A Study of “Wheat” and “Chaff” in Source Code

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Abstract—Natural language is robust against noise. The meaning of many sentences survives the loss of words, sometimes many of them. Some words in a sentence, however, cannot be lost without changing the meaning of the sentence. We call these words “wheat” and the rest “chaff”. The word “not” in the sentence “I do not like rain” is wheat and “do” is chaff. For human understanding of the purpose and behavior of source code, we hypothesize that the same holds. To quantify the extent to which we can separate code into “wheat” and “chaff”, we study a large (100M LOC), diverse corpus of real-world projects in Java. Since methods represent natural, likely distinct units of code, we use the ~9M Java methods in the corpus to approximate a universe of “sentences.” We “thresh”, or lex, functions, then “winnow” them to extract their wheat by computing the function’s minimal distinguishing subset (MINSET). Our results confirm that programs contain much chaff. On average, MINSETS have 1.56 words (none exceeds 6) and comprise 4% of their methods. Beyond its intrinsic scientific interest, our work offers the first quantitative evidence for recent promising work on keyword-based programming and insight into how to develop powerful, alternative programming systems.

I. INTRODUCTION

Words are the smallest meaningful units in most languages. We group them into sentences and sentences into paragraphs and paragraphs into novels and technical papers like this one. Some words in a sentence are more important to its meaning than the others. Indeed, from a few distinctive words in a sentence, we can often guess the meaning of the original sentence.

This paper studies whether this intuitive observation about the importance of some words to the meaning of sentences in a natural language also holds for programming languages.

This work follows recent, seminal studies on the “uniqueness” [9] and the “naturalness” [12] of code. We study a different dimension — the “essence” of code as captured in its syntax and amenable to human interpretation. Our study is inspired by recent work on keyword-based programming [14, 16, 17, 23]. Keyword programming is a technique that translates keyword queries into Java expressions [16] Sloppy programming is a general term that describes several tools and techniques that interpret, via translation to code, keyword queries [17, 23]. SmartSynth [14], another notable tool, combines techniques from natural language processing and program synthesis to generate scripts for smartphones from natural language queries.

This promising, new programming paradigm rests on the untested assumption that 1) small sets of distinctive keywords characterize code and 2) humans can produce them. Our work is the first to provide quantitative and qualitative evidence to validate this assumption. We show the existence of small distinctive sets that characterize code, establishing a necessary condition of this paradigm that allows programmers to write code naturally and easily using keyword queries, alleviating syntactic frustration.

We focus our study on a diverse corpus of real-world Java projects with 100M lines of code. The approximately 9M Java methods in the corpus form our universe of discourse as methods capture natural, likely distinct units of source code. Against this corpus, we compute a minimal distinguishing subset (MINSET) for each method. This MINSET is the wheat of the method and the rest is chaff. We develop procedures for “threshing” functions via lexing and “winnowing” them, by computing their MINSETS. A lexicon is a set of words. Like web search queries, MINSETS are built from words in a lexicon. We run our algorithms over different lexicons, ranging from raw, unprocessed source tokens to various abstractions of those tokens, all in a quest to find a natural, expressive and meaningful lexicon that culminated in the discovery of a natural lexicon to use for queries (Section IV-B).

Our results show programs do indeed contain a great deal of chaff. Using the most concrete lexicon, formed over raw lexemes, MINSETS compose only 4% of their methods on average. This means that about 96% of code is chaff. While the ratios vary and can be large, MINSETS are always small, containing, on average, 1.56 words, and none exceeds 6. We observed the same trend over other lexicons. Detailed results are in Section IV. Section V also discusses existing and preliminary applications of our work. Our project web site (http://jarvis.cs.ucdavis.edu/code_essence) also contains more information on this work, and interested readers are invited to explore it.

While our work is not code search, the results have direct implications in that area because they provide evidence that addresses an assumption of code search: humans can efficiently search for code. This assumption is closely related to the second part of the assumption on which keyword programming is based. Work on code search breaks the problem into three subproblems 1) how to store and index code [2, 20], 2) what queries (and results) to support [27, 28], and 3) how to filter and rank the results [2, 18, 21]. The programmer’s only concern is “What do I need to type to find the code I want?” We take a step back and ask, “Is there anything you can type?”, and answer, “Yes, a MINSET.”

Our main contributions follow:

• We define and formalize the MINSET problem for rigorously testing the “wheat” and “chaff” hypothesis (Section II-B);
• We prove that MINSET is NP-hard and provide a greedy algorithm to solve it (Section II-C);
• We validate our central hypothesis — source code contains much chaff — against a large (100M LOC), diverse corpus of real-world Java programs (Section IV); and
• We design and compare various lexicons to find one that is natural, expressive, and understandable (Section IV-B).

The rest of this paper is organized as follows. Section II describes threshing and winnowing source code. Section III describes our Java corpus, and implementations of the function thresher and winnowing tool (MINSET algorithm). Section IV presents our detailed quantitative and qualitative results. Section VI analyzes our results and their implications. Section VII places our work into the context of related work, and Section VIII concludes.

