Capture the Feature Flag: Detecting Feature Flags in Open-Source

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ABSTRACT

Feature flags (a.k.a feature toggles) are a mechanism to keep new features hidden behind a boolean option during development. Flags are used for many purposes, such as A/B testing and turning off a feature more easily in case of failures. While software engineering research on feature flags is burgeoning, examples of software projects using flags rarely come from outside commercial and private projects, stifling academic progress. To address this gap, in this paper we present a novel semi-automated mining software repositories approach to detect feature flags in open-source projects, based on analyzing the projects' commit messages and other project characteristics. With our approach we search over all open-source GitHub projects, finding multiple thousand plausible and active candidate feature flagging projects. We manually validate projects and assemble a dataset of 100 confirmed feature flagging projects. To demonstrate the benefits of our detection technique, we report on an initial analysis of feature flags in the validated sample of 100 projects, investigating practices that correlate with shorter flag lifespans (typically desirable to reduce technical debt), such as using the issue tracker and having a flag owner.

1 INTRODUCTION

Feature flags (aka. feature toggles) are becoming an increasingly important, but also controversial software-engineering practice with the advent of continuous deployment and delivery. Technically, feature flags are a design pattern to conditionally enable a code path (e.g., an if-statement controlled by a boolean flag), where the decision is typically controlled by an external configuration mechanism. Feature flags enable development of new features in the same branch, which can speed up releases while avoiding large merges [4, 8]. Flags are also used for experimentation in production [1, 14] and canary releases [12, 13]. Feature flags are widely discussed in blog posts and at practitioner conferences, and there are multiple competing startups offering tool support. Feature flags can be controversial and seen as a cause of *technical debt*, because they are easy to introduce, create additional complexity in a system, and are often hard to remove [6, 7, 9].

Unfortunately, there is little research on feature flagging *practices*, except for a handful of studies of Chromium [9, 10] and a few commercial projects [6, 7]. Unlike many other software engineering practices, where open-source software enabled a wealth of large-scale empirical research, studies of feature flags in open-source are rare. In part, this might be explained by feature flagging being a rather commercial practice, often used for A/B testing commercial web and mobile products. Another explanation is that feature flag use is non trivial to identify systematically, leaving uncertain how widespread and how diverse the practice is in open-source. Indeed, feature flag implementations can range from custom solutions to commercial software libraries, e.g., from *Split.io* or *LaunchDarkly*, to simple Boolean options in code or configuration files; Listing 1 shows an example of the latter—feature flags in `Automattic/wp-calypso`[1] are defined as a map in a json file.

Listing 1: Excerpt from a json file defining feature flags in `Automattic/wp-calypso`. Note that the file also contains other kinds of configuration options that are not feature flags.

```
"livechat_support_locales": ["en","es","pt-br"],
"features": {
    "async-payments": true,
    "ad-tracking": false,
    "automated-transfer": true,
    "blogger-plan": true,
    "calypsoify/plugins": true,
    "code-splitting": true,
    "comments/filters-in-posts": true,
```

To enable and encourage empirical research on feature flagging practices, in this paper we propose a novel mining software repositories technique to identifying open-source projects using feature flags, based on textual analysis of commit messages for patterns such as "feature flag" combined with a series of filters to remove likely false positives (§3). Applying our technique to all public repositories on GitHub uncovers 3 237 candidate feature flagging projects. To assemble a starting dataset for future research, we manually confirm 100 projects that actually use feature flagging, which together account for 7 593 different flags in total. We demonstrate the value of this dataset with a small *preliminary study* on feature flagging practices and changes to the feature flags over time (introductions and removals) (§4). Among others, our study reveals that high ownership (i.e., the author who introduces a flag also removes it later) is statistically significantly associated with shorter flag lifespans, suggesting that ownership can be an effective practice to keep technical debt in check. In short, *the goal of this work is to identify open-source repositories that use feature flagging and to provide a dataset, to help researchers study feature flagging practices on a variety of open-source projects.*

In summary, the contributions of this paper are:
- We propose a novel mining software repositories technique to

[1]https://github.com/Automattic/wp-calypso/blob/master/config/development.json

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identify repositories that likely use feature flags, resulting in 3 237 plausible candidates on GitHub.
- We provide a dataset of 100 projects and their 7 593 feature flags, including information on each flag's lifetime.
- We report on an initial analysis of this sample, showing that ownership of flags correlates with shorter flag lifespans.

