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Natural Language Processing
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Chapter 8
Sequence Labeling for Parts of Speech and Named Entities

- content is based on [1]
- certain elements (e.g. equations or tables) were taken over or taken over in a modified form from [1]
- citations of [1] or from [1] are omitted for legibility
- errors are fully in the responsibility of Georg Groh
- BIG thanks to Dan and James for a great book!

Part-of-Speech-Tags

- Parts-of-Speech (POS, word classes, syntactic categories)
- Examples: noun, pronoun, verb, adjective, ….
- important for
  - language models ("nouns are preceded by determines or adjectives"),
  - information extraction tasks such as Named Entity Recognition and Classification,
  - stemming,
  - auto-summarization,
  - pronunciation (e.g. CONtent vs conTENT)
  - etc.

Part-of-Speech-Tags

- POS: based on not primarily semantic categories (adjective ←→ property of smth) but rather
  - syntactic categories / functions (e.g. distributional properties (which other words usually in neighborhood)) and
  - morphological categories/functions (e.g. to carry similar suffixes)

- closed class (function words (e.g. *of, it*); fixed members (e.g. prepositions)) vs.
  open class (nouns, verbs, adjectives, adverbs; e.g. new nouns are continually created)

POS Overview

	Tag	Description	Example
Open Class	**ADJ**	Adjective: noun modifiers describing properties	*red, young, awesome*
	ADV	Adverb: verb modifiers of time, place, manner	*very, slowly, home, yesterday*
	NOUN	words for persons, places, things, etc.	*algorithm, cat, mango, beauty*
	VERB	words for actions and processes	*draw, provide, go*
	PROPN	Proper noun: name of a person, organization, place, etc..	*Regina, IBM, Colorado*
	INTJ	Interjection: exclamation, greeting, yes/no response, etc.	*oh, um, yes, hello*
Closed Class Words	**ADP**	Adposition (Preposition/Postposition): marks a noun's spacial, temporal, or other relation	*in, on, by, under*
	AUX	Auxiliary: helping verb marking tense, aspect, mood, etc.,	*can, may, should, are*
	CCONJ	Coordinating Conjunction: joins two phrases/clauses	*and, or, but*
	DET	Determiner: marks noun phrase properties	*a, an, the, this*
	NUM	Numeral	*one, two, first, second*
	PART	Particle: a preposition-like form used together with a verb	*up, down, on, off, in, out, at, by*
	PRON	Pronoun: a shorthand for referring to an entity or event	*she, who, I, others*
	SCONJ	Subordinating Conjunction: joins a main clause with a subordinate clause such as a sentential complement	*that, which*
Other	**PUNCT**	Punctuation	; , ()
	SYM	Symbols like $ or emoji	$, %
	X	Other	asdf, qwfg

Figure 8.1 The 17 parts of speech in the Universal Dependencies tagset (Nivre et al., 2016a). Features can be added to make finer-grained distinctions (with properties like number, case, definiteness, and so on).

Part-of-Speech-Tags

- Nouns:
  - occur with determiners (*a goat, its bandwidth*)
  - can take possessives (*husband's house*)
  - may occur in plural (*goats, hounds*)
  - Proper Nouns: specific entities, no *the* (*Regina, IBM, Colorado*) (usually capitalized)
  - Common Nouns:
    - Count Nouns: *one goat, two goats*
    - Mass Nouns: *snow, salt, communism*

- Verbs:
  - ←→ actions, processes, smth. dynamic,...
  - may be inflected: *eat, eats, eating, eaten*

- Adjectives
  - ←→ properties, qualities,...
  - *beautiful, tall, small*

Part-of-Speech-Tags

- Adverbs:
  - modify something: ***Unfortunately***, *John walked* ***home extremely slowly yesterday***
  - directional adverbs / locative adverbs: *home, here, downhill*
  - degree adverbs: *extremely, very, somewhat*
  - manner adverbs: *slowly, slinkily, delicately*
  - temporal adverbs: *yesterday, Monday*

- Prepositions:
  - occur before noun phrases: ***by*** *the house,* ***on*** *time,* ***with*** *gusto,* ***at*** *the gate*
  - indicate spatial, or temporal, or other relations

- Particle:
  - occur with verbs: *hand the paper* ***over****, throw the ball* ***at***
  - together with verb: phrasal verb (with non-compositional meaning): *turn down == reject, rule out == eliminate, go on == continue*

Part-of-Speech-Tags

- Determiners:
  - especially articles: definite: *the*; indefinite: *a, an*
  - also*: this, that, …*

- Conjunctions:
  - join phrases, sentences, clauses
  - Coordinating conjunctions*: and, or*
  - Subordinating conjunctions (Complementizers)*: I thought* ***that*** *you might fail*

