CS 6120/CS 4120: Natural Language Processing

Instructor: Prof. Lu Wang

College of Computer and Information Science

Northeastern University

Webpage: www.ccs.neu.edu/home/luwang

Logistics

- Deadline for assignment 2's questions 3 and 4 are extended to March 24, 11:59pm
- Checklist from piazza post @251 for submission
  - It shouldn't affect your implementation
  - Following it will help you get partial credit when your implementation has errors
- Sign up for project feedback at piazza post @221 (if you haven't done so). Comments and grades are available on blackboard.
- Presentation order will be randomly decided and posted on piazza. If you'd like to present on April 9^{th}, please inform instructors on piazza.

Goal: “Machine Reading”

Acquire structured knowledge from unstructured text

Information Extraction (IE)

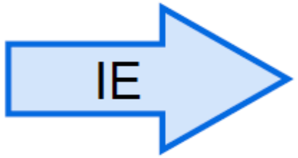
- Extract entities
  - People, organizations, locations, times, dates, prices, ...
  - Or sometimes: genes, proteins, diseases, medicines, ...
- Extract the relations between entities
  - Located in, employed by, part of, married to, ...
- Figure out the larger events that are taking place
  - attack, transport, die, …

Information Extraction (IE)

- IE systems extract clear, factual information
  - Roughly: *Who did what to whom when? (and maybe where too)*
- E.g.,
  - Gathering earnings, profits, board members, headquarters, etc. from company reports
    - The headquarters of BHP Billiton Limited, and the global headquarters of the combined BHP Billiton Group, are located in Melbourne, Australia.
    - headquarters("BHP Biliton Limited", "Melbourne, Australia")
  - Learn drug-gene interactions from medical research literature

Machine-readable summaries


Involvement of Tumor Necrosis Factor Receptor-associated Protein 1 (TRAP1) in Apoptosis Induced by β-Hydroxyisovalerylshikonin



Subject	Relation	Object
p53	**is_a**	protein
Bax	**is_a**	protein
p53	has_function	apoptosis
Bax	has_function	induction
apoptosis	involved_in	cell_death
Bax	is_in	mitochondrial outer membrane
Bax	is_in	cytoplasm
apoptosis	related_to	caspase activation
...	...	...

textual abstract:
summary for human

structured knowledge extraction:
summary for machine

More applications of IE

- Building & extending knowledge bases and ontologies
- Scholarly literature databases: Google Scholar, CiteSeer
- People directories: Rapleaf, Spoke, Naymz
- Shopping engines & product search
- Bioinformatics: clinical outcomes, gene interactions, …
- Patent analysis
- Stock analysis: deals, acquisitions, earnings, hirings & firings
- SEC filings
- Intelligence analysis for business & government

Information Extraction

- Named Entity Recognition
- Relation Extraction

Slides synthesized from Dan Jurafsky, Luke Zettlemoyer

Named Entity Recognition (NER)

- A very important sub-task: find and classify names in text, for example:
  - The decision by the independent MP Andrew Wilkie to withdraw his support for the minority Labor government sounded dramatic but it should not further threaten its stability. When, after the 2010 election, Wilkie, Rob Oakeshott, Tony Windsor and the Greens agreed to support Labor, they gave just two guarantees: confidence and supply.

Named Entity Recognition (NER)

- A very important sub-task: find and classify names in text, for example:
  - The decision by the independent MP Andrew Wilkie to withdraw his support for the minority Labor government sounded dramatic but it should not further threaten its stability. When, after the 2010 election, Wilkie, Rob Oakeshott, Tony Windsor and the Greens agreed to support Labor, they gave just two guarantees: confidence and supply.

Named Entity Recognition (NER)

- A very important sub-task: find and classify names in text, for example:

  - The decision by the independent MP Andrew Wilkie to withdraw his support for the minority Labor government sounded dramatic but it should not further threaten its stability. When, after the 2010 election, Wilkie, Rob Oakeshott, Tony Windsor and the Greens agreed to support Labor, they gave just two guarantees: confidence and supply.

Person
Date
Location
Organization

Named Entity Recognition (NER)

- The uses:
  - Named entities can be indexed, linked off, etc.
  - Sentiment can be attributed to companies or products
  - A lot of IE relations are associations between named entities
  - For question answering, answers are often named entities.

