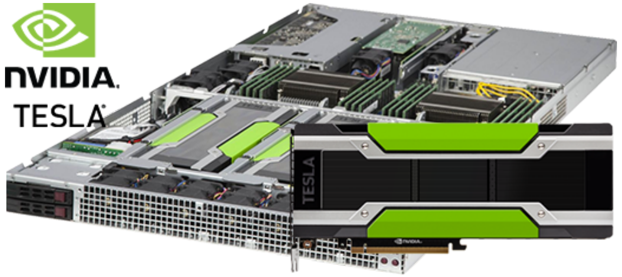
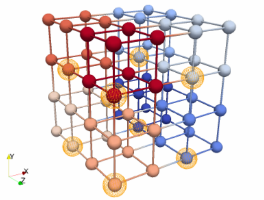
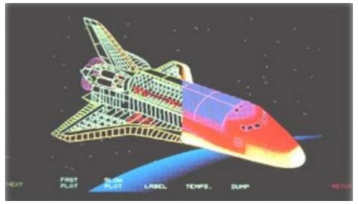
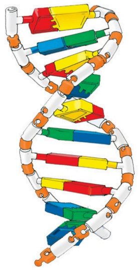
GPGPU in HPC



GPGPU



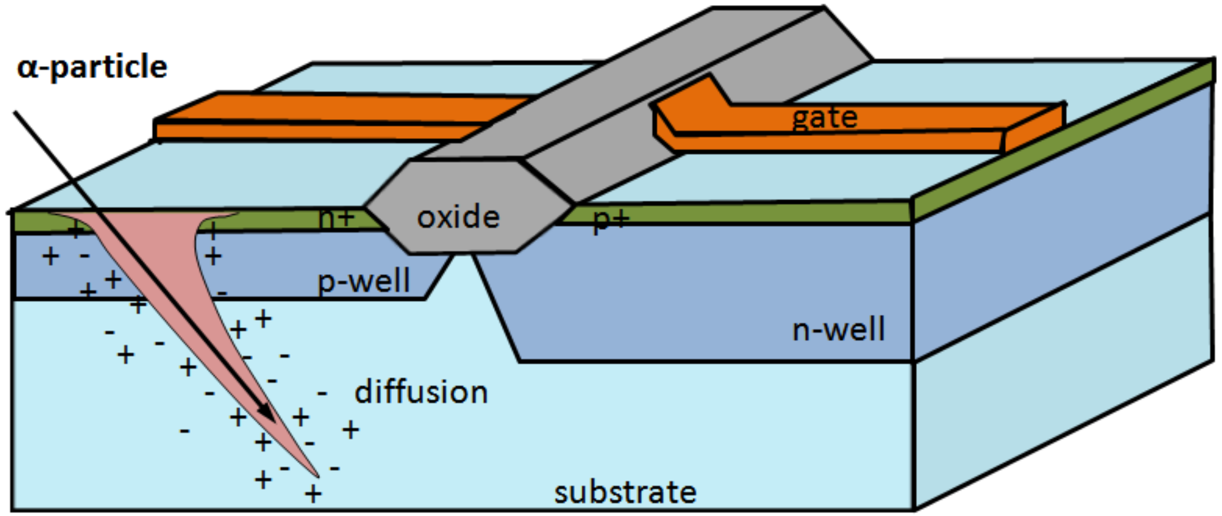


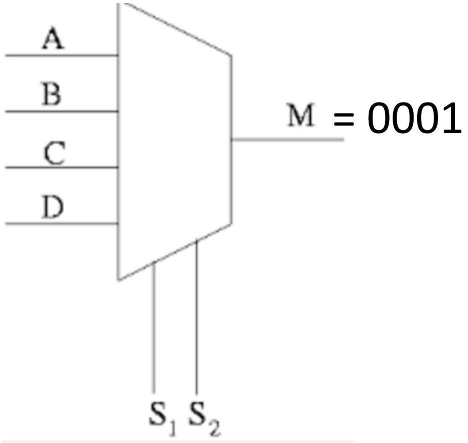


