732A54 / TDDE31 Big Data Analytics

Topic: Database Technologies for Data Analytics

Olaf Hartig olaf.hartig@liu.se



## Online Transactional Processing (OLTP)

- Most common use of relational DBs is for operational data
  - that is, data produced by the day to day operations of a business or an organization
  - e.g., students enrolling in courses, customers purchasing products, passengers purchasing airline tickets
- Workload characteristics:
  - simple queries (reads and writes)
  - many short transactions that make small changes
- Database systems that support the basic operations of a business are generally classified as *OLTP systems* 
  - tuned to maximize throughput of concurrent transactions



## Online Analytical Processing (OLAP)

- Enables analysts, managers, executives to gain insight into data as a basis for making decisions
- Primarily read-only workloads with complex queries
  - aggregations and grouping
  - touch large amounts of data
  - usually ad hoc



#### Data Warehouse

- Data warehouse: separate copy of the operational data, organized in a way that it can be used for executing decision support queries and/or data mining queries
  - usually a combination of data from multiple sources
  - data warehouses keeps years' worth of data (in contrast, operational data in OLTP systems is short-lived and changes frequently)



Figure from https://www.monitis.com/blog/top-5-data-warehouses-on-the-market-today/

![](_page_3_Picture_6.jpeg)

#### Why a separate system?

- Usually a combination of data from multiple sources
- Data organized differently, to better support OLAP queries
- Complexity of OLAP queries
  - take too much time to be executed in a transaction processing system with high throughput requirements
  - may lock the database for long periods of time and, thus, negatively affect all other OLTP transactions

![](_page_4_Figure_6.jpeg)

Figure from https://www.monitis.com/blog/top-5-data-warehouses-on-the-market-today/

![](_page_4_Picture_8.jpeg)

#### **Categories of OLAP Systems**

- Relational OLAP systems ("ROLAP")
  - Store data in relations
  - Queries written in SQL
- Special-purpose OLAP systems
  - Represent and store data in a multi-dimensional array
  - OLAP-specific query language or spreadsheet-like UI

![](_page_5_Picture_7.jpeg)

#### **Multidimensional Data Model**

![](_page_6_Picture_1.jpeg)

## Multidimensional Data Model

- Numeric measures that are the focus of the analysis
  - e.g., sales amount, budget, revenue, inventory counts
- Each such measure depends on a set of dimensions
  - e.g., dimensions of a sales amount may be product name, city, and date
- Each dimension described by a set of attributes
  - e.g., product dimension may consist of product category, industry of the product, year of introduction, and average profit margin
- Some attributes may form a hierarchy of relationships

Example from Chaudhuri and Dayal: An Overview of Data Warehousing and OLAP Technology. SIGMOD

![](_page_7_Figure_9.jpeg)

![](_page_7_Figure_10.jpeg)

![](_page_7_Picture_11.jpeg)

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## Multidimensional Model in an RDBMS

- Dimension tables with the attributes of the dimensions
- Fact table with a column for each dimension (foreign keys to the dimension tables) and for the numeric measures
  - i.e., one tuple/row per cell of the multidimensional array
- Star schema: single dimension table for each dimension

![](_page_8_Figure_5.jpeg)

![](_page_8_Picture_6.jpeg)

## Multidimensional Model in an RDBMS

- Snowflake schema: dimension tables normalized
  - hence, hierarchies represented explicitly
  - e.g., LOCATIONS(locid, city, state) and STATES(state, country)

![](_page_9_Figure_4.jpeg)

https://www.javatpoint.com/data-warehouse-star-schema-vs-snowfla

![](_page_9_Picture_6.jpeg)

#### **Operations over Multidimensional Data**

![](_page_10_Picture_1.jpeg)

