In Memory Parallel Hash Join Project Milestone Report

Authors: Zhidong Guo (zhidongg), Ye Yuan (yeyuan3)

1. Summary

We have implemented the sequential hash join and parallel shared hash join, where mulitple threads build and probe a shared hash table. The parallel implementation supports both static and dynamic scheduling. We have set up the benchmark framework which enables us to generate workloads of varying skewness and measure the per-stage (partition, build, probe) execution time.

A preliminary comparison of these two implementations gives us the following observations - 1. the parallel implementation almost achieves perfect speedup compared with the sequential version, 2. the computation is dominated by the probe phase so we should focus on read hash bucket's performance, 3. hash function adds to workload skewness even if the data is uniform.

For the remaining duration of the project, we will implement parallel partitioned hash join, where the tuples are partitioned into bottom-level-cache-sized chunks and joined locally, and perform a series of evaluation on synchronization cost, cache access, and workload distribution to figure out whether partitioning is beneficial for in-memory parallel hash join.

1. Work Completed So Far

1.1. Rust Language and Library Onboarding

We have spent some time onboarding Rust language and frameworks. We have familiarized ourselves with the Rust syntax, data structures, and concurrency model. We have also explored various Rust libraries that might be useful for our project, including:

- <u>rayon</u> for multi-threaded parallelism.
- <u>boxcar</u> for lock-free data structures implementation.
- <u>xxhash-rust</u> for hash function implementation. We choose xxhash as it is the fastest hash function without quality problems according to the <u>smhasher benchmark</u>.
- parking lot for smaller and faster locks than those in the standard library.
- <u>clap</u> for building the command line interface of our benchmark program.

1.2. Implementation of Benchmark Infrastructures

We have set up the benchmark infrastructure for different variants of the hash join.

- Work laod generator generates the tuples in the inner and outer relation. We can specify the number of tuples in both relations, the cardinality ratio, outer table foregin key distribution. Currently we support uniform distribution and zipfan distribution.
- Time measuring: the framework times the three phases in a hash join: partition, build, and probe.

1.3. Implementation of Sequential Hash Join

We have implemented a sequential hash join algorithm as a baseline. The pseudo code of the algorithm is as follows:

```
/**
 * Pesudo-code for the sequential hash join algorithm
 * @param Table R: The smaller table to join
 * @param Table S: The larger table to join
 * @param Attribute R key: The join attribute in table R
 * @param Attribute S key: The join attribute in table S
 * @return Result: The joined table containing all matching rows
 */
func SequentialHashJoin(Table R, Table S, Attribute R_key, Attribute S_key):
   // Step 1: Build phase
   HashTable = {}
   // Loop over each record in the smaller table
    for each row in R:
        hashKey = hash(row[R key])
        if hashKey not in HashTable:
            HashTable[hashKey] = []
        HashTable[hashKey].append(row)
   // Step 2: Probe phase
   Result = []
   // Loop over each record in the larger table
   for each row in S:
        hashKey = hash(row[S_key])
        if hashKey in HashTable:
            for R row in HashTable[hashKey]:
                if R_row[R_key] == row[S_key]:
                    // Combine matching rows
                    joinedRow = join(R_row, row)
```

1.4. Implementation of Parallel Shared Hash Join

The parallel shared hash join is essentially the same as the sequential version, except that we split both tables into chunks of data and let multiple threads process them in parallel. We compared the performance of implementing the hash bucket with Mutex<Vec> and boxcar::Vec (lock free vector), and found that the former provides better performance. We also implemented static scheduling and dynamic scheudling to account for the possible imbalance.

1.5. Evaluation of Parallel Shared hash Join v.s. Sequental

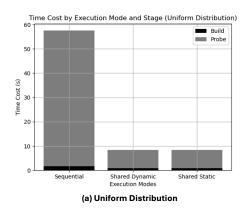
1.5.1. Workload

We are joining two relations R and S, where |R|=16000000, |S|=256000000, and each tuple comes in the form of (key, payload), where both key and payload takes up 8 bytes. The key column of the inner relation is its primary key (monotonically increasing integer sequence), while that of the outer relation is the foreign key following either

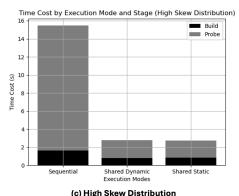
- Uniform distribution
- ullet Low skew: zipfan distribution with lpha=1.05
- High skew: zipfan distribution with $\alpha=1.25$

