Data Warehousing

Jens Teubner, TU Dortmund
jens.teubner@cs.tu-dortmund.de

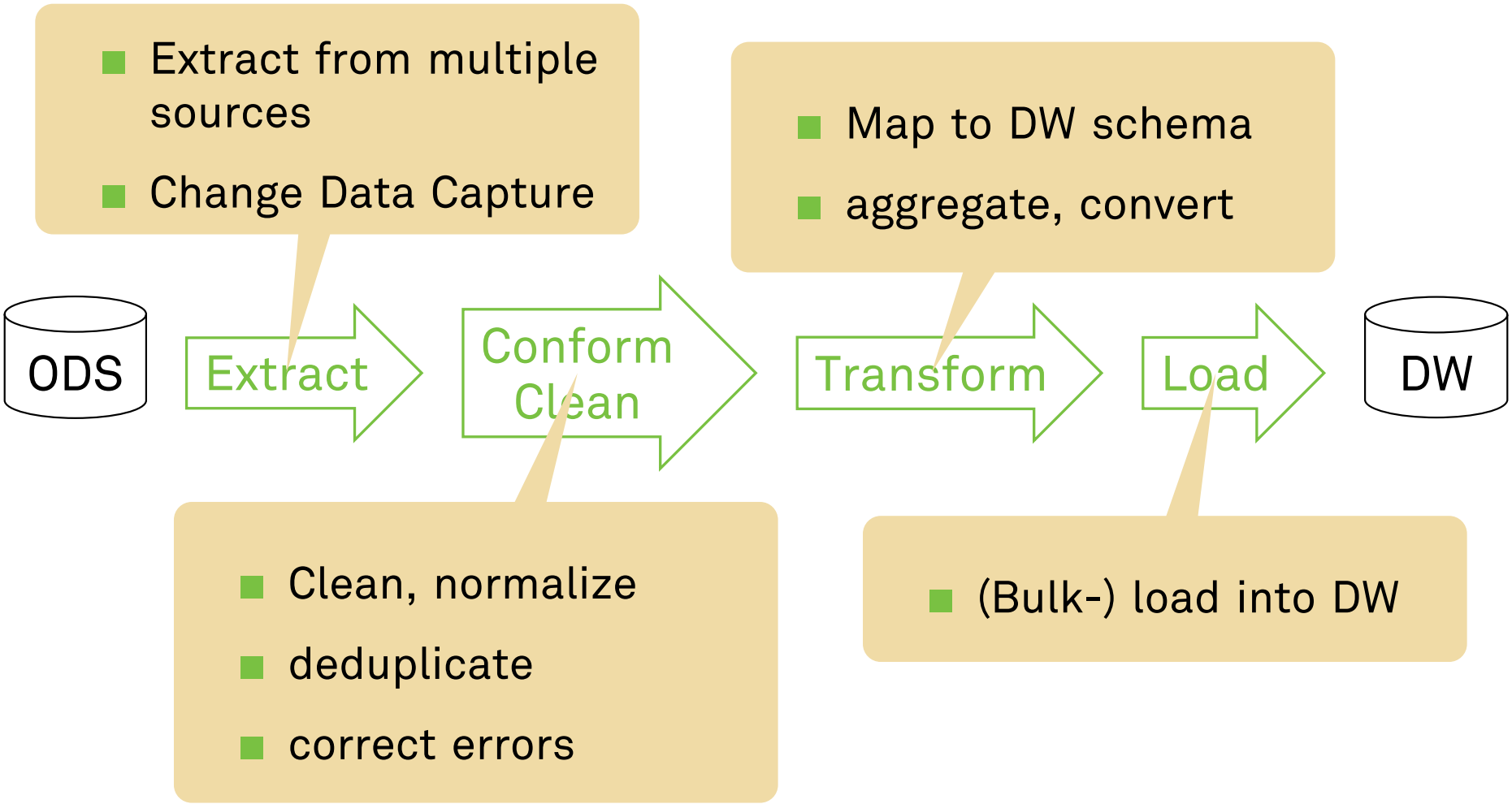
Winter 2015/16

Part VI

ETL Process

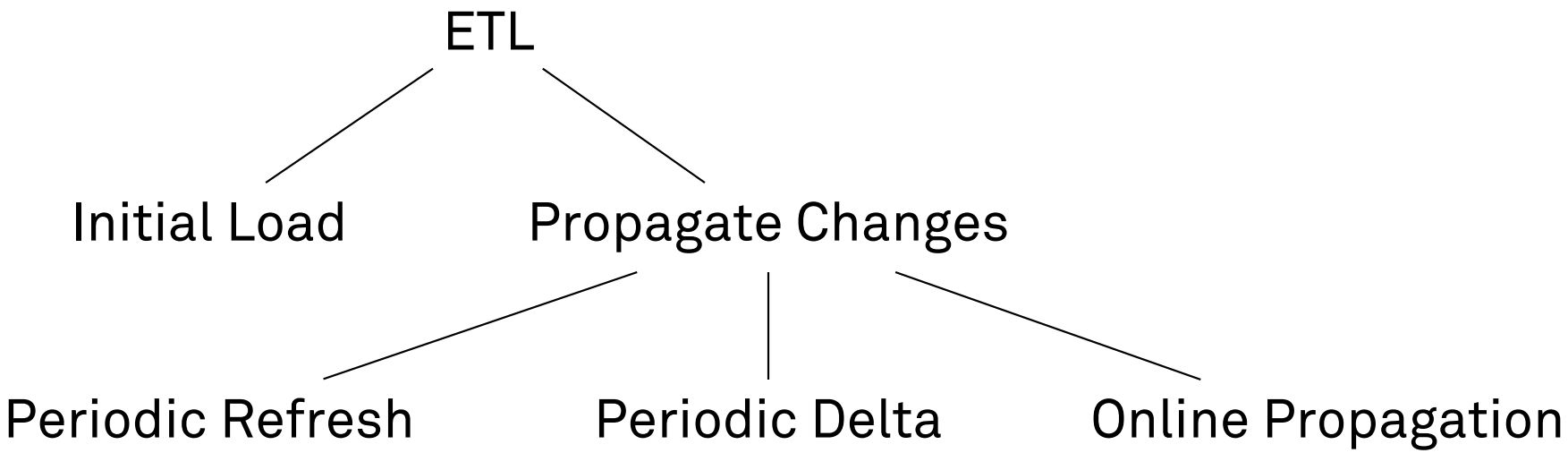
ETL Overview

In most DW systems, the most complex part is the **ETL process.**



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.

