Adapting Graph Application Performance Via Alternate Data Structure Representations

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ABSTRACT
Graph processing is used extensively in areas from social networking mining to web indexing. We demonstrate that the performance and dependability of such applications critically hinges on the graph data structure used, because a fixed, compile-time choice of data structure can lead to poor performance or applications unable to complete. To address this problem, we introduce an approach that helps programmers transform regular, off-the-shelf graph applications into adaptive, more dependable applications where adaptations are performed via runtime selection from alternate data structure representations. Using our approach, applications dynamically adapt to the input graph’s characteristics and changes in available memory so they continue to run when faced with adverse conditions such as low memory. Experiments with graph algorithms on real-world (e.g., Wikipedia metadata, Gnutella topology) and synthetic graph datasets show that our adaptive applications run to completion with lower execution time and/or memory utilization in comparison to their non-adaptive versions.

Keywords
runtime data structure selection, space-time trade-off

1. INTRODUCTION
Graph processing continues to increase in popularity with the emergence of applications such as social network mining, real-time network traffic monitoring, etc. Due to their data-intensive nature, the performance and dependability of such applications depends upon how well the choice of runtime data structure matches the input data characteristics and availability of memory (low memory can prevent the applications from completing).

Input Data Characteristics. Programmers often choose specific, fixed data structures when developing graph applications. The memory used by the data structure can be greatly influenced by the input data characteristics. Thus, it is possible that the characteristics of data may not match the choice of the data structure. This is particularly problematic when the application is expected to encounter a wide range of input data characteristics, and these characteristics may change during the course of execution. For example, matrices can be represented in the Compressed Column Storage (CCS) format, appropriate for sparse matrices, or the array representation, appropriate for dense matrices. An application, e.g., matrix multiplication, programmed to use the sparse CCS format, could take longer to complete when presented with a dense input. Similarly, evolving graphs [33], where nodes or edges are added during execution, are another example of changes in input data characteristics. The data structure selection based on input pre-analysis will fail under such scenario. Therefore, in our approach, adaptive applications tailor the choice of data structure at runtime.

Availability of Memory. Since real-world applications often do not run in isolation, they share the available memory resources with other applications. There could be times where the application experiences a resource crunch, caused by other running programs. In this scenario the performance of the application may be degraded, or the application may even be prematurely terminated. Therefore, in our approach, adaptive applications tailor the choice of data structure at runtime.

It is well known that for data-intensive applications, the choice of data structure is critical to memory usage and execution time. There has been previous work on data structure identification [10], as well as data structure prediction and selection [3, 17, 22]. While these prior approaches help in data structure selection, none of them support switching from one data structure to another as the application executes. There has also been work on dynamically adapting the representation of individual data items for impacting memory usage and performance—employing data compression [29] or replacing float data with int data [20]. These techniques are orthogonal to our work that switches between alternate high level data structures. Other approaches dynamically switch between implementations. Elastin [20] allows a program to switch between versions using dynamic software update techniques [21]; however, it does not consider switching between alternate high level data structures. IBM’s K42 Operating System [11, 3] supports hot-swapping classes as a mechanism for performing dynamic updates. Scenario Based Optimization [19], a binary level online optimization technique dynamically changes the course of execution through a route meant for a particular runtime scenario as predefined by developer. Wang et al. [32] proposed dynamic resource management techniques based on userspecific, application-specific and hardware-specific management policies. In contrast, our objective is to simultaneously support alternate data structures and switch between them.

In this paper we consider several widely-used graph applications and study how data structure representations impact execution time and memory consumption on a range of input graphs (Section 2). The input graphs consist of both real-world graphs such as Wikipedia metadata, Gnutella network topology (from the SNAP library [31]), and synthetic graphs. Based upon the observations from our study, we design a concrete adaptation system that supports switch-
ing between alternate representations of the data in memory (Section 3). We demonstrate that the cost of performing the runtime adaptations is quite small in comparison to the benefits of adaptation (Section 1). Moreover, the lightweight monitoring we employ to detect adaptation opportunities imposes acceptable overhead even when no adaptations are triggered at runtime. Thus, our adaptive versions have nearly the same performance as the most appropriate non-adaptive versions for various input characteristics. We compare our approach with related work in Section 5 and in Section 6 we conclude.

