# Comparing NLTK with other NLP tools for text analysis

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#### Introduction:

Natural language processing helps us to understand valuable texts in countless ways. It also forms the structure of the text and is useful in many applications, such as speech recognition, content or context analytics on Twitter or Facebook, and so on. The goal of this paper is to compare one of the most popular and powerful natural language processing tools NLTK with other popular ones like Textblob and stanfordNLP. NLTK is a useful Python package that provides the reader with the fundamentals of writing Python programs. It has plenty of tools to clean and pre-process the text data, working with corpora, categorizing text, analyzing linguistic structure, and more.

# Overview of different functionality and usage for text analysis between NLTK and other NLP tools:

- 1. Install and environment setting.
  - a. First of all, Install NLTK, Textblob and Standford coreNLP.
  - b. For StanfordNLP, we need to set up the environment:

cd ~ wget <a href="http://nlp.stanford.edu/software/stanford-corenlp-full-2016-10-31.zip">http://nlp.stanford.edu/software/stanford-corenlp-full-2016-10-31.zip</a> unzip stanford-corenlp-full-2016-10-31.zip && cd stanford-corenlp-full-2016-10-31 pip3 install -U <a href="https://github.com/stanfordnlp/python-stanford-corenlp/archive/master.zip">https://github.com/stanfordnlp/python-stanford-corenlp/archive/master.zip</a>

# On Mac export

CORENLP\_HOME=/Users/<username>/stanford-corenlp-full-2016-10-31/

# On linux export

CORENLP\_HOME=/home/<username>/stanford-corenlp-full-2016-10-31/

- 2. Pre-processing with NLTK and StandfordNLP.
  - a. Import libraries

Using NLTK

```
import nltk
import random
from nltk.corpus import state_union
from nltk.tokenize import PunktSentenceTokenizer
from nltk.corpus import movie_reviews
from nltk.corpus import stopwords
from textblob.classifiers import NaiveBayesClassifier
```

### Using StandfordNLP

```
: 1 import corenlp
```

#### b. Tokenizing

Using NLTK - word tokenizers and sentences tokenizers.

```
from nltk.tokenize import sent_tokenize, word_tokenize
example_text = "Hello Mr. Smith, how are you doing today? The weather is great and Python is awesome. "\
"the sky is pinkish-blue. You should not eat carboard."

print(sent_tokenize(example_text)) #creat a list.

['Hello Mr. Smith, how are you doing today?', 'The weather is great and Python is awesome.', 'the sky is pinkish-blu e.', 'You should not eat carboard.']
['Hello', 'Mr.', 'Smith', ',', 'how', 'are', 'you', 'doing', 'today', '?', 'The', 'weather', 'is', 'great', 'and', 'P ython', 'is', 'awesome', '.', 'the', 'sky', 'is', 'pinkish-blue', '.', 'You', 'should', 'not', 'eat', 'carboard', '.']
```

# Using StandfordNLP -

```
with corenlp.client.CoreNLPClient(annotators="tokenize ssplit".split()) as client:
    ann = client.annotate("Hello Mr. Smith, how are you doing today? The weather is great and Python is awesome. "\
    "the sky is pinkish-blue. You should not eat carboard.")
    sentence = ann.sentence[0]
[token.word for token in sentence.token]
    #['Hello', 'Mr.', 'Smith', ',', 'how', 'are', 'you', 'doing', 'today', '?', 'The', 'weather', 'is', 'great', 'and',
    #'.', 'You', 'should', 'not', 'eat', 'carboard', '.']
```

#### c. Removing stop words and POS Tagging with NLTK

```
example_sentence = "This is just a simple example to show off how to filter the stop words."

stop_words = set(stopwords.words("english")) # choose english as the language to get all stopwords in it.

words = word_tokenize(example_sentence)
filtered_sentence = []

# for word in words:
# if word not in stop_words:
# filtered_sentence.append(word)
filtered_sentence = [word for word in words if not word in stop_words]
print(filtered_sentence)

['This', 'simple', 'example', 'show', 'filter', 'stop', 'words', '.']
```

```
#Part of Speech Tagging
    import nltk
   from nltk.corpus import state_union
   sample_text = "I like that Movie." #loading some data as input.
   tokenized = custom sent tokenizer.tokenize(sample text)
   def process_content():
        try:
           for i in tokenized:
                words = nltk.word_tokenize(i)
tagged = nltk.pos_tag(words)
12
13
14
                print(tagged)
       except Exception as e:
           print(str(e))
17 process_content()
['I like that Movie.']
[('I', 'PRP'), ('like', 'VBP'), ('that', 'DT'), ('Movie', 'NNP'), ('.', '.')]
```

