CacheOptimizer: Helping Developers Configure Caching Frameworks for Hibernate-Based Database-Centric Web Applications

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ABSTRACT

To help improve the performance of database-centric cloud-based web applications, developers usually use caching frameworks to speed up database accesses. Such caching frameworks require extensive knowledge of the application to operate effectively. However, all too often developers have limited knowledge about the intricate details of their own application. Hence, most developers find configuring caching frameworks a challenging and time-consuming task that requires extensive and scattered code changes. Furthermore, developers may also need to frequently change such configurations to accommodate the ever changing workload.

In this paper, we propose *CacheOptimizer*, a lightweight approach that helps developers optimize the configuration of caching frameworks for web applications that are implemented using Hibernate. *CacheOptimizer* leverages readily-available web logs to create mappings between a workload and database accesses. Given the mappings, *CacheOptimizer* discovers the optimal cache configuration using coloured Petri nets, and automatically adds the appropriate cache configurations to the application. We evaluate *CacheOptimizer* on three open-source web applications. We find that i) *CacheOptimizer* improves the throughput by 27–138%; and ii) after considering both the memory cost and throughput improvement, *CacheOptimizer* still brings statistically significant gains (with mostly large effect sizes) in comparison to the application's default cache configuration and to blindly enabling all possible caches.

CCS Concepts

•**Software and its engineering** → **Software performance;** *Cloud computing; Object oriented frameworks;*

Keywords

Performance, application-level cache, ORM, web application

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1. INTRODUCTION

Web applications are widely used by millions of users worldwide. Thus, any performance problems in such applications can often cost billions of dollars. For example, a report published in 2012 shows that a one-second page load slowdown of the Amazon web applications can cost an average of 1.6 billion dollars in sales each year [25]. The complexity and scale of modern database-centric web applications complicate things further. As much as 88% of developers find their applications' performance is deeply impacted by their reliance on databases [29].

Application-level caching frameworks, such as Ehcache [54] and Memcached [38], are commonly used nowadays to speed up database accesses in large-scale web applications. Unlike traditional lower-level caches (e.g., hardware or web proxies) [3, 7, 18, 34], these application-level caching frameworks require developers to instruct them about what to cache; otherwise these frameworks are not able to provide any benefit to the application.

Deciding what should be cached can be a very difficult and time-consuming task for developers, which requires in-depth knowledge of the applications and workload. For example, to decide that the results of a query should be cached, developers must first know that the query will be frequently executed, and that the fetched data is rarely modified. Furthermore, since caching frameworks are highly integrated with the application, these frameworks are configured in a very granular fashion – with cache API calls that are scattered throughout the code. Hence, developers must manually examine and decide on hundreds of caching decisions in their application. Even worse, a recent study finds that most database-related code is undocumented [37], which makes manual configuration even harder.

Developers must continuously revisit their cache configuration as the workload of their application changes [22]. Outdated cache configurations may not provide as much performance improvement, and they might even lead to performance degradation. However, identifying workload changes is difficult in practice for large applications [53, 61]. Even knowing the workload changes, developers still need to spend great effort to understand the new workload and manually re-configure the caching framework.

In this paper, we propose *CacheOptimizer*, a lightweight approach that automatically helps developers decide what should be cached (and also automatically places the cache configuration code) in web applications that are implemented using Hibernate in order to optimize the configuration of caching frameworks. Using *CacheOptimizer*, developers can better manage the cost of their database accesses – greatly improving application performance [6, 11, 13–16, 48].

CacheOptimizer first recovers the workload of a web application by mining the web server access logs. Such logs are typically readily-available even for large-scale applications that are deployed in production environments. *CacheOptimizer* further analyzes the source code statically to identify the database accesses that are associated with the recovered workloads. To identify detail information about the recovered database accesses, such as the types of the access and the accessed data, *CacheOptimizer* leverages static taint analysis [30] to map the input variables of the web requests to the exact database accesses. Combining the recovered workload and the corresponding database accesses, *CacheOptimizer* models the workload, the database accesses, and the possible cache configurations as a coloured Petri net. By analyzing the Petri net, *CacheOptimizer* is able to determine an optimal cache configuration (i.e., given a workload, which objects or queries should be cached by the caching frameworks). Finally, *CacheOptimizer* automatically adds the appropriate configuration calls to the caching framework API into the source code of the application.

We have implemented our approach as a prototype tool and evaluated it on three representative open-source database-centric web applications (Pet Clinic [44], Cloud Store [20], and OpenMRS [41]) that are based on Hibernate [21]. The choice of Hibernate is due to it being one of the most used Java platforms for database-centric applications in practice today [58]. However, our general idea of automatically configuring a caching framework should be extensible to other database abstraction technologies. We find that after applying *CacheOptimizer* to configure the caching frameworks on the three studied applications, we can improve the throughput of the *entire application* by 27–138%.

The main contributions of this paper are:

1. We propose an approach, called *CacheOptimizer*, which helps developers in automatically optimizing the configuration of caching frameworks for Hibernate-based web applications. *CacheOptimizer* does not require modification to existing applications for recovering the workload, and does not introduce extra performance overhead.
2. We find that the default cache configuration may not enable any cache or may lead to sub-optimal performance, which shows that developers are often unaware of the optimal cache configuration.
3. Compared to having no cache (*NoCache*), the default cache configurations (*DefaultCache*), and enabling all caches (*CacheAll*), *CacheOptimizer* provides a better throughput improvement at a lower memory cost.

Paper Organization. The rest of the paper is organized as follows. Section 2 first discusses related work to our paper. Section 3 introduces background knowledge for common caching frameworks. Section 4 describes the design details of *CacheOptimizer*. Section 5 evaluates the benefits and costs of *CacheOptimizer*. Section 6 discusses threats to validity of our study. Finally, Section 7 concludes the paper.

2. RELATED WORK AND BACKGROUND

In this section, we discuss related work to *CacheOptimizer*. We focus on three closely related areas: software engineering research on software configuration, optimizing the performance of database-centric applications, and caching frameworks.

2.1 Software Configuration

Improving Software Configurations. Software configurations are essential for the proper and optimal operation of software applications. Several prior software engineering studies have proposed approaches to analyze the configurations of software applications. For example, Rabkin *et al.* [47] use static analysis to extract the configuration options of an application, and infer the types of these configurations. Xu *et al.* [2] conduct an empirical study on the configuration parameters in four open-source applications in order to help developers design the appropriate amount of configurability for their application. Liu *et al.* [57] focus on configuring client-slide browser caches for mobile devices.

Detecting and Fixing Software Configuration Problems. Rabkin *et al.* [46] use data flow analysis to detect configuration-related functional errors. Zhang *et al.* [59] propose a tool to identify the root causes of configuration errors. In another work, Zhang *et al.* [60] propose an approach that helps developers configure an application such that the application's behaviour does not change as the application evolves. Chen *et al.* [10] propose an analysis framework to automatically tune configurations to reduce energy consumption for web applications. Xiong *et al.* [56] automatically generate fixes for configuration errors using a constraint-based approach.

Prior research on software configuration illustrates that optimizing configurations is a challenging task. In this paper, we propose *CacheOptimizer*, which particularly focuses on helping developers optimize the cache configurations to improve the performance of large-scale web applications.

2.2 Improving Application Performance by Reducing the Overhead of Database Accesses

Most studies in literature propose frameworks to reduce the overhead of database accesses by batching [28], or reordering [6] database accesses. Ramachandra *et al.* [48] propose a framework for pre-fetching data from the database management system (DBMS) in batches in order to reduce database access overheads. Similarly, Cheung *et al.* [16] propose a framework for delaying database accesses as late as possible, and sending database access requests only when the data is needed in the application. Chavan *et al.* [9] propose a framework for sending queries asynchronously in order to improve application performance.

