

Evaluation of the Context-Free Path Querying Algorithm Based on Matrix Multiplication

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ABSTRACT

Recently proposed matrix multiplication based algorithm for context-free path querying (CFPQ) offloads the most performance-critical parts onto boolean matrices multiplication. Thus, it is possible to utilize modern parallel hardware and software to achieve high performance of CFPQ easily. In this work, we provide results of empirical performance comparison of different implementations of this algorithm on both real data and synthetic data for the worst cases.

CCS CONCEPTS

• **Information systems** → Query languages for non-relational engines; • **Theory of computation** → Grammars and context-free languages; *Parallel computing models*; • **Computing methodologies** → Massively parallel algorithms; • **Computer systems organization** → Single instruction, multiple data.

KEYWORDS

Context-free path querying, transitive closure, graph databases, context-free grammar, GPGPU, CUDA, boolean matrix, matrix multiplication

ACM Reference Format:

Nikita Mishin, Iaroslav Sokolov, Egor Spirin, Vladimir Kutuev, Egor Nemchinov, Sergey Gorbatyuk, and Semyon Grigorev. 2018. Evaluation of the Context-Free Path Querying Algorithm Based on Matrix Multiplication. In *Proceedings of GRADES-NDA 2019: the 2nd Joint International Workshop on Graph Data Management Experiences & Systems (GRADES) and Network Data Analytics (NDA) 2019 (GRADES-NDA 2019)*. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/1122445.1122456>

1 INTRODUCTION

Language-constrained path querying [6], and particularly Context-Free Path Querying (CFPQ) [15], allows one to use formal grammars

as constraints for path: concatenation of labels along the path is treated as a word, and constraint on the path is a specification of language which should contain specific words. CFPQ is widely used for graph-structured data analysis in such domains as biological data analysis, RDF, network analysis, and huge amount of the real-world data makes performance of CFPQ critical for practical tasks. Number of algorithms for CFPQ based on such parsing techniques as (G)LL, (G)LR, and CYK proposed recently [8, 10, 12–14, 16].

One of the most promising algorithms is a matrix-based algorithm, proposed by Rustam Azimov [5]. This algorithm offloads the most critical computations onto boolean matrices multiplication. As a result, it is easy to implement and allows one to utilize modern massive-parallel hardware for CFPQ. The implementation provided by authors utilizes GPGPU by using cuSPARSE¹ library which is a floating point sparse matrices multiplication library. Even it does not use advanced algorithms for boolean matrices, it outperforms existing algorithms.

It is necessary to investigate the effect of specific algorithms and implementation techniques on the performance of CFPQ. One of the problems is that there is no publically available standard dataset for CFPQ algorithms evaluation which includes both graph-structured data and queries.

In this work, we do an empirical performance comparison of different implementations of matrices multiplication based algorithm for CFPQ on both real data and synthetic data for the worst cases. We make the following contributions in this paper.

- (1) We provide a number of implementations of the matrix multiplication based CFPQ algorithm, which utilizes different modern software and hardware. Source code is available on GitHub: <https://github.com/SokolovYaroslav/fast-boolean-semiring-matrix-multiplication-for-CFPQ>
- (2) We present a dataset which contains both real data and syntactic data for worst cases. This dataset contains data and queries in the simple textual format, so it can be used for other algorithms evaluation easily. This dataset is published, and we hope that this dataset can form a base of the unified benchmark for CFPQ algorithms.

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GRADES-NDA 2019, June 30, 2019, Amsterdam, Netherlands

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ACM ISBN 978-1-4503-9999-9/18/06...\$15.00
<https://doi.org/10.1145/1122445.1122456>

¹cuSparse is a library for GPGPU utilization for sparse matrices multiplication. Official documentation: <https://docs.nvidia.com/cuda/cusparse/index.html>. Access date: 12.03.2019

- (3) We provide evaluation which shows that GPGPU utilization for CFPQ can significantly improve performance, and that there are many open questions in this area.

2 MATRIX-BASED ALGORITHM FOR CFPQ

Matrix-based algorithm for CFPQ was proposed by Rustam Azimov [5]. This algorithm can be expressed in terms of operations over matrices (see listing 1), and it is a sufficient advantage for implementation. It was shown that GPGPU utilization for queries evaluation can significantly improve performance in comparison to other implementations [5] even if float matrices are used instead of boolean matrices.

