# Towards the Assisted Decomposition of Large-Active Files

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Abstract—Tightly coupled and interdependent systems inhibit productivity by requiring developers to carefully coordinate their changes, even when modifying subsystems that should be independent of one another. Poor architectural decisions frequently lead to the presence of large, change-prone source files that are at the center of complexes of technical debt [11, 6]. This kind of technical debt quickly incurs interest both through coordination costs and error-proneness. In this paper, we present a new approach for decomposing these "large-active" files to pay down critical technical debt. We package our approach as a refactoring recommendation system. Each recommendation is determined by analyzing patterns of co-change and mutual dependency among files. Each recommendation corresponds to a responsibility the large-active file has in relation to the rest of the system. By moving recommended functionality from the largeactive file into smaller files, developers can reduce the impact of a debt-laden file and clarify its essential responsibilities. A key advantage of this approach over prior work is that we better focus effort; we avoid spending developer effort refactoring code that is only superficially problematic. We achieve this by incorporating revision history into both determining and ranking recommendations. Each recommendation corresponds to some change-prone responsibility. We present some examples of this approach in action and outline our future plans.

Index Terms—refactoring, design improvement, software architecture

#### I. INTRODUCTION

The difficulty of modularizing a system so that developers can work independently of one another is as old as software development [14]. While some development tasks are inherently sequential, even those that should be parallel often turn out to be coupled in frustrating ways. A common place where developers discover this coupling is deep within the bowels of large, ever-growing, and frequently changing source files. Because of their extensive influence on the rest of the system, these large-active files often need to be changed for seemingly unrelated reasons. Developers working on otherwise parallel tasks must therefore carefully coordinate with one another to successfully modify such files. These files are often identified by smells such as god file [3], unstable interface [11], or crossing [11]. Recently, this observation was given empirical backing when the presence of large-active files was shown to the strongest indicator of technical debt [6]. In this paper, we present our novel method of algorithmically recommending operations that can modularize a large-active file to increase the overall parallelism of the development team.

No existing refactoring recommendation system is able to directly eliminate a large-active file. Instead, most existing refactoring recommendation systems function by recommending operations that improve quality metrics [5, 13, 9, 10, 1]. These systems use quality metrics to measure global characteristics like coupling, cohesion, maintainability, etc. These measurements are then used as the targets of a multiobjective search algorithm to find a sequence of refactoring steps. However, no particular attention is paid to large-active files despite these often being the focal point of maintenance activities. In fact, no attention is paid at all to the activity or *co-activity* of files as change history is ignored by these existing systems. So while these systems will improve their selected quality metrics, and while some of these quality metrics will encourage smaller files, it is not likely that these systems will reliably decompose a large file into its constitutive parts, let alone a large-active file. Furthermore, because change history is not considered, it is possible that these approaches are not prioritizing code that is incurring the most effort and the greatest interest. Given the recent evidence suggesting that these files play a central role in the worsening of technical debt, it is especially important to have algorithms aimed specifically at the decomposition of excessively large and active files.

A large-active file with many dependents is problematic because of the extensive influence it has on the rest of the system that prevents parallel changes and inhibits modularity. This influence can be seen in the number of files dependent on it (direct or otherwise), and in the number of times it has cochanged with other files. Our approach is a form of ensemble clustering that uses these shared influences to calculate the similarity between members of the target file. The resulting clusters are served as recommendations to reduce the influence that this file has on the rest of the system. These refactoring recommendations identify clear responsibilities of the largeactive file and guide a developer to pull these out into their own file. When a developer refactors according to her choice of recommendation, she is reducing the influence of the target file while also narrowing its actual responsibilities to only the most essential.

The promise of our approach is already evident in our early results. These results indicate that our algorithm successfully recommends cohesive clusters of functionality, each associated with a distinct responsibility of the target file. Specifically, we have found the most promise in "utility" files that span many responsibilities of the system. These kinds of files are easy to evaluate because of their deliberate nature. Still, our goal with this approach is to find more subtle distinctions that a developer might miss. This evaluation is left as future work.

