CS 3813/780, Python Programming, Fall 2012

Final Project

December 6, 2012

1 Instructions

- This is a programming project on *machine translation* but we assume **no prior knowledge** in any of the languages involved in the examples (Chinese, French, or Spanish), nor any familiarity with computational linguistics or any linguistic theory.
- Please refer to the slides for high-level intuitions and visualizations.
- The submission deadline is **Friday Dec 21st** at midnight. **No late submissions are accepted.**
- There are other testcases on the course homepage.

2 The Problem - Syntax-Directed Translation

In this project, you will be building a machine translation system that translates from a source language to a target language, say, English-to-French. The translation method we use here is *syntax-directed translation*, which is originated in compiling, where the source program in a high-level language (say, C or Java) is first parsed into a syntax or expression tree which guides the generation of object program (say, in Assembly or Byte-code). We adapt this technique to the translation of human languages, where the source input is first parsed into a parse-tree and then we recursively convert the tree into a string in the target language.

2.1 An English-to-Chinese Example

Consider the following English sentence and its Chinese translation (note the reordering in the passive construction):

(1) the gunman was killed by the police .

qiangshou bei jingfang jibi 。
[gunman] [passive] [police] [killed] .

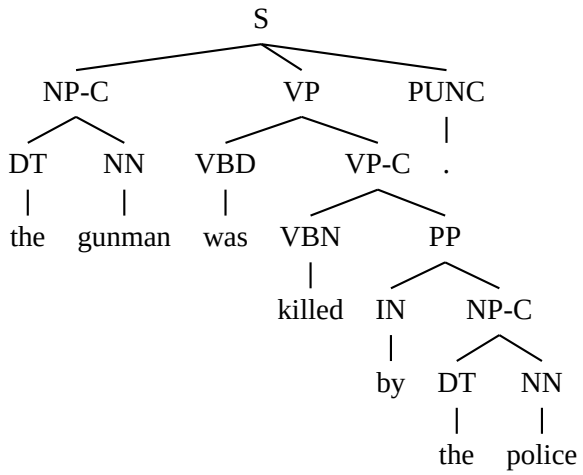
Figure 1 shows how the translation works. The English sentence (a) is first parsed into the tree in (b)[1] which is then recursively converted into the Chinese string in (e) through five steps. First, at the root node,

[1]The internal nodes in the parse tree are called *non-terminal tags* or *syntactic categories*. For example, VP stands for verb phrase and PP prepositional phrase. The tags right above leaf nodes are called *preterminals* or *part-of-speech tags*. For example, VBD and VBN correspond to verbs in past tense and past participle, respectively. Our tagset and grammar follows the Penn Treebank Style. For further information, please visit:
`http://www.cis.upenn.edu/~treebank`
`http://bulba.sdsu.edu/jeanette/thesis/PennTags.html`

(a) the gunman was killed by the police .

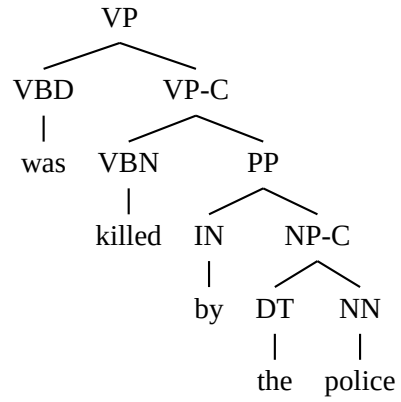
parser $\Downarrow$

(b)



$r_1, r_2 \Downarrow$

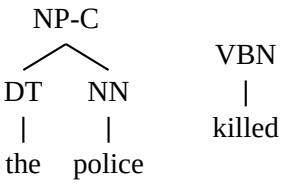
(c) *qiangshou*



。

$r_3 \Downarrow$

(d) *qiangshou* *bei*



。

$r_5 \Downarrow$ $r_4 \Downarrow$

(e) *qiangshou* *bei* *jingfang* *jibi* 。

Figure 1: A syntax-directed translation process.

