \\ & \quad \mathbb{P}_{i,j} \in \{0, 1\}, \forall i \in [n], j \in [m] \end{aligned}$$

where the first constraint limits the size of the memory-resident hash table, as 2 pages are reserved for input and join output, and m pages for the output buffer for each disk-resident partition.

The integer program above can be interpreted by first fixing the K_{disk} (i.e., which keys/records should be spilled out to disk), and then finding the optimal partitioning for K_{disk} . Our Algorithm OCAP can be invoked as a primitive for given K_{disk} . It remains to identify the optimal K_{disk} (i.e., which records should be spilled out

to disk) that leads to the overall minimum cost. Although there is an exponentially large number of candidates for K_{disk} , it is easy to see that records with low CT value should be spilled out to disk, while records with high CT values should be kept in memory. In other words, the consecutive property of Theorem 3.1 still applies for this hybrid partitioning – we can achieve the optimal cost by caching the top- k records from CT in memory, if restricting the size of K_{mem} to be k , where $k < c_R$ since at most c_R records can remain in memory. By extending Algorithm 5 to a hybrid version, we finally come to the OCAP in Algorithm 7.

Complexity Analysis. As the number of records that can remain in memory is at most $c_R = \lfloor b_R \cdot (B - 2)/F \rfloor$, we run Algorithm 5 at most c_R times. Recall that the complexity of Algorithm 5 can be reduced to $O(n^2 \log m / c_R^2)$, the time complexity for OCAP is now $O(n^2 \log m / c_R) = O(n^2 \log m / m)$. The space complexity is $O(n)$.

4 OUR PRACTICAL ALGORITHM

In practice, it is impossible to know the exact correlation between input relations for each key in advance; instead, a much smaller set of high-frequency keys are collected for skew optimization, such as the Most Common Values (MCVs) in PostgreSQL [44]. PostgreSQL supports skew optimization by assigning 2% memory to build a hash table for skewed keys if their total frequency is larger than 1% of the outer relation, but this heuristic uses fixed thresholds to trigger skew optimization, which may be sub-optimal for arbitrary correlation skewness. Hence, we present a practical algorithm built upon the theoretically I/O-optimal algorithm in the previous section. Instead of relying on the whole correlation CT table, our practical algorithm only needs the same amount of MCVs as PostgreSQL and generates a hybrid partitioning that can be adaptive to arbitrary correlation skewness, and constrained memory budget.

4.1 Hybrid Partitioning

Let K be the set of skew keys tracked from MCVs with their CT values known. Guided by the consecutive property and weakly-ordered property in Theorem 3.1, it is always efficient to keep as many skew keys as possible in memory if possible, so that we can avoid reading the corresponding records in S repeatedly. For the rest of keys not tracked by MCVs, we consider their frequency as low and can be tackled well by the traditional hashing method GHJ/DHH.

Framework. In a hybrid partitioning, we design a hash set HS_{mem} to store a subset of skew key (denoted as $K_{\text{mem}} \subseteq K$) that will be used to build the in-memory hash table HT_{mem} , a hash map f_{disk} to store a subset of skew keys (denoted as $K_{\text{disk}} \subseteq K$) with their designated partition identifiers, and the rest of skew keys (if there exists any) together with non-skew keys (denoted as K_{rest}) will be uniformly partitioned by GHJ/DHH with a certain memory budget m_{rest} (in pages). With HS_{mem} , f_{disk} and m_{rest} in hand, we can partition records in R using Algorithm 8. For each record in R , if its key is in HS_{mem} , we put the entire record in the in-memory hash table HT_{mem} (the hash set HS_{mem} only stores the key); if its key belongs to f_{disk} , we put it into the partition specified by f_{disk} , which will be spilled to disk later; otherwise, it will be assigned by GHJ/DHH along with the rest of the records using the m_{rest} pages reserved. We can partition records in S similarly using Algorithm 9. This hybrid partitioning workflow is visualized in Figure 5.

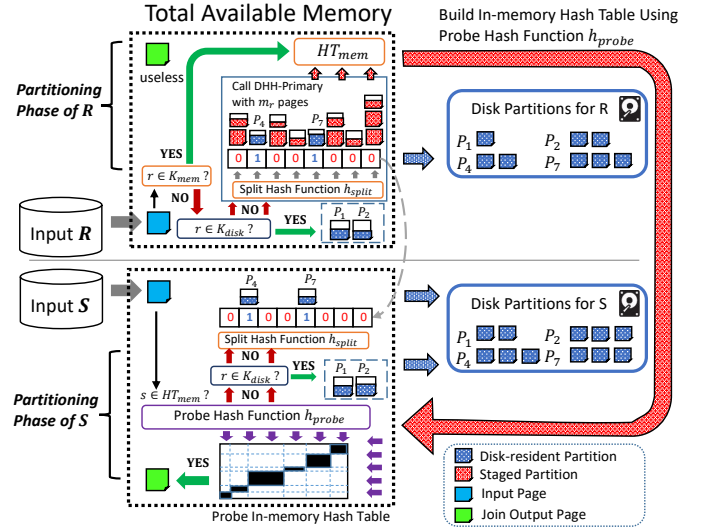


Figure 5: An illustration of hybrid partitioning workflow of NOCAP. Partitions P_4 and P_7 are spilled to disk when invoking DHH, while P_1 and P_2 are written to disk due to designated partitioning by f_{disk} . Other records in R either have keys from K_{mem} or stage in memory when invoking DHH, which will be inserted to the in-memory hash table HT_{mem} .