If you are interested in what stop words are, check <a href="here">here</a>. From above example, we can see all words were <a href="tagged">tagged</a> as part-of-speech. Upon my research, some of the pre-processing stages like removal of stopwords, punctuation, or special characters are not included in the StandfordNLP. However, we can run the Standford Pos Tagger on NLTK Using <a href="Java">Java</a> or <a href="Python">Python</a>.

d. There is another interesting example shows that how can we use Stanford Parser to get a dependency path. First of all, import the library:

```
import os
from nltk.parse import stanford
```

Then path java.exe and .jar files to your Stanford parser:

```
java_path = r'C:\Program Files (x86)\Common Files\Oracle\Java\javapath\java.exe' os.environ['JAVAHOME'] = java_path os.environ['STANFORD_PARSER'] = r'YOUR_PATH\stanford-parser-full-2014-10-31\stanford- parser.jar' os.environ['STANFORD_MODELS'] = r'YOUR_PATH\stanford-parser-full-2014-10-31\stanford- parser-3.5.0-models.jar' dependency_parser = stanford.StanfordDependencyParser(path_to_jar=r'YOUR_PATH\stanford-parser-full-2014-10-31\stanford-parser.jar', path_to_models_jar=r'YOUR_PATH\stanford-parser-full-2014-10-31\stanford-parser-3.5.0-models.jar')
```

Then we can get dependencies, see below:

```
sentence = "I like that movie."
result = dependency_parser.raw_parse(sentence)
dep = next(result)
print(list(dep.triples()))

[(('like', 'VBP'), 'nsubj', ('I', 'PRP')), (('like', 'VBP'), 'dobj', ('movie', 'NN')), (('movie', 'NN'), 'det', ('that', 'DT'))]
```

 e. Stemming - We can also use nltk.stem to identify the similar meanings of words/sentences.

```
1 from nltk.stem import PorterStemmer
 2 from nltk.tokenize import word_tokenize
 4 ps =PorterStemmer()
 example_words = ["call", "caller", "calling", "called", "Call", "cally"]

example_sentence = "It is very cool to be called while you are calling with caller"\
      . As a cally once, call is called."
 9 words = word_tokenize(example_sentence)
10 for w in words:
        print(ps.stem(w))
11
it
is
veri
cool
to
be
call
while
you
are
call
with
caller
as
calli
onc
call
call
```

In the above example, we can see NLTK converting "caller", "called", to "call".

#### WordNet with NLTK

We we can use nltk.corpus to identify the similarities and differences of the words.

```
#WordNet
from nltk.corpus import wordnet

#similarity
wl = wordnet.synset("woman.n.01") # synset function has an optional pos argument which
w2 = wordnet.synset("lady.n.01") #lets you constrain the part of speech of the word:

#compare the similarity between these two words.
print(wl.wup_similarity(w2))
#0.9473684210526315 this indicates woman and lady are 94.7% similar.

wl = wordnet.synset("woman.n.01")
w2 = wordnet.synset("boy.n.01")
print(wl.wup_similarity(w2))
#0.6666666666666666 woman and boy are 66.6% similar. (humans)

wl = wordnet.synset("woman.n.01")
w2 = wordnet.synset("woman.n.01")
print(wl.wup_similarity(w2))
#0.36363636363636365 woman and food are 36.36% similar.
```

From above example, we can see the similarities between "woman" and "lady" are

over 90 percent, compared to 36 percent between "woman" and "food", which makes sense.

