Analysis of Data Structures Involved in RPQ Evaluation

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Keywords: Graph Data Management, Regular Path Queries, Experimental Analysis.

Abstract: A fundamental ingredient of declarative graph query languages are regular path queries (RPQs). They provide an expressive yet compact way to match long and complex paths in a data graph by utilizing regular expressions. In this paper, we systematically explore and analyze the design space for the data structures involved in automaton-based RPQ evaluation. We consider three fundamental data structures used during RPQ processing: adjacency lists for quick neighborhood exploration, visited data structure for cycle detection, and the representation of intermediate results. We conduct an extensive experimental evaluation on realistic graph data sets and systematically investigate various alternative data structure representations and implementation variants. We show that carefully crafted data structures which exploit the access pattern of RPQs lead to reduced peak memory consumption and evaluation time.

1 INTRODUCTION

In recent years, the graph data model had a renaissance in the database community, positioning itself as an alternative to the traditional relational data model. The interest is mainly driven by novel, emerging use cases like the analysis of social networks. In such use cases the relationships between the entities and therefore the topology of the graph are as important as other data attached to the entities.

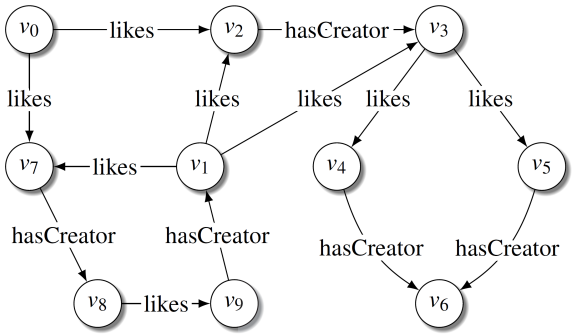
Major database vendors adopted graph data management and integrated it into their database systems, e.g., Oracle PGX (Raman et al., 2014) and SAP HANA Graph (Rudolf et al., 2013). Graph database systems excel in handling multi-hop relationships between entities, e.g., multi-hop stakeholder relationships between offshore profits and potential tax evaders. One expressive way to match multi-hop relationships are regular path queries (RPQs) (Wood, 2012). Many declarative graph query languages have support for RPQs, e.g., SPARQL (W3C, 2013), PGQL (van Rest et al., 2016), and G-Core (Angles et al., 2018).

RPQs are a compact way to match long paths in a data graph which conform to a given regular expression. The regular expression is defined over the set of edge labels in the data graph. Additionally, every label can be reversed which checks for incoming edges with the label instead of outgoing edges, e.g., expression `^likes` checks for incoming edges with label `likes`. This type of queries is also called two-way regular path queries (2RPQs). The concatenation of all edge labels on a path from the start vertex to the end vertex has to be in the language of the given regular expression, otherwise it is not a part of the result set. The result set is a distinct set of tuples consisting of the start vertex and the end vertex of each matched path.

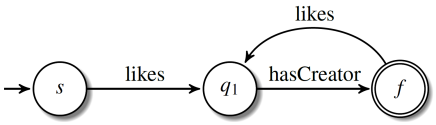
One state-of-the-art way to evaluate RPQs is to transform the regular expression to an equivalent automaton and use it to guide the search for matching paths in the data graph. An automaton consists of one initial state s and one or multiple final states f. The states are connected by directed transitions which have edge labels attached as predicates. Figure 1b shows an automaton for the regular expression `(likes/hasCreator)+`.

The search traverses synchronously the automaton and the data graph, starting at the initial state and all vertices if no additional index is available which limits the set of start vertices. The transitions in the automaton restrict which edges in the data graph can be followed. The edge labels have to be equivalent. When the traversal reaches one of the final states in the automaton, a result tuple is produced, consisting of the vertex from which the search in the data graph

Tetzel, F., Voigt, H., Paradies, M., Kasperovics, R. and Lehner, W.
Analysis of Data Structures Involved in RPQ Evaluation.
DOI: 10.5220/0006860303340343
In *Proceedings of the 7th International Conference on Data Science, Technology and Applications (DATA 2018)*, pages 334-343
ISBN: 978-989-758-318-6



(a) Data graph.



(b) Automaton for (likes/hasCreator)+.

start	end
v_0	v_3,v_6,v_8,v_1
v_1	v_4,v_6,v_8,v_1
v_3	v_6
v_8	v_1,v_8

(c) Result pairs grouped on the start vertex.

Figure 1: Example for RPQ evaluation.

started and the current vertex when the final state was reached. Figure 1 shows a small example. The resulting pairs are shown grouped on the start vertex.

