

An Expert System for Redesigning Software for Cloud Applications

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Abstract

Cloud-based software has many advantages. When services are divided into many independent components, they are easier to update. Also, during peak demand, it is easier to scale cloud services (just hire more CPUs). Hence, many organizations are partitioning their monolithic enterprise applications into cloud-based microservices.

Recently there has been much work using machine learning to simplify this partitioning task. Despite much research, no single partitioning method can be recommended as generally useful. More specifically, those prior solutions are “brittle”; i.e. if they work well for one kind of goal in one dataset, then they can be sub-optimal if applied to many datasets and multiple goals.

In order to find a generally useful partitioning method, we propose DEEPLY . This new algorithm extends the CO-GCN deep learning partition generator with (a) a novel loss function and (b) some hyper-parameter optimization. As shown by our experiments, DEEPLY generally outperforms prior work (including CO-GCN, and others) across multiple datasets and goals. To the best of our knowledge, this is the first report in SE of such stable hyper-parameter optimization.

To enable the reuse of this research, DEEPLY is available on-line at <https://bit.ly/2WhfFLB>.

Keywords: software engineering, microservices, deep learning, hyper-parameter

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1. Introduction

As more and more enterprises move to the cloud, new tools are needed. For example, IBM helps clients with millions of lines of code each year in this refactoring process. In one such effort, IBM worked with a Fortune 100 company to recommend partitions for a system with over one million lines of code. These partitions were manually inspected by subject matter experts and verified within weeks (as opposed to a year of manual effort)¹. Unfortunately, the tool support needed for this process is still in its infancy. For example, consider the problem of how to divide up old software for the cloud (i.e., into microservices). Informally, we need to encourage cohesion and minimize coupling. However, AI-based tools for doing this require more precise definitions of cohesion and coupling. In this paper, we show six state-of-the-art tools focused on that exact problem, which internally have several internal hyper-parameter choices. The challenge with these tools is to tame that large hyper-parameter space.

Data mining is a powerful tool but, like any other software system (Xu et al. (2015)), analysts are often puzzled by all the options for the control settings. For example, consider the task of converting monolithic enterprise software into cloud microservices. For the task, it is a common practice to apply some clustering algorithm to decide how to break up the code into k smaller microservices. A common question asked by programmers is “what is a good value for k ”? More generally, across all the learners used for microservice partitioning, currently there is little support for selecting appropriate control settings (Desai et al. (2021); Yedida et al. (2021a)).

Tools that can automatically learn settings for data miners are called *hyper-parameter optimizers* (HPO). These tools can learn (e.g.) good k values while also optimizing for other goals including cluster coherence (which should be maximized) and coupling (which should be minimized). But HPO suffers from *hyper-parameter brittleness*. For example, Tu & Nair (2018) reported that if an optimizer works well for one kind of

¹<http://tiny.cc/mono2micro>

goal in one data set, they can be sub-optimal if applied to multiple datasets and goals. In the case of redesigning software monoliths as cloud microservices, Yedida et al. (2021a) recently reported that different HPO tools perform best for different sets of goals being explored on different datasets. To say that another way, based on past results, no specific prior partitioning method can be recommended as generally useful. This we consider this as a significant problem. As designs get more complex, partitioning methods become very slow (Yedida et al. (2021a)). For example, at the time of this writing, we are running our algorithms for an industrial client. That process has taken 282 CPU hours for 1 application. Hence it is less-than-ideal to ask engineers to hunt through the output of multiple partitioning algorithms, looking for results that work best for their particular domain. This especially true when each of those algorithms runs very slowly. Instead, we should be able to offer them one partitioning method that is generally most useful across a wide range of problems.

To find a generally useful partitioning methods, this paper seeks HPO tools that perform best across multiple datasets and goals (and prior work (Kalia et al. (2021); Jin et al. (2019); Mazlami et al. (2017); Mitchell & Mancoridis (2006); Desai et al. (2021) tended to explore just one or two partitioning methods). Thus, we propose DEEPLY , which is a novel combination of optimization (using Bergstra’s hyperopt tool (Bergstra et al. (2013)) and a loss function. As shown by ur results, DEEPLY generally works well across multiple goals and data sets.

To understand the benefits of DEEPLY , we investigate five research questions.

RQ1: *How prevalent is hyper-parameter brittleness in automated microservice partitioning?* We verify Yedida et al. (2021a)’s results, who showed that hyper-parameter optimizers are “brittle”, i.e., they work well for a few metrics and datasets, but are not useful across multiple goals and data sets. The verification is crucial to set the motivation for our contribution.

RQ2: *Is hyper-parameter optimization enough to curb the aforementioned optimizer brittleness?* Here we will show that standard hyper-parameter optimization methods are insufficient for solving brittleness.

RQ3: *Since hyper-parameter optimization methods are not enough, How else might we fix the aforementioned brittleness problem?* To that purpose, we propose

DEEPLY , a novel combination of hyper-parameter optimizers with a new loss function.

RQ4: Does DEEPLY generate “dust” (where all functionality is loaded into one partition) or “boulders” (where all partitions contain only one class each)? Here, we show that DEEPLY avoids two anti-patterns. Specifically, DEEPLY does not create “boulders” or “dust”.

The rest of this paper is structured as follows. We provide a detailed background on the problem and the various attempts at solving it in §2. We then formalize the problem and discuss our method in §3. In §4, we discuss our experimental setup and evaluation system. We present our results in §5. Next, we show how the crux of our approach extends beyond this problem in §6. We discuss threats to the validity of our study in §7. Finally, we conclude in §8.

Before we begin, just to say the obvious, when we say that hyper-parameter optimization is becomes more generally useful method with DEEPLY , we mean “generally useful across the data sets and metrics **explored thus far**”. It is an open question, worthy of future research, to test if our methods apply to other datasets and goals.

2. Designing for the Cloud

To fully exploit the cloud, systems have to be rewritten as “microservices” comprising multiple independent, loosely coupled pieces that can scale independently. Microservice architectures have many advantages (Al-Debagy & Martinek (2018); Wolff (2016) such as technology heterogeneity, resilience (i.e., if one service fails, it does not bring down the entire application), and ease of deployment. Therefore, it is of significant business interest to port applications to the cloud under the microservice architecture. For example, Netflix states that the elasticity of the cloud and increased service availability are two of the primary reasons it switched to a microservice architecture². They use the cloud for distributed databases, big data analytics, and business logic. Further, they mention that moving to the cloud reduced their averaged cost. .

²<https://about.netflix.com/en/news/completing-the-netflix-cloud-migration>

Daya et al. (2016) report on the long queue of applications waiting to be ported to the cloud. Once ported to cloud-based microservices, code under each microservice can be independently enhanced and scaled, providing agility and improved speed of delivery. But converting traditional enterprise software to microservices is problematic. Such traditional code is *monolithic*, i.e., all the components are tightly coupled, and the system is designed as one large entity. Thus, some *application refactoring* process is required to convert the monolithic code into to a set of small code clusters.

