Text Mining

Week 6

(D. Jurafsky and C. Manning)

Information Extraction

- Finding structured information from unstructured (or lightly structured) 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

Example

WASHINGTON — Senate Republicans on Sunday kept up the drumbeat of blame against President Obama for what they say is his failure to negotiate with them on the fiscal crisis that will come to a head on Thursday, when the government will run out of money to pay its bills. As the Republicans pointed fingers at the White House, Senators Harry Reid and Mitch McConnell were set to sit down again on Sunday in an effort to come up with some sort of agreement — even one that will kick the most pressing problems down the road for a few weeks or months.

- Names: "Senate Republicans", "President Obama", "the Republicans", "the White House", "Senators Harry Reid", "Mitch McConnell"
- Entity Linking: e1={"Senate Republicans", "the Republicans"}, e2={"President Obama", "his", "the White House"}
- Title: title("President", "Obama"), title("Senator", "Harry Reid"), title("Senator", "Mitch McConnell")
- "Blame" Event: "X kept up the drumbeat of blame against Y", "X pointed fingers at Y".

http://www.nytimes.com/2013/10/14/us/politics/budget-and-debt-limit-debate.html?hp

Factoid Questions as Google Queries

Overview

- Name Tagging
  - sequence models for Name tagging
  - pattern learning
- co-reference resolution
- Slot Filling
- Bootstrapping
- Distant supervision

Name Tagging

- Identify the “Named Entities” in text.
  - Named Entity Recognition (NER)
- People
- Organizations including companies, teams, etc.
- Locations and/or Geo-political Entities (GPE)

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, AlchemyAPI, Yahoo's Term Extraction, …
  - Apple/Google/Microsoft/… smart recognizers for document content

Named Entity Recognition (NER)

- Initially, NAMED entities: People names, Locations, Company names, etc.
- What it is the first, most straight-forward feature?

- Now, more general: protein names, drug names, etc.

Information Extraction and Named Entity Recognition

The Named Entity Recognition Task ~ sequence labeling

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

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 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

Sequence Models for Named Entity Recognition

Maximum entropy sequence models

Maximum entropy Markov models (MEMMs) or Conditional Markov 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 one of labeling each item

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

POS tagging

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

Named entity recognition

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

Word segmentation

Text segmen-tation

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 usually explored via search

Local Context

Decision Point

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

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

Features

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

Example: POS Tagging

- Scoring individual labeling decisions is no more complex than standard classification decisions
  - We have some assumed labels to use for prior positions
  - We use features of those and the observed data (which can include current, previous, and next words) to predict the current label

Local Context

Decision Point

-3	-2	-1	0	+1
DT	NNP	VBD	???	???
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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	%

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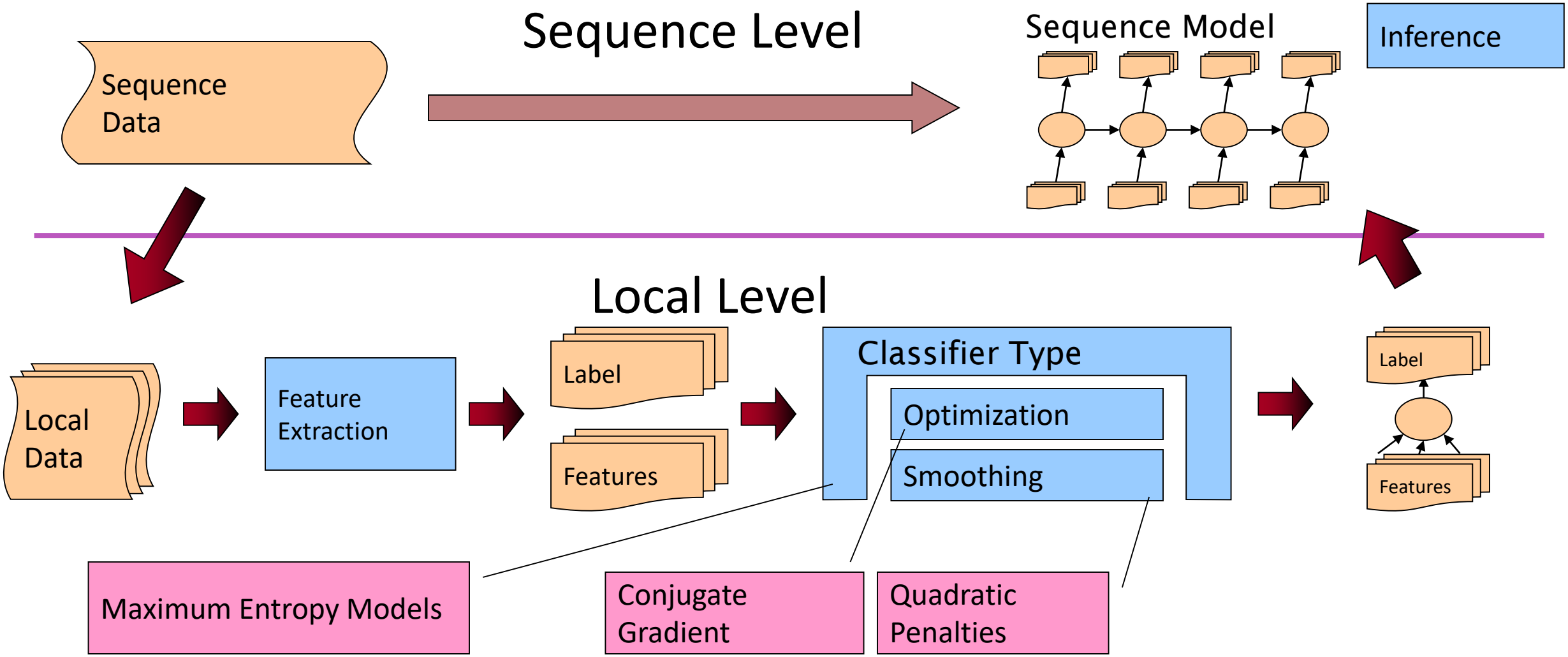
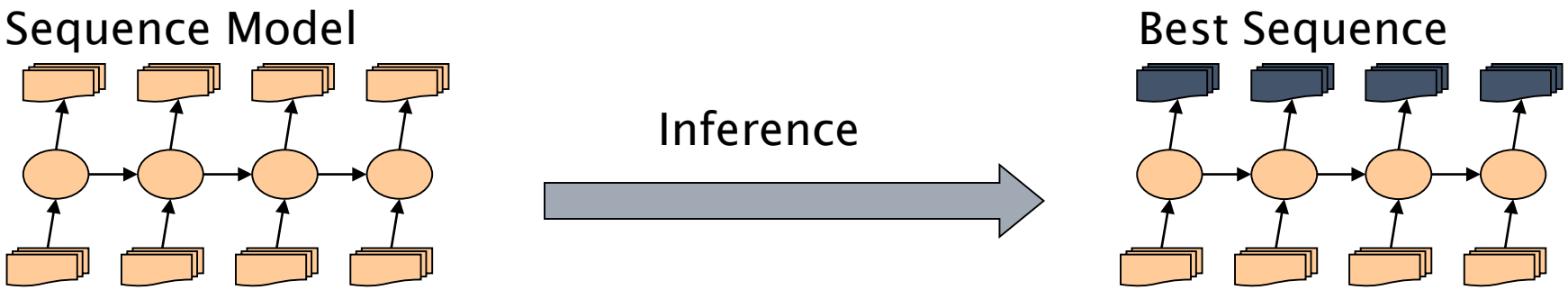
Inference in Systems



