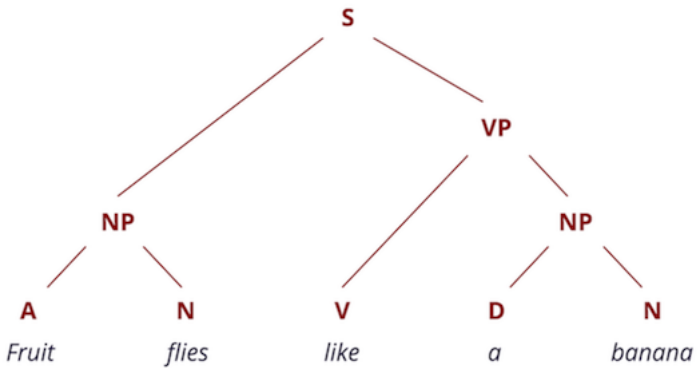
SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN

50.040 Natural Language Processing, Summer 2020
Homework 2

Due 3 July 2020, 5pm

Homework 2 will be graded by Li Haoran

Introduction Constituency parsing aims to extract a constituency-based parse tree from a sentence that represents its syntactic structure according to a phrase structure grammar. A typical constituency parse tree is shown below:



S is a distinguished start symbol, node labels such as NP(noun phrase), VP(verb phrase) are non-terminal symbols, leaf labels such as "a", "banana" are terminal symbols.

In this homework, we will implement a constituency parser based on probabilistic context-free grammars (PCFGs) and evaluate its performance.

Dataset We will be using a version of the "Penn Treebank" released in NLTK corpora to induce PCFGs and evaluate our algorithm. The preprocessing code has been provided, do not make any changes to the text and code unless you are requested to do so. Run the code we provide to load the training and test sets as Python lists, it will take 1 minute. Since we will not tune hyper-parameters in this homework, there will be no need for a development set.

Requirements nltk

PCFGs A probabilistic context-free grammar consists of:

1. A context-free grammar $G = (N,\ \Sigma,\ S,\ R)$ where N is a finite set of non-terminal symbols, Σ is a finite set of terminal symbols, R is a finite set of rules (e.g., $NP \rightarrow NP\ PP$), $S \in N$ is the start symbol.

2. One parameter $q(A \rightarrow \beta)$ for each rule $A \rightarrow \beta$ in R. Since the grammar is in Chomsky normal form, there are only two types of rules: $A \rightarrow B\ C$ and $A \rightarrow \alpha$, where A, B, $C \in N$, $\alpha \in \Sigma$.

We can estimate the parameter $q(A \rightarrow \beta)$ using maximum likelihood estimation:

$$q_{MLE}(A \rightarrow \beta) = \frac{count(A \rightarrow \beta)}{count(A)} \tag{1}$$

where $count(A \rightarrow \beta)$ refers to the number of occurences of the rule $A \rightarrow \beta$ in all the parse trees in the training set, and $count(A)$ refers to the number of occurences of the non-terminal symbol A.

(50 points)

Question 1 [written] (3 points) To better understand PCFG, let's consider the first parse tree in the training data "cnf_train" as an example. Run the code we have provided for you and then write down the roles of *.productions(), .rhs(), .lhs(), .leaves()* in the ipynb notebook.

Question 2 [code] (5 points) To count the number of unique rules, nonterminals and terminals, please implement functions *collect_rules*, *collect_nonterminals*, *collect_terminals*.

Question 3 [code] (5 points) Implement the function *build_pcfg* which builds a dictionary that stores the terminal rules and nonterminal rules.

Question 4 [code] (1 points) Estimate the probability of rule $NP \rightarrow NNP@NNP$ according to Eq.(1).

Question 5 [code] (1 points) Find the terminal symbols in "cnf_test[0]" that never appeared in the PCFG we built.

