Heavyweight Pattern Mining in Attributed Flow Graphs

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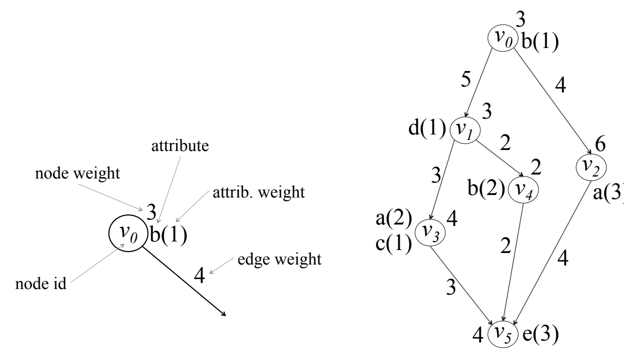
***Abstract*—This paper defines a new problem - heavyweight pattern mining in attributed flow graphs. The problem can be described as the discovery of patterns in flow graphs that have sets of attributes associated with their nodes. A connection between nodes is represented as a directed edge. The amount of load that goes through a path between nodes, or the frequency of transmission of such load between nodes, is represented as edge weights. A heavyweight pattern is a sub-set of attributes, found in a dataset of attributed flow graphs, that are connected by edges and have a computed weight higher than an user-defined threshold. A new algorithm called AFGMiner is introduced, the first one to our knowledge that finds heavyweight patterns in a dataset of attributed flow graphs and associates each pattern with its occurrences. The paper also describes a new tool for compiler engineers, HEPMiner, that applies the AFGMiner algorithm to Profile-based Program Analysis modeled as a heavyweight pattern mining problem.**

I. Introduction

Flow graphs are an abstraction used to represent elements (*e.g.,* digital data, goods, electric current) that travel through a network of nodes (*e.g.,* computers, physical locations, circuit parts). Flow graphs are often used in the modelling of logistics problems. Weights associated with the edges represent either the size of the load that is transmitted from the source to the destination node, or the frequency of transmission of a token between these nodes. The nodes of a flow graph may have associated weights that can represent, for instance, the capacity of the node, or the cost of storing payload at the node, or the delay of processing a token at that node. If additional data, in the form of attributes and their values, are associated with the nodes, we have attributed flow graphs. An attributed flow graph (AFG) is a single-entry/single-exit graph with a *source node* that has no incoming edges and a *sink node* with no outgoing edges. The flow starts in the source node and is directed to the sink node. All other nodes in the AFG, if they exist, must have at least one incoming and one outgoing edge. An example of an AFG is shown in Figure 1.

The presence of weights associated with edges, nodes and attributes allows AFGs — either a single AFG or a set of AFGs — to create a rich description of dynamic applications. It might be best to illustrate an AFG thtrough an example that models logistics. Figure 2 shows a snapshot of the transportation by air of goods between cities. In this illustrative example, an AFG models the volume of sea food, medicine, and flowers processed through the cargo terminals of several airports. Airports are represented as nodes, the type of goods processed at an airport as attributes of each node, the volume of each type of good handled in an airport as attribute weights, the storage capacity at each airport as node weights, and the volume capacity of the flights transporting goods between cities are represented as weighted directed edges. With similar data for multiple transportation companies, an analyst may use a set of AFGs to model a transportation network with each AFG, for instance, corresponding to a single company.



(a) Elements of an AFG (b) Example

Fig. 1. Example of attributed flow graph.

In many applications modelled by AFGs, complex structural sub-graph patterns may be prevalent. These sub-graphs are often unknown and non-trivial to detect, but they may represent important characteristics of the application. Given the richness of the model, the notion of "prevalence" or "support" of such patterns, as a measure of interestingness or importance to analysts, is often difficult to capture by simply counting the number of occurrences of the pattern in the AFG. Instead, when modelling an application with AFGs the interesting and useful patterns that an analyst wants to detect are also

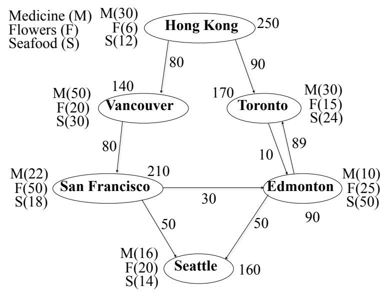


Fig. 2. AFG representing transportation of goods between airports.

characterized by node attributes and a notion of support that may include node weights, attribute weights and edge weights.

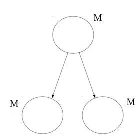


Fig. 3. Pattern in the goods distribution example.

Different applications may benefit from using other definitions of a support metric that takes more than the frequency of pattern occurrences into account. Section V discusses an application of AFGs in compiler optimization and software profiling. Although the remainder of this paper will not discuss logistics-based problems, the example in Figure 2 seeks to underscore that AFGs and methods to discover supported patterns in AFGs are broadly applicable. However, such a method that takes the full structural information present in AFGs into account while searching for patterns does not exist.

Existing graph-mining algorithms are all severely limited in their applicability to AFGs. None of them is able to find general sub-graph patterns in AFGs that take into account multiple node attributes as well as weights in nodes and edges. A number of algorithms proposed in the literature perform sub-graph mining only on undirected and unweighted graphs, with no attributes [1] [2] [3] [4] [5]. Such algorithms mine datasets of graphs for *frequent sub-graphs*, which are patterns that occur more than a certain number of times in the dataset.

The only work on mining patterns in AFGs is the FlowGSP algorithm proposed by *Jocksch et al.* [6]. However, FlowGSP can only find sub-path patterns, while the algorithm described in this work finds all the patterns that FlowGSP does and additional patterns that encompass multiple sub-paths in the dataset.