- Pronouns:
  - shorthand referring to noun phrase etc.
  - Personal pronoun: *you, I, he, she, it*
  - Possessive pronoun: *your, mine, his, her, its, one's*
  - Wh-pronouns: *what, whom, whoever, why*

Part-of-Speech-Tags

- Auxiliary verbs:
  - mark semantic features of verbs: *can, do, may, should, are, have*: whether action is completed, negated, necessary, possible, suggested, desired, ….
  - Copula *be* : connects: *he **is** a duck*
  - Modal verbs: *can, must*

- Other classes:
  - Interjections *oh, hey, um, hmmm*
  - Negatives *no, not*
  - Politeness markers *please, thank you*
  - Greetings *hello, goodbye*
  - …

Penn Treebank POS Tags

Tag	Description	Example	Tag	Description	Example	Tag	Description	Example
CC	coord. conj.	*and, but, or*	NNP	proper noun, sing.	*IBM*	TO	"to"	*to*
CD	cardinal number	*one, two*	NNPS	proper noun, plu.	*Carolinas*	UH	interjection	*ah, oops*
DT	determiner	*a, the*	NNS	noun, plural	*llamas*	VB	verb base	*eat*
EX	existential 'there'	*there*	PDT	predeterminer	*all, both*	VBD	verb past tense	*ate*
FW	foreign word	*mea culpa*	POS	possessive ending	*'s*	VBG	verb gerund	*eating*
IN	preposition/ subordin-conj	*of, in, by*	PRP	personal pronoun	*I, you, he*	VBN	verb past participle	*eaten*
JJ	adjective	*yellow*	PRP$	possess. pronoun	*your, one's*	VBP	verb non-3sg-pr	*eat*
JJR	comparative adj	*bigger*	RB	adverb	*quickly*	VBZ	verb 3sg pres	*eats*
JJS	superlative adj	*wildest*	RBR	comparative adv	*faster*	WDT	wh-determ.	*which, that*
LS	list item marker	*1, 2, One*	RBS	superlatv. adv	*fastest*	WP	wh-pronoun	*what, who*
MD	modal	*can, should*	RP	particle	*up, off*	WP$	wh-possess.	*whose*
NN	sing or mass noun	*llama*	SYM	symbol	*+,%, &*	WRB	wh-adverb	*how, where*

There/PRO/EX are/VERB/VBP 70/NUM/CD children/NOUN/NNS there/ADV/RB ./PUNC/.

Preliminary/ADJ/JJ findings/NOUN/NNS were/AUX/VBD reported/VERB/VBN in/ADP/IN today/NOUN/NN 's/PART/POS New/PROPN/NNP England/PROPN/NNP Journal/PROPN/NNP of/ADP/IN Medicine/PROPN/NNP

POS Labelled Corpora

- examples:
  - Brown corpus (1961, 10^6 words, different genre texts),
  - Wall Street Journal corpus (1989, 10^6 words),
  - Switchboard corpus (1991, $2*10^6$ words, telephone conversations)

- slight differences in using POS tags (e.g. in corpora)
  - e.g.
    -- Brown, WSJ: to/TO for both uses of to (preposition: *go to the store;* infinitive: *too dangerous to swim*)
    -- Switchboard: Well/UH ,/, I/PRP ,/, I/PRP want/VBP to/TO go/VB
    to/IN a/DT restaurant/NN

POS Labelled Corpora

- POS tag sets: pragmatic decisions:
  - Penn 45 is a subset of larger POS tagsets, leaving off syntactic information recoverable from a parse tree, e.g. in Penn, the tag IN is used for subordinating conjunctions
    after/IN spending/VBG a/DT day/NN at/IN the/DT beach/NN
    as well as prepositions:
    after/IN sunrise/NN
  - Penn 45 assumes tokenization of multipart words:
    a/DT New/NNP York/NNP City/NNP firm/NN (New York City as one word)

