Data Storage Systems

Dmitry Alimov

2018

$ whoami

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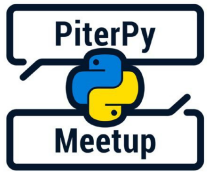
- Software Engineer
- SPbPython and PiterPy active member & speaker
- SPbPython drinkups co-organizer
- CTF player with SiBears team
- Python Software Foundation (PSF) contributing member



Outline

- Storage data structures
  - B-tree
  - LSM-tree
  - Other indices
- RUM conjecture
- OLTP, OLAP, HTAP
- SQL, NoSQL, NewSQL
- DB in CPython
- Books and references *

* References are in brackets “[ref num]”

Intro

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- Every year new databases appear, existing ones are improved
- Each database has its own trade-offs
- Understanding them helps to choose the right one
- Knowing and understanding of storage internals helps to make better design decisions, troubleshoot problems, tune database

Storage Data Structures

“Wer Ordnung hält, ist nur zu faul zum Suchen”

(He who keeps order is just too lazy
to spend his time searching)

German proverb

Simple datastore

```
def set(key, value):
    with open('main.db', 'a') as db_file:
        db_file.write('{},{}\n'.format(key, value))

def get(key):
    value = None
    with open('main.db', 'r') as db_file:
        for line in db_file:
            k, v = line.split(',')
            if k == key:
                value = v.rstrip()
    return value
```

Simple datastore

```
>>> set('a', 'one')
>>> set('b', 'two')
>>> set('c', 'three')
>>> set('b', 'four')

>>> print(get('a'))
one
>>> print(get('b'))
four
>>> print(get('z'))
None
```

```
$ cat main.db
a,one
b,two
c,three
b,four
```

Questions

- Escaping

```
>>> set('a,b', 'oops')

$ cat main.db
...
a,b,oops  # ???
...
```

Questions

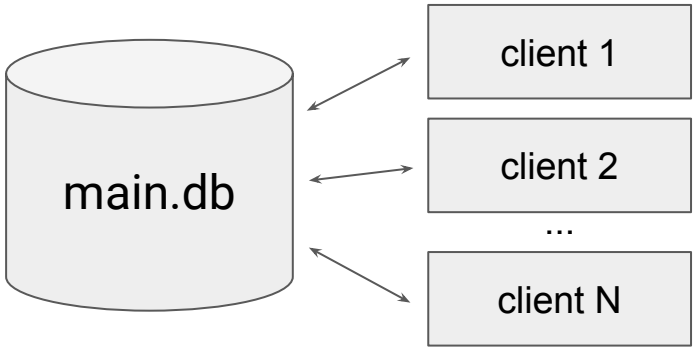
- Escaping
- Deleting

```
>>> delete('c')

$ cat main.db
...
c,<tombstone>
...
```

Questions

- Escaping
- Deleting
- Concurrency



More questions:
Locks
MVCC
Single-writer, multiple-reader
...

Questions

- Escaping
- Deleting
- Concurrency
- Compaction

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$ cat main.db
a,one
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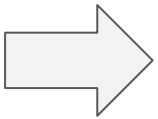
```

Compact



