AJoin: Ad-hoc Stream Joins at Scale

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ABSTRACT

The processing model of state-of-the-art stream processing engines is designed to execute long-running queries one at a time. However, with the advance of cloud technologies and multi-tenant systems, multiple users share the same cloud for stream query processing. This results in many ad-hoc stream queries sharing common stream sources. Many of these queries include joins.

There are two main limitations that hinder performing ad-hoc stream join processing. The first limitation is missed optimization potential both in stream data processing and query optimization layers. The second limitation is the lack of dynamicaly in query execution plans.

We present AJoin, a dynamic and incremental ad-hoc stream join framework. AJoin consists of an optimization layer and a stream data processing layer. The optimization layer periodically reoptimizes the query execution plan, performing join reordering and vertical and horizontal scaling at run-time without stopping the execution. The data processing layer implements pipeline-parallel join architecture. This layer enables incremental and consistent query processing supporting all the actions triggered by the optimizer. We implement AJoin on top of Apache Flink, an open-source data processing framework. AJoin outperforms Flink not only at ad-hoc multi-query workloads but also at single-query workloads.

PVLDB Reference Format:


1. INTRODUCTION

Stream processing engines (SPEs) process continuous queries on real-time data, which are series of events over time. Examples of such data are sensor events, user activity on a website, and financial trades. There are several open-source streaming engines, such as Apache Spark Streaming [4, 53], Apache Storm [48], and Apache Flink [15], backed by big communities.

With the advance of cloud computing [20], such as the Software as a Service model [51], multiple users share public or private clouds for stream query processing. Many of these queries include joins. Stream clouds continuously combine rows from two or more

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ping the execution. Note that the state-of-the-art streaming systems are optimized for maximizing the data throughput. However, in a multi-user cloud environment it is also important to maximize query throughput and the frequency of created and deleted queries.

Sharing Limitations in Ad-hoc SPEs. Ad-hoc query sharing has been studied both for batch and stream data processing systems. Unlike ad-hoc batch query processing systems, in ad-hoc SPEs query sharing happens between queries running on fundamentally different subsets of the data sets, determined by the creation and deletion times of each query. Below, we analyze the main limitations of modern ad-hoc SPEs.

Missed optimization potential: To the best of our knowledge, there is no ad-hoc SPE providing ad-hoc stream QEP optimization. Modern ad-hoc SPEs embed rule-based query sharing techniques, such as query indexing [17], in the data processing layer [35]. However, appending a query index payload to each tuple causes redundant memory and computation usage. As the number of running queries increases, each tuple carries more payload.

Modern ad-hoc SPEs materialize intermediate join results eagerly. Especially with low selectivity joins, the eager materialization results in high transfer costs of intermediate results between subsequent operators.

Also, the join operator structure in modern SPEs performs several costly computations, such as buffering stream tuples in a window, triggering the processing of a window, computing matching tuples, and creating a new set of tuples based on matching tuples. With more queries and $n$-way $(n \geq 3)$ joins, the join operation will be a bottleneck in the QEP.

Dynamicity: Modern ad-hoc SPEs consider ad-hoc query processing only with a static QEP and with queries with common join predicates. In stream workloads with fluctuating data and query throughput, this is inefficient.

AJoin. We propose AJoin, a scalable SPE that supports ad-hoc equi-join query processing. AJoin also supports selection operators. We overcome the limitations stated above by combining incremental and dynamic ad-hoc stream query processing in our solution:

Efficient distributed join architecture: Because the join operator in modern SPEs is computationally expensive, AJoin shares the workload of the join operator with a source and sink operator. The join architecture is not only data-parallel but also pipeline-parallel. Tuples are indexed in the source operator. The join operator utilizes indexes for an efficient join operation. AJoin incrementally computes multiple join queries. It performs a scan, data, and computation sharing between multiple join queries with different predicates. Our solution adopts late materialization for the intermediate join results. This technique enables the system to compress the intermediate results and pass them to downstream operators efficiently.

Dynamic query processing: AJoin supports dynamicity at the optimization and data processing layer: dynamicity at the optimization layer means that the optimization layer performs regular reoptimization, such as join reordering and horizontal and vertical scaling; dynamicity at the data processing layer means that the layer is able to perform all the actions triggered by the optimizer at run-time, without stopping the QEP.

Contributions and Paper Organization. The main contributions of the paper are as follows: (1) We present the first optimizer to process ad-hoc streaming queries in an incremental manner; (2) We develop distributed pipeline-parallel stream join architecture. This architecture also supports dynamicity (modify QEP on-the-fly in a consistent way); (3) We perform an extensive experimental evaluation with state-of-the-art streaming engines.

The rest of the paper is organized as follows. We present related work in Section 2. Section 3 gives the system overview. Section 4 presents the AJoin optimizer. We provide implementation details in Section 5 and run-time operations in Section 6. Experimental results are shown in Section 7. We conclude in Section 8.

2. RELATED WORK

Shared query processing. SharedDB is based on batch data processing model and handles OLTP, OLAP, and mixed workloads [22, 23]. Gicvea et al. adopt SharedDB ideas and implement shared query processing on multicores [25]. CJoin [12, 13] and DataPath [6] focus on ad-hoc query processing in data warehouses. Braun et al. propose a hybrid (OLTP and OLAP) computa- tion system, which integrates key-value-based event processing and SQL-based analytical processing on the same distributed store [11]. BatchDB implements hybrid workloads sharing for interactive applications [42]. SharedHive is a shared query processing solution built on top of MapReduce framework [18]. The works mentioned above are designed for batch data processing environments. Although we also embrace some ideas from shared join operators, we focus on stream data processing environments with ad-hoc queries.

