Learning Thesauruses and Knowledge Bases

Thesaurus induction and relation extraction

What is thesaurus induction?

Relation extraction

- Lexico-syntactic patterns (Hearst, 1992),
- LRA (Turney, 2005),
- Espresso (Pantel & Pennacchiotti, 2006),
- Distributional similarity…

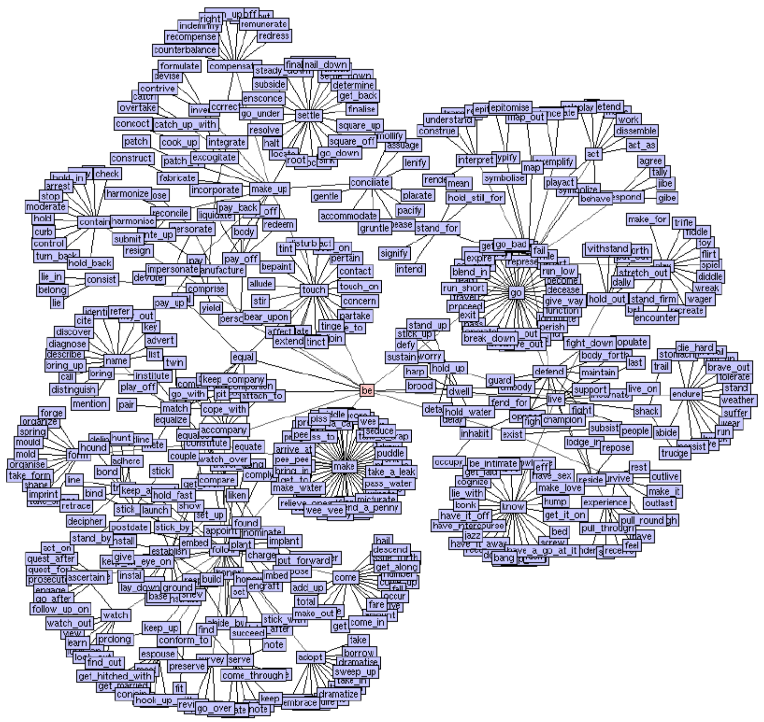
bambara ndang	IS-A	bow lute
ostrich	IS-A	bird
wallaby	is-like	kangaroo

And hundreds of thousands more…

Taxonomy Induction

A structured, consistent thesaurus of sense-disambiguated synsets

WordNet



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Thesaurus induction is a special case of relation extraction

- 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

- Co-ordinate term (co-hyponym)

  Chicago, Boston, Austin, Los Angeles

- Meronym

  Bumper is-part-of car

Extracting **relations** from text

- Company report: "International Business Machines Corporation (IBM or the company) was incorporated in the State of New York on June 16, 1911, as the Computing-Tabulating-Recording Co. (C-T-R)…"
- Extracted Complex Relation:

Company-Founding

Company	IBM
Location	New York
Date	June 16, 1911
Original-Name	Computing-Tabulating-Recording Co.

- But we will focus on the simpler task of extracting relation **triples**

Founding-year(IBM,1911)

Founding-location(IBM,New York)

