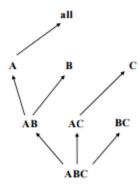
# **Data Cube Computation Methods:**

- Data cube computation is an essential task in data warehouse implementation.
  The precomputation of all or part of a data cube can greatly reduce the response
  time and enhance the performance of online analytical processing. However,
  such computation is challenging because it may require substantial
  computational time and storage space.
- Efficient methods for data cube computation methods are:
  - A. the multiway array aggregation (MultiWay) method for computing full cubes.
  - B. a method known as BUC, which computes iceberg cubes from the apex cuboid downward.
  - C. the Star-Cubing method, which integrates top-down and bottom-up computation.
  - D. High dimension OLAP

# A. Multi-Way Array Aggregation:

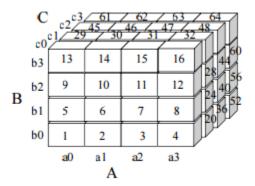
- Array-based "bottom-up" algorithm
- Using multi-dimensional chunks
- No direct tuple comparisons
- Simultaneous aggregation on multiple dimensions
- Intermediate aggregate values are re-used for computing ancestor cuboids
- Full materialization Cannot do Apriori pruning: No iceberg optimization

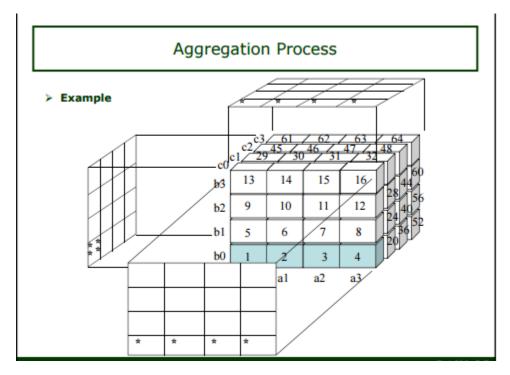


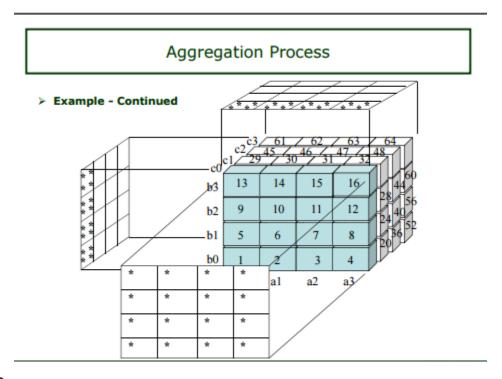
### **Aggregation Strategy**

- 1. Partitions array into chunks
- 2. Chunk: a small sub-cube which fits in memory

- 3. Data addressing
- 4. Uses chunk id and offset
- 5. Multi-way Aggregation
- 6. Computes aggregates in multi-way
- 7. Visits chunks in the order
  - 1. to minimize memory access
  - 2. to minimize memory space

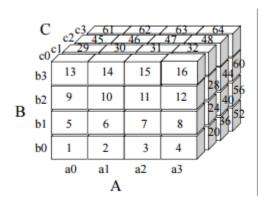






## **Example**

- Suppose the data size on each dimension A, B and C is 40, 400 and 4000, respectively.
- Minimum memory required when traversing the order, 1,2,3,4,5,..., 64
- Total memory required is 100×1000 + 40×1000 + 40×400



# **Summary of Multi-Way**

### Method

Cuboids should be sorted and computed according to the data size on each dimension

 Keeps the smallest plane in the main memory, fetches and computes only one chunk at a time for the largest plane

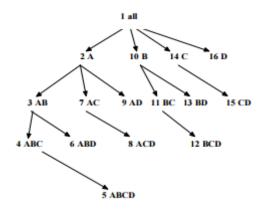
#### Limitations

- Full materialization
- Computes well only for a small number of dimensions ( high dimensional data → partial materialization )

# **B. Bottom-Up Computation (BUC)**

### **Characteristics**

- "Top-down" approach
- Partial materialization (iceberg cube computation)
- Divides dimensions into partitions and facilitates iceberg pruning
- No simultaneous aggregation



### **Iceberg Pruning Process**

### **Partitioning**

- Sorts data values
- Partitions into blocks that fit in memory

## **Apriori Pruning**

 For each block • If it does not satisfy min\_sup, its descendants are pruned • If it satisfies min\_sup, materialization and a recursive call including the next dimension

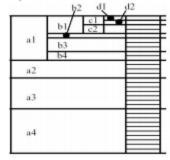
## Apriori Pruning Example

#### Description in SQL

Iceberg cube computation

compute cube iceberg\_cube as select A, B, C, D, count(\*) from R cube by A, B, C, D having count(\*) ≥ min\_sup

