CARGO: Al-Guided Dependency Analysis for Migrating Monolithic Applications to Microservices Architecture

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ABSTRACT

Microservices Architecture (MSA) has become a de-facto standard for designing cloud-native enterprise applications due to its efficient infrastructure setup, service availability, elastic scalability, dependability, and better security. Existing (monolithic) systems must be decomposed into microservices to harness these characteristics. Since manual decomposition of large scale applications can be laborious and error-prone, AI-based systems to detect decomposition strategies are gaining popularity. However, the usefulness of these approaches is limited by the expressiveness of the program representation and their inability to model the application's dependency on critical external resources such as databases. Consequently, partitioning recommendations offered by current tools result in architectures that result in (a) distributed monoliths, and/or (b) force the use of (often criticized) distributed transactions. This work attempts to overcome these challenges by introducing CARGO (short for **C**ontext-sensitive lAbel pRopaGatiOn)—a novel un-/semi-supervised partition refinement technique that uses a context- and flow-sensitive system dependency graph of the monolithic application to refine and thereby enrich the partitioning quality of the current state-of-the-art algorithms. CARGO was used to augment four state-of-the-art microservice partitioning techniques that were applied on five Java EE applications (one of which was a industrial scale proprietary project). Experiments demostrate that CARGO can improve the partition quality of all modern microservice partitioning techniques. Further, CARGO substantially reduces distributed transactions and a real-world performance evaluation of a benchmark application (deployed under varying loads) shows that CARGO also lowers the overall the latency of the deployed microservice application by 11% and increases throughput by 120% on average, across various sequences of simulated user actions.

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CCS CONCEPTS

Computer systems organization → Cloud computing.

ACM Reference Format:

1 INTRODUCTION

Businesses are gradually migrating their existing applications to the cloud as their enterprise applications outgrow their monolithic architectures. This allows them to leverage better scalability and reliability, faster development, easier maintenance and deployment, and better fault isolation, among others [1]. This migration requires a decomposition of monolithic applications into loosely connected compositions of specialized microservices [2-4]. However, modernizing an enterprise application with entrenched technology stacks is a challenging task. Manual approaches to modernization consume a significant amount of engineering time and resources [5] and a complete rebuild is rarely feasible. Therefore, big enterprises such as IBM [6], Amazon [7], and GitHub [8] frequently advocate for partitioning applications by identifying functional boundaries in the code that may be extracted as microservices. This has led to a rapid growth of research in using program analysis to automatically discover these functional boundaries and partitions within the application [9-17].

Existing work and limitations. A typical microservice extraction approach starts by converting a monolithic application into a call-graph or control-flow graph representation. Then, an off-the-shelf graph clustering algorithm is used to find loosely connected functional boundaries and make partitioning recommendations. These graph clustering algorithm's performance is directly influenced by the expressiveness and completeness of the graphs it uses. Unfortunately, the program graph used by current techniques are ill-suited to adequately model enterprise applications. The key limitations of current approaches include:

• Missing database interactions: Existing AI-guided microservice partitioning methods miss the interconnections between applications and databases. Transactional databases, which are stored and maintained centrally, are typically used by monolithic enterprise

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applications to execute and persist key business logic. If these interactions are not taken into account, the partitioning guidelines will force the adoption of distributed transactions (such as 2 Phase commits). This represents a considerable effort for developer who must now ensure state changes are coordinated across several services. Further, distributed transactions pose other challenges such as: a) lack of consistency in the data; b) probable safety violations; and c) loss of ACID isolation guarantees [18–20].

• Imprecise program analysis: Popular approaches such as CoGCN [21] and microservice extractor ¹ use context-insensitive staticanalysis which tends to be incomplete and imprecise. Further, these techniques use off-the-shelf static analysis tools such as SOOT [22] and WALA ² which are known to ignore crucial features used by enterprise java applications such as dependency injection [23], and centralized object store [24], among others. This often results in a sparse coverage of several critical sections of the application [25]. To overcome this challenge, certain approaches construct a dynamic call graph by instrumenting the program to amass light-weight traces as the application's many use-cases are exercised [6, 26]. However, for dynamic analysis to be useful, it must be run with sufficient inputs to expose as many different program behaviors as possible, and this can be hard to satisfy. Further, building call-graphs with dynamic tracing has additional drawbacks—it can: (a) be intrusive, (b) lead to a considerable performance degradation, and (c) produce a partially complete representation of the application. **Our approach.** To address the above challenges, we propose a microservice partitioning and refinement tool that statically analyze JEEs application to build a comprehensive, highly-precise, contextsensitive system dependency graph (SDG). Our SDG is a rich graphical abstraction of the Java EE application with various crucial relationships that exist in the application, namely: call-return edges, data-flow edges, heap-dependency edges, and database transaction edges. Our work also proposes a novel community detection algorithm called Context-sensitive lAbel pRopaGatiOn (when abbreviated as CARGO serves as an eponym for our general tool) that isolates "snapshots" of the system dependency graph under various contexts to discover and/or to refine existing partitions into highly-cohesive and loosely-coupled compositions of the program to partition as microservices.

Results summary. We evaluate CARGO on 5 monolithic applications (with 4 open source and 1 proprietary application) a suite of architectural metrics. Further, using CARGO's partitions we modernize a benchmark monolithic application (daytrader), to evaluate it's real-world performance in terms of latency and throughput. Our key findings are listed below:

- CARGO is able to almost eliminate distributed database transactions, both when applied in conjunction with a baseline approach and when applied stand-alone.
- We use CARGO to refine the partitions produced a baseline approach, find that the resulting microservice application has 11% less latency and 120% more throughput than the baseline.
- When we compare CARGO to baseline partitioning approaches on 4 architectural metrics, CARGO is better than the baselines on 3 metrics and inferior on 1.