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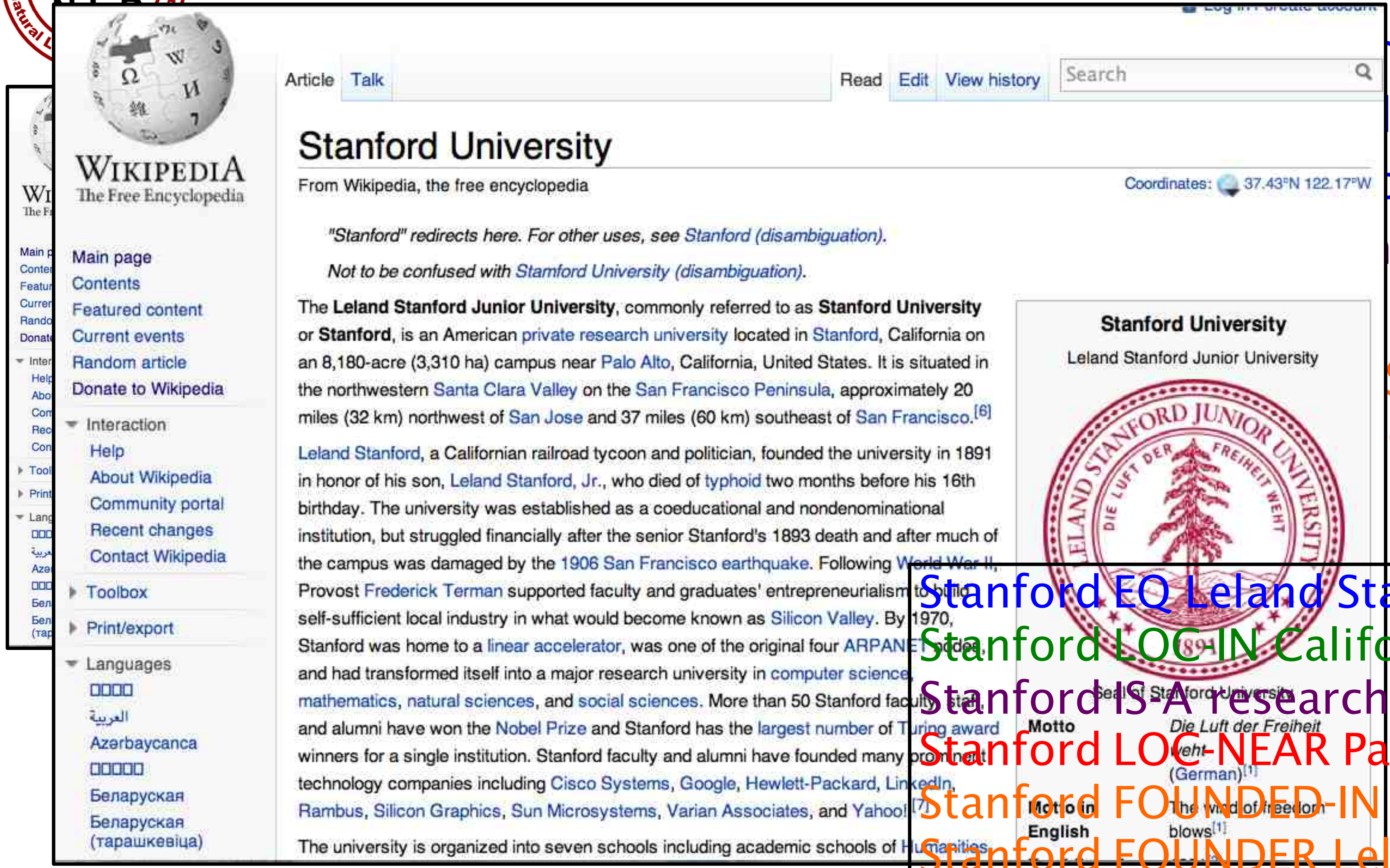
Extracting Relation Triples from Text



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Stanford University

From Wikipedia, the free encyclopedia

Coordinates: 37.43°N 122.17°W

"Stanford" redirects here. For other uses, see Stanford (disambiguation).

Not to be confused with Stamford University (disambiguation).

