CMPT-413 Computational Linguistics

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Human Supervision in Part of Speech Tagging

In unseen data, we wish to find the part of speech tags:

Input: In 1994, Hartnett said

Output: In_IN 1994_CD ,_ , Hartnett_NNP said_VBD

- The set of part of speech tags are decided by experts
- The experts also have to provide adequate amounts of data in which the part of speech tags have been listed for each word in context.
- This general approach is called supervised learning since the training data is provided by humans.

Trigram Models for Part of Speech Tagging

In_IN 1994_CD ,_, Hartnett_NNP said_VBD

THE_DT BONEYARD_NNP Northrop_NNP Grumman_NNP 's_POS modest_JJ flight_NN museum_NN occupies_VBZ a_DT corner_NN of_IN one_CD of_IN its_PRP\\$ power-seat_NN adjusters_NNS ,_, door_NN trim_JJ now_RB made_VBN in_IN South_NNP Korea_NNP 's_POS antiquated_JJ coal-fired_JJ power_NN plant_NN in_IN Canada_NNP ,_, to_TO a_DT 11.9_CD million_CD mark_NN investment_NN in_IN Samsung_NNP 's_POS Sachon_NNP plant_NN in_IN Taiwan_NNP as_IN part_NN of_IN a_DT steam_NN turbine_NN ,_, a_DT new_JJ high-yielding_JJ rice_NN plant_NN was_VBD reorganized_VBN into_IN a_DT big_JJ expansion_NN of_IN a_DT fuel-fabrication_NN plant_NN near_IN Nagoya_NNP in_IN Aichi_NNP Prefecture_NNP

From_IN October_NNP ,_, when_WRB they_PRP do_VBP not_RB need_VB it_PRP

Borges gives a vague reference to some work by Franz Kuhn allegedly commenting on the classification of animals by a Chinese encyclopedia called the _Celestial Emporium of Benevolent Knowledge_.

>> ... animals are divided into:

- (a) those that belong to the Emperor,
- (b) embalmed ones,
- (c) those that are trained,
- (d) suckling pigs,
- (e) mermaids,
- (f) fabulous ones,
- (g) stray dogs,
- (h) those that are included in this classification,
- (i) those that tremble as if they were mad,
- (j) innumerable ones,
- (k) those drawn with a very fine camel brush,
- (1) others,
- (m) those that have just broken a flower vase,
- (n) those that resemble flies from a distance. <<
- -- Jorge Luis Borges, "Other Inquisitions"

- Let the input sentence (word sequence) be w_0, w_1, \ldots, w_n
- Let the most likely tag sequence be $T^*=t_0^*,t_1^*,\ldots,t_n^*$
- In order to compare all possible tag sequences we build a probability model:

$$P(t_0, t_1, \ldots, t_n \mid w_0, w_1, \ldots, w_n)$$

The best (or most likely) tag sequence is:

$$T^* = \underset{t_0, \ldots, t_n}{\operatorname{arg max}} P(t_0, \ldots, t_n \mid w_0, \ldots, w_n)$$

$$P(t_0,\ldots,t_n\mid w_0,\ldots,w_n)$$

$$= \frac{P(w_0,\ldots,w_n\mid t_0,\ldots,t_n)\times P(t_0,\ldots,t_n)}{P(w_0,\ldots,w_n)}$$
(Bayes Rule)

$$= P(w_0,\ldots,w_n \mid t_0,\ldots,t_n) \times P(t_0,\ldots,t_n)$$

$$P(w_0, \dots, w_n \mid t_0, \dots, t_n)$$

$$= P(w_0 \mid t_0) \times P(w_1 \mid t_1) \times \dots \times P(w_n \mid t_n)$$

$$= \prod_{i=0}^n P(w_i \mid t_i)$$

$$P(t_0, ..., t_n)$$
= $P(t_0) \times P(t_1 | t_0) \times P(t_2 | t_0, t_1) \times ... \times P(t_n | t_{n-2}, t_{n-1})$
= $P(t_0) \times P(t_1 | t_0) \times \prod_{i=2}^{n} P(t_i | t_{i-2}, t_{i-1})$

$$P(t_{0},...,t_{n} \mid w_{0},...,w_{n})$$

$$= P(w_{0},...,w_{n} \mid t_{0},...,t_{n}) \times P(t_{0},...,t_{n})$$

$$= \left(\prod_{i=0}^{n} P(w_{i} \mid t_{i})\right) \times \left(P(t_{0}) \times P(t_{1} \mid t_{0}) \times \prod_{i=2}^{n} P(t_{i} \mid t_{i-2},t_{i-1})\right)$$

$$= \prod_{i=0}^{n} P(w_{i} \mid t_{i}) \times P(t_{i} \mid t_{i-2},t_{i-1})$$

 So, all we need to do to find the most likely tag sequence is to train the following two probability models:

$$P(w_i | t_i)$$
 and $P(t_i | t_{i-2}, t_{i-1})$

- Easy to do if we have training data with word and tag sequences.
- All we need after we have the probability models is an algorithm to find the most likely tag sequence
- Use the algorithm used to find the best tag sequence in Hidden Markov Models: the Viterbi algorithm

- **Evaluation**: *train* your model on the training data, *test* on unseen test data to obtain best tag sequence for each word sequence.
- Accuracy is measured as the percentage of correct tags for words in the test data.