When done manually, such refactoring is expensive, time-consuming, and error-prone. Hence, there is much current interest in automatically refactoring traditional systems into cloud services.

Some of the authors of this paper are part of the IBM “Mono2Micro” that helps client redesign their systems for the cloud. Some of that analysis is manual since it relies on extensive domain knowledge. That said, increasingly, there is automation applied to this task. For example, given a set of test cases or use cases, it is reasonable to ask “how does this knowledge of frequently use tests or use cases inform our microservices design?”. For that purpose, some AI clustering can be used.

But when we try to use AI tools for this task, we often encounter the same problem. Specifically, there are so many algorithms and partitioning goals:

- Table 1 lists the various coupling and cohesion goals used by prior work on partition generation. Note that in column one, any goal marked with “[-]” should be *minimized* and all other goals should be *maximized*.
- See also Table 2 which lists some of the partitioning tools, as well as their control parameters. In the table, the core idea is to understand what parts of the code call each other (e.g., by reflecting on test cases or use cases), then cluster those parts of the code into separate microservices. These algorithms assess the value of different partitions using scores generated from the Table 1 metrics.

In such a rich space or options, different state-of-the-art AI approaches may generate different recommendations. Yedida et al. (2021a) concluded that looking at prior work, we seem to have a situation where analysts might run several partitioning algorithms to find an algorithm that performs the best based on their business requirements. For example, analysts might prefer Mono2Micro (Kalia et al. (2020, 2021)) over others

Table 1: Yedida et al. (2021a) report five widely used metrics to assess the quality of microservice partitions. In this table, [-] denotes metrics where *less* is better and [+] denotes metrics where *more* is better. For details on how these metrics are defined, see §4.4.

Metric	Name	Description	Goal
BCS [-] (Kalia et al. (2020))	Business context sensitivity	Mean entropy of business use cases per partition	If minimized then more business cases handled locally
ICP [-] (Kalia et al. (2020))	Inter-partition call percentage	Percentage of runtime calls across partitions	If minimized then less traffic between clusters
SM [+] (Jin et al. (2019))	Structural modularity	A combination (see §4.4) of cohesion and coupling defined by Jin et al. (2019)	If maximized then more self-contained clusters with fewer connections between them
MQ [+] (Mitchell & Mancoridis (2006))	Modular quality	A ratio involving cohesion and coupling, defined by Mitchell & Mancoridis (2006)	If maximized then more processing is local to a cluster
IFN [-] (Mitchell & Mancoridis (2006))	Interface number	Number of interfaces needed in the microservice architecture	If minimized then fewer calls between clusters
NED [-] (Kalia et al. (2020))	Non-extreme distribution	Number of partitions with non-extreme values	If minimized , fewer “boulders” (large monolithic partitions) or “dust” (partitions with only one class)

considering the clean separation of business use cases where as they might prefer CoGCN (Desai et al. (2021)) and FoSCI (Jin et al. (2019)) for low coupling. As stated in the introduction, this is hardly ideal since these partitioning algorithms can be slow to execute. Accordingly, this paper seeks optimization methods that support partitioning

Table 2: Hyper-parameter choices studied in this paper. All the methods take runtime traces (or use cases) as their input. These methods return suggestions on how to build partitions from all the classes seen in the traces. For further details on these partitioning algorithms, see §3.

Algorithm	Hyper-parameter	(min, default, max)
Mono2Micro (Kalia et al. (2020, 2021))	Number of clusters	(2, 5, 10)
	Number of clusters	(5, 5, 13)
FoSCI (Jin et al. (2019))	Number of iterations to run	(1, 3, 6)
	NSGA-II	
	Population size for NSGA-II	(30, 100, 200)
	Parent size to use in NSGA-II	(10, 30, 50)
MEM (Mazlami et al. (2017))	Maximum partition size	(17, 17, 17)
	Number of partitions	(2, 5, 13)
Bunch (Mitchell & Mancoridis (2006))	Number of partitions	(3, 5, 13)
	Initial population size for hill climbing	(2, 10, 50)
	Number of neighbors to consider in hill-climbing iterations	(2, 5, 10)
	Number of clusters	(2, 5, 13)
CoGCN (Desai et al. (2021))	Loss function coefficients	(0, 0.1, 1)
	$\alpha_1, \alpha_2, \alpha_3$	
	Number of hidden units in each layer, h_1, h_2	(4, 32, 64)
	Dropout rate	(0, 0.2, 1)

for a wide range of data sets and goals.

3. Algorithms for Microservice Partitioning

Informally, partitioning algorithms take domain knowledge and propose partitions containing classes that often connect to each other. For example, given a set of use cases or traces of test case execution:

- Identity the entities (such as classes) used in parts of the use cases/test cases;
- Aggregate the frequently connecting entities;
- Separate the entities that rarely connect.

This can be formalized as follows. Consider classes³ in an application A as \mathcal{C}^A such that $\mathcal{C}^A = \{c_1^A, c_2^A, \dots, c_k^A\}$, where c_i^A represents an individual class. With this, we define a partition as follows:

Definition 1. A partition \mathcal{P}^A on \mathcal{C}^A is a set of subsets

$\{P_1^A, P_2^A, \dots, P_n^A\}$ such that

- $\bigcup_{i=1}^n P_i^A = \mathcal{C}^A$, i.e., all classes are assigned to a partition.
- $P_i^A \neq \phi \forall i = 1, \dots, n$, i.e., there are no empty partitions.
- $P_i^A \cap P_j^A = \phi \forall i \neq j$, i.e., each partition is unique.

Definition 2. A partitioning algorithm f is a function that induces a partition \mathcal{P}_A on an application with classes \mathcal{C}^A .

The goal of a microservice candidate identification algorithm is to identify a function f that jointly maximizes a set of metrics m_1, m_2, \dots, m_p that quantify the quality of the partitions, i.e., given an application characterized by its class set \mathcal{C}_A , we aim to find:

$$\mathcal{P}_A^* = \arg \max_{\mathcal{P} \in B_{\mathcal{C}_A}} \sum_{i=1}^p \alpha_i m_i(\mathcal{P}; f) \quad (1)$$

where $B_{\mathcal{C}_A}$ denotes the set of all partitions of \mathcal{C}_A and p is the number of partitions.

The following is structured as follows. We first discuss prior approaches, and the issues with them. These prior approaches come from a recent review of automated microservice partitioning (Yedida et al. (2021a)), which studied the effect of hyperparameter optimization on these approaches. Then, we will present the business case for a new algorithm, and finally, we will discuss our approach.