The **Leland Stanford Junior University**, commonly referred to as **Stanford University** or **Stanford**, is an American private research university located in Stanford, California on an 8,180-acre (3,310 ha) campus near Palo Alto, California, United States. It is situated in the northwestern Santa Clara Valley on the San Francisco Peninsula, approximately 20 miles (32 km) northwest of San Jose and 37 miles (60 km) southeast of San Francisco.[6]

Leland Stanford, a Californian railroad tycoon and politician, founded the university in 1891 in honor of his son, Leland Stanford, Jr., who died of typhoid two months before his 16th birthday. The university was established as a coeducational and nondenominational institution, but struggled financially after the senior Stanford's 1893 death and after much of the campus was damaged by the 1906 San Francisco earthquake. Following World War II, Provost Frederick Terman supported faculty and graduates' entrepreneurialism to build self-sufficient local industry in what would become known as Silicon Valley. By 1970, Stanford was home to a linear accelerator, was one of the original four ARPANET nodes, and had transformed itself into a major research university in computer science, mathematics, natural sciences, and social sciences. More than 50 Stanford faculty, staff, and alumni have won the Nobel Prize and Stanford has the largest number of Turing award winners for a single institution. Stanford faculty and alumni have founded many prominent technology companies including Cisco Systems, Google, Hewlett-Packard, LinkedIn, Rambus, Silicon Graphics, Sun Microsystems, Varian Associates, and Yahoo![7]

The university is organized into seven schools including academic schools of Humanities

rd Junior University,
to as Stanford
ord, is an American
iversity located in
… near Palo Alto,
Stanford…founded
91

Stanford EQ Leland Stanford Junior University
Stanford LOC-IN California
Stanford IS-A research university
Stanford LOC-NEAR Palo Alto
Stanford FOUNDED-IN 1891
Stanford FOUNDER Leland Stanford

Why Relation Extraction?

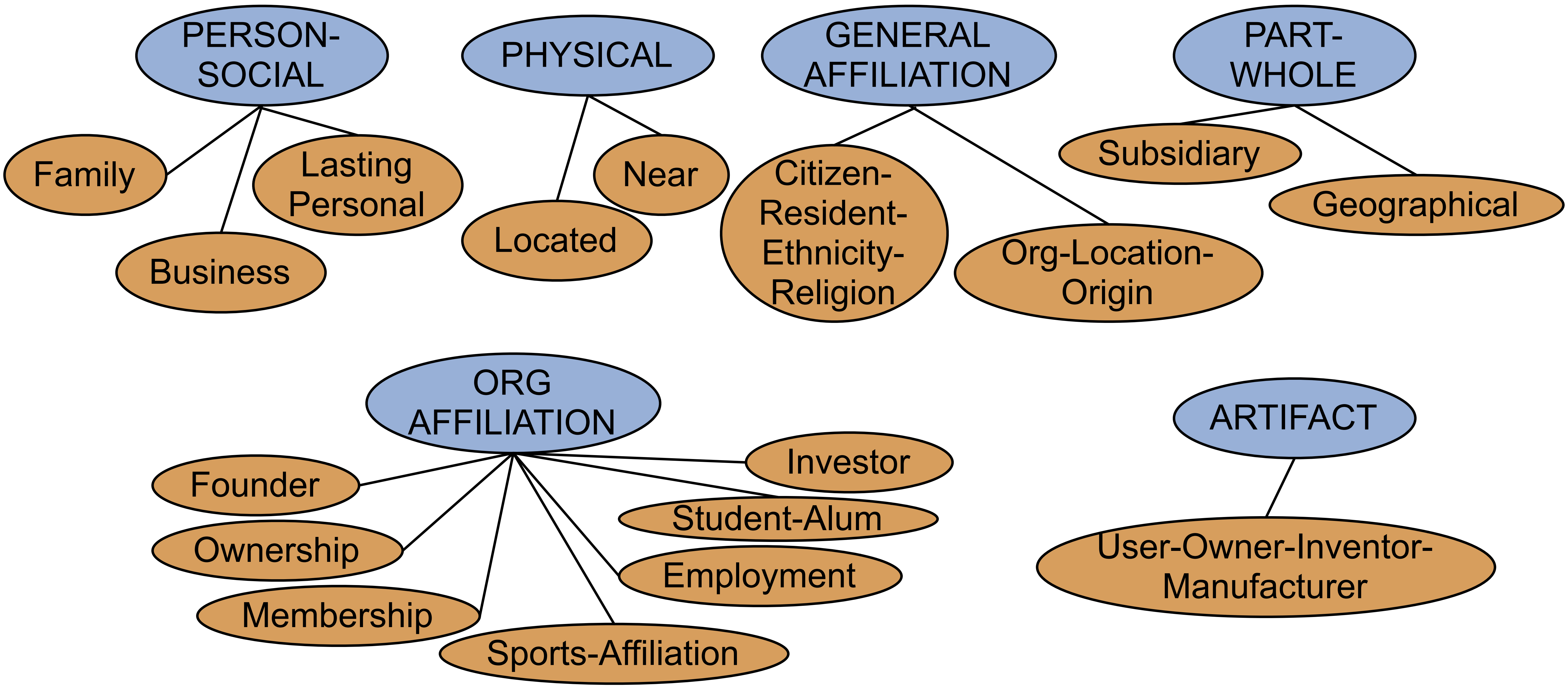
- Create new structured knowledge bases
- Augment current knowledge bases
  - Lexical resources: Add words to WordNet thesaurus
  - Fact bases: Add facts to FreeBase or DBPedia
- Sample application: question answering
  - The granddaughter of which actor starred in the movie “E.T.”?

```
(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…
-

Databases of Wikipedia Relations

Wikipedia Infobox