#### Example



```
( \bullet, \bullet, \bullet, \bullet ) \longrightarrow 0\text{-D cuboid}

(a1, \bullet, \bullet, \bullet ) \longrightarrow 1\text{-D cuboid}

(a1, b1, \bullet, \bullet ) \longrightarrow 2\text{-D cuboid}

(a1, b1, c1, \bullet ) \longrightarrow 3\text{-D cuboid}

(a1, b1, c1, d1) \longrightarrow \text{pruning}

(a1, b1, c2, \bullet) \longrightarrow 3\text{-D cuboid}

(a1, b2, \bullet, \bullet) \longrightarrow \text{pruning}
```

# **Summary of BUC**

#### Method

Computation of sparse data cubes

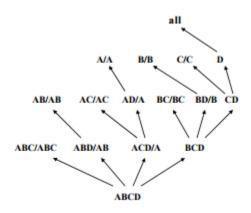
#### Limitations

- Sensitive to the order of dimensions
- → The most discriminating dimension should be used first
- → Dimensions should be in the order of decreasing cardinality
- → Dimensions should be in the order of increasing maximum number

# C. Star-Cubing

### **Characteristics of Star-Cubing**

- Integrated method of "top-down" and "bottom-up" cube computation
- Explores both multidimensional aggregation (as Multi-way) and apriori pruning (as BUC)
- · Explores shared dimensions
- e.g., dimension A is a shared dimension of ACD and AD
- e.g., ABD/AB means ABD has the shared dimension AB



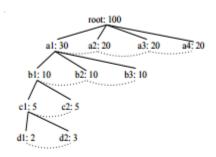
## **Iceberg Pruning Strategy**

- Iceberg Pruning in a Shared Dimension
- If AB is a shared dimension of ABD, then the cuboid AB is computed simultaneously with ABD
- If the aggregate on a shared dimension does not satisfy the iceberg condition (min\_sup), then all the cells extended from this shared

dimension cannot satisfy the condition either - If we can compute the shared dimensions before the actual cuboid, we can apply Apriori pruning

### **Cuboid Trees**

- Tree structure to represent cuboids
- Base cuboid tree, 3-D cuboid trees, 2-D cuboid trees, ...
- Each level represents a dimension
- Each node represents an attribute
- Each node includes the attribute value, aggregate value, descendant(s)
- The path from the root to a leaf represents a tuple
- Example count(a1,b1,,) = 10 count(a1,b1,c1,\*) = 5 → Pruning while aggregating simultaneously on multiple dimensions



### Star Nodes

• If the single dimensional aggregate does not satisfy min\_sup,

no need to consider the node in the iceberg cube computation

- The nodes are replaced by \*
- Example (min\_sup = 2)

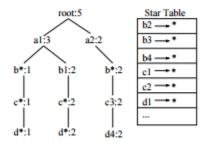
						Α	В	С	D	count
						a1	b1	•	•	1
						a1	b1	٠	٠	1
Α	В	C	D	count	_	a1	•	•	•	1
a1	b1	/c1\	/d1\	1		a2	•	c3	d4	1
a1	b1	c4	d3	1		a2	•	сЗ	d4	1
a1	/b2\	\c2/	\d2/	1	l '					
a2	b3	3	d4	1						
a2	\b4/	c3	d4	1		Α	В	С	D	count
						a1	b1	•	•	2
						a1	•	•	•	1
						a2		сЗ	d4	2

#### **Star Tree**

• A cuboid tree that is compressed using star nodes

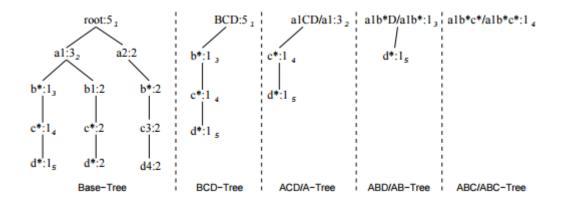
### **Star Tree Construction**

- Uses the compressed table
- Keeps the star table for lookup of star nodes
- · Lossless compression from the original cuboid tree



## Aggregation

- DFS (depth-first-search) from the root of a star tree
- Creates star trees for the cuboids on the next level

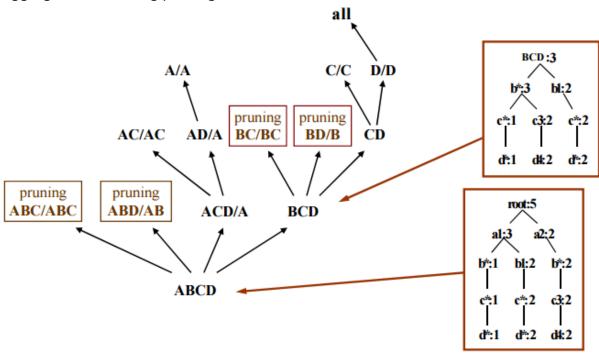


## **Pruning**

- Prunes if the aggregates do not satisfy min\_sup
- Prunes if all the nodes in the generated tree are star nodes

### Method\*

Multi-way aggregation & iceberg pruning



### Limitations

- Sensitive to the order of dimensions
- → The order of decreasing cardinality