Threats of Aggregating Software Repository Data

Martin P. Robillard and Mathieu Nassif
School of Computer Science
McGill University
Montréal, QC, Canada
Email: {martin,mnassif}@cs.mcgill.ca

Shane McIntosh
Department of Electrical and Computer Engineering
McGill University
Montréal, QC, Canada
Email: shane.mcintosh@mcgill.ca

***Abstract*—Software repository mining techniques can provide insights about software systems and their development processes through the use of metrics that aim to capture a construct of interest. However, linking development history metrics with high-level constructs is fraught with threats to validity. We conducted a case study in which we performed a critical review of the underlying artifacts used to compute a metric of knowledge at risk in software projects, proposed in prior work. The case study revealed eight major threats to validity that have the potential to generalize to other software process metrics derived from repository data. In addition to a detailed description of each threat, we contribute a questionnaire to facilitate their assessment in past and future studies.**

***Index Terms*—Mining software repositories, Software metrics, Knowledge loss, Threats to validity.**

I. Introduction

Software repository mining techniques can provide insights about software systems and their development processes to support developers and other stakeholders [1]–[3]. In particular, repository mining has recently been proposed to quantify the risk of knowledge loss in large software projects [4]. Because not all of the knowledge required to develop and maintain a software system can be encoded in project artifacts, some of that knowledge must remain tacit, and can be lost when contributors leave the organization [5]. There is thus an incentive to anticipate and mitigate knowledge loss in software projects, and repository mining provides the opportunity to act on this incentive.

One way to *detect* potential knowledge loss in a software project is through the analysis of contributor involvement in a project's history. For example, Rigby et al. leverage information about abandoned lines in a project to compute a Knowledge at Risk (KaR) metric that estimates the number of files that have a 5% chance of being abandoned within a given 3-month period [4]. The application of this KaR computation to two very large systems showed that the systems were susceptible to large losses.

Although software repository metrics, such as Knowledge at Risk, constitute a precise way to *summarize* the data in a software project, it remains an open question whether such computations can adequately capture the target construct (e.g., knowledge loss). Even in studies where metric validity is analyzed, such an analysis can only scratch the surface because thoroughly assessing the validity of a metric is a research project in itself.

Using the computation of Knowledge at Risk as a case study, we set out to investigate, in depth, the threats to validity associated with metrics that summarize typical software repository data: *commits* to *files* by *contributors*. Using as a starting point our replication [6] of Rigby et al.'s study [4], we retrieved and analyzed every file considered abandoned to investigate the properties of the files, including size, file type, and amount of comments. We conducted our analysis in two phases, termed macro- and micro-analysis. The goal of the macro-analysis (Section III) was to identify threats to validity by considering the entire data set, but along new dimensions that leveraged our extended set of file properties. The goal of the micro-analysis (Section IV) was to delve even deeper into the data, which can only be made tractable by focusing on a subset identified using a systematic procedure.

As a result, we documented eight specific threats to validity associated with the aggregation of software repository data (Section V). Although we identified the threats in the context of a case study of knowledge at risk, our approach supports a straightforward analytic generalization [7] to other metrics based on large-scale data aggregation from software repositories. We thus articulate our results as general threats, and develop them into an evaluation instrument designed to help mitigate these threats in future studies.

The contributions of this paper include *a)* a critical re-analysis of previously-published file abandonment computations for eight open-source systems; *b)* a new approach for analyzing software repository data based on a combination of macro- and micro-analysis; and *c)* a description of eight major threats to validity for software process metrics derived from repository data together with a questionnaire to facilitate their assessment in past and future studies.

II. Knowledge Loss Case Study Data

This case study is a critical review of the validity of the *Knowledge at Risk* (KaR) metric as originally proposed by Rigby et al. [4]. The KaR metric is the estimated number of files that has a 5% probability of being abandoned by developers in a given 3-month period. The related construct is *knowledge loss*, i.e., the loss of valuable software design knowledge held by developers who leave the project. In this study, we investigate what factors threaten the correspondence between the metric and the construct, i.e., factors that raise the

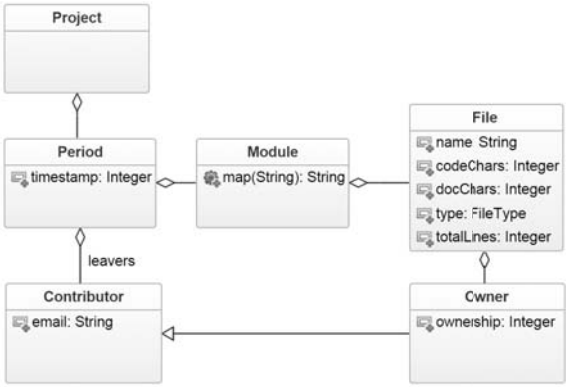


Fig. 1. The Extended Data Model

possibility that the KaR value may not really be representative of the risk of knowledge loss.

Basic Concepts for Computing Knowledge at Risk

The *period* is an arbitrary time interval of the development history of the *project* during which *contributors* can leave the project and thus become *leavers* [4], [8]. During a period, a project comprises several source *files*. Each *line* in each file can be attributed to (or *owned by*) one contributor. Because ownership can be detected at the granularity of lines, the ownership attribute for a contributor is the number of lines they own. If a line is owned by a leaver, it is said to be *abandoned*. If a file contains a high proportion of abandoned lines, it is said to be abandoned.

Extended Data Model

Figure 1 represents the data model that we instantiate for this study. This model adds two main additional types of information to the basic associations between periods, files, and authors used in the initial study. First, we add *file properties*, including the file *type* (represented by its extension, e.g., ".cpp"), the length of the file (in lines), the number of characters of code in the file (codeChars) and the number of characters of comments in the file (docChars). The rationale for considering file properties is that files are not atomic building blocks for software systems.

Second, we add a map between a file and a general concept of *module*. The rationale for considering modules is that files are rarely independent, and metrics that are based on files can lead to different interpretations whether or not these files are in the same module. For example, the impact of a leaver who owns a few files in many modules may be different from the impact of a leaver who owns many files of a few modules. We use the module-related information for the micro-analysis in Section IV.