Our regular expressions for identifying feature flags, together with the two lists of plausible candidate and manually verified projects, are all available publicly at DOI 10.5281/zenodo.3712227.

2 RELATED WORK ON FEATURE FLAGS

Feature flags are a topic frequently discussed by practitioners in blog posts and at practitioner conferences (e.g., [2, 3], Rahman et al. [9, 10] and Mahdavi-Hezaveh et al. [6] provide an extensive overview of grey literature on feature flags). According to an interview study with practitioners [7] there are three common use cases for feature flags: (a) parallel trunk-based development, where multiple features guarded by feature flags are developed simultaneously in the same branch, (b) canary releases, where features are released incrementally to different users, and (c) experimentation in production (A/B testing), where features are selectively activated to measure their impact on business objectives. In addition, they found that the boundary between feature flags (intended to be temporary) and configuration options (intended to be permanent) [11] is often fuzzy, and often the same mechanisms are used for both.

Academic research on feature flags is rather sparse. Meinicke et al. [7] interviewed and Mahdavi-Hezaveh et al. [6] surveyed practitioners about their feature flagging practices, finding among others than feature flag removal is a key pain point, that testing is rarely conducted systematically across feature flags and their interactions, and that concerns about technical debt abound. To the best of our knowledge, the only study on feature flags using mining software repository techniques is the analysis of feature flags in Chromium, the open-source implementation behind Google Chrome, by Rahman et al. [9, 10]; they found that feature flags are often long lived, confirming concerns expressed by practitioners.

3 CAPTURING FEATURE FLAGS

Finding open-source projects that use feature flags was a surprisingly challenging task. Many of our initial attempts (described briefly below) found barely any projects or overwhelmed us with false positives, such that we doubted whether feature flags would be used in open-source at all.[2] We incrementally developed and refined a method to identify and filter open-source feature-flagging projects at scale on GitHub.

Our approach is semi-automated, using various heuristics to identify promising candidate projects which we then manually validate. Our goal here is not to identify *all* feature-flagging projects on GitHub, but to build a substantial dataset of active feature-flagging projects that can be used (and expanded) in future research.

Heuristics and Initial Sampling. We initially explored many different strategies to identify open-source projects using feature flags, including (a) finding projects importing feature flagging libraries (finds only few open-source projects, often without serious feature flag use, and misses many projects such as Chromium with homegrown feature flag solutions), (b) looking for filename patterns such as `flags.*` (which finds mostly configuration settings, such as compiler options, not feature flags), and (c) searching for documentation of feature flags in wikis or issues (very few hits).

The heuristics that turned out to be the most promising are based on analyzing commit messages:

- *Keywords* (H_1). We match common terms used for feature flags in the existing literature and blog posts (see Sec. 2) with the pattern *"feature + (flag, toggle, flipper, switch, bit, gate)"*, in the project's commit messages. We consider only commits where the two search terms are no more than 50 characters apart, to increase the likelihood that the terms are related. We chose 50 after some experimentation when collecting the commits from GitHub; searching for commits that contain both keywords independent of their distance contained too many false positives where the keywords are unrelated.
- *Mentions of feature flag removal* (H_2). We match the pattern *"(remove, delete, cleanup) + (flag, toggle)"* in commit messages (again at most 50 characters apart). The intuition is that feature flags are meant to be removed more frequently than configuration flags and configuration options [5, 7, 15].

We used the search queries from H_1 and H_2 across all of GitHub using GitHub's API, identifying 231 223 non-fork repositories with 3 918 003 commits matching at least one search term.

Data Cleaning. Informal inspection of a sample of the projects identified previously revealed many small or toy projects, on the one hand, and many clones of different repositories that are not explicitly recorded as forks on GitHub, on the other hand.

