

# Algorithms for hard lattice problems

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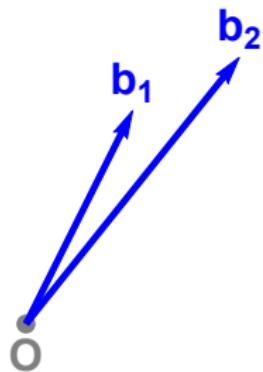
# Lattices

What is a lattice?



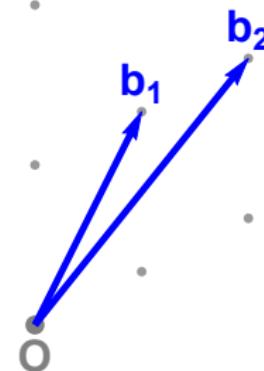
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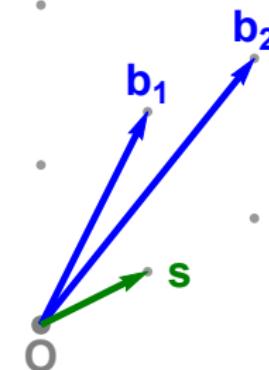
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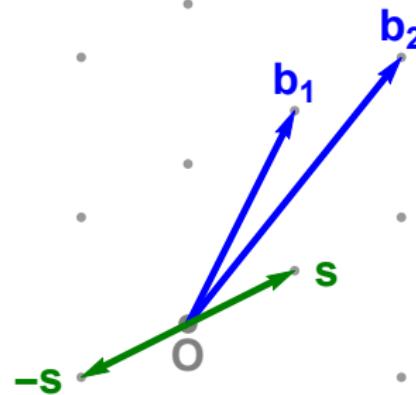
## Lattices

Shortest Vector Problem (SVP)



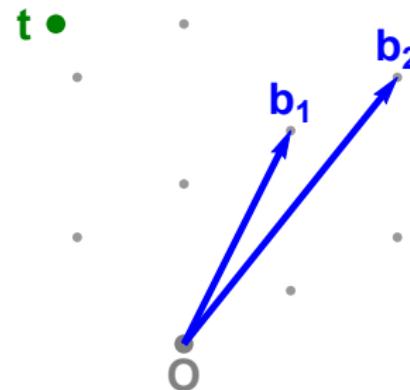
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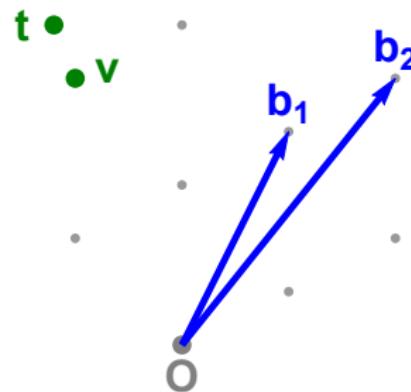
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Closest Vector Problem (CVP)



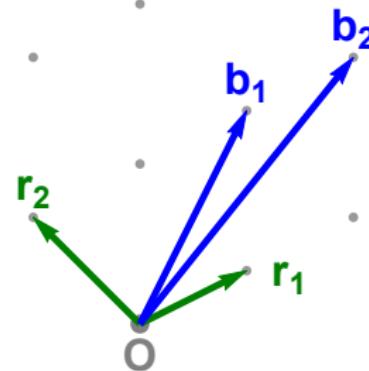
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Closest Vector Problem (CVP)



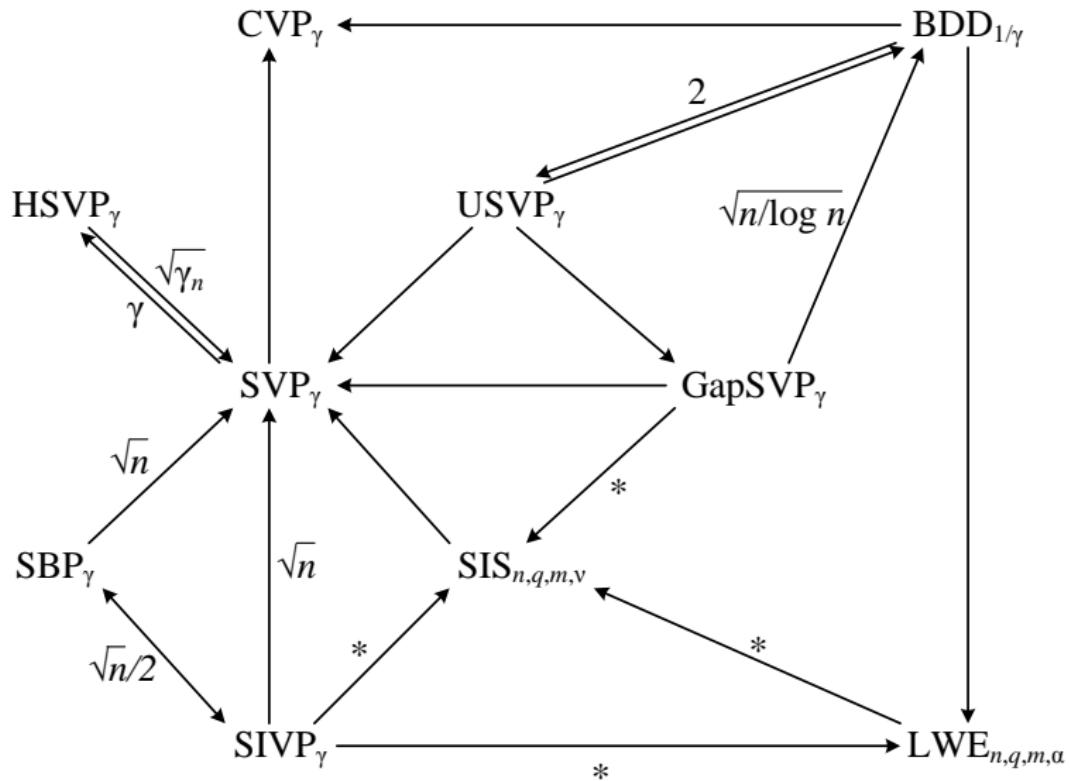
# Lattices

## Lattice basis reduction



## Lattices

Hard lattice problems [LvdPdW12]



# Lattices

## Lattice-based cryptography

**Problem:** Security of lattice-based cryptographic primitives

- Lattice-based crypto relies on hardness of lattice problems
- Most lattice problems reducible to (approximate) SVP
- State-of-the-art: BKZ basis reduction [Sch87, SE94, ...]
  - ▶ BKZ uses exact SVP algorithm as subroutine
  - ▶ Complexity of BKZ dominated by *exact* SVP calls

SVP costs  $\implies$  BKZ costs  $\implies$  Security estimates  $\implies$  Parameters

**Problem:** How hard is SVP in high dimensions?

# Outline

## SVP algorithms

- Enumeration

- Sieving

## SVP hardness

- Theory

- Practice

- NIST submissions

## Conclusion

# Outline

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- Enumeration

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## SVP hardness

- Theory

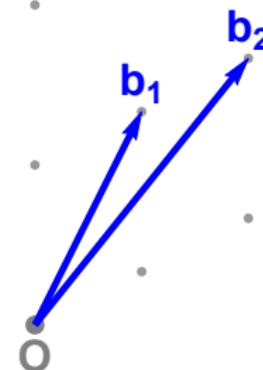
- Practice

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## Conclusion

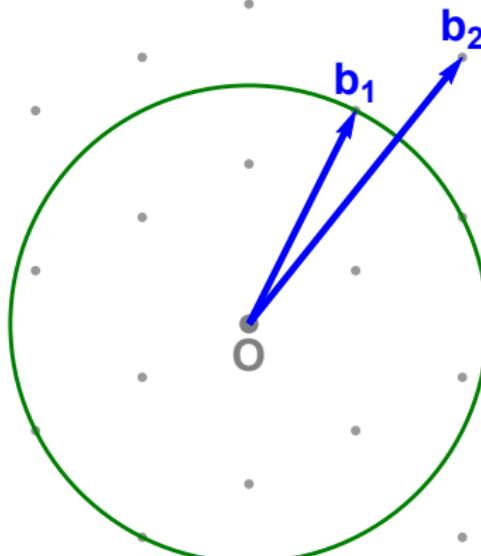
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1. Determine possible coefficients of  $b_2$