Contributions. CARGO makes the following contributions to improve the current state of the art:

- (1) CARGO builds a highly precise statically derived system dependency graph (SDG) with full context and flow sensitivity (detailed in §3). The nodes of the SDG represent the methods and database tables in the application. The various inter-procedural edges to express different types of program dependencies between one method and another and transactional edges to highlight relationships between methods and database tables. Together, the SDG constructed by CARGO offers a *fine-granular view* of the an application that includes all it internal and external (i.e., database) relationships.
- (2) CARGO introduces a novel partitioning algorithm based on label propagation (aka. LPA) [27] called *context-sensitive label propagation*. Context-sensitive label propagation (detailed in §3) extracts "context-snapshots" of the SDG, i.e. abstractions of the possible *dynamic state* of the program [28], applies label propagation across all contexts to identify the best functional boundaries in code.
- (3) CARGO offers multiple ways of usage: (i) as a stand-alone tool, wherein the partitions are discovered in an unsupervised manner; or (ii) as an add-on to existing tools, wherein the existing partitions are refined to improve their overall quality.
- (4) CARGO and the associated artifacts will be made available³.

2 BACKGROUND AND MOTIVATION

A recent report shows that only 20% of the enterprise workloads are in the cloud, and they were predominately written for native cloud architectures. This leaves 80% of applications as *monoliths* deployed on-premises, waiting to be refactored and modernized for the cloud. In a monolithic architecture the entire application is bundled into a single package, which includes source code, libraries, configurations, and any other dependencies required for it to execute. Monoliths aren't intrinsically bad, although they do have several drawbacks: (a) Deployment artifacts are often huge, sluggish to start, and consume a substantial amount of resources; (b) changing one component of the program necessitates rebuilding and redeploying the entire application, which slows developer productivity—a challenge that triggered GitHub to migrate away from monoliths to a microservice architecture⁴.

In comparison to monoliths, microservices split an application into discrete units that have clearly defined service boundaries. This offers a number of benefits such as: continuous delivery of large and complex applications, small and easily maintainable applications, low resource-intensiveness, independently deployable and scalable applications, easy fault isolation, and autonomy in development.

The migration from monolith to a microservice architecture is no mean feat. Even a small, seemingly trivial, upgrade to a monolithic software can be time consuming and resource intensive. For example, a rails upgrade to a 10 year old system at GitHub took a year and a half to complete [5]. Therefore, the best strategy to migrate monolithic applications to microservices is to do so incrementally by identifying boundaries in the application such that the functionalities encompassed by them are highly cohesive yet as loosely coupled as possible to other functionalities in the code.

¹https://aws.amazon.com/microservice-extractor/

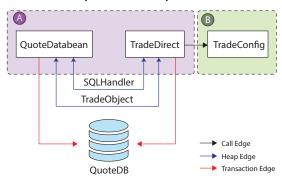
²https://github.com/wala/WALA

³Repository blinded to maintain anonymity

⁴https://www.infoq.com/articles/github-monolith-microservices/



(a) A typical partitioning recommendation for two important classes in Daytrader offered by FoSCI and CoGCN.



(b) Recommended partitioning considering the the high coupling between QuoteDataBean and TradeDirect.

Figure 1: An example from Daytrader that illustrates a distributed monolithic behavior. The two classes QuoteDatabean and TradeDirect lie in different partitions, yet they are tightly coupled by their: a) shared references to TradeObject and SQLConnector; and b) part-taking in a distributed transaction with QuoteDB.

The study of identifying these boundaries has seen a lot of interest lately with prominent industry tools such as Mono2Micro 5 and several others in academia [6, 9–17]. However, when confronted with enterprise applications, each of these approaches faces some difficulties. We will look at a common motivating scenario below and the rest of this paper will attempt to address this problem.

2.1 Motivation

In this section, we use a real-world example to highlight the challenges that may arise when attempting to partitioning a monolith. We use a state-of-the-art microservice partitioning algorithm to partition a monolithic version of a popular JEE trading application called daytrader⁶. Fig. 1 shows an example with three classes from daytrader: QuoteDatabean, TradeDirect, and TradeConfig. Fig. 1a shows the most common partitioning recommendation of these three classes where, partition A contains QuoteDatabean and partition B contains TradeDirect and TradeConfig.

At first glance, this may seem like a reasonable partitioning strategy (especially when inspecting the call-edges between the classes in Fig. 1a), a closer look (as seen in Fig. 1b) paints a very different picture. Several challenges will arise if a developer tried to partition according to the recommendations made by current approaches, as in Fig. 1a. Some of these are described below:

Challenge #1: Services are tightly coupled leading to distributed monolithic behavior. Coupling refers to the degree of separability between two classes. There exists a tight coupling between the QuoteDatabean and TradeDirect, although not apparent in Fig. 1a, due to heap-dependencies induced by SQLHandler and TradeObject. These objects carry the payload of information exchange between the two classes that is crucial to execute the business functionality. If partitioned according to Fig. 1a, one would have to rely on serialization/de-serialization protocols as well as tightly choreographed object state management to ensure the business logic is executed accurately. This makes the partition behave more like a monolith that is deployed as microservices (aka. a distributed monolith) rather than a true microservice.

Challenge #2: Services engage in transactions to the same database table. If partitioned according to Fig. 1a, we would be forced to reconcile a distributed transaction between QuoteDatabean, TradeDirect, and the database table QuoteDB (as is seen in Fig. 1b). This would require a developer to implement 2 Phase commits (or 2PCs) to coordinate the state change across QuoteDatabean, TradeDirect. The use of 2PC can be very problematic due a number of reasons including but not limited to (1) Loss of atomicity and/or isolation guarantees, (2) Non-trivial coordination of distributed locks, and (3) Very high latency. Therefore they must be avoided if possible lest one is forced to rely on expensive data centers and meticulously synchronized atomic clocks ⁷.

