Information Extraction

Lecture 8 – Relation Extraction

CIS, LMU München

Winter Semester 2015-2016

Dr. Alexander Fraser, CIS

Relation Extraction

- Up until now we have focused on early stages of the Information Extraction pipeline
  - We have emphasized named entity tagging
- Now we will discuss extracting facts about these entities
  - This can include IS-A facts (similar to named entity types), but also more complicated relations

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

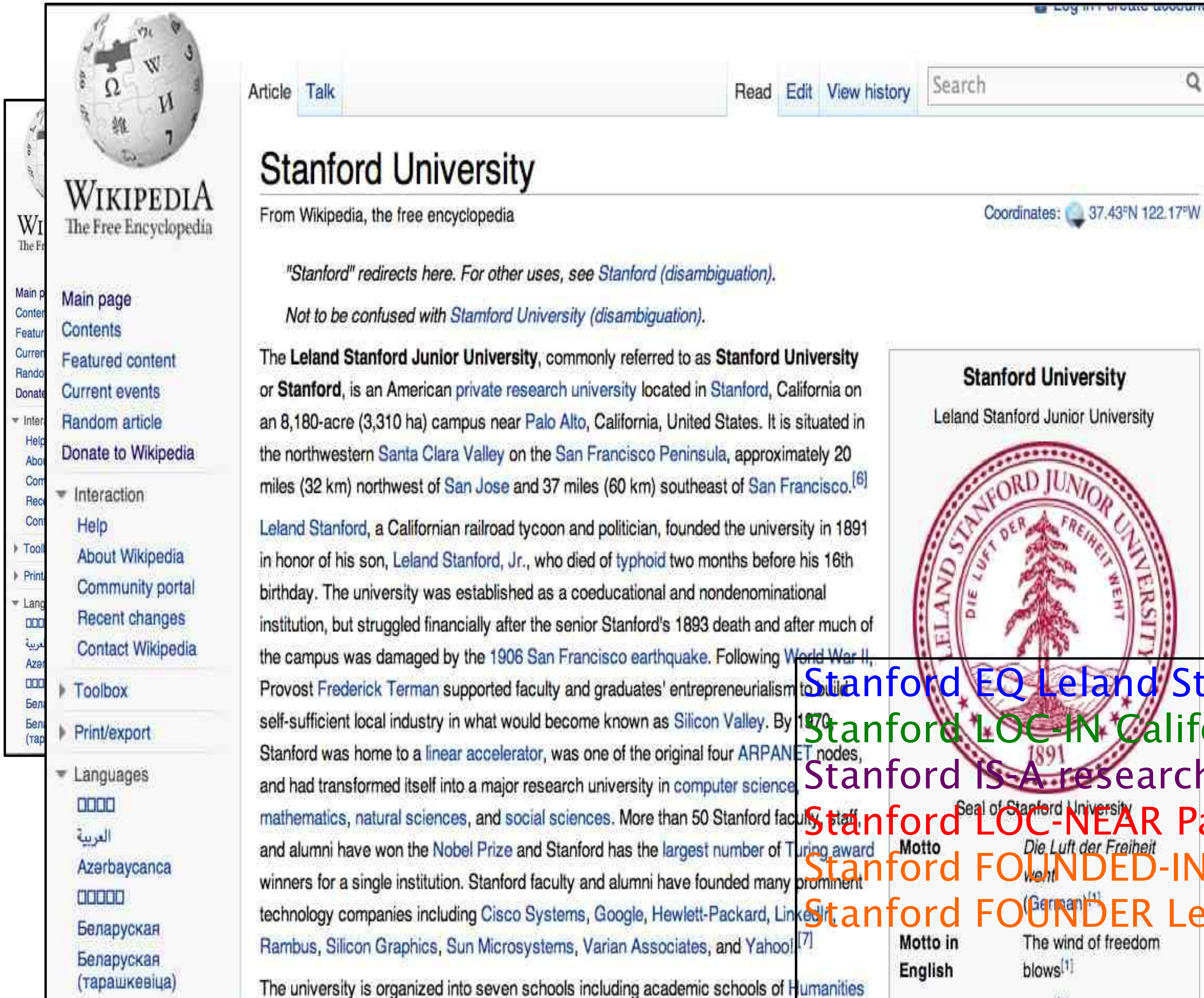
Company	IBM
Location	New York
Date	June 16, 1911
Original-Name	Computing-Tabulating-Recording Co.

