Experiments with Auto-generated Socratic Dialogue for Source Code Understanding

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Abstract: Intelligent Tutoring Systems have been proven to generate excellent learning outcomes in many domains such as physics, mathematics and computer programming. However, they have seen relatively little use in training and school classrooms due to the time and cost of designing and authoring. We developed an authoring tool for dialogue-based intelligent tutoring system for programming called Auto-author to reduce the time and cost. The tool allows teachers to create fully functional Socratic tutoring dialogue for learning programming from Java code. First, we conducted a controlled experiment on 45 introductory to programming students to assess auto-authored tutoring dialogues' learning outcomes. The result shows that the auto-authored dialogues improved students' programming knowledge by 43% in terms of learning gain. Secondly, we conducted a survey of auto-authored tutoring dialogues by introductory to programming course instructors to evaluate the dialogues' quality. The result shows that the instructors rated the questions as agree or strongly agree. However, the instructors suggested that more improvement is required to help students develop a robust understanding of programming concepts.

1 INTRODUCTION

Tutoring is one of the most effective forms of instruction. Students in human tutoring conditions show mean learning gains of 0.4–0.9 (non-expert) to 0.8–2.3 standard deviations (expert tutors) compared to students in traditional classroom instruction and other suitable controls (Bloom, 1984; Cohen et al., 1982; Graesser et al., 2009; Person et al., 2007; VanLehn et al., 2007). Therefore, Intelligent Tutoring Systems (ITS) that mimic human tutors have been built, hoping that a computer tutor could be provided to every student with access to a computer. As a result, the ITSs have been shown to be effective for one-to-one tutoring in many domains such as mathematics, physics and programming (Pillay, 2003; Freedman et al., 2000; Corbett et al., 1999; Alshaikh et al., 2020) and can generate impressive learning outcomes.

Despite many successful ITSs examples, they have seen relatively little use in training and school classrooms. In examining the barriers to ITS's widespread use, the time and cost for designing and authoring ITS have been widely cited as the primary obstacles (Sottilare and Holden, 2013). The costs are high because authoring content and other needed elements for ITSs is tedious, error-prone (Heffernan et al., 2006), and time-consuming (Blessing, 1997). Furthermore, the authoring process usually involves domain experts, pedagogical experts, cognitive scientists, linguistic experts in the case of dialogue-based ITSs, and software development expertise (Blessing, 1997). It is estimated that creating one hour of ITS instruction can take up to 200 hours (Woolf & Cunningham, 1987; Murray, 1999)

To overcome the challenge of authoring high-quality tutors is to automate the entire authoring process or as many parts of the process as possible (Aroyo et al., 2004). Therefore, authoring tools can reduce time, effort, cost and enable reuse and customization of content and lower the skill barrier (Ainsworth et al., 2003; Halff et al., 2003). Consequently, authoring systems were developed in many domains such as physics, mathematics, and public policy to increase both the accessibility and the affordability of ITSs (Heffernan et al., 2006). For instance, a successful example of an ITS authoring system was developed by Jordan and his colleagues (Jordan et al., 2001) in which they were able to build knowledge sources for their dialogue system in only

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3 man-months. The system uses a graphical interface for teachers to construct tutoring dialogues for physics. Another example of such a system was introduced by Aleven and his colleagues (Aleven et al., 2009) where they developed a graphical user interface to speed up the development of instructional components such as hints and just-in-time messages.

Intelligent tutoring systems with conversational dialogue form is a special category of educational technologies. These conversational ITSs are based on explanation-based constructivist theories of learning and the collaborative constructive activities that occur during human tutoring. They have been proven to promote student learning gains up to an impressive effect of 1.64 sigma when compared to students learning the same content in a canned text remediation condition that focuses on the desired content (VanLehn et al., 2007).

We focus on conversational ITSs that implement a Socratic tutoring style that relies on prompting students to think and provide information in the form of answers. The questions are designed to follow a directed, predefined line of reasoning (Rosé et al., 2001). Based on static analysis and dynamic simulations of code examples that learners are prompted to understand, we propose an automated method to generate a Socratic line of reasoning and corresponding questions necessary to implement a Socratic tutorial dialogue for code comprehension.

