Natural Language Processing

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Adapted from Info 256 - David Bamman, UC Berkeley

Named entity recognition

Citing high fuel prices, [$_{\text{ORG}}$ **United Airlines**] said [$_{\text{TIME}}$ **Friday**] it has increased fares by [$_{\text{MONEY}}$ **$6**] per round trip on flights to some cities also served by lower-cost carriers. [$_{\text{ORG}}$ **American Airlines**], a unit of [$_{\text{ORG}}$ **AMR Corp.**], immediately matched the move, spokesman [$_{\text{PER}}$ **Tim Wagner**] said. [$_{\text{ORG}}$ **United**], a unit of [$_{\text{ORG}}$ **UAL Corp.**], said the increase took effect [$_{\text{TIME}}$ **Thursday**] and applies to most routes where it competes against discount carriers, such as [$_{\text{LOC}}$ **Chicago**] to [$_{\text{LOC}}$ **Dallas**] and [$_{\text{LOC}}$ **Denver**] to [$_{\text{LOC}}$ **San Francisco**].

Named entity recognition

[tim cook]$_{PER}$ is the ceo of [apple]$_{ORG}$

- Identifying spans of text that correspond to typed entities that are proper names.

Named entity recognition

Type	Tag	Sample Categories	Example sentences
People	PER	people, characters	**Turing** is a giant of computer science.
Organization	ORG	companies, sports teams	The **IPCC** warned about the cyclone.
Location	LOC	regions, mountains, seas	The **Mt. Sanitas** loop is in **Sunshine Canyon**.
Geo-Political Entity	GPE	countries, states, provinces	**Palo Alto** is raising the fees for parking.
Facility	FAC	bridges, buildings, airports	Consider the **Golden Gate Bridge**.
Vehicles	VEH	planes, trains, automobiles	It was a classic **Ford Falcon**.

Figure 17.1 A list of generic named entity types with the kinds of entities they refer to.

ACE NER categories (+weapon)

Named entity recognition

- GENIA corpus of MEDLINE abstracts (biomedical)

We have shown that [interleukin-1]PROTEIN ([IL-1]PROTEIN) and [IL-2]PROTEIN control [IL-2 receptor alpha (IL-2R alpha) gene]DNA transcription in [CD4- CD8- murine T lymphocyte precursors]CELL LINE

