

GPU-Accelerated Static Timing Analysis and Beyond



Dr. Tsung-Wei Huang

Department of ECE

University of Utah, UT

Dr. Yibo Lin

Department of CS

Peking University, Beijing, China



Static Timing Analysis

- Static timing analysis (STA)

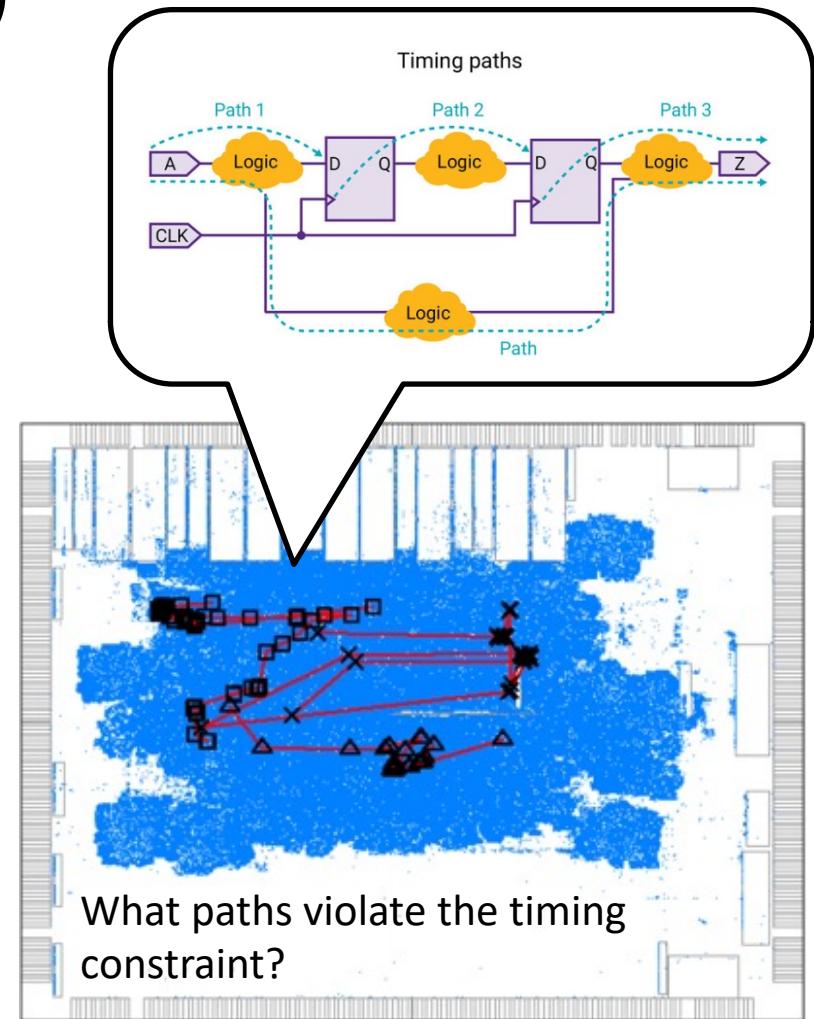
- Key step in the VLSI design
- Verify the circuit timing

- Analyze worst-case timing

- Minimum timing values
- Maximum timing values

- Challenges

- Compute giant graphs
- Analyze millions of paths
- Balance the loads
- ...



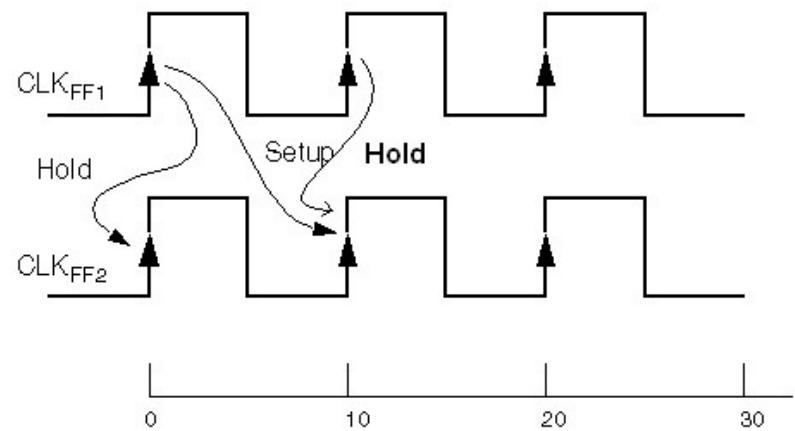
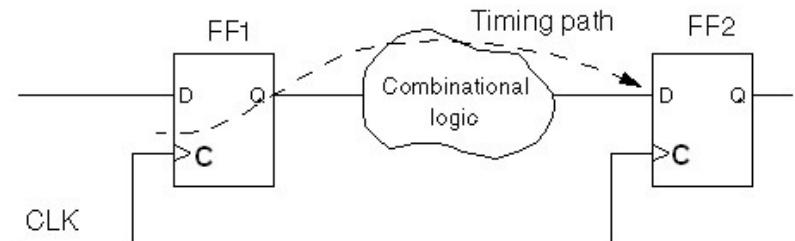
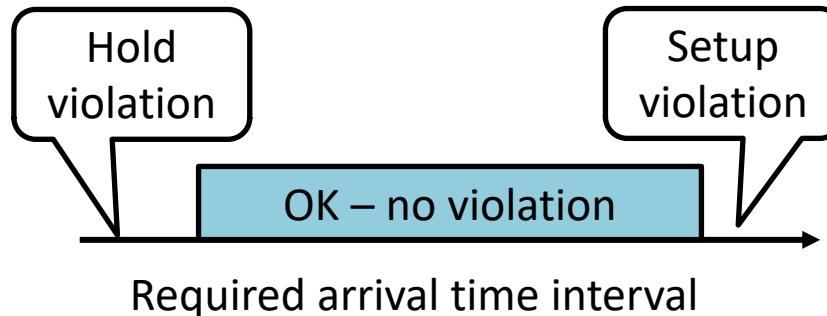
Timing Checks (Required Arrival Time)

- Modern circuits are sequential

- Drive data signal via clocks
- Capture data via flip-flops (FF)s

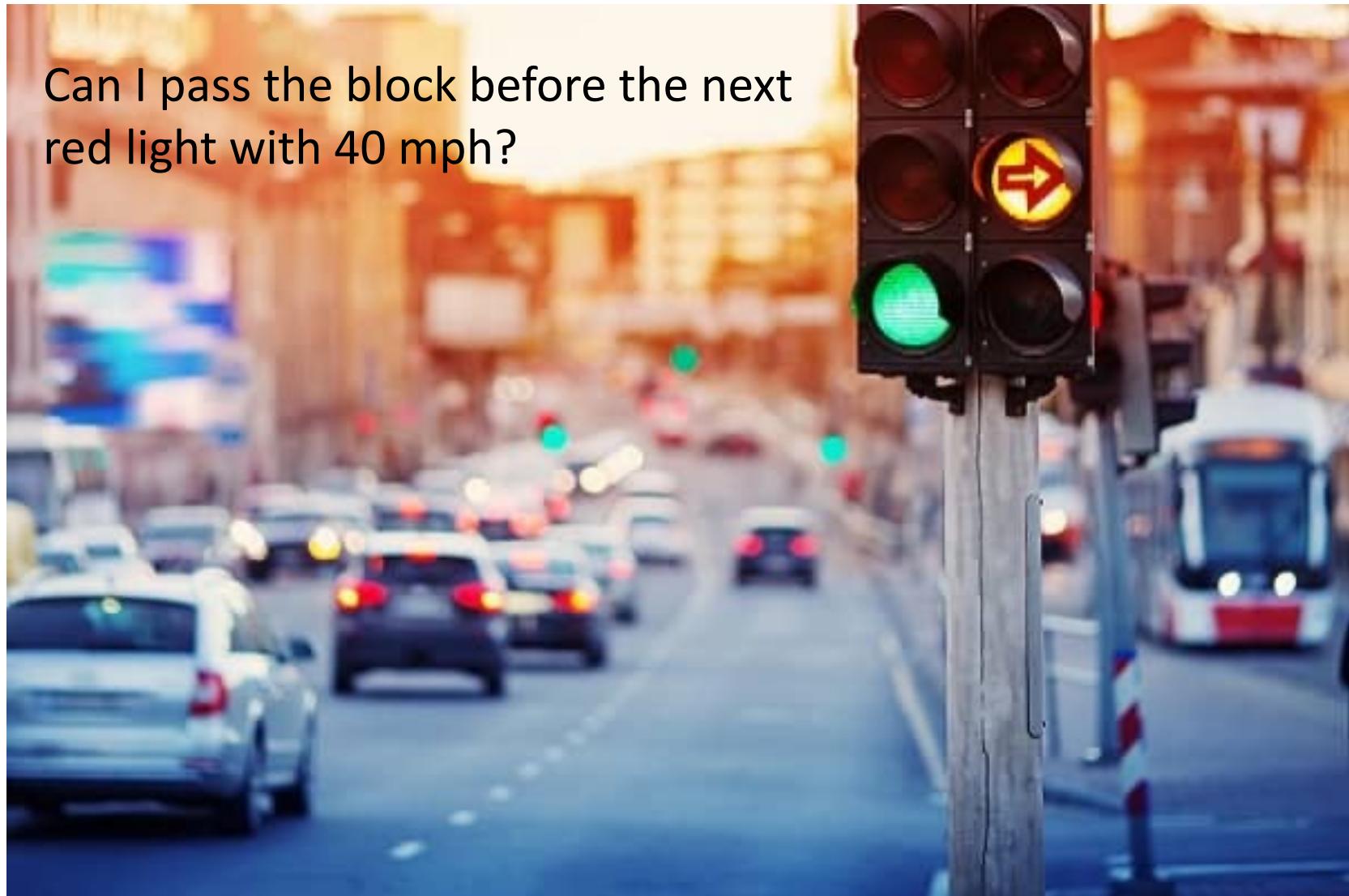
- Timing constraints

- Min required arrival time
 - After clock: hold
- Max required arrival time
 - Before clock: setup



The “Traffic Light” Analogy

Can I pass the block before the next red light with 40 mph?



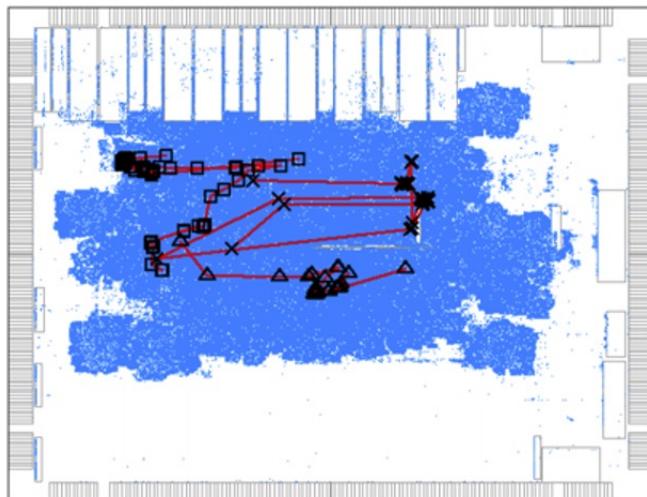
Building a Good Traffic System is Hard

- Trillions of sections and traffic lights to analyze ...



