Information Extraction: Coreference and Relation Extraction

Lecture #22

Introduction to Natural Language Processing
CMPSCI 585, Spring 2004
University of Massachusetts Amherst

Andrew McCallum

What is "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…

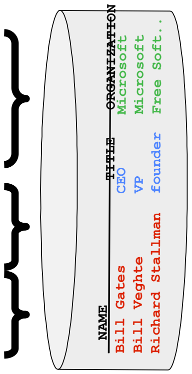
* Microsoft Corporation
CEO
Bill Gates

* Microsoft
Gates

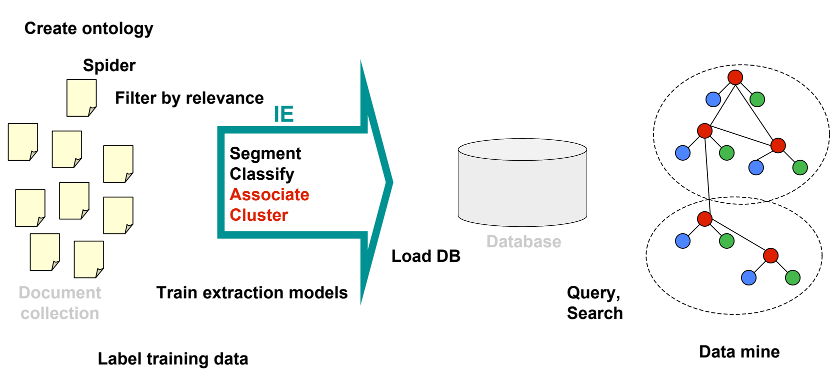
* Microsoft

Bill Veghte
* Microsoft
VP

Richard Stallman
founder
Free Software Foundation



IE in Context



Main Points

Co-reference
- How to cast as classification [Cardie]
- Measures of string similarity [Cohen]
- Scaling up [McCallum et al]

Relation extraction
- With augmented grammar [Miller et al 2000]
- With joint inference [Roth & Yih]
- Semi-supervised [Brin]

Coreference Resolution

AKA "record linkage", "database record deduplication", "citation matching", "object correspondence", "identity uncertainty"

Input

News article, with named-entity "mentions" tagged

Today Secretary of State Colin Powell met with . . . . he . . . . Condoleezza Rice . . . . Mr Powell . . . . .she . . . . Powell . . . . President Bush . . . . Rice . . . . Bush . . . .

Output

Number of entities, *N = 3*

#1
Secretary of State Colin Powell
he
Mr. Powell
Powell

#2
Condoleezza Rice
she
Rice

#3
President Bush
Bush

Inside the Traditional Solution

Pair-wise Affinity Metric

Mention (3): . . . Mr Powell . . .
Y/N?
Mention (4): . . . Powell . . .

N	Two words in common	29	
Y	One word in common	13	
Y	"Normalized" mentions are string identical	39	
Y	Capitalized word in common	17	
Y	> 50% character tri-gram overlap	19	
N	< 25% character tri-gram overlap	-34	
Y	In same sentence	9	
Y	Within two sentences	8	
N	Further than 3 sentences apart	-1	
Y	"Hobbs Distance" < 3	11	
N	Number of entities in between two mentions = 0	12	
N	Number of entities in between two mentions > 4	-3	
Y	Font matches	1	
Y	Default	-19	
	OVERALL SCORE =	98	> threshold=0

Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment...

Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment...

Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment...

Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment...

Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment...

Noun Phrase Coreference

Identify all noun phrases that refer to the same entity

Queen Elizabeth set about transforming her husband, King George VI, into a viable monarch. Logue, a renowned speech therapist, was summoned to help the King overcome his speech impediment...

IE Example: Input Text

SAN SALVADOR, 15 JAN 90 (ACAN-EFE) -- [TEXT] ARMANDO CALDERON SOL, PRESIDENT OF THE NATIONALIST REPUBLICAN ALLIANCE (ARENA), THE RULING SALVADORAN PARTY, TODAY CALLED FOR AN INVESTIGATION INTO ANY POSSIBLE CONNECTION BETWEEN THE MILITARY PERSONNEL IMPLICATED IN THE ASSASSINATION OF JESUIT PRIESTS.

"IT IS SOMETHING SO HORRENDOUS, SO MONSTROUS, THAT WE MUST INVESTIGATE THE POSSIBILITY THAT THE FMLN (FARABUNDO MARTI NATIONAL LIBERATION FRONT) STAGED THESE MURDERS TO DISCREDIT THE GOVERNMENT," CALDERON SOL SAID.

SALVADORAN PRESIDENT ALFREDO CRISTIANI IMPLICATED FOUR OFFICERS, INCLUDING ONE COLONEL, AND FIVE MEMBERS OF THE ARMED FORCES IN THE ASSASSINATION OF SIX JESUIT PRIESTS AND TWO WOMEN ON 16 NOVEMBER AT THE CENTRAL AMERICAN UNIVERSITY.

IE Example: Output Template

1. DATE	16 NOV 90
2. LOCATION	EL SALVADOR: CENTRAL AMERICAN UNIVERSITY
3. TYPE	MURDER
4. STAGE OF EXECUTION	ACCOMPLISHED
5. INCIDENT CATEGORY	TERRORIST ACT
6. PERP: INDIVIDUAL ID	"FOUR OFFICERS" "ONE COLONEL" "FIVE MEMBERS OF THE ARMED FORCES"
7. PERP: ORGANIZATION ID	"ARMED FORCES", "FMLN"
8. PERP: CONFIDENCE	REPORTED AS FACT; ACCUSED BY GOVT
9. HUM TGT: DESCRIPTION	"JESUITS" "WOMEN"
10. HUM TGT: TYPE	CIVILIAN: "JESUITS" CIVILIAN: "WOMEN"
11. HUM TGT: NUMBER	6: "JESUITS" 2: "WOMEN"
12. EFFECT OF INCIDENT	DEATH: "JESUITS" DEATH: "WOMEN"

IE Example: Coreference

SAN SALVADOR, 15 JAN 90 (ACAN-EFE) -- [TEXT] ARMANDO CALDERON SOL, PRESIDENT OF THE NATIONALIST REPUBLICAN ALLIANCE (ARENA), THE RULING SALVADORAN PARTY, TODAY CALLED FOR AN INVESTIGATION INTO ANY POSSIBLE CONNECTION BETWEEN THE MILITARY PERSONNEL IMPLICATED IN THE ASSASSINATION OF JESUIT PRIESTS.

