# 

**Introduction**

The most expensive, time consuming, and longest part of the software development life cycle is widely known to be maintenance, and work is always being done to try and simplify this lengthy portion of the life cycle. Our goal with this current research is to offer a method for detecting commented out code within a script, with the hopes that we can improve maintenance time and mitigate confusion later on when commented out code is found. Our thought process is that if we can detect commented out code rapidly throughout the development phase of the software when there is a direct route to question why it has either been added in or commented out at the time of origin rather than trying to decipher the meaning later on. Of course the benefits are not limited merely to maintenance, by detecting commented out code early we have the ability to protect companies from disclosing security vulnerabilities that may be outlined in sections of commented out code or to avoid sections of commented out code that have the potential to be accidently made active, for example comments held in an *if(0)* block.

*If(0){  
ResetTotal();*

*PrintTicket();}*

A prominent example of the need for more research into commented out code comes from the Knight Capital case which occurred on August 1, 2012. On that day, an updated copy of Knight Capital’s stock purchasing software was deployed on seven of their eight servers with a fatal flaw, a flag was set to active on a portion of dead code meant purely for simulation purposes. The activation of this commented out code led to the purchase of over seven billion dollars’ worth of stock in the span of one hour and even after all of the returns and buy backs would still leave the company at a net loss of 440 million dollars after just one hour of their software running.[Dolfing 2019] All of this trouble could have easily been avoided if dead code was not permitted to be in the final launch version of the companies’ software, but this is a task that is easier said than done with the sheer size of projects growing every day.

Research in this area is exceptionally limited and the debate on text detection is an ever changing and evolving field. In order to detect commented out code we break down every line in to individual characters and store them in a dictionary which is then further broken down into frequencies of each character in comparison to the total number of characters in the line. In order to automate the process we develop a data artifact that is read and evaluated by hand in order to create an environment that is optimized for training our automation process. Our research sets out to answer two questions, is it possible to use character frequency to identify commented out code and is it possible to automate this process within an acceptable margin of error, alpha = .05.

In Chapter 2, we go over related works focused primarily in natural language processing. In Chapter 3 we detail the process of data collection. Chapter 4 focuses on the analysis of the data that we have obtained and processed in the data artifact. Chapter 5 talks about the results of the automation process on test data. Chapter 6 focuses on our threats to validity as well as thoughts on solutions to them. Chapter 7 outlines our plans for future work based off of the results from this study. Finally, Chapter 8 is our conclusion, giving a brief overlay on all our results.

# 

**Related Work**

Because the detection of commented out code is a much newer field of research, we have made the decision to look into research that includes identifying the scope of comments and readability as well. Borstler and Paech conducted a study to investigate the effect method chain and code comments have on the ability for a programmer to comprehend software. The previous works reviewed prior to study focused on only one factor in rating the readability of source code. The study shifted focus to method chain and code comments. The questions being tested were: “How does the amount and quality of source code comments affect software readability and comprehension? and, “How does method chaining affect software readability and comprehension?”. The subjects who were reviewing code snippets first to assess readability, then parts of the code were removed, and the programmers were tasked to fill in the blanks with code that would achieve the original intention based on their understanding. There were originally 255 subjects, after filtering down the most qualified, there were 104 left. The code snippets were broken down into 6 types with a total of 36 snippets to review [Borstler and Paech 2016]. The results show a relationship between the quality of code comments and the readability of the code. The good comments were rated to contribute in a positive way an accurate representation of the source code, “Code snippets with good comments (GC) are perceived as the most readable and the variants without comments (NC) are perceived as the least readable”. The level of experience of the reviewer had an accuracy rating of the snippets as well. The more experience a subject/reviewer possessed reflected his or her ability to understand the code snippets and later fill in the blanks of missing code. “Overall, the student group without a naming preference finds the snippet variants more difficult to read than the other groups and also has the lowest answer accuracy (Acc).” The lack of significant effect method chains had the readability of the code was surprising the authors. “we can conclude that there are statistically significant differences in the perceived readability of the tested code snippets with respect to different comment variants (RQ1).”[Borstler and Paech 2016]

