In [1]:

```
%%html
<style>
table {display: block;}
td {
  font-size: 20px
}
.rendered_html { font-size: 20px; }
*{ line-height: 200%; }
</style>
<style type="text/css" media="print"> body { -webkit-print-color-adjust: exact;
```

# Natural Language Processing and the Web WS 2022/23 - Practice Class - Tutorial 3 ¶

We have seen in the previous practice classes how to access text data and tokenization issues. In this section, we will cover the following topics:

## Contents

- Revision - Lemmatization and POS tagging
- Parsing and Chunking text documents
- Description of building small Ontology using Hearst Pattern ( Assignment can be done in group!)

# Lemmatization

A lemma is the canonical, uninflected or dictionary form of a word. For example, the lemma of smallest is small, and the lemma of eating is eat. In many languages, the lemma for nouns is the nominative singular form, the lemma for adjectives is the nominative singular positive form, and the lemma for verbs is the infinitive. But given an inflected form, finding the lemma (a process called lemmatization) is not always as easy. Words often undergo regular spelling changes when inflected for example, in English, verbs and adjectives ending in -e often drop this letter when inflecting: bake → baking. Sometimes final consonants are doubled, as in (British) English travel → travelling.

An accurate algorithm for lemmatization must be aware of these sorts of inflectional rules and know how to undo them to arrive at the base form of the word. It must also know about completely irregular cases, such as go → went, mouse → mice, and good → better. Lemmatization is a difficult task for computers, and requires some basic understanding of the grammatical context and properties of the word. For example, the lemma of dove depends on whether the word is being used as a noun (as in the bird) or a verb (as in the past tense of dive).

However, lemmatization is an important task because, as with part-of-speech tagging, many NLP applications rely on lemmatized text.

Examples of lemmatization:

```
rocks : rock
corpora : corpus
better : good
```

# NLTK Lemmatizer

**optional --> coloring outputs**

```
COLOR = {
    'blue': '\033[94m',
    'default': '\033[99m',
    'grey': '\033[90m',
    'yellow': '\033[93m',
    'black': '\033[90m',
    'cyan': '\033[96m',
    'green': '\033[92m',
    'magenta': '\033[95m',
    'white': '\033[97m',
    'red': '\033[91m'
}
```

In [2]:

```
HR='\033[91m' # hilight in red
HD ='\x1b[0m'# hilight in default
```

In [3]:

```python
import nltk
# Lemmatize using WordNet's buil-in morphy function
# Returns the input unchanged if it cannot be found in WordNet
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
print("rocks :"+HR, lemmatizer.lemmatize("rocks") + HD)
print("corpora :"+HR, lemmatizer.lemmatize("corpora") +HD)
#Give the POS tag as a context to the tager,  a denotes adjective in "pos"
print("better :"+HR, lemmatizer.lemmatize("better", pos ="a") +HD)
print("drove of verb :"+HR, lemmatizer.lemmatize("drove", pos ="v") +HD)
print("drove as noun (bird): :"+HR, lemmatizer.lemmatize("drove", pos ="n") +HD)
#Lemmatizing sentence
sentence = "The striped bats are hanging on their feet for best"
word_list = nltk.word_tokenize(sentence)
print("words:",word_list)
# Lemmatize list of words and join
lemmatized_output = ',    '.join([lemmatizer.lemmatize(w) for w in word_list])
print("lemma: "+HR,lemmatized_output)
```

```
rocks : rock
corpora : corpus
better : good
drove of verb : drive
drove as noun (bird): : drove
words: ['The', 'striped', 'bats', 'are', 'hanging', 'on', 'their', 'fe
et', 'for', 'best']
lemma:  The,    striped,    bat,    are,    hanging,    on,    their,    foo
t,    for,    best
```

# spaCy Lemmatizer

In [4]:

```
import spacy
# Initialize spacy 'en_core_web_sm' model, keeping only tagger component needed
nlp = spacy.load('en_core_web_sm', disable=['parser', 'ner'])
sentence = "The striped bats are hanging on their feet for best"
# Parse the sentence using the loaded 'English' model object `nlp`
doc = nlp(sentence)
# Extract the lemma for each token and join
print(" ".join(["[" + token.text+"-->"+HR+token.lemma_ + HD for token in doc]))
```

```
[The-->the [striped-->striped [bats-->bat [are-->be [hanging-->hang [o
n-->on [their-->their [feet-->foot [for-->for [best-->good
```