Change Data Capture

Detecting changes is a challenge:

- **Audit Columns** (*e.g.*, “last modified” time stamp)
  - → Set time stamps 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 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

Data Cleansing

After extraction, data has to be **normalized** and **cleaned.**

	Name	Street	Clty	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

	Name	Street	Clty	Phone
s_1	Sweet legal Invesments Inc.	202 N	Redmond	
s_2	ABC Groceries Corpn.	Amphitheetre Parkway	Mountain View	
s_3	Cable Services	One Oxford Dr	Cambridge	6171234567

Data Cleansing / Normalization Tasks

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:

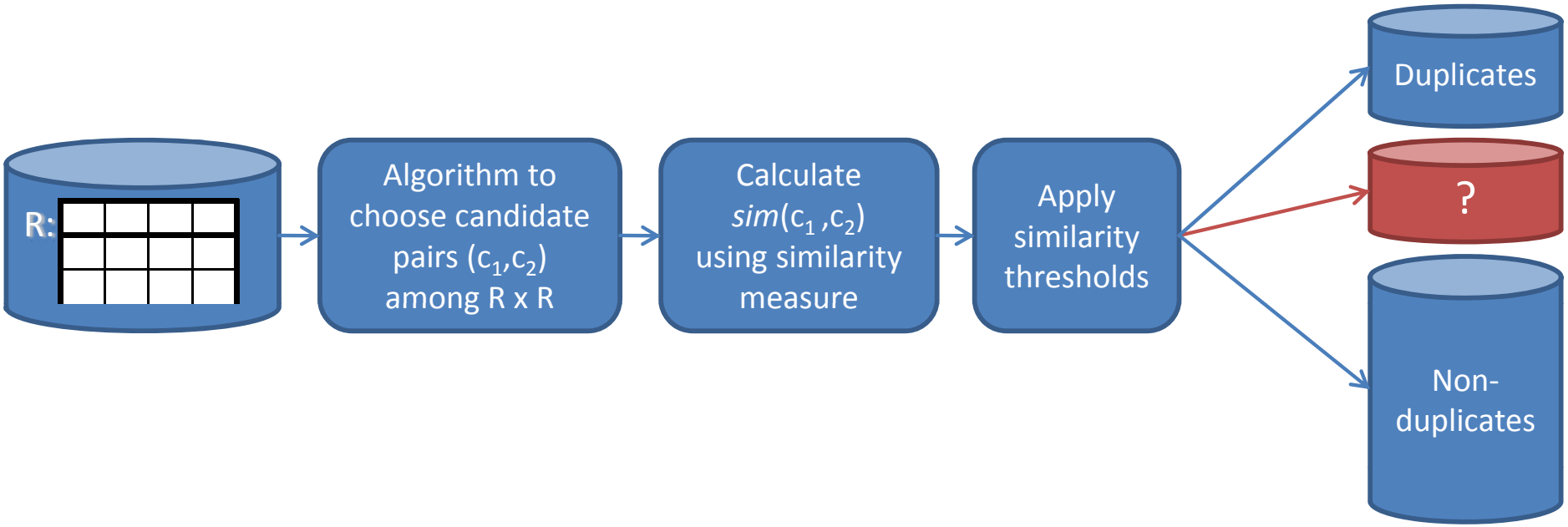
- Correct **spelling errors.**
- Identify **record matches** and **duplicates.**
- Resolve **conflicts** and **inconsistencies.**
- **Normalize** (“conform”) data.

Primitive Operations for Cleansing

1. **Similarity Join**
   - → Bring together similar data
   - → For record matching and deduplication
2. **Clustering**
   - → Put items into groups, based on “similarity”
   - → *E.g.*, pre-processing for deduplication
3. **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"`)

Similarity Join / Deduplication

Process of finding duplicates:



“Similarity”

What is the “similarity” of two strings s_1 and s_2?

1. **Edit Distance**

   $ed(s_1, s_2)$: shortest **edit sequence** that transforms s_1 into s_2

insert	ab → axb
delete	axb → ab
replace	axb → ayb
transpose	axyb → ayxb

   E.g. $s_1 =$ "Sweet"; $s_2 =$ "Sweat"

   → Levenshtein distance (insert, delete, replace allowed): ✎

   → Longest Common Subsequence (LCS) distance (insert, delete allowed) ✎

2 Jaccard Similarity

Intuition: similarity of two **sets** S_1 and S_2

$$\rightarrow \frac{\text{size of intersection}}{\text{size of union}} = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$$

Sets? String $s_i \rightarrow$ set S_i?