The model in Quality Analysis of Source Code Based Comments is based off of comment categorization which is based on four criteria to evaluate the quality of the comments generated using a heuristic approach. Similar studies that were conducted on comments analysis focused on a specific characteristic to evaluate the quality of the comments, unlike Steidl et al. who were focused on a more generalized evaluation of the effectiveness in the semi-automatic generated comment. Two separate training sets were created for the programs created in Java and C++. The code snippet was used on both types of code to find commented out code. A decision tree algorithm was used to classify the comments using the four preset criteria: coherence, usefulness, completeness, and consistency. The authors explain the model is based on entities, activities, and criteria to determine the effectiveness and how useful the comments are to developers to understand the source code. The criteria are used to give a positive or negative impact on a comment type. The first metric used was the extraction of words within the comment and compared against the words used in the method names. Two hypotheses were formed off this metric on the relationship coefficient being able to show how accurate the comment created is to the purpose of the source code. The second metric used was the length of the comments as a way to evaluate if there is coherence with comments and source code. Two more hypotheses were formed on the length metric which are based on the number of words in a comment reflects if it is too short to be useful or too long to properly be cohesive with the source code. The survey was created was online and taken by sixteen developers to rate the effectiveness of the semi-automatic comment generator. The coefficient was proven effective on predicting the coherence of the comment to the source code from the results of the survey. The length was proven to be an indicator as well, however, developers preferred the longer comment proving the first part of one of the hypotheses. A case study was conducted to evaluate the comment ratio (CR) of the number of characters found in the source code and the coefficient and length being indicators of effectiveness of the comment to the purpose of the source code. Based on the results the authors suggest using CR in conjunction with additional metrics. Finally, the study showed the coefficient and length were useful to improve the quality of the comment created.[Steidl et al. 2013] Here is where we see the mention of commented out code attempting to be detected directly, though they are relying on snippets and terms found within the code for detection, which our method is able to outperform for two reasons, first our method is not dependent on the code for which the comments are being scanned, and second abnormalities in commented out code such as unused functions may not be detected in a method like this.

In A Survey of Automatic Generation of Source Code Comments: Algorithms and Techniques it is stated early in the article that no matter the method used; a large issue is the lack of a unified data set to be used as a standard for testing. The paper is broken into six different sections. The first section is an introduction explaining how automatic commenting methods are a relatively new concept, and there is still much room for improvement. The second section breaks the basic concept of how an automatic system mines for information within the source code, the code is then put into natural language and finally it’s evaluated for how effective the summary is in explaining the key points. The research the authors have compiled as a basis shows a new trend of deep neural network-based method emerging. The third section explains the three main algorithms used for automatic comments generate: information retrieval (IR), deep neural networks, and other comment generation. IR uses target code against other source code and determines the relevant words to be returned to create the comments. The issue with IR is that data set need to be of high-quality data to find matching comments to use code clone detection to generate the comments. IR uses techniques such as VSM and LSI to retrieve information, however a drawback is these techniques don’t use the source code documents. Deep neural networks are broken into three kinds of networks: Convolutional Neural Network, Recurrent Neural Network (RNN) and Recursive Neural Network (RvNN). These networks use encoder-decoder structures to retrieve information and predict comments and is supplemented attention mechanism to improve accuracy of the comments. The third algorithm, other comment generation, uses previously established models and uses stereotype identification to create the comments. The fourth section begins by explaining the four main metrics used for automatic evaluation: BLEU, METEOR, ROUGEm and CIDEr. These automatic evaluation metrics are useful but have disadvantages to effectively review the comments generated. Next the authors discuss the high accuracy rate of human evaluation judging effectiveness of automated comments, however it’s slower and most costly than the automatic metrics. Section five discusses the authors’ thoughts on the future direction of source code commenting methods such as synergy of deep neural network and other models, and the unification of test datasets.[Song et al. 2019] This concept of automatic generation of comments by way of machine learning and analysis of source code is a concept which could be reverse engineered in the future to develop yet another method for detecting of commented out code.

The case study presented in On the Use of Automated Text Summarization Techniques for Summarizing Source Code -Literary Summary had four subjects who were computer science students. Each were given three days to become familiar with two Java software systems, then they are given a series of summaries generated by lead, VSM, LSI, and baseline techniques. Each technique was weighted by binary-entropy, tf-idf, and log schemes. The summaries were generated as both 5-term and 10-term summaries. The results were gathered by a four-level Likert scale. After marking 1-4 with (4 being “highly agree”) the students were then told to rate using 0 and 1 the relevance of the terms used for method or class. To improve the quality of the study and future research, a 3-question follow-up questionnaire to evaluate how developers choose their answers. There was no time limit on when the students had to be finished with their evaluations. Only two of the students displayed similar tactics when evaluating the effectiveness of the summaries, however, the articles selected as effective varied between the students. The data showed the students preferred lead summaries using 10-terms due. The result was concluded to be due to the number of terms deemed relevant being included in the summaries. VSM 10-term summaries were second on being favored. The surveyors then had the developers (after a 4-month gap between the first evaluation and second) evaluate a second set of summaries generated from a combination of lead and VSM techniques once again being divided in 5-term and 10-term length. Upon evaluation there was little intersection between the terms chosen by the two techniques to use in the summaries generated. The two techniques focused on different information within the code deemed relevant, specifically the information found in method and the class. The new hypothesis created for the second evaluation was the new summaries would score higher on effectiveness from the student than the summaries generated by the four individual techniques. The results of this second evaluation proved the hypothesis correct. The highest average score from the first evaluation was 2.89 on a 4-point scale versus the highest average for the second session was 3.54. The highest averages were for 10-term summaries as well. The conclusion of the study was combining text summarization techniques is more effective than using an individual summarization technique.[Haiduc et al. 2010] The methodology used in this case study holds much closer to the common conventions of Natural Language Processing, both for analysis and for generation of these summaries. One major difference about our work and theirs is that they do not care about the existence of commented out code. (pagebreak)