```
$ cat main.db
a,one
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```

Questions

- Escaping
- Deleting
- Concurrency
- Compaction
- Performance

```
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```

Insert: O(1), Search: O(n)

Indices

Database indices

- Hash indices [50]

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- B-tree [50]

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Indices speed up read queries, but slow down writes

Databases

B-tree

LSM-tree

B-tree

“B-trees are by far the most important access path structure in database and file systems”

Gray and Reuter, 1992 [31]

“It could be said that the world’s information is at our fingertips because of B-trees”

Goetz Graefe, 2011 [32]

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Optimized for paged data access [7]

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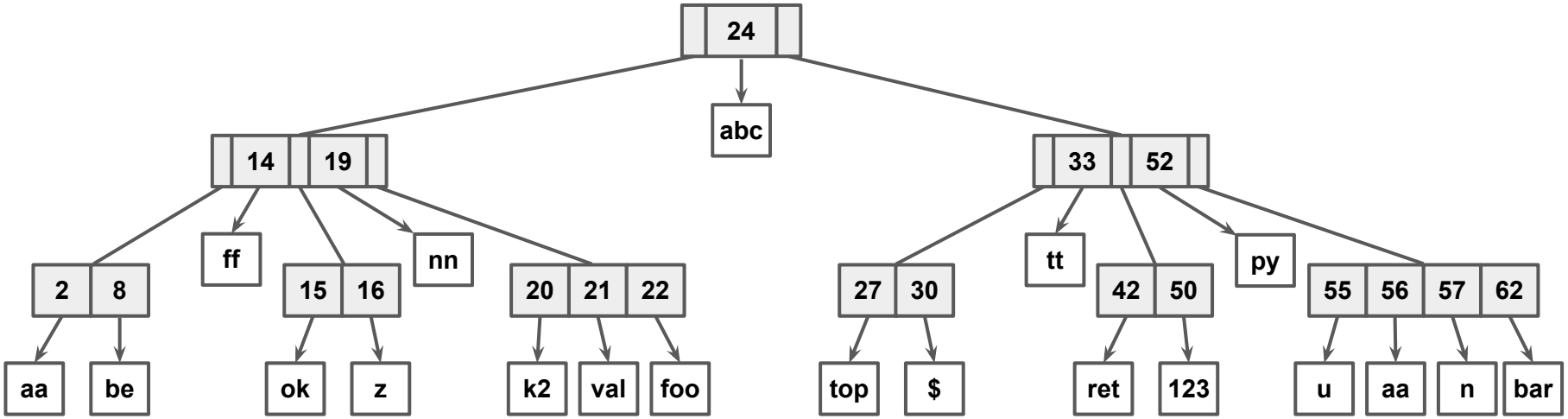
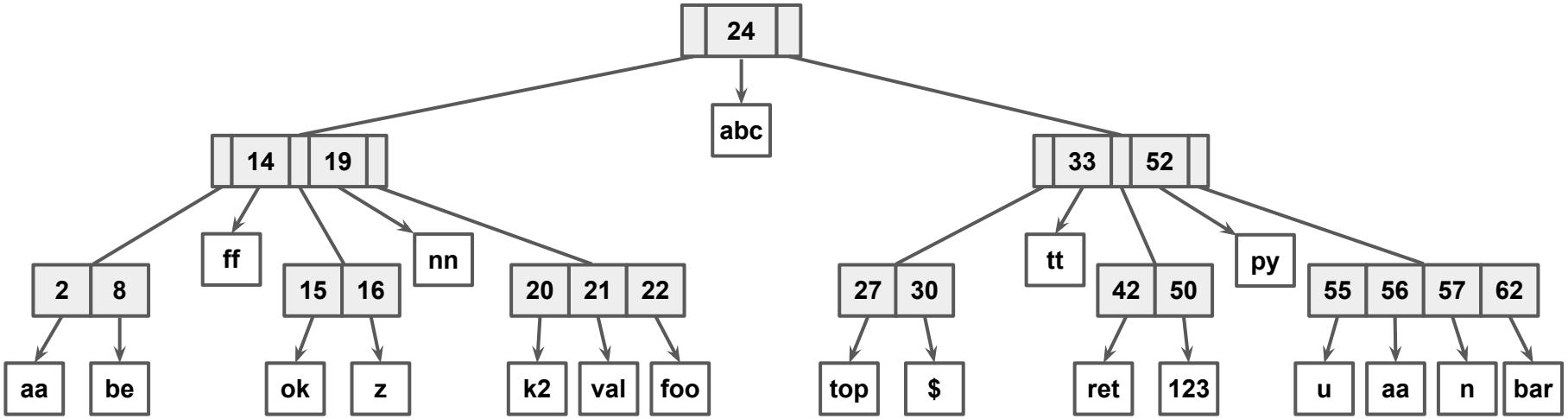
Typically faster for reads [39]

B-tree

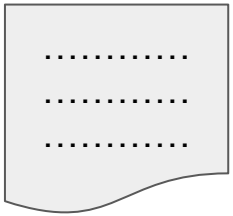


key	value
2	aa
8	be
14	ff
...	...

B-tree durability



Write-ahead log (WAL)



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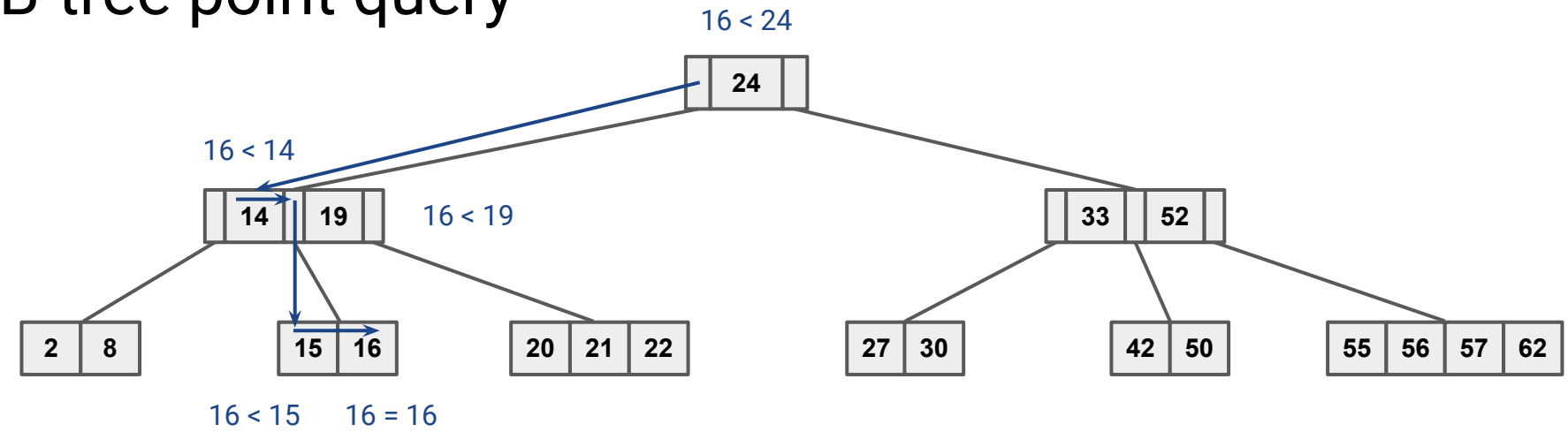
B-tree point query