Many graph database systems operate purely or mainly in main memory. One major challenge of RPQ evaluation in this context is the very high peak memory consumption in many queries, which can easily lead to slow-downs or out-of-memory situations. Especially RPQs with unbounded recursions, e.g., with a Kleene-star, produce large intermediate results, and also large result sets. To investigate how this memory consumption can be reduced we study the data structures involved in the RPQ evaluation, and search for mitigations and alternatives.

Our contributions in this paper are three-fold:

1. We revisit automaton-based RPQ evaluation, examine involved data structures, and discuss their usage in the algorithm. Section 2 outlines the algorithm with the relevant data structures.
2. We provide a detailed discussion of implementation variants for each involved data structure aiming to lower the memory footprint and improve the evaluation time. This is described in Section 3.
3. We experimentally evaluate the discussed variants of the data structures on data graphs of various sizes and different query sets. Section 4 discusses the experiments and our findings.

Section 5 examines related work and Section 6 concludes the paper.

2 AUTOMATON-BASED RPQ EVALUATION

Using an automaton representation of the regular expression is a state-of-the-art method to evaluate RPQs. The automaton is used to guide the search for matching paths in the data graph, similar to a pattern graph in graph pattern matching. Most often a deterministic finite automaton (DFA) is employed as it has only a single initial state which acts as a natural starting point for the search. Attached to every state transition in the DFA is an edge label predicate. It represents a traversal step in the data graph along an equivalent edge label. ε-transitions, which have the empty word as predicate on the transition, are not allowed.

The search has to keep track where it initially started from as the start vertex is part of the result pairs. The matched paths are not returned, so it is sufficient to just track the start vertex. Information to reconstruct the path is not required. Additionally, the search has to know the current state in the automaton and the current vertex in the data graph. Hence, the search state is a triple (v_s, s, v_i) consisting of the start vertex v_s, the state s, and the current vertex v_i.

Let S be the set of all valid start vertices in the graph. For each $v_i \in S$ we have one initial search state (v_i, s, v_i), e.g., in Fig. 1 one initial state is (v_0, s, v_0). S is either given by the user, a nesting query, or includes all vertices of the graph. All initial search states form the first intermediate results (IR).

The search proceeds in traversal steps. Each step transforms search states from IR into new search states or drops them. The edges of the current vertex are examined if they match an edge label predicate of an outgoing transition of the current state. As is standard in most graph processing engines, an adjacency list (ADJ) is used to provide quick access to all incoming and outgoing edges of each vertex. Each match produces a new search state consisting of the start vertex which is just copied over, the state where the matching transition leads to, and the vertex where the matching edge leads to. The new search states are then checked against a visited data structure (VIS) to make sure it is a search state which was not seen be-

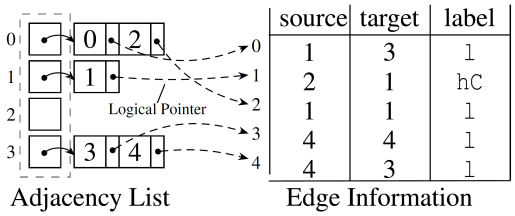


Figure 2: Mutable adjacency list consisting of a two-dimensional dynamic array with edge identifiers which refer to edge information like source, target and label of the referenced edge.

fore. If it is new, it is added to IR for the next step and also to VIS, otherwise it is dropped. In Fig. 1, the search state (v_0, s, v_0) would produce two new search states (v_0, q_1, v_2) and (v_0, q_1, v_7) as there are two matching edges leading to v_2 and v_7 which match the only outgoing transition of the initial state s to the state q_1.

When the search reaches a final state, a new tuple for the result set (RS) consisting of the start vertex and the current vertex is produced, additionally to the new search state. The search ends when there are no search states available anymore to explore. In other words, IR is empty.

The search can be conducted with two different traversal strategies: depth-first search (DFS) and breadth-first search (BFS). The major difference is that DFS does not materialize IR and always produces just one search state, and follows it. It employs backtracking to reach old search states and produces the next search states from them. Therefore, DFS is better suited for memory constraint situations.

3 DATA STRUCTURES

In the following sections, we investigate in detail various implementation variants of the data structures for adjacency list (ADJ), visited (VIS), and intermediate results (IR).

3.1 Adjacency List

The graph topology is commonly stored in an adjacency list to support fast access to adjacent edges and vertices. All edges have a unique identifier and provide the information about the edge label, source vertex and target vertex. Vertices have unique identifiers as well. As edge label predicates can be reversed in RPQs, the graph traversal has to follow not only outgoing but also incoming edges, from target vertex to source vertex. Hence, it is common practice to use two adjacency lists: one containing all outgoing edges per vertex and one for all incoming edges per vertex. In the following, we only discuss each variant for outgoing edges.