- Concretely:
  - Many web pages tag various entities, with links to bio or topic pages, etc.
  - Apple/Google/Microsoft/… smart recognizers for document content
  - Dialogue systems, like Alexa, Google Home, etc

Evaluation of Named Entity Recognition

The Named Entity Recognition Task

Task: Predict entities in a text

Foreign	ORG
Ministry	ORG
spokesman	O
Shen	PER
Guofang	PER
told	O
Reuters	ORG
:	:

Standard evaluation is per entity, *not* per token

Precision/Recall/F1 for IE/NER

- Recall and precision are straightforward for tasks like IR and text categorization, where there is only one grain size (documents)
- The measure behaves a bit funnily for IE/NER when there are *boundary errors* (which are *common*):
  - First Bank of Chicago announced earnings …

Precision/Recall/F1 for IE/NER

- Recall and precision are straightforward for tasks like IR and text categorization, where there is only one grain size (documents)
- The measure behaves a bit funnily for IE/NER when there are *boundary errors* (which are *common*):
  - First Bank of Chicago announced earnings …
- This counts as both a false positive and a false negative
- Selecting *nothing* would have been better

Precision/Recall/F1 for IE/NER

- Recall and precision are straightforward for tasks like IR and text categorization, where there is only one grain size (documents)
- The measure behaves a bit funnily for IE/NER when there are *boundary errors* (which are *common*):
  - First Bank of Chicago announced earnings …
- This counts as both a false positive and a false negative
- Selecting *nothing* would have been better
- Partial credit?

Sequence Models for Named Entity Recognition

The ML sequence model approach to NER

Training

1. Collect a set of representative training documents
2. Label each token for its entity class or other (O)
3. Design feature extractors appropriate to the text and classes
4. Train a sequence classifier to predict the labels from the data

Testing

1. Receive a set of testing documents
2. Run sequence model inference to label each token
3. Appropriately output the recognized entities

Encoding classes for sequence labeling

	IO encoding
Fred	PER
showed	O
Sue	PER
Mengqiu	PER
Huang	PER
‘s	O
new	O
painting	O

