Modular Data Storage with Anvil

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Motivation

- Data storage and databases drive modern applications
  - Facebook, Twitter, Google Mail, system logs, even Firefox
  - Yet hand-built data stores can outperform by 100x! [Boncz]
- Changing the layout of stored data can substantially improve performance
  - Recent systems implement custom storage engines
- Custom storage engines are hard to write
  - Reason: Must be consistent, fast for both reads and writes
  - What if you want to experiment with a new layout?

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Yes we can!

Anvil

- Fine-grained modules called *dTables*
  - Composable to build complex data stores from simple parts
  - Easy to implement new dTables to store specialized data
- Isolates all writing to dedicated writable dTables
  - Many data storage layouts only add or change read-only dTables, which are significantly easier to implement
  - Good disk access characteristics come as well
  - Unifying dTables combine write- and read-optimized dTables

Contributions

- Fine-grained, modular dTable design
- Core dTables
  - Overlay dTable, Managed dTable, Exception dTable
- Anvil implementation
  - Shows that such a system can be fast

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- Key/value store
  - Keys are integers, floats, strings, or blobs
  - Values are byte arrays
  - Iterators support in-order traversal
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bool  insert(key k, blob v)
bool  remove(key k)
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Slightly simplified, but not much!

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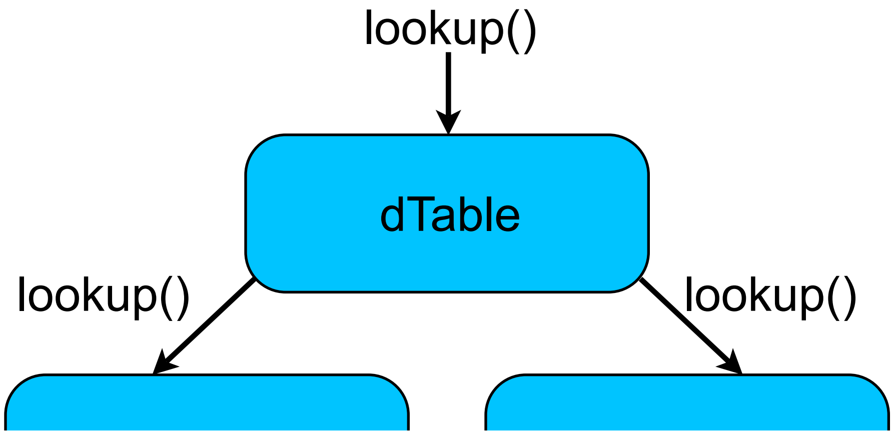

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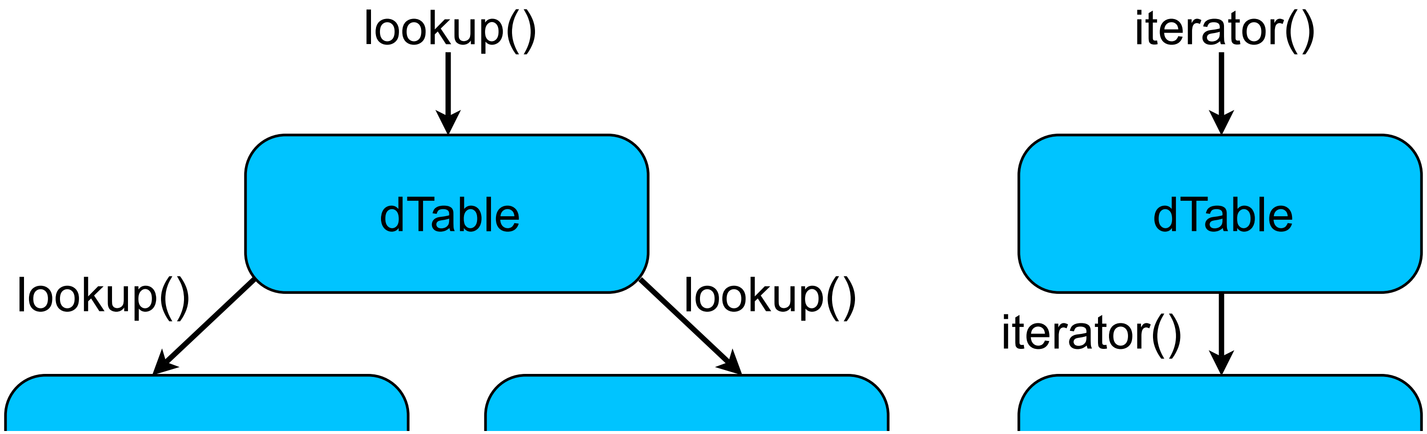

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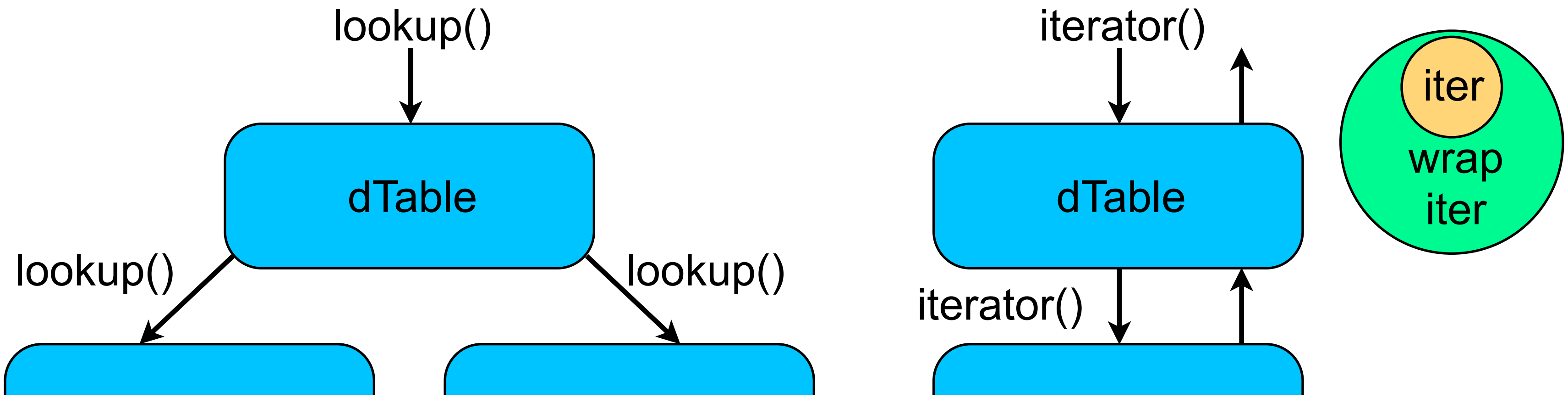

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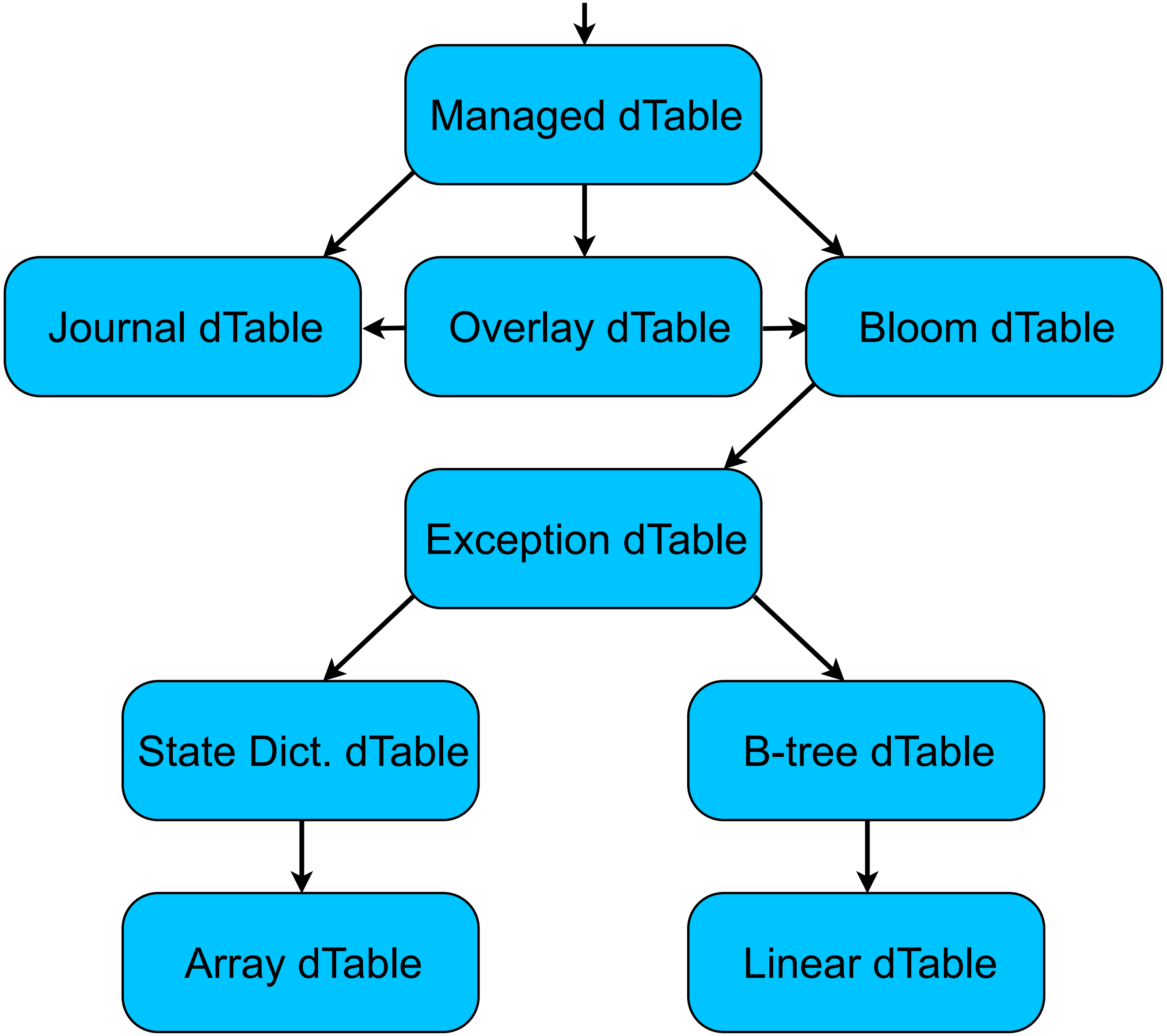

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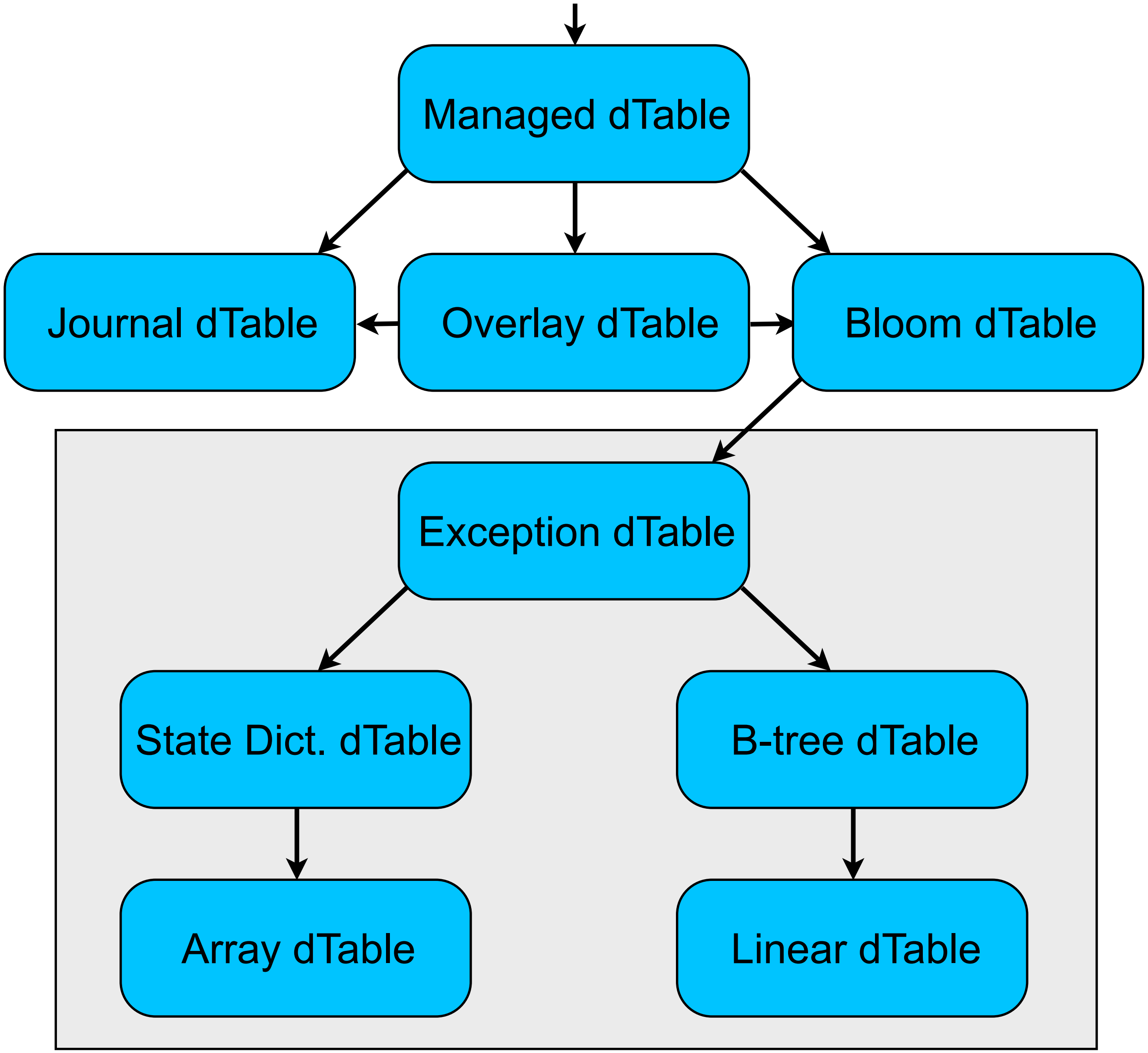

Application-Specific Data Example

- Want to store the state of residence of customers
  - Identified by mostly-contiguous IDs
  - Most live in the US, but a few don’t
  - Move between states occasionally
- Common case could be stored efficiently as an array of state IDs
  - But don’t want to penalize the uncommon case
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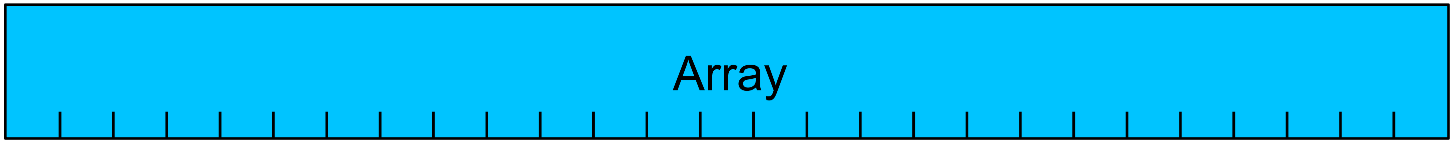
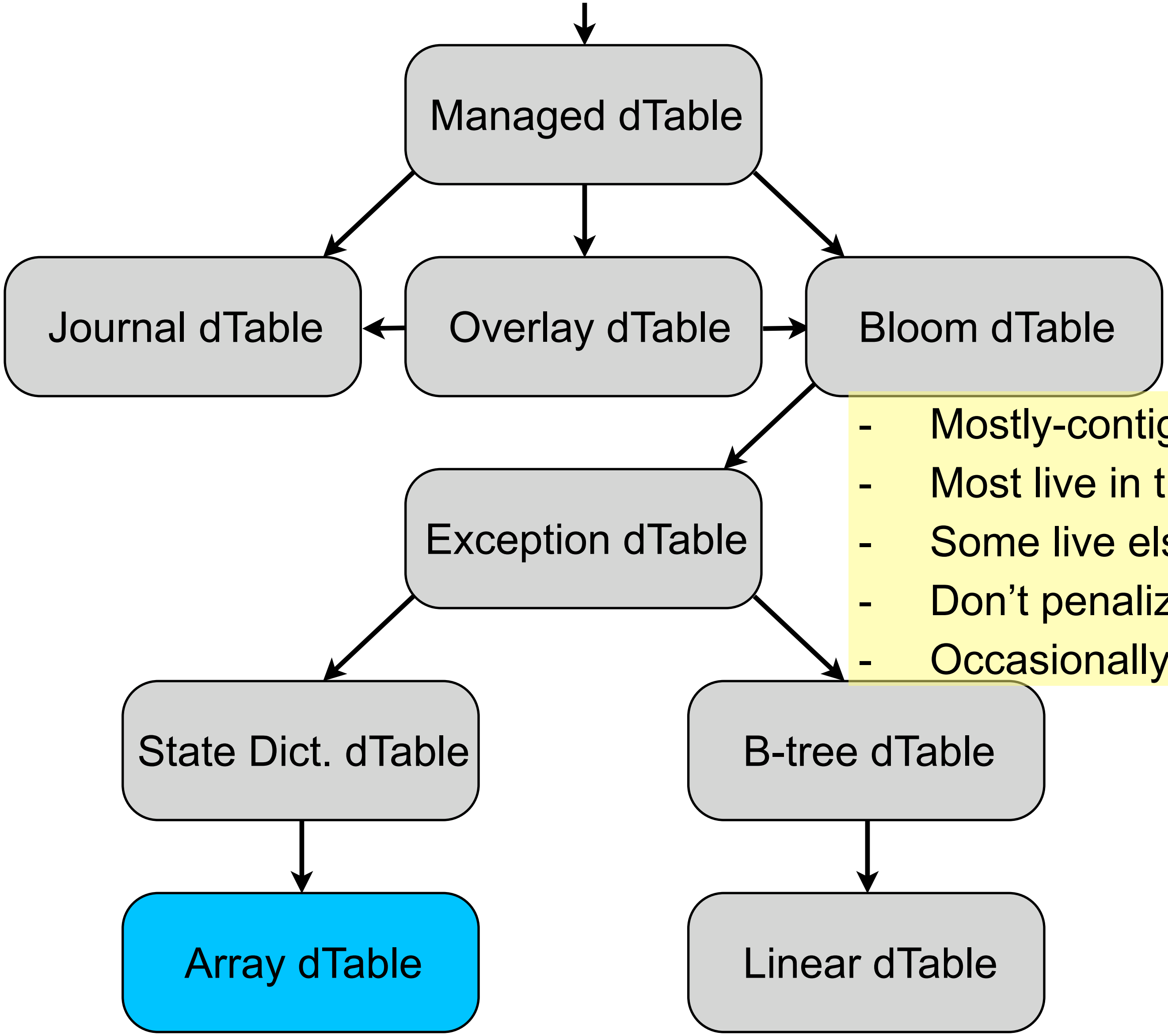
Array dTable