Algorithm 8: HYBRID-PARTITION-PRIMARY($R, HS_{\text{mem}}, f_{\text{disk}}, m_{\text{rest}}$)

```

1  $R' \leftarrow \{r \in R : r.\text{key} \notin HS_{\text{mem}} \text{ and } r.\text{key} \notin f_{\text{disk}}\}$ ;
2    $\triangleright$  Logically construct  $R'$  without instantiation;
3 foreach  $r \in R - R'$  do
4   if  $r.\text{key} \in HS_{\text{mem}}$  then add  $r$  to  $HT_{\text{mem}}[h_{\text{probe}}(r.\text{key})]$ ;
5   else assign  $r$  to disk-resident partition  $f_{\text{disk}}(r.\text{key})$ ;
6  $(HT'_{\text{mem}}, \text{POB}) \leftarrow \text{DHH-PRIMARY}(R', m_{\text{rest}})$ ;
7 return  $(HT'_{\text{mem}} \cup HT_{\text{mem}}, \text{POB})$ 

```

Algorithm 9: HYBRID-PARTITION-FOREIGN($S, HT_{\text{mem}}, f_{\text{disk}}, \text{POB}$)

```

1  $S' \leftarrow \{s \in S : s.\text{key} \notin f_{\text{disk}}\}$ ;
2    $\triangleright$  Logically construct  $S'$  without instantiation;
3 foreach  $s \in S'$  do
4   if  $s.\text{key} \in f_{\text{disk}}$  then
5     assign  $s$  to disk-resident partition  $f_{\text{disk}}(s.\text{key})$ 
6  $\text{DHH-FOREIGN}(S - S', HT_{\text{mem}}, \text{POB})$ ;

```

Regarding whether to use GHJ or DHH, we note the following difference. When the available memory is large, say $\lceil |K_{\text{rest}}|/c_R \rceil < m_{\text{rest}}$, we simply invoke DHH to partition the rest of keys K_{rest} using m_{rest} pages. When the available memory is small, as discussed in Section 2.2, the DHH just downgrades to the GHJ.

Enforcing Memory Constraints. State-of-the-art systems (e.g., MySQL and PostgreSQL) typically assign to each join operator a user-defined memory budget. The default memory limit for the join operator in MySQL is 256 KB [37] and the one in PostgreSQL is 4 MB [45]. Assuming the available buffer is in total B pages, we need

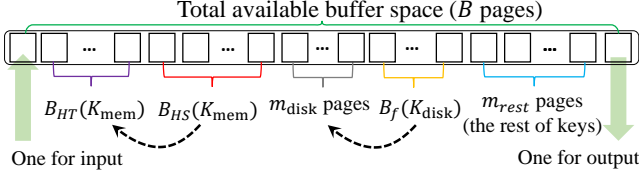


Figure 6: The memory breakdown when partitioning R .

to ensure that Algorithm 8 uses no more than B pages. We present a memory breakdown as illustrated in Figure 6.

- $B_{HS}(K_{\text{mem}})$: #pages for the hash set HS_{mem} with keys in K_{mem} ;
- $B_{HT}(K_{\text{mem}})$: #pages for the hash table HT_{mem} with records whose keys are in K_{mem} ;
- $B_f(K_{\text{disk}})$: #pages for the hash map f_{disk} with keys in K_{disk} ;
- m_{disk} : #pages as write buffer for all the on-disk partitions specified in f_{disk} (which is the same as #partitions specified in f_{disk});
- m_{rest} : #pages to partition records whose keys are in K_{rest} ;

Moreover, we denote ks as the size of each key (in bytes), and ps as the size of each page (in bytes). We can roughly have $B_{HT}(K_{\text{mem}}) = \lceil b_R \cdot |K_{\text{mem}}| / F \rceil$, $B_{HS}(K_{\text{mem}}) = \lceil ks \cdot |K_{\text{mem}}| / (F \cdot ps) \rceil$, and $B_f(K_{\text{disk}}) = \lceil (ks + 4) \cdot |K_{\text{disk}}| / (F \cdot ps) \rceil$, where a 4-byte integer is used to store the partition identifier in the hash map f_{disk} . Finally, we come to the memory constraint subject to the total number of pages as B :

$$B_{HS}(|K_{\text{mem}}|) + B_{HT}(|K_{\text{mem}}|) + B_f(|K_{\text{disk}}|) + m_{\text{disk}} + m_{\text{rest}} \leq B - 2$$

Cost function. Combining all these above together, we come to the cost function and integer programming as follows:

$$\begin{aligned}
 & \min_{K_{\text{mem}}, K_{\text{disk}}, \mathbb{P}_{\text{disk}}} \text{Join}(K_{\text{disk}}, \mathbb{P}_{\text{disk}}, m_{\text{disk}}) + g_{\text{DHH}}(|K_{\text{disk}}|, m_{\text{rest}}) \\
 & \text{s.t. } B_{HS}(|K_{\text{mem}}|) + B_{HT}(|K_{\text{mem}}|) + B_f(|K_{\text{disk}}|) \\
 & \quad \leq B - 2 - m_{\text{disk}} - m_{\text{rest}}, \\
 & \quad 0 \leq m_{\text{disk}}, 0 \leq m_{\text{rest}} \leq B - 2, \\
 & \quad K_{\text{mem}} \cap K_{\text{disk}} = \emptyset, K_{\text{mem}} \cup K_{\text{disk}} \subseteq K \\
 & \quad \sum_{j=1}^m \mathbb{P}_{i,j} = 1, \forall i \in [n] \\
 & \quad \mathbb{P}_{i,j} \in \{0, 1\}, \forall i \in [n], \forall j \in [m]
 \end{aligned}$$