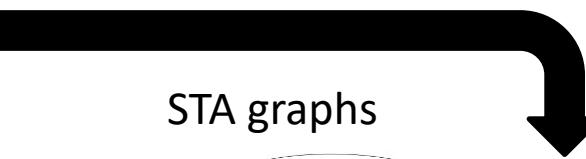
Same, STA is Computationally Challenging

- ❑ STA graphs is extremely large and irregular
 - ❑ Millions to billions of nodes and edges
 - ❑ Propagate timing information along giant graphs



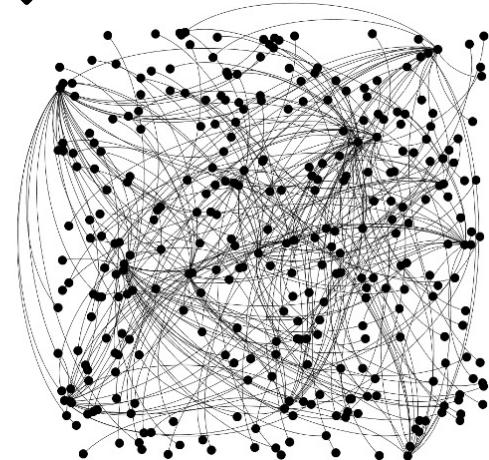
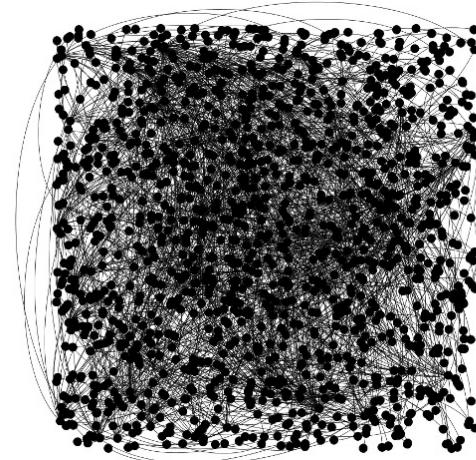
ISPD circuit design (10M gates)

Complete analysis can take **8 hours** and **800 GB RAM**



STA graphs

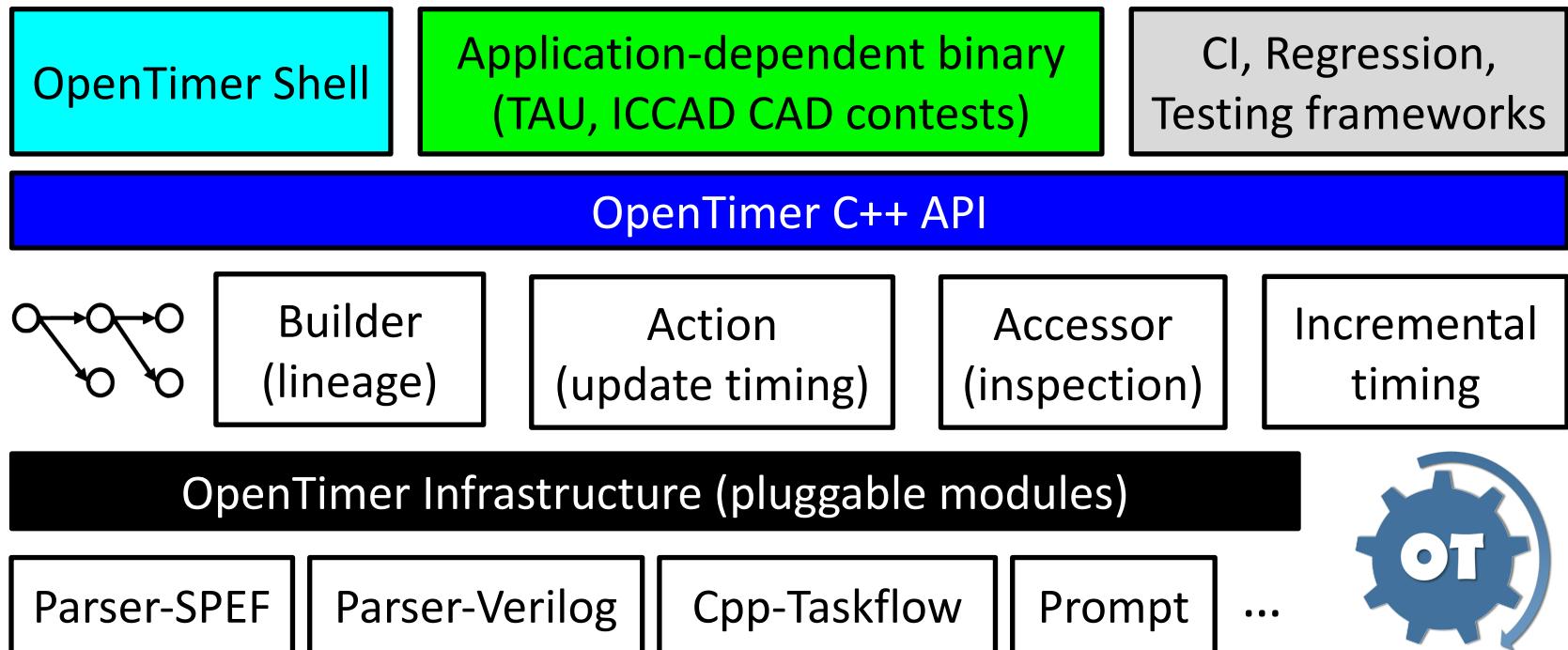
A datapath



STA graphs are extremely large and irregular

Our STA Solution: OpenTimer

- CPU-parallel timing analysis engine
 - Two major versions: v1 (2015) and v2 (2020)
 - <https://github.com/OpenTimer/OpenTimer>

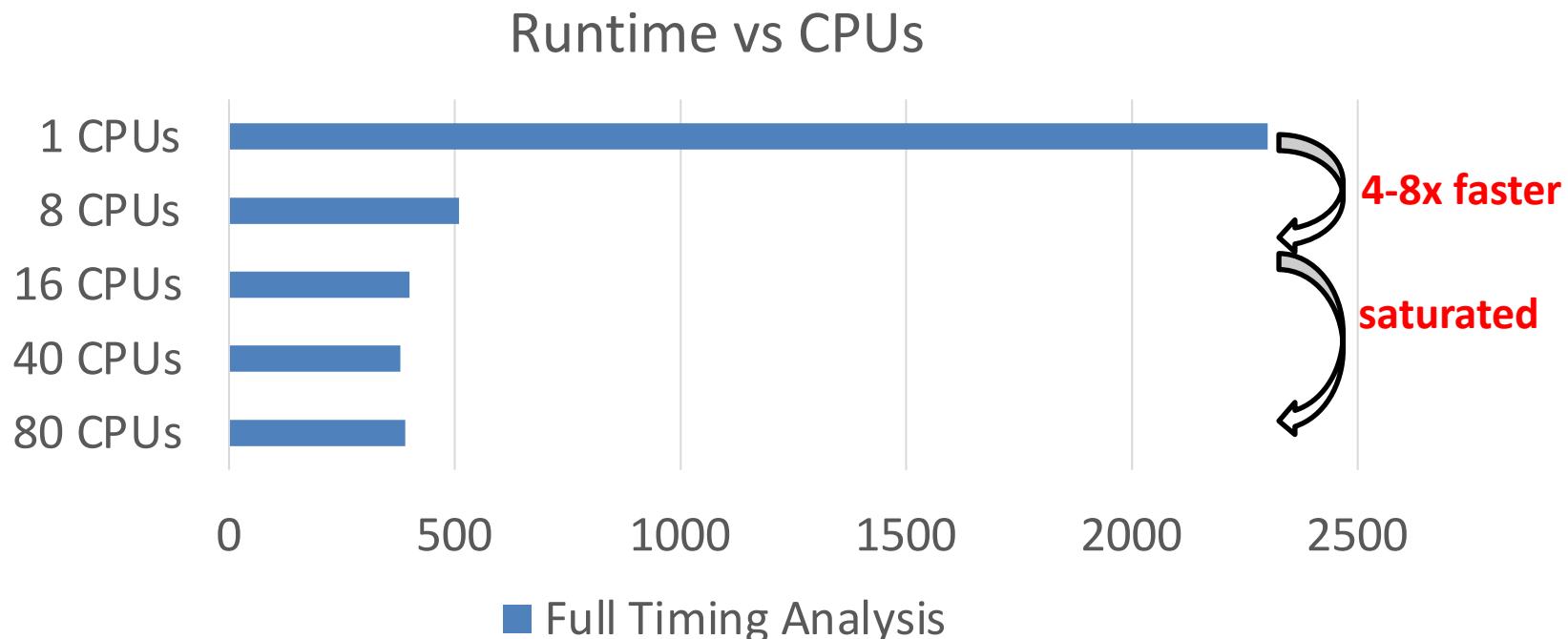


T.-W. Huang et al., “OpenTimer: A High-performance Timing Analysis Tool,” IEEE/ACM ICCAD15

T.-W. Huang et al., “OpenTimer v2: A New Parallel Incremental Timing Analysis Engine,” IEEE TCAD21

Key Idea: Parallel Timing Analysis

- ❑ Leverage many-core CPUs to speed up the runtime
 - ❑ Dramatic speed-up using 8 cores
 - ❑ Yet, scalability saturates at about 10–16 cores

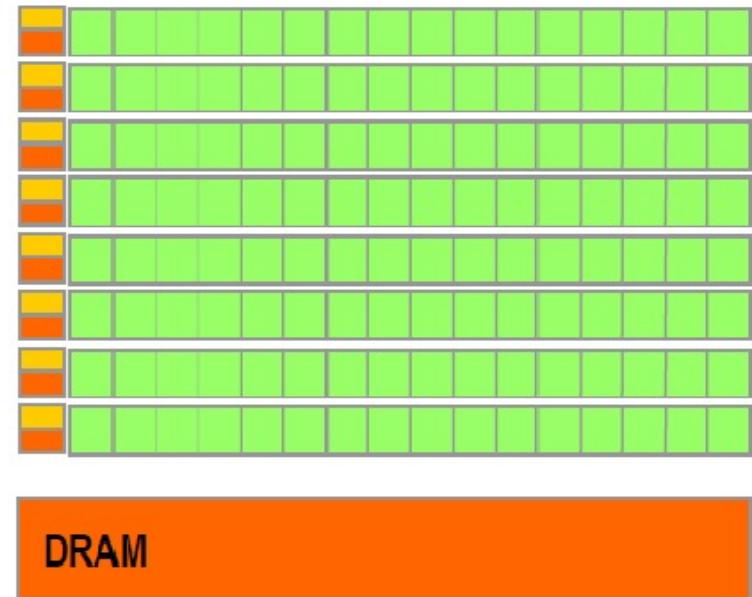
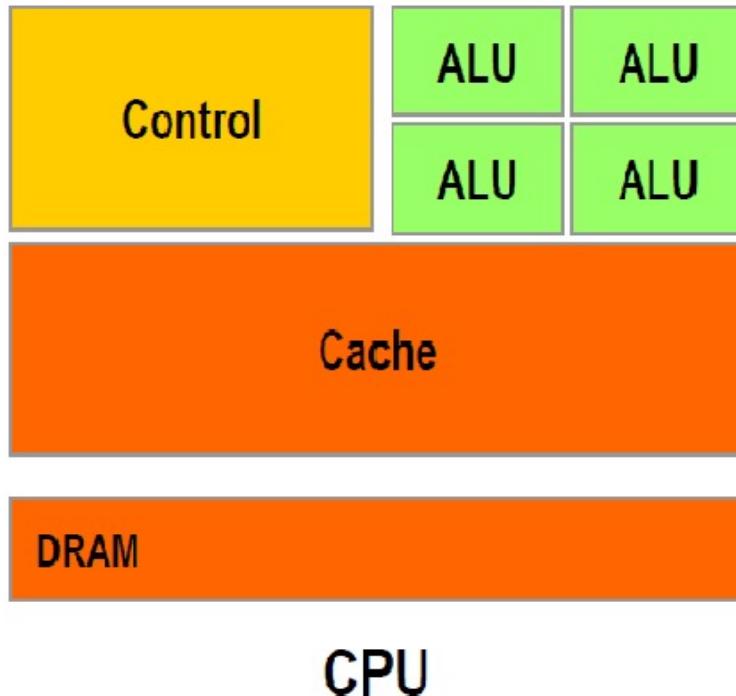


Observed Scalability Bottleneck

- CPU-only parallelism stagnates at about 10 cores
 - “Amdahl’s Law” limits the strong scalability
 - Circuit graph structures limits the maximum parallelism
 - If the graph has only 10 parallel nodes at a level, we won’t achieve 40x speed-up
 - Irregular computations limits the memory bandwidth
 - STA is graph-oriented, not cache-friendly
- Need to incorporate new parallel paradigms
 - GPU opens opportunities for new scalability milestones
 - e.g., 100x speed-up reported in logic simulation
 - e.g., 20—80x speed-up reported in placement

