String Matching

Shobeir Fakhraei
University of Southern California

Thanks to Pedro Szekely, Craig Knoblock
and your textbook authors for these slides

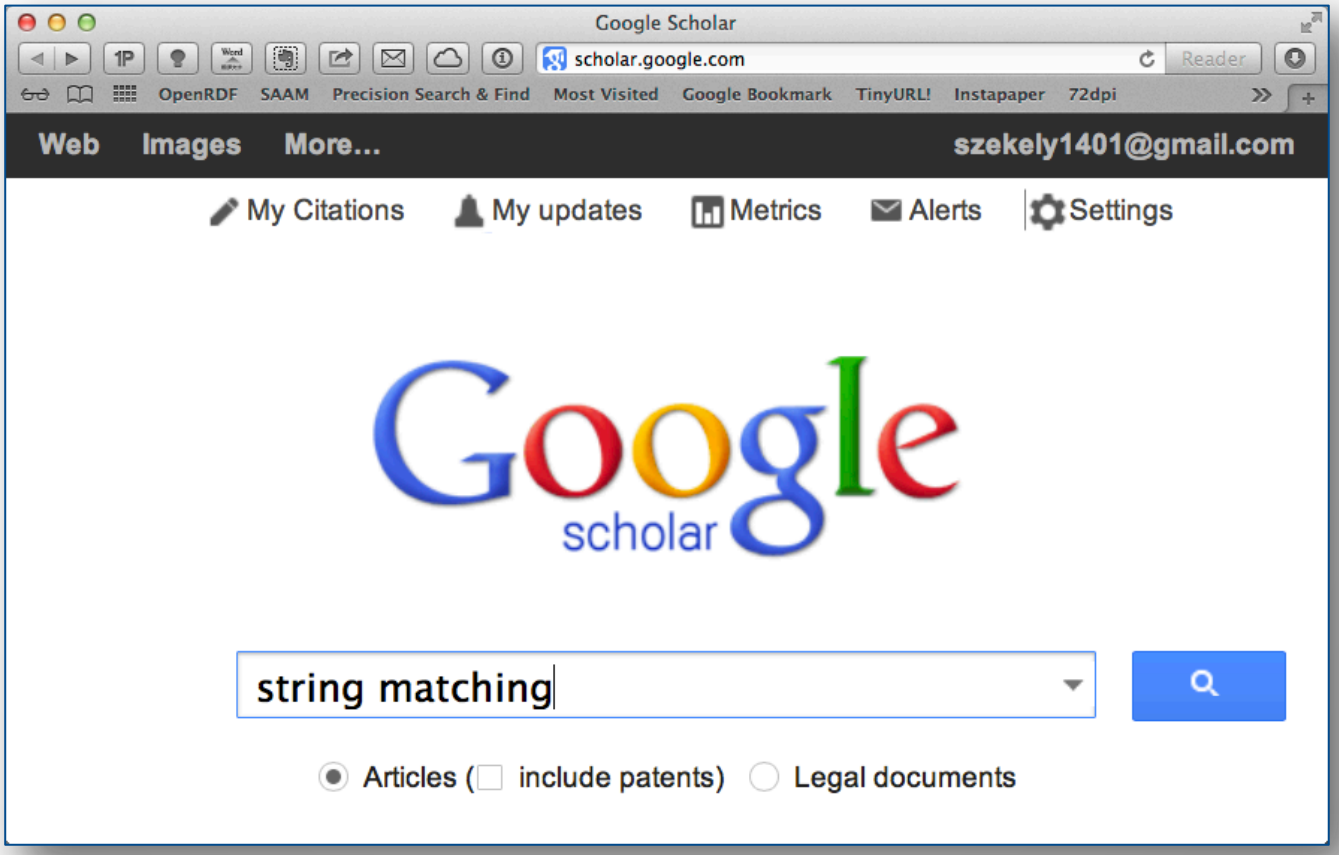
Where are we?

- Information Extraction
  - Semi-structured: Web, HTML
  - Unstructured: Text, Adds, Tweets, …
- Entity Linkage, Data Cleaning, Normalization
- Logical Data Integration
  - Mediators, Query Rewriting
  - Warehouse, Logical Data Exchange
- Automatic Source Modeling/Learning Schema Mappings
- Semantic Web
  - RDF, SPARQL, OWL, Linked Data
- Advanced Topics
  - Geospatial Data Integration, Knowledge Graphs

Isn't the Problem Solved?

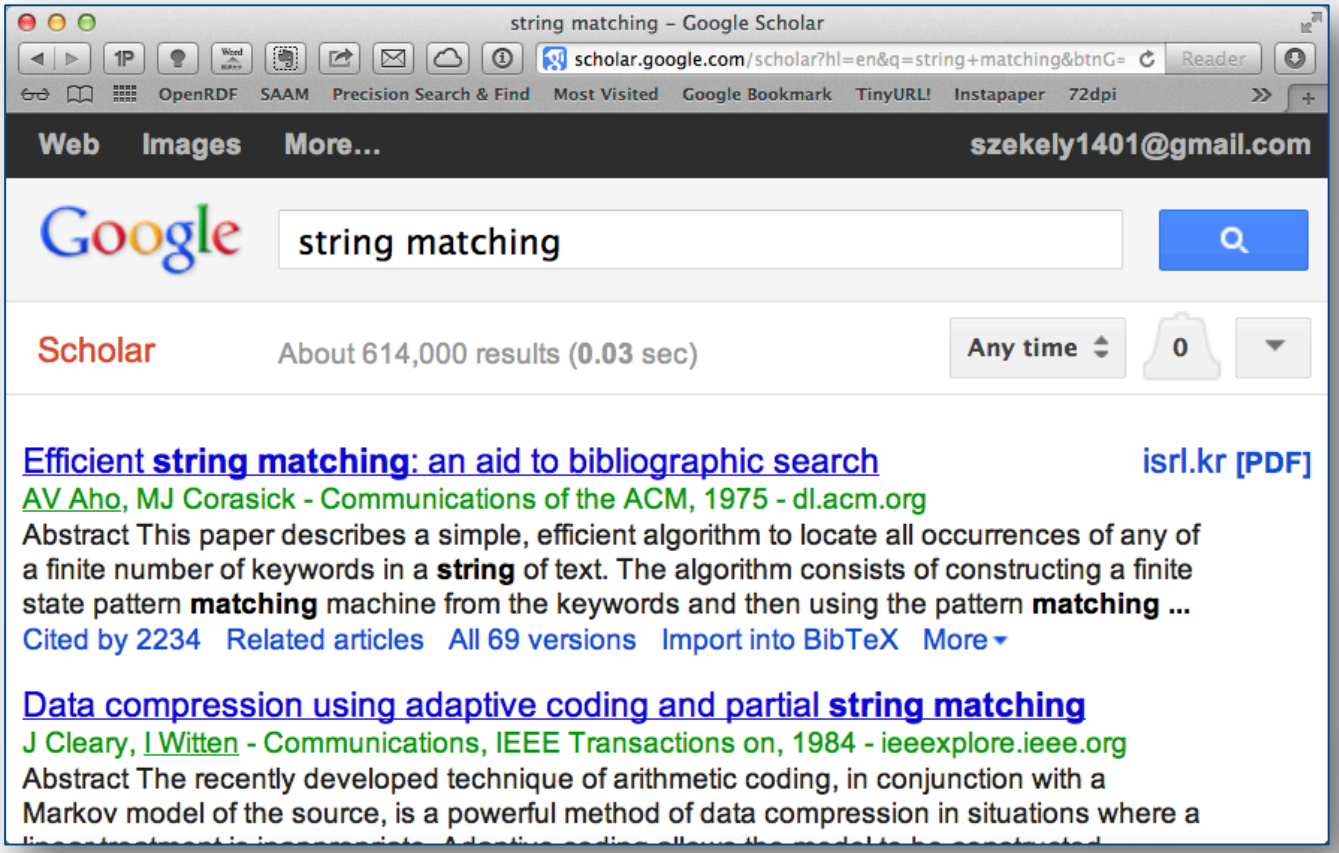
String.equalsIgnoreCase(String x)

How Many Publications?



slide by Pedro Szekely

Why So Many?



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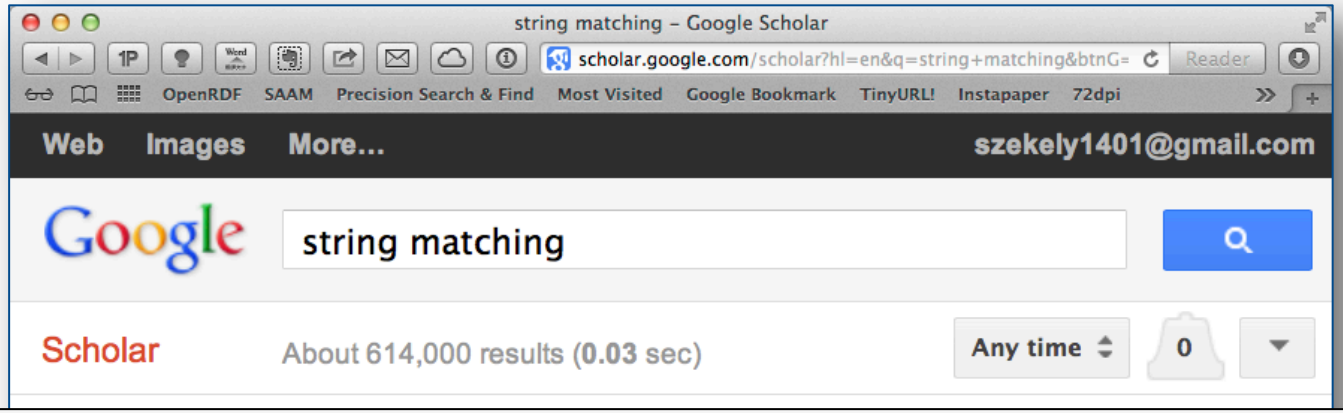
Why So Many?