In the objective function, the first term $\text{Join}(K_{\text{disk}}, f_{\text{disk}}, m_{\text{disk}})$ is the cost of partitioning K_{disk} into m_{disk} partitions, and the second term $g_{\text{DHH}}(|K_{\text{rest}}|, m_{\text{rest}})$ is the estimated cost of partitioning K_{rest} with m_{rest} pages using either GHJ or DHH, depending on how large m_{rest} is, as mentioned earlier. We will discuss $g_{\text{DHH}}(|K_{\text{disk}}|, m_{\text{rest}})$ in Section 4.2. In both estimation models of GHJ or DHH, we need to know the total number of records from S whose key falls into K_{rest} , which can be estimated by $n_S - \sum_{i \in K_{\text{mem}} \cup K_{\text{disk}}} \text{CT}[i]$, since the CT values of keys in K are known from MCVs.

To find out the best combination of K_{mem} , K_{rest} and f_{disk} (the optimal value of m_{rest} can be calculated using Equation (6)), we iterate all possible combinations of $|K_{\text{mem}}|$, $|K_{\text{disk}}|$ and f_{disk} , and pick the one with the minimum estimated cost, as described by Algorithm 10. Then, implied by the consecutive property and weakly-ordered property in Theorem 3.1 (i.e., keys with higher frequency should be kept in memory or in a small partition with higher priority), we always pick the top- $|K_{\text{mem}}|$ keys from K as K_{mem} and the next top- $|K_{\text{disk}}|$ keys from K as K_{disk} .

Algorithm 10: NOCAP(CT, k , n , m)

```

1   $c_{\text{opt}} \leftarrow +\infty, k_{\text{mem}} \leftarrow 0, k_{\text{disk}} \leftarrow 0, f_{\text{disk}} \leftarrow \emptyset;$ 
2  for  $i_1 \leftarrow 0$  to  $\min(k, c_R)$  do
3       $V \leftarrow \text{PARTITION}(\text{CT}[i_1 + 1 : k], k - i_1, \lceil \frac{k - i_1}{c_R} \rceil);$ 
4      for  $i_2 \leftarrow 0$  to  $\min(k, c_R) - i_1$  do
5          for  $j \leftarrow \min(i_2, 1)$  to  $\lceil \frac{i_2}{c_R} \rceil$  do
6               $m_{\text{rest}} \leftarrow B - 2 - B_{HT}(i_1) - B_{HS}(i_1) - B_f(i_2) - j;$ 
7               $c_{\text{probe}} \leftarrow V[i_2][j].\text{cost};$ 
8               $c_{\text{part}} \leftarrow \mu \cdot \left( \lceil \frac{i_2}{b_R} \rceil + \lceil \frac{1}{b_S} \cdot \sum_{j=i_1+1}^{j=i_2} \text{CT}[j] \rceil \right);$ 
9               $c_{\text{rest}} \leftarrow g_{\text{DHH}}(i_2 + 1, n, m_{\text{rest}});$ 
10              $c_{\text{tmp}} \leftarrow c_{\text{probe}} + c_{\text{part}} + c_{\text{rest}};$ 
11             if  $c_{\text{tmp}} < c_{\text{opt}}$  then
12                  $c_{\text{opt}} \leftarrow c_{\text{tmp}}, k_{\text{mem}} \leftarrow i_1, k_{\text{disk}} \leftarrow i_2;$ 
13                  $f_{\text{disk}} \leftarrow \text{GETCUT}(V, i_2, j);$ 
14 return  $k_{\text{mem}}, k_{\text{disk}}, f_{\text{disk}};$ 

```

4.2 Optimizations with Rounded Hash

In our implementation, we also design *rounded hash* (RH) in partitioning that can further reduce the I/O cost of scanning the outer relation in the per-partition join. This is motivated by the divisible property in Theorem 3.1, that the sizes of most partitions should be divisible by c_R in the optimal partitioning. To understand why this insight may help, let us consider an example in Figure 7.

We note that uniform partitioning namely assigns records using a uniform hash function $\text{PartID} = \text{hash}(\text{key}) \bmod m$, based on the modular function with respect to m (the number of partitions), which is denoted as *plain hash* (PH). To reduce the extra I/O cost using non-uniform partitioning, our RH uses an additional modular function with respect to $\lceil n/c_R \rceil$:

$$\text{PartID} = (\text{hash}(\text{key}) \bmod \lceil n/c_R \rceil) \bmod m \quad (2)$$

where $c_R = \lfloor b_R \cdot (B - 2) / F \rfloor$ is the chunk size of records. Intuitively, our RH maximizes the number of partitions with $\lfloor \lceil n/c_R \rceil / (B - 1) \rfloor$ chunks. In addition to reducing unnecessary passes, RH also merge small partitions to avoid fragmentation when partitioning [29].

Parametric Optimization. Since we rely on a hash function to partition records, partitions 1 and 2 in Figure 7 could occasionally “overflow” and grow larger than six pages due to randomness. In a skewed workload, overflowed partitions could result in higher cost compared to the cost of uniform partitioning. In fact, a more robust scheme in Figure 7 is to assign 2.5 pages to partition 4 and evenly distribute 15.5 pages to partitions 1, 2, and 3. Formally, we replace c_R with $c_R^* = \beta \cdot c_R$ in Equation (2), where β should be very close to 1 in the range $(0, 1]$ (we fix $\beta = 0.95$ in our implementation).

