

Parallel (Public-Key) Cryptanalysis

Joppe W. Bos



Summer school
on real-world crypto and privacy

What is Parallel cryptanalysis?

From the concise Oxford Dictionary (ninth edition)

Parallel

“Computing involving the simultaneous performance of operations”

Cryptanalysis

“the art or process of solving cryptograms by analysis; code-breaking”

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Parallel cryptanalysis can be applied in many different settings

- ✓ Brute force
- ✓ Public-key / symmetric cryptography
- ✓ Computation of higher-order correlation power analysis attacks



The working rebuilt bombe at Bletchley Park museum.

Picture by Antoine Taveneaux

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Use *parallel cryptanalysis* to solve mathematical problems which form the theoretical foundation of many public-key cryptographic schemes.



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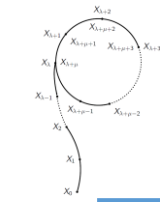
Outline



Integer factorization

- RSA

Still the most widely used public-key cryptosystem



Discrete Logarithm

- DH
- ElGamal
- DSA

In this talk
Elliptic curve
DLP

- ECDH(E)
- ECDSA



Post-Quantum

- Lattice-based R-LWE, NTRU
- Hash-based Merkle trees
- Code-based McEliece

Most common problems used to base public-key cryptography systems on

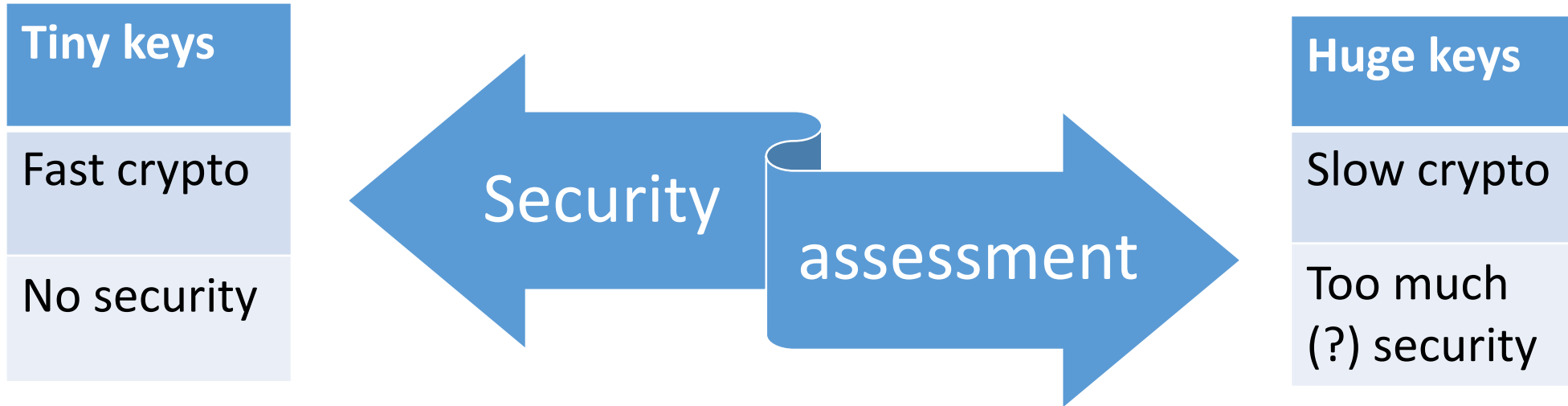
Goals

1. Show the *best* methods to cryptanalyze public-key cryptography
 - a) Explain some of the details
 - b) Effort estimates (security assessment)
2. From a computational and parallel point of view
3. Public-key cryptography is fun!

Tiny keys
Fast crypto
No security

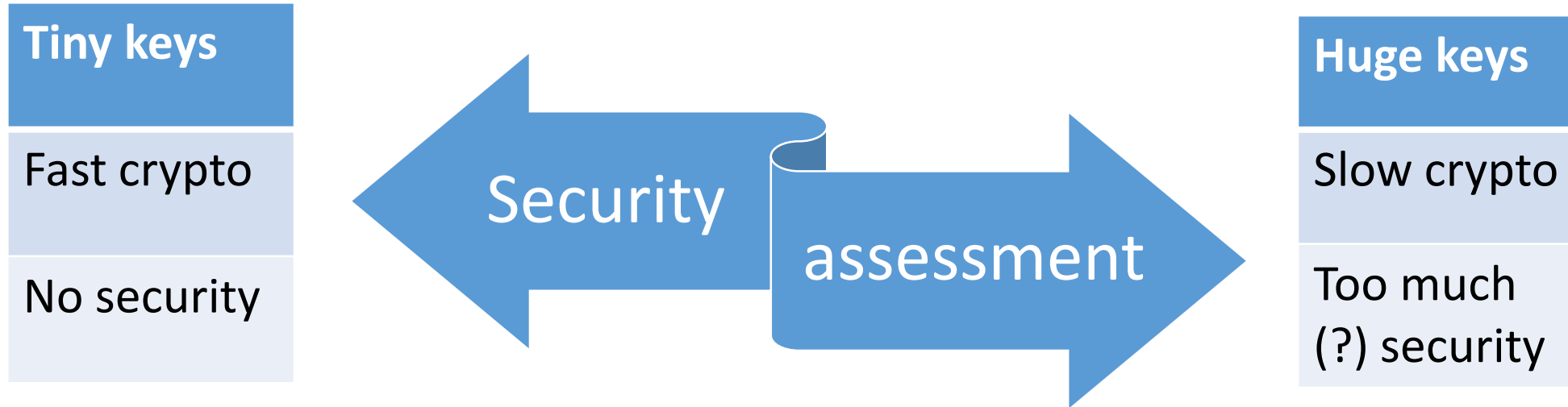


Huge keys
Slow crypto
Too much (?) security



Finding the “optimal” key size is difficult

Approach: Use the **best** parallelizable algorithms

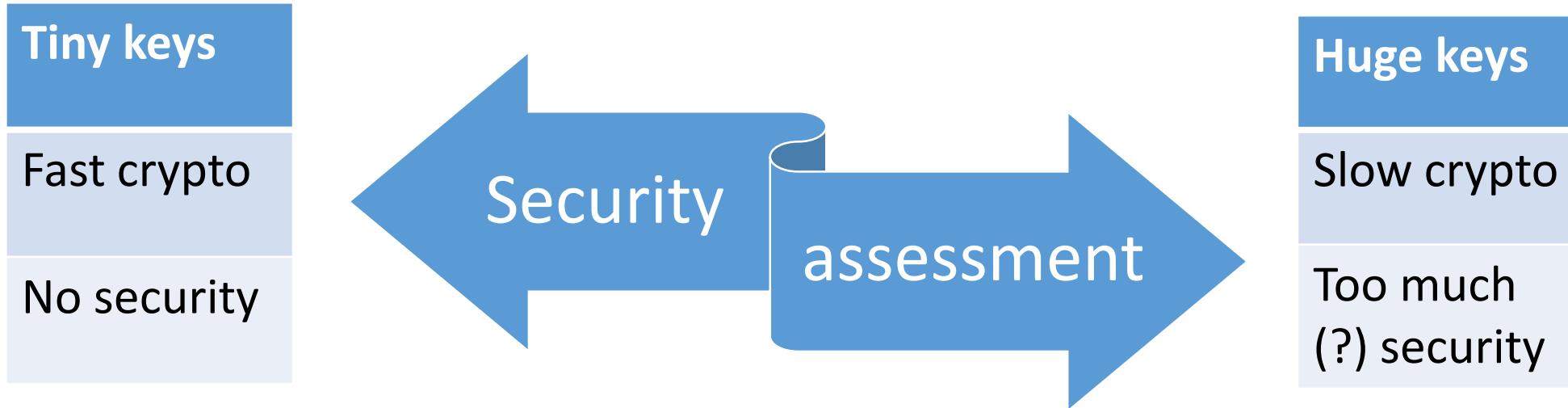


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Does it make sense to say the best attack?

- | | |
|----------------------------|---|
| Fastest | (time) |
| Minimize power consumption | (green) |
| Minimize investment | (re-use existing hardware) |
| Et cetera | (invent your own characterization for best) |



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Et cetera	(invent your own characterization for best)

This presentation: Minimize wall-clock time using commonly available compute power

Integer Factorization

Many **generic** integer factoring algorithms follow the same **old** approach.

Idea: an odd integer n can be written as the **difference of two squares**

For instance, idea behind

- Fermat factorization method
- Quadratic sieve (and variants)
- Number field sieve

Given a composite odd $n \in \mathbb{Z}$, find non-trivial factors p and q such that $p \cdot q = n$ ($q > p$).

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$$\begin{aligned} p \cdot q &= \left(\frac{p+q}{2} - \frac{q-p}{2} \right) \cdot \left(\frac{p+q}{2} + \frac{q-p}{2} \right) \\ &= (x-y) \cdot (x+y) \\ &= x^2 - y^2 \end{aligned}$$

Since p and q are odd the **average** $\frac{p+q}{2}$ is an integer and $\frac{q-p}{2}$ is the **distance** from this average to p (or q)

Integer Factorization: Fermat factorization method

Good at finding large divisors

Given n , try to find x and y such that $x^2 - n = y^2$, start with $\lceil \sqrt{n} \rceil$

Example.

$$2279 = 43 \times 53$$

$$\lceil \sqrt{2279} \rceil = 48$$

$$48^2 - 2279 = 25 = 5^2$$

$$(48 + 5)(48 - 5) = 43 \times 53 = 2279$$

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Generalization

Find x and y such that

$$x^2 \equiv y^2 \pmod{n} \text{ and } x \not\equiv y \pmod{n}$$

then with high probability

$$\gcd(x - y, n) \neq 1 \text{ or } n$$

Integer Factorization

1. Polynomial selection

Degree $d > 1$, integer $m \approx n^{1/d}$, radix- m representation of $n = f_d m^d + \dots + f_1 m + f_0$

Leads to $f_a(X) = \sum_{i=1}^d f_i X^i \in \mathbb{Z}[X]$ with $f_a(m) \equiv 0 \pmod{n}$ (one can do better!) and $f_r(X) = X - m$

2. Relation collection

Find co-prime $a, b \in \mathbb{Z} \times \mathbb{Z}_{\geq 0}$ such that $b f_r(a/b)$ and $b^d f_a(a/b)$ factors into small primes (“smooth”)

3. Matrix step

Find even sum of small prime exponent vectors, solve linear dependencies between the relations (find random elements of the null-space of the matrix)

4. Square root

Compute the square root of a large element of the number field

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< 1 CPU day

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Sieving identifies many pairs (a_i, b_i) such that $bf_r(a/b)$ and $b^d f_a(a/b)$ have many small factors (memory intensive)

Cofactorization (to check: is $bf_r(a/b)$ **B_r -smooth** and $b^d f_a(a/b)$ **B_a -smooth**)


1. Polynomial evaluation
2. Compositeness test (Miller-Rabin)
3. Trial division
4. Pollard $p - 1$ (stage 1 & 2)
5. Elliptic curve factorization method (stage 1 & 2) using twisted Edwards curves

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Modular arithmetic
(Montgomery multiplication)
Exact division

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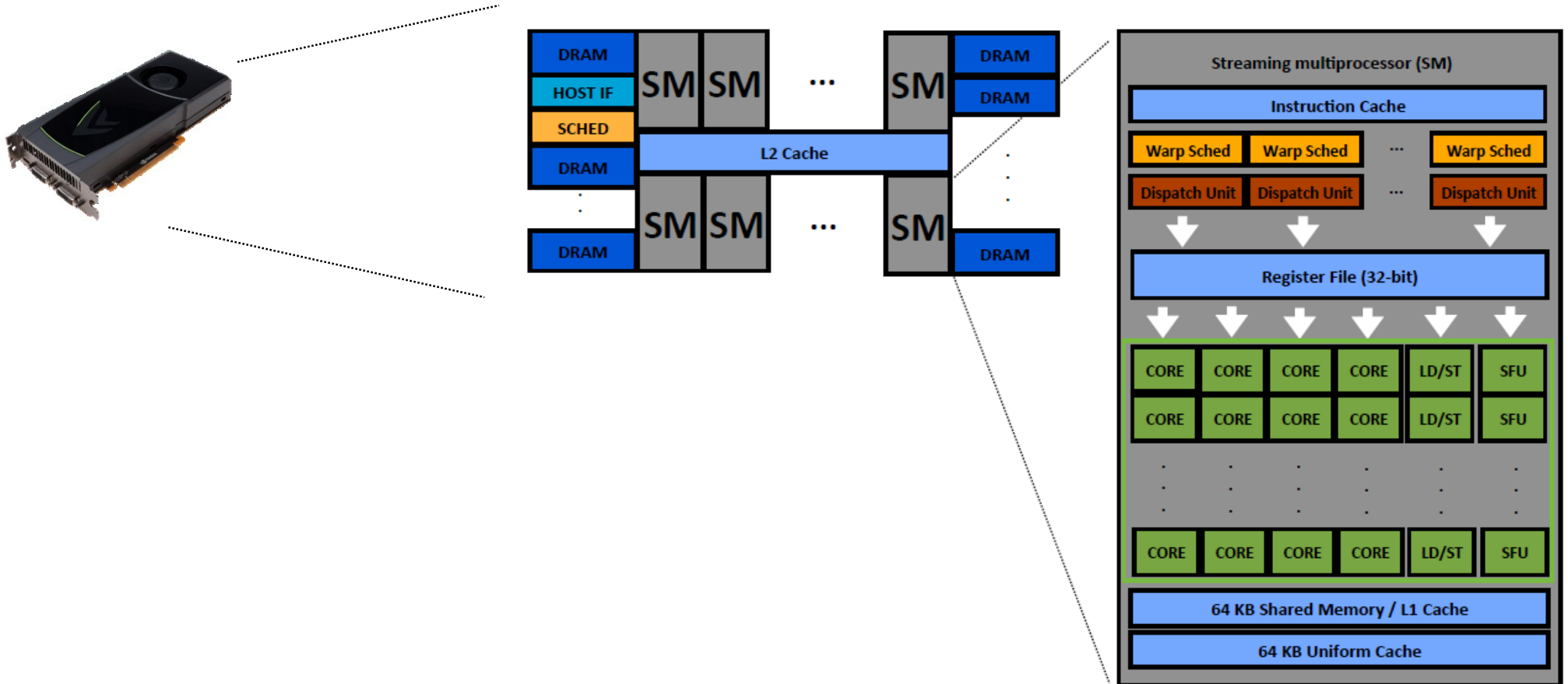
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Modular arithmetic
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Exact division

Cofactorization can check many pairs (a_i, b_i) simultaneously. Can we offload this to another device?
Possible answer: **Graphics processing unit**

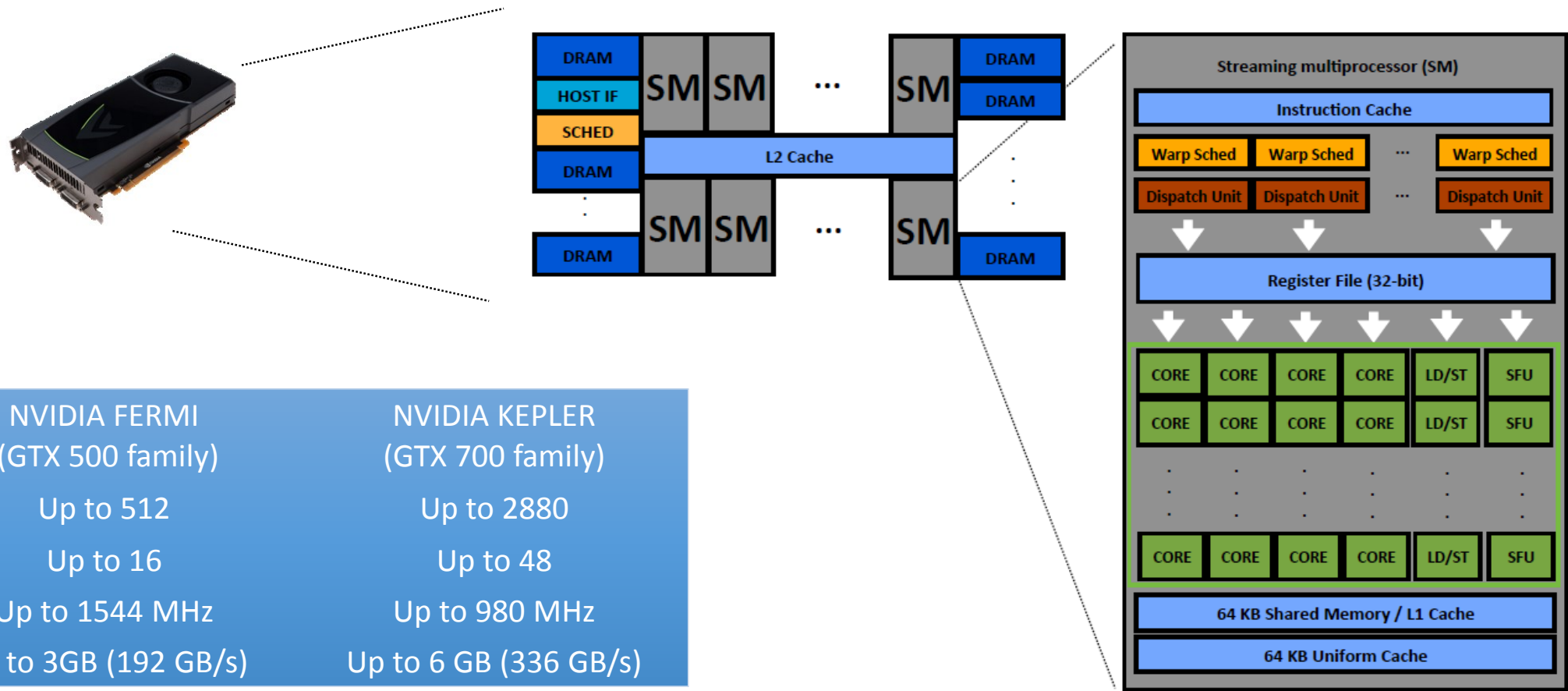
Graphics processing unit (Nvidia platform)

