Compact Hash Tables for Decision-trees[☆]

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Abstract

Decision-trees have been widely used in scientific computing. It is challenging to sustain high performance for large decision-trees. In this paper, we present a conversion technique translating a generic decision-tree into multiple compact hash tables; the conversion technique does not depend on the depth or shape of the decision-tree. All the compact hash tables are searched individually; the outcomes from all the tables are merged into the final result. To evaluate the performance, we prototype our design on state-of-the-art FPGA and multi-core General Purpose Processors (GPPs). Experimental results show that, for a typical 92-leaf decision-tree, we achieve 533 Million Classifications Per Second (MCPS) throughput and 26 ns latency on FPGA, and 134 MCPS throughput and 239 ns latency on multi-core GPP. We sustain $6\times$ and $2.7\times$ speedups, respectively.

Keywords: decision-tree, hash table, performance, FPGA, multi-core

1. Introduction

Tree structures [1] have been widely used for high-performance computation; a tree can be used as the underlying data structure for search or lookup operations. In particular, binary decision-tree has been widely studied due to its simple structure; elegant algorithms based on balanced BST have been proposed [2] for efficient searching of input data.

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State-of-the-art Field Programmable Gate Arrays (FPGAs) [3], with their flexibility and reconfigurability, are especially suitable for implementing a large tree structure [4]. Many hardware architectures have been proposed to enhance the performance for balanced tree structures [5], but it is still challenging to sustain high throughput for large trees on FPGA.

Using software accelerators and virtual machines is a new trend in parallel computing [6, 7]. State-of-the-art GPP [8] is an attractive platform for low-latency applications. Efficient algorithms are still needed to explore the parallelism and improve the performance of the multi-core processors [9–11].

In this paper, we present a conversion from the decision-trees to a set of *compact hash tables* for efficient implementation. We map this structure onto various platforms. Specifically, our contributions include the following:

- We provide the conversion technique from trees to compact hash tables; this technique does not depend on the depth or shape of a given decision-tree.
- We evaluate the performance on various state-of-the-art platforms including FPGA and multi-core GPP. We present a thorough performance comparison between these platforms.
- We sustain 533 MCPS throughput (26 ns latency) and 134 MCPS throughput (239 ns latency) for a typical decision-tree used for Internet traffic classification on FPGA and multi-core GPP, respectively. The corresponding speedups on these platforms are $6\times$ and $2.7\times$, respectively.

The rest of the paper is organized as follows: Section 2 covers the related work. We introduce the relevant data structures and algorithms in Section 3. Section 4 evaluates the performance. Section 5 concludes this paper.

2. Background

2.1. Generic Decision-tree

A *feature* is a distinct set of data (*e.g.*, Internet packet size, date, time, *etc.*). A generic decision-tree (not necessarily balanced) consists of N leaves. Each internal node specifies a criterion defined on a specific feature. The input data are checked against the criterion of an internal node; the comparison result determines the next-hop, until a leaf node has been reached. We

Figure 1: An example of a (static) decision-tree T

denote this tree traversal process as *classification*. The classification process stops at a leaf node, where a final decision can be made.

We show a toy example of a binary decision-tree used for holiday plans in Figure 1. In this example, the decision-tree are built on 3 features: weather, date, and money. Without loss of generality, in this paper, we always assume a left child is to be searched next if the criteria of a node is not satisfied (following a dashed “No”-edge in Figure 1); otherwise a right child is to be searched (following a solid “Yes”-edge). A feature can be used more than once along a path from the root to a leaf. We use M to denote the number of features examined by a decision-tree.

The design of a dynamic decision-tree [12] based on dynamic data is also an interesting problem. However, in this paper, we assume we are given an arbitrary static decision-tree, hence the discussion on dynamic updates of a decision-tree is beyond the scope of this paper.

2.2. Implementations for Trees

A lot of the existing works have used pipelining techniques to search binary trees on FPGA [5, 13]. In a pipelined implementation, each tree level is mapped into an individual pipeline stage; each stage consists of a logic component and a memory module. We denote this implementation [5, 13] as the *state-of-the-art implementation* on FPGA. Denoting Ω as the total number of nodes in a tree, the state-of-the-art implementation of a decision-tree is expensive: A tree (possibly imbalanced) may require $O(\Omega)$ pipeline

