CloneCloud: Boosting Mobile Device Applications Through Cloud Clone Execution
Byung-Gon Chun†, Sunghwan Ihm*, Petros Maniatis†, Mayur Naik†
†Intel Labs Berkeley, *Princeton University

Abstract

Mobile applications are becoming increasingly ubiquitous and provide ever richer functionality on mobile devices. At the same time, such devices often enjoy strong connectivity with more powerful machines ranging from laptops and desktops to commercial clouds. This paper presents the design and implementation of CloneCloud, a system that automatically transforms mobile applications to benefit from the cloud. The system is a flexible application partitioner and execution runtime that enables unmodified mobile applications running in an application-level virtual machine to seamlessly off-load part of their execution from mobile devices onto device clones operating in a computational cloud. CloneCloud uses a combination of static analysis and dynamic profiling to optimally and automatically partition an application so that it migrates, executes in the cloud, and re-integrates computation in a fine-grained manner that makes efficient use of resources. Our evaluation shows that CloneCloud can achieve up to 21.2x speedup of smartphone applications we tested and it allows different partitioning for different inputs and networks.

1 Introduction

Mobile cloud computing is the next big thing. In recent research done by ABI research [29], it has predicted that by the end of 2014 mobile cloud computing will deliver annual revenues of 20 billion dollars. Mobile devices as simple as phones and as complex as mobile Internet devices with Internet access via multiple technologies, camera(s), GPS, and other sensors are the current computing wave, competing heavily with desktops and laptops for market and popularity. The variety of flash-popular applications being featured on various on-line application stores like those of Apple, Google, Microsoft and others mean that mobile users have no shortage of interesting things to do with their devices, for a low fee or even free.

This blossoming of the mobile application market is pushing mobile users beyond the usual staples of personal information management and music playback. Now mobile users look up songs by audio samples; play games; capture, edit, and upload video; analyze, index, and aggregate their mobile photo collections; analyze their finances; and manage their personal health and wellness. Also, new rich media, mobile augmented reality, and data analytics applications that require heavy computation are emerging. Such applications recruit increasing amounts of computation, storage, and communications from a still limited supply on mobile devices—certainly compared to tethered, grid-powered devices like desktops and laptops—and an extremely limited supply of energy. As a result, mobile applications end up in one of two camps: 1) they are either designed for the lowest common denominator device, pushing most functionality at a service provider’s site, and leaving little computing done at the device as a thin client; or 2) they are built monolithically to run on the device, taking a long time to execute on low-end devices, even when a split client-server design might have been desired.

Fortunately, such devices often enjoy strong connectivity, especially in developed areas. What is more, there is increasingly broad availability of tethered computing, storage, and communications to spare on commercial clouds, at nearby wireless hotspots equipped with computational resources (e.g., cloudlet [32]), or at the user’s PC and plugged-in laptop. Putting these two trends together, we recently made the case for a flexible architecture that enables the seamless use of ambient computation to augment mobile device applications [12]. In this paper, we take a first step towards realizing this vision, by designing and implementing the first version of the CloneCloud system.

CloneCloud boosts unmodified mobile applications by seamlessly off-loading part of their execution from the mobile device onto device clones operating in a com-
It is designed to serve as a platform for generic mobile-device processing as a service. Conceptually, our system automatically transforms a single-machine execution (e.g., computation on a smartphone) into a distributed execution that is optimal given the network connection to the cloud, if needed, the relative processing capabilities of the mobile device and cloud, and the application’s computing patterns (Figure 1).

The underlying motivation for such a system lies in the following intuition: as long as execution on the cloud is significantly faster than execution on the mobile device (or more reliable, more secure, etc.), paying the cost for sending the relevant data and code from the device to the cloud and back may be worth it. Unlike partitioning a service by design between an undemanding mobile client and a computationally expensive server in a provider’s infrastructure, CloneCloud late-binds this kind of partitioning. Only when the metric (e.g., performance or energy) of the newly partitioned application is better than that of the existing application, it makes sense to partition an application. In practice, the partitioning decision may be more fine-grained than a yes/no answer (i.e., it may result in carving off different amounts of the original application for cloud execution). Furthermore, the decision may be impacted not only by the application itself, but also by the expected workload and the execution conditions, such as network connectivity and CPU speeds of both mobile and cloud devices. A fundamental design goal for CloneCloud is to allow such fine-grained flexibility on what to run where, which traditional client-server partitionings hardwire early on in the development process.

Another design goal for CloneCloud is to take the programmer out of the business of application partitioning. While we conjecture that automatic partitioning is unlikely to produce optimized applications that can rival what a competent programmer would hand-code, we assert that competent programmers are also unlikely to willingly do such a hand-coding job for every possible set of circumstances a user may face. The kinds of applications on mobile platforms that are featured on application stores and gain flash popularity tend to be low-margin products, whose developers have little incentive to optimize manually for different combinations of architectures, network conditions, battery lives, and hosting infrastructures. Consequently, CloneCloud aims to make application partitioning seamless, and based only on the deployed version of the application, without need for source code.

Our work in this paper applies primarily to application-layer virtual machines, such as the Java VM, DalvikVM from the Android Platform, and Microsoft’s .NET. The relative ease of manipulating application executables and migrating pieces thereof to computing devices of diverging architectures made the AppVM model a promising first platform on which to explore our work. We expect some—but not all—of our design decisions to carry over when addressing such partitioning at lower layers in the execution stack, e.g., to UNIX-level processes, to kernel-level process containers, or to mobile hypervisors.

