ADAPTIVITY IN DATABASE KERNELS

Adaptive Indexing: Self tuning access methods

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SUMARY

RECAP

- **New Problems**
- Adaptive vs Offline
- Database Cracking
 - Adaptive index for column stores
- Adaptive merging
 - Adaptive index for tuple based storage
- Concurrency





RECAP

FAST DATA, URGENT NEED FOR INSIGHTS

Data must be processed at least as quickly as it is produced!

Data layout must be flexible and specialized to the workload.

Tuning must be autonomous.



Figure: The Large Hadron Collider



LACK OF WORKLOAD KNOWLEDGE

In many modern applications e. g. big data exploration, the query pattern is unknown until it is actually processed





TIME FOR PHYSICAL DESIGN TUNING

Data is produced continuously, there is no time to fully optimize physical layout (offline tuning)



OPTIONS

Fast and large data analysis strategies:





DISTRIBUTED COMPUTING FRAMEWORKS

Scalable
Distributed
Comodity hardware
Map Reduce



Figure: Apache Hadoop

VOLUNTEER COMPUTING

Heterogeneous Social Autonomous



Figure: SETI @ Home





OPTIONS

What about DBMS?





ADAPTIVE VS OFFLINE

Offline indexes

- Require a decision on what to index
- One step operation (CREATE INDEX, DROP INDEX)
- Changes in workload demand rebuild





ADAPTIVE VS OFFLINE

Adaptive indexes

- Index selection is made on first query

 Physical design is tuned by incremental actions

 Changes occur in response to current query
 - Changes in workload are naturally handled





ADAPTIVE INDEXING CHANGES PHYSICAL LAYOUT

Query sequence —>



DATABASE CRACKING

DATABASE CRACKING

Developed for column stores (MonetDB)

Partitions an attribute at each query

In memory column copy and supporting AVL tree

Zero initialization







```
algorithm CrackInTwo(Low, High, Med)
    x1 := point at position Low
    x2 := point at position High
    while position(x1) < position(x2) do</pre>
        if value(x1) < Med then
            x1 := point at next position
        else
            while value(x2) >= Med and
            position(x2) > position(x1) do
                x2 := point at previous position
            end while
            Exchange(x1, x2)
            x1 := point at next position
            x2 := point at previous position
        end if
    end while
```

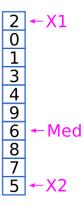
Idreos et. al. 2007 - Database Craking



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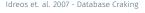




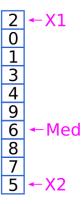




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Idreos et. al. 2007 - Database Craking







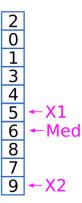
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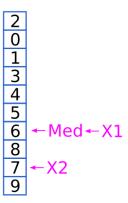












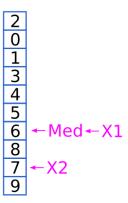




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```

Idreos et. al. 2007 - Database Craking









```
←Med←X1
```





```
\leftarrow Med\leftarrow X1\leftarrow X2
```





Partitions are stored in a tree structure (cracker index)





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More queries - more partitions - smaller pieces scanned

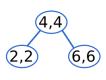






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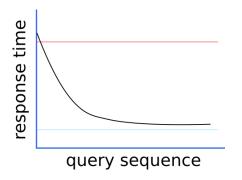






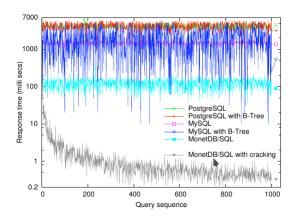
RESULTS

Response times are expected to decrease from the level of full scans (O(N)) to near the level of a binary search $(O(\log(n)))$





Database cracking - response times



Idreos et. al. 2007 - Database Cracking



ADDITIONAL BENEFIT

A histogram for free 1

Column partitions contain information on the distribution of the data attribute. i. e. they tell how many records lie in the given range.

¹Idreos et. al. 2007 - Database Craking



ADDITIONAL BENEFIT

Cracking aided joins ²

The same histogram-like information can be used to exclude partitions to consider while executing joins.

²Idreos et. al. 2007 - Database Craking



Stochastic cracking

- Partition ranges are not equal to query ranges
- Adds a random component to cracking
- Eventually cracks big partitions

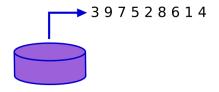
Holistic indexing

- Idle CPU cores are used to perform cracks
- Select operators still perform cracks
- Holistic cracks are performed on the biggest partitions



BLOCK STORAGE

Relational systems are typically stored in disk
B-tree based structures are suitable for block storage
Full sorting may be prohibitive (time)
And demands prior index selection (workload knowledge)



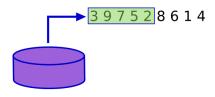


Figure: Collect run



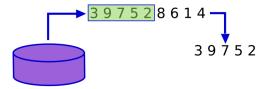


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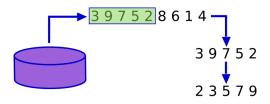
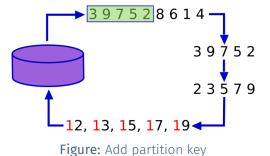