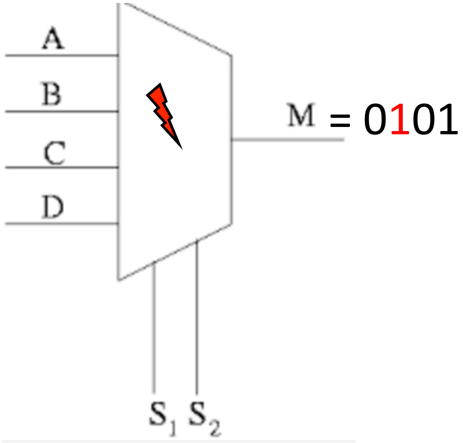
Scientific Applications

Soft Errors

Bauman et al. [TDMR, 2005]







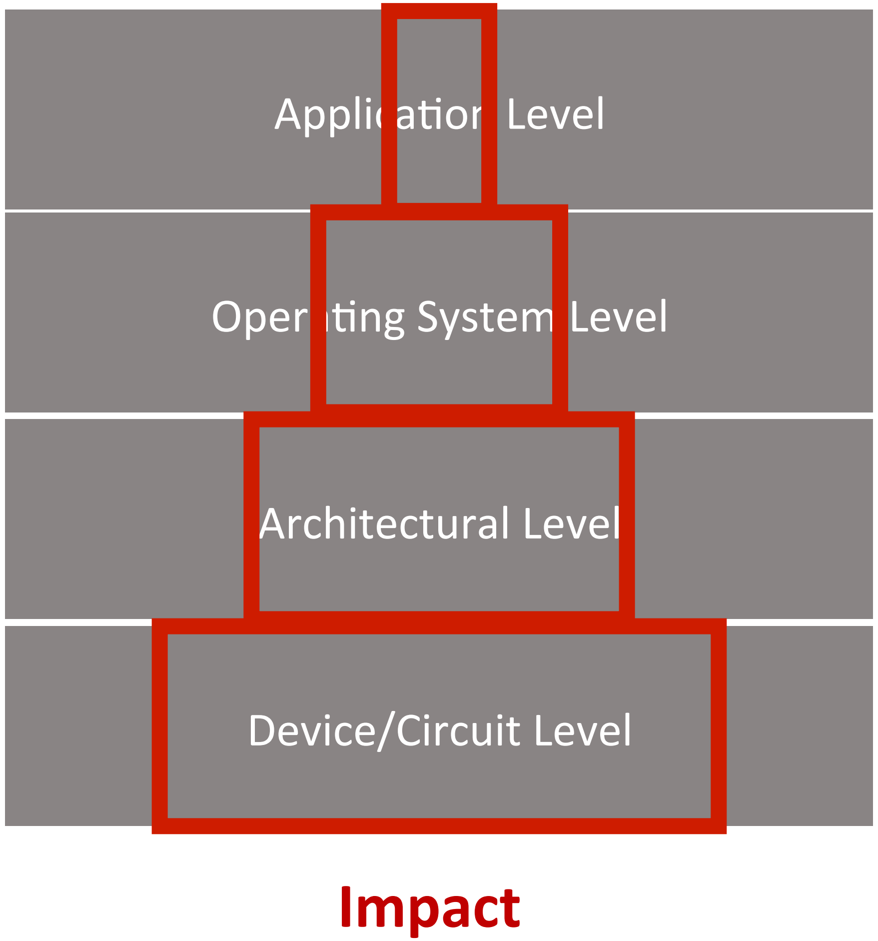
Traditional Method: DMR

Dual Modular Redundancy (DMR)

- Run 2 copies
- Compare for divergence

Too much energy consumption!

