2016 IEEE/ACM 13th Working Conference on Mining Software Repositories

From Query to Usable Code: An Analysis of Stack Overflow Code Snippets

Di Yang
Department of Informatics
University of California, Irvine
diy4@uci.edu

Aftab Hussain
Department of Informatics
University of California, Irvine
aftabh@uci.edu

Cristina Videira Lopes
Department of Informatics
University of California, Irvine
lopes@uci.edu

ABSTRACT

Enriched by natural language texts, Stack Overflow code snippets are an invaluable code-centric knowledge base of small units of source code. Besides being useful for software developers, these annotated snippets can potentially serve as the basis for automated tools that provide working code solutions to specific natural language queries.

With the goal of developing automated tools with the Stack Overflow snippets and surrounding text, this paper investigates the following questions: (1) How usable are the Stack Overflow code snippets? and (2) When using text search engines for matching on the natural language questions and answers around the snippets, what percentage of the top results contain usable code snippets?

A total of 3M code snippets are analyzed across four languages: C#, Java, JavaScript, and Python. Python and JavaScript proved to be the languages for which the most code snippets are usable. Conversely, Java and C# proved to be the languages with the lowest usability rate. Further qualitative analysis on usable Python snippets shows the characteristics of the answers that solve the original question. Finally, we use Google search to investigate the alignment of usability and the natural language annotations around code snippets, and explore how to make snippets in Stack Overflow an adequate base for future automatic program generation.

CCS Concepts

•**Software and its engineering** → Software libraries and repositories;

Keywords

code mining, automatic program generation

1. INTRODUCTION

Research shows that programmers use web searches extensively to look for suitable pieces of code for reuse, which they adapt to their needs [13, 4, 9]. Among the many good sites for this purpose, Stack Overflow (SO, from here onwards) is one of the most popular destinations in Google search results. Over the years, SO has accumulated an impressive amount of programming knowledge consisting of snippets of code together with relevant natural language explanations. Besides being useful for developers, SO can potentially be used as a knowledge base for tools that automatically combine snippets of code in order to obtain more complex behavior. Moreover those more complex snippets could be retrieved by matches on the natural language (i.e. non-coding information) that enriches the small snippets in SO.

As an illustrative example, consider searching for "java parse words in string" using Google Web search. This yields several results in SO, one of which is shown in Figure 1. The snippet of code provided with the answer that was accepted is almost executable as-is by copy-paste. The job of

Figure 1: Example of Stack Overflow question and answers. The search query was "java parse words in string".

MSR'16, May 14-15 2016, Austin, TX, USA

ISBN 978-1-4503-4186-8/16/05…$15.00

DOI: http://dx.doi.org/10.1145/2901739.2901767

programmers becomes, to a large extent, to glue together these snippets of code that do some generic functionality by themselves. The fact that a Web search engine returned this SO page as one of the top hits for our query closes in on one of the hardest parts of program synthesis, namely the expression of complex program specifications. Hence, it is conceivable that tools might be developed that would do that gluing job automatically given a high-level specification in natural language.

In pursuing this goal, the first challenge one faces is whether, and to what extent, the existing snippets of code that are suggested by Web search results are *usable* as-is. If there are not enough usable snippets of code, the process of repairing them automatically for further composition may be out of reach. This paper presents research in this direction, by showing the results of our investigation of the following questions:

(1) How usable are the SO code snippets?

(2) When using Web search engines for matching on the natural language questions and answers around the snippets, what percentage of the top results contain usable code snippets?

In order to compare the *usability* of different pieces of code, we need to define what *usability* is in the first place. We classified snippets of code based on the effort that would (potentially) be required by a program generation tool to use the snippet as-is. Usability is therefore defined based on the standard steps of parsing, compiling and running source code. For each of these steps, if the source code passes, the more likely it is that the tool can use it with minimum effort.

Given this definition of usability, there are situations where a snippet that does not parse is more useful than the one that runs, but passing these steps assures us of important characteristics of the snippet, such as the code being syntactically and structurally correct, or all the dependencies being readily available, which are of surmount importance for automation.

We first study the percentages of parsable, compilable and runnable (where these steps apply) snippets for each of the four most popular programming languages (C#, Java, JavaScript, and Python).[1] From the results, we saw a significant difference in repair effort (usability) between the statically-typed the dynamically-typed languages, the latter being far less effort. Next, we focused on the best performing language (Python) and conducted a 3-step qualitative analysis to see if the runnable snippets can actually answer questions correctly and completely. Finally, in order to close the circle, we use Google Search in order to find out the extent to which the SO snippets suggested by the top Google results are usable. Being able to find a large percentage of usable snippets among the top search results for informal queries, the idea of automating snippet repair and composition, and finding those synthetic pieces of code via informal Web queries becomes within the realm of possibility.

The remainder of this paper is organized as follows. In Section 2, we present the overall research methodology and environment of our work. The results of qualitative analysis are explained in Section 3. In Section 4 we investigate the usability and quality of top results from Google Web search. In Section 5, we present the related work in the areas of SO analyses, enhancing coding environments, and automated code generation. Section 6 concludes the paper.

[1]Based on the RedMonk programming language popularity rankings as of January 2015, four of the most popular programming languages are Java, C#, JavaScript and Python. We choose these four, also as representatives of statically-typed (the first two) and dynamically-typed languages (the last two).

2. USABILITY RATES

This section describes our usability study of SO snippets. In 2.1, we elaborate upon our goal. In 2.2, we describe the characteristics of the extracted snippets. In 2.3, we present the operations that were carried out on the snippets of each language. We also describe the libraries that were used to process the snippets for each of the languages, and highlight the limitations found[2]. In 2.4 and 2.6, we present the usability rates and error messages for each language. ÆŠ

2.1 Goal

Our goal is to compare the usability rates for the snippets of four programming languages (C#, Java, JavaScript, and Python) as they exist in SO, i.e., in small snippets of code. We also want compare the languages regarding their static or dynamic nature, and target the most usable language. In our study, snippets in Java and C#, which are statically-typed, are parsed and compiled in order to assess their usability level. JavaScript does not have the process of compilation, so we investigate only the parsing and running levels for it. Python is also a dynamic language but it can be compiled. However, this step is not as important as it is for Java and C#, as important errors (such as name bindings) are not checked at compile time. As such, for Python, like for JavaScript, we assess usability only by parsing and running the snippets.

