Context-dependent Natural Language Processing Based on Scene Analysis

（場面解析に基づく文脈依存自然言語処理）

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Abstract

We present a new framework for using scene knowledge in context-dependency analysis for natural language processing, together with an implementation method for its application to the machine translation of narrative stories.

The need for research on context dependency in natural language processing is widely acknowledged in the fields of computing, linguistics and psychology, but the problems are difficult, and progress is slow. The generality of existing frameworks is also poor, in that the only exstensible theories are those which can be adapted to resolving simple anaphora in highly specific application domains. These frameworks are based on syntactic rather than semantic methods, and so are difficult to extend to more complex context analysis such as those that require more general word sense disambiguation.

Here we classify the role of contextual knowledge according to its use, and examine the effectiveness of scene knowledge as a component of more general contextual analysis. We articulate measures for evaluating the advantages of using scene knowledge for word sense disambiguation. The evaluation is based on our concept of a scene identification method based on discourse structure analysis, which is tested on its application to real stories. The resulting system extracts "scenal" discourse segments from texts both by indentifying appropriate scenes and judging their breaks. Scene identification consists of three parts: detection of cohesive relations among words, determination of subject focus, and scene expectation according to lexical cohesion.

Our results show that scene knowledge is measurably effective for word sense disambiguation, and that the proposed scene identification method is relatively reliable within the scope of automatical coherence analysis.

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Chapter 1

Introduction

1.1 Objective and Background

Natural language processing systems generally require context-dependent disambiguating process for the following reason. As natural language is a mean of communication between people, it must provide efficient and smooth communication. Thus in most cases, it uses simple representation, assuming interpersonal common knowledge. However, such efficient communication produces problems of interpreting ambiguity in natural language. These problems appear in sentences as homonym, polysemy, ellipsis, anaphora, structural ambiguity and so on; they can be combined to cause more complex problems. To determine intended meaning in such cases leads to two issues: explosion in search space and impossibility of disambiguation. Consequently, for efficient search and acquisition of intended interpretation one must use context knowledge to change the search ordering so that more plausible candidates would be checked earlier.

The need for the research on context dependency in natural language interpretation is widely acknowledged in the field of computing, linguistics and psychology[1, 2, 3]. Yet, the problems are difficult, and progress is slow. The generality of existing frameworks is also poor, in that the only extensible theories are those which can be adapted to resolve simple anaphora in highly specific application domains. Most methods to resolve these anaphoric problems are based on syntactical analysis and do not need common semantic knowledge. However, solution to other types of context dependent problems like word sense ambiguity requires broader knowledge and appropriate processing methods.

Contrary to these traditional methods, two approaches have been recently proposed:

1. Cognitive and Linguistics

2. Statistical and Memory-based Translation

As for examples that handle such wide context explicitly, there is a few researches with cognitive approch and liguistical approach; the research with cognitive approach uses scripts, goals, and plans as knowledge context to constraint meanings of narrative stories; the research with linguistical approach analyzes discourse structures of stories to determine the precise mechanism of text-reading process in human information processing. However, these only propose how to represent knowledge context, showing neither proposals for processing methods with classified knowledge, nor robust acquisition method on real texts.

Other researchers use statistical or memory-based approaches without explicitly handling such context knowledge. Their systems are nevertheless poor in the ability of understanding precise relations in stories.

Consequently, research on novel systems which process and understand such complex relations is now needed.

Here we present a new framework for using scene knowledge in context-dependency analysis for natural language processing, together with an implementation method for its application to the machine translation of narrative stories.

1.2 Approach

Human communication is mostly based on everyday behavior. Hence it needs to deal with both inter-lingual and extra-lingual knowledge with adequate processing. This fact also applies to machine translation.

Among these types of knowledge, inter-lingual knowledge exists with strict form and its rule-based processing method, *i.e.* grammar and traditional parsing. Its ease of use has rapidly boosted the investigation into it up to the present day. Consequently such progress in rule-based method consequently produced powerful machine translation systems.

However, such logical processing is time consuming. We humankind can effectively understand situations by communication with reduced representations, assuming extra-lingual knowledge as common. Recent researches on machine translation lack the capability to such extra-lingual knowledge. Thus the traditional machine translation systems have two main disambiguation problems:

1. Low reliability
2. Low measurable efficiency

On the other hand, extra-lingual knowledge lacks visible form, especially in semantics. It has not been dealt with owing to the difficulty on defining and processing concepts.

This difficulty arise from the gap between the complexity in liguistics and the uniform traditional framework. Now it is necessary to divide this extra-lingual knowledge into several categories according to the differences on their processing type. From this, we approached the problem in the following way.

Firstly, we classify the role of contextual knowledge according to its use, and propose a way to represent scene knowledge as one kind of extra-lingual knowledge. The spatial scene knowledge is generally considered to be obvious in our daily communication. However, we must mention that such kind of knowledge often escapes our notice and sometimes we by ourselves leave it out without any representation. To make up the semantic gaps, we use common knowledge like 'scene'. This knowledge corresponds to R.Schank's *Script*. Schank takes a top-down approach by previously describing series of our typical actions in each scene, and storing it as a template. Hence his approach has difficulty in robustness to various stories, and lacks methods of constructing such knowledge. Thus we provide a way to get the knowledge source and to represent the knowledge context on translation systems. We also propose a robust method applied to real texts from narrative stories, with bottom-up approach.

Secondly, we examine the effectiveness of the knowledge as a component of more general contextual analysis.

Thirdly, we articulate measures for evaluating the advantages of scene knowledge for word sense disambiguation.

Lastly, we evaluate our concept of scene identification method based on discourse structure analysis, which is tested by applicating it to real stories.

Our method reduces the semantic ambiguity of words, imitating human text-reading process. It is also applicable to other disambiguation problems which require relatively highly abstracted relations, *i.e.* spatial-temporal relations and causal relations.

We illustrate the method of disambiguation by spatial scene, by example sentences from real texts(Fig.1.1). The current scene is specified by the first sentence as 'kitchen' (with ellipsis resolution). Here the system is required to set ordered priorities to the meaning of the word 'table' in the paragraph; the correct sense 'furniture table' is natural to be output from the system prior to another sense 'mathematical table'. The system uses the information 'table : furniture' in the kitchen scene knowledge, or the information that the frequency of the category 'furniture' exceeds other categories. The system prepares the table of words-senses pairs and the semantical distribution for each scene, and set priorities to the words' meaning calculating the likelihoods. The whole data flow of our

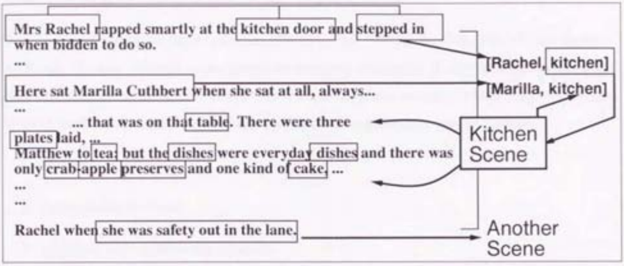


Figure 1.1: Noun disambiguation based on scene discourse analysis

proposing method and the architecture are illustrated in Fig. 5.1. It distinguishes itself from traditional natural language systems in the point that it identifies scenes by extracting discourse structures from stories, and set priorities to senses of words in the current and the following sentences according to its likelihood with the identified scenes.

1.3 Points of Originality

Our approach has the following points of originality:

1. to classify the role of contextual knowledge according to our associative processing.
2. to propose a way to represent scene knowledge as one kind of extra-lingual knowledge.
3. to provide a way to get a knowledge source and to represent a knowledge context on translation systems.
4. to propose a robust method applied to real texts from narrative stories, with bottom-up approach.
5. to implement on a system and evaluate our concept of scene identification method based on discourse structure analysis, which is tested by application to real stories.

1.4 Target Field of Our Approach

Our approach seeks to implement an efficient and reliable machine translation system. Although the aim is word sense disambiguation in sentences, it also provides a basis for resolving ambiguity in various fields. The current application fields which require development of such fundamental technologies in natural language processing include:

1. Machine translation
2. Information retrieval
3. Dialogue and multimedia interface
4. Text-processing support and information extraction

We will first summarize the target and the requirements in each field and later show how to apply our method to those requirements.

1. Machine translation :

   Machine translation is intended to translate sentences from a a source language into other target languages as precise and fast as possible. The current systems can produce a large amount of high-level output in many restricted, but are nevertheless useful, and in appropriate circumstances. A typical application is the translation of electrical manual documentations. Moreover, there is research on conference registration systems with limited amount of vocabularies and restricted class of grammar; there is room for improvement with these restrictions and the processing speed.

   However, their flexibility is poor, and their target fields and complexity of grammar are limited. Research on methods for translating highly-structured sentences with robustness to handle non-grammatical phrases is now desired. This would require the following subgoals:

   (a) to define word meanings appropriately
   (b) to develop evaluation methods of the output quality
   (c) to acquire knowledge from dictionaries and large corpora
   (d) to acquire a large number of bi-lingual corpus pairs
   (e) to construct a flexible framework for grammar

(f) to abstract and classify knowledge

2. Information retrieval :

   Users retrieve documents through index descriptions referring either to the full documents or surrogates like abstracts. Index descriptions may, in the limit, be the documents or surrogates themselves or, more commonly, be extracted natural language items for example, keywords or phrases, or items from a controlled vocabulary like a thesaurus or list of subject headings. Among these descriptions, keywords have been manually extracted or assigned in traditional way.

   However, as it is time consuming and less reliable to assign keywords with such approach to every document, an algorithm of automatic extraction and assignment of keywords is desirable. For this automatic labeling, both statistical and symbolic approaches have been proposed. In addition, some sequence ordering process of the retrieved documentations is often required, since it is time consuming to look precisely through them or, the amount of documentations may even exceed the range of our display peripherals.

   Therefore, there are some reseaches on extracting user's current topic and abstracting contexts of stored documents. Based on these, users can retrive appropriate documents with matching algorithm.

3. Dialogue and multimedia interface :

   In the field of man-to-machine dialogue and multimedia, natural interfaces on systems without jerky are desired. Realtime requirements focus attention on to efficient proceesings of various types of data like visions, sounds, languages and so on. The requirements for reduced representation of communication means that disambiguation without any extra-lingual knowledge will be extremely difficult.

   - Man-to-machine dialogue :

     Man-to-machine dialogue systems attempt to communicate with users, to understand situations including users' intentions, and to respond adequately to the users' requests. The systems are also required to ask questions of users and understand the users' replies to get an appropriate model of the users' knowledge levels.

   - Multimedia interface :

We often handle lingustic data or refer to objects with a combination of visual and sound information. This multimedia environment increases the ambiguity in individual processing on refering to objects. It requires data completion by a fusion process of vision, sound and so on, mediated by symbols like our language.

4. Text-processing support and information extraction :

   In text-processing, it is necessary to understand semantics and contexts to recognize cohesion in sentences. Information extraction is aimed to reduce verbose phrases in sentences, to add clarity, and generate suitable sentences. These processes reqire the ability to understand contexts and judge the importance of each part of them. They sometimes require one to guess the authors' intentions.

   In both of these fields, such deep understanding must be based on precise natural language analyses, especially at the semantic and pragmatic levels. Although very limited but useful systems, for example a spelling-checker, are widely in use, novel systems to check semantics are yet to be developed.

Our survey reveals several common characteristics, summarized below:

1. to solve fundamental problems like ambiguity, both efficiently and reliably. The ambiguity problems include: syntactic (or structural) ambiguity, word sense ambiguity, case assignment, and literalness.
2. to define and use contexts.
3. to develop a robust framework for non-grammatical sentences. The non-grammatical sentences include spontaneous speech.
4. to understand extra-lingual concepts used in sentences.

we propose an approach targeting to these problems in the following chapters.

1.5 Organization of the Thesis

The rest of the thesis is organized as follows:

In Chapter 2, we present a general abstraction of the problems of ambiguity in natural language processing. We will also clarify a measure of processing difficulty of context-dependency from an engineering viewpoint. In Chapter 3, we will survey related work on context-dependency and clarify their technical strengths. We will categorise the role of contextual knowledge according to our associative processing in Chapter 4. Then we will examine the necessity for handling scene knowledge, as one kind of extra-lingual knowledge; we also propose a way to acquire scene knowledge. Chapter 5 provides a method to representing a knowledge context; we describe an algorithm to disambiguate word meanings in sentences, together with a process of identifying scenes in narrative stories. Chapter 6 explains how to implement the above framework, for a machine translation system. In Chapter 7, we will evaluate the system applied to real texts from narrative stories and examine the results. In Chapter 8, we will discuss the algorithm proposed in this thesis. Finally in Chapter 9, after summarizing the results in the previous chapters, we will discuss some future problems in our approach and conclude the thesis.

Chapter 2

Ambiguity Problems and Semantic Disambiguation

2.1 Context-dependency Problems

The difficulty of semantic disambiguation in natural language processing originates with the complexity of defining disambiguating knowledge contexts[1]. These knowledge contexts must provide unique interpretations for co-dependent words, and help resolve "semantic garden path" sequences[4, 5].

Firstly, we will examine the importance of context inside sentences through famous examples. The first example shows a typical difficulty of word disambiguation:

```
John shot some bucks.
```

In this sentence, the words 'shot' and 'buck' have many meanings and this sentence contains the essential problem of ambiguity. Each word has dozens of meanings, and there are hundreds of combinations to translate these two words. We can easily interpret this sentence according to the contexts in the following two ways:

1. Hunting context : John fired at some deer.
2. Gambling context : John wasted some dollars.

In this sentence, a unique reading requires semantic agreement on "shot" and "bucks", suggesting either a hunting or gambling context. The semantic garden path can be illustrated by prefixing the above sentence with "John travelled to the woods," which might suggest the hunting context, but then appending "The illegal casino was hidden far from town," to dramatically change the interpretation suggested by the first sentence.

This problem appears with a simpler form in the next sentence, which suggests a strongly interactive associative processing by human beings from a cognitive process angle:

`The astronomer married the star.`

At first, a celestial body comes to our mind as the meaning of "star", but after a while, that meaning is distrained and the concept of a movie star replaces it. We recall an astronomical scene by the word "astronomer" at first and interpret "star" as a celestial body. Then we check the logical consistency of its meaning in the sentence, and search again to find another concept "movie star".

We further investigate into the cases of narrative story interpretation. Narrative stories have hierachical structure consisted of, for example, sentence, paragraph, section, and story. Under the surface structure, they also have a deep hierachical structure to organize their semantic relations including their coherence. From these facts, we must analyze the stories logically, together with capturing the correct relations of the characters or referred things.

For instance:

```
'Marilla retreated to the kitchen.
She set the candle firmly on the table.'
```

We immediately understand that 'she' refers to 'Marilla' and she is in the kitchen. According to this, we guess the meaning of 'table' not as a mathematical one but as a furniture. In such cases, the readers interpret sentences expecting current focuses, for example characters, and their environments. The focus enviroments include when, where, how, why, what it does. Using this expectation, writers efficiently pass the concepts and relations in reduced form as ambiguous sentences to readers.

While in machine translation, the core of the problem is the disciplined and dynamic construction of such a disambiguating knowledge context in a parsing system. Although it might be possible to write static rules which provide disambiguating information in the context of complete knowledge, such traditional bottom-up models are inefficient in the sense of both time and space. The inefficiency mainly arises from a search space explosion in the process of resolving combinated ambiguity. In addition, local constraints from surface information of the sentences are insufficient to narrow down the ambiguities. This fact often leads to misinterpretation. Accordingly, efficient and adequate interpretation of sentences requires context understanding to prune inadequate candidates and set low priority to them.

We always read such complex sentences and encounter the situation to disambiguate, so are accustomed to handle them without being aware. We are unconsciously extracting approriate knowledge from our stored memory, and use it as a knowledge context for efficient communication. Consequently, we have not yet clarified where we store the knowledge contexts, what kind of knowledge is useful, and how we utilize it, but it is now reqired for current natural language processings to analyze and provide a way of processing a knowledge context.

Here we divide the above goal into following subgoals:

- to define contexts and semantics
- to articulate an efficient processing method
- to provide a method to acquire a knowledge source
- to show a method to determine the context

These subgoals still have a difficulty that they mainly depend on the characteristics of the target fields in the real world. They depend on internal representation in semantic and syntactic analysis. They also depend on knowledge from other frontier technologies, *e.g.* vision processing and speech processing, and change according to their processing style.

In this chapter, we will survey the method and representaion of traditional natural language processing, together with the characteristics of the fundamental and combinated problems above.

2.2 Internal Representation

We illustrate a commonly used internal representation in traditional natural language systems by the example 'John shot some bucks.' in the hunting context. Current natural language processing system requires infomation of part-of-speech, syntax, and semantics. Internal representation of each information in the traditional system varies according to its characteristics.

1. Part-of-speech :

   Part-of-speech refers to one of the classes into which words are divided in grammar, *e.g.* noun, adjective, verb, etc, shown independently to another:

```
John shot some bucks.
---------------------
NOUN VERB ADJ  NOUN
```

2. Syntax :

   Syntactical information shows how sentences are constructed with phrases or words:

```
[S [NP [N John]
    [VP [V shoot] [T PASSED]
        [NP [DET some]
            [N bucks]]]]]
```

3. Semantics(Deep case frame) :

   Semantic information illustrates the conceptual meaning of the whole sentence. Since this is essentially formatless, several methods of representation have been proposed. Most practical systems adopt case frame representation shown in the example below:

```
Verb = shoot
Tense = PASSED
Actor = John
Object = some bucks
```

   This is mainly because the case frame representation explicitly points out the meaning and it can be handled with logical frameworks. Its other advantages are summarized below.

   (a) It can be described as a set of case slots accompanied to the verb

   (b) It itself represents the grammatical structure

   (c) It shows well about human behavior

   (d) Readable text format enables us to maintain easily

2.3 Ambiguity Problem and Processing Dependency

We explained the ambiguity problem by showing the above example and the meaning which we judge correct. However, translation systems must take all combinations as candidates if there is neither context nor semantic constraint. In such situations, the following ambiguity problems arise:

1. Syntactic(or Structural) Ambiguity :

```
John saw the Grand Canyon flying to New York.
Time flies like an arrow.
```

Is it John or the Grand Canyon flying? The answer depends on the ambiguous syntactic role of the word "flying" in this example. We can easily find an adequate solution to this with novel knowledge that Grand Canyon is a valley and does not fly. The question in the second example is whether it refers that time is flying, or we are talking about a species of insect called 'time flies'. It depends on whether 'flies' is a noun or a verb. These sentences requires us to inference with world knowledge to reach the right meanings.

2. Word Sense Ambiguity :

```
The man went to the bank | to get some cash.
                         | and jumped in.
```

In these sentences, the word "bank" refers either to a repository for money or the side of a river, depending on the two different continuations. Here we took the word "bank" in this example, but again, all the words in these sentences are ambiguous. The number of candidates is the product of the number of meanings of each word. Thus these sentences have more than dozens of sense candidates.

3. Case :

```
He ran the mile in | four minutes.
                   | the Olympics.
```

Linguistically, a "case" refers to the relation between a central organizing concept, here an act of running, and a subsidiary concept, here time or location. In both examples the same preposition, 'in', indicates the two quite different relationships. Case disambiguation generally requires both semantic and syntactic analysis.

4. Referential :

```
I took the cake from the table and ate it.
```

This example presents the question as to what was eaten, the cake or the table. Independent of real-world knowledge, 'it' could refer to either one. We check if we can 'eat' 'table', and prune this candidate. For instance, 'it' will have a different referent in the example above if we replace 'ate' with "cleaned".

5. Literalness :

```
Can you open the door?
I feel cold.
```

Here the problem is, what is the correct interpretation. There are some circumstances when the first question might be answered reasonably "yes" or "no". On the other hand, it is easy to think of circumstances whether the speaker wanted other replies from the listener. The second sentence might be a statement of fact or request to close a window. The ambiguities here lie in whether to treat it as an indirect speech act. They might be an implicit request to open the window.

6. Ellipsis :

```
I ate a hamburger and drank a cup of coke.
```

Sometimes we omit words or clauses which can easily be guessed and made up. Without such omission, contrary to our intuition, the sentence may be strange in our daily conversation. It might even lead to another interpretation.

7. Quantifier :

Mere inter-lingual information is insufficient to clarify scopes of quantifiers like 'small' or 'most'. They mainly base on extra-lingual and specific domain knowledge.

8. Negation :

Scope of negation is ambiguous. For instance, information retrieval system must decide whether to take phrases accompaning "not" as index keys or not.

9. Time, Tense :

To capture adequate time and tense information requires explicit processing of event ordering and relationship of cause and effects. Because of its complexity, most current natural language procesing systems can not handle such relations.

10. Ellipsis combinated with conjunctions :

    We sometimes join clauses into one sentences. If the sub-clauses in these sentences have the same subjects as main clauses, we omit them. This leads to a generation of complex sentence structures, which is very difficult to be analyzed. Thus some researches target to detect coordinate structures in such complex sentences.

11. Simile, Metaphor :

    According to Collins COBUILD dictionary, a simile is an expression which describes a person or thing as being similar to someone or something else. For example, the sentences 'She runs like a deer' and 'He is as white as a sheet' contain similes. Similes usually starts with 'like' or 'as'. While a metaphor is an imaginative way of describing something by referring to something else which has the quantities that we are trying to express. For example, if we want to say that someone is very shy and timid, we might say that they are a mouse.

    Understanding of these examples need guessing the words or phrases to indicate (associate) something different from (though related in some way to) the literal meaning. The guess requires extra-lingual knowledge with analogical inference.

12. Illness :

    Ill-sentences include non-grammatical sentences and ill-semantical sentences. Robust semantic understanding mechanisms of non-grammatical sentences and methods to point out semantical illness are necessary in practical systems.

The difficulty of the above example 'John shot some bucks.' originates from the combinations of the following problems:

- Context dependency (hunting / gambling)
- Part-of-speech ambiguity
- Word sense ambiguity
- Difficulty in defining word senses

Table2.1 shows the number of senses of each part-of-speech of the words in the sentence, according to Roget 5th ed. International Thesaurus and WordNet[6, 7].

Disambiguating process has dependencies like below:

Table 2.1: The number of senses of each word in 'John shot some bucks.' (the number in the left side of each cell is according to Roget Thesaurus, and that in the left side is according to WordNet [6, 7]).

	John	shot	shoot	some	buck
noun	4/1	26/15	10/0	2/0	8/5
verb	0/0	0/0	20/13	0/0	3/2
adj.	0/0	5/1	0/0	3/2	0/0
adv.	0/0	0/0	0/0	1/1	0/0

- Structural ambiguity depends on case information.
- Word sense ambiguity depends on part-of-speech information.
- Case ambiguity depends on both syntactics and word senses.
- Reference ambiguity:
  - Pronominal ambiguity depends on case and focussing information.
  - Noun reference ambiguity depends on morphological matching.

Consequently, the process has a characteristic of constraint satisfaction problem, in that it must find solutions to satisfy all of these constraints.

Traditional natural language processing systems use search which is a universal problem-solving mechanism. The sequence of actions reqired for solution are not known a priori but must be determined by a systematic trial-and-error exploration of alternatives. Without context, the systems search with brute-force techniques as in Fig.2.1.

The technique includes breadth-first and depth-first search.

Breadth-first search begins by generating all the successors of the root node (this is known as expanding a node). Next, all the successor nodes are expanded, generating all the nodes at level 2 in the search tree. This search continues by expanding one complete level of the tree at a time until a solution is found. Since this search never generates a node in the tree until all the nodes at shallower levels have been generated, once a path to a goal is found, it will be a path of shortest length. Thus, this search always finds an optimal solution by this measure. With a parallel computer with sufficient memory, this algorithm achieves the most time efficient search.

The main drawback of this search, however, is its memory requirement. Since each level of the tree must be entirely saved to generate the next level, and the amount of

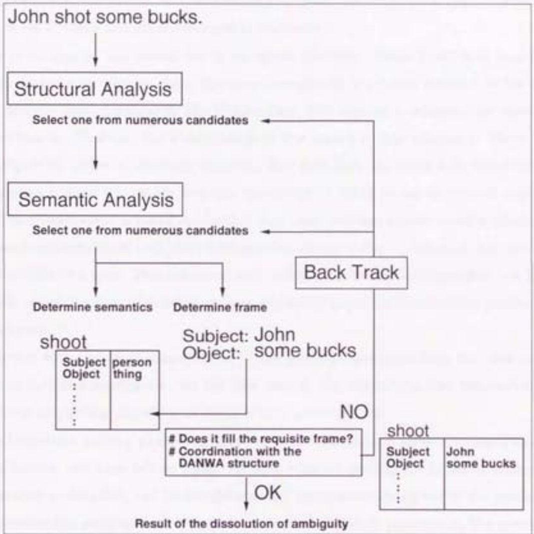


Figure 2.1: Data flow in traditional parser

memory is propotional to the number of nodes stored, the space complexity of this search is an exponential function of the depth. As a result, this search severely space-bound in practice and will exhaust the available memory in a matter of seconds on typical computer configurations.

An algorithm that remedies the space limitation of breadth-first search is depth-first search. This search proceeds by first generating one successor of the root node, then generating one of its successors, and continuing to extend this single path until it terminates. Then, it back tracks and generates another successor.

The advantage of this search lies in its space efficiency. Since depth-first search only requires to store the current path, the space complexity is a linear function of the depth. On a memory-limited computer like Workstation, this algorithm achieves the most space efficient search. However, the disadvantage of this search is time efficiency. These brute-force algorithm suffer in efficiency from the fact that they are essentially blind searches; they use no domain knowledge to guide the choice of which nodes to expand next. The idea of heuristic search is based on the fact that most problem spaces provide information, at a small computational cost, that distinguishes among states in terms of their likelihood of being close to a goal. This information is called a heuristic. Our approach is a kind of heuristic search, in that knowledge context effectively prunes and orders the pathes in the search space.

Together with the above classification of the parsing algorithms from the view point of search in artificial intelligence, we can also classify the algorithms into top-to-down and bottom-to-up parsing according to its style in generating trees.

Top-to-bottom parsing pieces together structural description trees systematically from top to bottom and from left to right. At each stage of parsing the leftmost unexpanded nonterminal is identified, and its daughter nodes are attached using one of the productions that rewrites the nonterminal. If there is more than one such production, the parser tries them all, following a separate continuation path in each case (nondeterministic).

Terminal symbols thus incorporated into a structural description are matched against the next symbols of the string being parsed. Failure in matching causes the continuation in question to fail or block. A continuation also fails if there are remaining input string symbols after the last nonterminal has been expanded.

While, bottom-to-top parsing pieces together structural description trees systematically from bottom to top and from left to right. We explain left-corner parsing as one of the bottom-to-top parsing. At each step in left-corner parsing, having determined a left-corner subtree of a structural description tree, it attempts to extend the subtree by scanning the productions for those whose right members begin with the root node of the left-corner subtree. Substituting that subtree for the first constituent of the right member of such a production gives a larger left-corner subtree; all of the daughter nodes of its root node except the first remain to be replaced by an appropriate structure, this being accomplished in left-to-right order, recursively using the same left-corner parsing algorithm.

This algorithm is also nondeterministic. There can be more than one production with a right member begining with a given constituent, leading to one type of nondeterminism. Another source of nondeterminism arises whenever a subtree is successfully build up to replace a constituent other than the first one in the right member of some production. Addition to making the replacement, it is also necessary to attempt to build the subtree up to a larger subtree with the same root node.

Adequate algorithm to take depends on whether we have global heuristics or local ones. Since global heuristics over the sentences constraint the upper part of the tree, they make top-to-bottom parsing efficient. While, local heuristics constraint the lower part of the tree; they make bottom-to-top parsing efficient.

Our approach targets to a time and space efficient bottom-to-top parser, with local heuristics from scene knowledge context. It disambiguates word sense and in consequence, reduces the number of parse tree effectively.

Chapter 3

Related Works on Context-dependent Natural Language Processing

Based on traditional natural language processing (Fig.3.1), there are two types of approach to context-dependent disambiguation, as shown in Fig.3.2.

One is to extend the traditional system by adding extra modules of context-processing and intution understanding, in line with the representation and parsing techniques for morphological, syntactical, and semantical analysis.

The other is based on statistical or memory-based methods. It is supposed to free us from the labor of precisely coding all kinds of complex semantics and contexts.

3.1 Context-dependent Processing on Traditional Systems

Traditional natural language processing systems base on symbolical representation and logical reasoning, mainly including morphological analysis, syntactical analysis, semantical analysis, and case-slot checking.

As to Context-dependent processing, there are two stances:

- Not to handle context-dependent processing :

  This results in the following:

  - The problem of search space explosion arises.
  - System's inability to select the candiates requires human to check the outputs.

- To handle parsing with context as topics, given in top-to-bottom fashion.

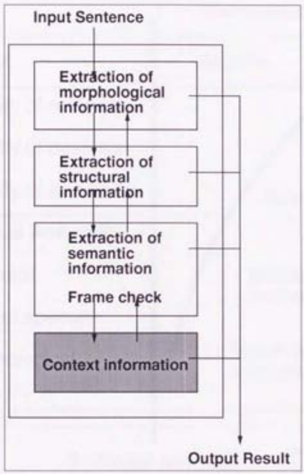


Figure 3.1: Conventional parser.

