CS447: Natural Language Processing

http://courses.engr.illinois.edu/cs447

Lecture 11: Part-of-Speech tagging

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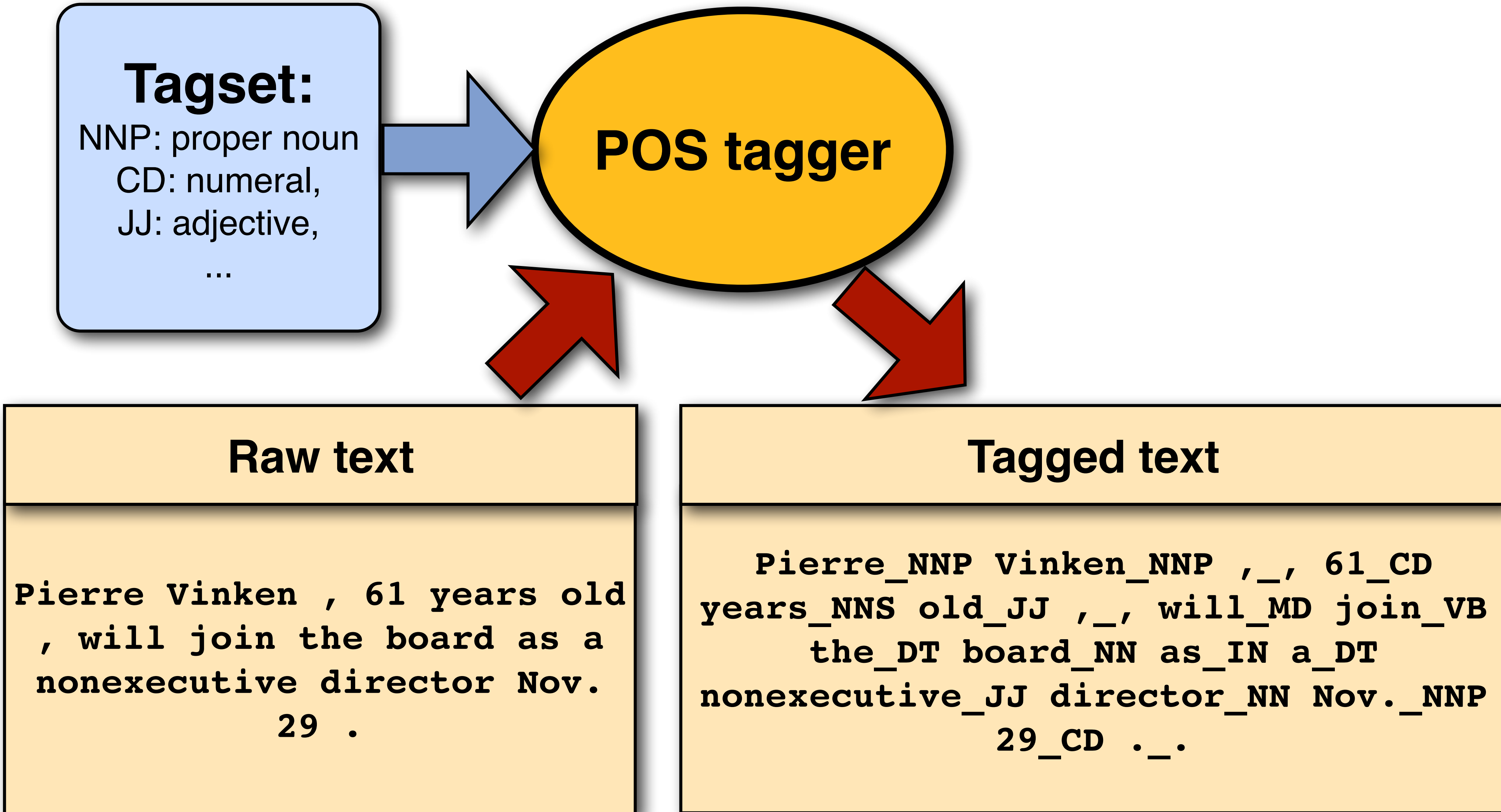
What are parts of speech?