To increase data throughput, MJoin proposes a multi-way join operator that operates over more than two inputs [52]. While the bucket data structure in AJoin also mimics the behavior of multi-way joins, the join operator of AJoin supports binary input streams. To increase data throughput, AJoin reoptimizes the QEP periodically. FluxQuery is a centralized main-memory execution engine based on the idea of continual circular clock scans and adjusted for interactive query execution [19]. Similarly, MQJoin supports efficient ad-hoc execution of main-memory joins [41]. Hammad et al. propose streaming ad-hoc joins [26]. The solution adopts a centralized router, extended from Eddies [7]. Also, the work adopts a selection pull-up approach, which might result in high bookkeeping cost of resulting joined tuples and intensive CPU and memory consumption. The above works are designed for a single-node environment. However, AJoin is designed for distributed environments. AJoin does not utilize any centralized computing structure. Dynamicity and progressive optimization, are more essential in distributed environments. Also, AJoin exploits pipeline-parallelism. In a single-node environment, however, task-fusion is more beneficial [55].

AJoin vs AStream. AJoin was inspired by AStream [35], the first shared ad-hoc SPE. AStream adds an additional attribute to each tuple that represents a bitset of potentially interested queries in that tuple. This attribute is called query-set. For example, a query-set `0011` means that the tuple matches selection predicates of the third and fourth queries. AStream also adopts changelog that is a special data structure consisting of i) query deletion and creations meta-data and ii) a changelog-set, a bitset encoding the associated query deletions and creations. By utilizing query-sets and changelog-sets, AStream ensures consistent query creation and deletion.

Figure 2 shows an architectural comparison between AJoin and AStream. AJoin inherits query-sets and changelogs from AStream. Also, AJoin enhances the rule-based optimizer of AStream. Instead of encoding all queries in a query-set, AJoin arranges queries with similar selection predicates into the same groups. This enables AJoin to lower the cost of sharing and the query-set payload. AJoin features a cost-based query optimizer that performs progressive query optimization periodically at run-time.
AJoin features a dynamic data processing layer that is able to perform join reordering without extra operators. The join operator buffers stream tuples in a window, finds matching tuples, and builds resulting tuples by assembling the matching tuples. The join operator also implements all the functionalities of a windowing operator. The sink operator pushes the resulting tuples to external output channels. Because most of the computation is performed in the join operator, it can easily become a bottleneck. With more concurrent n-way join queries (n ≥ 3), the join operator is more likely to be a limiting factor.

To overcome this issue, we perform two main optimizations. First, we perform pipeline parallelization sharing the load of the join operator between the source and sink operators. The source operator combines the input data acquired in the last t time slots and builds a bucket. With this, we transmit the windowing operation from the join operator to the source operator. Also, buckets contain indexed tuples, which are used at the downstream join operator to perform the join efficiently. Afterwards, the partitioner distributes buckets based on a given partitioning function. Then, the join operator performs a set intersection between the index entries of input buckets. Note that for all downstream operators of the source operator, the unit of data is a bucket instead of a stream tuple. Finally, the sink operator performs full materialization, i.e., it converts buckets into stream tuples, and outputs join results.

Second, we perform late materialization of intermediate join results. After computing the matching tuples (via intersecting index entries), the join operator avoids performing the cross-product among them. Figure 4b shows the join operation for Q1. Index entries from the two input buckets are joined. Then, tuples with the matched indexes are retained in the resulting bucket. The late materialization technique can also be used for n-way joins. For example, Figure 4e shows the resulting bucket of Q3. The bucket keeps indexes of matched tuples from stream sources W, C, and R.

All join predicates in Q3 use the same join attribute (usrID).
OPTIMIZER

Queries do not share data because of their selection predicates. Description when the optimizer decides to trigger each of them.

If the optimizer cannot find common subqueries, it will check the selection predicate and the cost. In this case, the optimizer will perform a cost-based analysis and reoptimizes the QEP, if necessary.

In this case, the late materialization can be easily leveraged with built-in indexes (Figures 4d and 4e). However, if join attributes are different (e.g. in Q2), then repartitioning is required after the first join. AJoin benefits from late materialization also in this scenario.

To compute Q3, AJoin computes the result of the upstream join operator (Figure 4b). Then, the resulting bucket (\( V \bowtie W \)) is reindexed w.r.t. \( W.\text{usrID} \) (Figure 3c, 3f). Note that reindexing is related to the tuples belonging to \( W \) because only these tuples contain attribute \( \text{usrID} \). Instead of materializing the intermediate result fully and iterating through it, AJoin avoids full materialization and only iterates over the tuples belonging to \( W \): (1) every tuple \( t_p \in W \) is reindexed w.r.t. \( W.\text{usrID} \); (2) a list of its matched tuples from \( V \) is retrieved (get list with index \( \text{idx} = t_p.\text{vID} \)); (3) the pointer of the resulting tuple is appended to \( tp \). When \( tp \) is eliminated in the downstream join operator, all its matched tuples from \( V \) are also automatically eliminated. For example, tuples with \( \text{usrID} = 3 \) in Figure 4c (d) are eliminated when joining with \( C \) (Figure 4d). In this case, the pointers are also eliminated without iterating through them.

4. OPTIMIZER

In this section, we discuss the query optimization process in AJoin. After a changelog ingestion, the optimizer eagerly shares the newly created query with the running queries (Q1 in this case), without considering the selection predicate and the cost. In this case, the optimizer deploys Q2 as (\( V \bowtie W \)) on \( C \) to reuse the existing stream sources and the join operator. In the following phases, the optimizer performs a cost-based analysis and reoptimizes the QEP, if necessary.