```
{{Infobox university
|image_name= Stanford University seal.svg
|image_size= 210px
|caption = Seal of Stanford University
|name =Stanford University
|native_name =Leland Stanford Junior Uni
|motto = {{lang|de|"Die Luft der Freiheit v
name="casper">{{cite speech|title=Die Lu d
Casper|first=Gerhard|last=Casper|author
05|url=http://www.stanford.edu/dept/pr tml}}</ref>
|mottoeng = The wind of freedom blows<
|established = 1891<ref>{{cite web |
url=http://www.stanford.edu/home/stan ty History |
publisher = Stanford University | accessda
|type = [[private university|Private]]
|calendar= Quarter
|president = [[John L. Hennessy]]
|provost = [[John Etchemendy]]
|city = [[Stanford, California|Stanford]]
|state = California
|country = U.S.
```

Type	Private
Endowment	US$ 16.5 billion (2011)[3]
President	John L. Hennessy
Provost	John Etchemendy
Academic staff	1,910[4]
Students	15,319
Undergraduates	6,878[5]
Postgraduates	8,441[5]
Location	Stanford, California, U.S.
Campus	Suburban, 8,180 acres (3,310 ha)[6]
Colors	Cardinal red and white

Relations extracted from Infobox

Stanford state California

Stanford motto "Die Luft der Freiheit weht"

Thesaurus relations

- 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

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- Meronym

  bumperis-part-of car

Relation databases that draw from Wikipedia

- Resource Description Framework (RDF) triples

  subject predicate object

  `Golden Gate Park location San Francisco`

  dbpedia:Golden_Gate_Park dbpedia-owl:location dbpedia:San_Francisco

- DBPedia: 1 billion RDF triples, 385 from English Wikipedia
- Frequent Freebase relations:

  people/person/nationality,
  people/person/profession,
  biology/organism_higher_classification