2.2 Snippets Extraction

All snippets were extracted from the dump available at the Stack Exchange data dump site[3].

In SO both questions and answers are considered as *posts*, which are stored with unique ids in a table called `Posts`. In this table, posts that represent questions and answers are distinguished by the field `PostTypeId`. Information about posts can be obtained by accessing the field `Body`.

There are two types of answers in SO, *accepted answer* and *best answer*. An accepted answer is the answer chosen by the original poster of the question to be the most suitable. All question posts have an `AcceptedAnswerId` field from which we can identify accepted answers when these exist. The best answer is the one which has the most number of votes from other SO users. The vote count is stored in the field `ViewCount` of the table `Posts`. Thus, an accepted answer may not always be the best answer.

Finally, in SO, questions are tagged with their subject areas, which include relevant information such as the language or the domain where the question is relevant (networking, text processing, etc.). We get the language information for each accepted answer from these tags, one example on how the social nature of SO helps categorizing and selecting pieces of code.

[2]Note to reviewers: code and data for this study are available upon request, and will be made publicly available upon publication of this paper.

[3]https://archive.org/details/stackexchange, obtained on April 2014.

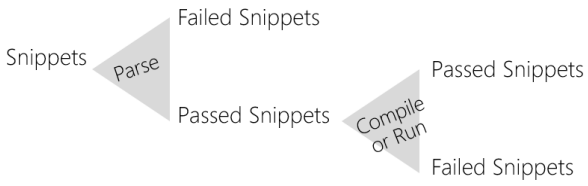


Figure 2: Sequence of operations

In this work, we only include snippets found in all **accepted answers**. We choose accepted these as we value the agreement from the original poster, accepting the fact that it is very likely this answer resolved the original problem. For all posts for a language we were interested in, we used the the markdown `<code>` to extract the code snippets from the field `Body`.

2.3 Snippets Processing

In Table 1 we present the operations we performed to analyze and rate each of language. All the snippets from all languages were parsed, but depending on the static or dynamic nature of the language we either compiled it and analyzed the (possible) errors, or ran the language (below we detail these processes).

Table 1: Operations performed for each language.

Operation	C#	Java	JavaScript	Python
Parse	x	x	x	x
Compile	x	x		
Run			x	x

Figure 2 shows the order in which these operations are performed. We compile (or run) only those snippets which passed parsing, since snippets which are unparsable have syntactic errors and therefore are also non-compilable/non-runnable.

We used a set of tools and APIs to process the snippets in the various languages, which we present next:

2.3.1 C#

For parsing we utilize a tool called Roslyn by Microsoft to obtain the parsable snippets. Roslyn provides for the Visual Studio languages rich APIs for different phases of compilation. In particular, Roslyn provides us with the API for getting the abstract syntax tree, which is the landmark of parsing process. Syntax errors will be detected in this step.

Compiling C# programmatically can be easily done by using a functionality provided by the .NET Framework and found in the `Microsoft.CSharp` and `System.CodeDom.Compiler` namespaces. We need to call the function that compiles the code, and results of whether a snippet compiles or not are returned together with errors if applicable.

2.3.2 Java

Eclipse's JDT (Java Development Tools) Parser (ASTParser) and the Javax.Tools were used for the parsing and compiling processes, respectively. We use JDT1.7 in our experiments since it's the latest version for our data dump.

Using the JDT's `ASTParser` we generated abstract syntax trees of the snippets, and any parse errors found during the process were extracted via the `IProblems` interface.

Javax.Tools compilation functionality first creates a dynamic source code file object of the Java snippet, from which it generates a list of compilation units, which are passed as parameters to the `CompilationTask` object for compilation. Issues during compilation are stored in a `Diagnostics` object. Issues could be of the following kinds: `ERROR, MANDATORY_WARNING, NOTE, OTHER, WARNING`. We only look for issues which are of kind `ERROR`, as they are the ones more likely prevent the normal completion of compilation.

2.3.3 JavaScript

A reflection of the SpiderMonkey parser is included in the SpiderMonkey JavaScript Shell and is made available as a JavaScript API. It parses a string as a JavaScript program and returns a `Program` object representing the parsed abstract syntax tree. Syntax errors are thrown if parsing fails. JavaScript Shell has also a built-in function `eval()` to execute JavaScript code, which we used if parsing succeed.

A limitation of the SpiderMonkey parser is that it terminates the processing of a snippet right when it encounters the first error. Therefore, it does not identify *all* the errors in a snippet, only the first one, but this suffices to detect problems in the code.

2.3.4 Python

Python's built-in AST module and `compile()` method can help us parse code strings. Python is a special language among dynamic languages: it has the process of building abstract syntax tree into Python code objects, so it has the `compile` function. But when we specify one of the function parameters to be AST only, it only parse the code by building the AST. `exec` statement provides functionality to run code strings.

One problem we encountered in processing Python snippets was that Python2 and Python3 have some incompatible language features. To deal with snippets written in different versions of Python, and to avoid being biased when rating these pieces of code, we first examined all Python snippets under Python2 engine, and examined the unparsable ones again under the Python3 engine and combine the results. The Python libraries share the same limitation as JavaScript's SpiderMonkey; they do not catch *all* the errors in a snippet, only the first one.

2.4 Findings

We present the results that were obtained after the initial parsing and compiling (or running) of the snippets.