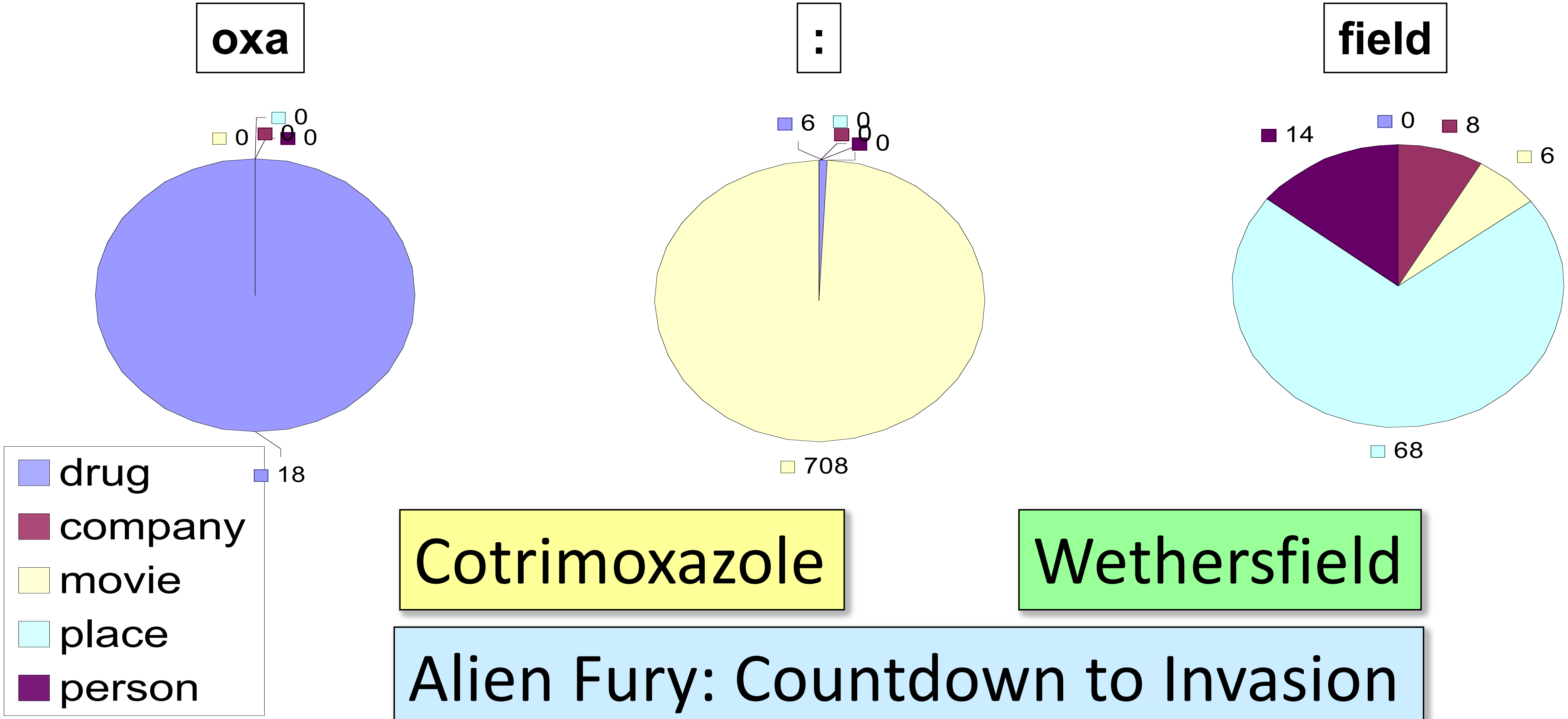
Encoding classes for sequence labeling

	IO encoding	IOB encoding
Fred	PER	B-PER
showed	O	O
Sue	PER	B-PER
Mengqiu	PER	B-PER
Huang	PER	I-PER
‘s	O	O
new	O	O
painting	O	O

Features for sequence labeling

- Words
  - Current word (essentially like a learned dictionary)
  - Previous/next word (context)
- Other kinds of inferred linguistic classification
  - Part-of-speech tags
- Label context
  - Previous (and perhaps next) label

Features: Word substrings



Cotrimoxazole

Wethersfield

Alien Fury: Countdown to Invasion

Features: Word shapes

- 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

Maximum Entropy Sequence Models

Sequence problems

- Many problems in NLP have data which is a sequence of characters, words, phrases, lines, or sentences …
- We can think of our task as: labeling each item in the sequence

VBG	NN	IN	DT	NN	IN	NN
Chasing	opportunity	in	an	age	of	upheaval

POS tagging

B	B	I	I	B	I	B	I	B	B
而	相	对	于	这	些	品	牌	的	价

Word segmentation

PERS	O	O	O	ORG	ORG
Murdoch	discusses	future	of	News	Corp.

Named entity recognition

Text segmentation / Topic segmentation

Maximum Entropy

- Make a probabilistic model from the linear combination $\Sigma\lambda_i f_i(c,d)$

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

Makes votes positive

Normalizes votes

- $f_1(c, d) \equiv [c = \text{LOCATION} \wedge w_{-1} = \text{“in”} \wedge \text{isCapitalized}(w)]$ -> weight 1.8
- $f_2(c, d) \equiv [c = \text{LOCATION} \wedge \text{hasAccentedLatinChar}(w)]$ -> weight -0.6
- $f_3(c, d) \equiv [c = \text{DRUG} \wedge \text{ends}(w, \text{“c”})]$ -> weight 0.3

Maximum Entropy Markov Model (MEMM)

- We want a classifier that makes a single decision at a time, conditioned on evidence from observations and previous decisions
- Using POS tagging as an example

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.)

Example: POS Tagging

- POS tagging Features can include:
  - Current, previous, next words in isolation or together.
  - Previous one, two, three tags.
  - Word-internal features: word types, suffixes, dashes, etc.

Local Context

Decision Point

-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.)

Information Extraction

- Named Entity Recognition
- Relation Extraction

Slides synthesized from Dan Jurafsky, Luke Zettlemoyer

Relation Extraction

Relation extraction example

CHICAGO (AP) — Citing high fuel prices, United Airlines said Friday it has increased fares by $6 per round trip on flights to some cities also served by lower-cost carriers. American Airlines, a unit of AMR, immediately matched the move, spokesman Tim Wagner said. United, a unit of UAL, said the increase took effect Thursday night and applies to most routes where it competes against discount carriers, such as Chicago to Dallas and Atlanta and Denver to San Francisco, Los Angeles and New York.