Table 1: Notations for converting the decision-tree to hash tables

$A_n = (S_0, S_1, \dots, S_{k_n}, \dots, S_{K_n-1}),$ $n = 0, 1, \dots, N - 1, k_n = 0, 1, \dots, K_n - 1$	N root-to-leaf paths in T , each path visiting K_n edges
$\text{par}\{S_{k_n}\}, \text{chi}\{S_{k_n}\}$	parent and child nodes connecting edge S_{k_n}
$u_i^{(m)}, m = 0, 1, \dots, M - 1,$ $i = 0, 1, \dots, q^{(m)} - 1$	Unique values for M features, $q^{(m)}$ unique values for feature m
$B_i^{(m)} = \overline{b_{i,0}^{(m)} b_{i,1}^{(m)} \dots b_{i,n}^{(m)} \dots b_{i,N-1}^{(m)}},$ $i = 0, 1, \dots, q^{(m)} - 1, n = 0, 1, \dots, N - 1$	$q^{(m)}$ BVs for feature m , each BV consisting of N bits
$f_0^{(m)}, f_1^{(m)}, \dots, f_p^{(m)}, \dots, f_{P-1}^{(m)}$	P hash functions for feature m
$H^{(m)}$	Hash table for feature m
$[\cdot]_m$	A set of data structures with different m

stages, while a lookup may take $O(\Omega)$ time. Besides FPGA, a thorough evaluation for decision-trees on state-of-the-art multi-core GPP is still to be studied.

3. Data Structures & Algorithms

3.1. Overview

Our work is inspired by the following observation on a decision-tree T : The classification process on T is a serial process incurring large latency. To reduce the processing latency, more parallelism has to be explored on T . In this paper, we examine all the M input features in parallel to reduce the processing latency. In addition, efficient hashing techniques [14] are exploited to examine each input feature. The searching outcomes for all the M inputs can be merged together to produce the final classification result. This final classification result indicates what the final decision should be if we use the M input features to search T .

3.2. Example: A Decision-tree used for Internet Traffic Classification

Before we present our algorithm, we revisit Bit Vector (BV) [14], a data structure used to efficiently merge the partial results. A BV consists of N bits; the n -th bit ($n = 0, 1, \dots, N - 1$) is set to “1” if and only if the input matches or satisfies the n -th condition. Note the number of leaf nodes (N) is

Algorithm 1 Converting the decision-tree to hash tables $[H^{(m)}]_m$

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1: for  $n = 0, 1, \dots, N - 1$  {every root-to-leaf path} do
2:   for  $m = 0, 1, \dots, M - 1$  {every feature} do
3:     if path  $A_n$  does not check feature  $m$  then
4:       for  $i = 0, 1, \dots, q^{(m)} - 1$  do
5:          $b_{i,n}^{(m)} \leftarrow 1$ 
6:       end for
7:     else
8:       for  $k_n = 0, 1, \dots, K_n - 1$  {along the path} do
9:         for  $i = 0, 1, \dots, q^{(m)} - 2$  {excluding  $\oslash$ } do
10:          if  $\text{par}\{S_{k_n}\}$  stores a unique value  $u_i^{(m)}$  then
11:            if  $S_{k_n}$  is a “YES-edge” then
12:               $b_{i,n}^{(m)} \leftarrow 1$ 
13:            else
14:               $b_{i,n}^{(m)} \leftarrow 0$ 
15:            end if
16:          end if
17:        end for
18:      end for
19:      construct  $u_{q^{(m)}-1}^{(m)} \leftarrow \oslash$  and  $B_{q^{(m)}-1}^{(m)}$ 
20:    end if
21:  end for
22: end for
23: for  $m = 0, 1, \dots, M - 1$  {every table} do
24:   for  $i = 0, 1, \dots, q^{(m)} - 1$  {every unique value} do
25:      $p \leftarrow 0$ 
26:     if location  $f_p(u_i^{(m)})$  in  $H^{(m)}$  is empty then
27:       store  $(u_i^{(m)}, B_i^{(m)})$  at location  $f_p(u_i^{(m)})$ 
28:     else
29:        $p \leftarrow p + 1$ 
30:       if  $p = P$  {already tried all the  $P$  functions} then
31:         enlarge  $H^{(m)}$ , reselect  $[f_p^{(m)}]_p$ , and  $p \leftarrow 0$ 
32:       end if
33:     go to Step 26
34:   end if
35: end for
36: end for

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Figure 2: Translating a decision-tree T into M hash tables

usually small in T ; merging a set of short BVs can be very fast. This is the reason why we choose to use BV to represent the partial searching results.

During the training phase, we convert T into M hash tables, each constructed for a specific feature. Using the notations in Table 1, we show the pseudo-code in Algorithm 1. After the conversion, each hash table stores a number of $q^{(m)}$ entries, each consisting of a unique value and a BV. A detailed explanation can be found in [14].

We show an example of translating a decision-tree T into M hash tables in Figure 2, where T is used for Internet traffic classification. 3 features are used in this example, including Source Port Number (SP), Destination Port number (DP), and Minimum Packet Size (MinPS).