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- One integer or floating point instruction/clock cycle per thread/core
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Relation Collection on GPUs

- GPUs have been considered as cryptanalytic coprocessors before (e.g., for ECM)
- First time for the entire relation collection phase

Transfer batch of (a_i, b_i) from CPU to GPU

Repeat in parallel until all (a_i, b_i) have been processed {

Thread receives (a_i, b_i)

Polynomial evaluation + Trial Division

Perform compositeness test and put results in correct bucket

Pick composite from bucket and perform dedicated Pollard $p - 1$

Perform compositeness test and put results in correct bucket

for $(i = 0; i < n; i++)$ {

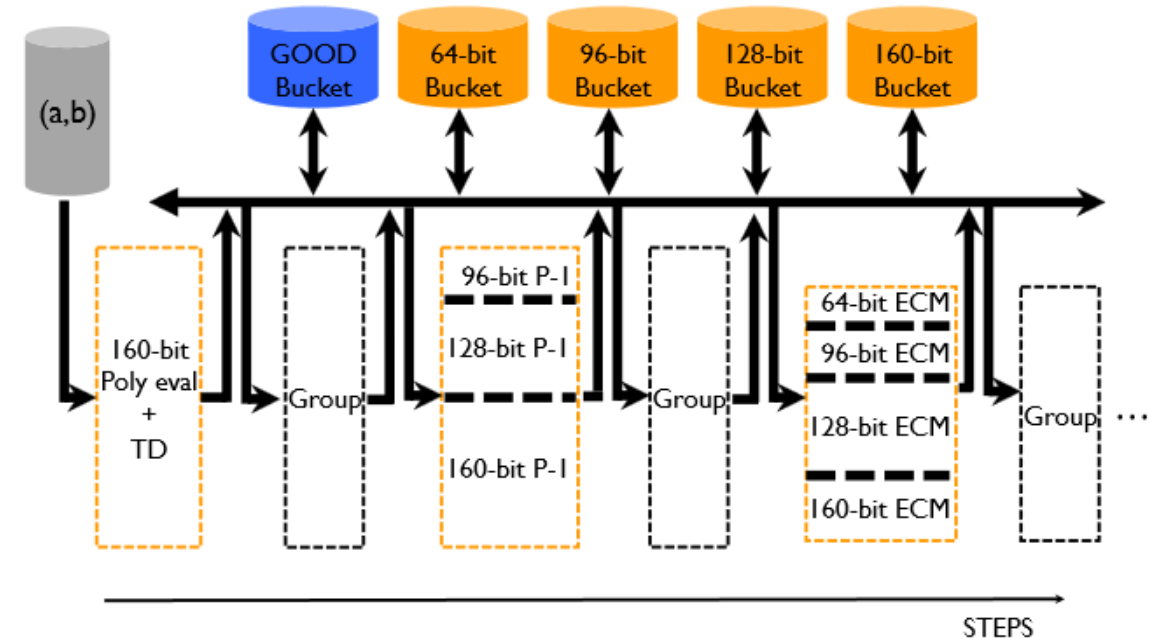
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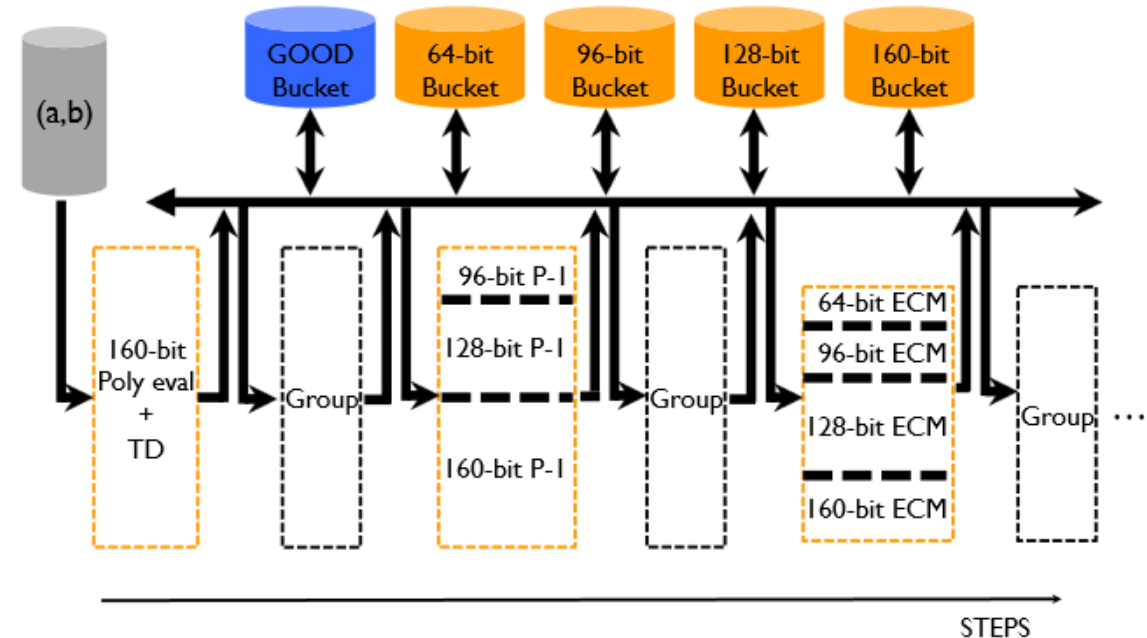
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All the Pollard $p - 1$ and ECM algorithms run concurrently
→ must use the same parameters
→ **how to optimize?**



Parameter determination

Observation: Varying the bounds of the Pollard $p - 1$ factoring (within reasonable ranges) does **not noticeably affect the yield**

Explanation: All missed prime factors are found by the subsequent ECM attempts.

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However, early removal of small primes reduce the size of the composite

→ reducing the ECM run time

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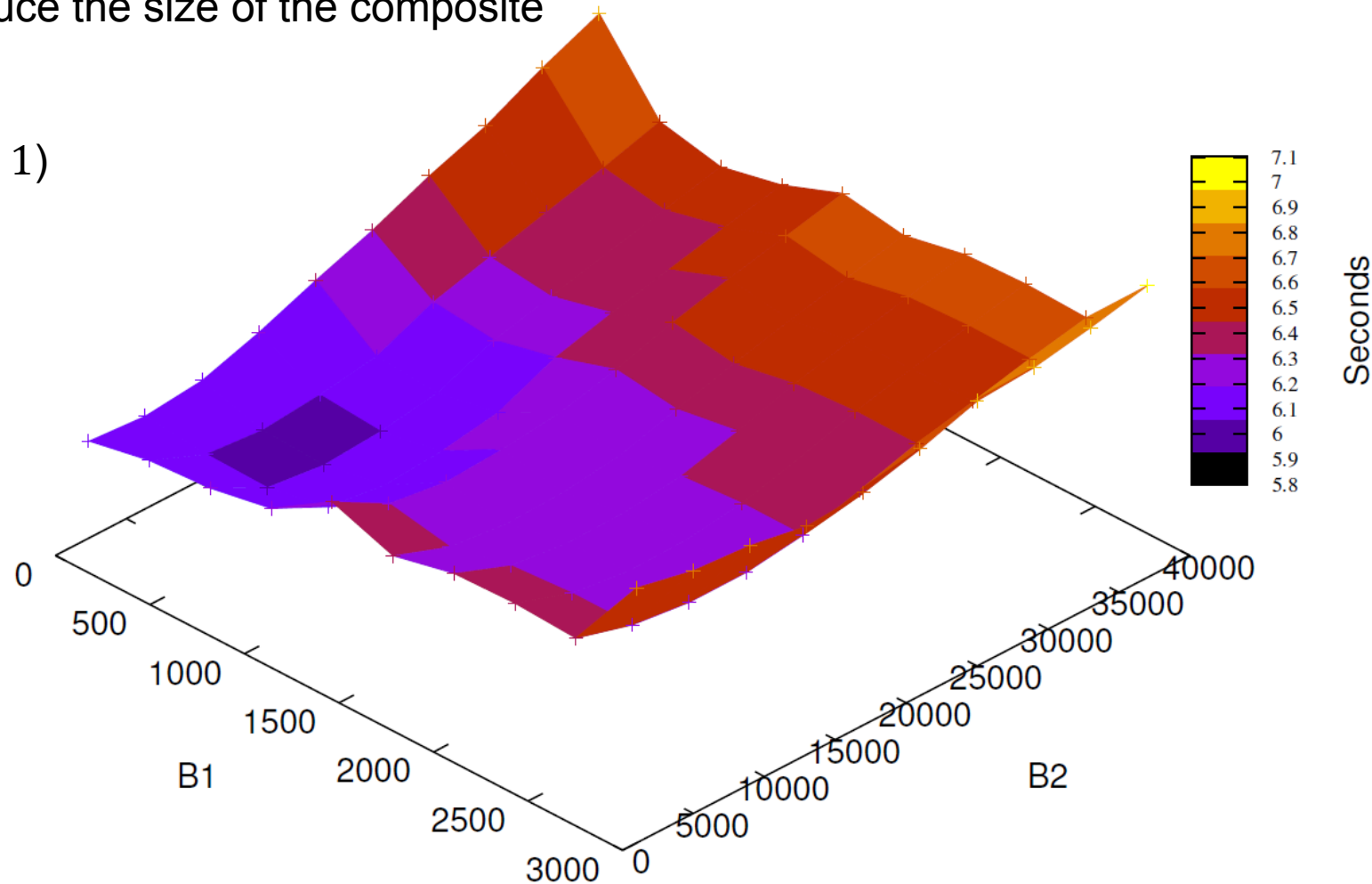
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The time difference for the entire cofactorization when the yield is *fixed* at 95% when varying the B_1 and B_2 bounds for Pollard $p - 1$ on the rational side



Results

CPU used: **Intel i7-3770K CPU**, with 4 cores, 3.5 GHz with 16 GB of memory
GPU used: **NVIDIA GeForce GTX 580**, with 512 CUDA cores, 1.5 GHz with 1.5 GB of global memory

Target number: RSA-768 (same polynomial as used for the factorization)

Processing multiple special primes with desired yield 99%.

Large primes	Number of pairs after sieving	Setting	Total seconds	Relations found	Relations per second
4	$\approx 5 \cdot 10^7$	CPU only	1602	6855	4.28
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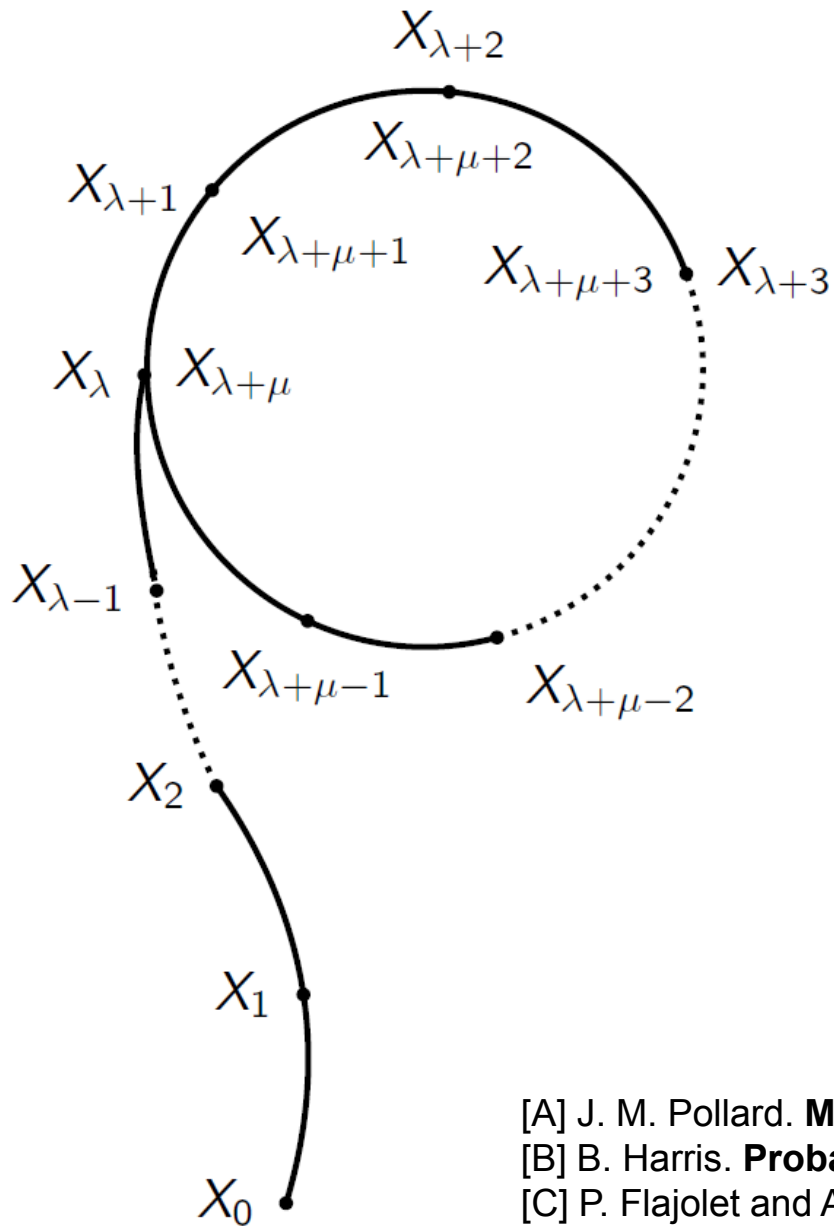
- ✓ Latency down by a factor 1.23
- ✓ Number of relations found up by 21.1%
- ✓ Yield / second up by a factor 1.49x

- Not considered
- Purchase cost GPU versus CPU
 - Power comparison GPU versus CPU

Pollard Rho

Given prime $p > 3$, $G \in E(\mathbf{F}_p)$ of order n , $H \in \langle G \rangle$
find integer m such that $mG = H$

- Originally an integer factorization method (1975)
- Three years later turned into approach for solving dlps [A]
- Perform a pseudo-random walk through the set of points
(length tail \approx length cycle $\approx \sqrt{\pi n/4}$ [B,C])