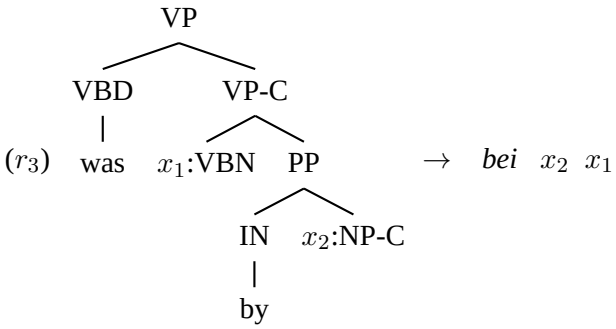
we apply the rule r_1 which preserves the top-level word-order and translates the English period into its Chinese counterpart:

(r_1) S (x_1:NP-C x_2:VP PUNC (.)) $\rightarrow$ x_1 x_2 。

Then, the rule r_2 grabs the whole sub-tree for "the gunman" and translates it as a phrase:

(r_2) NP-C (DT (the) NN (gunman)) $\rightarrow$*qiangshou*

Now we get a "partial Chinese, partial English" sentence "*qiangshou* VP 。" as shown in Fig. 1 (c). Our recursion goes on to translate the VP sub-tree. Here we use the rule r_3 for the passive construction:



which captures the fact that the agent (NP-C, "the police") and the verb (VBN, "killed") are always inverted between English and Chinese in a passive voice. Finally, we apply rules:

(r_4) VBN (killed) $\rightarrow$*jibi*

(r_5) NP-C (DT (the) NN (police)) $\rightarrow$*jingfang*

which perform phrasal translations for the two remaining sub-trees in (d), respectively, and get the completed Chinese string in (e).

You might also have other rules which lead to a different translation, say, replacing r_5 with another Chinese word for "police":

(r_5) NP-C (DT (the) NN (police)) $\rightarrow$*jingcha*

In this framework, every rule is associated with a *probability*, and your job is to search for the best translation (the one with the highest probability) given a parse tree.

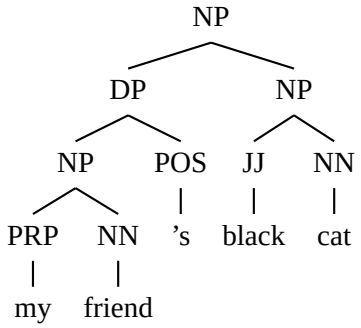
2.2 English-to-French/Spanish Example

If you have no idea what the previous example is all about, here is another example, but from English to French and Spanish (it's not a whole sentence).

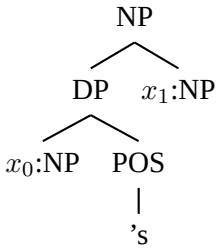
(2) my friend's black cat

le	chat	noir	de	mon	ami
el	gato	negro	de	mi	amigo
[the]	[cat]	[black]	[of]	[my]	[friend]

Again, assume the parse tree for the English phrase is:



We can first have a rule which takes care of the reordering of possessive ('s) construction between English and French/Spanish:

(r_1')  $\rightarrow \quad x_1 \quad \text{de} \quad x_0$

Then we use a rule to translate the English phrase "my friend":

(r_2') NP(PRP (my) NN (friend)) $\rightarrow$ mon ami / mi amigo

and a rule for reordering the adjective (black) with the noun (cat):

(r_3') NP(x_0:JJ x_1:NN) $\rightarrow \quad x_1 \quad x_0$

finally, we finish the translation with the following two lexical rules:

(r_4') black $\rightarrow$ noir / negro

(r_5') cat $\rightarrow$ le chat / el gato

Of course, you may decompose r_2' into three smaller rules and get the same translations.

2.3 Translation Algorithm

Given a fixed parse-tree τ^*, we are to search for the best derivation with the highest probability. This can be done by a simple top-down traversal (or depth-first search) from the root of τ^*: at each node η in τ^*, try each possible rule r whose source-side pattern $t(r)$ matches the subtree τ^*_η rooted at η, and recursively visit each descendant node η_i in τ^*_η that corresponds to a variable in $t(r)$. We then collect the resulting target-language

strings and plug them into the Chinese-side $s(r)$ of rule r, getting a translation for the subtree τ^*_η. We finally take the best of all translations.

