Chapter 1

Introduction

1.1 Motivation

Flourishing of the field of knowledge engineering is largely due to mechanization of deductive reasoning. On the other hand, non-deductive reasonings such as induction, analogical reasoning and abduction have been also investigated for a long time[32]. There has been desire to mechanize the non-deductive reasonings. Mechanized induction makes it possible to automatically generate general rules by giving many instances, implying resolution of the knowledge acquisition bottleneck, so far the largest obstacle in the area of knowledge engineering. Mechanized analogical reasoning makes a knowledge base system capable to use its knowledge not only under the predetermined applicable conditions but also in similar situations, implying resolution of the brittleness, the other major issue in the field. Mechanized abduction let a knowledge base system use incomplete knowledge, which is sometimes incorrect due to inconsistency, as well as complete knowledge, which is always true. That gives the knowledge base system a huge advantage of ability to deal with a hypothetical situation.

As results of huge efforts that have been made, the field of artificial intelligence (AI) has some fruits. On induction, classification rule learning systems have been widely studied. In a typical approach, they learn rules distinguishing a case that is an instance of goal concept from one that is not. The case is expressed in a list of attribute-value pairs. Effective methods like decision tree induction[67, 68] and neural network[69, 4] were proposed for the approach. Recently a commercial application called *data mining*, which finds hidden regularities among data in huge databases, is emerging and the methods are used as its key components. On analogical reasoning, a problem solver that uses a similar experience in the past was proposed.

It is called case-based reasoning (CBR)[38] and used in the fields such as planning[46]. On abduction, an efficient mechanism to manage consistency of sets of hypotheses is developed. It is called assumption-based truth maintenance system (ATMS)[9] and applied to diagnosis problems[10].

However the past studies also have problems. The first issue is on knowledge description. A way to describe a task of non-deductive reasoning system can hugely influence effectiveness of the system. In abduction, it has been well understood by researchers that knowledge description highly affects abduction system's efficiency and some methods have been established to preprocess the knowledge base so that it can be efficiently used by the abduction system[11]. However, in induction the issue has not been noticed until recently. In analogical reasoning the issue has been almost neglected at least by studies in AI. The second issue is on semantics. Induction and abduction have clear semantics. However application of abduction on logic programs is seldom discussed, though its semantics is widely studied. Moreover, in analogical reasoning, the desire to implement practical systems has somehow postponed analyzing semantic nature of analogical reasoning.

The thesis proposes the following solutions for the problems.

1. **Preprocessing for induction**[58]
   The inductive classification rule learner's performance is heavily influenced by a set of attributes that is used to describe the cases. One way to cope the problem is to include potentially redundant attributes in the set. However the approach does not work when the redundant attributes contain noises. Several studies have tried to resolve the problem and some have succeeded at the cost of computational expensiveness. The thesis proposes a new method that is effective and computationally efficient. The method is implemented with a common inductive learning system and its effectiveness is experimentally shown.

2. **Automatic partitioning for analogical reasoning**[63, 54]
   The analogical reasoning system's performance is also influenced by a set of symbols that is used to describe its initial knowledge. Furthermore it is also influenced by how the knowledge is partitioned into clusters called domains. There have been studies to deal with the former but few for the latter. Generally a pre-partitioned knowledge base has been given to the analogical reasoning system. In the thesis, importance that the system is able to change the partition at will is explained. Then an application that requires the feature, a creativity support system[52, 53, 6, 47], is implemented and experimentally tested.

3. **Semantics for analogical reasoning as abduction**[50, 51]
   Few studies have dealt with semantics for analogical reasoning. The thesis proposes a declarative semantics for analogical reasoning that is based on a semantics for abduction. The approach also gives a nice application to abduction on logic program. Properties of the semantics are investigated and a proof procedure for it is presented.

1.2 Background

1.2.1 Induction

First, terms used in the field of classification rule learning are explained.

A concept for which the system should learn the classification rules is called a *goal concept*. Cases given to the system are called *training examples*. The training example is given with information of its membership to the goal concept. A training example that is an instance of the goal concept is called a *positive example*. Otherwise it is called a *negative example*. Sometimes the membership information is regarded as an attribute and in that case the attribute is called *class*. A candidate of the classification rules is called *hypothesis*.

