

Data Warehousing

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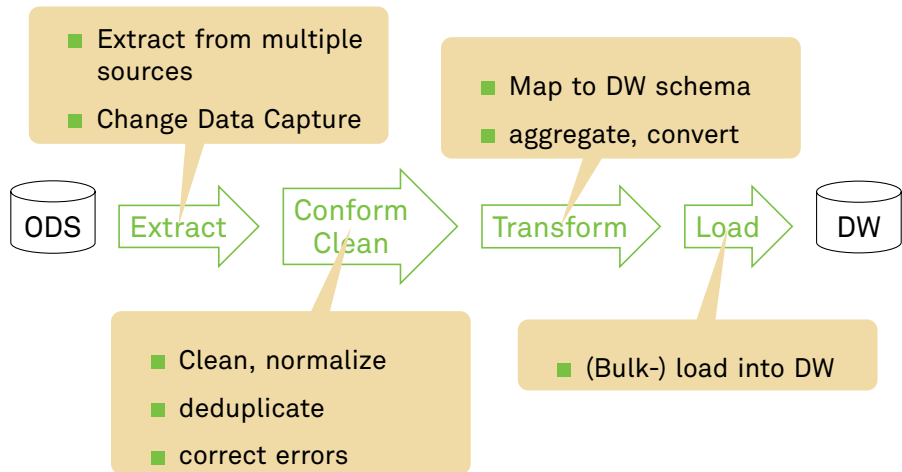
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Part VI

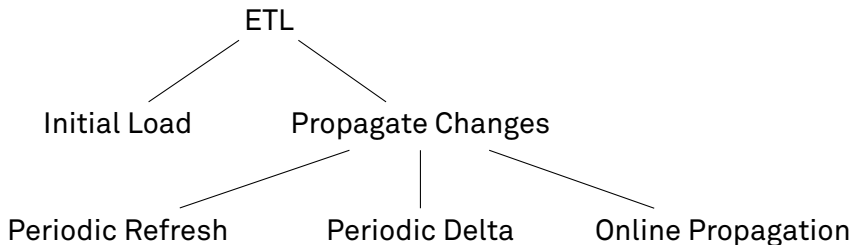
ETL Process

ETL Overview

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



When do we run the ETL process?





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.

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	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

	Name	Street	City	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

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.

1 Similarity Join

- Bring together similar data
- For record matching and deduplication

2 Clustering

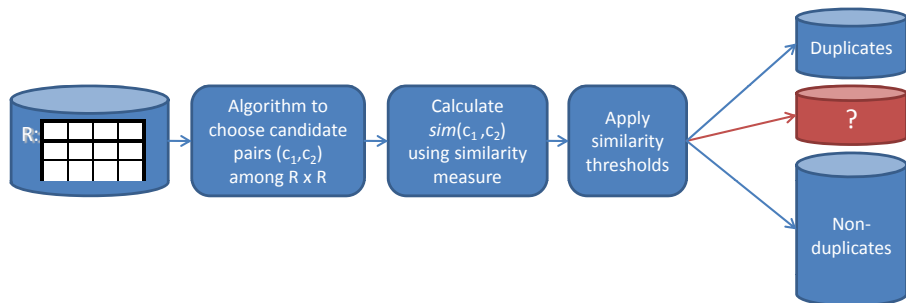
- Put items into groups, based on “similarity”
- *E.g.*, pre-processing for deduplication

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:



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 $ab \rightarrow axb$

delete $axb \rightarrow ab$

replace $axb \rightarrow ayb$

transpose $axyb \rightarrow ayxb$

E.g. $s_1 = \text{"Sweet"}; s_2 = \text{"Sweat"}$

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

$$\begin{aligned} \rightarrow \frac{|\{Sw, we, ee, et\} \cap \{Sw, we, ea, at\}|}{|\{Sw, we, ee, et\} \cup \{Sw, we, ea, at\}|} &= \frac{|\{Sw, we\}|}{|\{Sw, we, ee, et, ea, at\}|} \\ &= \frac{2}{6} = \frac{1}{3} \end{aligned}$$