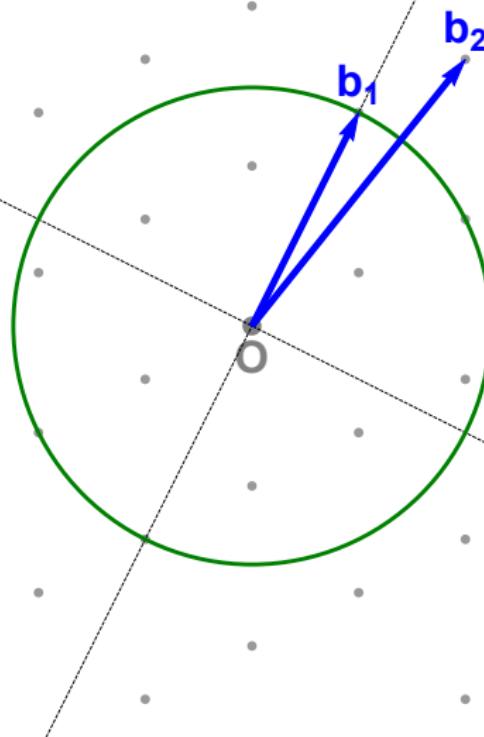
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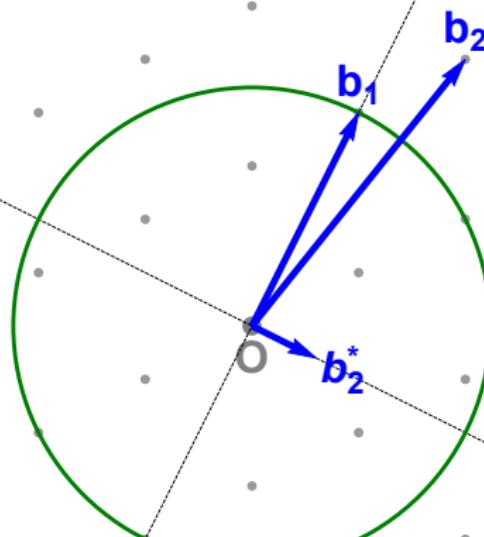
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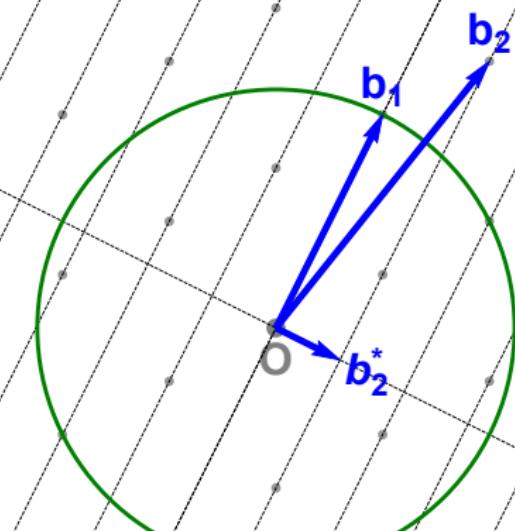
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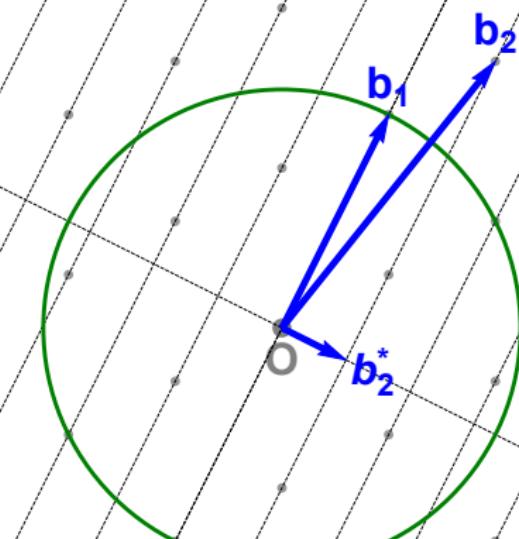
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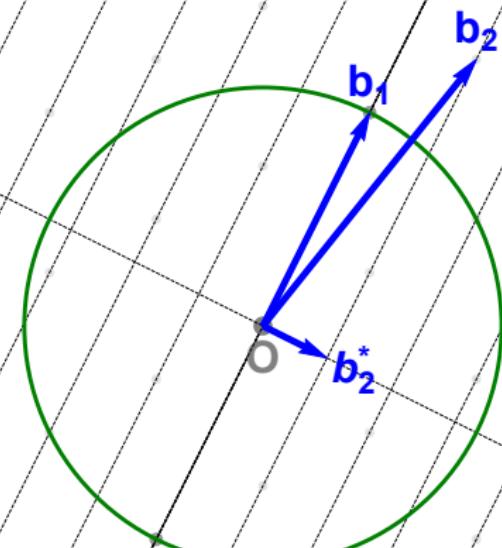
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2. Find short vectors for each coefficient of  $b_2$



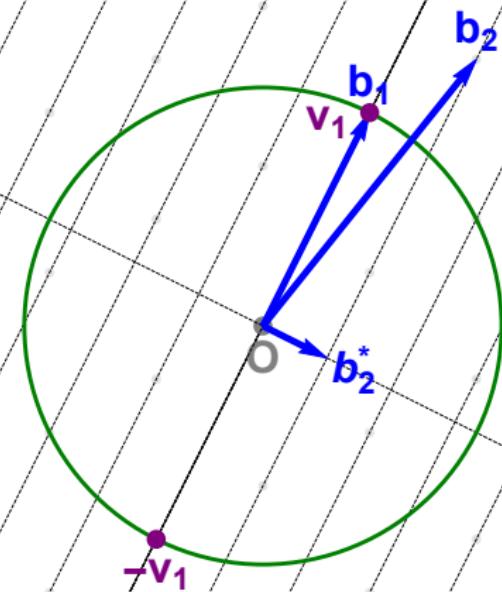
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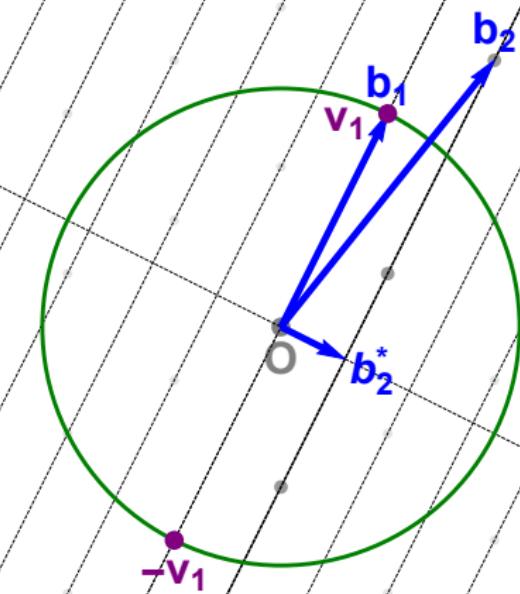
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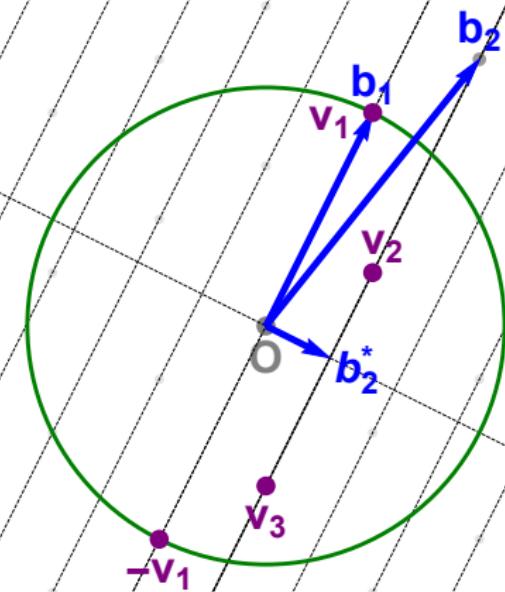
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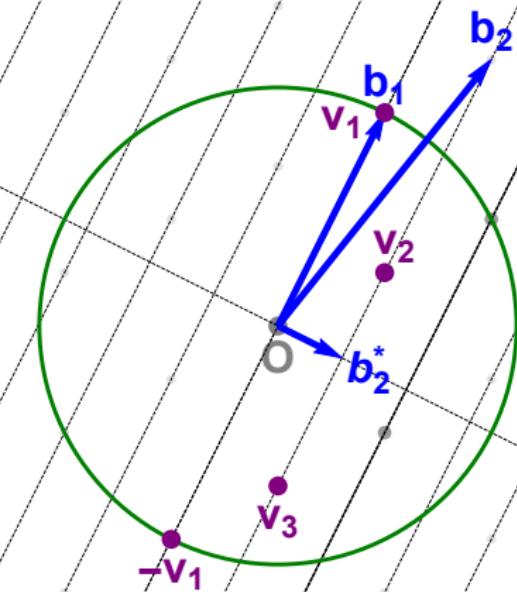
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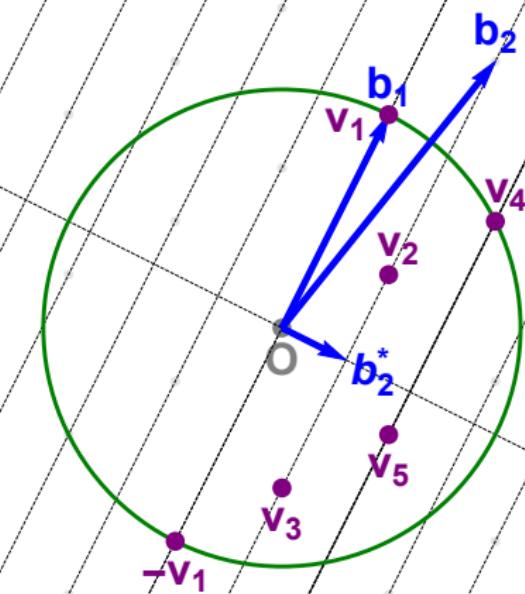
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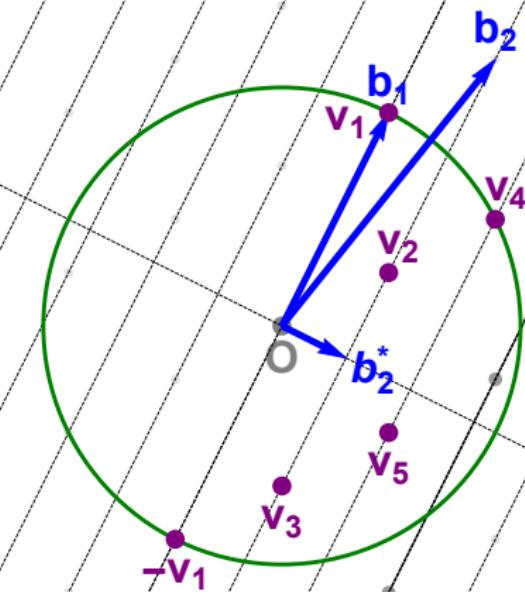
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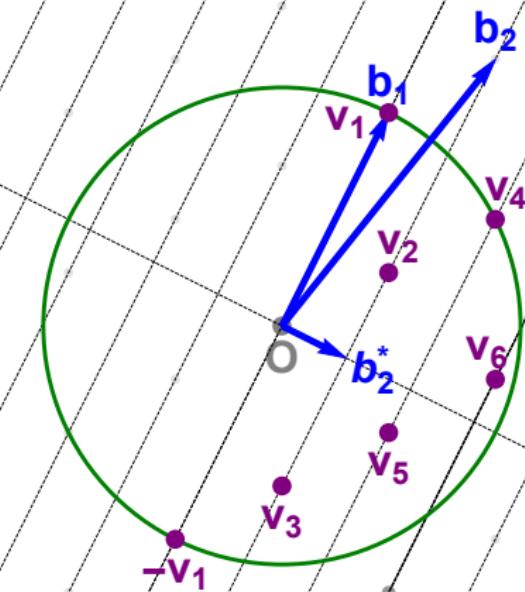
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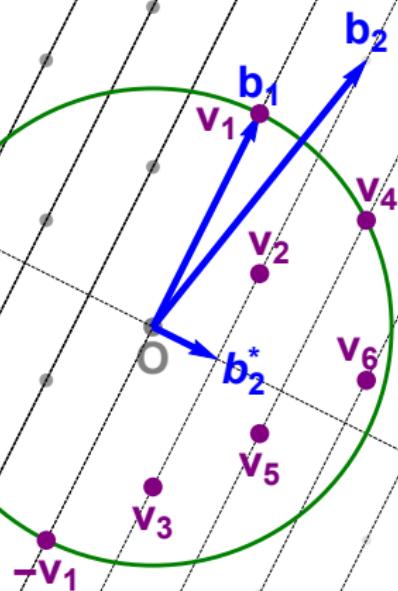
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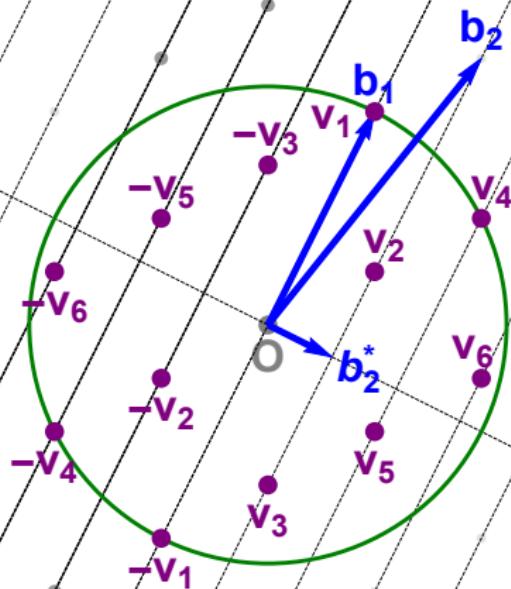
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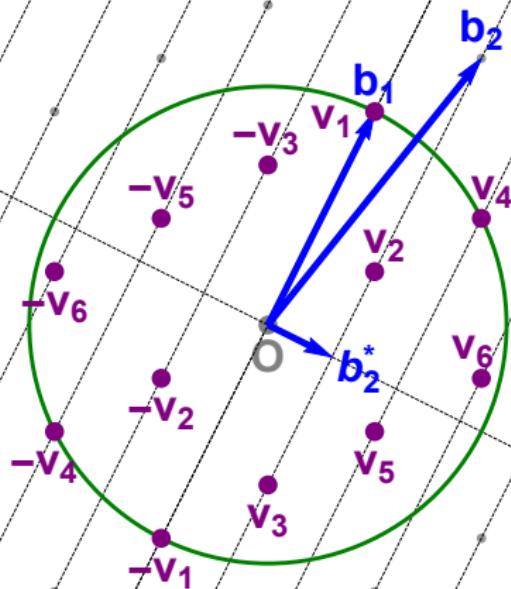
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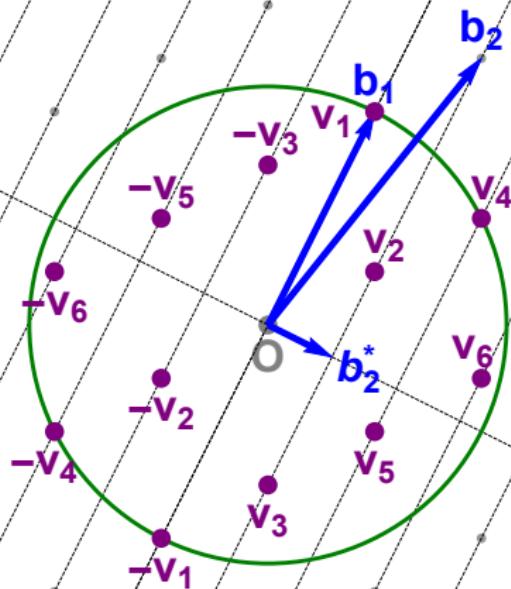
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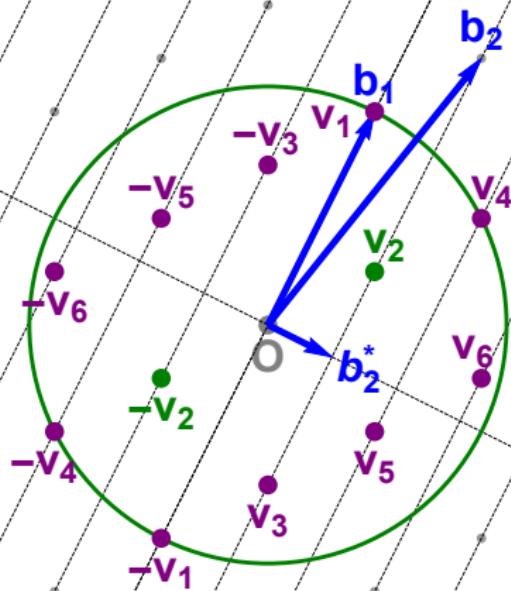
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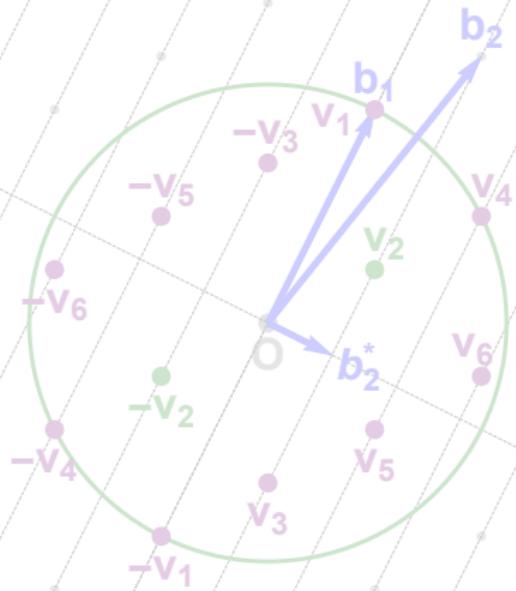
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# Enumeration

