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Automatic Source Code Summarization of Context for Java Methods

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Abstract—Source code summarization is the task of creating readable summaries that describe the functionality of software. Source code summarization is a critical component of documentation generation, for example as Javadocs formed from short paragraphs attached to each method in a Java program. At present, a majority of source code summarization is manual, in that the paragraphs are written by human experts. However, new automated technologies are becoming feasible. These automated techniques have been shown to be effective in select situations, though a key weakness is that they do not explain the source code's context. That is, they can describe the behavior of a Java method, but not why the method exists or what role it plays in the software. In this paper, we propose a source code summarization technique that writes English descriptions of Java methods by analyzing how those methods are invoked. We then performed two user studies to evaluate our approach. First, we compared our generated summaries to summaries written manually by experts. Then, we compared our summaries to summaries written by a state-of-the-art automatic summarization tool. We found that while our approach does not reach the quality of human-written summaries, we do improve over the state-of-the-art summarization tool in several dimensions by a statistically-significant margin.

Index Terms—Source code summarization, automatic documentation, program comprehension

1 Introduction

Programmers rely on good software documentation [11], [22], [27], [48]. Unfortunately, manually-written documentation is notorious for being incomplete, either because it is very time-consuming to create [6], [19], or because it must constantly be updated [10], [17], [38]. One result has been the invention of the *documentation generator*. A documentation generator is a programming tool that creates documentation for software by analyzing the statements and comments in the software's source code. The key advantage is that they relieve programmers of many tedious tasks while writing documentation. They offer a valuable opportunity to improve and standardize the quality of documentation.

Still, a majority of documentation generators are manual. They need considerable human intervention. Prominent examples include Doxygen [50] and Javadoc [23]. These tools streamline the task of writing documentation by standardizing its format and presentation. But, they rely on programmers to write the documentation's content (in particular, a *summary* of each function or method) as specially-formatted metadata in the source code comments. The tools cannot generate documentation without this metadata. The burden of writing the documentation still lies with the programmers.

Recent research has made inroads towards automatic generation of natural language descriptions of software [2], [29], [33], [42]–[44]. In particular, work by Sridhara *et al.* can form natural language summaries of Java methods [42]. The summaries can then be aggregated to create the software's documentation. The technique works by first selecting a method's most important statements, and then extracting keywords from the identifier names in those statements. Next, a natural language generator stitches the keywords into English sentences. Finally, these sentences are used to make a method summary. The process is automatic; so long as the source code contains meaningful identifiers, the summaries will describe the main behaviors of a given Java method.

What is missing from the method summaries is information about the *context* which surrounds the method being summarized. The context includes the dependencies of the method, and any other methods which rely on the output of the method [24]. A method's context is important for programmers to know because it helps answer questions about *why* a method exists and what role it plays in the software [7], [39], [40]. Because they summarize only those statements within a method, existing techniques will supply only limited context about a method. Programmers exploring a software system they are unfamiliar with can use summaries with context to more quickly understand how a given method in a project, at a high-level, fits in with the rest of the project.

In this paper, we hypothesize that existing documentation generators would be more effective if they included information from the context of the methods, in addition to the data from within the methods. We define "more effective" in terms of three criteria: programmers find the documentation's method summaries to be more helpful in understanding 1) what the methods do internally, 2) why the methods exist, and 3) how to use the methods. To test our hypothesis, we introduce a novel technique to automatically generate documentation that includes context. We then perform two case studies. Our first case study compares source summaries generated by our automatic approach to manually written source code summaries via Javadocs. Our second study compares source code summaries generated by our automatic approach to source code summaries generated by a state-of-the-art automatic approach.

Our tool works by collecting contextual data about Java methods from the source code, namely method calls, and then using the keywords from the context of a method to describe how that method is used. We use related work, the Software Word Usage Model, to identify the parts of speech for the different keywords. We choose the contextual information to summarize using the algorithm PageRank, which we compute for the program's call graph. We then build a novel Natural Language Generation system to interpret the keywords and infer meaning from the contextual information. Our system then generates a readable English description of the context for each method in a Java program. We will describe typical natural language generation systems and supporting technologies for our approach in Section 3, followed by our approach, our evaluation, and our evaluation results. Specifically, we contribute the following:

- A novel approach for generating natural language descriptions of source code. Our approach is different from previous approaches in that we summarize context as readable English text.
- An expanded case study of our previous work [31]. This case study evaluates summaries generated by our approach and compares these summaries against manually written documentation via Javadocs.
- A case study evaluating our approach and comparing it against documentation generated by a state-of-the-art approach. Our case study shows that our approach can improve existing documentation by adding important contextual information.
- A complete implementation of our approach for Java methods. For the purpose of reproducibility of our results, we have released our implementation to the public as an open-source project via our online appendix[1].

2 The Problem

The long-term problem we target in this paper is that much software documentation is incomplete [28], which costs programmers time and effort when trying to understand the software [11]. In Java programs, a typical form of this documentation is a list of inputs, outputs, and text summaries for every method in the software (e.g., JavaDocs). Only if these summaries are incomplete, do the programmers resort to reading the software's source code [37]. What they must look for are clues in the source code's *structure* about how the methods interact [16], [22], [47]. The term "structure" refers to both the control flow relationships and the data dependencies in source code. The structure is important because it defines the behavior of the program: methods invoke other methods, and the chain of these invocations defines how the program acts. In this paper, we aim to generate documentation that is more complete than previous approaches, in that our generated documentation contains structural information in each method's summary.

We include this structural information from the *context* surrounding each method in the program. A method's "context" is the environment in which the method is invoked [24]. It includes the statement which called the method, the statements which supplied the method's inputs, and the statements which use the method's output. *Context-sensitive program slicing* has emerged as one effective technique for extracting context [24]. Given a method, these techniques will return all statements in its context. However, some statements in the context are more relevant to the method than other statements. This issue of relevance is important for this paper because we must limit the size of the text summaries, and therefore select only a small number of statements for use in generating the summaries.

Consider the manually-written examples of method summaries from NanoXML, a Java program for parsing XML, below. Item 1 is an example method we selected. It demonstrates how the default summary from documentation can be incomplete. In isolation, the method summary leaves a programmer to guess: What is the purpose of reading the character? For what is the character used? Why does the method even exist?

Example method with default summary from JavaDocs

1) StdXMLReader.read() ◃ Method Name
"Reads a character." ◃ Method Summary

Methods from context of example, with summaries from JavaDocs

2) XMLUnit.skipWhitespace()
"Skips whitespace from the reader."
3) XMLElement.addChild()
"Adds a child element."
4) StdXMLBuilder.startElement()
"This method is called when a new XML element is encountered."
5) StdXMLBuilder.addAttribute()
"This method is called when a new attribute of an XML element is encountered."

These questions can be answered by reading the context. The example method may be easier to understand when we know that Items 2 through 5 are in the the example's context. These methods are in the context because they all rely on the method `read` (e.g., they either call `read` directly, or are called by `read`). We selected Items 2 through 5 above by hand to demonstrate this motivating example. However, in the remainder of this paper we will discuss how we automatically choose methods from the context and generate natural language descriptions, such as the one below in Item 6, for arbitrary Java methods. Our summaries provide programmers with key clues about how a method is used, and provides this information as English readable sentences:

Example method with summary including the method's contextual information

6) StdXMLReader.read()
"This method reads a character. That character is used in methods that add child XML elements and attributes of XML elements. Calls a method that skips whitespace."

3 Background

This section describes three supporting technologies for our work: the Software Word Usage Model (SWUM) [15], the design of Natural Language Generation (NLG) systems [36], and the algorithm PageRank [25]. These techniques were proposed and evaluated elsewhere. We emphasize them here because they are important concepts for our approach.

1. http://www.nd.edu/~pmcburne/summaries/

3.1 Software Word Usage Model

The Software Word Usage Model (SWUM) is a technique for representing program statements as sets of nouns, verbs, and prepositional phrases. SWUM works by making assumptions about different Java naming conventions, and using these assumptions to interpret different programs statements. Consider a method from NanoXML which has the signature `static String scanPublicId(StringBuffer, XMLReader, char, XMLEntityResolver)`. SWUM first splits the identifier names using the typical Java convention of camel case. Next, it reads verbs from the method as the starting word from the method identifier (e.g., "scan"). SWUM also extracts noun phrases, such as "public id", and deduces a relationship of the nouns to the verbs. For example, "public id" is assumed to be the direct object of "scan" because it follows "scan" in the method identifier. Other nouns, such as "string" or "xml reader", are read from the return types and arguments, and are interpreted under different assumptions. We direct readers to the relevant literature on SWUM for complete details [15].

