

# Shortest Lattice Vector Enumeration on Graphics Cards

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- 1 Introduction
- 2 Lattices: crash course
- 3 GPUs
- 4 The Algorithm
- 5 Results
- 6 The Future

# Why GPU?



(Source: MSI)

# CUDA framework

## Warning: sales talk

Your own personal supercomputer for  $< \text{€}500$ .

Nvidia CUDA Framework:

- Run 'general' programs on GPU
- More complex operations, data types, branching...
- Recent GPU required
- Theory: 1TFlop (practice: 200 GFlop)

# Crypto on GPU

Current applications:

- Ciphers:
  - RSA <sup>1</sup>, ECC <sup>2</sup>, AES <sup>3</sup>
- Cryptanalysis:
  - Factoring <sup>4</sup>
  - Brute force

Focus: high throughput, not latency

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<sup>1</sup>Moss, Page, Smart / Szerwinski, Guneyasu / Fleissner

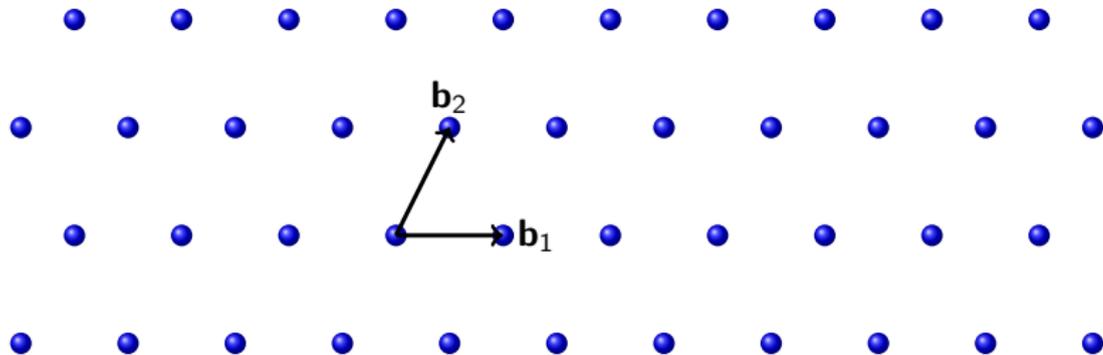
<sup>2</sup>Szerwinski, Guneyasu

<sup>3</sup>Manavski / Harrison, Waldron

<sup>4</sup>Bernstein, Chen, Cheng, Lange, Yang

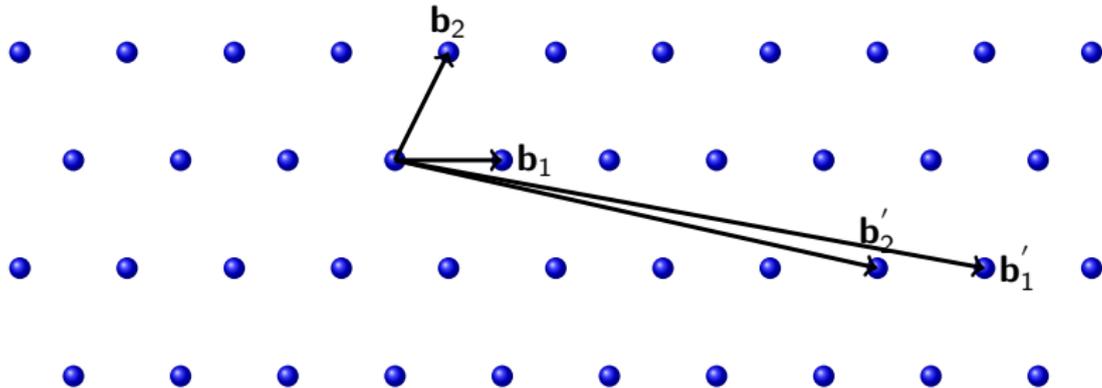
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# Lattices



- Basis matrix  $\mathbf{B} = \{\mathbf{b}_1, \dots, \mathbf{b}_n\}$  with  $\mathbf{b}_i \in \mathbb{R}^d$
- Lattice:  $L(\mathbf{B}) = \{\sum_{i=1}^n x_i \mathbf{b}_i, x_i \in \mathbb{Z}\}$

# Shortest Vector Problem (SVP)



- Basis not unique
- Idea: 'good' basis  $\mathbf{B}$  and 'bad' basis  $\mathbf{B}'$
- Finding  $\lambda_1(L)$  is hard with  $\mathbf{B}'$