Cost Estimation. To get a rough estimation of how many I/Os are used by RH, we first build the I/O model for PH-based partitioning. We actually consider a generalized problem by estimating the per-partition cost for partitioning records lying on the CT array from index s to index e into m partitions using PH, noted by $g_{\text{PH}}(s, e, m)$:

$$g_{\text{PH}}(s, e, m) = \sum_{j=1}^m \mathbb{E} \left[\left\lceil \frac{|P_j|}{c_R} \right\rceil \right] \cdot \sum_{i \in P_j} \text{CT}[i] = \left\lceil \frac{e - s + 1}{m \cdot c_R} \right\rceil \cdot \sum_{i=s}^e \text{CT}[i]$$

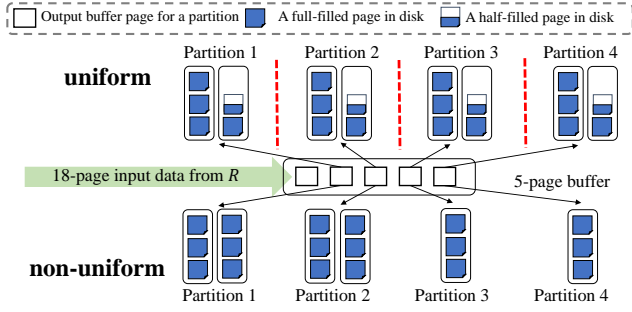


Figure 7: An illustration of the uniform and non-uniform partitioning on the inner relation R , with a 5-page buffer (with 4 pages for partitioning R and 1 page for streaming the input). In NBJoin, the maximum #chunks loaded at a time is 3-page long (with 1 page for streaming S and 1 page for the output assuming $F = 1.0$). Uniform hash partitioning generates 4 partitions with each having $18/4 = 4.5$ pages worth of data. One needs to read S twice for each partition. As a comparison, rounded hashing with $n/c_R = 6$ and $m = 4$ generates 2 partitions with each having 6 pages, and 2 partitions with each having 3 page worth of data. In that way, partitions 1 and 2 need two passes on the corresponding partitions in S , while partitions 3 and 4 only need a single pass.

where each $\|P_j\|$ is approximated as a Poisson distribution with $\lambda = \frac{e-s+1}{m}$. When estimating the cost of RH we need to know how much proportion (noted by γ) of data from S is scanned with one fewer pass ($1 - \gamma$ of data is scanned with one more pass):

$$\gamma = \left(\left(\left\lfloor \frac{e-s+1}{c_R^*} \right\rfloor \bmod m \right) \cdot \left\lfloor \frac{e-s+1}{m \cdot c_R^*} \right\rfloor \cdot c_R^* \right) / (e-s+1)$$

As such, the normalized number of rounded passes is:

$$\text{\#rounded_passes}(s, e) = \gamma \cdot \left\lfloor \frac{e-s+1}{m \cdot c_R^*} \right\rfloor + (1 - \gamma) \cdot \left\lfloor \frac{e-s+1}{m \cdot c_R^*} \right\rfloor + 1$$

We then have our cost model for rounded hash g_{RH} :

$$g_{RH}(s, e, m) = \text{\#rounded_passes}(s, e) \cdot \sum_{i=1}^e \text{CT}[i] \quad (3)$$

The cost of our original problem is captured by $g_{RH}(1, n, m)$.

Overestimation using Chernoff Bound. When the filling percent for each partition using PH reaches the predefined threshold β , $(\frac{e-s+1}{m} > \beta \cdot t \cdot c_R)$, where t is the largest positive integer such that $t \cdot c_R > \frac{e-s+1}{m}$, we disable RH. This is to avoid additional passes that are triggered by occasional overflow in the random process. We also need to take into account the possible overflow when estimating the cost. In fact, every element is distributed independently and identically using the same hash function, and thus we can apply Chernoff bound to overestimate the probability. For an arbitrary partition, we define $X = \sum_{i=1}^e X_i$ where $X_i = 1$ (i.e., i -th element is assigned to this partition) with the probability $\frac{1}{m}$, and $X_i = 0$ with probability $1 - \frac{1}{m}$. Then $\mathbb{E}[X] = \frac{e-s+1}{m}$. From Chernoff bound, $\Pr[X > t \cdot c_R] < \left(\frac{e^\sigma}{(1+\sigma)^{1+\sigma}} \right)^{\mathbb{E}[X]}$, where $\sigma = \frac{t \cdot c_R \cdot m}{e-s+1} - 1$. We thus

let $1 - \gamma = \left(\frac{e^\sigma}{(1+\sigma)^{1+\sigma}} \right)^{\mathbb{E}[X]}$ and set:

$$\text{\#rounded_passes}(s, e) = \gamma \cdot \left\lfloor \frac{e-s+1}{m \cdot c_R^*} \right\rfloor + (1 - \gamma) \cdot \left(\left\lfloor \frac{e-s+1}{m \cdot c_R^*} \right\rfloor + 1 \right)$$

We then reuse Equation (3) to estimate the I/O cost.

5 EXPERIMENTAL ANALYSIS

We now present experimental results for our practical method.

