

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 achieve high performance of CFPQ by means of modern parallel hardware and software. In this paper, we provide results of empirical performance comparison of different implementations of this algorithm on both real-world 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:

—, —, —, —, —, —, and —. 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 paths: concatenation of the labels along the path

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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>

is treated as a word, and a constraint on the path is a specification of the 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. Huge amount of the real-world data makes performance of CFPQ critical for practical tasks. Several algorithms for CFPQ based on such parsing techniques as (G)LL, (G)LR, and CYK are 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 the authors utilizes GPGPU by using cuSPARSE¹ library which is a floating point sparse matrices multiplication library. Although it does not use advanced algorithms for boolean matrices, it outperforms existing algorithms.

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

In this work, we do an empirical performance comparison of several implementations of matrices multiplication based algorithm for CFPQ on both real-world 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. The source code is available on GitHub: link to the repository is hidden for anonymization purposes
- (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 easily used to evaluate other algorithms. The dataset is available on GitHub via the same link, and we hope that this dataset can form a base of the unified benchmark for CFPQ algorithms.
- (3) We provide evaluation which shows that GPGPU utilization for CFPQ can significantly improve performance, and that there are still many open questions in this area.

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

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 the utilization of GPGPU improves the context-free path querying performance significantly in comparison to other implementations [5] even if float matrices are used instead of boolean matrices.

Listing 1 Context-free path querying 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 the labels along the path p . Thus, this algorithm solves reachability problem, or, according to Hellings [9], processes CFPQs by using relational query semantics.

The performance-critical part of the 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 operation of matrix update is $T_{N_j} \leftarrow T_{N_j} + (T_{N_i} \times T_{N_k})$ 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. In this paper, we compare the effects of different approaches to matrices multiplication. All our implementations are based on the optimized version of the algorithm.

3 IMPLEMENTATION

We implement the matrix-based algorithm for CFPQ by using several different programming languages and tools. We aim 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 a high-performance 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 chosen because it is a performant implementation 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 the GPGPU based implementations allocate all required memory on the GPGPU once, at the start of computations. This significantly reduces the overhead on data transferring: all input data is loaded to the GPGPU at the start, and the result is loaded from the 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 the worst cases specific to matrices representations.

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

The 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

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

for the following cases. Each case is a pair of a set of graphs and a set of grammars: each query (grammar) should be applied to each graph.

[RDF] The set of the real-world RDF files (ontologies) from [16] and two variants of the same generation query which describes hierarchy analysis. The first query is the grammar G_4 :

$$\begin{aligned} s &\rightarrow SCOR\ s\ SCO & s &\rightarrow TR\ s\ T \\ s &\rightarrow SCOR\ SCO & s &\rightarrow TR\ T \end{aligned}$$

The second one is the grammar G_5 : $s \rightarrow SCOR\ s\ SCO \mid SCO$.

[Worst] The theoretical worst case for CFPQ time complexity 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. Query is a grammar for the $A^n B^n$ language. The example of such graph and grammar is presented in figure 1.

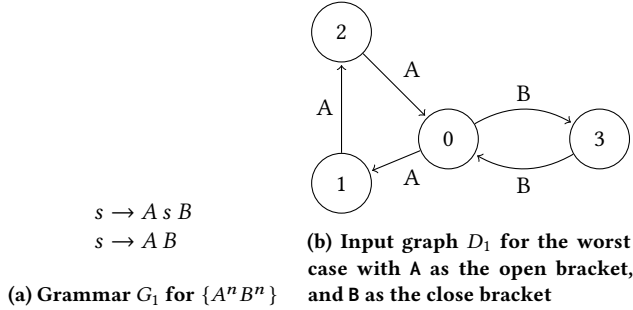


Figure 1: Graph and grammar for the worst case

[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 representations. 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 the sequence of tokens of arbitrary length: the simple ambiguous grammar G_2 : $s \rightarrow s\ s \mid A$, and the highly ambiguous grammar G_3 : $s \rightarrow s\ s\ s \mid A$.

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

5 EVALUATION

We evaluate all the described implementations on all the datasets and the queries presented. We compare our implementations with [5]. We exclude the 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.

The results of evaluation are summarized in the tables below. Time is measured in seconds unless specified otherwise. The result for each algorithm is averaged over 10 runs. The cell is left blank

if the time limit is exceeded, or if there is not enough memory to allocate the data.