# Algorithms for SVP

## Shortest vector problem

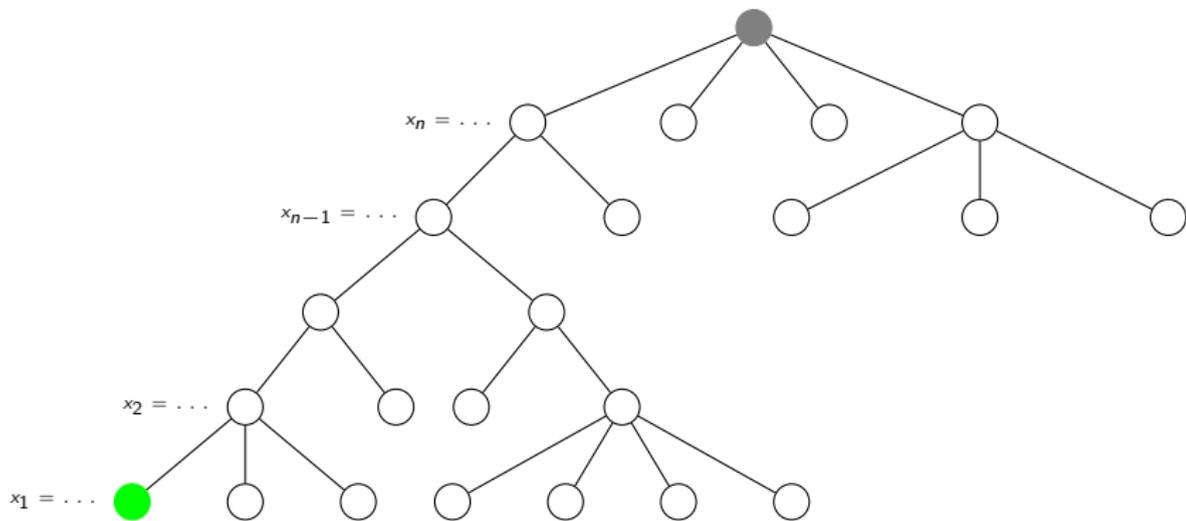
$$\text{Compute } \min_{\mathbf{x} \in \mathbb{Z}^n} \|\mathbf{B}\mathbf{x}\|_2$$

SVP algorithms:

- LLL (+variants): approximate solution, polynomial
- BKZ
- ...
- Enum: exact solution, exponential

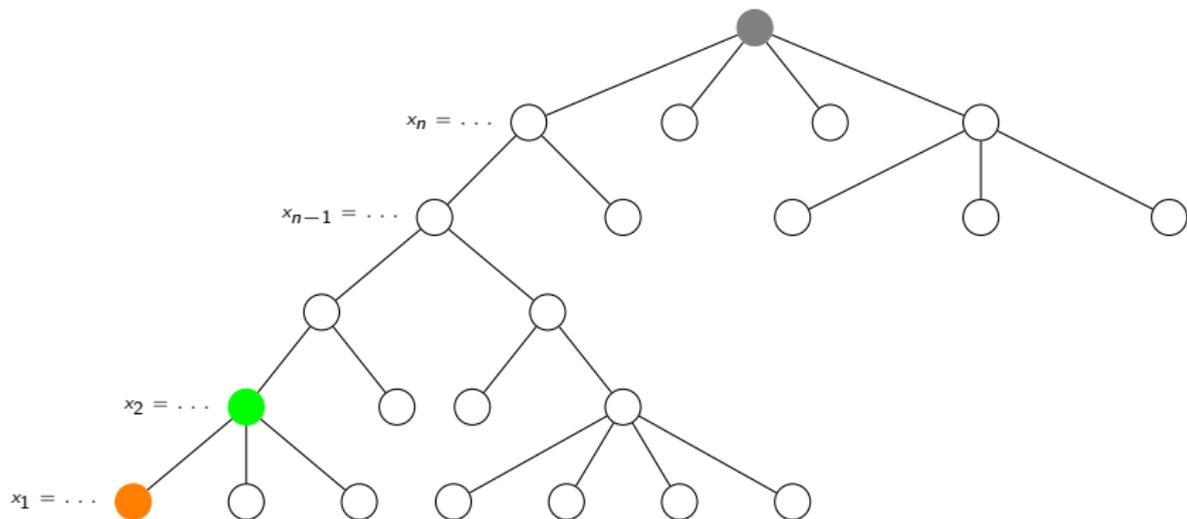
⇒ This talk: focus on enum.

