MEMM inference in systems

- For a Conditional Markov Model (CMM) a.k.a. a Maximum Entropy Markov Model (MEMM), the classifier makes a single decision at a time, conditioned on evidence from observations and previous decisions.
- A larger space of sequences is explored via search

Decision Point

Local Context

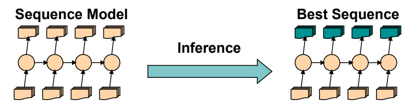
-3	-2	-1	0	+1
DT	NNP	VBD	???	???
The	Dow	fell	22.6	%

Features

W_0	22.6
W_{+1}	%
W_{-1}	fell
T_{-1}	VBD
T_{-1}-T_{-2}	NNP-VBD
hasDigit?	true
…	…

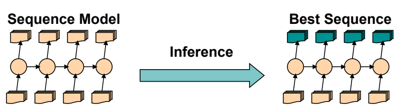
(Ratnaparkhi 1996; Toutanova et al. 2003, etc.)

Beam Inference



- Beam inference:
  - At each position keep the top k complete sequences.
  - Extend each sequence in each local way.
  - The extensions compete for the k slots at the next position.
- Advantages:
  - Fast; and beam sizes of 3–5 are as good or almost as good as exact inference in many cases.
  - Easy to implement (no dynamic programming required).
- Disadvantage:
  - Inexact: the globally best sequence can fall off the beam.

Viterbi Inference

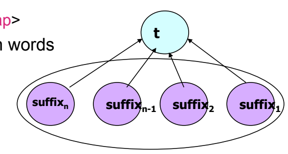


- Viterbi inference:
  - Dynamic programming or memoization.
  - Requires small window of state influence (e.g., past two states are relevant).
- Advantage:
  - Exact: the global best sequence is returned.
- Disadvantage:
  - Harder to implement long-distance state-state interactions (but beam inference tends not to allow long-distance resurrection of sequences anyway).

HMM Part-of-speech Tagging Models - Brants 2000

- Highly competitive with other state-of-the art models
- Trigram HMM with smoothed transition probabilities
- Capitalization feature becomes part of the state – each tag state is split into two e.g.
  NN → <NN,cap>,<NN,not cap>
- Suffix features for unknown words

$$P(w \mid tag) = P(suffix \mid tag)(w \mid suffix)$$
$$\approx \hat{P}(suffix)\tilde{P}(tag \mid suffix)/\hat{P}(tag)$$



$$\tilde{P}(tag \mid suffix_n) = \lambda_1\hat{P}(tag \mid suffix_n) + \lambda_2\hat{P}(tag \mid suffix_{n-1}) + \ldots + \lambda_n\hat{P}(tag)$$

MEMM Tagging Models -II

- Ratnaparkhi (1996): local distributions are estimated using maximum entropy models
  - Previous two tags, current word, previous two words, next two words, suffix, prefix, hyphenation, and capitalization features for unknown words
- Toutanova et al. (2003)
  - Richer features, bidirectional inference, better smoothing, better unknown word handling

Model	Overall Accuracy	Unknown Words
HMM (Brants 2000)	96.7	85.5
MEMM (Ratn. 1996)	96.63	85.56
MEMM (T. et al 2003)	97.24	89.04

CRFs [Lafferty, Pereira, and McCallum 2001]

- Another sequence model: Conditional Random Fields (CRFs)
- A whole-sequence conditional model rather than a chaining of local models.

$$P(c \mid d, \lambda) = \frac{\exp \sum_i \lambda_i f_i(c,d)}{\sum_{c'} \exp \sum_i \lambda_i f_i(c',d)}$$

- The space of c's is now the space of sequences
  - But if the features f_i remain local, the conditional sequence likelihood can be calculated exactly using dynamic programming
- Training is slow, but CRFs avoid causal-competition biases
- These (or a variant using a max margin criterion) are seen as the state-of-the-art these days

Summary of Tagging

For tagging, the change from generative to discriminative model **does not by itself** result in great improvement

One profits from discriminative models for specifying dependence on **overlapping features of the observation** such as spelling, suffix analysis,etc