Several proposed frameworks improve application performance by analyzing the source code. In our prior work [12, 14], we propose a static analysis framework to detect and rank database access performance anti-patterns. Developers can address these anti-patterns based on their priorities. Cheung *et al.* [17] leverage static analysis and code synthesis to automatically generate optimal SQL queries according to post-conditions and loop invariants. Grechanik *et al.* [31] propose a framework that combines both static and dynamic analysis to prevent database deadlocks. Chaudhuri *et al.* [8] use instrumented database access information

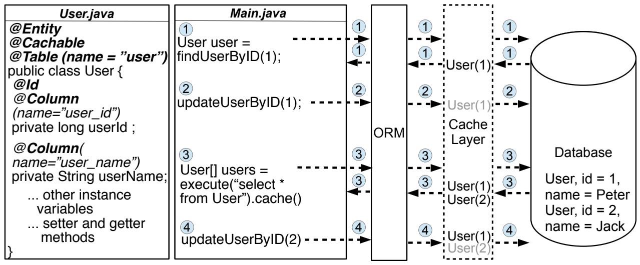


Figure 1: An example of simplified Hibernate code, Hibernate cache configuration code, and Hibernate cache mechanism. The numbers and the arrows indicate the flow for different workloads. The grey User objects in the cache layer means the objects are invalidated in the cache layer.

to find database-related performance problems in the code.

Compared to prior studies, we not do propose a new framework. Instead, *CacheOptimizer* helps developers optimize the configuration of the frameworks (in particular caching frameworks) that are already in use in practice today. Indepth knowledge of a software application is needed for software developers to optimally configure such frameworks.

2.3 Caching Frameworks

There are many prior studies on cache algorithms and frameworks. Many cache algorithms such as least recently used (LRU) [34], and most recently used (MRU) [18] are widely used in practice for scheduling lower-level caches. For example, such algorithms are used to improve the performance of web applications by caching web pages through proxies [7, 24]. Most of these caching algorithms operate in an unsupervised dumb fashion, i.e., these low-level caching algorithms do not require any application-level knowledge to operate.

Many modern applications generate dynamic content, which may be highly variable and large in size, based on data in the DBMS. Therefore, many low-level cache frameworks are becoming less effective. Many recent caching frameworks cache database accesses at the application level [27, 40]. When using these application-level caching frameworks, developers have full control of what should be cached in an application. However, to leverage these caching frameworks effectively, they must be configured properly.

Unlike most prior studies, *CacheOptimizer* does not try to manage cache scheduling. Instead, *CacheOptimizer* is designed to help developers optimize the configuration of application-level caching frameworks, which must be configured correctly for developers to fully leverage their benefits.

3. HIBERNATE AND CACHING MECHANISMS

3.1 Hibernate

CacheOptimizer automatically configure the caching framework for Hibernate-based web applications [21]. Hibernate is one of the most popular Java frameworks for abstracting database operations. Hibernate abstracts database accesses as object calls in Java instead of using SQL or JDBC directly. Hibernate is very popular among developers, because it helps reduce the amount of boilerplate code and development time [36]. For instance, a recent survey shows that among the 2,164 surveyed Java developers, 67.5% use Hibernate [58] instead of other database abstraction frameworks (including JDBC). Figure 1 shows an example of using Hibernate to abstract database accesses in Java. In this example, annotations (e.g., *@Entity*, *@Table*, and *@Column*) are added to User.java to specify the mapping between tables in a relational database and objects in Java. Based on such annotations, Hibernate automatically transforms user records to user objects and vice versa, and automatically translates the manipulation of the user object to the corresponding SQL queries. Hibernate is often used along caching frameworks like Ehcache [54]. These application-level caching frameworks aim to improve the performance of database-centric applications by reducing the number of database accesses.

3.2 Hibernate Caching Mechanism

Most caching frameworks act like an in-memory key-value store. When using Hibernate, these caching frameworks would store the database entity objects (objects that have corresponding records in the DBMS) in memory and assign each object a unique ID (i.e., the primary key). There are two types of caches in Hibernate:

- **Object cache.** As shown in workflow 1 (Figure 1), if the requested user object is not in the cache layer, the object will be fetched from the DBMS. Then, the user object will be stored in the cache layer and can be accessed as a key-value pair using its id (e.g., {*id: 1, User obj*}). If the object is updated, the cached data would be evicted to prevent a stale read (Workflow 2).

  To cache database entity objects, developers must add an annotation *@Cachable* at the class declaration (as shown in User.java in Figure 1). Then, *all* database entity object retrieved by ID (e.g., retrieved using *findUserById()*) would be cached. These annotations configure the underlying caching frameworks.

- **Query cache.** The cache mechanism for query cache is slightly different from object cache. For example, the cached data for a *select all* query on the user table (Workflow 3) would look as follows:

  $$\begin{Bmatrix} \textit{select * from User} \rightarrow \{id:1, id:2\} \\ \{id:1, id:2\} \rightarrow \{id:1, \text{User obj}\}, \{id:2, \text{User obj}\} \end{Bmatrix}$$

  The cache layer stores the *ids* of the objects (i.e., id 1 and 2) that are retrieved by the query, and uses the ids to find the cached objects (the corresponding User obj). Thus, the object cache must be enabled to use a query cache. When a user object is updated (workflow 4), the query cache needs to retrieve the updated object from the DBMS to prevent a stale read. Thus, if the queried entity objects are frequently modified, using a query cache may not be beneficial, and may even hinder performance [26].

  To cache query results, developers must call a method like cache() before executing the query (Main.java in Figure 1). Such method is used to configure the underlying caching frameworks.

Adding caches incorrectly can introduce overhead to the application. Caching a frequently modified object or query will cause the caching framework to constantly evict and

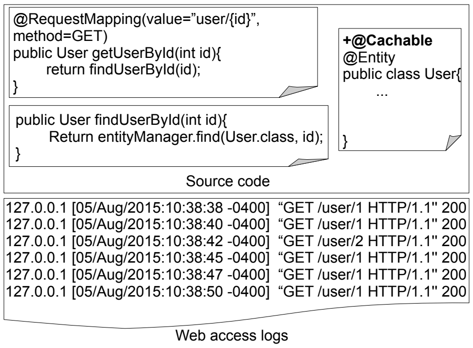


Figure 2: A working example of *CacheOptimizer*. The + sign in front of the @Cachable line indicates that the caching configuration is added by *CacheOptimizer*.

renew the cache, which not only causes cache renewal overhead but may also result in executing extra SQL queries. Therefore, blindly adding caches without understanding the workload may lead to performance degradation [51].

4. CACHE OPTIMIZER

CacheOptimizer optimizes the configuration of caches that are associated with database accesses that occur for a given workload. Hence, our approach needs to recover the workload of an application then to identify which database access occurs within that particular workload. In the following subsections, we explain each step of the inner workings of *CacheOptimizer* in detail using a working example. The input of the working example shown in Figure 2 consists of two parts: 1) source code of the application and 2) web access logs. Figure 3 shows an overview of *CacheOptimizer*.

4.1 Recovering Control and Data Flow Graphs

We first need to understand the calling and data flow relationships among methods, and determine which application-level methods are impacted by database caching (i.e., which methods eventually lead to a database access). We therefore extract the call and data flow graphs of the application by parsing the source code of the application using the Eclipse JDT. We opt to parse the source code instead of analyzing the binary since we need to locate the Hibernate annotations in the source code – such annotations are lost after compiling the source code to Java byte code. We mark all Hibernate methods that access the DBMS (e.g., query.execute()) in the call and data flow graphs. Such methods are easy to identify since they are implemented in the same class (i.e., in the EntityManager and the Query class of Hibernate). Once such methods are marked, we are able to uncover all the application-level methods that are likely to be impacted by optimizing the database cache. In our working example, after generating the call and data flow graphs, and identifying the Hibernate database access methods, we would know that the method getUserById contains one database access, and the parameter is passed in through a web request.