2. A STUDY OF GRAPH APPLICATIONS

In this section we study the execution time and memory usage behavior of a set of graph applications. The goal of this study is two fold. First, we want to quantify how input data characteristics and the choice of data structures used to represent the graphs impact memory usage and execution time. Second, we would like to develop a simple characterization of program behavior that can be used to guide data structure selection at runtime.

We considered six graph algorithms: Multiple Source Shortest Path (MSSP) finds the shortest path from all the nodes to every other node; Betweenness Centrality (BC) computes the importance of a node in a network; Breadth First Search (BFS) traverses the graph with each node as root per iteration; Boruvka’s Algorithm (MST-B) and Kruskal’s Algorithm (MST-K), finds the minimum spanning tree; Preflow Push (PP), finds out the maximum flow in a network. The inputs were selected such that the trade-offs could be exposed easily. The core data structure used in these applications is a graph. We consider two different representations of graphs: Adjacency List (ADJLIST); and Adjacency Matrix (ADJMAT). When the graph is sparse, it is expected that ADJLIST will use less memory than ADJMAT. On the other hand, for highly dense graphs ADJMAT may use less memory than ADJLIST. Determining whether a pair of nodes is connected by an edge can be done in constant time using ADJMAT while it may require searching through a list with ADJLIST. Thus, the runtime memory usage and execution time depend upon the sparsity, or conversely the density, of the input graph. The input graphs with relevant properties and densities were generated to study program behavior.

To observe the trade-offs of using the alternative representations of graphs, we executed each of the programs using the two representations. The programs were run on inputs consisting of randomly-generated graphs with varying density which is computed as $\frac{|E|}{|V|(|V|-1)}$, where $|V|$ and $|E|$ are number of nodes and edges in the graph. The inputs were selected such that the trade-offs could be exposed easily. The results of these executions are summarized as follows:

Impact of data structure selection on memory usage and execution time. We present the relative memory usage and execution time of program versions in Table 1. In particular, we computed the ratios of memory usages and execution times for ADJLIST and ADJMAT versions across all graph densities considered. The minimum and maximum values of observed ratios is given in Table 2. As we can see, in terms of both memory usage and execution time, the relative performances vary a great deal. Moreover, neither representation gives the best memory usage or execution time performance across all graph densities. Hence, it is crucial to select the data structure at runtime, based upon the input data characteristics.

| Application | ADJLIST / ADJMAT |
|-------------|------------------|
| Memory Usage | Execution Time |
| MSSP        | 0.68 - 8.02      | 0.40 - 4.00 |
| BC          | 0.40 - 4.00      | 0.59 - 2.88 |
| MST-K       | 0.72 - 2.44      | 0.35 - 3.83 |
| BFS         | 0.84 - 5.14      | 0.72 - 3.14 |
| MST-B       | 0.71 - 1.67      | 0.16 - 7.21 |
| PP          | 0.60 - 5.40      | 0.60 - 3.53 |

Table 1: Relative performance ranges.

We now present our approach for building adaptive applications; an overview is shown in Figure 1. The starting point is the annotated source code: in the source code, programmers add annotations to identify the alternative data structures, e.g., $DS_1$ and $DS_2$, and functions operating on them. The compiler takes heed of these annotations and generates the source code with transition logic, that is capable of dynamically switching among alternative data structure representations. The transitions are allowed at selected program points where the processing of an input item has just completed and that of another item is about to begin. Lastly, the adaptation module consists of the runtime monitors for tracking input data characteristics and memory usage as well as the code that implements the transition policy that triggers the switch from one data structure representation to another. The adaptation can be triggered by a mismatch between the input data characteristics and the data structure currently in use. To discover this mismatch the characterization of application behavior as performed in the previous section is used. The adaptation can also be triggered by the system during high memory usage.

3. ADAPTIVE APPLICATIONS

Characterization of application behavior. For the purpose of runtime data structure selection, we characterize the behavior of each application as shown in Table 2. Note that graph densities are divided into three subranges. In the first range (e.g., $< 9\%$ for MSSP) the ADJLIST is both more memory- and time-efficient than ADJMAT. In the second range (e.g., $9\% - 25\%$) ADJLIST is more memory-efficient while ADJMAT is more time-efficient. Thus, the selection can be made at runtime based upon memory availability. Finally, in the third range (e.g., $> 25\%$ for MSSP) ADJMAT is both more memory and time efficient than ADJLIST.