Software Solutions



Advantages

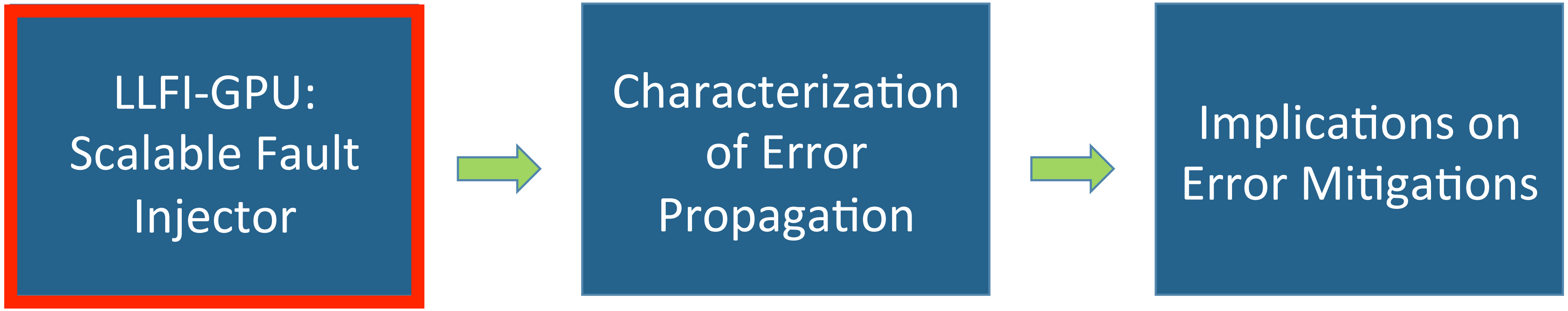
- No hardware modification
- Errors can be masked
- Allow selective protection

Challenges for GPGPU Resilience

- Different architecture and programming model from CPUs

- No scalable fault injection tools for HPC GPGPU applications

Our Contributions



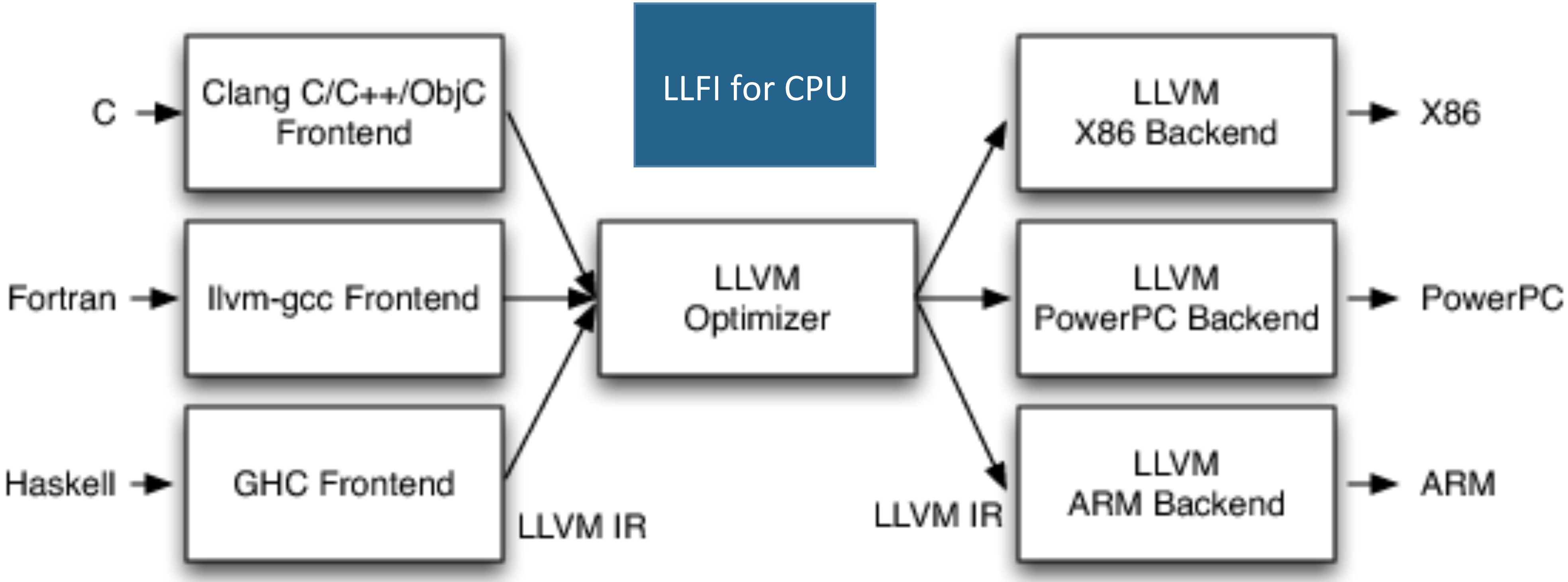
Existing Publicly Available GPU Fault Injectors

