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Data Warehousing & Mining Techniques

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Summary

Summary

- Last Week: Optimization -
  Indexes for multidimensional data
  – R-Trees
  – UB-Trees
  – Bitmap Indexes

- We continue this lecture with optimization…

5. Optimization

5. Optimization

- 5.1 Partitioning
- 5.2 Joins
- 5.3 Materialized Views

5.1 Partitioning

- Breaking the data into **several physical units** that can be handled separately
- Granularity and partitioning are key to **efficient implementation** of a warehouse
- The question is not **whether** to use partitioning, but **how** to do it

5.1 Partitioning

- Why partitioning?
  - **Flexibility** in managing data
  - Smaller physical units allow
    - Inexpensive indexing
    - Sequential scans, if needed
    - Easy reorganization
    - Easy recovery
    - Easy monitoring

5.1 Partitioning

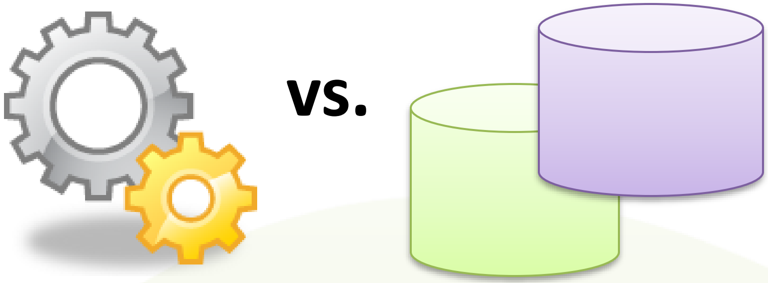
- In DWs, partitioning is done to improve:
  - **Business query performance**, i.e., minimize the amount of data to scan
  - **Data availability**, e.g., back-up/restores can run at the partition level
  - **Database administration**, e.g., adding new columns to a table, archiving data, recreating indexes, loading tables

5.1 Partitioning

- Possible approaches:
  - **Data partitioning** where data is usually partitioned by
    - Date
    - Line of business
    - Geography
    - Organizational unit
    - Combinations of these factors
  - **Hardware partitioning**
    - Makes data available to different processing nodes
    - Sub-processes may run on specialized nodes

5.1 Data Partitioning

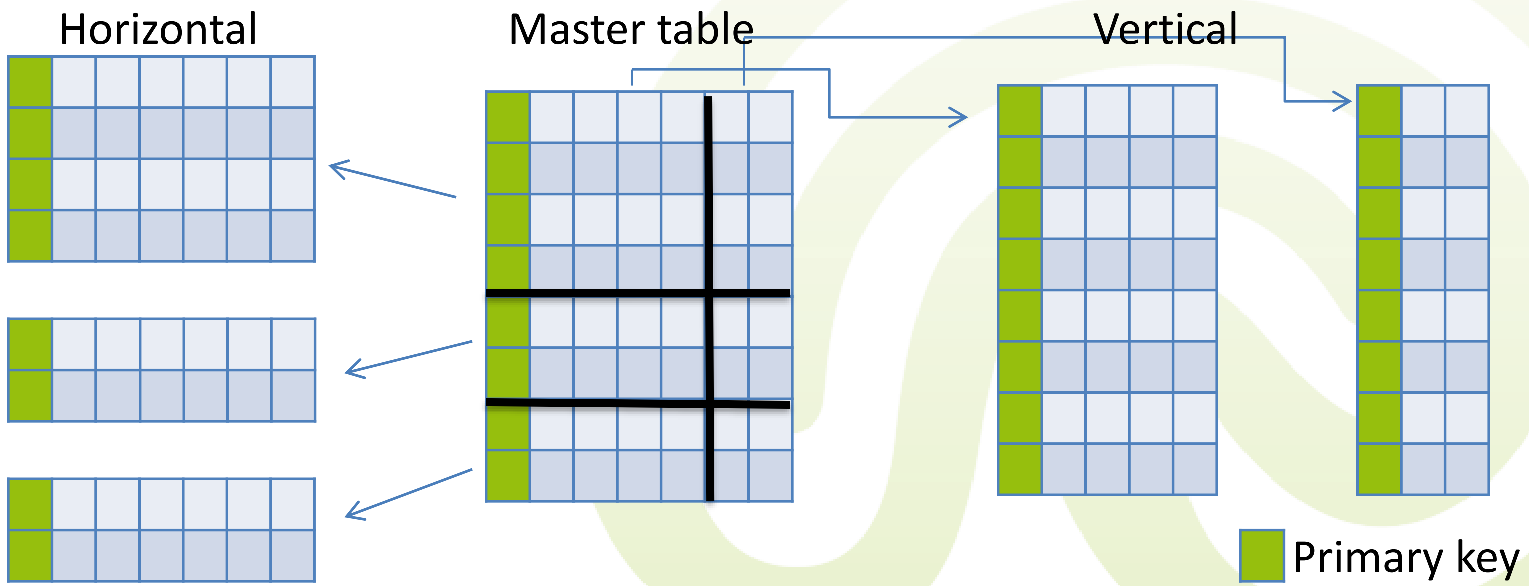
- Data partitioning **levels**
  - Application level
  - DBMS level



- Partitioning on DBMS level is obvious, but it also makes sense to partition at **application level**
  - E.g., allows different definitions for each year
    - Important, since DWs span many years and as business evolves DWs change, too
    - Think for instance about changing tax laws

5.1 Data Partitioning

- Data partitioning, involves:
  - Splitting out the rows of a table into multiple tables i.e., **horizontal partitioning**
  - Splitting out the columns of a table into multiple tables i.e., **vertical partitioning**



5.1 Data Partitioning

- **Horizontal partitioning**
  - The set of tuples of a table is split among **disjoint** table parts
  - Definition: A set of Relations $\{R_1,\ldots, R_n\}$ represent a **horizontal partitioning** of Master-Relation R, if and only if $R_i \subseteq R$, $R_i \cap R_j = \emptyset$ and $R = \cup_i R_i$, for $1 \leq i, j \leq n$
  - According to the partitioning procedure we have different horizontal partitioning solutions
    - Range partitioning, list partitioning and hash partitioning

5.1 Horizontal Partitioning

- **Range Partitioning**
  - Selects a partition by determining if the partitioning key is inside a certain **range**
  - A partition can be represented as a restriction on the master-relation
    - $R_i = \sigma_{P_i}(R)$, where P_i is the partitioning predicate. The partitioning predicate can involve more attributes
      - P_1: Country = 'Germany' and Year = 2016
      - P_2: Country = 'Germany' and Year < 2016
      - P_3: Country $\neq$ 'Germany'

5.1 Horizontal Partitioning

- **List Partitioning**
  - A partition is assigned for a **list of values**
    - If a row's partitioning key shows one of these values, it is assigned to this partition
      - For example: all rows where the column Country is either Iceland, Norway, Sweden, Finland or Denmark could be a partition for the Scandinavian countries
  - Can be expressed as a simple **restriction** on the master relation
    - The partitioning predicate involves just one attribute
      - P_1: City IN ('Hamburg', 'Hannover', 'Berlin')
      - P_2: City IN (DEFAULT) – represents tuples which do not fit P_1