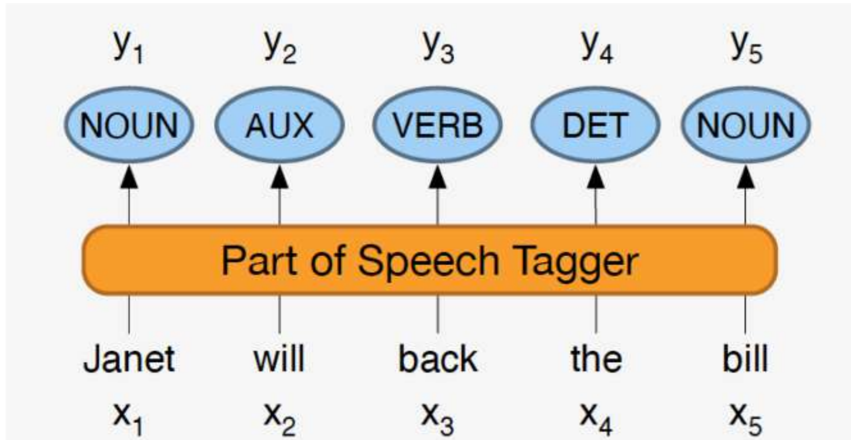
POS Tagging

- After tokenization: POS tagging for each word: disambiguation task (*book a flight, read a book*)
  Not many words ambiguous but ambiguous words are among the most common tokens:

		WSJ		Brown	
Types:					
Unambiguous	(1 tag)	44,432	(**86%**)	45,799	(**85%**)
Ambiguous	(2+ tags)	7,025	(**14%**)	8,050	(**15%**)
Tokens:					
Unambiguous	(1 tag)	577,421	(**45%**)	384,349	(**33%**)
Ambiguous	(2+ tags)	711,780	(**55%**)	786,646	(**67%**)

- Most frequent POS tag (class) baseline: always predict the most frequent POS tag among the possible POS tags for an ambiguous word:
  on WSJ: accuracy: ≈0.92 ←→ state of the art: accuracy: ≈0.97

POS Tagging



earnings growth took a **back/JJ** seat
a small building in the **back/NN**
a clear majority of senators **back/VBP** the bill
Dave began to **back/VB** toward the door
enable the country to buy **back/RP** debt
I was twenty-one **back/RB** then

Named Entity Recognition

- Named Entity: Anything referred to by a proper name, often extended to temporal or numerical expressions

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

- Entity Types:

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 **Tappan Zee Bridge**.
Vehicles	VEH	planes, trains, automobiles	It was a classic **Ford Falcon**.
…			

Named Entity Recognition

- Named entity recognition: finding spans of text that constitute NEs + classification

- categorial ambiguities:

Name	Possible Categories
Washington	Person, Location, Political Entity, Organization, Vehicle
Downing St.	Location, Organization
IRA	Person, Organization, Monetary Instrument
Louis Vuitton	Person, Organization, Commercial Product

[$_{\text{PER}}$ Washington] was born into slavery on the farm of James Burroughs.
[$_{\text{ORG}}$ Washington] went up 2 games to 1 in the four-game series.
Blair arrived in [$_{\text{LOC}}$ Washington] for what may well be his last state visit.
In June, [$_{\text{GPE}}$ Washington] passed a primary seatbelt law.
The [$_{\text{VEH}}$ Washington] had proved to be a leaky ship, every passage I made...

