UNIVERSITÉ DE MONTRÉAL

TITRE DE MON DOCUMENT

ALEXANDRE COUROUBLE
DÉPARTEMENT DE GÉNIE INFORMATIQUE ET GÉNIE LOGICIEL
ÉCOLE POLYTECHNIQUE DE MONTRÉAL

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M. NOM Prénom, Doct., président
Mme NOM Prénom, Ph. D., membre et directrice de recherche
M. NOM Prénom, Ph. D., membre

DEDICATION

To all friends at the lab,
I will miss you...

ACKNOWLEDGEMENTS

In the acknowledgements, the author points out the help that various people have provided, including advice or any other type of contribution as the author carried out their research. As appropriate, this is the section where the candidate must thank their thesis or dissertation supervisor, grant-awarding organizations, or companies that provided bursaries or research funds.

If the thesis or dissertation is in French and students wish to thank someone in particular in English, they must insert a second page and title it in English (i.e., “Acknowledgments”). If the thesis or dissertation is in English and students wish to thank someone in particular in French, they must insert a second page and title it in French (i.e., “Remerciements”).

RÉSUMÉ

The résumé (mandatory summary) is a brief explanation in French of the work's topic, its objectives, the research questions or hypotheses put forth, the experimental methods used, and the results analysis. It also includes the key research conclusions and future applications. In general, a summary does not exceed three pages.

The summary must provide an exact idea of the thesis or dissertation's content. It cannot be a simple enumeration of the manuscript's parts. The goal is to precisely and concisely present the nature and scope of the research. A summary must never include references or figures.

ABSTRACT

Written in English, the abstract is a brief summary similar to the previous section (Résumé). However, this section is not a word for word translation of the French.

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LOC	Lines of Code

CHAPTER 1 INTRODUCTION

10-12 lines to introduce the topic.

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1.1.1 Mining Software Repositories

1.2 Plan of the Thesis

CHAPTER 2 CRITICAL LITERATURE REVIEW

Texte.

CHAPTER 3 RESEARCH GENERAL WORKFLOW

My master research consisted of two different parallel projects. On one hand, in a collaboration with the linux foundation, I created and open-sourced 2 tools: Srcmap and Email2git. On the other hand, I created and evaluated an expertise detection model, which was submitted as a paper to the IEEE International Conference on Software Analysis, Evolution and Reengineering[1].

3.1 Srcmap

In the interest of offering more visibility to the authors of the Linux Kernel, we built a data visualization tool capable of displaying a wide array of information about directories or files found in the linux git repository. We wanted to display the following data points about each file and directory of the source code:

- Lines of Code (LOC)
- Median age of the LOC within a file/directory
- Number of lines of code modified since 2016
- A list of the 20 developers with the most lines of code
- A bar plot displaying the distribution of line of code age

We needed an interface that would allow the user to navigate the different files and direcotries of Linux while displaying our list of datapoints, which is why we chose to base the tool on a treemap. Treemaps, which were introduced by Shneiderman (Bederson et al., 2002) as a solution to display large hierarchical dataset on a 2 dimentional plane, were a great fit for our tool's requierments.

3.1.1 Srcmap 1.0

In the first version of Srcmap[2], we used the Google Chart treemap implementation[3]. This easy to use library allowed us to create a quick proof of concept.

[1] http://saner.unimol.it/
[2] http://mcis.polymtl.ca/~courouble/linux.html
[3] https://developers.google.com/chart/interactive/docs/gallery/treemap

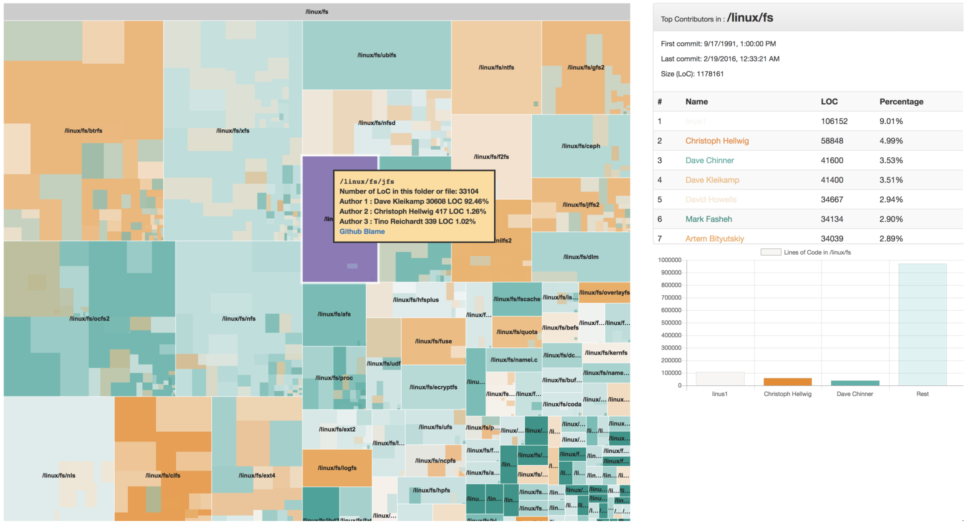

Figure 3.1 First version of srcmap

Figure 3.1 shows the first version of Srcmap. The diferent boxes represent subdirectories of the Linux Kernel. The different colors present within each box give a preview of the content of the box. In this version of the tool, the color represents the developer having contributed the most lines of code in the contained files. Furthermore, the size of the boxes is proportional to the number of lines of code existing within the file or directory represented by the box. The panel on the right of the screen and the tooltip contain most of the data: exact number of lines of code, age of the first and last lines of code to be added, and the top 20 authors and their percentage of lines of code contributed.

Even though the library offered by Google allowed us to quickly provide a strong proof of concept, we discovered some limitations when we tried adding new features to the tool. The tool had issues handling the size of the dataset. The actual data would take up to 30 seconds to load, and navigating between each node became very slow. This is why we decided to create a new version of the tool with a different treemap library.

3.1.2 Srcmap 2.0

After some research, we discovered a new treemap implementation[4] capable of handling large dataset and deeply nested stuctures, which we used for the second version of the tool[5]. This new version, shown in Figure 3.2, introduced three important features:

- Coloring the files and directories according to three metrics:

[4] `https://carrotsearch.com/foamtree/`
[5] `http://mcis.polymtl.ca/~courouble/dev/`

  - LOC
  - Median age
  - Number of commits since 2016, or "Hot files"
- File search
- A plot displaying the *age* distribution of LOC present in the file/directory.

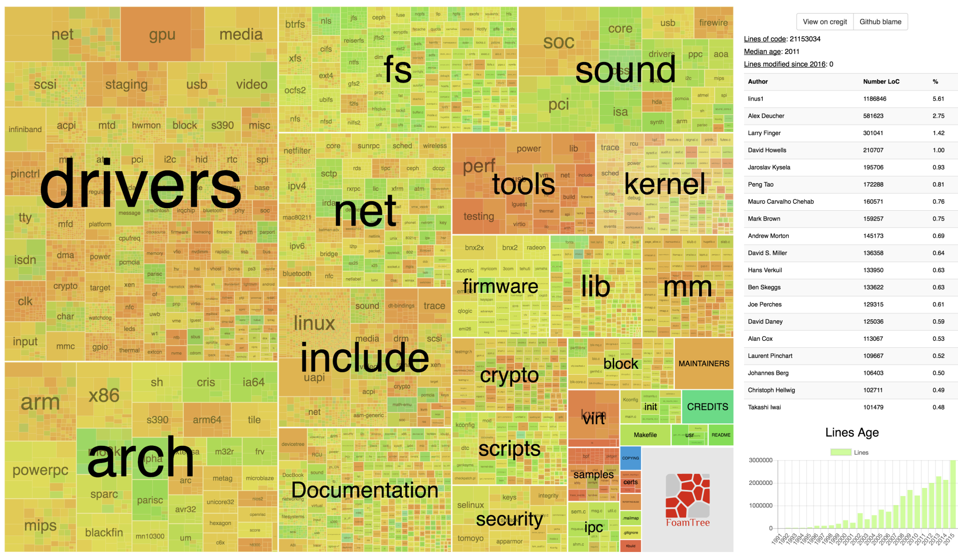

Figure 3.2 Second version of srcmap

Although the foamtree library had a steeper learning curve than the Google Charts Treemap library, the versatility provided by the foamtree library allow us to provide a much more pleasant user experience and easier access to the data.

