50.040 Natural Language Processing (Summer 2022) Homework 2

Due 1st July 2022, 5PM

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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:

tree

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.

PCFGs

A probabilistic context-free grammar consists of:

- 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.
- 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:

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

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.

In [1]:

```
import copy
from collections import Counter
from nltk.tree import Tree
from nltk import Nonterminal
from nltk.corpus import LazyCorpusLoader, BracketParseCorpusReader
from collections import defaultdict
import time
```

In [2]:

```
st = time.time()
```

In [3]:

```
import nltk
nltk.download('treebank')
!pip install svgling
```

```
[nltk_data] Downloading package treebank to /Users/skylee/nltk_dat
a...
[nltk_data]   Package treebank is already up-to-date!

Requirement already satisfied: svgling in /Users/skylee/.pyenv/versi
ons/3.8.10/lib/python3.8/site-packages (0.3.1)
Requirement already satisfied: svgwrite in /Users/skylee/.pyenv/vers
ions/3.8.10/lib/python3.8/site-packages (from svgling) (1.4.2)
WARNING: You are using pip version 21.1.1; however, version 22.1.2 i
s available.
You should consider upgrading via the '/Users/skylee/.pyenv/version
s/3.8.10/bin/python3.8 -m pip install --upgrade pip' command.
```

In [4]:

```
def set_leave_lower(tree_string):
    if isinstance(tree_string, Tree):
        tree = tree_string
    else:
        tree = Tree.fromstring(tree_string)
    for idx, _ in enumerate(tree.leaves()):
        tree_location = tree.leaf_treeposition(idx)
        non_terminal = tree[tree_location[:-1]]
        non_terminal[0] = non_terminal[0].lower()
    return tree

def get_train_test_data():
    '''
    Load training and test set from nltk corpora
    '''
    train_num = 3900
    test_index = range(10)
    treebank = LazyCorpusLoader('treebank/combined', BracketParseCorpusReader, r
'wsj_.*\.mrg')
    cnf_train = treebank.parsed_sents()[:train_num]
    cnf_test = [treebank.parsed_sents()[i+train_num] for i in test_index]
    #Convert to Chomsky norm form, remove auxiliary labels
    cnf_train = [convert2cnf(t) for t in cnf_train]
    cnf_test = [convert2cnf(t) for t in cnf_test]
    return cnf_train, cnf_test
def convert2cnf(original_tree):
    '''
    Chomsky norm form
    '''
    tree = copy.deepcopy(original_tree)

    #Remove cases like NP->DT, VP->NP
    tree.collapse_unary(collapsePOS=True, collapseRoot=True)
    #Convert to Chomsky
    tree.chomsky_normal_form()

    tree = set_leave_lower(tree)
    return tree
```

In [5]:

```
### GET TRAIN/TEST DATA
cnf_train, cnf_test = get_train_test_data()
```

In [6]:

```
cnf_train[0].pprint()
```

```
(S
  (NP-SBJ
    (NP (NNP pierre) (NNP vinken))
    (NP-SBJ|<,-ADJP-,>
      (, ,)
      (NP-SBJ|<ADJP-,>
        (ADJP (NP (CD 61) (NNS years)) (JJ old))
        (, ,))))
  (S|<VP-.>
    (VP
      (MD will)
      (VP
        (VB join)
        (VP|<NP-PP-CLR-NP-TMP>
          (NP (DT the) (NN board))
          (VP|<PP-CLR-NP-TMP>
            (PP-CLR
              (IN as)
              (NP
                (DT a)
                (NP|<JJ-NN> (JJ nonexecutive) (NN director))))
            (NP-TMP (NNP nov.) (CD 29))))))
    (. .)))
```

Question 1

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.