Trick: Determine q**-grams** of s_i

$\rightarrow$ q-gram: all substrings of size q

$\rightarrow$ $qgrams(\texttt{"Sweet"}) = \{\texttt{Sw}, \texttt{we}, \texttt{ee}, \texttt{et}\}$

$$\rightarrow \frac{|\{\texttt{Sw}, \texttt{we}, \texttt{ee}, \texttt{et}\} \cap \{\texttt{Sw}, \texttt{we}, \texttt{ea}, \texttt{at}\}|}{|\{\texttt{Sw}, \texttt{we}, \texttt{ee}, \texttt{et}\} \cup \{\texttt{Sw}, \texttt{we}, \texttt{ea}, \texttt{at}\}|} = \frac{|\{\texttt{Sw}, \texttt{we}\}|}{|\{\texttt{Sw}, \texttt{we}, \texttt{ee}, \texttt{et}, \texttt{ea}, \texttt{at}\}|}$$

$$= \frac{2}{6} = \frac{1}{3}$$

3 Soundex

Phonetic algorithm to index words by sound:

1. Retain first letter of word.
2. Replace following letters with numbers (drop other letters):

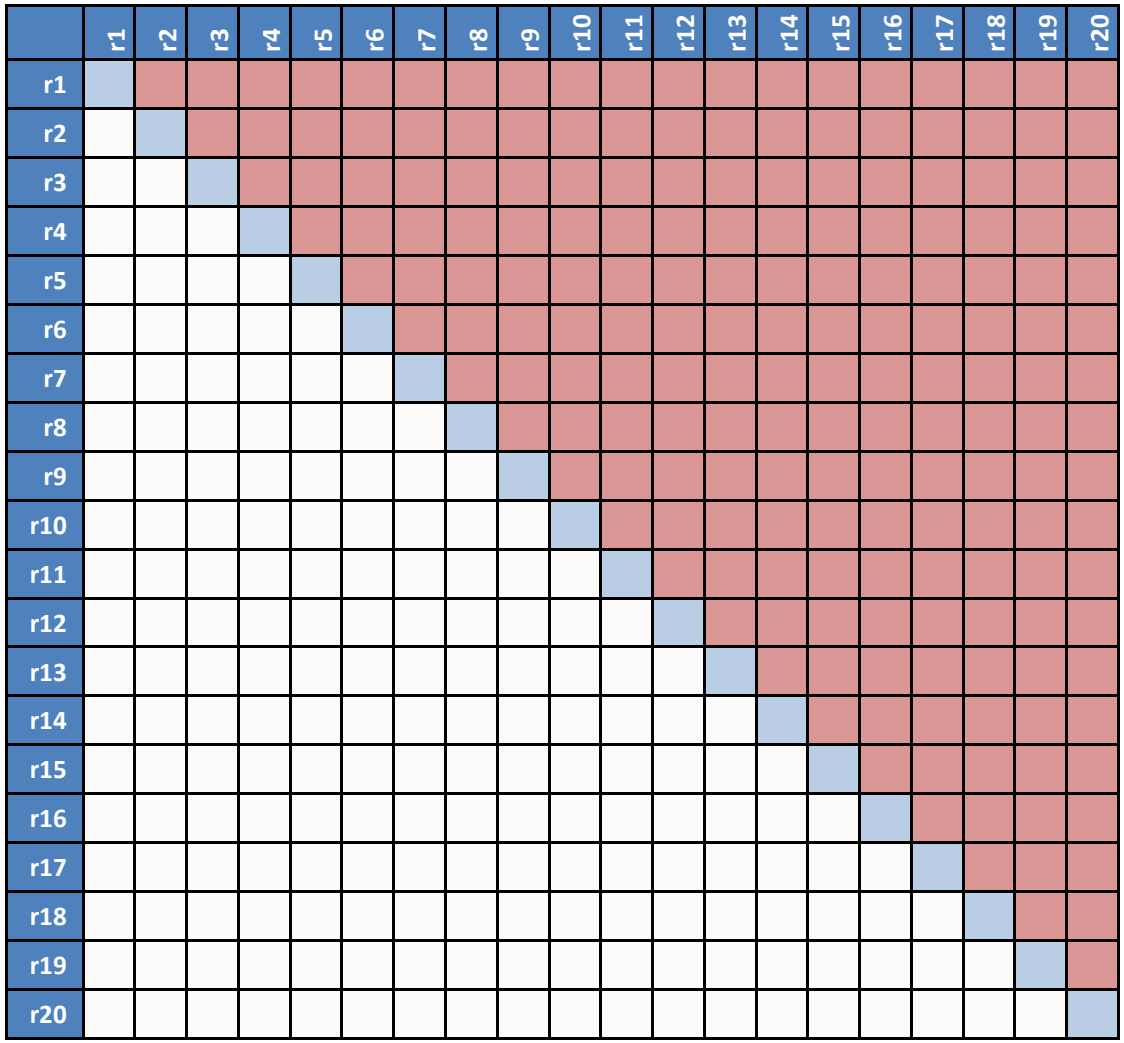
b, f, p, v	→	1
c, g, j, k, q, s, x, z	→	2
d, t	→	3
l	→	4
m, n	→	5
r	→	6

3. Drop letters where preceding letter yielded same number.
4. Collect three numbers, fill with 0 if necessary.

→ $\mathit{soundex}(\texttt{"Sweet"}) = \texttt{S300}$;
$\mathit{soundex}(\texttt{"Robert"}) = \mathit{soundex}(\texttt{"Rupert"}) = \texttt{R163}$.

