Dynamic Data Structures on the GPU

John Owens

Child Family Professor of Engineering and Entrepreneurship

University of California, Davis

Student principal authors: Saman Ashkiani, Muhammad Awad, Afton Geil

Joint work with Martin Farach-Colton (Rutgers, co-PI), Nina Amenta (UC Davis), Rob Johnson (VMWare Research)

Why data structures?

- Data structures organize sparsity
- Part of any programmer's toolbox!

```
#include <map>
#include <list>
#include <set>
```

And they just work!

What do we want to do?

- Queries (do not modify data structure)
  - Membership (is this key in the data set?)
    - Probabilistic membership (is this key probably in the dataset?)
  - Search (given key, return value associated with key)
    - SearchAll (given key, return all values associated with key)
- Successor (given key, what's the next key?)
- Range (given key range, return all keys / all values within that range)

What do we want to do?

- Change (mutate) data structure
  - Insert (add new key or key-value pair)
  - Replace (insert, but replaces old value with new value)
  - Delete (remove key and associated value(s))

- We can always just rebuild the data structure from scratch, but:

- Goal: Cost is *O*(update size) instead of *O*(dataset size)

What do we want to do?

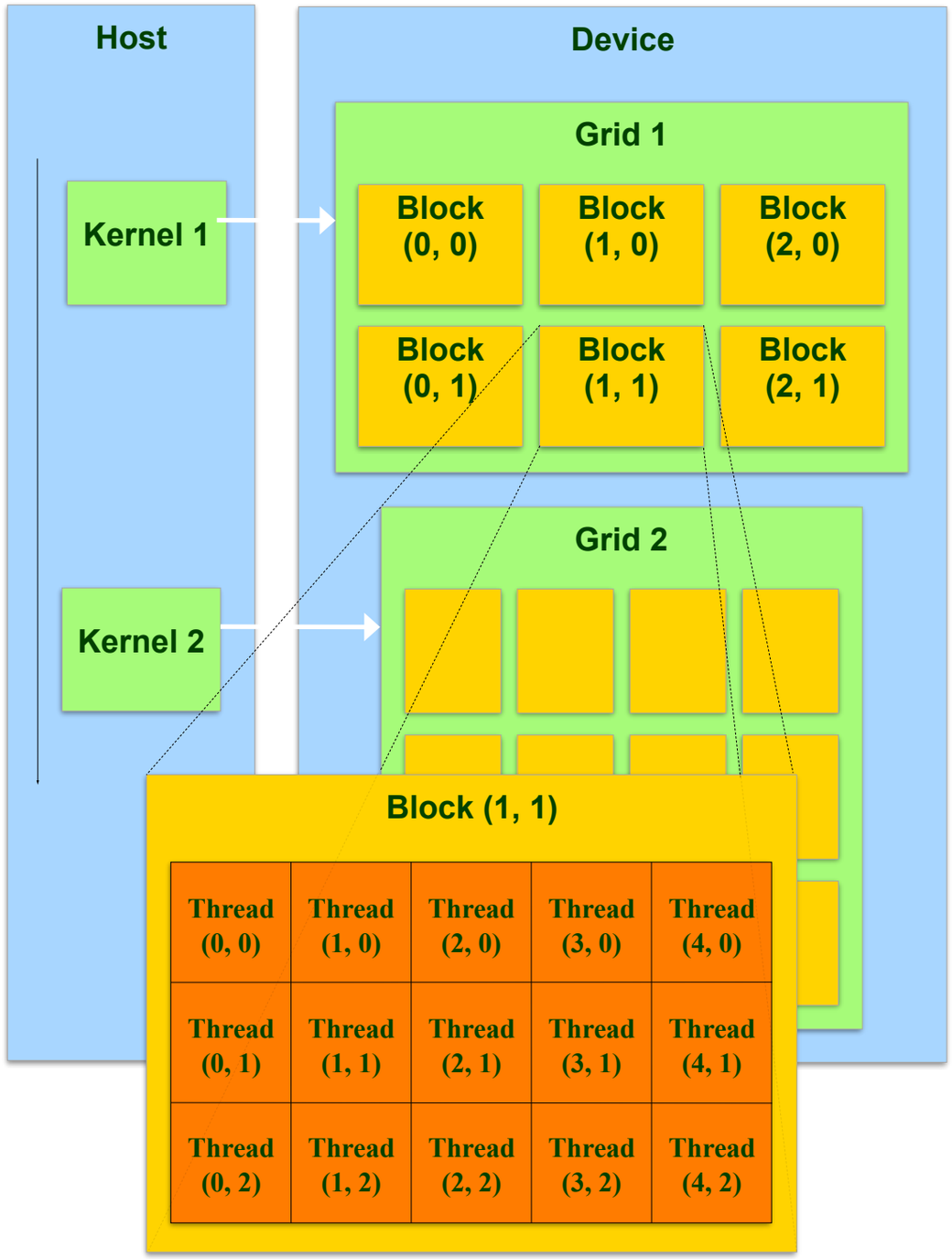
- **Build data structure**
  - "Bulk build" (build complete data structure from large amount of data)
  - Incremental build (e.g., data is streaming in and we want to build the data structure as we go)
    - What are the use cases for incremental build?
      - "Add and age": as data streams in, add new data & delete data older than a certain threshold [DARPA]
      - Use cases for this are not yet clear (more later)

Why is this hard?

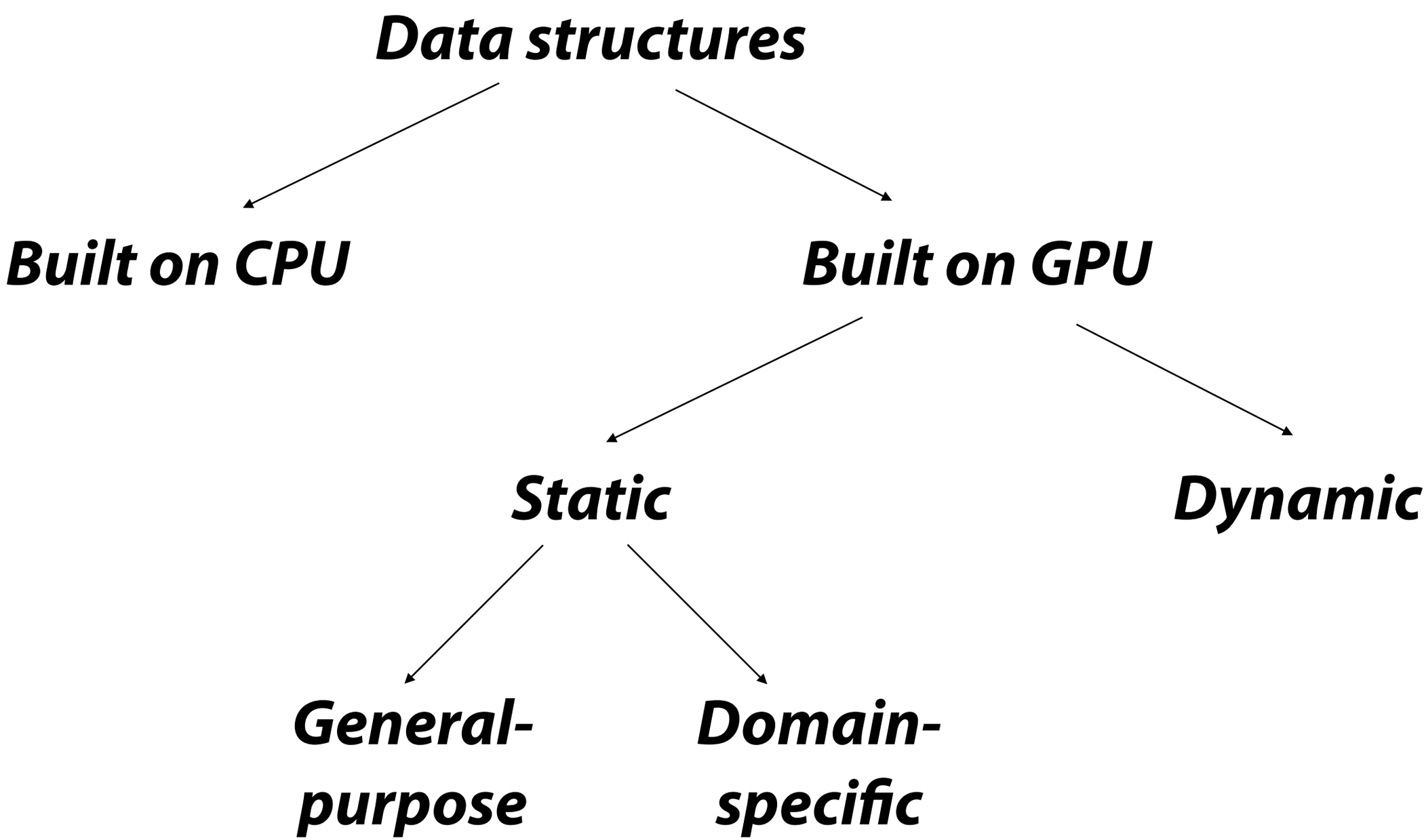
- Some data structures are simply a poor fit for the GPU
- Conventional data structures are typically defined and described serially
  - e.g., "insert item" == "find location for item in a tree, add it, rebalance the tree"
  - NOT described as bulk / parallel operations
- Even existing parallel data structures rarely see concurrency on a GPU scale