Sequence Labeling

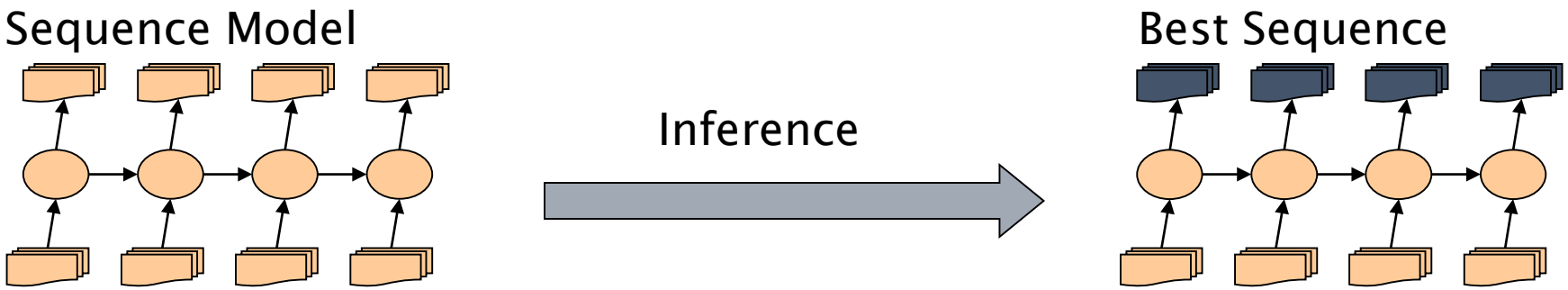
- Greedy
- Beam
- Viterbi

Greedy Inference



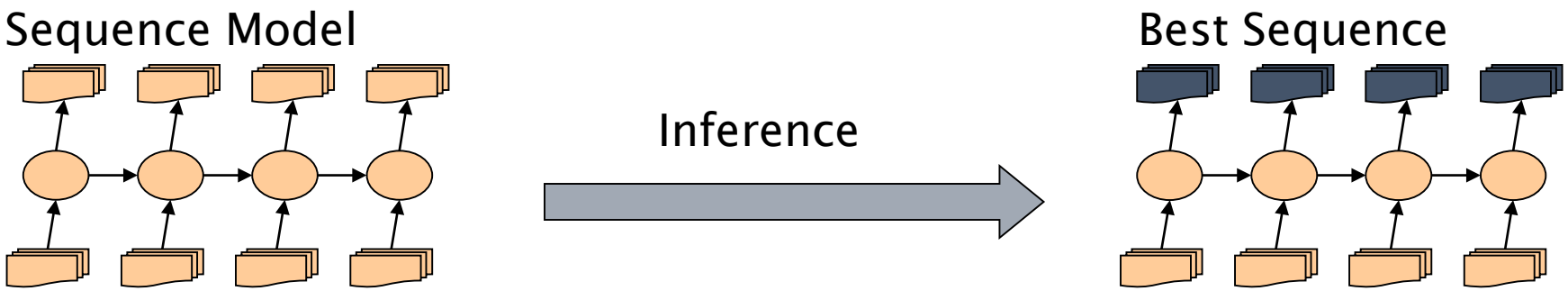
- Greedy inference:
  - We just start at the left, and use our classifier at each position to assign a label
  - The classifier can depend on previous labeling decisions as well as observed data
- Advantages:
  - Fast, no extra memory requirements
  - Very easy to implement
  - With rich features including observations to the right, it may perform quite well
- Disadvantage:
  - Greedy. We make commit errors we cannot recover from

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; beam sizes of 3–5 are 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).

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 slower, 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 … but in practice usually work much the same as MEMMs.