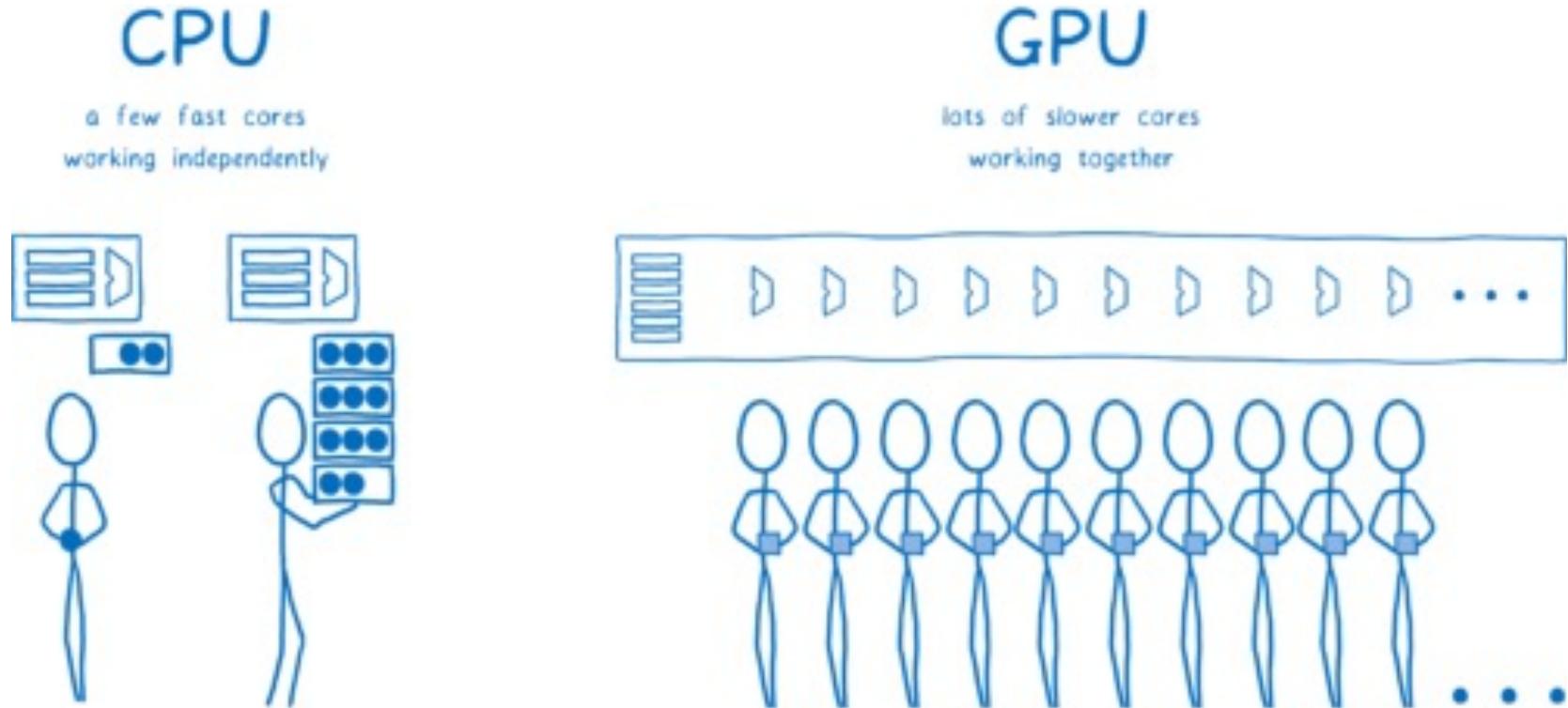
CPU vs GPU

- CPU is built for *compute-driven* applications
 - A few powerful threads to compute critical blocks fast
- GPU is built for *throughput-driven* applications
 - Many lightweight threads to compute data at one time



CPU vs GPU (cont'd)

- CPU: graph algorithms, irregular data structures, etc.
- GPU: matrix operations, gaming, video, etc.

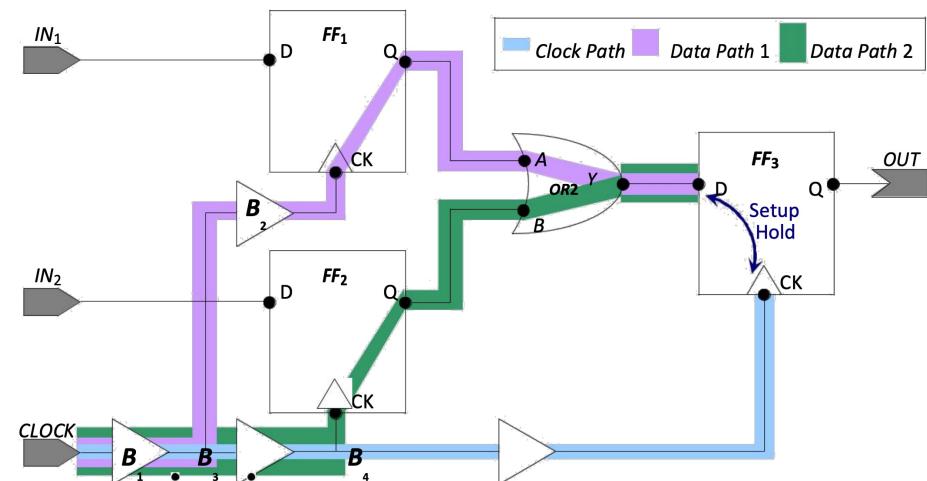
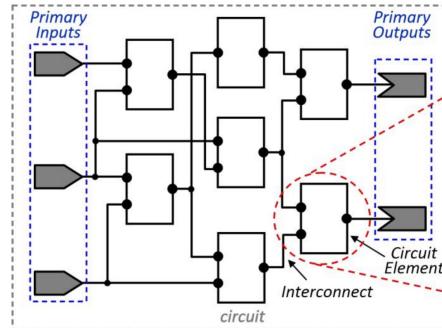


Leverage GPU to Accelerate STA

- We target two important STA steps:
 - Graph-based analysis (GBA)
 - Path-based analysis (PBA)
- We design CPU-GPU collaborative STA algorithms
 - CPU-GPU task decomposition
 - GPU kernels for timing update

PBA analyzes critical paths one by one on a updated graph

GBA computes the delay, slew, arrival time at each node and edge



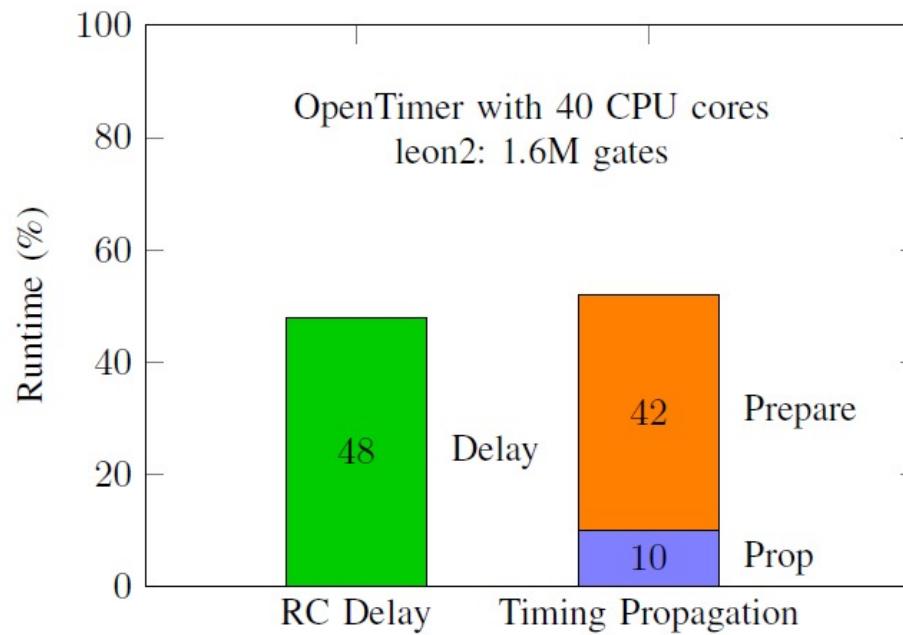
Z Guo, T-W Huang, and Y Lin, “GPU-Accelerated Static Timing Analysis,” *IEEE/ACM ICCAD*, 2020



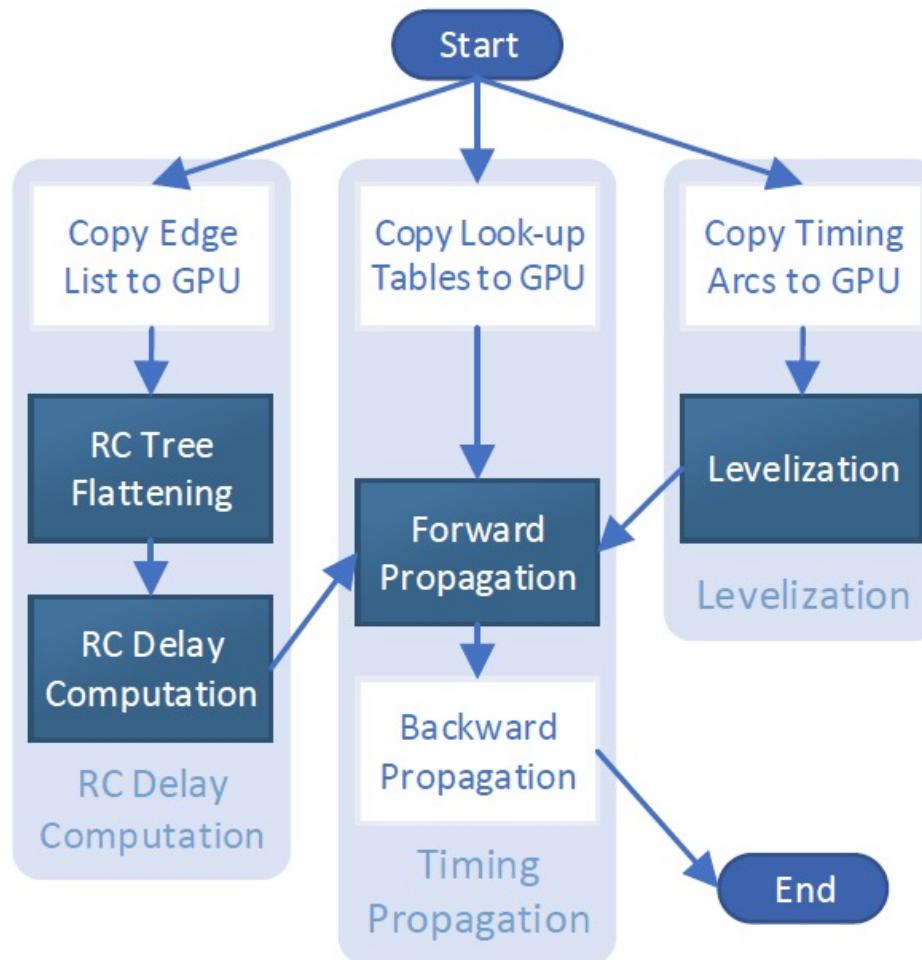
Runtime Breakdown of GBA

□ GBA has three time-consuming steps

1. Prepare tasks through levelization → 42% runtime
2. Compute RC delay → 48% runtime
3. Propagate timing → 10% runtime



GPU-Accelerated GBA Algorithm Flow



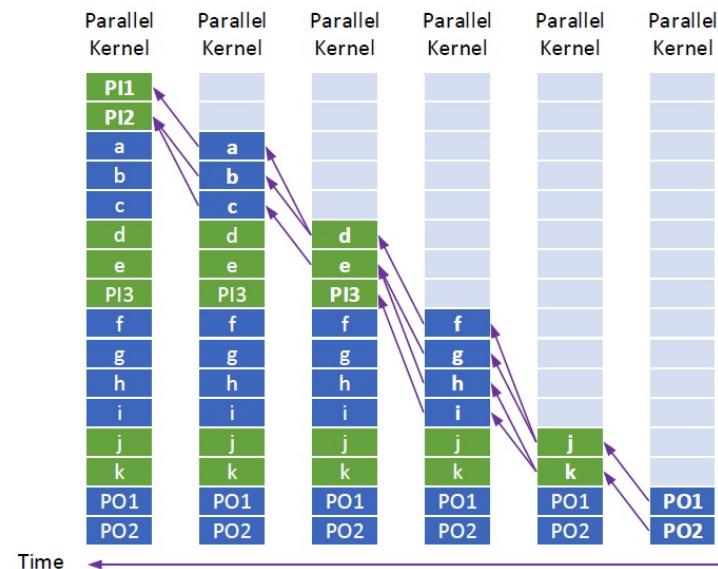
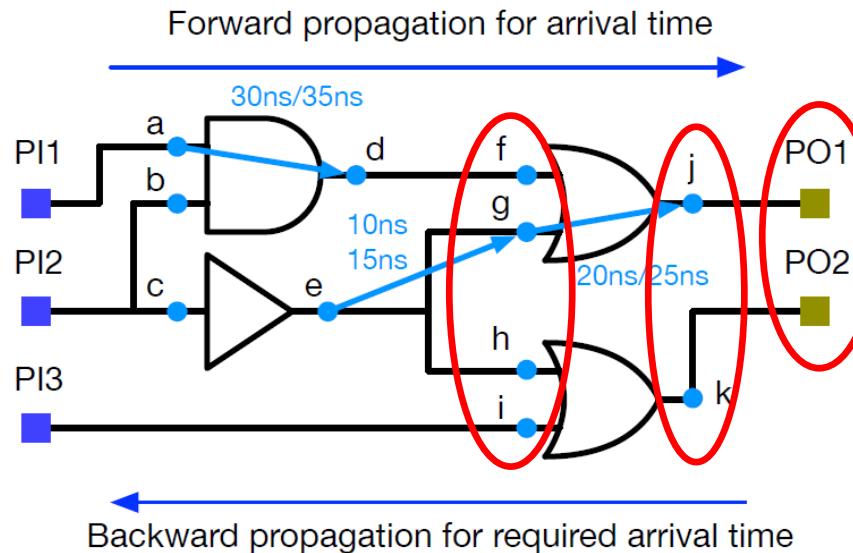
CPU Tasks

