Mix-and-Match: A Model-driven Runtime Optimisation Strategy for BFS on GPUs

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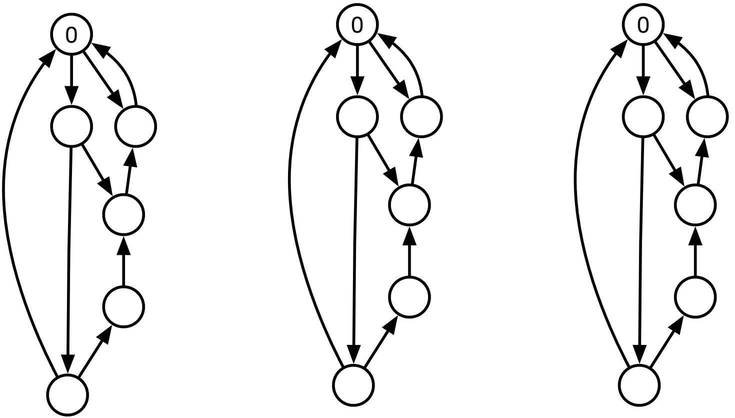
November 12, 2018

Breadth-First Search: Implementations

Edge-centric | **Vertex Push** | **Vertex Pull**



Useful Frontier Thread

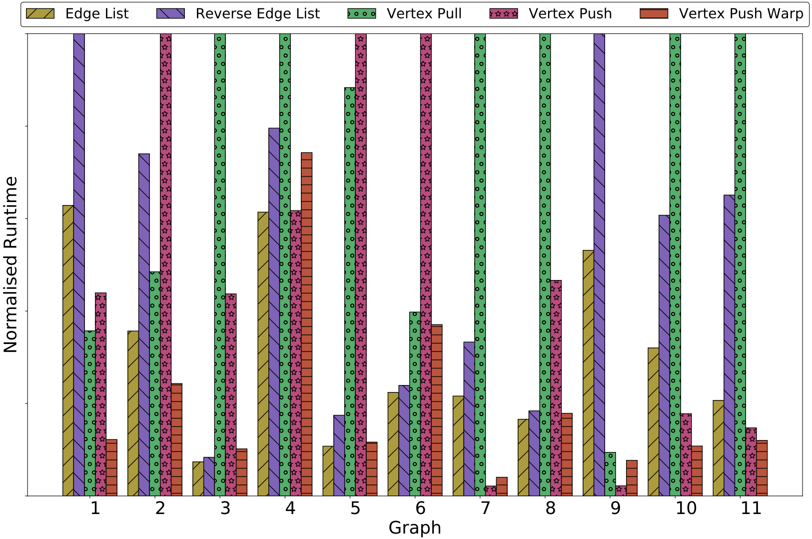
Useless Frontier Thread

Frontier Node

Updated Node

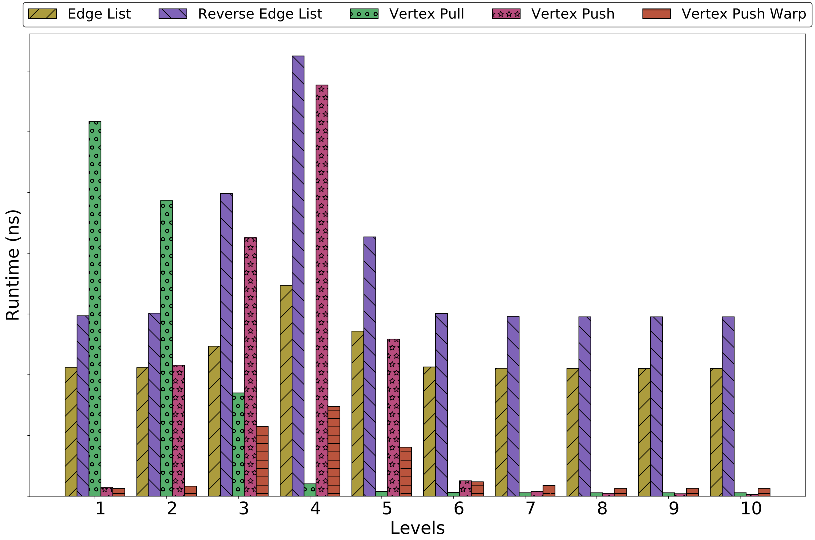
Accessed Node

Relative Performance of Implementations



There is no “best”!