# TextBlob Lemmatizer

In [5]:

```
from textblob import TextBlob, Word
# Lemmatize a word, use the WordNet's morphy function
word = 'stripes'
w = Word(word)
print(word +" " + HR+w.lemmatize())
```

```
stripes stripe
```

In [6]:

```
# Lemmatize a sentence
sentence = "The striped bats are hanging on their feet for best"
sent = TextBlob(sentence)
print(" ". join(["["+ w+"-->"+HR+w.lemmatize()+"]"+HD for w in sent.words]))
```

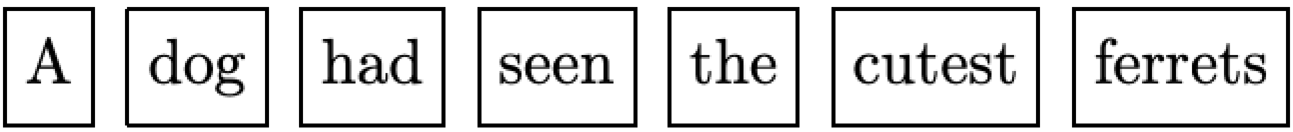
```
[The-->The] [striped-->striped] [bats-->bat] [are-->are] [hanging-->ha
nging] [on-->on] [their-->their] [feet-->foot] [for-->for] [best-->bes
t]
```

# Parts of speech tagging with NLTK

Part-of-speech tagging (POS tagging) is the process of marking up the words in a text with their corresponding part of speech (e.g., noun, verb, adjective). For example, take the following sentence:

A dog had seen the cutest ferrets.

A tokenizer would split it into the following tokens:




A part-of-speech tagger could then assign labels, or tags, to the tokens according to their respective parts of speech:


The Penn Treebank tags used here are as follows: DT determiner NN noun, singular or mass VBD verb, past tense JJS adjective, superlative NNS noun, plural VBN verb, past participle

The inventory from which these POS tags are drawn varies from language to language, and from application to application.

NLTK includes a Part-of-speech tagger, which assign a tag, or word class, or lexical category for a given token in a text. The default POS tagset for English is based on PennTreebank tagset< (https://www.ling.upenn.edu/courses/Fall_2003/ling001/penn_treebank_pos.ht

NLTK also include the Universal POS tagset (https://universaldependencies.org/u/pos/)

In [7]:

```
from nltk.tokenize import sent_tokenize, word_tokenize
from nltk.tag import pos_tag
import nltk
text = "I saw a man sawing the tree with a saw. He can't finish it ontime."
sentences = sent_tokenize(text)
for sentence in sentences:
    for token, pos in pos_tag(word_tokenize(sentence)):
        print(token +"  " + HR + pos + HD)
# to get information about a given tag
print("=====")
nltk.help.upenn_tagset("VB")
```

```
I PRP
saw VBD
a DT
man NN
sawing VBG
the DT
tree NN
with IN
a DT
saw NN
. .
He PRP
ca MD
n't RB
finish VB
it PRP
ontime RB
. .
=====
VB: verb, base form
    ask assemble assess assign assume atone attention avoid bake balka
nize
    bank begin behold believe bend benefit bevel beware bless boil bom
b
    boost brace break bring broil brush build ...
```

In [8]:

```
# you can also decide to use the Universal POS tagset
for sentence in sentences:
    for token, pos in pos_tag(word_tokenize(sentence), tagset='universal'):
        print(token +" "+ HR + pos + HD)
```

```
I PRON
saw VERB
a DET
man NOUN
sawing VERB
the DET
tree NOUN
with ADP
a DET
saw NOUN
. .
He PRON
ca VERB
n't ADV
finish VERB
it PRON
ontime ADV
. .
```

