

Logical dependencies: extraction from the versioning system and usage in key classes detection [★]

Adelina Diana Stana¹ and Ioana Șora²

¹ Stana Adelina Diana

Politehnica University, Piața Victoriei Nr. 2, ; 300006 Timișoara, jud. Timiș, România
stana.adelina.diana@gmail.com

² Șora Ioana

Politehnica University, Piața Victoriei Nr. 2, ; 300006 Timișoara, jud. Timiș, România
ioana.sora@cs.upt.ro

Abstract. The version control system of every software product can provide important information about how the system is connected. In this study, we first propose a language-independent method to collect and filter dependencies from the version control, and second, we use the results obtained in the first step to identify key classes from three software systems. To identify the key classes, we are using the dependencies extracted from the version control system together with dependencies from the source code, and also separate. Based on the results obtained we can say that, compared with the results obtained by using only dependencies extracted from code, the mix between both types of dependencies do not provide dramatically different results, only small improvements. And, by using only dependencies from the version control system, we obtained results that did not surpass the results previously mentioned, but are still acceptable. Even though the logical dependencies are not on pair with structural dependencies results, this might open an important opportunity for software systems that use dynamically typed languages such as JavaScript, Objective-C, Python, Ruby, or systems that use multiple languages. These types of systems, for which the code dependencies are harder to obtain, can use the dependencies extracted from the version control to gain better knowledge about the system.

Keywords: logical dependencies; logical coupling; mining software repositories; versioning system; key classes; co-changing entities; software evolution.

1. Introduction

The version control (also known as source control) system that tracks changes in source code during software development can provide useful information about the system's details. The usage of information extracted from the version control system is not new. Previous works have used version control information to detect design issues [28], predict fault incidence among modules [13], [4] or guide software changes [10], [3]. In software engineering literature, concepts like evolutionary coupling, evolutionary dependencies, logical dependencies, or logical coupling refer to the same sort of relationship among software entities. That relationship is extracted from the version control system and can

[★] If this is an extended version of a conference paper, it should be clearly stated here.

mean that the entities from the source code files that change together, evolve together, and might depend on one another. Studies show that dependency relationships found in the source code overlap only in a small percentage with dependency relationships found in the version control system, and suggest that these two types of relationships can be used together [14], [2]. But, in practice, dependencies extracted from the version management system are rarely used because of the size of the information extracted [20]. A relatively small source code repository with roundabout one thousand commits can lead to millions of connections. In this paper, by applying a set of filters with different thresholds to the information extracted, we intend to speed up the processing time, reduce the size of connections extracted from the version control and increase the confidence that the connections obtained might be related. In order to validate the results obtained, and to see if the filtering methods had or had not a favorable effect on the final result, we want to identify the key classes of different systems. The identification of key classes has been previously performed by using structural dependencies, so we intend to use the results obtained together with structural dependencies, and also separate, and see how the final results fluctuate.

We performed our analysis on three open source projects: Ant, Tomcat Catalina, and Hibernate. And we answered the following research questions:

RQ1: Will logical dependencies enhance results previously obtained by using only structural dependencies? Since previous researches and our studies show that logical dependencies overlap only in a small percentage with structural dependencies, we intend to combine both types of dependencies and provide them as input for key classes identification tools.

RQ2: Can logical dependencies provide good results if used instead of structural dependencies? In this research question, we want to focus more on the use of logical dependencies as stand-alone dependencies. Even though logical dependencies are not the same as structural dependencies, they can provide enough information about the system to be successfully used as input for tools like key classes detection tools.

RQ3: Does the connection strength filter has a favorable impact on the results obtained? In this paper, we use a new type of filter: the connection strength filter. This filter, together with the commit size filter, will be used to filter co-changes into logical dependencies. Now, the question is if this new filter will indeed do what we expect and provide better results.

Paper structure. The paper is organized as follows: Section 2 introduces the concepts of logical dependencies and the methods of obtaining them. Section 3 introduces the concept of key classes and the metrics used for results evaluation. The new approach of using logical dependencies to detect key classes can be found in section 4. Section 5 defines the data set used and presents the new results obtained with the data set. In section 6 we present the threats to the validity of the results presented in this paper. And finally, section 7 discusses the conclusions based on the results obtained.

2. The concept of logical dependencies

This section presents the definition of logical dependencies, previous works involving logical dependencies, and our contribution to this topic. In subsection 2.1, we define what logical dependencies are and the previous research involving them. In subsection 2.2, we

1 present our approach for identifying logical dependencies and the work we have done
 2 around this subject. Related to subsection 2.2, sections 2.3, and 2.4 present more details
 3 about the filtering techniques we used to identify logical dependencies.

4 2.1. Definition and previous related research

5 The concept of logical coupling (dependency) was first introduced by Gall et al. [12].
 6 They defined the logical dependency between two software entities (classes, modules,
 7 interfaces, etc.) as the fact that the entities repeatedly change together during the histor-
 8 ical evolution of a software system. Since then, logical dependencies have been used in
 9 multiple areas of software engineering, most commonly in fault and change prediction.
 10 Besides the studies on how logical dependencies can help gain knowledge about software
 11 systems, some studies also focused on the interplay between logical and structural de-
 12 pendencies. Ajienka et al. and Olivia et al. studied the interplay between structural and
 13 logical dependencies, and they concluded that, in most cases, structural dependencies do
 14 not lead to logical dependencies [14], [15], [2]. The above affirmation is also supported
 15 by Lanza et al., who consider that logical dependencies are important because they can
 16 reveal dependencies that are not visible via code analysis [9].

17 In previous research, the *support* and *confidence* metrics were used to measure the
 18 strength of a logical dependency. The logical dependencies are commonly represented as
 19 directed association rules. The association rule between A and B ($A \rightarrow B$) means that
 20 changes in entity A cause changes in entity B, where A is the antecedent, and B is the
 21 consequent of the rule. The support metric counts the number of commits in which both
 22 entities of an association rule change together. The confidence metric is the ratio between
 23 the support metric and the total number of commits in which the antecedent of the rule
 24 was involved.