Google Scholar

string matching

Articles

About 1,290,000 results (0.08 sec)

Any time
Since 2019
Since 2018
Since 2015
Custom range...

Sort by relevance
Sort by date

Efficient string matching: an aid to bibliographic search
AV Aho, MJ Corasick - Communications of the ACM, 1975 - dl.acm.org
This paper describes a simple, efficient algorithm to locate all occurrences of any of a finite number of keywords in a **string** of text. The algorithm consists of constructing a finite state pattern **matching** machine from the keywords and then using the pattern **matching** machine ...
Cited by 3819 Related articles All 43 versions

A guided tour to approximate string matching
G Navarro - ACM computing surveys (CSUR), 2001 - dl.acm.org
We survey the current techniques to cope with the problem of **string matching** that allows errors. This is becoming a more and more relevant issue for many fast growing areas such

Information Extraction

As a family of techniques:

Information Extraction = segmentation + classification + association + clustering

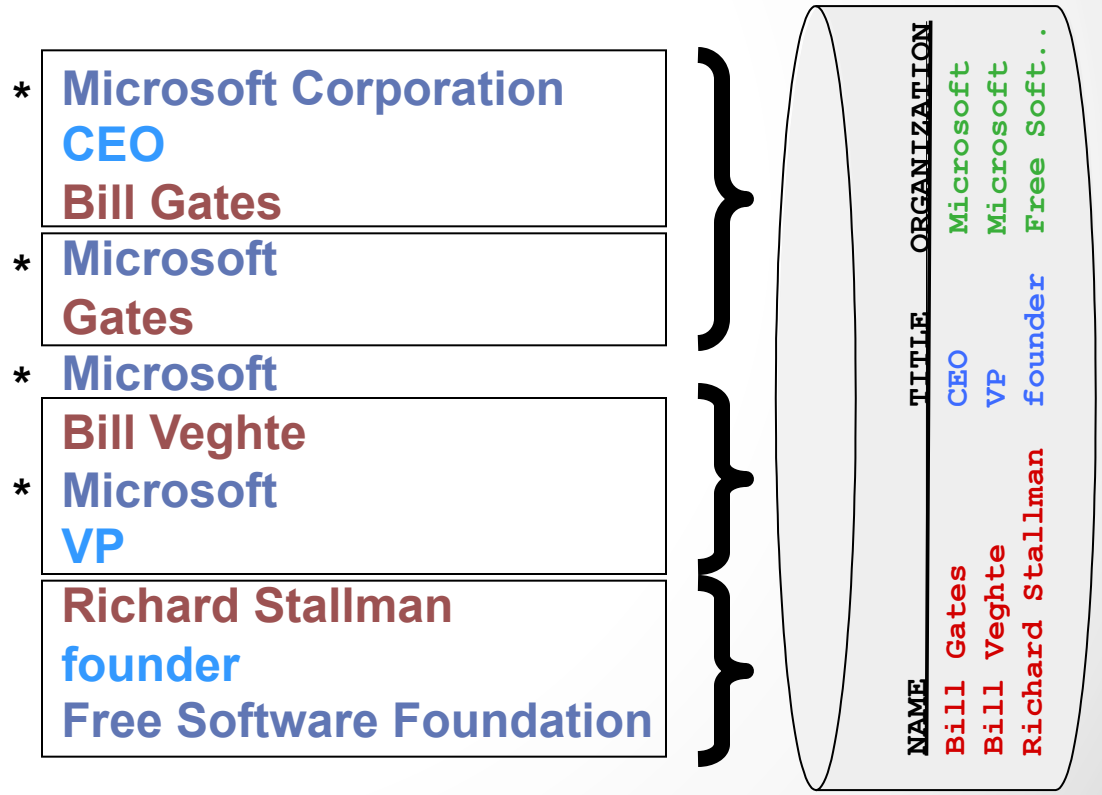
October 14, 2002, 4:00 a.m. PT

For years, Microsoft Corporation CEO Bill Gates railed against the economic philosophy of open-source software with Orwellian fervor, denouncing its communal licensing as a "cancer" that stifled technological innovation.

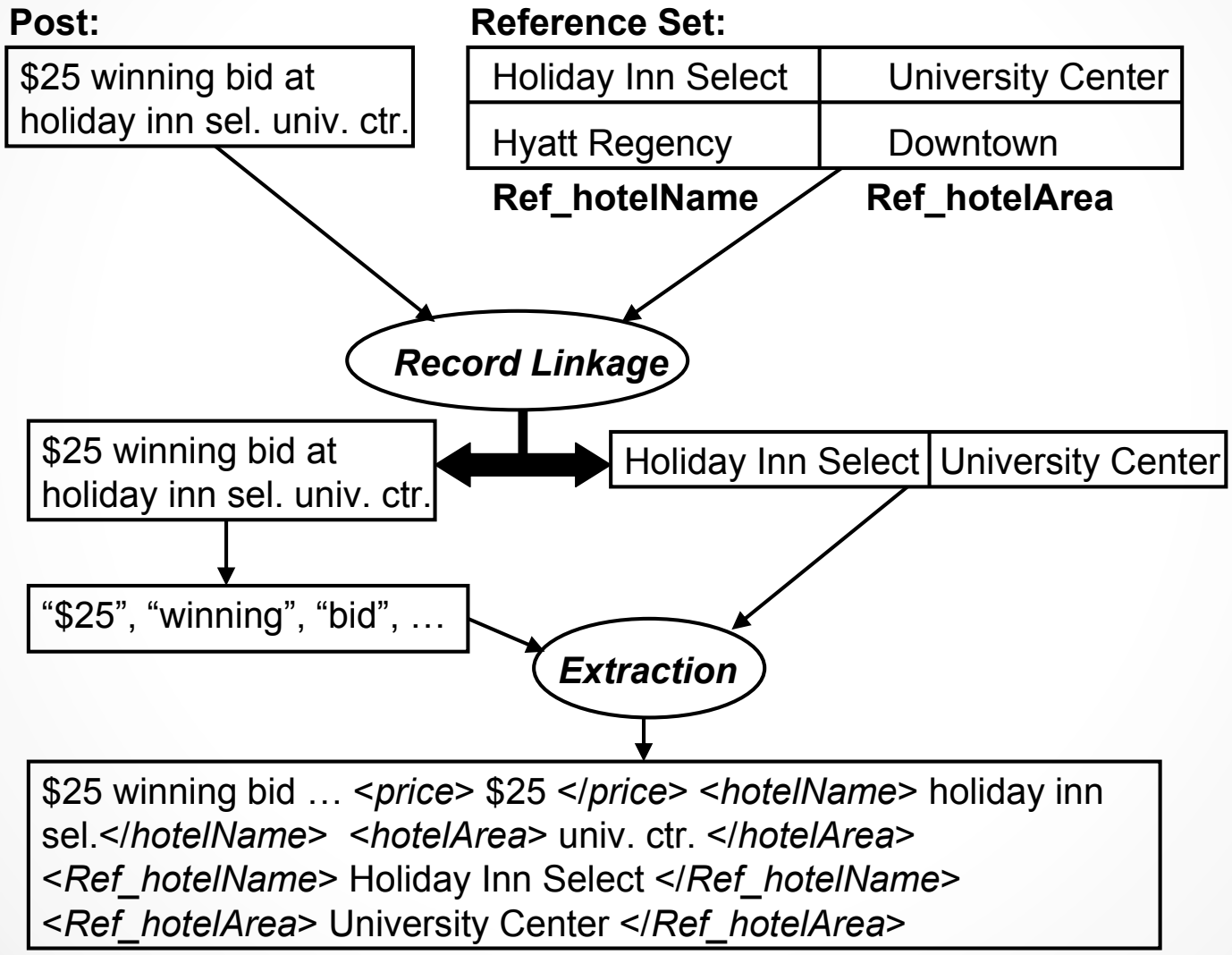
Today, Microsoft claims to "love" the open-source concept, by which software code is made public to encourage improvement and development by outside programmers. Gates himself says Microsoft will gladly disclose its crown jewels--the coveted code behind the Windows operating system--to select customers.

"We can be open source. We love the concept of shared source," said Bill Veghte, a Microsoft VP. "That's a super-important shift for us in terms of code access."

