Computer Workstations as Intelligent Agents

Tom M. Mitchell

Center for Automated Learning and Discovery Carnegie Mellon University

> SIGMOD Keynote Talk June, 2005

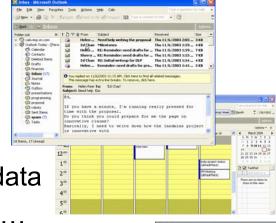
Thanks to many collaborators:
Vitor Carvalho, William Cohen, Dinesh Govindaraju,
Yifen Huang, Sophie Wang, and the entire CALO team

Our workstations are huge semi-structured databases

Why don't we have useful intelligent agents to operate over them?

Technical Challenges

- Interpreting all that text
 - and mix of structured/unstructured data
 - .jpg, .wav, .pdf, .dat, .ppt, .txt, .dba, ...
- Learning to customize to user
 - Scheduling, email preferences
 - Work routines
 - What parts of web and world does user (not) know about





- Perception of environment and user's world
 - Seeing/hearing office activity
 - Inferring work groups, friends, strangers, ...



What Structured Data Types Should We Extract from Workstations?

Person: WCohen@cs

• **Meeting**: M423

• A • | Project: SummerCourse

- 어 역 | Tasks: PlanCourse, Teach
 - Participants: CGuestrin, JLafferty, ...
 - Project Leader: EricXing
 - Associated emails: e1; ...
 - Associated files: f9; f7, ...
 - Associated meetings: m5; m423;...
 - Topic keywords: machine learning, Advanced,...

Person

Meeting

Project

Just a few dozen should do...

Task

Negotiation

File

WebPage

Date/Time

Deadline

Organization

• 1

• N

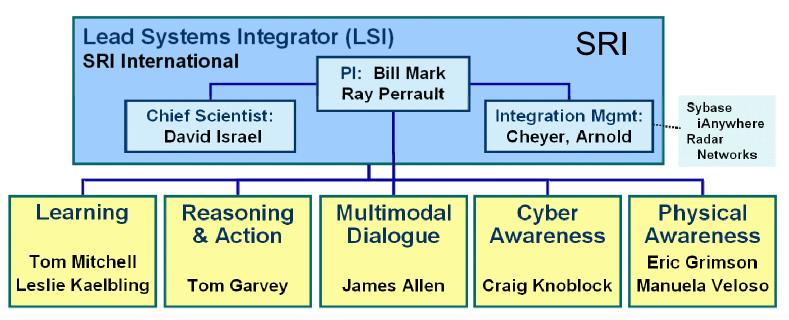
What Good Is Stuctured Data?

Person: WCohen@cs **Project**: SummerCourse Type: Course Offering Participants: CGuestrin, JLafferty, ... Project Leader: EricXing Associated emails: e1; ... Associated files: f9; f7, ... Associated Web pages: w5; w8;... Topic keywords: machine learning, Advanced,...

- File incoming information
- Prepare briefing folder before every meeting
- Alert user to time-critical emails
- Automate routine correspondence
- Help negotiate/schedule meetings
- Monitor pending action items per project

• . . .