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

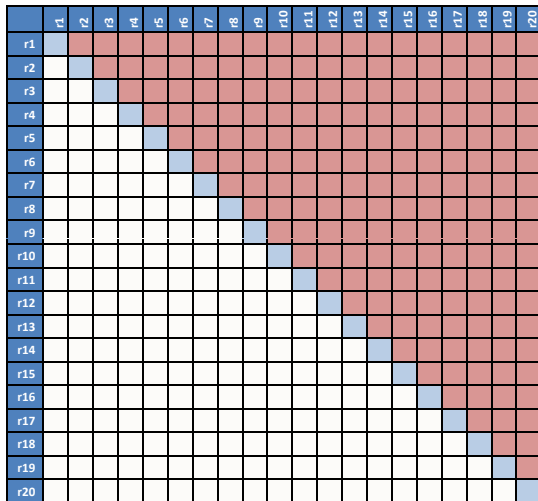
r → 6

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

→ *soundex*("Sweet") = S300;
soundex("Robert") = *soundex*("Rupert") = R163.


Similarity Join—Naïve Strategy

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

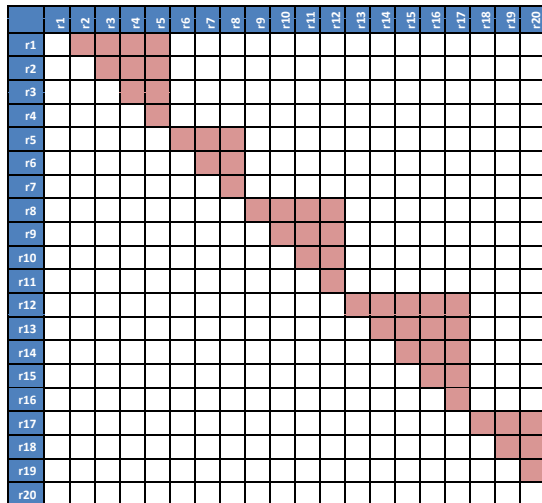


	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15	r16	r17	r18	r19	r20
r1	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r2	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r3	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r4	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r5	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r6	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r7	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r8	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r9	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r10	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r11	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r12	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r13	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r14	White	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red	Light Red
r15	White	White	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red	Light Red
r16	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red	Light Red
r17	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red	Light Red
r18	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red	Light Red
r19	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue	Light Red
r20	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	White	Light Blue

Similarity Join—Blocking

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

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



	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15	r16	r17	r18	r19	r20
r1																				
r2																				
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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**.

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:

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

	r1	r2	r3	r4	r5	r6	r7	r8	r9	r10	r11	r12	r13	r14	r15	r16	r17	r18	r19	r20
r1		■	■	■																
r2			■	■	■															
r3				■	■	■														
r4					■	■	■													
r5						■	■	■												
r6							■	■	■											
r7								■	■	■										
r8									■	■	■									
r9										■	■	■								
r10											■	■	■							
r11												■	■	■						
r12													■	■	■					
r13														■	■	■				
r14															■	■	■			
r15																■	■	■		
r16																	■	■	■	
r17																		■	■	■
r18																			■	■
r19																				■
r20																				

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.

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:

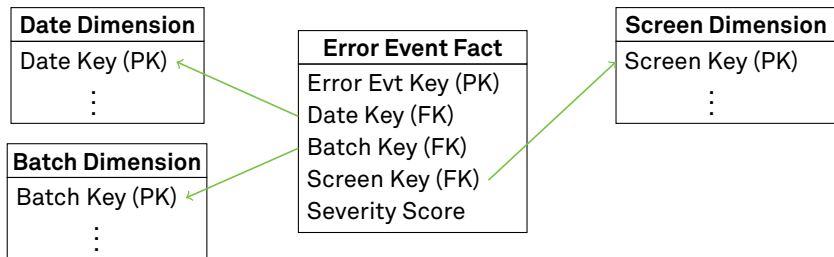
- Often a lot of **manual work** needed.