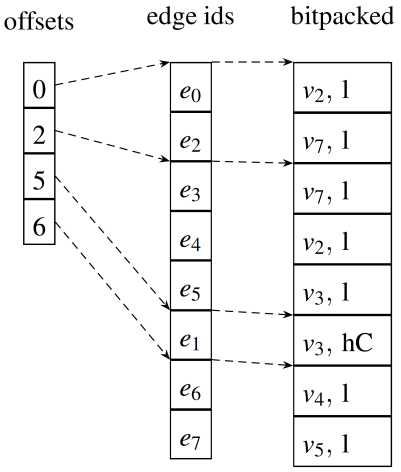


Figure 3: CSR with edge identifiers and CSR with bitpacked values consisting of vertex identifier and label identifier, both can share the offset array.

Vectors. A common representation is a two-dimensional dynamic array which contains edge identifiers, as illustrated in Fig. 2.

The first dimension is a dynamic array containing one entry per vertex. Each entry is yet another dynamic array containing all outgoing edges originating from the corresponding vertex. Edges are represented with edge identifiers, which can be used to lookup the edge information.

The use of dynamic arrays allows the insertion and removal of edges and vertices. The entries in the dynamic array are stored consecutively in memory which results in good cache locality and, therefore, good read performance. The name adjacency list might imply the use of linked lists, but the worse read performance of linked lists, because of pointer chasing, makes them a less appealing choice.

CSR. Another widespread representation is the CSR (compressed sparse row) format. It trades off mutability for a more compact and cache friendly representation. The arrays in the second dimension are collapsed into one single array which then contains one entry for each edge in the data graph, sorted in such a way that all outgoing edges of the first vertex are grouped together at the beginning of the array. Thereafter all outgoing edges of the second vertex are stored, then for the third vertex, and so on.

The entries in the first array are offsets into the second array, marking the beginning of the outgoing edges for the corresponding vertex. The end is marked with the beginning for the next vertex. The left side of Fig. 3 gives an illustration of CSR.

An insertion into a CSR structure is time-

consuming since it has to shift following existing entries to make space before adding the new entry. The order of the entries has to be kept. Therefore, CSR is usually employed when the data graph remains static.

Bitpacked. A CSR format optimized for RPQ evaluation uses bitpacked values instead of edge identifiers. A bitpacked value combines label and target vertex of the edge into a single value. It removes the additional indirection to lookup edge label and target vertex with the edge identifier. The lookup is in general an expensive random access with a cache miss which is avoided by having all the information already in the adjacency list.

Dictionary-encoded edge labels only require a few bits to be stored. Bitpacking reserves a fixed number of low bits for the edge label and encodes the target vertex identifier in the remaining high bits. For most data graphs it is possible to use 32-bit value types, e.g., LDBC scale factor 10 has 29 146 487 vertices and 15 different edge labels, which require 25 bits and 4 bits, respectively.

The array with bitpacked values can replace or complement the array with edge identifiers in a CSR structure as shown in Fig. 3. The complementing variant still allows access to further edge data, such as edge properties, if required, e.g., graph pattern matching with predicates on edge properties.

Vertical Partitioning. Another well-known variant of the CSR format is vertical partitioning. Most regular expressions in RPQs use only a small number of different edge label predicates. Additionally, if one looks at a single traversal step which corresponds to a single state transition in the automaton, the number of edge labels which have to be checked in the adjacency of a vertex shrinks even more.

This can be exploited by vertically partitioning the adjacency list by edge label. Each partition contains only edges of a single label and is represented by a CSR with target vertex identifiers in the second array. Hence, scanning of non-matching edges can be avoided and all matching target vertices can be easily extracted.

3.2 Visited

Next to the adjacency list one key data structure for good performance in RPQ evaluation is VIS, which keeps track of already discovered search states and avoids redundant exploration of the same graph regions. If the data graph and automaton are cyclic, it is also necessary to guarantee program termination.

The search state consists of the start vertex, the state in the automaton and the current vertex in the data graph. We assume for all following variants that the search state is grouped on the state. Hence, for each state in the automaton one separate data structure for VIS is used, storing a tuple consisting of start vertex and reached vertex.

It is sufficient to only keep track of discovered vertices as we do not store full path information during the RPQ processing. It is not relevant for the result over which edge a certain vertex has been reached as it is essentially only reachability information constrained by the regular expression.