GPUs in one slide

- Kernels run over a grid of thread blocks; blocks are independent
- Thread blocks are mapped to SMs
- Threads running within a thread block can communicate through local "shared memory"
- SMs have 32-wide SIMD hardware that runs one 32-wide "warp" of threads
- Warps accessing neighboring memory locations are "coalesced"
- Thread or memory divergence: bad



Taxonomy


Data structures
Built on CPU
Built on GPU
Static
Dynamic
General-purpose
Domain-specific

Taxonomy

Data structures

Built on CPU

Built on GPU

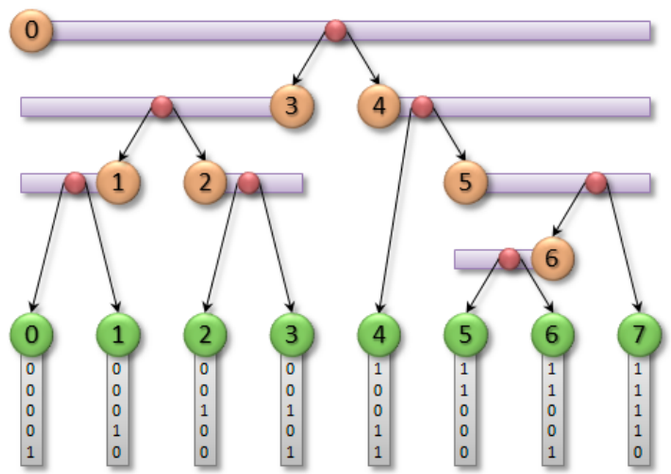
Static

Graphics data structures are typically rebuilt every frame

Dynamic

General-purpose

Domain-specific



e.g., BVH tree

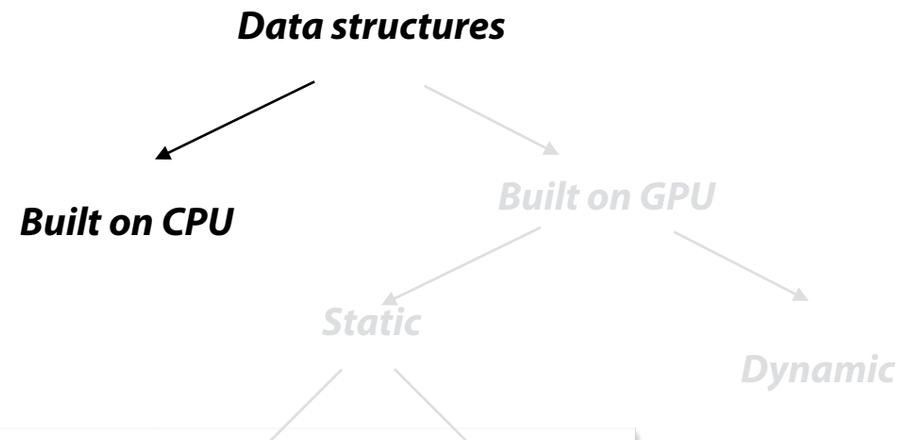
Tero Karras, Maximizing Parallelism in the Construction of BVHs, Octrees, and k-d Trees, Proc. of High Performance Graphics 2012

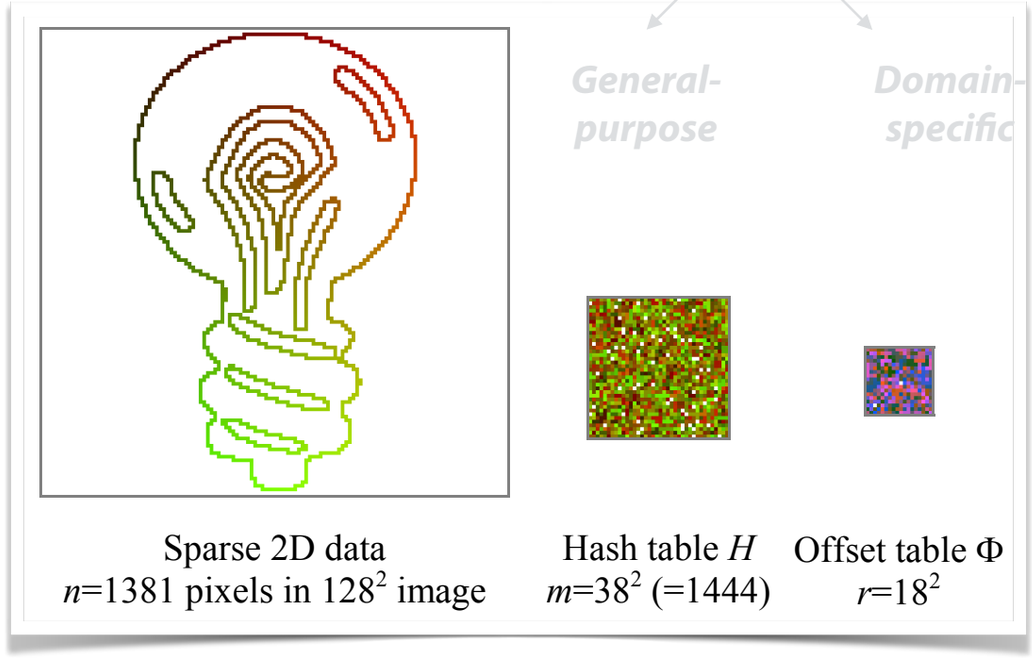
All data structures involve tradeoffs

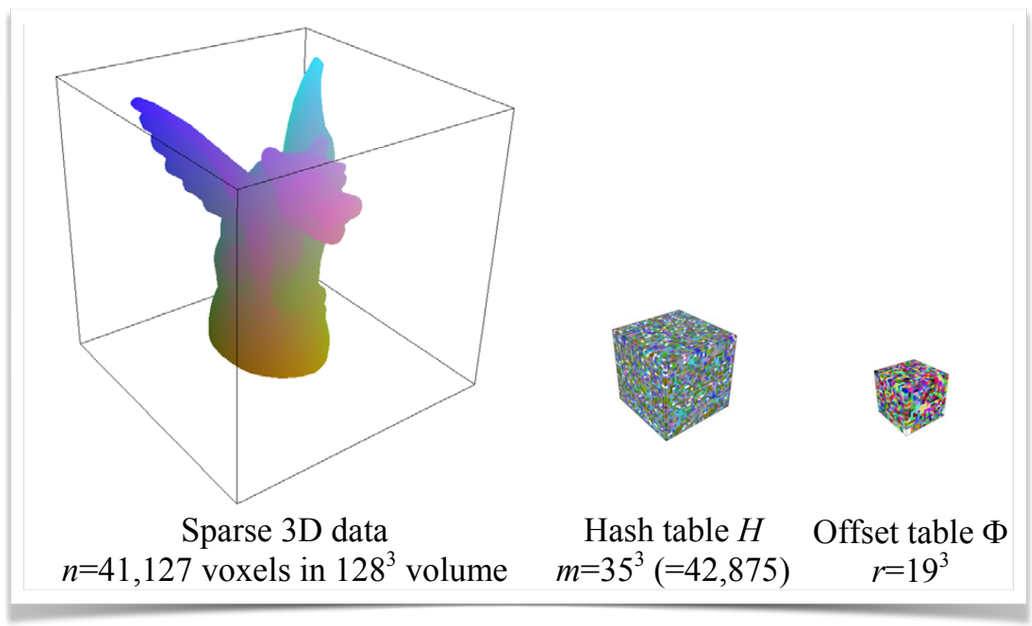
- GPU hash table implementations, for instance, typically balance:
  - Lookup time
  - Construction time
  - (Mutation time)
  - Memory usage (load factor)

Perfect Spatial Hashing

- Perfect hash function
- Built on CPU
  - Construction times: seconds to minutes
- Transferred to GPU
- Optimized for lookups

