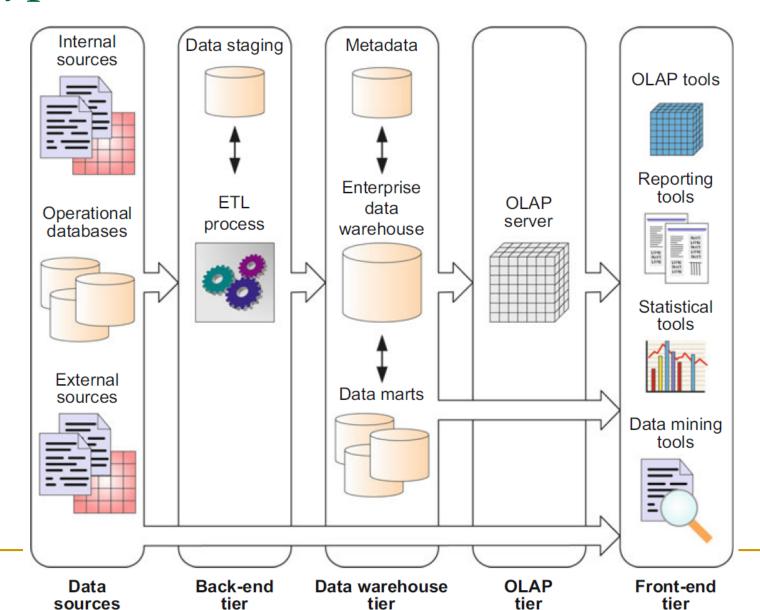
DS-306 Data Warehousing and Business Intelligence

Topic 4: Types of DW Schemas, Data Marts

Dr. Khurram Shahzad

Typical DW architecture



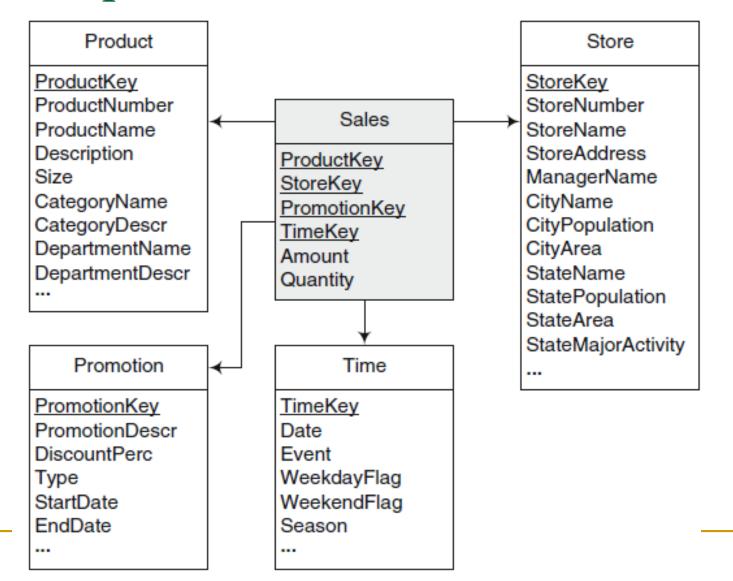
Star Schema

Dimension tables are not normalized

Therefore, they may contain redundant data

Especially, in the presence of hierarchies

Example Star Schema



Start Schema

Example: Product Dimension

All products belonging to the same category

So, all the category information will be

redundant

Product

<u>ProductKey</u>

ProductNumber

ProductName

Description

Size

CategoryName

CategoryDescr

DepartmentName

DepartmentDescr

...

Start Schema

- Example: Store Dimension
 - All stores (unique) belong to a city
 - So, all the category information will be redundant
 - All stores (unique) belongs to the same state
 - So, all the state information will be redundant

Store

StoreKey
StoreNumber
StoreName
StoreAddress
ManagerName
CityName
CityPopulation
CityArea
StateName
StatePopulation
StateArea
StateMajorActivity

••••

Star Schema Keys

- Primary keys (in dimension)
 - Identifying attribute in dimension table
 - Relationship attributes combine together to form P.K.
- Surrogate keys (in dimension)
 - Replacement of primary key
 - System generated
- Foreign keys (in fact, dimension)
 - Collection of primary keys of dimension tables
- Primary key to fact table
 - Collection of P.Ks