**Data Collection**

In order to ensure that all of the comments found in the source code are properly pulled for analysis the language parsing tool, srcML, is used [Collard and Maletic]. At its core srcML is a tool designed to take source code and automatically convert it into an XML representation. srcML processes source code independent of the preprocessor, which functions well for the purposes of this project because it means that when comments are being extracted from the source code we do not have to worry about things such as missing libraries needed to actually run the source code. Further, because srcML does not need to compile the code in order to analyze and extract information it is able to run extremely quickly, which is great for the purpose of this project due to the large number of files that are being analyzed. Another reason that srcML is selected as the extraction tool for this project is because of the tools ability to leave the original structure of the source code entirely intact, meaning that whitespace, comments, and all preprocessing comments are left untouched. Once source code has been converted to XML using srcML the user is able to write XPath, a query language for selecting nodes from an XML document, queries to pull any specific information needed from the original source code quickly and easily which allows us to ignore the actual code in the source and just the comments can be extracted. The original path of the files is preserved and in the case of scanning whole directories XSLT, a language for transforming XML documents into other XML documents, may be used in conjunction to create an archive of these queries. Currently, the greatest limitation of srcML is that it can only parse C, C++, C#, and Java, though for the purposes of this research this is not an issue.

To ensure that the quality of the base source code that is being used in this project is maintained and written by programmers with more experience it is decided that the best approach is to pull highly trafficked projects from GitHub. The reason for this is two-fold, first, projects that have higher rates of traffic are likely to be better maintained as there is greater scrutiny on the projects, and second, these projects are more likely to be written by programmers with greater experience and better represent the general population of programmers. Based on this, the 20 topmost trafficked C, C++, C# and Java projects have been selected and pulled for the use in building the data artifact used in this project. srcML currently only supports C, C++, C# and Java, however, as these are among the most popular languages used in industry and open source, we do not consider this a threat to validity in our current research.

To do this the first step is to convert the entire series of projects into one large archive XML file of all of the code present in all of the source code of each of the 20 projects. This archive can be simultaneously broken down into just the comments from these projects by including an XPATH query that looks for just the comments in the source code. The query we use is:

*srcml --xpath “//src:comment” project.xml -o comments.xml*

In the case of this research, this is the appropriate step to take as the rest of the source code is not needed. Since the long term goal of this research is to use automated verification of comments through machine learning it is important to ensure that the initial variables being given to the machine learning algorithm are as accurate as possible, to this end a manual verification approach was decided by reviewing thousands of lines of comments term by term.

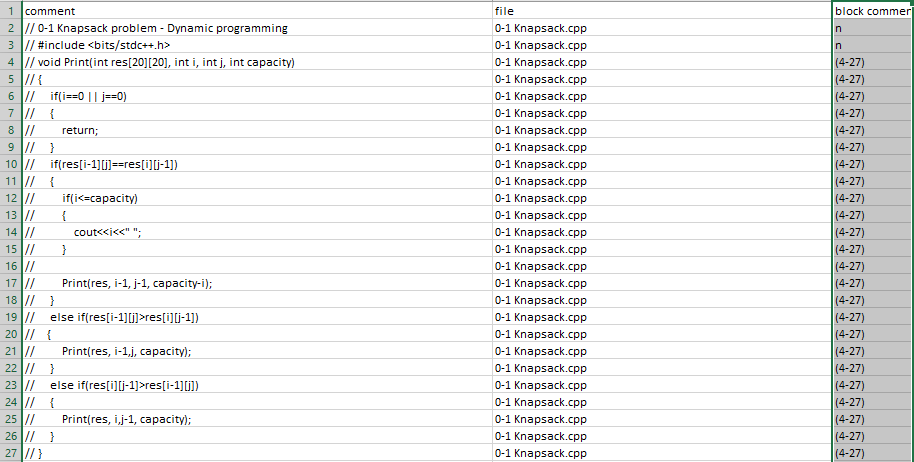
The entire process of manual verification covered a spread of 2,935 lines of comments from amongst the 20 different projects and covers a mix of all four languages selected for this project. We have decided that it is best to verify all comments on a line by line basis, this is to include block comments on a line to line basis, the reason for reviewing even block comments in this manner is that it is very possible to have a block comment that is a mix of both commented out code and standard English prose. The manual verification process took a total of 185 hours both of initial review and double verification over the course of two months. The results of this manual verification have been stored inside a data artifact in the form of a 7-column csv file for ease of use and the sake of future research regarding this topic. 