- Stores an array of fixed-size values
  - Keys must be contiguous integers
  - Locating data items becomes constant time
  - Can’t store some types of data
  - Read-only



Storing Common Case Data Efficiently



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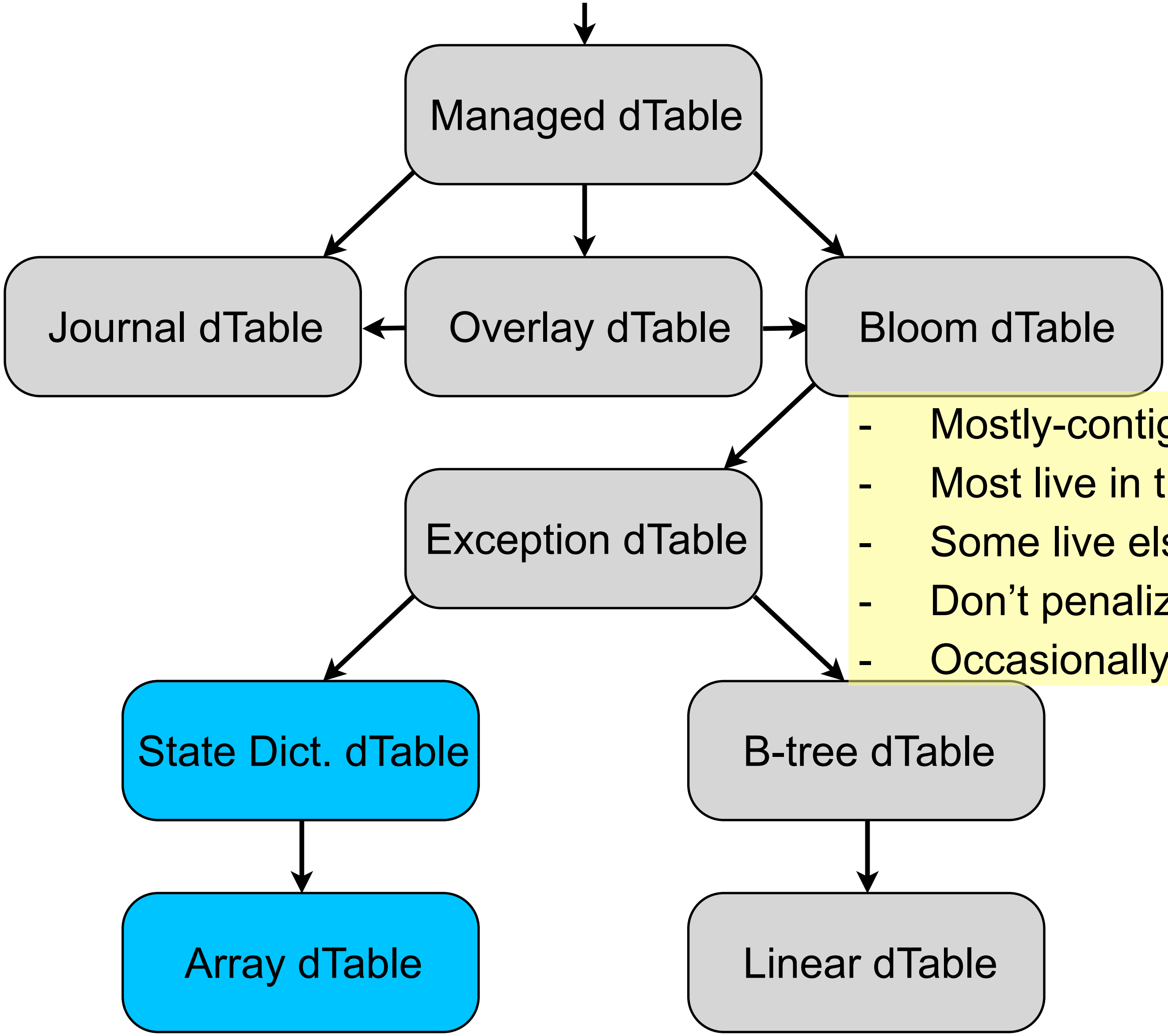

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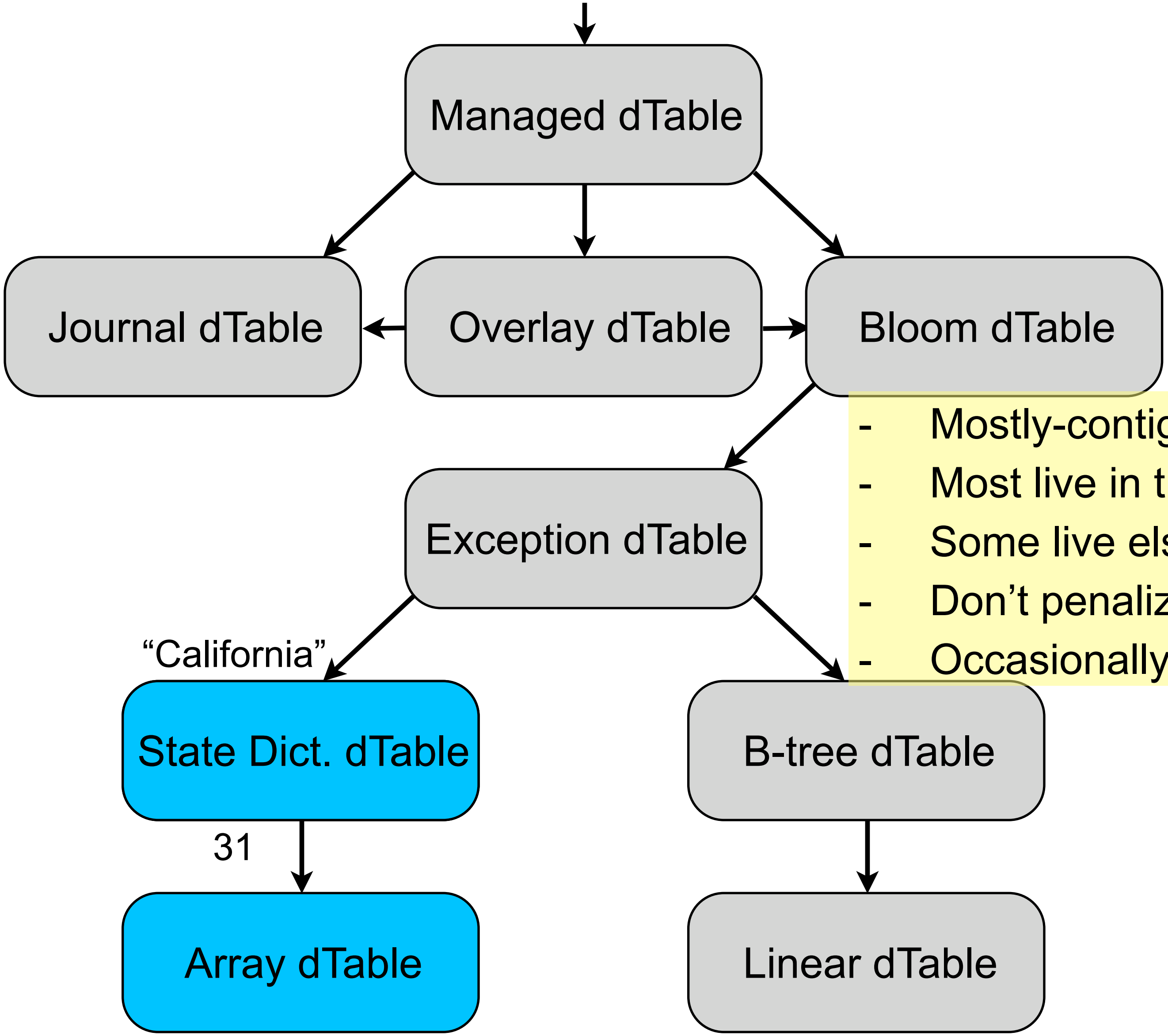

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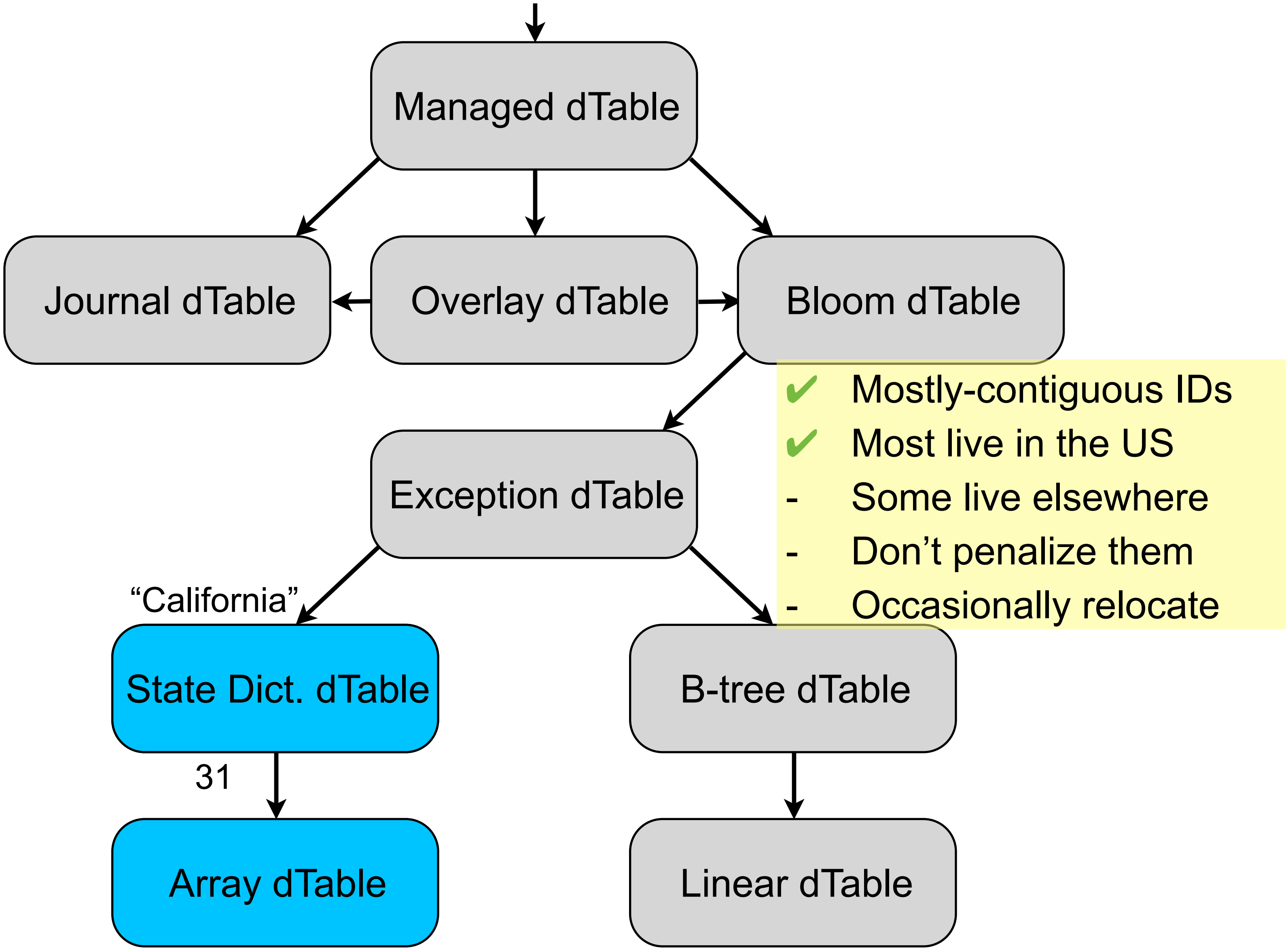

Managed dTable

Journal dTable

Overlay dTable

Bloom dTable

Exception dTable

"California"

State Dict. dTable

31

Array dTable

B-tree dTable

Linear dTable

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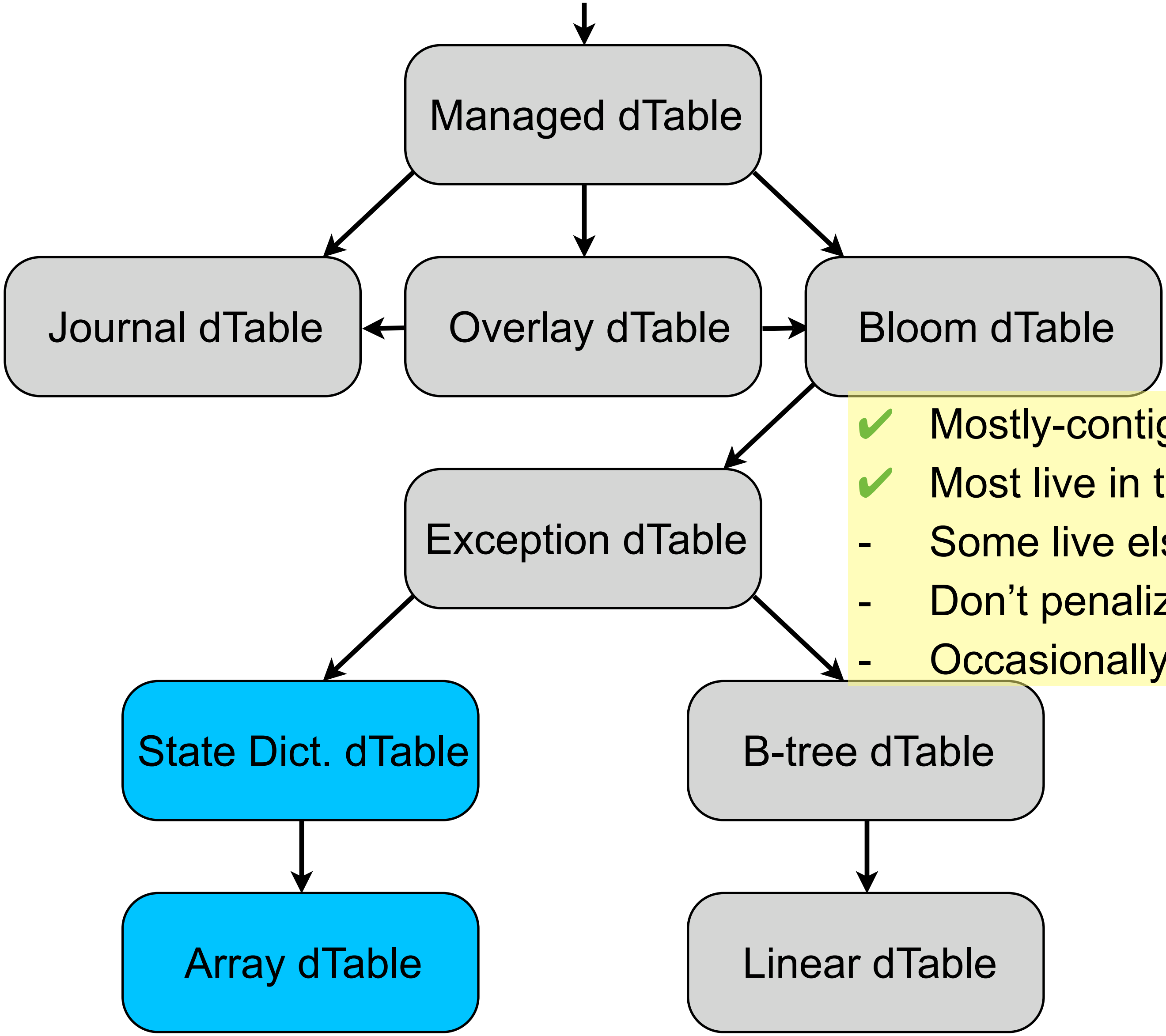
    - Sentinel value in restricted dTable indicates that the unrestricted dTable should be checked
- Simple unrestricted dTable: Linear dTable