This work is significant because it is the first to offer a way to directly decompose large-active source files, improving their cohesion, thus enabling parallel developer activity and reducing their unwarranted (bug-producing, churn producing) complexity. Large-active source files have repeatedly been shown to correlate with technical debt and software decay. This correlation stems for the extensive influence they have on the rest of the system. Our approach promises to reverse this influence, decreasing the influence of a large-active file on the rest of the system.

### II. APPROACH

Our refactoring recommendation approach is designed to disentangle large-active files. An excellent formulation of the problem is the unstable interface anti-pattern of Mo et al [11]. An *unstable interface* is a file with many dependents that also changes frequently with those dependents. We identify two core problems any unstable interface will exhibit.

- a) A poor separation of concerns. This file must be changed for many different reasons. Other files use this file for many different reasons.
- b) A poor separation between interface and client. This file must be changed with many of its clients in the same commits. This implies that a poor abstraction boundary was drawn between components. Implementation details of the unstable interface may be leaking into the clients.

We address these two problems separately using distinct algorithms. Then we aggregate and rank the recommendations from both algorithms. The top recommendations are given to the developer.

# A. Interface Splitting

The goal of the interface splitting algorithm is to reduce the responsibilities of the target file to its most essential by pulling other responsibilities out and placing them in their own file.

Let T be the set of functions found in the target file and D be the set of files that are dependent on the target file. Then for any target function  $t \in T$ , let  $d(t) \subseteq D$  denote the subset of dependents that use that function. This dependency could be a direct function call, a transitive function call, or a co-change dependency mined from the revision history.

To determine if two functions,  $t_i$  and  $t_j$ , serve the same responsibilities, we check the similarity of their respective dependent sets,  $d(t_i)$  and  $d(t_j)$ . The dependent set of any particular function captures the responsibilities it has to the rest of the system. Let the Jaccard index  $s_{ij} = |d(t_i) \cap d(t_j)|/|d(t_i) \cup d(t_j)|$  be this similarity. Notice that the more clients these two functions have in common, the higher  $s_{ij}$  is, and the fewer they have in common, the lower  $s_{ij}$ 

is. So pairs of functions with a high  $s_{ij}$  are considered to play a similar role in the wider system.

Then, to discover subsets of T that may serve as cohesive stand-alone files, we cluster the rows (or equivalently, columns) of the square similarity matrix  $\mathbf{S}_s = [s_{ij}]$  and take each resulting cluster as a candidate recommendation. Functions that serve similar sets of clients should be grouped together, while functions that serve not-so-similar sets of clients should be separate. There are many clustering algorithms of this sort in the literature [18], but for now, we simply assume that whichever algorithm is chosen is parameterized with some scalar or vector value  $\theta$ . For instance,  $\theta$  may be the desired number of clusters.

Because we do not want the developer to have to specify the parameter themselves, we require the use of a heuristic function  $g_q(\mathbf{S}_s) = \theta_q$  that "guesses" a good parameter for clustering the similarity matrix, where q = 1 is the highest quality guess, q = 2 is the second highest, etc. Examples of ginclude the silhouette coefficient [15] and the spectral gap [8].

The interface splitting algorithm proceeds as an ensemble clustering algorithm [17]. First, the similarity matrix  $S_s$  is calculated. Then, the best guess parameter  $\theta_1$  is derived from the similarity matrix. The clustering algorithm is executed with  $\theta_1$  and the resulting clusters are added to the multiset of recommendations R. Then, the next-best guess  $\theta_2$  is calculated,  $S_s$  is re-clustered, and the clusters are added to R. This process continues until  $q = q_{\text{max}}$ . Finally, each recommendation of R is ranked, first by multiplicity then by average change frequency, both in descending order.

### B. Interface Redrawing

The goal of the interface redrawing algorithm is to alter the boundary between the target file and its clients so that future changes are less likely to modify both sides of the interface. The interface redrawing algorithm is similar to the interface splitting algorithm but instead of only considering functions of the target file, functions of the client file are also considered. The algorithm recommends subsets containing functions from both sides of the interface to the developer. A recommended subset may then either be extracted into its own file so it is a new client of the interface, or it may be moved into the target file so it is "behind" the interface.