II. PROBLEM FORMULATION

After harvesting, farmers thresh and winnow the wheat. Threshing is the process of loosening the grain from the chaff that surrounds it. Winnowing is the process of separating the grain or kernels from the chaff. In this section, we define “wheat” and “chaff”, describe code threshing, and present MINSET, our winnowing algorithm.

A. Threshing

We view functions as the “stalks of wheat”. Functions are natural, likely distinct, units of code and functionality. One could also choose other units like individual statements, blocks, or classes. This granularity seems adequate. Functions are usually the building blocks of more complex components. To thresh, we parse a function to get its set of lexemes. Then, we map this set of lexemes to a set (or bag) of “words”.

What is a “word”? We are free to define the lexicon, the set of (allowed) words. A natural, basic lexicon is the set of lexemes; a lexeme is a delimited string of characters in code, where space and punctuation are typical delimiters; it is an atomic syntactic unit in a programming language. Under this lexicon, words are lexemes. New lexicons can be formed by abstraction over lexemes. In natural languages, for example, the words in a sentence can be replaced by their part of speech, like NOUN, VERB, or ADJECTIVE, to highlight structure. Similarly, code parsers tag each lexeme with one of a set of token types. Thus, another natural, but more abstract, lexicon consists of token types. New lexicons can also be defined by filtering specific lexemes. For example, we can allow all lexemes except delimiters, like ’(‘, and ’)’. Under this lexicon, a function’s set would be all its lexemes except the delimiters.

Figure 1 illustrates the threshing process. It shows the source code of a Java method that sorts numbers using bubble sort. It also shows the threshed function using a lexicon consisting of all raw lexemes, and a lexicon consisting only of lexer token types.

Varying the lexicon allows us to explore programming language-specific information. The lexicon consisting of all lexemes probably includes many elements that we suspect have little to do with the behavior of functions, i.e., delimiters and string literals like ’+Joe’. We can filter those lexemes, by not scooping them into the winnowing screen. We can also filter other lexemes, like the type annotation “int” in “int cars = 0;”, to explore how important they are in the model. Functions may also contain, to adapt a word from linguistics, homonyms: identical lexemes with distinct effects on behavior. For example, in Java, the lexeme ”get” could be a method call of “java.util.Map.get()” or “java.util.List.get()”. In Java, we fully qualify homonyms to distinguish them as shown.

In general, we can map lexemes to distinct words to capture the difference in behavior. We can also abstract distinct lexemes we suspect have the same effect on behavior, i.e., synonyms, to the same word. For example, variable identifiers can be replaced with their type under a language’s type system. In general, a lexicon that is fine-grained and concrete may exaggerate unimportant differences between functions, while one that is coarse and abstract may blur important differences. At both ends of the spectrum of lexicons, it may be difficult to separate the grain from the chaff later.

B. Winnowing

In threshing, we simplified the representation of a function by mapping its source code to a set of lexical features, words. Finding the wheat of function is thus reduced to finding a unique subset of code features. This unique subset distinguishes each function from all other functions (when all functions are represented as sets of words). We call any such subset a distinguishing subset, and define it precisely in Definition II.1. We call the problem of finding the minimum distinguishing subset (MINSET) the MINSET problem.

Definition II.1. Given a finite set $S$, and a finite collection of finite sets $C$, $S'$ is a distinguishing subset of $S$ if and only if:

1. $S' \subseteq S$ and $S'$ is a subset of $S$
2. $\forall C \in C$, $S' \not\subseteq C$ and $S'$ is only a subset of $S$

What is wheat and what is chaff in code? The wheat grain of a piece of code is the MINSET. A MINSET identifies a piece of code — wheat and chaff together. The MINSET are distinguishing features, a kind of semantic core. The MINSET, however, is not itself executable. Just as a wheat grain depends on chaff to grow, a MINSET depends on its surrounding context to execute and provide functionality. We call this surrounding context chaff: it consists of the low-level technological details
Algorithm 1 Given the universe $U$, the finite set $S$, and the finite set of finite sets $C$, $\text{MINSET}$ has type $2^U \times 2^2U \rightarrow 2^U$ and its application $\text{MINSET}(S,C)$ computes 1) $S^* \subseteq S$, a subset that distinguishes $S$ from sets in $C$, and 2) $C'$, a “remainder”, i.e. a subset of $C$ whose sets contain $S$ and therefore from which $S$ could not be distinguished; when $C' = \emptyset$, $S^*$ distinguishes $S$ from all the sets in $C'$; when $C' = C$, $S^* = \emptyset$.

Input: $S$, the set to minimize.
Input: $C$, the collection of sets against which $S$ is minimized.

1. $C_e = \{ C \mid C \in C \land e \in C \}$ are those sets in $C$ that contain $e$.
2. $S^* = \emptyset$
3. while $S \neq \emptyset \land C \neq \emptyset$
4. // Greedily pick an element that most differentiates $S$.
   4.1. $e := \text{CHOOSE}(\{ x \in S \mid |C_e| \leq |C_x|, \forall y \in S \})$
5. if $C_e \subseteq \emptyset \cup e$ break
6. $S^* := S^* \cup \{ e \}$
7. $S := S \setminus \{ e \}$
8. $C := C - e$
9. return $S^*, C$

Algorithm 1 computes distinguishes $S$ from a subset of $C$; when $C' = \emptyset$, $S^*$ is a minimally distinguishing subset of $S$.