For instance, for each target concept in the abstract syntax tree (AST), we generate a question that the correct answer is the target information. For example, the static analysis of the statement *"int num = 10;"* results in the following benchmark answer *declaring an integer variable num and initializing it to 10* . When students are prompted to answer the question, *what does the statement at line 1 do?*, the student response is automatically compared to the corresponding benchmark answer using semantic similarity. If the two match, positive feedback is provided to the students, e.g., *Great job!* Otherwise, the students receive negative feedback followed by an assertion indicating the correct answer. The students may also receive neutral feedback depending on how semantically close their answer is to the benchmark answer. In sum, we adopt the following Socratic Tutoring Framework for our automatically generated Socratic ITSs (see Figure 1).

The Socratic ITS Framework just presented can be implemented adaptively. In other words, not all students will receive all the prompts/questions. Some students, e.g., students who show mastery of certain concepts, e.g., conditions, will be asked fewer questions about it than students who have yet to master the conditions. Thus, this adaptive Socratic ITS uses instruction tailored to each learner should result in better learning outcomes for all learners.

It should be noted that the above framework covers the inner loop or within-task interaction of an ITS. We assume an instructional task has been selected for the learner to work on, e.g., a particular Java code example has been chosen for the learner to read to comprehend. Therefore, our task is to automate the interaction with the learner within such a task. The outer loop responsible for selecting an appropriate instructional task for a given learner is not described here (see VanLehn's two-loop ITS framework (Vanlehn, 2006)). How to automatically select the appropriate next instructional tasks in adaptive ITSs is a topic we plan to explore in the future.

It is important to add that our Socratic line of reasoning for a target code example only targets the program level or program model aspects of comprehension. Indeed, comprehension theories distinguish between the program model, the domain model, and the situation model (Pennington, 1987; Schulte et al., 2010).

This paper investigates and proposes an approach to generate Socratic dialogue for programming comprehension automatically. This work's research hypothesis is that auto-generated dialogues will help introductory to programming students learn programming and produce learning gain. The proposed approach was implemented and evaluated throughout a controlled experiment and survey.

2 SYSTEM DESCRIPTION

Socratic Author was designed and developed as a stand-alone tool that can be used by ITS developers. The authoring tool requires only source code examples as input to produce a full dialogue framework that can simply be played. The current implementation was developed for the Java language to help students understand Java code examples. The tool was developed in Python and the output dialogue is a JSON object (JavaScript Object Notation, or JSON, is a lightweight data-interchange format that is easy for machines to parse and generate). When porting to a new target language, e.g., Python, the only components that need to be changed are the static code analyzer and the underlying dynamic simulator of the code, which are typically available as off-the-shelf components.

The architecture of the authoring tool consists of five major components: question generation, benchmark answer generation, feedback generation, run

```
WHILE there are items to ask about in the AST {
        Prompt the student to answer a question for a target information
        in the AST or from the dynamic code simulation
        Automatically assess the correctness of the student answer.
        Provide short feedback followed by the assertion of the correct
        answer, if needed
}
```

Figure 1: The Socratic ITS Framework.

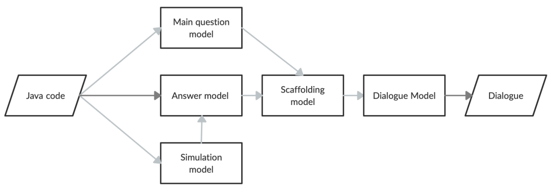


Figure 2: Architecture of Socratic Author.

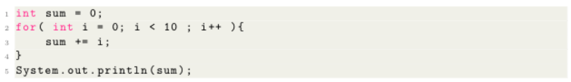
time information, and dialogue generation (see Figure 2). The dialogue generation module takes as input the output of the other four components or modules (question generation, answer generation, feedback generation, run time information) to generate a complete segment of dialogue. As already noted, the generated dialogue can be adaptively played by conversational ITSs. That is, all learners need not be asked all questions; questions can be chosen adaptively depending on learners' knowledge and other characteristics, such as their emotional state.

