Named Entity Recognition NER using spaCy | NLP

spaCy NLP Series Part 4

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Named Entity Recognition is the most important or I would say the starting step in Information Retrieval. Information Retrieval is the technique to extract important and useful information from unstructured raw text documents. Named Entity Recognition NER works by locating and identifying the named entities present in unstructured text into the standard categories such as person names, locations, organizations, time expressions, quantities, monetary values, percentage, codes etc. Spacy comes with an extremely fast statistical entity recognition system that assigns labels to contiguous spans of tokens.

Spacy provides option to add arbitrary classes to entity recognition system and update the model to even include the new examples apart from already defined entities within model.

Spacy has the **'ner'** pipeline component that identifies token spans fitting a predetermined set of named entities. These are available as the **'ents'** property of a Doc object.

```
# Perform standard imports
import spacy
nlp = spacy.load('en_core_web_sm')
```

```
#Write a function to display basic entity info:
def show_ents(doc):
    if doc.ents:
        for ent in doc.ents:
            print(ent.text+' - ' +str(ent.start_char) +' - '+ str(ent.end_char) +
                  ' - '+ent.label_+ ' - '+str(spacy.explain(ent.label_)))
    else:
        print('No named entities found.')
```

```
doc1 = nlp("Apple is looking at buying U.K. startup for $1 billion")

show_ents(doc1)
```

```
Apple - 0 - 5 - ORG - Companies, agencies, institutions, etc.
U.K. - 27 - 31 - GPE - Countries, cities, states
$1 billion - 44 - 54 - MONEY - Monetary values, including unit
```

Here we see tokens combine to form the entities `$1 billion`.

Text	Start	End	Label	Description
Apple	0	5	ORG	Companies, agencies, institutions.
U.K.	27	31	GPE	Geopolitical entity, i.e. countries, cities, states.
$1 billion	44	54	MONEY	Monetary values, including unit.

```
doc2 = nlp(u'May I go to Washington, DC next May to see the Washington Monument?')

show_ents(doc2)
```

```
Washington - 12 - 22 - GPE - Countries, cities, states
next May - 27 - 35 - DATE - Absolute or relative dates or periods
the Washington Monument - 43 - 66 - ORG - Companies, agencies, institutions, etc.
```

```
doc3 = nlp(u'Can I please borrow 500 dollars from you to buy some Microsoft stock?')

for ent in doc3.ents:
    print(ent.text, ent.start, ent.end, ent.start_char, ent.end_char, ent.label_)
```

```
500 dollars 4 6 20 31 MONEY
Microsoft 11 12 53 62 ORG
```

Entity Annotations

Doc.ents are token spans with their own set of annotations.

`ent.text`	The original entity text
`ent.label`	The entity type's hash value
`ent.label_`	The entity type's string description
`ent.start`	The token span's *start* index position in the Doc
`ent.end`	The token span's *stop* index position in the Doc
`ent.start_char`	The entity text's *start* index position in the Doc
`ent.end_char`	The entity text's *stop* index position in the Doc

Accessing Entity Annotations

The standard way to access entity annotations is the doc.ents property, which produces a sequence of Span objects. The entity type is accessible either as a hash value using **ent.label** or as a string using **ent.label_**.

The Span object acts as a sequence of tokens, so you can iterate over the entity or index into it. You can also get the text form of the whole entity, as though it were a single token.

You can also access token entity annotations using the token.ent_iob and token.ent_type attributes. token.ent_iob indicates whether an entity starts, continues or ends on the tag. If no entity type is set on a token, it will return an empty string.

```python
doc = nlp("San Francisco considers banning sidewalk delivery robots")

# document level
for e in doc.ents:
    print(e.text, e.start_char, e.end_char, e.label_)
# OR
ents = [(e.text, e.start_char, e.end_char, e.label_) for e in doc.ents]
print(ents)

# token level
# doc[0], doc[1] ...will have tokens stored.

ent_san = [doc[0].text, doc[0].ent_iob_, doc[0].ent_type_]
ent_francisco = [doc[1].text, doc[1].ent_iob_, doc[1].ent_type_]
print(ent_san)
print(ent_francisco)
```

```
San Francisco 0 13 GPE
[('San Francisco', 0, 13, 'GPE')]
['San', 'B', 'GPE']
['Francisco', 'I', 'GPE']
```

IOB SCHEME

I – Token is inside an entity.