Subject	Relation	Object
American Airlines	subsidiary	AMR
Tim Wagner	employee	American Airlines
United Airlines	subsidiary	UAL

example from Jim Martin

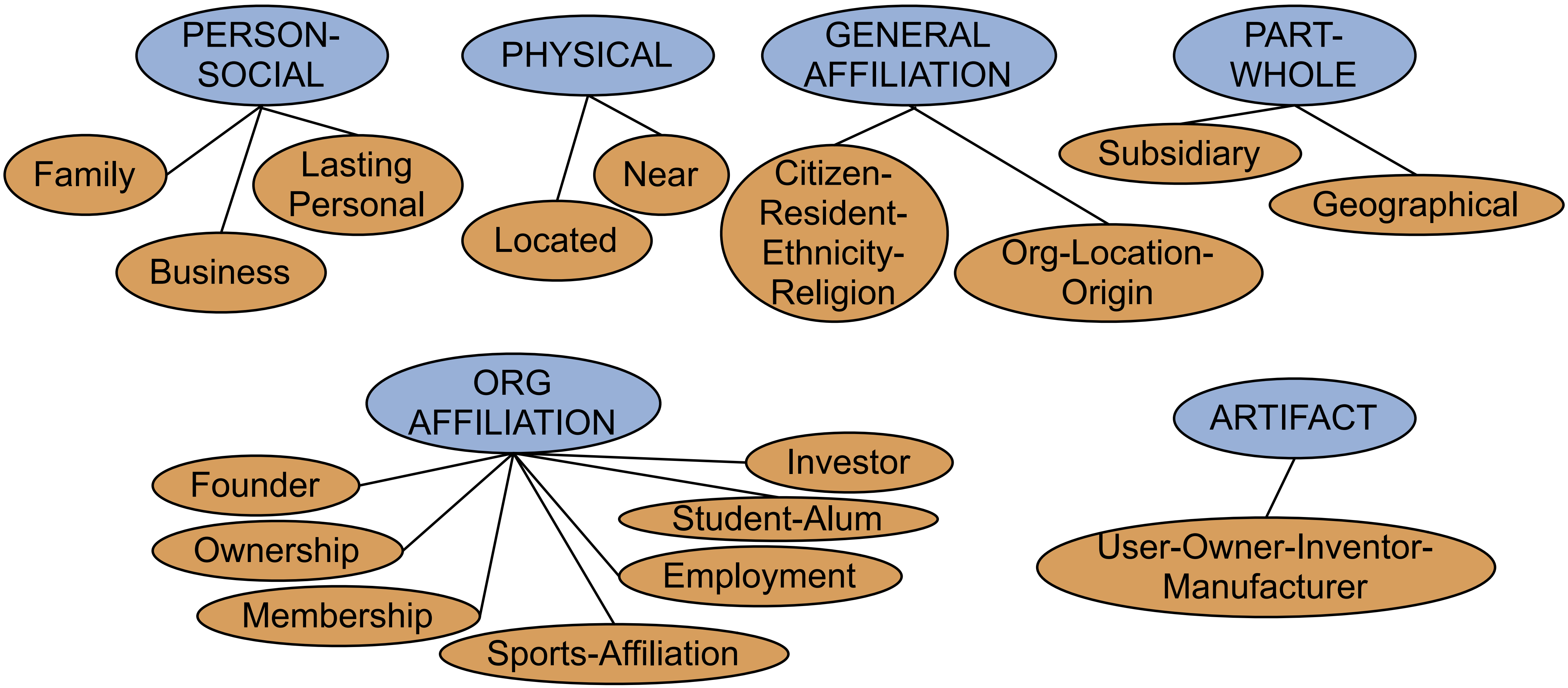
Why Relation Extraction?

- Create new structured knowledge bases, useful for any application
- Augment current knowledge bases
  - Adding words to WordNet thesaurus, facts to FreeBase or DBPedia
- Support question answering
  - The granddaughter of which actor starred in the movie “E.T.”?

  ```
  (acted-in ?x “E.T.”)(is-a ?y actor)(granddaughter-of ?x ?y)
  ```
- But which relations should we extract?

Automated Content Extraction (ACE)

17 relations from 2008 “Relation Extraction Task”



Automated Content Extraction (ACE)

- Physical-Located PER-GPE

  `He was in Tennessee`

- Part-Whole-Subsidiary ORG-ORG

  `XYZ, the parent company of ABC`

- Person-Social-Family PER-PER

  `John’s wife Yoko`

- Org-AFF-Founder PER-ORG

  `Steve Jobs, co-founder of Apple…`

Ontological relations

Examples from the WordNet Thesaurus

- IS-A (hypernym): subsumption between classes
  - Giraffe IS-A ruminant IS-A ungulate IS-A mammal IS-A vertebrate IS-A animal…
- Instance-of: relation between individual and class
  - San Francisco instance-of city

