

Sample Sort

14

The sample sort example demonstrates a partitioning-based sort that overcomes the scaling limitation of Quicksort described in Section 8.9.3, which arose because Quicksort’s partitioning operation is serial. Sample sort overcomes this deficiency by parallelizing partitioning. The key patterns in the example are **binning** and **packing** of data in parallel. Note that what we have defined as the **partition** pattern just provides a different view of data, whereas what is commonly meant in the description of sorting algorithms by “partitioning” actually reorganizes the data into **bins**. To avoid confusion we call this data reorganization operation “**binning**” in this chapter. This algorithm is also an interesting example of where a *serial scan* pays off as part of a practical parallel algorithm.

14.1 OVERALL STRUCTURE

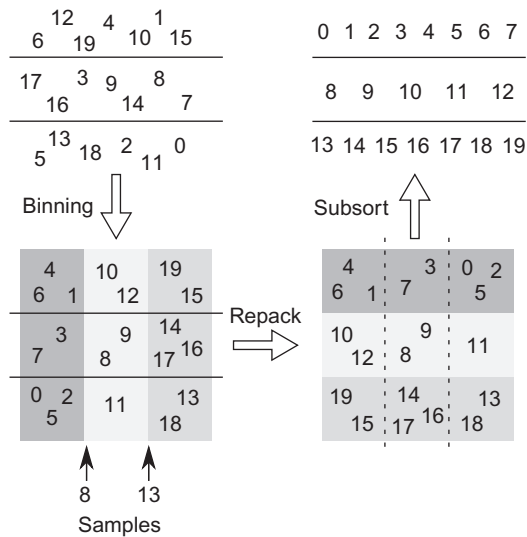
Sample sort divides keys into m bins by building an $m \times m$ matrix of empty buckets and filling the buckets with the keys. Each column corresponds to a bin. Separate rows can be filled concurrently. Figure 14.1 shows the overall phases of the algorithm:

- **Bin:** Split the input into m chunks. Move the contents of each chunk to a separate row of the matrix, dividing it among the buckets in that row.
- **Repack:** Move the contents of each column of buckets back to a contiguous section of the original array.
- **Subsort:** Sort each section.

In the first phase, separate rows are processed in parallel. In the second phase, separate columns are processed in parallel. There is some serial work before or after. The top-level code is shown in Listing 14.1. A production-quality C++ version would be generalized as a template with iterator arguments and a generic comparator and include extra code to ensure exception safety. These generalizations are omitted for the sake of exposition to readers who are not C++ experts.

Furthermore, our analysis will assume that the constructor $T()$ and destructor $\sim T()$ are trivial enough to generate no instructions, so that the construction and destruction of array y requires only $O(1)$ work. This is true of C-like types in C++ but generally not true if the constructor or destructor involves user-defined actions. In that case, the code shown has a $\Omega(N)$ bottleneck. Section 14.6 describes how a C++ expert can remove the bottleneck.

When the sequence is no longer than `SAMPLE_SORT_CUT_OFF`, the code calls Quicksort directly. The best value for `SAMPLE_SORT_CUT_OFF` will depend on the platform, though it should be at least big enough to subsume all cases where $m = 1$, since binning into a single bin is a waste of time and memory.

**FIGURE 14.1**

Sample sort example using a 3×3 matrix of buckets, where the samples for binning are 8 and 13. The keys are initially grouped into three rows of a matrix. The binning phase divides each row into buckets, one bucket for each subrange $[-\infty, 8)$, $[8, 13)$, and $[13, \infty)$. The repack phase copies the buckets in a way that transposes the matrix, so that buckets for identical subranges become contiguous in memory. The subsort phase sorts each row.

```

1  const size_t M_MAX = 32;
2
3  void parallel_sample_sort( T* xs, T* xe ) {
4      if( xe-xs<=SAMPLE_SORT_CUT_OFF ) {
5          parallel_quicksort(xs,xe);
6      } else {
7          size_t m = choose_number_of_bins(xe-xs);
8          size_t tally[M_MAX][M_MAX];
9          T* y = new T[xe-xs];
10         bin(xs, xe, m, y, tally);
11         repack_and_subsort(xs, xe, m, y, tally);
12         delete[] y;
13     }
14 }
```

LISTING 14.1

Top-level code for parallel sample sort. This code sequences the parallel phases and is independent of the parallel programming model.

14.2 CHOOSING THE NUMBER OF BINS

If the exact number of available hardware threads (workers) is known, then using one bin per worker is best. However, in work-stealing frameworks like Cilk or TBB, the number of *available* workers is unknown, since the sort might be called from a nested context. Instead, a strategy of **over-decomposition** is used. The number of bins will be chosen so that each bin is large enough to acceptably amortize per-bin overhead. Some of the logic in function `bin` requires that the number of bins be a power of two. The code is shown below:

```
size_t choose_number_of_bins( size_t n ) {
    const size_t BIN_CUTOFF = 1024;
    return std::min( M_MAX, size_t(1)<<floor_lg2(n/BIN_CUTOFF));
}
```

Function `floor_lg2` is presumed to compute the function $k \rightarrow \lfloor \lg k \rfloor$ —that is, the position of the most significant 1 in the binary numeral for k .

