Advanced NLP tasks

Contents

Named Entity Recognition (NER)

NER

Named entity recognition (NER), aims at identifying real-world entity mentions from texts, and classifying them into predefined types.

Gold Dataset

Suxamethonium infusion rate and observed fasciculations.

Suxamethonium chloride (Sch) was administred i.v.

NER

We wish to predict an output vector $\mathbf{y} = (y_1, y_1, \ldots, y_L)$, of random variables, given an observed characteristic vector $\mathbf{x} = (x_1, x_2, \ldots, x_L)$

$\mathbf{y}$ takes it value from a list of N possible values.

Part-of-Speech Tagging (POS)

POS is the process of mapping words in a text with a label corresponding to their grammatical class.

("He", "likes", "to", "drink", "tea"), $\rightarrow$ ("PERSONAL PRONOUN", "VERB", "TO", "VERB", "NOUN").

Part-of-Speech Tagging (POS)

There several levels of granularity.: using the tag set for english

("He", "likes", "to", "drink", "tea"), $\rightarrow$ ("PRP", "VBP", "TO", "VB", "NN").

Conditional Random Field (CRF)

Knowing that language models are good at generating vector spaces to better represent words:
for each token in a sentence we want to compute a probability p to belong to a class n.

$$p : f(\mathbf{x}, \theta)_l \mapsto ?$$

with $p \in [0, 1]$
Where $f(\mathbf{x}, \theta)_l$ are the language model's parameters for the $l_{1 \leq L}$-th token.

Conditional Random Field (CRF)

Using the softmax function?

$$p : f(\mathbf{x}, \theta)_l \mapsto \frac{e^{f(\mathbf{x},\theta)_l^{(n)}}}{\sum_{n'=1}^{N} e^{f(\mathbf{x},\theta)_l^{(n')}}}$$

The probability given by the softmax function will not encode non-local dependencies!

Conditional Random Field (CRF)

We need to take sequential decisions: what if we add transition scores into our softmax?

$$p : f(\mathbf{x}, \theta)_l \mapsto \frac{e^{f(\mathbf{x},\theta)_l^{(n)} + t(y_l^{(n)}, y_{l-1})}}{\sum_{n'=1}^{N} e^{f(\mathbf{x},\theta)_l^{(n')} + t(y_l^{(n')}, y_{l-1})}}$$

But this is the probability for one token to belong to a class, we want to compute the probability of a whole sequence of label at once...

Conditional Random Field (CRF)

$$P(\mathbf{y}|\mathbf{x}) = \prod_{l=2}^{L} p(\mathbf{y}|f(\mathbf{x},\theta)_l)$$

$$= \prod_{l=2}^{L} \frac{e^{f(\mathbf{x},\theta)_l^{(n)} + t(y_l^{(n)}, y_{l-1})}}{\sum_{n'=1}^{N} e^{f(\mathbf{x},\theta)_l^{(n')} + t(y_l^{(n')}, y_{l-1})}}$$

$$P(\mathbf{y}|\mathbf{x}) = \frac{exp[\sum_{l=2}^{L}(f(\mathbf{x},\theta)_l^{(n)} + t(y_l^{(n)}, y_{l-1}))]}{\sum_{n'=1}^{N} exp[\sum_{l=2}^{L}(f(\mathbf{x},\theta)_l^{(n')} + t(y_l^{(n')}, y_{l-1}))]}$$

$$= \frac{exp[\sum_{l=2}^{L}(U(\mathbf{x}, y_l^{(n)}) + T(y_l^{(n)}, y_{l-1}))]}{\sum_{n'=1}^{N} exp[\sum_{l=2}^{L}(U(\mathbf{x}, y_l^{(n')}) + T(y_l^{(n')}, y_{l-1}))]}$$

$$= \frac{exp[\sum_{l=2}^{L}(U(\mathbf{x}, y_l^{(n)}) + T(y_l^{(n)}, y_{l-1}))]}{Z(\mathbf{x})}$$

