Accelerating and Evaluation of Syntactic Parsing in Natural Language Question Answering Systems

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Abstract With the development of Natural Language Processing (NLP), more and more systems want to adopt NLP in User Interface Module to process user input, in order to communicate with user in a natural way. However, this raises a speed problem. That is, if NLP module cannot process sentences in durable time delay, users will never use the system. As a result, systems which are strict with processing time, such as dialogue systems, web search systems, automatic customer service systems, especially real-time systems, have to abandon NLP module in order to get a faster system response. This paper aims to solve the speed problem. In this paper, at first, the construction of a syntactic parser which is based on corpus machine learning and statistics model is introduced, and then a speed problem analysis is performed on the parser and its algorithms. Based on the analysis, two accelerating methods, Compressed POS Set and Syntactic Patterns Pruning, are proposed, which can effectively improve the time efficiency of parsing in NLP module. To evaluate different parameters in the accelerating algorithms, two new factors, PT and RT, are introduced and explained in detail. Experiments are also completed to prove and test these methods, which will surely contribute to the application of NLP.

Keywords: Parsing Algorithm, Evaluation, Corpus Learning, Question Answering, Natural Language Processing

1 Introduction

Natural Language Processing (NLP) is one of the most important fields in Artificial Intelligence researches, and it is applied more and more in application systems. For example, NLP could be used in Question Answering (QA) systems to understand users’ natural language inputs, and communicate with users in a natural way, such as LUNAR [1] and some service systems [2]. These applications have greatly improved the way users interact with computer systems and overcome the disadvantages of traditional QA systems which use pattern matching algorithms, for example ALICE [3].

However, with the development of NLP technology, a big problem has emerged. Most researchers spend a lot of time thinking of how to improve the precision of Part-of-Speech (POS) taggers and syntactic parsers, but there are few researches on how to save CPU time in tagging and parsing without precision decrease. Actually nowadays, NLP is applied more and more in real-time QA systems, such as dialogue, web search, cell phone and PDA etc. [4]. As a result, the processing time problem becomes more and more important for NLP applications, because users need the responses to their requests in an acceptable length of time. In fact, the speed problem is the very reason why most QA systems choose pattern matching algorithm but not NLP methods.

Then, how to accelerate the parsing speed of syntactic parser? A NLP system always includes several parts, such as a stemmer module, a word tagging module, and a syntactic parsing module etc. Many algorithms have been proposed for these modules. As we know, the syntactic parsing takes most of the processing time. So, improving syntactic parsing is one of the most important methods, and the optimization of other modules is also necessary.

Syntactic patterns are needed in syntactic parsing module. But it is possible for humans to construct a syntactic pattern. Firstly, it is hard to define a large amount of syntactic patterns. Sec-
2 Syntactic Parser Construction

In this section, we will introduce how to construct a parser which can learn from corpus, discuss how to parse sentences, and analyze the reason why the speed problem exists.

2.1 Corpus Machine Learning

Syntactic pattern learning generates syntactic pattern dictionary through machine learning from tagged and parsed corpus. In the learning process, all the appeared patterns should be extracted from corpus, and also their appearance counts and probabilities should be recorded for the further processing.

In this paper, $N$ stands for nonterminals, like “S“, “NP”, “VP”, and $N_j$ means $j$-th nonterminal in the nonterminal set.

For each syntactic pattern $N_j \rightarrow \zeta$, where $N_j$ and $\zeta$ are both Part-Of-Speech (POS), $C(N_j \rightarrow \zeta)$ is used to record appearance count of the pattern, and $P(N_j \rightarrow \zeta)$ represents its appearance probability. The following Formula 1 represents the relationship between the two variables:

$$P(N_j \rightarrow \zeta) = \frac{C(N_j \rightarrow \zeta)}{\sum_{\gamma} C(N_j \rightarrow \gamma)} \quad (1)$$

In this equation, $\gamma \in R$ and $R$ is the full POS Pattern Set. So $\sum_{\gamma} C(N_j \rightarrow \gamma)$ stands for the total amount of all the possible patterns which have the same left $N_j$.

2.2 Parsing and Speed Problem

Syntactic Parsing is defined to generate a syntactic tree from a given sentence. For example, we can use chart parsing algorithm to parse sentences, for more details, please see [7], [8] and [9].

