Improving Semantic Consistency of Variable Names with Use-Flow Graph Analysis

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Abstract—Consistency is one of the keys to maintainable source code and hence a successful software project. We propose a novel method of extracting the intent of programmers from source code of a large project (≈ 300 kLOC) and checking the semantic consistency of its variable names. Our system learns a project-specific naming convention for variables based on its role solely from source code, and suggest alternatives when it violates its internal consistency. The system can also show the reasoning why a certain variable should be named in a specific way. The system does not rely on any external knowledge. We applied our method to 12 open-source projects and evaluated its results with human reviewers. Our system proposed alternative variable names for 416 out of 1080 (39%) instances that are considered better than ones originally used by the developers. Based on the results, we created patches to correct the inconsistent names and sent them to its developers. Three open-source projects adopted it.

Index Terms—Program comprehension, Source code analysis, Dataflow analysis, Software maintenance, Naming, Semantic consistency

I. BACKGROUND

A large software project is typically developed and maintained by a number of people. Even if the project is relatively small in its size, it might eventually grow into a large project over time. It is therefore desirable to keep its code looks and feels consistent across the different components, so that each member can communicate smoothly. Many software projects adopt “style guides”, a set of coding standards to maintain a certain level of superficial consistency. While these guidelines help the project to achieve a certain aspect of the code consistency, they mostly address the stylistic aspects such as indentation or word capitalization. The other types of consistency, or “semantic consistency” such as word choice for concepts used in the code, is often left to each developer’s discretion.

One of the reasons why such a consistency is difficult to achieve is that they are highly subjective. It is relatively easy to prescribe the stylistic aspect of source code in a way that it can be checked automatically. On the other hand, it is hard to regulate all the names used in source code in advance. Programmers often encounter situations where they have to name a certain concept that is not so well-defined, yet necessary to be named. Some of these concepts might not be immediately comparable to any real-life objects, so the programmers have to be inventive. In general, naming is much more difficult to regulate than superficial coding styles.

One way to cope with such a problem is to maintain a list of words that are used for names and share them among the developers [1]. However, this is impractical because, unlike style guides, the concepts used in a program are often project specific, and the same word can mean different things in different projects. For example, the word “view” can mean a portion of a table when it is used in a database engine, while it can mean a visible window when it is used in a graphical application. Or “rate” can mean different things in a financial application and a network application, etc. To make it worse, different projects use different abbreviation for the same words (e.g. “att” versus “attr” for attributes). To date, there are still relatively few naming guidelines for a large project.

Yet, the importance of names in a program code has been emphasized by many researchers and practitioners [3], [4]. Programmers tend to heavily rely on meaningful identifier names to understand source code [5], and they generally prefer a long descriptive name than single-letter variables [6]. It is also reported that poor naming can lead to misunderstanding or confusion among programmers, which eventually result in poor code quality [7]. In many software projects, inconsistent naming is often considered as a bad smell. Sometimes they are actually treated as bugs (naming bugs [8]). While naming inconsistency does not immediately lead to a malfunction, it decays the code quality over time and developers become more prone to introduce serious bugs. A quick search over GitHub reveals that programmers keep being confused by wrongly named variables and methods. [2] Also, it is natural to assume that the problem of inconsistent names is exacerbated as the size of codebase grows. In large software projects, multiple programmers are involved in changing different parts of the code, sometimes with not enough communication to each other. Without the holistic view of the entire codebase, the inconsistent names can be often overlooked or neglected for a long time, which further degrade the code quality.

Naming issues have been an active topic of research in the software engineering community. Overall, two approaches exist; one is to provide accurate names based on source code, and the other is to detect and correct the naming inconsistency.

1News organizations took a similar approach to this by developing their in-house style guides [1].

2A search over GitHub issues with “wrong name” turns out over 1 million results.
in existing code. For the first approach, Allamanis et al. used machine learning algorithms to suggest method and class names from code [9]. Alon et al. converted source code into word embeddings [10] that correspond to a certain word in natural language [11], which can be used for identifiers. Raychev et al. recovered variable names from obfuscated JavaScript code [12]. For the second approach, Høst et al. [8] used manually crafted rules to detect naming bugs in a number of open source Java projects. Liu et al. used machine learning to capture the relationships between a method name and its body (code) to discover bad method names that do not properly describe its function [13]. Allamanis et al. proposed a method to automatically capture the stylistic conventions from source code, some of them are naming-related [14]. To our knowledge, our work is the first attempt to detect semantic inconsistency of variable names in a large software project.