"IT IS SOMETHING SO HORRENDOUS, SO MONSTROUS, THAT WE MUST INVESTIGATE THE POSSIBILITY THAT THE FMLN (FARABUNDO MARTI NATIONAL LIBERATION FRONT) STAGED THESE MURDERS TO DISCREDIT THE GOVERNMENT," CALDERON SOL SAID.

SALVADORAN PRESIDENT ALFREDO CRISTIANI IMPLICATED FOUR OFFICERS, INCLUDING ONE COLONEL, AND FIVE MEMBERS OF THE ARMED FORCES IN THE ASSASSINATION OF SIX JESUIT PRIESTS AND TWO WOMEN ON 16 NOVEMBER AT THE CENTRAL AMERICAN UNIVERSITY.

Why It's Hard

Many sources of information play a role

- head noun matches
  - IBM *executives* = the *executives*
- syntactic constraints
  - John helped himself to...
  - John helped him to…
- number and gender agreement
- discourse focus, recency, syntactic parallelism, semantic class, world knowledge, …

Why It's Hard

- No single source is a completely reliable indicator
  - number agreement
    - the assassination = these murders
- Identifying each of these features automatically, accurately, and in context, is hard
- Coreference resolution subsumes the problem of pronoun resolution…

A Machine Learning Approach

- Classification
  - given a description of two noun phrases, NP_i and NP_j, classify the pair as *coreferent* or *not coreferent*

coref ? *coref ?*

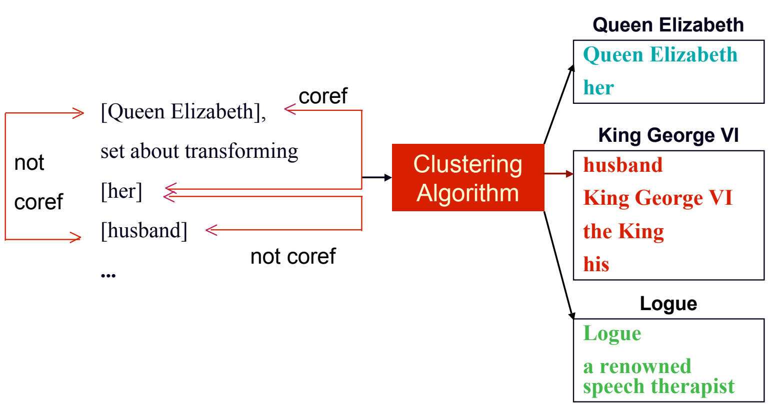
[Queen Elizabeth] set about transforming [her] [husband], ...

not coref ?

Aone & Bennett [1995]; Connolly et al. [1994]; McCarthy & Lehnert [1995]; Soon et al. [2001]; Ng & Cardie [2002]; …

A Machine Learning Approach

- Clustering
  - coordinates pairwise coreference decisions



Machine Learning Issues

- Training data creation
- Instance representation
- Learning algorithm
- Clustering algorithm

Supervised Inductive Learning

Examples of NP pairs (features + class)

↓

ML Algorithm

↓

(novel) pair of NPs (features) → Concept description (program) → label

Training Data Creation

- Creating training instances
  - texts annotated with coreference information
  - one instance *inst*(NP_i, NP_j) for each pair of NPs
    - assumption: NP_i precedes NP_j
    - feature vector: describes the two NPs and context
    - class value:

      coref pairs on the same coreference chain

      not coref otherwise

Instance Representation

- 25 features per instance
  - lexical (3)
    - string matching for pronouns, proper names, common nouns
  - grammatical (18)
    - pronoun, demonstrative (the, this), indefinite (it is raining), …
    - number, gender, animacy
    - appositive (george, the king), predicate nominative (a horse is a mammal)
    - binding constraints, simple contra-indexing constraints, …
    - span, maximalnp, …
  - semantic (2)
    - same WordNet class
    - alias
  - positional (1)
    - distance between the NPs in terms of # of sentences
  - knowledge-based (1)
    - naïve pronoun resolution algorithm

Learning Algorithm

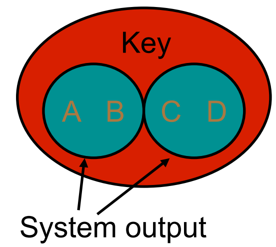
- RIPPER (Cohen, 1995)
  C4.5 (Quinlan, 1994)
  - rule learners
    - input: set of training instances
    - output: coreference classifier
- Learned classifier
  - input: test instance (represents pair of NPs)
  - output: classification
    confidence of classification

Clustering Algorithm

- Best-first single-link clustering
  - Mark each NP_j as belonging to its own class: $NP_j \in c_j$
  - Proceed through the NPs in left-to-right order.
    - For each NP, NP_j, create test instances, $inst(NP_i, NP_j)$, for all of its preceding NPs, NP_i.
    - Select as the antecedent for NP_j the highest-confidence coreferent NP, NP_i, according to the coreference classifier (or none if all have below .5 confidence);
      Merge c_j and c_j .

