MODELLING INDUCTIVE REASONING ABILITY FOR ADAPTIVE VIRTUAL LEARNING ENVIRONMENT

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ABSTRACT
Inductive reasoning is one of the important characteristics of human intelligence. Researchers have regarded inductive reasoning as one of the seven primary mental abilities that are accounted for intelligent behaviours; researches also showed that it is the best predictor for academic performance. Despite its recognised importance underlying the learning process of human beings, little effort is spent on research to support the inductive reasoning process in virtual learning environments (VLEs). This paper partially addresses this issue by asking the question of how to model inductive reasoning ability of a learner. In this paper, characteristics of inductive reasoning ability are studied in relation to domain knowledge, generalisation, working memory capacity, analogy, and hypothesis generation from the view of cognitive science to extract the manifestations of inductive reasoning ability which are in general observable patterns of learner behaviour. The manifestations listed in this paper can be used by virtual learning environment to model the inductive reasoning ability of the learner.

KEYWORDS
Inductive Reasoning Ability, Cognitive Trait, Student Modelling, Adaptivity, Virtual Learning Environment

1. INTRODUCTION
Inductive reasoning is one of the important characteristics of human intelligence: Researchers have regarded inductive reasoning as one of the seven primary mental abilities that are accounted for intelligent behaviours (Selst, 2003). Pallegrino and Glaster (cited by Harverty et al., 2000, p. 250) noted that the induction reasoning ability can be extracted in most aptitude and intelligence tests and is the best predictor for academic performance. Harverty et al. (2000) cited several other researches that viewed inductive reasoning as a significant factor for problem solving, concept learning, mathematic learning, and development of expertise (p. 250). Heller et al. (2001) showed that inductive reasoning is a necessary ability for extracting the knowledge of problem solving in physics.
Despite its recognised importance underlying the learning process of human beings, little effort is spent on researches to support learners’ inductive reasoning process in virtual learning environments (VLEs) (Lin, Kinshuk, & Patel, 2003). This paper presents important findings in a series of researches that aim to address this issue. The focus of this paper is placed on the question of how to model inductive reasoning ability of a learner during the learner’s interaction with virtual learning environments which could be web-based hypermedia system. This paper initially discusses the characteristics of inductive reasoning and then describes various manifestations of inductive reasoning ability that have been synthesized.

2. CHARACTERISTICS OF INDUCTIVE REASONING ABILITY

In order to formulate rules to support inductive reasoning ability in VLEs, we need to identify specific characteristics of inductive reasoning ability. This section discusses these characteristics in relation to domain knowledge, learning, working memory capacity, analogy, and hypothesis generation. The purpose is to find out manifestations of inductive reasoning ability, which can then be translated into learner behaviours observable through pattern analysis techniques on learners’ actions in the VLE.

2.1 Knowledge Background and Induction

SGW (1996) noted that the prior domain knowledge bears influence on the inductive behaviour of the learner in addition to the general intellectual ability to make induction. The latter is referred as generic knowledge that is the domain independent knowledge to systematise and relate objects of observation. SGW (1996, ¶ 8) cited the Klahr and Dunbar’s SDDS (Scientific Discovery as Dual Search) theory, which postulated that the discovery activities can be located in either of the two spaces, i.e. hypothesis space (HS) and experiment space (ES), and then used these two spaces to describe and analyse the discovery behaviours of the learner. SGW further correlated the predicted behaviours of the learner with different level of generic knowledge and domain knowledge, both in terms of high and low, to the two spaces stated in the SDDS theory. The categorisation is shown in table 1.

<table>
<thead>
<tr>
<th>Generic Knowledge</th>
<th>Domain Knowledge</th>
<th>High (HDK)</th>
<th>Low (LDK)</th>
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<tbody>
<tr>
<td>High (HGK)</td>
<td>Start with Hypothesis Space, only goes into Experiment Space to test the validity of hypothesis.</td>
<td>Constant switching between Hypothesis Space and Experiment Space</td>
<td></td>
</tr>
<tr>
<td>Low (LGK)</td>
<td>Start with Experiment Space and gradually into Hypothesis space</td>
<td>Stay and Struggle in the Experiment Space</td>
<td></td>
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</tbody>
</table>

(HGK: High Generic Knowledge, LGK: Low Generic Knowledge, HDK: High Domain Knowledge, LDK: Low Domain Knowledge)