How to build relation extractors

1. Hand-written patterns (also can be used as features)
2. Supervised machine learning
3. Semi-supervised and unsupervised
   - Bootstrapping (using seeds)
   - Distant supervision
   - Unsupervised learning from the web

Hand-written Patterns

Rules for extracting IS-A relation

Early intuition from **Hearst (1992)**

- "Agar is a substance prepared from a mixture of red algae, such as Gelidium, for laboratory or industrial use"

- What does *Gelidium* mean?
- How do you know?`

Rules for extracting IS-A relation

Early intuition from **Hearst (1992)**

- “Agar is a substance prepared from a mixture of **red algae, such as Gelidium,** for laboratory or industrial use”

- What does *Gelidium* mean?
- How do you know?`

Hearst's Patterns for extracting IS-A relations

(Hearst, 1992): Automatic Acquisition of Hyponyms

```
“Y such as X”
“such Y as X”
“X or other Y”
“X and other Y”
“Y including X”
“Y, especially X”
```

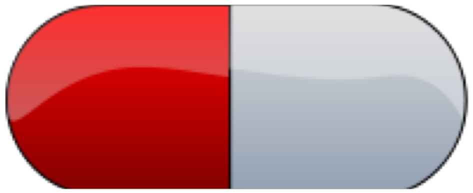
Hearst’s Patterns for extracting IS-A relations

Hearst pattern	Example occurrences
X and other Y	...temples, treasuries, and other important civic buildings.
X or other Y	Bruises, wounds, broken bones or other injuries...
Y such as X	The bowlute, such as the Bambarandang...
Such Y as X	...such authors as Herrick, Goldsmith, and Shakespeare.
Y including X	...common-law countries, including Canada and England...
Y , especially X	European countries, especially France, England, and Spain...

Extracting Richer Relations Using Rules

- Intuition: relations often hold between specific entities
  - located-in (ORGANIZATION, LOCATION)
  - founded (PERSON, ORGANIZATION)
  - cures (DRUG, DISEASE)
- Start with Named Entity tags to help extract relation!

Named Entities aren’t quite enough.
Which relations hold between 2 entities?



Drug

Cure?

Prevent?

Cause?

Disease

What relations hold between 2 entities?

PERSON

Founder?

Investor?

Member?

Employee?

President?

ORGANIZATION

Hand-built patterns for relations

- Plus:
  - Human patterns tend to be high-precision
  - Can be tailored to specific domains
- Minus
  - Human patterns are often low-recall
  - A lot of work to think of all possible patterns!
  - Don’t want to have to do this for every relation!
  - We’d like better accuracy

Supervised machine learning for relations

- Choose a set of relations we’d like to extract
- Choose a set of relevant named entities
- Find and label data
  - Choose a representative corpus
  - Label the named entities in the corpus
  - Hand-label the relations between these entities
  - Break into training, development, and test
- Train a classifier on the training set

How to do classification in supervised relation extraction

1. Find all pairs of named entities (usually in same sentence)
2. Decide if 2 entities are related
3. If yes, classify the relation

- Why the extra step?
    - Faster classification training by eliminating most pairs
    - Can use distinct feature-sets appropriate for each task.

Features

- Lightweight features — require little pre-processing
  - Bags of words & bigrams between, before, and after the entities
  - Stemmed versions of the same
  - The types of the entities
  - The distance (number of words) between the entities
- Medium-weight features — require base phrase chunking
  - Base-phrase chunk paths
  - Bags of chunk heads
- Heavyweight features — require full syntactic parsing
  - Dependency-tree paths
  - Constituent-tree paths
  - Tree distance between the entities
  - Presence of particular constructions in a constituent structure

Word Features for Relation Extraction

American Airlines, *a unit of AMR, immediately matched the move, spokesman* ***Tim Wagner*** *said*

Entity Mention 1 Entity Mention 2

Word Features for Relation Extraction

American Airlines*, a unit of AMR, immediately matched the move, spokesman* ***Tim Wagner*** *said*

Mention 1 Mention 2

- Headwords of M1 and M2, and combination

  Airlines Wagner Airlines-Wagner

- Bag of words and bigrams in M1 and M2

  {American, Airlines, Tim, Wagner, American Airlines, Tim Wagner}

- Words or bigrams in particular positions left and right of M1/M2

  M2: -1 spokesman

  M2: +1 said

- Bag of words or bigrams between the two entities

  {a, AMR, of, immediately, matched, move, spokesman, the, unit}

Named Entity Type and Mention Level Features for Relation Extraction

***American Airlines**, a unit of AMR, immediately matched the move, spokesman **Tim Wagner** said*

Mention 1 Mention 2

- Named-entity types
  - M1: ORG
  - M2: PERSON
- Concatenation of the two named-entity types
  - ORG-PERSON

