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# **MEDIATORBOT: AN INTELLIGENT CONVERSATIONAL BOT OF SUPPORTING STUDENTS WORKING TOGETHER IN A COLLABORATIVE E-LEARNING PLATFORM BY USING A INTELLIGENT TUTOR SYSTEM**

Vu Do Dung

## **ABSTRACT**

The interactivity of online learning is very important through it becomes popular. Moreover, the usage of Artificial Intelligence application is growing accelerated in modern years and in many sectors. In order to improve the interactivity and effectiveness of E-Learning environment in supporting students collaborate together, a conversational bot called MediatorBot is considered. As a part of Artificial Intelligence application, it generates hints to help users solve their obscure problem according to the given lecture or assignment. It can be integrated with an Intelligent Tutor System (ITS) as an add-in. MediatorBot contains the knowledge of a given specific domain (e.g., deep learning) which is valuable to deliver an appropriate answer to the users' questions. Especially, it monitors the conversations of each student groups, identifies the debated or clarified problem, and the opportunities for intervention. In the original ITS, the bot answers the question or inquiry of the user. In this research, the authors would like to overcome the ITS by improving its knowledge, determining intervention opportunities according to the group conversation within a given domain-specific online curriculum. As to encourage students knowledge approach, several features are being examined such as definition extractor, hints generator, intervention investigator, etc., This will allow the student to directly follow the maintenance of a specific topic and build their knowledge in an effective way. In addition, an enhancement to engage all the students following the conversation is proposed to help them come up with the lecture. With this enhancement, MediatorBot can give a recommendation of solutions for users to ask. All of the functions are measured using the users' experiment feedback in parallel with the experts' evaluation. **Keywords:** Intelligent Tutor, Artificial

Intelligence, Natural Language Processing



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## **LIST OF ABBREVIATIONS**

AI	Artificial Intelligence
ITS	Intelligent Tutoring Systems
CSCL	Computer-Supported Collaborative Learning
RNN	Recurrent Neural Network
MLE	Maximum Likelihood Estimation
NLP	Natural Language Processing
SVM	Support Vector Machine
CNNs	Convolution Neural Networkss



## INTRODUCTION

Intelligent Tutoring Systems (ITS) is developed in the early 1970s (1). One of the intentions in AI technologies is to create educational agents that can be adapted to the student. Because an ITS can perform various roles such as "knowledge presentation mechanisms", "knowledge processing tools", "communication tools" (2), it succeeds through each of these functions in exciting training and cognitive development of the learner:

- "Knowledge presentation mechanisms": By using these tools, information enhances more accessible, more up-to-date, and can be presented in various formats. It is a great stimulant for the learner's imagination, memorization, and comprehension.
- "Knowledge processing tools": These tools allowance for supervision of the student better, more personalized, and adaptive learning. The learner can do their self-evaluations, get recommendations, and feedback faster.
- "Communication tools": These tools are utilized for projects which have human and machine communication through intelligent agents. The better communication is, the better the teaching will be and hence the more effortful learning is.

According to the timeline of AutoTutor systems or Intelligent Tutor systems development in Figure 0.1, most of them have the mission "helped students explain good answers" rather than "recognizing and correcting misconceptions" such as:

- Help students construct expressions of material as answers to questions and solutions to challenging problems
- Ask questions that tap deep levels of reasoning and that involve collaboration
- Solve problems that involve deep argumentation

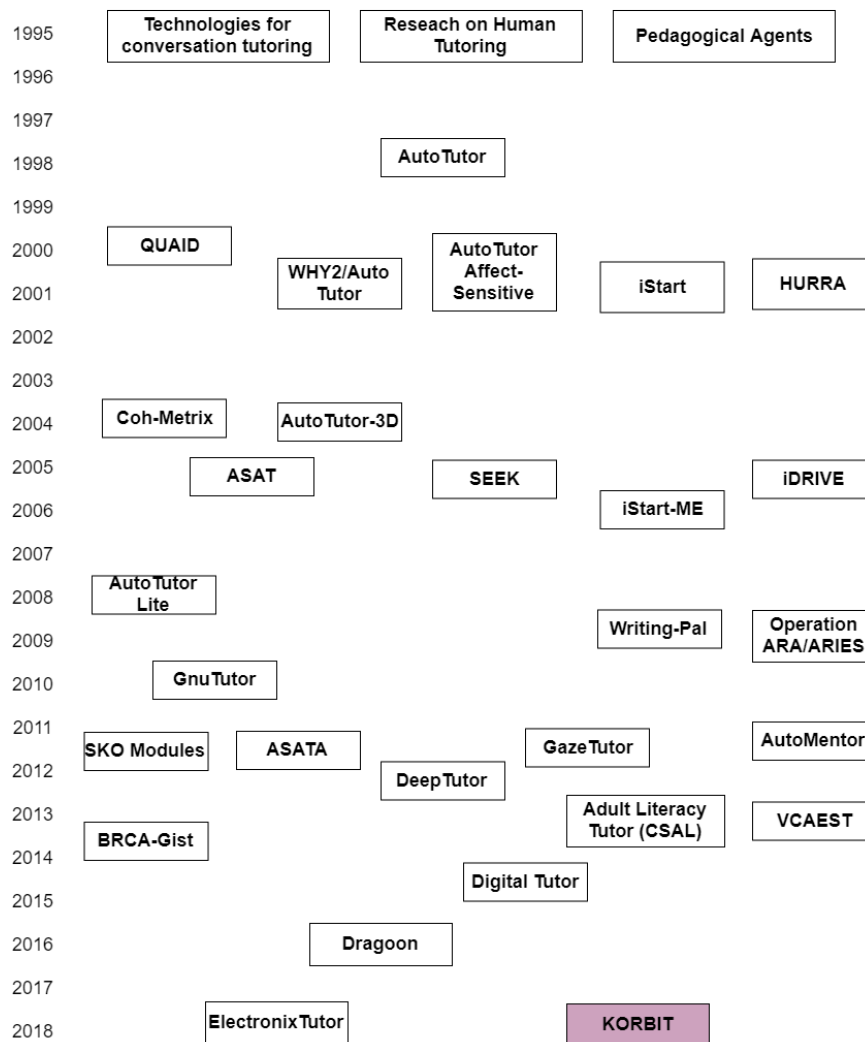


Figure 0.1 The time life of Intelligent Tutor System (ITS)

Conventional training or tutoring systems adapt to individual students, but they do so a level with limited options (e.g., two to five) at each point in the student intercommunication as following:

- (a) the student studies material presented in a lesson,
- (b) is tested with a multiple-choice test or another objective test with a small number of options,

- (c) receives feedback on the test performance,
- (d) re-studies,
- (e) progresses to a new topic if the performance in “c” exceeds the specified threshold