In a discovery task aimed at a problem solution, learners of HGK/HDK typically start by searching hypothesis space because they have understanding of the variables in the problem domain; what the learners focus on is the selection or creation of a hypothesis that can be applied in the problem at hand, and the learners only go to the experiment space to validate their hypotheses. Learning effect for the exploratory activities is best for this kind of learners. Learners of LGK/HDK may start by searching the hypothesis space because of the high stack of relevant domain knowledge. But due to the lack of systematic approach, the learners are likely fail to discover the right relationship among the objects and hence unable to select or create the right hypothesis to apply. This type of learners would be forced to search on the experiment space and go back and forth between the two spaces until the solution is found. Learners of HGK/LDK typically start with experiment space due to the lack of understanding of the domain variables, but will gradually discover the working patterns of the variables and start to work in the hypothesis space and they are very likely to become learners of HGK/HDK. Finally, typical learners of LGK/LDK start with experiment space and due to the lack of understanding about the domain and the inability to discover systematic patterns, they
will struggle and remain in the experiment space. Learning effect of the discovery task is therefore the worst for this kind of learners. The learning efficiency of the exploratory task decreases from HGK/HDK - HGK/LDK - LGK/HDK - LGK/LDK (SGW, 1996).

Heit (2000) showed that one form of inductive reasoning, the diversity-based reasoning, is demonstrated less by children than by adults, but further comparison of American adults and Itzaj (name of Mayan people in Guatemala) adults showed that diversity-based reasoning depends not only on processing but on prior knowledge. The result corresponds well to the view point of SGW (1996) with the efficiency of the HGK/HDK combination being greater than that of the HGK/LDK. Harverty et al.’s (2000) study in the formula-finding process of mathematics proposed that there are three main activities of inductive reasoning:

- data gathering: includes activities of data collection, organisation, and representation.
- pattern finding: includes activities of investigation and analysis of the data collected.
- hypothesis generation: includes activities of constructing, proposing, and testing hypothesis.

Hypothesis generation uses the data from data gathering and pattern finding, but the flow of data is not just unidirectional. The activities of hypothesis can also incur new insight for data gathering and pattern finding.

Harverty et al. (2000) observed the behaviours of the subjects in their experiment of mathematical formula-finding and noted that subjects who successfully completed the task employed common solution strategies. In the experiment, subjects were asked to find the mathematical formula (in terms of y and x) given the data of the formula. One solution strategy is local hypothesis strategy. In local hypothesis strategy, subjects formed a local hypothesis from a single instance of data and tested if the local hypothesis work for other data instance as well. They may have to generate many local hypotheses before they can find one working for another piece of instance, but this strategy is useful in finding the elements of the global hypothesis (solution).

Another strategy that the subjects employed successfully to solve the problems was called the pursuit strategy (Harverty et al., 2000). In pursuit strategy, subjects found a pattern expressed in quantity Q, besides the original quantities (x and y). The subjects then tried to understand the formula using Q, and decided whether Q is worthy or not for the pursuit.

These strategies listed by Harverty et al. (2000) were commonly found in the behaviours of learners who had successfully solved the problem. These strategies, even though found in experiment of mathematical formula finding, can be applied in many other daily contexts to solve other kinds of problems. Holland et al. (1987) had also listed several “rules” that are commonly employed in problem solving processes, including inferential rules, specialization rules, unusualness rules, law of large number heuristics and regulation schemas. The strategies or rules of this type are not domain specific and correspond to the generic knowledge for induction in SGW’s (1996) categorisation.

From the above discussion, it is clear that induction depends neither solely on prior knowledge nor on the generic knowledge. Novice learners, even though possess great generic knowledge, may still be limited by their domain knowledge to perform as accurate the induction as experts could be in a profession. Nonetheless, the amount of domain knowledge has a positive correlation to the ability of inductive reasoning. Domain knowledge of the learner, though beyond the scope of this discussion, is available in many VLEs in the form of performance-based student models. The representational value of the domain competencies can be retrieved from the performance-based model of the system and can therefore be used as a factor to determine how good learners can perform induction in a domain.

2.2 Inductive Reasoning Ability and Generalization

The term induction is derived from the Latin rendering of Aristotle’s *epagoge* that is the process for moving to a generalisation from its specific instances (Rescher, 1998). Bransford et al. (2000) pointed out that generalisations aimed at increasing transferability can result in (mathematical) models or global hypothesis (Harverty et al., 2000) that can be applied to a variety of contexts in an efficient manner.

Zhu and Simon (cited by Harverty et al., 2000) pointed out that the learners have to induce how and when to apply the problem solving method in worked-out examples. In reality, the learners also need to induce where to apply as well, with a contextual awareness. The induction here requires the learners to (1) recognise the similarities and differences of the parameters in the current and experienced contexts, (2) recognise and
match pattern of current context to experienced context(s), and/or (3) recognise/create the theory/method that
can be applied to solve the problem.