In the function “predictor” of chart parsing, patterns with the required left side $N_j$, like “$N_j \rightarrow \gamma$“, are all added into chart to predict next matching pattern. However, if the system has a large syntactic pattern dictionary, a lot of patterns will be added, including both important patterns and unimportant patterns which have low probability to appear. Actually in most cases, the unimportant patterns will contribute nothing to the parsing tree. In other words, it is most likely that the unimportant patterns are not part of the syntactic tree, but they spend most processing time in parsing. As a result, the system will spend much time in processing meaningless patterns and run very slowly.

An efficient method to accelerate speed of parser is to compress patterns set (combine similar patterns) and delete some unimportant patterns from the dictionary. But which patterns should be deleted or kept back is really a big problem, and it will be the main issue of the next section.

3 Accelerating Methods

In parsing experiments on Penn Treebank, for example using chart parsing, it is found that parsers can not parse sentences in durable time, because too many POS, nonterminal and syntactic pattern types have been generated. Obviously it is unacceptable for real-time systems.

There are mainly two solutions to this problem: using Compressed POS Set and Patterns Pruning. In this section, both the two algorithms will be discussed, and experiments will be performed to prove the algorithms.

3.1 Compressed POS Set

Compressed POS Set is a set of POS in which some POS in the full POS set have been combined, in order to decrease the number of different POS types. For example, we can combine “NNS” and “NNP”, so patterns “NP → NNS” and “NP → NNP” will be combined into “NP → NN”. In syntactic patterns, both terminal characters (e.g. NNS, VBD) and nonterminal characters (e.g. NP, VP) are used, so we have to compress both of them to decrease the amount of pattern types and then accelerate the parsing speed.
First, we combine terminals. For Penn Treebank style POS Set, compressed POS Set in table 1 is applied to decrease POS number. The POS in column “Original” will be combined into the POS in column “Compressed”. Thanks to the effect of this table, the number of terminals has decreased from 46 to 27.

Second, we should combine nonterminals. For example, “WHNP-22 → WDT”, “WHNP-23 → WDT”, and “WHNP-24 → WDT” are essentially the same, so they can be combined into one pattern “WHNP → WDT”. So do patterns “NP-SBJ-33 → DT NN”, “NP-SBJ-35 → DT NN” and so on.

Table 2 shows the statistical data of differences between using full POS set and compressed POS set. These data are based on Penn Treebank 10% version, in which there are total 10959 words and 94200 tag-tag pairs. In our experiments, it shows that the amount of tag-tag pair types decreases to 341 using Compressed POS Set, which is only 34% of full POS set. The amount of pattern types decreases to 4947, which is 61.8% of full POS set. The amount of nonterminal types decreases to 232, which is 35.2% of full POS set. The time elapsed in learning decreases by 16.7%. Memory and disk space occupied by learning result have also greatly decreased. All these data prove that Compressed POS Set can effectively improve tagging and parsing speed of a parser in a NLP module.

| Items                  | Full | Compressed |
|------------------------|------|------------|
| Terminal types         | 46   | 27         |
| Dimension of HMM Array | 46×46| 27×27      |
| Tag-tag pair types     | 1003 | 341        |
| Word-tag pairs         | 12726| 11787      |
| Pattern types          | 8001 | 4947       |
| Nonterminal types      | 659  | 232        |
| Time elapsed (ms)      | 60515| 50234      |

Table 2: Comparison of Different POS Sets

3.2 Syntactic Patterns Pruning

Syntactic Patterns Pruning (SPP) is to delete some unimportant patterns from pattern dictionary in order to save parsing time.

Compared with compressed POS Set, SPP is much more important for accelerating parser speed. In parsing process, the seldom appearing patterns waste much CPU time, but contribute nothing to improving precision and recall. So in the case that is strict with processing time and less important with precision, precision could decrease a little by SPP in order to decrease the time elapsed in parsing. That is a balance between precision and speed. Actually, in most cases, users input short sentences instead of long sentences or complex sentences in Penn Treebank, so the parsing precision will not decrease greatly.

There are mainly three ways for SPP, which will be discussed as follows.

