MUNI
FACULTY
OF INFORMATICS

PA220: Database systems for data analytics

ETL Process

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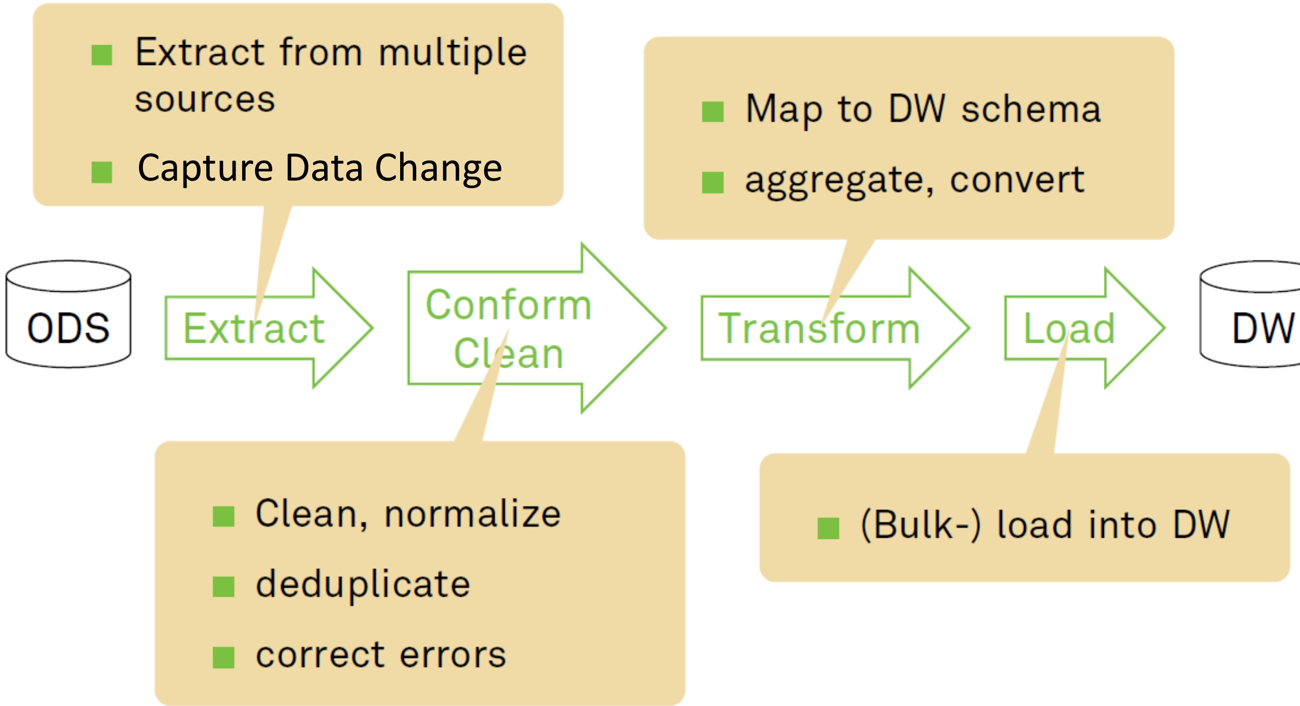
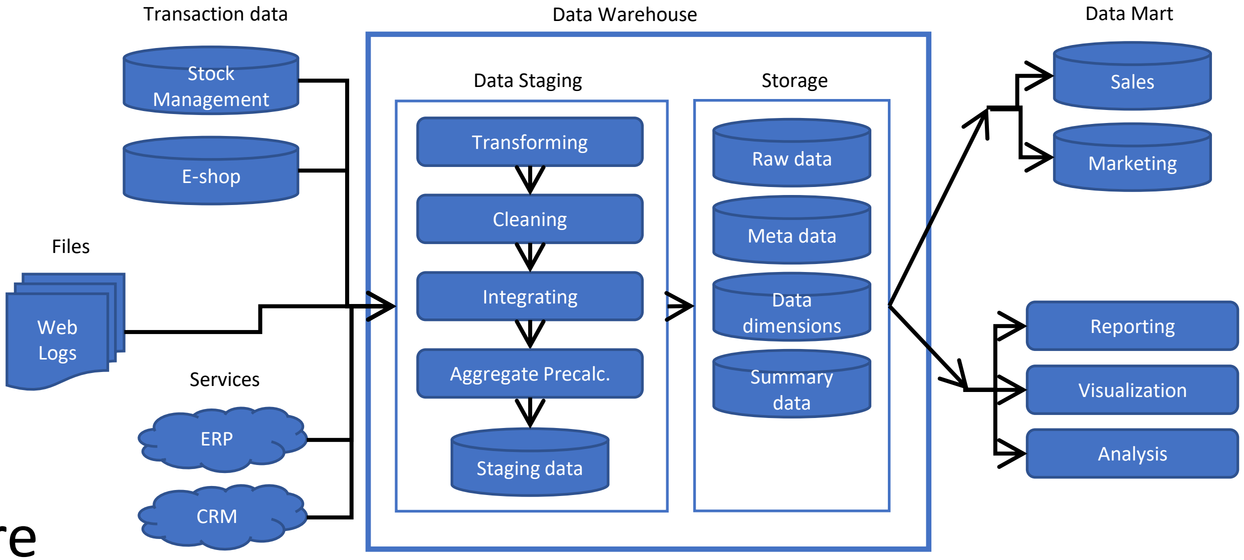
ETL Process Overview