Table 2 and Figure 3 shows the summary of usability results of all the snippets. A total of 3M code snippets were analyzed. Python and JavaScript proved to be the languages for which the most code snippets are usable: 537,767 (65.88%) JavaScript snippets are parsable and 163,247 (20.00%) of them are runnable; for Python, 402,249 (76.22%) are parsable and 135,147 (25.61%) are runnable. Conversely, Java and C# proved to be the languages with the lowest usability rate: 129,727 (16.00%) C# snippets are parsable but only 986 (0.12%) of them are compilable; for Java, only 35,619 (3.89%) are parsable and 9,177 (1.00%) compile.

As a result of finding such low parsable and compilable rates for Java and C#, we removed Java and C# snippets

Table 2: Summary of results

	C#	Java	JavaScript	Python
Total Snippets Processed	810,829	914,974	816,227	527,774
Parsable Snippets (Percentage)	129,727 (16.00%)	35,619 (3.89%)	537,767 (65.88%)	402,249 (76.22%)
Compilable Snippets (Percentage)	986 (0.12%)	9,177(1.00%)	–	–
Runnable Snippets (Percentage)	–	–	163,247 (20.00%)	135,147 (25.61%)

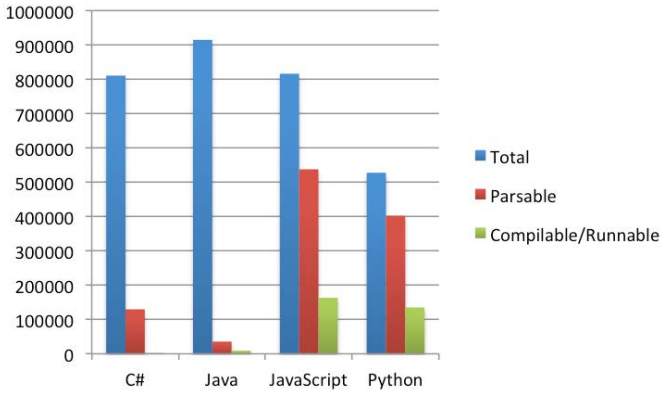


Figure 3: Parsable and compilable/runnable rates histogram

that only contained single words (i.e. tokens without non-alphabetical characters). The rationale behind this step was to that a single word in C# or Java is too insignificant a candidate for composability; by ignoring those snippets we might improve the usability rates for these two languages. We then parsed and compiled the remaining snippets, the results of which are shown in Table 3. We see that the rates of usability improve for both languages, and for both parsing and compilation. For Java, the parsable rate increases from 3.89% to 6.22%, and the compilable rate increases from 1.00% to 1.60%. For C#, the parsable rate increases from 16.00% to 25.18%, and the compilable rate increases from 0.12% to 0.19%.

Table 3: Summary of results for C# and Java after single-word snippets removal

	C#	Java
Total snippets after removal	514,992	572,742
Parsable	129,691 (25.18%)	35,619 (6.22%)
Compilable	986 (0.19%)	9,177 (1.60%)

2.5 Snippet Examples

Figures 4, 5, 6, and 7 show examples of SO snippets that passed and failed for each language. For those that failed, we also show the generated error messages. The examples are representative of the most common error messages.

The unparsable Python snippet in Figure 7 also illustrates a common occurrence in SO posts, where the example code is given more or less as pseudo-code that mixes the syntax of several languages.

2.6 Error Messages

During the usability analysis process, we log the common

C#

Parsable, Compilable

```
using System;
namespace ConsoleApplication1
{
    class Program
    {
        static void Main(string[] args)
        {
            MyClass foo = new MyClass();
            Console.ReadLine();
        }
    }
    class BaseClass
    {
        public BaseClass()
        {
            Console.WriteLine("BaseClass constructor called.");
        }
    }
    class MyClass : BaseClass
    {
        public MyClass()
        {
            Console.WriteLine("MyClass constructor called.");
        }
    }
}
```

Parsable, Uncompilable

```
public void RaisePostBackEvent(string eventArgument) { }

Error(s):
Expected class, delegate, enum, interface, or struct
```

Unparsable

```
Console.ReadLine()

Error(s):
Type or namespace definition, or end-of-file expected
A namespace cannot directly contain members such as fields or methods
```

Figure 4: Examples of C# Snippets.

Java

Parsable, Compilable

```
public class Gallow extends JPanel {
  public paintComponent(Graphics g){
    g.fillOval(10, 20, 40, 25);
  }
}
```

Parsable, Uncompilable

```
public enum Command
{
  START(StartCommand.class),
  END(EndCommand.class);

  private Class<? extends CommandInterface> mappedClass;
  private Command(Class<? CommandInterface> c) { mappedClass = c;
  public CommandInterface getInstance()
  {
    return mappedClass.newInstance();
  }
}

Example Error:
cannot find symbol [symbol: class CommandInterface,
location: class Command]
```

Unparsable

```
List<?> list = (List<?>) object;

Example Error:
Syntax error on token "List", interface expected before this toke
```

Figure 5: Examples of Java Snippets.

JavaScript

Parsable, Runnable

```
function setColor(element, color){
    element.style.backgroundColor = color
}
```

Parsable, Non-runnable

```
expression.call

Error(s):
ReferenceError: expression is not defined
```

Unparsable

```
<%= yield :window_name %>

Error(s):
SyntaxError: expected expression, got '<'
```

Figure 6: Examples of JavaScript Snippets.

Python

Parsable, Runnable

```
import sys
sys.stdout.write('\a')
sys.stdout.flush()
```

Parsable, Non-runnable

```
result = getattr(foo, 'bar')()

Error(s):
name 'foo' is not defined
```

Unparsable

```
p = Pita()
while p( next() ) != END:
   // do stuff with p.pocket!

Error(s):
invalid syntax
```

Figure 7: Examples of Python Snippets.

errors of the four languages. In total, we collected 3,347,674 parse errors and 359,783 compile errors for C#, 1,417,910 parse errors and 199,489 compile errors for Java, 278,460 parse errors and 374,520 runtime errors for JavaScript, and 125,525 parse errors and 267,102 runtime errors for Python.