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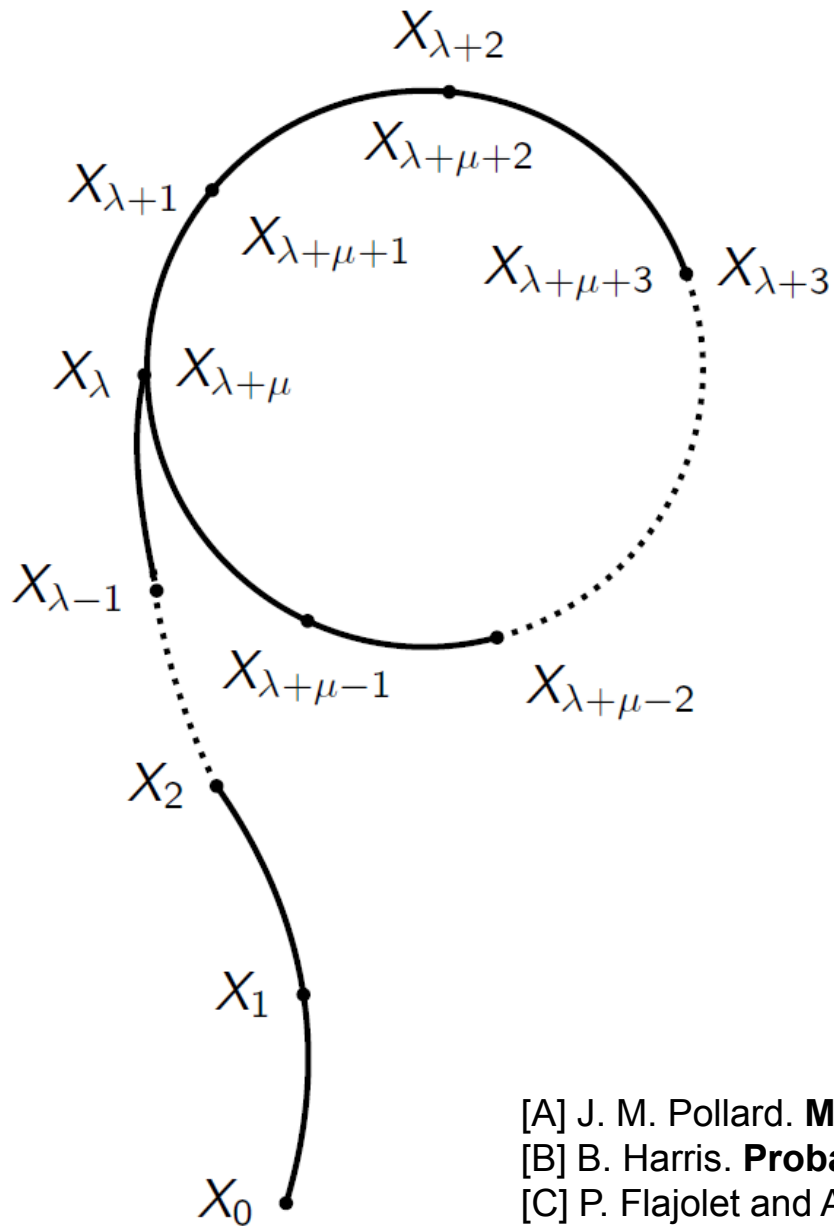
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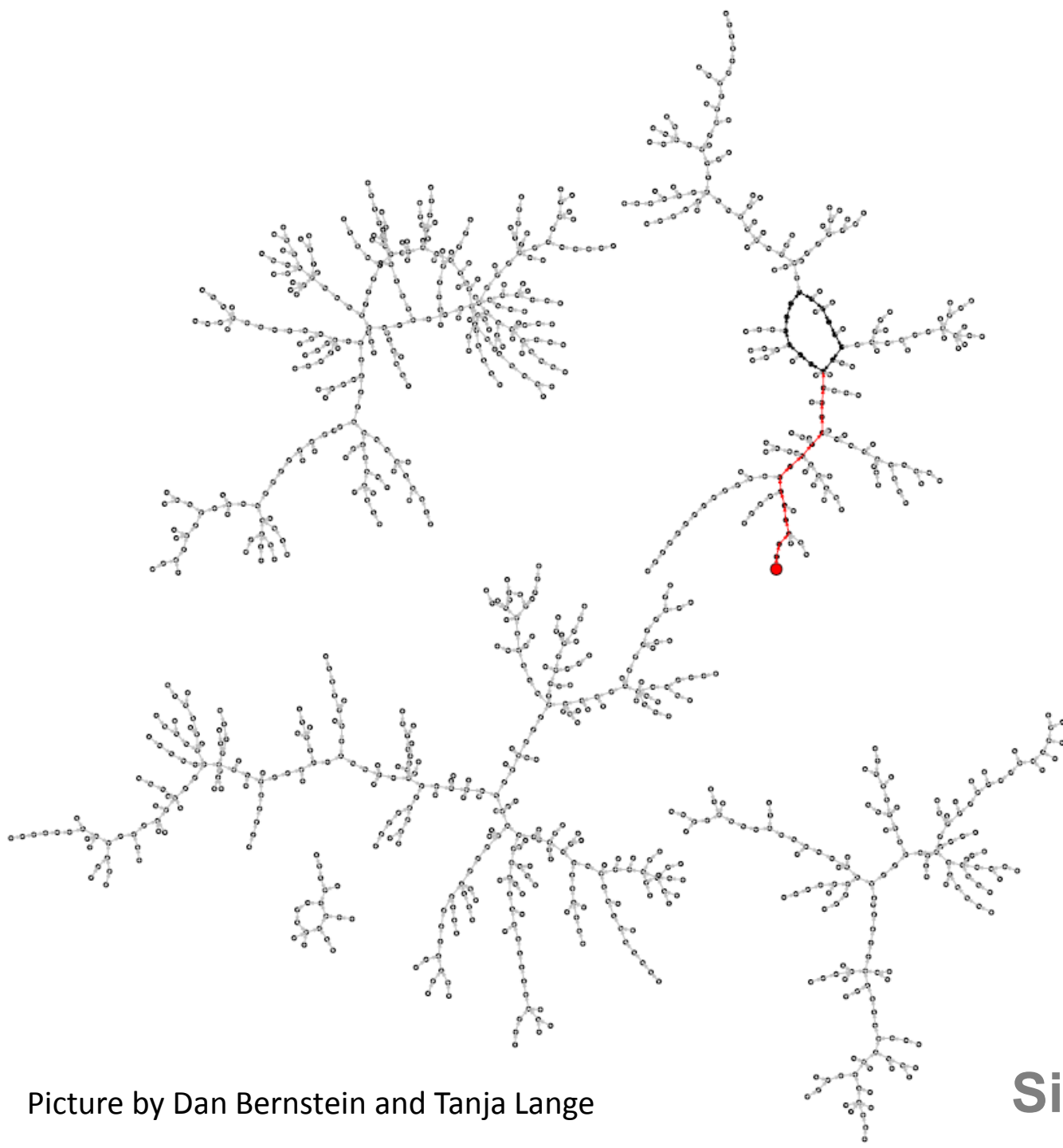
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r -adding walk

- Define index function $\ell : \langle G \rangle \mapsto [0, \dots, r-1]$
- ℓ -induced r -partition $\langle G \rangle = \bigcup_{i=0}^{r-1} g_i$ where $g_i = \{x : x \in \langle G \rangle, \ell(x) = i\}$
(all of approximately the same cardinality)
- Select random multipliers u_i and v_i to define r points $f_i = u_i G + v_i H$
- One step is defined as: $P_{i+1} = P_i + f_{\ell(P_i)}$

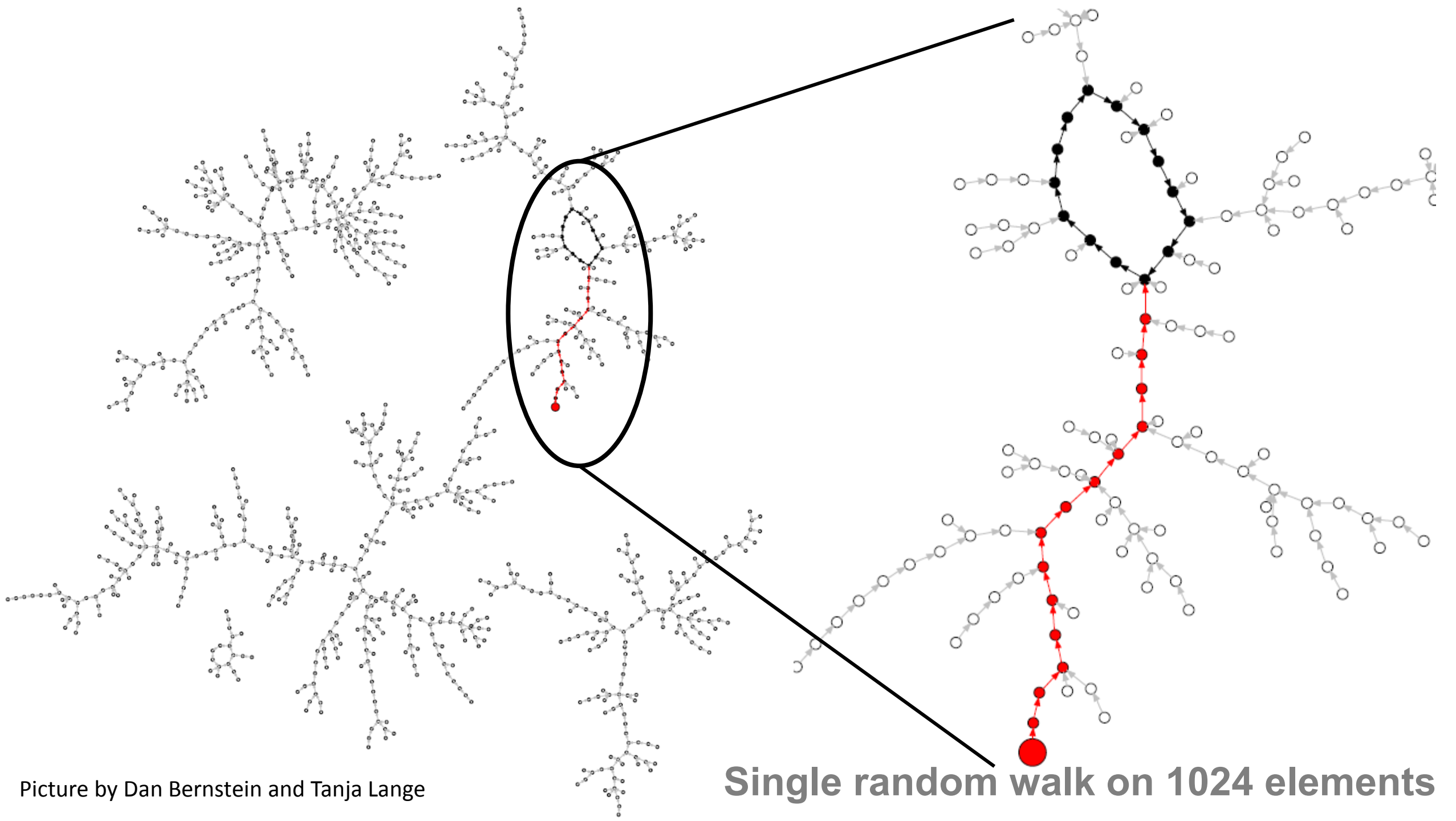


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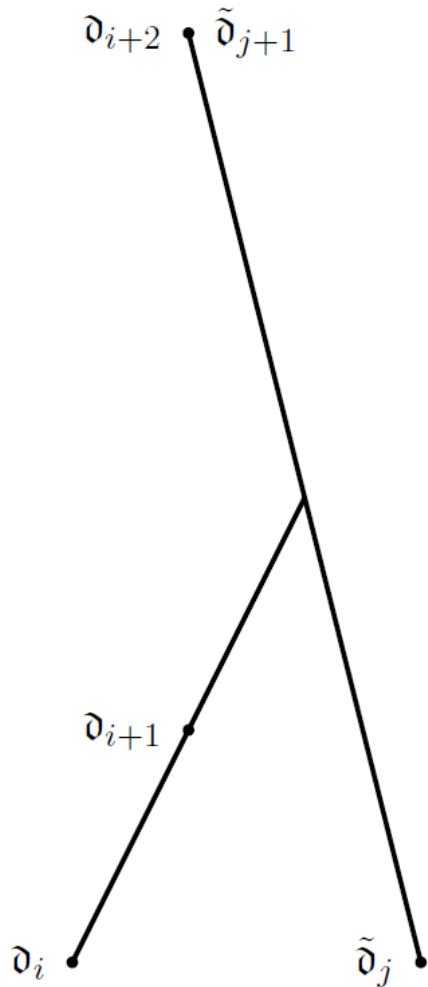
Picture by Dan Bernstein and Tanja Lange

Single random walk on 1024 elements



Picture by Dan Bernstein and Tanja Lange

Parallelization of Pollard Rho



Can we compute Pollard rho using multiple computational resources?

What happens if we run Pollard rho m times in parallel?

→ \sqrt{m} speedup

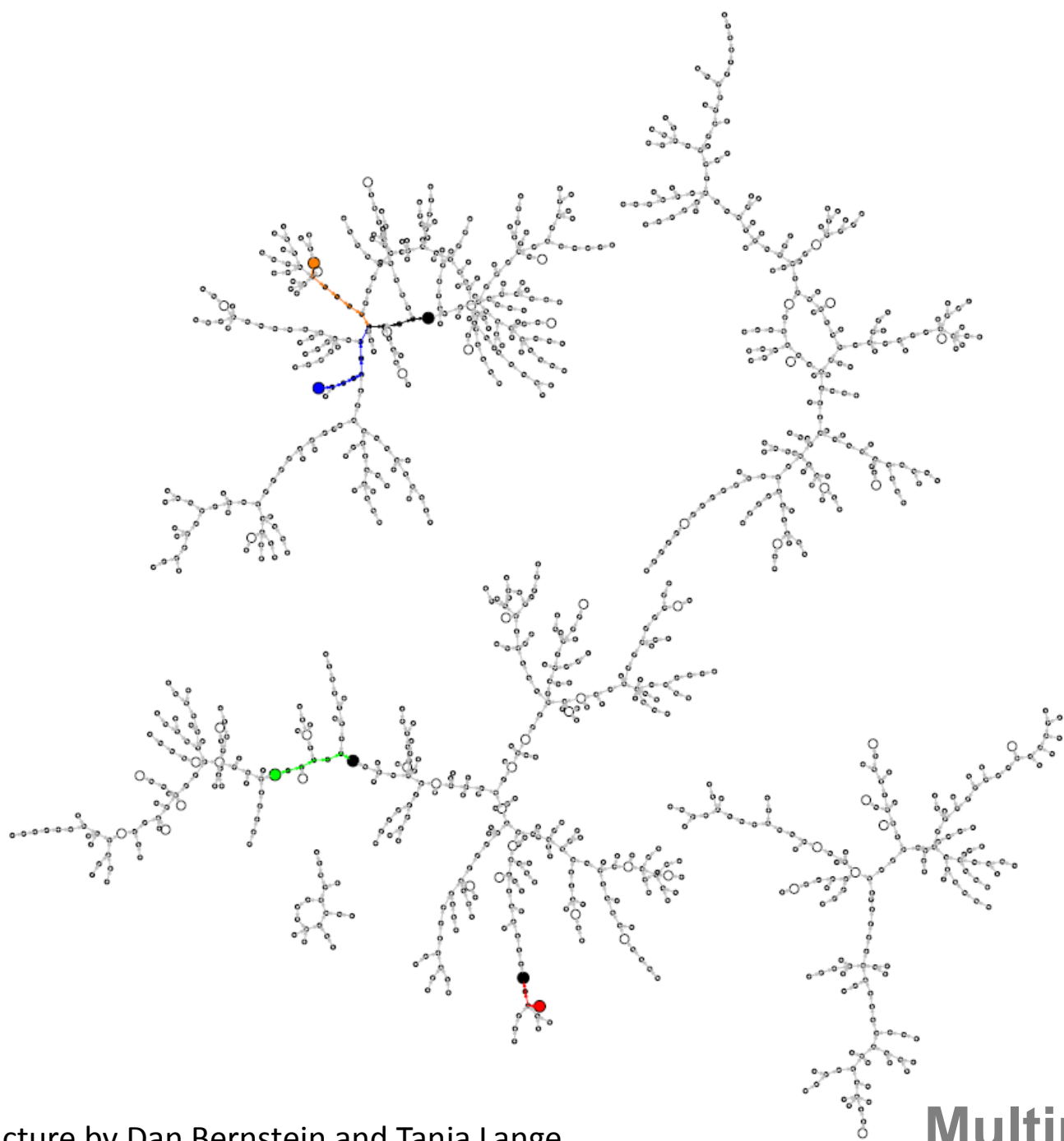
Can we do better?

Let the m parallel instance “work together”

→ share some points (distinguished points)

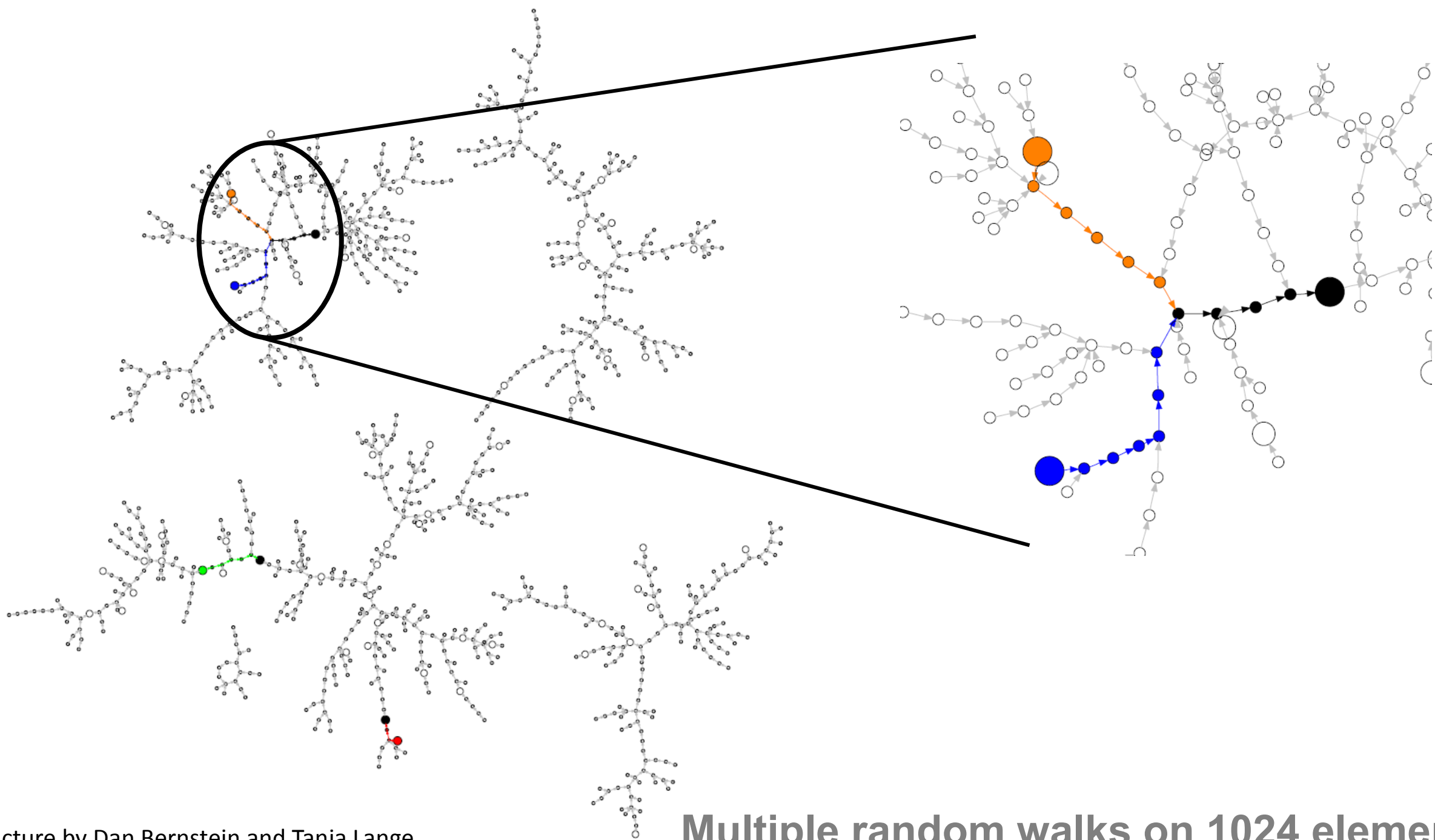
(Collected in a central database, collision search is performed here)

→ factor m speedup



Picture by Dan Bernstein and Tanja Lange

Multiple random walks on 1024 elements



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Multiple random walks on 1024 elements

Using Pollard Rho to solve ECDLPs

Advantages of Pollard rho

- ✓ Very low memory requirement (can run virtually on any device!)
- ✓ Can store a batch of distinguished points locally and sent them to the central database in batches.