Storing All Data



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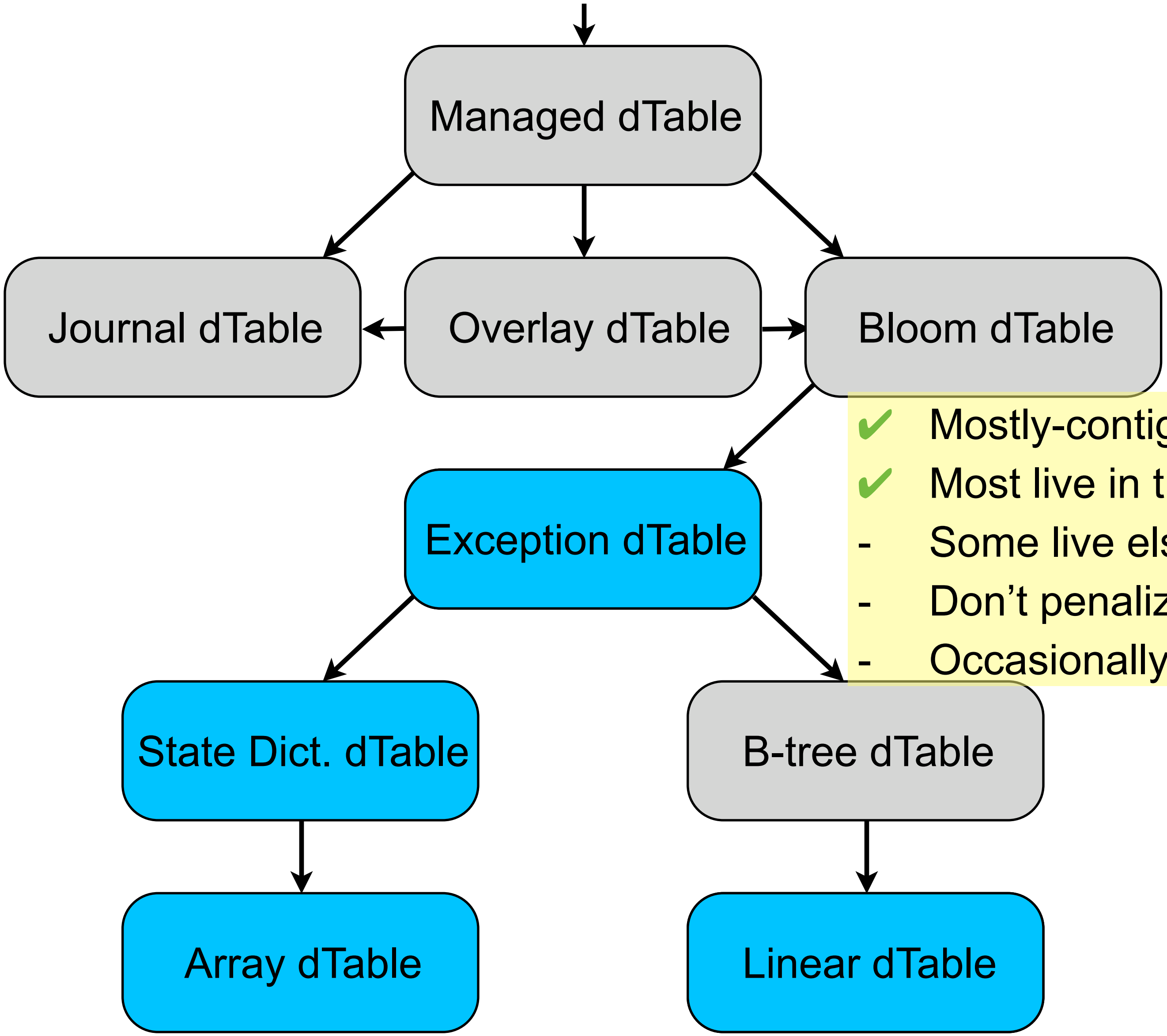

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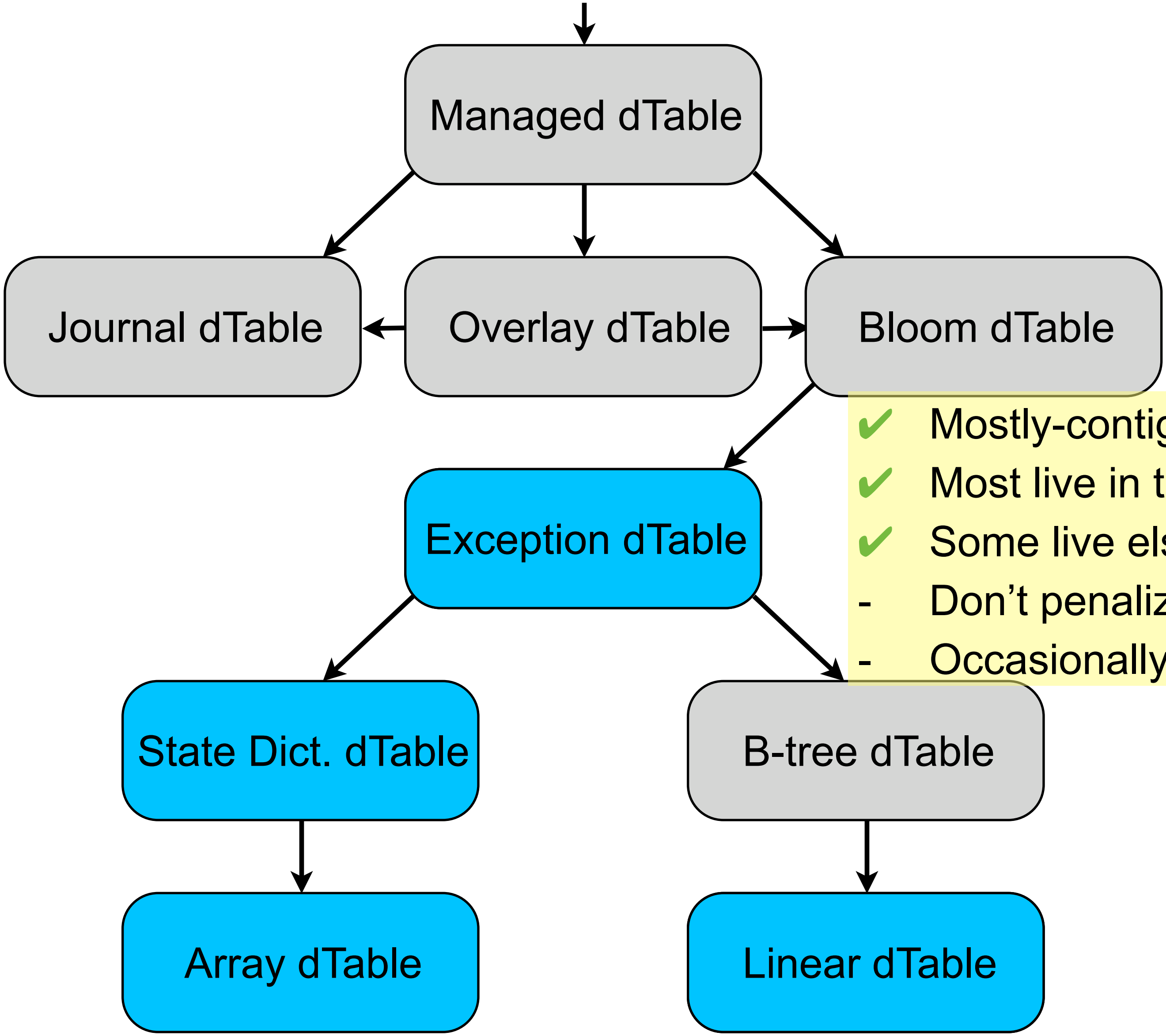

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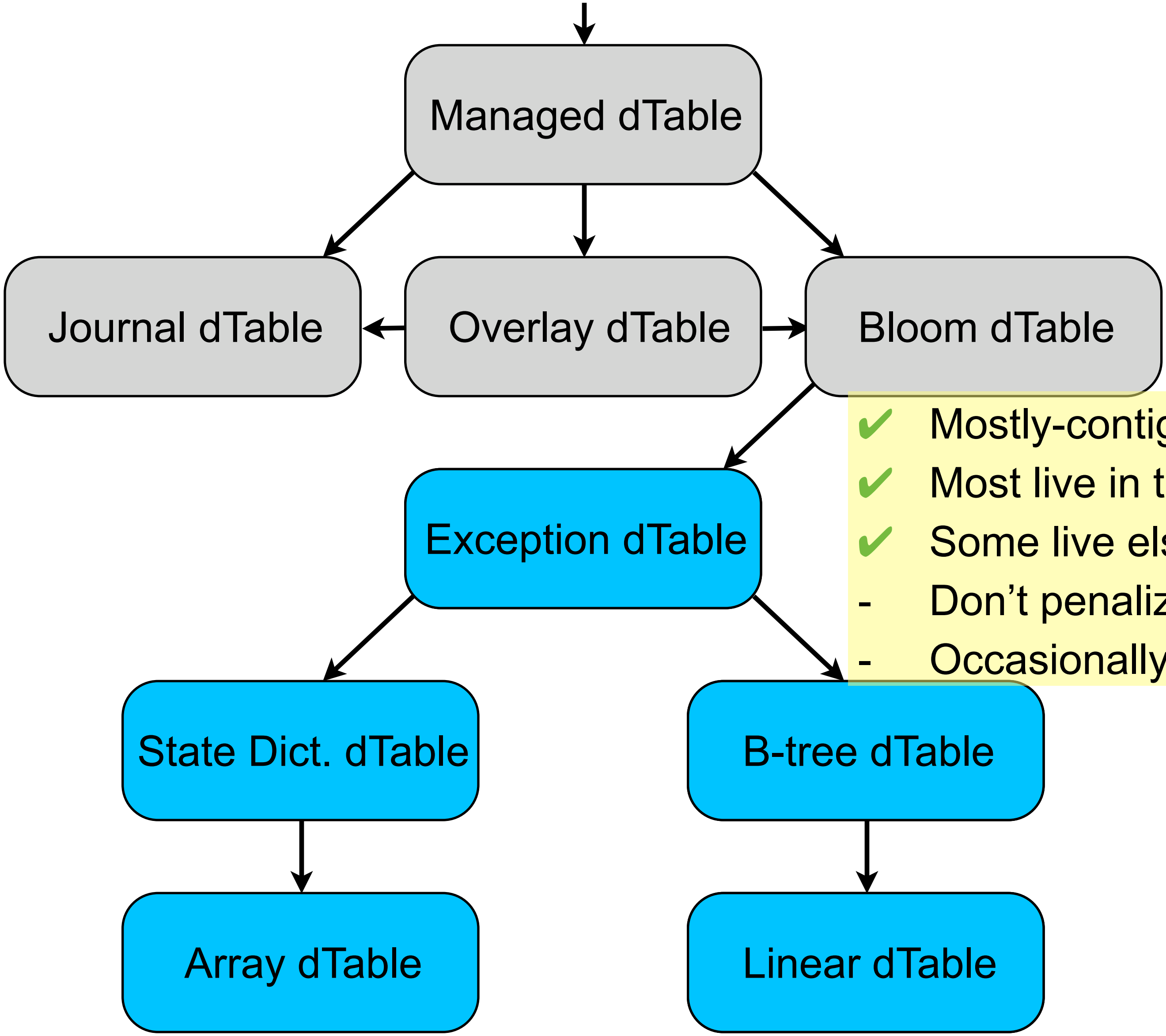

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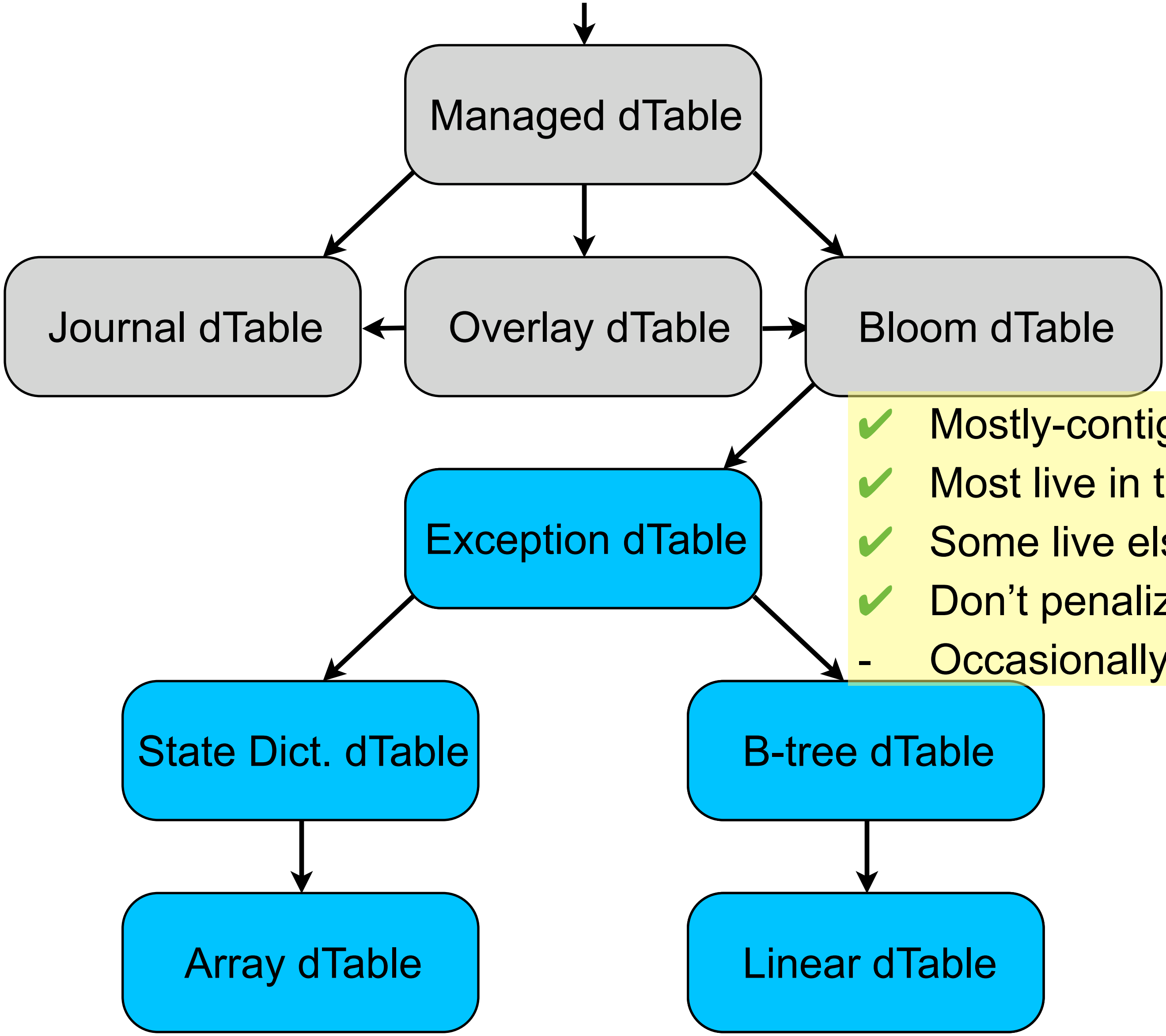

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General dTables

- We’ve seen how to build a read-only data store specialized for an application-specific layout
  - The pieces can be recombined for other layouts
- Next section shows how to build a writable store
  - Writable store dTables are common to many layouts
  - Split data write functionality and management policies