- Data is periodically brought from the ODS to the data warehouse.
- In most DW systems, the ETL process is the most complex part.
  - and the most underestimated and time-consuming part.
    - Often, 80% of development time is spent on ETL



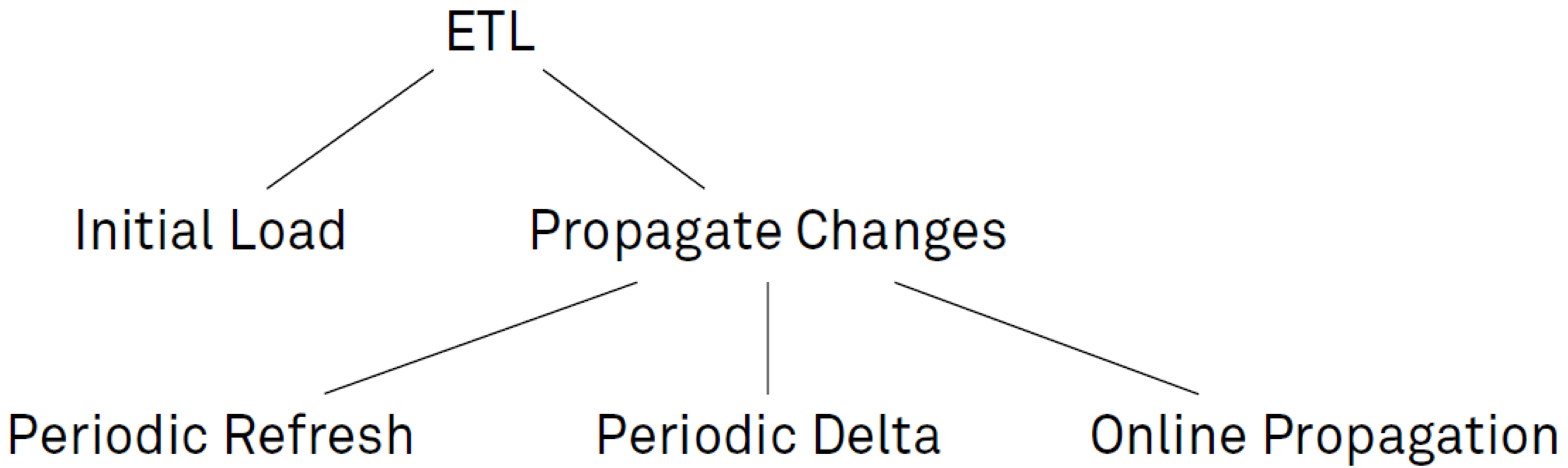
Data Staging Area



- Transit storage for data underway in the ETL process
  - Transformations/cleansing done here
- No user queries (some do it)
- Sequential operations (few) on large data volumes
  - Performed by central ETL logic
  - Easily restarted
  - No need for locking, logging, etc.
  - RDBMS or flat files? (DBMS have become better at this)
- Finished dimensions copied from staging area to relevant marts