protein
cell line
cell type
DNA
RNA

http://www.aclweb.org/anthology/W04-1213

BIO notation

B-PERS I-PERS O O O O B-ORG

tim cook is the ceo of apple

- **B**eginning of entity
- **I**nside entity
- **O**utside entity

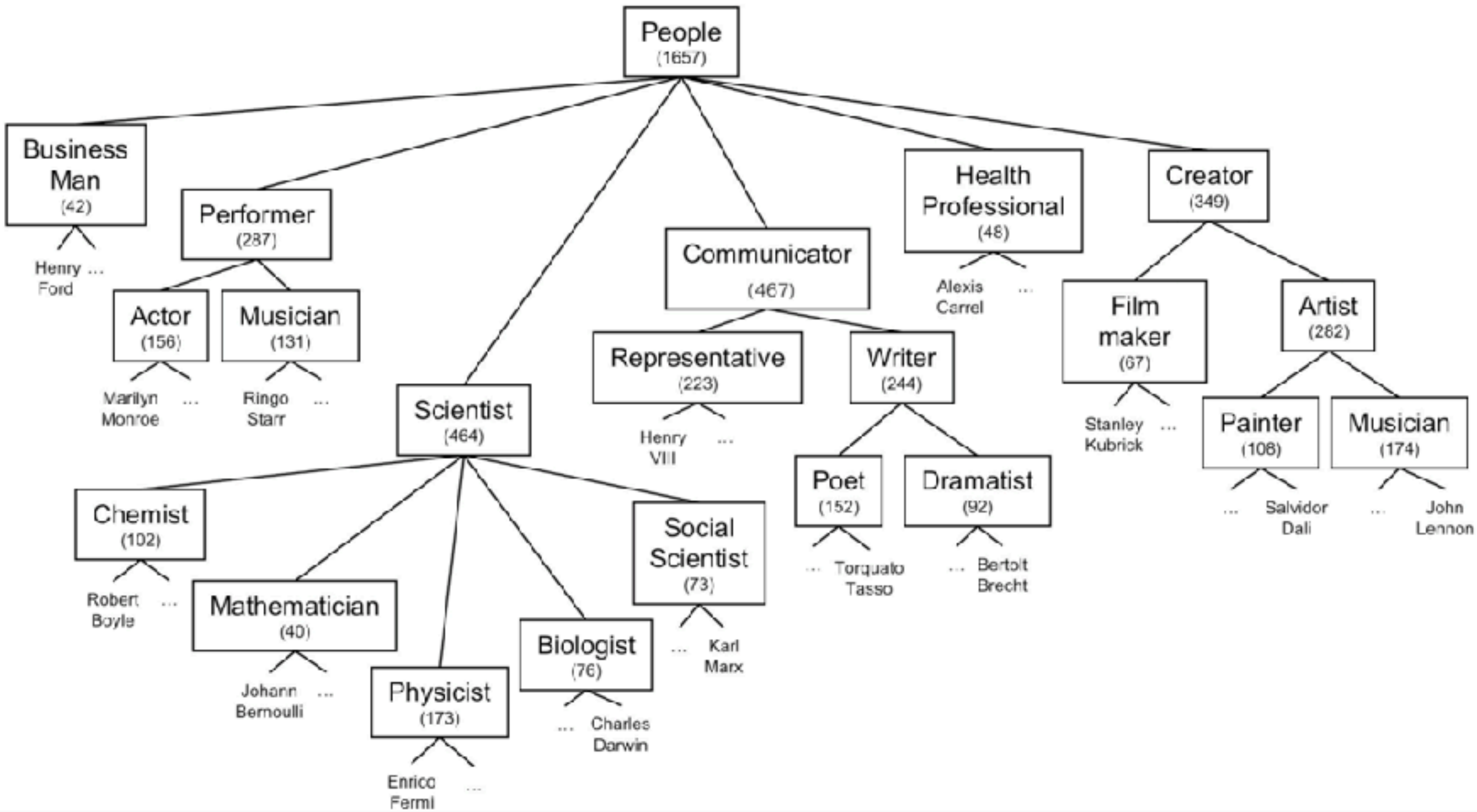
[tim cook]$_{\text{PER}}$ is the ceo of [apple]$_{\text{ORG}}$

Named entity recognition

B-PER B-PER

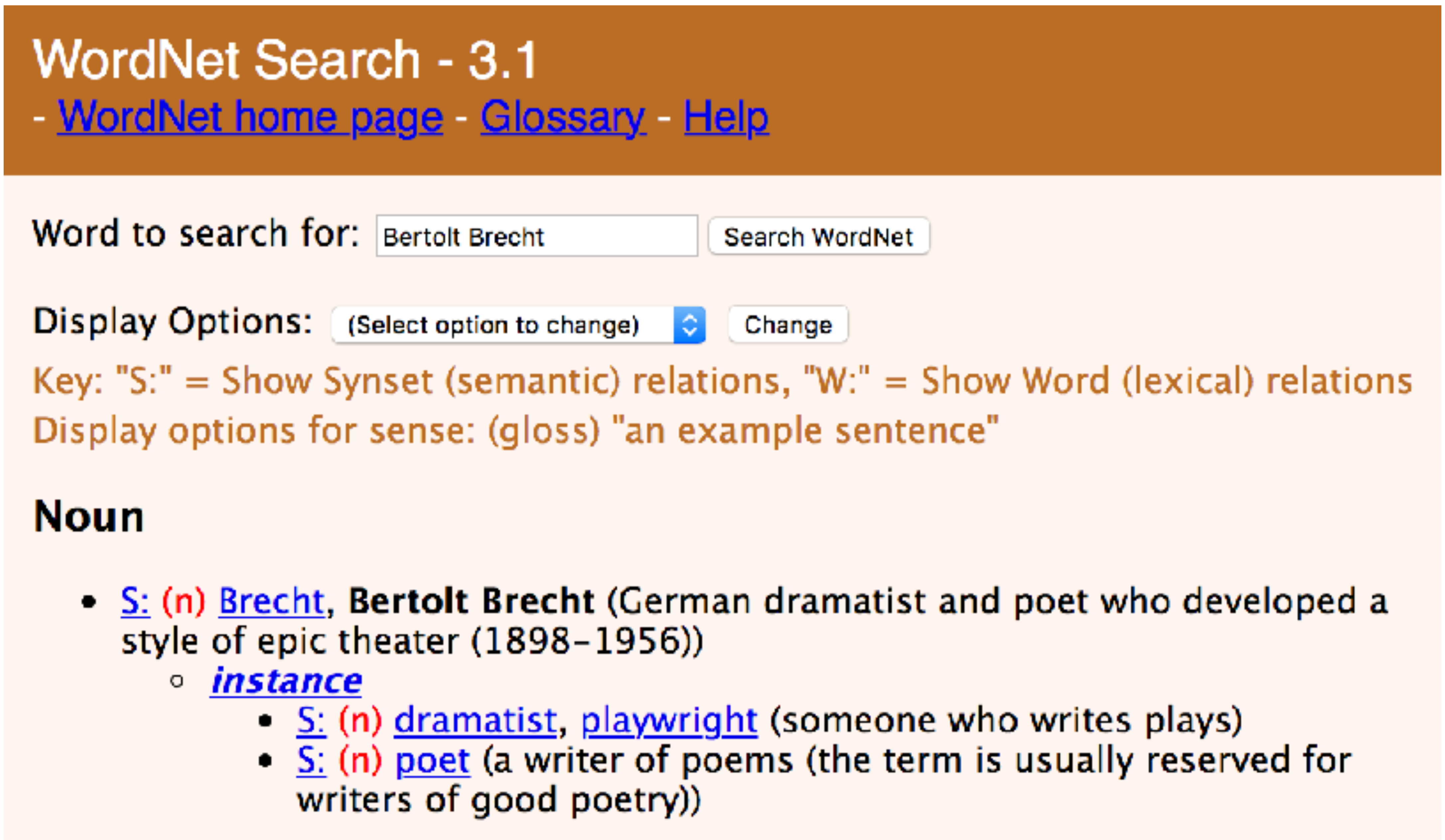
After he saw Harry Tom went to the store

