



Towards Chip-on-Chip Neuroscience

Fast Mining of Neuronal Spike Streams Using Graphics Hardware

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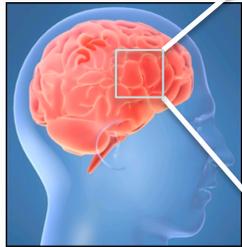
Virginia Polytechnic Institute and State University

Motivation

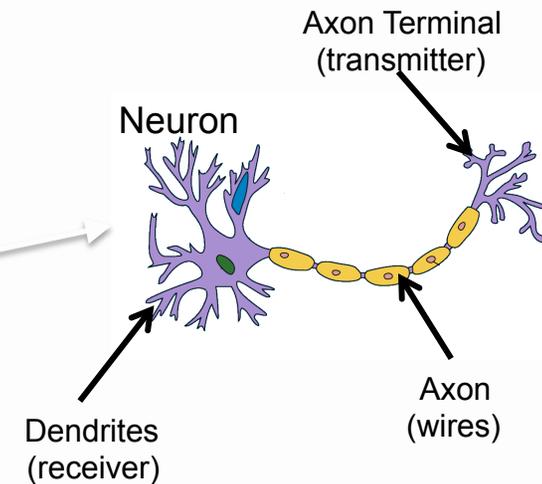
◆ Reverse-engineer the brain



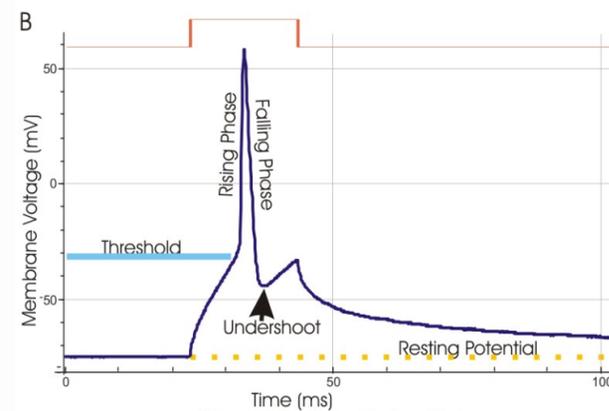
National Academy of Engineering Top 5 Grand Challenges



Cited from Sciseek.com



Question:
How are the neurons
connected?



Action Potentials (Spikes)

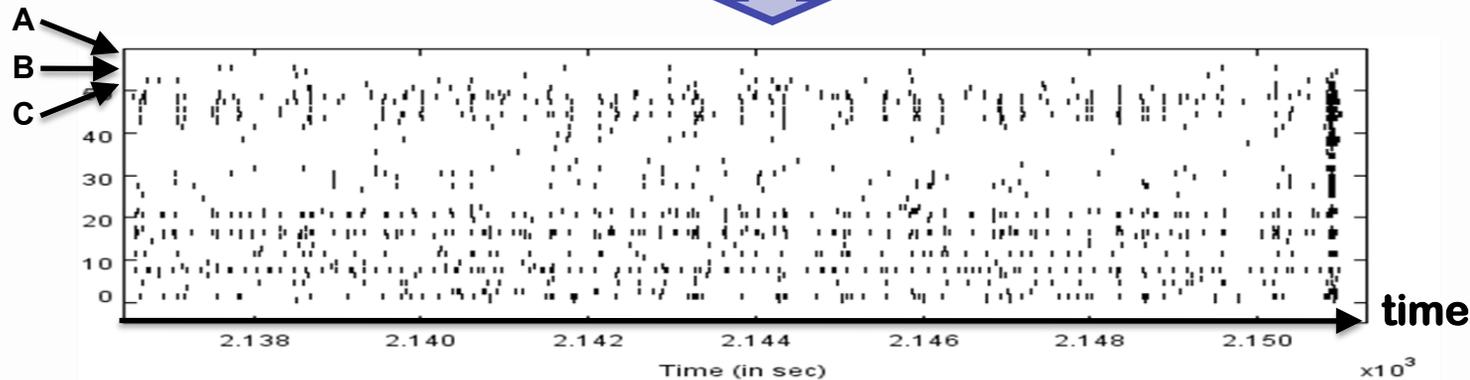
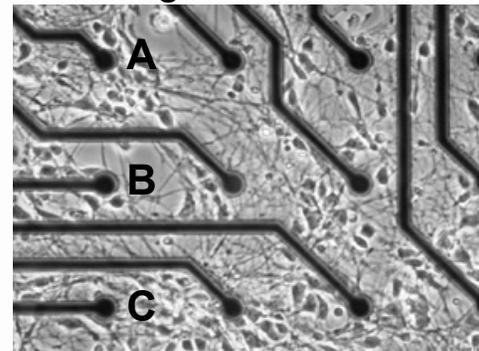
Motivation

◆ Reverse-engineer the brain



National Academy of Engineering Top 5 Grand Challenges

Multi-Electrode Array (MEA) Neurons grown on MEA Chip



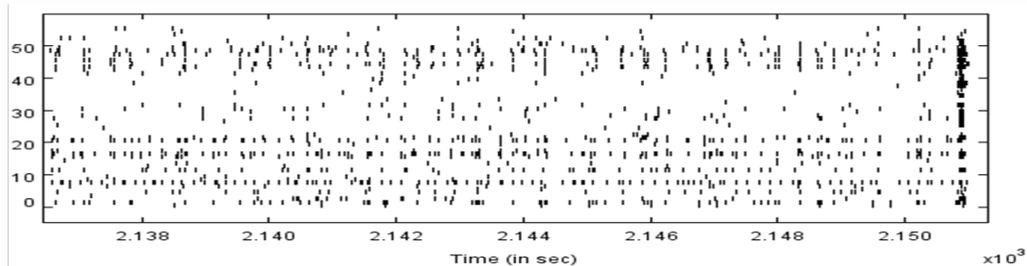
Spike Train Stream

Motivation

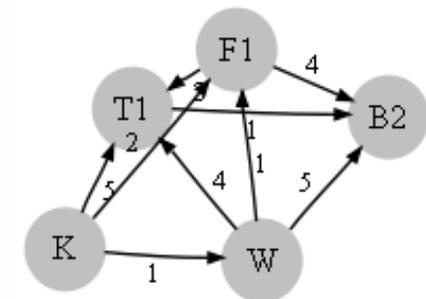
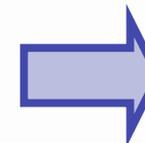
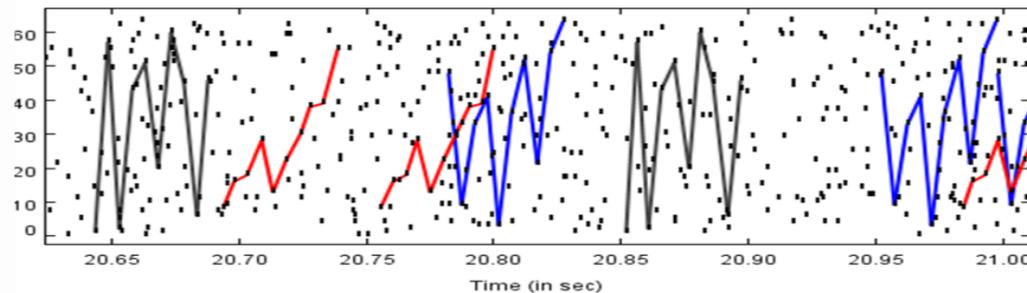
◆ Reverse-engineer the brain



National Academy of Engineering Top 5 Grand Challenges



Find Repeating Patterns

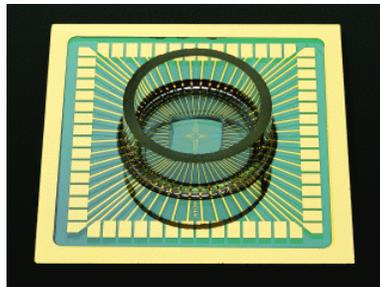


Infer Network Connectivity

Contributions

- ◆ Fast data mining of spike train stream on Graphics Processing Units (GPUs)

MEA Chip



Multi-Electrode Array
(MEA)