- Hauberk [IPDPS, 2011]
  - Source code level fault injection
  - Not representative for hardware errors
- GPU-Qin [ISPASS, 2014]
  - Debugger-based
  - Execution is slow
- GPGPU-Sim based fault injector [DSN, 2015]
  - Not full system simulation

Goals of LLFI-GPU

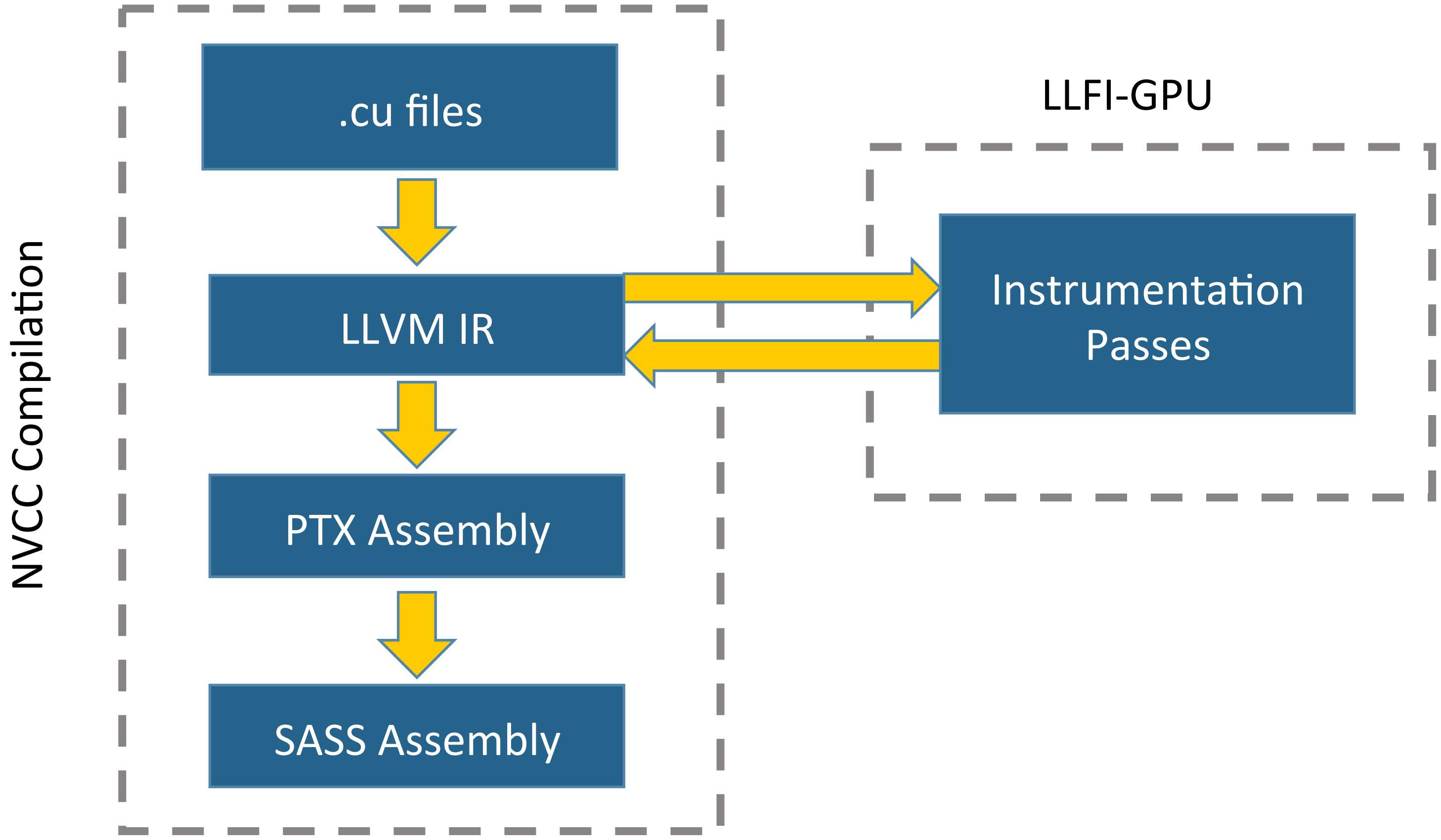
- **Native Speed**
  - Program-level fault injection
  - Compile to binary
- **Full system simulation**
  - Execute on real hardware
  - Able to simulate different failure outcomes
- **Representativeness**
  - LLVM IR level fault injection
  - Close to assembly, yet preserve high-level program symbols