One strategy for using SWUM for text generation is to define templates of natural language sentences, and use the output from SWUM to fill these templates [42]. For example, a template for method call statements is "*action theme args* and get *return-type*". The template may be further processed so that items such as *return-type* actually display as the variable name. Given a method call statement `systemID = XMLUtil.scanPublicID(publicID, reader, '& ', this.entityResolver);`, a summary for the statement is "scan public id and get system id". To summarize an entire method from these summaries of statements, Sridhara *et al.* selected a subset of key statements by defining rules for which statements are typically the most important (e.g., return or control-flow statements). A method summary was a combination of the summaries of these key statements.

3.2 Natural Language Generation Systems

The design of a Natural Language Generation (NLG) systems typically follows an architecture described by Reiter and Dale [36]. Figure 1 illustrates this architecture. Conceptually, the architecture is not complicated: a "communicative goal" is translated from a series of facts into readable natural language sentences, known as "surface text." The NLG system has three main components, each of which is made up of several individual steps.

The first main component is the *Document Planner*. The input to this component is a list of facts that need to be communicated to a human reader. Through "content determination", the document planner interprets the facts and creates "messages." Messages are an intermediate representation between the communicative goal and readable text. For example, in a weather forecast generator such as FOG [13], facts about the temperature on given days result in a message offering an interpretation of those facts, e.g., that it is colder today than it was yesterday. After the messages are created, "document structuring" takes place which sorts the messages into a sequence that makes sense to a human reader. This sequence of messages is known as the *document plan*.

The next main component, the *Microplanner*, decides which words will be used to describe each message. In "lexicalization", the microplanner assigns specific words as parts of speech in a "phrase" about each message. Typically, the subject, verb, and object for a given message are identified. Additionally, any modifiers such as adjectives and adverbs. Next, two steps smooth the phrases so that they are more naturally read. "Reference generation" decides how nouns will be referred to in the phrases, such as whether to use a proper name or a pronoun. Finally, "aggregation" joins phrases based on how they are related, e.g., causally (joined by because) or via coordination (joined by and/or).

The final component of NLG is the *Surface Realizer*. The surface realizer generates natural language sentences from the phrases. Different grammar rules for the natural language dictate how the sentences should be formed. The surface realizer follows these rules to create sentences that contain the parts of speech and words given by the microplanner. These sentences are the surface text. They are human-readable descriptions of the information in the messages, interpreted from the facts given to the document planner, and in the order defined in the document plan.

3.3 PageRank

PageRank is an algorithm for approximating the importance of the nodes in a graph [25]. While a complete discussion of PageRank is beyond the scope of this paper, in general, PageRank calculates importance based on the number of edges which point to a given node as well as the importance of the nodes from which those edges originate. PageRank is well-known for its usefulness in ranking web pages for web search engines. However, PageRank has seen growing relevance in its applications in software engineering. In particular, a body of work has shown how PageRank can highlight important functions or methods in a software program [5], [18], [32], [35]. A common and effective strategy is to model a software program as a "call graph": a graph in which the nodes are functions or methods, and the edges are call relationships among the methods. Methods that are called many times or that are called by other important methods are ranked as more important than methods which

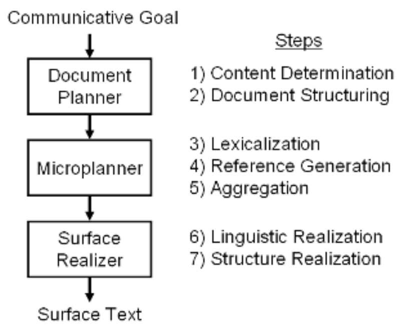


Fig. 1. The typical design of a Natural Language Generation system as described by Reiter and Dale [36]. We built our NLG system around each of these seven steps.

are called rarely, and thus have few edges in the call graph. We follow this model of using PageRank for this paper.

4 Approach

This section describes the details of our approach, including each step of our natural language generation system. Generally speaking, **our approach creates a summary of a given method in three steps:** 1) use PageRank to discover the most important methods in the given method's context, 2) use data from SWUM to extract keywords about the actions performed by those most important methods, and 3) use a custom NLG system to generate English sentences describing for what the given method is used.

The summaries our approach generates are designed to communicate high-level summaries of a method and its context. Our goal is to allow a programmer inexperienced with a given system to be able to understand not just what a method does, by why the method exists by examining its interactions. Our summaries point to examples of a given method being used. These examples are chosen to briefly inform the user how a method can be used. The examples, however, are designed to be simple and short as a summary that is inconcise can be a limiting factor to programmer comprehension. The examples do not describe all the neccessary pre-conditions or the resulting post-conditions of running a method, as the summaries would become inconcise as a result.

The architecture of our approach is shown in Figure 2. In theory our system could summarize functions in many languages, but in this paper we limit the scope to Java methods. The data we collect about these Java methods is our "communicative goal" (see Section 3.2) and is the basis for the information we convey via NLG.

4.1 Data Collection

The comment generator requires three external tools to produce the necessary input data: SWUM, the call graph generator, and PageRank. SWUM parses the grammatical structure from the function and argument names in a method declaration. This allows us to describe the method based on the contents of its static features. Specifically, SWUM outputs the keywords describing the methods, with each keyword tagged with a part of speech (Figure 2, area 3). Next, we produce a call graph of the project for which we are generating comments. Our call graph[2] allows us to see where a method is called so that we can determine the method's context (Figure 2, area 2). Finally, we obtain a PageRank value for every method by executing the PageRank algorithm with the procedure outlined in Section 3.3.

In addition to gleaning this information from the project to produce our comments, we also use the source code of the project itself. For every method call in the call graph, the Data Organizer searches through the code to find the statement that makes that call. The purpose of collecting these statements is to provide a concrete usage example to the programmer. The Data Organizer combines these example statements with the call graph and SWUM keywords to create the Project Metadata (Figure 2, area 4).

2. Generated using java-callgraph, available via https://github.com/gousiosg/java-callgraph, verified 9/12/2013

4.2 Natural Language Generation

This section covers our NLG system. Our system processes the Project Metadata as input (Figure 2, area 5), following each of the NLG steps shown in Table 1.

Content Determination. We create six different types of "messages" (see Section 3.2) that represent information about a method's context. These messages are briefly described in Table 1.

First, a *Quick Summary Message* represents a brief, high-level action summarizing a whole method. For example, "skips whitespace in character streams." We create these messages from the noun/verb labeling of identifier names extracted by SWUM from the method's signature. Our system makes a simplifying assumption that all methods perform some action on some input. If the keyword associated with the input is labeled as a noun by SWUM, and the keyword associated with the method name is a verb, we assume that there is a verb/direct-object relationship between the method name and the input name. This relationship is recorded as a Quick Summary Message.

The *Return Message* is a message created to reflect the return type of the message. This method uses the return type of a Java method signature. For primitive datatypes, we use the natural language interpretations of Java datatypes. For example, `int` is interpreted as Integer. For methods that return objects, we use SWUM to generate a natural language representation of the object name. This usually is a noun phrase where the object name is split on camel-casing. The return message is often combined with the Quick Summary Message (see Lexicalization below).

Another type of message is the *Importance Message*. The idea behind an importance message is to give programmers clues about how much time to spend reading a method. The importance message is created by interpreting both the PageRank value of the method and the PageRank values of all other methods. The importance message represents how high this value is above or below average. At the same time, an importance message will trigger our NLG system to include more information in the method's description if the method is ranked highly (see Aggregation below). It should be noted that the Importance Message was removed from our summarization tool after an initial study comparing our summaries to human written summaries. When we compared to the automatic state of the art approach, this message was omitted due to several programmers in our study specifically saying that the Importance Message was unnecessary and did not provide useful understanding of the method(see Section 8).

A third message type is the *Output Usage Message*. This message conveys information about the method's output, such as "the character returned by this method is used to skip whitespace in character streams." Our system uses data from quick summary messages, importance messages, and the call graph to create output usage messages. Given a method, our system creates an output usage message by first finding the methods in the call graph which depend on the given method. Then, it picks the two of those methods with the highest PageRank. It uses the quick summary message from those two methods to describe how the output is used.