Listing 1 Context-free path quering algorithm

```

1: function CONTEXTFREEPATHQUERYING( $D, G$ )
2:    $n \leftarrow$  the number of nodes in  $D$ 
3:    $E \leftarrow$  the directed edge-relation from  $D$ 
4:    $P \leftarrow$  the set of production rules in  $G$ 
5:    $T \leftarrow$  the matrix  $n \times n$  in which each element is  $\emptyset$ 
6:   for all  $(i, x, j) \in E$  do ▷ Matrix initialization
7:      $T_{i,j} \leftarrow T_{i,j} \cup \{A \mid (A \rightarrow x) \in P\}$ 
8:   while matrix  $T$  is changing do
9:      $T \leftarrow T \cup (T \times T)$  ▷ Transitive closure calculation
10:  return  $T$ 

```

Here $D = (V, E)$ is the input graph and $G = (N, \Sigma, P)$ is the input grammar. Each cell of the matrix T contains the set of nonterminals such that $N_k \in T[i, j] \iff \exists p = v_i \dots v_j$ —path in D , such that $N_k \xRightarrow{*}_G \omega(p)$, where $\omega(p)$ is a word formed by labels along the path p . Thus, this algorithm solves reachability problem, or, according to Hellings [9], process CFPQs by using relational query semantics.

The performance-critical part of this algorithm is matrix multiplication. Note, that the set of nonterminals is finite, and we can represent the matrix T as a set of boolean matrices: one for each nonterminal. In this case the matrix update operation is $T_{N_i} \leftarrow T_{N_i} + (T_{N_j} \times T_{N_k})$ for each production $N_i \rightarrow N_j N_k$ in P . Thus we can reduce CFPQ to boolean matrices multiplication. After such transformation, we can apply the next optimization: we can skip update if the matrices T_{N_j} and T_{N_k} have not been changed at the previous iteration.

Thus, the most important part is the efficient implementation of operations over boolean matrices, and in this work we compare effects of utilization of different approaches to matrices multiplication. All our implemetations are based on the optimized version of the algorithm.

3 IMPLEMENTATION

We implement the matrix-based algorithm for CFPQ by using a number of different programming languages and tools. Our goal is to investigate the effects of the following features of an implementation.

- **GPGPU utilization.** It is well-known that GPGPUs are suitable for matrices operations, but the performance of the whole solution depends on the implementation details. For

example, overhead on data transferring may negate the effect of parallel computations. Can GPGPUs utilization for CFPQ improve performance in comparison with the CPU version?

- **Existing libraries utilization** is a good practice in software engineering. Is it possible to achieve higher performance by means of existing libraries for matrices operations or do we need to create our own solution to get more control?
- **Low-level programming.** GPGPU programming traditionally involves low-level programming in C-based languages (CUDA C, OpenCL C). But can we achieve high-performant solution with high-level languages such as Python?
- **Sparse matrices.** Real graphs are often sparse. Can we gain more performance improvement by using sparse matrix representation for CFPQ?

We provide the following implementations for investigation.

- **CPU-based solutions**
 - [**Scipy**] Sparse matrices multiplication by using Scipy [11] in Python programming language.
 - [**M4RI**] Dense matrices multiplication by using m4ri² [2] library which implements the Method of Four Russians [4] in C language. This library is choosen because it is one of performant implementations of the Method of Four Russians [3].
- **GPGPU-based solutions**
 - [**GPU4R**] Our own implementation of the Method of Four Russians in CUDA C.
 - [**GPU_N**] Our own implementation of the naïve boolean matrix multiplication in CUDA C with boolean values treated as bits and packed into uint₃₂.
 - [**GPU_Py**] Manual implementation of naïve boolean matrix multiplication in Python by using numba compiler³. Boolean values are packed into uint₃₂.

As far as a set of matrices and its size can be calculated at the start of computations, all GPGPU based implementations allocate all required memory on the GPGPU once, at the start of computations. This way, it is possible to significantly reduce overhead on data transferring: all input data loads to GPGPU at the start, and the result loads from GPGPU to the host at the end. As a result, there is no active data transferring and memory allocating during query computation.

4 DATASET DESCRIPTION

We created and published a dataset for CFPQ algorithms evaluation. This dataset contains both the real-world data and synthetic data for different specific cases, such as the theoretical worst case, or matrices representation specific worst cases.