In Figure 2, 3 compact hash tables are constructed, each consisting of $q^{(m)}$ key-BV pairs ($m = 0, 1, 2$, and $q^{(m)} = 2, 3, 3$, respectively). In a specific key-BV pair, a key corresponds to a feature value tested in T (e.g., for feature SP, 45 is the value tested in the root node of T). A BV has N bits, each bit corresponding to a leaf node of T ; a bit is set to “1” only if the classification process based on the key can lead to the corresponding leaf node. Note each hash table also stores a “ $\emptyset$ ” as a key, in case the input feature does not match any value tested in T .

3.3. Searching and Merging

After the compact hash tables are constructed, the classification process is straightforward. Perfect hashing [15] is employed to search each feature, each returning an N -bit BV. All the M BVs are merged by bitwise AND operations to produce the final classification result. To continue the example in Figure 2, let us suppose the input features are: SP = 45, DP = 125, and MinPS = 100. The 3 BVs extracted from the compact hash tables are “001111”, “101101”, and “110110”, respectively. After bitwise ANDing, the final classification result is “000100”, indicating the final decision on the Internet traffic class is “MSN” (leaf node 3). Detailed space/time complexity analysis can be found in [14].

4. Performance Evaluation

Although the conversion technique leads to the same data structures on FPGA and on multi-core GPP, we use different implementations to achieve as high performance as possible on the two platforms¹:

- On FPGA, we customize the pipeline architecture to sustain high clock rate (**pipelined implementation**).
- On Multi-core GPP, we design parallel algorithms to achieve high performance (**parallel implementation**).

4.1. Experimental Setup

4.1.1. FPGA-based Implementation

We conducted experiments using Verilog on Xilinx Vivado Design Suite 2013.4, targeting Virtex-7 XC7VX1140t FLG1930 -2L FPGA [3]. This device has 1100 I/O pins, 218800 logic slices, 67 Mb BRAM, and can be configured to realize large amount of distributed RAM (distRAM, up to 17 Mb). Maximum achievable clock rate and resource consumption are shown using post-place-and-route timing reports and resource utilization reports, respectively.

The architecture of our FPGA-based implementations is shown in Figure 3. Based on the m -th input feature of width W_m ($m = 0, 1, \dots, M - 1$), the m -th Processing Element (PE) is responsible for extracting a BV from a

¹FPGA integrates reconfigurable logic with fast on-chip memory, while multi-core GPP consists of many parallel processor cores and a cache hierarchy.

Figure 3: Architecture of a single pipeline

hash table. A BV extracted from one PE is ANDed with the BV provided from the previous PE. Hash tables are stored using dual-port distRAM or BRAM; hence the throughput is twice the maximum achievable clock rate.

4.1.2. GPP-based Implementation

We conducted experiments on a $2 \times$ AMD Opteron 6278 processor and a $2 \times$ Intel Xeon E5-2470 processor. The AMD processor has 16 2.4 GHz cores. Each core is integrated with a 16 KB L1 data cache, 16 KB L1 instruction cache, and a 2 MB L2 cache. A 6 MB L3 cache (LLC) is shared among all the 16 cores; all the cores have access to 64 GB DDR3-1600 main memory. The AMD processor runs openSUSE 12.2 OS (64-bit 2.6.35 Linux Kernel, gcc version 4.7.1). The Intel processor has 16 2.3 GHz cores. Each core has a 32 KB L1 data cache, 32 KB L1 instruction cache, and a 256 KB L2 cache. All the 16 cores share a 20 MB L3 cache (LLC), and they have access to 48 GB DDR3-1600 main memory. This processor runs openSUSE 12.3 OS (64-bit 3.7.10 Linux Kernel, gcc version 4.7.2).

We use OpenMP on both the AMD and Intel processors. M searching threads were deployed for each set of input features; they were bound to a single core in order to mitigate the penalty of data movements among the cores [14]. We used *perf*, a performance analysis tool in Linux, to monitor the hardware and software events such as the number of cache misses.

Table 2: Throughput and latency of a single pipeline ($M = 7$)

Implementation No. of leaves	State-of-the-art [13]	This work
128	520 MCPS, 162 ns	533 MCPS, 26 ns
256	468 MCPS, 179 ns	530 MCPS, 26 ns
512	412 MCPS, 204 ns	523 MCPS, 27 ns
1024	360 MCPS, 233 ns	437 MCPS, 32 ns

4.1.3. Trees and Data Sets

We tested a typical decision-tree used for Internet traffic classification [13, 14], although our technique is not limited to decision-trees exclusively used for network applications. The imbalanced decision-tree has 42 levels, $N = 92$ leaves, $M = 7$ features, and classifies traffic into 8 application classes. Random traffic traces were used pessimistically² for worst-case analysis. For synthetic decision-trees having more than 92 leaves, we used the same setup as our prior work [14].