We note that these challenges are very common, and appear often in enterprise scale systems. As a consequence, the recommendations from certain microservice partitioning tools are often rendered useless due to the potential ramifications involved in implementing their recommendation. This inspired the construction of CARGO, where we attempt to refine the recommendations of existing approaches to reduce incidents of distributed monoliths and/or transactions. The partitions in Fig. 1b were derived from CARGO. Here, QuoteDatabean and TradeDirect have been grouped in the same partition, essentially overcoming the above challenges.

3 METHODOLOGY

This section describes CARGO and how it identifies (and/or refines) microservice partitions in monolithic enterprise Java applications to obtain loose coupling between services and high cohesion within the services. Fig. 2 illustrates an end-to-end workflow of the proposed approach. In the first stage (§3.1), we build a context and flow sensitive system dependence graph (SDG) notation of enterprise application which has methods and DB tables as nodes with various edges between them such as call-return edge, data-dependency edge, heap-dependency edge, and transactional edges. In the second stage (§3.2), we extract sub-graphs of the SDG under each context and the across all the transactional scopes, we refer to these as contextual snapshots. In the final stage (§3.2.3), we apply a novel label propagation algorithm across each contextual snapshot to group functionally similar components of the program together.

3.1 Building a System Dependency Graph

In this section, we describe the construction of a System Dependence Graph (SDG) [29, 30], which is an instrumental component of

⁵https://www.ibm.com/cloud/blog/announcements/ibm-mono2micro

⁶https://github.com/WASdev/sample.daytrader7

 $^{^{7}} https://www.youtube.com/watch?v=iKQhPwbzzxU\\$

Stage 1: Extract Context Sensitive Program dependency graph (PDG)

Stage 2: Generate context-/transactional-snapshots from the PDG

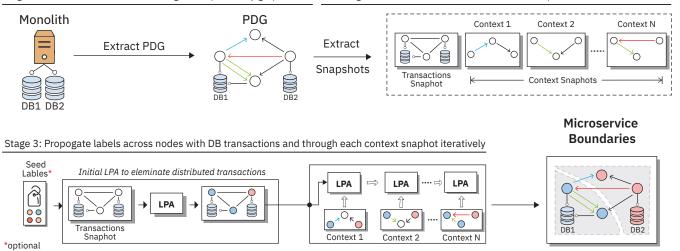


Figure 2: Overview of CARGO.

CARGO. The SDG captures the semantics of the whole program and are particularly well suited to study large enterprise applications as they are purpose-built for context-sensitive analyses, which offer a precise way to distinguish different invocations of the application without need for expensive dynamic tracing. The rest of this section first describes context-sensitivity followed by the various dependency (edge) types in the SDG (§3.1.2).

3.1.1 Context sensitivity. Context-sensitivity dictates that every relationship in the SDG is qualified by a context information. This ensures that different calls/information flows across a the method are annotated with a unique *identifier*. This enables us to distinguish between different paths through the same section of the code, thereby enhancing the precision and richness of our SDG.

Consider the sample program in Fig. 3: here, in lines 2 and 5, we allocate two objects a1 and a2 of type A, and for each of these objects, we call the class method A. foo(...) which in turn calls B. bar(...) (on line 12) and C.id(...) (on line 19). A context-insensitive view of this program as seen in 1, fails to distinguish between two *distinct* calls to B.bar(...). Whereas, a context-sensitive analysis as seen in 2 distinguishes between the call arising from a1.foo(...) and a2.foo(...) as separate edges.

Context-sensitivity may best be thought of as abstractions of the possible dynamic executions of a program, i.e., a method (and it's associated variables) under two different context represents non-overlapping program states that may be reached in one or more dynamic runs of the program. The main flavors of context sensitivity are call-site-sensitivity [31, 32], object-sensitivity [28], and type-sensitivity [33]. Of these, object-sensitivity has been shown to be remarkably precise for analyzing object-oriented programs like Java [33, 34]. Object-sensitivity qualifies contexts using the object allocation site the current method was invoked on, e.g., in Fig. 3 contexts are qualified at A/1, A/2, B/1, and C/1. Thus, the context of two invocations may differ even if their call-site is the same but the object method that was called was allocated in different places,

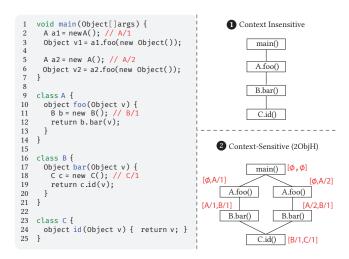
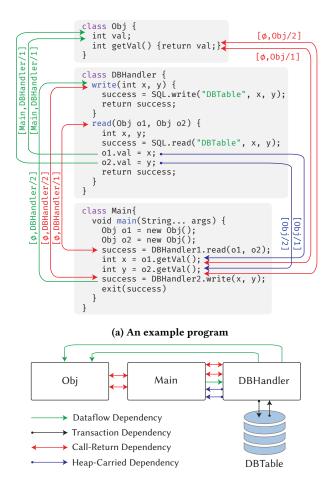


Figure 3: Difference between a context-sensitive and a context insensitive call graph. Context-insensitive analysis cannot differentiate between two calls to the same method, context-sensitive analysis uses object allocation sites (highlighted in red) to distinguish between calls.

e.g., in **2**, B.bar(...) appears in two contexts, even though it has the same call-site (on line 11).

In this paper, we use 2-object-sensitive-analysis with a context-sensitive heap (2objH) for all our analysis as this has been considered the standard for scalable yet precise analysis [34–36]. Although even more precise analysis are available, and can be developed, they seldom scale when applied to enterprise JAVA applications [34] 8 . A crucial property of the object-sensitivity analysis is the *inherent flow-sensitivity* imparted by the contexts. As illustrated in Fig. 3, each object allocation site is annotated with a numeric identifier

⁸A detailed discussion of context-sensitivity is beyond the scope of this work; we therefore direct interested readers to some influential work in this area [28, 34, 37].



