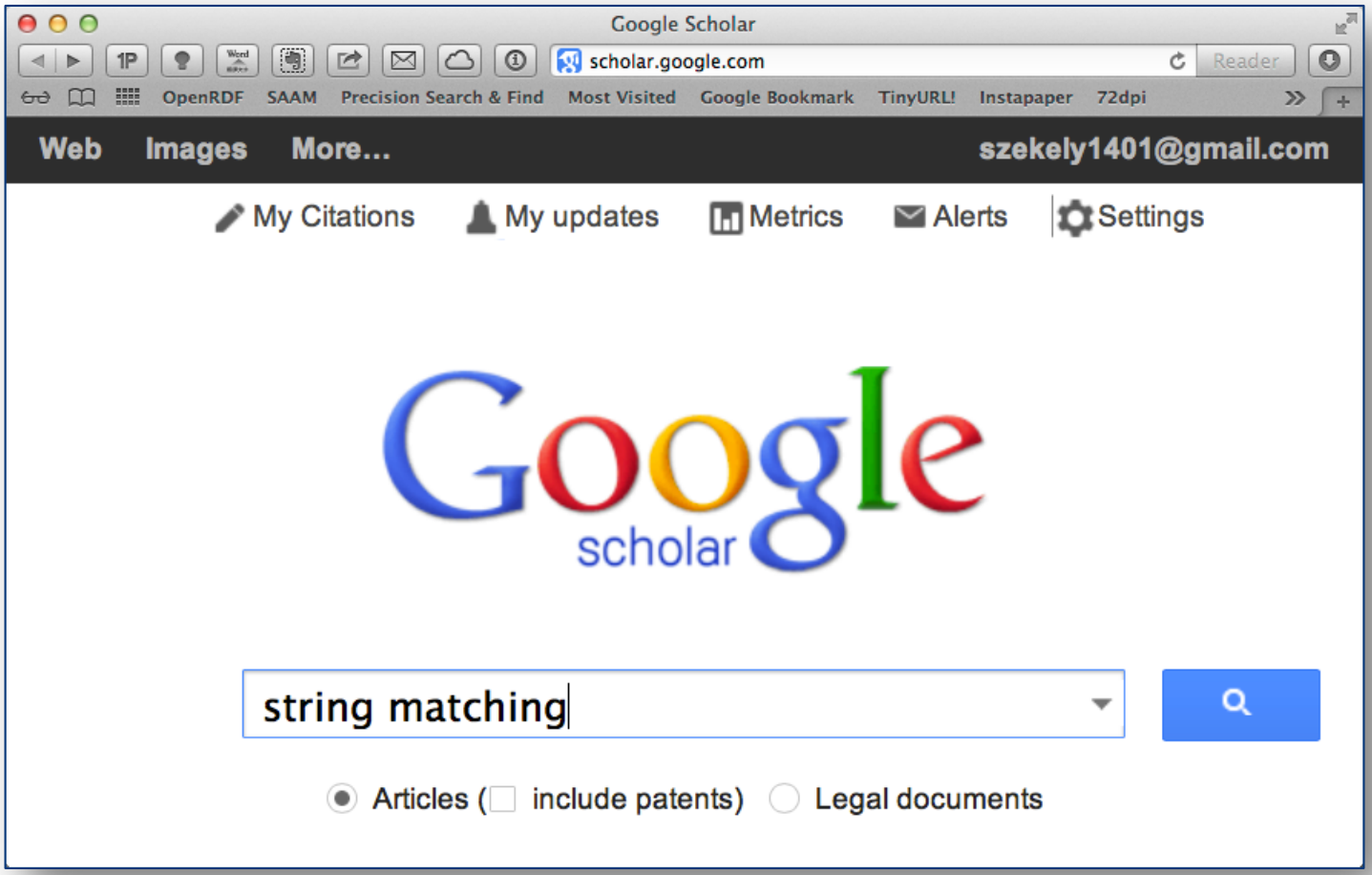
String Matching

Pedro Szekely & Craig Knoblock
University of Southern California

Isn't the Problem Solved?

String.equalsIgnoreCase(String x)

How Many Publications?



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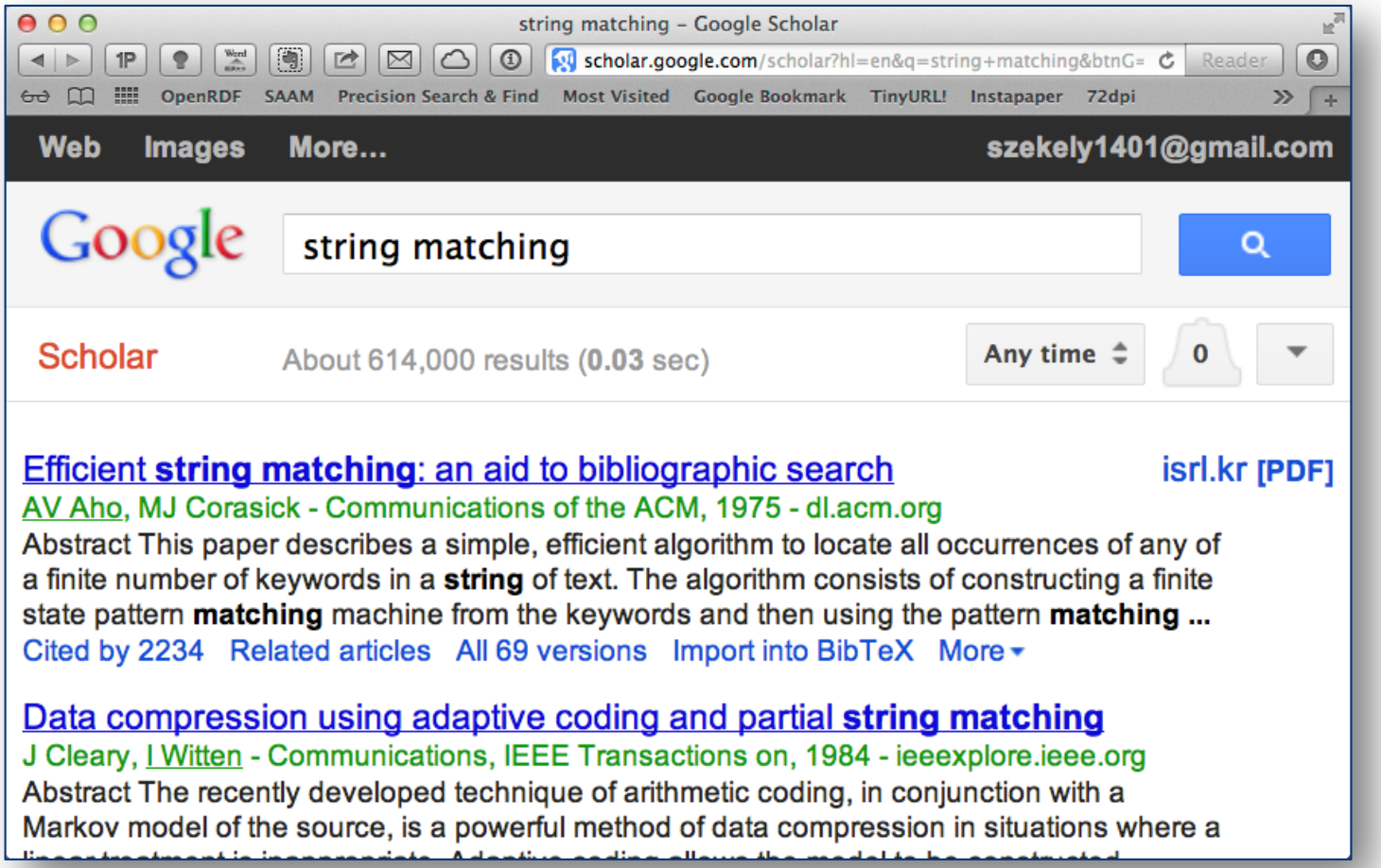
Why So Many?