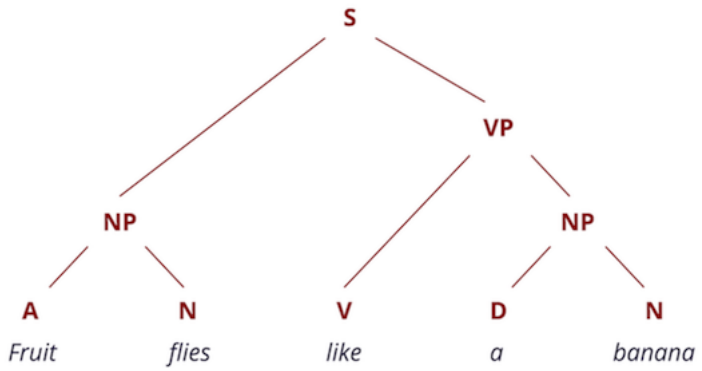
Question 6 [code] (10 points) To handle cases where terminals symbols in test data never appear in the training data, we introduce a simple smoothing technique. We first create a new "unknown" terminal symbol "unk". Next, for each original non-terminal symbol $A \in N$, we add one new rule "$A \rightarrow unk$" to the original PCFG. The smoothed probabilities for all rules can then be estimated as:

$$q_{smooth}(A \rightarrow \beta) = \frac{count(A \rightarrow \beta)}{count(A) + 1}$$

$$q_{smooth}(A \rightarrow unk) = \frac{1}{count(A) + 1}$$

Implement the function *smooth_rules_prob* which returns the smoothed rule probabilities. Then run the code we have provided for you.

CKY algorithm Similar to the Viterbi algorithm, the CKY algorithm is a dynamic-programming algorithm. Given a PCFG $G = (N,\ \Sigma,\ S,\ R)$, we can use the CKY algorithm described in class to find the highest scoring parse tree for a sentence. First, let us complete the CKY function from scratch using only Python built-in functions. The output should be two dictionaries π and bp, which store the optimal probability and backpointer information respectively. Given a sentence $w_0, w_1, ..., w_{n-1}$, $\pi(i, k, X)$, $bp(i, k, X)$ refer to the highest score and backpointer for the (partial) parse tree that has the root X (a non-terminal symbol) and covers the word span $w_i, ..., w_{k-1}$, where $0 \leq i < k \leq n$. Note that a backpointer includes both the best grammar rule chosen and the best split point.



Question 7 [code] (15 points) Implement *CKY* function according Algorithm 1 and run the test code to check your implementation.

Question 8 [code] (8 points) Implement *build_tree* function according to algorithm 2 to reconstruct the parse tree.

Question 9 [code] (2 points) Run the remaining code to test your model on *cnf_test*. The F1 score should be around 0.5.

How to submit

1. Fill up you student ID and name in the Jupyter Notebook.
2. Click the Save button at the top of the Jupyter Notebook.

Algorithm 1 CKY Algorithm

```
procedure CKY(sent, rules)
    Initialization: score, back, len
    for i = 0, ..., len − 1 do
        for A in nonterminals do
            if A → sent[i] in rules then
                Update score[(i,i+1)][A], back[(i,i+1)][A]
            end if
        end for
    end for
    for span=2,..., len do
        for begin = 0,..., (len-span) do
            end = begin + span
            for split = begin+1,..., end-1 do
                for A,B,C in nonterminals do
                    if A→B,C in rules then
                        Update score[begin,end][A], back[(begin, end)][A]
                    end if
                end for
            end for
        end for
    end for
end procedure
```

Algorithm 2 Build Tree algorithm

```
procedure BUILD_TREE(back, root)
    Initialization: begin, end, root_label
    Return: tree
    Read split point, left child node and right child node from back
    if right child node exists then
        build left_tree, right_tree
        tree = nltk.tree.Tree(root_label, [left_tree, right_tree])
    else
        tree = nltk.tree.Tree(root_label, [left_child])
    end if
end procedure
```

3. Select Cell - All Output - Clear. This will clear all the outputs from all cells (but will keep the content of all cells).

4. Select Cell Run All. This will run all the cells in order, and will take 20-25 minutes.

5. Once you've rerun everything, select File - Download as - PDF via LaTeX or print out the HTML as PDF.

6. Look at the PDF file and make sure all your solutions are there, displayed correctly. The PDF is the only thing your graders will see! Submit your PDF on eDimension.