Proof: By induction on $S^*$.

The worst case complexity of $\text{MINSET}(S,C)$ is $O(|S|^2 |C|)$. First, there are $|S|$ iterations and, in each call, for each element $x \in S$, we need to 1) compute $C_x$, each at a cost of $|C|$, for a total cost of $O(|S||C|)$, then 2) find the minimum $|C_x|$ at a cost of $O(|S|)$. Of course, $S$ and $C$ are smaller in each iteration, but we ignore this and over-approximate. Thus, we have $O(|S|(|S||C| + |S|)) = O(|S|^2 |C|)$.

As mentioned earlier, modeling functions as sets discards differences in methods due to multiplicity. We have also developed a multiset version of the $\text{MINSET}$ algorithm, which we omit due to lack of space.

III. SETUP AND IMPLEMENTATION

We selected a very popular, modern programming language, Java, and collected a large (100M lines of code), diverse corpus of real-world projects. Ignoring scaffolding and very simple methods, which we define as those containing fewer than 50 tokens, there are 1,870,905 distinct methods in our corpus. We selected a simple random sample of 10,000 methods$^2$. Our software and data is available$^3$.

A. Code Corpus

Over the summer of 2012, we downloaded almost one thousand of the most popular projects from four widely-used open source code repositories: Apache, Eclipse, Github, and Sourceforge.

Curation Since some projects in our corpus are hosted in multiple code repositories, we removed all but the most recent copy of each project. Also, since many project folders contained earlier or alternative versions of the same project, and even other projects, where we could, we identified the main project and kept only its most current version. Table I summarizes our curated corpus. After curation, clones may still exist in the corpus, for example, within projects. A search program we wrote helps us find clones. When we compute minsets, we assume no clones remain. Our results in Section IV-A give us confidence that this is the case.

Filtering Scaffolding Methods Java, in particular, requires that a programmer write many short scaffolding methods, for example, getters and setters. Many languages, like Ruby and Python, eliminate the need for such scaffolding code. After manual inspection, we found that such methods usually contain

$^2$Given the population size, this gives us a confidence level of 95%, and a margin of error of ±1%.

$^3$https://bitbucket.org/martinvelez/code_essence_dev/downloads.
TABLE II: Method counts.

| Methods                  | Count   |
|--------------------------|---------|
| Total (in corpus)        | 8,918,575 |
| Unique                   | 8,135,663 |
| Unique (50 or more tokens) | 1,870,905 |
| Unique (50 to 562 tokens) | 1,801,370 |

less than 50 tokens, or about 5 lines of code. This is consistent with other research [3, 15] that also ignores shorter methods. At this size, we also filter methods with very simple functionality. After filtering, 905 out of 908 projects are still represented. Table II shows the method counts.

B. The Function Thresher

We developed a tool, which we call JavaMT, that threshes all the functions in our corpus. JavaMT leverages the Eclipse JDT parser which parses Java code and builds the syntax tree. JavaMT can take as input .java, .class, and .jar files. Projects can contain these and other types of files. The tool builds a list of tokens for each method. It collects the lexeme of each token and additional information as it traverses the syntax tree.

To address the homonym problem, JavaMT collects the fully qualified method name (FQMN) for method name lexemes, and the fully qualified type name (FQTN) for variable identifiers and type identifiers. Collecting this information allows us later to classify methods and types based whether they are part of the Java SDK library or if they are local to specific projects. When projects are missing dependencies, resolving names to either FQMN or FQTN may not be possible. In our corpus, we encountered this problem with 0.03% of the tokens. JavaMT can also collect more abstract information like lexer token types as defined in the javac implementation of OpenJDK, an open-source Java platform [26].

C. The Winnowing Tool

All the information collected by JavaMT is stored in a PostgreSQL database. We developed a tool that runs MINSET for each method and stores the result in the same database. If a method does not have a minset, it stores a list of methods that are strict supersets and a list of methods that are duplicates after threshing.

IV. RESULTS AND ANALYSIS

Our core research question can be addressed in terms of absolute minset sizes, or in terms of minset ratios, minset size to threshed method size. While the minset sizes and minset ratios will almost undoubtedly vary across functions, we hypothesize that the mean minset size and the mean minset ratio are small — that there is a great deal of chaff in code. Our results show that code contains much chaff.

The data we present, and the database queries we used can be downloaded from Bitbucket.²

A. How Much of Code is Wheat?

Cast in terms of wheat, our core research question — How much of code is wheat? — can be answered in two ways: in terms of size of minsets, or the ratio of minsets to their function. We report both. There are also two natural views we can take of code: the raw sequence of lexemes the programmer sees when writing and reading code, and the abstract sequence of tokens the compiler sees in parsing code. We want to explore those two views, and capture each one as a lexicon, a set of words. LEX is the set of all lexemes found in code (5,611,561 words). LTT is the set of lexer token types defined by the compiler (101 words). Each word in LTT is an abstraction of a lexeme, like 3 into \texttt{INTLIT}.