Evaluation

- MUC-6 and MUC-7 coreference data sets
- documents annotated w.r.t. coreference
- 30 + 30 training texts (dry run)
- 30 + 20 test texts (formal evaluation)
- scoring program
  - recall
  - precision
  - F-measure: 2PR/(P+R)

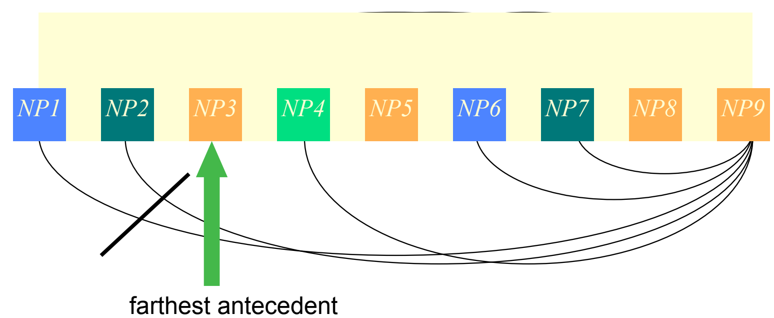


Baseline Results

	MUC-6			MUC-7		
	R	P	F	R	P	F
Baseline	40.7	73.5	52.4	27.2	86.3	41.3
Worst MUC System	36	44	40	52.5	21.4	30.4
Best MUC System	59	72	65	56.1	68.8	61.8

Problem 1

- Coreference is a rare relation
  - skewed class distributions (2% positive instances)
  - *remove some negative instances*



Problem 2

- Coreference is a discourse-level problem
  - different solutions for different types of NPs
    - proper names: string matching and aliasing
  - inclusion of “hard” positive training instances
  - *positive example selection*: selects easy positive training instances (cf. Harabagiu *et al.* (2001))

Queen Elizabeth set about transforming her husband,
King George VI, into a viable monarch. Logue,
the renowned speech therapist, was summoned to help
the King overcome his speech impediment...

Problem 3

- Coreference is an equivalence relation
  - loss of transitivity
  - need to tighten the connection between classification and clustering
  - *prune learned rules w.r.t. the clustering-level coreference scoring function*

coref ? *coref ?*

[Queen Elizabeth] set about transforming [her] [husband], ...

not coref ?

Results

	MUC-6			MUC-7		
	R	P	F	R	P	F
Baseline	40.7	73.5	52.4	27.2	86.3	41.3
NEG-SELECT	46.5	67.8	55.2	37.4	59.7	46.0
POS-SELECT	53.1	80.8	64.1	41.1	78.0	53.8
NEG-SELECT + POS-SELECT	63.4	76.3	69.3	59.5	55.1	57.2
NEG-SELECT + POS-SELECT + RULE-SELECT	63.3	76.9	69.5	54.2	76.3	63.4

- Ultimately: large increase in F-measure, due to gains in recall

Comparison with Best MUC Systems

	MUC-6			MUC-7		
	R	P	F	R	P	F
NEG-SELECT + POS-SELECT + RULE-SELECT	63.3	76.9	69.5	54.2	76.3	63.4
Best MUC System	59	72	65	56.1	68.8	61.8

Supervised ML for NP Coreference

- Good performance compared to other systems, but…**lots** of room for improvement
  - Common nouns < pronouns < proper nouns
  - Tighter connection between classification and clustering is possible
    - Rich Caruana's ensemble methods
    - Statistical methods for learning probabilistic relational models (Getoor *et al.,* 2001; Lafferty et al., 2001; Taskar *et al.*, 2003; McCallum and Wellner, 2003).
  - Need additional data sets
    - New release of ACE data from Penn's LDC
    - General problem: reliance on manually annotated data…

Main Points

Co-reference
- How to cast as classification [Cardie]
- **Measures of string similarity [Cohen]**
- Scaling up [McCallum et al]

Relation extraction
- With augmented grammar [Miller et al 2000]
- With joint inference [Roth & Yih]
- Semi-supervised [Brin]

Record linkage: definition

- *Record linkage:* determine if pairs of *data records* describe the same entity
  - I.e., find record pairs that are *co-referent*
  - Entities: usually people (or organizations or…)
  - Data records: names, addresses, job titles, birth dates, …
- Main applications:
  - *Joining* two heterogeneous relations
  - *Removing duplicates* from a single relation

Record linkage: terminology

- The term "*record linkage"* is possibly co-referent with:
  - For DB people: data matching, merge/purge, duplicate detection, data cleansing, ETL (extraction, transfer, and loading), de-duping
  - For AI/ML people: reference matching, database hardening, object consolidation,
  - In NLP: co-reference/anaphora resolution
  - Statistical matching, clustering, language modeling, …

Finding a technical paper *c.* 1995

- Start with citation:

> " Experience With a Learning Personal Assistant", T.M. Mitchell, R. Caruana, D. Freitag, J. McDermott, and D. Zabowski, *Communications of the ACM*, Vol. 37, No. 7, pp. 81-91, July 1994.

- Find author's institution (w/ INSPEC)
- Find web host (w/ NETFIND)
- Find author's home page and (hopefully) the paper by browsing

The data integration problem

internet host	*institution*
cs.ucsd.edu	computer science department, university of california, san diego
cs.stanford.edu	computer science department, stanford university, palo alto, california
(INSPEC)	Dept. of Comput. Sci., California Univ., San Diego, La Jolla, CA, USA.
(INSPEC)	Dept. of Comput. Sci. Stanford Univ., CA, USA.

String distance metrics: overview

- Term-based (e.g. TF/IDF as in WHIRL)
  - Distance depends on **set of words** contained in both *s* and *t*.
- Edit-distance metrics
  - Distance is **shortest sequence of edit commands** that transform *s* to *t.*
- Pair HMM based metrics
  - Probabilistic extension of edit distance
- Other metrics

String distance metrics: term-based

- Term-based (e.g. TFIDF as in WHIRL)
  - Distance between *s* and *t* based on **set of words** appearing in both *s* and *t.*
  - Order of words is **not** relevant
    - E.g, "Cohen, William" = "William Cohen" and "James Joyce = Joyce James"
  - Words are usually **weighted** so common words count less
    - E.g. "Brown" counts less than "Zubinsky"
    - Analogous to Felligi-Sunter's Method 1