25 By applying different thresholds to the metrics presented above, the logical dependen-
 26 cies to further use were selected [15], [2], [28].

27 2.2. Our approach for logical dependencies identification

28 To avoid confusion, we call *co-changing pairs* all the association rules of one system.
 29 The association rules are formed between two software entities that update together in
 30 the same commit. For example, a commit that contains seven entities will generate 21
 31 co-changing pairs ($C_k^n = \frac{n!}{k!(n-k)!} = \frac{7!}{2!(5)!} = 21$).

32 The *logical dependencies* are the association rules whose metrics fulfill certain condi-
 33 tions. So, the logical dependencies are a subset of the co-changing pairs.

34 The conditions that need to be met by a co-changing pair to be considered a logical
 35 dependency are called *filters*. Like in other research regarding logical dependencies, our
 36 filters are thresholds applied to the metrics of association rules.

37 Previously, we tried to filter logical dependencies from co-changing pairs by applying
 38 filters like the occurrence filter and commit size filter [22], [23]. The commit size filter,
 39 presented in more detail in section 2.3, and used by other authors [2], proved to be helpful,
 40 and it will be also used for this paper. But we cannot say the same for the occurrence filter.
 41 The filter consisted of different thresholds applied to the support metric and proved to not
 42 work well for systems with few commits.

1 Currently, we aim to refine the filtering method with a new filter applicable for all sorts
 2 of commit history sizes. This new filter, presented in section 2.4, will be used together
 3 with the commit size filter to filter logical dependencies from co-changing pairs. The
 4 entire process of extracting co-changing pairs from the versioning system, filtering them
 5 to obtain logical dependencies, and exporting the results, is done with a tool written in
 6 Python. The workflow is presented in figure 1.

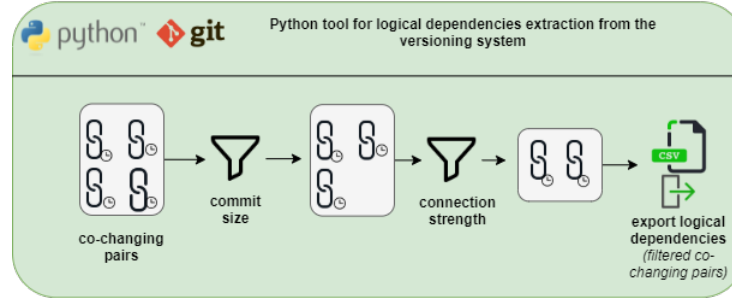


Fig. 1. Workflow for logical dependencies extraction.

7 2.3. Logical dependencies filtering: The commit size filter

8 The commit size filter filters out all co-changing pairs from commits with more than 10
 9 files changed. We consider that commits with more than 10 files changed tend to be code
 10 unrelated; we studied the commit size trend from several git open-source repositories, and
 11 we concluded that most of the commits contain less than 10 files. On average, only 10%
 12 of the total commits have more than 10 files changed.

13 This filter will also prevent the volume of data processed from going out of proportion.
 14 In some of the repositories studied, we found commits with more than 1000 files; these
 15 commits could generate over half a million co-changing pairs if the commit size filter is
 16 not applied [23], [22].

17 2.4. Logical dependencies filtering: The connection strength filter

18 The connection strength filter is new for our research regarding logical dependencies iden-
 19 tification, and it is based on our experience with the occurrence filter. An important con-
 20 clusion drawn from the results obtained with the occurrence filter is that setting a hard
 21 threshold for a filter is not always a good idea. A certain threshold can work well with a
 22 medium/large-sized system, but when applied to a small-sized system, it can reduce the
 23 co-changes filtered to 0. To avoid this kind of situation, we evaluated a filter that considers
 24 the system's specifications.

25 As we previously mentioned, a filter has two components: the metrics computed for
 26 each co-changing pair (association rule) and the threshold values. The connection strength
 27 metric derives from the support and the confidence metrics.

28 For an association rule (co-changing pair) formed from the antecedent A and conse-
 29 quent B ($A \rightarrow B$), the support count is the total number of commits in which both entities
 30 are involved,

$$\text{support}(A \rightarrow B) = \text{freq}_{\text{total commits}}(A \cup B) \quad (1)$$

1 and the confidence is the ratio between the support and the frequency of the antecedent
2 of the rule.

$$\text{confidence}(A \rightarrow B) = \frac{\text{support}(A \rightarrow B)}{\text{freq}_{\text{total commits}}(A)} \quad (2)$$

3 The only problem with the confidence metric, as it is defined above, is that it does
4 not include the big picture of the system. The best value for the confidence metric is 1,
5 meaning that in all commits in which entity A is present, entity B is also there. If, for
6 example, we have a co-changing pair $A \rightarrow B$, and A updates only once in the entire
7 history, and in that time, updates together with B, then the confidence metric associated
8 with the co-changing pair will be 1 (the best value possible). That is not a fair value
9 compared with other scenarios. For example, we can have the co-changing pair $A \rightarrow$
10 B , and A updates 100 in the entire history from which 80 times updates together with
11 B, leading to a confidence value of 0.8. Even though in the second scenario we have a
12 confidence value smaller than in the first scenario, the second scenario could lead to a
13 more trustworthy connection.

14 Figures 2 and 3 intend to offer the big picture of two systems, one small-sized (Ant)
15 and one medium-sized (Hibernate). In both figures, the dots represent the maximum number
16 of updates of one entity with another, and the blue line represents the average occur-
17 rence value of the system. It can be observed that both systems have multiple entities
18 that update only once (the dark line at the bottom), meaning that we might have many
19 confidence values of 1 (highest value possible) for entities that update only once together.