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

Table 2: Evaluation results for the worst case

| #V | Scipy | M4RI | GPU4R | GPU_N | GPU_Py | CuSprs |
|------|----------|---------|--------|---------|---------|----------|
| 16 | 0.032 | < 1 | 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) are presented in table 2. This case is really hard to process: even for a graph of 1024 vertices, the query evaluation time is greater than 10 seconds even for the most performant implementation. We can see, that the running time grows too fast with the 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 the **[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 the sparse matrices based implementation is as expected, but for dense matrices we can see, that more sparse graphs are processed faster. Reasons for such behaviour demand further investigation. Note that we estimate only the query execution time, so it is hard to compare our results with the results presented in [7]. Nevertheless the running time of our **[GPU_N]** implementation is significantly smaller than the one provided in [7].

The last dataset is **[Full]**, and results are shown in table 4. As we expect, this case is very hard for sparse matrices based implementations: the running time grows too fast. This dataset also demonstrates the impact of the grammar size. Both queries specify the same constraints, but the grammar G_3 in CNF contains 2

Table 1: RDFs querying results (time in milliseconds)

| 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 |
| atm-prim | 291 | 685 | 3 | 2 | 2 | 1 | 5 | 269 | 1 | < 1 | 1 | < 1 | 2 | 267 |
| biomed | 341 | 711 | 3 | 5 | 2 | 1 | 5 | 283 | 4 | < 1 | 1 | < 1 | 5 | 280 |
| foaf | 256 | 815 | 2 | 9 | 2 | < 1 | 5 | 270 | 1 | < 1 | 1 | < 1 | 2 | 263 |
| funding | 778 | 1480 | 4 | 7 | 4 | 1 | 5 | 279 | 2 | < 1 | 3 | < 1 | 4 | 274 |
| generations | 129 | 351 | 3 | 3 | 2 | < 1 | 5 | 273 | 1 | < 1 | 1 | < 1 | 2 | 263 |
| people_pets | 337 | 834 | 3 | 3 | 3 | 1 | 7 | 284 | 1 | < 1 | 1 | < 1 | 3 | 277 |
| pizza | 671 | 2604 | 6 | 8 | 3 | 1 | 6 | 292 | 2 | < 1 | 2 | < 1 | 5 | 278 |
| skos | 144 | 323 | 2 | 4 | 2 | < 1 | 5 | 273 | < 1 | < 1 | 1 | < 1 | 2 | 265 |
| travel | 131 | 397 | 3 | 5 | 2 | < 1 | 6 | 268 | 1 | < 1 | 1 | < 1 | 3 | 271 |
| unv-bnch | 179 | 413 | 2 | 4 | 2 | < 1 | 5 | 266 | 1 | < 1 | 1 | < 1 | 3 | 266 |
| wine | 733 | 2450 | 7 | 6 | 4 | 1 | 7 | 294 | 1 | < 1 | 3 | < 1 | 3 | 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 | < 1 | 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 | - | - |

times more rules than the grammar G_2 , so, the running time for big graphs differs by more than twice.

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, the high-level implementation ([GPU_Py]) is comparable with other GPGPU-based implementations. So, it may be a balance between implementation complexity and performance. Highly optimized existing libraries can be of some use: the implementation based on m4ri is faster than the reference implementation and the other CPU-based implementation. Moreover, it is comparable with some GPGPU-based implementations in some cases. Sparse matrices utilization demands more thorough investigation. 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 of implementation details.

The first direction for future research is a more detailed investigation of the CFPQ algorithms. We should do more evaluation on sparse matrices on GPGPUs and investigate techniques 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 a single GPGPU. We hope that it is possible to utilize existing techniques for huge matrices multiplication for this problem.

Another direction is the dataset improvement. First of all, it is necessary to collect more data, and more grammars/queries. It is of most importance to add more real-world graphs and more real-world queries to the dataset. 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.