Nouns, Pronouns, Proper Nouns,
Verbs, Auxiliaries,
Adjectives, Adverbs
Prepositions, Conjunctions,
Determiners, Particles
Numerals, Symbols,
Interjections, etc.

See e.g. https://universaldependencies.org/u/pos/
(and the appendix of this slide deck)

POS Tagging


Tagset:
NNP: proper noun
CD: numeral,
JJ: adjective,
...
POS tagger
Raw text
Pierre Vinken , 61 years old , will join the board as a nonexecutive director Nov. 29 .
Tagged text
Pierre_NNP Vinken_NNP ,_, 61_CD years_NNS old_JJ ,_, will_MD join_VB the_DT board_NN as_IN a_DT nonexecutive_JJ director_NN Nov._NNP 29_CD ._.

Why POS Tagging?

POS tagging is one of the first steps in the traditional NLP pipeline (right after tokenization, segmentation).

POS tagging is traditionally viewed as
a prerequisite for further analysis:

- Syntactic Parsing:
  What words are in the sentence?
- Information extraction:
  Finding names, dates, relations, etc.

NB: Although many neural models don't use POS tagging,
it is still important to understand what makes POS tagging difficult
(or easy), and how the basic models and algorithms work.

Ambiguity and Coverage

The POS tagging task:
Determine the POS tag for all tokens in a sentence.

Words often have more than one POS:

- *The **back** door* (adjective)
- *On my **back*** (noun)
- *Win the voters **back*** (particle)
- *Promised to **back** the bill* (verb)

Due to ambiguity (and unknown words), we cannot rely on a dictionary to look up the correct POS tags.

These examples from Dekang Lin

How Much Ambiguity is There?

Common POS ambiguities in English:

Noun—Verb: *table*

Adjective—Verb: *laughing*, *known*,

Noun—Adjective: *normal*

A word is ambiguous if has more than one POS

Unless we have a dictionary that gives all POS tags for each word,
we only know the POS tags with which a word appears in our corpus.

Since many words appear only once (or a few times) in any given corpus,
we may not know all of their POS tags.

Most **word *types*** appear with only one POS tag….

Brown corpus with 87-tag set: 3.3% of word types are ambiguous,
Brown corpus with 45-tag set: 18.5% of word types are ambiguous

… but a large fraction of **word *tokens*** are ambiguous

Original Brown corpus: 40% of tokens are ambiguous

Creating a POS Tagger

To handle ambiguity and coverage,
POS taggers rely on learned models.

For a **new language** (or domain)

- Step 0: Define a POS tag set
- Step 1: Annotate a corpus with these tags

For a **well-studied language** (and domain):

- Step 1: Obtain a POS-tagged corpus

For any language….:

- Step 2: **Choose a** POS tagging **model** (e.g. an HMM)
- Step 3: **Train** your model on your training corpus
- Step 4: **Evaluate** your model on your test corpus

Defining a Tag Set

We have to define an **inventory of labels for the word classes** (i.e. the tag set)

- Most taggers rely on models that have to be trained on **annotated (tagged) corpora**.
- **Evaluation** also requires annotated corpora.
- Since human annotation is expensive/time-consuming, the tag sets used in a few existing labeled corpora become the **de facto standard**.
- Tag sets need to capture **semantically or syntactically important distinctions** that can easily be made by trained human annotators.

