DATA WAREHOUSE FUNDAMENTALS

18 | 10 | 21

SRIHARI
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1. Data warehousing concepts

a. Introduction to Data Warehousing concepts.

What is DWH? Not same as Database

DWH usage DB platform

Data comes from elsewhere

↘ Possibly a dozen of them.

Data is copied.

4 Rules of DWH →

- Integrated environment
- Subject oriented
- Time variant (historical data)
- Non volatile (DWH remains stable as it is refreshed)

• Improvement in data quality.

⑥ Reasons to build DWH

Data driven decisions

Past
Present
Future
The unknown

BI
Business Intelligence

One stop shopping

Before DWH we need to get or explore more sources.

BI + DWH = Best Value

ⓒ Compare DWH and Data Lake

Traditional Data Warehousing → also on top of

built on top of RDBMS

Data Lake Built on top of Big Data

The 3 V's

Differences

- Volume (amount of data)
- Velocity (takes new and changed data rapidly)
- Variety (structured and unstructured) semi-structured.

DWH → (next gen) DL

Some companies have both DWH & DL

Blurring Differences

BI + DWH/DL = Business Value

ⓓ DWH and Data Virtualization

DWH History

1980's eoa extract files.

late 1980's Distributed DBMS → failed

DDBMS (technology was not powerful)

Data Virtualization

Data Warehousing

Data Virtualization (DV)

- Read-only DDBMS
- In-place data access
- Many name over the years.

Virtual Data Warehousing

Enterprise Information Integration (EII)

Enterprise Data Access (EDA)

Of course Data Virtualization

Technology has improved

DV use cases

- Simple transformations
- Smaller number of data sources
- Relaxed response time

BI + DWH / DL / DV = Best Value.

© Simple End to End DWH Environment

Typical DWH

Data Sources → Extract Transform Load → DWH → ETL → Data Marts

eg Suppliers → Wholesalers → Retailers

2. Data Warehousing Architecture

ⓐ Build a Centralized Data Warehouse

Single DWH Environment

Single database

One stop shop

Historical Challenges

- Technologies (solved)
- Work process (solved)
- Org. and human factors

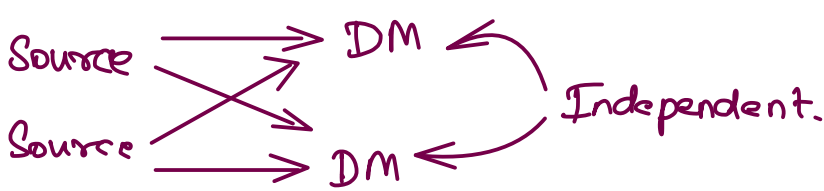
Today's challenges

ⓑ Compare a DWH to Data Mart (DM)

Data Sources → ETL → DWH → ETL → DM

Dependent DM → Existence depends on existence of DWH

Independent DM



Dependent DM (VS)	Independent DM
• Sourced from DWH • Uniform data across marts • Architecturally Straight-forward.	Sourced directly from applications and systems Little or no uniformity Spaghetti architecture

DWH vs. Independent DM

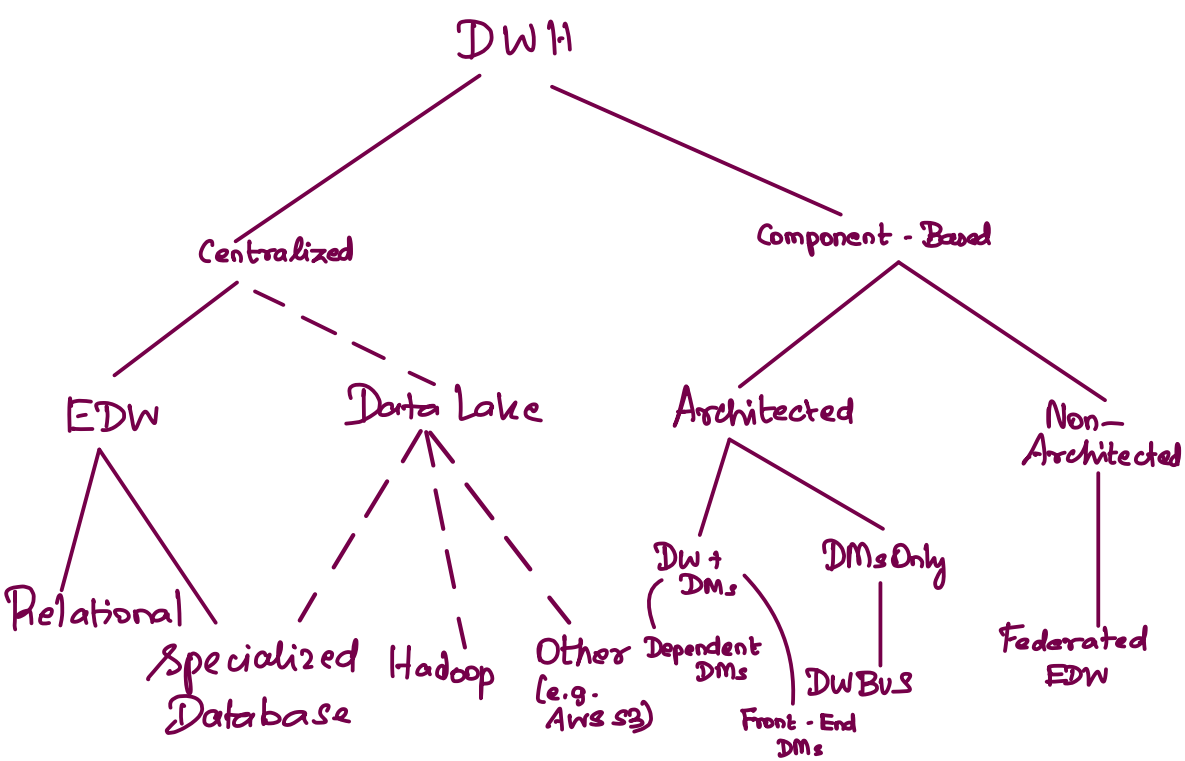
DWH

- Many Sources (dozens or even 100s)
- ETL from sources
- Probably large data volumes
- Dimensionally Organized data

Independent DM

- One or more sources (no specific number typically <10)
- ETL from sources
- Possibly large data volumes
- Dimensionally Organized data

© Your DWH Architectural Options



Centralized

Pros
- Default option
- One stop shopping
- Modern Technology

Cons
Requires
- High cross org cooperation
- High data governance
- Ripple effects

Component Based

Pros
- Decomposition
- Mix and match tech.
- "Bolt" together components
- Overcome org challenges

Cons
- Often inconsistent data
- Difficult to cross integrate

Centralized

EDW or Data Lakes
enterprise data warehouse

(refer the tree in previous page)

Component Based

Architected vs. Non Architected

(refer the tree in previous page)

C.B Architected

DMs Only

|

DW Bus

Confirmed Dimensions

Front-end DM

Instead of having DM behind a DWH, we have DM in front of the DWH. The DM is the place where business analytics takes place. We can have some data from the DM flowing into the DWH.

C.B Non-architected

Federated EDW

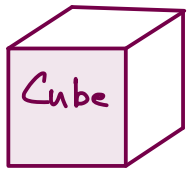
"Let's agree to disagree"

Collection of DMs

"Only as the last resort"

Better to use DWH & DL

ⓓ Including cubes in your DWH environment.



Cube = Multi Dimensional DB

Not a RDBMS

Specialized "dimensionally aware" databases

leading alternative for first gen. DWH

Today = Best for smaller-scale DWs, DMs

Advantages

Fast query response time

"Modest" data volumes

Dis-advantages

Less flexible data structures than RDBMS

More vendor variation than RDBMSs

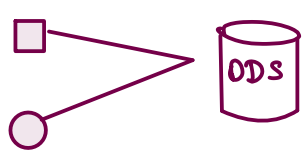
Today

RDBMS + MDBMS = BEST VALUE

ⓔ Include Operational Data Stores in your DWH Environment

What is Operational Data Store ODS

Multiple Data Sources



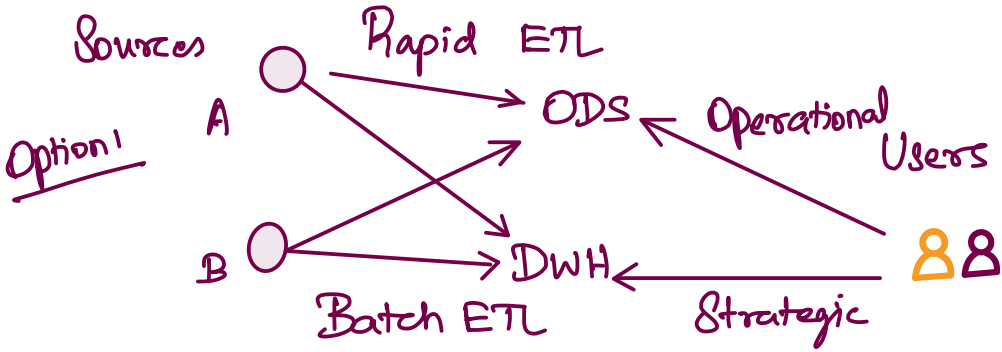
Integrates from multiple sources

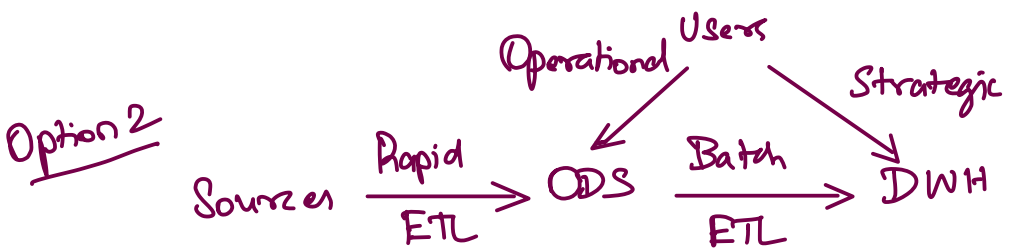
Often real time

Source → ODS data feeds (not batch)

IMP: Emphasis on current operational data

ODS ← Tell me what's happening right now!
Popular late 1990s / early 2000s.

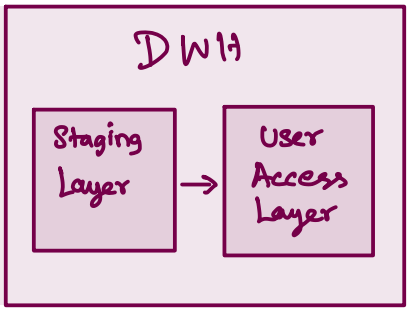




ODS → Less popular
Faster and more current DWs
Superceded by Big Data
ODS components within Data Lake
Traditional ODSs still used in mission critical situations.

BI + DWH and/or DL and/or DV and or ODSs = Best Value

⑥ Explore the role of Staging layer



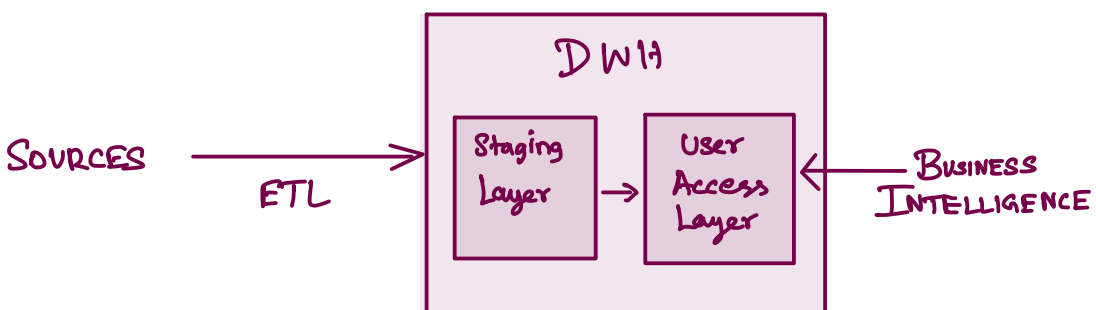
Staging Layer

- Landing zone
- "E" within ETL
- 2 Variations

"Pull the data in a non-intensive way"

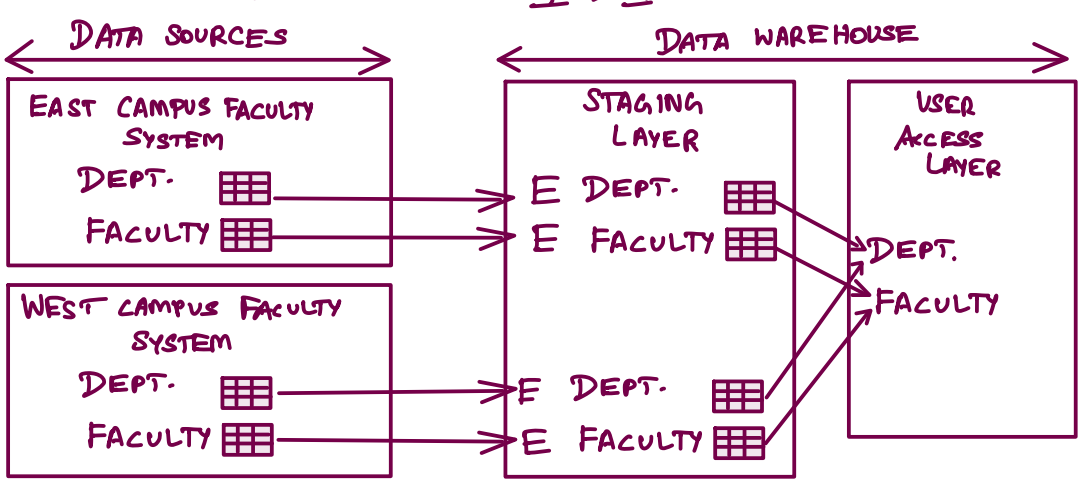
User Accen Layer

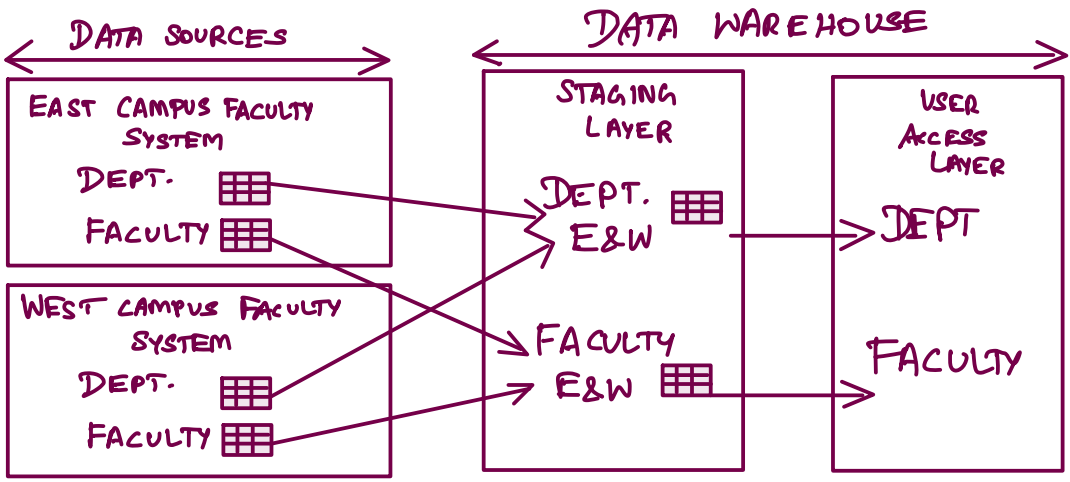
- Where users go
- Dimensional Data



Inside Staging layer

1 → 1 FEED





MANY → 1 FEED

Many to 1

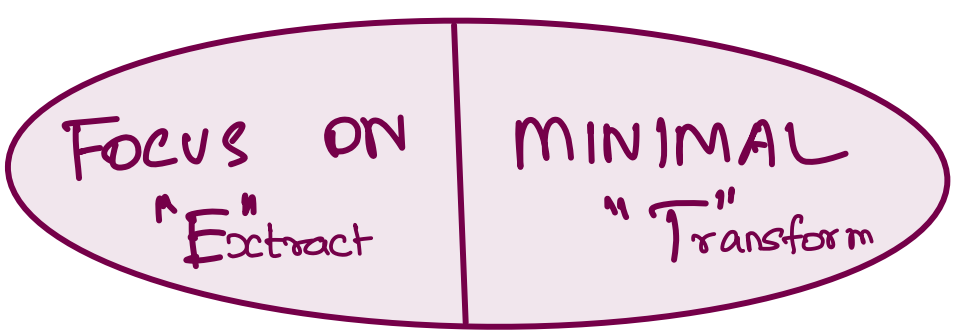
Multiple instances of identical source applications

(Mostly uniform across data marts)

1 to 1

Multiple customized instances of source applications

Different vendor apps for the same function



⑧ Comparing Two Types of Staging Layers

Two types

Non-Persistent

Prior to each update it is empty.