The CloneCloud prototype described here meets all our design goals, by rewriting an unmodified application executable. While the modified executable runs, at automatically chosen points individual threads migrate from the mobile device to a device clone in a cloud. There the thread executes, possibly accessing native features of the hosting platform such as the fast CPU, network, hardware accelerators, storage, etc. Eventually, the thread returns back to the mobile device, along with any state it created abroad, which it merges back into the original process. The choice of where to migrate off and back onto the mobile device is made by a partitioning component, which uses static analysis to discover constraints on possible migration points, and dynamic profiling to build a cost model for execution and migration. A mathematical optimizer chooses migration points that optimize execution time given the application and the cost model. Figure 2 shows the high-level architecture of our prototype.

Much research has attacked application partitioning and migration in the past (we present detailed related work in Section 7). We distill our novel contributions here as follows. First, unlike traditional suspend-migrate-resume mechanisms [21] for application migration, the CloneCloud migrator operates at thread granularity, an essential consideration for mobile applications, which tend to have features that must remain at the mobile device, such as those accessing the camera or managing the user interface. Second, unlike past application-layer VM migrators [8, 43], the CloneCloud migrator allows native system operations to execute both at the mobile device and at its clones in the cloud, harnessing not only raw CPU cloud power, but also system facilities or specialized hardware. Third, unlike mostly programmer-assisted approaches to application partitioning, the CloneCloud partitioner automatically identifies costs and constraints through static and dynamic code analysis, without the programmer’s

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1 Throughout this paper, we use the term “cloud” in a broader sense to include diverse ambient computational resources discussed above.
help, annotations, or application refactoring.

In what follows, we first give some brief background on application-layer VMs (Section 2). We then present the design of CloneCloud’s partitioning components (Section 3) and its distributed execution mechanism (Section 4). We describe our implementation (Section 5) and experimental evaluation of the prototype (Section 6). We survey related work in Section 7, discuss future research agenda in Section 8, and conclude in Section 9.

2 Background: Application VMs

An application-level VM is an abstract computing machine that provides hardware and operating system independence (Figure 3). Its instruction sets are platform-independent bytecodes; an executable is a blob of bytecodes. The VM runtime executes bytecodes of methods with threads. There is typically a separation between the virtual portion of an execution and the native portion; the former is only expressed in terms of objects directly visible to the bytecode, while the latter include management machinery for the virtual machine itself, data and computation invoked on behalf of a virtual computation, as well as the process-level data of the OS process containing the VM. Interfacing between the virtual and the native portion happens via native interface frameworks.

Runtime memory is split between VM-wide and per-thread areas. The Method Area, which contains the types of the executing program and libraries as well as static variable contents, and the Heap, which holds all dynamically allocated data, are VM-wide. Each thread has its own Virtual Stack (stack frames of the virtual hardware), the Virtual Registers (e.g., the program counter), and the Native Stack (containing any native execution frames of a thread, if it has invoked native functions).

Most computation, data structure manipulation, and memory management are done within the abstract machine. However, external processing such as file I/O, networking, using local hardware such as sensors, are done via APIs that punch through the abstract machine into the process’s system call interface.

3 Partitioning

The partitioning mechanism in CloneCloud aims to modify an application executable by deciding where to execute methods in the code. No special considerations are required for the executable beyond targeting the same application VM; that is, it need not be written in a particular idiom, e.g., a dataflow language. The output of the partitioning mechanism is the executable with partitioning points, optimal for a choice of execution conditions (network link characteristics between mobile device and cloud, relative CPU speeds). The partitioning mechanism can be run multiple times for different execution conditions, resulting in a database that maps partitioning to conditions. At runtime, the distributed execution mechanism we describe in Section 4 implements the choice of partitioning for the current execution conditions.

Partitioning of an application operates according to the conceptual workflow of Figure 4. Our partitioning framework combines static program analysis with dynamic program profiling to produce partitioning that optimizes goals while meeting correctness constraints.

The first component, the Static Analyzer, identifies legal partition choices for the application executable, according to a set of constraints (Section 3.1). Constraints codify the needs of the distributed execution engine used, as well as the particular usage model we target; however, different mechanisms can seamlessly be plugged into the partitioning component by changing these constraints.

The second component, the Dynamic Profiler (Section 3.2), runs the input executable on different platforms (the mobile device and on the cloud clone) under a set of inputs, and returns a set of profiled executions. Profiled executions are used to compose a cost model for the application under different partitionings.

Finally, the Optimization Solver finds a legal partitioning among those enabled by the static analyzer that mini-
class C {
    void a() {
        if () {b(); c();}
    }
    void b() {
        // lightweight processing
    }
    void c() {
        // expensive processing
    }
    void main () {
        C c; c.a();
    }
}

(a) program       (b) static control-flow graph            (c) partitioned graph

Figure 5: An example of a program, its corresponding static control-flow graph, and a partitioning

mizes an objective function, using the cost model derived by the profiler (Section 5.3). The resulting partitioning is used to modify the executable, yielding the final output of the partitioner. This partitioning is an offline process that generates a model that the runtime uses.

3.1 Static Analyzer

The partitioner uses static analysis to identify legal choices for placing migration and re-integration points in the code. In principle, these points could be placed anywhere in the code, but we reduce the available choices to make the optimization problem tractable. In particular, we restrict migration and re-integration points to the entry and exit points, respectively, of methods. In addition, to focus on our application program, we restrict these partitioning points to methods of application classes as opposed to methods of system classes (e.g., the core classes for Java) or native methods.

Figure 5 shows an example of a program, relevant parts of its static control-flow graph, and a particular legal partitioning of the program. Class C has three methods. Method a() calls method b(), which performs lightweight processing, followed by method c(), which performs expensive processing. The static control-flow graph approximates control flow in the program (inferring exact control flow is undecidable as program reachability is undecidable). The approximation is conservative in that if an execution of the program follows a certain path then that path exists in the graph (but the converse typically does not hold). In the depicted static control-flow graph, only entry and exit nodes of methods are shown, labelled as <class name>,<method name>,<entry | exit>; other kinds of nodes (e.g. those corresponding to instructions) are omitted since we restrict partitioning points to method entry and exit. A possible partitioning as shown in Figure 5 runs the body of method c() on the clone, and the rest of the program on the mobile device.