We instantiated the data model for all eight projects in our earlier replication study [6]. This work required a combination of straightforward extraction of the available data combined with new extraction procedures for the file properties and modules. Table I, adapted from the original work [6, Table 1], summarizes relevant project characteristics.

TABLE I
SUBJECT SYSTEMS (CF. NASSIF AND ROBILLARD [6])

System	Domain	Files	Devs
Apereo	Authentication service	900	99
Assimp	3D modeling library	600	152
Chromium	Web browser	30 000	6511
Gimp	Image editor	3200	210
Gitlab	Hosting platform	1500	1124
Kodi	Media player	4000	525
Linux	Operating system	35 000	6974
Trinity	Gaming framework	12 000	334

Basic Data Extraction

We used the replication package to obtain, for each project, the lists of (a) periods studied and their timestamps, (b) leavers for each period, and (c) files with their corresponding ownership information for each period. In this data model, periods are three months in length and files are considered abandoned if 90% of their lines are owned by leavers.

Extracting File Properties

To complete the model with file properties, we cloned each project from their Git repository to retrieve all the project's files for each period. Using the ownership information in the replication package, we compiled the list of all files in a project at the end of each period, and used the `git-show` command to retrieve the content of the file at the required timestamps.

To derive the type of the file, we used the extension of the file. This yielded a set of 20 different file types (e.g., "cpp", "cmake"). To obtain the number of characters of code and comments, respectively, we wrote lightweight parsers. The parsers read in each character in a source file, skip all whitespace characters, and sum up the characters in comments and non-comment regions, respectively. The parsers also skip copyright blocks using a simple heuristic: if the first block comment of a file contains the keyword "copyright", it is eliminated from further consideration.

Creating the Module Map

Because of the large size of some of the systems under investigation, we were also interested in partitioning the analysis in terms of modules. For this purpose, we needed a mapping between files and modules. Ideally, such a mapping would be constructed manually, by an architect of the system. For practical reasons, this strategy was not possible. Additionally, because partitioning files into modules can have an impact on the subsequent investigation, we sought a transparent and replicable process for identifying modules, that would reduce threats of investigator bias. We therefore designed the following procedure, which aims to be conceptually simple, partition the files in a project into a manageable number of modules, have modules of manageable size, and have modules that align with the general structure of the project. The general principle guiding our algorithm is to identify as a module any subdirectory of the project with between 2% and 20% of the total file namespace.

More specifically, for a given project:

1) We aggregate all of the files in each period under study into a single, merged directory tree. We then count the total number of files in this directory tree, which will henceforth be referred to as *total*.
2) We create an initial map that considers all first-level directories to be modules. We compute the cardinality of each such module, and place all of the files that are located directly in the root directory in a generic module called `General`.
3) We remove the mapping for any module whose cardinality is less than 2% of *total*. The corresponding files then become mapped to the `General` module.
4) For any module with cardinality of 20% or more of *total*, we create a module mapping for any subdirectory with cardinality of 2% or more of *total*. The remainder of the subdirectories get automatically mapped to the parent module, unless the remaining cardinality in less than 2%, in which case the parent module is removed and the remaining files are mapped to the `General` module.

The Trinity project was the only case where the procedure was modified, where an `sql` folder was excluded from the calculation because it contains a large number of source files that are versioned clones of each other.

Replication Package

Our extended data set is available at:
http://www.cs.mcgill.ca/~swevo/icsme2018/.

III. Macro-Analysis of File Abandonment

Empirical work on knowledge at risk concludes that the studied software projects are susceptible to large knowledge losses based on the observation that the probability distributions of file losses tend to have "spikes" that show a non-negligible probability of massive losses [4], [6]. However, it is not clear what these spikes truly indicate. In the first part of this case study, we dissect the probability distributions for knowledge at risk, as an exemplar metric, by reviewing the entire data set that was used to compute the metric.

File Abandonment Distributions

The visualization in Figure 2 summarizes the number of abandoned files for all of the studied projects. Each bar represents a time period in the history of the system, in chronological order from left to right. The height of the bar shows the number of files that became abandoned in that period (i.e., files that were abandoned in the period, and were either nonexistent or not abandoned in the previous period). To give a sense of the importance of file abandonment at any point, the dashed line shows 5% of the total number of files in the system at the end of each period. The two shades represent the distinction between implementation and non-implementation files, discussed below.

For each studied project, with the exception of Kodi, we observe that *there is at most one period exhibiting large losses* on the order of 5% or more of the system's files.