Once data is moved to DWH the NPSL is cleared

SL EMPTL
Source → SL
SL → UAL
EMPTY SL

Persistent

SL has the data

We don't empty out

Data is persisted.

SL has data
Source → SL
SL → UAL
SL has data

NPSL

Advantages

- Less storage space
- Data already moved to user access layer

Disadvantages

- Need to go back to source to rebuild user access layer
- Data QA also requires source systems.

PSL

Advantages

Rebuild user layer without source systems

Data QA: compare staging layer with user layer

Disadvantages

More storage space

Risk of ungoverned access.

3. Bring Data into your Data Warehouse

@ Compare ETL vs ELT

Extract Transform Load Extract Load Transform

Quickly pull data
Batches
Raw data ... with errors and all...
Land data in staging layer

Transform

- Apples to apples
- Prepare for uniform data in user access layer
- Can be very complex

Load

- Final stop along the data pathway
- Store uniform data in user access layer

Challenges around ETL

Significant business analysis } Before loading
Significant data modeling } the data.

Change the order

E L T instead of E T L

- Blast data into big data environment.
- Raw data in Hadoop HDFS, AWS S3, etc.
- Using big data environment computing power to transform when needed.

"Schema on read" vs. "Schema on write"

ETL	ELT
You need the schema before you read the data from source	Schema and the associated analytics preparatory work can happen just before write.

For traditional DWH ⟶ ETL

For DL or DWH · DL Hybrid ⟶ ELT

(b) Designing the initial load ETL

Source → ETL ⟶ DWH

Initial ETL and Incremental ETL

'first time' 'then on'

Initial ETL

Normally one time only.

Right before the DWH goes live.

All relevant data necessary for BI and analytics.

Redo if data warehouse blows up.

> DON'T BRING IN ALL POSSIBLE DATA
> BRING ONLY WHAT IS
> 'RELEVANT'

What to bring into DWH ?

- Data definitely needed for BI and analytics
- Data probably needed for BI and analytics
- Historical data

Once Ready to go!

from then on "Incremental ETL"

© Compare different models for incremental ETL

2 variations of ETL

Initial ETL

Incremental ETL

Incremental ETL

- Incrementally refreshes the DWH
- New data
- Modified data
- Special handling for deleted data: we keep data for historical purposes but mark it as deleted or inactive.

BRING THE DWH UP TO DATE ✓

4 MAJOR INCREMENTAL ETL PATTERNS

- Append - append new info on top of existing data
- In-place update - update data in place
- Complete replacement - total overwrite of the data
- Rolling append - you maintain only certain history. eg. You maintain only 36 months of data. You append data and the time window keeps rolling.

ETL Today

Append

In-place update.

ⓓ Explore the role of data transformation

Data transformation overarching goals

Uniformity

Apple ⟷ Apple

Restructuring

COMMON TRANSFORMATION MODELS

part of ⓓ
1. Data value unification
2. Data type and size unification
3. De-duplication

} Uniformity

Refer ⓔ
4. Dropping Columns (vertical slicing)
5. Value-based row filtering (horizontal slicing)
6. Correcting known errors

} Restructuring

1. Data Value Unification

eg Faculty Rank

System 1: Professor, Asst. Professor, Lecturer

System 2: P, AP, L

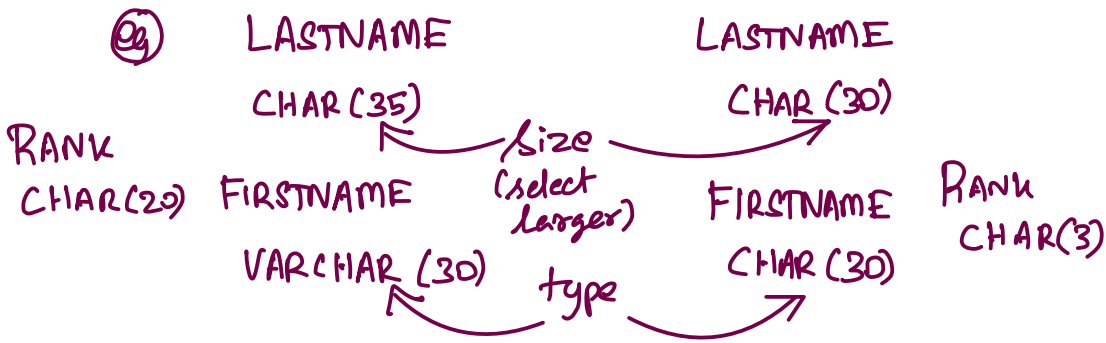
Rank

Unify the data values

eg Faculty Master Dimension

Lets say we chose Rank column values as P, AP, L

2. Data type and size unification



We need to unify the types and values

Faculty Master Dimension

LASTNAME	CHAR(35)
FIRSTNAME	CHAR(30)

If we decide to abbreviate the rank

RANK CHAR(3)

3. De-duplication

Say a student goes 2 campuses so the student appears in the student table of both campuses. Solution: De-duplication

④ More data transformations within your ETL

4. 5. 6. are discussed in this section

4. Dropping Columns

e.g. Some columns may not get used by business analytics. So we just go ahead and ignore these columns as part of ETL process.

FACULTY MASTER DIMENSION only has required columns → used for analytics.

5. Value based row filtering (Horizontal slicing)

Students

FN	LN	YEAR	MAJOR
			Business
			Engineering
			Literature

Assume we build a data mart for "College of Business"

The users might be interested in students who are having their major as "business"

6. Correcting Known Errors

Fix all the known data errors so that reports are accurate!

(f) Implementing Mix and Match Incremental ETL

Among ETL feeds ... frequency might differ

Daily, Hourly, Weekly

... approaches of handling data

Complete Replacement, Append, Replace, Rolling append

Mix and match within an ETL feed from various source systems

Design and build what makes sense for your environment

Context is the key

as in architecture "It depends"

4. Data Warehouse Design : Building Blocks

@ How will your data warehouse be used?

Making data-driven decisions

Past Present Future Unknowns

BI + DWH = Best value ← Remember?

BI Category drives data model

Basic Reporting	Dimensional
Online Analytical Processing (OLAP)	Dimensional
Predictive Analytics	Data Mining / Specialized
Exploratory Analytics	Data Mining / Specialized

ⓑ The basic principles of dimensionality

We will focus on first 2

- One or more measurement
- Dimensional context for each measurement

eg. 5312 ← some measurement

some ₹ sign on the front

₹ 5312 what does this amount mean

some more context ₹ 5312 payment

Now we know it is a payment for something, some service, we don't know much.

Absence of context is the problem!

Providing dimensional context

by using the words 'By' 'For'

eg Typical dimensional insights

- What is the average annual faculty salary by rank, by department, by academic year.
- What is the student loan balance by major, by class year, by campus?

MEASUREMENT

DIMENSIONAL CONTEXT

Some times the questions may be specific dimension out of all dimensional contexts

eg for assistant professors

for engineering majors

WORDING	USAGE (almost always)
By	"Sliced and grouped" by values of the entire dimension.
For	• One or more specific values from the entire dimension.

Implied wording → for

- What is the average annual faculty salary this academic year for asst. professors, by department ?

Using "by" instead of "for" for grammatical reasons

What is the total number of vacation days taken last academic year by administration employees ?

- last academic year → implied "for"
- by administration employees → sounds more natural than "for administration employees"

The critical lesson

MEASUREMENT + CONTEXT = INSIGHTS FOR DATA-DRIVEN DECISIONS

© Compare facts, fact tables, dimension, dimension tables

- Measurements → Facts
- Dimensional context → Dimensions

Facts Numeric Quantifiable, Think "measurement"

Eg
- Salary
- Number of credits
- Dollar amount
- Number of years

DWH fact is not the same as a logical fact

If we use RDBMS store facts in a fact table

Fact ≠ Fact Table

We will look at
- Deciding which facts can go into the same fact table
- Different types of fact tables
- How to connect fact tables and dimension tables.

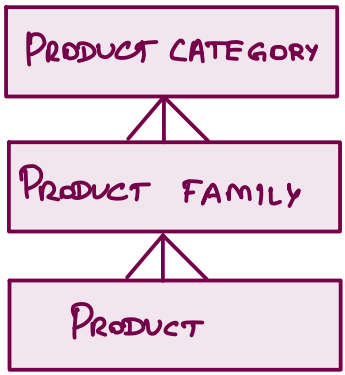
Eg Of dimensions

Academic Department, Major, Student, Employee

We store dimensions in dimensions table

Sometimes we interchange the phrases dimension and dimension table

Eg The product dimension

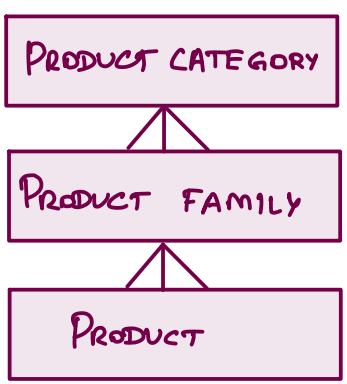


Hierarchy

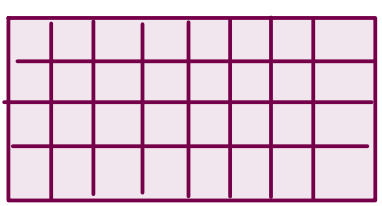
3 levels of dimensions

Why the confusion? Difference is between Star schema vs. Snowflake schema

Star Schema



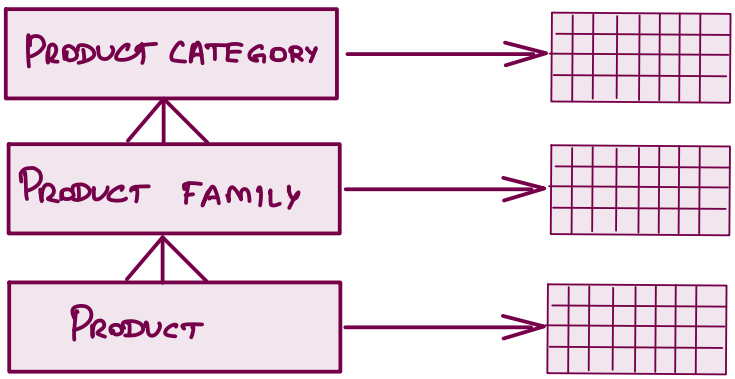
- 1 Dimension table known as product dimension (table)



- Actually 3 dimensions (from same hierarchy) in 1 table

Snowflake Schema

3 dimensions 3 dimension tables



(d) Compare different forms of additivity in facts

A data warehouse fact can be

Additive

An additive fact can be added under all circumstances

eg A faculty member salary

Say add all faculty member salaries

or Add salary of a faculty salary over the years

Non additive

Cannot be added!

Grade Point Average GPA

You cannot add average or ratios.

NOTE: Additivity means ability to add.

Typical non additive facts

Margins, Ratios, Percentages, Calculated average

Semi-additive

Sometimes you can add, but other times you cannot.

Typically used in "Periodic snapshot fact tables"

Non additive facts

- Store underlying components in fact tables
- Possibly store non-additive fact also for individual row easy access (minimal calculations)
- Calculate aggregate averages, ratios, percentages etc. from totals of underlying components.

ⓒ Compare Star schema to a snowflake schema

OLAP = Dimensional Analysis
→ supported by
→ Underlying dimensional data
→ Facts, Dimensions,
→ Fact tables and Dimension Tables

Star Schema

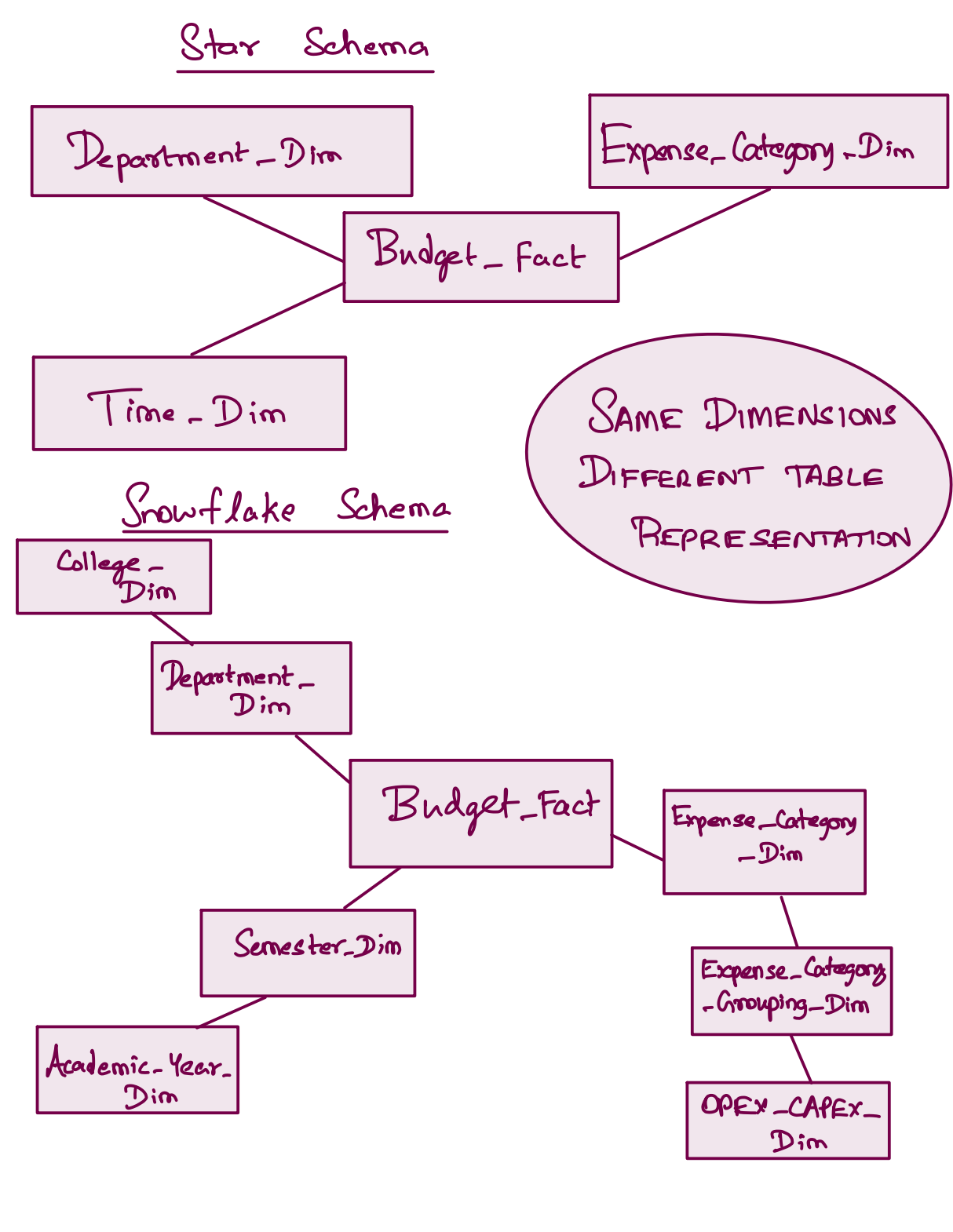
- All dimensions along a given hierarchy in one dimension table
- Only one level away from fact table along each hierarchy
- With one fact table visually resembles a star
- "Denormalized" dimension table data → means more repetitive data

Snowflake schema

Each dimension / dimension level in its own table

One or more levels away from fact table along each hierarchy

With one fact table visually resembles a snowflake.
"Normalized" dimension table data


Star Schema
Department_Dim
Expense_Category_Dim
Budget_Fact
Time_Dim
SAME DIMENSIONS
DIFFERENT TABLE
REPRESENTATION
Snowflake Schema
College_Dim
Department_Dim
Budget_Fact
Expense_Category_Dim
Semester_Dim
Expense_Category_Grouping_Dim
Academic_Year_Dim
OPEX_CAPEX_Dim

ⓕ Database keys for data warehousing

Fundamentals

- Star or Snowflake schemas implemented in RDBMSs
- RDBMSs use logical relationships to relate data across tables.
- Technically any data can be related to any other data
- "Official" relationships handled through keys

RDBMS Keys

Primary vs. Foreign Keys
Natural vs. Surrogate Keys

PRIMARY KEYS A unique identifier for each row in a database.
Single column or more than one column

Faculty Master Dimension eg. FacultyID

FOREIGN KEY Some other table's primary key
Used to indicate logical relationship
Helps improve query performance

Faculty Master	Department Master
Faculty_ID	Dept_ID ----- Dept_ID

NATURAL KEY

Might be cryptic

eg

Faculty_ID
32132
48789
83156

Or

Might be understandable

Dept_ID
ACCT1
MKT1
MGT1
COMP1
FIN1

> "Natural keys "travel" from source systems with the rest of the data"

> "Best practice is to use surrogate keys to relate data across tables"

Surrogate keys

- No business meaning
- Different than a cryptic natural key
- Generated by the database itself or a supplemental "key management" system.

Faculty Master

Faculty_key
12498
12349
41323

Faculty_ID
123892
564321
789321

This is used in the database to relate dimensions. eg. Faculty to Dept.