3.1. FoSCI

FoSCI (Jin et al. (2019)) uses runtime traces as a data source. They prune traces that are subsets of others, and use hierarchical clustering with the Jaccard distance

³This definition trivially extends to languages without classes; translation units such as functions could be used instead, for example.

Table 3: Deep learning: a tutorial. In this work, deep learning is used by both CO-GCN and DEEPLY .

<p>A deep learner is a directed acyclic graph. Nodes are arranged into “layers”, which are proper subsets of the nodes. Each node computes a weighted sum of its inputs, and then applies an “activation function”, yielding its output.</p>
<p>Deep learning (DL) (Goodfellow et al. (2016)) is an extension of prior work on multi-layer perceptrons, where the adjective “deep” refers to the use of multiple layers in the network.</p>
<p>The weights form the parameters of the model, which are learned via <i>backpropagation</i> (Rumelhart et al. (1986)) using the rule $\theta = \theta - \eta \nabla_{\theta} \mathcal{L}$ where θ represents the parameters of the model, η is the <i>learning rate</i>, and \mathcal{L} is the <i>loss function</i> (described below).</p>
<p>A deep learner with L layers produces a prediction \hat{y}, and the network learns parameters by using gradient descent to minimize the <i>loss function</i> $\mathcal{L}(y, \hat{y})$. This loss function can be arbitrarily designed, as done by the authors of CO-GCN (Desai et al. (2021)) to suit the specific needs of the application.</p>
<p>For static learning rates, there has been an increased interest in learning rate schedules, where η is replaced by a function $\eta(t)$, where t is the iteration. The proposed schedules have both theoretical (Seong et al. (2018); Yedida et al. (2021b)) and empirical (Smith & Topin (2017); Smith (2017)) backing. Generally, however, all the papers agree on the use of non-monotonic learning rate schedules. Specifically, Smith (2017) argues for cyclical learning rates, where the learning rate oscillates between (η_l, η_u), a preset range for a specified number of cycles. More recently, Smith & Topin (2019) proposed a “1cycle” learning rate policy, where a single cycle is used, and showed this to be effective, but simple.</p>
<p><i>Dropout</i> (Srivastava et al. (2014)) is a technique which involves removing some nodes with a probability p during training, and adjusting the weights of the model during testing. Srivastava et al. (2014) argues that this enforces sparsity in the model weights, which improves the model performance and makes it more robust to noise.</p>

to create “functional atoms”. These are merged using NSGA-II (Deb et al. (2002)), a multi-objective optimization algorithm to optimize for the various goals. Since FoSCI relies on a somewhat older optimization algorithm (from 2002 (Deb et al. (2002))), and all the goals are given equal priority, this can lead to suboptimal results if the different goals have, for example, different scales.

3.2. *Bunch*

Bunch (Mitchell & Mancoridis (2006)) is based on search techniques such as hill-climbing⁴ to find a partition that maximizes two specific metrics. It is well established that such greedy search algorithms can get stuck in local optima easily (Russell & Norvig (2002)).

3.3. *Mono2Micro*

Mono2Micro (Kalia et al. (2020, 2021)) collects runtime traces for different business use cases. Then, they use hierarchical clustering with the Jaccard distance to partition the monolith into a set of microservices. However, as noted by Yedida et al. (2021a), this approach takes as input the number of partitions, which different architects may disagree on, or may not know the value of.

3.4. *CO-GCN*

CO-GCN uses the deep learning technology discussed in Table 3. More specifically, **CO-GCN** (Desai et al. (2021)) uses the call graph (built from the code) as input to a graph convolutional neural network (Kipf & Welling (2016)). They develop a custom loss function (defined in Table 3) that relates to the metrics being optimized for, and thus, the neural network can be seen as a black-box system that optimizes for Equation (1). However, while their use of a custom loss function tailored to the goals is novel, their approach has several hyper-parameters that a non-expert may not know how to set, and their study did not explore hyper-parameter optimization .

⁴Their tool offers other heuristic-based approaches as well.

CO-GCN uses an exponential learning rate scheduling policy (see Table 3 for details), where the learning decays exponentially. In our approach, we instead use the 1cycle (Smith & Topin (2019)) policy, which has more experimental backing.

CO-GCN also uses *dropout* (Srivastava et al. (2014)), which involves removing some nodes with a probability p during training, and adjusting the weights of the model during testing. Srivastava et al. (2014) argues that this enforces sparsity in the model weights, which improves the model performance and makes it more robust to noise.

CO-GCN is controlled by the settings of Table 2. Later in this paper, we show that there are several benefits in using hyper-parameter optimization to automatically select good subsets of these hyper-parameters. Note that (a) all our partitioning methods (CO-GCN and all the others shown above) utilize hyper-parameter optimization; (b) even better results can be obtained via augmenting HPO with a novel loss function (and that combination of HPO+loss function is what we call DEEPLY).

3.5. The case for a new algorithm

The discussion so far shows that there are several approaches that perform automatic microservice partitioning, with different goals, i.e., businesses may be able to choose based on the goals they need, which application to use. However, our industry partners have stressed that these are not widely adopted for several reasons.

Key among these reasons is that these approaches all have *hyper-parameters*. Industry practitioners, having worked with their monolithic systems, may not know how many partitions would be “ideal” for a microservice architecture. Furthermore, there may be disagreements between different practitioners on the number of microservices (clusters), for example. Moreover, hiring an expert such as a system architect can be expensive, and even then provides no guarantees that just because the architect recommends, say, 4 microservices, that the system will build the microservices envisioned by the architect.

On top of the above, refactoring a monolithic application into microservices is *expensive*. It is a time-consuming process that can take months to complete, with rigorous testing required to ensure that the outward functionality of the system has

not been changed. Therefore, it is crucial to large enterprises that if and when such a change is made, that it is done well. What “well” means can vary from business to business, or even application to application. For example, while a commercial product that faces millions of users might have the non-functional requirement that it be fast, an internal tool may not have such a requirement.

Finally, we bring up the results of the study by Yedida et al. (2021a). Specifically, they studied microservice partitioning algorithms, and showed that “there is no best algorithm”. That is, each algorithm that they studied (when tuned with hyperparameter optimization) was an expert at one of the metrics, but did poorly on the rest. Of course, this does not inspire much confidence in businesses who might be open to adopting these automated systems, and whose requirements may be constantly changing.

3.6. DEEPLY

Summarizing the approaches in prior work, we note that they suffer from the following limitations:

- (a) They have hyper-parameters that practitioners may not understand or know how to set.
- (b) They rely on techniques that can easily get stuck in suboptimal, local minima.
- (c) They treat all the metrics as having equal priority, when it may not be the case (e.g., some feature scaling may be needed, or the business priorities are different).

