

Multi-column Substring Matching For Database Schema Translation

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The 32nd Very Large Database Conference, 2006

Database Integration

Objective

A generalisable method capable of resolving complex schema matches and the translation required to convert the instance data using substrings concatenation.

Example

- 1 leftmost characters of column lastname + 2 rightmost characters of column birthdate \rightarrow column userid
- Name in database $D \rightarrow$ First + Last in database D'
- 2005/05/29 in database $D \rightarrow$ 05/29/2005 in database D'
- PartNumber in database $D \rightarrow$ Number + PlantId + 2 rightmost digits in Year.

Database Integration

Why is this an important problem?

Issues:

- ...the number and size of databases growing. (+10,000 tables, +1,600 columns)
- ...integration is an every day issue. (Semantic web, smart clients, dynamic data sources...)
- ...multiple standards in use. (22 Locales)
- ...previously we have used top-down approaches. Here we use a data-driven, bottom up approach.

⇒ Need automation to deal with this problem.

Database Integration

Previous work

- Rahm and Bernstein present a good taxonomy and discussion of matching problem. [RB01b, RB01a]
 - Basic support for concatenating complete columns in the CUPID system. [MBR01]
 - Embley et al. made use of ontologies to discover such translations. [EXD04]
 - To deal with complex cases, Doan et al. proposed “format learners”. [DDH01]
 - The IMAP system makes use of specific matchers for mathematical relationships. [DLD⁺04]
- ⇒ No known generalisable solution to high-cardinality (n -to-1), substring concatenations schema translations.

Requirements and concerns

- 1 Automated, un-supervised and data driven.
- 2 Offload as much of the work to the databases. [KMS04]
- 3 Client side discovery process, bandwidth \ll database contents.
- 4 Part of a larger, automated, database integration system: partial notion of what could/should be a match.
- 5 “Entity” overlap between database tables unknown but present.

Problem formalization

Definition

For a given target database table T_2 with a target column A ...and a source table T_1 with a set of likely source columns (B_1, B_2, \dots, B_n)

Find a transformation such that:

$A = \omega_1 + \omega_2 + \dots + \omega_\nu$ Where ω_j represents a substring of column B_j

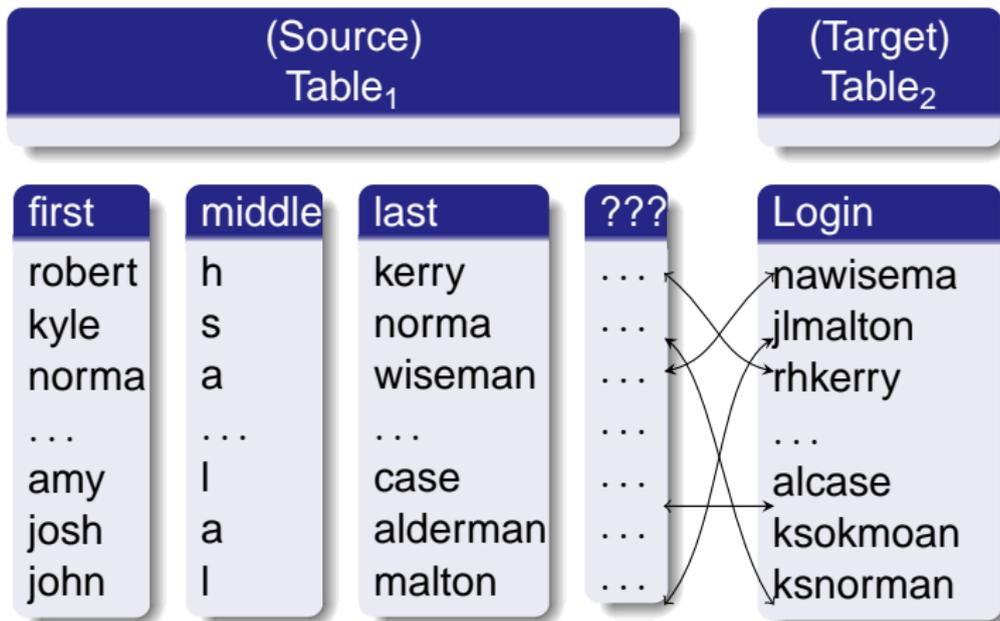
Translation model

$t' = t [\beta_1^{x_1 \dots y_1} + \beta_2^{x_2 \dots y_2} + \dots + \beta_\nu^{x_\nu \dots y_\nu}]$ (chars $x_\nu \dots y_\nu$ of col B_ν)