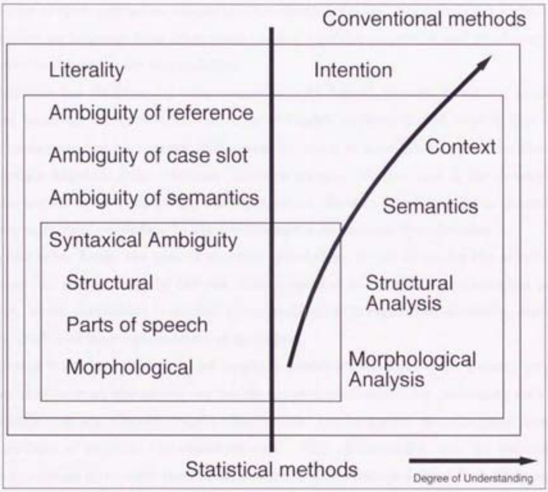


Figure 3.2: Approaches for disambiguation problems.

This results in the following:

- Topics is a too abstracted method to define a knowledge and obtain it from the real-world.
- Since it needs hand-coded classification of the world knowledge, it lacks scalability in practical use.

In this way, appropriate formulation and investigation of computationally effective mechanisms for context-dependent communication through natural language is yet to be found.

Research on language from other fileds, such a cognitive linguistics and psychology may be a clue to a solution for this problem.

Linguistics has traditionally been concerned with formal, general, structural models of natural language. Linguists, therefore, have tended to favor formal models that allow them to capture the regularities of language as much as possible and to make the most appropriate linguistic generalizations. Little or no attention was paid in the development of these models to their computational effectiveness. That is, linguistic models characterize the language itself, regardless to the mechanisms that produce it or decipher it.

On the other hand, the goal of cognitive psychology is not to model the structure of language but rather to model the use of language and to do it in a psychological plausible way, where plausibility is defined by correlations with experimental results, especially timing studies of language-understanding tasks.

Different from these fields, natural language processing does not study natural-language communication in an abstracted way but by devising mechanisms for performing such communication that are computationally effective, *i.e.*, can be turned into computer programs that perform or simulate the communication. This characteristic sets the natural language processing apart from traditional linguistics and other disciplines that study natural language.

However, natural language researchers have incorporated the fruit of the labor in these field, linguistics and psychology, into the computational algorithms on their systems. Here in addition to relating natural language processing to the study of language in other disciplines, we point out a major division that arises within natural language processing itself: general natural language processing and applied natural language processing.

We can think of general natural language processing as a way of tackling cognitive psychology from a computer science viewpoint. The goal is to make models of human language use and also to make them computationally effective. The vehicle for this kind of work is general story understanding. The common stance among linguistics, psychology, and general natural language processing concentrates into this modeling of human language use, and the fundamental technologies can be shareable. Our approach stands on this point, in that it targets to formalize and investigate computationally effective mechanisms for communication through natural language, based on psychologically proposed scene knowledge, which is required to be identified in narrative stories with discourse analysis. We introduce a linguistical and psychological framework into natural language processing, together with a context-dependent processing algorithm and a knowledge source from a dictionary.

Applied natural language processing is not concerned with cognitive simulation but rather with allowing people to communicate with machines through natural language. The emphasis is pragmatic. In applied natural language processing it is less important for the machine to understand a natural languge input in a cognitively plausible way than to respond to it in a way helpful to the user and in accordance with the desires expressed in it. Applied natural language includes the hopeful approach of analogical machine translation, *i.e.*, memory-based translation and example-based translation, which makes use of similarity of word usage, thesaurus, and a number of corpus-pairs. This approach is quite different from the traditional computational natural language processing method, hence we classify it into another category and make brief descriptions accompanied by surveys on these fields, below.

3.2 Cognitive Approaches and Linguistics

This section surveys the research on context in two fields, psychology and linguistics.

1. Schank's approach [8, 9, 10, 11] :

   This approach takes several types of knowledge representation according to the abstraction level:

   (a) Conceptual Dependency:

   This refers to verbal frame representation, abstracted way of commonly-used verbs, of human action,

   (b) Script:

   Top-to-bottom information to describe typical scene or typical human behavior as a series of sequence.

(c) Memory Organizing Packets(MOP):

space efficient representation with hierarchical structure of scripts.

(d) Goals and Plans:

to behave according to the messengers' intutions or aims.

2. Rumelhart's story grammars [12] :

This work attempts to analyze narrative stories into schematic outlines that represent the elements in a story that readers remember. These schemata are called 'story grammars'. Story grammars describe general structures of stories as a set of grammar rules giving top-to-bottom knowledge to the text reading process. According to these grammars, narrative stories are divided into elements including events and scenes.

3. (a) Preference Semantics by Wilks [13]

   (b) Pollaroid Word and Semantic Enquery Desk by Hirst [5]

These are heuristic approaches based on semantic network and activation propagation.

4. Subsymbolic Episode Memory Model by Miikkulainen [14, 15, 16, 17, 18] :

This model takes an approach of Parallel Distributed Processing (PDP).

5. Text linguistics :

In this field, discourse structure analysis based on functional grammar [19] have allowed investigation into the reading process and brought the current advances. This approach bases on semantic coherence in a series of sentences, without deriving from the traditional basic syntactic grammar. This functional grammar handles pronouns and determiners semantically as a kind of reference. In the traditional grammar, they have been thought to be very difficult to obtain functional roles. It also clarifies about the relations and connections between contexts and grammars, with mention to semantical processing in human-brains from cognitive psychology's viewpoint. Thus the introduction of focus and subject related concepts [20] naturally supports functional aspects in the English language. Unfortunately, it only offers an analysis of the reading process, and currently lacks computationally effective algorithm in natural language processing systems.

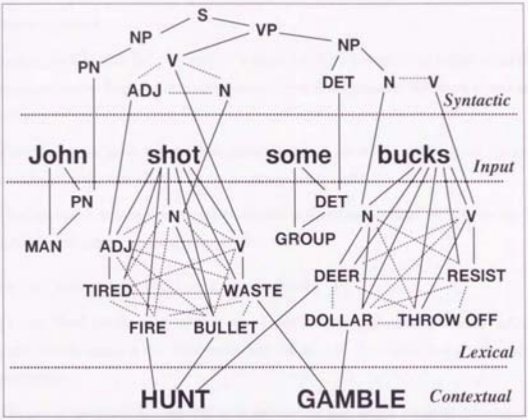


Figure 3.3: Activation propagation on connectionist model.

3.3 Statistical and Memory-based Approaches

Here we explain a statistical technique and an example-based technique. Their purpose is mainly disambiguation of words or sentences by not handling the context explicitly in a traditional manner, but by extracting required statistical parameters or similar sentences from a set of stored examples.

1. Connectionist approach :

   Research on connectionist approach by Waltz and Pollack[4] is fascinating because it is automatic and has global constraint satisfaction in the understanding of natural language. The original paper on this subject has pointed out the capacity of massively parallel parsing for natural language interpretation and for resolving ambiguities (Fig. 3.3). This is in line with a strongly interactive processing between all sentences such as, 'The astronomer married the star'. It also explains language interpretation by human beings from a cognitive process angle, particularly in reading semantic garden path sentences.

Tamura[21] and Tsunoda[22] formulated this approach for implementation on processing systems.

Veronis and Ide[23, 24] proposed a system on this approach, on which an activation propagation on English dictionary-based links disambiguate the word senses dynamically.

Their paper discusses about the limitation of their methods, pointing out the system's instability and poor effectivity to language complexity.

This approach is now considered to be one of the fundamental techniques to divided subgoals with less language complexity.

2. Baysian approach by Gale[25], Yarowsky[26, 27, 28] :

   This method firstly calculates a set of conditional probability of each meaning of words which appears in a 100 words window around the words in a number of stored sentences.

   The set of conditional probability is applied to the target sentece, to acquire post-probability of the word sense [29].

3. Example-based, Memory-based, and Analogical translation by ATR, Sato, Kitano et al.[30, 31, 32, 33, 34] :

   This kind of approach is based on the idea of performing translation by imitating translation examples of similar sentences[30]. In this type of translation system, a large amount of bi/multi-lingual translation examples has been stored in a textual database and input expressions are rendered in the target language by retrieving from the database an example most similar to the input.

   There are three key issues related to example-based translation:

   (a) establishment of correspondence between units in a bi/multi-lingual text at a sentence, phrase a word level
   (b) a mechanism for retrieving a unit that matches the input best
   (c) exploiting the retrieved translation example to produce the actual translation of the input sentence

4. Hidden Markov Model[35, 36] :

Currently this technique is used in syntactical analysis, particularly in part-of-speech tagging. It is also investigated as a means to approximate context-dependent grammar, but still lacks clue to semantic analysis and context-dependent processing.

3.4 Problems in Related Works

Although the need for context dependent processing in natural language processing is widely acknowledged, the problem is so difficult that there is no remark concerning its practical use. Knowledge representation and processing strategy of context-dependent analysis is for the present under consideration.

Contrary to this, human reading models from the two disciplines, cognitive psychology and traditional linguistics, have been proposed. Proposals from statistical and memory-based approach exist as well on the hypothesis that large corpora includes most kinds of linguistical information.

However current systems are yet to handle real world data and do examples without any knowledge source. Thus they have a problem that they lack computationally practical implementation methods and have poorness in scalability.

They are comparatively satisfactory to examples with limited complexity, but show little effectivity to complex processing like context dependent semantic analysis; they have not processed instances enough to cope with such structured sentences. Also the frameworks of practical systems are unable to understand inter-event relations deeply.

Another problem is that it is difficult to obtain a set of frequency of daily words from corpora such as newspapaers.

Among these approaches, the models from cognitive psychological discipline have an issue that they have not clarified knowledge source and method of detecting contexts. While, the statistical models handle various knowledge as a whole without consideration of natural language complexity. This causes a problem that they are unable to understand common, but deep knowledge.

The neck point common to these approaches is that they want to propose homogeneous framework without classifying the complex phenomena. Natural language has a highly organized structure with various levels from letters to stories. Contents of the information may vary with attentional states of listners or readers; the states are controlled to some degree by speakers or writers.

Thus, computationally effective and reliable communication requires following points:

1. to detect context by discourse analysis.

2. to classify context knowledge which we naturally handle according to the types of human behavior and knowledge source.

3. to acquire an appropriate knowledge source.

We classify our goals by analysis of real texts into several subgoals, and apply the most computationally effective and reliable way to each subgoal selecting from statistical method and traditional linguistics results.

Chapter 4

Context-dependent Processing Based on Scene Analysis

4.1 Overview

In this chapter we classify knowledge context according to its process stage and characteristics of data, and handle spatial scene knowledge both as one kind of the knowledge and also as one kind of discourse segment in discourse analysis.

On handling spatial scene knowledge, we propose three separated algorithms:

1. Disambiguation algorithm under a fixed scene.
2. Scene identification algorithm in narrative stories.
3. Method to acquire scene knowledge.

Here, our system is particularly targeted to word sense disambiguation among the other kinds of disambiguation problems mentioned above. It uses a table of words-senses pairs according to each context if the words are registered in the table, and guesses their meaning if they do not exist. That is, if the name of the target word is found on the list of the table (Fig. 4.1), the system shows the corresponding sense in the table as a result (symbolical processing), and if the name is not on the list, it guesses its sense with the sense distribution previously defined according to the context (statistical association).

Concerning the second algorithm, *i.e.*, scene identification, we figure it out in the context of discourse analysis and focus on detecting spatial scenes in narrative stories from real texts (Fig. 4.2). Spatial scenes can be identified in three situations: mentioned explicitly by location phrases in the sentences, specified implicitly by location of subject focus in the sentences, and estimated by relations with the words around (lexical cohesion). The explicit identification with the location information and the implicit specification with the

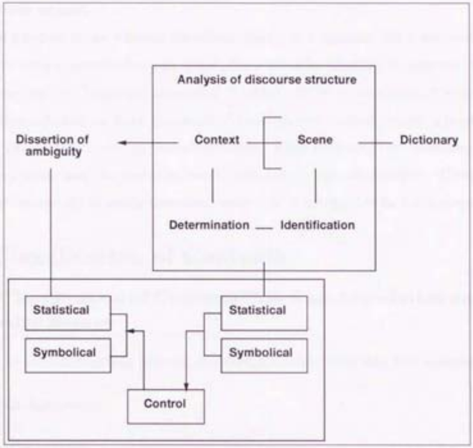


Figure 4.1: Scene extraction and sentence interpretation(1).

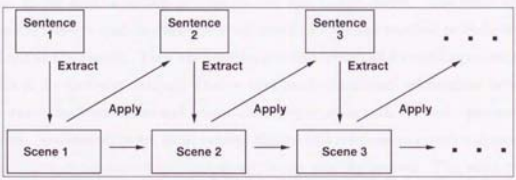


Figure 4.2: Scene extraction and sentence interpretation(2).

subject focus use symbolical processings. While, the lexical cohesion is based on word sense association implemented on statistical associative memory with the probability in relation with the words around.

Provided previous scene information exists, the system analyzes the input sentences with it and disambiguates senses of words. If not, the system behaves in the same way as analyses in traditional natural language processing systems. After the analysis, it either extracts scene location information from the result of case analysis (sometimes with focus stacked), or guesses the current scene by lexical cohesion. Then it checks the consistency between the assumed scene and the previous scene, and renews the information. These processes are applied repeatedly to every sentences input one after another to the system.

4.2 Classification of Contexts

4.2.1 Classification of Contexts Based on Association and Knowledge Source

According to human thinking process, knowledge context falls into four categories:

1. Domain knowledge
2. Attentional state
3. Situation in speech
4. Intution in speech

Among these knowledge types, since situation and intution in speech are implied in the problems in the field of speech act, we do not care in this paper. The other types are fundamental bases to analyze discourse structures in stories and required to be detected and understood in the system. They are used for interpretations of forwarding sentences with the result of the discourse analysis, That is, they are bi-directional information between the surface structures of sentences and semantical interpretation with internal representation in the system. Attentional states focus current objects and relations to detect and reconstruct coherent states of the sentences successively in the reading process. The main puropose is to detect current focus topics. Depending on the difference of the memorizing process, domain knowledge can be classified into the following four categories [37]:

1. Knowledge to support spatial association.

2. Knowledge to support temporal association.

3. Knowledge to support similarity.

4. Knowledge to support contrariness.

This classification corresponds to that of knowledge sources. Similarity and contrariness can be considered to support spatial and temporal association with introduction of viewpoints to them. Knowledge to support spatial associaton includes the generally referred 'scene', which we explain precisely below.

4.2.2 Scene as Settings

As naturally used in various situations like movies 'scene' refers to several kinds of concepts, of which the structure is shown below:

```
Abstract scene
Senseous scene --+ Non-vision based scene
                 + Vision based scene  --+ Acts, Experiences
                                         + Settings
```

Abstract scene implies conversations, psychological descriptions, abstracted concepts, topics, and so on but we do not mention them here. We also exclude the discussion about non-vision based scene, which can be regarded as a special type of characters' experience or attributes of settings and objects.

Here we concentrate on a setting scene, *i.e.* spatial scene in which characters and objects take actions, and examine the system's ability to detect the segments from texts [38].

This kind of scene corresponds almost to the location header in Schank's script(Schank77), for example 'Restaurant' in 'Restaurant script'. It corresponds to 'Hunting' in the previously described example of 'John shot some bucks' in hunting context, and corresponds to 'Gamble(roulette)' in gambling context.

'Scene' is defined as a place in where some typical action is made, in where someone's purpose is accomplished, in where some kind of objects naturally gather, and a typical collection of several objects. Taking account of robust processing, here we define it as a spatial information represented as a set of objects in it, without describing explicitly the necessity of each object that appears. Thus our stance is not to restrict strongly the meanings with the spatial scene context, but rather to help preference by cooccurrence and actions with other words or their senses.

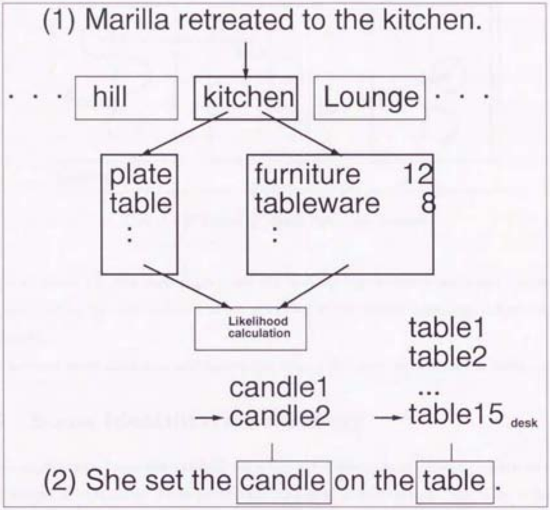


Figure 4.3: Disambiguation by spatial scene.

4.3 Disambiguation by Spatial Scene

We illustrate the method of disambiguation by spatial scene, by example sentences from real texts (Fig. 4.3).

```
Marilla retreated to the kitchen.
She set the candle on the table.
```

In this example, the current scene is specified by the first sentence as 'kitchen'. Here the system is desired to set ordered priorities to the meaning of the word 'table' in the next sentence; the correct sense 'furniture table' is natural to be output from the system faster than another sense 'mathematical table'. The system uses information 'table : furniture' in the 'kitchen' scene knowldge, or the information that the frequency of the category 'furniture' exceeds other categories according to the semantical distribution of the 'kitchen'

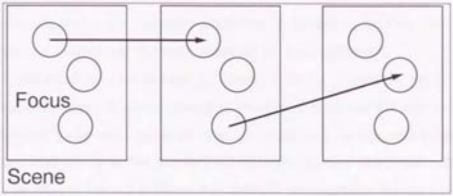


Figure 4.4: Links of scenes based on focuses.

in this situation *i.e.* the system prepares the table of words-senses pairs and the semantical distribution for each scene, and set priorities to the words' meanings calculating the likelihoods.

As to word sense definition and knowledge source of scene, we describe in later.

4.4 Scene Identification Strategy

Discourse structure bases semantically on a bundle of discourse segments called coherence. We undergo an optimistic stand point that requests: A text plainly has to be 'coherent' in that the concepts and relationships expressed should be relevant to each other, thus enabling us to make plausible inferences about the underlying meaning. The coherent discourse segments give the continuity of semantics, but it is generally difficult to define [39]. Abstracted relations like topics and causal relations have been investigated as one kind of discourse segments. However, discourse segments include all other kind of relations which focus on objects, situations, events, and actions.

Spatial scene is one of these relations where objects or characters action or enjoy the same situation (Fig. 4.4). Although the definition of scene knowledge depends on the characteristics of discourse structure, we discuss here the typical case in narrative stories where characters and objects take some state or take actions in the forefround of a spatial scene.

When we discuss scene structure, we must mention three cases: entering the scene, continuing the scene, and exiting the scene. Since it is time consuming, less reliable, and sensible to characteristics of the sentence to detect a scene for each sentence independently, here we concentrate on a paragraph level identification, continuation check, and structure construction.

Our system cuts down the discourse segments of spatial scene from the stories with cohesive factor, *i.e.*, structural patterns appeared on text surfaces.

To call a sequence of sentences a 'text' is to imply that the sentences display some kind of mutual dependence; they are not occurring at random. Sometimes the internal structure of a text is immedietely apparent, as in headings of a restaurant menu; sometimes it has to be carefully demonstrated, as in the network of relationships that enter into a literary work. In all cases, the task of textual analysis is to identify the linguistic features that cause the sentence sequence to 'cohere' – something that happens whenever the interpretation of one feature is dependent upon another elsewhere in the sequence. The ties that bind a text together are often referred to under the heading of 'cohesion'.

Several types of cohesive factor have been recognized:

- Conjunctive relations:

  What is about to be said is explicitly related to what has been said before, through such notions as contrast, result, and time:

  ```
  I left early. However, Mark stayed till the end.
  Lastly, there's the question of cost.
  ```

- Coreference:

  Features that can not be semantically interpreted without referring to some other feature in the text. Two types of relationships are recognized: anaphoric relations look backward for their interpretation, and cataphoric relations look forward:

  ```
  Several people approached. They seemed angry.
  Listen to this: John's getting married.
  ```

- Substitution:

  One feature replaces a previous expression:

  ```
  I've got a pencil. Do you have one?
  Will we get there on time? I think so.
  ```

- Ellipsis:

  A piece of structure is omitted, and can be recovered only from the preceding discourse:

  `Where did you see the car? In the street.`

- Repeated forms:

  An expression is repeated in whole or in part:

  `Canon Brown arrived. Canon Brown was cross.`

- Lexical relationships:

  One lexical item enters into a structural relationship with another:

  `The flowers were lovely. He liked the tulips best.`

- Comparison:

  A compared expression is presupposed in the previous discourse:

  `That house was bad. This one's far worse.`

Beside these, cohesive factor includes: reccurence, parallelism, paraphrase, tense and aspect, functional sentence perspective (focussing and reactivation), intonation [19]. They are key patterns to detect coherence, trading off the informativity and compactness according to the capacity of our short memory.

Detection of coherence from cohesion requires:

1. to understand anaphoric relations
2. to understand coherence relations, *i.e.*, to understand relations among referred events and states

As the total processing of coherence leads to processing explosion problem and ambiguous definition problem, we focus on the coherence on spatial scene here.

In this case, understanding anaphoric and coherence relations is achieved by two types of identification:

1. Identification of focuses, *e.g.* characters and objects:

   Mainly it is due to extracting subjects in the sentences. For example, a subject of 'Marilla retreated to the kitchen.' is 'Marilla'. As the next sentence 'She set the candle on the table.' has 'She' as a subject, the system search the focus stack to find a focus that resolves the pronoun 'she'. Thus it identifies the focus, 'Marilla'.

2. Identification of locations of focuses:

   Location of focuses can be identified by two majar methods: to analyze the sentence and extract location information from the case frame, with focus stack if necessary to guess its location by lexical cohesion with around words provided the sentence has no explicit location data.

Above identification approaches are translated into several cases below for practical use:

1. Identification of focus :

   (a) Explicitly given

  1

   Ex: <u>Marilla</u> said.

   The focus is Marilla, explicitly identified by the case analysis of this sentence.

   (b) Not explicitly given:

   i. included in subject but indirectly

  2

   Ex: <u>Marilla's</u> lips twitched.

   Marilla's lips belong to Marilla. This needs solution of inclusive relationship.

   ii. Without subject or pronoun subject:

   A. Search focus stack

  3

   Ex: She was sitting there. ← [<u>Rachel</u>, kitchen]

   In this example, 'she' refers to Mrs. Rachel. This needs anaphora resolvement.

   B. Knowledge that conversation lasts mutually

  4

Ex: 'I've never been in the depths of despair, so I can't say,' responded Marilla.

'Weren't you? Well, did you ever try to imagine you were in the depths of despair?'

'No, I didn't.'

This indicates focus switching.

C. End of chapter:

.......5

A change of chapter suggests a change of scene. Elements of the focus stack are cleared.

D. Focus refers to place

.......6

Ex: There was no mistaking.

This indicates only existance or non-existance and refers to no focus. Thus the focus is the previous focus.

Ex: The hall was cold.

The focus subject itself contaions location information.

E. Idiomatic words

.......7

Ex: All went merry.

This phrase refers to 'Everything went good,' which is idiomatic words.

2. Identification of location of focus :

   (a) Explicitly given

      i. place at

      ....A

      Ex: Anne recited <u>in the kitchen</u>.

      ii. place to

      ....B

      Ex: Marilla retreated <u>to the kitchen</u>.

   (b) Not explicitly given:

      i. Search focus stack:

.......C

Ex: She was sitting there. ← [Rachel, kitchen]

The extracted subject focus is matched in the focus stack. Since the focus in the stack has scene location information, the system can identify the scene.

ii. Lexical cohesion

.......D

Ex: Anne finished dishwashing.

If the focus stack has no information about Anne, the system must identify scene by lexical cohesion lead by 'dishwashing'. If it has information of Anne's location, the system must detect contradiction between the scene and the word 'dishwashing', which needs deep knowledge. Therefore we exclude such cases which need contradiction detection.

iii. Needs novel inference

.......E

Ex: She was downstairs.

This sentence requires the knowledge that 'downstairs' implies a kitchen, and a kitchen is not in 'upstairs'. We exclude such cases which needs novel inferences.

iv. Default:previous focus place

.......F

v. going out

.......G

Ex: She set out.

The verb itself suggests a change in location. The system happens to such cases in exiting scenes.

Here, focus is hypothesized to be the subject of the first sentence of the current paragraph.

4.5 Acquisition of Scene Information

Spatial scene knowledge consists of a frame specifying the setting and objects which appear typically in the scene. These objects generally share some common functions, or have some common characteristics in line with taxonomy, *e.g.* plants in forest scene. The shared setting is mainly defined as a scene or a background which includes these objects. Although

Table 4.1: Basic statistical information of OPED.

Total # of scenes	384 scenes
Registered # of words	27,500 words
Total # of words	11,711 words
Average # of words / scene	184.2 words
Max # of words in one scene	478 words

there are many kind of relations between these objects and scene or, among these objects, we regard them all as a variety of 'part-of' relation here, and leave the individual analysis for the future work.

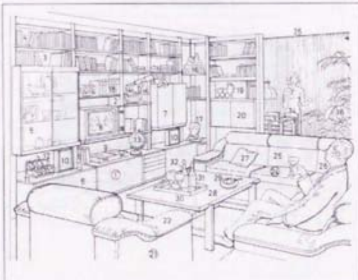
Spatial scene knowledge essentially requires reproduction of actual events in the real world, particularly vision processing, image recognition, image understanding to imitate the process of human acquisition and recognition of world knowledge. It is also necessary to fuse these vision processing and natural language processing with common representation and sharable processing technologies.

However, such technologies are not available yet. Thus as an approximation of spatial scene knowledge, we first propose to use pictorial dictionaries.

As one of such pictorial dictionaries, we examined OXFORD-DUDEN Pictorial English Dictionary (OPED), and input all the images with assigned symbols to every part. This pictorial dictionary claims to provide word sense meanings for most ordinary life scenes. The simple representation of pictorial knowledge based on the OPED makes the analysis simpler, and provides a potentially smooth connection to visual sensory data. As explained in the OPED, "The dictionary is edited regarding the depiction of everyday objects and situations, in order to allow greater scope for the treatment of these objects and situations in the context of English-speaking countries"[from *Forward* in OPED]. Each scene or pictorial entry in the OPED is accompanied by a word list of entries from the scene. Example and the structure of OPED is shown in Fig.4.5 and Fig.structure, respectively.

This dictionary entries 27,500 words. Its basic statistical information is shown in Fig.4.1. It has 384 categories under 11 rough classifications. These categories correspond to rough scenes we handle here, and have several pictures which contain many objects with corresponding symbols. The categories can be classified according to its usage into several types, as is shown in Fig.4.7. In this figure, category names are common nouns, for example, "Living room(Lounge)". They vary according to the type of prepositions in sentences; they can refer to 'sight', 'object', or 'type' which specifies some kind of set visually classi-

Living Room (Lounge) 42



1 wall units
2 side wall
3 bookshelf
4 row of books
5 display cabinet unit
6 cupboard base unit
7 cupboard unit
8 television set (TV set)
9 stereo system (stereo equipment)
10 speaker (loudspeaker)
11 pipe rack
12 pipe
13 globe
14 brass kettle
15 telescope
16 mantle clock
17 bust
18 encyclopaedia [in several volumes]
19 room divider
20 drinks cupboard
21-26 **upholstered suite** (seating group)
21 armchair
22 arm
23 seat cushion (cushion)
24 settee
25 back cushion
26 [round] corner section
27 scatter cushion
28 coffee table
29 ashtray
30 tray
31 whisky (whiskey) bottle
32 soda water bottle (soda bottle)
33-34 **dining set**
33 dining table
34 chair
35 net curtain
36 indoor plants (houseplants)

Figure 4.5: Living room scene in OPED.

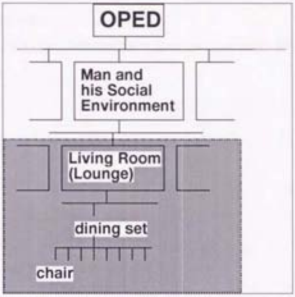


Figure 4.6: Structure of OPED

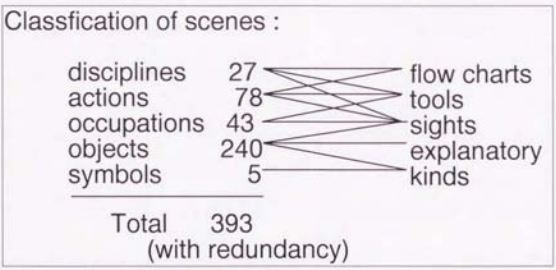


Figure 4.7: Types, classifications, and numbers of categories.

fied according to its shape, for example, various types of dwells. Thus the category names and their usages take many-to-many relations as in the figure. Furthermore, since some catogories include several names, *e.g.* "Roof and Roofer", the number of categories does not equal to the total number.

In the following chapter, we demonstrate how to use this dictionary as a knowledge source of spatial scenes.

Chapter 5

Knowledge Representation of Spatial Scene and Context-dependent Processing Algorithm

5.1 Data Flow and Architecture

Based on the purposes described in the previous section, this chapter proposes and describes the knowledge representation and algorithm of the method. Fig.5.1 illustrates the entire data flow in our method. It distinguishes itself from traditional natural language systems in the point that it identifies scenes by extracting discourse structures from stories, and set priorities to senses of words in the current and the following sentences according to its likelihood with the identified scene.