To address the limitations, we propose an extension to the CO-GCN (Desai et al. (2021)) deep learner. DEEPLY uses an hyper-parameter optimization technique that is known to deal with local optima better, and (b) a novel reweighting of the metrics based on data.

When algorithms produce a highly variable output, then hyper-parameter optimization, described in §3.6.2, can be used to automatically learn the control settings

that minimize the variance. Specifically, we use the fact that a hyper-parameter optimization algorithm, in searching for optimal parameters, must test different hyper-parameter configurations, each of which produces a different result. The results are aggregated together to form a frontier, from which we can pick the “best” sample. To do so, we notice that simply picking a model based on one metric sacrifices the performance in others. Moreover, using a sum of all metrics has the disadvantages of (a) different scales for different metrics (b) learners doing well in the “easy” metrics but not in the others (c) ignoring correlations among the metrics. Therefore, we design a custom *loss function* to choose the best sample.

For further details on all the concepts in the last two paragraphs, see the rest of this section.

3.6.1. Feature Engineering

DEEPLY uses the deep learning technology discussed in Table 3.

We format our datasets into the form required by a graph convolutional network (Kipf & Welling (2016)) as suggested in CO-GCN (Desai et al. (2021)). A graph convolutional network models a graph as a pair of matrices (A, X) , where A is the (binary) adjacency matrix and X is the feature matrix. Our graph is characterized by nodes corresponding to classes, and edges corresponding to function calls between two classes. If a class is not used by any of the APIs published by the software, then it is removed from the graph. The adjacency matrix is trivially defined as $M_{ij} = 1$ if an edge exists between the vertices i, j , and 0 otherwise.

For the feature matrix, we follow the approach of suggested in CO-GCN (Desai et al. (2021)). Specifically, we first define the *entry point matrix* $E \in \{0, 1\}^{|V| \times |P|}$ (where V is the set of classes, and P is the set of *entry points*). Entry points refer to APIs published by a software, each potentially for different functions. Then, for each such entry point (i.e., API), we consider the set of classes invoked in its execution. We consider the entry $E_{ij} = 1$ if class i is part of the execution trace of entry point j , and 0 otherwise. Additionally, we consider the *co-occurrence matrix* $C \in \{0, 1\}^{|V| \times |V|}$ such that $C_{ij} = 1$ if both classes i, j occur in the same execution trace, and 0 otherwise. Finally, we define the *dependence matrix* $D \in \{0, 1\}^{|V| \times |V|}$

as $D_{ij} = D_{ji} = 1$ if class i inherits from class j or vice versa, and 0 otherwise. The feature matrix $X \in \mathbb{R}^{|V| \times (|P| + 2|V|)}$ is the concatenation of E, C, D (in that order), and is then row-normalized.

CO-GCN also uses *dropout* (Srivastava et al. (2014)), which involves removing some nodes with a probability p during training, and adjusting the weights of the model during testing. Srivastava et al. (2014) argues that this enforces sparsity in the model weights, which improves the model performance and makes it more robust to noise.

3.6.2. Hyper-parameter Optimization

Hyper-parameter optimization is the systematic process of finding an optimal set of hyper-parameters for a model. In the specific case of optimizing CO-GCN, those parameters are shown in Table 2.

Several approaches for hyper-parameter optimization now exist. Of note is the work by Bergstra et al. (2011)⁵ which discusses three different approaches. In this paper, we use a newer, widely used hyper-parameter optimization algorithm called Tree of Parzen Estimators (TPE) (Bergstra et al. (2011)). TPE divides data points seen so far into *best* and *rest*, each of which are modeled by a Gaussian distribution. New candidates are chosen so that they are highly likely to be in the *best* distribution. Evaluating these candidates adds to the data points, and the algorithm continues. This algorithm was open-sourced by its authors in a package called *hyperopt* (Bergstra et al. (2013)). Therefore, in this paper, whenever we say “hyperopt”, we mean TPE as implemented by this package.

3.6.3. Loss Function

Table 3 discussed *loss functions* \mathcal{L} that offers weights to the feedback seen by the learner during the inner-loop of the learner process. Numerous researchers report that augmented loss functions can enhance reasoning:

⁵As of August 2021, this paper has 2,800 citations.

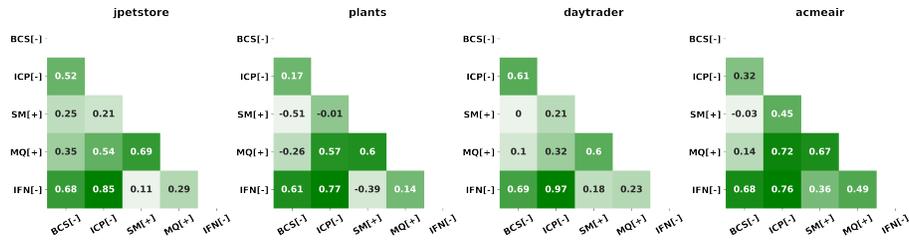


Figure 1: Spearman ρ among metrics from 1,000 runs.

- Ryu & Baik (2016) used reweighted Naive Bayes for cross-project defect prediction;
- In a similar approach, a reweighted Naive Bayes was used by Arar & Ayan (2017) for defect prediction and Yedida & Menzies (2021) explored weighted loss functions in deep learners for defect prediction.
- In the AI literature, Lin et al. (2017) propose a “focal loss” function that uses an exponential weighting scheme.

To the best of our knowledge, augmenting the loss function has not been previously attempted for improving microservice partitions.

One challenge with designing a loss function is how to obtain the required weights. In DEEPLY, we first run the algorithm 1,000 times to generate a set of metrics shown in Table 1. Then, we check the correlation among the metrics using the Spearman correlation coefficients. If any two metrics have strong correlations we prefer to keep one to remove the redundant metrics for the optimization. Figure 1 indicates the correlations among the metrics. Clearly, some of the metrics are highly correlated. Therefore, we use a reduced set of metrics for evaluating our approaches. We set a threshold of 0.6 to prune the set of metrics. We observe that MQ has higher correlations with other metrics than SM. Since IFN and ICP are highly correlated across all datasets, we arbitrarily choose ICP. This leads to the final set of metrics: BCS, ICP, and SM. Note that to ensure that we do not generate “dust” (individual classes in a partition) or “boulders” (monolithic partitions), we also include NED in the final metric set (for which we assigned a static weight of 0.2).

Based on these three metrics, we choose a loss function to pick one model from

the frontier of best solutions. This loss function is

$$\mathcal{L}_H(P) = \sum_i w_i m_i(P) \tag{2}$$

where w_i are *weights* assigned to each of the metrics m_i , and P is the partition. Additionally, we divide the BCS weight by 10 (for an overall weight of 0.1) to normalize its value to the same order of magnitude as the other metrics. Finally, we add in a term for the NED metric, so that we do not generate “dust” or “boulders” (e.g., a monolith with 20 classes is not partitioned into 19 and 1).