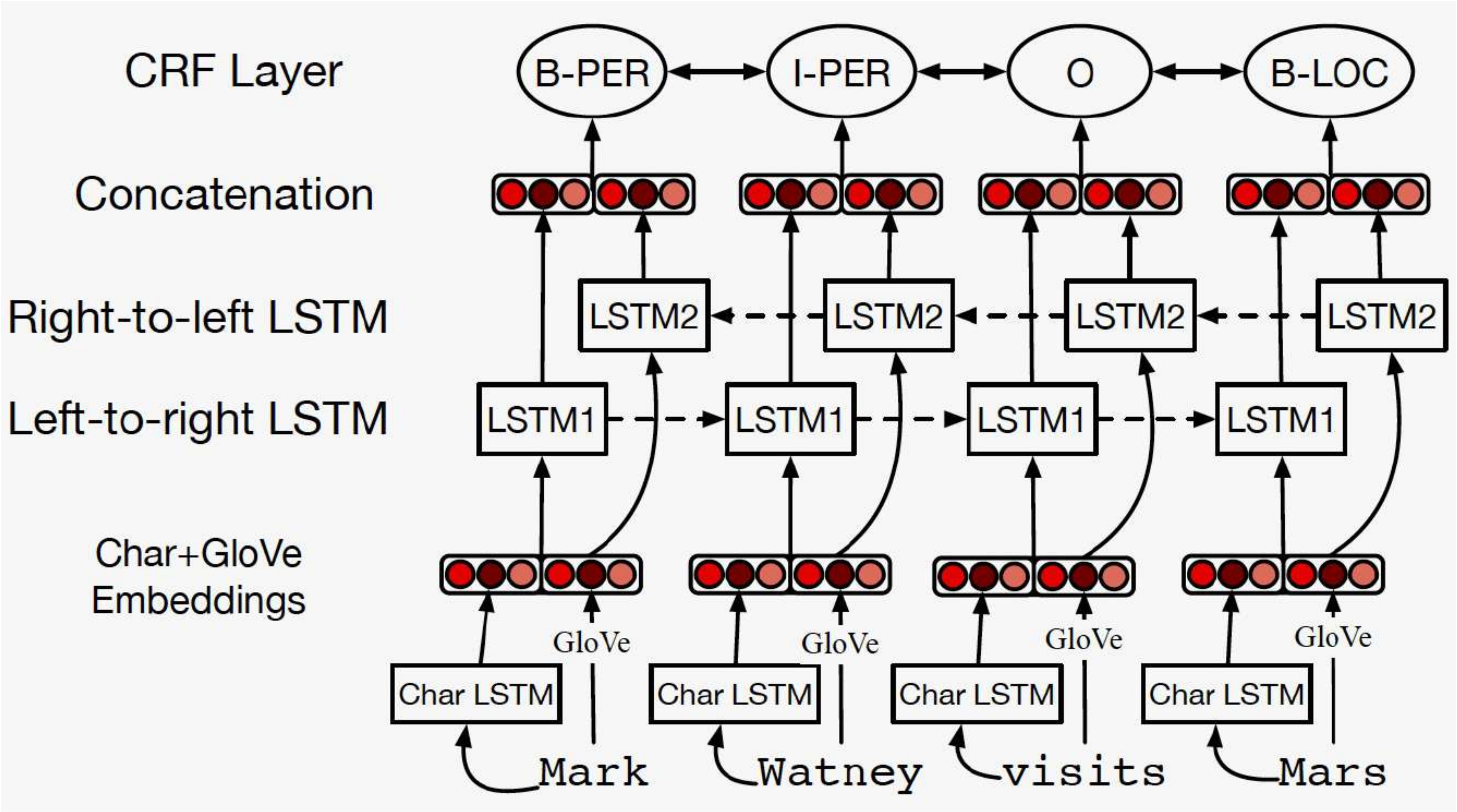
NER as Sequence Labeling Task

- use supervised sequence classifier such as HMM or RNN, with BIO tagging (for n entity types → 2n+1 corresp. BIO classes) or IO tagging (n+1 corresp. IO classes) or BIOES tagging (E=end, S=one word span):

[$_{\text{PER}}$ **Jane Villanueva**] of [$_{\text{ORG}}$ **United**] , a unit of [$_{\text{ORG}}$ **United Airlines Holding**] , said the fare applies to the [$_{\text{LOC}}$ **Chicago**] route.

Words	IO Label	BIO Label	BIOES Label
Jane	I-PER	B-PER	B-PER
Villanueva	I-PER	I-PER	E-PER
of	O	O	O
United	I-ORG	B-ORG	B-ORG
Airlines	I-ORG	I-ORG	I-ORG
Holding	I-ORG	I-ORG	E-ORG
discussed	O	O	O
the	O	O	O
Chicago	I-LOC	B-LOC	S-LOC
route	O	O	O
.	O	O	O

NER as Sequence Labeling Task – NN Methods



(more on the details in the second half of the lecture)

HMM for POS Tagging

If you do not know HMMs, study appendix A of Jurafsky and slide-set _A_HiddenMarkovModels

- States: tags; observations: words
- training on labelled data: MLE by counting for A and B separately (No Baum Welch necessary): → counting

$$P(t_i|t_{i-1}) = \frac{C(t_{i-1},t_i)}{C(t_{i-1})} \qquad P(w_i|t_i) = \frac{C(t_i,w_i)}{C(t_i)}$$

- POS-Tagging via Viterbi algorithm: find:

$$\hat{t}_{1:n} = \underset{t_1 \dots t_n}{\operatorname{argmax}} P(t_1 \dots t_n | w_1 \dots w_n)$$
$$= \underset{t_1 \dots t_n}{\operatorname{argmax}} P(w_1 \dots w_n | t_1 \dots t_n) P(t_1 \dots t_n)$$

- First oder Markov assumptions for A and B:

$$P(w_1 \dots w_n | t_1 \dots t_n) \approx \prod_{i=1}^{n} P(w_i|t_i)$$
$$P(t_1 \dots t_n) \approx \prod_{i=1}^{n} P(t_i|t_{i-1})$$