Very similar to the Output Usage Message, the *Call Message* is used to say what methods a given method calls.

TABLE 1
A quick reference guide for types of messages our approach creates.

Message Type	Explanation
Quick Summary Message	Short sentence that describes method
Return Message	Notes the return type of the method
Importance Message	States how important a method is based on PageRank
Output Used Message	Describe at most 2 methods that call this method
Call Message	Describe at most 2 methods that this method calls
Use Message	Gives an example of how the message can be used.

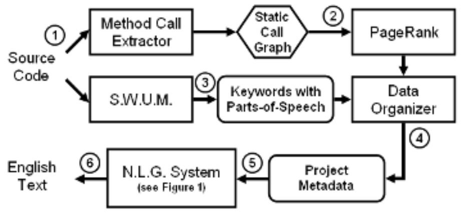


Fig. 2. Overview of our approach.

Saying what methods are called by a given method can help illuminate how the method performs a particular action. The call message, for example, could be "Calls a method that loads a file." This would illustrate to a programmer that this method is reliant on some form of file input to complete its task. Similar to how we handle the *Output Usage Message*, we consider all the methods called by the method being summarized, and select the two methods with the highest PageRank. The Call Message also used the Quick Summary Message from those selected methods.

The last message type we will examine in detail is the *Use Message*. This message serves to illustrate how a programmer can use the message by highlighting a specific example in the code. For example, one message we generated was "the method can be used in an assignment statement ; for example: `Date releaseDate=getReleaseDate();`." Our system can also generate a Use Message classifying a conditional statement. For example "The method can be used in an assignment statement ; for example: `if (getAddedFigure() != null & & !getCreatedFigure().isEmpty())`". Our system uses the call graph to find a line of code that calls the method for which we are generating the message. It then classifies, based on static features with the line of code, whether the calling statement is a conditional, iteration, assignment, or procedural statement.

Document Structuring. After generating the initial messages in the content determination phase, we organize all the messages into a single document plan. We use a templated document plan where messages occur in a predefined order: Quick Summary Messages, Return Messages, Output Used Messages, Called Messages, Importance Messages, and then Use Messages. This ordering was decided based on internal exploratory pilot studies. We decided on this order as we felt this order was the most natural to read. This order puts the Quick Summary Message first, which we believe is the most important piece of information. Due to Lexicalization (see below) the Quick Summary Message was usually combined with the Return Message. We believe the next most important piece of information is the Output Usage Message, which provides summary readers with some understanding of context, and can clarify the Quick Summary Message. The Usage Message is last as we believe readers already need to have a high level understanding of a method in order to understand a given usage example from source code. Note that this order may change during the Aggregation phase below.

Lexicalization. Each type of message needs a different type of phrase to describe it. This section will describe how we decide on the words to be used in each of those phrases, for the six message types described under Content Determination. Note that the phrases we generate are not complete sentences; they will be grouped with other phrases during Aggregation and formed into sentences during realization.

The *Quick Summary Message* records a verb/direct-object relationship between two words extracted by SWUM. The conversion to a sentence is simple in this case: the verb becomes the verb in the sentence, and likewise for the direct-object. The subject is assumed to be "the method", but is left out for brevity. The message is then created as "This method *verb direct object*." In some cases, the article "the" is added before the direct object.

The *Importance Message* holds both the method's PageRank and an average PageRank. To create a phrase for this type of message, we set the subject as "this method", the verb as "seems", and the object as "important." If the method's PageRank is more than 150% of the average, we add the modifier "far more." If it is between 100% and 150%, we consider it "slightly more", while if it is less than 100%, we use the modifier "less". We decided on these thresholds during exploratory pilot studies, though improving them is part of our future work (see Section 8). As the Importance Message was removed in our second study, we do not perform this lexicalization in the summaries we compare to a state-of-the-art approach.

We create a phrase for an *Output Usage Message* by setting the object as the return type of the method, and the verb as "is". The subject is the phrase generated from the Quick Summary Message. We set the voice of the phrase to be passive. We decided to use passive voice to emphasize how the return data is used, rather than the contents of the Quick Summary Message. An example of the phrase we output is under the Content Determination section.

The *Use Message* is created with the subject "this method", the verb phrase "can be used", and appending the prepositional phrase "as a *statement type*;". Statement type is pulled from the data structures populated in our content determination step. Additionally, we append a second dependent clause "for example: *code*".

Reference Generation and Aggregation. During Aggregation, we create more complex and readable phrases from the phrases generated during Lexicalization. Our system works by looking for patterns of message types, and then grouping the phrases of those messages into a sentence. For example, if two Output Usage Messages are together, and both refer to the same method, then the phrases of those two messages are conjoined with an "and" and the subject and verb for the second phrase is hidden. In another case, if a Quick Summary Message follows a Quick Summary Message for a different method, then it implies that the messages are related, and we connect them using the preposition "for". The result is a phrase such as "skips whitespace in character streams for a method that processes xml". Notice that Reference Generation occurs alongside Aggregation. Rather than hiding the subject in the phrase "processes xml", we make it explicit as "method" and non-specific using the article "a" rather than "the." We direct readers to our online appendix for a complete listing of the Aggregation techniques we follow.

Surface Realization. We use an external library, `simplenlg` [12], to realize complete sentences from the phrases formed during Aggregation. In the above steps, we set all words and parts of speech and provided the structure of the sentences. The external library follows English grammar rules to conjugate verbs, and ensure that the word order, plurals, and articles are correct. This step outputs an English summary of the method (Figure 2, area 6).

5 Example

In this section, we explore an example of how we form a summary for a specific method. We will elaborate on how we use SWUM, call graph, PageRank, and source code to form our messages. Note that in these examples, we do not discuss the *Importance Message*, as the more recent version of our approach in the second study left this off. To see how the Importance Message is generated, see the Lexicalization section in Section 4.2.

Consider `getResult()` from StdXMLBuilder.java in Nano-XML. The method's signature, `public Object getResult()`, is parsed by SWUM which will tell us the verb is "get"and the object is "result." Additionally, it will note the return type as "object." This will be used to generate the *Quick Summary Message* "This method gets the result and returns an Object." Then, using the call graph, we determine that the top two methods (as scored by PageRank) that call `getResult()` are `scanData()` and `parse()`. Initially, in the document planning phase, we generate two separate messages, one using the SWUM information for each function. However, these are combined in the aggregation step with the conjunction "and", and eventually produce the *Output Usage Message* "That Object is used by methods that scans the data and that parses the std XML parser."

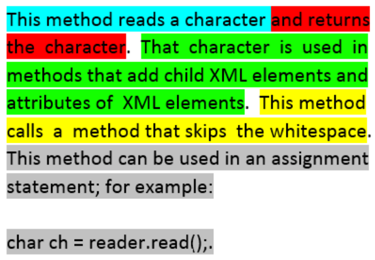
The last message we generate is the *Use Message*. We search through the most important calling method, which in this case is `scanData()`. We take a line of code that calls `getResult()`, and determine based on its content whether it is a conditional, iteration, assignment, or procedural statement. Using this information, we generate the *Use Message* "The method can be used in an iteration statement; for example: `while ((!this.reader.atEOF()) && (this.builder.getResult() == null)) {` ". Each of these messages are then appended together to make the final summary.

As a second example, we consider an abstract method. Abstract methods are not called directly, so when we generate messages, they will not have an *Output Usage Message* or a *Use Message*. For example, when we look at the signature `public IXMLElement CreatePCDataElement();` in IXMLElement.java, there will be no other methods connected to it on the callgraph. We can, however, still generate a *Quick Summary Message*. Doing so in the same way as we showed previously in the section, we get the summary "This method creates the PC data element and returns an IXMLElement." Similarly, API library methods, which are designed to be called by a programmer in an external program, may only be limited to a *Quick Summary Message*.

For a third example, we will look at the method `read()` in StdXMLReader.java. This was the method we examined in Section 2. To generate a *Quick Summary Message*, we examine the method signature `public char read()`. The method name, "read" is interpreted by SWUM to be a verb. This means the direct object is the return type, "char", or "character." This results the *Quick Summary Message* "This method reads a character." The *Return Message*, "This method returns the character," is then combined with the *Quick Summary Message* in aggregation to produce "This method reads a character and returns the character."