What devices can we use to solve ECDLPs?



```
[ free busy full down disabled absent ]
john@frontend ~ $ cluster-nodes
[ free busy full down disabled absent ]
-----
16 10.123.1.4567:10000 [CDEF]
15 10.123.1.4567:10000 [CDEF]
14 10.123.1.4567:10000 [CDEF]
13 10.123.1.4567:10000 [CDEF]
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Master: 0 Slave: 0
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Pollard Rho on Mobile Devices

Fun exercise (back in 2010) use Pollard rho with negation map to solve 115-bit ECDLP

Apple iPad family (2015)	250 million sold	Ipad (2010)	$530 \cdot 10^3$
Apple iPhone family (2015)	700 million sold	Apple A4 (= ARM Cortext A8, 1.0 GHz, single-core)	iterations per second
Android active monthly users (2014)	1000 million		

Idea use their compute power when they are charging (night time)

Effort: $\sqrt{\frac{\pi \cdot 2^{115}}{4}} \approx 1.8 \cdot 10^{17}$ iterations expected $\rightarrow 10^4$ Ipad years

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Newer models have multiple cores, 64-bit architecture, higher clock-speeds + better implementation



Home

Participate

Teams

Users

Sign in

Create an account

Grid computing on the move.



Grid computing system designed for cryptographic computation only based on smartphones and tablets.

Participate

100% FREE

Lattice-based cryptosystems -- Motivation

- Shortest Vector Problem (SVP) used as a theoretical foundation in many PQ-crypto schemes
 - Lattice based encryption / signature schemes, fully homomorphic encryption
 - Often compute in an ideal lattice for performance reasons

$$R = \mathbb{Z}[X]/(X^n + 1)$$

- Exact SVP is known to be NP-hard under randomized reductions
(In most applications approximations are enough)
- How efficient can we find short vectors in ideal lattices?

SVP solvers

Asymptotic rigorous proven runtimes (ignoring poly-log factors in the exponent)		
	Time	Memory
Voronoi	2^{2n}	2^n
List Sieve	$2^{2.465n}$	$2^{1.233n}$
Enumeration	$2^{O(n \log(n))}$	$\text{poly}(n)$

SVP solvers

Asymptotic rigorous proven runtimes (ignoring poly-log factors in the exponent)

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Asymptotic heuristic runtimes

BKZ 2.0	$n \cdot N \cdot \text{svp}(k)$	$\text{poly}(n)$