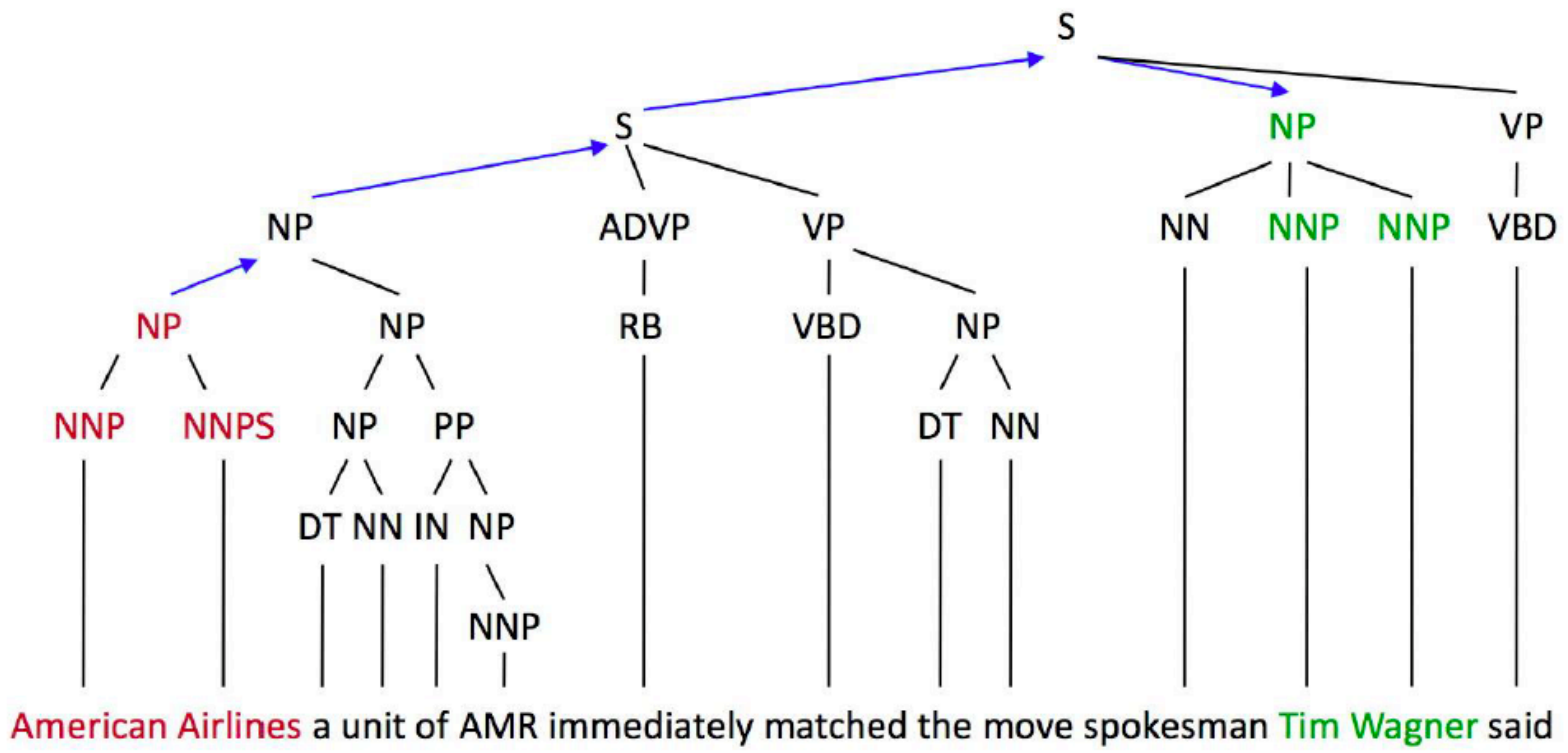
Parse Features for Relation Extraction

American Airlines*, a unit of AMR, immediately matched the move, spokesman* ***Tim Wagner*** *said*
Mention 1 Mention 2

- Base syntactic chunk sequence from one to the other

NP NP PP NP ADVP VP NP NP

$[_{NP}$ American Airlines], $[_{NP}$ a unit] $[_{PP}$ of] $[_{NP}$ AMR], $[_{ADVP}$ immediately] $[_{VP}$ matched] $[_{NP}$ the move], $[_{NP}$ spokesman Tim Wagner] $[_{VP}$ said].



