ABSTRACT

Every programmer has a characteristic style, ranging from preferences about identifier naming to preferences about object relationships and design patterns. Coding conventions define a consistent syntactic style, fostering readability and hence maintainability. When collaborating, programmers strive to obey a project’s coding conventions. However, one third of reviews contain feedback about coding conventions, indicating that programmers do not always follow them and that project members care deeply about adherence. Unfortunately, programmers are often unaware of coding conventions because inferring them requires a global view, one that aggregates the many local decisions programmers make and identifies emergent consensus on style. We present NATURALIZE, a framework that learns the style of a codebase, and suggests revisions to improve stylistic consistency. NATURALIZE builds on recent work in applying statistical natural language processing to source code. We apply NATURALIZE to suggest natural identifier names and formatting conventions. We present four tools focused on ensuring natural code during development and release management, including code review. NATURALIZE achieves 94% accuracy in its top suggestions for identifier names. We used NATURALIZE to generate 18 patches for 5 open source projects: 14 were accepted.

Categories and Subject Descriptors:
D.2.3 [Software Engineering]: Coding Tools and Techniques

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1 Introduction

To program is to make a series of choices, ranging from design decisions — like how to decompose a program into functions — to the choice of identifier names and how to format the code. While local and syntactic, the latter are important: names connect program source to its problem domain [13, 43, 44, 68]; formatting decisions usually capture control flow [36]. Together, naming and formatting decisions determine the readability of a program’s source code, increasing a codebase’s portability, its accessibility to newcomers, its reliability, and its maintainability [55, §1.1]. Apple’s recent, infamous bug in its handling of SSL certificates [7, 40] exemplifies the impact that formatting can have on reliability. Maintainability is especially important since developers spend the majority (80%) of their time maintaining code [2, 6].

A convention is an equilibrium that everyone expects in interactions that have more than one equilibrium” [74]. For us, coding conventions arise out of the collision of the stylistic choices of programmers. A coding convention is a syntactic restriction not imposed by a programming language’s grammar. Nonetheless, these choices are important enough that they are enforced by software teams. Indeed, our investigations indicate that developers enforce such coding conventions rigorously, with roughly one third of code reviews containing feedback about following them (Section 4.1).

Like the rules of society at large, coding conventions fall into two broad categories: laws, explicitly stated and enforced rules, and mores, unspoken common practice that emerges spontaneously. Mores pose a particular challenge: because they arise spontaneously from emergent consensus, they are inherently difficult to codify into a fixed set of rules, so rule-based formatters cannot enforce them, and even programmers themselves have difficulty adhering to all of the implicit mores of a codebase. Furthermore, popular code changes constantly, and these changes necessarily embody stylistic decisions, sometimes generating new conventions and sometimes changing existing ones. To address this, we introduce the coding convention inference problem, the problem of automatically learning the coding conventions consistently used in a body of source code.

Conventions are pervasive in software, ranging from preferences about identifier names to preferences about class layout, object relationships, and design patterns. In this paper, we focus as a first step on local, syntactic conventions, namely, identifier naming and formatting. These are particularly active topics of concern among developers, for example, almost one quarter of the code reviews that we examined contained suggestions about naming.

We introduce NATURALIZE, a framework that solves the coding convention inference problem for local conventions, offering suggestions to increase the stylistic consistency of a codebase. NATURALIZE can also be applied to infer rules for existing rule-based formatters. NATURALIZE is descriptive, not prescriptive: it learns what programmers actually do. When a codebase does not reflect consensus on a convention, NATURALIZE recommends nothing, because it has not learned anything with sufficient confidence to make recommendations. The naturalness insight of Hindle et al. [35], building on Gabel and Su [28], is that most short code utterances, like natural language utterances, are simple and repetitive. Large corpus statistical inference can discover and exploit this naturalness to improve developer productivity and code robustness. We show that coding conventions are natural in this sense.

Learning from local context allows NATURALIZE to learn syntactic restrictions, or sub-grammars, on identifier names like camelcase.

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1Prescriptivism is the attempt to specify rules for correct style in language, e.g., Strunk and White [67]. Modern linguists studiously avoid prescriptivist accounts, observing that many such rules are routinely violated by noted writers.
or underscore, and to unify named uses in similar contexts, which rule-based code formatters simply cannot do. Intuitively, NATURALIZE works by identifying identifier names or formatting choices that are surprising according to a probability distribution over code text. When surprised, NATURALIZE determines if it is sufficiently confident to suggest a renaming or reformattting that is less surprising; it unifies the surprising choice with one that is preferred in similar contexts elsewhere in its training set. NATURALIZE is not automatic; it assists a developer, since its suggestions, both renaming and even formatting, as in Python or Apple’s aforementioned SSL bug [7, 40], are potentially semantically disruptive and must be considered and approved. NATURALIZE’s suggestions enable a range of new tools to improve developer productivity and code quality:

1) A pre-commit script that rejects commits that excessively disrupt a codebase’s conventions; 2) A tool that converts the inferred conventions into rules for use by a code formatter; 3) An Eclipse plugin that a developer can use to check whether her changes are unconventional; and 4) A style profiler that highlights the stylistic inconsistencies of a code snippet for a code reviewer.