3.2.1 SPP on times thresholds

This method defines a threshold of pattern’s appearance times, and prunes patterns whose appearance times are less than the threshold. Table 3 shows the relationship between the threshold value and the amount of pattern types after pruning. And the relationship is also depicted in Figure 1 according to the data in the table.

According to the data in the Table 3, along with the elevation of threshold, the amount of both pattern types and nonterminal types decrease obviously, but the amount of patterns appearance times decreases only a little. For example, at the point \( N = 50 \), the amount of pattern types decreases to 3.23% of all pattern types, and the amount of nonterminal types decreases to 15.9% of all types, but...
the amount of pattern appearance times only decreases to 80% of all patterns.

The reason is that many patterns seldom appear, maybe only one or two times, and these patterns can not greatly improve the precision of the syntactic parser, but waste a lot of processing time. As a result, these patterns should be removed from pattern dictionary in order to improve speed.

In Figure 1, in N section [15, 50], the curve starts to change much more smoothly. Our experiment in the later section shows that the precision of the parser is still acceptable at the point \( N = 50 \).

After pruning, the remaining patterns are mainly like “NP \( \rightarrow \gamma \)” and “VP \( \rightarrow \gamma \)”, because NP and VP appear in the corpus much more frequently than other nonterminals do.

3.2.2 SPP on probability threshold

This method defines a threshold of pattern appearance probability, and prunes patterns whose appearance probability is smaller than the threshold. Table 4 shows the relationship between the threshold and the amount of pattern types. And the relationship is also shown in Figure 2 according to the data in the table.

According to the data in the Table 4, along with the elevation of threshold, the amount of pattern types decreases greatly, and the amount of patterns appearance times also decreases, but the amount of nonterminal types hardly decreases, especially in the section [0, 10\%] where it does not decrease at all. For example, at the point \( P = 10\% \), the amount of pattern types decreases to 7.43\% of all pattern types, and the amount of patterns appearance times decreases to 47.7\% of all patterns, but the amount of nonterminal types does not decrease.

The reason is that, the sum of the probabilities of all the patterns with the same left side equals to 1:

\[
\sum_\zeta P(N^j \rightarrow \zeta) = 1
\] (2)

As a result, when pruning on appearance probabilities threshold, if the threshold \( P \) is small, nonterminals will not be pruned, such as at the point \( P = 10\% \). But when the threshold is elevated, the patterns with the same left side and different right side, in which different constitutions of right side appear comparatively, will be pruned first. Unfortunately, these patterns are always the most common and important patterns. For example, an unimportant pattern only appears once, then its probability is 100\%, and it will not be pruned. So, nonterminals missing should be avoided if this

| Threshold P | PA | PT | NT |
|------------|----|----|----|
| \( P=0.00\% \) | 73460 | 4947 | 232 |
| \( P=0.60\% \) | 60459 | 1081 | 232 |
| \( P=2.00\% \) | 51568 | 728 | 232 |
| \( P=5.00\% \) | 45784 | 457 | 232 |
| \( P=10.00\% \) | 35057 | 368 | 232 |
| \( P=15.00\% \) | 26042 | 315 | 229 |
| \( P=20.00\% \) | 23573 | 284 | 223 |
| \( P=40.00\% \) | 17071 | 213 | 198 |
| \( P=80.00\% \) | 10329 | 139 | 139 |

Table 4: SPP on Probability Threshold
Table 5: Mixed SPP

| Threshold N | Threshold P | PA    | PT  | NT |
|-------------|-------------|-------|-----|----|
| 30          | 5%          | 44226 | 79  | 44 |
| 20          | 5%          | 44650 | 96  | 54 |
| 10          | 5%          | 45081 | 125 | 69 |
| 10          | 4%          | 46514 | 137 | 69 |
| 10          | 3%          | 47049 | 147 | 69 |
| 10          | 2%          | 50345 | 170 | 69 |

Method is adopted. In other words, a low threshold should be defined.

In the Figure, in P section [5, 10], the curve starts to change much more smoothly. Our experiment in a later section shows that the precision of syntactic parser is still acceptable at point \( P = 5 \).

### 3.2.3 Mixed SPP

When we use SPP on appearance probability threshold, a great number of syntactic patterns have to be reserved in order not to miss any non-terminals, which will slow down speed of parser. So Mixed SPP method, which prunes on both appearance times threshold and probability threshold, could be adopted to keep the advantages of both methods.