Basic example

(Source) Table ₁				(Target) Table ₂
first	middle	last	???	Login
robert	h	kerry	...	nawisema
kyle	s	norma	...	jmalton
norma	a	wiseman	...	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

Basic example



Basic example

(Source) Table ₁				(Target) Table ₂
norma	a	wiseman	...	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

How to infer translation?

```
select substring(first from 1 for 1) ||  
substring(middle from 1 for 1) || last as login  
into target_table from source_table.
```

Basic example

(Source)
Table₁

(Target)
Table₂

Solution:

Iteratively select substrings from “best-fit” columns while performing a simple form of record linkage.

...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

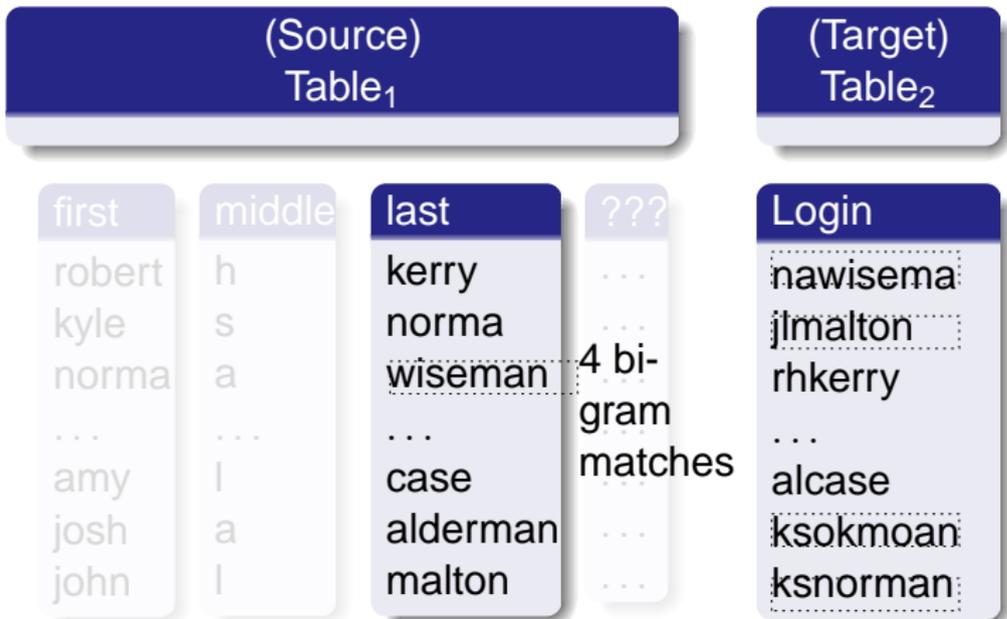
Basic example - Find initial column. (1)

(Source) Table ₁				(Target) Table ₂
first	middle	last	???	Login
robert	h	kerry	...	nawisema
kyle	s	norma	...	jmalton
norma	a	wiseman	?	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