NATURALIZE draws upon a rich body of tools from statistical natural language processing (NLP), but applies these techniques to a different kind of problem. NLP focuses on understanding and generating language, but does not ordinarily consider the problem of improving existing text. The closest analog is spelling correction, but that problem is easier because we have strong prior knowledge about common types of spelling mistakes. An important conceptual dimension of our suggestion problems also sets our work apart from mainstream NLP. In code, rare names often usefully signify unusual functionality, and need to be preserved. We call this the sympathetic uniqueness principle (SUP): unusual names should be preserved when they appear in unusual contexts. We achieve this by exploiting a special token UNK that is often used to represent rare words that do not appear in the training set. Our method incorporates SUP through a clean, straightforward modification to the handling of UNK. Because of the Zipfian nature of language, UNK appears in unusual contexts and identifies unusual tokens that should be preserved. Section 4 demonstrates the effectiveness of this method at preserving such names. Additionally, handling formatting requires a simple, but novel, method of encoding formatting.

As NATURALIZE detects identifiers that violate code conventions and assists in renaming, the most common refactoring [50], it is the first tool we are aware of that uses NLP techniques to aid refactoring.

The techniques that underlie NATURALIZE are language independent and require only identifying identifiers, keywords, and operators, a much easier task than specifying grammatical structure. Thus, NATURALIZE is well-positioned to be useful for domain-specific or esoteric languages for which no convention enforcing tools exist or the increasing number of multi-language software projects such as web applications that intermix Java, CSS, HTML, and JavaScript.

To the best of the authors’ knowledge, this work is the first to address the coding convention inference problem, to suggest names and formatting to increase the stylistic coherence of code, and to provide tooling to that end. Our contributions are:

- We built NATURALIZE, the first framework to solve the coding convention inference problem for local conventions, including identifier naming and formatting, and suggests changes to increase a codebase’s adherence to its own conventions;
- We offer four tools, built on NATURALIZE, all focused on release management, an under-todoed phase of the development process.
- NATURALIZE 1) achieves 94% accuracy in its top suggestions for identifier names and 2) never drops below a mean accuracy of 96% when making formatting suggestions; and
- We demonstrate that coding conventions are important to software teams, by showing that 1) empirically, programmers enforce conventions heavily through code review feedback and correct commits, and 2) patches that were based on NATURALIZE suggestions have been incorporated into 5 of the most popular open source Java projects on GitHub — of the 18 patches that we submitted, 14 were accepted.

Tools are available at groups.inf.ed.ac.uk/naturalize.

2 Motivating Example

Both industrial and open source developers often submit their code for review prior to check-in [61]. Consider the example of the class shown in Figure 1 which is part of a change submitted for review by a Microsoft developer on February 17th, 2014. While there is nothing functionally wrong with the class, it violates the coding conventions of the team. A second developer reviewed the change and suggested that res and str do not convey parameter meaning well enough, the constructor line is much too long and should be wrapped. In the checked in change, all of these were addressed, with the parameter names changed to queryResults and queryStrings.

Consider a scenario in which the author had access to NATURALIZE. The author might highlight the parameter names and ask NATURALIZE to evaluate them. At that point it would have not only have identified res and str as names that are inconsistent with the naming conventions of parameters in the codebase, but would also have suggested better names. The author may have also thought to himself “Is the constructor on line 3 too long?” or “Should the empty constructor body be on it’s own line and should it have a space inside?” Here again, NATURALIZE would have provided immediate, valuable answers based on the the conventions of the team. NATURALIZE would indicate that the call to the base constructor should be moved to the next line and indented to be consonant with team conventions and that in this codebase empty method bodies do not need their own lines. Furthermore it would indicate that some empty methods contain one space between the braces while others do not, so there is no implicit convention to follow. After querying NATURALIZE about his stylistic choices, the author can then be confident that his change is consistent with the norms of the team and is more likely to be approved during review.

Furthermore, by leveraging NATURALIZE, fellow project members wouldn’t need to be bothered by questions about conventions, nor would they need to provide feedback about conventions during review. We have observed that such scenarios occur in open source projects as well.

2.1 Use Cases and Tools

Coding conventions are critical during release management, which comprises committing, reviewing, and promoting (including releases) changes, either patches or branches. This is when a coder’s idiosyncratic style, isolated in her editor during code composition, comes into contact with the styles of others. The outcome of this interaction strongly impacts the readability, and therefore the maintainability, of a codebase. Compared to other phases of the development cycle like editing, debugging, project management, and issue tracking, release management is under-todoed. Code conventions are particularly pertinent here, and lead us to target three use cases: 1) a developer preparing an individual commit or branch for review or promotion; 2) a release engineer trying to filter out needless stylistic diversity from the flood of changes; and 3) a reviewer wishing to consider how well a patch or branch obeys community norms.

Any code modification has a possibility of introducing bugs [3, 51]. This is certainly true of a system, like NATURALIZE, that is based on statistical inference, even when (as we always assume) all of NATURALIZE’s suggestions are approved by a human. Because of this risk, the gain from making a change must be worth its cost. For
public class ExecutionQueryResponse : ExecutionQueryResponseBasic<QueryResults>
{
    public ExecutionQueryResponse(QueryResults res, IReadOnlyCollection<string> str, ExecutionStepMetrics metrics) : base(res, str, metrics) {}
}

Figure 1: A C# class added by a Microsoft developer that was modified due to requests by a reviewer before it was checked in.

Figure 2: A screenshot of the devstyle Eclipse plugin. The user has requested suggestion for alternate names of the each argument.

this reason, our use cases focus on times when the code is already being changed. To support our use cases, we have built four tools: devstyle A plugin for Eclipse IDE that gives suggestions for identifier renaming and formatting both for a single identifier or format point and for the identifiers and formatting in a selection of code.

styleprofile A code review assistant that produces a profile that summarizes the adherence of a code snippet to the coding conventions of a codebase and suggests renaming and formatting changes to make that snippet more stylistically consistent with a project.

genrule A rule generator for Eclipse’s code formatter that generates rules for those conventions that NATURALIZE has inferred from a codebase.

stylish? A high precision pre-commit script for Git that rejects commits that have highly inconsistent and unnatural naming or formatting within a project.