# Parts of speech tagging with spaCy

In [9]:

```python
import spacy
import pprint
# Load English tokenizer, tagger,
# parser, NER and word vectors
nlp = spacy.load("en_core_web_sm")
text = ("I saw a man sawing the tree with a saw. He can't finish it ontime!")
doc = nlp(text)
# Print token and Tag
for token in doc:
    print(str(token)+"  "+HR+  str(token.pos_) + HD)
# Example list of Verb tokens
print("Verbs:", [token.text for token in doc if token.pos_ == "VERB"])

```

```
I PRON
saw VERB
a DET
man NOUN
sawing VERB
the DET
tree NOUN
with ADP
a DET
saw NOUN
. PUNCT
He PRON
ca AUX
n't PART
finish VERB
it PRON
ontime ADV
! PUNCT
Verbs: ['saw', 'sawing', 'finish']
```

# Parts of speech tagging with TextBlob

In [10]:

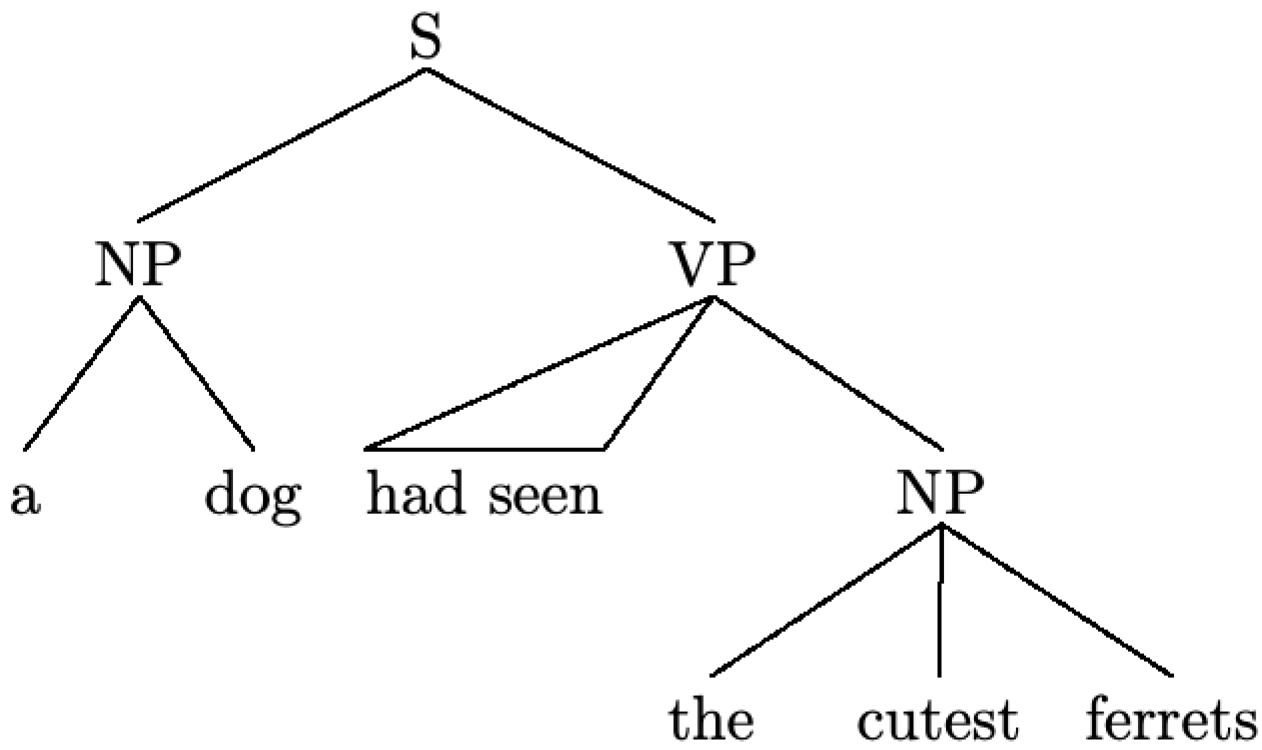
```
from textblob import TextBlob
text = ("I saw a man sawing the tree with a saw. He can't finish it ontime!")
# create a textblob object
blob_object = TextBlob(text)
# print word with pos tag.
for word, pos in blob_object.tags:
    print(word +" " +HR + pos + HD)
```

```
I PRP
saw VBD
a DT
man NN
sawing VBG
the DT
tree NN
with IN
a DT
saw NN
He PRP
ca MD
n't RB
finish VB
it PRP
ontime RB
```