2.1 The Question Generation Module

The question generation module uses a Java parser to identify programming concepts and sub-concepts in an abstract syntax tree as well as program run time information from the dynamic program simulation model to generate two types of questions. The first question type is based on the dynamic behavior of the code, e.g., *how many times a loop is executed* and *what are the values of the counter i* during the execution of the loop. The second type of questions are generated based on the static code analysis of the code, such as *What is the name of the integer variable declared in line 1?* These questions were generated from the code shown in Figure 3.

Based on the static analysis of the code, this system generated three types of questions. Definition questions check students' knowledge of basic programming concepts (e.g., *What is a variable?* or *What is an assignment statement about?*). Second are questions targeting syntactic knowledge of the target programming language (e.g., *Can you indicate the condition of the for loop in line 2?*). Third are complex questions or sequences of related questions targeting all aspects of statements. For instance, for a line of code declaring an integer variable and initializing it to 0, a generic question is generated (e.g., *What does the statement in line 1 do?*) and a sequence of two related questions (e.g., *What is the main purpose of the statement in line 1?* and *What value, if any, are the variables in the declaration statement in line 1 initialized to?*). That is, the sequence of questions targets the declaration and initialization aspects of a declaration statement. For more complex statements, e.g., *for* loops, a sequence of questions promoting deep understanding of this more complex statement is generated. Each question in the sequence targets an important aspect of the loop concept, such as the loop variable *i*, the initialization of the loop variable, the terminal condition, and the increment of the loop variable. For instance, the following questions are generated for the *for* loop, as shown in Figure 3: (1) What is the initialization statement of the *for* loop? (2) What is the stop condition of the loop? (3) What is the inc/decrement statement?

Finally, the question generation module generates questions for a block of statements as well. For a block, i.e., a group of statements between balanced braces, questions are generated to ask the learner to summarize the goal of the block, e.g., *functions, loops, and if-else*. For instance, a block question generated for the code in Figure 3 is *What does the code on the block from line 24 do?*



```
1 int sum = 0;
2 for( int i = 0; i < 10 ; i++ ){
3     sum += i;
4 }
5 System.out.println(sum);
```

Figure 3: Java for loop.

There is one challenge with these block-level questions. Generating a higher level benchmark response summarizing the function of the block in order to automatically assess student responses was beyond the scope of the current method, which focused on the program model as opposed to the domain model. Furthermore, automatically generating functional benchmark responses for a given block of code is a challenging task the researcher plans to tackle in the future. For this reason, the current solution to generate the benchmark responses for a given block is to concatenate the benchmark responses of the individual statements in the block, as detailed later.

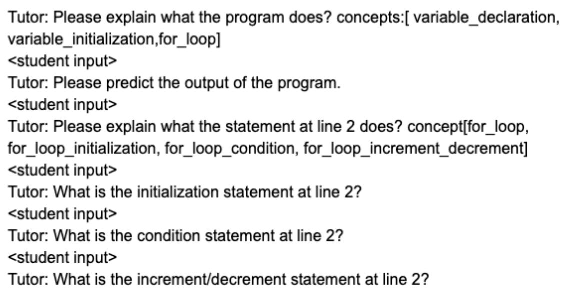

Tutor: Please explain what the program does? concepts:[variable_declaration, variable_initialization,for_loop]
<student input>
Tutor: Please predict the output of the program.
<student input>
Tutor: Please explain what the statement at line 2 does? concept[for_loop, for_loop_initialization, for_loop_condition, for_loop_increment_decrement]
<student input>
Tutor: What is the initialization statement at line 2?
<student input>
Tutor: What is the condition statement at line 2?
<student input>
Tutor: What is the increment/decrement statement at line 2?

Figure 4: Auto-generated questions from Figure 2 program.

