A Practitioner's Guide to Natural Language Processing (Part I) — Processing & Understanding Text

Proven and tested hands-on strategies to tackle NLP tasks

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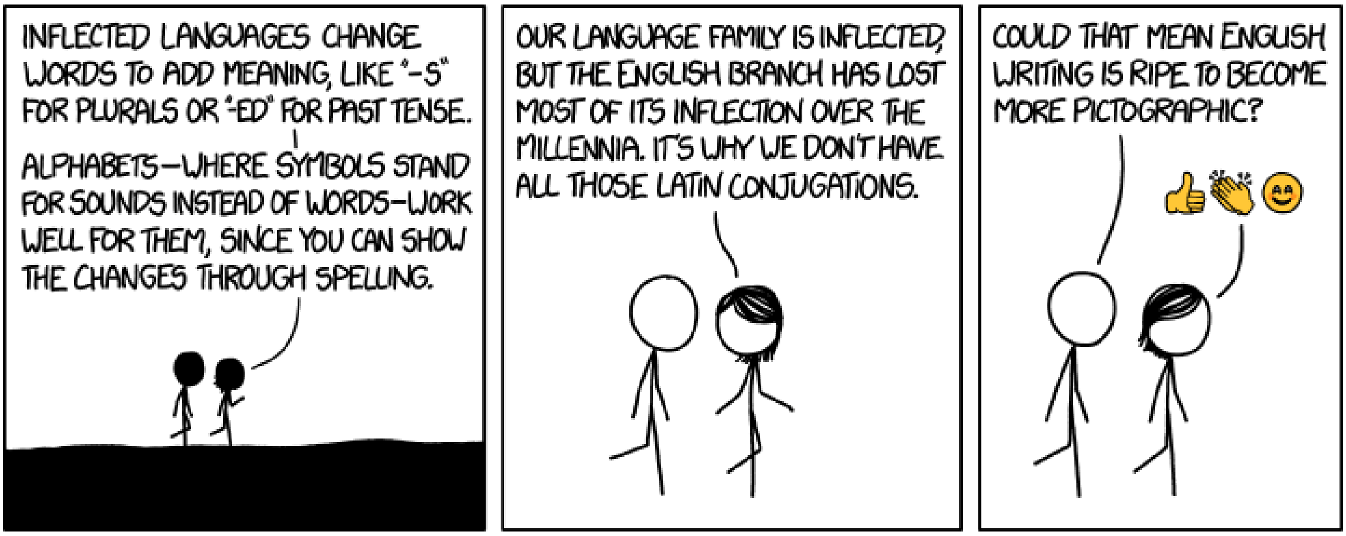
Introduction

Unstructured data, especially text, images and videos contain a wealth of information. However, due to the inherent complexity in processing and analyzing this data, people often refrain from spending extra time and effort in venturing out from structured datasets to analyze these unstructured sources of data, which can be a potential gold mine.



Natural Language Processing (NLP) is all about leveraging tools, techniques and algorithms to process and understand natural language-based data, which is usually unstructured like text, speech and so on. In this series of articles, we will be looking at tried and tested strategies, techniques and workflows which can be leveraged by practitioners and data scientists to extract useful insights from text data. We will also cover some useful and interesting use-cases for NLP. This article will be all about processing and understanding text data with tutorials and hands-on examples.

Outline for this Series

The nature of this series will be a mix of theoretical concepts but with a focus on hands-on techniques and strategies covering a wide variety of NLP problems. Some of the major areas that we will be covering in this series of articles include the following.

1. **Processing & Understanding Text**
2. **Feature Engineering & Text Representation**
3. **Supervised Learning Models for Text Data**
4. **Unsupervised Learning Models for Text Data**
5. **Advanced Topics**

Feel free to suggest more ideas as this series progresses, and I will be glad to cover something I might have missed out on. A lot of these articles will showcase tips and strategies which have worked well in real-world scenarios.

What this article covers

This article will be covering the following aspects of NLP in detail with hands-on examples.

1. **Data Retrieval with Web Scraping**
2. **Text wrangling and pre-processing**
3. **Parts of Speech Tagging**
4. **Shallow Parsing**
5. **Constituency and Dependency Parsing**
6. **Named Entity Recognition**
7. **Emotion and Sentiment Analysis**

This should give you a good idea of how to get started with analyzing syntax and semantics in text corpora.

Motivation

Formally, NLP is a specialized field of computer science and artificial intelligence with roots in computational linguistics. It is primarily concerned with designing and building applications and systems that enable interaction between machines and natural languages that have been evolved for use by humans. Hence, often it is perceived as a niche area to work on. And people usually tend to focus more on machine learning or statistical learning.

When I started delving into the world of data science, even I was overwhelmed by the challenges in analyzing and modeling on text data. However, after working as a Data Scientist on several challenging problems around NLP over the years, I've noticed certain interesting aspects, including techniques, strategies and workflows which can be leveraged to solve a wide variety of problems. I have covered several topics around NLP in my books *"Text Analytics with Python"* (I'm writing a revised version of this soon) and *"Practical Machine Learning with Python"*.

> *However, based on all the excellent feedback I've received from all my readers (yes all you amazing people out there!), the main objective and motivation in creating this series of articles is to share my learnings with more people, who can't always find time to sit and read through a book and can even refer to these articles on the go!* ***Thus, there is no pre-requisite to buy any of these books to learn NLP.***

Getting Started

When building the content and examples for this article, I was thinking if I should focus on a toy dataset to explain things better, or focus on an existing dataset from one of the main sources for data science datasets. Then I thought, why not build an end-to-end tutorial, where we scrape the web to get some text data and showcase examples based on that!

The source data which we will be working on will be news articles, which we have retrieved from **inshorts,** a website that gives us short, 60-word news articles on a wide variety of topics, and they even have an app for it!

Inshorts, news in 60 words !

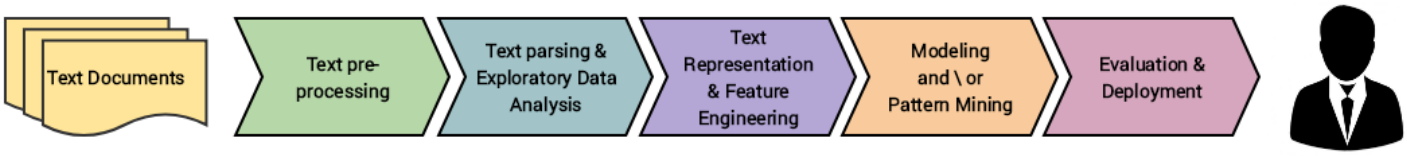
Edit description

inshorts.com

In this article, we will be working with text data from news articles on technology, sports and world news. I will be covering some basics on how to scrape and retrieve these news articles from their website in the next section.

Standard NLP Workflow

I am assuming you are aware of the CRISP-DM model, which is typically an industry standard for executing any data science project. Typically, any NLP-based problem can be solved by a methodical workflow that has a sequence of steps. The major steps are depicted in the following figure.

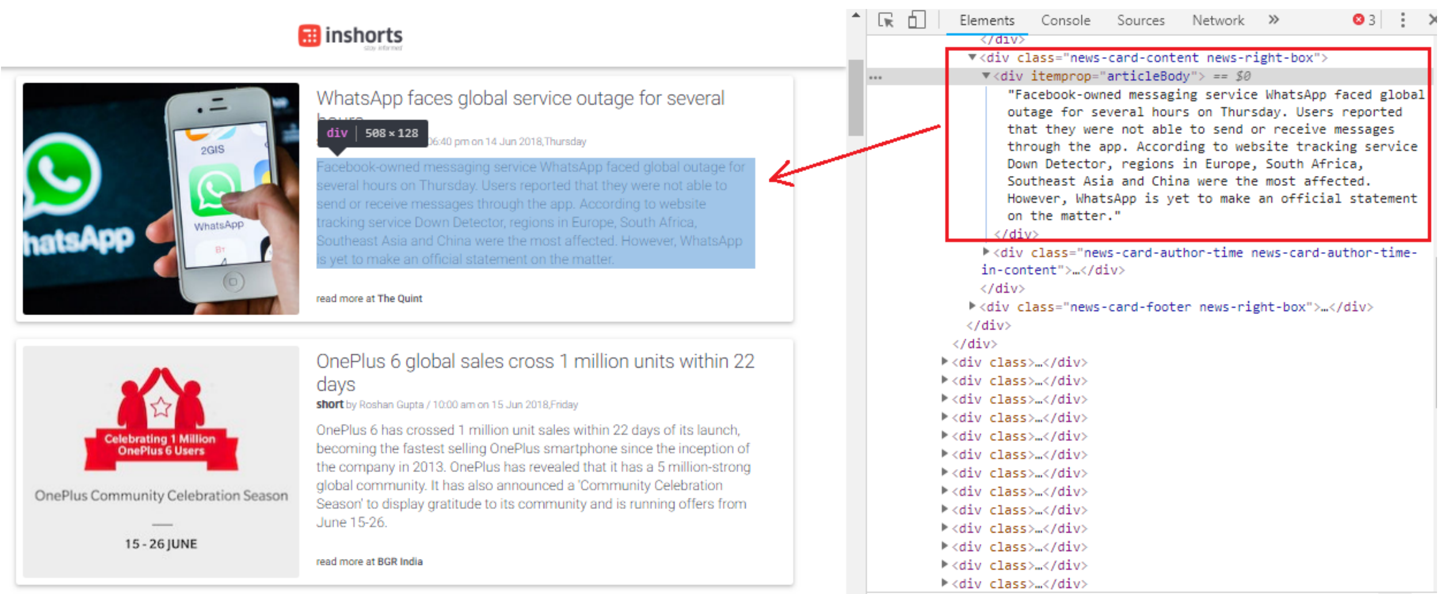


A high-level standard workflow for any NLP project

We usually start with a corpus of text documents and follow standard processes of text wrangling and pre-processing, parsing and basic exploratory data analysis. Based on the initial insights, we usually represent the text using relevant feature engineering techniques. Depending on the problem at hand, we either focus on building predictive supervised models or unsupervised models, which usually focus more on pattern mining and grouping. Finally, we evaluate the model and the overall success criteria with relevant stakeholders or customers, and deploy the final model for future usage.

Scraping News Articles for Data Retrieval

We will be scraping **inshorts**, the website, by leveraging python to retrieve news articles. We will be focusing on articles on technology, sports and world affairs. We will retrieve one page's worth of articles for each category. A typical news category landing page is depicted in the following figure, which also highlights the HTML section for the textual content of each article.