Similarity Join—Naïve Strategy

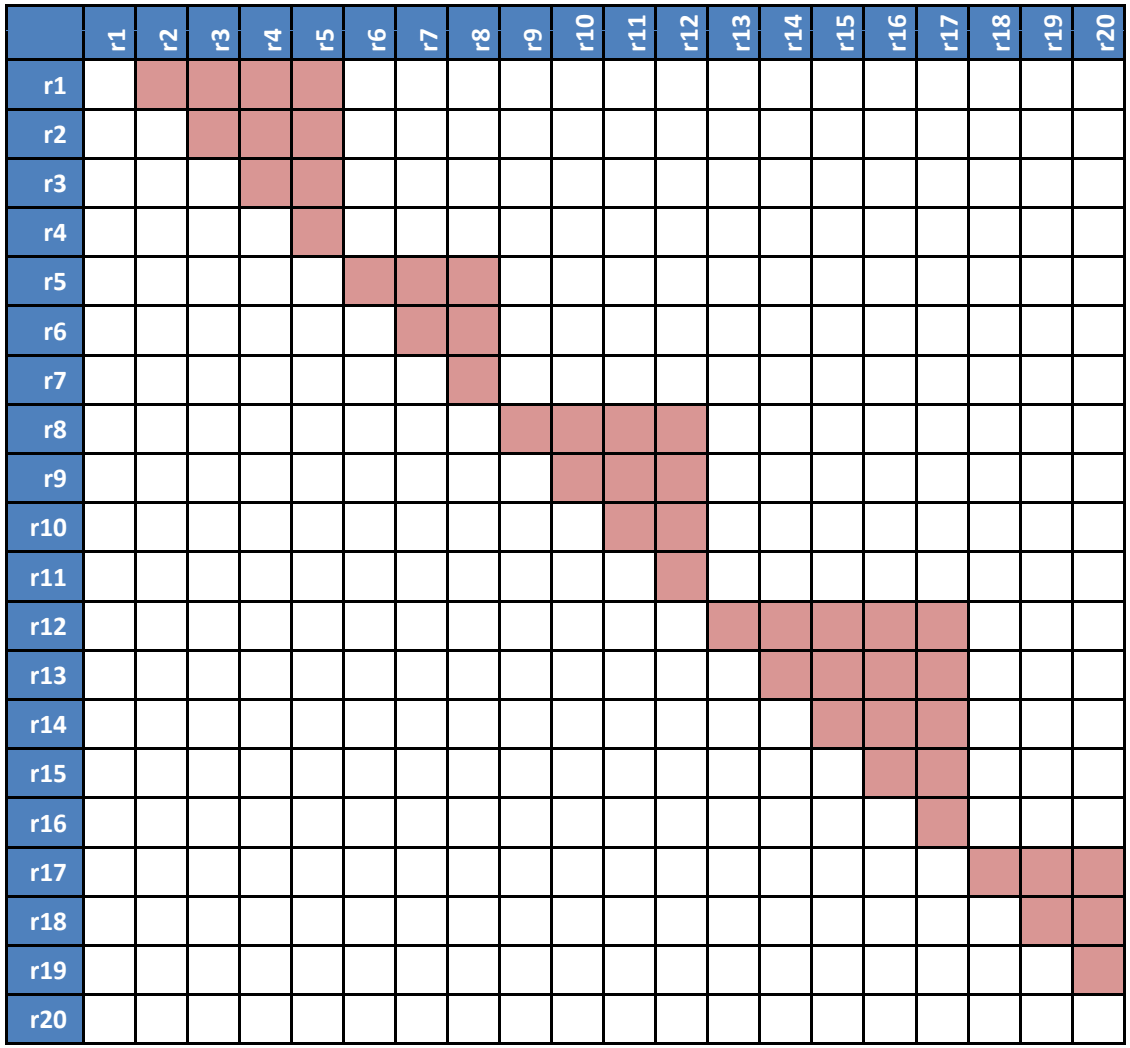
- Compare every record with every other
- Here: Deduplication ($R \bowtie_{\approx} R$)
- ✎ **Cost?**



Similarity Join—Blocking

- Partition data into **blocks**
- Compare only **within** blocks
- ✎ **Cost?**
  Assume n records and b blocks:

$$
\begin{aligned}
& b \cdot \frac{\frac{n}{b}\left(\frac{n}{b}-1\right)}{2} \\
&= \frac{n\left(\frac{n}{b}-1\right)}{2} \\
&= \frac{1}{2}\left(\frac{n^2}{b}-n\right)
\end{aligned}
$$



Similarity Join—Blocking

Observations:

- Must partition such that duplicates appear in same partition.
  - → Risk of **missing** duplicates.

Strategies:

- Use (prefix of) the ZIP code
  - → Assume no typo in the ZIP code and customer has not moved across ZIP code ranges.
- Use first character of last name
  - → Again, assume no typo there.

Typically leads to **uneven partition sizes.**

Similarity Join—Blocking

Refinement:

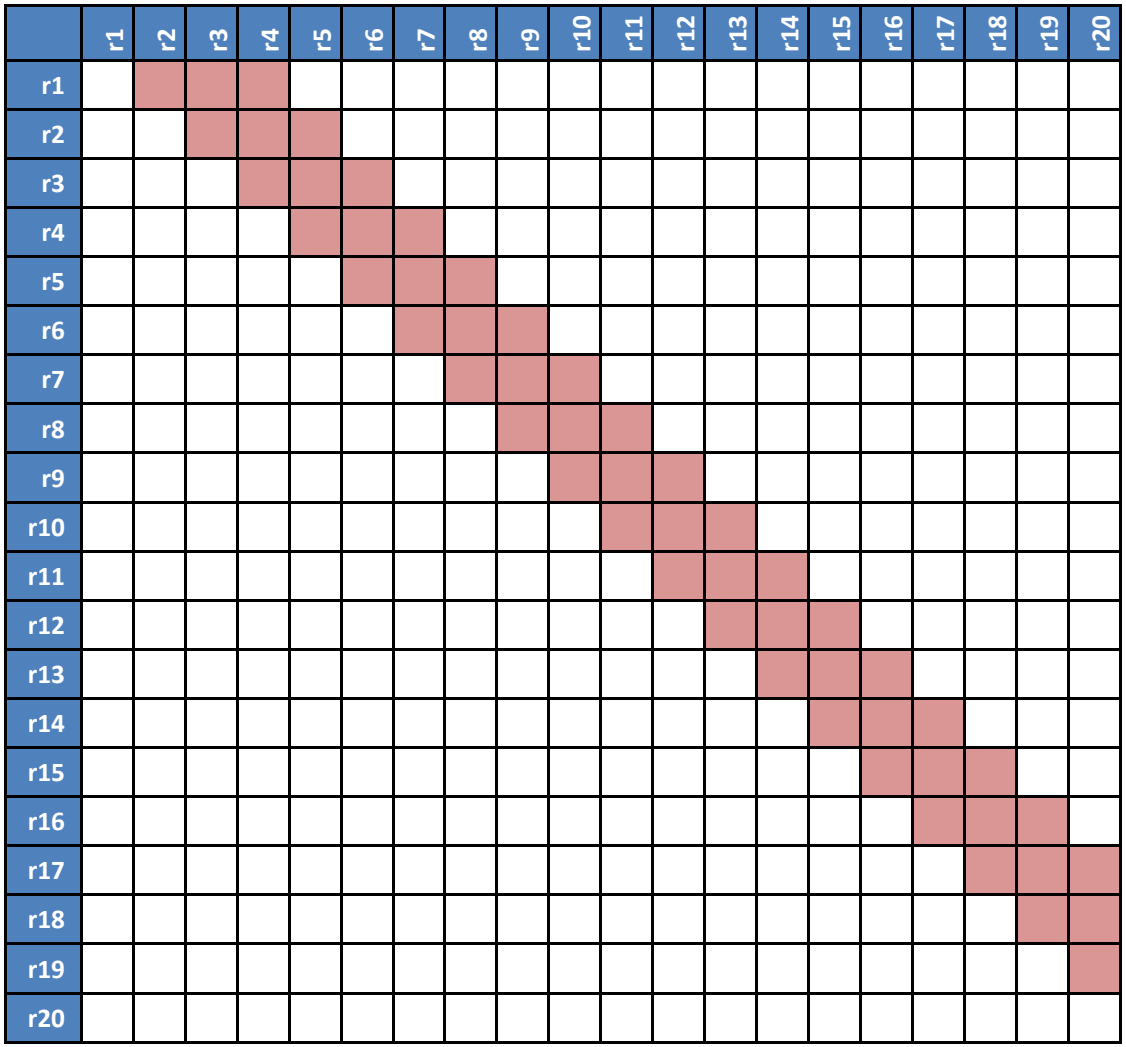
- Run **multiple passes** of the similarity join.
  - → Use **different partitioning** key in each pass.
  - → Assume duplicates agree in at least one partitioning key.

Similarity Join—Sorted Neighborhood

1. Assign a **sort key** to each record.
2. **Sort** accordingly.
3. **Slide window** of size w across sorted list and join within.

Number of comparisons:

$$(w-1)\cdot\left(n-\frac{w}{2}\right)$$



Similarity Join—Sorted Neighborhood

Observations:

- Need good sorting criterion
  - → Choose characters with low probability of errors

Example:

- Sort by
  - First 3 consonants of last name
  - First letter of last name
  - First 2 digits of ZIP code.

  (It is more likely to err in a vowel than in a consonant.)

Also:

- **Multi-pass processing** can be beneficial also here.

Detecting Conflicts / Inconsistencies

Data screening system:

1. **Column screens:** Test data within a column
   → Correct value ranges, value formatting, null values?
2. **Structure screens:** Relationship across columns
   → Foreign key relationships?
   → Combination of columns is a valid postal address?
3. **Business rule screens:** Data plausible according to business rules?
   → *E.g.*, customer status *X* requires *N* years of loyalty, *M* EUR total revenue, etc.

Cleansing: Tool Support

Lots of **tools** support typical cleaning tasks:

- Commercial offerings:
  - SAP Business Objects
  - IBM InfoSphere Data Stage
  - Oracle Data Quality and Oracle Data Profiling
- Open source tools:
  - Eobjects DataCleaner, Talend Open Profiler

→ Explore and profile source data
  - Analyze key properties, missing values, distributions, etc.

→ Rules for common filtering and normalization tasks
  - Regular expressions for phone numbers, credit card numbers, etc.
  - Convert dates, phone numbers, addresses, etc.

Schema Integration

Tools also help with **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 similar to **similarity joins** and **deduplication**.

Still:

- Often a lot of **manual work** needed.