This paper presents AFGMiner, the first algorithm, to the best of our knowledge, to address the problem of mining AFGs for general sub-graph patterns. AFGMiner takes as input a set of AFGs and a support measure $MinSup$ that may be formulated by taking into account the attribute weights, node weights and edge weights of the occurrences of patterns. AFGMiner returns all patterns P, called *heavyweight patterns*, whose support $MinSup(P)$ is higher than a threshold. This threshold is user-specified as commonly assumed in pattern-mining approaches. The main contributions of this paper are as follows:

1) Definition of the Attributed-Flow-Graph Mining problem to find Heavyweight Patterns.
2) Development of different versions of AFGMiner, an algorithm that mines for heavyweight patterns in attributed flow graphs, including a parallel version with a work-distribution heuristic to maintain workload balance between multiple threads.
3) Development of HEPMiner, a tool that automates the analysis of hardware-instrumented profiles. HEPMiner allows compiler developers to mine for heavyweight patterns that represent particular *execution patterns*. Discovered patterns indicate potential, non-obvious, opportunities for compiler and architecture-design improvements.
4) Complexity and scalability analysis of AFGMiner, comparison against the FlowGSP algorithm and qualitative analysis of patterns found by HEPMiner when applied to the DayTrader benchmark running on IBM's WebSphere Application Server [7].

II. Problem Definition

An attributed flow graph (AFG) G, that belongs to a dataset DS of AFGs, is defined as $G = \langle V, E, A, \alpha, w^E, w^V, w^{A,V}, l\rangle$ where:

1) V is a set of nodes.
2) E is a set of directed edges (v_a, v_b) where $v_a, v_b \in V$.
3) A is the set of all possible attributes.
4) α is a function mapping nodes $v \in V$ to a subset of attributes, *i.e.,* $\alpha(v) = \{a_1, ..., a_k\}$, $a_i \in A$, $1 \le i \le k$.
5) w^E is a function assigning a weight $w \in [0,1]$ to each edge $e \in E$ so that $\Sigma_{e \in E_{DS}} w^E(e) = 1$ where E_{DS} is the set of edges from all AFGs that belong to DS, *i.e.,* w^E is normalized over DS.
6) w^V is a function assigning a weight $w \in [0,1]$ to each node $v \in V$ so that $\Sigma_{v \in V_{DS}} w^V(v) = 1$ where V_{DS} is the set of nodes from all AFGs that belong to DS, *i.e.,* w^V is normalized over DS.
7) $w^{A,V}$ is a function assigning a weight $w \in [0,1]$ to each attribute a of each node $v \in V$, $a \in \alpha(v)$, with the constraint that $w^{A,V}(a) \le w^V(v)$.
8) l is a function assigning a unique integer label $l(v)$ to each node $v \in V$, according to a depth-first traversal of the graph. $l(V)$ denotes the result of applying the labeling function to all nodes in V. Given an edge (v_i, v_j), the edge is called a *forward* edge if $l(v_i) < l(v_j)$; otherwise, if $l(v_i) \ge l(v_j)$ the edge is called a *backward* edge or *back-edge*; the node v_i is called the edge's *from-node* and the node v_j is called the edge's *to-node*.
9) G is a flow graph, *i.e.,* for any node v^* it holds that $\Sigma_{(x,v^*) \in E} w^E((x, v^*)) = \Sigma_{(v^*,y) \in E} w^E((v^*, y))$.

A directed graph $g = \langle V_g, E_g, A_g, \alpha_g, w_g^E, w_g^V, w_g^{A,V}, l_g\rangle$ is a *sub-graph* of G, if V_g is a subset of the nodes in G, E_g is a subset of the edges in G that exist between nodes in V_g, A is a subset of the attributes in G, and the functions $\alpha_g, w_g^E, w_g^V, w_g^{A,V}, l_g$ are the corresponding functions in G, restricted to the corresponding domains of nodes, edges and attributes in g.

A *pattern* is a graph $P =< V_P, E_P, A, \alpha >$, where V_P is a set of nodes with attributes from A associated to them by α, and E_P is a set of directed edges; note that a pattern does not include weights. A pattern is an abstraction in which the nodes represent sets of attributes that are relevant under a *support criteria*, and the edges represent an ordering for such attribute sets.

An *occurrence* g of a pattern P is a sub-graph of G that "matches P with a maximum gap size k_{max}"; g *matches* P *with a maximum gap size* k_{max} if there is a function m that maps every node v in P to a node in g so that for every edge (v_i, v_j) in P, there is a path in g that starts at node $m(v_i)$ and ends at node $m(v_j)$, and that has at most k_{max} nodes between $m(v_i)$ and $m(v_j)$. This definition of an occurrence of a pattern allows a number k_{max} of "mismatches" or "don't-care nodes" when mapping each node in the pattern P to a sub-graph in G, and k_{max} can be chosen by a user in order to allow approximate matches in applications where such an approach is useful. A k_{max}-match of a pattern P is an occurrence g_P of P that was found by using a maximum gap size of k_{max}. As an example, in Figure 4 we have a pattern on the left and an AFG in which a 0-match, an 1-match and a 2-match of the pattern can be found.

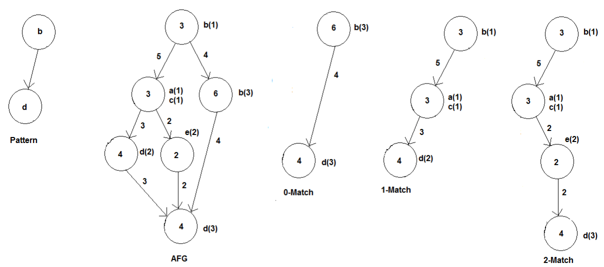


Fig. 4. Example of k-matches of a pattern.

Given a dataset DS of AFGs, a *support measure* $MinSup$ that defines the minimum support of patterns P in DS, the maximum number of attributes allowed in any given pattern node $MaxAttrs$ and a threshold value T. The problem we address in this paper is to find all patterns P with at most $MaxAttrs$ attributes in each node, for which $MinSup(P) > T$. We call the patterns for which $MinSup(P) > T$ *heavy-weight patterns*, and we call the problem itself **Heavyweight Pattern Mining in Attributed Flow Graphs** (for short, *heavyweight pattern mining*).