4.2 Linking Logs to Application-Level Methods

We recover the workload of the application by mining its web access logs. We leverage web access logs because of the following reasons. First, web access logs are typically readily available without needing additional instrumentation since many database-centric applications rely on RESTFul web service (based on HTTP web requests) [49] to accept requests from users [5]. For example, large companies like IBM, Oracle, Facebook and Twitter all provide RESTFul APIs[1]. Second, unlike application logs, web access logs have a universal structure (the format of all log lines are the same) [55]. Hence, compared to application logs, web access logs are easier to analyze and do not usually change as an application evolves [50].

Web access logs may contain information such as the requestor's IP, timestamp, time taken to process the request, requested method (e.g. GET), and status of the response. An example web access log may look like:

> *127.0.0.1 [05/Aug/2015:10:38:38 -0400] 1202 "GET /user/1 HTTP/1.1" 200*

This web access log shows that a request is sent from the local host at August 05, 2015 to get the information of the user whose ID is 1. The status of the response is 200, and the application took 1,202 milliseconds to respond to the request.

In order to know which application-level methods will be executed for each web request, we use static analysis to match the web access logs to application-level methods. *CacheOptimizer* parses the standard RESTful Web Services (JAX-RS) specifications in order to find the handler method for each web request [42]. An example of JAX-RS code is shown below:

```
@RequestMapping(value = "/user/{id}", method=GET)
public User getUserById(int id) {
        return findUserById(id);
}
```

In this example, based on the JAX-RS annotations, we know that all GET requests with the URL of form "/user/{id}" will be handled by the getUserById method.

For every line of web access log, *CacheOptimizer* looks for the corresponding method that handles that web request. After analyzing all the lines of web access logs, *CacheOptimizer* generates a list of methods (and their frequencies) that are executed during the run of the application.

In our working example, we map every line of web access log to a corresponding web request handling method, i.e., getUserById method.

4.3 Database Access Workload Recovery

We want to determine which database accesses are executed for the workload. Since application-level cache highly depends on the details of the database accesses, we need to recover the types of the database access (e.g., a query versus a select/insert/update/delete of a database entity object by id) and the data that is associated with the database access (e.g., accessed tables and parameters). Such detailed information of database accesses helps us in determining the optimal cache configurations. We first link each web access log to its request-handler method in the code (as described in Section 4.2). Therefore, for each workload, we know the list of request-handler-methods that are executed (i.e., entry points into the application). Then, we conduct a call graph and static flow-insensitive interprocedural taint analysis on

[1] http://www.programmableweb.com/apis/directory

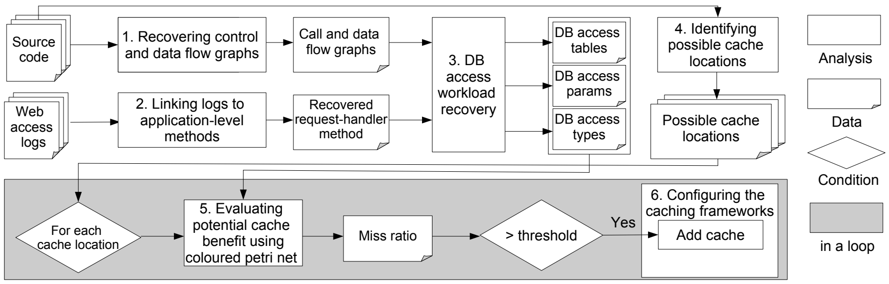


Figure 3: Overview of *CacheOptimizer*.

each web-request-handler method, using the generated call and data flow graphs (as describe in Section 4.1).

Our algorithm for recovering the database access workload is shown in Algorithm 1. For each web-request-handler-method, we identify all possible database accesses by traversing all paths in the call graph, and recording the type of the database access. After recovering the database access, we traverse the data flow graph of each web-request-handler method to track the usage of the parameters that are passed in through the web requests. We want to see if the parameters are used for retrieving/modifying the data in the DBMS. Such information helps us better calculate the optimized cache configuration. For example, we would be able to count the number of times a database entity object is retrieved (e.g., according to the id that is specified in the web requests), or how many times a query is executed (e.g., according to the search term that is specified in the web request). For POST, PUT, and DELETE requests, we track the URL (e.g., POST /newUser/1) to which the request is sent, which usually specifies which object the request is updating. If there is no parameter specified, then we assume that the request may modify any of the objects to be conservative on our advice on enabling the cache.

In our working example, we recover a list of database accesses. All of the accesses read data from the User table. In five of the accesses, the parameter is 1 and in one of the accesses, the parameter is 2.

Algorithm 1: Our algorithm for recovering database accesses.

```
Input: CG, DG, Mthd /* call graph, data flow graph,
       the request handler method */
Output: AccessInfo, Params /* accessed DB tables
        and DB func type (query or key-value
        lookup) and parameter of the request */
AccessInfo ← ∅; Params ← ∅;
/* Traverse the call graph from Mthd */
foreach path ∈ CG.findAllPathFrom(Mthd) do
    foreach call ∈ path do
        if isDBCall(call) then
            AccessInfo ← AccessInfo ∪
            (getAccessedTable(call), getMthdType(call));
        end
    end
end
/* Track the usage of the input params */
foreach param ∈ Mthd.getParams() do
    foreach path ∈ DG.findAllPathFrom(param) do
        foreach node ∈ path do
            node ← pointToAnalysis(node)
            if usedInDBAccessCall(node) then
                Params ←
                Params ∪ (dbAccessCall, node)
            end
        end
    end
end
```

4.4 Identifying Possible Caching Locations

After our static analysis step, we recover the location of all the database access methods in the code, and the mapping between Java classes and tables in the DBMS. Namely, we obtain all potential locations for adding calls to the cache configuration APIs. Thus, if a query needs to be cached, we can easily find the methods in the code that execute the query. If we need to add object caches, we can easily find the class that maps to the object's corresponding table in the DBMS. In our example, we identify that the class User is a possible location to place an object cache. Our static analysis step is very fast (23–177 seconds on a machine with 16G RAM and Intel i5 2.3GHz CPU) for our studied applications (see Table 1), and is only required when deploying a new release. Thus, the execution time has minimal impact.

We use flow-insensitive static analysis approaches to identify possible caching locations, because it is extremely difficult to recover precise dynamic code execution paths without introducing additional overhead to the application (e.g., using instrumentation). During our static analysis step, if we choose to assign different probabilities to code branches, we may under-count or over-count reads and writes to the DBMS. Under-counting reads may result in failing to cache frequently read objects, which has little or no negative performance impact (i.e., the same as not adding a cache). However, under-counting writes may result in caching frequently modified objects and thus has significant negative effects on performance. In contrast, we choose a conservative approach by considering all possible code execution paths (over-counting) to avoid under-counting reads and writes. We may over-count reads and writes to the DBMS, but over-counting reads has minimal performance impact, since in such cases we would only place cache configuring APIs on objects that are rarely read from the DBMS; over-counting writes means that we may miss some objects that should have been cached, but will not affect the system performance (the same as adding no cache). Hence, our conservative choice by intentionally considering all possible code execution paths (over-counting) ensures that the caching suggestions would not have negative performance impact after placing the suggested caches. Note that there may be some memory costs when turning on the cache (i.e., use more memory), and in RQ2 we evaluate the gain of our approach when considering such costs.

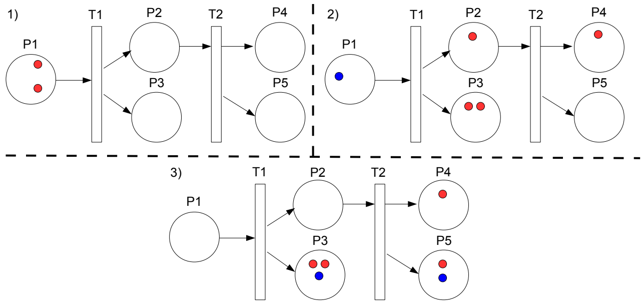


Figure 4: An example of modeling potential cache benefits using a coloured Petri net. A red token represents a read to a specific database entity object (e.g., *findUserById(1)*), and a blue token represents write to a specific database entity object (*updateUserById(1)*).