To generate the *Output Usage Message*, we first find the methods that call `read()` with the highest PageRank. In this case, the most important methods, the two with the highest PageRank, are `XMLElement.addChild()` and `StdXMLBuilder.addAttribute()`. The *Output Usage Message* is created by combining the *Quick Summary Messages* of those two methods. The *Quick Summary Message* of `XMLElement.addChild()` is "add child XML elements" and the *Quick Summary Message* of `XMLElement.addAttribute()` is "add attribute of XML element." These messages are combined with the *Return Message* to produce the sentence "That character is used in methods that add child XML elements and attributes of XML elements." Note that because both methods use the verb add, we do not repeat it. We combine the two direct objects into a complex verb phrase. The *Called Message* is generated by finding the most important methods that `read()` calls. The only meethod that `read()` calls is `skipsWhitespace()`, which is used to generate the sentence "This method calls a method that skips the whitespace."

The *Usage Message* is created by finding a line of code in one of the methods that calls `read()`. For example, we find a line of code `char ch = reader.read();`. This meets the definition of an assignment statement. Thus, we generate the message, "This method can be used in an assignment statement ; for example: `char ch = reader.read();`. Putting all the messages together, the final summary we generate for `read()` is "This method reads a character and returns the character. That character is used in methods that add child XML elements and attributes of XML elements. This method calls a method that skips the whitespace. This



This method reads a character and returns the character. That character is used in methods that add child XML elements and attributes of XML elements. This method calls a method that skips the whitespace. This method can be used in an assignment statement; for example:

char ch = reader.read();.

Fig. 3. An example of a summary produced by our approach with the different message types highlighted. The Quick Summary Message is highlighted blue. The Return Message is highlighted red. The Output Usage Message is highlighted Green. The Call Message is highlighted Yellow. The Use Message is highlighted grey. The Importance Message is not shown, as it was not used in the most recent version of our approach.

method can be used in an assignment statement; for example: `char ch = reader.read();`." The fully combined summary is shown in Figure 3.

6 Evaluation Comparing to Manual Summaries

Our first evaluation compared automatic summaries of our approach to the summaries written by human experts within the source code via Javadocs. The Javadocs for the program were embedded within the source code written by the developers. The goals of our evaluation were threefold: 1) to assess the degree to which our summaries mimic the high quality of summaries written by programmers, 2) to assess whether the summaries provide useful contextual information about the Java methods, and 3) to determine whether the generated summaries can be used to improve, rather than replace, existing documentation.

Assessing Overall Quality. We do not expect an automated approach to outperform human experts in terms of the overall quality of the summaries. Nevertheless, one goal of our evaluation is to quantify any difference in quality, and to determine in what areas the quality of the summaries can be most improved. We compare the summaries from our approach to summaries extracted from the documentation (e.g., the Javadocs) for different Java programs. To assess quality, we ask three different Research Questions (RQs):

RQ_1 To what degree do the automated and manually-written summaries differ in overall accuracy?

RQ_2 To what degree do the automated and manually-written summaries differ in terms of missing important information?

RQ_3 To what degree do the automated and manually-written summaries differ in terms of including unnecessary information?

These Research Questions are derived from two earlier evaluations of source code summarization [33], [42], where the "quality" of the generated comments was assessed in terms of accuracy, content adequacy, and conciseness. Content adequacy referred to whether there was missing information, while conciseness referred to the amount of unnecessary information in a summary. This strategy for evaluating generated comments is supported by a recent study of source code comments [45] in which quality was modeled as a combination of factors correlating to accuracy, adequacy, and conciseness.

Assessing Contextual Information. Contextual information about a method is meant to help programmers understand the behavior of that method. But, rather than describe that behavior directly from the internals of the method itself, context explains how that method interacts with other methods in a program. By reading the context, programmers then can understand what the method does, why it exists, and how to use it (see Section 2). Therefore, we study these three Research Questions:

RQ_4 Do the summaries help programmers understand what the methods do internally?

RQ_5 Do the summaries help programmers understand why the methods exist?

RQ_6 Do the summaries help programmers understand how to use the methods?

The rationale behind RQ_4 is that a summary should provide programmers with just enough details to understand the most important internals of the method – for example, the type of algorithm the method implements – without forcing them to read the method's source code. Our summaries aim to include this information solely from the context. If our summaries help programmers understand the methods' key internals, it means that this information came from the context. For RQ_5, a summary should help programmers understand why the method is important to the behavior of the program as a whole. For example, the programmers should be able to know, from reading the summary, what the consequences might be of altering or removing the method. Likewise, for RQ_6, the summary should explain the key details about how a programmer may use the method in his or her own code.

Orthogonality. While the ultimate goal of this research is to generate documentation purely from data in the source code, we also aim to improve existing documentation by adding contextual information. In particular, we ask:

RQ_7 Do the generated summaries contain orthogonal information to the information already in the manual summaries?

The idea behind this RQ is that to improve existing summaries, the generated summaries should contribute new information, not merely repeat what is already in the summaries. We generate summaries by analyzing the context of methods, so it is plausible that we add information from this context, which does not exist in the manually-written summaries.

6.1 Cross-Validation Study Methodology

To answer our Research Questions, we performed a cross-validation study in which human Java programmers read the source code of different Java methods, as well as summaries of those methods, for three different rounds. For

TABLE 2
The cross-validation design of our user study. Different participants read different summaries for different programs.

Round	Group	Summary	Program 1	Program 2
1	A	Generated	NanoXML	Jajuk
	B	Manual	Siena	JEdit
	C	Both	JTopas	JHotdraw
2	A	Both	Siena	Jajuk
	B	Generated	JTopas	JEdit
	C	Manual	NanoXML	JHotdraw
3	A	Manual	JTopas	Jajuk
	B	Both	NanoXML	JEdit
	C	Generated	Siena	JHotdraw

each method and summary, the participants answered eight questions that covered various details about the summary. Table 3 lists these questions. The first six correspond to each of the Research Questions above, and were multiple choice. The final two were open-ended questions; we study the responses to these two questions in a qualitative evaluation in Section 11. If a participant was unable to understand a method enough to evaluate the given summary, they were encouraged to not answer any questions about it and skip to the next method. Additionally, participants could leave the study at any point.

In the cross-validation study design, we rotated the summaries and Java methods that the human evaluators read. The purpose of this rotation was to ensure that all evaluators would read summaries from each different approach for several different Java programs, and to mitigate any bias from the order in which the approaches and methods were presented [30]. Table 2 shows our study design in detail. Upon starting the study, each participant was randomly assigned to one of three groups. Each of those groups was then assigned to see one of three types of summary: summaries from our approach, manually-generated summaries, or both at the same time.

For an example of what a "both" summary contains, in the case of `XMLElement.findAttribute()`, we combine the human-written Javadocs summary with our approach's generated summary in the order. The human-written Javadocs summary reads "Searches an attribute." Our approach's summary reads "This method finds the attribute and returns a XMLAttribute. That XMLAttribute is used by methods that gets the attribute." These are then combined to read "Searches an attribute. This method finds the attribute and returns a XMLAttribute. That XMLAttribute is used by methods that gets the attribute." This can result in some redundancy when our Quick Summary Message is similar to the Javadocs summary.

6.2 Subject Java Programs

The summaries in the study corresponded to Java methods from six different subject Java programs, listed in Table 4. We selected these programs for a range of size (5 to 117 KLOC, 318 to 7161 methods) and domain (including text editing, multimedia, and XML parsing, among others). During the study, participants were assigned to see methods from four of these applications. During each of three different rounds, we rotated one of the programs that the groups saw, but retained the fourth program. The reason is so that the group would evaluate different types of summaries

TABLE 3
The questions we ask during the user study. The first six are answerable as "Strongly Agree", "Agree", "Disagree", and "Strongly Disagree." The last two are open-ended.

Q_1-Accuracy	Independent of other factors, I feel that the summary is accurate.
Q_2-Content	The summary is missing important information, and that can hinder the understanding of the method.
Q_3-Concise	The summary contains a lot of unnecessary information.
Q_4-What	The summary contains information that helps me understand what the method does (e.g., the internals of the method).
Q_5-Why	The summary contains information that helps me understand why the method exists in the project (e.g., the consequences of altering or removing the method).
Q_6-How	The summary contains information that helps me understand how to use the method.
Q_7-Summary	In a sentence or two, please summarize the method in your own words.
Q_8-Comments	Do you have any general comments about the given summary?

for different programs, but also evaluate different types of summaries from a single application. From each application, we pre-selected (randomly) a pool of 20 methods from each application. At the start of each round, we randomly selected four methods from the pool for the rotated application, and four from the fixed application. Over three rounds, participants read a total of 24 methods. Because the methods were selected randomly from a pool, the participants did not all see the same set of 24 methods. The programmers could always read and navigate the source code for these applications, though we removed all comments from this code to avoid introducing a bias from these comments.