Defining a Tag Set

Tag sets have different granularities:

Brown corpus (Francis and Kucera 1982): 87 tags

Penn Treebank (Marcus et al. 1993): 45 tags

Simplified version of Brown tag set

(de facto standard for English now)

NN: common noun (singular or mass): *water*, *book*

NNS: common noun (plural): *books*

Prague Dependency Treebank (Czech): 4452 tags

Complete morphological analysis:

AAFP3----3N----: *nejnezajímavějším*

Adjective Regular Feminine Plural Dative….Superlative

[Hajic 2006, VMC tutorial]

Statistical POS tagging

	She	promised	to	back	the	bill
$\mathbf{w} =$	$w^{(1)}$	$w^{(2)}$	$w^{(3)}$	$w^{(4)}$	$w^{(5)}$	$w^{(6)}$
$\mathbf{t} =$	$t^{(1)}$	$t^{(2)}$	$t^{(3)}$	$t^{(4)}$	$t^{(5)}$	$t^{(6)}$
	PRP	**VBD**	**TO**	**VB**	**DT**	**NN**

What is the most likely sequence of tags $\mathbf{t} = t^{(1)} \dots t^{(N)}$ for the given sequence of words $\mathbf{w} = w^{(1)} \dots w^{(N)}$?

$$\mathbf{t}^* = \mathrm{argmax}_{\mathbf{t}} P(\mathbf{t} \mid \mathbf{w})$$

POS tagging with generative models

$$\begin{aligned}\operatorname*{argmax}_{\mathbf{t}} P(\mathbf{t}|\mathbf{w}) &= \operatorname*{argmax}_{\mathbf{t}} \frac{P(\mathbf{t},\mathbf{w})}{P(\mathbf{w})}\\ &= \operatorname*{argmax}_{\mathbf{t}} P(\mathbf{t},\mathbf{w})\\ &= \operatorname*{argmax}_{\mathbf{t}} P(\mathbf{t})P(\mathbf{w}|\mathbf{t})\end{aligned}$$

$P(\mathbf{t},\mathbf{w})$: the joint distribution of the labels we want to predict ($\mathbf{t}$) and the observed data ($\mathbf{w}$).

We decompose $P(\mathbf{t},\mathbf{w})$ into $P(\mathbf{t})$ and $P(\mathbf{w} \mid \mathbf{t})$ since these distributions are easier to estimate.

Models based on joint distributions of labels and observed data are called generative models: think of $P(\mathbf{t})P(\mathbf{w} \mid \mathbf{t})$ as a stochastic process that first generates the labels, and then generates the data we see, based on these labels.

Hidden Markov Models (HMMs)

HMMs are the most commonly used generative models for POS tagging (and other tasks, e.g. in speech recognition)

HMMs make specific **independence assumptions** in $P(\mathbf{t})$ and $P(\mathbf{w} \mid \mathbf{t})$:

1) $P(\mathbf{t})$ is an *n*-gram (typically **bigram** or **trigram**) model over tags:

$$P_{\text{bigram}}(\mathbf{t}) = \prod_i P(t^{(i)} \mid t^{(i-1)}) \qquad P_{\text{trigram}}(\mathbf{t}) = \prod_i P(t^{(i)} \mid t^{(i-1)}, t^{(i-2)})$$

$P(t^{(\mathrm{i})} \mid t^{(\mathrm{i}-1)})$ and $P(t^{(\mathrm{i})} \mid t^{(\mathrm{i}-1)}, t^{(\mathrm{i}-2)})$ are called **transition probabilities**

2) In $P(\mathbf{w} \mid \mathbf{t})$, each $\mathrm{w}^{(\mathrm{i})}$ depends only on [is generated by/conditioned on] $\mathrm{t}^{(\mathrm{i})}$:

$$P(\mathbf{w} \mid \mathbf{t}) = \prod_i P(w^{(i)} \mid t^{(i)})$$

$P(w^{(\mathrm{i})} \mid t^{(\mathrm{i})})$ are called **emission probabilities**

These probabilities don't depend on the position in the sentence $^{(\mathrm{i})}$,
but are defined over word and tag types.
With subscripts $_{\mathrm{i,j,k}}$, to index word/tag types, they become $P(t_i \mid t_j)$, $P(t_i \mid t_j, t_k)$, $P(w_i \mid t_j)$