Approaches Compared. We compare NOCAP with Grace Hash Join (GHJ), Sort-Merge Join (SMJ), and Dynamic Hybrid Hash join (DHH). For all the **partitioning-based** methods (GHJ, DHH, and ours), we apply a light optimizer that picks the most efficient algorithm according to Table 1 in the partition-wise join. We also augment GHJ by allowing it to fall back to NBJoin if the latter has a lower cost. For DHH, we follow prior approaches that use fixed thresholds to trigger skew optimization (2% of the available memory is used for an in-memory hash table for skew keys if the sum of their frequency is larger than 2% of the relation size). We also compare Histojoin (by setting the trigger frequency threshold as zero) as one of our baselines. All the approaches are implemented in C++, compiled with gcc 10.1.0, in a CentOS Linux with kernel 4.18.0. For NOCAP, DHH, and Histojoin, we assume top $k = 50K$ frequently matching keys are tracked (i.e., 5% of the keys when $n = 1M$). In PostgreSQL’s implementation of DHH, the frequent keys are stored using a small amount of system cache, which **does not consume the user-defined working memory budget unless they are inserted into the in-memory hash table**. Similarly, in our prototype, the top- k keys are given. Due to the pruning techniques (§3.1.3), computing the partitioning scheme (Alg. 10) with $k = 50K$ takes less than one second, so we omit its discussion.

5.1 Sensitivity Analysis

We now experimental results with synthetic data produced by our workload generator that allows us to customize the distribution of matching keys between two input relation to test the robustness of different join methods.

Experimental Setup. We use our in-house server, which is equipped with **375GB memory in total** and two Intel Xeon Gold 6230 2.1GHz processors, each having 20 cores with virtualization enabled. For our storage, we use a **350GB PCIe P4510 SSD** with direct I/O enabled. We can change the read/write asymmetry by turning the `O_SYNC` flag on and off. When `O_SYNC` is on, every write is ensured to flush to disk before the write is completed, and thus has higher asymmetry ($\mu_{sync} = 3.3$, $\tau_{sync} = 3.2$). When it is off, we have lower asymmetry ($\mu_{no_sync} = 1.28$, $\tau_{no_sync} = 1.2$). By default, sync I/O is off to accelerate joins.

Experimental Methodology. We first experiment with a synthetic workload, which contains two tables R and S with $n_R = 1M$ and $n_S = 8M$. The record size is 1KB for both R and S , and thus we have $\|R\| = 250K$ pages and $\|S\| = 2M$ pages (the page size is fixed as 4KB in all the experiments). In this experiment, we vary the buffer size from $0.5 \cdot \sqrt{F \cdot \|R\|} \approx 256$ pages to $\|R\| = 250K$ pages. We use #I/Os (reads + writes) and latency as two metrics, and when comparing #I/Os, we also run OCAP (§3.2) to plot the optimal (lower bound) #I/Os.

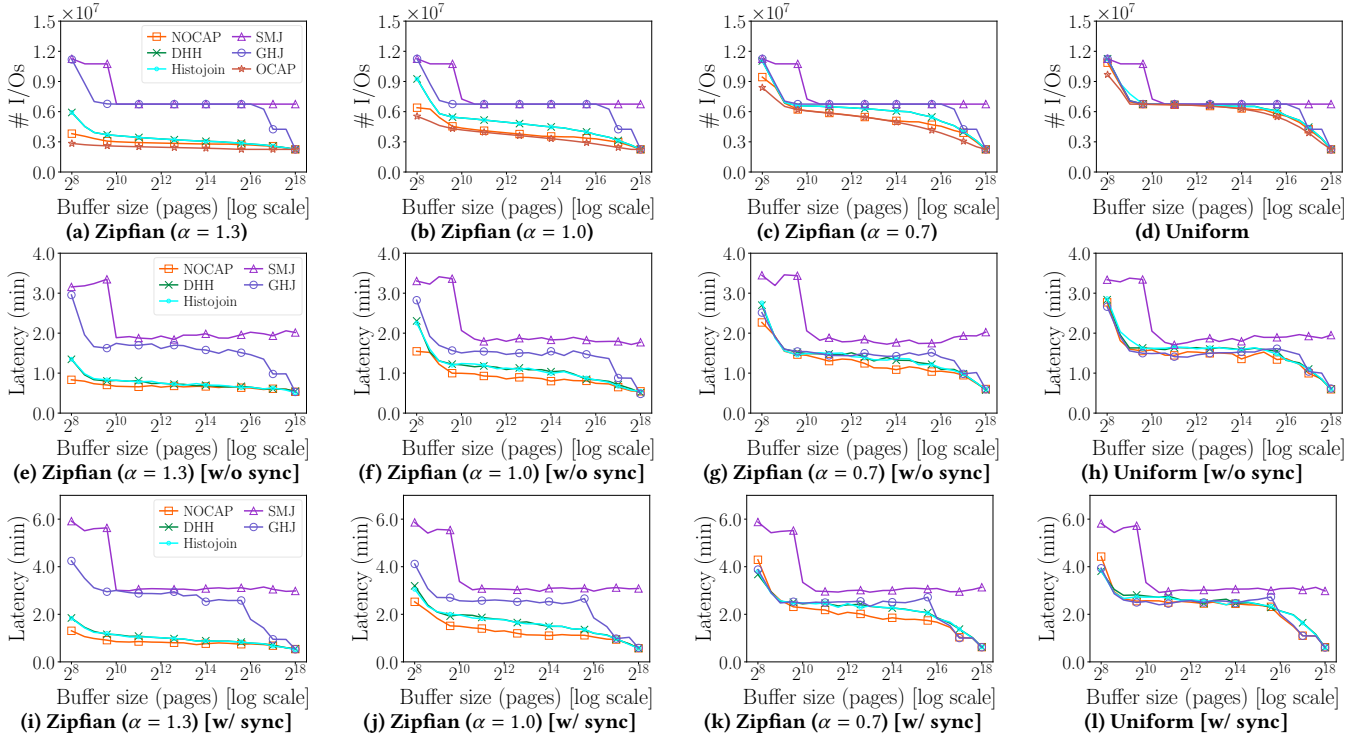


Figure 8: While state-of-the-art skew optimization in DHH helps reduce the I/O cost, NOCAP can better exploit the correlation skew to achieve even lower I/O cost and latency. The benefit of NOCAP is more pronounced with skew correlation.