For example, if patterns which appear less than 30 times or have a probability of less than 5% are pruned, there are 44 nonterminals and 44226 patterns left, which belong to 79 pattern types. In this case, a syntactic parser can hardly correctly parse very long sentences, but can effectively parse short sentences, which actually are most frequently used by users, very fast and precisely. For example, simple sentences could be parsed correctly, such as "The journal will report events of the past century" and "I want to find a job" etc.

Table 5 shows the relationship between the values of two thresholds and the amount of pattern types.

### 4 Evaluation

In previous sections, it has been demonstrated that Compressed POS Set and SPP can accelerate parsers’ speed very effectively. But because of the different definitions of thresholds \( N \) and \( P \), parsers with different thresholds will perform differently. A certain evaluation method should be proposed to evaluate different \( < N, P > \) pairs for Mixed SPP Method.

In this section, two new evaluation factors are defined to describe parsers’ efficiency. The higher its value is, the faster and more accurate the parser is.

#### 4.1 PT Factor

As what has been discussed in the previous sections, in order to accelerate parser, we should keep a balance between speed and precision, through using Compressed POS Set and SPP algorithm.

To get a high score in efficiency evaluation, parsers should process sentences correctly as many as possible in a time unit. Parameter \( \mu \) is defined to represent this concept:

\[
\mu = \frac{C^+}{T}
\]

In the formula, \( C^+ \) represents the amount of syntactic patterns correctly parsed by parser, and \( T \) represents the time elapsed in parsing.

Assume that parameter \( C \) represents the total amount of parsed syntactic patterns, including both correctly and incorrectly parsed patterns. Because tests on different parsers are based on the same test set, \( C \) values are equal. As a result, the ratio of \( \mu_1, \mu_2 \) equals to the following:

\[
\frac{\mu_1}{\mu_2} = \frac{C^+_1 T_2}{C^+_2 T_1} = \frac{C^+_1}{C^+_2} \frac{T_2}{T_1}
\]

Besides, the precision of a system, defined as \( P \), should be computed as the following:

\[
P = \frac{C^+}{C}
\]

So, formula 4 is transformed into the following formula:

\[
\frac{\mu_1}{\mu_2} = \frac{P_1}{P_2} \frac{T_1}{T_2}
\]

Here, magnitude of \( \mu \) is decided by the ratio of precision and time. So, factor \( PT \) is proposed to evaluate time efficiency of a parser, which is defined as the following:

\[
PT = \frac{P}{T}
\]

where \( P \) represents precision of parsing, and \( T \) represents time elapsed in parsing. An efficient parser should be of higher \( PT \) value.
4.2 RT Factor

Obviously, PT factor can evaluate parsers effectively. However, this situation exists: as a result of too much pruning, along with great decrease of time elapsed, precision also greatly decreases. In this situation, PT value is nearly the same as parser with high precision. To solve this problem, the balance between recall and speed should also be evaluated. That means, parser should correctly recall as many syntactic patterns as possible in a time unit. Variable $\lambda$ is defined to represent this concept:

$$\lambda = \frac{C^+_r}{T} \quad (8)$$

where, $C^+_r$ represents the amount of syntactic patterns correctly recalled by parser, and $T$ represents time elapsed in parsing. Also, tests on different parsers are based on the same test set, so $C$ values are equal. As a result, the ratio of $\lambda_1, \lambda_2$ equals to the following:

$$\frac{\lambda_1}{\lambda_2} = \frac{C^+_1}{C^+_2} \frac{T_2}{T_1} \frac{T_1}{C} \frac{C}{C^+_1} \quad (9)$$

The recall rate of the system, which is defined as $R$, should be computed as the following:

$$R = \frac{C^+_r}{C} \quad (10)$$

So, formula 9 is transformed into the following formula:

$$\frac{\lambda_1}{\lambda_2} = \frac{R_1}{T_1} \frac{R_2}{T_2} \quad (11)$$

Here, magnitude of $\lambda$ is decided by the ratio of recall rate and time elapsed. So, factor RT is also proposed to evaluating time efficiency of parser, which is defined as the following:

$$RT = \frac{R}{T} \quad (12)$$

In this formula, $R$ represents recall rate of parser, and $T$ represents time elapsed in parsing. RT represents the amount of correctly recalled patterns in a time unit. An efficient parser should be of higher RT value also, not only higher PT value.