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

  Founding-year(IBM, 1911)

  Founding-location(IBM, New York)

Extracting Relation Triples from Text


Article Talk Read Edit View history Search

Stanford University

From Wikipedia, the free encyclopedia

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

Not to be confused with Stanford 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

Stanford University

Leland Stanford Junior University

Motto: Die Luft der Freiheit weht (German)[1]

Motto in English: The wind of freedom blows[1]

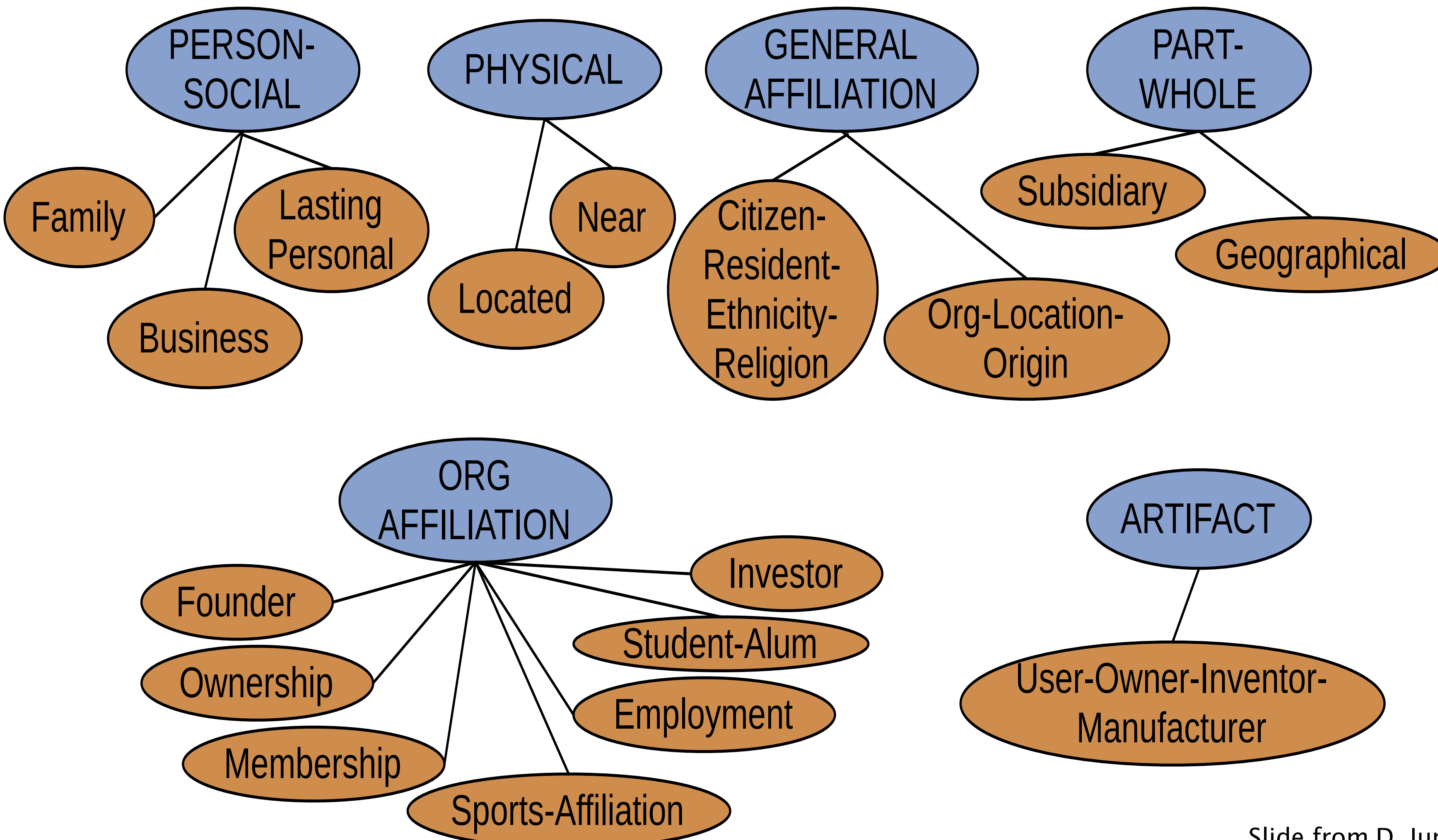
d Junior University,
to as Stanford
ord, is an American
iversity located in
… near Palo Alto,
Stanford…founded
91

