Exploring Regular Expression Feature Usage in Practice and the Impact on Tool Design

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***Abstract*—Regular expressions are used frequently in programming languages for form validation, ad-hoc file searches, and simple parsing. Due to the popularity and pervasive use of regular expressions, researchers have created tools to support their creation, validation, and use. Each tool has made design decisions about which regular expression features to support, and these decisions impact the usefulness of the tools and their power. Yet, these decisions are often made with little information as there does not exist an empirical study of regular expression feature usage to inform these design decisions.**

In this paper, we explore regular expression feature usage, focusing on how often features are used and the diversity of regular expressions from syntactic and semantic perspectives. To do this, we analyzed nearly 4,000 open source Python projects from GitHub and extracted nearly 14,000 unique regex patterns that were used for analysis. We also map the most common features used in regular expressions to those features supported by four common regex engines from industry and academia, brics, Hampi, Re2, and Rex. Our results indicate that the most commonly used regular expression features are also supported by popular research tools and that programmers frequently reinvent the wheel by writing identical or nearly identical regular expressions in different ways. We concluded by discussing the implications of omitting certain features in a tool's design and out like several directions of future work.

I. Introduction

Regular expressions (regexes) are an abstraction of keyword search that enables the identification of text using a pattern instead of an exact keyword. There is a saying about regexes: 'now you have two problems'. A skilled programmer can quickly solve problems such as form validation and parsing text using regular expressions. Regular expression languages also enable a valuable text search/string specification technique used frequently within text editors (e.g., emacs), command line tools (e.g., grep, sed) and IDEs (e.g., the search feature in the Eclipse IDE). Although regexes are powerful and versatile, they can be hard to understand, maintain, and debug, resulting in tens of thousands of bug reports [15].

Due in part to their pervasive use across programming languages and how susceptible regexes are to error, many researchers and practitioners have developed tools to support more robust creation [15] or to allow visual debugging [4]. To remove the human in the loop, other research has focused on learning regular expressions from text [3], [10]. Beyond supporting regular expression usage, the applications of regular expressions in research include test case generation [1], [7], [8], [16], solvers for string constraints [9], [17], and as queries in a data mining framework [5]. Regexes are also employed in critical missions like mysql injection prevention [19] and network intrusion detection [13], or in more diverse applications like DNA sequencing alignment [2].

In writing tools to support regular expressions, tool designers make decisions about which features to support and which not to support. These decisions are sometimes made casually and may be dependent on the regular expressions the designers happen to have experience with, the designers have seen in the wild, or the complexity of the implementation. The goal of this work is to bring more context and information about regular expression feature usage so these design decisions can be better informed.

In fact, this paper emerges out of a need to understand which features can be reasonably included in or excluded from a tool that supports regular expressions. For some features that could involve more complexity, such as lazy evaluation, it is important to understand the impact of omitting such features. In the absence of empirical research into how regular expressions are used in practice, this work emerged.

In this paper, to motivate the study of regular expressions in general, we explore how regular expressions are used in practice. For example, we measure how frequently regular expressions appear in projects, and after doing a feature analysis (e.g., kleene star, character classes, and capture groups are all features), we further measure how often such features appear in regular expressions and in projects. Then, we compare the features to those supported by four common regex support tools, brics [12], hampi [9], Rex [18], and RE2 [14]. We then explore the features not supported by these tools and, using a semantic analysis to cluster similar regular expressions, we explore the impact of omitting those features. Our results indicate that these tools support all of the top six most common features and that some of the omitted features, such as the lazy quantifier, are used in over 35% of projects containing regular expressions.

The contributions of this work are:

- An empirical analysis of the usage of regular expressions in 3,898 open-source Python projects
- A mapping of which features are omitted from common regular expression tools and the impact of ignoring those features
- A discussion on the semantic similarity of regular expressions in practice and identification of opportunities for future work in supporting programmers in writing regular expressions.

The rest of the paper is organized as follows. Section II motivates this work by discussing research in supporting programmers in the use, creation, and validation of regular expressions. Section III presents the research questions and study setup for exploring regular expressions in the wild. Results are in Section IV followed by a discussion in Section V and a conclusion in Section VII.

II. Related Work

Regular expressions have been a focus point in a variety of research objectives. From the user perspective, tools have been developed to support more robust creation [15] or to allow visual debugging [4]. Building on the perspective that regexes are difficult to create, other research has focused on removing the human from the creation process by learning regular expressions from text [3], [10].

Regarding applications, regular expressions have been used for test case generation [1], [7], [8], [16], and solvers for string constraints [9], [17]. Regexes are also employed in critical missions like mysql injection prevention [19] and network intrusion detection [13], or in more diverse applications like DNA sequencing alignment [2].

As a query language, lightweight regular expressions are pervasive in search. For example, some data mining frameworks use regular expressions as queries (e.g., [5]).

Within standard programming languages, regular expressions libraries are very common, yet there are differences between languages in the features that they support. For example, Java supports possessive quantifiers like `'ab*+c'` (here the '+' is modifying the '*' to make it possessive) whereas Python does not.

Since regular expression languages vary somewhat in their syntax and feature set, researchers and tool designers have typically had to pick what features to include or exclude. Thus, researchers and tool designers face a difficult design decision: supporting advanced features is always more expensive, taking more time and potentially making the tool or research project too complex and cumbersome to execute well. A selection of only the simplest of regex features is common in research papers and automata libraries, but this limits the applicability/relevance of that work in the real world.