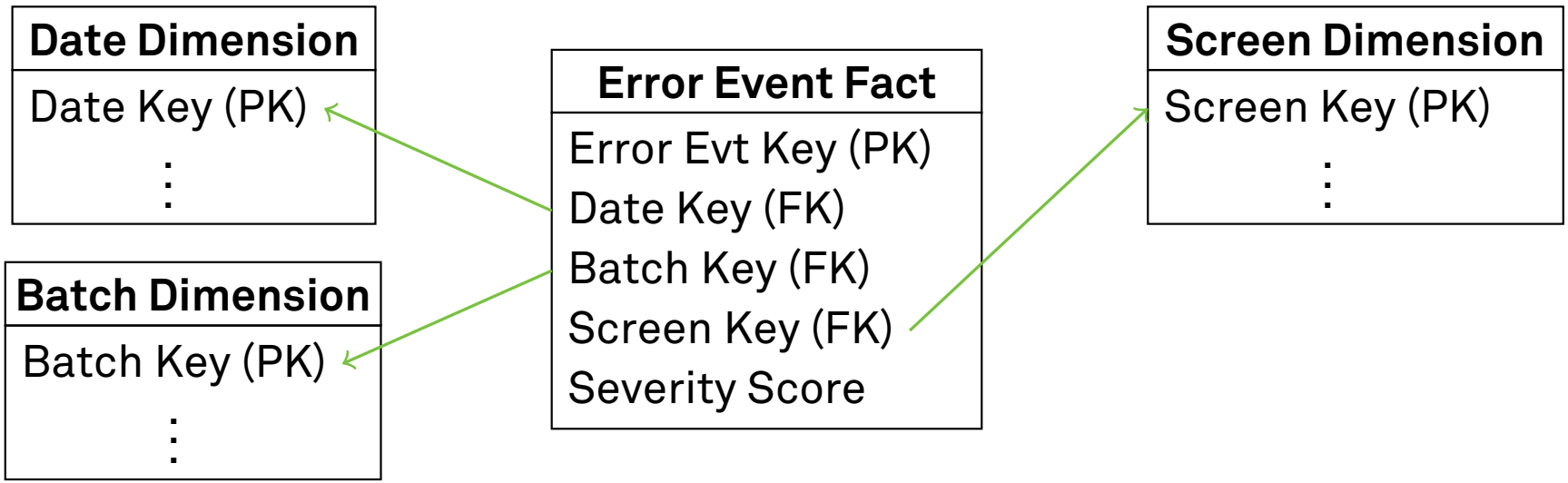
Error Events

What to do with detected errors/problems?

- Fix automatically if possible
- Otherwise: **report the error** → **How/Where?**

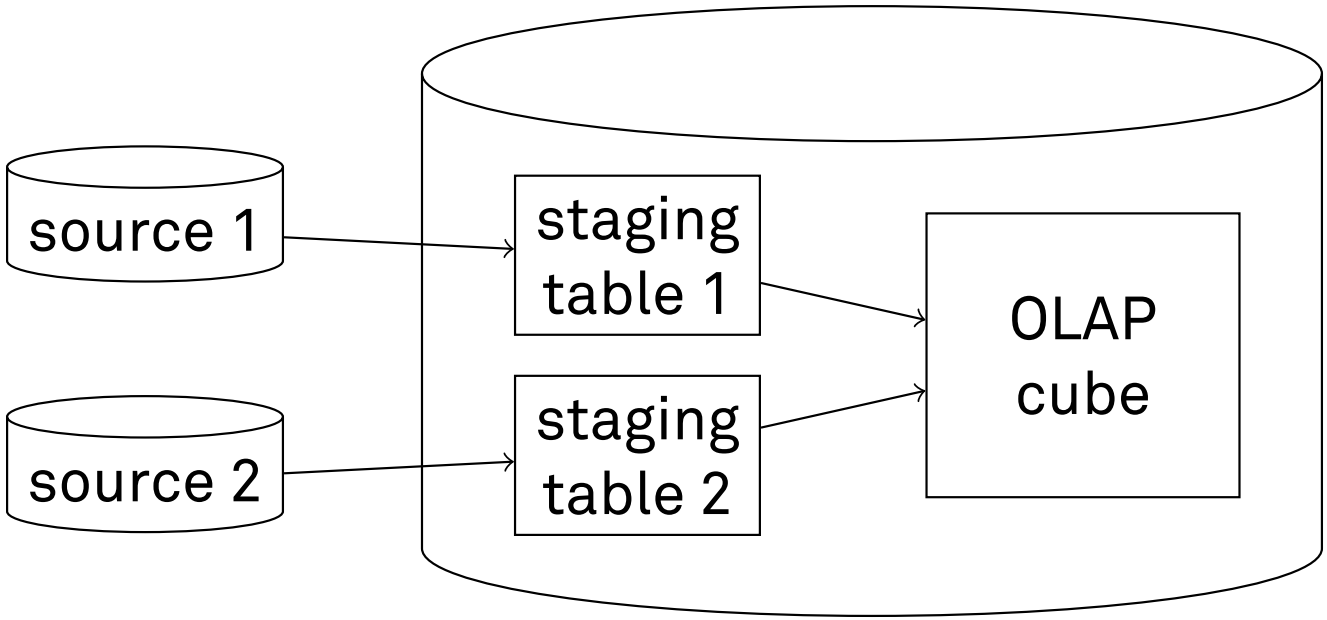
"Trick:" **Error event schema**

→ Star schema for the "error" business event



✎ **Advantage?**

Data Transformation



Source → Staging Table:

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

Dimension and Fact Tables

Complete load process will involve **fact and dimension tables.**

- Dependency *fact* $\xrightarrow{\text{foreign key}}$ *dimension*.
- Thus: **Load dimension table(s) first.**
  - $\rightsquigarrow$ All dimension keys available when fact table row is inserted.

Slowly Changing Dimensions—Type 1

Data updated/inserted in **source database**:

Products		
SKU	Description	Dept
A913-G	Mega Drill	Tools
A922-Z	IntelliKidz	Education

→

Products		
SKU	Description	Dept
A913-G	Mega Drill	Tools
A922-Z	IntelliKidz	Strategy
A944-V	Frizz Master	Cooking

Type 1 ("Overwrite") strategy in **data warehouse**:

Product Dimension			
Prod Key	SKU	Description	Department
10468	A913-G	Mega Drill	Tools
12345	A922-Z	IntelliKidz	Education