## Overview

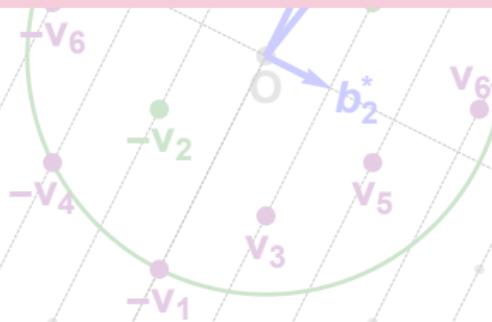


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## Overview

Theorem (Fincke–Pohst, Math. of Comp. '85)

Lattice enumeration solves SVP in time  $2^{O(n^2)}$  and space  $\text{poly}(n)$ .



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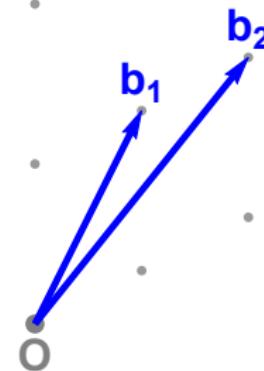
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Lattice enumeration solves SVP in time  $2^{O(n^2)}$  and space  $\text{poly}(n)$ .

Essentially reduces  $SVP_n$  ( $CVP_n$ ) to  $2^{O(n)}$  instances of  $CVP_{n-1}$ .

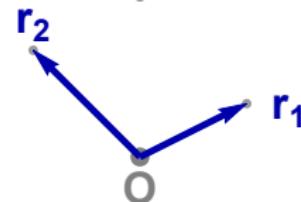
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Better bases



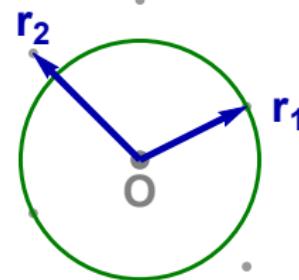
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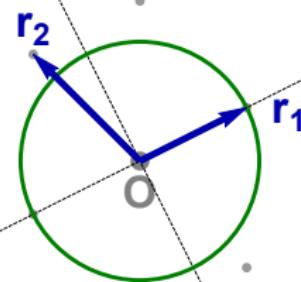
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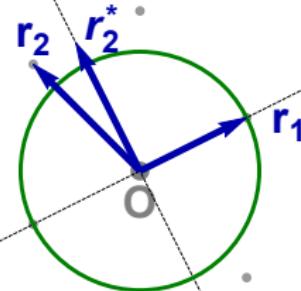
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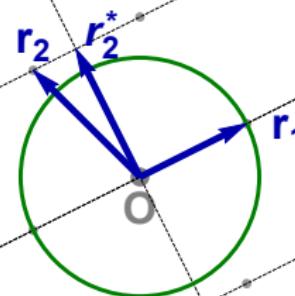
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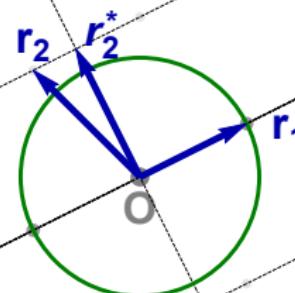
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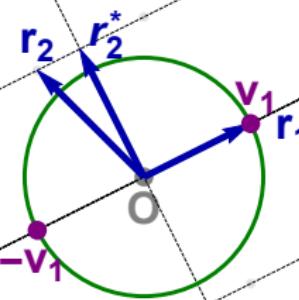
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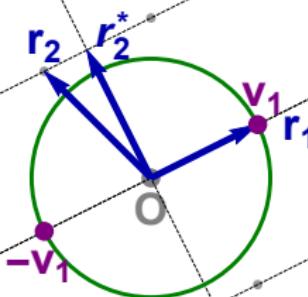
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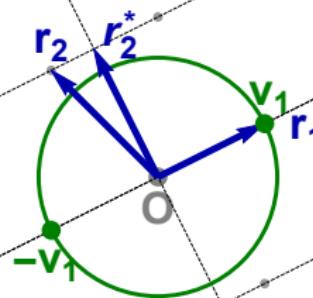
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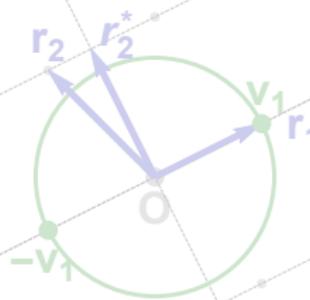
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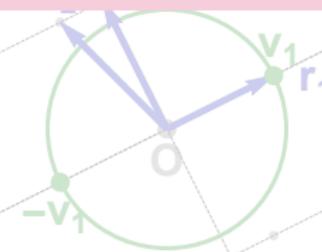


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Theorem (Kannan, STOC'83)

Combining enumeration with stronger basis reduction, one can solve SVP in time  $2^{O(n \log n)}$  and space  $\text{poly}(n)$ .