An ITS monitors the detail of students’ knowledge, skills, and other psychological characteristics and response to the student by applying computational algorithms in artificial intelligence and cognitive science (3)(4)(5). For an ITS, adaptivity is so fine-grained that most of the tutorial interactions on a given topic follow the unique sequence. ITSs have been developed for a wide range of Science, technology, engineering, and mathematics (STEM) subject matters. Many have targeted to mathematics and other well-formed, quantitatively precise topics. For example, there are the Cognitive Tutors (6)(7)(8) and ALEKS (9) were worked on the areas of algebra and geometry; one assessment compared these two systems on learning gains and resulted in a virtual tie (10). In the area of technology and engineering, there are ITSs on electronics (11)(12), digital information technology (13), and database retrieval (14). VanLehn and his colleagues have developed Andes (15) which was the ITS of physics. Some ITSs concentrate on knowledge specific-domains that have a stronger verbal foundation as opposed to mathematics and precise analytical reasoning (16). AutoTutor and its progenies (17)(18)(19)) help students learn by holding a conversation in natural language. Conversational agents (also known as interactive agents and pedagogical agents) are a general class of learning environments that are intelligently adaptive (20)(21)(28)(23)(24). Conversational agents have talking heads that speak, point, gesture, and exhibit facial expressions. They can guide the interaction with the learner, instruct the learner what to do, and interact with other agents to model ideal behavior, strategies, reflections, and social interactions (25)(26)(16)(27). These agents have been designed to represent different human instructional roles, such as experts (28)(29), tutors (18)(19), mentors (30)(29), and learning companions (31). Therefore, communication is one of the basic pillars of education, some intelligent tutoring systems proposed in the past

were based on conversational dialog (32)(33). On the other hand, construction of a complete system including all the necessary components (e.g., representing the domain, modeling the pedagogical knowledge, monitoring the students' progress to offer appropriate help, and constructing the appropriate user interface) is a hot challenging. However, ITS seem effective for improving students' learning outcomes (34)(35). One of the key aspects of these systems is the provision of instructional feedbacks or hints that are helpful and appropriate. Many systems are based on production rules or constraints (36) where the students' responses are matched against pre-organized solutions. In practice, this often returns in a high development and maintenance cost. However, the need for appropriate feedback (hint) is a major challenge for ITS. With recent advances in AI and Big data technologies, data-driven tutors are now proposed in (37). The personalized supports students (38) and often used in conjunction with conversational agents (39) are considered deeply. When a student fails to answer the question, which is issued by the system, the system may respond one of several tactics, such as short feedback (i.e., positive, neutral, negative), pumps (e.g. "Uh, tell me more"), prompts, suggestions, clues, assertions, scaffolding, corrections, and summaries (40). In early systems, such as AutoTutor, the hints were created by experts or professors manually. Naturally, this is a time-consuming and hard work process, which cannot be scaled to many domains. In some early systems, hints have been generated by applying pre-defined templates to generate textual hints (41)(42) which reduced some of the manual efforts, but they remained a time-consuming process. In later systems, hints have also been generated using a domain ontology, such as a knowledge base (43)(44). On the other hand, based on the study of (45) the investigation on the effects that conversational tutors which are the autonomous agents support teams of three (or more) students in a design task. The authors compare this tutor with a socially neutral baseline agent and human capability tutors to prove that the social ability tutor achieves significantly higher learning gains than the neutral, purely task concentrated tutor and learning gains not different from the human capability tutors. The framework named academically productive talk (APT) at (46)



is found that agent intervention aiming to link students' contributions to previously acquired knowledge can improve both individual and group studying when implemented in the context of a collaborative learning activity in higher education. Hence, facilitation of collaborating groups can be effectively automated through agile agent interventions is the big challenge in this study



## **CHAPTER 1**

### **PROBLEM DEFINITION.**

Online group learning or E-Learning, or sometimes referred to as computer-supported collaborative learning (CSCL), can provide an ideal environment in which interaction among students in the learning processes (49)(50). Why then is the online group learning not more widely implemented, particularly within university education? There are several possible reasons that could be supported with some justification. The seven most commonly found in the literature are the following:

- (1): the student antipathy works in the group
- (2): the selection of the groups is not good
- (3): the students don't have enough group-work skills
- (4): some students want to work alone or become the free-riders
- (5): the possible inequalities of student abilities appears in the group
- (6): some members do not commit to working in the group with their responsibilities
- (7): the assessment of individuals within the groups is not fair

Many of these problems above are inter-related. Hence, they can be the causes of many conflicts of the group conversation which make the group knowledge building worse and worse. The MediatorBot is proposed to solve these problems.

#### **1.1 Student antipathy works in the group**

Some students do not care the whole idea of group work and can be apathetic because their views against involvement the group work such as they study best on their own, they have no

need to work in a group, they cannot spare the time to meet and communicate with others, or others in the group are not worse than them. So how can the antipathy best be overcome?

- Solution 1: Tell the students the benefits of the group work
- Solution 2: Make the assessment criteria explicit

## **1.2 The selection of the groups is not good**

Selection of groups tends to be popular in an online environment. How large should each group be? There is no standard answer here that fits all circumstances or courses. Johnson and Johnson (55) and Kagan (52) suggest that teams of four work well in a face-to-face setting, while Bean (53) suggests groups of five or six work best. However, arguments based on group dynamics are less applicable in an online environment, where both small or large groups can work well which depend on the context, size, and complexity of the group task. How should the membership of each group be determined?

- Solution 1: Select randomly
- Solution 2: Deliberately select heterogeneous groups

## **1.3 The students don't have enough group-work skills**

In scenarios where students who have not previously been taught to group work, and lack the necessary or essential skills, any instructor who uses group work as a major component, and does not prepare the students appropriately, is almost inevitably condemning the students to a traumatic and probably unproductive experience. Hence, there is a major reason for many conflicts in group work. How to give students the essential group-work?

- Solution 1: Cover the skills required at the beginning of the course
- Solution 2: Identify the right time of intervention during the students' conversation

#### **1.4 Some students want to work alone or become the free-riders**

The free-rider effect (56) is probably the most commonly cited disadvantage of group work; that is, when one or more students in the group do little or no work or want to work alone, thereby contributing almost nothing of the group, and consequently decreasing the group's ability to perform to their potential. How to avoid the free-rider effect?

- Solution 1: Using the pressure from the instructor
- Solution 2: Using peer pressure openly and unashamedly.
- Solution 3: Employing a marking scheme that penalizes free-riders

#### **1.5 The possible inequalities of student abilities appear in the group**

There is always the possibility that the ablest students within a group may fall victim to the sucker effect which in many ways may be the reverse free-rider effect. The sucker in the group is the student who carries most of the workload and is perceived as the most capable in the group by the other members but he may not be evaluated as far as his effort because of the group work. However, the sucker effect is fairly easy to overcome.

- Identify potential suckers in advance
- Implement an appropriate reward scheme
- Using subgroups within the groups

#### **1.6 Some members do not commit to working in the group with their responsibilities**

Online courses are notoriously suffering from higher than average attrition rates, often because of a feeling of isolation (57). The student may be in an informal study group or have made a network with other students, but students learn and study on an individual basis. Hence,

with the group work, it is common for those students who remain in the group feel bad or disadvantage if one or more of members do not commit to working with their responsibilities. How to encourage the student to follow the tasks?

- Using a detail task strategy on the group work
- Monitoring the conversation of the group work and identify the opportunity of intervention when the problem occurs

### **1.7 The assessment of individuals within the groups is not fair**

The traditional view of assessment has always following the grading. But it is not fair if the assessment is only worked at the end of the courses. Therefore, it should play a vital part in the learning process itself. How can this be done fairly if group work is used?

