

Conditional Random Field Overview

Friday, January 14, 2022 10:14 AM

<https://github.com/ContentUpgrad/Syntactic-Processing/blob/master/Custom%20NER%20Code.ipynb>

<https://towardsdatascience.com/named-entity-recognition-and-classification-with-scikit-learn-11e3a2a2a2d>

https://colab.research.google.com/github/dipanjanS/nlp_workshop_odsc19/blob/master/Module%201%20-%20Introduction%20to%20NLP.ipynb

- 'I drove away in my Jaguar.'
- 'The deer ran away seeing the Jaguar.'

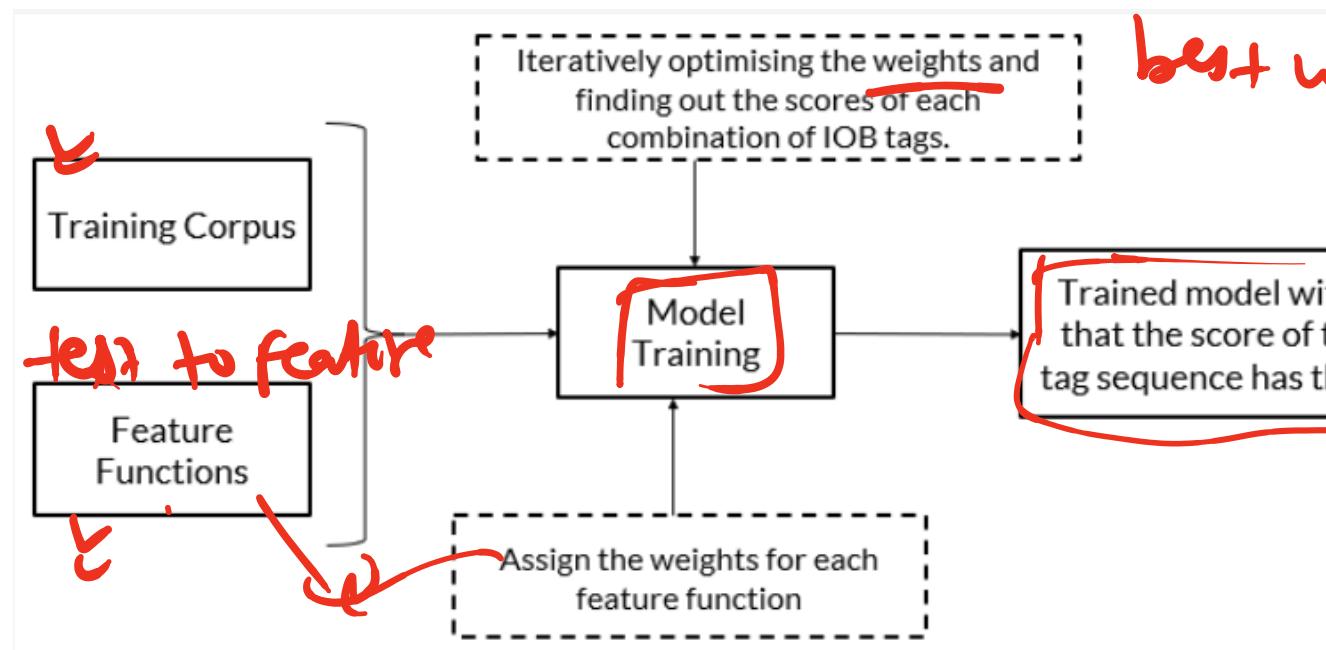
The word 'Jaguar' in the first sentence refers to a car manufacturing company, and in the second sentence it refers to a wild animal.

Python Example

The Conditional Random Field (CRF) can be used as a sequence labelling technique for performing NER.

Conditional Random Fields are the class of probabilistic models. There are two terms in the CRF:

- **Random fields:** These indicate that the CRF is probability a distribution-based model.
- **Conditional:** This indicates that the probabilities are conditional probabilities.