(b) A class-level SDG abstraction of the program in Fig. 4a.

Figure 4: An example program and it's corresponding SDG. While the program is analyzed at an instruction level granularity, the SDG is constructed at a class level abstraction. Edges in the SDG are implicitly qualified with a 20bjH context-sensitivity. Note: for the sake of simplicity, this example does not show all the inter-procedural dependencies.

(e.g., A/1, A/2). These identifiers indicate the flow of the program, with A/1 and all it's subsequent contexts appearing before A/2 and all the contexts that follow. This facilitates accurate reasoning about potential control-/data-flows in the program.

We note that context sensitivity is not limited to just call-graphs, it may be used for any static analysis such as data-flow analysis, alias analysis, heap-dependency analysis, and more.

3.1.2 Dependency (edge) types. An SDG represents the possible information flows in the form of a graph with nodes (which are classes in our case) and edges representing both the payload of the information as well as the nature of the information flow between method, i.e., the form of a call-return relationship, a data-flow relationship, and/or a heap-carried dependency relationship. Further, our formulation of the SDG also highlights the information flow

between classes and database tables (which are additional nodes in the SDG) in the form of *transaction reads and writes*.

Fig. 4 illustrates a simple example highlighting the various dependencies that are extracted from the application. Specifically, Fig. 4a highlights the inter-procedural dependencies between instructions in different classes where, each dependency is annotated with a 2objH context information. Fig. 4b, illustrates a class-level abstraction of the SDG in Fig. 4a. The dependency types are:

- (1) Call-Return dependencies: These are the cornerstone of interprocedural static analysis. Each edge represents a possible method invocation from an instruction in the source method to a target method. Being that Java is an object-oriented language, each source and target method have a fully qualified reference object associated with them. This enables us to associate an object-sensitive context to both the caller and the callee. In Fig. 4, the call-return edges are denoted with \longleftrightarrow . We note that each call return edge is qualified with a 20bjH context associated with it, e.g., in Fig. 4 (a) there are two call-graph edges from class Main.main() to the Obj.getVal() with different contexts $[\phi, Obj/1]$ and $[\phi, Obj/2]$.
- (2) Data Dependencies: These edges indicate a static abstraction of the data flows through the any two pairs of instructions in the program. Data flow edges (denoted by \longrightarrow in Fig. 4a) can arise in a number of ways: (a) arguments passed through a call-graph edge (e.g., in the call from Main.main to DBHandler.write(x,y)); or (b) variable reads/writes that are propagated across classes (e.g., in the field writes o1.val = x) in DBHandler.read(). It is possible to extract many of these dependencies with taint tracking.
- (3) Heap-carried Dependencies: These edges indicate if two statements access the same object on the heap. In order to detect heap-carried dependencies, we use points-to analysis in order to determine which objects each statement may access. Heap-carried edges (denoted by \longrightarrow in Fig. 4a) uses context-sensitivity to capture the heap-objects with a 1-heap-sensitivity (indicated by for the 'H' in 2objH). This heap-sensitivity allows us to precisely discover which instance of the heap-object are being used. A good example of this can be seen if Fig. 4a where we first write to o1.val=x in DBHandler.read() and then read it back in x = o1.getVal(). This is a typical heap carried dependency that arises due to a shared object [Obj/1]. Other heap-carried edges can be differentiated with their corresponding heap-context (e.g., [Obj/2] in Fig. 4a).
- (4) Transactions Dependencies: These edges identify sections of the code that part-take in database transactions. Database transactions are a critical and an irreplaceable component of Java EE applications. It is possible to discover transactions using static analyzers like WALA/SOOT/DOOP. To do this, we leverage JEE features such as Java Persistence API (JPA) and JAVA Transaction API (JTA). These APIs allow users to annotate their code with @Transactional to indicate that the following method is part of a transaction. We process these methods their instructions to identify the destination database of the transaction.

We note that, as per norm [30], we gather the dependencies at an instruction level, but abstract way the intra-partition dependencies to minimize the volume of the graph. Since the JEE based monoliths are often partitioned at a class-level, we conjecture that the intra-procedural dependencies play a minimal role in enabling that process when compared to the inter-procedural dependencies.

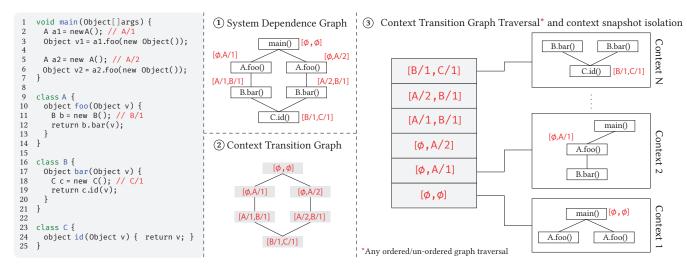


Figure 5: A sample workflow depicting the extraction of context-snapshot from the SDG. From left to right, the sample program from Fig. 3; the system dependence graph (1) and context transition graph (2); SDG sub-graphs under various contexts (3).

3.2 Partitioning with CARGO

In this section, we describe the *Context sensitive Label Propagation* (or CARGO)—a novel community detection algorithm that builds upon the principles of Label Propagation Approach (LPA) [27] to effectively leverage the rich context-sensitive dependencies in the SDG to identify and demarcate functional boundaries in the code. We first describe off-the-shelf label propagation (§3.2.1), then we discuss motivation for, and construction of, context and transactional snapshots from the SDG (§3.2.2), finally we describe CARGO and how label propagation across each snapshot can be used generate highly-cohesive and functionally isolated partitions (§3.2.3).