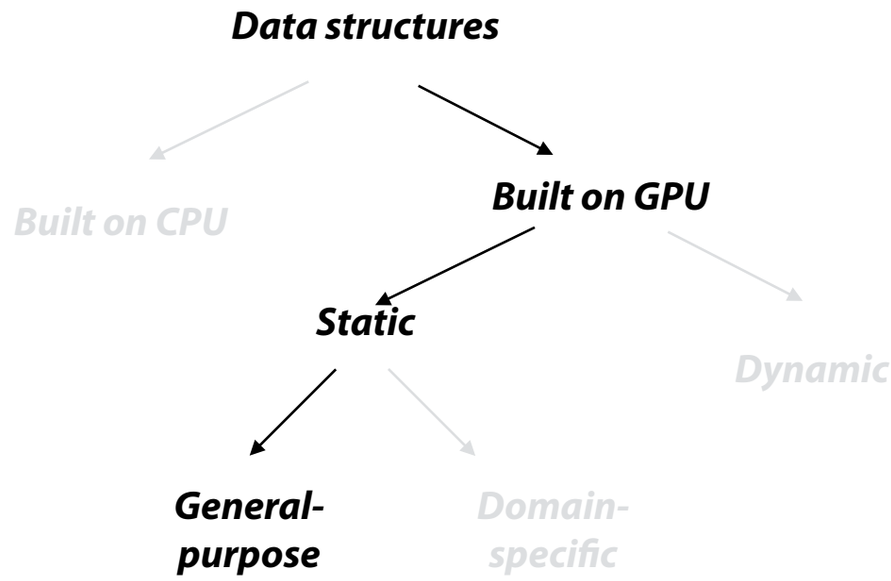




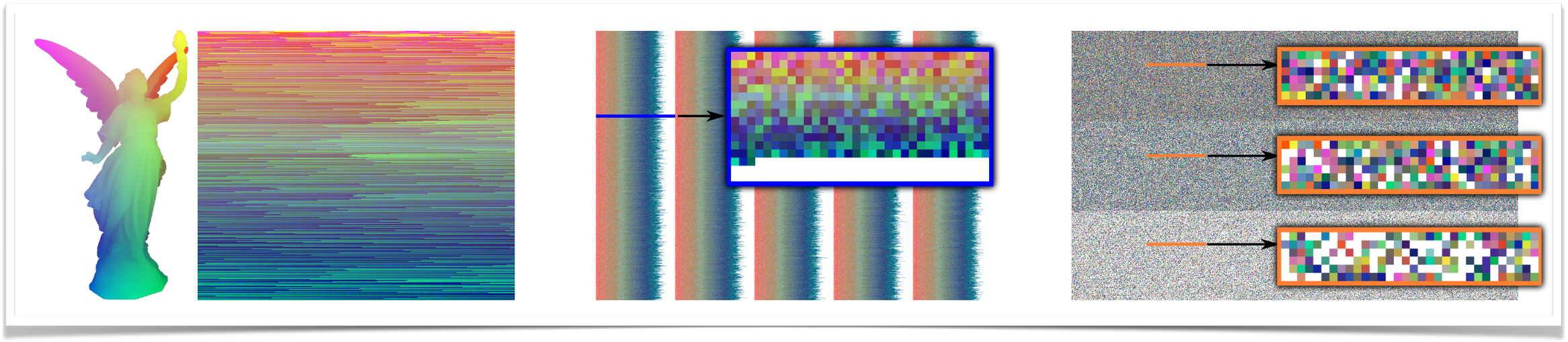


S. Lefebvre and H. Hoppe, Perfect Spatial Hashing, ACM Transactions on Graphics, 2006, vol. 25, no. 3, pp. 579–588.

GPU Cuckoo Hashing

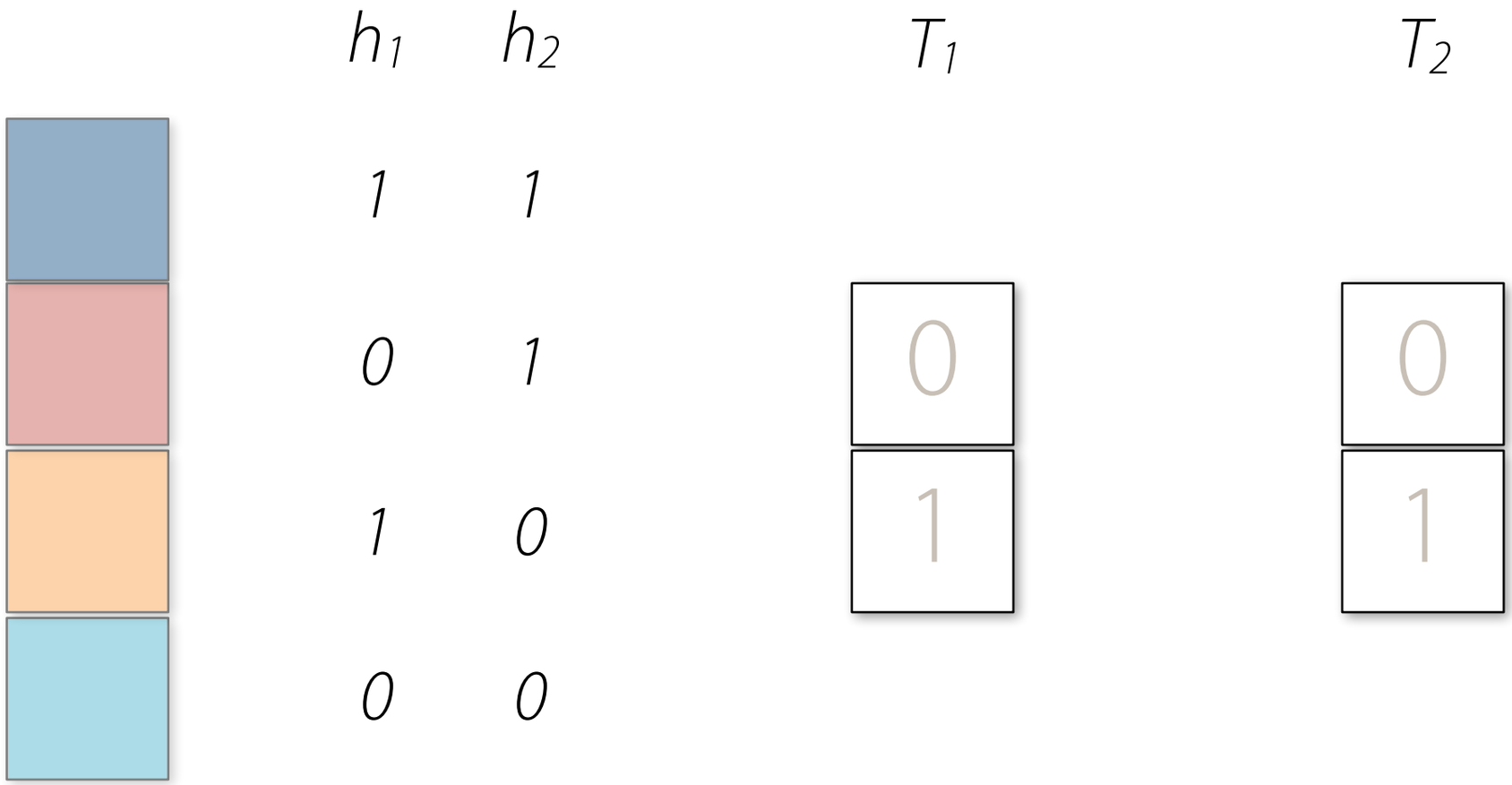


- First hash tables to be constructed on the GPU
- Cuckoo hashing: each element can be placed in one of *n* buckets; if full, ejects item already there
- Excellent best-case performance: one atomic exchange for insertion, one (non-atomic) read for query (note: stresses the TLB)
  - This is the best comparison for read & bulk build performance
- Incremental updates require a complete rebuild



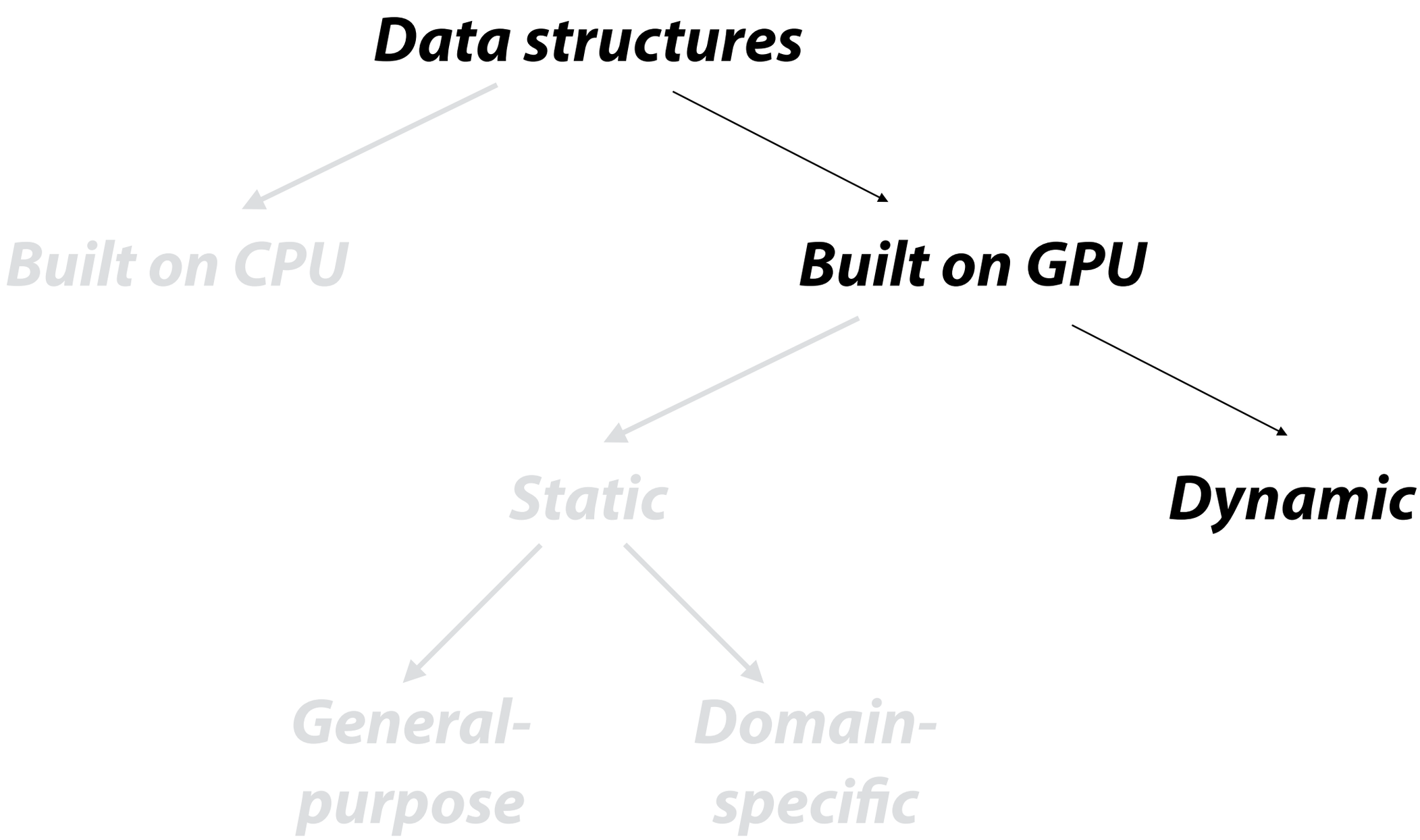
D. A. Alcantara, A. Sharf, F. Abbasinejad, S. Sengupta, M. Mitzenmacher, J. D. Owens, and N. Amenta, Real-time Parallel Hashing on the GPU, ACM Transactions on Graphics, 2009, vol. 28, no. 5, p. 1.