GPU Chip



NVIDIA GTX280
Graphics Card

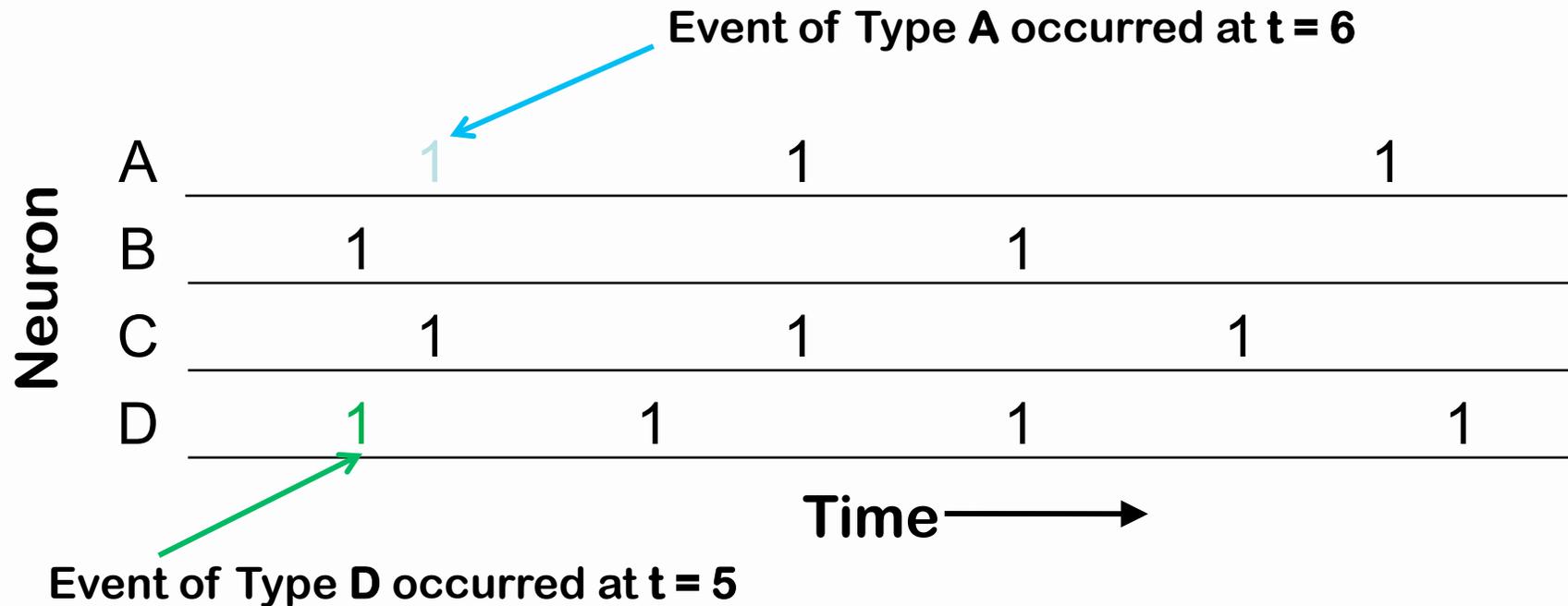
Contributions

- ◆ Fast data mining of spike train stream on Graphics Processing Units (GPUs)
- ◆ Two key algorithmic strategies to address scalability problem on GPU
 - ◆ A hybrid mining approach
 - ◆ A two-pass elimination approach

Background

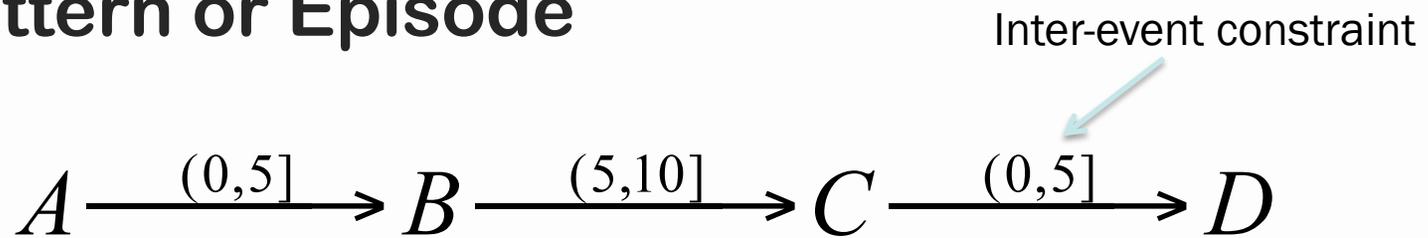
- ◆ Event stream data: sequence of neurons firing

$$\langle (E_1, t_1), (E_2, t_2), \dots, (E_n, t_n) \rangle$$

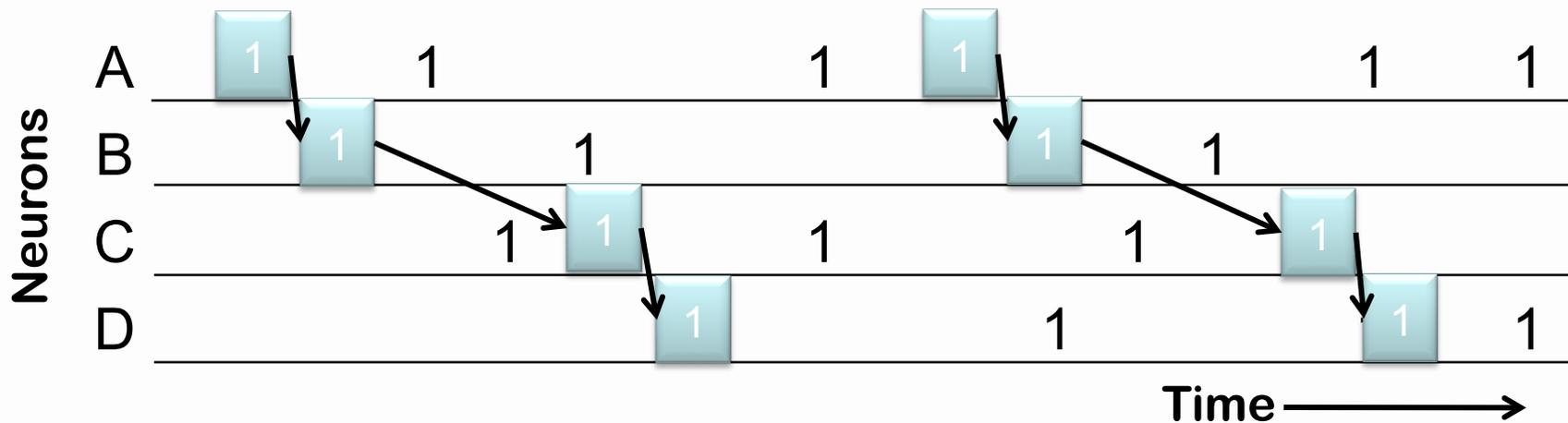


Background

◆ Pattern or Episode



◆ Occurrences (Non-overlapped)



Episode appears twice in the event stream.

Background

◆ Data mining problem:

Find all possible episodes / patterns which occur more than X-times in the event sequence.

◆ Challenge:

◆ Combinatorial Explosion: large number of episodes to count

Episode Size/Length:	1	2	3	4
	<i>A</i>	<i>A → B</i>	<i>A → B → C</i>	<i>A → B → C → D</i>	
	<i>B</i>	<i>B → A</i>	<i>A → C → B</i>	<i>A → C → B → D</i>	
	⋮	<i>A → C</i>	<i>B → A → C</i>	<i>A → C → D → B</i>	
	⋮	⋮	<i>B → C → A</i>	<i>A → D → B → C</i>	
		⋮	⋮	<i>A → D → C → B</i>	
			⋮	⋮	

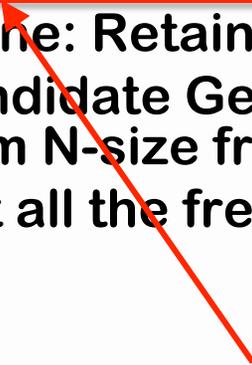
Background

◆ Mining Algorithm

(A level wise procedure to control combinatorial explosion)

- Generate an initial list of candidate *size-1* episodes
- Repeat until - no more candidate episodes
 - **Count:** Occurrences of *size-M* candidate episodes
 - Prune: Retain only frequent episodes
 - Candidate Generation: *size-(M+1)* candidate episodes from N-size frequent episodes
- Output all the frequent episodes