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

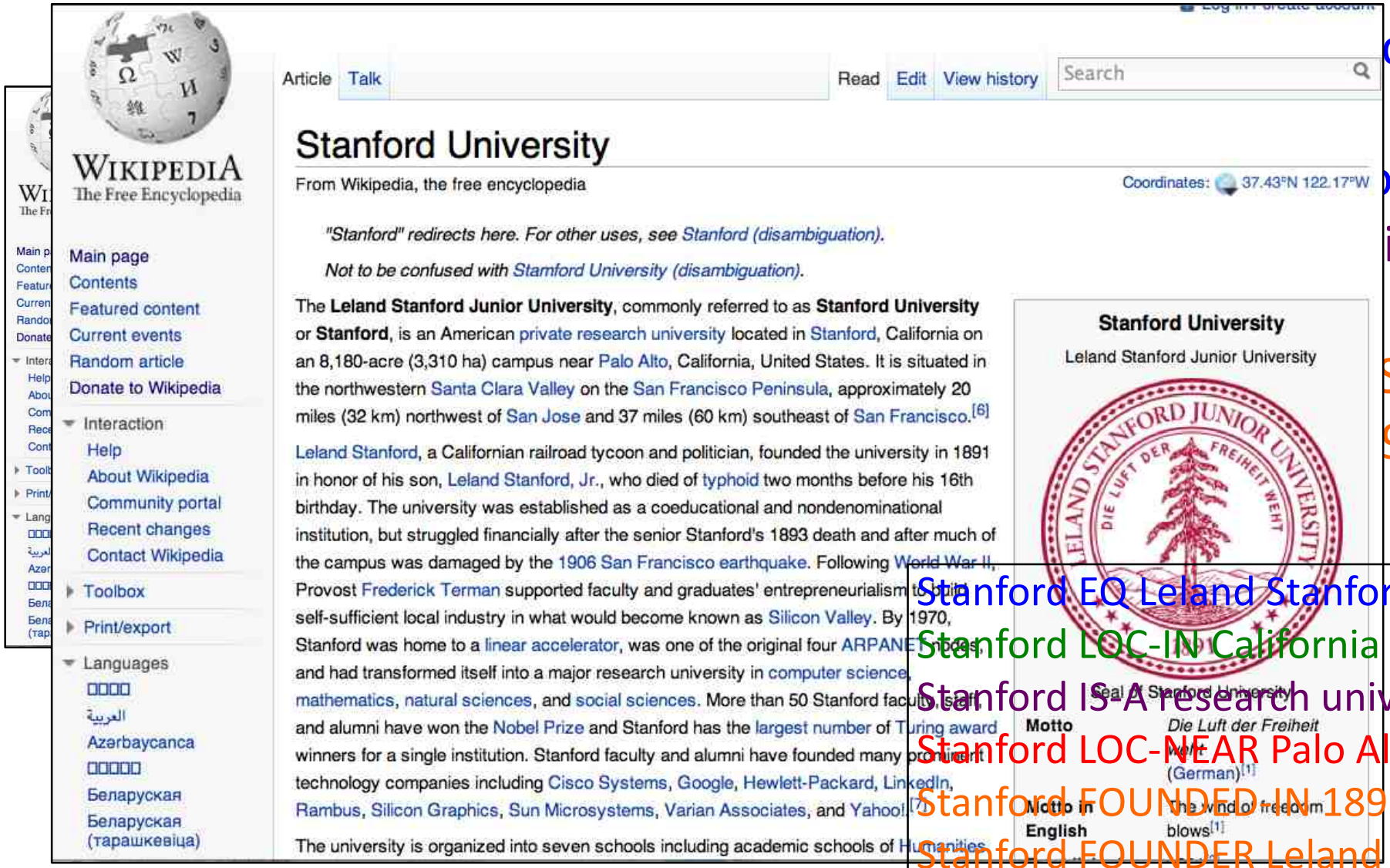
Company	IBM
Location	New York
Date	June 16, 1911
Original-Name	Computing-Tabulating-Recording Co.

- 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
rd, 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.”?

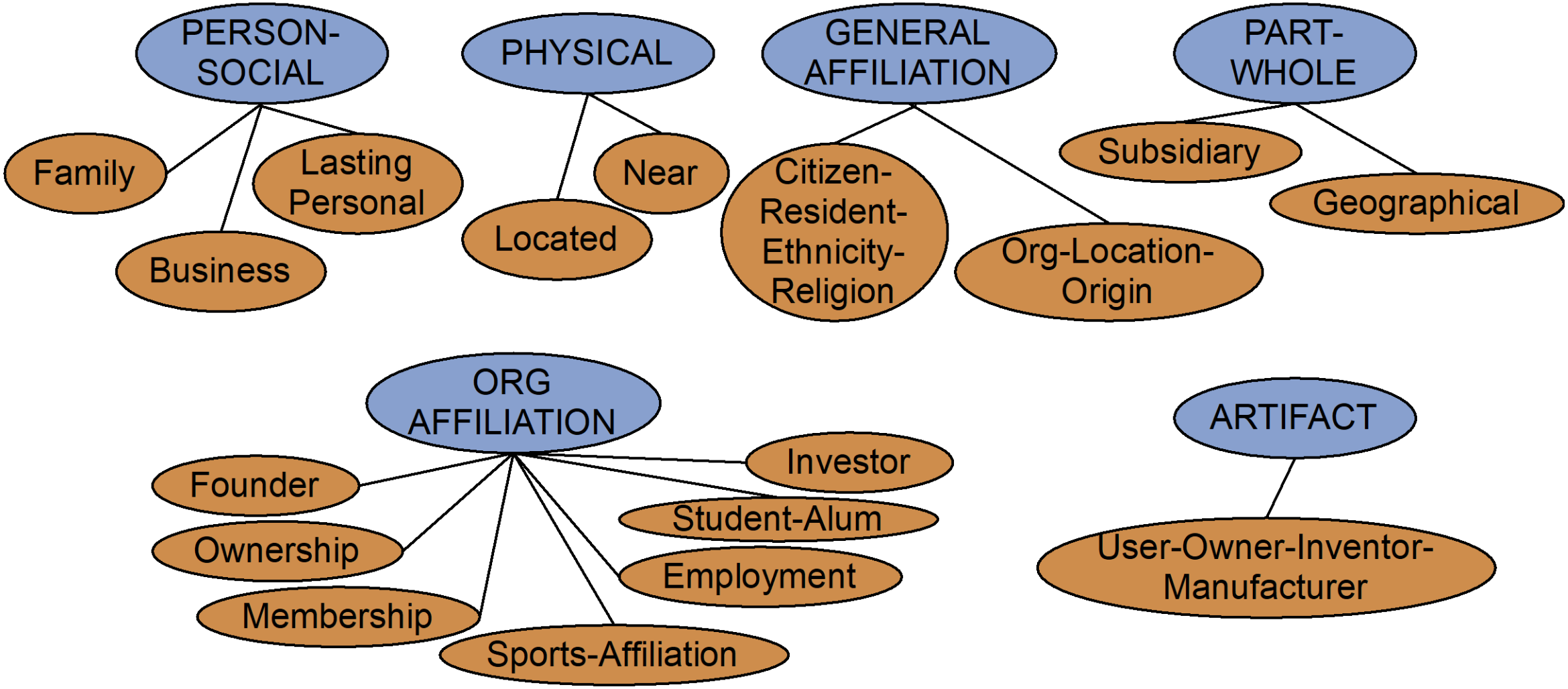
```
(acted-in ?x “E.T.”)(is-a ?y actor)(granddaughter-of ?x ?y)
```