To perform these processes computationally effectively, it has several separated processing modules as in Fig.5.2. They include a traditional parser for syntactic and semantic analysis, a part-of-speech identification module to extract part-of-speeches of words directly from senteces, a noun extraction module, a judging module to select from two kinds of scene knowledge representation, a calculating module to set priorities to the word senses depending on the scene information, and a scene identification module with discourse analysis.

5.2 Word Sense Definition Based on the Thesaurus

The first problem in the word sense disambiguation is the difficulty in defining the meaning. Word senses are ambiguous because they have no visible forms which can be found in syntax, *e.g.* grammars. They vary even among dictionaries that are considered to be describing them most objectively. Even if we decide one dictionary as a reference, scopes of the word senses are ambiguous depending on situations or viewpoints. This leads to the

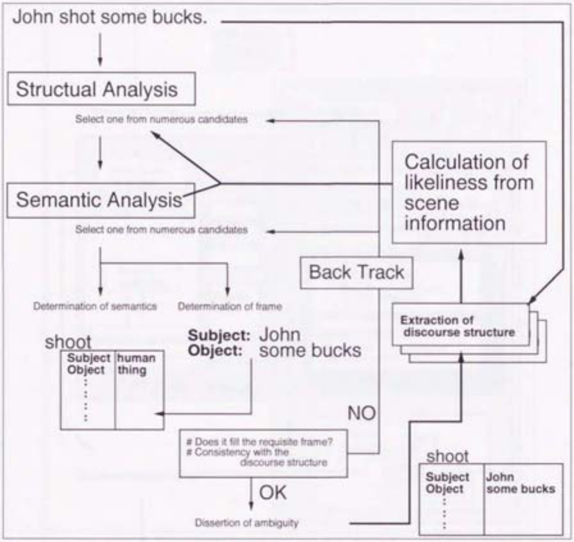


Figure 5.1: Whole data flow on our proposing method

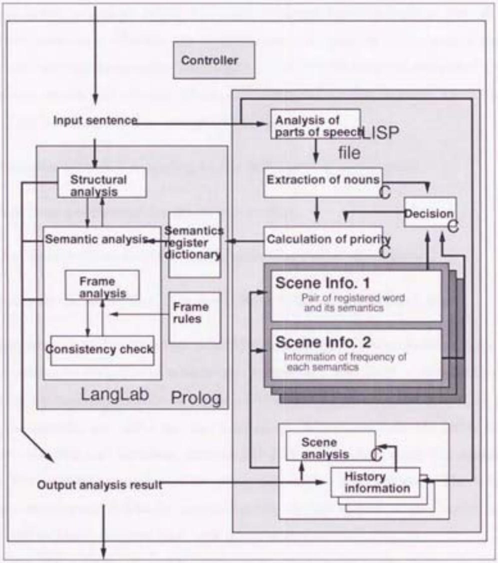


Figure 5.2: Architecture.

difficulty of judging their correctness. Here we suppose that such kind of problems would be resolved in the future, and currently use the classifications on a thesaurus, Roget 5th ed. International Thesaurus, to define word senses.

The thesaurus is originally based on Roget's classification. It is a device for finding specific words or phrases for general ideas. A dictionary tells us many things about a word – spelling, pronunciation, meanings and origins. We use a thesaurus when we have an idea but do not know, or cannot recall, the word or phrase that expresses it best or when we want a more accurate or effective way of expressing our intention. The range of possibilities includes not only the meaning as we usually think, but the special sense and force given by nonformal words and phrases (slang and informal), of which many are included and labeled. This latest edition has several advantages;

1. It classifies all words according to the difference on social usage.
2. It has been polished up for about one century.
3. It has been used all over the world, wider than other dictionaries.
4. As it is the latest edition, it is useful for looking up present-day words.

The classification is in line with top-to-bottom manner into fifteen classes ranging from our body and senses to decipline of science and technology, and further into 1,073 categories with ranges we ordinary handle as topics. Within each category the terms are presented in short paragraphs, and these are also numbered. References from the index to the text are made with two-part numbers such as 247.4, the first part being the number of the category, the second the number of the paragraph within that category. The terms within a category are organized also by part-of-speech, in this order: nouns, verbs, adjectives, adverbs, prepositions, conjunctions, and interjections.

This range of categories almost equals to that of categories in the dictionary OPED used in this research. Difference between them is that the thesaurus targets to classify words in top-to-bottom manner and is poor in constructing associational links like scene, while OPED targets to find words by pictorial keys, without any top-to-bottom classification.

With this classification on categorical level, our system disambiguate the meaning of each words, identifying a thesaurus category which specifies one of them. For example, this thesaurus contains sixteen categories which include 'table' as a noun sense, and three categories which include it as a verb sense (Fig.5.3). We assume that specifying one category

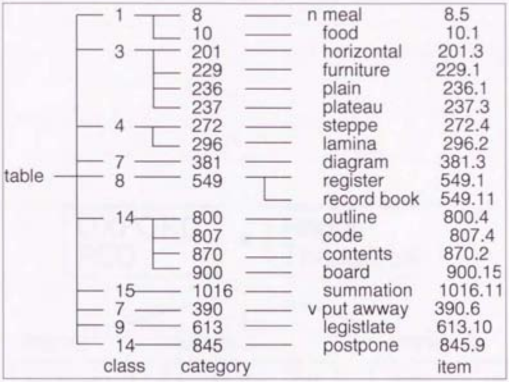


Figure 5.3: Structure of Roget 5th ed. International Thesaurus

among others leads to an identification of the word sense of 'table'. (The larger classification which includes fifteen classes has too large range of meaning to disambiguate.)

5.3 Knowledge Representation of Spatial Scene

We construct spatial scene knowledge in advance, both for word sense disambiguation and scene identifiation by the OPED and the Roget thesaurus, assigning the correct senses in the thesaurus to the symbols in the OPED. We can prepare three kinds of representation for this scene knowledge (Fig. 5.4):

1. Frame representation of the list of words in the thesaurus, without using the thesaurus:

   This is useful for scene identification based on lexical cohesion. Words in sentences are matched against the words in this list, and the combination of them are used to guess (identify) the current scene.

2. Word-Sense table:

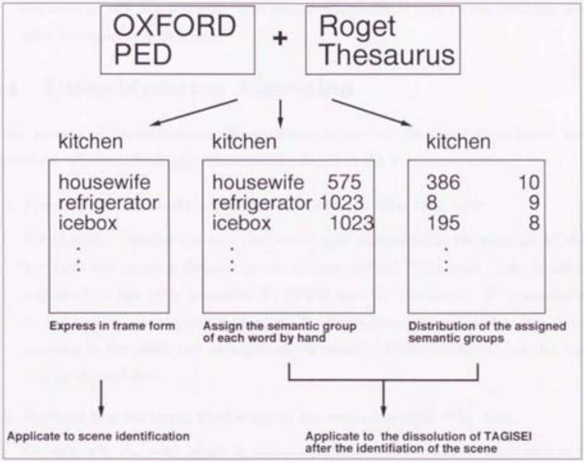


Figure 5.4: Knowledge representation of spatial scene.

This representation is constructed by reserving word senses assigned to the words in OPED according to the classification of the thesaurus. The categories in the thesaurus are used for this classification. This kind of knowledge is used to the disambiguation after scene identification.

3. Semantic distribution:

   This representation is constructed by the frequncy of senses assigned to the words in OPED according to the classification of the thesaurus. The categories in the thesaurus are used for this classification. This kind of knowledge is used to the disambiguation after the scene identification.

5.4 Disambiguation Algorithm

In the process of disambiguation, the usefulness of each of the information listed above depends on whether the target word could be found in the word-sense table or not.

1. Provided that the target word is in the word-sense table (Fig. 5.5):

   For example, consider the case that we want to disambiguate the meaning of 'dish' in 'Anne was washing dishes.' in the kitchen context. The word 'dish' is already registered to the table according to OPED and the thesaurus. To disambiguate it, the system uses semantic category ('8' in this example) assigned to the correct meaning in the table, and arranges search ordering in the parser so that this sense will be checked first.

2. Provided that the target word is not in the word-sense table (Fig. 5.6):

   For example, the word 'glass' in 'glass of cordial' is not explicitly registered in the word-sense table. In this case, the system uses the semantic distribution to guess the word sense. The meaning of dish with the highest frequency in the distribution corresponds to a category numbered 195, which refers to containers, in the thesaurus. In this way the system arranges search ordering in the parser so that this sense candidate will be checked first.

To evaluate this algorithm later, we formalize the representation and processing: Assume these:

- target word as W(ex: table),

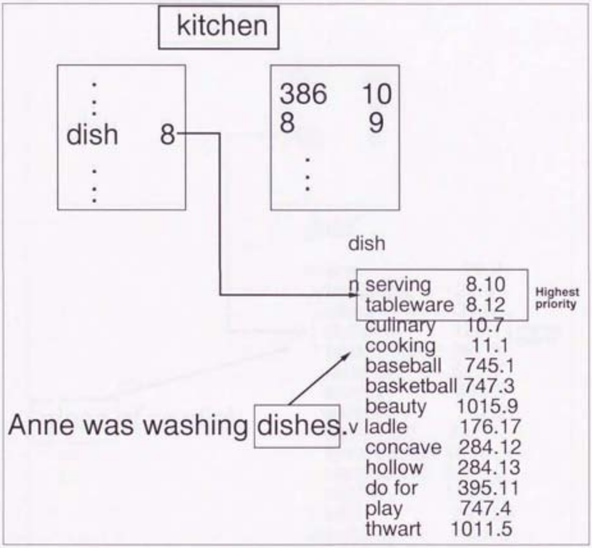


Figure 5.5: Disambiguation algorithm (1).

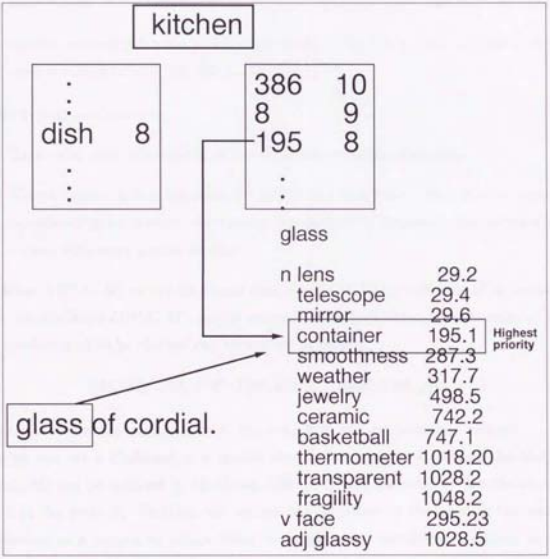


Figure 5.6: Disambiguation algorithm (2).

- word sense as M(ex: furniture table),
- context as C(entire set of input sentences),
- S(ex: kitchen),
- semantic classification as k(ex: 1.1 ~ 1073.14),
- correct sense of the target word as M_{c_j} (ex: 'furniture table' and 'support table'),
- correct sense classification of the target word as $k_{c_j}(1 \leq j \leq n_c, n_c$ is the number of correct classifications) (ex: 229.1, 900.15)

This system also assumes:

1. Each word sense corresponds to one classification in the thesaurus.
2. 'Correct sense' means the sense we selected to be correct. Even if some senses are considered to be correct, the system is supposed to determine one solution to be correct with more precise analysis.

We define $L(W, C, M)$ as the likelihood that a word W has a meaning M in context C. With this likelihood $L(W, C, M)$, partial ordered set $\mathbf{T}$ which determines the order of senses (the number is n) to be checked can be written as follows:

$$\{M_1, M_2, ...M_n \in \mathbf{T} : L(W, S, M_i) \geq L(W, S, M_{i+1})\} \tag{5.1}$$

Here the elements that satisfy $L(W, S, M_i) = L(W, S, M_j)$ are randomly ordered.

As we can use a likelihood in a special case that a scene is identified, the likelihood $L(W, C, M)$ can be replaced by likelihood $L(W, S, k)$ that the word W has the classification k in the scene S. Furthermore, we use the frequency of the word in the semantic distribution as a huristic to reduce effort to acquire prior distribution, without any context and conditional probability with each context to calculate posterior distribution and select the maximum category. This is mainly because prior distribution and conditional probability are generally unknown, and it is time consuming to get the whole data.

$$L(W, C, M) = L(W, S, k) = n(k, S) \tag{5.2}$$

Thus Eq.(5.1) can be rewrited as:

$$\{k_1, k_2, ...k_n \in \mathbf{T} : n(k_i, S) \geq n(k_{i+1}, S)\} \tag{5.3}$$

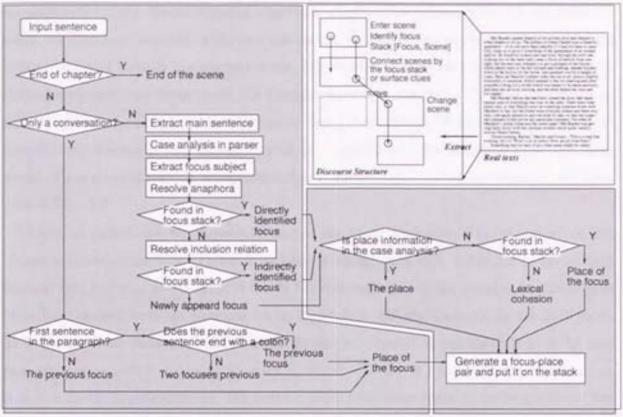


Figure 5.7: Scene identification algorithm

The system module outputs this result. To evaluate the correctness of the output, we furthermore define the iteration number I to check the number of candidates which appear until the system find the solution that does not lead any inconsistency.

As the practice system is assumed to take precise checks until it finds an unique solution, even if we judge several senses to be correct, we can not decide which candidate is the solution. Thus we approximate the system behavior by taking the average number of iterations to reach the solutions we judge to be correct.

$$I_j = \{i \mid k_i = k_{c_j}\} \tag{5.4}$$

$$I = \frac{\sum_j I_j}{n_c} \tag{5.5}$$

$$= \frac{1}{n_c} \sum_j \{i \mid k_i = k_{c_j}\} \tag{5.6}$$

Effects of scene knowledge to this mean value I are evaluated in a later section.

5.5 Scene Identification Algorithm

Scene identification is targeted to extract knowledge context to disambiguate word senses accompanied by the disambiguating algorithm above. The scene extraction algorithm is based on discourse analysis with four phases (as in the upper square of Fig. 5.7): (1) Enter scene and identify the current scene, (2) Identify the current focus and put on the [focus,scene] pair on a focus stack, (3) Connect scenes by the focus stack or surface clues, and (4) Detecting exitance from the scene or change in location. However, the system must handle every sentece in any situation with no suggestion of the situation from the outer world. Thus the sentence detection algorithm is rather complicated as shown in the lower part of Fig. 5.7.

Firstly, an end of chapter suggests an end of the scene. Secondly, if the sentence consists of only a conversation like "This is a real fine evening, isn't it?", detection of the subject focus of this sentence needs rules; if this is the first sentence in the paragraph, the subject focus has changed from the previous focus; if not, it is still the same to the previous focus. Thirdly, the focus subject of the main sentence (if it exists) is extracted from it by case analysis, and searched in the focus stack to check whether it has newly appeared or not. If it is a newly appeared focus, the system must find some clues to identify the current scene without any information from the focus stack, but if not, it can use the focus stack to get the place where the focus is. In this phase, the system resolves some anaphoric relationships like 'she' with 'Marilla' and so on. Fourthly, if the case analysis successed to extract place information from the sentence, the current place information will be changed according to the extracted scene information. Then the focus-place pair will be put on the focus stack for further analyses. Finally, if the sentence has neither explicit information nor subject focus corresponding to any focuses in the focus stack, the scene must be identified by analysis on lexical cohesion. In this way, the system can extract a series of spatial scene contexts on narrative stories from real texts.

The algorithm is precisely investigated here. It bases on focus tracking, resolution of focus location, and lexical cohesion:

The main algorithm is shown in Fig. 5.8:

- End of chapter?
  - YES → End.
  - NO : Only a conversation?
    - With main sentence → Extract only the main sentence to pass to the parser.
    - Only conversation → Process it without passing to the parser.

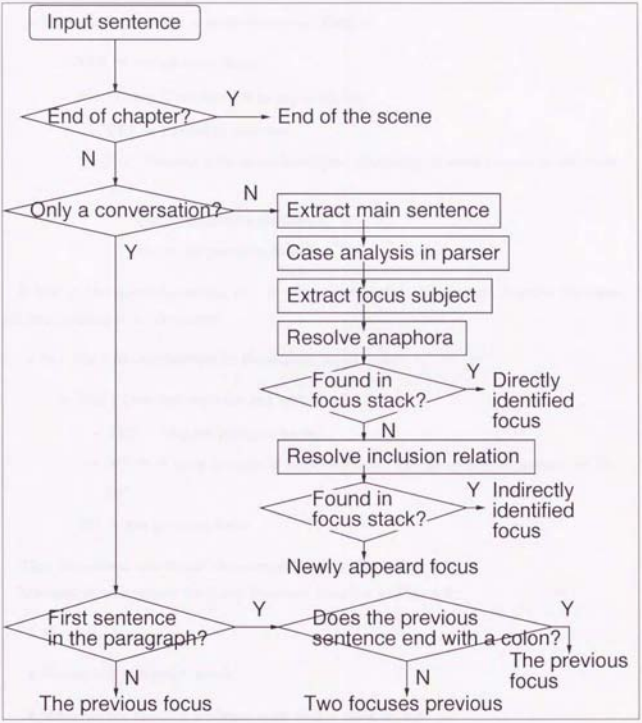


Figure 5.8: Scene identification algorithm (focus).

As a special case in these, after the extraction of the main sentence and passing it to the parser, this module accepts the result from the parser and extracts a focus of it.

The focus is resolved again using this algorithm:

- Does the focus refers to some place(*e.g.* There)?
    - YES → the previous focus.
    - NO : Check if the focus is in the stack list
        - YES → Explicitly matched.
        - NO : Recheck if the focus has a part-of relation to some focuses in the stack list?
            - YES → Implicitly resolved.
            - NO → the previous focus.

While in the main algorithm, if it is only conversation, the system handles the case without passing it to the parser:

- Is it the first conversation in the current paragraph?
    - YES : Does the sentence end with a colon?
        - YES → Output previous focus.
        - NO → It is in a series of conversations. The focus is the previous of the last.
    - NO → the previous focus.

Thus the system can detect the current focus in the sentence.

Memorable information for focus detection is shown in Fig. 5.9:

- Focus stack
- Position of paragraph break
- Whether the previous sentence ends with a colon or not

While, information to detect by morphological analysis is:

- End of chapter
- Conversation

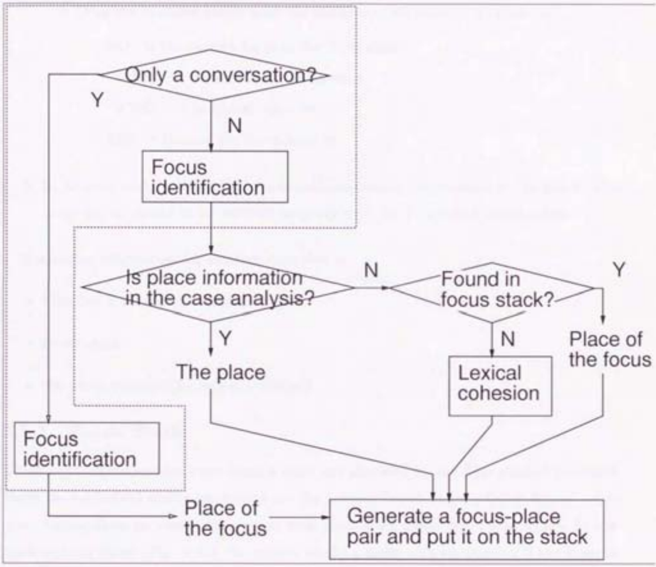


Figure 5.9: Scene identification algorithm (location).

- Position of paragraph break

Identification of focus location uses this focus information. It choose two types of processing algorithms depending on whether the module passed a sentence or not:

1. In the case it passed it to the parser, the algorithm is:
   - Does the analyzed result from the parser include location information?
     - NO : Is the current focus in the focus stack?
       * YES → Output the focus location
       * NO → Use lexical cohesion
     - YES → Output the focus location
2. In the case that it resolved the focus without passing the sentence to the parser, the focus was supposed to be resolved uniquely with the focus stack information.

Memorable information for location detection is:

- Whether it passed the sentence or not
- Focus stack
- the whole sentence(for lexical cohesion)

5.5.1 Focus Stack

These main algorithms for scene identification are attended by the finer grained processes based on symbolical reasoning, except for the process based on associative lexical cohesion. Among these processes, the process with focus stack needs detail description. In the stack making phase (Fig. 5.10), the system stacks a focus with its location if the focus is determined by the case analysis.

For example, assume that we want to analyze a sentence 'Marilla retreated to the kitchen'. The parser outputs a result like

```
[retreat, [act, change_in_location], [sfrm/p1_1]],
[marilla, [agt, [human], sbj], [human]],
[kitchen, [place_to, [place], mdf], [room],
[the, det2]]]
```

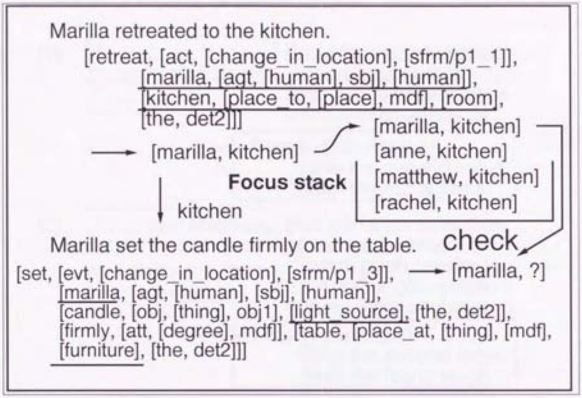


Figure 5.10: Focus stack.

for this sentence.

From this result, the focus processing module extracts Marilla as a subject (agent) and kitchen as a direction of movement (place_to), and stacks them with a representation [marilla, kitchen] on a focus stack. From this, now the system knows the current reading state is in a kitchen. With the knowledge context corresponding to this kitchen information, it changes the ordering of word senses in the semantic retrieving dictionary in the parser,

For example, following the above sentencs, a case analysis of sentence 'Marilla set the candle firmly on the table.' results in

```
[set, [evt, [change_in_location], [sfrm/p1_3]],
[marilla, [agt, [human], [sbj], [human]],
[candle, [obj, [thing], obj1], [light_source], [the, det2]],
[firmly, [att, [degree], mdf]], [table, [place_at, [thing], [mdf],
[furniture], [the, det2]]]]]
```

From this information, we immediately acknowledge that the 'furniture table' sense for 'table' exceeds other senses.

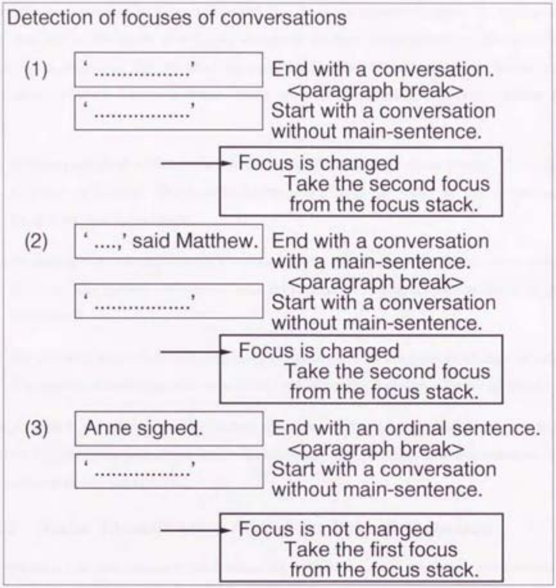


Figure 5.11: Three cases in detecting the focuses of conversations

Thus the system can extract the focus 'marilla', which leaves the hypothesis 'marilla in kitchen' unchanged, requiring no further case analysis.

Provided the result from the case analysis changes the current focus place explicitly, it needs the disambiguating module to change its scene knowledge and reanalyze the sentence. The set of focus and its location extracted from this sentence is stacked on the focus stack for further analyses of succeeding sentences.

5.5.2 Detection of Focuses of Conversations

There are two types of conversations: with and without main-sentences. Focuses of conversations with main-sentences can be easily identified by analyzing the main-sentences.

However, conversations without main-sentence have no explicit focuses. In typical cases when they are in the midst of ordinary sentences, focuses of the sentences are the same as the previous sentences. But we must be careful when the current paragraph begins with a conversation without a main-sentence. Such cases are classified into three situations: (Fig. 5.11).

1. the last paragraph ended with a conversatin without any main-sentence: this suggests a change of focuses. The system determines who in the focus by taking the second focus from the focus stack.

2. the last paragraph ended with a conversation a main-sentence: this suggests a change of focus. The system determines who is in focus by taking the second focus from the focus stack.

3. the previous paragraph included no conversations: this suggests no change of focuses. The system determines who is in focus by taking the first focus from the focus stack.

To cope with these situations, the system must detect the positions of paragraph breaks, whether the previous paragraph had conversations, and whether the conversation is the first sentence in the paragraph.

5.5.3 Scene Identification Based on Lexical Cohesion

The spatial scene identification mechanism[40] proposed in this section is one module of a general inference architecture called Parallel Distributed Associative Inference and Contradiction Detection (PDAI&CD)[22, 41, 42, 43], which uses an associative memory WAVE[44, 45, 46, 47] based on neural networks and a logical verification system. We have previously presented an application of this architecture to semantic disambiguation[22, 42, 43]. It features a cognitive model of fast disambiguation depending on context with bottom-up associative memory together with a more precise top-down feedback process (Fig.5.12). After one scene is selected by previously input words, the system can disambiguate meanings of the following words (Fig.5.14). In the future, we plan to combine natural language processing with visual image from sensory data. Our representation of the spatial data from the OPED is considered to be a simplest approximation of such visual sensory images.

Scene identification with a small set of words based on lexical cohesion implies an algorithm on an associative memory[40, 48, 49, 50, 51, 52, 53] to discriminate patterns into categories (Fig. 5.15). In most cases, the patterns consist of subsets of patterns memorized

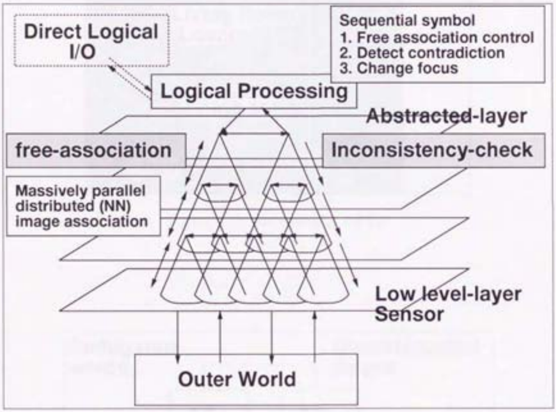


Figure 5.12: PDAI&CD architecture

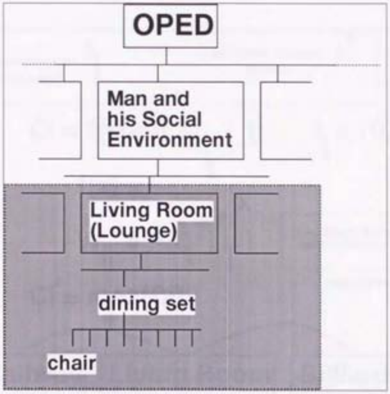


Figure 5.13: Structure of OPED

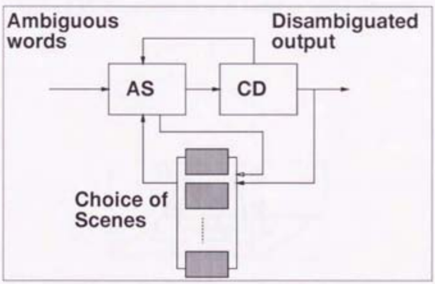


Figure 5.14: Diagram of PDAI&CD

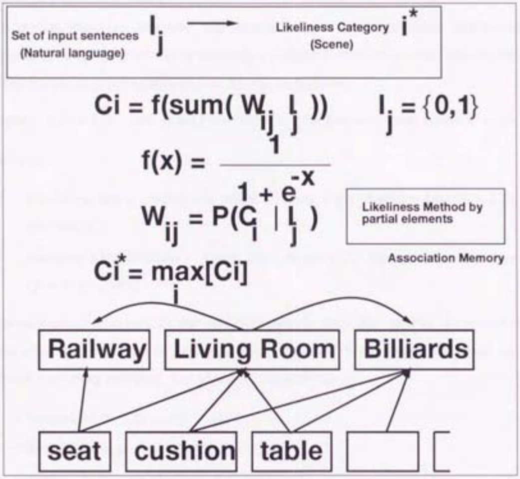


Figure 5.15: Scene identification based on lexical cohesion.

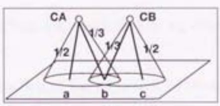


Figure 5.16: Weight of links and category selection

previously. $\mathbf{I}_i$ and C_i are set to be elements of input space S_I, scene space S_C, respectively.

In an ideal state, the appropriate scene C_i is uniquely indexed by association with a complete input vector: $\mathbf{I}_i \xrightarrow{A} C_i$.