What to do with detected errors/problems?

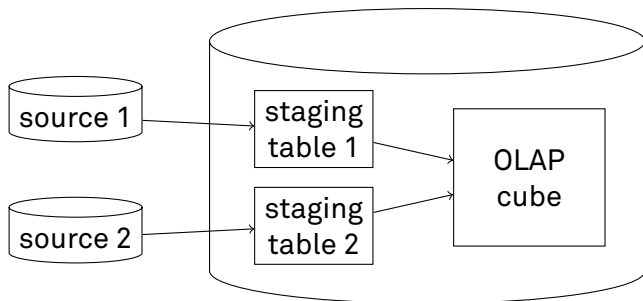
- Fix automatically if possible
- Otherwise: **report the error** → **How/Where?**

“Trick:” Error event schema

→ Star schema for the “error” business event



Advantage?



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

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

- Dependency *fact* $\xrightarrow{\text{foreign key}}$ *dimension*.
- Thus: **Load dimension table(s) first.**
 - ~> 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

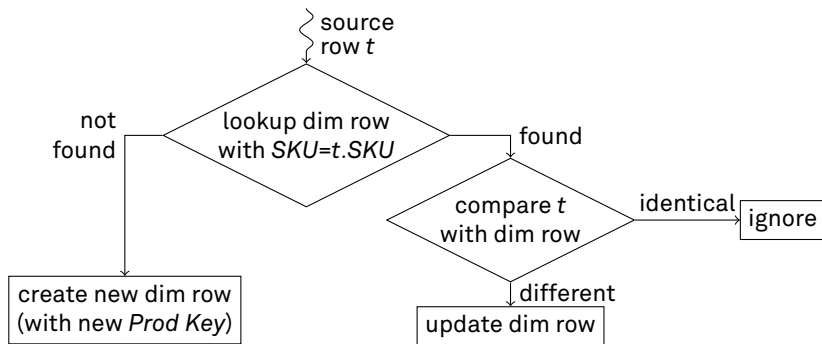
↓

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.

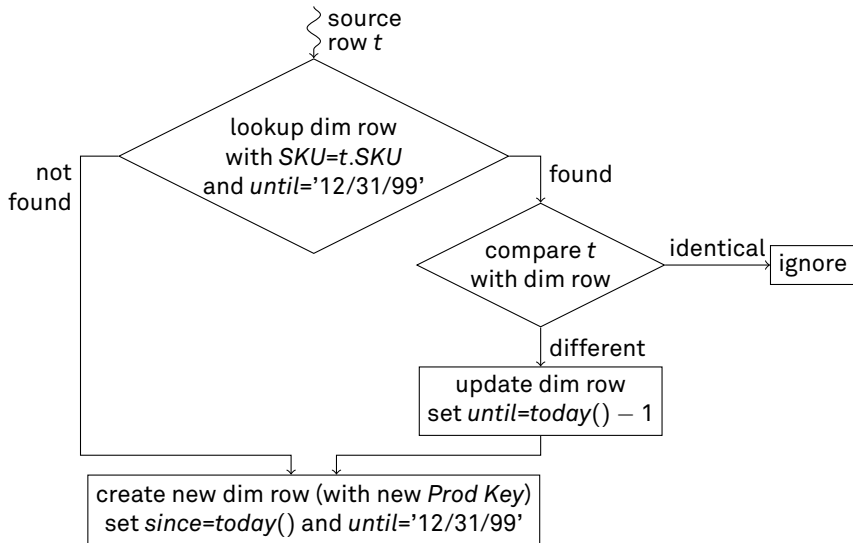
Product Dimension					
Prod Key	SKU	Description	Department	Since	Until
10468	A913-G	Mega Drill	Tools	2/4/12	12/31/99
12345	A922-Z	IntelliKidz	Education	1/1/12	2/28/13
63726	A922-Z	IntelliKidz	Strategy	3/1/13	12/31/99
46729	A944-V	Frizz Master	Cooking	3/1/13	12/31/99

- 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



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)

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.

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.

