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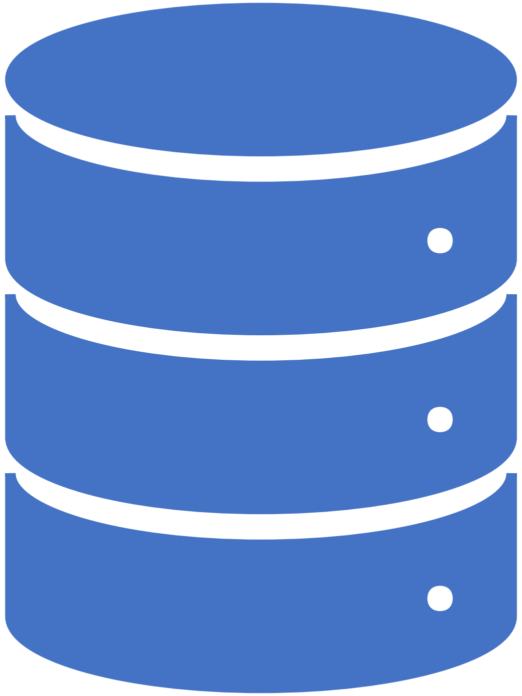


PA220: Database systems for data analytics

Data Warehouse Indexing & Optimization

Contents

- Approaches to indexing
- Data partitioning
- Joins
- Materialized views

Why Indexes?

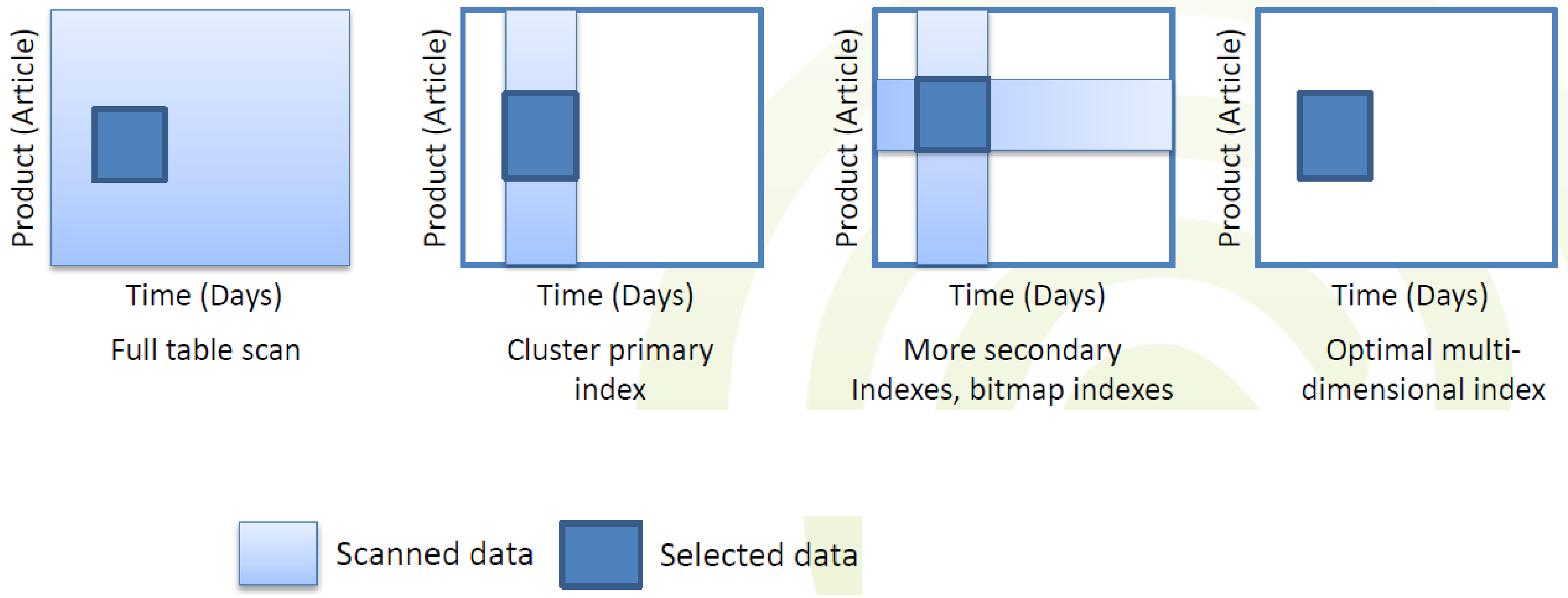
- Consider a 100 GB table; at 100 MB/s read speed we need 17 minutes for a full table scan
- Query for the number of “Bosch S500” washing machines sold in Germany last month
  - Applying restrictions (product, location) the **selectivity** would be strongly improved
    - If we have 30 locations, 10,000 products and 24 months in the DW, the selectivity value is 1/30 * 1/ 10,000 * 1/24 = 0,000 000 14
- So… we read 100 GB for 1,4KB of data

The low value of selectivity
→ Highly selective predicate!

- The problem is: *how to filter data in a fact table as much as possible*

Why Indexes?

- Reduce the size of read pages of data cube to a minimum with indexes

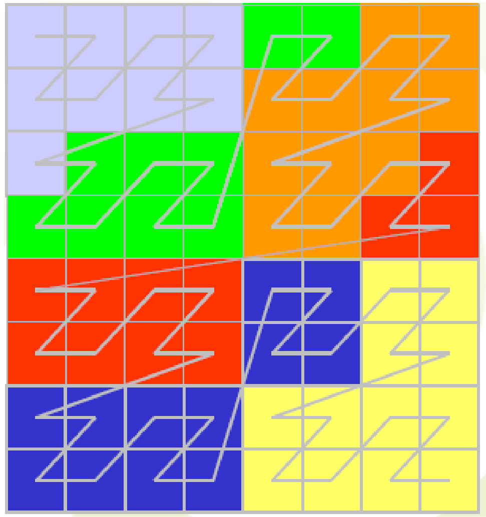


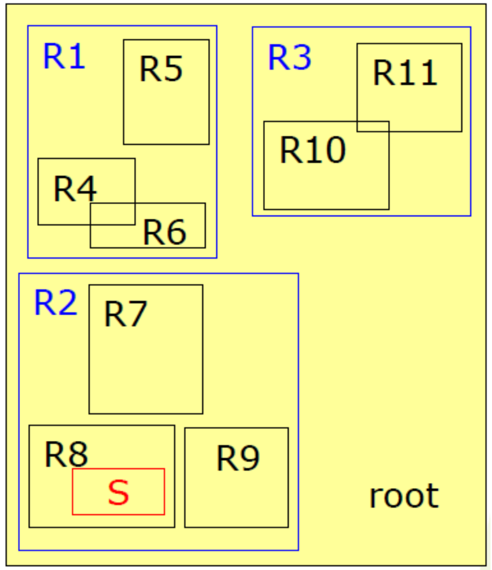
Index Types

- Tree structures
  - B^+-tree, R-tree, …
- Hash based
  - Dynamic hash table
- Special
  - Bitmap index
  - Block-Range INdex (in Pg)

Multidimensional Data

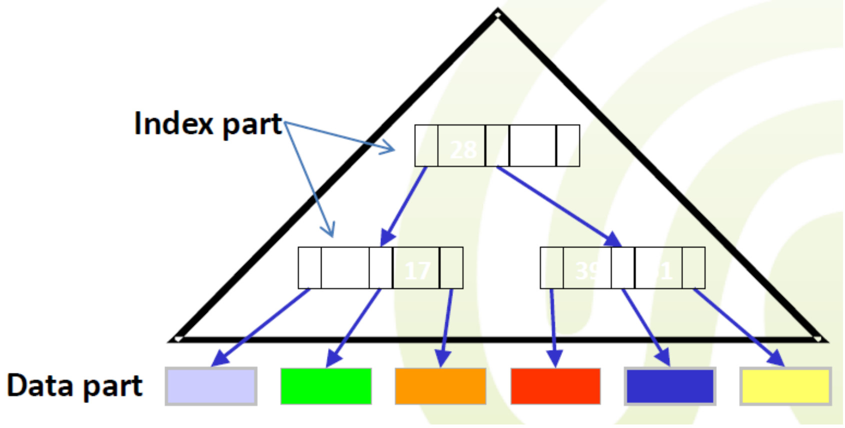
- B^+-tree
  - classic structure – very efficient in updates
  - supports point and range queries
  - limited to 1D data
- UB-tree
  - uses B*-tree and
  - Z-curve to linearize n-dim data
- R-tree
  - wrapping by n-dim rectangles
  - R^+, R*, X-tree