Cuckoo Hashing Construction



- Lookup procedure: in parallel, for each element:
  - Calculate h_1 & look in T_1;
  - Calculate h_2 & look in T_2; still $O(1)$ lookup

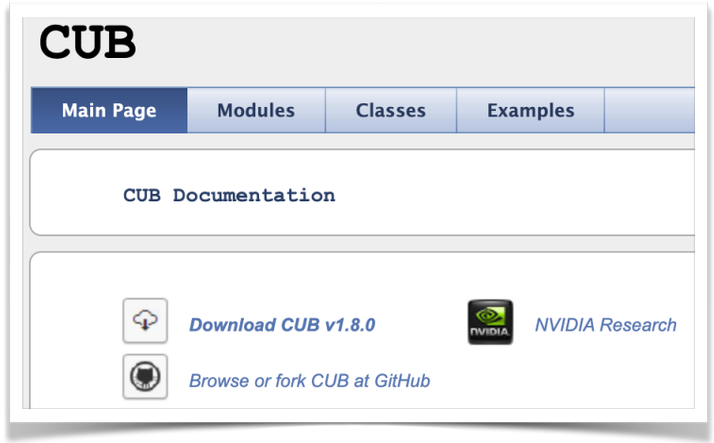
Our goal with this work



- **Goal: Cost is *O*(update size) instead of *O*(dataset size)**

Baseline data structure: sorted arrays

- Sorted arrays support point/range queries (binary search), insertions (merge), deletions (filter)
- Sort, merge, and filter are highly optimized and fast. Binary search is pretty fast.
- Sorted arrays are easy to write



- ∴ Sorted arrays are a pretty good comparison

What We Built

- Dictionary: membership, lookup, range queries, insertions/deletions
- Prioritize insert performance
- *Log-structured merge tree*

- Dictionary: membership, lookup, range queries, insertions/deletions, successor
- Prioritize query performance
- *B-tree*

- Approximate membership query: membership(k) may return "true" even if false with tunable probability 1/ϵ
- *Quotient filter*

- Dictionary: membership, lookup, insertions/deletions
- Prioritize competitiveness with static hash table
- *Hash table (& linked list & dynamic graph)*

There are no mutable GPU data structures

先有鸡还是先有蛋

There are no applications that benefit from mutable GPU data structures

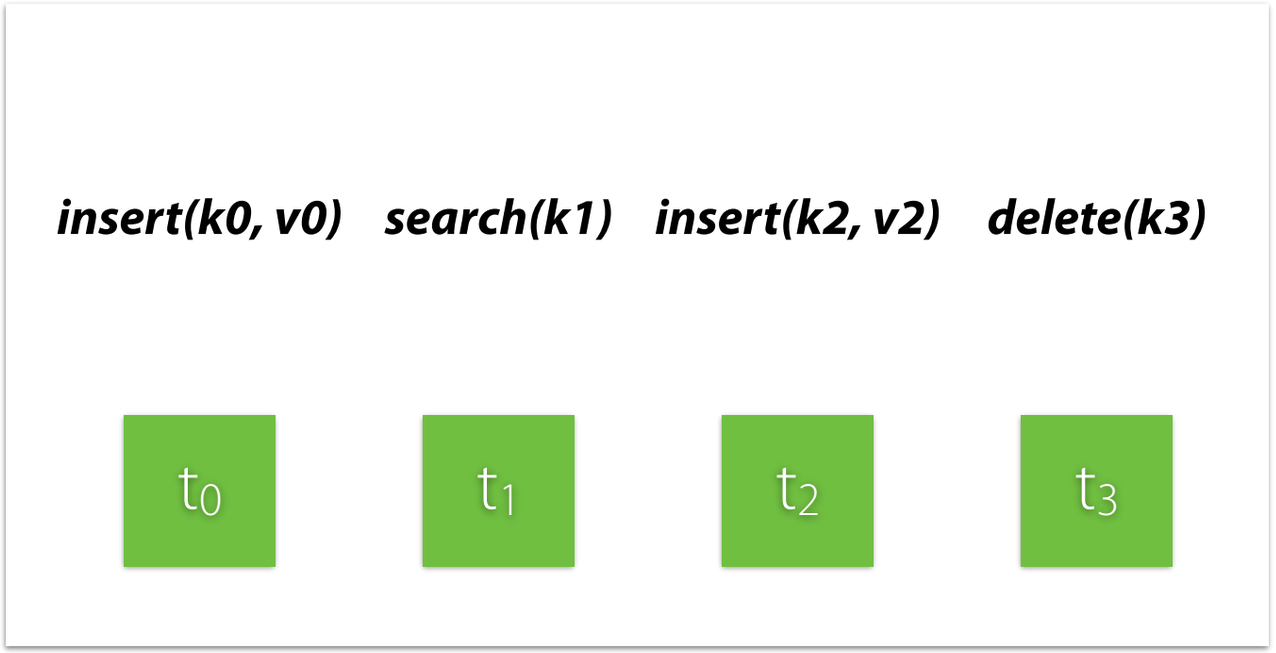
Scale of updates

- Update 1–few items
  - Fall back to serial case, slow, probably don't care
- Update very large number of items
  - Rebuild whole data structure from scratch
    - *O*(update size) ≅ *O*(dataset size)
      - Usually faster than incremental-update approach
      - May be an interesting parallel problem on its own
- Middle ground: our primary goal
  - Question: When do you do this in practice?

Operations: Coarse or Fine?

- GPU requires 100k+ threads to stay busy
- When we do lookups or mutations, we're probably going to do ~100k of them at a time, assigning one per thread
- For the underlying computation, are those threads:
  - All cooperating on a single task? (*coarse*)
  - Each performing an individual task? (*fine*)
- Another way to think about it: Do we treat the input to whatever operations we're doing as a bulk chunk of data or as a bunch of independent items?

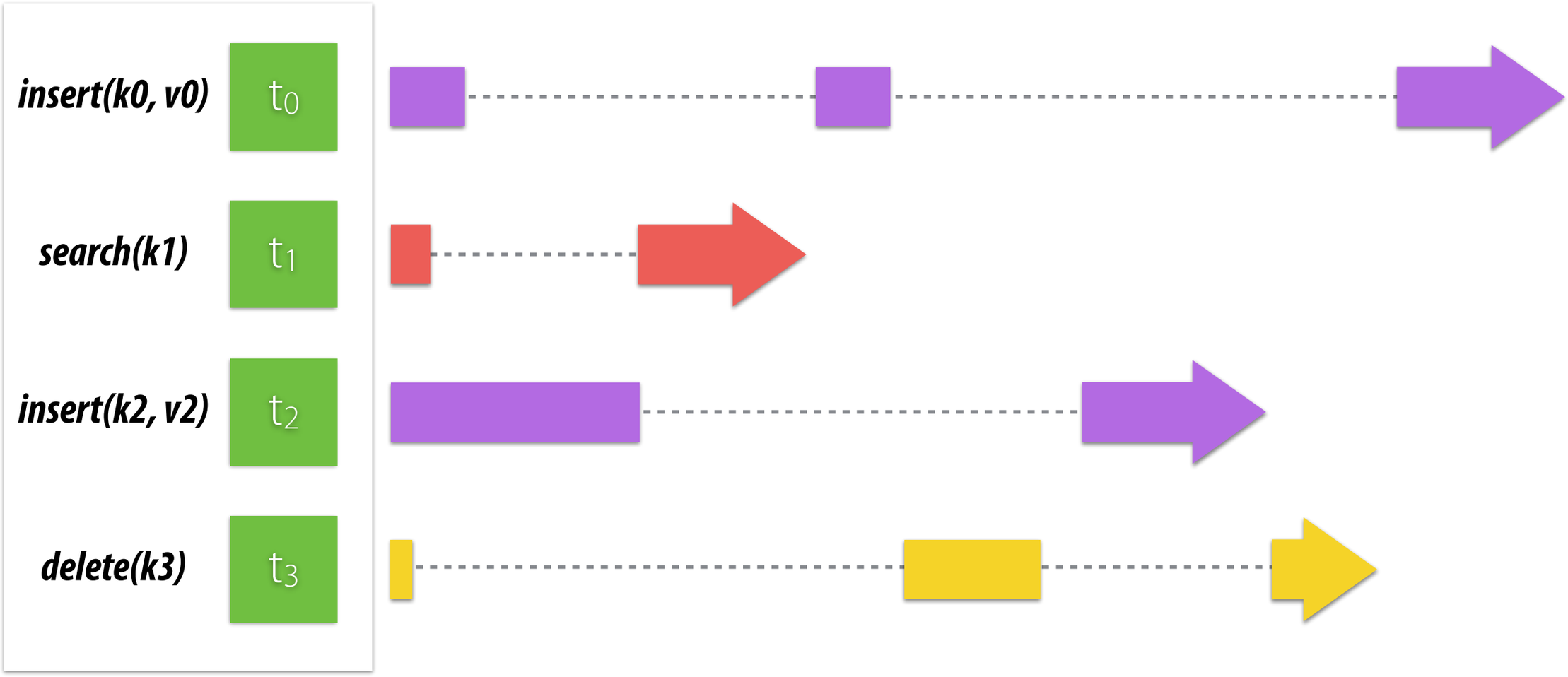
Traditionally: Each thread is independent



