Natural Language Processing
Session 5

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Session 5 Agenda

- Information extraction
- Named entity recognition
- Relation extraction
  - Automatic content extraction annotation guidelines for entities
- Natural language parsing
- Dependency parsing

Information Extraction and Named Entity Recognition

Introducing the tasks:

Getting simple structured information out of text

Information Extraction

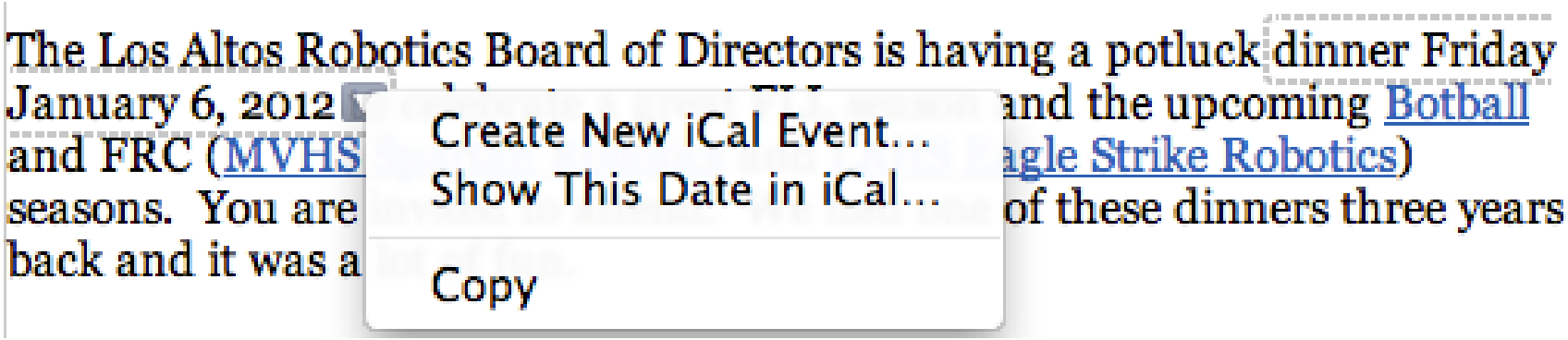
- Information extraction (IE) systems
  - Find and understand limited relevant parts of texts
  - Gather information from many pieces of text
  - Produce a structured representation of relevant information:
    - *relations* (in the database sense), a.k.a.,
    - a *knowledge base*
  - Goals:
    1. Organize information so that it is useful to people
    2. Put information in a semantically precise form that allows further inferences to be made by computer algorithms

Information Extraction (IE)

- IE systems extract clear, factual information
  - Roughly: *Who did what to whom when?*
- 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 product interactions from medical research literature

Low-level information extraction

- Is now available – and I think popular – in applications like Apple or Google mail, and web indexing



- Often seems to be based on regular expressions and name lists

Low-level information extraction

Google bhp billiton headquarters

Search About 123,000 results (0.23 seconds)

Everything
Images
Maps
Videos
News
Shopping

Best guess for BHP Billiton Ltd. Headquarters is Melbourne, London

Mentioned on at least 9 websites including wikipedia.org, bhpbilliton.com and bhpbilliton.com - Feedback

BHP Billiton - Wikipedia, the free encyclopedia
en.wikipedia.org/wiki/**BHP_Billiton**
Merger of BHP & Billiton 2001 (creation of a DLC). **Headquarters**, **Melbourne, Australia** (**BHP Billiton** Limited and **BHP Billiton** Group) **London, United Kingdom** ...
History - Corporate affairs - Operations - Accidents

As Google matured from rules to ML / AI

Exercise

What are the top 20 main **characters** (people) and **locations** in the “Book_CMC_AD” book?

And how frequently were they mentioned?

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.