Fine-grained NER



Giuliano and Gliozzo (2008)

Fine-grained NER



Entity recognition

Person	… named after [the daughter of a Mattel co-founder] …
Organization	[The Russian navy] said the submarine was equipped with 24 missiles
Location	Fresh snow across [the upper Midwest] on Monday, closing schools
GPE	The [Russian] navy said the submarine was equipped with 24 missiles
Facility	Fresh snow across the upper Midwest on Monday, closing [schools]
Vehicle	The Russian navy said [the submarine] was equipped with 24 missiles
Weapon	The Russian navy said the submarine was equipped with [24 missiles]

ACE entity categories
https://www.ldc.upenn.edu/sites/www.ldc.upenn.edu/files/english-entities-guidelines-v6.6.pdf

Named entity recognition

- Most named entity recognition datasets have flat structure (i.e., non-hierarchical labels).

✔ [The University of California]$_{\text{ORG}}$

✖ [The University of [California]$_{\text{GPE}}$]$_{\text{ORG}}$

- Mostly fine for named entities, but more problematic for general entities:

[[John]$_{\text{PER}}$'s mother]$_{\text{PER}}$ said …

Nested NER

named	after	the	daughter	of	a	Mattel	co-founder
						B-ORG	
					B-PER	I-PER	I-PER
		B-PER	I-PER	I-PER	I-PER	I-PER	I-PER

Sequence labeling

$$x = \{x_1, \ldots, x_n\}$$

$$y = \{y_1, \ldots, y_n\}$$

- For a set of inputs x with n sequential time steps, one corresponding label y_i for each x_i
- Model correlations in the labels y.

Maximum Entropy Markov Model (MEMM)