GPU Tasks



Step #1: Levelization

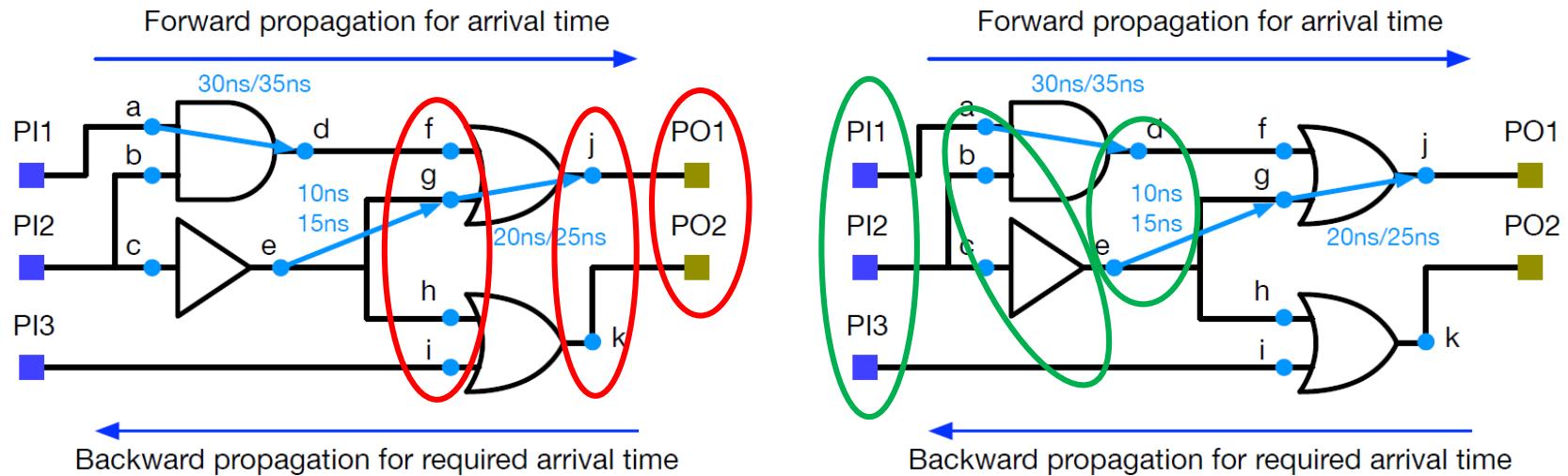
- ☐ Levelize the circuit graph to a 2D levellist
 - ☐ Nodes at the same level can run in parallel (red circle)
 - ☐ Nodes at the same level can be modeled as a batch



- ☐ GPU-accelerated levelization using parallel frontiers

Step #1: Levelization (cont'd)

- ☐ Levelize the graph backward rather than forward

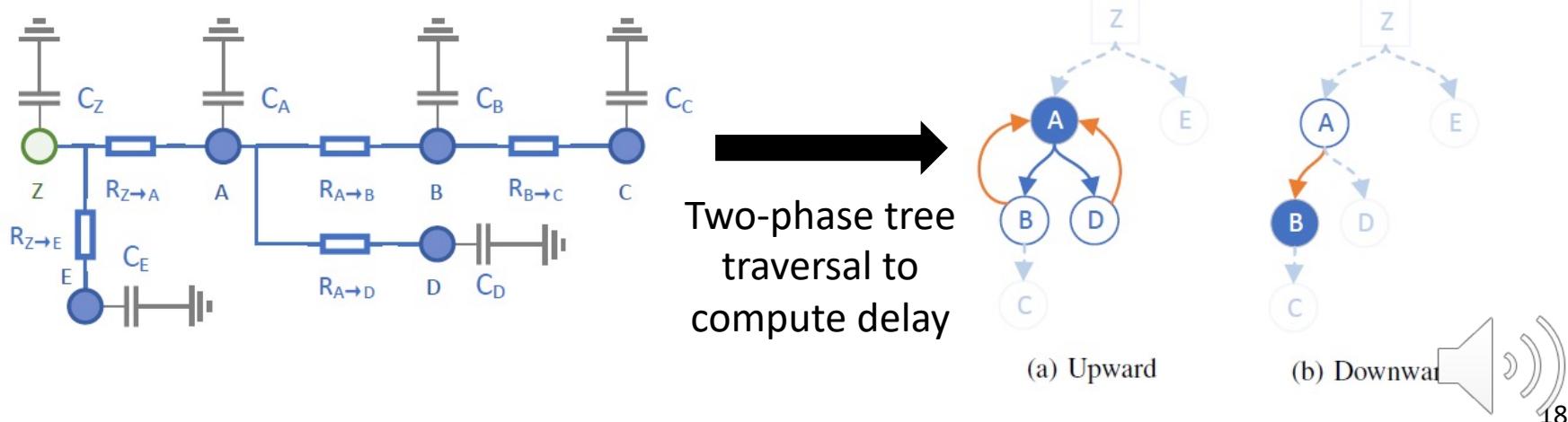


Benchmark	#nodes	Max In-degree	Max Out-degree
netcard	3999174	8	260
vga_lcd	397809	12	329
wb_dma	13125	12	95



Step #2: RC Update

- The Elmore delay model
- Phase 1: $load_u = \sum_{v \text{ is child of } u} cap_v$
 - For example, $load_A = cap_A + cap_B + cap_C + cap_D = cap_A + load_B + load_D$
- Phase 2: $delay_u = \sum_{v \text{ is any node}} cap_v \times R_{Z \rightarrow LCA(u,v)}$
 - For example, $delay_B = cap_A R_{Z \rightarrow A} + cap_D R_{Z \rightarrow A} + cap_B R_{Z \rightarrow B} + cap_C R_{Z \rightarrow B} = delay_A + R_{A \rightarrow B} load_B$



Step #2: RC Update Upward Phase

- Store the parent index of each node on GPU
- Perform dynamic programming on trees

DFS_load(u):

 load[u] = cap[u]

 For child v of u:

 DFS_load(v)

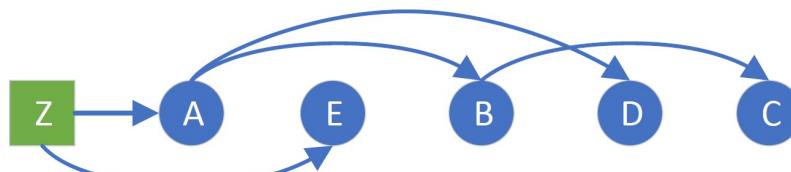
 load[u] += load[v]

GPU_load:

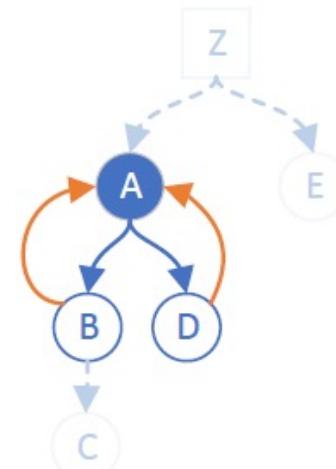
 For u in [C, D, B, E, A]:

 load[u] += cap[u]

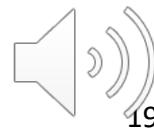
 load[u.parent] += load[u]



Parent list representation in memory



(a) Upward



Step #2: RC Update Downward Phase

- Store the parent index of each node on GPU
- Perform dynamic programming on trees

DFS_delay(u):

For child v of u:

temp := $R[u,v] * \text{load}[v]$

delay[v] = delay[u] + temp

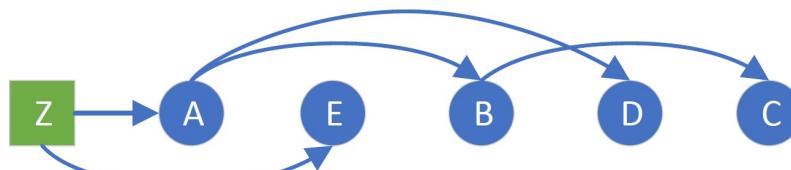
DFS_delay(v)

GPU_delay:

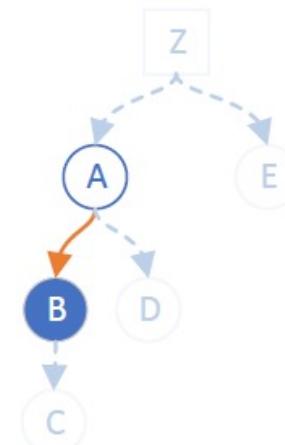
For u in [A, E, B, D, C]:

temp := $R[u.\text{parent},u] * \text{load}[u]$

delay[u]=delay[u.parent] + temp



Parent list representation in memory

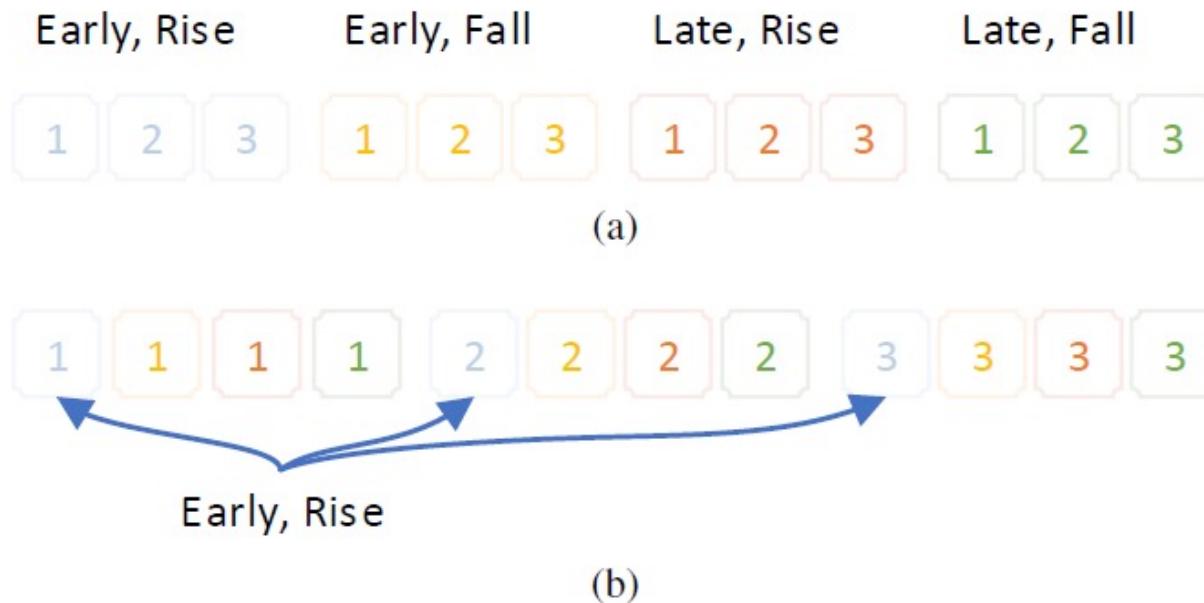


(b) Downward



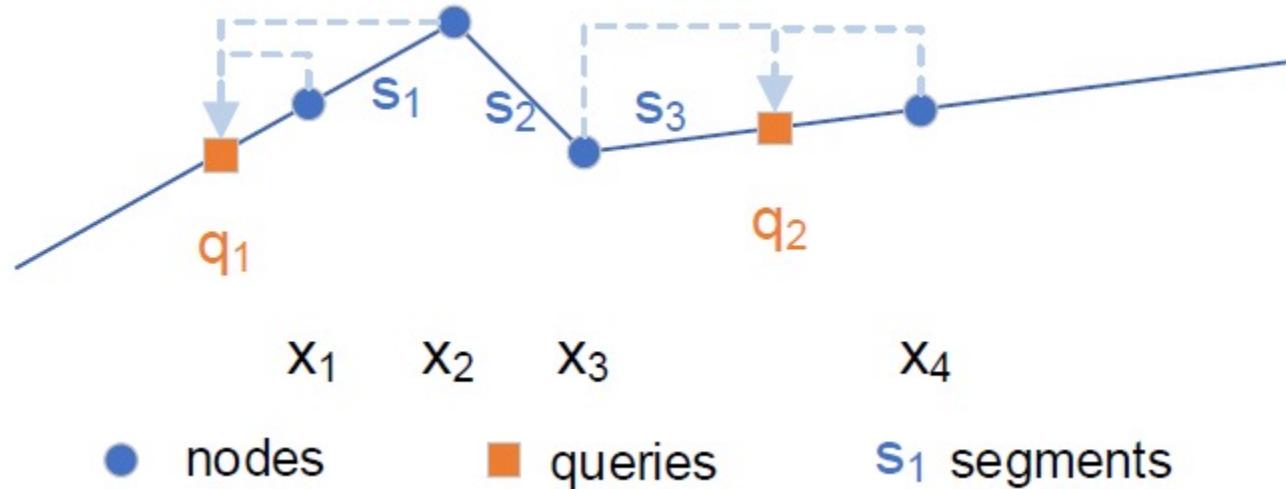
Step #2: RC Update Memory Coalesce

- Consecutive threads access consecutive memory
- RC update has four cases: {Rise, Fall} x {Early, Late}



Step #3: Cell Delay Update

- Perform linear inter- and extra-polation in batches
 - x-axis and then y-axis



Experimental Setting

❑ Machine configuration

- ❑ Nvidia CUDA, RTX 2080
- ❑ 40 Intel Xeon Gold 6138 CPU cores

❑ Execution parameters for GPU kernels

❑ RC Tree Flattening

- 64 threads per block with one block for each net

❑ Levelization

- 128 threads per block

❑ RC delay computation

- 4 threads for each net (one for each Early/Late and Rise/Fall condition) with a block of 64 nets

❑ Cell delay computation

- 4 threads for each arc, with a block of 32 arcs



Overall Performance

- Comparison with OpenTimer of 40 CPUs
 - Run on large TAU15 Benchmarks (>20K gates)

Benchmark	# PIs	# POs	# Gates	# Nets	# Pins	# Nodes	# Edges	OpenTimer Runtime (40 CPUs)	Our Runtime (40 CPUs 1 GPU)	
									Runtime	Speed-up
aes_core	260	129	22938	23199	66751	413588	453508	156 ms	138 ms	1.13×
vga_lcd	85	99	139529	139635	397809	1966411	2185601	829 ms	311 ms	2.67×
vga_lcd_iccad	85	99	259067	259152	679258	3556285	3860916	1480 ms	496 ms	2.98×
b19	22	25	255278	255300	782914	4423074	4961058	1831 ms	585 ms	3.13×
cordic	34	64	45359	45393	127993	7464477	820763	274 ms	167 ms	1.64×
des_perf	234	140	138878	139112	371587	2128130	2314576	832 ms	325 ms	2.56×
edit_dist	2562	12	147650	150212	416609	2638639	2870985	1059 ms	376 ms	2.86×
fft	1026	1984	38158	39184	116139	646992	718566	241 ms	148 ms	1.63×
leon2	615	85	1616369	1616984	4328255	22600317	24639340	10200 ms	2762 ms	3.69×
leon3mp	254	79	1247725	1247979	3376832	17755954	19408705	7810 ms	2585 ms	3.02×
netcard	1836	10	1496719	1498555	3999174	21121256	23027533	9225 ms	2571 ms	3.60×
mgc_edit_dist	2562	12	161692	164254	450354	2436927	2674934	1021 ms	368 ms	2.77×
mgc_matrix_mult	3202	1600	171282	174484	492568	2713241	2994343	1138 ms	377 ms	3.02×
tip_master	778	857	37715	38493	95524	533690	570154	163 ms	143 ms	1.14×

PIs: number of primary inputs # POs: number of primary outputs

Pins: number of pins # Nodes: number of nodes in the STA graph

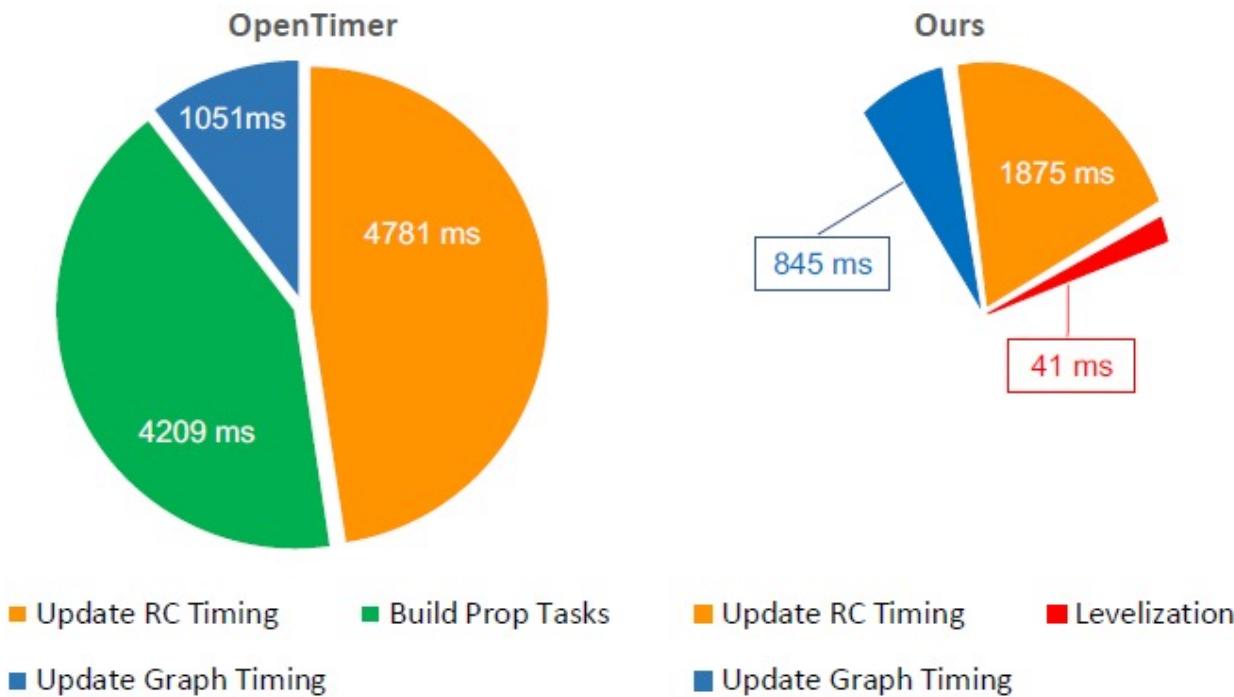
Gates: number of gates # Nets: number of nets

Edges: number of edges in the STA graph



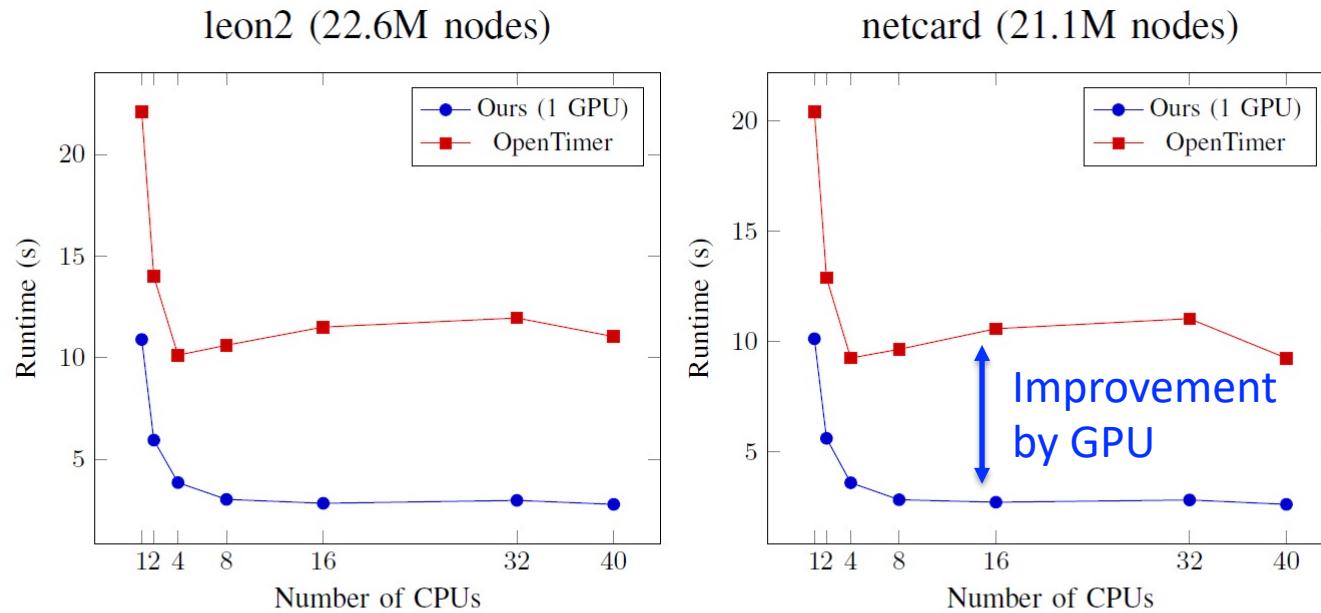
Runtime Breakdown

□ Circuit leon2 (21 M nodes)



Runtime vs CPUs

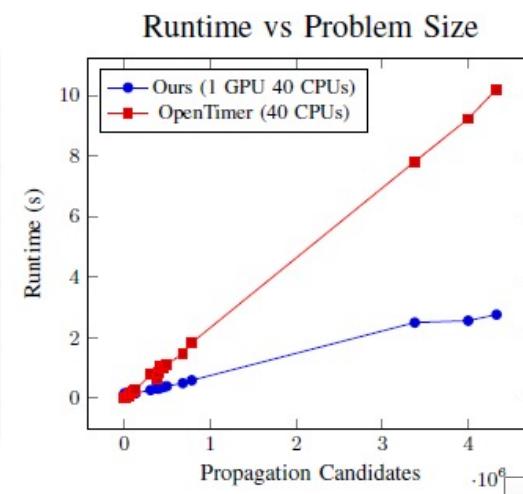
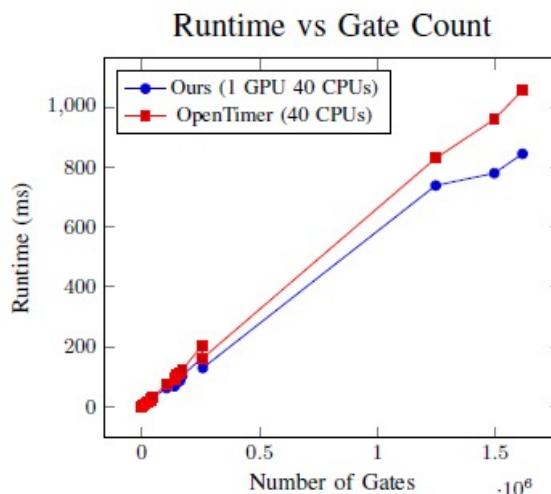
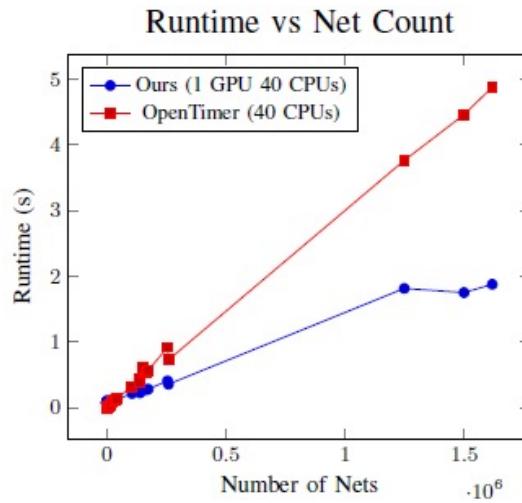
□ Significant performance gap between CPU and GPU