Jaccard Distance

S		William	Cohen	CM	Univ		Pgh
T	Dr.	William	Cohen	CM		University	
$\|S \cup T\|$	Dr.	William	Cohen	CM	Univ	University	Pgh
$\|S \cap T\|$		William	Cohen	CM			

$$\text{Jaccard Score} = \frac{|S \cap T|}{|S \cup T|} = \frac{3}{7}$$

String distance metrics: term-based

- Advantages:
  - Exploits **frequency** information
  - Efficiency: Finding { *t : sim(t,s)>k* } is sublinear!
  - Alternative word orderings ignored (William Cohen *vs* Cohen, William)
- Disadvantages:
  - Sensitive to spelling errors (Willliam Cohon)
  - Sensitive to abbreviations (Univ. vs University)
  - Alternative word orderings ignored (James Joyce *vs* Joyce James, City National Bank *vs* National City Bank)

String distance metrics: Levenshtein

- Edit-distance metrics
  - Distance is **shortest sequence of edit commands** that transform *s* to *t.*
  - Simplest set of operations:
    - Copy character from *s* over to *t*
    - Delete a character in *s* (cost 1)
    - Insert a character in *t* (cost 1)
    - Substitute one character for another (cost 1)
  - This is “Levenshtein distance”

Levenshtein distance - example

- distance(“William Cohen”, “Willliam Cohon”)

s	W	I	L	L	gap	I	A	M	_	C	O	H	E	N
t	W	I	L	L	L	I	A	M	_	C	O	H	O	N
op	C	C	C	C	**I**	C	C	C	C	C	C	C	**S**	C
cost	0	0	0	0	1	1	1	1	1	1	1	1	2	2

alignment

Computing Levenshtein distance - 1

D(i,j) = score of **best** alignment from *s1..si* to *t1..tj*

$$= \min \begin{cases} D(i-1,j-1), \text{ if } si=tj & \textit{//copy} \\ D(i-1,j-1)+1, \text{ if } si!=tj & \textit{//substitute} \\ D(i-1,j)+1 & \textit{//insert} \\ D(i,j-1)+1 & \textit{//delete} \end{cases}$$

Computing Levenshtein distance - 2

D(i,j) = score of **best** alignment from *s1..si* to *t1..tj*

$$= \min \begin{cases} D(i-1,j-1) + d(si,tj) & \textit{//subst/copy} \\ D(i-1,j)+1 & \textit{//insert} \\ D(i,j-1)+1 & \textit{//delete} \end{cases}$$

(simplify by letting d(c,d)=0 if c=d, 1 else)

also let D(i,0)=i *(for i inserts)* and D(0,j)=j

Computing Levenshtein distance - 3

$$D(i,j) = \min \begin{cases} D(i-1,j-1) + d(si,tj) & \textit{//subst/copy} \\ D(i-1,j)+1 & \textit{//insert} \\ D(i,j-1)+1 & \textit{//delete} \end{cases}$$

	C	O	H	E	N
M	1	2	3	4	5
C	1	2	3	4	5
C	2	2	3	4	5
O	3	2	3	4	5
H	4	3	2	3	4
N	5	4	3	3	3

= D(*s*,*t*)

Computing Levenshtein distance – 4

$$D(i,j) = \min \begin{cases} D(i-1,j-1) + d(si,tj) & \textit{//subst/copy} \\ D(i-1,j)+1 & \textit{//insert} \\ D(i,j-1)+1 & \textit{//delete} \end{cases}$$

A *trace* indicates where the min value came from, and can be used to find edit operations and/or a best *alignment*
(may be more than 1)

	C	O	H	E	N
M	**1**	2	3	4	5
C	**1**	2	3	4	5
C	**2**	3	3	4	5
O	3	**2**	3	4	5
H	4	3	**2**	**3**	4
N	5	4	3	3	**3**

Needleman-Wunch distance

$$D(i,j) = \min \begin{cases} D(i-1,j-1) + d(si,tj) & \textit{//subst/copy} \\ D(i-1,j) + \mathbf{\textit{G}} & \textit{//insert} \\ D(i,j-1) + \mathbf{\textit{G}} & \textit{//delete} \end{cases}$$

G = "gap cost"

d(c,d) is an arbitrary distance function on characters (e.g. related to typo frequencies, amino acid substitutibility, etc)

William Cohen
↓
Wukkuan Cigeb

Smith-Waterman distance

- Instead of looking at each sequence in its entirety, this compares segments of all possible lengths and chooses whichever maximise the similarity measure.
- For every cell the algorithm calculates all possible paths leading to it. These paths can be of any length and can contain insertions and deletions.

Smith-Waterman distance

$$D(i,j) = \max \begin{cases} \mathbf{0} & \textbf{//start over} \\ D(i-1,j-1) - d(si,tj) & \textit{//subst/copy} \\ D(i-1,j) - G & \textit{//insert} \\ D(i,j-1) - G & \textit{//delete} \end{cases}$$

G = 1

d(c,c) = -2

d(c,d) = +1

	C	**O**	**H**	**E**	**N**
M	0	0	0	0	0
C	**+2**	0	0	0	0
C	**+2**	0	0	0	0
O	0	**+4**	+3	0	0
H	0	+3	**+6**	**+5**	+3
N	0	+2	+5	+5	**+7**

Smith-Waterman distance: Monge & Elkan's WEBFIND (1996)

internet host	*institution*
cs.ucsd.edu	computer science department, university of california, san diego
cs.stanford.edu	computer science department, stanford university, palo alto, california
(INSPEC)	Dept. of Comput. Sci., California Univ., San Diego, La Jolla, CA, USA.
(INSPEC)	Dept. of Comput. Sci. Stanford Univ., CA, USA.

Table 1: Example of NETFIND and INSPEC fields.

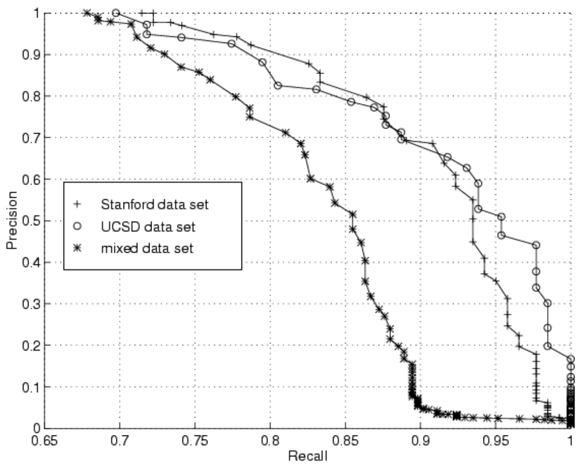
Smith-Waterman distance in Monge & Elkan's WEBFIND (1996)

Used a **standard version** of Smith-Waterman with hand-tuned weights for inserts and character substitutions.