2.2 The Benchmark Answer Generation Module

To generate a meaningful answer, the answer generation model starts with the abstract syntax tree of the input Java program obtained from Java parser. The model generates block- and statement-level answers by traversing the syntax tree. A complete pass of the tree statement nodes generates a complete sentence, where each type of node is associated with a predefined template. That is, this study followed a template-based text generation approach, which is widely used in natural language generation (Jurafsky and Martin, 2008). For instance, a complete pass over the tree of the statement *final static int = 10* produces the following benchmark answer Declare *a final static integer x* and initialize it to *10*. For block-level answers, the answer generation module first identifies the block by matching the node type with a predefined list of types, e.g., *function, loop, and if-else*, then analyzes the sub-tree to generate an answer for each statement in the block. Next, the module combines the answers for each individual statement in the block into a single paragraph. For example, the block-level answer for the *for* loop presented in Figure 3 is "The for loop in line 2 iterates over the counter *i from 0 to 9*, *increasing the counter by 1 in each iteration*. In each iteration, the value of *sum is incremented to its current value plus the value of i.*"

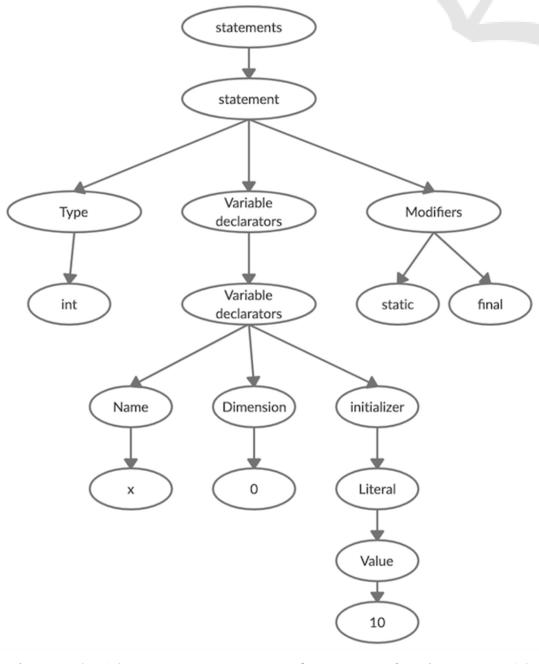


Figure 5: Abstract syntax tree for *static final int x = 10*.

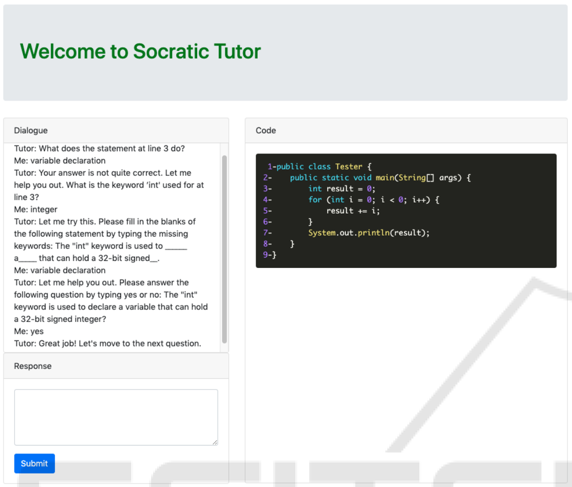
2.3 The Code Simulation Module

Generating answers from abstract syntax trees is not enough because the trees do not represent any run-time information. This is critical for code examples that require user input, in which case the behavior of the code will change depending on the user input. Therefore, a Java Debugger Interface (JDI) was used to simulate the execution of Java programs and record variable values. This information answers questions such as what the value of the variable *sum* is in line 3 when *i* is 4 or what the values of the counter i are during the execution of the *for* loop. Therefore, the simulation module offers the ability to trace the execution of Java code and generate questions based on the results of this dynamic execution of the code.

2.4 The Scaffolding Module

The scaffolding module uses the information from the answer generation module and a set of short predefined phrases expressing positive (*Good job*), neutral (*Good try*), or negative (*Not quite so*) feedback to generate a more complete feedback utterance, which consists of short feedback (e.g., *Good job*) followed by an assertion of the correct answer or a more informative follow-up hint. The system can generate three levels of Socratic hints, as shown in Figure 6. At the first level, the tutor may ask definition questions about the targeted programming concept, e.g., "What is the *int* keyword used for in line 1?" For level 2 questions, the tutor may ask a concept completion question in the form of a fill-in-the-blank question, e.g., "The *int* keyword is used to _______ a _______ that can hold a 32-bit signed _______." The expected keywords are *declare*, *variable*, and *integer*. Finally, at Level

3, the tutor asks a verification question in the form of a yes/no question, e.g., “The *int* keyword is used to declare a variable that can hold a 32-bit signed integer? Please answer the following question by typing yes or no.” Using yes/no questions allows the system to verify common misconceptions students may have and correct them. However, at this moment, no misconception information has been incorporated into the method to account for and correct misconceptions, but this feature will be added in the future.