The landing page for technology news articles and its corresponding HTML structure

Thus, we can see the specific HTML tags which contain the textual content of each news article in the landing page mentioned above. We will be using this information to extract news articles by leveraging the **BeautifulSoup** and **requests** libraries. Let's first load up the following dependencies.

```
import requests
from bs4 import BeautifulSoup
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os

%matplotlib inline
```

We will now build a function which will leverage **requests** to access and get the HTML content from the landing pages of each of the three news categories. Then, we will use **BeautifulSoup** to parse and extract the news headline and article textual content for all the news articles in each category. We find the content by accessing the specific HTML tags and classes, where they are present (a sample of which I depicted in the previous figure).

```
seed_urls = ['https://inshorts.com/en/read/technology',
             'https://inshorts.com/en/read/sports',
             'https://inshorts.com/en/read/world']

def build_dataset(seed_urls):
    news_data = []
    for url in seed_urls:
        news_category = url.split('/')[-1]
        data = requests.get(url)
        soup = BeautifulSoup(data.content, 'html.parser')

        news_articles = [{'news_headline': headline.find('span',
                                                         attrs={"itemprop": "headline"}).string
                          'news_article': article.find('div',
                                                       attrs={"itemprop": "articleBody"}).strin
                          'news_category': news_category}

                            for headline, article in
                             zip(soup.find_all('div',
                                               class_=["news-card-title news-right-box"]),
                                 soup.find_all('div',
```

```
                                  class_=["news-card-content news-right-box"]))
                    ]
        news_data.extend(news_articles)

    df =  pd.DataFrame(news_data)
    df = df[['news_headline', 'news_article', 'news_category']]
    return df
```

It is pretty clear that we extract the news headline, article text and category and build out a data frame, where each row corresponds to a specific news article. We will now invoke this function and build our dataset.

```
news_df = build_dataset(seed_urls)
news_df.head(10)
```

	news_headline	news_article	news_category
0	World's cheapest phone 'Freedom 251' maker's f...	The maker of world's cheapest smartphone 'Free...	technology
1	US unveils world's most powerful supercomputer...	The US has unveiled the world's most powerful ...	technology
2	FB bug changed 1.4 cr users' privacy setting t...	Facebook has said it recently found a bug that...	technology
3	Contest for 1st couple to marry in self-drivin...	The American Automobile Association has launch...	technology
4	China's ZTE to pay $1 billion fine to US to li...	Chinese telecommunications equipment maker ZTE...	technology
5	Android Co-founder's startup unveils magnetic ...	Android Co-founder Andy Rubin's startup Essent...	technology
6	Yahoo Messenger to shut down 20 years after la...	Yahoo has announced it is discontinuing its Me...	technology
7	Google won't design AI for weapons, surveillan...	Google CEO Sundar Pichai has clarified the com...	technology
8	Virgin Hyperloop One may allow riders to see t...	Richard Branson-led Virgin Hyperloop One has s...	technology
9	Apple patents wearable device to monitor blood...	Apple has been granted the patent for a wearab...	technology

Our news dataset

We, now, have a neatly formatted dataset of news articles and you can quickly check the total number of news articles with the following code.

```
news_df.news_category.value_counts()

Output:
-------
world         25
sports        25
technology    24
Name: news_category, dtype: int64
```

Text Wrangling & Pre-processing

There are usually multiple steps involved in cleaning and pre-processing textual data. I have covered text pre-processing in detail in ***Chapter 3 of 'Text Analytics with Python'*** (code is open-sourced). However, in this section, I will highlight some of the most important steps which are used heavily in Natural Language Processing (NLP) pipelines and I frequently use them in my NLP projects. We will be leveraging a fair bit of **nltk** and **spacy** , both state-of-the-art libraries in NLP. Typically a `pip install <library>` or a `conda install <library>` should suffice. However, in case you face issues with loading up `spacy's` language models, feel free to follow the steps highlighted below to resolve this issue (I had faced this issue in one of my systems).

```
# OPTIONAL: ONLY USE IF SPACY FAILS TO LOAD LANGUAGE MODEL
# Use the following command to install spaCy
> pip install -U spacy

OR

> conda install -c conda-forge spacy

# Download the following language model and store it in disk
https://github.com/explosion/spacy-
models/releases/tag/en_core_web_md-2.0.0

# Link the same to spacy
> python -m spacy link ./spacymodels/en_core_web_md-
2.0.0/en_core_web_md en_core

Linking successful
    ./spacymodels/en_core_web_md-2.0.0/en_core_web_md -->
./Anaconda3/lib/site-packages/spacy/data/en_core

You can now load the model via spacy.load('en_core')
```

Let's now load up the necessary dependencies for text pre-processing. We will remove negation words from stop words, since we would want to keep them as they might be useful, especially during sentiment analysis.

> *📝**IMPORTANT NOTE:** A lot of you have messaged me about not being able to load the contractions module. It's not a standard python module. We leverage a standard set of contractions available in the* `contractions.py` *file in **my repository**.Please add it in the same directory you run your code from, else it will not work.*

```
import spacy
import pandas as pd
import numpy as np
import nltk
from nltk.tokenize.toktok import ToktokTokenizer
import re
from bs4 import BeautifulSoup
from contractions import CONTRACTION_MAP
import unicodedata

nlp = spacy.load('en_core', parse=True, tag=True, entity=True)
#nlp_vec = spacy.load('en_vecs', parse = True, tag=True,
#entity=True)
tokenizer = ToktokTokenizer()
stopword_list = nltk.corpus.stopwords.words('english')
stopword_list.remove('no')
stopword_list.remove('not')
```

Removing HTML tags

Often, unstructured text contains a lot of noise, especially if you use techniques like web or screen scraping. HTML tags are typically one of these components which don't add much value towards understanding and analyzing text.

```python
def strip_html_tags(text):
    soup = BeautifulSoup(text, "html.parser")
    stripped_text = soup.get_text()
    return stripped_text

strip_html_tags('<html><h2>Some important text</h2></html>')
```

nlp_strategy_2.py hosted with ♡ by GitHub view raw

```
'Some important text'
```

It is quite evident from the above output that we can remove unnecessary HTML tags and retain the useful textual information from any document.

Removing accented characters

Usually in any text corpus, you might be dealing with accented characters/letters, especially if you only want to analyze the English language. Hence, we need to make sure that these characters are converted and standardized into ASCII characters. A simple example — converting **é** to **e**.

```
def remove_accented_chars(text):
    text = unicodedata.normalize('NFKD', text).encode('ascii', 'ignore').decode('utf-8', 'ignore
    return text

remove_accented_chars('Sómě Áccěntěd těxt')
```

nlp_strategy_3.py hosted with ♡ by GitHub view raw

```
'Some Accented text'
```

The preceding function shows us how we can easily convert accented characters to normal English characters, which helps standardize the words in our corpus.

Expanding Contractions

Contractions are shortened version of words or syllables. They often exist in either written or spoken forms in the English language. These shortened versions or contractions of words are created by removing specific letters and sounds. In case of English contractions, they are often created by removing one of the vowels from the word. Examples would be, ***do not*** to ***don't*** and ***I would*** to ***I'd***. Converting each contraction to its expanded, original form helps with text standardization.

> *We leverage a standard set of contractions available in the `contractions.py` file in **my repository**.*

```
def expand_contractions(text, contraction_mapping=CONTRACTION_MAP):

    contractions_pattern = re.compile('({})'.format('|'.join(contraction_mapping.keys())),
                                      flags=re.IGNORECASE|re.DOTALL)
    def expand_match(contraction):
        match = contraction.group(0)
        first_char = match[0]
        expanded_contraction = contraction_mapping.get(match)\
                               if contraction_mapping.get(match)\
                               else contraction_mapping.get(match.lower())
        expanded_contraction = first_char+expanded_contraction[1:]
        return expanded_contraction

    expanded_text = contractions_pattern.sub(expand_match, text)
    expanded_text = re.sub("'", "", expanded_text)
    return expanded_text

```

```
expand_contractions("Y'all can't expand contractions I'd think")
```

nlp_strategy_4.py hosted with ♡ by GitHub view raw

```
'You all cannot expand contractions I would think'
```

We can see how our function helps expand the contractions from the preceding output. Are there better ways of doing this? Definitely! If we have enough examples, we can even train a deep learning model for better performance.

Removing Special Characters

Special characters and symbols are usually non-alphanumeric characters or even occasionally numeric characters (depending on the problem), which add to the extra noise in unstructured text. Usually, simple regular expressions (regexes) can be used to remove them.

```
def remove_special_characters(text, remove_digits=False):
    pattern = r'[^a-zA-z0-9\s]' if not remove_digits else r'[^a-zA-z\s]'
    text = re.sub(pattern, '', text)
    return text

remove_special_characters("Well this was fun! What do you think? 123#@!",
                          remove_digits=True)
```

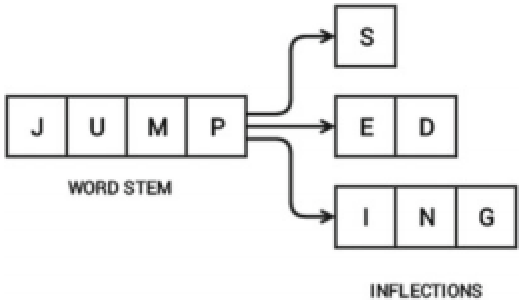
nlp_strategy_5.py hosted with ♡ by GitHub view raw

```
'Well this was fun What do you think '
```

I've kept removing digits as optional, because often we might need to keep them in the pre-processed text.

Stemming

To understand stemming, you need to gain some perspective on what word stems represent. Word stems are also known as the ***base form*** of a word, and we can create new words by attaching affixes to them in a process known as inflection. Consider the word ***JUMP***. You can add affixes to it and form new words like ***JUMPS***, ***JUMPED***, and ***JUMPING***. In this case, the base word ***JUMP*** is the word stem.



Word stem and its inflections (Source: Text Analytics with Python, Apress/Springer 2016)

The figure shows how the word stem is present in all its inflections, since it forms the base on which each inflection is built upon using affixes. The reverse process of obtaining the base form of a word from its inflected form is known as ***stemming***. Stemming helps us in standardizing words to their base or root stem, irrespective of their inflections, which helps many applications like classifying or clustering text, and even in information retrieval. Let's see the popular Porter stemmer in action now!

```
def simple_stemmer(text):
    ps = nltk.porter.PorterStemmer()
    text = ' '.join([ps.stem(word) for word in text.split()])
    return text

simple_stemmer("My system keeps crashing his crashed yesterday, ours crashes daily")
```

nlp_strategy_6.py hosted with ♡ by GitHub view raw

```
'My system keep crash hi crash yesterday, our crash daili'
```

The Porter stemmer is based on the algorithm developed by its inventor, Dr. Martin Porter. Originally, the algorithm is said to have had a total of five different phases for reduction of inflections to their stems, where each phase has its own set of rules.

> *Do note that usually stemming has a fixed set of rules, hence, the root stems may not be lexicographically correct. Which means, the* ***stemmed words may not be semantically correct,*** *and might have a chance of not being present in the dictionary (as evident from the preceding output).*

Lemmatization

Lemmatization is very similar to stemming, where we remove word affixes to get to the base form of a word. However, the base form in this case is known as the root word, but not the root stem. The difference being that the ***root word is always a lexicographically correct word*** (present in the dictionary), but the root stem may not be so. Thus, root word, also known as the ***lemma***, will always be present in the dictionary. Both `nltk` and `spacy` have excellent lemmatizers. We will be using `spacy` here.

```
def lemmatize_text(text):
    text = nlp(text)
    text = ' '.join([word.lemma_ if word.lemma_ != '-PRON-' else word.text for word in text])
    return text

lemmatize_text("My system keeps crashing! his crashed yesterday, ours crashes daily")
```

nlp_strategy_7.py hosted with ♡ by GitHub view raw

```
'My system keep crash ! his crash yesterday , ours crash daily'
```

You can see that the semantics of the words are not affected by this, yet our text is still standardized.