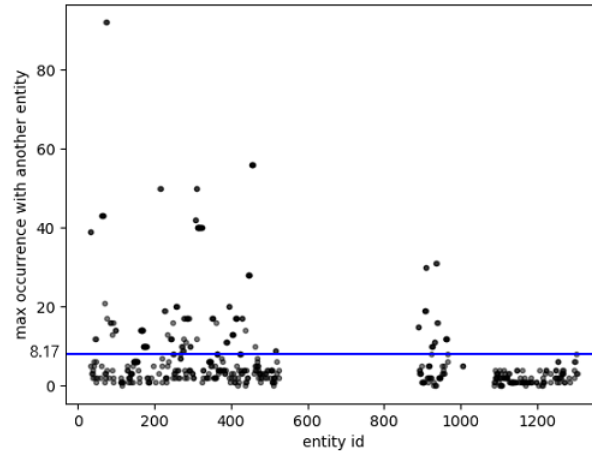


Fig. 2. Overview of the number of occurrences in Ant.

20 To take into account the big picture of the system, we defined a new metric for a
21 co-changing pair (association rule), called the *connection strength metric*.

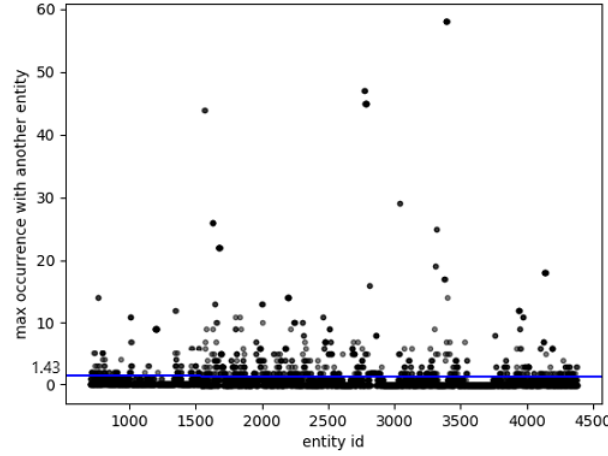


Fig. 3. Overview of the number of occurrences in Hibernate.

1 The connection strength metric is computing the same ratio as the confidence metric,
 2 a.k.a the ratio between the support metric and the frequency of the antecedent. And ad-
 3 ditionally, it multiplies it with a system factor and with 100. The *system factor* calculates
 4 the ratio between the support metric and the mean value for updates. The *system mean* is
 5 the mean value of all the support values for all the association rules from the system. We
 6 multiply with 100 because we want to scale the metric's values to structural dependencies
 7 metric's values that have, in most cases, supraunitary values. And we want both metrics
 8 to be comparable. The values obtained are clipped between 0 and 100, where 100 is the
 9 best value and 0 is the worst.

$$systemfactorfor(A \rightarrow B) = \frac{support(A \rightarrow B)}{system\ mean} \quad (3)$$

$$strength(A \rightarrow B) = \frac{support(A \rightarrow B) * 100}{freq_{total\ commits}(A)} * system\ factor \quad (4)$$

10 By using the strength metric, if we consider again the two scenarios presented above,
 11 and a system mean value of 10, we will have the following values: for the scenario in
 12 which the entities A and B update only once, and in that one update, they update together,
 13 the strength metric value is 10. For the scenario in which entity A updates 100 times in
 14 the entire history from which 80 times updates together with B, the strength metric value
 15 is 100.

16 Since the values can vary from 0 to 100, the filter threshold values begin at 10 and are
 17 repeatedly incremented by 10, until 100. We do not settle for one value because we want
 18 to see how the threshold values affect the number of remaining co-changing pairs and the
 19 output of their usage.

20 In figure 4 we plotted for two systems (one small-sized and one medium-sized) the
 21 number of structural dependencies, co-changing pairs before filtering, and co-changing
 22 pairs after filtering. With the connection strength filter, the small-sized system didn't lose

all the co-changing pairs once with the filtering. We compare the number of remaining co-changing pairs with the number of structural dependencies because, according to surveys [20], [11], the main reason why logical dependencies (filtered co-changes) are not used together with structural dependencies is their size. So, it is essential to get an overview of the comparison between the number of co-changing pairs and the number of structural dependencies at each filtering step.

We call the co-changing pairs that remain after filtering, logical dependencies. After this step, we will use the logical dependencies obtained with different threshold values and see which threshold value performs the best. Up until now, we only looked at the size of the resulting logical dependencies and decided if a filter and its threshold are good or not. Now, we can also look at the results obtained by using the logical dependencies and decide.

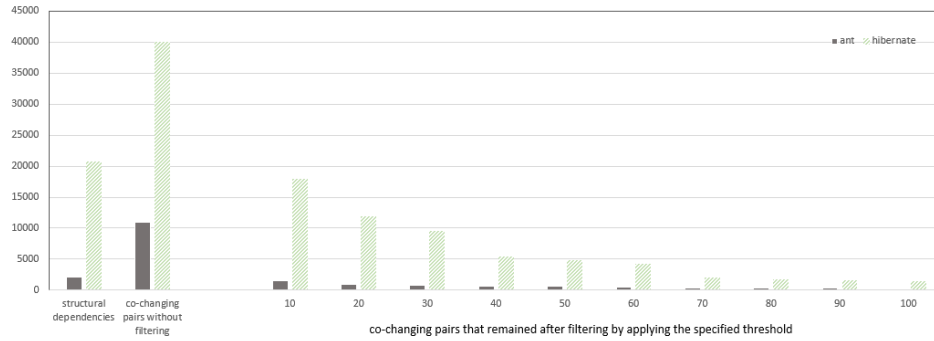


Fig. 4. Overview of the impact of connection strength filtering on the number of co-changing pairs.

3. The concept of key classes

This section presents the key classes definition, previous research regarding key classes identification, and metrics used to evaluate the results obtained. In section 3.1, we present a summary of previous researchers and their approaches for key classes identification. Section 3.2 focuses on one previous research that we consider as our baseline research in key classes identification. With the results of the baseline research, we will compare our results. In section 3.3, we present the metrics used in previous researches to evaluate the results obtained.