Key DWH design decision about keys

Question / Decision	Guidance
Use surrogate or natural keys as primary or foreign keys ?	Add surrogate keys as data brought into DWH.
Keep or discard natural keys in dimension table?	Keep as "secondary" keys
Keep or discard natural keys in fact tables ?	Experts differ but our guidance is to discard.

5. Design facts, fact tables, dimensions and dimension tables

@ Design dimension tables for star schemas and snowflake schemas

Recap

Dimension → context for measurements (facts)

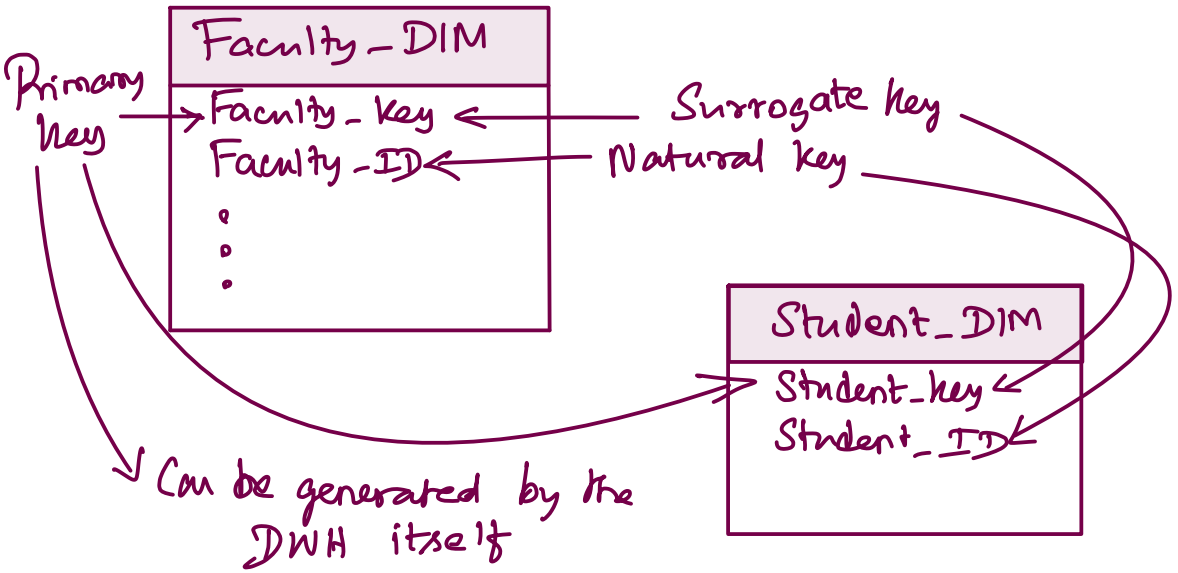
Dimension ≠ Dimension tables.

we used → Table → RDBMS

RDBMS table requires Primary 🔑

DWH Primary 🔑 = Surrogate 🔑

Representative Dimensions: Faculty | Students



Dimension tables

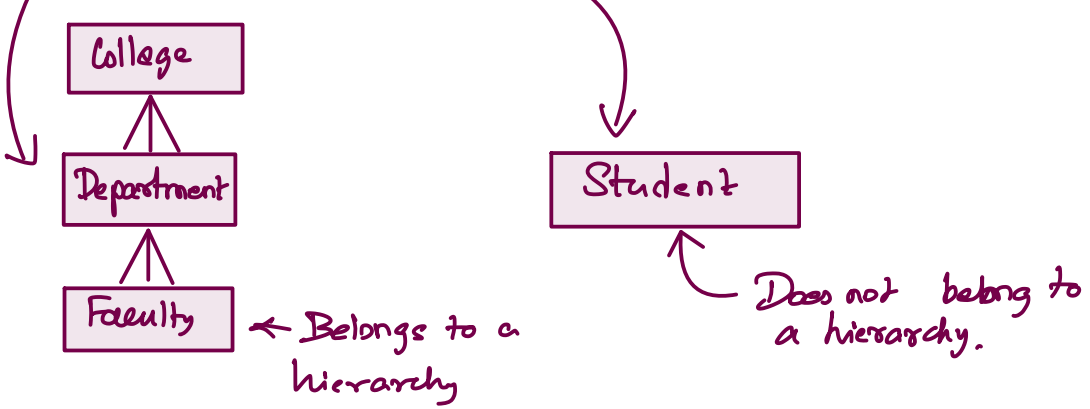
Key DWH subject areas

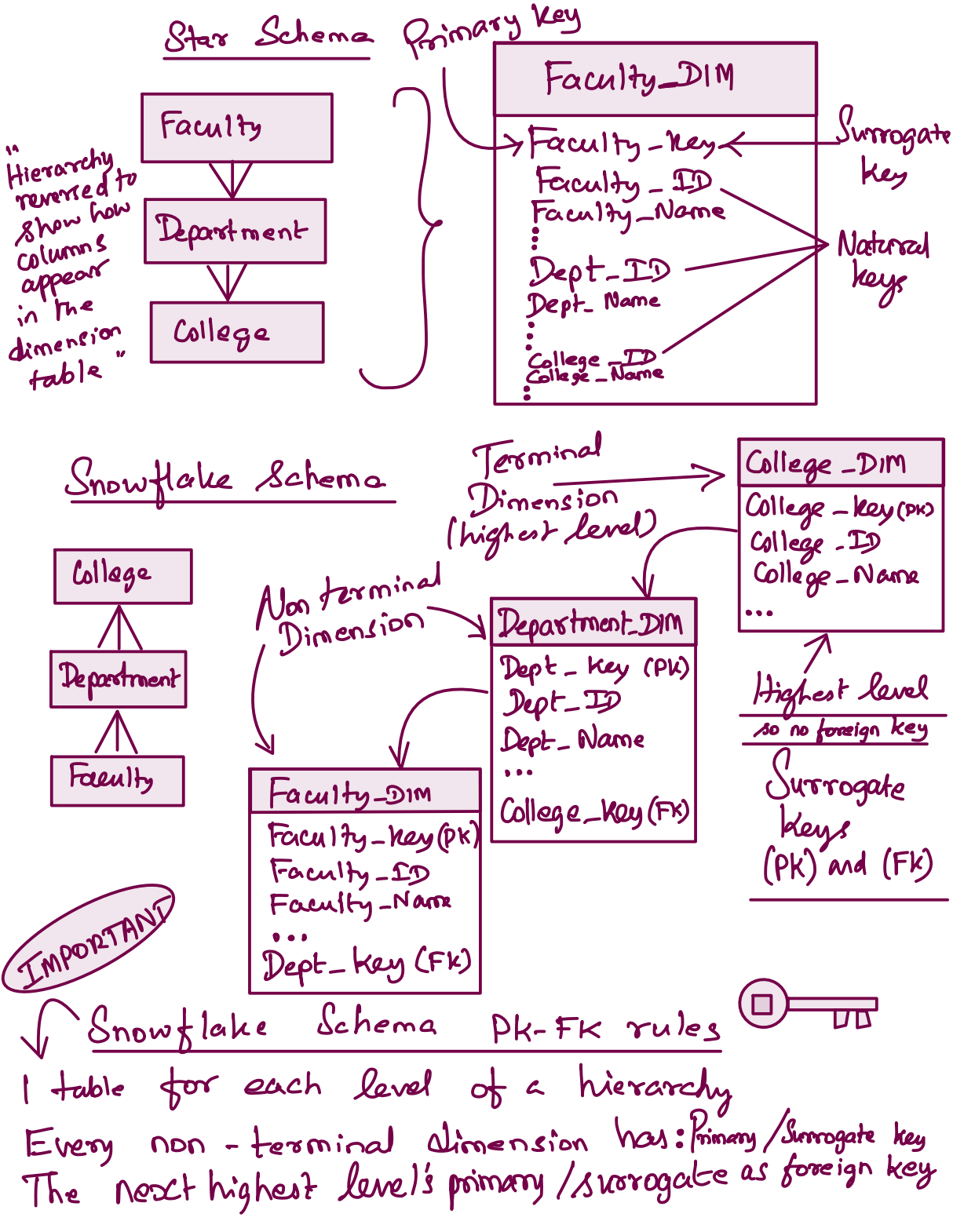
→ Provide context to measurement

All or most meaningful information

"One stop shop" for dimensional subjects.

Hierarchical vs Flat dimensions

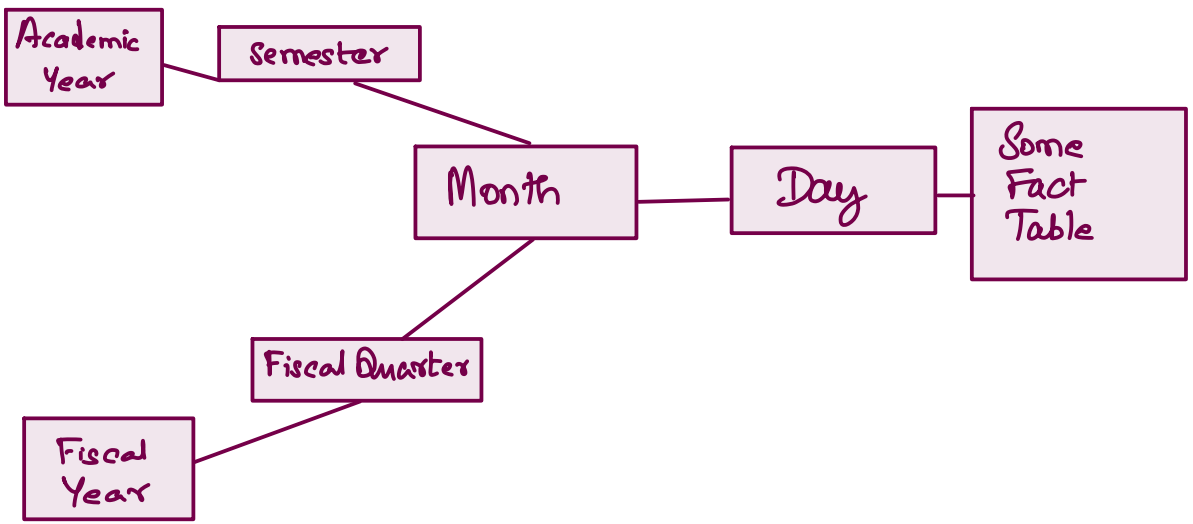


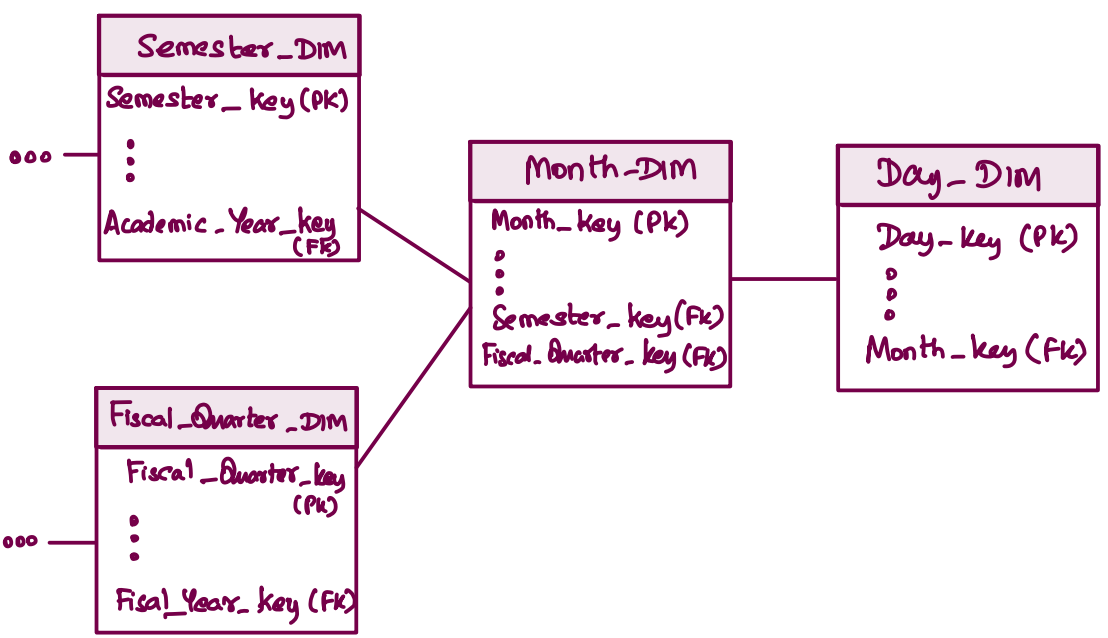

Star Schema
Primary key
Faculty_DIM
Faculty
Department
College
"Hierarchy reversed to show how columns appear in the dimension table"
Faculty_key
Surrogate key
Faculty_ID
Faculty_Name
Dept_ID
Dept_Name
College_ID
College_Name
Natural keys
Snowflake Schema
Terminal Dimension (highest level)
College_DIM
College_key (PK)
College_ID
College_Name
...
College
Department
Faculty
Non terminal Dimension
Department_DIM
Dept_key (PK)
Dept_ID
Dept_Name
...
College_key (FK)
Highest level
so no foreign key
Surrogate keys (PK) and (FK)
Faculty_DIM
Faculty_key (PK)
Faculty_ID
Faculty_Name
...
Dept_key (FK)
IMPORTANT
Snowflake Schema PK-FK rules
1 table for each level of a hierarchy
Every non-terminal dimension has: Primary/Surrogate key
The next highest level's primary/surrogate as foreign key

Every terminal dimension has primary/surrogate key

No hierarchy based FK (because no higher level)

Snowflake hierarchy with branching





(b) The four main types of DWH fact tables

Recap We store our facts in a fact table.

Fact ≠ Fact tables

4 types of fact tables

Transaction Fact Tables
- Record facts (measurements) from transactions.

Periodic Snapshot Fact Tables
- Track a given measurement at regular intervals

Accumulating Snapshot Fact Tables
- Track the progress of a business process through formally defined stages

Factless Fact Tables
- Record occurrence of a transaction that has no measurements
- Record coverage or eligibility relationships

(c) The role of transaction fact tables

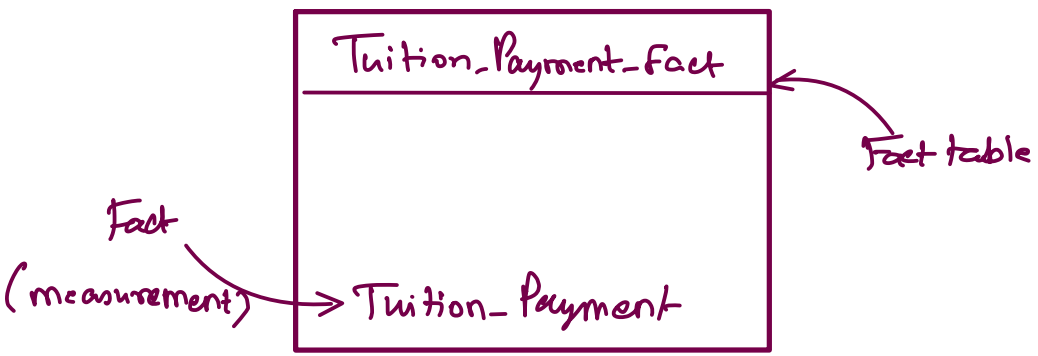
Transaction fact table

Formally - transaction-grained fact table
Heart of dimensional models

Literally - a table where we store facts from our transactions.

One or more facts stored together in a fact table

Rules tell us how many facts in each fact table.



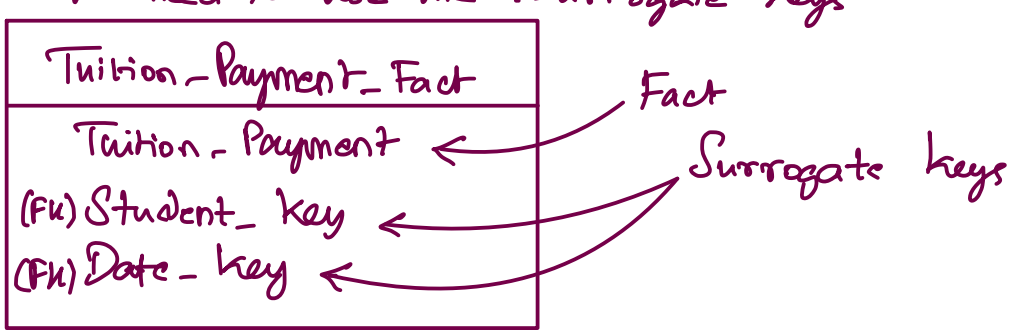
Fact + Context = Decision

What's missing — Student — Payment Date

We won't add the Student_ID and payment_Date

Remember:

We need to use the surrogate keys



Student_DIM
Student_Key (PK) Student_ID ...