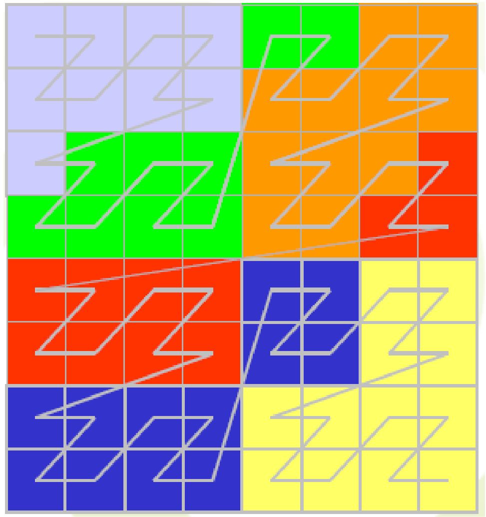




UB-Trees

- Convert n-dim data to a single dimension by the Z-curve
- and Index by B* tree

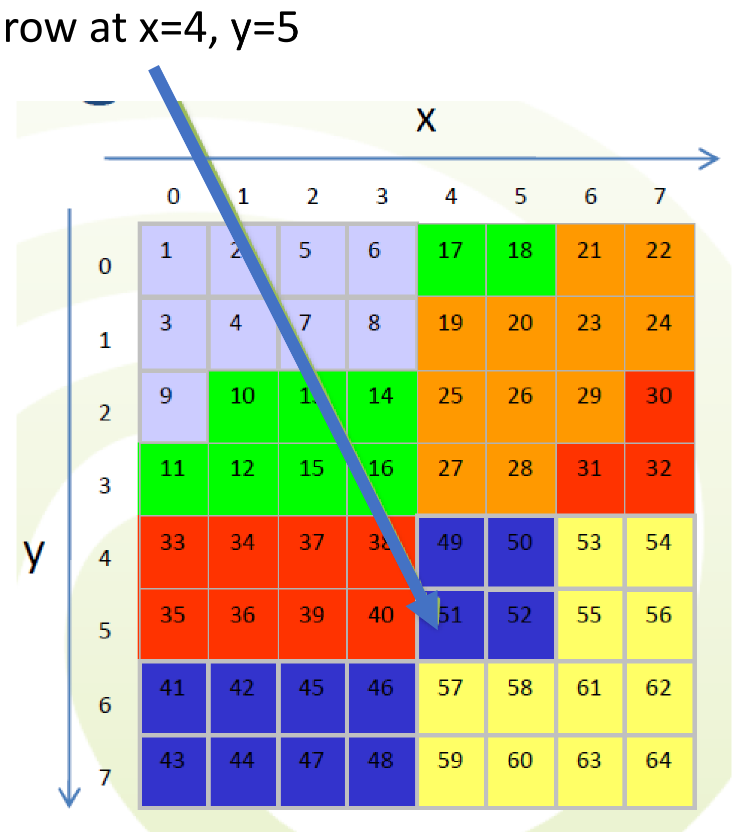




- The Z-curve provides for good performance for range queries!
  - Consecutive values on the Z-curve index similar data
  - Similarity by means of neighborhood

UB-Trees

- Z-Value address representation
  - Calculate the z-values such that neighboring data is clustered together
  - Calculated through bit interleaving of the coordinates of the tuple
  - To localize a value with coordinates one must perform de-interleaving



For Z-value 51, we have the offset 50.
50 in binary is 110010

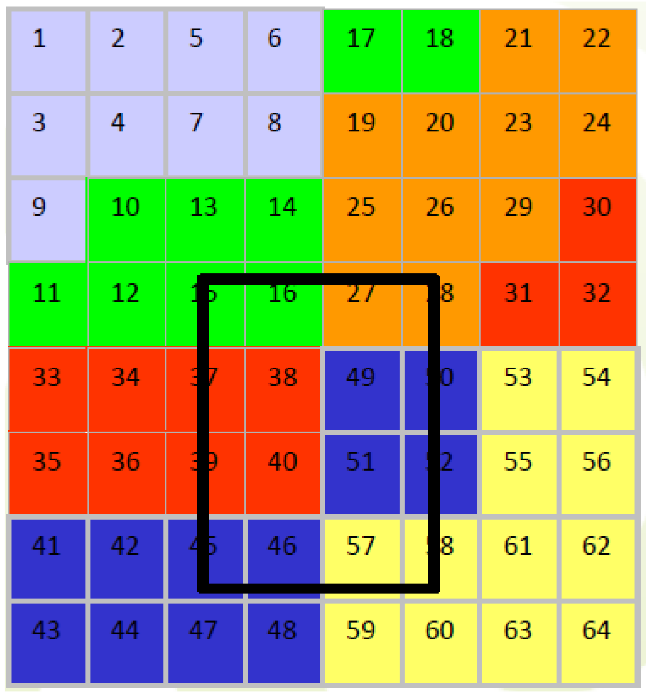
Z-value = 110010

Y = 101 = 5   X = 100 = 4

We have Z-regions – describes one block in storage.
E.g. [1-9], [10-18].

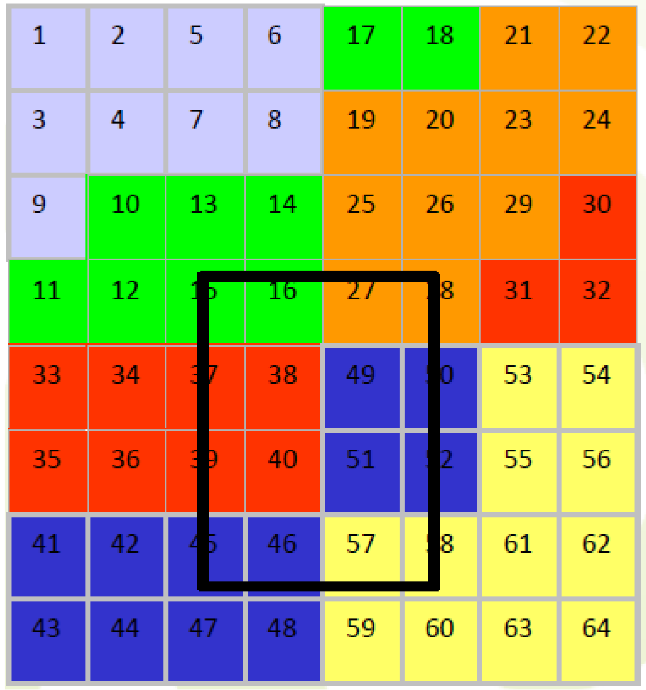
UB-Trees – Range Query

Q: $x \in [2;5]$, $y \in [3;6]$



- Range queries (RQ) in UB-Trees
  - Each query can be specified by 2 coordinates
    - q_a (the upper left corner of the query rectangle)
    - q_b (the lower right corner of the query rectangle)
- Range Query Algorithm
  1. Calculate z-values for q_a and q_b
  2. Get a node with Z-Region containing q_a
     - e.g., Z-Region of q_a is [10:18]
  3. The corresponding page is loaded and filtered with the query predicate
     - E.g., value 10 has after de-interleaving x=1 and y=2, which is outside the query rectangle

