

Data Cleaning for Data Integration

Advanced School on Data Exchange, Integration, and Streams (DEIS)

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Data integration:

- Combine data from various sources/applications
- Merge into a single database
- lacktriangle Requires a unified view over the data ightarrow cleaning

Challenges:

- Handling the various incoming schemata
- Dealing with the missing data values
- Entity Resolution
 - → combine the various descriptions or references for the same real world objects



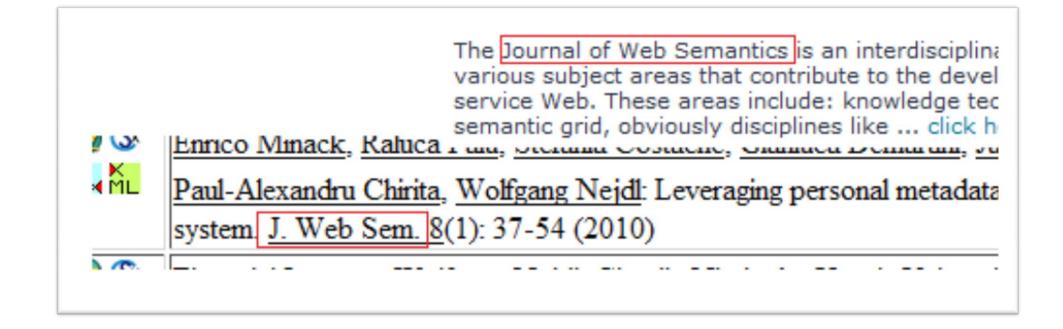


Text variations:

- Misspellings
- Acronyms
- Transformations
- Abbreviations
- etc.

Welcome to ICDE 2011

The IEEE International Conference on Data Engineering results and advanced data-intensive applications and dis The mission of the conference is to share research soluti identify new issues and directions for future research and







- Text variations
- Local knowledge:
 - Each source uses different formats
 e.g., person from publication vs. person from email
 - Lack of global coordination for identifier assignment

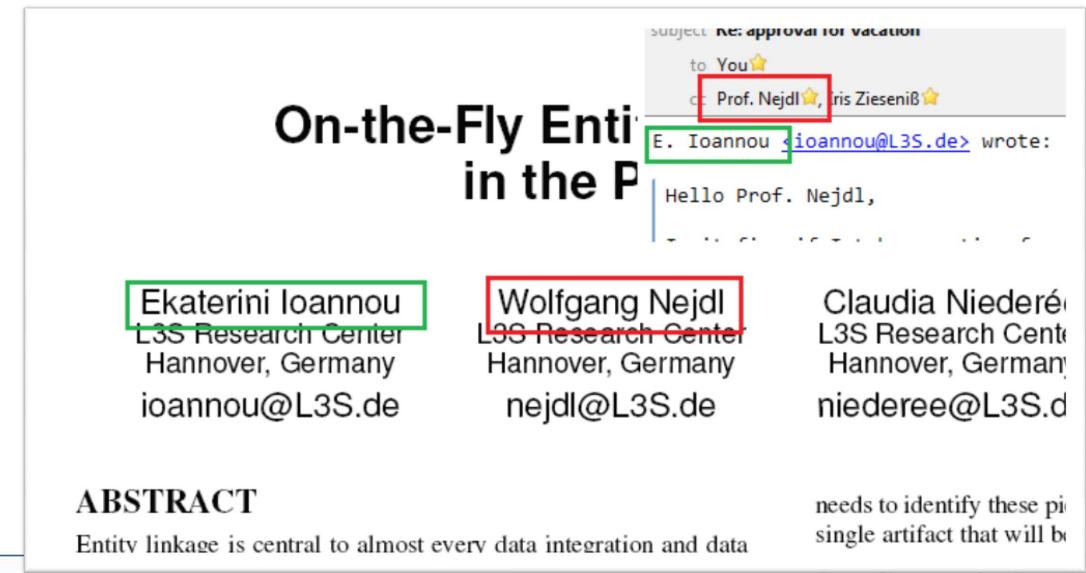
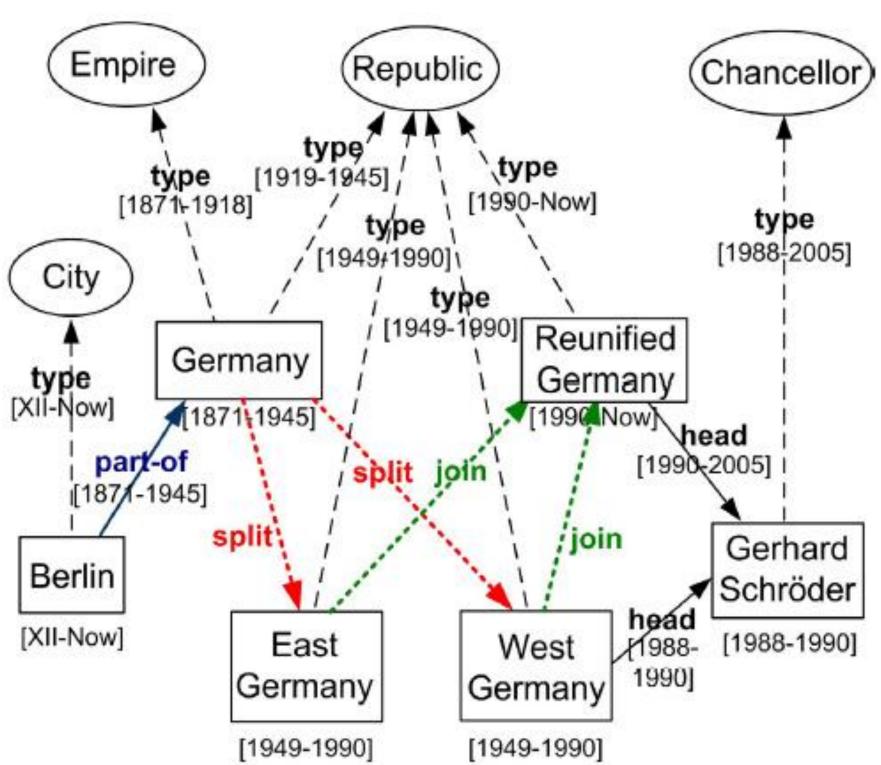




figure from [RVMB09]