If the optimizer cannot find common subqueries, it will check for common sources to benefit from scan sharing. The optimizer restarts the optimization process, if a new changelog has arrived. Below, we explain each phase of the optimization separately and describe when the optimizer decides to trigger each of them.

**Query Grouping.** Consider Q4 and Q5 in Figure 7a. These queries do not share data because of their selection predicates.
Assume that Q4 in Figure 7 is deleted, and Q7 = whole plan, but part of the QEP. Also, the optimizer does not recompute full materialization only at the sink operator.

Figure 7a shows our approach to calculate query groups. First, we compare the cost of sharing stream sources between two queries and executing them separately. If the cost of the former is less than the latter, we put the two queries into the same query group. Once we find query groups consisting of two queries, we eagerly check other queries, which are not part of any group, to include into the group. The only condition (to be accepted to the group) is that the cost of executing the new query and the queries inside the group in a shared manner must be less than executing them separately (e.g., Figure 6). Query grouping is performed periodically during the query execution. When join reordering is triggered, it utilizes recent query groups.

The optimizer must therefore support incremental computation.

When repartitioning is performed, \( b_m \) is also a boolean variable indicating if full materialization is required. A join performs full materialization only at the sink operator.

Figure 7b shows an example scenario for iterative QEP optimization. We enhance an iterative dynamic programming technique [37] and adapt it to ad-hoc stream query workloads. Our approach combines dynamic programming with iterative heuristics. In each iteration, the optimizer 1) calculates the shared cost of subqueries and 2) selects subplan based on the cost. The shared cost is the cardinality of a particular subquery divided by the number of QEPs, sharing the subquery.

Join Reordering. After discovering query groups, the optimizer performs iterative QEP optimization. We enhance an iterative dynamic programming technique [37] and adapt it to ad-hoc stream query workloads. Our approach combines dynamic programming with iterative heuristics. In each iteration, the optimizer 1) calculates the shared cost of subqueries and 2) selects subplan based on the cost. The shared cost is the cardinality of a particular subquery divided by the number of QEPs, sharing the subquery.

The second iteration is similar to the first one. Note that \( \text{T1} \bowtie \text{Q2}.C \) cannot be shared with \( \text{Q6} \) because \( \text{Q6}.V \boweq \text{Q2}.V \boweq \text{FRA} \) and \( \text{V}.\text{geo} = \text{ENG} \). Also, \( \text{Q1}.V \boweq \text{Q3} \boweq \text{V}.\text{geo} = \text{German} \) is no longer shared with \( \text{Q2} \) because \( \text{Q1} \) and \( \text{Q2} \) are in the same group (Figure 7a). Also, the cost of \( \text{Q1}.V \boweq W \) differs when exploiting all sharing opportunities (MaxShared) and executing it separately (MinShared). After the first iteration, the optimizer selects subplans with minimum costs. Then, the optimizer substitutes the selected subqueries with \( \text{T1} \) and \( \text{T2} \). If the cost is shared with other QEPs (e.g., \( \text{Q1}.V \boweq W \) is shared between \( \text{Q1} \) and \( \text{Q2} \)), then the optimizer assigns the shared cost to all other related queries.

The second iteration is similar to the first one. Note that \( \text{T1} \boweq \text{Q2}.C \) cannot be shared with \( \text{Q6} \) because \( \text{Q6}.V \boweq W \) and \( \text{Q2}.V \boweq W \) reside in different query groups. So, the optimizer prunes this possibility. Also, \( \text{Q3}.V \boweq W \) is no longer shared with \( \text{Q2} \) because in the first iteration the optimizer assigned \( \text{V}.\boweq \text{W} \boweq \text{W} \) to \( \text{Q2} \).

Computing the optimal QEP for multiple queries is an NP-Hard problem [24, 31]. For ad-hoc queries, this is particularly challenging, since queries are created and deleted in an ad-hoc manner. The optimizer must therefore support incremental computation. Assume that \( \text{Q4} \) in Figure 7 is deleted, and \( \text{Q7} = \text{whole plan, but part of the QEP} \). Also, the optimizer does not recompute query groups from scratch but reuses existing ones.
source operator (indexing S1 and S2), the cost of join operator (index set intersection), and the cost of sink operator (full materialization). The second requirement is that the cost computation should include joining information. We achieve this requirement by dividing $\text{COST}$ by the number of shared queries (Figure 7b, MaxShared). We select this cost computation semantics because it complies with our requirements, and it is simple.

Vertical and Horizontal Scaling. AJoin uses consistent hashing for assigning tuples to partitions. The partitioning function PF maps each tuple with key $k$ to a circular hash space of key-groups: $\text{PF}(k) = (\text{hash}(k) \mod |P|)$, where $|P|$ is the number of parallel partitions. At compile-time, partitions are distributed evenly among nodes.

The optimizer performs vertical scaling (3 in Figure 5), if the latency of tuples residing in specific partitions is high, and there are resources available on nodes, in which overloaded partitions are located. The optimizer checks for scaling up first, because scaling up is less costly than scaling out. Note that when scaling up, the partitioning function and the partition range assigned to each node remains the same. Instead, the number of threads operating on specific partitions is increased. When new operators are deployed, and existing operators exhibit low resource-utilization, the optimizer decides to scale down the existing operators.