5.1 Horizontal Partitioning

- **Hash Partitioning**
  - The value of a **hash function** determines membership in a partition
    - This kind of partitioning is often used in parallel processing
    - The choosing of the hash function is decisive: the goal is to achieve an equal distribution of the data
  - For each tuple t, of the master-table R, the hash function will associate it to a partition table R_i
    - $R_i = \{t_1, \ldots, t_m / t_j \in R \text{ and } H(t_j) = H(t_k) \text{ for } 1 \leq j, k \leq m\}$

5.1 Horizontal Partitioning

- In DW, data is partitioned by the
  - **Time dimension**
    - Periods, such as week or month can be used or the data can be partitioned by the age of the data
    - E.g., if the analysis is usually done on last month's data the table could be partitioned into monthly segments
  - **Some dimension** other than time
    - If queries usually run on a grouping of data: e.g. each branch tends to query on its own data and the dimension structure is not likely to change then partition the table on this dimension
  - **Table size**
    - If a dimension cannot be used, partition the table by a **predefined size**. If this method is used, metadata must be created to identify what is contained in each partition

5.1 Vertical Partitioning

- **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
  - Different physical storage might be used e.g., storing infrequently used or very wide columns on a different device

5.1 Vertical Partitioning

- In DW, common vertical partitioning means
  - Moving **seldom used** columns from a highly-used table to another table
  - Creating a **view** across the two newly created tables restores the original table with a performance penalty
    - However, performance will increase when accessing the highly-used data e.g. for **statistical analysis**

5.1 Vertical Partitioning

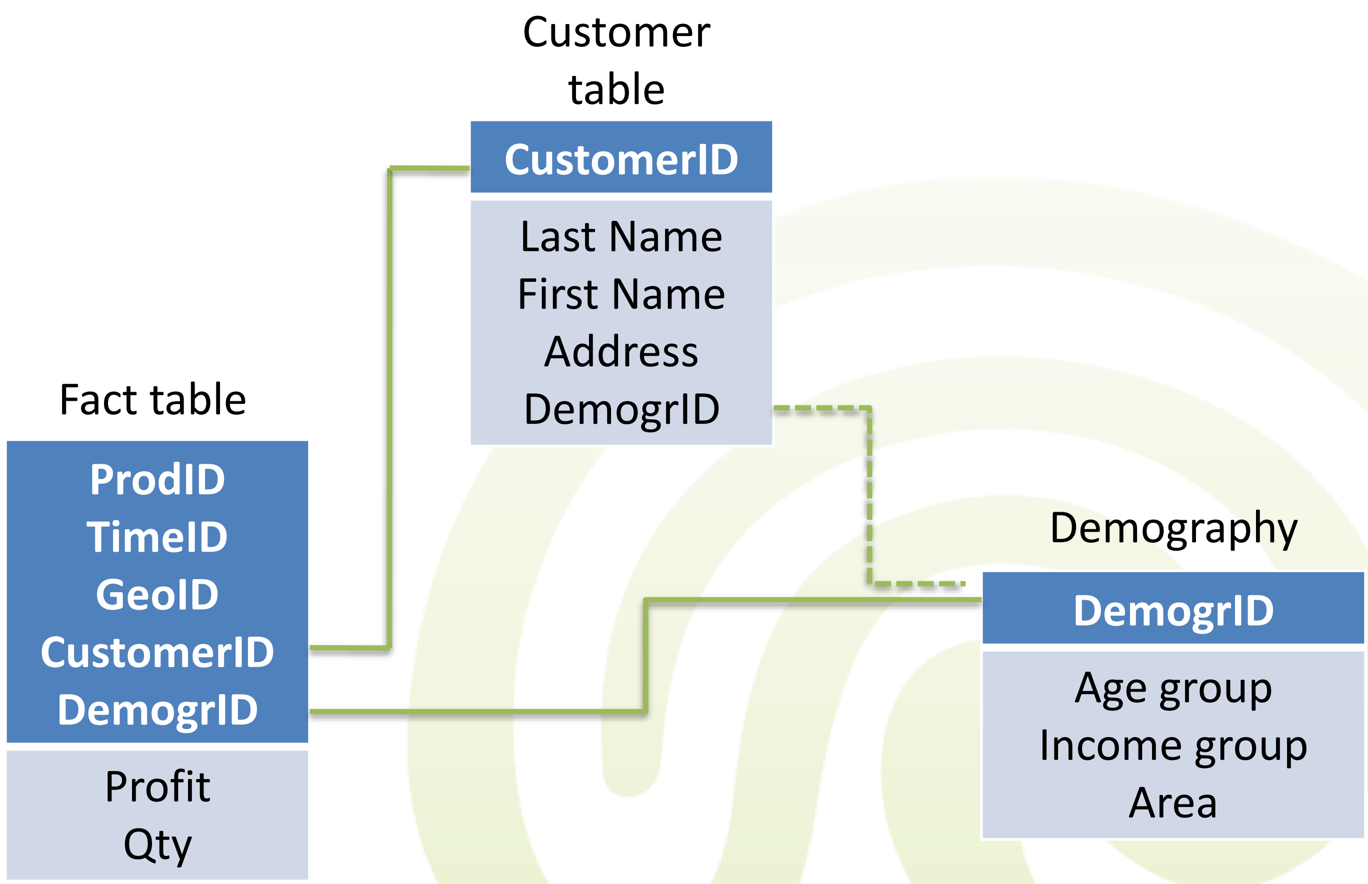
- In DWs with **very large** dimension tables like the customer table of Amazon (tens of millions of records)
  – Most of the attributes are rarely –if at all– queried
    - E.g. the address attribute is not as interesting for marketing as evaluating customers per age-group
  – But one must still maintain the link between the fact table and the **complete** customer dimension, which has **high performance costs!**

5.1 Vertical Partitioning

- The solution is to use **Mini-Dimensions,** a special case of vertical partitioning
  - 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

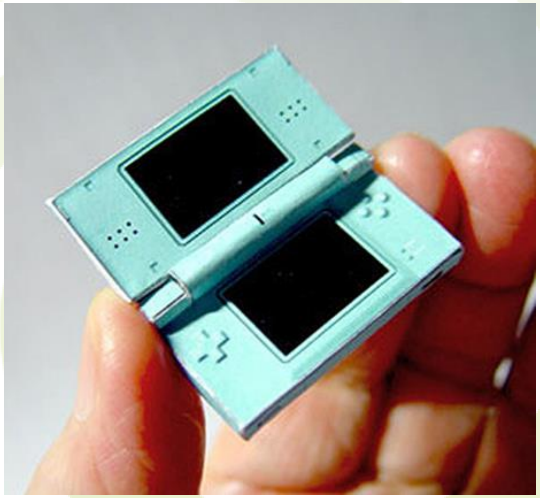
5.1 Vertical Partitioning

- Mini-Dimensions, e.g., the **Demography** table



5.1 Vertical Partitioning

- All variables in these mini-dimensions must be presented as **distinct classes**
- The key to the mini-dimension can be placed as a **foreign key** in **both** the fact and dimension table from which it has been broken off
- Mini-dimensions, as their name suggests, should be kept small and compact