- Text variations
- Local knowledge
- Evolving nature of data:
 - Entity alternative names appearing in time
 - Updates in entity data



Jacqueline Lee Bouvier

Alternate Names: Jackie Bouvier | Jackie Kennedy | Mrs. John F. Kennedy | Jackie Onassis | Jacqueline Kennedy Onassis | Jacqueline Onassis





- Text variations
- Local knowledge
- Evolving nature of data
- New functionality:
 - Web page extraction
 e.g., Calais, Cogito
 - Import data collections from various applications e.g., Wikipedia data used in Freebase
 - Mashups for easy and fast integration from various source e.g., yahoo pipes





Entity Resolution typical methodology:

- Indentify data describing the same real-world objects
- Decide how to merge the data
- Update the data collection

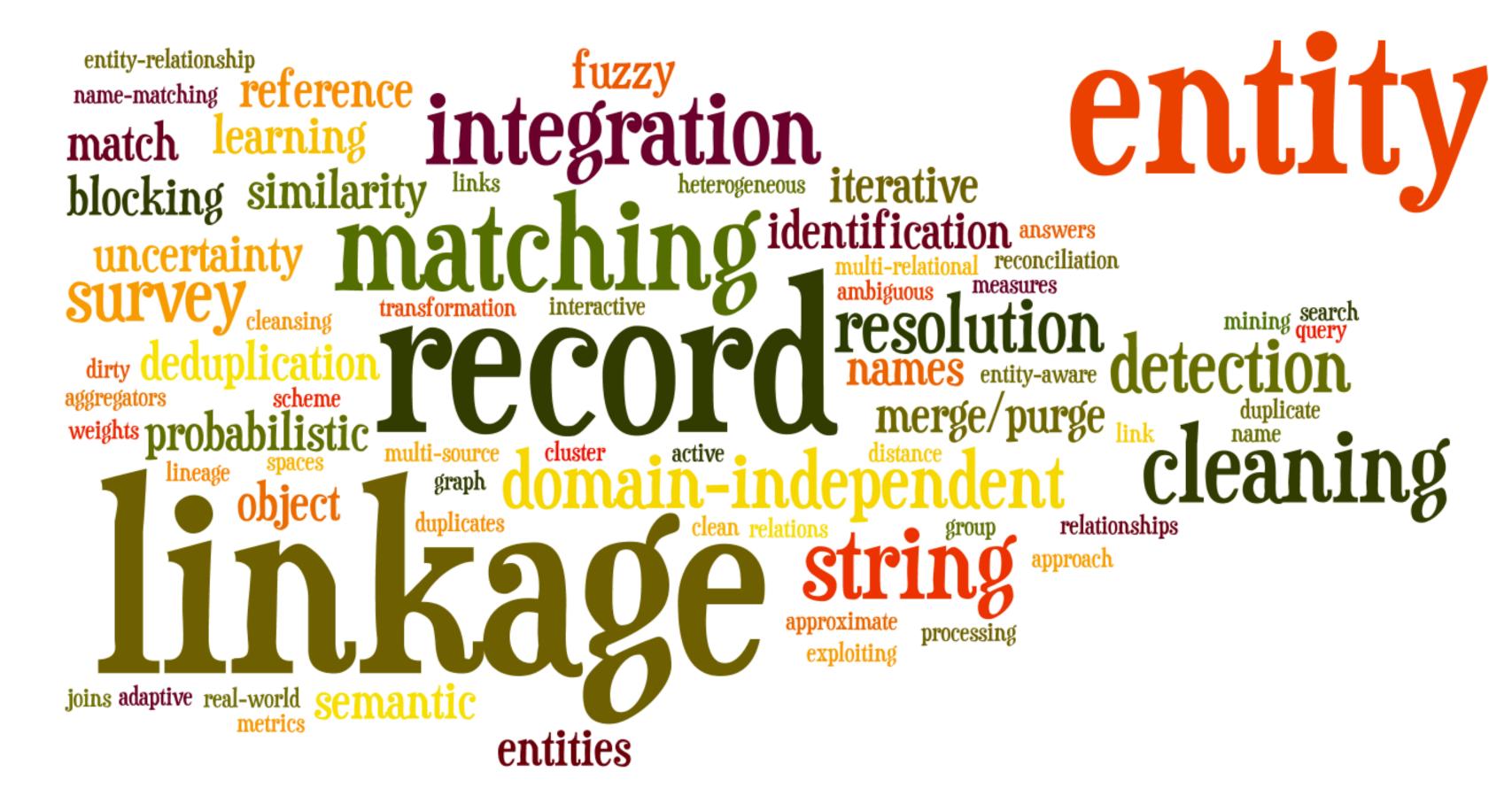
Solutions following various directions We present them through four categories:

- 1. Atomic similarity methods
- 2. Similarity methods for sets
- 3. Facilitating inner-relationships
- 4. Methods in uncertain data