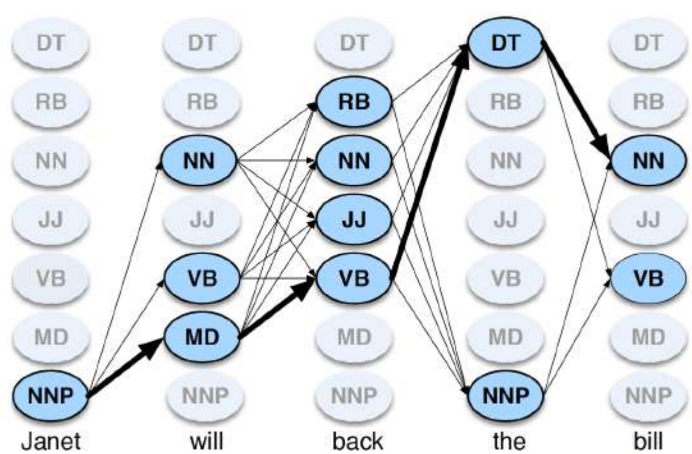
$$\hat{t}_{1:n} = \underset{t_1 \dots t_n}{\operatorname{argmax}} P(t_1 \dots t_n | w_1 \dots w_n) \approx \underset{t_1 \dots t_n}{\operatorname{argmax}} \prod_{i=1}^{n} \overbrace{P(w_i|t_i)}^{\text{emission}} \overbrace{P(t_i|t_{i-1})}^{\text{transition}}$$

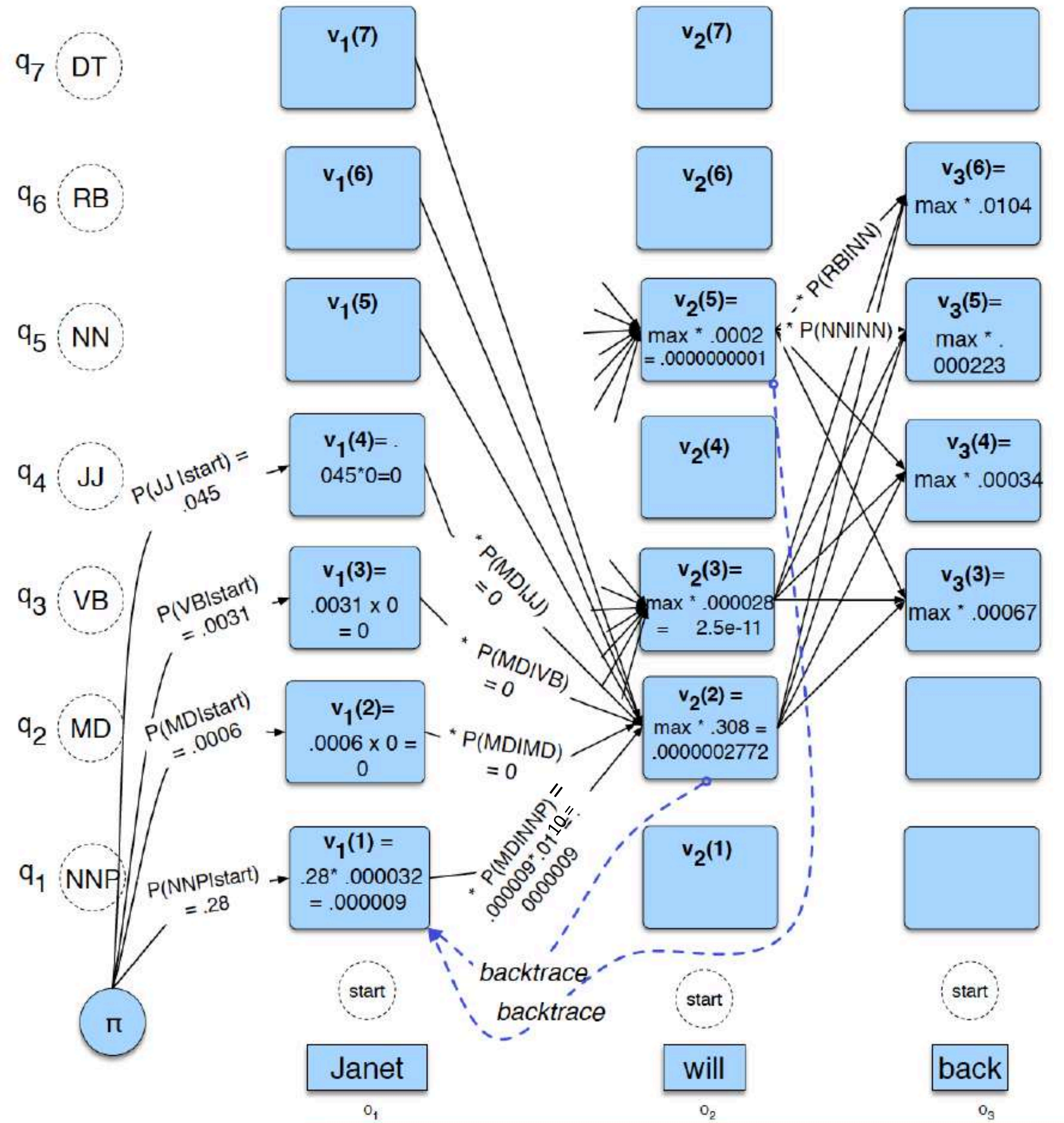
example: *Janet will back the bill* →
true POS tags:
Janet/NNP will/MD back/VB the/DT bill/NN