The common error messages for C# are shown in Figure 8a and 8b, for Java in Figure 9a and 9b, for JavaScript in Figure 10a and 10b, and for Python in Figure 11a and 11b. The error messages are listed in descending order of percentage. The token '[symbol]' is just a replacement for various specific strings appeared in error messages.

The error messages shown for Java and C# were obtained on the collection of snippets without single-words. It is important to note that the libraries used for Python and JavaScript can generate at most one error message for a snippet, so they do not show all problems that each snippet may have.

Main syntax problems are shown in parsing errors, for all four languages. For example for JavaScript, 50% of the parsing errors are not getting an expression. For Java, 25% of the parsing errors are tokens to be inserted.

Errors more related to code context, such as missing symbols, are revealed in compiling or running process. For C#, "type or namespace" is a main issue for usability. For Java, "cannot find symbol" dominates compiling error messages. When running a JavaScript snippet, we are most likely to stop at a reference error, while for Python, the most common runtime error is a specific name not defined.

The purpose for logging the error messages is to provide a knowledge base for repairing codes and increasing usability rates in the future. For example one of the main parsing errors for C# is missing semicolons, then a heuristic repair to C# codes to improve parsable rate can be locating missing semicolons and append them. In next section, we give example of two heuristic repairs for Java and C# snippets.

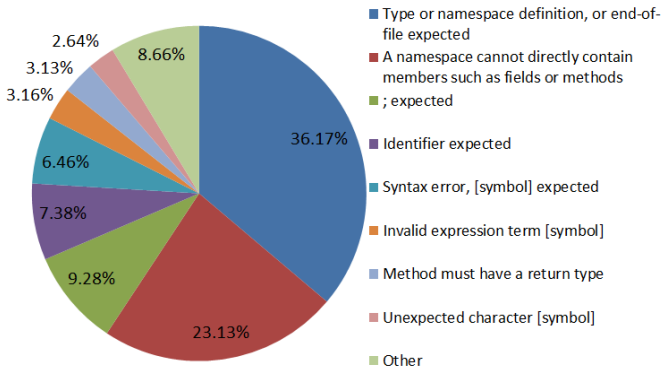
2.7 Heuristic Repairs for Java and C# Snippets

From the preliminary results above, we can see that the parsing rates for Python and JavaScript are significantly better than Java and C#. The parsing errors reveal the main syntax problems, while the compiling errors given above are more related to code context, such as missing symbols. In this case, compiling errors are hard to fix, because we need to look into the specific snippet to complement the missing symbols.

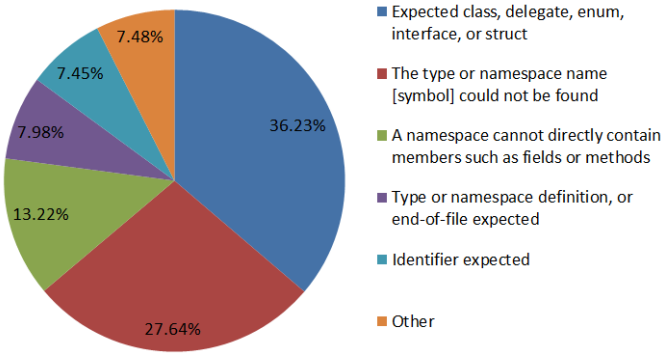
Based on the common error messages for Java and C#, we implemented two heuristic repairs on Java and one repair on C# snippets in order to improve their parsing and compilation rates.

2.7.1 Repair 1 - Class

Many Java snippets consist just of Java code without it being properly encapsulated in a class or a method. The `class` construct is essential for Java snippets. The `class` repair fixes Java code snippets that were found to be missing a class construct based on a heuristic check. This heuristic check works as follows: if the code snippet is found to contain any of the tokens `import`, `package`, or `class`, we assume that the `class` construct already exists in the snippet. The rationale behind this heuristic is that, based on our observations of the snippets, tokens `import` and `package` form scaffolding information of code in SO and are not