A CMM allows integration of rich features of the observations, but can suffer strongly from assuming independence from following observations; this effect can be relieved by adding dependence on following words

This additional power (of the CMM ,CRF, Perceptron models) has been shown to result in improvements in accuracy

The **higher accuracy** of discriminative models comes at the price of **much slower training**

Biomedical NER Motivation

- The biomedical field contains a large body of information, which is growing rapidly.
  - MEDLINE, the primary research database serving the biomedical community, currently contains over 12 million abstracts, with 60,000 new abstracts appearing each month.
  - There is also an impressive number of biological databases containing information on genes, proteins, nucleotide and amino acid sequences, including *GenBank*, *Swiss-Prot*, and *Fly-Base*; each contains entries numbering from the thousands to the millions and are multiplying rapidly.

Motivation

- Currently, all of these resources are curated by hand by expert annotators at enormous expense.
- The information overload from the massive growth in the scientific literature has shown the necessity to automatically locate, organize and manage facts relating to experimental results
- Natural Language Processing can aid researchers and curators of biomedical databases by automating these tasks.

Named Entity Recognition

- General NER vs. Biomedical NER

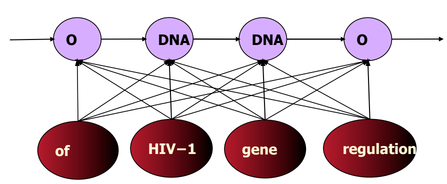
<PER> Christopher Manning </PER> is a professor at <ORG> Stanford University </ORG>, in <LOC> Palo Alto </LOC>.

<RNA> TAR </RNA> independent transactivation by <PROTEIN> Tat </PROTEIN> in cells derived from the <CELL> CNS </CELL> - a novel mechanism of <DNA> HIV-1 gene </DNA> regulation.

Why is this difficult?

- The list of biomedical entities is growing.
  - New genes and proteins are constantly being discovered, so explicitly enumerating and searching against a list of known entities is not scalable.
  - Part of the difficulty lies in identifying previously unseen entities based on contextual, orthographic, and other clues.
- Biomedical entities don't have strict naming conventions.
  - Common English words such as *period*, *curved*, and *for* are used for gene names.
  - Entity names can be ambiguous. For example, in FlyBase, “clk” is the gene symbol for the “Clock” gene but it also is used as a synonym of the “period” gene.
- Biomedical entity names are ambiguous
  - Experts only agree on whether a word is even a gene or protein 69% of the time. (Krauthammer *et al.*, 2000)
  - Often systematic polysemies between gene, RNA, DNA, etc.

Maximum Entropy Markov Model



$$P(t \mid h) = \frac{\exp(\sum_{j=1}^{m} f_j(h,t)\lambda_j)}{\sum_{k=1}^{K} \exp(\sum_{j=1}^{m} f_j(h,t_k)\lambda_j)}$$

Interesting Features

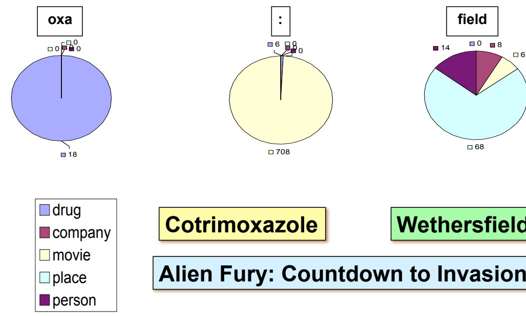
- Word, and surrounding context
- Word Shapes
  - Map words to simplified representation that encodes attributes such as length, capitalization, numerals, Greek letters, internal punctuation, etc.

Varicella-zoster	Xx-xxx
mRNA	xXXX
CPA1	XXXd

- Character substrings

#Dpp# → #Dpp#, #Dpp, Dpp#, #Dp, Dpp, pp#, #D, Dp, pp, p#, D, p

Features: What's in a Name?