The following example shows how to compute PT and RT values. A test, in which compressed POS set is used and the patterns that appears less than 50 times has been pruned, has been performed on the first 5854 lines of Penn Treebank. The precision of syntactic parsing is: $247/691 = 35.7\%$, and the recall rate is: $247/761 = 32.5\%$, 4048 seconds elapsed in the test. So PT and RT values could be calculated as follows:

$$PT = \frac{35.7}{4048} = 0.0088 \quad (13)$$

$$RT = \frac{32.5}{4048} = 0.0080 \quad (14)$$

Our experiment in the next section will discuss how to choose parameters in order to increase PT and RT values.

5 Experiments

Our experiments are performed on 10% version of Penn Treebank, obtained from NLTK [10]. Compressed POS Set is adopted in all the following experiments.

Firstly, precision of our tagger is tested on the first 9988 lines of Penn Treebank, and the result is 9479/9784 = 96.88%.

Then, parsers with different thresholds are tested on the first 5854 lines:

1. Threshold N=50, Precision = $247/691 = 35.7\%$, Recall = $247/761 = 32.5\%$.
2. Threshold N=60, Precision = $235/662 = 35.5\%$, Recall = $235/761 = 30.9\%$.
3. Threshold P=60%, Precision = 0, Recall = 0.
4. Threshold P=5%, Precision = $30/94 = 31.9\%$, Recall = $30/761 = 3.9\%$.
5. Threshold N=10, P=2%, Precision = $72/208 = 34.6\%$, Recall = $72/761 = 9.5\%$. Although test (5) gets a lower recall than (1), its parsing speed is far faster than (1).

All the related data of the tests is summarized in Table 6 and Table 7. Of the five tests, test (5), in which the amount of pattern types is about the same as other tests or even less than the others, has nearly both the highest PT and RT values. So thresholds in test (5) are the best parameters in the test for system which is strict with processing time.

But in the cases that systems are not strict with processing time, the pruning algorithm with lower PT and RT value but higher precision and recall should be adopted. For example, in the case of ignoring small differences of precision and recall between test (1) and test (2), test (2) is better than test(1).

Actually, in real systems, users always input short sentences, so precision and speed will be much higher than these experiments.
| Threshold N | Threshold P | Pattern Types | Precision | Time Elapsed | PT Value |
|------------|-------------|---------------|-----------|--------------|----------|
| 50         | 0%          | 160           | 35.7%     | 4048.578s    | 0.0088   |
| 60         | 0%          | 139           | 35.5%     | 3091.563s    | 0.0115   |
| 0          | 60%         | 163           | 0         | 250.421s     | 0        |
| 0          | 5%          | 457           | 31.9%     | 249.359s     | 0.1281   |
| 10         | 2%          | 170           | 34.6%     | 278.329s     | 0.1245   |

Table 6: PT Value after Pruning

| Threshold N | Threshold P | Pattern Types | Recall | Time Elapsed | RT Value |
|------------|-------------|---------------|--------|--------------|----------|
| 50         | 0%          | 160           | 32.5%  | 4048.578     | 0.0080   |
| 60         | 0%          | 139           | 30.9%  | 3091.563     | 0.0100   |
| 0          | 60%         | 163           | 0      | 250.421      | 0        |
| 0          | 5%          | 457           | 3.9%   | 249.359      | 0.0157   |
| 10         | 2%          | 170           | 9.5%   | 278.329      | 0.0342   |

Table 7: RT Value after Pruning

6 Future Work

In the future, more accelerating algorithms should be proposed to improve parser, which will greatly promote the application of NLP technology, especially in real-time systems. These methods may include:

1. Determine the importance level of syntactic patterns by their content and constitution. For example, some patterns frequently appear in written English corpus but seldom appear in oral English or user input, so these patterns should be removed from the dictionary and that will not influence precision and recall.

2. Instead of chart parsing, a new parsing algorithm may be proposed for the new speed demands. In the new algorithm, the disadvantages brought by step “predict” should be avoided.

As to the evaluation, actually, in different application background, different evaluation factors should be defined for the specified circumstance. In other words, Precision and Recall are not the only things we should pay attention to.

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