5.1 Partitioning

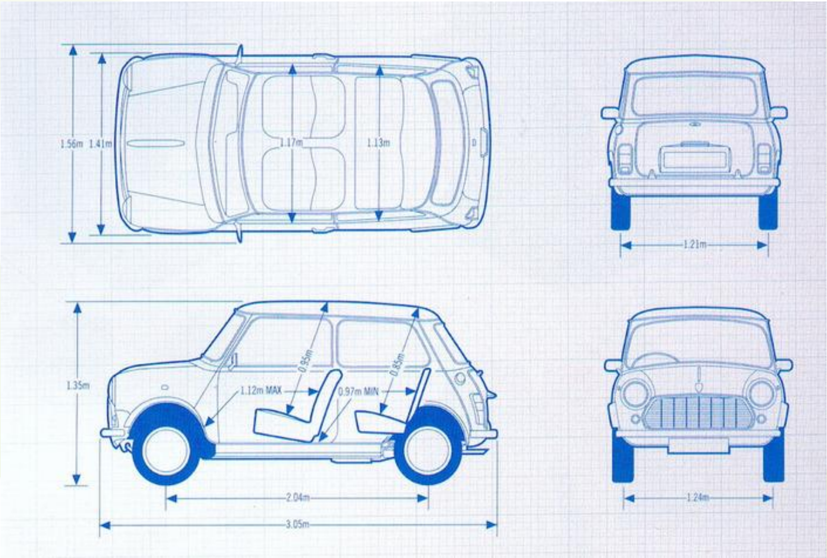
- **Advantages**
  - Records used together are grouped together
  - Each partition can be optimized for performance
  - Security, recovery
  - Partitions stored on different disks: contention
  - Take advantage of parallel processing capability
- **Disadvantages**
  - Slow retrieval across partitions (expensive joins)
  - Complexity

5.1 Partitioning

Detour

- Use partitioning when:
  - A table is larger than **2GB** (from Oracle)
  - A table has more than **100 Million rows** (practice)
  - Think about it, if the table has **1 million rows**

- **Partitioning does not come for free!**



5.1 Partitioning

Detour

- Partitioning **management**
  - Partitioning should be transparent outside the DBMS
    - The applications work with the Master-Table at logical level
    - The conversion to the physical partition tables is performed internally by the DBMS
    - It considers also data consistency as if the data were stored in just one table
  - Partitioning transparency is not yet a standard. Not all DBMS support it!

5.1 Partitioning Management

- Partitions in practice
  - Oracle supports Range-, List-, Hash-, Interval-, System-Partitions as well as combinations of these methods
  - E.g., partitioning in Oracle:
    - CREATE TABLE SALES(
      ProdID NUMBER,
      GeoID NUMBER,
      TimeID DATE,
      Profit NUMBER)
      PARTITION BY RANGE(timeID)(
      PARTITION before 2015
      VALUES LESS THAN (TO_DATE ('01-JAN-2015', 'DD-MM-YYYY')),
      PARTITION 2015
      VALUES LESS THAN (TO_DATE ('01-JAN-2016', 'DD-MM-YYYY'))
      );

- In Oracle partitioning is performed with the help of only one function - LESS THAN
  - Partition data in the current year
    - ALTER TABLE Sales
      ADD PARTITION after 2016 VALUES LESS THAN (MAXVALUE);

5.1 Partitioning Management

Detour

- Partitioning:

RowID	ProdID	GeoID	TimeID	Profit
…	…	…	…	…
121	132	2	05.2014	8K
122	12	2	08.2015	7K
123	15	1	09.2014	5K
124	14	3	01.2016	3K
125	143	2	03.2016	1,5K
126	99	3	05.2014	1K
	…	…	…	…

RowID	ProdID	GeoID	TimeID	Profit
…	…	…	…	…
121	132	2	05.2014	8K
123	15	1	09.2014	5K
126	99	3	05.2014	1K

RowID	ProdID	GeoID	TimeID	Profit
122	12	2	08.2015	7K

RowID	ProdID	GeoID	TimeID	Profit
124	14	3	01.2016	3K
125	143	2	03.2016	1,5K

- In the data cleaning phase, records can be updated. For partition split tables, this means **data migration:**
  - UPDATE Sales SET TimeID = '05.2015' WHERE RowID = 121;
    - ERROR at line 1: ORA-14402: updating partition key column would cause a partition change

RowID	ProdID	GeoID	TimeID	Profit
…	…	…	…	…
121	132	2	05.2014	8K
123	15	1	09.2014	5K
126	99	3	05.2014	1K

RowID	ProdID	GeoID	TimeID	Profit
122	12	2	08.2015	7K

RowID	ProdID	GeoID	TimeID	Profit
124	14	3	01.2016	3K
125	143	2	03.2016	1,5K

5.1 Partitioning Management

Detour

- Data migration between partitions is by default disabled
  - ALTER TABLE Sales ENABLE ROW MOVEMENT;
  - ROW MOVEMENT deletes the record from one partition and inserts it into another
    - The issue is that **RowID is automatically changed!**

RowID	ProdID	GeoID	TimeID	Profit
…	…	…	…	…
~~121~~	~~132~~	~~2~~	~~05.2014~~	~~8K~~
123	15	1	09.2014	5K
126	99	3	05.2014	1K

RowID	ProdID	GeoID	TimeID	Profit
122	12	2	08.2015	7K
13256	132	2	05.2015	8k

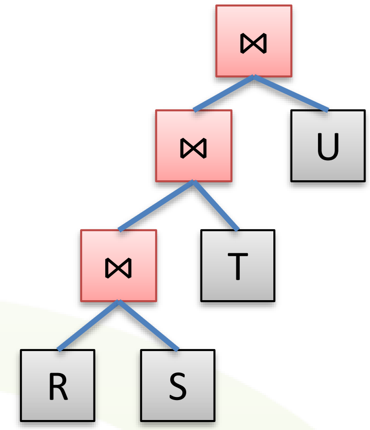
5.2 Join Optimization

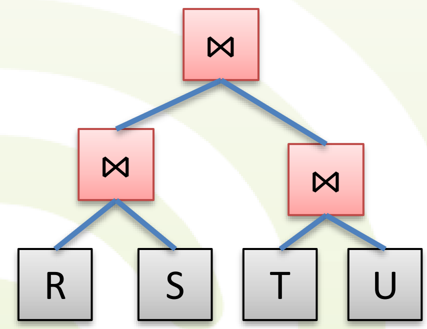
- Often queries over **several** partitions are needed
  - This results in **joins** over the data
  - Though joins are **generally expensive operations**, the overall cost of the query may **strongly differ** with the chosen evaluation plan for the joins

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

5.2 Join Optimization

- This allows to evaluate individual joins in **any order**
  - Results in **join trees**
    - Different join trees may show very different evaluation performance
  - Join trees have different **shapes**
  - Within a shape, there are different relation **assignments** possible
- Example: $R \bowtie S \bowtie T \bowtie U$





5.2 Join Optimization

- Number of **possible join trees** grows rapidly with number of join relations
  - For n relations, there are T(n) different tree shapes
    - $T(1) = 1$
    - $T(n) = \sum_{i=1}^{n-1} T(i)T(n-i)$
    - "Any number of 1 ≤ i ≤ n-1 relations may be in the left subtree and ordered in T(i) shapes while the remaining n-i relations form the right subtree and can be arranged in T(n-i) shapes."