The devstyle plugin offers two types of suggestions, single point suggestion under the mouse pointer and multiple point suggestion via right-clicking a selection. A screenshot from devstyle is shown in Figure 2. For single point suggestions, devstyle displays a ranked list of alternatives to the selected name or format. If devstyle has no suggestions, it simply flashes the current name or selection. If the user wishes, she selects one of the suggestions. If it is an identifier renaming, devstyle renames all uses, within scope, of that identifier under its previous name. This scope traversal is possible because our use cases assume an existing and compiled codebase. Formatting changes occur at the suggestion point. Multiple point suggestion returns a style profile, a ranked list of the top k most stylistically surprising naming or formatting choices in the current selection that could benefit from reconsideration. By default, k = 5 based on HCI considerations [23, 48]. To accept a suggestion here, the user must first select a location to modify, then select from among its top alternatives. The styleprofile tool outputs a style profile. genrule (Section 3.5) generates settings for the Eclipse code formatter. Finally, stylish? is a filter that uses Eclipse code formatter with the settings from genrule to accept or reject a commit based on its style profile.

NATURALIZE uses an existing codebase, called a training corpus, as a reference from which to learn conventions. Commonly, the training corpus will be the current codebase, so that NATURALIZE learns domain-specific conventions related to the current project. Alternatively, NATURALIZE comes with a pre-packaged suggestion model, trained on a corpus of popular, vibrant projects that presumably embody good coding conventions. Developers can use this engine if they wish to increase their codebase’s adherence to a larger community’s consensus on best practice. Projects that are just starting and have little or no code written can also use the training corpus a pre-existing codebase, for example another project in the same organization, whose conventions the developers wish to adopt. Here, again, we avoid normative comparison of coding conventions, and do not force the user to specify their desired conventions explicitly. Instead, the user specifies a training corpus, and this is used as an implicit source of desired conventions. The NATURALIZE framework and tools are available at groups.inf.ed.ac.uk/naturalize.

3 The NATURALIZE Framework

In this section, we introduce the generic architecture of NATURALIZE, which can be applied to a wide variety of different types of conventions and is language independent. NATURALIZE is general and can be applied to any language for which a lexer and a parser exist, as token sequences and abstract syntax trees (ASTs) are used during analysis. Figure 3 illustrates its architecture. The input is a code snippet to be naturalized. This snippet is selected based on the user input, in a way that depends on the particular tool in question. For example, in devstyle, if a user selects a local variable for renaming, the input snippet would contain all AST nodes that reference that variable (Section 3.3). The output of NATURALIZE is a short list of suggestions, which can be filtered, then presented to the programmer. In general, a suggestion is a set of snippets that may replace the input snippet. The list is ranked by a naturalness score that is defined below. Alternately, the system can return a binary value indicating whether the code is natural, so as to support applications such as stylish? The system makes no suggestion if it deems the input snippet to be sufficiently natural, or is unable to find good alternatives. This reduces the “Clippy effect” where users ignore a system that makes too many bad suggestions. In the next section, we describe each element in the architecture in more detail.

Terminology A language model (LM) is a probability distribution over strings. Given any string \( x = x_0, x_1, \ldots, x_M \) where each \( x_i \) is a token, a LM assigns a probability \( P(x) \). Let \( G \) be the grammar of a programming language. We use \( x \) to denote a snippet, that is, a string \( x \) such that \( ax\beta \in \mathcal{L}(G) \) for some strings \( \alpha, \beta \). We primarily consider snippets that are dominated by a single node in the file’s AST. That is, there is a node within the AST whose subtree comprises the entire snippet and nothing else. We use \( x \) to denote the input snippet to the framework, and \( y, z \) to denote arbitrary snippets.

3.1 The Core of NATURALIZE

The architecture contains two main elements: proposers and the scoring function. The proposers modify the input code snippet to produce a list of suggestion candidates that can replace the input snippet. In the example from Figure 1, each candidate replaces all occurrences of \( \text{res} \) with a different name used in similar contexts elsewhere in the project, such as results or queryResults. In principle, many implausible suggestions could ensue, so, in practice, proposers contain filtering logic.

A scoring function sorts these candidates according to a measure of naturalness. Its input is a candidate snippet, and it returns a real number measuring naturalness. Naturalness is measured with respect to a training corpus that is provided to NATURALIZE—thus allowing us to follow our guiding principle that naturalness must be measured with respect to a particular codebase. For example, the training corpus might be the set of source files \( A \) from the current application. A powerful way to measure the naturalness

\[ \text{naturalness} = \sum \text{score}(x) \]

In extreme cases, such systems can be so widely mocked that they are publicly disabled by the company’s CEO in front of a cheering audience: http://bit.ly/pmHoW1.

The application of NATURALIZE to academic papers in software engineering is left to future work.
of a snippet is provided by statistical language modeling. We use 
\( P_k(y) \) to indicate the probability that the language model \( P \), which
has been trained on the corpus \( A \), assigns to the string \( y \). The
key intuition is that an LM \( P_k \) is trained so that it assigns high
probability to strings in the training corpus, \( i.e., \) snippets with higher
log probability are more like the training corpus, and presumably
more natural. There are several key reasons why statistical language
models are a powerful approach for modeling coding conventions.
First, probability distributions provide an easy way to represent
soft constraints about conventions. This allows us to avoid many of the
pitfalls of inflexible, rule-based approaches. Second, because they
are based on a learning approach, LMs can flexibly adapt to
the conventions in a new project. Intuitively, because \( P_k \) assigns high
probability to strings \( t \in A \) that occur in the training corpus, it also
assigns high probability to strings that are similar to those in the
corpus. So the scoring function \( x \) tends to favor snippets that are
stylistically consistent with the training corpus.