> *Do note that the lemmatization process is considerably slower than stemming, because an additional step is involved where the root form or lemma is formed by removing the affix from the word if and only if the lemma is present in the dictionary.*

Removing Stopwords

Words which have little or no significance, especially when constructing meaningful features from text, are known as stopwords or stop words. These are usually words that end up having the maximum frequency if you do a simple term or word frequency in a corpus. Typically, these can be articles, conjunctions, prepositions and so on. Some examples of stopwords are ***a***, ***an***, ***the***, ***and*** the like.

```
def remove_stopwords(text, is_lower_case=False):
    tokens = tokenizer.tokenize(text)
    tokens = [token.strip() for token in tokens]
    if is_lower_case:
        filtered_tokens = [token for token in tokens if token not in stopword_list]
    else:
        filtered_tokens = [token for token in tokens if token.lower() not in stopword_list]
    filtered_text = ' '.join(filtered_tokens)
    return filtered_text
```

```
remove_stopwords("The, and, if are stopwords, computer is not")
```

nlp_strategy_8.py hosted with ♡ by GitHub view raw

```
', , stopwords , computer not'
```

There is no universal stopword list, but we use a standard English language stopwords list from `nltk` . You can also add your own domain-specific stopwords as needed.

Bringing it all together — Building a Text Normalizer

While we can definitely keep going with more techniques like correcting spelling, grammar and so on, let's now bring everything we learnt together and chain these operations to build a text normalizer to pre-process text data.

```
def normalize_corpus(corpus, html_stripping=True, contraction_expansion=True,
                     accented_char_removal=True, text_lower_case=True,
                     text_lemmatization=True, special_char_removal=True,
                     stopword_removal=True, remove_digits=True):

    normalized_corpus = []
    # normalize each document in the corpus
    for doc in corpus:
        # strip HTML
        if html_stripping:
            doc = strip_html_tags(doc)
        # remove accented characters
        if accented_char_removal:
            doc = remove_accented_chars(doc)
        # expand contractions
        if contraction_expansion:
            doc = expand_contractions(doc)
        # lowercase the text
        if text_lower_case:
            doc = doc.lower()
        # remove extra newlines
        doc = re.sub(r'[\r|\n|\r\n]+', ' ',doc)
        # lemmatize text
        if text_lemmatization:
            doc = lemmatize_text(doc)
        # remove special characters and\or digits
        if special_char_removal:
            # insert spaces between special characters to isolate them
```

```
                special_char_pattern = re.compile(r'([{.(-)!}])')
                doc = special_char_pattern.sub(" \\1 ", doc)
                doc = remove_special_characters(doc, remove_digits=remove_digits)
            # remove extra whitespace
            doc = re.sub(' +', ' ', doc)
            # remove stopwords
            if stopword_removal:
                doc = remove_stopwords(doc, is_lower_case=text_lower_case)

            normalized_corpus.append(doc)

        return normalized_corpus
```

Let's now put this function in action! We will first combine the news headline and the news article text together to form a document for each piece of news. Then, we will pre-process them.

```
# combining headline and article text
news_df['full_text'] = news_df["news_headline"].map(str)+ '. ' + news_df["news_article"]

# pre-process text and store the same
news_df['clean_text'] = normalize_corpus(news_df['full_text'])
norm_corpus = list(news_df['clean_text'])

# show a sample news article
news_df.iloc[1][['full_text', 'clean_text']].to_dict()
```

nlp_strategy_9.py hosted with ♡ by GitHub view raw

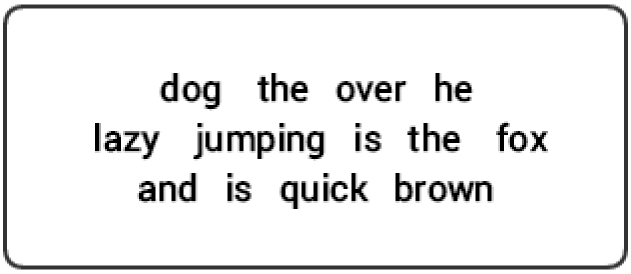
```
{'clean_text': 'us unveils world powerful supercomputer beat china
us unveil world powerful supercomputer call summit beat previous
record holder china sunway taihulight peak performance trillion
calculation per second twice fast sunway taihulight capable trillion
calculation per second summit server reportedly take size two tennis
court',

 'full_text': "US unveils world's most powerful supercomputer, beats
China. The US has unveiled the world's most powerful supercomputer
called 'Summit', beating the previous record-holder China's Sunway
TaihuLight. With a peak performance of 200,000 trillion calculations
per second, it is over twice as fast as Sunway TaihuLight, which is
capable of 93,000 trillion calculations per second. Summit has 4,608
servers, which reportedly take up the size of two tennis courts."}
```

Thus, you can see how our text pre-processor helps in pre-processing our news articles! After this, you can save this dataset to disk if needed, so that you can always load it up later for future analysis.

```
news_df.to_csv('news.csv', index=False, encoding='utf-8')
```

Understanding Language Syntax and Structure

For any language, syntax and structure usually go hand in hand, where a set of specific rules, conventions, and principles govern the way words are combined into phrases; phrases get combines into clauses; and clauses get combined into sentences. We will be talking specifically about the English language syntax and structure in this section. In English, words usually combine together to form other constituent units. These constituents include words, phrases, clauses, and sentences. Considering a sentence, ***"The brown fox is quick and he is jumping over the lazy dog"***, it is made of a bunch of words and just looking at the words by themselves don't tell us much.

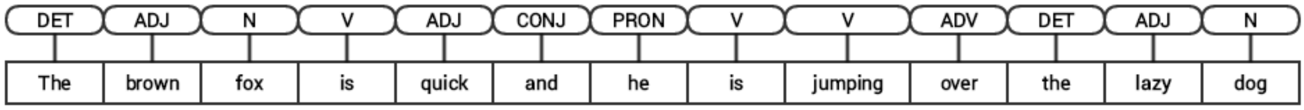


A bunch of unordered words don't convey much information

Knowledge about the structure and syntax of language is helpful in many areas like text processing, annotation, and parsing for further operations such as text classification or summarization. Typical parsing techniques for understanding text syntax are mentioned below.

- **Parts of Speech (POS) Tagging**
- **Shallow Parsing or Chunking**
- **Constituency Parsing**
- **Dependency Parsing**

We will be looking at all of these techniques in subsequent sections. Considering our previous example sentence ***"The brown fox is quick and he is jumping over the lazy dog"***, if we were to annotate it using basic POS tags, it would look like the following figure.



POS tagging for a sentence

Thus, a sentence typically follows a hierarchical structure consisting the following components,

> sentence → clauses → phrases → words

Tagging Parts of Speech

Parts of speech (POS) are specific lexical categories to which words are assigned, based on their syntactic context and role. Usually, words can fall into one of the following major categories.

- ***N(oun):*** This usually denotes words that depict some object or entity, which may be living or nonliving. Some examples would be fox , dog , book , and so on. The POS tag symbol for nouns is **N**.
- ***V(erb)***: Verbs are words that are used to describe certain actions, states, or occurrences. There are a wide variety of further subcategories, such as auxiliary, reflexive, and transitive verbs (and many more). Some typical examples of verbs would be running , jumping , read , and write . The POS tag symbol for verbs is **V**.
- ***Adj(ective)***: Adjectives are words used to describe or qualify other words, typically nouns and noun phrases. The phrase beautiful flower has the noun (N) flower which is described or qualified using the adjective (ADJ) beautiful . The POS tag symbol for adjectives is **ADJ** .
- ***Adv(erb):*** Adverbs usually act as modifiers for other words including nouns, adjectives, verbs, or other adverbs. The phrase very beautiful flower has the adverb (ADV) very , which modifies the adjective (ADJ) beautiful , indicating the degree to which the flower is beautiful. The POS tag symbol for adverbs is **ADV**.

Besides these four major categories of parts of speech , there are other categories that occur frequently in the English language. These include pronouns, prepositions, interjections, conjunctions, determiners, and many others. Furthermore, each POS tag like the *noun* (**N**) can be further subdivided into categories like *singular nouns* (**NN**), *singular proper nouns* (**NNP**), and *plural nouns* (**NNS**).

The process of classifying and labeling POS tags for words called *parts of speech tagging* or *POS tagging* . POS tags are used to annotate words and depict their POS, which is really helpful to perform specific analysis, such as narrowing down upon nouns and seeing which ones are the most prominent, word sense disambiguation, and grammar analysis. We will be leveraging both `nltk` and `spacy` which usually use the ***Penn Treebank notation*** for POS tagging.

```
# create a basic pre-processed corpus, don't lowercase to get POS context
corpus = normalize_corpus(news_df['full_text'], text_lower_case=False,
                          text_lemmatization=False, special_char_removal=False)

# demo for POS tagging for sample news headline
sentence = str(news_df.iloc[1].news_headline)
sentence_nlp = nlp(sentence)

# POS tagging with Spacy
spacy_pos_tagged = [(word, word.tag_, word.pos_) for word in sentence_nlp]
pd.DataFrame(spacy_pos_tagged, columns=['Word', 'POS tag', 'Tag type'])

# POS tagging with nltk
nltk_pos_tagged = nltk.pos_tag(sentence.split())
pd.DataFrame(nltk_pos_tagged, columns=['Word', 'POS tag'])
```

nlp_strategy_10.py hosted with ♡ by GitHub view raw

	Word	POS tag	Tag type
0	US	NNP	PROPN
1	unveils	VBZ	VERB
2	world	NN	NOUN
3	's	POS	PART
4	most	RBS	ADV
5	powerful	JJ	ADJ
6	supercomputer	NN	NOUN
7	,	,	PUNCT
8	beats	VBZ	VERB
9	China	NNP	PROPN

	Word	POS tag
0	US	NNP
1	unveils	VBZ
2	world's	VBZ
3	most	RBS
4	powerful	JJ
5	supercomputer,	JJ
6	beats	NNS
7	China	NNP

SpaCy POS tagging **NLTK POS tagging**

POS tagging a news headline

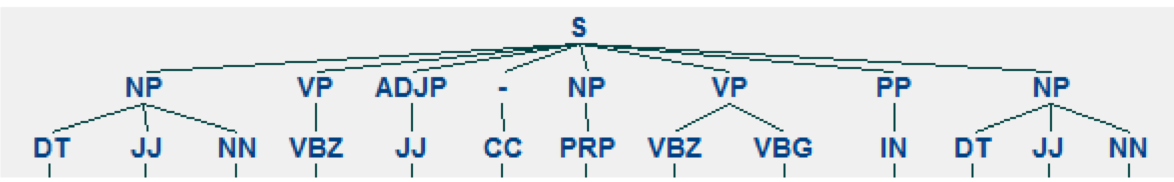
We can see that each of these libraries treat tokens in their own way and assign specific tags for them. Based on what we see, `spacy` seems to be doing slightly better than `nltk`.

Shallow Parsing or Chunking

Based on the hierarchy we depicted earlier, groups of words make up phrases. There are five major categories of phrases:

- **Noun phrase (NP):** These are phrases where a noun acts as the head word. Noun phrases act as a subject or object to a verb.
- **Verb phrase (VP):** These phrases are lexical units that have a verb acting as the head word. Usually, there are two forms of verb phrases. One form has the verb components as well as other entities such as nouns, adjectives, or adverbs as parts of the object.
- **Adjective phrase (ADJP):** These are phrases with an adjective as the head word. Their main role is to describe or qualify nouns and pronouns in a sentence, and they will be either placed before or after the noun or pronoun.
- **Adverb phrase (ADVP):** These phrases act like adverbs since the adverb acts as the head word in the phrase. Adverb phrases are used as modifiers for nouns, verbs, or adverbs themselves by providing further details that describe or qualify them.
- **Prepositional phrase (PP):** These phrases usually contain a preposition as the head word and other lexical components like nouns, pronouns, and so on. These act like an adjective or adverb describing other words or phrases.