Maximum Entropy Markov Models

MEMMs use a **logistic regression** ("Maximum Entropy") classifier for each $P(t^{(i)} \mid w^{(i)}, t^{(i-1)})$

$$P(t^{(i)} = t_k \mid t^{(i-1)}, w^{(i)}) = \frac{\exp(\sum_j \lambda_{jk} f_j(t^{(i-1)}, w^{(i)}))}{\sum_l \exp(\sum_j \lambda_{jl} f_j(t^{(i-1)}, w^{(i)}))}$$

Here, $t^{(i)}$: label of the i-th word vs. t_i = i-th label in the inventory

This requires the definition of a **feature function** $f(t^{(i-1)}, w^{(i)})$ that returns an *n*-dimensional feature vector for predicting label $t^{(i)}=t_j$ given inputs $t^{(i-1)}$ and $w^{(i)}$

Training returns weights λ_{jk} for each feature j used to predict label t_k

Conditional Random Fields (CRFs)

Conditional Random Fields have the same mathematical definition as MEMMs, but:

— CRFS are trained globally to maximize the probability of the overall sequence,

— MEMMs are trained locally to maximize the probability of each individual label

This requires dynamic programming

- Training: akin to the Forward-Backward algorithm used to train HMMs from unlabeled sequences)
- Decoding: Viterbi

Evaluation Metric: Test Accuracy

How many *words* in the unseen test data can you tag correctly?

State of the art on Penn Treebank: around 97%

⇨ **How many *sentences* can you tag correctly?**

Compare your model against a **baseline**

Standard: assign to each word its most likely tag

(use training corpus to estimate P(t|w))

Baseline performance on Penn Treebank: around 93.7%

… and a **(human) ceiling**

How often do human annotators agree on the same tag?

Penn Treebank: around 97%

Is POS-tagging a solved task?

Penn Treebank POS-tagging accuracy
≈ human ceiling

Yes, but:

Other languages with more complex morphology need much larger tag sets for tagging to be useful, and will contain many more distinct word forms in corpora of the same size.

They often have much lower accuracies.

Also: POS tagging accuracy on English text from other domains can be significantly lower.

Qualitative evaluation

Generate a confusion matrix (for development data):
How often was a word with tag *i* mistagged as tag *j*:

Correct Tags

Predicted Tags

	IN	JJ	NN	NNP	RB	VBD	VBN
IN	—	.2			.7		
JJ	.2	—	**3.3**	2.1	1.7	.2	**2.7**
NN		**8.7**	—				.2
NNP	.2	**3.3**	**4.1**	—	.2		
RB	**2.2**	2.0	.5		—		
VBD		.3	.5			—	**4.4**
VBN		**2.8**				**2.6**	—

% of errors caused by mistagging VBN as JJ

See what errors are causing problems:

- Noun (NN) vs ProperNoun (NNP) vs Adj (JJ)
- Preterite (VBD) vs Participle (VBN) vs Adjective (JJ)

Appendix: English Parts of Speech

Nouns

Nouns describe **entities and concepts**:

Common nouns: *dog, bandwidth, dog, fire, snow, information*

Count nouns have a plural (*dogs*) and need an article in the singular (*the dog barks*)

Mass nouns don't have a plural (**snows*) and don't need an article in the singular (*snow is cold, metal is expensive*).
But some mass nouns can also be used as count nouns:
Gold and silver are metals.

Proper nouns (Names): *Mary, Smith, Illinois, USA, IBM*

Penn Treebank tags:

NN: singular or mass common noun   NNS: plural common noun
NNP: singular proper noun   NNPS: plural proper noun

(Full) verbs

Verbs describe **activities, processes, events**:

eat, write, sleep, ….

Verbs have different morphological forms:
infinitive (*to eat*), present tense (*I eat*), 3rd pers sg. present tense (*he eats*), past tense (*ate*), present participle (*eating*), past participle (*eaten*)

Penn Treebank tags:

VB: infinitive (base) form

VBD: past tense

VBG: present participle

VBD: past tense

VBN: past participle

VBP: non-3rd person present tense

VBZ: 3rd person singular present tense

Adjectives

Adjectives describe **properties of entities**:

blue, hot, old, smelly,…

Adjectives have an...