In this work, we perform a feature analysis on regular expressions used in the wild and compare that set to the features supported by four popular regular expression tools. Research tools like Hampi [9], and Rex [18], and commercial tools like brics [12] and RE2 [14], all use regular expressions for various task. Hampi was developed in academia and uses regular expressions as a specification language for a strong constraint solver. Rex was developed by Microsoft Research and generates strings for regular expressions that can be used in several applications, such as test case generation [1], [16]. Brics is an open-source package that creates automata from regular expressions for manipulation and evaluation. RE2 is an open-source tool created by Google to power Code Search with a more efficient regex engine. While there are many regular expression tools available, in this work, we focus on the features support for these four tools, which offer diversity across developers (i.e., Microsoft, Google, open source, and academia) and across applications. Further, as the focus of this work is on tool designers and we wanted to perform a feature analysis, these four tools and their features are well-documented, allowing for easy comparison.

```
          function          pattern                flags
r1 = re.compile('(0|-?[1-9][0-9]*)$', re.MULTILINE)
```

Fig. 1. example of one regex utilization

Mining properties of open source repositories is a well-studied topic, focusing, for example, on API usage patterms [11] and bug characterizations [6]. To our knowledge, this is the first work to mine and evaluate regular expression usages from existing software repositories. Related to mining work, regular expressions have been used to form queries in mining framework [5], but have not been the focus of the mining activities.

III. Study

To understand how programmers use regular expressions in Python projects, we scraped 3,898 Python projects from GitHub, and recorded regex usages for analysis as described in Section III-B. Throughout the rest of this paper, we employ the following terminology:

Utilization: A *utilization* occurs whenever a developer uses a regex engine in a project. We detect utilizations by recording all calls to the `re` module in Python. Within a particular file in a project, a utilization is composed of a function, a pattern and 0 or more flags. Figure 1 presents an example of one regex utilization, with key components labeled. Specifically, `re.compile` is the function call, `(0|-?[1-9][0-9]*)$` is the regex string, or pattern, and `re.MULTILINE` is an (optional) flag. Thought of another way, a regular expression utilization is one single invocation of the `re` library in a project.

The utilization in Figure 1 will compile a regex object in the variable `r1` from the pattern `(0|-?[1-9][0-9]*)$`, with the `$` token matching at the end of each line because of the `re.MULTILINE` flag. The pattern in this *utilization* will match if it finds a zero at the end of a line, or a (possibly negative) integer at the end of a line (i.e., due to the `-?` sequence denoting zero or one instance of the `-`).

Pattern: A *pattern* is extracted from a utilization, as shown in Figure 1. In essence, it is a string, but more formally it is an ordered series of regular expression language feature tokens.

Notice that because the vast majority of regex features are shared across most all-purpose languages, a Python pattern will (almost always) behave the same when used in other languages, such as Java, C#, Javascript, or Ruby, whereas a utilization is not universal in the same way (i.e., it may not compile in other languages).

TODO: Carl: check the above paragraph

In this work, we primarily focus on patterns since they are cross-cutting across languages and are the primary way of specifying the matching behavior for every utilization. Next, we describe the research questions and how the data set was collected and analyzed.

A. Research Questions

Our overall research goal is to understand how regular expressions and regular expression features are used in practice. We aim to answer the following research questions:

RQ1: How is the `re` module used in Python projects?

To address this research question, we measure how often any calls are made to the `re` module per file and per project in Python projects.

Furthermore, we measure the frequency of usage for calls to the 8 functions of the `re` module (`re.compile`, `re.search`, `re.match`, `re.split`, `re.findall`, `re.finditer`, `re.sub` and `re.subn`) in Python projects scraped from GitHub.

We also measure usage of the 8 flags (`re.DEFAULT`, `re.IGNORECASE`, `re.LOCALE`, `re.MULTILINE`, `re.DOTALL`, `re.UNICODE`, `re.VERBOSE` and `re.DEBUG`) of the `re` module.

Further, to provide context as to the overlap among regular expression strings used in Python, we explore the most common regex patterns across all utlizations.

RQ2: Which regular expression language features are most commonly used in python?

We consider regex language features to be tokens that specify the matching behavior of a regex pattern, for example, the + in `ab+`. All studied features are listed and described in Section III-B with examples.

To measure feature usage, we parse Python regular expression patterns using Bart Kiers' PCRE parser[1], as described in Section III-B. We then count the number of usages of each feature per project, per file and as a percent of all distinct regular expression patterns.

RQ3: What is the impact of *not* supporting various regular expression features on tool designers and users?

To address, this question, we use semantic analysis to illustrate the impact of missing features on a tool's applicability by identifying what each feature (or group of features) is commonly used for.

At a high level, our semantic analysis clusters regular expressions by their behavioral similarity. Behavioral similarity is determined by a pairwise comparison among all patterns. Within each pair, a set of strings is generated for each regular expression and then tested against the other. The average percentage of matching regular expressions creates the similarity level. By calculating pairwise similarity among all regex patterns, a similarity matrix is constructed for use during clustering.

TODO: Finish this example - I will get back to this next pass For example, consider the following two regular expressions, denoted A and B for reference.

```
state regex A
state regex B
```

For each regex, the following strings are generated:

A	B
s1	s2
s3	s4

Each string in the A column matches regex A, and each string in the B column matches regex B. When testing the strings in B against regex A, X/5 = 0.Y% match. When testing the strings in the A column against regex B, Z/5 = 0.W% match. Thus, the similarity between these two regular expressions is 0.U%.

To perform this similarity analysis on each pair of regex patterns, we use Rex for string generation. We chose Rex to build matching strings because it supports the most features of any String-generation tool. To build the similarity matrix, we generated at least 384 strings per regular expression in an effort to balance the precision of the similarity metric (i.e., more strings lead to higher precision) with the speed of our analysis tool (i.e., more strings lead to longer runtimes).

Using the similarity matrix, clusters of regexes with similar behavior are discovered using Markov Clustering[2]. These clusters are used to see how programmers implement regular expressions that match similar strings and interpret what a feature is used for. We chose the mcl clustering tool because it offers a fast and tunable way to cluster items by similarity and it is particularly useful when the number of clusters is not known *a priori*.

Next, we describe in greater detail how the corpus of regex patterns was built, how features were analyzed, and how the clustering was performed.