Figure 1 Block Comment Sample

Each of the 7 columns of the csv file represent what we feel are the most important notes on each comment though only two of the columns will actually be used for the machine learning process, namely the comment itself and the column that specifies whether or not a line is code while the remainder is present for the purpose of continued research. The first of these columns contains the comments themselves, in the case of block comments, each line is stored independently and each of the 7 columns are filled out for each line, as described in the previous paragraph. In the interest of maintaining the integrity of the data, all of the blank lines within block comments have been kept as well and are stored on their own lines. To maintain comments of all different types the markers for the comments are also maintained in these lines. Some examples of this include ‘//’, ‘/\*’, ‘\*’, ‘///’ and in the case of C++ and C style block comments potentially no marker at all. The purpose of this was to determine if certain types of comments were more likely to generate false positives in the machine learning algorithm and, if this was the case, to ensure that we manipulate the comments by removing these markers before feeding them into the machine learning algorithm. The second through fourth columns are used primarily for bookkeeping purposes but do provide important information especially towards future research.

The second column is the name of the source-code file from which the comment has been pulled from. This file name is extracted from the path information provided by srcML in the XML archive used in the production of this data artifact. The third column of the csv file is labeled block comment, and there are two different ways that this is marked down. If this column is marked with a n then the line is not part of a block comment. If the line is given a range of numbers then those numbers represent the range of lines that are a block comment that the line is a part of, note here this number applies only to the csv document rows and not to the source code itself. The fourth column is labeled as language and represent the coding language that the source code was written in. We decided to add this column for the purpose of both future research and to ensure that anyone viewing the data artifact will know what language the comment was written in regardless of whether or not they are familiar with all of the different file endings attributed to a language. The language column is followed by two different column’s that are related to one another, the first is the contains code column and the second is the code column.

The first of these two columns, the contains code column, is the fifth column of the csv file and was determined to be extremely important when verifying false positives when catching commented out code with the machine learning algorithm. The primary thing that we check for when determining whether or not to mark this comment with a yes are function names and equations. While equations seem to be less common function names may be included in order to aid in the description of what a section of source code does or to mark what functions need to be called within an area of the source code. The sixth column, which is the column labeled is code, is the second column directly important to the machine learning algorithm. This column is very straight forward and is marked with either a y or n depending on whether or not it is determined that a comment line is commented out code. However, it is important to note that this has nothing to do with the actual source code itself, rather, we decided to mark anything that if uncommented a compiler would attempt to compile it as code. for example, in the C family any line that appears like the line below would cause a crash if any of the variables had not been declared beforehand.

*// totalCost = price + salesTax - discount*

The last columns purpose is purely for future research and the possibility of additional checks that can be made in a multilayered machine learning approach.

The seventh column, which is labeled contains standard terms, is only ever filled when a comment line is commented out code. The primary purpose of this column is to provide a list of terms that could be used as a bag of words when identifying lines of commented out code. for example, in C++ *#include, return, void, int, string, virtual, float, and double* are all fairly common within code and are terms that could be used to identify commented out code. We are also marking things such as if, else, else if etc. though these are less likely to be helpful due to the fact that they are common English words. In Figure 1 Block Comment Sample a sample section of the csv is shown to help visualize everything that has been discussed in this chapter.

**Data Analysis**

When attempting to determine whether or not a comment, or a line of a block comment, is a piece of commented out code things become much more complicated then when a trained programmer is simply able to review it. Over the progress of this research multiple approaches are considered with the final method being the one that is currently in use at this time. The first of these methods which had proven to be fairly ineffective on larger test cases is what we would call the syntax-based approach.

## Syntax-based Approach

In the syntax-based approach the method for analysis of lines is simplistic and is broken down into a series of different checks. The first check, run on every line, is whether or not the line contains a semicolon, which has the direct ability to generate a number of false positives depending on the writing style of the programmer (i.e., if they tend to use semicolons in standard comments). The second and third checks rely both on checking for the opening and closing of parenthesis and curly braces respectively [Bacchelli et al. 2010]. This was not something that we had at first expected to be a problem, and in fact it was, as in cases where optional snippets of code had been commented out, the automation process would disregard these sections as it did not find the opening or closing piece that it was looking for. The second approach, which was considered but never implemented is a bag of words approach.

This bag of words approach is not to be confused with the bag of words approach mentioned earlier in the data collection chapter, which proposes the use of common terms as an additional method of verification. Rather, the concept of this approach is to break down an entire piece of source code and create a bag of words from it, which could then be used to cross check comments for terms that are present in the line which are found to be frequent in the bag of words. For example, if we scan an entire script broken down by the spaces and then scan the comments for matching terms then we could potentially identify variables and function names held within the comments. While this could be helpful in finding commented out code that is modifying common variables or using common variables as part of a greater equation, it has a number of strong failing points. First, when considering variable names, one time use variables, variables created in a piece of commented out code, and commented out functions are all highly likely to be ignored due to the fact that in comparison to other terms in the bag of words they may only have an appearance rate of 1-3 times in the entire source code where as a term like int, void, or count will appear much more frequently. The other issue with this method comes down to explanations of how code functions, in the case of thorough documentation where a programmer may be referencing function names and variable names, to many of such references is likely to cause false positives. This brings us to our third and most current approach, what we call the frequency approach.

