Natural Language Processing

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

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September 15, 2022

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.
- Brill tagger has hundreds of rules.

Tags used in Penn Treebank

- Nine common parts of speech in English: noun, verb, article, adjective, preposition, pronoun, adverb, conjunction, and interjection.
- Most NLP researchers use Penn Treebank tags, which are finer than common English POSes mentioned above.
- https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.html

Why do we still need POS tagging?

- In DL era, models are end-to-end. Is POS tagging out of fashion?
- There are still many cases where training data is not enough or labeling is very costly.
- POS tags are a good intermediate feature, trained on large amounts of data.
- The hidden states of POS taggers can be considered as a syntactical representation of text.
- One way to look at POS tagging is to treate is an NP-Complete problem. It's a bridge.
- What's new today in NLP? Adept AI.

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.

	Natural	Language	Processing	is	a	field	of	computer	science.
$\mathbf{T}_1$	aj.	n.	n.	v.	dt.	n.	cj.	n.	n.
$\mathbf{T}_2$	n.	n.	n.	v.	n.	n.	cj.	n.	n.
$\mathbf{T}_3$	v.	n.	av.	v.	dt.	n.	cj.	n.	n.
$\mathbf{T}_4$	dt.	n.	n.	v.	v.	n.	aj.	v.	n.
$\mathbf{T}_5$	cj.	n.	n.	v.	dt.	n.	cj.	n.	n.

$\mathbf{T}_2$ - $\mathbf{T}_5$ apparently make no sense and hence their $P()$'s are very low.

- The goal is to find the most likely sequence of tags ($\mathbf{T}$), given the sequence of words ($\mathbf{W}$), i.e.,

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

A generative model for POS tagging

- Make use of Bayes' rule:

$$\operatorname*{argmax}_{\mathbf{T}} P(\mathbf{T}|\mathbf{W}) = \operatorname*{argmax}_{\mathbf{T}} \frac{P(\mathbf{W}|\mathbf{T})P(\mathbf{T})}{P(\mathbf{W})} \quad (1)$$

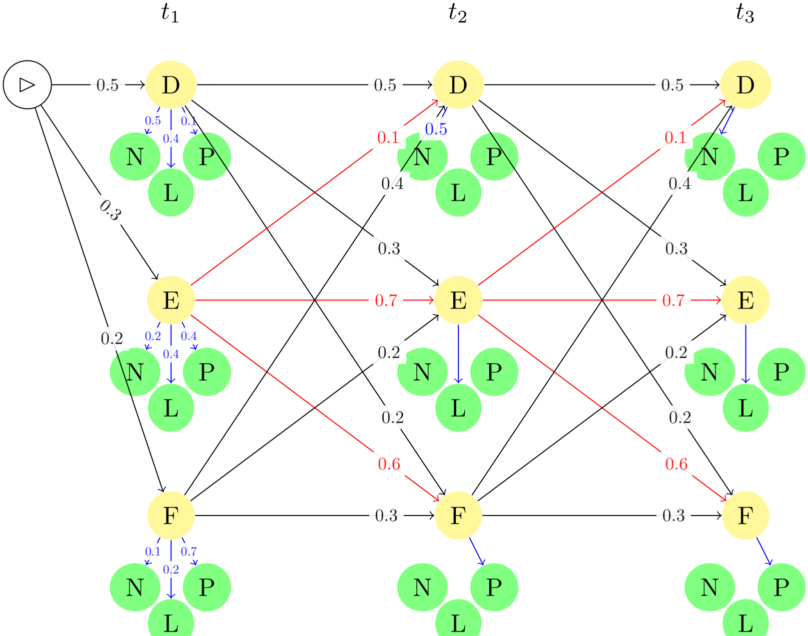
$$= \operatorname*{argmax}_{\mathbf{T}} P(\mathbf{W}|\mathbf{T})P(\mathbf{T}) \quad (2)$$

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.,
- the probability of the first tag sequence: $P(\mathbf{T_1}) = P_T(JJ|\triangleright) \times P_T(NN|JJ) \times P_T(NN|NN) \times \cdots$.
- tag-to-word *emission* probabilities: $P(\mathbf{W}|\mathbf{T}) = \Pi_{i=1}^{l} P_E(w_i|t_i)$: e.g., $P(\mathbf{W}|\mathbf{T_1}) =$ $P_E(\text{“}natural''|JJ) \times P_E(\text{“}language''|NN) \times P_E(\text{“}processing''|NN) \times \cdots$.

A generative model for POS tagging

- A sequence of words is generated in two phases:
  1. Produce a sequence of tags, e.g., $\triangleright$, NN, DET, ..., based on probability between each two consecutive tags.
  2. For each tag, produce a word, e.g., NN $\rightarrow$ "language", DT $\rightarrow$ "the".
- Yes, a semantically meaningless sentence can be tagged and further parsed correctly, e.g., "NLP is a automobile of GOP".



Tags/states: D, E, and F. Words/observations: N, L, and P.

A generative model for POS tagging

- 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.
- 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.
- Smarter way? Viterbi algorithm – a good example of dynamic programming.

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.

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: $\mathbf{W} = [w_1, w_2, w_3]$. <u>Given tags t_2 and t_3</u>,

$$\begin{aligned}
&\max P_T(t_1|\triangleright)P_E(w_1|t_1)P_T(t_2|t_1)P_E(w_2|t_2) \quad \overbrace{P_T(t_3|t_2)P_E(w_3|t_3)}^{\text{search only happens here}} \\
=&[\max P_T(t_1|\triangleright)P_E(w_1|t_1)P_T(t_2|t_1)P_E(w_2|t_2)] \quad P_T(t_3|t_2)P_E(w_3|t_3)
\end{aligned}$$

- 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 $P_T(t_3|t_2)P_E(w_3|t_3)$. Instead, check $N + 2N^2 \in \mathcal{O}(3N^2)$ combinations.

HMM decoding in Viterbi algorithm

- Let's generalize:

$$
\begin{aligned}
&\max \Pi P_T(t_i|t_{i-1}) P_E(w_i|t_i) \qquad P_T(t_{i+1}|t_i) P_E(w_{i+1}|t_{i+1}) \\
=&[\max \Pi P_T(t_i|t_{i-1}) P_E(w_i|t_i)] \qquad P_T(t_{i+1}|t_i) P_E(w_{i+1}|t_{i+1})
\end{aligned}
$$

- Denote $v(\overbrace{\quad i \quad}^{\text{step or word index}}, \overbrace{\quad j \quad}^{\text{state or tag index}})$ 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*.
-
$$
v(i,j) = \max_{j=1}^{N} v(i-1,j) P_T(t_i|t_j) P_E(w_i|t_i)
$$

- If we repeat this step by step, we can find the maximum $P(\mathbf{T}|\mathbf{W})$.
- Then a traceback allows us to find the tags that maximizes it.

HMM decoding in Viterbi algorithm

- Time complexity: $O(lN^2)$ instead of $O(N^l)$ 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 observations/words.
- Transition probabilities, from one state/tag to another, usually as an $N \times N$ matrix
- Emitting probabilities, from one state/tag to an observation/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.

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`

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.

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`
- Sklearn-CRFsuite `https://sklearn-crfsuite.readthedocs.io/en/latest/tutorial.html`

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`
- It seems that CRF is more widely used in NER than in POS tagging.

Modern ways?

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