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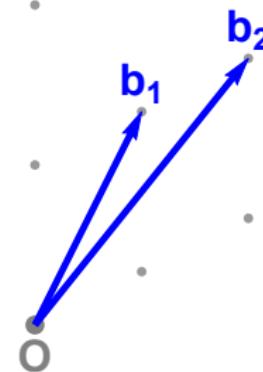
Combining enumeration with stronger basis reduction, one can solve SVP in time  $2^{O(n \log n)}$  and space  $\text{poly}(n)$ .

*"Our algorithm reduces an  $n$ -dimensional problem to polynomially many (instead of  $2^{O(n)}$ )  $(n - 1)$ -dimensional problems. [...] The algorithm we propose, first finds a more orthogonal basis for a lattice in time  $2^{O(n \log n)}$ ."*

– Kannan, STOC'83

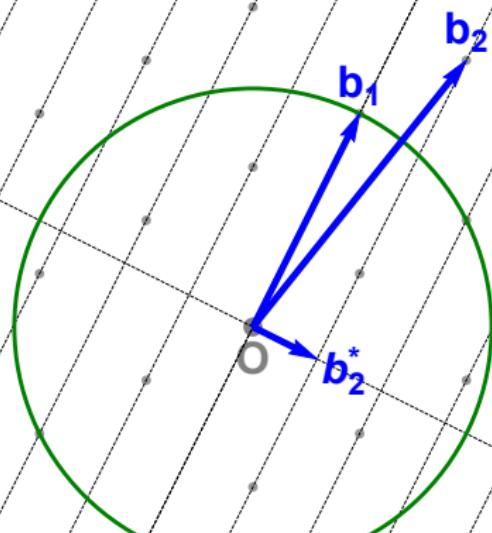
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Pruning the enumeration tree



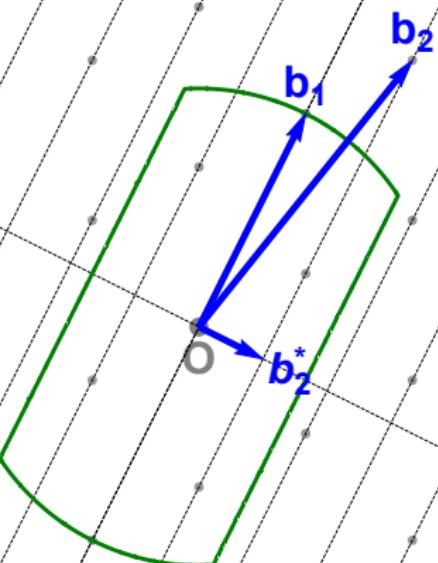
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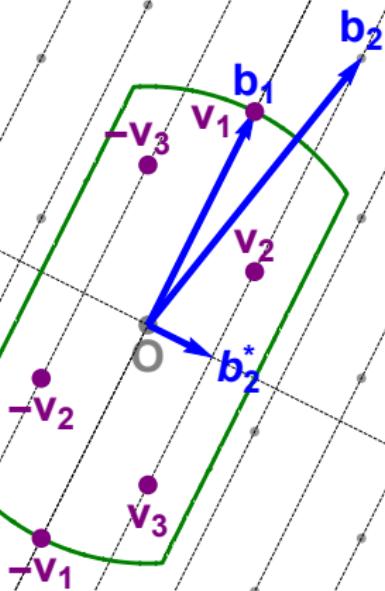
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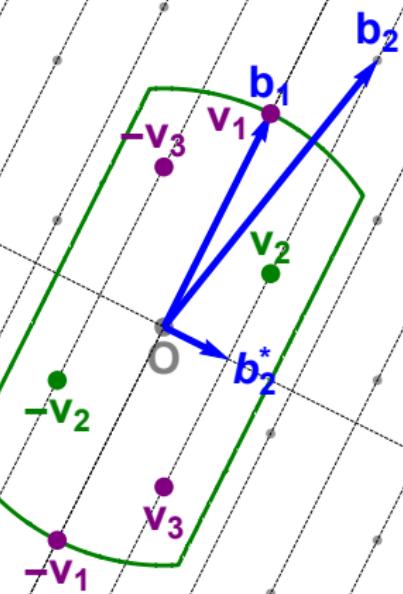
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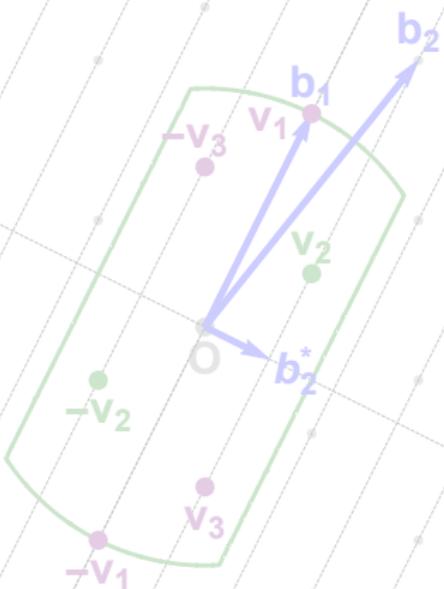
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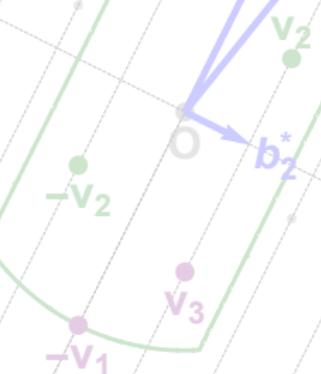


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## Pruning the enumeration tree

“Well-chosen bounding functions lead asymptotically to an exponential speedup of about  $2^{n/4}$  over basic enumeration, maintaining a success probability  $\geq 95\%$ . ”

– Gama–Nguyen–Regev, EUROCRYPT’10



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*“With extreme pruning, the probability of finding the desired vector is actually rather low (say, 0.1%), but surprisingly, the running time of the enumeration is reduced by a much more significant factor (say, much more than 1000). ”*

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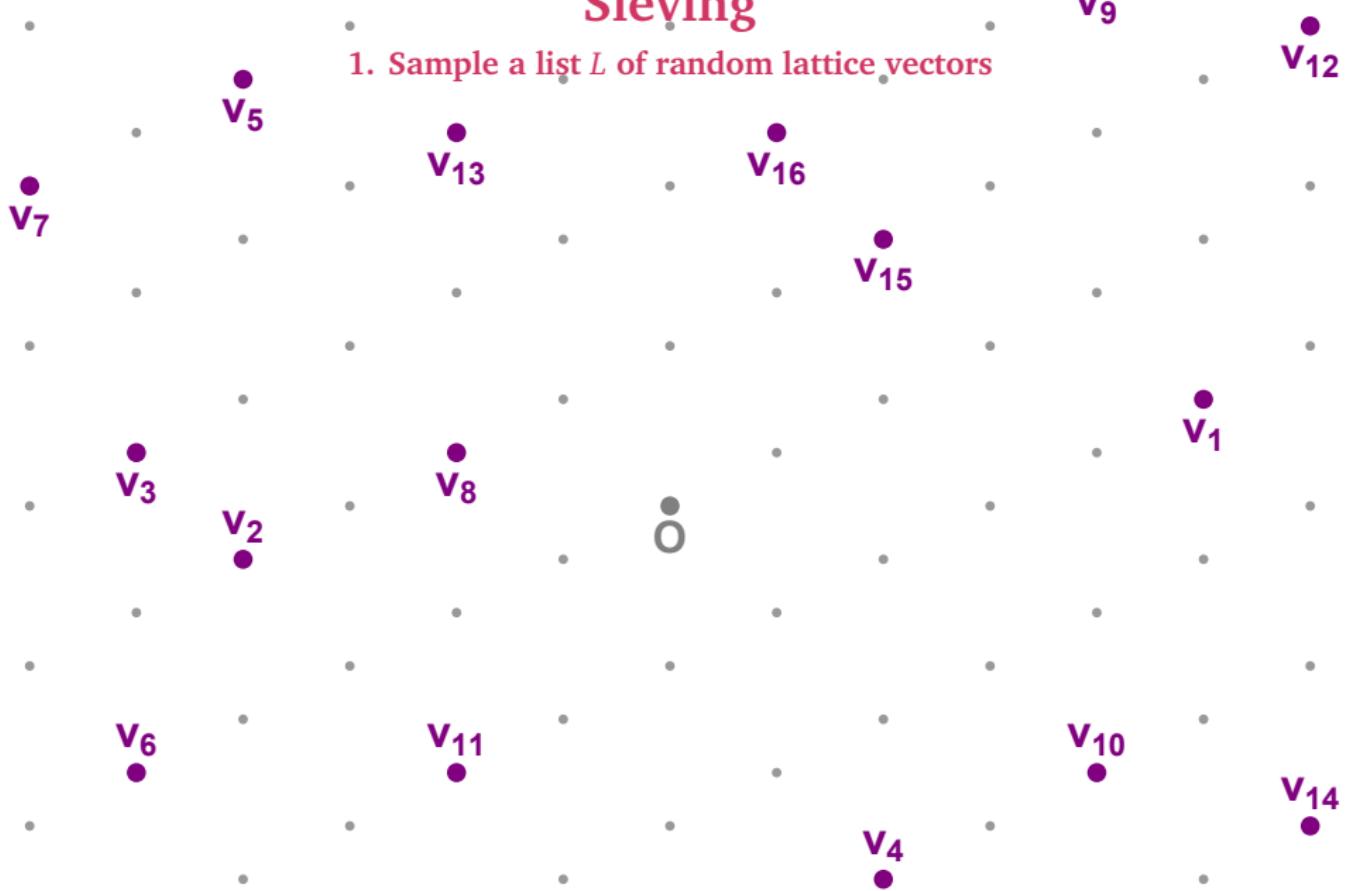
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1. Sample a list  $L$  of random lattice vectors