Shallow parsing, also known as light parsing or chunking , is a popular natural language processing technique of analyzing the structure of a sentence to break it down into its smallest constituents (which are tokens such as words) and group them together into higher-level phrases. This includes POS tags as well as phrases from a sentence.



An example of shallow parsing depicting higher level phrase annotations

We will leverage the **conll2000** corpus for training our shallow parser model. This corpus is available in **nltk** with chunk annotations and we will be using around 10K records for training our model. A sample annotated sentence is depicted as follows.

```python
from nltk.corpus import conll2000

data = conll2000.chunked_sents()
train_data = data[:10900]
test_data = data[10900:]

print(len(train_data), len(test_data))
print(train_data[1])
```

nlp_strategy_11.py hosted with ♡ by GitHub view raw

```
10900 48
(S
  Chancellor/NNP
  (PP of/IN)
  (NP the/DT Exchequer/NNP)
  (NP Nigel/NNP Lawson/NNP)
  (NP 's/POS restated/VBN commitment/NN)
  (PP to/TO)
  (NP a/DT firm/NN monetary/JJ policy/NN)
  (VP has/VBZ helped/VBN to/TO prevent/VB)
  (NP a/DT freefall/NN)
  (PP in/IN)
  (NP sterling/NN)
  (PP over/IN)
  (NP the/DT past/JJ week/NN)
  ./.)
```

From the preceding output, you can see that our data points are sentences that are already annotated with phrases and POS tags metadata that will be useful in training our shallow parser model. We will leverage two chunking utility functions, tree2conlltags , to get triples of word, tag, and chunk tags for each token, and conlltags2tree to generate a parse tree from these token triples. We will be using these functions to train our parser. A sample is depicted below.

```python
from nltk.chunk.util import tree2conlltags, conlltags2tree
```

```
wtc = tree2conlltags(train_data[1])
wtc
```

nlp_strategy_12.py hosted with ♡ by GitHub view raw

```
[('Chancellor', 'NNP', 'O'),
 ('of', 'IN', 'B-PP'),
 ('the', 'DT', 'B-NP'),
 ('Exchequer', 'NNP', 'I-NP'),
 ('Nigel', 'NNP', 'B-NP'),
 ('Lawson', 'NNP', 'I-NP'),
 ("'s", 'POS', 'B-NP'),
 ('restated', 'VBN', 'I-NP'),
 ('commitment', 'NN', 'I-NP'),
 ('to', 'TO', 'B-PP'),
 ('a', 'DT', 'B-NP'),
 ('firm', 'NN', 'I-NP'),
 ('monetary', 'JJ', 'I-NP'),
 ('policy', 'NN', 'I-NP'),
 ('has', 'VBZ', 'B-VP'),
 ('helped', 'VBN', 'I-VP'),
 ('to', 'TO', 'I-VP'),
 ('prevent', 'VB', 'I-VP'),
 ('a', 'DT', 'B-NP'),
 ('freefall', 'NN', 'I-NP'),
 ('in', 'IN', 'B-PP'),
 ('sterling', 'NN', 'B-NP'),
 ('over', 'IN', 'B-PP'),
 ('the', 'DT', 'B-NP'),
 ('past', 'JJ', 'I-NP'),
 ('week', 'NN', 'I-NP'),
 ('.', '.', 'O')]
```

The chunk tags use the IOB format. This notation represents Inside, Outside, and Beginning. The B- prefix before a tag indicates it is the beginning of a chunk, and I-prefix indicates that it is inside a chunk. The O tag indicates that the token does not belong to any chunk. The B- tag is always used when there are subsequent tags of the same type following it without the presence of O tags between them.

We will now define a function **conll_tag_ chunks()** to extract POS and chunk tags from sentences with chunked annotations and a function called **combined_taggers()** to train multiple taggers with backoff taggers (e.g. unigram and bigram taggers)

```
def conll_tag_chunks(chunk_sents):
    tagged_sents = [tree2conlltags(tree) for tree in chunk_sents]
    return [[(t, c) for (w, t, c) in sent] for sent in tagged_sents]

```

```

def combined_tagger(train_data, taggers, backoff=None):
    for tagger in taggers:
        backoff = tagger(train_data, backoff=backoff)
    return backoff
```

nlp_strategy_13.py hosted with ♡ by GitHub view raw

We will now define a class `NGramTagChunker` that will take in tagged sentences as training input, get their ***(word, POS tag, Chunk tag)* WTC triples**, and train a `BigramTagger` with a `UnigramTagger` as the backoff tagger. We will also define a `parse()` function to perform shallow parsing on new sentences

> *The `UnigramTagger` , `BigramTagger` , and `TrigramTagger` are classes that inherit from the base class `NGramTagger` , which itself inherits from the `ContextTagger` class , which inherits from the `SequentialBackoffTagger` class .*

We will use this class to train on the `conll2000` chunked `train_data` and evaluate the model performance on the `test_data`

```
from nltk.tag import UnigramTagger, BigramTagger
from nltk.chunk import ChunkParserI

# define the chunker class
class NGramTagChunker(ChunkParserI):

  def __init__(self, train_sentences,
               tagger_classes=[UnigramTagger, BigramTagger]):
    train_sent_tags = conll_tag_chunks(train_sentences)
    self.chunk_tagger = combined_tagger(train_sent_tags, tagger_classes)

  def parse(self, tagged_sentence):
    if not tagged_sentence:
        return None
    pos_tags = [tag for word, tag in tagged_sentence]
    chunk_pos_tags = self.chunk_tagger.tag(pos_tags)
    chunk_tags = [chunk_tag for (pos_tag, chunk_tag) in chunk_pos_tags]
    wpc_tags = [(word, pos_tag, chunk_tag) for ((word, pos_tag), chunk_tag)
                     in zip(tagged_sentence, chunk_tags)]
    return conlltags2tree(wpc_tags)

# train chunker model
ntc = NGramTagChunker(train_data)

# evaluate chunker model performance
```

```
print(ntc.evaluate(test_data))
```

```
ChunkParse score:
    IOB Accuracy:  90.0%%
    Precision:     82.1%%
    Recall:        86.3%%
    F-Measure:     84.1%%
```

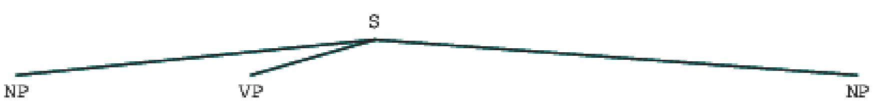
Our chunking model gets an accuracy of around 90% which is quite good! Let’s now leverage this model to shallow parse and chunk our sample news article headline which we used earlier, ***“US unveils world’s most powerful supercomputer, beats China”.***

```
chunk_tree = ntc.parse(nltk_pos_tagged)
print(chunk_tree)

Output:
-------
(S
  (NP US/NNP)
  (VP unveils/VBZ world's/VBZ)
  (NP most/RBS powerful/JJ supercomputer,/JJ beats/NNS China/NNP))
```

Thus you can see it has identified two noun phrases (NP) and one verb phrase (VP) in the news article. Each word’s POS tags are also visible. We can also visualize this in the form of a tree as follows. You might need to install **ghostscript** in case `nltk` throws an error.

```
from IPython.display import display

## download and install ghostscript from https://www.ghostscript.com/download/gsdnld.html

# often need to add to the path manually (for windows)
os.environ['PATH'] = os.environ['PATH']+";C:\\Program Files\\gs\\gs9.09\\bin\\"

display(chunk_tree)
```

nlp_strategy_15.py hosted with ♡ by GitHub view raw



Shallow parsed news headline

The preceding output gives a good sense of structure after shallow parsing the news headline.

Constituency Parsing

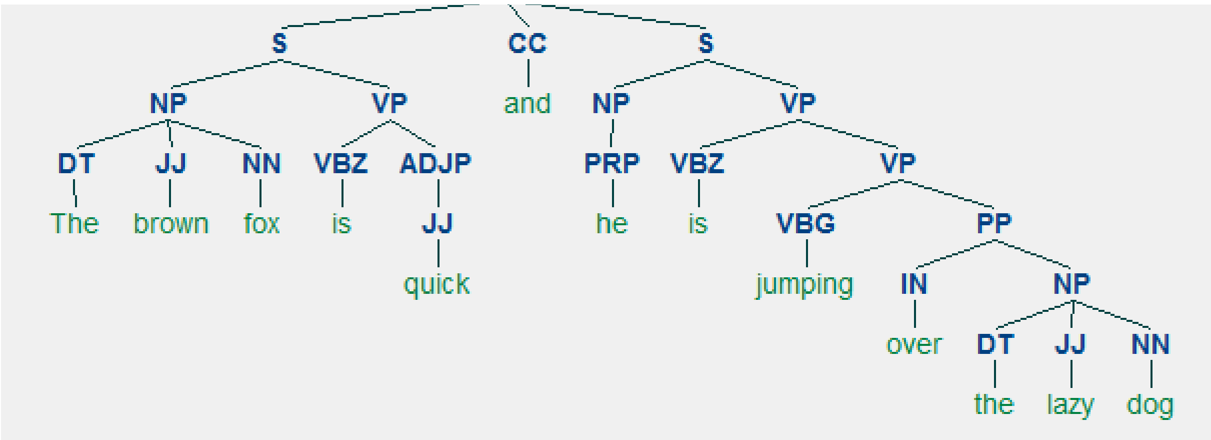
Constituent-based grammars are used to analyze and determine the constituents of a sentence. These grammars can be used to model or represent the internal structure of sentences in terms of a hierarchically ordered structure of their constituents. Each and every word usually belongs to a specific lexical category in the case and forms the head word of different phrases. These phrases are formed based on rules called *phrase structure rules*.

Phrase structure rules form the core of constituency grammars, because they talk about syntax and rules that govern the hierarchy and ordering of the various constituents in the sentences. These rules cater to two things primarily.

- They determine what words are used to construct the phrases or constituents.
- They determine how we need to order these constituents together.

The generic representation of a phrase structure rule is ***S → AB*** , which depicts that the structure ***S*** consists of constituents ***A*** and ***B*** , and the ordering is ***A*** followed by ***B*** . While there are several rules (*refer to Chapter 1, Page 19: Text Analytics with Python, if you want to dive deeper*), the most important rule describes how to divide a sentence or a clause. The phrase structure rule denotes a binary division for a sentence or a clause as ***S → NP VP*** where ***S*** is the sentence or clause, and it is divided into the subject, denoted by the noun phrase (***NP***) and the predicate, denoted by the verb phrase (***VP***).

A constituency parser can be built based on such grammars/rules, which are usually collectively available as context-free grammar (CFG) or phrase-structured grammar. The parser will process input sentences according to these rules, and help in building a parse tree.



An example of constituency parsing showing a nested hierarchical structure

We will be using `nltk` and the `StanfordParser` here to generate parse trees.