Split large text fields by separators like commas, etc, and found minimal cost over **all possible pairings** of the subfields (since S-W assigns a large cost to large transpositions)

Result **competitive** with plausible competitors.

Results: S-W from Monge & Elkan



Affine gap distances

- Smith-Waterman fails on some pairs that seem quite similar:

William W. Cohen

William W. 'Don't call me Dubya' Cohen

Intuitively, single long insertions are "cheaper" than a lot of short insertions

Affine gap distances - 2

- Idea:
  - Current cost of a "gap" of *n* characters: *nG*
  - Make this cost: *A + (n-1)B,* where *A* is cost of "opening" a gap, and *B* is cost of "continuing" a gap.

Affine gap distances - 3

$$D(i,j) = \max \begin{cases} D(i-1,j-1) + d(si,tj) \\ IS(I-1,j-1) + d(si,tj) \\ IT(I-1,j-1) + d(si,tj) \end{cases}$$

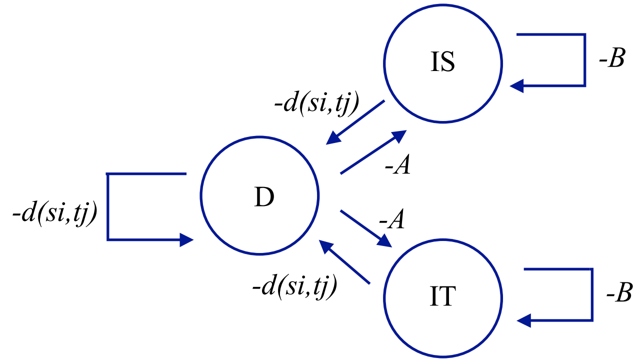
$$IS(i,j) = \max \begin{cases} D(i-1,j) - A \\ IS(i-1,j) - B \end{cases}$$

Best score in which si is aligned with a 'gap'

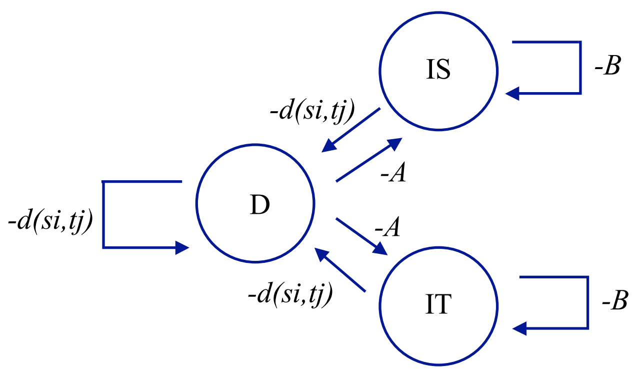
$$IT(i,j) = \max \begin{cases} D(i,j-1) - A \\ IT(i,j-1) - B \end{cases}$$

Best score in which tj is aligned with a 'gap'

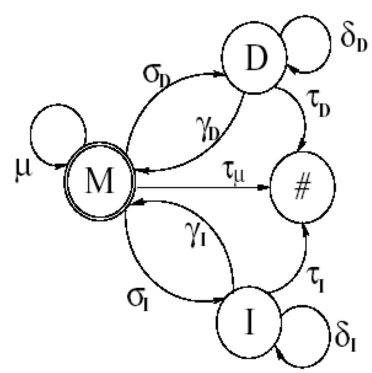
Affine gap distances - 4



Affine gap distances as automata



Generative version of affine gap automata (Bilenko&Mooney, TechReport 02)



HMM emits **pairs:** *(c,d)* in state *M*, pairs *(c,-)* in state *D*, and pairs *(-,d)* in state *I*.

For each state there is a **multinomial** distribution on pairs.

The HMM can trained with EM from a sample of pairs of **matched** strings *(s,t)*

E-step is forward-backward; M-step uses some *ad hoc* smoothing

Affine gap edit-distance learning: experiments results (Bilenko & Mooney)

Table 2: Sample duplicate records from the RESTAURANT database

name	address	city	phone	cuisine
Second Avenue Deli	156 2nd Ave. at 10th St.	New York	212/677-0606	Delicatessen
Second Avenue Deli	156 Second Ave.	New York City	212-677-0606	Delis

Table 3: Sample duplicate records from the MAILING database

first	last	street address	city
Tsy C	Dodgson	18 Lilammal Ave 3k1	Christina MT 59423
Tessy	Dodgeson	PO Box 3879	Christina MT 59428

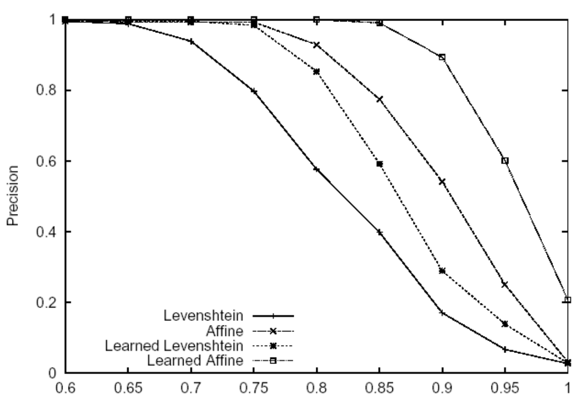
Experimental method: parse records into fields; append a few key fields together; sort by similarity; pick a threshold *T* and call all pairs with distance(*s*,*t*) < *T* "duplicates"; picking *T* to maximize F-measure.