+ Enumeration with extreme pruning	$n \cdot N \cdot 2^{O(k^2)}$	$\text{poly}(n)$
Gauss Sieve	" $2^{0.48n}$ "	$2^{0.2075n}$
Decomposition	$2^{0.3374n}$	$2^{0.2925n}$
Voronoi	"up to dimension 8"	

SVP solvers

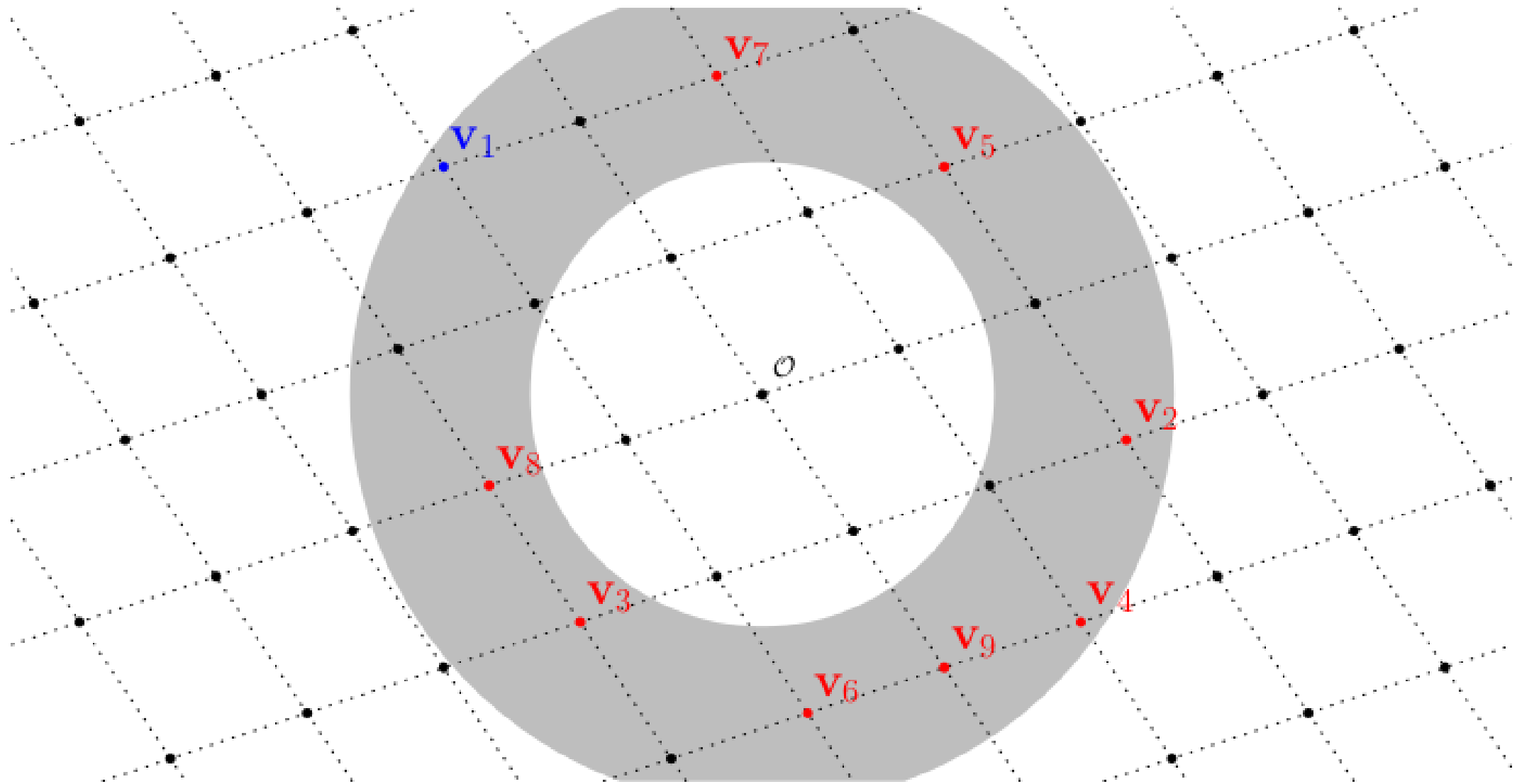
Asymptotic rigorous proven runtimes (ignoring poly-log factors in the exponent)

	Time	Memory
Voronoi	2^{2n}	2^n
List Sieve	$2^{2.465n}$	$2^{1.233n}$
Enumeration	$2^{O(n \log(n))}$	$\text{poly}(n)$

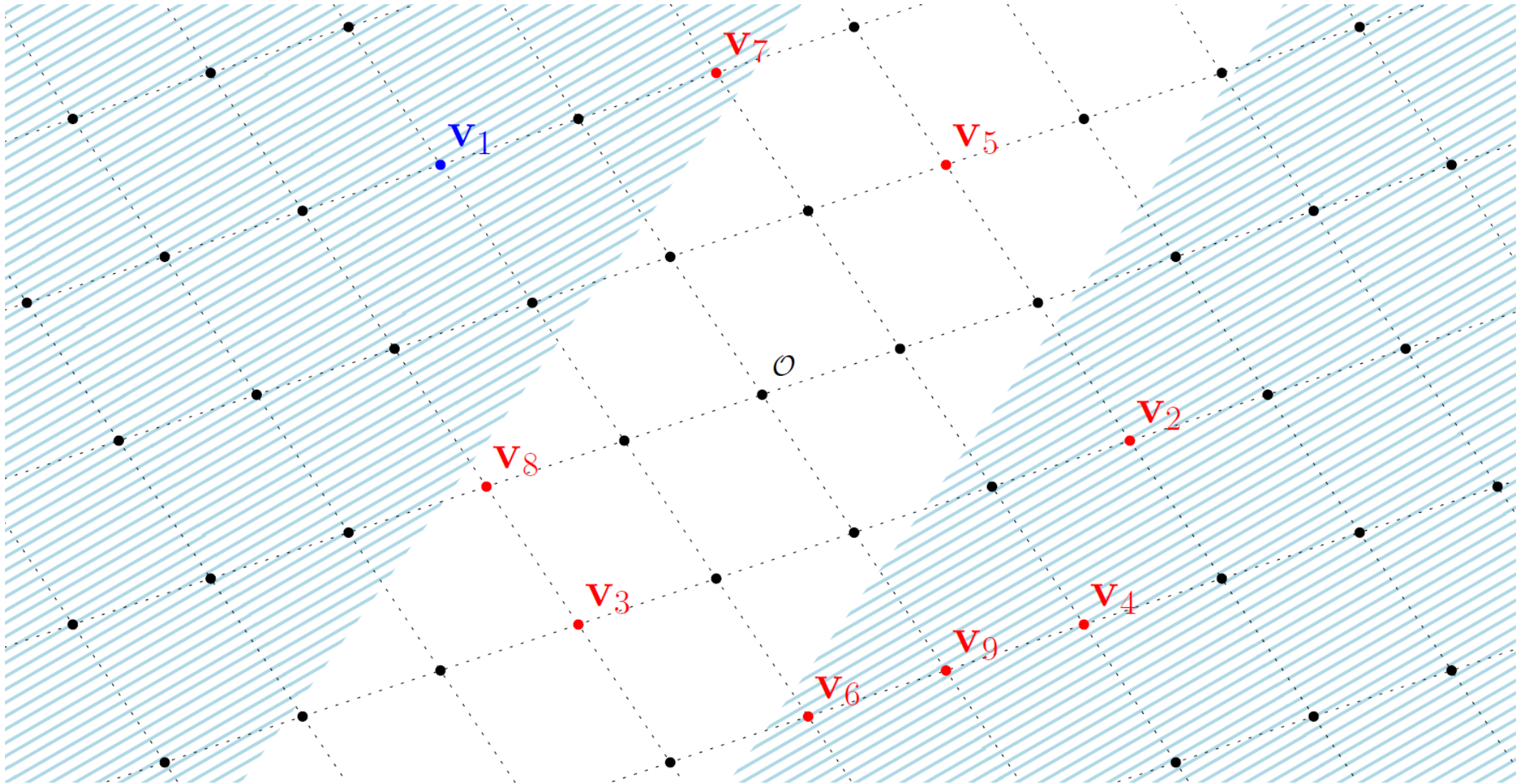
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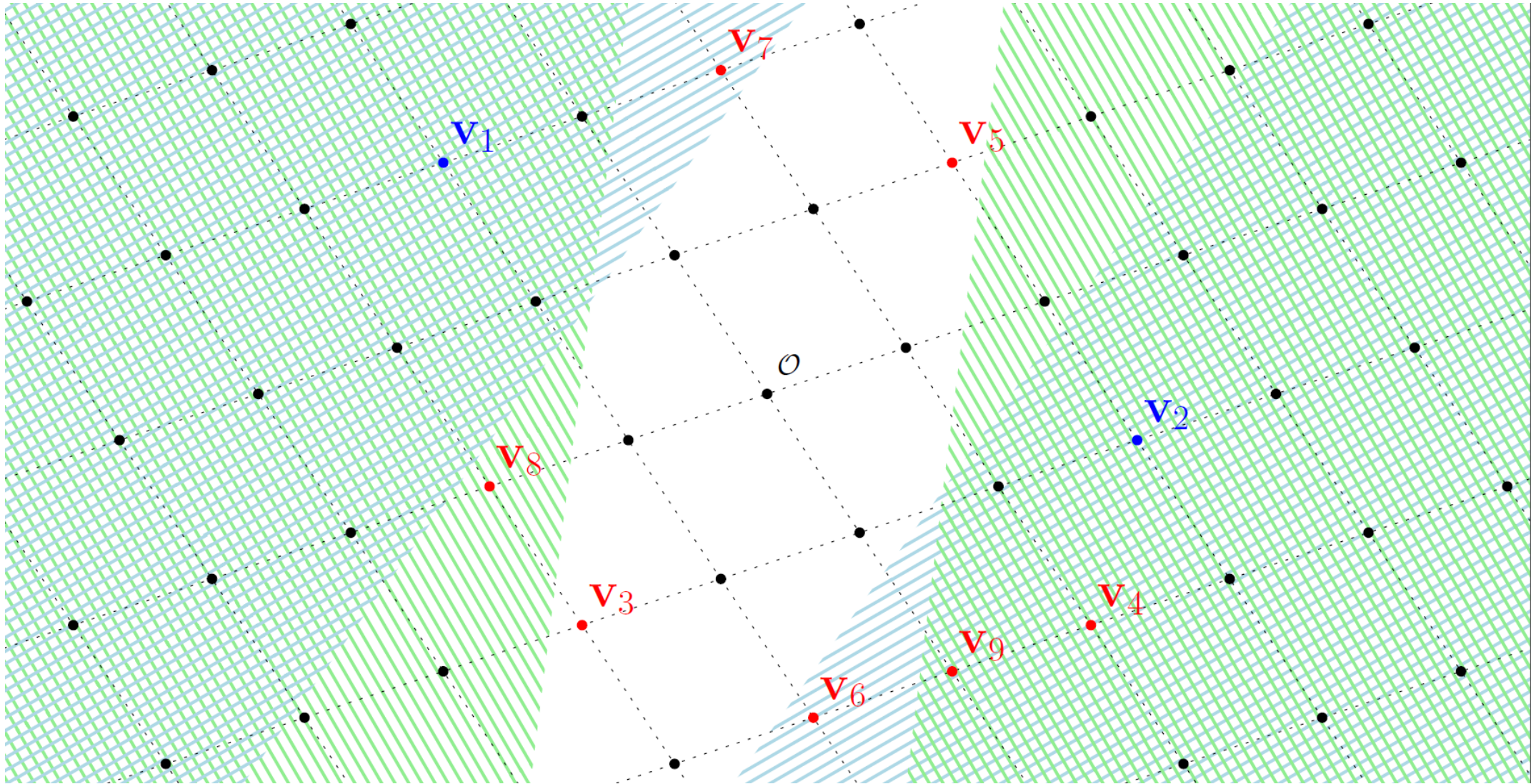
Only sieving algorithms take advantage of the ideal lattice structure



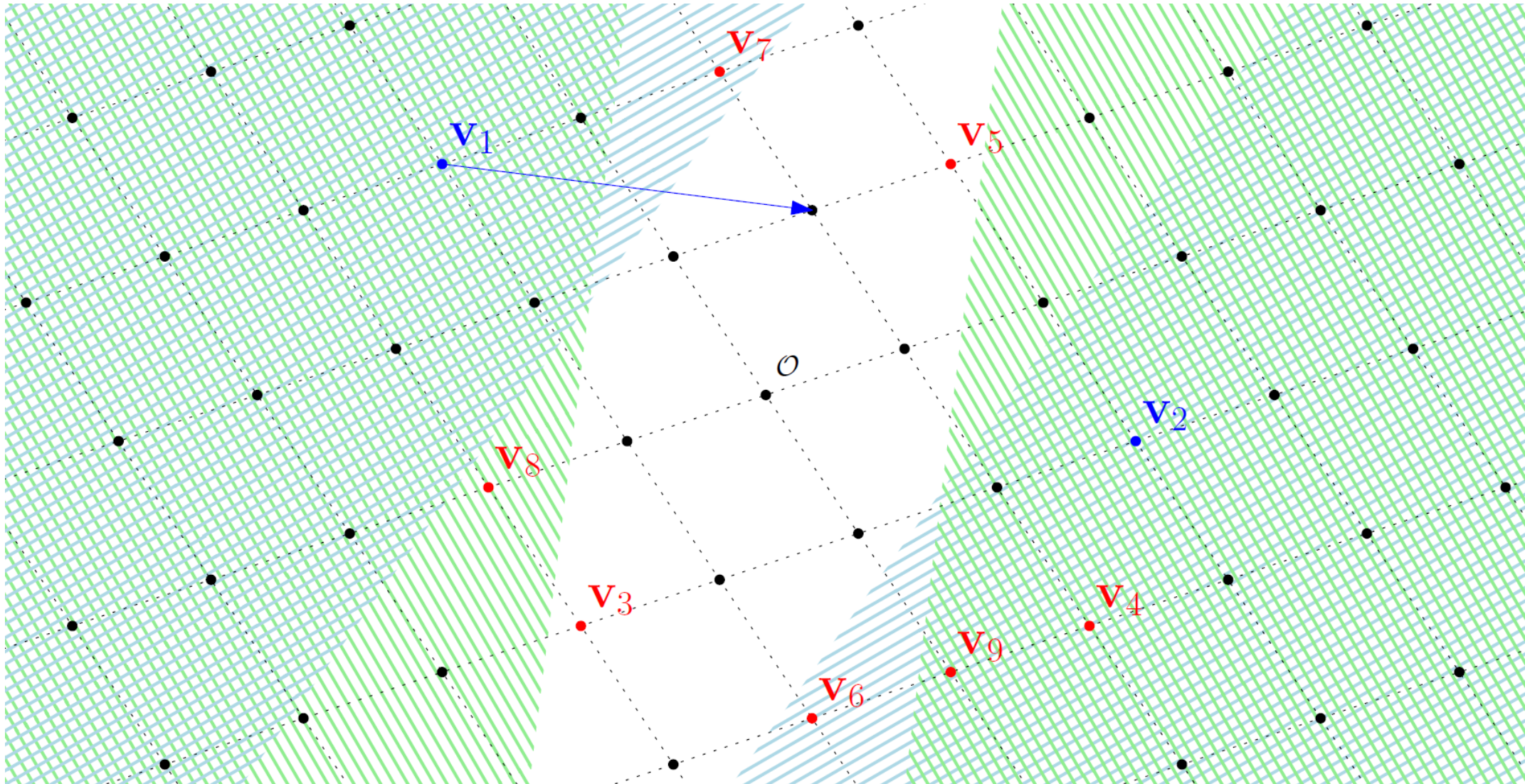
Sample a list of vectors and Gauss reduce all vectors with respect to each other



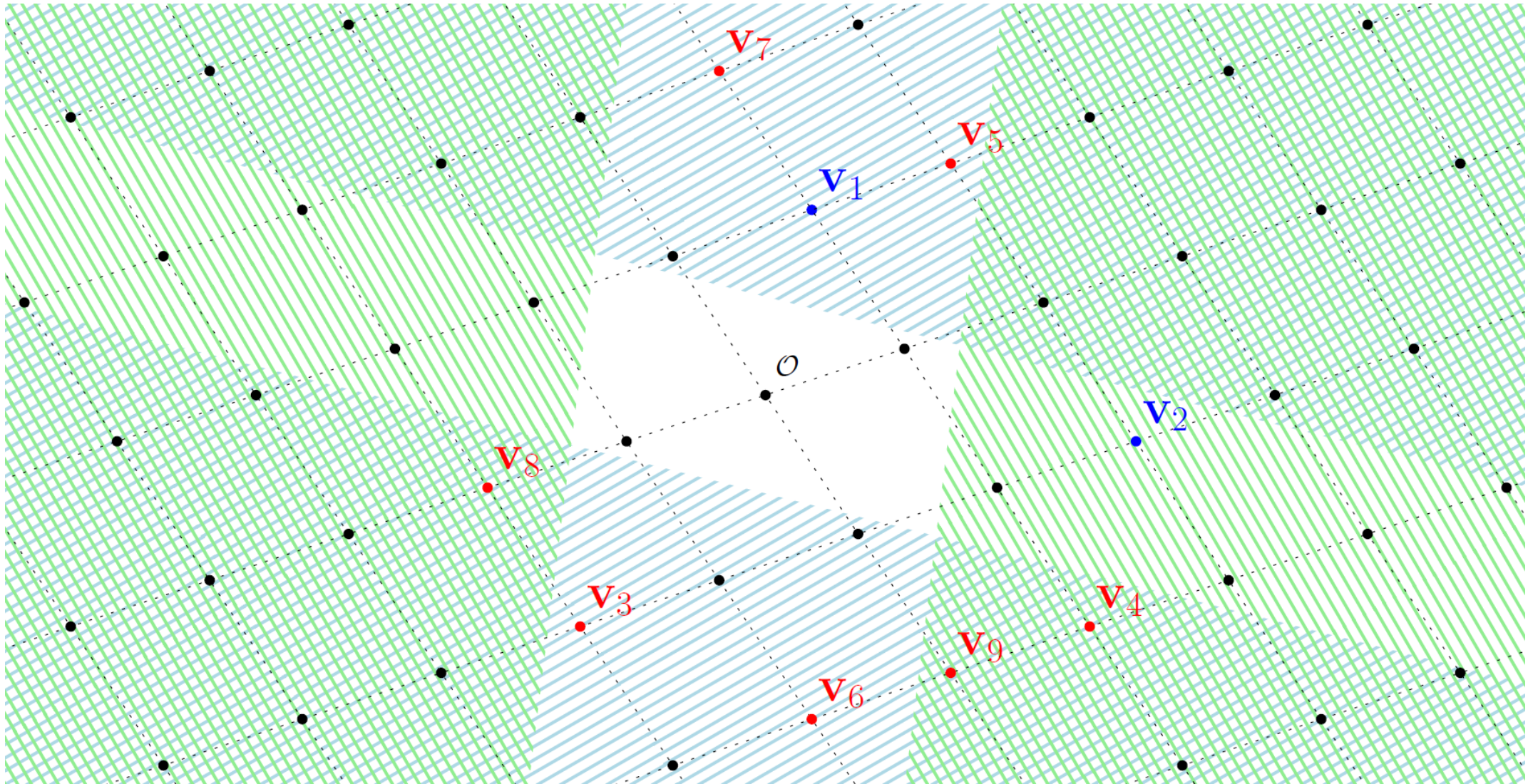
Each vector corresponds to two half spaces.
If a vector is in half-space of another previous vector, it can be reduced.



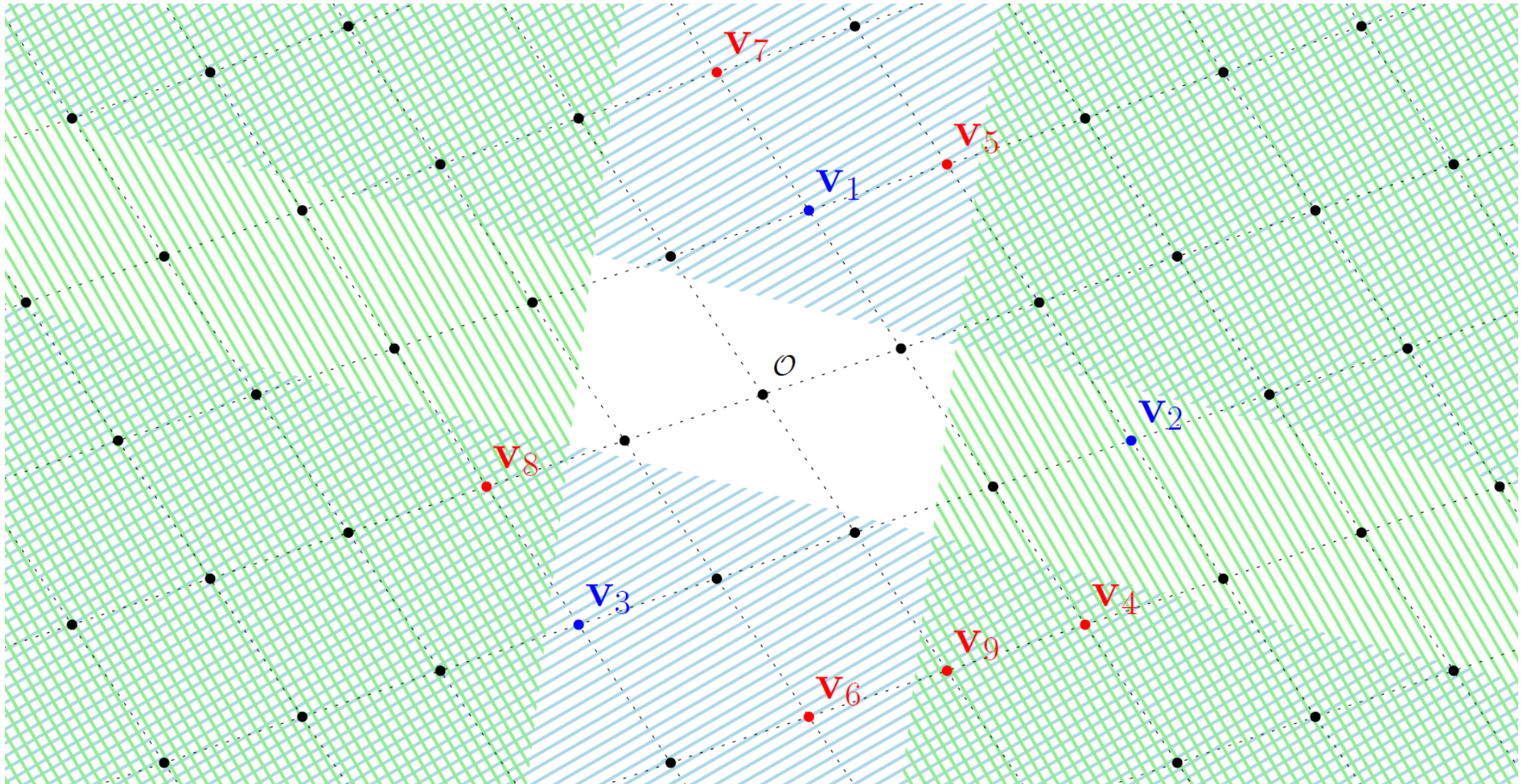
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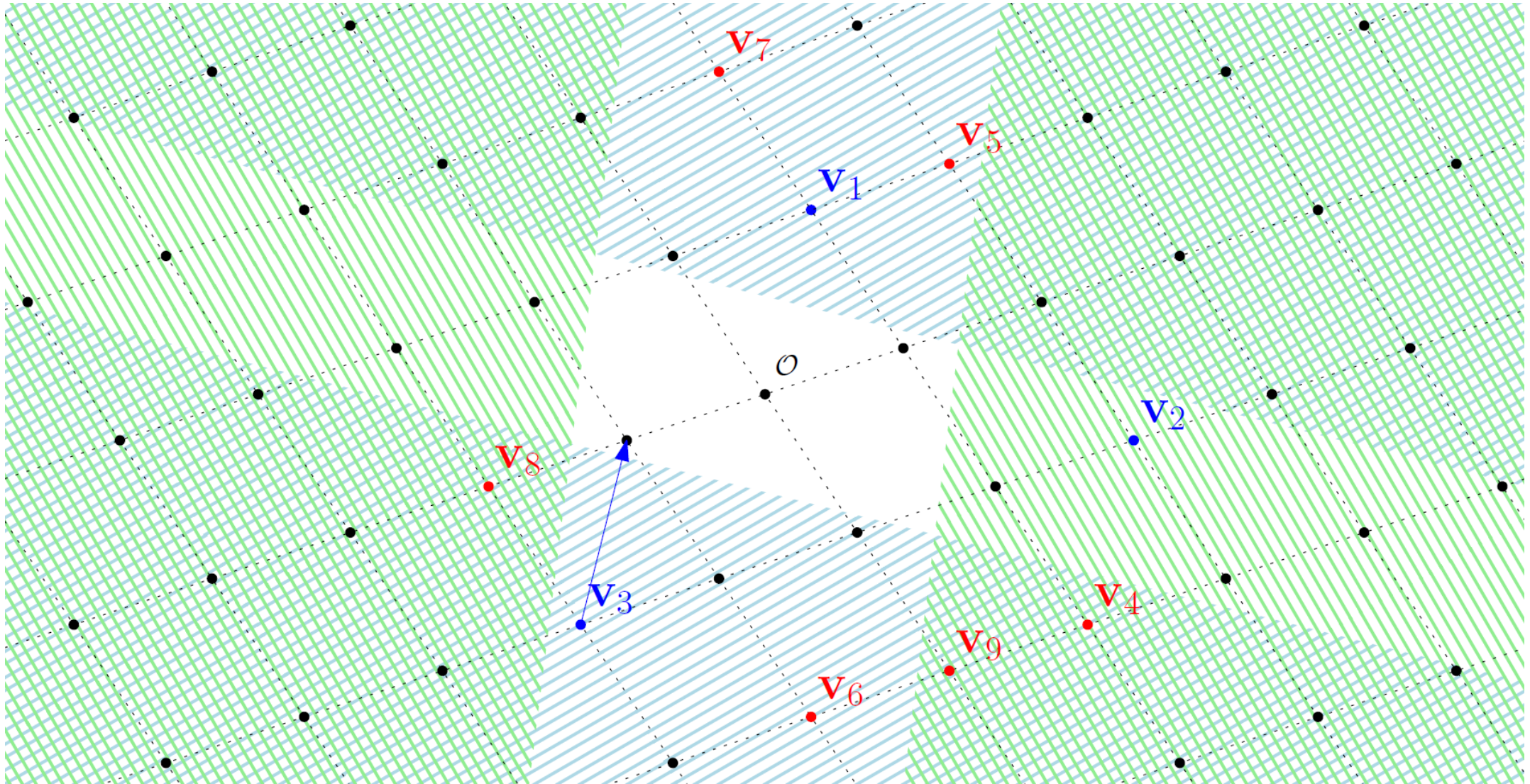
When two vectors can reduce each other, the shorter one reduces the longer one.



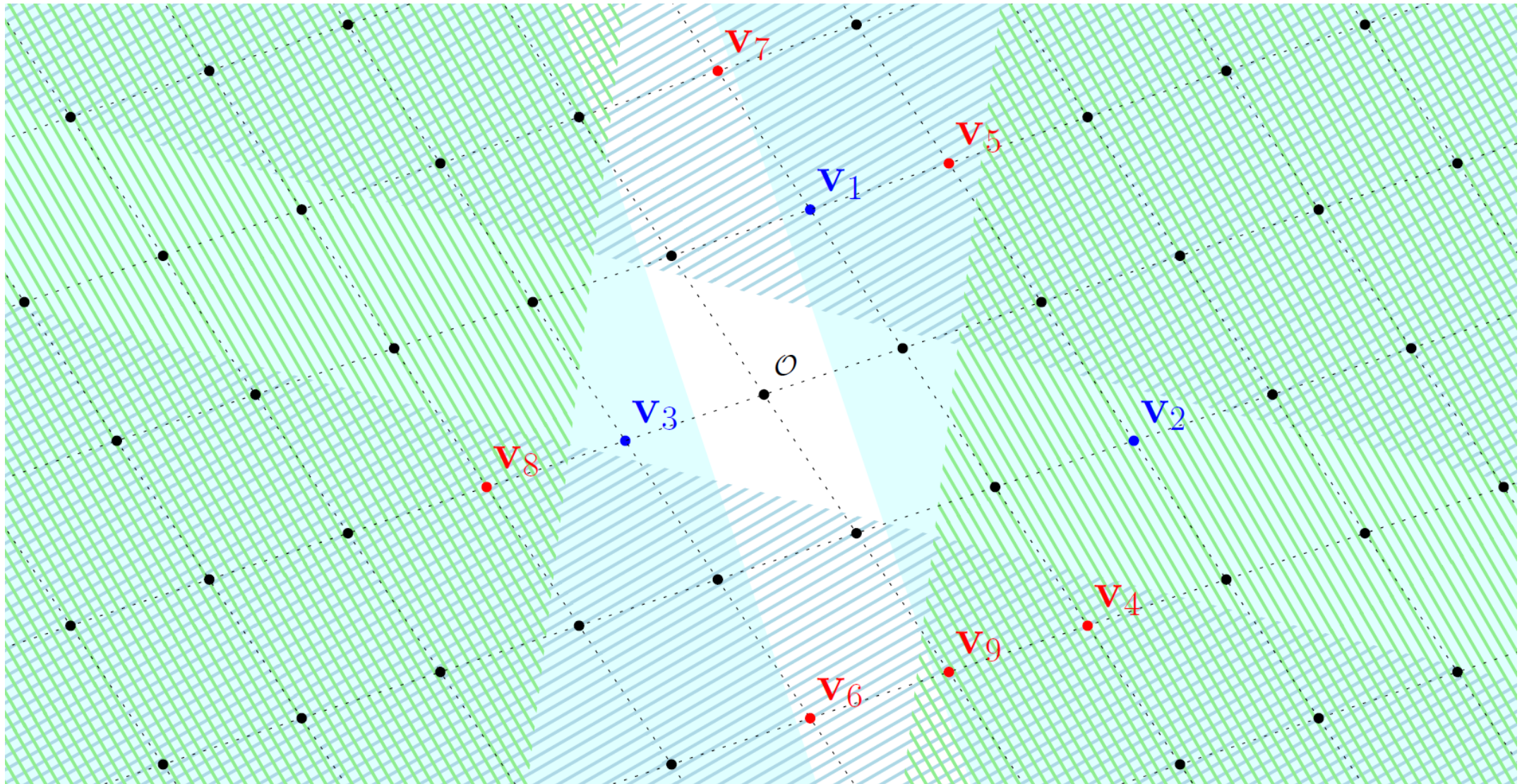
When two vectors can reduce each other, the shorter one reduces the longer one. The half-spaces increasingly cover more space.



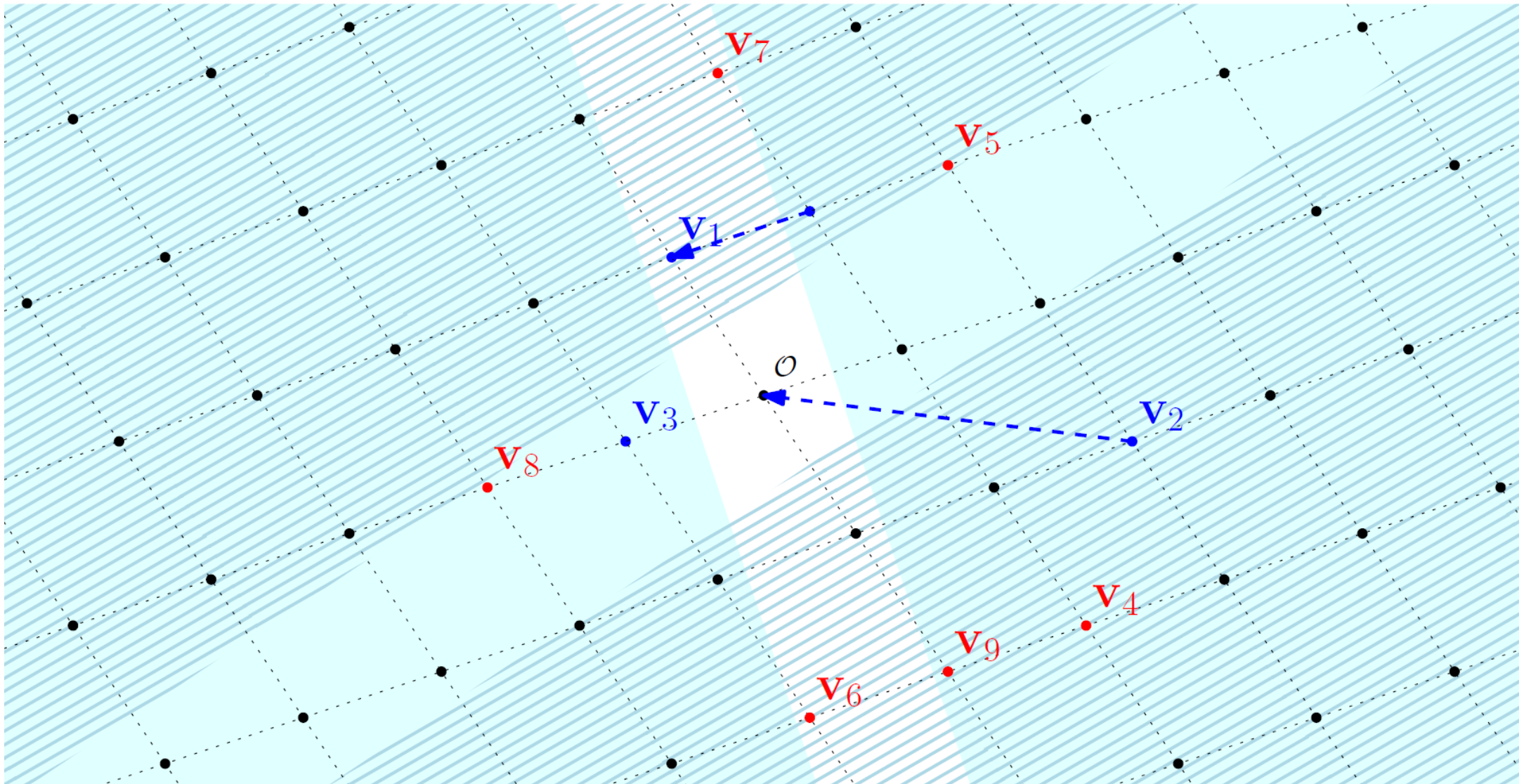
All vectors become pairwise Gauss reduced.



All vectors become pairwise Gauss reduced and the list consists of shorter and shorter vectors.

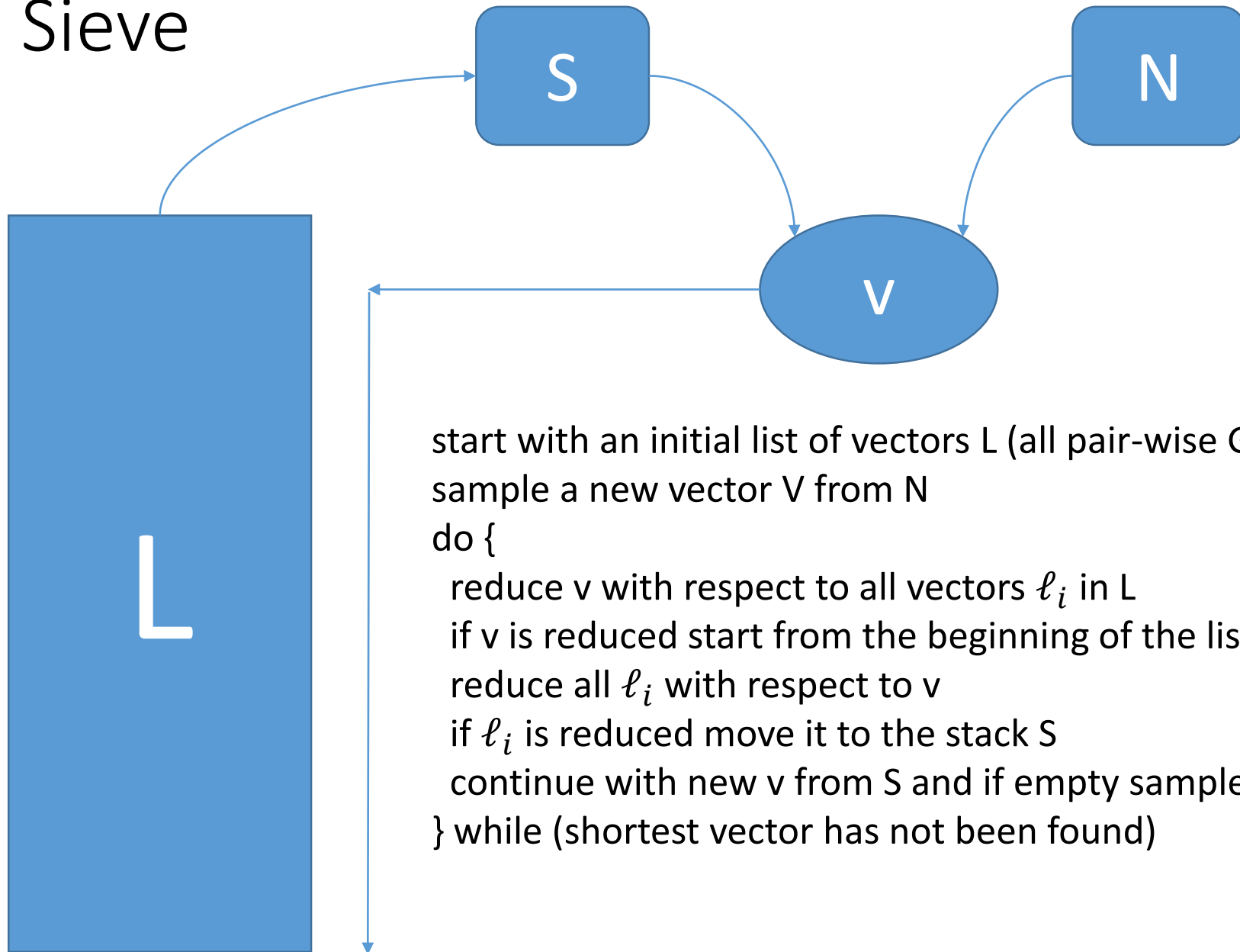


Repeat until we find a short vector or enough collisions.

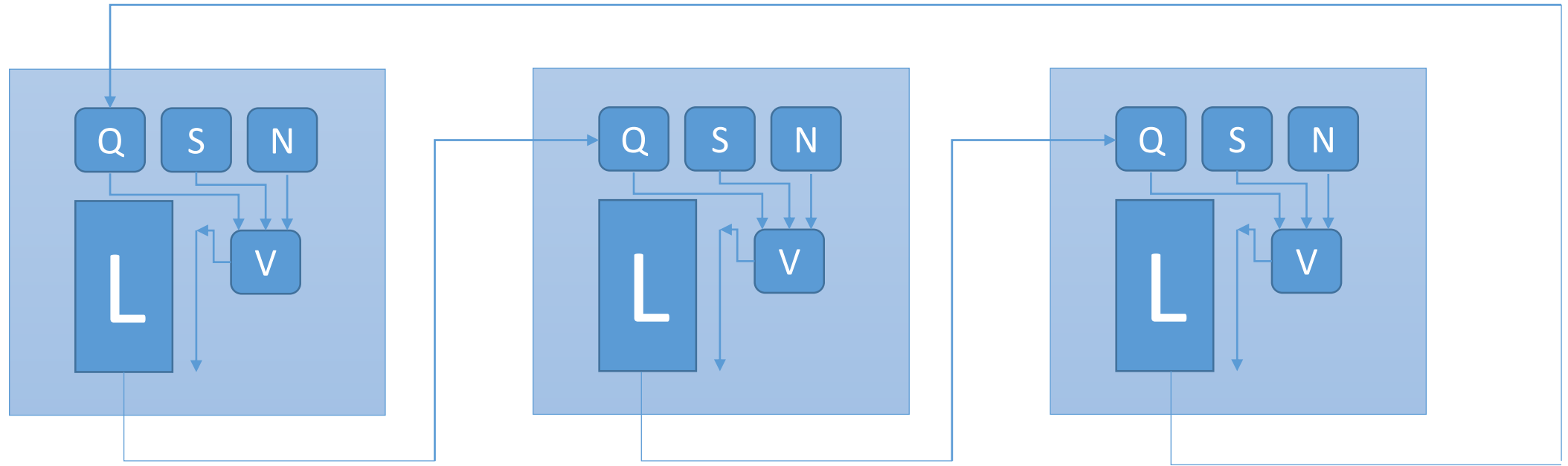


Repeat until we find a short vector or enough collisions.
Nothing can be proven about the collisions.

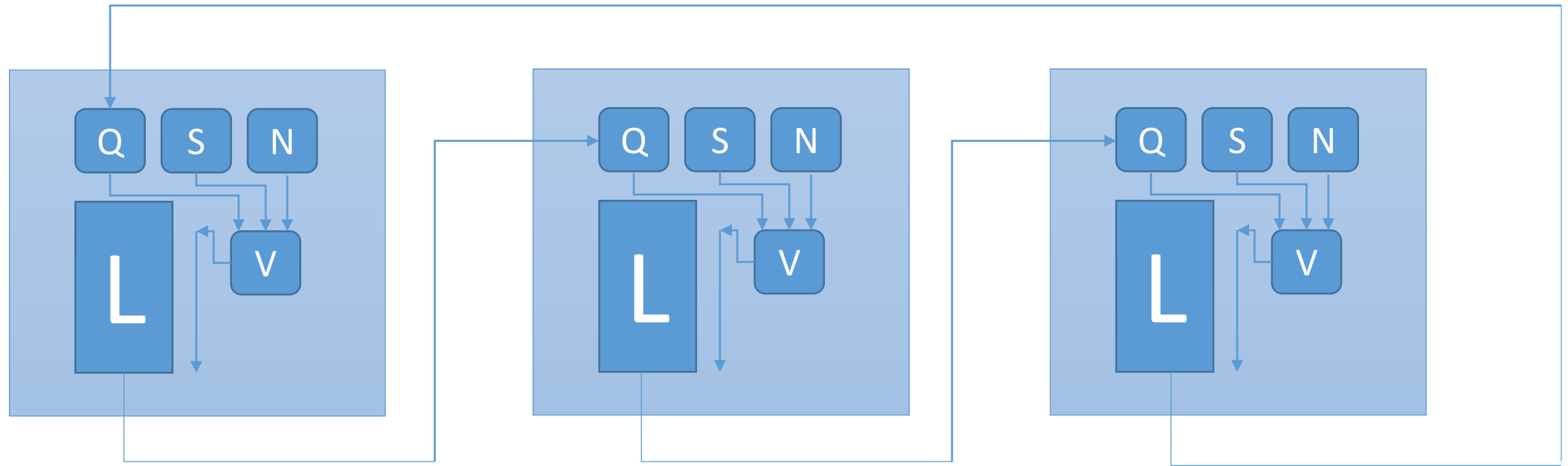
Gauss Sieve



Parallel Gauss Sieve

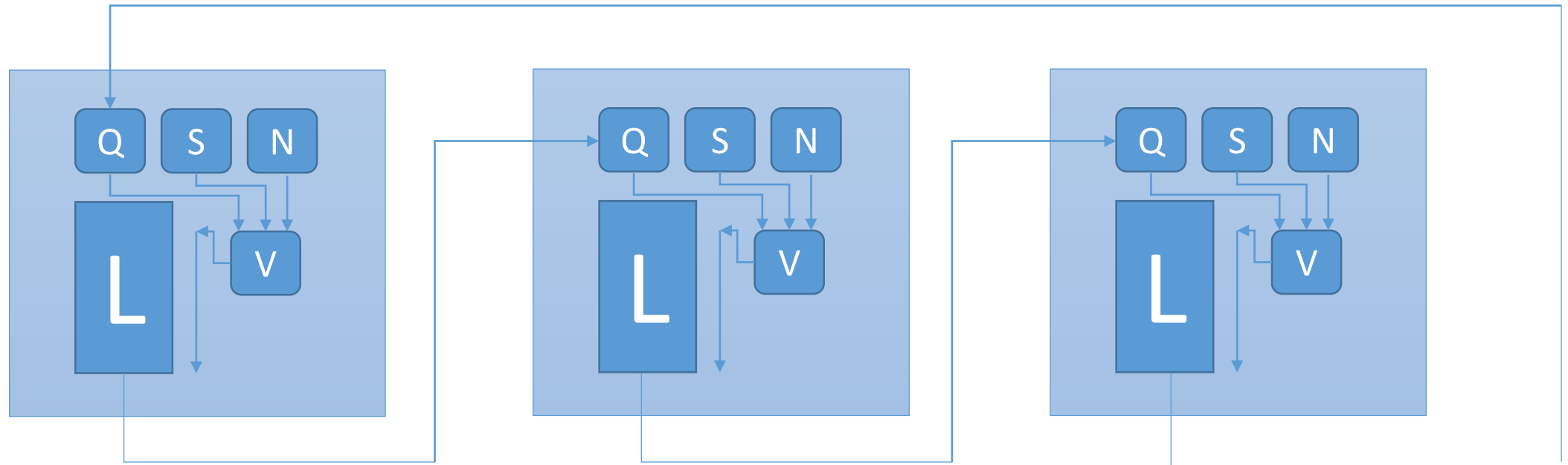


Parallel Gauss Sieve



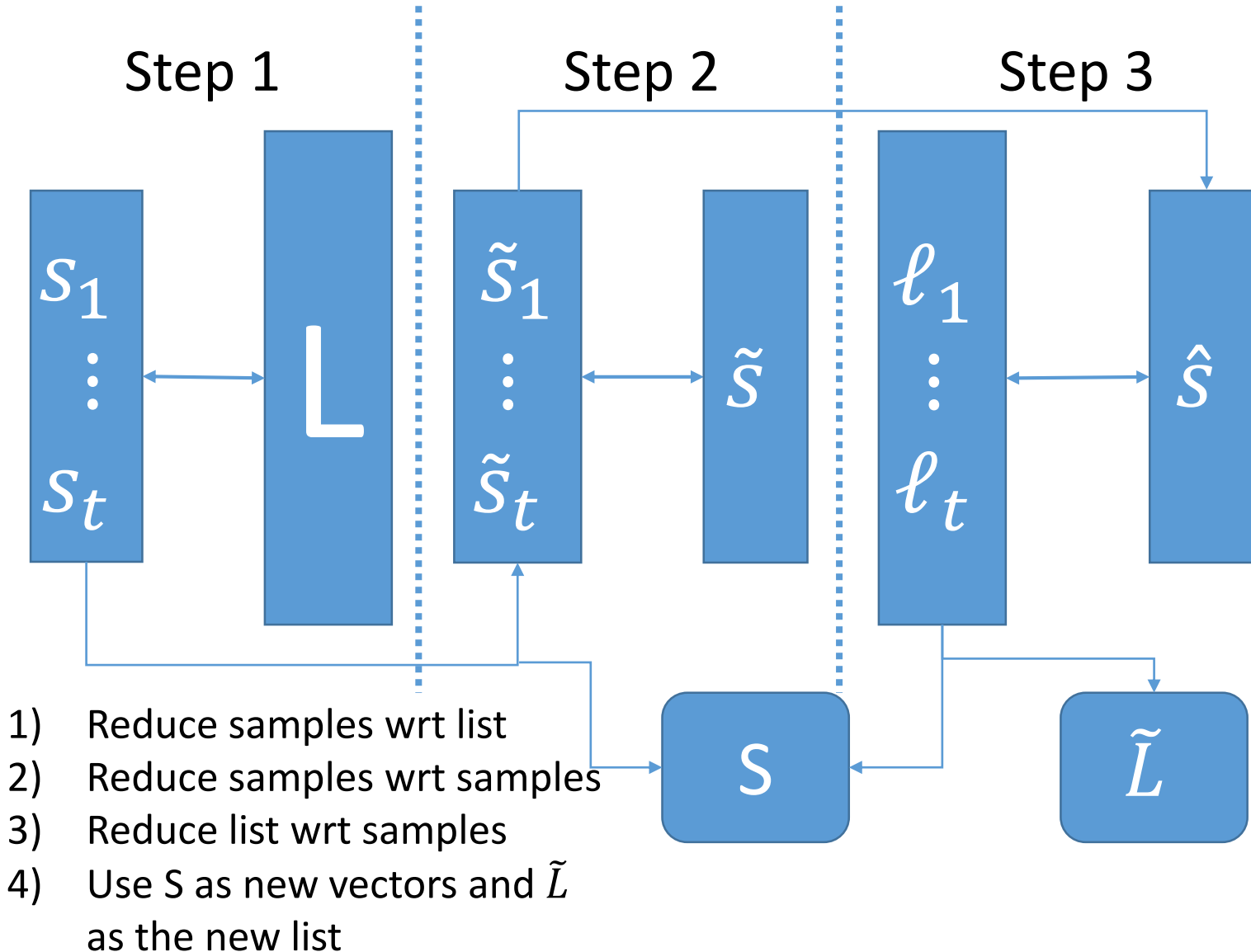
Pros	Cons
Easy parallel algorithm	
Total list size ($\sum L_i$) is distributed among nodes	

Parallel Gauss Sieve

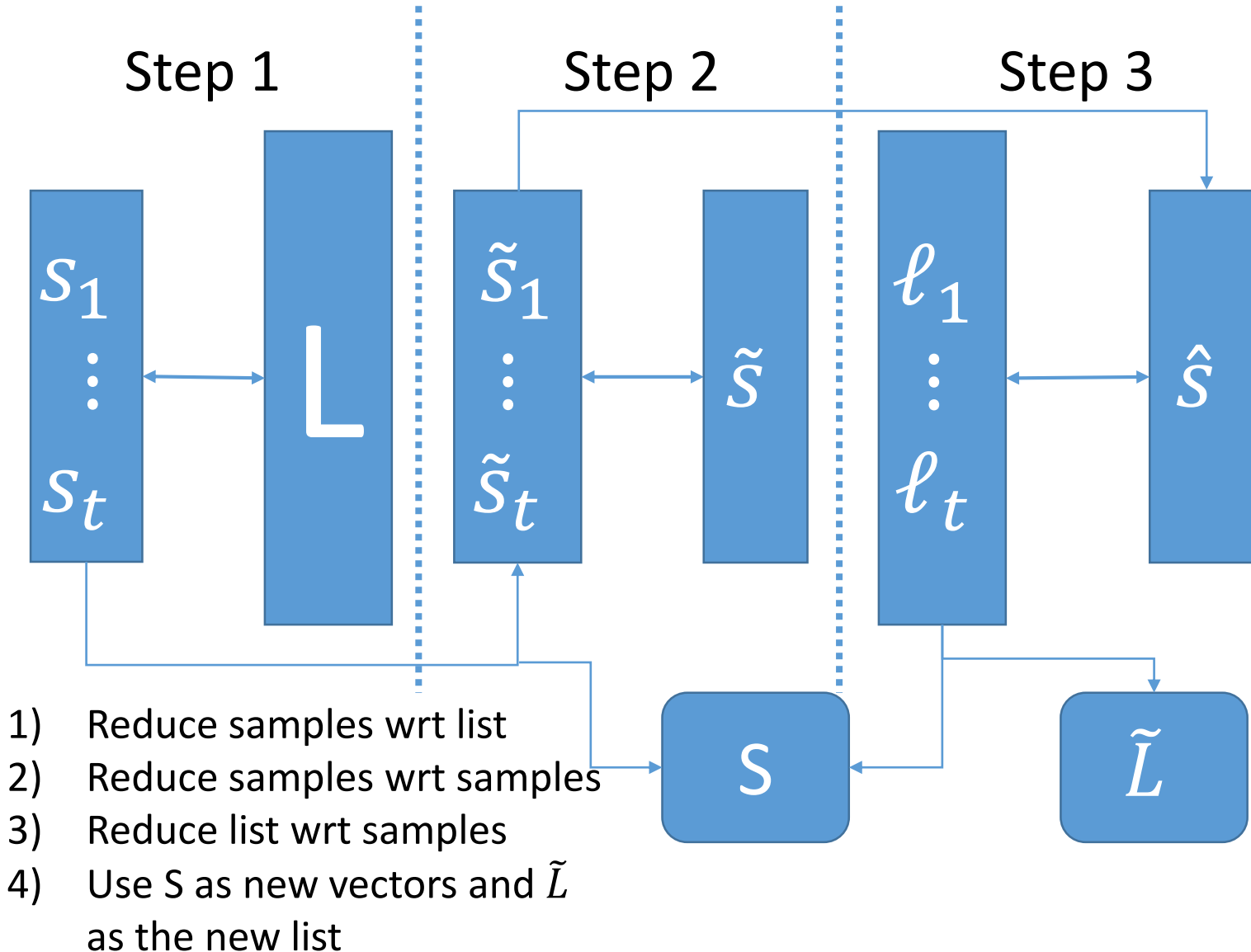


Pros	Cons
Easy parallel algorithm	$U_i L_i$ are not necessarily pair-wise Gauss reduced