3.1. Definition and previous research

Zaidman et al. [27] were the first to introduce the concept of key classes and it refers to classes that can be found in documents written to provide an architectural overview of the system or an introduction to the system structure. Tahvildari and Kontogiannis

1 have a more detailed definition regarding the key classes concept: “Usually, the most
 2 important concepts of a system are implemented by very few key classes which can be
 3 characterized by the specific properties. These classes, which we refer to as key classes,
 4 manage many other classes or use them in order to implement their functionality. The key
 5 classes are tightly coupled with other parts of the system. Additionally, they tend to be
 6 rather complex, since they implement much of the legacy system’s functionality” [24].

7 The key class identification can be done by using different algorithms with different
 8 inputs. In the research of Osman et al., the key class identification is made by using a
 9 machine learning algorithm and class diagrams as input for the algorithm [18]. Thung
 10 et al. built on top of Osman et al.’s approach and added network metrics and optimistic
 11 classification to detect key classes [25].

12 Zaidman et al. used a web mining algorithm and dynamic analysis of the source code
 13 to identify the key classes [27].

14 3.2. Baseline approach

15 We use the research of I. Șora et al. [17] as a baseline for our research involving the usage
 16 of logical dependencies to find key classes.

17 Șora et al. used the static analysis of the source code, a page ranking algorithm and
 18 other class attributes to find key classes [6], [16], [7], [21],[17]. The page ranking algo-
 19 rithm is a customization of PageRank, the algorithm used to rank web pages [19], and
 20 it works based on a recommendation system. If one node has a connection with another
 21 node, then it recommends the second node. In previous research, connections are estab-
 22 lished based on structural dependencies extracted from static code analysis. If A has a
 23 structural dependency with B, then A recommends B, and also B recommends A.

24 The ranking algorithm ranks all the classes from the source code of the system, ac-
 25 cording to their importance. To identify the important classes from the rest, a threshold
 26 for the top classes from the top of the ranking is set. We call this TOP threshold, and its
 27 value can range from 1 to the total number of classes found in the system.

28 3.3. Metrics for results evaluation

29 To evaluate the quality of the key classes ranking algorithm and solution produced, the
 30 key classes found by the algorithm are compared with a reference solution. The reference
 31 solution is extracted from the developer documentation. The classes mentioned in the
 32 documentation are considered key classes and form the reference solution (ground truth)
 33 used for validation [26].

34 For the comparison between both solutions, a classification model is used. The quality
 35 of the solution produced is evaluated by using the Receiver Operating Characteristic Area
 36 Under Curve (ROC-AUC) metric, a metric that evaluates the performance of a classifica-
 37 tion model.

38 *Receiver Operating Characteristic Area Under Curve*

39 The ROC graph is a two-dimensional graph that has on the X-axis plotted the false
 40 positive rate and on the Y-axis the true positive rate. By plotting the true positive rate and
 41 the false positive rate at thresholds that vary between a minimum and a maximum possible
 42 value, we obtain the ROC curve. The area under the ROC curve is called Area Under the
 43 Curve (AUC).

1 The true positive rate of a classifier is calculated as the division between the number
2 of true positive results identified, and all the positive results identified:

$$\text{True positive rate}(TPR) = \frac{TP}{TP + FN} \quad (5)$$

3 The false positive rate of a classifier is calculated as the division between the number of
4 false positive results identified, and all the negative results identified:

$$\text{False positive rate}(FPR) = \frac{FP}{FP + TN} \quad (6)$$

5 The True Positives (TP) are the classes found in the reference solution and also in the
6 top TOP ranked classes. False Positives (FP) are the classes that are not in the reference
7 solution, but are in the TOP ranked classes. True Negatives (TN) are classes that are found
8 neither in the reference solution, nor in the TOP ranked classes. False Negatives (FN) are
9 classes that are found in the reference solution, but are not found in the TOP ranked
10 classes.

11 In related research, the ROC-AUC metric has been used to evaluate the results for
12 finding key classes of software systems. For a classifier to be considered good, its ROC-
13 AUC metric value should be as close to 1 as possible. When the value is 1, then the
14 classifier is considered to be perfect. A metric value between 0.8 and 0.9 means that the
15 classifier is excellent. Between 0.8 and 0.7 means acceptable results, and between 0.7 and
16 0.5 means poor results [1].

17 Osman et al. obtained in their research an average ROC-AUC score of 0.750 [18].
18 Thung et al. obtained an average ROC-AUC score of 0.825 [25] and Şora et al. (the base-
19 line) obtained an average ROC-AUC score of 0.894 [17].

20 4. Key classes identification using logical dependencies

21 This section presents our approach for key classes identification by using logical depen-
22 dencies. In section 4.1, we describe the experimental setup and how we intend to integrate
23 logical dependencies with the baseline approach. Section 4.2 presents our investigation
24 plan and how this plan can respond to the research questions we enunciated at the begin-
25 ning of this paper.

26 4.1. Current approach

27 The baseline approach uses a tool that takes as an input the source code of the system and
28 applies ranking strategies to rank the classes according to their importance. We modified
29 the tool used by the baseline approach to take also the logical dependencies as input; the
30 rest of the workflow is the same as in the baseline approach (figure 5).

31 Below are some of the class metrics used in the baseline approach and in our current
32 research to rank the classes according to their importance.

33 The class metrics used can be separated into two categories: class connection metrics
34 and class PageRank values. The class connection metrics are CONN-TOTAL-W, which is
35 the total weight of all connections of the class, and CONN-TOTAL, the total number of
36 distinct classes that a class uses or are using the class [17].

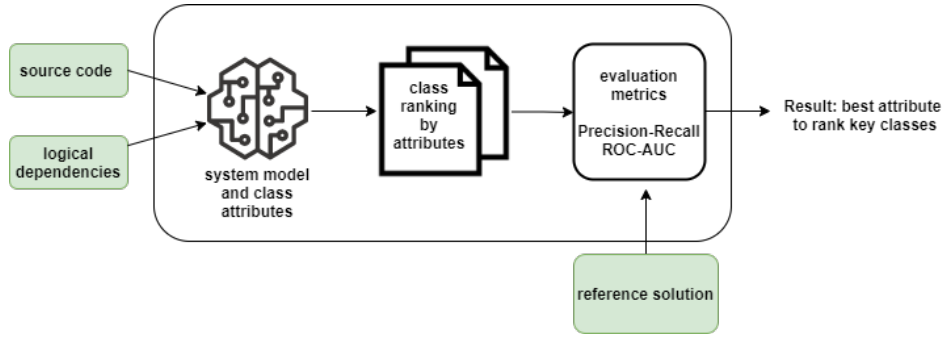


Fig. 5. Overview of the current approach.

