NLP Cheat Sheet

by sree017 via cheatography.com/126402/cs/24446/

Tokenization

Tokenization breaks the raw text into words, sentences called tokens. These tokens help in understanding the context or developing the model for the NLP. ... If the text is split into words using some separation technique it is called word tokenization and same separation done for sentences is called sentence tokenization.

```
# NLTK
import nltk
nltk.download('punkt')
paragraph = "write paragaraph here to convert into tokens."
sentences = nltk.sent_tokenize(paragraph)
words = nltk.word_tokenize(paragraph)
# Spacy
from spacy.lang.en import English
nlp = English()
sbd = nlp.create_pipe('sentencizer')
nlp.add_pipe(sbd)
doc = nlp(paragraph)
[sent for sent in doc.sents]
nlp = English()
doc = nlp(paragraph)
```

Tokenization (cont)

```
[word for word in doc]
# Keras
from keras.preprocessing.text import text_to_word_sequence
text_to_word_sequence(paragraph)
# genis
from gensim.summarization.textcleaner import split_sentences
split_sentences(paragraph)
from gensim.utils import tokenize
list(tokenize(paragraph))
```

Bag Of Words & TF-IDF

Bag of Words model is used to preprocess the text by converting it into a bag of words, which keeps a count of the total occurrences of most frequently used words

```
# counters = List of stences after pre processing like tokenization, stemming/lemmatization, stopwords
from sklearn.feature_extraction.text import CountVectorizer
cv = CountVectorizer(max_features = 1500)
```

Bag Of Words & TF-IDF (cont)

```
X = cv.fit_transform(counters).toarray()
```

Term Frequency-Inverse Document Frequency (TF-IDF):

Term frequency-inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.

T.F = No of rep of words in setence/No of words in sentence

IDF = No of sentences / No of sentences containing words

```
from sklearn.feature_extraction.text import TfidfVectorizer
cv = TfidfVectorizer()
X = cv.fit_transform(counters).toarray()
```

N-gram Language Model: An N-gram is a sequence of N tokens (or words).

A 1-gram (or unigram) is a one-word sequence.the unigrams would simply be: “I”, “love”, “reading”, “blogs”, “about”, “data”, “science”, “on”, “Analytics”, “Vidhya”.

Bag Of Words & TF-IDF (cont)

A 2-gram (or bigram) is a two-word sequence of words, like “I love”, “love reading”, or “Analytics Vidhya”.

And a 3-gram (or trigram) is a three-word sequence of words like “I love reading”, “about data science” or “on Analytics Vidhya”.

Stemming & Lemmatization

From Stemming we will process of getting the root form of a word. We would create the stem words by removing the prefix of suffix of a word. So, stemming a word may not result in actual words.

```
paragraph = ""
# NLTK
from nltk.stem import PorterStemmer
from nltk import sent_tokenize
from nltk import word_tokenize
stem = PorterStemmer()
sentence = sent_tokenize(paragraph)[1]
words = word_tokenize(sentence)
[stem.stem(word) for word in words]
# Spacy
```

Stemming & Lemmatization (cont)

```
No Stemming in spacy
# Keras
No Stemming in Keras
Lemmatization:
As stemming, lemmatization do the same but the only difference is that lemmatization ensures that root word belongs to the language
# NLTK
from nltk.stem import WordNetLemmatizer
lemma = WordNetLemmatizer()
sentence = sent_tokenize(paragraph)[1]
words = word_tokenize(sentence)
[lemma.lemmatize(word) for word in words]
# Spcay
import spacy as spac
sp = spac.load('en_core_web_sm')
ch = sp(u'warning warned')
for x in ch:
    print(ch.lemma_)
# Keras
No lemmatization or stemming
```

Word2Vec

```
In BOW and TF-IDF approach semantic information not stored. TF-IDF gives importance to uncommon words. There is definitely chance of overfitting.
 In W2v each word is basically represented as a vector of 32 or more dimension instead of a single number. Here the semantic information and relation between words is also preserved.
Steps:
1. Tokenization of the sentences
2. Create Histograms
3. Take most frequent words
4. Create a matrix with all the unique words. It also represents the occurence relation between the words
from gensim.models import Word2Vec
model = Word2Vec(sentences, min_count=1)
words = model.wv.vocab
vector = model.wv['freedom']
similar = model.wv.most_similar['freedom']
```

Stop Words

```
Stopwords are the most common words in any natural language. For the purpose of analyzing text data and building NLP models, these stopwords might not add much value to the meaning of the document.
# NLTK
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
stopwords = set(stopwords.words('english'))
word_tokens = word_tokenize(paragraph)
[word for word in word_tokens if word not in stopwords]
# Spacy
from spacy.lang.en import English
from spacy.lang.en.stop_words import STOP_WORDS
nlp = English()
my_doc = nlp(paragraph)
# Create list of word tokens
token_list = [token.text for token in my_doc]
# Create list of word tokens after removing stopwords
filtered_sentence =[]
```

Stop Words (cont)

```
for word in token_list:
    lexeme = nlp.vocab[word]
    if lexeme.is_stop == False:
        filtered_sentence.append(word)
# Gensim
from gensim.parsing.preprocessing import remove_stopwords
remove_stopwords(paragraph)
```

Tokenization

NLTK	Spacy	Keras	Tensorlfow
dfdfd			

Parts of Speech (POS) Tagging, Chunking & NER

```
The pos(parts of speech) explain you how a word is used in a sentence. In the sentence, a word have different contexts and semantic meanings. The basic natural language processing(NLP) models like bag-of-words(bow) fails to identify these relation between the words. For that we use pos tagging to mark a word to its pos tag based on its context in the data. Pos is also used to extract rlationship between the words
# NLTK
```

Parts of Speech (POS) Tagging, Chunking & NER (cont)

```
from nltk.tokenize import word_tokenize
from nltk import pos_tag
nltk.download('averaged_perceptron_tagger')
word_tokens = word_tokenize('Are you afraid of something?')
pos_tag(word_tokens)
# Spacy
nlp = spacy.load("en_core_web_sm")
doc = nlp("Coronavirus: Delhi resident tests positive for coronavirus, total 31 people infected in India")
[token.pos_ for token in doc]
```

Chunking:
Chunking is the process of extracting phrases from the Unstructured text and give them more structure to it. We also called them shallow parsing.We can do it on top of pos tagging. It groups words into chunks mainly for noun phrases. chunking we do by using regular expression.

```
# NLTK
word_tokens = word_tokenize(text)
```

Parts of Speech (POS) Tagging, Chunking & NER (cont)

```
word_pos = pos_tag(word_tokens)
chunkParser = nltk.RegexpParser(grammar)
tree = chunkParser.parse(word_pos)
```

Named Entity Recognization:
It is used to extract information from unstructured text. It is used to classy the entities which is present in the text into categories like a person, organization, event, places, etc. This will give you a detail knowledge about the text and the relationship between the different entities.

```
# Spacy
import spacy
nlp = spacy.load("en_core_web_sm")
doc = nlp("Coronavirus: Delhi resident tests positive for coronavirus, total 31 people infected in India")
for ent in doc.ents:
    print(ent.text, ent.start_char, ent.end_char, ent.label_)
```