LEX is the primordial lexicon; all others are abstractions of its words. Unfortunately, it is noisy: it is sensitive to any syntactic differences, including types or use of synonyms, so it tends to overstate the number of minsets and understate their sizes; spurious homonyms can have the opposite effect, but are unlikely in Java when one can employ fully qualified names. LTT is the minimal lexicon a parser needs to determine whether or not a string is in a language. We computed minsets with our winnowing tool of all the methods in our random sample of 10,000 using each lexicon, and display a summary of our results in Figure 3 and Figure 4.

Using LEX, wheat is a tiny proportion of code. The minset of a method, on average, contains 4.57% of the unique lexemes in a method which means that methods in Java contain a significant amount of chaff, 95.43% on average. More surprisingly, the number of lexemes in a minset is also just plain small. The mean minset size is 1.55. The minset sizes also do not vary much. In 85.62% of the methods, one or two unique lexemes suffices to distinguish the code from all others. The largest minset consists of only 6 lexemes. Minset ratios also do not vary much. 75% of all methods have a minset ratio of 6.35% or smaller. While the ratios are sometimes large, the absolute sizes never are. The method with the largest minset ratio, 33.3%, for example, consists of 18 unique lexemes but has a minset size of 6. The method with the second largest minset ratio, 29.41%, another example, consists of 17 unique lexemes and has a minset size of 5.

Minsets are surprisingly small; especially surprising is that the maximum size is small. One reason might be the compression inherent to representing functions as sets. We address this later when we experiment with multisets. To test the robustness of our results, we also focused our investigation on larger methods because they may encode more behavior and therefore have more information. Hence, they may have larger minsets. Selected uniformly at random, our sample set does not include many of the largest methods: the largest method in our random sample has 2025 lines of code while the largest one in our corpus contains 4,606 lines of code. To answer this question about minset properties conditioned on large methods, we selected the 1,000 largest methods, by lines of source code, and computed their minsets. The mean and maximum minset sizes of the largest methods are slightly lower but similar to the previous sample, 1.12 and 4, respectively. This shows that minsets are small and potentially effective indices of unique information even for abnormally large methods.

Using LTT, the proportion of wheat in code is larger but still small. The minset of a method, on average, contains 18.45% of the unique token types in a method. We observe again that

²http://www.eclipse.org/jdt/.
Fig. 3: The histogram of minset sizes tells us that minsets are small. Comparing minset sizes with method sizes shows that minsets are also relatively small. The minset ratio histogram confirms this.

Fig. 4: Random Sample of 10,000 Methods: (left) Proportion of Methods with Minsets: There is a stark difference in that proportion between LEX and LTT. (right) Proportion of Methods with Duplicates: LEX induces very few duplicates compared to LTT. LTT maps almost three quarters of the methods to the same set as another. It is too coarse, and does not thresh well.

sometimes minset ratios can be large but the absolute minsets sizes never are. It is not surprising that the minset ratio is larger. Information is lost in mapping millions of distinct lexemes to only 101 distinct lexer token types. Information is also lost as method sizes decrease from 42.7 using LEX to 18.2 using LTT.

These results show that code contains a lot of chaff, in relative and absolute terms. Given that we preserve a lot of information with LEX, we claim that the mean minset size, and mean minset ratios we found are approximate lower bounds. In essence, we can define a lexicon spectrum where LEX is one of the poles, and LTT is a more abstract point on the lexicon spectrum.

The yield of a lexicon is its percentage of threshable methods. Our exploration also shows that the yield decreases as the lexicon becomes coarser, measured roughly by the number of words. Our coarsest lexicon, LTT, does not loosen the grains from the chaff well. Its coarseness seems to cause 6640 methods to be threshed to the same set as another. Only 87 out of 10,000, 0.87%, methods have a minset using LTT. In contrast, LEX appears to preserve sufficient information so that 9,087 out of 10,000 methods have a minset.

### B. What is a Natural, Minimal Lexicon?

We have shown that a method can be threshed and winnowed to a small minset over LEX and LTT. Raw lexemes and token types are cryptic. We also want to determine whether we can thresh and winnow a method to a small and meaningful minset. By meaningful, we refer to how much information a minset reveals about functionality and behavior to us, humans. By the definition of minset, what they reveal should also be distinguishing.

We address this question by exploring the lexicon spectrum toward more abstract views of code. Our challenge is to find a lexicon that differentiates methods while being sufficiently small to be easily understandable and useful for humans. In short, we seek here to approximate the set of words a programmer might use to search for or synthesize code. We additively construct a bag of words a programmer might naturally use.