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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" .
```

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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

myMatchFunction(x, y)

yourMatchFunction(x, y)

What does it mean that one is better than the other?

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)
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We can use precision and recall to evaluate algorithms

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

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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 "Jock"

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

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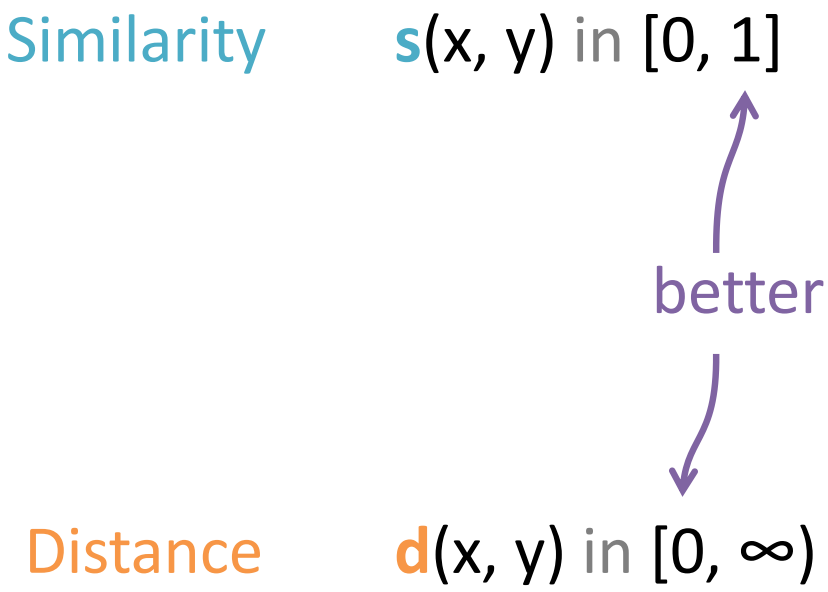
Similiarity Measure



Types of Similarity Metrics

- Sequence based
- Set based
- Hybrid
- Phonetic

Sequence Based Metrics

Edit Distance

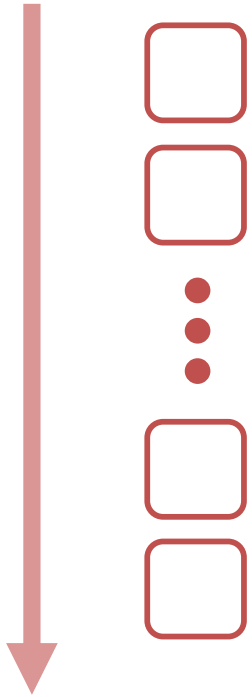
"J0n Singer Sargent"