III. The AFGMiner Algorithm

AFGMiner generates and tests candidate patterns of increasing number of edges, then extends those patterns considered heavyweight. It generates candidate patterns of k edges, starting with $k = 0$ (patterns composed of a single node and no edges), and searches for occurrences of such patterns in the dataset by using a sub-graph isomorphism detection algorithm. Each ocurrence found has its node weight and edge weight support values computed, and, when no more occurrences of a pattern are present in the dataset, the support value for the pattern itself is computed by aggregating the support values of its occurrences. If the support value for the pattern is higher than an user-defined threshold, the pattern is heavyweight. It is then output to the user and later extended into candidate patterns with an additional edge, a process called *edge-by-edge pattern extension*. If the pattern is not heavyweight, it is discarded.

Edge-by-edge pattern extension works by adding to a pattern either: (i) an edge that connects two of its nodes; (ii) or an edge that connects one of its nodes to a new node called the *extension node*. A pattern that generates other patterns by extension is called a *parent pattern*, while the generated patterns are *child patterns*.

A. Canonical Labeling

It is possible that two different patterns, when extended, generate child patterns that are isomorphic. It is inefficient to mine for redundant patterns, so redundancy should be detected. The well-known concept of *canonical labeling* of patterns is used to detect redundancy [1]. The idea is to map each sub-graph pattern to an identifier string called *DFS Code*. The string representation, or DFS Code of an AFG of n edges is $(e_0)(e_1)...(e_n)$, where each edge $e_i = (v_i, v_j)$ is represented by a string: $([l(v_i) : (a_{i_0})\ (a_{i_1})...(a_{i_m})]$ $[l(v_j) : (a_{j_0})(a_{j_1})...(a_{j_p})])$, where m and p are the number of attributes present in the edge's *from-node* and *to-node*, respectively. DFS Codes can be lexically ordered in such a way that, if two sub-graphs are isomorphic to each other, they provably have the same minimum DFS Code. The rules that define how to sort DFS Codes depend on the types of graphs being mined.

In order for a newly-generated sub-graph pattern to be considered redundant, and thus discarded, its DFS Code should be already present in H, a hash-set whose elements are the distinct DFS Codes of all patterns that have been processed. However, this approach may consume large amounts of memory because the number of candidate patterns generated may be very high. Instead, the approach adopted in the prototype implementation of AFGMiner is to record the DFS Codes only for patterns considered heavyweight.

When producing the DFS Code of a sub-graph pattern, it is a requirement to label the edges and nodes of the pattern. Nodes are labelled as follows. The attribute set of the node is used as its preliminary label, by forming a bit vector in which each attribute is represented by a bit presence or absence of the attribute. Edge labels are simply the labels of the edges's *from-node* and *to-node* in that order. The edge labels are sorted by considering that, given any two edge labels, the one with the lower *from-node* label comes first, and in case those are the same, the one with the lower *to-node* label comes first. The minimum DFS spanning tree of the sub-graph pattern is then computed using the sorting order of the edge labels *in lieu* of edge weights. Finally, the order in which pattern nodes are visited during a pre-order traversal of this minimum spanning tree determines their final and unique-per-pattern label, which is used to sort the edges. The resulting sorted edge labels of two patterns is the same if the patterns are isomorphic.

B. Support Value Policy

The process of generating and testing candidate patterns in AFGMiner may be understood as the exploration of the space of patterns that exist in the dataset of AFGs being mined. The algorithm searches for all the heavyweight patterns present in this space, which can be envisioned as a forest of trees with the root node of each tree being a 0-edge pattern, child nodes of the root node being the 1-edge patterns extended from the 0-edge patterns, etc. Pruning this search space as much as possible is desirable in order to decrease the run-time of the algorithm. AFGMiner adopts an *anti-monotonic* support value policy to enable the pruning of the search space. Under this policy, the support value of a pattern is always lower than or equal to the support value of any of its ancestor patterns. Therefore, if a pattern is not heavyweight, none of its descendants can be heavyweight. Thus all patterns that do not meet a minimum support criteria can be discarded. The anti-monotonic support value policy allows the algorithm to prune nodes in the search space that it identifies as non-heavyweight patterns.

The support value policy works as follows. For each occurrence g of a pattern p, two values are calculated: $S_n(g)$, the weight of the attribute with minimum weight amongst all attributes associated with nodes of g; and $S_e(g)$, the minimum edge weight amongst all edges of g. The $S_n(g)$ of all occurrences of p found in DS are then added up, resulting in $S_n(p)$, the node weight support of p. The $S_e(g)$ of all occurrences of p found in DS are also added up, resulting in $S_e(p)$, the edge weight support of p. The support value for p is $S_m(p)$, the maximum between $S_n(p)$ and $S_e(p)$. $S_m(p)$ is compared against the support threshold to decide whether p is a heavyweight pattern.

The principle behind separately computing the support values of node attributes and edges of a pattern and then choosing the maximum between the two values is that a pattern is relevant if either, or both, the attributes or edges of its occurrences have significant weight in comparison to the sum of all node weights and to the sum of all edge weights in the dataset. The support-value policy selected for AFGMiner is conservative because only the minimum edge weight and the minimum node attribute weight of each occurrence are used in the computation. Less conservative support-value policies could be adopted as long as they are anti-monotonic.

C. Matching Patterns to Occurrences

When a candidate pattern is generated, its DFS Code is computed and the algorithm checks if the DFS Code already exists in H. If the DFS Code is not present, the candidate pattern is not redundant and the process of mining for it in the dataset begins. The mining process finds sub-graphs g in AFGs of DS that match the candidate pattern p. AFGMiner may use any sub-graph isomorphism detection algorithm to match patterns and sub-graphs, as long as the algorithm is adapted to take node attributes into consideration when detecting isomorphism. The prototype implementation of AFGMiner adapts VF2 [8], an algorithm that is faster than alternatives for graphs that are relatively regular, have a large number of nodes and whose nodes have small valency [9]. For the case study described in this paper, AFGs meet this criteria.