3.1.1 Constraints

We next describe three properties required by the migration component of any legal partitioning and explain how we use static analysis to obtain constraints that express these properties.

Property 1. Methods that access specific features of a machine must be pinned to the machine.

If a method uses a local resource such as the location service (e.g., GPS) or sensor inputs (e.g., microphones) in a mobile device, the method must be executed on the mobile device. This primarily concerns native methods, but also the main method of a program. The analysis marks the declaration of such methods with a special annotation M—for Mobile device. We manually identify such methods in the VM’s API (e.g., VM API methods explicitly referring to the camera); this is done once for a given platform and is not repeated for each application. We also always mark the main method of a program. We refer to methods marked with M as the V_M method set.

Property 2. Methods that share native state must be colocated at the same machine.

An application may have native methods that create and access state below the VM. Native methods may share native state. Such methods must be collocated at the same machine as our migration component does not migrate native state (Section 4.1). To avoid a manual-annotation burden, native state annotations are inferred automatically by the following simple approximation, which works well in practice: we assign a unique annotation Nat_C to all native methods declared in the same class C; the set V_Nat_C contains all methods with that annotation.

Property 3. Prevent cyclic migration.

With one phone and one clone, this implies that there should be no nested suspends and no nested resumes. Once a program is suspended for migration at the entry point of a method, the program should not be suspended again without a resume, i.e., migration and re-integration points must be executed alternately. To enforce this property, the static analysis builds the static control-flow graph of an application, capturing the callee-callee method relation; it exports this as two relations, DC(m_1, m_2), read as “method m_1 directly calls method m_2,” and TC(m_1, m_2) read as “method m_1 transitively calls method m_2,” which is the transitive closure of DC. For the example in Figure 5, this ensures that if partitioning points are placed in a() then they are not placed in b() or c(). The other remaining legal partitionings place no migration points at a() but at b() or c(), or at both b() and c().
3.2 Dynamic Profiler

The job of the profiler is to collect the data that will be used to construct a cost model for the application under different execution settings. The cost metric can be different things, including energy expenditure, resource footprint, etc.; we focus on execution time in the prototype presented here.

The profiler is invoked on multiple executions of the application, each using a different set of input data (e.g., command-line arguments and user-interface events), and each executed once on the mobile device and once on the clone in the cloud. The profiler outputs a set $S$ of executions, and for each execution a profile tree $T$ and $T'$, from the mobile device and the clone, respectively.

A profile tree is a compact representation of an execution on a single platform. It is a tree with one node for each method invocation in the execution; it is rooted at the starting (user-defined) method invocation of the application (e.g., main). Specific method calls in the execution are represented as edges from the node of the caller method invocation (parent) to the nodes of the callees (children); edge order is not important. Each node is annotated with the cost of its particular invocation in the cost metric (execution time in our case). In addition to its called-method children, every non-leaf node also has a leaf child called its residual node. The residual node $i'$ for node $i$ represents the residual cost of invocation $i$ that is not due to the calls invoked within $i$; in other words, node $i'$ represents the cost of running the body of code excluding the costs of the methods called by it. Finally, each edge is annotated with the state size at the time of invocation of the child node, plus the state size at the end of that invocation; this would be the amount of data that the migrator (Section 4.1) would need to capture and transmit in both directions, if the edge were to be a migration point. Edges between a node and its residual child have no cost.

Figure 6 is an example of an execution trace and its corresponding profile tree. $a$ is called twice in main, one $a$ call invoking $b$ and $c$, and one $a$ call invoking no other method. A tree node on the right holds the execution time of the corresponding method in the trace (the length of the square bracket on the left). main’ and $a'$ are residual nodes, and they hold the difference between the value of their parent node and the sum of their sibling nodes. For example, node main’ holds the value $t_3 - t_2 = (t_4 - t_1) - ((t_4 - t_3) + (t_2 - t_1))$.

To fill in profile trees, we temporarily instrument method entry and exit points during each profile run on each platform. We focus only on application code to have low profiling overhead; we treat system or library methods as inline code executed in the body of the calling application method. For our execution-time cost metric, we collect timings at method entry and exit points, which we process trivially to fill in tree node annotations. For profile trees executed at the clone, we leave edge costs set to 0 (since those do not initiate migration). For mobile-device trees, we perform the suspend-and-capture operation of the migrator (Section 4.1), measure the state size, and discard the captured state, both when invoking the child node and when returning from it. Recall that for every execution $E$, we capture two profile trees, one per platform with different annotations.

For each invocation $i$ in profiling execution $E$, we define a computation cost $C_c(i, l)$ and a migration cost $C_m(i)$, where $l$ is the location of the invocation. We fill in $C_c(i, l)$ from the corresponding profile tree collected at location $l$; if $i$ is a leaf profile tree node, we set $C_c(i, l)$ to be the annotation of that node; otherwise, we set it to the annotation of the residual node $i'$. We fill $C_m(i)$ as the cost of making invocation $i$ a migrant invocation. This cost is the sum of a suspend/resume cost and a transfer cost. The former is the time required to suspend a thread and resume a thread. The latter is a volume-dependent cost, the time it takes to capture, serialize, transmit, deserialized, and reinitialize state of a particular size (assuming for simplicity all objects have the same such cost per byte). We precompute this per-byte cost $\mathcal{C}$ and use the edge annotations from the mobile-device profile tree to calculate the cost.