The original basis of the frequency approach is derived from the works of Dvorak [Nakic-Alfirevic and Durek] who is famous for designing alternate versions of the key board layout used on English typewriters and computers. To simplify the concepts explained in the related works chapter, Dvorak examined which letters are most frequently used in the English language and relocated their positions to allow for easier and less strenuous typing. This concept of common characters in English words brought forth a very powerful idea, what if we check the frequency of ASCII characters found in lines of both English prose style comments and commented out code and compared them against each other? What the data shows us when analyzing the results of these frequencies is that there are key differences between English prose and commented out code, and not only are these differences present, some of them are quite extreme. As shown in Figure 2 large frequency differences, there are thirteen symbols which have a frequency near to or greater than one percent more common in commented out code versus in a standard comment. The most staggering of these numbers is actually the frequency of spaces found in commented out code, for which a number of assumptions are made. Likely, one of the largest reasons for this is good indentation practices leaving large amounts of whitespace in commented out code. However, upon closer analysis of some samples where spacing rates were particularly high it was noted that the average character length of terms tended to be much shorter in commented out code, a prime example being:

Figure 2

*// i = a + b;*

In this example the average size of a term is roughly 1 character and a total of five non-space based characters being present, now when you consider the fact that there is also eight spaces in the line, that means that the spaces are making up over 50% of the lines total number of characters. Further, taking into consideration Mayzner’s [cite] work and Googles[cite] follow-on research using modern computational methods, it has been determined that the average length of an English word is 4.7 characters. This means that in the same space of total characters, fifteen, on average 3 words would fit, assuming that it ends in a period and contains 2 spaces. Importantly, what this means is that spaces would be making up about 13% of the total number of characters in the line which is roughly 80% less spaces than the commented-out code example. These methods continue to hold true at different frequencies for a wide variety of different characters besides the ones mentioned previously, though in smaller amounts.

One of the benefits of using a method like this is by scanning a variety of source code you are able to create frequency distributions that are consistent across the board. In the case of the final frequency distributions used in this research the values are pulled from code and comments from amongst different projects, ensuring that it gets a good general representation of what a frequency distribution should look like and helps with generalizability and avoiding overfitting. Of course, an added benefit to this is if you are examining code and comments that are required to follow a very specific structure then the process is equally as beneficially once the scanning process is complete. The way this is done is by taking each line one at a time and verifying each character converted to lowercase for normalization against a dictionary of characters and then consequently stored in the dictionary. Once the entire line has been read and all characters have been stored and a final count of characters is obtained the frequency of each character is calculated and stored in a list, ensuring that they remain in order by using key based verification. These frequencies can then be used individually, as a group, or averaged into a single working list as shown in Table 1 LINE BREAKDOWN SAMPLE.

**Decision Trees**

Within the field of machine learning there are many different options not just in algorithms but also in preconstructed implementations. Of course, one can also always take the option of producing an implementation of an algorithm themselves, however for the sake of transparency, reproducibility, and validity we use verified implementations from within the scikit-learn Python library. Choosing what type of algorithm, you are going to use for data is extremely important, sometimes an algorithm cannot function at all with the data you have available, other times using the incorrect algorithm will cause poor fit or present results that contradict the output.

For our data there are two major factors that we must consider, first, our data is completely non-linear meaning that any machine learning algorithms that rely on the data being linear immediately will not work. The second factor that is of particular importance is that we are working with classification of two distinct classes (i.e., standard comment or code), so choosing a machine learning algorithm that is known for classification is equally as important. Considering these two factors the obvious choice of machine learning algorithm is the decision tree.

In scikit-learn’s current state their decision tree algorithm is based off an optimized version of the Classification and Regression Trees (CART) algorithm. This is a variation of the popular C4.5 algorithm which proceeded ID3 style decision trees [scikit-learn developers]. One of the major changes that came with the C4.5 algorithm is the ability to handle non-categorical data, as well as a new method for pruning that focused on pruning if a rules precondition improved without the pruned node [scikit-learn developers]. Decision trees require the data used to train the tree to be as balanced as possible, so for the purpose of training our model we made our training data a perfect 50/50 split. This is because at its root, a decision tree is a series of if then else statements and the optimization of such a sorting method requires this sort of distribution[scikit-learn developers].

The ability to handle various types of data, non-linear data, and work well for both classification and regression are not the only reasons why we chose decision trees however. Decision trees can be fully visualized as shown in Figure 2 Decision Tree Sample, which makes them both very easy to understand and equally easy to explain. This is aided by scikit-learn further using their export method which can allow you to color code and label the tree to aid in interpretation [scikit-learn developers]. To add to this decision trees use a white box method, and all the rules created are made clearly visible; this allows all rules to be statistically verified unlike with other methods such as neural networks [scikit-learn developers].

**Results**

The results of this research are attained through the use of a CART decision tree style model present in the Sci-kit Learn module for Python. The reason for choosing to use a decision tree is based off of the benefits that are naturally present when using them. First, decision trees are easy to understand and the model itself can be fully graphically visualized such as in the sample section of our decision tree in Figure 2 Decision Tree Sample.



