POS Tagging

words are ambiguous

so tagging must resolve / disambiguate

Types:		WSJ	Brown
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%**)

Figure 10.2 The amount of tag ambiguity for word types in the Brown and WSJ corpora, from the Treebank-3 (45-tag) tagging. These statistics include punctuation as words, and assume words are kept in their original case.

Some words have up to 6 tags

1 earnings took a back/Adj seat

2 a small yard in the back/Noun

3 senators back/present tense verb the bill

4 He started to back/infinitival verb toward the four-

5 to buy back/particle stock
verb

6 I was young back/Adverb then
temporal

HMMs for tagging

Hidden Markov Models are trained on tagged corpora, instead of using the Baum-Welch algorithm. Fully supervised instead, with MLE parameter estimation

Basic eqn. for HMM tagging:

$$\hat{t}_1^N = \arg\max_{t_1^N} P(t_1^N | w_1^N)$$

Use Bayes Rule

$$= \arg\max_{t_1^N} \frac{P(w_1^N | t_1^N) P(t_1^N)}{P(w_1^N)}$$

$$= \arg\max_{t_1^N} P(w_1^N | t_1^N) P(t_1^N)$$

simplifying assumptions

Simplifying assumptions:

1. Probability of a word only depends on its own tag, and it is independent of neighboring words and tags:

$$p(w_1^N | t_1^N) \approx \prod_{i=1}^{N} p(w_i | t_i)$$

2. Bigram assumption. The probability of a tag depends only on prev. tag, not the whole tag sequence:

$$p(t_1^N) \approx \prod_{i=1}^{N} p(t_i | t_{i-1})$$

Combining everything

$$\hat{t}_1^N = \underset{t_1^N}{\operatorname{argmax}}\, p(t_1^N | w_1^N) \approx \underset{t_1^N}{\operatorname{argmax}} \prod_{1}^{N} p(w_i | t_i)\, p(t_i | t_{i-1})$$

emission probabilities, transition prob

Estimating probabilities

tag transition probabilities

MLE

$$P(t_i \mid t_{i-1}) = \frac{\text{Count}(t_{i-1}\ t_i)}{\text{Count}(t_{i-1})}$$

Example

$$P(VB \mid MD) = \frac{\text{Count}(MD\ VB)}{\text{Count}(MD)} = \frac{10471}{13124} = .8$$

Emission probabilities: probability that given a tag, we will see a given word

$$P(w_i \mid t_i) = \frac{\text{count}(t_i, w_i)}{\text{count}(t_i)}$$

Example

$$P(\text{will} \mid MD) = \frac{\text{Count}(\text{will MD})}{\text{count}(MD)}$$

$$= \frac{4061}{13124} = .31$$

P(house | NN)

Extending HMMs to trigrams

use more word history

$$p(t_1^n) \approx \prod_{i=1}^{n} p(t_i \mid t_{i-2}, t_{i-1})$$

estimation = MLE

Advanced features:

① Interpolation (just like LMs)

λ_3 Trigram tags $p(t_i \mid t_{i-1}, t_{i-2})$ +

λ_2 bigrams $p(t_i \mid t_{i-1})$ +

λ_1 unigrams $p(t_i) = \frac{count(t_i)}{N}$

② Dealing with Unknown words

Many new words are added to the lexicon

Most of our annotated corpora are 20+ years old.

Never contained the word google

- Morphological clues
  - wugs → plural noun
  - -ed → past tense verb
  - -able → adjective
  - -ly → adverb
- Capitalization