  location/location/contains
  people/person/place-of-birth
  film/film/genre

How to build relation extractors

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

Learning Thesauruses and Knowledge Bases

Using patterns to extract relations

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 ((, X)* (, and|or) X)”
“such Y as X”
“X or other Y”
“X and other Y”
“Y including X”
“Y, especially X”

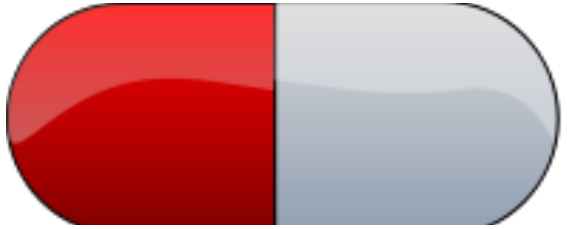
Hearst's Patterns for extracting IS-A relations

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 bow lute, such as the Bambara ndang...
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

Extracting Richer Relations Using Rules and Named Entities

Who holds what office in what organization?

PERSON, POSITION of ORG

- George Marshall, Secretary of State of the United States

PERSON (named|appointed|chose|*etc.*) PERSON Prep? POSITION

- Truman appointed Marshall Secretary of State

PERSON [be]? (named|appointed|*etc.*) Prep? ORG POSITION

- George Marshall was named US Secretary of State

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

Learning Thesauruses and Knowledge Bases

Using patterns to extract relations

Learning Thesauruses and Knowledge Bases

Supervised relation extraction

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.

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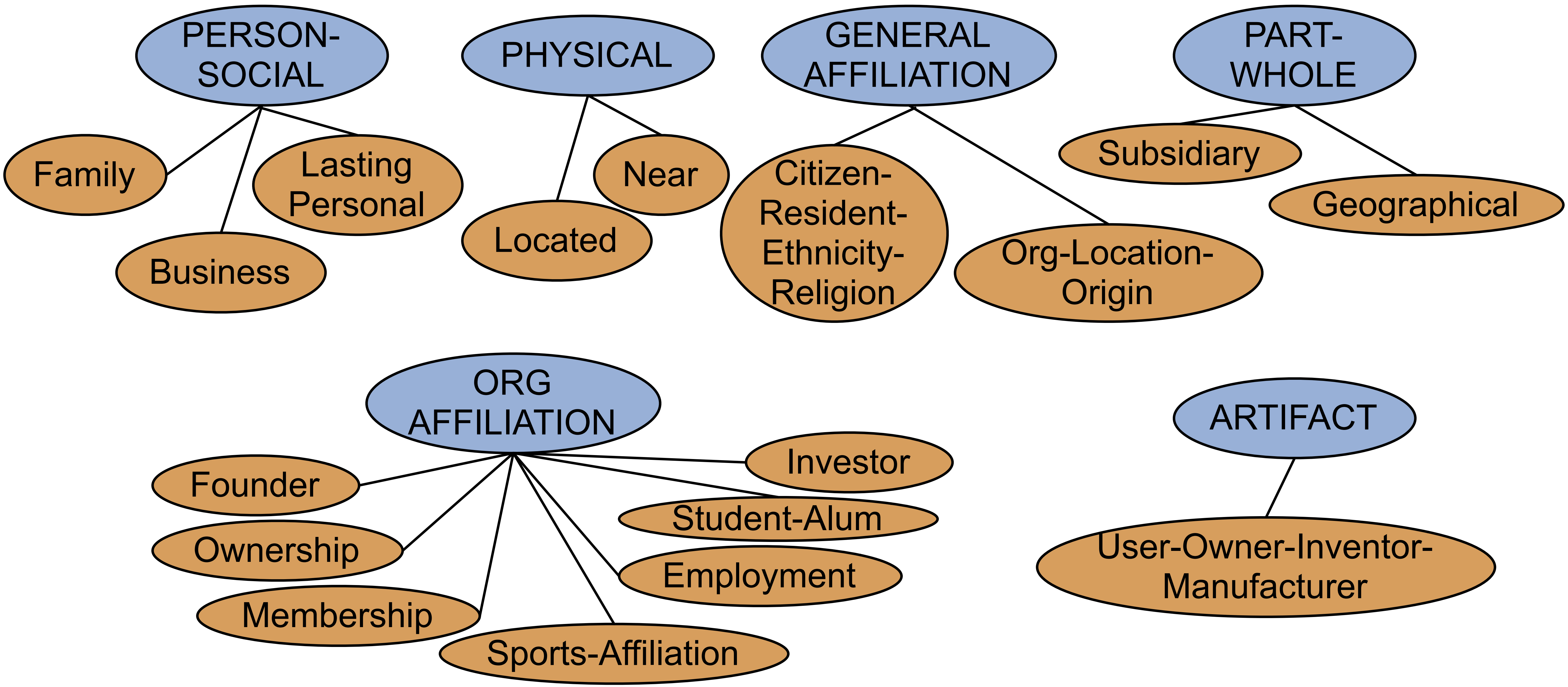
Automated Content Extraction (ACE)

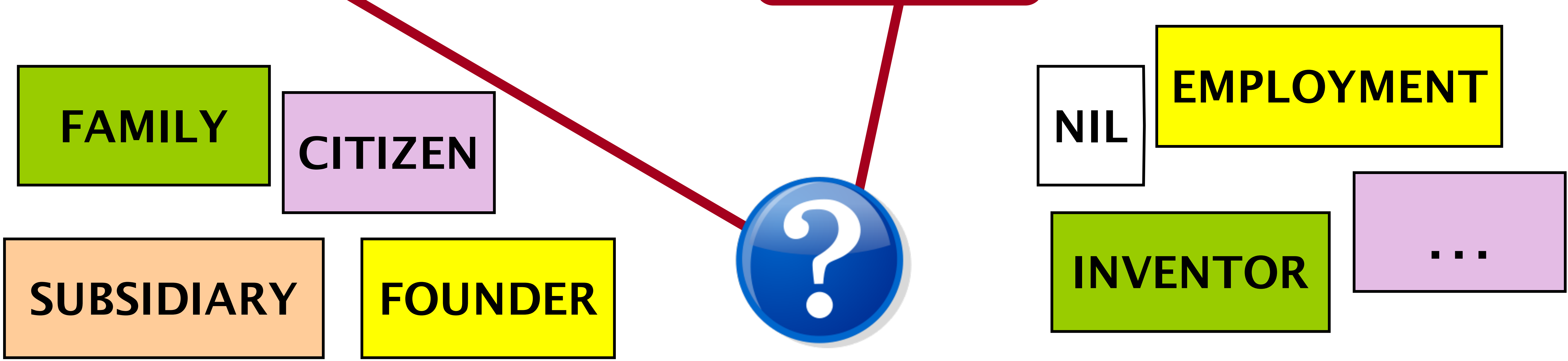
17 sub-relations of 6 relations from 2008 "Relation Extraction Task"



Relation Extraction

Classify the relation between two entities in a sentence

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



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