4.1.4. Performance Metrics

- **(Overall) Throughput:** total number of classifications performed per unit time (in MCPS).
- **(Processing) Latency:** average processing time per classification.

4.2. Performance on FPGA

4.2.1. Throughput

We first deploy a single pipeline as shown in Figure 3. We show the throughput of our implementation, along with the throughput achieved by the state-of-the-art implementation in Table 2. As can be seen, we achieve better throughput since the wire length of our pipelined architecture is reduced compared to the state-of-the-art implementation.

The resource consumption shown in post-place-and-route reports indicates that less than 30% of the total resources (logic slices and I/O pins) are used for a single pipeline. Hence we deploy 3 pipelines to improve the throughput of our classification engine; we show in Figure 4 the throughput with respect to various values of N and M . Large values of N deteriorate

²Low cache efficiency for our implementations on multi-core GPP.

Figure 4: Varying N (depleting FPGA resources using 3 pipelines)

the clock rate of each PE³; large values of M deteriorate the throughput⁴ and prolong the pipeline latency (see Section 4.2.2). However, as can be seen in Figure 4, the throughput loss is less than 8%.

4.2.2. Latency

For multiple pipelines deployed in parallel, the processing latency is the same as the single-pipeline latency. We show in Table 2 the worst-case latency performance. As can be seen, the state-of-the-art implementation incurs long latency (42 pipeline stages). However, our pipelined architecture only uses a small number of pipeline stages while sustaining high clock rate. Note we have a speedup of around $6 \sim 7\times$ for the latency performance.

4.3. Performance on Multi-core GPP

On multi-core GPP, a large number (denoted as P) of concurrent packet classifiers can be deployed; this is different from our designs on FPGA, where only a small number of pipelines can be employed. We choose $P = 32$ based on our prior work [14]. In addition, thanks to the memory hierarchy on multi-core GPP, larger decision-trees and more features can be supported.

We show in Figure 5 the throughput and latency performance on our AMD and Intel platforms, with respect to various values of M and N . As M or N increases, the performance tapers; the reasons are:

³This is because large hash tables are required in each PE for large N .

⁴More resources are used, leading to less place-and-route choices and inferior clock rate.

Figure 5: Performance on multi-core GPP ($P = 32$ concurrent classifiers)

1. More memory accesses are required for larger values of M since more hash tables need to be examined.
2. Cache performance degrades for large values of N . Given that the number of key-BV pairs $q^{(m)}$ is kept proportional to N , it is more difficult to fit larger hash tables in cache for larger N .

A detailed analysis [14] reveals that the searching time contributes 80% $\sim$ 90% of the processing latency. The AMD platform achieves better performance than the Intel platform; note the AMD processor has a higher clock frequency. Compared to the Intel platform, the AMD processor misses less in L2 cache but more in L3 cache [14], due to their different cache sizes; this can also result in better performance on the AMD platform. For $M = 7$, $N = 92$, and $P = 32$, we achieve 134 MCPS throughput and 239 ns latency on the AMD platform, and 102 MCPS throughput and 313 ns latency on the Intel platform, respectively.

Figure 6: Performance comparison

4.4. Comparison

As an example, we study a typical C4.5 decision-tree consisting of 42 levels, 92 leaves, and 7 features. In Figure 6, we show the throughput and latency performance for various implementations on software-based and hardware-based platforms. As baselines on multi-core GPPs, we denote the straightforward Binary Search Tree (BST) implementations on the AMD and Intel platforms as “Baseline_AMD” and “Baseline_Intel”, respectively; our implementations based on compact hash tables are denoted as “Proposed_AMD” and “Proposed_Intel”, respectively. Similarly, the state-of-the-art implementation of the decision-tree on FPGA is remapped onto our Virtex-7 FPGA, and denoted as “Baseline_FPGA”; our implementation based on compact hash tables are denoted as “Proposed_FPGA”. As can be seen:

- The FPGA-based approaches achieve better performance; this is because the application-specific architectures on FPGA are designed and optimized with parallel accesses to SRAM. However, multi-core GPPs can support much larger decision-trees (larger N) or a larger number of features (larger M) than FPGA, due to its memory hierarchy.
- On both the multi-core GPP and FPGA platforms, our proposed approaches using compact hash tables achieve better performance ($2.7\times$ and $6\times$ speedups, respectively).

5. Conclusion

In this paper, we presented a translation from a decision-tree to multiple compact hash tables. We evaluated and compared the performance on state-of-the-art platforms. Our future work includes exploring efficient merging of searching results and investigating the performance on GPU-based platforms.

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