1 Previous research used PageRank values computed on both directed and undirected,
 2 weighted and unweighted graphs. In the current research, we use the PR, which is the
 3 PageRank value computed on the directed and unweighted graph, the PR-U, which is the
 4 value computed on the undirected and unweighted graph, and the PR-U2-W, the value
 5 computed on the weighted graph with back-recommendations [6], [16], [17], [21].

6 4.2. Experimental plan

7 Our study aims to check whether logical dependencies can be usable. Previous research
 8 focused on filtering the co-changes extracted from the versioning system and studying
 9 how filtering affects their size or how they overlap with structural dependencies. We intend
 10 to use the resulting information after co-changes filtering (the logical dependencies)
 11 in a tool that usually receives structural dependencies as input.

12 Our research questions are the following: **RQ1:** *Will logical dependencies enhance*
 13 *results previously obtained by using only structural dependencies?* **RQ2:** *Can logical*
 14 *dependencies provide good results if used instead of structural dependencies?* **RQ3:** *Does*
 15 *the connection strength filter has a favorable impact on the results obtained?*

16 To answer the research questions, we defined the following experimental plan: We will
 17 use the tool mentioned in the above section. Previously the tool had as input the structural
 18 dependencies of the system and the reference solution, and the output was the ROC-AUC
 19 score. The closer the ROC-AUC score is to 1, the better the results. The slightly modified
 20 version of the tool, we be able to receive as input also logical dependencies.

21 For **RQ1**, we will give as input to the tool the structural and the logical dependencies,
 22 and we will compare the ROC-AUC scores obtained with the results obtained by using
 23 only structural dependencies.

24 *Hypothesis:* Key classes detection is better when we provide both types of dependencies
 25 as input to the tool. The output has a higher ROC-AUC score than the base approach.

26 Our findings for this research question can be found in section 5.3.

27 For **RQ2**, we will give as input to the tool only logical dependencies, and we will
 28 compare the ROC-AUC scores obtained with the results obtained by using only structural
 29 dependencies, and by using structural and logical dependencies combined. We do not

expect that the results will be better compared to the results previously obtained, but we expect results that have a ROC-AUC score close to those values. That would mean that logical dependencies can provide enough information to detect most of the key classes of the system.

Hypothesis: The output has a ROC-AUC score between 0.7 and 1.

Our findings for this research question can be found in section 5.4.

For **RQ3**, we generate two sets of logical dependencies. One set will be generated with the connection strength filter and one with the confidence filter. We will then use each set in two different scenarios: one when we only use logical dependencies to detect key classes and one when we use logical and structural dependencies for detection. Finally, we will compare the results obtained. We expect that the connection strength filter will generate better results.

Hypothesis: The results obtained by using the connection strength filter are better than the ones obtained with the confidence filter.

Our findings for this research question can be found in section 5.5.

5. Experimental results using logical dependencies

As presented in section 3, the key class detection was previously done only by using the structural dependencies of the system. In this section, we use the same tool used in the baseline approach presented in section 3, and we add a new input to it, the logical dependencies.

In subsection 5.1, we present the data set used to generate new results and, in subsection 5.2, we present the previously obtained results. Subsection 5.3 presents the conclusions and results obtained by using logical and structural dependencies together, subsection 5.4 presents the conclusions and results obtained by using only logical dependencies. And, finally, subsection 5.5 presents a comparison between results obtained with confidence metric versus results obtained with strength metric.

5.1. Data set used

The research of I. Sora et al. takes into consideration structural dependencies that were extracted using static analysis techniques, and were performed on the object-oriented systems presented in table 1 [17].

The requirements for a system to qualify as suited for investigations using logical dependencies are: has to be version controlled by Git, has to have releases for different code versions (previous research was done only on specific versions), and also has to have a significant number of commits. From the total of 14 object-oriented systems listed in the baseline [17], 13 of them have repositories in git 1, and from the found repositories, only 6 repositories have the same release tag as the specified version in previous research. The commits number found on the remaining 6 repositories varies from 19108 commits for Tomcat Catalina to 149 commits for JHotDraw. In order to have more accurate results, we need a significant number of commits (more than 5000 commits), so we concluded to use only 3 systems from the initial candidates for key classes detection using logical dependencies: Ant, Hibernate, and Tomcat Catalina.

Table 1. Systems and versions of the systems found in Git.

ID	System	Version	Release Tag name	Commits number
S1	Apache Ant	1.6.1	rel/1.6.1	6713
S2	Argo UML	0.9.5	not found	0
S3	GWT Portlets	0.9.5 beta	not found	0
S4	Hibernate	5.2.12	5.2.12	6733
S5	javaclient	2.0.0	not found	0
S6	jEdit	5.1.0	not found	0
S7	JGAP	3.6.3	not found	0
S8	JHotDraw	6.0b.1	not found	149
S9	JMeter	2.0.1	v2_1_1	2506
S10	Log4j	2.10.0	v1_2_10-recalled	634
S11	Mars	3.06.0	not found	0
S12	Maze	1.0.0	not found	0
S13	Neuroph	2.2.0	not found	0
S14	Tomcat Catalina	9.0.4	9.0.4	19108
S15	Wro4J	1.6.3	v1.6.3	2871

1 5.2. Measurements using only the baseline approach

2 In table 2 are presented the ROC-AUC values for different attributes computed for the
3 systems Ant, Tomcat Catalina, and Hibernate by using the baseline approach. We intend
4 to compare these values with the new values obtained by using also logical dependencies
5 in key class detection.