- Solution 1: Using the individual assessment
- Solution 2: Assess individual contributions

This analysis has attempted to point out that considering the online group learning, by listing seven of the most common problems and describing the traditional solutions for each. It may have anything which is far from an exhaustive list. Especially, in the Intelligence Tutor Technology based on Dialogue System, there are other potential problems in the online group learning that have not been dealt with here. Hence, the authors want to propose the MediatorBot who can generate the hints, identify the debated problem, the opportunities for intervention, and answer the related topic question of students to encourage the users to collaborate more effectively in the online group learning with low price in many specific-domain.

## CHAPTER 2

### CHALLENGES AND OBJECTIVES

#### 2.1 Challenges

Most of these problems above of online group learning are inter-related. For example, weak group-work skills of student (#3) and student antipathy (#1) may lead to free-riders within groups (#4), and even the working without their responsibilities of some group members (#6), and this, in turn, may cause issues for the assessment of individuals within the groups (#7). Indeed, it will happen that problem #7, in particular, is central. The rest problems such as selection (#2) or inequalities of student abilities appear in the groups (#5) come from the limited capabilities of the instructor who is not good enough to evaluate group members. According to (58), students who were dissatisfied with group work struggled with communication, finding a group, lack of a sense community, lack of commonality with group members, and lack of subject knowledge which is presented in the table 2.1.

Question terms	Satisfied group N=18. Mean(.std)	Unsatisfied group N=19. Mean(.std)
How satisfied were you with the group size in your project	4.33(.907)	3.11 (.994)
How satisfied were you with your role in your project	4.28 (.752)	3.11 (1.100)
How satisfied were you with your workload in the group work	3.89 (.758)	2.95 (1.129)
How satisfied were you with the way group decisions were made	4.11 (.676)	2.68 (.820)
How satisfied were you with your team members	4.00 (.840)	2.63 (1.012)

Table 2.1 Summary of factors that promote success in group work of an online course.

In the ideal case, we assume that all the conditions of hardware, bandwidth, or the other materials are satisfied the requirement of online group learning system based on dialogue methodology. Hence, the challenges come from both sides: one is from students and the other is from

the instructor. To support students working together in a collaborative online group learning or E-learning platform by the use of a dialogue system with low price is the most important challenges of encouraging the students learning.

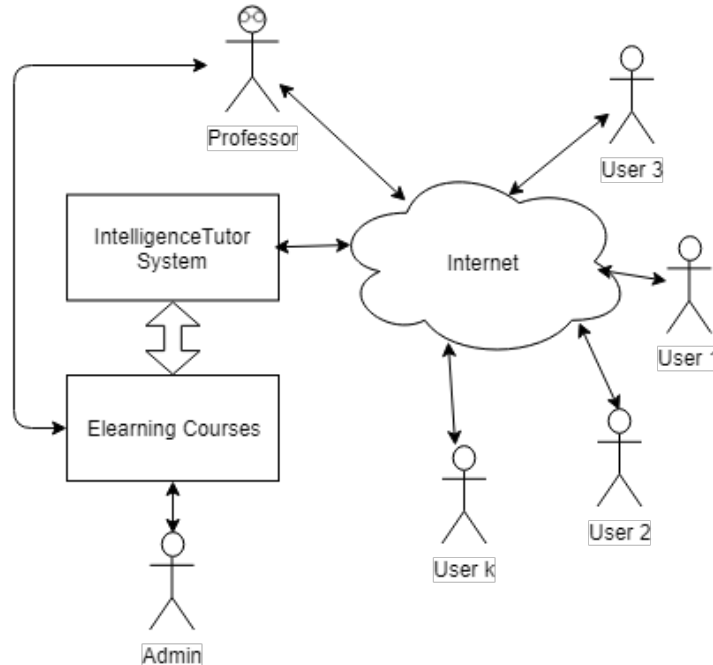


Figure 2.1 Intelligence Tutor System context

## 2.2 Objectives

According to the challenges of online group studying, we figure out that the most important problems are the problem #1 which is the students with their antipathy of group study or teamwork. When we solve this problem, the rest issues can be fixed quickly and effectively. To do so, we propose a smart MediatorBot with three objectives such as:

- Generate hints to help users solve the topic or problem automatically
- Identify the debated or clarify the problem
- Intervene in the conversation to clarify the problem: identify the opportunities for intervention, answer the related topic question of users



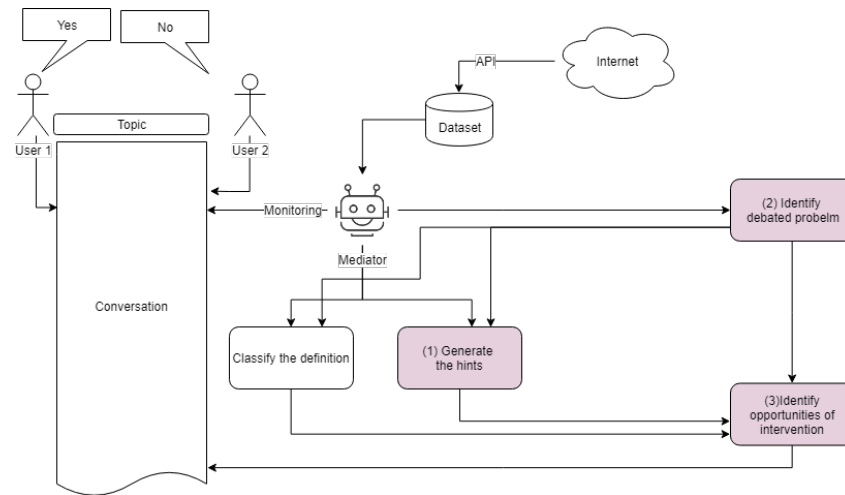


Figure 2.2 Mediator system

### 2.2.1 Generate the hints to help users solve the topic or problem automatically

The hint generation module is very useful to teach students how to find the correct solution and building their knowledge step-by-step, including how to write an answer, what do they need to focus on, and how to express and understand a concept. A major benefit of the automatic hint generation is that it can be personalized for each student and fix their knowledge gaps. Moreover, it is also a useful exploration for the future task of automatic generation of the content of courses. Additionally, these generated hints are beneficial for teachers or instructor. Furthermore, they could select one hint and refine them, which makes the generated hints more student-friendly. Especially for the online group learning, the generated hints can help the student want to work more in the group without their antipathy which is the most major reason for many problems group work. First, this module should ensure the contextual relevance between questions, answers, and considered concepts. This involves task complex contextual information, such as definitions which generally contain many aspects (e.g., concepts, ideas, equations). Second, it requires generating diversified hints for each concept, which makes the task more challenging.

### **2.2.2 Identify the debated problem**

According to the students' conversations based on the given topic or assignment, identify the debated problem makes more values for learning intelligence effort. Here we argue that depending on the type of question and its' following conversation, students' sentiments, a new system of automatically identify the debated problem is proposed. This system will enable to clarify the problem of conversation quickly and keep students on the right track of conversation to follow the assignment or topic, at low-cost in many different educational domains. This approach provides more detail result than the current practice of word cloud, while it is faster than sentiment analysis approach.