[de%20Demonstration/Code%20files/CRF.ipynb](#)

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[Module03%20-%20Text%20Understanding/Project%20-%20Building%20NER%20Taggers.ipynb](#)

and sentence, it refers to a species of animal

Custom NER tagging. CRF is used to perform custom NER.

For nomenclature that you need to keep in mind, which are as follows:
Machine learning model.

weights

With weights such
the correct IOB
the highest score.

[TF1 COF]
↓
→ WE

FE
↓

doc = "Google Inc. is headquartered in Silicon Valley."

4- feature function

X - token	Y - Right	Y' - wrong	Y''	Y'''
Google	B-ORG	B-LOC	B-LOC	B-ORG
Inc	I-ORG	I-ORG	I-LOC	I-ORG
is	O	O	O	B-ORG
headquartered	O	O	O	B-LOC
in	O	O	O	B-ORG
Silicon	B-LOC	O	B-LOC	B-ORG
Valley	I-LOC	O	I-LOC	B-ORG

So, for the input sentence 'X', there can be multiple combinations of IOB tags possible, and some are tagged manually in the training data set. The model needs to train itself or assign the weights in such a way that it can learn the right combination.

Now, apart from the training data set, you require features and their values to train a model. You can create features out of this text data, which you can feed into the model.

Feature Functions -

Some commonly used features in the CRF technique for NER applications are as follows:

- You can build logic on the input word 'xi' and on the surrounding words, which can be used to identify the entity.
- The PoS tag of the word 'xi' and surrounding words.
- Is a particular word present in a dictionary (dictionary of common names, dictionary of locations, etc.)
- Word shapes:
- 26-03-2021 => dd-dd-dddd
- 26 Mar 2021 => dd Xxx dddd
- W.H.O => X.X.X
- Presence of prefix and suffixes

Example -

doc = "Google Inc. is headquartered in Silicon Valley."

f1 (X, xi, xi-1, i) = 1 if xi= Xx+; otherwise, 0 (Words starting with an uppercase letter)

	f_1	f_2	f_3	y'
<u>Google</u>	1	0	0	<u>B-Loc</u>
<u>Inc</u>	1	0	-	<u>C-ORG</u>
<u>is</u>	0	0	1	/
<u>(</u>	0	0	1	,
<u>Silicon</u>	1	-	0	<u>1</u>
<u>Valley</u>	1	1	0	0

Some of them are shown in the above table. The highlighted one is the correct combination, which is done such a way that it assigns the highest score to the correct combination.

in a machine learning model. Here, the training corpus is nothing but the text data. You need to

should be ' x_{i-1} ' or ' x_{i+1} '.

vary of organic chemicals, etc.)

~~words starting with an uppercase letter,~~

f2 (X, xi, xi-1, i) = 1 if xi= Noun and xi-1 is Noun; otherwise, 0 (Continuous entity)

;	0q-wuqadfcx8z
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- The f1 feature indicates that if a particular word in the given sentence starts with an uppercase letter, assign 1 as the value of f1 to this word.
- The f2 feature indicates that if a particular word in the given sentence has a PoS tag of noun and the previous word is also a noun; otherwise, assign 0 as the value of f2 to this word.
- The f3 feature indicates that if a particular word in the given sentence is 'Inc' and the word before it is also 'Inc'; otherwise, assign 0 as the value of f3 to this word.

So, the model considers all the possible combinations of IOB tags of the given training examples and computes the score for each feature function. The model starts the computation by taking any random initial word and continues until where the score of the correct IOB tag sequence is the highest.

Let's first calculate the values of all three features for the Y' combination of IOB tags.