As for the naming guidelines and code readability, [15] offers an early work for the code documentation. Lawrie et al. [16] was one of the early attempts to give an insight to naming bugs. According to Lawrie et al., naming bugs are divided into two categories: homonym and synonym. If two different concepts are mapped into the same name (homonym), or a single concept is called by multiple names (synonym), it often causes confusion to the programmers [17]. Apart from naming, detecting semantic inconsistency in source code can be a powerful tool for finding potential bugs [18].

A. Importance of Variable Names

So far, most of the existing works focus on the method names. This is understandable because a method or function is often a meaningful chunk of code that is supposed to have a coherent name. However, we argue that it is a variable name, rather than a method name, that plays the crucial role for understanding the high-level meaning of the code because it reveals the type of information that the program handles. We have found that nouns often play a significant role in naming variables, and in turn help the overall understanding of the program. We also have found that each project has a fairly specific set of nouns that are related to its target domain.

Informally, this can be shown in the two steps: First, method names often rely on variable names. Table I shows the number of method names that are related to the variables it uses. By “related”, we mean that the method name contains a word that is also used by one of the variables it uses. From this table, we can say that about one third (or more) of method names rely on the variable names in its meaning, i.e. we first need to understand the meaning of each variable in order to understand the meaning of a method.

Next, many variable names are made up with nouns that refer to domain specific concepts. Note that many method names consist of both verbs and nouns. Again, this is understandable as a method is often an actor or agent of the objects while a variable usually contains a reference to certain objects. However, we observed that the verbs used in method names are fairly limited in its variety. Table II shows the popular words used in method names. One can see that the most popular verbs are get, set, add, remove, and create in nearly all projects, whereas the nouns are more diverse across different projects. One can also see that the nouns are often specific to each project topic, whereas the verbs are mostly generic.

From the above observations, we can conclude the following:

1) Nouns often play a significant role in naming identifiers, and in turn understanding the high-level meaning of the code.
2) Each project has a fairly specific set of nouns that are related to its target domain.

Relatively fewer attempts have been made for predicting field or variable names, possibly because of its variety and subjectivity. Typically, nouns are used for variable names whereas verbs are used for method names. WordNet [19] has 115k nouns while it has only 11k verbs. The software industry has a long history of using existing common nouns for representing abstract concepts, such as “tree”, “view” or “stream”. The naming of these words, however, are only loosely defined in each project. Raychev et al. obtained the characteristics of variable names from a large JavaScript codebase [12], which can be applied to general functions but not project specific

| Project | Related | Unrelated |
|---------|---------|-----------|
| ant     | 5,507   | 5,905     |
| antlr4  | 1,046   | 1,922     |
| bcel    | 1,113   | 2,243     |
| compress| 995     | 1,366     |
| jedit   | 3,068   | 4,630     |
| jhotdraw| 2,171   | 5,127     |
| junit4  | 396     | 943       |
| lucene  | 3,978   | 8,026     |
| tomatc  | 10,519  | 11,189    |
| weka    | 11,040  | 11,428    |
| xerces  | 3,820   | 4,272     |
| xz      | 224     | 464       |