Affine gap edit-distance learning: experiments results (Bilenko & Mooney)

Distance metric	CORA title	RESTAURANT name
Levenshtein	0.870	0.843
Learned Levenshtein	0.902	**0.886**
Affine	0.917	0.883
Learned Affine	**0.971**	**0.967**

Distance met	RESTAURANT address	MAILING name	MAILING address
Levenshtein	0.950	0.867	0.878
Learned Leve	0.975	**0.899**	0.897
Affine	0.870	0.923	0.886
Learned Affi	**0.929**	**0.959**	0.892

Affine gap edit-distance learning: experiments results (Bilenko & Mooney)



Precision/recall for MAILING dataset duplicate detection

Affine gap distances – experiments (from McCallum,Nigam,Ungar KDD2000)

- Goal is to match data like this:

Fahlman, Scott & Lebiere, Christian (1989). The cascade-correlation learning architecture. In Touretzky, D., editor, Advances in Neural Information Processing Systems (volume 2), (pp. 524-532), San Mateo, CA. Morgan Kaufmann.

Fahlman, S.E. and Lebiere, C., "The Cascade Correlation Learning Architecture," NIPS, Vol. 2, pp. 524-532, Morgan Kaufmann, 1990.

Fahlmann, S. E. and Lebiere, C. (1989). The cascade-correlation learning architecture. In Advances in Neural Information Processing Systems 2 (NIPS-2), Denver, Colorado.

Figure 2: Three sample citations to the same paper.

Affine gap distances – experiments (from McCallum,Nigam,Ungar KDD2000)

- Hand-tuned edit distance
- Lower costs for affine gaps
- Even lower cost for affine gaps near a "."
- HMM-based **normalization** to group title, author, booktitle, etc into **fields**

Affine gap distances – experiments

	TFIDF	Edit Distance	Adaptive
Cora	0.751	**0.839**	**0.945**
	0.721		**0.964**
OrgName1	**0.925**	0.633	0.923
	0.366	**0.950**	0.776
Orgname2	**0.958**	0.571	**0.958**
	0.778	0.912	**0.984**
Restaurant	0.981	0.827	**1.000**
	0.967	0.867	0.950
Parks	0.976	0.967	**0.984**
	0.967	0.967	**0.967**

String distance metrics: outline

- Term-based (e.g. TF/IDF as in WHIRL)
  - Distance depends on **set of words** contained in both *s* and *t*.
- Edit-distance metrics
  - Distance is **shortest sequence of edit commands** that transform *s* to *t.*
- Pair HMM based metrics
  - Probabilistic extension of edit distance
- **Other metrics**

Jaro metric

- Jaro metric is (apparently) tuned for personal names:
  - Given *(s,t)* define *c* to be *common in s,t* if it *si=c, tj=c,* and |*i-j*|*<min(*|s|,|*t*|*)/2.*
  - Define *c,d* to be a *transposition* if *c,d* are common and *c,d* appear in different orders in *s* and *t.*
  - Jaro(*s,t)* = average of *#common/*|s|, *#common/*|*t*|, and 0.5*#transpositions/#common*
  - Variant: weight errors early in string more heavily
- Easy to compute – note edit distance is O(|*s*||*t*|)

NB. This is my interpretation of Winkler's description

Jaro metric

	W	I	L	L	I	A	M
W	$\boxed{1}$	**0**	**0**	0	0	0	0
I	**0**	$\boxed{1}$	**0**	**0**	1	0	0
L	**0**	**0**	$\boxed{1}$	**1**	**0**	0	0
L	0	**0**	**1**	$\boxed{1}$	**0**	**0**	0
L	0	0	**1**	**1**	$\boxed{0}$	**0**	**0**
A	0	0	0	**0**	**0**	$\boxed{1}$	**0**
I	0	1	0	0	**1**	**0**	$\boxed{0}$
M	0	0	0	0	0	**0**	**1**

Illustration of the Jaro metric. Boxed entries are on the main diagonal, and every character in a row (column) which contains a boldfaces one is considered to be "in common" with the string "WILLIAM" ("WILLLAIM").

$$Jaro(s,t) = \frac{1}{3} \cdot \left(\frac{|s'|}{|s|} + \frac{|t'|}{|t|} + \frac{|s'| - T_{s',t'}}{|s'|} \right)$$

$|s'| = |t'| =$ no. of characters common to s and t.

$T_{s',t'} =$ no. of transpositions for s' and t'

Soundex metric

- Soundex is a coarse **phonetic** indexing scheme, widely used in genealogy.
- Every Soundex code consists of a letter and three numbers between 0 and 6, e.g. B-536 for "Bender". The letter is always the first letter of the surname. The numbers hash together the rest of the name.
  - Vowels are generally ignored: e.g. Lee, Lu => L-000. Later later consonants in a name are ignored.
  - Similar-sounding letters (e.g. B, P, F, V) are not differentiated, nor are doubled letters.
  - There are lots of Soundex variants….

N-gram metric

– Idea: split every string *s* into a set of *all* character n-grams that appear in *s,* for *n<=k.* Then, use term-based approaches.

– e.g. "COHEN" => {C,O,H,E,N,CO,OH,HE,EN,COH,OHE,HEN}

– For n=4 or 5, this is competitive on retrieval tasks. It doesn't seem to be competitive with small values of n on matching tasks (but it's useful as a fast approximate matching scheme)

Main Points

Co-reference

- How to cast as classification [Cardie]
- Measures of string similarity [Cohen]
- **Scaling up [McCallum et al]**

Relation extraction

- With augmented grammar [Miller et al 2000]
- With joint inference [Roth]
- Semi-supervised [Brin]

Reference Matching

- Fahlman, Scott & Lebiere, Christian (1989). The cascade-correlation learning architecture. In Touretzky, D., editor, Advances in Neural Information Processing Systems (volume 2), (pp. 524-532), San Mateo, CA. Morgan Kaufmann.
- Fahlman, S.E. and Lebiere, C., “The Cascade Correlation Learning Architecture,” NIPS, Vol. 2, pp. 524-532, Morgan Kaufmann, 1990.
- Fahlman, S. E. (1991) The recurrent cascade-correlation learning architecture. In Lippman, R.P. Moody, J.E., and Touretzky, D.S., editors, NIPS 3, 190-205.