X= Google (B-LOC) Inc (I-ORG) is (O) headquartered (O) in (O) Silicon (O) Valley (O). - ↴

- f1 (X, xi, xi-1, i) = 1 if xi= Xx+; otherwise, 0 (words starting with an uppercase letter)

	Y'	f1 - Xx+:
Google	B-LOC	1 (because 'Google' starts with an uppercase letter)
Inc	I-ORG	1 (because 'Inc' starts with an uppercase letter)
is	O	0
headquartered	O	0
in	O	0
Silicon	O	1 (because 'Silicon' starts with an uppercase letter)
Valley	O	1 (because 'Valley' starts with an uppercase letter)

- f2 (X, xi, xi-1, i) = 1 if xi= Noun and xi-1 is Noun; otherwise, 0 (Continuous entity)

ercase letter, then assign 1 as the value of f1; otherwise, assign 0 as the value of f1 to this word.
oun and the word before it also has a PoS tag of noun, then assign 1 as the value of f2 as to this

rd before it has the NER tag of B-ORG, then assign 1 the value of f3 to this word; otherwise, assign 0

ample and calculates the scores of each combination using the weights corresponding to
ights for each feature function and iteratively modifies the weights until it reaches a stage

— Reg ex

ase
ase
ter)

		f2
Google	B-LOC	0
Inc	I-ORG	0
is	O	0
headquartered	O	0
in	O	0
Silicon	O	0
Valley	O	1 (because 'Valley' is a noun and 'Silicon' is a noun)

- $f3(X, x_i, x_{i-1}, i) = 1$ if $x_i = \text{Inc}$ and $x_{i-1} = \text{B-Org}$; otherwise, 0 (Company names often end with 'Inc')

		f3
Google	B-LOC	0
Inc	I-ORG	0 (because the previous word 'Google' does have the B-ORG tag)
is	O	0
headquartered	O	0
in	O	0
Silicon	O	0
Valley	O	0

Weights calculation and optimization -

X= Google (B-LOC) Inc (I-ORG) is (O) headquartered (O) in (O) Silicon

Iso

with Inc)

not

(O) Valley (O).

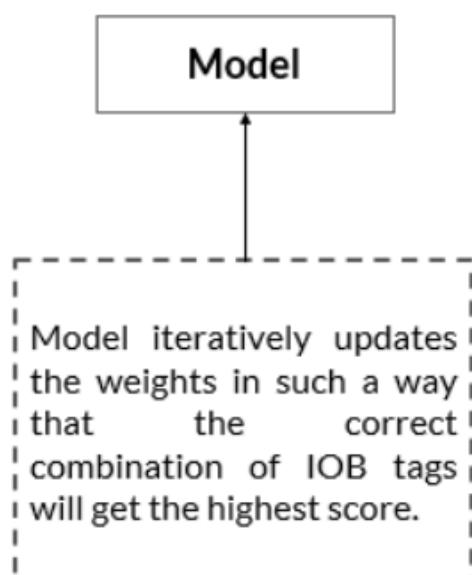
$$w_1 = 1 \quad w_2 = 2 \quad w_3 = 3$$

X	\hat{Y}_2	$f_1 * w_1$ ($w_1=1$)	$f_2 * w_2$ ($w_2=2$)	$f_3 * w_3$ ($w_3=3$)
Google	B-Loc	1	0	0
Inc	I-Org	1	0	0
is	O	0	0	0
headquartered	O	0	0	0
in	O	0	0	0
Silicon	O	1	0	0
Valley	O	1	2	0
SUM		4	2	0

So, the value of the score for this combination of NER tags will be $4+2+0 = 6$, which weights, as shown in the table above.

We keep continue this exercise -

Correct label



X	Y	Y^i
Google	B-Org	B-Loc
Inc	I-Org	I-Org
Is	O	O
headquartered	O	O
in	O	O
Silicon	B-Loc	O
Valley	I-Loc	O

Score 1 = 9

Score 2 = 6

Score 1 = 9 is the highest.

1-3



you will obtain after multiplying each feature function values with their corresponding

Y''
B-Loc
I-Loc
O
O
O
B-Loc
I-Loc

Score 3 = 6

Every sentence - \wedge - tag -

\hookrightarrow POS tag

\hookrightarrow NER +

detained

\hookrightarrow LSPacy

ML

~~# training~~

\hookrightarrow test -

CRF

X -
↓

new

The sentence

- context is missing

eg - Search

- with the tags

- down) → reflect the tags
↓

→ NERTAG

missing - John

in

X y

\hat{y} - pred

hoo, sig - B-org

Noun - Per

Per

Per

Use



weights max 1 min
best tags

u