| Project | Top Verbs | Top Nouns |
|---------|-----------|-----------|
| ant     | set, get, add, create, is | file, name, function, class, output |
| antlr4  | get, set, add, remove, visit | string, rule, token, code, name |
| bcel    | visit, get, accept, set, dump | constant, class, string, type, value |
| compress| get, set, read, write, close | stream, entry, archive, data, input |
| jedit   | get, set, add, is, run | JJ, action, line, string, buffer |
| jhotdraw| get, set, create, is, add | action, figure, color, name, property |
| junit4  | get, assert, run, test, validate | test, class, method, failure, runner |
| lucene  | get, set, compare, add, read | doc, next, string, value, bytes |
| tomatc  | get, is, add, name, remove | name, string, session, max, class |
| weka    | get, set, add, is | text, tip, options, action, string |
| xerces  | get, is, create, add | element, name, decl, type, impl |
| xz      | get, write, read, close, set | stream, input, size, output, memory |
There is another reason why we think variable names are important: ultimately, what a computer program handles is just a collection of bits; they are typically interpreted as numbers, vectors and strings. However, that is not the end – real applications need to handle concepts such as “counter”, “position” or “balance”. Fig. 1 shows two functions that are functionally identical (adding a value of one variable to another) but semantically different; one is to update the balance, and the other is to update the position. Similarly, a string can be used as “username”, “pathname” or “address”. In other words, they need to assign the meaning to these bits by naming them, and it is the primary function of variables. Variable names are particularly important to give programmers high-level views. They represent a fundamental building block of application domain.

In reality, maintaining consistency is not always a project’s top goal. Real world software faces constant challenge to be modified or improved. Sometimes one needs to break consistency in order to upgrade a part of the code to adapt for a newer requirement. Therefore, the naming rules are often a set of conventions rather than a strict dogma. Our goal is to capture these conventions and reuse them effectively in an automated manner to improve the code quality. In this paper, we first present our general framework of testing consistency, and then introduce an actual mechanism to apply it to source code.

II. WHAT IS CONSISTENCY?

In this section, we present a general framework of testing the consistency between two sets of inputs over a certain invariant. Suppose we have two sentences, $S_a$ and $S_b$, where each sentence has a pair of features $(F_{a1}, F_{a2})$ and $(F_{b1}, F_{b2})$, respectively. Furthermore, assume that $F_{a1}$ in general conveys a sufficient context to reliably predict $F_{a2}$, i.e. there is a function $K$ such that $K(F_{a1}) = F_{a2}$. Now, if we also find that $K(F_{b1}) = F_{b2}$, i.e. $F_{b1}$ has the same context to predict $F_{b2}$, we can say that $S_b$ is consistent with $S_a$ in regard to $K$.

To illustrate this framework, take a look at the following example:

(a) “It is rainy today so you should take an umbrella.”
(b) “It is [X] today so John should take an umbrella.”

Suppose that we obtained the knowledge ($K$) that there is a strong relationship between “rainy” and “umbrella” from sentence (a). It is fairly easy then to predict the word [X] according to our knowledge. If the word [X] is indeed “rainy”, sentence (b) is consistent with sentence (a) in regard to our knowledge, $K$. While this formulation is similar to a typical machine learning framework, the focus is different: instead of predicting the unknown value of [X], we are interested in measuring the consistency of $K$ over various inputs.

In reality, however, this kind of categorical knowledge is hard to obtain. Therefore, we extend our definition to include Bayesian inference, i.e. statements that have varying degrees of certainty. Suppose we have two statements, $S_a$ and $S_b$, pairs of their features $(F_{a1}, F_{a2})$ and $(F_{b1}, F_{b2})$. Now, if we find that $F_{a2}$ is likely to be predicted by $F_{a1}$, i.e. $P(F_{a2}|F_{a1})$ is high, and we also find that $P(F_{b2}|F_{b1})$ is high, we can say that $S_b$ is likely to be consistent with $S_a$ in regard to $P$. In other words, the consistency in our framework is equivalent to the predictability of answers.

A. MEASURING CONSISTENCY OF PROGRAM

Now, let us apply the above framework to a program code. Suppose we have two comparable code snippets A and B (Fig. 2). In snippet A, the name “out” is used for a return value of open(...) function and also for the first argument of write(...) function. Assume that we learned the relationship between the variable name “out” and these two statements. More formally put, we find that the snippet A has three features:

- $F_{A1}$: the variable is assigned with the return value of “open()”.
- $F_{A2}$: the variable is passed as the first argument of “write()”.
- $F_{A3}$: the variable has name “out”.