Point (1) and (2) corresponds to the pattern finding activity of Harverty et al.’s (2000) categorisation. Pattern finding is, in Holland et al.’s (1987) term, detection of co-variation from a stack of samples (or past experiences). In the research done by Heller et al. (2001), the instructors believed that the attainment of problem solving skill in physics comes from reflective practices to extract knowledge from previous experiences of working on other problems or from sample problem solutions. Point (3) corresponds to the hypothesis generation activity in Harverty et al.’s (2000) categorisation. Hypothesis generation differs from mere guessing in an important ways - having a rationale behind the hypothesis. The rationale of the hypothesis is primarily derived from the observed pattern. Without the activity to confirm the hypothesis, it can never be proved or disproved. It then forms a loose cognitive structure that is deemed as the source of “fundamental attribution error” that means “people’s judgment strategies in the social domain, like their empirical rules in the physical domain, are defective” (Holland et al., 1987, p222), and is accountable for wrong judgements at later time when this knowledge structure is used as a basis of induction.

In VLEs, row phenomena are often presented as examples or case studies trying to demonstrate some underlying principle in a contextual way. The measure of this skill is determined by the fact whether the learner can generalise the principles correctly from the presented examples or not. In courses that are constituted by nodes of concepts/html-pages, generalisation as a manifestation of inductive reasoning ability can be detected from the navigational trace of the learner in a pattern that includes visited example node(s) and failed evaluation node(s).

2.3 Working Memory Capacity and Pattern Matching

Transferability of learning is regarded as an important part on how people develop competencies (Bransford, et al. 2000). Transferability refers to the ability to apply the problem solving skills, which can contain only conceptual knowledge obtained from case studies or procedural knowledge obtained from previous hands-on exercises in the lab, in a novel context. Previous procedural knowledge does not guarantee the ability to solve a problem in a novel context, nor does mere understanding of concepts. Thus, curriculum with focus on transferability tries to provide as many contexts of the problem/case studies as possible to increase the success rate of transfer of problem solving knowledge to new contexts. Learners create sets of different mental models, all related to the concept at scrutiny, from the set of different contexts. Variables in the contexts are encoded to differentiate one mental model from the other.

Often transferability is used as a measure of the quality of learning (Bransford, 2000). For the assessment of the transferability to be fair, a “new” context must differ from any previously experienced contexts, but the differences can neither be 0% nor 100% – there must be similarities between the contexts. It is, then, up to the learner to induce which learned mental model to apply to current task. Selecting an appropriate mental model to apply requires pattern matching. It is important to note that the individual difference in the performance of pattern matching can be explained in terms of Holland et al.’s (1987) “adaptive default hierarchy” of mental models.

Holland et al. (1987) posited rule-based mental model as a framework to explain human induction behaviour. They postulated that there is a general default set of rules for every mental model, e.g. a permission mental model has the following rule: “if X is true then Y is allowed”. For example, a Chocolate-Permission mental model for a child could be like this: “if Mom says I cannot have chocolate, then I am not allowed to have the chocolate”. Their framework is adaptive because it allows exception to exist within a mental model to form a sub mental model. Sub mental model could be created under the Chocolate-Permission mental model such as “if Mom says I cannot have chocolate, and Dad is present and does not confirm her, then I am allowed to have the chocolate”. The sub mental model can have further sub mental models and thus forms a hierarchy of mental models. The mental models in the higher level of the hierarchy are usually more generic mental models, and in the lower levels more specific. The number of rules in the higher level is less than the ones in the lower level. Induction of which mental model is applicable for a given situation requires the comparison of the rules in a mental model to the variables observed in the environment. Comparison as a cognitive process is known to be highly related to working memory capacity, and is proportional to working memory capacity (Salthouse & Babcock, 1991; Lin, Kinshuk, & Patel, 2003). It is
therefore obvious that higher working memory capacity lays the foundation to higher inductive reasoning ability.

Another evidence suggesting that the inductive reasoning ability relates to working memory capacity is the fact that external representation (what the learners see) can indeed influence one’s internal cognitive processes. Wexler (1999) gave an example of rearranging the cards in one’s hand renders the relation of the cards more perceptually salient. It brings up the point that cognitive capacity of human being is limited in nature. One important factor to be able to perform generalization, as a form of induction, is to remember the particulars and their attributes. The remembering certainly has to occupy the available working memory capacity if external representation in any form is not available. Therefore, it is plausible to postulate that inductive reasoning ability depends also on working memory capacity.

Working memory capacity as a manifestation of inductive reasoning ability is simplified by the fact that working memory capacity is another cognitive trait that had been modeled by the Cognitive Trait Model (Lin, Kinshuk, & Patel, 2003), and the value of the learner’s working memory capacity is readily available as part of cognitive trait model.

2.4 Analogy and Induction

Use of analogy also plays an important role for inductive reasoning. Researchers of instructional technology had long recognised the important value of using analogies or parallel concepts to prop understanding of important concepts. Among them, Kinshuk et al. (1999) had identified parallel concept link as one of the major six types of navigational link in web-based educational systems.