Cotrimoxazole

Wethersfield

Alien Fury: Countdown to Invasion

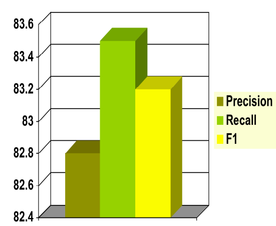
Interesting Features

- Part-of-Speech tags
- Parsing information
- Searching the web for the word in a given context
  - *X gene*, *X mutation*, *X antagonist*
- Gazetteer
  - list words whose classification is known
- Abbreviation extraction (Schwartz and Hearst, 2003)
  - Identify short and long forms when occurring together in text

… Zn finger homeodomain 2 (Zfh 2) …

Finkel et al. (2004) Results

- BioCreative task – Identify genes and proteins



Precision	Recall	F1
81.3%	86.1%	83.6%

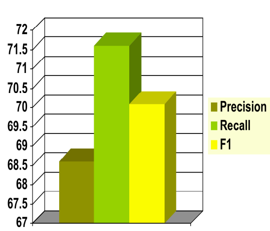
precision = tp / (tp + fp)

recall = tp / (tp + fn)

F1 = 2(precision)(recall) / (precision + recall)

Finkel et al. (2004) Results

- BioNLP task – Identify genes, proteins, DNA, RNA, and cell types



Precision	Recall	F1
68.6%	71.6%	70.1%

precision = tp / (tp + fp)

recall = tp / (tp + fn)

F1 = 2(precision)(recall) / (precision + recall)

Information Extraction and Integration

Following slides from:

William Cohen

Andrew McCallum

Eugene Agichtein

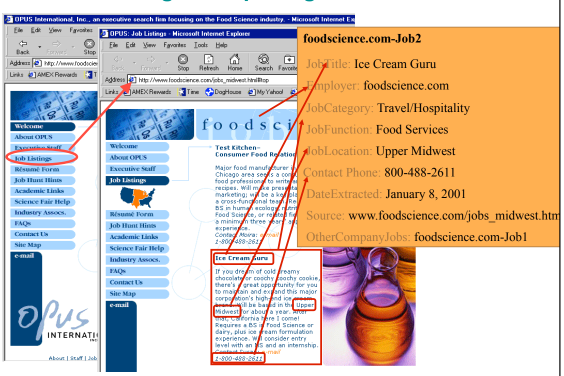
Sunita Sarawagi

The Value of Text Data

- "Unstructured" text data is the primary source of human-generated information
  - Citeseer, comparison shopping, PIM systems, web search, data warehousing
- Managing and utilizing text: information extraction and integration
- Scalability: a bottleneck for deployment
- Relevance to data mining community

Example: A Solution

Extracting Job Openings from the Web



Job Openings:
Category = *Food Services*
Keyword = *Baker*
Location = *Continental U.S.*

What is "Information Extraction"

As a task: Filling slots in a database from sub-segments of text.

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…

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IE

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Bill Veghte	VP	Microsoft
Richard Stallman	founder	Free Soft..

What is “Information Extraction”

As a family of techniques:

Information Extraction =
segmentation + classification + clustering + association

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aka “named entity extraction”

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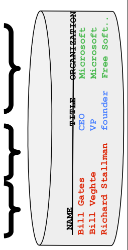


IE is different in different domains!

Example: on web there is less grammar, but more formatting & linking

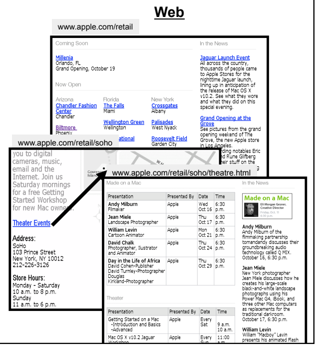
Newswire

Apple to Open Its First Retail Store in New York City

MACWORLD EXPO, NEW YORK--July 17, 2002--Apple's first retail store in New York City will open in Manhattan's SoHo district on Thursday, July 18 at 8:00 a.m. EDT. The SoHo store will be Apple's largest retail store to date and is a stunning example of Apple's commitment to offering customers the world's best computer shopping experience.

"Fourteen months after opening our first retail store, our 31 stores are attracting over 100,000 visitors each week," said Steve Jobs, Apple's CEO. "We hope our SoHo store will surprise and delight both Mac and PC users who want to see everything the Mac can do to enhance their digital lifestyles."