- Tag sequence

$$p(t_i \mid t_{i-1}\ t_{i-2})$$

Beyond HMMS: MEMM

Maximum entropy Markov Models

- discriminative sequence model

Instead of

$$\hat{T} = \underset{T}{\operatorname{argmax}}\ P(T \mid W)$$

$$\rightarrow = \underset{T}{\operatorname{argmax}}\ P(W \mid T)\ P(T)$$

Instead of

$$\hat{T} = \underset{T}{\operatorname{argmax}}\ P(T|W)$$

$$\rightarrow = \underset{T}{\operatorname{argmax}}\ P(W|T)\,P(T)$$

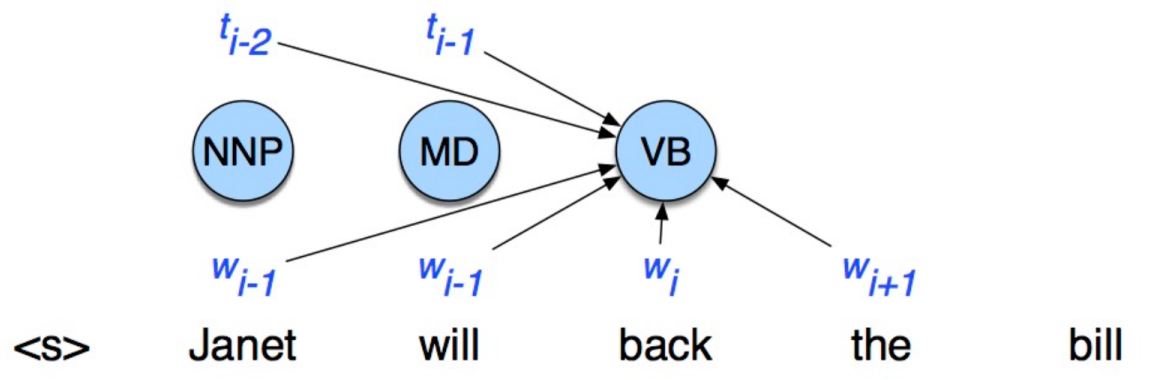
$$\rightarrow = \underset{T}{\operatorname{argmax}} \prod_i P(w_i|t_i) \prod P(t_i|t_{i-1})$$

MEMMs compute posterior directly, and train it to discriminate among tag sequences!

$$\hat{T} = \underset{T}{\operatorname{argmax}}\ P(T|W)$$

$$= \underset{T}{\operatorname{argmax}} \prod_i P(t_i|w_i, t_{i-1})$$

or use tons of features



$$= \underset{T}{\operatorname{argmax}} \prod_i p(t_i \mid w_{i-1}^{i+1}, t_{i-k}^{i-1})$$

$$= \underset{T}{\operatorname{argmax}} \prod_i \frac{\exp\left(\sum_i w_i f_i(t_i, \cdots)\right)}{\sum_{t' \in \text{tagset}} \exp\left(\sum_i w_i f_i(t', \cdots)\right)}$$

what does this remind you of?

logistic regression

What does this remind you of?

logistic regression

Most Frequent class baseline

92% accuracy

versus

97% SOA taggers

Q: Does that mean that POS tagging is "solved"?

```
ikr smh he asked fir yo last name so he can add u on fb lolololol
```

word	tag	confidence
ikr	!	0.8143
smh	G	0.9406
he	O	0.9963
asked	V	0.9979
fir	P	0.5545
yo	D	0.6272
last	A	0.9871
name	N	0.9998
so	P	0.9838
he	O	0.9981
can	V	0.9997
add	V	0.9997
u	O	0.9978
on	P	0.9426
fb	^	0.9453
lolololol	!	0.9664

- *"ikr"* means "I know, right?", tagged as an interjection.
- *"so"* is being used as a subordinating conjunction, which our coarse tagset denotes *P*.
- *"fb"* means "Facebook", a very common proper noun (^).
- *"yo"* is being used as equivalent to *"your"*; our coarse tagset has posessive pronouns as *D*.
- *"fir"* is a misspelling or spelling variant of the preposition *for*.
- Perhaps the only debatable errors in this example are for *ikr* and *smh* ("shake my head"): should they be *G* for miscellaneous acronym, or *!* for interjection?

```
:o :/ :'( >:o (: :) >.< XD -__- o.O ;D :-) @_@ :P 8D :1 >:( :D =| ") :> ....
```

word	tag	confidence
:o	E	0.9387
:/	E	0.9983
:'(	E	0.9975
>:o	E	0.9964
(:	E	0.9994
:)	E	0.9997
>.<	E	0.9952
XD	E	0.9938
-__-	E	0.9956
o.O	E	0.9899
;D	E	0.9995
:-)	E	0.9992
@_@	E	0.9964
:P	E	0.9996
8D	E	0.9961
:	E	0.6925
1	$	0.9194
>:(	E	0.9715
:D	E	0.9996
=|	E	0.9963
"	,	0.6125
)	,	0.9078
:	,	0.7460
>	G	0.7490
...	,	0.5223
.	,	0.9946

Challenge case for emoticon segmentation/recognition: 20/26 precision, 18/21 recall.

Most POS tagging work is evaluated on the WSJ. This is a well-edited formally written newspaper that obeys standard conventions. Twitte OTOH is...

- Conversational
- lacks conventional spelling — confefe!
- introduces abbreviations and other innovations to match the 140 character limit (now raised to 280).

CMU researchers introduced a new tagset for Twitter plus some manually annotated Tweets.

The performance of their system is in the mid-80% range instead of high 90s.

Other challenges

Other languages

Low resource languages

Dialects.

Q: Do all language share the same parts of speech?