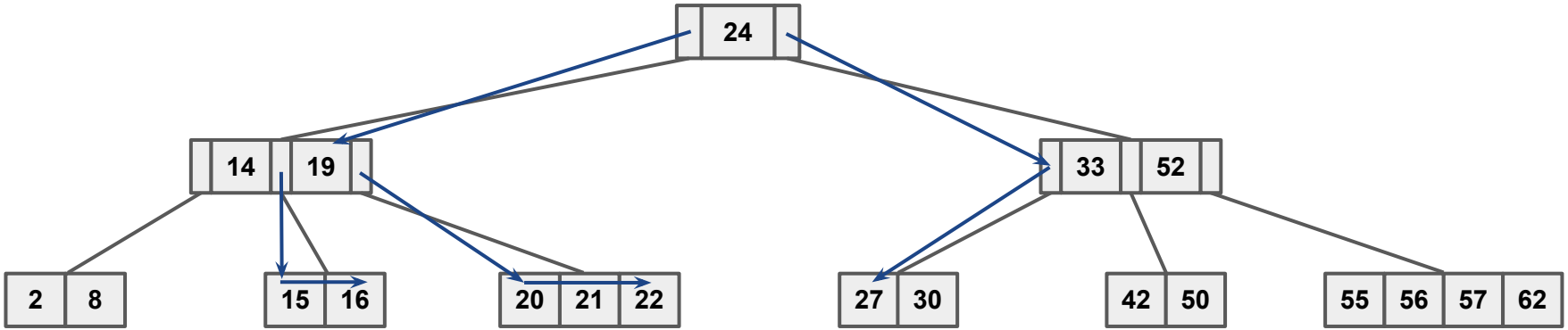


select value with key 16

Insert: $O(\log_B N)$

Search: $O(\log_B N)$

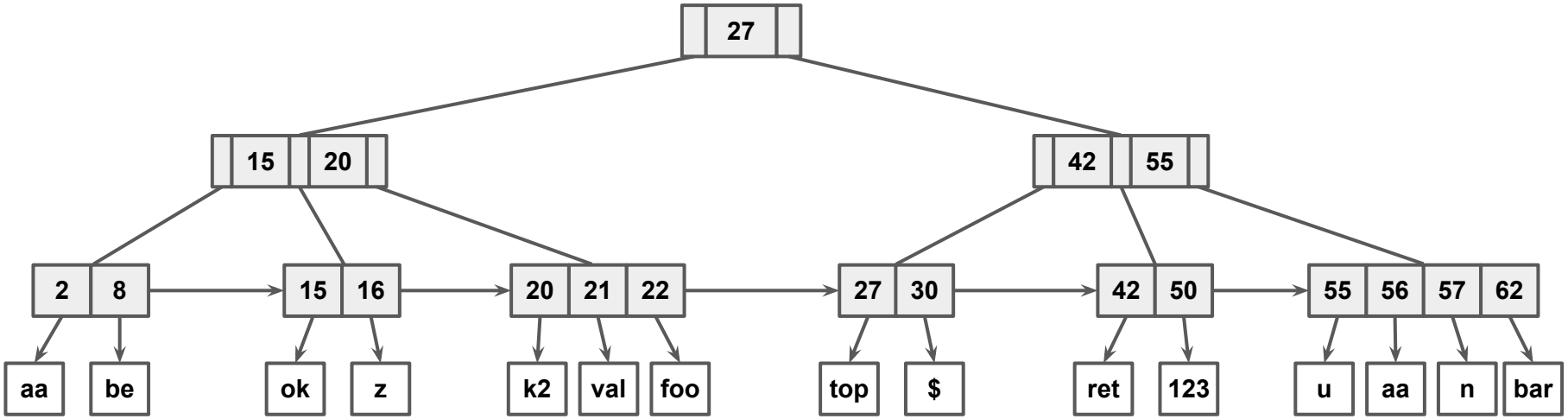
B-tree range query



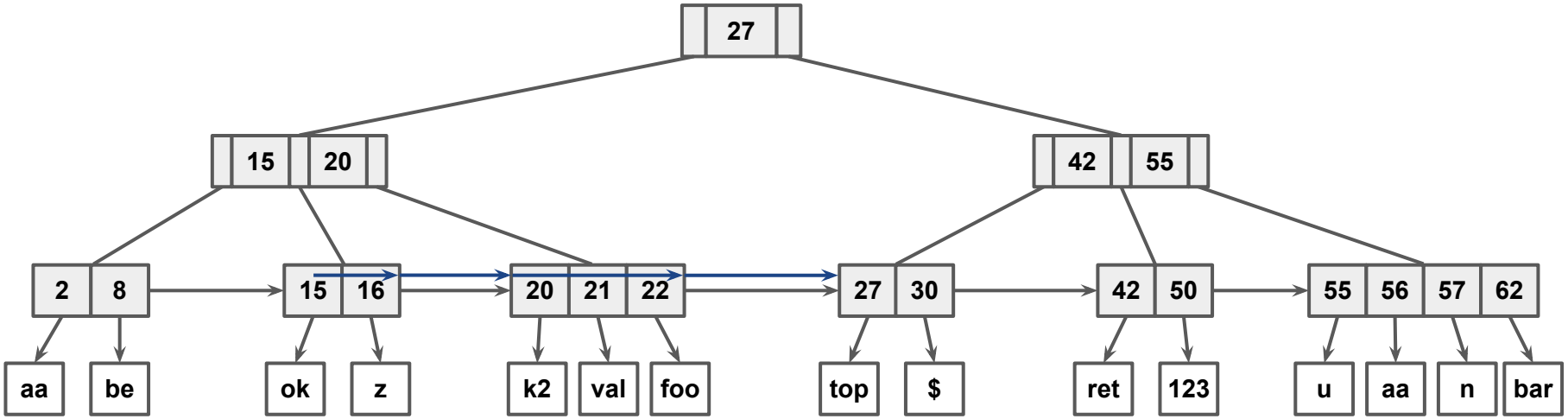
select values with keys in [15...27]

Non-optimal :(

B+ tree


27
15
20
42
55
2
8
15
16
20
21
22
27
30
42
50
55
56
57
62
aa
be
ok
z
k2
val
foo
top
$
ret
123
u
aa
n
bar

B+ tree range query



select values with keys in [15...27]

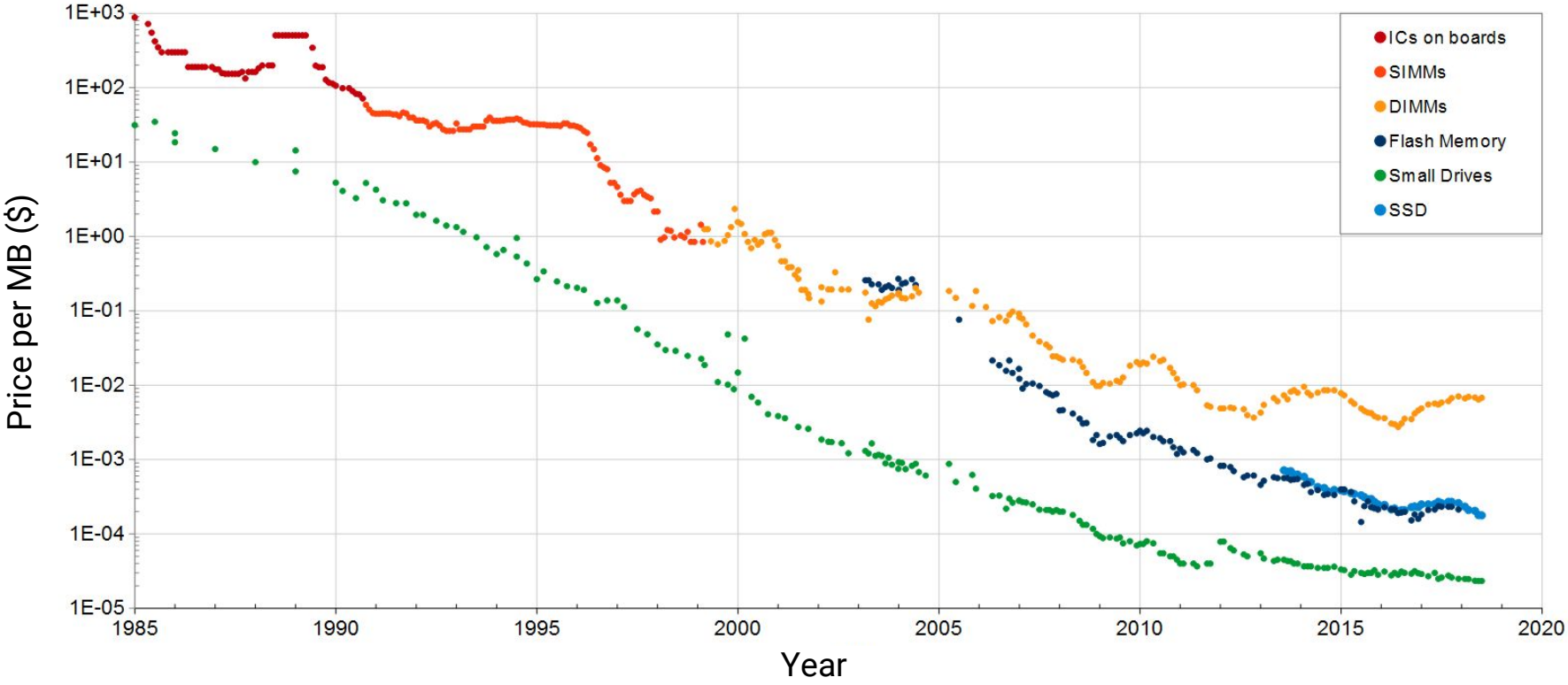
Insert: $O(\log_B N)$

Search: $O(\log_B N)$

RangeQuery: $O(\log_B N + k)$

Memory vs Disk

Memory Prices [34]



Memory vs Disk [56, 57, 58, 59]

Operation	Time, ns *	Comment
Memory access	100	
SSD random read	16 000 (16 µs)	
HDD seek	4 000 000 (4 ms)	
SSD I/O	50 000 - 150 000 (50 - 150)	
HDD I/O	1 000 000 - 10 000 000 (1 - 10 ms)	
Read 1 MB sequentially from memory	9 000 (9 µs)	
Read 1 MB sequentially from SSD	200 000 (200 µs)	22x memory
Read 1 MB sequentially from HDD	2 000 000 (2 ms)	10x SSD, 220x memory

* Numbers for 2015

LSM-tree

LSM-tree (Log-structured merge-tree)

Patrick O'Neil et al., introduced in 1996 [54]

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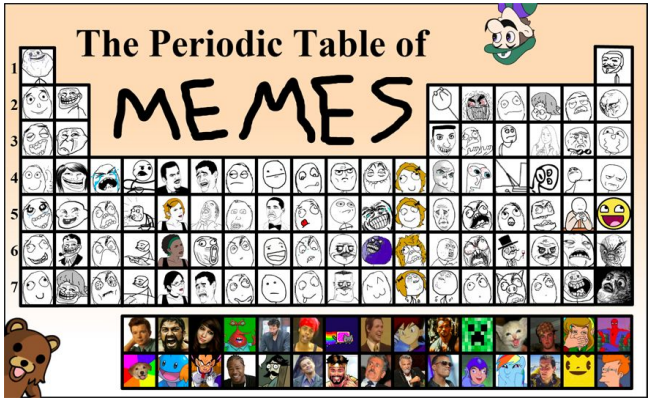