Context

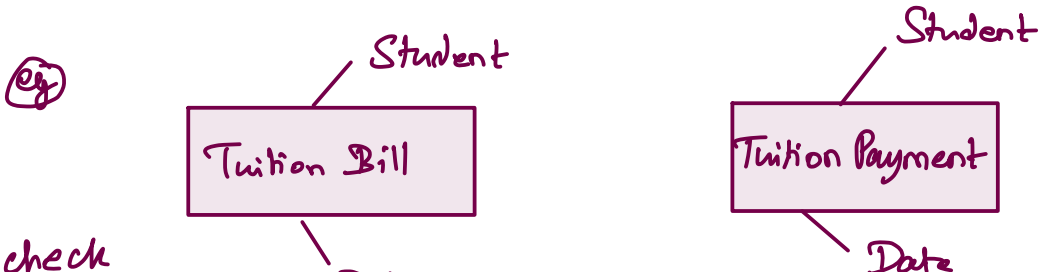
Date_DIM
Date_key (PK) ...

ⓓ The rules governing transaction fact tables

What are the rules?

Rule #1
Facts available at same grain (level of detail)

Rule #2
Facts occur simultaneously



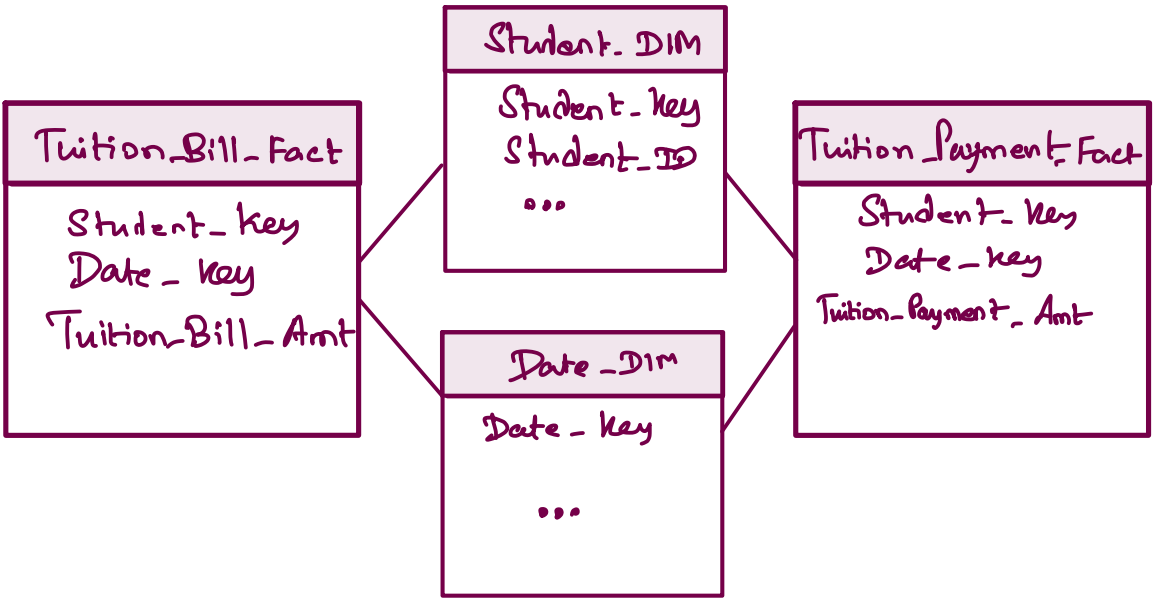
To check
Rule #1
look at dimensions

Available at same grain?
YES

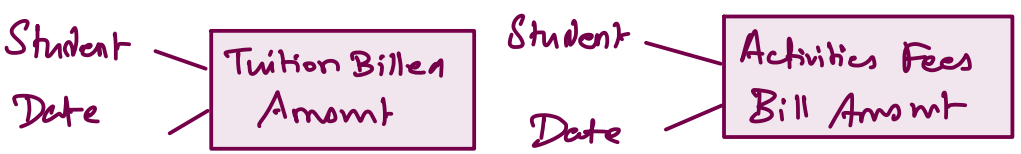
Rule #2 Do they occur simultaneously? NO
Student receives a bill and then they pay the bill.

Why not violate the two rules
Complicates data analysis. Requires SQL workarounds
Billing and Payments are 2 different business processes.
Business processes belong in their own separate fact tables.

How to represent ?

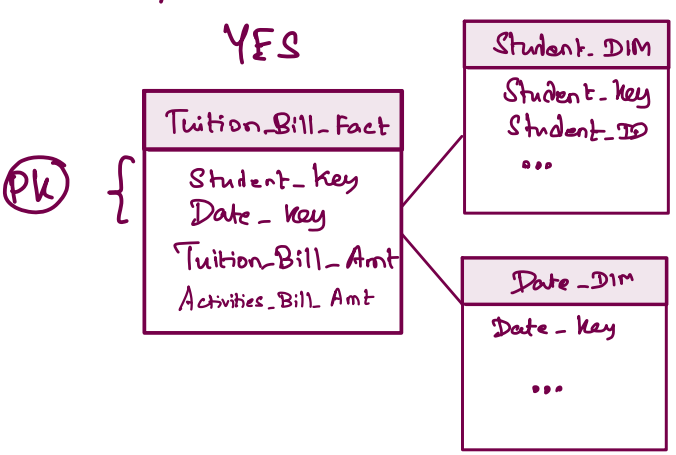


What facts can be stored together ?



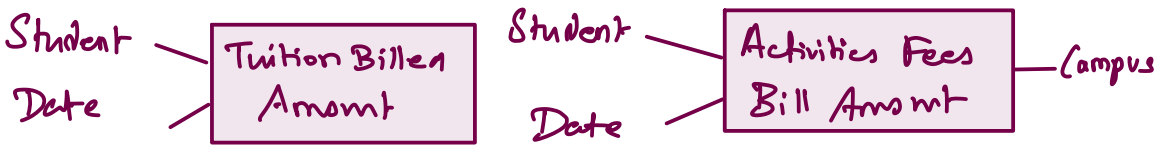
Rule 1 ✓
YES

Rule 2 ✓
Yes



Example of facts at different grains

Assume if activities fees also depends on the campus dimension



Rule #1 is not satisfied

⑥ Primary and Foreign Keys for Fact Tables

Recap PK - Primary key FK - Foreign key

For dimension table Student_key ← Surrogate key

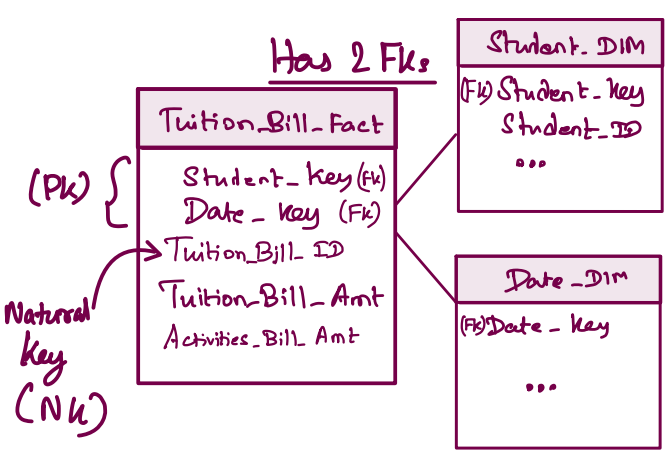
Student_ID ← Primary key

Natural key

Fact tables handled differently !

PK of fact tables → Combination of all foreign keys relating back to dimension tables.

Has 2 FKs



PK is still a combination of Surrogate key !!

(f) The role of periodic snapshot fact tables

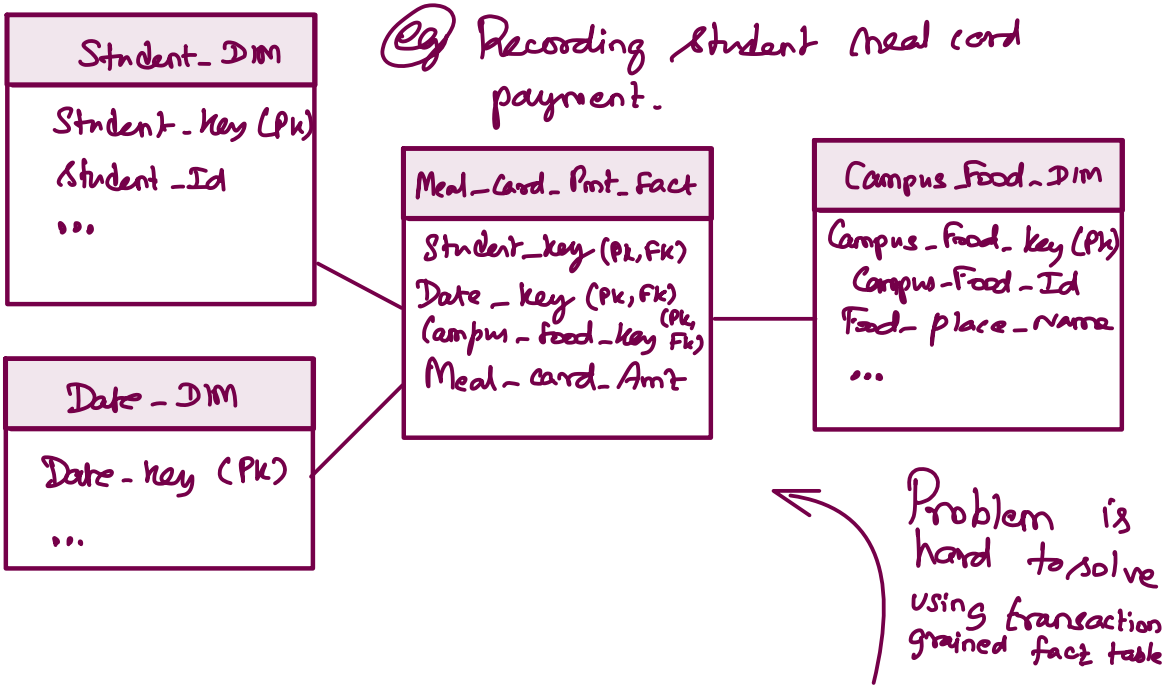
Sometimes called snapshots → Better use full name

Take and record regular periodic measurement.

2 types of periodic snapshot fact tables

Aggregate result of "regular" transactions

Levels that are not related to "regular" transactions

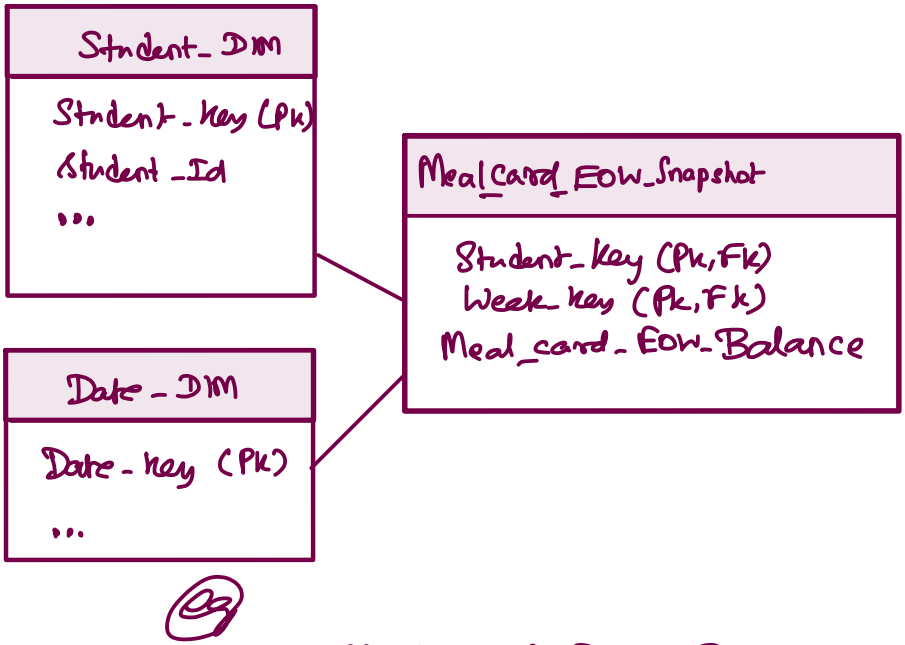


(eg) Recording student meal card payment.

Problem is hard to solve using transaction grained fact table

(eg) Track and analyze the end-of-week meal account balances throughout the semester.

We create a periodic snapshot fact table along side regular transaction grained fact table

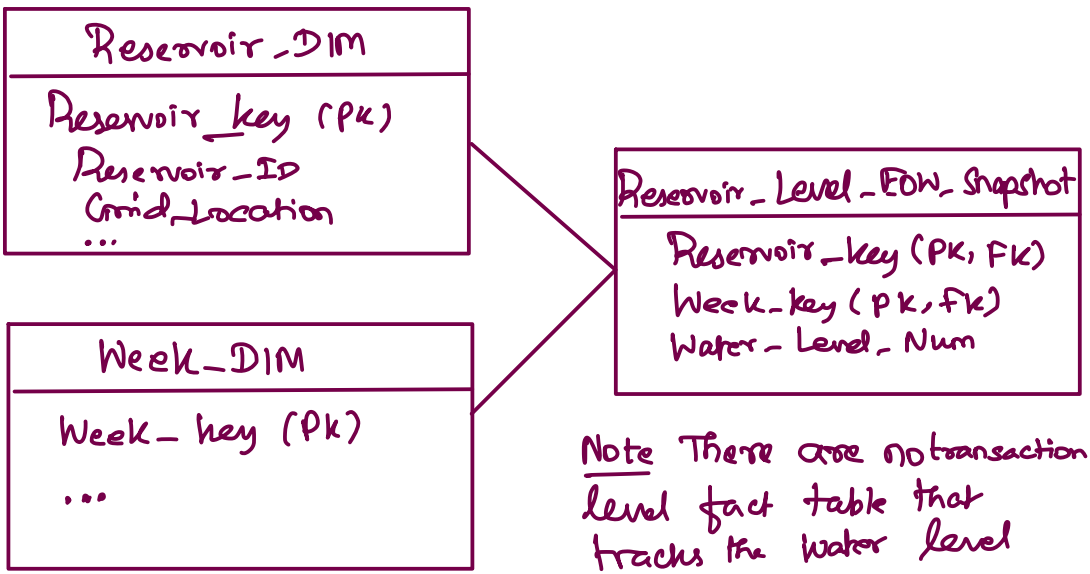


Meal_Card_EOW_Snapshot

Student_key	Week_key	Meal_Card_EOW_Balance
43232	34	$210.12
43232	35	$200.12
43232	38	$200.12
43232	39	$150.12
81768	34	$430.34
81768	35	$430.34
81768	38	$400.34
81768	39	$400.34
...	...	...

Much easier, more direct access for certain type of business questions.

2nd type of periodic snapshot fact table



Note There are no transaction level fact table that tracks the water level in a reservoir.

Comparing the 2 types of periodic snapshot fact tables

- Both are structurally the same.
- 2nd type: no transactions from which levels are built
- The levels "just exist" and can be measured.

COMPLICATION ALERT

Next - Semi additive facts

(9) Periodic Snapshot Fact Tables and Semi-Additive facts

Semi-additive facts Recap Additive, Non-additive and Semi-additive

★ Some times you can add
★ But other times you cannot add

* Typically used in periodic snapshot fact tables

(eg) What was the ending meal card balance for a student on any given week?

Meal_Card_EOW_Snapshot		
Student_key	Week_key	Meal_Card_EOW_Balance
14323	4313	$455.12
14323	4317	$388.65
14323	4318	$388.65
14323	4320	$319.76

Measurement

We cannot add the EOW_Balance along the time dimension!

Student_DIM		
Student_key	Student ID	Name
14323	SOACK32	Sally J

→ Total $1552.18 ← doesn't make sense.

We are doing a snapshot each week.

Non additive But you can perform other numeric operations along the time dimension.

Avg. of EOW Balance for 4 weeks $\frac{\$1552.18}{4}$

$= \$388.05$

Also you can lock time dimension to one specific value ... and then add values.

Meal_Card_EOW_Snapshot

Student_key	Week_key	Meal_Card_EOW_Balance
14323	4313	$455.12
14323	4317	$388.65
14323	4318	$388.65
14323	4320	$319.76
13531	4313	$561.23
14381	4313	$215.63

Measurement

We lock the time dimension Week 4313

Then we can sum up to get

The total remaining balances in meal accounts at the end of week 4313 was $1231.98

Then find average remaining account balance at the end of week 4313 was $410.66.

NOTE: Periodic snapshot fact tables can play a valuable role in your data warehouse.