NOCAP Dominates for any Correlation Skew and any Memory Budget. For all the join methods, #I/Os decreases as the buffer size increases, as shown Figures 8a-8d. We also observe that NOCAP achieves the lowest #I/Os (near-optimal) among all the join algorithms for any correlation skew and any memory budget. When we compare latency from Figures 8e-8h, we also conclude that GHJ and SMJ have a clear gap while they have nearly the same #I/Os regardless of the join correlation. This is because random reads in SMJ are $1.2\times$ slower than sequential reads in GHJ. While two traditional join methods have no optimization for skewed join correlations, DHH, Histojoin, and NOCAP can take advantage of correlation skew to alleviate #I/Os. However, DHH and Histojoin cannot fully exploit the data skew because it limits the space for high-frequency keys with a fixed threshold (2% of the total memory budget). Compared to DHH and Histojoin, NOCAP normally has fewer #I/Os because it freely decides the size of the in-memory hash table for frequent keys without any predefined thresholds. Figures 8f-8h show that the latency gap between NOCAP and DHH (Histojoin) is more pronounced when we have medium skew ($\alpha = 1$ or $\alpha = 0.7$), compared to the uniform correlation. However, when the correlation is highly skewed ($\alpha = 1.3$), the small hash table (2% of the available memory) in DHH is enough to capture the most frequent keys and, hence, issue near-optimal #I/Os (Figure 8a). As a result, the benefit of NOCAP for $\alpha = 1.3$ (Figure 8e) is smaller than for $\alpha = 1$ (Figure 8f). Nevertheless, NOCAP still issues 30% fewer #I/Os when the memory budget is small (2^8 pages).

DHH Cannot Adapt to Different Memory Budget. The skew optimization in DHH relies on two thresholds (memory budget and minimum frequency) and thus it cannot easily adapt to a different

memory budget. To verify this, we compare DHH with NOCAP under a given Zipfian correlation ($\alpha = 0.7$) using as memory budgets 2MB and 32MB. Figures 9a and 9b show the the percentage of reduced #I/Os using NOCAP based on DHH when we vary the two thresholds used by DHH. When $B = 2\text{MB}$, the best DHH (the darkest cell) does not trigger skew optimization by setting a high frequency trigger threshold or the memory budget as zero. In contrast, when $B = 32\text{MB}$, the best DHH assigns 8% memory to build the hash table for skewed keys. Note that even though DHH can achieve close-to-NOCAP performance by varying these two thresholds, this relies on well-tuned parameters, which may not be feasible when the workload and the buffer size changes.

NOCAP Outperforms DHH Even for Uniform Correlation with Small Memory Budget. We also examine the speedup when we have a lower memory budget. Although Figures 8l and 8h show that there *seems* no difference between DHH and NOCAP when the workload is uniform, we actually capture a larger difference after we narrow down the buffer range (128~512 pages). As shown in Figure 10a, NOCAP can even achieve up to 15% and 10% speedup when there are 480 and 352 pages. The step-wise pattern of DHH and GHJ comes from random (uniform) partitioning. When the memory is smaller than $\sqrt{\|R\|} \cdot F$, uniform partitioning easily makes each partition larger than the chunk size, as illustrated in Figure 7. On the contrary, rounded hash allows some partitions to be larger so that other partitions have fewer chunks and thus require fewer passes to complete the partition-wise joins. When the correlation becomes more skewed, NOCAP can be more than 30% faster than DHH under limited memory, as shown in Figure 10b.

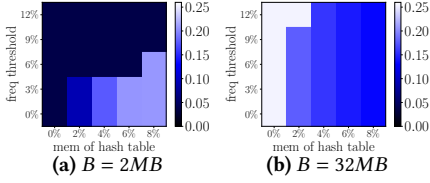


Figure 9: DHH requires careful manual tuning to achieve its best performance, which is still slower than NOCAP.

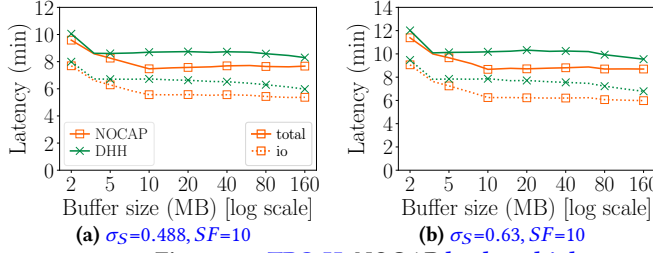


Figure 12: TPC-H: NOCAP leads to higher speedup when more data from S are joined in a query.

DHH and NOCAP Both Exhibit Robustness for Noisy MCVs. To examine how noisy CT can affect DHH and NOCAP, we add Gaussian noise to the CT values, with the average noise as 0 (the value of the average noise has no impact over MCVs) and $\sigma = n_S/n_R$. We reuse most of experimental settings so that $n_S/n_R = 8$ and thus $CT_{noise}[i] \in [CT[i]-8, CT[i]+8]$ with probability 68%. We redo the experiments with uniform and Zipfian join correlation ($\alpha = 0.7$), and the results are shown in Figure 11. We do not observe a significant difference between the results with noisy CT values and the original results in Figures 8. The rational behind this is that keys with high frequency are still likely to be prioritized (cached) during hybrid partitioning even after we add the Gaussian noise, thus having very similar performance to the results without noise.

5.2 Experiments with TPC-H, JCC-H, and JOB

We now experiment with TPC-H [53], JCC-H [11], and JOB [31], using DHH as our main competitor.