CALO Project Team























BOEING









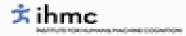




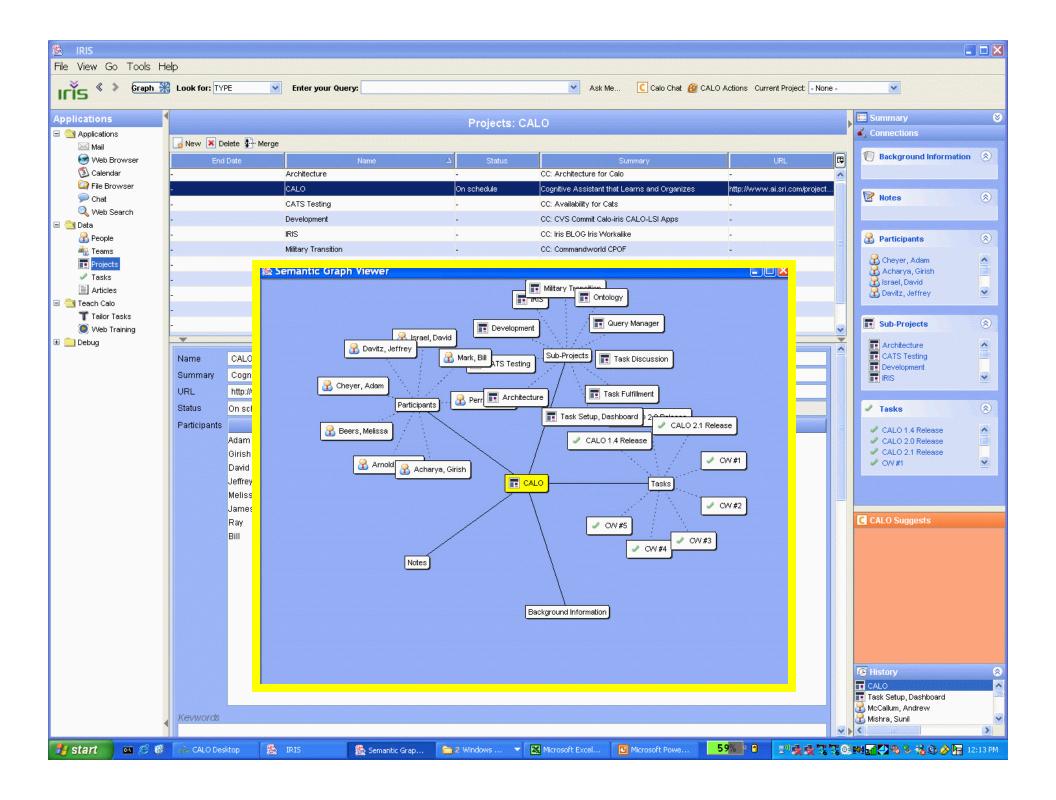


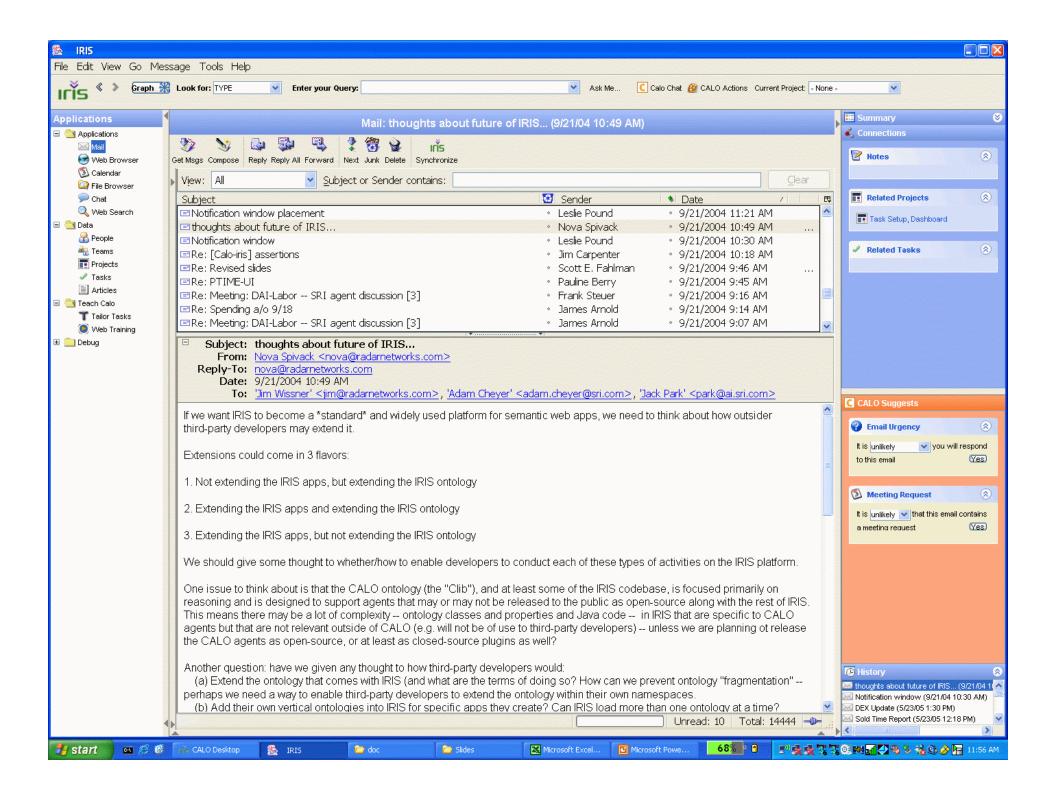


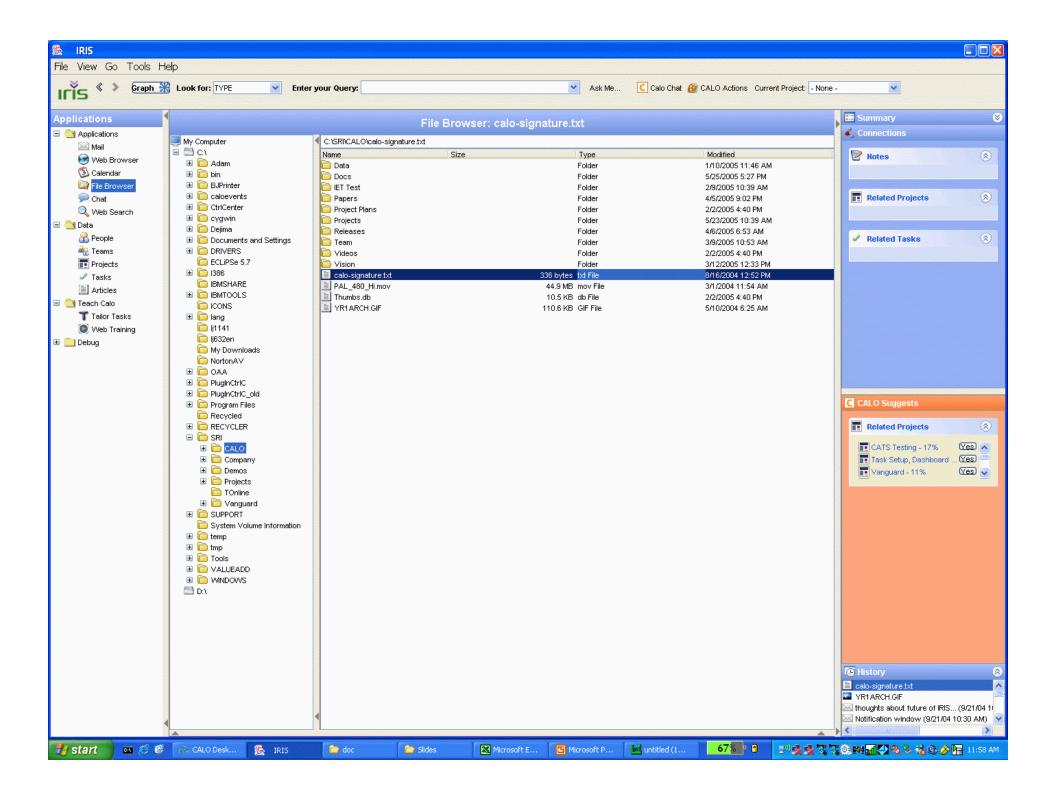


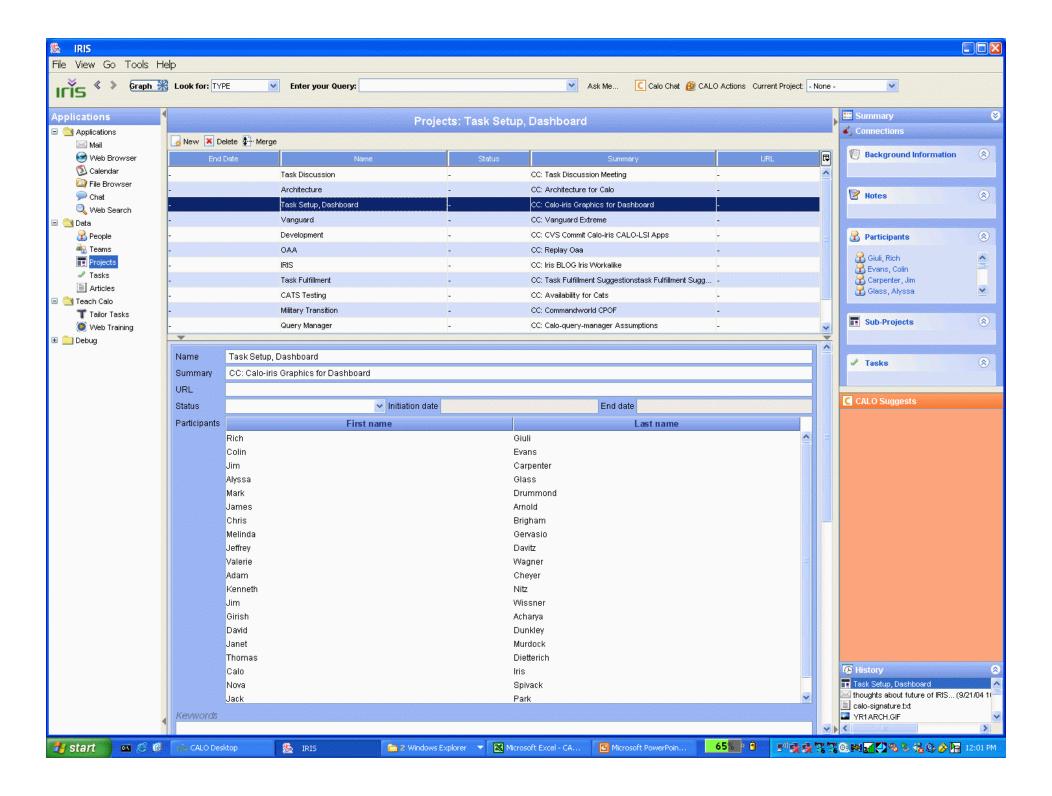


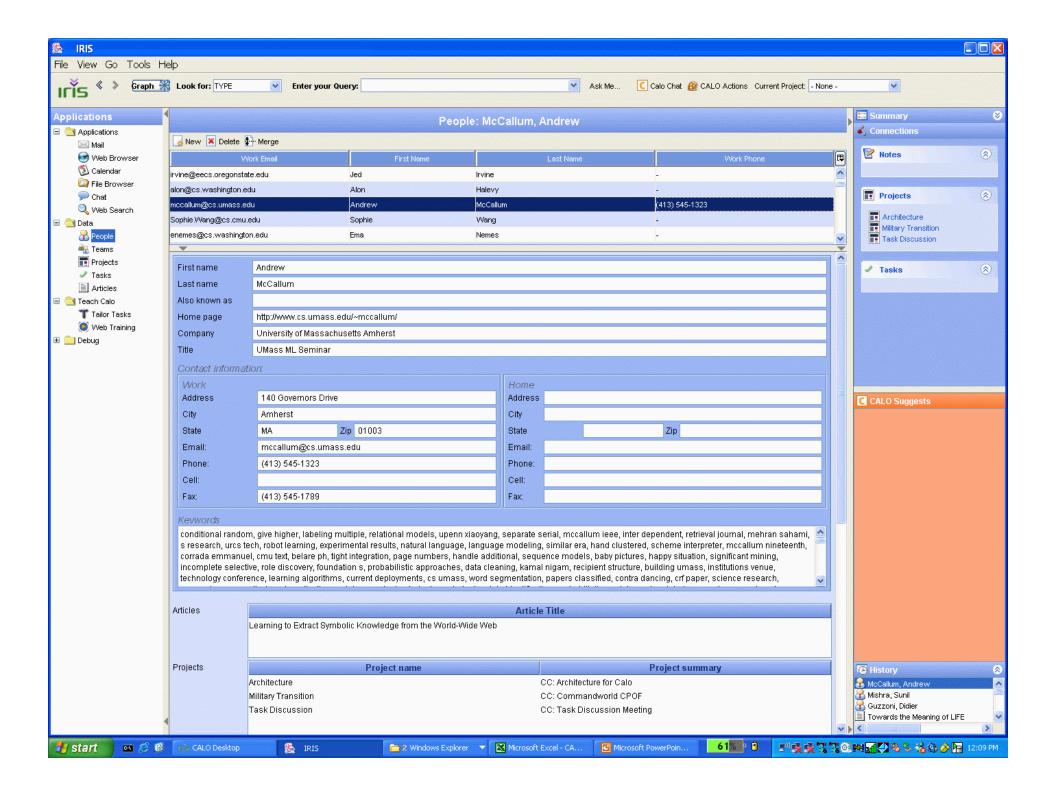


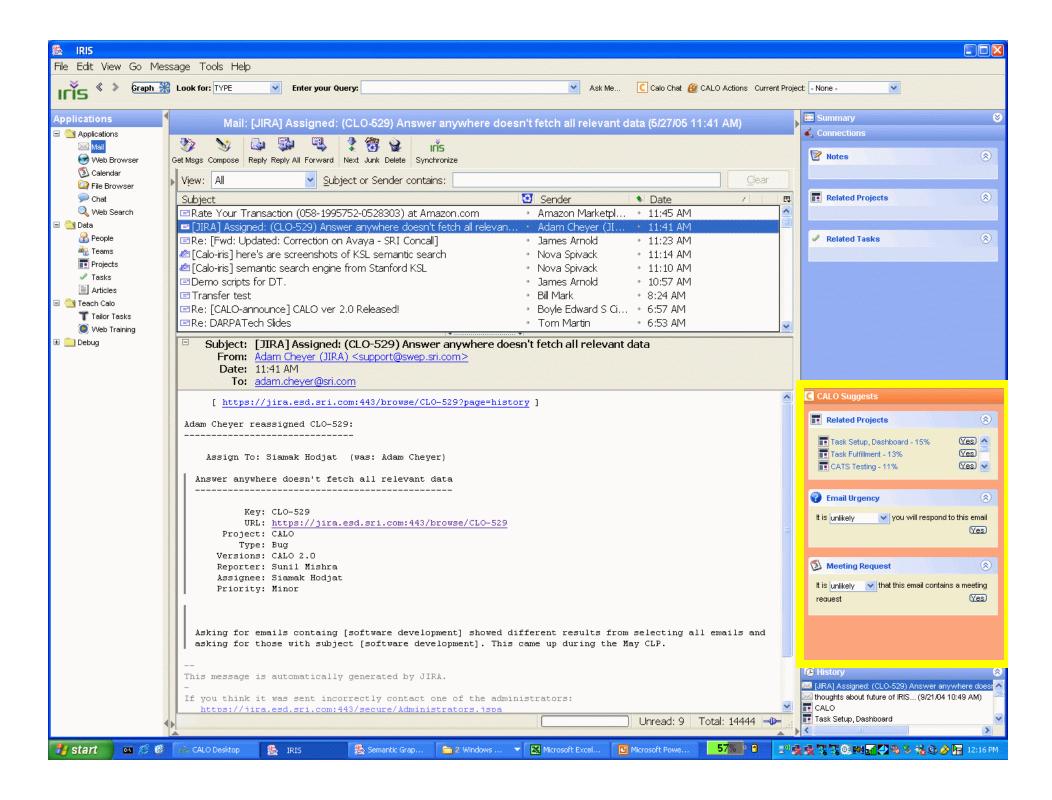


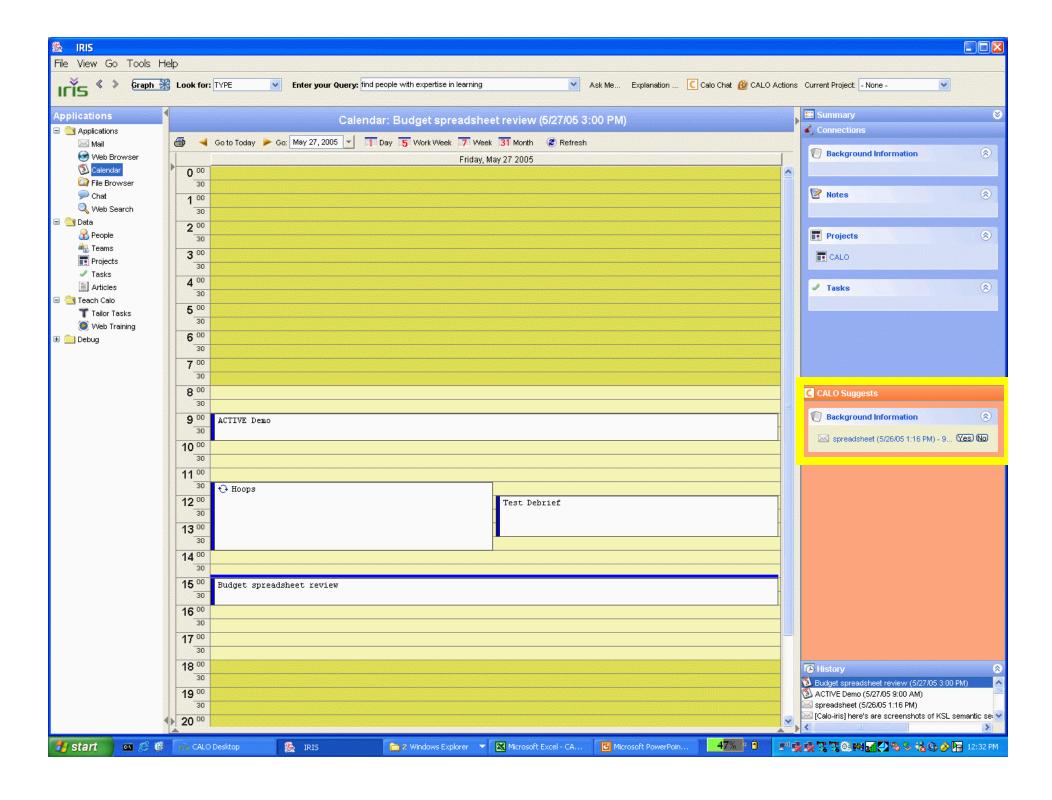












CALO Target Functionality

- Organize & Manage Information
 - Manage email, documents, web info
 - Organize information by tasks and user activities

- Prepare Information Products
 - Prepare meeting, event info packages
 - Organize and assemble reports, summaries
- Observe & Mediate Interactions
 - Monitor meetings, email threads, chat
 - Record meeting discussion, events, actions

- Monitor & Manage Tasks
 - Organize and monitor task execution
 - Monitor due dates, perform time management
- Schedule & Organize in Time
 - Schedule meetings, events, tasks
 - Organize task dependencies, preconditions

- Acquire, Allocate Resources
 - Locate, acquire, allocate resources (equipment, facilities, people) in response to needs

1. Can we extract structured descriptions of ongoing <u>projects</u> from user's email?

Approach

[with Y. Huang, S. Wang]

1. Cluster emails by headers

2. Cluster emails by body

Use both for better performance

To: Ann@ darpa.mil To: Bill@ cmu.edu Subj: ISAT study From: Sue@cmu I'm thinking about Subj: fMRI mtg proposing an ISAT We need to meet study on a new way to soon to disci in brains To: Sue @ cmu.edu · paper dead From: Bill@cmu Subj: Re: fMRI mtg Ok, I suggest cmu edu Wednesday at 4pm. **ISAT** study To: Bill@ cmu.edu That's a good idea, From: Sue@cmu.edu but I think they did Subj: Re: fMRI mtg such a study last See you then. year. It's at Attached is the current www.isat.darpa.mil draft.

People: Sue, Bill

Emails: 1423, 1644,

Keywords: paper,

draft, deadline,...

<u>Dates</u>: Wednesday

Times: 4pm

Unsupervised Learning of Projects

1. Cluster emails

- (Headers) Initialize clusters bottom-up
 - group emails with similar <u>subject lines</u>, then select initial groups with greatest TFIDF distance
- (Body) Refine clusters by applying EM algorithm,
 - Represent email by bag of words in subject and body
- (Social network) Subdivide each cluster based on graph of email co-recipients