Web



The directory structure, link structure, formatting & layout of the Web is its own new grammar.

Landscape of IE Tasks (1/4): Degree of Formatting

Text paragraphs without formatting

Astro Teller is the CEO and co-founder of BodyMedia. Astro holds a Ph.D. in Artificial Intelligence from Carnegie Mellon University, where he was inducted as a national Hertz fellow. His M.S. in symbolic and heuristic computation and B.S. in computer science are from Stanford University. His work in science, literature and business has appeared in international media from the New York Times to CNN to NPR.

Grammatical sentences and some formatting & links

Dr. Steven Minton - Founder/CTO
Dr. Minton is a fellow of the American Association of Artificial Intelligence and was the founder of the Journal of Artificial Intelligence Research. Prior to founding Fetch, Minton was a faculty member at USC and a project leader at USC's Information Sciences Institute. A graduate of Yale University and Carnegie Mellon University, Minton has been a Principal Investigator at NASA Ames and taught at Stanford, UC Berkeley and USC.

Frank Huybrechts - COO
Mr. Huybrechts has over 20 years of

- Press

Contact
- General information
- Directions maps

Non-grammatical snippets, rich formatting & links

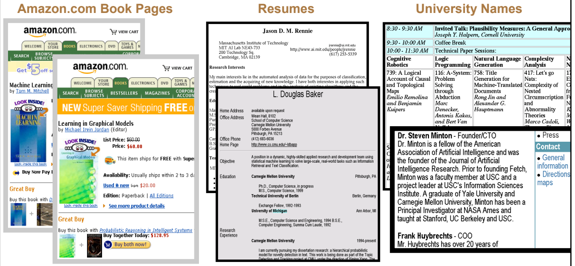
Barto, Andrew G.	(413) 545-2109	barto@cs.umass.edu	CS276
Professor. Computational neuroscience, reinforcement learning, adaptive motor control, artificial neural networks, adaptive and learning control, motor development.			
Berger, Emery D.	(413) 577-4211	emery@cs.umass.edu	CS344
Assistant Professor.			
Brock, Oliver	(413) 577-0334	oli@cs.umass.edu	CS246
Assistant Professor.			
Clarke, Lori A.	(413) 545-1328	clarke@cs.umass.edu	CS304
Professor. Software verification, testing, and analysis; software architecture and design.			
Cohen, Paul R.	(413) 545-3638	cohen@cs.umass.edu	CS278
Professor. Planning, simulation, natural language, agent-based systems, intelligent data analysis, intelligent user interfaces.			

Tables

8:30 - 9:30 AM	**Invited Talk: Plausibility Measures: A General Approach for Representing Uncertainty** *Joseph Y. Halpern, Cornell University*					
9:30 - 10:00 AM	Coffee Break					
10:00 - 11:30 AM	Technical Paper Sessions:					
Cognitive Robotics	**Logic Programming**	**Natural Language Generation**	**Complexity Analysis**	**Neural Networks**	**Games**	
739: A Logical Account of Causal and Topological Maps *Emilio Remolina and Benjamin Kuipers*	116: A-System: Problem Solving through Abduction *Marc Denecker, Antonis Kakas, and Bert Van Nuffelen*	758: Title Generation for Machine-Translated Documents *Rong Jin and Alexander G. Hauptmann*	417: Let's go Nats: Complexity of Nested Circumscription and Abnormality Theories *Marco Cadoli, Thomas Eiter, and Georg Gottlob*	179: Knowledge Extraction and Comparison from Local Function Networks *Kenneth McGarry, Stefan Wermter, and John MacIntyre*	71: Iterative Widening *Tristan Cazenave*	
549: Online-Execution of ccGolog Plans *Henrik Grosskreutz*	131: A Comparative Study of Logic Programs with	246: Dealing with Dependencies between Content Planning and	470: A Perspective on Knowledge Compilation	258: Violation-Guided Learning for Constrained	353: Temporal Difference Learning Applied to a	

Landscape of IE Tasks (2/4):
Intended Breadth of Coverage

Web site specific	Genre specific	Wide, non-specific
Formatting	Layout	Language
Amazon.com Book Pages	Resumes	University Names