- Entity Level of M1 and M2 (NAME, NOMINAL, PRONOUN)
  - M1: NAME [it or he would be PRONOUN]
  - M2: NAME [the company would be NOMINAL]

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 VP NP NP

- Constituent path through the tree from one to the other

  NP ↑ NP ↑ S ↑ S ↓ NP

- Dependency path

  Airlines matched Wagner said

  subj comp subj

Gazeteer and trigger word features for relation extraction

- Trigger list for family: kinship terms
  - parent, wife, husband, grandparent, etc. [from WordNet]
- Gazeteer:
  - Lists of useful geo or geopolitical words
    - Country name list
    - Other sub-entities

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
  - Naive Bayes
  - Logistic Regression (MaxEnt)
  - 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

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

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

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

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

Learning Thesauruses and Knowledge Bases

Supervised relation extraction

Learning Thesauruses and Knowledge Bases

Semi-supervised 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 for 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

Snowball

E. Agichtein and L. Gravano 2000. Snowball: Extracting Relations from Large Plain-Text Collections. ICDL

- Similar iterative algorithm

Organization	Location of Headquarters
Microsoft	Redmond
Exxon	Irving
IBM	Armonk

- Group instances w/similar prefix, middle, suffix, extract patterns
  - But require that X and Y be named entities
  - And compute a confidence for each pattern

.69 ORGANIZATION {'s, in, headquarters} LOCATION

.75 LOCATION {in, based} ORGANIZATION

Distant Supervision