Tutor: What does the statement at line 3 do?
Me: variable declaration
Tutor: Your answer is not quite correct. Let me help you out. What is the keyword 'int' used for at line 3?
Me: integer
Tutor: Let me try this. Please fill in the blanks of the following statement by typing the missing keywords: The "int" keyword is used to _____ a_____ that can hold a 32-bit signed__.
Me: variable declaration
Tutor: Let me help you out. Please answer the following question by typing yes or no: The "int" keyword is used to declare a variable that can hold a 32-bit signed integer?
Me: yes
Tutor: Great job! Let's move to the next question.

```
1-public class Tester {
2-    public static void main(String[] args) {
3-        int result = 0;
4-        for (int i = 0; i < 0; i++) {
5-            result += i;
6-        }
7-        System.out.println(result);
8-    }
9-}
```

Figure 6: Tutoring session.

2.5 The Dialogue Module

Once the questions, answers, feedback, and run-time simulations are produced, the dialogue module generates a complete segment dialogue in the form of a sequence of questions and corresponding expected benchmark answers, which are used to automatically assess whether student responses are correct using a semantic similarity approach (Khayi and Rus, 2019). Technically speaking, the dialogue is specified as an JSON object.

2.6 Enacting the Dialogue Model

The dialogue generated for a given code example needs to be played by a dialogue manager as part of a dialogue-based ITS. The role of the dialogue manager is to present the learner with questions in a particular order. Typically, the dialogue manager presents the questions in a sequence corresponding to the lines of code the questions are about. For blocks, the Socratic dialogue starts with questions about each statement within the code block. When all the statements in a block are covered, the ITS asks the students to summarize the block. Other orders of presenting the questions can be envisioned, such as the execution order of the lines of code for a given input.

Besides the questions generated from the abstract syntax trees and the dynamic execution of the code, there are two general types of questions or statements: a question or statement to elicit self-explanation (*Can you read the code and explain in your own words what the code does and what it means to you while you read the code?*) and a prediction question or statement (*Please read the code and predict its output*).

Each generated question is labeled internally according to its type and a list of concepts in order to track students’ mastery of key programming concepts. Therefore, this labeling mechanism gives the dialogue manager freedom to choose what questions to present. Various ITS developers may choose different question sequencing strategies. For instance, the following is a potential sequencing: the dialogue manager starts by asking the students to explain the code in detail and predict its output. The Socratic line of questioning is only triggered if the student’s explanation and prediction are incorrect or incomplete. For instance, for incomplete explanations, the sequencing strategy may be implemented to ask questions only about the parts of the code that were not explained in sufficient detail.

2.7 User Interface

The user interface is simple, easy to use, and consists of a text area to write or paste Java code and three buttons (see Figure 7). The interface offers authors two options: (1) generate a Socratic dialogue and save it as a JSON script or (2) start a tutoring session for testing purposes. Furthermore, the interface provides the ability to choose what concepts the author prefers to generate a dialogue for. For example, if an author wants to encourage students to practice *for* loops, they can select the *for* loop concept only.

The authoring tool also offers an interface for ITSs by using REST API technology. This allows ITSs to easily integrate the tool by requesting a dialogue script for a given Java code and getting as a response the corresponding Socratic dialogue as a JSON object.