6.3 Participants

We had 13 participants in our study. Six were graduate students and three were undergraduates from the Computer Science and Engineering Department at the University of Notre Dame. The remaining four were a mix of professionals and graduate students from three different organizations, not listed due to our privacy policy. Two participants failed to complete enough of the study and had their responses thrown out. Both of these participants were students at from the Computer Science and Engineering Department at the University of Notre Dame. One was an undergraduate student, and the other was a graduate student. Another user only completed the answers on 2 summaries before leaving the survey. The remaining 10 participants answered

TABLE 4
The six Java programs used in our evaluation. KLOC reported with all comments removed. All projects are open-source.

	Methods	KLOC	Java Files
NanoXML	318	5.0	28
Siena	695	44	211
JTopas	613	9.3	64
Jajuk	5921	70	544
JEdit	7161	117	555
JHotdraw	5263	31	466

the questions on an average of 19 summaries, skipping on average 5.

6.4 Metrics and Statistical Tests

Each of the multiple choice questions could be answered as "Strongly Agree", "Somewhat Agree", "Somewhat Disagree", or "Strongly Disagree." We assigned a values to these answers as 4 for "Strongly Agree", 3 for "Somewhat Agree", 2 for "Somewhat Disagree", and 1 for "Strongly Disagree." For questions 1, 4, 5, and 6, higher values indicate stronger performance. For questions 2 and 3, lower values are preferred. We aggregated the responses for each question by approach. For example, all responses to question 1 for automatically-generated summaries, and all responses to question 1 for the manually-written summaries.

To determine statistical significance between these groups, we use the `lrm` modeling function within the `rms` [3] package for the R scripting language [4]. The `rms:lrm` modelling function represents the data as an ordinal logistical regression model to account for difference in treatments. Specifically, we use `rms:lrm` to account for differences between individual participants, who may have their own biases, and individual methods, which may be easier or more difficult to summarize. As such, the inputs our logistical model consider are the summarization technique applied, the participant who is performing the evaluation, and the method the summary is generated to describe. We use ANOVA within the R scripting language to determine the p-values that the type of summary significantly affects the quality of the summary with respect to our six questions. If the p-value is $p < .05$, we consider the two compared populations to be significantly different.

6.5 Threats to Validity

As with any study, our evaluation carries threats to validity. We identified two main sources of these threats. First, our evaluation was conducted by human programmers, who may be influenced by factors such as stress, fatigue, or variations in programming experience. Stress and fatigue could make results later in the study less reliable, as programmers attempt to finish quickly. Additionally, very large summaries, such as those that can result from combining summaries from our approach with existing summaries, may result in the user not reading an entire summary. We attempted to mitigate these threats through our cross-validation study design, which altered the order in which the participants viewed the Java methods and summaries. We also recruited our participants from a diverse body of professionals and students, and confirmed our results with accepted statistical testing procedures. Still, we cannot guarantee that a different group of participants would not produce a different result.

Another source for a threat to validity is the set of Java programs we selected. We chose a variety of applications of different sizes and from different domains. In total, we generated summaries for over 19,000 Java methods from six projects, and randomly selected 20 of these methods from each project to be included in the study (four to twelve of which were ultimately shown to each participant). Even with this large pool of methods, it is still possible that our results would change with different projects. To help mitigate this threat, we have released our tool implementation and all evaluation data in an online appendix, so that other researchers may reproduce our work in independent studies.

A third threat to validity arises from the learning effect. In our study, in order to mitigate the fatigue effect, we present programmers with the same Program 2 in each round of the study. This is because the subset of possible second programs (jEdit, jajuk, and jHotDraw) are, programmatically, much larger than the other three programs in terms of number of methods. Our study relies on programmers looking at a method source code in order to evaluate method quality. Programmers, therefore, need to explore the context of a method within the source code itself in order to verify the correctness of given summaries. With large programs, this can create a large amount of fatigue. By using the same program, the programmer can gain understanding of the program in question to reduce the fatigue effect that would arise from switching programs. To reduce the impact of the learning effect, we change the order of summary type given to each group, such that each order is represented.

One final threat to validity emerged in our statistical analysis. We ran into one error using the *rms:lrm* modelling tool with R. One programmer responded to a combined summary (where a human summary was combined with our approach's generated summary) by saying they "Somewhat disagreed." This individual data element prevented *rms:lrm* from being able to fit a model to the data. When we removed this individual piece of data, or modified which method it referred to, the model was able to be fitted to the data. We chose to remove this data element from the statistical tests. As we will note in the results section, this could have an effect on the p-value generated for H_7. However, the p-value for H_7 was found to be .8917, which is substantially larger than our decision point of $p < .05$. As such, we feel confident that this single data element being removed would not change our decision regarding that hypothesis.

6.6 Reproducibility

To ensure reproducibility, we have included all data collected in an online appendix [5]. The online appendix includes our implementation of our approach as well as survey data. Survey data includes user responses to both quantitative and qualitative questions, as well as the methods in the study, the summaries for each approach, and the location in source code of each method.

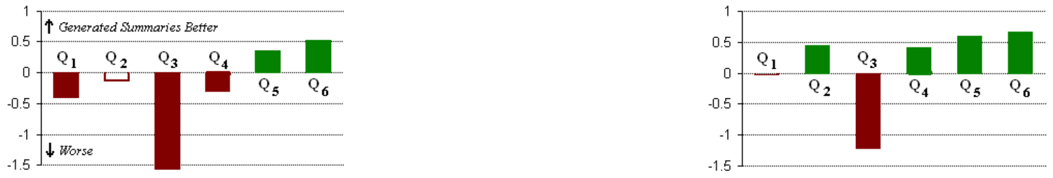
7 Empirical Results

This section reports the results of our evaluation. First, we present our statistical process and evidence. Then, we explain our interpretation of this evidence and answer our research questions.

3. http://cran.r-project.org/web/packages/rms/rms.pdf
4. http://www.r-project.org/
5. http://www.nd.edu/~pmcburne/summaries/

TABLE 5
Statistical summary of results for the participants' ratings for each questions. "Samp." is the number of responses for that question for a given summary type, for all rounds. χ^2 is calculated by applying ANOVA to the `rms:lrm` generated linear regression model and considering the difference caused by the type of summary. D.f. refers to the number of degrees of freedom within the type of summary. If the p-value is less than .05, we reject the null hypothesis.

H	Q	Summary	Samp.	$\tilde{x}$	μ	Vari.	χ^2	d.f.	p-value	Decision
H_1	Q_1-Accuracy	Our	63	3	2.635	0.558	5.19	1	0.023	Reject
		Manual	63	3	3.032	0.676				
H_2	Q_2-Content	Our	63	3	2.714	0.691	0.02	1	0.882	Not Reject
		Manual	63	3	2.587	0.956				
H_3	Q_3-Concise	Our	63	3	2.937	0.673	45.53	1	<.001	Reject
		Manual	63	1	1.381	0.304				
H_4	Q_4-What	Our	63	3	2.413	0.633	6.01	1	0.014	Reject
		Manual	63	3	2.714	0.917				
H_5	Q_5-Why	Our	63	3	2.524	0.512	7.14	1	0.008	Reject
		Manual	63	2	2.175	0.921				
H_6	Q_6-How	Our	63	3	2.698	0.730	14.54	1	<.001	Reject
		Manual	63	2	2.175	0.727				
H_7	Q_1-Accuracy	Combined	66	3	3.136	0.458	0.02	1	0.897	Not Reject
		Manual	63	3	3.032	0.676				
H_8	Q_2-Content	Combined	67	2	2.149	0.371	15.02	1	<.001	Reject
		Manual	63	3	2.587	0.956				
H_9	Q_3-Concise	Combined	67	3	2.597	0.547	39.54	1	<.001	Reject
		Manual	63	1	1.381	0.304				
H_{10}	Q_4-What	Combined	67	3	3.119	0.470	7.75	1	0.005	Reject
		Manual	63	3	2.714	0.917				
H_{11}	Q_5-Why	Combined	67	3	2.761	0.518	9.91	1	0.002	Reject
		Manual	63	2	2.175	0.921				
H_{12}	Q_6-How	Combined	67	3	2.856	0.685	27.71	1	<.001	Reject
		Manual	63	2	2.175	0.727				



(a) Generated vs. Manual Summaries (b) Both vs. Manual Summaries

Fig. 4. Performance comparison of the summaries. The chart shows the difference in the means of the responses to each question. For example in (a), the mean of Q_5-Why for our approach is 0.349 higher than for the Manual summaries. The sign is reversed for Q_2-Content and Q_3-Concise because lower scores, not higher scores, are better values for those questions. Solid bars indicate differences which are statistically-significant. In general, the manual summaries were more accurate and contained less unnecessary information, but our generated summaries provided more thorough contextual information.