> ***Prerequisites:*** *Download the official Stanford Parser from* ***here****, which seems to work quite well. You can try out a later version by going to* ***this website*** *and checking the* ***Release History*** *section. After downloading, unzip it to a known location in your filesystem. Once done, you are now ready to use the parser from* `nltk` *, which we will be exploring soon.*

The Stanford parser generally uses a ***PCFG (probabilistic context-free grammar) parser***. A PCFG is a context-free grammar that associates a probability with each of its production rules. The probability of a parse tree generated from a PCFG is simply the production of the individual probabilities of the productions used to generate it.

```
# set java path
import os
java_path = r'C:\Program Files\Java\jdk1.8.0_102\bin\java.exe'
os.environ['JAVAHOME'] = java_path

from nltk.parse.stanford import StanfordParser

scp = StanfordParser(path_to_jar='E:/stanford/stanford-parser-full-2015-04-20/stanford-parser.j
                     path_to_models_jar='E:/stanford/stanford-parser-full-2015-04-20/stanford-p

result = list(scp.raw_parse(sentence))
print(result[0])
```

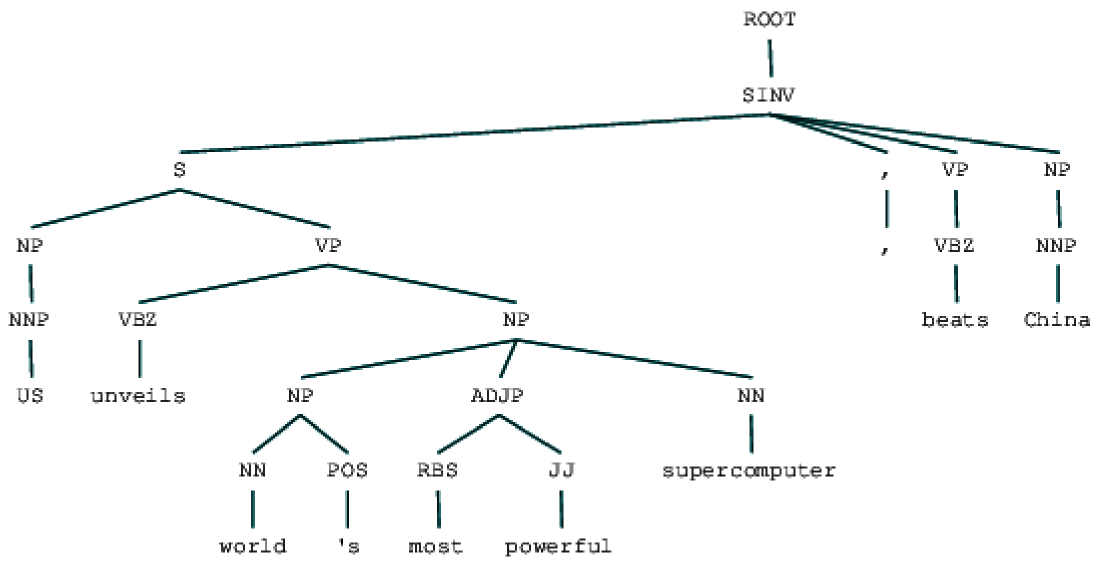
nlp_strategy_16.py hosted with ♡ by GitHub view raw

```
(ROOT
  (SINV
```

```
(S
  (NP (NNP US))
  (VP
    (VBZ unveils)
    (NP
      (NP (NN world) (POS 's))
      (ADJP (RBS most) (JJ powerful))
      (NN supercomputer))))
(, ,)
(VP (VBZ beats))
(NP (NNP China))))
```

We can see the constituency parse tree for our news headline. Let's visualize it to understand the structure better.

```
from IPython.display import display
display(result[0])
```



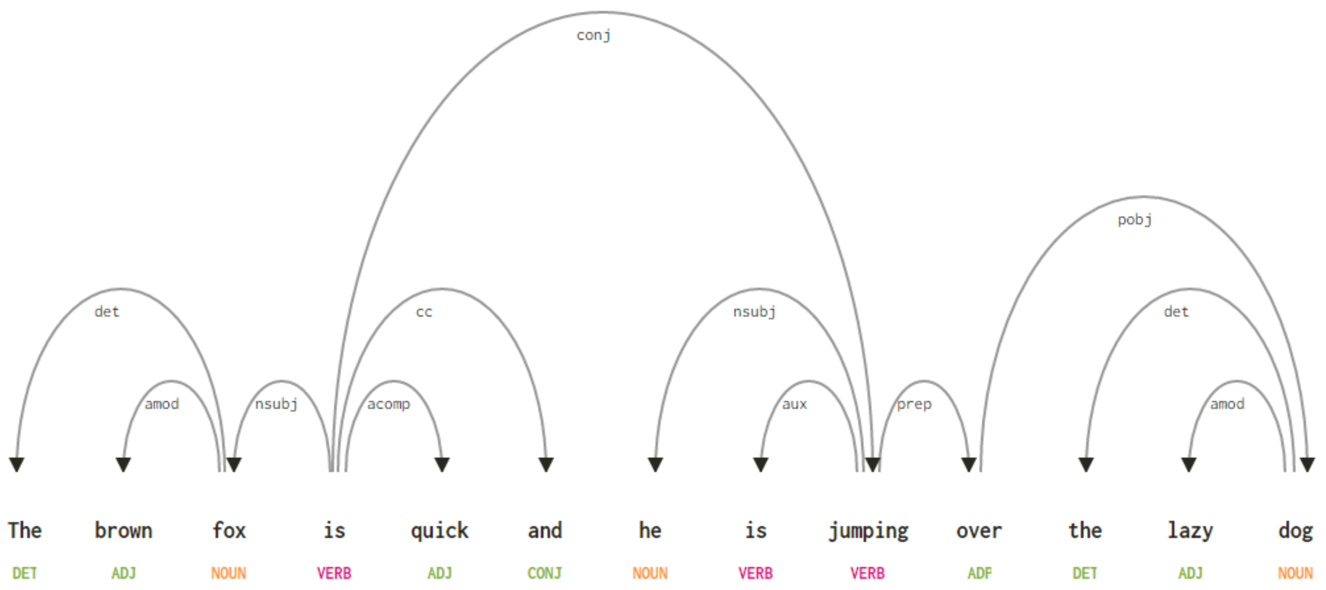
Constituency parsed news headline

We can see the nested hierarchical structure of the constituents in the preceding output as compared to the flat structure in shallow parsing. In case you are wondering what ***SINV*** means, it represents *an Inverted declarative sentence*, i.e. one in which the subject follows the tensed verb or modal. Refer to the ***Penn Treebank reference*** as needed to lookup other tags.

Dependency Parsing

In dependency parsing, we try to use dependency-based grammars to analyze and infer *both structure and semantic dependencies* and relationships between tokens in a sentence. The basic principle behind a dependency grammar is that in any sentence in the language, all words except one, have some relationship or dependency on other words in the sentence. The word that has no dependency is called the root of the sentence. The verb is taken as the root of the sentence in most cases. All the other words are directly or indirectly linked to the root verb using links , which are the dependencies.

Considering our sentence ***"The brown fox is quick and he is jumping over the lazy dog"*** , if we wanted to draw the dependency syntax tree for this, we would have the structure



A dependency parse tree for a sentence

These dependency relationships each have their own meaning and are a part of a list of universal dependency types. This is discussed in an original paper, *Universal Stanford Dependencies: A Cross-Linguistic Typology by de Marneffe et al, 2014*). You can check out the exhaustive list of dependency types and their meanings ***here***.

If we observe some of these dependencies, it is not too hard to understand them.

- The dependency tag ***det*** is pretty intuitive — it denotes the determiner relationship between a nominal head and the determiner. Usually, the word with POS tag **DET** will also have the ***det*** dependency tag relation. Examples include **fox → the** and **dog → the** .

- The dependency tag ***amod*** stands for adjectival modifier and stands for any adjective that modifies the meaning of a noun. Examples include **fox → brown** and **dog → lazy** .
- The dependency tag ***nsubj*** stands for an entity that acts as a subject or agent in a clause. Examples include **is → fox** and **jumping → he** .
- The dependencies ***cc*** and ***conj*** have more to do with linkages related to words connected by coordinating conjunctions . Examples include **is → and** and **is → jumping** .
- The dependency tag ***aux*** indicates the auxiliary or secondary verb in the clause. Example: **jumping → is** .
- The dependency tag ***acomp*** stands for adjective complement and acts as the complement or object to a verb in the sentence. Example: **is → quick**
- The dependency tag ***prep*** denotes a prepositional modifier, which usually modifies the meaning of a noun, verb, adjective, or preposition. Usually, this representation is used for prepositions having a noun or noun phrase complement. Example: **jumping → over** .
- The dependency tag ***pobj*** is used to denote the object of a preposition . This is usually the head of a noun phrase following a preposition in the sentence. Example: **over → dog** .

Spacy had two types of English dependency parsers based on what language models you use, you can find more details ***here***. Based on language models, you can use the ***Universal Dependencies Scheme*** or the ***CLEAR Style Dependency Scheme*** also available in **NLP4J** now. We will now leverage **spacy** and print out the dependencies for each token in our news headline.

```
dependency_pattern = '{left}<---{word}[{w_type}]--->{right}\n--------'
for token in sentence_nlp:
    print(dependency_pattern.format(word=token.orth_,
                                  w_type=token.dep_,
                                  left=[t.orth_
                                            for t
                                            in token.lefts],
                                  right=[t.orth_
                                             for t
                                             in token.rights]))
```

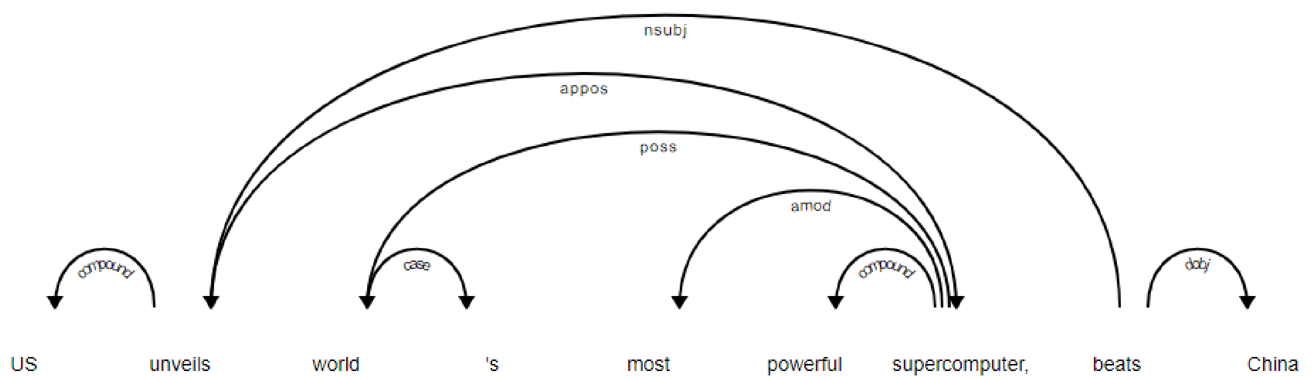
nlp_strategy_17.py hosted with ♡ by GitHub view raw

```
[]<---US[compound]--->[]
--------
['US']<---unveils[nsubj]--->['supercomputer', ',']
--------
[]<---world[poss]--->["'s"]
--------
[]<---'s[case]--->[]
--------
[]<---most[amod]--->[]
--------
[]<---powerful[compound]--->[]
--------
['world', 'most', 'powerful']<---supercomputer[appos]--->[]
--------
[]<---,[punct]--->[]
--------
['unveils']<---beats[ROOT]--->['China']
--------
[]<---China[dobj]--->[]
--------
```