Experimental Setup. We experiment with a modified TPC-H Q12. Q12 selects data from table `lineitem`, and joins them with orders on `l_orderskey=o_orderskey`, followed by an aggregation. As we have already seen, DHH has only a minor difference from NOCAP when the correlation is uniform. Here, we focus on a skew correlation in TPC-H data. To achieve this, we modify the TPC-H dbgen codebase – all the keys are classified into *hot* or *cold* keys, and the frequency of hot keys and cold keys, respectively, follows two different uniform distributions, which controls the overall skew and the average matching keys [13, 15]. In this experiment, we focus on a skew correlation where 0.5% of the `o_orderkey` keys match 500 `lineitem` records on average and the rest keys only match 1.5 `lineitem` records on average.

We further remove the filtering condition on `l_shipmode` and `l_receiptdate` so that the size of the filtered `lineitem` is larger than orders (since we focus on the case when $|R| < |S|$). We then have two conditions left, `l_receiptdate < l_shipdate` and `l_shipdate < l_commitdate`, which has separately selectivity 0.488 and 0.63. We choose one of filter conditions to vary the selectivity. We run our experiments with these two selectivity and two scale factors ($SF=10, SF=50$), as shown in Figure 12. In these experiments,

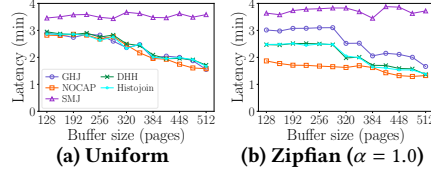


Figure 10: When the memory is limited, NOCAP can reach 10% speedup even if the workload is uniform.

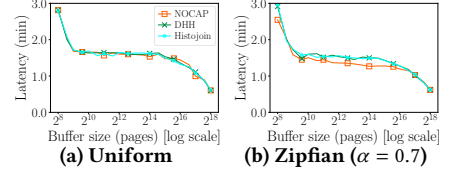


Figure 11: With noisy MCVs, both DHH and NOCAP have similar performance to Figures 8h and 8g.

we employ storage-optimized AWS instances (*i3.xlarge*) and we turn off `O_SYNC`. The device asymmetry is $\mu = 1.2$ and $\tau = 1.14$.

NOCAP Accelerates TPC-H Joins. We observe that the difference in the total latency between NOCAP and DHH is not so large as we see in previous experiments on skew correlation in Figure 12a. In fact, we find that the proportion of time spent on I/Os is lower in the TPC-H experiment due to extra aggregations in Q12. In earlier experiments (e.g., Figures 8f and 8g), the time spent on CPU is 10~20 seconds out of a few minutes (the total latency). In contrast, we observe that in both Figures 12a and 12b, the proportion of time spent on I/Os is less than 85%. This explains why the speedup of NOCAP diminishes when we have more CPU-intensive operations (e.g., aggregation) in a query. In addition, when we adjust the selectivity so that more data from `lineitem` are involved in the join, we observe a higher benefit in Figure 12b. We have similar observation when we move to a larger data set ($SF=50$), as shown in Figures 12c and 12d. In fact, in both cases, when we have larger `lineitem` data involved in the join, NOCAP usually leads to higher speedup.

NOCAP Outperforms DHH for JCC-H and JOB. To further validate the effectiveness of NOCAP, we experiment with JCC-H (Join Cross Correlation) and JOB (Join Order Benchmark). JCC-H is built on top of TPC-H with adding join skew, so we reuse our TPC-H experimental setup (running the modified Q12 with $SF = 10$ and $\sigma_S = 0.488$). In the original JCC-H dataset, the majority (i.e., $300K \cdot SF$) of `lineitem` records only join with 5 orders records. To vary the skew, we tune the code by allowing around $5100 \cdot SF$ orders records to match 600 `lineitem` records on average. In addition to JCC-H, we also compare DHH and NOCAP by executing a PK-FK join between two tables from the JOB dataset. Specifically, `cast_info` stores the cast info between movies and actors, which are respectively stored in tables `title` and `name`. The number of movies per actor is highly skewed where the top 50 actors match 0.6% records in `cast_info`, while the number of actors per movie is less skewed where the top 50 movies match less than 0.1% records in `cast_info` (“top” in terms of the number of occurrences in `cast_info`). As we can observe in Figures 13a-d, when the correlation is extremely skewed (i.e., the original JCC-H

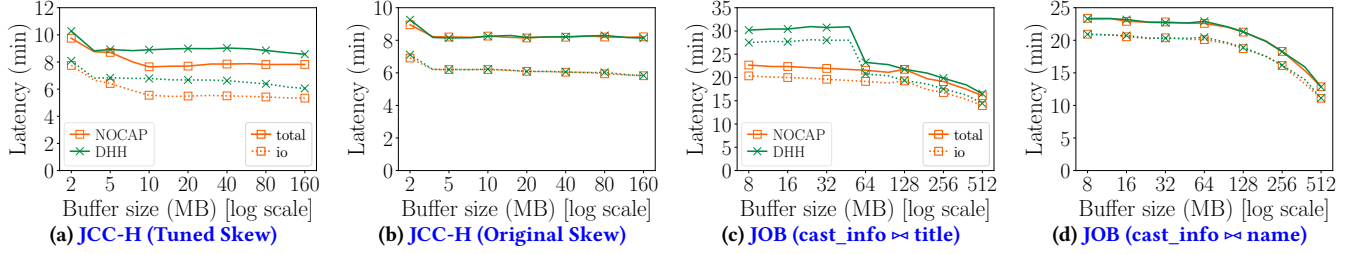


Figure 13: While DHH sometimes performs as close as NOCAP, NOCAP is more adaptive when the workload varies.

and `cast_info <=> name`), DHH with fixed thresholds can identify the skew and exploit it to achieve close-to-NOCAP performance. However, when it comes to medium skewed (i.e., tuned JCC-H and `cast_info <=> title`), DHH with fixed thresholds results in suboptimal performance compared to NOCAP.