LLVM (Low Level Virtual Machine)



LLFI for CPU: https://github.com/DependableSystemsLab/LLFI

LLFI-GPU: Overview



...

R0 = add R1, R2

R0 = injectFault(R0)

R4 = mul R0, R3

...

Advantages of LLFI-GPU

- Compile on large GPGPU programs
  - 1000x faster compared to GPU-Qin (MatrixMul)
- Represented simulation
  - Full system simulation of soft errors
- Open-source
  - https://github.com/DependableSystemsLab/LLFI-GPU

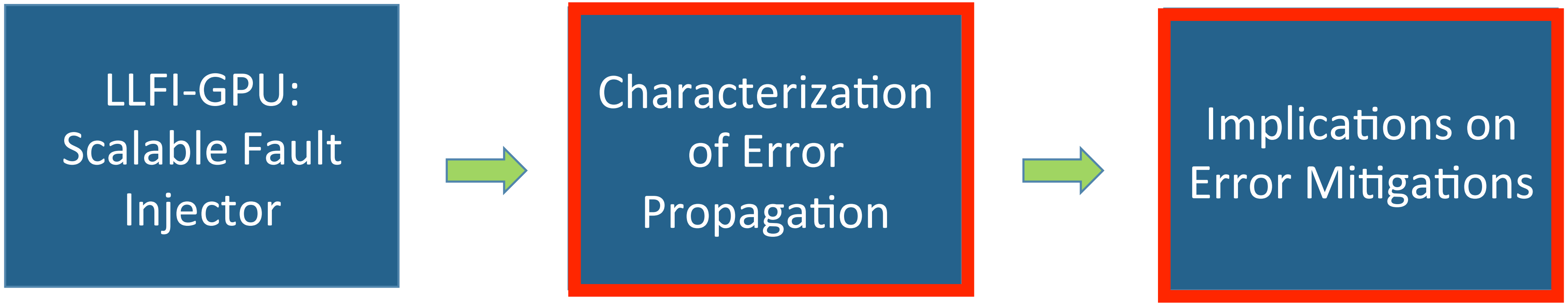
Experiment Setup: Nvidia K20

- 12 Benchmarks
  - Rodinia & Parboil suites
  - Lulesh (LLNL), Barns-Hut (Texas State Univ.), Fiber (Northeastern Univ.), Circuit Solver (Rice Univ.) and NMF (UC Berkley)
- Fault Injection
  - 10,000 per application (Error bar: 0.22%-2.99% , 95% confidence level)
- Fault Model
  - Single bit-flip
  - Transient faults in execution units

Failure Outcomes

- Silent Data Corruption (SDC)
  - Mismatch in program outputs from golden run and fault injection run
- Crash
  - CUDA exceptions (e.g, illegal memory address)
  - Cause kernel execution to halt
- Benign
  - No effect on program output