UB-Trees – Range Query



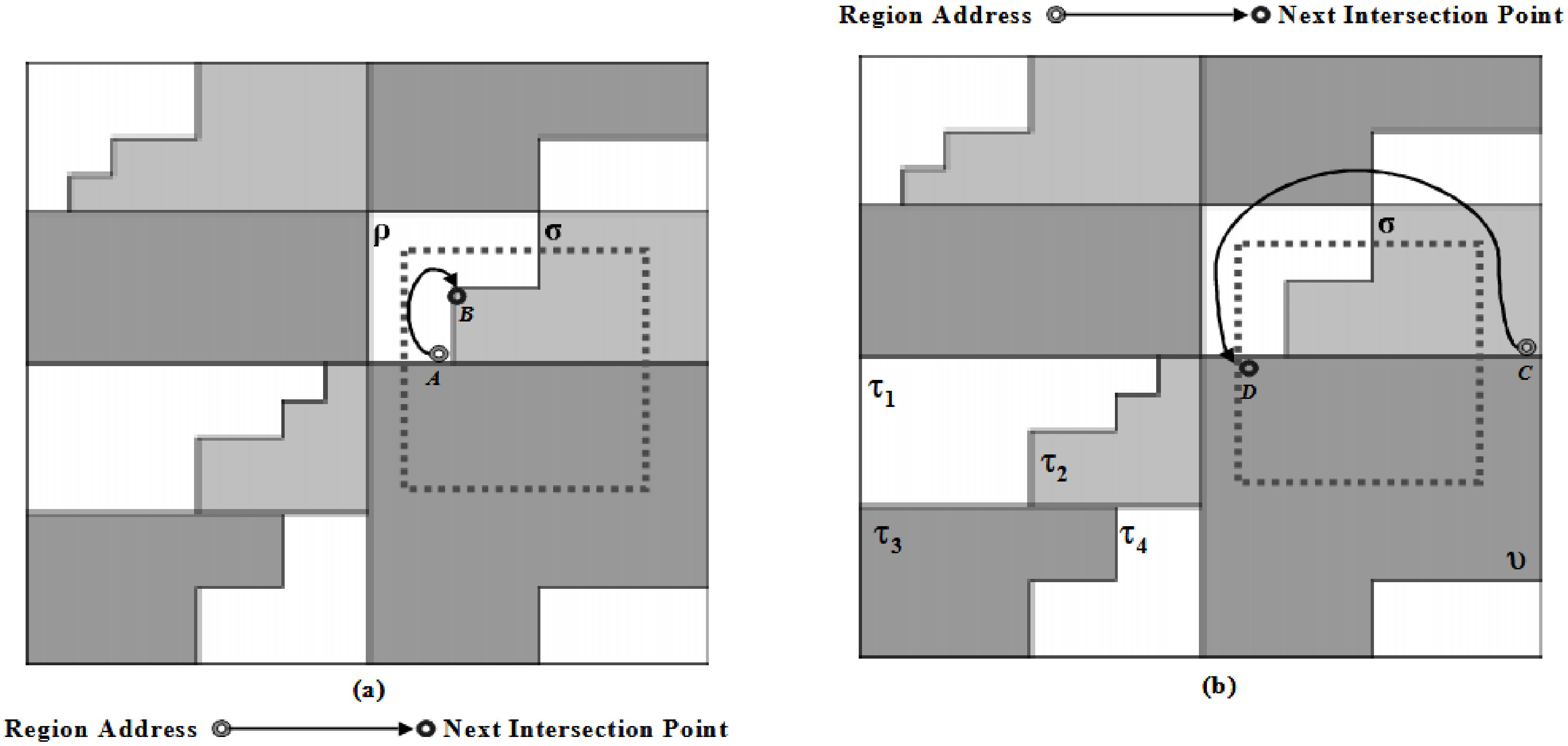
- Range Query Algorithm (cont.)
  4. After q_a, all values on the Z-curve are de-interleaved and checked by their coordinates
     - The data is only accessed from the disk.
     - The next jump point on the Z-curve is 27.
  5. Repeat Steps 2 and 3 until the decoded end-address of the last filtered region is bigger than q_b

Calculating the *jump point* mostly involves:

- Performing **bit operations** and comparisons
- 3 points: q_a, q_b and the current Z-Value

UB-Trees – next “jump” point

- Idea of getting next jump point

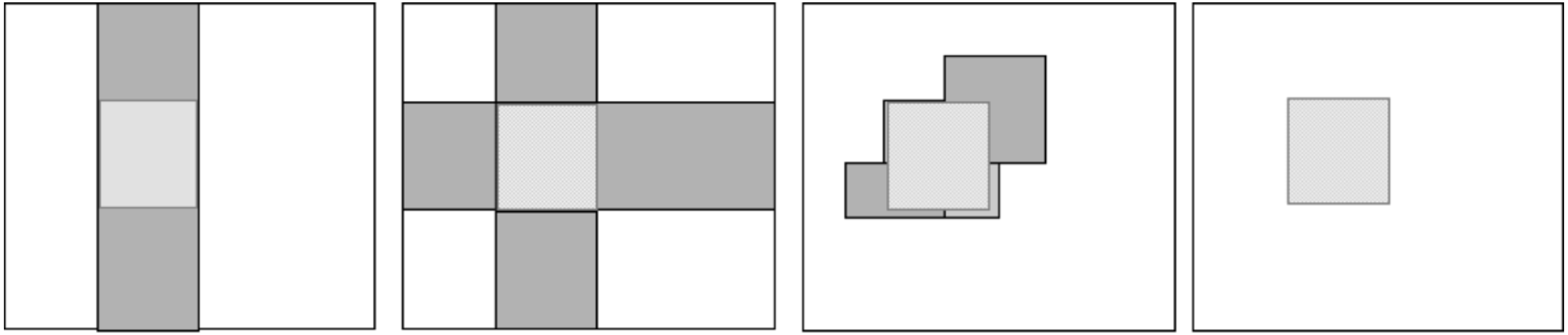



```
BP changeBP=BP(d,outstep); //we start with the minimal bit position that has to be changed
int i;
if (flag[d] == 1) // we cannot set this bit to 1, therefore we have to find a lower bit position we can safely set
then {
        changeBP=max({bp|bp<changeBP and bp >= saveMax[Dim(bp)] and Val(nisp,bp)=0}); //maximal bitposition that is save to set to 1
        saveMin[DIM(changeBP)]=STEP(changeBP);
        flag[DIM(changeBP)]=0;
        }
// now we can change the rest of the Z-value
for(i=0;i<dimno;i++) { //for each dimension we determine how to change the bits
if(flag[i]>=0) // we have not fallen below the minimum in this dimension
then {
     if(changeBP > BP(i,saveMin[i]))
     then "set all bits of dim with bit positions > changeBP to 0"
     else "set all bits of dim with bit positions > changeBP to the minimum of the query box in this dim"
}
else { // if we have fallen below the min in this dimension the lowest possible value is the min itself
     "set the bits to the minimum of the query box in this dim"
}}
```

Figure 4-4 Pseudo code for parts of getNextZvalue

Index comparison

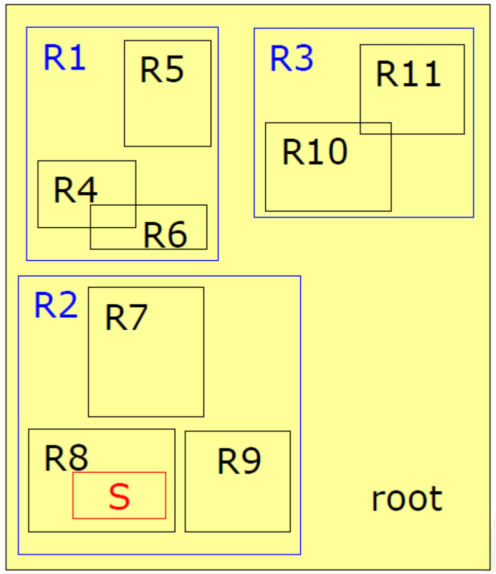
- Area of records to scan (dark-grey) to get the answer (light-grey)

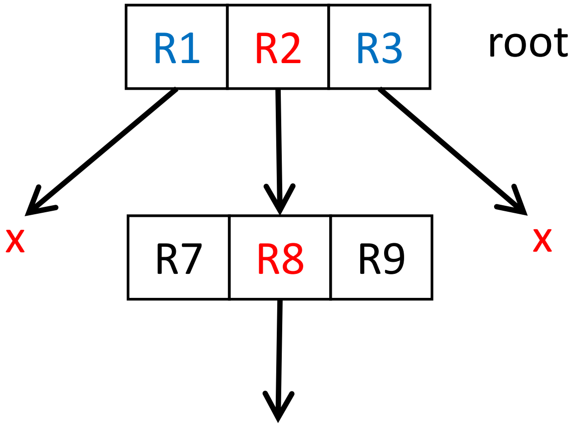


compound primary B-Tree | multiple secondary B-Trees | UB-Tree | ideal case

R-Trees

- Like B-trees
  - Data objects stored in leaf nodes
  - Nodes represented by minimum bounding rectangles
  - High-balanced structure



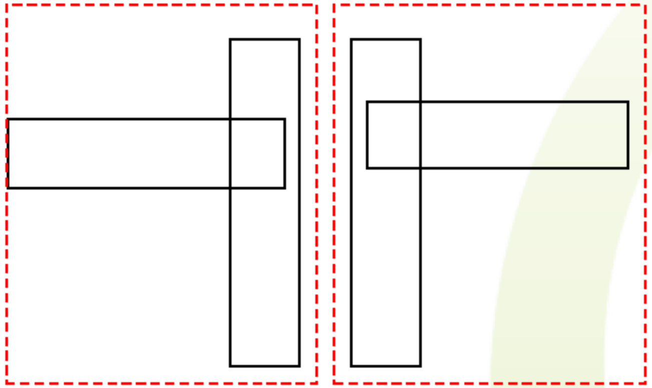


Check all the objects
in node R8.