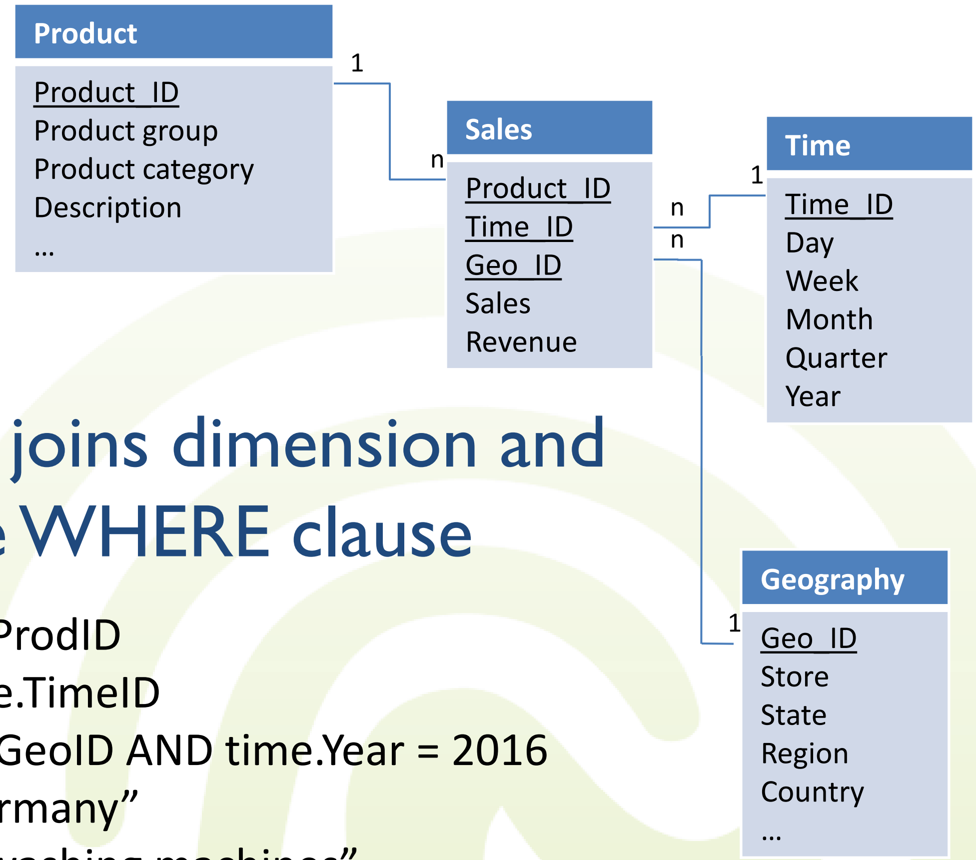
5.2 Join Optimization

- Optimizer has 3 choices
  - Consider all possible join trees
    - Generally prohibitive
  - Consider a subset of all trees
    - Restrict to trees of certain shapes
  - Use heuristics to pick a certain shape

- Classical **join order optimization** is discussed in more detail in the RDB2 lecture

5.2 Join Optimization in DW

- Relational optimization of **star-joins**
  - Star schema comprises a **big** fact table and many **small** dimension tables

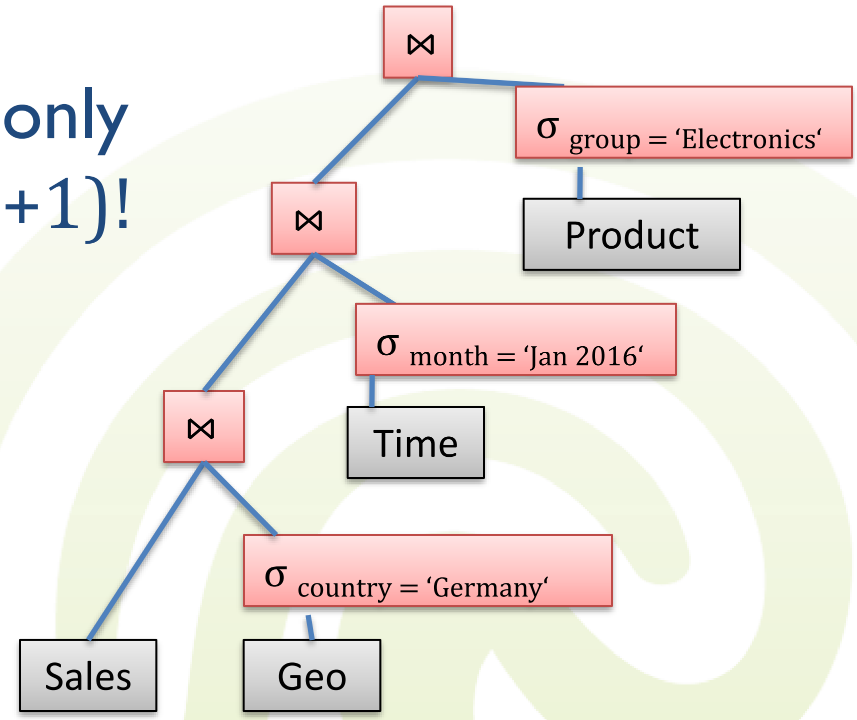


  - An **OLAP SQL** query joins dimension and fact tables usually in the WHERE clause

sales.ProdID = product.ProdID
AND sales.TimeID = time.TimeID
AND sales.GeoID = geo.GeoID AND time.Year = 2016
AND geo.Country = “Germany”
AND product.group = “washing machines”