"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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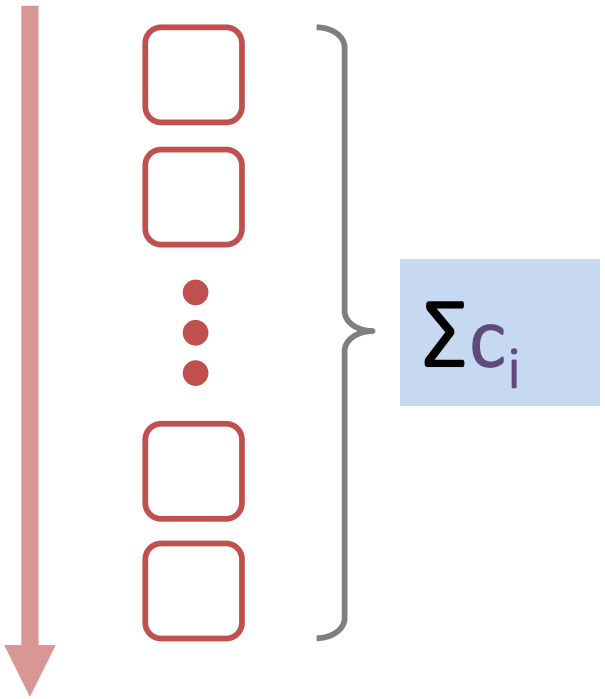
Edit Distance

"J0n Singer Sargent"



"John S. Sargent"

costs

insert character	c_1
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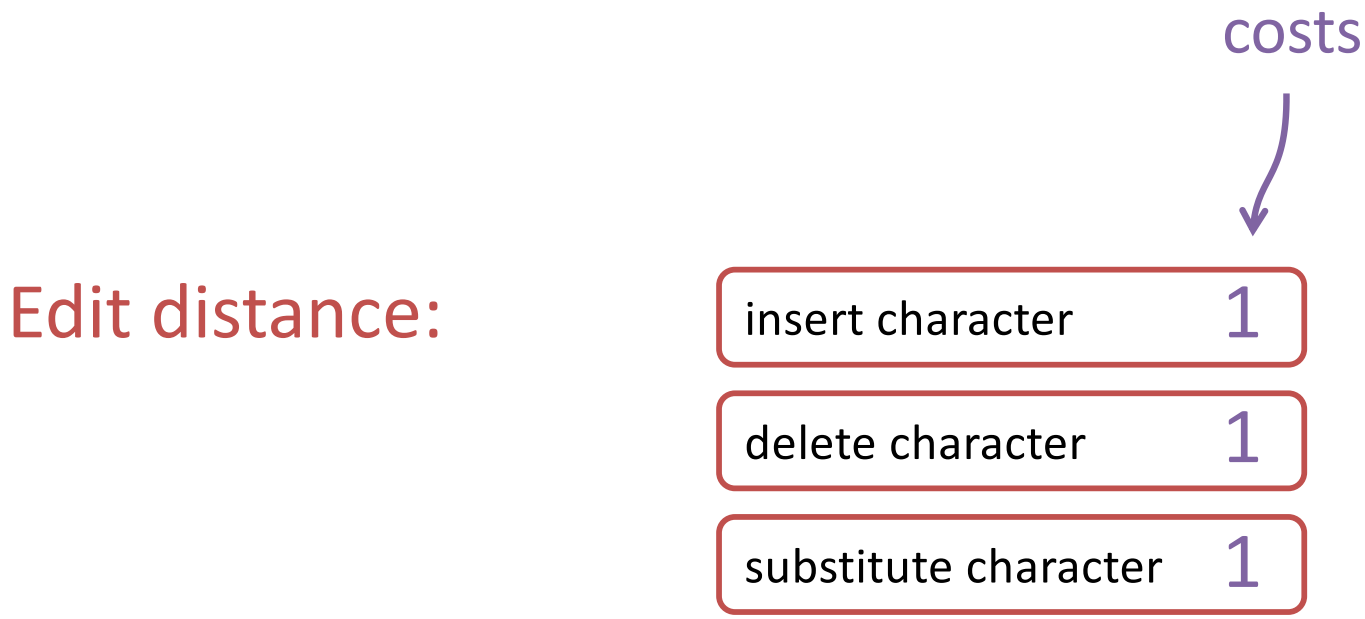
transpose character	c_4
…	c_i

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 suffix of x $y_1 y_2 \ \ldots \ y_{j-1} y_j$ is a suffix of y

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 $y_1 y_2 \ \ldots \ y_{j-1} y_j$ is a prefix of y

Case	Distance	Operation
$x_i = y_j$	$d(i-1,j-1)$	keep x_i
$x_i \ != \ y_j$		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 $y_1 y_2 \ldots y_{j-1} y_j$ 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 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 $y_1 y_2 \ldots y_{j-1} y_j$ is a prefix of y

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

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$x_1 x_2 \ldots x_{i-1} x_i$ 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