14.3 BINNING

The binning phase involves several steps:

1. Select sample keys to demarcate the bins.
2. Organize the samples so that a key can be mapped to its bin index quickly.
3. Compute the bin index of each key.
4. Compute the starting address of each bucket.
5. Scatter the keys into the buckets.

A poor choice of demarcation samples can lead to grossly unbalanced bins. Over-sampling improves the odds against bad choices. An over-sampling factor o is chosen and om keys are selected and sorted. Then m evenly spaced samples are extracted from the sorted sequence. A good way to choose o is to make it proportional to the logarithm of the number of keys [BLM+98].

Given a linear array of sorted samples, the bin index of a key can be computed by binary search. The code for the binary search can be tightened into branchless code by rearranging the array to be an implicit binary tree. The root of the tree is stored at index 0. The children of a node with index k are stored at indices $2k + 1$ and $2k + 2$. [Listing 14.2](#) shows the technique.

The code uses an implicit binary tree with $m-1$ nodes to map n keys in x to their respective bin indices. For $i \in [0, n)$, the routine sets `binindex[i]` to the bin index of $x[i]$. Type `binindex_type` is an integral type big enough to hold an integer in the range $[0, m)$. The routine also generates a histogram tally of bin indexes, defined as `tally[b]`, of the number of keys with bin index b . The histogram is the sizes of the buckets in a row of our conceptual matrix.

Now the binning routine can be built. The routine divides keys in the interval $[x_s, x_e)$ among m bins, and copies the keys to buckets in y .

```

1 void map_keys_to_bins( const T x[], size_t n, const T tree[], size_t m,
    binindex_type binindex[], size_t freq[] ) {
2     size_t d = floor_lg2(m);
3     freq[0:m] = 0;
4     for( size_t i=0; i<n; ++i ) {
5         size_t k = 0;
6         for( size_t j=0; j<d; ++j )
7             k = 2*k+2 - (x[i] < tree[k]);
8         ++freq[binindex[i] = k-(m-1)];
9     }
10 }

```

LISTING 14.2

Code for mapping keys to bins.

The conceptual matrix of buckets is represented by `y` and `tally`. Each bucket of the matrix is stored in `y`, ordered left-to-right and top-to-bottom, with the elements within a bucket stored consecutively. Each row of `tally` is a running sum of bucket sizes; `tally[i][j]` is the sum of the sizes of buckets $0 \dots j$ in row i .

This information suffices to reconstitute pointer bounds of a bucket. The beginning of the leftmost bucket for row i is `y+i*block_size`. The beginning of any other bucket is the end of the previous bucket. The end of bucket (i,j) is `y+i*block_size+tally[i][j]`.

14.3.1 TBB Implementation

Listing 14.3 can be translated to TBB by replacing the `cilk_for` loop with a `tbb::parallel_for` and a **lambda expression**, so it looks like this:

```

tbb::parallel_for( size_t(0), m, [=,&tree](size_t i) {
    ...
});

```

The lambda captures all variables **by value**, except for array `tree`, which is captured **by reference**, to avoid the overhead of copying an array. A subtle C++ technicality is that, although `tally` is captured by value, its underlying array is *not* copied. This is because in C and C++, a formal parameter declared as an array is treated as a pointer to its zeroth element. Hence, the lambda expression copies only the address of the array, not the array itself.

14.4 REPACKING AND SUBSORTING

The final phase of sample sort has two subphases:

1. Compute where each bin should start in the original array.
2. Move the keys from buckets into their bins, and sort them.

```

1 void bin(T* xs, T* xe, size_t m, T* y, size_t tally[M_MAX]
    [M_MAX] ) {
2     T tree[M_MAX-1];
3     build_sample_tree( xs, xe, tree, m );
4
5     size_t block_size = ((xe-xs)+m-1)/m;
6     bindex_type* bindex = new bindex_type[xe-xs];
7     cilk_for( size_t i=0; i<m; ++i ) {
8         size_t js = i*block_size;
9         size_t je = std::min( js+block_size, size_t(xe-xs) );
10
11         // Map keys to bins
12         size_t freq[M_MAX];
13         map_keys_to_bins( xs+js, je-js, tree, m, bindex+js, freq );
14
15         // Compute where each bucket starts
16         T* dst[M_MAX];
17         size_t s = 0;
18         for( size_t j=0; j<m; ++j ) {
19             dst[j] = y+js+s;
20             s += freq[j];
21             tally[i][j] = s;
22         }
23
24         // Scatter keys into their respective buckets
25         for( size_t j=js; j<je; ++j )
26             *dst[bindex[j]]++ = std::move(xs[j]);
27     }
28     delete[] bindex;
29 }

```

LISTING 14.3

Parallel binning of keys using Cilk Plus.