I was given the oportunity to travel to Santa Fe, New Mexico to present Srcmap and Cregit at the Linux Plumbers Conference. After discussing srcmap and my research to a series of linux developers, it became evident that there was real interest for another aspect of linux development: linking Linux git commits to email patches and code reviews.

3.2 Email2git

The linux contribution process has been a reliable way to pipe code contributions (patches) from developers around the world, to the main Linux repository. With a working copy of the Linux Kernel on their computers, developer can modify the source code and, if desired, submit their changes for review, in hope to integrate the main tree. These changes are submitted as patches, files that contain the lines that are to be removed and the lines that are to be added. To submit a patch, developer send the patch file(s) to a linux maintainer in an *email* with a description of the changes brought by the patch. If accepted, the maintainer will *commit* the changes to his local git repository, and submit the changes *upstream* to another maintainer.

Although this system has been very reliable, it has one major drawback: once committed, it is impossible to easily find the email conversation that eventually led to the creation of the patch. We addressed this drawback by creating an algorithm capable of backtracking the origin of commits in the Linux Git repository. The algorithm is described in chapter 4.

The data generated by the algorithm consists of a list of commit to patch matches. The matches are accessible online through two interfaces: as a commit ID search through the Email2git interface[6], or though the Cregit interface[7].

3.3 Integrating Email2git with Cregit

Cregit is a project that aim at providing a finer grain approach to *git blame*. The blame option in git returns the name of the developer who last changed a line of code in the source code. It provides a great way to quickly unmask the developers responsible for code in the Source Code. However, it has a serious limitation: git blame assigns a line to a developer even after a small modification to that line. For instance, if developer A writes `print "Hello world"`, this line will then become associated with developer A. However, if developer B modifies the line to read `print "Hello world!"`, git blame will associate the line with devloper B even though developer B only added a character.

Cregit addresses this limitation by tokenizing the source code in a git repository to enables git blame at a token level, instead of a line level. This provides a better understanding of the true authors of the source code. A tokensize version of the Linux kernel source code is available online through the cregit interface[8].

Figure 3.3 shows tokenized linux code as it appears on the Cregit interface. In an effort to ease the access to email2git data, we decided to provide access to the matches through cregit. To this end, I modified the user interface to display a window containing all the available patches after clicking on a token, as shown in Figure 3.4.

[6]`http://mcis.polymtl.ca/~courouble/email2git/`
[7]`https://cregit.linuxsources.org/`
[8]`https://cregit.linuxsources.org/`

```
static void dio_bio_end_aio(struct bio *bio)
{
        struct dio *dio = bio->bi_private;
        unsigned long remaining;
        unsigned long flags;

        /* cleanup the bio */
        dio_bio_complete(dio, bio);

        spin_lock_irqsave(&dio->bio_lock, flags);
        remaining = --dio->refcount;
        if (remaining == 1 && dio->waiter)
                wake_up_process(dio->waiter);
        spin_unlock_irqrestore(&dio->bio_lock, flags);

        if (remaining == 0) {
                if (dio->result && dio->defer_completion) {
                        INIT_WORK(&dio->complete_work, dio_aio_complete_work);
                        queue_work(dio->inode->i_sb->s_dio_done_wq,
                                      &dio->complete_work);
                } else {
                        dio_complete(dio, 0, true);
                }
        }
}
```

Contributors

Person	Tokens	Prop	Commits	CommitProp
Zach Brown	68	49.28%	4	50.00%
Christoph Hellwig	42	30.43%	2	25.00%
Andrew Morton	27	19.57%	1	12.50%
Neil Brown	1	0.72%	1	12.50%
Total	138	100.00%	8	100.00%

Figure 3.3 Tokenized source code as it appears on Cregit.

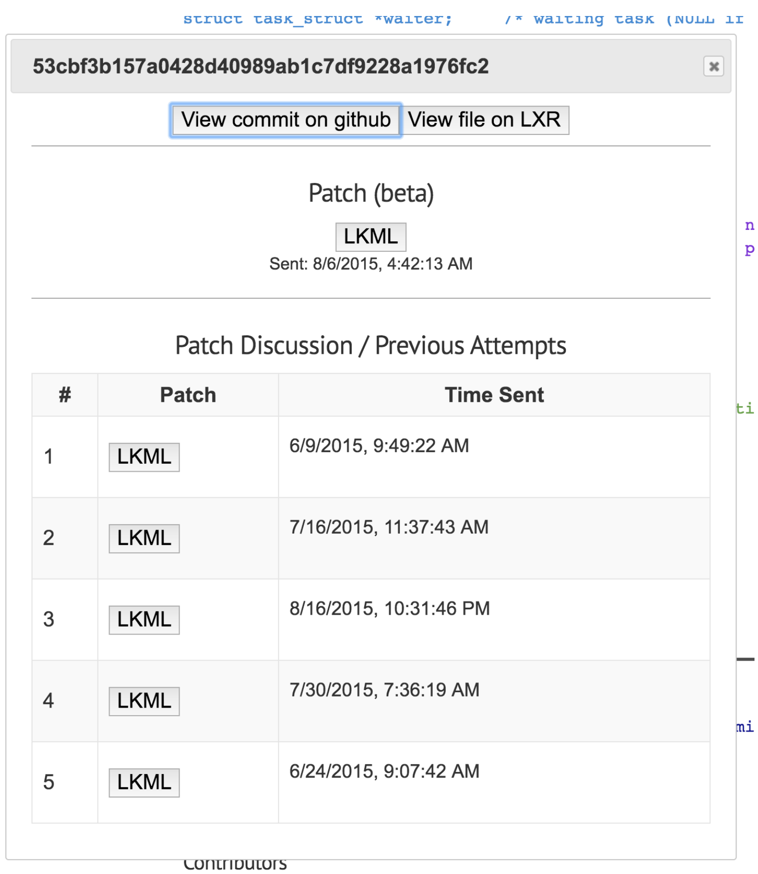

Figure 3.4 Window containing the patches that introduced the commit associated with the clicked token

CHAPTER 4 EMAIL2GIT: FROM ACADEMIC RESEARCH TO OPEN-SOURCE SOFTWARE

4.1 Previous Publications and Original Algorithm

The original algorithm capable of backtracking patches from commits was introduced in two papers (Jiang et al., 2013, 2014) published by Jiang, a former member of the MCIS Lab. Originally written in Perl, the script was a great proof of concept. The general idea of the script was to compare the +/- lines from both the git commits and the email patches. A match was found if the proportion of identical +/- lines was above a certain threshold. Although this script was a great proof of concept, it had difficulties scalling to 8 years of emails and commits.

4.2 Scalling the Algorithm

Because we wanted Email2git to be a usable and practical tool, we needed a way to display the patches and the code reviews in a browser. Fortunatly, a great existing open-source tool called **Patchwork**[1] perfectly answers our requirements. Patchwork is a tool designed to assist maintainers of open source projects using an email-based contribution process. It tracks the mailing lists used by developers to submit patches and recieve code reviews. The tool extracts each detected patch as well as its associated reviews, then displays them in a web-based user interface.

We were granted read access to the MySQL database behind a patchwork instance hosted on kernel.org[2]. This instance has been tracking 69 of the many linux subsystems mailing lists since 2009, giving us the oportunity to analyse over *1.4 million* patches.

In addition to being a great data source, patchwork.kernel.org is also a great way for us to display the patches and the code reviews associated with commits to the users. The only limitation of this patchwork instance is that it does not track some major mailing lists, particularly some of the `Net` mailing lists.

Since we had access to email patches dating back to 2009, we decided to extract git commits from the Linux git repository from the same date, which represent over *500,000 commits* to analyse. Unfortunatly, this amount of data was too large for the orignal algorithm to parse in a timely fashion, which called for a new, scalable algorithm that applies exploits mentioned

[1] `https://github.com/getpatchwork/patchwork`
[2] `https://patchwork.kernel.org/`

in (Jiang et al., 2013, 2014).

4.3 The Data

There are two sides to this matching process: the Linux git repository and the archives containing the patches sent in mailing lists over the years. We need to extract data from both sides.

4.3.1 Extracting the Commits

4.3.2 Extracting the Patches

4.4 Serving the Matches

CHAPTER 5 ARTICLE: ON HISTORY-AWARE MULTI-ACTIVITY EXPERTISE MODELS

5.1 Abstract

As software evolves, a developer's contributions will gradually vanish as they are being replaced by other developers' code, slowly eroding the developer's footprint in the software project. Even though this developer's knowledge of the file did not disappear overnight, to outsiders, the developer and her expertise have become invisible. Through an empirical study on 5 years of Linux development history, this paper analyses this phenomenon of expertise erosion by building a 2-dimensional model of developer expertise involving a range of developer activities and involving activity data on more than one release. Using these models, we found that although many Linux maintainers' own coding footprint has regressed over time, their expertise is perpetuated through involvement in other development activities such as patch reviews and committing upstream on behalf of other developers. Considering such activities over time further improves the expertise models.