# Enumeration



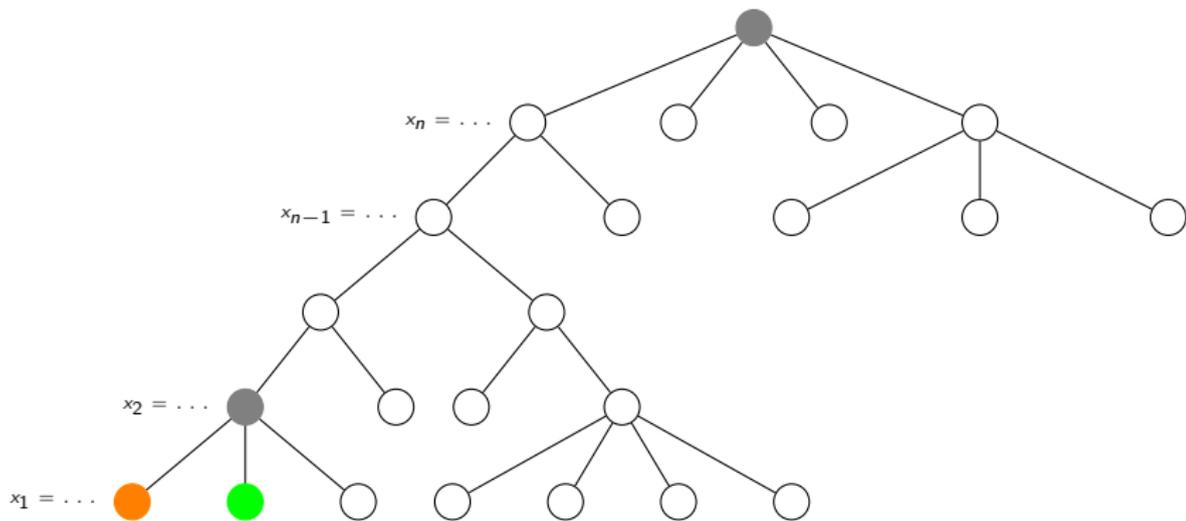
Optimum  $A = \|\mathbf{B}\mathbf{x}\|_2^2$  and  $\mathbf{x} = [1, 0, \dots, 0]$

# Enumeration



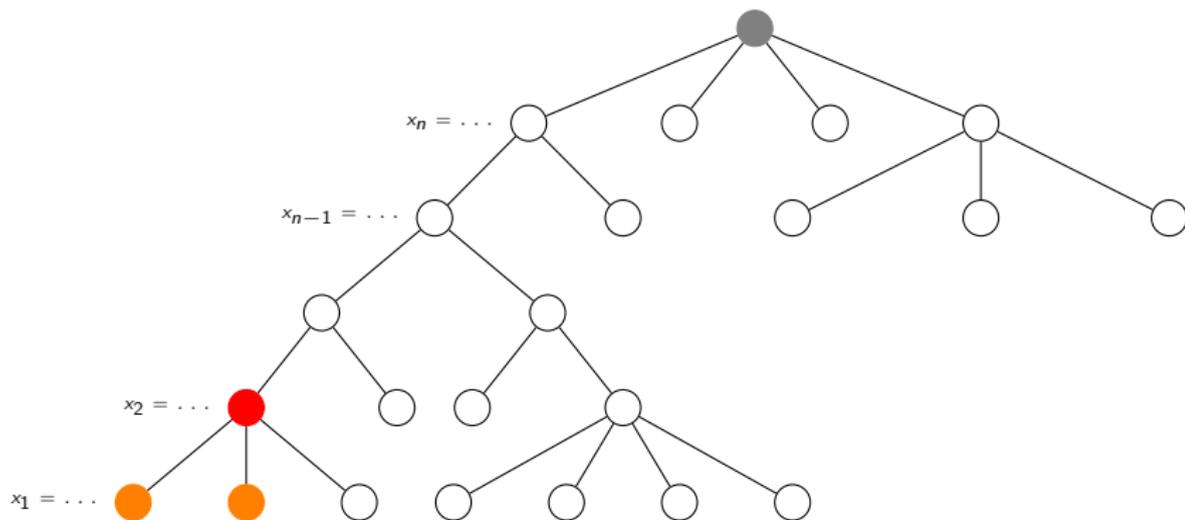
Intermediate norm  $l_2$  s.t.  $l_i \geq l_{i+1}$  (with  $l_1 = \|\mathbf{B}\mathbf{x}\|_2^2$ )