Our runtime of 1 CPU and 1 GPU is very close to OpenTimer of 40 CPUs

Runtime vs Problem Sizes

- Problem size matters for GPU acceleration
- When to enable GPU acceleration?
 - Net count > 20K
 - Gate count > 50K
 - Propagation candidate count > 15K

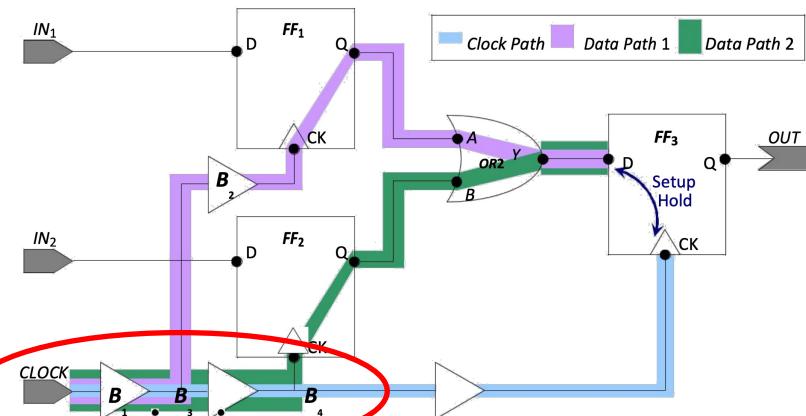
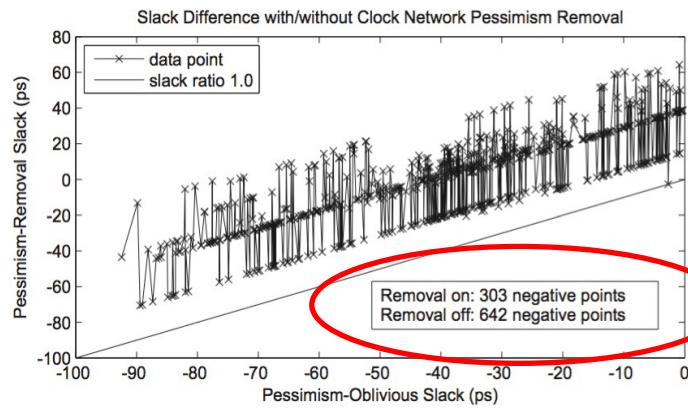


G Guo, T-W Huang, Y Lin, and M Wong, “GPU-Accelerated Path-based Timing Analysis,” *IEEE/ACM DAC*, 2021

Path-based Analysis (PBA)

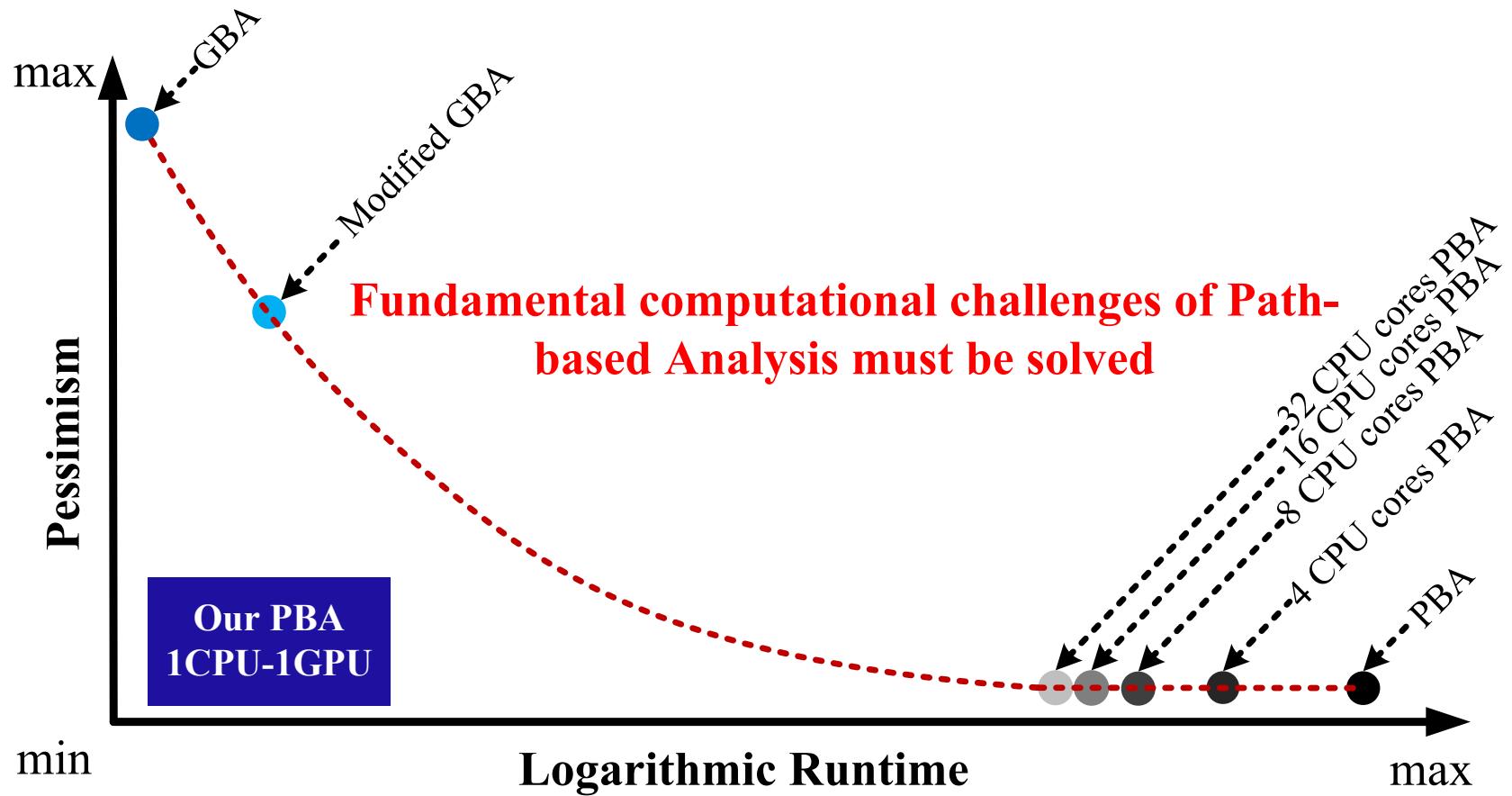
- Identify a set of critical paths from a updated graph
 - Exponential number of paths in the circuit graph
- Re-analyze each path with path-specific update
 - Re-propagate the slew and remove pessimism
 - Advanced on-chip variation (AOCV)
 - Common path pessimism removal (CPPR)
 - ...

Paths marked failing at GBA may become passing after PBA!