Let C be the set of commits found in this project and  $c(f) \subseteq C$  be the set of commits where the function  $f \in (T \cup D)$  changed. Let  $\mathbf{S}_r = [s_{ij}]$  be a rectangular similarity matrix where rows correspond to target functions and columns correspond to client functions. Each entry is the Jaccard index  $s_{ij} = |c(t_i) \cap c(d_j)|/|c(t_i) \cup c(d_j)|$ . This is the similarity between the change history of the target function  $t_i$ and the client function  $d_j$ . It does not matter if  $d_j$  actually calls  $t_i$  because their co-change relationship alone indicates that they depend on one another. We conjecture that these co-change relationships reveal locations where implementation details of the target file are being leaked to clients.

By clustering the rows and columns of  $S_r$  at the same time we discover portions of the interface that are prone

TABLE I INTERFACE SPLITTING – SELECTED RECOMMENDATIONS

-	
	Recommendation
1	Utils.java > getApplicationLabel
	Utils.java > getBadgedIcon
3	Utils.java > getFaceManagerOrNull
	Utils.java > getFingerprintManagerOrNull
	Utils.java > hasFaceHardware
	Utils.java > hasFingerprintHardware
	Utils.java > isMultipleBiometricsSupported
6	Utils.java > getCredentialOwnerUserId
0	Utils.java > getUserIdFromBundle
9	Utils.java > getSecureTargetUser
	Utils.java > hasMultipleUsers
10	Utils.java > getBatteryPercentage
10	Utils.java > isBatteryPresent
	Utils.java > createAccessibleSequence
	Utils.java > enforceSameOwner
12	Utils.java > getCredentialOwnerUserId
	Utils.java > getCredentialType
	Utils.java > getUserIdFromBundle

to instability and leakage. Each resulting cluster contains functions from both sides of the interface that tend to change together. In general, this form of clustering is known as co-clustering [2]. As before, we sidestep discussion of specific co-clustering algorithms and instead focus on the parameter  $\theta$ . Here, we also require a heuristic function  $g_q(\mathbf{S}_r) = \theta_q$  that can provide promising parameters for co-clustering the similarity matrix.

The interface redrawing algorithm proceeds as an ensemble clustering algorithm [17]. First, the similarity matrix  $S_r$  is calculated. Then, the best guess parameter  $\theta_1$  is derived from the similarity matrix. The co-clustering algorithm is executed with  $\theta_1$  and the resulting co-clusters are added to the multiset of recommendations R. Then, the next-best guess  $\theta_2$  is calculated,  $S_r$  is re-clustered, and the co-clusters are added to R. This process continues until  $q = q_{\text{max}}$ . Finally, each recommendation of R is ranked, first by multiplicity then by average change frequency, both in descending order.

## III. EARLY RESULTS

To demonstrate the promise of our approach, we present the results of our recommendation system on a large-active file from the Android operating system. The Utils.java<sup>1</sup> source file of the Settings<sup>2</sup> application is the third most depended-on file in the system with 243 clients and the sixth most changed file with 271 commits over a two-year period.<sup>3</sup> Our approach successfully recommends cohesive refactoring operations that would reduce the influence of the large-active file and potentially enable further developer parallelism.

### A. Example of Interface Splitting

We implemented the interface splitting algorithm as described in the previous section. We found the most success

 TABLE II

 INTERFACE SPLITTING – DEPENDENT FILES OF NO. 3 IN TABLE I WITH

 # OF OCCURRENCES

File	
CombinedBiometricStatusPreferenceController.java	
BiometricSettingsAppPreferenceController.java	
FaceSettings.java	
FaceStatusPreferenceController.java	
FingerprintEnrollFinish.java	
FingerprintEnrollSuggestionActivity.java	
FingerprintStatusPreferenceController.java	
BiometricFaceStatusPreferenceController.java	
BiometricFingerprintStatusPreferenceController.java	
BiometricsSettingsBase.java	
FaceEnrollIntroduction.java	
FaceSettingsAppPreferenceController.java	
FaceSettingsKeyguardPreferenceController.java	
FingerprintEnrollIntroduction.java	
FingerprintSuggestionActivity.java	
ChooseLockGeneric.java	
SetNewPasswordController.java	

