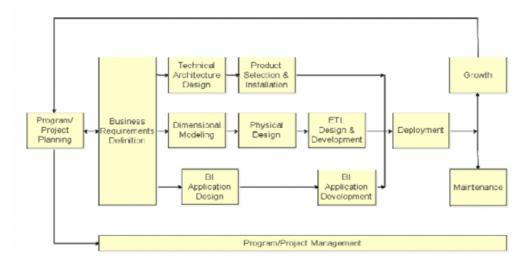


# What is a Dimensional Modelling

- I. Dimensional Modelling
  - a. Suited for Data Warehouse and Business Intelligence applications
  - b. Denormalized structure, optimized for faster retrieval of data
  - c. Easier to understand and to use by business users
  - d. Groups the data according to business categories
  - e. Dimensional models stored are often referred to as star schemas
  - f. Both the dimensional models and the 3NF models are logical models of data that can be physically stored in relational databases
  - g. Part of the data warehouse lifecycle

### II. Kimball Data Warehouse Lifecycle



# III. Program/Project Planning

- a. Program
  - a. Long term strategic approach, no fixed deadline
  - b. Contain multiple projects, can be linked
  - c. Governed by senior stakeholders
  - d. Planning
    - i. Why is data warehouse project is required
    - ii. Access Readiness
      - Sponsor support, investment, culture, resources, and business motivation

# iii. Benefits/ROI new data warehouse project will bring in

- b. Project
  - a. Aim is to deliver one or more business products
  - b. Is time-bound, has an end date
  - c. Contains project team
  - d. Planning
    - i. Develop project plan (Cost, Resourcing, Start Date, Completion Date)
    - ii. Project team assemble

### IV. Requirement Gathering

- a. Interview with Business Users & Executives
  - a. Understand the needs of the business
  - Understand KPI, process, issues, all the information to support their analytical needs
- b. Data source analysis or data profiling
- c. Documentation write up
  - a. Findings from interviews
  - b. Success criteria
  - c. Data sources list
  - d. Business Processes identified
    - i. Operational activities performed by your organization
    - ii. Generate or capture performance metrics that translate into facts in a fact table
    - iii. Fact tables focus on the results of a single business process
    - iv. Defines a specific design target
    - v. Allows to define the grain, dimensions, and facts
    - vi. Corresponds to a row in the bus matrix
  - e. Users stories
  - f. Business Processes laid out in Enterprise Bus Matrix
    - i. Essential tool to implement the Dimensional Data Warehouse
    - ii. Defines high level entities
    - iii. Rows are business processes
    - iv. Columns are dimensions
    - v. Helps prioritize the project direction and workload

# V. Concept and Steps of Dimensional Modeling

### a. Dimension

- a. A dimension is essentially a descriptive information about facts
- b. Example: Customer, Date, Products
- Attributes defines characteristic of a dim (customer\_name, product\_description)

### b. Fact

- a. A "fact" indicates business measurements or business activity (Transaction, sales)
- b. Example Business Activity: Product was sold for \$50
- c. Measurement in fact defines quantitative values (count, sum, avg)
- d. Example measure: price \$50
- c. 4 Steps of Dimensional Modeling
  - a. Select the business process
    - i. Operational activities performed by your organization
    - ii. Capture performance metrics that will get translated into fact tables
  - b. Declare the grain
    - i. A critical process that establishes what a single row of fact table represents
    - ii. Must be declared before anything else as it dictates the design of dim and fact tables
  - c. Identify the Dimensions
    - i. Who, what, where, when, why, how context of a business process
    - ii. Whenever possible a dim should be a single value when associated with a given fact
  - d. Identify the Facts
    - i. Measurements in numeric values that result from a business process
    - ii. Only facts consistent with the declared grain are allowed

### VI. Declare the Grain

- a. Declare the grain means defining the level of detail for your star schema
- b. Indicates the lowest level at which data is captured (Daily, hourly, monthly, etc.)
- c. Both Dim and Fact table contains some level of details
- d. In a fact table, individual transactions, line item of order contains level of detail

- e. Data should be stored as granular as possible
- f. Granularity should be defined before identifying dim and fact

### VII. Dimensions

- a. Dimension tables contain descriptive fields
- b. Usually flat denormalized table
- c. Have a single primary key column
- d. Attributes are the primary target for declaring constraints
- e. Dimension characteristics should be verbose (full words), descriptive, and complete (no missing values)
- f. Usually represent many-to-one hierarchical relationships

# VIII. Types of Dimensions

- a. Conformed Dimensions
  - a. Common dimensions that are joined to multiple facts
  - b. Provides same structure, attributes, and same meaning in every fact table
  - c. Improved data consistency
  - d. Every row is unique and is at atomic level
  - e. Enables cross process analysis by allowing various fact in same query
  - f. Easy to update as all business rules are in one place
  - g. Contains primary and surrogate keys
  - h. Date dimension is common conformed dimension (year, month, week, days, etc.)
  - i. Conformed Dimensions are needed to build Dimensional Data Warehouse