3.3 Optimization Solver

The purpose of our optimizer is to pick which application methods to migrate to the clone from the mobile device, so as to minimize the expected cost of the partitioned application. Given a particular execution $E$ and its two profile trees $T$ on the mobile device and $T'$ on the clone, one might intuitively picture this task as optimally replacing annotations in $T$ with those in $T'$, so as to minimize the total node and weight cost of the hybrid profile tree. Our static analysis dictates the logical ways to fetch annotations from $T'$ into $T'$, and our dynamic profiling dictates the actual trees $T$ and $T'$. We do not differentiate among diff-

\footnote{One could also estimate this per-byte cost from memory, processor, and storage speeds, as well as network latency and bandwidth, but we took the simpler approach of just measuring it.}
different executions $E$ in the execution set $S$; we consider them all equiprobable, although one might assign non-uniform frequencies in practice to match a particular expected workload.

More specifically, the output of our optimizer is a value assignment to binary decision variables $R(m)$, where $m$ is every method in the application. If the optimizer chooses $R(m) = 1$ then the partitioner will place a migration point at the entry into the method, and a re-integration point at the exit from the method. If the optimizer chooses $R(m) = 0$, method $m$ is unmodified in the application binary. For simplicity and to constrain the optimization problem, our migration strategy chooses to migrate or not migrate all invocations of a method. Despite its simplicity, this conservative strategy provides us with undeniable benefits (Section 5); we leave further refining differentiations depending on calling stack, method arguments, etc., to future work.

Not all partitioning choices for $R(\cdot)$ are legal (Section 3.1.1). To express these constraints in the optimization problem, we define an auxiliary decision variable $L(m)$ indicating the location of every method $m$, and three relations $I$, as well as $DC$ and $TC$ computed during static analysis. $I(i, m)$ is read as “$i$ is an invocation of method $m$,” and is trivially defined from the profile runs. Whereas $DC$ and $TC$ are computed once for each application, $I$ is updated with new invocations only when the set $S$ of profiling executions changes.

Using the decision variables $R(\cdot)$, the auxiliary decision variables $L(\cdot)$, the method sets $V_M$ and $V_{NatC}$ for all classes $C$ defined during static analysis, and the relations $I$, $DC$ and $TC$ from above, we formulate the optimization constraints as follows:

$$L(m_1) \neq L(m_2), \quad \forall m_1, m_2 : DC(m_1, m_2) = 1$$

$$\land R(m_2) = 1 \quad (1)$$

$$L(m) = 0, \quad \forall m \in V_M \quad (2)$$

$$L(m_1) = L(m_2), \quad \forall m_1, m_2, C : m_1, m_2 \in V_{NatC} \quad (3)$$

$$R(m_2) = 0, \quad \forall m_1, m_2, C : TC(m_1, m_2) = 1$$

$$\land R(m_1) = 1 \quad (4)$$

The first is a soundness constraint. Constraint 1 requires that if a method causes migration to happen, it cannot be collocated with its callers. The remaining three correspond to the three properties defined in the static analysis. Constraint 2 requires that all methods pinned at the mobile device run on the mobile device (Property 1). Constraint 3 requires that methods dependent on the native state of the same class $C$ are collocated, at either location (Property 2). And constraint 4 requires that all methods transitively called by a migrated method cannot be themselves migrated (Property 3).

The cost of a (legal) partitioning $R(\cdot)$ of execution $E$ is defined as follows, in terms of the auxiliary variables $L(\cdot)$, the relation $I$ and the cost variables $C_c$ and $C_s$ from the dynamic profiler:

$$C(E) = \text{Comp}(E) + \text{Migr}(E)$$

$$\text{Comp}(E) = \sum_{i \in E, m} [(1 - L(m))I(i, m)C_c(i, 0) + L(m)I(i, m)C_c(i, 1)]$$

$$\text{Migr}(E) = \sum_{i \in E, m} R(m)I(i, m)C_s(i)$$

$\text{Comp}(E)$ is the computation cost of the partitioned execution $E$ and $\text{Migr}(E)$ is its migration cost. For every invocation $i \in E$, the computation cost takes its value from the mobile-device tree annotation $C_c(i, 0)$, if the method $m$ being invoked is to run on the mobile device, or from the clone tree annotation $C_c(i, 1)$ otherwise. The migration cost sums the individual migration costs of only those invocations whose methods are migration points.

Finally, the optimization objective is to choose $R(\cdot)$ so as to minimize $\sum_{E \in S} C(E)$. We use a standard integer linear programming (ILP) solver to solve this optimization problem with the above constraints.

4 Distributed Execution

The purpose of the distributed execution mechanism in CloneCloud is to implement a specific partitioning of an application process running inside an application-layer virtual machine, as determined during partitioning (Section 3).

The lifecycle of a partitioned application is as follows. When the user attempts to launch a partitioned application, current execution conditions (availability of cloud resources and network link characteristics between the mobile device and the cloud) are looked up in a database of pre-computed partitions. The lookup result is a binary, modified with particular migration and re-integration points (special VM instructions in our prototype), which is then launched in a new process. When execution of the process on the mobile device reaches a migration point, the executing thread is suspended and its state (including virtual state, program counter, registers, and stack) is packaged and shipped to a synchronized clone. There, the thread state is instantiated into a new thread with the same stack and reachable heap objects, and then resumed. When the migrated thread reaches a re-integration point, it is similarly suspended and packaged as before, and then shipped back to the mobile device. Finally, the returned packaged thread is merged into the state of the original process. When conditions change, or upon explicit user input via a simple configuration interface, a different partition and corresponding binary can be substituted for subsequent invocations of the application.

CloneCloud migration operates at the granularity of a thread. This allows a multi-threaded process to off-load
functionality, one thread-at-a-time. CloneCloud enables threads, local and migrated, to use—but not migrate—native, non-virtualized features of the platform on which they operate: this includes the network, unvirtualized hardware accelerators, natively implemented API functionality (such as expensive-to-virtualize image processing routines), etc. In contrast, most prior work providing application-layer virtual-machine migration keeps native features and functionality exclusively on the original platform, only permitting the off-loading of pure, virtualized computation.