Since we expect that projects with more feature flags may be more interesting for future researchers, we impose a filter of at least 10 "feature flagging" commits per repository, i.e., each project should match H_1 or H_2 at least 10 times, and we do not consider projects below this threshold further; We arrived at the 10 threshold after some experimentation and our results are robust to other values (i.e., the projects we manually analyzed would not change).

To identify clones, we compare repositories in terms of their (i) commit SHAs and (ii) commit message titles and names of files changed. This step revealed `Chromium`, `linux`, `llvm`, and `WordPress` as the four largest projects in our dataset with over 1 000 copies each (not tracked as forks by GitHub). We removed all copies of these projects from further consideration.

After filtering out projects with fewer than 10 matching commits and removing clones, 3 239 projects remained, with 126 067 commits total matching our search heuristics.

Assembling a Dataset of Feature Flagging Projects. Not all of the 3 237 remaining projects actually use *feature* flags. To assemble the final dataset, we manually inspect projects by systematically looking for two signals in their their repositories: 1) temporarily guarding functionality using flags (i.e., typical use cases of feature flags); 2) documentation on continuous deployment. We marked all projects where either signal was clearly present as 'Confirmed' (Figure 1). We marked all projects where the two signals were unclear as 'Unclear'. If the project uses flags for other purposes, such as compiler options, we mark it as 'Denied'. Thus, we are confident that the probability of having false positives is small.

[2]At some point we even had a bet among team members whether we would ever find more than 20 open-source projects with serious feature flag use.

However, we did not manually inspect all 3 237 projects. Instead, to guide our inspection process to focus on more likely candidates first, we developed the following process. First, we inspected the 50 projects with the largest numbers of commits matching our search terms. This revealed a significant number (about 50%) of false positives among those projects, i.e., projects that use flags for other purposes than feature flagging, such as compiler flags, preprocessor flags, or configuration options. We then analyzed what distinguished feature flagging projects from false positives in this initial set, developing two further prioritization heuristics:

- We compared the fraction of commit messages that match individual search terms used in H_1 and H_2 above, in the first 50 manually classified projects. A closer inspection of the matched terms reveals that non-feature-flagging projects tend to have a high percentage of messages matching flag removal, i.e, "remove flag" and "delete flag" (H_2) compared to feature-flagging projects, which have higher percentages for "feature flag" and "feature toggle" (H_1). Feature-flagging projects also have commit messages matching removal (H_2), however in a lower proportion; it is possible that these projects contain more feature-flagging-related tasks, such as adding new flags or changing the flag values. Figure 1 shows how the analyzed projects cluster with respect to their number of feature-flagging commits and the percentage of commits matching H_1. Note how the manually confirmed non-flagging projects (labeled 'Denied') are on the bottom, while the manually confirmed flagging projects are on the top, with high percentages of commits matching H_1. Based on this insight we used the ratio of flag removal mentions to all flag mentions as a prioritization heuristic to aid our manual validation effort (H_3).
- We inspected the changes made in feature-flagging commits (H_1 and H_2) with the goal of identifying the files that define the feature flags. Such files commonly store the flag in a single field or as an entry in a map-like data structure. Thus, changes to feature flags in these files, such as adding or removing a flag, tend to only involve a few lines of code. We ranked the files touched by feature-flagging commits by median number of line changes and number of commits touching them. Analyzing the manually classified projects we found that repositories with changes to file names containing 'feature' and either 'flag' or 'toggle' are very likely to be actual feature-flagging projects. Based on this insight we used the names of the files defining the flags as a prioritization heuristic to aid our manual validation effort (H_4).

These prioritization heuristics (H_3 and H_4) were effective in guiding the rest of our inspection process, having few false positives among the highly ranked projects. Using H_3 and H_4 we continued to validate candidate projects until reaching 100 confirmed feature-flagging projects total. Note that H_4 uncovered 185 additional likely feature-flagging projects (labeled 'Likely' in Figure 1), but we have yet to manually validate these. If more feature flagging projects are needed, we are confident that, with further manual analysis, one can find many more among the remaining candidate projects.