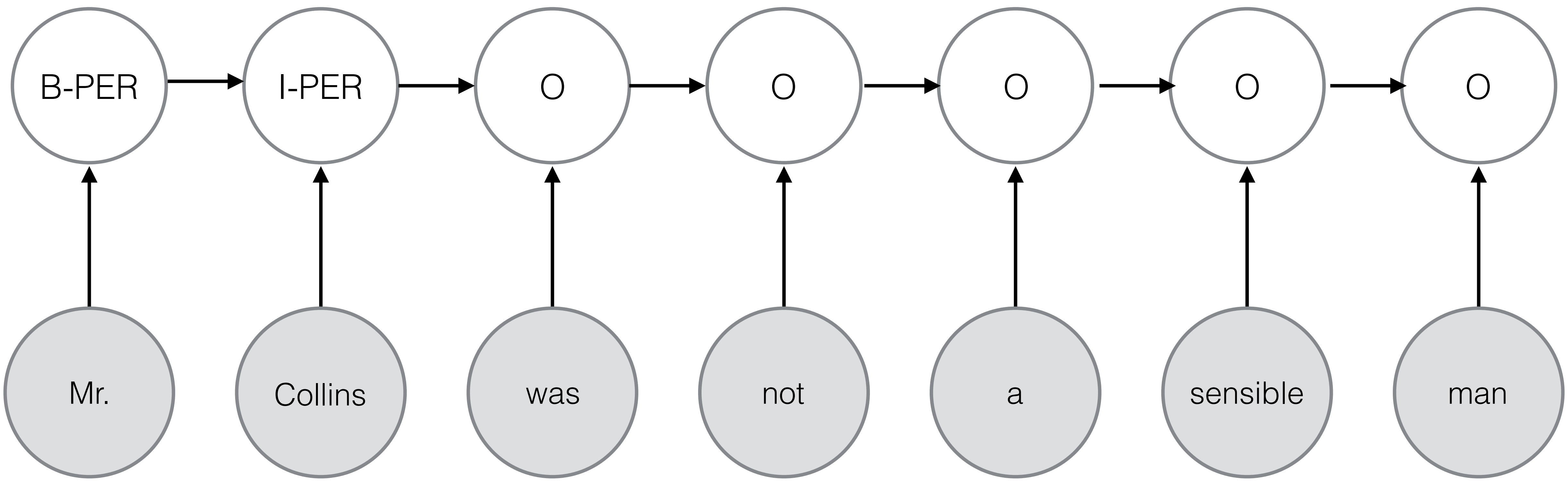
General maxent form

$$\arg\max_{y} P(y \mid x, \beta)$$

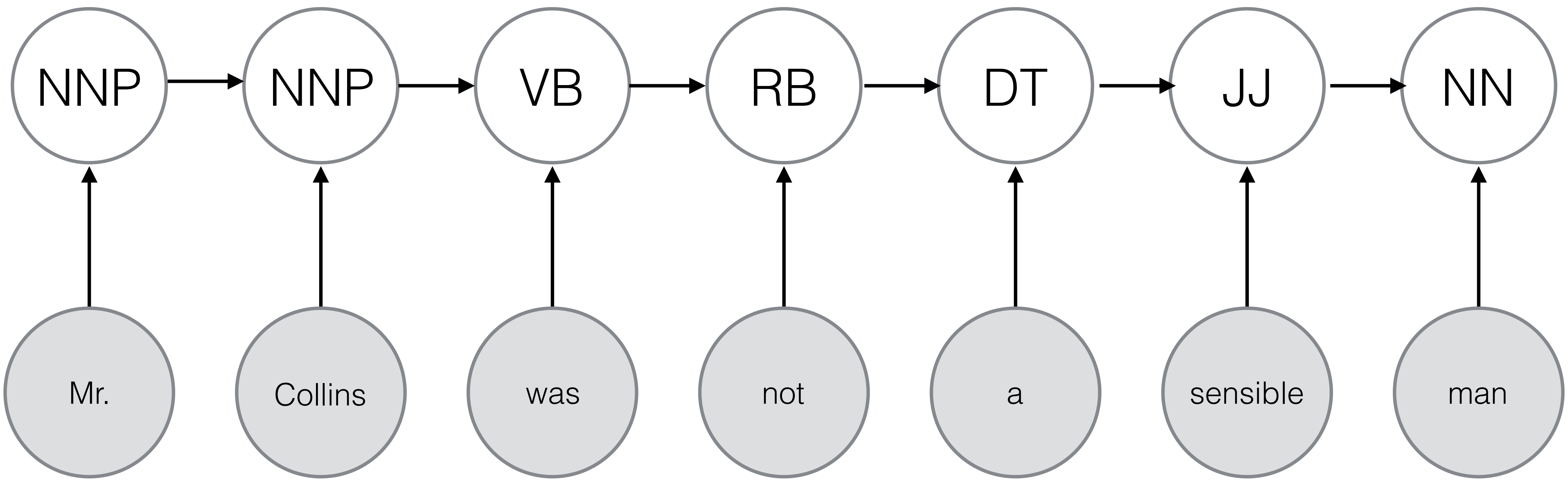
Maxent with Markov assumption: Maximum Entropy Markov Model