#### b. Junk Dimensions

- a. Dim with simple attributes (flags, yes/no, true/false, id/description)
- b. Values that do not change frequently
- c. Eliminate small dimensions for performance and better management
- d. Group highly correlated attributes into a single dimension
- e. Reduce the number of dimensions (<= 26 dimensions per fact table)
- f. Reduce the number of columns in the fact table
- g. Reduce joins between facts and dimensions

# c. Degenerate Dimensions

- a. Dimension without attributes
- b. Receipt/Invoice number, tracking number, order number, etc.
- c. It is stored inside a fact table to reduce duplications (Fact dimensions)
- d. Degenerate dimensions are added due to grain of fact tables

# d. Role-Playing Dimensions

- a. Same dimension used for multiple purpose
- b. Used multiple times within the same fact giving different business context
- c. Best example is date dimension
- d. fact\_order contains (order\_date, due\_date, cancelled\_date etc.)
- e. Don't create multiple dim, instead create one dim\_date

# e. Slowly Changing Dimensions

- a. Dimensions that change over time
- b. Manages current and historical version
- c. Build to track changes
- d. There are different types of SCD such as:
  - i. Type 0 Retain original
    - 1. There is essentially no change
    - 2. The attribute will never change
    - 3. Facts always grouped by the original value
  - ii. Type 1 Overwriting the Old Value
    - 1. Overwrite Old Value
    - Attributes always reflect the most recent assignment, disregarding historical changes
    - 3. This is easy to implement but not the most optimum solution as we lose track of historical data

### iii. Type 2 – New Additional Record

- 1. Create new additional record
- 2. New primary key (SK), flag column, and date columns added to track

- iv. Type 3 Adding a New Attribute Column
  - Add a new column to the dimension to preserve historical information
  - 2. Allows to query in 2 different realities
- v. Type 4 Using Historical Table
  - Historical table used to track any changes separate to the dimension table
  - 2. The main dimension only keeps current data based on the present time period
- vi. Store as Snapshots
  - 1. Use table partitions and store as snapshot for dimensions
  - 2. All data is added to snapshot daily or weekly
- e. Bridge Tables
  - i. Used to resolve many-to-many relationships
  - ii. Sits between Fact and Dimension
  - iii. Only contain key columns for the various tables
  - iv. Access requirement before implementing
  - v. Loading of table can be complex

### IX. Facts

- a. Contains the measurement created by an operational system
- b. At the lowest granularity captured by the business process
- c. Design entirely based on a physical activity, not influenced by the report
- d. Contain foreign keys for each dimension associated
- e. Measures are used for queries and aggregations
- f. Primary key is usually a composite key

### IX. Types of Facts

- a. Measures
  - a. Additive
    - i. Measures that can be summed across any of the dimension within the fact table
    - Results we get from aggregations is useful and gives us business meanings
    - iii. SUM, GROUP BY

### b. Semi-Additive

- i. Measures that can be summed across some of the dimensions within the fact table
- ii. Some values do not provide business value or is misleading
- c. Non-Additive Facts
  - i. Measures that cannot be summed across any of the dimensions within the fact table
  - ii. Percentage and unit price are examples

### b. Tables

- a. Transaction Fact Tables
  - i. Most common in dimensional modeling
  - ii. Grain one row per transaction
  - iii. Lowel level of granularity and date dimension
  - iv. Additive measures
  - v. Can grow very large quick
  - vi. No update happens in these tables
- b. Periodic Fact Tables
  - i. Snapshot of data for specific time (Day, Week, Month, Hours, etc.)
  - ii. Grain is one row per time period
  - iii. Semi-additive
  - iv. Usually built from Transaction Fact Table
  - v. Smaller table size compared to Transaction Fact Table
  - vi. Useful to get overview of KPI's
- c. Accumulating Fact Tables
  - i. One row per entire lifetime of an event or product
  - ii. Has beginning and an end date
  - iii. Contains multiple date columns
  - iv. Update happens when each milestone is completed
  - v. Example: Processing of an order, insurance processing, material processing
  - vi. Aggregation can be difficult to perform
  - vii. Smallest in table size

# X. Star Schema

- a. Pros
  - a. Simpler queries compared to a normalized model
  - b. Simplified business reporting logic
  - c. Better performing queries

### b. Cons

- a. Data integrity not enforced
- b. Does not inform many to many relationships
- c. Dependent on business process

### XI. Snowflake Schema

### a. Pros

- a. Improved data quality as data is more structured
- b. Uses less storage space than a denormalized schema
- c. Suitable for data with deep hierarchies
- d. Easier to design and develop

### b. Cons

- a. Requires more complex queries
- b. Increase number of joins potentially impacting on performance
- c. Level of integrity still lower than a highly normalized schema
- d. Difficult for Business Users to understand data