6 DISCUSSION

What If $\|R_j\| \geq \|S_j\|$ for some $j \in [m]$ in Section 3? We first focus on a simple case that $\|R_j\| \geq \|S_j\|$ holds for each $j \in [m]$. Then, the join cost of the general case will be upper bounded by the sum of cost for the case discussed in Section 3 and the case discussed below. In this case, NBJ builds an in-memory hash table for $\|S_j\|$, and thus the join cost function becomes:

$$\begin{aligned} \text{Join}(\mathbb{P}, m) &= \|S\| + \sum_{j=1}^m \left\lceil \frac{\|S_j\|}{(B-2)/F} \right\rceil \cdot \|R_j\| \\ &\leq \|S\| + \sum_{j=1}^m \left(\frac{\|S_j\|}{(B-2)/F} + 1 \right) \cdot \|R_j\| \\ &\leq \|S\| + \frac{1}{c_S \cdot b_R} \cdot \left(\sum_{i=1}^n \text{CT}[i] \cdot |\mathcal{N}_f(i)| \right) + \frac{n_S}{c_S} + 2 \cdot m + \|R\| \end{aligned}$$

where $c_S = \lfloor b_S \cdot (B-2)/F \rfloor$. To minimize $\text{Join}(\mathbb{P}, m)$, it suffices to minimize the term $\sum_{i=1}^n \text{CT}[i] \cdot |\mathcal{N}_f(i)|$, which inherits the same spirit as the other case in Section 3. Hence, our main theorem in Section 3.1.2 with consecutive property and ordered property still holds (divisible property does not hold), and it can be solved by the dynamic programming in Section 3.1.3.

General (Many-to-Many) Joins. In many-to-many joins, we have two CT lists that store the frequency per key in each relation, and thus we need to create a new cost function (with two CT lists) to use as the main objective function. Despite that, we can still reuse our dynamic programming algorithm 5 and replace CalCost by considering extra CT values, however, the error bound is no longer guaranteed since our main theorem does not hold. In practice, even this crude approximation of the optimal partitioning for general joins is worth exploring since the CPU cost of enumerating partitioning schemes is very low, and it covers the design space of DHH with variable values for its two thresholds. As a result, NOCAP is still expected to outperform DHH for general joins. We leave the complete formulation for many-to-many joins as future work.

On-the-fly Sampling. On-the-fly sampling can give us more accurate CT values because it takes into account the applied predicate while MCVs rely only on the estimated selectivity. However, relying on sampling without knowledge of MCVs makes the partitioning operation not pipelineable with the scan/select operator. This is because partitioning relies on the exact join correlation, but in case

of sampling we need one complete pass first to acquire this information. In this case, we may downgrade NOCAP into DHH to avoid the additional pass. Another approach proposed by Flow-join [48] is to employ a streaming sketch to obtain an approximate distribution during partitioning. However, this requires scanning S first to build the histogram, which conflicts with partitioning R first in the hybrid join. On the other hand, if we already have MCVs (note that it is acceptable to be noisy), sampling on-the-fly to enable sideways information passing (SIP) [40] can be helpful. Specifically, we can sample R on-the-fly during partitioning and build a Bloom Filter, which is later used when partitioning/scanning S . The additional Bloom Filter makes the estimated CT more accurate, and thus the partitioning generated by NOCAP can get closer to expected #I/O cost. However, adding a BF in the memory also introduces new trade-offs between performance and memory consumption.

7 RELATED WORK

In-Memory Joins. When the memory is enough to store the entire relations, in-memory join algorithms can be applied [6, 7, 34, 43, 50, 52]. Similar to storage-based joins, in-memory join algorithms can be classified as hash-based and sort-based (e.g., MPSM [1] and MWAY [4]). Hash joins can be further classified into partitioned joins (e.g., parallel radix join [4]) and non-partitioned joins (e.g., CHT [5]). GPUs can also be applied to accelerate in-memory joins [22, 35, 49]. Although storage-based joins focus on #I/Os, when two partitions both fit in memory after the partitioning phase, NOCAP can still benefit from optimized in-memory joins.

Distributed Equi-Joins. In a distributed environment, the efficiency of equi-joins also relies on load balance and communication cost. When the join correlation distribution is skewed, uniform partitioning may overwhelm some workers by assigning excessive work to do [54]. More specifically, when systems like Spark [57] rely on in-memory computations, the overall performance drops when the transmitted data for a machine do not fit in memory. Several approaches [8, 32, 48, 56] are proposed to tackle the data (and thus, workload) skew for distributed equi-joins.

8 CONCLUSIONS

In this paper, we propose a new cost model for partitioning-based PK-FK joins that allows us to find the optimal partitioning strategy assuming accurate knowledge of the join correlation. Using this optimal partitioning strategy, we show that the state-of-the-art Dynamic Hybrid Hash Join (DHH) yields sub-optimal performance since it does not fully exploit the available memory and the correlation skew. To address DHH's limitations, we develop a practical near-optimal partitioning-based join with variable memory requirements (NOCAP) which is based on OCAP. We show that NOCAP dominates the state-of-the-art for any available memory budget and for any join correlation, leading to up to 30% improvement.

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