3.2.1 Label propagation. LPA is a semi-supervised algorithm for identifying communities of densely connected regions in a network that works based just on network structure, without a need for predefined objective functions or apriori knowledge about the communities [27]. Our intuition is based on the idea that if sections of the code are cohesive, then they tend to be densely connected and therefore the labels from LPA will propagate quickly through them and a single label will come to dominate that section of the code. Whereas, for sections of the code that are only loosely coupled, these labels will fail to propagate to those regions. This essentially isolates loosely coupled regions of the code while coalescing cohesive sections of the code. Consequently, as the Label Propagation converges, each highly cohesive group of nodes (classes) will acquire a consensus on a single label and each loosely coupled regions of the code will have their own unique labels.

3.2.2 Context and Transactional Snapshots. Using off-the-shelf label propagation on the entire SDG is inaccurate and it may limit us from leveraging the precision and completeness properties the SDG. This is because, the SDG-in it's entirety-represents a superposition of all the possible contextual states of the program. At any given point, the program may only exist under only one of these contexts (and not all of them simultaneously). Consider the sample program shown in Fig. 5 and it's system dependency graph (1). Here, the

SDG consists of two versions of the same methods A.foo() and B.bar() under different contexts. At a given instance, these methods can exist under one context, but not both. Therefore, to process the SDG accurately, we need extract sub-graphs of the SDG that represent all the individual program states under various contexts. We denote these sub-graphs with the term "context snapshots".

To extract the context snapshots, we first construct a context transition graph to capture all possible context transitions in the program. This can derived from the SDG by analyzing all pairs of vertices connected by an edge and recording their contexts. For example, in Fig. 5, we analyze the SDG (1) to obtain the contexts of each pair of vertices to build the context transition graph seen in (2). Next, for each context (say ctx_i) in the context transition graph, we extract all the nodes from the SDG belonging to the current context ctx_i as well as the nodes the belonging to the preceding context (ctx_{i-1}) and the succeeding context (ctx_{i+1}) . The key intuition here is that, for any given context, one must be able to know three things: (a) what is my current state (i.e., ctx_i)?, (b) how did I get to my current state (i.e., the previous contexts ctx_{i-1})?, and (c) which program state can I transition to (i.e., the next contexts ctx_{i+1})? Together, these nodes represent a "snapshot" of the program's state. This is repeated for all contexts to get a list of "context-snapshots".

In a spirit similar to that of context-snapshots, we also generate a *transactional snapshot* which is a sub-graph of the SDG that includes vertices that are databases and those classes which engage in transactions with this database. It produces a perspective of the application that is centered explicitly around databases. Our key intuition for including this view is to encourage the our label propagation to explicitly collect classes that share transactional dependencies with one another. This should, in theory, reduce incidences of distributed transactions.

3.2.3 Context Sensitive Label Propagation (CARGO). Context Sensitivity Label Propagation (CARGO) is a novel variant of LPA that attempts to leverage the SDG (particularly, the context- and transactional-snapshots) to identify functionally similar and loosely

coupled components of the application. It comprised of 3 steps, namely (1) Initialization with seed labels; (2) Initial LPA with the transactional snapshot; and (3) Iterative LPA over context snapshots. Each of these are described in detail below:

- **Step 1:** *Initialization with seed labels.* Label propagation, and by extension CARGO, are required to be seeded with initial partitioning labels. In the presence of an existing partitioning assignments via the use of existing algorithms (or a user-preferred partitioning assignment), we may use that to seed CARGO. In the absence of these seeds, we assign each class it's own partition ID. In this sense, CARGO can be fully unsupervised, or it may be semi-supervised. • **Step 2:** *Initial LPA with the transactional snapshot.* In the first stage, we apply LPA over the transactional snapshot of the SDG. This identifies classes that engage in distributed transactions and propagates seed labels between them. If more than one class share transaction edges with a the same DB table, then LPA attempts to apportion the same seed labels to them. For two or more classes that do not write to the same table, their labels will remain unchanged. While LPA doesn't guarantee that distributed transactions will be eliminated, this initial seeding guarantees that incidents of distributed transactions are reduced in the subsequent stages as other class nodes to adapt to the seeds from this stage.
- Step 3: Iterative LPA over context-snapshots. In this stage, we iteratively apply label propagation on each context snapshot of the SDG. The underlying intuition is as follows—in a significant number of snapshots, if a group of classes seems to be connected to one another (through call, data, or heap-dependency), they are likely cohesive and must thus belong together. In contrast, if classes are rarely connected across all context snapshots, they are weakly tied and must exist in different partitions. As we apply LPA to each context snapshot, classes that are cohesive, frequently co-occurring, and related will quickly share the same label. For classes that do not frequently co-occur, a separate label will be used. This means that CARGO can isolate weakly connected portions of the code while combining cohesive portions of the code in a single partition.

4 EVALUATION

4.1 Benchmark Applications

We use 5 commonly used Java applications as our benchmarks to perform evaluation. These include: (1) Daytrader [38]: A Java EE7 application built around the paradigm of an online stock trading system. The application allows users to login, view their portfolio, and buy or sell stock shares.; (2) Plants [39]: a simple Java EE 6 application which uses CDI managed beans, Java Server Faces (JSF), and Java Server Pages (JSP); (3) AcmeAir [40]: a Java web application for a fictious airline company which allows users to book and manage flights; JPetStore [41]: a Java web application for a pet store where users shop for pets online; (5) one proprietary app which we call Proprietary1. They contain 109, 33, 66, 37 and 82 classes respectively. We note that of the above benchmark applications, Daytrader makes uses of 6 SQL databases for its business logic.

4.2 Implementation

We use Doop [42] and datalog to implement all our static analysis as described in §3. We also leverage JackEE [25], a framework that performs scalable and precise analysis of Java Enterprise applications.