In [7]:

```
rules = cnf_train[0].productions()
print(rules, type(rules[0]))
```

```
[S -> NP-SBJ S|<VP-.>, NP-SBJ -> NP NP-SBJ|<,-ADJP-,>, NP -> NNP NN
P, NNP -> 'pierre', NNP -> 'vinken', NP-SBJ|<,-ADJP-,> -> , NP-SBJ|<
ADJP-,>, , -> ',', NP-SBJ|<ADJP-,> -> ADJP ,, ADJP -> NP JJ, NP -> C
D NNS, CD -> '61', NNS -> 'years', JJ -> 'old', , -> ',', S|<VP-.> -
> VP ., VP -> MD VP, MD -> 'will', VP -> VB VP|<NP-PP-CLR-NP-TMP>, V
B -> 'join', VP|<NP-PP-CLR-NP-TMP> -> NP VP|<PP-CLR-NP-TMP>, NP -> D
T NN, DT -> 'the', NN -> 'board', VP|<PP-CLR-NP-TMP> -> PP-CLR NP-TM
P, PP-CLR -> IN NP, IN -> 'as', NP -> DT NP|<JJ-NN>, DT -> 'a', NP|<
JJ-NN> -> JJ NN, JJ -> 'nonexecutive', NN -> 'director', NP-TMP -> N
NP CD, NNP -> 'nov.', CD -> '29', . -> '.'] <class 'nltk.grammar.Pro
duction'>
```

In [8]:

```
rules[0].rhs(), type(rules[0].rhs()[0])
```

Out[8]:

```
((NP-SBJ, S|<VP-.>), nltk.grammar.Nonterminal)
```

In [9]:

```
rules[10].rhs(), type(rules[10].rhs()[0])
```

Out[9]:

```
(('61',), str)
```

In [10]:

```
rules[0].lhs(), type(rules[0].lhs())
```

Out[10]:

```
(S, nltk.grammar.Nonterminal)
```

In [11]:

```
print(cnf_train[0].leaves())
```

```
['pierre', 'vinken', ',', '61', 'years', 'old', ',', 'will', 'join',
'the', 'board', 'as', 'a', 'nonexecutive', 'director', 'nov.', '29',
'.']
```

ANSWER HERE

- .productions(): It returns a grammar production where each of them maps a single symbol on the "left hand side" to a sequence of symbols on the "right hand side"
- .rhs(): It returns the right-hand side of a production(it's children nodes)
- .lhs(): It returns the left-hand side of a production (it's parent node)
- .leaves(): It returns the leaves of the tree when joined from the whole sentence, the order reflects the order of leaves in the tree hierarchical structure

Question 2

To count the number of unique rules, nonterminals and terminals, please implement functions **collect_rules**, **collect_nonterminals**, **collect_terminals**

In [12]:

```
def collect_rules(train_data):
    '''
    Collect the rules that appear in data.
    params:
        train_data: list[Tree] --- list of Tree objects
    return:
        rules: list[nltk.grammar.Production] --- list of rules (Production objec
ts)
        rules_counts: Counter object --- a dictionary that maps one rule (nltk.N
onterminal) to its number of
                                                  occurences (int) in train data.
    '''
    rules = list()
    rules_counts = Counter()
    ### YOUR CODE HERE

    for train in train_data:
        for rule in train.productions():
            rules.append(rule)
            rules_counts[rule] += 1

    ### YOUR CODE HERE
    return rules, rules_counts

def collect_nonterminals(rules):
    '''
    collect nonterminals that appear in the rules
    params:
        rules: list[nltk.grammar.Production] --- list of rules (Production objec
ts)
    return:
        nonterminals: set(nltk.Nonterminal) --- set of nonterminals
    '''
    ### YOUR CODE HERE

    nonterminals = list()

    for rule in rules:
        nonterminals.append(rule.lhs())
        for r in rule.rhs():
            if type(r) == str:
                continue
            else:
                nonterminals.append(r)

    nonterminals = set(nonterminals)
    ### END OF YOUR CODE

    return nonterminals

def collect_terminals(rules):
    '''
    collect terminals that appear in the rules
    params:
        rules: list[nltk.grammar.Production] --- list of rules (Production objec
ts)
    return:
        terminals: set of strings --- set of terminals
    '''
```

```
    ### YOUR CODE HERE

    terminals = list()

    for rule in rules:
        for i in rule.rhs():
            if type(i) != nltk.grammar.Nonterminal:
                terminals.append(i)

    terminals = set(terminals)
    ### END OF YOUR CODE

    return terminals
```

In [13]:

```
train_rules, train_rules_counts = collect_rules(cnf_train)
nonterminals = collect_nonterminals(train_rules)
terminals = collect_terminals(train_rules)
```

In [14]:

```
len(train_rules), len(set(train_rules)), len(terminals), len(nonterminals)
```