Table 2. ROC-AUC metric values extracted.

Metrics	Ant	Tomcat Catalina	Hibernate
PR_U2_W	0.95823	0.92341	0.95823
PR	0.94944	0.92670	0.94944
PR_U	0.95060	0.93220	0.95060
CONN_TOTAL_W	0.94437	0.92595	0.94437
CONN_TOTAL	0.94630	0.93903	0.94630

6 5.3. Measurements using combined structural and logical dependencies

7 The tool used in the baseline approach runs a graph-ranking algorithm on a graph that
8 contains all the structural dependencies extracted from static source code analysis. Each
9 edge in the graph represents a dependency. The entities that form a structural dependency
10 are represented as vertices in the graph. As mentioned in section 3, we modified the tool
11 to take structural and logical dependencies as input. For this subsection's measurements,
12 we add the logical dependencies in the graph that contains all structural dependencies.
13 Since it is a weighted graph, if a structural dependency is also a logical dependency, then
14 the final weight of the connection is the sum of the weight computed for the structural
15 dependency and the connection strength metric associated with the logical dependency.

16 In tables 3, 4, and 5, on each line, we have the computed the key class metric gen-
17 erated with logical dependencies extracted with the connection strength threshold that is
18 specified in the columns header.

We started with logical dependencies that have a connection strength metric greater than 10, then we repeatedly increased the value by 10 until we reached 100. The last column of the table contains the results previously obtained by the tool by only using structural dependencies (the results presented in section 5.2).

So, to answer *RQ1: Will logical dependencies enhance results previously obtained by using only structural dependencies?*:

The results obtained by combining structural and logical dependencies are close to the previously registered values but, in most cases, do not surpass them. Underlined are the values that are better than the previously registered values. We can observe that for all 3 systems, the best values obtained are for connection strength between 40-70.

Table 3. Measurements for Ant using structural and logical dependencies combined

Metrics	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100	Baseline
PR_U2_W	0.877	0.880	0.883	0.888	0.884	0.880	0.901	0.924	0.900	0.891	0.929
PR	<u>0.955</u>	<u>0.932</u>	<u>0.936</u>	<u>0.936</u>	0.880	0.884	0.887	0.889	0.888	<u>0.890</u>	0.855
PR_U	0.933	<u>0.937</u>	<u>0.936</u>	<u>0.939</u>	<u>0.940</u>	<u>0.939</u>	<u>0.941</u>	<u>0.943</u>	<u>0.942</u>	<u>0.940</u>	0.933
CON_T_W	0.841	0.839	0.836	0.838	0.835	0.849	0.859	0.872	0.870	0.874	0.934
CON_T	0.920	0.919	0.921	0.923	0.923	0.932	0.934	0.939	0.937	0.937	0.942

Table 4. Measurements for Tomcat Catalina using structural and logical dependencies combined

Metrics	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100	Baseline
PR_U2_W	0.862	0.883	0.898	0.901	0.907	0.909	0.910	0.916	0.918	0.918	0.923
PR	0.879	0.885	0.888	0.882	0.869	0.869	0.863	0.863	0.863	0.863	0.927
PR_U	0.924	0.930	0.931	0.932	0.932	0.932	0.932	0.932	0.932	0.932	0.932
CON_T_W	0.868	0.888	0.901	0.909	0.914	0.917	0.918	0.923	0.925	0.925	0.926
CON_T	0.925	0.934	0.937	0.938	0.938	0.938	0.938	0.938	0.938	0.938	0.939

Table 5. Measurements for Hibernate using structural and logical dependencies combined

Metrics	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100	Baseline
PR_U2_W	0.903	0.909	0.916	0.928	0.930	0.932	0.946	0.947	0.947	0.949	0.958
PR	0.956	0.959	0.961	0.962	0.962	0.962	0.953	0.953	0.953	0.954	0.949
PR_U	0.937	0.941	0.943	0.947	0.948	0.948	0.950	0.950	0.950	0.950	0.951
CON_T_W	0.864	0.872	0.879	0.896	0.898	0.900	0.929	0.930	0.931	0.934	0.944
CON_T	0.920	0.927	0.932	0.940	0.940	0.940	0.945	0.945	0.945	0.945	0.946

Some other details about the systems are presented in tables 6 and 7. In table 6 are the overlappings between structural and logical dependencies expressed in percentages. Each column represents the percentage of logical dependencies that are also structural. The values obtained confirm that, indeed, the logical dependencies overlap with structural dependencies in a small percentage, and they must be treated as different dependencies.

1 In table 7 are the ratio numbers between structural dependencies and logical depen-
 2 dependencies. We added this table to highlight how different the numbers of both dependencies
 3 are.

Table 6. Percentage of logical dependencies that are also structural dependencies

System	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
Ant	17.628	19.872	20.461	20.858	21.078	23.913	24.688	21.807	20.000	19.776
Tomcat Catalina	10.331	14.931	15.862	16.221	16.427	16.302	16.598	18.336	19.207	19.149
Hibernate	8.005	8.971	9.755	12.060	12.348	12.254	18.426	19.105	18.836	19.371

Table 7. Ratio between structural and logical dependencies (SD/LD)

System	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100
Ant	1.373	2.251	2.870	3.133	3.461	4.604	5.282	6.598	7.060	7.903
Tomcat Catalina	0.445	0.936	1.302	1.543	1.660	1.967	2.218	3.057	3.376	3.440
Hibernate	1.159	1.747	2.184	3.867	4.283	4.877	10.547	11.920	12.464	14.851

4 In most cases, for all systems, the results tend to become better once with increasing
 5 the value of the connection strength threshold up until one point, after which the results
 6 obtained begin to drop. If we look at table 6, we can observe that the bigger the threshold
 7 for the connection strength filter, the smaller the number of total logical dependencies
 8 becomes. For example, in Hibernate, the value 70 for the connection strength threshold
 9 makes the structural dependencies outnumber 10 times the logical dependencies.

