Natural Language Processing

Lecture IV. Part-of-speech (POS) tagging and Named Entity Recognition (NER)

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Outline

What is POS tagging

POS tagging in HMM

CRF for POS tagging and NER

POS

Natural	Language	Processing	is	a	field	of	computer	science.
Adj.	n.	n.	v.	dt.	n.	cj.	n.	n.

Part of speech tagging

- "In traditional grammar, a part of speech (abbreviated form: PoS or POS) is a category of words (or, more generally, of lexical items) which have similar grammatical properties. "
- "In corpus linguistics, part-of-speech tagging (POS tagging or POST), also called grammatical tagging or word-category disambiguation, is the process of marking up a word in a text (corpus) as corresponding to a particular part of speech,
- based on both its definition and its context, i.e., its relationship with adjacent and related words in a phrase, sentence, or paragraph."
- Brill tagger (circa. 1993): the first English POS tagger, rule-based. It assigns initial tags to words first and then use rules to iteratively update tags based on, e.g., context.
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Tags used in Penn Treebank

- Nine common parts of speech in English: noun, verb, article, adjective, preposition, pronoun, adverb, conjunction, and interjection.
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Probabilistic Model for Tagging

- Problem of using rule-based system: Very difficult to verify and to scale.
- Probabilistic approach: there are many sequences of tags, but only one yields (i.e., argmax) the highest probability.

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$\mathbf{T}_3$	v.	n.	av.	v.	dt.	n.	cj.	n.	n.
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A generative model for POS tagging

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Note that we go from Eq. (1) to Eq. (2) because $P(\mathbf{W})$ is not a function of $\mathbf{T}$.

- tag-to-tag *transition* probabilities: $P(\mathbf{T}) = \Pi_{i=1}^{l+1} P_T(t_i|t_{i-1})$: e.g., NN comes after DET
- tag-to-word *emission* probabilities: $P(\mathbf{W}|\mathbf{T}) = \Pi_{i=1}^{l} P_E(w_i|t_i)$: e.g., "natural" is probably a JJ.
- A sequence of words is generated in two phases:
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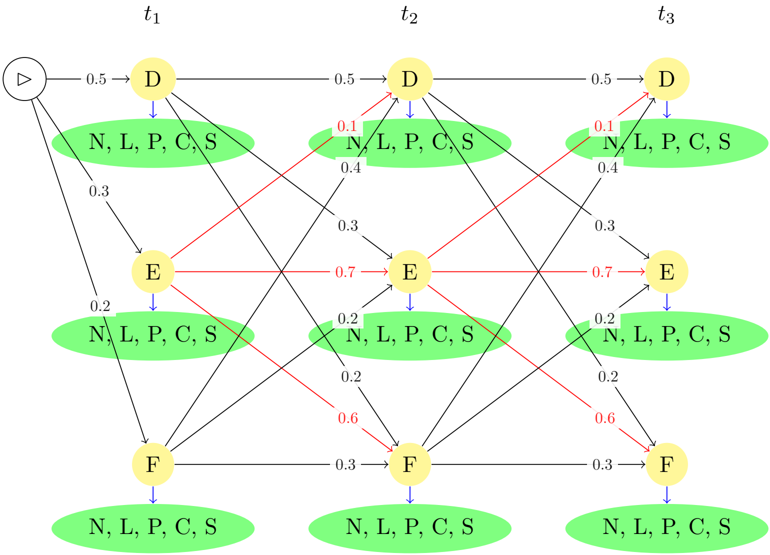

Three tags/states: D, E, and F. Five words/obserations: N, L, P, C, and S.

A generative model for POS tagging

$\mathbf{W}$	Natural	Language	Processing	is	a	field	of	computer	science.
$\mathbf{T_1}$	JJ	NN	NN	VBZ	DT	NN	IN	NN	NN.

- The generative model we just see is a typical Hidden Markov Model (HMM), where a tag is a *state* and a word is an *observation*.
- In each state/tag, a word/observation emits. After each emission, transit to the next state/tag and emit a word/observation again.
- Why Markovian? The probably of a tag is only conditioned on the previous tag. No further history. First-order Markovian.
- For example, the probability of the first tag sequence: $P(\mathbf{T_1}) = P_T(JJ|\triangleright) \times P_T(NN|JJ) \times P_T(NN|NN) \times \cdots$
- Also, the probability for generating the sentence from the first tag sequence: $P(\mathbf{W}|\mathbf{T_1}) =$ $P_E(\text{“}natural''|JJ) \times P_E(\text{“}language''|NN) \times P_E(\text{“}processing''|NN) \times \cdots$
- The transition and emission probabilities can be obtained by scanning the corpus once.

A generative model for POS tagging

- In principle, we just need to enumerate all possible tag sequences, $\mathbf{T}_1, \mathbf{T}_2, \ldots$ and find the one that yields the largest $P(\mathbf{W}|\mathbf{T})P(\mathbf{T})$.
- But this is costly: If we have N different tags and l words in the sentence, there are N^l possible/hidden tag sequences.
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HMM decoding in Viterbi algorithm

- The problem of estimating the sequence of hidden states given a sequence of observations is known as *decoding* in HMM.
- Basic principle (Lemma 1): $\max(x \cdot y) = \max(x) \cdot y$, if x is a real variable and y is a real constant.
- In each step i (except the start and end), we have N possible states/tags t_i's, each of which can come from N possible t_{i-1}'s.