We might say that this is the “knowledge” $K$ that we learned about the use of this variable. Furthermore, we have another code snippet B where a certain variable $x$ is used in the exactly same manner; it has three features and we find $F_{A1} = F_{B1}$ and $F_{A2} = F_{B2}$. If we find $F_{A3}$ is also equal to $F_{B3}$, i.e. the name of the variable $x$ is indeed “out”, we can say that the variable name is consistent in regard to our knowledge $K$. The key idea here is that most variables exist with relationship with other variables, and the relationship defines the role (name) of each variable which can be inferred from various aspects of source code.

So far, the framework we presented here is general in that we did not put any assumption on how each feature should look like or what their relationship can be. We later create a more concrete mechanism to express a usage of a variable, and a probabilistic model (knowledge) to measure its semantic consistency in a similar process described above. If the program is not consistent with our model, we can suggest a better name for variables that aligns with our understanding of the program. However, the general framework can be applied to any kind of elements in source code. For example, it is

Fig. 1. Functionally Identical But Semantically Different Functions

Fig. 2. Comparable Code Snippets
possible to measure the consistency between method names and its calling convention, if such features are available. In the rest of this paper, however, we focus on improving the consistency of variable names to improve the code readability using the above framework.

III. PROPOSED METHOD

In this section, we describe how to apply the above framework of naming consistency to program variables. First, we need to capture the usage of each variable in a systematic way. For this purpose, we introduce a graph structure called “Use-Flow Graph” (UFG). The idea of UFG is similar to a dataflow diagram and program dependence graph (PDG). A typical dataflow diagram describes how data is processed and transmitted from one part of a system to another. In most settings, the parts involved in a dataflow diagram are processors or storage devices. UFG involves with a more granular kind of storage: variables and fields in a program. In this sense, UFG is similar to a PDG. However, while a typical PDG only shows the data dependence of each statement, UFG shows the data dependence between each variable. The idea of using a graph for representing the dataflow among variables was disseminated by [20]. We added operators and function (method) arguments as a location. Fig. 3 shows a sample UFG. Note that the graph not only shows how the value is transmitted from each variable (a, b, c, x and y), but also shows how various operators (+, − and *) are applied in the process. This way, we can see how the value of each variable is treated in a series of processing. A comparable PDG for the same program could be written as in Fig. 4.

We further added a way to express conditional branches and loops to UFG, which is explained later. In short, UFG can present how values (variables, fields or constants) are treated at each operation in a precise manner without depending on a language syntax. A path in UFG can show how a particular value is given as an input, processed and tested, and passed to other variables. We then define the “usage pattern” of a variable as a UFG path that is originating from that variable. By traversing the edges in Fig. 3, we obtain the following usage patterns:

- a \rightarrow L + \rightarrow L * \rightarrow x \rightarrow R + \rightarrow return
- a \rightarrow \rightarrow y \rightarrow L + \rightarrow return
- b \rightarrow R + \rightarrow L * \rightarrow x \rightarrow R + \rightarrow return
- c \rightarrow R * \rightarrow x \rightarrow R + \rightarrow return

After obtaining such patterns, we construct and use a probabilistic model that we explained in Section II to test if each variable name is consistent with its usage pattern. In the next subsection, we first explain how to construct UFGs from source code.

A. Constructing Use-Flow Graph

We now illustrate how to construct a UFG from typical language constructs in Java. UFG can be constructed in a linear time for a given program size, allowing to analyze a large project in a reasonable time.

Let us revisit the UFG shown in Fig. 3. In this graph, every operator is represented as a separate node, and the transmission of each value is shown as directed edges. The label of each edge shows at which side of the binary operator that a value is used (either L or R). Note that the order of execution can be recovered by following the edges at each node and each variable is still distinguished as a different path in a graph. So it is still possible to reconstruct the equivalent program from a given graph. We expect that the overall structure of UFG is generally preserved across different programming styles because all the basic operations still have to be applied in the same order to have the same effect. The UFG of a program shows how each piece of data at various locations in a program is interacted with each other. If one takes a look at the UFG around a certain variable, its subgraph is likely to show how the variable is used at the other parts of the program; namely, they are showing its usage.

B. Tracking Multiple Variables

When a program is purely functional, i.e. its output is solely determined by its inputs and there is no side effect, the program can be represented by a single connected UFG with one sink node. When multiple independent variables are modified, however, there will be multiple sinks or disjointed

One of the major differences between our graph and the work by Raychev et al. [12] is that our graph is directional; we only consider a relationship that reflects an actual execution order. For example, there is no direct relationship between variable x and y in this graph.

