**A pruning hierarchical graph method using in A\* algorithm in Vietnamese parsing technique**

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*Abstract* — this paper presents our research on pruning hierarchical tree method in A\* (A-star) in Vietnamese parsing technique in order to improve the speed of Vietnamese parsing system. Based on the virtual node method proposed in [ref], we will describe our replace method: pruning hierarchical tree method. Unlike the virtual node method, PHGM process only significant candidates and do not generate new redundancy candidates for each step of A\* algorithm. With this method, the speed of parsing system could be improved so much.

Keywords – A\*, parsing technique, PHGM, algorithm, Vietnamese

# Introduction

### [Probabilistic context free grammar](http://www.cs.utexas.edu/%7Emooney/cs388/slides/stats-parsing.ppt) (PCFG) and lexical probabilistic context free grammer (LPCFG) in parsing technique are very well-known models. In the parsing system using these models, the final result is determined based on the score of candidates. The candidate with highest score will be the predict outcome. With these models, especially LPCFG, the accuracy of parsing system is relatively high. However, when dealing with wide-coverage grammars and very long sentence, the parsing process is very complicated and the cost for processing time is too expensive. To solve this problem, many speedy algorithm has been researched to reduce the work. Some of them like Beam Search, Greedy algorithm, and Dijkstra algorithm. But all of algorithms above also have its problem. Beam Search use the beam to remove the underrated candidates, so it is not guaranteed to find the best result. The Greedy algorithm only follows the best path in each step, so it got a very fast parsing time but it cannot be guaranteed to find the best result, too. The Dijkstra algorithm will find the best result, but its speed, in many cases, is too slow.

### A\* parsing algorithm which proposed by Dan Klein and Christopher D.Manning could correct those two problems: best result and speed. A\* which is belong to Best-First-Search algorithm group is considered as one of the best searching algorithm in the world. It uses a heuristic f(x) to determine the best candidate for each step of parsing process:

f(x) = g(x) + h(x)

In which:

g(x) - the path-cost function, which is the cost from the starting *node* to the current *node*.

h(x) - an admissible "heuristic estimate" of the distance to the goal.

And the most important figure is h(x), it will determine how fast the parsing process leads to the target.

There are many algorithms which have been researched and developed in Vietnamese like Beam Search, Greedy algorithm and Machine learning... But in our knowledge, there is no research about A\* algorithm. So, A\* algorithm for parsing is a good choice to research.

In this paper, we present you two main major parts. The first major heading presents about A\* parsing algorithm. The second major heading which is a mainly focus of our research, presents you about the pruning hierarchical tree method, denoted as PHGM. This method is a replacement for the classical virtual node method in order to reducing the estimating cost of parsing process. Therefore, the speed of A\* parsing algorithm could be improved.

Some abbreviations:

G – The grammar rules. Each production in G has a corresponding weight w.

POS – part of speech, is a tag which appears in G

# A\* ALGORITHM FOR PARSING

## Basic concept

A\* algorithm operates on basically items called “*node*”. A *node* includes three attributes: *name, start,* and *end.* *Name* attribute indicates the POS of *node*. And the attribute couple (*start, end*) is the start and end position of the text which is covered by *node* in the sentence. Its format is *name* [*start, end*].

The parsing system maintains two data structures: a chart (note as CHART) which records *nodes* for which (best) parses have already been found, and an agenda of newly-formed *nodes* needs to be processed (note as AGENDA).

The initial CHART is empty.

The input string is tokenized into *n* words a1…an. And then, these words are POS tagged to create an initial AGENDA: *{(Xi [i, i+1], wi ),}*, wi is an initial weight of each tagged word Xi.

A context for *node* X[i,j] (with input string a1…an) is a parse tree whose leaf nodes labels with a1…ai-1Xaj...an. The weight of a context is sum of the weights of the productions appearing in the parse tree. A function h(X[i,j]) - a real number will be called an admissible heuristic for parsing if h(X[i, j]) is a lower bound on the weight of any context for X[i, j].

## A\* parsing process

While AGENDA is not empty and CHART does not contain S [1, n+1] (S is a POS of sentence) do

*Remove a candidate node (Y[i,j],w) with highest w + h(Y[i,j]*

*If CHART does not already contain Y[i,j] then:*

*\* Combine Y with AGENDA (1)*

* For each *node* (Z[j,k],w’) in CHART where G contains a production , add the *node* (X[i,k], w+w’+w’’) to AGENDA.
* For each *node* (Z[k,j], w’) in CHART where the G contains a production , add the *node* (X[k,j],w+w’+w’’) to AGENDA.

