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Slowly changing dimensions and fast changing facts - the story of the traditional Datawarehouse



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Video Recording: https://www.youtube.com/watch?v=BcttdN rbBhk

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• Inmon, W. H. (1992). Building the Data Warehouse. Wiley.

The beginnings

- Codd, E. F., Codd, S. B., & Salley, C. T. (1993). Providing OLAP (on-line analytical processing) to user-analysts. *An IT Mandate. White Paper. Arbor Software Corporation*, *4*.
- Kimball, R. (1996). The Data Warehouse Toolkit: The Definitive Guide to Dimensional Modeling (1st ed.). Wiley.

Example of a business insight:

Company ABC made \$234,567 from the sale of 13" MacBookPro to customer XYZ

How do we generate this?

_	Α	В	C	D	E
			Opening Balance		900.00
	Date	Total Sales	Payments To Bank	Cumulative Total Sales	Cumulative Balance
	01/12/12	2000.00		2000.00	-1100.00
	02/12/12	1000.00	800.00	3000.00	-1300.00
	03/12/12	2300.00		5300.00	-3600.00
	04/12/12	1100.00	2500.00	6400.00	-2200.00
	05/12/12	500.00		6900.00	-2700.00
	06/12/12	1200.00	1000.00	8100.00	-2900.00
)	07/12/12	700.00		8800.00	-3600.00
	08/12/12	800.00		9600.00	-4400.00
	09/12/12	1200.00	5600.00	10800.00	0.00
}	10/12/12	200.00		11000.00	-200.00
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Take 1: Generate insights from existing databases



What is the problem?

Take 2: Generate the aggregates during the night when systems are not busy and store them in efficient data structures (data cube)



Dimensions of the cube: Subject, Student, Year Numbers in the subcubes: GPA





There's still a problem!

Insights require data from many sources, some of which may not even be databases (files, spreadsheets, etc) => need to Extract, Transform, and Load

Need to preserve historical data with a specific need to find temporal patterns

Performance does not scale as analytical processing needs grow; transaction processing cannot take a hit

Normalization can come in the way of efficient analytical query processing => need for a different way to model data

=> Cannot mix OLTP (operational) and OLAP (informational) systems!





An Example Fact Table: Sales

sale_id	product_id	time_id	location_id	branch_id	quantity_sold	amount
1	101	1	1	1	5	150
2	102	2	2	2	3	90
3	101	3	1	1	2	60
4	103	4	3	3	7	210
5	102	5	2	2	4	120



Dimensions are descriptive => They are wide => Mostly contain strings and some numbers => Less number of rows compared to fact table => Short and stout!

NO

Dimension Table: Time

time_id	date	day_name
1	2023-05-10	Monday
2	2023-05-11	Tuesday
3	2023-05-12	Wednesday
4	2023-05-13	Thursday
5	2023-05-14	Friday

Dimension Table: Location

location_id	location_name
1	City A
2	City B

Dimension Table: Product

product_id	product_name	category_id
101	Laptop	1
102	Smartphone	2
103	Tablet	1

Dimension Table: Branch

branch_id	branch_name
1	Store A
2	Store B
3	Store C

What are the total sales amount for each product in City A during the month of May 2023?

SELECT p.product_name, SUM(s.amount) AS total_sales_amount FROM Sales s JOIN Product p ON s.product_id = p.product_id JOIN Location I ON s.location_id = l.location_id JOIN Time t ON s.time_id = t.time_id WHERE l.location_name = 'City A' AND t.date BETWEEN '2023-05-01' AND '2023-05-31' GROUP BY p.product_name;



8/29/23





Key considerations

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What are the dimensions and how many of them?

I/O bound queries => minimize storage



What numeric quantities will be stored in the Fact table?



At what granularity will be facts be captured?

Tradeoff: finer grain => better detail for drilling down, but more rows

An example

Suppose there are 60 dimensional attributes and 3 facts to be captured in the fact table How do we design the star schema? How many dimension tables? Choices:

- A.One dimension with all 60 attributes
- B.Each attribute gets its own dimension table
- **C.Four dimensions**

FK	Fact 1	Fact 2	Fact 3

A: One dimension with all 60 attributes

B: Each attribute gets its own dimension table





C: Four dimensions



- Option A is the worst dimension can have as many rows as the fact table!
- Option B dimensions occupy less storage, but the fact tables will be very wide and occupy huge storage, still less than in Option A
- Option C is the best do the math!



How do we handle rarely occurring changes to dimensions?

- Do nothing ignore the changes (type 0)
- Overwrite the existing values erase history (type 1)!
- Find ways to preserve the history – Type 2, 3, 4, …



Silver

Los Angeles

SCD Type 1: In-Place Update

	customer_id	customer_name	city	loyalty_status
Initial Customer	101	John Smith	New York	Gold
Dimension	102	Jane Doe	Los Angeles	Silver
Requested	customer_id	customer_name	city	loyalty_status
Customer update	101	John Smith	Boston	Platinum
	customer_id	customer_name	city	loyalty_status
Opdated Customer	101	John Smith	Boston	Platinum
Dimension	400			0.1

Jane Doe

SCD Type 2: Historical Tracking

102

	customer_i	d cı	usto	mer_name	city		loyalt	y_status
Initial Customor	101		John Smith		New York		Gold	
Dimonsion	102	Ja	ane [Doe	Los Angeles		Silver	
Dimension								
Requested	customer_id		customer_name		city		loyalty_status	
Customer update	101		John Smith		New York		Platinum	
	customer_ id	custom name	er_	city	loyalty_st atus	effect date	tive_	end_date
Updated Customer	101	John Sm	nith	New York	Gold	2023- 01	01-	2023-08- 10
Dimension	101	John Sm	nith	New York	Platinum	2023-	08-11	(null)
	102	Jane Do	e	Los Angeles	Silver	(null)		(null)

SCD Type 3: Alternate Reality

	customer_id	customer_nar	ne city		loya	lty_status	
Initial Customor	101	John Smith	New Yo	ork	Gold		
Dimension	102	Jane Doe	Los An	geles	Silve	er	
Dimension							
Requested	customer id	customer nar	ne citv		lova	ltv status	
Customer update	101	John Smith	New Yo	ork	Plati	Platinum	
Undeted Customer	customer_id	customer_name	city	loyalty_sta	atus	prev_loyalt y_status	
Dimonsion	101	John Smith	New York	Platinum		Gold	
Dimension	102	Jane Doe	Los Angeles	Silver		(null)	

SCD Type 4: Monster / Mini Dimension

	customer_id	custo	mer_name	city		loyalty_status	
Initial Customor	101	John	Smith	New York		Gold	
Dimension	102	Jane	Doe	Los Angeles		Silver	
Dimension				-			
	customer_id		customer_r	name	city		
	101		John Smith		New York		
Loyalty_status is	102		Jane Doe		Los Angeles		
changing rapidly =>							
create a new mini	customer_id	loyalt	y_status	start_date		end_date	
dimension for it	101	Gold		2023-01-01		2023-08-10	
Undated Mini	customer_id	loyalt	y_status	start_date		end_date	
Dimension	101	Gold		2023-01-01		2023-08-10	
Dimension	101	Platinum		2023-08-11		(null)	