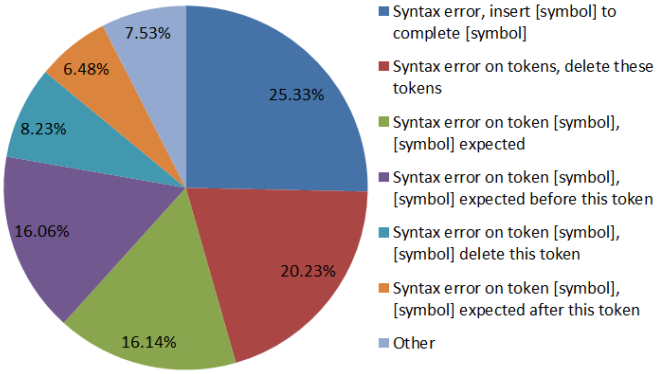


(a) Most common parse errors for C#

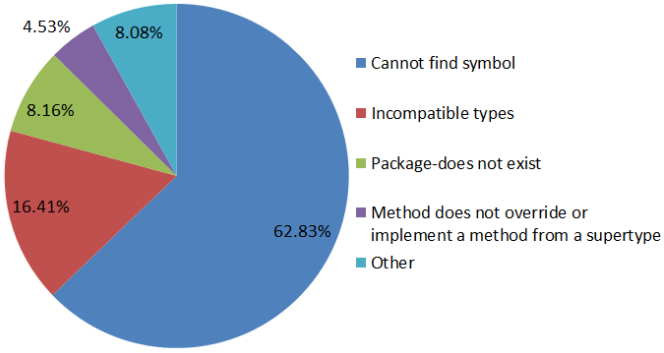


(b) Most common compile errors for C#

Figure 8: Most common error messages for C#

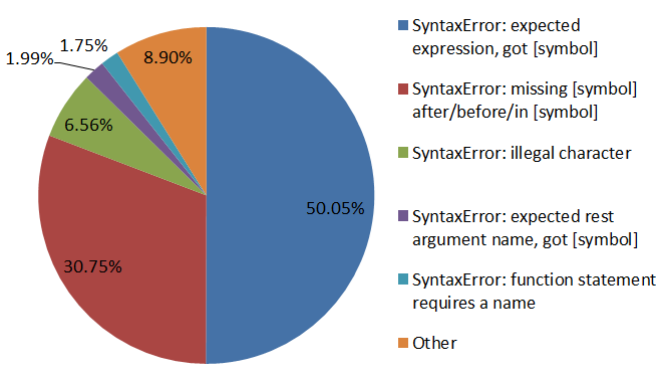


(a) Most common parse errors for Java

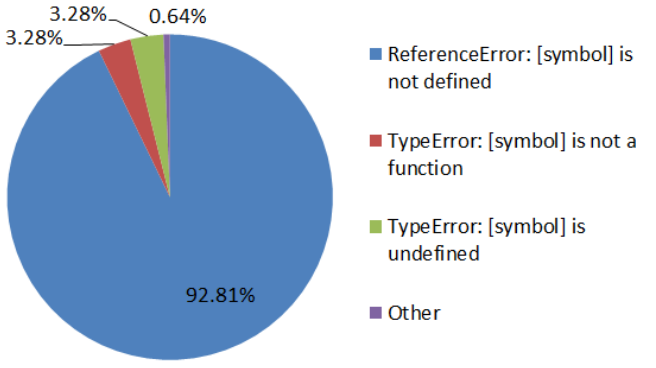


(b) Most common compile errors for Java

Figure 9: Most common error messages for Java

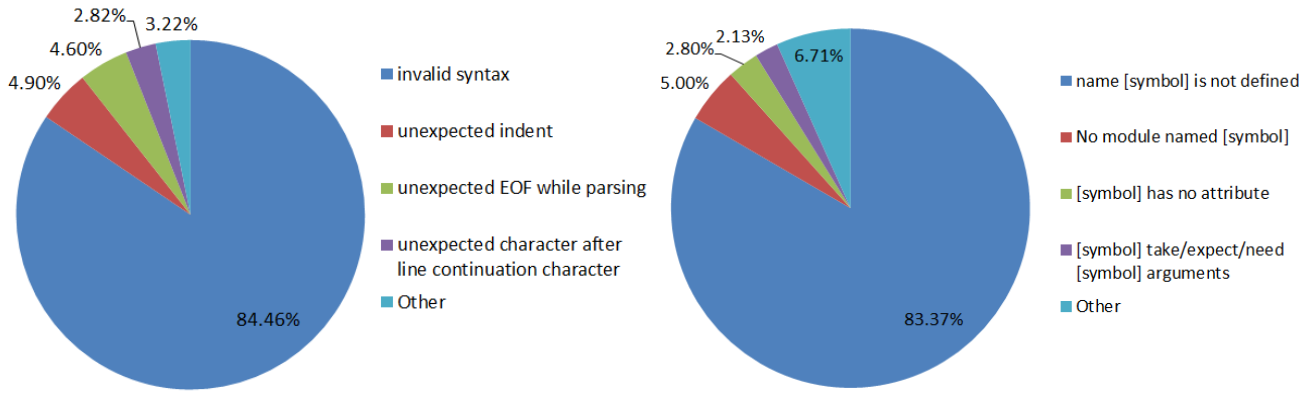


(a) Most common parse errors for JavaScript



(b) Most common runtime errors for JavaScript

Figure 10: Most common error messages for JavaScript



(a) Most common parse errors for Python

(b) Most common runtime errors for Python

Figure 11: Most common error messages for Python

the focus of SO answers. Hence any code that uses one of them is likely to use the `class` construct also. We also assume if a token `class` is present in a code, it exists with enclosing braces and as a keyword and not a part of a string or comment.

Example:

```
\\Repair 1 Candidate
public void main(String args []){
  System.out.println("Hello World");
}
\\After Repair 1
class Program{
  public void main(String args []){
    System.out.println("Hello World");
  }
}
```

Unlike Java, C# does not require a class construct for error-free parsing and compilation, and thus this repair was only applied to Java snippets.

2.7.2 Repair 2 - Semicolon

Java and C# statements require a semicolon (";") at the end in order to parse and compile correctly. To decide whether a ";" should be added to a statement, we run a set of heuristic checks on each line of the snippet; we add the semicolon if all the following conditions are true:

1. If the line does not contain any of the tokens `;`, `{`, `(`, and
2. if the line does not contain any of the tokens `class`, `if`, `else`, `do`, `while`, `for`, `try`, `catch`, and
3. if the line does not end with the tokens = and `}`.

With check 1, we avoid double-adding ";" and avoid adding a ";" at the line of an opening brace, before the opening brace has been closed. With check 2 and 3 we avoid corrupting originally parsable code. With check 2 we avoid the following situation:

```
\\Repair 2
try; <--  will corrupt
{  <code>
}catch...
```

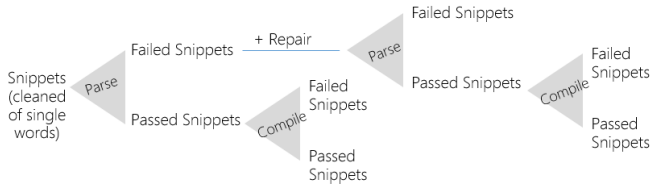


Figure 12: Sequence of operations while applying repairs

With check 3 we avoid the following situations:

```
\\Repair 2 inside assignment
 Double s_dev = ; <-- will corrupt
     Math.pow(sum(mean_sq(al))/al.size(),0.5);
\\Repair 2 between if-else
if ()
{   <code>
} ; <-- will corrupt
else
{   <code>
}
```

2.7.3 Study Workflow for Repairs

The workflow for studying the effect of repairs is similar to the one used for the initial parsing/compiling processes (as shown in Figure 2), except that now we have also incorporated repairs. The process is depicted in Figure 12.