Computational bottleneck



Background

◆ Counting Algorithm (for one episode)

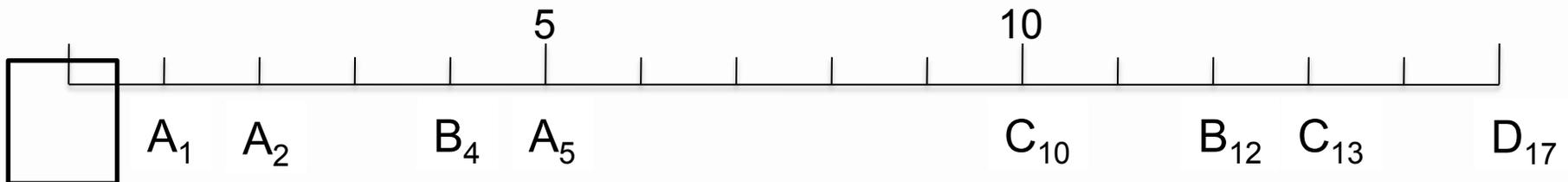
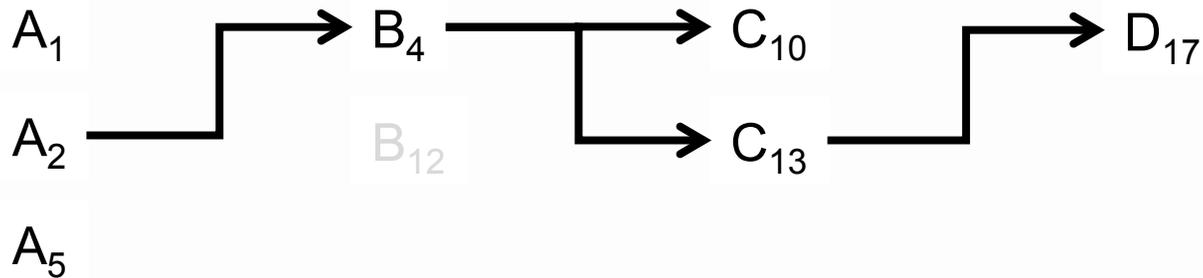
Episode: $A \xrightarrow{(0,5]} B \xrightarrow{(5,10]} C \xrightarrow{(0,5]} D$

Accept_A()

Accept_B()

Accept_C()

Accept_D()



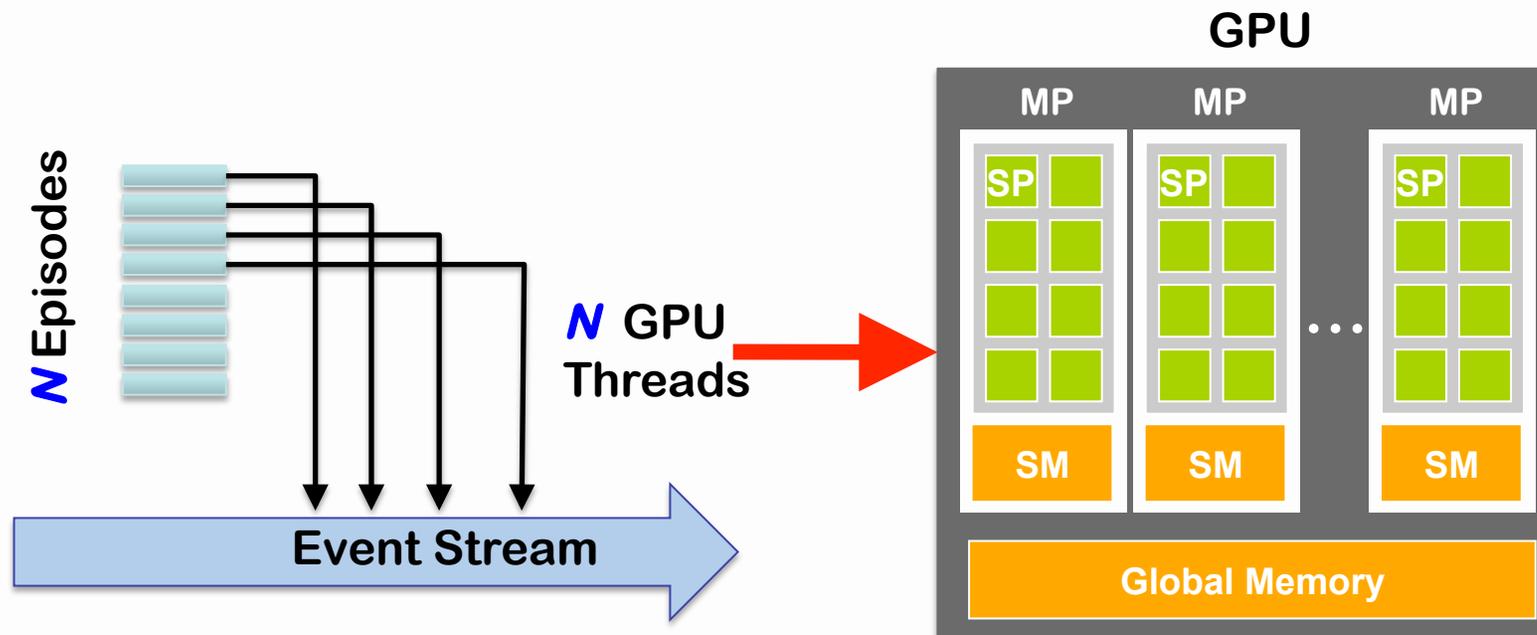
Event Stream

Problem Statement

- ◆ Find an efficient counting algorithm on GPU to count the occurrences of N size- M episodes in an event stream.
- ◆ Address scalability problem on GPU's massive parallel execution architecture.

A Naïve Approach

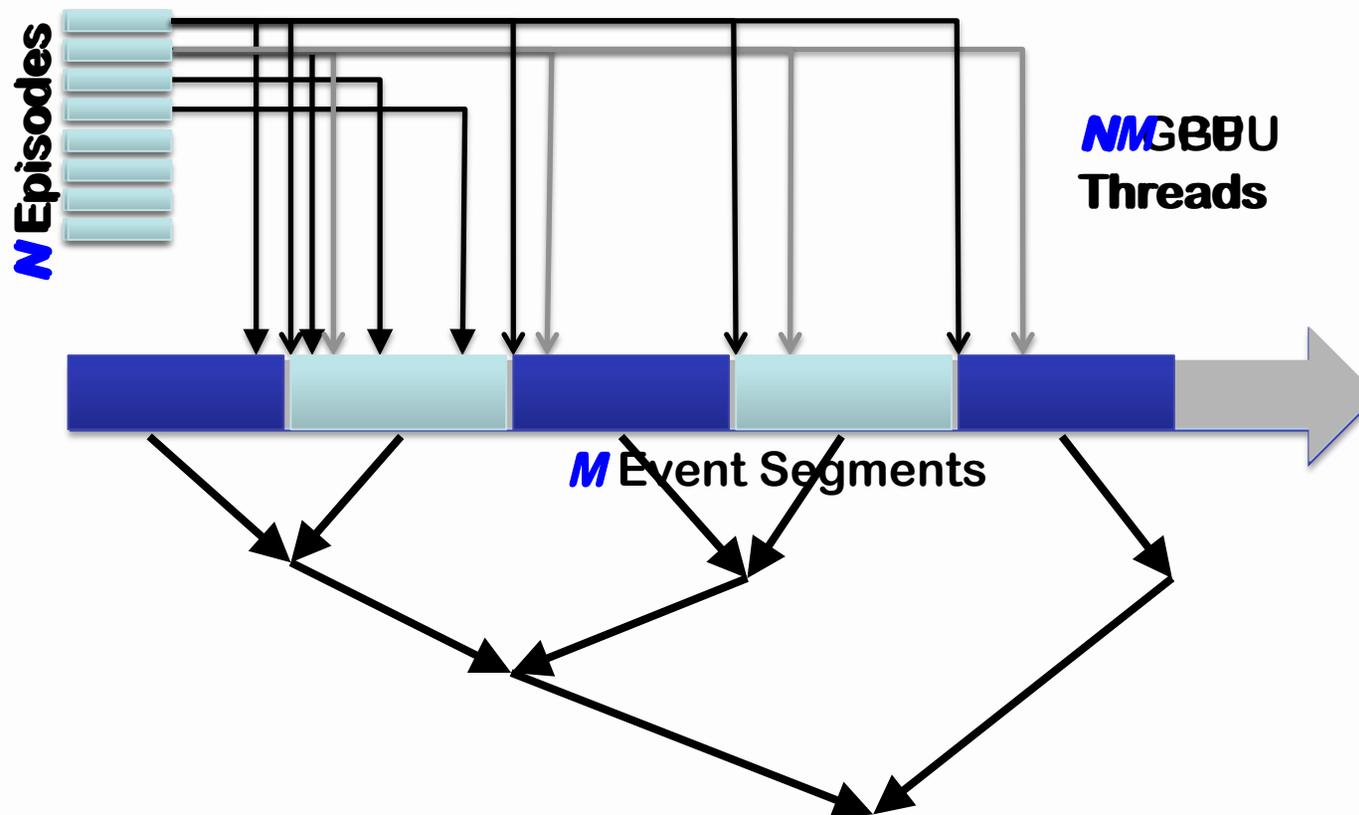
- ◆ One episode per GPU thread (PTPE)
 - ◆ Each thread counts one episode
 - ◆ Simple extension of serial counting



- ◆ Efficient when the number of episode is larger than the number of GPU cores.