Two issues confounds this search: lexicon specialization can overfit while lexicon abstraction introduces imprecision. To ameliorate overfitting, we restricted our search to natural lexicons. By natural, we mean simple and intuitive. We pursue natural abstractions to avoid unnatural abstractions that overfit our corpus, like one that maps every function in our corpus to a unique meaningless word. In our context, imprecision leads spurious homonyms which reduces yield\(^5\). To handle this problem, we relax the definition of threshability, to \(k\)-threshability: a method is \(k\)-threshable if its minset has \(k\) or fewer supersets. Henceforth, when we say threshable we mean

\[^5\text{Although LEX is rife with synonyms, our candidate lexicons have almost none.}\]
10-threshold. We chose 10 because that is consistent with what humans can process in a glance or two. Humans can rapidly process short lists [22].

We considered four lexicons. Table III shows their names and sizes. Our results appear in Figure 5 and Figure 6. We focused on the absolute minset size. In searching or synthesizing code using minsets, the minset size is likely more important to the programmer than the minset ratio. We also focused on yield, the proportion of threshable methods. It approximates the proportion of methods a programmer can synthesize or search for using a given lexicon. Broadly, it gives us a sense of the effectiveness and usefulness of a programming model involving minsets.

First, we considered Min1, a lexicon including only method names and operators. For public API methods, we used fully qualified method names to prevent the spurious creation of homonyms. For local methods, we abstracted all names to a single abstract word to capture their presence. Local methods tend to implement project-specific functionality not provided by the public API, and are not generally aimed for general use. The intuition in including method names is that a lot of the semantics is captured in method calls. They are the verbs or action words of program sentences. Our intuition is further supported by the effectiveness of API birthmarking [31]. We also included operators because all primitive program semantics are applications of operators. Using this lexicon, the mean and maximum minset size are small, 2.73 and 7, respectively. The imprecision of Min1 manifests itself in the low yield of 26.86%.

To try to improve yield, we created lexicon Min2 by including control flow keywords as well; there are 13 in Java. From the programmer’s perspective, these words reveal a great deal about the structure of a method that is critical to semantics. For example, the word for alone immediately tells us that some behavior is repeated. Using this lexicon, the mean and maximum minset sizes are still small, 2.88 and 9, respectively. The yield does not increase much. Only an additional 288 methods become threshable. The likeliest and simplest explanation for the small change is that these words are very common; at least one of them is present in at least three quarters of the methods. It is more difficult to interpret this change. On the one hand, it is small. On the other hand, it is the result of adding only 13 new, semantically-rich words. In balancing the size of the lexicon with the interpretability of minsets, this appears to be a good trade-off.

In our quest to improve yield, we defined Min3 to include the types of variable identifiers (names). Those of a public type were mapped to their fully qualified type name. Those of a locally-defined type were mapped to a single abstract word to signal their presence. Locally-defined types, like local methods, tend to be project-specific and not of general use. Our reason for focusing on types is that they tell the programmer the kind of data on which methods and operators act. It is also a simple way of considering variable identifiers. Again, the mean and maximum minset size are small, 2.96 and 9, respectively. There is a notable increase in the yield, from 29.72% to 41.44%. It is now close to what we would imagine might be practical. In a Minset-based programming model, a programmer would find 4 out of 10 methods. The lexicon also grew substantially by 36,260 words. This trade-off appears reasonable considering as well that it is natural to supply the programmer with the convenience of a variety of primitive and composite types.

We defined a final lexicon, Min4, which includes false, true, and null, object reference keywords, like this and new, and the token types of constant values, such as the token type Character-Literal for ‘Z’ or, for 5, Integer-Literal. In total, we added 13 new words. Our intuition is that the use of hard-coded strings and numbers is connected to semantics. Certainly,
reading hard-coded values can be informative. Also, in a new programming model, a programmer may need to indicate that some constant string or number will be used. For example, if the programmer wishes to find a method that calculates the area of a circle, then it would be natural to indicate that target method likely contains $3.14$ or $\pi$. After including these words, the mean and maximum minst size remain small, 3.06 and 10, respectively. The yield increased from 41.44% to 44.79%. Adding this small number of semantically-rich words to the lexicon seems to be another reasonable exchange for a noticeable gain in yield: under this lexicon, the words are easier to interpret (see Section IV-D for our analysis of the interpretability of minsets built from these words) while remaining small enough for humans to work with, e.g. a human could potentially write a minset from scratch while programming using key words [16].

C. Improving Threshing and Winnowing

Instead of continuing our search for lexicons generated from ever more complex abstractions over lexemes, we reconsidered multiplicity, the number of copies of a word in a method. We hypothesized that modeling methods as multisets would recapture some textual and semantic differences, and thereby increase the yield of the lexicons MIN1 through MIN4. We used the multiset version of Algorithm 1 to recompute minsets, and show our results in Figure 7.