Out[14]:

```
(196646, 31656, 11367, 7869)
```

In [15]:

```
print(train_rules_counts.most_common(5))
```

```
[(, -> ',', 4876), (DT -> 'the', 4726), (. -> '.', 3814), (PP -> IN
NP, 3273), (S|<VP-.> -> VP ., 3003)]
```

Question 3

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

In [16]:

```
def build_pcfg(rules_counts):
    '''
    Build a dictionary that stores the terminal rules and nonterminal rules.
    param:
        rules_counts: Counter object --- a dictionary that maps one rule to its
 number of occurences in train data.
    return:
        rules_dict: dict(dict(dict)) --- a dictionary has a form like:
                    rules_dict = {'terminals':{'NP':{'the':1000,'an':500}, 'AD
J':{'nice':500,'good':100}},
                                  'nonterminals':{'S':{'NP@VP':1000},'NP':{'NP@N
P':540}}}
    When building "rules_dict", you need to use "lhs()", "rhs()" funtion and con
vert Nonterminal to str.
    **All the keys in the dictionary are of type str**.
    '@' is used as a special symbol to split left and right nonterminal strings.
    '''
    ### YOUR CODE HERE
    rules_dict = dict()
    rules_dict['terminals'] = defaultdict(dict)
    rules_dict['nonterminals'] = defaultdict(dict)

    for rule in rules_counts:
        temp = []

        rhs = rule.rhs()
        lhs = str(rule.lhs())

        if len(rhs) == 1:
            if type(rhs[0]) == str:
                rules_dict['terminals'][lhs][rhs[0]] = rules_counts[rule]

        else:
            for r in rhs:
                temp.append(str(r))
            at_str = '@'.join(temp)
            rules_dict['nonterminals'][lhs][at_str] = rules_counts[rule]


    ### END OF YOUR CODE
    return rules_dict
```

In [17]:

```
train_rules_dict = build_pcfg(train_rules_counts)
```

Question 4

Count and find all the terminal symbols in ''cnf_test'' that never appeared in the PCFG we built.

In [18]:

```
unseen_symbols = []
for i in cnf_test:
    test_rules, test_rules_counts = collect_rules([i])
    test_terminals = collect_terminals(test_rules)
    for t in test_terminals:
        if t not in terminals:
            unseen_symbols.append(t)

print(f"count of unseen symbols: {len(unseen_symbols)}")
print(f"terminal symbols that never appeared in PCFG:\n{unseen_symbols}")
```

```
count of unseen symbols: 19
terminal symbols that never appeared in PCFG:
['constitutional-law', 'kurland', 'tribe', 'laurence', 'professors',
'procedure', 'scuttle', 'procedure', 'implicitly', 'kennedy', 'spect
rum', 'kurland', 'tribe', 'professors', 'professors', 'authorizes',
'partial', 'lawmaking', 'shared']
```

Question 5

We can use smoothing techniques to handle these cases. A simple smoothing method is as follows. 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:

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

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

where $|V|$ is the count of unique terminal symbols.

Implement the function **smooth_rules_prob** which returns the smoothed rule probabilities

In [19]:

```
def smooth_rules_prob(rules_counts):
    '''
    params:
        rules_counts: dict(dict(dict)) --- a dictionary has a form like:
                            rules_counts = {'terminals':{'NP':{'the':1000,'an':500},
 'ADJ':{'nice':500,'good':100}},
                                        'nonterminals':{'S':{'NP@VP':1000},'NP':
{'NP@NP':540}}}

    return:
        rules_prob: dict(dict(dict)) --- a dictionary that has a form like:
                                rules_prob = {'terminals':{'NP':{'the':0.6,'an':
0.3, '<unk>':0.1},
                                                            'ADJ':{'nice':0.6,'goo
d':0.3,'<unk>':0.1},
                                                            'S':{'<unk>':0.01}}}
                                            'nonterminals':{'S':{'NP@VP':0.99}}
    '''
    rules_prob = copy.deepcopy(rules_counts)
    unk = '<unk>'
    ### YOUR CODE HERE

    for dicts in rules_prob['terminals'].values():
        summ = 0

        for count in dicts.values():
            summ += count

        for word, count in dicts.items():
            dicts[word] = count / (summ + 1)

        dicts[unk] = 1 / (summ + 1)

    for key, dicts in rules_prob['nonterminals'].items():
        summ = 0

        for count in dicts.values():
            summ += count

        for word, count in dicts.items():
            dicts[word] = count / (summ + 1)

        if key not in rules_prob['terminals']:
            rules_prob['terminals'][key] = {unk:(1/(summ+1))}
    ### END OF YOUR CODE
    return rules_prob
```

