CS474 Natural Language Processing

- **Last classes**
  - N-gram models
- **Today**
  - Part-of-speech tagging
    - Introduction
    - Transformation-based learning

Part of speech tagging

"There are 10 parts of speech, and they are all troublesome."

-*Mark Twain*

- POS tags are also known as word classes, morphological classes, or lexical tags.

- Typically much larger than Twain's 10:
  - Penn Treebank: 45
  - Brown corpus: 87
  - C7 tagset: 146

Part of speech tagging

- **Assign the correct part of speech (word class) to each word/token in a document**

  "The/DT planet/NN Jupiter/NNP and/CC its/PRP moons/NNS are/VBP in/IN effect/NN a/DT mini-solar/JJ system/NN ,/, and/CC Jupiter/NNP itself/PRP is/VBZ often/RB called/VBN a/DT star/NN that/IN never/RB caught/VBN fire/NN ./."

- **Needed as an initial processing step for a number of language technology applications**
  - Answer extraction in Question Answering
  - Base step in identifying syntactic phrases for IR systems
  - Critical for word-sense disambiguation (WordNet apps)
  - Information extraction
  - …

Why is p-o-s tagging hard?

- **Ambiguity**
  - He will race/VB the car.
  - When will the race/NOUN end?
  - The boat floated/VBN down the river sank.

- **Average of ~2 parts of speech for each word**

- **The number of tags used by different systems varies a lot. Some systems use < 20 tags, while others use > 400.**

Hard for Humans

- **particle vs. preposition**
  - He talked *over* the deal.
  - He talked *over* the telephone.
- **past tense vs. past participle**
  - The horse *walked* past the barn.
  - The horse *walked* past the barn fell.
- **noun vs. adjective?**
  - The *executive* decision.
- **noun vs. present participle**
  - *Fishing* can be fun.

To obtain gold standards for evaluation, annotators rely on a set of tagging guidelines.

From Ralph Grishman, NYU

Penn Treebank Tagset

Tag	Description	Example	Tag	Description	Example
CC	Coordin. Conjunction	*and, but, or*	SYM	Symbol	+,%, &
CD	Cardinal number	*one, two, three*	TO	"to"	*to*
DT	Determiner	*a, the*	UH	Interjection	*ah, oops*
EX	Existential 'there'	*there*	VB	Verb, base form	*eat*
FW	Foreign word	*mea culpa*	VBD	Verb, past tense	*ate*
IN	Preposition/sub-conj	*of, in, by*	VBG	Verb, gerund	*eating*
JJ	Adjective	*yellow*	VBN	Verb, past participle	*eaten*
JJR	Adj., comparative	*bigger*	VBP	Verb, non-3sg pres	*eat*
JJS	Adj., superlative	*wildest*	VBZ	Verb, 3sg pres	*eats*
LS	List item marker	*1, 2, One*	WDT	Wh-determiner	*which, that*
MD	Modal	*can, should*	WP	Wh-pronoun	*what, who*
NN	Noun, sing. or mass	*llama*	WP$	Possessive wh-	*whose*
NNS	Noun, plural	*llamas*	WRB	Wh-adverb	*how, where*
NNP	Proper noun, singular	*IBM*	$	Dollar sign	$
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	#
PDT	Predeterminer	*all, both*	"	Left quote	(' or ")
POS	Possessive ending	*'s*	"	Right quote	(' or ")
PP	Personal pronoun	*I, you, he*	(	Left parenthesis	([, (, {, <)
PP$	Possessive pronoun	*your, one's*	)	Right parenthesis	( ],), }, >)
RB	Adverb	*quickly, never*	,	Comma	,
RBR	Adverb, comparative	*faster*	.	Sentence-final punc	(. ! ?)
RBS	Adverb, superlative	*fastest*	:	Mid-sentence punc	(: ; ... – -)
RP	Particle	*up, off*			

Among easiest of NLP problems

- **State-of-the-art methods achieve ~97% accuracy.**
- **Simple heuristics can go a long way.**
  - ~90% accuracy just by choosing the most frequent tag for a word (MLE)
  - To improve reliability: *need to use some of the local context.*
- **But defining the rules for special cases can be time-consuming, difficult, and prone to errors and omissions**

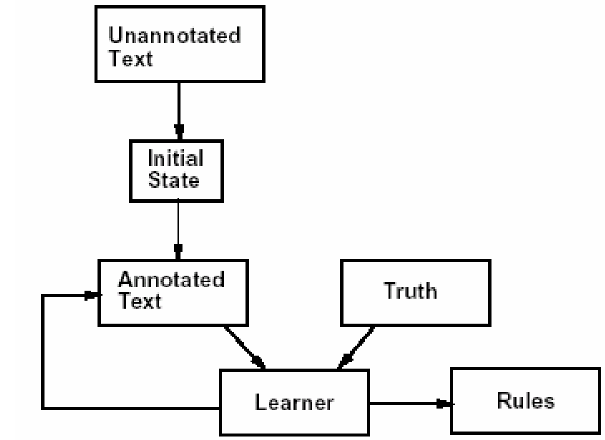
Approaches

1. **rule-based**: involve a large database of hand-written disambiguation rules, e.g. that specify that an ambiguous word is a noun rather than a verb if it follows a determiner.
2. **probabilistic**: resolve tagging ambiguities by using a training corpus to compute the probability of a given word having a given tag in a given context.
   - HMM tagger
3. **hybrid corpus-/rule-based**: E.g. transformation-based tagger (Brill tagger); learns symbolic rules based on a corpus.
4. **ensemble methods**: combine the results of multiple taggers.