We score the naturalness of a snippet \( y = y_{1:N} \) as
\[
s(y, P_k) = \frac{1}{N} \log P_k(y);
\]
that is, we deem snippets that are more probable under the LM as
more natural in the application \( A \). Equation 1 is cross-entropy multi-
plied by -1 to make \( s \) a score, where \( s(x) > s(y) \) implies \( x \) is more
natural than \( y \). Where it creates no confusion, we write \( s(y) \), eliding
the second argument. When choosing between competing candidate
snippets \( y \) and \( z \), we need to know not only which candidate the LM
prefers, but how “confident” it is. We measure this by a gap function
\( g \), which is the difference in scores \( g(y, z, P) = s(y, P) - s(z, P) \).
Because \( s \) is essentially a log probability, \( g \) is the log ratio of proba-
bilities between \( y \) and \( z \). For example, when \( g(y, z) > 0 \) the snippet
\( y \) is more natural — \( i.e., \) less surprising according to the LM — and
thus is a better suggestion candidate than \( z \). If \( g(y, z) = 0 \) then both
snippets are equally natural.

Now we define the function \( \text{suggest}(x, C, k, t) \) that returns the
top candidates according to the scoring function. This function
returns a list of top candidates, or the empty list if no candidates are
sufficiently natural. The function takes four parameters: the input
snippet \( x \), the list \( C = (c_1, c_2, ..., c_r) \) of candidate snippets, and two
thresholds: \( k \in \mathbb{N} \), the maximum number of suggestions to return,
and \( t \in \mathbb{R} \), a minimum confidence value. The parameter \( k \) controls
the size of the ranked list that is returned to the user, while \( t \) controls
the suggestion frequency, that is, how confident NATURALIZE needs
to be before it presents any suggestions to the user. Appropriately
setting \( t \) allows NATURALIZE to avoid the Clippy effect by making
no suggestion rather than a low quality one. Below, we present an
automated method for selecting \( t \).

The suggest function first sorts \( C = (c_1, c_2, ..., c_r) \), the candidate
list, according to \( s \), so \( s(c_1) \geq s(c_2) \geq ... \geq s(c_r) \). Then, it trims
the list to avoid overburdening the user: it truncates \( C \) to include
only the top \( k \) elements, so that \( \text{length}(C) = \min(k, r) \). and removes
candidates \( c_i \in C \) that are not sufficiently more natural than the
original snippet; formally, it removes all \( c_i \) from \( C \) where \( g(c_i, x) < t \).
Finally, if the original input snippet \( x \) is the highest ranked in \( C \),
\( i.e., \) if \( c_1 = x \), suggest ignores the other suggestions, sets \( C = \emptyset \) to
decline to make a suggestion, and returns \( C \).

**Binary Decision** If an accept/reject decision on the input \( x \) is
required, \( i.e., \) as in \( \text{suggest} \) \( x \)? NATURALIZE must collectively
consider all of the locations in \( x \) at which it could make suggestions.
We propose a score function for this binary decision that measures
how good is the best possible improvement that NATURALIZE
is able to make. Formally, let \( L \) be the set of locations in \( x \) at which
NATURALIZE is able to make suggestions, and for each \( f \in L \), let \( C_f \)
be the system’s set of suggestions at \( f \). In general, \( C_f \) contains name or
formatting suggestions. Recall that \( P \) is the language model. We
define the score
\[
G(x, P) = \max_{t \in L} \max_{c \in C_f} g(x, c).
\]
If \( G(x, P) > T \), then NATURALIZE rejects the snippet as being
excessively unnatural. The threshold \( T \) controls the sensitivity of
NATURALIZE to unnatural names and formatting. As \( T \) increases,
fewer input snippets will be rejected, so some unnatural snippets
will slip through, but as compensation the test is less likely to reject
snippets that are in fact well-written.

**Setting the Confidence Threshold** The thresholds \( r \) in the suggest
function and \( T \) in the binary decision function are on log probabili-
ties of strings, which can be difficult for users to interpret. Fortu-
nately, these can be set automatically using the false positive rate
(FPR), \( i.e., \) the proportion of snippets \( x \) that in fact follow convention
but that the system erroneously rejects. We would like the FPR to
be as small as possible, but, unless we wish the system to make no
suggestions at all, we must accept some false positives. So we set
a maximum acceptable FPR \( \alpha \), and search for a threshold \( t \) or \( T \nthat ensures that NATURALIZE’s FPR is at most \( \alpha \). The principle
is similar to statistical hypothesis testing. To make this work, we
estimate the FPR for a given \( t \) or \( T \). To do so, we select a random
set of snippets from the training corpus, \( e.g., \) random method bod-
ies, and compute the proportion of these snippets that are rejected
using \( T \). Again leveraging our assumption that our training corpus
contains natural code, this proportion estimates the FPR. We use
a grid search [11] to find the greatest value of \( T < \alpha \) \((t < \alpha)\), the
user-specified acceptable FPR bound.

### 3.2 Choices of Scoring Function
The generic framework described in Section 3.1 can, in principle,
employ a wide variety of machine learning or NLP methods for
its scoring function. Indeed, a large portion of the statistical NLP
literature focuses on probability distributions over text, including language models, probabilistic grammars, and topic models. Very few of these models have been applied to code; exceptions include [4, 35, 46, 49, 53]. We choose to build on statistical language models, because previous work of Hindle et al. [35] has shown that they are particularly able to capture the naturalness of code.

