# Cuckoo Hashing Cuda Lab

Yiwei YANG 2018533218

YANGYW@SHANGHAITECH.EDU.CN

### 1. The introduction of cuckoo hashing

Hash table, one of the most fundamental data structure, have been implemented on Graphics Processing Units (GPUs) to accelerate a wide range of data analytics workloads. Most of the existing works focus on the static scenario and try to occupy as much GPU device memory as possible for maximizing the insertion efficiency. In many cases, the data stored in the hash table gets updated dynamically and existing approaches takes unnecessarily large memory resources, which tend to exclude data from concurrent programs to coexist on the device memory. In this paper, we design and implement a dynamic hash table on GPUs with special consideration for space efficiency. To ensure the insertion performance under high filled factor, a novel coordination strategy is proposed for resolving massive thread conflicts.

#### 1.1 The challenge of Cuckoo Hashing in GPU

- 1. The aim of a universal hash function set is to distribute the input keys into random entries of a hash table uniformly. The nearly random accessing to memory actually destroy the space locality within the warp which contains the consecutive threads, which makes it hard to manipulate shared memory and cause high hit missing rate of cache.
- 2. Cuckoo hashing is a variant of open addressing hashing method, the addressing iteration could introduce much divergence between threads in a warp. With the increasing of load factor of a hash table, the probability of the thread divergence grows quickly either.
- 3. As for a cuckoo hashing table with only two hashing function, any multiple loops in a connected component could lead a failure. For any failure, the original algorithm invokes a rehashing, which could be painful with high expected cost. Besides, we don't double the size of the hash table while rehashing, which can not guarantee the rehashing to work and it will interrupt all working thread.

#### 1.2 The Algorithm of Cuckoo Hashing in GPU

I proposed the cuckoo hashing in Zhou and Zeng (2015).

```
Algorithm A2 Parallel cuckoo hashing on a GPU
 1: procedure Cuckoo-Hash-Insert(\mathcal{H}, T, k)
         \mathbf{for}\ i \leftarrow 0\ \mathbf{to}\ k-1\ \mathbf{do}
             T[i] \leftarrow \emptyset
         end for
         for all t \in T do
                                                                       \triangleright dispatch nodes according to h(x)
 5:
            Push-Back(T[h(t)], t)
         for i \leftarrow 0 to k-1 in parallel do
             for j \leftarrow 1 to |T[i]| in parallel do call Insert(\mathcal{H}[i], T[i][j]) on block i
10:
11:
              end for
        end for
13: end procedure
14: procedure Insert(H, t)
15:
         z \leftarrow -1
         while true do
16:
              \mathbf{for}\ i \leftarrow 0\ \mathsf{to}\ d-1\ \mathbf{do}
18:
                  if H[h_i(t)] is empty then
                      H[h_i(t)] \leftarrow t
19:
                       z \leftarrow i
20:
21:
                      break
22:
                  end if
23:
              end for
              thread synchronization
24:
              if z \neq -1 and H[h_z(t)] = t then
25:
26:
              Let r be a random number in \{0,1,\ldots,d-1\}
28:
              Атоміс-Swap(H[h_r(t)], t)
29:
         end while
31: end procedure
```

Figure 1: Parallel cuckoo hashing on a GPU

## 2. Environment Setup

- 1. NVIDIA V100, CUDA 11.0
- 2. The software is cross platform, tested on MSCV on windows, clang on mac and icc on linux.
- 3. Deploy Mersenne Twister 19937 generator to generate random integers.

To deploy the project, just

```
mkdir build
cd build
cmake ..
make
```

./CuckooHashing.

## 3. Experiment

## 3.1 Experiment 1

Cuckoo Hashing	Insertion size	Performance
	$2^{1}$	$1.665~\mathrm{ms}$
	$2^{2}$	$2.291 \mathrm{\ ms}$
	$2^{3}$	$4.257 \mathrm{\ ms}$
	$2^{4}$	$2.616~\mathrm{ms}$
	$2^5$	$3.858 \mathrm{\ ms}$
	$2^{6}$	$2.589 \mathrm{\ ms}$
	$2^{7}$	$2.315 \mathrm{\ ms}$
	$2^{8}$	$9.164~\mathrm{ms}$
	$2^{9}$	$4.281 \mathrm{\ ms}$
	$2^{10}$	$2.742~\mathrm{ms}$
	$2^{11}$	$2.676~\mathrm{ms}$
	$2^{12}$	$4.700~\mathrm{ms}$
	$2^{13}$	$7.928~\mathrm{ms}$
	$2^{14}$	$2.405 \mathrm{\ ms}$
	$2^{15}$	$5.150 \mathrm{\ ms}$
	$2^{16}$	$7.061~\mathrm{ms}$
	$2^{17}$	$6.978~\mathrm{ms}$
	$2^{18}$	$6.582~\mathrm{ms}$
	$2^{19}$	$6.653~\mathrm{ms}$
	$2^{20}$	$9.412~\mathrm{ms}$
	$2^{21}$	$15.54~\mathrm{ms}$
	$2^{22}$	$25.42~\mathrm{ms}$
	$2^{23}$	$43.83 \mathrm{\ ms}$
	$2^{24}$	$115.5 \mathrm{\ ms}$

Here the performance is quite competitive compared to many public benchmark. With the scale of insertion increasing, the inserting speed will go up (Better Occupancy) and finally go down (the high load factor of hash table introduce too much collision).

#### 3.2 Experiment 2

Cuckoo Hashing	percentile	Performance
	$S_0$	25.062000  ms
	$S_1$	24.761000  ms
	$S_2$	24.801001 ms
	$S_3$	24.785999  ms
	$S_4$	24.948999  ms
	$S_5$	25.292000  ms
	$S_6$	25.968000  ms
	$S_7$	24.972000  ms
	$S_8$	24.790001  ms
	$S_9$	25.865000  ms
	$S_{10}$	24.771000  ms

Since the lookup operation exactly take O(1) time, here are no obvious difference for random input or existed keys. Besides, here indicates the drawback of my design, the lookup time cost is nearly close to the insert operation, the extra cost is introduced by my auxiliary linear probing table, since it may lead to traverse all the auxiliary table in the worst case.

#### 3.3 Experiment 3

Cuckoo Hashing	Ratios	Performance
	1.9	38.073002 ms
	1.8	23.381001 ms
	1.7	23.188999  ms
	1.6	25.606001  ms
	1.5	23.326000  ms
	1.4	21.899000 ms
	1.3	24.674999 ms
	1.2	23.295000  ms
	1.1	24.481001 ms
	1.05	24.409000 ms
	1.02	30.268000  ms
	1.01	23.343000 ms

The experiment result reveal the rules of efficiency of hashing: low load factor leads to better performance.

## 3.4 Experiment 4

Cuckoo Hashing	Bound	Performance
	0	39.252998 ms
	1	25.014999  ms
	2	25.364000  ms
	3	29.417999  ms
	4	24.982000  ms
	5	28.659000  ms
	6	24.945000  ms
	7	24.924000  ms
	8	24.877001  ms
	9	24.905001  ms
	10	26.068001  ms

The result of this experiment of mine would be quite different to others. Here you can see the lower bound lead to better performance, which is actually promised by the auxiliary. Most elements will be successfully hashed to proper position at the first time, it's the long tail effect, the lower bound we set, the less divergence in warp either. However, it can't be too small as the auxiliary table can't be too large.

## References

Yichao Zhou and Jianyang Zeng. Massively parallel a\* search on a gpu. In *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.