- But which relations should we extract?

Automated Content Extraction (ACE)

17 relations from 2008 “Relation Extraction Task”

Does it remind anything to the CS people?



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…
-

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,
  people/person/profession,
  biology/organism_higher_classification

  location/location/contains
  people/person/place-of-birth
  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`

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

Relation Extraction

What is relation extraction?

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

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

Relation Extraction

Using patterns to extract relations

Relation Extraction

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

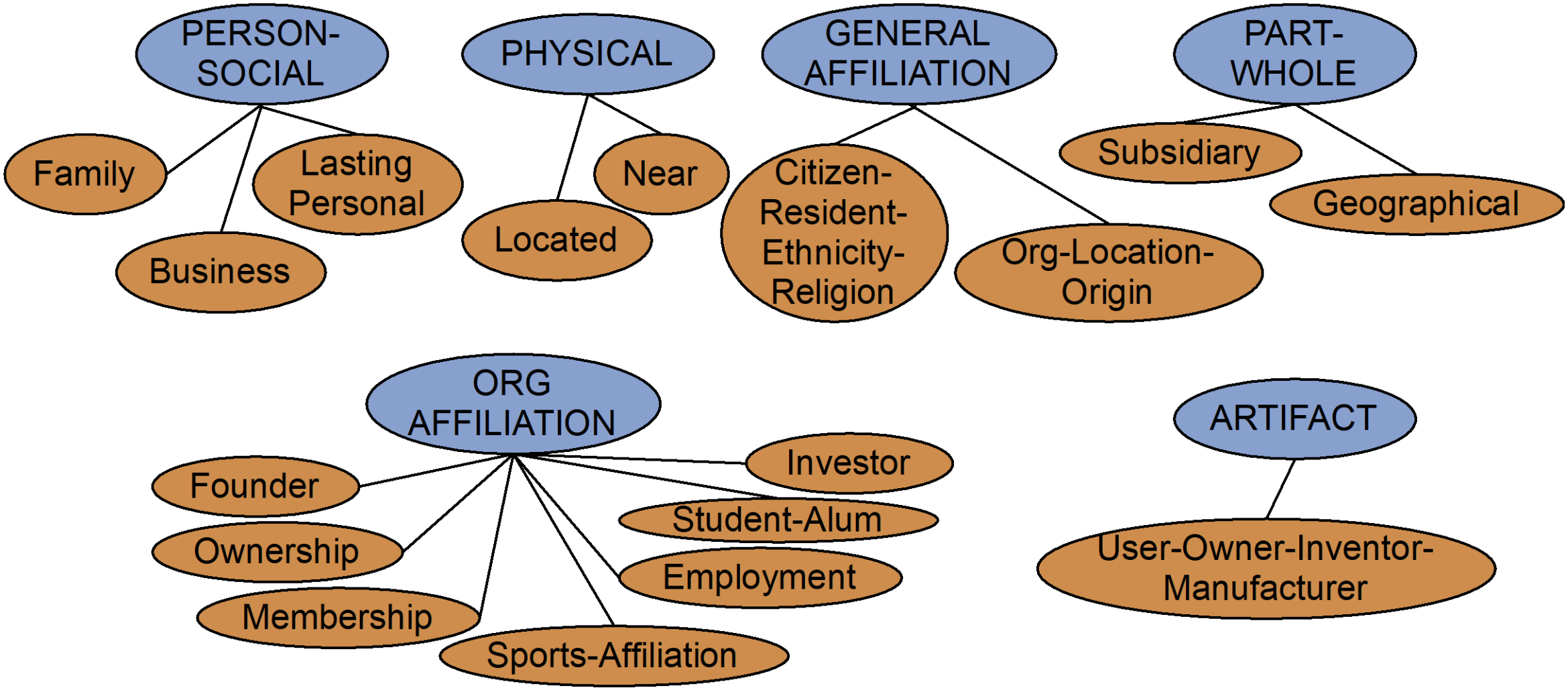
How to do classification in supervised relation extraction

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.