Writable dTables

- Array dTable is hard to update transactionally
- Idea: use separate writable dTables
  - Can be optimized for writing (e.g. a log)
- Several design questions
  - Implementation of write-optimized dTable
  - Building an efficient store from write-optimized and read-only pieces

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- Appends new/updated data to a shared journal

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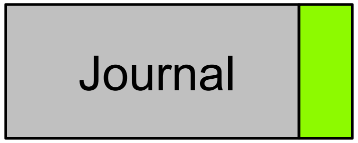

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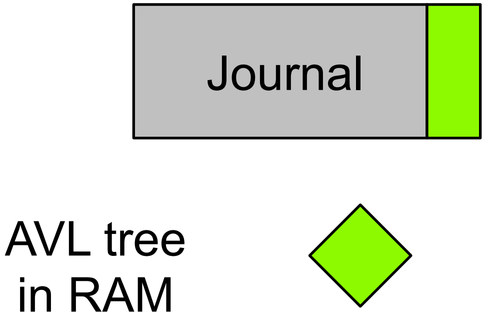
- Appends new/updated data to a shared journal
- All data also cached in an AVL tree in RAM



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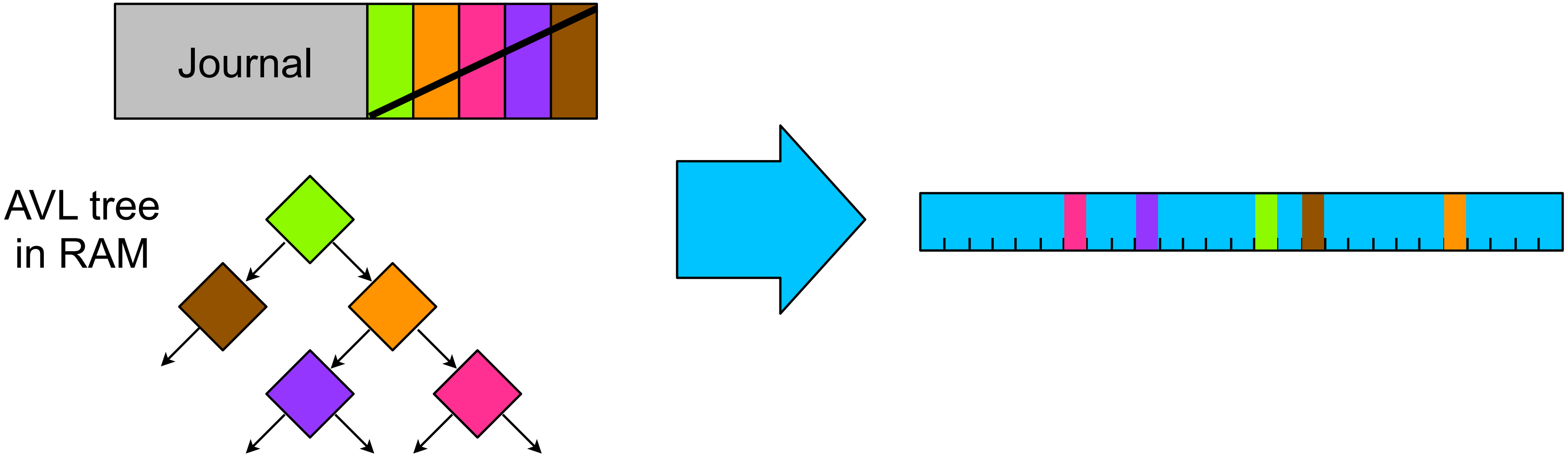
- Appends new/updated data to a shared journal

- All data also cached in an AVL tree in RAM

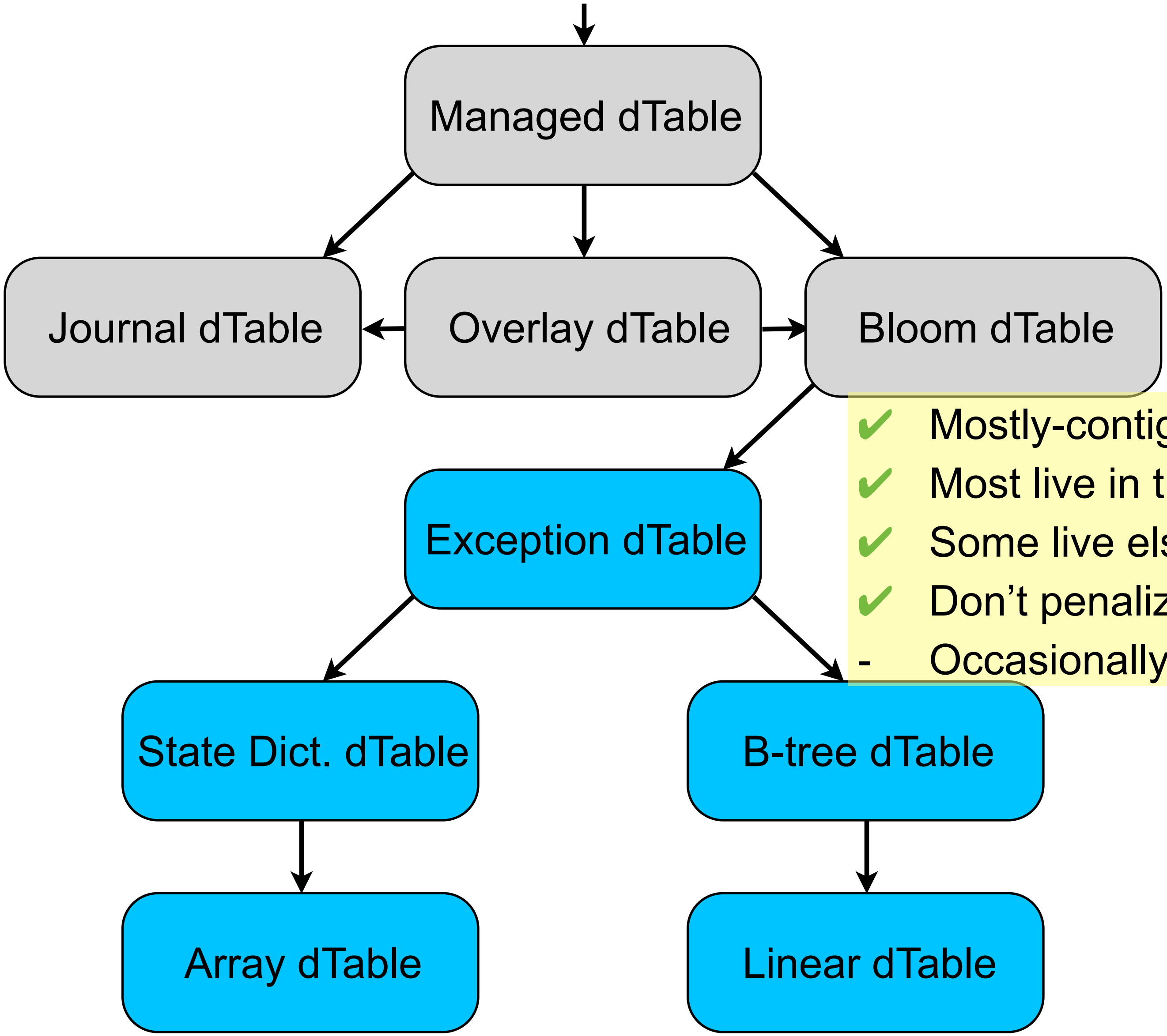
- Should be “digested” when it gets large



System Journal

- Chronological order, append-only data store
  - Fast, contiguous writes on disks and other storage devices like Flash memory
  - Data later rewritten elsewhere in batches from cache
- *Clean* the system journal periodically to reclaim space
  - Data already written elsewhere can be omitted
  - Optimization: just delete it and restart if totally empty
- Uses a transaction system described in the paper
  - Client code chooses start and end of each transaction
  - Durability optional, consistency always provided

Handling Writes



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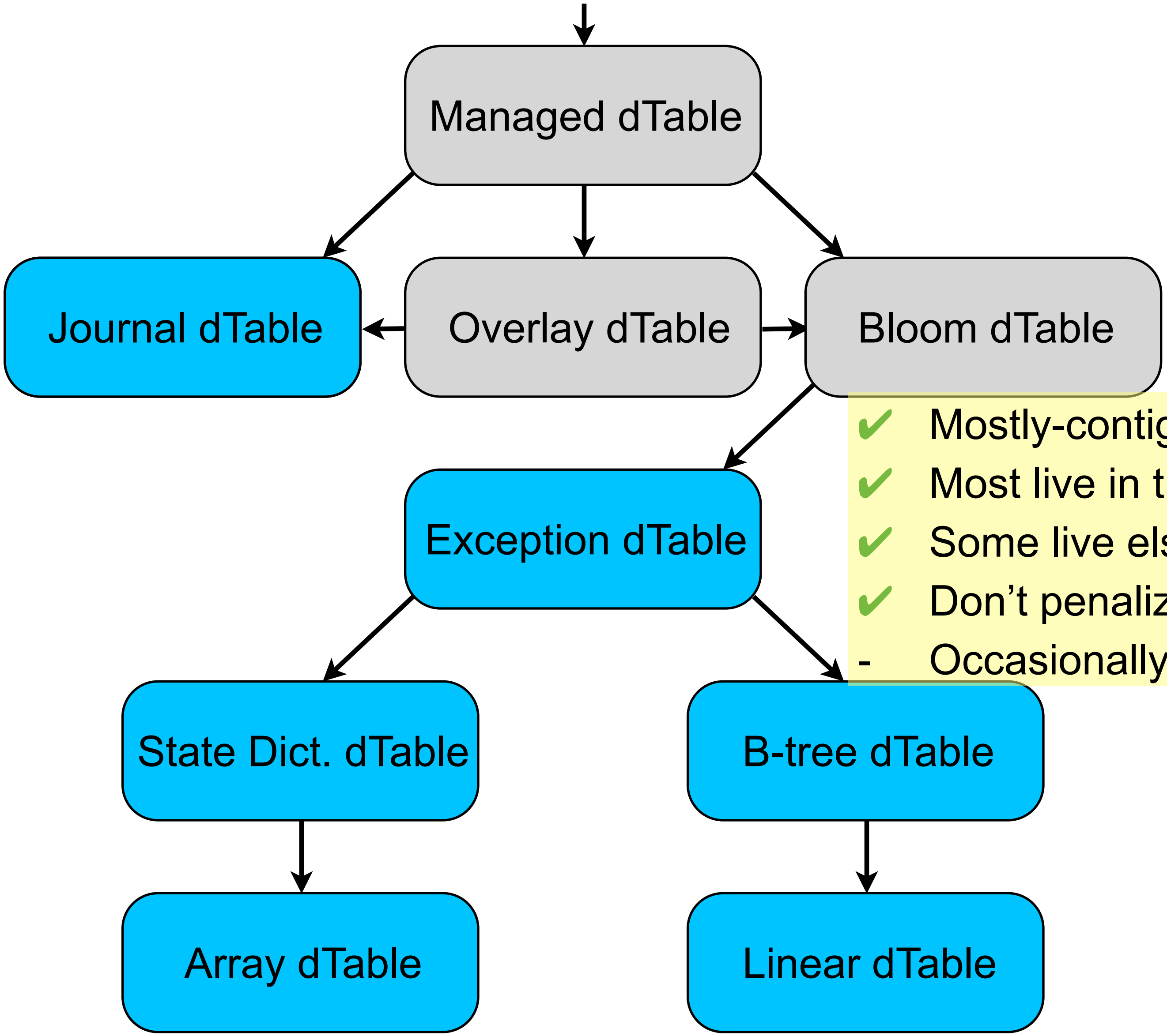

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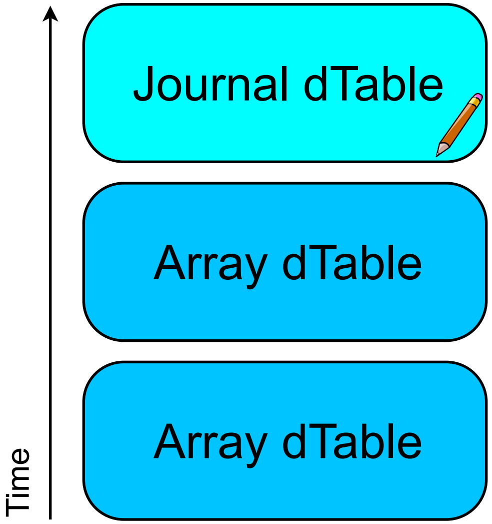

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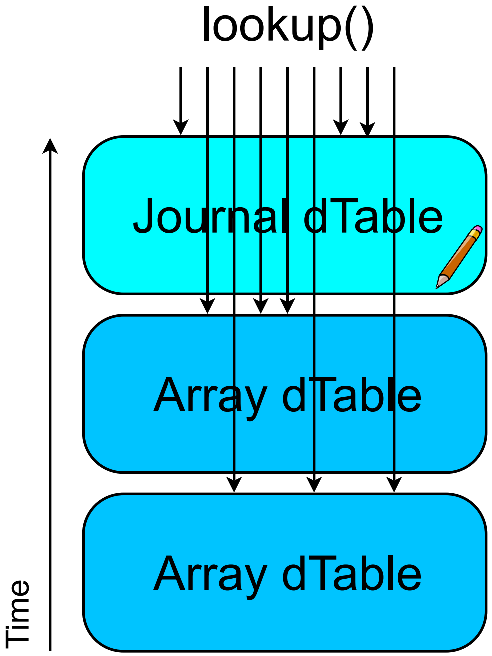

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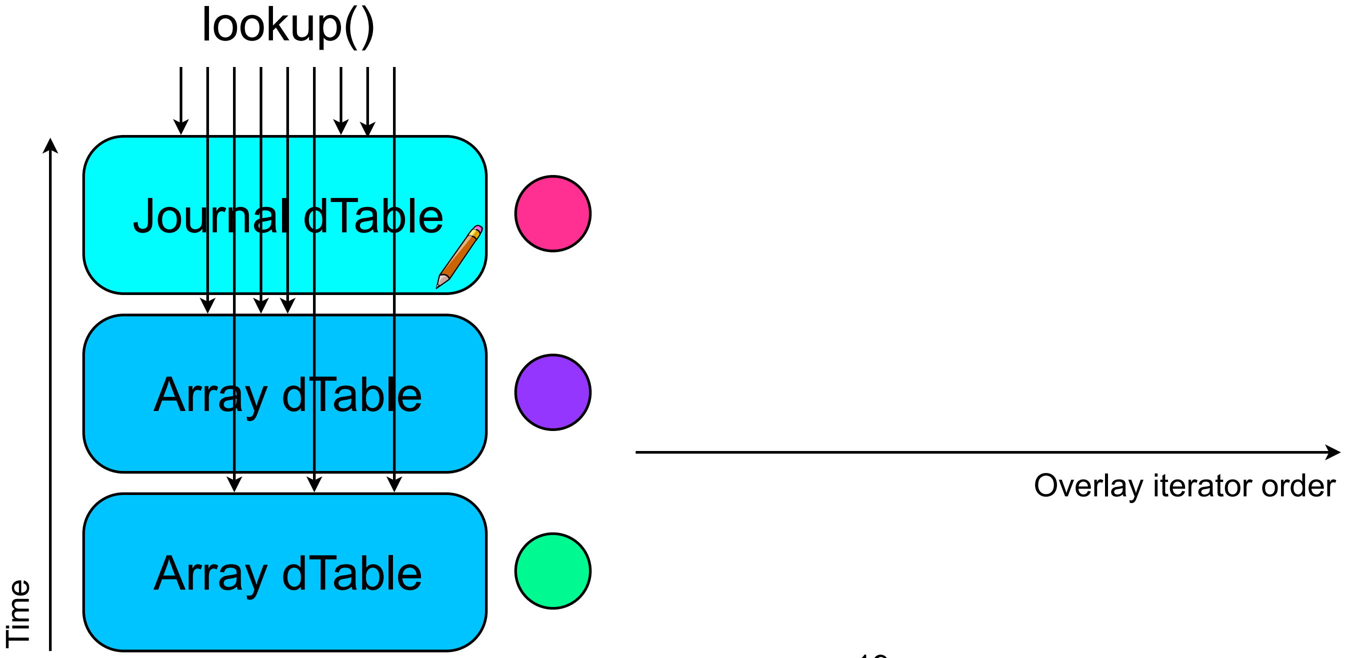