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

- Combine bootstrapping with supervised learning
  - Instead of 5 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

Distantly supervised learning of relation extraction patterns

1. For each relation — Born-In
2. For each tuple in big database — <Edwin Hubble, Marshfield> <Albert Einstein, Ulm>
3. Find sentences in large corpus with both entities — Hubble was born in Marshfield; Einstein, born (1879), Ulm; Hubble's birthplace in Marshfield
4. Extract frequent features (parse, words, etc) — PER was born in LOC; PER, born (XXXX), LOC; PER's birthplace in LOC
5. Train supervised classifier using thousands of patterns — $P(\text{born-in} \mid f_1, f_2, f_3, \ldots, f_{70000})$

Distantly supervised learning of IS-A extraction patterns

Snow, Jurafsky, Ng 2005

1. For each X IS-A Y in WordNet

<sarcoma, cancer>
<deuterium, atom>

2. Find sentences in large corpus with X and Y

an uncommon bone **cancer** called osteogenic **sarcoma**

in the doubly heavy hydrogen **atom** called **deuterium.**

3. Extract parse path between X and Y

N called N

4. Represent each noun pair as a 70,000d vector with counts for each of 70,000 parse patterns

$$P(\text{IS-A},X,Y \mid f_1,f_2,f_3,\ldots,f_{70000})$$

5. Train supervised classifier

Using Discovered Patterns to Find Novel Hyponym/Hypernym Pairs

<hypernym> *called* <hyponym>

Learned from:

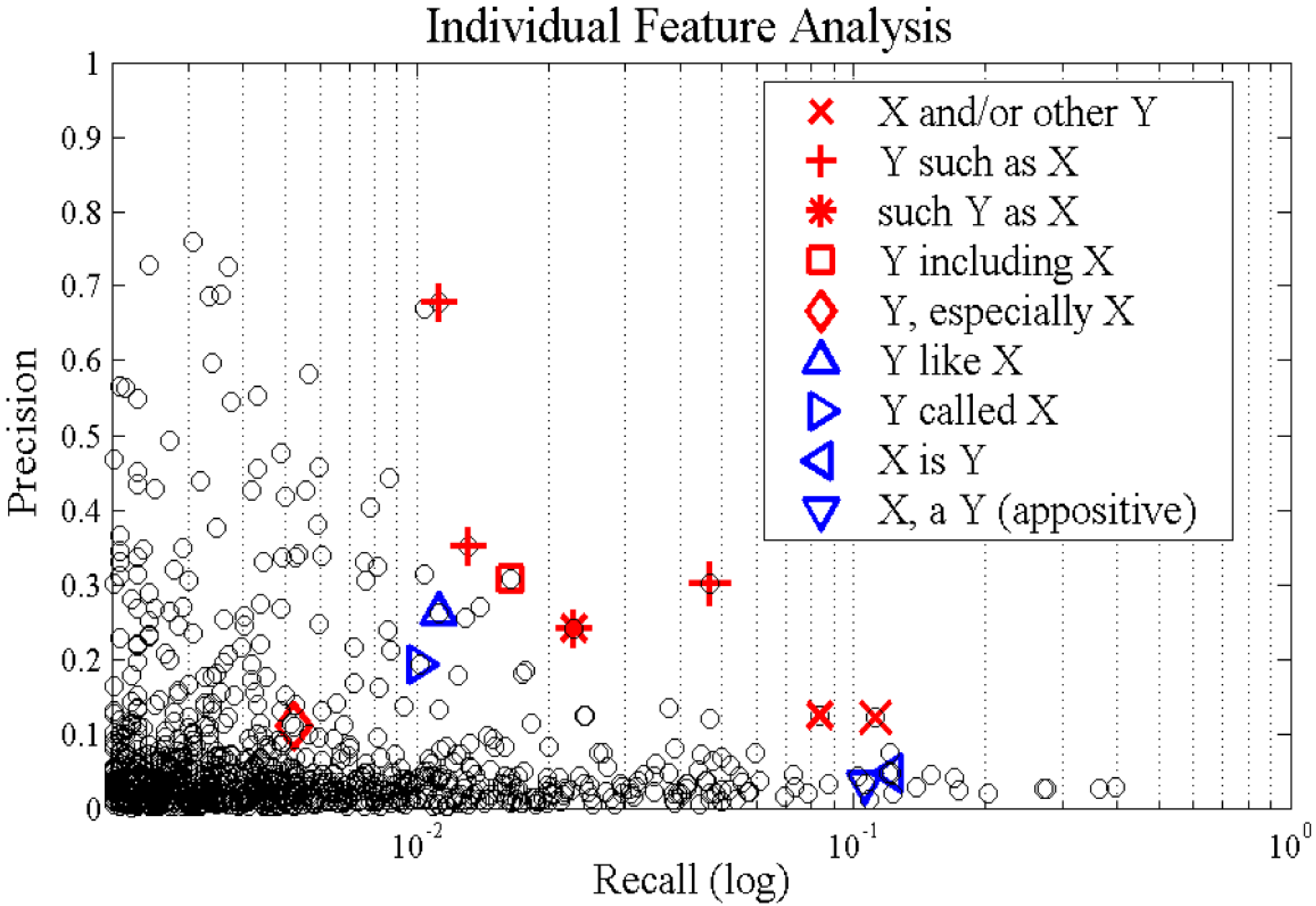
"sarcoma / cancer": …an uncommon bone **cancer called osteogenic sarcoma** and to…
"deuterium / atom" ….heavy water rich in the doubly heavy hydrogen **atom called deuterium**.

Discovers new hypernym pairs:

"*efflorescence / condition*": …and a **condition called efflorescence** are other reasons for…