Semantically, "correct induction" is clearly defined. Suppose E^+ to be a set of positive examples, E^- to be a set of negative examples, $A(x)$ to be information on attributes of training example x and P to be a goal concept. Then induction should result a hypothesis H described as below, where $\mathcal{M}(X)$ denotes X's model.

$$
\begin{array}{l}
\forall x(x \in E^+ \supset \mathcal{M}(H \cup A(x)) \models P(x)) \\
\wedge \\
\forall x(x \in E^- \supset \mathcal{M}(H \cup A(x)) \not\models P(x))
\end{array}
$$

However, from a practical point of view the clarity means little. For example, a disjunction of all positive instances' attribute information and class information clearly satisfies above, but is clearly useless too. We implicitly expect the following to be achieved by induction[24].

- The classification rules can be used to predict a class of an unknown individual, namely generalization is done.

- The classification rules *compactly* express regularity in the training examples.

To obtain meaningful rules, a format of hypotheses is usually restricted. Typically that is a rule whose if-part is a conjunction of atoms. There is another merit of the restriction. Because a learning algorithm is typically implemented as a search in a space of hypotheses, the restriction helps the search finish within a reasonable time.

Furthermore, in most study, symbols that may be used to describe the rules must appear in the description of the training examples. Therefore learnability of the rules depends on relevancy of the attributes to be used to describe the training examples. Although one can think the issue as a part of problem formulation, we must deal with it to apply the classification rule learning to practical applications. There are two approaches.

1. *Selective induction*: When the training examples are described, information on all the available attributes, no matter how relevant it is or not, should be given. The rule learner selects necessary attributes to construct a hypothesis from the whole set.

2. *Constructive induction*: Another piece of information called background knowledge is additionally provided. Predicates and functions that are not used to describe the training examples appear in the background knowledge along with their relationship with attributes that are used to describe the training examples. Using the information the rule learner can use the symbols that are not used to describe the training examples as needed.

In the approach 2, studies such as inductive logic programming[5] has been conducted, but so far they have not reached to a practical level due to problems such as computational expensiveness. The approach 1 is a current mainstream and used in data mining. However algorithms like C4.5[68], which exhibit great performance under ideal conditions, are known to degrade its performance when they faced to many noisy attributes. They require attribute selection by preprocess systems to maintain the performance.

1.2.2 Analogical reasoning

First, terms used in the field of analogical reasoning are explained.

Analogical reasoning is an approach to problem solving that invokes knowledge on known situations at an unknown situation. A situation is called a *domain*. The known situation is called a *base domain*. The unknown situation is called a *target domain*. The knowledge is invoked according to similarity recognized between the base domain and the target domain. The similarity is called *analogy*. The invocation is implemented as transformation of knowledge in the base domain into one in the target domain taking the analogy into account. The transformation is called *transcription*.

There are two major ways in logical approaches to analogical reasoning.

1. Formalize a domain as an individual constant. Knowledge on the domain is described as formulae that include the constant.

2. Formalize a domain as a set of formulae. Knowledge on the domain is described as the formulae that are included in a set that corresponds to the domain.

In the case 2, if we classify the formulae according to constants included in them then we will have the case 1. In that sense the case 1 is a special case of the case 2.

The first issue in the analogical reasoning is its ambiguous semantics. Because a study of the analogical reasoning in AI usually aimed a very practical objective of increasing problem-solving ability of knowledge base systems, the most of the effort has been devoted to implement an analogical reasoning mechanism as an add-in to the problem solver. As a result semantical analysis has been relatively overlooked. The issue is common to both approaches.

An analogical reasoning mechanism as a procedure raises an issue too. Its inference rules typically define how to find new correspondences of symbols based on already known correspondences between domains. Initially no symbols correspond each other. Symbols shared between the domains are the start of the search for the correspondences. Rules to augment the correspondences under some conditions are given. For example, if a symbol a in a domain A and a symbol b in a domain B correspond each other, a symbol a' that has a relation R with a in A and a symbol b' that has R with b in B should correspond each other too. Therefore the correspondences are found depending on what symbols are used and how domains are partitioned.

