



Problem Statement

Memory traffic is a bottleneck of GPGPU programs. There are cases of data analysis when some of kernel parameters are fixed during many kernel runs.

- Patterns in substring matching
- HMM in homology search
- Query in graph database quying

Known parameters are still increase memory traffic. **Can we automatically optimize procedire when parameters are partially known?**

Results

- It is possible to optimize procedures with partially known parameters by using **partial evaluation** [1]
 - Optimized procedure for substring matching is up to 2 times faster
 - !!!

Future Research

- Switch to CUDA C partial evaluator.
 - LLVM.mix: partial evaluator for LLVM IR.
- Reduce specialization overhead to make it applicable in run-time.
- Integrete with shared memory register spilling [2].
- Evaluate on real-world examples.
 - Homology search in bioinformatics.
 - Graph processing.

Example

Parameters of filter are fixed during one data processing session which may contains many procedure runs.

```
__global__ void handleData
(int* filterParams, int* data, ...)
{
    __shared__ int cachedFilterParams[size];

    /*some code to load filterParams
    to cachedFilterParams*/
    ...
}
```

In real-world cases we have a huge number of data chunks. Thus we have multiple procedure runs.

Filter params are read only and common for all threads, so we usually copy it into shared memory to reduce memory traffic. In some cases this data can be placed in the constant memory

Partial Evaluation [1]

$$\underbrace{\llbracket handleData \rrbracket}_{handleData}[\underbrace{filterParams, data}_{\text{partial evaluator}}] = \underbrace{\llbracket mix \rrbracket}_{handleData_{mix}}[\llbracket handleData, filterParams \rrbracket][data]$$

$$\llbracket mix \rrbracket[\llbracket handleData, [[2; 3]] \rrbracket]$$

handleData (filterParams, data)

handleData (data)

```
{
    res = new List()
    for d in data
        for e in filterParams
            if d % e == 0
                then res.Add(d)
    return res
}
```

```
{
    res = new List()
    for d in data
        if d % 2 == 0 ||
           d % 3 == 0
            then res.Add(d)
    return res
}
```

We Need More Real-World Data

Graph: classical ontologies (RDFs)
Query: same-generation query over type and SubClassOf relations
Grammar: $S \rightarrow scor\ S\ sco \mid tr\ S\ t \mid scor\ sco \mid tr\ t$

RDF			Algorithms				
Name	#V	#E	Scipy	M4RI	GPU	CuSprs	CYK
atm-prim	291	685	3 ms	2 ms	1 ms	269 ms	8.5 min
biomed	341	711	3 ms	5 ms	1 ms	283 ms	7.1 min
pizza	671	2604	6 ms	8 ms	1 ms	292 ms	54 min
wine	733	2450	7 ms	6 ms	1 ms	294 ms	68 min

- 2019 (GPU) is 10^6 times faster than 2016 (CYK) on real-world data
 - Reasonable time even for CPU based implementations
- We should find bigger RDFs
- We should find other real-world cases for CFPQ
 - Both graphs and queries

We Should Do More Research on the Algorithms Scaling

	Graph	Scipy	M4RI	GPU	CuSprs
Sparse graphs are generated by GTgraph Query: $S \rightarrow a\ S\ b \mid a\ b$	G10k-0.001	37 s	2 s	0.2 s	35 s
	G10k-0.1	601 s	1 s	0.1 s	395 s
	G40k-0.001	-	97 s	8.1 s	-
	G80k-0.001	-	1142 s	65 s	-
Graph is a cycle Query: $S \rightarrow S\ S \mid a$	G25k	-	33 s	5 s	-
	G50k	-	360 s	44 s	-
	G80k	-	1292 s	190 s	-

- We can handle graphs with 80k vertices in a reasonable time by using GPGPU
 - Technical bound: GPGPU RAM does not fit bigger graphs
- We should evaluate multi-GPU systems
- We should evaluate distributed solutions
- We should implement a sparse boolean matrices library for GPGPU

Contact Us

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Both dataset and implementations are available on GitHub:

<https://github.com/SokolovYaroslav/CFPQ-on-GPGPU>

References

[1] Neil D. Jones, Carsten K. Gomard, and Peter Sestoft. *Partial Evaluation and Automatic Program Generation*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1993.

[2] Putt Sakdhnagool, Amit Sabne, and Rudolf Eigenmann. Regdem: Increasing GPU performance via shared memory register spilling. *CoRR*, abs/1907.02894, 2019.

[3] Roland Leissa, Klaas Boesche, Sebastian Hack, Arsène Pérard-Gayot, Richard Membarth, Philipp Slusallek, André Müller, and Bertil Schmidt. Anydsl: A partial evaluation framework for programming high-performance libraries. *Proc. ACM Program. Lang.*, 2(OOPSLA):119:1–119:30, October 2018.

Acknowledgments

The research is supported by the JetBrains Research grant and the Russian Science Foundation grant 18-11-00100