$$v_t(j) = \max_{q_{1:t-1}} P(q_{1:t-1}, q_t = j, o_{1:t} \mid \lambda)$$
$$= \max_{i=1}^{N} v_{t-1}(i)\, a_{ij}\, b_j(o_t)$$

	NNP	MD	VB	JJ	NN	RB	DT
<s>	0.2767	0.0006	0.0031	0.0453	0.0449	0.0510	0.2026
NNP	0.3777	0.0110	0.0009	0.0084	0.0584	0.0090	0.0025
MD	0.0008	0.0002	0.7968	0.0005	0.0008	0.1698	0.0041
VB	0.0322	0.0005	0.0050	0.0837	0.0615	0.0514	0.2231
JJ	0.0366	0.0004	0.0001	0.0733	0.4509	0.0036	0.0036
NN	0.0096	0.0176	0.0014	0.0086	0.1216	0.0177	0.0068
RB	0.0068	0.0102	0.1011	0.1012	0.0120	0.0728	0.0479
DT	0.1147	0.0021	0.0002	0.2157	0.4744	0.0102	0.0017

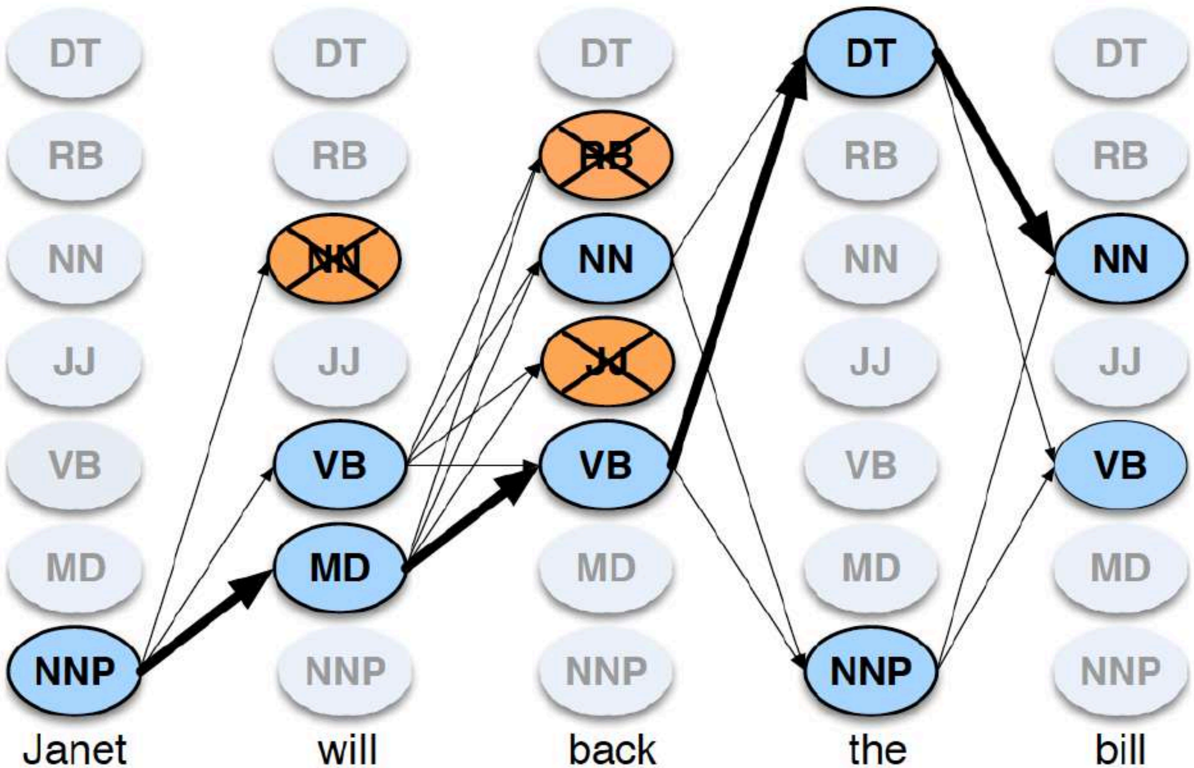
	Janet	will	back	the	bill
NNP	0.000032	0	0	0.000048	0
MD	0	0.308431	0	0	0
VB	0	0.000028	0.000672	0	0.000028
JJ	0	0	0.000340	0.000097	0
NN	0	0.000200	0.000223	0.000006	0.002337
RB	0	0	0.010446	0	0
DT	0	0	0	0.506099	0





