Towards Quantifying the Development Value of Code

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ABSTRACT

Quantifying the value of developers' code contributions to a software project requires more than simply counting lines of code or commits. We define the *development value* of code as a combination of its structural value (the amount of work it represents and the amount of work it saves other code) and its non-structural value (the impact of the change in development). We propose techniques to automatically calculate both components of development value and combine them using Learning to Rank. Our preliminary empirical study shows that our analysis yields richer results than human assessment or simple counting methods, and demonstrates the potential of our approach.

1 INTRODUCTION

Developers contribute code to software project repositories. Those code contributions are typically characterized by simple metrics such as the number of commits (NOC) or lines of code (LOC). For example, GitHub uses NOC to rank developers of a project [13]. Expertise Browser [33], a classic tool for identifying developers' expertise, uses the number of changed LOCs as an indicator. Such metrics measure the *amount* of code contributions, rather than their *value*. For example, a function at the core of the application logic is probably more valuable than an auxiliary script.

There are many use cases where we need to compare and recognize the *value* of different developers' contributions. While traditional value-based software engineering [3, 5, 32] focuses on creating *economic value* as a way to prioritize resource allocation and scheduling, other measurements of value may be more relevant in some of the use cases. One example is that instructors need a tool to evaluate individual students' contributions to group project code in team projects. Such valuation of code contributions has nothing to do with economic returns. As a second example, an engineering manager may need a quantitative measurement of team members' performance. Additionally, for free and open source software (FOSS) projects, it is not necessarily meaningful to assign economic value to contributions, yet developers' contributions heavily influence collaboration, coordination, and leadership [26, 38]. Finally, software engineering researchers observe development activities *per se*, but not necessarily their economic returns. As the above Expertise Browser case shows, a new quantitative tool for the code value would help better understand software development processes.

In this paper, we outline our work to *quantify the value of code contributions in software development*, that is, the *effect on development activities* of contributed code. In general, code that addresses a time consuming development task has higher value than code that addresses an easier task; code that saves a huge amount of other developers' effort has higher value than code that saves little. Therefore, we define *development value* as a quantification of the development effort embodied in a code contribution and the development effort that the code contribution saves other developers.

We factor the development value into *structural* and *non-structural* components. The structural value reflects the effect of the code structure on development activities: A function that is called by many callers "reduces the workload" on those callers and thus tends to be of high value. Based on this observation, we design *DevRank*, a variant of PageRank to derive development value from the function call graph. On the other hand, not all development value is reflected in code structure. Through interviewing three open source developers, we find that developers judge the value by classifying the impact of commits. We explore the possibility to automate the commit classification by utilizing the commit messages that usually describe what impact the code makes. We apply natural language processing (NLP) and machine learning (ML) techniques. Finally, we train a learning-to-rank (L2R) model to find the best combination of the structural and non-structural value to generate an overall score of development value.

The rest of the paper describes structural analysis, non-structural analysis and their combination in §2, and our preliminary empirical study in §3. We discuss the next steps in §4 and related work in §5.

2 DEVELOPMENT VALUE

We postulate that a code contribution carries two kinds of value. The *structural value* reflects its role in the structure of the program (§2.1). The *non-structural value* reflects the impact to the project in a way that code structure alone does not (§2.2). This section describes how we compute both kinds of value, and how we combine them to get an overall value of a code contribution (§2.3).

2.1 Structural Value: DevRank

In most imperative programming languages, a function (procedure, method) is a basic unit of program structure. Functions both provide a way to divide a complex task into subtasks and enable reuse of code that is called from multiple sites. Therefore, the development value of a function is based not only on the effort spent creating the function, but also the effort saved when other code calls the function. The structural component of the development value (structural value) is captured by our graph-based algorithm *DevRank*, which is an extension of the original PageRank algorithm.