VF2 produces a mapping M between nodes in p and nodes in G, where G contains at least as many nodes as p. M is expressed as a set of pairs $\{n, m\}$, where $n \in p$ and $m \in G$ are nodes. The mapping is said to be an isomorphism if M is a bijective function that preserves the branch structure of both p and G. This mapping is represented as a state s in a State Space Representation (SSR). This state, which we call a *miner state*, goes from empty (no mapping between nodes in p and nodes in G) to a goal state (all nodes in p mapped to respective nodes in G) during the process of finding M. A state transition between any miner state s_1 and its successor s_2 represents the addition of a new pair $\{n, m\}$ to the collections of known pairs that compose M. The addition of new pairs only occurs if n and m form a feasible pair. The rules for a pair of nodes to be considered feasible, in the case of AFGs, are as follows: (i) attributes of m should be a proper superset of attributes in n; (ii) topological structure around n and m should be the same.

D. Generation of Candidate Patterns

The input to AFGMiner is a list A_0 of attributes that occur in the dataset. Each one of the possible attributes is used to create a set of 0-edge candidate patterns with a single attribute in their nodes, as shown in Figure 5. The support value threshold in this example is $T = 1/23$. Each one of the candidate patterns p is mined for in the dataset DS, and, if p is heavyweight, its only attribute is added to A_1. A_1 is the list of distinct attributes that belong to 0-edge heavyweight patterns and that are used in the generation of 1-edge candidate patterns.

After all 0-edge heavyweight patterns of a single attribute are found, the attributes in A_1 are combined in pairs and AFGMiner searches for the generated 0-edge candidate patterns that have two attributes each (Figure 6). The attributes that compose the 0-edge candidate patterns of two attributes found to be heavyweight are then combined into sets of three attributes, which form the 0-edge candidate patterns of three attributes each. This continues until no more 0-edge heavyweight patterns with a certain number of attributes can be found.

The process of mining for candidate patterns with an increasing number of attributes in their single node (in the case of 0-edge patterns) or in their extension node (in the case of k-edge patterns with $k > 0$) is called *attribute-set growth*. Attribute-set growth is useful because an attribute set is only used to generate a pattern if all of its sub-sets generated heavyweight patterns.

Each one of the 0-edge heavyweight patterns spans multiple child candidates, one for every attribute in A_1, in which the extension node contains a single attribute from A_1. Thus, all the pairs of nodes connected by an edge in Figure 7 are child candidates for the example. AFGMiner searches for matches for each candidate child pattern in the dataset as soon as the pattern is generated. If a candidate pattern is found to be heavyweight, all its attributes are added to A_2. Attributes in A_2 are then used to generate 1-edge candidate patterns that have two attributes in their extension node. In Figure 8 a candidate is generated for each pair of nodes connected by an edge. For clarity, only candidates generated by the pattern $a \rightarrow a$ are shown. The attribute-set growth process then proceeds until no more 1-edge candidate patterns of certain number of attributes in their extension node can be found. In Figure 9, 2-edge patterns are shown.

A set of patterns that have the same number of edges is called a *generation*. AFGMiner produces and mines for candidate patterns generation by generation as described above. Patterns of a certain generation are only created and mined after all the heavyweight patterns of the previous generation have been found. This is important because it allows the algorithm to use only the A_k set of distinct attributes present in the $(k-1)$-th generation to compose the patterns of the k-th generation, thus restricting the number of candidate patterns produced.

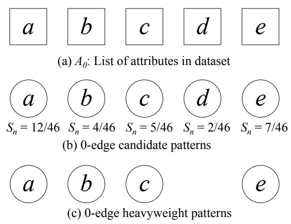


Fig. 5. 0-edge candidate patterns.

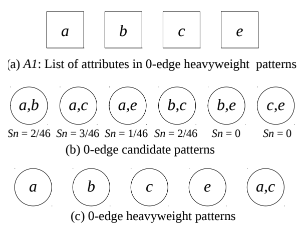


Fig. 6. Attribute-set growth for 0-edge candidate patterns.

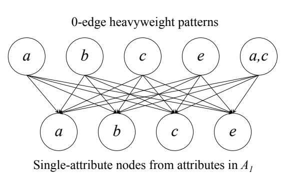


Fig. 7. 1-edge candidate patterns.

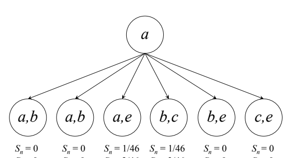


Fig. 8. Attribute-set growth for 1-edge candidate pattern node $a \rightarrow a$.

IV. Algorithm Improvements

The previous section described the original version of AFGMiner, called **AFGMiner-iso** (*iso* stands for isomorphism detection). AFGMiner-iso visits all nodes in the dataset for every pattern searched, making it potentially slow when analyzing large datasets composed of thousands of AFGs with hundreds of nodes each, as in the case study presented in this

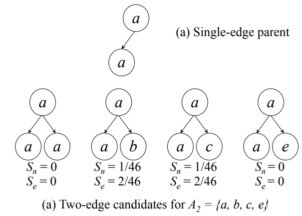


Fig. 9. 2-edge candidate patterns.

work. Another version of AFGMiner, **AFGMiner-locreg**, addresses this performance issue. It uses the concept of location registration.

Location Registration is the complete mapping, including nodes and edges, between a candidate pattern p and each of its occurrences g. If p is found to be heavyweight, this mapping is kept, otherwise it is discarded. Then, when a heavyweight pattern p is extended into its child patterns c, in order to find occurrences of c the algorithm only checks the mappings between p and its occurrences g. In order to generate c, p has one of its nodes, v, extended by adding to it an edge e, and may also have an extension node q connected to e. The idea of location registration is to check each mapping between p and occurrences g for: (i) the node v_g in g that corresponds to v; (ii) if v_g is connected to an edge e_g that corresponds to e and (iii) in case c was extended from p by adding an extension node, check if e_g connects a node q_g, corresponding to node q, to v_g. If the algorithm is able to find appropriate v_g, e_g and q_g attached to the occurrence g, then the sub-graph that is composed of g plus e_g and q_g is an occurrence of c.