ETL Process Types

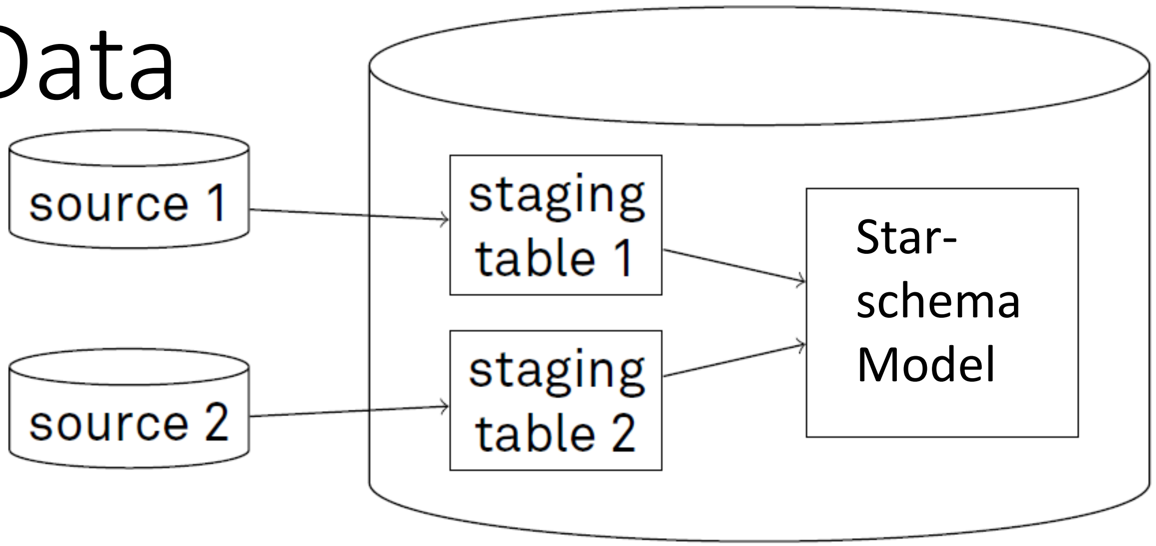
- When do we run the ETL process?



ETL Process Types

- Considerations:
  - **Overhead** on data warehouse and source sides.
    - E.g., online propagation puts a permanent burden on both sides; cannot benefit from bulk loading mechanisms
  - **Data Staleness**
    - Frequent updates reduce staleness but increase overhead.
  - **Debugging, Failure Handling**
    - With online/stream-based mechanisms, it may be more difficult to track down problems.
  - Different process for different flavors of data?
    - E.g., periodic refresh may work well for small (dimension) tables.