PageRank [7] is the basis for Google Web Search, and finds applications in various domains [15]. The algorithm runs over a

directed graph of web pages. It hypothesizes a *web surfer* with assumed visiting behavior, and iteratively calculates the probability that the surfer visits each page. The meaning of the calculated probabilities depend on the behavior of the surfer. In the original PageRank, the surfer does two random actions: (1) upon arriving at a page, with probability α, the surfer randomly selects a link on that page to follow, and visits the linked page; (2) with probability $1 - \alpha$, the surfer teleports to a random page and continues. The damping factor α is a fixed probability chosen in advance. Based on the behavior, the resulting probability reflects how likely a page is visited according to the link structure of pages. Intuitively, what is reflected is the popularity or importance of a page on the web.

To compute each function's structural value, we analyze the code repository's *function call graph*. Of course, program *execution* never randomly jumps to an irrelevant function as in PageRank. However, we find that PageRank is a surprisingly convenient model to characterize code *development*. First, we interpret random teleportation as navigating the *development activities* of the code, rather than execution behavior. Second, we consider not only the instantaneous state of the function call graph, but its development *history* as revealed by revisions in a revision-control system over time.

In DevRank, the hypothetical "surfer" becomes a *development sniffer*, whose task is to detect development effort. To construct the behavior of the sniffer, we assume that the development effort spent on a function is revealed by the total LOCs of all changes that result in the function across the development history. We believe it can more precisely quantify the development effort than only counting the LOCs at a specific snapshot. Based on this assumption, the sniffer performs two random actions. (1) Upon arriving at a function, with probability α, it visits one of the called functions with probabilities proportional to the development efforts of those functions. That means the more development effort associated with a called function, the more likely it is visited. As we regard calling a function as a way to save development effort on the caller, this behavior reflects how much development effort is saved by coding a call to each function. (2) With probability $1 - \alpha$, the sniffer teleports to a random function with a probability proportional to the development effort of the function. Such teleportation can be explained as the sniffer's search for development effort. Overall, we can see that the resulting probability of the sniffer showing up on each function reflects the development effort spent on the function and that the function saves other developers' effort. Therefore, it reflects the development value of a function.

A *commit* is a group of changes made atomically to a subset of files in the repository. After computing DevRank scores for functions, we can distribute development value of functions to commits, and further to developers. This is done by allocating the value of a function to all commits that change the function, proportionally to their LOCs and then assigning the value of commits to their corresponding authors. In this way, developers receive credits for their contributions to the development value.

2.2 Non-Structural Value: Impact Coding

Not all development value is embodied in the code structure. A code contribution also has a *non-structural impact* on the whole project, e.g., fixing a bug, making an improvement, creating a new feature, or maintaining a document.

Our proposal for measuring non-structural value is inspired by how human developers assess a code contribution's non-structural impact on the project. We interviewed three open source developers: an author of a popular Twitter client and two FreeBSD developers each with over ten years of experiences. Specifically, we asked them to give a free-form answer to the following question: what procedure would they use to compare the values of two randomly-chosen commits from a project? Despite the vast answer space, all three interviewees mentioned that they would start with commit classification by what kind of impact a commit has on the project. One of the FreeBSD developers even gave a comprehensive list of his personal hierarchy of commit-value as follows: "fix for build errors > fix for severe non-build errors > important new features > fix for severe speculative errors > fix for minor errors > regular new features > cosmetic errors > source code hygiene".

Although we hesitate to use the above hierarchy as ground truth, as it is subjective and may vary among developers, we do think that the impact type of a commit is an important feature for determining its non-structural value. Therefore, we introduce *impact coding* to capture such non-structural value. Impact coding classifies a commit according to a predefined set of impact categories. Previous work defines related categories of development activities [17, 23], but focuses on only certain aspects of software development (e.g., maintenance). To construct a set of impact categories that comprehensively represent non-structural value, we plan to conduct a large-scale survey and let developers freely express their reasons for commit value comparisons, and analyze their responses following the grounded theory approach [14]. This approach will inductively generate impact categories during the labeling of data.

The impact coding is aided by the fact that many communications among developers are computer-mediated [35, 41]. Each code commit is associated with a *context* developers implicitly build in development activities. The context records a natural-language description of the commit in bug/issue tracking systems, pull requests or commit messages [10, 39]. Those natural-language descriptions provide an adequate corpus for constructing a machine learning model to infer the impact category of a commit. We refer to this approach as *context learning* and give a concrete example in §3.3.