Multiplicity improved yield at the cost of larger absolute minset sizes. The yield increased for all lexicons. The new yields ranged from 32.64%–53.63%. The smallest increase in yield was using MIN1 (3.18%) and the largest was using MIN4 (8.84%). More concretely, using MIN4, the number of threshable methods increased by 884. Multiplicity also improved the minset ratios over all lexicons. For example, using MIN4, the mean minset ratio decreased from 15.47% to 5.35%. The cost of considering multiplicity, however, was an overall increase in minset sizes; the range of mean minset sizes shifted, 2.73–3.06, shifted and got a bit wider, 7.06–9.56. The outliers of minset sizes moved farther to the right. Previously, they ranged from 7–10 and now they range from 258–438. The right tails have grown longer. For example, using MIN4, 75.67% of the minsets have fewer than 10 words. Another cost of the gain in yield was in minset computation where we observed an approximate slowdown factor ranging from 4 to 7. For example, computing multiset minsets using MIN1 took 44 hours instead of 6. In practice, the slowdown is much better than Algorithm 1’s complexity implies. Overall, despite its cost, modeling methods as multisets over MIN4 produces a yield with practical value: it easily distinguishes more than half of the methods in our sample set.

Multiplicity appears to also improve the how well methods are threshed. Threshing maps a method to a set (or multiset), and can map two unique methods to the same set or multiset. When this happens, the MINSET algorithm cannot distinguish them. We can use the proportion of methods with duplicates to gauge the precision of threshing. LEX gave us a baseline of 37% non-treshable methods, entirely and no multiplicity, we observed the portion improved from 66.4% using MIN1 down to 41.64% using MIN4 (Figure 8). Multiplicity cut those portions nearly in half. For example, using MIN4, the portion is now 23.59%.

The remaining portion of non-threshable methods is intriguing. There are still 46.37% non-threshable methods, entirely subsumed by more than 10 other methods. We certainly expected some methods to subsume others because of their sheer size. We also expected families of semantically-related methods where some subsume others. However, given that methods are not that small, containing, on average, 72.8 words over MIN4, and that the the portion of methods with duplicates is small, we suspected another reason. We hypothesized that there are abnormally large methods subsuming a great number.
of methods.

We conducted an experiment where we gradually filtered large methods to observe the effect on yield (Figure 9). We initialized the filter size to 72,028, the maximum method size (in tokens) in our corpus, and repeatedly halved it down to 70; the minimum size of a method is 50. If we filter methods with more than 562 tokens, or about 56 lines of code, then the yield improves from 53.67% to 61.74%. This filter means that, in a new programming model, what the programmer is coding would not be compared against abnormally large methods, by default. With such a filter, 6 out of 10 methods can be easily distinguished from others via their minset. If we doubled the filter size, we would reconsider 55,953 methods, and the yield would still be higher at 57.32% than without the filter. Since there is a relatively low number of these large methods, 69,535 out of 1,870,905 (or 3.7%), the trade-off seems reasonable. A maximum size filter would clearly add practical value in a new programming model.

MIN4 is a natural lexicon suited for code search, synthesis, and robust programming. We recomputed minsets using MIN4 considering multiplicity, and the filter size set to 562. As we already mentioned, the yield is 61.74%. The mean minset size increases with the filter from 9.56 to 11.03. The minset sizes vary but have a clear positive skew where fewer than 25% contain more than 12 words. That right tail of the distribution is significantly shorter; the maximum size decreased from 689 to 173 because of the filter.

D. Minset Case Studies

Recall that our definition of a MINSET, the wheat of a method, does not imply that a MINSET is unique. Nor does it imply that chaff is meaningless, containing little information about the method. A MINSET is also not executable. To be useful, a MINSET should capture core, distinguishing functionality in a method, and be easily understandable. We studied whether this is the case.

From these case studies, we learned that minsets computer over LEX are small but do not reveal much about the behavior of the method. Minsets over MIN4, on the other hand, are still small but also give insight into the functionality of a method.

Study of LEX Since there are thousands of minsets, we took a broad view. For all minsets, we partitioned lexemes by type, leveraging information collected JavaMT; the types we defined are similar to lexer token types but broader in some cases and narrower in others. We provide a list of the lexeme types we defined, along with the counts of lexemes belonging to that type in Table IV.

Public type variable identifiers, and string and character literals dominate minsets. String literals are constant string values like “Joda”. The strings can represent error or information messages, IP addresses, names, pretty much anything. Perhaps this is why are at the top of the list: they can be unique or very rare. We divide certain classes of words depending if they are public or local — method invocations, type identifiers, and variable names. Public words are more standard and common whereas local words are more specialized and rare. Not surprisingly then, we observe that standard language features, like keywords and operators, and public types and methods are less common in minsets. The only exceptions are variable identifiers of public types. Their distinctiveness is due in part to synonyms and homonyms. A programmer has great freedom in creating them. For example, dir appears 8017 times, as a variable name in methods, while directory appears only 2774 times. Another reason is that variable identifiers are more prevalent than other type of identifiers, like types and method calls.

Study of MIN4 We studied the minsets produced in our last experiment in Section IV-C. We selected nine minsets (Figure 10); we partitioned the methods into low, medium, and high minset ratios and picked three uniformly at random from each subset. For each minset, we tried to understand each element and what they revealed together about the behavior of a method. Then we inspected the method source code more carefully to assess how well the minsets capture method functionality. Due to lack of space, we discuss only three in detail.