Alternative names for Entity Resolution





- 1. Motivation: Entity Resolution
- 2. Atomic similarity methods
- 3. Similarity methods for sets
- 4. Facilitating inner-relationships
- 5. Methods in uncertain data
- 6. Conclusions



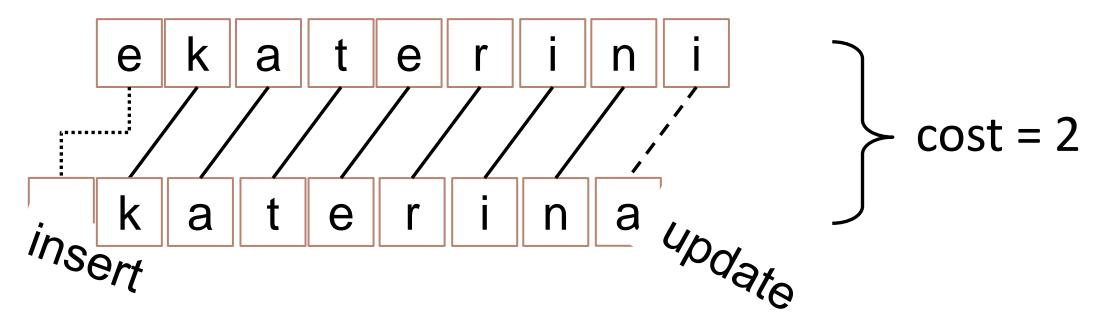


Examples of targeting cases:

- Publication authors: "John D. Smith" vs. "J. D. Smith"
- Journal names: "Transactions on Knowledge and Data Engineering"
 vs. "Trans. Knowl. Data Eng."

Edit Distance:

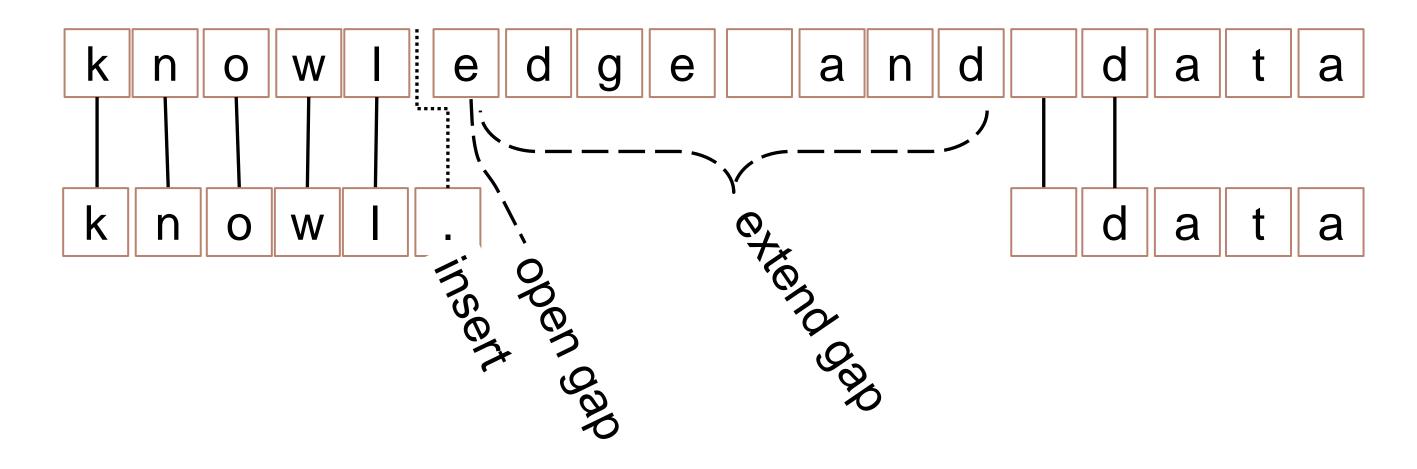
- Number of operations to convert from 1st to 2nd string
- Operations in Levenstein distance [Lev66]
 - → delete, insert, and update a character with cost 1





Gap Distance:

- Overcome limitation of edit distance with shortened strings
- Considers two extra operations [Nav01]
 - → open gap, and extend gap (with small cost)



cost = 1 + o + 8e



Jaro similarity [Jar89]:

■ Small string, e.g., first and last names

JaroSim(s₁, s₂) =
$$\frac{1}{3} \left(\frac{C}{|s_1|} + \frac{C}{|s_2|} + \frac{C-T}{C} \right)$$

C

common characters in S1 and S2

T \rightarrow transpositions/2 transposition is a k in which $s_1[k] != s_2[k]$

Example: "DEIS"vs. "DESI"

C=4, T=2/2, JaroSim=
$$\frac{1}{3} \left(\frac{4}{4} + \frac{4}{4} + \frac{4-1}{4} \right) = 0.9167$$

Jaro-Winkler similarity [Win99]:

- Extension that gives higher weight to matching prefix
- Increasing it's applicability to names



Soundex:

- Coverts each word into a phonetic encoding by assigning the same code to the string parts that sound the same
- Similarity between the corresponding phonetic encodings

Remarks:

- Surveys: [CRF03], [Win06]
- Existing API with these methods:
 - SecondString: http://secondstring.sourceforge.net/
 - SimMetrics: http://www.dcs.shef.ac.uk/~sam/simmetrics.html





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Database community:

- Each record is an entity
- A simple example:

| <u>Name</u> | <u>Email</u> | <u>Journal</u> |
|---------------|---------------|--|
| John D. Smith | smith@uni.edu | Transactions on Knowledge and Data Engineering |
| Smith, J. | smith@uni.edu | IEEE Trans. Knowl. Data Eng. |