Relative Performance Within a Single Traversal



Sticking to one implementation costs us!

Let's Choose an Algorithm!

Choosing the best algorithm:

- Depends on algorithm + platform + graph
- Predict "best" implementation each level

Challenge?

How to model the algorithm + graph + platform

Is it worth it? It depends on...

- ...gain
- ...prediction cost
- ...data representation for implementations

Modelling the Problem

Analytical model:

1. Build a parametrised work model of the algorithm
2. Use graph properties as parameters
3. Calibrate using hardware microbenchmarking

Result: Prediction accuracy below 50%...

What's going wrong?

Intuition vs Results

Intuition & experience say this should work.

Results say it doesn't! But why?

Problem: Sequential workload $\rightarrow$ Parallel GPU execution

But: Best implementation stable over several GPU generations

What now?

Machine Learning: Decision Trees

Training Parameters:

- Degree distribution
- Frontier size
- Percentage discovered
- Vertex count
- Edge count

Pros:

- Black-box approach
- Fast! (Training & prediction)
- **Variable importance!**

Cons:

- Can overfit on non-uniform parameters
- Bad with large numbers of parameters

Two Questions

Do the models actually work?

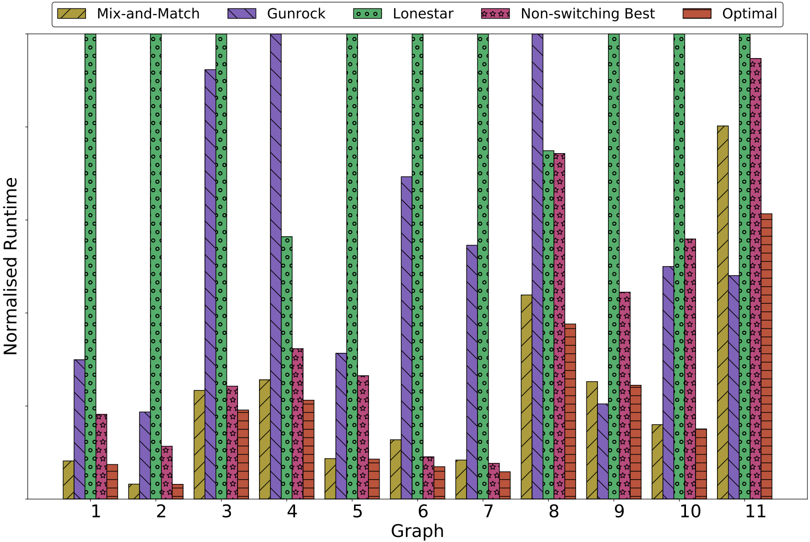
Do the models match our intuitions?

Feasibility:

Average Prediction Time:	144 ns ($\sigma = 165$ ns)
Mininum BFS Step:	20 ms
(Re)loading graph representation:	Stupidly slow

Classic time-space trade-off.

Comparison with State-of-the-Art: Best & Worst



Even better if we include Gunrock in model?

Overall Results

Algorithm	1–2×	>5×	>20×	Average	Worst
Mix-and-Match	92%	2.5%	0.4%	2.04×	498×
Non-switching Best	65%	8%	0%	2.44×	37×
Edge List	49%	22%	2.2%	4.16×	61×
Rev. Edge List	39%	33%	8.8%	7.04×	108×
Vertex Pull	16%	58%	30%	48.41×	2,495×
Vertex Push	23%	53%	28%	55.61×	1,980×
Vertex Push Warp	18%	25%	4.9%	5.42×	88×

Averaged over 248 KONECT graphs.

Model & Intuition

Parameter importance matches intuition

Investigating "poor" predictions reveals new insights

Not investigated (yet):

- Handle implementations with similar results
- Minimising training data
- Model portability across datasets, hardware & algorithm
- Relating BDTs to analytical model

Summary

The Good:

- Prediction works!
- Predictions are fast enough at runtime
- Our Mix-and-Match outperforms state-of-the-art (on average)
- Models provide new insights

The Bad:

- Training set to big
- Training set non-uniformity

Takeaway

No single best implementation for irregular GPU algorithms

Large potential performance gains for graph algorithms

Mix-and-Match is a generalisation of direction-optimised BFS

Significant performance improvement for many graphs

Method applicable to any BSP graph algorithm

Will revisit analytical models using decision tree models

Questions?