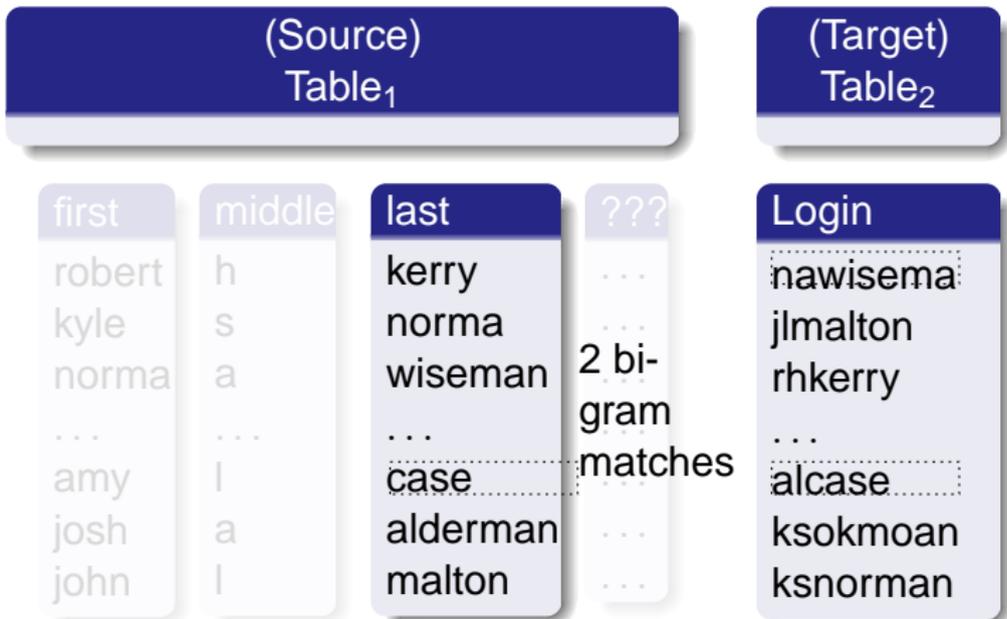
Basic example - Find initial column. (2)

(Source) Table ₁				(Target) Table ₂
first	middle	last	???	Login
robert	h	kerry	...	nawisema
kyle	s	norma	...	jmalton
norma	a	wiseman	1 bi-gram match	rhkerry
...
amy	l	case		alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

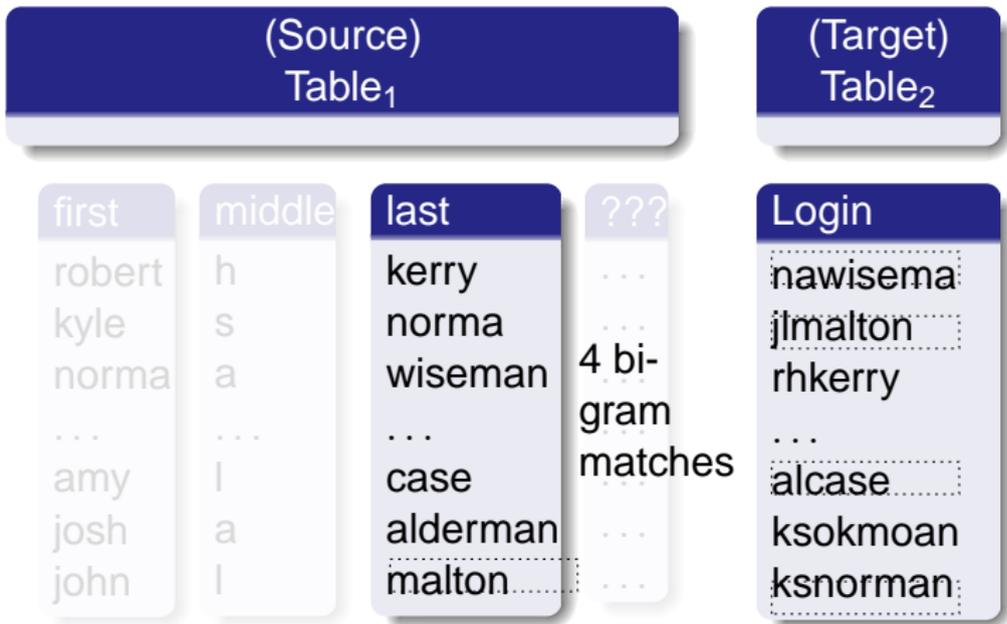
Basic example - Find initial column. (2)



Basic example - Find initial column. (2)



Basic example - Find initial column. (2)



Basic example - Find initial column. (2)

(Source)

(Target)

Column Scoring Formula

$$\text{ScoreCol} = \left(\sum_{j=1}^t \frac{\text{HitCount}(j)}{t * \text{length}(\text{key}_j)} \right)^q \quad (1)$$