Merge-purge [HS95],[HS98]:

- Idea: same entities will share information
- Create a key for each record (e.g., email)
- Sort records according to key
- Compare only a limited set of records in each iteration

e1

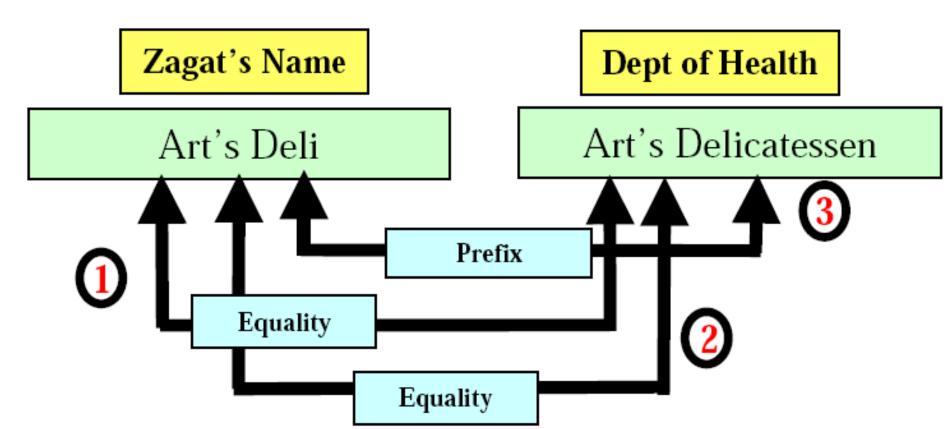
e2





Using transformations [TKM02]:

- 1. Analyze data to generate transformations
- Unary transform:
 - Equality, Stemming, Soundex,
 Abbreviation (e.g., 3rd or third)
- N-ary transformations:
 - Initial, Prefix, Suffix, Substring
 Acronym, Abbreviation, Drop



- 2. Calculate transformation weights
- 3. Apply on candidate mappings



Group Linkage [OKLS07]:

- Considers groups of relational records
 - not individual relational records
- Groups match when:
 - 1. High similarity between data of individual records
 - 2. Large fraction of matching records, i.e., no. 1

Some additional methods

→ [DLLH03]

Surveys for methods in this category

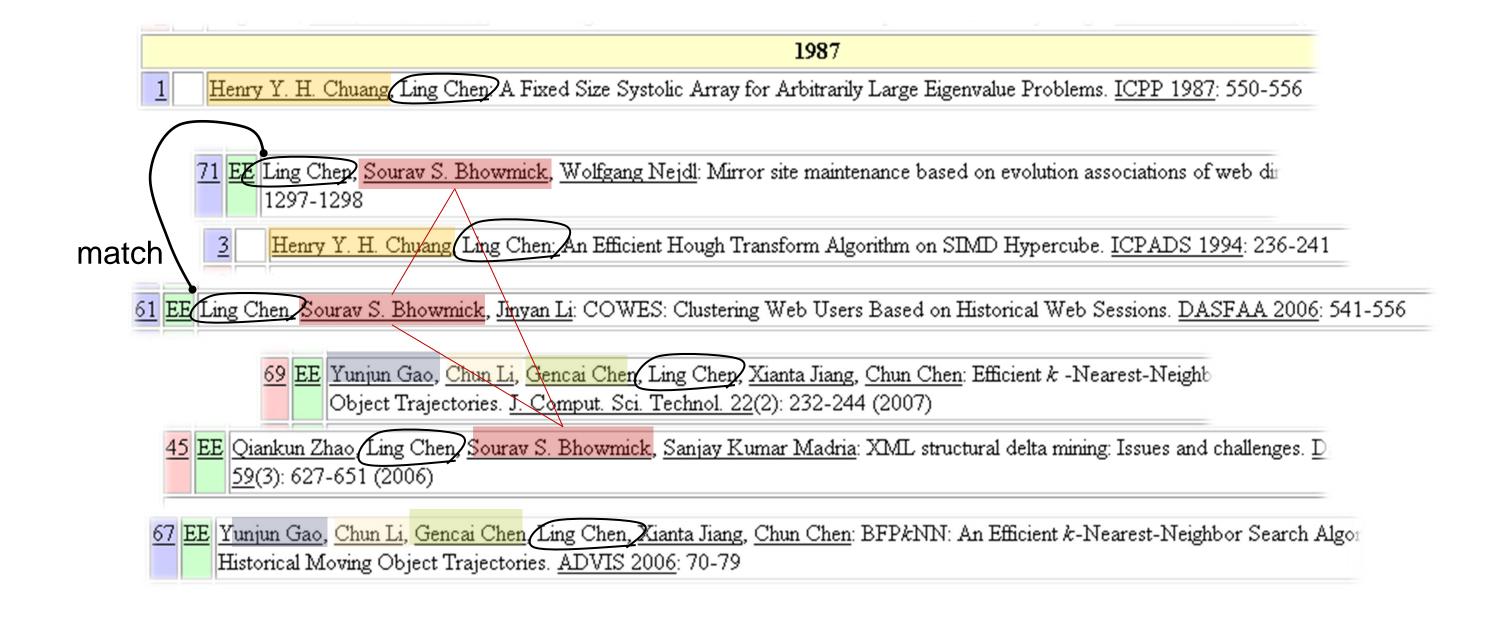
→ [DH05], [EIV07], [OS99]





Remarks:

- Methods do not consider semantics of data
- Currently used as a first step of Entity Resolution