### **2.2.3 Intervene in the conversation to clarify the problem**

We propose developing a module, which interactively identifies the opportunities for intervention, answers the related topic question of students. An intelligent tutoring system with this module will solve the above-mentioned problems as follows:

- Not only prevent the conflict problem but also encourage students to work together in the online group learning
- No need mentors if students need help, support
- Students can get multiple levels of hints, find their files, media, text, etc., to approach concepts or solve a given question, problems.
- Monitoring of learning progress become easier because one can both automatically evaluate and measure the number of hints and quality of students' answers and intervene in the right way the problems of group learning
- Interactively generating content from unstructured text, preventing the conflicts conversation and encouraging students learning automatically help the professors save a lot of time because they will be able to quickly review and modify the existing content to approach the best quality of training with low cost.

Hence, dealing with the problem of generating appropriate and effective learning content is our third objective.



## CHAPTER 3

### RESEARCH METHODOLOGY

This research tackles the problem of intervening students' conversation to encourage them to study and build their knowledge. The conversational ITS identifies the chance of intervention, gives hints to the student, and then analyzes their answer using machine learning algorithms during students' conversation. When the students' conversations based on the given topic have the signals of conflict which can be recognized by the emoticons, contradict description, it is classified as being a positive, negative, or unknown problem. The system must analyze the main reason for conflict, the opportunities for intervention, and give an appropriate hint to help them answer the question, reconcile the conflict, and encourage the study or understand the topic, assignment. The system at Figure 3.1 is powered by a database of questions, answers,

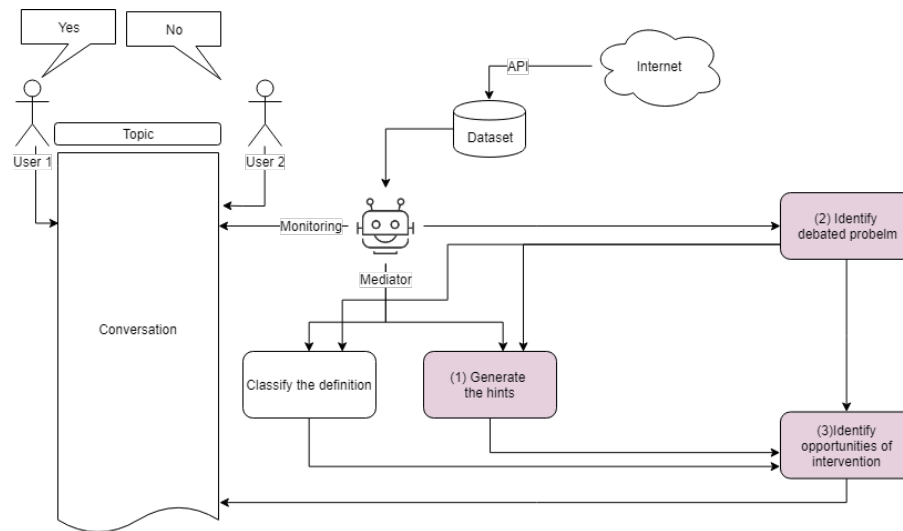


Figure 3.1 MediatorBot System

hints, emoticons, concept descriptions. The component generating the hints is called the “hint generator” model. To this end, we propose a feedback and hint generation model capable of generating meaningful, personalized, pedagogical hints based on the right definitions of many concepts. Identify the debated problem and opportunity of intervention models are proposed to monitor, keep, and encourage students to study with their positive feeling. In addition, we

also investigate how the system may be capable of efficiently adapting its content and tutoring strategies to individual group students.

### 3.1 Methodology for Sub-objective 1

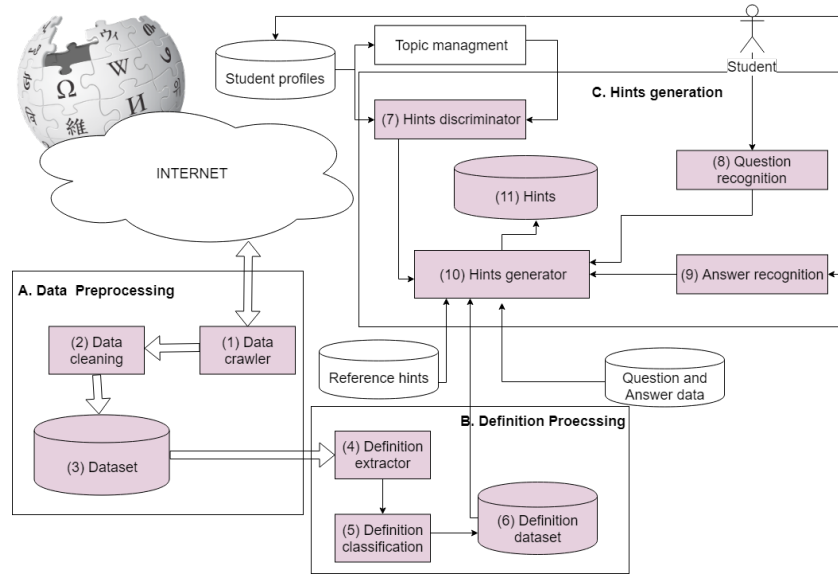


Figure 3.2 Hints generator system

We propose a method to generate new hints which can be integrated into the Intelligent tutor system as the new advantage of value. The hint generator is presented in Figure 3.2, is built on three components: Data preprocessing, Definition processing, and Hints generation. We introduce an attention mechanism and relevance control mechanism to boost it.

We crawl the text stream from unstructured data sources such as Wikipedia with a given domain-specific (e.g., Machine learning) which is presented in Figure 3.3. By using the wikipedia-api<sup>1</sup> which is easy to access and parse data from Wikipedia, we extract the list of relevance recursive subcategories according to the given domain-specific.

<sup>1</sup> <https://pypi.org/project/wikipedia/>

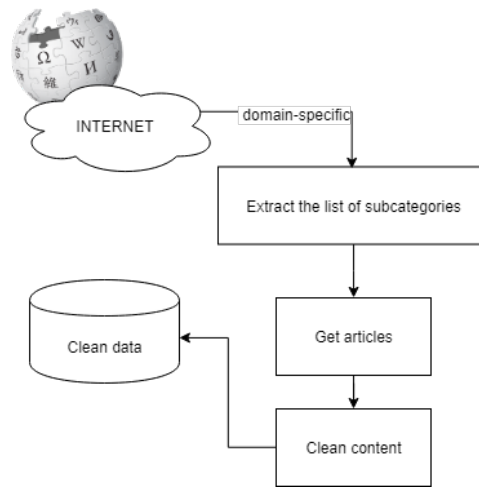


Figure 3.3 Data preprocessing

Based on the structure content list of wikipedia article<sup>2</sup>, we extract the section "See also" by another recursive function to get more relevance keyword of this domain-specific. According to the list of relevance keywords, we crawl the articles, respectively. After cleaning all of the Unicode and converting all the mathematical expression to the standard string we save the clean-content to the clean-data which is used for definition extraction component.

The component of definition extractor is presented in Figure 3.4. Based on the clean data, we extract all the sentence tokens of articles and acronyms of technical keywords. According to the list of sentence tokens, we extract the subject of each sentence by using the Spacy API<sup>3</sup> which is the *Doc* and the *Vocab*. The *Doc* object owns the sequence of tokens and all their annotations. The *Vocab* object owns a set of look-up tables that make common information available across documents. On the other hand, the acronyms of technical keyword is extracted by using algorithm which proposed by Schwartz and Hearst<sup>4</sup>. After get the description of concept and the first sentence of relevance wikipedia article, we save them to the list of concept description.