Richard Stallman, founder of the Free Software Foundation, countered saying…



IE form Ungrammatical Text



Multiple John Singer Sargents?

```
dallas:John_Singer_Sargent
  a foaf:Person;
  :dateOfBirth "1856" ;
  :dateOfDeath "1925" ;
  :name "John Singer Sargent" .
```

```
ima:John_Singer_Sargent
  a foaf:Person;
  :dateOfBirth "1856" ;
  :dateOfDeath "1925" ;
  :name "John S. Sargent" .
```

slide by Pedro Szekely

Multiple John Singer Sargents?

```
dallas:John_Singer_Sargent
  a foaf:Person;
  :dateOfBirth "1856" ;
  :dateOfDeath "1925" ;
  :name "John Singer Sargent" .
```

string_match("John Singer Sargent", "John S. Sargent") = ???

```
ima:John_Singer_Sargent
  a foaf:Person;
  :dateOfBirth "1856" ;
  :dateOfDeath "1925" ;
  :name "John S. Sargent" .
```

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String Matching Problem

Problem Definition

Given X and Y sets of strings

Find pairs (x, y)
such that both x and y
refer to the same real world entity

"John S. Sargent"

"John Singer Sargent"

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Problem Definition

Given X and Y sets of strings

Find pairs (x, y)
such that both x and y
refer to the same real world entity

We can use precision and recall to evaluate algorithms

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Problem Definition

Given X and Y sets of strings

Find pairs (x, y)
such that both x and y
refer to the same real world entity

fraction of pairs found that are correct

We can use precision and recall to evaluate algorithms

fraction of pairs found

Why Strings Don't Match Perfectly?

typos "Joh" vs "John"

OCR errors "J0hn" vs "John"

formatting conventions "03/17" vs "March 17"

abbreviations "J. S. Sargent" vs "John Singer Sargent"

nick names "John" vs "Jack"

word order "Sargent, John S." vs "John S. Sargent"

Similarity Measure

Similiarity **s**(x, y) in [0, 1]

Inverse relation

Distance **d**(x, y) in [0, ∞)

Types of Similarity Metrics

- Sequence based
  Levenshtein edit distance, Needleman-Wunch, affine gap, Smith-Waterman, Jaro, Jaro-Winkler
- Set based
  overlap, Jaccard, TF/IDF
- Hybrid
  generalized Jaccard, soft TF/IDF, Monge-Elkan
- Phonetic
  Soundex

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Sequence Based Metrics

Edit Distance

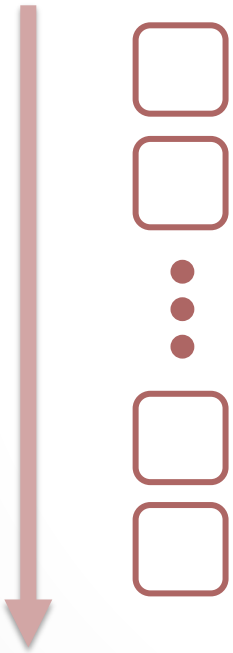
"J0n Singer Sargent"

"John S. Sargent"

- insert character
- delete character
- substitute character
- transpose character
- …

Edit Distance

"J0n Singer Sargent"



"John S. Sargent"

costs

insert character	c_1
delete character	c_2
substitute character	c_3
transpose character	c_4
…	c_i

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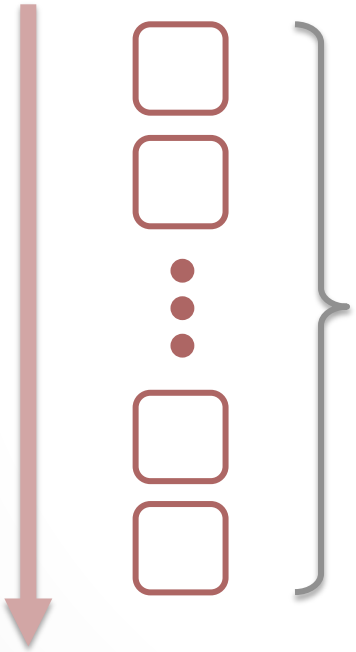
Edit Distance

"J0n Singer Sargent"



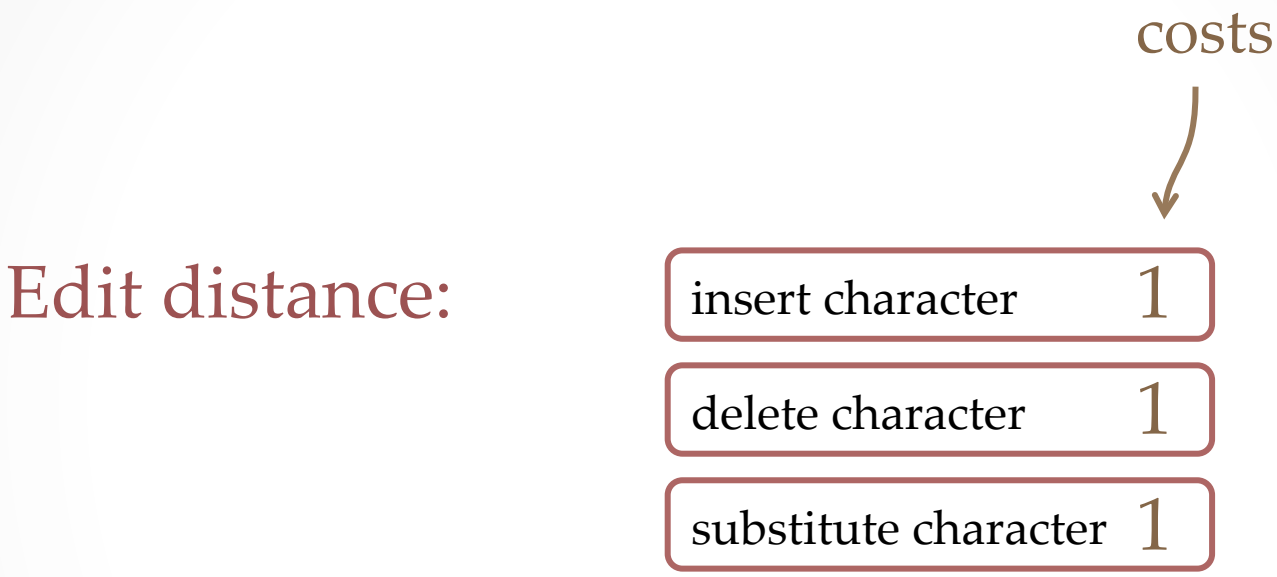
Σc_i

costs

insert character	c_1
delete character	c_2
substitute character	c_3
transpose character	c_4
…	c_i

"John S. Sargent"

Levenshtein Distance



lev(x, y) is the minimum cost to transform x to y

Online calculator: http://planetcalc.com/1721/

Computing Levenshtein Distance

lev(x, y) is the minimum cost to transform x to y

Definitions

$x = x_1 x_2 \ldots x_n$

$y = y_1 y_2 \ldots y_m$

$d(i,j) = lev(x_1 x_2 \ldots x_i, y_1 y_2 \ldots y_j)$

$d(0,0) = lev(\text{“”},\text{“”}) = 0$

We want d(n, m)

Computing Levenshtein Distance

```
d(0,0) = 0
```

Computing Levenshtein Distance

$d(0,0) = 0$

$x_1 x_2 \ldots x_{i-1} x_i$ is a prefix of x $\quad$ $y_1 y_2 \ldots y_{j-1} y_j$ is a prefix of y

$d(i-1,j-1) \rightarrow d(i,j)$?

Computing Levenshtein Distance

$d(0,0) = 0$

$x_1 x_2 \ldots x_{i-1} x_i$ is a prefix of x $y_1 y_2 \ldots y_{j-1} y_j$ is a prefix of y

Case	Distance	Operation
$x_i = y_j$	$d(i-1,j-1)$	keep x_i

Computing Levenshtein Distance

$d(0,0) = 0$

$x_1 x_2 \ldots x_{i-1} x_i$ is a prefix of x $\quad$ $y_1 y_2 \ldots y_{j-1} y_j$ is a prefix of y

Case	Distance	Operation
$x_i = y_j$	$d(i-1,j-1)$	keep x_i
$x_i \mathrel{!}= y_j$		delete x_i insert y_j after x_i replace x_i with y_j

slide by Pedro Szekely

Computing Levenshtein Distance

`d(0,0) = 0`

$x_1 x_2 \ldots x_{i-1} x_i$ is a prefix of x $y_1 y_2 \ldots y_{j-1} y_j$ is a prefix of y

Case	Distance	Operation
$x_i = y_j$	`d(i-1,j-1)`	keep x_i
x_i != y_j	`d(i-1,j) + 1`	delete x_i insert y_j after x_i replace x_i with y_j

Computing Levenshtein Distance

$d(0,0) = 0$

$x_1 x_2 \ldots x_{i-1} x_i$ is a prefix of x $\quad$ $y_1 y_2 \ldots y_{j-1} y_j$ is a prefix of y

Case	Distance	Operation
$x_i = y_j$	$d(i-1,j-1)$	keep x_i
$x_i \mathrel{!}= y_j$	$d(i-1,j) + 1$	delete x_i
	$d(i,j-1) + 1$	insert y_j after x_i
		replace x_i with y_j

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Computing Levenshtein Distance

$d(0,0) = 0$

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$x_i = y_j$	$d(i-1,j-1)$	keep x_i
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	$d(i-1,j-1) + 1$	replace x_i with y_j

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Computing Levenshtein Distance

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$x_1 x_2 \ldots x_{i-1} x_i$ is a prefix of x $\quad$ $y_1 y_2 \ldots y_{j-1} y_j$ is a prefix of y

Case	Distance	Operation
$x_i = y_j$	$d(i-1,j-1)$	keep x_i
$x_i \mathrel{!}= y_j$	$d(i-1,j) + 1$	delete x_i
	$d(i,j-1) + 1$	insert y_j after x_i
	$d(i-1,j-1) + 1$	replace x_i with y_j

$d(i,j) =$ minimum

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Computing Levenshtein Distance Using Dynamic Programming

- x = dva, y = dave

		y0	y1	y2	y3	y4
			d	**a**	**v**	**e**
x0		0	1	2	3	4
x1	**d**	1	0	1		
x2	**v**	2				
x3	**a**	3				

Computing Levenshtein Distance Using Dynamic Programming

- x = dva, y = dave

		y0	y1	y2	y3	y4
			d	**a**	**v**	**e**
x0		0	1	2	3	4
x1	**d**	1	0	1		
x2	**v**	2				
x3	**a**	3				

		y0	y1	y2	y3	y4
			d	**a**	**v**	**e**
x0		0	1	2	3	4
x1	**d**	1	0	1	2	3
x2	**v**	2	1	1	1	2
x3	**a**	3	2	1	2	2

x = d – v a
| | | |
y = d a v e

substitute a with e
insert a (after d)