 - Make each clique of co-recipients a subcluster
- 2. For each cluster, extract information from the email text and headers

Naïve Bayes classifier (supervised)

Train:

For each class c_j of documents

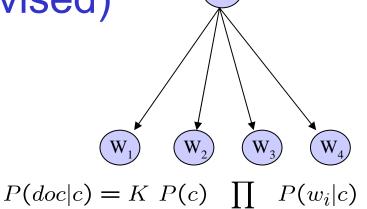
- 1. Estimate $P(c_i)$
- 2. For each word w_i estimate $P(w_i / c_i)$

Classify (doc):

Assign doc to most probable class

$$\underset{j}{\operatorname{arg\,max}} P(c_j) \prod_{w_i \in doc} P(w_i \mid c_j)$$

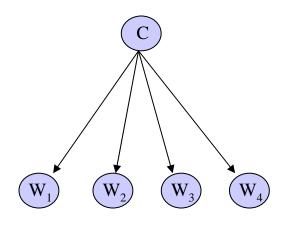
* assuming words are conditionally independent, given class



 $w_i \in doc$

EM for Text Clustering

 Like supervised learning, but no training labels



EM:

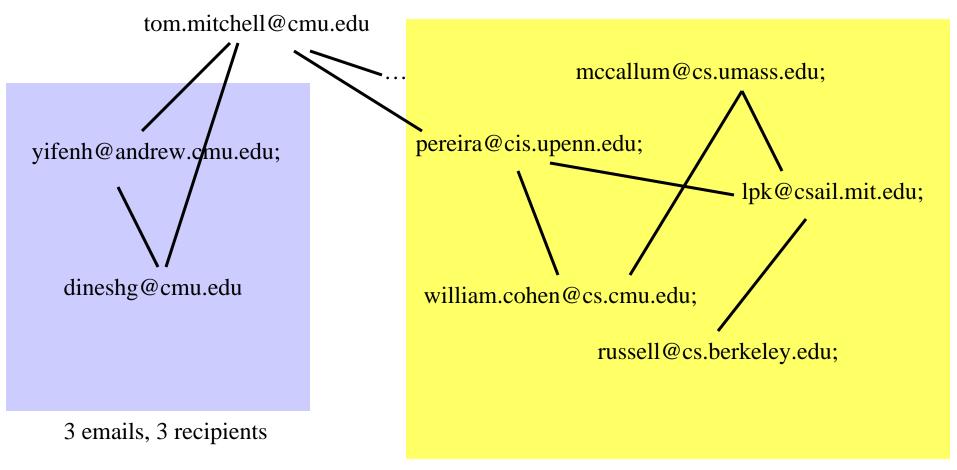
- Initialize labels, then train Naïve Bayes classifier
- Repeat until convergence
 - E: use current classifier to assign probabilistic labels
 - M: retrain Naïve Bayes classifier using these probabilistic labels

Results: <u>Discovered topic words</u> and <u>User labels</u> (from 1481 emails during one month)

- CS faculty discussions (158)
 - Faculty, SCS, Qatar, LTI, wishlist
- Recruiting in AI (137)
 - CSD, host, hiring, RI, interviews
- Research1 (93)
 - RADAR, fluid, Siemens, lead,
 Bloomberg, IDA, letter, parkway
- Research2 (105)
 - CALO, TFC, SRI, examples, heads, labeled, Leslie, HMM
- CALD management (54)
 - SAS, software, color, GSIA, ATT, license, consulting, CALD, NYU
- Family and friends (63)
 - Joan, Paris, Petra, wet, water, towels, restaurant, night, weekend
- Professional conversations (299)
 - UnitedTechnologies, Diane,
 Howard, house, Dewey, research

- Professional organizations (45)
 - PASCAL, Hamilton, Southampton, Amari, Shawe, network, Carol
- AAAI Fellows committee (38)
 - AAAI, fellows, selection, committee, nominations, Hamilton, Carol
- Writing activities (109)
 - Vitor, Melissa, nouns, noun, paper,
 Beers, Vincent, verbs, classification
- Computer facilities support (59)
 - DVD, root, purchase, upgrade, Natural, bookkeeping, hardware, toolbox
- Seminar announcements (123)
 - CNBC, cognitive, fMRI, code, activation, brain, data, theory, model
- Research props, grant reporting (148)
 - Lecture, news, miles, Keck, grade, hall
- Health-related seminars/RFP's (6)
 - NIH, RFA, grants, pathways, scientific
- Recommendation letters (11)

Email co-recipient subgraph cliques (cluster 4)



51 emails, 129 recipients

Cluster 4: 105 emails total.