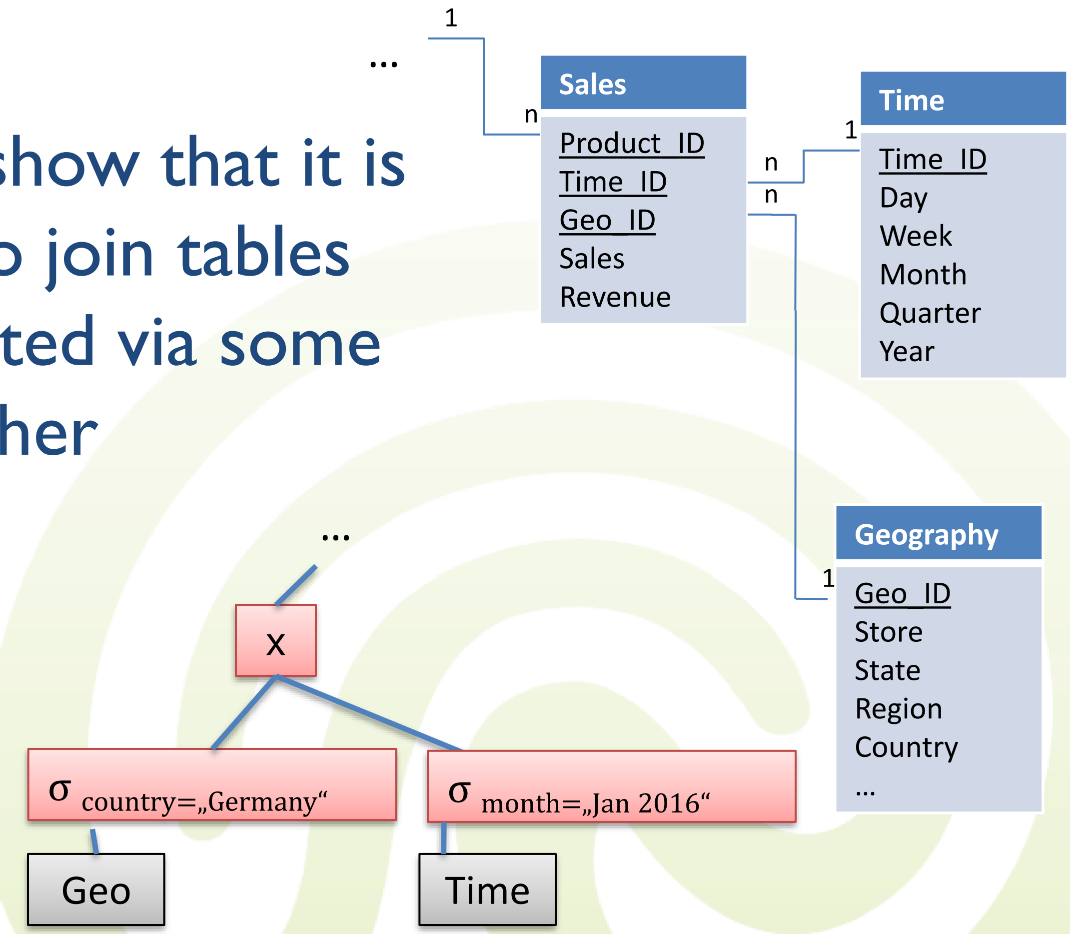
5.2 Join Optimization in DW

- If the OLAP query specifies **restrictions** or **group by's** on n dimensions, an $n+1$ order join is necessary
  - Joins can be performed only pair-wise, resulting in $(n+1)!$ possible join orders



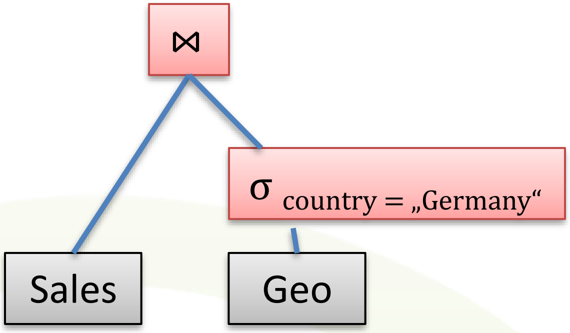
5.2 Join Heuristics

- To reduce the number of join-orders, **heuristics** are used
  - In OLTP heuristics show that it is **not a good idea** to join tables that are not connected via some attribute to each other
    - E.g., Geo with Time relation leads to a Cartesian product



5.2 Join Heuristics

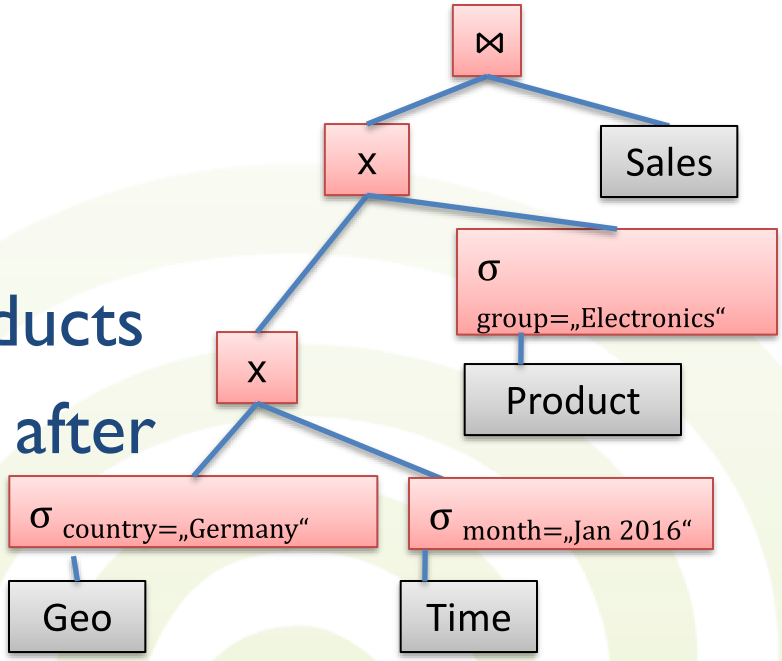
- But this heuristic rule from OLTP is **not suitable** for DW!
  - E.g., join Sales with Geo in the following case:
    - Sales has 10 mil records, in Germany there are 10 stores, in January 2016 there were products sold in 20 days, and the Electronics group has 50 products



  - If 20% of our sales were performed in Germany, the selectivity is small and an index would not help that much
    - The intermediate result would still comprise 2 mil records

5.2 Dimensional Cross Product

- In star-joins a **cross product** of the dimension tables is recommended
  - Geo dimension – 10 stores
  - Time dimension – 20 days
  - Product dimension – 50 products
  - 10*20*50 = 10 000 records after performing the cross product of the dimensions
  - The total selectivity is in this case 0.1% which is fit for using an index



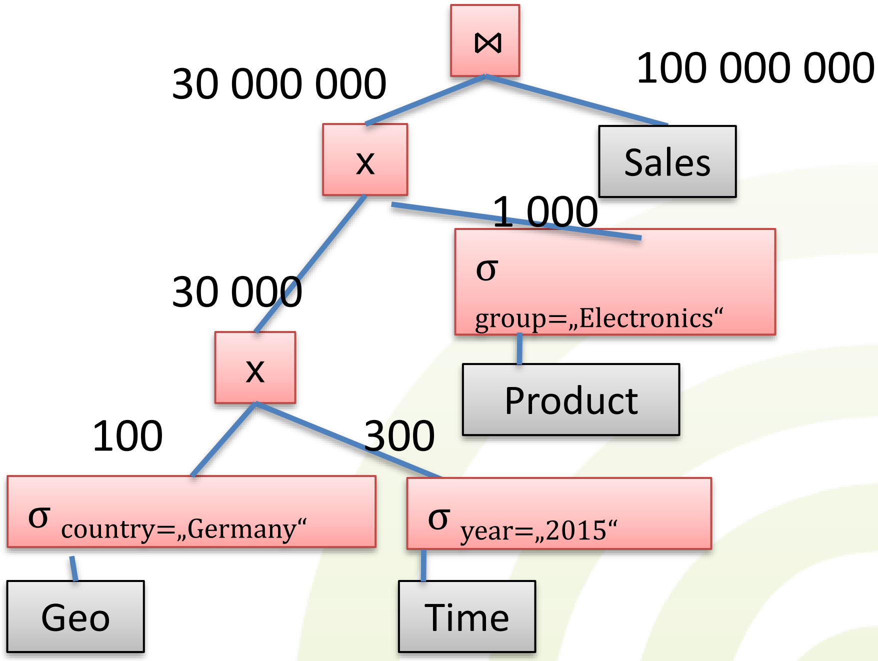
5.2 Dimensional Cross Product

Detour

- But dimension cross products can also become **expensive**
  - If the restrictions on the dimensions are **not restrictive enough** or if there are many dimension tables
- E.g. query for the sales of all electronic products of a company in 2015:
  - The company has **100 stores** in Germany and it sells **1000** types of electronics **products**
  - In 2015 it sold products in **300 working days**