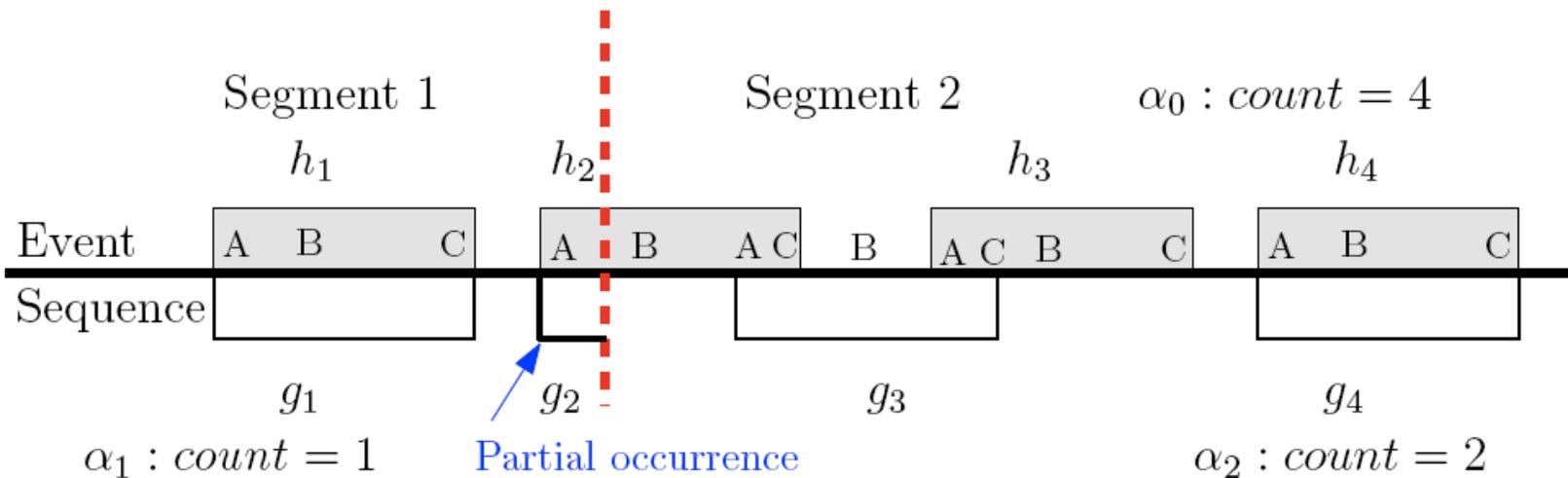
Small Scale

- ◆ Not enough episodes/thread, some GPU cores will be idle.
- ◆ Solution: Increase the level of parallelism.
Multiple Thread per Episode (MTPE)



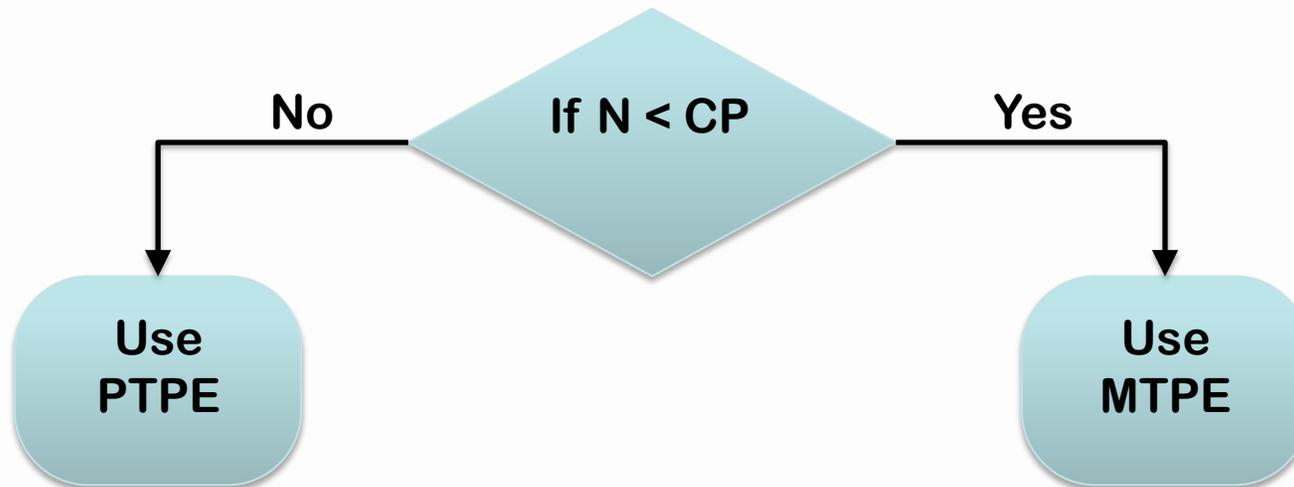
Small Scale

◆ Problem with simple count merge.



A Hybrid Approach

- ◆ Choose the right algorithm with respect to the number of episodes N .
- ◆ Define a switching threshold - **Crossover point (CP)**



GPU
computing
capacity

$$CP = MP \times B_{MP} \times T_B \times f(\text{size})$$

MP : Number of multi-processors

B_{MP} : Block per multi-processor

T_B : Thread per block

Performance
Penalty
Factor

Large Scale

- ◆ Problem: Original counting algorithm is too complex for a GPU kernel function.

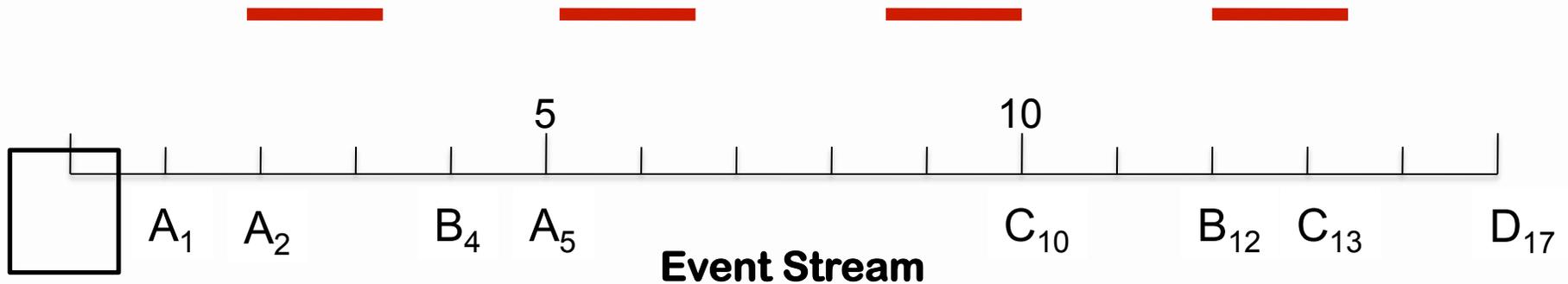
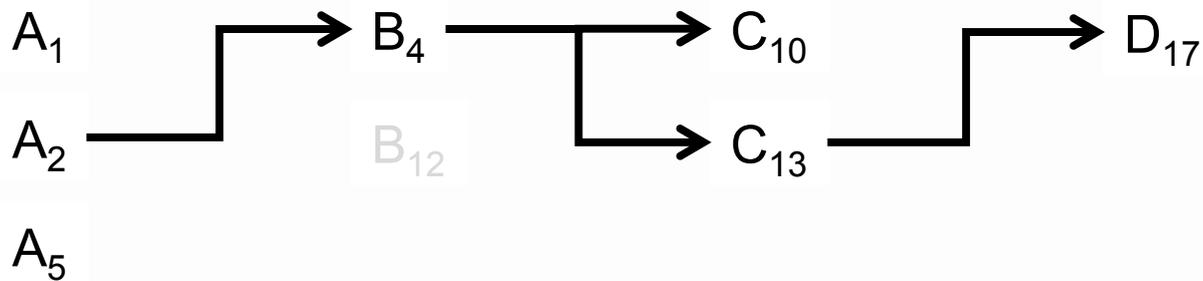
Episode: $A \xrightarrow{(0,5]} B \xrightarrow{(5,10]} C \xrightarrow{(0,5]} D$