3 EVALUATION

3.1 Method

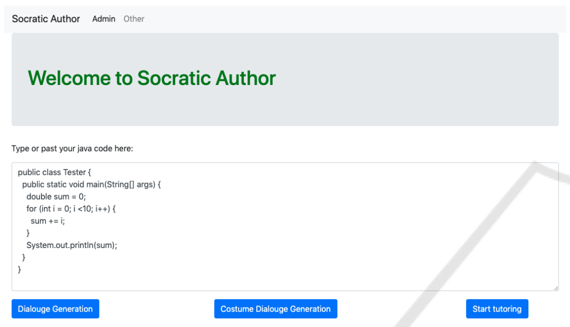
We carried out two evaluations to assess the quality of auto-generated dialogue and its effect on programming comprehension. The first evaluation was

Table 1: Mean and Stander Deviation of pre-test, post-test, and learning gain.

		Pre-test		Post-test		Learning gain	
Section	n	Mean	SD	Mean	SD	Mean	SD
Group-1	14	58	21	86	13	51%	21
Group-2	15	56	16	70	11	43%	19
Group-3	15	57	35	61.3	33	12%	9.1

Table 2: Mean and Stander Deviation of turns, words, sentences and content-words.

Section	Turns		Words		Sentences		Content-words	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Group-1	123	13	402	217	45	8	191	164
Group-2	115	28	334	183	35	18	154	106


Socratic Author
Admin
Other
Welcome to Socratic Author
Type or past your java code here:
Dialouge Generation
Costume Dialouge Generation
Start tutoring

```
public class Tester {
  public static void main(String[] args) {
    double sum = 0;
    for (int i = 0; i <10; i++) {
      sum += i;
    }
    System.out.println(sum);
  }
}
```

Figure 7: Socratic Authoring Tool Interface.

to let a group of programming instructors evaluate the auto-generated dialogues to explore if this approach is educationally useful. The second evaluation was conducted as a control experiment by letting introductory to programming course's students use either auto-authored, expert-authored Socratic dialogue or output only. The goal of the second evaluation is to analyze the learning outcomes to see how easy, efficient, and friendly the system is.

3.2 Participants

In the first evaluation, participants (n=13) were instructors teaching Java programming courses. Moreover, the second study participants were undergraduate students (n=45) who enrolled in the introductory to programming course at a major 4-year Asian university. The participants were divided into three groups of 15 students. The first group (Group-1) was assigned to a tutoring session where experts generated the tutoring dialogues. The second group (Group-2) was assigned to a condition in which they used auto-generated tutoring dialogues. And finally, the last group (Group-3) was assigned to a scaled-down version of the system. The scaled-down version presents Java code examples and asks about the output without providing any feedback.

3.3 Materials

Materials for the first evaluation study included fifteen auto-generated dialogues from Java code examples covering the following concepts: variables, *if* and *if-else* conditionals, *for* loop, *while* loop and array. The dialogues were formatted in a human readable form and then shown one by one to each rater. At the end of each dialogue, a survey consists of 10 questions using a 5-point Likert scale presented (see Table 4) where 1 is strongly disagree and 5 is strongly agree.

Materials for the controlled experiment included a pre- and post-test measuring participants' knowledge on a number of key computer programming concepts and a survey that contains 7 questions to evaluate the authored dialogues. The pre- and post-test have similar difficulty levels and contain 6 Java programs where each question assessed students' understanding of a particular programming concept. For each question in the pre- and post-test, the participants were asked to predict the code example's output.

3.4 Procedure

For the first evaluation, we emailed the survey link to introductory to programming courses instructors. The instructors were given five days to complete the survey.

On the other hand, the controlled experiment was conducted in a computer lab under supervision. First, participants were debriefed about the purpose of the experiment and were given a consent form. Those who consented started by taking a pre-test. Once they have finished the pre-test, an approximately 60-minute tutoring session started. Finally, participants took the post-test and an evaluation survey. For group-3, there was no survey at the end of the experiment since they did not interact with the dialogue ITS.

Table 3: Mean and Stander Deviation of scaffolding questions and success rate.

Section	Feedback		First		Second		Third	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Group-1	28	4	55%	16	70%	23	61%	37
Group-2	31	7.5	41%	21	47%	13	73%	24

Table 4: Mean and Stander Deviation of survey questions for evaluating tutoring dialogues by students.