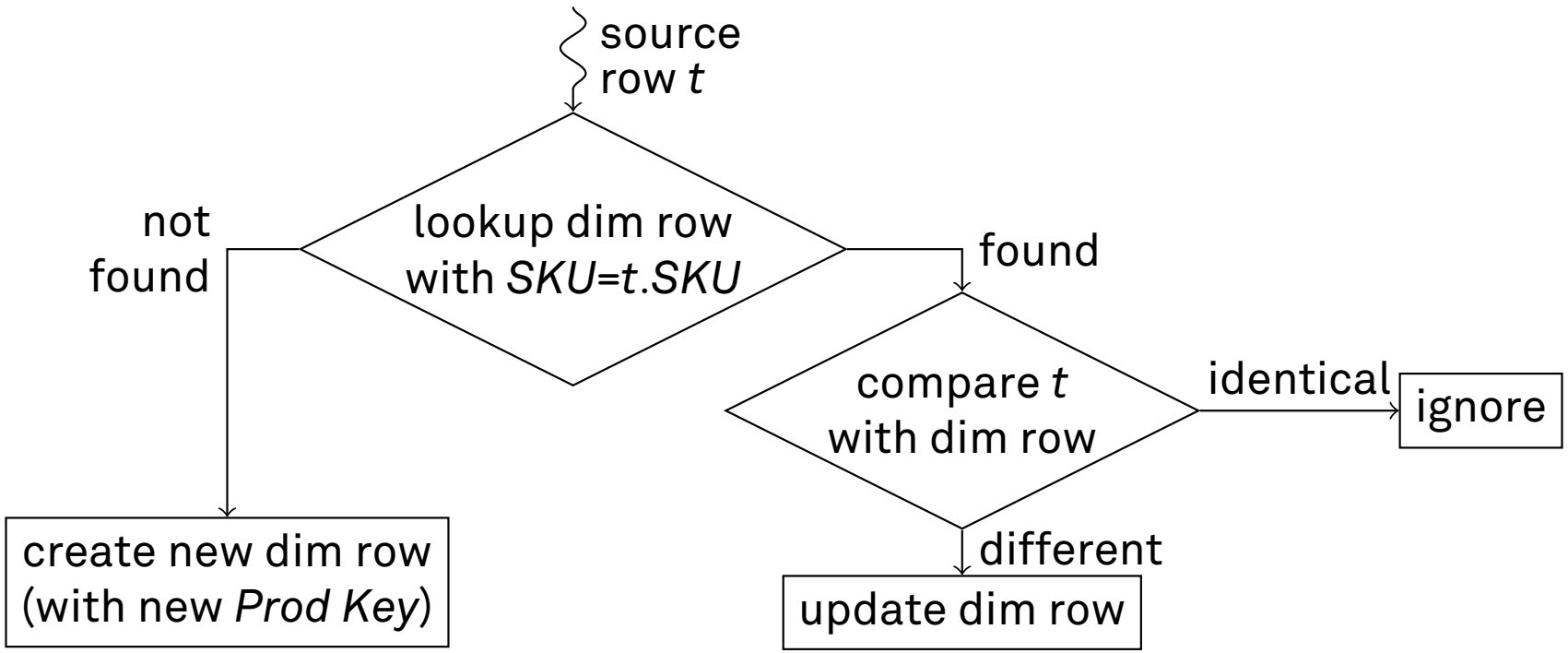
↓

Product Dimension			
Prod Key	SKU	Description	Department
10468	A913-G	Mega Drill	Tools
12345	A922-Z	IntelliKidz	Strategy
46729	A944-V	Frizz Master	Cooking

Slowly Changing Dimensions—Type 1

For every source row *t*:

1. Search in dimension table **by operational key (“natural key”).**
2. If found, **compare** existing dimension row with *t*.
   → Apply changes to dimension row if necessary.
3. If not found, **insert** new row in dimension table.
   → Create a **new surrogate key.**



Slowly Changing Dimensions—Type 2

Type 2 Dimensions: Keep a **History** of Changes

→ Create a new dimension row for **every change**.

→ Mark validity with *since*/*until* fields.