Table 2: Density ranges where each data structure prevails.

| Application | ADJLIST | ADJLIST | ADJMAT |
|-------------|---------|---------|--------|
| Memory Usage | best space & time | best space, ADJMAT | best space & time |
| MSSP        | $< 9\%$ | $9\% - 25\%$ | $> 25\%$ |
| BC          | $< 10\%$ | $10\% - 25\%$ | $> 25\%$ |
| MST-K       | $< 25\%$ | $25\% - 37\%$ | $> 37\%$ |
| BFS         | $< 8\%$ | $8\% - 25\%$ | $> 25\%$ |
| MST-B       | $< 10\%$ | $10\% - 40\%$ | $> 40\%$ |
| PP          | $< 2\%$ | $2\% - 34\%$ | $> 34\%$ |

Figure 1: High level overview of our approach.
Programming for adaptation. To enable adaptation, the programmer implements the alternate data structures. In addition, a compute-intensive function during whose execution adaptation may be performed, must be coded as follows. First, it should contain a variable that tracks the progress in terms of processing steps defined as either the amount of input processed or results produced. Second, it should be written so that it can commence execution from any point between two processing steps. The latter is needed because we allow execution to switch from one data representation to another at these points. We used a set of pragmas in our approach to identify alternate data structure representations, enable generation of code that transfers code from one representation to another, and identify program points where transitions may be performed. First, the programmer identifies the data structure to the compiler. The programmer annotates the alternate representation of data structures in multiple files with \#pragma ADP(\$SRC_FILENAME, "data1_def"). \$SRC_FILENAME’s presence clearly differentiates the alternate representation of the data structure in multiple files. If there are multiple data structures with alternate representations in different files, then they could be annotated with a different index, e.g., \#pragma ADP(\$SRC_FILENAME, "data2_def"). Second, the programmer uses several pragmas to identify the key methods (insert, delete, traverse, and fetch) that manage data stored in the data structure. Another pragma allows access to the initialization parameters which must be migrated from one data structure to another. All of this information is used to generate the code for data and function migration when we switch between data structures.

Triggering adaptations. The adaptation module decides whether or not to switch between data structures based upon the input from runtime monitors and the transition policy. Since the adaptation could be program-triggered or system-triggered, there are two kinds of monitors which are required by the adaptation module. The input data monitor captures input data characteristics and the memory monitor reports the available system memory. The transition policy defines which data structure representation is better for what range of input data characteristics in terms of execution time and memory consumption. Its specification consist of three parts, as illustrated below:

```
/* EXECUTION TIME */
DS1 [0.9]
DS2 [9,100]

/* MEMORY */
DS1 [0.25]
DS2 [25,100]

/* THRESHOLD */
MEMORY 100
```

The first part indicates the ranges for which a particular data structure representation is best in terms of execution time: under \texttt{EXECUTION TIME} in the figure, the input data property for which \texttt{ADJLIST} (DS1) is better is denoted by directives DS1, which means that \texttt{ADJLIST} is favorable in terms of execution time if the input data property or density of the graph (in case of MSSP) is in between 0% and 9%. The second part consists of the ranges of the input data property for which a particular data structure representation is better in terms of memory. According to the figure, under \texttt{MEMORY}, we see that \texttt{ADJLIST} (DS1) is better when the density of the input graph is between 0% and 25% while \texttt{ADJMATRICE} (DS2) is better when the density of the graph is between 26% and 100%. The third part is the threshold for memory, defined by the programmer to notify the system that if the available memory is below this threshold then, regardless of input characteristics always use the representation requiring least memory; in the figure (under \texttt{THRESHOLD}) the threshold is set to 100MB.

```
dataMigrationDS1DS2(void* DS1, void* DS2)
{
    initializationParameters* ip;
    ip = getInitializationParameter(DS1);
    initializeDS2(ADDS2, ip);
    transferDataDS1DS2(DS1, DS2);
    deleteDS1(DS1);
}
```

Figure 2: Data migration.

Switching between data structure representations. The data structure transition logic is inserted into the source files by the compiler, guided by the pragmas. This transition logic carries out on-the-fly transitions from one data structure representation to another whenever required. To accomplish the transition, the in-memory data must be transformed from one representation to another, along with the functions operating on them. The transition logic handles this by function migration and in-memory data methods contained in the logic. When the code for transition logic is inserted, appropriate header files are also inserted such that source code after modification compiles and links properly. To avoid recomputation of already-computed results, the result transfer logic (injected into code along with the transition logic) will transfer the already-computed results from one representation to the other representation.