A. A Parallel Implementation of AFGMiner

A parallel version of AFGMiner benefits from the multiple cores available in many computing systems. An important challenge in the implementation of a parallel version of AFGMiner-locreg, **p-AFGMiner**, is the distribution of the workload to improve load balancing.

p-AFGMiner executes the following steps while a queue Q of heavyweight patterns is not empty (s signals a sequential step, while p signals a parallel step): (i-s) fork into n threads to start the processing of a new generation composed of patterns with k edges.

For $k = 0$, (ii-s) divide the set A_0 among the threads and (iii-p) each thread generates 0-edge candidate patterns using their part of A_0 and searches the database for these patterns — heavyweight patterns form a local queue Q_{TL} and the set of attributes in Q_{TL} form A_{TL}, the local set of attributes.

For $k > 0$, (ii-s) distribute the queue Q of k-edge heavyweight patterns among n thread-local queues Q_{TL}; (iii-p) each thread generates $(k+1)$-edge candidates from patterns in Q_{TL} and computes their support, generating A_{TL} and adding the patterns found to be heavyweight to Q_{TL};

Then: (iv-s) synchronize when all threads finish step (iii) and unify all Q_{TL}s into a single queue Q, and all A_{TL}s into a single A_{k+1} set of attributes; and (v) start processing the next generation, if Q is not empty. The dataset of AFGs, DS, is read-only during the entire run of p-AFGMiner, allowing the maintenance of thread-local versions of variables and thus reducing synchronization.

The distribution of Q among threads should balance the workload to improve the performance of p-AFGMiner. The number of occurrences of the parent of a pattern p in DS is the most important factor determining the time required to search for occurrences of p. A reasonable heuristic tries to balance the number of parent-pattern occurrences assigned to each thread.

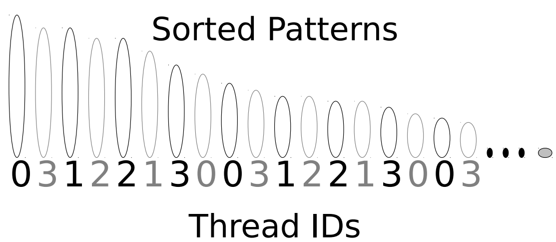


Fig. 10. Illustration of pattern distribution heuristic.

The pattern-distribution heuristic created for p-AFGMiner sorts the m patterns in Q by decreasing order of the number of parent-pattern occurrences. The heuristic then does a round-robin assignment of patterns to threads following an increasing order for the patterns with an even position in the sorted Q and in decreasing order for patterns with an odd position in the sorted Q as illustrated in Figure 10 — assume that numbering in Q starts at zero. In this illustration each ellipse represents a pattern in Q and the size of the ellipse stands for the number of occurrences of the pattern's parent in the database. This simple $O(n)$ heuristic is effective for a moderate number of threads and for limited variations in the number of parent-pattern occurrences. Experimental evaluation revealed that this workload-distribution heuristic lowered the execution time of p-AFGMiner, on average, by 6% when compared with a naive workload distribution method that simply distributes patterns among the threads without any sorting.

V. Case Study: Using AFGMiner for Program Analysis

The process of optimizing computer systems, compilers, computer architecture and computer applications often involves the analysis of the dynamic behaviour of an application. When this optimization is performed offline it involves the analysis of the runtime profile collected over a single, or many, executions of an application. For many applications it is possible to identify *hot-spots* in the application profile that consist of segments of the application's source code that account for a larger portion of the execution time. The effort to improve any part of the computer system that influences the application performance can then easily focus on these hot-spots. However, there is a class of computer applications that have no such hot-spots. Instead, the execution time is distributed over a very large code base, with no method taking up signicant execution time (*i.e.,* no more than 2 or 3%). Such applications are said to have *flat profiles*.

The execution of such applications also generates very large profiles that are difficult to analyze by manual inspection. Thus, the **Profile-based Program Analysis** (PBPA) problem is defined as follows. Given a profile *Prof* obtained from an execution of a computer program, automatically discover operation patterns in the execution of *Prof* that, in aggregation, account for a sufficiently large fraction of the program's execution time. Developers are then able to focus their optimization efforts on those areas in the program code that correspond to occurrences of the relevant operation patterns. In order to solve PBPA, we convert it to a heavyweight pattern mining problem, by modeling the program as a dataset of attributed flow graphs named *Execution Flow Graphs* (EFGs). EFGs are control flow graphs with attributes and weights provided by profile information, and represent profiled program methods.

This section discusses the run-time complexity of AFGMiner when mining EFGs. In general, the complexity of AFGMiner depends on the type of attributed flow graph being mined.

The section also presents a practical application of AFGMiner to PBPA. HEPMiner is a tool that targets compiler and architecture developers and intends to facilitate the analysis of programs that have been profiled by hardware instrumentation[10].

A. Sub-Graph Mining in Bounded Treewidth Graphs

Tree-width is a measure of how similar to a tree a graph is. It is a very useful property because several NP-hard problems on graphs become tractable for the class of graphs with bounded tree-width, including sub-graph isomorphism detection and, as a consequence, frequent sub-graph mining of connected graphs [11]. *Horvarth and Ramon* discovered a level-wise sub-graph mining algorithm that lists frequent connected sub-graphs in incremental polynomial time in cases when the tree-width of the graphs being mined is bounded by a constant [11]. *Thorup* shows that graphs representing the control flow of structured programs (*i.e.,* control flow graphs) have tree-width of at most six [12]. Therefore, CFGs of structured programs have bounded tree-width.

Because CFGs have bounded tree-width, so do EFGs. In the application of AFGMiner shown in this paper, AFGMiner runs in incremental polynomial time because the problem being solved is fundamentally finding frequent connected sub-graphs in a dataset of EFGs. The addition of weights in nodes and edges and weighted attributes to nodes does not change the complexity of the algorithm, but the generation of attribute sets of increasing size when creating new candidate patterns does. However, the number of attributes that an extension node of a k-edge candidate pattern with $k > 0$ or that the single node of a 0-edge candidate pattern can have is bounded by the size of A, *i.e.,* by the number of possible attributes that each pattern node may contain. As a consequence, the attribute-set growth component of the algorithm has a constant complexity, while the sub-graph mining component has incremental polynomial complexity. We can thus say that AFGMiner has incremental polynomial complexity when applied to PBPA.