In the following paragraphs, we introduce four data structures, which we employed as VIS.

hashset. One obvious choice for VIS is a hashset, e.g., C++'s std::unordered_set. It stores tuples of vertex identifiers for start vertex and visited vertex. Since vertex identifiers are 32-bit values, we essentially store one 64-bit value per entry.

hashmapset. A variation of a single hashset is a hashmapset which maps each start vertex to its own hashset of reached vertices. Splitting the hashset into multiple smaller hashsets reduces the overhead of rehashing. It is hard to estimate the size of VIS in advance, which results in a lot of resizing and, therefore, rehashing of the hashset. Since rehashing is less expensive for smaller hashsets, it is beneficial to split the single hashset.

roaring. Another obvious choice next to hashsets are bitsets, in case of roaring, a compressed bitset. The number of possible values for a tuple of start and reached vertex is too large for a fixed-size bitset. It requires $|V|^2$ bits with V being the set of vertices in the data graph, additionally multiplied by the number of states in the automaton. For a graph with 3 141 713 vertices like LDBC scale factor 1, the required memory has to encompass several terabytes which is unreasonable. Hence, we investigated into compressed bitsets, and settled for the recently proposed Roaring Bitmap (Chambi et al., 2016; Lemire et al., 2016). A Roaring Bitmap prunes unset regions in the bitset very efficiently and still provides fast random access which is required for the frequent lookups in VIS.

bitset. One simple trick to still make use of a fixed-size bitset is to treat start vertices separately and unset the bitset when the traversal for one start vertex is done and the traversal for the next one starts. That way, the size of the bitset is limited to the number of vertices in the graph. One bit per vertex, multiplied by the number of states in the automaton as we have visited per state, is an affordable memory size for most graphs. Unsetting the bitset has to be very fast to not become the bottleneck during execution. SIMD instructions are used to efficiently unset the whole bitset. For queries which only visit a small portion of the graph, we only partially unset the bitset by keeping

track of changed words in the bitset.

3.3 Intermediate and End Results

The number of paths matched by an RPQ can be large, especially for RPQs with unbounded recursions. Materializing and storing the end result set can already be challenging. For some queries intermediate results are even larger than the end result set. Intermediate results are only materialized during a BFS graph traversal, but not during a DFS traversal. Hence, a DFS has much lower peak memory consumption for most RPQs. We briefly introduce two basic data structures to store the end result set in the following paragraphs.

vector. The simplest data structure to store the end result set in is a dynamic array, e.g., a C++ std::vector. It simply stores all tuples in an array of consecutive memory. One major drawback is the necessary resizing as the result set size is not known in advance. During resizing more than twice the amount of memory is allocated for a short moment as the data is copied to the newly allocated memory. Copying a large amount of data is a costly operation. The use of overprovisioned allocation, which allocates more memory than strictly needed, reduces the number of resizes considerably.

realloc. Another technique to grow a dynamic array is reallocation. How reallocation works depends on the used memory allocator. The default allocator in Linux[1] uses various allocation schemes depending on the size of the allocation, and this also changes how reallocation works. We will only discuss the large allocation scheme as this is used for the large result sets. When the allocation size is very large (around 128 KiB[2]), the default allocator employs anonymous memory mapping to allocate memory from the operating system. In case of a reallocation, the operating system enlarges the allocated memory without copying. The operating system can relocate memory in the virtual address space efficiently by manipulating page table entries.

In addition to the two resizing strategies introduced above, we investigated various grouping strategies for the intermediate results (IR). IR is conceptual set of search states which are triples. Storing triples runs easily out-of-memory for many RPQs. Hence, we always group on the start vertex and therefore only have to store a tuple consisting of state and current vertex. The tuples are stored in a dynamic array which either utilizes copying or reallocation as resizing strategy.

[1]Other operating systems have similar mechanisms.

[2]the threshold is dynamic, see manpage for mallopt() and parameter M_MMAP_THRESHOLD for details

Table 1: LDBC social network with various scale factors.

	SF1	SF3	SF10
vertices	3 141 713	8 967 247	29 146 487
edges	17 080 008	50 711 019	171 506 420

stategroup. The tuple can be grouped once more, in this case on state. For each state, we now only store a simple list of current vertices. We employed an array with one entry for each state in the automaton. The number of states is usually small in most RPQs. The list of current vertices is realized with a dynamic array utilizing reallocation for resizing. The memory footprint is reduced considerably as many tuples share the same state during the traversal of most RPQs.

vertexgroup. Grouping on vertex instead of state is also possible but gives no benefit for most RPQs. There are not many vertices in the data graph reached in the same traversal step in different states, such that tuples share the same vertex and have different states. Another problem is the diversity of the reached vertices in one traversal step. An array with one entry per vertex in the graph would waste a lot of memory. We used a hash map instead to map the reached vertex to a bitset which represents the different shared states.

4 EXPERIMENTAL EVALUATION

We experimentally study the impact of the various data structures described in Section 3 on the LDBC[3] social network graph. We choose three different scale factors with an increasing number of vertices and edges (cf. Table 1). By default, we use *vertical partitioning* for ADJ, *bitset* for VIS, *stategroup* for IR and *realloc* for RS. In each experiment we only vary one data structure; all other data structures remain fixed.