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

Slide from D. Jurafsky

Automated Content Extraction (ACE)

17 relations from 2008 “Relation Extraction Task”



Slide from D. Jurafsky

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…

-

Slide from D. Jurafsky

UMLS: Unified Medical Language System

- 134 entity types, 54 relations

Injury	disrupts	Physiological Function
Bodily Location	location-of	Biologic Function
Anatomical Structure	part-of	Organism
Pharmacologic Substance	causes	Pathological Function
Pharmacologic Substance	treats	Pathologic Function

Slide from D. Jurafsky

Extracting UMLS relations from a sentence

Doppler echocardiography can be used to diagnose left anterior descending artery stenosis in patients with type 2 diabetes

↓

Echocardiography, Doppler DIAGNOSES Acquired stenosis

Slide from D. Jurafsky

Databases of Wikipedia Relations

Wikipedia Infobox

Relations extracted from Infobox
Stanford state California
Stanford motto “Die Luft der Freiheit weht”

```
{{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 | accessd
|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

Slide from D. Jurafsky

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

Patterns for Relation Extraction

- Hand-written rules for relation extraction were used in MUC (such as the Fastus system)
- Recently there has been a renewed wide interest in learning rules for relation extraction focused on precision
  - The presumption is that interesting information occurs many times on the web, with different contexts
    - e.g., how many times does "Barack Obama is the 44th President of the United States" occur on the web?
  - Focusing on high precision is reasonable because the high redundancy will allow us to deal with recall

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?`

Slide from D. Jurafsky

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?`

Slide from D. Jurafsky

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"

Slide from D. Jurafsky

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...