Detour

- 100 stores * 300 days * 1.000 products = **30 mil records…**

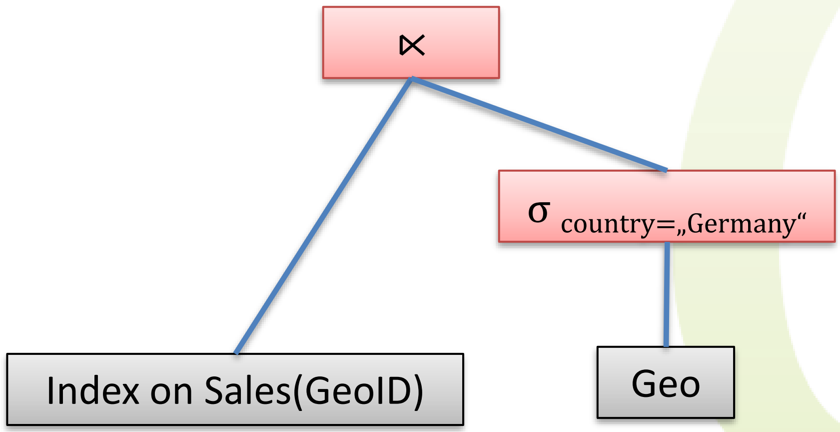


- Very **expensive** to compute

5.2 Star-Join Optimization

Detour

- **IBM DB2** solution for expensive dimension cross products
  - Build B*-Tree **indexes** on the fact table **for each dimension**
  - Apply a semi-join on each index and the corresponding dimension



Keep all index entries for the Sales fact table for sales in Germany

5.2 Star-Join Optimization

Detour

GeoID	ID
1	1
1	2

$\ltimes$

Index on Sales for GeoID

GeoID	ID
1	1
1	2
4	3
…	…

Geo

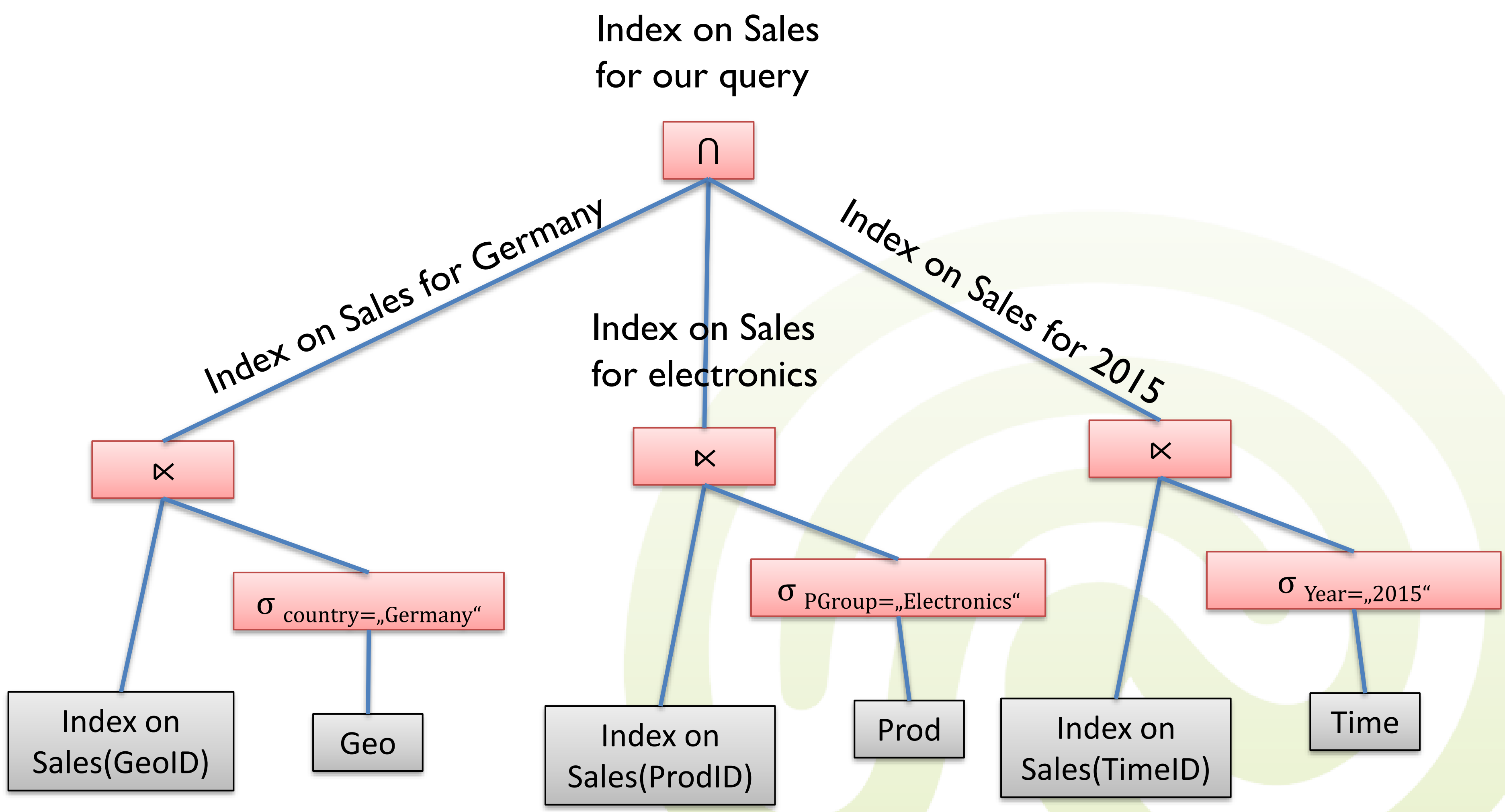
GeoID	Store	City	Country
1	S1	BS	Germany
2	S2	BS	Germany
3	S3	HAN	Germany
4	S4	Lyon	France

$\sigma_{\text{country=„Germany“}}$

GeoID	Store	City	Country
1	S1	BS	Germany
2	S2	BS	Germany
3	S3	HAN	Germany

5.2 Star-Join Optimization

Detour



5.3 Materialized Views

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

5.3 Materialized Views

- How can we use MV in DW?
  - E.g., we have queries requiring us to join the Sales table with another 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 an already **materialized view**

5.3 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 2 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