Our prototype provides a columnar, dictionary-encoded storage for the graph data. Edges are stored in an edge table consisting of source vertex, target vertex, and edge label. Other edge or vertex properties are not imported as they are not relevant for the RPQ evaluation. All columns are dictionary-encoded, i.e., a dense domain of integer values are stored in the columns. Source and target share a common dictionary for all vertices.

All experiments were conducted on a Haswell two-socket machine (Intel(R) Xeon(R) CPU E5-2660 v3) running at 2.6 GHz. The machine has 20 cores (with SMT up to 40 hardware threads) and 128 GB of RAM. The RPQ evaluation utilizing a depth-first traversal is trivially parallelized by running up to 40 traversals starting in different start vertices in paral-

[3]http://ldbcouncil.org/

lel. The breadth-first traversal is additionally internally parallelized.

We define our own set of queries as there is no benchmark readily available which includes RPQs. The LDBC benchmarks only consider rudimentary RPQs: a path of variable length consisting only of one edge label, e.g., `knows+`. The queries $Q1-Q4$ are larger recursive queries, matching a long, repeated path. They exemplify the expressiveness of RPQs. According to a recent study of SPARQL query logs (Bonifati et al., 2017) most real world RPQs are surprisingly simple. That is why we added three additional queries, $Q5$, $Q6$ and $Q7$, which are less complex and also have a much smaller result set. The query set written in the syntax of SPARQL property paths looks as follows:

$Q1$: `(likes/hasCreator)+`
$Q2$: `(hasInterest/^hasTag/hasCreator)+`
$Q3$: `(likes/isLocatedIn/^isLocatedIn/^workAt)+`
$Q4$: `(likes/isLocatedIn/^isPartOf/^isLocatedIn/^studyAt)+`
$Q5$: `knows+`
$Q6$: `knows/(likes|^hasCreator)`
$Q7$: `^isLocatedIn/(hasInterest|hasTag)`

The first experiments we conducted analyze the different data structures used for ADJ.

4.1 Adjacency List

Time Measurements. We first run the more complex recursive queries $Q1-Q4$ on the smallest data set with scale factor 1 (SF1). Figures 4a and 4b show our results. All queries have very similar behavior. The performance of the DFS is not really impacted by changing the data structure for ADJ which is not surprising as a DFS reads only one edge from ADJ and moves forward with it. Avoiding the lookup into the edge table only gives a very small speedup.

The BFS on the contrary, gets a lot of speedup from avoiding the additional lookup as can be seen by the big drop in evaluation time from CSR with edge identifiers to CSR with bitpacked values. Vertical partitioning gives yet another small boost as all adjacent vertices with the correct label can be extracted directly from the data structure without any additional check.

Another set of experiments was conducted with different scale factors of the graph (SF1, SF3 and SF10). As the more complex recursive RPQs $Q1-4$ run out-of-memory for SF10, we opted for the less complex query $Q5$ which has a much smaller result set with less pressure on the memory system. Figures 4c and 4d show our results.

Table 2: Memory consumption in MB of different data structures for ADJ on the LDBC dataset of various scale factors.

	SF1	SF3	SF10
vectors	143.7	418.1	1385.5
CSR	80.9	238.7	802.6
bitpacked	80.9	238.7	802.6
partitioned	256.8	740.9	2434.8

We observe the same general behavior as in the previous experiment. Changing the data structure for ADJ has little to no impact on the runtime of the DFS traversal. For BFS on the other hand, avoiding the lookup in the edge table gives about a two times speedup. Vertical partitioning gives again another boost in performance.

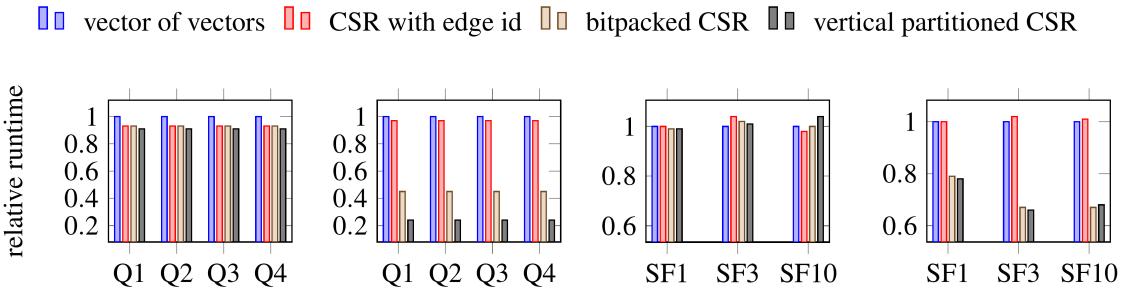
Memory Consumption. We imported the data sets into the various data structures for ADJ and measured the memory consumption of each data structure separately. Table 2 summarizes our findings. As one would expect, the compact format CSR has the smallest memory footprint. The bitpacked values have the same size as the edge identifiers. Therefore, the whole data structure requires the same amount of memory. The mutable adjacency list *vectors* with dynamic arrays is bigger than CSR because the dynamic arrays overprovision their internal memory usage. They allocate more memory than strictly required by their content to avoid growing the data structure too often when new data is inserted. Growing a dynamic array is an expensive operation.