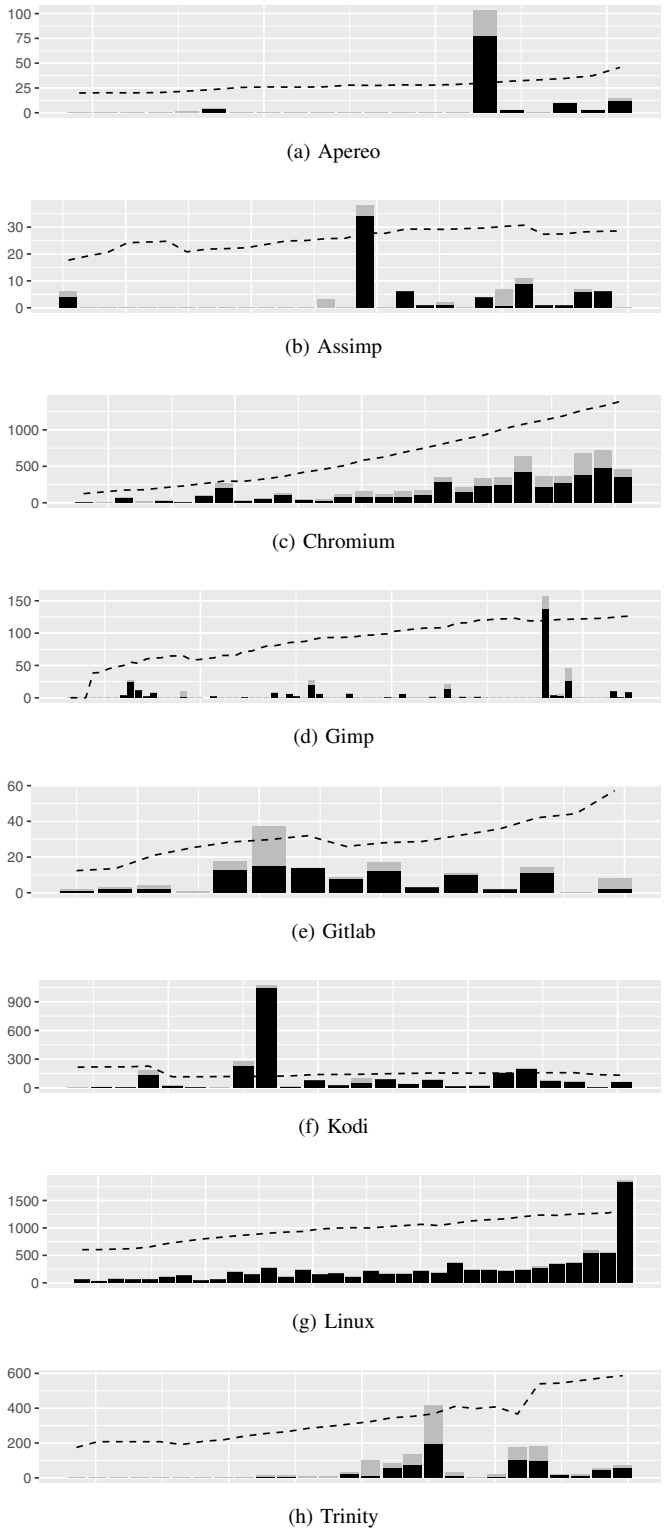


Fig. 2. File Abandonment per period. Each bar represents a time period in the history of the system, in chronological order from left to right. The height of the bar shows, respectively, the number of implementation (black) vs. non-implementation (gray) files that became abandoned in that period. The dashed line shows 5% of the total number of files in the system (both implementation and non-implementation) at the end of each period.

Fragility Threat: The transformation of a small number of rare events into a probability may misrepresent the underlying phenomenon.

In our case, the precise probability is simply an artifact of the number of periods considered.

Implementation vs. Non-Implementation Files

After a preliminary manual investigation of abandoned files, we realized than many of these files were unlikely to contain software development knowledge at risk. In particular, we noted that in addition to implementation source code, abandoned files also consisted of build scripts, tests, or object data, or were small stubs or boilerplate code (e.g., exception class declarations, enumerated values, etc.). To investigate this issue, we created a distinction between *implementation* and *non-implementation* files. We automatically classify a file as a non-implementation file if:

- It is a data or build file according to its file type;[1]
- It is a test file, as determined by the presence of the string "test" in the file's path.
- It is a *tiny file*, which has less than 10 lines or less than 50 characters of non-comment content. These thresholds were selected after a preliminary inspection of the files, to represent a file equivalent to a class stub.

In Figure 2, the black portion of the data bars shows the proportion of abandoned files that were implementation files. Table III adds some precision to the analysis. In the table, *Largest Event* provides the maximum number of implementation files that were abandoned in one period, and the percentage of the total project it represents. *Implementation* is the ratio of abandoned files that were implementation files over all instances of file abandonment.

We make three observations about the ratio of abandoned files that are implementation files. First, for some systems, *the ratio of implementation meaningfully affects the amount of abandoned files*; For both Gitlab and Trinity, considering only implementation files would decrease the loss ratio by close to 50% for the period with the largest amount of abandonment. Second, *the ratio of implementation files varies across periods.* A stable implementation ratio across periods would support an easy correction of corresponding metrics. However, for most systems, the abandonment history shows periods where almost all abandoned files are implementation files (entire black bars), whereas in other periods the ratios vary, somewhat unpredictably. Third, *the ratio of implementation files varies across systems*. This observation is best made using the *implementation* column of Table III. At the lower extreme, we find Trinity, whose lower proportion of implementation files is explained by the reliance of the project on a large number of short SQL scripts. On the other hand, Linux and Kodi have large proportions of implementation files because of the almost complete lack of tests in the projects at the time of analysis.

[1]That is, it has one of the following file extensions: .cob, .object, .x, .am, .in, .classic, .cmake. We only considered the types of files in the data set, so this list is internally exhaustive.

TABLE II
DETAILED ABANDONMENT DATA.

System	Largest Event	Implementation
Apereo	77 (13%)	77%
Assimp	34 (6%)	80%
Chromium	479 (2%)	70%
Gimp	138 (6%)	81%
Gitlab	15 (3%)	66%
Kodi	1046 (44%)	93%
Linux	1837 (7%)	98%
Trinity	198 (3%)	53%

File Content Threat: The quantity and complexity of code is not uniformly distributed across files.

Size Distributions

It is clear that the File Content threat also results from variations in file size. We assessed the impact of this threat for knowledge loss. Figure 3 shows the distribution of file *instance* sizes (in number of lines), with a distinction between abandoned and owned (i.e., not abandoned) file instances. We use the term file *instance* to clarify that in our analysis a data point is a file in a given period, so for any file that survives a single period, the simple term *file* becomes ambiguous. The figure thus represents all file instances across all periods for a given project. Within the figure, we also report the p-value of an unpaired Wilcoxon test that gauges the probability that owned and abandoned file instances are issued from the same size distribution, and the interquartile range (IQR) of the distribution of the sizes of abandoned file instances. We employ a logarithmically scaled Y-axis and use interquartile ranges as a measure of dispersion because the distribution of file instance sizes is skewed, with some systems exhibiting very large file instances.