Next, we change the clustering method used in CO-GCN (Desai et al. (2021)). Rather than using the k-means clustering, which assumes globular clusters, we use spectral clustering, which can produce more flexible cluster shapes (Yedida & Saha (2021)). We also change the cluster loss function to

$$\mathcal{L}_{clus} = \sum_i \min_j |x_i - x_j| \tag{3}$$

where x_i and x_j are data points.

Next, we update the learning rate scheduling policy to the “1cycle” policy (Smith (2017); Smith & Topin (2019)), which has been shown to lead to faster convergence (see Table 3 for details). We update the learning rate every 200 steps.

Finally, we change all the activation functions in the network to ReLU ($f(x) = \max(0, x)$) (Nair & Hinton (2010)), except the last layer (which we leave unchanged to $f(x) = x$). Specifically, like Desai et al. (2021), we use an encoder-decoder architecture with 2 layers per each layer; each layer being a graph convolution as defined by Kipf & Welling (2016). Therefore, for an input *feature matrix* X , we consider

$$E \leftarrow \text{ReLU}(\hat{A}(\text{ReLU}(\hat{A}XW_1))W_2) \tag{4}$$

$$D \leftarrow \text{ReLU}(\hat{A}(\text{ReLU}(\hat{A}EW_3))W_4) \tag{5}$$

Algorithm 1 shows the overall approach. In the algorithm **the lines in red** (19-22,25) are from the CO-GCN algorithm (and all else is our extension). We first collect correlation statistics using a Monte Carlo-style data collection (lines 1-4). Then we set weights (lines 4-7) and run hyperopt for 100 iterations (lines 10-15), while collecting

the results of each run. The weighted loss function then picks the “best” candidate in line 16, and returns the optimal hyper-parameters in line 17. The actual model training itself is delegated to `CO-GCN-modified`.

We form the graph Laplacian in lines 18-20, and pretrain (for 1 epoch) the encoder (see Eq. (4)) and decoder (see Eq. (5)). We initialize the clusters in line 23, but use spectral clustering instead. Then, we run the actual training for 300 epochs.

In summary, our new method `DEEPLY` differs from `CO-GCN` in the following ways:

- We use a better learning rate scheduling policy from deep learning literature (discussed in Table 3).
- We update the activation functions used in the neural network (also see Table 3).
- We run hyper-parameter optimization and choose from the Pareto frontier using a custom loss function over a reduced space of metrics (discussed in §3.6.2).
- We update the clustering method employed, and the corresponding term in the deep learner loss function (see §3.6.3).

4. Experimental Design

In this section, we detail our experimental setup for the various parts of our research. Broadly, we follow the same experimental setup as Yedida et al. (2021a). However, that paper concluded that different optimizers performed differently across datasets and metrics, and that there was no one winning algorithm. In this paper, using the method described in §3.6, we show that our approach wins most of the time across all our datasets and metrics.

4.1. Case studies

We use four open source projects to evaluate our approach against prior work. These are *acmeair*⁶ (an airline booking application), *daytrader*⁷ (an online stock trad-

⁶<https://github.com/acmeair/acmeair>

⁷<https://github.com/WASdev/sample.daytrader7>

Algorithm 1: DEEPLY . Note *CO-GCN-modified* is a sub-routine containing our changes to the original CO-GCN system. The **the lines in red** (18-21,24) are from the original CO-GCN algorithm (and all else is our extension).

```

1 Algorithm DEEPLY
  Input : graph dataset  $D$ 
  Output: optimal hyper-parameters  $\theta^*$ 
2 for 1,000 iterations do
3   | run CO-GCN-modified( $D$ ) with random settings and collect metrics
4 end
5  $w_{SM} \leftarrow -1/corr(SM, MQ)$  // initialize weights
6  $w_{ICP} \leftarrow 1/corr(BCS, ICP)$ 
7  $w_{NED} \leftarrow 0.2, w_{BCS} \leftarrow 0.1$ 
8  $\theta = \phi$  // initialize our history to empty set
9  $M = \phi$  // initialize results to empty
10 for  $i=1..100$  do
11   |  $\theta_i \leftarrow \text{hyperopt}(\theta)$ 
12   |  $M_i \leftarrow \text{CO-GCN-modified}(D; \theta_i)$  // run the model
13   | append  $\theta_i$  to  $\theta$  // log hyper-params
14   | append  $M_i$  to  $M$  // log results
15 end
16  $\theta^* = \arg \min_{\theta} \sum_{j=1}^4 w_j M_j$ 
17 return  $\theta^*$ 

18 Algorithm CO-GCN-modified
  Input : graph dataset  $D = (A, X)$ 
  Output: partitioned microservices
  // compute the graph Laplacian
19  $\tilde{A} \leftarrow A + I$ 
20 define diagonal matrix  $\tilde{D}$  such that  $\tilde{D}_{ii} = \sum_j \tilde{A}_{ij}$ 
21  $\hat{A} \leftarrow \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}}$ 
22 pretrain the encoder and decoder using (4) and (5) respectively
23 initialize the clusters using spectral clustering on embeddings
24 train the network ( $E, D$ ) for 300 epochs using Alg. 1 lines 5-9 from (Desai et al.
  (2021)) and 1cycle (Smith & Topin (2019))
25 get embeddings using (4)
26 cluster the embeddings using spectral clustering
27 return clusters

```

Table 4: Statistics about the datasets used in this study.

Application	#classes	#methods	#Runtime traces	Class coverage	Method coverage
acmeair	33	163	11	28 (84%)	108 (66%)
daytrader	109	969	83	73 (66%)	428 (44%)
jpetstore	66	350	44	36 (54%)	236 (67%)
plants	37	463	43	25 (67%)	264 (57%)

ing application), *jpetstore*⁸ (a pet store website), and *plants*⁹ (an online web store for plants and pets). These applications are built using Java Enterprise Edition (J2EE), and common frameworks such as Spring and Spring Boot.

In Table 4, we show statistics about the datasets (number of classes and methods) and the runtime traces that we used (number of traces, and their class and method coverage). While the coverage here may seem low, we note that applications tend to have a significant amount of “dead”, or unreachable code. For example, Brown et al. (1998) found between 30 to 50% of an industrial software system was dead code. Eder et al. (2012) found that for an industrial software system written in .NET, 25% of method genealogies were dead. Therefore, we were not worried about the coverage seeming low.

4.2. Hyper-parameter Optimization

We use the Tree of Parzen Estimators (TPE) (Bergstra et al. (2011)) algorithm from the hyperopt (Komer et al. (2014)) package for hyper-parameter optimization . As discussed in §3.6, we use $\mathcal{L}_H(P)$ from (2) to guide hyperopt towards an optimal set of hyper-parameters. Table 2 lists the hyper-parameters that we tune, along with their ranges. We run the hyper-parameter optimizer for 100 iterations. We train for 300 epochs using an initial learning rate of 0.01.