Holland et al. (1987) pointed out that analogous thinking enables one to view a novel situation using familiar concepts, and showed that many great scientific discoveries could be attributed to the use of analogy as a basis for induction. The wave nature of light was discovered by drawing analogy to the wave of liquid for observed properties such as reflection, and diffraction. Analogy, in their view, provides an already-structured framework of which the information available in the new context can be filled in. Structural information and the information of how operations can change the problem state are readily available from the analogy and thus greatly facilitate the learning process. Metaphors, according to their perspective, serve the similar role.

Inducing and hence understanding the theories could be facilitated by the use of analogies. Analogy presents learners an alternative angle to look at current problem. The alternative point of view supplies a certain degree of familiarity from already-learned knowledge to make solving a problem or learning a concept easier. A parallel concept to the concept of how sound waves travel in air could link to an explanation of how waves travel in pond. By first seeing the already-familiar analogy of pond wave and then presented the new concept of sound wave, the learner certainly has higher possibility to induce the properties of sound wave.

In VLEs, analogous concepts to the current concept at hand are often implemented by parallel concept links which “leads to the analogous domain unit for comparative learning or to the unit related to another aspect of the currently being learnt domain content” (Kinshuk et al., 1999). Therefore, the ability to learn from analogy as a manifestation of inductive reasoning can be detected from the navigational trace of the learner in a pattern that includes visited parallel concept node(s) and failed evaluation nodes.

2.5 Hypothesis Generation and Induction

Hypothesis formation is an essential step for induction no matter whether the hypothesis is local or global. Hypothesis, once formed, can then be proved to become part of legitimate knowledge or disapproved to allow identification of wrong path. Either ways, it contributes, directly or indirectly, to the overall knowledge building in the learning process.

However, hypothesis primarily exists only as a mental construct in learners when they are reading or exploring to learn. It then poses a great problem for any online learning system to detect the formation of hypothesis since there is no explicit way to examine what is happening in a learner’s mind. However, once the learner had constructed a hypothesis, the learner will need to confirm it, no matter whether the result is positive or negative. According to Popper (cited by Holland et al. 1987, p328), a philosopher of science, the primary function of scientific laws and theories is prediction. “The process of inductive reasoning which
moves from an observed uniformity across the examined cases of a certain sort to the conclusion that all cases of this sort have the feature in question” (Rescher, 1980, p39).

Without the action to confirm, the hypothesis is literally of no use – it cannot be used either to predict or not to predict (in the case of confirmed wrong hypothesis). Thus, it is logical to say that in the case of learner’s online learning experience, the lack of action to confirm a hypothesis has the equivalent result as no hypothesis at all.

In VLEs, a learner can navigate to a concept’s example node, which is the primary arena for the hypothesis generation process. If any of the hypotheses is formed during the viewing of the example, the best way to confirm it is to follow the original trace to come back to the concept node. Thus, this navigational pattern can be used to detect the existence of this manifestation of inductive reasoning ability.

2.6 Manifestations of Inductive Reasoning Ability

Based on the previous discussion, certain behaviours of the learners, called the manifestations of inductive reasoning ability, can be used to indicate their inductive reasoning abilities. The manifestations of inductive reasoning ability are listed below:

- Higher generalisation ability manifests higher inductive reasoning ability.
- Inability to learn from analogy manifests lower inductive reasoning ability.
- Activities to confirm hypotheses indicate the formation of hypotheses and therefore manifests higher inductive reasoning ability.
- Higher domain knowledge manifests higher inductive reasoning ability.
- Higher working memory capacity manifests higher inductive reasoning ability.

Manifestations of inductive reasoning ability are generally observable learner behaviours. In the cases of domain knowledge and working memory capacity, the manifestations are readily available from student models created by the VLE. The technique of relation-based browsing pattern analysis (Lin, Kinshuk, & Patel, 2003), which performs domain-independent analysis based on learning object relations, can be used as a tool to analysis the learner’s interaction with the VLE.

3. CONCLUSION

This paper presented a solution to address the issue of inadequate support for inductive reasoning ability in virtual learning environments by providing a theoretical background to model the inductive reasoning ability of the learner. The focus of this paper is theoretical; other researches (Lin, Kinshuk, & Patel, 2003) along the same line had addressed the technical issues. However, despite the intensive literature review on human cognition and induction, the list of manifestations of inductive reasoning ability is not exhaustive. The list is in part limited by the diverse viewpoints of inductive reasoning among researchers as well as the novel requirement of translatability of each manifestation into machine observable patterns in our work.

The findings in this paper are domain independent and they provide a practical starting point for researches in adaptive support for inductive reasoning ability. Further researches will be conducted to create an adaptive framework for inductive reasoning ability. The framework will allow instructional content researchers and developers to create content that can be adapted to suit different learner’s inductive reasoning ability in virtual learning environments.

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