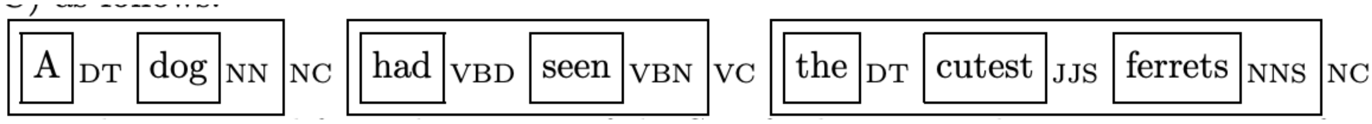
---

# Parsing vs. chunking

Parsing is the process of analyzing a text to determine its grammatical structure. It goes beyond part-of-speech tagging (though that is often a first step) by grouping words within sentences into hierarchical grammatical structures. Here is a possible parse tree for the example sentence "A dog had seen the cutest ferrets."




Proper parsing is a hard problem in computational linguistics. While identifying some sort of sentence structure is important for many NLP applications, not all of them require something as detailed and complicated as a parse tree. Chunking, also known as shallow parsing, is a simplified form of sentence analysis which identifies basic constituents (noun groups, verb groups, etc.) but does not specify their internal structure. For the POS-tagged sentence example above, a chunker might identify noun chunks (NC) and verb complexes (VC) as follows:




# Chunking with NLTTK

Chunking works on top of POS tagging, it uses pos-tags as input and provides chunks as output.

We can create rules to create noun phrase, for example, we can define noun phrase chunking as an optional determiner (DT) followed by any number of adjectives (JJ) and then a noun (NN).

In [11]:

```python
import nltk
sentence = "the little yellow dog barked at the cat."
#Define your grammar using regular expressions
grammar = ("Noun-Chunk: {<DT>?<JJ>*<NN>} # NP")
chunkParser = nltk.RegexpParser(grammar)
postags = nltk.pos_tag(nltk.word_tokenize(sentence))
for word, pos in postags:
    print(word +"  " + HR+ pos + HD)
tree = chunkParser.parse(postags)
for subtree in tree.subtrees():
    print(subtree)
tree.draw()
```

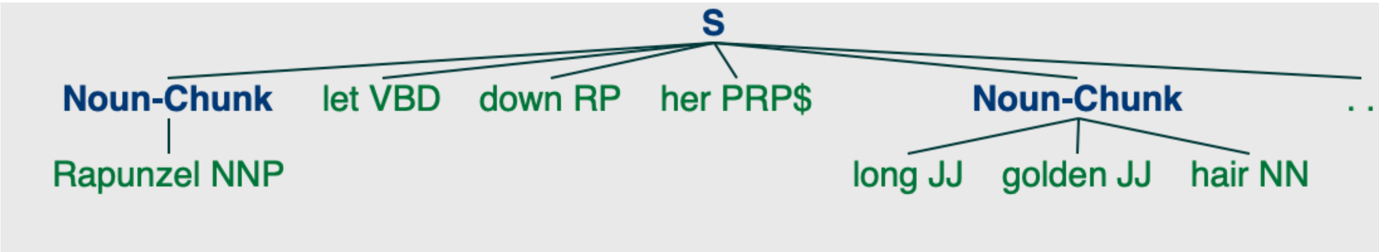
```
the DT
little JJ
yellow JJ
dog NN
barked VBD
at IN
the DT
cat NN
. .
(S
  (Noun-Chunk the/DT little/JJ yellow/JJ dog/NN)
  barked/VBD
  at/IN
  (Noun-Chunk the/DT cat/NN)
  ./.)
(Noun-Chunk the/DT little/JJ yellow/JJ dog/NN)
(Noun-Chunk the/DT cat/NN)
```