B. A Tool for Compiler Developers and Computer Architects

HEPMiner is a program performance analysis tool that requires information about the static control flow of the program and its behavior at run-time. Dynamic information about the program is obtained by profiling its methods and includes which instructions are executed and which hardware events are triggered as a result of instruction execution. When the program is profiled, compiler log files (typically one per running thread) are created with edge profiling information, *i.e.,* basic blocks and flow edges of each method and their execution frequency measured in CPU cycles. A hardware profile is also generated and contains sequences of instructions and associated hardware events, captured by performance counters during run-time. Each instruction has a corresponding number of cycles during which it was executed, and the number of cycles in which each event was active.

The information from compiler log files and hardware profile goes into database tables later read by HEPMiner, that assembles one EFG per profiled method. An EFG node is created for each assembly instruction in the profile; instructions in the same basic block are connected by new flow edges and the frequency of such edges is the same as the frequency of those basic blocks that they connect. The nodes at the end of each basic block are connected to the first nodes of all subsequent basic blocks as determined by edges in the CFG of the method, and the frequency of these edges is set to the frequency of the corresponding CFG edges. The weight of each EFG node is the number of sampling ticks associated with the corresponding assembly instruction that the node represents, and the attributes of a node are the events associated with the same instruction.

With all EFGs assembled, HEPMiner uses the AFGMiner algorithm to find *heavyweight execution patterns* (HEP). HEPs are sets of hardware-related events captured by performance counters and associated with assembly instructions that were executing when the hardware-related events happened. Examples of such events are the occurrence of instruction and data cache misses, address-generation interlocks. These events affect program performance and it is thus important for compiler and architecture developers to understand when and why they happen, and which sets of events, correlated with which sets of instructions, take up more execution time. HEPMiner automates this process, and finds non-obvious correlations represented by execution patterns that take up significant execution time when their occurrences are considered in aggregation.

VI. Performance Evaluation Methodology

Experiments for HEPMiner were performed on an Intel Core 2 Quad CPU Q6600 machine, running at 2.4 GHz and with 3 GB of RAM.

A. HEPMiner Evaluation

The experimental evaluation of the algorithm in the context of HEPMiner used profiles from the DayTrader Benchmark, running on IBM's WebSphere Application Server, on an IBM z196 mainframe [13] and JIT-compiled using the IBM Testarossa JIT compiler. The WebSphere Application Server is a Java® Enterprise Edition (JEE) server [7]. It has a very flat profile, with its execution time spread relatively evenly over 2,566 methods, as is typical of large business applications.

AFGMiner-locreg had its run-time scalability tested in 4 experiments: **A**, **B**, **C** and **D**, described in more detail below. All experiments were run on DayTrader methods that were profiled using hardware instrumentation. Three important parameters in the experiments are: the minimum support threshold (MinSup) and the maximum allowed size of the attribute set in each candidate pattern node (MaxAttrs), both described in Section II; and the *Minimum Hotness Method* (MMH) value. The MMH is calculated by dividing the sum of all CPU cycles associated with each one of DayTrader's profiled methods by the cycles associated with the entire program run. This parameter is used in the experiments simply to limit the methods analyzed by the algorithm to those that contribute most significantly to total program run-time, and are thus more likely to contain patterns of interest to compiler engineers.

For experiments **A**, **B** and **C**, the MMH is kept at 0.001, meaning that only methods with execution time that exceeds 0.1% of program run-time are selected for mining (*i.e.* in DayTrader, 278 of 2,566). For experiment **D**, the MMH has values 0.001 (278 methods), 0.003 (56 methods) and 0.005 (23 methods). For all experiments except **A**, MaxAttrs is kept at 5.

Experiment **A** compares the run-times of AFGMiner-locreg with respect to changes in MaxAttrs. MinSup is kept at 0.001, meaning that only those patterns consuming more than 0.1% of program run-time are considered heavyweight. Increasing MaxAttrs potentially causes more candidate patterns to be generated, which is why modifying this parameter is a way of controlling the memory consumed by the algorithm and also its run-time.

Experiment **B** compares the run-times of AFGMiner-locreg with respect to changes in the number of EFG nodes visited by the algorithm. The number of EFG nodes visited is controlled by changing MinSup.

Experiment **C** compares run-times of AFGMiner-locreg and p-AFGMiner with 2, 4, 6 and 8 threads, by changing MinSup.

Experiment **D** compares run-times of AFGMiner-locreg and p-AFGMiner with 2, 4, 6 and 8 threads by changing MMH. MinSup is kept at 0.001.

Patterns found by AFGMiner-locreg were also compared to the ones found by the FlowGSP algorithm. FlowGSP was modified to support variations in MMH, MinSup and MaxAttrs, and run on DayTrader methods with the same parameter values used for Experiment **B** above. In addition, expert compiler engineers from IBM's JIT Compiler Development team verified the usefulness of patterns identified by the HEPMiner tool, as described in Section VIII.

VII. Performance Evaluation

In our experiments using HEPMiner, AFGMiner-locreg was always faster than AFGMiner-iso. As an example, when running with MMH and MinSup of 0.001, AFGMiner-iso took approximately 11 hours to complete the mining process, while AFGMiner-locreg took 40 minutes and p-AFGMiner with 8 threads took 15 minutes. The dramatic decrease in run-time when comparing AFGMiner-locreg to AFGMiner-iso is expected because location registration decreases the number of dataset sub-graphs that must be tested for isomorphism with candidate patterns.

We also compared patterns found by AFGMiner and FlowGSP. Figure 11 shows the number of output patterns for different MinSup values. As expected, AFGMiner found all patterns found by FlowGSP, but also found additional patterns composed of multiple sub-paths. For flat profiles, the trend is for AFGMiner to find many more patterns than FlowGSP as the MinSup is decreased, with the sequential patterns found by both being the parent patterns of the sub-graph patterns found exclusively by AFGMiner.