4.5 Evaluating Potential Cache Benefits Using Coloured Petri Net

After linking the logs to handler methods and recovering the database accesses, *CacheOptimizer* then calculates the potential benefits of placing a cache on each database access call. We use Petri nets [45], a mathematical modeling languages for distributed applications, to model the activity of caches such as cache renewal and invalidation. Petri nets allow us to model the interdependencies, so the reached caching decisions are global optimal, instead of focusing on top cache accesses (greedy). Petri nets model the transition of states in an application, and a net contains *places*, *transitions*, and *arcs*. Places represent conditions in the model, transitions represent events, and arcs represent the flow relations among places. Formally, a Petri net N can be defined as:

$$N = (P, T, A) \text{ and } A \subset (P \times T) \cup (T \times P),$$

where P is the set of places, T is the set of transitions, and A is the set of arcs. Places may contain *tokens*, which represent the execution of the net. Any distributions of the tokens in the places of a net represent a set of *configurations*. A limitation of Petri nets is that there is no distinction between tokens. However, to use Petri nets to evaluate potential cache benefits, we need to model different data types (e.g., a Hibernate query versus an entity lookup by id) and values (e.g., query parameter). Thus, we use an extension of Petri nets, called coloured Petri net (CPN) [33]. In a CPN, tokens can have different values, and the values are represented using colours. Formally, a CPN can be defined as:

$$CPN = (P, T, A, \Sigma, C, N, E, G, I),$$

where P, T, and A are the same as in Petri nets. Σ represents the set of all possible colours (all possible tokens), C maps P to colours in Σ (e.g., specify the types of tokens that can be in a place), and N is a node function that maps A into $(P \times T) \cup (T \times P)$. E is the arc expression function, G is the guard function that maps each transition into guard expressions (e.g., boolean), and finally I represents an initialization function that maps each place to a multi-set of token colours.

In our CPN (shown in Figure 4), we define P to be the states of the data in the cache. P3 is a repository that stores the total number of database accesses, P4 stores the total number of cache hits, and P5 stores the number of invalidated caches. P2 is an intermediate place for determining whether the data would be cached or invalidated. We define T to be all database accesses that are recovered from the logs. We define Σ to distinguish the type of the database access call (e.g., read/write using ids or queries), and the parameters used for the access (obtained using Algorithm 1). Thus, our C defines that P4 can only have colours of database access calls that are reads, and P1, P2, P3, and P5 may contain all colours in Σ. The transition function on T1 always forwards the tokens in the initial place P1 to P2 and P3. There are two guard functions on T2, where one allows a token to be moved to P4 if there are two or more tokens of the same colour in P2 (i.e., multiple reads to the same data, so a cache hit), and another guard function makes sure that if there is a write in P2, all the same write tokens and the corresponding read tokens are moved to P5 (e.g., the cache is invalidated).

In our example (Figure 4), we let red tokens represent the database access call findUserById(1), and blue tokens represent updateUserById(1). In (1), there are two red tokens, and T1 is triggered, so the two red tokens are stored in P2 and P3. Since there are two red tokens in P2, T2 is triggered, and moves one red token to P4 (a cache hit). The resulting CPN is shown in (2). When a blue token appears in P1, T1 is triggered and moves the blue token to both P2 and P3. Since there is a blue token in P2, T2 is triggered, and we move both the red and blue token to P5 (cache invalidation). The final resulting Petri net is shown in (3). Note that T2 acts slightly different for tokens that represent query calls. When an object is updated, the query cache needs to retrieve the updated object from the DBMS to prevent a stale read. Thus, to model the behaviour, T2 would be triggered to move the query token to P5 from P2 if we see any token that represents a modification to the query table.

We use the recovered database accesses of the workload to execute the CPN. For *all tokens* that represent the database access to the same data (e.g., a read and write to user by id 1), we examine their total counts in P3 and P4 to calculate the miss ratio (MR) of the cache. MR can be calculated as one minus the total number of cache hits in P4 divided by the total number of calls in P3. We choose MR because it is used in many prior studies to evaluate the effectiveness of caching (e.g., [24, 43, 62]). If MR is too high, caching the data would not give any benefit. For example, if a table is constantly updated, then data in that table should not be cached. Thus, we define a threshold to decide whether a database access call should be cached. In our CPN, if MR is smaller than 35%, then we place the cache configuration code for the corresponding query (query cache) or table (object cache). Since object cache must be turned on to utilize query cache, we enable query cache only if the MR of the object cache is under the threshold. Such that, there would not exist conflicting decisions for object and query cache. We choose 35% to be more conservative on enabling caches so that we know the cached data would be invalidated less frequently (lower cache renewal cost). We also vary MR to 45% and do not see any difference in terms of the suggested cache configurations. However, future work should further investigate the impact of MR.

4.6 Configuring the Caching Frameworks

CacheOptimizer automatically adds the appropriate calls to the cache configuration API. Since the locations that require adding cache configuration APIs may be scattered across the code, *CacheOptimizer* helps developers reduce manual efforts by automatically adding these APIs to the appropriate locations. For example, if the query that is executed by the request "/user/?query=Peter" should be cached, *CacheOptimizer* would automatically call the caching framework's API to cache the executed query in the corresponding handler method searchUserByName. In our example shown in Figure 2, the miss ratio of caching objects in the User class is 0.33, which is smaller than our threshold 0.35. *CacheOptimizer* automatically adds the *@Cachable* annotation to the source code to enable cache for the User class.

5. EVALUATION

In this section, we present the evaluation of *CacheOptimizer*. We first discuss the applications that we use for our evaluation. Then we focus on two research questions: 1) what is the performance improvement after using *CacheOptimizer*; and 2) what is the gain of *CacheOptimizer* when considering the cost of such caches.

Experimental Setup. We evaluate *CacheOptimizer* on three open-source web applications: Pet Clinic [44], Cloud Store [20], and OpenMRS [41]. Table 1 shows the detailed information of these three applications. All three applications use Hibernate as the underlying framework to access database, and use MySQL as the DBMS. We use Tomcat as our web server, and use Ehcache as our underlying caching framework. Pet Clinic, which is developed by Spring [52], aims to provide a simple yet realistic design of a web application. Cloud Store is a web-based e-commerce application, which is developed mainly for performance testing and benchmarking. Cloud Store follows the TPC-W performance benchmark standard [1]. Finally, OpenMRS is large-scale open-source medical record application that is used worldwide. OpenMRS supports both web-based interfaces and RESTFul services.

We use one machine each for the DBMS (8G RAM, Xeon 2.67GHz CPU), web server (16G RAM, Intel i5 2.3GHz), and JMeter load driver (12G RAM, Intel Quad 2.67GHz). The three machines are all connected on the same network. We use performance test suites to exercise these applications when evaluating *CacheOptimizer*. Performance test suites aim to mimic the real-life usage of the application and ensure that all of the common features are covered during the test [4]. Thus, for our evaluation, performance test suites are a more appropriate and logical choice over using functional tests. We use developer written tests for Pet Clinic [23], and work with BlackBerry developers on creating the test cases for the other applications. For Cloud Store, we create test cases to cover searching, browsing, adding items to shopping carts, and checking out. For OpenMRS, we use its RESTFul APIs to create test cases that are composed of searching (by patient, concept, encounter, and observation etc), and editing/adding/retrieving patient information. We also add randomness to our test cases to better simulate real-world workloads. For example, we add randomness to ensure that some customers may checkout, and some may not. We use, for our performance tests, the MySQL backup files that are provided by Cloud Store and OpenMRS developers. The backup file for Cloud Store contains data for over 5K patients and 500K observations. The backup file for Cloud Store contains about 300K customer data and 10K items.