7.1 Statistical Analysis

The main independent variable was the type of summary rated by the participants: summaries generated by our solution, summaries from Javadocs written by programmers, or both presented together. The dependent variables were the ratings for each question: 4 for "Strongly Agree" to 1 for "Strongly Disagree".

For each question, we compare the mean of the participants' ratings for our generated summaries to the manual summaries. We also compare the ratings given when both summaries were shown, versus only the manual summaries. We compared these values using ANOVA on the `rms:lrm` modelling function in the R scripting language (see Section 6.4). Specifically, we posed 12 hypotheses of the form:

H_n	The difference in the reported ratings of the responses for Q_m is not statistically-significant.

where n ranges from 1 to 12, and m ranges from 1 to 6, depending on which question is being tested. For example, in H_{11}, we compare the answers to Q_5-Why for the manual summaries to the answers to Q_5-Why for the combined summaries.

Table 5 shows the statistical analysis of our null hypotheses and notes which ones were rejected (e.g., the means with a statistically-significant difference). We made a decision to reject a hypothesis only when the calculated p-value was less than .05.

7.2 Interpretation

Figure 4 showcases the key evidence we study in this evaluation. We use this evidence to answer our Research Questions along the three areas highlighted in Section 9.

Overall Quality. The manually-written summaries are superior in overall quality to the generated summaries. Figure 4(a) shows the difference in the means of the responses for survey questions. Questions Q_1-Accuracy through Q_3-Concise refer to aspects of the summaries related to overall quality, in particular to our Research Questions RQ_1 to RQ_3. In short, participants rated the generated summaries as less accurate and as including more unnecessary information by a statistically-significant margin. While these results may be expected when comparing computer-generated text to text written by human experts, it nevertheless points to a need to improve in these areas. In particular, in Section 8, we explore what information that the participants felt was unnecessary in our summaries.

Contextual Information. The generated summaries included more contextual information than the manual summaries. The differences in responses for questions Q_5-Why and Q_6-How are significantly higher for the generated summaries. These results mean that, in comparison to the manual summaries, the generated summaries helped the programmers understand *why* the methods exist and *how to use* those methods. Therefore, we answer RQ_5 and RQ_6 as a positive result. However, we found RQ_4 to be a negative result. That is, on average, programmers disagreed our summaries explained what a method does to a statistically signficant margin. However, the answers to RQ_5 and RQ_6 point to an important niche filled by our approach: the addition of contextual information to software documentation.

Orthogonality. We found substantial evidence showing that our generated summaries improve the manually-written summaries. When participants read both types of summary for a given method, the responses for Q_5-Why and Q_6-How improved by a significant margin, pointing to an increase in useful contextual information in the documentation. Overall quality did not decrease as sharply as when only the generated solutions were given. Consider Figure 4(b): Accuracy was nearly identical, with no statistical difference. The amount of missing information dropped, as indicated by better responses to Q_2-Content. Additionally, the responses to Q_4-What increased by a statistically significant margin. While the combined summaries did show a marked increase in unnecessary information, we still find evidence to positively answer RQ_7: the information added to manual summaries by our generated summaries is orthogonal. This answer suggests that our approach can be used to improve existing documentation.

8 Qualitative Results

Participants in the evaluation study had the opportunity to write an opinion about each summary (see Q_8-Comments in Table 3). In this section, we explore these opinions for feedback on our approach and directions for future work.

One result from the survey was the substantial amount of information in the generated summaries that participants rated as unnecessary (see Q_3-Concise in Figure 3). Several of these complaints centered around the *Importance Message*. One source of confusion seems to be that the structure implies that the number of calling functions is the primary determinant of importance, when in fact importance is derived from PageRank. Still, several users found the *Importance Message* altogether unnecessary. The following comments about our summaries or the combination of our summaries and the manual summaries illustrate this:

- "It doesn't seem meaningful to say that the method has less importance than average by counting the number of calls. Maybe the method is very important for external users of the library. If so, then it should be annotated as part of the external API."
- "The name of the method alone is about all the description it needs, and I also don't think being called by 1 method merits the "far more important than average" description."
- "'IsKeyword() seems far more important than average because it is called by 1 method' is unnecessary."
- "First 3 sentences have a very good summary. 4th sentence [*Importance Method*] seems unnecessary. 5th sentence [*Use Message*] is a good example"

As a result of this feedback paired with our approaches poor performance in Q_3-Concise, we removed the *Importance Message* from our summaries in the study comparing our approach to the state-of-the-art automatic summarization approach.

One positive result is the dramatic increase in the scores for Q_5-Why and Q_6-How, which deal with how a programmer can use the method within the system. This appears to be drawn primarily from the *Use Message* – several users cite it either directly or indirectly in their comments. For example, the last comment in the list above refers to the *Use Message* as a good example. Some additional examples follow:

- "I like that the comment describes how to use the method."
- "...The information about how it is used is useful."
- "I think an example of how to use the method is not really needed, though it might be useful for convenience."

Additionally, in a method that did not generate a *Use Message*, one user noted "...it would be nice to have an example of how it is used like others have."

Along with our empirical results, these comments show that our approach improves programmer understanding of why a method exists and how a method is used. We believe that this fills our target niche of improving context in software documentation. Typically, programmers try to understand a system so that they can use the system effectively. By providing contextual information, we help improve a programmers understanding of the structure of the source code.

Several of our generated summaries had grammar issues that distracted users. These complaints seemed less common in the combined summaries than when the user was just given our summary, possibly because the user was given a human-written sentence that explains the code alongside our generated comment. However, poor grammar can be a hindrance to effectively conveying a message. These grammar errors usually result from incorrect interpretation of part-of-speech by SWUM or by selecting incorrect articles or subject-verb agreement within the framework of our natural language generation tool. In some method signatures, the direct object of the verb phrase is misidentified, such as using the object name as the direct object when the argument name should be the direct object, or vice versa. We aim to correct these issues in future work with refinement of our NLG tool.

It is worth noting that several users, when commenting on the manually-generated comments alone (without our generated summary as a supplement) said that many of the comments were insufficient. The following comments were pulled from sections where the programmer was only given the manually-generated comment:

- "Should be a little more clear about what the wrapping process is, I think."
- "More information would be appreciated for this one."
- "Why is this method important?"

9 Evaluation Comparing to Automatic Summaries

Our second evaluation compares our approach to the state-of-the-art approach described by Sridhara *et al.* [42]. The objective of our evaluation is three-fold: 1) to assess the degree to which our summaries meet the quality of summaries generated by a state-of-the-art solution, 2) to assess whether the summaries provide useful contextual information about the Java methods, and 3) to determine whether the generated summaries can be used to improve, rather than replace, existing documentation.

Our study design is very similar to the study design for our previous approach. In this section, we will only include changes to our evaluation, such as the number of participants in our second study and changes in the research questions. For information on how the study is conducted, see Section 6.

9.1 Approach Modification

For this evaluation, we removed the *Importance Message* from our approach's summaries. Our rationale for this decision is that in our first study, participants found our approach's summaries to contain a large amount of unneccesary information. The qualitative results (Section 8) suggest that the *Importance Message* is to blame. No other modifications to our approach are made.

9.2 Research Questions

This section defines the research questions for our second evaluation. These research questions are very similar to those in Section 6.

Assessing Overall Quality. In this evaluation, we seek to quantify the difference in summary quality between our approach and the existing state-of-the-art approach. To assess quality, we propose the three following Research Questions (RQs):

RQ_8 To what degree do the summaries from our approach and the state-of-the-art approach differ in overall accuracy?

RQ_9 To what degree do the summaries from our approach and the state-of-the-art approach differ in terms of missing important information?

RQ_{10} To what degree do the summaries from our approach and the state-of-the-art approach differ in terms of including unnecessary information?