With the extended LHS of our transducer, there may be many different rules applicable at one tree node. As a result, the number of derivations is exponential in the size of the tree, since there are exponentially many decompositions of the tree for a given set of rules. This problem can be solved by *memoization*: we cache each subtree that has been visited before, so that every tree node is visited *at most* once. This results in a dynamic programming algorithm that is guaranteed to run in $O(npq)$ time where n is the size of the parse tree, p is the maximum number of rules applicable to one tree node, and q is the maximum size of an applicable rule. For a given rule-set, this algorithm runs in time linear to the length of the input sentence, since p and q are considered grammar constants, and n is proportional to the input length. The full pseudo-code is worked out in Algorithm 1.

Algorithm 1 Top-down Memoized Recursion

function TRANSLATE(η)
  if $cache[\eta]$ defined **then** ▷ this sub-tree visited before?
    return $cache[\eta]$
  $best \leftarrow 0$
  for $r \in \mathcal{R}$ **do** ▷ try each rule r
    $matched,\ sublist \leftarrow$ PATTERNMATCH$(t(r), \eta)$ ▷ tree pattern matching
    if $matched$ **then** ▷ if matched, $sublist$ contains a list of matched subtrees
      $prob \leftarrow \Pr(r)$ ▷ the probability of rule r
      for $\eta_i \in sublist$ **do**
        $p_i, s_i \leftarrow$ TRANSLATE(η_i) ▷ recursively solve each sub-problem
        $prob \leftarrow prob \cdot p_i$
      if $prob > best$ **then**
        $best \leftarrow prob$
        $str \leftarrow [x_i \mapsto s_i]s(r)$ ▷ plug in the results
  $cache[\eta] \leftarrow best,\ str$ ▷ caching the best solution for future use
  return $cache[\eta]$ ▷ returns the best string with its prob.

3 I/O Specifications and Samples

Command-line format:

```
cat <tree_file> | ./translate.py <rule_file> [-d|-k <K>]
```

where `<...>` and `[...]` denote required and optional arguments, respectively.

There are two input files:

- a tree file (through `sys.stdin`): a list of source-language parse trees, which contains several lines, with each line representing one parse tree.
- a rule file (filename specified by the command-line): one line for each rule in the format of

$$lhs \texttt{ -> } rhs \texttt{ ### prob=} p$$

where lhs is the left-hand-side (source-language) tree pattern (trees with variables), and rhs is the right-hand-side (target-language) string (with the same set of variables, possibily permutated). The variables will be in the form of `x0`, `x1`, and so on. The real number p is the probability of this rule.

Sample input files:

input1.txt:

```
NP(DP(NP(PRP("my") NN("friend")) POS("'s")) NP(JJ("black") NN("cat")))
NP(DP(NP(PRP("my") NN("friend")) POS("'s")) NP(JJ("white") NN("cat")))
```

rules1.txt:

```
NP(DP(x0:NP POS("'s")) x1:NP) -> x1 "de" x0 ### prob=1.0
NP(PRP("my") NN("friend")) -> "mon" "ami" ### prob=0.51
NP(PRP("my") NN("friend")) -> "mon" "amie" ### prob=0.49
NP(x0:JJ x1:NN) -> x1 x0 ### prob=0.7
NP(x0:JJ x1:NN) -> x0 x1 ### prob=0.3
JJ("black") -> "noir" ### prob=0.6
JJ("black") -> "noire" ### prob=0.4
NN("cat") -> "le" "chat" ### prob=1.0
NP(x0:JJ NN("cat")) -> "le" "chat" x0 ### prob=1
NP(JJ("black") x0:NN) -> x0 "noir" ### prob=0.55
NP(JJ("black") x0:NN) -> x0 "noire" ### prob=0.45
```

To run the program, type in the terminal

```
cat input1.txt | ./translate.py rules1.txt
```

and you will get the output

```
my friend 's black cat -> le chat noir de mon ami ### prob=0.306
my friend 's white cat -> *** failed ***
```

The output contains one line for each source-language tree in `input.txt`. As shown in the above example, the format is quite similar to the rules file, except there are no quotes, and the probability of the best translation is printed to the 3rd decimal digit (i.e., `'%.3f' % prob`).

Note:

1. if the search fails, simply print `*** failed ***` in place of the best translation. (see the above example).
2. each individual word in the input (e.g., `"my"`) is surrounded by a pair of double quotes, and we assume that white spaces, double quotes, or parentheses are *not* part of any word.
3. The sample case is available online as `input1.txt`, `rules1.txt`, and `output1.txt` under the homework page, where you can also find a more complicated example.