In [20]:

```
s_rules_prob = smooth_rules_prob(train_rules_dict)
terminals.add('<unk>')
```

In [21]:

```
print(s_rules_prob['nonterminals']['S']['NP-SBJ@S|<VP-.>'])
print(s_rules_prob['nonterminals']['S']['NP-SBJ-1@S|<VP-.>'])
print(s_rules_prob['nonterminals']['NP']['NNP@NNP'])
print(s_rules_prob['terminals']['NP'])
```

```
0.1300172371337109
0.025240088648116228
0.039506305917861376
{'<unk>': 5.389673385792821e-05}
```

In [22]:

```
len(terminals)
```

Out[22]:

```
11368
```

Question 6

Estimate the probability of the first parse tree in the testing data "cnf_test" by using "s_rules_prob".

In [23]:

```
probability = 1
try:
    for rule in cnf_test[0].productions():
        lhs = rule.lhs()
        rhs = rule.rhs()
        if len(rhs) == 1: #terminal
            probability *= s_rules_prob['terminals'][lhs][rhs[0]]
        else:
            child = str(rhs[0]) + '@' + str(rhs[1])
            probability *= s_rules_prob['nonterminals'][lhs][child]
except KeyError: # nonterminal not found = (prob -> 0)
    probability = 0

print("Probability of the first parse tree in cnf_test is:", probability)
```

```
Probability of the first parse tree in cnf_test is: 0
```

CKY Algorithm

Similar to the Viterbi algorithm, the CKY algorithm is a dynamic-programming algorithm. Given a PCFG $G = (N,\ \Sigma,\ S,\ R,\ q)$, 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 and the Numpy package.

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.

tree

Question 7

Implement **CKY** function and run the test code to check your implementation.

In [24]:

```
def CKY(sent, rules_prob):
    '''
    params:
        sent: list[str] --- a list of strings
        rules_prob: dict(dict(dict)) --- a dictionary that has a form like:
                                           rules_prob = {'terminals':{'NP':{'th
e':0.6,'an':0.3, '<unk>':0.1},
                                                                     'ADJ':{'ni
ce':0.6,'good':0.3,'<unk>':0.1},
                                                                     'S':{'<unk
>':0.01}}}
                                                         'nonterminals':{'S':{'N
P@VP':0.99}}
    return:
        score: dict(dict) --- score[(i,i+span)][root] represents the highest sco
re for the parse (sub)tree that has the root "root"
                         across words w_i, w_{i+1},..., w_{i+span-1}.
        back: dict(dict) --- back[(i,i+span)][root] = (split , left_child, right
_child); split: int;
                         left_child: str; right_child: str.
    '''
    score = defaultdict(dict)
    back = defaultdict(dict)
    sent_len = len(sent)
    ### YOUR CODE HERE

    for i in range(0, sent_len):
        term = sent[i]
        for A, dicts in rules_prob['terminals'].items():
            if term in dicts:
                score[(i, i+1)][A] = dicts[term]
                back[(i, i+1)][A] = (-1, term, '')

    for span in range(2, sent_len + 1):
        for begin in range(0, sent_len - span + 1):
            end = begin + span

            for split in range(begin + 1, end):
                for A in rules_prob['nonterminals'].keys():
                    for key in rules_prob['nonterminals'][A].keys():
                        B = key.split('@')[0]
                        C = key.split('@')[1]

                        if (B in score[(begin, split)].keys()) and (C in score[(
split, end)].keys()):
                            updated_score = rules_prob['nonterminals'][A][key] *
\
                                            score[(begin, split)][B] *\
                                            score[(split, end)][C]

                            if (A not in score[(begin, end)]) or (updated_score
> score[(begin, end)][A]):
                                score[(begin, end)][A] = updated_score
                                back[(begin, end)][A] = (split, B, C)

    ### END OF YOUR CODE
    return score, back
```

Question 8

Implement **build_tree** function to reconstruct the parse tree.