Table 1: Statistics of the studied applications.

	Total lines of code	Number of Java files
Pet Clinic	3.8K	51
Cloud Store	35K	193
OpenMRS	3.8M	1,890

Table 2: Performance improvement (throughput) against *NoCache* after applying different cache configurations.

	Throughput			
	NoCache	*CacheOptimizer*	*CacheAll*	*DefaultCache*
Pet Clinic	98.7	125.1 (+27%)	108.4 (+10%)	—
Cloud Store	110.7	263.4 (+138%)	249.3 (+125%)	114.7 (+4%)
OpenMRS	21.3	30.8 (+45%)	25.5 (+20%)	27.7 (+30%)

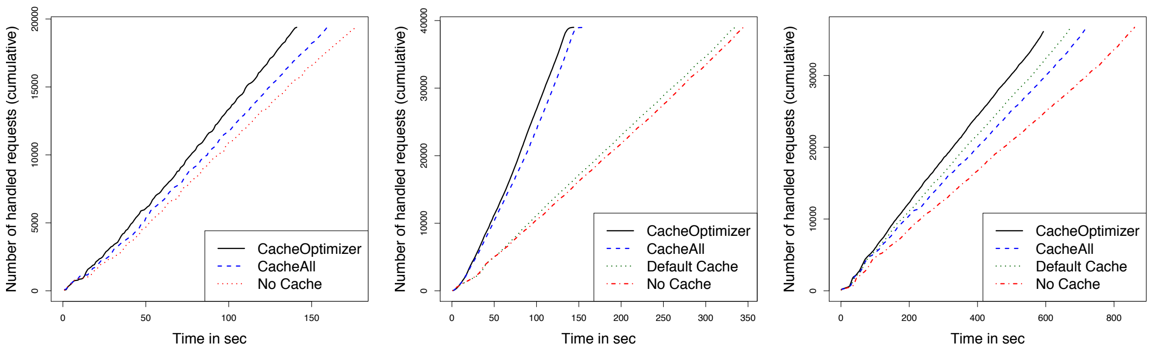
RQ1: What is the performance improvement after using CacheOptimizer?

Motivation. In this RQ, we want to examine how well the performance of the studied database-centric web applications can be improved when using *CacheOptimizer* to configure the caching framework.

Approach. We run the three studied applications using the performance test suites under four different sets of cache configurations: 1) without any cache configuration (*NoCache*), 2) with default cache configuration (*DefaultCache*, cache configurations that are already in the code, which indicates what developers think should be cached), 3) with enabling all possible caches (*CacheAll*), and 4) with configurations that are added by *CacheOptimizer*. We compare the performance of the applications when configured using these four different sets of cache configurations. We work with performance testing experts from BlackBerry to ensure that our evaluation steps are appropriate, accurate, and realistic. We use throughput to measure the performance. The throughput is measured by calculating the number of requests per second throughout the performance test. A higher throughput shows the effectiveness of the cache configuration, as more requests can be processed within the same period of time.

There may exist many possible locations to place the calls to the cache configuration APIs. Hence, configuring the caching framework may require extensive and scattered code changes, which can be a challenging and time-consuming task for developers. Therefore, to study the effectiveness of *CacheOptimizer* and how it helps developers, we also compare the number of cache configurations that are added by *CacheOptimizer* relative to the total number of all possible caching configurations that could be added, and the number of cache configurations that exist in *DefaultCache*.

Results. *CacheOptimizer* outperforms *DefaultCache* and *CacheAll* in terms of application performance improvement. Table 2 shows the performance improvement of the applications under four sets of configurations. We use *NoCache* as a baseline, and calculate the throughput improvement after applying *CacheOptimizer*, *CacheAll*, and *DefaultCache*. The default cache configuration of Pet Clinic does not enable any cache. Therefore, we only show the performance improvement of *DefaultCache* for Cloud Store



(a) Pet Clinic. (b) Cloud Store. (c) OpenMRS.

Figure 5: Number of handled requests overtime (cumulative).

Table 3: Total number of possible places to add cache in the code, and the number of location that are enabled by *CacheOptimizer* and that exist in the *DefaultCache*.

	Object Cache			Query Cache		
	Total	*CacheOptimizer*	*DefaultCache*	Total	*CacheOptimizer*	*DefaultCache*
Pet Clinic	11	6 (55%)	0	4	3 (75%)	0
Cloud Store	33	2 (6%)	10 (30%)	24	9 (38%)	1 (4%)
OpenMRS	112	16 (14%)	7 (6%)	229	2 (0.9%)	0

and OpenMRS. Using *CacheOptimizer*, we see a throughput improvement of 27%, 138% and 45% for Pet Clinic, Cloud Store and OpenMRS, respectively. The throughput improvement of applying *CacheOptimizer* is always higher than that of *DefaultCache* and *CacheAll* for all the studied applications. Figure 5 further shows the cumulative throughput overtime. We can see that for the three studied applications, the throughput is about the same at the beginning regardless of us adding cache or not. However, as more requests are received, the benefit of caching becomes more significant. The reason may be that initially when the test starts, the data is not present in the cache. *CacheOptimizer* is able to discover the more temporal localities (reuse of data) in the workload and help developers configure the application-level cache more optimally. Therefore, as more requests are processed, frequently accessed data is then cached, which significantly reduces the overhead of future accesses. We see a trend that the longer the test runs, the more benefit we get from adding cache configuration code using *CacheOptimizer*. We also observe that the performance of Cloud Store with *DefaultCache* is close to the performance with no cache. Such an observation shows in some instances developers do not have a good knowledge of optimizing cache configuration in their own application.

***CacheOptimizer* enables a small number of caches to improve performance.** *CacheOptimizer* can help developers change cache configurations quickly without manually investigating a large number of possible cache locations. Table 3 shows the total number of possible locations to place calls to object and query cache APIs in the studied applications. We also show the number of *CacheOptimizer* enabled caches, and the number of *DefaultCache* enabled caches. *CacheOptimizer* suggests adding object cache configuration APIs to a fraction (6–55%) of the total number of possible cache locations. In OpenMRS and Cloud Store, where there are more Hibernate queries, *CacheOptimizer* is able to improve performance by enabling 0.9% and 38% of all the possible caches, respectively. For the object cache of Cloud Store, *CacheOptimizer* even suggests enabling a smaller number of caches than *DefaultCache*. For large applications like OpenMRS with 112 possible object caches and 229 possible query caches, manually identifying the optimized cache configuration is time-consuming and may not even be possible.

Discussion. In our evaluation of *CacheOptimizer*, we observe a larger improvement in Cloud Store. After a manual investigation, we find that *CacheOptimizer* caches the query results that contain large binary data, e.g., pictures. Since the sizes of pictures are often larger, caching them significantly reduces the network transfer time, and thus results in a large performance improvement. We see less improvement when using *DefaultCache*, because most database access calls are done through queries (like workflow 3 in Figure 1), while the default cache configurations of Cloud Store are mostly for object cache (Table 3). Thus, enabling only object caches does not help improve performance. In OpenMRS, both *CacheOptimizer* and *DefaultCache* cache some database entity objects that are not often changed. However, *CacheOptimizer* is able to identify more object caches and queries that should be cached to further improve performance. We also see that the overhead of *CacheAll* causes OpenMRS to run slower when compared to *DefaultCache*. In Pet Clinic, we find that caching the owner information significantly improves the performance of searches. Moreover, since the number of vets in the clinic is often unchanged, caching the vet information also speeds up the application.