B. Building the Corpus

Github is a popular project hosting site containing over 100,000 Python projects. The GitHub API assigns an integer identifier to each repository and can be used to clone relevant repositories for analysis. Using the http://api.github.com/repositories?since=N interface page, we launched 32 scrapers to find repositories containing Python code. The Github interface provides information about the first 100 repository IDs since the `N` value on a single results page. Each scraper used this information to identify repositories containing Python. When a scraper was done with one page, it continued on to the next 100 repository IDs by using the interface again with `N` now equal to the last repository ID on the current page. Using this process, each scraper paged through the next available 1,000 repositories, cloning and scanning Python projects as they were found. Each scraper started at a different `N` value, with the first scraper starting at 0. Scraper start indices were spaced by 262,144 so as to investigate within the first 8 million repositories. At the time scraping was performed, the highest repoID was over 32 million, so we were cloning projects in the lowest fourth of the available space of IDs. After this process was complete, 3,898 Python projects had been cloned and scanned.

For each project, we used Astroid[3] to build the AST of each Python file and find utilizations of Python's `re` module. This

[1] https://github.com/bkiers/PCREParser

[2] http://micans.org/mcl/

[3] https://bitbucket.org/logilab/astroid

ensured that all utliizations of the `re` module were captured for analysis.

Using git, each project's commit history was scanned at 20 evenly-spaced commits. If the project had fewer than 20 commits, then all commits were scanned. The most recent commit was always included, and the spacing between all other chosen commits was determined by dividing the remaining number of commits by 19 (rounding as needed).

Within one project, we define a duplicate utilization as a utilization having the same function, pattern and flags within the same file (same relative path). We ignored duplicate utilizations across project versions to protect against over-counting the same utilization as we rewind the project through its history. We observed and recorded 53,894 non-duplicate regex utilizations in 3,898 projects.

C. Extracting Patterns

As the focus of this study is regex features, our analysis targets the patterns. Thus, we ignore the 12.7% of utilizations using flags that can alter regex behavior. An additional 6.5% of utilizations contained patterns that could not be compiled because the pattern was non-static (e.g., used some runtime variable), or because of other unknown parsing failures.

The remaining 80.8% (43,525) utilizations were collapsed into 14,113 distinct pattern strings using sql. Each of the pattern strings was pre-processed by removing Python quotes(`'\\W'` becomes `\\W`), unescaping escaped characters (`\\W` becomes `\W`) and parsing the resulting unescaped string using an ANTLR-based, open source PCRE parser released by Bart Kiers[4].

This parser was unable to support 0.5% (76) of the patterns due to unsupported unicode characters. Another 0.2% (27) of the patterns used regex features that we have chosen to exclude in this study because they did not appear often enough (e.g., Reference Conditions). The 13,912 distinct pattern strings that remain were each assigned a weight value equal to the number of distinct projects the pattern appeared in. We refer to this set of weighted, distinct pattern strings as the *corpus*.

D. Analyzing Features

For each escaped pattern, the PCRE-parser produces a tree of feature tokens. Note that features such as capture groups or logical 'OR' can contain sub-patterns composed of more tokens. For each of these trees, we counted the number of tokens, creating a frequency-of-appearance vector or '*featureCount*' for each pattern. A pattern is said to contain a feature at an index if the value of the featureCount at that index is non-zero.

TODO: fill in this paragraph for a bridge between paragraphs For example, consider again the pattern in Figure 1. This pattern has X different features, specifically, Y, Z, and W. The Y feature appears X times. The set if distinct fears forms the feature set for the pattern.

Once the feature set was established, we mapped the features from the corpus to those features supported by

[4]https://github.com/bkiers/pcre-parser

```
strings = ["abc","abbc","abbcyz","bc","abcdefg","xyz"]
r1 = re.compile('abb*c')
r2 = re.compile('ab+c') #r2 is equivalent to r1
r3 = re.compile('.*bc') #r3 is similar to r1,r2
r4 = re.compile('.*yz') #r4 is not similar
len(filter(r1.match,strings)) # r1 matches 4 strings
len(filter(r2.match,strings)) # r2 matches 4 strings
len(filter(r3.match,strings)) # r3 matches 5 strings
len(filter(r4.match,strings)) # r4 matches 2 strings
```

Fig. 2. An Example of Patterns With Similar and Dissimilar Behavior

the four regular expression engines described in Section II: brics, hampi, RE2, and Rex. To create the tool mappings, we consulted documentation for each of the selected regular expression engines. For brics, we collected the set of supported features using the formal grammar[5]. For hampi, we manually inspected the set of regexes included in the `lib/regex-hampi/sampleRegex` file within the hampi repository[6] (this may have been an overestimation, as this included more features than specified by the formal grammar[7]). For RE2, we used the supported feature documentation[8]. For Rex, we were able to use trial and error because we tried to parse all patterns with Rex, and Rex provides good error feedback when a feature is unsupported.

TODO: Were there any features supported by the tools that we did not find in the corpus? Explain either way...tomorrow. There are many, it seems less critical

E. Clustering and Semantic Analysis

We are interested in what behaviors users are trying to get when using regexes, and we know that the exact same behavior, or very similar behavior can be specified in many ways, as shown in Figure 2. **TODO: need to explain figure 2! guide the reader in understanding what figure 2 is illustrating - also inflate to just be an example of the actual process instead of a conceptual guide**

Rex can be used to generate a set of strings that will all match a pattern. For each of the 13,912 distinct patterns, we use Rex to generate a set of at least 384 *matching strings*. If fewer strings were generated, we did not include that pattern in the similarity analysis. The average number of generated strings per pattern was **TODO: X** with a standard deviation of **TODO: Y**. The maximum number generated was **TODO: Z-these3:programming project for later tonight**. The number 384 was selected to balance the runtime of the similarity analysis with the precision of the calculations. Since Rex does not support all the features present in the corpus, we could only generate sets of matching strings for 9,727 (70%) of the 13,912 patterns in the corpus (omitted features are indicated in Table III as described in Section IV-C).