*\* Add (<Y,i,j>,w) to CHART*

Final, if AGENDA contains an assignment to (S,1,n+1) then the parsing process is successful (a parse has been found) else terminate with failure (there is no parse).

# pruning hierarchical tree method (PHGM)

## The context for proposition

In step (1), here are two situations that happened when combining candidate *node* with CHART:

*The relevant production is a Chomsky-form,* means that it has *less-than or equal to* two elements on the extension part. In this case, the combination follows step (1) in A\* algorithm.

*The relevant production is not a Chomsky-form;* it has more than two elements on the extension part. In this case, the parser uses a virtual node method (VNM) with the *wait* parameter which denotes the *POS tags* which are remained to complete the rule. It means that when A *node* and B *node* are combined together using a rule like “E → A B C D”, they will form a virtual *node* E[wait = “CD”]. Later, if the virtual node E[wait=”CD”] meets C *node*, this combination will form the *node* E[wait=“D”].

After the parsing process ends, the successful of parsing process will be determined if the *node* S[1,n+1,wait=“”] is founded in CHART.

The problem is that the cost of VNM is too expensive to deal with. Because of the huge of the grammar rules (approximately over 10000 rules!!), the combination using VNM will generate a large quantity of redundancy *nodes.* Specified as table 1, the combination of two instance elements has formed so many new elements, and only few of them are significant.

1. all the *nodes* was formed when combined N(2,7) and V(7,8)

|  |  |
| --- | --- |
| *NP[2,8, wait=""]* | *NP[2,8, wait=", A"]* |
| *NP[2,8, wait="AP"]* | *NP[2,8, wait="AP NP"]* |
| *NP[2,8, wait="AP PP"]* | *NP[2,8, wait="MP"]* |
| *NP[2,8, wait="N"]* | *NP[2,8, wait="NP"]* |
| *NP[2,8, wait="NP PP"]* | *NP[2,8, wait="NP VP"]* |
| *NP[2,8, wait="P"]* | *NP[2,8, wait="PP"]* |
| *NP[2,8, wait="PP PP"]* | *NP[2,8, wait="VP"]* |

## The PHGM model

### The basic idea

Instead of using VNM, PHGM uses *combinable chain* to overcome the *Chomsky production*. A *combinable chain* is a *node* sequencewhich has the continuous position*.* For example, a simple combinable chain: (NP[1,3] PP[3,5] VP[5,8]). In PHGM model, all the combinable chains of a candidate *node* and CHART will be used in step (1) of A\* algorithm. Unlike virtual node method, PHGM model does not form the redundancy virtual *nodes* and it decreases the number of *node* in parsing process.

For instance, the candidate *node* has the start-end position as X[7,10] and the content of CHART has been shown in Table 2.

1. the *nodes in* CHART

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| X1[1,8] | X2[6,16] | X3[13,35] | X4[5,20] | X5[2,7] | X6[10,11] |
| X7[8,27] | X8[2,21] | X9[9,11] | X10[2,13] | X11[6,14] | X12[15,26] |
| X13[14,23] | X14[5,18] | X15[1,7] | X16[9,16] | X17[12,17] | X18[7,18] |
| X19[6,25] | X20[13,26] | X21[11,26] | X22[9,24] | X23[11,20] | X24[8,18] |
| X25[7,16] | X26[14,16] | X27[4,6] | X28[13,21] | X29[4,8] | X30[11,13] |

From this input data (candidate and CHART *nodes* position), the PHGM will process and use the combinable chains which are presented in Table 3:

1. the combinable chains of the candidate with CHART *nodes.*

|  |  |  |
| --- | --- | --- |
| 1 | Position | *node* |
| 2 | [2-7] **[7-10]** | X5**X** |
| 3 | [1-7] **[7-10]** | X15**X** |
| 4 | [1-7] **[7-10]** [10-11] [11-13] | X15 **X** X6 X30 |
| 5 | [2-7]**[7-10]**[10-11] [11-13] [13-26] | X5 **X** X6 X30 X20 |
| 6 | **[7-10]** [10-11] [11-20] | **X** X6 X23 |
| 7 | **[7-10]** [10-11] [11-13] | **X** X6 X30 |
| 8 | **[7-10]** [10-11] [11-13] [13-26] | **X** X6 X30 X20 |
| 9 | **[7-10]** [10-11] [11-13] [13-21] | **X** X6 X30 X28 |
| 10 | [2-7] **[7-10]** [10-11] | X5 **X** X6 |
| 11 | [2-7] **[7-10]** [10-11] [11-16] | X5 **X** X6 X21 |
| 12 | [2-7] **[7-10]** [10-11] [11-20] | X5 **X** X6 X23 |
| 13 | [2-7] **[7-10]** [10-11] [11-13] | X5 **X** X6 X30 |
| 14 | **[7-10]** [10-11] [11-16] | **X** X6 X21 |
| 15 | [1-7] **[7-10]** [10-11] | X15 **X** X6 |
| 16 | [2-7] **[7-10]** [10-11] [11-13] [13-21] | X5 **X** X6 X30 X28 |
| 17 | [1-7] **[7-10]** [10-11] [11-16] | X15 **X** X6 X21 |
| 18 | [1-7] **[7-10]** [10-11] [11-20] | X15 **X** X6 X23 |
| 19 | **[7-10]** [10-11] | **X** X6 |
| 20 | [1-7] **[7-10]** [10-11] [11-13] [13-26] | X15 **X** X6 X30 X20 |
| 21 | [1-7] **[7-10]** [10-11] [11-13] [13-21] | X15 **X** X6 X30 X28 |

Thus, assuming that there is a production (A → X5 **X** X6 X30 X28)relevant to the 16th chain in the table 3, the *node* A(2,21) will be formed and will be added to AGENDA.

### PHGM combinable-chains generator model

PHGM combinable-chains generator model includes two phases: *classification phase* and *combinable chains generation phase*.

*Classification phase* (CP)(1): the parser classifies the *nodes* in CHART into the difference blocks.

*Combinable chains generation phase* (CGP)(2): the parser generates all the combinable chains and uses them to create a new *node* which is added into AGENDA.

#### Classification phase

The PHGM classification phase is based on *pigeon hole sort* algorithm idea. There are holes which are created for adding pigeon. But the holes in PHGM are used for CGP(2) instead of sorting.

The holes in the PHGM are divided into two types: the *left hole*s and the *right hole*s (Figure 1). Let assuming that X is a candidate *node*.

We have two kind of *node* in CHART:

* *Left node of X*: This is a set of *nodes* that have their *end* position <= *start* position of X. All the *nodes* which have the same *end* position will be grouped in a block labeled as *end* position of them*.* And a set of all these blocks is called as *left holes*.
* *Right node of X*: This is a set of *nodes* that have their *start* position >= *end* position of X. All the *nodes* that have the same *start* position will be grouped in a block labeled as *start* position of them*.* And a set of these blocks is called as *right holes*.

#### Combinable chains generation phase

With the input as the classified CHART, the parsing system begins generating the combinable chains. This phase includes three main parts: “generating *left chain*s”, “generating *right chain*s” and “*generating combinable chains*”.

***1. Generating left chains****:* this module generates all the combinable chains which end with candidate X, it is called as the *left chain*s. We imply that S(E) is the block in a ***left hole*** which is labeled as a *start* position of node E. This part can be described as below:

* Parsing system processes the X *node*, save the left combinable chain corresponding to X and get the S(X) from *left holes*.
* This progress is done recursively for all the *nodes* in the S(X).

Figure 1 – The instance example for generating *left chain*s.

***2. Generating right chains****:* the same progress as the “generating *left chain*s” is realized.

Figure 2 – The instance example for generating *right chain*s.

We imply that E(S) is the block in a ***right hole*** which is labeled as a start position of node S. This part can be described as:

* Parsing system processes the X *node*, save the right combinable chain corresponding to X and get the E(X) from *right holes*.
* This progress is done recursively for all the *nodes* in the E(X).

***3. Generating combinable chain****:* from two first phases we got the *left chain* and *right chain* of the candidate. The connection of three factors “*left chain*”, “*right chain*” and X will form the real combinable chains of X.