Data Extraction: Getting Data



- **Source → Staging Table**:
  - Tool selection depends on data source
    - database, XML, flat files, etc.
  - Use SQL, XQuery, Perl, awk, etc. to query the source system
  - Often:
    - Extract to flat file (e.g., CSV)
    - Then bulk-load into staging table

  - Data compression for large data transfers
  - Data encryption if transfer over public networks

Data Extraction: Capturing Data Changes

- Detecting changes is a challenge:
  - **Audit Columns**
    - E.g., “last modified” timestamp
    - Set timestamps or “new” flags on every row update. How?
    - Unset “new” flags on every load into the DW. Why?
  - **Full Diff**
    - Keep old snapshot and diff it with the current version.
    - Thorough, will detect any change
    - Resource-intensive: need to move and scan large volumes
    - Optimization: Hashes/checksums to speed up comparison
  - **Database Log Scraping**
    - The database’s write-ahead log contains all change inform.
    - Scraping the log may get messy, though.
    - Variant: create a message stream ODS → DW
  - **Message Queue Monitoring**
    - source system must use a messaging framework; then low overhead

Data Cleansing

- After extraction, data must be **normalized** and **cleaned**.

	Name	Street	CIty	Phone
r_1	Sweetlegal Investments Inc	202 North	Redmond	425-444-5555
r_2	ABC Groceries Corp	Amphitheatre Pkwy	Mountain View	4081112222
r_3	Cable television services	One Oxford Dr	Cambridge	617-123-4567

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Data Quality (Revision)

- Data almost never has decent quality
- Data in DW must be:
  - Precise
    - DW data must match known numbers - or explanation needed
  - Complete
    - DW has all relevant data, and the users know
  - Consistent
    - No contradictory data: aggregates fit with detail data
  - Unique
    - The same thing is called the same and has the same key (customers)
  - Timely
    - Data is updated ”frequently enough” and the users know when

Data Cleansing

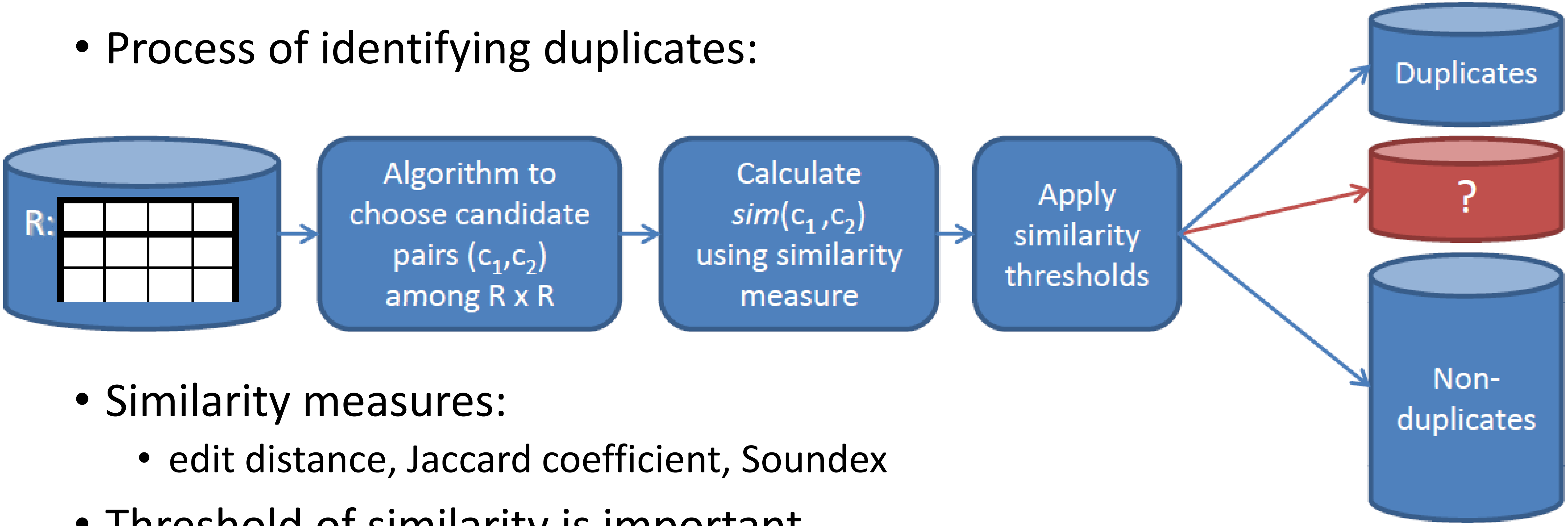
- Problem:
  - Real-world data is messy.
  - Consistency rules in the OLTP system?
    - A lot of data is still entered by people.
    - Data warehouses serve as an integration platform.
- Typical cleaning and normalization tasks:
  - Correct spelling errors.
  - Handle missing / null values
  - Identify record matches and duplicates.
  - Resolve conflicts and inconsistencies.
  - Normalize (“conform”) data.