These two unique features of CloneCloud, thread-granularity migration and native-everywhere operation, enable new execution models. For example, a mobile application can retain its user interface threads running and interacting with the user, while off-loading worker threads to the cloud if this is beneficial. This would have been impossible with monolithic process or VM suspend-resume migration, since the user would have to migrate to the cloud along with the code. Similarly, a mobile application can migrate a thread that performs heavy 3D rendering operations to a clone with GPUs, without having to modify the original application source; this would have been impossible to do seamlessly if only migration of virtualized computation were allowed.

CloneCloud migration is effected via three distinct components: (a) a per-process migrator thread that assists a process with the mechanics of suspending, packaging, resuming, and merging thread state; (b) a per-node node manager that handles node-to-node communication of packaged threads, clone image synchronization and provisioning; and (c) a simple partition database that determines what partitioning to use.

The migrator functionality manipulates internal state of the application-layer virtual machine; consequently we chose to place it within the same address space as the VM, simplifying the procedure significantly. A manager, in contrast, makes more sense as a per-node component shared by multiple applications, for several reasons. First, it enables application-unspecific node maintenance, including file system synchronization between the device and the cloud. Second, it amortizes the cost of communicating with the cloud over a single, possibly authenticated and encrypted, transport channel. Finally, it paves the way for future optimizations such as chunk-based or similarity-enhanced data transfer. Our current prototype has a simple configuration interface that allows the user to manually pick out a partition from the database, and to choose new configurations to partition for. We next delve more deeply into the design of the distributed execution facilities in CloneCloud.

Figure 7: Migration overview.

4.1 Suspend and Capture

Upon reaching a migration point, the job of the thread migrator is to suspend a migrant thread, collect all of its state, and pass that state to the node manager for data transfer. The thread migrator is a native thread, operating within the same address space as the migrant thread, but outside the virtual machine. As such, the migrator has the ability to view and manipulate both native process state and virtualized state.

To capture thread state, the migrator must collect several distinct data sets: execution stack frames and relevant data objects in the process heap, and register contents at the migration point. Virtualized stack frames—each containing register contents and local object types and contents—are readily accessible, since they are maintained by the VM management software. Starting with local data objects in the collected stack frames, the migrator recursively follows references to identify all relevant heap objects, in a manner similar to any mark-and-sweep garbage collector. For each relevant heap object, the migrator stores its field values, and collects all relevant static fields as well (e.g., static class fields).

Captured state must be conditioned for transfer to be portable. First, object field values are stored in network byte order to allow for incompatibilities between different processor architectures. Second, whereas typically a stack frame contains a local native pointer to the particular class method it executes (which is not portable across address spaces or processor architectures), we store instead the class name and method name, which are portable.

4.2 Resume and Merge

As soon as the captured thread state is transferred to the target clone device, the node manager passes that state to the migrator of a newly allocated process. To resume that migrant thread, the migrator must overlay the thread context over the clean process address space. This overlaying process is essentially the inverse of the capture process.
The executable text is loaded (it can be found under the same filename in the synchronized file system of the clone). Then all captured classes and object instances are allocated in the virtual machine’s heap, updating static and instance field contents with those from the captured context. As soon as the address space contains all the data relevant to the migrant thread, the thread itself is created, given the stack frames from the capture, the register contents are filled to match the state of the original thread at the migration point in the mobile device, and the thread is marked as runnable to resume execution.

As described above, the cloned thread will eventually reach a reintegration point in its executable, signaling that it should migrate back to the mobile device. Reintegration is almost identical conceptually to the original migration: the clone’s migrator captures and packages the thread state, the node manager transfers the capture back to the mobile device, and the migrator in the original process is given the capture for resumption. There is, however, a subtle difference in this reverse migration direction. Whereas in the forward direction—from mobile device to clone—a captured thread context is used to create a new thread from scratch, in the reverse direction—from clone to mobile device—the context must update the original thread state to match the changes effected at the clone. We call this process a state merge.

A successful design for merging states in such a fashion depends on our ability to map objects at the original address space to the objects they “became” at the cloned address space; object references themselves are not sufficient in that respect, since in most application-layer VMs, references are implemented as native memory addresses, which look different in different processes, across different devices and possibly architectures, and tend to be reused over time for different objects.

Our solution is an object mapping table, which is only used during state capture and reinstatement in either direction, and only stored while a thread is executing at a clone. We instrument the VM to assign a per-VM unique object ID to each data object created within the VM, using a local monotonically increasing counter. For clarity, we call the ID at the mobile device MID and at the clone CID. Once migration is initiated at the mobile device, a mapping table is first created for captured objects, filling for each the MID but leaving the CID null; this indicates that the object has no clone counterpart yet. After instantiation at the clone, the clone recreates all the objects with null CIDs, assigning valid fresh CIDs to them, and remembers the local object address corresponding to each mapping entry. At this point, all migrated objects have valid mappings.

During migration in the reverse direction, objects that came from the original thread are captured and keep their valid mapping. Newly created objects at the clone have the locally assigned ID placed in their CID, but get a null MID. Objects from the original thread that may have been deleted at the clone are ignored and no mapping is sent back for them. During the merge back at the mobile device, we know which objects should be freshly created (those with null MIDs) and which objects should be overwritten with the contents fetched back from the clone (those with non-null MIDs). “Orphaned” objects that were migrated out but died at the clone become disconnected from the thread object roots and are garbage-collected subsequently. Note that the mapping table is constructed and used only during capture and reintegration, not during normal memory operations either at the mobile device or at the clone.