It is evident that the verb beats is the ROOT since it doesn't have any other dependencies as compared to the other tokens. For knowing more about each annotation you can always refer to the ***CLEAR dependency scheme***. We can also visualize the above dependencies in a better way.

```python
from spacy import displacy

displacy.render(sentence_nlp, jupyter=True,
                options={'distance': 110,
                         'arrow_stroke': 2,
                         'arrow_width': 8})
```

nlp_strategy_18.py hosted with ♡ by GitHub view raw



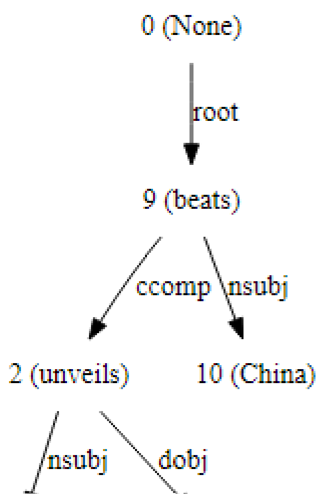
PROPN NOUN NOUN PART ADJ NOUN NOUN NOUN PROPN

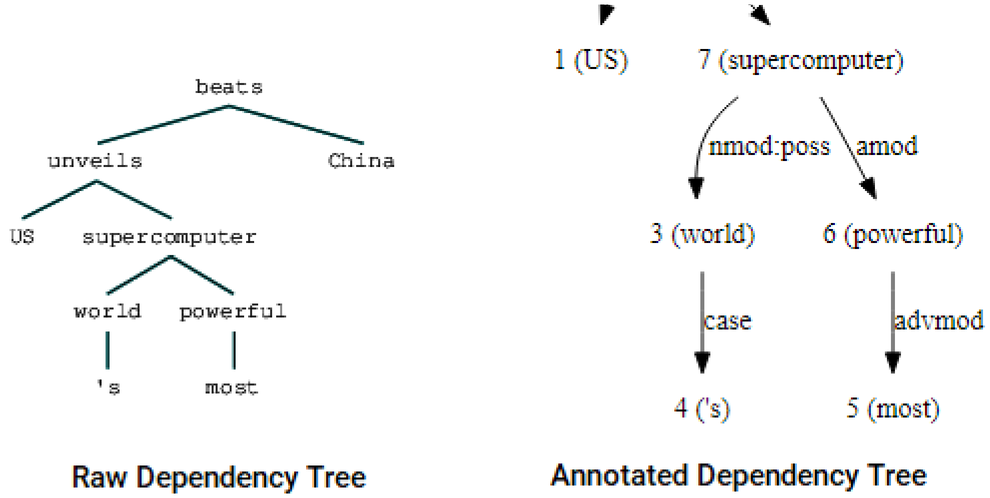
News Headline dependency tree from SpaCy

You can also leverage **nltk** and the **StanfordDependencyParser** to visualize and build out the dependency tree. We showcase the dependency tree both in its raw and annotated form as follows.

```
from nltk.parse.stanford import StanfordDependencyParser
sdp = StanfordDependencyParser(path_to_jar='E:/stanford/stanford-parser-full-2015-04-20/stanfor
                               path_to_models_jar='E:/stanford/stanford-parser-full-2015-04-20/

result = list(sdp.raw_parse(sentence))

# print the dependency tree
dep_tree = [parse.tree() for parse in result][0]
print(dep_tree)

# visualize raw dependency tree
from IPython.display import display
display(dep_tree)

# visualize annotated dependency tree (needs graphviz)
from graphviz import Source
dep_tree_dot_repr = [parse for parse in result][0].to_dot()
source = Source(dep_tree_dot_repr, filename="dep_tree", format="png")
source
```

```
(beats (unveils US (supercomputer (world 's) (powerful most)))
 China)
```





Dependency Tree visualizations using nltk's Stanford dependency parser

You can notice the similarities with the tree we had obtained earlier. The annotations help with understanding the type of dependency among the different tokens.

Named Entity Recognition

In any text document, there are particular terms that represent specific entities that are more informative and have a unique context. These entities are known as named entities , which more specifically refer to terms that represent real-world objects like people, places, organizations, and so on, which are often denoted by proper names. A naive approach could be to find these by looking at the noun phrases in text documents. Named entity recognition (NER) , also known as entity chunking/extraction , is a popular technique used in information extraction to identify and segment the named entities and classify or categorize them under various predefined classes.

SpaCy has some excellent capabilities for named entity recognition. Let's try and use it on one of our sample news articles.

```python
sentence = str(news_df.iloc[1].full_text)
sentence_nlp = nlp(sentence)

# print named entities in article
print([(word, word.ent_type_) for word in sentence_nlp if word.ent_type_])

# visualize named entities
displacy.render(sentence_nlp, style='ent', jupyter=True)
```

nlp_strategy_20.py hosted with ♡ by GitHub view raw

```
[(US, 'GPE'), (China, 'GPE'), (US, 'GPE'), (China, 'GPE'),
 (Sunway, 'ORG'), (TaihuLight, 'ORG'), (200,000, 'CARDINAL'),
 (second, 'ORDINAL'), (Sunway, 'ORG'), (TaihuLight, 'ORG'),
 (93,000, 'CARDINAL'), (4,608, 'CARDINAL'), (two, 'CARDINAL')]
```

US GPE unveils world's most powerful supercomputer, beats China GPE . The US GPE has unveiled the world's most powerful supercomputer called 'Summit', beating the previous record-holder China GPE 's Sunway TaihuLight ORG . With a peak performance of 200,000 CARDINAL trillion calculations per second ORDINAL , it is over twice as fast as Sunway TaihuLight ORG , which is capable of 93,000 CARDINAL trillion calculations per second. Summit has 4,608 CARDINAL servers, which reportedly take up the size of two CARDINAL tennis courts.

Visualizing named entities in a news article with spaCy

We can clearly see that the major named entities have been identified by `spacy` . To understand more in detail about what each named entity means, you can refer to ***the documentation*** or check out the following table for convenience.

TYPE	DESCRIPTION
PERSON	People, including fictional.
NORP	Nationalities or religious or political groups.
FAC	Buildings, airports, highways, bridges, etc.
ORG	Companies, agencies, institutions, etc.
GPE	Countries, cities, states.
LOC	Non-GPE locations, mountain ranges, bodies of water.
PRODUCT	Objects, vehicles, foods, etc. (Not services.)
EVENT	Named hurricanes, battles, wars, sports events, etc.
WORK_OF_ART	Titles of books, songs, etc.
LAW	Named documents made into laws.
LANGUAGE	Any named language.
DATE	Absolute or relative dates or periods.
TIME	Times smaller than a day.
PERCENT	Percentage, including "%".
MONEY	Monetary values, including unit.

Named entity types

Let's now find out the most frequent named entities in our news corpus! For this, we will build out a data frame of all the named entities and their types using the following code.

```python
named_entities = []
for sentence in corpus:
    temp_entity_name = ''
    temp_named_entity = None
    sentence = nlp(sentence)
    for word in sentence:
        term = word.text
        tag = word.ent_type_
        if tag:
            temp_entity_name = ' '.join([temp_entity_name, term]).strip()
            temp_named_entity = (temp_entity_name, tag)
        else:
            if temp_named_entity:
                named_entities.append(temp_named_entity)
                temp_entity_name = ''
                temp_named_entity = None

entity_frame = pd.DataFrame(named_entities,
                            columns=['Entity Name', 'Entity Type'])
```


We can now transform and aggregate this data frame to find the top occuring entities and types.

```python
# get the top named entities
top_entities = (entity_frame.groupby(by=['Entity Name', 'Entity Type'])
                           .size()
                           .sort_values(ascending=False)
                           .reset_index().rename(columns={0 : 'Frequency'}))
top_entities.T.iloc[:,:15]

```


	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Entity Name	US	India	Indian	Singapore	Kim Jong - un	one	Apple	two	first	Messenger	China	Canadian	Facebook	Yahoo	Trump
Entity Type	GPE	GPE	NORP	GPE	PERSON	CARDINAL	ORG	CARDINAL	ORDINAL	PRODUCT	GPE	NORP	ORG	ORG	ORG
Frequency	30	12	12	11	11	10	9	8	8	7	7	6	6	6	6

Top named entities and types in our news corpus

Do you notice anything interesting? ***(Hint:** Maybe the supposed summit between Trump and Kim Jong!)*. We also see that it has correctly identified 'Messenger' as a product (from Facebook).

We can also group by the entity types to get a sense of what types of entites occur most in our news corpus.

```
# get the top named entity types
top_entities = (entity_frame.groupby(by=['Entity Type'])
                           .size()
                           .sort_values(ascending=False)
                           .reset_index().rename(columns={0 : 'Frequency'}))
top_entities.T.iloc[:,:15]
```

nlp_strategy_23.py hosted with ♡ by GitHub view raw

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Entity Type	PERSON	GPE	ORG	DATE	CARDINAL	NORP	EVENT	ORDINAL	PRODUCT	MONEY	TIME	LOC	FAC	QUANTITY	WORK_OF_ART
Frequency	165	126	105	67	66	58	23	21	15	11	7	5	5	3	1

Top named entity types in our news corpus

We can see that people, places and organizations are the most mentioned entities though interestingly we also have many other entities.

Another nice NER tagger is the **StanfordNERTagger** available from the **nltk** interface. For this, you need to have Java installed and then download the ***Stanford NER resources***. Unzip them to a location of your choice (I used `E:/stanford` in my system).

Stanford's Named Entity Recognizer is based on an implementation of linear chain Conditional Random Field (CRF) sequence models. Unfortunately this model is only trained on instances of ***PERSON***, ***ORGANIZATION*** and ***LOCATION*** types. Following code can be used as a standard workflow which helps us extract the named entities using this tagger and show the top named entities and their types (extraction differs slightly from **spacy**).

```
from nltk.tag import StanfordNERTagger
import os

# set java path
java_path = r'C:\Program Files\Java\jdk1.8.0_102\bin\java.exe'
os.environ['JAVAHOME'] = java_path

# initialize NER tagger
sn = StanfordNERTagger('E:/stanford/stanford-ner-2014-08-27/classifiers/english.all.3class.dist
                       path_to_jar='E:/stanford/stanford-ner-2014-08-27/stanford-ner.jar')

# tag named entities
```

```
# tag named entities
ner_tagged_sentences = [sn.tag(sent.split()) for sent in corpus]

# extract all named entities
named_entities = []
for sentence in ner_tagged_sentences:
    temp_entity_name = ''
    temp_named_entity = None
    for term, tag in sentence:
        if tag != 'O':
            temp_entity_name = ' '.join([temp_entity_name, term]).strip()
            temp_named_entity = (temp_entity_name, tag)
        else:
            if temp_named_entity:
                named_entities.append(temp_named_entity)
                temp_entity_name = ''
                temp_named_entity = None

#named_entities = list(set(named_entities))
entity_frame = pd.DataFrame(named_entities,
                            columns=['Entity Name', 'Entity Type'])


# view top entities and types
top_entities = (entity_frame.groupby(by=['Entity Name', 'Entity Type'])
                           .size()
                           .sort_values(ascending=False)
                           .reset_index().rename(columns={0 : 'Frequency'}))
top_entities.head(15)


# view top entity types
top_entities = (entity_frame.groupby(by=['Entity Type'])
                           .size()
                           .sort_values(ascending=False)
                           .reset_index().rename(columns={0 : 'Frequency'}))
top_entities.head()
```

	Entity Name	Entity Type	Frequency
0	US	LOCATION	31
1	Donald Trump	PERSON	13
2	India	LOCATION	13
3	Trump	PERSON	12
4	Singapore	LOCATION	11
5	Kim Jong-un	PERSON	9