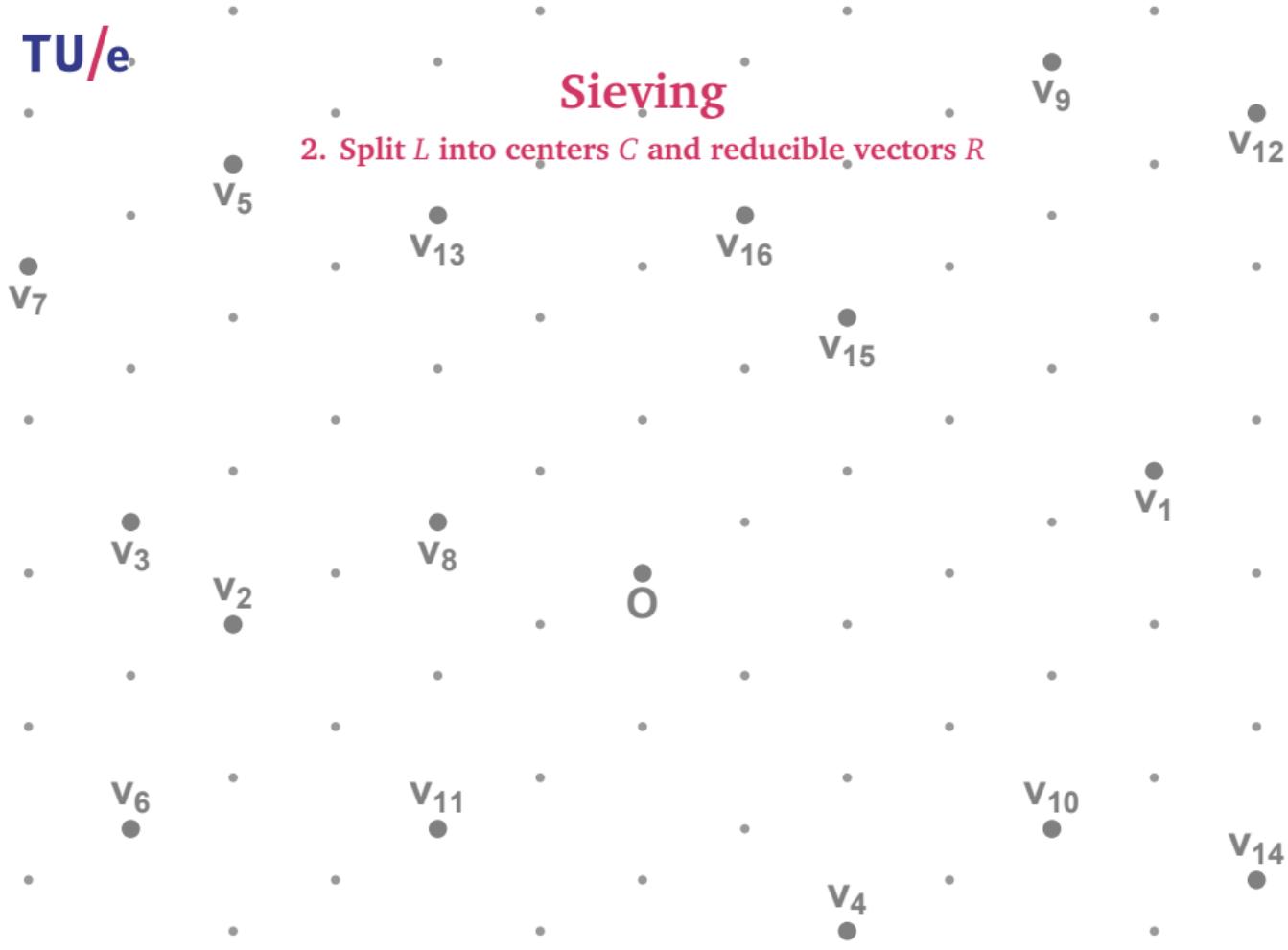
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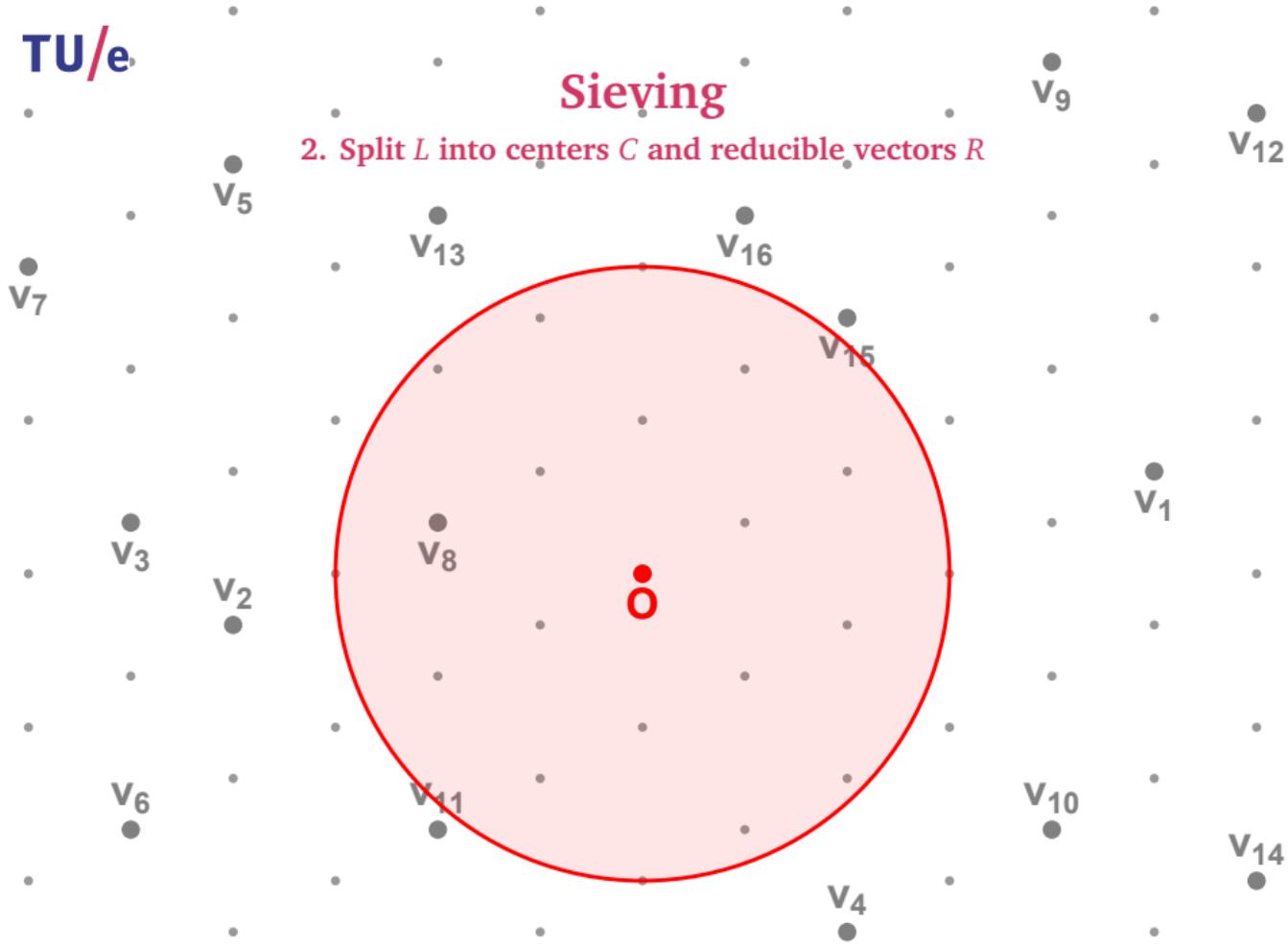
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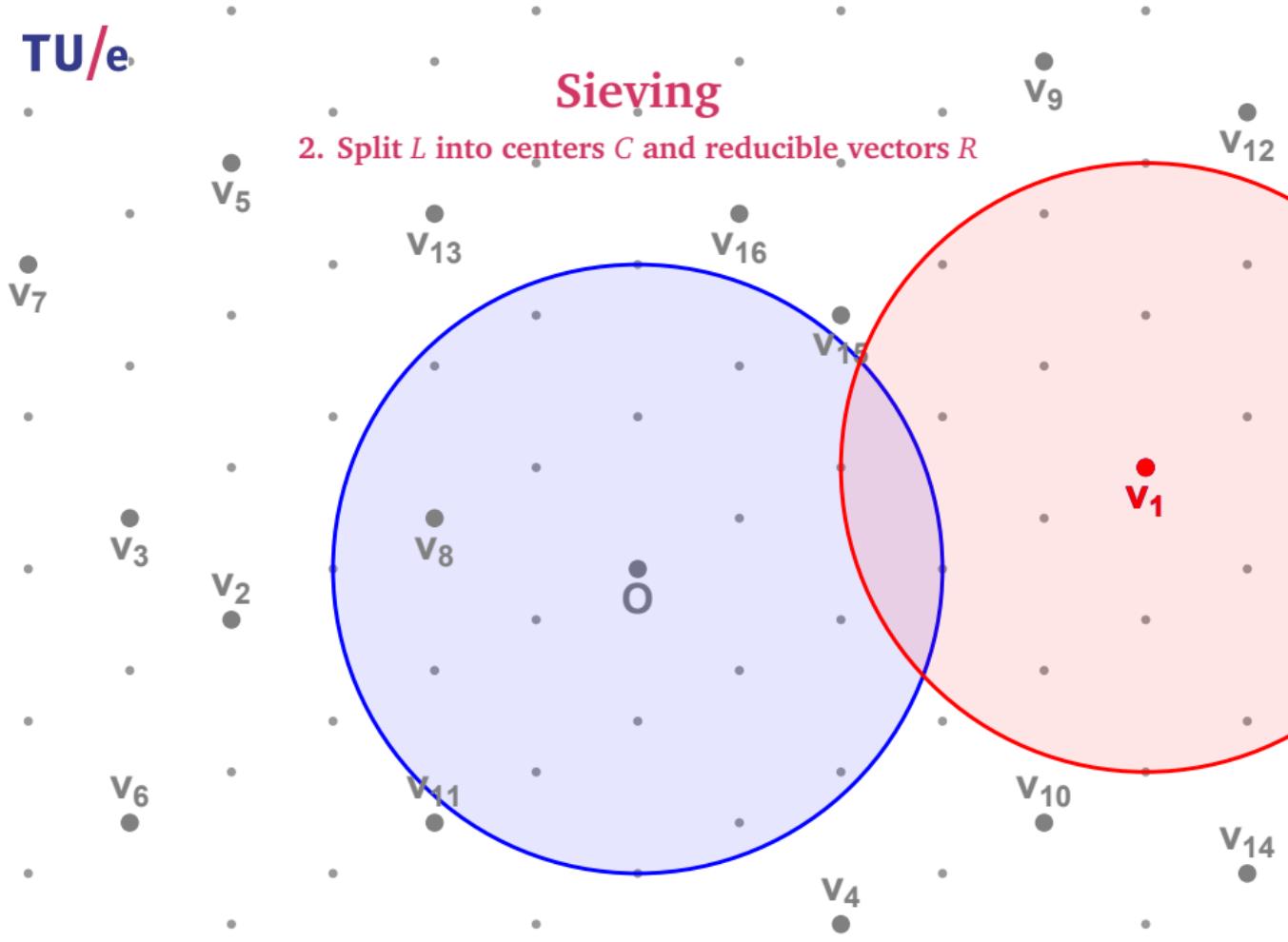