# Enumeration



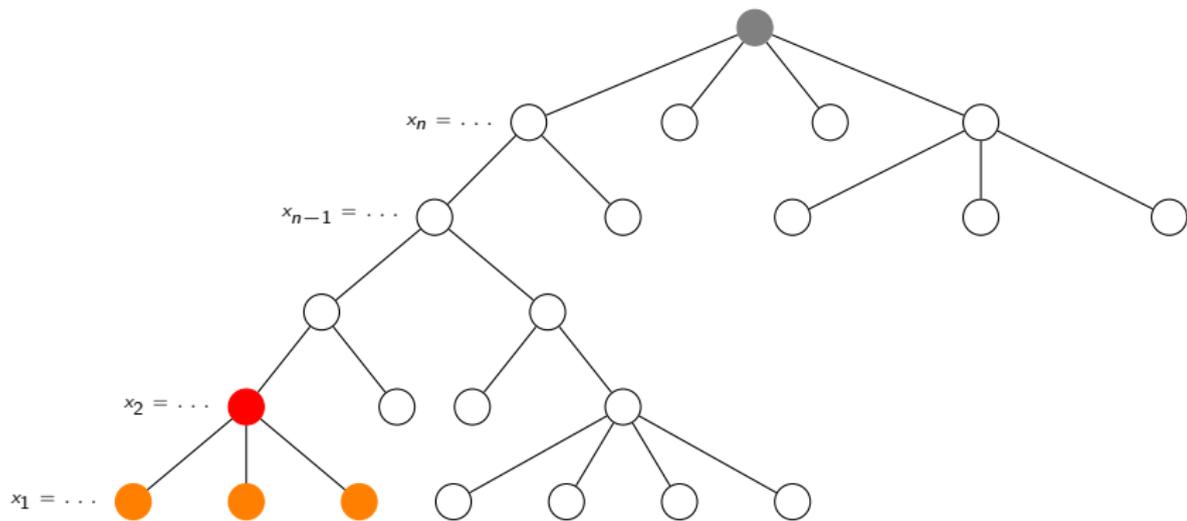
New optimum  $A = \|\mathbf{B}\mathbf{x}\|_2^2$

# Enumeration

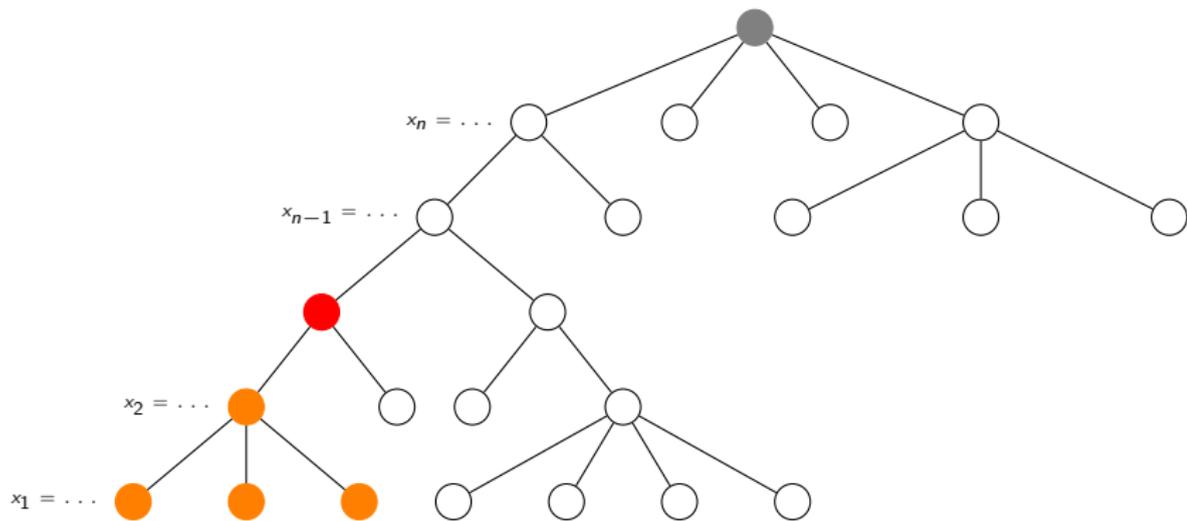


Cut off branch if  $l_i > A$ .