Types of Dimensions

- Based on size (columns and data)
 - Large dimensions
 - Small dimensions
- Based on changes to data
 - Slowly Changing Dimensions
 - Rapidly Changing Dimensions

Dimensions Types: Size

- Based on size
 - Large dimensions
 - Small dimensions

Large Dimensions

- A dimension is considered large based on two factors
 - A large dimension is deep i.e., large no of rows
 - A large dimension is wide i.e., large no of columns
- For example, customer, product and time dimension may be gigantic
- Multiple hierarchies
 - Large dimensions tend to have multiple hierarchies

Example Large Dimension

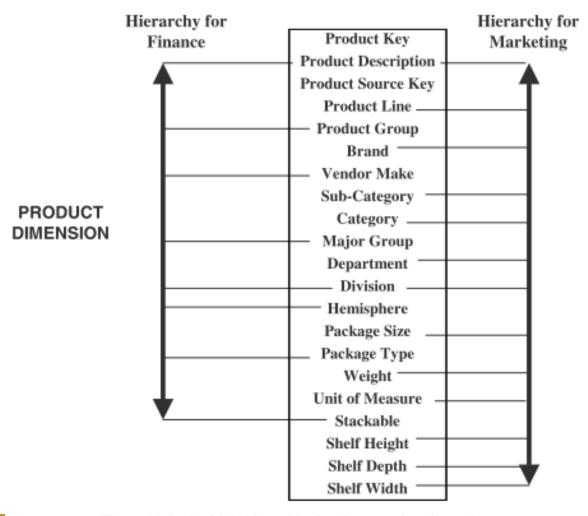


Figure 11-5 Multiple hierarchies in a large product dimension.

Small Dimensions

- Little deep
 - Fewer rows
- Little wide
 - Fewer columns
- Typically, single hierarchy
- Examples
 - Small Customer dimension
 - Small Product dimension
 - Small time dimension

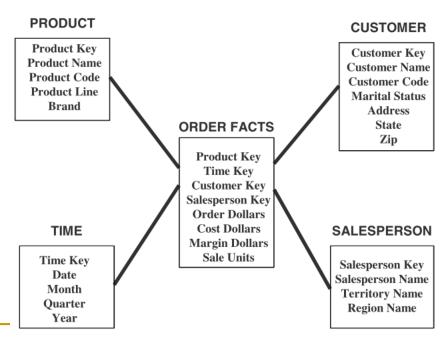
Types of Dim: Data Changes

- Based on changes to data of dimension
 - Slowly Changing Dimensions
 - Rapidly Changing Dimensions

Beforehand, lets discuss what are data changes

Updates to dimensions

- Fact: sales units
- Dimension: Product
 - Change: A new product is added
- Dimension: Customer
 - New customer is added
 - Customer is relocated
 - Marital status is changed



Types of Changes

- Type 1 Changes: Correction of errors
- Type 2 Changes: History preservation
- Type 3 Changes: Tentative revisions

Incremental load

- DW is updated once
- Next time update / incremental update

Type 1: Correction of Error

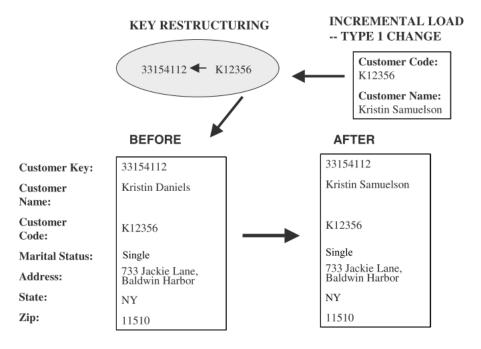
- For example, spelling of customer name is changed from Hammad Ikram to Hammad Akram
 - No need to preserve old value of Hammad "Akram"

Types 1: Correction of Error

- Kristian Daniel to Kristian Denial and the martial status is changed from single to married
 - No need to preserve old value of name
 - But change in martial status is slightly different
- Affect on result
 - Number of perfume products bought by married persons

Types 1: Correction of Errors

- Changes to DW
 - Solution, over-write old values with new values
 - Old value is not preserved
 - Key is not affected
 - Easiest to implement