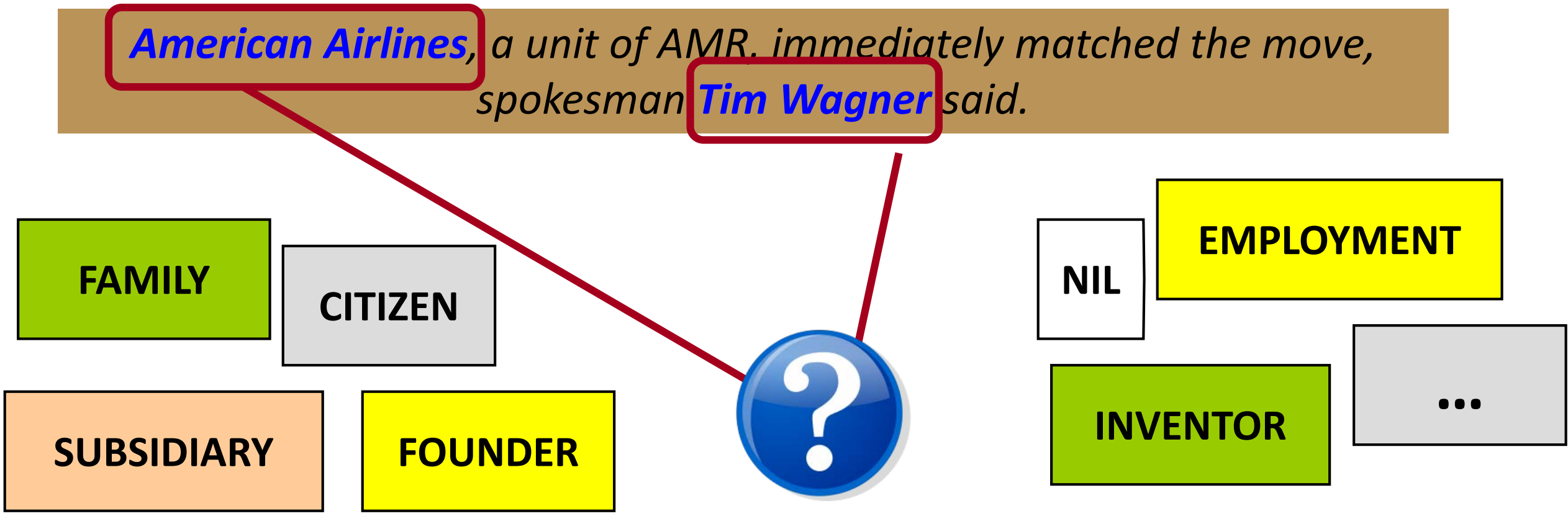
Automated Content Extraction (ACE)

17 sub-relations of 6 relations from 2008 “Relation Extraction Task”



Relation Extraction

Classify the relation between two entities in a sentence



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

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
  - 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

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

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

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

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

Relation Extraction

Supervised relation extraction

Relation Extraction

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 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 Wikipeida. 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

2. For each tuple in big database

3. Find sentences in large corpus with both entities

4. Extract frequent features (parse, words, etc)

5. Train supervised classifier using thousands of patterns

Born-In

<Edwin Hubble, Marshfield>
<Albert Einstein, Ulm>

Hubble was born in Marshfield

Einstein, born (1879), Ulm

Hubble's birthplace in Marshfield

PER was born in LOC

PER, born (XXXX), LOC

PER's birthplace in LOC

$$P(\text{born-in} \mid f_1, f_2, f_3, \ldots, f_{70000})$$

Unsupervised relation extraction

M. Banko, M. Cararella, S. Soderland, M. Broadhead, and O. Etzioni. 2007. Open information extraction from the web. IJCAI

- Open Information Extraction:
  - extract relations from the web with no training data, no list of relations

1. Use parsed data to train a “trustworthy tuple” classifier
2. Single-pass extract all relations between NPs, keep if trustworthy
3. Assessor ranks relations based on text redundancy

(FCI, specializes in, software development)

(Tesla, invented, coil transformer)

Evaluation of Semi-supervised and Unsupervised Relation Extraction

- Since it extracts totally new relations from the web
  - There is no gold set of correct instances of relations!
    - Can't compute precision (don't know which ones are correct)
    - Can't compute recall (don't know which ones were missed)
- Instead, we can approximate precision (only)
  - Draw a random sample of relations from output, check precision manually

$$\hat{P} = \frac{\#\text{ of correctly extracted relations in the sample}}{\text{Total }\#\text{ of extracted relations in the sample}}$$

- Can also compute precision at different levels of recall.
  - Precision for top 1000 new relations, top 10,000 new relations, top 100,000
  - In each case taking a random sample of that set
- But no way to evaluate recall

Embedding Methods for NLP (tutorial)

- http://emnlp2014.org/tutorials/8_notes.pdf
- (IE starts at slide 43)