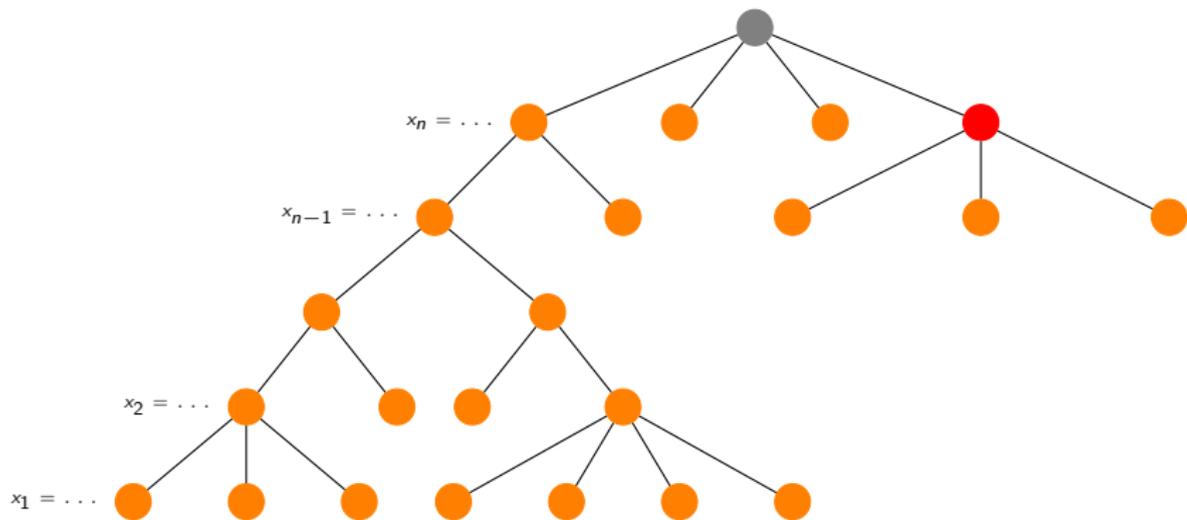
# Enumeration



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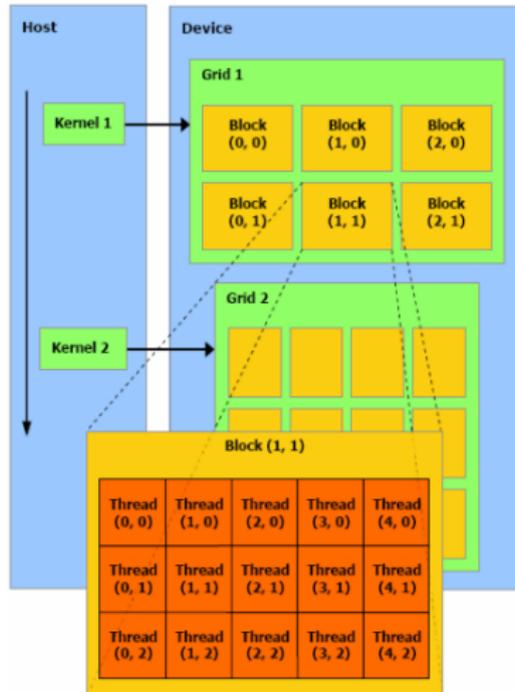
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# Processor

Nvidia GTX280:

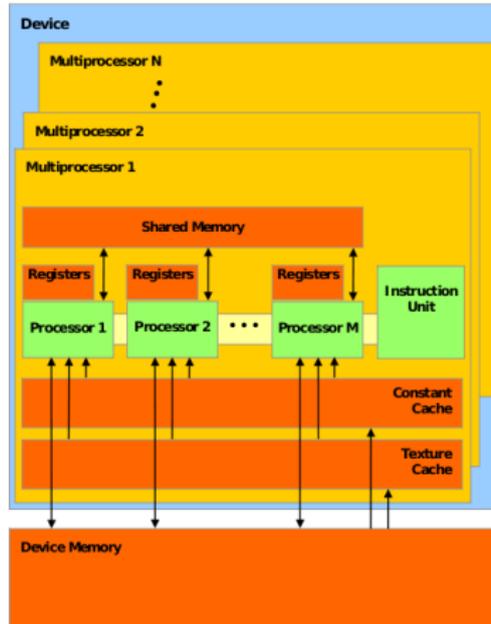
- 240 cores, scalar processors
- 30 multiprocessors (8 cores each)
- 1.3 GHz
- 1GB Global Memory
- 32 & 64-bit integers, FP

# Programming model



(Source: CUDA programming guide)

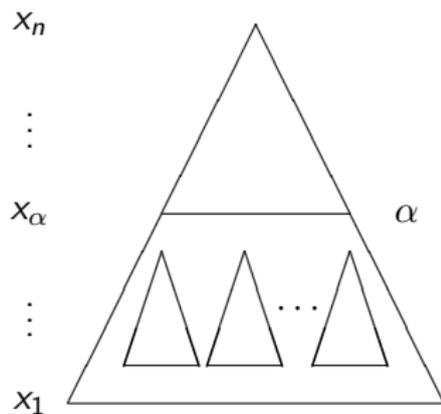
# Memory types



(Source: CUDA programming guide)

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# Algorithm Flow



# Basic idea

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**Input:**  $\mathbf{B}, A, \alpha, n$

1 Compute the Gram-Schmidt decomposition of  $\mathbf{b}_i$

2

3

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

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# Basic idea

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**Input:**  $\mathbf{B}$ ,  $A$ ,  $\alpha$ ,  $n$

- 1 Compute the Gram-Schmidt decomposition of  $\mathbf{b}_i$
- 2 CPU: generate  $\mathbf{x}_i = [0, \dots, 0, x_\alpha, \dots, x_n]$
- 3

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

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# Basic idea

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- 3 GPU thread: run a sub-enum on  $\mathbf{x}_i$ , if new optimum  $\rightarrow$  store in  $\mathbf{x}$

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$\implies$  horrible performance

# Early termination...

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**Input:**  $\mathbf{B}$ ,  $A$ ,  $\alpha$ ,  $n$

- 1 Compute the Gram-Schmidt decomposition of  $\mathbf{b}_i$
- 2 CPU: generate  $\mathbf{x}_i = [0, \dots, 0, x_\alpha, \dots, x_n]$

8

9

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

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## Early termination...