Levenshtein Distance Complexity

Dynamic programming algorithm

Time Complexity = O (N * M),
Space Complexity = O (N * M)

Polylogarithmic Approximation for Edit Distance and the Asymmetric Query Complexity

Alexandr Andoni, Robert Krauthgamer, Krzysztof Onak

We present a near-linear time algorithm that approximates the edit distance between two strings within a polylogarithmic factor; specifically, for strings of length n and every fixed epsilon>0, it can compute a $(\log n)^{O(1/\epsilon)}$ approximation in $n^{(1+\epsilon)}$ time.

http://arxiv.org/abs/1005.4033

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Levenshtein Distance to Similarity

$$s(x,y) = 1 - \frac{d(x,y)}{max(length(x), length(y))}$$

$$\text{s(David Simths, Davidd Smith)} = 1 - \frac{4}{max(12,12)} = 0.67$$

Levenshtein Distance Examples

```
lev(John Singer Sargent,
    John S. Sargent)
```

=

Levenshtein Distance Examples

```
lev(John Singer Sargent,
    John S. Sargent)
```

= 5

Levenshtein Distance Examples

```
lev(John Singer Sargent,
    John S. Sargent)
```
= 5

```
lev(John Singer Sargent,
    Jane Klinger Sargent)
```
=

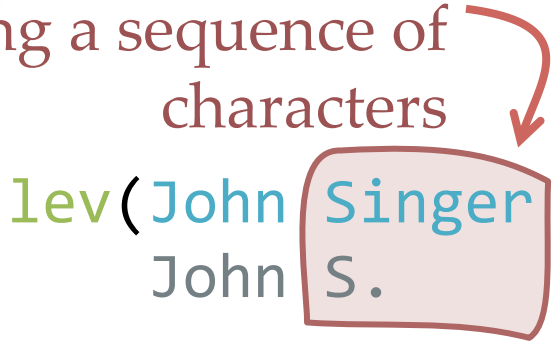
Levenshtein Distance Examples

```
lev(John Singer Sargent,
    John S. Sargent)
```
= 5

```
lev(John Singer Sargent,
    Jane Klinger Sargent)
```
= 5

Levenshtein Distance Examples

Too high a cost for deleting a sequence of characters

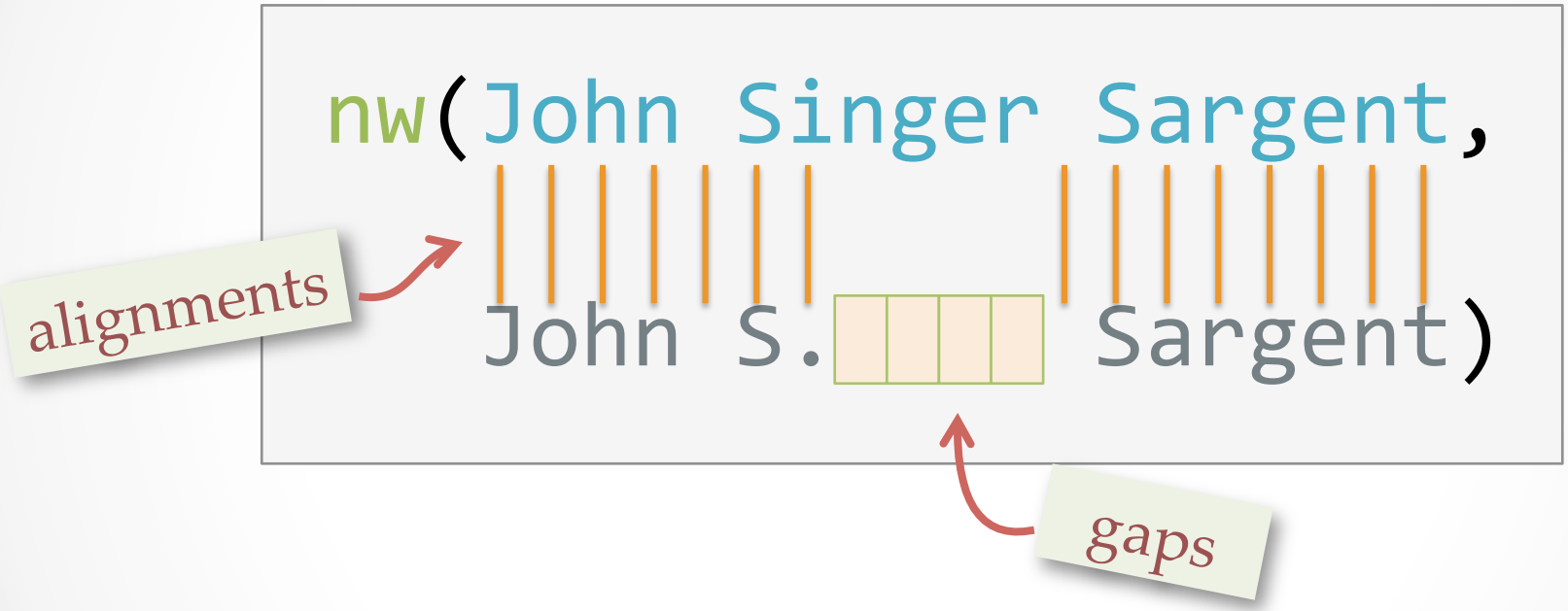


```
lev(John Singer Sargent,
    John S.     Sargent)   =  5
```

```
lev(John Singer Sargent,
    Jane Klinger Sargent)  =  5
```

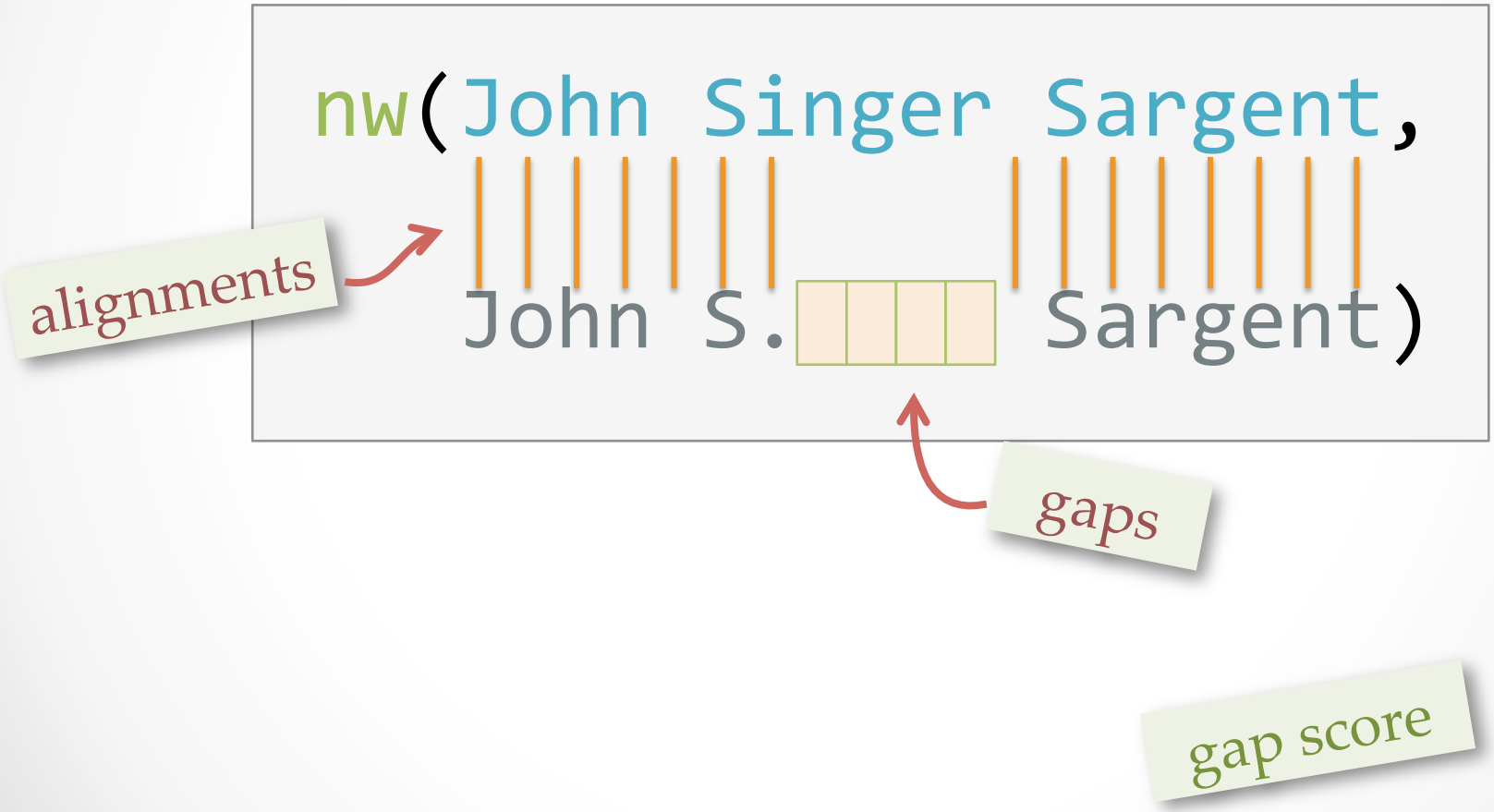
Needleman-Wunch Measure

Generalization of levenstein(x, y)