Adding cache configuration code, as suggested by CacheOptimizer , improves throughput by 27–138%, which is higher than using the default cache configuration and enabling all possible caches. The sub-optimal performance of DefaultCache shows that developers have limited knowledge of adding cache configuration.

RQ2: What is the gain of CacheOptimizer when considering the cost of such caches?

Motivation. In the previous RQ, we see that *CacheOptimizer* helps improve application throughput significantly. However, caching may also bring some memory overhead to the application, since we need to store cached objects in the memory. As a result, in this RQ, we want to evaluate *CacheOptimizer*-suggested cache configuration when considering both the cost (increase in memory usage) and the benefit (improvement in throughput).

Approach. In order to evaluate *CacheOptimizer* when considering both benefit and cost, we define the *gain* of applying a configuration as:

$$Gain(c) = Benefit(c) - Cost(c), \quad (1)$$

where c is the cache configuration, $Gain(c)$ is the *gain* of applying c, while $Benefit(c)$ and $Cost(c)$ measure the benefit and the cost, respectively, of applying c. In our case study, we measure the throughput improvement in order to quantify the benefit of caching, and we measure the memory overhead in order to quantify the cost of caching. We use the throughput and memory usage when no cache is added to the application as a baseline. Thus, $Benefit(c)$ and $Cost(c)$ are defined as follows:

$$Benefit(c) = TP(c) - TP(no\ cache), \quad (2)$$

$$Cost(c) = MemUsage(c) - MemUsage(no\ cache), \quad (3)$$

where $TP(c)$ is the average number of processed requests per second with cache configuration c, and $MemUsage(c)$ is the average memory usage with cache configuration c.

Since the throughput improvement and the memory overhead are not in the same scale, the calculated *gain* by Equation 1 may be biased. Therefore, we linearly transform both $Benefit(c)$ and $Cost(c)$ into the same scale by applying min-max normalization, which is defined as follows:

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})}, \quad (4)$$

where x and x' are the values of the metric before and after normalization, respectively; while x_{max} and x_{min} are the maximum and the minimum values of the metric, respectively. We note that if one wants to compare the *gain* of applying multiple configurations, the maximum and the minimum values of the metric are calculated by considering all the values of the metrics across the different configurations, including having no cache. For example, if one would like to compare the *gain* of applying *CacheOptimizer* and *CacheAll*, $throughput_{max}$ is the maximum throughput of applying *CacheOptimizer*, *CacheAll*, and *NoCache*.

To evaluate *CacheOptimizer*, in this RQ, we compare the *gain* of applying *CacheOptimizer*, *CacheAll*, and *DefaultCache* against *NoCache*. The larger the *gain*, the better the cache configuration. If the *gain* is larger than 0, the cache configuration is better than using *NoCache*. In order to understand the *gain* of leveraging cache configuration throughout the performance tests, we split each performance test into different periods. Since a performance test with different cache configurations runs for a different length of time (see Figure 5), we split each test by each thousand of completed requests. For each period, we calculate the *gain* of applying *CacheOptimizer*, *CacheAll*, and *DefaultCache*.

We study whether there is a statistically significant difference in *gain*, between applying *CacheOptimizer* and *CacheAll*, and between applying *CacheOptimizer* and *DefaultCache*. To do this we use the Mann-Whitney U test [39] on the *gains*, as the *gains* may be highly skewed. Since the Mann-Whitney U test is a non-parametric test, it does not have any assumptions on the distribution. A p-value smaller than 0.05 indicates that the difference is statistically significant. We also calculate the effect sizes in order to quantify the differences in *gain* between applying *CacheOptimizer* and *CacheAll*, and between applying *CacheOptimizer* and *DefaultCache*. Unlike the Mann-Whitney U test, which only tells us whether the difference between the two distributions is statistically significant, the effect size quantifies the difference between the two distributions. Since reporting only the statistical significance may lead to erroneous results (i.e., if the sample size is very large, the p-value are likely to be small even if the difference is trivial) [35], we use Cliff's d to quantify the effect size [19]. Cliff's d is a non-parametric effect size measure, which does not have any assumption of the underlying distribution. Cliff's d is defined as:

Table 4: Comparing the *gain* of the application under three different configurations: *CacheOptimizer*, *CacheAll*, and *DefaultCache*

	gain(*CacheOptimizer*) > *gain*(*CacheAll*)?		*gain*(*CacheOptimizer*) > *gain*(*DefaultCache*)?	
	p-value	Cliff's d	p-value	Cliff's d
Pet Clinic	<< 0.001	0.81 (large)	—	—
Cloud Store	< 0.01	0.32 (small)	<< 0.001	0.61 (large)
OpenMRS	<< 0.001	0.95 (large)	<< 0.001	0.95 (large)

$$Cliff's\ d = \frac{\#(x_i > x_j) - \#(x_i < x_j)}{m * n}, \quad (5)$$

where # is defined the number of times, and the two distributions are of the size m and n with items x_i and x_j, respectively. We use the following thresholds for Cliff's d [19]:

$$\text{effect size} = \begin{cases} \text{trivial} & \text{if } Cliff's\ d < 0.147 \\ \text{small} & \text{if } 0.147 \le Cliff's\ d < 0.33 \\ \text{medium} & \text{if } 0.33 \le Cliff's\ d < 0.474 \\ \text{large} & \text{if } 0.474 \le Cliff's\ d \end{cases}$$

Results. *CacheOptimizer* outperforms *DefaultCache* and *CacheAll* when considering the cost of cache. Table 4 shows the result of our Mann-Whitney U test and Cliff's d value when comparing the *gain* of applying *CacheOptimizer* with that of *CacheAll* and *DefaultCache*. We find that in all three studied applications, the *gain* of *CacheOptimizer* is better than the *gain* of *CacheAll* and *DefaultCache* (statistically significant). We also find that the effect sizes of comparing *CacheOptimizer* with *CacheAll* on *gain* are large for Pet Clinic (0.81) and OpenMRS (0.95). The only exception is Cloud Store, where the Cliff's d value indicates that the effect of *gain* is small (0.32) when comparing *CacheOptimizer* with *CacheAll*. On the other hand, when compared to *DefaultCache*, *CacheOptimizer* has a large effect size for both Cloud Store and OpenMRS.

Discussion. We investigate the memory overhead of applying *CacheOptimizer*, *CacheAll*, and *DefaultCache*. We use the Mann-Whitney U test and measure effect sizes using Cliff's d to compare the memory usage between applying *CacheOptimizer* and the memory usage of having no cache, *CacheAll*, and *DefaultCache*, respectively. The memory usage of applying *CacheOptimizer* and having no cache is statistically indistinguishable for Pet Clinic and OpenMRS; while for Cloud Store, applying *CacheOptimizer* has statistically significantly more memory usage than having no cache with a large effect size (0.78). This may explain why we see larger throughput improvement in Cloud Store. For OpenMRS, the memory usage of applying *CacheOptimizer* and

*DefaultCache*is statistically indistinguishable. Finally, when comparing *CacheOptimizer* with *CacheAll*, we find that for Pet Clinic and Cloud Store, the difference in memory usage is statistically indistinguishable; while for OpenMRS, *CacheOptimizer* uses statistically significantly less memory than *CacheAll* (p-value < 0.01) with an effect size of 0.61 (large effect). Nevertheless, after considering both the improvement and cost, *CacheOptimizer* out-performs all other cache configurations.

When considering both the benefit (throughput improvement) and cost (memory overhead), the gain of applying CacheOptimizer is statistically significantly higher than CacheAll and DefaultCache.

6. THREATS TO VALIDITY

External Validity. We only evaluated *CacheOptimizer* on three applications, so our findings may not generalize to other applications. We choose the studied applications with various sizes across different domains to improve the generalizability. However, evaluating *CacheOptimizer* on other applications would further show the generalizability of our approach. We implement *CacheOptimizer* specifically for Hibernate-based web applications. However, the approach in *CacheOptimizer* should be applicable to applications using different object-relational mapping frameworks or other database abstraction technologies. For example, our approach for recovering the database accesses from logs may also be used by non-Hibernate based applications. With minor modifications (e.g., changes are needed to the definitions of the tokens and transition functions in the coloured Petri net), *CacheOptimizer* can be leveraged to improve cache configurations of other applications.