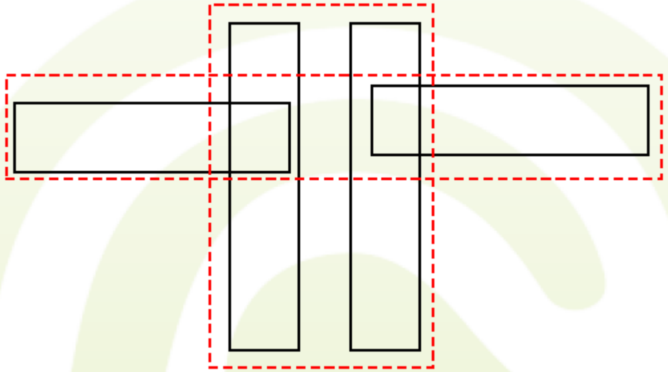
Query S:
3 out of 11 nodes are checked.
(root, R2, R8)

R-Trees Querying

- Many MBR overlaps deteriorate query performance
  - All nodes get visited in the worst case.
- Key is insertion/split optimization
  - Minimize volume by MBR → overlaps.



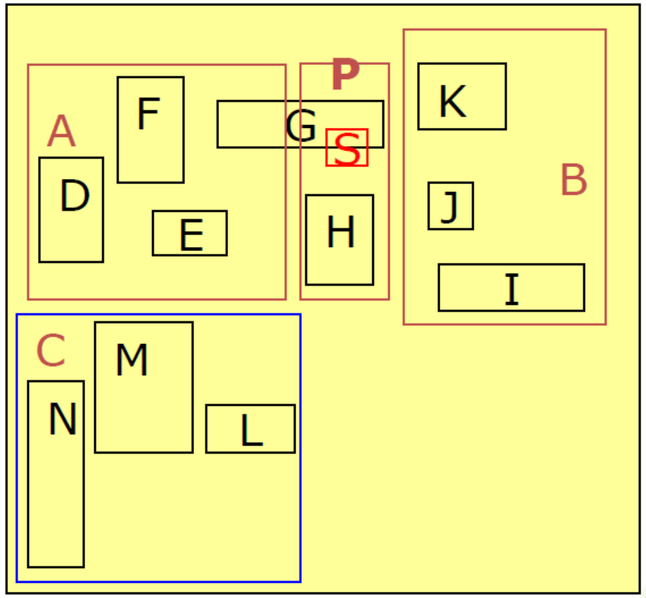
Bad split

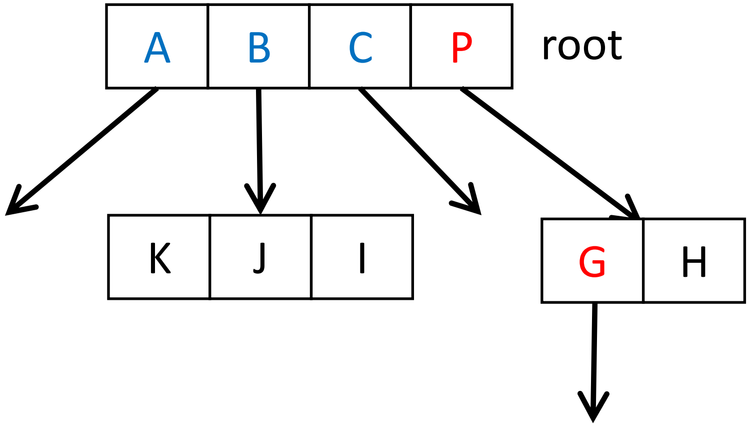


Better split

R+ Tree

- Eliminates overlaps by replication of objects in leaves





- Improves performance of point queries

Bitmap Index

- A bitmap index for an attribute is a data structure composed of:
  - A collection of bitmaps (bit-vectors)
    - The number of bit-vectors represents the count of distinct values of an attr. in the relation
  - Bitmap (bit vector/array) is an array data structure that stores individual bits
    - Bit signals the presence of value in the row with the relative index of the bit’s position.
    - The length of each bit-vector is the cardinality of the relation.
    - It is compressed by Run-length encoding.

Shop dim

Nr	Shop
1	Saturn
2	Real
3	P&C

Sales fact

Nr	Shop_ID	Sum
1	1	150
2	2	65
3	3	160
4	2	45
5	1	350
6	2	80

Bitmap on Shop of Sales

Value	Bitmap
3	001000
2	010101
1	100010

Bitmap Index

- Records are allocated under permanent numbers.
  - There is a mapping between record numbers and record addresses.
- Insertion
  - bit-vectors are extended, and the new record is appended to the table
- Update
  - toggle the bits in the old bit-vector array and in the new one.
- Deletion
  - in the fact table → tombstones
  - in the index → bit is cleared

Bitmap Index – Queries

- Combine OR/AND values
  - OR/AND bit ops on vectors
  - E.g., Saturn | P&C

Nr	Shop
1	Saturn
2	Real
3	P&C

Value	Bitmap
3	001000
2	010101
1	100010

100010
001000

101010

- Combine different indexes on the same table

Bitmap Index

- Good for data which has a “small” number of distinct values
  - E.g., gender data, clothing sizes
  - Thus, the selectivity value is *low.*
    - Combinations of multiple indexes lead to highly-selective predicates.

  - Similar performance as B+ tree for static (read-only) data
    - also, when all values are distinct
- Many distinct values cause many bit arrays.
  - Transform to multiple components and project to decrease it.
  - → Multi-component Bitmap Index
- Not very good for range queries on values.
  - → Range-encoded Bitmap Index

Multi-component Bitmap Index

- Encoding using a different numeration system to reduce storage space
  - E.g., <div,mod> classes
- Idea:
  - transform values into more dimensions and project
  - intersection of projections gives the original value
- E.g., the month attribute has values between 0 and 11.
  - Encode by X = 3*Z+Y

	Q1	Q2	Q3	Q4
1st	Jan	Apr	Jul	Oct
2nd	Feb	May	Aug	Nov
3rd	Mar	Jun	Sep	Dec

X	Y			Z			
M	$A_{2,\_}$	$A_{1,\_}$	$A_{0,\_}$	$A_{\_,3}$	$A_{\_,2}$	$A_{\_,1}$	$A_{\_,0}$
5	1	0	0	0	0	1	0

Multi-component Bitmap Index

- Encoding using a different numeration system to reduce storage space, e.g., <div,mod> classes
- Idea:
  - transform values into more dimensions and project
  - intersection of projections gives the original value
- E.g., the month attribute

	Q1	Q2	Q3	Q4
1^{st}	Jan	Apr	Jul	Oct
2^{nd}	Feb	May	Aug	Nov
3^{rd}	Mar	**Jun**	Sep	Dec

Encode by X = 3*Z+Y
i.e., June: 5=3*1+2

New bit-arrays

X	Y			Z			
M	$A_{2,\_}$	$A_{1,\_}$	$A_{0,\_}$	$A_{\_,3}$	$A_{\_,2}$	$A_{\_,1}$	$A_{\_,0}$
5	1	0	0	0	0	1	0

Multi-component Bitmap Index

- If we have 100 (0..99) different days to index we can use a multi-component bitmap index with the basis of <10,10>
- The storage is reduced from 100 to 20 bitmap-vectors
  - 10 for y and 10 for z
- The read-access for a point query (1 day out of 100) needs however 2 read operations instead of just 1
  - plus, the bit-and operation on the bit-arrays

Range-encoded Bitmap Index

- Requires a logical ordering of values
- Idea:
  - set the bit in all bit-vectors of the values following this current one
  - range queries will check just 2 bit-vectors
    - matches are: NOT previous AND current

- Disadvantage:
  - a point query requires reading 2 vectors

Range-encoded Bitmap Index

- Query: Persons born between March and August
  - So, persons who didn't exist in February but existed in August.
  - Just 2 vectors read: ((NOT A1) AND A7)

Index on month of birth

	Dec	Nov	Oct	Sep	Aug	Jul	Jun	Mai	Apr	Mar	Feb	Jan
Person	A_{11}	A_{10}	A_9	A_8	A_7	A_6	A_5	A_4	A_3	A_2	A_1	A_0
1	1	1	1	1	1	1	1	0	0	0	0	0
2	1	1	1	1	1	1	1	1	1	0	0	0
3	1	1	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	0	0	0
5	1	0	0	0	0	0	0	0	0	0	0	0

- Normal bitmap would require 6 vectors to read.