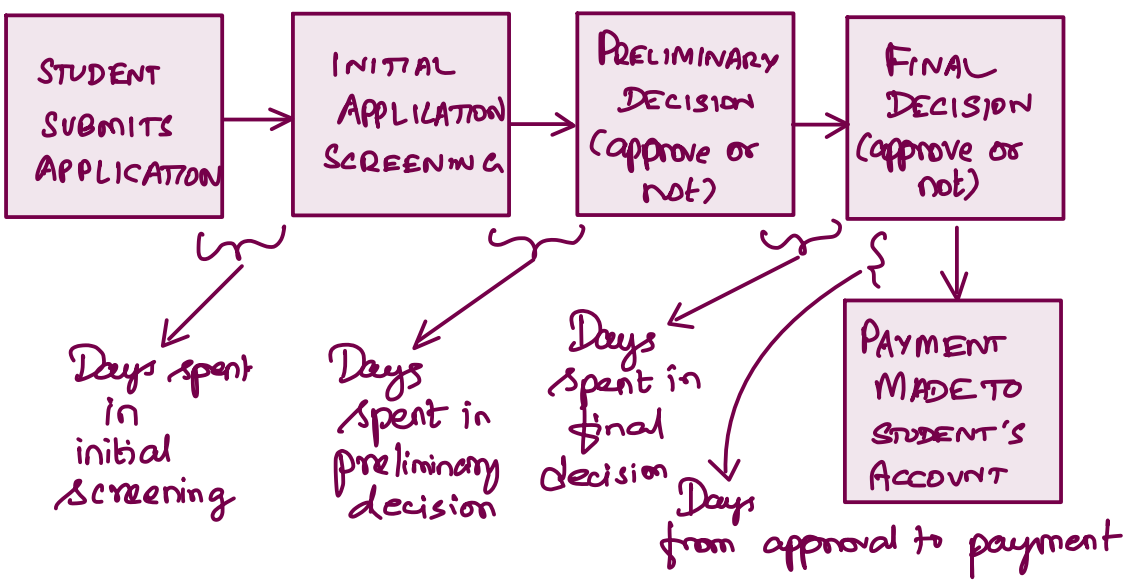
(6) The role of accumulating snapshot fact tables

Accumulating snapshot → Track the progress of a business process through formally defined stages

Tracking the progress of a business process

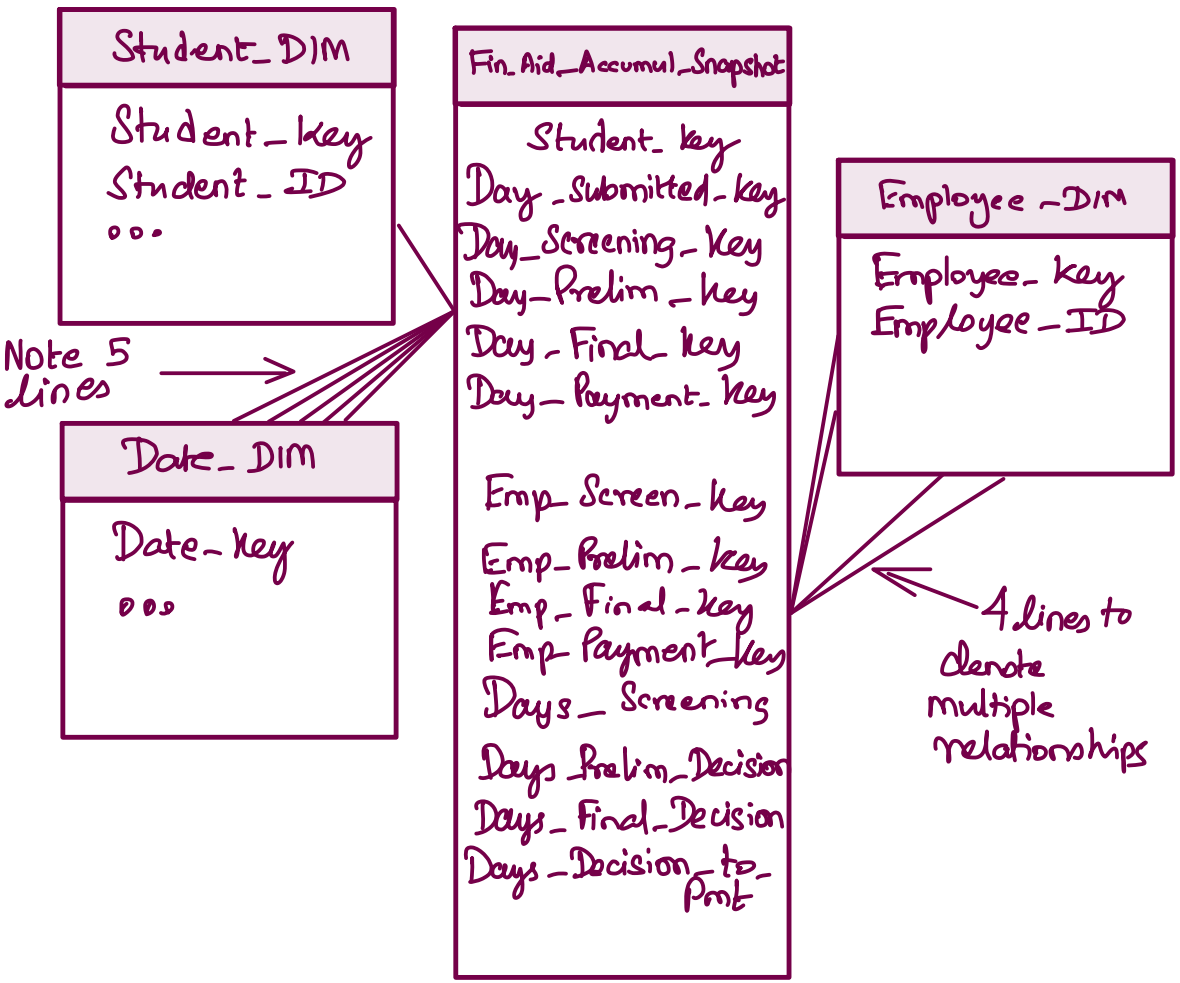
Elapsed time spent in each phase
Include both completed and in-progress phases
Can also track other measures as a process proceeds
Introduces concept of multiple relationship from fact table to a single dimension table. We have seen from multiple dimensions to a single fact table.

Eg Student financial aid application process

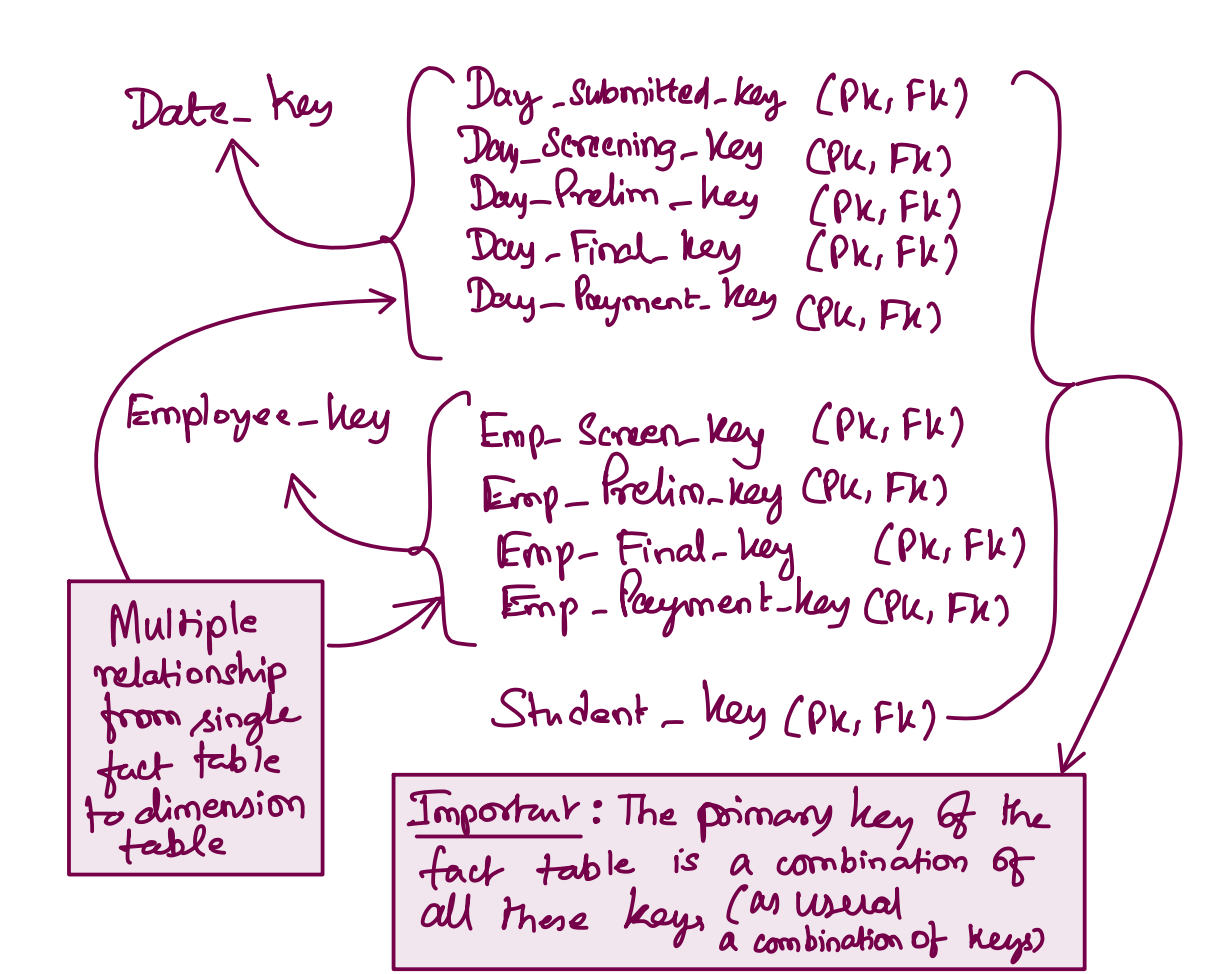


Dimensions for this process

Student
Time (Specific day a phase begins)
College employee responsible for each phase



The name of key in accumulating snapshot fact table is not the same as the name of the primary key dimension table.



① Accumulating Snapshot fact table example

Richard applies for $8000 on 8/11/2020

Student_key	Date_Submitted_key	....	Employee_Screen_key	...
48101234	832128		986531	

Other columns in Fin_Aid_Accumnl_Snapshot

... Day_Screening ...

1

"Day_Screening" is incremented to 2

Day 2 → Application still being screened

Day 3 → Screening completed

... Day_Screening_key 638321 ... Days_Screening 3

Day 4 ... Employee_Prelim_key 532128 ... Days_Screening 3

Some other employee has handled the stage.

... Days_Prelim_Decision 1 ...

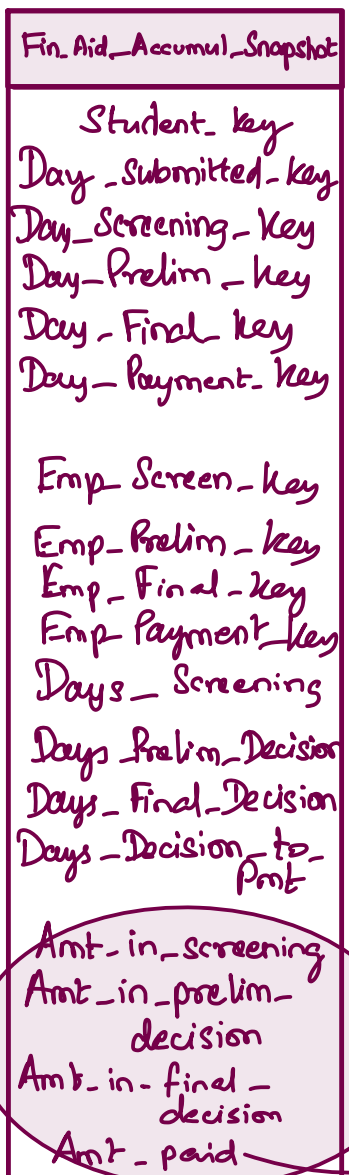
Day 5 Still in processing ... Days_Prelim_Decision... 2

and Eventually the entire record is filled in!

Fin_Aid_Accumul_Snapshot	Data
Student_key	48101234
Day_Submitted_key	832128
Day_Screening_key	638321
Day_Prelim_key	739432
Day_Final_key	861542
Day_Payment_key	976852
Emp_Screen_key	986531
Emp_Prelim_key	532128
Emp_Final_key	638714
Emp_Payment_key	639813
Days_Screening	3
Days_Prelim_Decision	4
Days_Final_Decision	3
Days_Decision_to_Pmt	6

Meanwhile other students are also applying for financial aid.

Can track other facts along the business process. Assume Richard is not paid the whole aid amount and gets paid $5000. We can track these additional facts.



Much more powerful and easier than using a transaction grained fact table

We can build additional reports like

- ✓ Average amount in screening
- ✓ Total amount in screening
- ✓ Average amount in final decision
- ✓ Total amount paid.

etc.

Additional facts

Sample values

$8000
$8000
$5000
$5000

(j) Why a factless fact table isn't a contradiction in terms

Recap Facts → Measurements

Fact ≠ Fact table

Factless

1. Record occurrence of a transaction that has no measurements
2. Record coverage or eligibility relationships.

Factless fact table

An event occurs that we want to track...

(eg) Students can register for online webinars throughout the semester.

Track

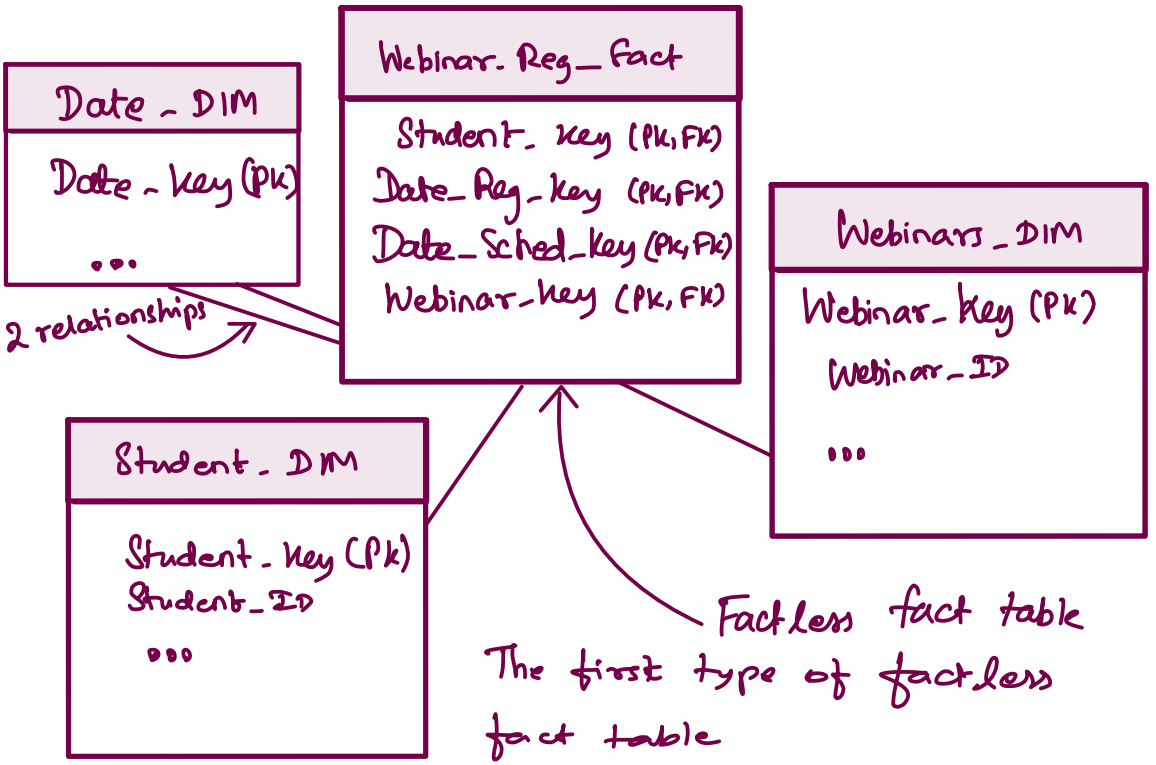
Which students register

which webinar

The date each student registers for a given webinar

The scheduled date for each webinar

Recording registrations in a fact table



Factless fact table

The first type of factless fact table

The "measurement" is actually the occurrence of the event.