Total list size ($U_i L_i$) is distributed among nodes	One node might sample a lot of new vectors: “traffic jams” + idle nodes
	Suggested solution: skip jams → more vectors in ($U_i L_i$) are not pair-wise Gauss reduced → increased list size → increased running time

Parallel Gauss Sieve – another approach

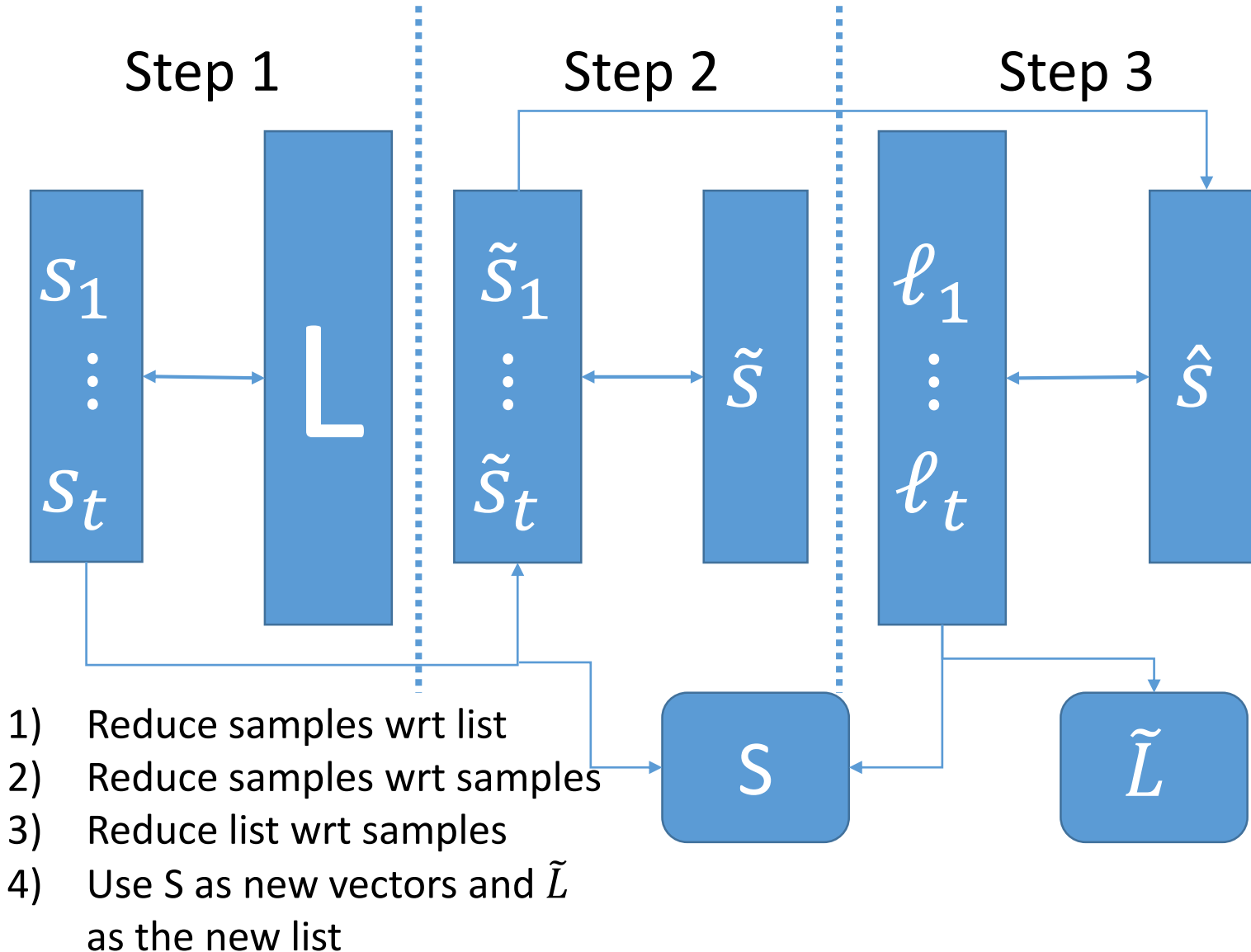


Parallel Gauss Sieve – another approach



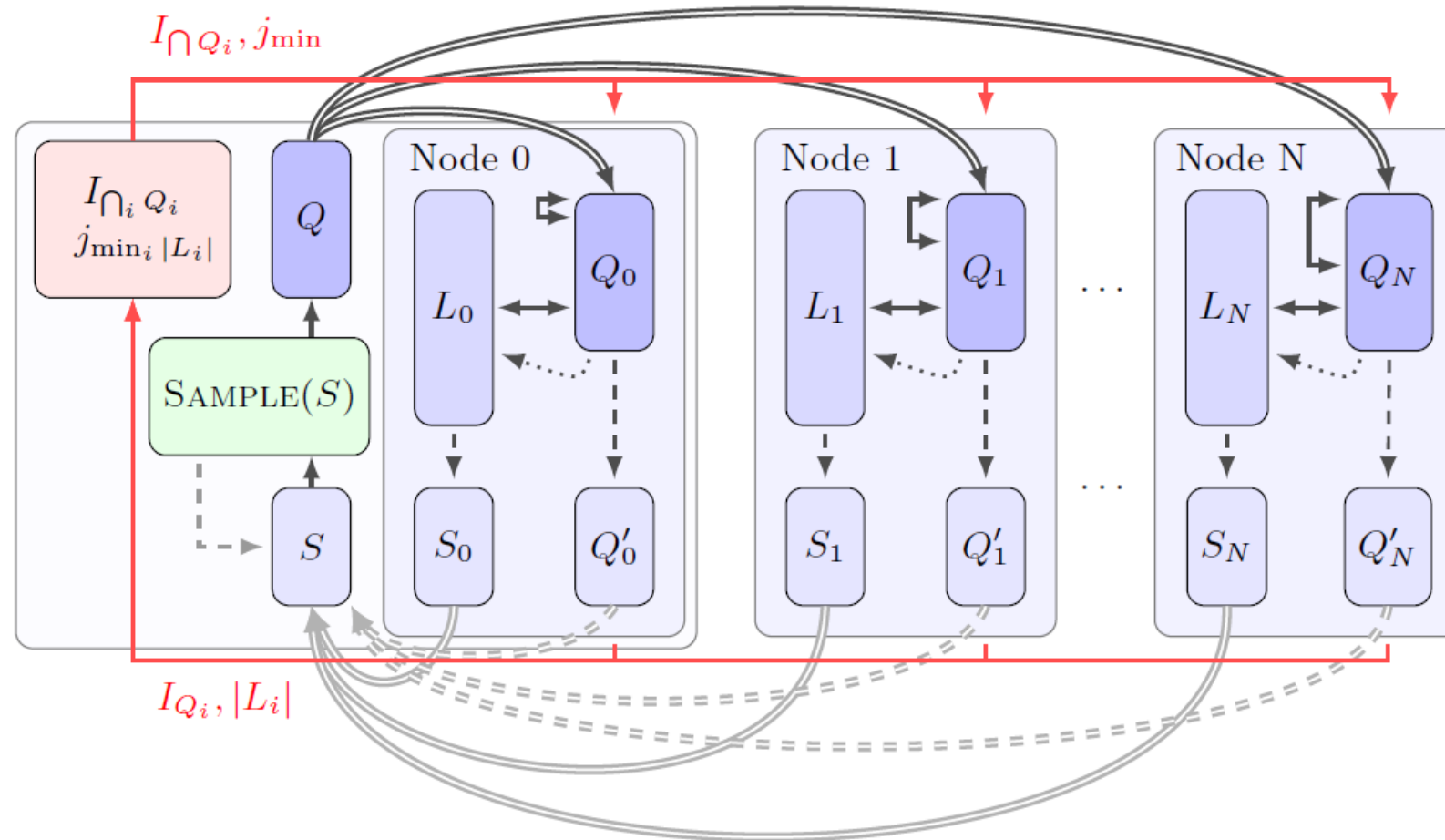
- ✓ After step 3 all vectors in \tilde{L} are pairwise Gauss reduced
- ✓ Avoids the traffic jam problem
- ✓ Every node requires the complete list L and all samples S
- ✓ Conservative estimated max. list size for (non-ideal) dim. 128 is $2^{28} \rightarrow 64$ GB

Parallel Gauss Sieve – another approach



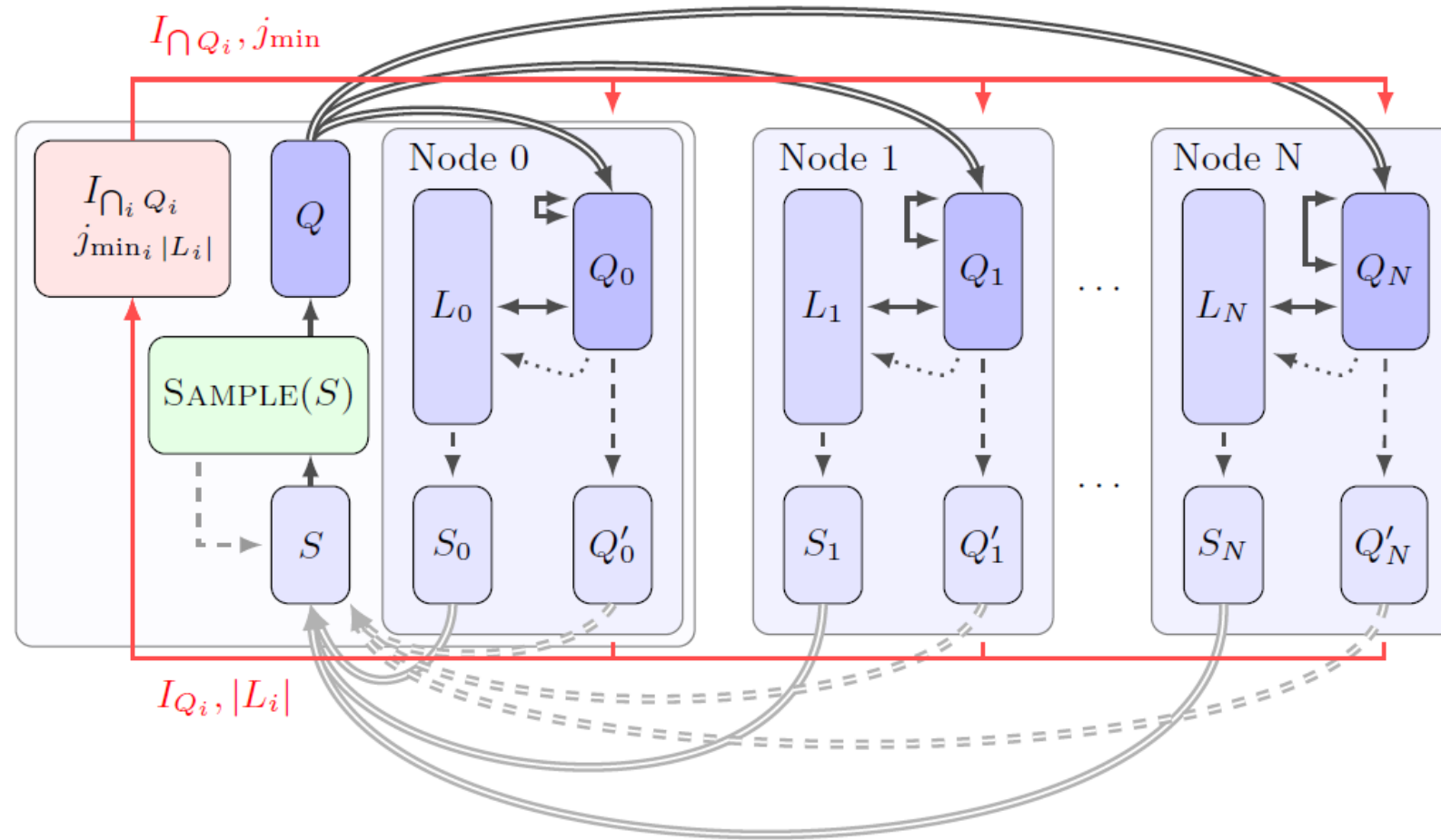
- ✓ After step 3 all vectors in \tilde{L} are pairwise Gauss reduced
- ✓ Avoids the traffic jam problem
- ✓ Every node requires the complete list L and all samples S
- ✓ Conservative estimated max. list size for (non-ideal) dim. 128 is $2^{28} \rightarrow 64$ GB
- ✓ Used to solve ideal lattice challenge of dim. 128 in
 ≈ 15 days on 1344 CPUs
 ≈ 55 CPU years

Parallel Gauss Sieve – combining both approaches



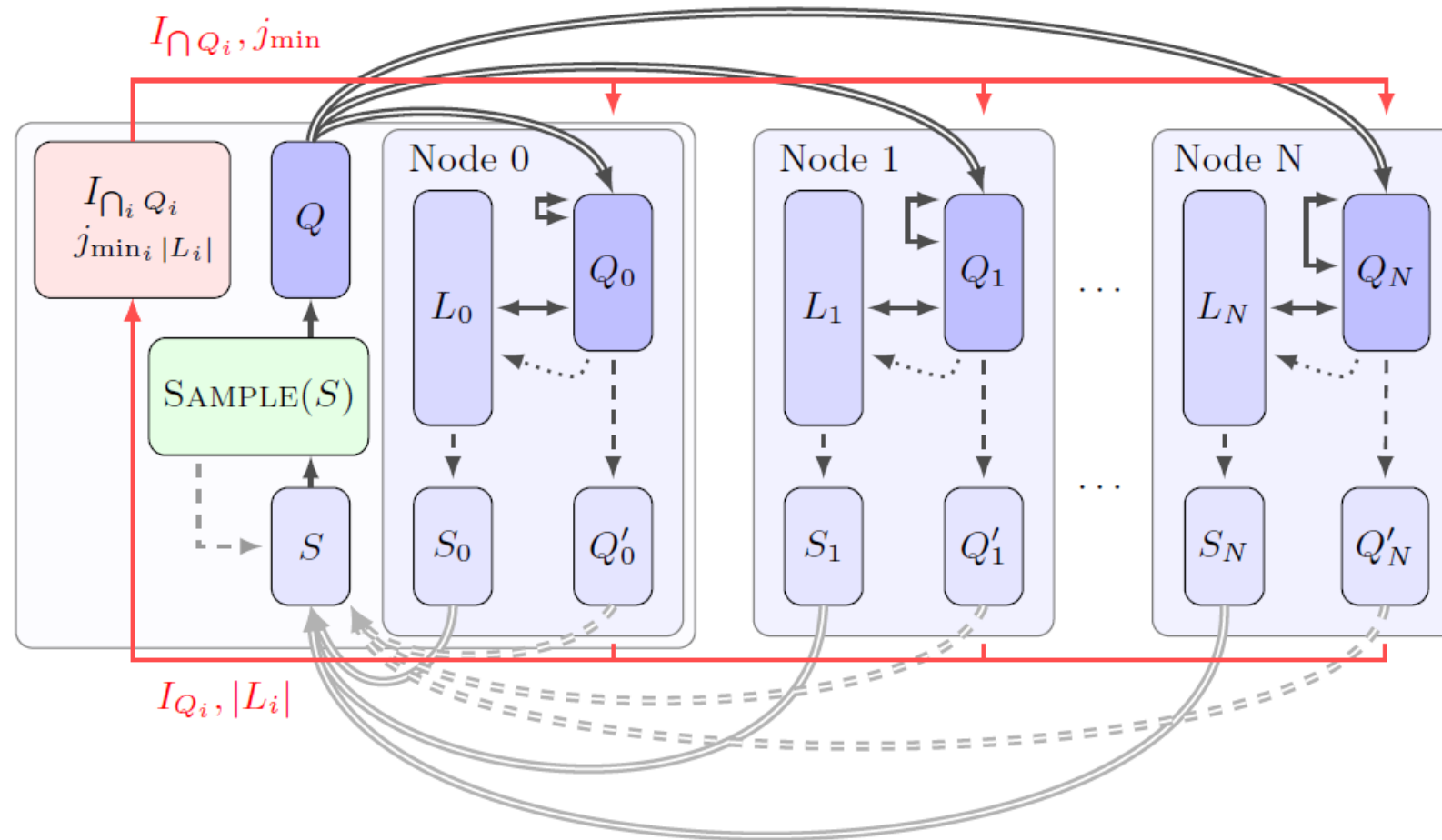
- 1) Collectively obtain new batch Q_i
- 2) Reduce vectors from Q_i wrt L_i and vice-versa
- 3) Reduce Q_i wrt to Q_i (divide work)
- 4) Reduced vectors from L_i go to S_i
- 5) Reduced vectors from Q_i go to Q'_i

Parallel Gauss Sieve – combining both approaches



- Locally L_i is replaced by $L_i \setminus S_i$
- Compute j s. t. $|L_j|$ is minimal and update L_j as $L_j \cup \cap_i Q_i$
- This avoids traffic jams
- List size ($\cup_i L_i$) is distributed among nodes
- All vectors are pairwise Gauss reduced

Parallel Gauss Sieve – combining both approaches



- The same vector $v \in Q$ might be reduced by different L_i at different nodes \rightarrow collisions
- Propagate the vector with minimal norm

Ideal lattice

- ✓ Ideal lattice: additional structure \rightarrow also ideals in a ring R
- ✓ Most crypto settings restrict to

$$R = \mathbb{Z}[X]/(\Phi_m(X)),$$

$$\text{where } m = 2n, n = 2^\ell, \ell > 0 \text{ s.t. } \Phi_m(X) = X^n + 1$$

- If $a(X)$ belongs to an ideal then $X^i a$ for $i \in \mathbb{Z}$ also belongs to the ideal