6	Facebook	ORGANIZATION	9
7	Yahoo	ORGANIZATION	6
8	Kim	PERSON	6
9	Nadal	PERSON	6
10	Google	ORGANIZATION	5
11	Trudeau	PERSON	5
12	China	LOCATION	5
13	North Korean	LOCATION	4
14	Chhetri	PERSON	4

Named entities and types

	Entity Type	Frequency
0	PERSON	186
1	LOCATION	125
2	ORGANIZATION	54

Named entities

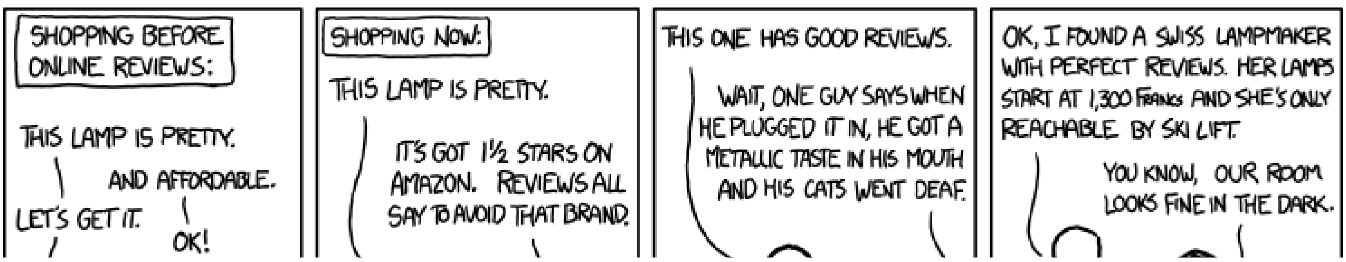
Top named entities and types from Stanford NER on our news corpus

We notice quite similar results though restricted to only three types of named entities. Interestingly, we see a number of mentioned of several people in various sports.

Emotion and Sentiment Analysis

Sentiment analysis is perhaps one of the most popular applications of NLP, with a vast number of tutorials, courses, and applications that focus on analyzing sentiments of diverse datasets ranging from corporate surveys to movie reviews. The key aspect of sentiment analysis is to analyze a body of text for understanding the opinion expressed by it. Typically, we quantify this sentiment with a positive or negative value, called ***polarity***. The ***overall sentiment*** is often inferred as *positive*, *neutral* or *negative* from the sign of the polarity score.

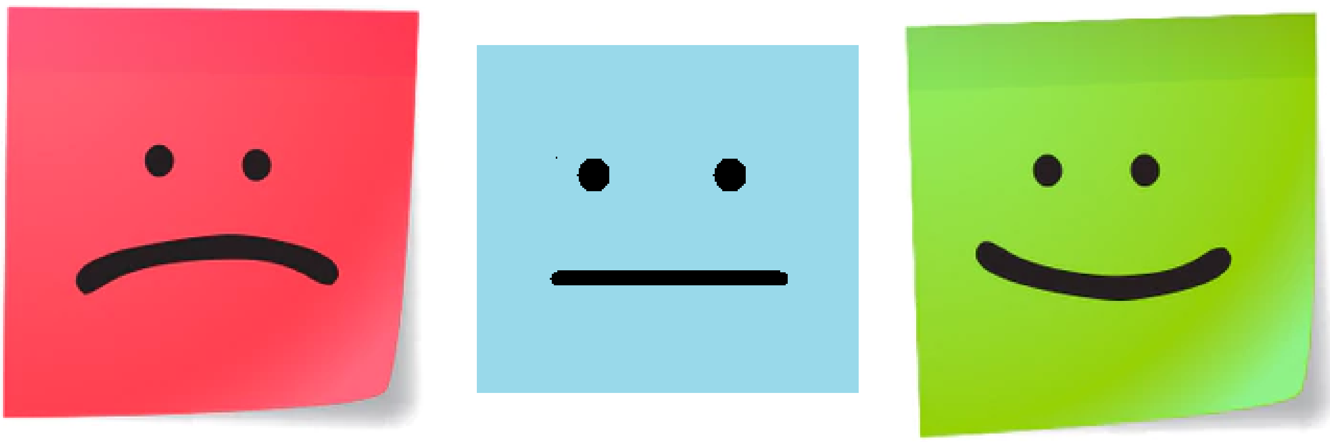
Usually, sentiment analysis works best on text that has a subjective context than on text with only an objective context. Objective text usually depicts some normal statements or facts without expressing any emotion, feelings, or mood. Subjective text contains text that is usually expressed by a human having typical moods, emotions, and feelings. Sentiment analysis is widely used, especially as a part of social media analysis for any domain, be it a business, a recent movie, or a product launch, to understand its reception by the people and what they think of it based on their opinions or, you guessed it, sentiment!



Typically, sentiment analysis for text data can be computed on several levels, including on an individual sentence level, paragraph level, or the entire document as a whole. Often, sentiment is computed on the document as a whole or some aggregations are done after computing the sentiment for individual sentences. There are two major approaches to sentiment analysis.

- Supervised machine learning or deep learning approaches
- Unsupervised lexicon-based approaches

For the first approach we typically need pre-labeled data. Hence, we will be focusing on the second approach. For a comprehensive coverage of sentiment analysis, refer to *Chapter 7: Analyzing Movie Reviews Sentiment, Practical Machine Learning with Python, Springer\Apress, 2018*. In this scenario, we do not have the convenience of a well-labeled training dataset. Hence, we will need to use unsupervised techniques for predicting the sentiment by using knowledgebases, ontologies, databases, and lexicons that have detailed information, specially curated and prepared just for sentiment analysis. A lexicon is a dictionary, vocabulary, or a book of words. In our case, lexicons are special dictionaries or vocabularies that have been created for analyzing sentiments. Most of these lexicons have a list of positive and negative polar words with some score associated with them, and using various techniques like the position of words, surrounding words, context, parts of speech, phrases, and so on, scores are assigned to the text documents for which we want to compute the sentiment. After aggregating these scores, we get the final sentiment.



Various popular lexicons are used for sentiment analysis, including the following.

- **AFINN lexicon**
- **Bing Liu's lexicon**
- **MPQA subjectivity lexicon**
- **SentiWordNet**
- **VADER lexicon**
- **TextBlob lexicon**

This is not an exhaustive list of lexicons that can be leveraged for sentiment analysis, and there are several other lexicons which can be easily obtained from the Internet. Feel free to check out each of these links and explore them. We will be covering two techniques in this section.

Sentiment Analysis with AFINN Lexicon

The ***AFINN lexicon*** is perhaps one of the simplest and most popular lexicons that can be used extensively for sentiment analysis. Developed and curated by Finn Årup Nielsen, you can find more details on this lexicon in the paper, *"A new ANEW: evaluation of a word list for sentiment analysis in microblogs", proceedings of the ESWC 2011 Workshop.* The current version of the lexicon is ***AFINN-en-165. txt*** and it contains over 3,300+ words with a polarity score associated with each word. You can find this lexicon at the author's *official GitHub repository* along with previous versions of it, including ***AFINN-111***. The author has also created a nice wrapper library on top of this in Python called `afinn`, which we will be using for our analysis.

The following code computes sentiment for all our news articles and shows summary statistics of general sentiment per news category.

```
# initialize afinn sentiment analyzer
from afinn import Afinn
af = Afinn()

# compute sentiment scores (polarity) and labels
sentiment_scores = [af.score(article) for article in corpus]
sentiment_category = ['positive' if score > 0
                          else 'negative' if score < 0
                              else 'neutral'
```

```
                          for score in sentiment_scores]


# sentiment statistics per news category
df = pd.DataFrame([list(news_df['news_category']), sentiment_scores, sentiment_category]).T
df.columns = ['news_category', 'sentiment_score', 'sentiment_category']
df['sentiment_score'] = df.sentiment_score.astype('float')
df.groupby(by=['news_category']).describe()
```

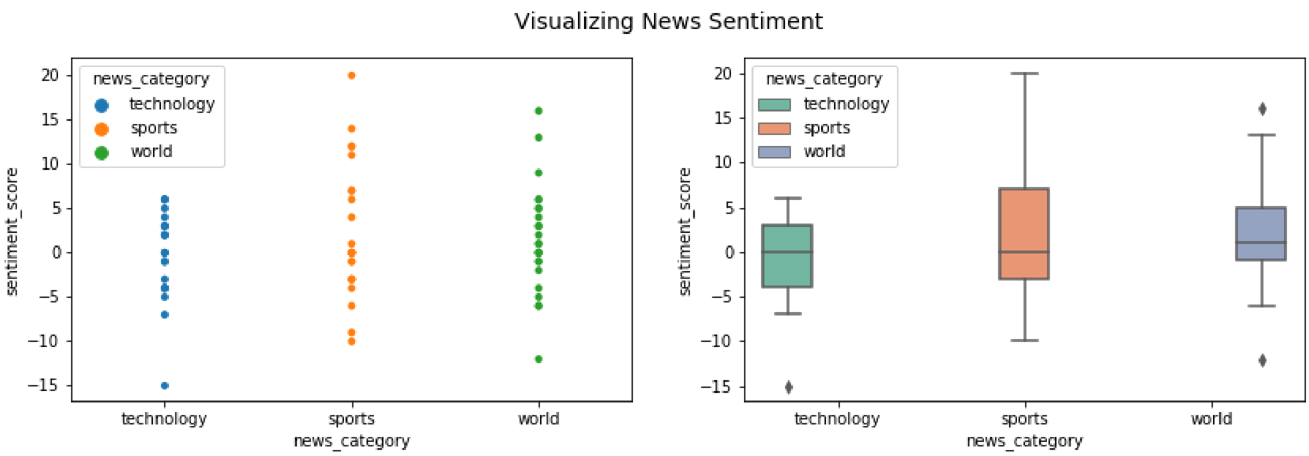
nlp_strategy_25.py hosted with ♡ by GitHub view raw

	sentiment_score							
	count	mean	std	min	25%	50%	75%	max
news_category								
sports	25.0	2.16	7.363649	-10.0	-3.0	0.0	7.0	20.0
technology	24.0	-0.25	4.936554	-15.0	-4.0	0.0	3.0	6.0
world	25.0	1.48	6.042351	-12.0	-1.0	1.0	5.0	16.0