Landscape of IE Tasks (3/4):
Complexity

E.g. word patterns:

Closed set

U.S. states

He was born in Alabama…

The big Wyoming sky…

Regular set

U.S. phone numbers

Phone: (413) 545-1323

The CALD main office can be reached at 412-268-1299

Complex pattern

U.S. postal addresses

University of Arkansas
P.O. Box 140
Hope, AR 71802

Headquarters:
1128 Main Street, 4th Floor
Cincinnati, Ohio 45210

Ambiguous patterns, needing context and many sources of evidence

Person names

…was among the six houses sold by Hope Feldman that year.

Pawel Opalinski, Software Engineer at WhizBang Labs.

Landscape of IE Tasks (4/4):
Single Field/Record

Jack Welch will retire as CEO of General Electric tomorrow. The top role at the Connecticut company will be filled by Jeffrey Immelt.

Single entity

Person: Jack Welch

Person: Jeffrey Immelt

Location: Connecticut

Binary relationship

Relation: Person-Title
Person: Jack Welch
Title: CEO

Relation: Company-Location
Company: General Electric
Location: Connecticut

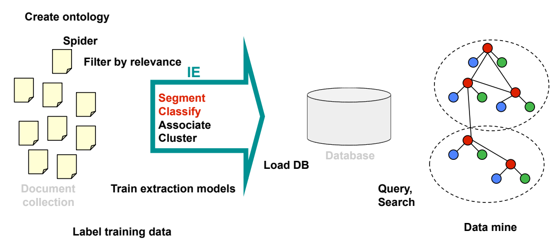
N-ary record

Relation: Succession
Company: General Electric
Title: CEO
Out: Jack Welsh
In: Jeffrey Immelt

"Named entity" extraction

Broader View

Up to now we have been focused on segmentation and classification



Steps 1 & 2: Hand Coded Rule Example: Conference Name

```
# These are subordinate patterns
$wordOrdinals="(?:first|second|third|fourth|fifth|sixth|seventh|eighth|ninth|tenth|eleventh|twelfth|thirtee
fourteenth|fifteenth)";
my $numberOrdinals="(?:\\d?(?:1st|2nd|3rd|1th|2th|3th|4th|5th|6th|7th|8th|9th|0th))";
my $ordinals="(?:$wordOrdinals|$numberOrdinals)";
my $confTypes="(?:Conference|Workshop|Symposium)";
my $words="(?:[A-Z]\\w+\\s*)"; # A word starting with a capital letter and ending with 0 or more spaces
my $confDescriptors="(?:international\\s+|[A-Z]+\\s+)"; # .e.g "International Conference ...' or the confer
name for workshops (e.g. "VLDB Workshop ...")
my $connectors="(?:on|of)";
my $abbreviations="(?:\\([A-Z]\\w\\w+[\\W\\s]*?(?:\\d\\d+)?\\))"; # Conference abbreviations like "(SIGMOD
# The actual pattern we search for.  A typical conference name this pattern will find is
# "3rd International Conference on Blah Blah Blah (ICBBB-05)"
my $fullNamePattern="((?:$ordinals\\s+$words*|$confDescriptors)?$confTypes(?:\\s+$connectors\\s+.*?
$abbreviations?)(?:\\n|\\r|\\.|<)";
############################## ##################################
# Given a <dbworldMessage>, look for the conference pattern
################################################################
lookForPattern($dbworldMessage, $fullNamePattern);
#############################################################
# In a given <file>, look for occurrences of <pattern>
# <pattern> is a regular expression
#############################################################
sub lookForPattern {
   my ($file,$pattern) = @_;
```

Machine Learning Methods

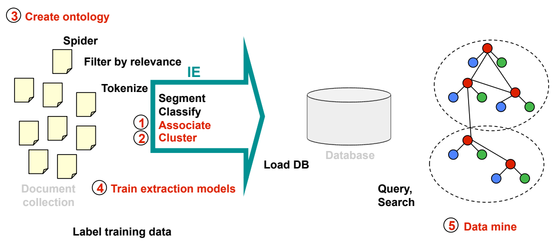
- Sequence models: HMMs, CMMs/MEMMs, CRFs
- Can work well when training data is easy to construct and is plentiful
- Can capture complex patterns that are hard to encode with hand-crafted rules
  - e.g., determine whether a review is positive or negative
  - extract long complex gene names

The human T cell leukemia lymphotropic virus type 1 Tax protein represses MyoD-dependent transcription by inhibiting MyoD-binding to the KIX domain of p300."