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General idea

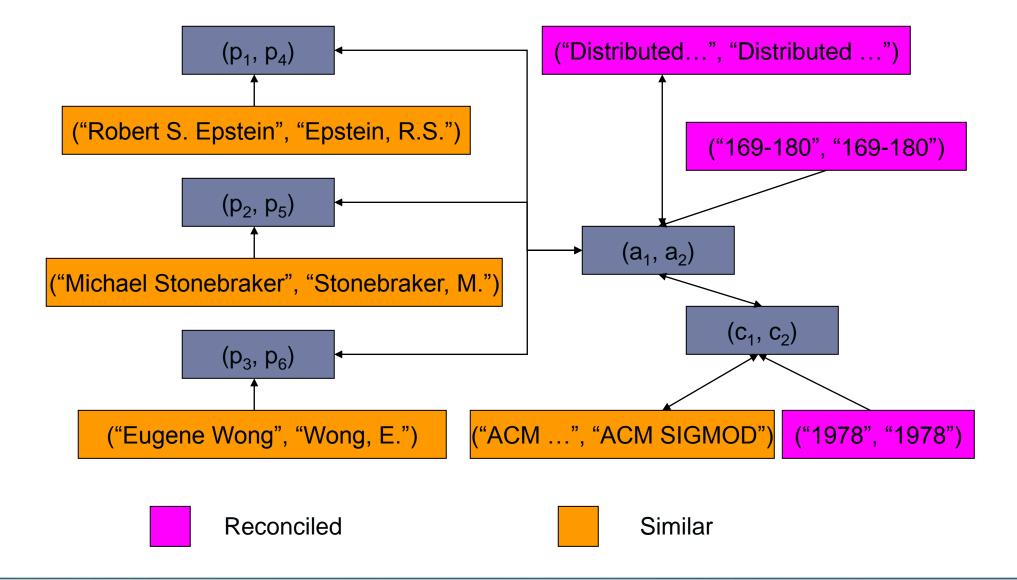
- Heterogeneous data
 - Lack of schema information
 - Variations in entity descriptions
 - Incomplete or missing values
- Improve effectiveness by considering data semantics
- Example → Reference Reconciliation





Reference Reconciliation [DHM05]