…**attributive use** (modifying a noun): *the blue book*

…**predicative use** (as arguments of be): *the book is blue.*

Many **gradable** adjectives also have a…

...**comparative form**: *greater, hotter, better, worse*

...**superlative form:** *greatest, hottest, best, worst*

Penn Treebank tags:

JJ: adjective JJR: comparative JJS: superlative

Adverbs

Adverbs describe **properties of events/states**.

- **Manner** adverbs: *slowly (slower, slowest) fast, hesitantly*,
- **Degree** adverbs: *extremely, very, highly…*
- **Directional** and **locative** adverbs: *here, downstairs, left*
- **Temporal** adverbs: *yesterday, Monday,…*

Adverbs modify verbs, sentences, adjectives or other adverbs:

Apparently, the ***very*** *ill man walks* ***extremely slowly***

NB: certain temporal and locative adverbs (*yesterday*, *here, Monday*) can also be classified as nouns

Penn Treebank tags:

RB: adverb   RBR: comparative adverb   RBS: superlative adverb

Auxiliary and modal verbs

Copula: *be* with a predicate

She is a student. I am hungry. She was five years old.

Modal verbs: *can*, *may*, *must*, *might*, *shall*,…

She can swim. You must come

Auxiliary verbs:

– *Be*, *have*, *will* when used to form complex tenses:

He was being followed. She has seen him. We will have been gone.

– *Do* in questions, negation:

Don’t go. Did you see him?

Penn Treebank tags:

MD: modal verbs

Prepositions

Prepositions describe **relations** between entities or between entities and events.

They occur before noun phrases to form prepositional phrase (PP):

on/in/under/near/towards the wall,

with(out) milk, by the author, despite your protest

PPs can modify nouns, verbs or sentences:

I drink [coffee [with milk]]
I [drink coffee [with my friends]]

Penn Treebank tags:

IN: preposition
TO: ‘to’ (infinitival ‘to eat’ and preposition ‘to you’)

Conjunctions

Coordinating conjunctions conjoin two elements:

X *and/or/but* X

[[*John*]$_{NP}$ *and* [*Mary*]$_{NP}$] $_{NP}$,

[[*Snow is cold*]$_{S}$ *, but* [*fire is hot*]$_{S}$]$_{S}$.

Subordinating conjunctions

introduce a subordinate (embedded) clause:

[*He thinks that* [*snow is cold*]$_{S}$]$_{S}$

[*She wonders whether* [*it is cold outside*]$_{S}$]$_{S}$

Penn Treebank tags:

CC: coordinating

IN: subordinating (same as preposition)

Particles

Particles resemble prepositions (but are not followed by a noun phrase) and appear with verbs:

come on
he brushed himself off
turning the paper over
turning the paper down

Phrasal verb: a verb + particle combination that has a different meaning from the verb itself

Penn Treebank tags:

RP: particle

Pronouns

Many pronouns function like noun phrases, and refer to some other entity:

- **Personal** pronouns: *I, you, he, she, it, we, they*
- **Possessive** pronouns: *mine, yours, hers, ours*
- **Demonstrative** pronouns: *this, that*,
- **Reflexive** pronouns: *myself, himself, ourselves*
- **Wh**-pronouns (question words)
  what, who, whom, how, why, whoever, which

Relative pronouns introduce relative clauses

*the book **that** [he wrote]*

Penn Treebank tags:

PRP: personal pronoun   PRP$ possessive   WP: wh-pronoun

Determiners

Determiners precede noun phrases:

the/that/a/every *book*

– **Articles**: *the, an, a*
– **Demonstratives**: *this, these, that*
– **Quantifiers**: *some, every, few,…*

Penn Treebank tags:

DT: determiner