The first subphase is merely a matter of summing the columns of `tally`. Each row of `tally` is a running sum of bucket sizes, so the sum of the columns yields a running sum of bin sizes. Since the value of m is typically several orders of magnitude smaller than n , the quadratic time $O(m^2)$ for computing the sums is not a major concern. It is typically too small for effective fork-join parallelism. However, it does lend itself to vector parallelism, and the array notation to do so even simplifies the source code slightly.

The second subphase does most of the work. Each parallel iteration copies a column of buckets into a bin. The bucket boundaries are found via the formulae mentioned in the discussion of method `bin`.

[Listing 14.4](#) shows a Cilk Plus routine implementation of both phases.

A TBB equivalent is a matter of replacing the `cilk_for` statement with `tbb::parallel_for`, similar to the the translation in [Section 14.3.1](#).

```

1 void repack_and_subsort( T* xs, T* xe, size_t m, const T* y, const size_t
    tally[M_MAX][M_MAX] ) {
2     // Compute column sums of tally, forming the running sum of bin sizes
3     size_t col_sum[M_MAX];
4     col_sum[0:m] = 0;
5     for( size_t i=0; i<m; ++i )
6         col_sum[0:m] += tally[i][0:m];
7     assert( col_sum[m-1]==xe-xs );
8
9     // Copy buckets into their bins and do the subsorts
10    size_t block_size = ((xe-xs)+m-1)/m;
11    cilk_for( size_t j=0; j<m; ++j ) {
12        T* x_bin = xs + (j==0 ? 0 : col_sum[j-1]);
13        T* x = x_bin;
14        for( size_t i=0; i<m; ++i ) {
15            const T* src_row = y+i*block_size;
16            x = std::move( src_row+(j==0?0:tally[i][j-1]), src_row+tally[i][j],
                x );
17        }
18        parallel_quicksort(x_bin,x);
19    }
20 }

```

LISTING 14.4

Repacking and subsorting using Cilk Plus. This is the final phase of sample sort.

14.5 PERFORMANCE ANALYSIS OF SAMPLE SORT

The asymptotic work for sample sort can be summarized as:

- $\Theta(m \lg m o)$ work to sort the input samples, over-sampled by o , where o is $\Theta(\lg n)$.
- $\Theta(n \lg m)$ work to bin keys into buckets.
- $\Theta(m^2)$ work to compute bin sizes.
- $\Theta(n \lg(n/m))$ work to repack/subsort, assuming a subsort of k keys takes time $O(k \lg k)$.

Keeping m sufficiently small ensures that the work is dominated by the binning and repack/subsort phases, both of which scale linearly if $m = \Theta(p)$ and the $\log p$ startup time of a parallel map is insignificant.

In practice, memory bandwidth is likely to become the bottleneck. The communication between the binning and repack/subsort phases changes ownership of the bucket matrix from columns to rows. Hence, there are inherently $\Omega(n)$ memory transfers required.

There is one other potential hardware-related problem of which to be aware. If m comes close to the number of entries in the translation lookaside buffer, and each bucket is at least a page in size, then the scattering of keys among the m buckets during the binning phase may incur a severe penalty from TLB thrashing (Section 2.4.1, page 44).

```

1  template<typename T>
2  T* destructive_move( T* first, T* last, T* output ) {
3      size_t n = last-first;
4      []( T& in, T& out ){
5          out = std::move(in);
6          in.~T();
7      }( first[0:n], output[0:n] );
8      return output+n;
9  }

```

LISTING 14.5

Using Cilk Plus to move and destroy a sequence, without an explicit loop!

14.6 FOR C++ EXPERTS

As [Section 14.1](#) remarked, our analysis assumes that `new T[...]` and `delete[]` take constant time. This is true if the constructor `T()` and destructor `~T()` do nothing, as is the case for C-like types, but not always true for types with non-trivial constructors or destructors. To handle those efficiently requires rethinking the allocation/deallocation of `y`.

One solution is to construct the array elements in parallel and destroy them likewise. But doing so adds two more parallel phases, adding to synchronization costs and memory traffic. A faster approach is to allocate and deallocate array `y` as a raw memory buffer. The binning phase can copy-construct the elements into the buffer directly. The repack phase can destroy the copies as it moves them back to the original array.

A combination of array notation ([Section B.8](#)) and C++11 lambda expressions enables a concise way to write the routine that destroys the copies after moving them back to the original array, without writing any loop, as shown in [Listing 14.5](#).

The lambda expression creates a functor that moves ([Section D.3](#)) the value of `out` to `in`, and then explicitly invokes a destructor to revert the location referenced by `in` to raw memory. The code is unusual in what it does with the functor. Instead of passing it to another routine, it immediately applies the functor to some arguments. The trick here is that those arguments are array sections, so the compiler has license to apply the functor in parallel.

14.7 SUMMARY

The sample sort example showed how to do binning and packing in parallel. The key to efficient binning is over-sampling and *not* trying to do the binning in place as Quicksort does. The packing relied on a serial prefix scan over a histogram to calculate where items should be packed. Most of the work occurs in two parallel map operations, one for binning and one for packing. In both cases, the work is over-decomposed to provide parallel slack ([Section 2.5.6](#)).