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Person
Date
Location
Organi-
zation

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.
    - Reuters' OpenCalais, Evri, IBM NLU, Yahoo's Term Extraction, …
  - Apple/Google/Microsoft/… smart recognizers for document content

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 …
- This counts as both a fp and a fn
- Selecting *nothing* would have been better
- Some other metrics (e.g., MUC scorer) give partial credit (according to complex rules)

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

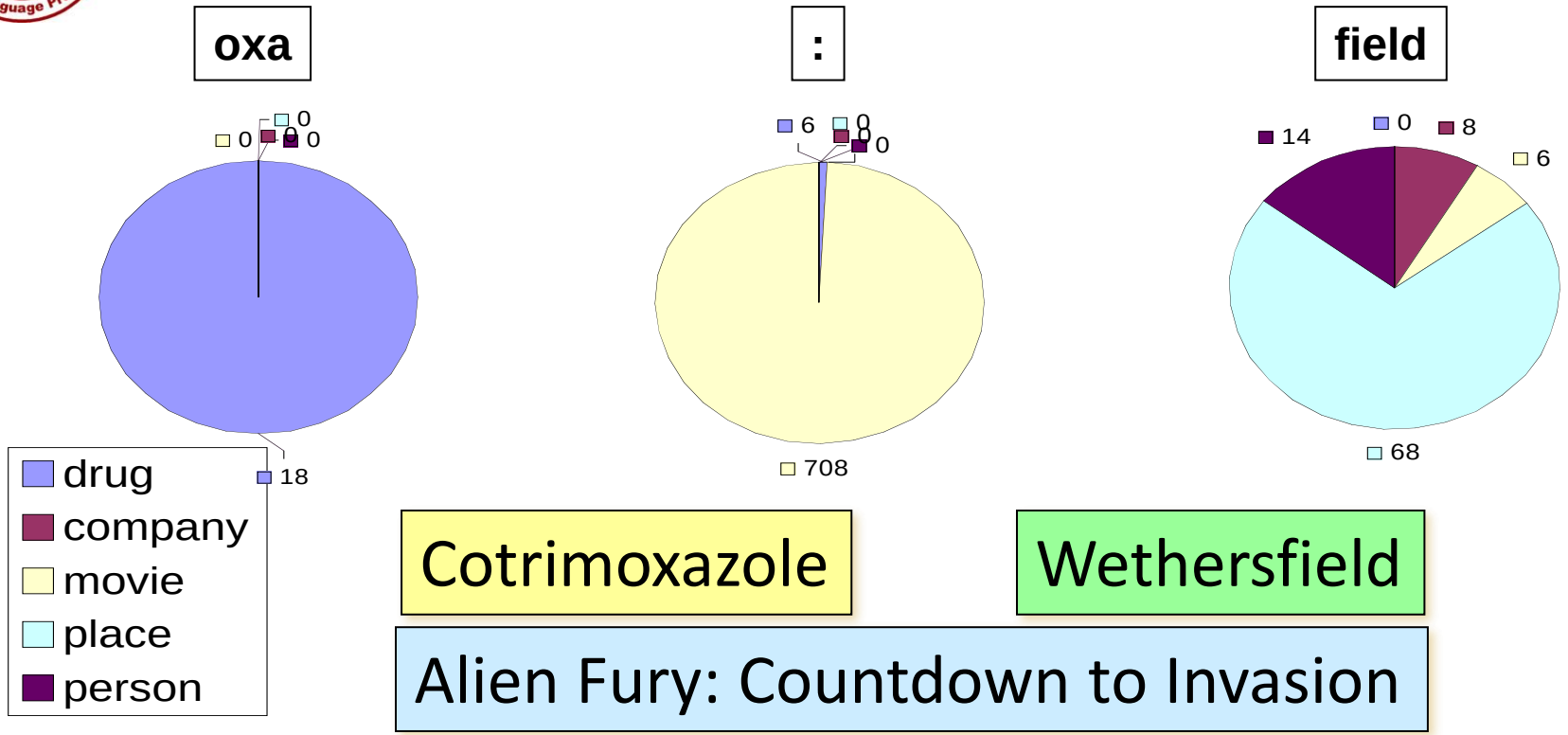
	IO encoding	IOB encoding
Fred	PER	B-PER
showed	O	O
Sue	PER	B-PER
Mengqiu	PER	B-PER
Huang	PER	I-PER
‘s	O	O
new	O	O
painting	O	O

B-PER indicates the beginning of a person name, *I-PER* indicates inside a person name, and so forth

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



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

NER in Python

Relation Extraction

What is relation extraction?