TABLE III INTERFACE REDRAWING – SELECTED RECOMMENDATIONS

	Recommendation
1	Utils.java > getCredentialType
	ConfirmDeviceCredentialActivity.java > onCreate
6	Utils.java > getSecureTargetUser
	SetNewPasswordController.java > launchChooseLock
7	Utils.java > isDemoUser
	<pre>FactoryResetPreferenceController.java &gt; isAvailable</pre>
10	Utils.java > isProfileOf
	SecondaryUserController.java > setSize
12	Utils.java > getManagedProfile
	AccountPreferenceBase.java > onAccountsUpdate
15	Utils.java > getBatteryPercentage
	PowerUsageSummary.java > onCreate
	PowerUsageSummary.java > onPause
	PowerUsageSummary.java > onResume

with the following configuration: (a) the clustering algorithm is the normalized cut spectral algorithm of Shi and Malik [16]; (b)  $\theta$  is the number of clusters; (c)  $g_q$  is the index of qth largest spectral gap [8]; (d)  $q_{\text{max}} = 3$ ; (e) the client set d(t)of any target function t includes both client files that directly call t and those that call t indirectly via a path of intermediate functions.<sup>4</sup>

In Table I, we present some of the more interesting recommendations for splitting Utils.java. Each row in this table is a recommendation to pull these functions out into their own file; otherwise known as an "extract class" refactoring [4].

The promise of this approach is that it frees the developer from having to comb through hundreds of related files and functions to determine an ideal decomposition of a large-active file. Notice how each recommendation corresponds to a clear responsibility of the target file. This is evident in the highly related function names despite lexical information not being used as input. In a large-active file, which functions correspond

<sup>&</sup>lt;sup>1</sup>See src/com/android/settings/Utils.java.

<sup>&</sup>lt;sup>2</sup>See https://android.googlesource.com/platform/packages/apps/Settings.

<sup>&</sup>lt;sup>3</sup>Ending at tags/android-12.0.0\_r3.

<sup>&</sup>lt;sup>4</sup>All intermediate functions must also be inside the target file.

to which responsibilities are far from obvious. This approach saves the developer's effort by providing principled guidance on how to decompose the target file.

For instance, consider Table II which contains the clients of Recommendation 3 from the first table. Clearly, the algorithm has identified the biometrics responsibility of Utils.java and has marked it for extraction because it is change-prone. While this pattern is self-evident when isolated and presented as it is here, noticing this unassisted is a far more challenging task. This approach gives the developer this ability on-demand.

A unique advantage of our approach over existing refactoring systems (discussed in Section V) is that, because we sort by change frequency, we are ensuring that the most highly ranked recommendations are those portions of the file that are incurring the highest maintenance penalties. We avoid recommending refactorings that look attractive purely when looking at the program structure. This avoids introducing needless code churn that would result from refactoring inactive code.

Another novelty of our approach is that we offer a complete "extract class" refactoring as a single recommendation instead of dispersing the recommendations across a series of "move method" operations. The advantage of this is that a developer can immediately see the end result and make a decision without having move forward and backward through a sequence of steps.

## B. Example of Interface Redrawing

We implemented the interface redrawing algorithm with a similar configuration to our interface splitting implementation. The only difference is that we use the co-clustering algorithm of Dhillon [2] which is also based on the spectral algorithm of Shi and Malik [16].

In Table III, we present some of the more interesting recommendations for redrawing Utils. java. Each row in this table is a recommendation to either move these functions into their own file or to move these functions into a relevant client file. We do not yet make the distinction between these cases and instead leave it to the developer to decide. The difference from interface splitting is that we offer functions from both sides of the interface and it is powered entirely by change history. Each of these recommendations is a set of functions that are frequently changing together across the boundary of an interface. By recommending them, we are encouraging the developer to look closely for possible implicit coupling and consider moving them onto the same side of the interface.

No existing approach can locate the specific regions of an interface that are unstable. This provides the antidote to the unstable interface anti-pattern [11] by generating concrete refactoring advice.

## IV. DISCUSSION

This refactoring recommendation approach has the potential to increase the parallelism of developer resources. Large and overactive files are common locations to discover inappropriate coupling between components. This coupling requires careful coordination between developers to work around. The techniques we have outlined in this paper are a first step towards removing these obstacles so developers can work more independently on their desired tasks.