Our Contributions

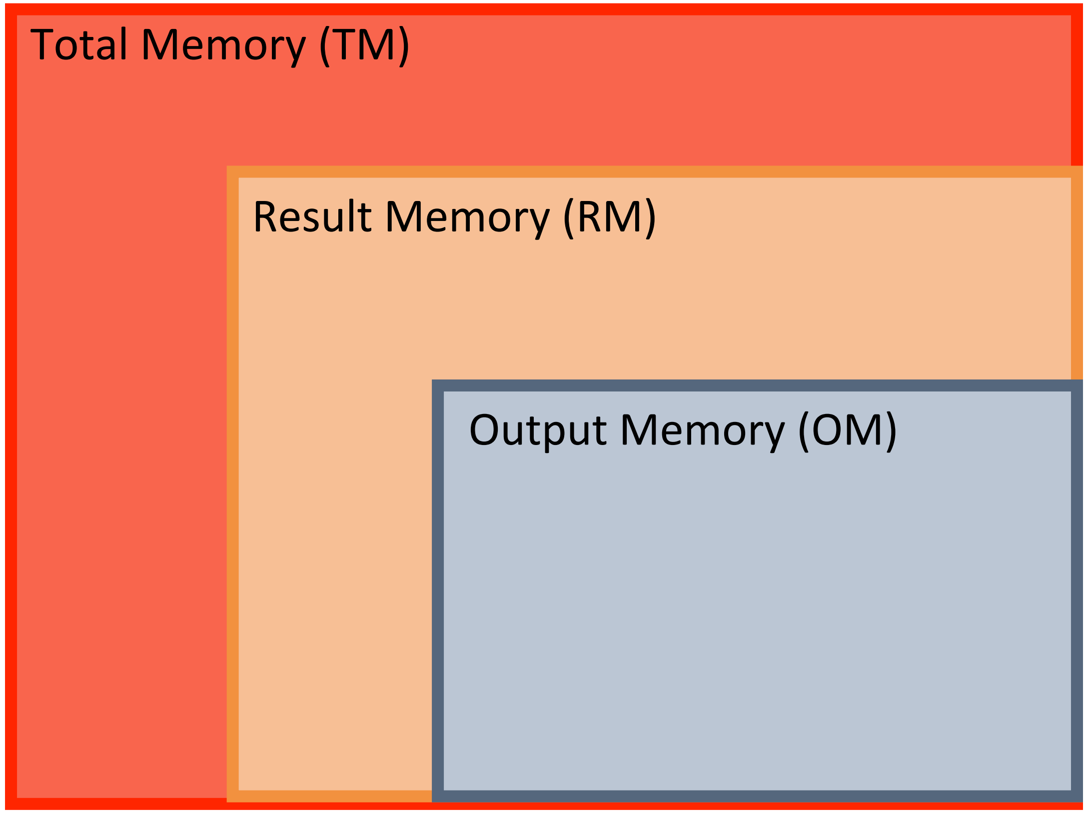


Research Question 1

What is the percentage of SDCs in different memory states?

Memory State

```
…
cudaMalloc( M1 )
cudaMalloc( M2 )
cudaMemcpy(M1, …)
cudaMemcpy(M2, …)
…
Kernel<<<>>>, …
…
cudaMemcpy(…, M2)
…
Foreach(M2): if(ele>0) {print(ele)}
…
```



SDC in Different Memory States

SDC of States

	bfs	barneshut	nmf
SDC_{TM} - SDC_{RM}	0.00%	0.20%	0.00%

Most of the faults in TM propagate RM

Average of $SDC_{(TM-RM)}$ in all benchmarks: 0.09%

Size of States

	bfs	barneshut	nmf
RM	14.29%	37.50%	0.03%
TM	100%	100%	100%

Checking RM reduces ~86% overhead while retaining coverage

Average size of RM in all benchmarks: 13.56%

Example of Checkers

Pattabiraman et al. [TDSC, 2011]
Hari et al. [DSN, 2012]