https://www.themarysue.com/periodic-meme-table/

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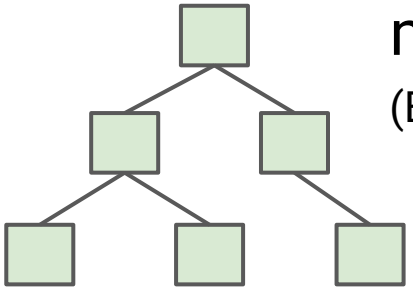


memtable

(B-tree, Skip List, etc)

Memory

Disk

SSTable index

key	file offset
aaaa	0
...	...

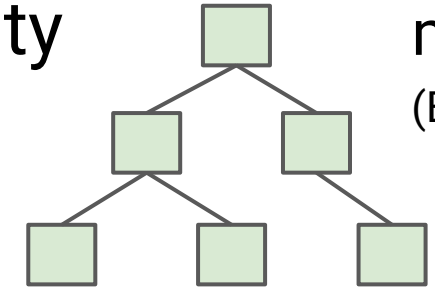
Bloom filter

0	1	0	1	1

SSTable data

key	value
aaaa	124
bbb	7351
...	...
zzzz	7

LSM-tree durability



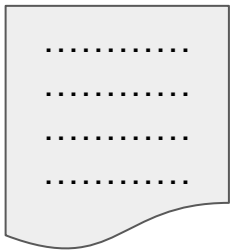
memtable

(B-tree, Skip List, etc)

Memory

Disk

Commit log



SSTable index

key	file offset
aaaa	0
...	...

Bloom filter

0	1	0	1	1

SSTable data

key	value
aaaa	124
bbb	7351
...	...
zzzz	7

SSTables compact & merge

SSTable (old)

key	value
aaaa	123
aab	1
...	...
zzzz	7

SSTable (new)

key	value
aaaa	124
foo	7351
...	...
zzzz	<deleted>

SSTable (merged)

key	value
aaaa	124
aab	1
foo	7351
...	...
yy	222

Leveled & Size-tiered compaction

Bloom filter [73]

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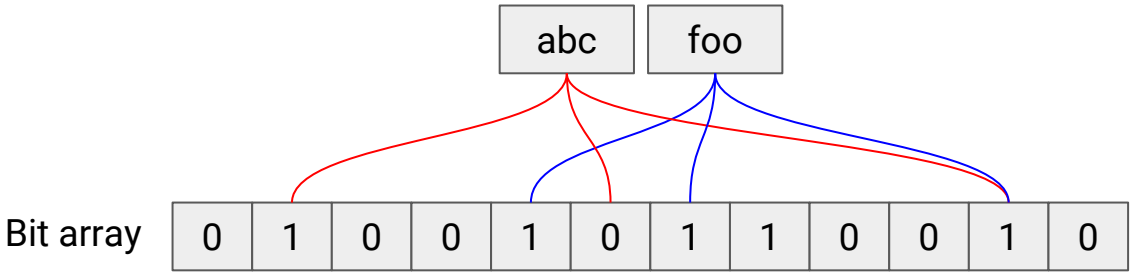
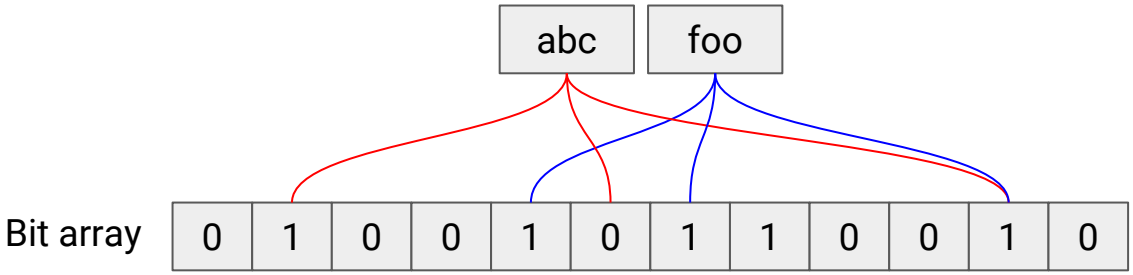
The Google Chrome - to identify malicious URLs
Medium - to avoid recommending articles a user has previously read

Bloom filter

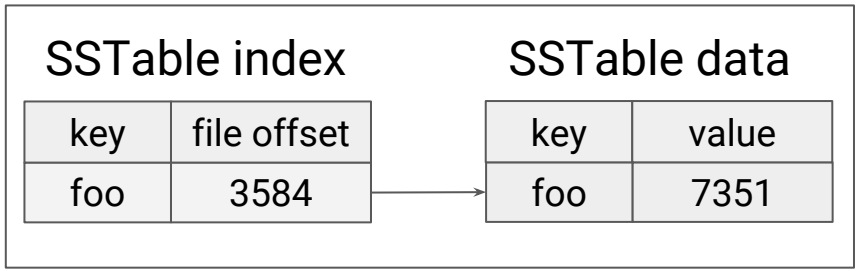


key “foo” probably exists in SSTable
key “abc” definitely not