Language	Source	# Tags	O/O	U/U	O/U
Arabic	PADT/CoNLL07 (Hajič et al., 2004)	21	96.1	96.9	97.0
Basque	Basque3LB/CoNLL07 (Aduriz et al., 2003)	64	89.3	93.7	93.7
Bulgarian	BTB/CoNLL06 (Simov et al., 2002)	54	95.7	97.5	97.8
Catalan	CESS-ECE/CoNLL07 (Martí et al., 2007)	54	98.5	98.2	98.8
Chinese	Penn ChineseTreebank 6.0 (Palmer et al., 2007)	34	91.7	93.4	94.1
Chinese	Sinica/CoNLL07 (Chen et al., 2003)	294	87.5	91.8	92.6
Czech	PDT/CoNLL07 (Böhmová et al., 2003)	63	99.1	99.1	99.1
Danish	DDT/CoNLL06 (Kromann et al., 2003)	25	96.2	96.4	96.9
Dutch	Alpino/CoNLL06 (Van der Beek et al., 2002)	12	93.0	95.0	95.0
English	PennTreebank (Marcus et al., 1993)	45	96.7	96.8	97.7
French	FrenchTreebank (Abeillé et al., 2003)	30	96.6	96.7	97.3
German	Tiger/CoNLL06 (Brants et al., 2002)	54	97.9	98.1	98.8
German	Negra (Skut et al., 1997)	54	96.9	97.9	98.6
Greek	GDT/CoNLL07 (Prokopidis et al., 2005)	38	97.2	97.5	97.8
Hungarian	Szeged/CoNLL07 (Csendes et al., 2005)	43	94.5	95.6	95.8
Italian	ISST/CoNLL07 (Montemagni et al., 2003)	28	94.9	95.8	95.8

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Italian	ISST/CoNLL07 (Montemagni et al., 2003)	28	94.9	95.8	95.8
Japanese	Verbmobil/CoNLL06 (Kawata and Bartels, 2000)	80	98.3	98.0	99.1
Japanese	Kyoto4.0 (Kurohashi and Nagao, 1997)	42	97.4	98.7	99.3
Korean	Sejong (http://www.sejong.or.kr)	187	96.5	97.5	98.4
Portuguese	Floresta Sintá(c)tica/CoNLL06 (Afonso et al., 2002)	22	96.9	96.8	97.4
Russian	SynTagRus-RNC (Boguslavsky et al., 2002)	11	96.8	96.8	96.8
Slovene	SDT/CoNLL06 (Džeroski et al., 2006)	29	94.7	94.6	95.3
Spanish	Ancora-Cast3LB/CoNLL06 (Civit and Martí, 2004)	47	96.3	96.3	96.9
Swedish	Talbanken05/CoNLL06 (Nivre et al., 2006)	41	93.6	94.7	95.1
Turkish	METU-Sabanci/CoNLL07 (Oflazer et al., 2003)	31	87.5	89.1	90.2

Does it make sense to have a "universal" pos tag set?

A Universal Part-of-Speech Tagset

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Abstract

To facilitate future research in unsupervised induction of syntactic structure and to standardize best-practices, we propose a tagset that consists of twelve universal part-of-speech categories. In addition to the tagset, we develop a mapping from 25 different treebank tagsets to this universal set. As a result, when combined with the original treebank data, this universal tagset and mapping produce a dataset consisting of common parts-of-speech for 22 different languages. We highlight the use of this resource via two experiments, including one that reports competitive accuracies for unsupervised grammar induction without gold standard part-of-speech tags.

forms across languages. These categories are often called *universals* to represent their cross-lingual nature (Carnie, 2002; Newmeyer, 2005). For example, Naseem et al. (2009) used the Multext-East (Erjavec, 2004) corpus to evaluate their multi-lingual POS induction system, because it uses the same tagset for multiple languages. When corpora with common tagsets are unavailable, a standard approach is to manually define a mapping from language and treebank specific fine-grained tagsets to a predefined universal set. This was the approach taken by Das and Petrov (2011) to evaluate their cross-lingual POS projection system for six different languages.

To facilitate future research and to standardize best-practices, we propose a tagset that consists of twelve universal POS categories. While there

sentence:	The	oboist	Heinz	Holliger	has	taken	a	hard	line	about	the	problems	.
original:	DT	NN	NNP	NNP	VBZ	VBN	DT	JJ	NN	IN	DT	NNS	.
universal:	DET	NOUN	NOUN	NOUN	VERB	VERB	DET	ADJ	NOUN	ADP	DET	NOUN	.

Figure 1: Example English sentence with its language specific and corresponding universal POS tags.

inflectional morphology - pluralization
tense

derivational morphology - oboe
→ oboist
"one who plays" verbs the noun
piano
→ pianist

agglutinative languages
words contain a lot of morphemes
joined together, which would be
expressed with seperate words in other
languages