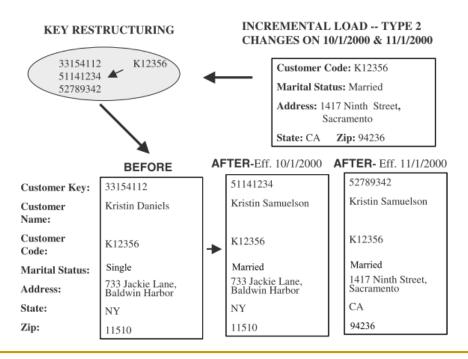


Type 2 changes: Preservation of History

- Assume that in DW an essential requirement is to track orders by marital status
 - If change happed on 1 Jan 2024 all order before that should be included in martial status single.
 - Similarly orders after that under marital status married
 - Assume city is also changed from LHR to ISL so both changes must be saved
- Principles:
 - Relate to true change in source systems
 - There is a need to preserve history in DW

Type 2 changes: Preservation of History

- Applying Type 2 changes in DW
 - There are no change to the original row in dimension table
 - Add a new dimension table row
 - The key of the original row is not affected
 - The new row is inserted with a new surrogate key

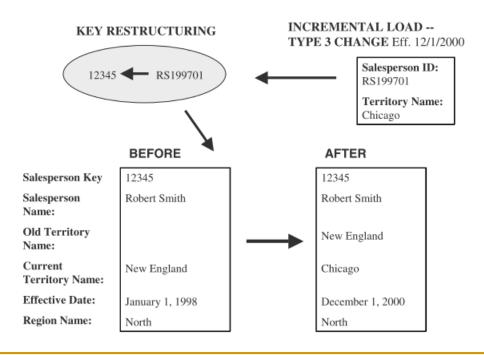


Type 3 changes: Tentative Soft Revisions

- We apply Type 2 change to a certain date (the date is a cut off point)
 - What if you need to count the orders on or after the cut-off date in both groups? This cannot be handled with type 2
 - i.e. sometimes there is a need to track both old and new values for a certain period
 - For instance, realigning territories

Type 3 changes: Tentative Soft Revisions

- Solution
- Add a new field in the dimension table
 - Push down the existing values from current to old
 - Keep the new values of the attribute in the "current" field



Summary of Types of changes

- Change 1. Correction of errors
 - Problem, Name of a person is changed, to correct error
 - Solution, over-write old value
 - Old value is not saved
 - Key is not affected, Easiest to implement
- Change 2. History preservation
 - Problem, Name is changed, marital status & address
 - Solution, Inserting new row for each change
 - Change has certain affect on analysis
 - Key is not affected, new surrogate key
- Change 3. Tentative revisions
 - Problem, Old address of customer is not known
 - Solution, Insert another attribute, with date
 - New row is not needed

Recall Types of Dim: Data Changes

- Based on changes to data of dimension
 - Slowly Changing Dimensions
 - Rapidly Changing Dimensions

Slowly Changing Dimension

- Consideration of the changes to dimension table
 - Many dimension, though not constant over time, change slowly
 - Product key of source record does not change
 - Description and other attributes change slowly over time
 - In OLTP new values overwrite old ones
 - Overwriting not always appropriate option in DW

Rapidly Changing Dimension

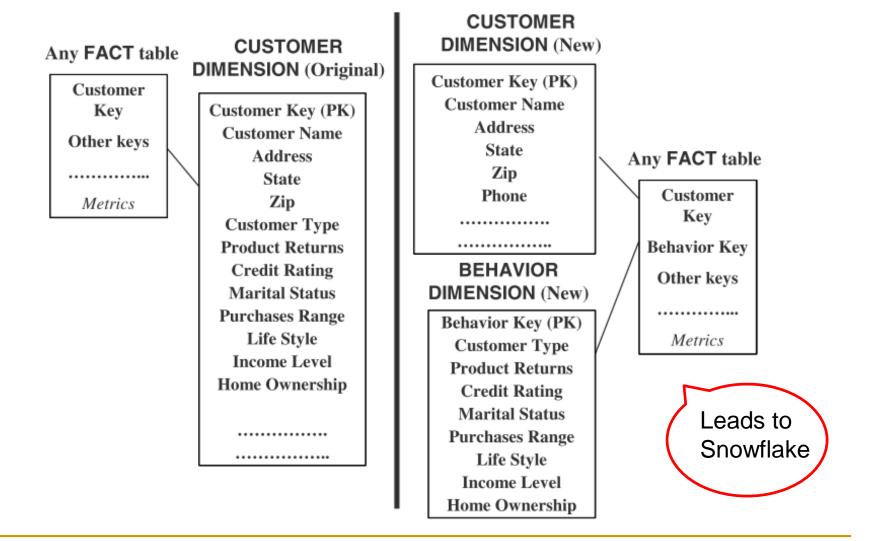
- For Type 2 changes, a new row is created with new attribute value
 - Preserve the history
- What if the change occurs too many times?
- This dimension is no longer a slowly changing dimension
- Particularly, in Large dim. frequent changes cannot be handled with any type of change