The Dataset. Both our candidate set of 3 237 projects as well as our validated set of 100 projects, the latter also including the exact names of the feature flags used, are part of our dataset.

In Figure 2 (b–e), we characterize the validated set of 100 feature flagging projects in our dataset. The projects are mostly large,

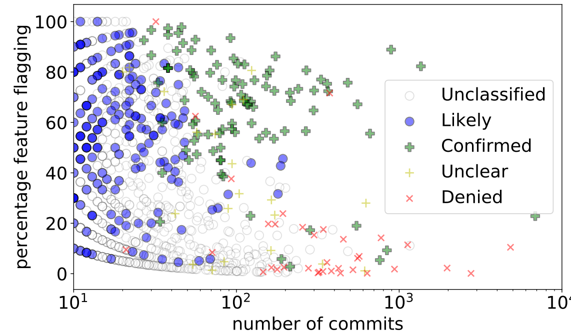


Figure 1: Classified and potential feature-flagging projects.

Listing 2: Example of definition for collecting flag data.

```
"gocd__gocd": {
    "owner": "gocd",
    "project": "gocd",
    "files":
        ["server/src/main/resources/available.toggles"],
    "regex": ["[+-]\\s*\"key\":\\s*\"([\\w_]*)\""]}
```

active, and popular, and written in a large number of different programming languages, showing that feature flags are indeed used in practice in open-source. Although we cannot be certain that our dataset is representative of all feature flag use in open-source, our data suggests that feature flagging is most common in web applications—this is expected, as websites (in contrast to say desktop applications) allow to roll-out features to subsets of users and for A/B testing on the server side.

4 PRELIMINARY FEATURE-FLAG STUDY

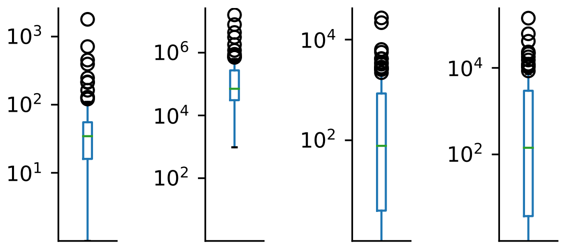
Our dataset of 100 open-source projects confirmed to use feature flags, which contains many large and active projects, will be a valuable resource to study feature-flag practices in public repositories. To demonstrate the potential, we report on a preliminary study of these 100 projects, that analyzes some aspects of feature-flag use.

Flag Data Collection. Informed by the previous manual inspection of each project, we collect data about individual feature flags, including how flags are used, introduced, and removed.

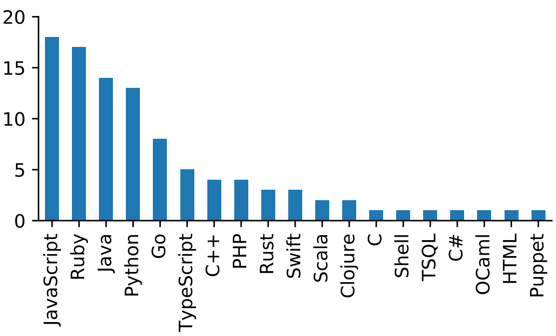
Most of the projects define their flags in a single file, usually either as field, or in a data structure (e.g., a map). We developed tooling, such that we only need to define the *file path(s)* to files storing flags, and a *regular expression* that we use to identify the flags' names and locations. We manually created these flag specifications for all 100 projects, which we release as part of our dataset. We show one such definition in Listing 2.

We then mined the git history of each project to record when flags are added and removed and by whom. In total, we collected data for 7 593 feature flags in the 100 projects of our dataset (distribution in Figure 2a). The median number of flags per project is 34 and `Chromium` has the maximum number of flags with 1 790.

Preliminary Analysis and Results. We analyzed the lifespan of feature flags to observe how frequently flags are cleaned up in open-source projects. Figure 3 shows the *Kaplan-Meier estimate* of



(a) Flags (b) Size (c) Forks (d) Stars



(e) Language

Figure 2: Statistics on 100 feature flagging projects (size, forks, and stars are metrics provided by GitHub).