In [25]:

```
def build_tree(back, root):
    '''
    Build the tree recursively.
    params:
        back: dict() --- back[(i,i+span)][X] = (split , left_child, right_chil
d); split:int; left_child: str; right_child: str.
        root: tuple() --- (begin, end, nonterminal_symbol), e.g., (0, 10, 'S
    return:
        tree: nltk.tree.Tree
    '''
    begin = root[0]
    end = root[1]
    root_label = root[2]
    ### YOUR CODE HERE

    split, left_node, right_node = back[(begin, end)][root_label]
    if right_node != '':
        left_tree = build_tree(back, (begin, split, left_node))
        right_tree = build_tree(back, (split, end, right_node))

        tree = nltk.tree.Tree(root_label, [left_tree, right_tree])
    else:
        tree = nltk.tree.Tree(root_label, [left_node])

    ### END OF YOUR CODE
    return tree
```

Question 9 & 10

- Use **CKY** function to compute the max probability for the sentence of the first parse tree in the testing data "cnf_test".
- Generate and display the parse tree of the sentence.

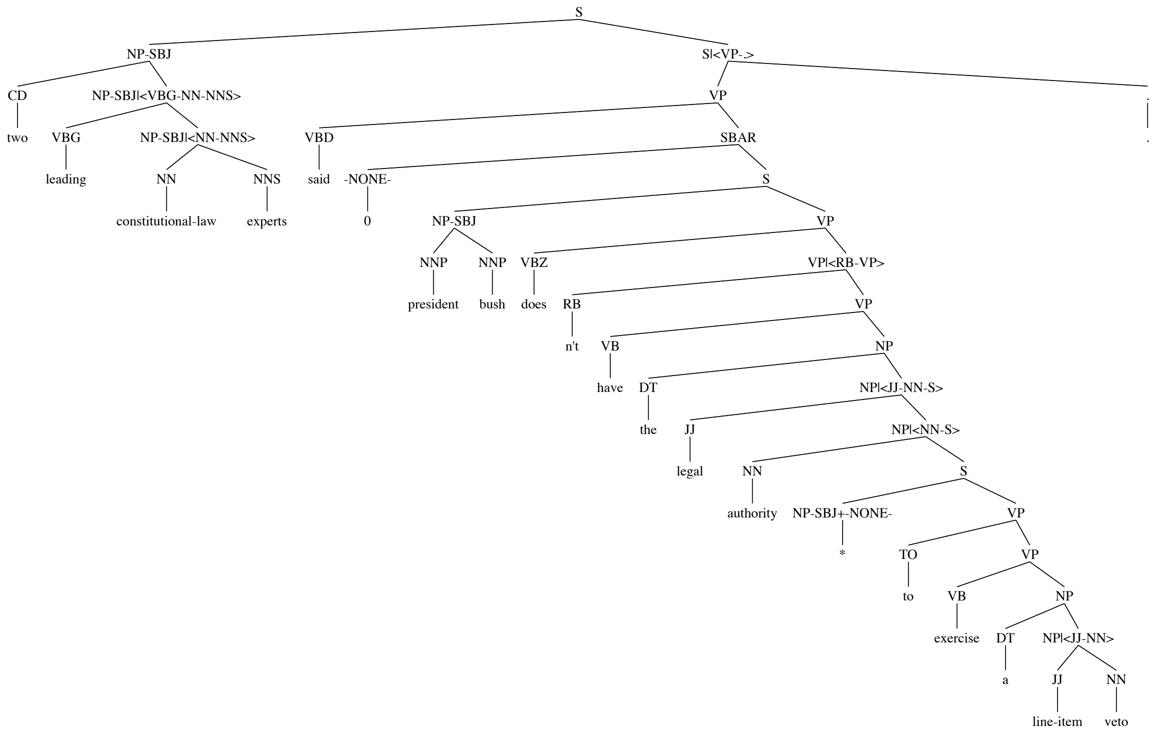
In [26]:

```
test_rules, test_rules_counts = collect_rules(cnf_test)
test_nonterminals = collect_nonterminals(test_rules)
test_terminals = collect_terminals(test_rules)

test_rules_dict = build_pcfg(test_rules_counts)

test_rules_prob = smooth_rules_prob(test_rules_dict)
test_terminals.add('<unk>')

test_sent = cnf_test[0].leaves()
test_score, test_back = CKY(test_sent, test_rules_prob)
```

In [27]:

```
test_tree = build_tree(test_back, (0, len(test_sent), 'S'))
test_tree
```