Rapidly changing dimensions

- But consider a large customer dimension, where millions of customers may exist
 - But significant attributes in a customer dimension may change many times in a year (rapidly changing dimension)
- In the case if dimension table is too large and changing too rapidly

Solution????

Rapidly changing dimensions



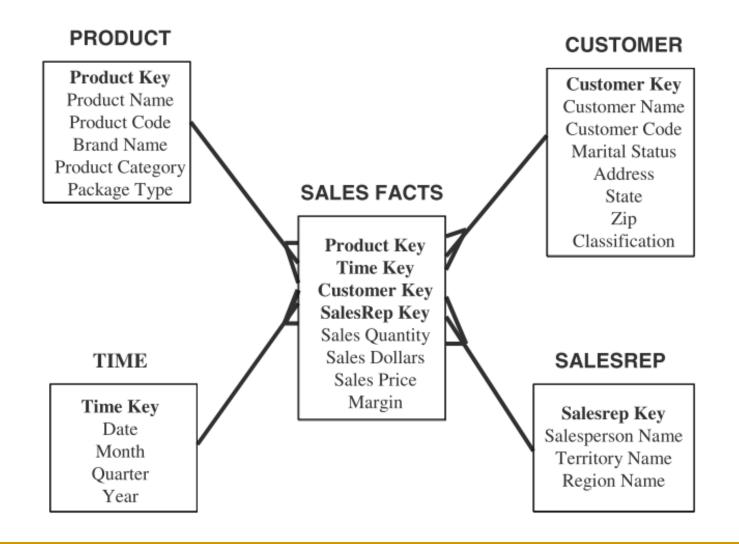
Types of Dimensional Models

- Star Schema (discussed)
- Snowflake Schema
- Starflake Schema
- Constellation Schema

Snowflake Schema

- Snowflake avoids the redundancy of star schemas by **normalizing** the dimension tables
- Therefore, a dimension is represented by several tables related by referential integrity
- Referential integrity constraints is also between fact table and the dimension tables at the fines level of details