10 We can identify 3 scenarios based on tables 3, 4, 5 and 7. In the 1st scenario, the
 11 connection strength threshold is too small, and we remain with a lot of logical depen-
 12 dependencies after filtering. The high volume of logical dependencies introduced in the graph
 13 might cause an erroneous detection of the key classes, in consequence, less performing
 14 measurements/results. This affirmation is sustained by the fact that, when the threshold
 15 begins to be more restrictive, and the total number of logical dependencies begins to de-
 16 crease, the key classes detection starts to improve. The 2nd scenario assumes that the
 17 connection strength threshold is too big, significantly decreasing the number of logical
 18 dependencies. In this case, the logical dependencies introduced in the graph are too few
 19 to improve the detection, and, instead, will create noise in the graph and less performing
 20 results. This leads us to the 3rd scenario, in which the connection strength threshold is
 21 'just right'. Not too small, because it will introduce too many logical dependencies in the
 22 graph and produce less performing results. And not too high, because it will decrease too
 23 much the number of logical dependencies, producing less performing results.

24 The 'just right' value can differ from one system to another, depending on the size of
 25 the system. If we look at Ant (the smaller size system), we can see that the results begin
 26 to decrease sooner than for Hibernate. On average, all the systems perform well between
 27 40 and 70 for the connection strength threshold value.

5.4. Measurements using only logical dependencies

In the previous subsection, we added the logical and structural dependencies in the graph based on which the ranking algorithm works. Currently, we add only the logical dependencies to the graph.

In tables 8, 9, and 10 are presented the results obtained by using only logical dependencies to detect key classes.

For the second research question: '**RQ2: Can logical dependencies provide good results if used instead of structural dependencies?**', the initial hypothesis is confirmed by the results obtained.

The measurements obtained are not as good as the ones using logical and structural dependencies combined or using only structural dependencies. But the values obtained are above 0.7, which means that a good part of the key classes is detected by using only logical dependencies. As mentioned in section 3.3, a classifier is good if it has the ROC-AUC value as close to 1 as possible.

Table 8. Measurements for Ant using only logical dependencies

Metrics	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100	Baseline
PR_U2_W	0.679	0.695	0.738	0.799	0.822	0.883	0.890	0.901	0.846	0.862	0.929
PR	0.868	0.776	0.767	0.825	0.822	0.850	0.834	0.863	0.844	0.860	0.855
PR_U	0.801	0.792	0.757	0.806	0.822	0.854	0.856	0.867	0.848	0.860	0.933
CON_T_W	0.819	0.825	0.818	0.817	0.813	0.828	0.843	0.861	0.845	0.854	0.934
CON_T	0.856	0.836	0.819	0.803	0.801	0.816	0.831	0.855	0.840	0.851	0.942

Table 9. Measurements for Tomcat Catalina using only logical dependencies

Metrics	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100	Baseline
PR_U2_W	0.775	0.810	0.834	0.828	0.819	0.815	0.805	0.816	0.820	0.813	0.923
PR	0.813	0.813	0.836	0.831	0.820	0.814	0.804	0.816	0.820	0.813	0.927
PR_U	0.772	0.815	0.835	0.831	0.820	0.814	0.804	0.816	0.819	0.813	0.932
CON_T_W	0.805	0.823	0.842	0.835	0.822	0.815	0.805	0.817	0.820	0.813	0.926
CON_T	0.787	0.812	0.835	0.832	0.821	0.814	0.804	0.817	0.820	0.813	0.939

Table 10. Measurements for Hibernate using only logical dependencies

Metrics	≥ 10	≥ 20	≥ 30	≥ 40	≥ 50	≥ 60	≥ 70	≥ 80	≥ 90	≥ 100	Baseline
PR_U2_W	0.721	0.733	0.743	0.700	0.700	0.703	0.741	0.742	0.744	0.751	0.958
PR	0.735	0.747	0.756	0.704	0.702	0.706	0.745	0.745	0.746	0.752	0.949
PR_U	0.738	0.740	0.749	0.699	0.701	0.704	0.744	0.743	0.745	0.752	0.951
CON_T_W	0.730	0.739	0.747	0.701	0.702	0.706	0.746	0.747	0.748	0.754	0.944
CON_T	0.740	0.743	0.750	0.700	0.700	0.704	0.746	0.746	0.747	0.753	0.946

One explanation for the less performing results is that the key classes may have a better design than the rest of the classes, which means that are less prone to change. If the

1 key classes are less prone to change, then the associated connection strength metric has a
2 lower value than for other entities.

3 Tables 11 and 12, provide us a better overview of the update behavior of key classes
4 in the versioning system. The commit count column presents the number of commits in
5 which the entity was involved. The column 'Max occurrence with another entity' con-
6 tains the maximum number of updates with another entity from the system (the strongest
7 connection with another entity).

8 It can be observed that some key classes change a lot in the versioning system, for
9 example, Configuration for Hibernate and ProjectHelper for Ant. Also, some classes cre-
10 ate strong connections with other entities, like IntrospectionHelper for Ant and Table for
11 Hibernate. But, in most cases, the key classes are not the entities that update the most in
12 the versioning system. So, by setting too high the connection strength threshold, we risk
13 filtering out the key classes.

Table 11. Ant key classes update overview.

Key class name	Commit count	Max occurrence with another entity
org.apache.tools.ant.Task	40	13
org.apache.tools.ant.Target	39	16
org.apache.tools.ant.IntrospectionHelper	52	43
org.apache.tools.ant.RuntimeConfigurable	38	16
org.apache.tools.ant.ProjectHelper	67	17
org.apache.tools.ant.TaskContainer	6	2
org.apache.tools.ant.Main	56	21
org.apache.tools.ant.UnknownElement	47	16
org.apache.tools.ProjectHelper2\$ElementHandler	21	14

Table 12. Hibernate key classes update overview.