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- 3 GPU thread:
- 4 **while** *there are  $\mathbf{x}_i$  left.* **do**
- 5 | Start enum for a certain  $\mathbf{x}_i = [0, \dots, 0, x_\alpha, \dots, x_n]$
- 6 | Stop enum after  $\mathbf{S}$  steps, store the state  $\{l_i, \bar{\mathbf{x}}_i, s_i = \mathbf{S}\}$
- 7 **end**
- 8
- 9

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

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## Early termination...

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## Early termination...

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- 6 |   Stop enum after  $\mathbf{S}$  steps, store the state  $\{l_i, \bar{\mathbf{x}}_i, s_i = \mathbf{S}\}$
- 7 **end**
- 8 CPU: Get enum state  $\bar{\mathbf{x}}_i = [\bar{x}_1, \dots, \bar{x}_{\alpha-1}, x_\alpha, \dots, x_n]$
- 9 CPU: Continue enum if  $\mathbf{S}$  was reached

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

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$\implies$  solves length difference problem, still not so good

# Iterating

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**Input:**  $\mathbf{B}$ ,  $A$ ,  $\alpha$ ,  $n$

- 1 Compute the Gram-Schmidt decomposition of  $\mathbf{b}_i$
- 2 **while** *true* **do**
- 3     CPU: generate some  $\mathbf{x}_i = [0, \dots, 0, x_\alpha, \dots, x_n]$
- 9     CPU: Get enum state  $\bar{\mathbf{x}}_i = [\bar{x}_1, \dots, \bar{x}_{\alpha-1}, x_\alpha, \dots, x_n]$
- 10 **end**

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

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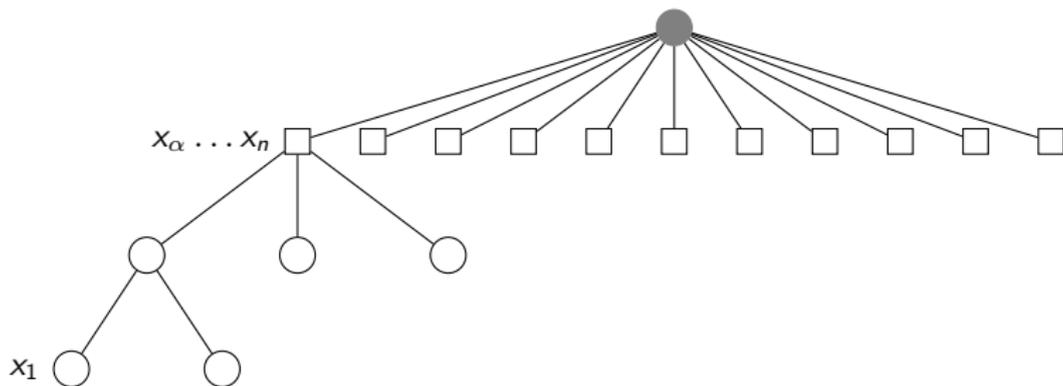
# Iterating

**Input:**  $\mathbf{B}$ ,  $A$ ,  $\alpha$ ,  $n$

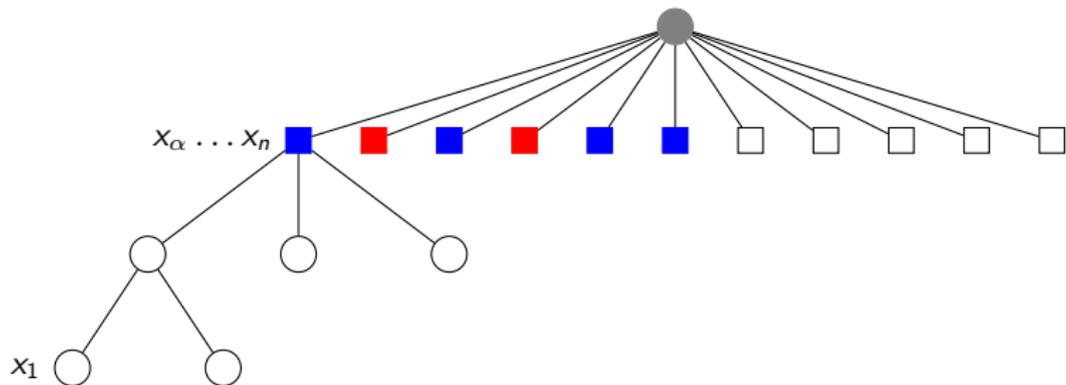
- 1 Compute the Gram-Schmidt decomposition of  $\mathbf{b}_i$
- 2 **while** *true* **do**
- 3     CPU: generate some  $\mathbf{x}_i = [0, \dots, 0, x_\alpha, \dots, x_n]$
- 4     GPU thread:
- 5     **while** *there are  $\mathbf{x}_i$  left.* **do**
- 6         Start enum for a certain  $\mathbf{x}_i$  or continue enum for  $\bar{\mathbf{x}}_i$
- 7         Stop enum after  $\mathbf{S}$  steps, store the state  $\{j_i, \bar{\mathbf{x}}_i, s_i = \mathbf{S}\}$
- 8     **end**
- 9     CPU: Get enum state  $\bar{\mathbf{x}}_i = [\bar{x}_1, \dots, \bar{x}_{\alpha-1}, x_\alpha, \dots, x_n]$
- 10 **end**