Summary of Indexes

- B-Trees are not fit for multidimensional data
  - UB-trees can be applicable
- R-Trees may not scale to many dimensions
- Bitmap indexes are typically only a fraction of the size of the indexed data in the table
- Bitmap indexes reduce response time for large classes of ad hoc queries

Data Partitioning

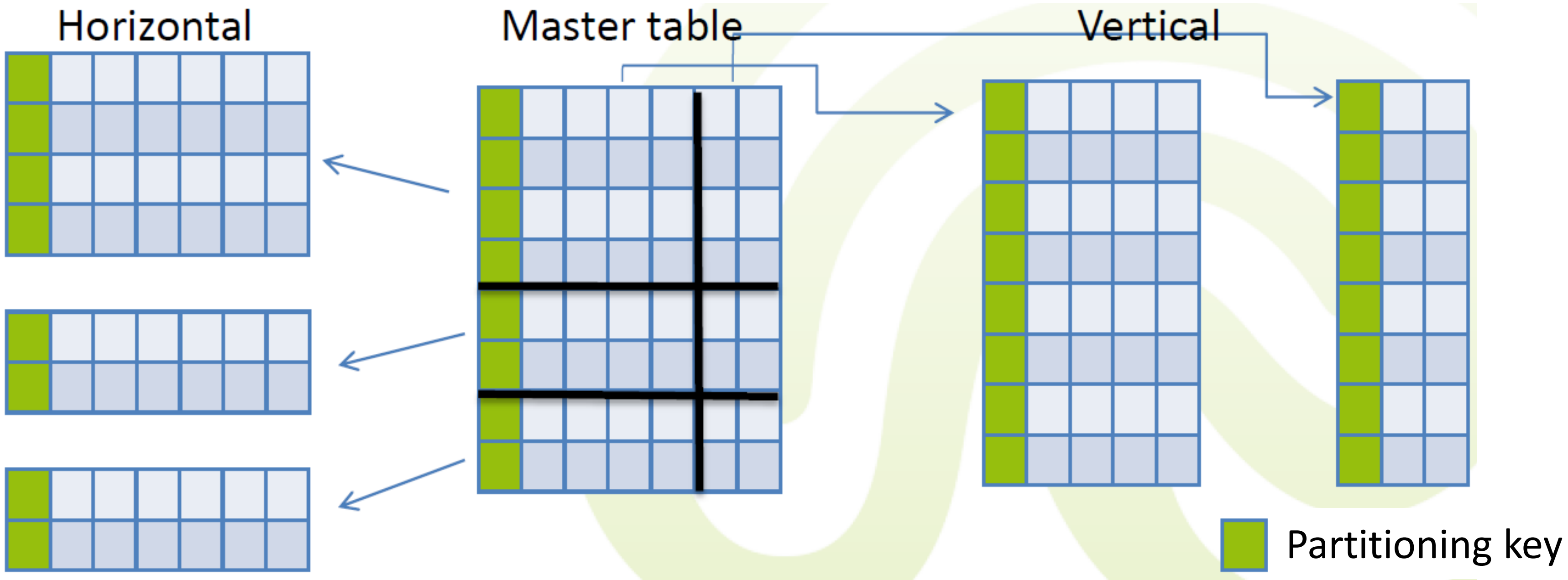
- Breaking data into “non-overlapping” parts
- May correspond to the granularity of a dimension and use ranges to define partitions of a fact table.
- Improves:
  - Business query performance,
    - i.e., minimize the amount of data to scan
  - Data availability,
    - e.g., back-up/restore can run at the partition level
  - Database administration,
    - e.g., archiving data, recreating indexes, loading tables

Data Partitioning

- Approaches:
  - Logical partitioning by
    - Date, Line of business, Geography, Organizational unit, Combinations of these factors, …
  - Physical partitioning
    - Makes data available to different processing nodes
    - Possible parallelization on multiple disks/machines
- Implementation:
  - Application level
  - Database system

Data Partitioning: Two Options

- Horizontal – splitting out the rows of a table into multiple tables
- Vertical – splitting out the columns of a table into multiple tables



Horizontal Partitioning

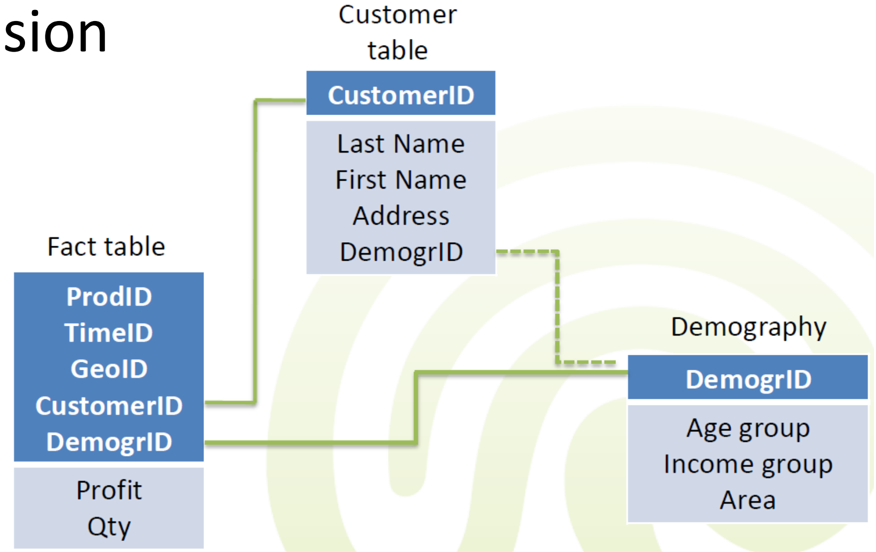
- Distributes records into disjoint “tables”
- Typically, “view” over the union of the table is created
- Types of partition function:
  - range – a range of values per table
  - list – enumeration of values per table
  - hash – result of a hash function determines the table
- Data warehouse context:
  - Fact table is partitioned by, e.g.,
    - Time dimension – weeks, months, or age of data
    - Another dim if it does not change often – branch, region
  - Individual partitions (tables)
    - require defining constraints on their contents
      - to use a subset of partitions in query execution

Vertical Partitioning

- Involves creating tables with fewer columns and using additional tables to store the remaining columns
  - Usually called row splitting
  - Row splitting creates one-to-one relationships between the partitions
    - Create a view that merges them
- Different physical storage might be used
  - E.g., storing infrequently used or very wide columns on a different device
- Data warehouse context :
  - move seldom-used columns from a highly-used table to another
    - Sometimes done as a side effect when an “outrigger” dimension is used.
    - This is relevant to fact tables and their measure columns!

Vertical Partitioning (contrast to dimensions)

- Mini-dimension with outrigger is a solution
  - Many dimension attributes are used very frequently as browsing constraints
    - In big dimensions these constraints can be hard to find among the lesser used ones
  - Logical groups of often used constraints can be separated into small dimensions
    - which are very well indexed and easily accessible for browsing
  - E.g., demography dimension
    - Notice the foreign key in customer



Summary of Data Partitioning

- Advantages
  - Records used together are grouped together
  - Each partition can be optimized for performance
  - Security, recovery
  - Partitions stored on different disks reduce contention
  - Take advantage of parallel processing capability
- Disadvantages
  - Slow retrieval across partitions (expensive joins in vertical partitioning)
  - Complexity
- Recommendations
  - A table is larger than 2GB (from Oracle)
  - A table has more than 100 million rows (practice)

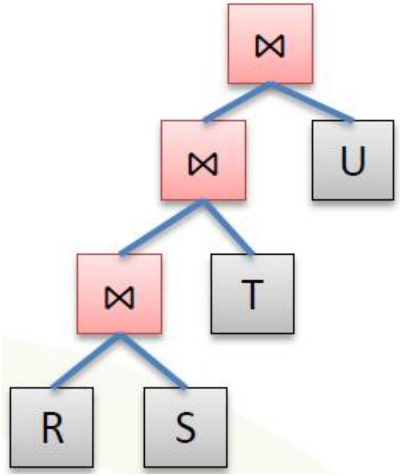
Join Optimization in DWH

- Queries over several dimensions are often needed
  - This results in joins over the tables
  - Though joins are generally expensive operations, the overall cost of the query may strongly differ with the chosen evaluation plan for the joins

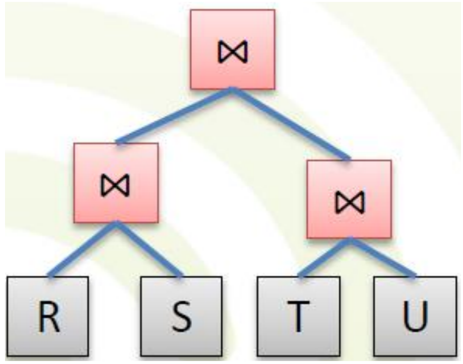
- Joins are commutative and associative
  - $R \bowtie S \equiv S \bowtie R$
  - $R \bowtie (S \bowtie T) \equiv (S \bowtie R) \bowtie T$