As explained in Section III-A, we used these sets of matching strings to measure the pairwise similarity between regular expressions and create a behavioral similarity matrix. We will refer to a cell of this matrix with row index `i` and

[5]http://www.brics.dk/automaton/doc/index.html?dk/brics/automaton/RegExp.html

[6]https://code.google.com/p/hampi/downloads/list

[7]http://people.csail.mit.edu/akiezun/hampi/Grammar.html

[8]https://re2.googlecode.com/hg/doc/syntax.html

column index `j` as `M[i][j]`. For each pattern at index `i`, we used Rex to create a set of matching strings which we will refer to as `matching_strings_i`. Then for every pattern at index `j`, we set the value of `M[i][j]` equal to the fraction of strings in `matching_strings_i` that the pattern at index `j` matched.

Once the matrix was complete, the values of cells reflected across the diagonal of the matrix were averaged to create a half-matrix of undirected similarity edges. Using all similarity values in this half-matrix above 0.75, we created a text file specifying the edges of a graph. This process is illustrated in Figure 3.

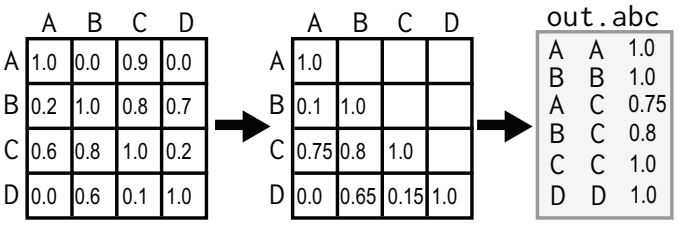

Fig. 3. Creating A Similarity Graph From A Similarity Matrix

TODO: in progress!

With 9,727 patterns there were 94,614,529 cells in the matrix, and although we were able to match them at a rate of about 8,300 cells per second, we had to save time by not

Markov clustering can be tuned using many parameters, including inflation and filtering out all but the top-k edges for each node. After exploring the quality of the clusters using various tuning parameter combinations[9], the best clusters were found using an inflation value of 1.8 and k=83.

There was an operational error in pulling patterns from our database and 227 patterns (2.3%) were omitted from the semantic analysis.

Note that the filteredCorpus is of size 9727, and at least one pattern from the fc can be found in 1375 of the original 3900 or whatever. Most patterns do not belong in a cluster (for example a very specific pattern like `<title>[^<]*Revision \d+:`), so after clustering is done only 2727 patterns are included, and only 999 projects have any of these patterns in them.

IV. Results

In this section, we present the results of each research question.

A. RQ1: How is the `re` module used in Python projects?

To address this research question, we look at regex utilizations, flags, and the most frequently observed pattern strings.

1) Saturation of Projects with Utilizations: Out of the 3,898 projects scanned, 42.2% (1,645) contained at least one regex utilization. For context about how saturated these projects were with utilizations, we consider how many utilizations were observed per project, how many files the average project scanned contained, how many of those files contained utilizations, and how many utilizations occurred per file in Table I.

[9]www.details.#thistopic

TABLE I. How Saturated are Projects with Utilizations? (RQ1)

source	Q1	Avg	Med	Q3	Max
utilizations per project	2	32	5	19	1,427
files per project	2	53	6	21	5,963
utilizing files per project	1	11	2	6	541
utilizations per file	1	2	1	3	207

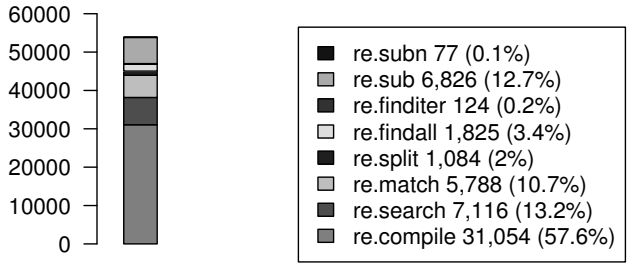

Fig. 4. How often are the 8 re functions used? (RQ1)

The average regex utilizations per project was 32, but this is offset by a high maximum value of 1,427. This value appeared in a C# project[10] that maintained a collection of source code for 20 Python libraries, including larger libraries like `pip`, `celery` and `ipython`, which contain many utilizations.

From Table I, we see that each project had an average of 11 files containing any utilization, and each of these files had an average of 2 utilizations. Because we scanned 3,898 projects, we would expect to have seen $11 * 2 * 3898 = 85756$ regex usages, which is higher than the actual 53,894 usages observed.

2) Usage Frequency of `re` Module Functions: The number of projects that use each of the `re` functions are shown in Figure 4. The y-axis denotes the total utilizations, with a maximum of 53,894. The `re.compile` function encompasses 57.6% of all utilizations, presumably because each usage of those functions can accept a regex compiled using `re.compile` as an argument.

[10]https://github.com/Ouroboros/Arianrhod

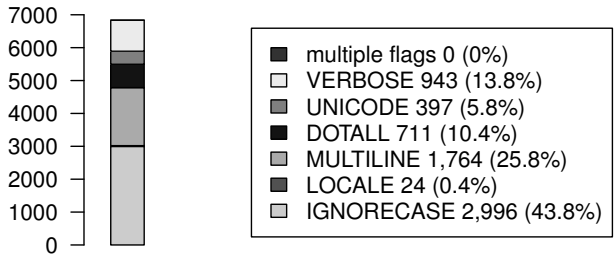

Fig. 5. Which behavioral flags are used? (RQ1)

TABLE II. TOP 10 PATTERNS BY NPROJECTS (RQ1)

pattern	nProjects
`'\\s+'`	181
`'\\s'`	78
`'\\d+'`	70
`'[\\x80-\\xff]'`	69
`'\nmd5_data = {\n([^}]+)}'`	69
`'\\\\(.)'`	67
`'([\\\\"]|[^\\ -~])'`	66
`'(-?(?:0|[1-9]\\d*))(\\.\\d+)?([eE][-+]?\\d+)?'`	61
`'[^]]+?\\] +([0-9.]+): (\\w+) <-(\\w+)'`	60
`'.*rlen=([0-9]+)'`	57

3) Usage Frequency of `re` *Module Flags:* When considering flag use, we excluded the default flag, which is built into the `re` module, and present internally whenever no flag is used. Of all utlizations, 87.3% had no flag, or explicitly specified the default flag (which is equivalent). The debug flag, which causes the `re` regex engine to display extra information about its parsing process, was never observed.