The above code will draw the parsed tree structure (with chunk labels) of the sentence. It should look like the following

In [12]:

```python
# another noun-chunk pattern
# 1) DT or PP$ followed by JJ and end by NN or
# 2) a number of proper noun sequences NNP+
grammar = r"""
  Noun-Chunk: {<DT|PP\$>?<JJ>*<NN>}   # chunk determiner/possessive, adjectives
      {<NNP>+}                # chunk sequences of proper nouns
"""
cp = nltk.RegexpParser(grammar)
sentence = "Rapunzel let down her long golden hair."
postags = nltk.pos_tag(nltk.word_tokenize(sentence))
tree = cp.parse(postags)
print(tree)
tree.draw()
```

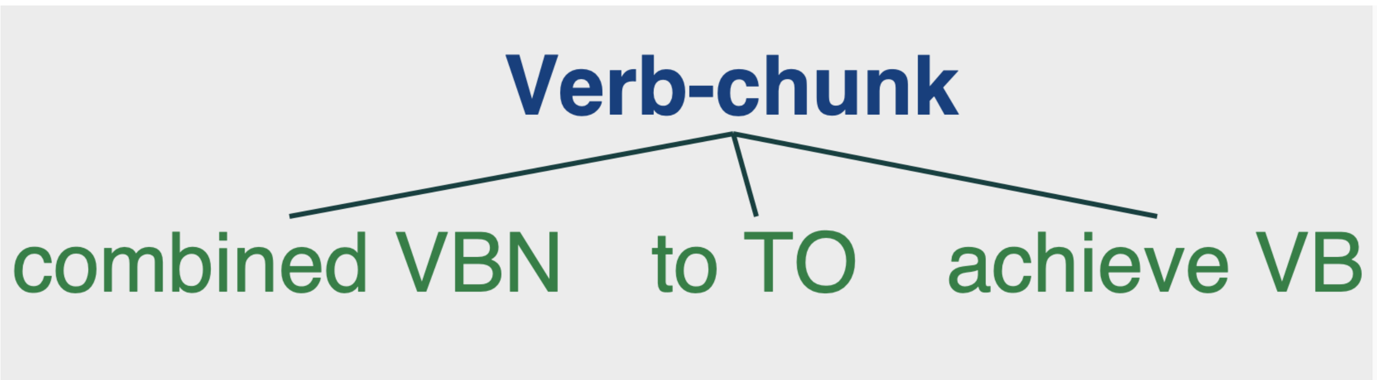
```
(S
  (Noun-Chunk Rapunzel/NNP)
  let/VBD
  down/RP
  her/PRP$
  (Noun-Chunk long/JJ golden/JJ hair/NN)
  ./.)
```



In [13]:

```python
# List verb chunks from the brown corpus
cp = nltk.RegexpParser('Verb-chunk: {<V.*> <TO> <V.*>}')
brown = nltk.corpus.brown
verbchunks = []
for sent in brown.tagged_sents():
    tree = cp.parse(sent)
    for subtree in tree.subtrees():
        if subtree.label() == 'Verb-chunk':
            verbchunks.append(subtree)
# print the first ten chunks
print(verbchunks[:10])
# draw the first Verb-chunk
verbchunks[0].draw()
```

```
[Tree('Verb-chunk', [('combined', 'VBN'), ('to', 'TO'), ('achieve', 'V
B')]), Tree('Verb-chunk', [('continue', 'VB'), ('to', 'TO'), ('place',
'VB')]), Tree('Verb-chunk', [('serve', 'VB'), ('to', 'TO'), ('protec
t', 'VB')]), Tree('Verb-chunk', [('wanted', 'VBD'), ('to', 'TO'), ('wa
it', 'VB')]), Tree('Verb-chunk', [('allowed', 'VBN'), ('to', 'TO'),
('place', 'VB')]), Tree('Verb-chunk', [('expected', 'VBN'), ('to', 'T
O'), ('become', 'VB')]), Tree('Verb-chunk', [('expected', 'VBN'), ('t
o', 'TO'), ('approve', 'VB')]), Tree('Verb-chunk', [('expected', 'VB
N'), ('to', 'TO'), ('make', 'VB')]), Tree('Verb-chunk', [('intends',
'VBZ'), ('to', 'TO'), ('make', 'VB')]), Tree('Verb-chunk', [('seek',
'VB'), ('to', 'TO'), ('set', 'VB')])]
```