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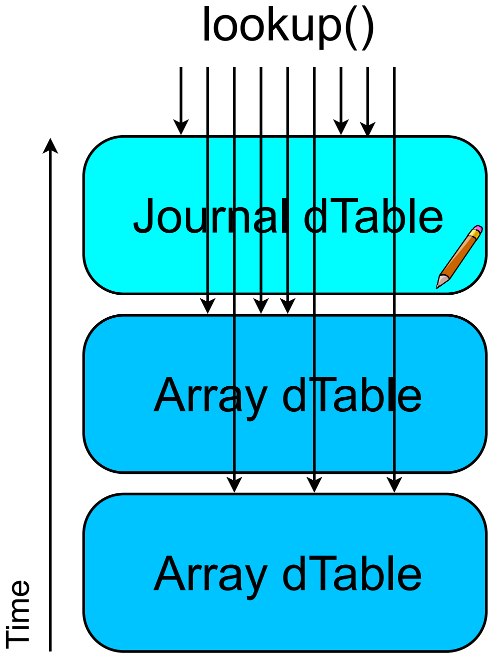

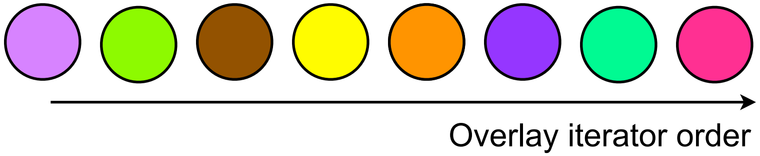

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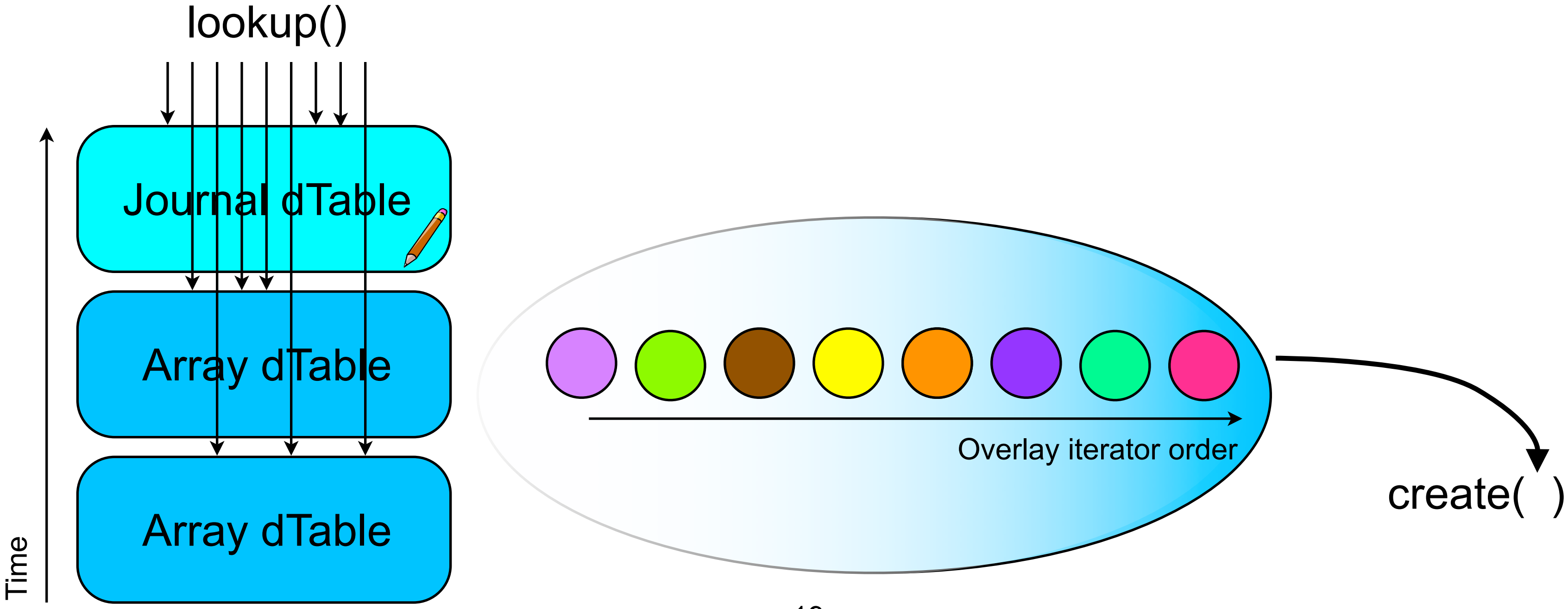

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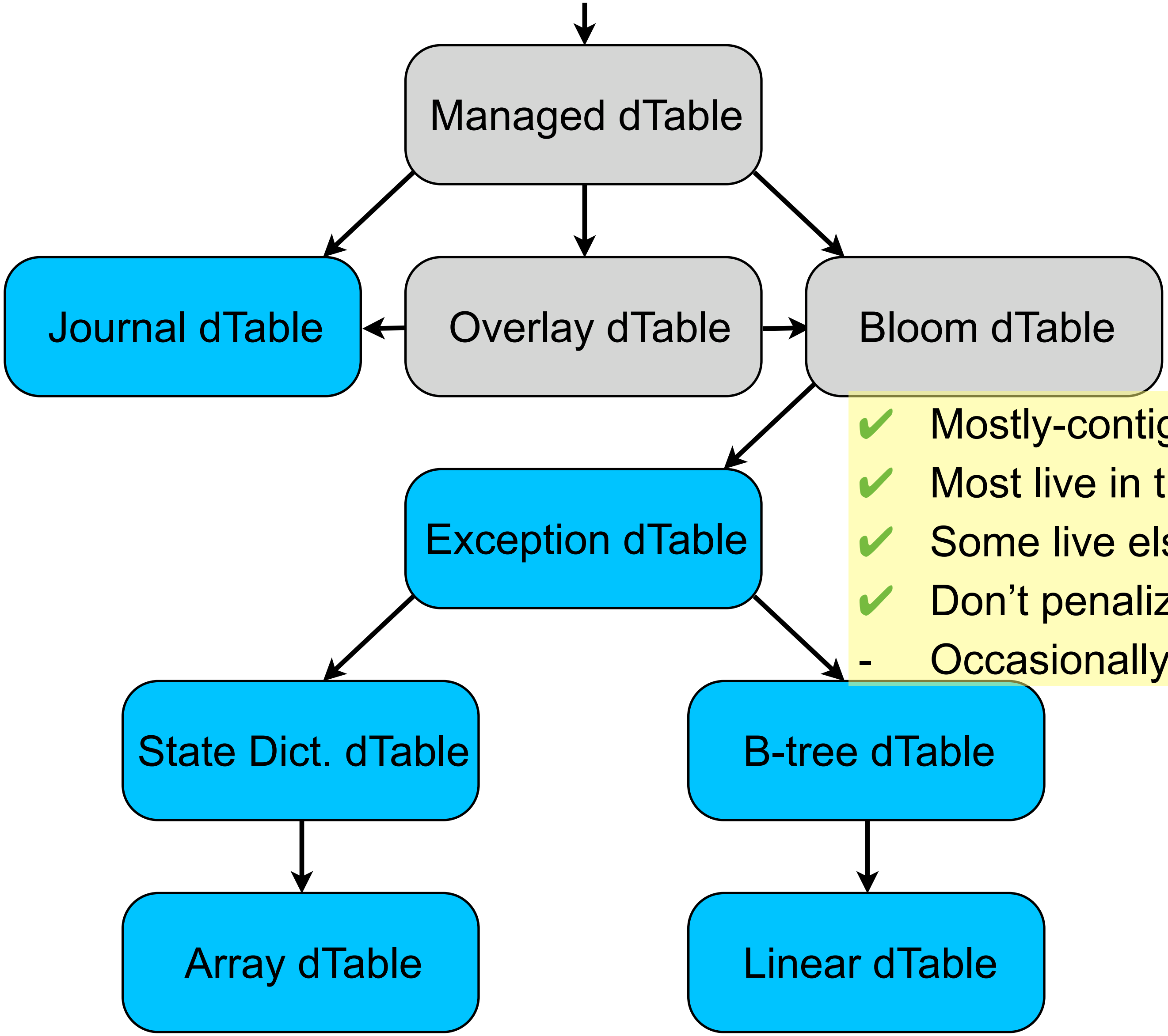

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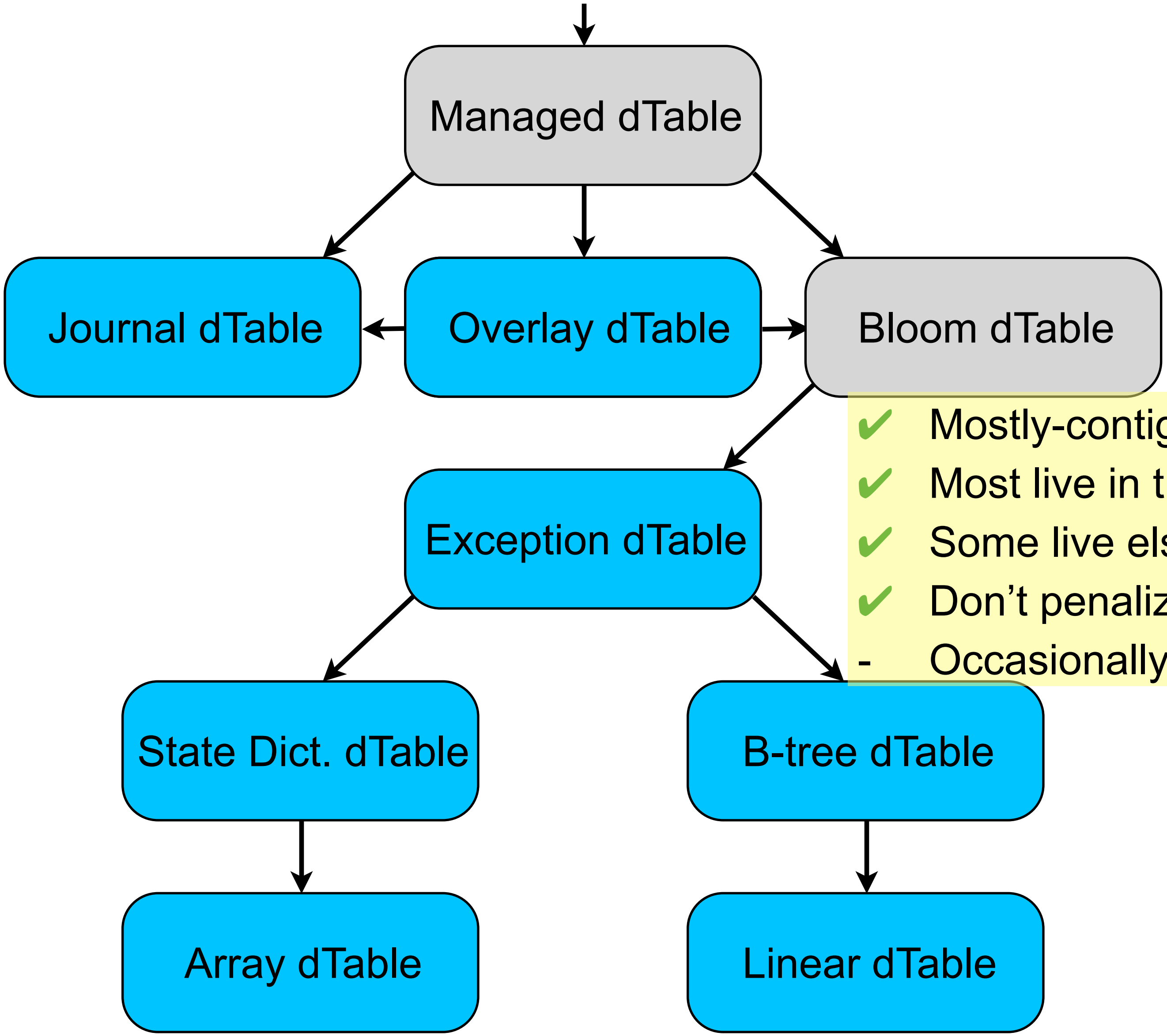

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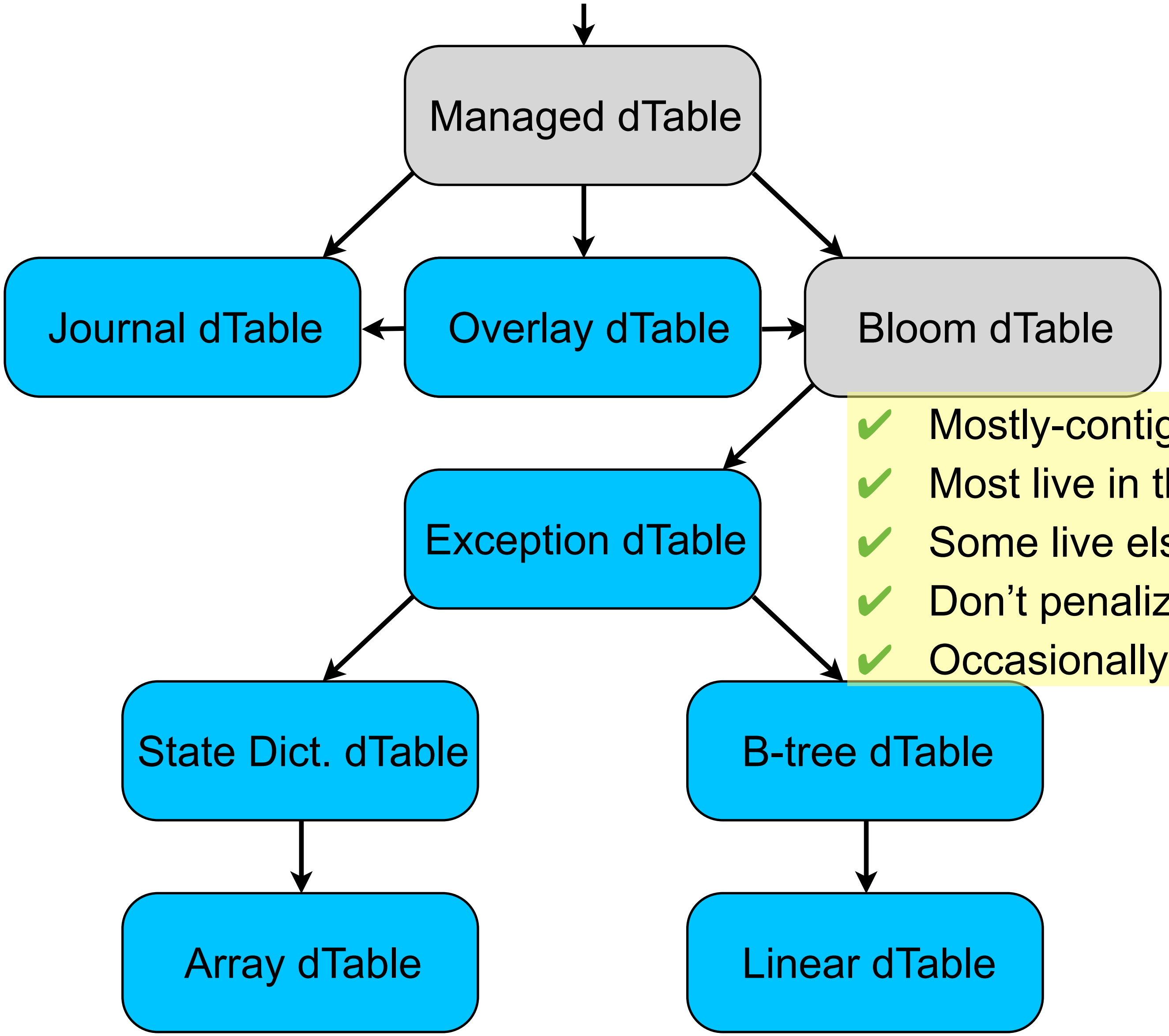

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  - Decreases overlay performance, but frees memory
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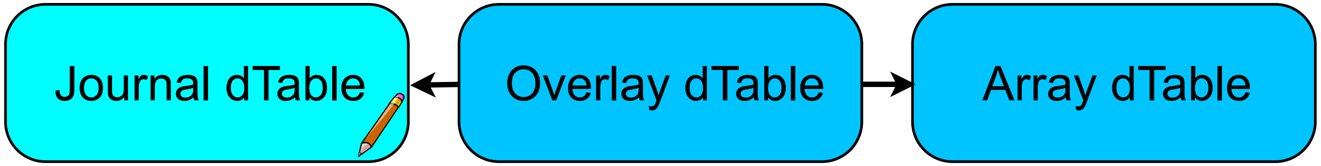
  - Restore overlay performance, consolidate data
- Must balance these goals efficiently