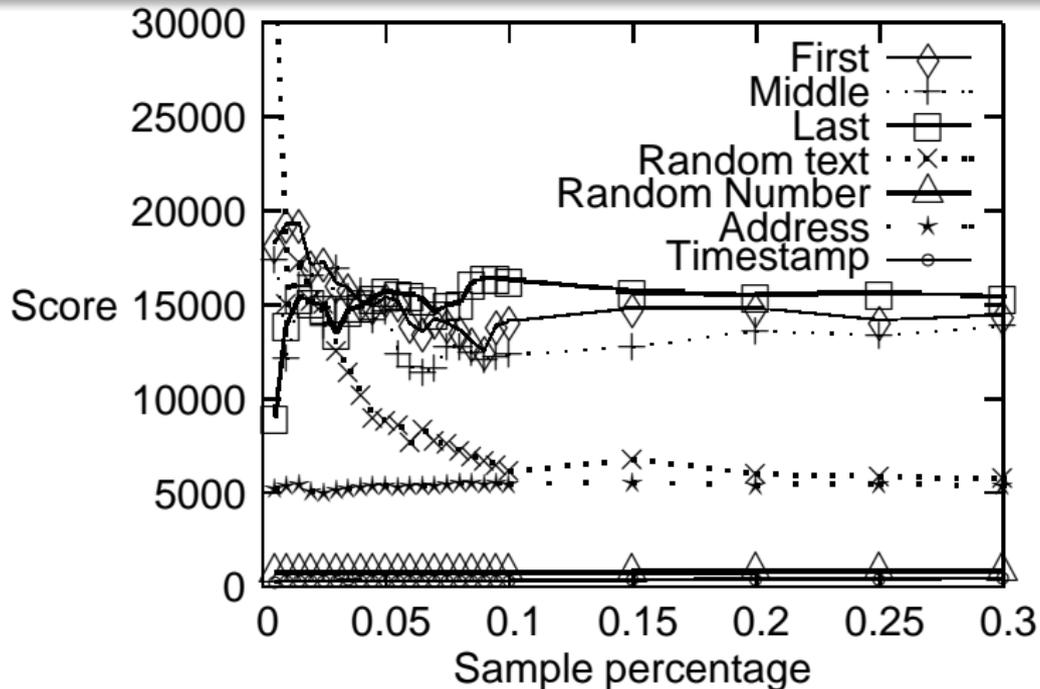
Where:

t is the number of sampled values from source column.

key_j is the j -th sampled value.

HitCount is the number of q -gram matches for key_j .

Basic example - Find initial column. (3)



Basic example - Find a partial translation. (1)

(Source) Table ₁				(Target) Table ₂
first	middle	last	???	Login
robert	h	kerry	...	nawisema
kyle	s	norma	...	jmalton
norma	a	wiseman	...	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

Use string edit distance to create candidate translation.

Basic example - Find a partial translation. (1)

(Source)	(Target)
Generate candidate translations	
malton + wiseman	→ %[1-2]%
malton + jmalton	→ %[1-EOL]
malton + alcasa	→ %[2-3]%
...	
kerry + rhkerry	→ %[1-EOL]
...	
Highest occurrence: %[1-EOL]	

john a algerman ... ksnorman

john l malton ... ksnorman

Use string edit distance to create candidate translation.

Basic example - Search for additional columns. (1)

(Source) Table ₁				(Target) Table ₂
first	middle	last	???	Login
robert	r	kerry	...	nawisema
kyle	s	norma	...	jmalton
norma	a	wiseman	...	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

Sample the tuples formed from translation formula.

Basic example - Search for additional columns. (1)

(Source)			(Target)
Table			Table
Generate candidate translations			
robert + rhkerry → %[1-EOL]			
...			
...			
(Keep track of all candidates and their frequencies.)			
norman	a	wiseman	rhkerry
...
amy	l	case	alcase
josh	a	alderman	ksokmoan
john	l	malton	ksnorman

Sample the tuples formed from translation formula.