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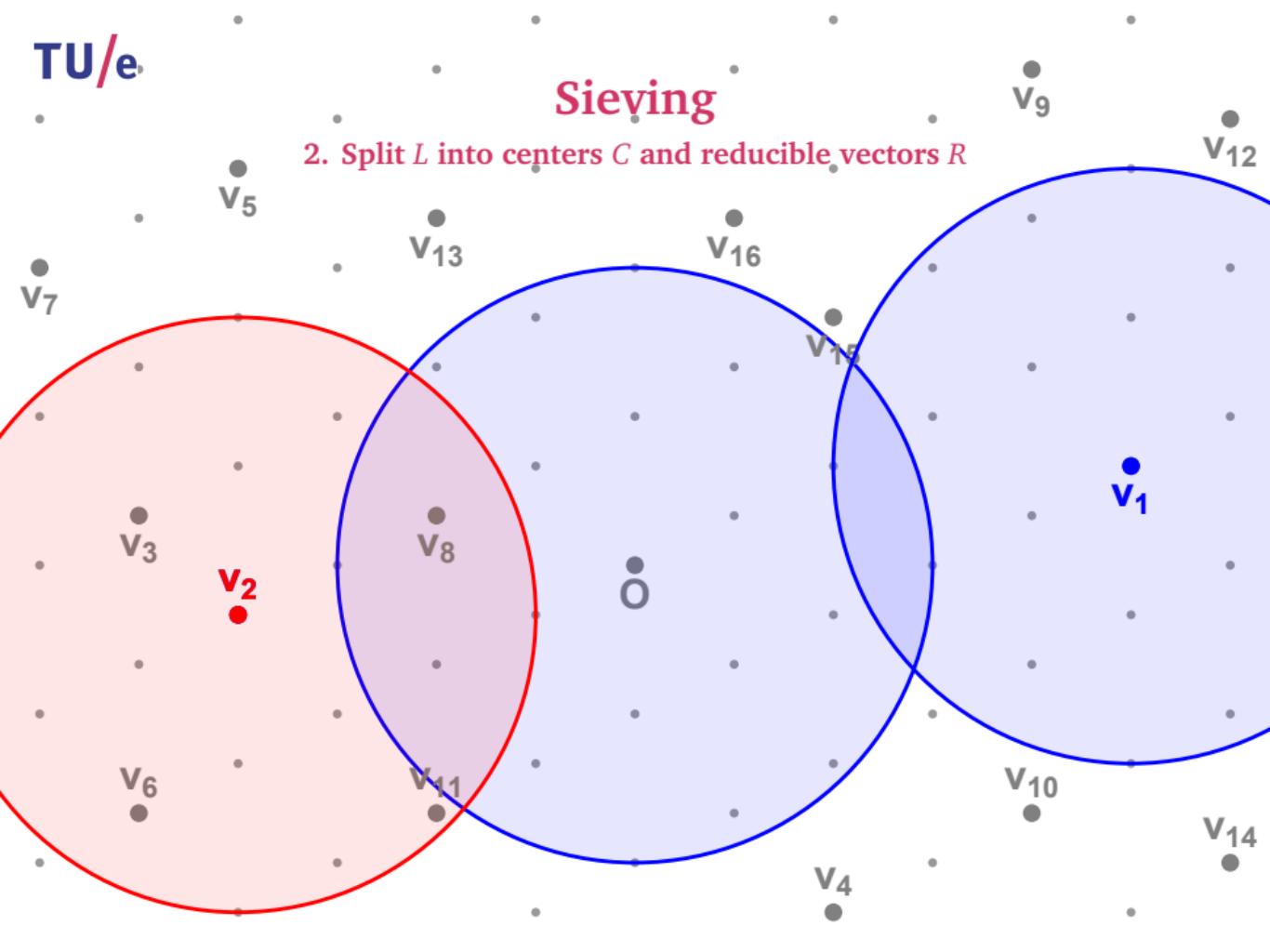
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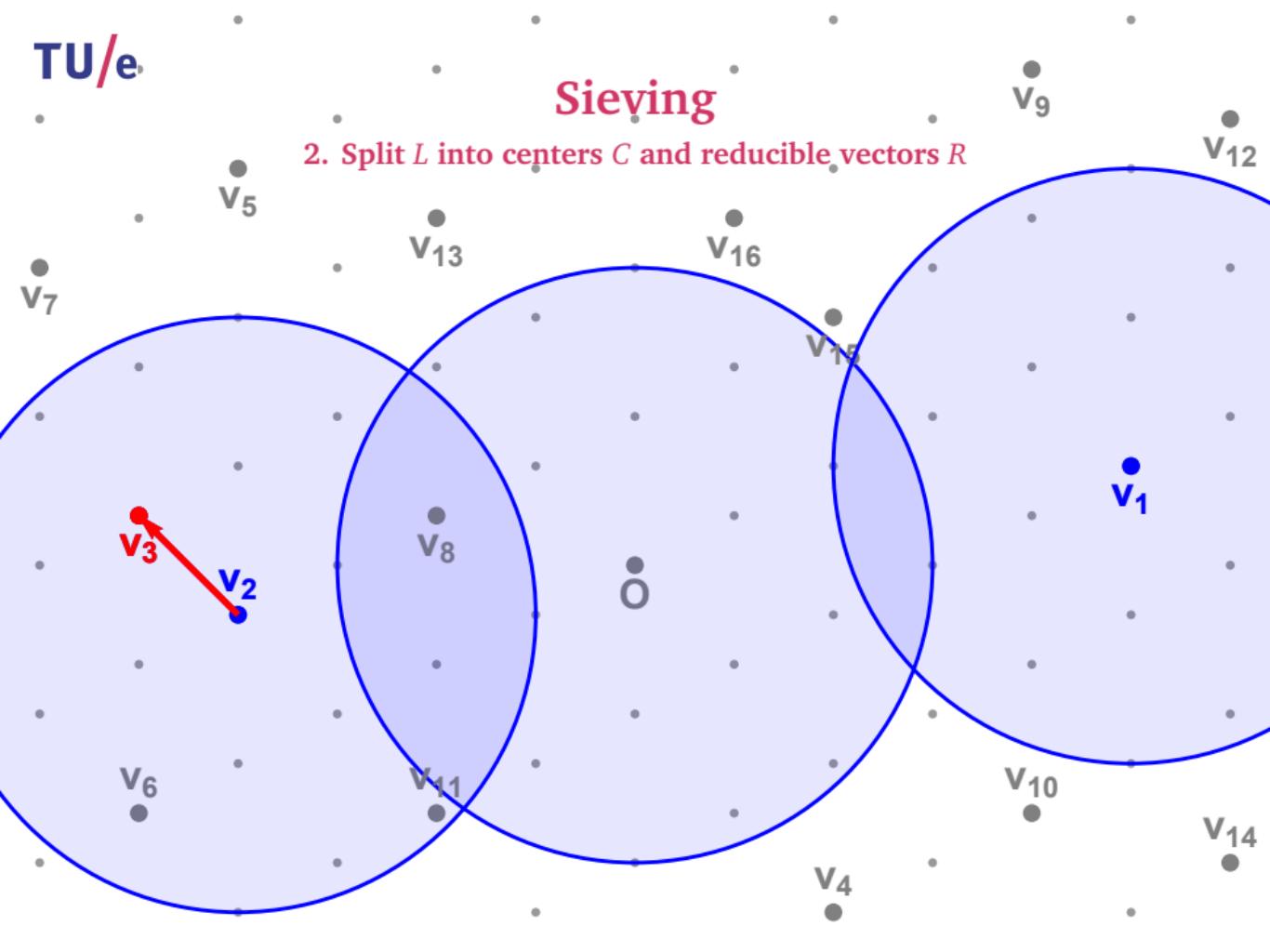
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