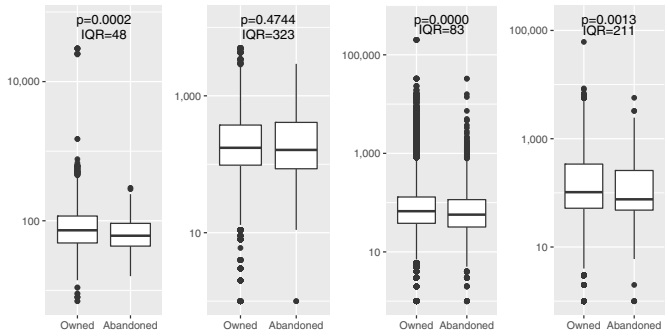
From the figure, we readily observe that half of the systems have interquartile ranges in the hundreds of lines.

Interestingly, we also observe that abandoned file instances are statistically significantly shorter than non-abandoned file instances (the only exception is for Assimp, which is by far the smallest project). However, this appears to be a good example of a statistically significant yet practically insignificant result. First, the effect size is minimal, and second, the result is at serious risk of being an artifact of the bias of large files, an issue that we now discuss in detail.

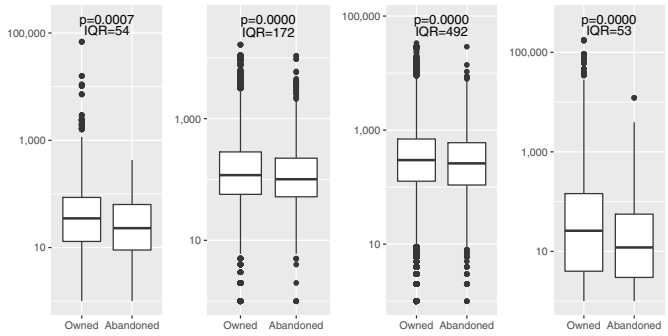
Large Files

The distributions in Figure 3 include some unusually large values, such as a 200kLOC file instance in Chromium and a 176kLOC file instance in Trinity. We investigated these unusual data points by manually inspecting every file instance over 20kLOC. Of the 291 file instances that exceed this threshold in the studied projects, only three were abandoned, so clearly very large files are unusual data points.

To facilitate the analysis of large files, we first merged all duplicates (same path in different periods), and obvious clones (same name stem in different directories, identical or

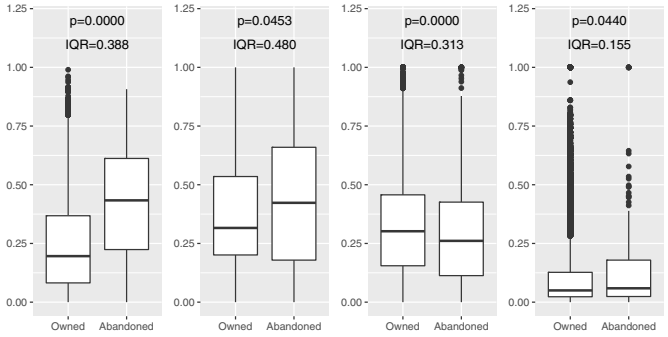


(a) Apereo (b) Assimp (c) Chromium (d) Gimp

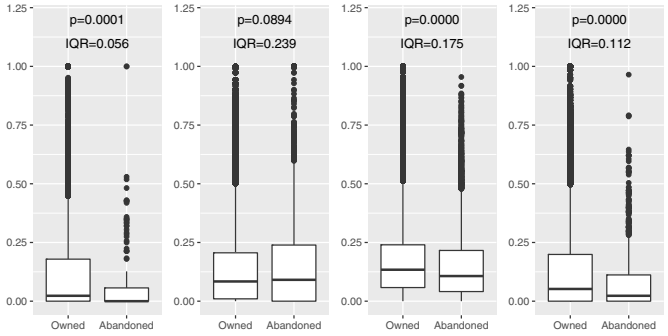


(e) Gitlab (f) Kodi (g) Linux (h) Trinity

Fig. 3. Size distribution of file instances collected from all periods. The right box plot shows the size distribution of abandoned file instances. The p-value was computed using an unpaired Wilcoxon test. The interquartile range values for abandoned file instances is also included.



(a) Apereo (b) Assimp (c) Chromium (d) Gimp



(e) Gitlab (f) Kodi (g) Linux (h) Trinity

Fig. 4. Comment distribution of file instances. For a project the left box plot shows the comment ratios distribution of owned file instances. The right box plot shows the comment ratio distribution of abandoned file instances. The p-value was computed using a Wilcoxon test. The interquartile range for abandoned file instances is also included.

similar size). This straightforward procedure left us with only 26 large files, each with approximately $\frac{291}{26} = 11.2$ instances on average. These included: one generated file, three Javascript libraries, 21 resource files (both application and test data), and a single true implementation file, the god class `Player.cpp` in Trinity (a 27kLOC class definition).

File Role Threat: File type is an imperfect way to detect the role that a file plays in a system. Review by project experts may be necessary to reliably recover file roles.

Comment Ratio Distributions

Source files contain a combination of formal and informal information (i.e., code vs. comments), a distinction that is not always considered when aggregating process metrics from software repositories. We investigated this issue by analyzing the *comment ratios* for each file in our data set. For our case study, the relevance of comment ratios is based on the hypothesis that if a file is commented, the knowledge that it contains has been partially externalized (if not perfectly), and is thus at a lower risk of loss because even if the file is abandoned, part of the knowledge that it captures is explicit.

We define the *comment ratio* of a file as the number of non-whitespace characters within syntactically-defined comments (excluding the copyright block), over the total number of non-whitespace characters in a file (still excluding the copyright block). Figure 4 presents the results, also with the p-value expressing the likelihood that the distributions are from the same population according to an unpaired Wilcoxon test, and the interquartile range for abandoned file instances.