The intuition behind language modeling is that since there is an infinite number of possible strings, obviously we cannot store a probability value for every one. Different LMs make different simplifying assumptions to make the modeling tractable, and will determine the types of coding conventions that we are able to infer. One of the most effective practical LMs is the n-gram language model. N-gram models make the assumption that the next token can be predicted using only the previous n − 1 tokens. Formally, the probability of a token \( y_m \) conditioned on all of the previous tokens \( y_1 \ldots y_{m−1} \) is a function only of the previous \( n − 1 \) tokens. Under this assumption, we can write

\[
P(y_1 \ldots y_M) = \prod_{m=1}^{M} P(y_m | y_{m−1} \ldots y_{m−n+1}).
\]

To use this equation we need to know the conditional probabilities \( P(y_m | y_{m−1} \ldots y_{m−n+1}) \) for each possible n-gram. This is a table of \( V^n \) numbers, where \( V \) is the number of possible lexemes. These are the parameters of the model that we learn from the training corpus. The simplest way to estimate the model parameters is to set \( P(y_m | y_{m−1} \ldots y_{m−n+1}) \) to the proportion of times that \( y_m \) follows \( y_{m−1} \ldots y_{m−n+1} \). In practice, this simple estimator does not work well, because it assigns zero probability to n-grams that do not occur in the training corpus. Instead, n-gram models are trained using smoothing methods [22]. In our work, we use Katz smoothing.

**Implementation** When an n-gram model is used, we can compute the gap function \( g(y, z) \) very efficiently. This is because when \( g \) is used within suggest, ordinarily the strings \( y \) and \( z \) will be similar, i.e., the input snippet and a candidate revision. The key insight is that in an n-gram model, the probability \( P(y) \) of a snippet \( y = (y_1 \ldots y_N) \) depends only on the multiset of n-grams that occur in \( y \), that is,

\[
NG(y) = \{y_i y_{i+1} \ldots y_i+n−1 | 0 \leq i \leq N−(n−1)\}.
\]

An equivalent way to write a n-gram model is

\[
P(y) = \prod_{a_1 \ldots a_n \in NG(y)} P(a_n|a_1, a_2 \ldots a_{n−1}).
\]

Since the gap function is \( g(y, z) = \log[P(y)/P(z)] \), any n-grams that are members both of \( NG(y) \) and \( NG(z) \) cancel, so to compute \( g \), we only need to consider those \( n \)-grams not in \( NG(y) \cap NG(z) \). Intuitively, this means that, to compute the gap function \( g(y, z) \), we need to examine the n-grams around the locations where the snippets \( y \) and \( z \) differ. This is a very useful optimization if \( y \) and \( z \) are long snippets that differ in only a few locations.

When training an LM, we take measures to deal with rare lexemes, since, by definition, we do not have much data about them. We use a preprocessing step — a common strategy in language modeling — that builds a vocabulary with all the identifiers that appear more than once in the training corpus. Let \( count(v, b) \) return the number of appearances of token \( v \) in the codebase \( b \). Then, if a token has \( count(v, b) \leq 1 \) we convert it to a special token, which we denote UNK. Then we train the n-gram model as usual. The effect is that the UNK token becomes a catchall that means the model expects to see a rare token, even though it cannot be sure which one.

### 3.3 Suggesting Natural Names

In this section, we instantiate the core NATURALIZE framework for the task of suggesting natural identifier names. We start by describing the single suggestion setting. For concreteness, imagine
Figure 4: A code snippet from TextRunnerTest.java in JUnit and the corresponding formatting tokenization.

function could be good at the single source problem but bad at the multiple source problem, e.g., if the score values have a different dynamic range when applied at different locations.

We adapt NATURALIZE slightly to address the multiple point setting. For all identifier names v that occur in x, we first compute the candidate suggestions S_v as in the single suggestion case. Then the full candidate list for the multiple point suggestion is \( S = \cup_{v \in \mathcal{S}} S_v \); each candidate arises from proposing a change to one name in x. For the scoring function, we need to address the fact that some names occur more commonly in x than others, and we do not want to penalize names solely because they occur more often. So we normalize the score according to how many times a name occurs. Formally, a candidate c \( \in S \) that has been generated by changing a name v, we use the score function \( s'(c) = |C|-1 s(c) \).

3.4 Suggesting Natural Formatting

We apply NATURALIZE to build a language-agnostic code formatting suggester that automatically and adaptively learns formatting conventions and generates rules for use by code formatters, like the Eclipse formatter. An n-gram model works over token streams; for the n-gram instantiation of NATURALIZE to provide formatting suggestions, we must tokenize whitespace. We change the tokenizer to encode contiguous whitespace into tokens using the grammar

\[
S ::= \text{T} \ \text{SPACE} | \text{LINE}
\]

\[
T ::= \text{IDENT} | \text{ID} \ \text{SPACE} | \text{LINE}
\]

\[
\text{SPACE} ::= \text{SPACE}/\text{tab} | \text{SPACE}/\text{tabs}
\]

\[
\text{LINE} ::= \text{ID} | \text{LET} | \{ \} | \text{keywords}
\]

\[
\text{keywords} ::= \text{class} | \text{enum} | \text{interface} | \text{method} | \text{package} | \text{private} | \text{static} | \text{volatile}
\]

Finally, to complement the automatic evaluation, we perform two qualitative evaluations of the effectiveness of NATURALIZE suggestions. First, we manually examine the output of NATURALIZE, showing that even high quality projects contain many entities for which other names can be reasonably considered (Section 4.4). Finally, we submitted patches based on NATURALIZE suggestions (Section 4.5) to 5 of the most popular open source projects on GitHub — of the 18 patches that we submitted, 12 were accepted by the core members of these projects.