⁸<https://github.com/mybatis/jpetstore-6>

⁹<https://github.com/WASdev/sample.plantsbywebsphere>

4.3. Baselines

Following our literature review, we use the baselines shown in Table 2. All these approaches, except Mono2Micro and CO-GCN, were either open-source, or re-implemented by us. For a fair evaluation, we tune each algorithm with hyperopt for 100 iterations (which is the same as our approach). We use the same loss function $\mathcal{L}_H(P)$ shown in (2), but set all the weights to either 1 (for metrics we wish to minimize), or -1 (for metrics we wish to maximize), since the correlation-based weights are a novel idea for our approach.

4.4. Metrics

For a fair comparison with prior work, we must compare using the same set of metrics. We choose a total of five metrics to evaluate our core hypothesis that hyperparameter tuning improves microservice extraction algorithms. These are detailed below. These metrics have been used in prior studies, although different papers used different set of metrics in their evaluations. For fairness, we use metrics from all prior papers. These metrics evaluate different aspects of the utility of an algorithm that might be more useful to different sets of users (detailed in the RQ1), e.g., BCS evaluates how well different business use cases are separated across the microservices.

Inter-partition call percentage (ICP) (Kalia et al. (2020)) is the percentage of runtime calls across different partitions. For lower coupling, *lower* ICP is better.

Business context sensitivity (BCS) (Kalia et al. (2020)) measures the mean entropy of business use cases per partition. Specifically,

$$BCS = \frac{1}{K} \sum_{i=1}^K \frac{BC_i}{\sum_j BC_j} \log_2 \left(\frac{BC_i}{\sum_j BC_j} \right)$$

where K is the number of partitions and BC_i is the number of business use cases in partition i . Because BCS is fundamentally based on entropy, *lower* values are better.

Structural modularity (SM), as defined by Jin et al. (2019), combines cohesion and coupling, is given by

$$\begin{aligned}
SM &= \frac{1}{K} \sum_{i=1}^n \frac{coh_i}{N_i^2} - \frac{1}{N_i(N_i - 1)/2} \sum_{i < j < K} coup_{i,j} \\
coh_i &= \frac{2}{m(m-1)} \sum_{\substack{c_i, c_j \in C \\ i < j}} \sigma(c_i, c_j) \\
coup_{i,j} &= \frac{\sum_{\substack{c_1 \in C_i \\ c_2 \in C_j}} \sigma(c_1, c_2)}{|C_i||C_j|}
\end{aligned}$$

where N_i is the number of classes in partition¹⁰ i , K is the number of partitions, coh_i is the cohesion of partition i , and $coup_{i,j}$ is the coupling between partitions i and j , c_i refers to a class in the subset, C_i, C_j are two partitions, σ is a general similarity function bounded in $[0, 1]$, and the $i < j$ condition imposes a general ordering in the classes. Higher values of SM are better.

Modular quality (MQ) (Mitchell & Mancoridis (2006)), coined by Mitchell & Mancoridis (2006), is defined on a graph $G = (V, E)$ as

$$\begin{aligned}
MQ &= \frac{2\mu_i}{2\mu_i + \epsilon} \\
\mu_i &= \sum_{(e_1, e_2) \in E} \mathbb{1}(e_1 \in C_i \wedge e_2 \in C_i) \\
\epsilon &= \sum_{\substack{(e_1, e_2) \in E \\ i \neq j}} \mathbb{1}(e_1 \in C_i \wedge e_2 \in C_j)
\end{aligned}$$

where $\mathbb{1}$ is the indicator function, and C_i, C_j are clusters in the partition. Higher values of MQ are better.

The *interface number (IFN)* (Mitchell & Mancoridis (2006)) of a partition is the number of interfaces needed in the final microservice architecture. Here, an interface is said to be required if, for an edge between two classes in the runtime call graph, the two classes are in different clusters.

¹⁰Note that we use the term "partition" to refer to both the set of all class subsets, as well as an individual subset, but it is typically unambiguous.

Finally, the *non-extreme distribution (NED)* is the percentage of partitions whose distributions are not “extreme” (in our case, these bounds were set to min=5, max=20).

However, as shown in Figure 1, some of these metrics are highly correlated with others. Therefore, to avoid bias in the evaluation and the loss function (i.e., if metrics M_1 and M_2 are correlated, and optimizer O performs best on M_1 , it likely performs best on M_2 as well), we use a subset of these metrics. Specifically, we prune the metric set as discussed in §3.6.3. Note that across all our figures and tables, a “[−]” following a metric means lower values are better, and a “[+]” following a metric means that higher values are better.

4.5. Statistics

For comparing different approaches, we use statistical tests due to the stochastic nature of the algorithms. According to standard practice (Ghotra et al. (2015)), we run our algorithms 30 times to get a distribution of results, and run a Scott-Knott test as used in recent work (Agrawal et al. (2019); Yedida & Menzies (2021)) on them. The Scott-Knott test is a recursive bi-clustering algorithm that terminates when the difference between the two split groups is insignificant. The significance is tested by the Cliff’s delta using an effect size of 0.147 as recommended by Hess & Kromrey (2004). Scott-Knott searches for split points that maximize the expected value of the difference between the means of the two resulting groups. Specifically, if a group l is split into groups m and n , Scott-Knott searches for the split point that maximizes

$$\mathbb{E}[\Delta] = \frac{|m|}{|l|} (\mathbb{E}[m] - \mathbb{E}[l])^2 + \frac{|n|}{|l|} (\mathbb{E}[n] - \mathbb{E}[l])^2$$

where $|m|$ represents the size of the group m .

The result of the Scott-Knott test is *ranks* assigned to each result set; higher the rank, better the result. Scott-Knott ranks two results the same if the difference between the distributions is insignificant.

5. Results

RQ1: *How prevalent is hyper-parameter brittleness in automated microservice partitioning?*

Here, we ran the approaches from Table 2, 30 times each, then compared results from those treatments with the statistical methods of §4.5. The median results are shown in Table 5a and the statistical analysis is shown in Table 5b.

In those results, we see that across different datasets and metrics, those ranks vary widely, with little consistency across the space of datasets and metrics. For example:

- For jpetstore, we see that the best algorithms for the three metrics are Mono2Micro, CO-GCN, and MEM respectively;
- For acmeair, the best algorithms are Mono2Micro, and Bunch;
- For plants, the best algorithms are FoSCI, CO-GCN, and MEM;
- For daytrader, the best are Mono2Micro, CO-GCN, and Bunch.

Hence we say:

For all the data sets and goals studied here, there is widespread performance brittleness.