- Can be labor intensive to construct training data
  - Question: how much training data is sufficient?

Broader View

Now touch on some other issues



Relation Extraction: Disease Outbreaks

- **E**xtract structured relations from text

May 19 1995, Atlanta -- The Centers for Disease Control and Prevention, which is in the front line of the world's response to the deadly **Ebola** epidemic in **Zaire**, is finding itself hard pressed to cope with the crisis...

Information Extraction System (e.g., NYU's Proteus)

Disease Outbreaks in ***The New York Times***

Date	*Disease Name*	*Location*
Jan. 1995	Malaria	Ethiopia
July 1995	Mad Cow Disease	U.K.
Feb. 1995	Pneumonia	U.S.

Example: Protein Interactions

„We show that CBF-A and CBF-C interact with each other to form a CBF-A-CBF-C complex and that CBF-B does not interact with CBF-A or CBF-C individually but that it associates with the CBF-A-CBF-C complex."

CBF-A $\xleftrightarrow[\text{complex}]{\text{interact}}$ CBF-C

CBF-B $\xrightarrow{\text{associates}}$ CBF-A-CBF-C complex

Relation Extraction

- Typically requires Entity Tagging as preprocessing
- Knowledge Engineering
  - Rules defined over lexical items
    - "<company> located in <location>"
  - Rules defined over parsed text
    - "((Obj <company>) (Verb located) (*) (Subj <location>))"
  - Proteus, GATE, …
- Machine Learning-based
  - Learn rules/patterns from examples
    Dan Roth 2005, Cardie 2006, Mooney 2005, …
  - Partially-supervised: bootstrap from "seed" examples
    Agichtein & Gravano 2000, Etzioni et al., 2004, …
- Recently, hybrid models [Feldman2004, 2006]

Example Extraction Rule [NYU Proteus]

```
;;; For <company> appoints <person> <position>

(defpattern appoint
   "np-sem(C-company)?  rn?  sa?  vg(C-appoint) np-sem(C-person) ','?
    to-be?  np(C-position) to-succeed?:
    company-at=1.attributes, sa=3.span, lv=4.span, person-at=5.attribute:
    position-at=8.attributes |
...
(defun when-appoint (phrase-type)
    (let ((person-at (binding 'person-at))
         (company-entity (entity-bound 'company-at))
         (person-entity (essential-entity-bound 'person-at 'C-person))
         (position-entity (entity-bound 'position-at))
         (predecessor-entity (entity-bound 'predecessor-at))
         new-event)
     (not-an-antecedent position-entity)
     ;; if no company is specified for position, use agent
...
```

Example Extraction Patterns: Snowball [AG2000]

ORGANIZATION	{<'s 0.7> <in 0.7> <headquarters 0.7>}	*LOCATION*
LOCATION	{<- 0.75> <based 0.75>}	*ORGANIZATION*

(1) Association as Binary Classification

Christos Faloutsos conferred with Ted Senator, the KDD 2003 General Chair.

Person — Person — Role

Person-Role (Christos Faloutsos, KDD 2003 General Chair) → NO

Person-Role (Ted Senator, KDD 2003 General Chair) → YES

Do this with SVMs and tree kernels over parse trees.