An example data migration function is shown in Figure 2. The code in the figure transfers the data from the data structure representation DS1 to another representation DS2. It begins with initialization of the DS2 data structure representation. The initialization parameters are fetched from DS1 and they consist of standard parameters that are invariant in both DS1 and DS2. For example, in the MSSP benchmark the invariant data is the number of nodes. In the PP benchmark the invariant data consists of number of nodes, the height, capacity and flow of each node. The \texttt{transferData} function is generated from \texttt{traverseData} function of DS1 as provided by the developer. This function traverses through the data by reading each data value, migrating it to DS2 representation using \texttt{insertDataDS2} and also deleting data from DS1 using \texttt{deleteDataDS1} thus releasing memory. The \texttt{deleteDS1} clears memory which contains the data regarding the initialization parameters.

The transition between implementations, i.e., switching from one set of functions operating on representation DS1 to functions operating on representation DS2 must be carefully orchestrated. The developer denotes an operation with a directive such as \#pragma ADP("DS1", "data1_op1"), which forms the compiler that the function is compute-intensive, as shown in Figure 2. Any call to that function is replaced by our customized method, which checks and executes operations with the suitable data structure. In this example \texttt{computeMSSP_DS1} is replaced by \texttt{call0P1}. The additional parameter, \texttt{startDS}, denotes the type of the current data structure representation in memory. The other three parameters are the data structure, a progress gauge, and the result set for storing the result. For example in the
Figure 3: Function migration method before compilation (left) and after compilation (right).

```c
void callOP1(void* ds, void* rs, int progress, currentDS){
  extern int changeReq; void* newDS; void* newRS;
  while (progress < 100) {
    if(changeReq == 1) {
      switch (currentDS) {
        case 1:
          currentDS = 2; dataMigrationDS1DS2(ds, newDS);
          resultMigrationRS1RS2(rs, newRS);
          computeMSSPDS2(ds, rs, progress);
          break;
        case 2:
          currentDS = 1; dataMigrationDS2DS1(ds, newDS);
          resultMigrationRS2RS1(rs, newRS);
          computeMSSPDS1(ds, rs, progress);
          break;
      }
    }
  }
}
```

Figure 4: Switching between implementations.

```c
void computeMSSP_DS1(void* graph, void* rs, int* progress)
{ //pragma ADP("DS1", "ds1_op1")
    void* graph, void* rs,
    int* progress);
    computeMSSP_DS1(graph, rs, progress);
    ...
}
```

Figure 5: Adaptation module interrupt before compilation (left) and after compilation (right).

| App. | Non-Adaptive Ex. Time (sec) | Adaptive: ADJLIST→ADJMAT (sec) | Benefit Realized |
|------|-----------------------------|----------------------------------|------------------|
| MST-B | 1.454 | 1.214 | 1.465 | 3.15 | 98.35 |
| MST-K | 1.454 | 1.214 | 1.465 | 3.15 | 98.35 |
| BFS | 1.454 | 1.214 | 1.465 | 3.15 | 98.35 |
| BC | 1.386 | 2.489 | 1.408 | 3.00 | 98.05 |
| PP | 0.81 | 2.566 | 0.87 | 3.2 | 96.35 |

Figure 6: Adaptive vs. non-adaptive performance.

4. EVALUATION

In this section we evaluate the performance of adaptive versions of graph algorithms and compare them with corresponding non-adaptive versions of the applications. The goals of these experiments are as follows. First, we evaluate the efficiency of our approach by measuring its benefits and overhead. Second, we consider the benefits of adaptation under two scenarios: adaptation triggered by the input characteristic, i.e., graph density; and system triggered adaptation. All experiments were run on a 24-core machine (4 six-core AMD Opteron™ 8431 processors) with 32GB RAM. The system ran Ubuntu 10.04, Linux kernel version 2.6.32-21-server. The sources were compiled with Gcc 4.4.3.