The Citation Clustering Data

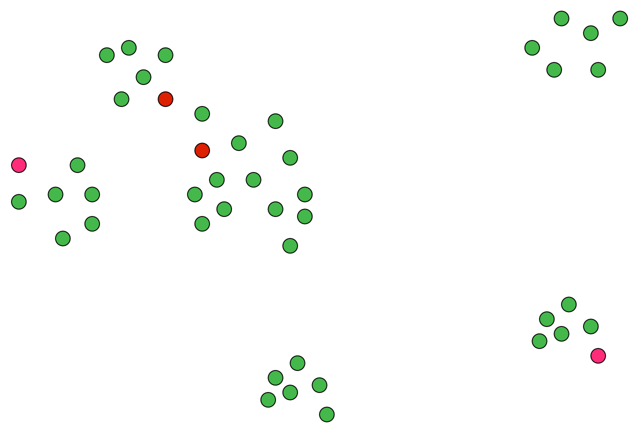
- Over 1,000,000 citations
- About 100,000 unique papers
- About 100,000 unique vocabulary words

- Over 1 trillion distance calculations

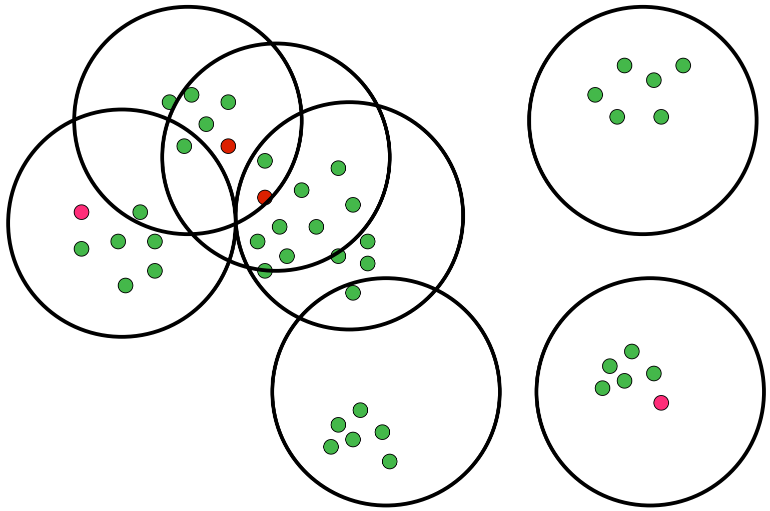
The Canopies Approach

- Two distance metrics: cheap & expensive
- First Pass
  - very inexpensive distance metric
  - create overlapping canopies
- Second Pass
  - expensive, accurate distance metric
  - canopies determine which distances calculated

Illustrating Canopies

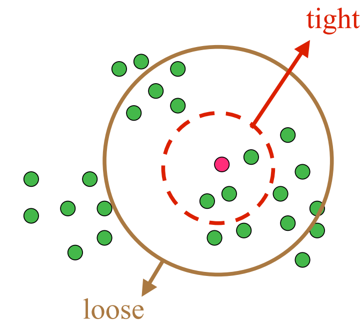


Overlapping Canopies



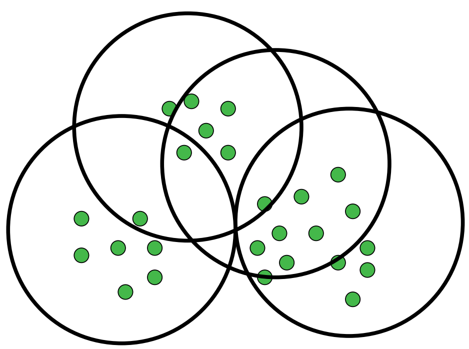
Creating canopies with two thresholds

- Put all points in D
- Loop:
  - Pick a point X from D
  - Put points within K_{loose} of X in canopy
  - Remove points within K_{tight} of X from D



Using canopies with Greedy Agglomerative Clustering

- Calculate expensive distances between points in the same canopy
- All other distances default to infinity
- Sort finite distances and iteratively merge closest



Computational Savings

- inexpensive metric << expensive metric
- # canopies per data point: f (small, but > 1)
- number of canopies: c (large)

- complexity reduction:

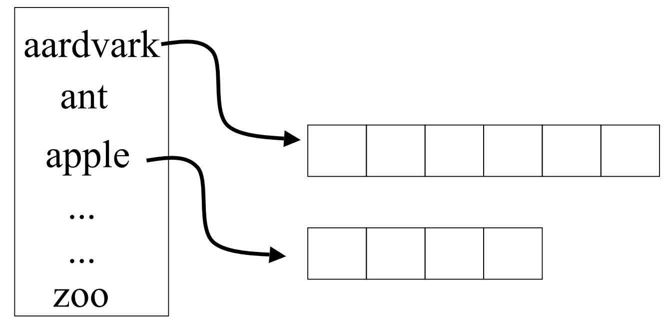
$$O\left(\frac{f^2}{c}\right)$$

The Experimental Dataset

- All citations for authors:
  - Michael Kearns
  - Robert Schapire
  - Yoav Freund
- 1916 citations
- 121 unique papers
- Similar dataset used for parameter tuning

Inexpensive Distance Metric for Text

- Word-level matching (TFIDF)
- Inexpensive using an inverted index



Expensive Distance Metric for Text

- String edit distance
- Compute with Dynamic Programming
- Costs for character:
  - insertion
  - deletion
  - substitution
  - ...

		S	e	c	a	t
	0.0	0.7	1.4	2.1	2.8	3.5
S	0.7	0.0	0.7	1.1	1.4	1.8
c	1.4	0.7	1.0	0.7	1.4	1.8
o	2.1	1.1	1.7	1.4	1.7	2.4
t	2.8	1.4	2.1	1.8	2.4	1.7
t	3.5	1.8	2.4	2.1	2.8	2.4

do Fahlman vs Falman

Extracting Fields using HMMs

Fahlman, S.E. and Lebiere, C., “The Cascade Correlation Learning Architecture,” NIPS, Vol. 2, pp. 524-532, Morgan Kaufmann, 1990.