As to why this issue has not been reported before in the literature, we note that much of the prior work was focused on one algorithm exploring one case study. To the best of our knowledge, this is first to perform a comparison across the same datasets and metrics and also propose a novel approach.

RQ2: *Is hyper-parameter optimization enough to curb the aforementioned optimizer brittleness?*

Here we check if brittleness can be solved by tuning the partitioning methods.

Since all the algorithms in our study were tuned by hyperopt, the results of Table 5 show that even post-tuning, there is a large brittleness problem. Accordingly, we say:

Hyper-parameter optimization does not suffice to fix performance brittleness.

Since hyper-parameter optimization is not enough to tame brittleness, we ask:

RQ3: *How else might we fix the aforementioned brittleness problem?*

When we added the novel loss function (discussed above in §3.6.3), we obtained the results shown in the last line of the two tables of Table 5b. When measured in

Table 5: Results on all datasets. The top row shows our median performance scores over 30 runs, while the bottom row shows the Scott-Knott ranks (lower is better). Gray cells indicate the best result according to the Scott-Knott test. All algorithms were tuned by hyperopt.

(a) Median performance scores over 30 runs

Algorithm	jpetstore			acmeair			plants			daytrader		
	BCS [-]	ICP [-]	SM [+]	BCS [-]	ICP [-]	SM [+]	BCS [-]	ICP [-]	SM [+]	BCS [-]	ICP [-]	SM [+]
Bunch	2.43	0.48	0.21	1.67	0.55	0.17	2.29	0.56	0.22	1.86	0.57	0.27
Mono2Micro	1.67	0.53	0.05	1.58	0.4	0.06	2.49	0.39	0.07	1.58	0.4	0.07
CO-GCN	2.79	0.27	0.2	1.89	0.47	0.15	2.46	0.35	0.24	2.09	0.05	0.13
FoSCI	1.99	0.66	0.05	2.08	0.54	0.07	1.94	0.45	0.07	2.04	0.48	0.07
MEM	2.74	0.48	0.22	2.13	0.69	0.03	2.04	0.42	0.25	2	0.59	0.09
DEEPLY	2.35	0.06	0.2	1.41	0.18	0.16	1.87	0.02	0.27	1.74	0.03	0.17

(b) Scott-Knott ranks. For all metrics, lower is better.

Algorithm	jpetstore			acmeair			plants			daytrader		
	BCS [-]	ICP [-]	SM [+]	BCS [-]	ICP [-]	SM [+]	BCS [-]	ICP [-]	SM [+]	BCS [-]	ICP [-]	SM [+]
Bunch	4	3	2	2	4	1	4	6	4	3	5	1
Mono2Micro	1	5	5	1	2	4	6	3	5	1	3	6
CO-GCN	6	2	2	3	3	3	5	2	3	6	2	3
FoSCI	2	6	4	4	4	5	2	5	6	5	4	5
MEM	5	4	1	5	5	6	3	4	2	4	6	4
DEEPLY	3	1	3	1	1	2	1	1	1	2	1	2

terms of ranks seen amongst the different populations, the last line of Table 5b is most insightful. Here we see that in general, DEEPLY performs better compared to all other optimizers across all our case studies. Hence we say:

Weighted losses together with hyper-parameter optimization fix the brittleness problem.

RQ4: Do we generate “dust” or “boulders”?

Two anti-patterns of partitioning are “dust” (generating too many partitions) and “boulders” (generating too few partitions).

To analyze this, Figure 2 shows the distribution of partition sizes seen in 30 random

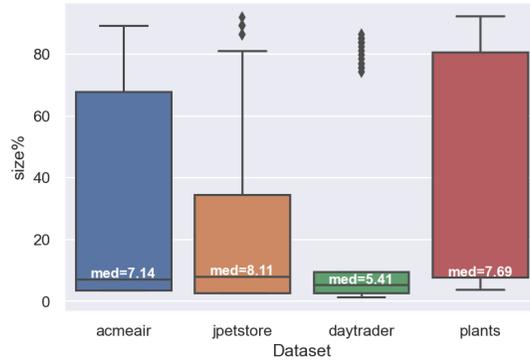


Figure 2: Analysis of partitions generated by our approach. Distribution of class size percentages across datasets (median results).

samples. From that figure we say that our methods usually generate small number of partitions. Also, since we are usually dealing with classes ranging from 33 in acmeair to 109 in daytrader, Figure 2 tells us that we are not generating partitions with only one item per partition (for example, on plants, the median size is $5.4\% \times 111 = 6$ classes). Hence we say:

Our partitions are neither “boulders” nor “dust”.

6. Discussion

6.1. Lessons Learned

Yedida et al. (2021a) listed four lessons learned from their study. Our results suggest that some of those lessons now need to be revised.

1. We fully concur with Yedida et al. when they said “*do not use partitioning methods off-the-shelf since these these tend to have subpar results.*” That said, currently we are planning to package (in Python) the DEEPLY system. Once that is available then Algorithm 1 should accomplish much of the adjustments required to commission DEEPLY for a new domain.
2. Yedida et al. said “*the choice of tuning algorithm is not as important as the decision to tune. The random and hyperopt optimizers performed differently on different metrics*”

and datasets, but in a broader view, shared the same number of highest statistical rankings. Therefore, the decision to tune is important, but the choice of algorithm may not be as important.”. We disagree since, as shown by Table 5b, our methods demonstrate overall better results (as indicated by the statistical ranks).

3. Yedida et al. said “More research is required on tuning. While our results shows that tuning is better than non-tuning, we also show that no single approach is a clear winner across multiple datasets or multiple performance goals.”. We concur but add that DEEPLY seems to resolve much of their pessimism about the state of the art in hyper-parameter optimization.
4. Yedida et al. said “There is no best partitioning algorithm... there is no one best algorithm across all metrics.” We agree, but only partially. The last row of Table 5b shows that even our preferred method DEEPLY does not always obtain top rank. That said, DEEPLY often performs as well or better than anything else.

6.2. On the value of dynamic traces

It is notable that one of the prior approaches we choose to compare against is Bunch and its hill-climbing algorithm. Several years ago, an extensive empirical study by Garcia et al. (2013) demonstrated that Bunch performs poorly in identifying meaningful abstractions in real-world systems it analyzes. However, we still chose Bunch as a comparative system, since that study used static attributes as the input to Bunch, while our inputs come from dynamic, runtime traces, which we believe makes it meaningfully different. That is, we use the results of Garcia et al. (2013) as an indication that static traces may not be sufficient for the microservice partitioning problem, and this study explores dynamic traces instead.