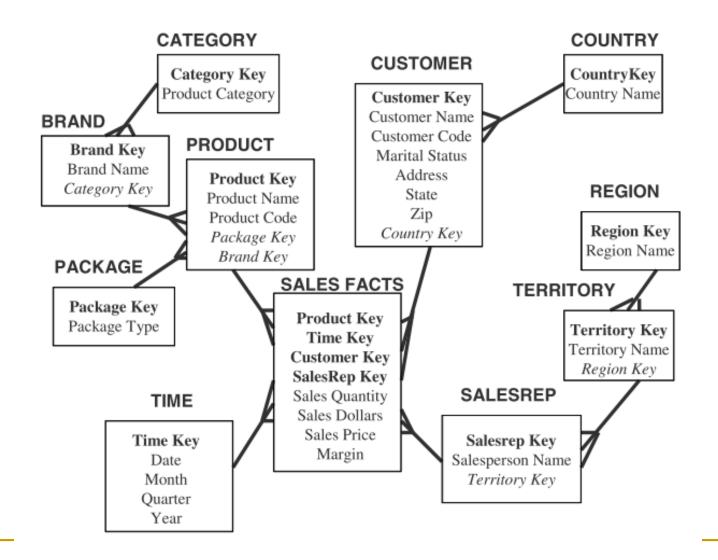
From Star to Snowflake Schema



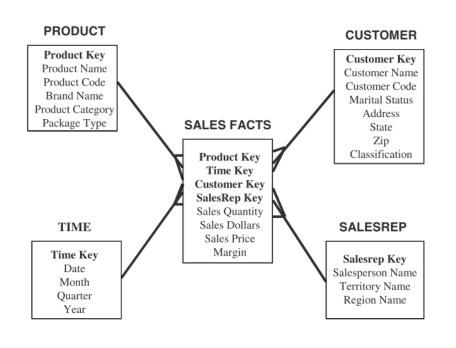
Normalization of Dimensions

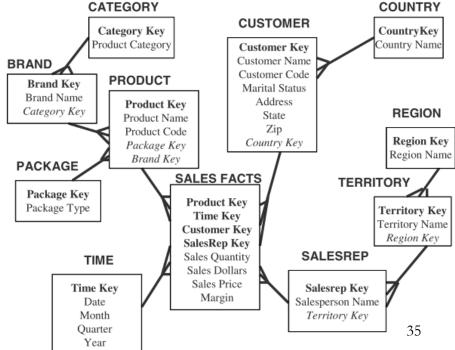
- 1st Normal Form
- 2nd Normal Form
- 3rd Normal Form

From Star to Snowflake Schema



From Star to Snowflake Schema





Search Reduction in Snowflake

- Assume there are 500,000 product dimension rows
- And 500 product brands, 10 product categories
- Query about 1 product category
 - Searching will be performed on 500,000 rows
 - But, if it partially normalized by product brands and product category
 - Initial search, 10 rows

Product Category Department ProductKey CategoryKey DepartmentKey ProductNumber CategoryName DepartmentName Another Example Snowflake Description ProductName Description DepartmentKey Description Size CategoryKey Promotion Sales Time PromotionKey ProductKey TimeKey PromotionDescr StoreKey Date DiscountPerc PromotionKey Event Type TimeKey WeekdayFlag StartDate Amount WeekendFlag **EndDate** Quantity Season Store City State StoreKey StoreNumber CityKey **StateKey** CityName StateName StoreName CityPopulation StatePopulation StoreAddress CityArea StateArea ManagerName StateMajorActivity CityKey StateKey

Snowflake: Advantages & Disadvantages

- Advantages
 - Small saving in storage
 - Normalized structures are easier to update
- Disadvantages
 - Schema is less intuitive (complex)
 - Ability to browse through content difficult
 - Degraded query performance due to joins

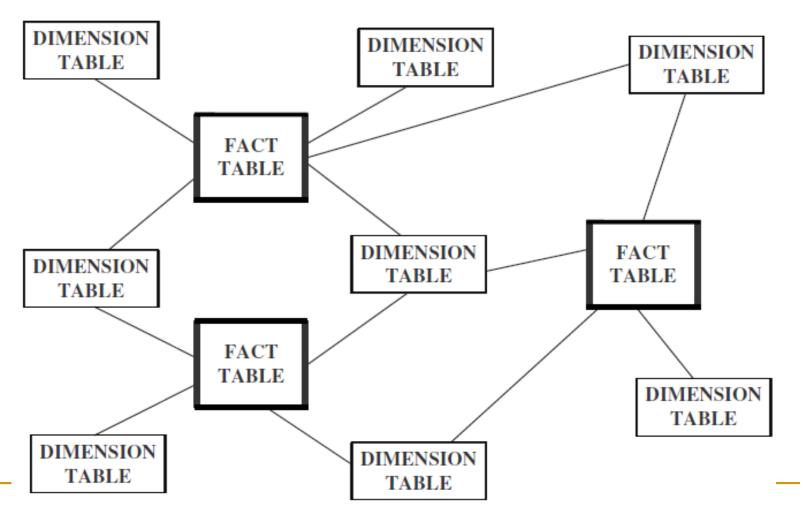
Starflake Schema

- A combination of star and snowflake.
- Some dimensions are normalized while others are not