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

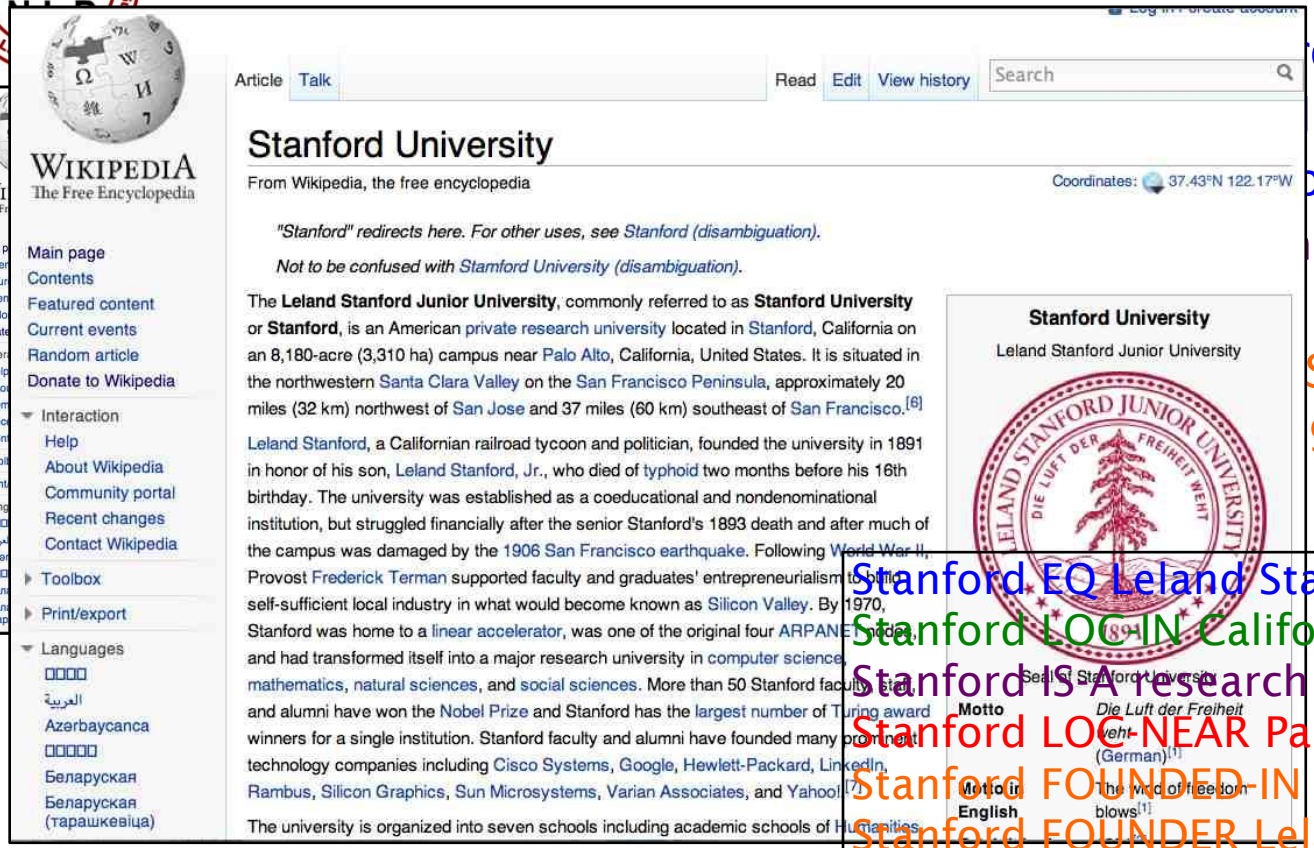
Company	IBM
Location	New York
Date	June 16, 1911
Original-Name	Computing-Tabulating-Recording Co.

- 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



...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

Why Relation Extraction?