The data shows considerable amounts of variability both between and within projects. In terms of between-project variability, we first notice major differences in commenting practices, from minimal (Gimp) to extensive (Assimp). Although the fact that different projects have different commenting practices is hardly surprising, the analysis provides a concrete illustration of the difference in expected impact for file abandonment between projects. The same reasoning can be made within a project, given that we observe large interquartile ranges in some projects. For example, in the case of Assimp, half of the comment ratio distribution is between 0.179 and 0.660, which exposes particular file abandonment events to a large amount of uncertainty about the true amount of undocumented knowledge in the file.

As an illustration of the meaning of comment ratios, we consider two abandoned files from Assimp. One file, `AiConfigOptions.java`, has 662 lines when it becomes abandoned, so it could naïvely be considered to represent an important amount of knowledge at risk. However, upon closer inspection, we see that it is an enumerated type, where 98% of the lines in the file are comments. At the other end of the spectrum, we have `OgreStructs.cpp`, a 1.2kLOC implementation file with very few comments (6%).

Comment Threat: A source code file is both a container of code and a repository of comments about this code. Code and comments have radically different roles in software construction. The extent to which a given file contains comments is variable. Even when accounting for the commenting practices of a project, important within-project variability means that different samples of files may represent very different amounts of comments.

Finally, we point out that for some projects, abandoned files contain a statistically significantly higher rate of comments (Apereo, Assimp, Gimp), a statistically significantly lower rate of comments (Chromium, Gitlab, Linux, Trinity), and in one case, commenting rates are more or less equivalent in abandoned and owned files (Kodi). Although we conducted the statistical test for thoroughness, we do conclude that this statistical difference is not practically meaningful given the file size bias described above, the small effect size for most projects, and the fact that, although different, the distributions of abandoned files still exhibit a high degree of variance.

IV. Micro-Analysis of File Abandonment

In the previous section, we reported on threats that were derived from properties of the entirety of the data from the studied projects. We also investigated the potential for threats related to the more specific context in which files were added, removed, or changed in a software repository. Such a fine-grained analysis is only possible for a subset of the data. We thus employed a systematic procedure to identify specific *File Abandonment Events* and closely scrutinized to what extent these events really corresponded to the expected construct of *Knowledge Loss Events*.

Identifying File Abandonment Events

We sought to sample large file abandonment events which, according to the hypothesis of Rigby et al. [4], could threaten the integrity of a project. We were also interested in sampling from different modules and different periods. To keep the investigation tractable, we identified three events from each project using the following procedure. For a project:

1) We compute the variance in the number of abandoned *implementation* (see Section III) files per modules over time, for each module.
2) We select the three modules with the highest variance (excluding the `General` module).
3) For each module, we select the period with the highest absolute increase in number of abandoned files.

We excluded the last period of Apereo because it features a major refactoring that threatened the usefulness of our selection. Table III summarizes the resulting events. In the table, the Abandon. column lists the number of module files that became abandoned during the period and the total number of module files abandoned in the period. The Module Size column shows the total number of files in the module. The Lea. column lists the number of leavers that contributed to at least two files of the module.

TABLE III
File Abandonment Events.

Event Name	Period (End)	Abandon. (Period/Total)	Module Size	Lea.
Apereo–core	Oct 2014	45/46	214	1
Apereo–ldap	Oct 2014	8/8	27	1
Apereo–x509	Oct 2014	9/9	36	1
Assimp–pyassimp	Nov 2008	6/6	6	1
Assimp–jassimp	Aug 2012	37/37	37	1
Assimp–main	Aug 2014	8/16	319	1
Chromium–tools	Jul 2014	84/170	1312	7
Chromium–components	Jan 2015	90/135	1333	2
Chromium–browser	Jul 2015	109/404	4965	11
Gimp–app	May 2005	27/30	305	1
Gimp–core	Feb 2013	15/20	350	1
Gimp–widgets	Feb 2013	33/33	391	1
Gitlab–db	Aug 2013	26/30	157	1
Gitlab–features	Aug 2013	6/10	57	1
Gitlab–spec	Nov 2013	4/7	38	1
Kodi–filesystem	Mar 2012	151/158	289	1
Kodi–viz	Mar 2012	217/451	460	1
Kodi–xbmc	Mar 2012	327/350	784	1
Linux–arch	Apr 2013	83/204	1836	1
Linux–drivers	Oct 2015	567/1854	7310	122
Linux–drivers-net	Oct 2015	161/591	2502	46
Trinity–dep	Feb 2013	27/27	88	1
Trinity–sql	Aug 2014	173/610	5623	4
Trinity–server-game	Feb 2015	13/18	481	4

Contributor Involvement

Like most software repository-based metrics, file abandonment is largely related to the activity of the contributors to a system. Because large projects can have different kinds of contributors, from one-time committers to long-term developers [9], we investigated the impact of such diversity on the interpretation of file abandonment events.

For each event, we extracted the set of leavers who played a role in the event by selecting all who left the project while owning some lines in at least two different files (to exclude trivial contributions) that became abandoned during the event.

For 17 of the 24 events, a single leaver contributed to close to 100% of the files of the event. The Chromium-components event was similar, with one contributor who owned lines in 85 of the 90 abandoned files, and the next largest contributor owning lines in only four files. We chose to treat this event like the previous 17 events. To understand the importance of the contributions of these impactful leavers, Figure 5 shows the commits that were made by each leaver prior to their departure.

The figure immediately reveals two issues with leavers. First, *we observe the richness of the phenomenon of departure*, previously abstracted as a binary classification by the rule that a contributor becomes a "leaver" after their last commit. For example, contributor `neo` essentially left the Gimp project over two years prior to the threshold, having made only a handful of commits in the intervening time. The same reasoning can apply, to a lesser extent, to `Helvetix` (Gimp) and `AlTheKiller` (Kodi). At the other end of the spectrum, we

Fig. 5. Commits made by each significant leaver prior to the knowledge loss event. The time axis is expressed in years before the loss event, and was limited to five years for clarity. Hence, the actual dates do not align from one series to the other. The leaver's identifiers are the user part of their email.

note the sudden departure of `serya`, `ialpert`, etc. Second, *we observe the significant quantitative differences in involvement*. Considering that these contributors were entirely responsible for the detection of a major file abandonment event, the impact of the departure of `neo` (who committed heavily for five years) and that of `scholza`, who made a single contribution and left, is incomparable. We further investigated this intriguing pattern of *immediate abandonment*, and report our findings under *Ownership Acquisition Events*, below. In our case, six impactful leavers participated in their projects for less than a year, three of them for even less than a quarter.