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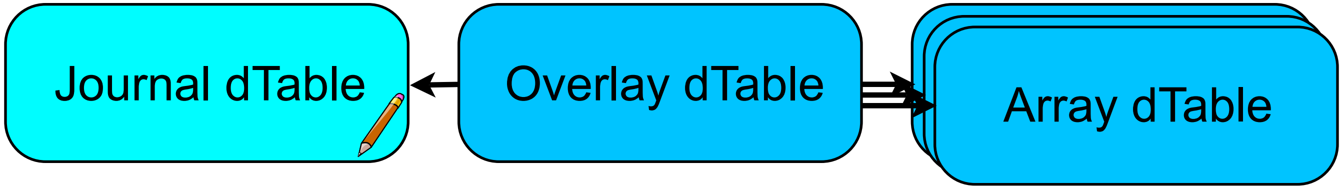

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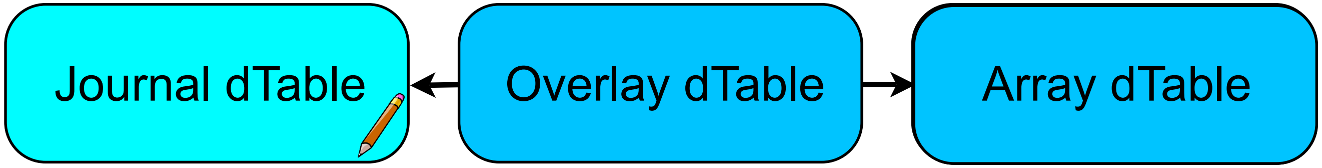

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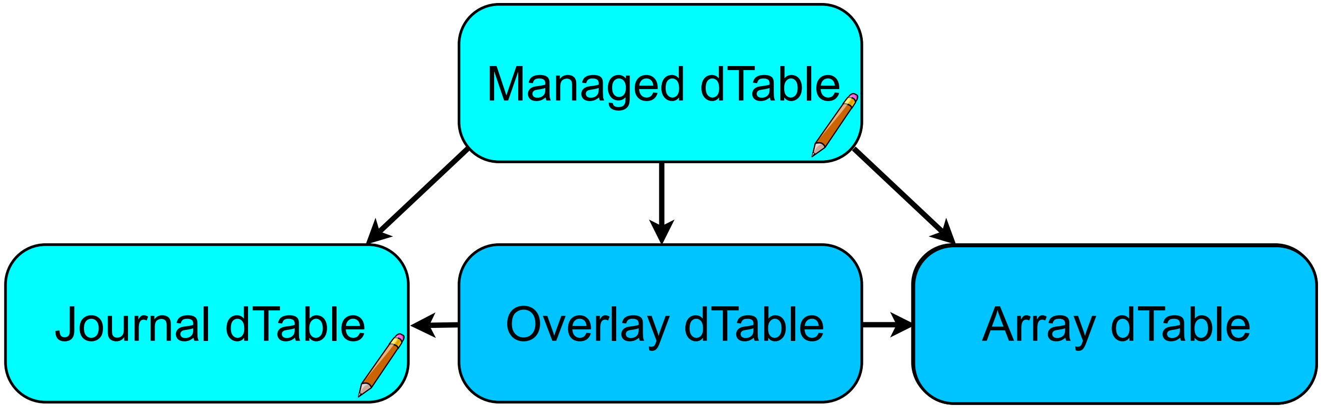
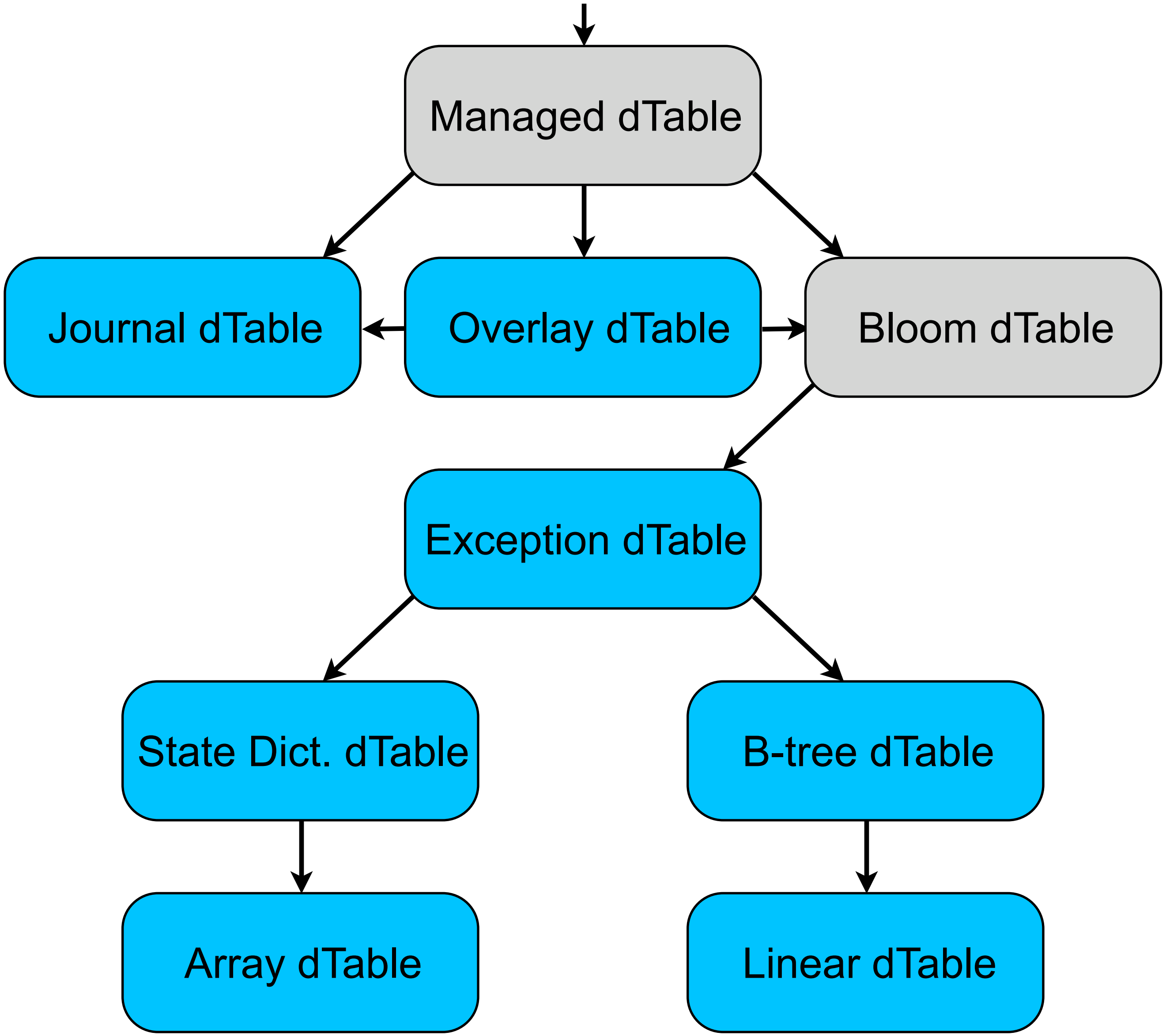


- Interfaces with transaction library
  - Allows all other dTables to ignore transactions

Managing Long-Term Efficiency



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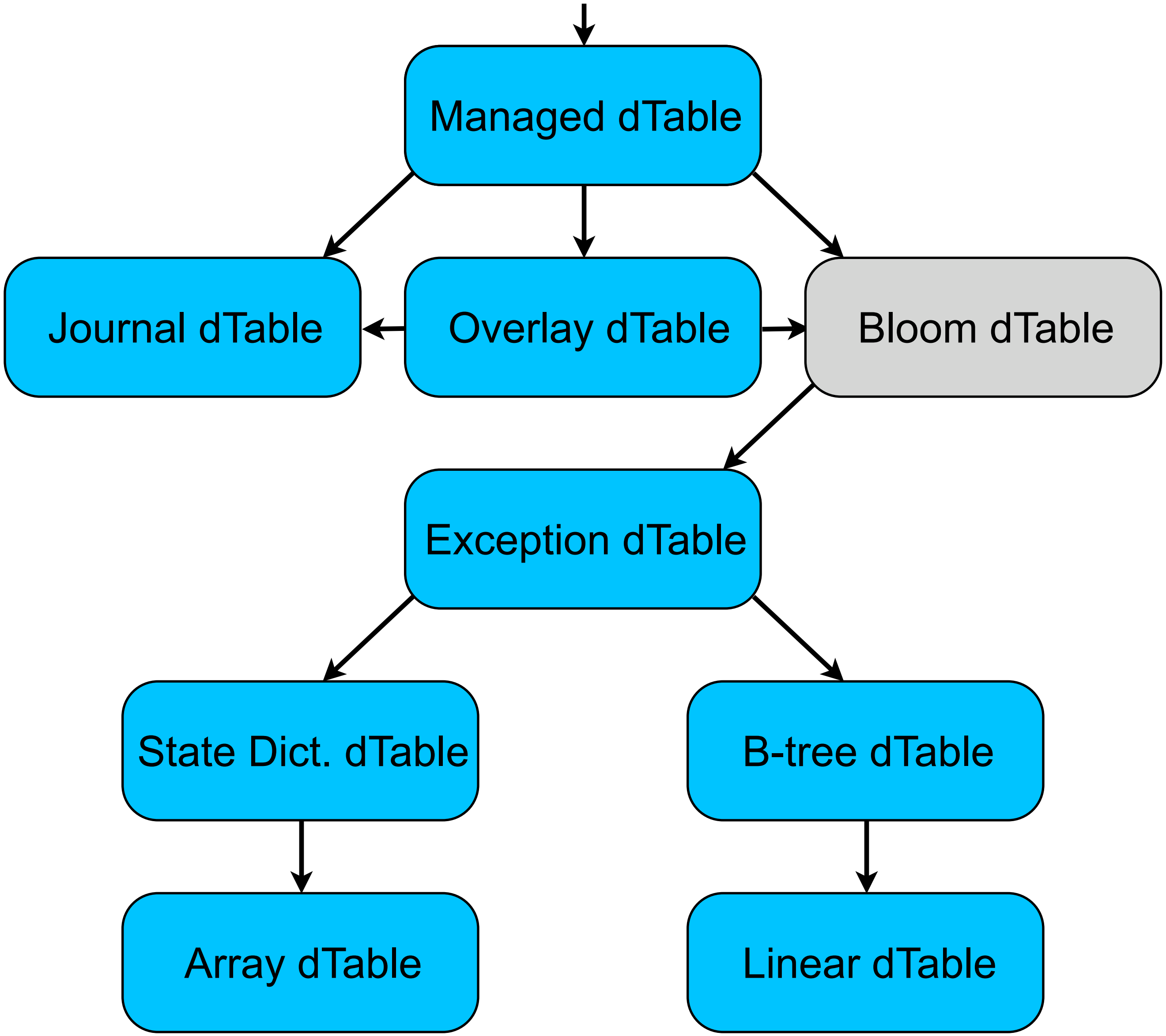

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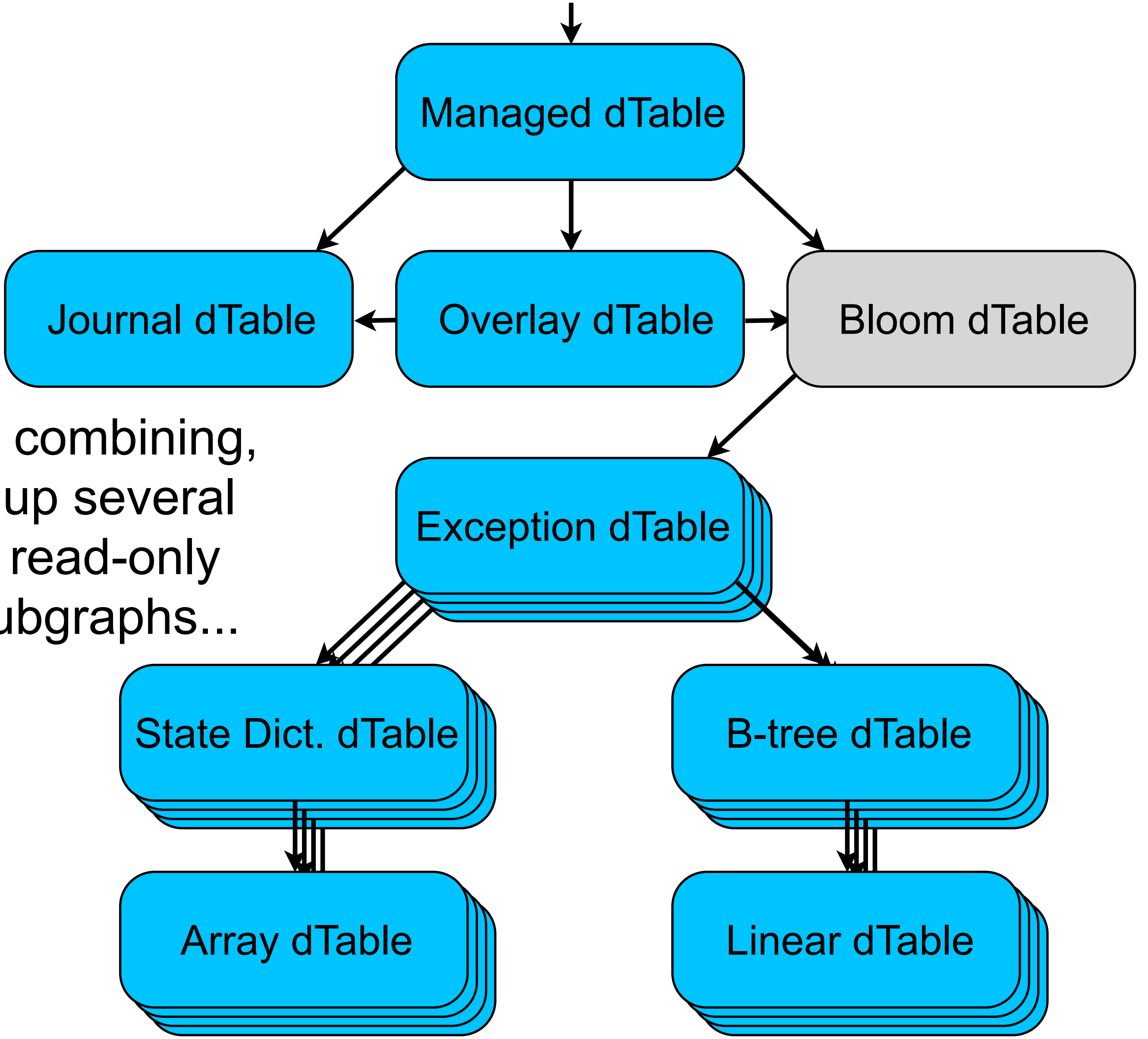

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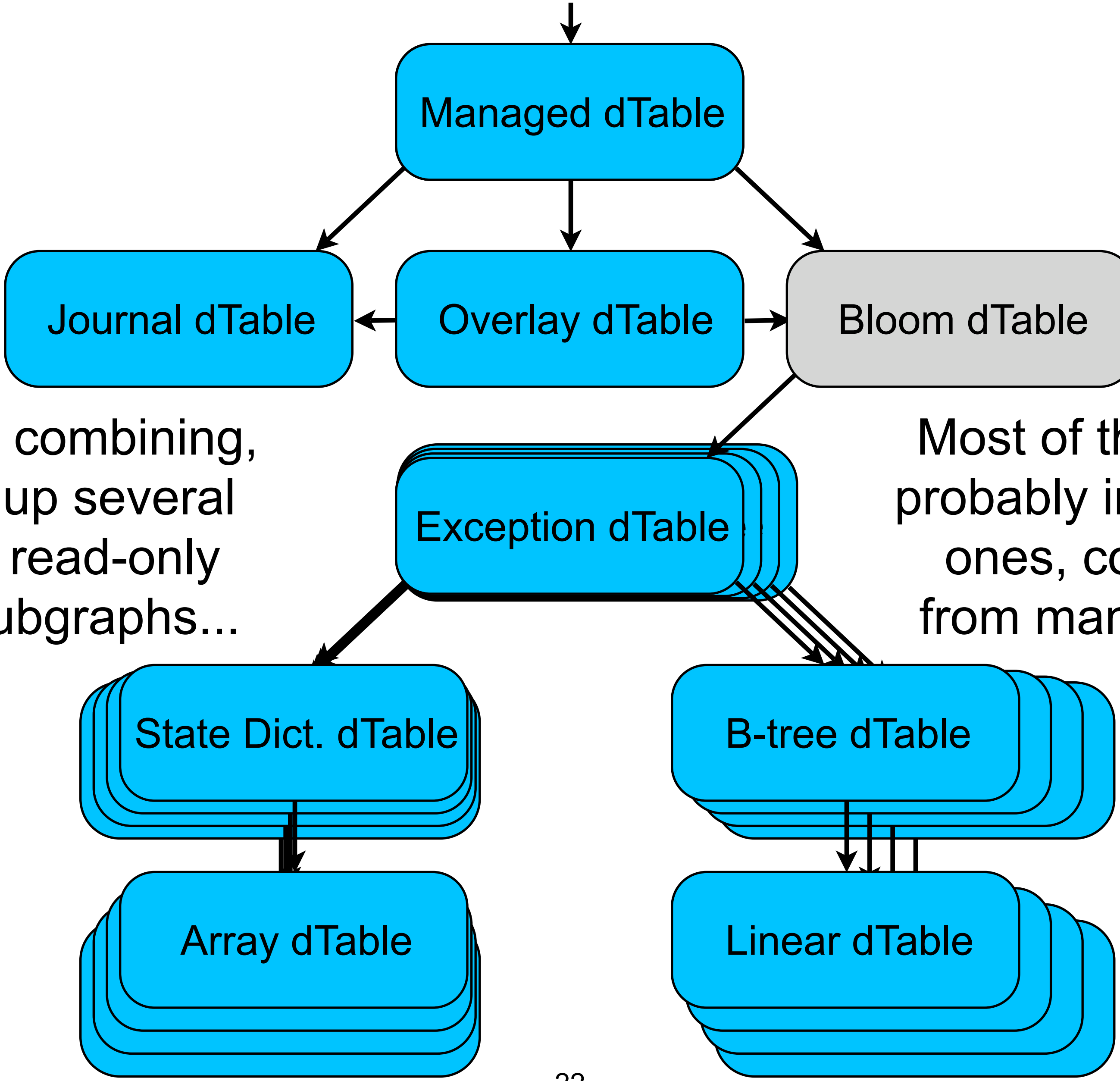

Even with combining, we build up several overlaid read-only dTable subgraphs...