Data Cleansing: Primitives

- Similarity Join
  - Bring together similar data
  - For record matching and deduplication
- Clustering
  - Put items into groups, based on “similarity”
  - E.g., pre-processing for deduplication
- Parsing
  - E.g., source table has an ‘address’ column; whereas target table has ‘street’, ‘zip’, and ‘city’ columns
  - Might have to identify pieces of a string to normalize (e.g., “Road” → “Rd”)

Data Cleansing: Similarity Join

- Process of identifying duplicates:



- Similarity measures:
  - edit distance, Jaccard coefficient, Soundex
- Threshold of similarity is important
  - Limits the number of candidates for duplicates!

Data Cleansing: Detecting Inconsistencies

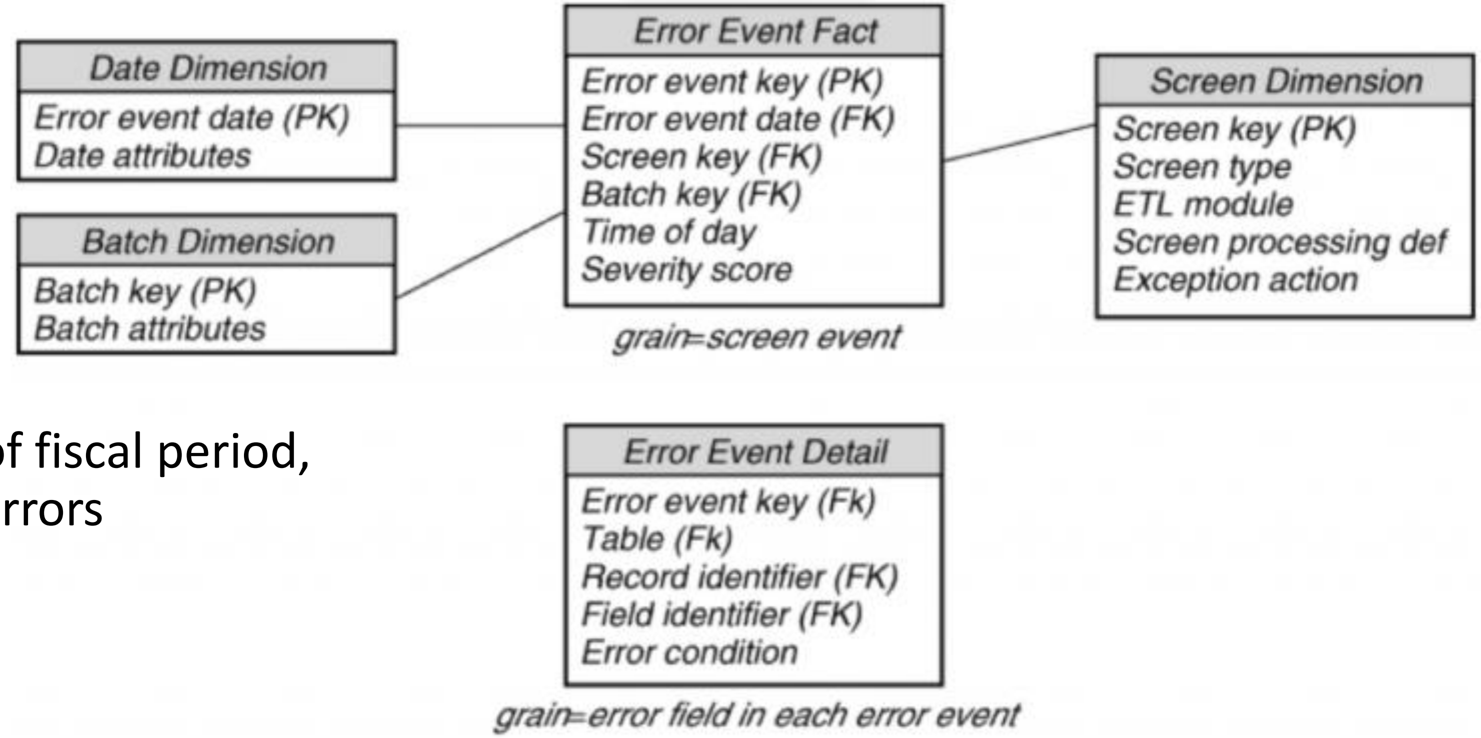
- Data (quality) screening system:
  - Column screens: Test data within a column
    - Correct value ranges, value formatting, null values?
    - Detect random/noise values
  - Structure screens: Relationship across columns
    - Two or more columns implement a hierarchy (e.g., a series of m:n relationships)
    - Foreign key relationships between tables
    - Combination of columns is a valid item, e.g., an existing postal address
  - Business rule screens: Data plausible according to business rules?
    - E.g., customer status X requires Y years of loyalty, Z EUR total revenue, etc.