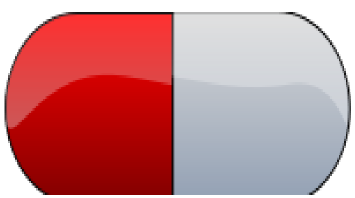
Slide from D. Jurafsky

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!

Slide from D. Jurafsky

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



Drug

Cure?

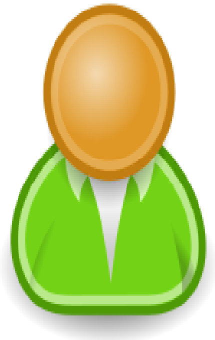
Prevent?

Cause?

Disease

Slide from D. Jurafsky

What relations hold between 2 entities?



PERSON

Founder?

Investor?

Member?

Employee?

President?

ORGANIZATION

Slide from D. Jurafsky

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

Slide from D. Jurafsky

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 Methods

- For named entity tagging, statistical taggers are the state of the art
- However, for relation extraction, this is not necessarily true
  - Still many hand-crafted rule-based systems out there that work well
  - But hand-crafting such systems takes a lot of work, so classification approaches are very interesting (and they are improving with time)
- I'll now discuss how to formulate relation extraction as a supervised classification problem

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

Slide from D. Jurafsky

How to do classification in supervised relation extraction

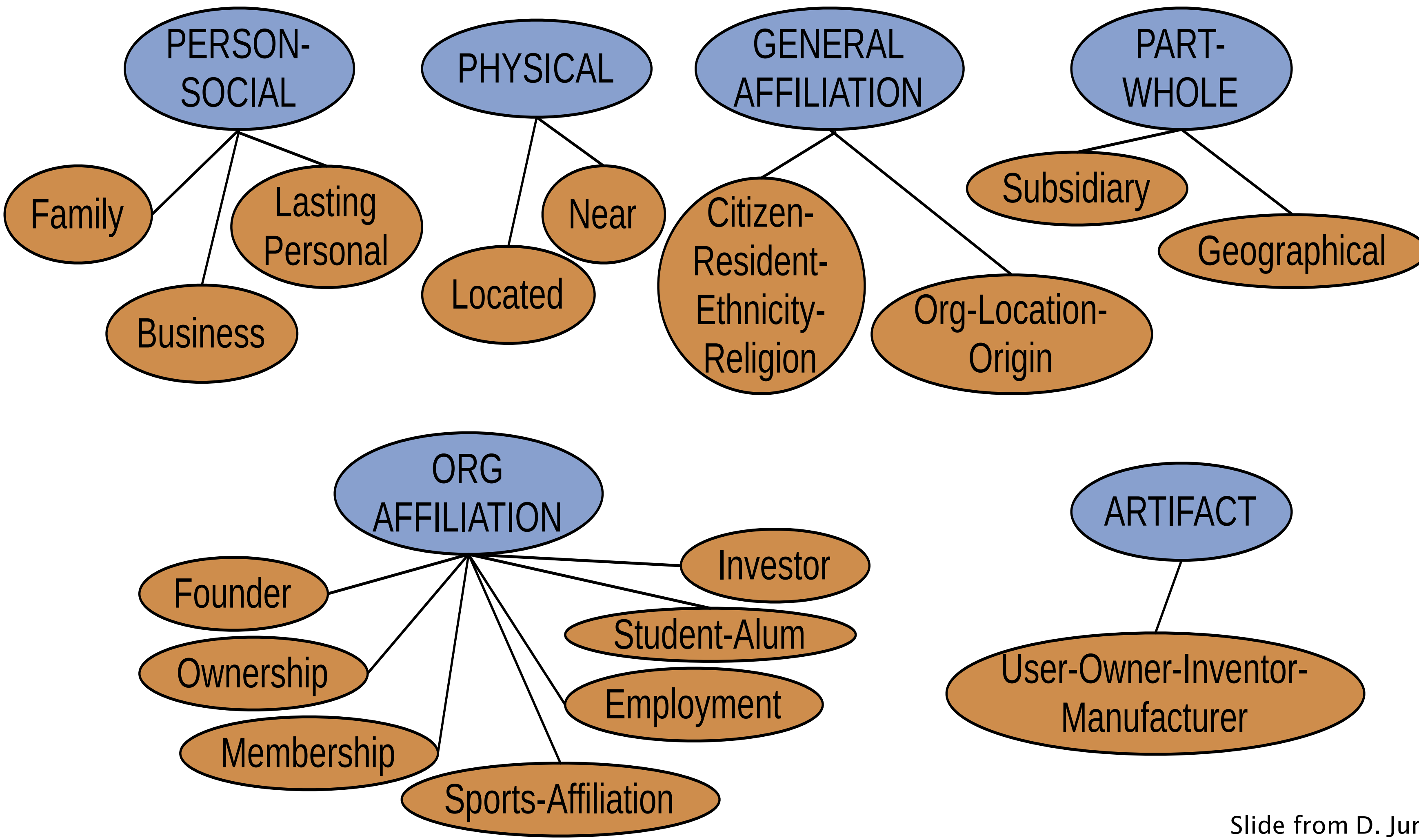
1. Find all pairs of named entities (usually in same sentence)
2. Decide if 2 entities are related
3. If yes, classify the relation

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

Slide from D. Jurafsky

Automated Content Extraction (ACE)

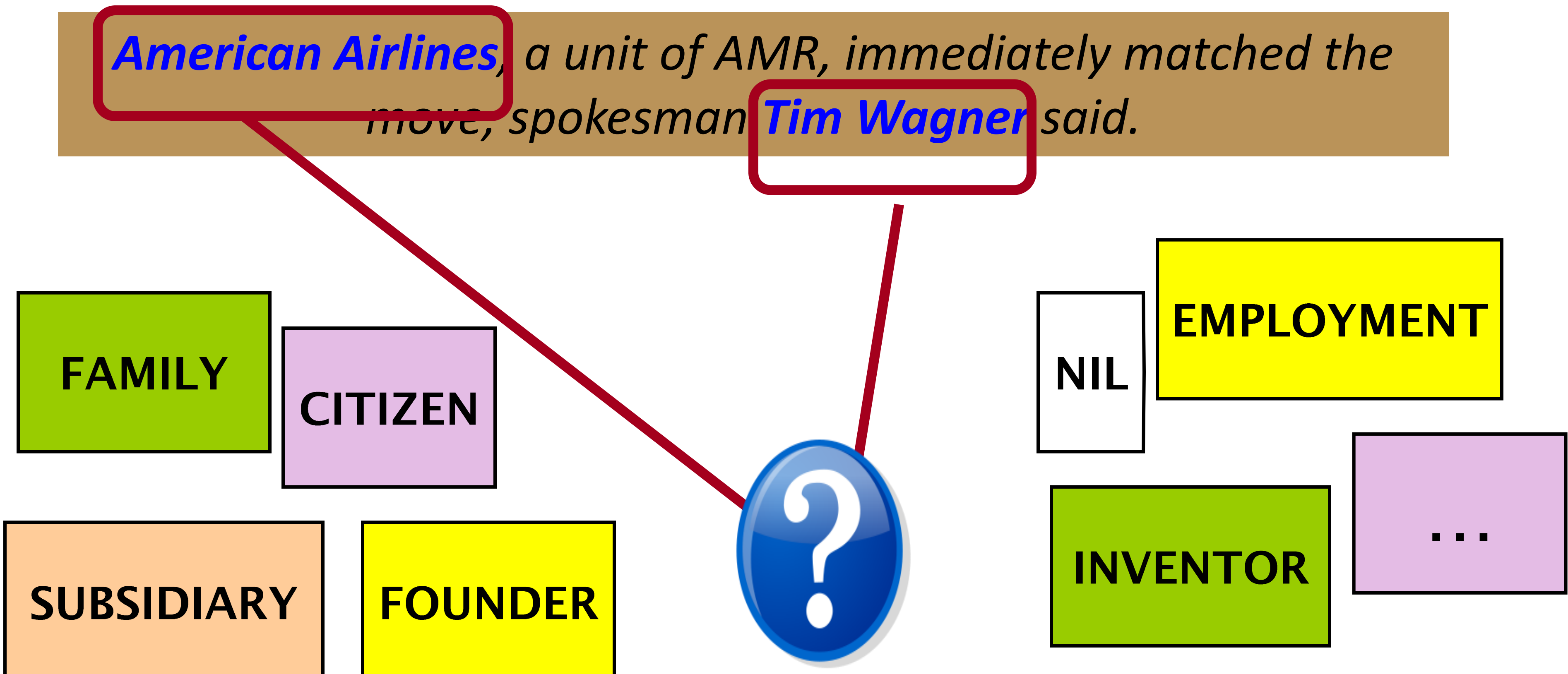
17 sub-relations of 6 relations from 2008 "Relation Extraction Task"



Slide from D. Jurafsky

Relation Extraction

Classify the relation between two entities in a sentence



Slide from D. Jurafsky

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}

Slide from D. Jurafsky

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]

Slide from D. Jurafsky

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

Slide from D. Jurafsky

Gazetteer and trigger word features for relation extraction

- Trigger list for family: kinship terms