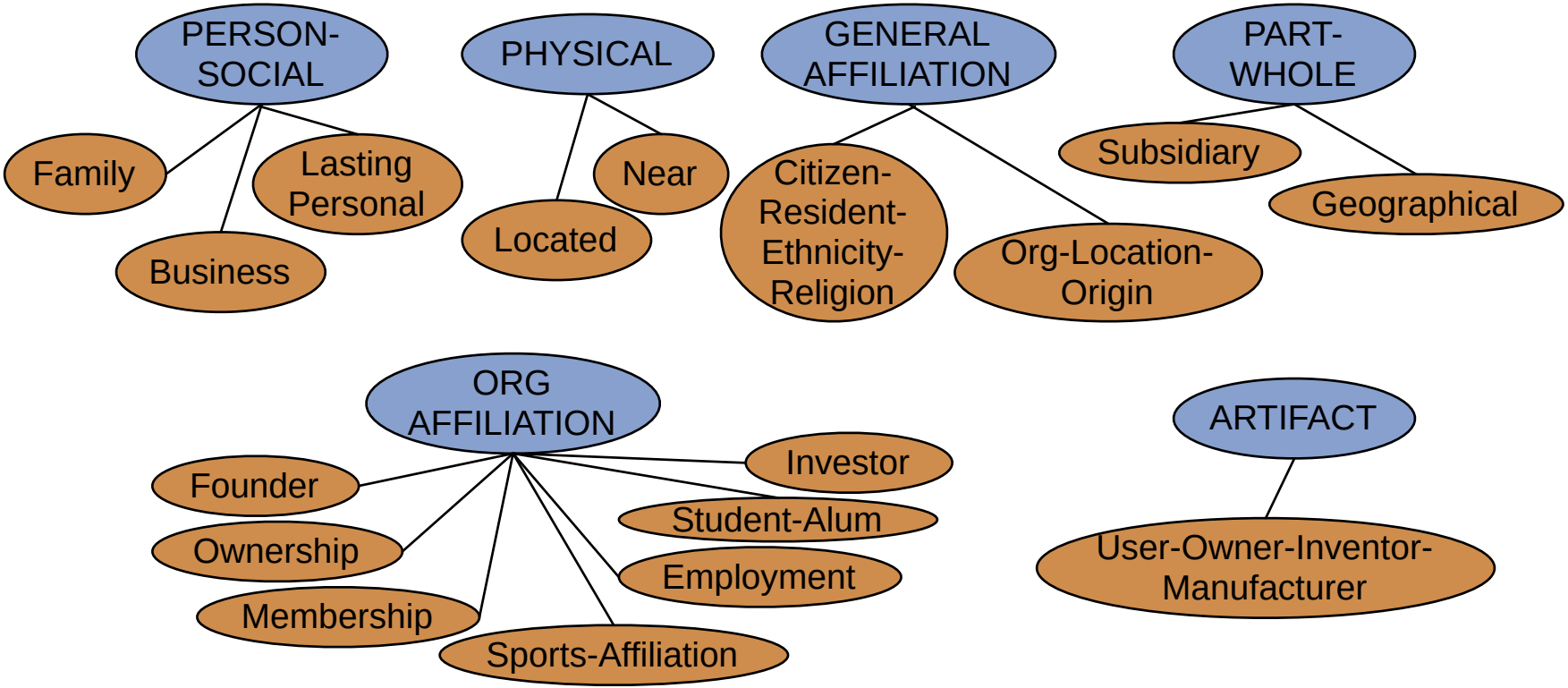
- Create new structured knowledge bases, useful for any app
- Augment current knowledge bases
  - Adding words to WordNet thesaurus, facts to FreeBase or DBPedia
- Support question answering
  - The granddaughter of which actor starred in the movie “E.T.”?

```
(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…

Persons (PER)
Geographical (GPE)
Organizations (ORG)

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

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

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
Casper|first=Gerhard|last=Casper|author
05|url=http://www.stanford.edu/dept/pr
|mottoeng = The wind of freedom blows<
|established = 1891<ref>{{cite web |
url=http://www.stanford.edu/home/stan
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”

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

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`

Relation Extraction

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

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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

Dan 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