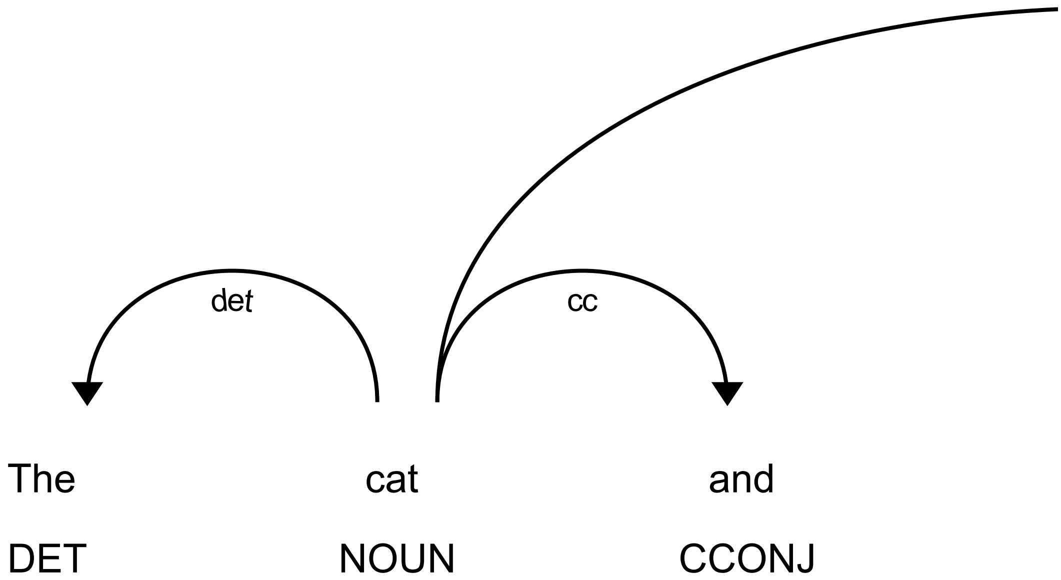



## Parsing and Chunking with spaCy

In dependency parsing the syntactic structure of a sentence is described solely in terms of directed binary grammatical relations between the words. Relations among the words are illustrated above the sentence with directed, labeled arcs from heads to dependents. We call this a **typed dependency structure** because in typed dependency the labels are drawn from a fixed inventory of grammatical relations. A root node explicitly marks the root of the tree, the head of the entire structure. Read more [here (https://web.stanford.edu/~jurafsky/slp3/14.pdf)](https://web.stanford.edu/~jurafsky/slp3/14.pdf)

In [14]:

```
#Dependency parsing with spaCy
import spacy
nlp = spacy.load('en_core_web_sm')
doc = nlp(u"The cat and the dog sleep in the basket near the door.")
spacy.displacy.render(doc, style='dep')
```



# noun chunks in spaCy

In [15]:

```
import spacy
nlp = spacy.load('en_core_web_sm')
doc = nlp(u'The cat and the dog sleep in the basket near the door.')
for np in doc.noun_chunks:
    print(np.text)
```

```
The cat
the dog sleep
the basket
the door
```

# Chunking with TextBlob

TextBlob currently has two noun phrases chunker implementations, textblob.np_extractors.FastNPExtractor (default, based on [Shlomi Babluki's implementation (https://thetokenizer.com/2013/05/09/efficient-way-to-extract-the-main-topics-of-a-sentence/)](https://thetokenizer.com/2013/05/09/efficient-way-to-extract-the-main-topics-of-a-sentence/) and textblob.np_extractors.ConllExtractor, which uses the CoNLL 2000 corpus to train a tagger.