5Our current UFG generator fully supports Java 8 syntax. In future, we plan to extend this to other popular procedural languages such as C# or C++.

6Exact reconstruction of the original code is not always guaranteed, because not all the side effects and indirect access are preserved. We assume that the lack of these properties do not cause a significant loss of accuracy for our purposes in this paper.

7Note that we do not intend to identify the functional equivalence. Two mathematically equivalent expressions (e.g. a+b and b+a) does not necessarily result in the same UFG. Our goal here is to preserve the intent of programmers as much as possible while removing stylistic differences.
graphs, as shown in Fig. 5. A different graph concerns a different set of data that are unrelated to each other. Note that the original order of execution is not preserved because there is no dependence between statements, and these unrelated statements could be executed in parallel.

C. Conditional Statement
To represent conditional statements such as if, we introduce special nodes. When a value of a certain variable is determined conditionally, all the possible flows are connected to a single Join node (Fig. 6). The idea is to interpret a Join node as something like a railroad switch, or a conditional operator. When the conditional statement is executed, only one of these edges (true or false in this example) is used. Each edge is labeled with its condition so that they can still be distinguished. When multiple variables are modified in the if statement, a similar structure is created for every variable that changed. Note that each statement is converted to nodes in UFG whether or not the statement is actually executed.

D. Loop
We introduce another set of special nodes, Begin and End, to represent a loop. (Fig. 8). For each variable that is modified in the loop, its Use-Flow subgraph is sandwiched with Begin and End nodes. In the case of do loop, as shown in Fig. 8 the conditional test is performed at the end of the loop, and the End node behaves like the Join node in the previous example. The interpretation of this graph is that the subgraph between the Begin and End nodes are repeated by an unknown number of times, and for every time the conditional value p is reevaluated. Note that the purpose of this graph is to show in which context each variable is modified, but not to show how the loop actually runs. A UFG is not suitable for inferring the loop invariant or comparing different loop structures.

E. Function/Method Call
A function or method call in a UFG is simply treated as yet another operator node (Fig. 9). The callee function is referenced. Each function call node has all possible references to the functions that has the same signature, including virtual functions. Each edge for the function arguments is labeled as #arg0, #arg1 and #arg2 and the return value as #return. When we want to obtain a relationship of nodes across multiple functions, however, we can internally treat each call node as if there was another UFG embedded within the node, in a similar manner to code inlining, i.e. the callee function is embedded (Fig. 7). This allows us to consider the relationship of value operations in an interprocedural context.

F. Collecting Usage Patterns
Realistic software usually contains thousands of functions. Since we want to collect a usage pattern of a value in a long context, we want to track how the value is handled and passed across multiple functions. This is done in the following steps. The key idea here is to start from a node of interest (a variable in this case) and gradually incorporate other nodes to multiple functions that are being called:

1) Start from every variable node (a node referring to a variable). This is an initial pattern for this variable usage.
2) Pick the next node by tracing its outgoing edges. Incorporate it as a part of the pattern.
3) If the node is a function call, push the current node to the stack and connect a value node of the caller function to the corresponding argument node of the callee function. This is done by connecting the UFGs of both functions. Incorporate this connection to the pattern.

8The initial variable node itself is not included in a usage pattern.
9In this paper, we limit the number of possible virtual functions that are potentially referenced to 5. When there are 6 or more possible virtual functions, we picked the virtual methods for the five most specific class.
private BufferedReader fp;
public String getName() {
    String line = fp.readLine();
    int i = line.indexOf(' ');
    return line.substring(0, i);
}
public void show() {
    String name = getName();
    System.out.println(name+"!!");
}
public String getField() {
    String buf = fp.readLine();
    return buf.substring(0, buf.indexOf(':'));
}
public String getColumn() {
    String buf = fp.readLine();
    return buf.substring(0, buf.indexOf(','));
}

Fig. 10. Sample Java Code

4) If the node is a return node and the stack is not empty, pop the previous node from the stack. Connect the return node of the callee function with the receiving node of the caller function.
5) If the node is a return node and the stack is empty, Connect the return node of the callee function with the receiving node of a function call node for every function that it potentially calls that function. Multiple patterns are generated.
6) Repeat this process until a pattern grows to a maximum predefined length \[10\]

There are actually two kinds of usage patterns: forward and backward. The process described above is one for obtaining forward usage patterns. For backward patterns, the same process is used for the opposite direction of the edges. From now on, we just use the term “usage patterns” for forward and backward patterns, combined.