21 subcliques, containing from 1 to 51 emails

Activity Clustering Algorithm

1. Cluster emails

- (Headers) Initialize clusters bottom-up
 - group emails with similar <u>subject lines</u>, then select initial groups with greatest TFIDF distance
- (Body) Refine clusters by applying EM algorithm to all emails,
 - Represent email by bag of words in subject and body
- (Social network) Subdivide each cluster based on graph of email co-recipients
 - Make each clique of co-recipients a subcluster
- 2. For each cluster, extract information from the email bodies

Example: Learned Project Description

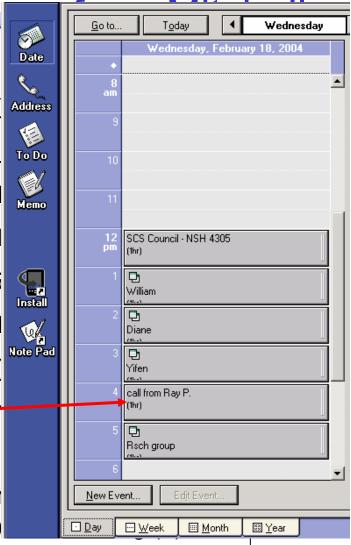
ActivityCluster4.1 (51 emails)

- <u>Keywords</u>: TFC, heads, CALO, Leslie, estimation, capabilities, baseline, capture, DarpaTech, calendar, SRI, goals, HMM, extraction
- PrimarySenders: Mitchell(21), McCallum(6), Leslie(5), Cohen(3),...
- <u>UserActivityFraction</u>: 71/1210 of total email (0.058 of total)
- *IntensityOfUserInvolvement:* created 29% of traffic; (default 31%)
- ExtractedNames: Tom (64), Leslie(11), Andrew (11), Dave (9), ...
- ExtractedDates: 2004(32), today(12), tomorrow(11), Wednesday(10), February 18(9), Tuesday(8), Monday (8)
- <u>ExtractedTimes</u>: 5(4), 11:30am(3), 5pm(2), morning(2), 2PM(2), 4pm(2), about 2PM(2), 9:15 PM(1), 4:30-6 p.m.(1), this morning (1)...
- <u>RequestEmails</u>: <emailA>, <emailB>, ...

Example: Learned Activity Fra email corpus

ActivityCluster4.1 (51 emails, from initial clusters)

- <u>Keywords</u>: TFC, heads, CALO, Leslie, estimation baseline, capture, DarpaTech, calendar, SRI, goal
- PrimarySenders: Mitchell(21), McCallum(6), Lesl
- <u>UserActivityFraction:</u> 71/1210 of total email (0.05)
- IntensityOfUserInvolvement: created 29% of traff
- <u>ExtractedNames</u>: Tom (64), Leslie(11), Andrew (
- <u>ExtractedDates</u>: 2004(32), today(12), temorrow(*) February 18(9), Tuesday(8), Monday (8)
- ExtractedTimes: 5(4), 11:30am(3), 5pm(2), morn 4pm(2), about 2PM(2), 9:15 PM(1), 4:30-6 p.m.(1)
- <u>RequestEmails</u>: <emailA>, <emailB>, ...



Example: Learned Activity Frame from Mitchell email corpus

ActivityCluster4.1 (51 emails, from initial cluster containing 105)

- Keywords: TFC, heads, CALO, Leslie, estimation, capabilities, baseline, capture, DarpaTech, calendar, SRI, goals, HMM, extraction
- PrimarySenders: Mitchell(21), McCallum(6), Leslie(5), Cohen(3),
- IntensityOfUserInvolvement: cr
- <u>ExtractedNames</u>: Tom (64), Le
- <u>ExtractedTimes</u>: 5(4), 11:30am 4pm(2), about 2PM(2), 9:15 PM

 <u>UserActivityFraction:</u> 71/1210 d I need to get to DARPA by COB tomorrow a list of CALO participants who need access to the IPTO booth. It seems to me we should ask for this for any of you who is • ExtractedDates: 2004(32), toda likely to be there. Could you let me know February 18(9), Tuesday(8), Mo asap if you *might* be there? No big deal if you end up not going.

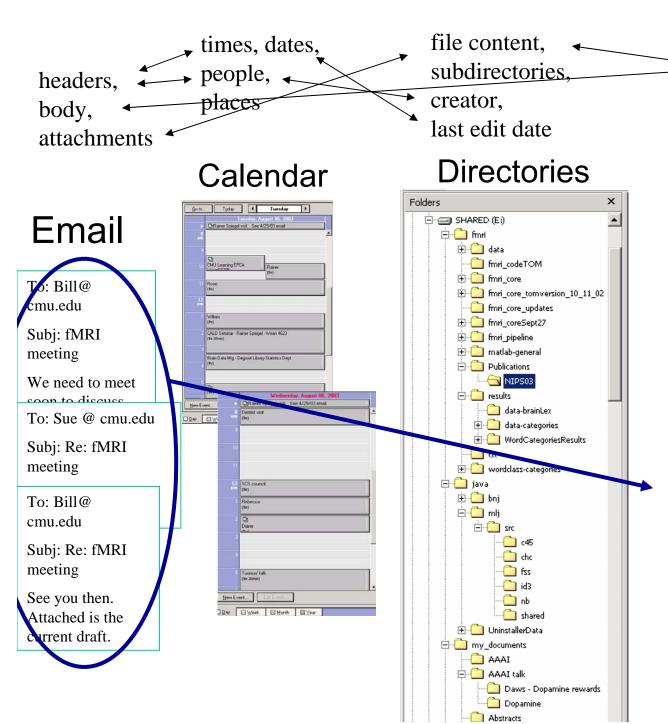
<u>RequestEmails</u>: <emailA>, <emailB>, ...

1. Can we extract structured descriptions of ongoing <u>projects</u> from user's email?

Yes! (though plenty of room to improve)

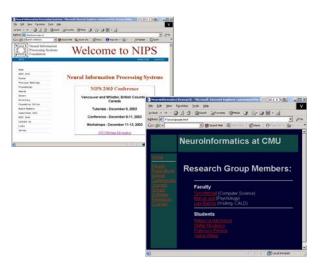
Accuracy is imperfect (e.g., in TM's "CALO" cluster, only ~half the emails were truly relevant)

Nevertheless, the project descriptions are often useful, because they describe aggregate statistics



page content, hyperlinks, host site structure

Web Activity



fMRI paper writing

People: Sue, Bill

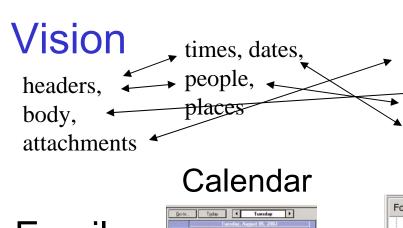
Document: <fileptr>

Meetings: Aug 24,

Emails: 1423, 1644,

Leader: Bill

Deadline: Jan 15



file content. subdirectories. creator, last edit date

page content, hyperlinks, host site structure

Directories





Email

mu.edu Subj: fMRI meeting

To: Bill@

We need to meet coon to discuss

To: Sue @ cmu.edu

Subj: Re: fMRI

meeting

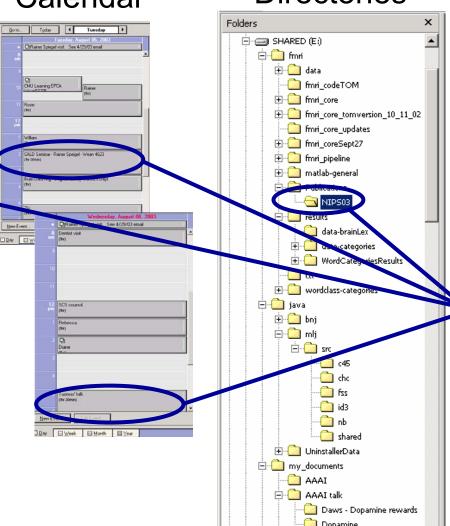
To: Bill@ cmu.edu

Subj: Re: fMRI

meeting

See you then.