## Pruning graph in PHGM model

As mentioned above, PHGM model is proposed in order to improving the speed of parsing system, to reduce the number of *node* in parsing process. However, the PHGM model is still not optimal because of the combinable chain redundancy.

From our experiment on testing performance of PHGM model, we found that there are approximately 8% of the combinable chains that could be used. Because of this, PHGM model is not only slower than virtual node algorithm in some case, but also got stuck when the number of CHART is high.

To solve this problem, PHGM model uses a pruning graph. Instead of processing all the combinable chains, the parser will use this graph to prune the redundancy combinable chains; it means that they are not relevant to any production in G. This algorithm is not only increasing the speed of parser but also reduce the complication of parsing process.

### The idea

A *node* has two informations: position and POS. PHGM basic model only uses the *node* position to generate chain, but the POS of *node* is not used.

For instance, if we have two nodes: NP(1,7) and PP(1,7). In the basic PHGM model, they are just the same, even their POS is difference. So, a pruning graph in PHGM model will show you how to use the POS to reduce the processing time of PHGM.

The algorithm using pruning graph in PHGM model includes two phases:

* *Statistic training phase*: create a pruning graph with the training corpus is G.
* *Pruning phase*: integrate pruning graph into PHGM model.

### Statistic training phase

As described, the training data of the PHGM pruning graph is G.

Specifically, with each “T” POS in G, the system creates two graphs:

#### The left-POS graph

The left-POS graph of “T” POS is a graph which stores the information about the POS being left-adjacent to “T” POS in G.

The creating algorithm of left-POS map:

* Process all the productions in the graph.
* For each production whose extension part likes [Pn … P2 P1 T…]:
  + - If P1 is not child of T, then add P1 into T children.
    - For i from 2 to n: if Pi is not child of Pi-1, then add Pi into Pi-1 children.

#### The right-POS graph

The right-POS graph of “T” POS is a graph which stores the information about the POS being right-adjacent to “T” POS in G.

The creating algorithm of right-POS map:

* Process all the productions in the graph.
* For each production whose extension part likes […T P1 P2 … Pm]:
  + - If P1 is not child of T, then add P1 into T children.
    - For i from 1 to m: if Pi is not child of Pi-1, then add Pi into Pi-1 children.

### Pruning phase

As described, the PHGM model uses the combinable chain to overcome the Chomsky problem. For each loop step, the candidate *node* from AGENDA combines with the *nodes* in CHART through three major part: “Generating left chains”, “Generating right chains” and the collection part of those two “Generating combinable chains”.

The input is still the classified CHART; The PHGM process will perform normally with the support of pruning graph. The system get pruning graph for POS of candidate *node* and use it to prune the bad combinable chains (cannot lead to any production) at two phase “generating left chains” and “generating right chains”. With an X *node*, if S(X) contains any *node* whose POS is not contained in “X” POS children in pruning graph, they will be pruned. The figure 3 below is an illustration of pruning graph in the PGHM model.

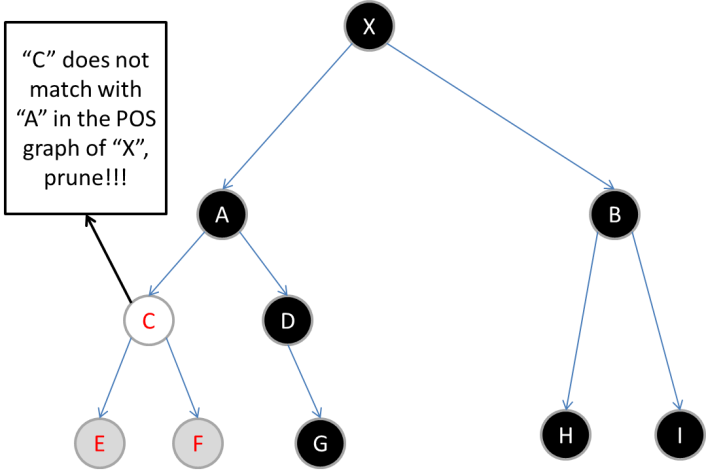


Figure 3 – the illustration of the PHGM model using pruning graph.

# experiment and result

This section presents the preparation and the result of experiment to illustrate the performance of A\* parsing algorithm using PHGM model.

## Preparation for experiment

Training corpus

Testing corpus

Test case

## Results

# conclusion and future works

# acknowledgements

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