Like the workflow of Figure 2, here at each stage we only compile snippets that have passed the prior step. Failed snippets are repaired and parsed again. The snippets that succeed at parsing are in turn compiled. For Java, we carry out two repairs sequentially, whereas for C# one repair is applied.

2.7.4 Results after Repairs

Table 4 shows the parsing and compilation results obtained for C# and Java after repairing the snippets. Again, the numbers here reflect the collection of non-single-word snippets.

Although the repairs did not significantly increase the usability rates for C#, the improvements were quite significant for parsing Java snippets. The parse rate of C# improved

Table 4: Summary of results for C# and Java snippets after repairs

	C#	Java
Total snippets after removal	514,992	572,742
Parsable snippets after repairs	135,421 (26.30%)	110,203 (19.24%)
Compilable snippets after repairs	986 (0.19%)	17,286 (3.02%)

Figure 13: Example of an incomplete answer in Stack Overflow

by only 1.12% (from 25.18% to 26.30%), whereas for Java the improvement was 13.02% (from 6.22% to 19.24%). The compilation rate did not change for C#, whereas for Java it improved by 1.42% (from 1.6% to 3.02%). There's a significant improvement on the parsable rate of Java.

Again, our approaches are heuristic, and may break some previously parsable or compilable snippets. But we can still see an increase in usability rates.

Even though the parsing and compilation rates improved for Java, the number of usable snippets is still one order of magnitude lower than the numbers for JavaScript and Python.

3. QUALITATIVE ANALYSIS

Based on the usability and popularity, we choose Python as the target language for further analysis. In order to investigate whether the runnable Python snippets can answer the questions *correctly* and *completely*, we perform a 3-step qualitative analysis on randomly selected snippets. By *correctness*, we mean the snippet giving a concise solution to the question; for specific coding questions with bugs, as in Figure 13, the answer is *correct* if it points out the erroneous part and fixes particular lines of code. By *completeness*, we mean that the snippet itself is a full answer to the question; we do not need to add any additional code to answer the question. Figure 13 is an example of correct but incomplete answer, the snippet fixes the bug in the original code but we have to mix the question and answer snippets to get the full answer.

Table 5: Features used to assess the quality of the snippets.

1. Votes for the question
2. Votes for accepted answer
3. Total number of answers
4. Is the accepted answer also the best answer?
5. Questioner's reputation score
6. Answerer's reputation score
7. Does the title correctly summarize the question described?
8. Is the question's description clear?
9. Is it a specific coding question?
10. Does the snippet answer the question correctly and completely?
11. Is it a single word snippet?
12. Is it a single line snippet?
13. Is there any surrounding context/explanation?
14. Number of comments
15. Is there any questioner's compliment in comments?
16. Question's tags

The 3-step qualitative analysis is as following:

Step 1

We randomly chose 50 runnable Python snippets. For each snippet, we investigate the features listed in Table 5. We found out that the proportion of snippets that answer the question is low (16%). We discovered a strong correlation between single word snippets and snippets answering the question, that is, among the 50 selected snippets, none of single word snippets answer the question, and all of the snippets that answer the question are non-single word snippets. The proportion of single word snippets is 64%.

Step 2

Based on the results of Step 1, we removed single word snippets from all runnable Python snippets, and then randomly chose another 50 snippets. We investigated the same aspects as in Step 1, except for No.11 (Is it a single word snippet?).

After removing single word snippets, the proportion of snippets that answer the question increases to 44%. From Step 2, we discovered another negative correlation between single line snippets and snippets answering the question. Among the 21 snippets that answer the question, 19 are multiple line snippets, and among the 20 single line snippets, only 2 answer the question.

Step 3

Finally, we removed the single line snippets, and chose 50 snippets randomly again. We investigated the same aspects as in Step 1, except for No.11 (Is it a single word snippet?) and No.12 (Is it a single line snippet). Again, the propor-

Table 6: Usability Rates of Top Results from Google

	Parsable	Runnable
Top 1	78.1%	30.8%
Top 10	77.9%	29.3%

tion of snippets that answer the question increases, to 66%. Moreover, for the 17 snippets that do not answer the question, 12 of them are incomplete, but correct, answers.

From the result of 3-step qualitative analysis, we can see that multiple-line snippets can best answer the questions. This subset contains 40,245 runnable snippets (29.8% of all runnable Python snippets).

4. GOOGLE SEARCH RESULTS

In this section, we explore the overlap between Google search results and the usable Python snippets. Specifically, we check if the top results from Google for several queries contain parsable or runnable snippets, as well as these snippets' overall quality.

The methodology was as follows. We selected 100 programming related questions from SO's highest voted questions about Python, and use them as queries using the Google search API. We add the constraint "site:stackoverflow.com" and the keyword "Python" in the in the queries. Moreover, because our database was downloaded in April 2014, we also add a date range restriction.

The accepted answers' usability rates of the Top 1 and Top 10 results from Google are shown in Table 6. They are high. As described in Section 2.4, we had found that the usability rates of all the Python snippets in SO are 76% parsable and 25% runnable. The top results on 100 queries to Google on the same SO data have usability rates above those averages. Moreover, the Top 1 results have an even higher usability rate than the Top 10 results.

Also, we find that 33.7% of Top 1 results and 32.5% of Top 10 results are multiple line snippets. Both higher than the average of 30%. So, both from our usability perspective and qualitative analysis perspective, the Google Top 10 search results are better than average, and the Top 1 results are the best.

From the results above, we can also see that the Google top results have a low runnable rate, although higher than average. The main problems encountered in the parsable but not runnable snippets from Google results are those already described for the entire SO snippets (see Section 2.6). Specifically, the majority of them suffered from undefined names or modules. An example of a parsable but not runnable Google search result to the query "Check if a given key already exists in a dictionary" is shown in Figure 14.