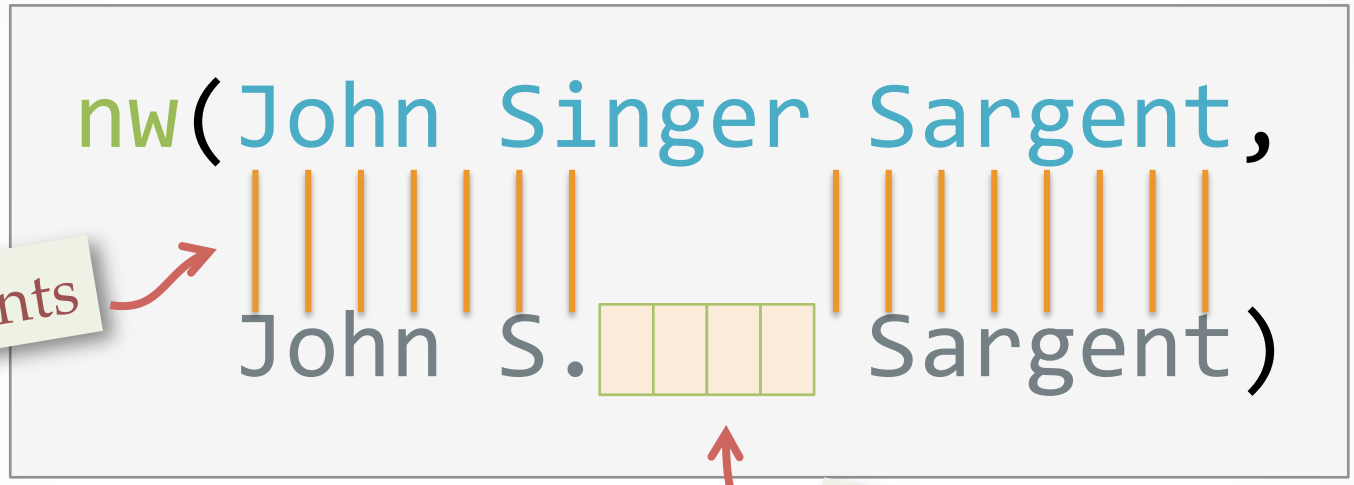
Needleman-Wunch Measure

Generalization of levenstein(x, y)



Needleman-Wunch Measure

Generalization of levenstein(x, y)

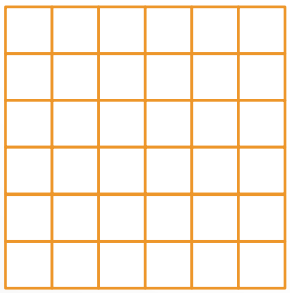


alignments

gaps

Alignment score matrix

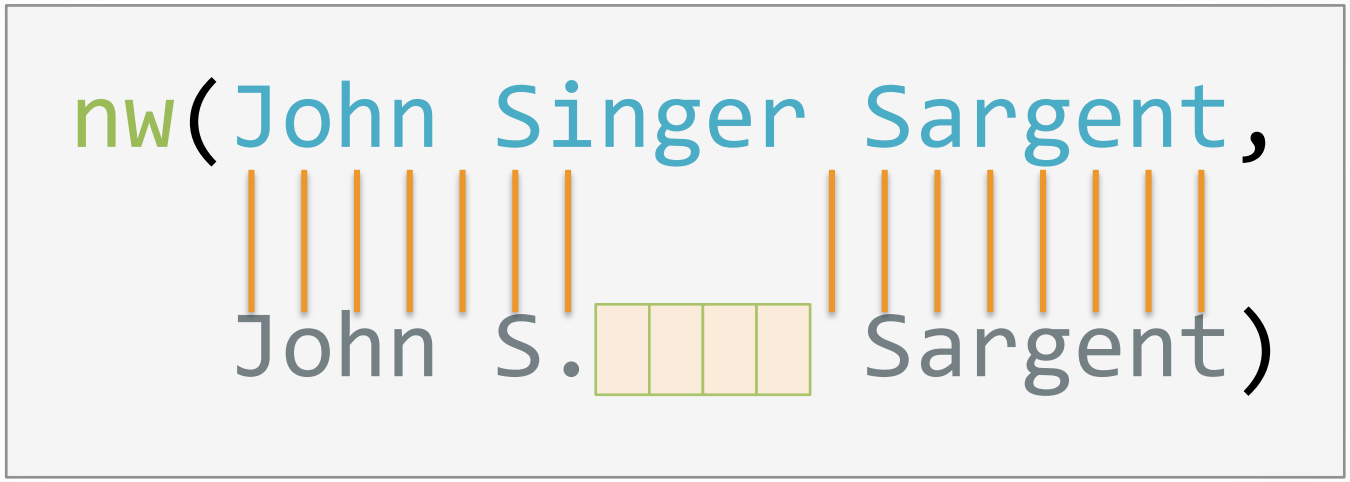
$s(c_i, c_j)$



gap score

Needleman-Wunch Measure

Generalization of levenstein(x, y)



$$s(c_i, c_j) = \begin{cases} 2 & \text{if } c_i = c_j \\ -1 & \text{if } c_i \mathrel{!}= c_j \end{cases}$$

gap-score = -0.5

slide by Pedro Szekely

Needleman-Wunch Measure

Generalization of levenstein(x, y)

```
nw(John Singer Sargent,
   |||||||    |||||||||
   John S.____ Sargent)
```

$2 * 14 + (-1) * 1 + (-0.5) * 4 = 25$

$$s(c_i, c_j) = \begin{cases} 2 & \text{if } c_i = c_j \\ -1 & \text{if } c_i \mathrel{!}= c_j \end{cases}$$

gap-score = -0.5

slide by Pedro Szekely

Needleman-Wunch Generalizes Levenshtein in Three Ways

	Levenshtein	Needleman-Wunch
Costs	1	matrix
Operations	insert/delete	gaps
Computes	distance	similarity

OCR errors `"J0hn"` vs `"John"`

```
score(o,0) = -0.2
score(m,0) = -1.0
```

lower penalty

Computing Needleman-Wunch Score with Dynamic Programming

$$s(i,j) = \max \begin{cases} s(i-1,j-1) + c(xi,yj) \\ s(i-1,j) - c_g \\ s(i,j-1) - c_g \end{cases}$$

$$s(0,j) = - jc_g$$
$$s(i,0) = -ic_g$$

		d	**e**	**e**	**v**	**e**
	0	-1	-2	-3	-4	-5
d	-1	2	1	0	-1	-2
v	-2	1	1	0	2	1
a	-3	0	0	0	1	1

d - - v a
d e e v e

Needleman-Wunch Example

```
nw(John Singer Sargent,
   John S.      Sargent)
```

2 * 14 + (-1) * 1 + (-0.5) * 4 = 25

2 * 14 + (-1) * 3 + (-0.5) * 1 = 24.5

```
nw(John S inger Sargent,
   Jane Klinger Sargent)
```

Needleman-Wunch Example

```
nw(John Singer Sargent,
   John S.      Sargent)
```

2 * 14 + (-1) * 1 + (-0.5) * 4 = 25

2 * 14 + (-1) * 1 + (-0.5) * 8 = 23

```
nw(John Stanislaus Sargent,
   John S.         Sargent)
```

Needleman-Wunch Example

```
nw(John Singer Sargent,
   John S.     Sargent)
```

$+ (-1) * 1 + (-0.5) * 4 = 25$

Longer gaps are penalized more

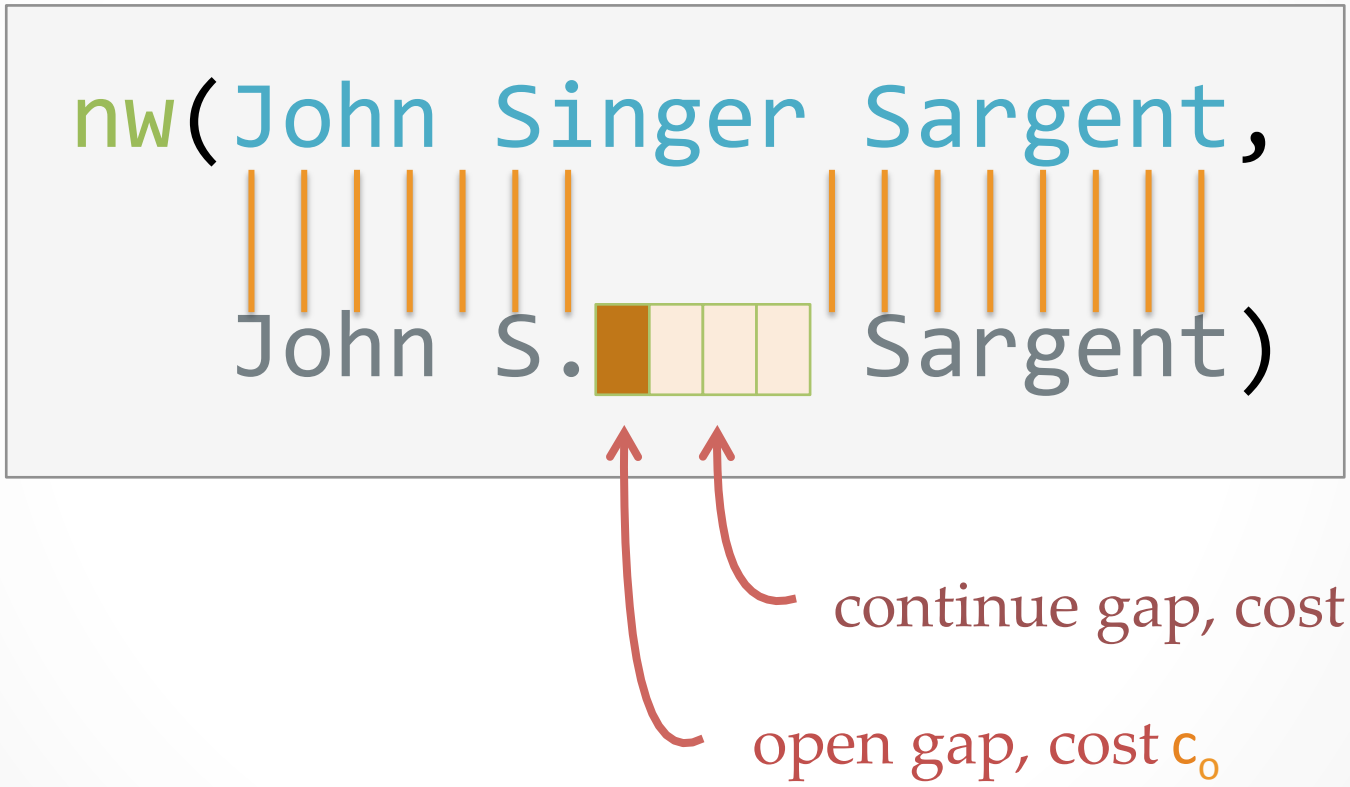
Bad for names

$14 + (-1) * 1 + (-0.5) * 8 = 23$

```
nw(John Stanislaus Sargent,
   John S.         Sargent)
```