In the typical situation, however, the complete index is not provided and we require a way of ranking competing scenes by defining a weighted activation value which depends on the partial input, or a set of ambiguous words, as follows:

- Input : $x_i(i = 1, 2, ..., n)$ (a set of words) *i.e.* in a feature vector space $X = \{\mathbf{x} \in R^N\}$
- Output :
  - Disambiguation : select one sense y_{ij} from a set of senses $\{y_{ij}\ (j = 1, 2, ..., m)\}$ for each x_i
  - category identification : select one category C_j from a set of categories $\{C_j\ (j = 1, 2, ..., m')\}$

  These two concentrates on the same problem in that they aim at the specification of one solution with a set of ambiguous information. For convenience, here we discuss about the latter problem, *i.e.* category identification.

  - Class $C_j(j = 1, 2, ..., k)$
  - Set of concepts $\Omega = \{C_j\}_{j=1}^{k}$
  - $P(C_j)$: prior distribution of each class C_j ($\sum P(C_j) = 1$)
  - $p(\mathbf{x} \mid C_j)$: Conditional probability distribution ($\int p(\mathbf{x} \mid C_j)d\mathbf{x} = 1$)
  - $p(C_j \mid \mathbf{x}) = \frac{P(C_j)p(\mathbf{x}|C_j)}{\sum_j P(C_j)p(\mathbf{x}|C_j)}$
- Decision : use a statistical decision procedure
  - $a = d(\mathbf{x})$: decision function which decides an action a of the input vector (a set of words)
  - $r(C_i \mid C_j)$: risk function of the algorithm to error as $C_j \rightarrow C_i$

  In this situation, the problem requires a decision function $d(\mathbf{x})$ that minimize:

$$R[d] = \sum_j \int r(d(\mathbf{x}) \mid C_j)P(C_j \mid \mathbf{x})p(\mathbf{x})d\mathbf{x}$$

  Implementation of this algorithm causes several problems below:

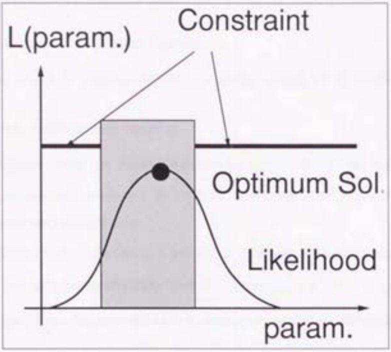


Figure 5.17: Selection of maximum likelihood solution and evaluation in goal function (constraints)

- The first problem : As the risk function $r(C_i \mid C_j)$ is unknown until the aim is fixed (the aim was not fixed in the learning phase), the algorithm must guess it. In addition, sometimes it posesses non-linearity.
  - Solution to the first problem : Therefore, we take a generate-and-test method by evaluating the maximum likelihood solution as follows:
    1. Associative memory with 0-1 cost function
    2. Discrete goal function by logical function (Fig.5.17)

    We adopt 0-1 cost function, *i.e.*, $r(C_i \mid C_j) = 1 - \delta_{ij}$ assuming that we ourselves are estimating maximum likelihood distribution in our learning phase. Thus, $d(\mathbf{x})$ results in Baysean discrimination[54].

$$\mathbf{x} \in C_i . if \;\; p(C_i \mid \mathbf{x}) \geq p(C_j \mid \mathbf{x}), \forall j = 1, 2, ..., k.$$

- The second problem : Taking acconut of the fact that $\mathbf{x}$ may be incomplete, or with some noise – unknown words which was not in the learned instances, for example, it is impossible to calculate all of $p(C_j \mid \mathbf{x})$. In such cases, they fall into non-probability and stops the inference. In addition, information fusion is generally an ill-defined problem.

Thus we propose a compromise plan:

1. Approximate it with some function
2. Set its target to a discrimination on quite a small set of words

– Solution to the second problem :

1. Approximate the discrimination function with a linear function
2. Assume independency and exponential family to the distribution of each element's probability.
3. Evaluate the likelihood function on a likelihood to one element.
4. Assume prior probability of each category as uniform. $(\forall i, j. P(C_j) = P(C_i))$

The likelihood discrimination function is set in the following fashion:

$$
\begin{aligned}
L(C_j \mid \mathbf{x}) &= f(\sum_i W_{ji} x_i) && (5.7)\\
f(x) &= \frac{1}{1+e^{-x}} && (5.8)\\
W_{ji} &= P(C_j \mid x_i) && (5.9)\\
&= \frac{p(x_i \mid C_j)P(C_j)}{\sum_j p(x_i \mid C_j)P(C_j)} && (5.10)\\
&= P(x_i \mid C_j) && (5.11)\\
L(C_{j*} \mid \mathbf{x}) &= \max_j [L(C_j \mid \mathbf{x})] && (5.12)
\end{aligned}
$$

The last equation refers to the selection of maximum likelihood solution, which is implemented on a winner-take-all network on a hardware level. The solution is evaluated by the goal function with logical function described above.

To put it simply with an example, it refers to the problem whether the system can identify 'Living room' or not with a set of words like 'seat', 'cushion', 'table', and so on, which is both a subset of words registered in OPED and found in the target sentence.

This type of associative memory has the following features:

- Unlike correlative models[55], neither distortion of pattern nor pseudo local minimum solutions arise from memorizing other patterns.
- Memory capacity is $O(mn)$ compared to $O(n^2)$ of correlative model, where m is the average number of words per scene, and n is the total number of possible words.

- Unlike back-propagation learning algorithms, incremental learning is possible at any time in WAVE.

We will evaluate and discuss about the talent of the associative memory with OPED.

Chapter 6

Implementation of System Modules

This chapter describes how to implement the proposed algorithm on a workstation system, and how to handle data in it.

6.1 Target Parser

As described previously, a parser generally has two types of approaches; a top-to-bottom approach which constructs a parsing tree from its top to the bottom, and a bottom-to-top approach which constructs the tree from its bottom to the top. A parser has another classification according to its search algorithm; depth-first and breadth-first. The former has an advantage in required memory space, while the latter is effective for search time provided it can use an utility function to a total path or some parallel processing material.

Here use an ordinal sequential processing workstation and decided to implement our algorithm with a bottom-to-top and breadth-first searching parser, since the algorithm targets to disambiguate by ordering the word sense level rather than the sentence level. We apply this to a parser[56](Fig. 6.1) implemented on Prolog as a implementation example. This parsr uses a 'Trie' type dictionary, which leads to a measurably effective search.

The original usage of this dictionary requires that the word in it must be registered

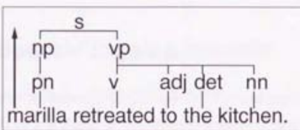


Figure 6.1: Bottom-to-top parser.

previously, and the searching order of the words is fixed. However, we take a different approach such that the words and the sense search ordering are dynamically rewritten being reconsulted over and over in the system. Grammers and lexicons to the parser are written on our own terms. We added a case analysis part to this parser, which semantically restricts the ranges of word senses on the thesaurus-base classification. As controlling module for the entire system is originally written in C language while the parser is implemented on Prolog, the system dynamically calls the Prolog runtime system from the controlling program, with data transfer by files.

An example sentence 'Marilla set the candle firmly on the table .' results as follows:

```
No. 1    time : 110 msec
 |-sentence
    |-sent
    |  |-s
    |     |-np
    |     |  |-nou2 -- marilla
    |     |-vp
    |        |-vp
    |        |  |-vp
    |        |  |  |-vrb1
    |        |  |  |  |-set
    |        |  |  |  |-suffix -- ed
    |        |  |  |-np
    |        |  |     |-det2 -- the
    |        |  |     |-np
    |        |  |        |-nou1 -- candle
    |        |  |-adp
    |        |     |-adv1 -- firmly
    |        |-prp
    |           |-pr -- on
    |           |-np
    |              |-det2 -- the
    |              |-np
    |                 |-nou1 -- table
    |-prd -- .
[set,
  [evt,[change_in_location],[sfrm/p1_3]],
  [marilla,[agt,[human],sbj],[human]],
  [candle,[obj,[thing],obj1],[light_source],
       [the,det2]],
       [firmly,[att,[degree],mdf]],
  [table,[place_at,[thing],mdf],[furniture],
       [the,det2]]]
```

6.2 Part-of-Speech Tagging Module

We use the XEROX Part-Of-Speech (POS) Tagger[36] for tagging the words in the sentence with part-of-speeches. The algorithm of this tagger bases on a Hidden Markov Model, and identifies common nouns, propernons, verbs, adjectives, adverbs, and defines at a precision of 96 % from the test result for words in about one hundred thousands sentences on the

Brown corpus. As the controlling module for the entire system is originally written in C language, while the tagger is implemented on LISP, the system dynamically calls the LISP runtime system from the controlling program, with data transfer by files. It costs several seconds to start up the tagger. To avoid this time cosuming problem at the start phase, the system taggs the words in all of the sentences once at an early stage of the processing.

6.3 Sense Preference Ordering Module

Here we explain about the sense preference ordering module, the main part of the system. Firstly the system assigns part-of-speeches with the tagging module shown above, to all of the words in the input sentences. From the tagged corpus, this ordering module extracts only nouns, calculates the likelihood for each sense assigned to each noun according to the currently identified scene, and finally rewrite the 'Trie' sense dictionary (Fig. 6.2) reflecting the set of likelihood parameters.

An example of the 'Trie' dictionary is, illustrating only the noun sense of 'table', `trie(table, [[nou1, [[sem/n_table4, sem/n_table15, sem/n_table1, sem/n_table2, ..., sem/n_tab []], head(nou1)]]], [])`. Provided a verb sense of it is written as `trie(table, [[vrb1, ...` following the noun sense description, the parser checks a sense sem/n_table4 – the first sense in the noun which corresponds to a furniture table, following checks of other senses if necessary. Verb sense checking succeeds to the noun checks if they are unsatisfactory to all of the constraints.

Thus the sense preference ordering module controls the sense ordering dictionary, to process computationally effective search. This ordering module is implemented on C language, which controls the entire system including the parser, the part-of-speech tagging module, and the scene identifying module.

6.4 Scene Identification Module

The scene identification module consists of:

1. an associative memory based on lexical cohesion,

2. a module for the extraction of focus from the case analysis module

3. a module for controlling the focus stack

4. a module for detecting the conversation

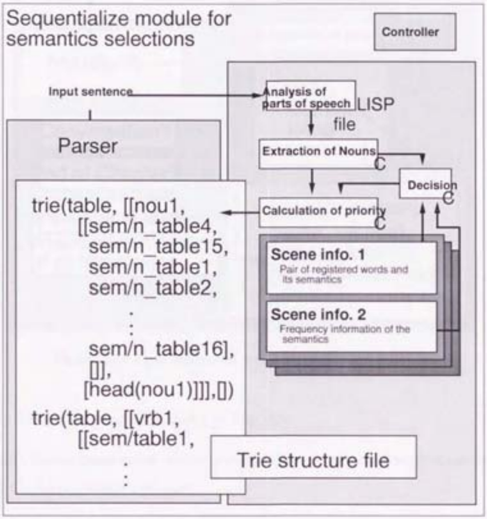


Figure 6.2: Usage of the trie dictionary

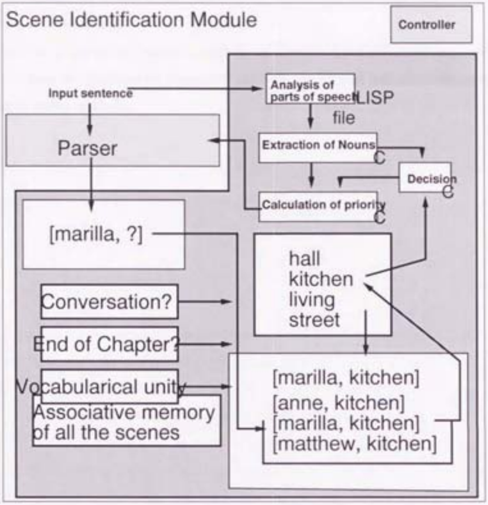


Figure 6.3: Flow control of scene identification module.

It typically follows the procedure shown in Fig. 6.3:

1. identify the sentence focus with the result of case analysis described above resolved with the focus stack if necessary.

2. specify the focus location (scene).

3. check the inconsistency with the sentence.

4. stack the focus list on the focus stack.

The focus stack is described in a file, from which the system reads a stack, and onto which it adds a stack list.

The focus stack in pratical use makes a stack at each sentences and renews the scene information in this manner. However, in the experimental phase, we prepare a focus stack for each paragraph to evaluate the validity of the system behavior and the focus stack modification independently.

The other parts use morphological analysis to detect logical relations, *e.g.* conversation sequences. These modules are implemented on C language, and transfer information among each other or extra modules.

Chapter 7

Performance Evaluation on Real Texts from Narrative Story

7.1 Real Text Data

System performance evaluation of an implementation system with data from the real world avoids falling into a pitfall into which hand analyses with our consideration may fall, since such hand analyses turns a spotlight only on a rather limited range of linguistic phenomema. Thus the main purpose of it is to examine the behavior of the actual system in the complicated real world. The real world data in natural language processing refers to some objective lexical data like dictionaries applied to non-arbitrary sentences with an actual implemented system. We cope with this request by:

1. Dictionaries : OPED, Roget thesaurus are used.
2. Real text : an original narrative story 'Anne of Green Gables' is used.
3. System : implemented on a parser.

We evaluate the system performance according to the following manner:

1. Evaluation of the sense preference ordering module
2. Evaluation of the scene identification module
3. Total evaluation on the implemented system

7.2 Evaluation of Sense Preference Ordering Module

The sense preference ordering module is evaluated by an amount of effectivity in setting priorities to sense candidates of ambiguous words, under a fixed scene[57, 58]. It targets

Table 7.1: Basic information of selected nouns relevant to kitchen scene

Nouns relevant to kitchen	357
Nouns registered in the thesaurus	341
Averaged ambiguity	4.13
Averaged backtracking number to finally select the answer(random)	2.71
Nouns registered in the kitchen	114
Nouns non-registered in the kitchen	227

Table 7.2: Semantic distribution to construct kitchen scene knowledge

Order	category	category name	frequency
1	386	Store, Supply	10
2	8	Eating	9
3	195	Container	8
3	239	Channel	8
5	11	Cooking	7
6	742	Ceramics	6
7	79	Cleanness	4
7	293	Closure	4
7	1023	Refrigeration	4
-	others	-	55
	total		115

to nouns, which are relevant to kitchen, selected from sentences of 'Anne of Green Gables'. Table 7.1 illustrates the basic information of the nouns. Table 7.2 shows a semantic distribution in the kitchen.

Based on this data, the sense preference ordering module is evaluated as follows. Fig. 7.1 illustrates a distribution of the number of ambiguous senses of selected nouns found in the thesaurus, together with a distribution of backtracking number until the system finds a right solution. Since the number of ambiguity refers to the worst backtracking number, it equals to about half of the backtracking number, as is shown in the figure.

In this section, we show the distributions of the backtracking number under several conditions, with discussions on them in later sections.

In Table7.3 we illustrate the average backtracking number to disambiguate nouns registered in the kitchen information under four types of conditions:

1. the senses are randomly selected without any scene knowledge

2. the senses are selected according to the word-sense knowledge in the kitchen scene

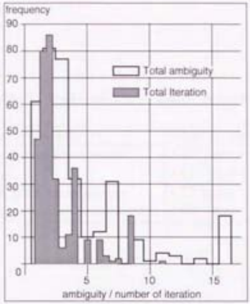


Figure 7.1: A distribution of the number of ambiguous senses of selected nouns found in the thesaurus, together with a distribution of backtracking number until the system finds a correct solution (without any context).

3. the senses are selected according to the kitchen scene knowledge on an item level classification

4. the senses are selected according to the kitchen knowledge on a category level classification

Here, each level refers to the classification level on the thesaurus.

Looking into the average numbers allows us to roughly grasp measurable effects regardless to fluctuations of backtracking numbers or their reduction ratios depending on words. Fig. 7.2 indicates the distribution of each conditions, and Fig. 7.3 indicates the selction probability to find correct senses until the sytem backtracks for each number of times. This implies that the selection according to the word-sense knowledge achieves an extraction speed of more than twice as the randomly selected case, while the knowledge on item level classification is not so satisfactory, and the knowledge on category level classification is worse.

While, Fig.7.4 shows distributions of difference between each conditions above. On the horizontal axis in this figure, the negative direction means the reduction of backtracking, which shows the measurable effectiveness of the knowledge, and the positive direction means an excess of backtracking, which leads to worse performance. We can conclude from

Table 7.3: Average number of backtracking of nouns registered in the kitchen scene.

Scene knowledge representation	Average number of backtracking
Random(without any scene knowledge)	3.43 times
Word-sense knowledge	1.47 times
Knowledge with item level classfication	1.72 times
Knowledge with category level classification	1.82 times

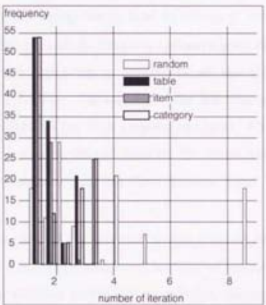


Figure 7.2: Distribution of backtracking number of senses of nouns registered in the kitchen information.

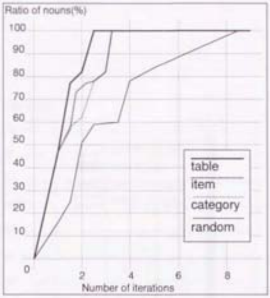


Figure 7.3: Probability to find correct senses for nouns registered in the kitchen information until the system backtracks for each number of iteration times.

this figure naturally that sense preference ordering with scene knowledge has a significance compared to randomly selecting strategy, and that knowledge on item level classification in the thesaurus is slightly advantageous to that on category level classification.

Comparison of backtracking numbers between category level classification and item level classification with which the algorithm is applied to all the selected nouns, is shown in Table 7.4, Fig. 7.5, and 7.7. Fig. 7.6 indicates the selction probability to find correct senses until the sytem backtracks for each number of times. Although the selected nouns include both registered and non-registered ones in the scene, these implies the result, *i.e.* the average backtracking numbers and the distributions, from the application to all the nouns selected.

The backtracking number for all the selected nouns without any scene knowledge shown in the first line in Table7.4 is small, compared to that of nouns registered in the kitchen scene knowledge, but also without any scene knowledge, shown in the first line in Table 7.3. This suggests that the group of the nouns registered in the scene knowledge has more ambiguous senses compared to that of not registered nouns.

Fig.7.3 also shows that the backtracking number for word senses in the category level classification exceeds that in the item level classification. This indicates the insufficiency of knowledge information, which leads to the necessity of information completion by the classification expansion from the item level to the category level. Average backtracking

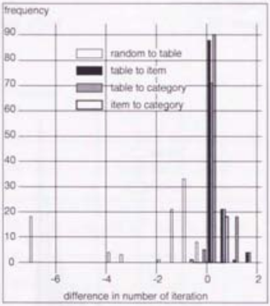


Figure 7.4: Distribution of differences of backtracking number of senses of nouns registered in the kitchen information.

Table 7.4: Average number of backtracking for all the selected nouns.

Knowledge type	number of backtracking(ave.)
Randomly selected(without scene knowledge)	2.71 times
item level classification	2.08 times
category level classification	1.83 times

Table 7.5: Average number of backtracking for nouns not regsitered in the kitchen scene knowledge.

Knowledge type	number of backtracking(ave.)
Randomly selected(without scene knowledge)	2.35 times
item level classification	2.26 times
category level classification	1.83 times

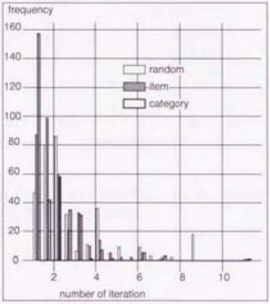


Figure 7.5: Distirbution of backtracking number for all the selected nouns.

numbers for nouns not registered in the scene knowledge under the knowledge types are shown in Table7.5. In this case, effectivity of the scene knowledge is not clear, since the number of the senses of the implied nouns is relatively small.

Thus, we concluded to take the following strategy, and show its result in Table 7.6.

- Order the sense of the nouns registered in the scene knowledge according to the word-sense table.
- Order the sense of the nouns not registered in the scene knowledge according to the semantic distribution in the category level classification of the thesaurus.

7.2.1 Discussion

In this section we discuss about the reason of the case that the scene knowledge did not effect the backtracking number, together with an examination of the difference of the

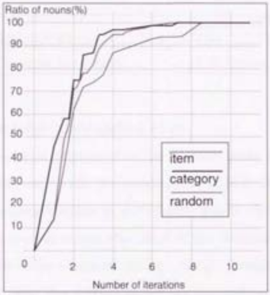


Figure 7.6: Probability to find correct senses for all the selected nouns until the system backtracks for each number of iteration times.

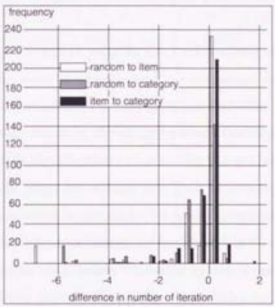


Figure 7.7: Distribution of difference in backtracking number according to knowledge types, for all the selected nouns.

Table 7.6: Average backtracking number for all the selected nouns with senses ordered according to the kitchen scene knowledge.

Knowledge type	number of backtracking(ave.)
Randomly selected(without scene knowledge)	2.71 times
After ordering with scene knowledge	1.71 times

effectivity among the knowledge types applied above.

Firstly, an example of a noun registered in the kitchen scene knowledge with relatively large number of backtracks even with the word-sense table is 'dish' with 2.5 times backtracks. The large backtracking number is not mainly due to the number of its ambiguity but rather because it has several senses classified in the thesaurus refers to the same object. For example, 'dish' includes senses of 'eating', 'food', 'cooking' and so on, all of which we consider them correct. But the system is assumed to take only one sense as a unique solution, resulting a rather disadvantege in this experiment. Another example is 'shelf', which implies senses of 'store, supply', 'layer', and 'support', separately classified in the thesaurus.

This fact indicates the difficulty of avoiding redundancy of word sense classification in a thesaurus. It requires an introduction of 'viewpoint' to identify correct meanings of words depending on each situation to cope with the similarity differences between one sense and another.

The instances which have negative value in the backtracking number difference between the nouns registered in the scene knowledge and the nouns not registered indicates insufficiency of the knowledge information. For example, the fact that the backtracking number for the registered nouns with senses in the category level classification is small compared to that of other cases, indicates the effectivity of counting the senses of the words themselves. Without these words in the scene knowledge may lead to serious disadvantages. Provided sufficient data would be corrected to construct the scene knowledge, the system will achieve performance even for disambiguating nouns not registered in the knowledge as effective as this case of registered nouns with senses classified in the item level. However, we can not always expect such ideal states. If sufficient knowledge is not available, completion with upper classification levels, *e.g.* the category level, will cause good effects as in this experiment.

While the problem of such completion with upper level classifications is the interference between sense distributions. Even in the item level classification, some word senses are interfered by senses of other words. For example, the word 'table' has a meaning 'layer', whose frequency is badly excessed, being affected by 'plate' including the sense in this scene. An example of the problem of completion with classification by category level is, 'table' which is registered in the scene knowledge and sometimes refers to 'eating'. By this analysis in the texts, most of the appeared words 'table' mean 'furniture table', but we sometimes use 'table' as 'cooking' in the same kitchen scene. This suggests a rather complicated difficulty of disambiguation.

As to nouns not registered in the scene knowledge, 'cream' is a good example. The knowledge supports 'washing cream' as its meaning in the influence of a category 'cleanness' in the semantic distribution, but it refers to 'soft cream for cakes' in the texts.

We can easily consider the case that several objects with different meanings with the same expressions may simultaneously appear in the scene knowledge, which results in disadvantages even with the word-sense table, though it did not appear in our target texts. For instance, the scene knowledge includes two 'plate's, one refers to 'dish plate' and the other refers to 'counter' of 'hotplate'. However, such cases are relatively rare.

7.3 Analysis of Scene Identification

We analyzed a set of kitchen scene paragraphs in real texts from a narrative story, 'Anne of Green Gables' by L. M. Montgomery. Its organization is illustrated in Fig. 7.8. It includes about fifty spatial scenes, which can be classified as follows:

- Around house:
  - Indoor: kitchen, entrance, hall, room, cellar, living, daily room, dining, stairs, hallway, washing room, bedroom
  - Outdoor: entrance, gate, roof, wall, garden, yard, barn
- On road: road, path, basin, field, orchard, farm, forest, pasture, town, hill, lake, pond, stream, marsh, port, spring, bridge, cape, seashore, inlet, seashore road
- Others(other building): station, railway, school, church, hotel, public hall, grocer, flat

These scenes almost correspond to the pictures in the OPED. In the text analysis, paragraph breaks are used to approximate discourse scene segments, from which we extracted all the scene segments referring to kitchen (309 paragraphs) to evaluate the system performance. The purpose of analyzing the real texts is to clarify what kind of knowledge is required for each identification case to detect; some conditional resolution may need only several rules, while others may be based on wider knowledge or deeper inference beyond our scope. Real texts imply natural combinations of ways to construct discourse, and require us various kinds of knowledge to extract the discourse segmentations. Text analysis is siginificant to resolve this kind of complexity and to find computationally effective and reliable algorithms.

In accordance with the classfication described above, we classified the 309 paragraphs we checked, into three cases: (1) Entering the scene : 34 paragraphs including 31 analyzable (Table 7.10), (2) Continuing the scene : 275 paragraphs including 241 analyzable (Table 7.11), and (3) Exiting the scene : 34 paragraphs including 31 analyzable (Table 7.12). Here we excluded 37 paragraphs from our analysis, since they were not confidenced to be kitchen scenes. They commonly require non-monotonical inference, which could puzzle even human readers.

Table 7.7, Table 7.8, and Table 7.9 illustrate the analysis results according to the knowledge classification discussed in Chapter 4.4, listed again below:

1. Identification of focus :
   (a) Explicitly given (ex: <u>Marilla</u> said.) 1
   (b) Not explicitly given:
      i. included in subject but indirectly (ex: <u>Marilla's</u> lips twitched.) 2
      ii. Without subject or pronoun subject:
         A. Search focus stack (ex: She was sitting there. ← [<u>Rachel</u>, kitchen]) 3
         B. Knowledge that conversation lasts mutually 4
         C. End of chapter 5
         D. Focus refers to place (ex: There was no mistaking.) 6
         E. Idiomatic words 7
2. Identification of location of focus :
   (a) Explicitly given
      i. place at (ex: Anne recited <u>in the kitchen</u>.) ....A

Table 7.7: Scene identification method in entering the kitchen scene.

	A	B	C	D	E	F	G
1	11	8		2	3		
2				1			
3	1	4		2			
4							
5							
6							
7							
8							

Table 7.8: Scene identification method in continuing the kitchen scene.

	A	B	C	D	E	F	G
1		1	139	1	4	4	
2			6				
3			43				
4			34				
5							
6							
7						1	
8						1	

ii. place to (ex: Marilla retreated to the kitchen.) ....B

(b) Not explicitly given:

i. Search focus stack: (ex: She was sitting there. ← [Rachel, kitchen]) C

ii. Lexical cohesion (ex: Anne finished dishwashing.) ....D

iii. Needs novel inference (ex: She was downstairs.) ....E

iv. Default:previous focus place ....F

v. going out (ex: She set out.) ....G

Entering the scene phase consists of two parts(Table 7.10): focus identification and identification of the place in focus. When the system enters a new scene, it must detect the place and focuses (characters or objects) which apprear in the place and stack a combinated list of the pairs [focus, place] for further analysis. This table implies the number of focuses required to identify the scene of succeeding paragraphs, and the number of the succeeding paragraphs (The number of paragraphs which includes the entrace to the scene

Table 7.9: Scene identification method in exiting the kitchen scene.

	A	B	C	D	E	F	G
1	5	8					8
2							
3	1	1					2
4				1			
5							6
6							
7							
8							

"kitchen" is 31). The focus identification consists of direct references and anaphoric references. An example for direct reference is an analyzed focus 'Marilla', which requires no anaphoric resolution. While anaphoric references like 'they'(labeled (C2)) need domain specific knowledge, and/or more common knowledge like sex-check, and/or sometimes more complicated inference with contradiction checks. Direct identification of the place in focus implies 'In kitchen'(A). This refers to explicit place specification like 'in the kitchen' or 'at the kitchen'. 'By kitchen objects'(B) refers to implicit place specification intermediated by some objects in the scene, *e.g.* 'at the kitchen door' or 'by the kitchen window' which are explicitly modified by the scene name. Another implicit place specification intermediated by objects uses lexical cohesion(E) to identify from objects like 'breakfast', which includes no surface key for relevance to the scene, rather with semantical connections. The instance which needs ellipsis resolution(H) appeares in Fig. 1.1, *i.e.* 'Mrs Rachel rapped smartly at the kitchen door and stepped in [ ]'. This sentence implies that she stepped in the kitchen. The indirect identification of the place in focus, *i.e.* place of the current scene or place of another focus, consists of 'anaphoric resolution'((C1): 'here', 'there' and so on), 'continuing verbs'((D): 'was smoking' and so on), 'first in the chapter'((G): not appeared previously in the focus stack. This suggests a usage of the place of the current scene), 'in the same paragraph'((F): equalify the place in focus to that of the current focus), 'in conversation series'((I): mutual talks), and 'as objects'((J) : not as subjects but as objects like 'her'). Among these, (F), (G), and (I) require a small set of rules, while others require a lexical knowledge source.