5.2 Introduction

As reported by Damien et al. (Joseph et al., 2007), employee turnover is a major challenge of information technology organizations. Estimations of the cost of losing an employee amount to between 0.5 and 1.5 times her salary, with the cost of replacing a software engineer in particular exceeding $100,000 (eco, 2000). These costs are not limited to the software engineer's company, but also spread to open source development. In their 2017 Linux kernel report, Corbet et al. (Corbet and Kroah-Hartman, 2017) noted that "well over 85 percent of all kernel development is demonstrably done by developers who are being paid for their work". In fact, only 8.2% of all kernel commits were made by volunteer developers. Hence, developer turn-over in companies risks to impact open source development as well!

Apart from improving the working conditions and onboarding procedures, software organizations (both closed and open source) need to invest time in finding the "right" expert to replace a parting developer. While it is possible to train newcomers and bring them up to speed (e.g., one third of the kernel contributors in the last 12 months were newcomers, and 60% of those made their contribution as employee), the term "right" refers to having a similar profile, allowing the new expert to seamlessly fit in and continue his or her predecessor's work, without significant loss of knowledge. Thanks to the widespread adoption of agile development and open source development models, software development has become a collaborative endeavor, in which knowledge is shared across the members of an organization, hence in principle it should be possible to find contributors with similar profiles.

Unfortunately, there is no consensus on how to measure the profile of a developer, and how to determine whether such a profile indicates the developer to be an expert. The simplest way to measure someone's development activities is to count the number of code changes (e.g., Git commits) authored. This is for example how Corbet et al. determine the most active developers and organizations in Linux kernel development (Corbet and Kroah-Hartman, 2017). Yet, at the same time, they note that "The total number of patches signed off by Linus Torvalds (207, or 0.3 percent of the total) continues its long-term decline. That reflects the increasing amount of delegation to subsystem maintainers who do the bulk of the patch review and merging." Worse, developer rankings based on the number of commits differed substantially based on the period during which this metric was measured (e.g., ranking based on last 10 years vs. last year). At a minimum, one needs to be careful interpreting these and other measures such as a developer's code legacy as shown by "git blame" (Bhattacharya et al., 2014; Mockus and Herbsleb, 2002; McDonald and Ackerman, 2000; Fritz et al., 2007).

To make developer expertise measures more robust and reliable, this paper proposes a 2-dimensional developer expertise footprint, addressing two important issues with current expertise models. First of all, while the amount of code written by a person can be an important indicator of expertise, it does not take into consideration the actions of people who do not directly contribute source code, such as those who review it or discuss it on mailing lists or issue repositories. Our footprint measure combines indicators of multiple kinds of developer activities.

Second, as indicated by the Corbet et al., current measures focus on a given software release or development period, basically ignoring the development activities that happened before. While a person who wrote 50% of the code changes of the previous release could be less of an expert than a person who wrote 50% of the code changes of the current release, the former developer might have been ill or absent, or might have been the one mentoring the latter developer. As such, both developers should be considered as experts, not just the latter developer. Our footprint measure allows to consider a developer's activities across different time periods.

We empirically evaluate the expertise footprint models on 5 years of Linux kernel development history, addressing the following research questions:

RQ1) *How does expertise evolve in an open source project?*

Almost 1 out of 4 subsystems has seen a change in maintainership during the last 22 Linux kernel releases, with the code footprint of maintainers gradually decreasing over time.

RQ2) *How well does dimension 1 explain expertise?*

Models involving a maintainers' own code footprint and coordination activities (committing and/or reviewing) perform the best.

RQ3) *How well does dimension 2 explain expertise?*

Expertise models considering the last R releases perform better than single-release models.

5.3 Background and Related Work

Maintainers ensure the longevity of the Linux kernel by not only contributing new code, but also by reviewing and integrating code submitted to their subsystems by other developers. They are the backbone of Linux kernel development, yet few studies have been done to study their work (Zhou et al., 2017).

In particular, a maintainer's departure of her subsystem calls for her immediate replacement. However, only a developer with extensive experience in the subsystem can take on the task of maintainer. Software expertise and knowledge have been extensively studied in the past (Bhattacharya et al., 2014; Mockus and Herbsleb, 2002; McDonald and Ackerman, 2000; Fritz et al., 2007). Many different models were created to attempt to assess developer expertise.

Earlier expertise models (McDonald and Ackerman, 2000; Mockus and Herbsleb, 2002) made the assumption that expertise is related to coding activities. They both extracted data describing the changes in the source code from the version control system. In other words, they measured a developer's expertise in terms of the number of changes made to the system.

Fritz et al. (Fritz et al., 2007) later expressed their concern about the assumption that activity indicates expertise. Their review of psychology studies indicated a lack of evidence proving that activity can be an indicator of knowledge. However, after a qualitative study consisting of 19 java developers interviews, they were able to confirm a relationship between commit frequency and expertise. In addition to that, they foud evidence proving that authorship (as obtained from the amount of churn contributed, or through "git blame") is also capable of indicating expertise.

Bhattacharya et al. (Bhattacharya et al., 2014) explored the suitability of different expertise indicators depending on the developer's role. They argue that state-of-the-art metrics (lines of code and commits added), being unaware of the developer's role, can lead to inaccurate results. They add that code activity metrics like the number of lines of code added, only describe expertise at a local level and poorly capture global expertise.

Even though the goal of each study mentioned above varies, they all introduced expertise detection models relying on two simple metrics to measure expertise: the number of lines of code contributed and/or the number of commits.

Although these state-of-the-art techniques are well suited to detect experts among regular developers, we believe that they do not properly evaluate more complex expertise, such as that of subsystem maintainers. Most of the daily tasks, such as reviewing, of maintainers are ignored, creating an inherent bias in the expertise models.

We address this bias by building expertise models based on a variety of metrics capturing the full breadth of software development activities, and also considering a longer the evolution of such activities over time.

5.4 Measuring the Expertise Footprint of Contributors

This section discusses the two-dimensional model of expertise footprint proposed by this paper to enable identification of experienced team members (e.g., developers, testers, etc.). The first dimension of the footprint model considers a wide range of activities performed by a project member, not only focusing on code changes, but also code review or even a developer's code "legacy" (i.e., contributed code that still survives in the code base). The second dimension enhances the first dimension by not only considering the range of activities in the latest release, but *across the last N releases*. As such, accidental lulls or shifts in project activity are accounted for.

Note that the expertise we are interested in is expertise about the *internals* of a particular source code file or component. An alternative form of expertise would consider knowledge on how to *use* a particular component (API). We focus on the former kind of expertise, since it is at the heart of a software organizations needs. For example, it allows to measure the expertise of a particular individual, allowing the organization to better use her skills, evaluate her value to the organization, and assess the risk of her potential departure. Furthermore, it is important for an organization to know—for any section of the system—who are its experts, and their level of expertise. Finally, in both cases, it is also important to know how this expertise is changing over time (e.g., the areas where a person is gaining and losing expertise, and, for a given area, how it is losing or gaining experts).

5.4.1 Dimension 1: Contributor Activities

The expertise footprint model that we propose explicitly considers a wide range of development activities instead of focusing only on review- or code-related activities. Table 5.1 provides a non-exhaustive list of activities, from very technical to outreach activities. Any activity by a contributor to one of these, can increase (or at least maintain) the contributor's knowledge about the subsystem she is working in. The more measures are considered, the more comprehensive the expertise footprint model becomes, hence the better the expected performance for identification of experts in a project under study, provided the activities are weighted based on their relevance for a given project.

This flexibility comes at the expense of additional effort for mining these activity measures. Fortunately, when developers contribute code to an open or closed source project, data about each code change, code review or other activity is automatically stored in the project's software repositories. The most trivial example are the code changes (commits) recorded in a version control system like git. However, information about the contributor's activity in issue report discussions is also readily available from the project's issue repository (e.g., bugzilla or jira), code review activity from the review repository (e.g., gerrit or mailing list) and mailing list activity from the mailing list archive. Of the metrics in Table 5.1, `represented` and `planned` are the hardest to obtain data for.