Figure 8 shows an example scenario demonstrating the use of object mapping. During initial migration, objects at addresses 0x01, 0x02, and 0x03 are captured. The migrator creates the mapping table with three entries, one for each object, with the local ID of each object—1, 2, and 3, respectively—in MID, and null CIDs. At the clone, the mapping table is stored, updating each entry with the local address of each object (0x21, 0x22, and 0x23, respectively). When the thread is about to return back to the mobile device, new entries are created in the table for captured objects whose IDs are not already in the CID column (objects with IDs 14 and 15). Entries in the table whose CID does not appear in captured objects are deleted (the second entry in the figure). Remaining entries belong to objects that came from the original thread and are also going back (those with CID 11 and 13). Note that memory address 0x22 was reused at the clone after the original object was destroyed, but the object has a different ID from the original object, allowing the migrator to differentiate between the two. Back at the mobile device, new objects are created for entries with null MIDs (bottom two entries), objects with non-null MIDs are updated with the returned state (first and third entries), and one object (with local address 0x02) is left to be garbage-collected.
4.3 Optimization

The VM offers a unique opportunity for optimizing the amount of information transferred during migration. Because new processes are forked as copies of a “template” process—the Zygote, in the Android nomenclature—and because that template exists in all booted instances of the Android platform, we can avoid transmitting all system heap objects that have not changed since an application was copied from Zygote. This typically saves about 40,000 object transmissions with every migration operation, a significant time and bandwidth overhead reduction. Furthermore, even ignoring the transmission cost, some of those objects are static or platform-dependent system objects, so should not be migrated anyway.

We obviate migration for system objects in a manner similar to how we map objects to platform-independent IDs (in Section 4.2), with one major difference: whereas application processes are first created at the mobile device under our control, and then partially copied out and back in again as differences from that original single copy, Zygote processes are created independently at the mobile device and the clone. This creates the challenge of mapping objects from two independent instances of Zygote on possibly different platforms. To address the challenge, we name each Zygote object according to its class name and invocation sequence among all objects of that class—this assumes that objects from each class are constructed in the same order at Zygote processes on different platforms, an assumption that holds true in all Zygote instances we have seen so far.

5 Implementation

We implemented our prototype of CloneCloud partitioning and migration on the “cupcake” branch of the Android OS. We tested our system on the Android Dev Phone 1 (an unlocked HTC G1 device) equipped with both WiFi and 3G connections, and on clones running within the Android x86 virtual machine. We ported an ARM-based Android virtual machine to x86 for this purpose. Clones execute on a Dell Desktop with a 2.83GHz CPU and 4GB RAM, running Ubuntu 8.04. We modified the Dalvik VM (Android’s application-level, register-based VM, principally targeted by a Java compiler front-end) for dynamic profiling and migration. These modifications comprised approximately 8,000 lines of C code. We also implemented static analysis, bytecode rewriting, and the CloneCloud node manager in Java.

For partitioning, we perform all static analysis and bytecode rewriting with Java bytecode and convert Java bytecode into Dalvik bytecode. We implemented our static analysis in jchord and modified jchord to support root methods of analysis that are different from main. We modified Dalvik VM tracing to trace migration cost and to trace only application methods in which we are interested. The profiling is done both on the phone and on the clone. Then, we use Mosek to solve the ILP program we defined to produce a partition for each chosen execution environment. We use Javassist to rewrite bytecode to insert suspend and resume points, which are enabled or disabled at run time depending on policies.

For migration, we modified the Dalvik VM interpreter. For the suspend mechanism, we use Dalvik VM’s implementation of thread suspension. Each VM thread has a suspend counter which indicates if there is any pending suspend request. It checks this counter whenever it finishes the execution of a bytecode instruction, so that we can suspend the thread at a safe point. Even if a thread was executing a native frame, it also checks the counter when it finishes. The calling (migrator) thread waits until all other threads are suspended with a condition variable, and continues its execution.

We use hprof as a basis for capturing and representing the execution state. It provides a well-defined format for storing all the classes and heap objects efficiently. Also, since it traverses all the objects and thread stacks to collect information, we extend this format to store the thread stacks and class file paths. Also, we add the CID and MID to each object data for the mapping table. We implemented the object mapping table as a separate hashtable inside Dalvik VM. With our hashtable implementation, the hashtable is created only when migration is actually started, and destroyed after the migration. To track the object creation and destruction, we modified corresponding functions in Dalvik VM.

Migration is currently initiated and terminated by the (modified) application. To pass control from the application to the migrator thread, we define two CloneCloud APIs: ccStart() indicates the start point of the migration, and ccStop() defines the end point of the migration. In partitioning, we insert these function calls to the original application bytecode. The application thread calling these operations notifies the migrator thread inside Dalvik, and suspends itself. Once the migrator thread gets the notification and gains control, it checks with the policy engine if the decision is to migrate or not. If the decision is yes, it handles the rest of the migration.

6 Evaluation

For the evaluation of our prototype, we implemented three mobile applications. We evaluated running those applications either on an Android Dev Phone 1—representing the status quo, monolithic execution—or by optimally partitioning them for two execution settings: one with WiFi.
Table 1: Execution times of virus scanning, image search, and behavior profiling applications. For each application we show three rows, one per input size—each application measures input size differently. For each input size, the data shown include (from left to right) execution time at the phone alone ("monolithic" execution), execution time at the clone alone, CloneCloud execution time, partitioning choice, and speedup (for 3G connectivity), and the same information for WiFi connectivity.