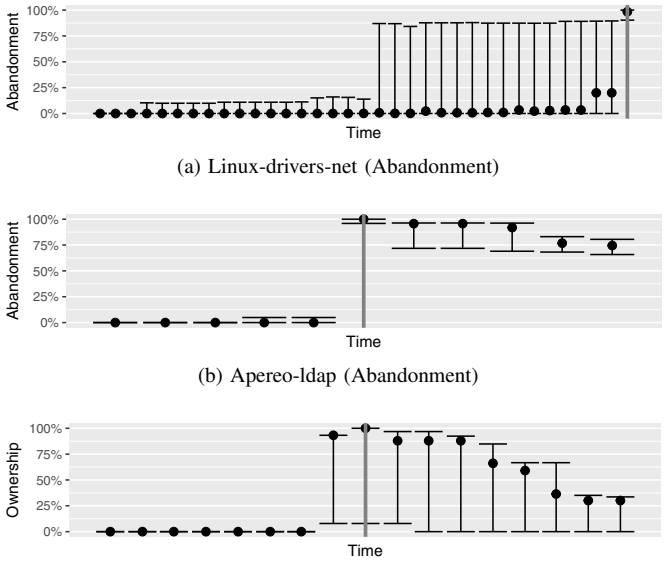
Contributor Involvement Threat: Interpretation of metrics that are derived from the activity of a few contributors may be significantly impacted by the actual involvement of these contributors.

We also analyzed the contributor activity for the six remaining events but found that they provided no additional insight.

One additional threat to validity when analyzing contributions to software repositories is *email aliasing*, i.e., the use of different emails by the same developer. This, however, is a well-known threat to validity [10] that is routinely controlled for through the use of a dealiasing procedure (the heuristic-based semi-automated clustering of email addresses that are presumed to belong to the same person). Such a dealiasing procedure was used in the original studies [4], [6] and reused for the present work. Because this threat is already well documented, and because it directly compounds the other threats presented in this paper, we do not include it as part of our contribution.

Abandonment Evolution

Abandonment is a normal part of the evolution of a software system, as developer turnover is almost inevitable. However, a metric to quantify knowledge loss within a period suggests a sudden, abnormal, and deleterious event. The so-called *bus factor* metric is an example, which evokes imagery of suddenness (in the form of a traffic accident). Yet in practice, the abandonment of a module may grow slowly, eventually passing the detection threshold. This situation poses a risk to the detection of the events, if several files simply happen to exceed the detection threshold during the same period.



(a) Linux-drivers-net (Abandonment)

(b) Apereo-ldap (Abandonment)

(c) Gitlab-spec (Ownership)

Fig. 6. Evolution of the distribution of the proportions of lines abandoned (abandonment) or owned by the event's leavers (ownership) for each file abandoned during three events. Each black line corresponds to one period, and stretches from the 2.5th to the 97.5th percentiles of the proportions for that period. The large dot shows the median of the distribution. The thick red line represents the period of the event.

To investigate this possibility, we plotted the evolution of the proportion of abandoned lines in the files involved in the 24 events under investigation. We show two representative patterns. For some of the events, such as Linux-drivers-net (Figure 6a), the ratio of abandoned lines in the module slowly grows, with occasional steps. In this case, the event may artificially be the point where the abandonment happens to cross the arbitrary 90% threshold. This contrasts with other events, such as Apereo-ldap (Figure 6b), where all files in the module grow from an abandonment rate of less than 10% to over 90% from one period to the next.

The incremental accretion of abandoned files (as opposed to lines) also poses a threat to the detection (or prediction) of loss events. When files are gradually abandoned in a module and never recovered, attempts to detect events based on discontinuities or variance in the data will not succeed despite the fact that the concept of interest (knowledge loss) will be present.

Quantization Threat: Using thresholds to classify development artifacts according to property values may create events where none exist. Conversely, progressive software evolution may make concepts of interest undetectable.

Ownership Acquisition Events

When analyzing the contribution history of leavers and the abandonment evolution, we observed abnormal patterns of ownership acquisition. Upon further investigation, we noted that some abandonment events were artifacts of unusual ownership acquisition by contributors. The most salient example is the `jassimp` module of Assimp, which was added to the

system by a contributor who immediately left. Therefore, the whole module appears to be abandoned all at once, yet this does not constitute a loss of the knowledge previously present in the system, especially in the case of bulk imports, migration from another repository, or other similar types of contributions.

A more subtle example relates to Gitlab-spec. This event involves files that were present in the module for a long time, with very low abandonment rates, which suddenly jumped to over 90% in one period. At first glance, this event appears to be similar to the Apereo-ldap event. However, looking at the evolution of the ratio of lines that were attributed to the leavers in the files involved in the event (Figure 6c), we can clearly see a jump from near 0% to high values in the period just before the abandonment event. This observation leads to the idea that the event is simply the consequence of a punctual, unusual, and large ownership acquisition event. This can be due, for example, to a minor contributor doing a simple automated refactoring that results in numerous line changes, which would thus create large amounts of artificial ownership for the contributor. In such cases, the event is a false positive.

Exceptional Action Threat: Subsets of the data that are presumed to be relevant to a construct of interest may only be an artifact of tool-supported activities, such as reverting deleted files or reformatting code files.

Cohesion of Abandoned Files

We concluded our micro-analysis of file abandonment events by investigating the relation between the files that were detected to be abandoned as part of an event.

Some of the files that are associated with an event immediately emerged as representing the loss of a cohesive unit of functionality of the system, even to an outside observer. For example, the Assimp-pyassimp and Assimp-jassimp events represent the complete abandonment of the entire ports of the library to Python and Java, respectively.