As shown in figure 5, of all behavioral flags used, ignorecase (43.8%) and multiline (25.8%) were the most frequently used. It is also worth noting that although multiple flags can be combined using a bitwise or, this was never observed.

4) Most Frequently Observed Patterns: Table II contains the most frequently used patterns, ordered by the number of projects that the pattern appears in. The patterns are quoted to show the presence of spaces, if any. The top pattern, `'\s+'` uses the WSP character class, which (as described in Table III) represents one or more whitespace characters, which (when no flags are used) is equivalent to a character class composed of spaces, tabs, newlines, vertical whitespace, carriage returns or form feeds. The + (the ADD feature in Table III) at the end of the pattern means that it must match one or more whitespace characters. The pattern `'\s+'` is often used to split sentences into separate words which may have more than one space between them.

The second pattern, `'\s'` uses the WSP character class like same the first pattern, but does not match several whitespace characters (though it would match the first of several).

The third pattern, `\d+` uses the DEC character class, which is composed of the digits from 0 to 9. Like the first pattern, the third uses the ADD feature to match one or more digits.

The fourth pattern, `[\x80-\xff]`, uses the CCC feature to create a custom character class, and the RNG feature to specify a range of characters. When hexadecimal values are used within a character class like this (and the UNICODE flag is not active), it signifies the corresponding characters in an ASCII lookup table. The range specified by this pattern is highlighted on the right side of Figure 6. Table image found at: https://courses.engr.illinois.edu/ece390/books/labmanual/ascii-code/quickref.png. **TODO: run program again to unescape pattern strings**

TODO: more of the topN patterns if there is space

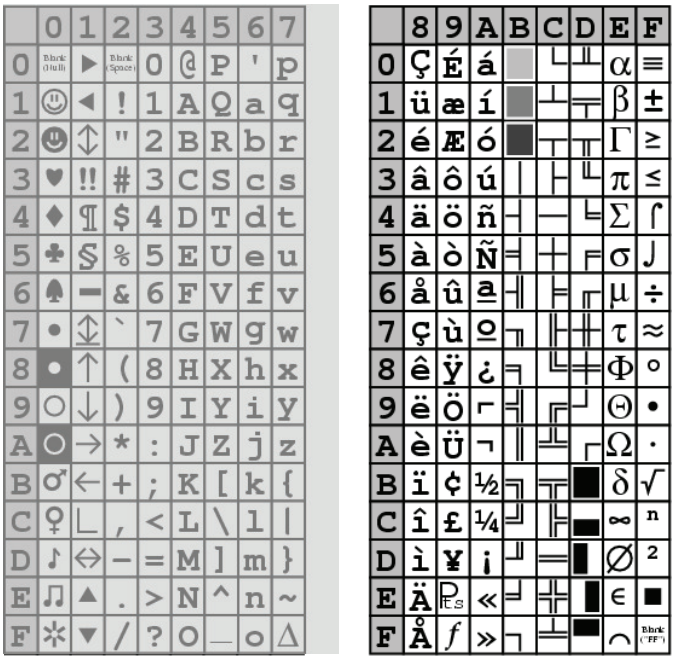

Fig. 6. On the Right, ASCII Characters Matching `'[\x80-\xff]'` (RQ1)

TODO: add patternStats table back in and describe it if there is enough time. Note the longest pattern present in patternLength.csv in analysis folder was probably automatially generated from text and is monstrous!

5) Summary of Results for RQ1: **TODO: Insert summary of results for RQ1**

B. RQ2: Which regular expression language features are most commonly used in python?

Table III lists all the regex features observed in at least 10 projects. The first column, *rank*, lists the features in order of popularity, determined by the percentage of projects in which they appear. The next column, *code*, gives a succinct reference string for the feature followed by a `description` and `example` usage from the corpus. For example, the most common feature observed in the corpus is the + token, denoting *one-or-more repetition*s, and is abbreviated `ADD`. After the tool mapping (see Section IV-C), the usage statistics are presented for the number and percent of patterns that the feature appears in, the number and percent of total files in which the appears at least once, and the number and percent of total projects in which that feature appears at least once.

Literal tokens were found in 97.5% of patterns, and accounted for 70.6% of all tokens. We consider literal tokens to be ubiquitous in all utilizations, and necessary for any regex related tool, and so exclude them from the rest of the feature analysis. In table III, we display a large body of information about feature usage and relate it to four major regex related projects. **TODO: needs more complete description of feature usage**

TODO: Insert summary of results for RQ2

TABLE III. HOW FREQUENTLY DO FEATURES APPEAR IN PROJECTS, AND WHICH FEATURES ARE SUPPORTED BY FOUR MAJOR REGEX PROJECTS? (RQ2)