Bloom filter



key “foo” probably exists in SSTable
try to get its value



SSTable

R-tree

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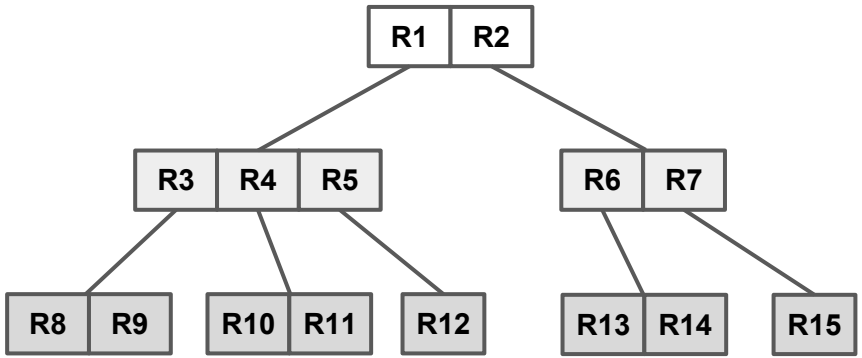
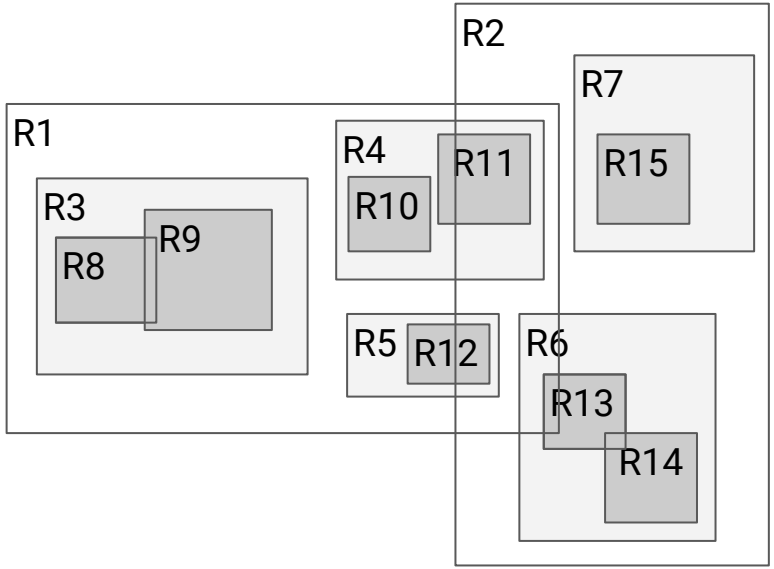
Tree data structure for indexing spatial information such as geographical coordinates, rectangles or polygons [82]
Common operation on spatial data is a search for all objects in an area [83], e.g.: “Find all shops within 1 km of my current location”

R-tree


R1
R2
R3
R4
R5
R6
R7
R8
R9
R10
R11
R12
R13
R14
R15


R2
R7
R1
R4
R11
R15
R3
R10
R9
R8
R5
R12
R6
R13
R14

BRIN

Block Range Index (BRIN) [80]

Proposed by Alvaro Herrera of 2ndQuadrant in 2013 as Minmax index [80, 81]

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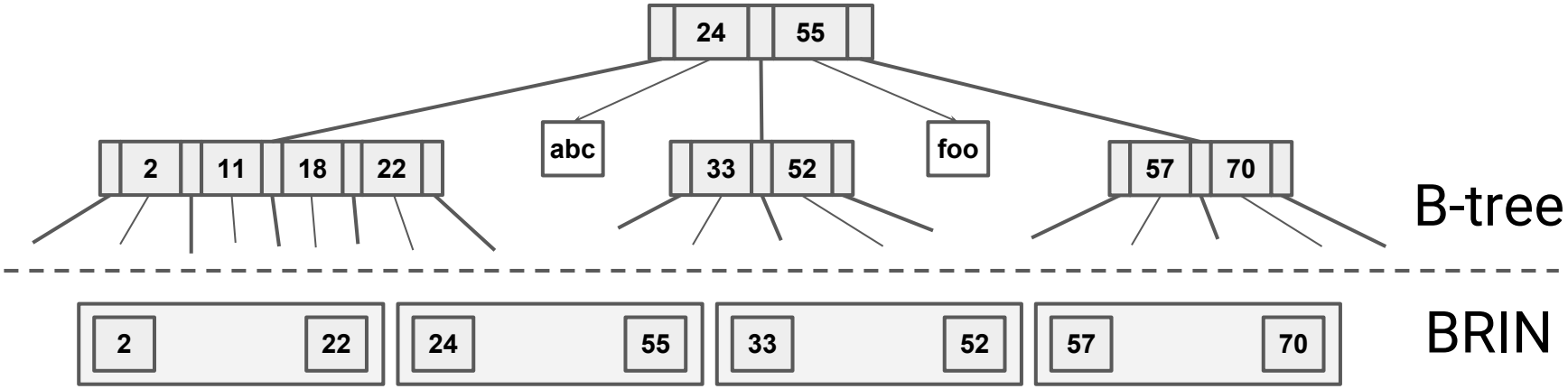
Other vendors have similar features: Oracle "storage indexes", Netezza “zone maps”, Infobright “data packs”, MonetDB, Apache Hive, ORC, Parquet [80, 81]

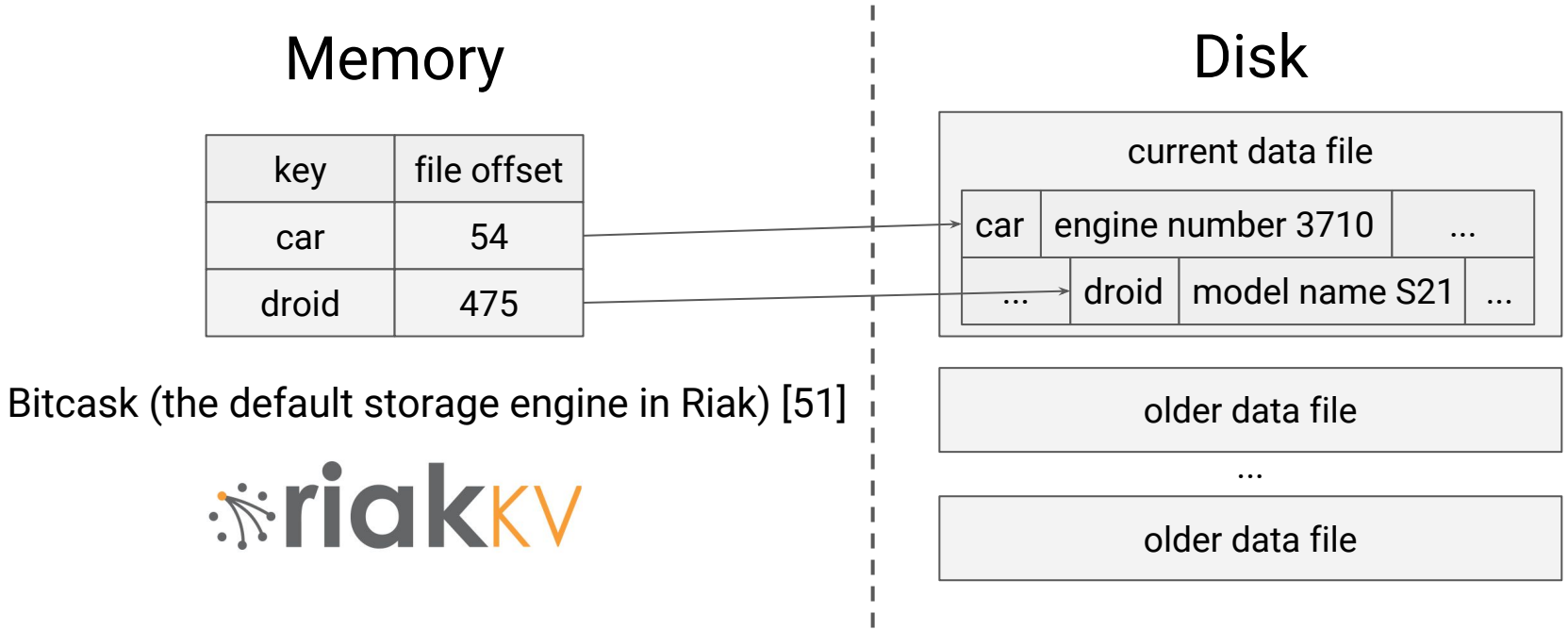
B-tree vs BRIN



block range	min value	max value
1	2	22
2	24	55
3	33	52
4	57	70

Log-Structured Hash Table

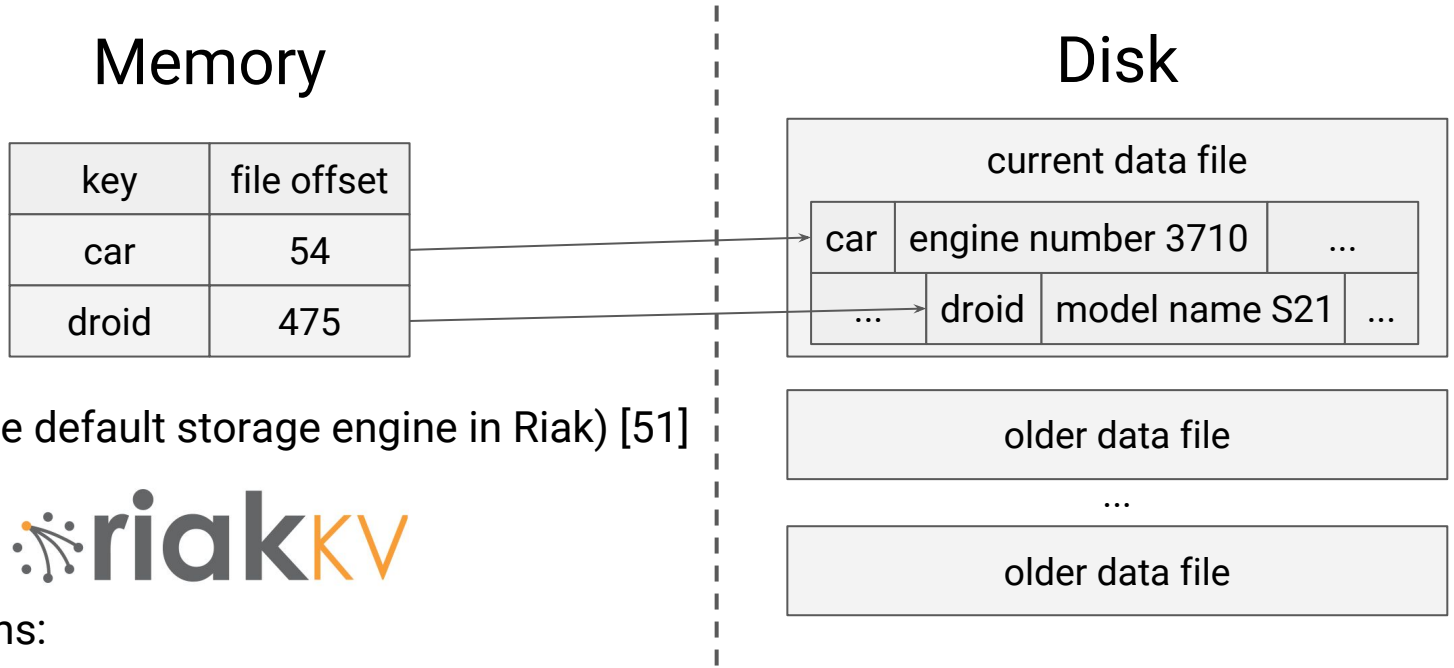
Log-Structured Hash Table



Bitcask (the default storage engine in Riak) [51]

riakKV