Accept_A()

Accept_B()

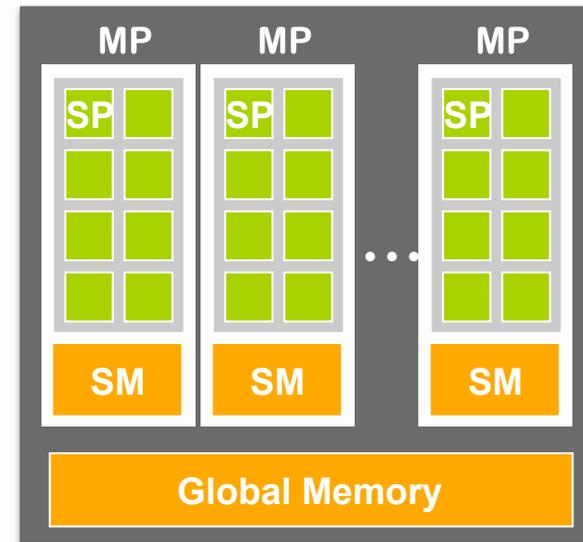
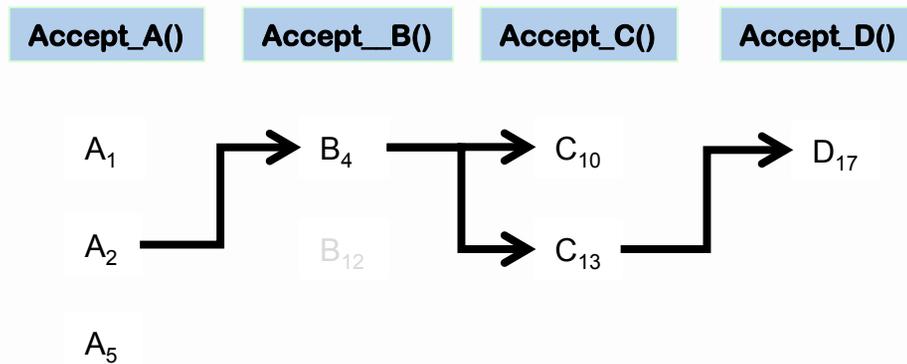
Accept_C()

Accept_D()



Large Scale

- ◆ Problem: Original counting algorithm is too complex for a GPU kernel function.



- ◆ Large shared memory usage
- ◆ Large register file usage
- ◆ Large number of branching instructions

Large Scale

◆ Solution: *PreElim* algorithm

- ◆ Less constrained counting → Simple kernel function
- ◆ Upper bound only

Episode: $A \xrightarrow{(-,5]} B \xrightarrow{(-,10]} C \xrightarrow{(-,5]} D$

Accept_A()

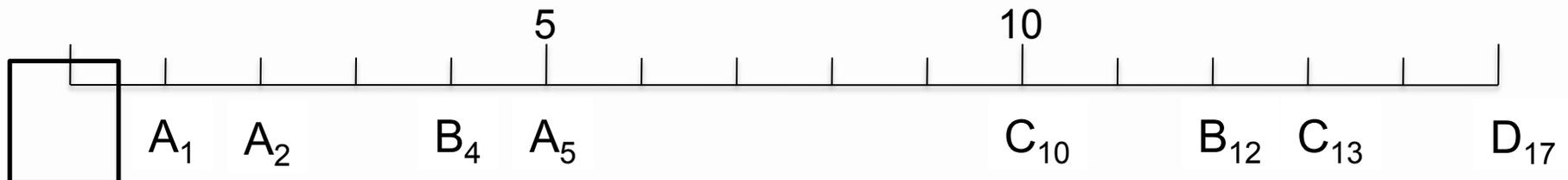
Accept_B()

Accept_C()

Accept_D()

$A_5 \longrightarrow B_4 \longrightarrow C_{13} \longrightarrow D_{17}$

B_{12}



Event Stream

Large Scale

◆ A simpler kernel function

	Shared Memory	Register	Local Memory
<i>PreElim</i>	4 x Episode Size	13	0
<i>Normal Counting</i>	44 x Episode Size	17	80

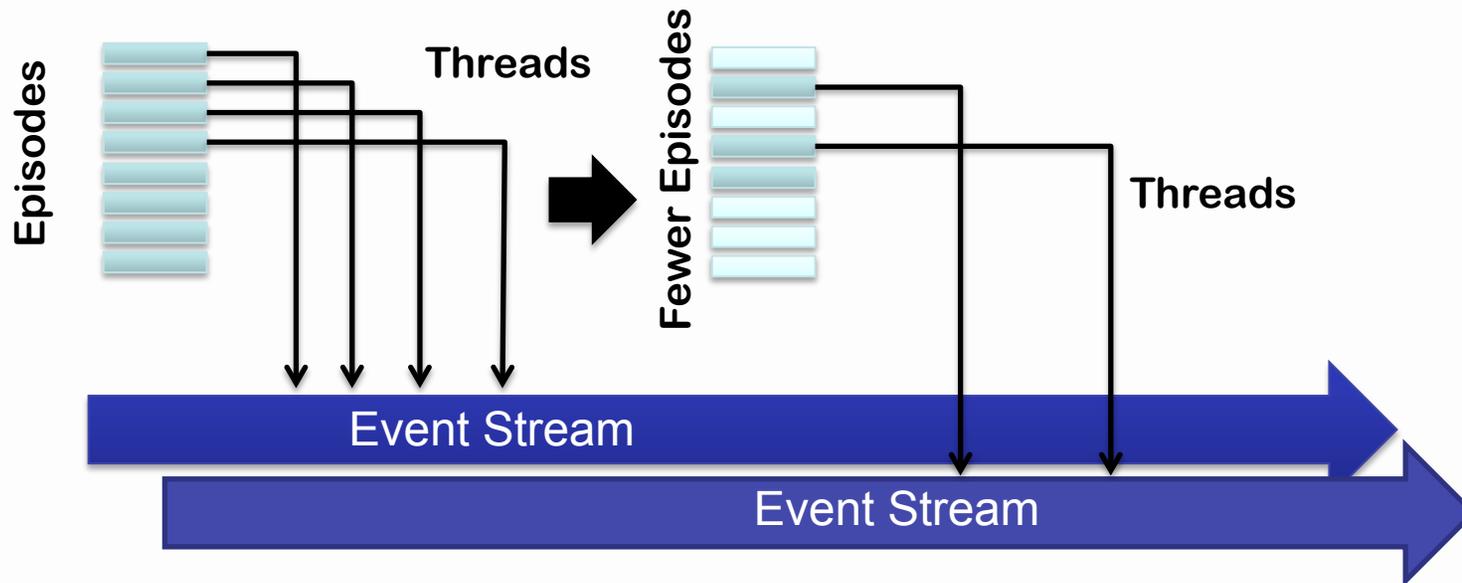
Large Scale

◆ Solution:

- ◆ Two-pass elimination approach

PASS 1: Less Constrained Counting

PASS 2: Normal Counting



Large Scale

◆ A simpler kernel function

Compile Time Difference

	Shared Memory	Register	Local Memory
<i>PreElim</i>	4 x Episode Size	13	0
<i>Normal Counting</i>	44 x Episode Size	17	80