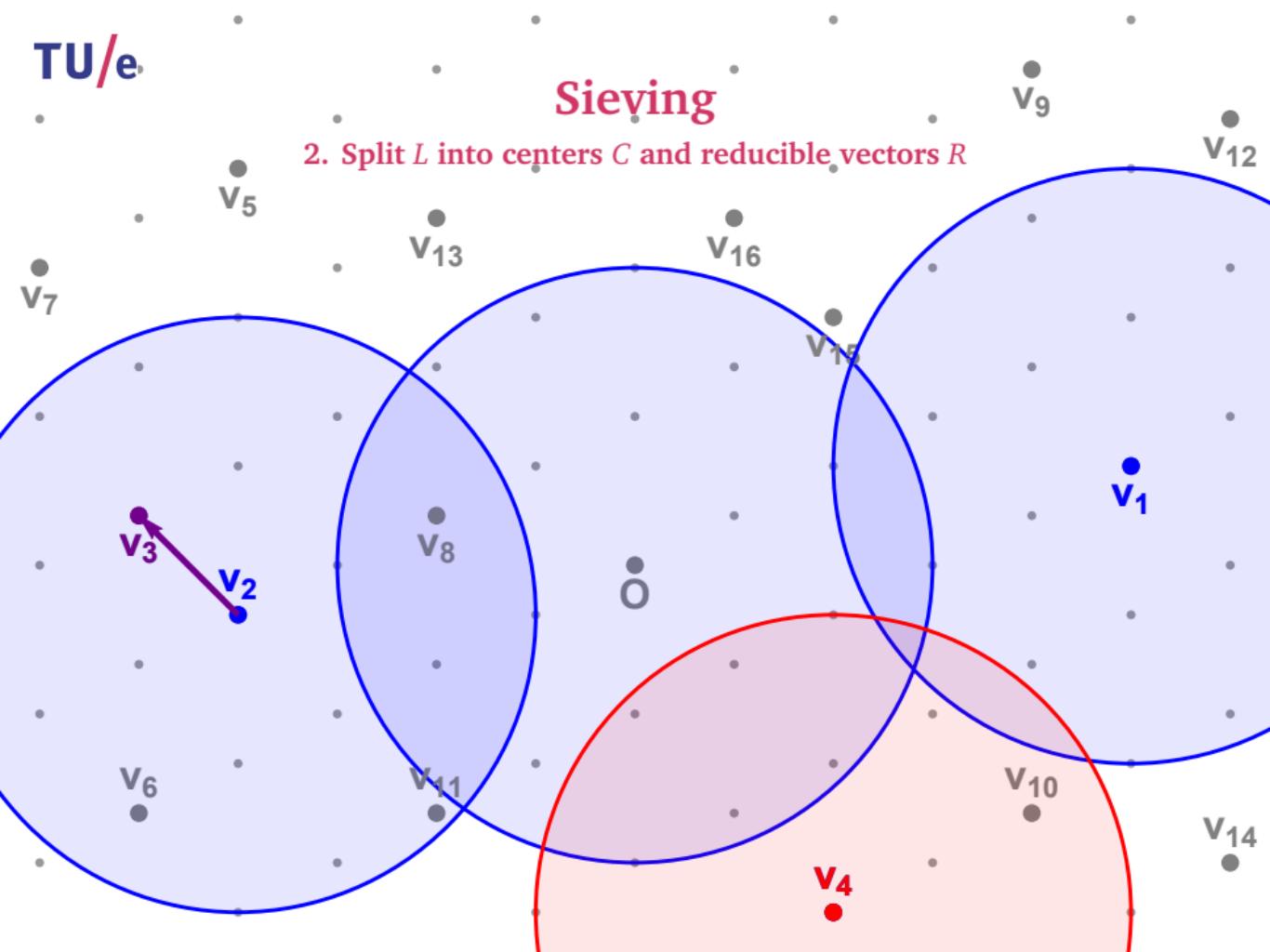
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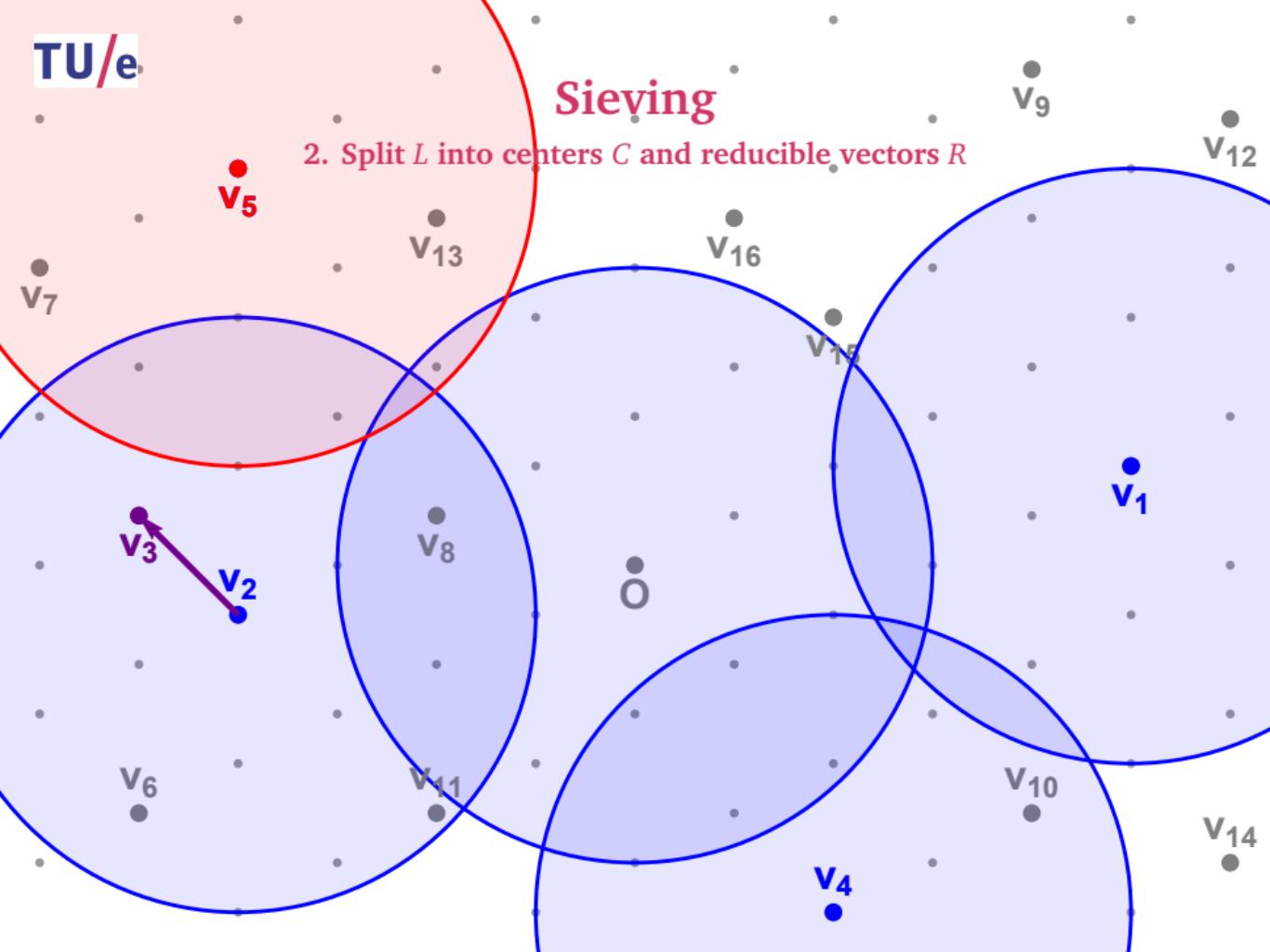
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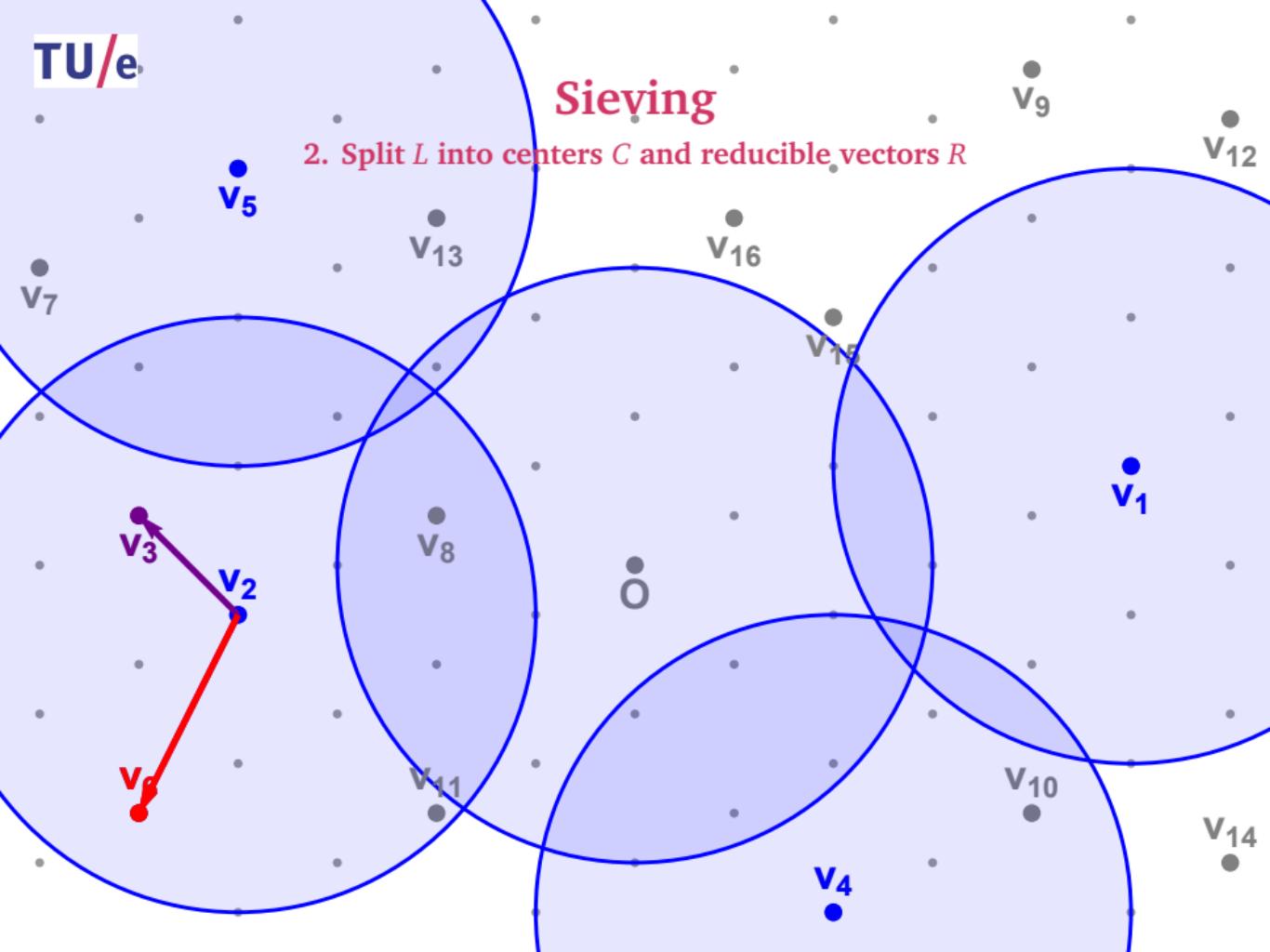