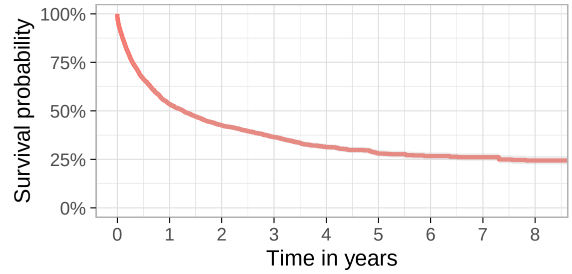


Figure 3: Survival curve for the feature flags in our sample.

the survival probability for flags in our sample, accounting for right censorship (flags that have been introduced recently, that may or not be removed in the future). The estimator suggests that most flags are expected to be eventually removed, that half of the flags are removed within 15 months, but also that 25 % of flags remain for a very long time or forever (more than 8 years).

Overall, we found that cleanup practices differ across projects; most projects clean up most flags, but few projects keep flags alive for a long time. Note though that the distinction of temporary feature flags and permanent configuration options is not always clear from the outside and a flag initially introduced as temporary might evolve into a permanent option in practice, without the ability of external observers to distinguish this in the implementation [3, 7, 9].

We further analyzed how ownership and tracking flags in issues associates with the lifespan of feature flags, for those flags that get removed (4 032 out of 7 593). First, *flag ownership* is a suggested practice to encourage the cleanup of flags by expecting the creator (i.e., the owner) of the flag to remove the flag after the feature is complete [6]. We identify all flags as having ownership if they were removed by the same Git user who introduced them in an earlier commit. Second, another suggested practice is to create a *"cleanup" issue* per feature flag, stating that the flag should be removed when the feature is finished, and assign the issue with a future date to a team or developer as a reminder [6]. We identified flags linked to issues by looking for patterns "(#nr)" in the commit messages that introduce or remove the flag.

We then estimated a mixed-effects linear regression, modeling flag age (days) as a function of the presence of an associated cleanup issue (boolean) and flag ownership (boolean), while controlling for project size (number of commits) and with a random effect for project, to account for the hierarchical nature of our data (flags nested within projects). The model has a total explanatory power (conditional R2) of 63 %; the fixed effects alone explain 36 % of the variance (marginal R2). Within this model, the effect of flag ownership is significant (beta = -189.13, SE = 10.14, 95 % CI [-209.02, -169.25], t(3964) = -18.65, p < .001) and can be considered as medium (std. beta = -0.55, std. SE = 0.03). The effect of cleanup issues is negligible. Results suggest that flags removed by their owner have, on average, a 189 days shorter lifespan than flags removed by others, which suggests that ownership could be an effective practice to keep the project clean of stale flags and thus reduce technical debt. The weak correlation between cleanup issues and the lifetime of flags warrants more in depth future analyses.

5 CONCLUSION AND OPEN QUESTIONS

Research on feature flagging is sparse and focuses on interviews with practitioners. Beyond the `Chromium` study by Rahman et al. [9, 10], we are not aware of any mining software repository studies of feature flags, possibly because it is difficult to identify projects using the practice, as there are no obvious identifiers. In this work, we describe our semi-automated process to assemble a dataset of 100 open-source feature flagging projects, and we additionally collect data about the individual flags used in these projects, and their lifecycle. Our preliminary analysis demonstrates that this dataset provides promising research opportunities; among others we found that flag ownership is a promising practice which correlates with faster flag cleanup and may help control technical debt pending confirmation through experimental methods. There are many more practices recommended by practitioners (see grey literature overviews [6, 9]), and we hope that our dataset can be used to collect evidence about which practices are effective. Also follow up qualitative studies of the implementations or interviews with open-source practitioners using feature flags can be facilitated with our dataset. We hope that our work contributes to fighting technical debt in projects using feature flags and to evidence-based guidelines about effective practices.

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