In continuing the scene phases(Table 7.11), the algorithm needs four types of focus identification methods: by exact match ((a): 'Marilla' to [marilla,kitchen] in the stack), by resolving anaphora ((b): 'she' to [marilla,kitchen] in the stack), by inclusion relation ((c):

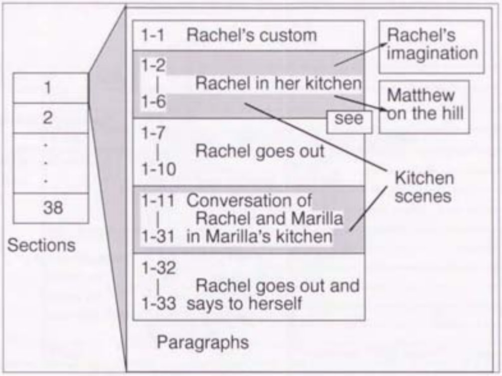


Figure 7.8: Structure of the text "Anne of Green Gables"

'Marilla's astonishment' to [marilla,kitchen] in the stack), and by detecting conversation ((d): 'I've never been in the depths of despair, so I can't say,' responded Marilla. [NEXT PARAGRAPH] 'Weren't you?...' – this focus is not Marilla.). Here, a small set of knowledge is necessary for these types of resolution.

In exiting scene phases(Table 7.12), an example for explicit scene change into another scene(labeled (1)) is 'she was safety out in the lane.' Inclusive relation((2)) refers to objects modified explicitly by a scene, *e.g.* 'flew to the porch door', in the scene 'porch'. Besides these, detection of exitance from the scene is based on four types of knowledge: exiting verbs((3): 'set out' and so on), idioms((4): 'go to bed'), end of chapter detection((5)), lexical cohesion((6): 'sitting on the sofa'). Like the knowledge for scene entrance detection, these kind of knowledge also require a wide lexical knowledge source.

7.3.1 Discussion

These results suggest that in entering the scene, the focus is explicitly refered or requires a search in the focus stack in most cases. The references to the focus stack are mainly required by resolutions of pronouns. The number of cases that locations are explicitly refered amounts to the half of the identification of the focus location, while the number

Table 7.10: Result of usage frequency of each identification algorithm for cases of entering scene

Entering the scene "kitchen"				label
Focus identification	Direct	56 / 247		(C2)
	Anaphora	16 / 61		
	Total	72 focuses / 308 succeeding paragraphs		
Identification of the place in focus	Direct	In kitchen	14 /73	(A)
		By kitchen objects	15 / 44	(B)
		By lexical cohesion	10 / 51	(E)
		Resolving ellipsis	1 / 12	(H)
	Place of the current scene or place of another focus	Anaphora	11 / 31	(C1)
		Continuing verbs	3 / 11	(D)
		First in the chapter	5 / 8	(G)
		In the same para.	7 /44	(F)
		In conversations	4 / 27	(I)
		as objects	2 / 7	(J)
	Total		72 focuses / 308 suceeding paragprahs	

Table 7.11: Result of usage frequency of each identification algorithm for cases of continuing scene

Continuing the scene "kitchen"		label
Focus id. by exact match	158	(a)
By resolving anaphora	22	(b)
By inclusion relation	3	(c)
By detecting conversation	58	(d)
Total	241 paragraphs	

of lexical cohesive cases amounts to 30 % of all. Other cases require extremely difficult inferences, for example, backward non-monotonical reasoning; therefore we do not discuss about such situations.

While, the cases of focus identification on continuing a scene are mainly due to explicit subject references, references of the focus stack, and regular common knowledges about the sequence of conversation.

Focus locations are mostly resolved by searching the corresponding focuses from the focus stack. We can interpret this fact that human being communicate efficiently without explicit reference to each location at every points, with clever confidence on the memory

Finally, many cases of exiting from scenes use explicit location changes, or changes of

Table 7.12: Result of usage frequency of each identification algorithm for cases of exiting scene

Exiting the scene "kitchen"			label
Explicit scene change	In another scene	15	(1)
	Inclusive relation	2	(2)
By exiting verbs		3	(3)
By idioms		3	(4)
End of chapter		6	(5)
By lexical cohesion		1	(6)
Hard to resolve		1	(7)
Total		31 paragraphs	

story by the end of a chapter.

Next, we discuss about the required knowledge to identify the kitchen scene in the text. Although little rules are required for continuing scenes by the focus stack, *i.e.* for simple anaphora resolution, many types of knowledge are needed to detect change in locations. Anaphoric relations for focus identification (labeled C2 in Table 7.10) implies 'she', 'he', 'her', which can be easily resolved with the focus stack, and 'it', 'they', 'them', 'the latter', which can not be resolved because of their ambiguous scope. Knowledge to identify the kitchen scene with lexical cohesion (labeled E in Table 7.10 and (5) in Table 7.12) implies 'sat down to supper', 'the dinner table', 'breakfast, dinner, and supper', 'proceeded to make her cake', 'had the breakfast ready', 'at breakfast'(twice), 'sitting on the sofa'. Anaphoric relations to equalify the place to another focus or the current scene (C1) are 'there', 'here', 'that', 'all', 'this', which our system can resolve, and six specifiers 'the ...' which are beyond the ability. Continuing verbs(D) including 'be ...ing', 'come', 'come in', exiting verbs((3) in Table 7.12) including 'set out', 'go back', 'go out of doors', and idioms((4)) including 'go to bed'(twice),'go home' requires extra knowledge sources for practical scalable systems.

7.4 Evaluation of Scene Identification Module on Lexical Cohesion

7.4.1 Recalling Probability and Estimation of Required Quantity of Information

The aim of using associative memory for detection of lexical cohesion is to select the most likely scene based on incomplete word data from sentences. The measure of scene selectivity is reduced to the condition whether given words are unique to the scene. If all input words are common to plural scenes, they can not determine the original scene uniquely. For example, the system can not determine whether to choose category CA or CB only by seeing element 'b' in Fig.5.16. If 'a' or the set {a, b} is given, it can select CA. Here we estimate the selectivity by the ratio of successful cases to all the possible cases as follows(n is the number of total elements, k is the number of elements related to each scene, and m is the total number of scenes; incomplete information is defined as a partial vector of elements number s $(0 < s < k)$).

The probability that s elements are shared simultaneously by two patterns is

$$V(n,k,s) = \frac{{}_kC_{s-1}\ {}_{n-k}C_{k-s-1}}{{}_nC_k} \tag{7.1}$$

To extend this probability to generalized cases of m patterns, we use the number s of elements of the (partial) input vector. It can be estimated by counting the negative case where more than one pattern shares elements.

$$\begin{aligned} & P(n,k,s,m) && (7.2)\\ = \ & (\sum_{r=1}^{s} V(n,k,r))^{m-1} - P(n,k,s-1,m) && (7.3)\\ = \ & (p_1 - p_2)(\sum_{q=0}^{m-2} p_1^q p_2^{m-2-q}) && (7.4)\\ = \ & \underline{V(n,k,s)(\sum_{q=0}^{m-2} p_1^q p_2^{m-2-q})} && (7.5) \end{aligned}$$

$$\left(p_1 = \sum_{r=1}^{s} V(n,k,r),\ \ p_2 = \sum_{r=1}^{s-1} V(n,k,r)\right)$$

The results using this formula are shown in the next section.

7.4.2 Information Entropy

As an alternative method of the evaluation of the spatial-scene information of OPED, we consider here self-information entropy and mutual-information entropy along with the information theory of Shannon[59].

- **Self-information entropy**:

  Fig.7.9 illustrates a talking scene. Although sentences involving many ambiguous words are handed from the speaker to the listener, the listener can disambiguate them with some kind of knowledge common to these people. Conversely, the listner can

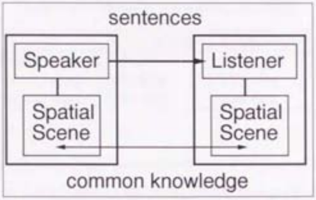


Figure 7.9: Common knowledge between speaker and listener to disambiguate semantics of handed sentences.

determine a scene by the handed sentences. The entropy of scene selection ambiguity is reduced by the interaction. We can define a concept of self-information (SI) of the spatial-scene idetification module as the entropy of ambiguous words or scenes. Assuming equal probability to the scene selection with no handed word, the entropy of the spatial-scene identification can be calcualted.

$$SI_0 = -\sum_j P(C_j)\log_2 P(C_j) = \log_2 384 = 8.59bits$$

After the identification, the meaning of each word can be selected according to each a selection distribution function updated by the Bayesian rule.

$$\begin{aligned} SI_1 &= CE(C \mid X) && (7.6)\\ &= <-\sum_{ji} P_{ji}\log P_{ji}> && (7.7)\\ P_{ji} &= P(C_j \mid x_i) = P(x_i \mid C_j) && (7.8) \end{aligned}$$

Each P_{ij} is equal to W_{ij} as in Eq.(2). <> represents the ensemble average over each x_i.

- **Mutual-information entropy**:

  Mutual-information entropy (MIE) can be defined as the contribution of additional words to identify a scene, and consequently, the selectiveness of the target word or scene. In order to select a word meaning or scene from the possible space Y, the space C of all other words are considered in the calculation of conditional entropy (CE). Mutual-information entropy per word is calculated by the following formula:

$$MIE(\theta;\theta') = CE(C \mid \theta) - CE(C \mid \theta')$$

Table 7.13: Mutual-information of OPED

	Scene entropy	Mutual-inform.
Without input	8.59 bits	—
1 word input	0.80 bits	7.79 bits
2 words input	0.32 bits	0.48 bits

Here, θ is a set of previous state parameters, and θ' is that of the next one. Mutual-inforamtion can be interpreted as the reduction from a previous conditional entropy to corresponding updated conditional entropy with additional words. We provide a theoretical estimation of self-information of spatial-scenes with the dictionary in Table 7.13. The result suggests that it has the spatial-scene identification ability with a few words preservation. It also supports the consequence of a logical-summation algorithm shown in the next section.

7.4.3 Analyses of Identification Module

Here we propose an analysis of OPED and the results of the theoretical simulations. As formula (7.10) is computationally expensive(11711! times), we use a Monte-Carlo simulation to abstract its characteristics. The iteration time in each case is 1,000.

- Fig.7.10 (a) shows a distribution of the number of elements involved in each scene in OPED. It approximated a Gaussian distribution and has a average value of 184.2. This value is used in the theoretical simulations.

- Fig.7.10 (b) shows a distribution of the number of scenes which are related to one element. The region where more than 100 scenes are related to one word are those for trivial words like 'a', 'the', 'of', 'that', 'to', 'in', 'and', 'for', 'with', 's'. Although we could ignore these words for an actual application, here we use them for fairness.

- Selection probability in the case that partial words of scenes are input to the associative memory is illustrated in Fig.7.11. The recall rate increases as the input vector (set of words) becomes more similar to the complete vector (set of words) pattern. About five words are sufficient for identifying each scene at a recognition rate of 90 %. Compared to the average number of 184 words in each scene, this required number is sufficiently small. It proves the good performance of the associative memory used in this module. Theoretical results of a random distribution

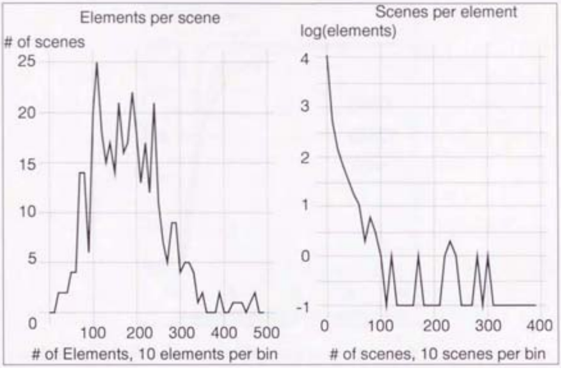


Figure 7.10: (a) Distribution of number of elements per scene and (b) distribution of number of scenes per elements

model is also shown in Fig.7.11. The cause of the discrepancy between the experiment and the theory is described later. The dotted line 'EXACT' in the figure is a result using logical-summation. The crossing point of the 'OPED' line and the 'EXACT' line is remarkable. The former has the advantage of expecting with relatively high-probability (likelihood) using input words of small number. Though with more additional words, the algorithm is defeated by the simple logical-summation. As our architecture PDAI&CD uses a dual-phase of expectation and evaluation, we can achieve a solution with the maximum-likelihood satisfying the constraints automatically.

- Fig.7.12 shows the distribution of the number of elements contributing to identify each scene uniquely.

- In order to clarify the discrepancy of the experimental and theoretical results, the number of elements overlapped in any two scenes are counted. As in Fig.7.13, the number of overlapping elements in the theoretical calculation is very small compared to the experiments with OPED. OPED-2 in the figure illustrates the same value without using trivial words like 'a', 'the', 'of', 'that', 'to', 'in', 'and', 'for', 'with', 's'.

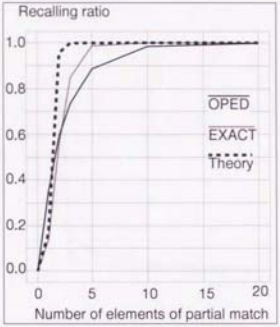


Figure 7.11: Recalling probability to number of partial input elements

But the existence of these words does not explain the whole discrepancy. This will be described in the next section in more detail.

- We investigate further on in order to explain the discrepancy of 'EXACT'(logical-summation) and 'OPED'(with our associative memory). The distribution of the weight values is shown in Fig.7.14. Logical-summation method is achieved by a special algorithm similar to the associative memory. The only difference is that it uses equal weight value without any variance. But in practical, the experimental result of 'OPED' as in Fig.7.14 shows an existence of an enormous variance in the distribution of the weight value. Though the variance helps the selectivity with a few words, it disturbs the expectivity with more than three words conversely. Here we summarize the interpretation of the gaps among the theoretical expectation, the result of logical-summation('EXACT'), and the system('OPED'):

  1. Exsistence of trivial words in most of the scenes

  2. Variance of the weight distribution

  3. Difference of the characteristics between each algorithm

- Abstracted results are summarized in Table.7.14. In this table, the number of registered words in the dictionary itself is different from the number of the total words

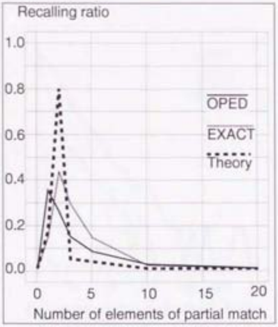


Figure 7.12: Distribution of number of partial input elements to identify scenes

analyzed by our system. The discrepancy arises mainly from the fact that we analyzed compound words into simple words (*e.g.* 'research laboratory' to 'research' and 'laboratory').

7.5 Total Evaluation on the Implemented System

We evaluate the implemented system by the part of the story, which is in the scene "kitchen" and analyzed above. It includes:

1. 27 sentences including nouns which are relevant to kitchen. They are applied to evaluating the disambiguating algorithm.

2. 133 paragraphs which are in the scene "kitchen". They are applied to evaluating the scene identification algorithm.

    - 1-(1): from the second to the seventh paragraph of the first chapter
    - 1-(2): from the tenth to the thirty-first paragraph of the first chapter
    - 3-(1): from the thirty-second to the fourty-first paragraph of the third chapter
    - 3-(2): from the fifty-third to the sixty-ninth paragraph of the third chapter
    - 7-(1): the seventh paragraph only

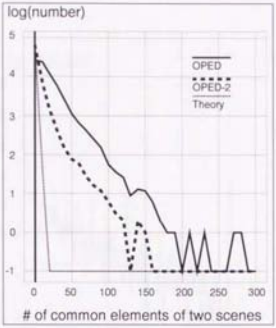


Figure 7.13: Distribution of number of elements common to two scenes

- 8-(2): from thirty-first paragraph of the eighth chapter to the fifty-fourth
- 18-(1): from the third paragraph of the eighteenth chapter to the twenty-sixth
- 18-(2): from the twenty-ninth paragraph of the eighteenth chapter to the tirty-sixth
- 18-(3): from the fourtyth paragraph of the eighteenth chapter to the fifty-first
- 27-(1): from the third paragraph of the eighteenth chapter to the seventh

The purpose of the experiment is to clarify the effectivity and the limitation of the algorithms, and knowledge necessary for the system to analyze the texts.

7.5.1 Noun Disambiguation

The 27 sentences evaluated are shown below. Nouns which are relevant to kitchen are underlined.

1. Mrs. Rachel had fairly closed the door.
2. There was three plates laid on the table.
3. Marilla expected someone home with Matthew to tea.
4. The dishes were everyday dishes.

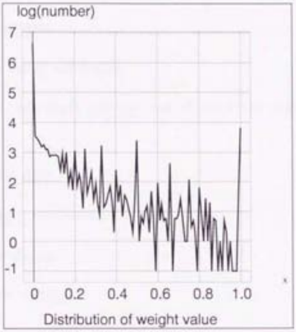


Figure 7.14: Distribution of weight value

Table 7.14: Summarized results

Total # of scenes Registered # of words Total # of words Average # of words / scene Max # of words in one scene	384 scenes 27,500 words 11,711 words 184.2 words 478 words
Required # of words to identify scenes at 90% ratio	5 words
Required # of words to identify scenes at 90% ratio by exact match algorithm	4 words
Theoretical estimation of required # of words to identify scenes at 90% ratio	2 words

5. There was only a crab-apple preserve on the table.
6. There was only one kind of cake on the table.
7. They sat down to supper.
8. she nibbled at the bread and butter.
9. she pecked at the crab-apple preserve out of the little scalloped glass dish by her plate.
10. She slipped into the chair.
11. Anne held her tongue obediently.
12. You may wash the dishes.
13. You have finished the dishes.
14. Anne washed the dishes deftly enough.
15. Crystals were shining on the window panes.
16. Anne studied at the table.
17. Anne turned her back on the clock shelf.
18. She lay on the kitchen sofa.
19. She desceneded to the kitchen.
20. Marilla entered the kitchen.
21. He was waiting for his tea.
22. Marilla washed the dishes.
23. Matthew nodded on the sofa.
24. The fire blacked out.
25. She must prepare the meal.
26. Anne had the kitchen.
27. A fire was glowing in the stove.

Table 7.15 shows the results of theoretical analysis and experiments of sentence disambiguation which requires unique and correct reading of the sentence. The number of trees in the second column refers to the product of the number of ambiguous senses and the number of structural ambiguous trees. The third column shows the probability that the first output sentence is correct under the condition that no scene information is applied to the system, and the fourth column shows the probability that the first or the second output sentence is correct under the condition that no scene information is applied to the system. The fifth column indicates the expectation value of the order of the first correct solution in the parsed trees. Each expectation value is calculated according to this formula:

$$E(n,m) = \sum_{k=1}^{n-m} k \left(\frac{{}_{n-m}C_{k-1}}{{}_{n}C_{k-1}} - \frac{{}_{n-m}C_{k}}{{}_{n}C_{k}} \right) + \frac{n-m+1}{{}_{n}C_{n-m}} \quad (7.9)$$

Here, n is the number of the ambiguous senses of each word, and m is the number of the correct senses.

The averaged value is 4.53, which means that the system must try over four times to check if the candidates are correct without any scene information. However, if the system has the scene information of "kitchen", the average number of candidates to readch the first correct solution is 1.37. The distribution is shown in the seventh column.

From these results, their average values are summarized in Table 7.16. If the system has no scene information, the probability that the first sentence has one of the correct solutions is only about 39 %. While, if the system has a scene knowledge, the probability is 89 %. The progress in the performance is due to the effectivity of the scene knowledge. Furthermore, under the same condition, the probability that the first and the second sentence have one of the correct solutions is 96 %.

Table 7.17 shows the results of theoretical analysis and experiments of word sense disambiguation which requires unique and correct reading of the sentence. In the third column, 'Correct' refers to the number of correct senses while 'Ambiguity' refers to the number of all senses of each word. The fourth column shows the probability that the first output sentence is correct under the condition that no scene information is applied to the system, and the fifth column shows the probability that the first or the second output sentence is correct under the condition that no scene information is applied to the system. The sixth column indicates the expectation value of the order of the first correct solution in the parsed trees. The averaged value is 2.30, which means that the system must try over twice to check if the candidates are correct without any scene information. However, if the system has the scene information of "kitchen", the average number of candidates to reach

Table 7.15: Result of sentence disambiguation

sentence #	Trees	Probability (without scene info.)		Order of the first correct solution		
		1st sentence	Until 2nd sentence	Expectation value (without scene info.)	Example of Randomly selected (without scene info.)	Set priority by scene info.
1	8	0.500	0.833	1.667	1	2
2	288	0.125	0.241	5.667	2	1
3	684	0.333	0.667	2.000	1	1
4	49	0.327	0.551	2.941	17	1
5	48	0.042	0.082	16.30	2	1
6	288	0.063	0.123	11.00	2	1
7	4	1.000	1.000	1.000	1	1
8	160	0.200	0.368	4.200	21	9
9	4536	0.021	0.042	38.00	111	2
10	12	0.333	0.600	2.333	2	1
11	18	0.111	0.222	5.000	3	1
12	7	0.571	0.857	1.600	3	1
13	7	0.571	0.857	1.600	3	1
14	14	0.571	0.857	1.600	3	1
15	288	0.500	1.000	1.500	1	1
16	64	0.125	0.242	5.667	5	1
17	2160	0.750	0.964	1.286	10	1
18	72	0.500	0.786	1.800	1	1
19	56	0.500	0.833	1.667	1	1
20	4	0.500	0.833	1.667	1	1
21	6	0.333	0.667	2.000	1	1
22	7	0.571	0.857	1.600	3	1
23	18	1.000	1.000	1.000	1	1
24	11	0.273	0.491	3.000	3	1
25	4	0.750	1.000	1.250	1	1
26	4	0.500	0.833	1.667	1	1
27	308	0.273	0.481	3.286	57	1
Average		0.39	0.64	4.53	9.56	1.37

Table 7.16: Probability to find the correct sentence

	Without scene info. (calculation)	An example of randomly selected (without scene info.)	Set Priority by scene info.
1st sentence	0.39	0.41	0.89
Until 2nd sentence	0.64	0.56	0.96

the first correct solution is 1.28. The distribution is shown in the seventh column. The result shows that most of these nouns are disambiguated at the first check.

From these results, their average values are summarized in Table 7.18. If the system has no scene information, the probability that the first sentence has one of the correct solutions is only about 50 %. While, if the system has a scene knowledge, the probability that the first sentence has one of the correct solutions is 92 %. The progress in the performance is due to the effectivity of the scene knowledge. Furthermore, under the same condition, the probability that the first and the second sentence have one of the correct solutions is 97 %.

These results refers to the fact that, if the system uses a scene knowledge, it can disambiguate the sense of listed nouns with the precision of 92 % without any additional help. We can also assume the case that the system output the two of the highest ordered candidates to us, and leave us or some additional modules to select the correct sense. Then the system is able to propose candidates with the precision of 97 %. It can effectively reduce our labor to check all the parsed trees which count up to the numbers shown in the second columns in Fig. 7.15 and Fig. 7.17.

7.5.2 Scene Identification

The original sentences used to evaluate the scene identification algorithm are shown in Appendix A. For simple analysis, they were transformed according to several rules:

- Conversations are transformed to two types of representation depending on whether they have main sentences or not; if they have main sentences, they are transformed to 'QQQ,' with the main sentences, *e.g.* " QQQ, said Matthew.", and if they have no main sentences, they are transformed to 'QQQ.'
- Paragraph numbers are assigned to the beginning of the paragraphs.
- Basically, only the first sentence from each paragraph is extracted from the texts; we assume that the extracted sentences can approximately trace the focus and place transitions.

The transformed format of the sentences in Appendix A is shown in Appendix B.

Furthermore, we set three assumptions below for convinience:

- Scene can be identified by analyzing the first sentence in each paragraph
- Only human subjects are handled as focuses

Table 7.17: Result of noun disambiguation

Sent. #	word	Correct /Ambiguity	Probability (without scene info.)		Order of the first correct solution		
			1st sentence	Until 2nd sentence	Expectation value (without scene info.)	Example of randomly selected (without scene info.)	Set priority by scene
1	door	2/4	0.500	0.833	1.667	1	2
2	table	2/16	0.125	0.241	5.667	2	1
3	tea	1/3	0.333	0.667	2.000	1	1
4	dish	4/7	0.571	0.857	1.600	15	1
	dish	4/7	0.571	0.857	1.600	3	1
5	preserve	1/3	0.333	0.667	2.000	1	1
	table	2/16	0.125	0.242	5.667	2	1
6	cake	1/2	0.500	1.000	1.500	1	1
	table	2/16	0.125	0.242	5.667	2	1
7	supper	1/1	1.000	1.000	1.000	1	1
8	bread	2/5	0.400	0.700	2.000	17	1
	butter	2/4	0.500	0.833	1.667	5	9
9	preserve	1/3	0.333	0.667	2.000	1	1
	dish	4/7	0.571	0.857	1.600	109	1
	plate	1/9	0.111	0.222	5.000	3	2
10	chair	2/6	0.333	0.667	2.333	2	1
11	tongue	1/9	0.111	0.222	5.000	3	1
12	dish	4/7	0.571	0.857	1.600	3	1
13	dish	4/7	0.571	0.857	1.600	3	1
14	dish	4/7	0.571	0.857	1.600	3	1
15	window	1/2	0.500	1.000	1.500	1	1
16	table	2/16	0.125	0.242	5.667	5	1
17	clock	2/2	1.000	1.000	1.000	1	1
	shelf	3/4	0.750	1.000	1.250	10	1
18	kitchen	2/4	0.500	0.833	1.667	1	1
	sofa	2/2	1.000	1.000	1.000	1	1
19	kitchen	2/4	0.500	0.833	1.667	1	1
20	kitchen	2/4	0.500	0.833	1.667	1	1
21	tea	1/3	0.333	0.667	2.000	1	1
22	dish	4/7	0.571	0.857	1.600	3	1
23	sofa	2/2	1.000	1.000	1.000	1	1
24	fire	3/11	0.273	0.491	3.000	3	1
25	meal	3/4	0.750	1.000	1.250	1	1
26	kitchen	2/4	0.500	0.833	1.667	1	1
27	fire	3/11	0.273	0.491	3.000	57	1
	stove	2/2	1.000	1.000	1.000	1	1
Average			0.50	0.73	2.30	7.42	1.28

Table 7.18: Probability to find the correct noun sense

	Without scene info. (calculation)	An example of randomly selected (without scene)	Set Priority by scene info.
1st sentence	0.50	0.47	0.92
Until 2nd sentenc	0.73	0.58	0.97

Table 7.19: Result of identification of scene in the entering phase

1-(1)	at her kitchen window	Success
1-(2)	stepped in [the kitchen]	Success
3-(1)	sat down to supper	Failure
3-(2)	went down to the kitchen	Success
7-(1)	retreated to the kitchen	Success
8-(2)	to decorate the dinner table	Failure
18-(1)	had the cheerful kitchen	Success
18-(2)	lay on the kitchen sofa	Success
18-(3)	desceneded to the kitchen	Success
27-(1)	entered her kitchen	Success

- The results of disambiguation do not affect the scene identification and vice versa; the system behavior is monotonic and deterministic.

Entering the scene "kitchen"

Table 7.19 indicates the result of identification of the scene "kitchen" in the entering phase on the implemented system. Scene identification is successful except for the part 3-(1) and 8-(2), which requires lexical cohesion understanding. Since the keyword 'supper' is not registered in the knowledge sourse, it did not suggest the system to identify the scene 'kitchen'. We discuss the scene identification based on lexical cohesion later. The scene of part 1-(1) is identified by resolving an inclusive relationship that 'kitchen window' is included in the scene 'kitchen'. The scene of part 1-(2) is identified by resolving an ellipsis problem that the omitted place is 'the kitchen'. Identification of the scene of part 3-(2) requires ordinary case analysis of the sentence, which leads the system to understand that the subject changed its place to the kitchen.

Focus identification is significant since it makes an initial state of the focus stack. The result of focus identification is shown in Table 7.20. The only required focus 'Rachel' in part

1-(1) can be identified by a simple exact-match algorithm. Part 1-(2) includes two focuses which are successfully identified by a simple exact-match algorithm, and three focuses which are beyond our assumption since they are not human subjects. In identification of the focuses in part 3-(1), the focus stack was used; 'they' refers to all of the humans listed in the focus stack, *i.e.* Anne, Marilla and Matthew. But in general, this kind of anaphoric relation requires wider knowledge or deeper domain specific knowledge. Part 18-(2) includes four focuses; two of which are characters which can be identified by ordinal analysis, and one 'It' is not a character. The rest character 'doctor' is not identified since it does not appear in the first sentence of the paragraph. It firstly appears not as a subect but as an object in the mid of the paragraph. The focus-place identification 'Marilla' in Part 18-(3) was unsuccessful in this algorithm, since it requires analysis of the conversation of the previous paragraph. Lastly, 'the warning' in Part 18-(3) and 'It' in Part 27-(1) are not characters.

In this way, the initial focus-place pairs are generated, which will be handed from paragraph to paragraph with the continuing scene algorithms below.