2.3 Combining DevRank and Impact Coding

As structural and non-structural analyses capture two fundamental aspects of development value, we combine the two to calculate overall development value. Suppose a commit has structural value d and non-structural value $\mathbf{t}$. Our goal is to find a function φ that combines them: $v = \varphi(d, \mathbf{t})$. In our solution, d is the DevRank score, and $\mathbf{t}$ is a one-hot vector encoding of the commit category.

If we had reliable ground truth—that is, a large set of commits with the known overall development value of each commit—we could pose the task as an optimization problem: from the data set, determine the weight vector $\mathbf{w}$ in

$$\varphi(d, \mathbf{t}) = \mathbf{w}^\mathsf{T} \begin{bmatrix} d \\ \mathbf{t} \end{bmatrix},$$

so that the average error between the true value and $\varphi(d, \mathbf{t})$ of every commit is minimized.

Unfortunately, developers find it very hard to directly score code values, e.g., giving one commit 0.17 and another 0.06, so we lack the reliable ground truth in that form. Instead, we can ask developers to compare many pairs of commits and identify which of each pair is more valuable. It is a much easier question to answer. Based on this "pairwise ground truth," we can use a learning to rank (L2R) algorithm to determine φ. There are several established algorithms for training the model, including Ranking SVM [16], IR SVM [8] and RankBoost [11]. We use the DevRank score d and the one-hot encoded commit category $\mathbf{t}$ as the input features to, for example, Ranking SVM. After training, we take the weight vector of the SVM as $\mathbf{w}$ in $\varphi(d, \mathbf{t})$. This method allows us to combine the structural and non-structural value scores for each commit to determine its overall development value score.

3 PRELIMINARY EXPERIMENTS

Our current experiments make three points: a case study in the education setting shows the limitation of human assessment and motivates our quantification approach; the different results of DevRank and LOC-counting show the effects of capturing structural value; the performance of mainstream ML models in classifying non-structural impacts reveals both opportunities and challenges.

To collect empirical evidence, we assemble two data sets: (1) course surveys of students required to assess teammates' contributions in a software engineering course; (2) over 250k issues and associated commit messages collected from Apache Software Foundation projects, for training the context learning models.

3.1 Human Assessment Is Not Reliable

Developers may assess code value through their understanding of the code, and their experience with and impressions of other developers. However, those factors are biased by social factors and personal interests. To better understand the limitations and the validity of human assessment, we surveyed 10 teams of students (58 students total) in an undergraduate software engineering course of a major research university. Each 8-week-long project is divided into four 2-week-long agile development iterations. After each iteration, individual students are asked to evaluate their teammates' code contributions during that iteration, by assigning team members (including themselves) shares normalized to 100% total.

We keep statistics of each student's self-assigned share and shares received from teammates. First, we see that most students receive very different amounts of shares from their teammates, showing the subjectivity in human value assessment. We examined the average correlation between students' ratings. For each possible pair of students in a team, we computed the Pearson's r coefficient between their ratings. By averaging all teams and pairs, the overall Pearson's r is 0.52, only indicating moderate level of agreement among students. Second, students' self-assigned shares are 18.36% more than their peer-assigned shares on average, suggesting that their self-assessment is subjectively more optimistic than their peer assessment. This reflects the influence of personal interests.

3.2 LOCs Incompletely Capture Value

To observe the effects of DevRank, we performed a comparison experiment on the Linux kernel project. We evaluated the code contributions in the Linux kernel code at the function level using DevRank and LOC separately and compared their results.

We first extracted LOC information for each function by parsing the source code of release version v4.14 using a static analysis tool named srcML [25]. We collected 458,054 functions from 45,959 source files. Then we computed DevRank values for all functions by analyzing 5,000 commits on the master branch before release v4.14. Since DevRank values sum up to 1, we normalized LOCs by dividing individual functions' numbers with their sum to make them comparable to DevRank values. We experimented with multiple α values and empirically set α to 0.5 for most following analysis.