Log-Structured Hash Table



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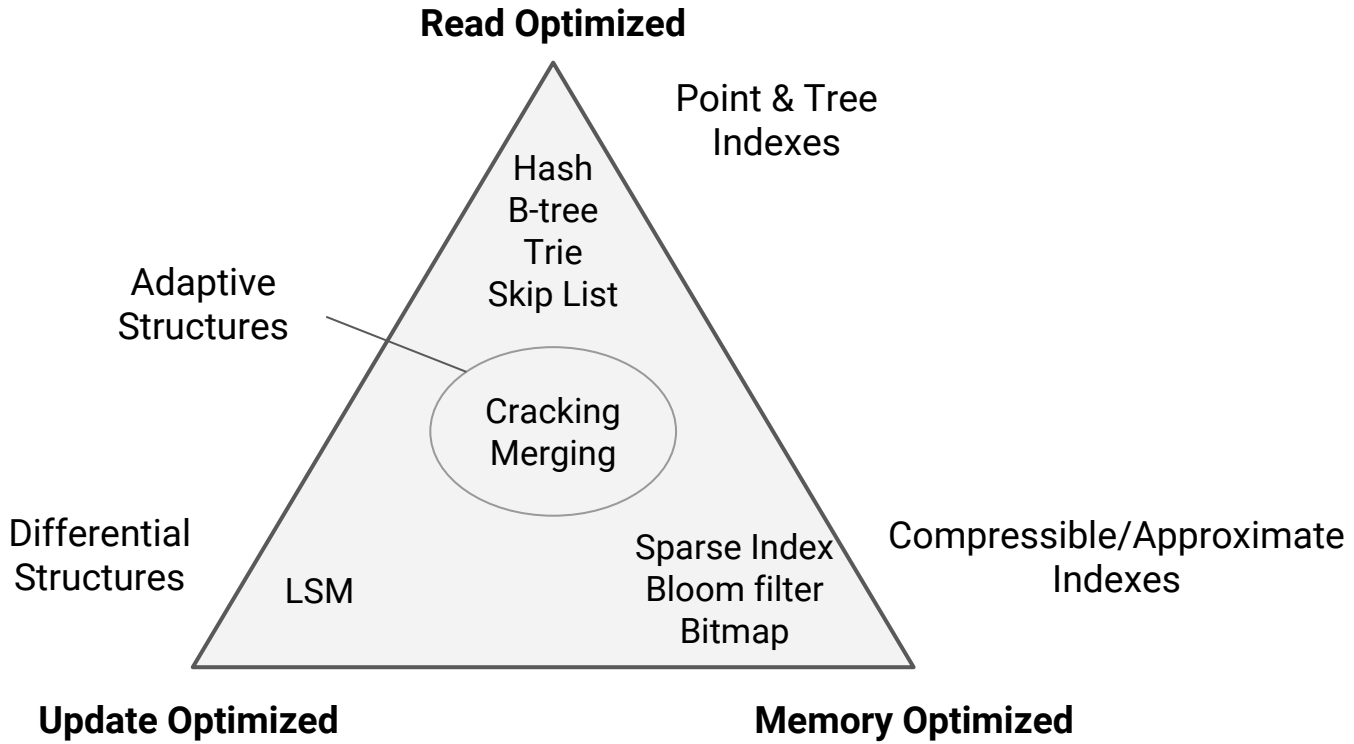
riakKV

Limitations:

1) must fit in memory
2) ranges not efficient

RUM Conjecture

RUM Conjecture [38, 39]



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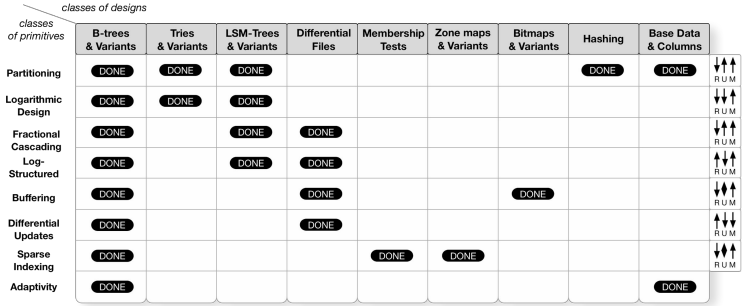
Amplification and other issues are heavily dependent on workload, configuration of the engine, and the specific implementation [48]

Interesting projects

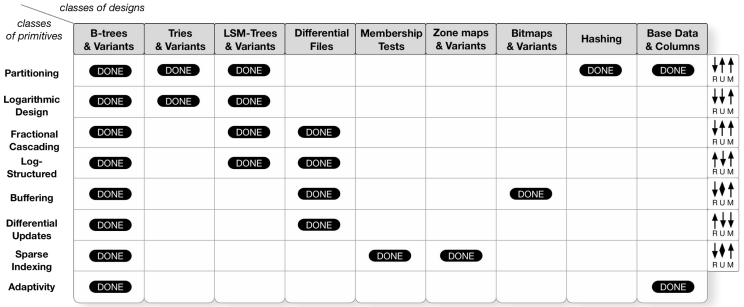
The periodic table of data structures [41]



Interesting projects

The periodic table of data structures [41]

Data calculator [42, 43]
Interactive, semi-automated design of data structures

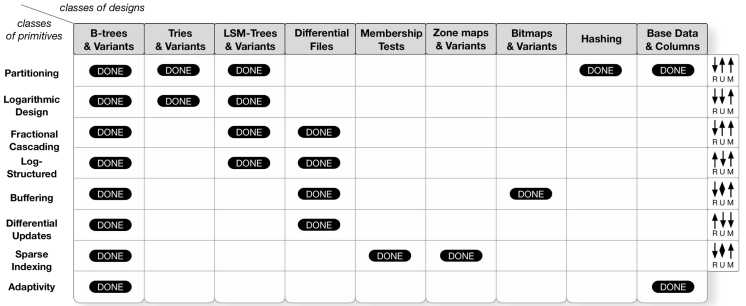


Interesting projects

The periodic table of data structures [41]

Data calculator [42, 43]
Interactive, semi-automated design of data structures

CrimsonDB [45]
A self-designing key-value store



OLTP/OLAP

OLTP vs OLAP

In the early days of business data processing, a write to the database typically corresponded to a commercial transactions [1]

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Hybrid transaction/analytical processing (HTAP) [84]

Row oriented vs Column oriented DBMS