Data Cleansing: Error Handling

- Halting the process on error
  - requires manual intervention – diagnose, restart/resume the job or abort it
- Create a suspense file
  - Log the errors in a side channel for later processing
  - Not clear when to handle its contents – fix the records and re-introduce to the job?
    - until these data items are restored, the overall DB integrity is questionable
- Tag the data and continue
  - Bad fact records – create an audit dimension
  - Bad dimension data – use unique error values
  - Best solution whenever possible

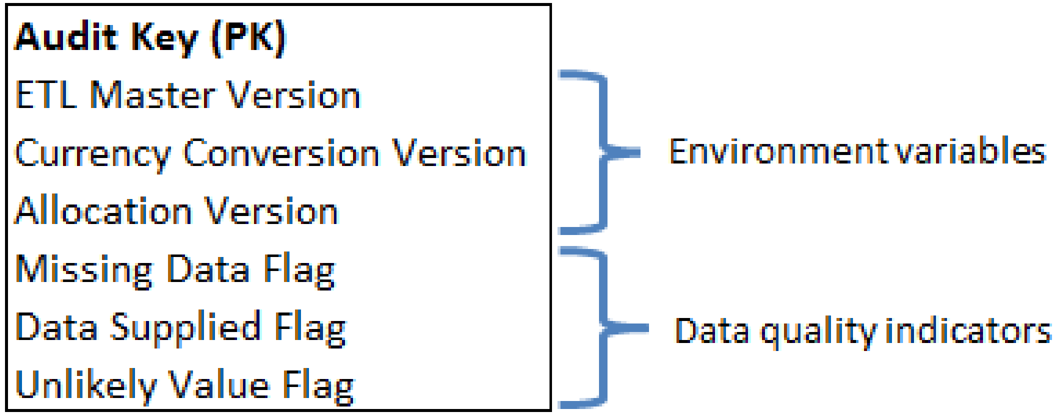
Data Cleansing: Error Handling

- A special error event schema can be created
  - as a result of “Tag the data and continue“
- Grain corresponds to the error appearance
  - Batch dim – info of the job
  - Date dim – not a minute and sec of the error
    - rather a weekday, last day of fiscal period, to constraint / summarize errors
  - Time of day – timestamp when the error occurred