rank	code	description	example	brics	hampi	Rex	RE2	nPatterns	% patterns	nFiles	%files	nProjects	% projects
1	ADD	one-or-more repetition	`z+`	●	●	●	●	6,122	44	9,330	50.3	1,209	73.5
2	CG	a capture group	`(caught)`	●	●	●	●	7,248	52.1	9,759	52.6	1,197	72.8
3	KLE	zero-or-more repetition	`.*`	●	●	●	●	6,104	43.9	8,323	44.9	1,100	66.9
4	CCC	custom character class	`[aeiou]`	●	●	●	●	4,581	32.9	7,808	42.1	1,027	62.4
5	ANY	any non-newline char	`.`	●	●	●	●	4,708	33.8	6,394	34.5	1,006	61.2
6	RNG	chars within a range	`[a-z]`	●	●	●	●	2,698	19.4	5,196	28	849	51.6
7	STR	start-of-line	`^`	○	●	●	●	3,660	26.3	5,622	30.3	847	51.5
8	END	end-of-line	`$`	○	●	●	●	3,258	23.4	5,549	29.9	828	50.3
9	NCCC	negated CCC	`[^qwxf]`	●	●	●	●	1,970	14.2	4,027	21.7	777	47.2
10	WSP	\t \n \r \b \f or space	`\s`	○	●	●	●	2,908	20.9	4,812	25.9	764	46.4
11	OR	logical or	`a|b`	●	●	●	●	2,161	15.5	4,039	21.8	711	43.2
12	DEC	any of: 0123456789	`\d`	○	●	●	●	2,385	17.1	4,366	23.5	694	42.2
13	WRD	[a-zA-Z0-9_]	`\w`	○	●	●	●	1,457	10.5	3,004	16.2	652	39.6
14	QST	zero-or-one repetition	`z?`	●	●	●	●	1,922	13.8	3,821	20.6	647	39.3
15	LZY	as few reps as possible	`z+?`	○	●	○	●	1,318	9.5	2,291	12.4	606	36.8
16	NCG	group without capturing	`a(?:b)c`	○	●	○	●	813	5.8	1,748	9.4	404	24.6
17	PNG	named capture group	`(?P<name>x)`	○	●	○	●	934	6.7	1,517	8.2	354	21.5
18	SNG	exactly n repetition	`z{8}`	●	●	●	●	623	4.5	1,359	7.3	340	20.7
19	NWSP	any non-whitespace	`\S`	○	●	●	●	490	3.5	788	4.2	271	16.5
20	DBB	$n \leq x \leq m$ repetition	`z{3,8}`	●	●	●	●	384	2.8	692	3.7	242	14.7
21	NLKA	sequence doesn't follow	`a(?!yz)`	○	○	●	○	137	1	503	2.7	184	11.2
22	NWRD	non-word chars	`\W`	○	●	●	●	97	0.7	315	1.7	169	10.3
23	LWB	at least n repetition	`z{15,}`	●	●	●	●	97	0.7	337	1.8	167	10.2
24	WNW	word/non-word boundary	`\b`	○	○	○	●	248	1.8	438	2.4	166	10.1
25	LKA	matching sequence follows	`a(?=bc)`	○	○	○	○	114	0.8	360	1.9	159	9.7
26	OPT	options wrapper	`(?i)CasE`	○	●	○	●	232	1.7	378	2	154	9.4
27	NLKB	sequence doesn't precede	`(?<!x)yz`	○	○	○	○	102	0.7	321	1.7	139	8.4
28	LKB	matching sequence precedes	`(?<=a)bc`	○	○	○	○	82	0.6	262	1.4	120	7.3
29	ENDZ	absolute end of string	`\Z`	○	○	○	●	91	0.7	154	0.8	94	5.7
30	BKR	match the i^{th} CG	`\1`	○	○	○	○	60	0.4	129	0.7	84	5.1
31	NDEC	any non-decimal	`\D`	○	●	●	●	36	0.3	92	0.5	58	3.5
32	BKRN	references NCG	`\g<name>`	○	●	○	○	17	0.1	44	0.2	28	1.7
33	VWSP	matches U+000B	`\v`	○	○	●	●	13	0.1	16	0.1	15	0.9
34	NWNW	negated WNW	`\B`	○	○	○	●	4	0	11	0.1	11	0.7

C. RQ3: What is the impact of not supporting various regular expression features on tool designers and users?

We guide the results analysis for this research question based on the features *not* supported by popular regex tools. Table III shows the mapping from features to regex tools. The mappings for each regex tool to the features are shown using ● to denote when a feature is supported by the tool and ○ when it is not.

Our behavioral clustering technique found 952 clusters over 2727 patterns, with at least one cluster present in 999 of the 9727 projects that were compatible with Rex.

TODO: Need to know why MCL is behaving like this

Table IV provides an example of a smaller behavioral cluster, representing 13 patterns, with at least one pattern from this cluster present in 100 different projects.

On first glance this cluster may seem to revolve around the '`\s*`' parts of these patterns, but actually this cluster was formed because each of these patterns has a comma literal, and other details did not interfere with matching the Rex-generated strings with commas in them.

It is not a coincidence that the smallest pattern in this cluster gives the best idea of what all the patterns within it have in common (the smallest pattern is just the single comma character, at index 1). All of the clusters we found follow this trend: the shortest pattern describes the rest of the pattern's behavior very well. In table V, I show the top 10 clusters,

TABLE IV. AN EXAMPLE CLUSTER (RQ3)

index	pattern	nProjects
1	`'\s*,\s*'`	54
2	`','`	30
3	`'\s*,'`	16
4	`' ,\s*'`	13
5	`' *, *'`	12
6	`',\S'`	5
7	`',.*$'`	3
8	`'(\S+)\s*,\s*'`	2
9	`',+'`	1
10	`',\ ?'`	1
10	`',\s*(\S)'`	1
11	`'\s*(,)\s*'`	1
12	`'\s*\,\s*'`	1

TABLE V. TOP 10 CLUSTERS BY NPROJECTS (RQ3)

rank	nProjects	nPatterns	example
1	227	31	`'\s'`
2	208	83	`'\W'`
3	193	87	`'\d'`
4	138	44	`'[^!-~]'`
5	122	54	`'[a-zA-Z]'`
6	114	31	`'\\'`
7	110	49	`'\w'`
8	100	13	`','`
9	91	32	`':'`
10	78	14	`'^\d+$'`

ranked by the number of projects they appear in, using the shortest pattern from the cluster as an example. The cluster in Table IV appears in the seventh row of Table V.

1) Feature Groups Overview: Instead of analyzing every feature independently, we chose small groups of conceptually related features. For each of these groups, we selected all clusters that had at least one of the features in at least one pattern within the cluster to form a 'feature group'-focused cluster set.