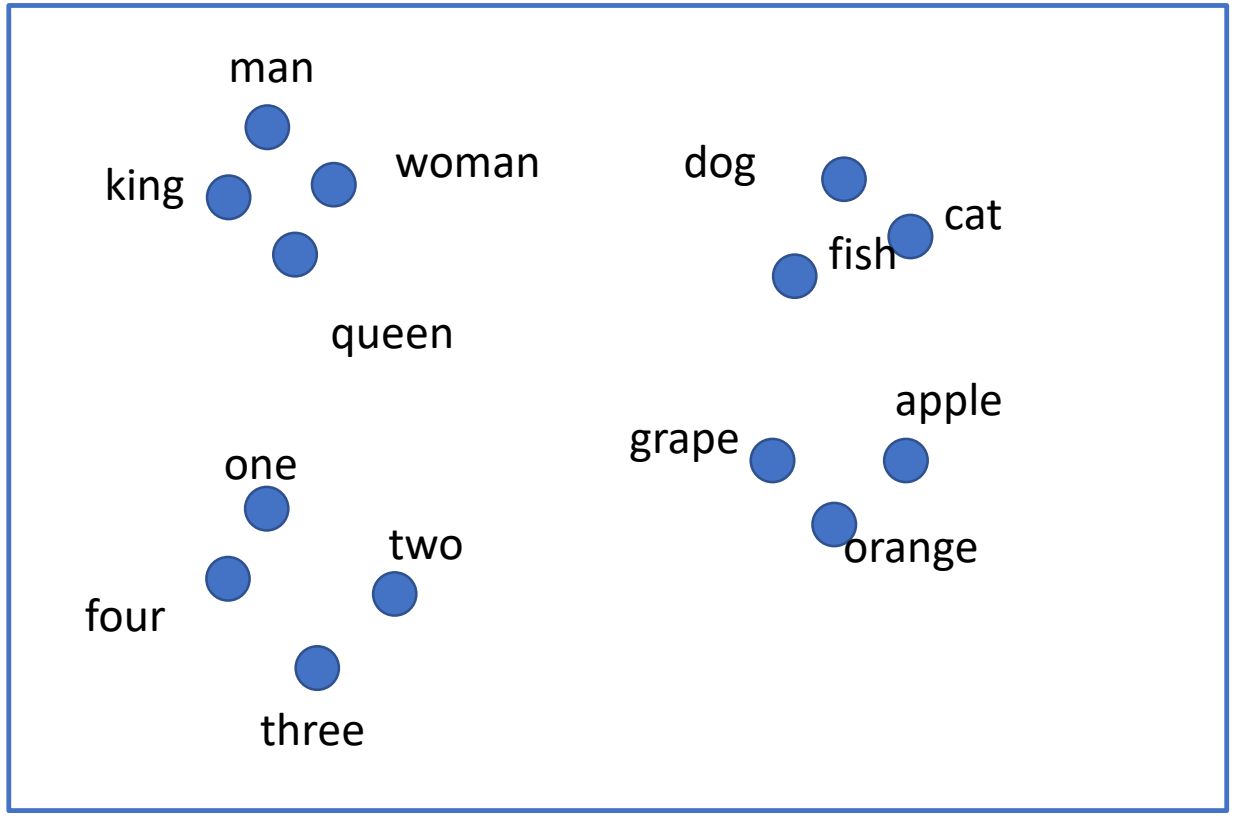
Featurized Representation: Word Embeddings (Andrew Ng)

300 features

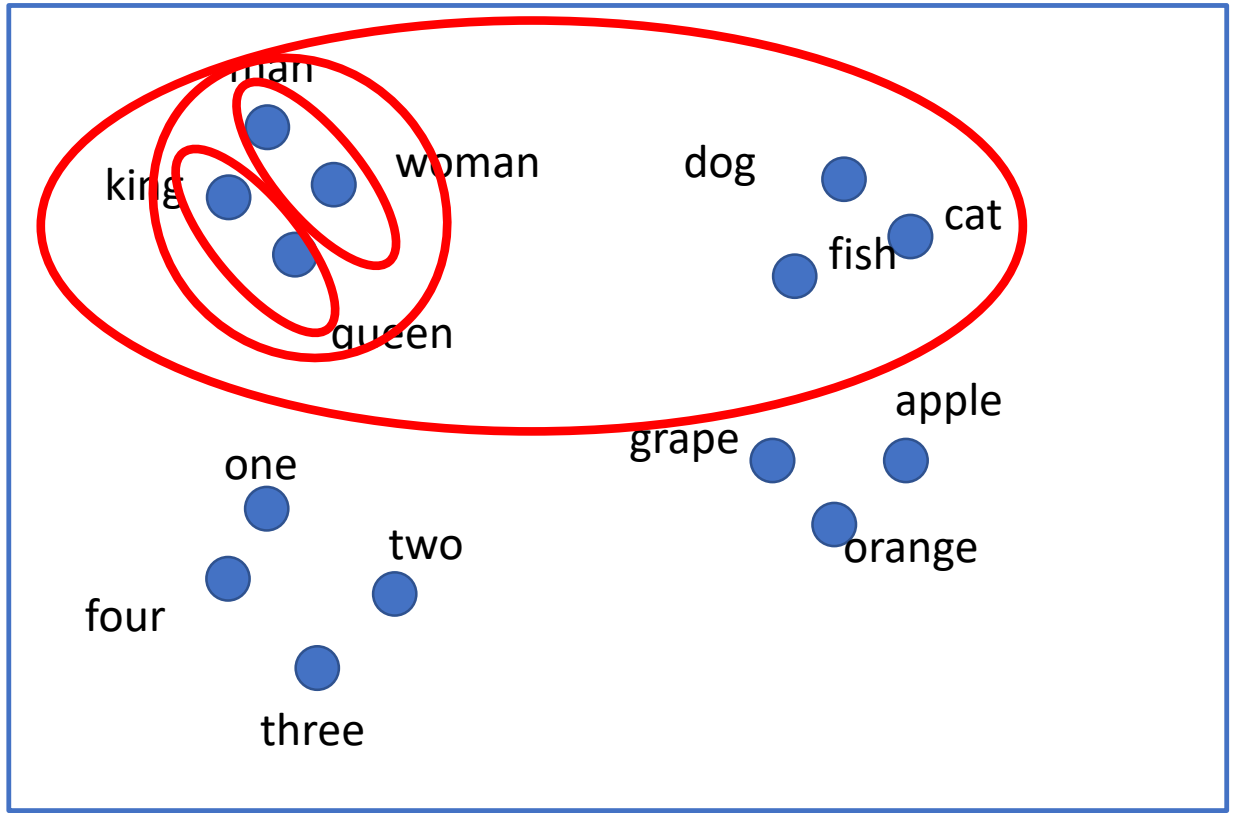
	Man	Woman	King	Queen	Apple	Orange
Gender	-1	1	-0.95	0.97	0.00	0.01
Royal	0.01	0.02	0.93	0.95	-0.01	0.00
Age	0.03	0.02	0.7	0.69	0.03	-0.02
Food	0.04	0.01	0.02	0.01	0.95	0.97
…						
….						