Key class name	Commit count	Max occurrence with another entity
org.hibernate.Query	9	1
org.hibernate.engine.spi.SessionFactoryImplementor	26	10
org.hibernate.SessionFactory	20	3
org.hibernate.mapping.Table	39	25
org.hibernate.criterion.Projection	2	0
org.hibernate.criterion.Criterion	2	0
org.hibernate.engine.spi.SessionImplementor	16	2
org.hibernate.cfg.Configuration	88	9
org.hibernate.mapping.Column	16	3
org.hibernate.type.Type	10	0
org.hibernate.Transaction	9	0
org.hibernate.engine.ConnectionProvider	2	0
org.hibernate.Session	25	14
org.hibernate.Criteria	10	1

5.5. Comparison between results obtained with strength versus confidence metric

As mentioned in section 2.4, we did not use the confidence metric because it does not consider the big picture of the system. A co-changing pair $A \rightarrow B$, where A updates only once in the entire history, and when it updates, it updates together with B, will have the best confidence value that we can get. This is why we introduced the strength metric, to balance the metric in the favor of those which update more frequently. Since both metrics require the same inputs and only the calculation method is different, we computed with our tool the confidence metric and applied the same threshold to it as to the strength metric. The only difference from how other authors computed the metric is that we multiplied its value by 100. So, the confidence values can fluctuate between 0 and 100. In the graph used by the key classes detection tool, the structural dependencies weights are supraunitary values. So, we multiplied with 100 the confidence value to scale it to the structural dependencies weights. Otherwise, if we add a subunitary value (confidence value) to a high value (the structural weight), it will not make a difference, so we will not be able to see the impact of the logical dependencies in the graph.

Table 13. Average results obtained with strength versus confidence metric.

Metric used	Using	
	Only logical dependencies	Structural and logical dependencies
Average values obtained for all systems		
strength	0.791	0.916
confidence	0.731	0.893
Average values obtained for Ant		
strength	0.826	0.903
confidence	0.741	0.873
Average values obtained for Tomcat Catalina		
strength	0.816	0.910
confidence	0.752	0.878
Average values obtained for Hibernate		
strength	0.732	0.935
confidence	0.699	0.929

The comparison between the average values obtained by using the confidence metric and the strength metric, can be found in table 13.

These results help us answer the third research question: *RQ3: Does the connection strength filter has a favorable impact on the results obtained?*. As we expected in our initial hypothesis and now based on the results, we can say that the connection strength metric is more suited for logical dependencies detection. So, by considering the mean update frequency of the entire system in the filtering process, we improve the detection of logical dependencies.

6. Threats to validity

We will present in this section some aspects that can constitute threats to the validity of the results from this paper. First, we extract co-changes only from main (master) branch commits. Development branches are not taken into consideration, which might cause some information loss. Especially if there are many branches in development with many commits

1 in them. On the other hand, if we designed the tool that extracts co-changes to consider
 2 also development branches, that would have constituted another threat to the validity.
 3 Some branches are just for try and error or prototyping, or sometimes they never get in-
 4 tegrated into the main branch, which means that we risk analyzing information that does
 5 not reflect the reality of the system. Another threat to the validity of the results is that we
 6 do not consider the age of the co-changes. It can happen that two entities updated together
 7 a lot because they were also structurally related entities, but, at some point in time, that
 8 connection was removed from the code, and they do not update together any longer. In
 9 this case, it can happen that the tool still considers them logical dependencies due to the
 10 frequency of updates. In future works, we will try to identify outdated connections.

11 7. Conclusions

12 In this paper we studied the filtering and the usage co-changes extracted from the version-
 13 ing system. In the first part of the paper we focused on the co-changes filtering, and in the
 14 second part we used the filtered co-changes (logical dependencies) to detect key classes.
 15 For co-changes filtering, we applied the commit size filter and the filter based on connec-
 16 tion strength. The co-changes that remained after filtering, called logical dependencies,
 17 were provided as input for a tool that detects key classes.

18 We approached two scenarios to detect key classes by using logical dependencies. In
 19 the 1st scenario, we used logical dependencies together with structural dependencies and
 20 in the 2nd, we used only logical dependencies to detect the key classes. We modified
 21 the tool used in the baseline approach to use also logical dependencies, and then we
 22 performed the key class identification.

23 Based on the results obtained, compared with the baseline results, we did saw a slight
 24 improvement in key class detection when both logical and structural dependencies were
 25 used together. The best results were obtained with a connection strength threshold of 40-
 26 70. When we used only logical dependencies to detect key classes, the results were less
 27 performing than using only structural or structural and logical dependencies combined.

28 To give some context on the results that we obtained, we will enumerate in this para-
 29 graph what other authors had obtained. Even though the approaches were not the same,
 30 most of them used the ROC-AUC metric to evaluate the quality of the results, same as us.
 31 Osman et al. obtained in their research an average ROC-AUC score of 0.750 [18]. Thung
 32 et al. obtained an average ROC-AUC score of 0.825 [25] and Şora et al. (our baseline
 33 approach) obtained an average ROC-AUC score of 0.894 [17].

34 In the current research, we obtained an average ROC-AUC score of 0.916 when us-
 35 ing logical and structural dependencies combined and a score of 0.791 when using only
 36 logical dependencies to detect key classes.

37 So, when using both dependencies combined, we can obtain a slightly better ROC-
 38 AUC score than the one from the baseline approach. And, when using only logical de-
 39 pendencies, even though we do not obtain a better score than the baseline approach, we
 40 obtain results that can be compared with results obtained by other researchers.

41 We consider this a very positive result because this research uses a different type
 42 of input than the previous ones, the logical dependencies. It is also an open door for
 43 new research in multiple fields that use structural dependencies to gain knowledge about
 44 software systems. And since logical dependencies are easy and fast to extract from the

1 versioning system and do not depend on the language of the software system, the cost of
 2 integrating them is small.

3 To sum up the findings of this paper, logical dependencies can be used to gain knowl-
 4 edge about software systems. We consider that the advantage of using only logical depen-
 5 dencies is that it only uses data extracted from the versioning system and can be general-
 6 ized to various programming languages.

7 In the future, we want to check if there are also other areas that can be improved by
 8 using logical dependencies, like software clustering [8], [20], [5].

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