| Application          | Input Size | Phone Exec. (sec) | Clone Exec. (sec) | Max Speedup | CloneCloud 3G Exec. (sec) | CloneCloud Part. | Speedup | CloneCloud WiFi Exec. (sec) | CloneCloud Part. | Speedup |
|----------------------|------------|-------------------|-------------------|-------------|--------------------------|------------------|---------|-----------------------------|------------------|---------|
| Virus scanning       | 100KB      | 5.70              | 0.30              | 19.00       | 5.70                     | Local            | 1.00    | 5.70                        | Local            | 1.00    |
|                      | 1MB        | 59.70             | 2.95              | 20.24       | 59.70                    | Local            | 1.00    | 20.30                       | Offload          | 2.94    |
|                      | 10MB       | 640.90            | 30.90             | 20.74       | 114.52                   | Offload          | 5.60    | 45.60                       | Offload          | 14.05   |
| Image search         | 1 image    | 22.20             | 0.97              | 22.89       | 22.20                    | Local            | 1.00    | 15.90                       | Offload          | 1.40    |
|                      | 10 images  | 212.20            | 8.40              | 25.26       | 98.40                    | Offload          | 2.16    | 23.60                       | Offload          | 8.99    |
|                      | 100 images | 2096.70           | 83.20             | 26.20       | 193.10                   | Offload          | 10.86   | 98.90                       | Offload          | 21.20   |
| Behavior profiling   | depth 3    | 3.60              | 0.20              | 18.00       | 3.60                     | Local            | 1.00    | 3.60                        | Local            | 1.00    |
|                      | depth 4    | 46.80             | 2.00              | 23.40       | 46.80                    | Local            | 1.00    | 14.50                       | Offload          | 3.23    |
|                      | depth 5    | 315.80            | 12.00             | 26.32       | 77.50                    | Offload          | 4.07    | 25.40                       | Offload          | 12.43   |

Table 1: Execution times of virus scanning, image search, and behavior profiling applications. For each application we show three rows, one per input size—each application measures input size differently. For each input size, the data shown include (from left to right) execution time at the phone alone (“monolithic” execution), execution time at the clone alone, CloneCloud execution time, partitioning choice, and speedup (for 3G connectivity), and the same information for WiFi connectivity.

The applications we consider are a virus scanner, image search, and privacy-preserving targeted advertising; we briefly describe each next. The virus scanner scans the contents of the phone file system against a library of 1000 virus signatures, one file at a time. We vary the total size of the file system between 100KB and 10 MB. The image search application finds all faces in images stored in the phone file system. We use a face-detection Android library that returns the mid-point between the eyes, the distance between the eyes, and the pose of every face detected. We only use images smaller than 100KB each, due to memory limitations of the Android face-detection library. We vary the number of images from 1 to 100. The privacy-preserving targeted advertising application uses behavioral tracking across websites to infer the users’ preferences, and selects ads accordingly to a resulting model; by doing this tracking at the user’s device, privacy can be protected (see Adnostic [38]). We implement Adnostic’s web page categorization on the mobile device, which maps a user’s keywords to one of the hierarchical interest categories—down to nesting levels 3-5—from the DMOZ open directory [1]. The application computes the cosine similarity between user interest keywords and predefined category keywords.

Table 1 collects all our results for the three applications, under three different workload sizes each. The third column shows the execution time for each experiment when running on the phone monolithically. As a point of comparison, the fourth column shows execution time when the application runs on the clone in its entirety. CloneCloud cannot achieve this performance, since in practice some part of the application must run on the phone, and there is non-trivial overhead in migrating the remainder to the clone. However the comparison of these two columns, as shown in the maximum speedup column coming next, captures the speedup opportunity available due to the disparity between phone and cloud computation resources, when offloading computation to a single clone.

We now turn to the choices CloneCloud makes when executing each application using the 3G network or the WiFi network. The execution times reported are the average of five runs. In the 3G case, communication is performed via an SSH tunnel between the phone and the clone, to punch through our lab firewall. Our 3G connection averaged latency of 415 ms, download bandwidth of 0.91 Mbps, and upload bandwidth of 0.16 Mbps, while our WiFi connection had a latency of 66 ms, download bandwidth of 7.29 Mbps, and upload bandwidth of 3.06 Mbps.

An obvious difference between the two execution environments is that CloneCloud chooses to keep local more workloads (5 out of 9) in the 3G case, than in the WiFi case (2 out of 9). This can be explained given the overhead differences between the two networks. Migration costs about 10-15 seconds in the WiFi case, but shoots up to 60 seconds in the 3G case, due to the greater latency and lower bandwidth in the latter case. In both cases, migration costs include a network-unspecific thread-merge cost—patching up references in the running address space from the migrated thread—and the network-specific transmission of the thread state. The former dominates the latter for WiFi, but is dominated by the latter for 3G. A secondary effect in the results is that larger workloads benefit from off-loading more; this is due to amortization of the migration cost over a larger computation at the clone that receives a significant speedup. Nevertheless,
the WiFi case displays significant speed-ups in all applications: 14x, 21x, and 12x for the largest workload of each of the three applications, for a completely automatic modification of the application binary without programmer input. We expect these benefits to increase with a number of optimizations targeting the network overheads (in particular, 3G network overheads): redundant transmission elimination and compression.

Next, we analyze the time to run the partitioning framework. First, we report the time to perform partitioning analysis for the image search application. In our evaluation, we report the average of five runs. We profile 35 methods in the application program. Note that we do profiling of only methods appeared in the application; thus profiling is done with low overhead. We profile the application on the phone and on the clone. Profiling execution time takes 29.4 seconds on the phone and 1.2 seconds on the clone. Profiling migration cost takes 98.4 seconds on the phone. Then, running static analysis using jchord takes 19.4 seconds with sun jdk 1.5.0_16 on the desktop machine. Generating an optimizer (ILP) script from the profile trees and constraints and solving the generated ILP take less than one second.

7 Related Work

CloneCloud is built upon previous research work done in automatic partitioning, migration, and remote execution, and it combines these technologies in a non-trivial way. First, it uses a partitioning framework that combines static program analysis with dynamic program profiling. It does partitioning in a method level, allows placing methods that access native state remotely if they meet partitioning constraints generated by the partitioning framework, and uses partitioning that optimizes certain metrics. CloneCloud performs migrating specific threads with relevant execution state including relevant reachable heap objects. It performs migration on demand if doing so is beneficial, and can merge migrated state back to the original process.