Construct Validity. The performance benefits of caching highly depends on the workloads. Thus, we use performance tests to evaluate *CacheOptimizer*. It is possible that the workload from the performance tests may not be representative enough for field workload. However, *CacheOptimizer* does not depend on a particular workload, nor do we have any assumption on the workload when conducting our experiments. *CacheOptimizer* is able to analyze any given workload and find the optimal cache configuration for different workloads. If the workload changes greatly and the cache configuration is no longer optimal, *CacheOptimizer* can save developers' time and effort by automatically finding a new optimal cache configuration. For example, developers can feed their field workloads on a weekly or monthly basis, and *CacheOptimizer* would help developers optimize the configuration of their caching frameworks. To maximize the benefit of caching, our approach aims to "overfit" the cache configurations to a particular workload. Thus, similar to other caching algorithms or techniques, our approach will not work if the workload does not contain any repetitive reads from the DBMS.

Our approach for recovering the database access. Prior research leverages control flow graphs to recover the executed code paths using logs [61]. We do not leverage control flow graphs to recover the database accesses from web access logs for two reasons. First, as a basic design principal of RESTFul web services, typically one web-request-handing method maps to one or very few database accesses [32, 49]. Second, although leveraging control flows may give us richer information about each request, it is impossible to know which branch would be executed based on web access logs. Heuristics may be used to calculate the possibility of taking different code paths. However, placing the cache incorrectly can even cause performance degradation. Thus, to be conservative when enabling caching and to ensure that *CacheOptimizer* would always help improve performance, we consider all possible database access calls. Our overestimation ensures that *CacheOptimizer* would not cache data that has a high likelihood of being frequently modified, so the *CacheOptimizer* added cache configurations should not negatively impact on the performance. Future research should consider the use of control flow information for optimizing the cache configurations.

Cache concurrency level. There are different cache concurrency levels, such as read-only and read/write. In this paper we only consider the default level, which is read/write. Read/write cache concurrency strategy is a safer choice if the application needs to update cached data. However, considering other cache concurrency levels may further improve performance. For example, read-only caches may perform better than read/write cache if the cached data is never changed. Future research should to add cache concurrency level information to *CacheOptimizer* when trying to optimize cache configuration.

Distributed cache environment. Cache scheduling is a challenging problem in a distributed environment due to cache concurrency management. Most caching frameworks provide different algorithms or mechanisms to handle such issues. Since the goal of *CacheOptimizer* is to instruct these caching frameworks on what to cache, we rely on the underlying caching frameworks for cache concurrency management. However, the benefit of using *CacheOptimizer* may not be as pronounced in a distributed environment.

7. CONCLUSION

Modern large-scale database-centric web applications often leverage different application-level caching frameworks, such as Ehcache and Memcached, to improve performance. However, these caching frameworks are different from traditional lower-level caching frameworks, because developers need to instruct these application-level caching frameworks about what to cache. Otherwise these caching frameworks are not able to provide any benefit. In this paper, we propose *CacheOptimizer*, an automated lightweight approach that determines what should be cached in order to utilize such application-level caching frameworks for Hibernate-based web applications. *CacheOptimizer* combines static analysis of source code and logs to recover the database accesses, and uses a coloured Petri net to model the most effective caching configuration for a workload. Finally, *CacheOptimizer* automatically updates the code with the appropriate cache configuration code. We evaluate *CacheOptimizer* on three open source applications (Pet Clinic, Cloud Store, and OpenMRS). We find that *CacheOptimizer* improves the throughput of *the entire application* by 27–138% (compared to *DefaultCache*and *CacheAll*), and the increased memory usage is smaller than the applications' default cache configuration and turning on all caches. The sub-optimal performance of the default cache configurations highlights the need for automated techniques to assist developers in optimizing the cache configuration of database-centric applications.

8. REFERENCES

[1] Transactional web e-commerce benchmark. http://www.tpc.org/tpcw/. Last accessed March 3 2016.

[2] T. , L. Jin, X. Fan, and Y. Zhou. Hey, you have given me too many knobs! understanding and dealing with over-designed configuration in system software. In *Proceedings of the 10th Joint Meeting of the European Software Engineering Conference and the ACM SIGSOFT Symposium on the Foundations of Software Engineering*, ESEC/FSE '15, 2015.

[3] M. Altinel, C. Bornhövd, S. Krishnamurthy, C. Mohan, H. Pirahesh, and B. Reinwald. Cache tables: Paving the way for an adaptive database cache. In *Proceedings of the 29th International Conference on Very Large Data Bases*, VLDB '03, pages 718–729, 2003.

[4] R. Binder. *Testing Object-oriented Systems: Models, Patterns, and Tools*. Addison-Wesley, 2000.

[5] J. Bloomberg. *The Agile Architecture Revolution: How Cloud Computing, REST-Based SOA, and Mobile Computing Are Changing Enterprise IT*. Wiley, 2013.

[6] I. T. Bowman and K. Salem. Optimization of query streams using semantic prefetching. *ACM Trans. Database Syst.*, 30(4):1056–1101, Dec. 2005.

[7] K. S. Candan, W.-S. Li, Q. Luo, W.-P. Hsiung, and D. Agrawal. Enabling dynamic content caching for database-driven web sites. In *Proceedings of the 2001 ACM SIGMOD International Conference on Management of Data*, SIGMOD '01, pages 532–543, 2001.

[8] S. Chaudhuri, V. Narasayya, and M. Syamala. Bridging the application and DBMS profiling divide for database application developers. In *VLDB*, 2007.

[9] M. Chavan, R. Guravannavar, K. Ramachandra, and S. Sudarshan. Program transformations for asynchronous query submission. In *Proceedings of the 2011 IEEE 27th International Conference on Data Engineering*, ICDE '11, pages 375–386, 2011.

[10] F. Chen, J. Grundy, J.-G. Schneider, Y. Yang, and Q. He. Stresscloud: A tool for analysing performance and energy consumption of cloud applications. In *Proceedings of the IEEE/ACM 37th IEEE International Conference on Software Engineering*, ICSE '15, pages 721–724, May 2015.

[11] T.-H. Chen. Improving the quality of large-scale database-centric software systems by analyzing database access code. ICDE '15, pages 245–249, 2015.

[12] T.-H. Chen, S. Weiyi, A. E. Hassan, M. Nasser, and P. Flora. Detecting problems in the database access code of large scale systems - an industrial experience report. ICSE '16, 2016.

[13] T.-H. Chen, S. Weiyi, h. M. Jiang, A. E. Hassan, M. Nasser, and P. Flora. Finding and evaluating the performance impact of redundant data access for applications that are developed using object-relational mapping frameworks. *IEEE Transactions on Software Engineering*, 2016.

[14] T.-H. Chen, S. Weiyi, Z. M. Jiang, A. E. Hassan, M. Nasser, and P. Flora. Detecting performance anti-patterns for applications developed using object-relational mapping. ICSE, 2014.

[15] T.-H. Chen, S. Weiyi, J. Yang, A. E. Hassan, M. W. Nasser, Godfrey, Mohamed, and P. Flora. An empirical study on the practice of maintaining object-relational mapping code in Java systems. In *Proceedings of the 13th International Conference on Mining Software Repositories*, MSR '16, pages 165–176, 2016.

[16] A. Cheung, S. Madden, and A. Solar-Lezama. Sloth: Being lazy is a virtue (when issuing database queries). In *Proceedings of the 2014 ACM SIGMOD International Conference on Management of Data*, SIGMOD '14, 2014.