5.3 Materialized Views

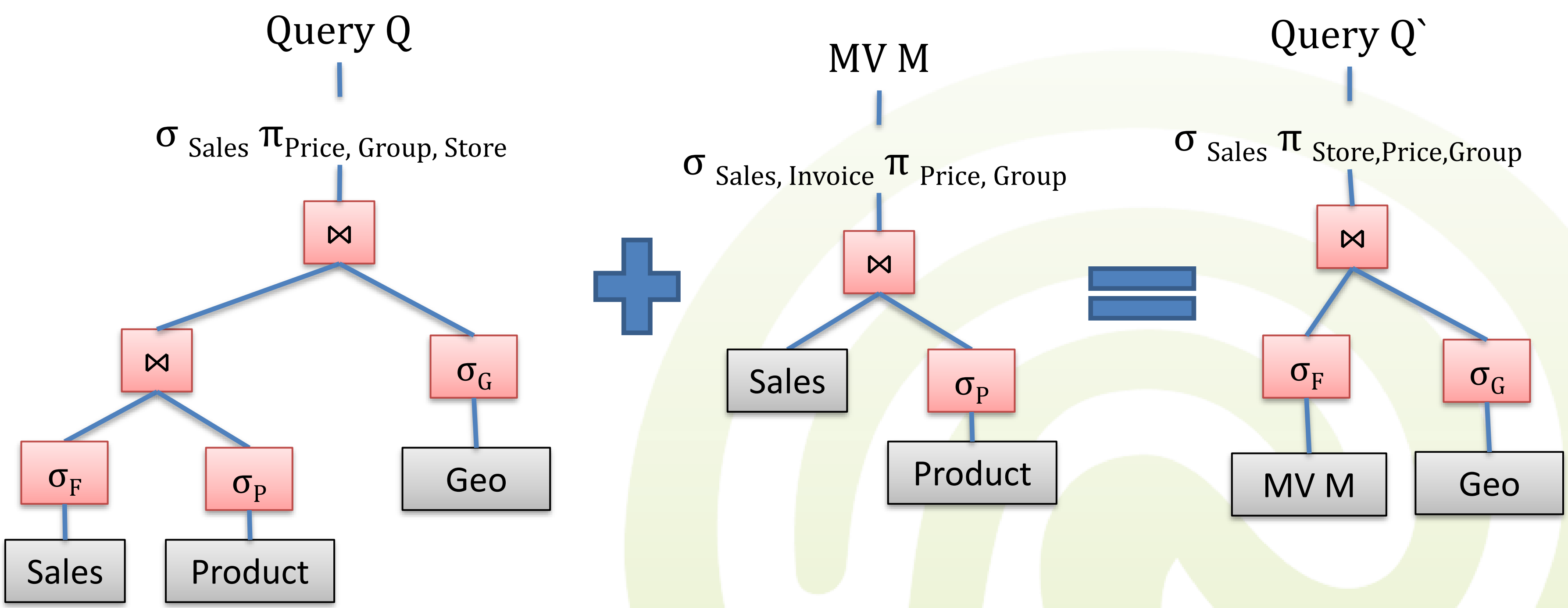
- MV issues
  - **Utilization**
    - What views should we materialize, and what indexes should we build on the pre-computed results?
  - **Choice** of materialized views
    - Given a query and a set of materialized views, can we use the materialized views to answer the query?
  - **Maintenance**
 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

5.3 Utilization of MVs

- Materialized views **utilization** has to 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**

5.3 Utilization of MVs

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



5.3 Integration of MVs

- **Integration** of MV
  - **Valid replacement:** 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 set
  - For general relational queries, the problem of finding a valid replacement is **NP-complete**
    - But there are practically relevant solutions for special cases like star-queries

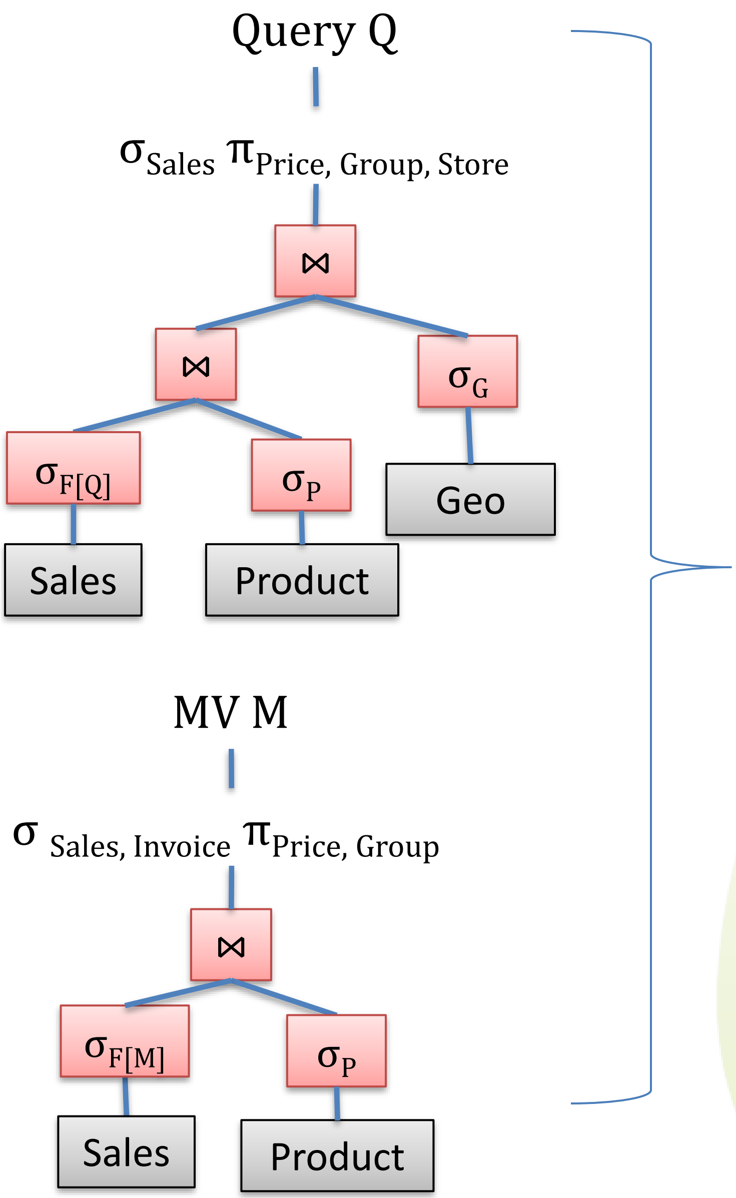
5.3 Integration of MVs

- In order to be able to integrate MV M in Q and obtain Q`, the following **conditions** need to be respected
  - The selection condition in M cannot be more restrictive than the one in Q
  - The projection from Q has to be a subset of the projection from M
  - It has to be possible to derive the aggregation functions of $\pi(Q)$ from $\pi(M)$
  - Additional selection conditions in Q have to be possible also on M

5.3 Integration of MVs

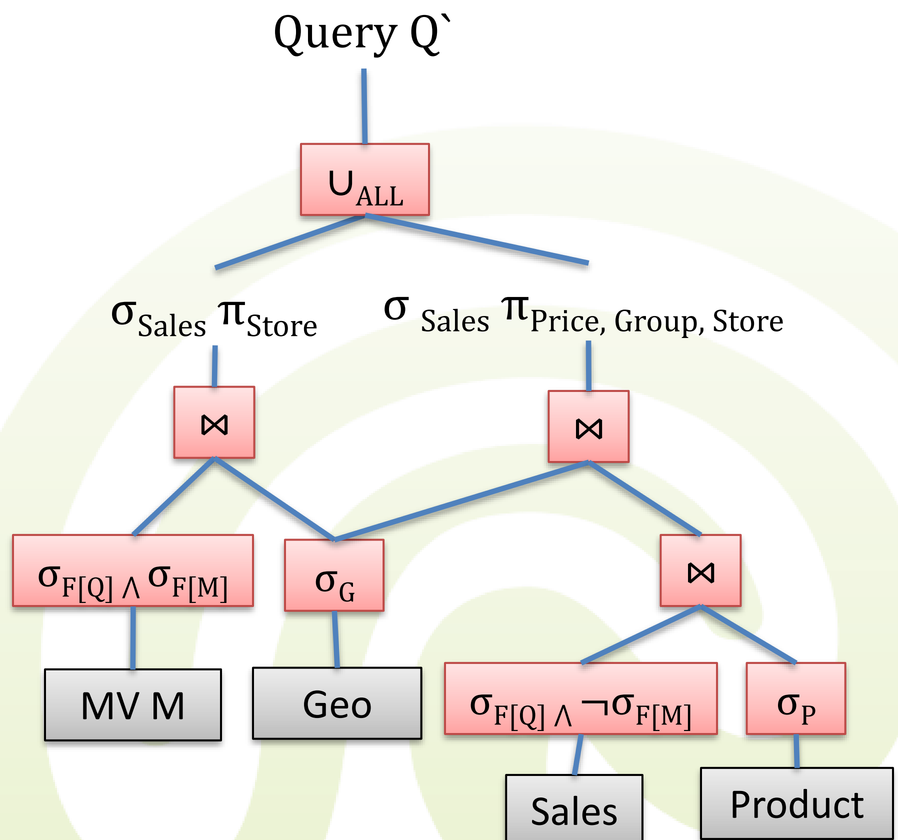
- How do we use MV even when there is no perfect match? (Multi-block queries)
- If the selection in M is more restrictive than the selection in Q
  - Split the query Q in two parts, Q_a and Q_b such that $\sigma(Q_a) = (\sigma(Q) \wedge \sigma(M))$ and $\sigma(Q_b) = (\sigma(Q) \wedge \neg\sigma(M))$