Figure 3 DECISION TREE SAMPLE

Second, decision trees are able to handle blank data very well, this is extremely important when considering our data, this is because even if a line does not contain a symbol from the portion of selected ASCII characters that we are analyzing such as in this sample:

Table 1 LINE BREAKDOWN SAMPLE

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **a** | **b** | **c** | **d** | **e** | **f** | **g** | **h** | **i** | **j** |
| *0.0208* | *0.0208* | 0 | 0 | *0.0416* | *0.0208* | 0 | 0 | *0.0208* | 0 |
| **k** | **l** | **m** | **n** | **o** | **p** | **q** | **r** | **s** | **t** |
| *0.0208* | *0.0208* | 0 | 0 | *0.0625* | *0.0416* | 0 | *0.0208* | *0.0416* | *0.0625* |
| **u** | **v** | **w** | **x** | **y** | **z** | **!** | **@** | **#** | **$** |
| *0.0208* | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **%** | **^** | **&** | **\*** | **(** | **)** | **1** | **2** | **3** | **4** |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **5** | **6** | **7** | **8** | **9** | **0** | **-** | **\_** | **+** | **=** |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **{** | **[** | **}** | **]** | **|** | **\** | **:** | **;** | **‘** | **“** |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| **<** | **,** | **>** | **.** | **?** | **/** | **space** | **~** | **`** | **\t** |
| 0 | 0 | 0 | 0 | 0 | 0 | *0.5625* | 0 | 0 | 0 |
| **\n** | **\f** | **\r** | **\b** | **\v** | **\0** | **unk** |  |  |  |
| *0.0208* | 0 | 0 | 0 | 0 | 0 | 0 |  |  |  |

It is still very relevant to our decision-making process. Third, because decision trees are a white box model, we can verify all of the decisions through either Boolean or mathematical approaches. Finally, when considering the immense size of software projects today and the rapid rate at software is growing the fact that the prediction process is logarithmic is extremely important.

In order to ensure that we are receiving high quality and statistically sound results the decision tree was trained using stratified K-fold cross validation utilizing five folds. The reason behind choosing to utilize five folds is because there was a minimal change in using 5x2 but by cutting down to a single 5-fold run we are able to cut the runtime in half. We chose to use K-fold over naïve-bayes style verification because studies show the benefits of using K-fold are very clear and help to ensure that we are not having any issues with overfitting.[Kohavi]

Initial tests were then preformed on smaller samples of 250 lines of true comments and 250 lines of commented out code to prevent a training bias based on a dominate class and then mathematically verified to ensure that the results were holding true. Afterwards the questions generated by the tree were checked against the initial findings of the research that they were all mathematically sound questions. For example, the first question at the root of the tree asks whether or not a line is composed of less than or equal to 26.7% spaces and if the statement is true then the sample is likely a comment. This is a highly reliable question as initial research indicated that on average comments are constructed of approximately 24% spaces while commented out code is constructed of approximately 33% spaces.

Once the integrity of both the initial results and the decision tree model have been verified it is time to move on to larger data set to evaluate the overall quality of this identification approach, and the results are very promising. Over a series of 10 tests randomly selecting 1000 lines of comments from the 20 different projects we show an accuracy of 96.5%, a precision of 97.6%, a recall of 94.3% and a F1 score of 96.6%. All of these results were calculated automatically using metrics from Sci-kit Learn, the calculations for each metric are shown in Table 3 HEURISTICS EQUATIONS. Below is a breakdown sample of all 5 folds built into Table 2 HEURISTICS.

Table 2 HEURISTICS

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Fold Number** | **accuracy** | **precision** | **recall** | **F1** |
| 1 | 98.50 | 98.15 | 99.07 | 98.60 |
| 2 | 97.00 | 100.00 | 94.00 | 96.91 |
| 3 | 97.50 | 95.65 | 98.88 | 97.23 |
| 4 | 98.50 | 99.00 | 98.02 | 98.51 |
| 5 | 98.00 | 99.01 | 97.09 | 98.04 |

Table 3 HEURISTICS EQUATIONS

|  |  |
| --- | --- |
| **Accuracy**  **Equation** |  |
| **Precision**  **Equation** |  |
| **Recall**  **Equation** |  |
| **F1**  **Equation** |  |

# 

**Threats to Validity**

Throughout the duration of our research there have been a few different points that point to threats to validity that we hope to both mitigate and eliminate in our future research. The first issue that we have encountered is the overall quality of the code and comments written in the 20 projects that we have pulled all of our data. In 6.1. External Validity we will present our concerns about the validity brought by our choices in projects that our data artifact is based on. In 6.2. Internal Validity we consider the second threat to validity that we face, which has to do with the way that we deal with unique or less common coding styles.