Figure: Sort run







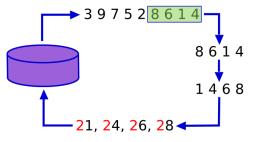


Figure: Repeat for other partitions



12, 13, 15, 17, 19, 21, 24, 26, 28

Figure: Final sorted data



Structure creation

- Runs become the data in the leaf level of a B+ tree
- A bulk load procedure is used to build the tree





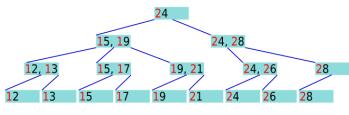


Figure: Complete tree



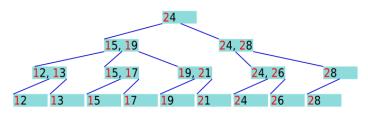


Figure: Answering a query



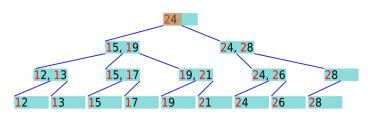


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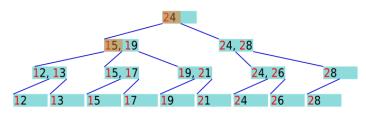


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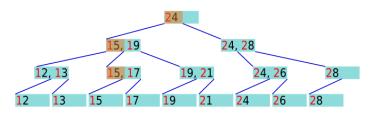


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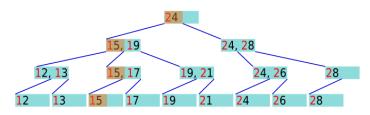


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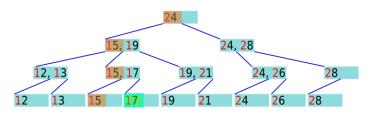


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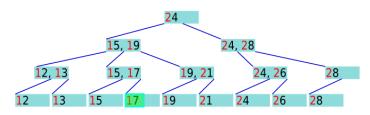


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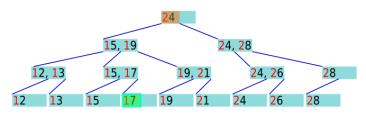


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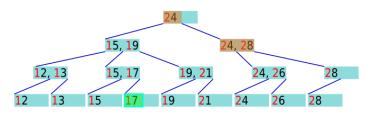


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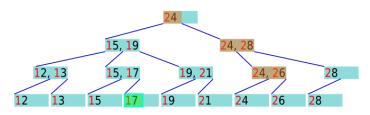


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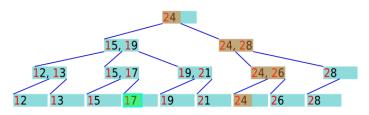


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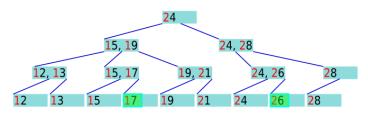


Figure: Answering a query



MERGE SELECTIONS

Each query walks the tree and move the qualifying tuples to the final partition



MERGE SELECTIONS

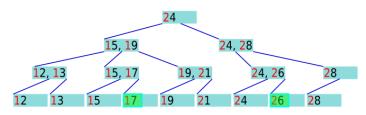


Figure: Adaptive Merging



MERGE SELECTIONS

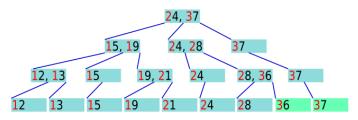


Figure: Short Query Ranges



Adaptive Merging - overhead per query

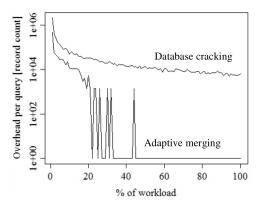


Figure: Short Query Ranges

Grafe et. al. 2010 - Self-selecting, self-tuning incrementally optimized indexes



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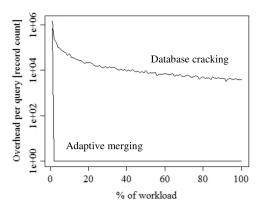


Figure: Long Query Ranges

Grafe et. al. 2010 - Self-selecting, self-tuning incrementally optimized indexes





The problem

Updating index structures while processing queries requires concurrency control and the system may incur additional lock contention



Index structure VS index contents ³

Index logical contents do not change Index refinement is not transactional Lightweight latches instead of locks

³Graefe et. al. 2012 - Concurrency Control for Adaptive Indexing



Locks VS Latches

SeparateLocksLatchesProtectDB ContentIn-memory dataDuringEntire TransactionsCritical sections



Incremental granularity of locking 4

Increasingly smaller key ranges affected Conflicts can be avoided

⁴Graefe et. al. 2012 - Concurrency Control for Adaptive Indexing



BEYOND ADAPTIVITY

AI/ML guided layout optimization

- Incremental physical layout tuning enables learning
 Current request X Workload pattern
- Workload forecasting (tune in anticipation)





CONCLUSION

Flexible physical design tuning
Autonomous
Enable the use of workload pattern recognition
Fits modern query processing