Vertical partitioning has the worst memory footprint. The edges are partitioned per edge label which requires no additional memory, but the offsets array which has as many entries as vertices in the graph is copied per edge label. In most graphs the number of edges is way bigger than the number of vertices. The number of distinct edge labels is also small in most data sets. Therefore, the increased memory consumption is noticeable but bearable considering the benefits it yields in evaluation time.

4.2 Visited

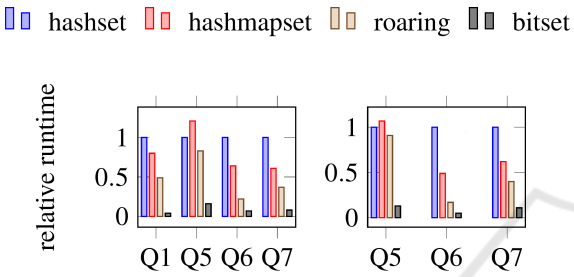
To evaluate variants of VIS we fixed all other data structures to the fastest variant, e.g., employing the vertical partitioned adjacency list, and only varied visited data structure. Since the BFS and DFS traversal strategies resulted in very similar behavior, we only report our findings with the DFS traversal.

Time Measurements. Fig. 5 shows the relative runtime of each variant, relative to the hashset variant, in various queries for scale factor 1 and 3. The me-



(a) DFS traversal on SF1 (b) BFS traversal on SF1 (c) DFS traversal with Q5 on different graph sizes (d) BFS traversal with Q5 on different graph sizes

Figure 4: fig:plot-adj-recursive



(a) DFS on SF1 (b) DFS on SF3

Figure 5: Relative evaluation time for variants of VIS.

mory consumption, especially for the hashset, was too big to run the experiments on larger graphs. Complex queries like $Q1$ ran out of memory already for scale factor 3 with the hashset as visited data structure.

The hashmapset gives only a small speedup, and it heavily depends on the query. It still suffers from frequent resizing and, therefore, rehashing. As the hashset also employs overprovisioning, it is not always better to split it into multiple parts. $Q5$ shows a slowdown for hashmapset. Due to overprovisioning, a large hashset grows faster than many small hashsets which leads to less frequent rehashing.

Roaring is a promising bitset compression scheme which works better than hashset and hashmapset. But again, it heavily depends on the query and which vertices are reached in the traversals. If the vertex identifiers are nicely clustered together, the compression and pruning is very efficient in roaring as it relies on partitioning. A more compact storage leads also to faster access times.

As obvious from the plots, the fixed-size bitset with special handling of unsetting is the fastest variant by far, improving evaluation time by a factor of 5 to 14. The bitset fits in both investigated graphs into the last-level cache which makes the random accesses less costly. The data structure is completely preallocated, i.e., it never has to be resized, which allows it to reside in the cache for the whole RPQ evaluation. Additionally, the adaptive strategy for unsetting exploits the different characteristics of the traversals, only unsetting changed values when just a few vertices got visited and utilizing vector instructions when a lot of vertices got visited.

Table 3: Comparison of memory consumption in MB for VIS across various queries on SF1.

VIS	Q1	Q5	Q6	Q7
hashset	34 978.3	3 774.8	9 079.3	135.8
hashmapset	44 570.4	2 562.3	11 063.7	128.3
roaring	2 486.5	80.6	745.1	7.5
bitset	1.2	0.8	1.2	1.2

Memory Consumption. To explain the considerable runtime difference we measured the memory consumption of each data structure for various queries. Table 3 shows the results of our experiment. The memory consumption heavily depends on the query and how many vertices the graph traversal visits. Query $Q1$ produces a large result set and visits a big portion of the graph. Therefore, all visited data structures require a lot of memory compared to the other queries, except bitset. It has a fixed size: as many bits as there are vertices in the data graph, multiplied by the number of states in the automaton. It does not depend on the query.

The bitset is also way smaller than all other data structures as it is only used for one start vertex and then unset for the next. All other visited data structures have the problem of a huge input domain they have to cover. Every vertex in the graph can potentially be a start vertex, and every vertex could be reached from each start vertex. Additionally, a separate visited data structure is required per state in the automaton.