## External Validity

The problem here is twofold, our sample size is limited, and the quality of writing is very high. The first issue is relatively simple to resolve and mainly only requires that we increase our sample sizes, though this comes with a number of computational challenges it is overall something that we can fix. The second part of this issue however is more complex, due to the fact that the code and comments are written in a very clean and consistent manner it has the direct potential to skew our results. An example of this is when programmers use very poor or no spacing methods, when this happens it throws off the root of our decision tree which first checks whether or not there is a high frequency of spaces on the given line. This is the same issue that we encounter if programmers don’t use proper indentation as it throws off spacing counts again, which are as previously stated, the root of our tree. The majority of the code that we are working with for this project also tend to have concise and standard naming conventions. Now of course traditionally this allows for increased readability of code, but not everyone uses this coding practice, if a programmer prefers to use long variable names that fully describe what a variable is, this will cause the ratio of alphabetic variables to increase, which in rare cases can lead to a piece of commented out code failing to be identified.

## Internal Validity

A second threat to validity that we intend to fix with our future research comes from well-established styles of coding, two prominent examples of this is Hungarian Notation and Whitesmiths style. Both of these styles cause new symbols to have increased prominence in our research though the cause is different between the two of them. Whitesmith style causes distribution changes because of its necessity to have minimalistic and concise lines. An example of this is that in Whitesmith style all curly braces should be on their own lines, this means that any line of code containing a curly brace is made of only a curly brace and an end-line marker.

|  |
| --- |
| *If(total > 0)*  *{*  *salesTax = total \* taxRate;*  *}* |

Figure 4 WHITESMITH SAMPLE

Of course, this causes a massive increase in the frequency distribution of curly braces and end-lines even though these symbols do not generally have a lot of importance when reviewing individual lines to determine if it is commented out code or not. Hungarian Notation provides a unique addition to this issue that has been the topic of many thoughts on the future development of this research. Hungarian Notation uses a standard method of labeling variables so that by looking at only a variable name you can gain a basic understanding of both what it is and what purpose it may have. An example of this is the use of the lowercase letter *m* to indicate that a variable is a class member.

|  |
| --- |
| *mDiceRoll;* |

Figure 5 HUNGARIAN SAMPLE

Hungarian notation provides a unique problem, namely, variables are very repetitious and depending on what the script does different letters become extremely important in identifying commented out code, but only when it is written in this style. Because of this there is some debate on whether Hungarian Notation should either be excluded from the tool as an outlier or if a special tree should be used to handle cases like Hungarian Notation.

**Future Works**

We envision four primary enhancements that we believe need to be handled in the future to extend the power and validity of this research. The first subject that we would like to see extended upon is handling specific coding styles such as Hungarian Notation, vertical alignment, Whitesmiths style, and indentation styles. The second focus of our future research is to extend the number of languages that our method works with. The third focus of our future research is to handle the various levels of coding skill as well as bad coding practices that are in use today. The final focus of our future research is to be able to search merge history within version control to identify exactly when and by whom code has been commented out.

When dealing with unique and specific coding styles such as Hungarian notation, vertical alignment, Whitesmiths style, and various indentation styles there are many different problems that must be considered. As discussed in further depth in the threats to validity section, Hungarian notation and Whitesmiths style cause different values that would not normally indicate commented out code to indicate commented out code. In these cases, it needs to be decided if unique trees need to be created for these problems or if there is a way to incorporate these styles into the current tree without causing trouble for the more common coding styles. Vertical alignment and various indentation styles that involve large amounts of spacing also provide a unique problem as the incorporation of excessive spaces can skew our values, again this is a problem that will either warrant the creation of unique trees for lines with excessive spacing or a way to modify the values without creating bias when integrating them into the tree. There is some argument that if they are not included in the tree creation however, that they will likely be properly identified in either case, though this is something that will require further analysis.

In the Chapter 6, it is discussed that the scope of this study is limited, because it has only worked with twenty projects from GitHub. This choice was made with the idea in mind that we wanted to have a very well written sample of code to work with for the first iteration of this project and it did give us access to almost 100,000 lines of comments. However, the code in these projects tend to be very well written and fairly uniform, and while this does give us a good example of what code and comments should look like it does not account for junior and veteran programmers who use out of date coding styles. Of course, a third group of coders, those who are self-taught, and who lack common and good practices and standards within our field also provide an additional layer of content that we wish to explore. When looking at these groups of programmers and their coding styles they have to potential to cause shifts in the data similar to the highly specific coding styles discussed earlier in this chapter. However, the difficulty here is that unlike with those coding styles which have established rules within their designs, the coding styles that we are talking about here are much harder to identify and will require a lot of research to automate their identification.

Finally, a big part of our future research, and one of the long-term purposes for this research is the ability to automate the process of locating exactly when commented out code has been introduced into the code base. Once we can identify when commented out code has been commented, then we can also figure out who actually commented out the code in the script. This allows us to ask the programmer exactly why they commented out the code in the first place hopefully find good solutions to the removal of this commented out code so that when a project is finally shipped it will be much easier to maintain. Additionally, we gain the ability to track commented out code as it enters and exits source code, develop a method for automatic removal and correcting developer behavior over time in order to prevent future issues and need for constant tracking.