[17] A. Cheung, A. Solar-Lezama, and S. Madden. Optimizing database-backed applications with query synthesis. PLDI '13, pages 3–14, 2013.

[18] H.-T. Chou and D. J. DeWitt. An evaluation of buffer management strategies for relational database systems. VLDB '85, pages 127–141, 1985.

[19] N. Cliff. Dominance statistics: Ordinal analyses to answer ordinal questions. *Psychological Bulletin*, 114(3):494–509, Nov. 1993.

[20] CloudScale. Cloud store. http://www.cloudscale-project.eu/, 2016. Last accessed July 25 2016.

[21] J. Community. Hibernate. http://www.hibernate.org/, 2016. Last accessed July 26 2016.

[22] S. Dar, M. J. Franklin, B. T. Jónsson, D. Srivastava, and M. Tan. Semantic data caching and replacement. VLDB '96, pages 330–341, 1996.

[23] J. Dubois. Improving the performance of the spring-petclinic sample application. http://blog.ippon.fr/2013/03/14/improving-the-performance-of-the-spring-\petclinic-sample-application-part-4-of-5/, 2016. Last accessed July 25 2016.

[24] L. Fan, P. Cao, J. Almeida, and A. Z. Broder. Summary cache: A scalable wide-area web cache sharing protocol. *IEEE/ACM Trans. Netw.*, 8(3):281–293, June 2000.

[25] FastCompany. How one second could cost Amazon 16 billion sales. http://www.fastcompany.com/1825005/how-one-second-could-cost-amazon-16-billion-sales, 2012. Last accessed March 3 2016.

[26] V. Ferreira. Pitfalls of the Hibernate second-level / query caches. https://dzone.com/articles/pitfalls-hibernate-second-0. Last accessed March 3 2016.

[27] B. Fitzpatrick. Distributed caching with memcached. *Linux J.*, 2004(124), Aug. 2004.

[28] G. Giannikis, G. Alonso, and D. Kossmann. Shareddb: Killing one thousand queries with one stone. *Proc. VLDB Endow.*, 5(6):526–537, Feb. 2012.

[29] Gleanster. Application performance starts with database performance analysis. http://www.gleanster.com/report/application-//performance-starts-with-database-performance-//analysis, 2015. Last accessed June 20 2015.

[30] D. Gollmann. *Computer Security*. Wiley, 2011.

[31] M. Grechanik, B. M. M. Hossain, U. Buy, and H. Wang. Preventing database deadlocks in applications. ESEC/FSE 2013, pages 356–366, 2013.

[32] IBM. Restful web services: The basics. http:

//www.ibm.com/developerworks/library/ws-restful/, 2016. Last accessed July 25 2016.
[33] K. Jensen. *Coloured Petri Nets: Basic Concepts, Analysis Methods and Practical Use*. Coloured Petri Nets. Springer, 1997.
[34] T. Johnson and D. Shasha. 2q: A low overhead high performance buffer management replacement algorithm. VLDB '94, pages 439–450, 1994.
[35] V. B. Kampenes, T. Dybå, J. E. Hannay, and D. I. K. Sjøberg. Systematic review: A systematic review of effect size in software engineering experiments. *Inf. Softw. Technol.*, 49(11-12):1073–1086, Nov. 2007.
[36] N. Leavitt. Whatever happened to object-oriented databases? *Computer*, 33(8):16–19, Aug. 2000.
[37] M. Linares-Vasquez, B. Li, C. Vendome, and D. Poshyvanyk. How do developers document database usages in source code? (n). In *Proceedings of the 30th IEEE/ACM International Conference on Automated Software Engineering*, ASE '15, pages 36–41, 2015.
[38] Memcached. Memcached. http://memcached.org/, 2015.
[39] D. Moore, G. MacCabe, and B. Craig. *Introduction to the Practice of Statistics*. W.H. Freeman and Company, 2009.
[40] R. Nishtala, H. Fugal, S. Grimm, M. Kwiatkowski, H. Lee, H. C. Li, R. McElroy, M. Paleczny, D. Peek, P. Saab, D. Stafford, T. Tung, and V. Venkataramani. Scaling Memcache at Facebook. In *Proceedings of the 10th USENIX Conference on Networked Systems Design and Implementation*, NSDI'13, pages 385–398, 2013.
[41] OpenMRS. Openmrs. http://openmrs.org/, 2016. Last accessed July 25 2016.
[42] Oracle. Java EE platform specification. https://java.net/projects/javaee-spec/pages/Home, 2016. Last accessed July 25 2016.
[43] S. Paul and Z. Fei. Distributed caching with centralized control. *Comput. Commun.*, 24(2):256–268, Feb. 2001.
[44] S. PetClinic. Petclinic. https://github.com/SpringSource/spring-petclinic/, 2016. Last accessed July 25 2016.
[45] J. L. Peterson. *Petri Net Theory and the Modeling of Systems*. Prentice Hall PTR, 1981.
[46] A. Rabkin and R. Katz. Precomputing possible configuration error diagnoses. ASE '11, pages 193–202, 2011.
[47] A. Rabkin and R. Katz. Static extraction of program configuration options. ICSE '11, pages 131–140, 2011.
[48] K. Ramachandra and S. Sudarshan. Holistic optimization by prefetching query results. SIGMOD '12, pages 133–144, 2012.
[49] L. Richardson and S. Ruby. *RESTful Web Services*. O'Reilly Media, 2008.
[50] W. Shang, Z. M. Jiang, B. Adams, A. E. Hassan, M. W. Godfrey, M. Nasser, and P. Flora. An exploratory study of the evolution of communicated information about the execution of large software systems. In *Proceedings of the 2011 18th Working Conference on Reverse Engineering*, WCRE '11, pages 335–344, 2011.
[51] A. J. Smith. Cache evaluation and the impact of workload choice. In *Proceedings of the 12th Annual International Symposium on Computer Architecture*, ISCA '85, pages 64–73, 1985.
[52] SpringSource. Spring framework. www.springsource.org/, 2016. Last accessed July 25 2016.
[53] M. D. Syer, Z. M. Jiang, M. Nagappan, A. E. Hassan, M. Nasser, and P. Flora. Continuous validation of load test suites. In *Proceedings of the 5th ACM/SPEC International Conference on Performance Engineering*, ICPE '14, pages 259–270, 2014.
[54] Terracotta. Ehcache. http://ehcache.org/, 2015.
[55] A. Tomcat. Logging in tomcat. https://tomcat.apache.org/tomcat-8.0-doc/logging.html, 2015.
[56] Y. Xiong, A. Hubaux, S. She, and K. Czarnecki. Generating range fixes for software configuration. ICSE '12, pages 58–68, 2012.
[57] X. z. Liu, Y. Ma, Y. Liu, T. Xie, and G. Huang. Demystifying the imperfect client-side cache performance of mobile web browsing. *IEEE Transactions on Mobile Computing*, PP(99), 2015.
[58] ZeroturnAround. Java tools and technologies landscape for 2015. http://zeroturnaround.com/rebellabs/java-tools-and-technologies-landscape-for-2014/, 2014. Last accessed July 24 2016.
[59] S. Zhang and M. D. Ernst. Automated diagnosis of software configuration errors. ICSE '13, pages 312–321, 2013.
[60] S. Zhang and M. D. Ernst. Which configuration option should i change? ICSE 2014, pages 152–163, 2014.
[61] X. Zhao, Y. Zhang, D. Lion, M. F. Ullah, Y. Luo, D. Yuan, and M. Stumm. Lprof: A non-intrusive request flow profiler for distributed systems. OSDI'14, pages 629–644, 2014.
[62] Y. Zhou, J. Philbin, and K. Li. The multi-queue replacement algorithm for second level buffer caches. In *Proceedings of the General Track: USENIX Annual Technical Conference*, ATC '01, pages 91–104, 2001.