Attached is the current draft.



fMRI paper writing

People: Sue, Bill

Document: <fileptr>

Meetings: Aug 24,

Emails: 1423, 1644,

Leader: Bill

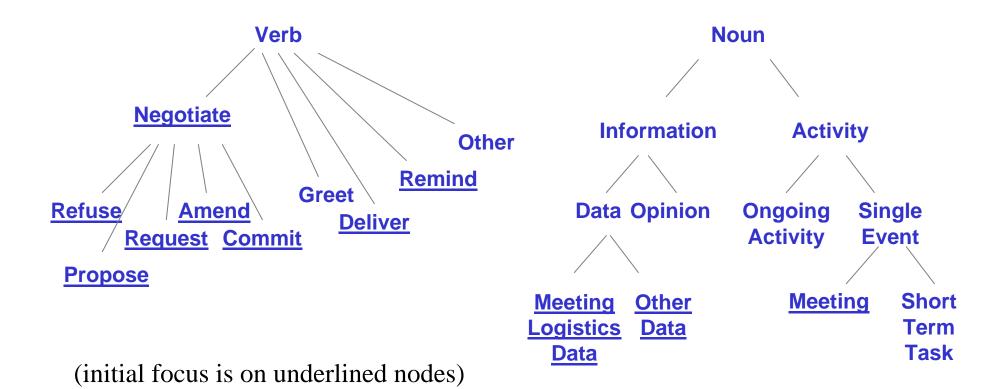
Deadline: Jan 15

2. How can we classify email according to the senders intent?

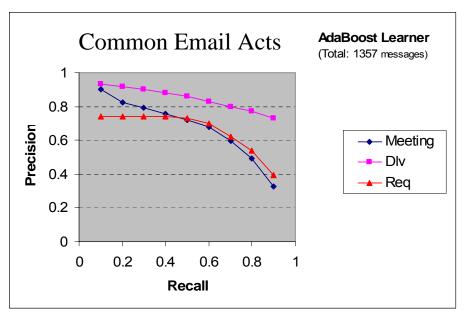
Emails as noun-verb "speech acts"

[Cohen, et al. 2004]

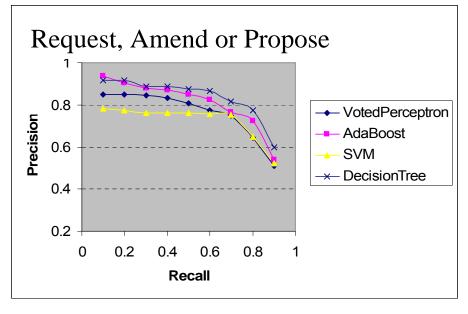
Learn to classify email sender's *intent*, according to a taxonomy of "email speech acts" defined by <verb,noun> (e.g., "Request meeting," "Deliver data")



Accuracies for Best-Learned Email Acts







Classification Errors and F1 Scores

VP: voted perceptron

AB: AdaBoost

SVM: linear Support

Vector Machine

DT: decision tree

'request' 'amend' or 'propose'	→
'commit' or 'deliver'	•

Act		VP	AB	SVM	DT
Request	Error	0.25	0.22	0.23	0.20
(450/907)	F1	0.58	0.65	0.64	0.69
Proposal	Error	0.11	0.12	0.12	0.10
(140/1217)	F1	0.19	0.26	0.44	0.13
Delivery	Error	0.26	0.28	0.27	0.30
(873/484)	F1	0.80	0.78	0.78	0.76
Commit-	Error	0.15	0.14	0.17	0.15
ment	F1	0.21	0.44	0.47	0.11
(208/1149)					
Directive	Error	0.25	0.23	0.23	0.19
(605/752)	F1	0.72	0.73	0.73	0.78
Commis-	Error	0.23	0.23	0.24	0.22
sive	F1	0.84	0.84	0.83	0.85
(993/364)					
Meet	Error	0.187	0.17	0.14	0.18
(345/1012)	F1	0.573	0.62	0.72	0.60

Speech Acts and Factored Classification

Standard classification: learn f: X → Y
Factored classification: learn f: X → Y1 x Y2
e.g., f: email → Noun x Verb

Our initial approach:

- Learn f_Y: email → Y, for each Y ∈ {N ∪ V}
- i.e., treat as |N|+|V| independent classifiers

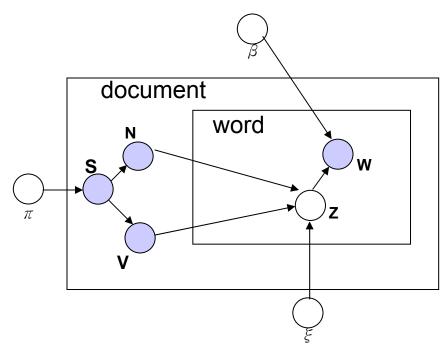
Idea:

 Assume Noun and Verb are <u>not independent</u>, and each email word is generated <u>either</u> by the Noun or Verb

Emails Words Generated by SpeechAct Nouns and Verbs

Current work, Qiong Chen, Yifen Huang

Motivation: (1) more accurate classification, (2) localize relevant text segments



Parameters to be learned:

$$eta_{wx}$$
 = p(W=w |Z=x)
 $lpha_{nv}$ = p(X=n | N=n,V=v)
 π_{nv} = p(S=)

- 1. Each document has speech act S, which specifies a noun N, verb V
- 2. Each word W in a document, is generated either by its N or V.
- 3. The hidden variable Z takes on either the value of N or value of V, for each word W,
- 4. Word W is generated by P(W|Z).

$$P(W_i|N,V,\theta) = P(W_i|Z_i)P(Z_i|N,V)$$

4. Parameters can be estimated using an EM algorithm.

Variant of LDA [Blei, Ng, Jordan, 2003]

Preliminary results: Words associated with Commit vs. Meeting

Speech act = <commit, meeting>

Subject: Re: Monday's meeting

commit

meeting

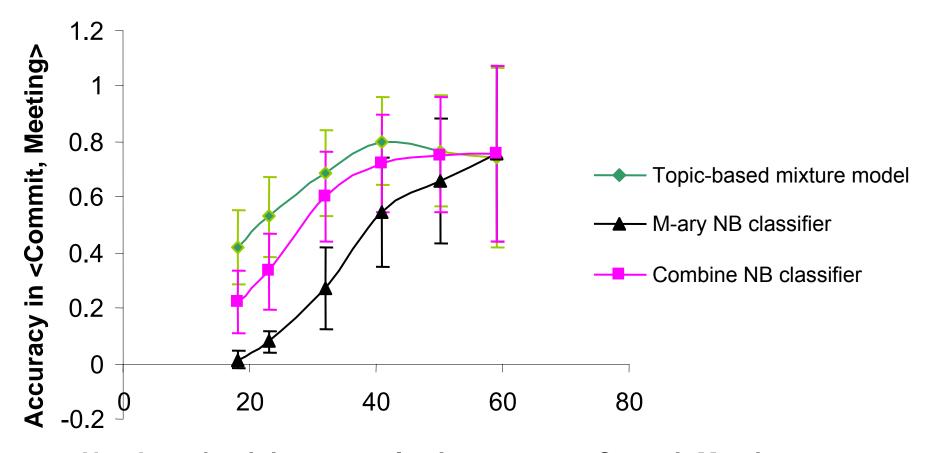
Hi , <u>everyone</u>

Monday <u>at</u> 10: <u>30</u> am is okay with me. <u>Let</u>'s just plan <u>on meeting</u> in <u>the</u> commons <u>at</u> 10: <u>30</u>. Like I <u>mentioned</u> previously, <u>we</u> should only take about 45 minutes just to decide what each of <u>us plans</u> to accomplish <u>over</u> the summer.

Good luck on all of you finals.

Supervised learning of Noun-Verb topic models

[Preliminary results, Qiong, 2005]

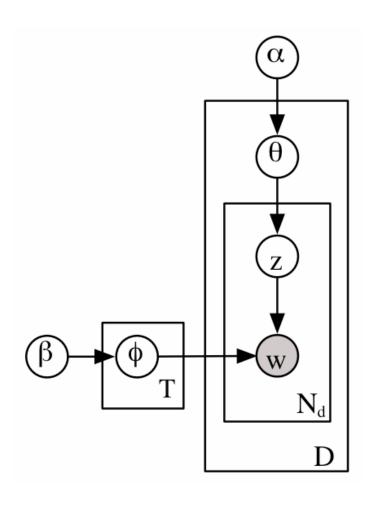


Number of training examples in category <Commit Meeting>

Bags of Words, or Bags of Topics?

Clustering words into topics with Latent Dirichlet Allocation

[Blei, Ng, Jordan 2003]



Probabilistic model for generating document D:

- 1. Pick a topic distribution $P(z|\theta)$ according to $P(\theta|\alpha)$
- 2. For each word w
 - Pick topic z from $P(z \mid \theta)$
 - Pick word w from P(w |z, φ)

Training this model defines topics (i.e., ϕ which defines P(W|Z))

