SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN

50.040 Natural Language Processing, Fall 2024

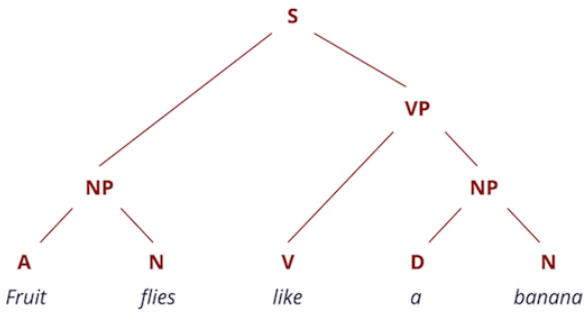
Homework 2

Due 28 October 2024, 23:59pm

Homework 2 will be graded by Chen Huang

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, and 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 around 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:

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

where $\text{count}(A \rightarrow \beta)$ refers to the number of occurrences of the rule $A \rightarrow \beta$ in all the parse trees in the training set, and $\text{count}(A)$ refers to the number of occurrences 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 explain the roles of *.productions()*, *.rhs()*, *.lhs()*, *.leaves()* in the ipynb notebook.

Question 2 [code] (5 points)

Implement functions *collect_rules*, *collect_nonterminals*, *collect_terminals* to count the number of unique rules, nonterminals, and terminals.

Question 3 [code] (4 points)

Implement the function *build_pcfg* which builds a dictionary that stores the terminal rules and nonterminal rules.

Question 4 [code] (1 point)

Find the terminal symbols in "cnf_test[0]" that never appeared in the PCFG we built.

Question 5 [code] (10 points)

To handle cases where terminal 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:

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

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

Implement the function *smooth_rules_prob* which returns the smoothed rule probabilities. Then run the sanity check code.

Question 6 [code] (2 points)

Estimate the probability of "cnf_train[0]", which is the first parse tree in the training data "cnf_train" by using *s_rules_prob*.

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 $w_0, w_1, \ldots, w_{n-1}$, $\pi(i, k, X)$, $bp(i, k, X)$ 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 $w_i, \ldots, w_{k-1}$, 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] (14 points)

Implement *CKY* function according to Algorithm 1.

Question 8 [code] (2 points)

What is the time complexity of CKY function (in worst case), please verify.

Question 9 [code] (6 points)

Implement *build_tree* function according to Algorithm 2 to reconstruct the parse tree.

Question 10 [code] (2 points)

- Given a parse tree, the original sentence can be obtained by arranging the terminal symbols from left to right. Use *CKY* function to compute the max probability for the sentence from "cnf_train[0]", which is the first parse tree in the training data "cnf_train".
- Generate and display the parse tree of the sentence.

Question 11 [code] (1 point)

Run the remaining code to test your model on "cnf_test".

How to submit

1. Fill up your student ID and name in the Jupyter Notebook.
2. Click the Save button at the top of the Jupyter Notebook.
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 several minutes.
5. Once you've rerun everything, select File – Download as – PDF via LaTeX.
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!**
7. Submit your PDF on eDimension.

Algorithm 1 CKY Algorithm

procedure CKY(sent, rules)
Initialization: score, back, len
for $i = 0, \ldots, len - 1$ **do**
  for A in nonterminals **do**
    if A $\rightarrow$ sent[i] in rules **then**
      Update score[$(i, i+1)$][A], back[$(i, i+1)$][A]
    end if
  end for
end for
for $span = 2, \ldots, len$ **do**
  for $begin = 0, \ldots, (len - span)$ **do**
    end = begin + span
    for $split = begin + 1, \ldots, end - 1$ **do**
      for A, B, C in nonterminals **do**
        if A $\rightarrow$ 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