Basic example - Search for additional columns. (1)

(Source) Table

(Target) Table

Score each candidate translation using formula.

$$\text{ScoreTrans}(\tau_j) = \frac{\text{Frequency}(\tau_j)}{\max(1, \text{AvgLength}(B_i) - \sigma)} \quad (2)$$

norma	a	wiseman	...	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

Sample the tuples formed from translation formula.

Basic example - Search for additional columns. (2)

(Source) Table ₁				(Target) Table ₂
first	middle	last	???	Login
robert	h	kerry	...	nawisema
kyle	s	norma	...	jmalton
norma	a	wiseman	...	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

Sample the tuples formed from current translation formula

Basic example - Search for additional columns. (2)

(Source)				(Target)
Table				Table
Generate candidate translations				
h + rhkerry → %[1-1]				
...				
...				
(Keep track of all candidates and their frequencies.)				
norman	a	wiseman	...	rhkerry
...
amy	l	case	...	alcas
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

Sample the tuples formed from current translation formula

Basic example - Search for additional columns. (2)

(Source)		(Target)	
Table	Table	Table	Table
Ending condition			
No unknowns remain within:			
$t' = t [\beta_1^{x_1 \dots y_1} + \beta_2^{x_2 \dots y_2} + \dots + \beta_\nu^{x_\nu \dots y_\nu}]$			
Login = first[1-1] + middle[1-1] + last[1-EOL]			
... amy josh john	... l a l	... case alderman malton	... alcase ksokmoan ksnorman

Sample the tuples formed from current translation formula

Experimental setup - Noise column

Add and populate the following noise columns:

- A random RFC-2822 timestamp.
- A random street address.
- A random long integer.
- A random value, variable length string.

Definition

Simulate noisy matching environment and ensure proper algorithmic behavior.

Login Dataset

(Source) Table ₁				(Target) Table ₂
first	middle	last	???	Login
robert	h	kerry	...	nawisema
kyle	s	norma	...	jmalton
norma	a	wiseman	...	rhkerry
...
amy	l	case	...	alcase
josh	a	alderman	...	ksokmoan
john	l	malton	...	ksnorman

(6,000 rows, $q=2$, 10% sample)

Time Dataset

(Source) Table ₁				(Target) Table ₂
second	middle	hours	???	time
55	59	02	...	355407
43	23	05	...	330011
12	55	07	...	135741
...
33	00	11	...	004107
34	54	07	...	192609

(10,000 randomly generated timestamps, $q=2$, sample=10%).

Name Dataset

(Source)
Table₁

first	last
robert	kerry
kyle	norman
norma	wiseman
...	...
amy	case
josh	alder
john	galt

(Target)
Table₂

???	full
...	robertkerry
...	kylenorman
...	normawiseman
...	...
...	amycase
...	joshalder
...	johngalt

(700,000 rows, $q=2$, sample=10%)

CiteSeer & DBLP Dataset

CiteSeer

Extracted 526,000 records from OAI dump.
Created Title, Year and Author (15) columns.
Created Citation column from Title, Year and First Author.
(Successfully matched at 1% sampling.)

DBLP

Extracted 233,000 records from web dump.
Created Title, Year and Author (15) columns.
Created Citation column from Title, Year and First Author.
(Successfully matched at 1% sampling.)

Cross Citeseer and DBLP Dataset translation

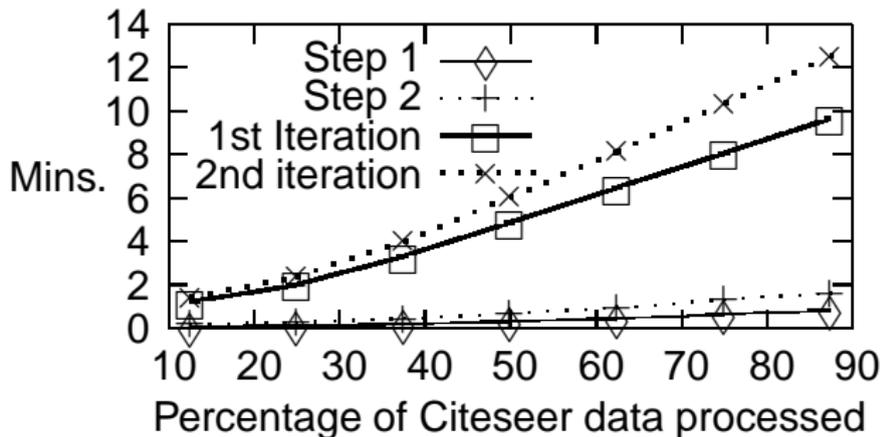
Expected result

Match Citeseer Citation column to DBLP source table.
Only 714 records match across Title, Year and First Author.