The optimizer checks for horizontal scaling (1 in Figure 5) when new and potentially non-shared queries are created. Also, the optimizer decides to scale out if CPU or memory is a bottleneck. When the optimizer detects a latency skew, and there are no available resources to scale up, it triggers scaling out. In this case, the optimizer distributes the partition range, which is overloaded, among new nodes added to the cluster. Therefore, at runtime, the partition range might not be distributed evenly among all nodes.

5. IMPLEMENTATION DETAILS

Bucketing. Bucketing is performed in the source operator. The source operator is the first operator in the AJoin QEP. Each index entry inside a bucket points to a list of tuples with the common key. If there are multiple indexes, pointers are used to reference stream tuples. The main intuition is that buckets are read-only; so, sharing the stream tuples between multiple concurrent queries (with different indexes) is safe. Each source operator instance assigns a unique ID to the generated bucket; however, bucket IDs are not unique between different partitions. The bucket ID is an integer indicating the generation time of the bucket.

Join. Let $L_{in}$ and $L_{out}$ be lists inside a join operator storing buckets from inner and outer stream sources, respectively. When the join operator receives buckets, $b_{in}$ from the inner and $b_{out}$ from the outer stream source, it (i) joins all the buckets inside $L_{out}$ with $b_{in}$, all the buckets inside $L_{in}$ with $b_{out}$, and combines the two results in one output bucket, (ii) emits the output bucket, and (iii) removes unnecessary buckets from $L_{in}$ and $L_{out}$.

The join operator handles join queries with different join predicates and window constraints. The operator receives query changelog from upstream operators and updates its query metadata. Figure 8 shows an example scenario for incremental ad-hoc join query computation. At time T1 Q1 is initiated. At time T2 the join operator receives the query changelog indicating the creation of Q2. Also, first buckets from both streams are joined and emitted. Since the joined buckets are no longer needed, they are deleted. Q1 and Q2 have the same join predicates but different window length. Therefore, $3|4|3$ is shared between Q1 and Q2, but $2|3$ and $3|2$ are associated with only Q2. Since buckets support multiple indexes, the join operator can share join queries with different join predicates. The rest of the example follows a similar pattern.

The join operation between two buckets is performed as follows. Firstly, queries with similar stream sources and join predicates are grouped. We perform scan sharing for the queries in the same group. The join operation is a set intersection of indexes, as we use a grace join [36] for streaming scenarios. AJoin supports out-of-order stream tuples if they reside within the same bucket.

Partitioning. The partitioner is an operator that partitions buckets among downstream operator instances. This operator accepts and outputs buckets. Given an input bucket, the partitioner traverses over existing indexes of the bucket. It maps each index entry and corresponding stream tuples to one output bucket. In this way, the partitioner traverses only indexes instead of all stream tuples.

The partitioning strategy of AJoin with multiple queries is similar to one with a single query. If queries have the same join predicate, the partitioner avoids copying data completely. That is, each index entry and its corresponding tuples are mapped to only one downstream operator instance. If queries possess different join predicates, AJoin is able to avoid data copy partially. For example, in Figure 9 the input bucket is partitioned into two downstream operator instances. Note that tuples that are partitioned to the same node w.r.t. both partitioning attributes (e.g., (1, 1), (8, 4)) are serialized and deserialized only once, without data copy.

Materialization. The sink operator performs full materialization. Basically, it traverses all indexes in a bucket, performs the cross-product of tuples with the same key, constructs new tuples, and pushes them to output channels.

Exactly-Once Semantics. AJoin guarantees exact-once semantics, meaning every stream tuple is only processed once, even under failures. AJoin inherits built-in exactly-once semantics of Apache Flink [14]. Whether the unit of data is a stream tuple or a bucket, under the hood the fault tolerance semantics is the same.

Optimizer. We implement the AJoin optimizer as part of the Flink’s optimizer. Flink v1.7.2 lacks a run-time optimizer. Therefore, the AJoin optimizer can be easily integrated into Flink’s optimizer. We also integrate the AJoin optimizer with Flink’s compile-
time optimization. The compile-time optimization process consists of three main phases. In the first phase, AJoin performs logical query optimization. Then, Flink’s optimizer receives the resulting plan, applies internal optimizations, and generates the physical QEP. Afterwards, the AJoin optimizer analyzes the resulting physical QEP. For n-way join queries, the AJoin optimizer inspects if each node contains at least one operator instance of all join operators in the query. For example, the physical QEP of (A ∘ B) ∘ C should contain at least one instance of the upstream (A ∘ B) and the downstream join operators (((...) ∘ C)) in each node. Also, the optimizer checks if all join operator instances are evenly distributed among the cluster nodes. It is acceptable if some nodes have free (idle) task slots. The free task slots provide flexibility for scaling up during the run-time. If there are join operators that share the same join partitioning attribute, the optimizer schedules them in the same task slot and notifies Flink to share the task slot between the two join operator instances. For example, in a query like (A ∘ B ∘ B) ∘ C, the instances of the upstream join operator (A ∘ B) share the same task slot with the instances of the downstream join operator C. The reason is to ensure the data locality, as the resulting stream of the upstream join operator is already partitioned w.r.t. attribute B. B. The optimizer performs the necessary changes in the physical QEP generated by Flink (second phase) to perform the optimizations listed above.

6. RUN-TIME QEP CHANGES

It is widely acknowledged that streaming workloads are unpredictable [8]. Supporting ad-hoc queries for streaming scenarios leads to more dynamic workloads. Therefore, AJoin supports several run-time operations updating the QEP on-the-fly.