A major novelty of this refactoring recommendation approach compared to existing work is its use of revision history. Each recommendation has been empirically shown to require more maintenance than the rest of the system. This is advantageous firstly because developers avoid introducing unnecessary code churn to repair code that is not causing problems. Some files might, for example, have alarming metric values but if they seldom change and incur few bugs they are not in fact problematic for the project. Secondly, the use of revision history to identify recommendations reveals instances of implicit coupling that would be missed by systems that do not consider revision history. Our approach recommends making these implicit dependencies explicit.

Another advantage of this approach is its focus on resolving the specific problem of large-active files rather than the generalist approach taken by other methods which aim to improve global quality metrics. Large and overactive files have repeatedly been shown to be a source of technical debt and a hurdle to developer parallelism. Our approach directly resolves this issue by offering complete recommendations that would narrow the responsibilities of the target file and improve the stability of its interface.

Because our approach is not global, it is suitable for both root canal and floss-style refactorings [12]. Developers may set aside some time to completely remove a particular large-active file by repeatedly querying for recommendations until there is nothing left of the target file. Or they may simply act upon a single recommendation when they are working on a file. For instance, they may choose to extract the biometric functions out of Utils.java when working on biometric code. Our approach is flexible enough to fit into any developer workflow.

However, our approach suffers from a limitation that prevents it from practical use in its current state: it does not filter out illegal recommendations. First, it is possible that an "extract class" recommendation will create a cyclic dependency between the target file and the newly created file if taken by the developer. Secondly, our approach does not consider constraints introduced by the type system. Our algorithms will recommend refactorings that would break an interface implementation or a class inheritance if taken. We are currently working on solutions to these limitations.

#### V. RELATED WORK

Automated and semi-automated refactoring has received considerable attention in the field of search-based software engineering (SBSE.) An influential approach taken by Harman and Tratt [5] is to optimize for two global quality metrics: coupling and cohesion. Ouni et al. [13] and Mkaouer et al. [10] continued this line of research by introducing new metrics that address the shortcomings of Harman and Tratt. Later, semiautomated approaches were introduced by Mkaouer et al. [9], Alizadeh et al. [1], and Lin et al. [7]. These improved on prior work by allowing the developer to give feedback to the system while refactoring. To our knowledge, our approach is the first to directly target large-active files.

## VI. FUTURE PLANS

As discussed, while our novel approach has the substantial promise of addressing the limits of prior refactoring systems, it is not yet suitable for practical use. Some of the refactorings recommended are illegal. Broadly, this can be remedied by either only searching through legal refactorings, or by tweaking illegal refactorings until they are legal. Further research is required to determine the most suitable method.

Once our approach is ready for practical use, we plan to evaluate our techniques with our industrial partners. Our claim of promise rests on three points: (a) our approach clarifies the responsibilities of the members of large-active files, (b) our approach is flexible enough to fit into any workflow, and (c) our approach reduces future maintenance costs by limiting or even removing the influence of the most debt-laden files. We plan to evaluate the first two points through interviews and extended collaboration with teams. The third point can be evaluated quantitatively through controlled experiments.

In the near future, we are interested in extending this research by using lexical information in the program to recommend names for the newly extracted files. This would further explain the responsibilities of the recommended files and improve the usability and adoption of our approach.

# VII. CONCLUSION

Complex, debt-laden code does not appear overnight. It is created over months and years of gradual erosion of the design. Large-active files are clear examples of this erosion. We have introduced a novel method of decomposing large-active files by using a project's revision history and the shared dependents of functions within the file to form recommendations. Each recommendation highlights a single responsibility. By moving responsibilities of the large-active file out and into their own files, we reduce the overall coupling of the system. When coupling is reduced, developers are more able to work more effectively in parallel and the overall complexity of the system is reduced, which should lead to fewer bugs and simpler changes.

Our approach is the first of its kind to directly target largeactive files and decompose them using their influences. The key advantage of our approach is its use of revision history to ensure recommendations isolate meaningful technical debt. Although our approach is not yet fully-featured, we plan to address its limitations and provide a full evaluation of these techniques soon.

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