Methodology Our corpus is a set of well-known open source Java projects. From GitHub\(^4\), we obtained the list of all Java projects that are not forks and scored them based on their number of “watchers” and forks. The mean number of watchers and forks differ, so, to combine them, we assumed these numbers follow the normal distribution and summed their z-scores. For these evaluations reported here, we picked the top 10 scoring projects that are not in the training set of the GitHub Java Corpus [4]. Our original intention was to also demonstrate cross-project learning, but have no space to report these findings. Table 1 shows the selected projects.

Like any experimental evaluation, our results are susceptible to the standard threat of external validity. Interestingly, this threat does not extend to the training corpus, because the whole point is to bias NATURALIZE toward the conventions that govern the training set. Rather, our interest is to ensure that NATURALIZE’s performance on our evaluation corpus matches that of projects overall, which is why we took such care in constructing our corpus.

Our evaluations use leave-one-out cross validation. We test on each file in the project, training our models on the remaining files.

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We also examined discussions that occurred in reviews of source code changes. Code review is practiced heavily at Microsoft in an effort to ensure that changes are free of defects and adhere to team standards. Once an author has completed a change, he creates a code review and sends it to other developers for review. They then inspect the change, offer feedback, and either sign off or wait for the author to address their feedback in a subsequent change. As part of this process, the reviewers can highlight portions of the code and begin a discussion (thread) regarding parts of the change (for more details regarding the process and tools used, see Bacchelli et al. [10]).

We examined 169 code reviews selected randomly across Microsoft product groups during 2014. Our goal was to include enough reviews to examine at least 1,000 discussion threads. In total, these 169 reviews contained 1093 threads. We examined each thread to determine if it contained feedback related to a) code conventions in general, b) identifier naming, and c) code formatting. 18% of the threads examined provided feedback regarding coding conventions of some kind. 9% suggested improvements in naming and 2% suggested changes related to code formatting (subsets of the 18%). In terms of the reviews that contained feedback of each kind, the proportions are 38%, 24%, and 9%.

4.1 The Importance of Coding Conventions

To assess whether a) code conventions, specifically following formatting and naming conventions, are important to software teams today, we conducted two empirical studies that we present in this section. But first, we posit that coding style is both an important and a contentious topic. The fact that many languages and projects have style guides is a testament to this assertion. For example, we found that the Ruby style guide has at least 167 un-merged forks and the Java GitHub Corpus [4] has 349 different .xml configurations for the Eclipse formatter.

Commit Messages We manually examined 1,000 commit messages drawn randomly from the commits of eight popular open source projects looking for mentions of renaming, changing formatting, and following other code conventions. We found that 2% of changes contained formatting improvements, 1% contained renamings, and 4% contained any changes to follow code conventions (which include formatting and renaming). We observed that not all commits that contain changes to adhere to conventions mention such conventions in the commit messages. Thus, our percentages likely represent lower bounds on the frequency of commits that change code to adhere to conventions.

Code Review Discussions We also examined discussions that occurred in reviews of source code changes. Code review is practiced heavily at Microsoft in an effort to ensure that changes are free of defects and adhere to team standards. Once an author has completed a change, he creates a code review and sends it to other developers for review. They then inspect the change, offer feedback, and either sign off or wait for the author to address their feedback in a subsequent change. As part of this process, the reviewers can highlight portions of the code and begin a discussion (thread) regarding parts of the change (for more details regarding the process and tools used, see Bacchelli et al. [10]).

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4.2 Suggestion

In this section we present an automatic evaluation of NATURALIZE’s suggestion accuracy. First we evaluate naming suggestions (Section 3.3). We focus on suggesting new names for (1) locals, (2) arguments, (3) fields, (4) method calls, and (5) types (class names, primitive types, and enums) — these are the five distinct types of identifiers the Eclipse compiler recognizes [26]. Recall from Section 3.3 that when NATURALIZE suggests a renaming, it renames all locations where that identifier is used at once. Furthermore, as described earlier, we always use leave-one-out cross validation, so we never train the language model on the files for which we are making suggestions. Therefore, NATURALIZE cannot pick up the correct name for an identifier from other occurrences in the same file; instead, it must generalize by learning conventions from other
files in the project.

**Single Point Suggestion** First, we evaluate NATURALIZE on the single point suggestion task, that is, when the user has asked for naming suggestions for a single identifier. To do this, for each test file, for each unique identifier we collect all of the locations where the identifier occurs and names the same entity, and ask NATURALIZE to suggest a new name, renaming all occurrences at once. We measure accuracy, that is, the percentage of the time that NATURALIZE correctly suggests the original name. This is designed to reflect the typical usage scenario described in Section 2, in which a developer has made a good faith effort to follow a project’s conventions, but may have made a few mistakes.