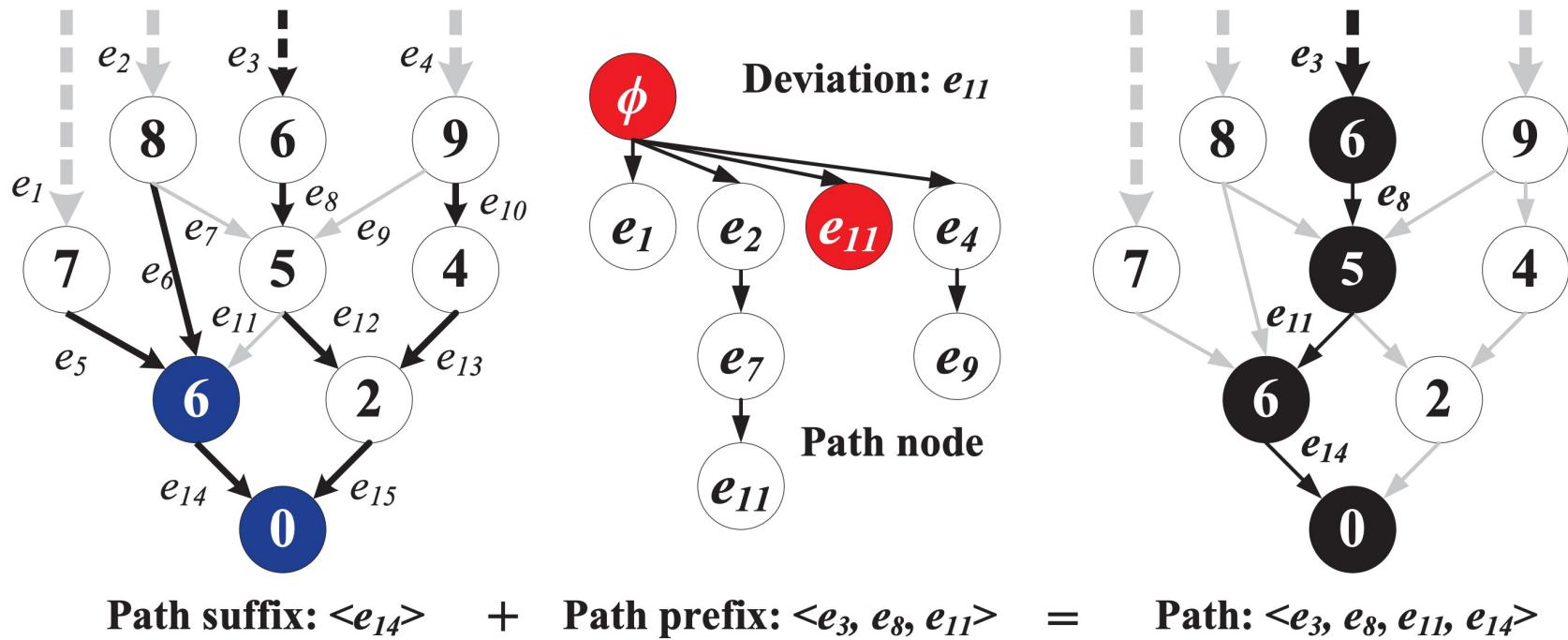
PBA is Extremely Time-Consuming

- Speed vs Accuracy (pessimism removal) tradeoff

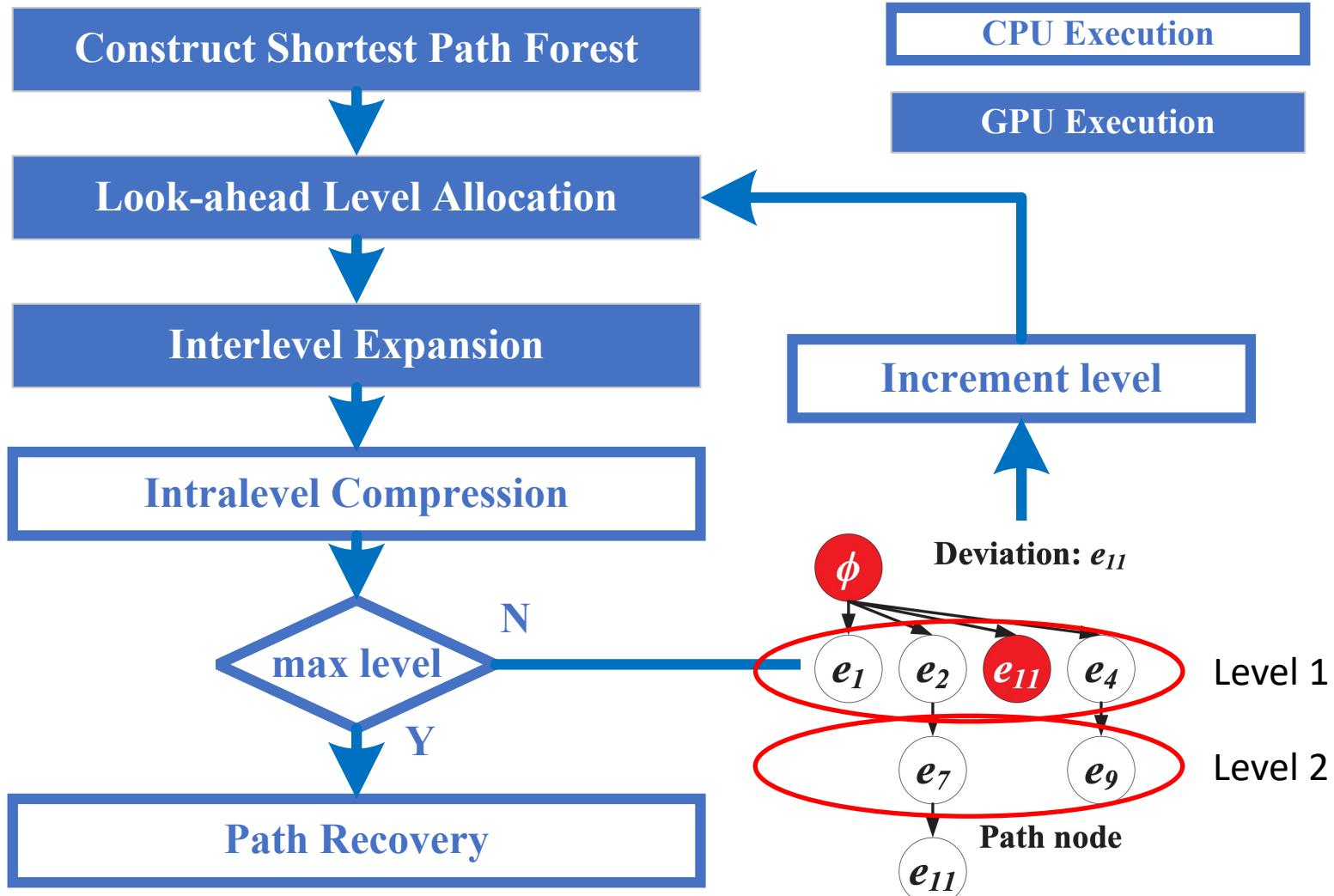


A Key Step: Generate Critical Paths

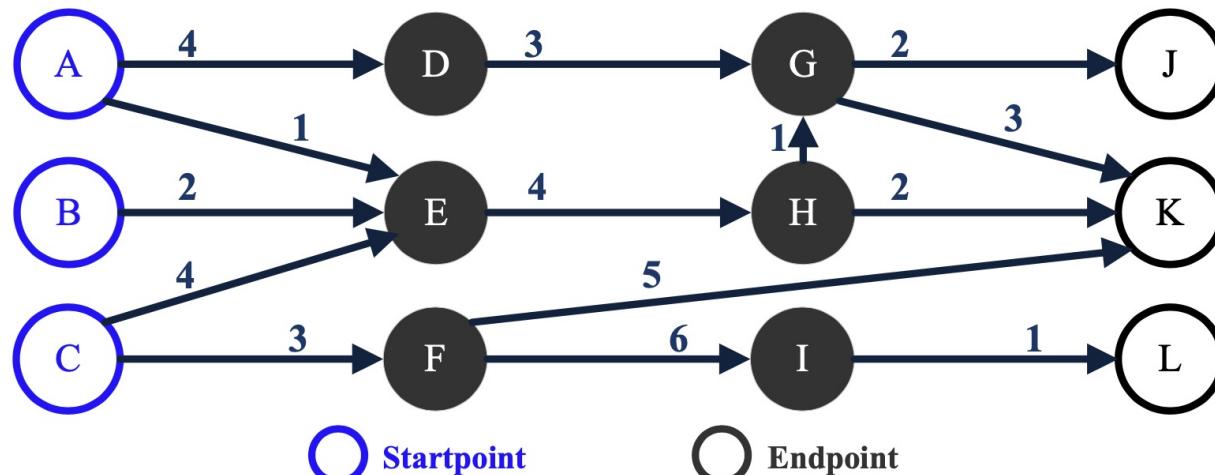
- OpenTimer adopts implicit path representation
 - Each path is represented using $O(1)$ space and time
 - Each path is ranked through a *prefix tree* & a *suffix tree*



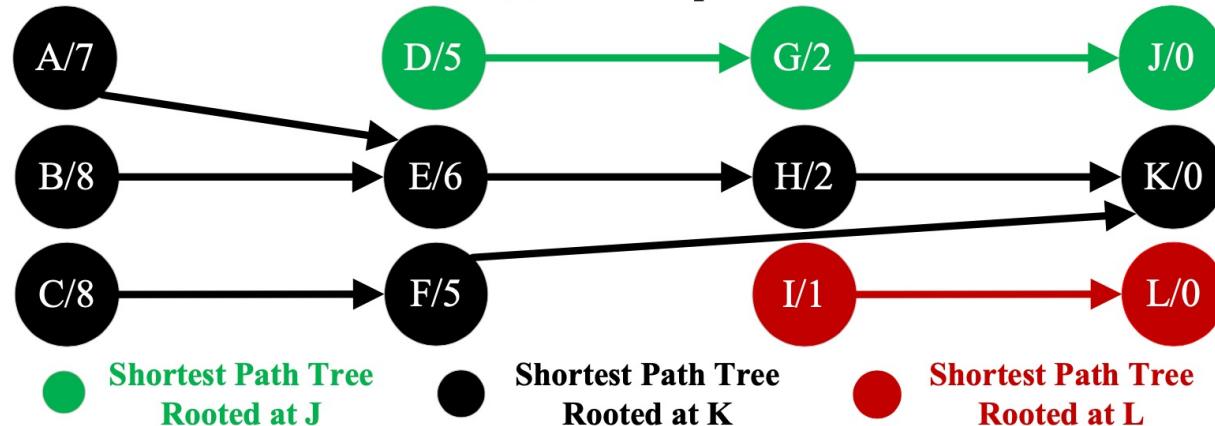
GPU-Accelerated PBA Algorithm Flow



Step #1: Generate Suffix Tree on GPU

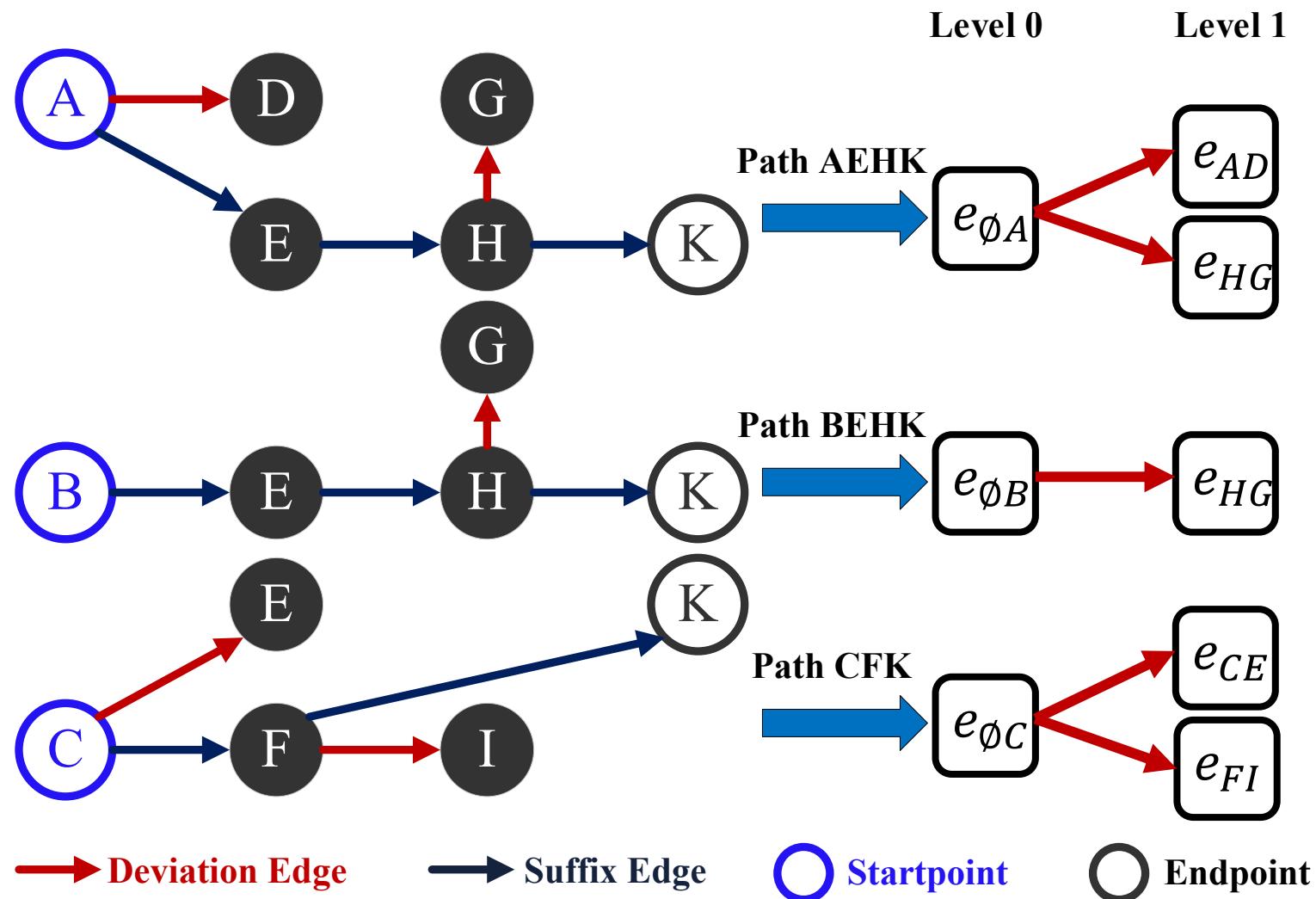


(a) STA Graph.



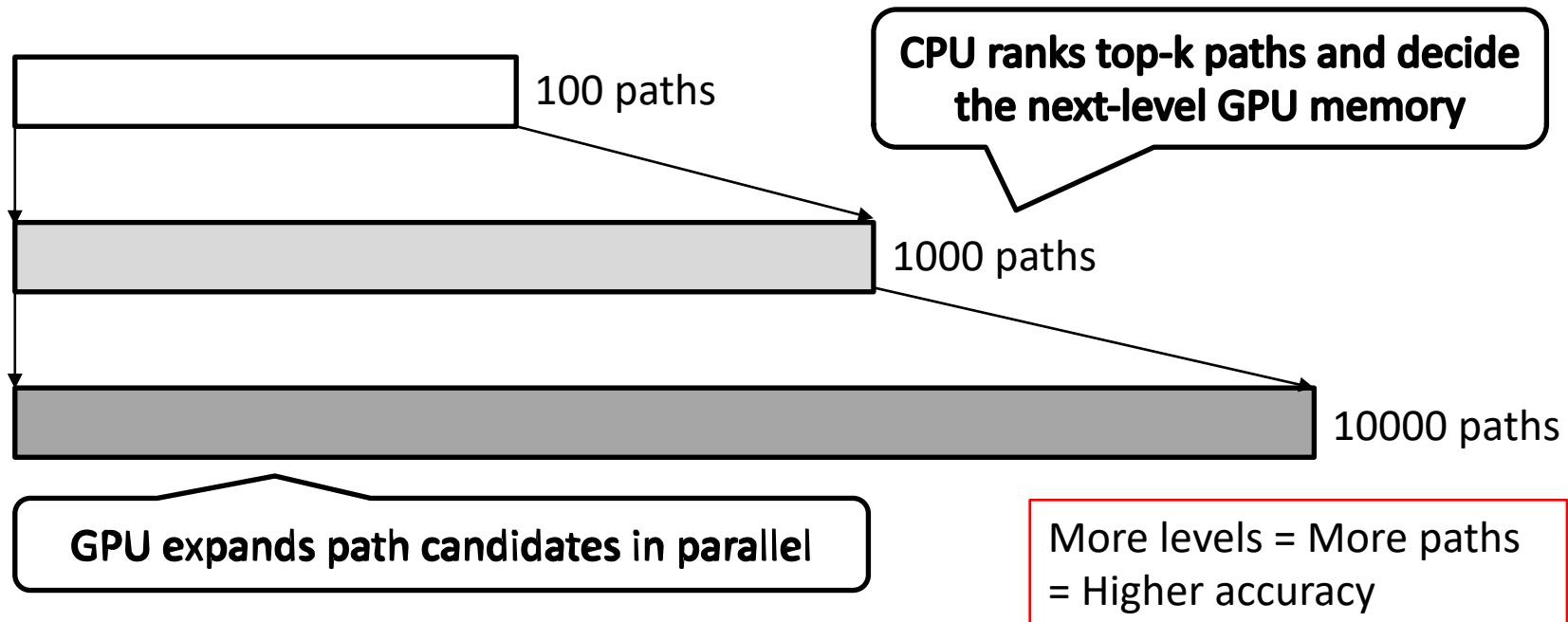
(b) Shortest path forest.