For the former, there is a study that employs background knowledge and deductive reasoning as a subsystem of the analogical reasoning system[20]. The analogical reasoning system can perform deduction as needed to get relevant descriptions of knowledge for finding the correspondences. For the latter, there has been no detailed analysis of it in AI because it is usually regarded as a part of problem formulation[16, 74]. However, from a cognitive-scientific standpoint, human can use her/his experiences from various views[56]. An experience can be used in different ways if situations she/he is facing are different[1]. Thinking partitioning as an issue *before* the

[1] The approach has been pursued by studies on metaphor[25, 26, 73, 55].

analogical reasoning is equivalent to thinking that every experiences are indexed just to be fine for later problem-solving, and hardly acceptable. This is the second issue in analogical reasoning.

1.2.3 Abduction

First, terms used in the field of abduction are explained.

Abduction is reasoning to build an explanation for an observation assuming appropriate hypotheses from incomplete knowledge when the observation is not explainable by complete knowledge only. The complete knowledge is called *background knowledge*. The incomplete knowledge is called *abducibles*. The set of abducibles assumed by the reasoner is called a *hypothesis* or *belief*. The observation is called a *goal*.

Semantically, "correct abduction" is clearly defined.

Suppose H to be a set of abducibles, g to be a goal and Σ to be background knowledge. Then abduction should result a hypothesis $h \subset H$ described as below, where $\mathcal{M}(X)$ denotes X's model and $\Sigma \cup h$ does not cause inconsistency.

$$\mathcal{M}(\Sigma \cup h) \models g$$

Because assuming the hypothesis usually takes its toll, minimality is often required for h.

Abduction was first introduced by a philosopher and logician Charles Sanders Peirce (1839–1914) as a distinctive pattern of reasoning wherein explanatory hypotheses are formed and accepted, either in science or everyday life[32]. Because of its knowledge producing nature, abduction is often regarded as an essence of scientific discovery, or even a fundamental mechanism of human perception that creates a higher level representation from a lower level representation[32]. Although as the essence of scientific discovery it is important to clarify how an abducible is brought into consideration in the first place as we will see in chapter 3, abduction with a predetermined set of abducibles is what has been mostly studied in AI. Even so the AI approach to abduction is important, because it is the simplest form of nonmonotonic reasoning and it has an obvious and important application of diagnosis[28].

There are two major ways in logical approaches to abduction.

1. Formalize abduction on propositional logic.

2. Formalize abduction on predicate logic.

Because abduction is essentially search in a large space of hypotheses, efficiency is important. For the case 1, an efficient way to record dependencies between hypotheses[9] and preprocessing methods to prepare a knowledge base for the search[11]. They are successfully used for application such as diagnosis[10] and design[43]. Applications to natural language processing are also common[23]. For the case 2, abduction on logic programs, especially its semantics, is widely studied, probably because of relationship between nonmonotonicity of abduction and meaning of negation in the logic programs. However they have not found any unique applications yet.

Structure of the thesis

The thesis provides solutions to the issues in past studies in non-deductive reasonings and shows effectiveness of the solution by implementing application systems.

First, in chapter 2, a new method for preprocessing in the classification rule learning is introduced[57]. The method is a variant of the wrapper model[31], where a relevant set of attributes is calculated by iterating trial learnings changing a tentative set of attributes of training examples. The method achieves huge acceleration by employing an evaluation function that takes harmfulness of attributes into account. The method is effective even to a task with many noisy attributes. The effectiveness is experimentally shown.

Next, in chapter 3, a framework for analogical reasoning that does not require beforehand partitioning by human is presented, in the approach of regarding a set of formulae as a domain[63]. The framework is called *paraphrasing-based analogical reasoning(***PAR***)*[2]. The framework can model analogical reasoning processes in which the beforehand partitioning is impossible. An example of such processes is analogical reasoning as a basic mechanism of human creativity.

In chapter 4, a creativity support system that assists human by providing fragments of ideas using its analogical reasoning system based on **PAR** is implemented in order to show importance of partitioning within the analogical reasoning framework[54]. The creativity support system has another feature that it has a very simple but effective Japanese language input system.

Then in chapter 5, an application of abduction on logic programs, primitive analogical reasoning on logic programs, is shown[50, 51]. The basic idea is regarding the analogical reasoning as a form of abduction. By doing so semantics for analogical reasoning can be given based on *generalized stable model* semantics for abduction[33]. This is also an attempt to give declarative

[2]The abbreviation was **PA** in the previous paper[63]. The change has been made for clarity because **PA** usually means *Peano Arithmetic*.

semantics for analogical reasoning in the approach of regarding a constant as a domain.

Finally in chapter 6, the studies are summed up and their importance and future directions are discussed.