If we rank functions by their normalized LOCs and DevRank values respectively, the generated rankings by LOC and DevRank are very different: the Kendall's τ between these two rankings is 0.64, only indicating moderate level of agreement.

We further explore DevRank's effects on different functions by computing the ratio between each function's DevRank value and normalized LOC. Figure 1 shows this ratio for all functions in log-scale and descending order. A positive log-scale ratio suggests that the function's DevRank value is larger than its normalized LOC. In other words, DevRank amplifies this function's contribution, compared to normalized LOC. We observe from Figure 1 that DevRank amplifies contributions of a small portion of functions, which account for 20.9% of the total number of functions.

However, the small portion of functions get huge contribution gains while the rest majority's contributions do not change much. For example, `memset`'s DevRank value is more than 8,000 times of its normalized LOC. The scale of the amplification effect is moderated by the parameter α of DevRank. As α decreases, this amplification effect would diminish. In fact, when α becomes 0, the DevRank value would converge to the normalized LOC. One limitation of DevRank algorithm is that it may over-estimate the contributions of some simple utility functions because of their high in-degrees in the call graph. For example, `check_memory_region` is ranked among the most valuable functions under the `mm` directory. To avoid this issue, we filtered out these simple utility functions by setting a threshold of the number of LOCs (20 by default) before ranking.

Table 1 shows the 5 most valuable functions under the `mm` (memory management) directory by DevRank and LOC counting after filtering out the simple utility functions. We look into the top functions `slob_free` and `shrink_page_list` on the two rankings, respectively, and showcase how DevRank better models the development value of code. `shrink_page_list` performs page frame reclamation, while `slob_free` is used to free SLOB blocks. `shrink_page_list` has a larger LOC number than `slob_free`, but both have to check and deal with many cases in their algorithms. If we only compare LOCs, `shrink_page_list` seems likely to embody more development value, but `slob_free` is called about 3,500 times[1] more than `shrink_page_list`. Every time `slob_free` is called, the slob allocator saves developers effort to deal with the memory allocation issue. That is also a form of development value we should consider.

[1] Most of the calls are through `kfree`.

Moreover, as the memory allocator is so frequently used, many efforts have been spent on improving its efficiency in Linux [6, 21, 27]. We believe that taking into account the call structure as in DevRank gives a fairer evaluation of `slob_free`'s development value.

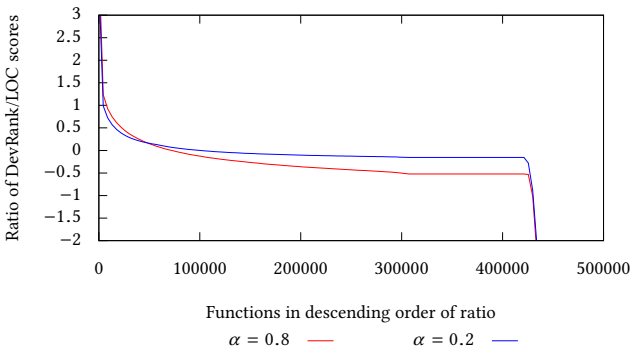

Figure 1: Ratios between a function's DevRank score and its LOC. $y = 1$ means both scores for a function are identical. Legend keys, i.e., 0.2, 0.8, are the values of α in DevRank.

	#	Function	File
DevRank	1	slob_free	mm/slob.c
	2	mempool_alloc	mm/mempool.c
	3	dma_pool_free	mm/dmapool.c
	4	kasan_slab_free	mm/kasan/kasan.c
	5	mempool_free	mm/mempool.c
LOC	1	shrink_page_list	mm/vmscan.c
	2	shmem_getpage_gfp	mm/shmem.c
	3	__vma_adjust	mm/mmap.c
	4	balance_dirty_pages	mm/page-writeback.c
	5	__alloc_pages_slowpath	mm/page_alloc.c

Table 1: Most valuable functions under `mm` directory

3.3 Automatic Impact Classification

We leverage the JIRA issue database[2] used by many Apache Software Foundation projects. In the database, developers label issues with predefined types (feature, improvement, bug fix, maintenance). We collect 267,446 issues and their associated commit messages from 139 Apache projects that have top most issues.