Phrase label paths

PTP = [NP, S, NP]

PTPH = [NP:Airlines, S:matched, NP:Wagner]

***American Airlines**, a unit of AMR, immediately matched the move, spokesman **Tim Wagner** said.*

Entity-based features	
Entity$_1$ type	ORG
Entity$_1$ head	*airlines*
Entity$_2$ type	PERS
Entity$_2$ head	*Wagner*
Concatenated types	ORGPERS
Word-based features	
Between-entity bag of words	{ *a, unit, of, AMR, Inc., immediately, matched, the, move, spokesman* }
Word(s) before Entity$_1$	NONE
Word(s) after Entity$_2$	*said*
Syntactic features	
Constituent path	$NP \uparrow NP \uparrow S \uparrow S \downarrow NP$
Base syntactic chunk path	$NP \rightarrow NP \rightarrow PP \rightarrow NP \rightarrow VP \rightarrow NP \rightarrow NP$
Typed-dependency path	$Airlines \leftarrow_{subj} matched \leftarrow_{comp} said \rightarrow_{subj} Wagner$

Classifiers for supervised methods

- Now you can use any classifier you like
  - MaxEnt
  - Naïve Bayes
  - SVM
  - ...
- Train it on the training set, tune on the dev set, test on the test set

Evaluation of Supervised Relation Extraction

- Compute P/R/F_1 for each relation

$$\text{P} = \frac{\text{\# of correctly extracted relations}}{\text{Total \# of extracted relations}}$$

$$F_1 = \frac{2PR}{P+R}$$

$$R = \frac{\text{\# of correctly extracted relations}}{\text{Total \# of gold relations}}$$

Summary: Supervised Relation Extraction

+ Can get high accuracies with enough hand-labeled training data, if test similar enough to training

- Labeling a large training set is expensive

- Supervised models are brittle, don't generalize well to different genres

Semi-supervised and Unsupervised Relation Extraction

Seed-based or bootstrapping approaches to relation extraction

- No training set? Maybe you have:
  - A few seed tuples or
  - A few high-precision patterns
- Can you use those seeds to do something useful?
  - Bootstrapping: use the seeds to directly learn to populate a relation

Relation Bootstrapping (Hearst 1992)

- Gather a set of seed pairs that have relation R
- Iterate:
  1. Find sentences with these pairs
  2. Look at the context between or around the pair and generalize the context to create patterns
  3. Use the patterns to grep for more pairs

Bootstrapping

- <Mark Twain, Elmira> Seed tuple
  - Grep (google) for the environments of the seed tuple

    "Mark Twain is buried in Elmira, NY."

      X is buried in Y

    "The grave of Mark Twain is in Elmira"

      The grave of X is in Y

    "Elmira is Mark Twain's final resting place"

      Y is X's final resting place.
- Use those patterns to grep for new tuples
- Iterate

Dipre: Extract <author,book> pairs

Brin, Sergei. 1998. Extracting Patterns and Relations from the World Wide Web.

- Start with 5 seeds:

Author	Book
Isaac Asimov	The Robots of Dawn
David Brin	Startide Rising
James Gleick	Chaos: Making a New Science
Charles Dickens	Great Expectations
William Shakespeare	The Comedy of Errors