"*hat_creek_outfit / ranch*" …run a small **ranch called the Hat Creek Outfit**.
"*tardive_dyskinesia / problem*": ... irreversible **problem called tardive dyskinesia**…
"*bateau_mouche / attraction*" …local sightseeing **attraction called the Bateau Mouche**…

Precision / Recall for each of the 70,000 parse patterns considered as a single classifier

Snow, Jurafsky, Ng 2005



Can even combine multiple relations

IS-A (hypernym):

Learn by distant supervision

San Francisco IS-A city IS-A municipality IS-A populated area IS-A geographic region…

Co-ordinate term (co-hyponym)

Learn by distributional similarity

Chicago, Boston, Austin, Los Angeles, San Diego

Overcoming Hypernym Sparsity with Distributional Information

Snow, Jurafsky, Ng (2006)

San Diego →

Coordinate Classifier:
“is similar to”

What is the hypernym of San Diego?

San Diego
San Francisco
Denver
Seattle
Cincinnati
Pittsburgh
New york city
Detroit
Boston
Chicago

Hypernym Classifier:
“is a kind of”

----
city

----
place, city
----
city

Learning Thesauruses and Knowledge Bases

Semi-supervised relation extraction

Summary

- Thesaurus Induction
  - Hypernymy, meronymy
- Mostly modeled as **relation extraction**
  - Pattern-based
  - Supervised
  - Semisupervised and bootstrapping
- Then combined with synonymy from distributional semantics

Computing Relations between Word Meaning: Summary from Lectures 1-6

- Word Similarity/Relatedness/Synonymy
  - Graph algorithms based on human-built Wordnet (Lec 2)
  - Learn from distributional/vector semantics (Lec 3,4)
- Word Connotation (Lec 5)
  - Human hand-labeled
  - Supervised from Reviews
  - Semisupervised from seed words
- Hypernymy (IS-A) (Lec 6)
  - Modeled as relation extraction
    - Supervised, semisupervised