As in our first study, these research questions are derived from work by Moreno *et al.* [33] and Sridhara *et al.* [42]. The questions address, respectively, a summary's accuracy, content adequacy, and conciseness.

Assessing Contextual Information. In the evaluation, we want to examine which automatic summarization approach better provides programmers with contextual information. Our questions are designed to determine if summaries generated by our approach are better than the state-of-the-art approach in helping programmers understand what a method does, why the method exists, and how to use it. We evaluate the following research questions:

RQ_{11} Do the summaries help programmers understand what the methods do internally?

RQ_{12} Do the summaries help programmers understand why the methods exist?

RQ_{13} Do the summaries help programmers understand how to use the methods?

The rationale for these questions is the same as in our first study (see Section 6)

Orthogonality. While the ultimate goal of this research is to generate documentation purely from data in the source code, we also aim to improve upon the state-of-the-art approach by adding contextual information. In particular, we ask:

RQ_{14} Do the summaries generated by our solution contain orthogonal information to the information already in the summaries from the state-of-the-art solution?

The idea behind this RQ is that to improve existing summaries, the generated summaries should contribute new information, not merely repeat what is already in the summaries. We generate summaries by analyzing the context of methods, so it is plausible that we add information from this context, which does not exist in the summaries from the state-of-the-art solution.

9.3 Cross-Validation Study Methodology

To answer our Research Questions, we performed a cross-validation study in which human experts (e.g., Java programmers) read the source code of different Java methods, as well as summaries of those methods, for three different rounds. The structure of this study is the same as our first study (see Section 6.1). Again in our cross-validation study, we rotate the projects programmers saw summaries from in order to avoid bias. Table 6 shows the ordering of our study.

TABLE 6
The cross-validation design of our user study. Different participants read different summaries for different programs.

Round	Group	Summary	Program 1	Program 2
1	A	Our	NanoXML	Jajuk
	B	S.O.T.A.	Siena	JEdit
	C	Combined	JTopas	JHotdraw
2	A	Combined	Siena	Jajuk
	B	Our	JTopas	JEdit
	C	S.O.T.A.	NanoXML	JHotdraw
3	A	S.O.T.A.	JTopas	Jajuk
	B	Combined	NanoXML	JEdit
	C	Our	Siena	JHotdraw

9.4 Subject Java Programs

In our second evaluation, we use the same subject Java programs as our first evaluation. Information about these subject Java programs can be found in Section 6.2 and in Table 4. Our approach to selecting method summaries is the same as in Section 6.2.

9.5 Participants

We had 12 participants in our study. Nine were graduate students and from the Computer Science and Engineering Department at the University of Notre Dame. The remaining three were professional programmers from two different organizations, not listed due to our privacy policy. Of our 12 participants, 3 did not complete enough of the study and had their results thrown out. One of these students was a graduate student at from the Computer Science and Engineering Department at the University of Notre Dame. The remaining two were among our professional programmers from different organizations. On average, the participants answered questions on 20.2 summaries, skipping an average of 3.8. Additionally, some participants occasionally failed to answer one of the six questions. Given the sporadic nature of when an individual question was not answered, we assume it was unintentional.

9.6 Metrics and Statistical Tests

We define the metrics identically as in the first study. See Section 6.4 for our statistical analysis, including information on statistiscal tests used.

9.7 Threats to Validity

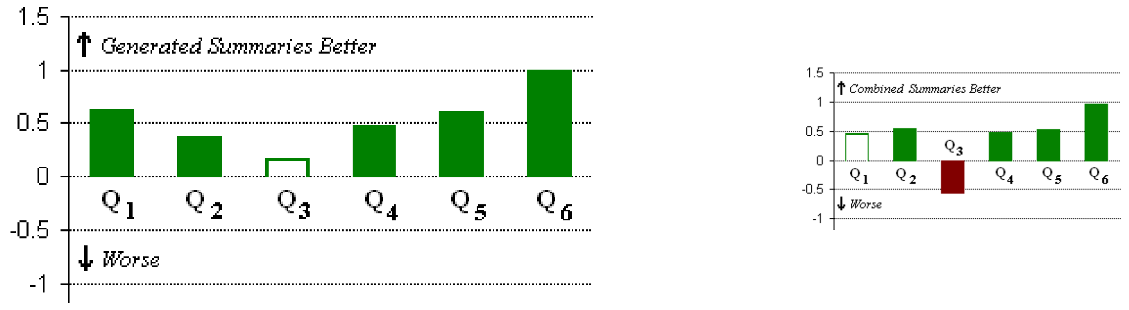
This study shares the same threats to validity as our first study. We address these threats in Section 6.5, as well as discuss how we mitigate their effect.

10 Empirical Results

This section reports the results of our evaluation. First, we present our statistical process and evidence. Then, we explain our interpretation of this evidence and answer our research questions.

TABLE 7
Statistical summary of results for the participants' ratings for each questions. "Samp." is the number of responses for that question for a given summary type, for all rounds. χ^2 is calculated by applying ANOVA to the `rms:lrm` generated linear regression model and considering the difference caused by the type of summary. D.f. refers to the number of degrees of freedom within the type of summary. If the p-value is less than .05, we reject the null hypothesis.

H	Q	Summary	Samp.	$\tilde{x}$	μ	Vari.	χ^2	d.f.	p-value	Decision
H_1	Q_1-Accuracy	Our	65	3	3.015	0.863	13.90	1	<.001	Reject
		S.O.T.A.	59	3	2.390	0.863				
H_2	Q_2-Content	Our	65	3	2.492	0.973	7.08	1	0.008	Reject
		S.O.T.A.	58	3	2.862	1.139				
H_3	Q_3-Concise	Our	65	2	1.815	0.497	0.15	1	0.702	Not Reject
		S.O.T.A.	59	2	1.983	0.982				
H_4	Q_4-What	Our	65	3	2.877	0.641	15.11	1	<.001	Reject
		S.O.T.A.	59	3	2.407	0.832				
H_5	Q_5-Why	Our	65	3	2.585	0.809	16.58	1	<.001	Reject
		S.O.T.A.	58	3	1.983	0.930				
H_6	Q_6-How	Our	65	3	2.769	0.649	31.92	1	<.001	Reject
		S.O.T.A.	58	3	1.776	0.773				
H_7	Q_1-Accuracy	Combined	59	3	2.847	0.580	2.96	1	0.085	Not Reject
		S.O.T.A.	59	3	2.390	0.863				
H_8	Q_2-Content	Combined	59	2	2.322	0.843	13.36	1	<.001	Reject
		S.O.T.A.	58	3	2.862	1.139				
H_9	Q_3-Concise	Combined	59	2	2.542	1.149	4.73	1	0.030	Reject
		S.O.T.A.	59	2	1.983	0.982				
H_{10}	Q_4-What	Combined	58	3	2.879	0.564	7.85	1	0.005	Reject
		S.O.T.A.	59	3	2.407	0.832				
H_{11}	Q_5-Why	Combined	59	3	2.508	0.634	10.32	1	0.001	Reject
		S.O.T.A.	58	2	1.983	0.930				
H_{12}	Q_6-How	Combined	59	3	2.746	0.503	26.63	1	<.001	Reject
		S.O.T.A.	58	2	1.776	0.773				



(a) Our vs. S.O.T.A. Summaries (b) Combined vs. S.O.T.A. Summaries

Fig. 5. Performance comparison of the summaries. The chart shows the difference in the means of the responses to each question. For example in (a), the mean of Q_5-Why for our approach is 0.602 higher than for the state-of-the-art summaries. The sign is reversed for Q_2-Content and Q_3-Concise because lower scores, not higher scores, are better values for those questions. Solid bars indicate differences which are statistically-significant. In general, the our summaries were more accurate and provided more thorough contextual information.

10.1 Statistical Analysis

We perform our statistical analysis in this study identically to the analysis in our first study (see Section 7.1). We again define our null hypotheses as follows:

H_n The difference in the reported ratings of the responses for Q_m is not statistically-significant.

where n ranges from 1 to 12, and m ranges from 1 to 6, depending on which question is being tested. For example, in H_{11}, we compare the answers to Q_5-Why for the state-of-the-art summaries to the answers to Q_5-Why for the combined summaries. Table 7 shows the the result of our statistical analysis.

10.2 Interpretation

Figure 5 showcases the key evidence we study in this evaluation. We use this evidence to answer our Research Questions along the three areas highlighted in Section 9.