Example topics induced from a large collection of text

DISEASE	WATER	MIND	STORY	FIELD	SCIENCE	BALL	JOB
BACTERIA	FISH	WORLD	STORIES	MAGNETIC	STUDY	GAME	WORK
DISEASES	SEA	DREAM	TELL	MAGNET	SCIENTISTS	TEAM	JOBS
GERMS	SWIM	DREAMS	CHARACTER	WIRE	SCIENTIFIC	FOOTBALL	CAREER
FEVER	SWIMMING		CHARACTERS	NEEDLE	KNOWLEDGE	BASEBALL	EXPERIENCE
CAUSE	POOL	IMAGINATION	AUTHOR	CURRENT	WORK	PLAYERS	EMPLOYMENT
CAUSED	LIKE	MOMENT	READ	COIL	RESEARCH	PLAY	OPPORTUNITIES
SPREAD	SHELL	THOUGHTS	TOLD	POLES	CHEMISTRY	FIELD	WORKING
VIRUSES	SHARK	OWN	SETTING	IRON	TECHNOLOGY	PLAYER	TRAINING
INFECTION	TANK	REAL	TALES	COMPASS	MANY	BASKETBALL	
VIRUS	SHELLS	LIFE	PLOT	LINES	MATHEMATICS	S COACH	CAREERS
MICROORGANISM		IMAGINE	TELLING	CORE	BIOLOGY	PLAYED	POSITIONS
PERSON	DIVING	SENSE	SHORT	ELECTRIC	FIELD	PLAYING	FIND
INFECTIOUS	DOLPHINS	CONSCIOUSNES	S FICTION	DIRECTION	PHYSICS	HIT	POSITION
COMMON	SWAM	STRANGE	ACTION	FORCE	LABORATORY		FIELD
CAUSING	LONG	FEELING	TRUE	MAGNETS	STUDIES	TEAMS	OCCUPATIONS
SMALLPOX	SEAL	WHOLE	EVENTS	BE	WORLD	GAMES	REQUIRE
BODY	DIVE	BEING	TELLS	MAGNETISM		SPORTS	OPPORTUNITY
INFECTIONS	DOLPHIN	MIGHT	TALE	POLE	STUDYING	BAT	EARN
CERTAIN	UNDERWATER	HOPE	NOVEL	INDUCED	SCIENCES	TERRY	ABLE

[Tennenbaum et al]

Example topics induced from a large collection of text

Significance:

- Learned topics reveal hidden, implicit semantic categories in the corpus
- In many cases, we can represent documents with 10² topics instead of 10⁵ words
- Especially important for short documents (e.g., emails). Topics overlap when words don't!

FIELD	SCIENCE	BALL	JOB
MAGNETIC	STUDY	GAME	WORK
MAGNET	SCIENTISTS	TEAM	JOBS
WIRE	SCIENTIFIC	FOOTBALL	CAREER
NEEDLE	KNOWLEDGE	BASEBALL	EXPERIENCE
CURRENT	WORK	PLAYERS	EMPLOYMENT
COIL	RESEARCH	PLAY	OPPORTUNITIES
POLES	CHEMISTRY	FIELD	WORKING
IRON	TECHNOLOGY	PLAYER	TRAINING
COMPASS	MANY E	BASKETBALL	SKILLS
LINES	MATHEMATICS	COACH	CAREERS
CORE	BIOLOGY	PLAYED	POSITIONS
ELECTRIC	FIELD	PLAYING	FIND
DIRECTION	PHYSICS	HIT	POSITION
FORCE	LABORATORY	TENNIS	<u>FIELD</u>
MAGNETS	STUDIES	TEAMS	OCCUPATIONS
BE	WORLD	GAMES	REQUIRE
MAGNETISM	[SCIENTIST	SPORTS	OPPORTUNITY
POLE	STUDYING	BAT	EARN
INDUCED	SCIENCES	TERRY	ABLE

[Tennenbaum et al]

3. Can we analyze roles and relationships between people by analyzing email word or topic distributions?

Author-Recipient-Topic model for Email

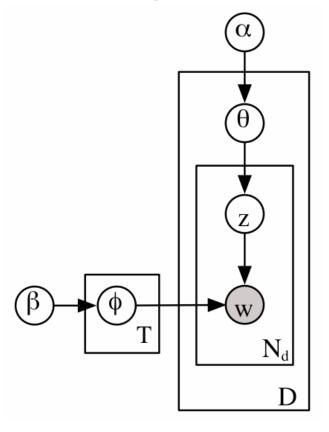
Latent Dirichlet Allocation

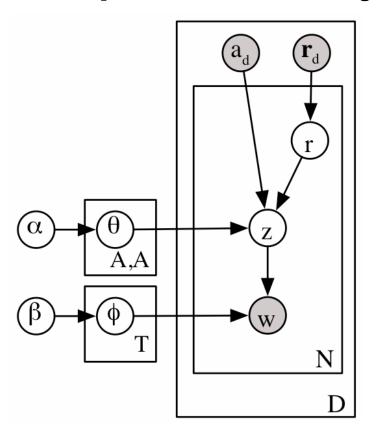
(LDA)

[Blei, Ng, Jordan, 2003]

Author-Recipient Topic (ART)

[McCallum, Corrada, Wang, 2004]





Enron Email Corpus

- 250k email messages
- 23k people

```
Date: Wed, 11 Apr 2001 06:56:00 -0700 (PDT)
From: debra.perlingiere@enron.com
To: steve.hooser@enron.com
Subject: Enron/TransAltaContract dated Jan 1, 2001
Please see below. Katalin Kiss of TransAlta has requested an
electronic copy of our final draft? Are you OK with this? If
so, the only version I have is the original draft without
revisions.
DP
Debra Perlingiere
Enron North America Corp.
Legal Department
1400 Smith Street, EB 3885
Houston, Texas 77002
dperlin@enron.com
```

Topics, and prominent sender/receivers discovered by ART [McCallum et al, 2004]

Top words within topic:

Top
author-recipients
exhibiting this
topic

T	Topic 17		Topic	27	Topic 45	
	"Document Review"		"Time Scheduling"		"Sports Pool"	
T	attached	0.0742	day	0.0419	game	0.0170
	agreement	0.0493	friday	0.0418	draft	0.0156
	review	0.0340	morning	0.0369	week	0.0135
	questions	0.0257	monday	0.0282	team	0.0135
	draft	0.0245	office	0.0282	eric	0.0130
	letter	0.0239	wednesday	0.0267	make	0.0125
	comments	0.0207	tuesday	0.0261	free	0.0107
	copy	0.0165	time	0.0218	year	0.0106
	revised	0.0161	good	0.0214	pick	0.0097
	document	0.0156	thursday	0.0191	phillip	0.0095
T	G.Nemec	0.0737	J.Dasovich	0.0340	E.Bass	0.3050
	B.Tycholiz		R.Shapiro		M.Lenhart	
T	G.Nemec	0.0551	J.Dasovich	0.0289	E.Bass	0.0780
	M.Whitt		J.Steffes		P.Love	
1	B.Tycholiz	0.0325	C.Clair	0.0175	M.Motley	0.0522
	G.Nemec		M.Taylor		M.Grigsby	

Topics, and prominent sender/receivers discovered by ART

Topic 34		Topic 37		Topic 41		Topic 42	
"Operations"		"Power Market"		"Government Relations"		"Wireless"	
operations	0.0321	market	0.0567	state	0.0404	blackberry	0.0726
team	0.0234	power	0.0563	california	0.0367	net	0.0557
office	0.0173	price	0.0280	power	0.0337	www	0.0409
list	0.0144	system	0.0206	energy	0.0239	website	0.0375
bob	0.0129	prices	0.0182	electricity	0.0203	report	0.0373
open	0.0126	high	0.0124	davis	0.0183	wireless	0.0364
meeting	0.0107	based	0.0120	utilities	0.0158	handheld	0.0362
gas	0.0107	buy	0.0117	commission	0.0136	stan	0.0282
business	0.0106	customers	0.0110	governor	0.0132	fyi	0.0271
houston	0.0099	costs	0.0106	prices	0.0089	named	0.0260
S.Beck	0.2158	J.Dasovich	0.1231	J.Dasovich	0.3338	R.Haylett	0.1432
L.Kitchen		J.Steffes		R.Shapiro		T.Geaccone	
S.Beck	0.0826	J.Dasovich	0.1133	J.Dasovich	0.2440	T.Geaccone	0.0737
J.Lavorato		R.Shapiro		J.Steffes		R.Haylett	
S.Beck	0.0530	M.Taylor	0.0218	J.Dasovich	0.1394	R.Haylett	0.0420
S.White		E.Sager		R.Sanders		D.Fossum	

Beck = "Chief Operations Officer"

Dasovich = "Government Relations Executive"

Shapiro = "Vice Presidence of Regulatory Affairs"

Steffes = "Vice President of Government Affairs"

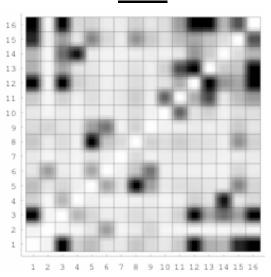
Discovering Role Similarity

Traditional SNA

16 : teb.lokev 15 : steven.harris 14 : kimberly.watson 13 : paul.y'barbo 12 : bill.rapp 11 : kevin.hvatt 10 : drew.fossum 9 : tracy.geaccone 8 : danny.mccarty 7 : shelley.corman 6 : rod.hayslett 5 : stanley.horton 4 : lynn.blair 3 : paul.thomas 2 : larry.campbell 1 : joe.stepenovitch

1 2 3 4 5 6 7 8 9 1 0 1 1 1 2 1 3 1 4 1 5 1 6

ART



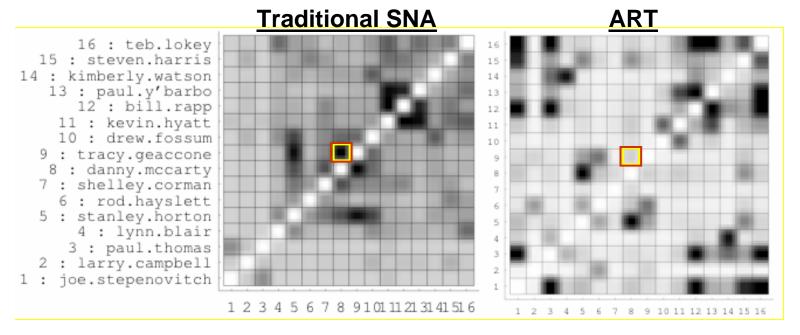
connection strength (A,B) =

Similarity in recipients they sent email to

Similarity in authored topics, conditioned on recipient

Discovering Role Similarity

Tracy Geaconne ⇔ Dan McCarty



Similar (send email to same individuals)