Given a set of activity measures $\mathbb{A} = \{a_i | a_i \textit{ is activity measure}\}$, we compute the expertise footprint of a release j as:

$$footprint_j(\mathbb{A}) = \sum_i \frac{w_i \times a_i}{a_i^{tot}}$$

, where w_i is a weight factor given to a_i ($\sum_i w_i = 1$) and a_i^{tot} is the total number of activities of a given type (e.g., number of source code lines, commits or reviews) recorded for a given activity and release. In other words, each activity is normalized, and the weighted sum of the normalized activities yields the $footprint_j(\mathbb{A})$ percentage. Hence, to instantiate the generic $footprint_j(\mathbb{A})$ measure, an organization first has to select the activity measures $\mathbb{A}$ relevant to its context, then determine the relative weight w_i of each selected activity.

It is necessary to normalize each activity's measure to provide a better understanding of the true impact of developers' contributions in the subsystem. This is because the studied subsystems differ in size and the heuristic counts are inherently uneven by nature. For

activity	definition
`legacy`	influential code contributed by C that still survives in R_i
`authored`	code authored by C since R_{i-1}
`committed`	code committed by C since R_{i-1}
`reviewed`	code changes reviewed by C since R_{i-1}
`translated`	involvement in translating/localizing textual strings for R_i
`integrated`	effort spent by C integrating code changes since R_{i-1}
`discussed`	effort spent by C discussing issue reports since R_{i-1}
`represented`	effort spent by C representing S on social media since R_{i-1}
`planned`	effort spent by C planning R_i

Table 5.1 Non-exhaustive list of activity measures that can be measured for a particular contributor C of a specific subsystem S in a given release R_i.

example, the value for `legacy` (in number of lines of code) will likely be much larger than the values of `authored` or `reviewed` (in number of commits).

5.4.2 Dimension 2: Historical Perspective

While the definition of $footprint_j(\mathbb{A})$ takes into account a wide range of activities, it only considers a contributor's activity for one specific release j. As such, this measure might still provide misleading information when used to find the most appropriate expert for a given subsystem (e.g., to help debug a coding issue).

First of all, contributors in both closed and open source development evolve according to a particular career path. Even in open source, many contributors start out translating textual strings, before contributing smaller code fixes and ever larger changes until they are trusted enough to be able to review or even accept other contributors' code. This not only implies that a contributor's volume of contributions is scattered across different activities, but also that this scattering (and volume) might change over time. Hence, depending on the release under study, different $footprint_j(\mathbb{A})$ values are obtained, as if a specific contributor suddenly would have "lost" or "gained" a substantial percentage of expertise (footprint). To counter this noise, one should incorporate past experience to obtain a more robust footprint model.

Second, even when a contributor's responsibilities are stable across a time period, accidental life events such as illness or busy periods at work, or project events such as the scope of the upcoming release (major release vs. bug fix release) could lead to increases or decreases for certain activities. Again, if the contributor was an expert in the previous release, she will not have lost all of this expertise in one release due to illness. Hence, a release-specific

$footprint_j(\mathbb{A})$ measure again would yield the wrong impression.

For this reason, the second dimension of our footprint model explicitly takes into account history by taking the weighted sum of $footprint_j(\mathbb{A})$ over the last R releases. In particular:

$$footprint_j^R(\mathbb{A}) = \sum_{i=j}^{j-R} W_i \times footprint_i(\mathbb{A})$$

, where W_i is a weight factor given to the specific footprint of release i ($\sum_i W_i = 1$). Note that $footprint_j(\mathbb{A}) = footprint_j^0(\mathbb{A})$, i.e., the footprint model obtained based on the first dimension is a special case of the second dimension ($R = 0$).

While the choice of weights w_i for dimension 1 could be chosen arbitrarily based on relevance of individual activities, the weights W_i typically will be decreasing, since recent activity typically is at least as important as older activity. For example, the weights could be linearly decaying (e.g., $[0.33, 0.27, 0.20, 0.13, 0.07]$ for $R = 4$), giving each older release proportionally less influence on the footprint model. Alternatively, an exponential ($[0.64, 0.23, 0.09, 0.03, 0.01]$) or logarithmic ($[0.34, 0.29, 0.23, 0.14, 0.00]$) decay could be used to give older release less or more influence, or (less likely) even a uniform ($[0.20, 0.20, 0.20, 0.20, 0.20]$) decay to give all considered releases the same importance.

5.4.3 Use Cases for Expertise Footprint

Given the footprint models $footprint_j(\mathbb{A})$ and $footprint_j^R(\mathbb{A})$, a number of use cases can be imagined.

The main use case considered in this paper is the identification of experts in a software project. Newcomers to a project typically are not aware who to ask for advice when encountering a specific technical issue. Similarly, when the maintainer of a specific component or library decides to retire, finding a good replacement is not always straightforward for an organization, as important development knowledge (across a range of development activities) risks to be lost.

A less straightforward application was suggested at one of the 2017 OPNFV Summit's panels, where substantial attention went to the issue of non-responsive Linux kernel maintainers. These are experts responsible for a given subsystem who, due to personal events, loss of interest or other reasons, start becoming non-responsive in communication with other developers or management. Having a reliable expertise measure in place would enable monitoring over time of maintainers' activities to spot long-term periods with sub-par performance. Such pro-active detection of issues could also suggest alternative maintainers.

Similarly, an expertise footprint can help an organization guard itself against accidental loss of manpower. For example, the bus factor (Mens et al., 2014) is a known measure of the risk that key personnel might disappear from a project, either out of free will or due to an accident. Organizations with a high bus factor could leverage an expertise footprint to identify backups for key developers or managers. As such, for each subsystem, an organization could have a list of the main people working in it as well as their expertise level.

In order to use the footprint models to find the most appropriate expert of a given subsystem, one needs to calculate $footprint_j(\mathbb{A})$ and/or $footprint^R_j(\mathbb{A})$ for each person who contributed at least once to one of the activities in $\mathbb{A}$. Then, the resulting footprint values should be ranked from high to low. Ideally, the contributor with the highest footprint value is recommended as first candidate expert, followed by the contributor with the next highest footprint value, etc.

5.5 Case Study Setup

This section presents the design of an empirical study on the Linux kernel to evaluate the 2-dimensional footprint model introduced in the previous section. The study addresses the following research questions:

RQ1: How does expertise evolve in an open source project?

RQ2: How well does dimension 1 explain expertise?

RQ3: How well does dimension 2 explain expertise?

5.5.1 Subject Data

Our study evaluates the expertise footprint models in the context of the Linux kernel. First of all, the Linux kernel is one of the hallmark open source projects, with a long history, large code base and vast supply of contributors. Second, the kernel is one of the few open source projects in which expertise is documented explicitly. The code base contains a file named `MAINTAINERS` that lists, for each subsystem, the experts in charge. Just as for source code, changes in maintainership are recorded through regular commits. This provides us with a unique oracle for our expertise measures.

Furthermore, the Linux Foundation (who governs and mentors the development of the Linux kernel and related open source initiatives) recently has started up the CHAOSS committee on Community Health Analytics for Open Source Software[1]. Amongst others, the aim of this committee is to identify explicit measures of expertise that can help prospective adopters of open source projects in choosing the right developer or maintainer to contact. As such, our study can help this concrete initiative, and we are in contact with the CHAOSS consortium.

Determining expertise footprints in the Linux kernel, especially taking into account the second dimension of our measure, requires a large set of historical data. We conducted our analysis on a set of 27 releases of the Linux kernel, spanning releases *v3.5* to *v4.11*, which corresponds to approximately 5 years of development and release history.

5.5.2 Filtering of the Data

Because of the constantly changing nature of the kernel, new subsystems are being added to the Linux kernel in every release to meet the demands associated with new hardware and changes in user expectations. Furthermore, it is not uncommon to see a subsystem disappearing, or, more precisely, becoming obsolete or orphaned (lin, v4.11, `MAINTAINERS`, Line 84).

On the other hand, the importance of the historical aspect of our analysis forces us to choose long-standing subsystems that would best reflect the evolution of expertise of the subsystems' maintainers. Hence, we filter our Linux kernel data set to keep only subsystems that existed throughout the studied timespan. This subset reduces the number of subsystems from 1,662 to 734 subsystems.

For RQ2 and RQ3, we need further filtering to ensure a data set of subsystems for which there is ongoing activity in each studied release. To achieve this, we parsed, for each release, the `MAINTAINERS` file to extract each *active* subsystem along with its name, list of maintainer names, and the list of files and directories belonging to that subsystem.