Our datalog rules will be made available as part of our published code. We then use networkx [43] to parse the generated edges and build an SDG that represents the program. We run CARGO in two modes:

- (1) **Native mode:** This is a purely unsupervised version of the algorithm, where we are provided only with a maximum number of partitions K. We take a random ordering of the nodes of the SDG, and initialize the i^{th} node with the label (i % K). We then run CARGO as described in §3 using these initial labels to arrive at partition assignments for each node.
- (2) **Refinement mode:** This is a semi-supervised version of the algorithm, where we are provided with an initial set of seed labels obtained from another partitioning approach. These labels are assigned to the corresponding nodes of the SDG, and the rest of the SDG nodes are initialized with "-1", denoting no label. We then run CARGO to propagate these initial labels. When the algorithm finishes, if nodes are still labeled "-1", these are unreachable classes. **Note:** In the rest of the paper, each algorithm ALGORITHM refined with CARGO is denoted by ALGORITHM++. The name CARGO refers to the algorithm run in native mode, unless specified otherwise.

4.3 Metrics

4.3.1 Database Transactional Purity. To minimize distributed transactions, we would like each database object to be accessed by classes from one partition only. To design a metric that quantifies this, we use entropy [44] which measures the homogeneity of a set of samples. A low value of entropy indicates a high purity of the samples and vice-versa.

For each database table, find the list of partitions from which it is accessed. Let the entropy of this list be h; then transactional purity for this database table is defined as 1 - h. If a database table is accessed only by classes from a single partition, the transactional purity for that table will be 1.0. The transactional purity of the whole program is the average across all database tables in the program. Higher transactional purity is indicative of fewer distributed transactions, which is a desirable property for a partitioning scheme.

- 4.3.2 Run-time Performance Metrics. These measures evaluate the run-time behavior of the program.
- Latency measures how long, in milliseconds, it takes to perform a user action. We calculate average latency of all the requests made by all the users.
- Throughput measures how many requests are completed per second, averaged over the entire run time of the program.
- 4.3.3 Architectural Metrics. Using our PDG and dynamic call graphs, we define four metrics to measure the effectiveness of partitions:
- Coupling [45] measures the degree of interaction between different partitions of the microservice. Coupling for each partition is the number of edges in the SDG going from or to the partition. We calculate the sum of coupling across all partitions, and divide this by the total number of edges in the SDG.
- Cohesion [45] measures the degree of interconnectedness between classes in a partition. For each partition, it is computed as (internal edges)/(internal edges+external edges). We calculate cohesion for each partition separately and compute the mean across all partitions.

- Inter-call Percentage (ICP) [6] measures the percentage of the overall call volume occurring between two partitions. $ICP_{i,j} = c_{i,j}/\sum_{i\neq j}^{M} c_{i,j}$, where $c_{i,j}$ represents the number of calls between partition i and partition j. Lower the ICP, better the partitioning.
- Business Context Purity (BCP) [46] measures the average entropy of business use cases per partition. Each class is associated with one use case, so each partition has a list of use cases. To maintain semantic and functional coherence of the partitions, we would like each partition to not handle too many different use cases. A list consisting of many different kinds of use cases would have high entropy and high BCP, so lower BCP means better partitions.

5 EXPERIMENTAL RESULTS

We evaluate our approach with the following questions:

- **RQ1: Mitigating distributed Transactions.** How effective is our approach in minimizing distributed transactions?
- **RQ2: Run-time performance.** How do the latency and throughput of a refined microservice application compare to those of the original application?
- **RQ3**: **Performance on architectural metrics**. How does our approach perform on architectural metrics?

5.1 RQ1: Distributed Database Transactions

Mitigating distributed transactions is crucial for a microservice application. In this section we evaluate how effective our approach is in minimizing distributed transactions.

Evaluation: We run CARGO to refine the output of other partitioning algorithms. We also run CARGO stand-alone. Since Daytrader is the only dataset that uses external databases, we run all partitioning algorithms only on Daytrader. We run each algorithm with K = [3, 5, 7, 9, 11, 13] and 5 random seeds, and measure the average transactional purity across all seeds and values of K.

Discussion: The transactional purity is shown in Fig. 6. CARGO increases the transactional purity of all baseline approaches (i.e., approaches suffixed with ++ perform better than the ones without the suffix). When used in native mode (CARGO), and when used to refine the outputs of FoSCI (FoSCI++) and MEM (MEM++), CARGO achieves transactional purity of 1.0. This indicates that there is no database table that is accessed by classes from multiple partitions.

Summary: For each of the 4 baselines, the refined partitions have higher transactional purity. Further, FoSCI++, MEM++ and CARGO have transactional purity of 1.0, implying that there can be no distributed transactions with these partitioning schemes.

5.2 RQ2: Run-time Performance

In this section, we evaluate the performance of our partitioning algorithm in a real world setting. When we implement the recommended partitioning scheme as a microservice application, we want the application to have **low latency** and **high throughput**.

Evaluation: The Daytrader application has the largest number of classes among our benchmark applications, so we choose it for these performance evaluations. Daytrader is also the only benchmark to use external databases. We use Mono2Micro [47] to construct a microservice version of the monolithic Daytrader application, and repeat this process for Mono2Micro++. Both these apps are

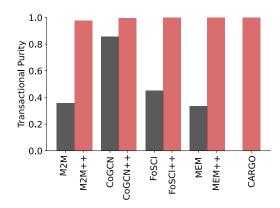


Figure 6: Transaction purity for CARGO and other approaches. The transactional purity of the refined partitions is higher than that of the original partitions for all approaches. FoSCI++, MEM++ and CARGO achieve transactional purity of 1.0, indicating that no database objects is accessed by classes belonging to different partitions.

deployed by using individual Docker containers for each partition, and orchestrated using docker-compose.