Step #2: Expand Prefix Tree on GPU



Step #2: Expand Prefix Tree on GPU (cont'd)

- Iteratively grow GPU memory at each expansion
 - Each iteration uses GPU to decide path candidates
 - Each iteration uses CPU to prune path candidates
 - Each path candidate takes $O(1)$ space “deviation edge”



Experimental Setting

- ❑ Machine configuration

- ❑ Nvidia CUDA, RTX 2080
 - ❑ 40 Intel Xeon Gold 6138 CPU cores

- ❑ Measure the accuracy-runtime tradeoff

- ❑ “MDL” stands for maximum deviation level

- ❑ Execution parameters for GPU kernels

- ❑ Suffix tree kernel
 - 1024 threads per block

- ❑ Prefix tree kernel
 - 1024 threads per block

Overall Performance

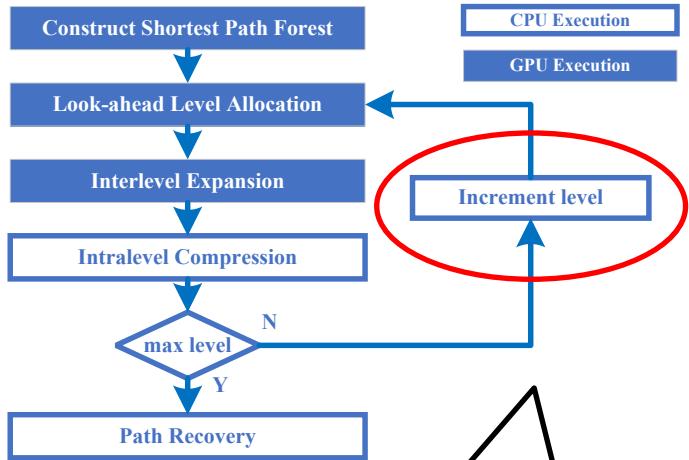
- ❑ Compare with OpenTimer's CPU-based PBA
 - ❑ Report speed-up at different MDLs

Benchmark	#Pins	#Gates	#Arcs	OpenTimer Runtime	Our Algorithm #MDL=10		Our Algorithm #MDL=15		Our Algorithm #MDL=20	
					Runtime	Speed-up	Runtime	Speed-up	Runtime	Speed-up
leon2	4328255	1616399	7984262	2875783	4708.36	611×	5295.49ms	543×	5413.84	531×
leon3mp	3376821	1247725	6277562	1217886	5520.85	221×	7091.79ms	172×	8182.84	149×
netcard	3999174	1496719	7404006	752188	2050.60	367×	2475.90ms	304×	2484.08	303×
vga_lcd	397809	139529	756631	53204	682.94	77.9×	683.04ms	77.9×	706.16	75.3×
vga_lcd_iccad	679258	259067	1243041	66582	720.40	92.4×	754.35ms	88.3×	766.29	86.9×
b19_iccad	782914	255278	1576198	402645	2144.67	188×	2948.94ms	137×	3483.05	116×
des_perf_ispd	371587	138878	697145	24120	763.79	31.6×	766.31ms	31.5×	780.56	30.9×
edit_dist_ispd	416609	147650	799167	614043	1818.49	338×	2475.12ms	248×	2900.14	212×
mgc_edit_dist	450354	161692	852615	694014	1463.61	474×	1485.65ms	467×	1493.90	465×
mgc_matric_mult	492568	171282	948154	214980	994.67	216×	1075.90ms	200×	1113.26	193×

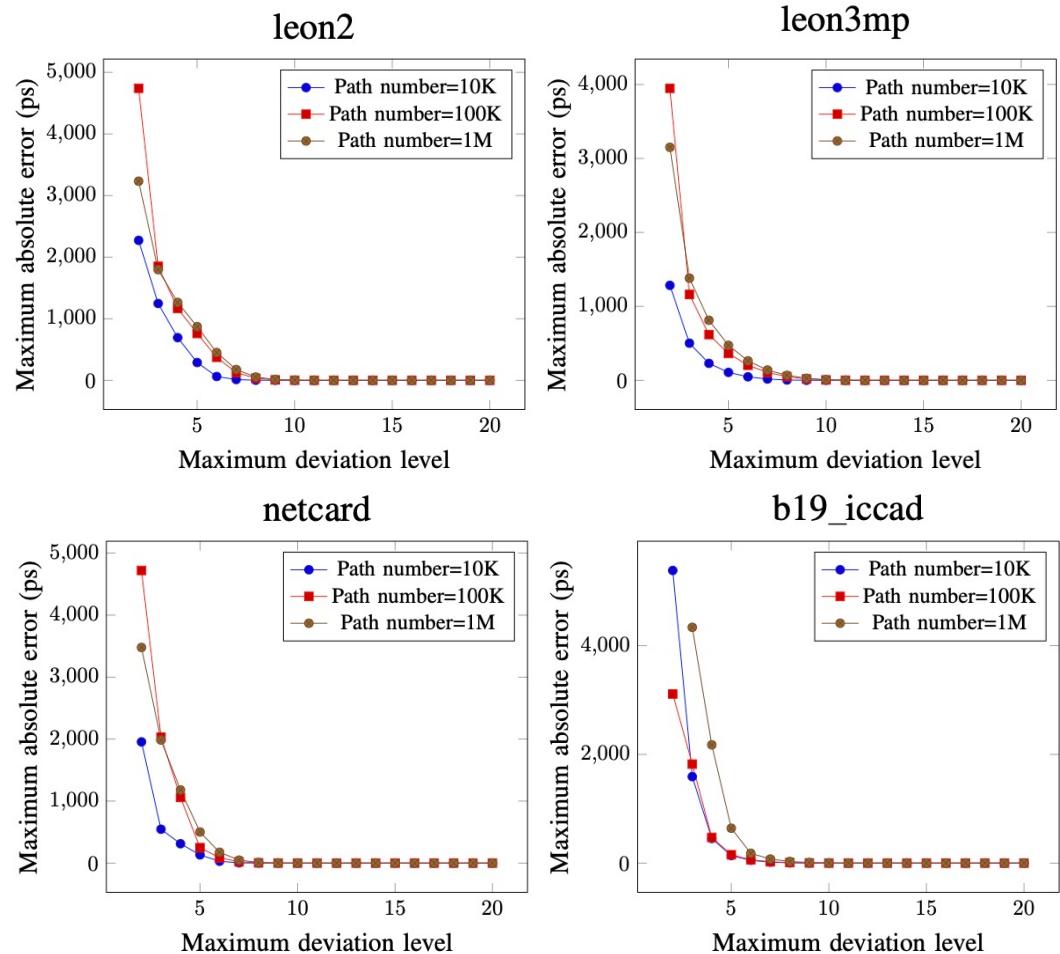
- ❑ Achieve significant speed-up at large designs
 - ❑ 611x speed-up in leon2 (1.3M gates)
 - ❑ 221x speed-up in leon3mp (1.2M gates)

Path Accuracy vs MDL

□ Achieve decent accuracy at 10–12 GPU iterations



**More GPU expansions
(iterations) lead to higher
numbers of paths and thus
better accuracy**

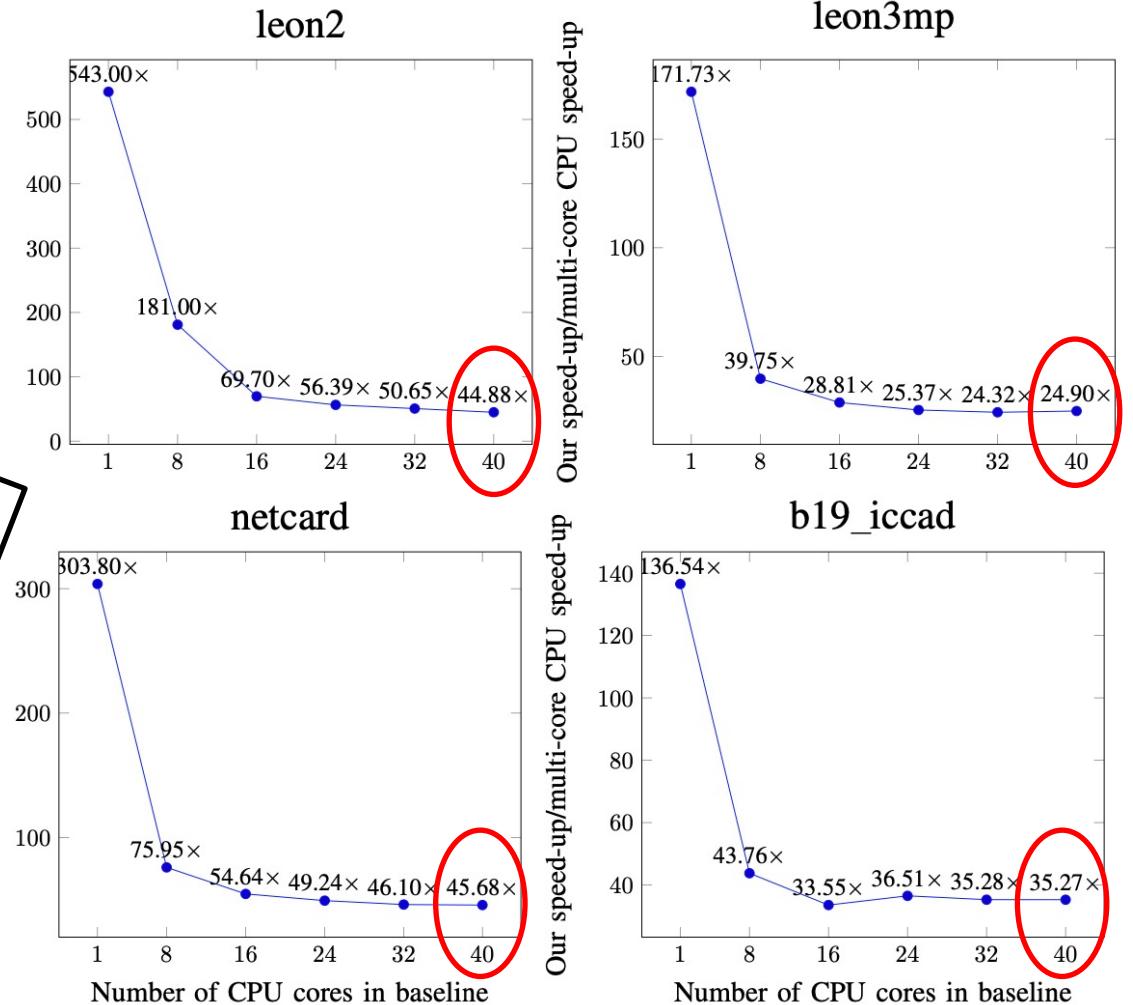


Path Accuracy vs MDL

- ❑ one GPU is even faster than OpenTimer with 40 CPUs

- ❑ 44x on leon2
- ❑ 25x on leon3mp
- ❑ 46x on netcard
- ❑ 35x on b19

In fact, according to our experiments, our GPU-accelerated PBA is always faster than OpenTimer's CPU baseline regardless of the core count



Conclusion

- ❑ **Introduced the runtime challenges of STA**
 - ❑ Knew graph-based analysis
 - ❑ Knew path-based analysis
- ❑ **Accelerated the graph-based analysis using GPU**
 - ❑ Achieved 4x speed-up on large designs
- ❑ **Accelerated the path-based analysis using GPU**
 - ❑ Achieved 600x speed-up on large designs
- ❑ **Future work**
 - ❑ Design GPU-accelerated incremental timing
 - ❑ Design load-balanced PBA algorithms on GPU
 - ❑ Leverage modern GPU graph parallelism

*Thank
you*

Dr. Tsung-Wei Huang

tsung-wei.huang@Utah.edu

Dr. Yibo Lin

yibolin@pku.edu.cn