- Check value range of particular states
  - Calculating angle: if (angle > 60 or angle < 0) {error detected}
- Overhead is directly proportional to the number of states checked
  - Checking RM reduces ~86% overhead
  - Small loss of coverage

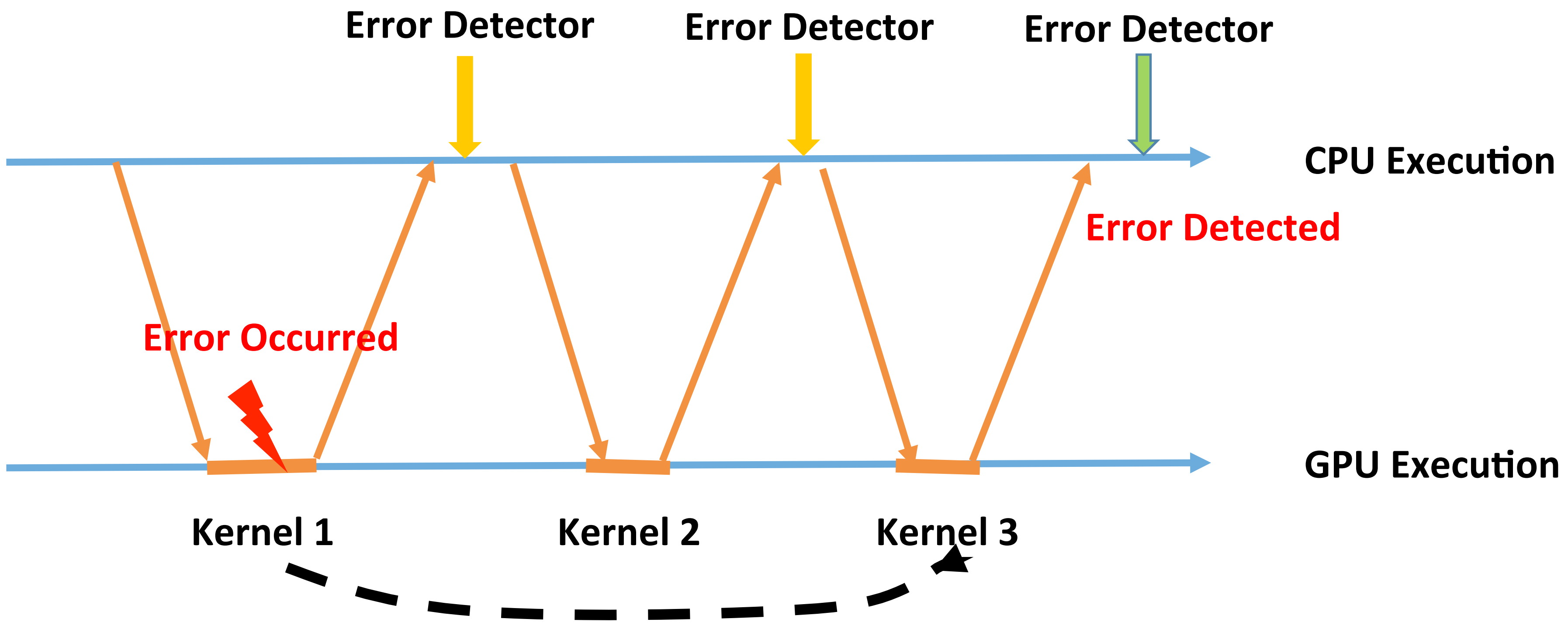
Research Question 2

How long do errors take to propagate to the RM?