We use Apache JMeter to measure latency and throughput of the application under varying loads. We simulate various use cases consisting of sequences of user actions. We test the application with multiple users executing multiple concurrent requests every second. The number of users is varied from $2^{11} \approx 2K$ to $2^{20} \approx 1M$ in exponents of 2.

Discussion: The latency and throughput are plotted as a function of the number of users, for different use cases. The results are shown in Figure 7. We observe that:

- When the number of users is sufficiently high, the Mono2Micro++ partitioning scheme achieves lower latency and higher throughput than the original Mono2Micro partitioning scheme. As the load on the application increases, the coupling between microservices becomes more of an impediment to performance. We hypothesize that Mono2Micro++ performs better than Mono2Micro under high loads because it has less inter-partition coupling.
- This holds true across all the use cases that we have considered.
- We compute the average percentage improvement in latency and throughput across all use cases, and find that Mono2Micro++ represents a 11% improvement in latency and a 120% improvement throughput, over Mono2Micro.

Summary: When we use our approach to re-partition a microservice application, the resulting application has **11**% lower latency and **120**% higher throughput on average across use cases than the original application.

5.3 RQ3: Performance on Architectural Metrics

RQ1 measured how effectively CARGO minimizes distributed transactions, and RQ2 evaluated the real-world performance of CARGO. In this section, we evaluate CARGO on architectural metrics that

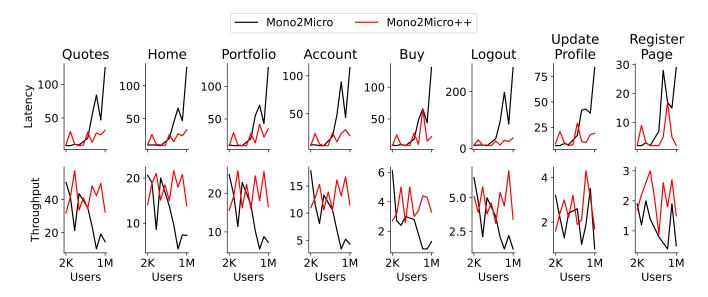


Figure 7: Latency and Throughput for Mono2Micro versus Mono2Micro++, for different use cases in Daytrader. We simulate each application with the number of users varying from $2^{11} \approx 2K$ to $2^{20} \approx 1M$ in exponents of 2. Mono2Micro++ achieves lower latency and higher throughput than Mono2Micro, indicating better performance.

use PDG and call-graph information to measure the quality of partitions. We would like to see loose coupling between partitions, and high cohesion within classes of the same partition.

Evaluation: We use four baseline partitioning approaches - Mono2Micro (M2M) [6], CoGCN [21], FoSCI [26] and MEM [48]. We run these approaches on our benchmark set of five monolithic applications. Each of these approaches allows one to specify a maximum number of partitions, K. We run each algorithm with K = [3, 5, 7, 9, 11, 13], and use CARGO to refine the partitions produced for each value of K. Additionally, we run CARGO in native mode with the same values of K. Both when refining existing partitions and while running CARGO stand-alone, we run the algorithm five times with different random seeds. For each metric, we report the average across all seeds and values of K.

Discussion: The results are shown in Table 1. The best results are highlighted in blue We make the following observations:

- Cohesion and Coupling: When used to refine the partitions produced by another algorithm, CARGO always improves the Cohesion and Coupling. Further, when used stand-alone, CARGO achieves the best Cohesion and Coupling across all algorithms.
- *ICP:* When used to refine the partitions produced by another algorithm, the refined partitions are noticeably better than the original partitions in terms of ICP. When used in native mode, CARGO performs significantly better than all the other approaches in 3 out of 5 datasets.
- *BCP*: BCP measures the semantic coherence of each partition in terms of business use cases that it handles. When CARGO is used stand-alone on Daytrader, it outperforms all other approaches on this metric. However when used to refine existing partitions, it performs poorly. The definition of BCP depends heavily on the quality of the generated business use cases for each class, which

is information that CARGO does not have access to. This is one possible explanation for its poor performance.

Finally, we note that CARGO when used stand-alone with randomly initialized labels achieves state-of-the-art performance on all four metrics on Daytrader. This shows that even in the absence of domain knowledge, CARGO can effectively learn the structure of the program and form partitions.

Summary: In 3 out of the 4 metrics, the refined partitions are better than the original partitions for a majority of the approaches. Further, CARGO used in native mode achieves state-of-the-art performance on all 4 metrics on the Daytrader benchmark.

6 RELATED WORK

Software Modularization: Microservice decomposition is a specific instance of the Software Modularization problem, which has seen a long line of work. In general, software modularization approaches construct a Module Dependence Graph (MDG), and perform various analyses on this graph. Doval et al. [49], Mitchell and Mancoridis [50] and Harman et al. [51] define a modularity metric based on intra-cluster and inter-cluster connections and optimize this metric using genetic algorithms or hill climbing. Sarkar et al. [52] define information-theory based metrics to evaluate the quality of software modularization. Bavota et al. [53] quantify the cohesion between classes using the volume of information flowing between functions, and the semantic similarity of the identifiers and comments used.