- Negative exponents: $X^{-1} = -X^{n-1}$

Notation: An element $a \in R$ is of the form

$$a(X) = \sum_{i=0}^{n-1} a_i X^i$$

and given by the coefficient vector

$$\mathbf{a} = (a_0, a_1, \dots, a_{n-1})$$

Ideal lattice

Previous work: store one vector, represent n vectors.

Observation 1: Checking if all n^2 pairs of rotations of a vector \mathbf{a} with a vector \mathbf{b} are Gauss reduced can be done with only n comparisons and n scalar products.

Lemma 1.

Let $a, b \in R = \mathbb{Z}[X]/(X^n + 1)$ for n a power of 2 and $i, j \in \mathbb{Z}$. Then we have:

$$\begin{aligned} X^i \cdot (X^j \cdot \mathbf{a}) &= X^{i+j} \cdot \mathbf{a}, & X^i \cdot (\mathbf{a} \cdot \mathbf{b}) &= X^i \cdot \mathbf{a} + X^i \cdot \mathbf{b}, & X^n \cdot \mathbf{a} &= -\mathbf{a}, \\ \langle X^i \cdot \mathbf{a}, X^i \cdot \mathbf{b} \rangle &= \langle \mathbf{a}, \mathbf{b} \rangle, & \langle X^i \cdot \mathbf{a}, X^j \cdot \mathbf{b} \rangle &= \langle \mathbf{a}, -X^{n-i+j} \cdot \mathbf{b} \rangle. \end{aligned}$$

Lemma 2.

Let $a, b \in R = \mathbb{Z}[X]/(X^n + 1)$ for n a power of 2 and $i, j \in \mathbb{Z}$.

If $2|\langle \mathbf{a}, X^\ell \cdot \mathbf{b} \rangle| \leq \min\{\langle \mathbf{a}, \mathbf{a} \rangle, \langle \mathbf{b}, \mathbf{b} \rangle\}$ for all $0 \leq \ell < n$, then $X^i \cdot \mathbf{a}$ and $X^j \cdot \mathbf{b}$ are Gauss reduced for all $i, j \in \mathbb{Z}$.

Ideal lattice

Observation 1. Checking if all n^2 pairs of rotations of a vector \mathbf{a} with a vector \mathbf{b} are Gauss reduced can be done with only n comparisons and n scalar products.

Observation 2. The n scalar products can be computed using a single ring product.

Define the reflex polynomial $b^{(R)}(X)$ as

$$b^{(R)}(X) = X^{n-1} \cdot b(X^{-1}) \text{ such that } \mathbf{b}^{(R)} = (b_{n-1}, b_{n-2}, \dots, b_0)$$

Lemma 3. Let

$$c(X) = a(X) \cdot \left(-X \cdot b^{(R)}(X) \right) \bmod (X^n + 1)$$

And let $c = (c_0, c_1, \dots, c_{n-1}) \in \mathbb{Z}^n$ be its coefficient vector. Then

$$c_i = \langle a, X^i \cdot b \rangle \text{ for } 0 \leq i < n.$$

Ideal lattice

Observation 1. Checking if all n^2 pairs of rotations of a vector \mathbf{a} with a vector \mathbf{b} are Gauss reduced can be done with only n comparisons and n scalar products.