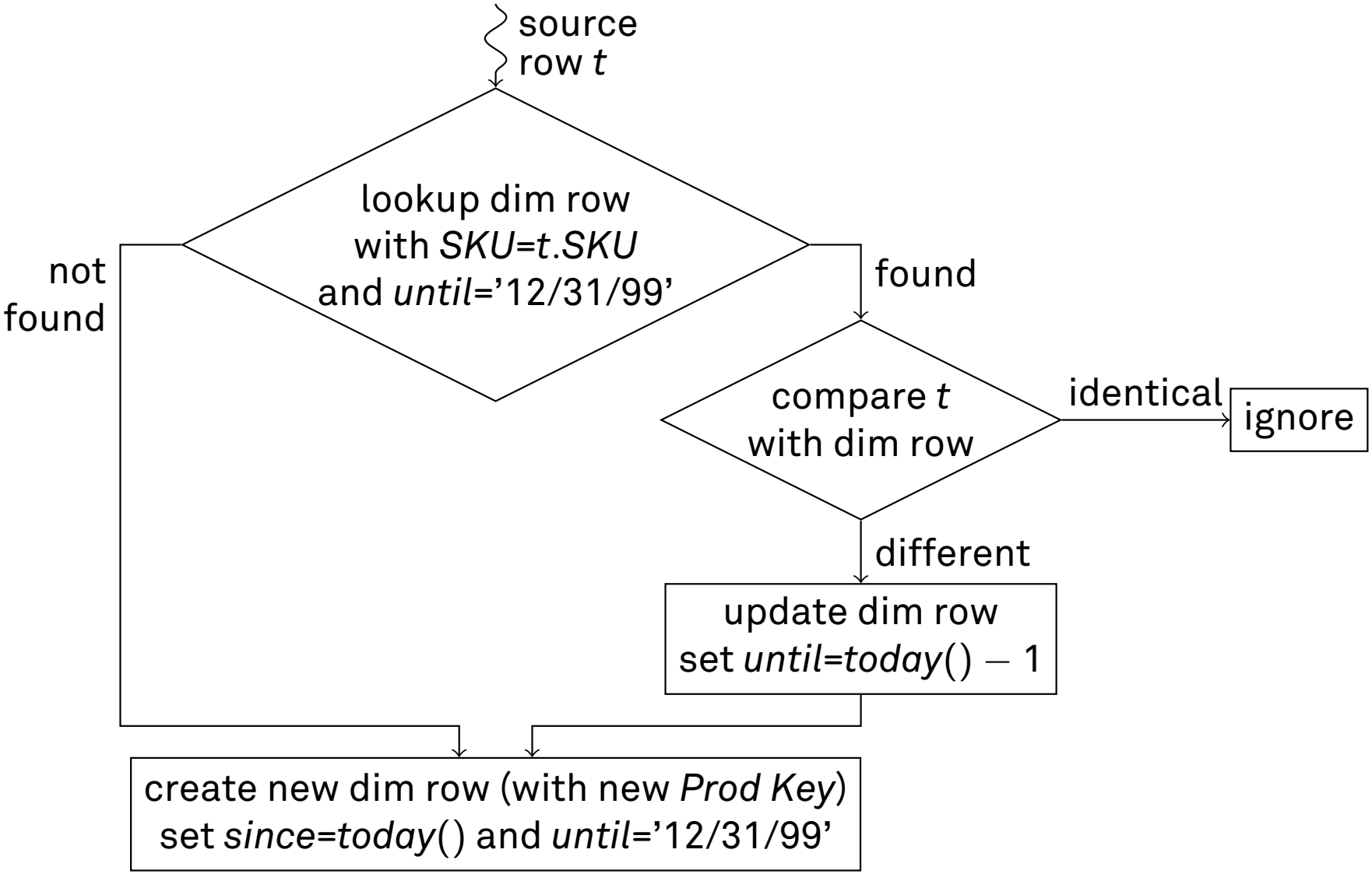
Product Dimension					
Prod Key	SKU	Description	Department	Since	Until
10468	A913-G	Mega Drill	Tools	2/4/12	12/31/99
12345	A922-Z	IntelliKidz	Education	1/1/12	2/28/13
63726	A922-Z	IntelliKidz	Strategy	3/1/13	12/31/99
46729	A944-V	Frizz Master	Cooking	3/1/13	12/31/99

→ Current value is the one with *until*='12/31/99' (or ∞, ...)

Alternative:

- Boolean *valid* field (*true* for current version, *false* for old versions)

Slowly Changing Dimensions—Type 2



Slowly Changing Dimensions

Notes:

- Types 1/2 may also be mixed
  - → Keep history for only some columns.

Single-row operations (lookup, update, create) may be **expensive.**

- → **Cache** lookup results (also for later fact loading)
  - ✎ **Implementation?**
- → Merge tuple creation into single **data flow.**
  - → **bulk-load** inserts
- → Use **dedicated syntax** (such as SQL Server's `MERGE` statement)

Loading Data

Tricks to load data **fast**:

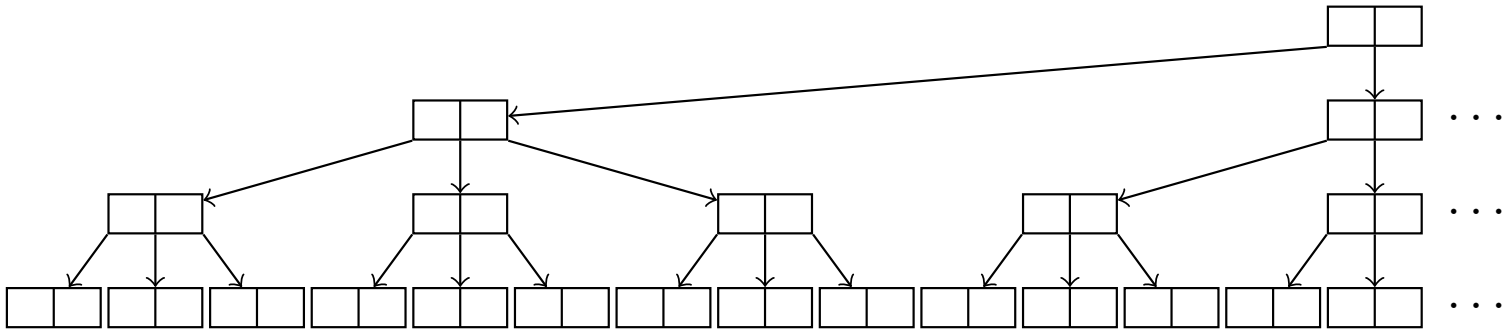
1. **Turn off logging**
   - → Databases maintain a **write-ahead log** to implement **failure tolerance** mechanisms.
   - → Row-by-row logging causes huge **overhead.**
2. **Pre-sort data**
   - → Depending on system, may speed up **index construction.**
   - → Additional benefit: may result in better **physical layout**
3. **Truncate table first**
   - → Makes (not) logging and failure tolerance even easier.

Loading Data

4. **Enable “fast mode”**
   - → If data is **prepared properly**, database may use **faster parsing mechanisms**
5. **Make sure data is correct**
   - → Transformation, field truncation, error reporting may slow down bulk-loading significantly
6. **Temporarily disable integrity control**
   - → Avoid checking during load, but do it in bulk, too.

Example: Bulk Loading and B-Tree Indexes

Building a B^+-tree is particularly easy when the input is **sorted.**



- Build B^+-tree **bottom-up** and **left-to-right.**
- Create a parent for every $2d + 1$ unparented nodes.
- If data is not sorted already, database will typically sort it before loading/re-building the index.