Actual result

Citeseer Citation = DBLP Title + DBLP Year + DBLP Second Author.
378 citations have their First and Second authors reversed!
Returned mapping is “correct” according to the data.

Incremental wall-clock performance



Estimated complexity

$$O(w * n * s_1 * s_2)$$

Overall

- Previous approaches required specialized domain specific matchers to form both the match and the translation.
- This algorithm is a generalized algorithm for string-based concatenations matches.
- Meant to function as part of larger database integration framework.

The future

- Remove or estimate parameter selection.
- Improve string editing algebra.
- Allow use of independent and concurrent translation formulas.

Name Dataset - Special Cases

(Source)
Table₁

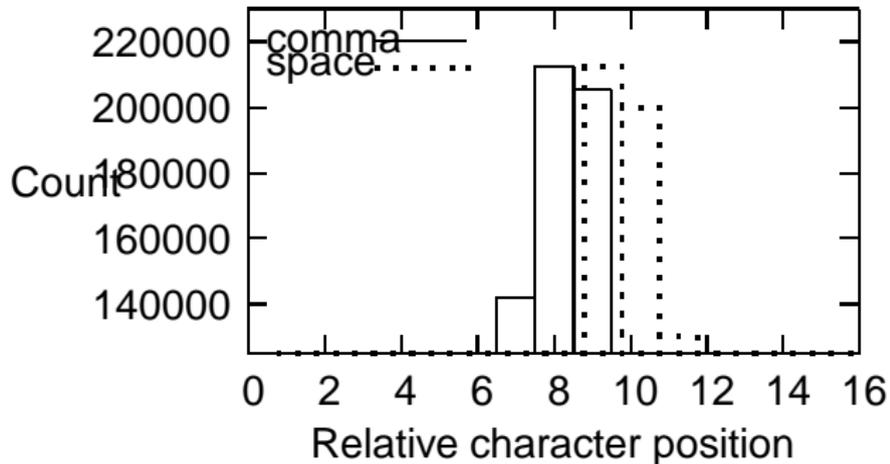
first	last
robert	kerry
kyle	norman
norma	wiseman
...	...
amy	case
josh	alder
john	galt

(Target)
Table₂

???	full
...	kerry, robert
...	norman, kyle
...	...
...	...
...	case, amy
...	alder, josh
...	galt, john

(700,000 rows, q=2, sample=10%)

Name Dataset - Separator Histogram



m-to-n linkages

Source				Target	
birth day	first	middle	last	login	DOB
12-21-1923	robert	h	kerry	nawisema	5/6/73
11-13-1956	kyle	s	norman	jlmalton	8/11/48
5-6-1973	norma	a	wisema	rhkerry	12/21/23
...
1-3-1981	amy	l	case	alcase	1/3/81
5-29-1989	josh	a	alderman	ksokmoan	2/20/73
8-11-1948	john	l	malton	ksnorman	11/13/56

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-  Robin Dhamankar, Yoonkyong Lee, AnHai Doan, Alon Halevy, and Pedro Domingos, *imap: discovering complex semantic matches between database schemas*, Intl. Conf. ACM SIGMOD, 2004, pp. 383–394.
-  David W. Embley, Li Xu, and Yihong Ding, *Automatic direct and indirect schema mapping: experiences and lessons learned*, SIGMOD Rec. **33** (2004), no. 4, 14–19.
-  Nick Koudas, Amit Marathe, and Divesh Srivastava, *Flexible string matching against large databases in practice.*, VLDB, 2004, pp. 1078–1086.

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-  Erhard Rahm and Philip A. Bernstein, *A survey of approaches to automatic schema matching*, The VLDB Journal **10** (2001), no. 4, 334–350.