Input: A set of independent operations, one per thread

Traditional way: per-thread processing

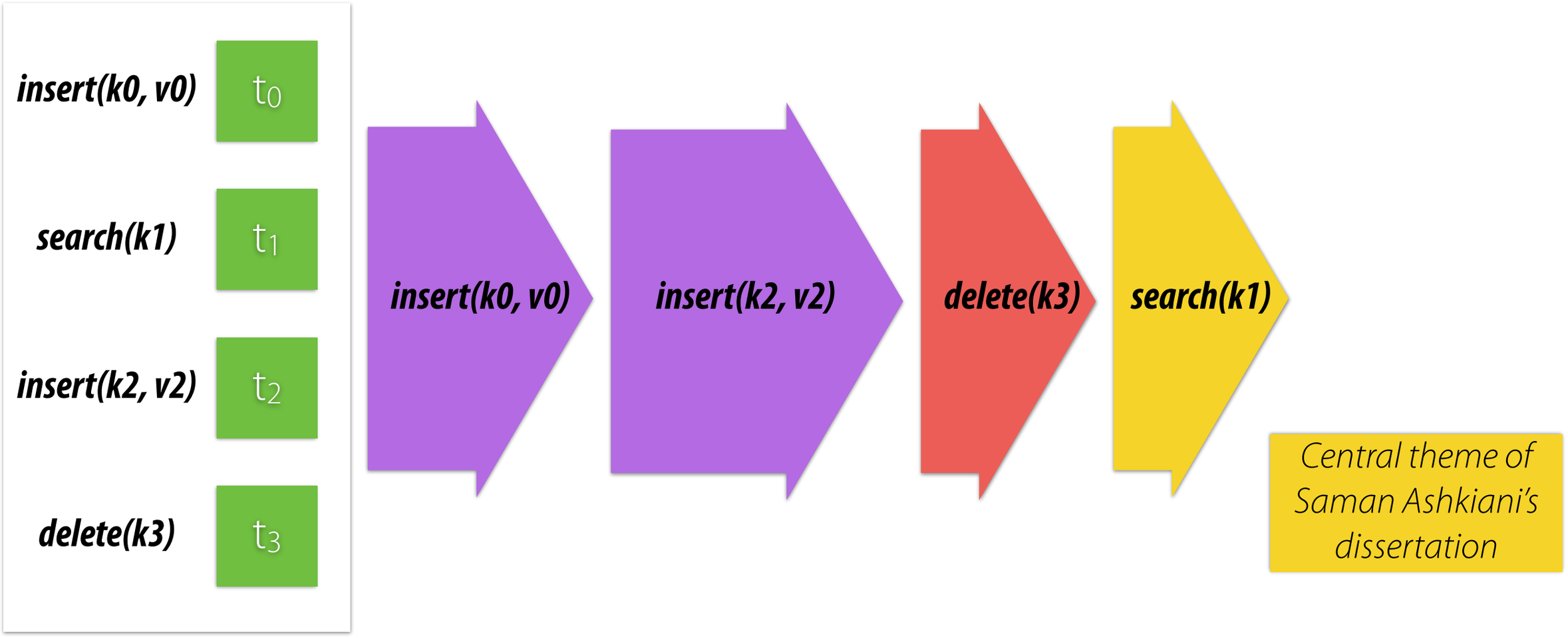
Downsides to independence



- A set of independent operations: per thread work assignment
- Traditional way: per-thread processing
- Poor performance on GPU because of uncoalesced memory accesses and branch divergence

Warp-cooperative work sharing strategy

Design Decision



Central theme of Saman Ashkiani's dissertation

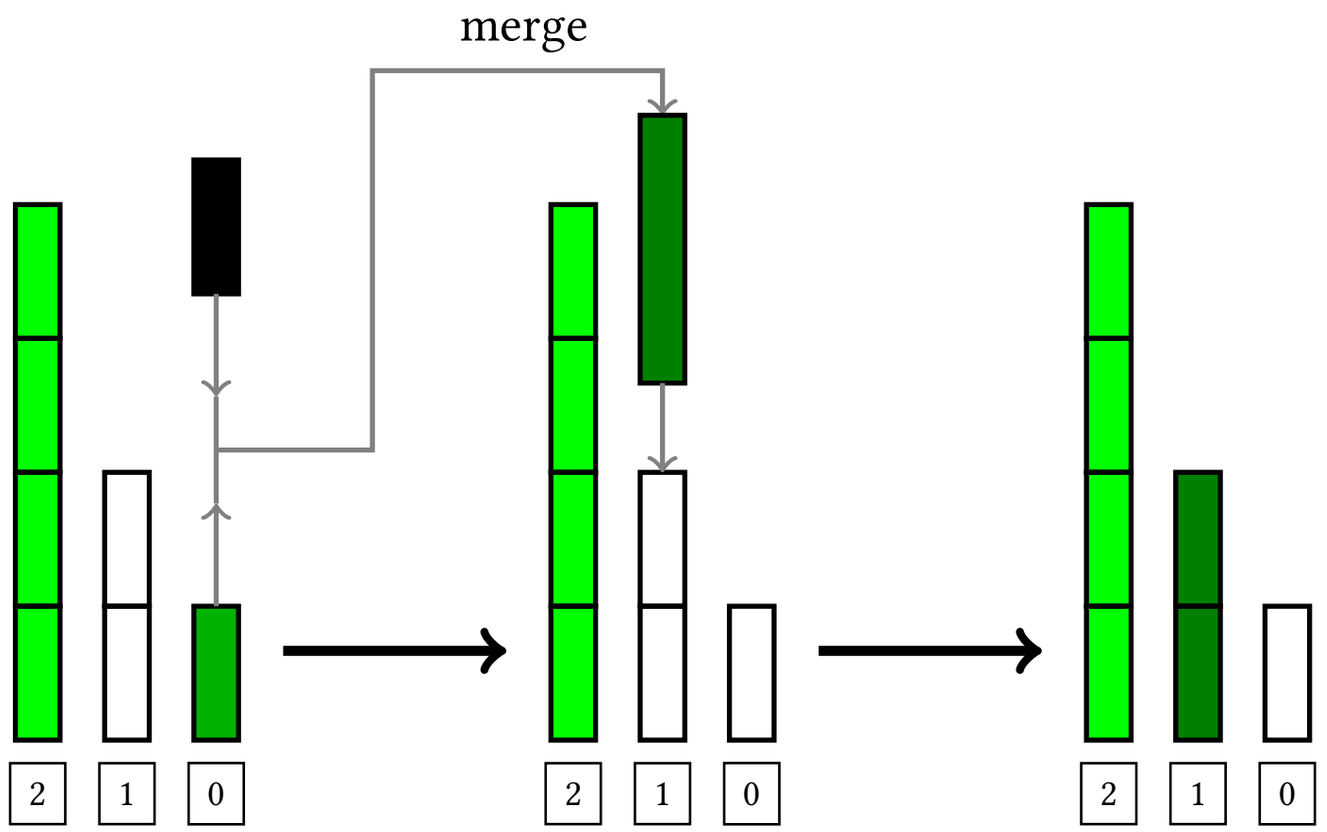
All threads within a warp cooperate to perform operations in parallel, one at a time

- **coalesced memory accesses**
- **minimal branch divergence**
- **parallel intra-warp implementation using ballots/shuffles**

Requires designing data structure to target warp-wide operations

Note: We can perform different operations concurrently!

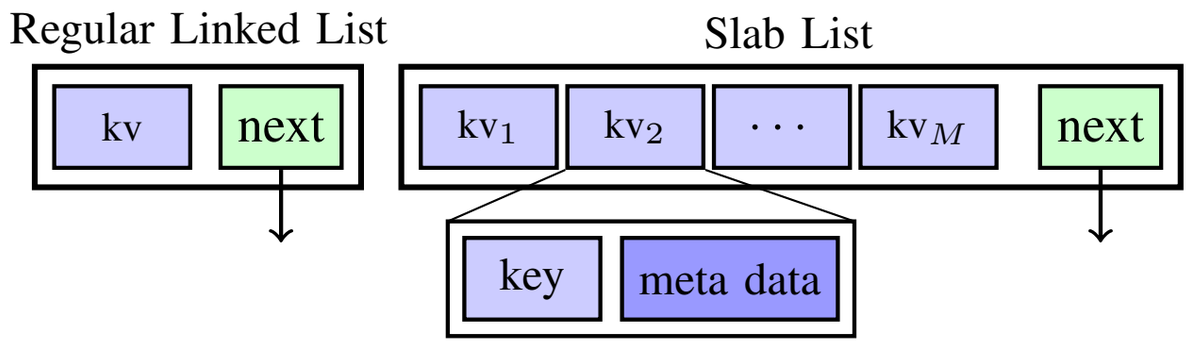
Log-structured merge tree



- Supports dictionary and range queries
- log *n* sorted levels, each level 2x the size of the last
- Insert into a filled level results in a merge, possibly cascaded. Inserts are fast. Operations are *coarse* (threads cooperate).