5.3 Integration of MVs



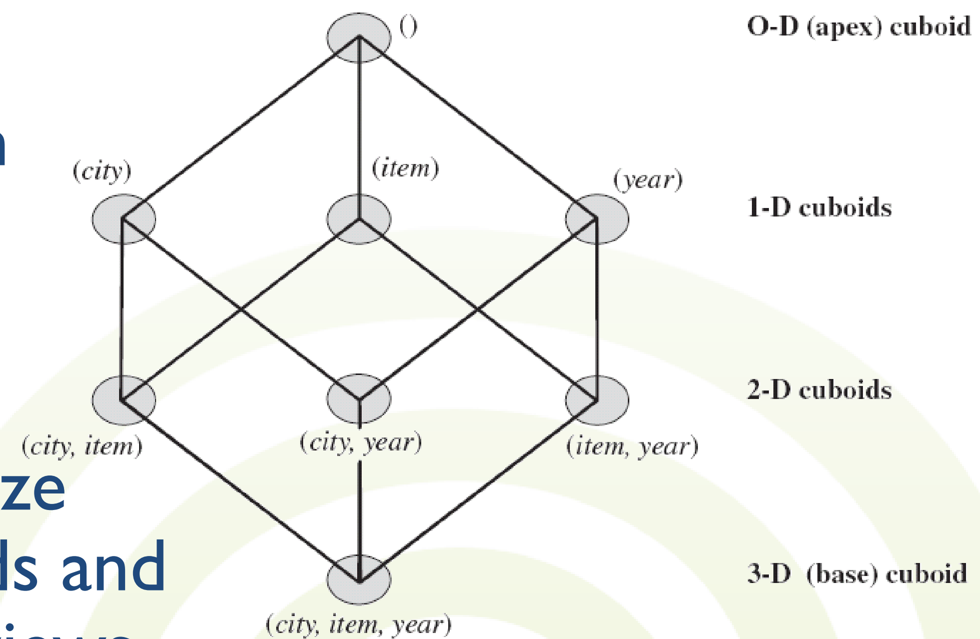
$\sigma_{F[Q]}$ - all sales

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



5.3 MVs in DWs

- In DW, materialized views are often used to store **aggregated results**
  - The number of nodes in the lattice of cuboids is
    - $|n| = \prod_{j=1}^{n} 2 = 2^n$
  - n = 3, |n| = 8 and we would need to materialize 2-D cuboids 1-D cuboids and 0D cuboids; in total 7 views
  - n = 16, |n| = 65534, … too much to materialize
  - **What should we materialize?**



5.3 Choosing the MV to Use

- **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
  - Dynamical choice:
    - The MV set adapts itself according to new queries

5.3 Static Choice

- **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

5.3 Static Choice

- The problem of choosing what to materialize is now a classical **knapsack problem**
  - We have a maximum MV storage size and the cost of each node in the lattice
- The choice algorithm is **greedy**
  - 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

5.3 Choosing the MV to Use

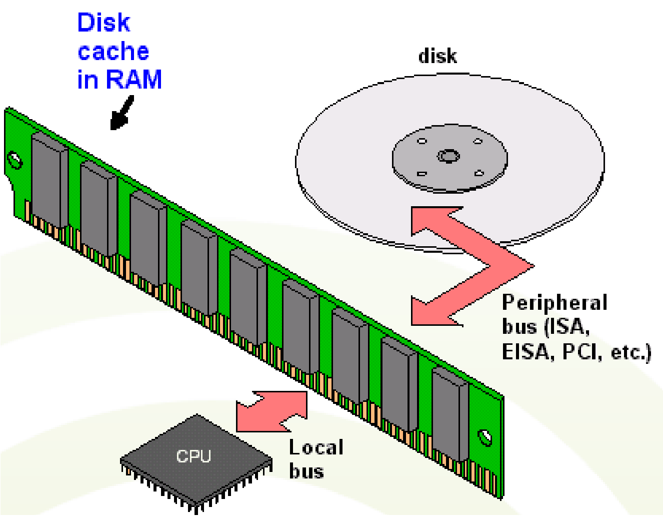
- **Disadvantages** of static choice
  - OLAP applications are interactive
    - Usually, the user runs a series of queries to explain a behavior he has observed, which happened for the first time
      - So now the query set comprises hard to predict, ad-hoc queries
  - Even if the query pattern would be observed after a while, it is unknown for how much time it will remain used
    - 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

5.3 Choosing the MV to Use

- **Dynamic choice** of MV
  - 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 (in background)
  - Decide on the views to be materialized
  - Reorganize the existing views

5.3 Dynamic Choice of MV

- It works on the same principle as **caching,** but with **semantic** knowledge
- Considered factors for calculating the **benefit** are:
  – Time of the last access
  – Frequency
  – 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



5.3 Dynamic Choice of MV

- **Dynamic update** of the cache
  - In each step, the benefit of MV in the cache as well as of the query are calculated
  - All MVs as well as the query result are sorted according to the benefit
  - The cache is then filled with MV in the order of their benefit, from high to low
    - This way it can happen that one or more old MVs are replaced, to insert the result of the current query

5.3 Maintenance of MV

- Maintenance of MV
  - Keeping a materialized view **up-to-date** with the underlying data
  - Important questions
    - **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?

5.3 How to Refresh a MV

- Materialized views can be maintained by re-computation on **every update**
  - Not the best solution
- A better option is **incremental view maintenance**

5.3 How to Refresh a MV

- **Incremental view 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 respectively inserted tuples

5.3 When to Refresh a MV

- **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

5.3 When to Refresh a MV

- **Deferred refresh** comes in 3 flavors
  - **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 for DW**
  - **Event-based:** e.g., refresh after a fixed number of updates to underlying data tables

Summary

- Partitioning: Horizontal or Vertical
  - Records used together are grouped together
  - However: slow retrieval across partitions
  - Mini-Dimensions
- Joins: for DW it is sometimes better to perform cross product on dimensions first
- Materialized Views: we can't materialize everything
  - Static or Dynamic choice of what to materialize
  - The benefit cost function is decisive

Next lecture

- Queries!
  - OLAP queries
  - SQL for DW
  - MDX