Expecting snippets to be runnable as-is may be too strong of a constraint. Parsable snippets seem to be a much more fertile groud as the base for future automatic code generation. Given our analysis of the causes of runtime errors, it seems it should be possible to repair a large percentage of them automatically. For example for Python, missing symbol names often indicate a piece of information that needs to come from elsewhere – another snippet, or some default initialization.

Note that we used the questions as-is as queries for Google; not surprisingly, Google always returned those SO questions as the Top 10 hits in each query. Out of the 100 queries we

Search Query

```
Check if a given key already exists in a dictionary
```

URL of One Search Result

```
http://stackoverflow.com/questions/17308754/
python-how-to-check-if-keys-exists-and-retrieve-
value-from-dictionary-in-descen/17308754#17308754
```

Snippet of Accepted Answer

```
value = None
for key in keySet:
    if key in myDict:
        value = myDict[key]
        break
```

Runtime Error

```
name 'keySet' is not defined
```

Figure 14: Example of Google Search Result

selected, 85 original ones were returned as the first hit by Google. Although 15 original links were not ranked as Top 1, 12 of them were in Top 10. The reason for them not being the first one is that Google seems to have a special heuristic to dealing with "daterange" restrictions. If we remove the "daterange" restriction in our search query, the original ones will appear in Top 1. However, 3 out of 100 queries were not in Top 10 list by Google. We looked at these three cases: one is because of the date range restriction, the second one is because it is a new query out of our date range, and the last one seems to genuinely be because of Google ranking algorithms.

The very high hit rate and, in particular, the top 1 results, confirm Google's efficiency in retrieving relevant information from the Web, something that our work leverages, by design. However, the usability rates on the top hits were encouragingly high, and that is orthogonal to Google's efficiency in finding the most relevant results. These higher-than-average usability rates may be because we used the most popular queries; users of SO value complete answers that have good code snippets, so it is not surprising that the most popular queries have snippets that are better than average.

In general, users search using words that are not exactly the same as the words in the SO questions, so the best snippet of code for their needs may not be in the first position; but, as it is usually the case with Google, it is likely in the top 10 positions. The usability of the snippets in the top 10 positions were not as high, but they were still very high (78% parsable, 29% runnable), and above average of the entire set of Python snippets.

The Google search results over SO snippets are very encouraging. They show that it is possible to go from informal queries in natural language to relatively usable, and correct, code in a large percentage of cases, opening the door to the old idea of programming environments that "do what I mean" [12]. This is possible now due to the emergence of very large mixed-language knowledge bases such as SO.

5. RELATED WORK

Various studies have been done on SO, but focus primarily on user behavior and their interactions with one another. These works made attempts at identifying correlations between different traits of SO users. For example [5] showed a correlation between the age and reputation of a user by exploring hypotheses such as the fact that older users having a

bigger knowledge of more technologies and services. Shaowei et al. [14] provided an empirical study on the interactions of developers in SO, revealing statistics on developers' questioning and answering habits. For instance, they found that a few developers ask and answer many questions. This social research might be important for our prioritization of snippets of code.

Among the works that utilize code available in the public domain for enhancing development is that of Wong et al. [15]. They devised a tool that automatically generates comments for software projects by searching for accompanying comments to SO code that are similar to the project code. They did so by relying on clone detection, but never tried to actually use the snippets of code. This work is very similar to Ponzanelli et al. [10] in terms of the approach adopted. Both mine for SO code snippets that are clones to a snippet in the client system, but Ponzanelli et al.'s goal was to integrate SO into an Integrated Development Environment (IDE) and seamlessly obtain code prompts from SO when coding.

Ponzanelli was involved in another work [1], where they presented an Eclipse plugin, Seahawk, that also integrates SO within the IDE. It can add support to code by linking files to SO discussions, and can also generate comments to IDE code. Similarly, Thummalapenta et al. [11] present a tool called PARSEWeb that assists in reusing open source frameworks or libraries by providing an efficient means for retrieving them from open source code.

With regards to assessing the usability of code, our central motivation, our study comes close to Nasehi et al.'s work [6]. They also analyzed SO code with the motivation of finding out how easy it is to reuse it. In particular, they delved into finding the characteristics of a good example. The difference for our approach was their criteria for assessing the usability of the code. They adopted a holistic approach and analyzed the characteristics of high voted answers and low voted answers. They enlisted traits related to a wide range of attributes of the answers by analyzing both the code and the contextual information. They looked into the overall organization of the answer - the number of code blocks used in the answer, the conciseness of the code, the presence of links to other resources, the presence of alternate solutions, code comments, etc. The execution behavior of the code was not among their usability criteria.

Semi-automatic or automatic programming, a development realm towards which this work takes an initial step, has also been explored in different ways by software practitioners. For instance, Budinskey et al. [2] and Frederick et al. [3], analyze how design patterns could assist in automatically generating software code. Other similar works include [7], [16], and [8]. The similarity in these works is that structured abstractions of code provide a good indicator about the actual implementation. They built tools that exploit this narrative and generate implementations from design patterns. Such a strategy would be highly challenging to use when trying to reproduce usable SO code (with respect to compilation), as those codes are usually small snippets that do not follow familiar patterns.

6. DISCUSSION AND CONCLUSION

Some of our experiment choices deserve an explanation:

- In SO, the concepts of accepted answer and best answer are different. Accepted answer is the one approved by the questioner, while best answer is voted by all viewers. We chose accepted answer in this work because we believe that in a Question&Answer forum as SO, the questioner the one who has the best judgement of whether the answer solves the problem. However, it is possible that the questioner makes mistakes and that the answer voted the best by other viewers is most usable. In the future we will evaluate the usability of best answers and compare the results with those of presented here.