Our goal is to evaluate querying algorithms, not graph storages or graph databases, so all data is presented in a text-based format to simplify usage in different environments. Grammars are in Chomsky Normal Form, and graphs are represented as a list of triples

²Actually we use pull request which is not merged yet: <https://bitbucket.org/malb/m4ri/pull-requests/9/extended-m4ri-to-multiplication-over-the/diff>. The original library implements operations over $GF(2)$, and this pull request contains operations over boolean semiring

³Numba is a JIT compiler which supports GPGPU for a subset of Python programming. Official page: <http://numba.pydata.org/>. Access date: 03.05.2019

(edges). Some details of the data representation can be found in Appendix.

It is known that variants of the *same generation query* [1] are an important example of queries that are context-free but not regular, so we use this type of queries in our evaluation. The dataset includes data for the following cases. Each case is a pair of set of graphs and a set of grammars: each query (grammar) should be applied to each graph.

[RDF] The set of real-world RDF files (ontologies) from [16] and two variants of the same generation query (figure 4 in appendix) which describes hierarchy analysis.

[Worst] Theoretical worst case for CFPQ time complexity which is proposed by Hellings [10]: the graph is two cycles of coprime lengths with a single common vertex. The first cycle is labeled by the open bracket and the second cycle is labeled by the close bracket. The example of such graph is presented in figure 2a in appendix. Query is a grammar for $A^n B^n$ language (grammar G_1 , figure 1 in appendix).

[Full] The case when the input graph is sparse, but the result is a full graph. Such a case may be hard for sparse matrices representation. As an input graph, we use a cycle, all edges of which are labeled by the same token. As a query we use two grammars which describe sequence of tokens of arbitrary length: simple ambiguous grammar G_2 and highly ambiguous grammar G_3 (figure 3 in appendix).

[Sparse] Sparse graphs from [7] generated by the GTgraph graph generator, and emulates realistic sparse data. Names of these graphs have a form G_n-p , where n represents the total number of vertices, probability that a pair of vertices is connected is p . The query is the same generation query represented by the grammar G_1 (figure 1 in appendix).

5 EVALUATION

We evaluate all described implementations on all data sets and queries presented. We compare our implementations with [5]. We exclude time required to load data from files. The time required for data transfer is included.

For evaluation, we use a PC with Ubuntu 18.04 installed. It has Intel core i7 8700k 3,7HGz CPU, Ddr4 32 Gb RAM, and Geforce 1080Ti GPGPU with 11Gb RAM.

Results of evaluation are summarized in the tables below. Time is measured in seconds. Result for each algorithm is an average time of 10 runs. Time is not presented if the time limit is exceeded, or if no memory enough to allocate the data necessary.

The results of the first dataset **[RDF]** are presented in a table 1. We can see, that in this case running time for all our implementations smaller than time for the reference implementation, and that **[GPU_N]** is faster than other implementations while other implementations demonstrate similar performance. Also, it is obvious that performance improvement in comparison with the first implementations is huge and it is necessary to extend dataset with new RDFs of the significantly biggest size.

Table 2: Worst case evaluation results

#V	Scipy	M4RI	GPU4R	GPU_N	GPU_Py	CuSprs
16	0.032	< 0.001	0.008	0.002	0.027	0.309
32	0.118	0.001	0.034	0.008	0.136	0.441
64	0.476	0.041	0.133	0.032	0.524	0.988
128	2.194	0.226	0.562	0.129	2.751	3.470
256	15.299	1.994	3.088	0.544	11.883	15.317
512	121.287	23.204	13.685	2.499	43.563	102.269
1024	1593.284	528.521	88.064	19.357	217.326	1122.055
2048	-	-	-	325.174	-	-

Results of the theoretical worst case (**[Worst]** dataset) is presented in table 2. This case is really hard to process: even for a graph of 1024 vertices, query evaluation time is greater than 10 seconds even for most performant implementation. Also, we can see, that time grows too fast with a number of vertices.

Table 3: Sparse graphs querying results

Graph	Scipy	M4RI	GPU4R	GPU_N	GPU_Py	CuSprs
G5k-0.001	10.352	0.647	0.113	0.041	0.216	5.729
G10k-0.001	37.286	2.395	0.435	0.215	1.331	35.937
G10k-0.01	97.607	1.455	0.273	0.138	0.763	47.525
G10k-0.1	601.182	1.050	0.223	0.114	0.859	395.393
G20k-0.001	150.774	11.025	1.842	1.274	6.180	-
G40k-0.001	-	97.841	11.663	8.393	37.821	-
G80k-0.001	-	1142.959	88.366	65.886	-	-

The next is a **[Sparse]** dataset presented in table 3. The evaluation shows that sparsity of graphs (value of parameter p) is important both for implementations which use sparse matrices and for implementations which use dense matrices. Note that the behavior of sparse matrices based implementation is as expected, but for dense matrices we can see, that more sparse graphs processed faster. Reasons of such behaviour demand further investigation. Note that we estimate only query execution time, so it is hard to compare our results with the results presented in [7]. But it would be interesting to do such a comparison in the future because the running time of our **[GPU_N]** implementation is significantly smaller than the provided in [7].