Table VI shows the total number of projects that contain at least one pattern from at least one cluster in the cluster set, and some selected clusters represented by the shortest string in the cluster. These clusters were selected not because of being within the largest number of projects, but because they illustrate some interesting usage of a feature that will be explored in detail later.

(note that for the ANY group, all but two of the top 30 clusters used '.*', but that .* as a pattern alone only appeared in 23 projects)

tell them how the cluster groups in the first part are all drawn from a subset of the corpus limited by what Rex can support, whereas the cluster groups in the second part are all drawn from the complete corpus, but are not guaranteed to have behavioral similarity like in the first part.

TODO: Insert summary of results for RQ3

```
x* = x{0,MAX}     x? = x{0,1}       x{5,} = x{5,MAX}
x+ = x{1,MAX}     x{3} = x{3,3}     x{7,9} = x{7,9}
```

Fig. 7. How DBB Subsumes All Other Repetition Features

```
\d = [0123456789]
\s = [ \t\n\r\f\v]
\w = [abcdefghijklmnopqrstuvwxyzABCDEFGHIJKLMNOPQRSTUVWXYZ0123456789_]
```

Fig. 8. How CCC Subsumes DEC, WSP and WRD

V. DISCUSSION

The results of the research questions have implications for **TODO: finish me**

regex usage is usually concentrated in a few files

Although 42.2% of the projects observed had at least one regex usage, only 11.2% of the files observed had at least one regex usage. This indicates that regex usage is usually concentrated in a few files. **TODO: so what?**

Observation 1: Utilizations May Be More Common In Python Library Code Than In User Code. The project with the most files containing utilizations: Arianrhod[11] which is a Japanese Anime game, mostly written in C# (over 18K files), but containing 3404 Python files, most of which are source code for various libraries. Of these library files, 541 (15.9%) contain at least one utilization. **TODO: so what?**

ACKk somesection about flags: notice how rarely the LOCALE flag was used.

Notice that the presence of the Verbose flag implies usage of the comment feature!

A. DBB subsumes repetition, CCC subsumes character classes

TODO: explain subsumption

$a \equiv b\{0, MAX\}$

TODO: what features does DBB subsume?

The DBB feature subsumes all other repetition features. Consider the equivalences shown in Figure 7

Similarly, the CCC feature subsumes NCCC, RNG, ANY, DEC, NDEC, WSP,NWSP, WRD, NWRD because each of these features is equivalent to a set of characters. We provide an example of how CCC subsumes DEC, WSP and WRD in Figure 8 (other equivalences not shown for brevity).

[11] https://github.com/Ouroboros/Arianrhod

TABLE VI. FEATURE GROUPS WITH SELECTED CLUSTER EXAMPLES (RQ3)

index	feature set	nProjects	% of Projects	selected cluster examples (nProjects for that cluster)
1	ADD,KLD,QST	970	97.1	`\W+'(208), `[A-Z]?[:;.A-Z]'(47), `:+'(91), `https?://'(13)
2	CCC,NCCC,RNG	953	95.4	`[0-9]'(193), `[^!-~]'(122), `[aeiou]'(4), `^[a-f0-9]{40}$'(34)
3	CG	943	94.4	`coding[:=]\s*([-\w.]+)'(48), `<(.*)>'(63), `"(.*)"'(42), `\\(.)'(110s)
4	STR,END	807	80.8	`^\d+$'(78), `^\\s*$'(59), `,.*$'(100), `=.*$'(52), `^(.*)<(.*)>(.*)$'(63),
5	ANY	801	80.2	`\s.*'(277), `(\d+)(.*)'(193), `-.*'(74), `(.)([A-Z])'(47), `<.+>'(63)
6	WSP,NWSP	775	77.6	`\s'(277), `\S'(53), `:\s*'(91), `,\S'(100), `<\\S[^>]*>'(63)
7	OR	759	76.0	`((the|a|an)\\s+)?[0-9]+'(193), `([ ]+_)|(_[ ]+)|([ ]+)'(66), `<.*>|</.*>'(63)
8	DEC,NDEC	622	62.3	`\d'(193), `\D'(65), `\.\d+$'(14), `[^\w\d_]'(208), `(\D)[.]'(61)
9	WRD,NWRD	595	59.6	`\W'(208), `\w'(114), `[a-zA-Z]\w*'(138), `(\w*)=(\w*)'(52), `\\(\W)'(110)
10	DBB,LWB,SNG	459	45.9	`^[0-9]{1,5}$'(78), `\d{2}'(193), `[.]{2,}'(21), `^[0-9A-Za-z._-]{0,100}$'(27)

TABLE VII. TOP 10 PATTERNS IN TOP 3 CLUSTERS (RQ3)

example	example	example
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'
`\s'	`\s'	`\s'

1) character classes are important: In replacing keyword search with an abstracted search, one of the most fundamental abstractions is that one element of a sequence can be one of several characters. This abstraction is realized in custom character classes.

2) default character classes are widely used: The pattern language for Python and most major regex engines supports a few default character classes (and their negations) which we have described as the features ANY, DEC, WSP, WRD, NDEC, NWSP, NWRD. Throughout this analysis it was obvious that these default character classes were widely used. Specifically, `\s`, `\d` and `\W` were the top three behavioral clusters (as shown in Table V). In Table VII we show the top 10 patterns from these top three clusters. **TODO: implication for tool designers**

One surprising result of our clustering is that behaviorally speaking, the negation of the word class was more heavily used (208 projects) than the word class itself (114 projects). One

The character class of all letters `[a-zA-Z]` appears so often that it is an excellent candidate for a new a character class.

The largest cluster using custom character classes (cluster N in Table V whose shortest member is `[^ -~]`) has 44 patterns which create a more permissive word class. Inspection of the source code of several projects using this pattern indicates that these permissive word classes were typically used when trying to create system-friendly object names, which indicates that there is a demand for a word class that includes more characters (but not dashes, tildes or the first 9 unicode characters).