Question	Group-1		Group-2	
	Mean	SD	Mean	SD
I think the questions were clear and easy to understand.	3.6	0.9	3.4	0.8
I think the system was able to understand my answers and response accordingly	4.6	1.2	4.3	0.9
I think the scaffolding questions from the system helped me produce the correct answer.	4.4	0.5	4.2	0.4
I think the system was effective at helping me understand the code examples.	4.6	0.5	4.4	0.7
I think the system was effective at helping me understand core programming concepts.	3.6	1.1	3.7	1.2
I think the system helped me to understand Java programming.	4	0.8	4.3	1.2
I think the system provides a useful learning experience.	4.5	0.5	3.4	1.3

3.5 Assessment

The pre and post-test questions were scored 1 when the student answer was correct and 0 otherwise. The learning gain score (LG) was calculated for each participant as follows (Marx and Cummings, 2007).

$$Learning\ gain = \begin{cases} \frac{post\text{-}test - pre\text{-}test}{100 - pre\text{-}test} & post\text{-}test > pre\text{-}test \\ \frac{post\text{-}test - pre\text{-}test}{pre\text{-}test} & post\text{-}test < pre\text{-}test \\ drop & pretest = posttest = 100 \text{ or } 0 \\ 0 & post\text{-}test = pretest \end{cases} \tag{1}$$

4 RESULT

To understand each type of tutoring method's overall effectiveness on students' knowledge, we report the knowledge change in terms of learning for each group. Table 1 shows the average scores of the pre-test for each group 1, 2, and 3 are 58%, 56% and 57%, respectively, in which they are in the range of 2% difference. Thus, the pre-test scores indicate that participants in both groups have, to some extent, similar knowledge—however, the post-test scores improved by 28% in group-1, 14% in group-2 and 4% in group-1. Therefore, the difference between pre- and post-test scores result in learning gain of 51%, 34% and 12% for group 1,2 and 3, respectively. Thus, the result indicates that the auto-authoring dialogues improved students' knowledge by 34% and outperformed the output only group by 22%.

Despite the difference in learning gain between group-1 and 2, the result from a two-tailed t-test showed that there is no statistically significant difference *(t=0.83, df=19, p>0.05)*. Furthermore, the results from the two-tailed t-test also showed that there is a statistically significant difference between group-3 and other groups *(t=3.1, df=52, p<0.05)* in terms of learning gain.

To evaluate dialogue efficiency, we analyzed the students' responses from dialogue logs in terms of turns, word, sentence and content-word for each group (see Table 2). For group-1, the results show that, on average, each tutoring session consist of 123 turns and participants produced 402 words, 45 sentences, and 191 content-words. On the other hand, group-2 students produced 334 words, 35 sentences, and 154 content-words within 115 turns. Therefore, students assigned to expert-written dialogues interact more with the tutor and produce more words, sentences, and content-words. However, the result from a two-tailed t-test showed that there is only a statistically significant difference *(t=6.13, df=19, p<0.05)* in terms of sentences.

We further analyzed the scaffolding questions to understand the difference between expert- and auto-generated help. Table 3 shows the average number of help received by students and the success rate. The question would be considered a success if the student was able to provide the correct answer. Table 3 shows that students in group-1 received more questions and have a higher success rate in the first and second levels. Furthermore, the result shows that the auto-generated third level has a 12% higher success rate. However, the result from a two-tailed t-test showed only a statistically significant difference in first *(t=3.6, df=25, p>0.05)* and second *(t=-4.1,* *df=25, p<0.05)* level.

To understand how efficient and user-friendly the system was to the students, we analyzed the result from after session survey, as shown in Table 4. The survey contains 7 questions using a 5-point Likert scale where 5 is strongly agree and 1 is strongly disagree. Students in group-1 gave a higher rate in all questions except the answer to the question "the system was effective at helping me understand core programming concepts" and "the system helped me to understand Java programming." We further calculated Fleiss' kappa for inter-rater reliability, and the result shows that (Fleiss' Kappa = 0.52) for group-1 and (Fleiss' kappa = 0.43) for group-2. Therefore, the Fleiss' kappa score suggests that the agreement between subjects in group-1 is higher than the subjects in group-2.