$x_i \mathrel{!}= y_j$	$d(i-1,j) + 1$	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

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)

- Cost of dynamic programming is O(|x||y|)

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 $(\log n)^{O(1/\text{epsilon})}$ approximation in $n^{(1+\text{epsilon})}$ time.

http://arxiv.org/abs/1005.4033

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Levenshtein Distance Examples

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

=

Levenshtein Distance Examples

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

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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

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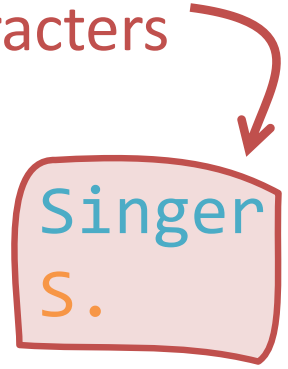
Levenshtein Distance Examples

Too high a cost for deleting a sequence of characters

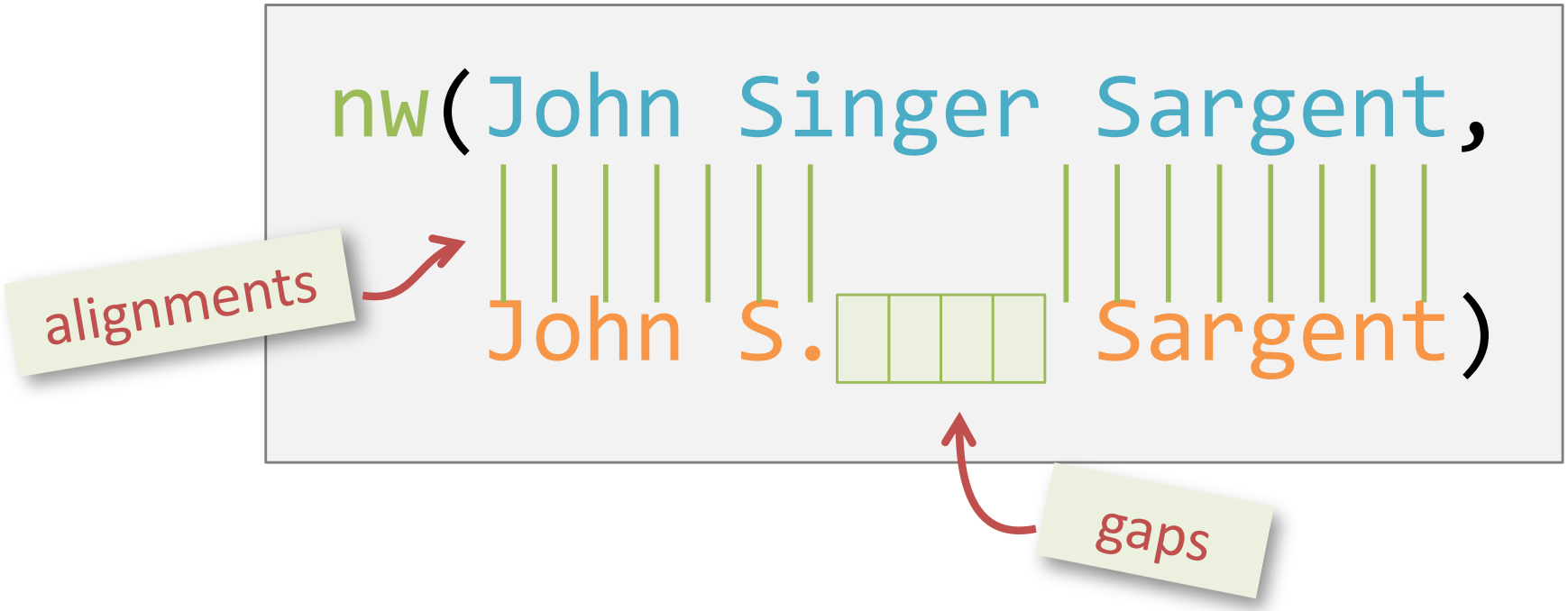


lev(John Singer Sargent, John S. Sargent) = 5

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

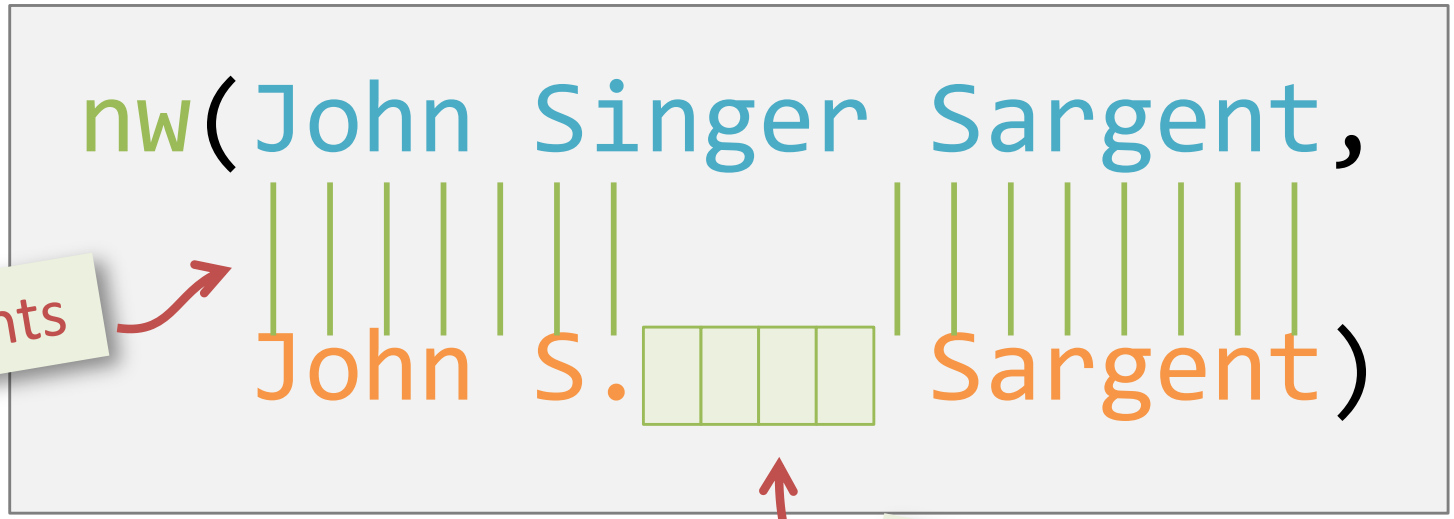