Beam Search

- no of states N large → Viterbi ($O(N^2T)$) inefficient →
- instead of keeping all N=45 possibilities at each column, just concentrate on the β most probable ones (prune the possible hidden sequence tree);
- β : beam width



Conditional Random Fields (CRFs)

- Problems of HMMs: unknown words. Possible remedies:
  -- use morphological features: ___-*ed* → VBN or VBD more likely
  -- deviate from Markov first order (use previous word or next word)

- Generative Models (like HMM): incorporate those features: cumbersome → switch to discriminative model (compare Naïve Bayes → Logistic Regression): new features easy to include in conditioning side

- discriminative sequence processing model: linear chain CRF

HMM:

tag-sequence

word-sequence

$$
\begin{aligned}
\hat{Y} &= \underset{Y}{\operatorname{argmax}}\, p(Y|X) \\
&= \underset{Y}{\operatorname{argmax}}\, p(X|Y)\,p(Y) \\
&= \underset{Y}{\operatorname{argmax}} \prod_i p(x_i|y_i) \prod_i p(y_i|y_{i-1})
\end{aligned}
$$

CRF:

$$
\hat{Y} = \underset{Y \in \mathcal{Y}}{\operatorname{argmax}}\, P(Y|X)
$$

CRFs

$$p(Y|X) = \frac{\exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right)}{\sum_{Y' \in \mathcal{Y}} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y')\right)}$$

$$p(Y|X) = \frac{1}{Z(X)} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right)$$

$$Z(X) = \sum_{Y' \in \mathcal{Y}} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y')\right)$$

$$\underbrace{F_k(X,Y)}_{\text{global feature}} = \sum_{i=1}^{n} \underbrace{f_k(y_{i-1}, y_i, X, i)}_{\text{local feature}}$$

CRFs

$$p(Y|X) = \frac{\exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right)}{\sum_{Y' \in \mathcal{Y}} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y')\right)}$$

$$p(Y|X) = \frac{1}{Z(X)} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right)$$

$$Z(X) = \sum_{Y' \in \mathcal{Y}} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y')\right)$$

$$F_k(X,Y) = \sum_{i=1}^{n} f_k(y_{i-1}, y_i, X, i)$$

restriction to current and previous tags: „linear chain" → variants of HMM algorithms (e.g. Viterbi) can be used

CRF Features for POS Tagging

- any feature constructed from (y_{i-1}, y_i, X, i) e.g.

$$\mathbb{1}\{x_i = \textit{the},\ y_i = \text{DET}\}$$
$$\mathbb{1}\{y_i = \text{PROPN},\ x_{i+1} = \textit{Street},\ y_{i-1} = \text{NUM}\}$$
$$\mathbb{1}\{y_i = \text{VERB},\ y_{i-1} = \text{AUX}\}$$

- e.g. using feature templates such as

$$\langle y_i, x_i \rangle, \langle y_i, y_{i-1} \rangle, \langle y_i, x_{i-1}, x_{i+2} \rangle$$

example : for Janet/NNP will/MD back/VB the/DT bill/NN and x_i=*back:*

$$f_{3743}\colon y_i = \text{VB and } x_i = \text{back}$$
$$f_{156}\colon y_i = \text{VB and } y_{i-1} = \text{MD}$$
$$f_{99732}\colon y_i = \text{VB and } x_{i-1} = \text{will and } x_{i+2} = \text{bill}$$

CRF Features for POS Tagging

- useful for unknown words: word shape features: x: letter; X: uppercase letter; d: number; punctuation.
  examples: I.M.F. → X.X.X DC10-30 → XXdd-dd

- useful for unknown words: prefix- or suffix-features:

x_i contains a particular prefix (perhaps from all prefixes of length ≤ 2)
x_i contains a particular suffix (perhaps from all suffixes of length ≤ 2)
x_i's word shape
x_i's short word shape

example: *well-dressed*:

$$\text{prefix}(x_i) = \texttt{w}$$
$$\text{prefix}(x_i) = \texttt{we}$$
$$\text{suffix}(x_i) = \texttt{ed}$$
$$\text{suffix}(x_i) = \texttt{d}$$
$$\text{word-shape}(x_i) = \texttt{xxxx-xxxxxxx}$$
$$\text{short-word-shape}(x_i) = \texttt{x-x}$$

CRF Features for NER

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
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)
word shape of w_i, word shape of neighboring words
short word shape of w_i, short word shape of neighboring words
gazetteer features

Figure 8.15 Typical features for a feature-based NER system.