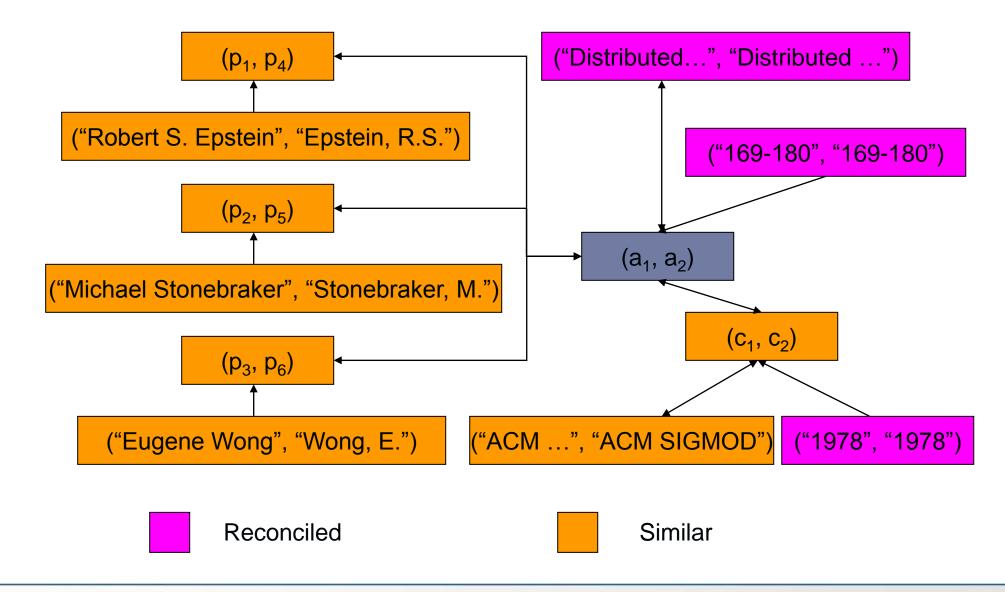
1. Build a dependency graph





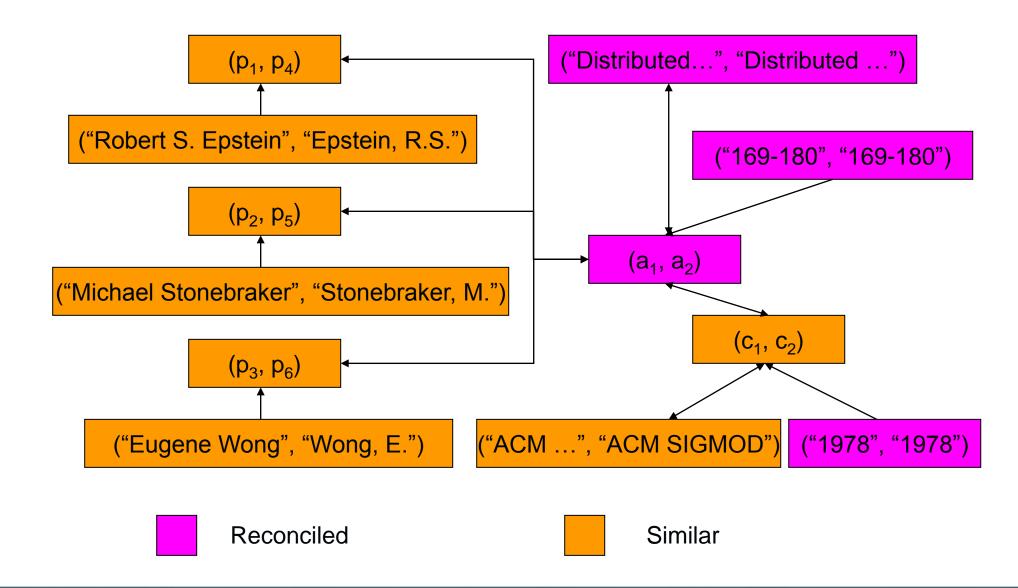


- 1. Build a dependency graph
- 2. Exploit information and relationships





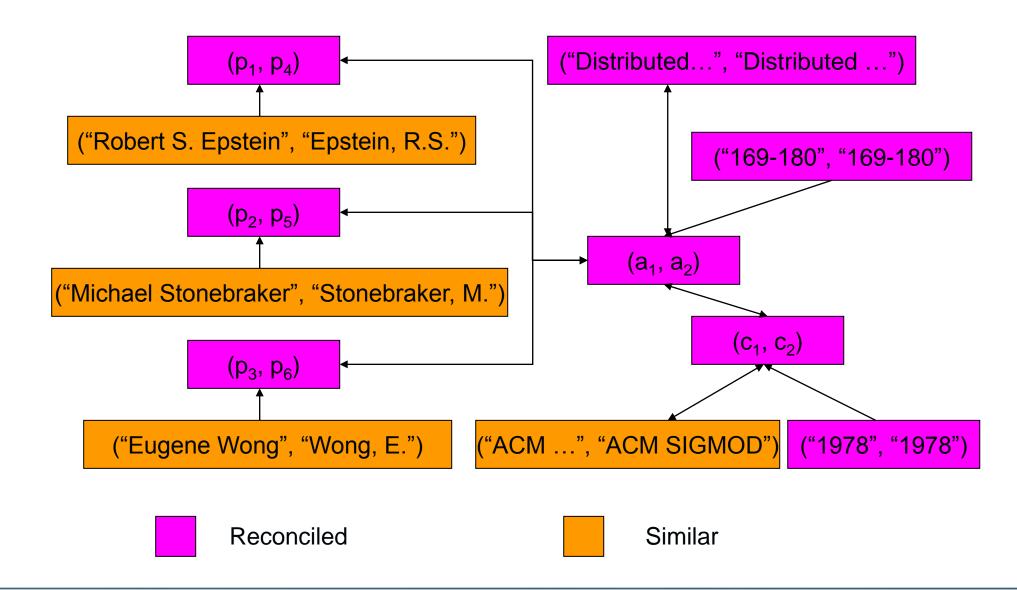
- 1. Build a dependency graph
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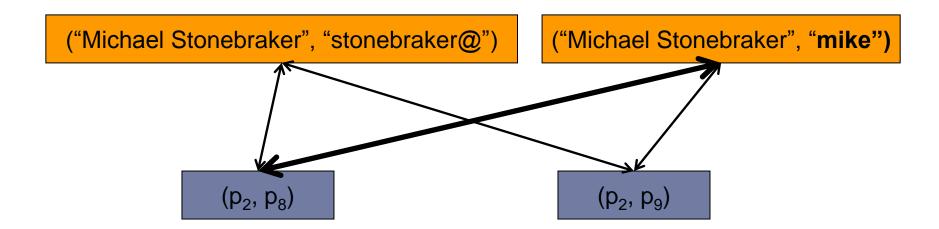
- 1. Build a dependency graph
- 2. Exploit information and relationships







- 1. Build a dependency graph
- 2. Exploit information and relationships
- 3. Propagate information \rightarrow enrich relationships





Analysis of entity-relationship graph [KM06], [KMC05]:

```
Publication table (to be cleaned)

(A1, 'Dave White', 'Intel')

(A2, 'Don White', 'CMU')

(A3, 'Susan Grey', 'MIT')

(A4, 'John Black', 'MIT')

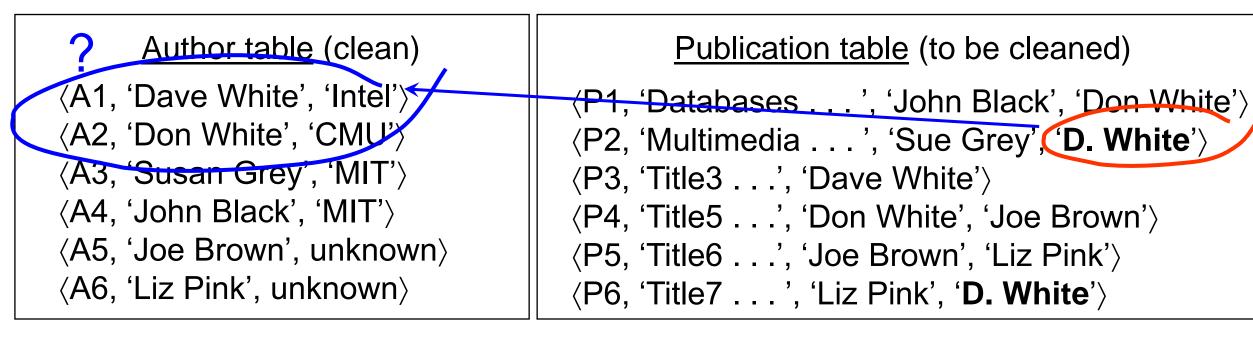
(A5, 'Joe Brown', unknown)

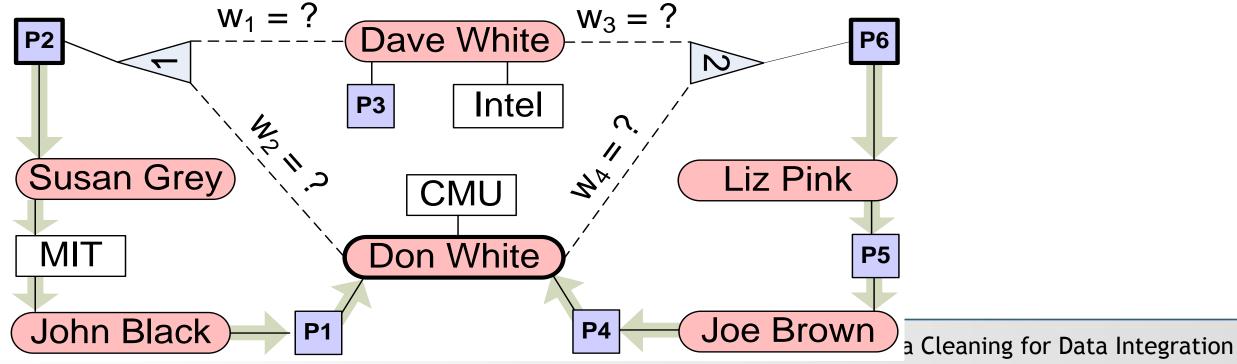
(A6, 'Liz Pink', unknown)
```