Most queries have a considerably smaller number of reached vertices and therefore only a sparse number of entries to store in VIS. The use of a compact data structure like roaring bitmaps has a lot of benefits. It stores sparse data efficiently in memory and the previous experiment showed that it still provides faster access to the data than the hash-based containers.

Table 4: Varying return type on SF1 with different queries.

	result size	**vector**[ms]	**realloc**[ms]	**speedup**
Q1	79 438 658	10 881.0	5 780.0	1.88
Q5	96 353 856	7 222.7	925.2	7.81
Q6	373 252 434	25 717.8	1 460.9	17.6
Q7	761 791	89.1	71.0	1.25

In the end the best choice for the visited data structure is the bitset. It has by far the lowest memory footprint and also provides the fastest evaluation time. The only limitation is that it can only be used by one start vertex at a time.

4.3 Intermediate and End Results

We first run a simple experiment where we only vary the return type. The goal is to see the impact reallocation can have when materializing a large result set. We used the DFS graph traversal so that no intermediate results are materialized.

Time Measurements. Table 4 summarizes our findings for scale factor 1. The speedup achievable by employing reallocation instead of copying greatly depends on the result size which has to be materialized. Copying gets more and more expensive with a larger amount of entries. With reallocation, the operating system kernel only has to relocate all memory pages which make up the dynamic array in the worst case. A very cheap operation compared to copying. Larger scale factors did not provide any new insights which is why we omitted them here.

Memory Consumption. Using a different resizing strategy does not change the memory consumption as both data structures employ overprovisioned allocations in the same way.

The second experiment we conducted focuses on IR. We use the BFS graph traversal as DFS does not materialize IR. For the result set we use reallocation as it was consistently faster in the first experiment.

Time Measurements. Utilizing reallocation for IR gives consistently a small speedup as is shown in Fig. 6. The difference is small as IR is not resized often. When the frontier of the BFS traversal gets larger, IR also has to get larger, but the size is not decreased for a small frontier. It stays at the large size.

Grouping the tuple additionally on state (*stategroup*) gives another speedup in most queries. Many entries in IR share the same value for state and can therefore benefit from grouping as less data is stored. The grouping operation increases the code complexity of the data structure and adds runtime overhead to the access method. Therefore, not all queries show an improved runtime. It depends on how many entries share the value the grouping operation works on.

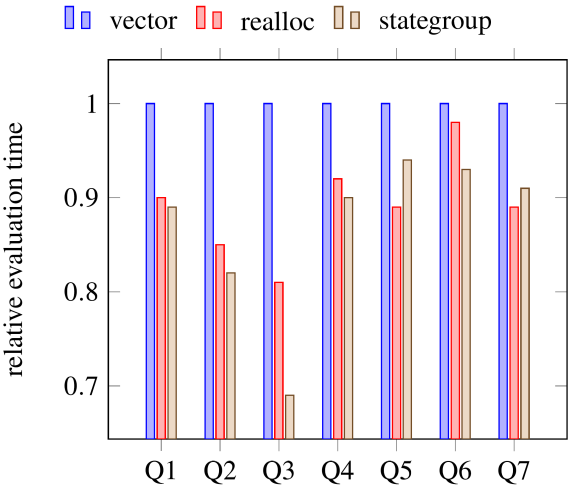


Figure 6: Relative evaluation time for intermediate representations.

Table 5: Memory consumption of variants for IR.

	vector	**realloc**	**stategroup**
Q1	2 097 152	2 097 152	1 122 304
Q2	16 777 216	16 777 216	8 658 944
Q5	131 072	131 072	73 728
Q6	4 194 304	4 194 304	2 113 536
Q7	1 572 864	1 572 864	892 928

Grouping on vertex (*vertexgroup*) instead of grouping on state, was consistently four times slower in each query which is why we omitted it from the plot. Not many entries in IR share the same vertex in different states and rehashing of the employed hash map created a performance bottleneck.

Memory Consumption. Table 5 shows the memory consumption of the variants of IR. *vertexgroup* is omitted as the employed hash map used too much memory to be competitive to the non-grouping tuples. *vector* and *realloc* both simply store tuples in the same format, only the resizing strategy is different. Hence, both data structures have the exact same memory consumption.

stategroup uses considerable less memory than *vector* and *realloc* as a lot of entries in IR share the same state. The grouping removes the redundant storage of state and reduces the memory consumption consistently by a factor of two. Therefore, it is advisable to always group IR on state.

4.4 Discussion

The adjacency list is a key data structure which is frequently accessed in the RPQ evaluation and a lot of other graph algorithms. Specialization for the access pattern during RPQ evaluation resulted in a conside-

rable speedup. RPQs consist only of edge label predicates, so it is advisable to integrate edge label information into the adjacency list. We exemplified it by using bitpacked values in the adjacency list, consisting of the edge label and the vertex identifier of the adjacent vertex. We showed that this approach reduces the evaluation time considerably by having the same memory footprint as an adjacency list with edge identifiers. Vertical partitioning of the adjacency list provides even more runtime improvements, but requires also more memory.