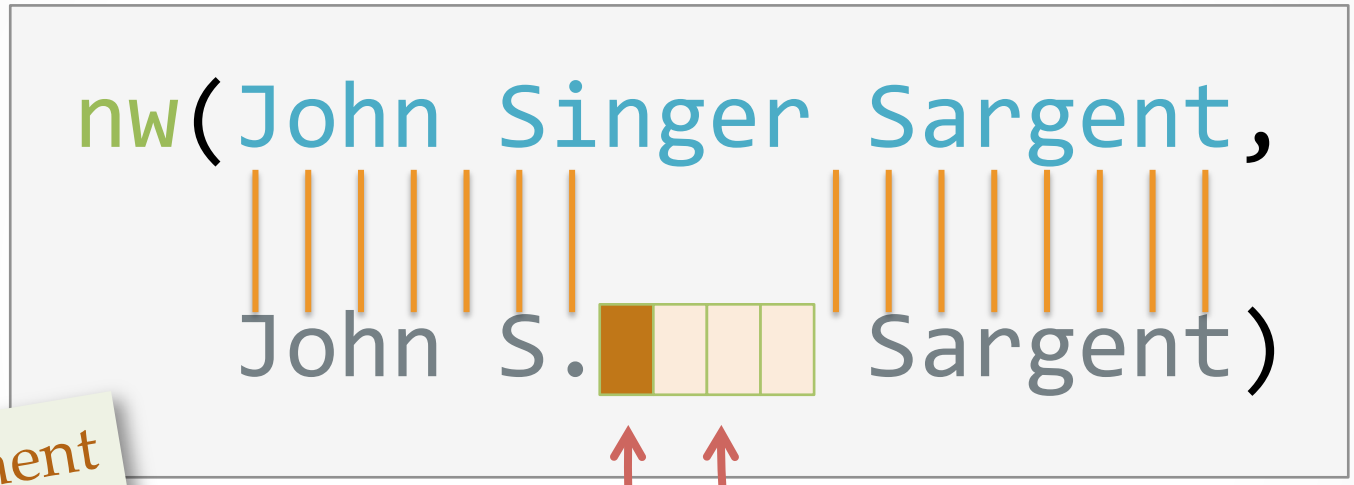
Affine Gap Measure

Generalization of needleman-wunch(x, y)



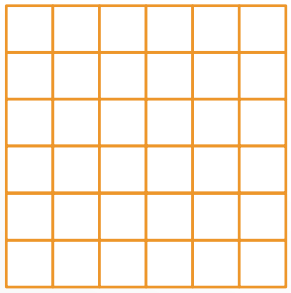
Affine Gap Measure

Generalization of needleman-wunch(x, y)



Alignment score matrix

$s(c_i, c_j)$



continue gap, cost c_r

open gap, cost c_o

total gap cost: $c_o + (|gap| - 1) * c_r$

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Smith-Waterman

Global alignment
fully align sequences,
opening gaps as needed

```
F T F T A L I L L A V A V
F - - T A L - L L A - A V
```

Needleman-Wunch

Local alignment
find best subsequences to
align

```
F T F T A L I L L A V A V
- - F T A L - L L A V - -
```

Smith-Waterman: local alignment version of Needleman-Wunch

slide by Pedro Szekely

Smith-Waterman Example

```
match(John Sargent, american painter,
      American artist John S. Sargent)
```

```
nw(                 John S   argent, american painter,
   American artist John S. Sargent                    )
```

Needleman-Wunch: significant gap penalty

Smith-Waterman Example

```
match(John Sargent, american painter,
      American artist John S. Sargent)
```

```
nw(                  John S   argent, american painter,
   American artist John S. Sargent                    )
```

Needleman-Wunch: significant gap penalty

Smith-Waterman Example

```
match(John Sargent, american painter,
      American artist John S. Sargent)
```

```
nw(                    John S  argent, american painter,
   American artist John S. Sargent                     )
```

Needleman-Wunch: significant gap penalty

```
sw(                    John S  argent, american painter,
   American artist John S. Sargent                     )
```

Smith-Waterman: identifies similar subsequences

Computing Smith-Waterman Score using Dynamic Programming

$$s(i,j) = \max \begin{cases} 0 \\ s(i-1,j-1) + c(xi,yj) \\ s(i-1,j) - c_g \\ s(i,j-1) - c_g \end{cases}$$

$$s(0,j) = 0$$
$$s(i,0) = 0$$

		d	**a**	**v**	**e**
	0	0	0	0	0
a	0	0	2	1	0
v	0	0	1	4	3
d	0	2	1	3	3

Jaro Similarity Measure

- Get points for having characters in common
  - but only if they are "close by"
- Get points for common characters in the same order
  - lose points for transpositions

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Jaro Similarity Measure

$$\text{max-distance} = \frac{\max(\,|x|\,,\,|y|\,)}{2} - 1$$

x_i matches y_j if $\begin{cases} x_i = y_j \\ |i - j| <= \text{max-distance} \end{cases}$

m = number of matching characters

t = number of transpositions
(of matching characters)

Jaro Similarity Measure

$$\text{max-distance} = \frac{\max(\,|x|\,,\,|y|\,)}{2} - 1$$

m = number of matching characters

t = number of transpositions/2

$$\text{jaro}(x, y) = \begin{cases} 0 & \text{if } m = 0 \\ \frac{1}{3}\left(\frac{m}{|x|} + \frac{m}{|y|} + \frac{m - t}{m}\right) \end{cases}$$

Jaro Example

```
lev(DIXON, DICKSONX)  = 4     (1 - 4/8 = 0.5)

jaro(DIXON, DICKSONX) = ???
```

Jaro Example

	D	I	X	O	N
D	1	0	0	0	0
I	0	1	0	0	0
C	0	0	0	0	0
K	0	0	0	0	0
S	0	0	0	0	0
O	0	0	0	1	0
N	0	0	0	0	1
X	0	0	1	0	0

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Jaro Example

	D	I	X	O	N
D	1	0	0	0	0
I	0	1	0	0	0
C	0	0	0	0	0
K	0	0	0	0	0
S	0	0	0	0	0
O	0	0	0	1	0
N	0	0	0	0	1
X	0	0	0	0	0

$|x| = 5$

$|y| = 8$

$\text{max-distance} = (8/2) - 1 = 3$

$m = 4$

$t = 0$

Jaro Example

	D	I	X	O	N
D	1	0	0	0	0
I	0	1	0	0	0
C	0	0	0	0	0
K	0	0	0	0	0
S	0	0	0	0	0
O	0	0	0	1	0
N	0	0	0	0	1
X	0	0	0	0	0

$$|x| = 5$$

$$|y| = 8$$

$$m = 4$$

$$t = 0$$

$$\frac{1}{3}\left(\frac{m}{|x|} + \frac{m}{|y|} + \frac{m - t}{m}\right)$$

$$\frac{1}{3}\left(\frac{4}{5} + \frac{4}{8} + \frac{4 - 0}{4}\right)$$

$$= 0.767$$

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Repeated characters

	D	I	X	O	N
D	1	0	0	0	0
I	0	1	0	0	0
C	0	0	0	0	0
I	0	0	0	0	0
S	0	0	0	0	0
O	0	0	0	1	0
N	0	0	0	0	1
X	0	0	0	0	0

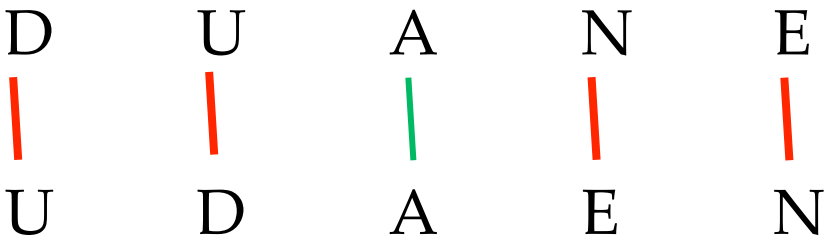
Suppose we replace K with I in the orange string

The 'second' I will not match with the I in Dixon, even though it's in the 'window' (the I in Dixon is already taken)

Thus Jaro similarity is still 0.767

Transposition

- Write down sequence of matching characters from each string
  - By definition, the set of matching characters in both strings are identical!



m = 5, transpositions = 4, t =4/2=2

Jaro Example

```
lev(DIXON, DICKSONX)  = 4     (1 - 4/8 = 0.5)

jaro(DIXON, DICKSONX) = 0.767
```

Jaro-Winkler Measure

Give a bonus if there is a common prefix

$$\text{jaro–winkler}(x,y) = \text{jaro}(x,y) + P_L.P_W.(1-\text{jaro}(x,y))$$

```
jaro(DIXON, DICKSONX) = 0.767

jaro-winkler(DIXON, DICKSONX) = 0.8136
```

Set-Based Metrics

Set-Based Metrics

Generate set of tokens from the strings

Measure similarity between the sets of tokens

Tokenizing a String

Words

Tokenizing a String

Words

n-grams: substrings of length n

"david smith" 3-grams
{##d, #da, dav, avi, …, h##}

Jaccard Measure

$$B_x = \text{tokens}(x)$$

$$B_y = \text{tokens}(y)$$

$$\text{jaccard}(x,y) = \frac{|B_x \cap B_y|}{|B_x \cup B_y|}$$

jaccard(dave, dav)

B_x = {#d, da, av, ve, e#}

B_y = {#d, da, av, v#}

jaccard(x,y) = 3/6

TF/IDF Measure

TF = term frequency
IDF = inverse document frequency

x = Apple Corporation, CA
y = IBM Corporation, CA
z = Apple Corp
...
blah blah Corporation

$$lev(x, y) \begin{vmatrix} > \\ = \\ < \end{vmatrix} lev(x, z)$$

???