Consistency Protocols. AJoin features two consistency protocols: atomic and non-atomic. The atomic protocol is a three-phase protocol. Figure 10 shows an example scenario for this protocol. In the first phase, the job manager requests bID, the current bucket ID, and ts, the current time in the task manager, from all task managers. In the second phase, the job manager proposes the task managers to ingest the changelog after the bucket with bID=6. If the job manager receives ack from all task managers, it sends a confirmation message to the task managers to ingest the changelog. In the non-atomic protocol, on the other hand, the job manager sends the changelog without any coordination with task managers.

Vertical Scaling. AJoin features two buffering queues between operators: a broadcast queue and a unicast queue. Let S be a set of subscribers to a queue. In the broadcast queue, the head element of the queue is removed if all subscribers in S pull the element. Any subscriber si ∈ S can pull elements up to the last element inside the queue. Afterwards, the subscriber thread is put to sleep mode and awakened once a new element is pushed into the broadcast queue. In a unicast queue, on the other hand, the head element of the queue is removed if one subscriber pulls it. The consequent subscriber pulls the new element in the queue.

The join operation is distributive over union (A ∘ (B ∘ C)) = (A ∘ B) ∪ (A ∘ C). We use this feature and the two queues to scale up and down efficiently. Each join operator subscribes to two upstream queues: one broadcast and one unicast queue. When a new join operator is initiated in the same worker node (scale up), it also subscribes to the same input channels. For example, in Figure 11, there are two queues. If we increase the number of join instances, then both instances would get the same buckets from the broadcast queue but different buckets from the unicast queue. As a result, the same bucket is joined with different buckets in parallel.

We use the non-atomic protocol for the vertical scaling. Let S1 and S2 be the two joined streams(S1 ∪ S2) and Π = (p1, p2, ..., pk) be parallel partitions in which the join operation is performed. Vertical scaling in AJoin is performed on a partition of a stream (i.e., a vertical scaling affects only one partition). So, we show that the scaled partition produces correct results. Assume that k new task managers are created at partition p1, which output join results to p1, p2, ..., pk. Since |S1∪S2|=p1+p2+...+pk (distributivity over union), the result of vertical scaling is correct. Since there is no synchronization among partitions, and since each vertically scaled partition is guaranteed to produce correct results, vertical scaling is performed in an asynchronous manner.

Horizontal Scaling. AJoin scales horizontally in two cases: when a new query is created (or deleted), and when an existing set of queries needs to scale out (or scale in). We refer to the first case as query pipelining. We assume that created or deleted queries share a subquery with running queries. Otherwise, the scaling is straightforward—adding new resources and starting a new job.

Query pipelining consists of three main steps. Let the existing query topology be E and the pipelined query topology be F. In the first step, the job manager sends a changelog to the task managers of E. Upon receiving the changelog, the task managers switch sink operators of E to the pause state and ack to the job manager. In the second step, the job manager arranges the input and output channels of the operators deployed inside the task managers, such that the input channels of F are piped to the output channels of E. In the third step, the job manager resumes the paused operators. If the changelog contains deleted queries, the deletion of the queries is performed similarly. The job manager pauses upstream operators of deleted stream topologies. Then, the job manager pipelines a sink operator to the paused operators. Lastly, the job manager resumes the paused operators.

Query pipelining is performed via the non-atomic protocol. Thus, all the partitions of the pipelined query are not guaranteed to start (or stop) processing at the same time. However, modern SPEs [54], [48], [15] also connect to data sources, such as Apache Kafka [1], in an asynchronous manner. Also, when a stream query in the modern SPEs is stopped, there is no guarantee that all sink operators stop at the same time.

Scaling out and in can be generalized to changing the partitioning function and computation resources. We explain the partitioning strategy in Section 4. Assume that AJoin scales out by N new nodes, and each node is assigned to execute P’ partitions. Then, the new partitioning function becomes F’(k)=(Hash(k) mod (1P’*1N))). Also, each new node is assigned a partition range. The partition range is determined via further splitting the overloaded partitions. For example, if a partition with hashed key range [0,10] is overloaded, and one new partition is initiated in the new node, then the hashed key ranges of the two partitions become...
W.usrID, instead of W.vID. At time T3, the changelog marker arrives at the first join operator. Having received the changelog, the job manager pushes the changelog marker via the non-atomic protocol. Once the partitioner receives this marker, it starts double-partitioning, meaning partitioned buckets contain data both w.r.t. the old and new partitioning function. The partitioner performs double-partitioning at most B time, then partitions only w.r.t. the recent partitioning function. In the third step, new task managers are launched (scale out) or stopped (scale in).

In order to guarantee the correctness of results, there are two main requirements: i) all partition operators must change the partitioning function at the same time and ii) downstream operators must ensure the consistency between the data partitioned w.r.t. the new and old partitioning functions. To achieve the first requirement, we use the atomic triple-phase protocol. To achieve the second requirement, we use a custom join strategy in which we avoid to double-partition and ensure that any joined two tuples are partitioned w.r.t. the same partitioning function. We apply the similar technique, mentioned above, when query groups are changed.

We use the atomic protocol when changing the partitioning function. Changing the partitioning function possibly affects all partitions. In order to guarantee the correctness of results, there are two main requirements: i) all partition operators must change the partitioning function at the same time and ii) downstream operators must ensure the consistency between the data partitioned w.r.t. the new and old partitioning functions. To achieve the first requirement, we use the atomic 3-phase protocol. To achieve the second requirement, we use a custom join strategy in which we avoid to join old-partitioned and new-partitioned data. Instead, we perform double-partitioning and ensure that any joined two tuples are partitioned w.r.t. the same partitioning function. We apply the similar technique, mentioned above, when query groups are changed.