presence of a row is therefore the measurement

Can count rows with or without filters

Factless fact table = PK/FK columns only *

Questions

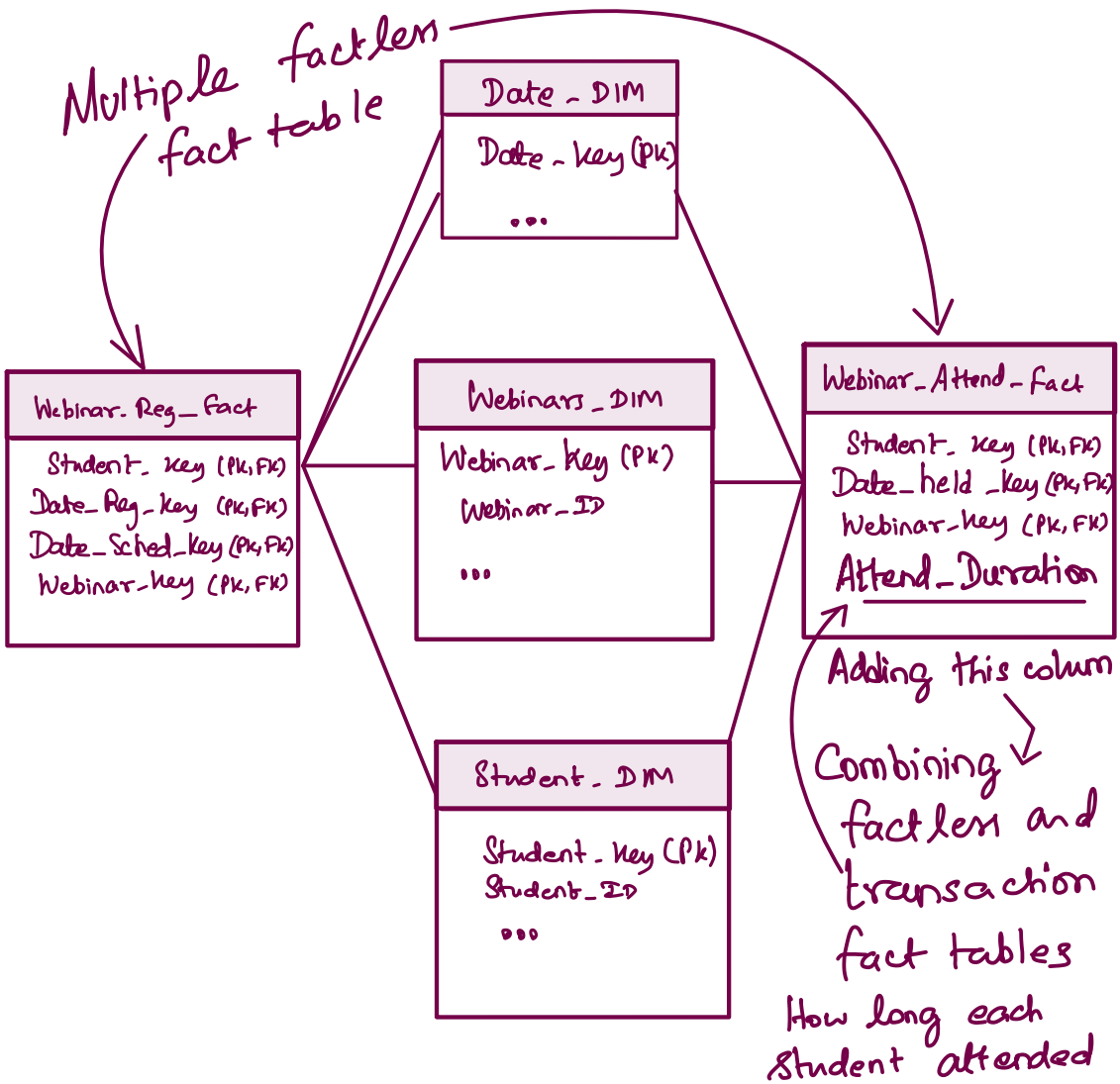
How many webinars were held last semester?

How many webinars has Rob registered for since becoming a student.

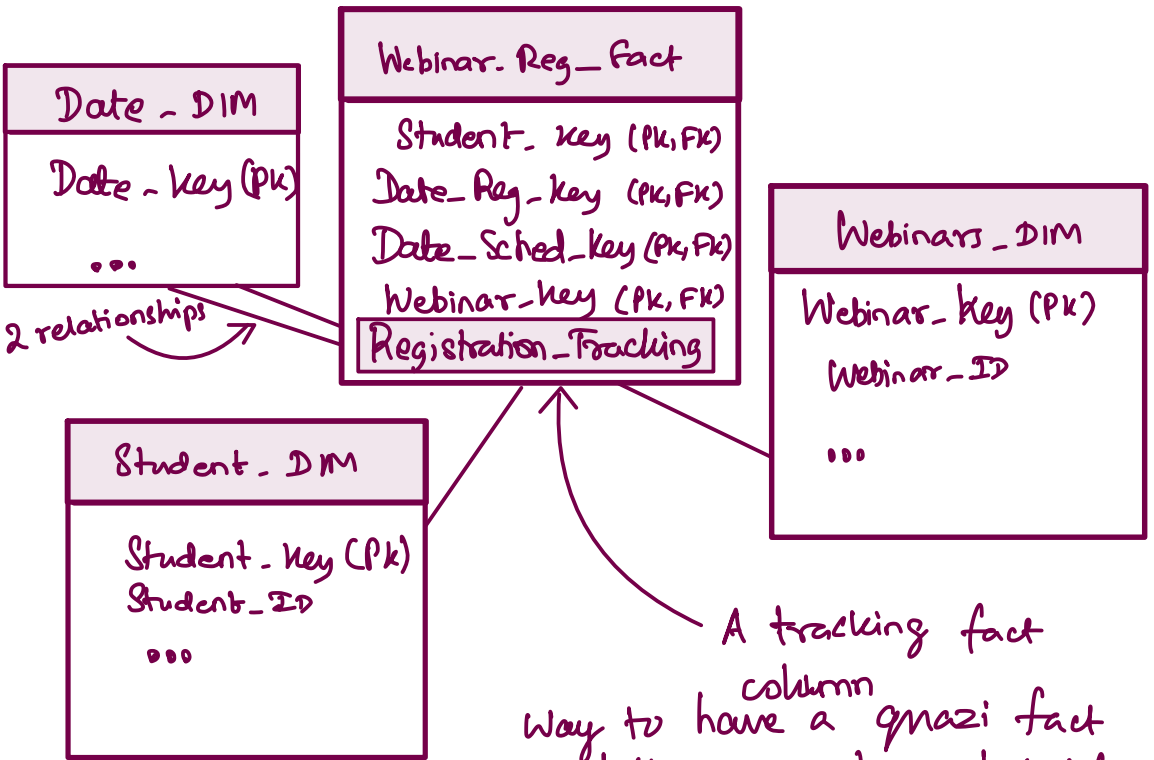
* See p.52

You can essentially query by a dimension and count the records in the factless fact table.

Can have multiple factless fact table in the same schema.



Sometimes use a "tracking fact"



A tracking fact column

Way to have a quazi fact

Some folks are not comfortable with a fact table without facts.

"Tracking fact" — Value is always = 1

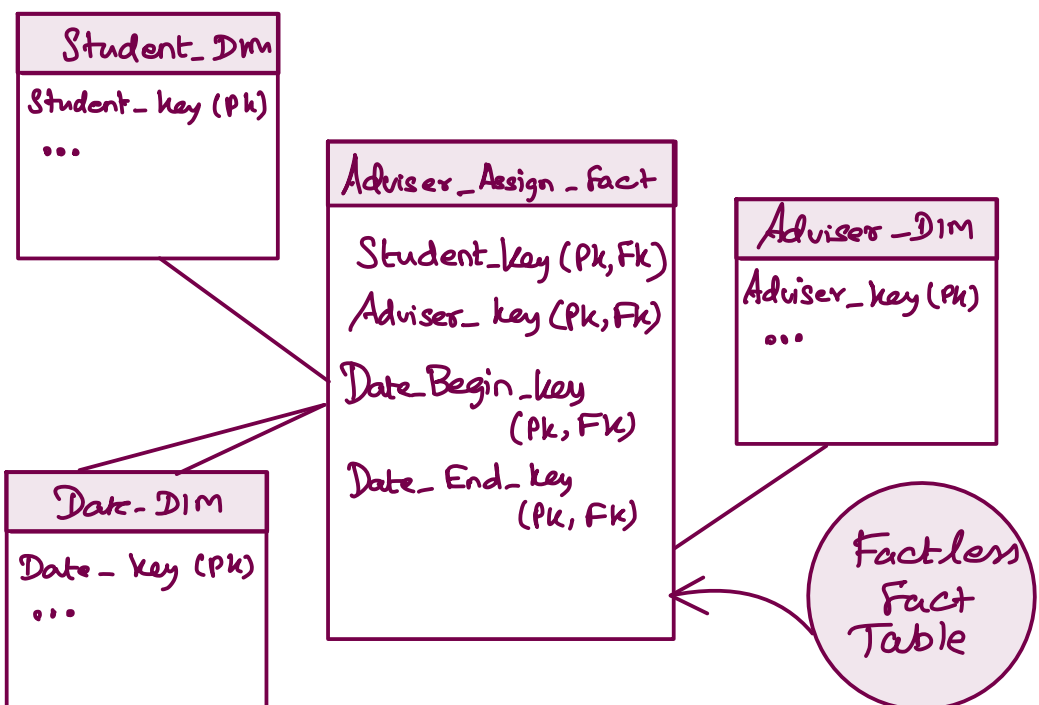
Allows you to use SQL SUM() function rather than COUNT() function.

More readable and understandable but it is less efficient in execution.

2nd type of factless fact table

Allows
- Record coverage or eligibility relationships among multiple parties
- Even if no transactions occurred.
- Typically (but not always) between a starting and ending date or time.

Academic Advisers assigned to students



If student visited advisor we can use the first type of factless fact table, to record that occurrence.

If we record duration of visit, could use a regular transaction-grained fact table.

* What if a student never visited his/her adviser?

Still we want to record the assignment.

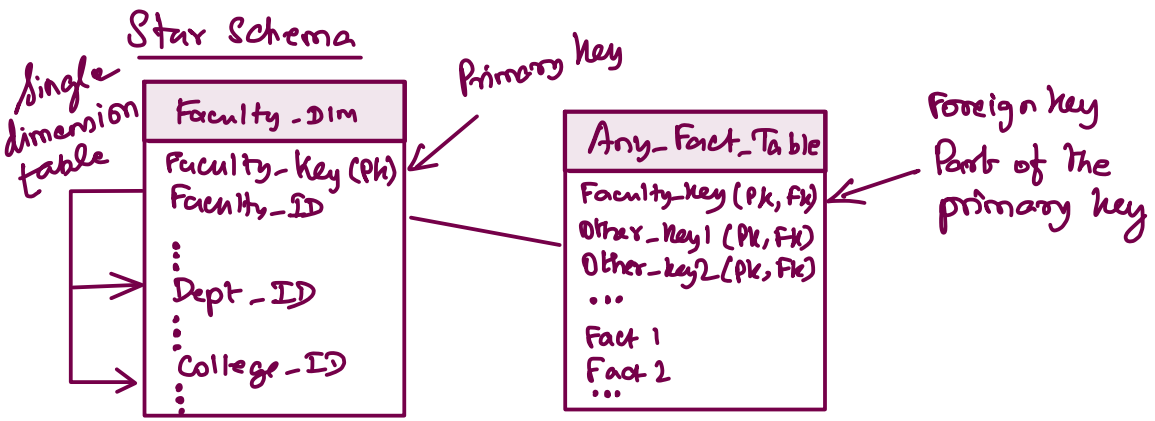
> Which students were assigned to an adviser from <from_date> to <to_date>

(K) Compare structure of fact tables in star vs. snowflake schema

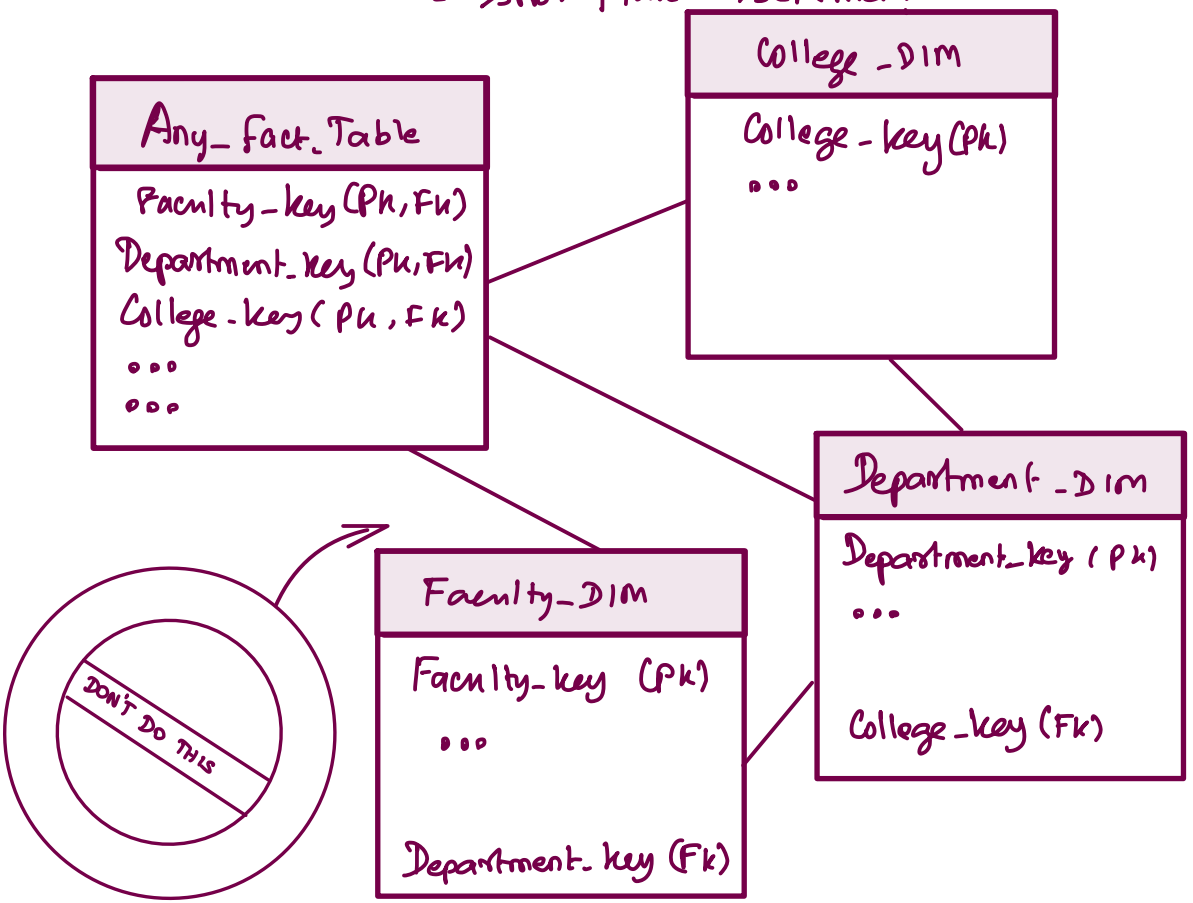
Star vs Snowflake schema

Recap Star vs Snowflake schemas for dimension tables.

Star schema	Snowflake schema
one primary key	primary key and foreign key



What about snowflake schema?



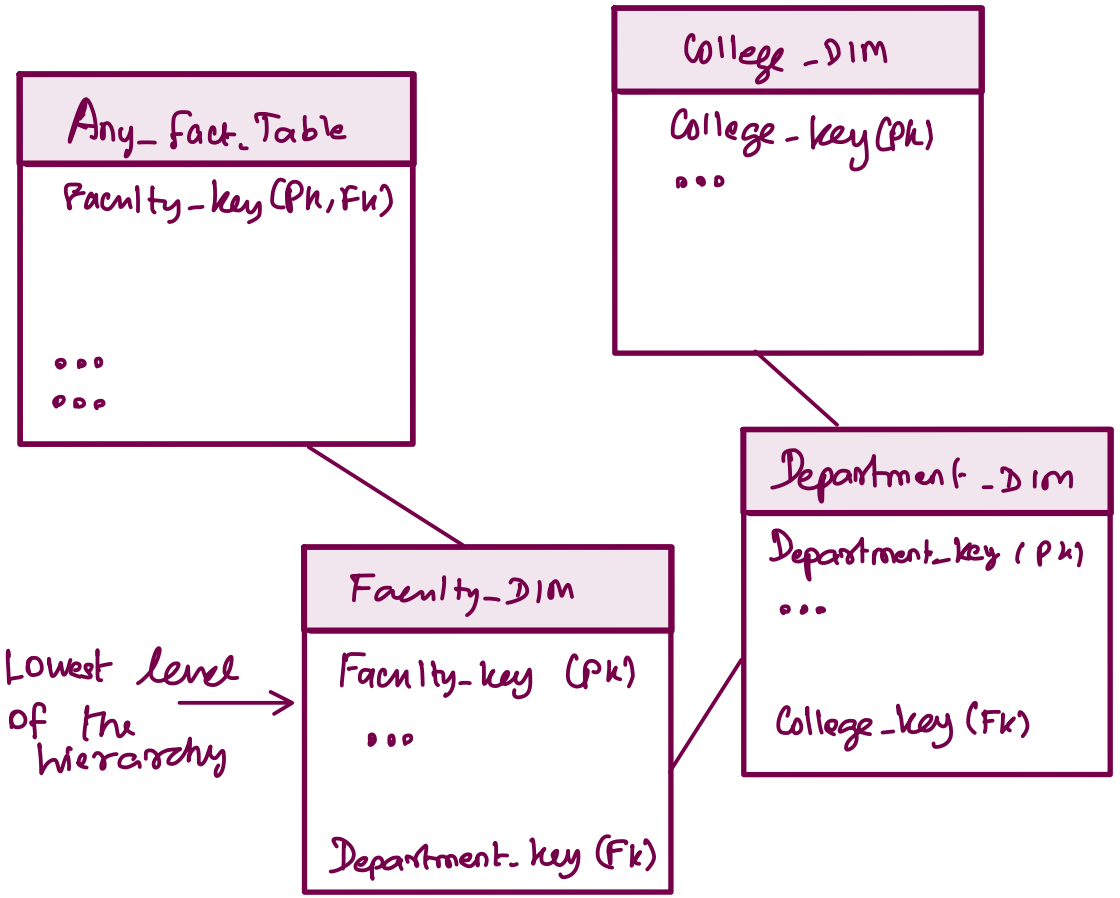
PK-FK links to every level of every hierarchy

- Unwieldy and complicated
- "Centipede" fact tables

} Not the most elegant solution.