<sup>2</sup> [https://en.wikipedia.org/wiki/Main\\_Page](https://en.wikipedia.org/wiki/Main_Page)

<sup>3</sup> <https://spacy.io/api>

<sup>4</sup> <http://www.cnts.ua.ac.be>

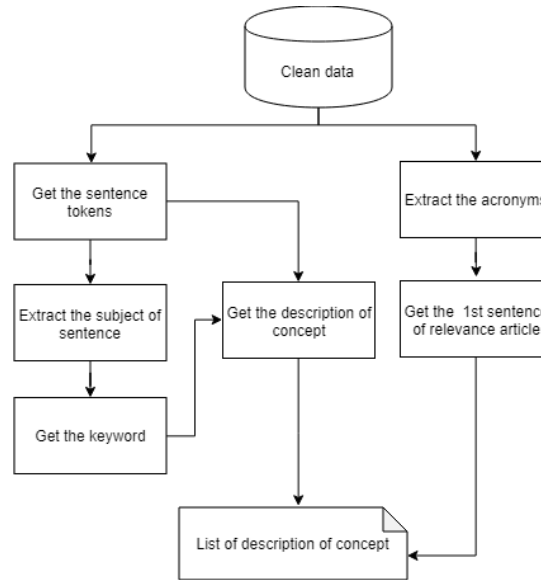


Figure 3.4 Definition extractor

According to the extraction definition dataset, we observe that one concept may have one or many description, hence we compute the score for each descriptions by features as in Table 3.1. We define that the first sentence of the wikipedia article is the good definition and the rest is the not good definition. By using logistic classification algorithm, we train our model to classify the good and not good definition. However, we observe the oversampling scenario, so we increase the weight of good samples to approximately the not good ones. After classifying the definitions to good and not good definition where good definition class is the class contained the exactly definitions, the other contained the explained definitions.

Given a conversation, we observe that users often use different types of questions as:

- (a) definition
- (b) definition and explanation
- (c) two or more definitions contrasting each other
- (d) explanation
- (e) list of properties



Features	Summary
length_of_keyword	the number words in the keyword
length_of_description	the number words in the description
score_keyword	inverse document frequency of keyword
score_description	inverse document frequency of concepts description
ner_in_description	name of entity recognition within the description
coreference_in_description	compute the coreference resolution score
type_of_word	recognize type of word (verb, noun, etc.,)
non_of_word	recognize the none of word (symbol, number, etc.,)
pronouns_rate	the rate of $\frac{\text{pronouns}}{\text{nouns}}$
keyword_rate	the rate of $\frac{\text{keyword\_position}}{\text{length\_of\_description}}$
perplexity	the real value of perplexity of description
likelihood_score	the log-likelihood probability score of description based on sum of probability output by using language model

Table 3.1 Features of definition

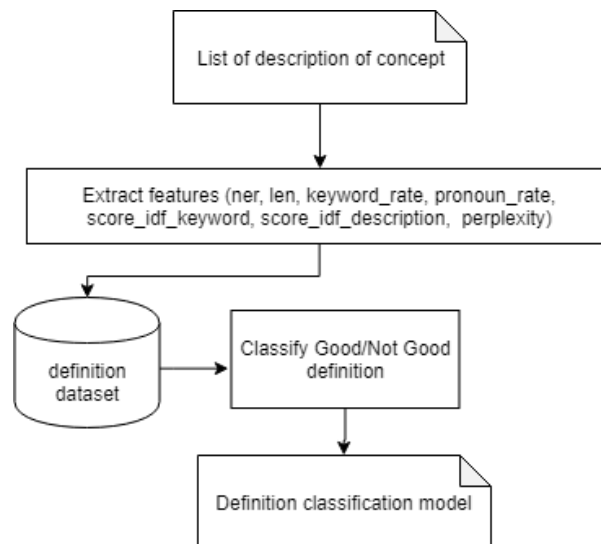


Figure 3.5 Definition classification system

These properties will be used in the future to evaluate if the student’s response is satisfactory. For example, with a question type (b) “definition and explanation” the system would expect to get some sort of a definition with accompanying explanation, and one of information only should not be considered as satisfactory. Hence, when the system identified the definitions are

correct, it should explain more details or in another aspect of this issue. For type (c) “contrast”, the system should expect to get 2 contradict definitions.

Features	Summary
length_of_hint	the number words in the hint
overlap_question_hint	the rate of overlap between question and hint
score_keyterm	inverse document frequency of keyterm in hint
keyhint_keyquestion_ratio	the ratio of $\frac{\text{number\_of\_keyhint}}{\text{number\_of\_keyquestion}}$
topic_overlap	content overlap between the question and hint
pronouns_rate	the rate of $\frac{\text{pronouns}}{\text{nouns}}$ in hint
keyword_rate	the rate of $\frac{\text{keyword\_position}}{\text{length\_of\_hint}}$
perplexity	the real value of perplexity of hint
ner_in_hint	name of entity recognition within the hint
score_of_hint	the log-likelihood probability score of hints based on sum of probability terms by using language model based on RNN

Table 3.2 Features of hints

Accordingly, the hints used for each type of the questions are different: e.g., the hints of type (b) encourage the students to address both of definition and explanation, and if one of them is missed, the system will explain more. The hints for type (c) should encourage contrasting the concepts.

The questions are recognized by keywords or question structure:

- Recognize question words “what”, “is this/that” or the prompt word “define”
- Identified by the question words “what”, “is this/that” and the prompt “explain”
- Most reliably identified by the keywords “difference” or ”contrast” + “between”
- Explored the question words “why”, “how” or the prompt word “explain”

Based on the reference of question and answer data, the features of hints are represented in Table 3.2. On the other hand, the hints discriminator is considered based on the student answer and topic management to make the right hint for the learning student. The generator in Figure

3.6 uses an encoder-decoder LSTM framework. In order to ensure the contextual relevance with the hints, we propose the way of learning soft alignments between generated hints and news context and adaptively computes encoder-side context vectors. Moreover, it selects the amount of contextual information to predict the next word. In order to generate diversified hints, we use random sample strategy to generate hints with diverse topics. Our model is proposed based on a recurrent neural network (RNN). In the earlier of training, we use the maximum likelihood estimation (MLE) to pre-train the hint generator on training set until the generator reaches convergence. Afterward, MLE is utilized to pre-train hint classifier with real hints and auto hints generated by our generator. After the pre-training, the generator and classifier are trained alternatively until convergence. In order to evaluate our method, we use both automatic evaluation metrics to show that the generated new hints are close to human hints and manual annotations to evaluate their quality. Our goal is to generate diversified hints for different topics and with various degrees of relevance by utilizing a random sample and a relevance control mechanism.