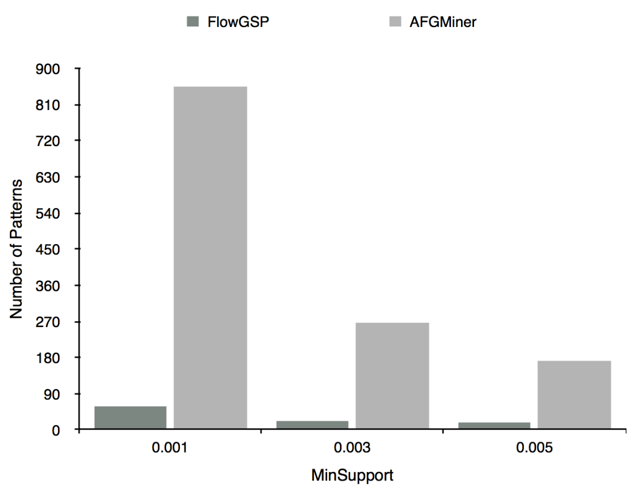


Fig. 11. Patterns found by FlowGSP and AFGMiner

A. Scalability Analysis

From the results of Experiments **A** (Figure 12) and **B** (Figure 13) we conclude that the MaxAttrs value is not as relevant a factor in the run-time performance of AFGMiner as the number of EFG nodes visited during the mining process. Figure 12 shows that, in the DayTrader Benchmark, it is more likely that heavyweight patterns have around 7 attributes per node, because making MaxAttrs higher than 7 does not produce statistically significant differences in run-time. It is worth noting that the effects of MaxAttrs on the performance of AFGMiner is dependent on the program being analyzed. If the program's run-time behavior causes more hardware events to happen, then the influence of MaxAttrs is more visible.

Experiment **B** changes the support value in order to increase the number of EFG nodes that the algorithm must visit. Figure 13 shows that the run-time of AFGMiner scales well enough with the number of EFG nodes visited. The performance of HEPMiner was deemed sufficient for it to be adopted as a handy tool by compiler developers in difficult analysis cases such as applications with flat profiles. However, better candidate pruning techniques could be developed to make AFGMiner faster. If more application-specific versions of the algorithm are developed in the future, those could take into account knowledge about which attributes are more likely to appear in the heavyweight patterns leading to more effective pruning of candidates.

Experiments **C** (Figure 14) and **D** (Figure 15) show run-times for AFGMiner-locreg and p-AFGMiner, with the number of threads used in parenthesis. As expected, mining becomes faster with more threads being used. However, using more threads has a diminishing effect on run-time decrease as the MinSup or MMH increase. The reason is that, with fewer patterns to mine due to the increase in MinSup/MMH, time spent on data loading and temporary bookkeeping of patterns and pattern occurrences - both done serially by p-AFGMiner - start dominating the total run-time.

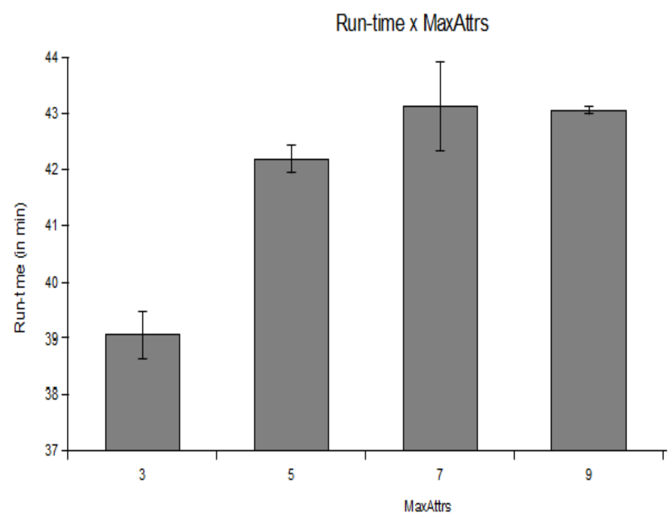


Fig. 12. Experiment A.

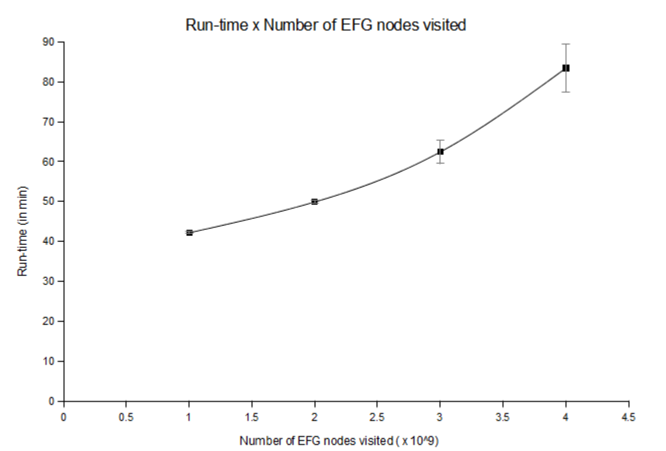


Fig. 13. Experiment B.

VIII. Qualitative Analysis

This section discusses the patterns obtained by both HEP-Miner. Results were analyzed by expert developers from the IBM Canada Software Laboratory.

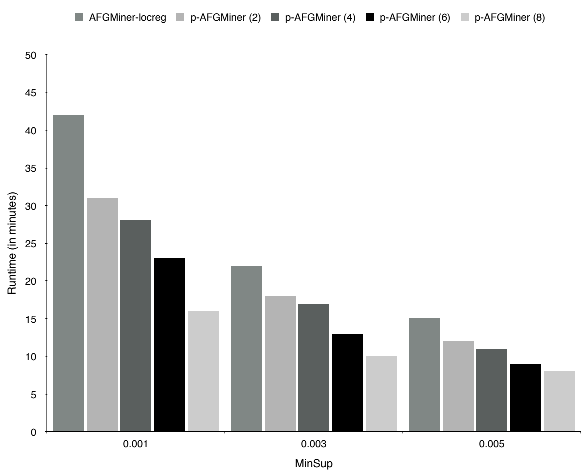


Fig. 14. Experiment C.