Join Optimization

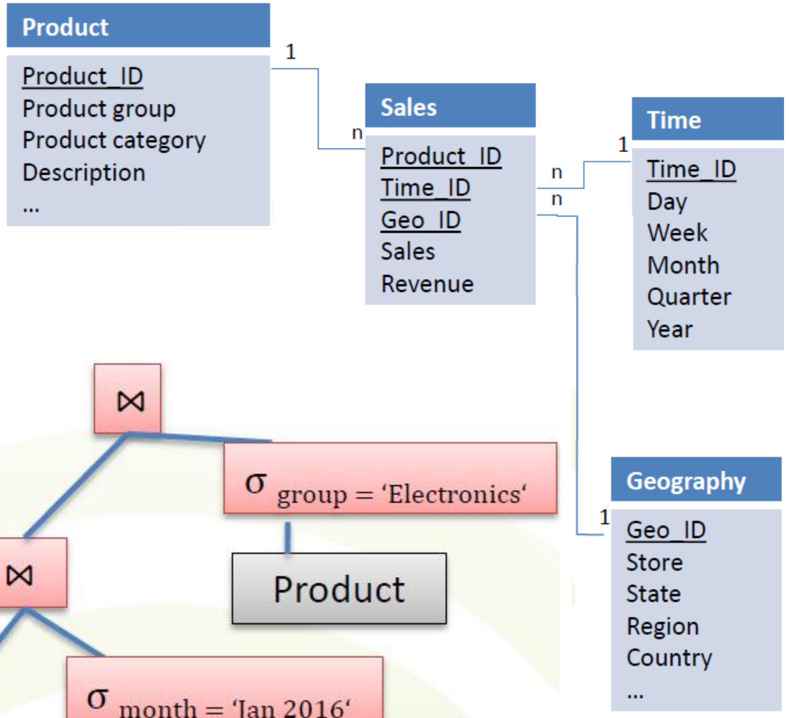
- This allows evaluating individual joins in any order
  - Results in join trees
    - Different join trees may show very different evaluation performance
  - Number of possible join trees may grow rapidly (n!)



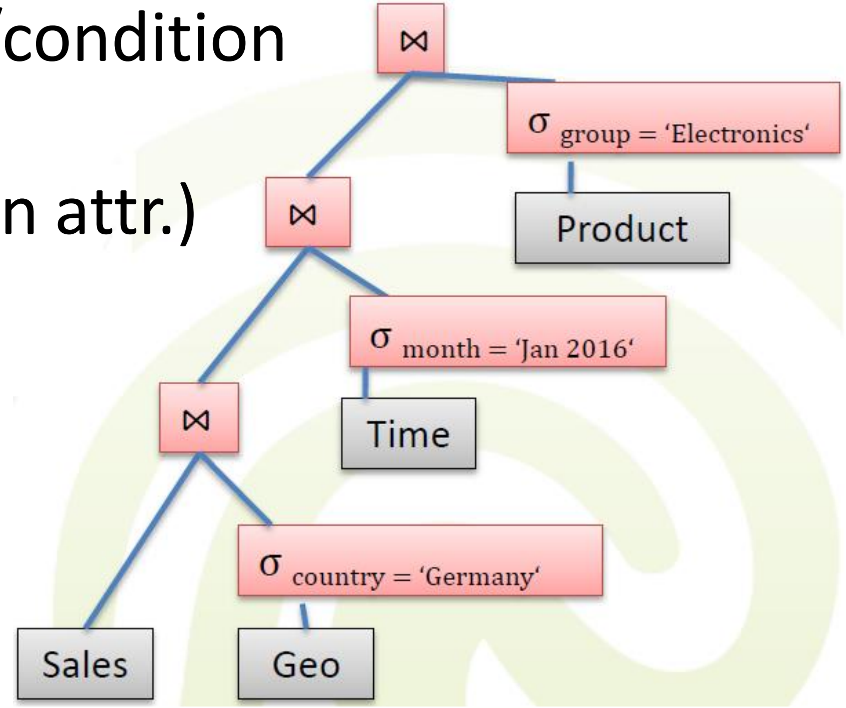
- DBMS optimizer considers
  - statistics to minimize result size
    - all possibilities → impossible for large *n*
  - heuristics to pick promising ones
    - when the number of relations is high (e.g., >6)
    - e.g., genetic algorithms



Join Selection Heuristics



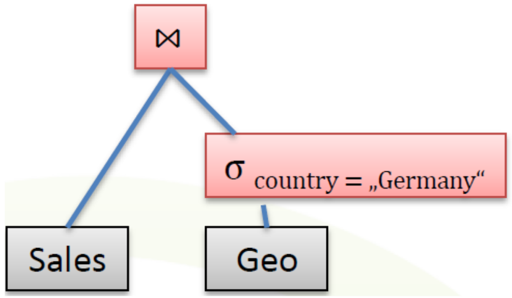
- Join relations that relate by an attribute/condition
  - which avoids cross joins
- Minimize the result size (A is the common attr.)
  - $\frac{T(R)*T(S)}{\max(V(R,A),V(S,A))}$
- Availability of indexes and selectivity of other conditions



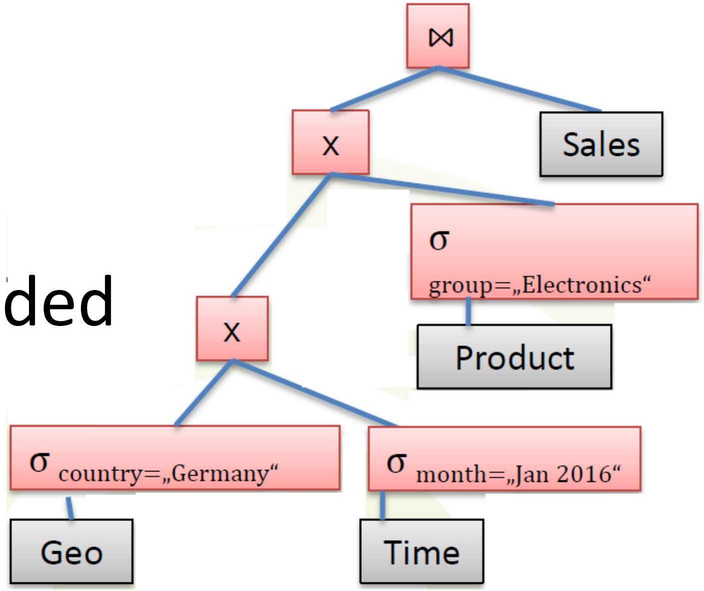
- User tuning
  - Hints in Oracle
  - Change **join_collapse_limit** in PostgreSQL

Join Selection Heuristics in DWs

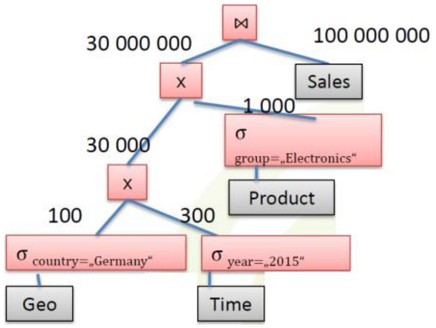
- OLTP's heuristics are not suitable in DWs
  - E.g., join Sales with Geo in the following case:
    - Sales has 10 mil records, in Germany there are 10 stores, in January 2016 there were products sold in 20 days, and the Electronics group has 50 products
  - If 20 % of our sales were performed in Germany,
    - the selectivity value is high.
    - so, an index would not help that much
  - The intermediate result would still comprise 2 mil records