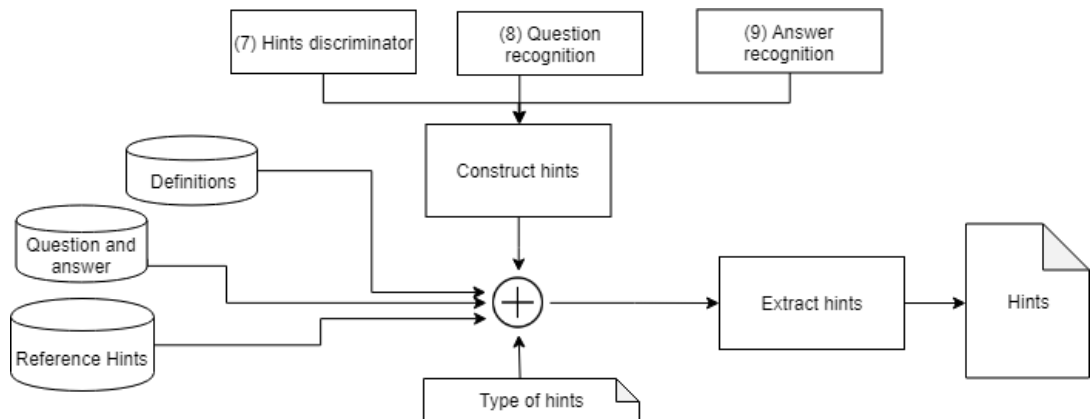


Figure 3.6 Hints generator component system

### 3.2 Methodology for Sub-objective 2

We next present a brief overview of the system identified the debated problem system based on the conversation of students which is illustrated in Figure 3.7

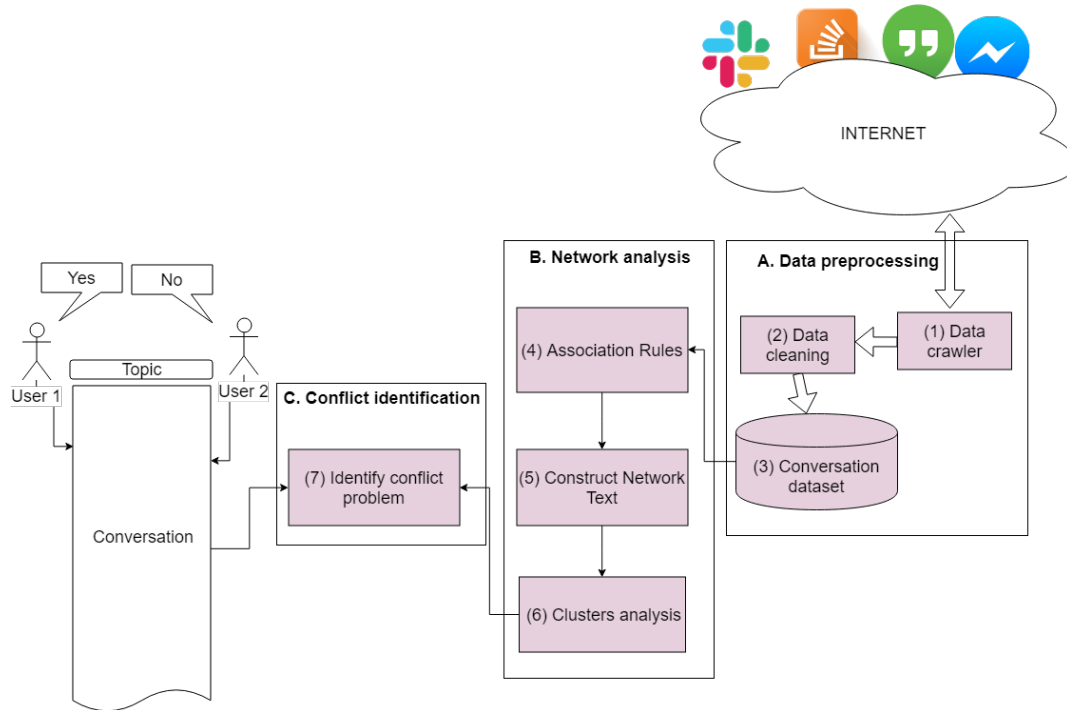


Figure 3.7 Identify debated problem

In this system, the conversations of a specific-domain (e.g., deep learning) are crawled from slack, StackOverflow, hangout, messenger via their application protocol interfaces (APIs). After we get a large volume of conversations, we conduct pre-process, which clean all the Unicode types (e.g., Chinese, Japanese) or any symbol and delete irrelevant conversations to the topic which we investigate at Figure 3.8

The dominant words are found by using a word cloud applications. We remove unsuitable dominant words to opinion words, this includes removing conjunction, pronoun, numbers, date, URL links, and others. After that, the association rules between dominant words are calculated. They find the interesting association and/or correlation relationship among a large set of data items and show attribute value conditions that occur frequently in the conversation dataset. We construct the network text of dominant words, which include weight edge result for association rules process. Then, we analyze the data by creating context, keyword, and sense from network text. In network analysis, we employ centrality the most important words in the

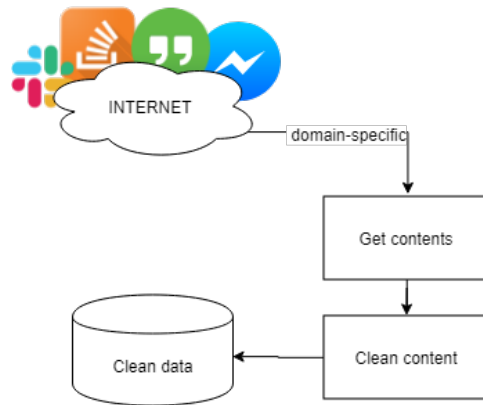


Figure 3.8 Identify debated problem

networks. Hence by analyzing the students' conversations, we identify the debated problem and recognize the clarify problem scales.

### 3.3 Methodology for Sub-objective 3

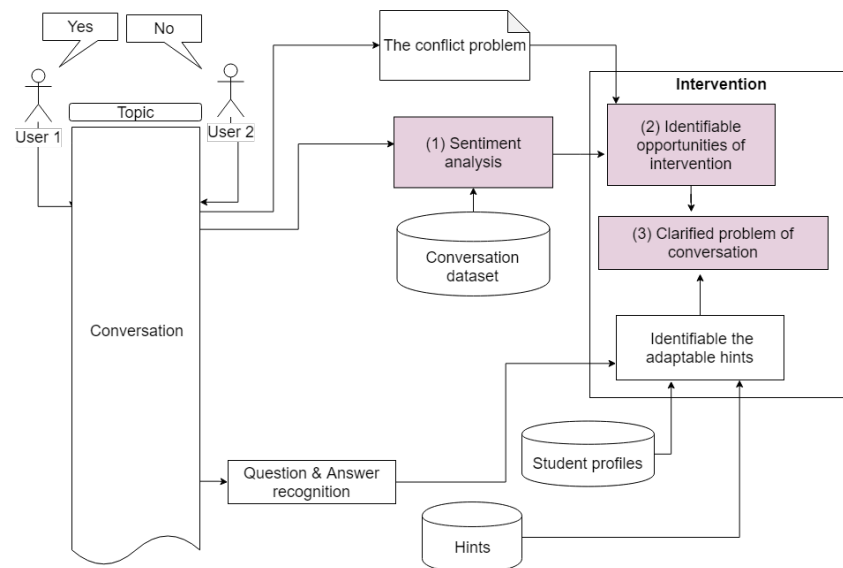


Figure 3.9 Intervention system

Figure 3.9 illustrates the architecture of the third system, which interactively identifies the opportunities for intervention and helps students solve their problems during conversations.