For the visited data structure, we found that a fixed-size bitset with a specialized way for unsetting all bits gives the best results. It provides the fastest evaluation time and smallest memory footprint. The only limitation is that it can only be used by a single start vertex at the time.

Roaring bitmaps provide a nice alternative when the traversal should start from multiple start vertices at the same time. It stores sparse data considerably more efficiently in a compact data structure compared to hash-based containers like a hashset. Therefore, the memory footprint is smaller and the evaluation time does not suffer from the compact storage as it still provides fast random access.

Reallocation is a preferable resizing technique for intermediate results and for the result set. It is consistently faster than copying and avoids sharp spikes in the memory consumption. Grouping of intermediate results on the automaton state results in considerable smaller memory consumption and a small speedup compared to the handling of tuples.

5 RELATED WORK

The broad applicability of RPQs has spurred the development of various extensions to the class of 2RPQ queries (Calvanese et al., 2000; Deutsch and Tannen, 2002). PGQL (van Rest et al., 2016) supports arbitrary predicates on any attribute of an edge or vertex along the path, not just edge label equivalence. G-Core (Angles et al., 2018) goes one step further with existential subqueries on sub-branches of the matching path.

Conjunctive regular path queries (CRPQs) combine several RPQs to a more complex pattern matching query. Since the general data access patterns to the underlying data structures are the same as for 2RPQs, we focus in our analysis on the less complex 2RPQs without conjunctions of multiple RPQs.

Extended conjunctive RPQ (ECRPQ) (Barcelo et al., 2010) extends 2RPQs further by allowing access to the matched paths as a result, instead of just pairs of vertices. The added functionality comes at the expense of making ECRPQs computationally *intractable*, which is typically not desirable for practical graph query languages. Therefore, we omit ECRPQs and paths as a result type from our analysis.

Naturally, the performance of RPQs is sensitive to the order in which parts of the RPQ are evaluated, effectively providing an opportunity for query optimization. An interesting approach are so-called *rare labels*, i.e., edge labels appearing only seldom on edges in the data graph (Koschmieder and Leser, 2012). Rare labels are used to split the regular expression into subexpressions, which can be evaluated independently using a bidirectional BFS traversal. Finally, all partial solutions are combined into the final result set. Since *rare labels* are an optimization technique, they are orthogonal to our study of data structures for RPQ evaluation.

WAVEGUIDE (Yakovets et al., 2015) provides another technique to speedup RPQ processing by introducing *waveplans*, which allow changing the evaluation direction in each traversal step. WAVEGUIDE supports the materialization of intermediate results (subexpressions) through *views*, which can be reused in the query, e.g., a transitive closure over a path segment. Both techniques employed by WAVEGUIDE—match ordering and views—are orthogonal to the choice of data structures used for RPQ evaluation.

EmptyHeaded (Aberger et al., 2016) introduced an adaptive adjacency list handling density skew. The degree of a vertex can vary by a large margin, especially in social graphs which usually contain supernodes. The layout of the list of adjacent vertices is chosen according to the degree and picks either a simple array layout or a compact bitset layout.

6 CONCLUSION

We systematically investigated variants of the data structures involved in the evaluation of RPQs. Carefully crafted data structures specialized for their use in RPQ evaluation showed considerable runtime improvements and decreased memory consumption compared to general purpose data structures.

It is advisable to integrate the edge label information into the adjacency list as the RPQ evaluation accesses label information very frequently. In the form of bitpacked values, it leads to considerable runtime improvements and no increased memory consumption. Vertical partitioning of the adjacency list results in even better runtime performance, but requires also additional memory. Another specialization is grouping on common values in the intermediate re-

presentation, e.g., grouping on the state of the automaton reduces the memory consumption by half and results additionally in a small runtime improvement as less data must be written and read. Reallocation also avoids spikes in the memory consumption and therefore reduces peak memory consumption considerably.

In the future, we want to investigate how succinct data structures affect RPQ evaluation. They are expected to trade off evaluation time for a very compact representation, e.g., the K^2-Tree (Brisaboa et al., 2009), which is a compact adjacency representation. Another direction we would like to study is the use of bidirectional traversal instead of unidirectional DFS and BFS, especially how to detect that both directions meet each other and how it influences the choice of intermediate representations. Furthermore, omitting the check against VIS in some states of the automaton is an interesting algorithmic variation. Depending on the query and the data graph it can lead to reduced memory consumption as less data has to be stored in VIS, but also to multiple explorations of the same search states and therefore increased evaluation time.

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