4 Recommended Design

- a Tree class

  A separate class for trees is highly recommended. It should work for both parse-trees and tree patterns (trees with variables), and implements the following two functions:

  - Tree Parsing

    the static method `from_string(s)` implements the parsing of a tree represented in string input into a Tree instance. This might be the most difficult part of this project. You may want to write a "pretty-print" function inside the Tree class to help you debug this part.

  - Tree Pattern Matching

    the method `patternmatch(self, pattern)` takes a tree pattern as input and returns a pair `(matched, sublist)`, where `matched` is a boolean (whether the matching succeeds or not), and `sublist` is a list of matched subtrees in case of success. See Algorithm 1.

- a Rule class: This is optional. In fact, a tuple of `(pattern, rhs, prob)` would suffice.

- search: This module implements the memoized depth-first search (Algorithm 1).

5 Extensions (Extra Credit Problems)

5.1 Outputing the derivation (easy)

What if we want to look into the derviation (see Figure 1)? How is the source sentence translated to the foreign sentence and what rules are used? We add another option `-d` to the command line for outputing the derivation of the best translation (if any). For example,

```
cat input1.txt | ./translate.py rules1.txt -d
```

should output the following:

```
my friend 's black cat -> le chat noir de mon ami ### prob=0.306
 NP (DP (x0:NP POS ('s)) x1:NP) -> x1 de x0 ### prob=1.000
 | x0: NP (PRP (my) NN (friend)) -> mon ami ### prob=0.510
 | x1: NP (x0:JJ NN (cat)) -> le chat x0 ### prob=1.000
 | | x0: JJ (black) -> noir ### prob=0.600
 | black cat -> le chat noir ### prob=0.600
 my friend 's black cat -> le chat noir de mon ami ### prob=0.306
my friend 's white cat -> *** failed ***
```

This output is available online as `output1-d.txt`. A derivation basically outputs all the rules involved in a tree-like format. For each subtree, we first output the top-level rule, e.g.

```
 NP (DP (x0:NP POS ('s)) x1:NP) -> x1 de x0 ### prob=1.000
```

and then recursively output the sub-derivations for the subtrees corresponding to the two variables (x0 and x1) with one more level of indentation. Finally, we output the best translation for this subtree in the standard format.

There is a more complicated example online.

5.2 Rule Indexing (easy)

In line 5 of Algorithm 1, we enumerate each rule and check if its LHS tree-pattern matches the current tree. This is rather inefficient in general when we have a very large rule set. However, you can index the rules using a dictionary, where the keys are the top-level productions of the tree pattern. For example, for the rule

```
NP (DP (x0:NP POS ('s)) x1:NP) -> x1 de x0 ### prob=1.000
```

the top-level production is

```
NP => DP NP
```

Now when you are translating a tree T whose top-level production is γ, you only need to look at rules indexed under γ (because other rules are certainly incompatible with T).

You can further group rules with same LHS tree pattern together, as a second-level of indexing, which will save some time by reducing redundant calls of `PatternMatch()`.

5.3 k-best translations (challenging but very interesting)

Clearly, there are many possible translations given a ruleset and an input tree. Can you also output the 2nd-best, 3rd-best, or up to kth-best translations? We add another option `-k` to the command line to request "top-k" translations. For example,

```
cat input1.txt | ./translate.py rules1.txt -k 3
```

will output

```
my friend 's black cat -> le chat noir de mon ami ### prob=0.306
my friend 's black cat -> le chat noir de mon amie ### prob=0.294
my friend 's black cat -> le chat noire de mon ami ### prob=0.204
my friend 's white cat -> *** failed ***
```

Note: do not print duplicate translations (say, there might be another way of deriving the best translated string). Be sure to include in `debrief.txt` your algorithm or thoughts if you attempted this question.

References: see (Huang and Chiang, 2005) and (Huang et al., 2006).

6 debrief.txt

1. How many hours did you spend on this project?
2. If you did any extra credit problem, describe your algorithms or methods.
3. If you had discussed with another student, what's his or her name?

References

Huang, Liang and David Chiang. 2005. Better k-best Parsing. In *Proceedings of the Ninth International Workshop on Parsing Technologies (IWPT-2005)*.

Huang, Liang, Kevin Knight, and Aravind Joshi. 2006. Statistical syntax-directed translation with extended domain of locality. In *Proceedings of AMTA*, Boston, MA, August.