The input data is a collection of various different materials such as hints, clarify a problem, sentiment analysis, questions and answers, students' questions and answers recognition. We extract the fact of sentiment words included emoticons from the students' conversations, then match all the emoticon symbols to its' meaning. After that, we analysis the sentimental of each student according to their conversation. Based on the clarify problem scales and sentimental analysis, the opportunity of intervention is identified by using the hidden Markov chain algorithm. Each state of sentiments is processed by the Sentiment Analysis which is recorded as an input recommendation system. In order to automatically help and encourage students to study, a system for processing a variety of data related to the topic and language is proposed based on Natural Language Processing (NLP) technology. By considering these questions and answers respected with the students' answers and their profile, the relevance and adapter hints are generated. The scoring and confidence model is finally applied to evaluate the quality of the output data. Sentiment analysis also is aware of conversation mining which needs to be analyzed, processed, reasoned and induced texts with emotional labels. It extracts polarity and subjectively from the semantic orientation which refers to the strength of words and polarity text or phases. We approach the to machine learning method where sentiment detection is labeled as emoticons. Emoticon and Contratict term classification is the core problem of sentiment analysis technology, is to judge tendency in the review, then is considered as the weight of the relevance term. According to the limited data information, we use Support Vector Machine (SVM) (59) to find the best compromise between the complexity and the learning ability, in order to get the best generalization ability up to 80% of accuracy on the test set. The feature vector is created as the table 3.3

Features	Summary
number_of_positive_word	the number positive words
number_of_negative_word	the number negative words
tag_of_emoticons	the tag of emoticons
scale_of_sentiment_adjective	the scale score of sentiment adjective
frequency_of_sentiment_adjective	the frequency of sentiment adjective

Table 3.3 Table features of sentiment analysis

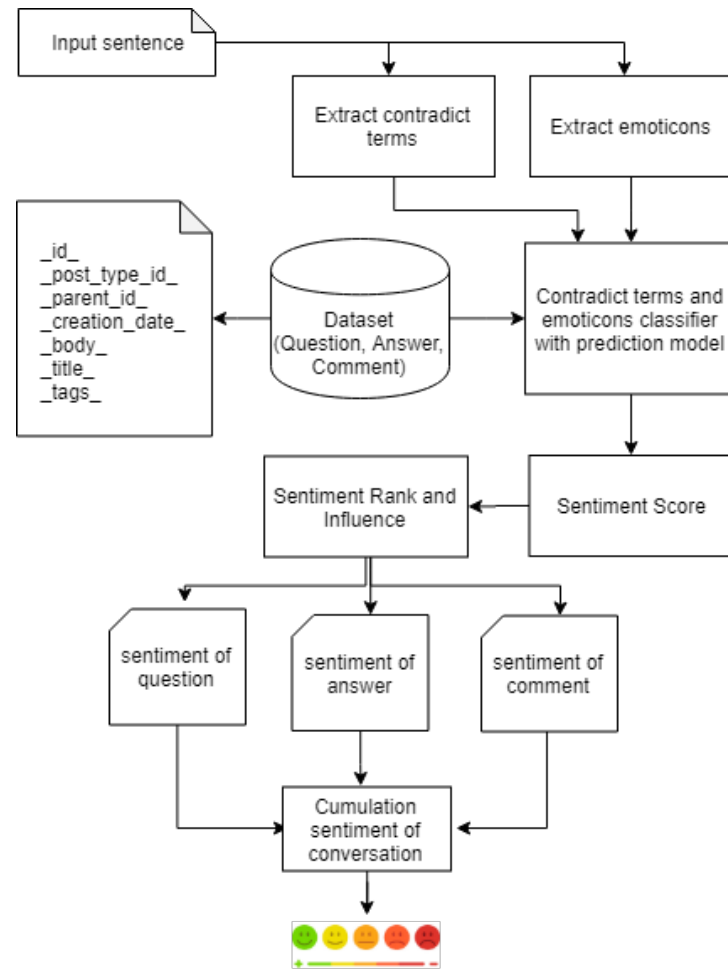


Figure 3.10 Sentiment analysis

On the other hand, Convolution neural networks (CNN) is good at learning the characteristics of the invariance, and SVM can find the optimal classification surface for the characteristics. In our methodology, we combine both SVM and CNN to solve text analysis. Because the output vectors of the pooling layer of CNN are represented by distributed features of input samples, the distributed feature representation can be used as feature input in SVM. Therefore, CNN is utilized as an automatic feature investigator, then SVM is used as an emoticon classifier, and both of them are combined to deal with sentiment analysis to generate the weight (label) of each student. (54) applied the idea of CNN to text classification, and implemented a CNN-based text classification model for classifying sentences. show that CNN-based text classification

method is more accurate than the best at that time. Moreover, the using of word order for text categorization with convolutional neural network is proposed in (55).

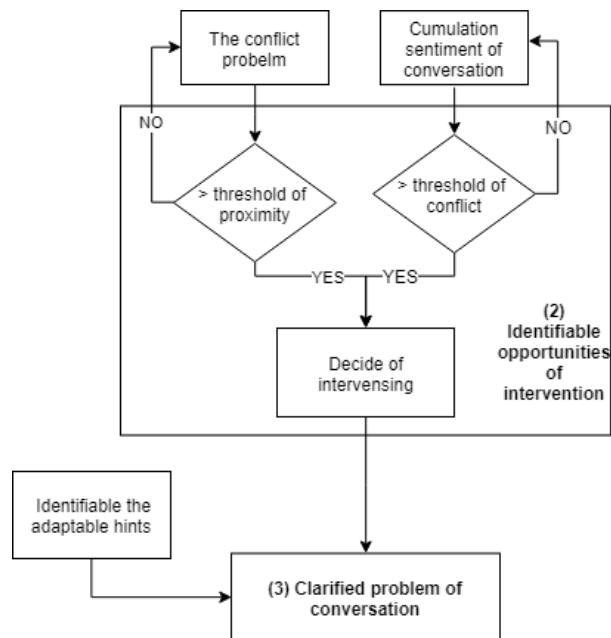


Figure 3.11 Intervention decision

In addition to the text classification model based on CNN, as shown in Figure 3.10, is the input layer, the convolution layer, the pool layer, and the output layer. Figure 3.10 text emotion classification model based on CNN The last layer of text sentiment based on CNN is the full connection layer. The input of this layer is the feature vector outputted from the pool layer, and the output of each category label classified according to the probability size. However, SVM the theory of VC theory and the minimum structural risk. So SVM represents the data feature vectors in the feature space, classified hyperplane. For linear, SVM can map space through a kernel function, and then transform the linear non-separable problem into a separable problem. That is, CNN the characteristics of the invariance and SVM can find the optimal classification surface for the characteristics based on the given emoticon dictionary<sup>5</sup>. Hence, the opportunity for intervention is identified based on the serious of conversation and the debated problem. To give the right intervention, the system analysis students' questions and answers including the

<sup>5</sup> <https://emojipedia.org>



adaptable hints. In the question and answer analysis, we focus on analyzing and quantifying the relation with question and answer. We use bidirectional LSTM model to measure the relevance between them. Then, we use a feed-forward network with shared parameters to learn the relevance between question and answer. The output is a relevance score between question and answer, so it is the particular feature of identifying the adaptable hints.