Real World Data-sets: We evaluate our system on some of the real-world graphs from the SNAP graph library [31]. The first graph, wiki-Vote, contains the who-votes-for-whom graph in Wikipedia administrator elections. This graph has 7,115 nodes and 103,689 edges. The second graph, p2p-Gnutella, is a snapshot of Gnutella, a decentralized peer to peer file sharing network from August 9, 2002. This graph
has 8,114 nodes representing hosts and 26,013 edges representing the connections between these hosts. For experiments, in cases where a more dense graph was needed, we added edges in both the graphs to raise the required density.

### 4.1 Programming Effort

The programmers need to add annotations to transform off-the-shelf applications to adaptive ones. In addition to this, programmers also need to modify the compute-intensive methods so they can be executed in incrementalized fashion. The number of pragmas added and the number of additional lines of code added to modify the methods are shown in Table 4. As we can see, these numbers are fairly modest.

### 4.2 Input Triggered Adaptation

In this scenario we study how adaptive applications respond to the mismatch between the data structure representation fixed a priori at compile time and the density of the input graph. We compute the benefit realized by our approach for various applications. In particular, we start the program by using the \texttt{ADJMAT} representation and select a real world graph (p2p-Gnutella) which is 0.004\% dense, which makes \texttt{ADJLIST} the ideal representation. Therefore, when the adaptive application is run, it dynamically switches from the \texttt{ADJMAT} to the \texttt{ADJLIST} representation.

In Table 5 we present the execution times of the non-adaptive (\texttt{ADJLIST} and \texttt{ADJMAT} representations) and adaptive (\texttt{ADJMAT}→\texttt{ADJLIST}) versions of the applications. For the latter version, we also present the transition latency which is the execution time after which the program has completed the transition to the \texttt{ADJLIST} representation. From the results in Table 5 we observe the following. The execution time of the adaptive version, on average, is 2.49\% higher than the non-adaptive \texttt{ADJLIST} version; but 48.09\% lower than the non-adaptive \texttt{ADJMAT} version. For example, for MSSP, the execution of the adaptive version is 1,408 seconds which is 1.54\% higher than the execution time of the non-adaptive \texttt{ADJLIST} version (1,386 seconds) and 56.55\% lower than the execution time of the non-adaptive \texttt{ADJMAT} version (2,489 seconds). In addition, we observe that the transition latency of the adaptive version is small in comparison to the total execution time. For example, for MSSP, the transition latency of 3 seconds is approximately 0.21\% of the total execution time of 1,408 seconds. That is, the adaptation is performed quickly (low transition latency) and efficiently (low transition overhead). Thus, nearly all the benefits of using \texttt{ADJLIST} over \texttt{ADJMAT} are realized by the adaptive version.

We quantify the benefit realized by our approach as follows. The maximum possible benefit is given by the difference in the execution times of the non-adaptive \texttt{ADJMAT} and non-adaptive \texttt{ADJLIST} versions. The benefit our approach realizes is the difference between the execution times of the non-adaptive \texttt{ADJLIST} version and the adaptive version. The realized benefit, as a percentage of maximum possible benefit, is given in the last column of Table 5. As we can see, the realized benefit is over 96\% for these applications.

The additional execution time taken by the adaptive version over the non-adaptive \texttt{ADJLIST} version can be divided into three categories: time spent on converting from one data structure representation to another; time spent on runtime monitoring and transition logic to trigger adaptation; and the time lost due to running the application in suboptimal mode, i.e., with the \texttt{ADJMAT} data structure. The breakdown of the extra execution time into the three categories is shown in Table 5. As we can see, the majority of the time is spent on runtime monitoring and transition logic. The next significant component is the time spent due to running the program in the suboptimal configuration before the transition occurs. Note that the time spent on converting one data structure into another (column 2) is the least.

An intuitive way to visualize adaptation is to plot how the memory used by applications varies before, during, and after adaptation. In Figure 7 we show how memory (y-axis) varies over time (x-axis) when starting the application in the \texttt{ADJMAT} representation and then through adaptation, the application transitions to \texttt{ADJLIST}. The charts point out several aspects. First, since we are using sparse graphs, as expected, the memory used is reduced significantly (tens of megabytes) when we switch from the \texttt{ADJMAT} to \texttt{ADJLIST} representation. Second, the switch from one data structure to the other takes place fairly early in the execution of the program. Third, the time to perform adaptation and the extra memory used during adaptation are very low.