- Our definition of usability is purely technical, and does not include the concept of usefulness other than indirectly, by the fact that the analyzed snippets are in the accepted answers. It is possible that a snippet that does not parse is more useful than the one that runs; or that a snippet that does not parse or run is still useful to the answer the question. For example, if the question asked in SO is not a specific programming query, people may answer with pseudo code, which is not usable in our case, but may also answer the original question. Those cases, however, will always be out of reach of automatic tools, as they will require many more repairs or even translation from pseudo-code to actual code. As such, this study focused conservatively on those snippets that are part of accepted answers and that show good potential to being used as-is or with little repairs.

In this paper, we examined the usability of code snippets in Stack Overflow. The purpose of our usability analysis is to understand the extent to which human-written snippets of code in sites like SO could be used as basic blocks for automatic program generation. We analyzed code snippets from all the accepted answers for four popular programming languages. For the two statically-typed, compiled languages, C# and Java, we performed parsing and compilation, and for the two dynamic languages, Python and JavaScript, we performed parsing and running experiments. The results show that usability rates for the two dynamic languages is substantially higher than that of the two statically-typed, compiled languages. Heuristic repairs improved the results for Java, but not for C#. Even after the repairs, the compilable rates for both Java and C# are very low. The results lead us to believe that Python and JavaScript are the best choices for program synthesis explorations.

Usability as-is, however, is not enough to ensure that the snippets have high information quality. Our qualitative analysis on the most usable snippets showed that multiple line snippets have the highest potential to answer the questions. We found 40K+ of these for Python, meaning that there is a good potential for processing them automatically.

Finally, in order to close the circle on our original vision, we investigated the extent to which the top results of queries on SO using Google Web search contain these usable snippets. The results are very encouraging, and show a viable path from informal queries to usable code.

7. ACKNOWLEDGMENTS

This work was partially supported by grant No. 1218228 from the National Science Foundation and by a grant from the DARPA MUSE program.

8. REFERENCES

[1] A. Bacchelli, L. Ponzanelli, and M. Lanza. Harnessing stack overflow for the ide. In *Proceedings of the 2012 Third International Workshop on Recommendation Systems for Software Engineering (RSSE)*, pages 562–567. ACM, 2013.

[2] F. J. Budinsky, M. A. Finnie, J. M. Vlissides, and P. Yu. Automatic code generation from design patterns. *IBM Systems Journal*, 35:151–171, 1996.

[3] G. Frederick, P. Bond, and S. Tilley. Vulcan: A tool for automatically generating code from design patterns. In *Proceedings of the 2nd Annual IEEE Systems Conference*, pages 1–4, 2008.

[4] R. E. Gallardo-Valencia and S. Elliott Sim. Internet-scale code search. In *Proceedings of the 2009 ICSE Workshop on Search-Driven Development-Users, Infrastructure, Tools and Evaluation*, SUITE '09, pages 49–52, Washington, DC, USA, 2009. IEEE Computer Society.

[5] P. Morrison. Is programming knowledge related to age? an exploration of stack overflow. In *Proceedings of the 10th IEEE Working Conference on Mining Software Repositories (MSR), 2013*, pages 69–72. IEEE, 2013.

[6] S. M. Nasehi, J. Sillito, F. Maurer, and C. Burns. What makes a good code example? - a study of programming q and a in stackoverflow. In *Proceedings of the 28th IEEE International Conference on Software Maintenance (ICSM)*, pages 102–111. ACM, 2012.

[7] J. Noble and R. Biddle. Patterns as signs. In *Proceedings of the 16th European Conference on Object-Oriented Programming*, ECOOP '02, pages 368–391, London, UK, UK, 2002. Springer-Verlag.

[8] M. Ohtsuki, A. Makinouchi, and N. Yoshida. A source code generation support system using design pattern documents based on sgml. In *Proceedings of the Sixth Asia Pacific Software Engineering Conference*, APSEC '99, pages 292–, Washington, DC, USA, 1999. IEEE Computer Society.

[9] K. Philip, M. Umarji, M. Agarwala, S. E. Sim, R. Gallardo-Valencia, C. V. Lopes, and S. Ratanotayanon. Software reuse through methodical component reuse and amethodical snippet remixing. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, CSCW '12, pages 1361–1370, New York, NY, USA, 2012. ACM.

[10] L. Ponzanelli, G. Bavota, M. D. Penta, R. Oliveto, and M. Lanza. Mining stackoverflow to turn the ide into a self-confident programming prompter. In *Proceedings of the 10th IEEE Working Conference on Mining Software Repositories (MSR), 2014*, pages 102–111. ACM, 2014.

[11] T. Suresh, C. Luigi, A. Lerina, and D. P. Massimiliano. An empirical study on the maintenance of source code clones. *Empirical Software Engineering*, 15(1):1–34, 2010.

[12] W. Teitelman. *PILOT: A Step towards Man-Computer Symbiosis*. PhD thesis, September 1966.

[13] M. Umarji, S. Sim, and C. Lopes. Archetypal internet-scale source code searching. In B. Russo, E. Damiani, S. Hissam, B. Lundell, and G. Succi, editors, *Open Source Development, Communities and Quality*, volume 275 of *IFIP – The International Federation for Information Processing*, pages 257–263. Springer US, 2008.

[14] S. Wang, D. Lo, and L. Jiang. An empirical study on developer interactions in stackoverïňĆow. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing)*, pages 1019–1024. ACM, 2013.

[15] E. Wong, J. Yang, and L. Tan. Autocomment: Mining question and answer sites for automatic comment generation. In *Proceedings of the 2013 IEEE/ACM 28th International Conference on Automated Software Engineering (ASE)*, pages 562–567. ACM, 2013.

[16] Y. Zheng. 1.x-way architecture-implementation mapping. In *Proceedings of the 33rd International Conference on Software Engineering*, ICSE '11, pages 1118–1121, New York, NY, USA, 2011. ACM.