Overall Quality. The summaries from our approach are superior in overall quality to the summaries from the state-of-the-art approach. Figure 5(a) shows the difference in the means of the responses for survey questions. Questions Q_1-Accuracy through Q_3-Concise refer to aspects of the summaries related to overall quality, in particular to our Research Questions RQ_8 to RQ_{10}. In short, participants rated our summaries as more accurate and as missing less required information by a statistically-significant margin. While these results are encouraging progress, they nevertheless still point to a need to improve. In Section 11, we explore what information that the participants felt was unnecessary in our summaries.

Contextual Information. The summaries from our approach included more contextual information than the state-of-the-art summaries. The differences in responses for questions Q_4-What, Q_5-Why, and Q_6-How are higher for our summaries by a statistically-significant margin. These results mean that, in comparison to the state-of-the-art summaries, our summaries helped the programmers understand *why* the methods exist and *how to use* those methods. Therefore, we answer RQ_{11}, RQ_{12}, and RQ_{13} as a positive result. The answers to these research questions point to an important niche filled by our approach: the addition of contextual information to software documentation.

Orthogonality. We found substantial evidence showing that our summaries improve the state-of-the-art summaries. When participants read both types of summary for a given method, the responses for Q_4-What, Q_5-Why, and Q_6-How improved by a significant margin, pointing to an increase in useful contextual information in the documentation. Overall quality did not decrease by a significant margin compared to when only our solutions were given, except in terms of unnecessary information added. Consider Figure 5(b): Accuracy and missing information scores showed similar improvement. While the combined summaries did show a marked increase in unnecessary information, we still find evidence to positively answer RQ_{14}: the information added to state-of-the-art summaries by our approach is orthogonal. This answer suggests that our approach can be used, after future work to reduce unnecessary information, to improve existing documentation.

11 Qualitative Results

Participants in the evaluation study had the opportunity to write an opinion about each summary (see Q_8-Comments in Table 3). In this section, we explore these opinions for feedback on our approach and directions for future work.

One of the results in our study was the significantly worse performance of Q_3-Concise in the combined comments, suggesting an increase in the amount of unnecessary information. Several user comments from our survey note concerns of repetitious information, as well as difficulties in processing the longer comments that result of the combination.

- "The description is too verbose and contains too many details."
- "The summary contains too much information and confuses the purpose of the method..."
- "The summary seems accurate but too verbose."
- "Too much information, I cannot understand the comment."

Another result is the increase in the scores for Q_5-Why and Q_6-How, which deal with how a programmer can use the method within the system. This increase appears to be due to the *Use Message*. Several users noted a lack of any form of usage message in the state-of-the-art approach. A selection of these comments follows.

- "Nice and concise, but lacking information on uses..."
- "The summary is clear. An example is expected."

- "The summary...does not tell me where the method is called or how it is used."

Additionally, in a method summary from our approach that did not generate a *Use Message*, a participant noted "I feel that an example should be provided." However, one participant in our study had a largely negative opinion of the *Use Message*. This participant repeatedly referred to the "last sentence" (the *Use Message*) as "unnecessary", even stating "Assume every one of these boxes comments about removing the last line of the provided comment."

Participants often felt the state-of-the-art approach lacked critical information about the function. Comments indicating a lack of information appeared consistently from many participants. The following comments (each from a different participant) support this criticism:

- "A bit sparse and missing a lot of information."
- "Comment details the inner workings but provides no big picture summary."
- "Only provides a detail for one of the possible branches."
- "It seems the summary is generated only based on the last line of the method."

These comments occur more frequently with the state-of-the-art compared to our approach. A possible reason for this is our approach focuses much more on method interactions (e.g., method calls), and avoids the internal details of the function. By contrast, the state-of-the-art approach focuses on a method's internal execution, selecting a small subset of statements to use in the summary. Participants felt this selection often leaves out error checking and alternate branches, focusing too narrowly on particular internal operations while ignoring others. We believe that these comments point to the contextual information we add in our summaries as being the key improvement over the state-of-the-art approach.

Several of our generated summaries and the state-of-the-art generated summaries had grammar issues that distracted users. Additionally, the state-of-the-art approach often selected lines of source code, but did not generate English summaries for those lines. Several users commented on these issues, noting that it made the summaries either impossible or difficult to understand. Our aim is to correct these issues going forward with refinement of our NLG tool.

Another common theme of participant comments in both our approach and the state-of-the-art centered on function input parameters. Many participants felt an explanation of input parameters was lacking in both approaches, as well as the combination approach. A selection of these comments follows. These comments were selected from our approach, the state-of-the-art, and the combined approach respectively:

- "The input parameters publicID and systemID are not defined – what are they exactly?"
- "The summary could mention the input required is the path for the URL"
- "... It would be better if the summary described the types of the inputs..."

12 Related Work

The related work closest to our approach is detailed in a recent thesis by Sridhara [41]. In Section 3, we summarized certain elements of this work that inspired our approach. Two aspects we did not discuss are as follows. First, one approach creates summaries of the "high level actions" in a method [43]. A high level action is defined as a behavior at a level of abstraction higher than the method. The approach works by identifying which statements in a method implement that behavior, and summarizing only those statements. A second approach summarizes the role of the parameters to a method. This approach creates a description of key statements related to the parameter inside the method. Our approach is different from both of these approaches in that we create summaries from the context of the method – that is, where the method is invoked. We help programmers understand the role the method plays in the software.

There are a number of other approaches that create natural language summaries of different software artifacts and behaviors. Moreno *et al.* describe a summarization technique for Java classes that match one of 13 "stereotypes." The technique selects statements from the class based on this stereotype, and then uses the approach by Sridhara [42] to summarize those statements. Work by Buse *et al.* focuses on Java exceptions [3]. Their technique is capable of identifying the conditions under which an exception will be thrown, and producing brief descriptions of those conditions. Recent work by Zhang *et al.* performs a similar function by explaining failed tests [51]. That approach modifies a failed test by swapping different expressions into the test to find the failure conditions. Summary comments of those conditions are added to the test. Another area of focus has been software changes. One approach is to improve change log messages [4]. Alternatively, work by Kim *et al.* infers change rules, as opposed to individual changes, that explain the software's evolution [21]. The technique can summarize the high-level differences between two versions of a program.

The key difference between our approach and these existing approaches is that we summarize the context of the source code, such as how the code is called or the output is used. Structural information has been summarized before, in particular by Murphy [34], in order to help programmers understand and evolve software. Murphy's approach, the software reflexion model, notes the connections between low-level software artifacts in order to point out connections between higher-level artifacts. There are techniques which give programmers some contextual information by listing the important keywords from code. For example, Haiduc *et al.* use a Vector Space Model to rank keywords from the source code, and present those keywords to programmers [14]. The approach is based on the idea that programmers read source code cursorily by reading these keywords, and use that information to deduce the context behind the code. Follow-up studies have supported the conclusions that keyword-list summarization is useful to programmers [1], and that VSM is an effective strategy for extracting these keywords [8].

Tools such as Jadeite [47], Apatite [9], and Mica [46] are related to our approach in that they add API usage information to documentation of those APIs. These tools visualize the usage information as part of the interface for exploring or locating the documentation. We take a different strategy by summarizing the information as natural language text. What is similar is that this work demonstrates a need for documentation to include the usage data, as confirmed by studies of programmers during software maintenance [20], [26], [49].

13 Conclusion

We have presented a novel approach for automatically generating summaries of Java methods. Our approach differs from previous approaches in that we summarize the *context* surrounding a method, rather than details from the internals of the method. We use PageRank to locate the most important methods in that context, and SWUM to gather relevant keywords describing the behavior of those methods. Then, we designed a custom NLG system to create natural language text about this context. The output is a set of English sentences describing why the method exists in the program, and how to use the method. We performed two cross-validation studies to evaluate the quality of summaries generated by our approach. In the first cross-validation study, we compared the summaries generated from our approach to summaries written by human experts. We found our approach provided better contextual information than manually written summaries. However, the human written summaries were significantly more accurate and concise. In the second cross-validation study, we compared the summaries from our approach to summaries written by a state-of-the-art solution. We found that our summaries were superior in quality and that our generated summaries fill a key niche by providing contextual information. That context is missing from the state-of-the-art summaries. Moreover, we found that by combining our summaries with the state-of-the-art summaries, we can improve existing software documentation. Finally, the source code for our tool's implementation and evaluation data are publicly available for future researchers.

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