We then retrieved the list of commits made to each subsystem, for each release that we considered. This allows us to compute, for each subsystem, the average number of commits across its releases. After matching each commit to its code reviews (see below), we also compute the average proportion of matched commits per release.

We then set minimum thresholds of 50 commits per release and 60% matched commits per release. This filtering reduces the 734 subsystems to a set of 78 subsystems for RQ2 and RQ3. This subset contains well know subsystems like `ARM PORT`, `XEN HYPERVISOR INTERFACE`, `SOUND`, `SCHEDULER`, and `CRYPTO API`.

[1] `https://chaoss.community/`

5.5.3 Instantiation of the Footprint Models

Table 5.2 shows the five concrete activity measures considered in our empirical study on the Linux kernel. These measures cover influential source code contributed (`legacy`), the volume of code changes since the last release (`authored` and `committed`), and code review activities since the last release (`attributed` and `reviewed`).

Our $footprint_j(\mathbb{A})$ and $footprint_j^R(\mathbb{A})$ models are calculated based on the above metrics, using $w_i = 0.20$ as weights for dimension 1 and a linear decay with $R = 4$ (i.e., $W_i \in [0.33, 0.27, 0.20, 0.13, 0.07]$) for dimension 2. A more judicious choice of w_i and/or W_i could improve the results in RQ2 and RQ3, however our empirical study aims to provide a lower bound on the expected performance.

5.5.4 Git-related Activity Measures

To calculate the Git-related activity measures of Table 5.2, i.e., all measures excluding `reviewed`, we cloned the official Linux kernel git repository, then checked out the Git tag corresponding to each analyzed release.

Bread-and-butter analysis of the Git log commits in the time span since the previous official release yields `authored` and `committed`, while simple regular expressions of the commit messages in the same logs obtains `attributed`. Finally, a standard git blame command yields, for each code line in the release under analysis, the last person touching it. This information allows to calculate `legacy`.

In kernel development, tags like “Signed-off-by”, “Reviewed-by” and “Acked-by” are used as “a loose indication of review, so [...] need to be regarded as approximations only” (Corbet and Kroah-Hartman, 2017). Despite the warning of Corbet et al., `attributed` information is straightforward to obtain from commit messages, which is why we included this measure to complement the more strictly defined `reviewed` measure (calculated from reviewing data).

The next step is to lift up each contributor’s Git-related activity measures to the subsystem-level, leveraging the file path information for each subsystem in the `MAINTAINERS` file. To do this, we identify for each commit the changed files, then map the commit to the subsystem(s) to which these files belong and aggregate the file-level measures to the subsystem level, for each contributor.

activity	source	definition
`legacy`	git blame	#lines of code contributed by C that still survive in R_i
`authored`	git log	#commits authored by C since R_{i-1}
`committed`	git log	#commits committed by C since R_{i-1}
`attributed`	git log	#commits since R_{i-1} for which C is credited in the commit message under "
`reviewed`	mailing list	#commits since R_{i-1} for which C has written at least one code review email

Table 5.2 Concrete activity measures used for our empirical study on the Linux kernel. Each activity is measured for a particular contributor C of a specific subsystem S in a given release R_i.

5.5.5 Linking Commits to Review Emails

In contrast to the developer `attributed` data obtained from the Git repository, the `reviewed` metric considers a second repository, i.e., the review environment. For the Linux kernel, code reviews are performed through mailing list discussions (Armstrong et al., 2017; Jiang et al., 2013, 2014). Patches are sent to one or more of the various linux mailing lists (typically one per kernel subsystem), where anyone can step up and provide review comments simply by replying to the patch email. As such, the review comments of a specific patch are spread across one or more email threads.

Jiang et al. (Jiang et al., 2013, 2014) have introduced a number of heuristics to link an accepted patch stored as a commit in the official Git repository to the (different versions of the) reviewed patch in the mailing list. We adopted the best performing heuristic of Jiang et al., which uses simple set intersection of the changed code lines between each email patch and Git commit. The heuristic matches a given Git commit C to the email patch P with which the change code line intersection is the largest and exceeds a given threshold of 4%. All emails in P's email thread are said to correspond to the review comments on P (and hence C).

To improve the line-based heuristic of Jiang et al., we have combined it with other heuristics. First of all, we observed that more and more kernel developers are using the commit message summary as the subject of their email threads. This summary is recommended to be between 50 and 72 characters[2] and appears before the body of a commit message. Hence, before applying the line-based matching of Jiang et al., we first check if there is a unique email patch P with subject identical to a commit C's commit summary. If so, we consider P and C to be a match, and do not need to run the more complex line-based matching algorithm.

[2] `https://medium.com/@preslavrachev/what-s-with-the-50-72-rule-8a906f61f09c`

If there is no such P, or multiple patches P have been found, we extract for each remaining commit the *author* and the *changed files*. We do the same for each remaining email patch. This information is then used to narrow down the search space of the line-based matching, by trying to match a commit only to email patches authored by the same developer and/or touching the same files. This substantially speeds up the matching process.

The remaining commits, i.e., the commits still not matched to a review, introduce noise to our measures. The reason for not finding a code review could be due to the reviews being sent to a mailing list that we did not analyze, or not being reviewed at all. We were granted read access to the database behind the Patchwork mailing list archive hosted by linux.org[3]. This Patchwork instance has been tracking 69 different Linux mailing lists since 2009, providing us with about 1.4 million patches. However, patches that were submitted through untracked mailing lists are not in our dataset, which explains the variability of matched commits across subsystems. Alternatively, the code change in the accepted commit could also have undergone substantial changes compared to the reviewed commit, for example due to rebasing, cherry-picking or squashing (Bird et al., 2009).

Figure 5.1 shows the total percentage of matched commits from 2009 to the time of writing this paper, across the largest subdirectories of the kernel. It shows that this percentage varies greatly among the different subdirectories, with a minimum of 25% for the "net" subdirectory. This is why, in subsection 5.5.2, we filter out those subsystems whose average percentage of matched commits across the studied releases is lower than 60%. Note that we do not show the percentage of unmatched *patches* (only unmatched *commits*), since the unmatched email patches include those patches that were rejected during code review, and hence never showed up in the Git repository.

5.6 Case Study Results

This section discusses for each research question its motivation, specific approach and results.

RQ1. How does expertise evolve in an open source project?

Motivation:

Open source software maintainers are responsible for the health of their subsystem. For example, each Linux kernel maintainer manages the changes proposed by developers to the subsystem they are responsible for, and shepherd those changes upstream towards the Git

[3] `https://patchwork.kernel.org/`

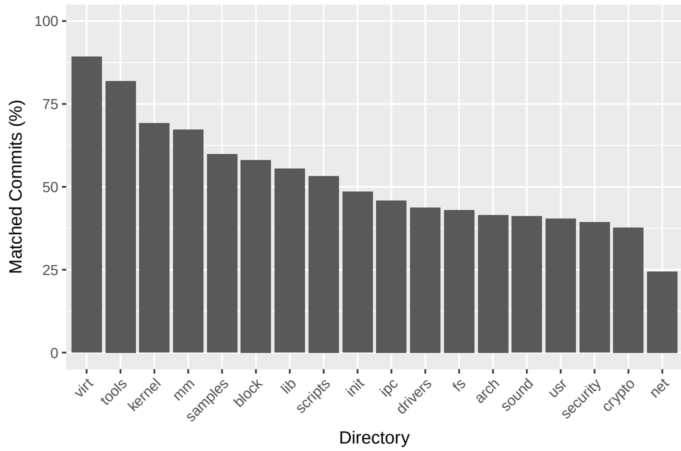

Figure 5.1 Percentage of matched commits in Linux subdirectories, from 2009 to the time of writing this paper.

repository of Linus Torvalds (i.e., the official Linux kernel repository). Hence, their presence is vital to the kernel community.

Unfortunately, due to the unpredictable nature of life in general and open source software development in particular (Wu et al., 2007; Zhou and Mockus, 2015), maintainers, for various reasons, one day will be forced to give up their responsibilities. In most cases, this means that another developer will have to take over the responsibility of maintainer.

Hence, this research question aims to analyze how often maintainership changes in kernel development. Furthermore, we are interested in understanding how much of the code base of official releases is "owned" by the subsystem maintainers, i.e., was originally developed by a maintainer. Since "git blame" is a popular means for finding experts (Rahman and Devanbu, 2011), our results will help us understand to what extent such a measure is reliable to measure expertise.