Observation 2. The n scalar products can be computed using a single ring product.

Observation 3. Since the ring product is a negacyclic convolution we can use a (symbolic) FFT

Nussbaumer's symbolic FFT

Decompose $\mathbb{Z}[X]/(X^n + 1)$ into two extensions. Let $n = 2^k = s \cdot r$ such that $s|r$. Then

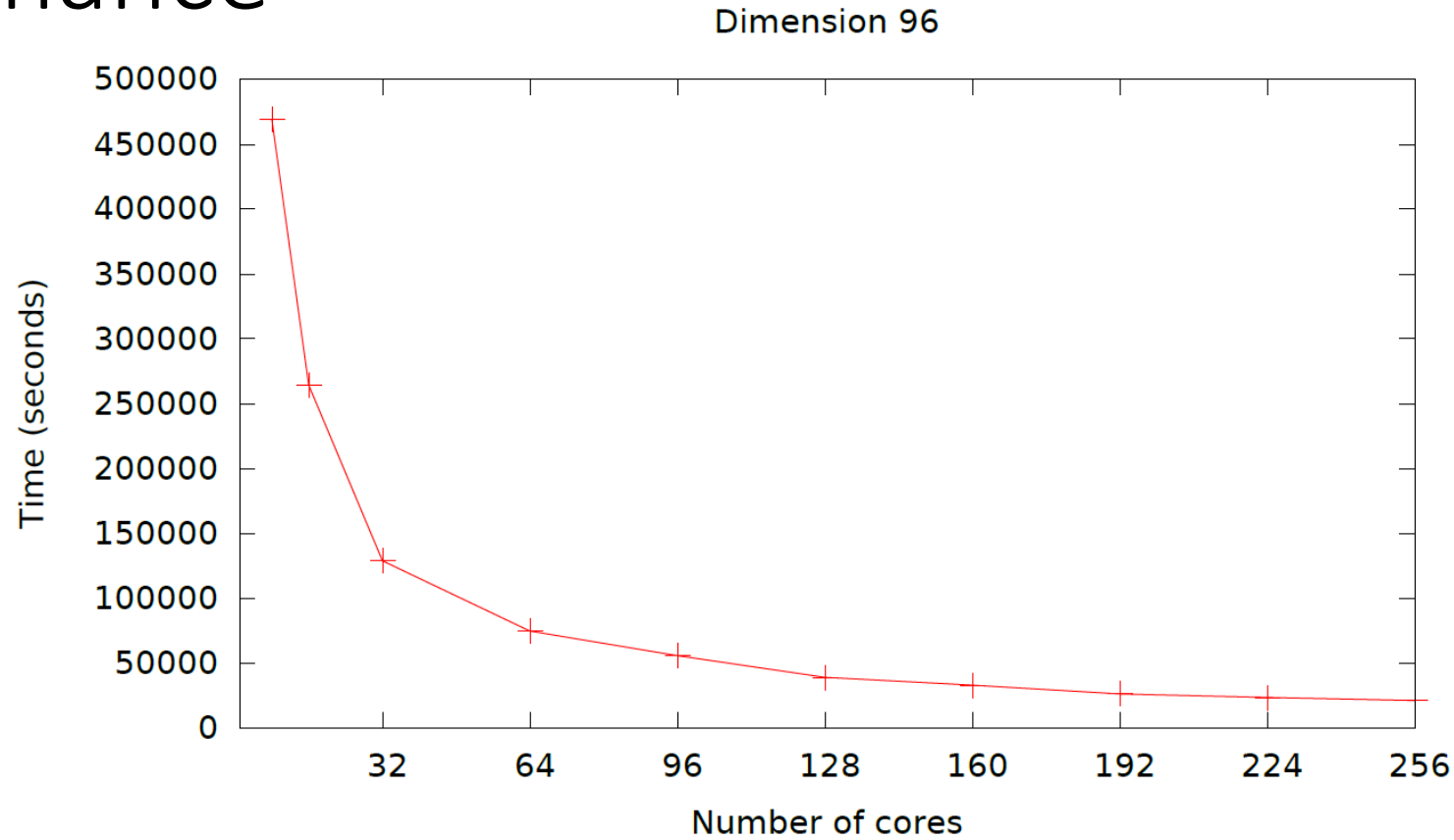
$$\mathbb{Z}[X]/(X^n + 1) \cong S = T[X]/(X^s - Z), \text{ where } T = \mathbb{Z}[Z]/(Z^r + 1)$$

Note: $Z^{r/s}$ is an s^{th} root of -1 in T and $X^s = Z$ in S

Allows to compute the DFT symbolically in T

Use $\mathcal{O}(n \ln n)$ instead of $\mathcal{O}(n^2)$ arithmetic operations

Performance

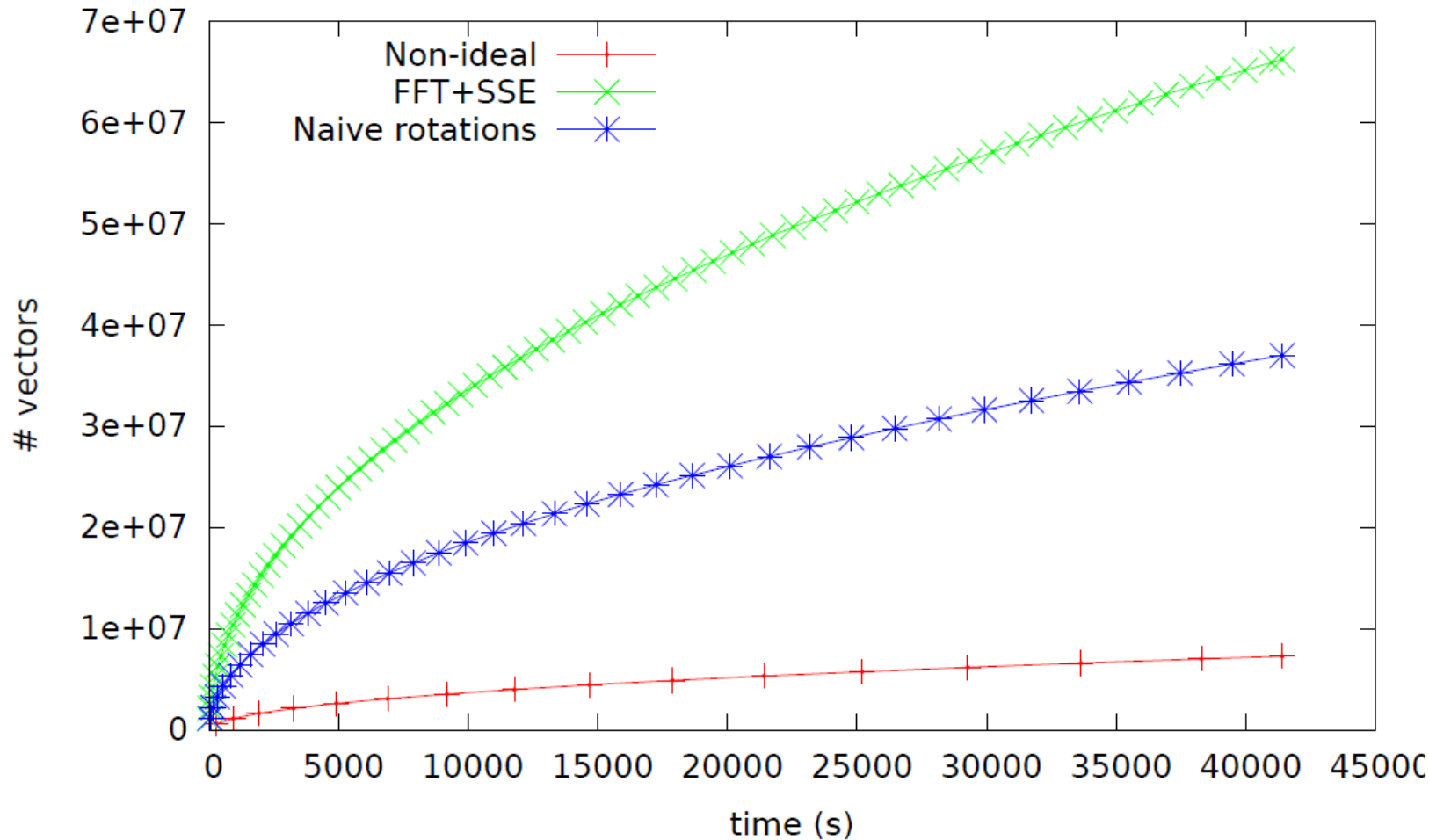


Lattices obtained from the SVP challenge, preprocess with BKZ with blocksize 30.

Speedup	
8 CPU versus 32 CPU	3.6
8 CPU versus 256 CPU	22.1

Experiments run on the BlueCrystal Phase 2 cluster of the Advanced Computing Research Centre at the University of Bristol

Performance



- Ishiguro et al. found a short vector in a dim. 128 ideal lattice in 14.88 days on 1334 CPUs ≈ 55 CPU years
- Our algorithm using FFT on the same lattice challenge on the same hardware (Bristol cluster) on 8.69 days on 1024 CPUs ≈ 25 CPU years
- More than twice as efficient
- Running challenge again with better load balancing, expect better results soon

○ Source code available (public domain):

<http://www.joppebos.com/src/ParallelGaussSieve-1.0.tgz>

Conclusions

- Number field sieve (*Integer factorization*)
 - Cofactorization step in parallel
 - When using the NVIDIA GeForce GTX 580 **1.5x improved yield** over quad-core Intel i7-3770K CPU
 - Matrix step is still difficult run in parallel
- Pollard rho (*Elliptic curve discrete logarithm*)
 - Highly-parallel and needs no memory → can utilize the power of low-cost and widely available devices
 - Example: mobile phones
- Gauss sieve (*shortest vector*)
 - Entire algorithm can be run in parallel, how does it scale exactly to thousands of nodes?
 - High communication cost, all nodes need to be online (?)

	Entire algorithm in parallel?	Can run on low- end devices?	Low communication?
Number field sieve	✗	✗	✓ ✗
Pollard rho	✓	✓	✓
Gauss sieve	✓	✗	✗