# Slicing and Dicing

- Slicing: reduce the dimensions by selecting a single value Campingausrüstung for one of the dimensions
  - like Outdoor-Schutzausrüstung ... WHERE *dimattr* = *xyz*
- Dicing: produce a sub-cube by selecting a range of values for one or more of the dimensions
  - like
    - ... WHERE *dimattr* > *xyz*
    - ... WHERE dimattr BETWEEN x AND y
    - ... WHERE dimattr IN (x,y,z)

Figures from Wikimedia Commons (https://en.wikipedia.org/wiki/File:OLAP slicing.png and https://en.wikipedia.org/wiki/File:OLAP dicing.png)

200

200

2004

Nordeuropa

Nordeuropa

Südeurop

Südeurop

Mitteleuropa

Mitteleuropa

Accessoires

Golfausrüstung

Bergsteigerausrüstung

Campingausrüstung

Outdoor-Schutzausrüstung

Bergsteigerausrüstung

Accessoires

Golfausrüstung

![](_page_11_Picture_9.jpeg)

2004

Nordeuropa

2006 -

Nordeuropa

2005

2004

Accessoires

Golfausrüstung

Outdoor-Schutzausrüstung

Südeuro

Mitteleuropa

Südeurop

Mitteleuropa

Campingausrüstung

Outdoor-Schutzausrüstung

Bergsteigerausrüstung

Accessoires

Golfausrüstung

## Roll-Up and Drill-Down

- Roll-up: aggregate the data along one or more dimensions (usually by moving up the hierarchy in these dimensions)
  - e.g., sum up by months instead of days, or by countries instead of cities
- Drill-down: opposite of roll-up
  - i.e., produce a more fine-grained view

![](_page_12_Figure_5.jpeg)

Figure from Bolt and Van der Aalst: Multidimensional Process Mining Using Process Cubes. In BPMDS 2015.

![](_page_12_Picture_7.jpeg)

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#### Pivoting

• Pivoting: rotate the cube to show a different orientation of the axes

![](_page_13_Figure_2.jpeg)

Figure from https://visibledata.wordpress.com/data/datacloud/datacube/

![](_page_13_Picture_4.jpeg)

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#### **Building a Data Warehouse**

![](_page_14_Picture_1.jpeg)

# **Building a Data Warehouse**

![](_page_15_Figure_1.jpeg)

- Identify desired data sources
- Scope the analytics needs that the project is meant to solve
- Define the data model/schema that the analysts and other end users need
- Build an extract-transform-load pipeline
- Conduct analytics work, extract insights

![](_page_15_Figure_7.jpeg)

Figures from https://fivetran.com/blog/etl-vs-elt and https://www.monitis.com/blog/top-5-data-warehouses-on-the-market-today/

![](_page_15_Picture_9.jpeg)

## ETL

![](_page_16_Figure_1.jpeg)

**Extract**: query the operational databases to retrieve relevant data, and run scripts to extract from other types of sources

Transform: clean the data (i.e., delete or repair tuples with missing or invalid information) and reorganize it to fit the schema of the warehouse

Load: populate the warehouse with the data, build indexes

![](_page_16_Figure_5.jpeg)

Figures from https://fivetran.com/blog/etl-vs-elt and https://www.monitis.com/blog/top-5-data-warehouses-on-the-market-today/

![](_page_16_Picture_7.jpeg)

#### Data Warehouse Systems

- On premise (now also with cloud offerings)
  - Teradata
  - Oracle
  - Vertica
  - Netezza
  - Actian Vector (formerly Vectorwise)
  - SAP IQ (formerly Sybase)
  - etc.
- Cloud native
  - Snowflake
  - Amazon Redshift
  - Google BigQuery
  - Azure Synapse Analytics
  - etc.