Let us illustrate the above algorithm with a more realistic example (Fig 10). Suppose that we are interested in taking a usage pattern of the variable “line” at Line 4. We start from the assignment expression, incorporate the .indexOf() and .substring() node, and reach the end of the getName() function at the return statement. Then we further extend the pattern by incorporating the nodes that are receiving the value of getName() function. In this example, the name node is added to the pattern. We repeat the same process for the backward pattern. At the end, we obtain the following usage pattern for the variable “line”.
- fp.readLine() → line → this.indexOf() → arg1 substring() → name → L + → arg0 println()

G. Detecting Inconsistent Names

In the snippet shown in Fig. 10, there are other functions named getField() and getColumn(). We obtain the usage pattern of their variables “buf” as follows:
- fp.readLine() → buf → this.indexOf() → arg1 substring()

The above pattern is similar to the one obtained for the variable “line”. However, this pattern appears more frequently throughout the program than the previous one, hence the pattern is more strongly associated with the name “buf” rather than “line”. This way, the system can learn that “line” should be better named as “buf” to achieve more consistency.

Note that this sort of knowledge is acquired entirely from the project source code. The system does not use any external knowledge. Naturally, this allows the system to tune to a specific project.

To recapitulate, the overall algorithm of our proposed method is the following:

1) Extract UFGs from source code and collect the usage patterns for each variable.
2) Construct a probabilistic model to test if each variable name is consistent with its usage pattern.
3) If a variable name is found not to be consistent, suggest an alternative name that is more strongly associated with its usage pattern.

H. Constructing and Using Probabilistic Model

After extracting UFGs from source code and obtaining its usage patterns for each variable, we construct a probabilistic model. We try to learn a model that predicts a variable name from a given usage pattern as explained in Section II. In this paper, we used a simple Bayesian inference, i.e. we assume that every node in a usage pattern independently affects the choice of its variable name. In the case of the previous Java example, the features that influence the prediction include: the origin of the value, the way it is used, and its destination (the variable name it is assigned), and so on. A usage pattern is converted to a set of features by encoding the sequence of its adjacent node pairs.

For example, a usage pattern like this
- indexOf() → arg1 substring() → name → L + → arg0 println()

is converted into the following features:
- indexOf():arg1:substring()
- substring():name
- name:L:+
- +:arg0:println()

To give the model more flexibility, names are not treated as a single feature but a set of features based on its tokens. For example, “outputBufferName” is tokenized into three distinct features: “output”, “buffer” and “name”.\[11\] Other than tokenization, the system does not have any prior knowledge about the natural language used in variable names. The list of features for each node of a usage pattern is shown in Table 111.

After learning the model using all the usage patterns throughout the program, the system re-applies them to every variable and see if its prediction matches its original name. If it does, its name is consistent with its usage. If it does not, the

\[11\]Our tokenizer assumes that variable names are either the form of camelCase or snake_case.
We conducted three experiments for the following questions: 

• RQ1. Are usage patterns an effective representation for a variable usage? 
• RQ2. Did the system predict a correct variable name? 
• RQ3. Did the system provide convincing evidences to support the suggested alternatives?

Our results were evaluated by nine reviewers. None of the reviewers were familiar with the source code of a target project. Reviewers were asked not to talk about specific results during the experiments. In the following subsections, we conducted experiments to answer the above questions.

Our experimental setup was a standard desktop PC running Arch Linux. Extracting UFGs and collecting usage patterns from source code took from a few minutes to several hours, depending on the project size. Building a probabilistic model and generating suggestions took several minutes. All the tools and datasets that we used for this experiment are publicly available.