Partitioning We first summarize previous work on partitioning of distributed systems. Coign [21] automatically partitions a distributed application composed of Microsoft COM components to reduce communication cost of partitioned components. The application must be structured to use COM components and partitioning points are COM boundaries, and the work focuses on static partitioning and assumes that a COM component can be placed anywhere. Wishbone [27] and Pleiades [23] compile a central program into multiple code pieces with stubs for communication mostly for sensor networks. Wishbone is a system that takes an acyclic dataflow graph of operators written in a high-level stream-processing language and partitions the dataflow graph between server and a set of embedded nodes for sensor computing applications. It uses a compiler that generates partitioned source code with communication stubs based on profiling CPU and network bandwidth consumption. Pleiades [23] compiles a central program written in an extended C language with the model of accessing the entire network into multiple units to run on sensor nodes. MAUI [14] partitions applications using dynamic profiling and optimization, focusing on energy consumption. For offloaded execution, it performs method shipping with relevant heap objects. J-Orchestra [36] creates partitioned applications automatically by a compiler that classifies anchored unmodifiable, anchored modifiable, or mobile classes. After the analysis, it rewrites all references into indirect references (i.e., references to proxy objects) for a cluster of machines, and places classes with location constraints (e.g., ones with native state constraints) to proper locations. Finally, for distributed execution of partitioned applications, it relies on the RMI middleware.

There are also Java program partitioning systems for mobile devices whose limitation is that only Java classes without native state can be placed remotely [20,25,28]. The general approach is to partition Java classes into groups using adapted MINCUT heuristic algorithms to minimize the component interactions between partitions. Also, different proposals consider different additional objectives such as memory, CPU, or bandwidth. This previous work does not consider partitioning constraints like our work does, the granularity of partitioning is coarse since it is a class level, and it focuses on static partitioning.

On a related front, Links [13], Hops [33], and UML-based Hilda [40] aim to statically partition a client-server program written in a high-level functional language or a high-level declarative language into two or three tiers. Yang et. al. [39] examine partitioning of programs written in Hilda based on cost functions for optimizing user response time. Swift [11] statically partitions a program written in the Jif programming language into client-side and server-side computation. Its focus is to achieve confidentiality and integrity of the partitioned program with the help of security labels in the program annotated by programmers.

Migration There has been previous work on supporting migration in Java. MERPATI [35] provides JVM migration using checkpointing the entire heap and all the threads with their execution environment (the call stack, the local variables, and the operand stacks) and resuming from a checkpoint. In addition, there has been different approaches on distributed Java virtual machines (DJVMs). They assume a cluster environment where homogeneous machines are connected via fast interconnect, and try to provide a single system image to users. One approach is to build a DJVM upon a cluster enabled infrastructure below the JVM. Jessica [24] and Java/DSM [42]
As a result, CloneCloud focuses on migrating at execution (after migration) is significantly higher, given processor architecture differences, and the complexity of integrating such captures into the migrator would have to collect such context for transfer as well. However, the complexity of capturing such information in a portable fashion (and the complexity of integrating such captures after migration) is significantly higher, given processor architecture differences, differences in file descriptors, etc. As a result, CloneCloud focuses on migrating at execution points where no native state (in the stack or the heap) need be collected and migrated.

A related limitation is that CloneCloud does not virtualize access to native resources that are not virtualized already and are not available on the clone. For example, if a method accesses a camera/GPS on the mobile device, CloneCloud requires that method to remain pinned on the mobile device. In contrast, networking hardware or an unvirtualized OS facility (e.g., Android’s image processing API) are available on both the mobile device and the clone, so a method that needs to access them need not be pinned. An alternative design would have been to permit migration of such methods, but enable access to the unique native resource via some RPC-like mechanism. We consider this alternative a complementary point in the design space, and plan to pursue it in conjunction with thread-granularity migration in the future.

The system presented in this paper allows only per-method concurrency between the unmigrated threads and the migrated thread: pre-existing state on the mobile device remains unmodifiable until the migrant thread returns. As long as local threads only read existing objects and modify only newly created objects, they can operate in tandem with the clone. Otherwise, they have to block. A promising direction, whose benefits may or may not be borne out by the associated complexity, lies in extending this architecture to support full concurrency between the mobile device and clones. To achieve this, we need to add thread synchronization, heap object synchronization, on-demand object paging to access remote objects, etc.

While in this paper we assume that the environment in which we run clone VMs is trusted, the future of roaming devices that use clouds where they find them demands a more careful approach. For instance, many have envisioned a future in which public infrastructure machines such as public kiosks and digital signs are widely available for running opportunistically off-loaded computations. We plan to extend our basic system to check that the execution done in the remote machine is trusted. Automatically refactoring computation around trusted features on the clone is an interesting research question.

In our related position paper, we discussed a rich design space for automatic off-loading. Our work here covers some aspects of primary and background augmentation, and we would like to continue to explore hardware augmentation and multiplicity augmentation that uses multiple copies of the system image executed in different ways.

8 Discussion and Future Work

CloneCloud is limited in some respects by its inability to migrate native state and to export unique native resources remotely. Conceptually, if one were to migrate at a point in the execution in which a thread is executing native code, or has native heap state, the migrator would have to collect such native context for transfer as well. However, the complexity of capturing such information in a portable fashion (and the complexity of integrating such captures after migration) is significantly higher, given processor architecture differences, differences in file descriptors, etc. As a result, CloneCloud focuses on migrating at execution
execution of mobile applications on the cloud, representing the whole-sale transfer of control from the device to the cloud and back. We combine partitioning, migration with merging, and on-demand instantiation of partitioning to address these challenges. Our prototype delivers up to 21.2x speedup for applications we tested, without programmer involvement, demonstrating feasibility for the approach, and opening up a path for a rich research agenda in hybrid mobile-cloud systems.

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