Needleman-Wunch Measure

Generalization of levenstein(x, y)



Needleman-Wunch Measure

Generalization of levenstein(x, y)

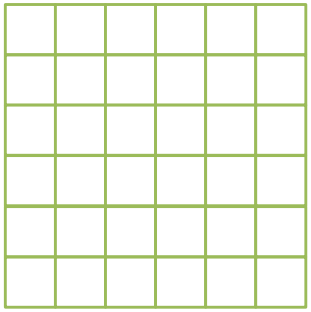


alignments

gaps

alignment score matrix

$s(c_i, c_j)$



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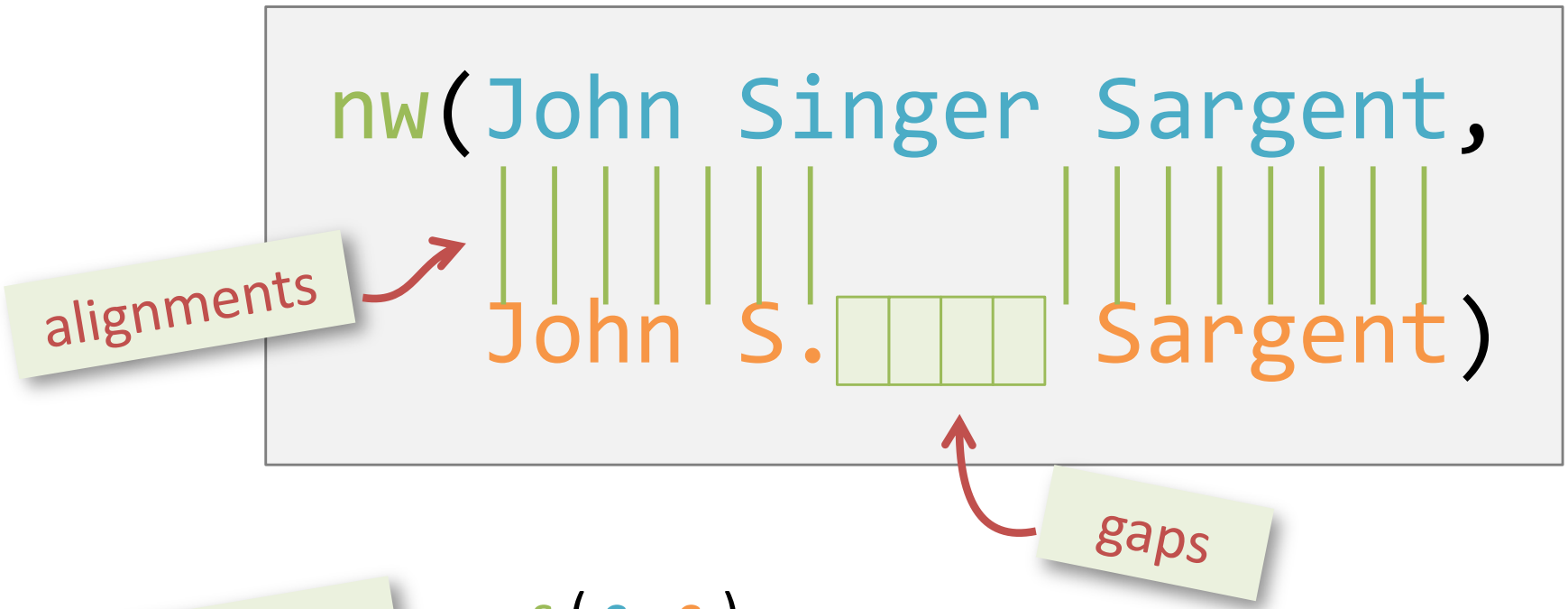
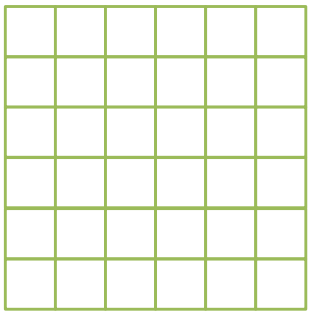
Needleman-Wunch Measure

Generalization of levenstein(x, y)



Alignment score matrix

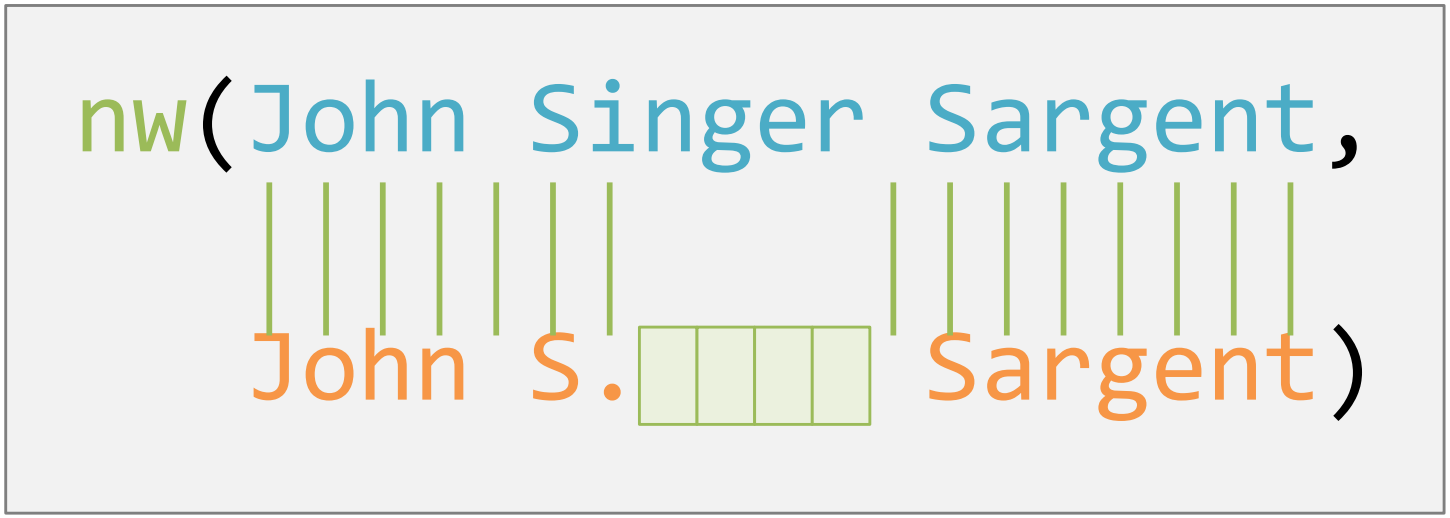
$s(c_i, c_j)$



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

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Needleman-Wunch Measure

Generalization of levenstein(x, y)

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

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

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

gap-score = -0.5

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Comparison

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

OCR errors "J0hn" vs "John"