Join reordering. Suppose at time $T_{1D}$, the optimizer triggers to change the QEP of Q2 from $(VW_{oldID=\text{W userid}})$ to $(VW_{\text{W userid}})$ at time $T_{1D}$. The main idea behind reordering joins. At time $T_{1}$, the job manager pushes the changelog marker via the non-atomic protocol. The marker passes through the partitioner at time T2. The marker informs the partitioner to partition based on $W_{\text{userid}}$, instead of $W_{\text{vID}}$. At time $T_{3}$, the changelog marker arrives at the first join operator. Having received the changelog, the join operator emits the join result, if any, and asks to the job manager. The job manager then i) pauses the join operator and ii) unsubscribes it from stream V. At time $T_{4}$, the marker arrives at the second join operator. Similarly, the second join operator emits the join result, if any. It informs the job manager about the successful emission of results. The job manager pauses the operator and unsubscribes it from input channels. Afterward, the second join operator switches its state with the upstream join operator. Finally, the job manager subscribes both join operators to modified input channels and resumes computation.

We use the non-atomic protocol for join reordering. Join reordering is performed in all partitions, independently. Assume that S1, S2, and S3 are streams, W denotes window length, WS and WE are window start and end timestamps, and T1 and T2 are timestamps in which the changelog arrives to the first and to the second window. Figure 13 shows the formal definition of the join reordering. When the changelog arrives at the first join operator, the intermediate join result (IR1 in Figure 13) is computed and emitted. At this point, AJoin switches the window states of S1 and S3. Then, unjoined parts of S3 and S2 are joined (IR2 in Figure 13). Finally, the job manager subscribes both join operators to modified input channels and resumes computation.

7. EXPERIMENTS

Experimental design. Our benchmark framework consists of a distributed driver and four systems under test (SUT): AJoin, AStream, Spark Streaming 2.4.4, and Apache Flink v1.7.2. The driver maintains two queues: one for stream tuples and one for window configurations. In the first step, the job manager combines all intermediate results to the final output (R in Figure 13) which is correct and does not include any duplicated data.
for user requests (query creation or deletion). The tuple queue receives data from tuple generators inside the driver. The driver generates tuples at maximum sustainable throughput [34]. A SUT pulls records from the data queue with the highest throughput it can process. So, the longer the tuple stays in the queue, the higher its event-time latency. The working principle of the user request queue is similar to the tuple queue.

If a SUT exhibits backpressure, it automatically reduces the pull rate. Contrary to data tuples, user requests are periodically pushed to the client module of the SUT. The SUT acquires the data after receiving the user request. If the ack timeout is exceeded or every subsequent ack duration keeps increasing, then the SUT cannot sustain the given query throughput. Similarly, if there is an infinite backpressure, then the SUT cannot sustain the given workload. In these cases, the driver terminates the experiment and tests the SUT again with a lower query and data throughput.

**Metrics.** Query deployment latency is the duration between a query create or delete request and the actual query create or delete time at a SUT. Overall data throughput is the sum of data throughputs of all running queries. Query similarity is the similarity between the generated query and the pattern query.

**Data generation.** Equation 3 shows the calculation of the query similarity. To evaluate the similarity between a query Q (e.g., A1,B1,AND A2,B2,B3) and the pattern query PQ (e.g., A1,B1,B2,A3,B4), we find the number of the common sources (ComS) between Q and PQ (A and B), find the number of the common sources with common join attributes (ComSJA) between Q and PQ (only A,a), and divide the multiplication of the two with square of all sources (AllS) in PQ (i.e., \( \frac{\text{ComS} \times \text{ComSJA}}{\text{AllS}} \)).

\[
\text{Similarity(ComS,ComSJA,AllS)} = \frac{\text{ComS} \times \text{ComSJA}}{(\text{AllS})^2}
\]

To generate query Q with n% similarity with PQ, we apply the following approach. Assume that n is 75% and PQ is \( A^1, A^2, A^3, B^1, B^2, B^3 \). (Step 1.) We randomly select ComS, which is between 1 and AllS (e.g., ComS=2). (Step 2.) Given ComS=2 and AllS=3, we calculate ComSJA from Equation 3. If a stream is a source stream, it is partitioned by the join attribute of the downstream join operator. If a stream is an intermediate result, two join operators affect the sharing possibility of this stream: the upstream join operators (how the stream was partitioned) and the downstream join operator (how the stream will be partitioned). Therefore, each stream can be affected by maximum of two partitioning attributes. If ComSJA number of join attributes cannot be used with ComS number of sources (e.g., 1 stream source can be affected by maximum of 2 join attributes), then we increase ComS by one and repeat this step. (Step 3.) We select ComS number of random stream sources from PQ, such that these stream sources are joined with each other with a join predicate and not via cross-product (e.g., A \( \times \) C is not acceptable). Similarly, we select random ComSJA number of join attributes from the selected sources.

Figure 14 shows a query template used in our experiments. \( S_n(i) \) means \( i^{th} \) attribute of stream \( n \). \( A_i \) (join attribute) and \( S_i \) (selection attribute) \((0 \leq i \leq n, S_i < |i|)\) are random variables (e.g., \( S_n(A_i) \) is \( S_n(i)^{th} \) attribute of stream \( S_n \)). FV, (filtering value) is a randomly assigned value used to filter streams.

![Figure 14: Query template used in our experiments.](image)

Figure 15: Overall data throughput of AJoin, AStream, Spark, and Flink with 1, 5, 20, 100, and 500 parallel queries on 4- and 8-node cluster configurations. qP at the legend means query parallelism.