Saman Ashkiani, Shengren Li, Martin Farach-Colton, Nina Amenta, and John D. Owens. **GPU LSM: A Dynamic Dictionary Data Structure for the GPU**. In *Proceedings of the 32nd IEEE International Parallel and Distributed Processing Symposium*, IPDPS 2018, pages 430–440, May 2018.

Slab Lists & Slab Hash

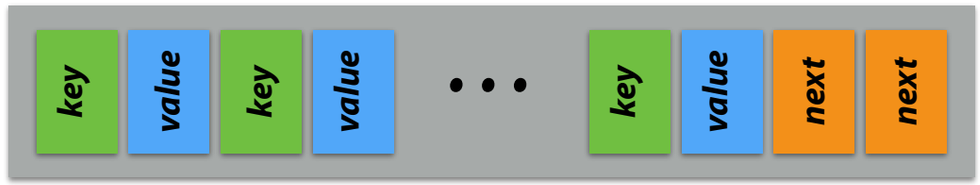


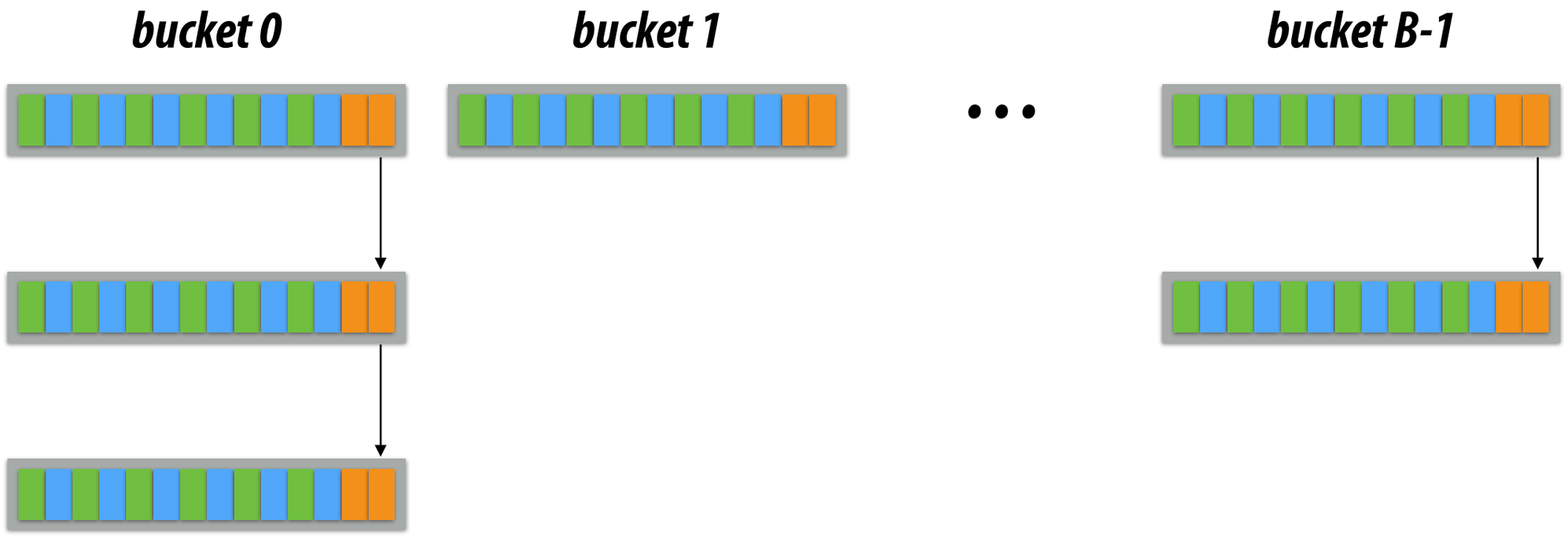
- **Linked lists are flexible, but are poorly suited for GPUs**
  - **Space inefficient. Poor locality (uncoalesced). Poor branch divergence.**
- **The "slab list" stores multiple items per "atom", allowing good parallel performance**
- **The "slab hash" (hash table) is a bucketing hash table with a slab list per bucket**

Saman Ashkiani, Martin Farach-Colton, and John D. Owens. **A Dynamic Hash Table for the GPU**. In *Proceedings of the 32nd IEEE International Parallel and Distributed Processing Symposium*, IPDPS 2018, pages 419–429, May 2018.

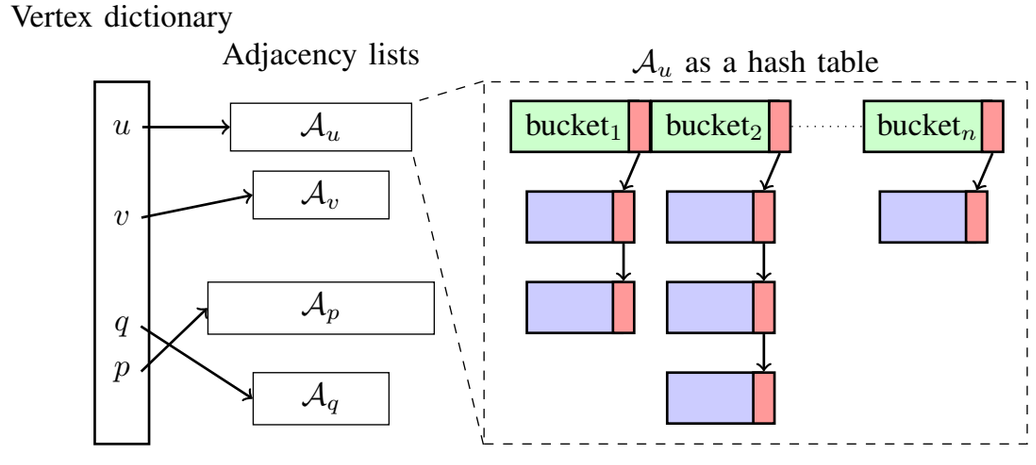
Slab Lists & Slab Hash

1. A hash table with *B* buckets, each represented by a slab list
2. Each slab is 128 bytes wide: 30 × 4B data elements + 2 × 4B next pointers
3. Green elements: keys, Blue elements: values, orange elements: next pointers and/or auxiliary





Dynamic Graphs

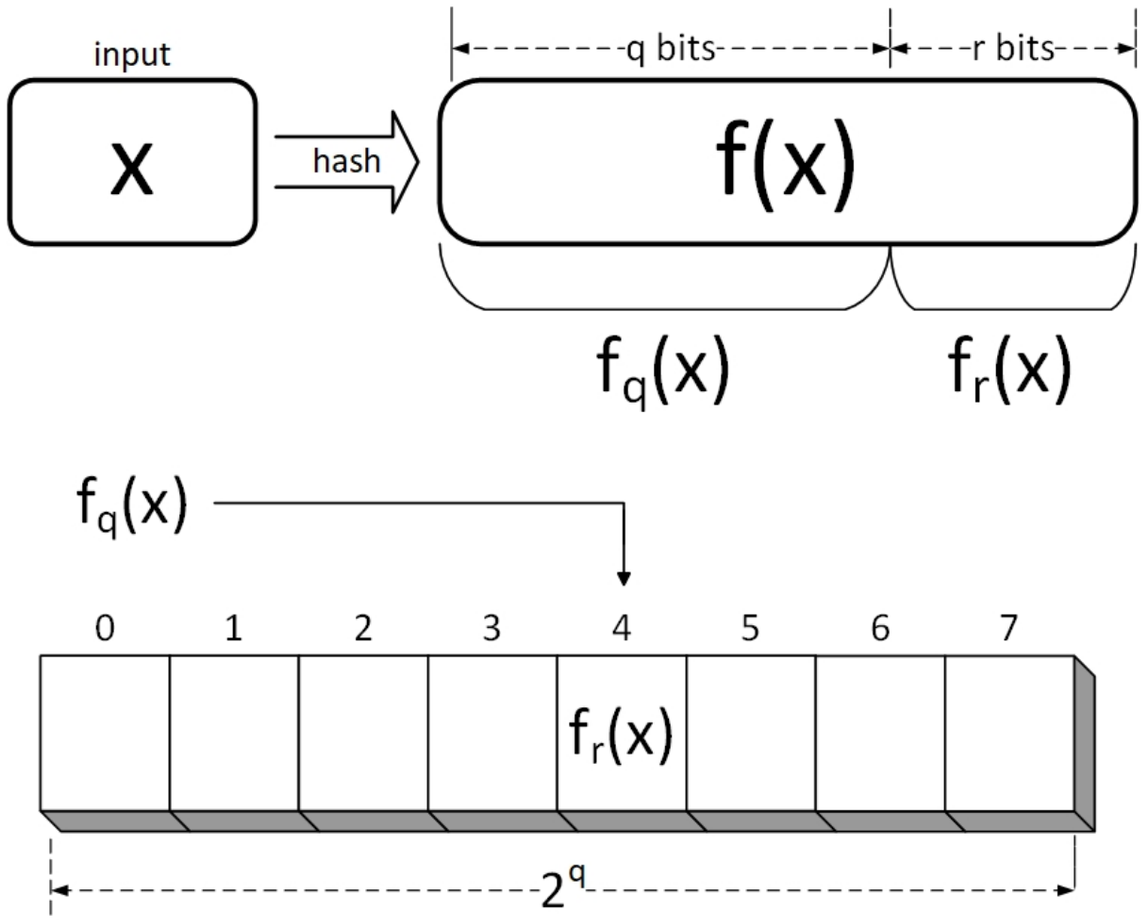


- Consider the query "does *u* have *v* as a neighbor?"
- Consider that vertex adjacencies are stored in a list
  - If that list is unsorted, the query requires visiting all elements
  - If that list is sorted, then the framework has to keep it sorted
- Conclusion: List data structures aren't a good fit for dynamic graphs
- Our work uses a hash table per vertex to store adjacencies