Scene identification based on lexical cohesion

Here we discuss the scene identification ability based on lexical cohesion particularly. Its purpose is to apply several words in sentences to identify the current scene with the associative memory, as described in Chapter 5. Input words have two types:

1. Only the words in the sentence
2. All words (synonyms) related to the all meanings of the words according to the thesaurus

In the text, the phrases which require lexical cohesion to identify the scene 'kitchen' are shown below:

- chap.3 – par.32 : sat down to supper
- chap.8 – par.31 : to decorate the dinner-table
- chap.10 – par.6 : Breakfast, dinner, and supper
- chap.29 – par.15 : had the breakfast ready
- chap.36 – par.27 : at breakfast

Table 7.20: Result of focus identification in the entering phase

1-(1)	Rachel	Success
1-(2)	Rachel	Success
	Marilla	Success
	Something	—
	This	—
	This job	—
3-(1)	they (include Marilla)	Success
	they (include Anne)	Success
	they (include Matthew)	Success
3-(2)	Marilla	Success
	Matthew	Success
7-(1)	Marilla	Success
8-(2)	Anne	Success
	Marilla	Success
18-(1)	Anne	Success
	Matthew	Success
	Diana	Success
18-(2)	Minnie	Success
	Anne	Success
	doctor	Failure
	It	—
18-(3)	Anne	Success
	Marilla	Failure
	The warning	—
27-(1)	Marilla	Success
	Matthew	Success
	It	—

Table 7.21: Result of scene identification based on lexical cohesion

	Categories (activation value > 0)		Order of the scene "kitchen"	
	(1)	(2)	(1)	(2)
cake	7	41	195.5(ave.)	212.5(ave.)
breakfast	0	51	192(ave.)	9
supper	0	51	192(ave.)	9
dinner	4	51	3	9
table	69	153	326.5(ave.)	78
dinner table	71	163	4	39

We extracted the words for objects from these phrases, prepared two types of clue words according to the manner shown above, and applied them to the associative memory. The result is shown in Table 7.21. Categories are ordered according to their activation value, where categories with the same activation value are ordered randomly.

In no case the system has been successful in finding the scene "kitchen" as the category with highest priority. Thus the system requires additional knowledge sources to identify the scene. This module supports preference ordering of scenes to speed up the identification.

The effect of using the synonyms in the thesaurus depends on the target words; 'cake' does not support the scene kitchen even with the synonyms, while the synonyms of 'breakfast', 'supper', and 'dinner' take effect in giving higher priority to the scene "kitchen". Contrary to this, 'dinner' and 'dinner table' without the synonyms are advantageous to those with the synonyms.

Table 7.22 indicates the top five scenes according to priority for the clue words. The existance of the scenes 'tableware', 'kitchen utensils', and 'dining room' which are relevant to the scene 'kitchen' in the top priorities also suggests the difficulty of discrimination from these relevant scenes.

These results require the system to acquire more accurate knowledge source to identify the scene. The dictionaries used here have rather less information to represent various sense of words. Most effective knowledge is based on verb processing, which strictly constraints each situation:

- sat down to supper → to <u>eat</u> supper → dining room or kitchen

- <u>make</u> her cake → kitchen

Table 7.22: Top five scenes for the clue words by lexical cohesion

	Top five scenes	
	(1)	(2)
cake	bakery	coking plant
	supermarket	meadow flowers
	synthetic fibers	bakery
	kitchen utensils	meteorology
	porcelain	geography
breakfast	—	tableware
	—	restaurant
	—	butcher's shop
	—	tropical plants
	—	fish farming
supper	—	tableware
	—	restaurant
	—	butcher's shop
	—	tropical plants
	—	fish farming
dinner	dining room	tableware
	men's ware	restaurant
	kitchen	butcher's shop
	tableware	tropical plants
	—	fish farming
table	ball games	geography
	jewelry	doctor
	machine tools	meteorology
	joiner	school
	playground	town
dinner table	dining room	geography
	tableware	doctor
	men's wear	restaurant
	kitchen	meterology
	ball games	geography'

Other reqiurements are appropriate setting of weights of links between categories and words, and acquisition of prior probability of each scene. Focus or viewpoint dependency will be a clue to solve this problem, in that it biases the set of prior probability depending on their importance under each situation:

- dinner table → dinner → dining room or kitchen
- breakfast, supper, dinner → dining room or kitchen

Continuing the scene "kitchen"

The algorithm of continuing the scene is evaluated both by checking whether it resolves the focus of each paragraph(in the first sentence) or not, and by checking whether it appropriately updates the focus stack or not.

1. Evaluate the scene identification ability with a prepared stack

   The result of the focus resolution with a prepared stack is shown in Table 7.23, Table 7.24, Table 7.25, Table 7.26, Table 7.27, Table 7.28, Table 7.29, and Table 7.30. The paragraphs 1-13, 1-23 and 1-27 were not analyzed since they lack of any human subject. It requires more precise semantic analysis with inference together with knowledge that 'lips' belong to persons. The grammatical difficulty of implementing the sentence 'Marilla's astonishment could not have been greater if Matthew had expressed a predilection for standing on his head.' in the paragraph 3-59 did not allow us to analyze and extract its focus on the parser. 'Marilla's lips' in the paragraph 1-16 does not refers to a character. The focuses 'It' in the paragraph 18-33, 'the warning' in the paragraph 18-45, and 'It' in the paragraph 27-7 are not characters. They are beyond our scope and the analysis was not successful.

   A remarkable instance is paragraph 1-4, which is in a scene "hill", nested in the other paragraphs in the scene "kitchen". This paragraph describes the view of Rachel from the kitchen. Understanding this relationship requires a precise analysis of the character's focus, or its viewpoint. Such complex relations are beyond our scope, but are discussed later.

2. Evaluate the ability of updating the focus stack

   The result of the focus stack updating ability is shown in Table 7.31, Table 7.32, Table 7.33, Table 7.34, Table 7.35, Table 7.36, Table 7.37, and Table 7.38. The stack

Table 7.23: Result of identification ability with a prepared stack (chapter 1)

1-(1)	1-3	she → [Rachel,kitchen]	Success
	1-4	(another scene) inclusion	—
	1-5	Rachel → [Rachel, kitchen]	Success
	1-6	the worthy woman → [Rachel, kitchen]	Success
1-(2)	1-11	Rachel → [Rachel, kitchen]	Success
	1-12	Marilla → [Marilla, kitchen]	Success
	1-13		—
	1-14	Marilla → [Marilla, kitchen]	Success
	1-15	Rachel → [Rachel, kitchen]	Success
	1-16	Marilla's lips → [Marilla, kitchen]	Failure
	1-17	she → [Marilla, kitchen]	Success
	1-18	Rachel → [Rachel, kitchen]	Success
	1-19	she → [Rachel, kitchen]	Success
	1-20	Marilla → [Marilla, kitchen]	Success
	1-21	Rachel → [Rachel, kitchen]	Success
	1-22	she → [Rachel, kitchen]	Success
	1-23		—
	1-24	Marilla → [Marilla, kitchen]	Success
	1-25	Rachel → [Rachel, kitchen]	Success
	1-26	(conversation) → [Rachel, kitchen]	Success
	1-27		—
	1-28	(conversation) → [Marilla, kitchen]	Success
	1-29	Rachel → [Rachel, kitchen]	Success
	1-30	Marilla → [Marilla, kitchen]	Success
	1-31	Rachel → [Rachel, kitchen]	Success

Table 7.24: Result of identification ability with a prepared stack (chapter 3)

3-(1)	3-33	Marilla → [Marilla,kitchen]	Success
	3-34	Anne → [Anne, kitchen]	Success
	3-35	(conversation) → [Anne, kitchen]	Success
	3-36	Marilla → [Marilla, kitchen]	Success
	3-37	(conversation) → [Anne, kitchen]	Success
	3-38	(conversation) → [Marilla, kitchen]	Success
	3-39	(conversation) → [Anne, kitchen]	Success
	3-40	Matthew → [Matthew, kitchen]	Success
	3-41	Marilla → [Marilla, kitchen]	Success
3-(2)	3-54	she → [Marilla, kitchen]	Success
	3-55	Matthew → [Matthew, kitchen]	Success
	3-56	(conversation) → [Marilla, kitchen]	Success
	3-57	(conversation) → [Matthew, kitchen]	Success
	3-58	(conversation) → [Marilla, kitchen]	Success
	3-59	Marilla's astonishment → [Marilla, kitchen]	Failure
	3-60	Matthew → [Matthew, kitchen]	Success
	3-61	(conversation) → [Marilla, kitchen]	Success
	3-62	Matthew → [Matthew, kitchen]	Success
	3-63	(conversation) → [Marilla, kitchen]	Success
	3-64	Matthew → [Matthew, kitchen]	Success
	3-65	(conversation) → [Marilla, kitchen]	Success
	3-66	Matthew → [Matthew, kitchen]	Success
	3-67	Marilla → [Marilla, kitchen]	Success
	3-68	Matthew → [Matthew, kitchen]	Success

Table 7.25: Result of identification ability with a prepared stack (chapter 7)

7-(1)	7-29	(conversation) → [Marilla,kitchen]	Success

Table 7.26: Result of identification ability with a prepared stack (chapter 8)

8-(2)	8-32	she → [Anne,kitchen]	Success
	8-33	Marilla → [Marilla,kitchen]	Success
	8-34	Anne → [Anne,kitchen]	Success
	8-35	she → [Anne,kitchen]	Success
	8-36	(conversation) → [Marilla,kitchen]	Success
	8-37	(conversation) → [Anne,kitchen]	Success
	8-38	(conversation) → [Marilla,kitchen]	Success
	8-39	Anne → [Anne,kitchen]	Success
	8-40	(conversation) → [Anne,kitchen]	Success
	8-41	(conversation) → [Marilla,kitchen]	Success
	8-42	Marilla → [Marilla,kitchen]	Failure
	8-43	Anne → [Anne,kitchen]	Success
	8-44	(conversation) → [Anne,kitchen]	Success
	8-45	Marilla → [Marilla,kitchen]	Success
	8-46	(conversation) → [Anne,kitchen]	Success
	8-47	Marilla → [Marilla,kitchen]	Success
	8-48	(conversation) → [Anne,kitchen]	Success
	8-49	(conversation) → [Marilla,kitchen]	Success
	8-50	Anne → [Anne,kitchen]	Success
	8-51	(conversation) → [Marilla,kitchen]	Success
	8-52	Anne → [Anne,kitchen]	Success
	8-53	(conversation) → [Marilla,kitchen]	Success
	8-54	Anne → [Anne,kitchen]	Success

Table 7.27: Result of identification ability with a prepared stack (chapter 18-(1))

18-(1)	18-4	(conversation) → [Anne,kitchen]	Success
	18-5	Matthew → [Matthew,kitchen]	Success
	18-6	Anne → [Anne,kitchen]	Success
	18-7	Matthew → [Matthew,kitchen]	Success
	18-8	Matthew → [Matthew,kitchen]	Success
	18-9	Anne → [Anne,kitchen]	Success
	18-10	Matthew → [Matthew,kitchen]	Success
	18-11	Anne → [Anne,kitchen]	Success
	18-12	Matthew → [Matthew,kitchen]	Success
	18-13	(conversation) → [Anne,kitchen]	Success
	18-14	Matthew → [Matthew,kitchen]	Success
	18-15	Anne → [Anne,kitchen]	Success
	18-16	(conversation) → [Anne,kitchen]	Success
	18-17	Matthew → [Matthew,kitchen]	Success
	18-18	(conversation) → [Anne,kitchen]	Success
	18-19	Matthew → [Matthew,kitchen]	Success
	18-20	Anne → [Anne,kitchen]	Success
	18-21	Anne → [Anne,kitchen]	Success
	18-22	Diana → [Diana,kitchen]	Success
	18-23	Matthew → [Matthew,kitchen]	Success
	18-24	Anne → [Anne,kitchen]	Success
	18-25	Diana → [Diana,kitchen]	Success
	18-26	Anne → [Anne,kitchen]	Success
	18-27	the girls → [Anne,kitchen]	Success
		→ [Diana,kitchen]	Success

Table 7.28: Result of identification ability with a prepared stack (chapter 18-(2))

18-(2)	18-30	Anne → [Anne,kitchen]	Success
	18-31	(conversation) → [Anne,kitchen]	Success
	18-32	Minnie → [Minnie,kitchen]	Success
	18-33	It	—
	18-34	Anne → [Anne,kitchen]	Success
	18-35	doctor → [doctor,kitchen]	Success
	18-36	(conversation) → [doctor,kitchen]	Success
	18-37	Anne → [Anne,kitchen]	Success

Table 7.29: Result of identification ability with a prepared stack (chapter 18-(3))

18-(3)	18-41	Anne → [Anne,kitchen]	Success
	18-42	Marilla → [Marilla,kitchen]	Success
	18-43	Marilla → [Marilla,kitchen]	Success
	18-44	(conversation) → [Marilla,kitchen]	Success
	18-45	the warning	—
	18-46	(conversation) → [Anne,kitchen]	Success
	18-47	Marilla → [Marilla,kitchen]	Success
	18-48	Anne → [Anne,kitchen]	Success
	18-49	she → [Anne,kitchen]	Success
	18-50	Marilla → [Marilla,kitchen]	Success
	18-51	Anne → [Anne,kitchen]	Success

Table 7.30: Result of identification ability with a prepared stack (chapter 27-(1))

27-(1)	27-4	Marilla → [Marilla,kitchen]	Success
	27-5	Matthew → [Matthew,kitchen]	Success
	27-6	Marilla → [Marilla,kitchen]	Success
	27-7	It	—

generation just before entering the paragrpah 1-11 was not successful beacause an additional sentence in the mid of the paragraph 1-10 was required to be analyzed for it. According to the assumption we set previously, such a case can not be resolved. The update phase of the stack of 1-16 needs resolution of inclusive relationship that 'Marilla's lips' belongs to 'Marilla', which can not be resolved yet in the system. The analysis in the paragraph 1-27 is difficult, since it requires a solution to an anaphoric relationship in the series of sentences, 'This Job's comforting seemed neither to offend nor alarm Marilla. She knitted steadily on.' The information who is 'she' is acuired from the object of the previous sentence. Also the sentence 'She knitted steadily on.' is not the first sentence in the paragraph. The failure of focus generation in the paragraph 3-53 is due to the fact that it needs an analysis of the second sentence in the paragraph. The first sentence in the paragraph 8-31 has a complex and knowledge dependent structure: 'Anne set the card up against the jugful of apple blossoms she had brought in to decorate the dinner-table – Marilla had eyed that decoration askance, but had said nothing – propped her chin on her hands, and fell to studying it intently for several silent minutes.' Focus identification in this sentence requires a resolvement of spatial-time relationships between Anne and the apple blossoms, between Anne and the dinner-table, and between the decoration and Marilla. This is beyond our scope. The character 'doctor' in the paragraph 18-33 is not identified since it does not appear in the first sentence of the paragraph. It firstly appears not as a subect but as an object in the mid of the paragraph.

Exiting the scene "kitchen"

The result of detecting the phase of exiting the scene "kitchen" is illustrated in Table 7.39. Location of the focuses were explicitly changed by the case analysis. The only failed instance had a non-human subject, which is not handled in this analysis.

7.6 Discussion on the Experimental Results

7.6.1 Noun Disambiguation

The result of noun disambiguation is consistent with the analysis described in setion 7.3. The scene knowledge dynamically updates the sense ordering in the dictionary, which is the same as that used in the analysis. While, the sentence disambiguation reflects the complexity by the combination of sense ambiguity and structural ambiguity. The result can not be estimated deterministically and thus requires an experiment like this. These experiments support the usefulness of scene knoledges in the practical application of sense disambiguation. They reduce effectively the cost of checking candidates by ordering the senses at high precision.

7.6.2 Scene Identification

The experimental result of the scene identification leads to several remarkable points below:

- Knowledge bases necessary for scene identification: The knowledge implemented for this experiment can be classified as follows:

  1. Rule-based knowledge:

     - Inference based on surface clues:

       * Detection of end of chapters
       * Tracking of focus change of conversations

     These types of knowledge requires small amount of rules and easily implemented on natural language processing systems.

Table 7.31: Result of stack generation ability(chapter 1)

1-(1)	1-2 → 1-3	[[Rachel,kitchen]]	Success
	1-3 → 1-4	[[Rachel,kitchen]]	Success
	1-4 → 1-5	[[Rahcel,kitchen]]	Success
	1-5 → 1-6	[[Rahcel,kitchen]]	Success
	1-6 → 1-7	[[Rahcel,kitchen]]	Success
1-(2)	1-10 → 1-11	[[Rachel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Failure
	1-11 → 1-12	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-12 → 1-13	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-13 → 1-14	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-14 → 1-15	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-15 → 1-16	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-16 → 1-17	[[Marilla,kitchen],[Rachel,kitchen]]	Failure
	1-17 → 1-18	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-18 → 1-19	[[Rachel,kitchen],[Marilla,kitchen]]	Success
	1-19 → 1-20	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-20 → 1-21	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-21 → 1-22	[[Rachel,kitchen],[Marilla,kitchen]]	Success
	1-22 → 1-23	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-23 → 1-24	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-24 → 1-25	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-25 → 1-26	[[Rachel,kitchen],[Marilla,kitchen]]	Success
	1-26 → 1-27	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-27 → 1-28	[[Marilla,kitchen],[Rachel,kitchen]]	Failure
	1-28 → 1-29	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-29 → 1-30	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success
	1-30 → 1-31	[[Rahcel,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Rachel,kitchen]]	Success

Table 7.32: Result of stack generation ability(chapter 3)

3-(1)	3-32 → 3-33	[[Marilla,kitchen],[Anne,kitchen],[Matthew,kitchen]] or its combinations	Success
	3-33 → 3-34	[[Marilla,kitchen],[Anne,kitchen],[Matthew,kitchen]] or its combinations	Success
	3-34 → 3-35	[[Anne,kitchen],[Marilla,kitchen][Matthew]]	Success
	3-35 → 3-36	[[Anne,kitchen],[Marilla,kitchen],[Matthew,kitchen]] or its combinations	Success
	3-36 → 3-37	[[Marilla,kitchen],[Anne,kitchen],[Matthew,kitchen]]	Success
	3-37 → 3-38	[[Anne,kitchen],[Marilla,kitchen],[Matthew,kitchen]]	Success
	3-38 → 3-39	[[Marilla,kitchen],[Anne,kitchen],[Matthew,kitchen]]	Success
	3-39 → 3-40	[[Anne,kitchen],[Marilla,kitchen],[Matthew,kitchen]] or its combinations	Success
	3-40 → 3-41	[[Matthew,kitchen],[Anne,kitchen],[Marilla,kitchen]] or its combinations	Success
3-(2)	3-53 → 3-54	[[Marilla,kitchen],[Matthew,kitchen]]	Failure
	3-54 → 3-55	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-55 → 3-56	[[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-56 → 3-57	[[Marilla,kitchen],[Matthew,kitchen]]	Success
	3-57 → 3-58	[[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-58 → 3-59	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-59 → 3-60	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-60 → 3-61	[[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-61 → 3-62	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-62 → 3-63	[[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-63 → 3-64	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-64 → 3-65	[[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-65 → 3-66	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	3-66 → 3-67	[[Matthew,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Matthew,kitchen]]	Success
	3-67 → 3-68	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success

Table 7.33: Result of stack generation ability(chapter 7)

7-(1)	7-28 → 7-29	[[Marilla,kitchen]]	Success

Table 7.34: Result of stack generation ability(chapter 8)

8-(2)	8-31 → 8-32	[[Anne,kitchen],[Marilla,kitchen]]	Failure
	8-32 → 8-33	[[Anne,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Anne,kitchen]]	Success
	8-33 → 8-34	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success
	8-34 → 8-35	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-35 → 8-36	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-36 → 8-37	[[Marilla,kitchen],[Anne,kitchen]]	Success
	8-37 → 8-38	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-38 → 8-39	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success
	8-39 → 8-40	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-40 → 8-41	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-41 → 8-42	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success
	8-42 → 8-43	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success
	8-43 → 8-44	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-44 → 8-45	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success
	8-45 → 8-46	[[Marilla,kitchen],[Anne,kitchen]]	Success
	8-46 → 8-47	[[Anne,kitchen],[Marilla,kitchen]] or [[Marilla,kitchen],[Anne,kitchen]]	Success
	8-47 → 8-48	[[Marilla,kitchen],[Anne,kitchen]]	Success
	8-48 → 8-49	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-49 → 8-50	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success
	8-50 → 8-51	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-51 → 8-52	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success
	8-52 → 8-53	[[Anne,kitchen],[Marilla,kitchen]]	Success
	8-53 → 8-54	[[Marilla,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Marilla,kitchen]]	Success

Table 7.35: Result of stack generation ability(chapter 18-(1))

18-(1)	18-3 → 18-4	[[Anne,kitchen],[Matthew,kitchen]]	Success
	18-4 → 18-5	[[Anne,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Anne,kitchen]]	Success
	18-5 → 18-6	[[Matthew,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Matthew,kitchen]]	Success
	18-6 → 18-7	[[Anne,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Anne,kitchen]]	Success
	18-7 → 18-8	[[Matthew,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Matthew,kitchen]]	Success
	18-8 → 18-9	[[Matthew,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Matthew,kitchen]]	Success
	18-9 → 18-10	[[Anne,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Anne,kitchen]]	Success
	18-10 → 18-11	[[Matthew,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Matthew,kitchen]]	Success
	18-11 → 18-12	[[Anne,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Anne,kitchen]]	Success
	18-12 → 18-13	[[Matthew,kitchen],[Anne,kitchen]]	Success
	18-13 → 18-14	[[Anne,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Anne,kitchen]]	Success
	18-14 → 18-15	[[Matthew,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Matthew,kitchen]]	Success
	18-15 → 18-16	[[Anne,kitchen],[Matthew,kitchen]]	Success
	18-16 → 18-17	[[Anne,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Anne,kitchen]]	Success
	18-17 → 18-18	[[Matthew,kitchen],[Anne,kitchen]]	Success
	18-18 → 18-19	[[Anne,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Anne,kitchen]]	Success
	18-19 → 18-20	[[Matthew,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Matthew,kitchen]]	Success
	18-20 → 18-21	[[Anne,kitchen],[Diana,kitchen],[Matthew,kitchen]] or its combinations	Success
	18-21 → 18-22	[[Anne,kitchen],[Diana,kitchen],[Matthew,kitchen]] or its combinations	Success
	18-22 → 18-23	[[Diana,kitchen],[Anne,kitchen],[Matthew,kitchen]] or its combinations	Success
	18-23 → 18-24	[[Matthew,kitchen],[Diana,kitchen],[Anne,kitchen]] or its combinations	Success
	18-24 → 18-25	[[Anne,kitchen],[Matthew,kitchen],[Diana,kitchen]] or its combinations	Success
	18-25 → 18-26	[[Diana,kitchen],[Anne,kitchen],[Matthew,kitchen]] or its combinations	Success
	18-26 → 18-27	[[Anne,kitchen],[Diana,kitchen],[Matthew,kitchen]] or its combinations	Success

Table 7.36: Result of stack generation ability(chapter 18-(2))

18-(2)	18-29 → 18-30	[[Minnie,kitchen],[Anne,kitchen]]	Success
	18-30 → 18-31	[[Anne,kitchen],[Minnie,kitchen]]	Success
	18-31 → 18-32	[[Anne,kitchen],[Minnie,kitchen]] or [[Minnie,kitchen],[Anne,kitchen]]	Success
	18-32 → 18-33	[[Minnie,kitchen],[Anne,kitchen]] or [[Anne,kitchen],[Minnie,kitchen]]	Success
	18-33 → 18-34	[[Minnie,kitchen],[Anne,kitchen],[doctor,kitchen]] or its combinations	Failure
	18-34 → 18-35	[[Anne,kitchen],[Minnie,kitchen],[doctor,kitchen]] or its combinations	Success
	18-35 → 18-36	[[doctor,kitchen],[Anne,kitchen],[Minnie,kitchen]]	Success
	18-36 → 18-37	[[doctor,kitchen],[Anne,kitchen],[Minnie,kitchen]] or its combinations	Success

Table 7.37: Result of stack generation ability(chapter 18-(3))

18-(3)	18-40 → 18-41	[[Anne,kitchen],[Marilla,kitchen]]	Success
	18-41 → 18-42	[[Anne,kitchen],[Marilla,kitchen]]	Success
	18-42 → 18-43	[[Marilla,kitchen],[Anne,kitchen]]	Success
	18-43 → 18-44	[[Marilla,kitchen],[Anne,kitchen]]	Success
	18-44 → 18-45	[[Marilla,kitchen],[Anne,kitchen]]	Success
	18-45 → 18-46	[[Marilla,kitchen],[Anne,kitchen]]	Success
	18-46 → 18-47	[[Anne,kitchen],[Marilla,kitchen]]	Success
	18-47 → 18-48	[[Marilla,kitchen],[Anne,kitchen]]	Success
	18-48 → 18-49	[[Anne,kitchen],[Marilla,kitchen]]	Success
	18-49 → 18-50	[[Anne,kitchen],[Marilla,kitchen]]	Success
	18-50 → 18-51	[[Marilla,kitchen],[Anne,kitchen]]	Success

Table 7.38: Result of stack generation ability(chapter 27-(1))

27-(1)	27-3 → 27-4	[Marilla,kitchen]	Success
	27-4 → 27-5	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	27-5 → 27-6	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success
	27-6 → 27-7	[[Marilla,kitchen],[Matthew,kitchen]] or [[Matthew,kitchen],[Marilla,kitchen]]	Success

[illegible]

[illegible]	[illegible]	[illegible]

[illegible]

- [illegible]
- [illegible]
- [illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

1. [illegible]
2. [illegible]

[illegible]

Table 7.39: Result of identification of scene in the exiting phase

1-(1)	set out	Success
1-(2)	when she was out in the lane	Success
3-(1)	the hall was ...	Failure
3-(2)	went to bed	Success
7-(1)	END OF CHAPTER	Success
8-(2)	retreated to the east gable	Success
18-(1)	hastened out	Success
18-(2)	had gone home	Success
18-(3)	END OF CHAPTER	Success
27-(1)	went up to the east galbes	Success

- Inference based on semantic analysis:
    * Resolvement of inclusive relationships
    * Ellipsis resolvement
    * Anaphora resolvement

2. Dictionary-based knowledge:
    - Verbs standing for location changes

  This requires gothering a large vocabulary as a dictionary.

- Difficulty of scene identification based on lexical cohesion:

  Although the associative part of the scene identification algorithm is effective according to the analysis on the dictionary, it still has a weakness in deep inference and common knowledge of 'action'. This research is targetted to clarify the usefulness of a spatial scene, but the fundamental technology requires the system to handle such temporal knowledge, which remains as a future work.

  The analysis on real texts indicates the inferiority of scene identification ability compared to the analysis on the dictionary itself. This is mainly due to following two reasons:

  1. Lack of vocabulary
  2. Lack of appropriate prior probability

  Both of these can be coped with by acquisition of real world knowledge through vision processing and visual image understanding. Another candidate is text processing on very large scale corpus. It has a potential to extract common knowledge provided appropriate corpus selection is applied.

- Necessity to analyze all sentences in paragraphs:

  Some cases of scene identification and focus-place pair generation to update the focus stack, used the information of case analyis of sentences which are not the first sentences in the paragraphs. Although we concentrated on the analysis of the first sentence in each paragraphs for convinience, all the sentences in the text are necessary to acquire information to reconstruct the discourse structure.

- Difficulty of analysis on anaphoric relationships:

  Some reference which strictly specifies objects are easy to resolve. For example, 'she' specifies one woman and is not ambiguos; the system resolves this by getting focuses from the focus stack and checking their sex. However, 'this' or 'they' are ambiguous in the sense that they do not specify the search range of candidates to the system. Some cases in this experiment are resolved using the focus stack skillfuly, but general resolution of such kinds of anaphric relationships is still an open problem.

- Necessity of handling non-human subjects:

  For ideal discourse analysis, all subjects must be analyzed and added to the focus stack accompanying their place information, particularly for scene identification and exitance decision. Nevertheless, analyzing the whole paragraph is both time and space cosuming. This experiment handled only human subjects for making a space efficient focus stack, and traced the discourse at high precision.

- Coping with highly-structured sentences in paragraphs:

  In the narrative story, the scene 'on the hill' of the fourth paragraph in the first chapter is nested in the scene 'kitchen'. Nest of scenes detected by paragraph breaks can be handled by this identification algorithm. However, analysis of finer grained strutcture in paragraphs – not within the scope of this research – requires knowledge of relationships between nested scenes and deeper inference to manage the stack changing.

Chapter 8

Discussion and Directions for Further Research

8.1 Preference Balancing between Association and Logic

The scene identification algorithm implies implicitly the problem of preference balancing between an associational reasoning and a logical inference. We took an approach to give priority to the logical inference on the viewpoint that the associational reasoning is not a strict rule but is rather based on preference heurisitcs, so that the logical inference finally determines the disambiguated solution.

However, in the situation that such strict knowledge is not available to the system, *i.e.*, if there is no rule to decide whether a candidate is correct or not, it will be best for the system to use the associational reasoning as a heuristic to minimize the processing cost.

8.2 Combinated Progress in Performance with Co-occurrence

Although the purpose of this research is mainly concentrated on noun sense disambiguation, a combination of the result and preference knowledge of noun-verb co-occurrence pairs will bring a progress in verb sense disambiguation. If a verb sense is disambiguated, it constraints the type of case frame, which accelarates the noun disambiguation ability since it prunes the search space of candidates.