$$\arg\max_{y} \prod_{i=1}^{n} P(y_i \mid y_{i-1}, x)$$

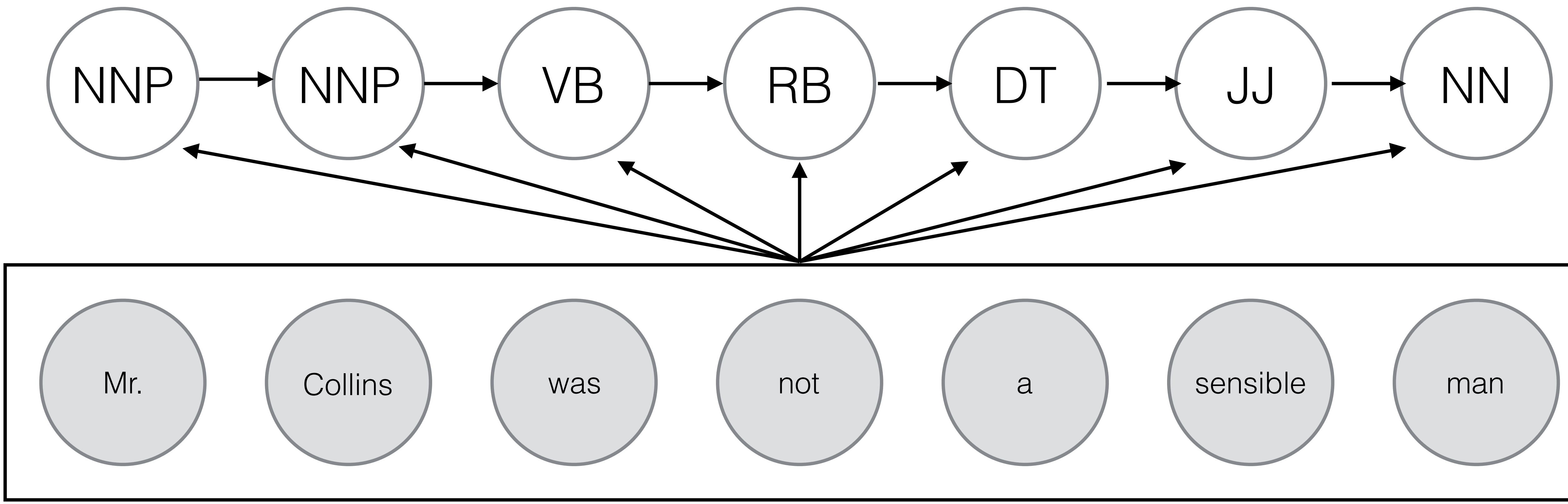
MEMM



MEMM

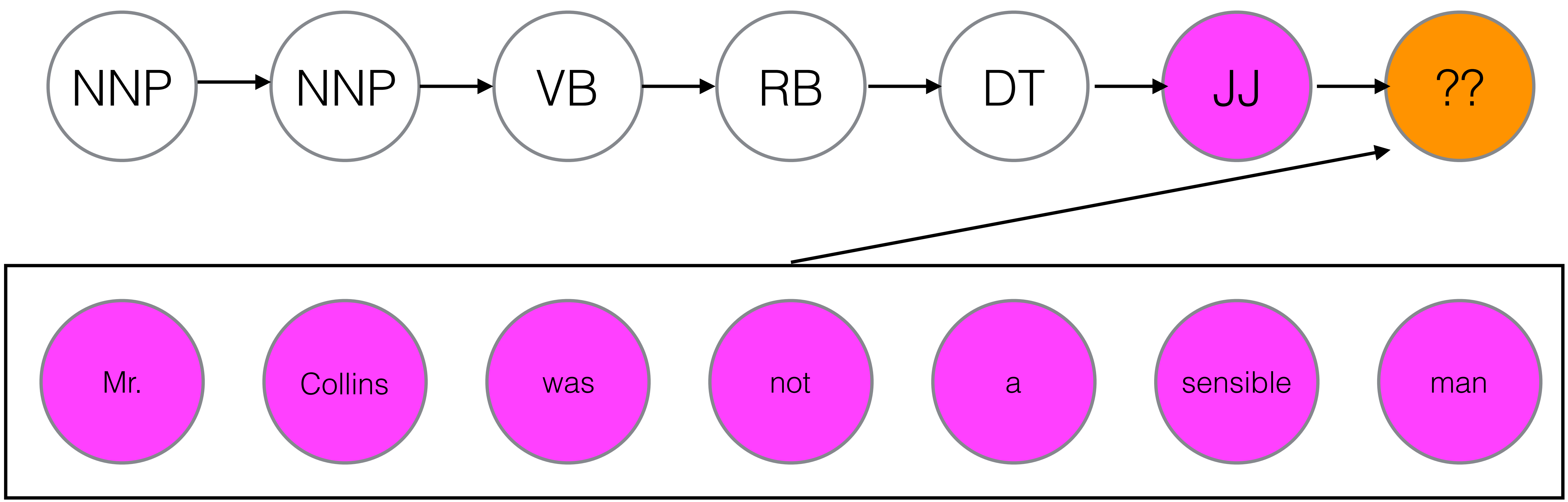


MEMM



MEMMs condition on the *entire* input

MEMM



Features

$$f(y_i, y_{i-1}; x_1, \ldots, x_n)$$

Features are scoped over the previous predicted tag and the entire observed input

feature	example
x_i = man	1
y_{i-1} = JJ	1
i=n (last word of sentence)	1
x_i ends in -ly	0

NER sequence labeling

identity of w_i, identity of neighboring words
embeddings for w_i, embeddings for neighboring words
part of speech of w_i, part of speech of neighboring words
base-phrase syntactic chunk label of w_i and neighboring words
presence of w_i in a **gazetteer**
w_i contains a particular prefix (from all prefixes of length ≤ 4)
w_i contains a particular suffix (from all suffixes of length ≤ 4)
w_i is all upper case
word shape of w_i, word shape of neighboring words
short word shape of w_i, short word shape of neighboring words
presence of hyphen

Figure 17.5 Typical features for a feature-based NER system.

Gazetteers

- List of place names; more generally, list of names of some typed category
- GeoNames (GEO), US SSN (PER), Getty Thesaurus of Geographic Placenames, Getty Thesaurus of Art and Architecture

Bun Cranncha
Dromore West
Dromore
Youghal Harbour
Youghal Bay
Youghal
Eochaill
Yellow River
Yellow Furze
Woodville
Wood View
Woodtown House
Woodstown
Woodstock House
Woodsgift House
Woodrooff House
Woodpark
Woodmount
Wood Lodge
Woodlawn Station
Woodlawn
Woodlands Station
Woodhouse
Wood Hill
Woodfort
Woodford River
Woodford
Woodfield House
Woodenbridge Junction Station
Woodenbridge
Woodbrook House
Woodbrook
Woodbine Hill
Wingfield House
Windy Harbour

Training

$$\prod_{i=1}^{n} P(y_i \mid y_{i-1}, x, \beta)$$