TF/IDF Measure

TF = term frequency
IDF = inverse document frequency

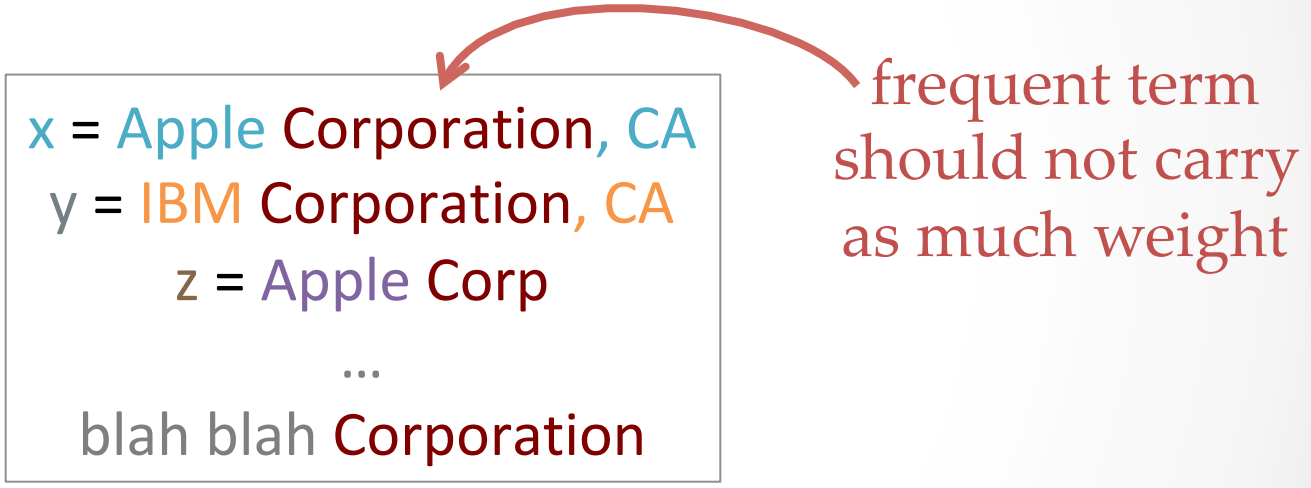
x = Apple Corporation, CA
y = IBM Corporation, CA
z = Apple Corp
…
blah blah Corporation

$$lev(x, y) > lev(x, z)$$

… but intuitively (x, z) is a better match

TF/IDF Measure

TF = term frequency
IDF = inverse document frequency



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TF/IDF Measure

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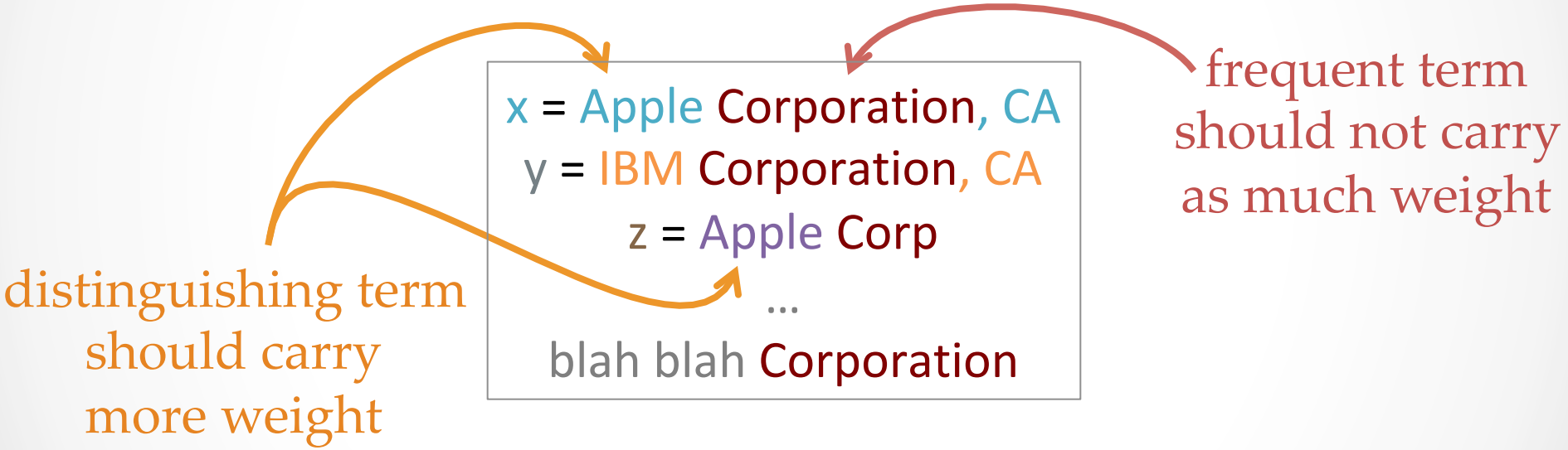

$$lev(x, y) > lev(x, z)$$

… but intuitively (x, z) is a better match

Term Frequencies and Inverse Document Frequencies

- Assume x and y are taken from a collection of strings
- Each string is converted into a bag of terms called a document
- term frequency tf(t,d) =
  - number of times term t appears in document d
- inverse document frequency idf(t) =
  - N / $\mathbf{N}_d$, number of documents in collection divided by number of documents that contain t
  - note: in practice, idf(t) is often defined as log(N / $\mathbf{N}_d$)

slide from Anhai Doan, Alon Halevy, Zachary Ives

Example

$x = aab \Rightarrow B_x = \{a, a, b\}$

$y = ac \Rightarrow B_y = \{a, c\}$

$z = a \Rightarrow B_z = \{a\}$

$tf(a, x) = 2$

$tf(b, x) = 1$

...

$tf(c, z) = 0$

$idf(a) = 3/3 = 1$

$idf(b) = 3/1 = 3$

$idf(c) = 3/1 = 3$

Feature Vectors

- Each document d is converted into a feature vector $\mathbf{v}_d$
- $\mathbf{v}_d$ has a feature $\mathbf{v}_d(\mathbf{t})$ for each term t
  - value of $\mathbf{v}_d(\mathbf{t})$ is a function of TF and IDF scores
  - here we assume $\mathbf{v}_d(\mathbf{t})$ = tf(t,d) * idf(t)

$x = aab \Rightarrow B_x = \{a, a, b\}$

$y = ac \Rightarrow B_y = \{a, c\}$

$z = a \Rightarrow B_z = \{a\}$

tf(a, x) = 2
tf(b, x) = 1
...
tf(c, z) = 0

idf(a) = 3/3 = 1
idf(b) = 3/1 = 3
idf(c) = 3/1 = 3

	a	**b**	**c**
$\mathbf{v}_x$	2	3	0
$\mathbf{v}_y$	1	0	3
$\mathbf{v}_z$	1	0	0

TF/IDF Similarity Score

- Let p and q be two strings, and T be the set of all terms in the collection
- Feature vectors $\mathbf{v}_p$ and $\mathbf{v}_q$ are vectors in the |T|-dimensional space wher each dimension corresponds to a term
- TF/IDF score of p and q is the cosine of the angle between $\mathbf{v}_p$ and $\mathbf{v}_q$
  - $s(p,q) = \sum_{t \in T} v_p(t) * v_q(t) \; / [\sqrt{\sum_{t \in T} v_p(t)^2} * \sqrt{\sum_{t \in T} vq(t)^2}]$

slide from Anhai Doan, Alon Halevy, Zachary Ives

TF/IDF Similarity Score

- Score is high if strings share many frequent terms
  - terms with high TF scores
- Unless these terms are common in other strings
  - i.e., they have low IDF scores
- Dampening TF and IDF as commonly done in practice
  - use v_d(t) = log(tf(t,d) + 1) * log(idf(t)) instead of
    v_d(t) = tf(t,d) * idf(t)
- Normalizing feature vectors
  - v_d(t) = v_d(t) / $\sqrt{\sum_{\{t \in T\}} v_d(t)^2}$