Muhammad A. Awad, Saman Ashkiani, Serban D. Porumbescu, and John D. Owens. **Dynamic Graphs on the GPU**.
In *Proceedings of the 34th IEEE International Parallel and Distributed Processing Symposium*, IPDPS 2020, May 2020. [bib | http]

Quotient Filters

- Probabilistic membership query (cf.: Bloom filter)
- Hash all inputs into fingerprints
- Use quotienting to divide fingerprints into *quotient* and *remainder* bits
- Quotient bits determine the slot number
- Remainder bits are stored in slot



Afton Geil, Martin Farach-Colton, and John D. Owens. **Quotient Filters: Approximate Membership Queries on the GPU**.
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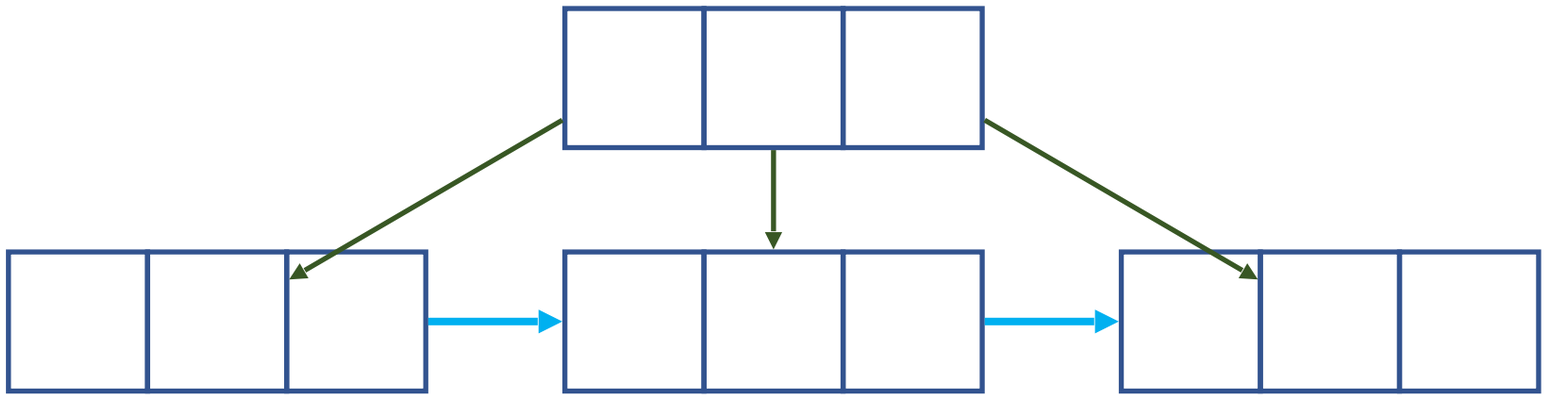
GPU B-Trees



Intermediate Node	$\{Pivot, Ptr\}_0$	$\{Pivot, Ptr\}_1$	…	$\{Pivot, Ptr\}_{14}$	$Link\{Min, Ptr\}$
Leaf Node	$\{Key, Value\}_0$	$\{Key, Value\}_1$	…	$\{Key, Value\}_{14}$	$Link\{Min, Ptr\}$

- **Key design decisions:**
  - **All blocks are warp-sized and processed with warp-cooperative work sharing**
  - **Side links reduce need for locking**

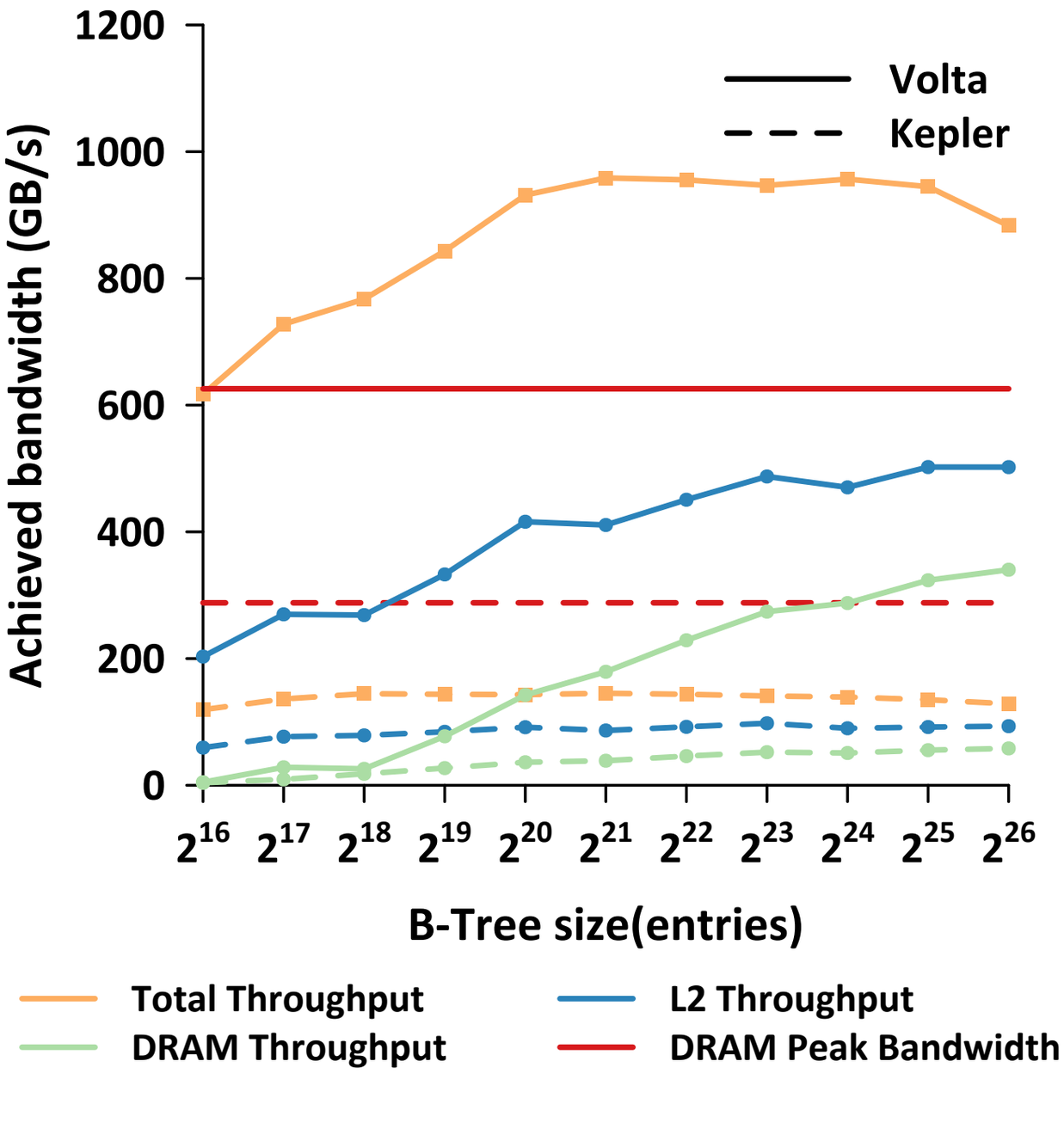
Muhammad A. Awad, Saman Ashkiani, Rob Johnson, Martín Farach-Colton, and John D. Owens. **Engineering a High-Performance GPU B-Tree**. In *Proceedings of the 24th ACM SIGPLAN Symposium on Principles and Practice of Parallel Programming*, PPoPP 2019, pages 145–157, February 2019. [bib | DOI | http]