**Conclusion**

The field of natural language processing is old, and fraught with a number of large problems, not the least of which is how to deal with the complexities of human language. Our research has provided two major findings in the analysis of comments within scripts that we hope will allow our further research in natural language processing to progress. The first of these findings is that the analysis of the individual characters rather than the analysis of whole words is something that, as our research shows, produces tangible data that can be used with powerful machine learning methods at a low, order log(n), to produce effective results. These results as shown in Table 1 Heuristics demonstrate that we meet our 5% confidence level in all heuristics as we had hoped to achieve. The importance here is that the overall computational cost of dealing with these numbers within data frames is much lower than say a bag of words approach which requires the storage of and analysis of a constantly varying list of words that must also account for lemmatization and stemming if it is going to work properly. With our approach stemming and lemmatization has a very limited effect, as in the end we are looking at frequency of the occurrence of certain characters, chosen by an optimized machine learning algorithm.

Our second major finding that builds off of our first is that while there are an extremely large number of different characters that may be included when any one programmer is writing code, in reality only a small number of them truly matter when identifying commented out code. As has been repeatedly mentioned the greatest of these is spaces, which is a subject that we intend to research further as we deal with extraneous cases that seem to break this mold. That being said, our results are clear, when looking at the difference between a line of code and English prose the first and greatest difference that we are going to notice is the frequency of special characters and spaces. After reviewing our data, this is something that we cannot help but notice with the naked eye and defied our original expectations of what we thought that we were going to find.

Abid, N.J., Dragan, N., Collard, M.L., and Maletic, J.I. 2015. Using stereotypes in the automatic generation of natural language summaries for C++ methods. *2015 IEEE International Conference on Software Maintenance and Evolution (ICSME)*, IEEE, 561–565.

Bacchelli, A., Lanza, M., and Robbes, R. 2010. Linking e-mails and source code artifacts. *Proceedings of the 32nd ACM/IEEE International Conference on Software Engineering - ICSE ’10*, ACM Press, 375.

Borstler, J. and Paech, B. 2016. The Role of Method Chains and Comments in Software Readability and Comprehension—An Experiment. *IEEE Transactions on Software Engineering* *42*, 9, 886–898.

Chen, H., Huang, Y., Liu, Z., Chen, X., Zhou, F., and Luo, X. 2019. Automatically detecting the scopes of source code comments. *Journal of Systems and Software* *153*, 45–63.

Collard, M.L. and Maletic, J.I. srcML. *srcML*.

Cortes-Coy, L.F., Linares-Vasquez, M., Aponte, J., and Poshyvanyk, D. 2014. On Automatically Generating Commit Messages via Summarization of Source Code Changes. *2014 IEEE 14th International Working Conference on Source Code Analysis and Manipulation*, IEEE, 275–284.

Dolfing, H. 2019. Case Study 4: The $440 Million Software Error at Knight Capital. In: *The Project Success Model*. Amazon.com Services LLC.

Flisar, J. and Podgorelec, V. 2019. Identification of Self-Admitted Technical Debt Using Enhanced Feature Selection Based on Word Embedding. *IEEE Access* *7*, 106475–106494.

Haiduc, S., Aponte, J., Moreno, L., and Marcus, A. 2010. On the Use of Automated Text Summarization Techniques for Summarizing Source Code. *2010 17th Working Conference on Reverse Engineering*, IEEE, 35–44.

Kohavi, R. A Study of Cross-Validation and Bootstrap for Accuracy Estimation and Model Selection. *IJACAI ’95*, 7.

Linares-Vasquez, M., Cortes-Coy, L.F., Aponte, J., and Poshyvanyk, D. 2015. ChangeScribe: A Tool for Automatically Generating Commit Messages. *2015 IEEE/ACM 37th IEEE International Conference on Software Engineering*, IEEE, 709–712.

Nakic-Alfirevic, T. and Durek, M. The Dvorak keyboard layout and possibilities of its regional adaptation. 6.

Ren, Y. and Ji, D. 2019. Learning to Detect Deceptive Opinion Spam: A Survey. *IEEE Access* *7*, 42934–42945.

scikit-learn developers. 1.10. Decision Trees. *scikit-learn*. https://scikit-learn.org/stable/modules/tree.html.

Song, X., Sun, H., Wang, X., and Yan, J. 2019. A Survey of Automatic Generation of Source Code Comments: Algorithms and Techniques. *IEEE Access* *7*, 111411–111428.

Steidl, D., Hummel, B., and Juergens, E. 2013. Quality analysis of source code comments. *2013 21st International Conference on Program Comprehension (ICPC)*, IEEE, 83–92.

Zhou, S., Xu, X., Liu, Y., Chang, R., and Xiao, Y. 2019. Text Similarity Measurement of Semantic Cognition Based on Word Vector Distance Decentralization With Clustering Analysis. *IEEE Access* *7*, 107247–107258.