Most of the data is probably in the older ones, combined from many others.

Bloom dTable

- Creates a Bloom filter for the keys in another dTable
  - Accelerates (most) nonexistent key lookups: O(1)!
  - Slightly slows down extant key lookups
  - Takes additional disk space in a separate file
- Read-only
  - No need to worry about key removal
  - Creates Bloom filter bitmap during create()
- Particularly useful under overlay dTables

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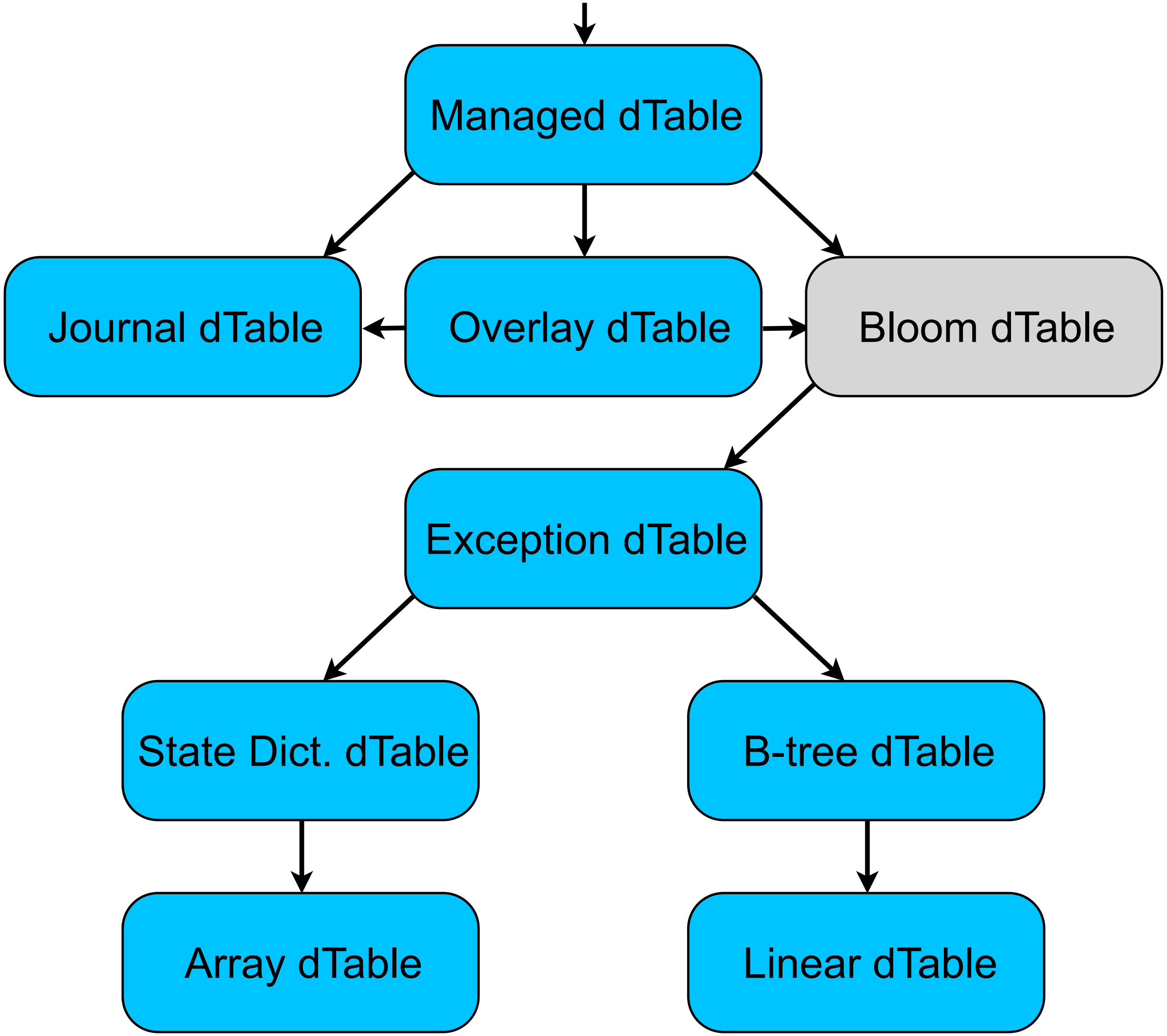

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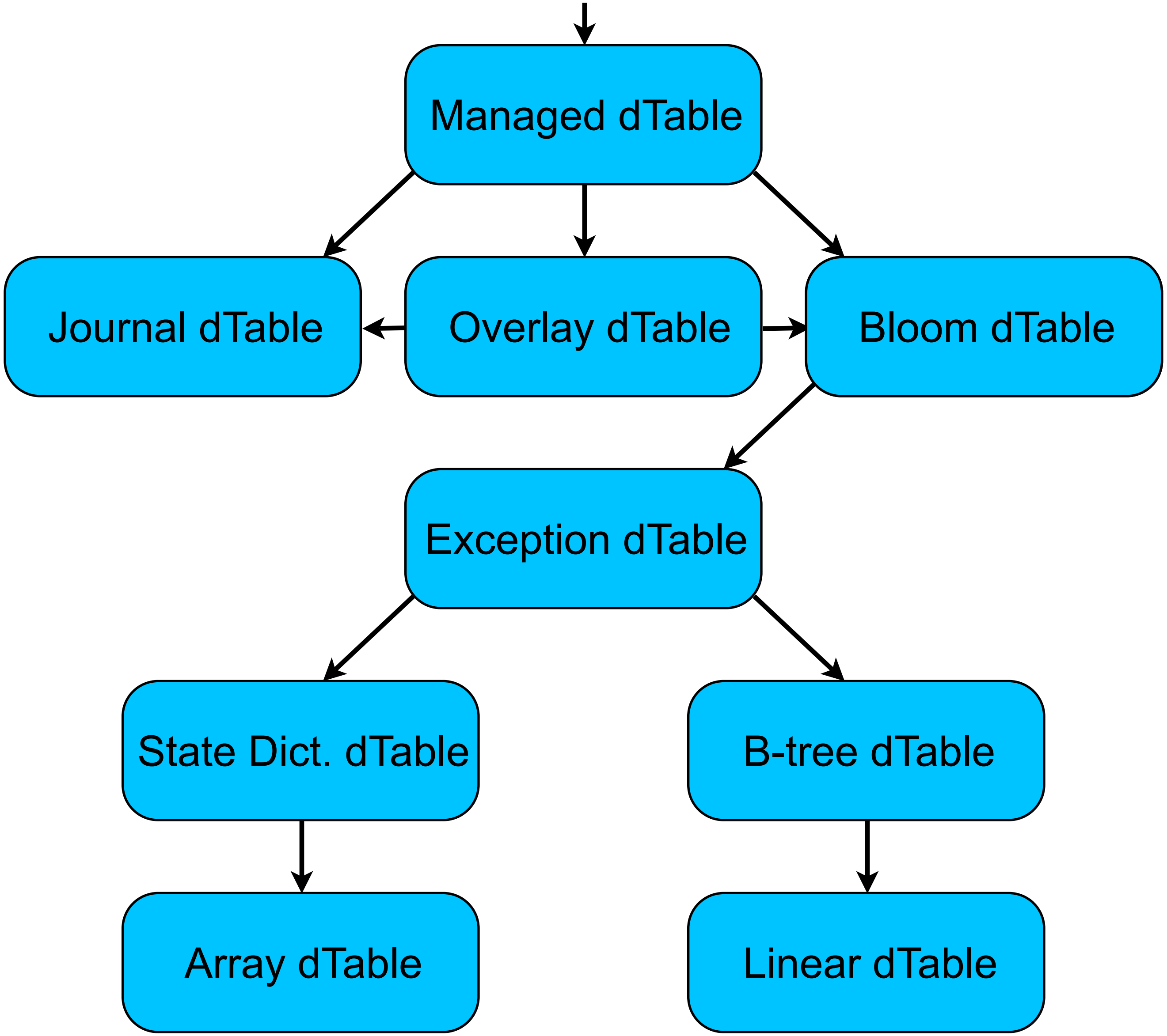


Additional dTables

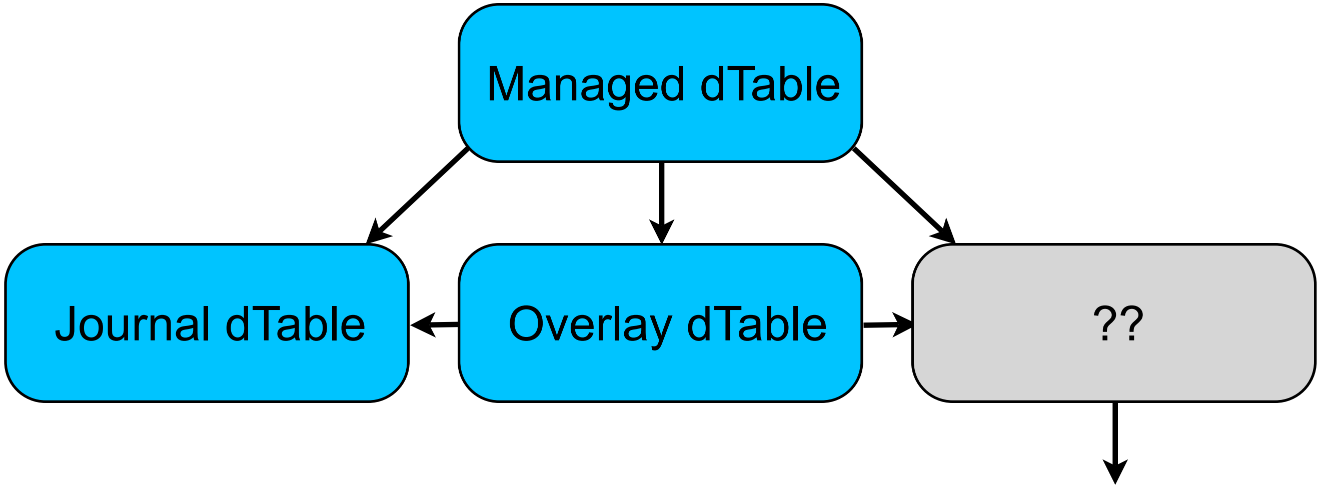
• Fixed-size	Combination array/linear
• Unique-string	Deduplicates strings
• Empty	Always empty
• Memory	Not persistent
• Cache	Memory cache
• Small integer	Strips leading zero bytes
• Delta integer	Stores differences

Performance Hypothesis

- Simple configuration changes can improve performance for specialized workloads
  - Benefits of tailoring dTable configurations to data
- Performance is good for conventional workloads
  - Replaced SQLite's update-in-place backend with Anvil
  - Can run a TPC-C-like benchmark (DBT2)
- Overhead of digesting and combining can be reduced by background processing

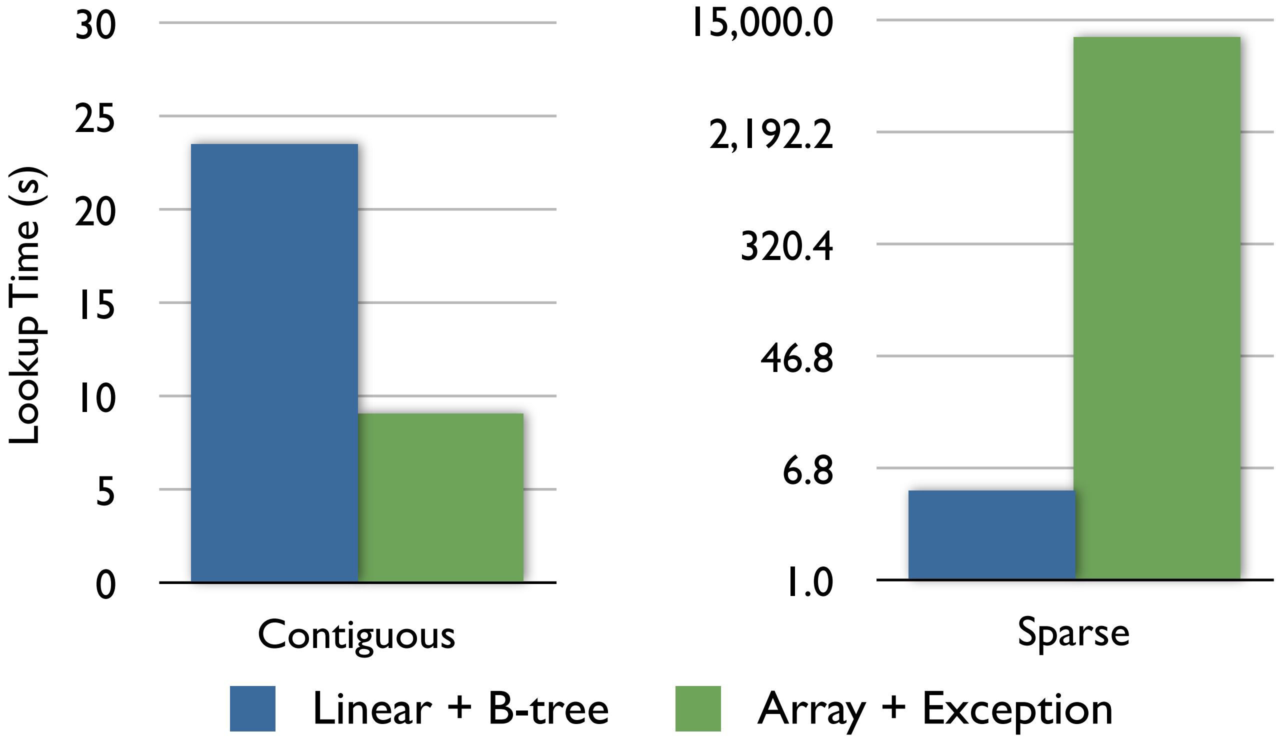
Evaluating dTable Modularity

- Load a given dTable configuration with 4M values
  - 0.2% of them 7 bytes, others 5 bytes
- Look up 2M random keys



dTable Choice Depends On Data

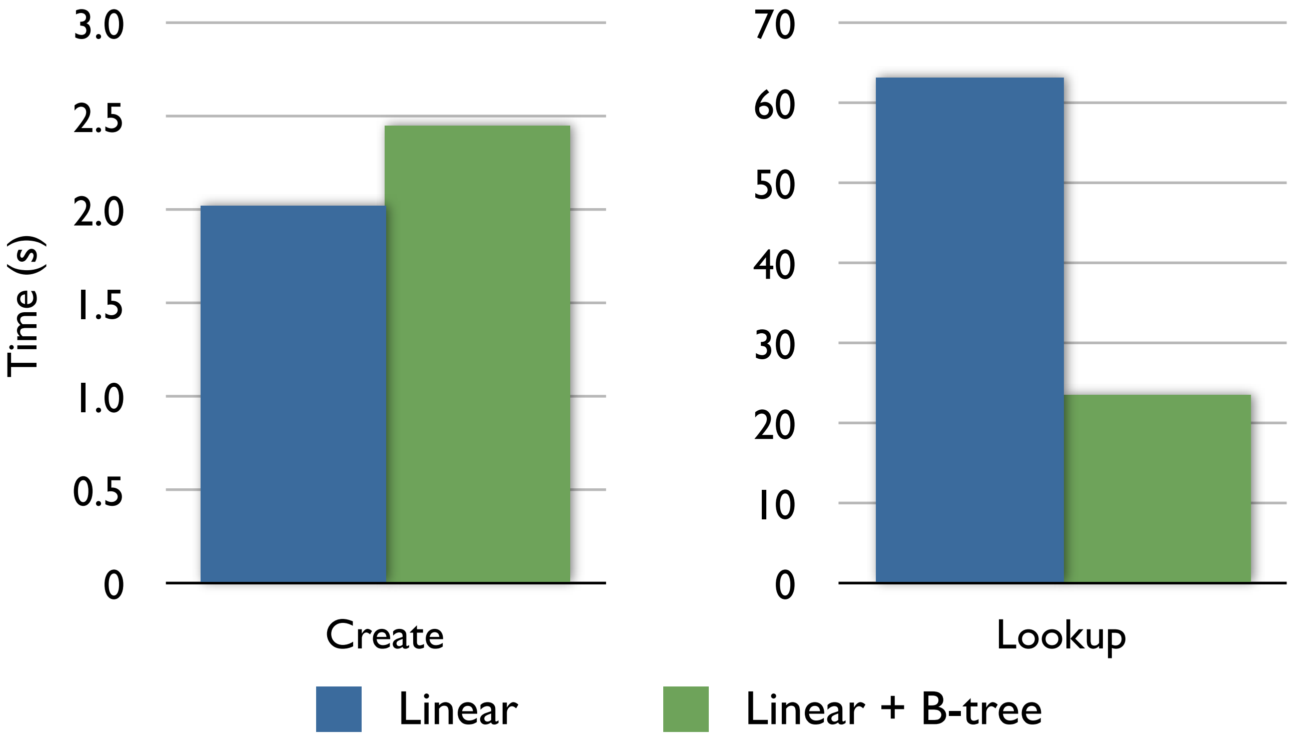
- Linear + B-tree vs. Array + Exception
  - Keys: contiguous or spaced 1000 apart