TF/IDF Similarity Score

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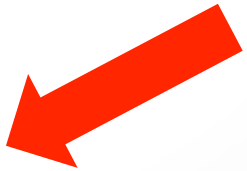
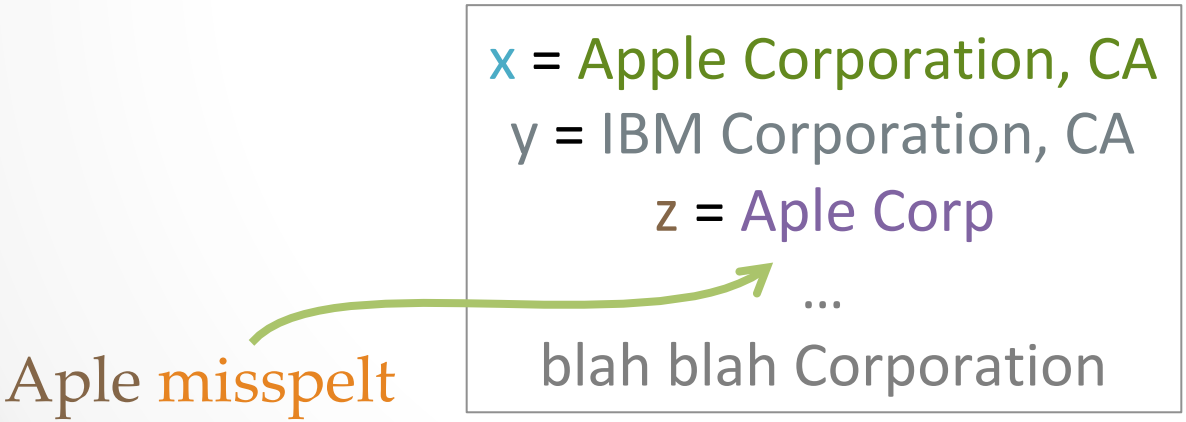
cosine -> dot product



Hybrid Similarity Measures

Hybrid Measures

Do the set-based thing
but
use a similiarity metric for each element of the set



Generalized Jaccard Measure

- **Jaccard measure**
  - Considers overlapping tokens in both x and y
  - A token from x and a token from y must be identical to be included in the set of overlapping tokens
  - This can be too restrictive in certain cases

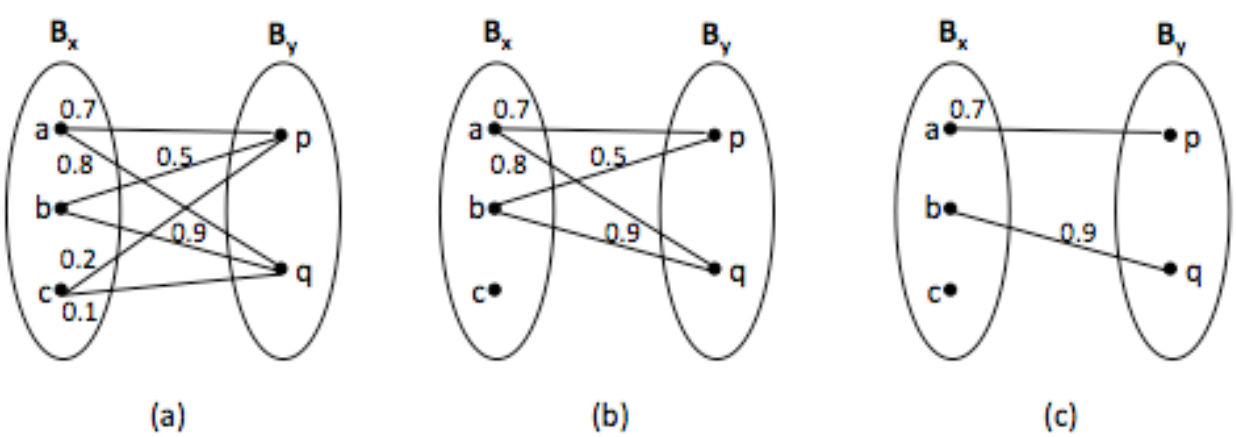
- **Example:**
  - Matching company sections
  - "Energy & Transportation" vs. "Transportation, Energy, & Gas"
  - In theory Jaccard is well suited here, in practice Jaccard may not work well if tokens are commonly **misspelled**
    - **e.g., energy vs. eneryg**
  - Generalized Jaccard measure can help such cases

Generalized Jaccard Measure

- Let $B_x = \{x_1, \ldots, x_n\}$, $B_y = \{y_1, \ldots, y_m\}$
- Step 1: find token pairs that will be in the "softened" overlap set
  - apply a similarity measure s to compute sim score for each pair (x_i, y_j)
  - keep only those score > a given threshold α, this forms a bipartite graph G
  - find the maximum-weight matching M in G
- Step 2: return normalized weight of M as generalized Jaccard score

$$GJ(x,y) = \frac{\sum_{(x_i,y_j)\in M} s(x_i,y_j)}{|B_x| + |B_y| - |M|}$$

Generalized Jaccard Example



$$GJ(x,y) = \frac{\sum_{(x_i,y_j)\in M} s(x_i,y_j)}{|B_x| + |B_y| - |M|}$$

Threshold = 0.5

Generalized Jaccard score: (0.7 + 0.9)/(3 + 2 – 2) = 0.53

The Soft TF/IDF Measure

- Similar to generalized Jaccard measure, except that it uses TF/IDF measure as the "higher-level" sim measure
  - e.g., "Apple Corporation, CA", "IBM Corporation, CA", and "Aple Corp", with Apple being misspelled

- Step 1: compute close(x,y,k):
  set of all terms $t \in B_x$ that have at least one close term $u \in B_y$, i.e., $s'(t,u) >= k$
  - s' is a basic sim measure (e.g., Jaro-Winkler), k pre-specified

- Step 2: compute s(x,y) as in traditional TF/IDF score, but weighing each TF/IDF component using s'
  - $s(x,y) = \sum_{t \in close(x,y,k)} v_x(t) * v_y(u^*) * s'(t,u^*)$
  - $u^* \in B_y$ maximizes $s'(t,u) \ \forall \ u \in B_y$

Soft TF/IDF Example

$$s(x,y) = \sum_{t \in close(x,y,k)} v_x(t) \cdot v_y(u_*) \cdot s'(t,u_*)$$

x = abcd

y = aa'b'cd'

B_x = {a, b, c, d}

1 0.7 0.8 1 0.6

B_y = {a, a', b', c, d'}

close (x, y, 0.75) = {a, b, c}

$s(x,y) = v_x(a) \cdot v_y(a) \cdot 1 + v_x(b) \cdot v_y(b') \cdot 0.8 + v_x(c) \cdot v_y(c) \cdot 1$

Monge-Elkan Measure

- Break strings x and y into multiple substrings
  - x = A_1 … A_n , y = B_1 … B_m
- Compute
  - s(x,y) = 1/n * $\sum_{i=1}^{n} max_{j\ =\ 1}^{m}$ s'($\mathbf{A_i}$,$\mathbf{B_j}$)
  - s' is a secondary sim measure, such as Jaro-Winkler
  - Intuitively, we ignore the order of the matching of substrings and only consider the best match for substrings of x in y
- E.g., match two strings

  "Comput. Sci. and Eng. Dept., University of California, San Diego"

  "Department of Computer Science, Univ. Calif., San Diego"

slide from Anhai Doan, Alon Halevy, Zachary Ives

Monge-Elkan Measure

$$s(x,y) = 1/n * \sum_{i=1}^{n} max_{j\_1}^{m} s'(A_i,B_j)$$

$x = A_1A_2$ $\quad$ $y = B_1B_2B_3$

$$\frac{\max(\ s'(A_1,B_1),\ s'(A_1,B_2),\ s'(A_1,B_3)\ ) + \max(\ s'(A_2,B_1),\ s'(A_2,B_2),\ s'(A_2,B_3))}{2}$$

s' could be any metric, e.g., levenshtein

slide by Pedro Szekely

Phonetic Similarity Measures

Phonetic Similarity Measures

- Match strings based on their sound, instead of appearances
- Very effective in matching **names**, which often appear in different ways that sound the same
  - e.g., Meyer, Meier, and Mire;
  - Smith, Smithe, and Smythe
- Soundex is most commonly used

The Soundex Measure

- Used primarily to match **surnames**
  - maps a surname x into a 4-letter code
  - two surnames are judged similar if share the same code

- Algorithm to map x into a code:
  - **Step 1:** keep the first letter of x,
    subsequent steps are performed on the rest of x:
  - **Step 2:** remove all occurrences of W and H.
    Replace the remaining letters with digits as follows:
    B, F, P, V with 1
    C, G, J, K, Q, S, X, Z with 2
    D, T with 3, L with 4
    M, N with 5, R with 6
  - **Step 3:** replace sequence of identical digits by the digit itself
  - **Step 4:** drop all non-digit letters, return the first four letters as the soundex code

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The Soundex Measure

- Example: x = Ashcraft
  - after Step 2: A226a13, after Step 3: A26a13, Step 4 converts this into A2613, then returns **A261**
  - Soundex code is padded with 0 if there is not enough digits
- Example: Robert and Rupert map into R163
- Soundex fails to map Gough and Goff, and Jawornicki and Yavornitzky
  - designed primarily for **Caucasian** names, but found to work well for names of many different origins
  - does not work well for names of **East Asian** origins which uses vowels to discriminate, Soundex ignores vowels

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Other Readings

- http://en.wikipedia.org/wiki/String_metric
- http://en.wikipedia.org/wiki/Approximate_string_matching
- http://en.wikipedia.org/wiki/Edit_distance
- http://en.wikipedia.org/wiki/Levenshtein_distance
- http://en.wikipedia.org/wiki/Jaro–Winkler_distance
- http://en.wikipedia.org/wiki/Smith–Waterman_algorithm
- http://en.wikipedia.org/wiki/Jaccard_index

- http://alias-i.com/lingpipe/demos/tutorial/stringCompare/read-me.html
- http://www.gettingcirrius.com/2011/01/calculating-similarity-part-2-jaccard.html
- http://en.wikipedia.org/wiki/Sequence_alignment#Pairwise_alignment