1.5.2. Performance Analysis

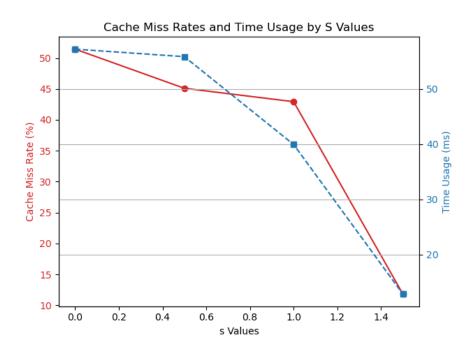
The figure below shows the performance comparison of three hash join variants under three workloads. The three variants are: sequential, shared hash table with static scheduling, and shared hash table with dynamic scheduling. The parallel hash joins are run with 8 threads. From this figure, we can see that under all workloads, the parallel variants reach a speedup of around 7.3x, and the probe phase dominates the execution time. This observation suggests that we should focus on optimizing the hash bucket's read performance.





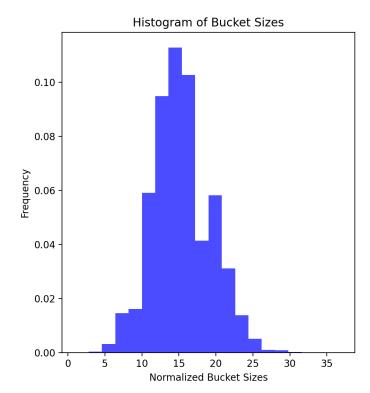


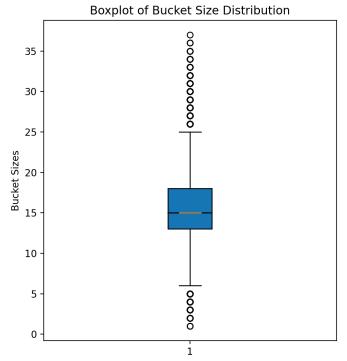
From the figure above, we also found that for the sequential hash join, the high skew workload has a shorter execution time than the uniform workload. We hypothesize that high skewness in the data distribution may lead to better cache hit rate. The following plot illustrates the cache hit rate and probe phase execution time under various skew workloads. The data distribution follows the zipfian distribution $f(r;s,N)=\frac{1}{\sum_{n=1}^{N}\frac{1}{n^s}}$, within which the factor s controls the skewness of the distribution. When s=0, the distribution is uniform, and as s increases, the distribution becomes more skewed.



From the figure above, we can see that the cache miss rate drops as the skewness of the data distribution increases. Also the probe phase execution time decreases as the skewness increases. This observation suggests that the more skewed the data distribution is, the better the cache hit rate, and the shorter the probe phase execution time.

Another interesting observation is that xxhash introduces skewness to the hash bucket sizes even if the input is uniform. This implies that if partitioning also uses xxhash (with a different seed), **the number of tuples in the partitions may be skewed**.





2. Problems

- 1. The description of how partitioned hash join should be implemented and why the increased cache hit rate would offset partition cost are vague in the paper that we based our project proposal on. Further investigation is needed as to implement it in the optimal way.
- 2. GHC's non-standard Rust installation prevents our program from compiling since it's using some unstable features. Therefore, we are switching to PSC machines for the benchmark.

3. Updated Goals

Considering the progress we have made so far is on track with our initial plan, we will continue to work on the following goals for the final presentation:

- 1. Implement parallel partitioned hash join.
- 2. Refine the benchmark infrastructure to measure workload imbalance through the distribution hash bucket sizes that outer tuples fall in.
- 3. Perform the following evaluations and analysis.
 - 1. Stage-by-stage exeuciton time comparison of sequential, parallel shared, and parallel partitioned variants under uniform, low skew, and high skew workload.
 - 2. Synchronization cost analysis through flamegraph.
 - 3. Cache analysis using performance counter.
- 4. Time permitting, we will explore utilizing prefetch to further increase cache hit rate.

4. Updated Schedule

End Date	Task
4-20	Investigate the optimial implementation of partitioned variant
4-24	Implement partitioned hash join
4-27	Perform execution time comparision and synchronization cost evaluation
4-30	Perform cache evaluation
5-5	Report writing