datetime	name	age
10/10/2018 12:01:23	John	54
10/10/2018 12:01:24	Alice	22

Columns

datetime
10/10/2018 12:01:23
10/10/2018 12:01:24

name
John
Alice

age
54
22

Rows

datetime	name	age
10/10/2018 12:01:23	John	54
10/10/2018 12:01:24	Alice	22

Compression:
RLE, LZW, etc

Column oriented & time series DBs

Apache Parquet, ClickHouse, C-Store, Greenplum, MonetDB, Vertica, etc.

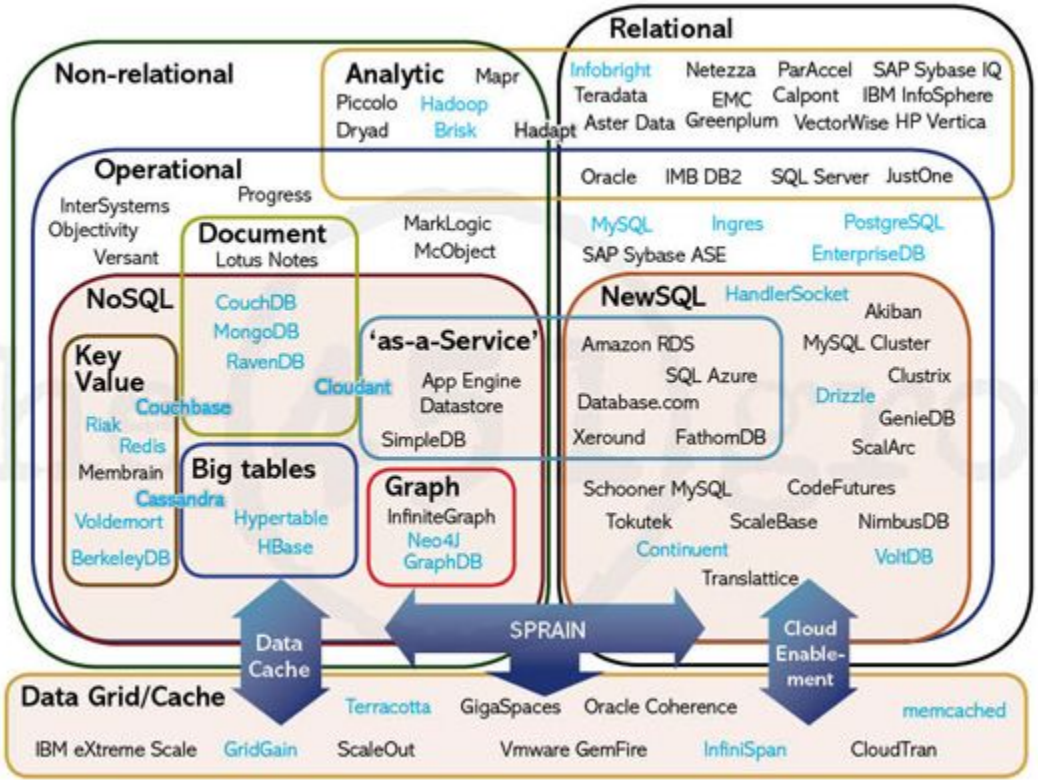
Time series databases (TSDB): Druid, Akumuli, InfluxDB, Riak TS, etc.

C-Store

SQL, NoSQL, NewSQL

RDBMS/SQL, NoSQL, NewSQL [72]

	RDBMS/SQL	NoSQL	NewSQL
Relational	Yes	No	Yes
ACID transactions	Yes	No	Yes
SQL support	Yes	No	Yes
Horizontal scalability	No	Yes	Yes
Schemaless	No	Yes	No



Matthew Aslett, The 451 Group [55]

DB in CPython

Python DB API Specification

PEP 248 - v1.0 (Release-Date: 09 Apr 1996 [74])

Python DB API Specification

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PEP 249 - v2.0 (Release-Date: 07 Apr 1999 [75])

Python DB API Specification

PEP 248 - v1.0 (Release-Date: 09 Apr 1996 [74])
PEP 249 - v2.0 (Release-Date: 07 Apr 1999 [75])

Implementations are available for:
- PostgreSQL (psycopg2, txpostgres, ...)
- MySQL (mysql-python, PyMySQL, ...)