Approach:

To confirm the presence of changes in maintainership during the evolution of the Linux kernel, we analyzed the maintainers recorded in the `MAINTAINERS` file of releases *v3.5* to *v4.11* to identify how often maintainers (dis)appeared. Furthermore, for each studied release, we measure and plot these maintainers' `legacy`, which corresponds to the number of surviving code lines of a maintainer, as given by "git blame". We then validated the statistical significance of the change in `legacy` distribution between the first and last analyzed release using a Wilcoxon paired test. In case of a significant test result, we also provide the Cliff Delta effect size ((Cite Romano stats paper)). An effect size smaller than 0.147 is deemed a "negligible" difference, smaller than 0.33 a "small" difference, smaller than 0.474 a "medium" difference and otherwise a "large" difference.

Results:

23% of the studied subsystems saw changes in maintainership over the last 5 years. Out of the 734 subsystems studied for RQ1, we counted 168 subsystems that experienced some sort of maintainership change. We counted 100 maintainer arrivals, 63 departures, and 88 replacements. These numbers confirm that maintainership change is common, even in mature open source systems like the Linux kernel. Furthermore, the median percentage of developers who are maintainers in the analyzed subsystems is 0.50% (mean of 0.90%), indicating that it is not straightforward to guess the next maintainer. These observations strengthen our case for more advanced expertise measures.

The median maintainer `legacy` significantly decreases over time. Figure 5.2 shows the evolution of the median percentage of maintainer `legacy` across all subsystems in each studied release. The plot shows a clear, steady decrease of this measure across releases in terms of median and variance. We confirm the significance of this decrease with a Wilcoxon paired test ($\alpha = 0.01$) between the first and last studied version, which yields a p-value of 2.2e-16.

Although the Cliff Delta value of 0.07 indicates only a negligible difference, this decreasing trend suggests that, if one limits the measure of expertise to the amount of surviving code originally authored by a maintainer, as was done by earlier work (Rahman and Devanbu, 2011), the expertise of maintainers globally seems to be decreasing over time. The next two research questions evaluate the use of a wider range of activity measures, across a range of releases, to obtain a more accurate measure of expertise.

RQ2. How well does dimension 1 explain expertise?

Motivation:

Prior work on expertise measures (Anvik et al., 2006; Bhattacharya et al., 2014; McDonald and Ackerman, 2000; Minto and Murphy, 2007; Mockus and Herbsleb, 2002) primarily are based on code activity, which can be defined in terms of `legacy` and `committed`. As motivated in subsection 5.4.3, we believe that these two metrics do not capture the full breadth of contributor expertise activities. Indeed, the results in RQ1 indicate that the `legacy` of long-standing maintainers crumbles over time. Unless one assumes that this reflects a real drop in expertise over time, the only explanation is that existing experts reorient their focus to other activities, such as code review and email communication. Hence, this research question

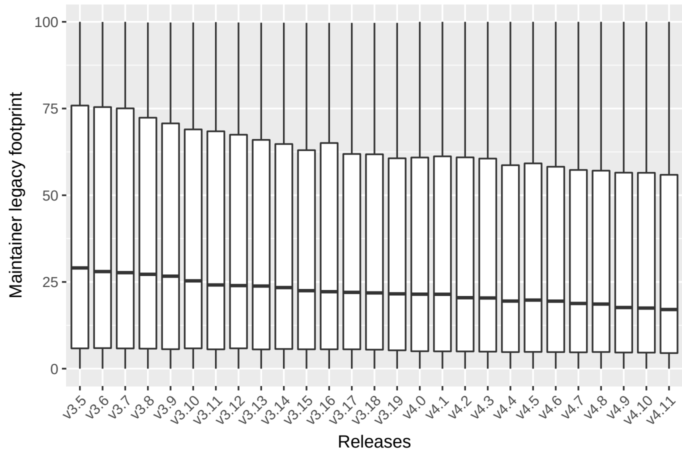

Figure 5.2 Median maintainer `legacy` across releases.

evaluates whether considering such additional activities is able to improve the identification of experts.

Approach:

To validate the ability of the measures in Table 5.2 to explain expertise, we evaluate how well the $footprint_j(\mathbb{A})$ measure involving those measures is able to identify the maintainers of Linux kernel subsystems. Those maintainers are the experts listed in the `MAINTAINERS` file of a kernel release.

For a given release and subsystem, we should find the maintainers in the top positions when ranked based on footprint values. The combination of activity measures $\mathbb{A}$ that is able to systematically yield the correct maintainers across subsystems and releases could be assumed to be a better indication of expertise.

In particular, we calculate two performance metrics:

POS_N Percentage Of Subsystems for which at least one maintainer was ranked in the top N expert candidates

POM_N Percentage Of Maintainers in the *whole* project who were ranked in the top N expert candidates for their subsystem

For these performance metrics, N is a threshold that can be varied. Our case study uses thresholds ranging from 1 to 5. It is important to note that, if the number of maintainers of a subsystem is larger than N, POM_N could be penalized. To avoid this, we slightly changed the definition of POM_N to be calculated only for the maintainers of all subsystems with at most N maintainers, instead of for all maintainers of the whole project. For example, POM_1 measures the percentage of top-recommended maintainers of subsystems with at most 1 maintainer.

To structure our analysis, we analyzed the performance of expertise models involving only one metric of Table 5.2, then analyzed models involving all combinations of `legacy` with one of the other 4 measures, and finally one model with all measures combined. We focus explicitly on models involving `legacy` because it is a commonly used measure (Rahman and Devanbu, 2011), and hence we use its performance as baseline.

Since, for a given release, there is one POS_N value and one POM_N value, we calculate these metrics for each release, then study their distribution across the analyzed releases using boxplots. Figure 5.3 and Figure 5.4 show for each analyzed $\mathbb{A}$ the distributions of POS_N for N=1 and N=3, respectively, across the 22 studied Linux releases, while Figure 5.5 and Figure 5.6 the distributions of POM_N for N=1 and N=3, respectively. We only show the plots for N=1 and N=3, as for higher values of N the plots remain more or less stable.

Results:

`attributed` is the only single-measure model able to keep up with the multi-measure models.

The results in Figure 5.3 and Figure 5.5 indicate that the first two individual measures, i.e., `legacy` and `authored`, are bad indicators of expertise compared to the other studied metrics. For example, in Figure 5.3, `legacy` only reaches a median POS_N value of 47.22%, while `attributed` reaches a median POS_N percentage of 58.4%.

The models combining `legacy` with `committed`, `attributed` and/or `reviewed` perform the best. Figure 5.3 shows indeed how only these four models read median percentages of 69.9%, while the other multi-measure models, especially the one involving only `legacy` and `authored`, are not able to outperform the best individual measure models.

These findings confirm the intuition that maintainers shifted focus from doing development (`authored`) themselves to mentoring others by controlling access to their subsystem's Git repository through committing and/or reviewing. As such, an expertise model only involving their own development (i.e., `legacy` and `authored`) is unable to explain the current kernel maintainers' expertise. In other words, modern expertise models should take into account the time spent reviewing code and pushing changes upstream.

POS_N **increases to a median of 87.5% for larger N, with multi-measure models outperforming single-measure models by at least 17%.** Comparing Figure 5.4 to Figure 5.3 shows how the top multi-measure models for N=1 are able to increase their

Type	Measure	N = 1	N = 3
POS_N	P-value	4.27e-05	4.28e-05
POS_N	Cliff's delta	0.99	1.0
POM_N	P-value	4.27e-05	4.77e-07
POM_N	Cliff's delta	0.84	1.0

Table 5.3 P-values and Cliff's delta values for the Wilcoxon paired tests ($\alpha = 0.01$) between `attributed` and `legacy + committed` for ranking thresholds N=1 and N=3 and for POS_N and POM_N.

distance compared to even the best single-measure models (`attributed`). This, compared with a change in best performing single-measure models, indicates that a larger diversity in activity measures enables better identification of the two additional candidate maintainers. Indeed, by considering top performing contributors across a wider range of activities, there is a larger chance at least one real maintainer is found. Although the percentages of Figure 5.5 and Figure 5.6 cannot be compared directly to each other (cf. modified definition of POM_N), Figure 5.6 (for POM_N) shows a similar ranking of models as Figure 5.3 (for POS_N), confirming the findings for POS_N.

Table 5.3 shows the p-value and effect size of the Wilcoxon test between `attributed` and `legacy + committed` for figures 5.3, 5.4, 5.5, and 5.6. Each effect size being close to 1, we notice a **large** performance increase between `attributed` and `legacy + committed`.