#### 4. Naive Bayes and Sentiment analysis

## a. Using NLTK

```
1 #Naive Baves with NLTK
 2 featuresets = [(find_features(rev), category) for (rev, category) in documents]
 3 training_set = featuresets[:1900]
    testing_set = featuresets[1900:] #we define two different sets to avoid bias.
 6 # posterior = prior occurences * likelihood / evidence - Naive Bayes
 7 classifier = nltk.NaiveBayesClassifier.train(training_set)
 8 print("Naive Bayes Algo accuracy: ", (nltk.classify.accuracy(classifier, testing_set))*100)
 9 classifier.show_most_informative_features(15) # negs numbers vs positive numbers
Naive Bayes Algo accuracy: 76.0
Most Informative Features
                       sucks = True
                                                                              17.3 : 1.0
                      justin = True
                                                      neg : pos
                                                                              9.1:1.0
                     annual = True
                                                      pos : neg
                                                                              8.9 : 1.0
               silverstone = True
                                                      neg : pos
                                                                               7.8 : 1.0
             unimaginative = True
                                                                               7.8 : 1.0
                                                      neg : pos
                    frances = True
                                                                              7.6 : 1.0
                                                      pos : neg
                 schumacher = True
                                                                              7.5 : 1.0
                                                      neg : pos
                                                                             7.5 : 1.0
7.3 : 1.0
7.1 : 1.0
7.1 : 1.0
6.7 : 1.0
                    idiotic = True
                                                     neg : pos
                  crappy = True
  shoddy = True
atrocious = True
                                                      neg : pos
                                                     neg : pos
                                                      neg : pos

    Notified
    neg : pos = 6.7 : 1.0

    turkey = True
    neg : pos = 6.7 : 1.0

    kudos = True
    pos : neg = 6.5 : 1.0

    regard = True
    pos : neg = 6.5 : 1.0

    cindy = True
    neg : pos = 6.4 : 1.0
```

# b. Using Textblob

```
1 #Naive Bayes with Textblob
 2 new_train, new_test = documents[0:1900], documents[1900:]
 3 c1 = NaiveBayesClassifier(new_train)
 4 print("Naive Bayes Algo accuracy with textblob: ", 100*c1.accuracy(new_test))
 5 cl.show informative features(15)
Naive Bayes Algo accuracy with textblob: 82.0
Most Informative Features
         contains(sucks) = True
                                                                      17.3 : 1.0
                                                  neg : pos
                                                                = 17.3 : 1.0
= 13.5 : 1.0
= 12.8 : 1.0
= 12.2 : 1.0
= 11.2 : 1.0
= 11.2 : 1.0
                                                 pos : neg
   contains(outstanding) = True
                                                 pos : neg
        contains(avoids) = True
    contains(astounding) = True
                                                 pos : neg
     contains(insulting) = True
                                                 neg : pos
                                                                = 11.2 : 1.0
= 11.2 : 1.0
= 10.8 : 1.0
= 10.8 : 1.0
= 10.6 : 1.0
    contains(unbearable) = True
                                                 neg : pos
         contains(damon) = True
                                                 pos : neg
                                                pos : neg
   contains(fascination) = True
          contains(slip) = True
     contains(ludicrous) = True
                                                 neg : pos
                                                                = 10.5 : 1.0
= 10.5 : 1.0
          contains(3000) = True
                                                 neg : pos
                                                 neg : pos
            contains(dud) = True
      contains(thematic) = True
contains(hudson) = True
                                             pos : neg = 10.2 : 1.0
neg : pos = 9.8 : 1.0
neg : pos = 9.8 : 1.0
          contains(jolie) = True
```

From the results as above, both NLTK and Textblob work well on text analysis, the accuracy was 76% vs 82%. Since Naive Bayers classifier in Textblob is based on NLTK (see line 188), so the result is similar which was indicated as above. In a word, we can use both to do the sentiment analysis.

#### Conclusion

From the above implementation, we can conclude that NLTK has more robust libraries and support many third-party extensions and interfaces. Both NLTK and Stanford NLP support a great number of languages but when it comes to tokenization, NLTK tends to be faster than Stanford NLP, and the size of the language models in the latter is too large, it takes a bit longer time to download. Furthermore, NLTK is quick about scripting a prototype but StanfordNLP requires more codes to chunk out the features. However, NLTK is only supported by Python. Instead, StanfordNLP was written in java, yet it is supported by multiple languages like Python, Java, and Jython. NLTK processes strings that are not very practical for the object-oriented language python either. In a word, NLTK is very powerful on handling unstructured texts, especially If you are new to text retrieval and analysis on English, NLTK would be one of the best choices.

#### Reference

https://www.nltk.org/howto.html

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