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

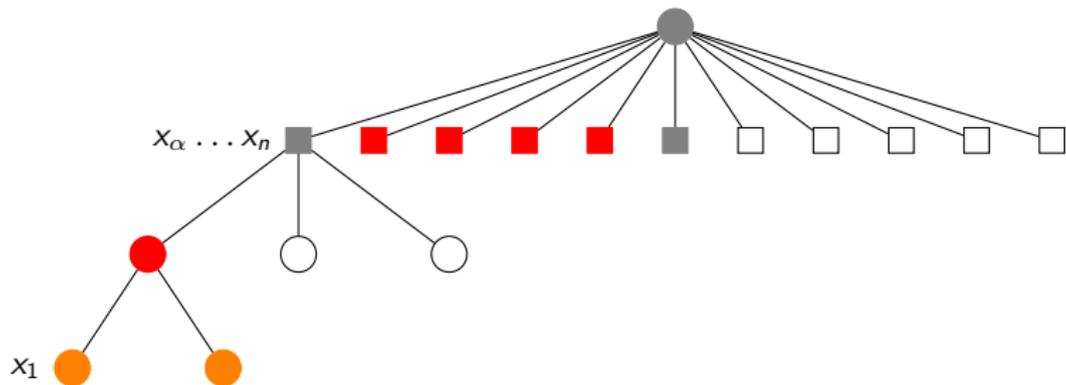
# GPU Enumeration



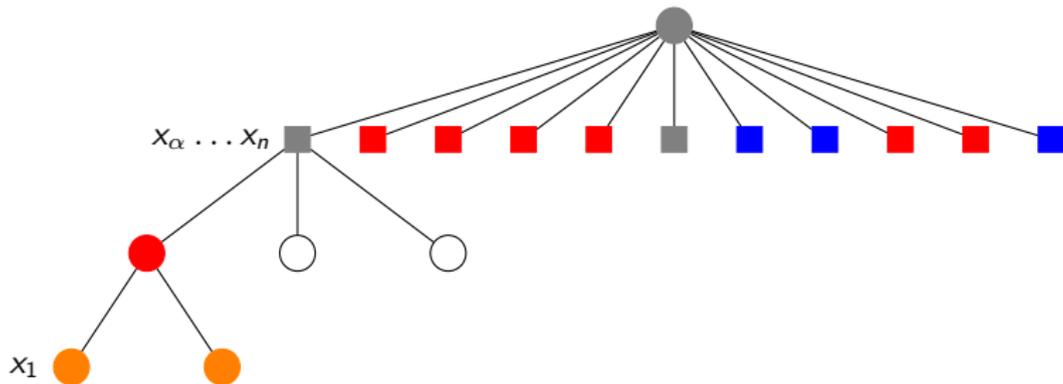
# GPU Enumeration



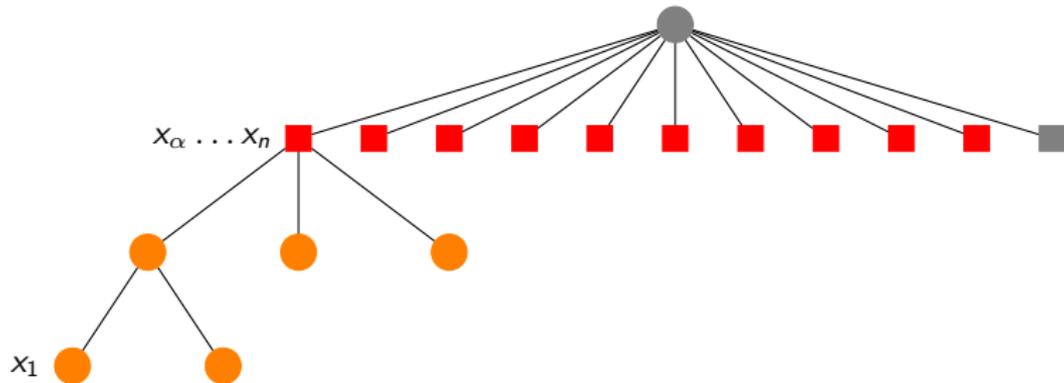
# GPU Enumeration



# GPU Enumeration



# GPU Enumeration



# Implementation details

Some facts & figures:

- Dimension 50, 100000 starting vectors  $\rightarrow$  upload & download  $\sim$  20 MB of data to GPU
- CPU top enum: very fast (low dimension)
- GPU runs for  $>$  10 seconds per iteration, iteration overhead is limited
- Share new optimal values among GPU threads

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# Throughput

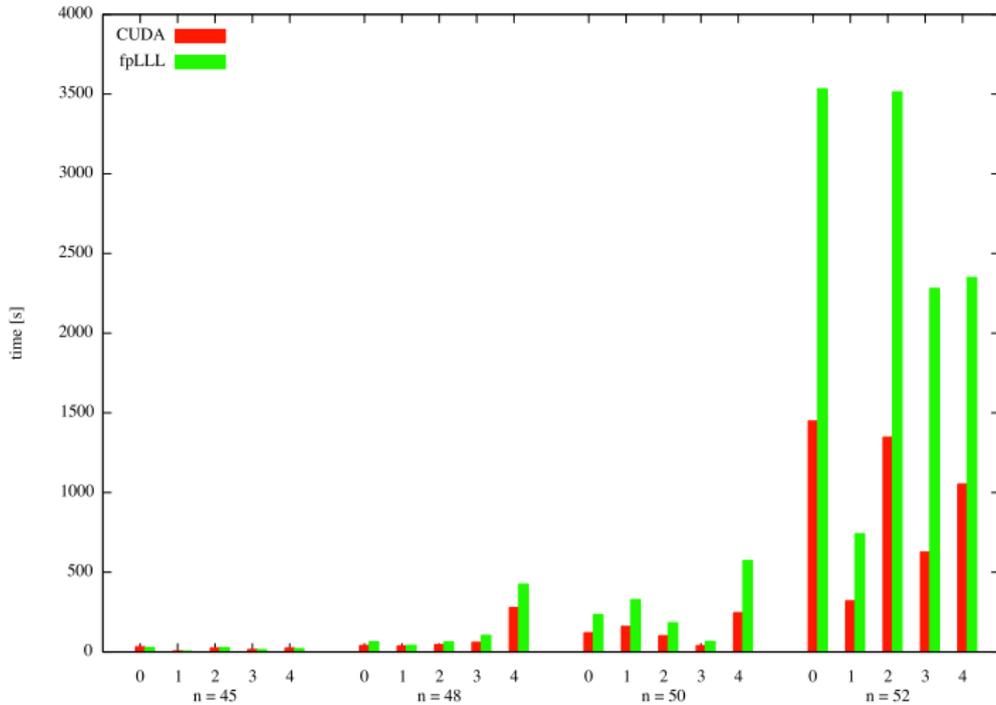
Throughput:

- CPU: around  $25 \cdot 10^6$  steps/s
- GPU: up to  $100 \cdot 10^6$  steps/s

Throughput on GPU depends on:

- Lattice dimension  $n$
- Length of sub-enumerations
- Number of parallel threads, uploaded points...

# Results



# Results

n	45	48	50	52	54
fpLLL	18.3s	139s	277s	2483s	6960s
CUDA	20.2s	92s	133s	959s	2599s
	110%	66%	48%	39%	37%

**Table:** Average time needed for enumeration of lattices in each dimension  $n$ .

# Ideas for the Future

Future:

- Generalize ideas (not specific for gpu's... clusters?)
- Use full power of CPU (now: idle during gpu-time)
- Gaussian heuristic

# The end...

Questions?

# Algorithm

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## Algorithm 1: High-level GPU ENUM Algorithm

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**Input:**  $\mathbf{b}_i, A, \alpha, n$

- 1 Compute the Gram-Schmidt decomposition of  $\mathbf{b}_i$
- 2 **while** *true* **do**
- 3      $S = \{(\mathbf{x}_i, \Delta \mathbf{x}_i, \Delta^2 \mathbf{x}_i, l_i = \alpha, s_i = 0)\}_i \leftarrow$  Top enum: generate at most  
 NUMSTARTPOINTS  $- \#T$  vectors
- 4      $R = \{(\bar{\mathbf{x}}_i, \Delta \mathbf{x}_i, \Delta^2 \mathbf{x}_i, l_i, s_i)\}_i \leftarrow$  GPU enumeration, starting from  $S \cup T$
- 5      $T \leftarrow \{R_i : s_i \geq \mathbf{S}\}$
- 6     **if**  $\#T < \text{CPUTHRESHOLD}$  **then**
- 7         Enumerate the starting points in  $T$  on the CPU.
- 8         Stop
- 9     **end**
- 10 **end**

**Output:**  $(x_1, \dots, x_n)$  with  $\|\sum_{i=1}^n x_i \mathbf{b}_i\| = \lambda_1(L)$

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