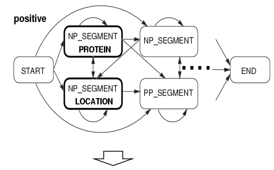
[Zelenko et al, 2002]

(1) Association with Finite State Machines

[Ray & Craven, 2001]

… This enzyme, UBC6, localizes to the endoplasmic reticulum, with the catalytic domain facing the cytosol. …

DET	this
N	enzyme
N	ubc6
V	localizes
PREP	to
ART	the
ADJ	endoplasmic
N	reticulum
PREP	with
ART	the
ADJ	catalytic
N	domain
V	facing
ART	the
N	cytosol



Subcellular-localization (UBC6, endoplasmic reticulum)

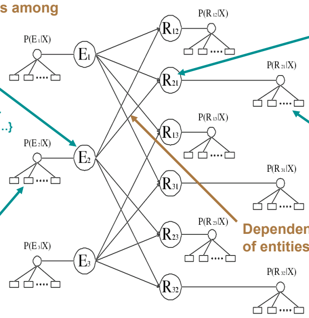
(1) Association with Graphical Models

[Roth & Yih 2002]

Capture arbitrary-distance dependencies among predictions.

Random variable over the class of entity #2, 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.

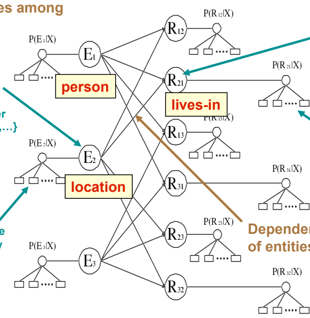
(1) Association with Graphical Models

[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.

Accuracy of Information Extraction

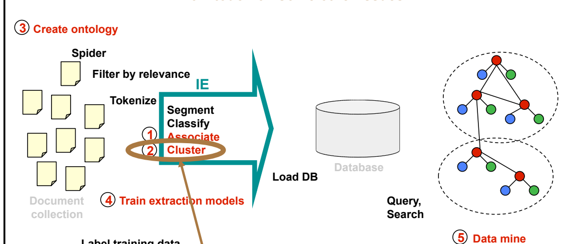
Information Type	Accuracy
Entities	90-98%
Attributes	80%
Facts	60-70%
Events	50-60%

[Feldman, ICML 2006 tutorial]

- Errors cascade (error in entity tag → error in relation extraction)
- This estimate is optimistic:
  - Holds for well-established tasks
  - Many specific/novel IE tasks exhibit lower accuracy

Broader View

Now touch on some other issues



When do two extracted strings refer to the same object?

Extracted Entities: Resolving Duplicates

Document 1: *The Justice Department has officially ended its inquiry into the assassinations of* **John F. Kennedy** *and Martin Luther King Jr., finding ``no persuasive evidence'' to support conspiracy theories, according to department documents. The House Assassinations Committee concluded in 1978 that* **Kennedy** *was ``probably'' assassinated as the result of a conspiracy involving a second gunman, a finding that broke from the* ***Warren Commission*** *'s belief that Lee Harvey Oswald acted alone in* ***Dallas*** *on Nov. 22, 1963.*

Document 2: *In 1953, Massachusetts* **Sen. John F. Kennedy** *married Jacqueline Lee Bouvier in Newport, R.I. In 1960, Democratic presidential candidate* **John F. Kennedy** *confronted the issue of his Roman Catholic faith by telling a Protestant group in Houston, ``I do not speak for my church on public matters, and the church does not speak for me.''*

Document 3: David Kennedy *was born in Leicester, England in 1959. ...***Kennedy** *co-edited The New Poetry (Bloodaxe Books 1993), and is the author of New Relations: The Refashioning Of British Poetry 1980-1994 (Seren 1996).*

[From Li, Morie, & Roth, AI Magazine, 2005]

Important Problem

- Appears in numerous real-world contexts
- Plagues many applications
  - Citeseer, DBLife, AliBaba, Rexa, etc.

(2) Information Integration

[Minton, Knoblock, et al 2001], [Doan, Domingos, Halevy 2001], [Richardson & Domingos 2003]

Goal might be to merge results of two IE systems:

Name:	Introduction to Computer Science
Number:	CS 101
Teacher:	M. A. Kludge
Time:	9-11am
Name:	Data Structures in Java
Room:	5032 Wean Hall

Title:	Intro. to Comp. Sci.
Num:	101
Dept:	Computer Science
Teacher:	Dr. Klüdge
TA:	John Smith
Topic:	Java Programming
Start time:	9:10 AM