Decomposition into Microservices: There have been several recent papers that attempt to decompose monolithic applications into microservices [9–17]. Escobar et al. [12] present a rule-based algorithm to partition JEE applications that separates classes according

Table 1: Performance of different approaches on four architectural metrics computed on 5 applications. We evaluate Mono2Micro (M2M), CoGCN, FoSCI and MEM, along with their refined partitions denoted with a "++". We also evaluate CARGO stand-alone. The symbol \triangle next to a metric indicates that higher is better, while ∇ indicates that lower is better. For each approach and refined approach, we shade the better of the two blue. We count the number of wins, ties and losses for the refined approaches versus the original approaches across all the datasets, and shade the corresponding cell green if wins outnumber the losses. The best performing approach in each row is bold. If CARGO is the best performing approach, then we shade its cell orange

	Coupling ∇										Cohesion △									
	M2M	M2M++	CoGCN	CoGCN++	FoSCI	FoSCI++	MEM	MEM++	CARGO	M2M	M2M++	CoGCN	CoGCN++	FoSCI	FoSCI++	MEM	MEM++	CARGO		
Daytrader	0.78	0.02	0.25	0.02	0.68	0.02	0.12	0.01	0.01	0.30	0.62	0.37	0.61	0.23	0.54	0.26	0.46	0.71		
PLANTS	0.31	0.04	0.40	0.29	0.75	0.31	0.29	0.11	0.05	0.32	0.61	0.39	0.46	0.24	0.40	0.39	0.44	0.6		
Acmeair	0.58	0.04	0.52	0.13	0.71	0.22	0.51	0.15	0.03	0.27	0.48	0.21	0.32	0.16	0.51	0.37	0.55	0.96		
JPETSTORE	0.77	0.03	0.78	0.06	0.79	0.03	0.77	0.05	0.03	0.27	0.29	0.20	0.24	0.18	0.36	0.30	0.44	0.94		
Proprietary	0.42	0.03	0.22	0.04	0.48	0.02	0.27	0.03	0.04	0.57	0.78	0.69	0.73	0.37	0.57	0.48	0.67	0.75		
Win/Tie/Loss	5 / 0 / 0		5 / 0 / 0		5 / 0	5 / 0 / 0		5 / 0 / 0		5 / 0 / 0		5 / 0 / 0		5/0/0		5 / 0 / 0				

	BCP ∇										ICP ∇									
	M2M	M2M++	CoGCN	CoGCN++	FoSCI	FoSCI++	MEM	MEM++	CARGO	M2M	M2M++	CoGCN	CoGCN++	FoSCI	FoSCI++	MEM	MEM++	CARGO		
Daytrader	2.31	2.57	1.40	1.90	2.55	2.26	2.23	2.32	1.31	0.60	0.05	0.16	0.05	0.48	0.07	0.04	0.07	0.00		
Plants	1.68	2.20	1.96	1.54	2.37	1.71	1.93	1.53	1.79	0.54	0.11	0.65	0.11	0.70	0.12	0.28	0.11	0.06		
Acmeair	1.29	1.48	1.18	1.12	1.75	1.61	1.94	1.95	1.75	0.91	0.35	0.67	0.63	0.85	0.63	0.41	0.72	0.32		
JPETSTORE	2.25	2.35	1.71	1.77	2.26	2.45	2.54	2.74	2.87	0.13	0.41	0.33	0.35	0.24	0.40	0.26	0.42	0.30		
Proprietary	1.23	1.53	1.27	1.42	1.49	1.48	1.48	1.95	1.55	0.02	0.35	0.17	0.25	0.37	0.32	0.32	0.32	0.37		
Win/Tie/Loss	0/0/5 2/0/3) / 3	4/0/1 1/0,) / 4		3 / 0 / 2		3 / 0 / 2		4 / 0 / 1		1/1/3					

to the data that they manipulate. [17] define 3 coupling criteria between classes based on an analysis of commit patterns and semantic similarity. They then construct a graph where the weight of an edge connecting two classes is proportional to the strength of the coupling between them, and use clustering algorithms on this graph. Gysel et al. [13] propose a similar algorithm, except that they define 16 coupling criteria instead of 3.

There are also some approaches that use dynamic traces to cluster classes into microservices. Jin et al. [54] identify functional atoms, or groups of classes that frequently occur together in a trace, and define four optimization objectives to group these functional atoms. Desai et al. [55] construct a co-occurrence graph between classes that occur in the same execution trace, and use a Graph Neural Network (GNN) to obtain node embeddings and cluster nodes on this graph. [6] measure the number of direct and indirect

calls between classes in a dynamic trace, and apply hierarchical clustering on the similarity graph thus obtained.

7 THREATS TO VALIDITY

As with any evaluation study, biases can affect the final results. Therefore, any conclusions of this work must be considered with the following issues in mind:

- Evaluation Bias: In **RQ1** and **RQ3**, we compare the performance of CARGO using a set of architectural metrics (defined in §4.3). The results and the conclusions of these RQs are scoped by the efficacy of the metrics to evaluate the architecture. Since these metrics are statically computed, there may be slightly different conclusions with other measurements. This is to be explored in future research.
- Construct Validity: At various places in this paper, we made engineering decisions about program graph granularity, traversal

orders, and so on. While these decisions were made using advice from the literature, we acknowledge that other constructs might lead to other conclusions. To enable further exploration of our design decisions and in the interest of open science, we make available our replication package.

• External Validity: For this study, we have selected a diverse set of subject systems, including a proprietary application. We also use a number of microservice partitioning algorithms for comparison. There is a possibility that our outcomes may vary for a different set of applications. Therefore, one has to be careful when generalizing our findings to other applications or algorithms. Even though we tried to run our experiment on a variety of applications, we do not claim that our results generalize beyond the specific case studies explored here. That said, to enable reproducibility, we have shared our scripts and the gather performance data.

8 CONCLUSION

Microservices Architecture (MSA) has evolved into a de-facto standard for developing cloud-native enterprise applications during the last decade. A number of automated approaches are being developed to recommend functional partitions in monolithic code that can be extracted away and modernized as microservices. However, many of these approaches produce recommendations that are not actionable as they result in (a) distributed monoliths, and/or (b) force the use of distributed transactions. This work attempts to overcome these challenges by introducing CARGO—a novel un-/semi-supervised partition refinement technique that was used to refine and thereby enrich the partitioning quality of the current state-of-the-art algorithms. Our findings over several Java EE projects suggest that CARGO can improve the partition quality of the existing approach and steer the recommendations towards generating better microservice recommendations.

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