Metrics: Kernel Call

… to measure propagation time of error

Error detection latency is 2



Tracking Error Propagation

…

Kernel1<<<>>>

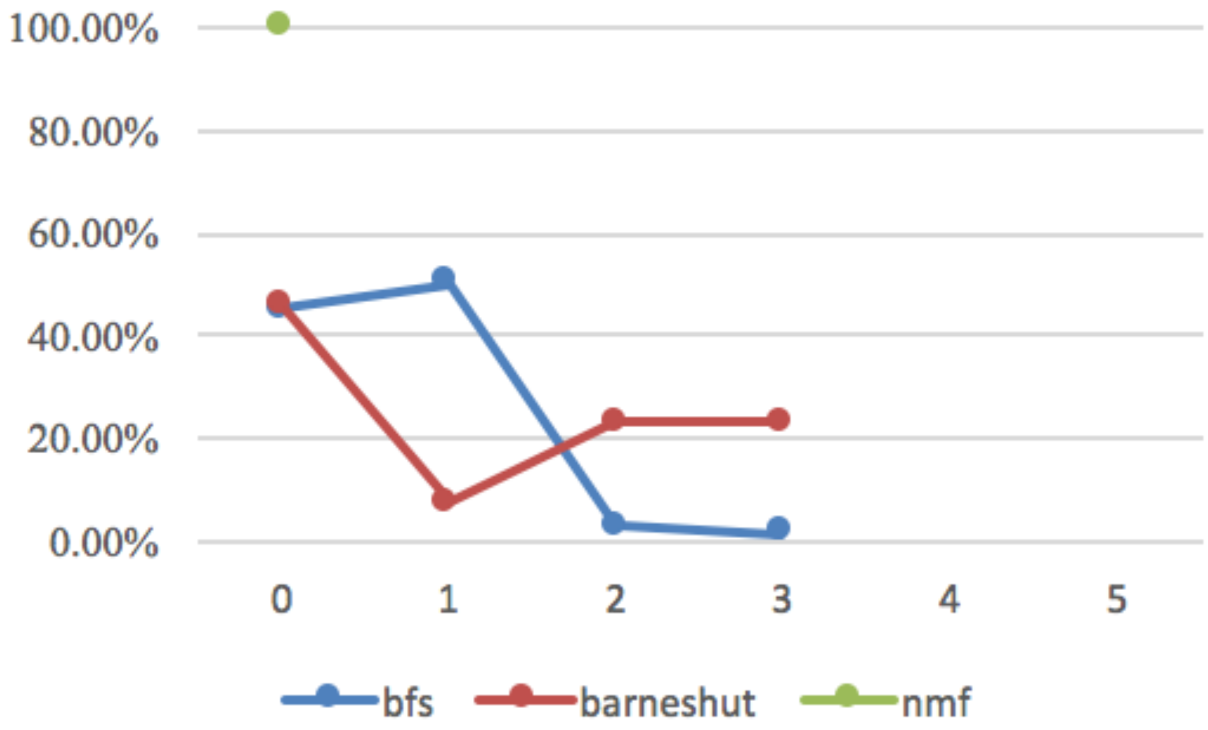
DumpToDisk(TM)
DumpToDisk(RM)
DumpToDisk(OM)

Kernel2 <<<>>>

…

Compared with golden copy for any data corruptions

Propagation Latency to RM



Checking RM provides short detection latency

Implications

- RM is a narrow tunnel where faults frequently propagate through
  - Checking RM for SDC is a better trade-off
- Crash-causing faults rarely propagate across kernel calls
  - Deploying high frequency checkpoints for GPGPU can avoid checkpoint corruptions
- Studied on 2 GPGPU platforms (Nvidia GTX 960 & Nvidia K20)
  - Results are statistically indistinguishable
- Investigated in error spread & masking etc
  - … more interesting findings can be found in the paper !

Summary

- Designed a scalable fault injector for GPGPUs: LLFI-GPU
- Characterized error propagation patterns in GPGPU applications
- Discussed their implications on error mitigation techniques

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- Website: ece.ubc.ca/~gpli
- LLFI-GPU:
  - https://github.com/DependableSystemsLab/LLFI-GPU
- Results:
  - https://www.dropbox.com/s/xrvojidskkcrj4y/FI_data.xlsx?dl=0

Acknowledgements

NSERC
CRSNG

DARPA

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