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

lower penalty

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

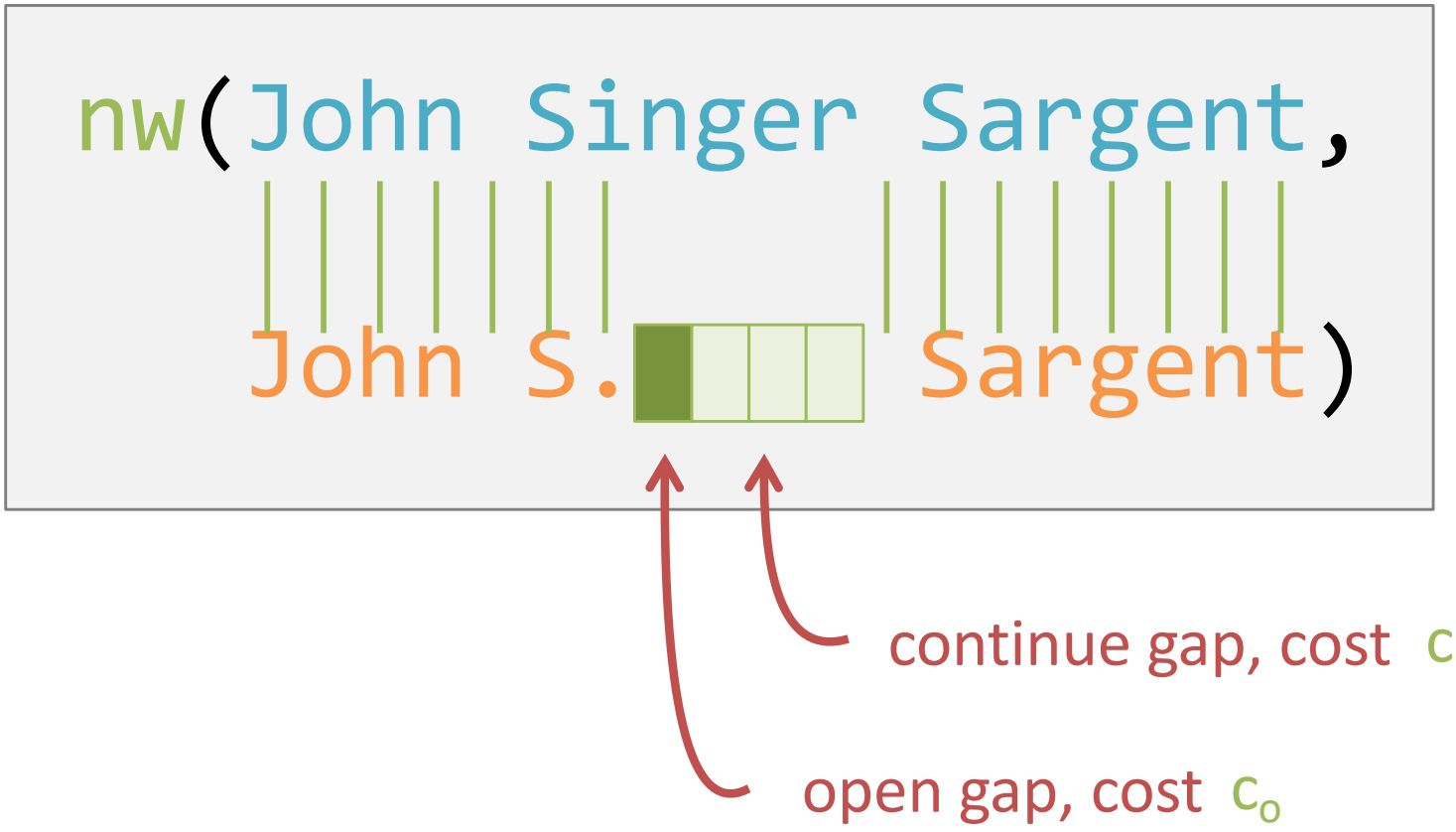
Bad for names

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

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

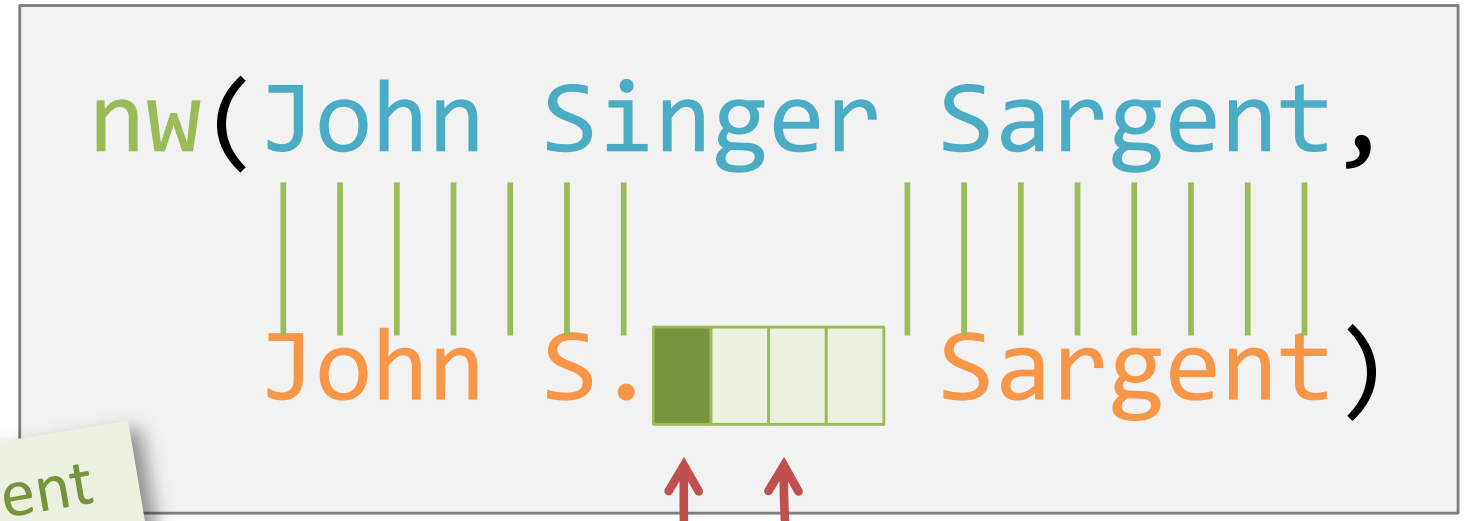
Affine Gap Measure

Generalization of needleman-wunch(x, y)



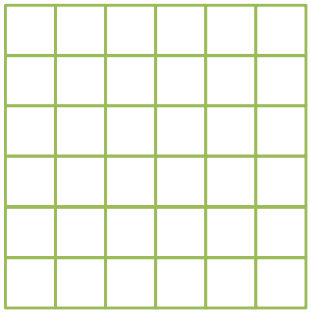
Affine Gap Measure

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

Needleman-Wunch

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

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

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)

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

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

Jaro Similarity Measure jaro(x, y)

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

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

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

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

Jaro Example