Hand-built patterns for relations

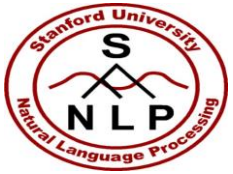
- Plus:
  - Human patterns tend to be high-precision
  - Can be tailored to specific domains
- Minus
  - Human patterns are often low-recall
  - A lot of work to think of all possible patterns!
  - Don’t want to have to do this for every relation!
  - We’d like better accuracy

Relation Extraction in Python

Dependency Parsing

Introduction

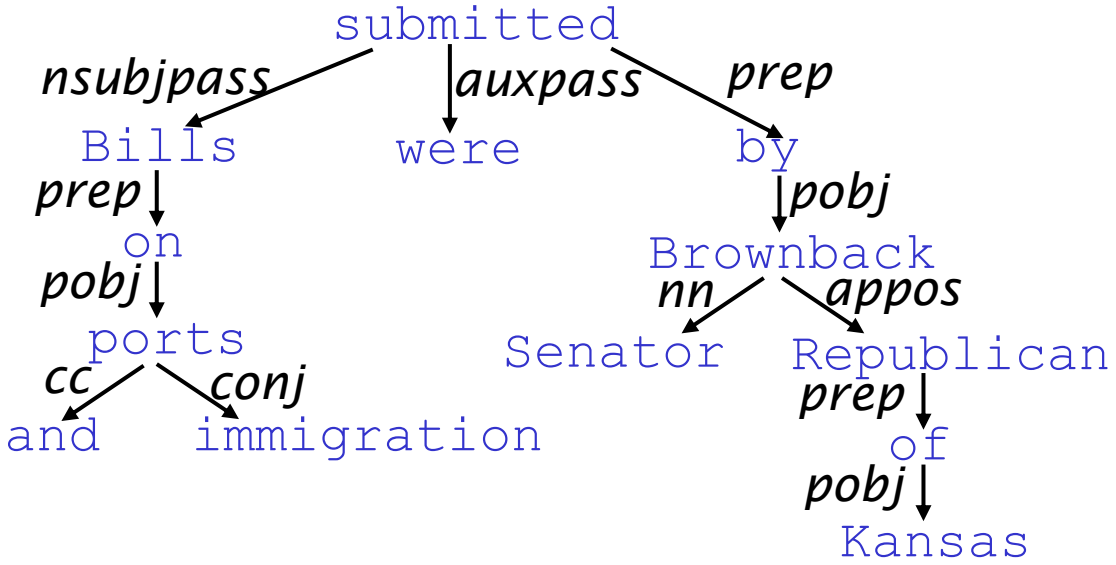
Christopher Manning



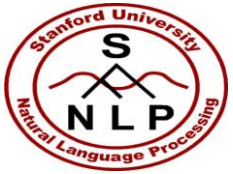
Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of lexical items linked by binary asymmetric relations ("arrows") called dependencies

The arrows are commonly typed with the name of grammatical relations (subject, prepositional object, apposition, etc.)



Christopher Manning



Dependency Grammar and Dependency Structure

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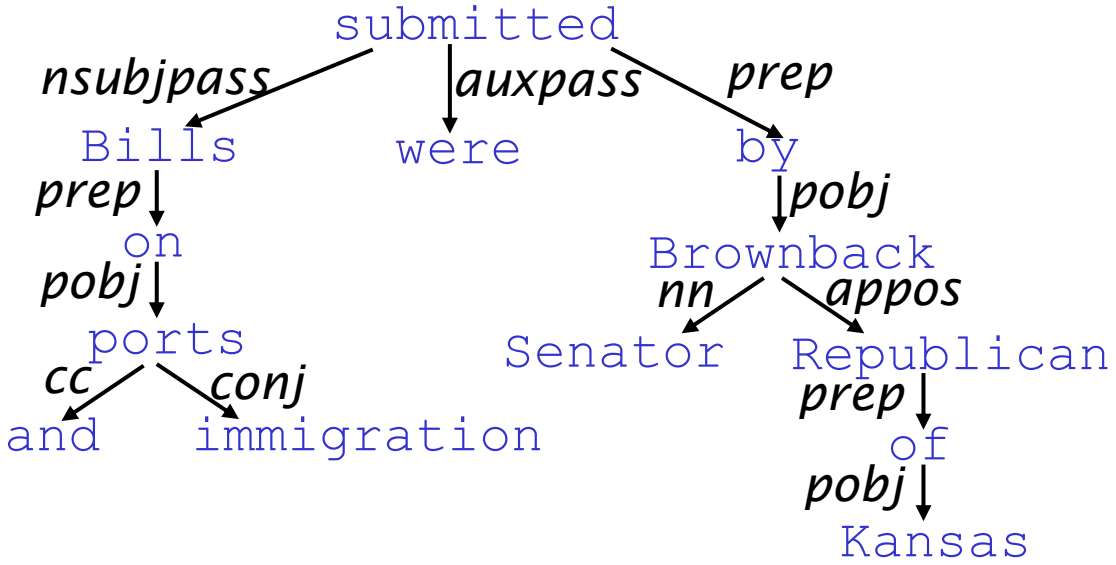
The arrow connects a head (governor, superior, regent) with a dependent (modifier, inferior, subordinate)

Usually, dependencies form a tree (connected, acyclic, single-head)



Dependency Parsing in Python

Watson NLU Demo

Thank You!