Author: Fahlman, S.E. and Lebiere, C.

Title: The Cascade Correlation Learning Architecture

Venue: NIPS

Year: 1990

Experimental Results

	F1	Minutes
Canopies GAC	0.838	7.65
Complete GAC	0.835	134.09
Existing Cora	0.784	0.03
Author/Year	0.697	0.03

Add precision, recall along side F1

Main Points

Co-reference
- How to cast as classification [Cardie]
- Measures of string similarity [Cohen]
- Scaling up [McCallum et al]

Relation extraction
- **With augmented grammar [Miller et al 2000]**
- With joint inference [Roth & Yih]
- Semi-supervised [Brin]

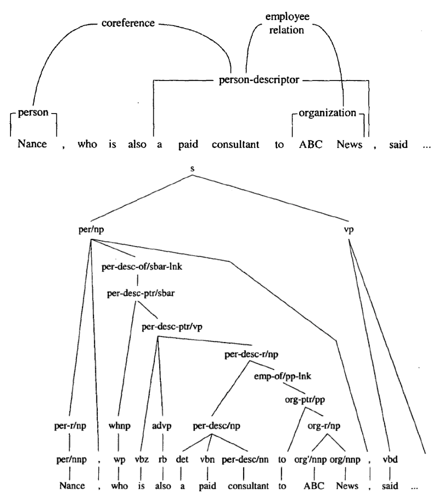
Main Points

Co-reference
- How to cast as classification [Cardie]
- Measures of string similarity [Cohen]
- Scaling up [McCallum et al]

Relation extraction
- With augmented grammar [Miller et al 2000]
- **With joint inference [Roth & Yih]**
- Semi-supervised [Brin]

(1) Association using Parse Tree

Simultaneously POS tag, parse, extract & associate! ***[Miller et al 2000]***



Increase space of parse constitutes to include entity and relation tags

Notation	Description
c_h	head constituent category
c_m	modifier constituent category
X_p	X of parent node
t	POS tag
w	word

Parameters	e.g.
$P(c_h \mid c_p)$	P(vp|s)
$P(c_m \mid c_p, c_{hp}, c_{m-1}, w_p)$	P(per/np|s,vp,null,said)
$P(t_m \mid c_m, t_h, w_h)$	P(per/nnp|per/np,vbd,said)
$P(w_m \mid c_m, t_m, t_h, w_h)$	P(nance|per/np,per/nnp,vbd,said)

(This is also a great example of extraction using a tree model.)

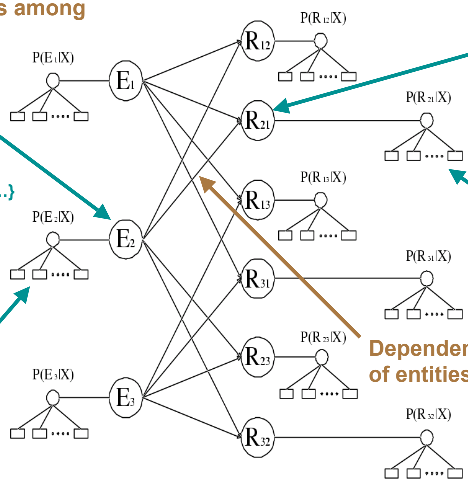
(1) Association with Graphical Models

[Roth & Yih 2002]

Capture arbitrary-distance dependencies among predictions.

Random variable over the class of entity #1, e.g. over {person, location,…}

Local language models contribute evidence to entity classification.



Random variable over the class of relation between entity #2 and #1, e.g. over {lives-in, is-boss-of,…}

Local language models contribute evidence to relation classification.

Dependencies between classes of entities and relations!

Inference with loopy belief propagation.

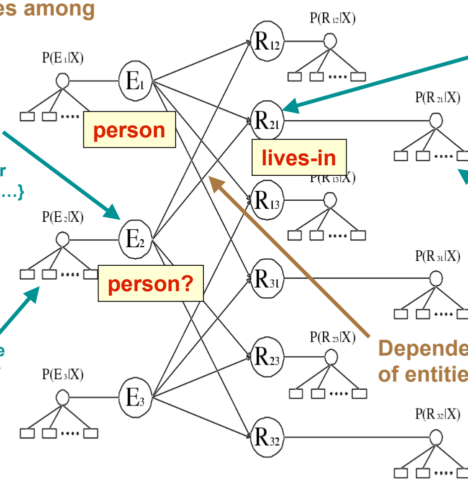
(1) Association with Graphical Models

[Roth & Yih 2002]

Also capture long-distance dependencies among predictions.

Random variable over the class of entity #1, e.g. over {person, location,…}

Local language models contribute evidence to entity classification.



Random variable over the class of relation between entity #2 and #1, e.g. over {lives-in, is-boss-of,…}

Local language models contribute evidence to relation classification.

Dependencies between classes of entities and relations!

Inference with loopy belief propagation.

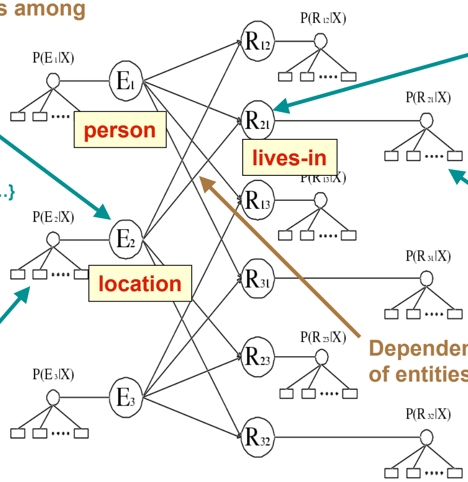
(1) Association with Graphical Models

[Roth & Yih 2002]

Also capture long-distance dependencies among predictions.

Random variable over the class of entity #1, e.g. over {person, location,…}

Local language models contribute evidence to entity classification.



Random variable over the class of relation between entity #2 and #1, e.g. over {lives-in, is-boss-of,…}

Local language models contribute evidence to relation classification.

Dependencies between classes of entities and relations!

Inference with loopy belief propagation.