REFERENCES

- [1] Serge Abiteboul, Richard Hull, and Victor Vianu. 1995. Foundations of Databases.
- [2] Martin Albrecht and Gregory Bard. 2019. *The M4RI Library*. The M4RI Team. <https://bitbucket.org/malb/m4ri>
- [3] MR Albrecht, GV Bard, and W Hart. 2008. Efficient multiplication of dense matrices over GF (2). *arXiv preprint arXiv:0811.1714* (2008).
- [4] Vladimir L'vovich Arlazarov, Yefim A Dinitz, MA Kronrod, and IgorAleksandrovich Faradzhev. 1970. On economical construction of the transitive closure of an oriented graph. In *Doklady Akademii Nauk*, Vol. 194. Russian Academy of Sciences, 487–488.
- [5] Rustam Azimov and Semyon Grigorev. 2018. Context-free Path Querying by Matrix Multiplication. In *Proceedings of the 1st ACM SIGMOD Joint International Workshop on Graph Data Management Experiences & Systems (GRADES) and Network Data Analytics (NDA) (GRADES-NDA '18)*. ACM, New York, NY, USA, Article 5, 10 pages. <https://doi.org/10.1145/3210259.3210264>
- [6] Chris Barrett, Riko Jacob, and Madhav Marathe. 2000. Formal-language-constrained path problems. *SIAM J. Comput.* 30, 3 (2000), 809–837.
- [7] Zhiwei Fan, Jianqiao Zhu, Zuyu Zhang, Aws Albarghouthi, Paraschos Koutiris, and Jignesh Patel. 2018. Scaling-Up In-Memory Datalog Processing: Observations and Techniques. *arXiv preprint arXiv:1812.03975* (2018).
- [8] Semyon Grigorev and Anastasiya Ragozina. 2017. Context-free Path Querying with Structural Representation of Result. In *Proceedings of the 13th Central & Eastern European Software Engineering Conference in Russia (CEE-SECR '17)*. ACM, New York, NY, USA, Article 10, 7 pages. <https://doi.org/10.1145/3166094.3166104>
- [9] Jelle Hellings. 2014. Conjunctive context-free path queries. In *Proceedings of ICDT'14*. 119–130.
- [10] Jelle Hellings. 2015. Querying for Paths in Graphs using Context-Free Path Queries. *arXiv preprint arXiv:1502.02242* (2015).
- [11] Eric Jones, Travis Oliphant, Pearu Peterson, et al. 2001–2019. SciPy: Open source scientific tools for Python. <http://www.scipy.org/> [Online; accessed 5.3.2019].
- [12] Ciro M. Medeiros, Martin A. Musicante, and Umberto S. Costa. 2018. Efficient Evaluation of Context-free Path Queries for Graph Databases. In *Proceedings of the 33rd Annual ACM Symposium on Applied Computing (SAC '18)*. ACM, New York, NY, USA, 1230–1237. <https://doi.org/10.1145/3167132.3167265>
- [13] Fred C. Santos, Umberto S. Costa, and Martin A. Musicante. 2018. A Bottom-Up Algorithm for Answering Context-Free Path Queries in Graph Databases. In *Web Engineering*, Tommi Mikkonen, Ralf Klamma, and Juan Hernández (Eds.). Springer International Publishing, Cham, 225–233.
- [14] Ekaterina Verbitskaia, Ilya Kirillov, Ilya Nozkin, and Semyon Grigorev. 2018. Parser Combinators for Context-free Path Querying. In *Proceedings of the 9th ACM SIGPLAN International Symposium on Scala (Scala 2018)*. ACM, New York, NY, USA, 13–23. <https://doi.org/10.1145/3241653.3241655>
- [15] Mihalis Yannakakis. 1990. Graph-theoretic methods in database theory. In *Proceedings of the ninth ACM SIGACT-SIGMOD-SIGART symposium on Principles of database systems*. ACM, 230–242.
- [16] X. Zhang, Z. Feng, X. Wang, G. Rao, and W. Wu. 2016. Context-free path queries on RDF graphs. In *International Semantic Web Conference*. Springer, 632–648.

A DETAILS OF DATASET DESCRIPTION

Here we present some details on the collected dataset. Grammars (queries) are stored in the files with the yrd extension. Each line is a rule in the form of a triple or a pair. Graphs are stored in the files with the txt extension. Example of the graph is presented in figure 2.

Cases for evaluation can be found in folders with the case-specific name. Grammars and graphs are in subfolders with the names Grammars and Matrices respectively.

| | |
|--------|-------|
| s a b | 0 A 1 |
| s a s1 | 1 A 2 |
| s1 s b | 2 A 0 |
| a A | 0 B 3 |
| b B | 3 B 0 |

(a) Grammar G_1 in yrd file (b) Input graph D_1 in txt file

Figure 2: Graph and grammar representation in the dataset