Transformation-based learning

- **Supervised machine learning technique**
  - For acquiring simple default heuristics and rules for special cases
  - Rules are learned by iteratively collecting errors and generating rules to correct them.
- **Requires a large (training) corpus of manually tagged text**

TBL: high-level algorithm



Learns an ordered list of transformations (i.e. rewrite rules)

Rewrite rules

- **Rule**
  - Change ***modal*** to ***noun***, if preceding word is a ***determiner***
- **Example**
  - Determiner: the, a, an, this, that …
  - Modals: can, will, should, would, may, might…followed by the main verb
  - The/*det* can/*modal* rusted/*verb* ./.
  - The/*det* can/*noun* rusted/*verb* ./.

Transformation-based learning

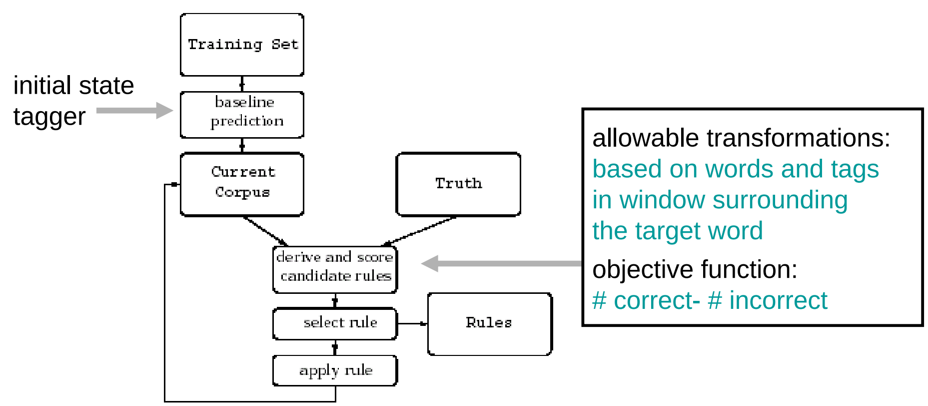


Figure 1: Transformation-based Learning

[Brill 1993]

Learning algorithm: greedy search

- **Specify**
  - An initial state annotator
  - Space of allowable transformations
  - Objective function for comparing corpus to truth
- **Algorithm**
  - Iterate
    - Try each possible transformation
    - Choose the one with the best score
    - Add to list of transformations
    - Update the training corpus
  - Until no transformation improves performance

Transformation templates

- **Change tag A to B when:**
  - preceding/following word is tagged Z
  - word two before/after is tagged Z
  - one of the two preceding/following words is tagged Z
  - one of the three preceding/following words is tagged Z
  - preceding word is tagged Z and following word is tagged W
  - preceding/following word is tagged Z and word two before/after is tagged W

Generating transformations

- Apply the initial tagger and compile types of tagging errors. Each type of error is of the form:
  - <incorrect tag, desired tag ,# of occurrences>
- For each error type, instantiate <u>all</u> templates to generate candidate transformations.
- Apply each candidate transformation to the corpus and count the number of corrections and errors that it produces. Save the transformation that yields the greatest improvement.
- Stop when no transformation can reduce the error rate by a predetermined threshold.

Example

- Suppose that the initial tagger mistags 159 words as verbs when they should have been nouns.
- Produces the error triple:

  < *verb, noun,* 159>
- Suppose template #3 is instantiated as the rule:

  Change the tag from verb to noun if one of the two preceding words is tagged as a determiner.
- When this template is applied to the corpus, it corrects 98 of the 159 errors. But it also creates 18 new errors. Error reduction is 98-18=80.

Learned rules

1. **NN→VB if the previous tag is TO**
   I wanted to/TO win/NN→VB a Subaru WRX…
2. **VBP→VB if one of the prev-3 tags is MD**
   The food might/MD vanish/VBP→VB from sight.
3. **NN→VB if one of prev-2 tags is MD**
   I might/MD not reply/NN→VB
4. **VB→NN if one of the prev-2 tags is DT**
5. **VBD→VBN if one of the prev-3 tags is VBZ**
6. **VBN→VBD if one of the previous tag is PRP**

Tagging new text

- **The resulting tagger consists of two phases:**
  - Use the initial tagger to tag all the text
  - Apply each transformation, in order, to the corpus to correct some of the errors.
- **The order of the transformations is very important!**
  - For example, it is possible for a word's tag to change several times as different transformations are applied. In fact, a word's tag could thrash back and forth between the same two tags.

Evaluation

- **Training: 600,000 words from the Penn Treebank WSJ corpus**
- **Testing: separate 150,000 words from PTB**
- **Assumes all possible tags for all test set words are known.**
- **97.0% accuracy**
- **Tagger learned 378 rules.**

Problems?

- **Not lexicalized**
  - Transformations are entirely tag-based; no specific words were used in the rules.
  - But certain phrases and lexicalized expressions can yield idiosyncratic tag sequences, so allowing the rules to look for specific words should help…
  - Add additional templates
    - E.g. when the preceding/following word is *w*…
  - Tagger achieves 97.2% accuracy
    - First 200 rules achieved 97.0%
    - First 100 rules achieved 96.8%
  - Learns 447 rules
- **Unknown words**

Transformation-based learning

- **Part-of-speech tagging**
  [Brill 1995; Ramshaw & Marcus 1994]
- **Prepositional phrase attachment**
  [Brill & Resnik 1995]
- **Syntactic parsing**
  [Brill 1994]
- **Noun phrase chunking**
  [Ramshaw & Marcus 1995, 1999]
- **Context-sensitive spelling correction**
  [Mangu & Brill 1997]
- **Dialogue act tagging**
  [Samuel et al. 1998]