Interesting to note is that, across all analyzed releases, the boxplots show a remarkable small variance, especially for N=3. Although this is partially due to the fact that less than 25% of the subsystems saw at least one maintainer change, it also indicates that our measures are stable across changes in the 5 activity measures used.

RQ3. How well does dimension 2 explain expertise?

Motivation:

The metrics analyzed in RQ2 reveal that traditional expertise metrics based solely on a contributor's own development productivity are not well suited to identify maintainers. Expertise models exploiting only the information available for the release under study, are able to obtain median POS_N performance of up to 75% (N=1) and 90% (N=3).

However, we believe that adding a historical dimension considering also the activity in the last R releases would assist the model in two ways. On the one hand, long standing kernel developers' contributions should carry more weight than newcomers' contributions. On the other hand, analyzing data on multiple releases would control for cases where contributors' productivity was lower due to a variety of reasons, such as illness, vacation or work on other projects.

Approach:

For each studied kernel release, we calculated $footprint_j^R(\mathbb{A})$ for R=4, since this covers a time span of 60 to 70 days. For example, when looking at experts in release *v4.11*, we need to take into account data found for releases *v4.7, v4.8, v4.9, v4.10, and v4.11.* We repeat such analysis for each of the 22 releases. In this paper, we use linearly decaying weights W_i to combine the individual $footprint_j(\mathbb{A})$ values across the five considered releases, since this scheme is less extreme than the exponential and logarithmic ones.

Similar to RQ2, we then use the footprint values to create, for each subsystem and release, a ranking of all contributors active in the five considered releases. We also use the same performance metrics as for RQ2, which allows us to compare the results of RQ3 to those of RQ2 to validate whether the historical dimension improves the model.

To save space, and since we found that, similar to RQ2, the combination of `legacy` and `committed` performs the best, we only show the results for this model (the rest of the data will be made available after the double-blind review). In particular, Figure 5.7 and Figure 5.8 show the POS_N performance of the combined `legacy+committed` model without and with the history dimension, for ranking thresholds N ranging from 1 to 5. Figure 5.9 and Figure 5.10 show the corresponding POM_N results.

Table 5.4 contains the results of Wilcoxon paired tests between the POS_N values without and with history, for each N, and (similarly) between the POM_N values without and with history, for each N. For each test, we also provide the Cliff Delta effect size(((cite romano))).

Results:

The history-aware `legacy+committed` footprint models perform significantly better than the history-unaware models. Figure 5.7 and Figure 5.8 show how, except for N=3, the median performance of the history-aware expertise measure improves upon the history-unaware measure. If one considers only the first recommendation of the measure, there is a median 73.6% chance that at least one maintainer is identified for a history-aware expertise model compared to 69.9% with the single-release model. This difference progressively decreases for higher N, which means that, for higher N, an expertise model considering `legacy+committed` on one release only is robust enough to assess expertise.

We find similar improvements for Figure 5.9 and Figure 5.10, except that the improvements due to history increase for larger N (and for N=1 there is no significant improvement). This is clearly shown by the p-values and effect sizes of the Wilcoxon paired tests in Table 5.4

Fig.	Measure	1	2	3	4	5
5.7/5.8	P-value	1.12e-4	8.76e-3	1.15e-2	1.57e-3	7.70e-4
5.7/5.8	Cliff's delta	0.62	0.50	-	0.55	0.51
5.9/5.10	P-value	1.27e-2	4.63e-3	5.13e-4	1.57e-5	1.88e-4
5.9/5.10	Cliff's delta	-	0.46	0.56	0.66	0.69

Table 5.4 P-values and Cliff's delta values for the Wilcoxon paired tests ($\alpha = 0.01$) between the POS_N results of Figure 5.7 and Figure 5.8, and of Figure 5.9 and Figure 5.10, for ranking thresholds N=1 to N=5. A Cliff delta "-" indicates a non-significant test result, with p-value$> \alpha$

($alpha = 0.01$). As an effect size greater than 0.474 indicates a **large** increase in performance, we notice that 7 of the 8 significant differences have an effect size of at least 0.50.

5.7 Discussion

Threats to validity:

Threats to external validity prevent generalization of empirical results to other contexts. In particular, due to the abundant volume of data and presence of an oracle for expertise, our empirical evaluation only focused on 22 releases of the Linux kernel project. Hence, the study should be expanded to cover not only more kernel releases, but also other open (and closed) source projects. Furthermore, we considered only 5 expertise measures for our footprint models. Other measures, such as those mentioned in Table 5.1, should be studied to understand their impact on expertise.

Threats to construct validity involve risks regarding the measures used in the empirical study. Of the five considered expertise measures, `reviewed` was the only one requiring noisy approximations. Except for cases where the email patch subject was identical to the Git commit message summary, there is a definite risk of false positive and false negative matches, as identified earlier by Jiang et al. (Jiang et al., 2013, 2014). This might explain the relatively weak performance of expertise models involving `reviewed`. However, no better alternatives exist for projects that use mailing lists for code review. Projects using web-based review environments like Gerrit do not have this issue, and will have perfect matching between commits and their reviews.

Finally, regarding threats to internal validity (i.e., confounding factors potentially explaining our findings), we mention the limited number of subsystems considered for RQ2 and RQ3. This number was the result of the data filtering in subsection 5.5.2 used to eliminate temporarily inactive subsystems. Furthermore, we used the `MAINTAINERS` file as oracle for expertise. Although this is the known reference in the Linux kernel community for finding the right maintainer to contact, this is a manually maintained text file that hence could contain inconsistencies (even though changes to it are peer-reviewed).

Finally, although maintainership is a form of expertise, there are other forms of expertise that our footprint models be indicators of that were not considered in our empirical study. As such, some of the false positive recommendations of our footprint rankings might actually be correct suggestions based on a different interpretation of expert, in which case our POS_N and POM_N results are lower bounds for the actual performance.

Future work:

Apart from addressing the threats to validity, other future work should consider different weights w_i and W_i. The former weights consider different activities to be more relevant than others, while the latter weights would give more or less weights to older vs. newer releases. For example, comparison of exponential and logarithmic decaying weights to the linear decay used in our study could be interesting. Similarly, different values of R for $footprint_j^R(\mathbb{A})$ should be evaluated.

Finally, whereas we used a top-down approach from expertise model to evaluation on an actual open source project, a bottom-up approach starting from the analysis of a project's or subsystem's maintainers before formulating expertise measures and models could provide complementary insights into different kinds expertise.

5.8 Conclusion

This paper argued about the need for expertise models considering a wide range of developer and other activities, and doing so across different snapshots of a project instead of just for one snapshot. Through an empirical study on 22 releases of the Linux kernel, we empirically showed how measures about an expert's own coding footprint (`legacy`) and her involvement in coordinating other project members (e.g., committing their commits and/or reviewing their code changes) significantly improves on coding-only expertise models. Furthermore, considering those measures across different releases significantly improved performance, with large effect size.

The simplest incarnation of our expertise model that software organizations should consider adopting involves (1) a developer's code `legacy` and number of changes `committed`, which are both readily obtainable from a Git log, calculated across (2) the last 5 releases. In future work, we will consider additional activity measures and empirically analyze other open source projects.

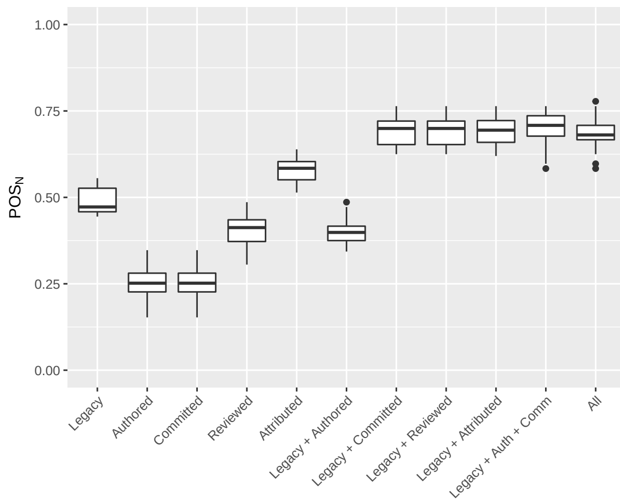

Figure 5.3 Distribution of POS_N for each combination of activity measures, for ranking threshold N = 1.