**Workload.** The first workload scenario (SC1) is applicable when a user activity is higher on specific time periods. Also, in this workload scenario, users execute long-running queries. The second workload scenario (SC2) is relevant for fluctuating workloads. Modern SPEs cannot execute ad-hoc stream queries. Therefore, there is no industrial workload for ad-hoc stream query processing. Therefore, we use the workload used in AStream [35], which is similar to cloud workloads [9, 3, 50, 47, 40, 30]. Nevertheless, the design of AJoin is generic and not specific to the workloads explained above.

**Setup.** We conduct experiments in 4- and 8-node cluster configurations. Each node features 16-core Intel Xeon CPU (E5620 2.40GHz) and 48 GB main memory. We configure the batch size of queries (in the client module) to be 1 second and ack timeout is 15 seconds, as these configurations are the most suitable for our workloads. The latency threshold for scaling up and out is 5 seconds. The threshold is derived from the latency-aware elastic scaling strategy for SPEs [27]. We measure the sustainable performance of the SUTs [34, 33] to detect if the latency spike is due to backpressure or unsustainable workload. If the latency value is higher than a given threshold because the system cannot sustain the workload, then AJoin scales up or out. Each created query in AJoin features this threshold value. For simplicity, we set the same threshold value for all queries. However, the overall methodology remains the same with different threshold values for each query. Because of the space constraints, we will include the related experimental results in the technical report of this paper.

**7.1 Scalability.**

Figure 15 shows the impact of scalability on the performance of the SUTs. All the queries are submitted to the SUTs at compile-time. The queries are 2-way joins and have 50% query similarity. For this experiment, we remove selection predicates from input queries to measure the performance of pure join operation. We can observe that the performance of all SUTs increases with more resources. Also, with more parallel queries, the overall data throughput of AJoin increases dramatically. The reason is that sharing opportunities increase with more parallel queries. The throughput of AStream is significantly lower than AJoin.
Because AJoin supports cost-based optimization, AJoin performs windowing in the source operator. While the join operator in AStream, Spark, and Flink remains idle with single query setups. The reason is the join implementation of AStream performs scan, data, and computation sharing in AStream is not always beneficial. The computation sharing in AStream is not always beneficial because there is no selection predicate. For queries with selection predicates, Spark cannot share the computation and data. For joins with different join predicates, Spark deploys a new QEP. Also, Spark does not utilize late materialization. The hashing phase in Spark is blocking. It uses blocking stage-oriented architecture.

AJoin performs better than AStream, Spark, and Flink even with single query setups. The reason is the join implementation of AJoin. AJoin uses not only data parallelism (like AStream, Spark, and Flink) but also pipeline parallelism for the join operation. The join operator in AStream, Spark, and Flink remains idle and buffers input tuples until the window is triggered. AStream and Flink perform nested-loop join after the window is triggered. AJoin performs windowing in the source operator. While the tuples are buffered, they are indexed on-the-fly. Therefore the load of join operator is lower in AJoin, as it performs the set-intersection operation. After the join is performed, AStream, Spark, and Flink create many new data objects. These new objects cause extensive heap memory usage. AJoin reuses existing objects, keeps them un-joined (late materialization), and performs full materialization at the sink operator. Because the data tuples are indexed, AJoin avoids to iterate all the data elements while joining them, but only indexes. Also, at the partitioning phase, AJoin iterates over indexes to partition a set of tuples with the same index at once, rather than iterating over each data tuple. Different from Flink, AJoin performs incremental join computation. Quantifying the impact of each component (e.g., indexing, grace join usage, late materialization, object reuse, task-parallelism, etc.) stated above, is nontrivial because these components function as an atomic unit. If we detach one component (e.g., indexing), then the whole join implementation would fail to execute. However, there is a significant improvement in throughput from 0.1 M t/s in Flink to 2.04 M t/s in AJoin.

Figure 16 shows the space used to buffer tuples and indexes in AJoin. With more queries, AJoin buffers more tuples and indexes. However, AJoin shares tuples among different queries and avoids new object creation and copy. The buffer size increases more for indexes than for tuples. The reason is that each tuple might be reused by different indexes. In this figure, the key space is between 0 and 500. When we increase the key space in the orders of millions, the index buffer space also increases significantly. Although this increase did not cause significant overhead in our setup (48GB memory per node), with low-memory setups and with very large key space, index usage causes significant overhead for AJoin.

Figure 17 shows the effect of distinct keys and the selectivity of selection predicates on the performance of AJoin, AStream, Spark, and Flink. Values on the x-axis show the selectivity of selection operators.

Figure 17 shows the effect of distinct keys and the selectivity of selection predicates on the performance of AJoin, AStream, Spark, and Flink. Values on the x-axis show the selectivity of selection operators.
The experiment is executed in a 4-node cluster. The query simulation overhead is based on the event-time latency of stream tuples. Figure 19 shows the breakdown of the overhead for SC1. $q/s$ $qp$ indicates that $i$ queries per second were created until the query parallelism is $i$.

Figure 18b shows the deployment latency for SC1 in AJoin. Figure 18 shows the average and max boundaries for SC1.

Figure 19 shows the average event-time latency for SC1 in AJoin. The query throughput is higher with 3- and 4-way joins, the overhead of on-the-fly QEP reordering also increase. To avoid stopping the QEP, it also has an impact on the overall latency. With 3-way and 4-way joins, the cost of query pipelining and join reordering also increase. Therefore, the overhead of parallelism is one of the major components causing latency. The reason is that tuples have to be fully materialized, copied, serialized, and sent to different physical output channels. We notice that similar overhead of source, join, and materialization leads to a higher data throughput (e.g., the throughput of 2-way is higher than others). The reason is that when $n$ (n-way join) increases, new stream sources, join operators, and sink operators are deployed. Therefore, the overhead for these operators remains stable. The overhead of the optimizer also increases as $n$ (n-way join) gets higher and as query throughput increases. The reason is that the sharing opportunities increase with more queries and with 3- and more $n$-way joins.