Brief History of Part of Speech Tagging

- Corpus building: English
 - Brown Corpus: 1979 (87 tags)
 - Penn Treebank Corpus: 1993 (45 tags)
 - British National Corpus (BNC): 1997
 - LOB corpus
- Other languages: Chinese, Czech, German, Korean, Turkish, . . .

Brief History of Part of Speech Tagging

- Models and Algorithms:
 - ngram models for tagging: Church 1988
 - extension of ngram model using HMMs: Xerox (Cutting et al) 1992
 - Transformation-Based Learning: Brill 1995
 - Maximum Entropy Models: Ratnaparkhi 1997

Applications of Part of Speech Tagging

- Other applications in NLP can be represented as POS tagging:
 - Chunking
 - Named-entity recognition (name-finding)
 - Cascaded Chunking
 - Word segmentation

Standard Part of Speech Tagging

- Part of speech tagging: finding the best sequence of POS tags for an input sentence (word sequence)
 - Representation: what does each POS tag represent?
 - Tagset: standard POS tags (NN=noun, VB=verb, etc.)
 - Training: word sequences with corresponding tag sequences
 - Input: word sequences (sentence)
 - Output: tag sequence

Noun Phrase Chunking

- Noun phrase chunking: e.g. input: *The man the news demonized* . . ., output: [The man] [the news] demonized . . .
 - Representation: is each word inside an NP or not?
 - Tagset: 3 tags: I (inside NP), O (outside NP), B (boundary of 2 NPs) e.g. The/I man/I the/B news/I demonized/O . . .
 - Training: word sequences with chunk tag sequences
 - Input: word sequences (sentence)
 - Output: chunk sequence

Noun Phrase Chunking

- Noun phrase chunking: The/I man/I the/B news/I demonized/O . . .
 - Tagset: Different options for the tags, as long as they correspond to the bracketing: [The man] [the news] demonized...
 - For example, another representation could be: I (inside NP), O (outside NP), E (end of NP)
 e.g. The/I man/E the/I news/E demonized/O . . .
 - If training data is in one representation, then we can transform from one tagset to another
- What about other kinds of phrases?

General Chunking

Intuition for Noun Phrase chunking: In the sentence

The company with the highest gain yesterday collapsed in today's market

The relationship between the verb *collapsed* is to the entire phrase The company with the highest gain yesterday

 Similar intuition about other phrases, like prepositional phrases: in today's market

General Chunking

- General chunking is non-overlapping:
 - e.g. input: The company with the highest gain yesterday collapsed in today's market,
 - output: [B-NP The company] [B-PP with] [B-NP the highest gain] [B-NP yesterday] [B-VP collapsed] [B-PP in] [B-NP today's market]
 - Representation: is each word inside a chunk or not?
 - Tagset: O tag for outside chunk, B- or E- prefix to the types of chunks we want, for instance NP, VP, PP
 e.g. The/B-NP company/E-NP with/B-PP the/B-NP highest/B-NP gain/E-NP yesterday/B-NP collapsed/B-VP in/B-PP today's/B-NP market/B-NP

General Chunking

- General chunking is non-overlapping
 - Representation: is each word inside a chunk or not?
 - Tagset: O tag for outside chunk, B- or E- prefix to the types of chunks we want, NP, VP, PP
 - Training: word sequences with corresponding chunk tag sequences
 - Input: word sequences (sentence)
 - Output: chunk sequence

Named Entity Recognition

In the sentence

Mr. Vinken is chairman of Elsevier N. V., a publishing group based in the Netherlands.

 We want to find names, such as person names, corporation names of locations:

[PER Mr. Vinken] is chairman of [ORG Elsevier N. V.], a publishing group based in the [LOC Netherlands].

Named Entity Recognition

- A named entity is a chunk that contains only names of persons, organizations or locations
 - Representation: a word or group of words as a named entity
 - Tagset: O tag for outside any named entity, B- or E- prefix to the types of named entities we want: PER = person, LOC = location,
 ORG = organization
 - Training: word sequences with corresponding named-entity tag sequences
 - Input: word sequences (sentence)
 Output: named-entity tag sequence

Cascaded Chunking

Input:	Mr.	Vinken	is	chairman	of	Elsevier	N.	V.
POS:	NNP	NNP	VBZ	NN	IN	NNP	NNP	NNP
NP:	I-NP	E-NP		I-NP		I-NP	I-NP	I-NP
PP:					I-PP	I-PP	I-PP	I-PP
VP:			I-VP	I-VP	I-VP	I-VP	I-VP	I-VP
S:	I-S	I-S	I-S	I-S	I-S	I-S	I-S	I-S

Cascaded Chunking

- A sequence of tagging steps
- Each step adds some more information
- Chunking had the disadvantage of not having overlapping chunks, cascaded chunking does not have this problem
 However, later steps cannot fix errors in earlier steps. For instance, a part of speech tagging error can cause errors in every successive step of cascaded chunking
- Later we will look at trees which generalize cascaded chunking in a principled way.

Summary: Part of Speech (POS) Tagging

- POS tagging is very similar to Hidden Markov Models
- POS tagging models are different from HMMs in the following ways:
 - The state sequences correspond to a particular representation
 - The training data always has to contain the right tag for each word in the word (or observation) sequence
- Viterbi algorithm provides the best sequence of tags for a given input
 Part of speech tagging can be applied to many applications like chunking, name finding, among others