Table 5 shows the result in terms of average and standard deviation for 10 questions using a 5-point Likert scale where 5 is strongly agree and 1 is strongly disagree. Questions 1 and 2 target the quality of the auto-generated questions, feedback, and model answers regarding their syntactic and semantic quality. Moreover, the third question asks about the coherence and consistency of the dialogue. The rest of the questions focus on educational goals and the raters' overall likelihood of using the system in their teaching in the future.

The result shows an average score above 4 for all questions except the fifth question that asking if the generated dialogue would help students develop a robust understanding of programming concepts. Furthermore, the instructors agreed that the auto-generated dialogues would help students understand Java programs better and learn programming concepts *(Fleiss' Kappa = 0.51)*. We also allowed the raters to provide voluntary feedback at the end of the survey, and the voluntary feedback was positive. For instance, one of the raters stated that "the system looks promising and the dialogue looks coherent to the point you feel it is not auto-generated."

5 DISCUSSION

The controlled experiment results show that the auto-generated Socratic dialogue for programming comprehension can improve students' knowledge. The average learning gain of group-2 students is 43% comparing with 12% group-3 students. However, group-1 students outperform both group-2 and group-3 in which we expected; however, it was not statistically significant.

Analyzing tutoring logs shows that group-1 students produced more words, sentences and content-words and were more interactive in terms of turns. Furthermore, group-1 students received more scaffolding questions and have higher success rates in providing the correct answer to the first and second levels. However, group-2 students achieved a higher success rate on the third level; however, the difference was not statistically significant.

Post tutoring survey shows that on average group-2 students rated the evaluation questions of auto-authored dialogues as agree or strongly agree. However, the rating dropped to neither agree nor disagree for questions 1, 5 and 7 (see Table 4). On the other hand, group-1 students rated questions 1 and 5 as neither agree nor disagree. The overall result suggests that students preferred to interact with expert-written dialogues. On the other hand, the evaluation by programming instructors shows that they chose to agree or strongly agree to every question except question 5 (see Table 5) suggesting that more improvement is required to help students developing a robust understanding of programming concepts.

To conclude, expert-written tutoring dialogues outperformed auto-generated dialogues in many aspects. However, auto-generated dialogue can be created from java code examples in less than a minute and requires no technical or educational knowledge. We believe that considering the cost, skills and time required to generate expertly written dialogues, the tool offers a great opportunity to students and teachers.

6 CONCLUSION

Intelligent Tutoring Systems can generate impressive learning outcomes in many domains such as physics, mathematics and computer programming. However, they have seen relatively little use in training and school classrooms due to the time and cost of designing and authoring ITS. We developed an authoring tool for programming dialogue intelligent tutoring system called Auto-author to reduce the time and cost. The tool allows instructors to create fully functional Socratic tutoring dialogue for teaching programming from Java code examples.

A controlled experiment on 45 introductory to programming students was carried out to evaluate auto-authored tutoring dialogues' learning outcomes. The result shows that the auto-authored dialogues improved students' programming knowledge by 43% in terms of learning gain. Furthermore, we conducted a survey of auto-authored tutoring dialogues by programming instructors to evaluate the dialogues' qual-

Table 5: Mean and Stander Deviation of survey questions for evaluating auto-generated tutoring dialogues by instructors.

Question	Mean	SD
I think the generated questions, feedback, and answers are syntactically correct.	4.2	0.55
I think the generated questions, feedback, and answers are semantically correct.	4.5	0.84
I think the generated dialogue is coherent and consistent.	4.4	0.45
I think the generated dialogue (questions, feedback) would help students understand Java code.	4.2	0.84
I think the generated dialogue (questions, feedback) would help students develop a robust understanding of programming concepts.	3.8	0.55
I think the generated scaffolding questions would help students learn and understand the corresponding Java code.	4.6	0.55
I think the generated dialogue covers all important programming concepts presented in the code.	4.8	0.45
I think I may use this system in the classroom.	4.2	0.84
I think the system is effective at helping students understand Java code.	4.2	0.45
I think the system is effective at helping students understand programming concepts.	4.2	0.84

ity. The result shows that the teachers believe the dialogues as good. However, the instructors believed that more improvement is required to help students developing a robust understanding of programming concepts.

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