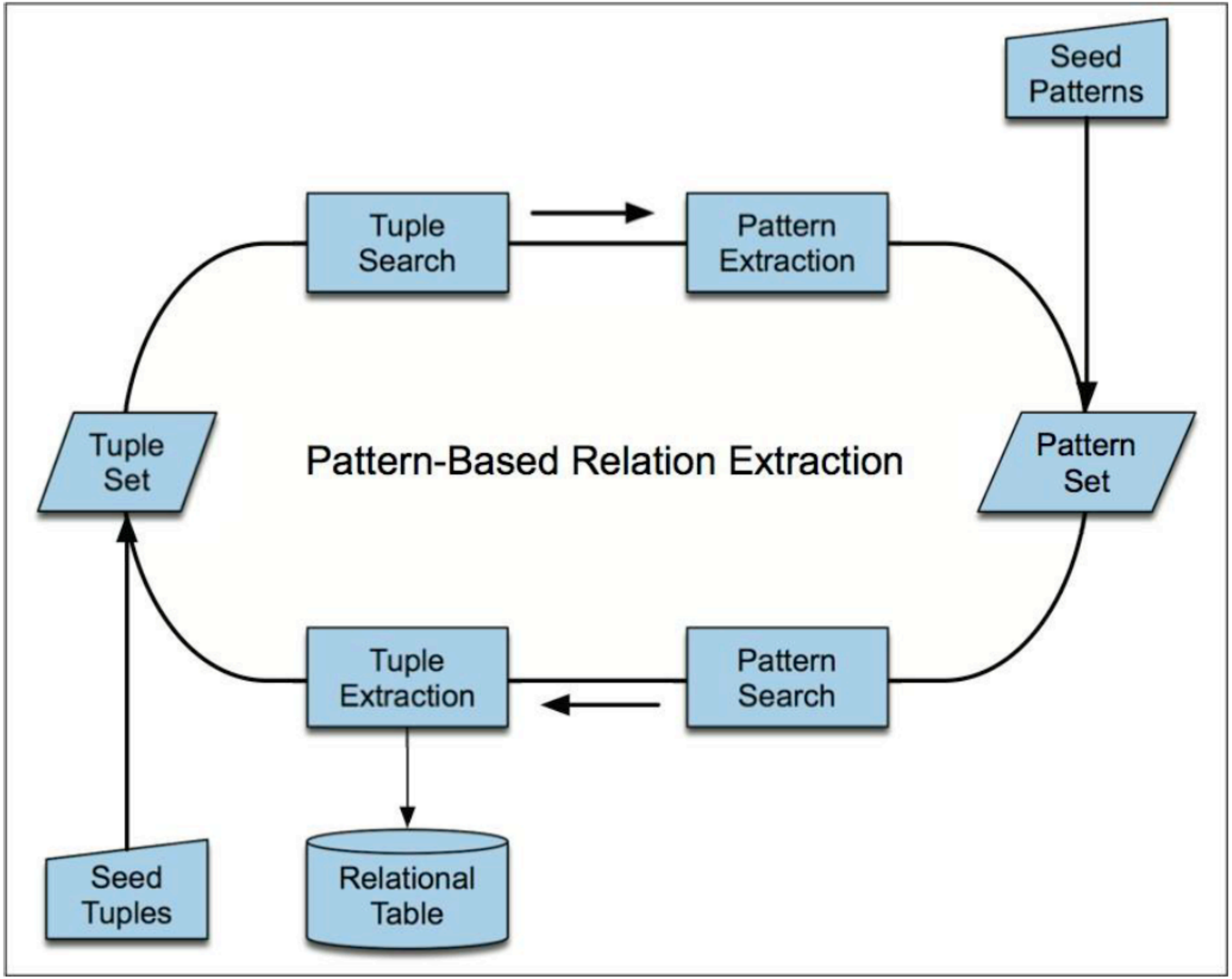
- Find Instances:

  The Comedy of Errors, by William Shakespeare, was
  The Comedy of Errors, by William Shakespeare, is
  The Comedy of Errors, one of William Shakespeare's earliest attempts
  The Comedy of Errors, one of William Shakespeare's most

- Extract patterns (group by middle, take longest common prefix/suffix)

  `?x , by ?y ,`   `?x , one of ?y ‘s`

- Now iterate, finding new seeds that match the pattern


Seed Patterns
Tuple Search
Pattern Extraction
Tuple Set
Pattern-Based Relation Extraction
Pattern Set
Tuple Extraction
Pattern Search
Seed Tuples
Relational Table

Distant Supervision

Snow, Jurafsky, Ng. 2005. Learning syntactic patterns for automatic hypernym discovery. NIPS 17
Fei Wu and Daniel S. Weld. 2007. Autonomously Semantifying Wikipeida. CIKM 2007
Mintz, Bills, Snow, Jurafsky. 2009. Distant supervision for relation extraction without labeled data. ACL09

- Combine bootstrapping with supervised learning
  - Instead of small number of seeds,
    - Use a large database to get huge # of seed examples
  - Create lots of features from all these examples
  - Combine in a supervised classifier

Distant supervision paradigm

- Like supervised classification:
  - Uses a classifier with lots of features
  - Supervised by detailed hand-created knowledge
  - Doesn’t require iteratively expanding patterns
- Like unsupervised classification:
  - Uses very large amounts of unlabeled data
  - Not sensitive to genre issues in training corpus