6.3. Business Implications

At a higher level, hyper-parameter tuning is akin to searching for various options and guessing which one is the best; weighted loss functions directly encode business goals in this process, making it a more focused effort. For example, changing business

goals can be trivially implemented in our framework, since the weighted loss function used in the hyper-parameter tuning is based on the metrics (i.e., no additional mathematical derivations need to be done).

Importantly, business users can (a) make a choice among many from the frontier of best solutions of a size that they can choose, with the understanding that higher sizes mean more options but takes slightly longer (b) see the trade-offs between different architectural design choices directly in terms of metrics (c) easily choose new metrics if they see fit. That is, our approach provides businesses with flexibility and transparency into the working of the model. While the deep learner itself is a black box, end users typically do not care about the internal workings of the model; only in interpretable ways to do better in their goals (this was studied by Chen et al. (2019)).

For businesses, we offer the following advantages:

- **Stability:** Business can be assured that our approach will perform well across any dataset, no matter the metric used. This stability is important for time-constrained businesses who need some guarantees of good results before using a new approach.
- **Performance:** Our approach achieved state-of-the-art performance across different and uncorrelated metrics on four open-source datasets. This high performance inspires confidence in our approach for businesses looking to adopt an automated system for the architectural change.
- **Openness:** Our code is fully open-source, but also modular. That is, businesses are not limited to our specific approach (which builds upon CO-GCN and uses hyperopt); rather, they are free to use our techniques to build upon any existing infrastructure that they may have (e.g., IBM Mono2Micro).

6.4. Research Implications

The ideas of this paper extend to other tasks and domains. In this section, we elaborate on the specific ideas and their broader utility.

Our approach is a general method that can be applied to any dataset, since the components themselves can be changed. For example, a different hyper-parameter op-

optimizer such as Optuna (Akiba et al. (2019)) can be used instead of hyperopt, and a different weighting mechanism can be chosen instead of our correlation-based weights. Finally, a different set of preprocessing can be used. Therefore, a generalized version of our approach is:

- (1) **Feature extraction.** Different features sets can be extracted from code. For example, one might use code2vec Alon et al. (2019), which transforms code snippets to fixed-length vectors.
- (2) **Hyper-parameter optimization.** Any hyper-parameter optimization approach can be plugged in here, such as random sampling, TPE, DODGE, etc.
- (3) **Loss-based selection.** Any loss function can be applied to the frontier of best solutions to select a configuration. Moreover, the loss function of the learner itself can be modified, as done in CO-GCN.

From a research standpoint, we offer the following:

- **Advancing the state-of-the-art:** Our approach consistently outperforms all the prior state-of-the-art approaches we tested against across three different metrics, on four datasets.
- **Modular approach:** Our approach can be adapted by changing the base algorithm (CO-GCN) and hyper-parameter optimization algorithm (hyperopt) and used on any dataset as discussed above.
- **Documenting the success of weighted losses:** Our paper adds to the body of literature that documents the success of using weighted losses for different problems, possibly motivating future work to also use them. More generally, our idea can be applied to any multi-objective optimization problem, using the general method from our paper: produce a frontier of best solutions (through hyper-parameter optimization, swarm optimization, etc.) and use a weighted loss to choose the best candidate. This idea has been used implicitly in the deep learning field. In particular, Santurkar et al. (2018); Li et al. (2017) show that a smoother loss function surface is beneficial for optimization. In the case

of Santurkar et al. (2018), the adding of “skip-connections” in the deep learner modify its loss function, making it smoother and therefore easier to optimize in. This idea has also been used by Chaudhari et al. (2019), who change the loss function to shape it into a more amenable form.

7. Threats to Validity

Sampling bias: With any data mining paper, it is important to discuss sampling bias. Our claim is that by evaluating on four different open-source projects across different metrics, we mitigate this. Nevertheless, it would be important future work to explore this line of research over more data.

Evaluation bias: While we initially considered comparing across all the metrics we found in the literature, we noticed large correlations between those metrics. Therefore, to reduce the effect of correlations, we chose a subset of the metrics and evaluated all the approaches across those. Moreover, in comparing the approaches, we tuned all of them using the same hyper-parameter optimization algorithm, for the same number of iterations.

External validity: We tune the hyper-parameters of the algorithm, removing external biases from the approach. Our baselines are also tuned using hyperopt for the same number of iterations.

Internal validity: All algorithms compared were tuned using hyperopt. Because our approach involves using weighted losses and other tweaks to CO-GCN, these were not applied to the other algorithms.

8. Conclusion

In this paper, we presented a systematic approach for achieving state-of-the-art results in microservice partitioning. Our approach consists of hyper-parameter optimization and the use of weighted losses to choose a configuration from the frontier of best solutions.

Broadly, the lesson from this work is:

At least for microservice partitioning, weighted loss functions can work together with tuning to achieve superior results.

We first analyzed the existing state-of-the-art. Through this review, we noticed (a) highly correlated, and therefore redundant, metrics used in the literature (b) inconsistent comparisons being made in prior work (c) prior work showing performance brittleness across different goals and datasets. We argued that this creates an issue for businesses looking to use a microservice partitioning tool for internal software. Through Monte Carlo-style sampling, we chose a reduced, less correlated set of metrics, and used those as data for choosing weights for each goal, accounting for their different scales. We built upon an existing tool, CO-GCN (Desai et al. (2021)), to build DEEPLY in this paper, which fixes the issues listed above. To the best of our knowledge, ours is the first structured attempt at (a) reviewing the literature for a list of state-of-the-art microservice partitioning approaches (b) comparing all of them on the same datasets and the same metrics (c) fixing the performance brittleness issue using weighted losses and tuning. Finally, we discussed the broader impacts of the approach specified in this paper, generalizing the concept beyond the specific case of microservice partitioning.

Our approach is extensible and modular, consistently outperforms other approaches across datasets and metrics, and can easily be adapted to any metric that an enterprise is interested in. Moreover, the two loss functions (for the deep learner and the hyper-parameter optimization algorithm) can be tweaked to suit business goals.

9. Future Work

Our approach being modular leads to several avenues of future work, which we discuss in this section.

Because we apply weighted losses at the hyper-parameter optimization level, we can apply the same approach using a different base algorithm than CO-GCN. Specifically, we could build a Pareto frontier using a different state-of-the-art algorithm and then use our weighted loss function to choose a “best” candidate.

Further, it would be useful to explore our methods on more datasets and metrics. In particular, it would be beneficial to test our methods on large enterprise systems. In addition, businesses might be interested in how much faster our system is compared to human effort.

Finally, our method (using weighted losses to guide exploration of the Pareto frontiers) is a general method that is not specific to microservice partitioning. Specifically, since our losses choose from a Pareto frontier generated by a hyper-parameter optimizer, (a) the choice of optimizer is left to the user (b) the application that the optimizer is applied to can be freely changed. Therefore our methods might offer much added value to other areas where hyper-parameter optimization has been applied.

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