We can get a good idea of general sentiment statistics across different news categories. Looks like the average sentiment is very positive in ***sports*** and reasonably negative in ***technology***! Let's look at some visualizations now.

```
f, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 4))
sp = sns.stripplot(x='news_category', y="sentiment_score",
                   hue='news_category', data=df, ax=ax1)
bp = sns.boxplot(x='news_category', y="sentiment_score",
                 hue='news_category', data=df, palette="Set2", ax=ax2)
t = f.suptitle('Visualizing News Sentiment', fontsize=14)
```

nlp_strategy_26.py hosted with ♡ by GitHub view raw

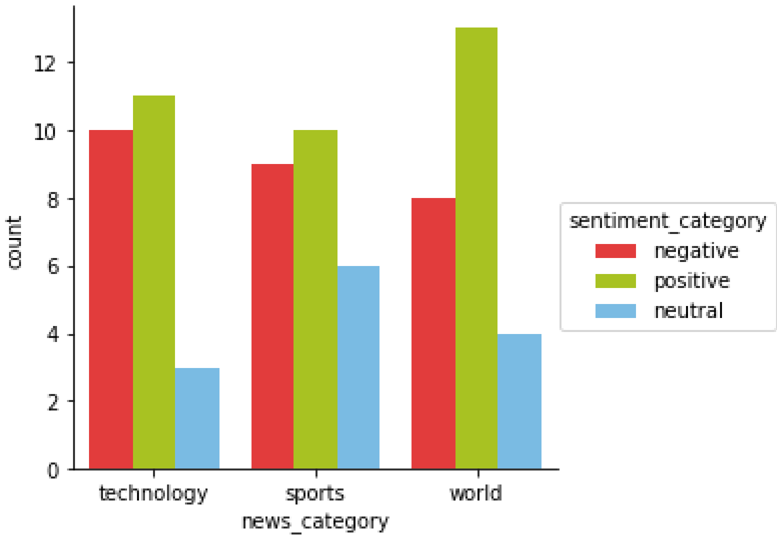


Visualizing news sentiment polarity

We can see that the spread of sentiment polarity is much higher in ***sports*** and ***world*** as compared to ***technology*** where a lot of the articles seem to be having a negative polarity. We can also visualize the frequency of sentiment labels.

```
fc = sns.factorplot(x="news_category", hue="sentiment_category",
                    data=df, kind="count",
                    palette={"negative": "#FE2020",
                             "positive": "#BADD07",
                             "neutral": "#68BFF5"})
```

nlp_strategy_27.py hosted with ♡ by GitHub view raw



Visualizing sentiment categories per news category

No surprises here that ***technology*** has the most number of negative articles and ***world*** the most number of positive articles. ***Sports*** might have more neutral articles due to the presence of articles which are more objective in nature (talking about sporting events without the presence of any emotion or feelings). Let's dive deeper into the most positive and negative sentiment news articles for ***technology*** news.

```
pos_idx = df[(df.news_category=='technology') & (df.sentiment_score == 6)].index[0]
neg_idx = df[(df.news_category=='technology') & (df.sentiment_score == -15)].index[0]

print('Most Negative Tech News Article:', news_df.iloc[neg_idx][['news_article']][0])
print()
print('Most Positive Tech News Article:', news_df.iloc[pos_idx][['news_article']][0])
```

nlp_strategy_28.py hosted with ♡ by GitHub view raw

```
Most Negative Tech News Article: The maker of world's cheapest smartphone 'Freedom 251' priced at ₹251, Ringing Bells' founder M
ohit Goel was arrested along with two more people by the Delhi Police on Sunday. The three were allegedly trying to extort money
```

```
in lieu of settling a rape case. Last year, Goel was arrested over allegations of fraud and an alleged non-payment of ₹16 lakh.

Most Positive Tech News Article: The American Automobile Association has launched a contest to find the first couple to get marr
ied in one of its self-driving shuttles in Las Vegas. The contestants will have to write a 400-word essay describing how an auto
nomous vehicle would have changed their road trip experience with their partner. The winning couple will be married on June 30.
```

Looks like the most negative article is all about a recent smartphone scam in India and the most positive article is about a contest to get married in a self-driving shuttle. Interesting! Let's do a similar analysis for ***world*** news.

```python
pos_idx = df[(df.news_category=='world') & (df.sentiment_score == 16)].index[0]
neg_idx = df[(df.news_category=='world') & (df.sentiment_score == -12)].index[0]

print('Most Negative World News Article:', news_df.iloc[neg_idx][['news_article']][0])
print()
print('Most Positive World News Article:', news_df.iloc[pos_idx][['news_article']][0])
```

nlp_strategy_29.py hosted with ♡ by GitHub view raw

```
Most Negative World News Article: Slamming Canadian Prime Minister Justin Trudeau's comments on US tariffs during the G7 summit,
US President Donald Trump's trade adviser Peter Navarro said, "Trudeau deserves a special place in hell." Navarro also accused T
rudeau of backstabbing Trump. The Canadian PM had called US tariffs "insulting", saying the country won't be pushed around and p
lans to apply retaliatory tariffs.

Most Positive World News Article: Pope Francis on Sunday said he is praying that the upcoming summit between US President Donald
Trump and North Korean leader Kim Jong-un succeeds in laying the groundwork for peace. Urging people around the world to pray fo
r the summit, the pontiff said, "I want to offer the beloved people of Korea an especial thought of friendship."
```

Interestingly Trump features in both the most positive and the most negative ***world*** news articles. Do read the articles to get some more perspective into why the model selected one of them as the most negative and the other one as the most positive (no surprises here!).

Sentiment Analysis with TextBlob

TextBlob is another excellent open-source library for performing NLP tasks with ease, including ***sentiment analysis***. It also an a ***sentiment lexicon*** (in the form of an XML file) which it leverages to give both polarity and subjectivity scores. Typically, the scores have a normalized scale as compare to Afinn. The ***polarity*** score is a float within the range `[-1.0, 1.0]`. The ***subjectivity*** is a float within the range `[0.0, 1.0]` where `0.0` is very *objective* and `1.0` is very *subjective*. Let's use this now to get the sentiment polarity and labels for each news article and aggregate the summary statistics per news category.

```python
from textblob import TextBlob

# compute sentiment scores (polarity) and labels
sentiment_scores_tb = [round(TextBlob(article).sentiment.polarity, 3) for article in news_df['
```

```
sentiment_category_tb = ['positive' if score > 0
                             else 'negative' if score < 0
                                 else 'neutral'
                                     for score in sentiment_scores_tb]


# sentiment statistics per news category
df = pd.DataFrame([list(news_df['news_category']), sentiment_scores_tb, sentiment_category_tb])
df.columns = ['news_category', 'sentiment_score', 'sentiment_category']
df['sentiment_score'] = df.sentiment_score.astype('float')
df.groupby(by=['news_category']).describe()
```

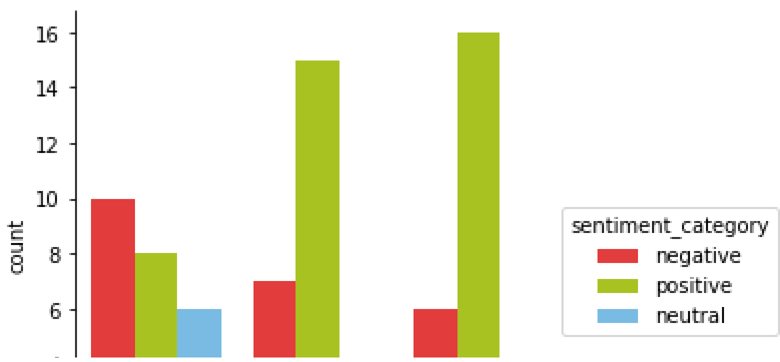
nlp_strategy_30.py hosted with ♡ by GitHub view raw

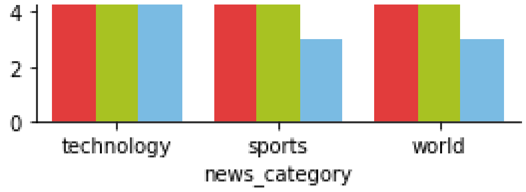
	sentiment_score							
	count	mean	std	min	25%	50%	75%	max
news_category								
sports	25.0	0.084040	0.149114	-0.200	-0.01700	0.075	0.15900	0.381
technology	24.0	0.010458	0.203315	-0.500	-0.07525	0.000	0.05925	0.500
world	25.0	0.120760	0.221134	-0.296	0.00000	0.075	0.21100	0.700

Looks like the average sentiment is the most positive in ***world*** and least positive in ***technology***! However, these metrics might be indicating that the model is predicting more articles as positive. Let's look at the sentiment frequency distribution per news category.

```
fc = sns.factorplot(x="news_category", hue="sentiment_category",
                    data=df, kind="count",
                    palette={"negative": "#FE2020",
                             "positive": "#BADD07",
                             "neutral": "#68BFF5"})
```

nlp_strategy_27.py hosted with ♡ by GitHub view raw





Visualizing sentiment categories per news category

There definitely seems to be more positive articles across the news categories here as compared to our previous model. However, still looks like technology has the most negative articles and world, the most positive articles similar to our previous analysis. Let's now do a comparative analysis and see if we still get similar articles in the most positive and negative categories for ***world*** news.

```
pos_idx = df[(df.news_category=='world') & (df.sentiment_score == 0.7)].index[0]
neg_idx = df[(df.news_category=='world') & (df.sentiment_score == -0.296)].index[0]

print('Most Negative World News Article:', news_df.iloc[neg_idx][['news_article']][0])
print()
print('Most Positive World News Article:', news_df.iloc[pos_idx][['news_article']][0])
```

nlp_strategy_31.py hosted with ♡ by GitHub view raw

```
Most Negative World News Article: A Czech woman drowned after being trapped inside Prague's underground drainage system while pa
rticipating in a global GPS-based treasure hunt, police officials said. The woman was geocaching when heavy downpours led to rap
idly rising water. The body of the 27-year-old victim, who has not been identified, was found in the Vltava river.

Most Positive World News Article: Pope Francis on Sunday said he is praying that the upcoming summit between US President Donald
Trump and North Korean leader Kim Jong-un succeeds in laying the groundwork for peace. Urging people around the world to pray fo
r the summit, the pontiff said, "I want to offer the beloved people of Korea an especial thought of friendship."
```

Well, looks like the most negative ***world*** news article here is even more depressing than what we saw the last time! The most positive article is still the same as what we had obtained in our last model.

Finally, we can even evaluate and compare between these two models as to how many predictions are matching and how many are not (by leveraging a confusion matrix which is often used in classification). We leverage our nifty **model_evaluation_utils** module for this.

```
import model_evaluation_utils as meu
meu.display_confusion_matrix_pretty(true_labels=sentiment_category,
                                    predicted_labels=sentiment_category_tb,
                                    classes=['negative', 'neutral', 'positive'])
```

nlp_strategy_32.py hosted with ♡ by GitHub view raw

		Predicted:		
		negative	neutral	positive
Actual:	negative	16	5	6
	neutral	3	2	8
	positive	4	5	25

Comparing sentiment predictions across models

In the preceding table, the ***'Actual'*** labels are predictions from the ***Afinn*** sentiment analyzer and the ***'Predicted'*** labels are predictions from `TextBlob`. Looks like our previous assumption was correct. `TextBlob` definitely predicts several *neutral* and *negative* articles as *positive*. Overall most of the sentiment predictions seem to match, which is good!

Conclusion

This was definitely one of my longer articles! If you are reading this, I really commend your efforts for staying with me till the end of this article. These examples should give you a good idea about how to start working with a corpus of text documents and popular strategies for text retrieval, pre-processing, parsing, understanding structure, entities and sentiment. We will be covering feature engineering and representation techniques with hands-on examples in the next article of this series. Stay tuned!

. . .

All the code and datasets used in this article can be accessed from my **GitHub**

The code is also available as a **Jupyter notebook**

*I often mentor and help students at **Springboard** to learn essential skills around Data Science. Thanks to them for helping me develop this content. Do check out **Springboard's DSC bootcamp** if you are interested in a career-focused structured path towards learning Data Science.*

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A lot of this code comes from the research and work that I had done during writing my book ***"Text Analytics with Python"***. The code is open-sourced on **GitHub**. *(Python 3.x edition coming by end of this year!)*

Text Analytics with Python - A Practical Real-World Approach to Gaining Actionab...
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"Practical Machine Learning with Python", my other book also covers text classification and sentiment analysis in detail. The code is open-sourced on **GitHub** for your convenience.

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Thanks to *Durba* for editing this article.

Machine Learning Data Science Python Artificial Intelligence Towards Data Science