In Figure 6 we show the execution time of the adaptive version for varying input densities over the range where we expect the adaptive application to switch from the \texttt{ADJLIST} to the \texttt{ADJMAT} representation. For these experiments, we have used graph size of 4000 nodes and varied densities. The execution times of the non-adaptive versions that use fixed representations (\texttt{ADJLIST} and \texttt{ADJMAT}) are also shown. As we can see, the performance of the adaptive application is very close to the best of the two non-adaptive versions.

### 4.3 System Triggered Adaptation

In this section we study the second scenario, i.e., when the adaptation is triggered by the system. The graph used for these experiments was p2p-Gnutella at 20\% density. However, we select \texttt{ADJMAT} as the initial data structure representation so that no adaptation was triggered due to the mismatch between the data structure and graph density. Instead we provided the program with a system trigger that forces the program to reduce its memory consumption.
decreases, our applications adapt to decrease their memory usage and execution time. For example, for the agglomerative clustering benchmark, when we tried using two alternate data structures of kd-tree and r-tree, we observed no significant trade-off between memory usage and execution time. Since there is a need to bulk load the data, the kd-tree always outperforms the r-tree. Second, our approach is only useful when the application is sufficiently compute and data intensive to justify the cost of runtime monitoring and transition logic. For example, in the case of the Max Cardinality Bipartite Matching benchmark, although the trade-off exists, the benchmark is not sufficiently compute-intensive to justify the adaptation cost.

4.4 Limitations of Our Approach

First, our approach is only useful when the alternative data structures offer a significant trade-off between memory usage and execution time. For example, for the agglomerative clustering benchmark, when we tried using two alternate data structures of kd-tree and r-tree, we observed no significant trade-off between memory usage and execution time. Since there is a need to bulk load the data, the kd-tree always outperforms the r-tree. Second, our approach is only useful when the application is sufficiently compute and data intensive to justify the cost of runtime monitoring and transition logic. For example, in the case of the Max Cardinality Bipartite Matching benchmark, although the trade-off exists, the benchmark is not sufficiently compute-intensive to justify the adaptation cost.

5. RELATED WORK

There is a large body of work on program transformations applied at compile-time or runtime to enhance program performance, which also influences resource usage. Some of these techniques can be used to support adaptation. Compiler-enabled adaptation techniques include altering of the contentions of an application [11, 16], which enables co-location of applications without interfering with their performance; data spreading [13] migrates the application across multiple cores; adaptive loop transformation [7] allows a program to execute in more than one way during execution based on runtime information. Multiple applications that are running on multicore systems can significantly impact each other’s performance as they must share hardware resources (e.g., last level cache, access paths to memory) [27]. The impact of interference on program performance can be predicted and estimated [10, 15], and contention management techniques guided by last level shared cache usage and lock contention have been developed [2, 24, 26, 13, 25, 12].

Huang et al. proposed Self Adaptive Containers [8] where they provide the developer with a container library which adjusts the underlying data structure associated with the container to meet Service Level Objectives (SLO); adaptation occurs during SLO violations. Similarly, CoCo [28] allows adaptation by switching between Java collections during execution depending on the size of collection. These methods are orthogonal to our approach as they do not have scope for user-defined data structures, and the space-time tradeoff is not taken into consideration.