Analysis of entity-relationship graph [KM06], [KMC05]:

1. Dataset modeled as a graph







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- 2. Data more strongly connected when sharing relationships

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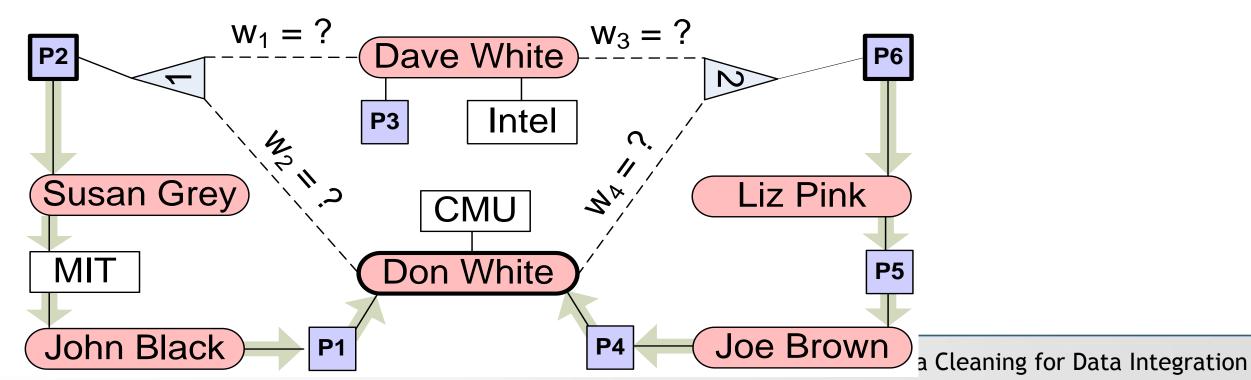
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A5, 'Joe Brown', unknown)

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```





Analysis of entity-relationship graph [KM06], [KMC05]:

- 1. Dataset modeled as a graph
- 2. Data more strongly connected when sharing relationships
- 3. Measure the connection strengths (details in paper)

```
? Author table (clean)

(A1, 'Dave White', 'Intel')

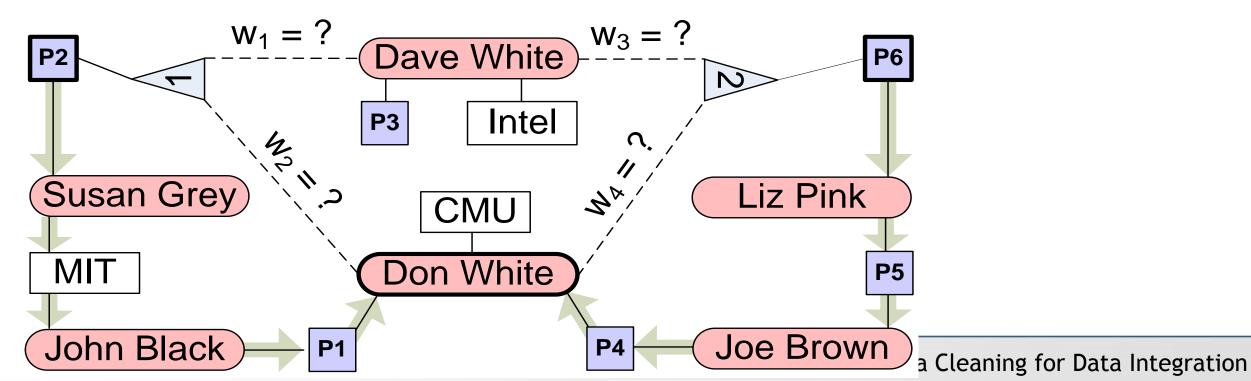
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(A6, 'Liz Pink', unknown)
```





Some additional methods:

- Relationship-based clustering [BG04a], [BG04b]:
 - Common references for a match increase our belief
 - o For this we need to identify common references
 - Iterative process: common matches → identifying additional matches
- Incremental & adaptive [INN08], [MPC+10]:
 - Targets data that are constantly changing and evolving
 - Bayesian network to model entities, relationships, and evidences (possible linkages)
 - Enables flexible update of the network

Surveys for methods in this category

→ [GD05], [KSS06]





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General idea:

- Keep conflicting relations, e.g., [AFM06], [RDS07], [DS07a], [DHY07]
 - Lack of resolution rules to correctly resolve and merge relations
 - No merging, but maintain results in the database
 - Relation are alternative representations of the same real world object
- Entity representation with probability indicates...
 - Reliability of the source
 - Output of the matching process
 - o Etc.