- MS SQL Server (adodbapi, pymssql, mxODBC, pyodbc, ...)
- Oracle (cx_Oracle, mxODBC, pyodbc, ...)
- etc.

DBs in Python

dbm, gdbm or bsddb

dbm — interfaces to Unix “databases” [76]

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shelve
“shelf” — persistent, dictionary-like object
The values can be arbitrary Python objects — anything that the **pickle** module can handle, but the keys are strings [77]

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https://pixnio.com/food-and-drink/bell-pepper-jar-carfiol-vegetable-food-diet-glass-organic

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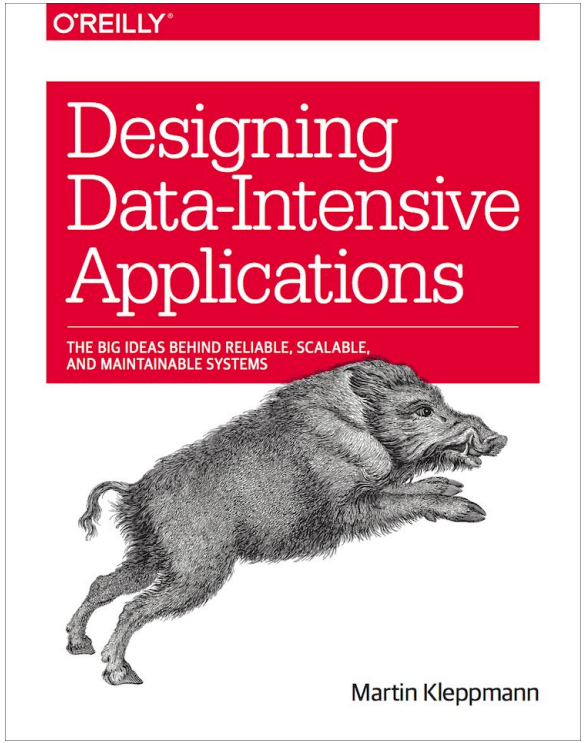
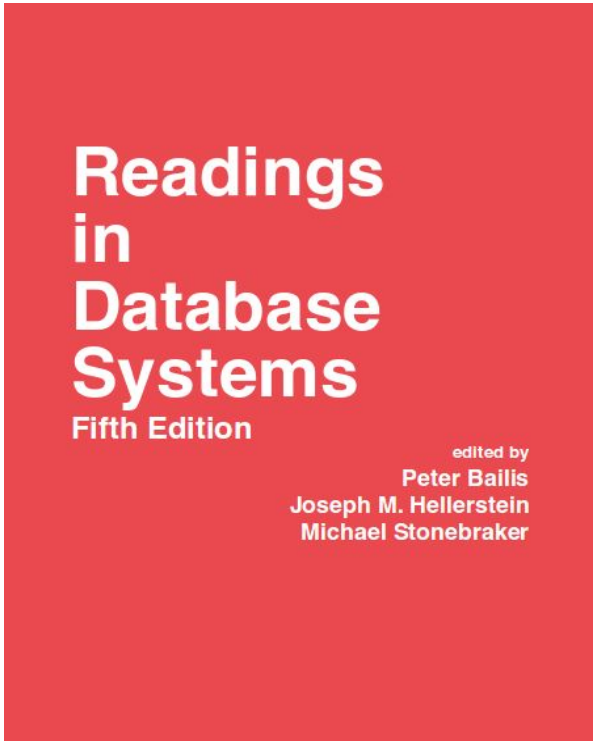
sqlite3
sqlite3 — DB-API 2.0 interface for SQLite databases [78]

Summary

- OLTP and OLAP
- OLTP:
  - B-tree
  - LSM-tree
  - Other indices
  - RAM, SSD
- OLAP
  - Column-oriented storage
- RUM Conjecture
- Amplifications


O'REILLY
Designing Data-Intensive Applications
THE BIG IDEAS BEHIND RELIABLE, SCALABLE, AND MAINTAINABLE SYSTEMS
Martin Kleppmann


Readings in Database Systems
Fifth Edition
edited by
Peter Bailis
Joseph M. Hellerstein
Michael Stonebraker

Books [1, 28]

Thank you!

Happy databasing!

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Questions