I want a glass of orange _____
I want a glass of apple _____

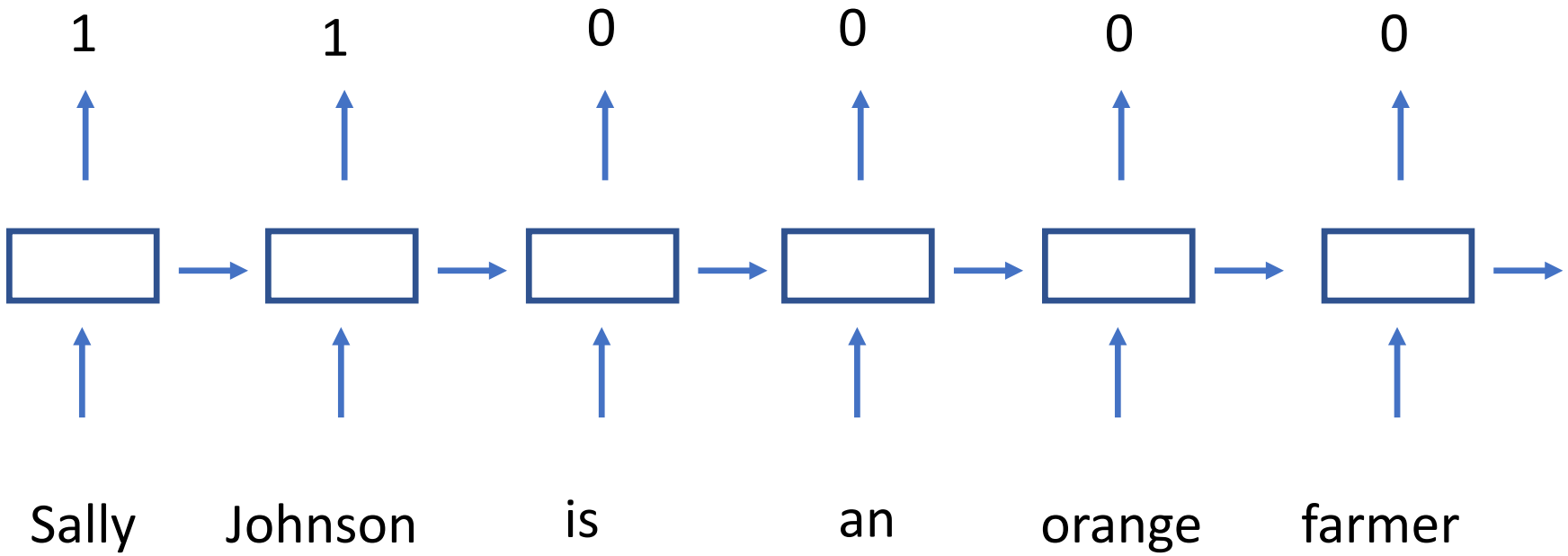
Visualizing word embeddings (Andrew Ng)



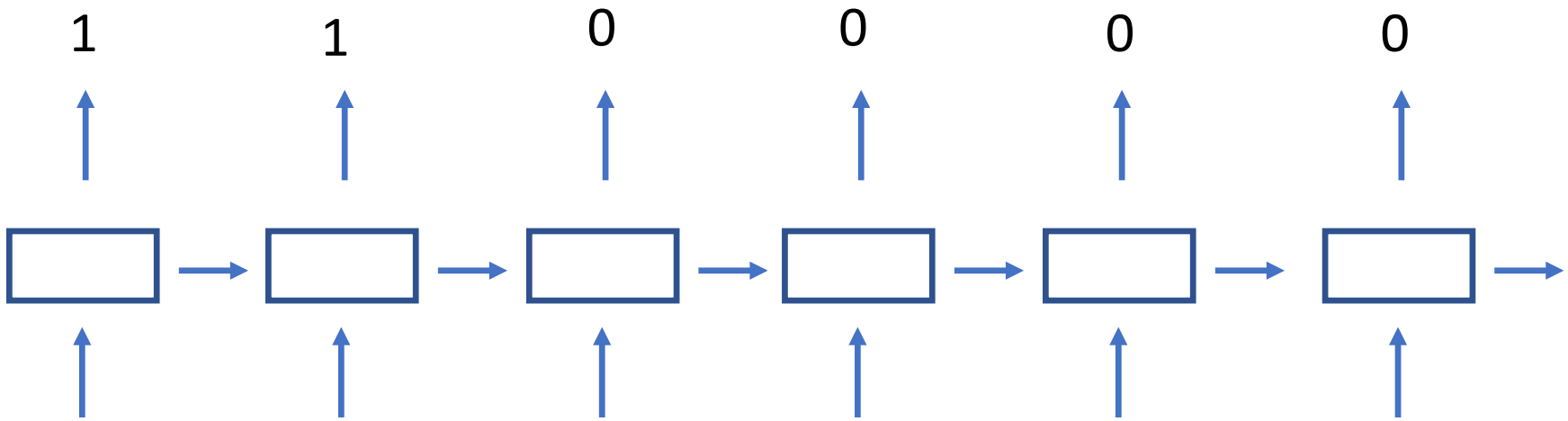
Visualizing word embeddings (Andrew Ng)