The last dataset is a **[Full]**, and results are shown in table 4

As we expect, this case is very hard for sparse matrices based implementations: running time grows too fast. Also, we can see, that the grammar size is important. Both queries specify the same restriction, but grammar G_3 in CNF contains 2 times more rules than grammar G_2 , and as a result, the running time for big graphs differs more than 2 times.

Finally, we can conclude that GPGPU utilization for CFPQ can significantly improve performance, but more research on advanced optimization techniques should be done. On the other hand, high-level implementation (**[GPU_Py]**) is comparable with other GPGPU-based implementations. So, it may be balance between implementation complexity and performance. Highly optimized existing libraries can be useful: implementation based on m4ri is faster than reference implementation and other CPU-based implementation.

Table 1: RDFs querying results

RDF			Query G ₄						Query G ₅					
Name	#V	#E	Scipy	M4RI	GPU4R	GPU_N	GPU_Py	CuSprs	Scipy	M4RI	GPU4R	GPU_N	GPU_Py	CuSprs
atom-primitive	291	685	0.003	0.002	0.002	0.001	0.005	0.269	0.001	< 0.001	0.001	< 0.001	0.002	0.267
biomed.-measure-primitive	341	711	0.003	0.005	0.002	0.001	0.005	0.283	0.004	< 0.001	0.001	< 0.001	0.005	0.280
foaf	256	815	0.002	0.009	0.002	< 0.001	0.005	0.270	0.001	< 0.001	0.001	< 0.001	0.002	0.263
funding	778	1480	0.004	0.007	0.004	0.001	0.005	0.279	0.002	< 0.001	0.003	< 0.001	0.004	0.274
generations	129	351	0.003	0.003	0.002	< 0.001	0.005	0.273	0.001	< 0.001	0.001	< 0.001	0.002	0.263
people_pets	337	834	0.003	0.003	0.003	0.001	0.007	0.284	0.001	< 0.001	0.001	< 0.001	0.003	0.277
pizza	671	2604	0.006	0.008	0.003	0.001	0.006	0.292	0.002	< 0.001	0.002	< 0.001	0.005	0.278
skos	144	323	0.002	0.004	0.002	< 0.001	0.005	0.273	< 0.001	< 0.001	0.001	< 0.001	0.002	0.265
travel	131	397	0.003	0.005	0.002	< 0.001	0.006	0.268	0.001	< 0.001	0.001	< 0.001	0.003	0.271
univ-bench	179	413	0.002	0.004	0.002	< 0.001	0.005	0.266	0.001	< 0.001	0.001	< 0.001	0.003	0.266
wine	733	2450	0.007	0.006	0.004	0.001	0.007	0.294	0.001	< 0.001	0.003	< 0.001	0.003	0.281

Table 4: Full querying results

#V	Query G ₂						Query G ₃					
	Scipy	M4RI	GPU4R	GPU_N	GPU_Py	CuSprs	Scipy	M4RI	GPU4R	GPU_N	GPU_Py	CuSprs
100	0.007	0.002	0.002	< 0.001	0.003	0.278	0.023	0.076	0.005	0.001	0.007	0.290
200	0.040	0.003	0.002	0.001	0.004	0.279	0.105	0.098	0.004	0.001	0.007	0.296
500	0.480	0.003	0.003	0.001	0.004	0.329	1.636	0.094	0.007	0.001	0.010	0.382
1000	3.741	0.007	0.005	0.001	0.006	0.571	13.071	0.106	0.009	0.001	0.009	0.839
2000	40.309	0.063	0.019	0.003	0.017	1.949	93.676	0.108	0.030	0.005	0.026	3.740
5000	651.343	0.366	0.125	0.038	0.150	99.651	1205.421	0.851	0.195	0.075	0.239	201.151
10000	-	1.932	0.552	0.315	0.840	1029.042	-	4.690	1.055	0.648	1.838	-
25000	-	33.236	7.252	5.314	15.521	-	-	70.823	15.240	10.961	36.495	-
50000	-	360.035	58.751	44.611	129.641	-	-	775.765	130.203	91.579	226.834	-
80000	-	1292.817	256.579	190.343	641.260	-	-	-	531.694	376.691	-	-

Moreover, it is comparable with some GPGPU-based implementations in some cases. Sparse matrices utilization should be investigated more. The main question is if we can create an efficient implementation for sparse boolean matrices multiplication.