Data Cleansing: Error Handling

- Audit dimension
  - attached to the resulting fact table
  - created in data cleansing
  - stores audit conditions
- Example
  - an ETL job finished with no error
    - a new audit rec. describing it is created
    - all new fact records are associated to it
  - if an error occurred (e.g., out of bounds)
    - another audit rec is created, and the failing fact records get attached



Improving Data Quality

- Appoint ”data stewards” - responsible for data quality
  - A given steward has the responsibility for certain tables
  - Includes manual inspections and corrections!
- DW-controlled improvement
  - Default values
  - ”Not yet assigned 157” note to data steward
- Source-controlled improvements
  - The optimal?
- Construct programs that check data quality
  - Are totals as expected?
  - Do results agree with alternative source?
- Do not fix **all** problems with data quality
  - Allow management to see ”weird” data in their reports?

Data Transformation: Schema Integration

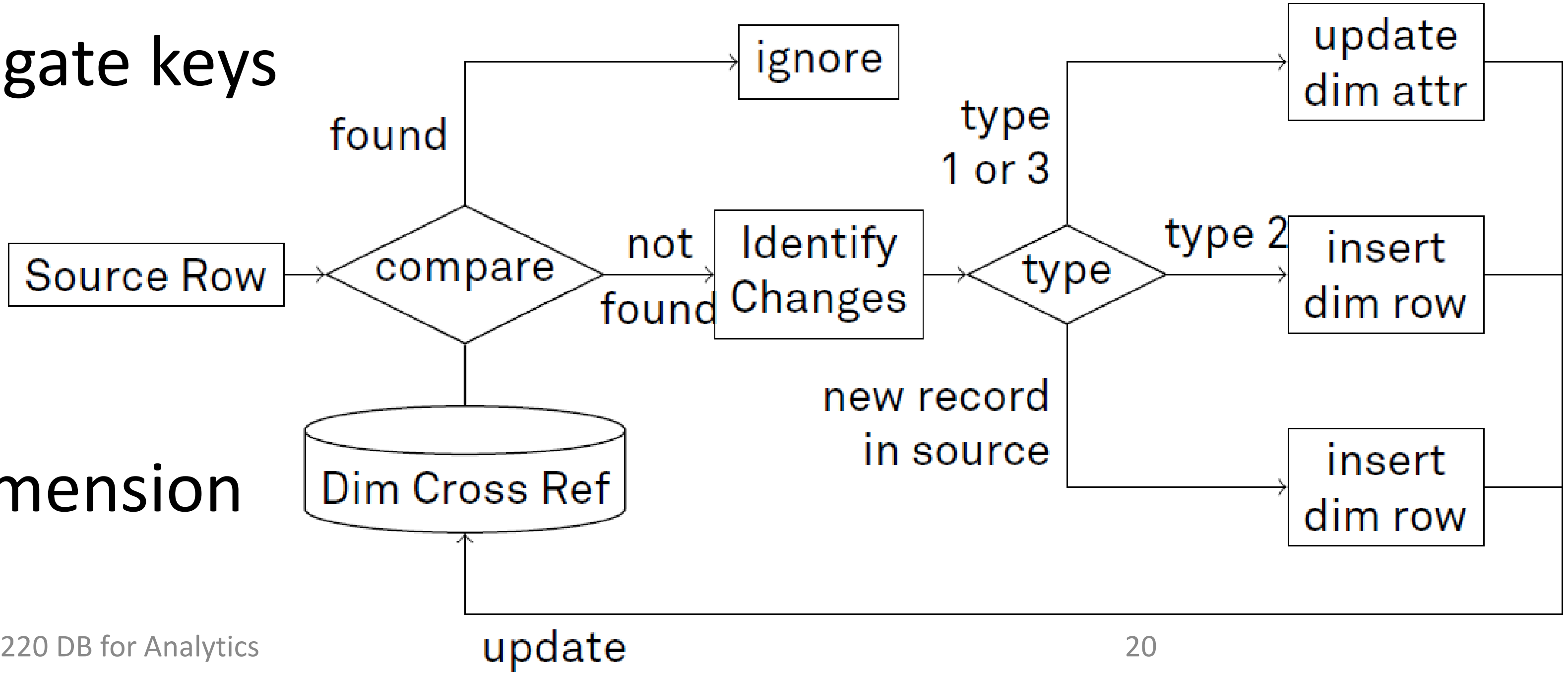
- Different source systems, types, and schemas must be integrated.
- Infer mapping between schemas (automatically)?