```
lev(DIXON, DICKSONX)  = 4     (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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Jaro-Winkler Measure

Give a bonus if there is a common prefix

```
jwProximity(x,y,boostThreshold,prefixSize)
      = jaro(x,y) <= boostThreshold
      ? jaro (x,y)
      : jaro (x,y)
        + 0.1 * prefixMatch(x,y,prefixSize)
              * (1.0 - jaro(x,y))

prefixMatch(x,y,prefixSize) =
  min(prefixSize, common-prefix(x,y))

boostThreshold = 0.7
    prefixSize = 4
```

Jaro-Winkler Measure

```
jwProximity(x,y,boostThreshold,prefixSize)
     = jaro(x,y) <= boostThreshold
     ? jaro (x,y)
     : jaro (x,y)
       + 0.1 * prefixMatch(x,y,prefixSize)
             * (1.0 - jaro(x,y))
```

boostThreshold = 0.7
prefixSize = 4

jaro(DIXON, DICKSONX) = 0.767

jwProximity(DIXON, DICKSONX) = 0.767 + 0.1*2*(1 – 0.767)
= 0.767 + 0.2*0.233
= 0.767 + 0.0466
= 0.8136

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Set-Based Metrics

Set-Based Metrics

Generate set of tokens from the strings

Measure similarity between the sets of tokens

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Tokenizing a String

Words

Tokenizing a String

Words

q-grams: substrings of length q

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

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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) > = < 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

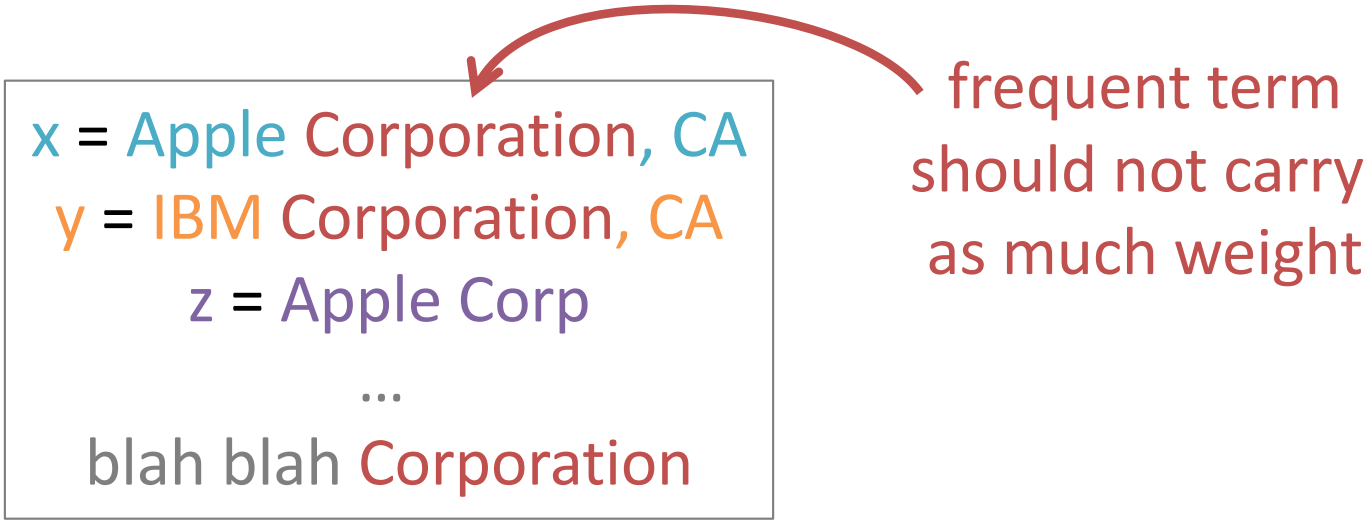
lev(x, y) < lev(x, z)

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

TF/IDF Measure

TF = term frequency

IDF = inverse document frequency



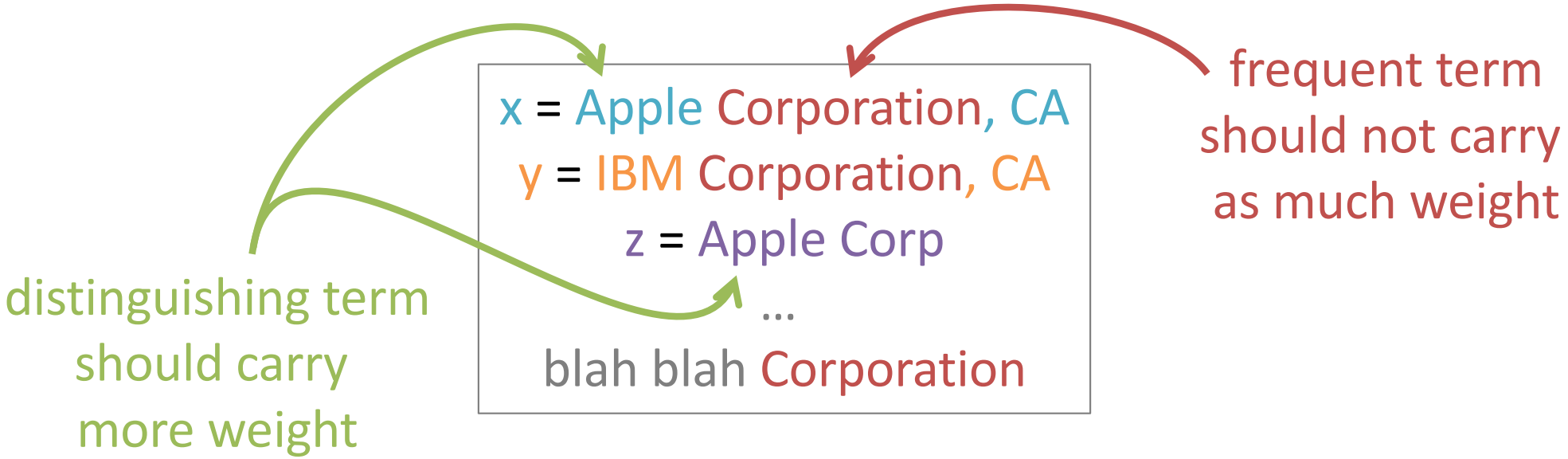
lev(x, y) > lev(x, z)

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

TF/IDF Measure

TF = term frequency

IDF = inverse document frequency



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 / $\mathbf{N}_d$)

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Example

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

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

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

$tf(a, x) = 2$

$tf(b, x) = 1$

...