A. Variable Equivalence Test (RQ1)

In the first experiment, we tested if two variables with similar usage patterns have indeed a similar role. This was done by collecting pairs of variables whose usage patterns are similar to each other (the similarity > 0.90), and check if the two variables have a similar name (role). The similarity is computed by taking the cosine distance of two usage patterns as TF-IDF vectors, as in

\[
Sim(p_1, p_2) = \frac{V_1 \cdot V_2}{|V_1||V_2|}, \quad V_i = \sum TF(n_i) \times IDF(n_i).
\]

where \( p_1 \) and \( n_i \) is a pattern and its nodes, respectively.

\[12\text{ TF is the frequency of the pattern that is associated with the variable. } \]
\[13\text{ IDF is the inverse frequency of the pattern over all the outputs. } \]
\[14\text{ Three are the authors of this paper. The other six are graduate students who has a basic experience of Java programming. } \]
\[15\text{ Intel i5, 1.8GHz, 32GB memory. } \]
\[16\text{ https://github.com/euske/fgyama } \]
Then we presented the pairs of variables to the reviewers while hiding the actual variable names by replacing them with “xxx”. The reviewers were asked to look at each variable pair with its surrounding code snippets and choose one of the following options:

(a) Variables must have the same name. (Must-Eq.)
(b) Variables can have the same name. (Can-Eq.)
(c) Variables must have a different name. (Must-Neq.)
(d) Undecidable. (Unk.)

The nine reviewers are presented with randomly selected five variable pairs for 12 projects each. Table V shows the responses. Out of 540 answers, 369 (68%) was either Must-Eq. or Can-Eq.. This suggests that usage patterns are a strong indicator of the role of a variable. The average cosine similarity of Must-Eq. or Can-Eq. pairs was 0.980, whereas the similarity of Must-Neq. was 0.976.

### B. Name Suggestion Test (RQ2)

In the second experiment, we tested if our proposed method can actually check the usage of variable names and suggest a better alternative for those which are found inconsistent with the other parts of the program. This experiment is twofold; first, we presented candidates of a variable name to the reviewers and let them choose the best name among them, where one of the candidates is produced by our system. We also manually created a patch for correcting some of the prominent suggestions by our system and sent it to the original developers of the projects.

1) Evaluating System Outputs by Reviewers: In the first part of the experiment, we presented code snippets to the nine reviewers. For each question, a reviewer is presented with one code snippet with one variable highlighted, and another snippet with a different variable whose usage is similar to the first one, but whose name is hidden. The reviewers were asked to compare the two snippets and infer an appropriate variable name for the hidden one. They can choose from the following candidates, or choose undecided (Unk.):

(a) A name suggested by our system. (System)
(b) A name suggested by a baseline system. (Base.)
(c) The original name (chosen by the developer). (Orig.)

The baseline system here was only to suggest the most common name for each data type. The system produces a number of suggestions for each project. We ranked them by its confidence score and present the top 10 suggestions to the reviewers. The total number of generated suggestions (including ones that were not reviewed) and its score distribution are shown in VI. The screenshot of the evaluation tool is shown in Fig. 12.

Each reviewer answers 120 questions in total. Table VII shows the reviewers’ responses. Out of 1080 (= 9 × 120) answers, 416 (39%) was System. This means that for about 40% of the cases, our system can discover inconsistent variable names and suggest alternatives which are considered better than the ones from the original developers.

Since there is no gold standard for a variable name, we calculated the Fleiss’ Kappa [21] for measuring the inter-reviewers agreement. Fleiss’ Kappa is commonly used for measuring agreement between N people where N ≥ 3. In case of N = 2, Cohen’s Kappa is typically used. The Fleiss’ Kappa for our experiment was $K = 0.45$ (moderate agreement).

For exploring different ways of generating usage patterns, we changed some parameters for feature generation and measured its accuracy against our best output. Table VIII shows how different parameters can affect the system performance.

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17For example, an int variable is always considered to be named i.
2) Sending Patches to Developers: In the second part of the experiment, we manually created a patch for correcting some of the prominent suggestions by the system. The patches were sent to the original developers of the projects. We have gotten 6 responses so far. Three projects adopted our patch, two are still discussing it, and one is rejected because “this is not a high priority” according to the developer.