Different (discuss different topics)

Geaconne = "Secretary" McCarty = "Vice President"

Discovering Role Similarity

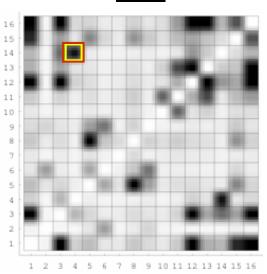
Lynn Blair ⇔ Kimberly Watson

Traditional SNA

16 : teb.lokey 15 : steven.harris 14 : kimberly.watson 13 : paul.y'barbo 12 : bill.rapp 11 : kevin.hyatt 10 : drew.fossum 9 : tracy.geaccone 8 : danny.mccarty 7 : shelley.corman 6 : rod.hayslett 5 : stanley.horton 4 : lynn.blair 3 : paul.thomas

2 : larry.campbell
1 : joe.stepenovitch

<u>ART</u>



Different (send to different individuals)

1 2 3 4 5 6 7 8 9 1 0 1 1 1 2 1 3 1 4 1 5 1 6

Similar (discuss same topics)

Blair = "Gas pipeline logistics"
Watson = "Pipeline facilities planning"

So far: what structure can we extract from email?

- 1. Projects
- 2. Email intent
- 3. Latent semantic topics
- 4. User relationships/roles
- 4. Why not use entire workstation contents? and the web...

Entity Descriptions from Workstation

[with S. Wang, W. Cohen]

Idea:

- Represent every entity (person, project, organization,...) by the distribution of words associated with it across entire workstation
- Simple implementation: type the name of the entity into Google Desktop Search, and form histogram of all associated words in all returned files, emails, webpages on the workstation
- Use this to find which entities are related, how

Word Vector Representation for Entities

 Type name of entity into Google desktop search, collect the returned snippets of text



- Create vector with one feature per word. It's value is based on the number of word occurrences in the returned Google snippets.
- Assign each feature its TFIDF value. Then normalize vectors to unit length.

Measuring Distance Between Entity Word Vectors

Distance between vectors is their dot product:

$$dist(x,y) = \sum_{i} x_i y_i$$

• Use distance to automatically construct descriptions for every entity, describing it by its most closely related organization, department, discipline, conference, funder, and person

Simple Experiment

Create word distribution vectors for 20k words. Type in simple ontology and instances:

People: widom faloutsos wcohen mccallum yifen huang indra rustandi rebecca hutchinson stefan niculescu john ramish jay pujara sharon cavlovich woodside diane stidle randy bryant jeannette wing wei wang sophie zhenzhen daniel neill kaustav carlos guestrin murphy marcel

Organizations: cmu stanford mit pitt upenn sri umass mitre lockheed

Departments: csd cald lti ri hci cnbc

<u>Disciplines</u>: ai databases biology cogsci neuroscience datamining robotics psychology

Conferences: aaai sigmod nips pakdd hbm ijcai

Funders: darpa nih keck nsf

Automatically Constructed Descriptions

Per	con c	antity: Widom					
1	Person entity: McCallum						
OR		Person entity: Indra					
	ORG						
DEF		ORGANIZATION: cmu, (lockheed)					
	DEPA						
DIS		DEPARTMENT: csd, (cald)					
	DISC						
COI		DISCIPLINE: neuroscience, (robotics)					
	CON						
FUN		CONFERENCE: nips, pakdd					
	FUND						
CLC		FUNDER: nih, keck					
	CLOS						
		CLOSEST PERSON: rebecca hutchinson					

Automatically Constructed Descriptions

```
Confere
        Conference entity: IJCAI
PERSON
        PERSON: indra, (guestrin)
ORGANI
        ORGANIZATION: lockheed, (pitt)
DEPART
        DEPARTMENT: csd, (hci)
DISCIPL
        DISCIPLINE: ai (databases)
CLOSES
        CLOSEST CONFERENCE: aaai, sigmod
FUNDEF
        FUNDER: nsf, nih
```

Summary: Workstation Word Vectors

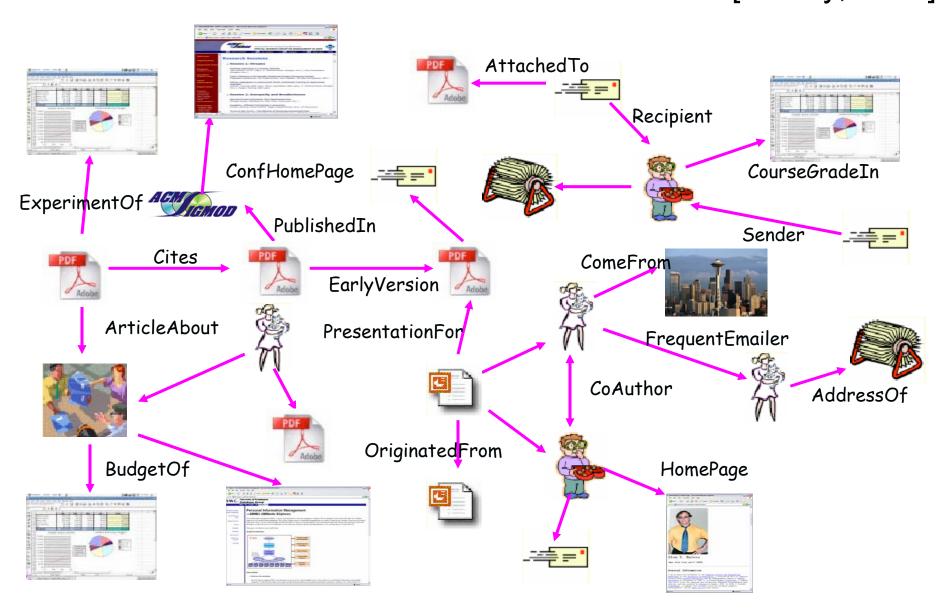
 Surprisingly accurate descriptions of entities by simply typing their *names* into Desktop Search engine

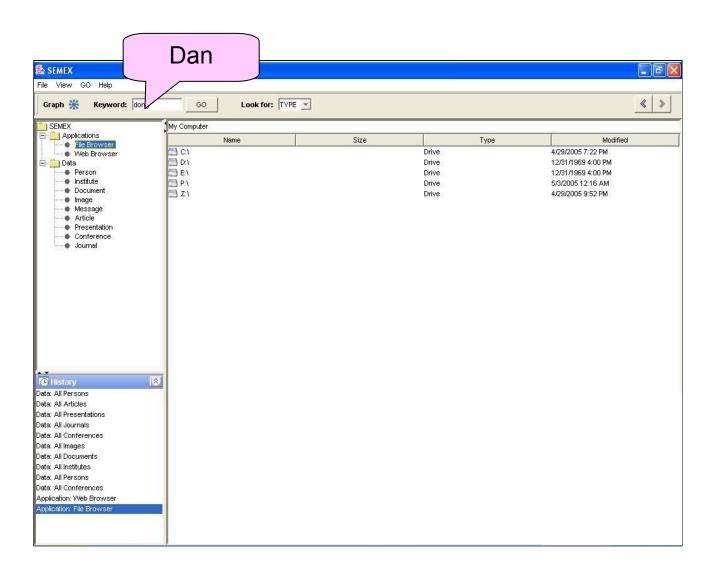
Leverages huge redundancy in workstation contents

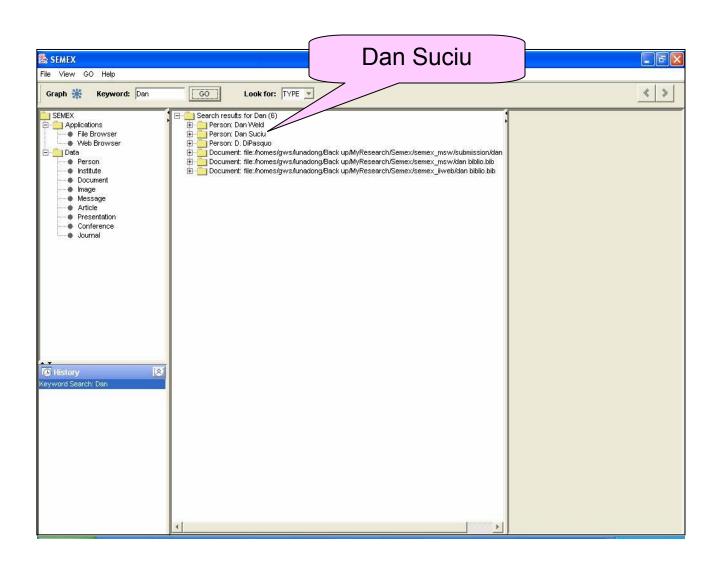
Future work: represent and infer more subtle relations