Just have the PK and FK between the fact table and the related dimension table

In this case between Fact table and faculty dimension table.



(1) SQL for dimension and fact tables.

CREATE TABLE examples

- Star schema dimension table.
- Snowflake schema non-terminal dimension table.
- Snowflake schema terminal dimension table.
- Transaction-grained fact table.
- Periodic snapshot fact table.

- Star Schema Dimension Table

```
CREATE TABLE Faculty_DIM (
    Faculty_key                 INT NOT NULL,
    Faculty_ID                  VARCHAR(10) NOT NULL,
    Faculty_Last_Name           VARCHAR(40) NOT NULL,
    Faculty_First_Name          VARCHAR(20) NOT NULL,
    Year_Joined                 INT,
    Faculty_Rank                VARCHAR(20) NOT NULL,
    ...
    Dept_ID                     VARCHAR(10) NOT NULL,
    Dept_Name                   VARCHAR(40) NOT NULL,
    Dept_Year_Founded           INT,
    ...
    College_ID                  VARCHAR(10) NOT NULL,
    College_Name                VARCHAR(40) NOT NULL,
    College_Year_Founded        INT,
    Dean                        VARCHAR(50) NOT NULL,
    ...
    PRIMARY KEY (Faculty_key)
),
```

Single key only in a star schema dimension.

- Snowflake schema non-terminal dimension tables

```
CREATE TABLE Faculty_DIM (
    Faculty_key                 INT NOT NULL,
    Faculty_ID                  VARCHAR(10) NOT NULL,
    ...
    ...
    Department_key              INT NOT NULL,
    PRIMARY KEY (Faculty_key),
    FOREIGN_KEY (Department_key) REFERENCES
);          Department_DIM (Department_key)
```

Non terminal dimension table has PK, FK relationship.

Similarly for Department table

```
CREATE TABLE Department_DIM(
    Department_key      INT NOT NULL,
    ...
    ...
    PRIMARY KEY (Department_key),
    FOREIGN KEY ((College_key) REFERENCES
                College_DIM (college_key)
);
```

- Snowflake schema for terminal dimension tables

```
CREATE TABLE College_DIM(
    College_key     INT NOT NULL,
    ...
    PRIMARY KEY (College_key)
);
```

No Fk as it is the terminal dimension.

- Transaction grained fact table

```
CREATE TABLE Tuition_Bill_Fact(
    Student_key             INT NOT NULL,
    Date_key                INT NOT NULL,
    Tuition_Bill_Amt        DECIMAL (8,2) NOT NULL,
    Activities_Bill_Amt     DECIMAL (8,2),
    PRIMARY KEY (Student_key, Date_key),
    FOREIGN_KEY (Student_key) REFERENCES
            Student_DIM(Student_key),
    FOREIGN_KEY (Date_key)  REFERENCES
            Date_DIM (Date_key)
);
```

Pk is combination of Fks

FK for each dimension

- Periodic snapshot fact table

e.g. Meal card balance

```
CREATE TABLE Meal_Card_Payment_fact (
    Student_key          INT NOT NULL,
    Date_key             INT NOT NULL,
    Campus_key           INT NOT NULL,
    Meal_Card_Balance    DECIMAL (8,2) NOT NULL,
    PRIMARY KEY (Student_key, Date_key, Campus_key),
    FOREIGN KEY (Student_key) REFERENCES
        Student_DIM (Student_key),
    FOREIGN KEY (Date_key) REFERENCES
        Date_DIM (Date_key),
    FOREIGN_KEY (Campus_key) REFERENCES
        Campus_DIM (Campus_key)
);
```

Primary key is Combination of FKs

Foreign key clauses for each dimension

If you have more than one reference to same dimension you will have appropriate number of FOREIGN KEY clauses

⑥ Managing DW History through Slowly changing dimensions

SCD ⟶ Slowly Changing Dimensions.

@ SCDs and DW History

- Techniques to manage history within DW.
- Multiple techniques based on various historical data policies
- Enables DW to appropriately manage history regardless of policies in transactional applications.

3 main policies

Overwrite old data : no history retention	Type 1
Maintain unlimited history	Type 2
Maintain limited history	Type 3

SCD Type	Technique	Implications
Type 1	"In-place update" ETL pattern.	Simplest... but no history maintained.
Type 2	Create new dimension table row for each new version of history	Most architecturally complex, but robust representation of history
Type 3	Small number of dimension table columns for multiple "versions" of history	Easily switch back and forth between "as-is" and "as-was" reporting.. but limited use cases.

Even more SCD types

- Type 0 (always retain original value)
- Type 4 (mini-dimension)
- Types 5, 6, 7 (various hybrid techniques)

Our Focus

Type 1	overwrite
Type 2	new row
Type 3	new column

(b) Designing a type 1 SCD.

Replace old value with new value

Before → Column: old_value

After → column: new_value

Old_value lost ✓

Eg. Correcting errors with type 1 SCD

eg. Fixing student's birthdate that was entered incorrectly

Advantages	Disadvantages
Simplest and most straightforward	Might still want history of errors for auditing purposes
DW content errors are purged forever	Reporting before and after type 1 change could vary
Best for error correction and any other "don't need any history" situations.	Tendency to overuse type 1 changes as it is easier than type 2.

5) Designing a type 2 SCD

Type 2

existing row remains as-is.
new row added to dimension table
new row reflects current state of all attributes
complications with reporting and analytics.

Before — Column: Old_value

e.g. Student relocating from one state to another → we need the history

After — Column: Old_value, New_value } Both old and new

Note: The Student_key (Dimension table's PK is auto generated. is a surrogate key)

Student_key	Name	State	
456312	Ted	CA	← Old version
458643	Ted	CO	← current version

Why would we need both versions?

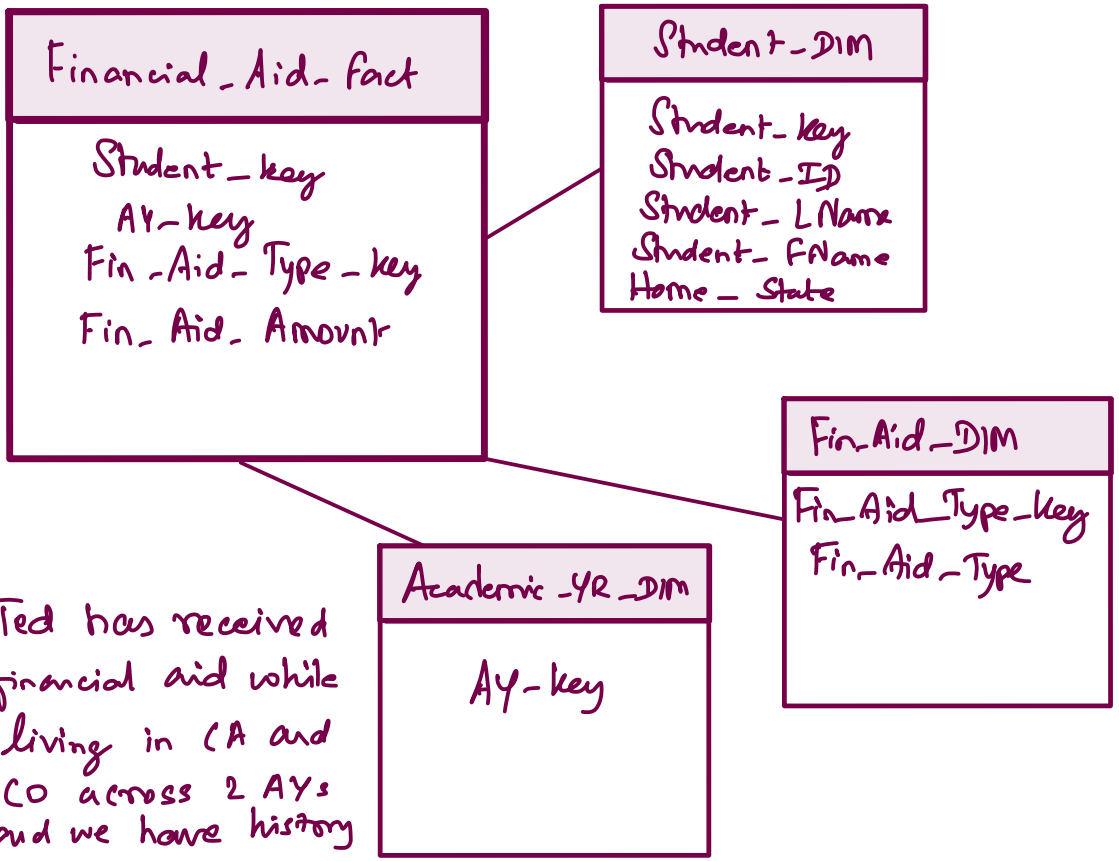
Reasons for Type 2 SCD

Reporting and analytics before the type 2 change needs to accurately reflect data values.

Report average student financial aid amt for last year by home state.

Last year Ted's home state was CA. So we need history for these kind of reports.

Fact table complications with type 2 SCDs



Ted has received financial aid while living in CA and CO across 2 AYs and we have history

Student_key	Student_ID	Student_LName	Student_FName	Home_State
985631	TYOUNG21	Young	Ted	CA
384081	TYOUNG21	Young	Ted	CO

Student_key	AY_key	Fin_Aid_Type_key	Fin_Aid_Amount
985631	221323	1181	$7500.00
384081	581233	1181	$2500.00

In the above example if you want to report all the aid that Ted received, we have a small problem. 2 records have different Student_keys.

Correct reporting with type 2 SCDs

Could include natural keys also in fact tables

Student_key	Student_ID	AY_key	Fin_Aid_Type_key	Fin_Aid_Amount
985631	TYOUNG21	221323	1181	$7500
384081	TYOUNG21	581233	1181	$2500

Natural key

WAIT! Unwieldy and takes significant storage for fact tables with many dimensions and billions of rows!

Recommendation Do not include the natural keys also in fact tables.

Best handled through careful multi-step SQL between dimension tables and fact tables.

First: find all surrogate keys for desired student.

Next: retrieve all fact table rows for all of the relevant surrogate keys.

There is yet another challenge

"Maintain correct data order with type 2 SCDs"

ⓓ Maintain correct data order with type 2 SCDs

SCD type 2 change → We have before and after records – how do we know which is which?

Type 2 SCDs and historical sequencing

"Base" type 2 change maintains limitless versions. But doesn't indicate the order of those versions.

2 main solutions. **First : Current_Flag column**

Dimension table

Col 1	Col 2	Col 3	Col 4	...	Current_Flag
—	—	—	—		Y
—	—	—	—		Y
—	<Some data>				

Before change

Indicates record is current.

Col 1	Col 2	Col 3	Col 4	...	Current_Flag
—	—	—	—		Y
—	—	—	—		N
—	—	—	—		Y

Indicates old record.

Indicates record is current.

After change

"What if a row changes more than once?"

What if Ted moves from CO (Colorado) to NM (New Mexico)

2 rows will have current flag set to 'N'

Home_State	Current_flag	
CA	N	Which is first?
CO	N	
NM	Y	

Solution 2 : Instead of one flag we have 2 columns

Home_State	Effective_Date	Expiry_Date	
CA	8/11/2017	8/14/2020	Obsolete
CO	8/15/2020	11/2/2020	Obsolete
NM	11/3/2020	12/31/2199	This date way into the future indicates it is current.

Third Solution

Combination of 1 and 2

Effective_Date	Expiration_Date	Current_flag

use this for use cases involving count!

⑥ Designing a Type 3 SCD

Type 2 robust but architecturally complex.

- Add a new column rather than new row to reflect changes.

- Old value column and new value column
- Supports back-and-forth switching for flexible reporting and analytics.

Type 3 SCD example

Textbook publishers sales divisions being reorganised

Formerly NORTH and SOUTH

Now EAST, WEST, CENTRAL

All sales reps reassigned to 1 of the 3 new divisions

Reorganization effective 01 01 2021

We want to report

> 2020 (and earlier) sales data "sliced" by the old NORTH and SOUTH divisions.

> 2021 (and forward) sales data "sliced" by the new EAST, WEST and CENTRAL divisions.

But also:

We want to report:

2020 (and earlier) sales data sliced by new EAST, CENTRAL and WEST divisions.

2021 (and forward) sales data sliced by old NORTH and SOUTH divisions.

Old and new sales data together, 'sliced' by either old or new division structures.

"We could use type 2 changes but queries are very complex"

A "Better" Solution

Sales_Rep_Dim

Sales_Rep_key	...	...	Current_Div	Previous_Div
4367			E	S
8316			E	N
3612			C	N
4319			W	S

Report / Analytic	Column to use
2020 (and earlier) by N & S	Previous_Div
2021 (and forward) by E, W & C	Current_Div
2020 (and earlier) by E, W, & C	Current_Div
2021 (and forward) by N & S	Previous_Div
Old and new by either old or new	Current_Div or Previous_Div

It seems easy? Because it is easy.

Type 3 SCD limitations

Use cases where every row in a dimension table is (or might) change at the same time

Reorganisations → classic use case

Not suited for random changes such as students' addresses.

Final Points: Type 3 SCD

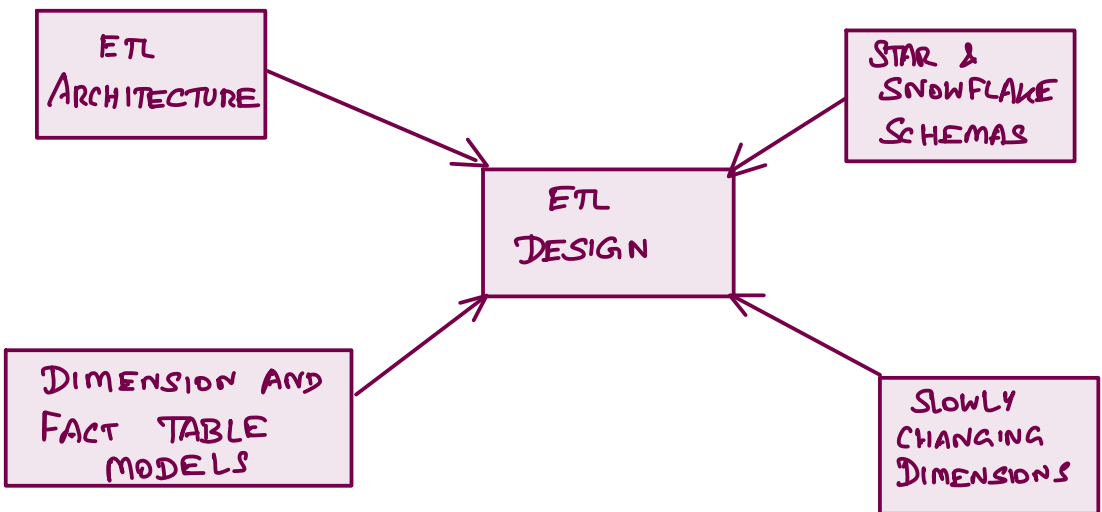
Not limited to only 2 columns (prev. vs. current). Could have 3 or 4 e.g. Reorganization history over time.

A large # of columns becomes unwieldy and better to use Type 2

⑦ Designing Your ETL

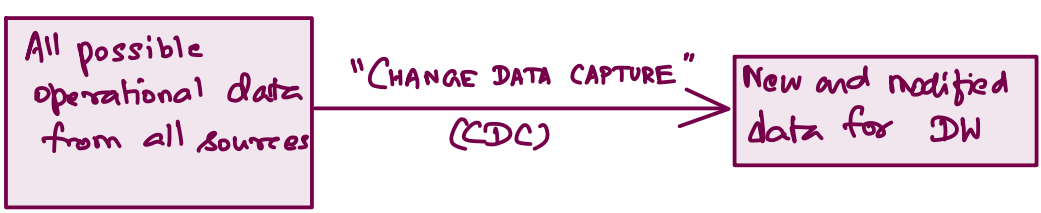
@ Build your ETL design from your ETL Architecture

Data Sources —ETL→ DW

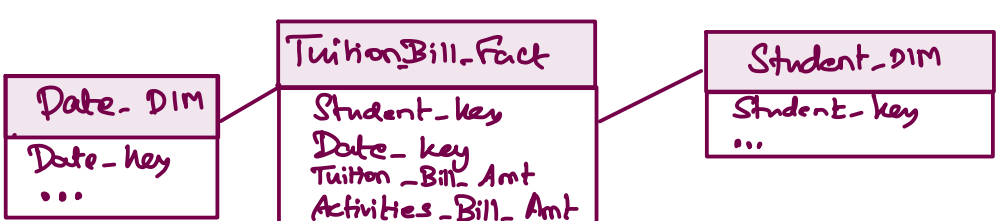


ETL Best Practices and Guidelines

- Limit the amount of incoming data to be processed.