8.3 Exceptions and Novel Situations

- More highly abstracted reasoning including non-monotonic reasoning:

We classified the role of contextual knowledge according to its use, and examined the effectiveness of scene knowledge as a component of more general contextual analysis. The rest part of it includes more highly abstracted reasoning like subject-to-subject relationships, viewpoint dependent inference, causal relationships, and non-monotonic reasoning. Subject-to-subject relationships and viewpoint dependent inference need more precise handling of spatial scene relationships. While, causal relationships and non-monotonic reasoning are based on spatial-temporal association and are required to manage reasoning directions.

- Nested relationships

  Nested relationships control strongly the readers' attentional states, since they specify the range of the current reading scope. They help us consturct a highly structured image of the world with the combination of a small set of relationships, standing on the viewpoint that all things and relationships could be described in spatial scene elements and several kind of relationships among them. Such kinds of characteristics in texts are also useful in context dependent natural language analysis, since it requires a relatively small set of knowledge and rules compared to a system which handles every sentences homogeneously without detecting the current context.

8.4 Directions for Further Research

There are still many areas for further investigation about this method as listed below:

- Combination with other fundamental techniques and knowledge bases
- More robust algorithm and acquisition of knowledge sources applicable to any kind of texts
- Other types of discourse analysis
- Disambiguation of parts-of-speech other than noun and structural ambiguity
- knowledge acquisition from the real world

Chapter 9

Conclusions

In this chapter, we summarize the accomplishments of our work and describe concluding remarks.

9.1 Summary of Accomplishments

Computationally effective and reliable semantic disambiguation requires the process of defining the appropriate knowledge context. The disambiguation difficulty originates from the knowledge complexity and processing dependency. The need for research on context dependency in natural language processing is widely acknowledged in the field of computing, linguistics and psychology, but lacks of appropriate approach as explained in Chapter 2 and 3.

In Chapter 4, 5 and 6, we clarified the necessity of providing a new framework for using dictionary-based scene knowledge in context-dependency analysis, according to the fundamental problems of ambiguity. Spatial scene knowledge based on the pictorial dictionary produces measurably effective noun sense disambiguation, which is one of the fundamental technologies neccesary for natural language processing, particularly in machine translation. The representation of the scene knowledge useful for disambiguation consists of two types: a word-sense pair table and a semantic distribution of senses. The senses of each word are looked up in the table, and if the search is unsuccessful, it is guessed according to the semantic distribution. While, the discourse scene analysis is based on two types of reasoning: logical inference and associational reasoning. The logical part handles the case analysis and surface structure analysis, and the associational part detects the coherence of the texts.

The evaluation is based on a scene identification method based on discourse structural analysis, which is tested on its application to real stories, and the reduction of backtracking times in disambiguating the sense of a noun, as described in Chapter 7. The results on the implemented system supports that scene knowledge is measurably effective for word sense disambiguation, and that the proposed scene identification method including focus tracking stack is relatively reliable within the scope of automatical coherence analysis.

In Chapter 8, we discussed the strategy in preference balancing between associational reasoning and logical inferece, a further approach to verb sense disambiguation and effective case ristriction with knowledge of noun-verb co-occurrence pairs, and the limitation of this research.

9.2 Conclusions

We classified the role of contextual knowledge according to its use, and examined the effectiveness of scene knowledge as a component of more general contextual analysis. We articulated measures for evaluating the advantages of using scene knowledge for word sense disambiguation. Our evaluation is based on the concept of a scene identification method based on discourse structure analysis, which we have tested on its application to real stories.

The resulting system extracts "scenal" discourse segments from texts both by identifying appropriate scenes and judging their breaks. Scene identification consists of three parts: detection of cohesive relations among words, determination of subject focus, and scene expectation according to lexical cohesion. Our results show that scene knowledge is measurably effective for word sense disambiguation, and that the proposed scene identification method is relatively reliable within the scope of automatical coherence analysis.

Future work implies to clarify the effectivity of scene knowledge combinated with the knowledge of co-ocurrence between verbs and nouns, to acquire a part of identification method which requires deep inference and knowledge, and to investigate the computational effectivity of handling other contexts together with its knowledge sources.

Appendix A

Analyzed Texts for Evaluating the Implemented System

A.1 Chapter 1-(1)

(1-2) There are plenty of people, in Avonlea and out of it, who can attend closely to their neighbours' business by dint of neglecting their own; but Mrs Rachel Lynde was one of those capable creatures who can manage their own concerns and those of other folks into the bargain. She was a notable housewife; her work was always done and well done; she 'ran' the Sewing Circle, helped run the Sunday-school, and was the strongest prop of the Church Aid Society and Foreign Missions Auxiliary. Yet with all this Mrs Rachel found abundant time to sit for hours at her kitchen window, knitting 'cotton warp' quilts – she had knitted sixteen of them, as Avonlea housekeepers were wont to tell in awed voices – and keeping a sharp eye on the main road that crossed the hollow and wound up the steep red hill beyond. Since Avonlea occupied a little triangular peninsula jutting out into the Gult of St Lawrence, with water on two sides of it, anybody who went out of it or into it had to pass over that hill road and so run the unseen gauntlet of Mrs Rachel's all-seeing eye.

(1-3) She was sitting there one afternoon in early June. The sun was coming in at the window warm and bright; the orchard on the slope below the house was in a bridal flush of pinky-white bloom, hummed over by a myriad of bees. Thomas Lynde – a meek little man whom Avonlea people called 'Rachel Lynde's husband' – was sowing his late turnip seed on the hill field beyond the barn; and Matthew Cuthbert ought to have been sowing his on the big red brook field away over by Green Gables. Mrs Rachel knew that he ought because she had heard him tell Peter Morrison the evening before in William J. Blair's store over at Carmody that he meant to sow his turnip seed the next afternoon. Peter had asked him, of course, for Matthew Cuthbert had never been known to volunteer information about anything in his whole life.

(1-4) And yet here was Matthew Cuthbert, at half past three on the afternoon of a busy day, placidly driving over the hollow and up the hill; moreover, he wore a white collar and his best suit of clothes, which was plain proof that he was going out of Avonlea; and he had the buggy and the sorrel mare, which betokened that he was going a considerable distance. Now where was Matthew Cuthbert going, and why was he going there?

(1-5) Had it been any other man in Avonlea, Mrs Rachel, deftly putting this and that together, might have given a pretty good guess as to both questions. But Matthew so rarely went from home that it must be something pressing and unusual which was taking him; he was the shyest man alive and hated to have to go among strangers or to any place where he might have to talk. Matthew, dressed up with a white collar and driving in a buggy, was something that didn't happen often. Mrs Rachel, ponder as she might, could make nothing of it, and her afternoon's enjoyment was spoiled.

(1-6) 'I'll just step over to Green Gables after tea and find out from Marilla where he's gone and why,' the worthy woman finally concluded. 'He doesn't generally go to town this time of year and he *never* visits; if he'd run out of turnip seed he wouldn't dress up and take the buggy to go for more; he wasn't driving fast enough to be going for a doctor. Yet something must have happened since last night to start him off. I'm clean puzzled, that's what, and I won't know a minute's peace of mind or conscience until I know what has taken Matthew Cuthbert out of Avonlea today.'

(1-7) Accordingly, after tea Mrs Rachel set out; she had not far to go; the big, rambling, orchard-embowered house where the Cuthberts lived was a scant quater of a mile up the road from Lynde's Hollow. To be sure, the long lane made it a good deal farther. Matthew Cuthbert's farther, as shy and silent as his son after him, had got as far away as he possibly could from his fellow-men without actually retreating into the woods when he founded his homestead. Green Gables was buit at the furthest edge of his cleared land, and there it was to this day, barely visible from the main road along which all the other Avonlea houses were so sociably situated. Mrs Rachel Lynde did not call living in such a place *living* at all.

A.2 Chapter 1-(2)

(1-10) Mrs Rachel rapped smartly at the kitchen door and stepped in when bidden to do so. The kitchen at Green Gables was a cheerful apartment – or would have been cheerful if it had not been so painfully clean as to give it something of the appearance of an unused parlour. Its windows looked east and west; through the west one, looking out on the back yard, came a flood of mellow June sunlight; but the east one, whence you got a glimpse of the bloomwhite cherry-trees in the left orchard and nodding, slender birches down in the hollow by the brook, was greened over by a tangle of vines. Here sat Marilla Cuthbert when she sat at all, always slightly distrustful of sunshine, which seemed to her too dancing and irredponsible a thing for a world which was meant to be taken seriously; and here she sat now, knitting, and the table behind her was laid for supper.

(1-11) Mrs Rachel, before she had fairly closed the door, had taken mental note of everything that was on that table. There were three plated laid, so that Marilla must be expecting someone home with Matthew to tea; but the dishes were everyday dishes and there was only crab-apple preserves and one kind of cake, so that the expected company could not be any particular company. Yet what of Matthew's white collar and the sorrel mare? Mrs Rachel was getting fairly dizzy with this unusual mystery about quiet, unmysterious Green Gebles.

(1-12) 'Good evening, Rachel,' Marilla said briskly. 'This is a real fine evening, isn't it? Won't you sit down? How are all your folks?'

(1-13) Something that for lack of any other name might be called friendship existed and always had existed between Marilla Cuthbert and Mrs Rachel, in spite of – or perhaps because of – their dissimilarlity.

(1-14) Marilla was a tall, thin woman, with angles and without curves; her dark hair showed some grey streaks and was always twisted up in a hard little knot behind with two wire hairpins stuck aggaressively through it. She looked like a woman of narrow experience and rigid conscience, which she was; but there was a saving something about her mouth which, if it had been ever so slightly developed, might have been considered indicative of a sense of humour.

(1-15) 'We're all pretty well,' said Mrs Rachel. 'I was kind of afraid *you* weren't, though, when I saw Matthew starting off today. I thought maybe he was goint to the doctor's.'

(1-16) Marilla's lips twitched understandingly. She had expected Mrs Rachel up; She had known that the sight of Matthew jaunting off so unaccountably would be too much for her neighbour's curiosity.

(1-17) 'Oh, no, I'm quite well, although I had a bad headache yesterday,' she said. 'Matthew went to Bright River. We're getting a little boy from an orphan asylum in Nova Scotia, and he's coming on the train tonight.'

(1-18) If Marilla had said that Matthew had gone to Bright River to meet a kangaroo from Australia Mrs Rachel could not have been more astonished. She was actually stricken dumb for five seconds. It was unsupposable that Marilla was making fun of her, but Mrs Rachel was almost forced to suppose it.

(1-19) 'Are you in earnest, Marilla?' she demanded when voice returned to her.

(1-20) 'Yes, of course,' said Marilla, as if getting boys from orphan asylums in Nova Scotia were part of the usual spring work on any well-regulated Avonlea farm instead of being an unheard-of innovation.

(1-21) Mrs Rachel felt that she had received a severe mental jolt. She thought in exclamation points. A boy! Marilla and Matthew Cuthbert of all people adopting a boy! From an orphan asylum! Well, the world was certainly turning upside down! She would be surprised at nothing after this! Nothing!

(1-22) 'What on earth put such a notion into your head?' she demanded disapprovingly.

(1-23) This had been done without her advice being asked, and must perforce be disapproved.

(1-24) 'Well, we've been thinking about it for some time – all winter in fact.' returned Marilla. 'Mrs Alexander Spencer was up here one day before Christmas and she said she was going to get a little girl from the asylum over in Hopetown in the spring. Her cousin lives there and Mrs Spencer has visited her and knows all about it. So Matthew and I have talked it over off and on ever since. We thought we'd get a boy. Matthew is getting up in years, you know – he's sixty – and he isn't so spry as he once was. His heart troubles him a good deal And you know how desperate hard it's got to be to get hired help. There's never anybody to be had but those stupid, half-grown little French boys, and as soon as you do get one broke into your ways and taught something he's up and off to the lobster canneries or the States. At first Matthew suggested getting a "Home" boy. But I said "no" flat to that. "They may be all right – I'm not saying they're not – but no London street arabs for me," I said. "Give me a native born at least. There'll be a risk, no matter who we get. But I'll feel easier in my mind and sleep sounder at nights if we get a born Canadian." So in the end we decided to ask Mrs Spencer to pick us out one when she went over to get her little girl. We heard last week she was going, so we sent her word by Richard Spencer's folks at Carmody to bring us a smart, likely boy of about ten or eleven. We decided that would be the best age – old enough to be of some use in doing chores right off and young enough to be trained up proper. We mean to give him a good home and schooling. We had a telegram from Mrs Alexander Spencer today – the mail-man brought it from the station – saying they were coming on the five-thirty train tonight. So Matthew went to Bright River to meet him. Mrs Spencer will drop him off there. Of course she goes on to White Sands station herself.'

(1-25) Mrs Rachel prided herself on always speaking her mind; she proceeded to speak it now, having adjusted her mental attitude to this amazing piece of news.

(1-26) 'Well, Marilla, I'll just tell you plain that I think you're doing a mighty foolish thing – a risky thing, that's what. You don't know what you're getting. You're bringing a strange child into your house and home, and you don't know a single thing about him not what his disposition is like nor what sort of parents he had nor how he's likely to turn out. Why, it was only last week I read in the paper how a man and his wife up west of the Island took a boy out of an orphan asylum and he set fire to the house at night – set it *on purpose*, Marilla – and nearly burnt them to a crisp in their beds. And I know another case where an adopted boy used to suck the eggs – they couldn't break him of it. If you had asked my advice in the matter – which you didn't do, Marilla – I'd have said for mercy's sake not to think of such a thing, that's what.'

(1-27) This Job's comforting seemed neither to offend nor alarm Marilla. She knitted steadily on.

(1-28) 'I don't deny there's something in what you say, Rachel. I've had some qualms myself. But Matthew was terrible set on it. I could see that, so I gave in. It's so seldom Matthew sets his mind on anything that when he does I always feel it's my duty to give in. And as for the risk, there's risks in people's having children of their own if it comes to that – they don't always turn out well. And then Nova Scotia is right close to the Island. It isn't as if we were getting him from England or the States. He can't be much different from ourselves.'

(1-29) 'Well, I hope it will turn out all right,' said Mrs Rachel in a tone that plainly indicated her painful doubts. 'Only don't say I didn't warn you if he burns Green Gables down or puts strychnine in the well – I heard of a case over in New Brunswick where an orphan asylum child did that, and the whole family died in fearful agonies. Only, it was a girl in that instance.'

(1-30) 'Well, we're not getting a girl,' said Marilla, as if poisoning wells were a purely feminine accomplishment and not to be dreaded in the case of a boy. 'I'd never dream of taking a girl to bring up. I wonder at Mrs Alexander Spencer for doing it. But there, *she* wouldn't shrink from adopting a whole orphan asylum if she took it into her head.'

(1-31) Mrs Rachel would have liked to stay until Matthew came home with his imported orphan. But, reflecting that it would be a good road to Robert Bell's and tell them the news. It would certainly make a sensation second to none, and Mrs Rachel dearly loved to make a sensation. So she took herself away, somewhat to Marilla's relief, fo the latter felt her doubts and fears reviving under the influence of Mrs Rachel's pessimism.

(1-32) 'Well, of all things that ever were or will be!' ejaculated Mrs Rachel when she was safety out in the lane. 'It does really seem as if I must be dreaming. Well, I'm sorry for that poor young one and no mistake. Matthew and Marilla don't know anything about children and they'll expect him to be wiser and steadier than his own grandfather, if so be's he ever had a grandfather, which is doubtful. It seems uncanny to think of a child at Green Gables somehow; there's never been one there, for Matthew and Marilla were grown up when the new house was built – if they ever *were* children, which is hard to believe when one looks at them. I wouldn't be in that orphan's shoes for anything. My, but I pity him, that's what.'

A.3 Chapter 3-(1)

(3-32) Anne took off her hat meekly. Matthew came back presently and they sat down to supper. But Anne could not eat. In vain she nibbled at the bread and butter and pecked at the crab-apple preserve out of the little scalloped glass dish by her plate. She did not really make any headway at all.

(3-33) 'You're not eating anything,' said Marilla sharply, eyeing her as if it were a serious shortcoming.

(3-34) Anne sighed.

(3-35) 'I can't. I'm in the depths of despair. Can you eat when you are in the depths of despair?'

(3-36) 'I've never been in the depths of despair, so I can't say,' responded Marilla.

(3-37) 'Weren't you? Well, did you ever try to imagine you were in the depths of despair?'

(3-38) 'No, I didn't.'

(3-39) 'Then I don't think you can understand what it's like. It's a very uncomfortable feeling indeed. When you try to eat a lump comes right up in your throat and you can't swallow anything, not even if it was a chocolate caramel. I had one chocolate caramel once two years ago and it was simply delicious. I've often dreamed since then that I had a lot of chocolate caramels, but I always wake up just when I'm going to eat them. I do hope you won't be offended because I can't eat. Everything is extremely nice, but still I cannot eat.'

(3-40) 'I guess she's tired,' said Matthew, who hadn't spoken since his return from the barn. 'Best put her to bed, Marilla.'

(3-41) Marilla had been wondering where Anne should be put to bed. She had prepared a couch in the kitchen chamber for the desired and expected boy. But, although it was neat and clean, it did not seem quite the thing to put a girl there somehow. But the spare room was out of the question for such a stray waif, so there remained only the east gable room. Marilla lighted a candle and told Anne to follow her which Anne spiritlessly did, taking her hat and carpet-bag from the hall table as she passed. the hall was fearsomely clean; the little gable chamber in which she presently found herself seemed still cleaner.

A.4 Chapter 3-(2)

(3-53) Marilla went slowly down to the kitchen and proceeded to wash the supper dishes. Matthew was smoking - a sure sign of perturbation of mind. He seldom smoked, for Marilla set her face against it as a filthy habit; but at certain times and seasons he felt driven to it, and then Marilla winked at the practice, realized that a mere man must have some vent for his emotions.

(3-54) 'Well, this is a pretty kettle of fish,' she said wrathfully, 'This is what comes of sending word instead of going ourselves. Robert Spencer's folks have twisted that message somehow. One of us will have to drive over and see Mrs Spencer tomorrow, that's certain. This girl will have to be sent back to the asylum.'

(3-55) 'Yes, I suppose so,' said Matthew reluctantly.

(3-56)'You suppose so! Don't you know it?'

(3-57)'Well now, she's a real nice little thing, Marilla. It's kind of a pity to send her back when she's so set on staying here.'

(3-58) 'Matthew Cuthbert, you don't mean to say you think we ought to keep her!'

(3-59) Marilla's astonishment could not have been greater if Matthew had expressed a predilection for standing on his head.

(3-60) 'Well, now, no, I suppose not - not exactly,' stammered Matthew, uncomfortably driven into a corner for his precise meaning. 'I suppose - we could hardly be expected to keep her.'

(3-61) 'I should say not. What good would she be to us?'

(3-62) 'We might be some good to her,' said Matthew suddenly and unexpectedly.

(3-63) 'Matthew Cuthbert, I believe that child has bewitched you! I can see as plain as plain that you want to keep her.'

(3-64) 'Well now, she's a really interesting little thing,' persisted Matthew. 'You should have heard her talk coming from the station.'

(3-65) 'Oh, she can talk fast enough. I saw that at once. It's nothing in her favour, either. I don't like children who have so much to say. I don't want an orphan girl, and if I did she isn't the style I'd pick out. There's something I don't understand about her. No, she's got to be dispatched straightway back to where she came from.'

(3-66) 'I could hire a French boy to help me,' said Matthew, 'and she'd be company for you.'

(3-67) 'I'm not suffering for company,' said Marilla shortly. 'And I'm not going to keep her.'

(3-68) 'Well now, it's just as you say, of course, Marilla,' said Matthew, rising and putting his pipe away. 'I'm going to bed.'

(3-69) To bed went Matthew. And to bed, when she had put her dishes away, went Marilla, frowning most resolutely. And upstairs, in the east gable, a lonely, heart-hungry, friendless child cried herself to sleep.

A.5 Chapter 7-(1)

(7-28) Marilla retreated to the kitchen, set the candle firmly on the table, and glared at Matthew.

(7-29) 'Matthew Cuthbert, it's about time somebody adopted that child and taught her something. She's next door to a perfect heathen. Will you believe that she never said a prayer in her life till tonight? I'll send to the manse tommorrow and borrow the Peep of Day series, that's what I'll do. And she shall go to Sunday school just as soon as I can get some suitable clothes made for her. I foresee that I shall have my hands full. Well, well, we can't get through this world without our share of trouble. I've had a pretty easy life of it so far, but my time has come at last and I suppose I'll just have to make the best of it.'

A.6 Chapter 8-(2)

(8-31) Anne set the card up against the jugful of apple blossoms she had brought in to decorate the dinner-table – Marilla had eyed that decoration askance, but had said nothing – propped her chin on her hands, and fell to studying it intently for several silent minutes.

(8-32) 'I like this,' she announced at length. 'It's beautiful. I've heard it before – I heard the superintendent of the asylum Sunday-school say it over once. But I didn't like it then. He had such a cracked voice and he prayed it so mournfully. I really felt sure he thought praying was a disagreeable duty. This isn't poetry, but it makes me feel just the same way poetry does. "Our Father which art in heaven, hallowed be Thy name." That is just like a line of music. Oh, I'm so glad you thought of making me learn this, Miss – Marilla.'

(8-33) 'Well, learn it, and hold your tongue,' said Marilla shortly.

(8-34) Anne tipped the vase of apple blossoms near enough to bestow a soft kiss on a pink-cupped bud, and then studied diligently for some moments longer.

(8-35) 'Marilla,' she demanded presently, 'do you think that I shall ever have a bosom friend in Avonlea?'

(8-36) 'A – a what kind of a friend?'

(8-37) 'A bosom friend – an intimate friend, you know – a really kindred spirit to whom I can confide my inmost soul. I've dreamed of meeting her all my life. I never really supposed I would, but so many of my loveliest dreams have come true all at once that perhaps this one will, too. Do you think it's possible?'

(8-38) 'Diana Barry lives over at Orchard Slope, and she's about your age. She's a very nice little girl, and perhaps she will be a playmate for you when she comes home. She's visiting her aunt over at Carmody just now. You'll have to be careful how you behave yourself, though. Mrs Barry is a very particular woman. She won't let Diana play with any little girl who isn't nice and good.'

(8-39) Anne looked at Marilla through the apple blossoms, her eyes aglow with interest.

(8-40) 'What is Diana like? Her hair isn't red, is it? Oh, I hope not. It's a bad enough to have red hair myself, but I positively couldn't endure it in a bosom friend.'

(8-41) 'Diana is a very pretty girl. She has black eyes and hair and rosy cheeks. And she is good and smart, which is better than being pretty.'

(8-42) Marilla was as fond of morals as the Duchess in Wonderland, and was firmly convinced that one should be tacked on to every remark made to a child who was being brought up.

(8-43) But Anne waved the moral inconsequently aside and seized only on the delightful possibilities before it.

(8-44) 'Oh, I'm so glad she's pretty. Next to being beautiful oneself – and that's impossible in my case – it would be best to have a beautiful bosom friend. When I lived with Mrs Thomas she had a bookcase in her sitting-room with glass doors. There weren't any books in it; Mrs Thomas kept her best china and her preserves there – when she had any preserves to keep. One of the doors was broken. Mr Thomas smashed it one night when he was slightly intoxicated. But the other was whole and I used to pretend that my reflection in it was another little girl who lived in it. I called her Katie Maurice, and were very intimate. I used to talk to her by the hour, especially on Sunday, and tell her everything. Katie was the comfort and consolation of my life. We used to pretend that the bookcase was enchanted and that if I only knew the spell I could open the door and step right into the room where Katie Maurice lived, instead of into Mrs Thomas's shelves of preserves and china. And then Katie Maurice would have taken me by the hand and led me out into a wonderful place, all flowers and sunshine and fairies, and we would have lived there happy for ever after. When I went to live with Mrs Hammond it just broke my heart to leave Katie Maurice. She felt it dreadfully, too. I know she did, for she was crying when she kissed me good-bye through the bookcase door. There was no bookcase at Mrs Hammond's. But just up the river a little way from the the house there was a long green little valley, and the loveliest echo lived there. It echoed back every word you said, even if you didn't talk a bit loud. So I imagined that it was a little girl called Violetta and we were great friends and I loved her almost as well as I loved Katie Maurice – not quite, but almost, you know. The night before I went to the asylum I said good-bye to Violetta, and oh, her good-bye came back to me in such sad, sad tones. I had become so attached to her that I hadn't the heart to imagine a bosom friend at the asylum, even if there had been any scope for imagination there.'

(8-45) 'I think it's just as well there wasn't,' said Marilla dryly. 'I don't approve of such goings-on. You seem to half believe your own imaginations. It will be well for you to have a real live friend to put such nonsense out of your head. But don't let Mrs Barry hear you talking about your Katie Maurices and your Violettas or she'll think you tell stories.'

(8-46) 'Oh, I won't. I couldn't talk of them to everybody – their memories are too sacred for that. But I thought I'd like to have you know about them. Oh, look here's a big bee just tumbled out of an apple blossom. Just think what a lovely place to live – in an apple blossom! Fancy going to sleep in it when the wind was rocking it. If I wasn't a human girl

I think I'd like to be a bee and live among the flowers.'

(8-47) 'Yesterday you wanted to be a seagull,' sniffed Marilla. 'I think you are very fickle-minded. I told you to learn that prayer and not talk. But it seems impossible for you to stop talking if you've got anybody that will listen to you. So go up to your room and learn it.'

(8-48) 'Oh, I know it pretty nearly all now – all but just the last line.'

(8-49) 'Well, never mind, do as I tell you. Go to your room and finish learning it well, and stay there until I call you down to help me get tea.'

(8-50) 'Can I take the apple blossoms with me for company?' pleaded Anne.

(8-51) 'No; you don't want your room cluttered up with flowers. You should have left them on the tree in the first place.'

(8-52) 'I did feel a little that way, too,' said Anne. 'I kind of felt I shouldn't shorten their lovely lives by picking them – I wouldn't want to be picked if I were an apple blossom. But the temptation was irresistible. What do you do when you meet with an irresistible temptation?'

(8-53) 'Anne, did you hear me tell you to go to your room?'

(8-54) Anne sighed, retreated to the east gable, and sat down in a chair by the window.

A.7 Chapter 18-(1)

(18-3) Hence, while Marilla and Mrs Rachel were enjoying themselves hugely at the mass meeting, Anne and Matthew had the cheerful kitchen at Green Gables all to themselves. A bright fire was glowing in the old-fashioned Waterloo stove and blue-white frost crystals were shining on the window-panes. Matthew nodded over a Farmer's Advocate on the sofa and Anne at the table studied her lessons with grim determination, despite sundry wistful glances at her that day. Jane had assured her that it was warranted to produce any number of thrills, or words to that effect, and Anne's fingers tingled to reach out for it. But that would mean Gilbert Blythe's triumph on the morrow. Anne turned her back on the clock shelf and tried to imagine it wasn't there.

(18-4) 'Matthew, did you ever study geometry when you went to school?'

(18-5) 'Well now, no, I didn't,' said Matthew, coming out of his doze with a start.

(18-6) 'I wish you had,' sighed Anne, 'because then you'de be able to sympathize with me. You can't sympathize properly if you've never studied it. It is casting a cloud over my whole life. I'm such a dunce at it, Matthew.'

(18-7) 'Well now, I dunno,' said Matthew soothingly. 'I guess you're all right at anything. Mr Phillips told me last week in Blair's store at Carmody that you was the smartest scholar in school and was making rapid progress. "Rapid progress" was his very words. There's them as runs down Teddy Phillips and says he ain't much of a teacher; but I guess he's all right.'

(18-8) Matthew would have thought anyone who praised Anne was 'all right'.

(18-9) 'I'm sure I'd get on better with geometry if only he wouldn't change the letters,' complained Anne. 'I learn the proposition off by heart, and then he draws in on the blackboard and puts different letters from what are in the book and I get all mixed up. I don't think a teacher should take such a mean advantage, do you? We're studying agriculture now and I've found out at last what makes the roads red. It's a great comfort. I wonder how Marilla and Mrs Lynde are enjoying themselves. Mrs Lynde says Canada is going to the dogs the way things are being run at Ottawa, and that it's and awful warning to the electors. She says if women were allowed to vote we would soon see a blessed change. What way do you vote, Matthew?'

(18-10) 'Conservative,' said Matthew promptly. To vote Conservative was part of Matthew's religion.

(18-11) 'Then I'm Conservative too,' said Anne decidedly. 'I'm glad, because Gil – because some of the boys in school are Grits. I guess Mr Phillip is a Grit too, because Prissy Andrew's father is one, and Ruby Gillis says that when a man is courting he always has to agree with the girl's mother in religion and her father in politics. Is that true, Matthew?'

(18-12) 'Well now, I dunno,' said Matthew.

(18-13) 'Did you ever go courting, Matthew?'

(18-14) 'Well now, no, I dunno's I ever did,' said Matthew, who had certainly never thought of such a thing in his whole existence.

(18-15) Anne reflected with her chin in her hands.