Words	POS	Short shape	Gazetteer	BIO Label
Jane	NNP	Xx	0	B-PER
Villanueva	NNP	Xx	1	I-PER
of	IN	x	0	O
United	NNP	Xx	0	B-ORG
Airlines	NNP	Xx	0	I-ORG
Holding	NNP	Xx	0	I-ORG
discussed	VBD	x	0	O
the	DT	x	0	O
Chicago	NNP	Xx	1	B-LOC
route	NN	x	0	O
.	.	.	0	O

Figure 8.16 Some NER features for a sample sentence, assuming that Chicago and Villanueva are listed as locations in a gazetteer. We assume features only take on the values 0 or 1, so the first POS feature, for example, would be represented as $\mathbb{1}\{\text{POS} = \text{NNP}\}$.

CRF Inference & Training

state sum

$$
\begin{aligned}
\hat{Y} &= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}} P(Y|X) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}} \frac{1}{Z(X)} \exp\left(\sum_{k=1}^{K} w_k F_k(X,Y)\right) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}} \exp\left(\sum_{k=1}^{K} w_k \sum_{i=1}^{n} f_k(y_{i-1}, y_i, X, i)\right) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}} \sum_{k=1}^{K} w_k \sum_{i=1}^{n} f_k(y_{i-1}, y_i, X, i) \\
&= \underset{Y \in \mathcal{Y}}{\operatorname{argmax}} \sum_{i=1}^{n} \sum_{k=1}^{K} w_k f_k(y_{i-1}, y_i, X, i)
\end{aligned}
$$

CRF Inference & Training

- For HMM we had:

$$\hat{t}_{1:n} = \underset{t_1 \ldots t_n}{\operatorname{argmax}} P(t_1 \ldots t_n | w_1 \ldots w_n) \approx \underset{t_1 \ldots t_n}{\operatorname{argmax}} \prod_{i=1}^{n} \overbrace{P(w_i|t_i)}^{\text{emission}} \overbrace{P(t_i|t_{i-1})}^{\text{transition}}$$

Viterbi: $$v_t(j) = \max_{i=1}^{N} v_{t-1}(i)\, P(s_j|s_i)\, P(o_t|s_j) \quad 1 \le j \le N, 1 < t \le T$$

$$= \max_{i=1}^{N} v_{t-1}(i)\, a_{ij}\, b_j(o_t); \quad 1 \le j \le N, 1 < t \le T$$

- HMM Viterbi formulated in terms of tags t (also denoted as states s) as y and outputs w (also denoted as o) as x:

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i) P\left(y_j \middle| y_i\right) P(x_t|y_j) \quad 1 \le j \le N, 1 < t \le T$$

- Linear chain CRF version of Viterbi

freedom to add new features

$$v_t(j) = \max_{i=1}^{N} v_{t-1}(i) \sum_{k=1}^{K} w_k f_k(y_{t-1}, y_t, X, t) \quad 1 \le j \le N, 1 < t \le T$$

Practical Variation for POS and NER

→ difficult data to label, subjective, hidden - - meanings, etc.

- Combine rule-based with ML-based:

> 1. First, use high-precision rules to tag unambiguous entity mentions.
> 2. Then, search for substring matches of the previously detected names.
> 3. Use application-specific name lists to find likely domain-specific mentions.
> 4. Finally, apply supervised sequence labeling techniques that use tags from previous stages as additional features.

- POS-Tagging for morphologically rich languages: use morphologically rich POS tags to be able to deal with unseen variants of words (→ 4-10 times larger tag-set)

1. Yerdeki **izin** temizlenmesi gerek. **The trace** on the floor should be cleaned.	iz + Noun+A3sg+Pnon+Gen
2. Üzerinde parmak **izin** kalmiş **Your** finger **print** is left on (it).	iz + Noun+A3sg+P2sg+Nom
3. Içeri girmek için **izin** alman gerekiyor. You need **permission** to enter.	izin + Noun+A3sg+Pnon+Nom

Bibliography

(1) Dan Jurafsky and James Martin: Speech and Language Processing (3rd ed. draft, version Jan 2023); Online: https://web.stanford.edu/~jurafsky/slp3/ (URL, Oct 2023) (this slide-set is especially based on chapter 8)

Recommendations for Studying

- minimal approach:

  work with the slides and understand their contents! Think beyond instead of merely memorizing the contents

- standard approach:

  minimal approach + read the corresponding pages in Jurafsky [1]

- interested students

  == standard approach + do a selection of the assignments in Jurafsky