O – Token is outside an entity.

B – Token is the beginning of an entity.

Text	ent_iob	ent_iob_	ent_type_	Description
San	3	B	"GPE"	beginning of an entity
Francisco	1	I	"GPE"	inside an entity
considers	2	O	""	outside an entity
banning	2	O	""	outside an entity
sidewalk	2	O	""	outside an entity
delivery	2	O	""	outside an entity
robots	2	O	""	outside an entity

Note: In the above example only San Francisco is recognized as named entity. Hence rest of the tokens are described as outside the entity. And in San Francisco San is the starting of the entity and Francisco is inside the entity.

User Defined Named Entity and adding it to a Span

Normally we would have spaCy build a library of named entities by training it on several samples of text. Sometimes, we want to assign specific token a named entity which is not recognized by the trained spacy model. We can do this as shown in below code.

Example 1

```
doc = nlp(u'Tesla to build a U.K. factory for $6 million')

show_ents(doc)
```

```
U.K. - 17 - 21 - GPE - Countries, cities, states
$6 million - 34 - 44 - MONEY - Monetary values, including unit
```

Right now, spaCy does not recognize "Tesla" as a company.

```
from spacy.tokens import Span
```

```


# Get the hash value of the ORG entity label
ORG = doc.vocab.strings[u'ORG']

# Create a Span for the new entity
new_ent = Span(doc, 0, 1, label=ORG)

# Add the entity to the existing Doc object
doc.ents = list(doc.ents) + [new_ent]
```

In the code above, the arguments passed to `Span()` are:

- `doc` - the name of the Doc object
- `0` - the *start* index position of the token in the doc
- `1` - the *stop* index position (exclusive) in the doc
- `label=ORG` - the label assigned to our entity

Example 2

```
doc = nlp("fb is hiring a new vice president of global policy")
ents = [(e.text, e.start_char, e.end_char, e.label_) for e in doc.ents]
print('Before', ents)
# the model didn't recognise "fb" as an entity :(

fb_ent = Span(doc, 0, 1, label="ORG") # create a Span for the new entity
doc.ents = list(doc.ents) + [fb_ent]

ents = [(e.text, e.start_char, e.end_char, e.label_) for e in doc.ents]
print('After', ents)
# [('fb', 0, 2, 'ORG')]
```

```
Before []
After [('fb', 0, 2, 'ORG')]
```

Adding Named Entities to All Matching Spans

What if we want to tag *all* occurrences of a token? In this section we show how to use the PhraseMatcher to identify a series of spans in the Doc:

```
doc = nlp(u'Our company plans to introduce a new vacuum cleaner. '
          u'If successful, the vacuum cleaner will be our first product.')

show_ents(doc)
```

```
first - 99 - 104 - ORDINAL - "first", "second", etc.
```

```
# Import PhraseMatcher and create a matcher object:
from spacy.matcher import PhraseMatcher
matcher = PhraseMatcher(nlp.vocab)
```

```
# Create the desired phrase patterns:
phrase_list = ['vacuum cleaner', 'vacuum-cleaner']
phrase_patterns = [nlp(text) for text in phrase_list]
```

```
# Apply the patterns to our matcher object:
matcher.add('newproduct', None, *phrase_patterns)

# Apply the matcher to our Doc object:
matches = matcher(doc)

# See what matches occur:
matches
```

```
[(2689272359382549672, 7, 9), (2689272359382549672, 14, 16)]
```

```
# Here we create Spans from each match, and create named entities from them:
from spacy.tokens import Span

PROD = doc.vocab.strings[u'PRODUCT']

new_ents = [Span(doc, match[1],match[2],label=PROD) for match in matches]
# match[1] contains the start index of the the token and match[2] the stop index (exclusive) of the token in the doc.

doc.ents = list(doc.ents) + new_ents
```

```
show_ents(doc)
```

```
vacuum cleaner - 37 - 51 - PRODUCT - Objects, vehicles, foods, etc. (not services)
vacuum cleaner - 72 - 86 - PRODUCT - Objects, vehicles, foods, etc. (not services)
first - 99 - 104 - ORDINAL - "first", "second", etc.
```