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Viterbi algorithm in math induction

- If the sentence has only one word: $\mathbf{W} = [w_1]$. The best tag t_1 should maximize $P_T(t_1|\triangleright)P_E(w_1|t_1)$ where $\triangleright = t_0$ is the beginning of the sentence.
- If it has two: $\mathbf{W} = [w_1, w_2]$. The best tags t_1 and t_2 shall maximize $\Pi_{i=1}^{2} P_T(t_i|t_{i-1})P_E(w_i|t_i) =$ $P_T(t_1|\triangleright)P_E(w_1|t_1)P_T(t_2|t_1)P_E(w_2|t_2)$. Just search over the N^2 combinations of t_1 and t_2, time complexity $O(N^2)$.
- If it has three: $\mathbf{W} = [w_1, w_2, w_3]$. Given tags t_2 and t_3,

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- No need to check N^3 combinations of tags t_1, t_2 and t_3, many of which will not maximize the final number regardless of the value of $P_T(t_3|t_2)P_E(w_3|t_3)$.

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$$= [\max P_T(t_1|\rhd)P_E(w_1|t_1)P_T(t_2|t_1)P_E(w_2|t_2)] \quad P_T(t_3|t_2)P_E(w_3|t_3)$$

- No need to check N^3 combinations of tags t_1, t_2 and t_3, many of which will not maximize the final number regardless of the value of $P_T(t_3|t_2)P_E(w_3|t_3)$.

HMM decoding in Viterbi algorithm

- Let's generalize:

$$\max \Pi P_T(t_i|t_{i-1})P_E(w_i|t_i) \qquad P_T(t_{i+1}|t_i)P_E(w_{i+1}|t_{i+1})$$
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- Denote $v(\overbrace{i}^{\text{step or word index}}, \overbrace{j}^{\text{state or tag index}})$ as the probability that the HMM is in state j after seeing the first i observations and passing through **the most probable** preceding sequence of states. We call $v(i,j)$ the *previous Viterbi path probability*.
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$$v(i,j) = \max_{j=1}^{N} v(i-1,j)P_T(t_i|t_j)P_E(w_i|t_i)$$

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HMM decoding in Viterbi algorithm

- Time complexity: $O(lN^2)$ instead of $O(N^3)$ where N is the number of tags and l is the length of the sentence under POS-tagging.
- For details, read chapter 9.4 of `https://web.stanford.edu/~jurafsky/slp3/9.pdf`.

What do you need?

- A set of N states/tags.
- A set of M obserations/words.
- Transition probabilities, from one state/tag to another, usually as an $N \times N$ matrix
- Emitting probabilities, from one state/tag to an obseration/word, usually as another matrix $N \times M$.
- Initial state/tag probabilities, usually denoted as pi. But this can be easily resolved by introducing a origin state and the transition probabilities from the origin state to all other states.

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Computational problems

- What is the problem of multiplying a lenghty list of probabilities?
- Like gradient vanishing, the product becomes very very small.
- Hence, a solution is to logarithmize all probabilities and use summation rather than multiplication.
- See Neubig's slide 8 on HMM. `http://www.phontron.com/slides/nlp-programming-en-04-hmm.pdf`

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Conditional Random Fields

- HMM uses Bayes theorem to find the most likely tag sequences $\underset{T}{\operatorname{argmax}} P(\mathbf{T}|\mathbf{W})$.
- CRFs directly estimates it.
- It works by evaluting the chances of each tag sequence over all possible tag sequences in a softmax fashion:

$$P(\mathbf{T}|\mathbf{W}) = \frac{\exp\left(\sum_{k=1}^{K} u_k F_k(\mathbf{W}, \mathbf{T})\right)}{\sum_{\mathcal{T}' \in \mathcal{T}} \exp\left(\sum_{k=1}^{K} u_k F_k(\mathbf{W}, \mathbf{T}')\right)}$$

- Then just need to find $\underset{T \in \mathcal{T}}{\operatorname{argmax}} P(T|W)$.
- u_k is the weight for the k-th feature F_k which is a function of both word sequence and tag sequence.
- Linear-chain CRF: $F_k(\mathcal{W}, \mathcal{T}) = \sum_{i=1}^{l} f_k(w_{i-1}, w_i, \mathcal{T}, i)$ The sum of a function of the word sequence and only the current and previous tags.

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Features of using CRFs in POS tagging

- Manually engineered features
- See §8.5.1 of Jurafsky's book.
- Also see https://towardsdatascience.com/pos-tagging-using-crfs-ea430c5fb78b
- It's now even common to use DL to extract features and then hook up to CRF, e.g., BiLSTM-CRF (NAACL 2016) https://arxiv.org/pdf/1508.01991.pdf
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Named Entity Recognition (NER)

- NEs are proper nouns. It is not rare for them to contain more than one word, e.g., New York City.
- Common categories of NEs: organization, people, location, etc.
- Just like POS tagging, NER can be modeled as a tagging problem.
- Instead of deciding the POS tags, we decide a different kind of tags.
- A common type of tags used in NER is BIO: begin, inside, and outside. See `https://medium.com/analytics-vidhya/bio-tagged-text-to-original-text-99b05da6664`
- See also `https://github.com/scofield7419/sequence-labeling-BiLSTM-CRF`
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Modern ways?

Neural network-based generative models, e.g., seq2seq.