We explore three main NLP + ML models: bag-of-words (BoW) [20], a convolutional neural network (CNN) [22], and a recurrent neural network (RNN). For each model, we experiment with two types of inputs: the commit message title and the complete message. We adopt ConceptNet Numberbatch (CN) word embeddings [37]. For all issue types, we show F1 scores in Table 2. We can see that CNN and RNN have comparable performance but outperform the bag-of-words model. The best average F1 score that our CNN model achieves among all classes is 0.60, using full commit messages; similarly, the best average F1 score of our RNN model is 0.59, using commit titles. In contrast, the best F1 score of the bag-of-words model is only 0.55, using commit titles.

[2]https://issues.apache.org/

The models show that some categories of commits are easier to infer than others. For example, the best F1 score for classifying Bug commits is 0.87 (precision 0.88 and recall 0.87, by the RNN model using commit messages), while the best F1 score for classifying maintenance commits is only 0.46 (precision 0.58 and recall 0.38, by the CNN model using full text of commit messages). These differences may be due to the number of commits of each category in the data set: Bug fixes are dominant and numerous, so training for them is more effective.

As a first step, our analysis shows the possibility of automatically classifying commit impact using solely the commit message and a neural network model. Overall, identification of Bug fixes and Improvements can be regarded as usable for DevRank, but that of less-represented categories is still too low. As part of our future work, we hope to improve the accuracy of automatic classification with a more comprehensive data set and optimized models.

	Maint.	Feature	Improv.	Bug
# commits	329	1517	14136	28818
BoW-title	0.28	0.34	0.63	0.85
BoW-message	0.2	0.33	0.62	0.85
CNN-title	0.37	0.39	0.65	0.86
CNN-message	0.46	0.39	0.64	0.87
RNN-title	0.4	0.35	0.67	0.86
RNN-message	0.33	0.36	0.68	0.87

Table 2: Performance (F1 score) of three NLP + ML models for context learning.

4 ONGOING WORK

We are planning a larger-scale survey of developers to collect commit-comparison reasons and results from developers as the ground truth for analysis and training. Such a data set will help us construct the impact categories for non-structural analysis and also allow us to experiment with more advanced machine learning models: both context learning and L2R should improve with more training data. We will open the data set for public use, to hopefully stimulate collaborative efforts in this research direction.

Our current implementation only supports C/C++ and Java. We are adding support for dynamic languages such as Python and JavaScript, which requires implementing static typing [1, 2].

5 RELATED WORK

PageRank-like algorithms have been used to portray developers [12, 18, 30] or their social relationships [4, 24, 29, 34]. Our DevRank is a variant of PageRank adapted to reflect the development value.

Effort-aware models [28, 31] consider the development effort in software engineering, and different effort estimation schemes have been proposed [9, 19, 36, 40]. A key difference of our work is to additionally consider the effort that is saved, instead of merely the effort that is spent, as we have seen in the `slob_free` example in §3.2. Meanwhile, DevRank can be extended to use a more advanced effort estimation scheme (e.g., polynomial, churn). The framework and methodologies of our work are orthogonal and remain applicable.

6 CONCLUSION

There are commercial, pedagogical, and stewardship reasons to evaluate the impact of individual code contributions to a large code

base. This task is difficult for developers to do manually, not only because of the subjectivity inherent in the task but also because few developers have a wide enough view of the entire project to do it effectively and in a manner well-calibrated to their fellow developers. To make the process both objective and amenable to automation, we postulated that a given code contribution has both structural and non-structural value, and proposed a combination of a PageRank-inspired algorithm and an impact coding scheme through manual labels or a machine learning model trained from developer's artifacts. We hope this on-going research work will finally enable and support an even stronger ecosystem of contribution-based projects with a "very long tail" of contributors as well as giving developers and project leaders better insights on the relative strengths of their own contributors and code.

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