  - parent, wife, husband, grandparent, etc. [from WordNet]
- Gazetteer:
  - 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	$Airlines \leftarrow_{subj} matched \leftarrow_{comp} said \rightarrow_{subj} Wagner$

Slide from D. Jurafsky

Classifiers for supervised methods

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

Slide modified from D. Jurafsky

Evaluation of Supervised Relation Extraction

- Compute P/R/F_1 for each relation

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

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

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

Slide from D. Jurafsky

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 domains (topics and genres)

Slide modified from D. Jurafsky

Semi-Supervised Methods

- We'd like to minimize our reliance on having a large training set
- Instead, given a few examples or a few high-precision patterns, we'd like to generalize
  - This is sometimes referred to as "bootstrapping"

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

Slide from D. Jurafsky

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

Slide from D. Jurafsky

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

- Slide sources
  - Most of the slides today came from a lecture of Dan Jurafsky's in Chris Manning and Dan Jurafsky's online NLP course at Stanford (covers very broad range of NLP and Machine Learning topics)

- (Last words on next slide)

Last words

- As discussed in Sarawagi, traditional IE and web-based IE differ
  - Traditional IE: find relation between entities in one text (think of CMU Seminars for instance)
  - Web IE: find relation between "real-world" entities. Relations may occur on many different pages expressed in different ways
  - There are also tasks that are in between these two extremes
- Event extraction is like relation extraction
  - The difference is that we fill out templates
  - We have seen examples of these templates several times (for instance: outbreak – location – date)
  - We'll see more on event extraction next time

- Thank you for your attention!