Out[27]:



Question 11

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

In [28]:

```
def set_leave_index(tree):
    '''
    Label the leaves of the tree with indexes
    Arg:
        tree: original tree, nltk.tree.Tree
    Return:
        tree: preprocessed tree, nltk.tree.Tree
    '''
    for idx, _ in enumerate(tree.leaves()):
        tree_location = tree.leaf_treeposition(idx)
        non_terminal = tree[tree_location[:-1]]
        non_terminal[0] = non_terminal[0] + "_" + str(idx)
    return tree

def get_nonterminal_bracket(tree):
    '''
    Obtain the constituent brackets of a tree
    Arg:
        tree: tree, nltk.tree.Tree
    Return:
        nonterminal_brackets: constituent brackets, set
    '''
    nonterminal_brackets = set()
    for tr in tree.subtrees():
        label = tr.label()
        #print(tr.leaves())
        if len(tr.leaves()) == 0:
            continue
        start = tr.leaves()[0].split('_')[-1]
        end = tr.leaves()[-1].split('_')[-1]
        if start != end:
            nonterminal_brackets.add(label+'-('+start+':'+end+')')
    return nonterminal_brackets

def word2lower(w, terminals):
    '''
    Map an unknow word to "unk"
    '''
    return w.lower() if w in terminals else '<unk>'
```

In [29]:

```
correct_count = 0
pred_count = 0
gold_count = 0
for i, t in enumerate(cnf_test):
    #Protect the original tree
    t = copy.deepcopy(t)
    sent = t.leaves()
    #Map the unknow words to "unk"
    sent = [word2lower(w.lower(), terminals) for w in sent]

    #CKY algorithm
    score, back = CKY(sent, s_rules_prob)
    candidate_tree = build_tree(back, (0, len(sent), 'S')) #, nonterminals)

    #Extract constituents from the gold tree and predicted tree
    pred_tree = set_leave_index(candidate_tree)
    pred_brackets = get_nonterminal_bracket(pred_tree)

    #Count correct constituents
    pred_count += len(pred_brackets)
    gold_tree = set_leave_index(t)
    gold_brackets = get_nonterminal_bracket(gold_tree)
    gold_count += len(gold_brackets)
    current_correct_num = len(pred_brackets.intersection(gold_brackets))
    correct_count += current_correct_num

    print('#'*20)
    print('Test Tree:', i+1)
    print('Constituent number in the predicted tree:', len(pred_brackets))
    print('Constituent number in the gold tree:', len(gold_brackets))
    print('Correct constituent number:', current_correct_num)

recall = correct_count/gold_count
precision = correct_count/pred_count
f1 = 2*recall*precision/(recall+precision)
```

```
####################
Test Tree: 1
Constituent number in the predicted tree: 20
Constituent number in the gold tree: 20
Correct constituent number: 14
####################
Test Tree: 2
Constituent number in the predicted tree: 54
Constituent number in the gold tree: 54
Correct constituent number: 30
####################
Test Tree: 3
Constituent number in the predicted tree: 30
Constituent number in the gold tree: 30
Correct constituent number: 23
####################
Test Tree: 4
Constituent number in the predicted tree: 17
Constituent number in the gold tree: 17
Correct constituent number: 16
####################
Test Tree: 5
Constituent number in the predicted tree: 32
Constituent number in the gold tree: 32
Correct constituent number: 26
####################
Test Tree: 6
Constituent number in the predicted tree: 40
Constituent number in the gold tree: 40
Correct constituent number: 18
####################
Test Tree: 7
Constituent number in the predicted tree: 22
Constituent number in the gold tree: 22
Correct constituent number: 7
####################
Test Tree: 8
Constituent number in the predicted tree: 18
Constituent number in the gold tree: 18
Correct constituent number: 6
####################
Test Tree: 9
Constituent number in the predicted tree: 28
Constituent number in the gold tree: 28
Correct constituent number: 16
####################
Test Tree: 10
Constituent number in the predicted tree: 40
Constituent number in the gold tree: 40
Correct constituent number: 8
```

In [30]:

```
print('Overall precision: {:.3f}, recall: {:.3f}, f1: {:.3f}'.format(precision,
recall, f1))
```

```
Overall precision: 0.545, recall: 0.545, f1: 0.545
```