AN ACCURATE MODEL OF SOFTWARE CODE READABILITY

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Abstract: *In this paper we present the role of software readability on software development cost. We dispute that the upfront cost of incorporating software readability pays off attractively at later stages in the life cycle, especially at the maintenance phase which is where most of the life cycle cost of software is expended. We explore the concept of code readability and investigate its relation to software quality. We build an automated readability measure and show that it can be 75 percent effective and better than a human, on average, at predicting readability judgments. We also measure the snippets on over million lines of code, as well as longitudinally, over many releases of selected projects. At last, we discuss the suggestions of this study on Programming language design and engineering practice.*

Index Terms - Software readability, code readability, software maintenance.

1. INTRODUCTION

Aggarwal claims that source code readability and documentation readability
are both critical to the maintainability of a project [10]. Our analysis of different software development activities shows that software readability has a global effect on
Software development cost and is independent of software size (i.e., KSLOC). We also discover the concept of code readability and examine its relation to software quality [1]. This is a new advance to measuring the complexity of software systems [2]. Software industry uses software metrics to measure the complexity of software systems for software cost estimation, software development control, software assurance, software testing, and software maintenance [3], [7], [5]. We find out the concept of code readability and study its relation to software quality. With data collected from open source, we derive associations

between a simple set of local code features and human notions of readability. We construct an automated readability measure and show that it can be 80% effective, and better than a human on average, at predicting readability judgments. This model of software readability correlates strongly with human annotators and also with external (widely available) notions of software quality. To understanding the usefulness of the objective model of software readability, we have to consider the readability metrics in natural languages. A number of readability measure and formulas were defined, but only few succeeded to conform validation standards. Few of the most popular readability formulas include: Flesch's Reading Ease Score [12], Dale-Chall's Readability Formula [13], SPACHE Readability Formula, FryGraph Readability Formula, SMOG Grading, Cloze Procedure, Lively-Pressey's Formula and Gunning's Fog Index (or FOG).

2. BACKGROUND

In addition, readability factors may vary significantly based on application domain. This research is needed to determine the extent of this variability, and whether specialized models would be useful. Another possibility for improvement would be an extension of our notion of local code readability to include broader features. While most of our features are calculated as average or maximum value per line, it may be useful to consider the size of compound statements, such as the number of simple statements within an if block. For this study, we intentionally avoided such features to help ensure that we were capturing readability rather than complexity. However, in practice, achieving this separation of

concerns is likely to be less compelling.Readability measurement tools present their own challenges in terms of programmer access. We suggest that such tools could be integrated into an IDE, such as Eclipse, in the same way that natural language readability metrics are incorporated into word processors. Finally, in line with conventional readability metrics, it would be worthwhile to express our metric using a simple formula over a small number of features. Using only the truly essential and predictive features would allow the metric to be adapted easily into many development processes. In addition, with a smaller number of coefficients the readability metric could be parameterized or modified in order to better describe readability in certain environments, or to meet more specific concerns.

3. METHODOLOGY

3.1 SELECT THE SNIPPET

In the generation of readability model, first collected the snippets from different project open source software repository. Snippet is small part of the code. A snippet does include preceding or in-between lines that are not simple statements, such as comments, function Headers, blank lines, or headers of compound statements like if-else, try-catch, while, switch, and for. These snippets must be too short to aid feature discrimination. However, if snippets are too short, then they may obscure important readability considerations. Second, snippets should be logically coherent to allow annotators the context to appreciate their readability. These snippets are given to the annotators; these are the people who can write the functionality of the code.

Table 2.1 snippets from different project

SNO	PROJECT NAME	NUMBER OF LINES
1	2D GAMES	2623
2	BSPMAP	8442
3	GAME	1526
4	LIBRARY RECORD STYSTEM	836
5	PAYROLL	535

3.2 SCORING READABILITY

We can give ratings to the snippets in given order from 1 to 5. If the code is "more readable" the metric value is 5,

if less the metric value is 1or 2, if in the average case the metric value is 3. According to given instructions they are gave ratings for the snippets from different project in the given order. First, forms a set of features that can be detected statically from a snippet or other block of code. For any code it contains some of local code features those are to be Line length (# character), identifiers,
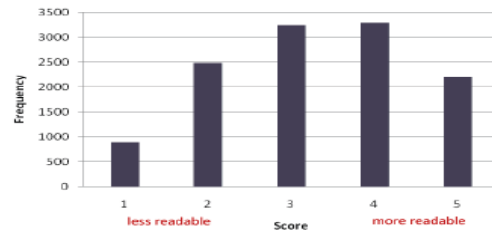