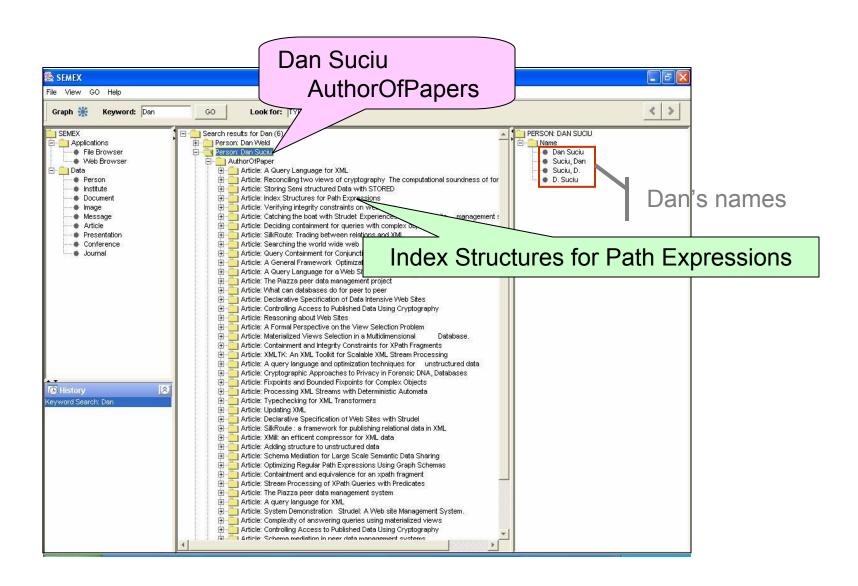
SEMEX – Alon Halevy

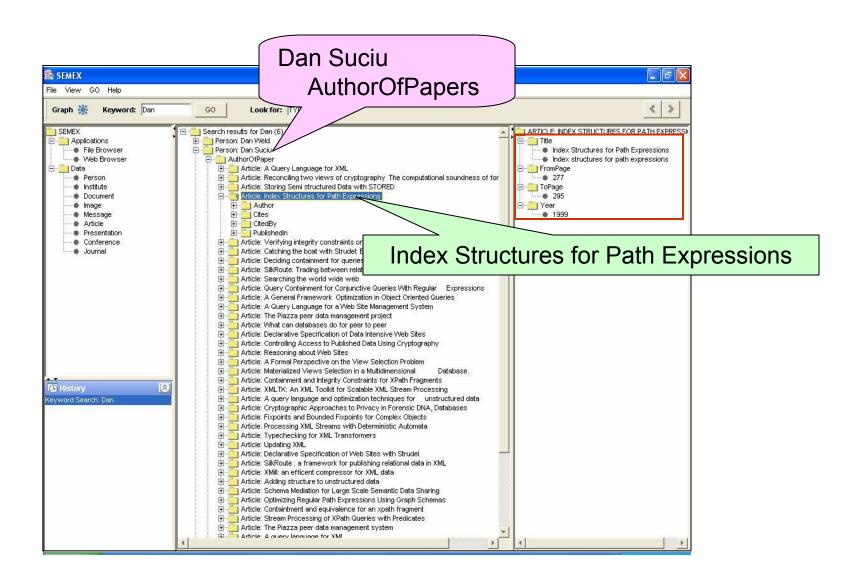
SEMEX Goal: Network of Associations Between Object Instances on One's Desktop [Halevy, 2004]

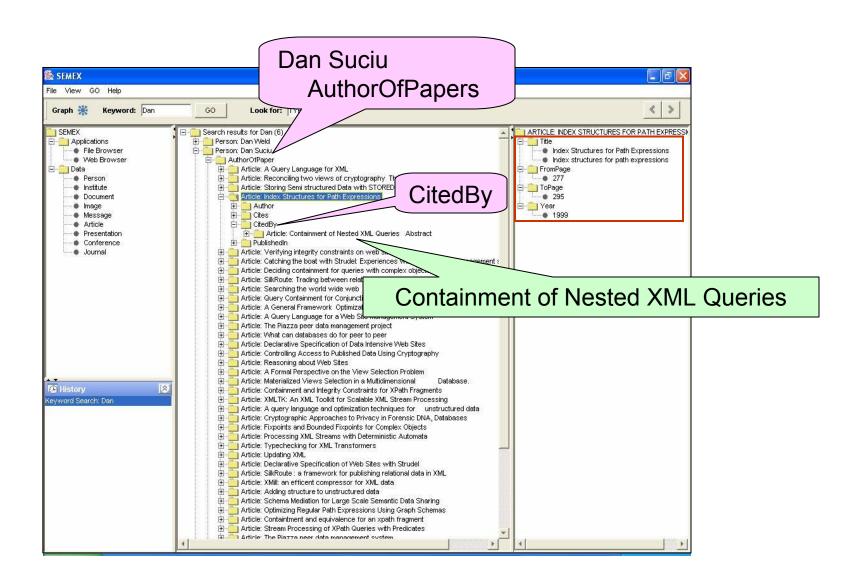


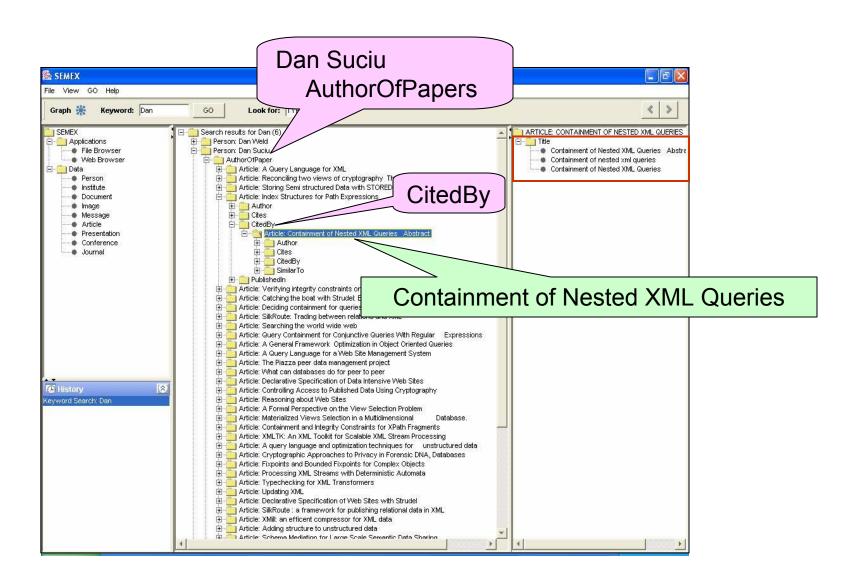










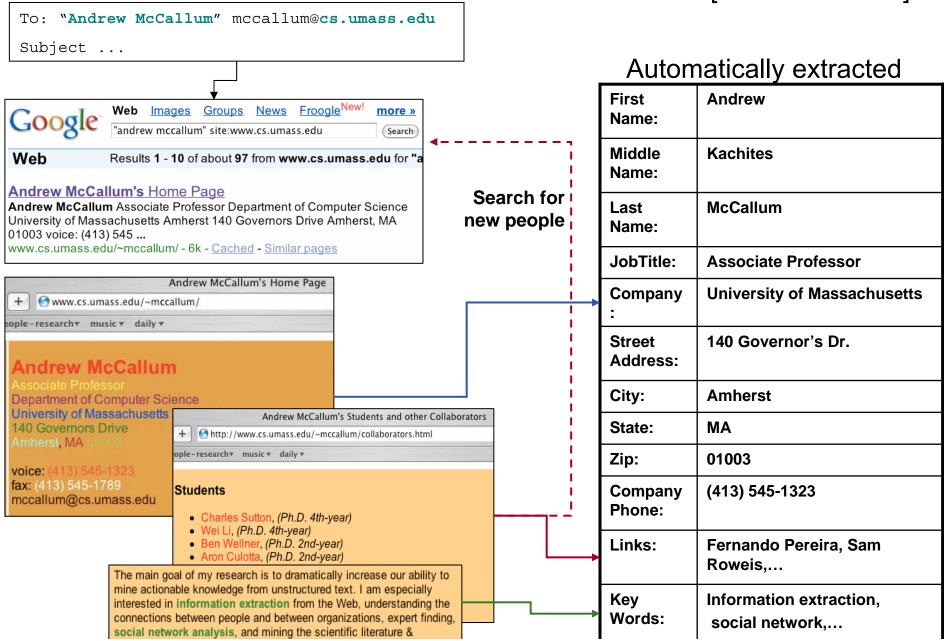


DEX

Andrew McCallum

Extracting Contact Information from the Web

[McCallum 2004]



Example keywords extracted

Person	Keywords
William Cohen	Logic programming Text categorization Data integration Rule learning
Daphne Koller	Bayesian networks Relational models Probabilistic models Hidden variables
Deborah McGuiness	Semantic web Description logics Knowledge representation Ontologies
Tom Mitchell	Machine learning Cognitive states Learning apprentice Artificial intelligence

Results Summary

Contact info and name extraction performance (25 fields)

Token	Field	Field	Field
Acc	Prec	Recall	F1
94.50	85.73	76.33	80.76

Summary: Much Progress, More Needed

- Extracting structured knowledge
 - Email classification
 - Information extraction from text
 - Social network analysis
 - Discovering latent structures (projects, semantic topics, ...)
 - Entity semantics as word distribution across workstation
 - Linking workstation and web information
 - Coreference resolution
 - Leading toward structured database/knowledge base of
 - people, projects, tasks, roles, deadlines, ...
- Tools like Google Desktop Search suddenly make it easy to do this kind of experimental research