An evaluation of string similarity measures on pricelists of computer components

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AND producer IS hp OR producer IS UNKNOWN
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Toner pro LaserJet 4/4M, 4/4M Plus, 5/5N/5M (8800)
```

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Example (2)

```
category IS accesories OR category IS UNKNOWN
AND producer IS logitech OR producer IS UNKNOWN
description IS SIMILAR TO
Pilot Optical Mouse, USB+PS/2, 3 tlačítka, černá
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AND producer IS logitech OR producer IS UNKNOWN
description IS SIMILAR TO
Pilot Optical Mouse, USB+PS/2, 3 tlačítka, černá

Logitech myš Pilot Optical Mouse Black, USB/PS/2, retail
```

Problem description

- We have pricelists of computer components from seven different resellers - some with more than 30,000 components.

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- Part numbers provide a very reliable matching.
- Unfortunatelly, many items in pricelists do not have any part number assigned.

A fulltext search method

- As a reference method we used the fulltext search of MySQL: `http://dev.mysql.com/doc/refman/5.0/en/fulltext-search.html`

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- The search string is treated as a phrase in free text.
- The MySQL stopword list was applied.
- Words present in more than 50% of the records were considered common and were not matched.
- Also words shorter than four characters were not matched.
- We denote the similarity value of two strings S_1 and S_2 provided by this fulltext search method as $Sim_1(S_1, S_2)$.

A string edit distance measure

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- We do not require the substrings of S_1 to be disjoint, which means that parts of substrings of S_1 longer than two are counted several times.
- In the experiments we used the relative string similarity defined as

$$Sim_2(S_1, S_2) = \frac{Sim(S_1, S_2)}{Sim(S_1, S_1)}$$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 1$

$Similarity(R_1, R_2) = 0$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 1$

$R = "WI"$

$Length(R) = 2$

$Similarity(R_1, R_2) = 2$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 1$

$R =$ "WIN"

$Length(R) = 3$

$Similarity(R_1, R_2) = 2 + 3$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 2$

$Similarity(R_1, R_2) = 2 + 3$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 2$

$R = "IN"$

$Length(R) = 2$

$Similarity(R_1, R_2) = 2 + 3 + 2$

The string edit distance measure

Example

R_1

W	I	**N**	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 3$

$Similarity(R_1, R_2) = 2 + 3 + 2$

The string edit distance measure

Example

R_1

W	I	N	**D**	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 4$

$Similarity(R_1, R_2) = 2 + 3 + 2$

The string edit distance measure

Example

R_1

W	I	N	D	**O**	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 5$

$Similarity(R_1, R_2) = 2 + 3 + 2$

The string edit distance measure

Example

R_1

W	I	N	D	O	**W**	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 6$

$Similarity(R_1, R_2) = 2 + 3 + 2$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	**S**		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 7$

$Similarity(R_1, R_2) = 2 + 3 + 2$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S	_	T	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 8$

$$Similarity(R_1, R_2) = 2 + 3 + 2$$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S	_	T	E	R	M

R_2

W	I	N	_	T	R	M	N	L

$k = 8$

$R ='' \ \text{T}''$

$Length(R) = 2$

$Similarity(R_1, R_2) = 2 + 3 + 2 + 2$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		**T**	E	R	M

R_2

W	I	N		T	R	M	N	L

$k = 9$

$$Similarity(R_1, R_2) = 2 + 3 + 2 + 2$$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	**E**	R	M

R_2

W	I	N		T	R	M	N	L

$k = 10$

$$Similarity(R_1, R_2) = 2 + 3 + 2 + 2$$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	**R**	M

R_2

W	I	N		T	R	M	N	L

$k = 11$

$Similarity(R_1, R_2) = 2 + 3 + 2 + 2$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	**R**	M

R_2

W	I	N		T	R	M	N	L

$k = 11$

$R =$ "RM"

$Length(R) = 2$

$Similarity(R_1, R_2) = 2 + 3 + 2 + 2 + 2$

The string edit distance measure

Example

R_1

W	I	N	D	O	W	S		T	E	R	M

R_2

W	I	N		T	R	M	N	L

$$Similarity(R_1, R_2) = 2 + 3 + 2 + 2 + 2 = 11$$

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- $n(S)$ be the total number of tokens in string S,
- m be the total number of all strings in the data, and
- $m(x)$ be the number of strings containing token x.
- The weight of a token x in string S is defined as

$$w(x, S) = \frac{n(x, S)}{n(S)} \log \frac{m}{m(x)} .$$

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$$\mathbf{v}(S) \quad = \quad \frac{\mathbf{w}(S)}{\sqrt{\sum_{i=1}^{d} w(x_i, S)^2}}$$

- Similarity of two strings S_1 and S_2 is then computed as the scalar product of normalized weight vectors $\mathbf{v}(S_1)$ and $\mathbf{v}(S_2)$