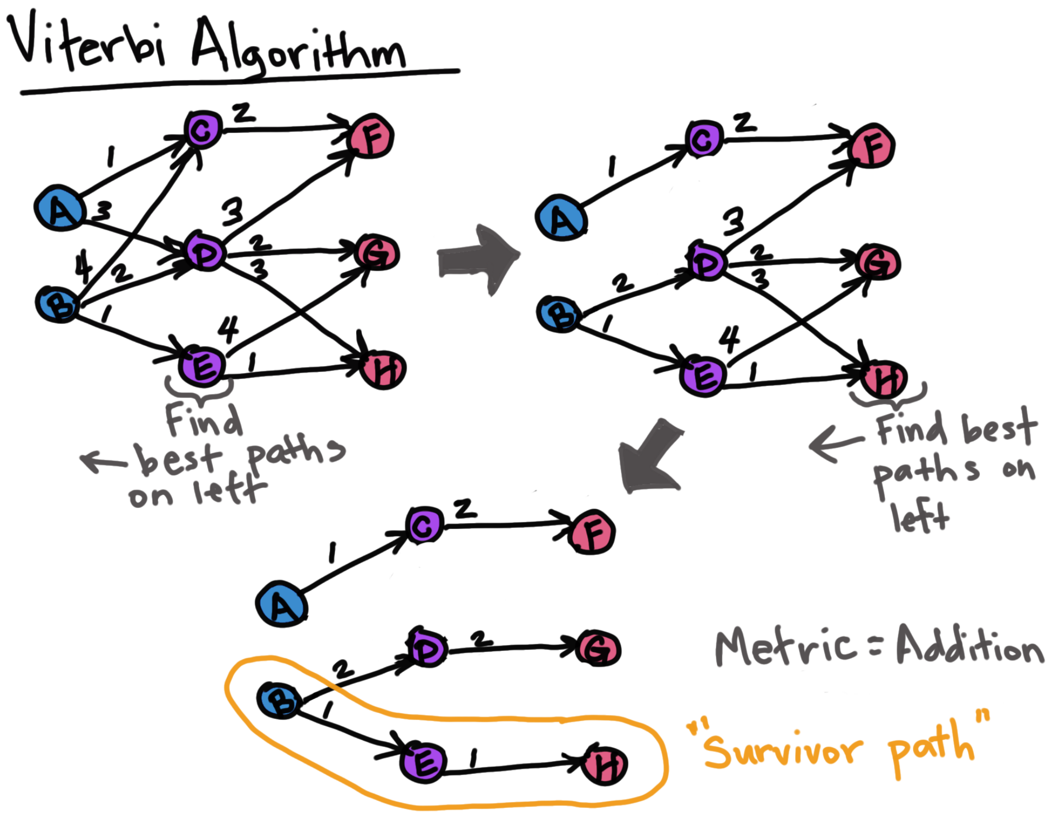
Conditional Random Field (CRF)

$Z(\mathbf{x})$ is commonly referred as the partition function. However, its not trivial to compute: we'll end up with a complexity of $\mathcal{O}(N^L)$.

Where N is the number of possible labels and L the sequence length.

How do we proceed?

Conditional Random Field (CRF)



Conditional Random Field (CRF)

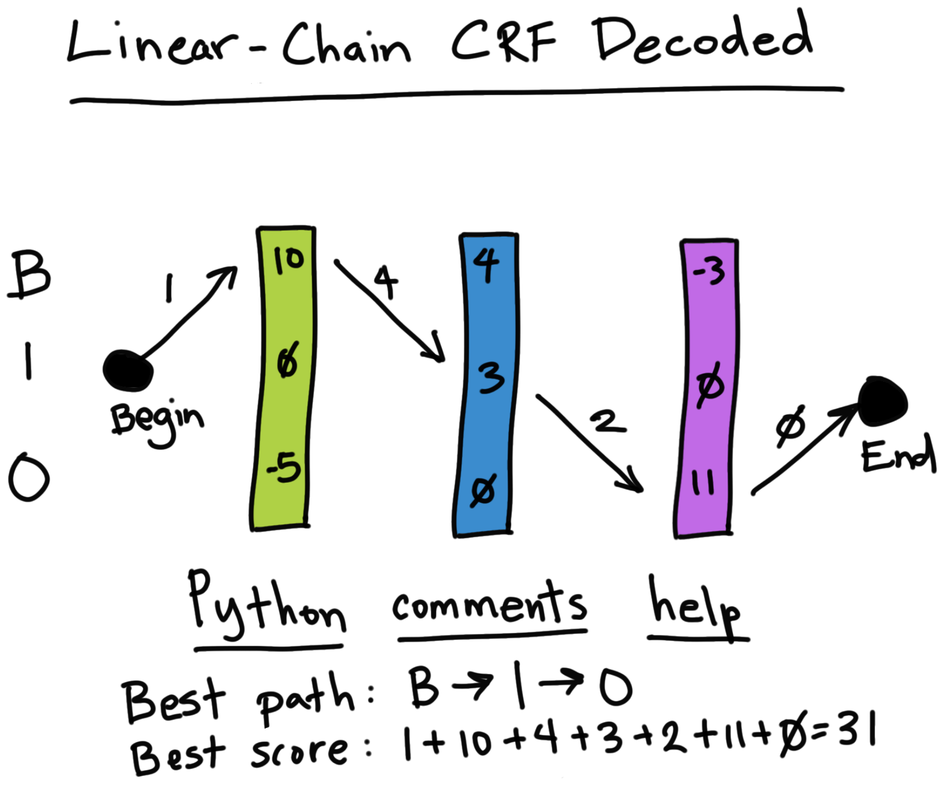
NER Transition Matrix

	B	I	O
B	C(B→B)	C(B→I)	C(B→O)
I	C(I→B)	C(I→I)	C(I→O)
O	C(O→B)	∞	C(O→O)

C = cost function

∞ = wouldn't happen

Conditional Random Field (CRF)



Conditional Random Field (CRF)

What do we learn?

Questions?

References

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