In contrast, other events consists of a large number of files with no obvious relation other than being located in the same sub-directory. In our case, if the proportion of abandoned files within a folder is relatively low, the knowledge at risk is mitigated by the other contributors who have contributed to related files from the same folder.

Furthermore, even among events that represent the abandonment of a cohesive unit of functionality, the consequences may differ depending on the architecture of the system. The abandonment of functionalities on which many other parts of the system depend will likely have a larger impact than the abandonment of functionalities that do not affect any others, such as independent plug-ins or library wrappers for other programming languages.

Architectural Sensitivity Threat: The contribution of different artifacts in a software repository to a construct may be a function of the architecture of the system, which is rarely formally documented in a manner that lends itself to automatic analysis.

V. Threat Assessment and Mitigation Strategies

Our case study of the detailed assessment of the validity of the Knowledge at Risk metric exposes how detailed aspects of software development history can be overlooked when aggregating data from software repositories. To help derive clear implications from this study, we organized our findings in terms of eight major threats to the validity of software process constructs that are to be captured from data aggregation.

Table IV presents these threats together with an assessment question and an example of aggregation that is exposed to the threat. The table is thus contributed as an *assessment instrument* for metrics. The instrument is designed so that if the answer to any of the questions is affirmative, the metric is subject to the threat and the corresponding data or construct should be carefully reviewed to assess the extent of the risk to validity. We emphasize that a *threat* is not a *flaw*: a positive answer may not point to an invalid inference if proper measures are in place to control for the risk of bias. However, mitigation factors should not be accidental, and the role of the assessment instrument is to support the systematic review of data aggregation for software repositories.

In terms of mitigation, we offer the following insights, derived from our investigation and subsequent reflection.

The *Fragility Threat* is not limited to software repositories, as computing probabilities for rare events (e.g., 100-year floods) relies on strong assumptions about the conditions in which the phenomenon is observed and involves unknown amounts of uncertainty when these assumptions are violated. As part of an idea he called "black swan", Taleb has argued extensively that empirically-derived probabilities for extreme events are not reliable [11].[2] The particular risk with software repositories is that the richness of the available data makes it possible to easily compute past frequencies for any number of rare event types, from file abandonments to very large commits, massive test failures, etc. In accordance with Taleb's philosophy, our recommendation is simply to avoid using the past as a model for the future when rare events are involved.

For the *File Content* threat, the self-evident but simplistic implication is to take the content of the file into account. Although weighting file-based metrics according to their length is a straightforward first step [6], other factors come into play that are project-specific and thus less easily controlled (such as the presence of constant declarations, cloned build scripts, etc.).

The threat of file content dependence is also closely related to the *File Role* and *Comment* threats. The File Role threat is especially problematic because the role of a file may be impossible to confidently detect without insider knowledge (e.g., whether a large file is a cloned-and-owned library or a large initial commit). To mitigate the File Role threat, approximate techniques such an analysis of outliers (e.g., large commits [12]) and explicit detection heuristics can serve as a

[2]This statement applies to natural events with probabilities computed from empirical data. For artificial systems such as games and lotteries, it is obviously possible to reliably compute probabilities for any event.

TABLE IV
THREATS OF AGGREGATING SOFTWARE REPOSITORY DATA

Threat	Assessment Question	Example
Fragility	Does the metric express a probability computed from a *small selection* of data items?	Estimating the *empirical probability* that a commit will be a single empty file.
File Content	Is the metric intended to represent the amount of code in the system?	Using the *total number of files of any kind* to represent the amount of development effort.
File Role	Does the metric assume that files play a uniform role in the construction of the system?	Considering *all files as equivalent* development artifacts to measure development effort.
Comment	Does the metric assume that the content of files or contributions correspond to source code?	Computing the length of files *without accounting for comments*.
Contributor Involvement	Is the metric intended to capture the contributions of a *selection* of contributors to the project?	Using the *total number of developers who committed* as a proxy for team size.
Quantization	Does the metric rely on a selection of information that involves thresholds?	Filtering large commits based on a *fixed size threshold*.
Architectural Sensitivity	Does the metric consider project artifacts as independent units in terms of the role they play in the system?	Using the *total number of makefiles* to represent the amount of configuration code.
Exceptional Action	Is the metric computed indiscriminately of outliers	Including *unusually large commits* into aggregated metrics such as averages.

starting point. The *Comment* threat directly compounds the File Content threat by further degrading the relation between the concept of a line in a file and an amount of software code. The *Comment* threat can be mitigated by parsing files for comments and accounting for the resulting ratio, as we did in this study. However, this mitigation is only partial, since comments can also represent different constructs, such as conversations between developers [13], [14], or dead code. For applicable metrics, for a strong mitigation of the Comment threat, one would also need to implement heuristics to classify comments, similarly to the content of messages in developer mailing lists [15].

Conceptually, the *Contributor Involvement* threat is similar to that of file content, in that contributors, like files, should not be considered identical atomic data points. The threat can thus be controlled through characterization of contributors.

For the *Quantization Threat*, for certain analyses, it may be possible to detect and leverage "natural" periods in the data [16], or at least implement discontinuity detection algorithms to avoid artificially severing continuously evolving variables. When a threshold is inevitable due to the nature of the construct (as is the case for file abandonment), enhancing threshold detection with a hysteresis mechanism will at least eliminate cases where a variable close to a threshold creates artificial discontinuities by repeatedly crossing the threshold back and forth.

By their nature, the *Architectural Sensitivity* and *Exceptional Action* are difficult to avoid algorithmically, and the best defense may simply be diligent investigation of the underlying data and additional extended case studies of specific data items [17].

VI. THREATS AND LIMITATIONS

Even a study on threats to validity cannot escape the grips of its own threats and limitations.

First, as a necessary way to analyze and visualize the huge amount of data we investigated, we employed various classification rules that are based on assumptions (e.g., to classify files as tests). Although we experimentally designed the thresholds and other rules to be as effective as possible, the classifications have their own error rates. The two main mitigating factors for these threats are that *(a)* we released our entire data set, so that the accuracy of the classification can independently be assessed, and *(b)* none of the threats (outcomes) is directly based on a single classification result.