![](_page_17_Figure_15.jpeg)

![](_page_17_Picture_16.jpeg)

# Challenges of Data Warehouses and ETL

![](_page_18_Figure_1.jpeg)

- Data in the warehouse needs to be refreshed periodically
- Building and maintaining a data warehouse is a huge effort, may easily go into millions of \$

Figure from https://fivetran.com/blog/etl-vs-elt

![](_page_18_Picture_5.jpeg)

# Challenges of ETL

![](_page_19_Figure_1.jpeg)

- transformation code needs to be extended or rewritten

Figure from https://fivetran.com/blog/etl-vs-elt

![](_page_19_Picture_4.jpeg)

# Data Integration for Analytics in the Age of Cloud Services

![](_page_20_Picture_1.jpeg)

#### Data Integration

- Data integration is the problem of combining data [from] different sources [into a single] unified view of these data<sup>\*</sup>
  - schema mapping
  - record linkage (entity resolution)
  - inconsistent formats or units
- Modern technologies for data integration
  - Integration Platform as a Service (iPaaS)
  - ELT (Extract, Load, and Transform)
  - Reverse ETL

\*Quote from Lenzerini: Data Integration: A Theoretical Perspective. PODS 2002

![](_page_21_Picture_10.jpeg)

## Integration Platform as a Service (iPaaS)

- Enable users to integrate applications with one another
  - in practice: an event in an application / system is transmitted to the iPaaS (via an API call or a Webhook) which then performs some predefined actions
- Data moves between applications directly through the iPaaS
- Little to no transformation takes place in the iPaaS

Figure from https://www.celigo.com/what-is-ipaas-integration-platform-as-a-service/

![](_page_22_Picture_6.jpeg)

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![](_page_22_Figure_8.jpeg)

**Olaf Hartig** 

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- Popular iPaaS
  - tray.io
  - workato
  - integromat
  - zapier
  - automate.io

![](_page_23_Figure_11.jpeg)

![](_page_23_Picture_12.jpeg)

## ELT: Extract, Load, and Transform

- Cloud data warehouses have become extremely fast and reliable, which enables transformations to take place inside the warehouse itself
- ELT: Data moves directly from (cloud) applications to the data warehouse; afterwards, transformation in the data warehouse *via SQL* Data Sources Fully Managed Data Warehouse
  - No coding required!

![](_page_24_Figure_4.jpeg)

Figure from https://fivetran.com/blog/etl-vs-elt

![](_page_24_Picture_6.jpeg)

#### **ELT Tools**

- Modern ELT tools don't even offer in-built transformation capabilities
  - which was one of the major parts of traditional ETL tools
- Instead, to handle transformations in the data warehouse they integrate purpose-built solutions

🚺 dbt

- e.g., dbt
- Leading companies:
  - Fivetran
  - Stitch
  - Matillion
  - Airbyte

Fivetran Estitch

![](_page_25_Picture_11.jpeg)

IRBYTE

## Workflows ETL versus ELT

![](_page_26_Figure_1.jpeg)

- Identify desired data sources
- Automatically extract & load (can be outsourced, scaled up and down)
- Scope the analytics needs
- Define and create the data model needed for the analytics work

Figures from https://fivetran.com/blog/etl-vs-elt

![](_page_26_Picture_7.jpeg)

## Workflows ETL versus ELT

![](_page_27_Figure_1.jpeg)

#### **Reverse ETL**

- Main use case: sync customer data from the data warehouse to sales, marketing and analytics tools
  - consistent view of the customer across all systems
  - enable operational analytics
- Main functionality of reverse ETL tools:
  - extract data from a data warehouse on a regular basis and load it into sales, marketing, and analytics tools
  - trigger a webhook or make an API call when data changes
  - move extracted data to a production database

![](_page_28_Picture_8.jpeg)

Figure from https://medium.com/memory-leak/reverse-etl-a-primer-4e6694dcc7fb

![](_page_28_Picture_10.jpeg)

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- Reverse ETL tools offer connectors for many cloud apps
- Startups that are building reverse ETL products: Hightouch,Census, Grouparoo, Headsup, Polytomic, SeekWell

hightouch Census 🚽 Grouparoo HEADSUP 👗 🔾 SEEKWELL

![](_page_29_Picture_11.jpeg)

www.liu.se

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