C. Evidence Persuasiveness Test (RQ3)

Our system can provide the evidences for suggested variable names. An “evidence” is a code snippet where the prominent usage patterns for the target variable were obtained from. This way, a user can review the system outputs and decide if they can accept its result. Since each usage pattern has a weight and is associated with its original location, the system can retrieve top $N$ usage patterns and its originating source code. In this experiment, the reviewers are asked to review a variable name suggestion with its original name and decide if the suggestion is sensible based on the accompanying evidences (snippets). The reviewers are asked to choose the following options regarding the evidences.

(a) It provides strong support for the name. (Strong)
(b) It provides reasonable support for the name. (Weak)
(c) It provides little support for the name. (Poor)
(d) Undecidable. (Unk.)

Table IX shows the reviewers’ responses. Out of 540 answers, 162 (30%) of them are considered as somewhat supportive to the suggested names. The relationship between the reviewers’ ratings and the system-generated confidence score is shown in Table X. It is observable that suggestions with a lower confidence score tend to be considered as a poor evidence.

D. Anecdotal Examples

Here are a couple of anecdotal results (suggestions) that our system produced:

- Make the name more task oriented.

```java
+ void normalize(int normalizationOffset
- void normalize(int normalizeOffset
```

- Use a synonym which aligns better with the other parts of the code.

```java
+ String pkgName = className.substring(...);
- String packageName = className.substring(...);
```

- Correct typo.

```java
+ void normalize(int normalizeOffset
- void normalize(int normalizationOffset
```

V. DISCUSSIONS

Our experiments showed that UFGs and usage patterns can be effectively used for discerning the use of variables. The system does not rely on any predefined knowledge other than the language syntax, and can be applied to a realistic project with modest computational resource.

As for the relevance of the experiment, note that our reviewers were not familiar with the codebase used for the evaluation. We made sure that all the reviewers (including the authors) be
not familiar with a target project in advance, and they do not discuss a specific example during the experiment. However, the reviewers had an advantage of seeing the different parts of the code side-by-side and being presented a direct evidence of inconsistency, whereas the original developers worked on only one part of the code. This way, we argue that it is possible that the reviewers made a better decision for variable naming than the original developers who are obviously more knowledgeable about the code.

A. Threats to Validity

There are a couple of threats to internal validity of our experiments. First, our evaluation is subjective; it is affected by the number of reviewers and their programming knowledge. One could argue that nine reviewers are not enough. However, our Fleiss’ Kappa $K = 0.45$, which is far from random, suggests that our reviewers had some common standard about variable naming. Another concern is the fairness of the reviews. To address the reviewers’ bias, we randomized the order of the system output that is presented to a reviewer so that they cannot know which name was produced by the system. However, in the Variable Equivalence Test (RQ1) we used variables that already have a certain similarity ($Sim > 0.90$).

As a result, this test was not completely blinded.

When generalizing our results to a wider use, the threats to its external validity are the following: There are not enough projects tested. The target language for now is limited to Java. There is a limitation of our UFG extraction program that cannot track dynamic dispatch and variable aliasing, which could be problematic for expanding our method to pointer-rich programming languages like C++. A bigger concern is that our experiment only measured the accuracy (precision) of the system output, but not the overall coverage (recall).

There are concerns related to the performance of the machine learning algorithm. In this paper, we tried to focus on our overall framework and keep the learning part lean. However, we expect that better algorithms (such as Recurrent Neural Network or Conditional Random Field) can produce a better result. One could use a better metrics for comparing usage patterns than ours (Cosine similarity, TF-IDF).

VI. CONCLUSION

In this paper, we presented a novel way of testing the semantic consistency of variable names. We presented a graph structure called Use-Flow Graph which is intended to capture the intent of programmers from source code. Our system learned a naming convention of variables by collecting usage patterns that are represented as a path of UFG nodes. We built a probabilistic model to infer a variable name from its usage patterns. We applied our method to 12 open-source projects and evaluated its results with human reviewers. The experiment showed that our system identified inconsistent variable names and suggest better names reasonably well compared to human developers. We plan to extend the concept of UFGs to apply other program comprehension tasks in future.

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