- Tools:
  - Compare table and attribute names; consider synonyms and homonyms
  - Infer data types/formats and mapping rules
  - Techniques like similarity joins and deduplication.

- Still:
  - Often a lot of manual work needed.

Data Loading: Prepare Dimension Tables

- Checks
  - dimension row is new
  - attributes in dimension have changed
  - handle updates respecting SCD type of dimension
- Generates the surrogate keys



- All done for each dimension

Data Loading: Prepare Dimension Tables - Problems

- "upsert" – update if exists, else insert (aka SQL-based update)
  - often a real performance killer
  - better: separate updates and bulk-load inserts
- Generate and find dimension surrogate keys
  - e.g., use key generator of back-end DB
  - Maintain "Dim Cross Ref" table in memory or in back-end DB
- Dimensions must be updated before facts
  - The relevant dimension rows for new facts must be in place
  - Special key considerations if initial load must be performed again
- May re-compute aggregates (Type 1 updates)
  - again, bulk-loading/changing is a good choice

Data Loading: Performance Tips

1. Turn off logging
   - Databases maintain a write-ahead log to implement failure tolerance mechanisms.
   - Row-by-row logging causes huge overhead.
2. Disable indexes and reindex after updates
3. Pre-sort data
   - Depending on system, may speed up index construction.
   - Additional benefit: may result in better physical layout
4. Truncate table
   - When loading from scratch

Loading Data – Performance Tips

5. Enable “fast mode”
    - If data is prepared properly, database may use faster parsing mechanisms
    - e.g., “copy from” command
6. Make sure data is correct
    - Transformation, field truncation, error reporting may slow down bulk-loading significantly
7. Temporarily disable integrity control
    - Avoid checking during load, but do it in bulk, too.
    - e.g., foreign keys in the fact table

Loading Data – Performance Tips

8. Parallelization
   - Dimensions can be loaded concurrently
   - Fact tables can be loaded concurrently
     - Partitions can be loaded concurrently
       - when horizontal partitioning of fact tables is used

Hints on ETL Design

- Do **not** try to implement all transformations in one step!

- Do **one** (or just a few) thing(s) at the time
  - Copy source data one-one to staging area
  - Compute deltas
    - Only if doing incremental load
  - Handle versions and generate DW keys
    - Versions only if handling slowly changing dimensions
  - Implement complex transformations
  - Load dimensions
  - Load facts

Issues

- Files versus streams/pipes
  - Streams/pipes: no disk overhead, fast throughput
  - Files: easier restart, often the only possibility
- ETL tool or not
  - Code: easy start, co-existence with IT infrastructure
  - Tool: better productivity on subsequent projects
- Load frequency
  - ETL time depends on processed data volumes.
    - Daily load is much faster than monthly.
  - Applies to all steps in the ETL process
- Should DW be on-line 24/7?
  - Use partitions or several sets of tables

Summary

- ETL is very time consuming (80% of entire project)
  - Needs to be implemented as a sequence of many small steps
  - Data quality is crucial - fixed in ETL
- Extraction of data from source systems might be very time consuming
  - Incremental approach is suggested
- Transformation into DW format includes many steps, such as
  - building key, cleansing the data, handle inconsistent/duplicate data, etc.
- Load includes the loading of the data in the DW, updating indexes, computing pre-aggregates, etc.