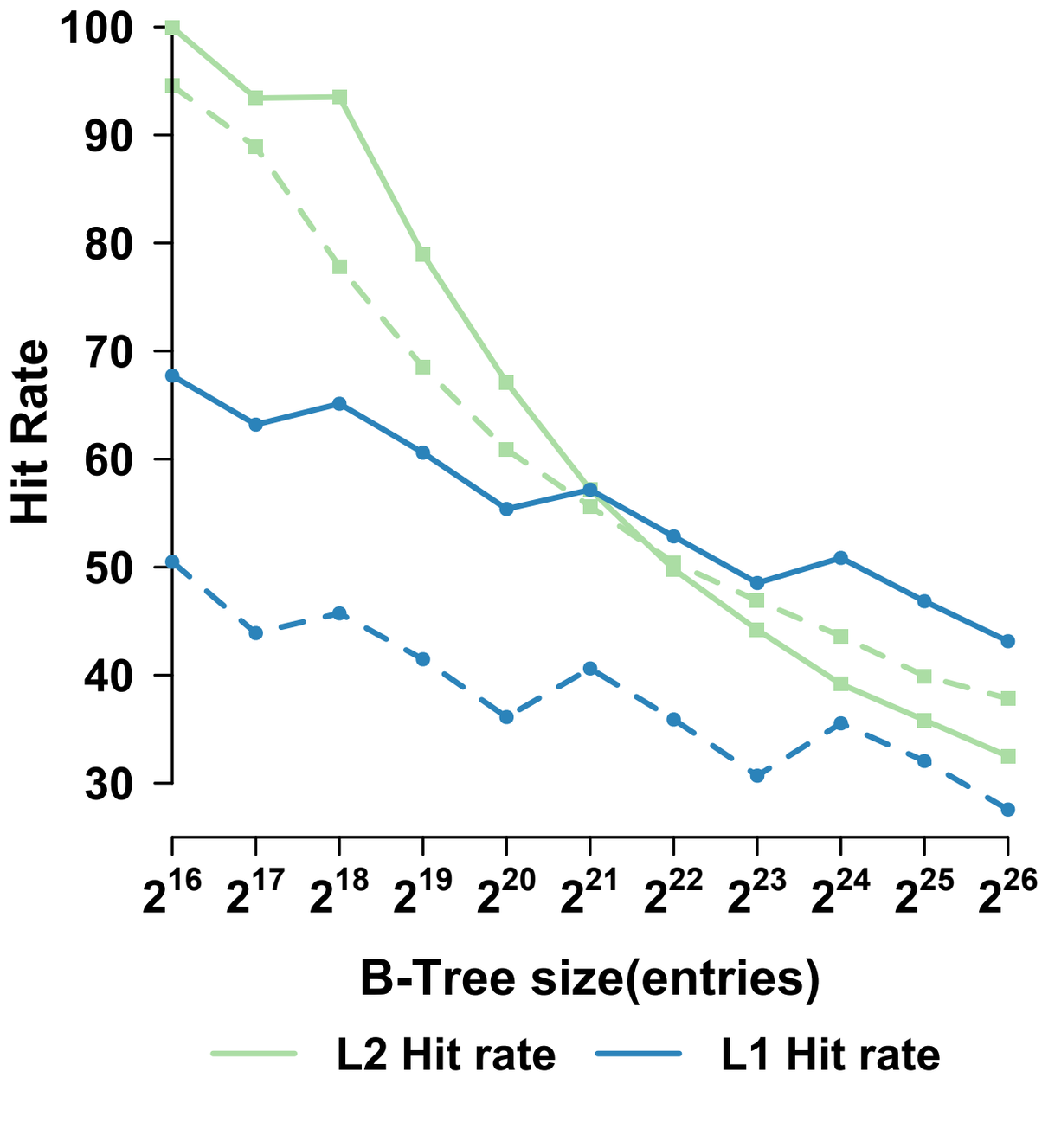
B-Tree: Contention is #1

- Side links & proactive splitting remove need for locking parents of node insertions
- Reads are latch-free; more work to switch to write but fewer locks are worth it
- Restarts instead of spinlocks

- Baseline (latch coupling, proactive splitting): 0.166 MKey/s
- Above design: 182.9 MKey/s

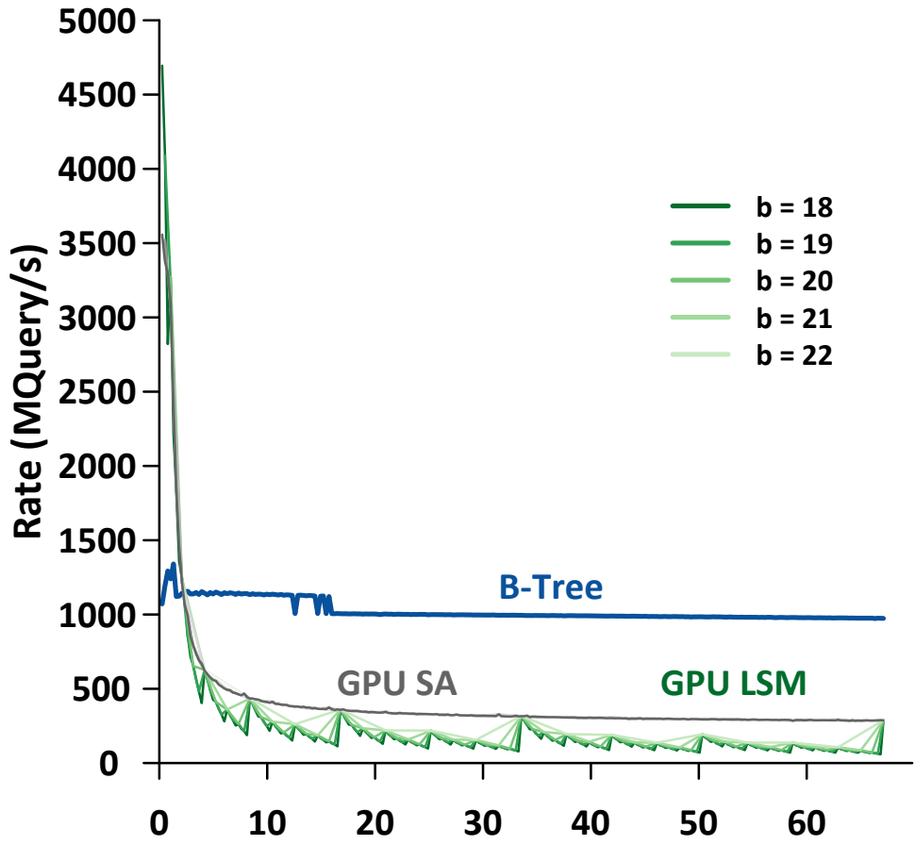
B-Tree: Caches Work





B-Tree vs. LSM

- No surprise that B-tree queries are faster than LSM …



- … but so are insertions of small batches.
- In general 10k–1M elements are necessary to approach peak performance

Millions of elements

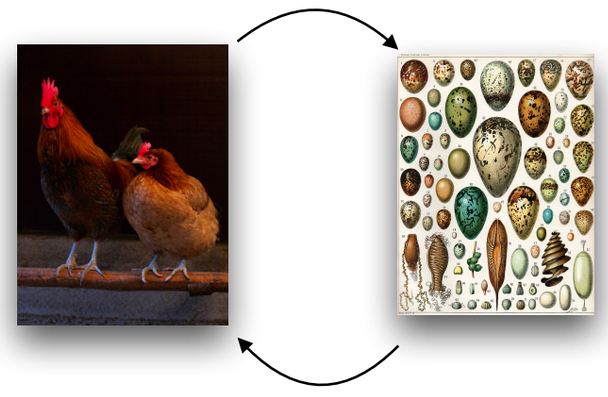
batch size	B-Tree	GPU LSM	GPU SA
2^{16}	168.0	61.5	44.9
2^{17}	139.7	121.3	87.6
2^{18}	171.7	218.6	160.6
2^{19}	190.3	402.5	292.6
2^{20}	205.1	685.9	543.0
2^{21}	211.9	1103.8	907.5
2^{22}	223.0	1603.1	1472.7
Mean	182.9	202.6	149.1

Issues with Hash Tables (that are actually general issues)

- Memory allocation was critical for performance
  - Built custom allocator just to allocate new slabs (cost: 2 registers)
  - Default allocators are terrible at small allocations
- Ideal item count per bucket approaches filling one slab
  - Performance suffers when that changes
  - In general: is stop-and-rebuild (garbage collection) a viable strategy?
- For mutable graphs:
  - We store outgoing edges with a hash table per vertex
  - Unbalanced inputs (e.g., neighbors in a scale-free graph) will be problematic for performance

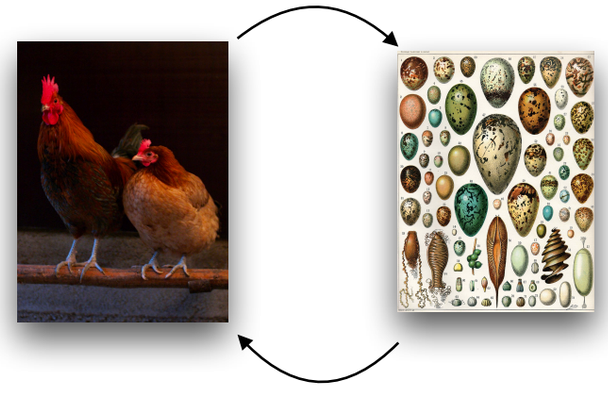
Do our APIs work?

- High priority: Build something programmers can use
  #include <data_structure.h>
- Generally, those look like “every thread has an item”
- Is that what programmers want?



Semantics

- GPUs (generally) operate with bulk semantics
  - What does this mean for ordering?
  - Within a batch of updates, how do we handle "collisions"?
- Do applications actually do updates and queries simultaneously or not?
  - Do updates and queries occur in different *phases*?
  - If not, what should happen when an insert, a delete, and a query all happen at the same time?
  - Need more applications to understand need for phases



The Future

- Dynamic graph data structure integration (cf. NVIDIA RAPIDS)
  - This work is already in Gunrock
- Revisit open-addressing hash tables
- Functional programming data structures
  - Persistent data structures
  - Data structures used in (e.g.) Haskell, Scala, Clojure
- Better understanding of interesting workloads
- Integrate into languages (~higher level than CUDA) that target the GPU
- Motivates investigating GPU runtimes

Thank you!

- NSF award CCF-1637442 (“Algorithms in the Field” program), Martin Farach-Colton, co-PI. Thanks to PM Tracy Kimbrel.
- NVIDIA AI Lab at UC Davis (est. 2019)
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- Bill Dally, Joe Eaton, Michael Garland, Ujval Kapasi, Steve Keckler, Lars Nyland, Josh Patterson, Brad Rees, Nikolay Sakharnykh (NVIDIA)

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Muhammad Awad, Saman Ashkiani, Serban D. Porumbescu, and John D. Owens. *Dynamic Graphs on the GPU*. In Proceedings of the 34th IEEE International Parallel and Distributed Processing Symposium, IPDPS 2020, pages 739–748, May 2020. [bib | http]

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