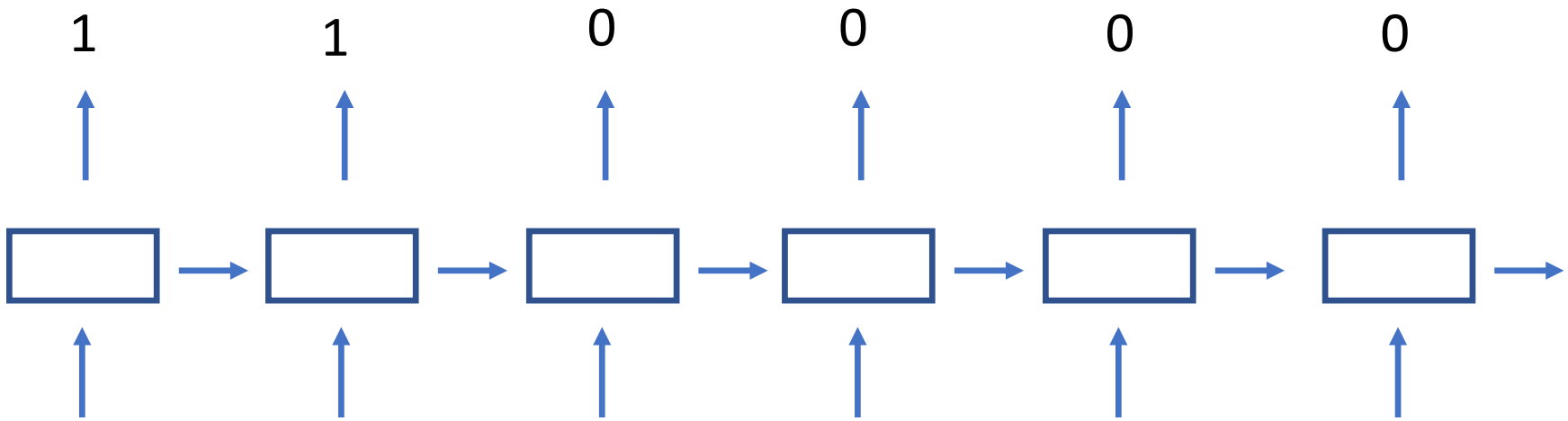
NE recognition (Andrew Ng)



NE recognition (Andrew Ng)

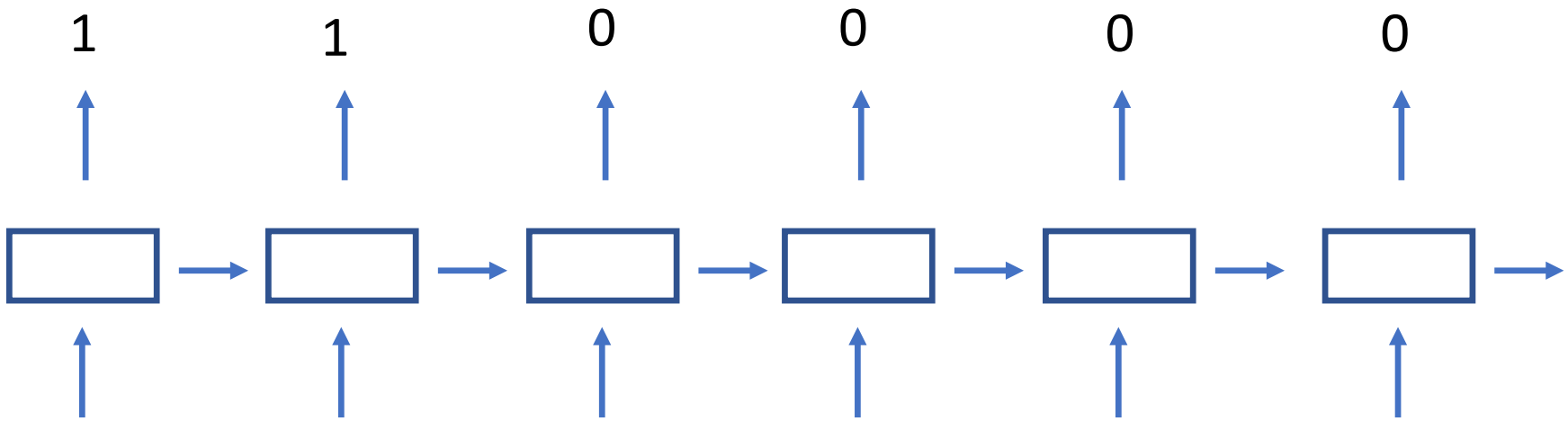


NE recognition (Andrew Ng)



Sally	Johnson	is	an	orange	farmer
Robert	Lin	is	~~an~~	~~apple~~	~~farmer~~
			a	durian	cultivator

NE recognition (Andrew Ng)



Sally Johnson is an orange farmer

Robert Lin is an apple farmer

a durian cultivator

fruits

Transfer Learning and word embeddings (Andrew Ng)

- Learn word embeddings from large corpora (1 -100B words)
  - Download pre-trained embeddings online
- Transfer embeddings to new task with smaller training set
- Optional: continue to finetune the word embeddings with new data (only if the new training set is big enough)

Analogies (Andrew Ng)

300 features

	Man	Woman	King	Queen	Apple	Orange
Gender	-1	1	-0.95	0.97	0.00	0.01
Royal	0.01	0.02	0.93	0.95	-0.01	0.00
Age	0.03	0.02	0.7	0.69	0.03	-0.02
Food	0.04	0.01	0.02	0.01	0.95	0.97

Man → Woman as King → ????

$e_{Man} - e_{Woman}$

$e_{king} - e_{?}$

$e_{Man} - e_{Woman} \sim \begin{vmatrix} -2 \\ 0 \\ 0 \\ 0 \end{vmatrix}$ $e_{king} - e_{queen} \sim \begin{vmatrix} -2 \\ 0 \\ 0 \\ 0 \end{vmatrix}$