Join Selection Heuristics in DWs



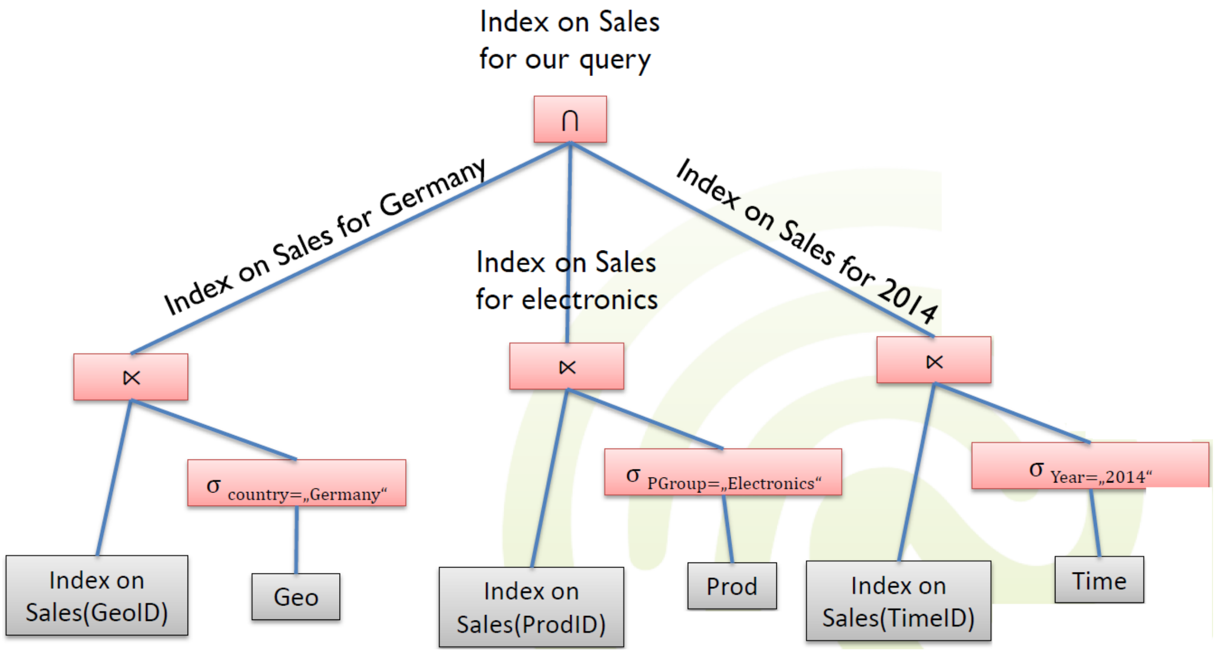
- The **cross join** of the dimension tables is recommended
  - Geo dimension – 10 stores in Germany
  - Time dimension – 20 days in Jan 2016
  - Product dimension – 50 products in Electronics
  - 10m facts in Sales
  - 10*20*50 = 10,000 records after performing the cross product
- But can also be expensive!



- Cross-join of dimensions allows
  - a single pass over Sales
  - using an index on the most selective attribute yet.

Join Selection Heuristics in DWs

- If cross join is too large, **intersect partial joins**
  - applicable when all dimension FKs are indexed
  - in fact, it is a **semi-join** (no record duplication can take place)



Summary of Joins

- Prefer a cross-join on dimensions
  - If not all dimension FKs are indexed
- Intersect semi-joins otherwise

- Avoid standard DBMS’s plans
  - But check the plan first ☺

Materialized Views

- Views whose tuples are stored in the database are said to be materialized
- They provide fast access, like a (very high-level) cache
- Need to maintain the view’s contents as the underlying tables change
    - Ideally, we want incremental view maintenance algorithms

Materialized Views

- How can we use MV in DW?
  - E.g., we have queries requiring us to join the Sales table with another dimension table and aggregate the result
    - SELECT P.Categ, SUM(S.Qty) FROM Product P, Sales S WHERE P.ProdID=S.ProdID GROUP BY P.Categ
    - SELECT G.Store, SUM(S.Qty) FROM Geo G, Sales S WHERE G.GeoID=S.GeoID GROUP BY G.Store
    - …
  - There are more solutions to speed up such queries
    - Pre-compute the two joins involved (product with sales and geo with sales)
    - Pre-compute each query in its entirety
    - Or use a common and already materialized view

Materialized Views

- Having the following view materialized
  - CREATE MATERIALIZED VIEW Totalsales(ProdID, GeoID, total) AS **SELECT S.ProdID, S.GeoID, SUM(S.Qty) FROM Sales S GROUP BY S.ProdID, S.GeoID**
- We can use it in our queries
  - SELECT P.Categ, SUM(T.Total) FROM Product P, Totalsales T WHERE P.ProdID=T.ProdID GROUP BY P.Categ
  - SELECT G.Store, SUM(T.Total) FROM Geo G, Totalsales T WHERE G.GeoID=T.GeoID GROUP BY G.Store

Materialized Views - Issues

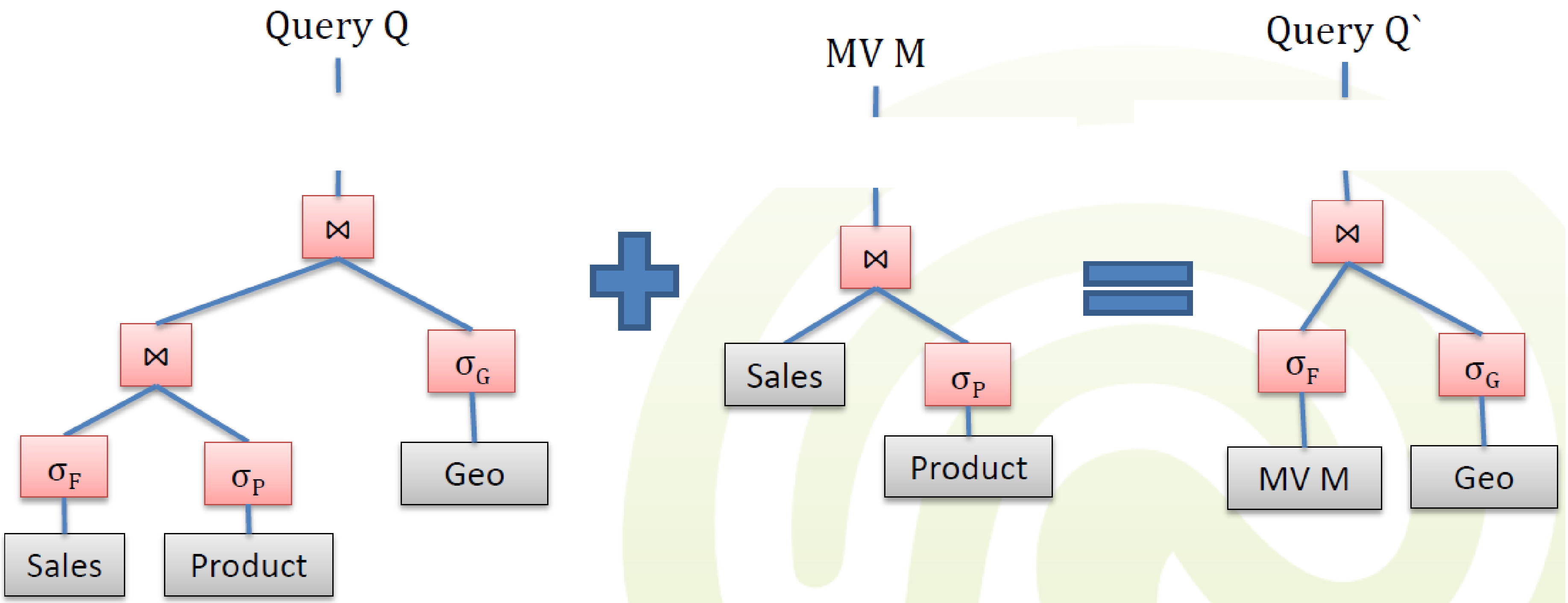
- Choice of materialized views
  - What views should we materialize, and what indexes should we build on the pre-computed results?
- Utilization
  - Given a query and a set of materialized views, can we use the materialized views to answer the query?
- Maintenance
  - How frequently should we refresh materialized views to make them consistent with the underlying tables?
  - And how can we do this incrementally?

Materialized Views: Utilization

- Utilization must be transparent
  - Queries are internally rewritten to use the available MVs by the query rewriter
  - The query rewriter performs integration of the MV based on the query execution graph

Materialized Views: Utilization

- E.g., mono-block query (perfect match)