In [16]:

```
from textblob import TextBlob
#from textblob.np_extractors import FastNPExtractor
from textblob.np_extractors import ConllExtractor
extractor = ConllExtractor()
sentence ="Swayy is a beautiful new dashboard for discovering and curating onlir
parse = TextBlob(sentence, np_extractor=extractor)
print(parse.noun_phrases)
```

```
['swayy', 'beautiful new dashboard', 'online content']
```

# Excercise (15 pts)

## Building small Ontology using Hearst Pattern

In this problem, you will employ the POS, lemma and chunking information to discover lexical relationships in a corpus.

Hearst patterns are lexico-syntactic patterns first used by Marti Hearst (http://people.ischool.berkeley.edu/~hearst/papers/coling92.pdf) to discover hyponyms in large text corpora. (A **hyponym** is a term which denotes a more specific or subordinate group of another term, called a hypernym. For example, tiger is a hyponym of mammal, which is in turn a hyponym of animal. Therefore animal is a hypernym of mammal, and mammal is a hypernym of tiger.)

Hearst observed that certain linguistic constructions can be used to infer hyponymy relationships. For example, in the phrase “works by such authors as Herrick, Goldsmith, and Shakespeare”, it is obvious that Herrick, Goldsmith, and Shakespeare are all hyponyms of author. In general, any phrase of the pattern “such NP0 as NP1, . . . , and NPn” implies that the noun phrases NP1 through NPn are hyponyms of NP0. The following table shows some patterns originally proposed by Hearst, along with examples.

| **Hearst pattern** | **Example** |
|---|---|
| $NP_0$ such as NP (... and/or NP) | ... played stringed instruments, such as the guitar, with ... |
| such $NP_0$ as NP (... and/or NP) | ... works by such authors as Herrick, Goldsmith, and Shakespeare ... |
| NP (...) and/or other $NP_0$ | ... bruises, wounds, broken bones or other injuries ... |
| $NP_0$, including NP (... and/or NP) | ... all common-law countries including Canada and England ... |
| $NP_0$, especially NP (... and/or NP) | ... most European countries, especially France, England, and Spain ... |

---

Write a Python program which looks for hyponyms by finding Hearst patterns in a collection of documents.

1. Write a program that will read a file or list of files, iterate over each sentences and extract possible hyponym/hypernym relations. ( 10 pts)
2. Once the relations are extracted, report the total number of relations/patterns as follows ( 5 pts) :

   - Print out the most commonly found hyponym-hypernym relations

Example output:

| **count** | **Hyponym** | **Hypernym** |
|---|---|---|
| 45 | house | building |
| 32 | Herrick | author |
| 11 | France | country |

- Print the top five most productive Hearst patterns

Example output:

| count | Hearst pattern |
| --- | --- |
| 1302 | NP such as NP |
| 800 | such NP as NP |
| 452 | NP, including NP |
| 121 | NP, especially NP |
| 32 | NP and/or other NP |

In this exercise, you can use either NLTK, TextBlob, or spaCy chunkers, or a combination of them to implement Hearst Pattern. We will run your script to test sentences to determine how much patterns your implementation covers.

You can use the corpus `wiki-1000.txt` in the folder `HearstPaternData`. You can compare your output to some of the files there such as `pattern_out_0.txt`.

# Resources

- [Learning POS Tagging & Chunking in NLP (https://medium.com/greyatom/learning-pos-tagging-chunking-in-nlp-85f7f811a8cb)](https://medium.com/greyatom/learning-pos-tagging-chunking-in-nlp-85f7f811a8cb)
- [TextBlob Chunking (https://textblob.readthedocs.io/en/dev/advanced_usage.html#noun-phrase-chunkers)](https://textblob.readthedocs.io/en/dev/advanced_usage.html#noun-phrase-chunkers)

- [Chunking in NLTK (https://www.nltk.org/book/ch07.html)](https://www.nltk.org/book/ch07.html)
- Hearst Pattern
- [Dependency Parsing (https://web.stanford.edu/~jurafsky/slp3/14.pdf)](https://web.stanford.edu/~jurafsky/slp3/14.pdf)

In [ ]:

```

```