Second, as discussed in Section II, focusing on some subset of the data requires a systematic procedure to select the data to put under the magnifying lens. In the absence of reliable architectural documents, we designed a procedure that is based on the existing directory structure. Other procedures would have resulted in different data being selected for the micro-analysis. The potential of a false positive is mitigated by our experimental approach, where we used the data to illustrate potential threats, as opposed to making claims about their presumed frequency. The main risk with our procedure is the converse: that we may have missed a threat worth reporting because the data that exemplified it was distributed across module boundaries.

Finally, we generalize to other software repository-based metrics. Given our case-study inspired research methods, the logic of inference is analytic rather than statistical [7]. We propose threats that apply to a specific context, with a specific description of the context which we aimed to capture as the assessment question in Table IV. The threat with analytic generalization is that an observed phenomenon may be unique to the case studied. In our case we mitigate this risk by orienting the outcomes in terms of general repository mining concepts (files, lines of code), as opposed to concepts specific to the case (i.e., knowledge at risk).

VII. RELATED WORK

We review work related to knowledge loss assessment as an illustration of the role and importance of process metrics derived from repository data, and then discuss work on research methods that offer perspectives that are complementary to our catalog of threats.

Knowledge Loss Assessment

Identifying which stakeholders have knowledge about modules within a codebase has long been of interest in the software engineering community. To identify stakeholders with relevant experience, Mockus and Herbsleb [18] developed the idea of Experience Atoms (EAs), i.e., completed development tasks (e.g., commits). Since EAs can also be associated with modules, the EA concept can identify stakeholders with expertise in a module. Challenging the hypothesis underlying EAs, Fritz et al. [19] found that developer commit activity was not strongly associated with module knowledge. Indeed, Negara et al. [20] argue that solely using version control records may underestimate the amount of knowledge of the code a developer has, since many of their interactions with a system are not recorded. Hence, more recent work replaces or augments change-based EAs with activities derived from API usage [21], IDE builds [22], IDE interactions [23], [24], and participation in peer code review [25].

Consolidation of knowledge within individuals has been observed to share a relationship with software quality. Rahman and Devanbu [26] found that developers with deep local experience produced code that was less frequently implicated in future defect fixes than that of developers with a breadth of general experience. Similarly, Bird et al. [27] found that the degree to which a module is predominantly developed by a single author shared a strong decreasing relationship with the likelihood of the module containing post-release defects.

By the same token, however, knowledge consolidation exposes an organization to the risk of knowledge loss because of developer turnover. For example, the degree to which an organization is exposed to turnover-induced knowledge loss is colloquially operationalized using the "bus" factor, which is the minimum number (or ratio) of developers who would need to leave the organization to stall development progress. The lower the bus factor value for an organization, the greater the organizational exposure to turnover-related risk of tacit knowledge being lost. Recent work has attempted to estimate this factor in large open source organizations [28]–[30].

More recent work has focused on identifying areas of a codebase that are at risk. As part of the seminal work on knowledge loss, Izquierdo-Cortazar et al. [8] developed the concept of *orphaned code*, i.e., code that was contributed by developers who are no longer in the organization, to study knowledge loss and how open source organizations recover from it. Rigby et al. [4] proposed Knowledge-at-Risk (KaR), an adapted version of the Value-at-Risk measure from the financial analysis domain. They used KaR to quantify turnover-induced knowledge loss and proposed strategies to mitigate organizational exposure in Chromium and a project developed by Avaya. Nassif and Robillard [6] then extended the KaR measure to allow for changes in the time period and the weight of files, and used it to study turnover-induced knowledge loss in seven additional open source projects.

Meta-Analyses of Repository Mining

Software repositories are noisy and incomplete sources of software data. Herbsleb and Grinter [31] found that (collocated) development teams often make project decisions in face-to-face (offline) meetings. Traces of these decisions are not present in software repositories. Moreover, Aranda and Venolia [17] found that issue trackers and version control repositories only contained partial or even erroneous information with respect to the resolution of issues at Microsoft.

In addition, others have sounded the alarm about of the risks of taking at face value results that have been mined from software repositories. In particular, Bird et al. [32] warned of the perils of mining Git repositories. In contrast to the present study, their work focused on the technical aspects of the Git source code management system. Others have pointed out that version control data includes non-essential [33], tangled [34], and non-meaningful changes [35]. The presence of these types of noise in repository data further threaten the meaning of the line ownership data upon which aggregated measures are based. In a different vein, Kalliamvakou et al. [36] warn against the indiscriminate sampling of projects from GitHub. This threat is, however, orthogonal to the threats that we identified, which apply to data aggregation for a given project.

Threat assessment and mitigation mechanisms have also been recently proposed. For example, Nagappan et al. [37] propose a *sample coverage* measure to quantify the threat of external validity to a population of interest. Munaiah et al. [38] propose Reaper, a tool to assess the likelihood that a GitHub repository contains an "engineered" software project. Similar to these past efforts, we propose an evaluation instrument to assess threats to construct validity that may be present when aggregating software repository data.

VIII. Conclusion

Countless benefits can be derived from the analysis of software repositories, as actionable insights can be produced at little cost once an analysis technique is in place. However, care must be taken to ensure that insights are based on a valid interpretation of the data.

To appreciate first hand the risk to the relation between a metric and the construct it is intended to represent, we conducted an in-depth critical review of the file abandonment computations described in previous work. The case study raised our awareness of the validity threats for metrics derived from aggregated software repository data. We organized our findings in terms of eight major threats to validity to consider when designing new software repository mining studies or techniques, and report these threats as an instrument with assessment questions and examples. The instrument can be used both to evaluate existing metrics and to help design further repository-based metrics and mining techniques.

Acknowledgment

The authors thank the anonymous reviewers for constructive feedback. This work was funded by NSERC.

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