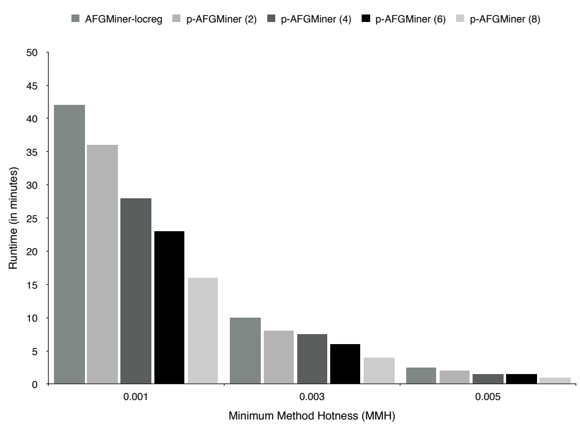


Fig. 15. Experiment D.

A. HEPMiner Results

The compiler engineers found HEPMiner to be a useful tool and were able to not only validade results according to previous knowledge about the benchmark, but also to make new observations about the run-time behavior of DayTrader when executed by the z196 hardware. The observations are summarized below.

1) AFGMiner found heavyweight patterns that contain an edge from a branch instruction leading to a node that has instruction cache misses as one of its attributes. Reviewing the occurrences of such patterns shows that this edge represents the taken path from the branch, which confirms expectation that instruction cache misses should be observed only on the taken branch target.
2) From prior analysis, the experts at IBM know that 30% of overall CPU cycles in JITted code are assigned to method prologues, and 40% of instruction cache misses are correlated with method prologues. This was confirmed in the results output by AFGMiner.
3) An attribute that represents a non-taken, correct-direction branch prediction was found to be dominant by AFGMiner. The fact that this attribute shows up highlights that the JIT compiler performs well when ordering basic blocks to optimize for fall-through paths. This discovery led to the creation of performance counters that take into account the ratio of taken and non-taken branches.
4) The output by AFGMiner shows patterns with low support value that have a certain attribute that is actually an instruction which is part of an asynchronous check sequence. This check sequence is used as a cooperative point in the method to allow for garbage collection and/or JIT compilation-related sampling mechanisms that determine which method is being executed. Such checks are placed at method entries and within hot loops. The experts at IBM confirmed that, given that DayTrader is a very flat benchmark, it is correct that the pattern should have such a low support.
5) The relative support values for a sequence of three attributes, present in several patterns, were found to be relevant by the IBM developers. The attributes are an address-generation interlock, followed by a directory or data cache miss, and then an instruction used to load a compressed referenced field from an object. This discovery led to the implementation of the pattern in the compiler's instruction scheduler in order to reduce its negative effect on the run-time of future compiled applications.

IX. Related Work

FlowGSP is a sequential-pattern mining algorithm that finds patterns whose occurrences are sub-paths of AFGs [14], [6]. AFGMiner differs from FlowGSP in that it is able to find not only sequential patterns, but also patterns whose occurrences are sub-graphs of AFGs. AFGMiner takes less time than FlowGSP to find each pattern. In addition, AFGMiner is able to map each pattern to all its occurrences and output this mapping to the user.

gSpan is a classic sub-graph mining algorithm. The main difference between AFGMiner and gSpan is that AFGMiner is able to handle multiple node attributes and uses breadth-first search with eager pruning when generating candidate patterns, while gSpan follows a depth-first approach [1]. *Fast Frequent Subgraph Mining* (FFSM) is another well-known sub-graph mining algorithm for undirected graphs, and its novelty was the introduction of embeddings that make the mining process faster. AFGMiner-locreg also uses embeddings, but has to record the complete mapping between sub-graph patterns and occurrences, making them more memory-consuming. Gaston is a more recent frequent path, tree and graph miner integrated into a single algorithm. In contrast to AFGMiner, however, Gaston only mines for patterns in non-attributed, undirected and unweighted graphs [2]. *Horvart et al.* describes a sub-graph mining algorithm for outerplanar graphs [15]. Similarly to AFGMiner the algorithm runs in incremental polynomial time due to outerplanar graphs being similar enough to trees.

A work related to HEPMiner is that of *Dreweke et al.*. It uses sub-graph mining as part of a code transformation to extract code segments [16]. HEPMiner differs from this work in that it is an external performance analysis tool that helps compiler developers to reach conclusions about the performance of applications of interest, and detect improvement opportunities.

X. Future Work

SCPMiner is another application of AFGMiner and currently a work in progress. It uses AFGMiner to perform profile-based program analysis at the source-code level, finding patterns composed of lines of source-code that, in aggregation, contribute significantly to the total execution time of analyzed flat-profile applications.

In addition, applications of AFGMiner in different domains, such as logistics and social networking, could be developed. The algorithm could also be tuned to take domain-specific knowledge into consideration when searching for candidate patterns and evaluating whether a candidate pattern is heavyweight.

Conclusion

This work defined heavyweight patterns and the problem of Heavyweight Pattern Mining. It presented AFGMiner, a heavyweight pattern mining algorithm that is generic enough to be applied to any problem that requires mining of attributed flow graphs, and is able to find sub-path and sub-graph patterns. AFGMiner was improved from its original version to use location registration. In addition, a parallel version of AFGMiner with location registration was developed that uses a workload distribution heuristic to better balance the mining work performed by different threads.

The tool HEPMiner, used for profile-based program analysis, was created as an useful application of AFGMiner. Heavyweight patterns discovered by this tool were positively evaluated by compiler engineers from the IBM Canada Software Laboratory in the context of analyzing flat-profile applications. The tool gave them useful insights on the behavior of such applications, leading to the creation of new performance counters and improvements to instruction scheduling in IBM's Testarossa JIT Compiler.

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