For all training data, we want probability of the true label y_i conditioned on the previous true label y_{i-1} to be high.

This is simply multiclass logistic regression

Decoding

- With logistic regression, our prediction is simply the argmax y:

$$P(y \mid x, \beta)$$

- With an MEMM, we know the true y_{i-1} during training but we never of course know it at test time

$$P(y_i \mid y_{i-1}, x, \beta)$$

Decoding

- Greedy: proceed left to right, committing to the best tag for each time step (given the sequence seen so far)

Fruit	flies	like	a	banana
NN	VB	IN	DT	NN

Decoding

DT	NN	VBD	IN	DT	NN	???
The	horse	raced	past	the	barn	fell

Decoding

DT	NN	VBD	IN	DT	NN	???
The	horse	raced	past	the	barn	fell
DT	NN	VBN	IN	DT	NN	VBD

Information later on in the sentence can influence the best tags earlier on.

All paths

END							
DT							
NNP							
VB							
NN							
MD							
START							
	^	Janet	will	back	the	bill	$

Ideally, what we want is to calculate the joint probability of each path and pick the one with the highest probability. But for N time steps and K labels, number of possible paths = K^N

5 word sentence with 45 Penn Treebank tags

45^5 = 184,528,125 different paths

45^{20} = 1.16e33 different paths

Viterbi algorithm

- Basic idea: if an optimal path through a sequence uses label L at time T, then it must have used an optimal path to get to label L at time T

- We can discard all non-optimal paths up to label L at time T

Evaluation

- We evaluate NER with precision/recall/F1 over typed chunks.

Evaluation

	1	2	3	4	5	6	7
	tim	cook	is	the	CEO	of	Apple
gold	B-PER	I-PER	O	O	O	O	B-ORG
system	B-PER	O	O	O	B-PER	O	B-ORG

<start, end, type>

Precision	1/3
Recall	1/2

gold

<1,2,PER>
<7,7,ORG>

system

<1,1,PER>
<5,5,PER>
<7,7,ORG>