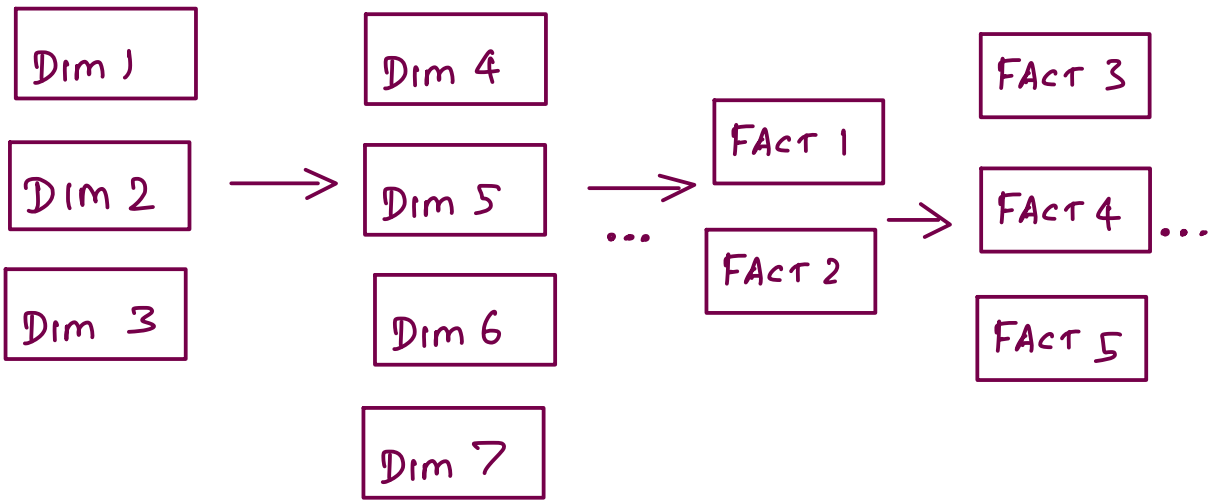


- Process dimension tables before fact tables.



We need to process Dim before fact as we need the surrogate key (PK). Process all Dim tables and then create the fact table.

- Opportunities for parallel processing.



ETL for

Boundary indicates our focus areas.

SCD Type 1 SCD Type 2 SCD Type 3	Star Schema Snowflake schema
Append In-place update Complete Replacement Rolling Append	Transaction grained fact table Periodic Snapshot fact table Accumulating Snapshots Factless fact table

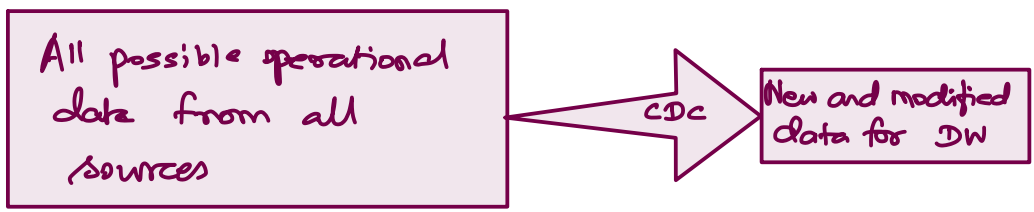
⑥ Dimension table ETL

Star Schema ETL (not Snowflake schema)

ETL for snowflake schema is complex given the hierarchy.

Dimension table incremental ETL

Step 1: Data preparation



"Change Data Capture" Techniques

- Transaction data timestamps ← Compare with last ETL run's timestamp.
- Database logs (if not)
- Last resort: database scan and compare.

Step 2 Data transformation

Refer to common transformation models discussed earlier.

Data value unification
Data type and size unification
De-duplication
Dropping columns (vertical sizing)
Value based row filtering (horizontal slicing)
Correcting known errors.

Step 3 Process new dimension rows

Step 4 Process SCD type 1 changes

Step 5 Process SCD type 2 changes

More accurately :

For each row:

If new: add to DIM table ← Here every new row gets brand new surrogate key.

If not new: process any type 1 and type 2 changes

Faculty → Faculty_DIM

As new records are added new surrogate keys get added to the dimension.

© Process SCD Type 1 changes to a dimension table

Correcting errors with type 1 SCD. "History is lost forever."

Basic in-place update.

SCD Type 1 complication

Even though it might be a simple in-place update we may need to apply that to more than one row

> Why? If we had a type 2 change that occurred before the type 1 change

The type 2 change leaves more than one row!

Apply type 1 change to all relevant rows.

How to handle this? IMPORTANT

Look for all dimension table rows for the natural key

If you make a type 1 change you need to handle that for all possible cases.

④ Process SCD Type 2 changes to dimension table.

Basic append with a new surrogate key

Use the natural key as a guide

After type 2 SCD

Student_key	Student_ID	Student_LName	Student_Fname	Home State	DOB
43621	TYOUNG21	TED	YOUNG	CA	11/4/2004
53123	TYOUNG21	TED	YOUNG	CO	11/4/2004

53123 ← New Record with new surrogate key.

43621 ← Old record

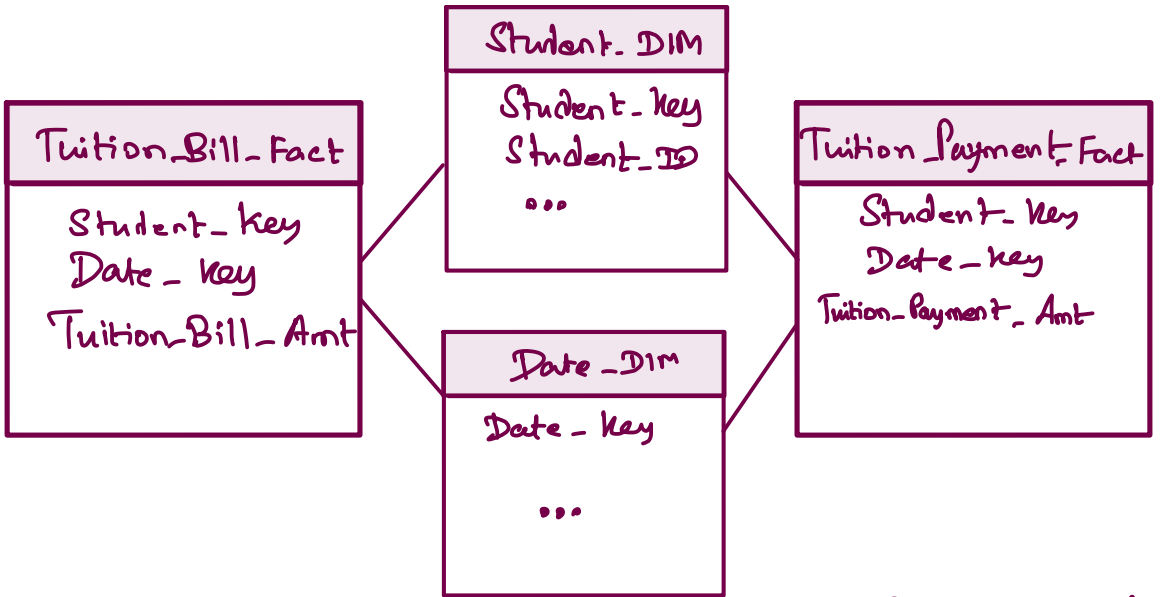
⑤ Design ETL for Fact tables

Process fact tables — Basic append but with a twist.

Refer to image in next page

2 fact tables.
2 dimension tables.

} Multiple fact tables and shared dimension tables



This example is going to use 'Tuition_Payment_Fact'

Tuition_payment_fact before ETL

Student_key	Date_key	Tuition_Payment_Amt
73273222	83853	$4500.00
83291245	46467	$3400.00
73678122	35356	$7000.00

Included in the next incremental ETL run

Ted Young pays $5000 in tuition

Transactional system provides natural keys

TYOUNG21 8/12/2021 $5000

But which Ted young?

↳ Meaning which version of Ted Young?

As other type 2 changes in Student_DIM happened.

Student_DIM

Student_key	Student_ID	Student_LName	Student_FName	Home_State	DOB
436431	TYOUNG21	Young	Ted	CA	4/16/2004
532215	TYOUNG21	Young	Ted	CO	4/16/2004
6167892	TYOUNG21	Young	Ted	NM	4/16/2004

We could assume the current version if we knew it.

Suppose if we are loading historical data?

Recollect the third solution (Kimball DW, toolkit)

Student_key	...<Other_columns>...	Effective_Date	Expiry_Date	Cur_Flag
436431		8/11/2017	8/15/2020	N
532215		8/16/2020	7/11/2021	N
6167892		7/12/2021	12/31/2199	Y

Handle versioning using Effective Date, Expiry Date, Cur_Flag

So for ETL" we need natural keys and relevant date"

Here for 8/12/2021 $5000 paid by TYOUNG21 there dimension table record is the one with Student_key 6167892 as the payment date is between effective date and expiry date.

Take this key and add an entry into the fact table!

Tuition_payment_fact after ETL

Student_key	Date_key	Tuition_Payment_Amt
73273222	83853	$4500.00
83291245	46467	$3400.00
73678122	35356	$7000.00
6167892	73864	$5000.00

new fact

ETL for a type 2 change in Fact table requires us to go to the dimension table.

"If we were loading historical data ..."

TYOUNG21 - 8/13/2018 - $4000

Record in dimension table for this date is Student_key 436431

Add entry into fact table using this student_key

After loading historic data !

Student_key	Date_key	Tuition_Payment_Amt
73273222	83853	$4500.00
83291245	46467	$3400.00
73678122	35356	$7000.00
6167892	73864	$5000.00
436431	89231	$4000.00

historic fact

IMPORTANT LESSON

Watch out for complications with all dimension and fact table data during ETL!

---

(8) Selecting your DW Environment

@ Decide between cloud and on premises settings for your Data Warehouse

On premises

IT megatrends

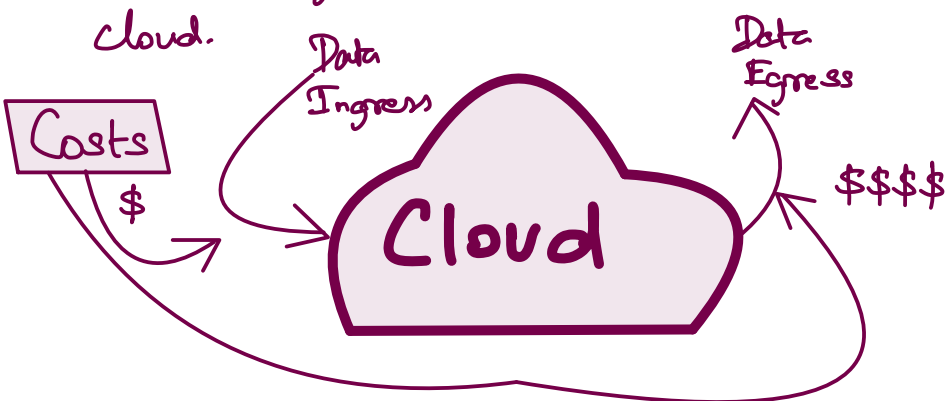
Big data and modern analytics
Social Media
Mobile technology
IoT and edge analytics
Cloud Computing ← Platform and hosting implications

→ Advantages

Offload routine system maintenance and upgrades
(Likely) lower initial platform investment.
Disaster Recovery
Data lake / big data synergies

Challenges

- Security (2 edged sword) (some responsibility gets delegated to cloud providers)
- Migrating existing DWs from on-premises to cloud.
- cloud to cloud data transport
  eg. OLTP (Azure) OLAP (AWS) ?
- Data transfer between corporate data center to cloud.



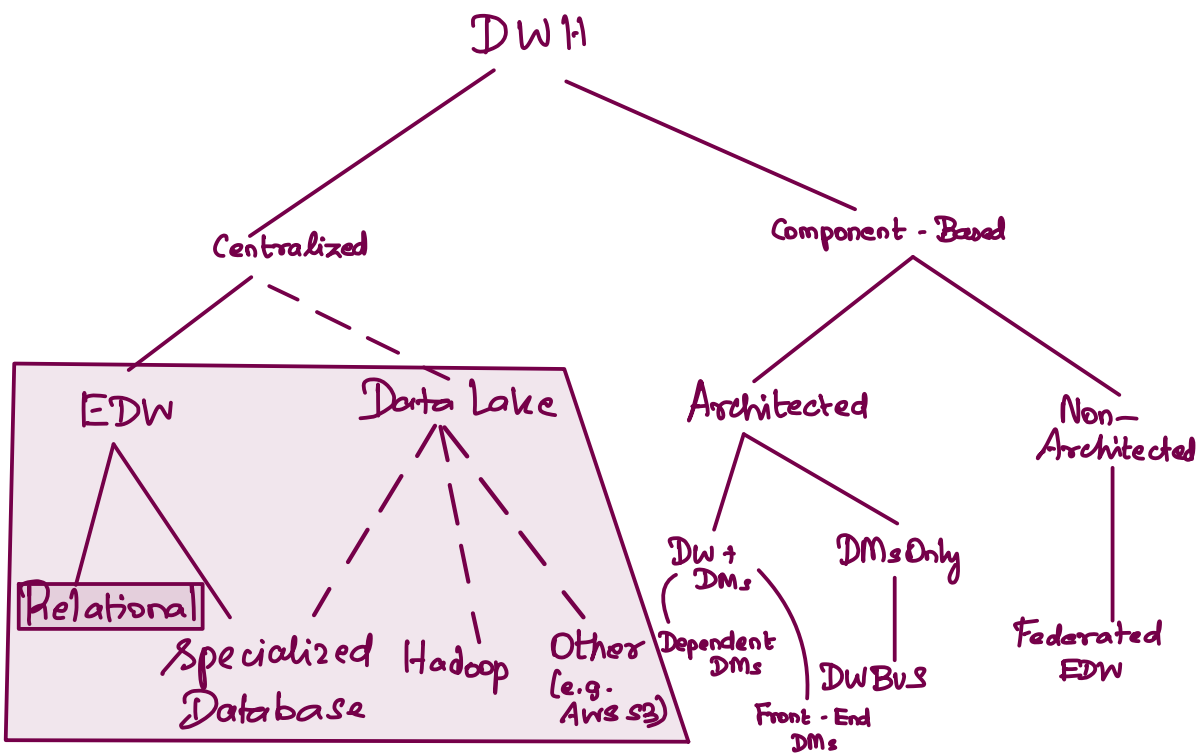
Data Egress Cost challenges

- Cost for large data volumes
- Not just operational data egress costs.
- Development, testing, QA, problem chasing...
- Experimental or exploratory analytics.

(b) Architecture and Design Implications for your selected platform

The diagram below is from section 1.

Our focus was on Relational EDW



Platform	User View (*)	Physical data model
On-prem RDBMS	Dimensional	Star / snowflake schema
On-prem DM Cube	Dimensional	Multidimensional
On-prem Specialized DB	Dimensional	Columnar, in-memory, etc.
cloud Hadoop	Dimensional	HDFS (SQL Access)
Cloud Aws S3	Dimensional	S3 Buckets (SQL Access)
Cloud RDBMS	Dimensional	Star / Snowflake schema
Cloud DM Cube	Dimensional	Multidimensional
Cloud Specialized DB	Dimensional	Columnar, in memory, etc.

(*) for OLAP / BI

Cloud based

Highlighted items trending upward as DW Platform

Implications

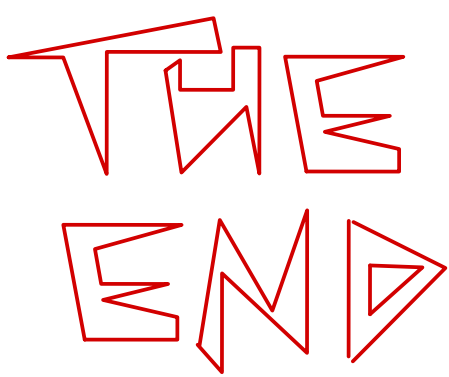
- DW shifting to the cloud
- Data lakes alongside or succeeding data warehouses
- RDBMSs still prevalent
- ...but being supplemented or replaced even for OLAP / BI

Think Dimensional!
(at least for user-facing BI)

Thank you for investing your time reading this. Thanks to Alan Simon for the wonderful course.

Additional Resources

Star Schema : The Complete Reference
The Data Warehouse Toolkit 3Ed.



SRIHARI SRIDHARAN