Figure 5 reports on the quality of the suggestions. Each point on these curves corresponds to a different value of the confidence threshold \( t \). The \( x \)-axis shows the suggestion frequency, i.e., at what proportion of code locations where NATURALIZE is capable of making a suggestion does it choose to do so. The \( y \)-axis shows suggestion accuracy, that is, the frequency at which the true name is found in the top \( k \) suggestions, for \( k = 1 \) and \( k = 5 \). As \( t \) increases, NATURALIZE makes fewer suggestions of higher quality, so frequency decreases as accuracy increases. These plots are similar in spirit to precision-recall curves in that curves nearer the top right corner of the graph are better. Figure 5a, 5b, and 5c show that NATURALIZE performance varies with both project and the type of identifiers. Figure 5a combines locals, fields, and arguments because their performance is similar. NATURALIZE’s performance varies across these three categories of identifiers because of the data hungriness of n-grams and because local context is an imperfect proxy for type constraints or function semantics. The results show that NATURALIZE effectively avoids the Clippy effect, because by allowing the system to decline to suggest in a relatively small proportion of cases, it is possible to obtain good suggestion accuracy. Indeed, NATURALIZE can achieve 94% suggestion accuracy across identifier types, even when forced to make suggestions at half of the possible opportunities.

**Multiple Point Selection** To evaluate NATURALIZE’s accuracy at multiple point suggestion, e.g., in devstyle or styleprofile, we mimic code snippets in which one name violates the project’s conventions. For each test snippet, we randomly choose one identifier and perturb it to a name that does not occur in the project, compute the style profile, and measure where the perturbed name appears in the list of suggestions. NATURALIZE’s recall at rank \( k = 7 \), chosen because humans can take in 7 items at a glance [23, 48] is 64.2%. The mean reciprocal rank is 0.47: meaning that, on average, we return the bad name at position 2.

**Single Point Suggestion for Formatting** To evaluate NATURALIZE’s performance at making formatting suggestions, we follow the same procedure as the single-point naming experiment to check if NATURALIZE correctly recovers the original formatting from the context. We train a 5-gram language model using the modified token stream (\( g = 20 \)) discussed in Section 3.4. We allow the system to make only \( k = 1 \) suggestions to simplify the UI. We find that the system is extremely effective (Figure 9) at formatting suggestions, achieving 98% suggestion accuracy even when it is required to reformat half of the whitespace in the test file. This is remarkable for a system that is not provided with any hand-designed rules about what formatting is desired. Obviously if the goal is to reformat all the whitespace an entire file, a rule-based formatter is called for. But this performance is more than high enough to support our use cases, such as providing single point formatting suggestions on demand, rejecting snippets with unnatural formatting and extracting high confidence rules for rule-based formatters.

**Binary Snippet Decisions** Finally, we evaluate the ability of stylish? to discriminate between code selections that follow conventions well from those that do not, by mimicking commits that contain unconventional names or formatting. Uniformly at random, we selected a set of methods from each project (500 in total), then uniformly \((\frac{1}{2})\), we either made no changes or perturb one identifier or whitespace token to a token in the n-gram’s vocabulary. This method for mimicking commits is probably a worst case for our method, because the perturbed methods will be very similar to existing methods, which are likely to be conventional.

We run stylish? and record whether the perturbed snippet is rejected because of its names or its formatting. stylish? is unaware of the perturbation (if any), identifier or whitespace, made to the snippet. Figure 6 reports NATURALIZE’s rejection performance as ROC curves. In each curve, each point corresponds to a different choice of threshold \( T \), and the \( x \)-axis shows FPR (estimated as in Equation 3.1), and the \( y \)-axis shows true positive rate, the proportion of the perturbed snippets that we correctly rejected. NATURALIZE achieves high precision, making it suitable for use as a filtering pre-commit script. When the FPR is at most 0.05, we are able to correctly reject 40% of the snippets. NATURALIZE is somewhat worse at rejecting snippets whose variable names have been perturbed; in part, this is because predicting identifier names is more difficult than predicting formatting. New advances in language models for code [46, 53] are likely to improve these results. Nonetheless, these results are promising: stylish? still rejects enough perturbed snippets that if deployed at 5% FPR, it would enhance convention adherence with minimal disruption to developers.

### 4.3 Robustness of Suggestions

We show that NATURALIZE avoids two potential pitfalls in its identifier suggestions: first, that it does not simply rename all tokens to common “junk” names that appear in many contexts, and second, that it retains unusual names that signify unusual functionality, adhering to the SUP.
A junk name is a semantically uninformative name when using only identifiers, only formatting or both. A junk name is a semantically uninformative name when using only identifiers, only formatting or both.

**Junk Names** A junk name is a semantically uninformative name used in disparate contexts. It is difficult to formalize this concept: for instance, in almost all cases, `foo` and `bar` are junk names, while `i` and `j`, when used as loop counters, are semantically informative and therefore not junk. Despite this, most developers “know it when they see it.” One might at first be concerned that NATURALIZE would often suggest junk names, because junk names appear in many different n-grams in the training set. We argue, however, that in fact the opposite is the case: NATURALIZE actually resists suggesting junk names. This is because if a name appears in too many contexts, it will be impossible to predict a unsurprising follow-up, and so code containing junk names will have lower probability, and therefore worse score.

To evaluate this claim, we randomly rename variables to junk names in each project to simulate low quality corpus. The x-axis is percentage of resulting low quality suggestions. Note log-log scale. The dotted line shows y = x. The boxplots are across the 10 evaluation projects.

**Sympathetic Uniqueness** Surprise can be good in identifiers, where it signifies unusual functionality. Here we show that NATURALIZE preserves this sort of surprise. We find all identifiers in the test file that are unknown to the LM, *i.e.* are represented by an UNK.
each project before starting on a new project. In fact, the evaluators required much less time than allocated, averaging about 5 minutes per example. The human evaluations can be found on our project’s webpage. Surprisingly, given the quality of our evaluation codebases, 50% of the suggestions were determined to be useful by both evaluators. Further, no suggestion works well for everyone: when we consider \textsc{naturalize}'s performance in terms of whether at least one evaluator found a suggestion useful, 63% of the suggestions are useful, with an inter-rater agreement (Cohen’s kappa [21]) of $\kappa = 0.73$. The quality of suggestions is strikingly high given that these projects are mature, vibrant, high-profile projects.