One obvious character class to consider is hexidecimal characters, and we see the pattern [a-fA-F0-9] appear many times.

For tools that do not support the default character classes, this is a significant obstacle for users trying to test the regexes that they already have.

3) use of repetition:

4) Anchors matter: The endpoint anchor features STR and END are the only way specify that an entire line has to match. Consider the following example, comparing the pattern `'^\s*$'` (found in 48 projects) to the pattern `'\s*'` (found in X projects) when looking for lines devoid of content. Without the endpoint anchors, the pattern matches every line, since there are always at least zero whitespace characters on every line. But with the endpoint anchors, only lines that contain nothing but whitespace will match, allowing the user to find all lines that don't have any content.

B. Opportunities for Future Work

1) New library feature for properties of a line:

2) Regexes need refactoring: We see the same features implemented many ways, and we don't know why. It might be that some methods of implementation are more understandable. However, if tool designers do not support that, refactoring may be needed.

example with anchors and `.*` in the middle which could be replaced by a comma?

3) Using 0-9 instead of d: Out of the 9727 patterns acceptable to Rex, 1498 contained the range `0-9` within a character class, even though this is exactly equivalent to using `\d` within a character class (which appeared within a character class only 237 times). Why are users specifying digits using the RNG feature when a default character class already exists? Is it to aid readability, or does this represent an opportunity for refactoring?

```
fruitDiary = "Day1: Apples, Oranges, Apples, Peaches
             Day2: Kumquats, Berries, Pears, Peaches
             Day3: Oranges, Pears, Apples, Pears"
print(len(re.findall('Apples.*',fruitDiary))) # 2
```

Fig. 9. An Example of Using .* to Count Lines Containing 'Apples'

```
found = re.match('.*cde.*', 'abcdefg')   # found=true
found = re.match('cde', 'abcdefg')       # found=false
found = re.search('cde', 'abcdefg')      # found=true
```

Fig. 10. An Example of Using .* to get Search Behavior From The Match Function

4) dot-star at the end - refactoring?: One of the most ubiquitous sub-patterns, `'.*'` appeared in 1937 of the 9727 patterns acceptable by Rex, and appeared within the last four characters in 1161 of the 9727 patterns. Out of the top 30 clusters containing the ANY feature, 26 also had `'.*'` within the last four characters.

One reasonable explanation for this tendency to put `'.*'` at the end of a pattern is that users want to disregard all matches after the first match on a single line in order to count how many distinct lines the match occurs on, as illustrated in Figure 9.

In many cases, this `'.*'` at the end of the string may not actually contribute any new behavior to the pattern, and may in fact be extraneous. Or users may be trying to bypass the whole-string nature of the `re.match` function, without realizing that they could instead use the `re.search` function. Consider the comparison shown in Figure 10

Are programmers using the dot-star sub-pattern unnecessarily? More research is needed into this question to find out if these patterns are a candidate for refactoring.

Fun fact: while creating similarity matrix, row 5464 took 2 hours, or almost 1 second per cell avg, only suffering 18 timeouts (1.2 secs). What is this pesky pattern?

We do not assume that Python projects represent a perfect sample of regular expression usage in all environments, but to make the work of collecting data for the paper reasonable, we had to choose one language to focus on (we hope to compare results across languages in future work). Python is an attractive choice because the culture of Python programming makes it seem likely that someone would write the pattern directly in the function, not trying to over-complicate things with some extra Classes or functions. Other attractive choices are Perl (which probably has the most active regex community), javascript and ruby (which may emphasize web tasks like form validation), sql or a general purpose language like java or C#.

VI. Threats to Validity

The threats to validity of this work stem primarily from sampling bias, tool limitations, and language selection.

We mined only 3,898 Python projects from GitHub, which is very small in comparison with the over 100,000 available Python projects on that platform. The projects were mined using the GitHub API which sorts the projects by **TODO: how were they sorted?**. By using the API, the goal was to reduce any sampling bias introduced by the researchers.

We did not scrape all commits in every project for regular expression utilizations, rather, we grabbed each project every 20 commits. It is possible that in between the scanned commits, a regular expression utilization was added and then removed, leading to fewer utilizations in our final data set.

In extracting patterns for analysis, we omit utilizations that contain flags since flags provide refinements on the functionality of the pattern as it is used in the project. Given that only 12.7% of all utilizations used flags, the impact on the clusters should be minimal.

Regular expression patterns were clustered using strings generated by the Rex tool. This introduces two threats to validity. First, we assume that the strings generated by Rex are reasonably diverse to help characterize the regular expression behavior. To mitigate this threat, Rex generated at least 384 strings per regular expression. Second, since the similarity between two regular expressions was calculated empirically using Rex rather than through analysis, we may have over-estimated the similarly. For this reason, in our clustering algorithm, we require a similarity level of Y so that we do not over-estimate the similarity between regular expressions **TODO: what is Y?**.

The final threat to validity comes from the fact that we only explore regular expressions in Python projects so these results many not generalize to other languages. Future work will replicate this study in other languages and compare the results.

VII. Conclusion

A. Empirical Analysis of Regex Utilizations

B. Frequency of Feature Usage

conclusion II

1) A Suggested Feature Implementation Priority List: One key consideration for Tool designers is what features are most important to implement in order of priority. We provide a prioritized list of feature groups to implement in Figure 11, based on the frequency of feature usage displayed in Table III.

TODO: need to list all the subsumed features for CCC and DBB. It's not clear

C. How Features Are Used In Practice

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1) literals, sequences of tokens
2) CCC (and all subsumed features)
3) CG (without back-references)
4) DBB (and all subsumed features)
5) STR, END
6) OR
7) LZY
8) NCG
9) NLKA, LKA, NLKB, LKB
10) WNW, NWNW
11) ENDZ
12) BKR

Fig. 11. A Suggested Feature Implementation Priority List

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