6 CONCLUSION AND FUTURE WORK

We provide a number of implementations of the matrix-based algorithm for context-free path querying, collect a dataset for evaluation and provide results of evaluation of our implementation on the collected dataset. Our evaluation shows that GPGPU utilization for boolean matrices multiplication can significantly increase the performance of CFPQs evaluation, but requires more research on implementation details.

The first direction for future research is a more detailed CFPQ algorithms investigation. We should do more evaluation on sparse matrices on GPGPUs and investigate technics for high-performance GPGPU code creation. Also, it is necessary to implement and evaluate solutions for graphs which do not fit in RAM, and for big queries which disallow to allocate all required matrices on single

GPGPU. We hope that it is possible to utilize existing technics for huge matrices multiplication for this problem.

Another direction is dataset improvement. First of all, it is necessary to collect more data, and more grammars/queries. Especially it would be important to add to the dataset more real-world graphs and more real-world queries. Secondly, it is necessary to discuss and fix the data format to be able to evaluate different algorithms. We believe that it is necessary to create a public dataset for CFPQ algorithms evaluation, and collaboration with the community is required.

ACKNOWLEDGMENTS

The research was supported by the Russian Science Foundation grant 18-11-00100 and a grant from JetBrains Research.

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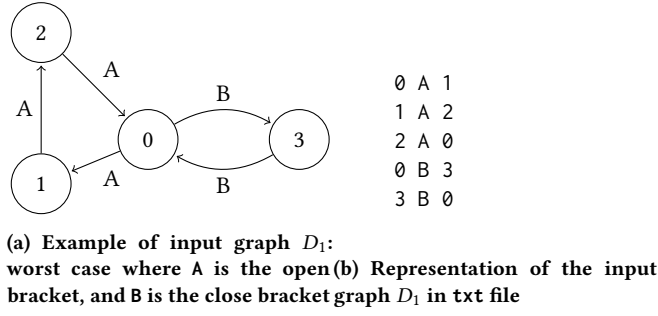


Figure 2: Example of graph representation in txt file

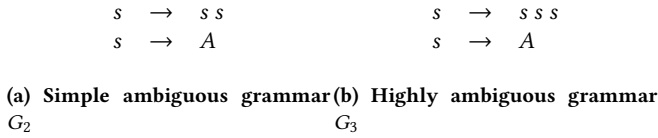


Figure 3: Queries for the [Full] dataset

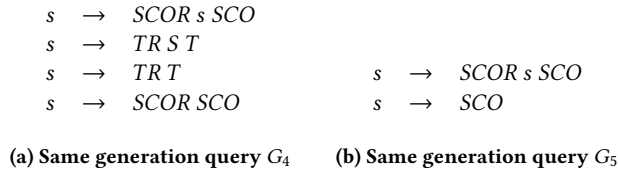


Figure 4: Queries for the [RDF] dataset

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A DETAILS OF DATASET DESCRIPTION

Here we present details on collected dataset. Grammars (queries) are stored in the files with yrd extension. Each line is a rule in the form of a triple or a pair. The example of grammar representation is presented in figure 1.

Graphs and are stored in the files with txt extension. Example of graph is presented in figure 2.

Cases for evaluation are placed in folders with the case-specific name. Grammars and graph are placed in subfolders with names Grammars and Matrices respectively.

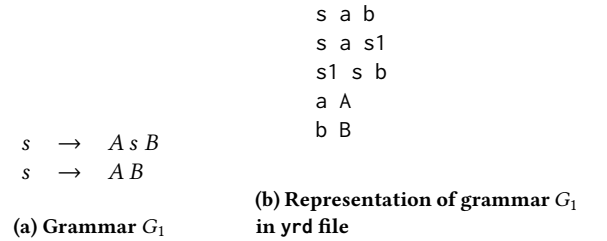


Figure 1: Example of grammar representation in the yrd file

Queries which we use for evaluation presented in figures ??.