customer

| | <u>custId</u> | name | income | prob |
|-------|---------------|--------|--------|------|
| s_1 | c1 | John | \$120K | 0.9 |
| s_2 | c1 | John | \$80K | 0.1 |
| s_3 | c2 | Mary | \$140K | 0.4 |
| s_4 | c2 | Marion | \$40K | 0.6 |

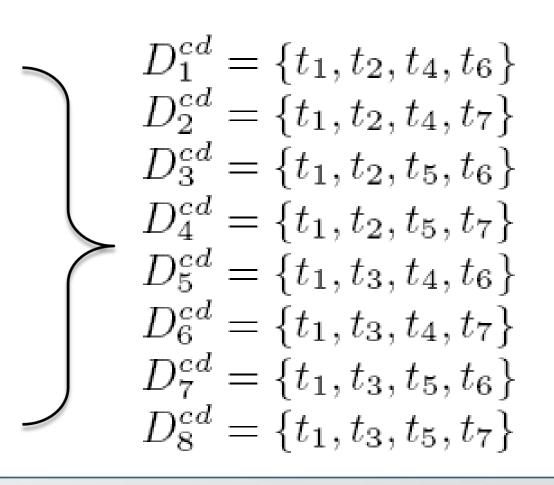


Clean answers over dirty databases [AFM06]:

- Dirty database represents several possible databases
- Result set for queries should include the entity resolution results
- Query rewriting mechanism with efficient computation of probability for each answer

| order | id | orderId | custFk | cIdFk | quantity | prob |
|-------|----|---------|--------|-------|----------|------|
| t_1 | о1 | 11 | m1 | c1 | 3 | 1 |
| t_2 | о2 | 12 | m2 | с1 | 2 | 0.5 |
| t_3 | о2 | 13 | m3 | c2 | 5 | 0.5 |

| customer | id | custId | name | balance | prob |
|----------|----|--------|--------|---------|------|
| t_4 | c1 | m1 | John | \$20K | 0.7 |
| t_5 | c1 | m2 | John | \$30K | 0.3 |
| t_6 | с2 | m3 | Mary | \$27K | 0.2 |
| t_7 | с2 | m4 | Marion | \$5K | 0.8 |





Clean answers over dirty databases [AFM06]:

Query rewriting

```
select A_1, \ldots, A_n \longrightarrow select A_1, \ldots, A_n, \text{sum}(R_1 .\text{prob.*} \ldots \ast R_m .\text{prob}) from R_1, \ldots, R_m where \mathcal{W} where \mathcal{W} group by A_1, \ldots, A_n
```

- Groups the result by the attributes
- For each group: sums the product of relation probabilities
- (applicable only to rewritable queries)



Entity-Aware querying over prob. linkages [INNV10]:

- Not merging the entities using threshold
- Keep probabilistic linkages alongside the original data
- Use them during query processing

Query:

o "J. K. Rowling" movies in "2002"

Assume no linkages:

o zero results

Possible answer with linkages:

- o merge(e₁, e₂)
- o merge(e₁, e₂, e₃)

| (| title: Harry Potter and the Chamber of Secrets | 0.6 |
|-------------------------|--|-----|
| | starring: Daniel Radcliffe | 0.7 |
| • <i>e</i> ₁ | starring: Emma Watson | 0.4 |
| | writer: J.K. Rowling | 0.6 |
| | genre: Fantasy | 0.6 |
| 0.9 | | |
| , | | ~ = |
| - - | title: Harry Potter and the Chamber of Secrets | 0.7 |
| • e ₂ | date: 2002 | 0.8 |
| - 2 | starring: Daniel Radcliffe | 0.5 |
| <u>-</u> | starring: Emma Watson | 0.9 |
| · ' | | |
| 0.6 | | |
| - (| title: Harry Potter and the Chamber of Secrets | 0.8 |

author: J.K. Rowling

0.8





Entity-Aware querying over prob. linkages [INNV10]:

- Linkage prob. represent several possible *l*-worlds
- Attribute prob. represent several possible worlds
- Efficient query processing:
 - Analyze query conditions
 - Identify the required entity merges
 - Decide useful possible *l*-worlds
 - Generate possible worlds
 - Compute probability

| | | title. Harry Folici and the Chamber of Secrets | 0.0 |
|---|-----------------|--|-----|
| | | starring: Daniel Radcliffe | 0.7 |
| | \bullet e_1 | starring: Emma Watson | 0.4 |
| | | writer: J.K. Rowling | 0.6 |
| - | - | genre: Fantasy | 0.6 |
| - | 0.9 | | |
| - | (| title: Harry Potter and the Chamber of Secrets | 0.7 |
| | • e2 | date: 2002 | 0.8 |
| | <u> </u> | starring: Daniel Radcliffe | 0.5 |
| | | starring: Emma Watson | 0.9 |
| | Α. | _ | |

title: Harry Potter and the Chamber of Secrets 0.6

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title: Harry Potter and the Chamber of Secrets 0.8 genre: Fantasy 0.8 author: J.K. Rowling 0.7

• e3



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Conclusions

Discussed methods entity resolution Four categories of methods Not presented:

- Blocking mechanisms:
 - Split data into blocks and compare inner-block data
 - Improves efficiency for large-size datasets
 - Examples: [WMK+09], [PINF11]
- Active learning approaches:
 - Use a subset of the data to learn matching rules
 - Apply the rules to remaining data
 - o Examples: [SB02], [CR01]
- Similarity Joins [GIJ+1]
- Schema matching
- •





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