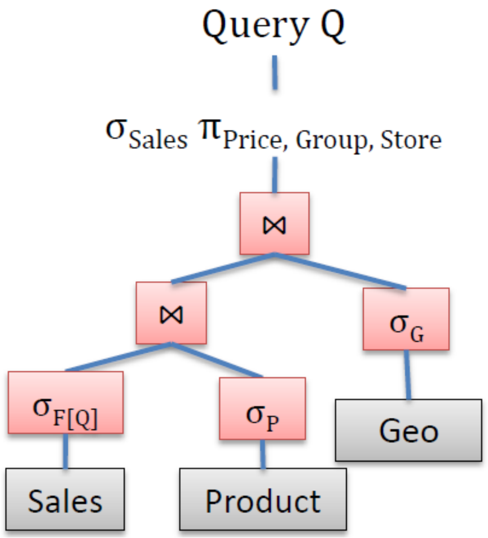


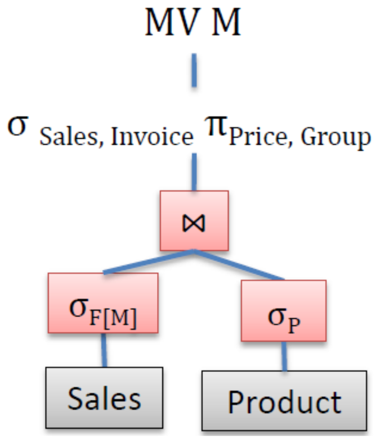
Materialized Views: Utilization

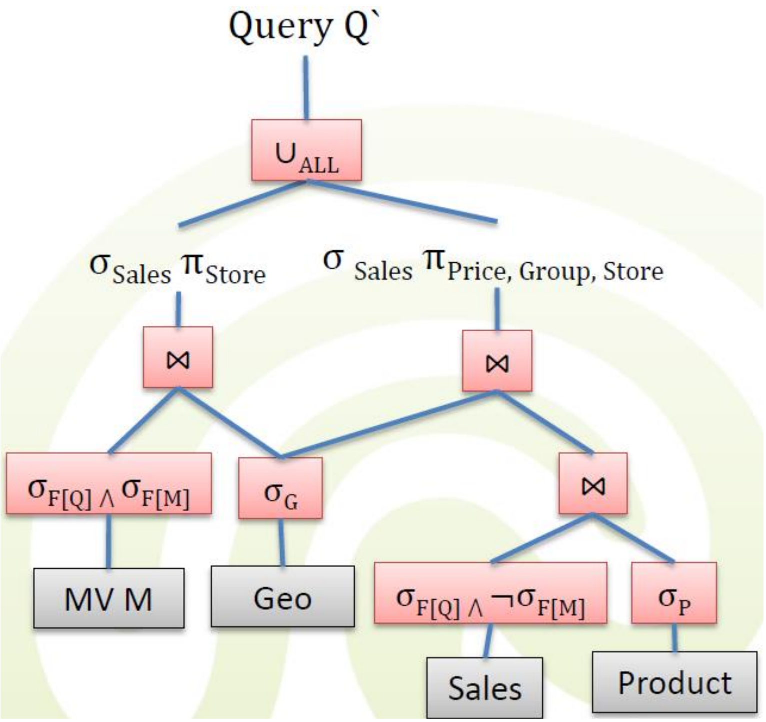
- Correctness:
  - A query Q` represents a valid replacement of query Q by utilizing the materialized view M, if Q and Q` always deliver the same result.
- Implementation requires the following:
  - The selection condition in M cannot be more restrictive than the one in Q.
  - The projection from Q must be a subset of the projection from M.
  - It must be possible to derive the aggregation functions in Q from ones in M.
  - Additional selection conditions in Q must also be possible on M.

Materialized Views: Integration

- A way to integrate a more restrictive view:
  - Split the query Q in two parts, Q_a and Q_b, such that
    - $\sigma(Q_a) = (\sigma(Q) \land \sigma(M))$ and
    - $\sigma(Q_b) = (\sigma(Q) \land \neg\sigma(M))$





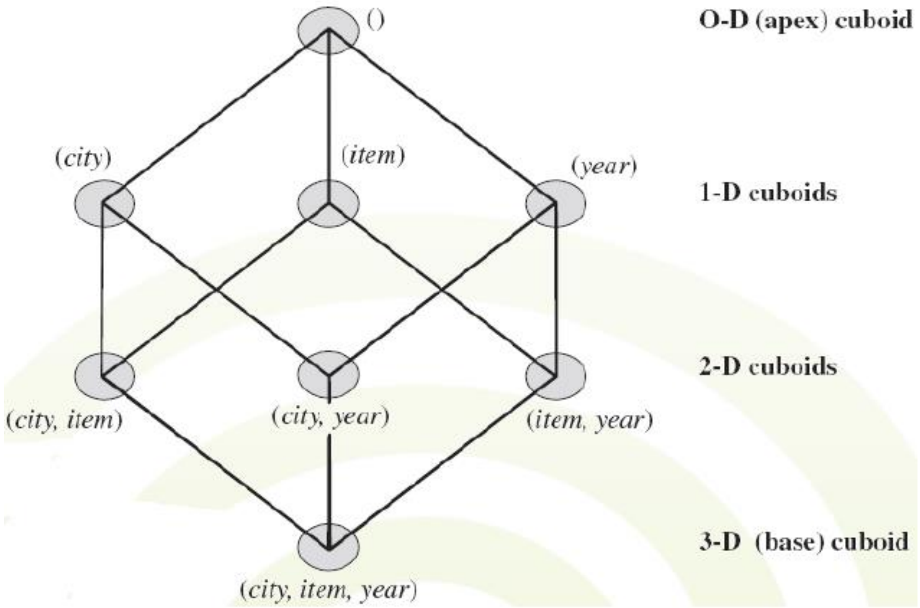


$\sigma_{F[Q]}$ - all sales

$\sigma_{F[M]}$ - More restrictive:
all sales above a threshold

Materialized Views & DWs

- Often store aggregated results
- For a set of "n" group-by attributes, there are 2^n possible combinations
  - Too many to materialize all
  - What to materialize?



Materialized Views & DWs

- Choosing the views to materialize
  - Static choice:
    - The choice is performed at a certain time point
      - by the DB administrator (not very often) or by an algorithm
    - The set of MVs remains unmodified until the next refresh
    - The chosen MVs correspond to older queries
  - Dynamic choice:
    - The MV set adapts itself according to new queries

Views to Materialize

- Static choice
  - Choose which views to materialize, in concordance with the “benefit” they bring
    - The benefit is computed based on a cost function
  - The *cost function* involves
    - Query costs
    - Statistical approximations of the frequency of the query
    - Actualization/maintenance costs
  - Classical knapsack problem – a limit on MV storage and the cost of each MV
  - Greedy algorithm
    - Input: the lattice of cuboids, the expected cardinality of each node, and the maximum storage size available to save MVs
    - It calculates the nodes from the lattice which bring the highest benefit according to the cost function, until there is no more space to store MVs
    - Output: the list of lattice nodes to be materialized

Views to Materialize

- Disadvantages of static choice
  - OLAP applications are interactive
    - Usually, the user runs a series of queries to explain a behavior he has observed, which happened for the first time
      - So now the query set comprises hard to predict, ad-hoc queries
  - Even if the query pattern is observed after a while, it is unknown for how much time the pattern will remain valid
    - Queries are always changing
  - Often modification to the data leads to high update effort
- There are, however, also for OLAP applications, some often repeating queries that should in any case be statically materialized.

Views to Materialize

- Dynamic choice
  - Monitor the queries being executed over time
  - Maintain a materialized view processing plan (MVPP) by incorporating most frequently executed queries
  - Modify MVPP incrementally by executing MVPP generation algorithm
    - as a background process
  - Decide on the views to be materialized
  - Reorganize the existing views

  - It works on the same principle as caching, but with semantic knowledge

Views to Materialize

- Dynamic choice
  - Updates of cached MV:
    - In each step, the cost of MV in the cache as well as of the query is calculated
    - All MVs as well as the query result are sorted according to their costs
    - The cache is then filled with MV in the order of their costs, from high to low
    - This way it can happen that one or more old MVs are replaced with the current query
  - Factors consider in the *cost function*:
    - Time of the last access
    - Frequency of query
    - Size of the materialized view
    - The costs a new calculation or actualization would produce for a MV
    - Number of queries which were answered with the MV
    - Number of queries which could be answered with this MV

Maintenance of Materialized Views

- Keeping a materialized view up-to-date with the underlying data
  - How do we refresh a view when an underlying table is refreshed?
  - When should we refresh a view in response to a change in the underlying table?
- Approaches:
  - Re-computation – re-calculated from the scratch
  - Incremental – updated by new data, not easy to implement

  - Immediate – as part of the transaction that modifies the underlying data tables
    - Advantage: materialized view is always consistent
    - Disadvantage: updates are slowed down
  - Deferred – some time later, in a separate transaction
    - Advantage: can scale to maintain many views without slowing updates
    - Disadvantage: view briefly becomes inconsistent

Maintenance of Materialized Views

- Incremental maintenance
  - Changes to database relations are used to compute changes to the materialized view, which is then updated
  - Considering that we have a materialized view V, and that the basis relations suffer modifications through inserts, updates or deletes, we can calculate V` as follows
    - $V' = (V - \Delta^-) \cup \Delta^+$, where Δ^- and Δ^+ represent deleted and inserted tuples, respectively

Maintenance of Materialized Views

- Deferred update options:
  - Lazy
    - delay refresh until next query on view, then refresh before answering the query
  - Periodic (Snapshot)
    - refresh periodically – queries are possibly answered using outdated version of view tuples
    - widely used in DWs
  - Event-based
    - e.g., refresh after a fixed number of updates to underlying data tables

Summary

- The term **selectivity** and its interpretation.
- Bitmap indexes are universal, space-efficient
- UB-trees, R*-trees, X-trees for multidimensional data
- Partitioning
  - Records used together should be stored together
  - Mini-dimension
- Joins
  - Computing cross join on dimension table is an option
- Materialized views can replace parts of a query
  - Select what to materialize (not everything) statically or dynamically