Low: L1 The method named javax.xml.bind.Unmarshaller.unmarshal from (javax.xml.transform.Source) deserializes XML documents and returns a Java content tree object; java.awt.Image is an abstract classes that represents graphical images. From this minset, we infer that this method handles images and XML files. Since it reads the XML file, we also infer that it uses XML data in some manner. Perhaps the file contains a list of images, or the data in the file is used to create or alter an image. After inspecting the source code, we find that it is a method in the LargeInlineBinaryTestCases class of the Eclipse Link project, which manages XML files and other data stores. Our understanding was not far off: the method does read a binary XML file that contains images.

Medium: M1 The java.lang.Class.isInstance(java.lang.-Object) method checks if a given object is an object of type Class or assignment-compatible with its calling object. The java.sql.Date. toString() method converts a Date object,
TABLE IV: Types of lexemes (or words) in the minsets we computed over the lexicon LEX.

| Grain Type | Count | Examples |
|------------|-------|----------|
| Variable Identifier (of Public Type) | 3235 | abilityType (java.lang.StringBuffer), defaultValue (int), lostCandidate (boolean), twsItem (java.util.List) |
| String and Character Literal | 3202 | "au203F", '&', "192.168.1.36", "audit.pdf", "Error: 3", "Joda", "Record Found", "secret4" |
| Method Call (Local) | 2942 | classNameForCode, getInstanceProperty, isUserDefaultAdmin, makeDir, shouldAutoComplete |
| Variable Identifier (of Local Type) | 1574 | arcTgt, component, iVRPlayPropertiesTab, nestedException, this_TemplateCS_1, wordFSA |
| Type Identifier (a Local Type) | 1413 | ErrorApplication, IWorkspaceRoot, Literals, NNSingleElectron, PickObject, TrainingComparator |
| Method Call (a Public Method) | 308 | currentTimMillis (java.lang.System.currentTimMillis()), replace (java.lang.String.replace(char, char)) |
| Number Literal (integer, float, etc.) | 310 | 0, 1, 3, 150, 2010, 0xDD, 0x7Bede42, 255.0f, 0x1000000000041L, 46.666660 |
| Type Identifier (a Public Type) | 265 | int, ArrayList, Collection, IllegalArgumentException, PropertyChangeSupport, SimpleDateFormat |
| Operator | 260 | <, <=, =, ==, >, >=, <<=, |, |=, ||, -, -=, –, !, !=, ?, /, /=, @, *, &, &&, +, +=, ++ |
|_keyword (except Types) | 196 | break, catch, do, else, extends, final, finally, for, instanceof, new, return, super, synchronized, this, try, while |
| Separator | 148 | false, null, true |
| Reserved Words (Literals) | 104 | COLUMNNAME_PostingType, E, ec2, element, ModelType, org, T, TC |
| Other | 112 |

In the source, we confirm that it is a constructor in the HsqlSocketFactorySecure class in the CloverETL project. It wraps code that instantiates a Provider class and adds it to the Security object in a try block. If adding the provider fails, it catches the exception, as we had inferred.

V. APPLICATIONS

Though our study is primarily empirical, in this section, we describe existing and new applications for minsets.

SmartSynth (Existing) As we mentioned earlier, the clearest and, perhaps, most promising application for minsets is in keyword-based programming. SmartSynth [14] is a recent, modern incarnation. SmartSynth generates a smartphone script from a natural language description (query). “Speak weather in the morning” is an example of a successful query. SmartSynth uses NLP techniques to parse the query and map it to a set of “components” (words) in its underlying programming language. Combining a variety of techniques, it then infers relationships between the words to generate and rank candidate scripts. At its heart is the idea that usable code can be constructed from a small set of words. This subset is a minset or another distinguishing subset.

Code Search Engine (New) A major problem of code search is ranking results [2, 18, 21]. We built a code search engine that uses a new ranking scheme. Relevant methods are ranked by the similarity between their minsets and the user’s query. For example, the query “sort array int” returns 135 methods. The top result, with minset “sort array parslet 16”, returns a sorted array of integers, if the ‘sort’ flag is set.

Code Summarizer (New) From our case studies of Min4 minsets, we realized that minsets can effectively summarize code. We built a code summary web application. A user enters the source code of a method, our tool computes a minset, and presents it as a concise summary. Due to space constraints, we omit a full example and invite interested readers to explore our web application. Figure 10 shows examples of minsets summarizing methods.

VI. DISCUSSION

The main purpose of this study was to test our “wheat and chaff” hypothesis. We have shown, over a variety of lexicons, that functions can be identified by a subset of their words, that those subsets tend to be very small, and suggested a

[^http://jarvis.cs.ucdavis.edu/code_essence]
lexicon, MIN4, that induces those minsets to be more natural and meaningful. Thus, our results clearly support our “wheat and chaff” hypothesis.

Our results offer insight into how to develop powerful, alternative programming systems. Consider an integrated development environment (IDE), like Eclipse or IntelliJ, that can search a MINSET indexed database of code and requirements to 1) propose related code that may be adapted to purpose, 2) auto-complete whole code fragments as the programmer works, 3) speed concept location for navigation and debugging, and 4) support traceability by interconnecting requirements and code [6].