(18-16) 'It must be rather interesting, don't you think, Matthew? Rubby Gillis says when she grows up she's going to have ever so many beaux on the string and have them all crazy about her; but I think that would be too exciting. I'd rather have just one in his right mind. But Ruby Gillis knows a great deal about such matters because she has so many big sisters, and Mrs Lynde says the Gillis girls have gone off like hot cakes. Mr Phillip goes up to see Prissy Andrews nearly every evening. He says it is to help her with her lessons, but Miranda Sloane is studying for Queen's, too, and I should think she needed help a lot more than Prissy because she's ever so much stupider, but he never goes to help her in the evenings at all. There are a great many things in this world that I can't understand very well, Matthew.'

(18-17) 'Well now, I dunno as I comprehend them all myself,' acknowledged Matthew.

(18-18) 'Well, I suppose I must finish up my lessons. I won't allow myself to open that new book Jane lent me until I'm through. But it's a terrible temptation, Matthew. Even when I turn my back on it I can see it there just as plain. Jane said she cried herself sick over it. I love a book that makes me cry. But I think I'll carry that book into the sitting-room and lock it in the jam closet and give you the key. And you must not give it to me, Matthew, until my lessons are done, not even if I implore you on my bended knees. It's all very well to say resist temptation, but it's ever so much easier to resist it if you can't get the key. And then shall I run down the cellar and get some russets, Matthew? Wouldn't you like some russets?'

(18-19) 'Well now, I dunno but what I would,' said Matthew, who never ate russets but knew Anne's weakness for them.

(18-20) Just as Anne emerged triumphantly from the cellar with her plateful of russets came the sound of flying footsteps on the icy boardwalk outside and the next moment the kitchen door was flung open and in rushed Diana Barry, white-faced and breathless, with a shawl wrapped hastily around her head. Anne promptly let go of her candle and plate in her surprise, and plate, candle, and apples crashed together down the cellar ladder and were found at the bottom, embedded in melted grease, the next day, by Marilla, who gathered them up and thanked mercy the house hadn't been set on fire.

(18-21) 'Whatever is the matter, Diana?' cried Anne. 'Has your mother relented at last?'

(18-22) 'Oh, Anne, do come quick,' implored Diana nervously. 'Minnie May is awful sick – she's got croup, Young Mary Joe says – and Father and Mother are away to town and there's nobody to go for the doctor. Minnie May is awful bad and Young Mary Joe doesn't know what to do – and oh, Anne, I'm so scared!'

(18-23) Matthew, without a word, reached out for cap and coat, slipped past Diana and away into the darkness of the yard.

(18-24) 'He's gone to harness the sorrel mare to go to Carmody for the doctor,' said Anne, who was hurrying on hood and jacket. 'I know it as well as if he'd said so. Matthew and I are such kindred spirits I can read his thoughts without words at all.'

(18-25) 'I don't believe he'll find the doctor at Carmody,' sobbed Diana. 'I know that Doctor Blair went to town and I guess Doctor Spencer would go too. Young Mary Joe never saw anybody with croup and Mrs Lynde is away. Oh, Anne!'

(18-26) 'Don't cry, Di,' said Anne cheerily. 'I know exactly what to do for croup. You forget that Mrs Hammond had twins three times. When you look after three pairs of twins you naturally get a lot of experience. They all had croup regularly. Just wait till I get the ipecac bottle – you mayn't have any at your house. Come on now.'

(18-27) The two little girls hastened out hand in hand and hurried through Lover's Lane and across the crusted field beyond, for the snow was too deep to go by the shorter wood away. Anne, although sincerely sorry for Minnie May, was far from being insensible to the romance of the situation and to the sweetness of once more sharing that romance with a kindred spirit.

A.8 Chapter 18-(2)

(18-29) Minnie May, aged three, was really very sick. She lay on the kitchen sofa, feverish and restless, while her hoarse breathing could be heard all over the house. Young Mary Joe, a buxom, broad-faced French girl from the Creek, whom Mrs Barry had engaged to stay with the children during her absence, was helpless and bewildered, quite incapable of thinking what to do, or doing it if she thought of it.

(18-30) Anne went to work with skill and promptness.

(18-31) 'Minnie May has croup all right; she's pretty bad, but I've seen them worse. First we must have lots of hot water. I declare, Diana, there isn't more than a cupful in the kettle! There, I've filled it up, and, Mary Joe, you may put some wood in the stove. I don't want to hurt your feelings, but it seems to me you might have thought of this before if you'd any imagination. Now, I'll undress Minnie May and put her to bed, and you try to find some soft flannel cloths, Diana. I'm going to give her a dose of ipecac first of all.'

(18-32) Minnie May did not take kindly to the ipecac, but Anne had not brought up three pairs of twins for nothing. Down that ipecac went, not only once, but many times during the long, anxious night when the two little girls worked patiently over the suffering Minnie May, and Young Mary Joe, honestly anxious to do all she could, kept on a roaring fire and heated more water than would have been needed for a hospital of croupy babies.

(18-33) It was three o'clock when Matthew came with the doctor, for he had been obliged to go all the way to Spencervale for one. But the pressing need for assistance was past. Minnie May was much better and was sleeping soundly.

(18-34) 'I was awfully near giving up in despair,' explained Anne. 'She got worse and worse until she was sicker than ever the Hammond twins were, even the last pair. I actually thought she was going to choke to death. I gave her every drop of ipecac in that bottle, and when the last dose went down I said to myself - not to Diana or Young Mary Joe, because I didn't want to worry them any more than they were worried, but I had to say it to myself just to relieve my feelings – "This is the last lingering hope and I fear 'tis a vain one." But in about three minutes she coughed up the phlegm and began to get better right away. You must just imagine my relief, doctor, because I can't express it in words. You know there are some things that cannot be expressed in words.'

(18-35) 'Yes, I know,' nodded the doctor. He looked at Anne as if he were thinking some things about her that couldn't be expressed in words. Later on, however, he expressed them to Mr and Mrs Barry.

(18-36) 'That little red-headed girl they have over at Cuthbert's is as smart as they make 'em. I tell you she saved that baby's life, for it would have been too late by the time I got here. She seems to have a skill and presence of mind perfectly wonderful in a child of her age. I never saw anything like the eyes of her when she was explaining the case out to me.

(18-37) Anne had gone home in the wonderful, white-frosted winter morning, heavy-eyed from loss of sleep, but still talking unweariedly to Matthew as they crossed the long white field and walked under the glittering fairly arch of the Lover's Lane maples.

A.9 Chapter 18-(3)

(18-40) Anne accordingly went to bed and slept so long and soundly that it was well on in the white and rosy winter afternoon when she awoke and descended to the kitchen where Marilla, who had arrived home in the meantime, was sitting kinitting.

(18-41) 'Oh, did you see the Premier?' exclaimed Anne at once. 'What did he look like, Marilla?'

(18-42) 'Well, he never got to be Premier on account of his looks,' said Marilla. 'Such a nose as that man had! But he can speak. I was proud of being a Conservative. Rachel Lynde, of course, being a Liberal, had no use for him. Your dinner is in the oven, Anne; and you can get yourself some blue-plum preserve out of the pantry. I guess you're hungry. Matthew has been telling me about last night. I must say it was fortunate you knew what to do. I wouldn't have had any idea myself, for I never saw a case of croup. There now, never mind talking till you've had your dinner. I can tell by the look of you that you're just full up with speeches, but they'll keep.'

(18-43) Marilla had something to tell Anne, but she did not tell it just then, for she knew if she did Anne's consequent excitement would lift her clear out of the region of such material matters as appetite or dinner. Not until Anne had finished her saucer of blue plums did Marilla say:

(18-44) 'Mrs Barry was here this afternoon, Anne. She wanted to see you, but I wouldn't wake you up. She says you saved Minnie May's life, and she is very sorry she acted as she did in that affair of the currant wine. She says she knows now you didn't mean to set Diana drunk, and she hopes you'll forgive her and be good friends with Diana again. You're to go over this evening if you like, for Diana can't stir outside the door on account of a bad cold she caught last night. Now, Anne Shirly, for pity's sake don't fly clean up into air.'

(18-45) The warning seemed not unnecessary, so uplifted and aerial was Anne's expression and attitude as she sprang to her feet, her face irradiated with the flame of her spirit.

(18-46) 'Oh, Marilla, can I go right now – without washing my dishes? I'll wash them when I come back, but I cannot tie myself down to anything so unromantic as dish-washing at this thrilling moment.'

(18-47) 'Yes, yes, run along,' said Marilla indulgetly. 'Anne Shirley – are you crazy? Come back this instant and put something on you. I might as well call to the wind. She's gone without a cap or wrap. Look at her tearing through the orchard with her hair streaming. It'll be a mercy if she doesn't catch her death of cold.'

(18-48) Anne came dancing home in the purple winter twilight across the snowy places. Afar in the south-west was the greatest shimmering, pearl-like sparkle of an evening star in a sky that was pale golden and ethereal rose over gleaming white spaces and dark glens of spruce. The tinkles of sleigh-bells among the snowy hills came like elfin chimes through the frosty air, but their music was not sweeter than the song in Anne's heart and on her lips.

(18-49) 'You see before you a perfectly happy person, Marilla.' she announced. 'I'm perfectly happy – yes, in spite of my red hair. Just at present I have a soul above red hair. Mrs Barry kissed me and cried and said she was so sorry and she could never repay me. I felt fearfully embarrassed, Marilla, but I just said as politely as I could, "I have no hard feelings for you, Mrs Barry. I assure you once for all that I did not mean to intoxicate Diana and henceforth I shall cover the past with the mantle of oblivion." That was a pretty dignified way of speaking, wasn't it, Marilla ? I felt that I was heaping coals of fire on Mrs Barry's head. And Diana and I had a lovely afternoon. Diana showed me a new fancy crochet stitch her aunt over at Carmody taught her. Not a soul in Avonlea knows it but us, and we pledged a solemn vow never to reveal it to anyone else. Diana gave me a beautiful card within a wreath of roses on it and a verse of poetry:

If you love me as I love you
Nothing but death can part us two.

And that is true, Marilla. We're going to ask Mr Phillips to let us sit together in school again, and Gertie Pye can go with Minnie Andrews. We had an elegant tea. Mrs Barry had the very best china set out, just as if I was real company. I can't tell you what a thrill it gave me. Nobody ever used their very best china on my account before. And we had fruit-cake and pound-cake and dough-nuts and two kinds of preserves, Marilla. And Mrs Barry asked me if I took tea and said, "Pa, why don't you pass the biscuits to Anne?" It must be lovely to be grown up, Marilla, when just being treated as if you were is so nice.'

(18-50) 'I don't know about that,' said Marilla, with a brief sigh.

(18-51) 'Well, anyway, when I am grown up,' said Anne decidedly, 'I'm always going to talk to little girls as if they were, too, and I'll never laugh when they use big words. I know from sorrowful experience how that hurts one's feelings. After tea Diana and I made taffy. The taffy wasn't very good, I suppose because neither Diana nor I had ever made any before. Diana left me to stir it while she buttered the plates and I forgot and let it burn and then when we set it out on the platform to cool the cat walked over one plate and that had to be thrown away. But the making of it was splendid fun. Then when I came home Mrs Barry asked me to come over as often as I could and Diana stood at the window and threw kisses to me all the way down to Lover's Lane. I assure you, Marilla, that I feel like praying tonight and I'm going to think out a special brand-new prayer in honour of the occasion.'

A.10 Chapter 27-(1)

(27-3) Consequently, when Marilla entered her kitchen and found the fire black out, with no sign of Anne anywhere she felt justly disappointed and irritated. She had told Anne to be sure and have tea ready at five o'clock, but now she must hurry to take off her second-best dress and prepare the meal herself against Matthew's return from ploughing.

(27-4) 'I'll settle Miss Anne when she comes home,' said Marilla grimly, as she shaved up kindlings with a carving knife and more vim than was strictly necessary. Matthew had come in and was waiting patiently for his tea in his corner. 'She's gadding off somewhere with Diana, writing stories or practising dialogues or some such tomfoolery, and never thinking once about the time or her duties. She's just go to be pulled up short and sudden on this sort of thing. I don't care if Mrs Allan does say she's the brightest and sweetest child she ever knew. She may be bright and sweet enough, but her head is full of nonsense and there's never any knowing what shape it'll break out in next. Just as soon as she grows out of one freak she takes up with another. But there! Here I am saying the very thing I was so riled with Rachel Lynde for saying at the Aid today. I was real glad when Mrs Allan spoke up for Anne, for if she hadn't I know I'd have said something too sharp to Rachel before everybody. Anne's got plenty of faults, goodness knows, and far be it from me to deny it. But I'm bringing her up and not Rachel Lynde, who'd pick faults in the Angel Gabriel himself if he lived in Avonlea. Just the same, Anne has no business to leave the house like this when I told her she was to stay home this afternoon and look after things. I must say, with all her faults, I never found her disobedient or untrustworthy before and I'm real sorry to find her so now.

(27-5) 'Well now, I dunno,' said Matthew, who, being patient and wise and, above all, hungry, had deemed it best to let Marilla talk her wrath out unhindered, having learned by experience that she got through with whatever work was on hand much quicker if not delayed by untimely argument. 'Perhaps you're judging her too hasty, Marilla. Don't call her untrustworthy until you're sure she has disobeyed you. Mebbe it can all be explained – Anne's great hand at explaining.'

(27-6) 'She's not here when I told her to stay,' retorted Marilla. 'I reckon she'll find it hard to explain that to my satisfaction. Of course I knew you'd take her part, Matthew. But I'm bringing her up, not you.'

(27-7) It was dark when supper was ready, and still no sign of Anne, coming hurriedly over the long bridge or up Lover's Lynde, breathless and repentant with a sense of neglected duties. Marilla washed and put away the dishes grimly. Then, wanting a candle to light her down cellar, she went up to the east gable for the one that generally stood on Anne's table. Lighting it, she turned around to see Anne herself lying on the bed, face downward among the pillows.

Appendix B

Analyzed Text with Reduced Format

B.1 Chapter 1-(1)

#1-2

mrs. rachel found abundant time at her kitchen window.

#1-3

she was sitting there in one afternoon.

#1-4

matthew was placidly driving over the hollow.

#1-5

mrs. rachel might have given a pretty good guess.

#1-6

QQQ,

the worthy woman finally concluded.

QQQ.

#1-7

mrs. rachel set out after tea.

B.2 Chapter 1-(2)

#1-10

mrs. rachel rapped at the kitchen door smartly.

mrs. rachel stepped in the kitchen.

#1-11

mrs. rachel had fairly closed the door.

mrs. rachel had taken mental note of everything.

there were three plates laid on the table.

marilla must be expecting someone home with matthew to tea.

the dishes were everyday dishes.

there was only a crabapple preserve on the table.

there was only one kind of cake on the table.

the expected company could not be any particular company.

#1-12

QQQ,

marilla said briskly.

QQQ.

#1-13

#1-14

marilla was a tall woman with angles.

marilla was a thin woman without curves.

#1-15

QQQ,

mrs. rachel said.

QQQ.

#1-16

marilla_s lips twitched understandingly.

#1-17

QQQ,

she said.

QQQ.

#1-18

mrs. rachel could not have been more astonished.

#1-19

QQQ,

she demanded.

#1-20

QQQ,

marilla said.

#1-21

mrs. rachel felt.

she had recieved a severe mental jolt.

#1-22

QQQ.

she demanded disapprovingly.

#1-23

#1-24

QQQ.

marilla returned.

QQQ.

#1-25

mrs rachel prided herself on always speaking her mind.

#1-26

QQQ.

#1-27

#1-28

QQQ.

#1-29

QQQ.

mrs. rachel said in a tone.

the tone plainly indicated her painful doubts.

QQQ.

#1-30

QQQ.

marilla said.

QQQ.

#1-31

mrs. rachel would have liked to stay.

matthew came home with his imported orphan.

B.3 Chapter 3-(1)

#3-32

matthew came back presently.

they sat down to supper.

anne could not eat.

she nibbled at the bread and butter.

she pecked at the crabapple preserve out of the little scalloped glass dish by her plate.

#3-33

QQQ,

marilla said.

#3-34

anne sighed.

#3-35

QQQ.

#3-36

QQQ,

marilla responded.

#3-37

QQQ.

#3-38

QQQ.

#3-39

QQQ.

#3-40

QQQ,

matthew said.

#3-41

marilla was wondering.

B.4 Chapter 3-(2)

#3-53

marilla went slowly to the kitchen.

she proceeded.

#3-54

QQQ,

she said wrathfully.

QQQ.

#3-55

QQQ,

matthew said reluctantly.

#3-56

QQQ.

#3-57

QQQ.

#3-58

QQQ.

#3-59

marilla_s astonishment could not have been greater.

#3-60

QQQ,

matthew stammered.

#3-61

QQQ.

#3-62

QQQ,

matthew said.

#3-63

QQQ.

#3-64

QQQ,

matthew persisted.

QQQ.

#3-65

QQQ.

#3-66

QQQ,

matthew said.

QQQ.

#3-67

QQQ.

marilla said shortly.

QQQ.

#3-68

QQQ.

matthew said.

QQQ.

#3-69

matthew went to bed.

marilla went to bed.

B.5 Chapter 7-(1)

#7-28

marilla retreated to the kitchen.

she set the candle firmly on the table.

#7-29

QQQ.

B.6 Chapter 8-(2)

#8-31

Anne set the card.

she had brought the jugful of apple blossoms in.

she decorated the dinner table.

marilla had eyed that.

#8-32

QQQ.

she announced.

QQQ.

#8-33

QQQ,

marilla said shortly.

#8-34

anne tipped the vase.

#8-35

QQQ,

she demanded.

QQQ.

#8-36

QQQ.

#8-37

QQQ.

#8-38

QQQ.

#8-39

anne looked at marilla.

#8-40

QQQ.

#8-41

QQQ.

#8-42

marilla was fond of morals.

#8-43

anne waved the moral.

#8-44

QQQ.

#8-45

QQQ,

marilla said dryly.

QQQ.

#8-46

QQQ.

#8-47

QQQ,

marilla sniffed.

QQQ.

#8-48

QQQ.

#8-49

QQQ.

#8-50

QQQ,

anne pleaded.

#8-51

QQQ.

#8-52

QQQ,

anne said.

QQQ.

#8-53

QQQ.

#8-54

anne sighed.

she retreated to the east gable.

B.7 Chapter 18-(1)

#18-3

anne and matthew had the cheerful kitchen.

a brightful fire was glowing in the stove.

crystals were shining on the window panes.

matthew nodded on the sofa.

anne studied at the table.

anne turned her back on the clock shelf.

#18-4

QQQ.

#18-5

QQQ,

matthew said.

#18-6

QQQ,

anne sighed.

QQQ.

#18-7

QQQ,

matthew said.

QQQ.

#18-8

matthew would have thought.

#18-9

QQQ,

anne complained.

QQQ.

#18-10

QQQ,

matthew said.

#18-11

QQQ,

anne said.

#18-12

QQQ,

matthew said.

#18-13

QQQ.

#18-14

matthew said.

#18-15

anne reflected.

#18-16

QQQ.

#18-17

QQQ,

matthew acknowledged.

#18-19

QQQ,

matthew said.

#18-20

anne emerged form the cellar.

she opened the kitchen door.

diana barry rushed in.

plate, candle and apples crashed together.

#18-21

QQQ,

anne cried.

#18-22

QQQ,

diana implored.

#18-23

matthew slipped away into the yard.

#18-24

QQQ,

anne said.

QQQ.

#18-25

QQQ,

diana sobbed.

QQQ.

#18-26

QQQ,

anne said.

QQQ.

#18-27

the girls hastened out.

B.8 Chapter 18-(2)

#18-29

minnie may was really very sick.

she lay on the kitchen sofa.

#18-30

anne went to work.

#18-31

QQQ.

#18-32

minnie_may did not take kindly to the ipecac.

#18-33

it was three o'clock.

#18-34

QQQ.

#18-35

QQQ,

the doctor nodded.

#18-36

QQQ.

#18-37

anne had gone home.

B.9 Chapter 18-(3)

#18-40

anne went to bed.

she descended to the kitchen.

#18-41

QQQ,

anne exclaimed.

QQQ.

#18-42

QQQ,

marilla said.

QQQ.

#18-43

marilla had something.

#18-44

QQQ.

#18-45

the warning seemed not necessary.

#18-46

QQQ.

#18-47

QQQ,

marilla said.

QQQ.

#18-48

anne came home.

#18-49

QQQ,

she announced.

QQQ.

#18-50

QQQ,

marilla said.

#18-51

QQQ,

anne said.

QQQ.

B.10 Chapter 27-(1)

#27-3

marilla entered the kitchen.

the fire blacked out.

she had told anne.

she must prepare the meal.

#27-4

QQQ,

marilla said.

matthew had come in.

he was waiting for his tea.

QQQ.

#27-5

QQQ,

matthew said.

QQQ.

#27-6

QQQ,

marilla retorted.

QQQ.

#27-7

it was dark.

marilla washed the dishes.

she went up to the east gable.

Appendix C

Prepared Focus Stack

C.1 Chapter 1-(1)

#1-2

[rachel,window]

#1-3

[rachel,kitchen]

#1-4

[peter,???]

[rachel,kitchen]

[matthew,field]

#1-5

[matthew,hill]

[rachel,kitchen]

#1-6

[rachel,kitchen]

[matthew,hill]

#1-7

[rachel,kitchen]

[matthew,hill]

C.2 Chapter 1-(2)

#1-10

[one,yard]

[rachel,yard]

#1-11

[marilla,kitchen]

[rachel,kitchen]

#1-12

[rachel,kitchen]

[marilla,kitchen]

#1-13

[marilla,kitchen]

[rachel,kitchen]

#1-14

[marilla,kitchen]

[rachel,kitchen]

#1-15

[marilla,kitchen]

[rachel,kitchen]

#1-16

[rachel,kitchen]

[marilla,kitchen]

#1-17

[marilla,kitchen]

[rachel,kitchen]

#1-18

[marilla,kitchen]

[rachel,kitchen]

#1-19

[rachel,kitchen]

[marilla,kitchen]

#1-20

[rachel,kitchen]

[marilla,kitchen]

#1-21

[marilla,kitchen]

[rachel,kitchen]

#1-22

[rachel,kitchen]

[marilla,kitchen]

#1-23

[rachel,kitchen]

[marilla,kitchen]

#1-24

[rachel,kitchen]

[marilla,kitchen]

#1-25

[marilla,kitchen]

[rachel,kitchen]

#1-26

[rachel,kitchen]

[marilla,kitchen]

#1-27

[rachel,kitchen]

[marilla,kitchen]

#1-28

[marilla,kitchen]

[rachel,kitchen]

#1-29

[marilla,kitchen]

[rachel,kitchen]

#1-30

[rachel,kitchen]

[marilla,kitchen]

#1-31

[marilla,kitchen]

[rachel,kitchen]

#1-32

[marilla,kitchen]

[rachel,?]

C.3 Chapter 3-(1)

#3-32

#3-33

[anne,kitchen]

[matthew,kitchen]

[marilla,kitchen]

#3-34

[marilla,kitchen]

[anne,kitchen]

[matthew,kitchen]

#3-35

[anne,kitchen]

[marilla,kitchen]

[matthew,kitchen]

#3-36

[anne,kitchen]

[marilla,kitchen]

[matthew,kitchen]

#3-37

[marilla,kitchen]

[anne,kitchen]

[matthew,kitchen]

#3-38

[anne,kitchen]

[marilla,kitchen]

[matthew,kitchen]

#3-39

[marilla,kitchen]

[anne,kitchen]

[matthew,kitchen]

#3-40

[anne,kitchen]

[marilla,kitchen]

[matthew,kitchen]

#3-41

[matthew,kitchen]

[anne,kitchen]

[marilla,kitchen]

C.4 Chapter 3-(2)

#3-53

[anne,bedroom]

[marilla,bedroom]

#3-54

[marilla,kitchen]

[matthew,kitchen]

#3-55

[marilla,kitchen]

[matthew,kitchen]

#3-56

[matthew,kitchen]

[marilla,kitchen]

#3-57

[marilla,kitchen]

[matthew,kitchen]

#3-58

[matthew,kitchen]

[marilla,kitchen]

#3-59

[marilla,kitchen]

[matthew,kitchen]

#3-60

[marilla,kitchen]

[matthew,kitchen]

#3-61

[matthew,kitchen]

[marilla,kitchen]

#3-62

[marilla,kitchen]

[matthew,kitchen]

#3-63

[matthew,kitchen]

[marilla,kitchen]

#3-64

[marilla,kitchen]

[matthew,ktichen]

#3-65

[matthew,kitchen]

[marilla,kitchen]

#3-66

[mariila,kitchen]

[matthew,kitchen]

#3-67

[matthew,kitchen]

[marilla,kitchen]

#3-68

[marilla,kitchen]

[matthew,kitchen]

#3-69

[matthew,kitchen]

[mariila,kitchen]

C.5 Chapter 7-(1)

#7-29 [marilla,kitchen]

C.6 Chapter 8-(2)

#8-32
[anne,kitchen]
[marilla,kitchen]
#8-33
[anne,kitchen]
[marilla,kitchen]
#8-34
[marilla,kitchen]
[anne,kitchen]
#8-35
[anne,kitchen]
[marilla,kitchen]
#8-36
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#8-41
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[anne,kitchen]
[marilla,kitchen]
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[marilla,kitchen]
[anne,kitchen]
#8-51
[anne,kitchen]
[marilla,kitchen]
#8-52

[marilla,kitchen]
[anne,kitchen]
#8-53
[anne,kitchen]
[marilla,kitchen]
#8-54
[marilla,kitchen]
[anne,kitchen]

C.7 Chapter 18-(1)

#18-4
[anne,kitchen]
[matthew,kitchen]
#18-5
[anne,kitchen]
[matthew,kitchen]
#18-6
[matthew,kitchen]
[anne,kitchen]
#18-7
[anne,kitchen]
[matthew,kitchen]
#18-8
[matthew,kitchen]
[anne,kitchen]
#18-9
[matthew,kitchen]
[anne,kitchen]
#18-10
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#18-11
[matthew,kitchen]
[anne,kitchen]
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[matthew,kitchen]
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[matthew,kitchen]
[anne,kitchen]
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[matthew,kitchen]
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[matthew,kitchen]
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[matthew,kitchen]
#18-17
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[matthew,kitchen]
#18-18
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[anne,kitchen]
#18-19
[anne,kitchen]
[matthew,kitchen]
#18-20
[matthew,kitchen]
[anne,kitchen]
#18-21
[anne,kitchen]
[diana,kitchen]
[matthew,kitchen]
#18-22

[anne,kitchen]

[diana,kitchen]

[matthew,kitchen]

#18-23

[diana,kitchen]

[anne,kitchen]

[matthew,kitchen]

#18-24

[matthew,yard]

[diana,kitchen]

[anne,kitchen]

#18-25

[anne,kitchen]

[matthew,yard]

[diana,kitchen]

#18-26

[diana,kitchen]

[anne,kitchen]

[matthew,yard]

#18-27

[anne,kitchen]

[diana,kitchen]

[matthew,kitchen]

C.8 Chapter 18-(2)

#18-30

[minnie,kitchen]

[anne,kitchen]

#18-31

[anne,kitchen]

[minnie,kitchen]

#18-32

[anne,kitchen]

[minnie,kitchen]

#18-33

[minnie,kitchen]

[anne,kitchen]

#18-34

[minnie,kitchen]

[anne,kitchen]

#18-35

[anne,kitchen]

[minnie,kitchen]

[doctor,kitchen]

#18-36

[doctor,kitchen]

[anne,kitchen]

[minnie,kitchen]

#18-37

[doctor,kitchen]

[anne,kitchen]

[minnie,kitchen]

C.9 Chapter 18-(3)

#18-41

[anne,kitchen]

[marilla,kitchen]

#18-42

[anne,kitchen]

[marilla,kitchen]

#18-43

[marilla,kitchen]

[anne,kitchen]

#18-44

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[anne,kitchen]
[marilla,kitchen]
#18-51
[marilla,kitchen]
[anne,kitchen]

C.10 Chapter 27-(1)

#27-4
[marilla,kitchen]
#27-5
[marilla,kitchen]
[matthew,kitchen]
#27-6
[matthew,kitchen]
[marilla,kitchen]
#27-7
[marilla,kitchen]
[matthew,kitchen]

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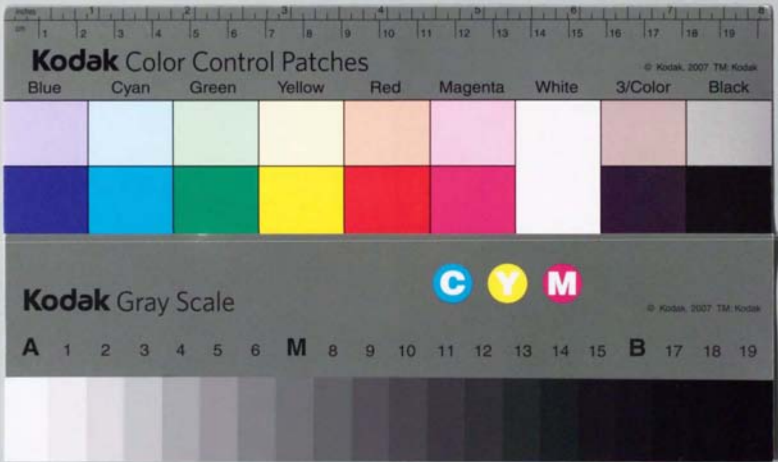
Kodak Color Control Patches
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Kodak Gray Scale
C Y M
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A 1 2 3 4 5 6 M 8 9 10 11 12 13 14 15 B 17 18 19