This provides evidence that the naming suggestions provided by \textsc{naturalize} are qualitatively reasonable. Of course, an obvious threat to validity is that the evaluators are not developers of the test projects, and the developers themselves may well have had different opinions about naming. For this reason, we also provided the \textsc{naturalize} naming suggestions to the project developers themselves, as described in the next section.

\textbf{4.5 Suggestions Accepted by Projects}

Using \textsc{naturalize}'s style profile, we identified high confidence renamings and submitted 18 of them as patches to the 5 evaluation projects that actively use GitHub. Table I shows the pull request ids and their current status. Four projects merged our pull requests (14 of 15 commits); the last ignored them without comment. Developers in the projects that accepted \textsc{naturalize}'s patches found the \textsc{naturalize} useful: one said “Wow, that’s a pretty cool tool!” [31]. JUnit did not accept two of the suggested renamings as-is. Instead, the patches sparked a discussion. Its developers concluded that another name was more meaningful in one case and that the suggested renaming of another violated the project’s explicit naming convention: “Renaming g to t is no improvement, because we should consistently use e.” [30]. We then pointed them to the code locations that supported \textsc{naturalize}’s suggestion. This triggered them to change all the names that had caused the suggestion in the first place — \textsc{naturalize} pointed out an inconsistency, previously unnoticed, that improved the naming in the project. Our project webpage has links to these discussions.

\textbf{5 Related Work}

Coding conventions, readability, and identifiers have been extensively studied in the literature. Despite this, \textsc{naturalize} is — to our knowledge — the first to infer coding conventions from a codebase, spanning naming and formatting.

\textbf{Coding conventions} are standard practice [15, 34]. They facilitate consistent measurement and reduce systematic error and generate more meaningful commits by eliminating trivial convention enforcing commits [73]. Some programming languages like Java and Python suggest specific coding styles [55, 64], while consortia publish guidelines for others, like C [8, 34].

High quality \textbf{identifier names} lie at the heart of software engineering [6, 16, 20, 24, 42, 66, 69, 54]; they drive code readability and comprehension [12, 19, 20, 41, 44, 68]. According to Deißenböck and Pizka [17], identifiers represent the majority (70%) of source code tokens. Eshtevvari et al. [27] explored how identifiers change in code, while Lawrie et al. [41] studied the consistency of identifier namings. Abebe et al. [1] discuss the importance of naming to concept location [59]. Caprile and Tonella [20] propose a framework for restructuring and renaming identifiers based on custom rules and dictionaries. Gupta et al. present part-of-speech tagging on split multi-word identifiers to improve software engineering tools [33]. Høst and Østvold stem and tag method names, then learned a mapping from them to a fixed set of predicates over bytecode. Naming bugs are mismatches between the map and stemmed and tagged method names and their predicates in a test set [37]. In contrast, our work considers coding conventions more generally, and takes a flexible, data-driven approach. Several styles exist for engineering consistent identifiers [14, 20, 24, 65]. Because longer names are more informative [44], these styles share an agglutination mechanism for creating multi-word names [5, 60].

Many rule-based \textbf{code formatters} exist but, to our knowledge, are limited to constraining identifier names to obey constraints like CamelCase or underscore and cannot handle conventions like the use of i as a loop control variable. Pylint [58] checks if names match a set of regular expressions (e.g., variable names must be lowercase); astyle, aspell and GNU indent [9, 32] only format whitespace tokens. gofmt formats the code aiming to “eliminating an entire class of argument” among developers [57, slide 66] but provides no guidance for naming. Wang et al. have developed a heuristic-based method to automatically insert blank lines into methods (vertical spacing) to improve readability [72].

\textsc{naturalize} is unique in that it does not require upfront agreement on hard rules but learns soft rules that are implicit in a codebase. The soft rules about which \textsc{naturalize} is highly confident can be extracted for a formatter.

\textbf{API recommenders, code suggestion and completion systems} aim to help during editing, when a user may not know the name of an API she needs [63], the parameters she should pass to the API [75], or that the API call she is making needs to preceded by another [29, 70, 71, 76]. Code suggestion and completion tools [18, 35, 52, 53, 62] suggest the next token during editing, often from a few initial characters. Essentially these methods address a search problem, helping the developer find an existing entity in code. Our focus is instead on release management and improving code’s adherence to convention. For example, code completion engines will not suggest renaming parameters like $\texttt{str}$ in Figure 1.

Language models are extensively used in \textit{natural language processing}, especially in speech recognition and machine translation [22, 38]. Despite this extensive work, LMs have been under-explored for non-ambiguous (e.g., programming) languages, with only a few recent exceptions [4, 35, 46, 53]. The probabilistic nature of language models allows us to tackle the suggestion problem in a principled way. There is very little work on using NLP tools to suggest revisions to improve existing text. The main exception is spelling correction [39], to which LMs have been applied [47]. However, spelling correction methods often rely on strong assumptions about what errors are most common, a powerful source of information which has no analog in our domain.

\textbf{6 Conclusion}

We have presented \textsc{naturalize}, the first tool that learns local style from a codebase and provides suggestions to improve stylistic consistency. We have taken the view that conventions are a matter of \textit{mores} rather than \textit{laws}: we suggest changes only when a codebase evinces stylistic consensus. We showed that \textsc{naturalize} effectively makes natural suggestions, achieving 94% accuracy in its top suggestions for identifier names, and even suggests useful revisions to mature, high quality, open source projects.

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7 References