Run Time Difference

	Local Memory Load and Store	Divergent Branching
<i>Two Pass</i>	24,770,310	12,258,590
<i>Hybrid</i>	210,773,785	14,161,399

Results

◆ Hardware

◆ Computer (custom-built)

- ◆ Intel Core2 Quad @ 2.33GHz

- ◆ 4GB memory

◆ Graphics Card (Nvidia GTX 280 GPU)

- ◆ 240 cores (30 MPs * 8 cores) @ 1.3GHz

- ◆ 1GB global memory

- ◆ 16K shared memory for each MP

Results

◆ Datasets

◆ Synthetic (*Sym26*)

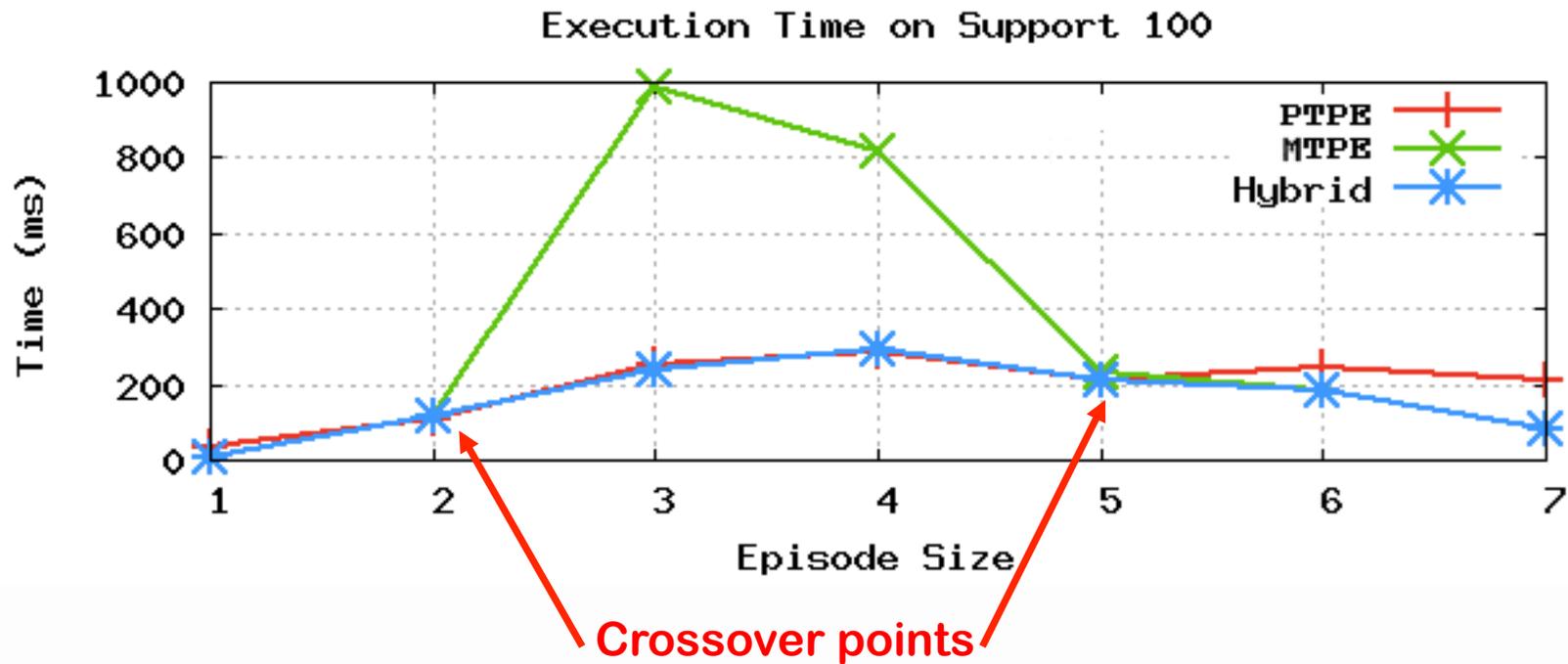
- ◆ 60 seconds with 50,000 events

◆ Real (Culture growing for 5 weeks)

- ◆ Day 33: *2-1-33* (333478 events)
- ◆ Day 34: *2-1-34* (406795 events)
- ◆ Day 35: *2-1-35* (526380 events)

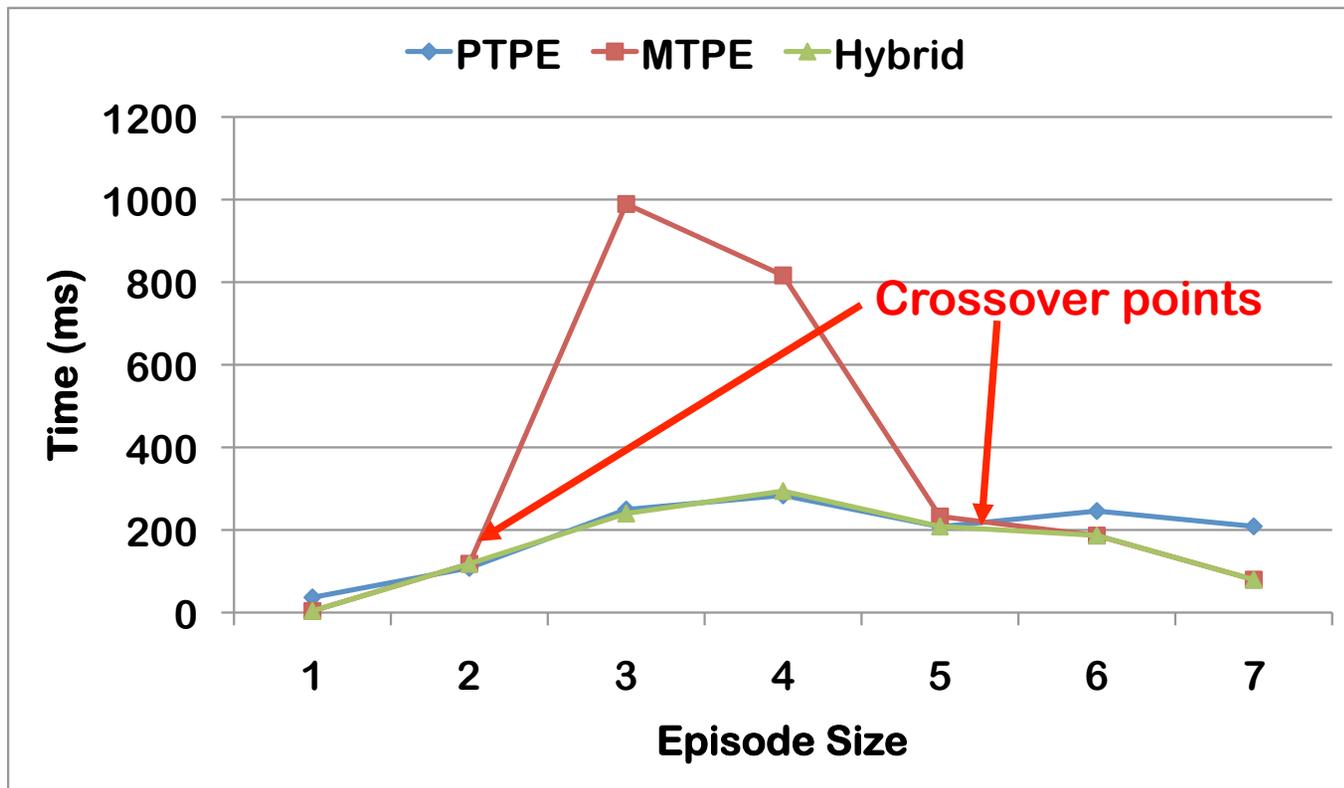
Results:

◆ PTPE vs MTPE



Results:

◆ Performance of the Hybrid Approach



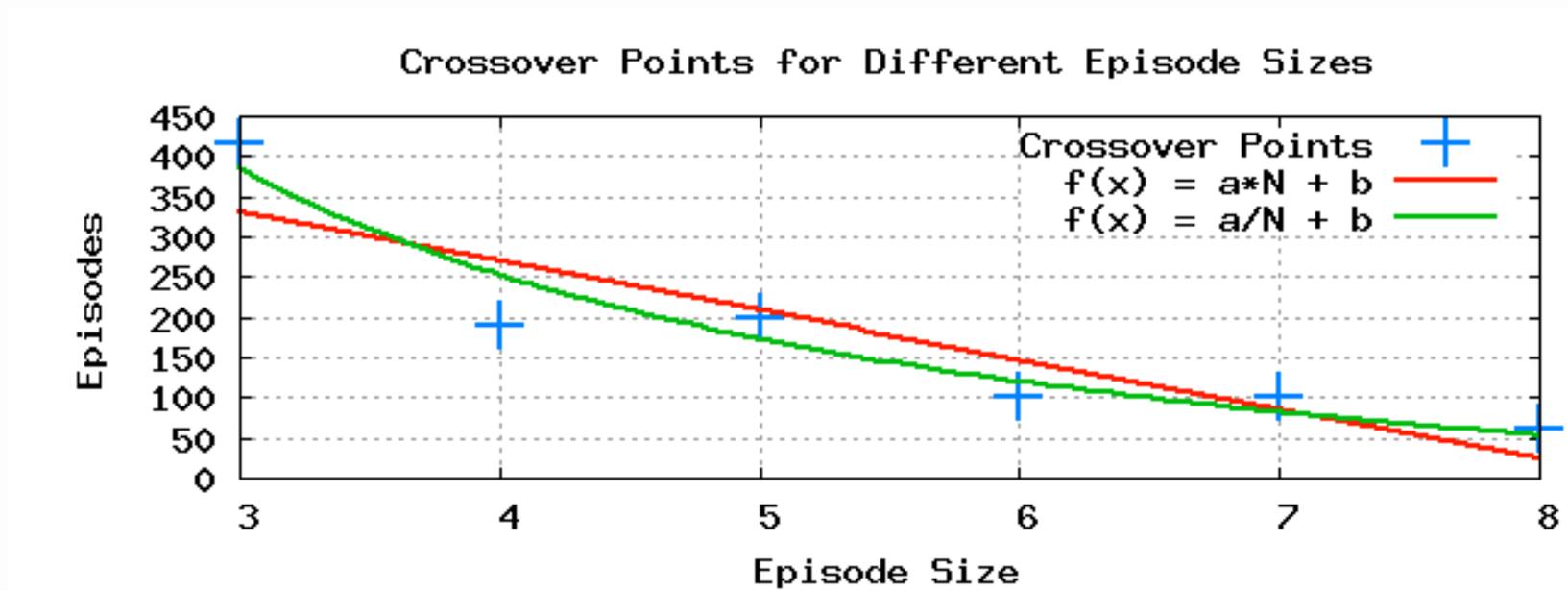
Episode Number:

26	650	4075	1288	228	63	3
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Sym26 dataset, Support = 100

Results:

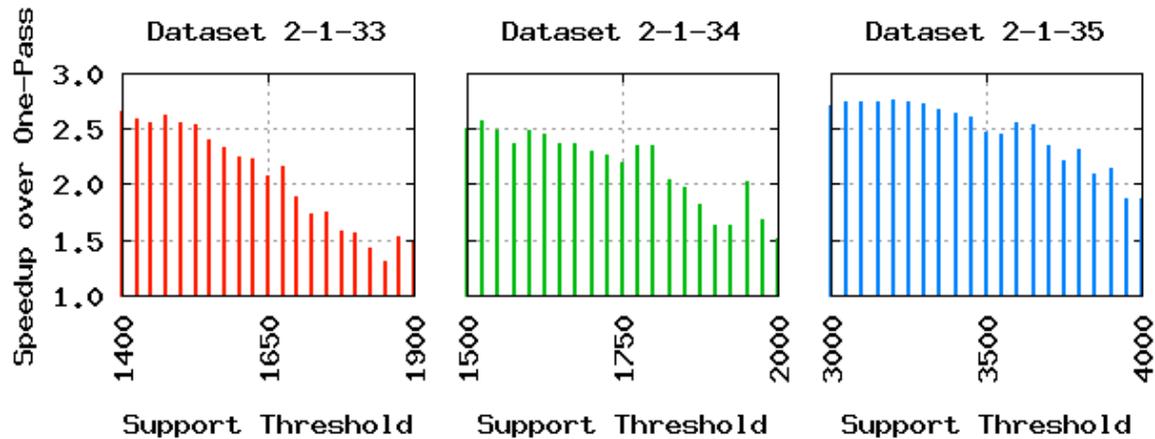
◆ Crossover Point Estimation



- ◆ $f(\text{size}) = \frac{a}{\text{size}} + b$ is a better fit.
- ◆ A least square fit is performed.

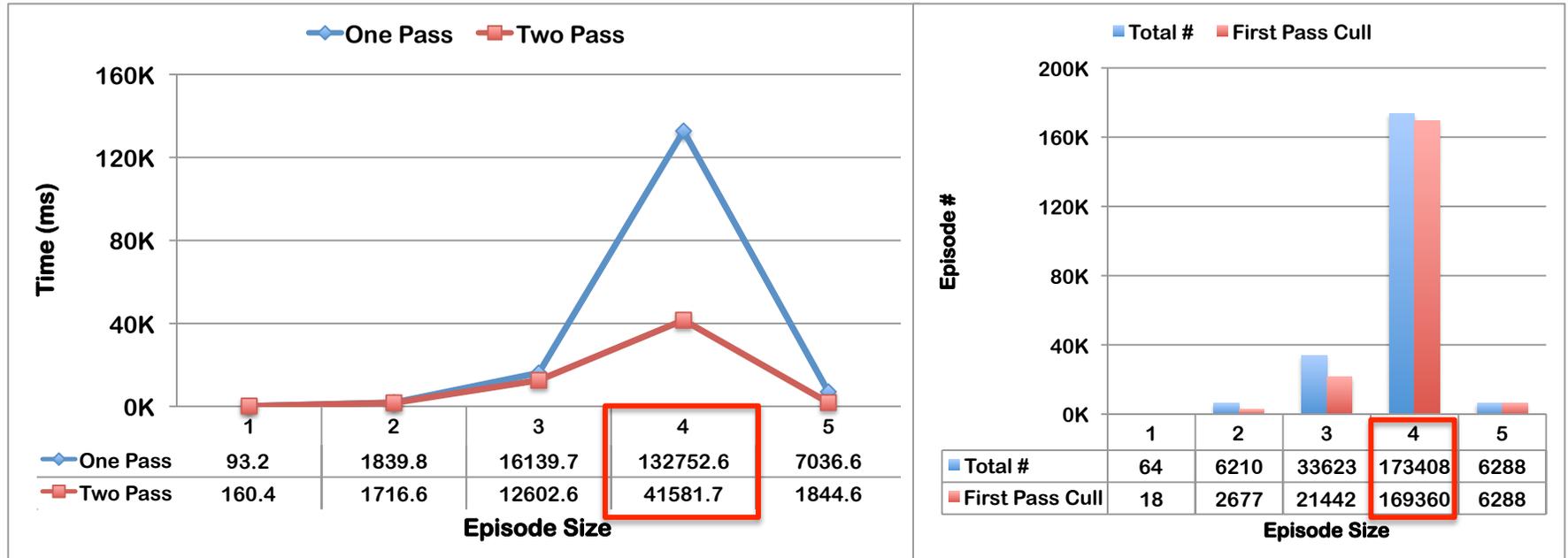
Results:

◆ Two-pass approach vs Hybrid approach



Results:

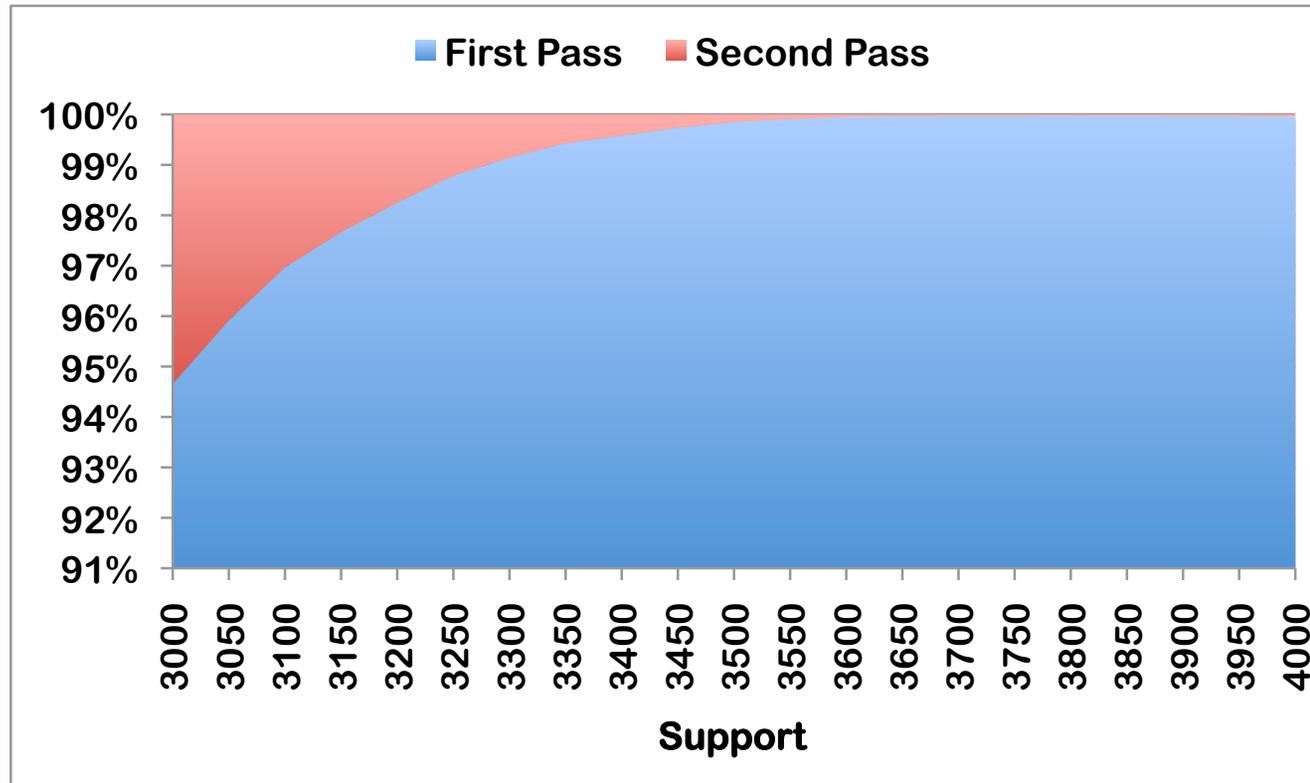
◆ Performance of the Two-pass approach



2-1-35 dataset, Support = 3150

Results:

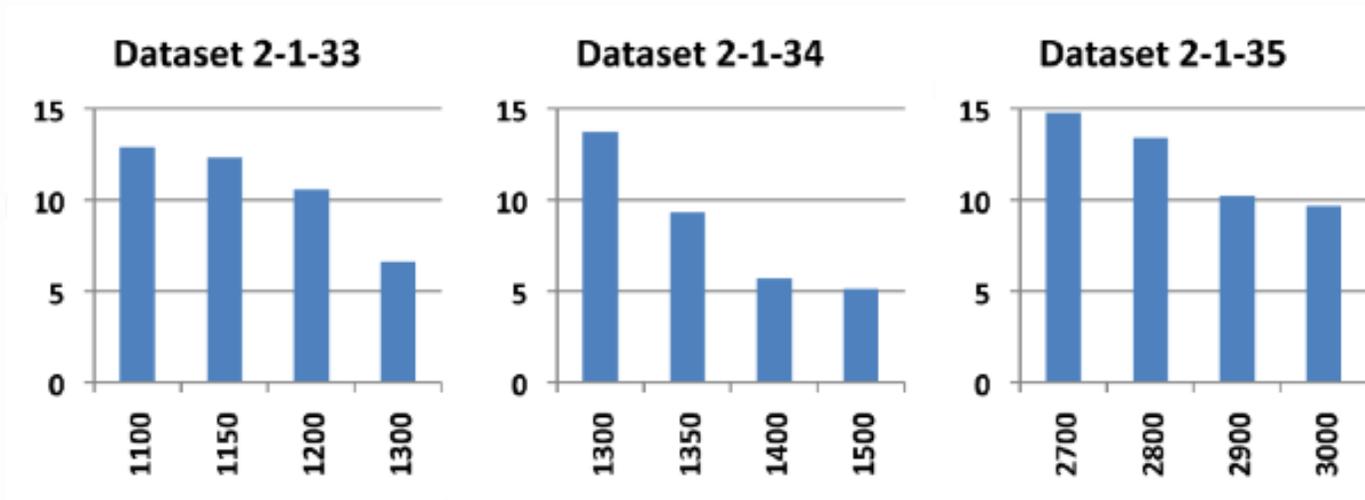
◆ Percentage of episodes eliminated by each pass



2-1-35 dataset, episode size = 4

Results:

◆ GPU vs CPU



- **GPU is always faster than CPU**
 - 5x - 15x speedup
 - Fair comparison
 - Two-pass algorithm used
 - Maximum threading for both

Conclusion and future work

- ◆ Massive parallelism is required for conquering near exponential search space
 - ◆ GPU's far more accessible than high performance clusters
- ◆ Frequent episode mining – Not data parallel
 - ◆ Redesigned algorithm
- ◆ Framework for real-time and interactive analysis of spike train experimental data

Conclusion

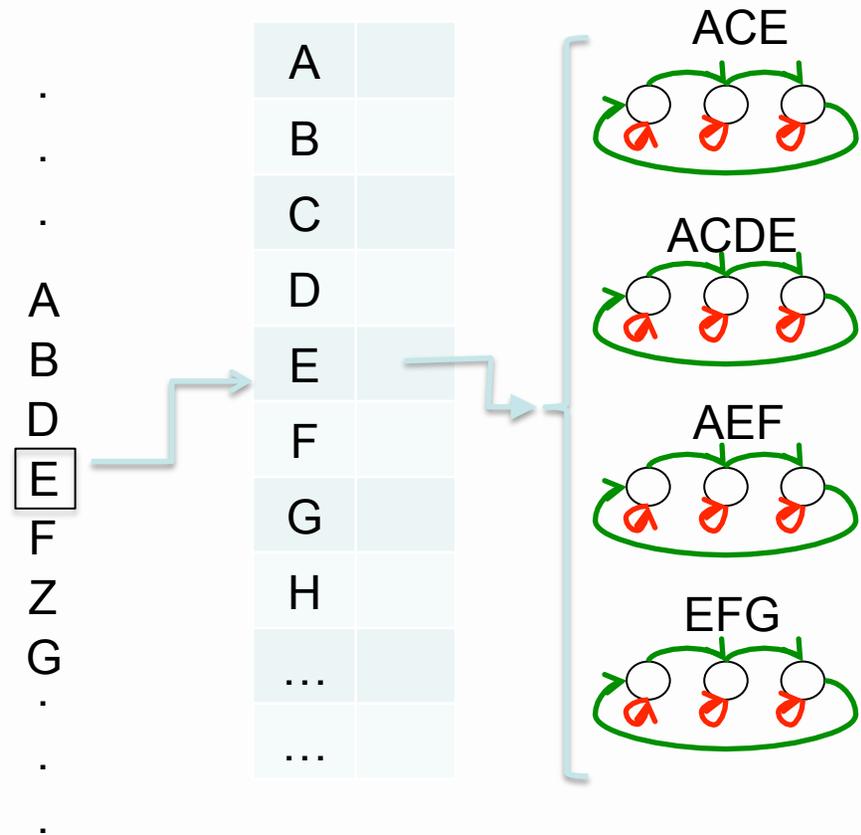
- ◆ A fast temporal data mining framework on GPUs
 - ◆ Commoditized system
 - ◆ Massive parallel execution architecture
- ◆ Two programming strategies
 - ◆ A hybrid approach
 - ◆ Increase level of parallelism
(data segmentation + map-reduce)
 - ◆ Two-pass elimination approach
 - ◆ Decrease algorithm complexity
(Task decomposition)

Thank you.

Questions.

CPU Implementation

- ◆ Parallel Execution via pthreads
- ◆ Optimized for CPU execution
 - ◆ Minimize disk access
 - ◆ Cache performance
- ◆ Implements Two-Pass Approach
 - ◆ PreElim – Simpler/ Quicker state machine
 - ◆ Full State Machine – Slower but is required to eliminate all unsupported episodes



Candidate Generation

- ◆ Level-wise

- ◆ N-size frequent episodes => (N+1)-size candidates