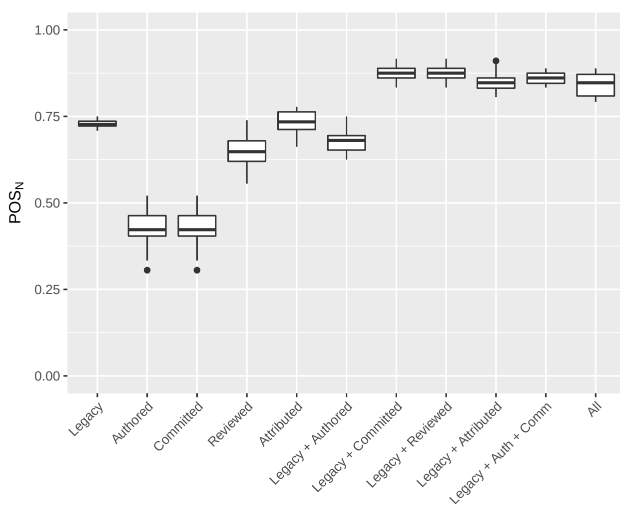

Figure 5.4 Distribution of POS_N for each combination of activity measures, for ranking threshold N = 3.

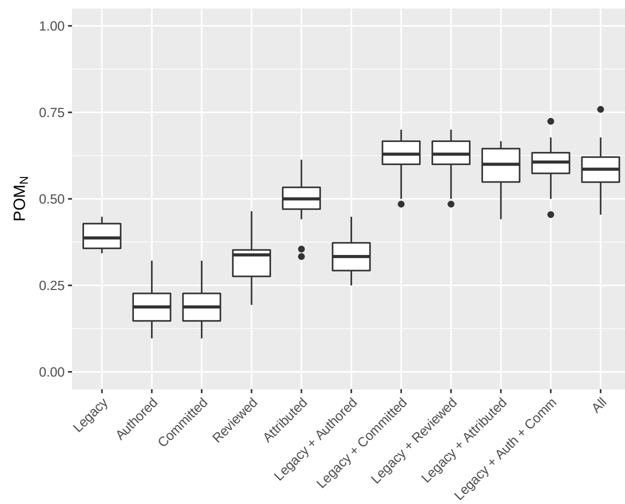

Figure 5.5 Distribution of POM_N for each combination of activity measures, for ranking threshold N = 1. These boxplots only consider subsystems with at most 1 maintainer.

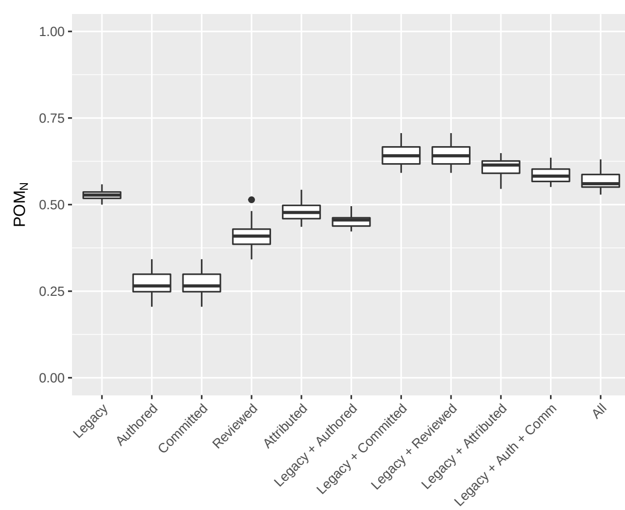

Figure 5.6 Distribution of POM_N for each combination of activity measures, for ranking threshold N = 3. These boxplots only consider subsystems with at most 3 maintainers.

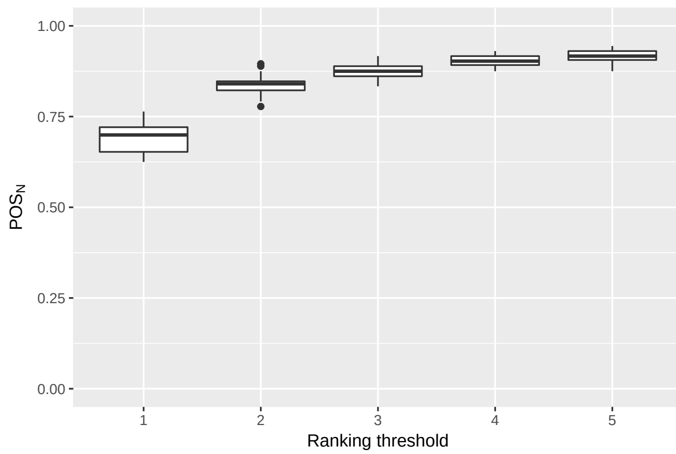

Figure 5.7 Distribution of POS_N for the combined `legacy+committed` model (**without** history dimension), for different N.

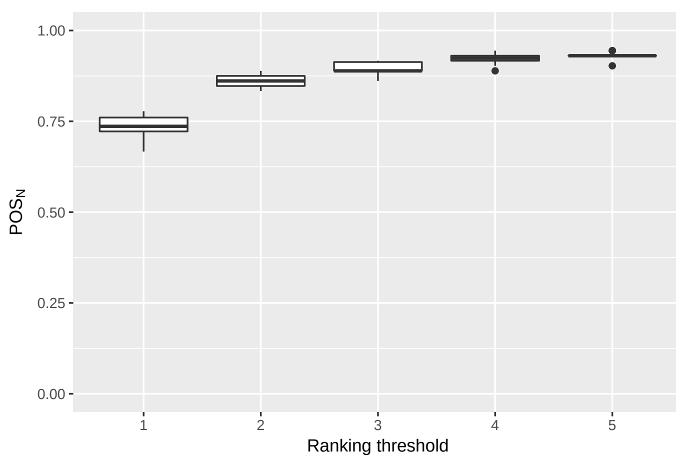

Figure 5.8 Distribution of POS_N for the combined `legacy+committed` model (**with** history dimension), for different N.

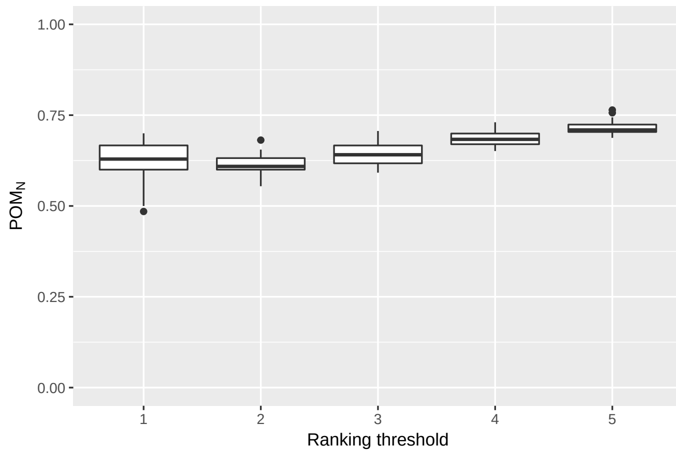

Figure 5.9 Distribution of POM_N for the combined `legacy+committed` model (**without** history dimension), for different N. For each N, the boxplot only considers subsystems with at most N maintainers.

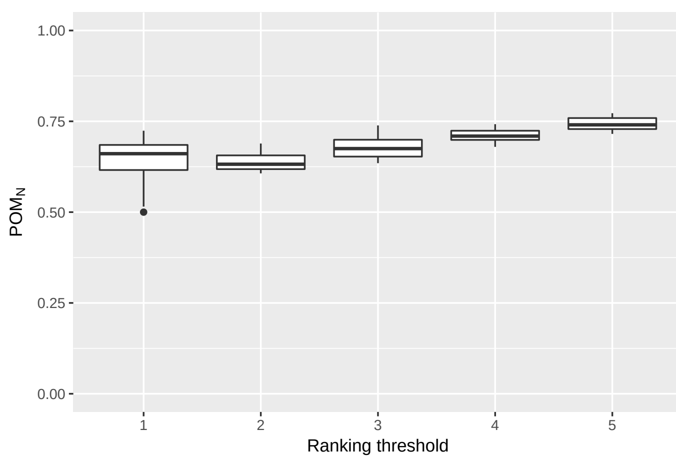

Figure 5.10 Distribution of POM_N for the combined `legacy+committed` model (**with** history dimension), for different N. For each N, the boxplot only considers subsystems with at most N maintainers.

CHAPTER 6 CONCLUSION

Text.

6.1 Advancement of knowledge

Text.

6.2 Limits and constraints

Text.

6.3 Recommendations

Text.

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