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# **Appendices**



## APPENDIX A

### IMPLEMENTATION AND RESULTS

In this experiment we had undergraduate and graduate students from McGill University (COMP-551) try to use our system (Korbit). The experiment was carried out in-class. We introduced the system to students for first 5 minutes which was followed the demo video, then highlighted how to write natural language answers and the concept tree building auxiliary task. After that, the students spent 30-40 minutes trying out the system for their studying. Students gave us the feedback after finishing their work. The experiment was conducted on the evenings of February 6th and February 8th, 2019. To solve disengaged students, students with less than 05 user utterances are excluded from this analysis. We also excluded 4 other students who were clearly abusing or playing around with the system instead of following the exercises given. There are four evaluated components in this experiment:

- 1) Automatically generated hints
- 2) New student model
- 3) Concept tree visualization
- 4) Concept tree building
- 5) Selection task.

We evaluated three variants of our system<sup>1</sup>: The text-based hints generated by humans or by a machine automatically perform reasonably well. In previous experiments, we found that human-generated hints helped users to improve their answer by on average 10-30% points (i.e. the probability of being “CORRECT” after a hint increased by 10-30% points). The table above suggests that the hints in this experiment help improve the student answers 20% - 50% of the time and that 10% - 30% of the time the student’s next solution attempt is “CORRECT”. When comparing the human-generated hints to the machine-generated hints, the table above shows that the machine-generated hints perform better. This may be an artefact of the fact that the machine-generated hints are created based on the reference solutions and therefore may reveal more information to the students. These numbers should therefore be interpreted with a

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<sup>1</sup> Source: Ai-educate

	Human-Generated Hints	Machine-Generated Hints
Sessions (Users)	36	36
Number of times text-based hint was shown (including the times it was shown after the user clicked “I don’t know”)	30 (100%)	19 (100%)
Number of times users improved their next solution attempt after hint was shown	8 (26.67%)	8 (42.11%)
Number of times users gave a “CORRECT” next solution attempt after hint was shown	5 (16.67%)	6 (31.58%)

Table 1.1 The experiment of generated hints

grain of salt. If we stay on the conservative side, we may conclude that the machine-generated hints are overall comparable to the human-generated hints. This is still good news, because it means that we can automate one of the most important parts of the content creation pipeline.

## APPENDIX B

### PLAN OF RESEARCHING

Activity	2017		2018			2019			2020			2021		
	S	F	W	S	F	W	S	F	W	S	F	W	S	F
DGA1005														
DGA1031														
MTI830														
DGA1032														
DGA1033														
Conference														
Mitacs proposal for PhD grant														
Literature review														
Experiement														
Research ethics board certificate														
Publication								[1]		[2]			[3]	
Writing thesis													(*)	(*)

Figure 2.1 Work schedule

#### Journals:

[1] Journal of Artificial Intelligence Research

[2] Technology, Knowledge and Learning

[3] Education and Information Technologies

#### Finished courses:

(1) DGA1005

(2) MTI830





## **APPENDIX C**

### **EVALUATION QUESTION BANK**

# Supporting instructor

## 1. How effective were the group topic in meeting the goals of this course?

Mark only one oval.

1	2	3	4	5	6	7	8	9	10
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 2. Was the hints difficult?

Mark only one oval.

1	2	3	4	5	6	7	8	9	10
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 3. Are the interventions fair?

Mark only one oval.

1	2	3	4	5	6	7	8	9	10
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 4. How would you rate the contribution of the instructor to the course?

Mark only one oval.

1	2	3	4	5	6	7	8	9	10
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 5. Is helpful about the field observations/feedback you received from your instructor?

Tick all that apply.

- ☐ Strong Agree
- ☐ Agree
- ☐ Disagree
- ☐ Strong Disagree
- ☐ Other: \_\_\_\_\_

# General evaluation question

## 1. Are the objectives of the course clear

*Tick all that apply.*

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly agree

## 2. Evaluate the course in terms of its ability to challenge you, to push you, to strengthen your ability to think and learn, and to contribute to your education.

*Tick all that apply.*

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly agree

## 3. This instructor fostered intellectual growth.

*Tick all that apply.*

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly agree

## 4. This instructor helped you improve your skills in team work

*Tick all that apply.*

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly agree

# Hints and Intervention

## 1. Hints and solutions were effective tests of student learning and understanding

*Tick all that apply.*

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neutral
- ☐ Agree
- ☐ Strongly agree

## 2. Were the hints difficult?

*Mark only one oval.*

1	2	3	4	5	6	7	8	9	10
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 3. Are the interventions fair?

*Tick all that apply.*

- ☐ Unfair
- ☐ Fair
- ☐ Other: \_\_\_\_\_

## 4. How effective was the instructor in conversation the goals of this course?

*Tick all that apply.*

- ☐ Good
- ☐ Not good
- ☐ Bad
- ☐ Very bad
- ☐ Other: \_\_\_\_\_

## 5. Hints and solutions for the course are available and you could use them effectively.

*Tick all that apply.*

- ☐ Strongly agree
- ☐ Agree
- ☐ Neutral
- ☐ Disagree
- ☐ Strongly Disagree

# Instructor action

## 1. Is she/he actively helpful when students have difficulty?

*Tick all that apply.*

- ☐ Always
- ☐ Often
- ☐ Sometimes
- ☐ Rarely
- ☐ Never

## 2. The system creates an atmosphere in class such that students feel free to ask questions, disagree and express their ideas.

*Tick all that apply.*

- ☐ Strongly Agree
- ☐ Agree
- ☐ Disagree
- ☐ Strongly Disagree
- ☐ Other: \_\_\_\_\_

## 3. The instructor respects students, recognizing their dignity and integrity.

*Tick all that apply.*

- ☐ Strongly Agree
- ☐ Agree
- ☐ Disagree
- ☐ Strongly Disagree
- ☐ Other: \_\_\_\_\_

## 4. Does she/he appear sensitive to students' feelings and problems?

*Tick all that apply.*

- ☐ Unaware
- ☐ Responsive
- ☐ Other: \_\_\_\_\_

## 5. Does she/he demonstrate originality and introduce interesting ideas?

*Tick all that apply.*

- ☐ Dwells on Obvious
- ☐ Introduces Interesting Ideas
- ☐ Other: \_\_\_\_\_

# Student Performance and Background

**1. You did your best to participate fully in this class.**

*Tick all that apply.*

- ☐ Yes
- ☐ No
- ☐ Maybe

**2. Evaluate your performance in this course. Do you think that you made a reasonable contribution through attendance, preparation for class, and participation in discussions?**

*Tick all that apply.*

- ☐ Yes
- ☐ No
- ☐ Maybe

**3. What might have improved your performance ?**

*Tick all that apply.*

- ☐ The conversation with my friends without the instructor
- ☐ The conversation with my friend with the instructor
- ☐ None of above

**4. What grade do you anticipate earning in this course?**

*Tick all that apply.*

- ☐ A
- ☐ B
- ☐ C
- ☐ D

**5. Did you come to class fully prepared (i.e., completing reading, etc.)?**

*Tick all that apply.*

- ☐ Always
- ☐ Often
- ☐ Sometime
- ☐ Never