$tf(c, z) = 0$

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

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

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

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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
$\mathbf{v}_y$	3	0	3
$\mathbf{v}_z$	3	0	0

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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 $\mathbf{v}_q$
  - $s(p,q) = \sum_{t \in T} v_p(t) * v_q(t) \; / [\sqrt{\sum_{t \in T} v_p(t)^2} * \sqrt{\sum_{t \in T} vq(t)^2}]$

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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) / $\sqrt{\sum_{\{t \in T\}} v_d(t)^2}$

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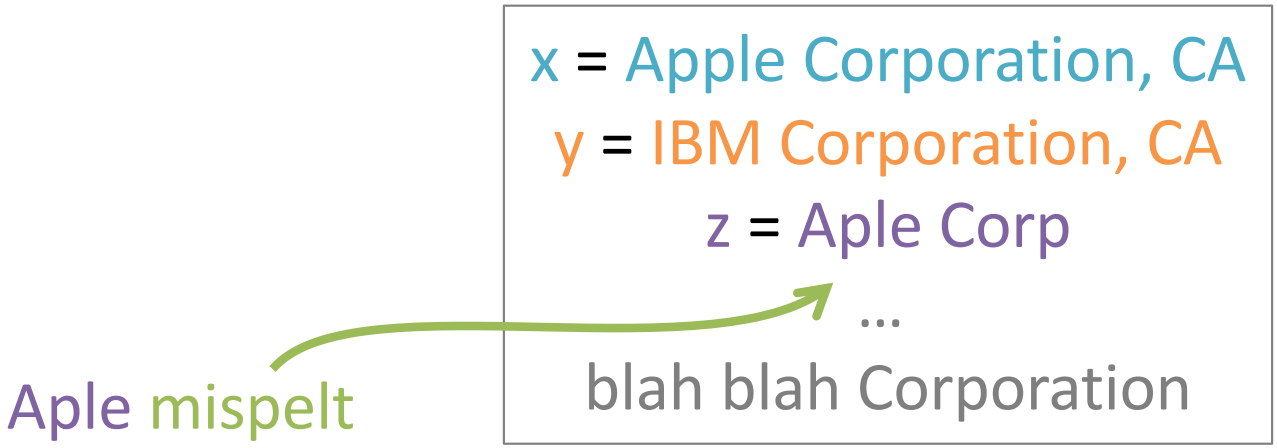
Hybrid Similarity Measures

Hybrid Measures

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



slide by Pedro Szekely

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 taxonomic nodes that describe companies
  - "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

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

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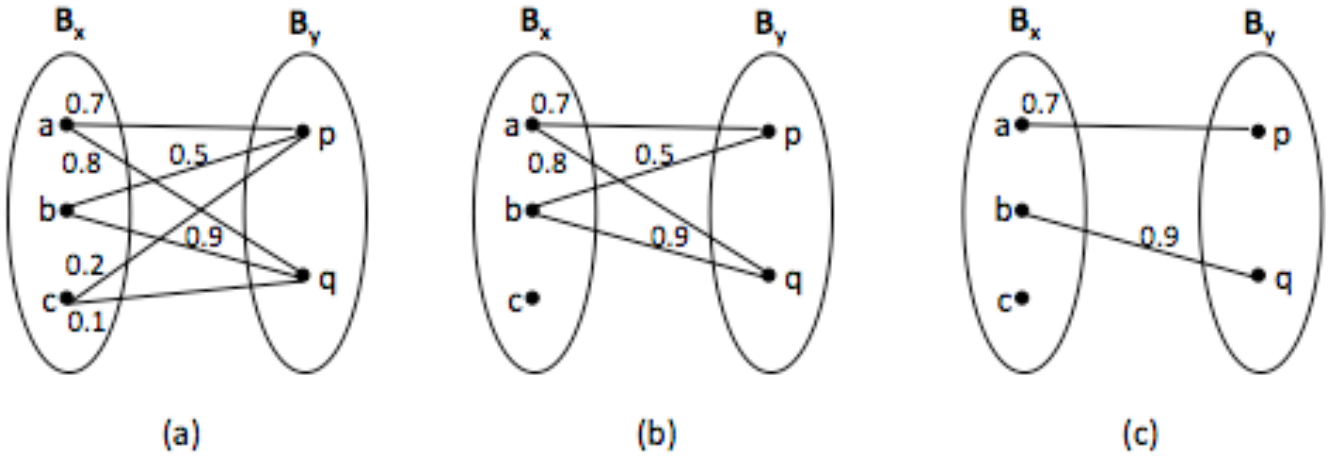
Generalized Jaccard Example



$\alpha = 0.5$

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

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

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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

Monge-Elkan Measure

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

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

y = Department of Computer Science, Univ. of Calif., San Diego

what s' should we use?

levenshtein
needleman-wunch
affine-gap
smith-waterman
jaro
jaro-winkler

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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 occurences of W and H. Replace the remaining letters with digits as follows:
    - replace 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
- https://web.archive.org/web/20160303200731/http://www.gettingcirrius.com/2011/01/calculating-similarity-part-2-jaccard.html
- http://en.wikipedia.org/wiki/Sequence_alignment#Pairwise_alignment

Software

- http://code.google.com/p/java-similarities/source/browse/trunk/simmetrics/src/main/java/uk/ac/shef/wit/simmetrics/
- http://sourceforge.net/projects/secondstring/
- http://planetcalc.com/1721/ (Levenshtein calculator)

Source path: svn/ trunk/ simmetrics/ src/ main/ java/ uk/ ac/ shef/ wit/ simmetrics

Directories	Filename
simmetrics	AbstractStringMetric.java
arbitrators	BlockDistance.java
basiccontainers	ChapmanLengthDeviation.java
math	ChapmanMatchingSoundex.java
metrichandlers	ChapmanMeanLength.java
similaritymetrics	ChapmanOrderedNameCompoundSimilarity.java
costfunctions	CosineSimilarity.java
task	DiceSimilarity.java
tokenisers	EuclideanDistance.java
utils	InterfaceStringMetric.java
wordhandlers	JaccardSimilarity.java
	Jaro.java
	JaroWinkler.java
	Levenshtein.java
	MatchingCoefficient.java
	MongeElkan.java
	NeedlemanWunch.java
	OverlapCoefficient.java
	QGramsDistance.java

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