Counting Entities

While spaCy may not have a built-in tool for counting entities, we can pass a conditional statement into a list comprehension:

In [33]:
```
doc = nlp(u'Originally priced at $29.50, the sweater was marked down to five dollars.')

show_ents(doc)
```

```
29.50 - 22 - 27 - MONEY - Monetary values, including unit
five dollars - 60 - 72 - MONEY - Monetary values, including unit
```

In [34]:
```
len([ent for ent in doc.ents if ent.label_=='MONEY'])
```

Out[34]: 2

Visualizing NER

Spacy has a library called "**displaCy**" which helps us to explore the behaviour of the entity recognition model interactively.

If you are training a model, it's very useful to run the visualization yourself.

You can pass a Doc or a list of Doc objects to displaCy and run displacy.serve to run the web server, or displacy.render to generate the raw mark-up.

In [62]:
```
text = "When Sebastian Thrun started working on self-driving cars at Google in 2007, \
few people outside of the company took him seriously."
doc = nlp(text)
displacy.render(doc, style="ent", jupyter=True)
```

When Sebastian NORP Thrun started working on self-driving cars at Google ORG in 2007 DATE , few people outside of the company took him seriously.

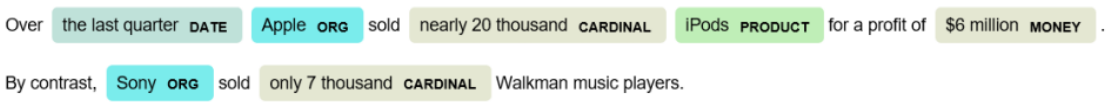
In [46]:
```
doc = nlp(u'Over the last quarter Apple sold nearly 20 thousand iPods for a profit of $6 million. '
          u'By contrast, Sony sold only 7 thousand Walkman music players.')

displacy.render(doc, style='ent', jupyter=True)
```

Over the last quarter DATE Apple ORG sold nearly 20 thousand CARDINAL iPods PRODUCT for a profit of $6 million MONEY . By contrast, Sony ORG sold only 7 thousand CARDINAL Walkman music players.

Visualizing Sentences Line by Line

```
In [47]: for sent in doc.sents:
             displacy.render(nlp(sent.text), style='ent', jupyter=True)
```



Viewing Specific Entities

You can pass a list of entity types to restrict the visualization:

```
In [48]: options = {'ents': ['ORG', 'PRODUCT']}

         displacy.render(doc, style='ent', jupyter=True, options=options)
```

Styling: customize colour and effects

You can also pass background colour and gradient options:

```
In [58]: colors = {'ORG': 'linear-gradient(90deg, #aa9cde, #dc9ce7)', 'PRODUCT': 'radial-gradient(white, red)'}

         options = {'ents': ['ORG', 'PRODUCT'], 'colors':colors}

         displacy.render(doc, style='ent', jupyter=True, options=options)
```

This is all about Named Entity Recognition NER and its Visualization using spaCy. Hope you enjoyed the post. Next Article I will write about Sentence Segmentation. Stay Tuned!

If you have any feedback to improve the content or any thought please write in the comment section below. Your comments are very valuable.

I would love to connect with you on LinkedIn so please do not forget to add me to your network. https://www.linkedin.com/in/ashutoshtripathi1/

References:

- https://spacy.io/usage/spacy-101
- https://www.udemy.com/course/nlp-natural-language-processing-with-python/