6. CONCLUSION

Graph applications have resource requirements that vary greatly across runs due to differences in graph characteristics; moreover, the required memory might not be available due to pressure from co-located applications. We have observed that data structure choice is crucial for allowing the application to get the best out of available resources. We propose an approach that uses programming and runtime support to allow graph applications to be transformed into adaptive applications by choosing the most appropriate data structure. Experiments with graph-manipulating applications which adapt by switching between data structure representations show that our approach is easy to use on off-the-shelf applications, is effective at performing adaptations, and imposes very little overhead.
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7. REFERENCES
[1] A. Baumann, J. Appavoo, D. D. Silva, J. Kerr, O. Krieger, and R. W. Wisniewski. Providing dynamic update in an operating system. USENIX ATC’05.
[2] M. Bhadauria and S. A. McKee. An approach to resource-aware co-scheduling for cmps. ICS’10.
[3] C. A. N. Soules, J. Appavoo, D. D. Silva, M. Auslander, G. R. Ganger, M. Ostrowski, and et al.. System support for online reconfiguration. USENIX ATC’03.
[4] C. Ghezzi, M. Pradella, and G. Salvaneschi. Programming language support to context-aware adaptation: a case-study with erlang. SEAMS’10.
[5] C. Jung, S. Rus, B. P. Railing, N. Clark, and S. Pande. Brainy: effective selection of data structures. PLDI’11.
[6] E. Schonberg, J. T. Schwartz, and M. Sharir. An automatic technique for selection of data representations in setl programs. ACM TOPLAS’81.
[7] R. Gupta and R. Bodik. Adaptive loop transformations for scientific programs. IPDPS’95.
[8] W.-C. Huang and W. J. Knottenbelt. Self-adaptive containers: Building resource-efficient applications with low programmer overhead. SEAMS 2013.
[9] I. Neamtiu, M. Hicks, G. Stoye, and M. Oriol. Practical dynamic software updating for C. PLDI’06.
[10] J. Mars, L. Tang, R. Hundt, K. Skadron, and M. L. Soffa. Bubble-up: increasing utilization in modern warehouse scale computers. In MICRO-44 ‘11.
[11] C. Jung and N. Clark. Ddt: design and evaluation of a dynamic program analysis for optimizing data structure usage. MICRO-42 ‘09.
[12] K. Kumar Pusukuri, R. Gupta, and L. N. Bhuyan. Adapt: A framework for coscheduling multithreaded programs. In ACM TACO’13.
[13] K. Pusukuri, R. Gupta, and L. Bhuyan. No more backstabbing... a faithful scheduling policy for multithreaded programs. PACT’11.
[14] L. Tang, J. Mars, and M. L. Soffa. Compiling for niceness: mitigating contention for qos in warehouse scale computers. CGO’12.
[15] L. Tang, J. Mars, N. Vachharajani, R. Hundt, and M. Soffa. The impact of memory subsystem resource sharing on datacenter applications. ISCA’11.
[16] L. Tang, J. Mars, W. Wang, T. Dey, M. Soffa, Reqos: Reactive static/dynamic compilation for qos in warehouse scale computers. ASPLOS’13.
[17] L. Liu and S. Rus. Perflint: A context sensitive performance advisor for C++ programs. CGO’09.
[18] M. Kamruzzaman, S. Swanson, and D. M. Tullsen. Software data spreading: leveraging distributed caches to improve single thread performance. PLDI’10.
[19] J. Mars and R. Hundt. Scenario based optimization: A framework for statically enabling online optimizations. In CGO, pages 169–179, 2009.
[20] I. Neamtiu. Elastic executions from inelastic programs. SEAMS’11.
[21] I. Neamtiu and M. W. Hicks. Safe and timely updates to multi-threaded programs. PLDI’09.
[22] O. Shacham, M. Vechev, and E. Yahav. Chameleon: adaptive selection of collections. PLDI’09.
[23] K. Pingali, D. Nguyen, M. Kulkarni, M. Burtscher, M. A. Hassaan, R. Kaleem, T.-H. Lee, A. Lenharth, R. Manevich, M. Méndez-Lojo, D. Praunzros, and X. Sui. The Tao of Parallelism in Algorithms. PACT’11.
[24] R. Knauerhase, P. Brett, B. Hohlt, T. Li, and S. Hahn. Using os observations to improve performance in multicore systems. Micro’03.
[25] S. Blagodurov, S. Zhuravlev, A. Fedorova, and A. Kamali. A case for numa-aware contention management on multicore systems. PACT’10.
[26] S. Zhuravlev, S. Blagodurov, and A. Fedorova. Addressing shared resource contention in multicore processors via scheduling. ASPLOS’10.
[27] W. Wang, T. Dey, J. Mars, L. Tang, J. Davidson, and M. Soffa. Performance analysis of thread mappings with a holistic view of the hardware resources. ISPASS’12.
[28] Guoqing Xu, Coco: Sound and Adaptive replacement of java collections. In ECOOP, pages 1–26, June 2013.
[29] Y. Zhang and R. Gupta. Data compression transformations for dynamically allocated data structures. LNCS 2304 ‘02.
[30] J. Eastep, D. Wingate and A. Agarwal. Smart Data Manager: A case study with erlang. SEAMS’10.
[31] J. Leskovec et al. Stanford Network Analysis Platform. http://snap.stanford.edu/snap/index.html
[32] Wei Wang et al. REEact: A Customizable Virtual Execution Manager for Multicore Platforms. VEE’12.
[33] Kunegis, Jérôme. KONECT: The Koblenz Network Collection. WWW ’13.