$$Sim_3(S_1, S_2) \quad = \quad \sum_{i=1}^{d} v(x_i, S_1) \cdot v(x_i, S_2) \quad = \quad \mathbf{v}(S_1)^T \cdot \mathbf{v}(S_2) \ .$$

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- Note that since both vectors are sparse the computation of the scalar product can be efficiently implemented.

The vector based method

Example

S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

The vector based method

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S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

S_2 `samsung␣toner␣magenta␣pro␣clp510/n␣(5000str␣)`

The vector based method

Example

S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

S_2 `samsung␣toner␣magenta␣pro␣clp510/n␣(5000str␣)`

- For simplicity assume tokens from these two strings only:

  `toner, magenta, pro, clp, 510, 510n, az, 5000, stran, samsung, clp510, n, 5000str`

The vector based method

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S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

S_2 `samsung␣toner␣magenta␣pro␣clp510/n␣(5000str␣)`

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- $w(\texttt{toner}, S_1) = \frac{1}{9} \log \frac{36478}{274} = 0.236$

The vector based method

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S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

S_2 `samsung␣toner␣magenta␣pro␣clp510/n␣(5000str␣)`

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  `toner, magenta, pro, clp, 510, 510n, az, 5000, stran, samsung, clp510, n, 5000str`

- $w(\texttt{toner}, S_1) = \frac{1}{9} \log \frac{36478}{274} = 0.236$
- $w(\texttt{toner}, S_2) = \frac{1}{7} \log \frac{36478}{274} = 0.303$

The vector based method

Example

S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

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- $w(\texttt{toner}, S_2) = \frac{1}{7} \log \frac{36478}{274} = 0.303$
- $w(\texttt{magenta}, S_1) = \frac{1}{9} \log \frac{36478}{59} = 0.310$

The vector based method

Example

S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

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The vector based method

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S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

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- $w(\texttt{magenta}, S_2) = \frac{1}{7} \log \frac{36478}{59} = 0.399$
- $\mathbf{w}(S_1) = (0.236, 0.310, 0.285, 0.420, 0.235, 0.345, 0.034, 0.121, 0.097, 0.000, 0.000, 0.000, 0.000)$

The vector based method

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S_1 `toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran`

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- $\mathbf{w}(S_1) =$ (0.236, 0.310, 0.285, 0.420, 0.235, 0.345, 0.034, 0.121, 0.097, 0.000, 0.000, 0.000, 0.000)
- $\mathbf{w}(S_2) =$ (0.303, 0.399, 0.366, 0.000, 0.000, 0.000, 0.000, 0.000, 0.000, 0.056, 0.451, 0.023, 0.456)

The vector based method

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S_1 toner␣magenta␣pro␣clp-510/510n,␣az␣5000␣stran

S_2 samsung␣toner␣magenta␣pro␣clp510/n␣(5000str␣)

- $\mathbf{v}(S_1) = \frac{\mathbf{w}(S_1)}{\sqrt{\sum_{i=1}^{d} w(x_i, S_1)^2}} = \frac{\mathbf{w}(S_1)}{0.780}$

The vector based method

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- $\mathbf{v}(S_2) = \frac{\mathbf{w}(S_2)}{\sqrt{\sum_{i=1}^{d} w(x_i, S_2)^2}} = \frac{\mathbf{w}(S_2)}{0.794}$

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- $\mathbf{v}(S_1) = (0.302, 0.397, 0.365, 0.538, 0.301, 0.442, 0.044, 0.155, 0.124, 0.000, 0.000, 0.000, 0.000)$

The vector based method

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$$\begin{aligned} Sim_3(S_1, S_2) &= \mathbf{v}(S_1)^T \cdot \mathbf{v}(S_2) \\ &= 0.302 \cdot 0.339 + 0.397 \cdot 0.446 + 0.365 \cdot 0.409 = 0.429 \end{aligned}$$

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where $\mathbf{c} = (c_1, c_2, c_3)$ was set to $(0.3, 1, 1)$, $(0, 1, 1)$, and $(0, 1, 2)$.

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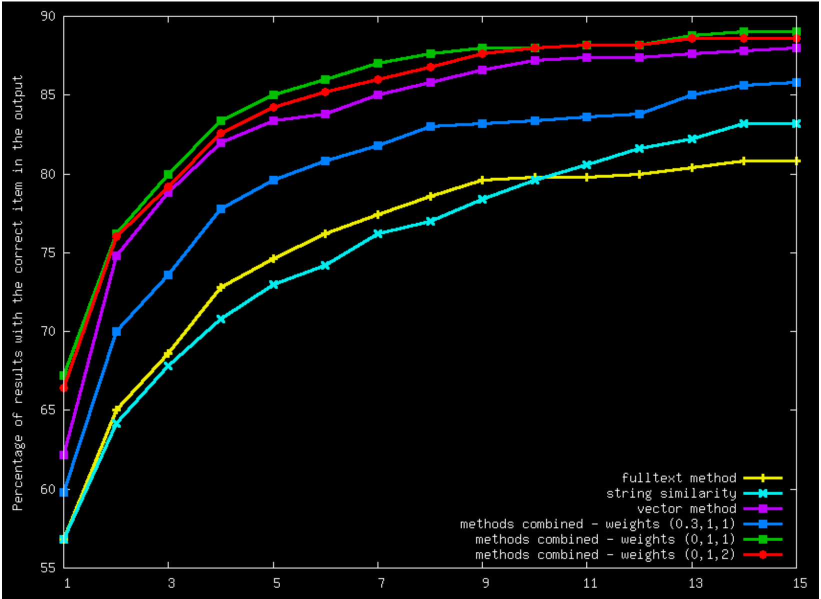
- We counted the number of these cases and computed the relative success rate for each method with respect to k.

Results of experiments



Examples of unmatched components

Example (Acer server)

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AAG320 PD 940 (3.2 GHz, 2x 2MB, 800 MHz FSB),
1x 512 MB DDR2 533/16x DVD-ROM
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- For example, the space symbol is a separator between `PD940` and `3.2 GHz` but "`3.2 GHz`" should be one token.

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Examples of unmatched components

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+ GOLD MAINT 1YR IN VALUE BAND F(5
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- the vector method as a basis for further improvements

Future work

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- This leads to a natural generalization of the vector method:

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- Since the matrix **P** and vectors $\mathbf{v}(S_1), \mathbf{v}(S_2)$ are sparse the computations can be efficiently implemented.