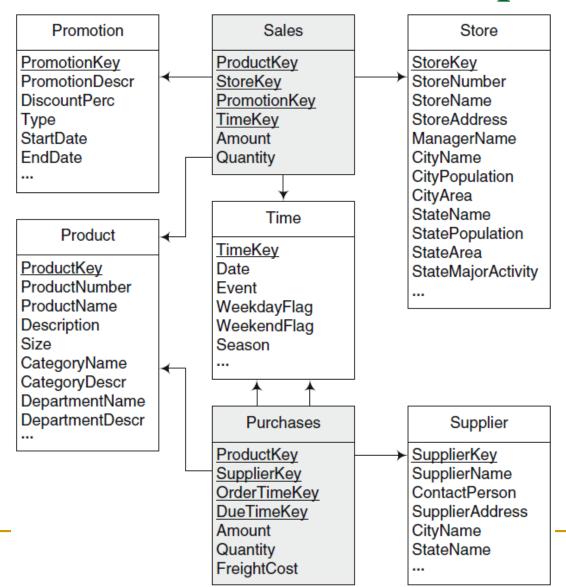
Constellation Schema

 Schema has multiple fact tables that share dimension tables

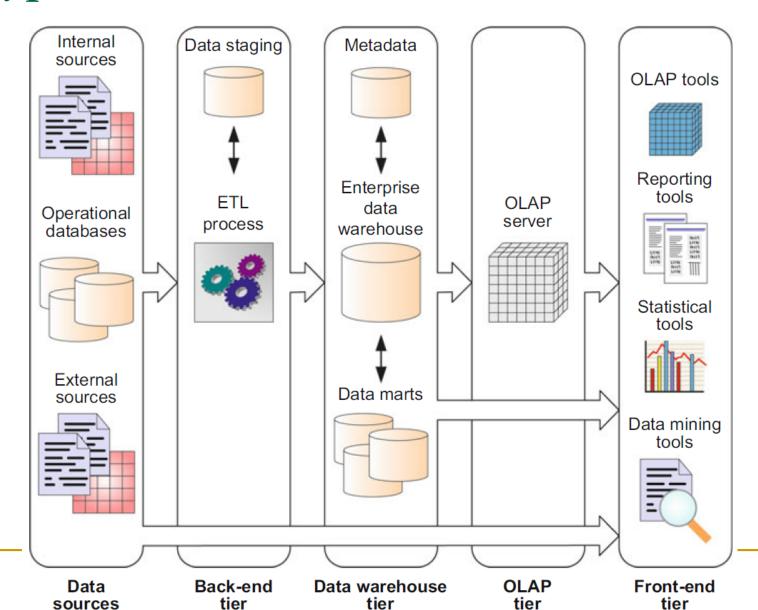
Constellation Schema



Constellation Schema Example



Typical DW architecture



Data Marts

- DW aims at analyzing the data of entire organization
- Sometimes, departments or division requires portion of the data warehouse
- They have specialized needs
 - Sales department needs sales data
 - HR department need demographic data and employee data
- Departmental data warehouses are called data marts

Data Marts

- Marts can be derived from DW or from data sources
- Can have Star or Snowflake schemas
- DW can be seen as a collection of data marts
- Marts are easier to build than an enterprise DW

Data Marts

- Two types of design approach
 - Bottom-up approach
 - Marts → DW
 - Top-down approach
 - DW → Marts

Top-down Approach

Advantages

- A truly corporate effort, enterprise view of data
- Inherently architecture not a union of marts
- Single, central storage
- Disadvantages
 - Takes longer to build
 - High risk of failure
 - Needs high level of cross-functional skills

Bottom-down Approach

Advantages

- Faster and easier implementation
- Favorable return on investment for PoC
- Inherently incremental
- Allows project team to learn and grow
- Disadvantages
 - Data mart has its own narrow view of data
 - Redundant data in every mart
 - Perpetuates inconsistent and irreconciled data

When to use DW or Mart?

- Questions that determine DW or Data Marts
 - Top-down or bottom-up approach
 - Enterprise-wide or departmental
 - Which first data warehouse or data mart
 - Build pilot or go with full-fledge implementation
 - Dependent or independent data marts

DW vs Marts Summary

DATA WAREHOUSE	DATA MART
 Corporate/Enterprise-wide Union of all data marts Data received from staging area Queries on presentation resource Structure for corporate view of data Organized on E-R model 	 Departmental A single business process Star-join (facts & dimensions) Technology optimal for data access and analysis Structure to suit the departmental view of data

Case Study: Draw Snowflake