Fig:3.1 Distribution of readability score on code snippets taken from several open source projects

identifier length, Indentation (preceding whitespace), Keywords, Parenthesis, Numbers, Comments, Periods, branches, loops likewise nearly 18 features are there. Each feature can be applied to an arbitrary sized block of Java source code, and each represents either an average value per line, or a maximum value for all lines. For example, we have a feature that represents the average number of identifiers in each line and another that represents the maximum number in any one line. There are several machine learning algorithms are available for this situation. Such algorithms typically take the form of a classifier which operates on instances. For our Purposes, an instance is a feature vector extracted from a single snippet. In the training phase, we give a classifier a set of instances along with a labeled "correct answer" based on the readability data from our annotators. The labeled correct answer is a binary judgment partitioning the snippets into "more readable" and "less readable" based on the human annotator data. We group the remaining snippets and consider them to be "more readable." Furthermore, the use of binary classifications also allows us to take advantage of a wider variety of learning algorithms [9]. After making the training and testing phases we generated a readability model. Using this readability the readability of the code is calculated. The readability is to be comes between 0-1, means a fractional value[10]. The readability model which is to be developed is to be incorporated into the graphical user inter phase such as to be NetBeans or Eclipse we can easily

understand the readability and we can also generate graphs to the readability of the code which is to be taken to calculate the readability.

The graphical representation is to be for the better understanding purpose. NetBeans and Eclipse are to be the IDEs (Integrated Development Environment), and if we incorporate this model into the IDEs, we can make more friendliness to the users to use the readability model in nature. Many organizations can be using this to check their code readability. If code readability is less then automatically the quality of the code also to be less. Readability and quality both are to be interrelated in nature. If readability is less then they try to increase the readability of the code by changing the code. Then automatically quality of the code also increases. Anyone can automatically judge readability about as well as the "average" human can.

4. RESULT

Unlike other formulas, it is easy to calculate and is regarded as more accurate readability index. Total number of words, syllables and sentences are the basic counts of the formula. Then it uses average sentence length and average number of syllables per word to compute a final readability score for a given text. The original Flesch Reading Ease Formula is as below:

R:E: = 206.835 - (0.846 *wl) - (1.015 * sl)

Here:

R.E. = Reading Ease

wl = Word Length (The number of syllables in a 100 word sample).

sl = Average Sentence Length (the number of words divided by the number of sentences, in a 100 word sample).

Below is the modified form of the formula in case of text having more than 100 words:

R:E: = 206.835 - (84.6 * ASW) - (1.015 *ASL)

Here:

ASW = Average Number of Syllables per Word (total number of syllables divided by the total number of words).

ASL = Average Sentence Length (the number of words divided by the number of sentences).

Constants in the formula are selected by Flesch after years of observation and trial [14]. The R.E. value ranges from 0 to 100 and higher value implies easier the text is to read. Abram and Dowling [14] use interpretations for FRES, originally specified by Klare and Campbell.

The above mentioned is one example for the natural language readability metrics. These metrics can help organizations gain some confidence that their documents meet goals for readability very cheaply, and have become ubiquitous for that reason. We believe that similar metrics, targeted specifically at source code and backed with empirical evidence for effectiveness, can serve an analogous purpose in the software domain. Most of the classical readability formulas, including FRES, are based on the count of lexical tokens or entities, e.g., total number of words, unique words, sentences, syllables, and paragraphs. In order to apply readability formulas to computer programs, one has to find the equivalents of these lexical entities for a program text. Programming languages at present are not exactly same as natural languages are, however the basic lexical units are similar. They have their own set of characters equivalent to alphabets, keywords and user defined identifiers equivalent to words, statements equivalent to sentences, block structures equivalent to paragraphs or sections, and modules equivalent to chapters.

An experiment is to be conducted on to the small part of the java code called snippet. This experiment is conducted using the IDE as Netbeans tocalculate the readability of the code. For this experiment given the snippet as

```
Class clas = object.getClass();
Field field = Reflect.resolveJavafield
( clas, name, false/*onlyStatic*
if ( field != null )
return new Variable(
name,field.getType(),new
LHS(object,field ) );
```

The above used a snippet from the java code and this is used as a input to my model and the output generated is the readability score. The readability score is

0.5342345566
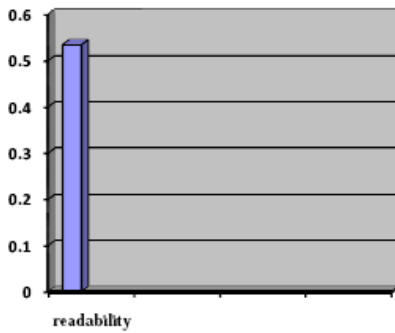
The above mentioned graph is to be the calculated readability of the given snippets. Using the model like above it can be calculated for any snippets

Conclusion

The techniques presented in this paper should provide an excellent platform for conducting readability formula, especially with respect to unifying even a very large number of judgments into an accurate model of readability. While we have shown that there is significant agreement between our annotators on the factors that contribute to code readability, we would expect each annotator to have personal preferences that lead to a somewhat different weighting of the relevant factors. It also investigates whether a personalized or organization-level model, adapted over time, would be effective in characterizing code readability.

5. REFERENCE

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Biography

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