- Anvil’s modularity allows us to choose the right configuration for this data

Layered Index dTable Speeds Lookups

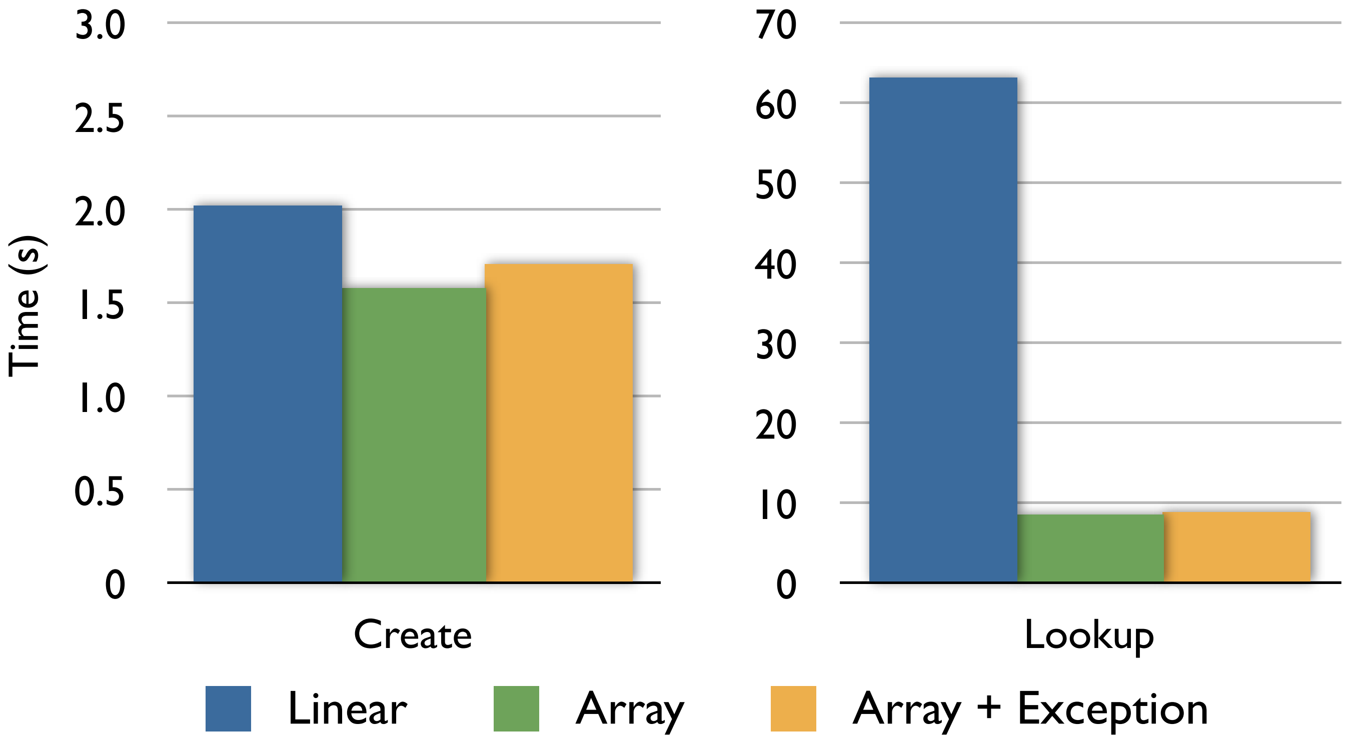
- Linear vs. Linear + B-tree
  - Also measure time to create data store



- Usually a good configuration choice: many lookups will make up the create cost

Exception dTable Has Low Overhead

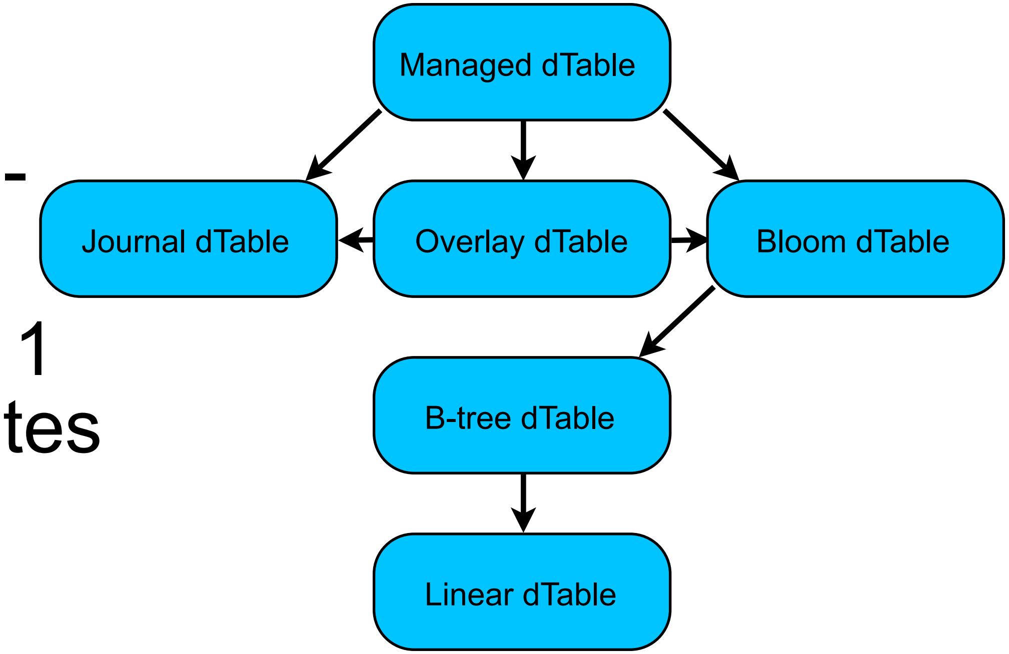
- Linear vs. Array vs. Array + Exception
  - Plain array can store only fixed size values



- Exception dTable is low overhead vs. array (4% slower lookups here), but restores full functionality

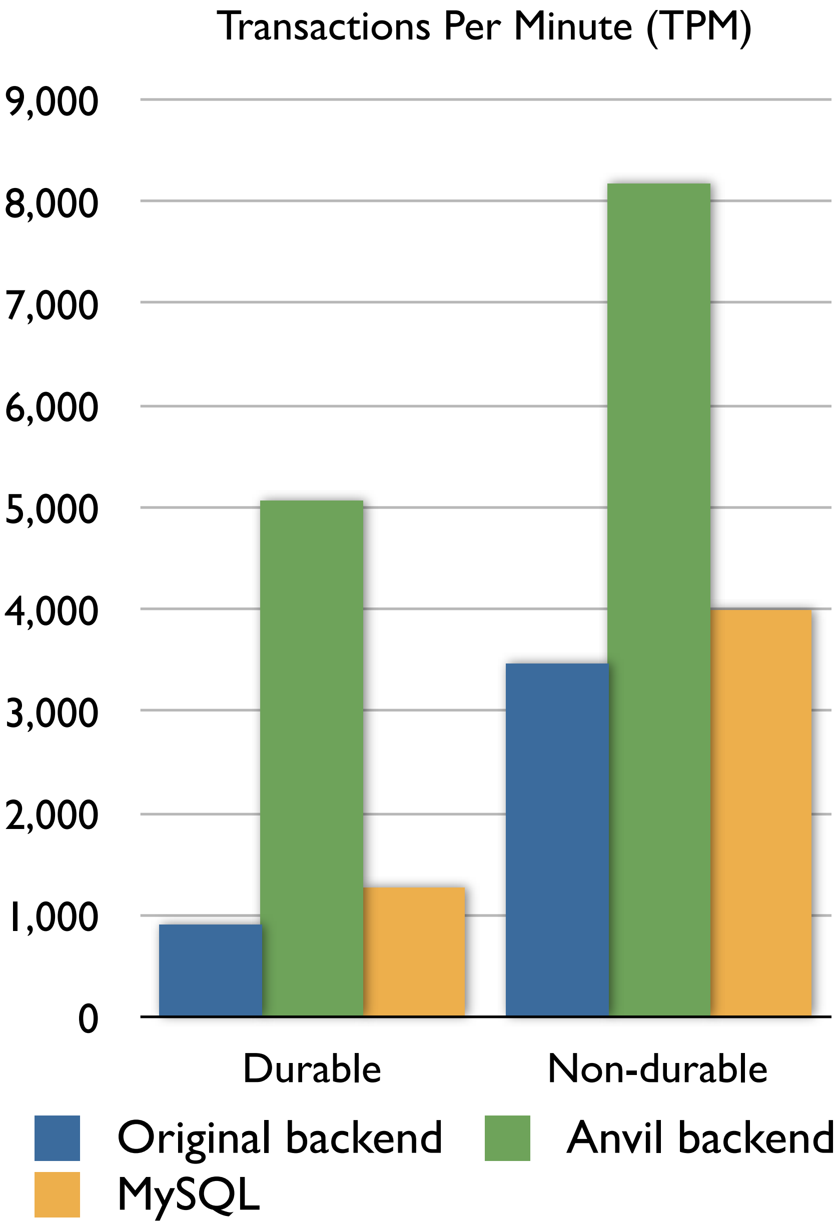
How Does Read/Write Separation Perform?

- Anvil separates reads and writes into different dTables in our configurations
- How does this perform relative to an update-in-place backend?
- Run DBT2 TPC-C with 1 warehouse for 15 minutes
  - Simple row store Anvil configuration
- Digesting, combining, and system journal cleaning all set to occur frequently

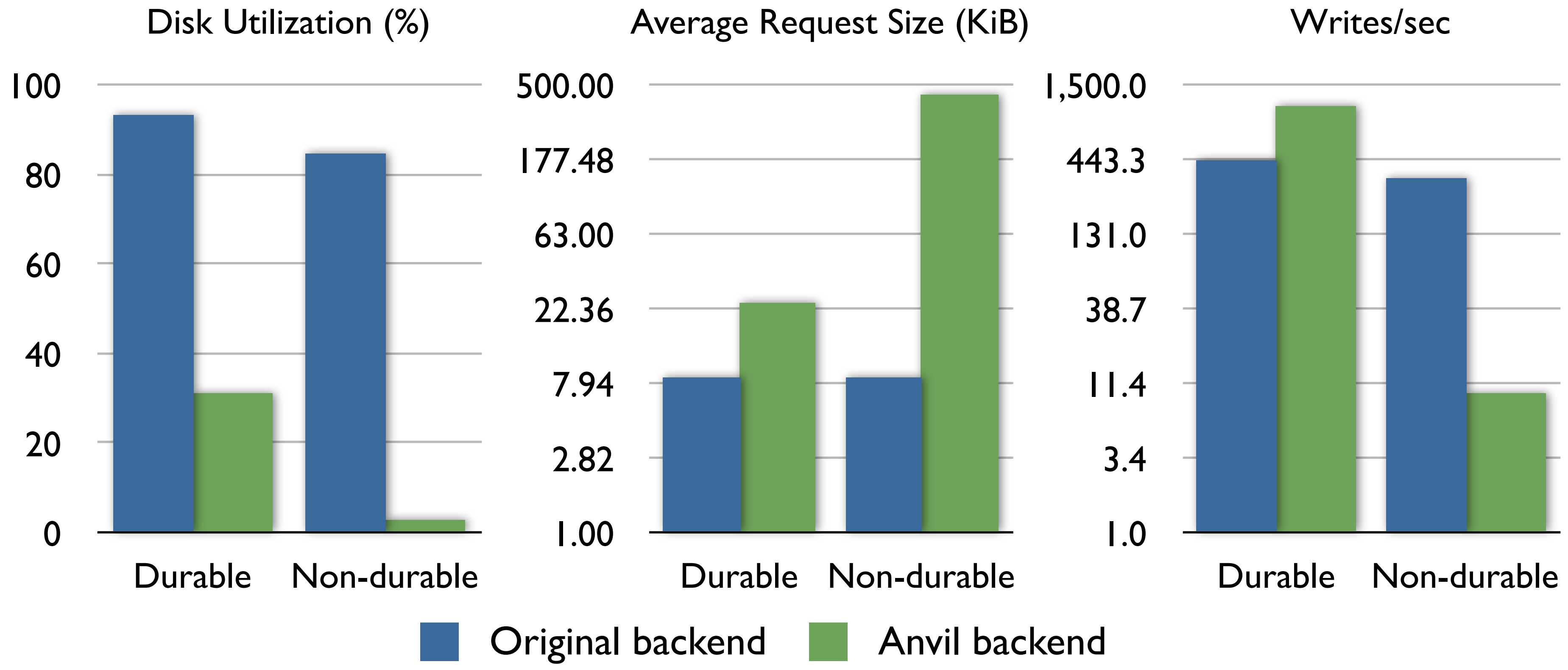


Separated Read/Write dTables Are Fast

- Anvil's durable configuration outperforms original durable configuration
- Anvil's non-durable (but consistent, i.e. safe) configuration outperforms original "async" (i.e. unsafe) configuration



Better Disk Access Makes Anvil Fast



- Both Anvil configurations have significantly better disk access characteristics
  - Larger, contiguous writes, better laid out on disk
  - Can write *more* data in *less* time with faster seeks

Digesting and Combining

- Anvil’s performance benefits don’t come for free
  - Digesting, combining, and cleaning are the price
- These tasks can be done in the background
  - Read-only source data makes a background thread safe
  - Takes advantage of additional cores and spare I/O bandwidth
- Bulk loading a dTable with ~1GiB of data
  - Digest every few seconds
  - 50 seconds with background digest/combine
  - 82 seconds without

Related Work

- Bigtable [Chang et al. ’06]
  - Some aspects of Anvil resemble Bigtable SSTables
  - Write-optimized logs, read-optimized data
  - Higher-level distribution system complimentary
- C-Store [Stonebraker et al. ’05]
  - Data-specific optimizations and finer control of data layout
- Abstraction-providing libraries
  - Stasis transaction framework [Sears, Brewer ’06]
  - BerkeleyDB persistent data structure library

Conclusions

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  - Desired functionality can be composed from fine-grained dTable modules
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  - Easy to write new dTables for novel storage strategies

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  - Aborting transactions, full concurrency

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  - Simple configuration changes allow storing data in many different useful ways
  - Easy to write new dTables for novel storage strategies
- Still lacks some features, but they seem compatible
  - Aborting transactions, full concurrency
- Performance overhead is small compared to potential benefits for applications
  - Prototype faster than SQLite's B-trees for TPC-C

More info:
http://read.cs.ucla.edu/anvil