**Throughput.** Figure 20 shows the effect of n-way joins, query groups, and query similarity to the performance of the SUTs. We show the performance improvement of AJoin when submitting queries at compile-time above the dashed lines in the figure. As $n$ increases in n-way joins, the throughput of AJoin drops (Figure 20a). The performance drop is sharp from 2-way join to 3-way join. The reason is that 3- and more n-way joins benefit from the late materialization more. Also, the performance difference between ad-hoc and compile-time query processing increases as the query throughput and $n$ increase.

Figure 20b shows the throughput of AStream, Spark, and Flink with n-way join queries. Because of the efficient join implementation, Spark performs better than other SUTs with single query execution. The performance of Flink and AStream decreases with more join operators. In some 4- and 5-way join experiments, Flink and AStream were stuck and remained unresponsive. The reason is that each join operator creates new objects in memory, which leads to intensive, CPU, network usage and garbage collection stalls. While Spark also performs data copy, its Catalyst optimizer efficiently utilizes on-heap and off-heap memory to reduce the effect of data copy on the performance.

Figure 20c shows the effect of the number of query groups on the performance of AJoin. With more query groups the throughput of AJoin decreases. However, the decreasing speed slows down gradually. Although there are less sharing opportunities with more query groups, updating the QEP becomes cheaper (as a result of incremental computation). The incremental computation also leads to a decrease in the overhead of executing queries ad-hoc.

Figure 20d shows the effect of query similarity on the performance of the SUTs. Both AStream and AJoin perform better with more similar queries. However, the performance increase is higher in AJoin. AStream lacks all the run-time optimization techniques AJoin features. As a result, AStream shares queries only with the same structure (e.g., 2-way joins can be shared only with 2-way joins) and the same join predicates. The effect of executing queries in an ad-hoc manner decreases as the query similarity increases. The overall picture in SC2 is similar with SC1.

**Impact of each component.** Figure 21 shows the impact of AJoin’s optimization components on the performance. In this experiment, we disable one optimization component (e.g., join reordering) and measure the performance drop. When the number of join operations in a query increases, the impact of join reordering and query pipelining also increase. Also, with more query throughput, the optimizer shares input queries aggressively. Therefore, the impact of the query pipelining increases with higher
The throughput of AJoin with n-way joins in Figure 6 is significant when it is too high (24 seconds in Figure 22b), there is a loss when the proportion of shared data is small.

The latency threshold value, which is 5 seconds in our experiments, needs to be configured carefully. When it is too low (3 seconds in Figure 22b), we experience an overhead for frequent optimizations. The reason is that AJoin also outperforms AStream, Spark, and Flink. With more similar queries, the effect of other components, especially the join reordering component, increases.

The overall picture is similar in SC2. The most noticeable difference is the impact of scaling out and in is less, and the impact of join reordering is more. The execution time and the query throughput in SC1 are higher than SC2. In SC2, queries are not only created but also deleted with lower throughput. This leads to a higher impact on join reordering.

Cost of sharing. Figure 22a shows the performance of AStream and AJoin with four input streams: 5%, 25%, 50%, and 75% shared. For example, 50% shared data source means that tuples are shared among 50% of all queries. We omit experiments with 0% shared data source, as in this scenario all the data tuples are filtered and no join operation is performed. We perform this experiment with a workload suitable for AStream (i.e., all join queries have the same join predicate and the same number of join operators) and disable the dynamicity property (except query grouping) of AJoin. This setup enables us to measure the cost of sharing and query-set payload to the throughput of AJoin and AStream.

Impact of the latency threshold value. Figure 22b shows the throughput of AJoin with different latency threshold values. The latency threshold value with 3-way join queries leads to a higher impact on join reordering.

Impact of the latency threshold value. Figure 22b shows the throughput of AJoin with different latency threshold values. The latency threshold value, which is 5 seconds in our experiments, needs to be configured carefully. When it is too low (3 seconds in Figure 22b), we experience an overhead for frequent optimizations. When it is too high (24 seconds in Figure 22b), there is a loss in optimization potential.

8. CONCLUSION

In this paper we present AJoin, an ad-hoc stream join processing engine. We develop AJoin based on two main concepts: (1) Efficient distributed join architecture: AJoin features pipeline-parallel join architecture. This architecture utilizes late materialization, which significantly reduces the amount of intermediate results between subsequent join operators; (2) Dynamic query processing: AJoin features an optimizer, which reoptimizes ad-hoc stream queries periodically at run-time, without stopping the QEP. Also, the data processing layer supports dynamicity, such as vertical and horizontal scaling and join reordering.

We benchmark AJoin, AStream, Spark, and Flink. When all the queries are submitted at compile-time, AJoin outperforms Flink by orders of magnitude. With single query workloads, AJoin also outperforms AStream, Spark, and Flink. With more join operators in a query (3-, 4-, 5-way joins) the performance gap between AJoin and the other systems even increases. With ad-hoc stream query workloads, Flink and Spark cannot sustain the workload, and AStream’s performance is less than AJoin’s. In the future, we envision to further distribute concepts of AJoin into an Internet of Things data processing system that we are currently developing at TU Berlin.

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9. REFERENCES