Other Lexicons  Our lexicon exploration avoided variable names because they are so unconstrained, noisy, and rife with homonyms and synonyms. Minsets over lexicons, like LEX, that incorporated them could include trivial, semantically insignificant differences, like user vs. usr in Unix. At the same time, variable names are an alluring source of signal. Intuitively, and in this corpus, they are the largest class of identifiers, which comprise 70% of source code [8], and connect a program’s source to its problem domain [4]. In future work, we plan to separate the “wheat from the chaff” in variable names.

Alternatives to Functions  We chose functions as our semantic unit of discourse. However, we can apply the same methodology at other semantic levels. One alternative is to study blocks of code. A single function can have many blocks. This could be very useful in alternative programming systems where the user seeks a common block of code but for which there is no individual function. Another alternative is to use abstract syntax trees (AST).

Threats to Validity  We identify two main threats. The first is that we only studied Java. However, we have no reason to believe that the “wheat and chaff” hypothesis does not hold for other programming languages. Java, though more modern, was designed to be very similar to C and C++ so that it could be adopted easily. The second threat comes from our corpus: size and diversity. We downloaded a very large corpus, by any standard. In fact, we downloaded all the Java projects listed as “Most Popular” in the four code repositories we crawled. Those code repositories are known primarily for hosting open-source projects. Thus, there is no indication that they are biased toward any specific types of projects. We plan to replicate this study on a larger Java corpus and with language of different paradigms like List and Prolog to help us understand to what extent the “wheat and chaff” phenomenon varies.

VII. RELATED WORK

Although we are the first to study the phenomenon of “wheat” and “chaff” in code⁹, a few strands of related work exist.

Code Uniqueness  At a basic level, our study is about uniqueness. Gabel and Su also studied uniqueness [9]. They found that software generally lacks uniqueness which they measure as the proportion of unique, fixed-length token sequences in a software project. We studied uniqueness differently. We captured the distinguishing core semantics (the essence) of a piece of code in a unique subset of syntactic features, a MINSET, whose elements may not be unique or even rare but together uniquely identify a piece of code. We keep in mind that syntactic differences do not always imply functional differences as Jiang and Su demonstrated [13]. Thus, in some cases two minsets may represent the same high-level behavior.

Code Completion and Search  Observations about natural language phenomenon provide a promising path toward making programming easier. Hindle et al. focused on the ‘naturalness’ of software [12]. They showed that actual code is “regular and predictable”, like natural language utterances. To do so, they trained an n-gram model on part of a corpus, and then tested it on the rest. They leveraged code predictability to enhance Eclipse’s code completion tool. Their work followed that of Gabel and Su who posited and gave supporting evidence that we are approaching a ‘singularity’, a point in time where all the small fragments of code we need to write already exist [9].

When that happens, many programming tasks can be reduced to finding the desired code in a corpus. Our work suggests that small, natural set of words, captured in a MINSET, can index and retrieve code. As for code completion, a MINSET-based approach could exploit not just the previous n−1 tokens, but on all the previous tokens and complete not just the next token but whole pieces of code.

Sourcerer and Portolio, two modern code search engines, support basic term queries, in addition to more advanced queries [2, 20]. Our research suggest the natural and efficient term query is a MINSET. Results may differ in granularity. Portfolio focuses on finding functions [20] while Exemplar, another engine, finds whole applications [11]. MINSET easily generalizes to arbitrary code fragments. Finally, code search must also be ‘internet-scale’ [10], and with a modest computer, we can compute minsets for corpora of code of various languages, and update them regularly as new code is added.

Code completion tools suggest code a programmer might want to use. They infer relevant code and rank it. Many diverse, useful tools and strategies exist [5, 24, 25, 32]. Our work suggests a different, complementary MINSET-based strategy: If what the programmer is coding contains the MINSET of some piece of code, suggest that.

Genetics and Debugging  At a high-level, Algorithm 1 isolates a minimal set of essential elements. Central to synthetic biology is the search for the ‘minimal genome’, the minimal set of genes essential to living organisms [1] [19]. Delta debugging is very similar in that it finds a minimal set of lines of code that trigger a bug [7]. Both approaches rely on an oracle who defines what is ‘essential’ whereas we define ‘essentialness’ with respect to other sets.

VIII. CONCLUSION AND FUTURE WORK

We imagine that code, to the human mind, is amorphous, and ask: “If a programmer were reading this code, what features would be semantically important?” and “If a programmer were trying to write this piece of code, what key ideas would the programmer communicate?” A MINSET is our proposal of a useful, formal definition of these key ideas as ‘wheat.’ Our definition is constructive, so a computer can compute Minsets to generate or retrieve an intended piece of code.

We evaluated Minsets, over a large corpus of real-world Java programs, using various, natural lexicons: the computed minsets are sufficiently small and understandable for use in code search, code completion, and natural programming.

⁹Others have used the “wheat and chaff” analogy in the computing world but in different domains [29, 30].
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