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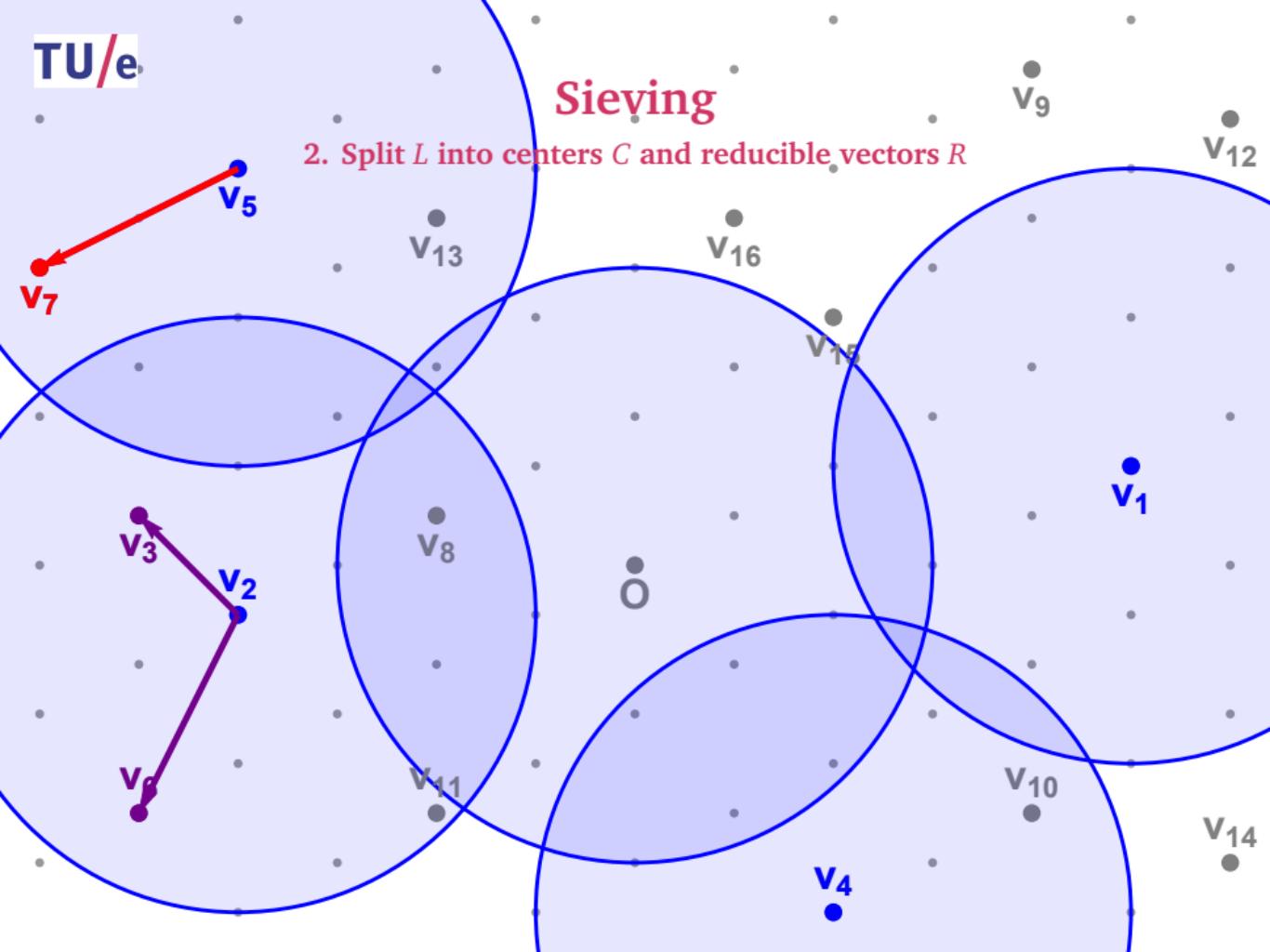
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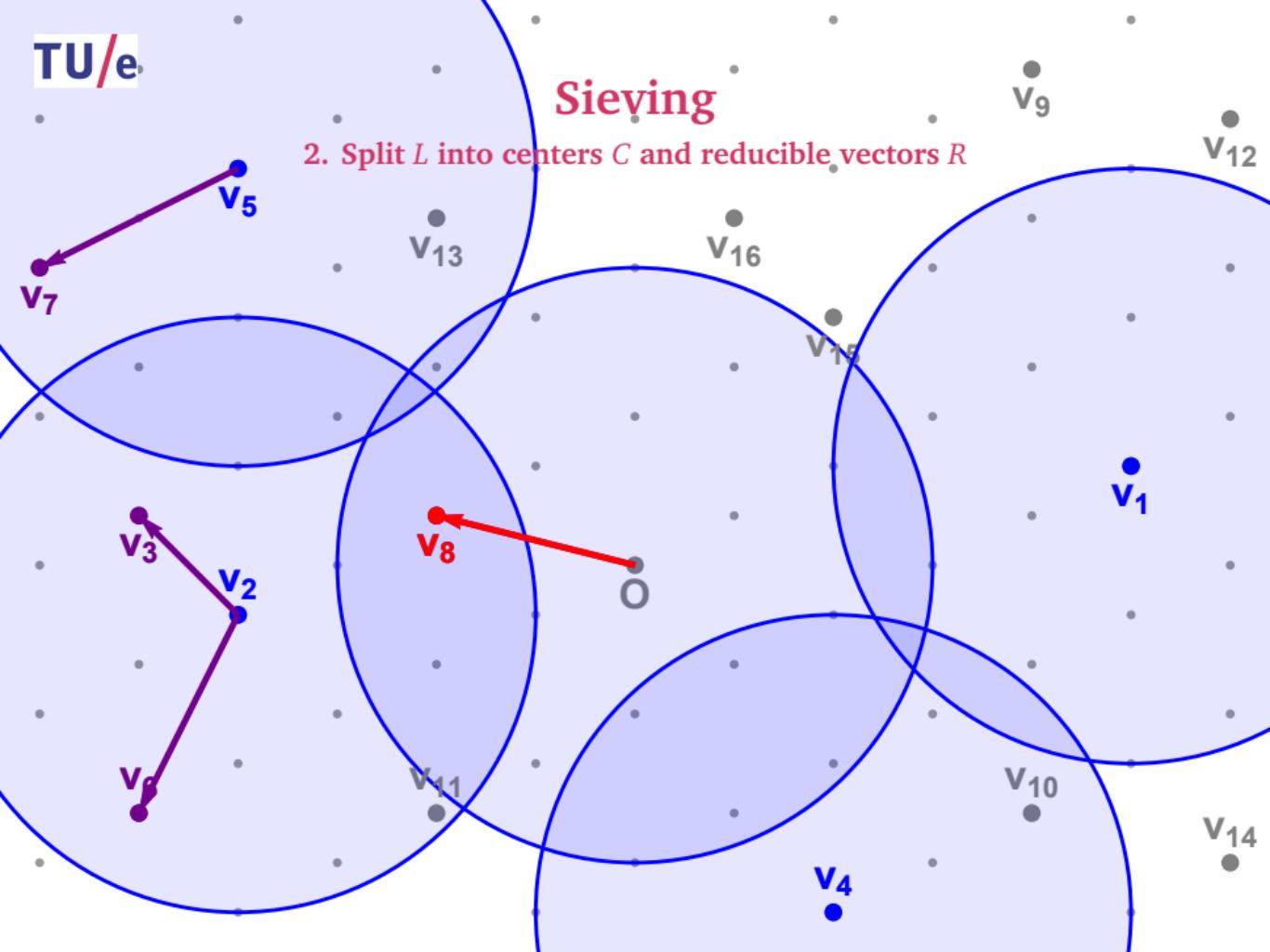
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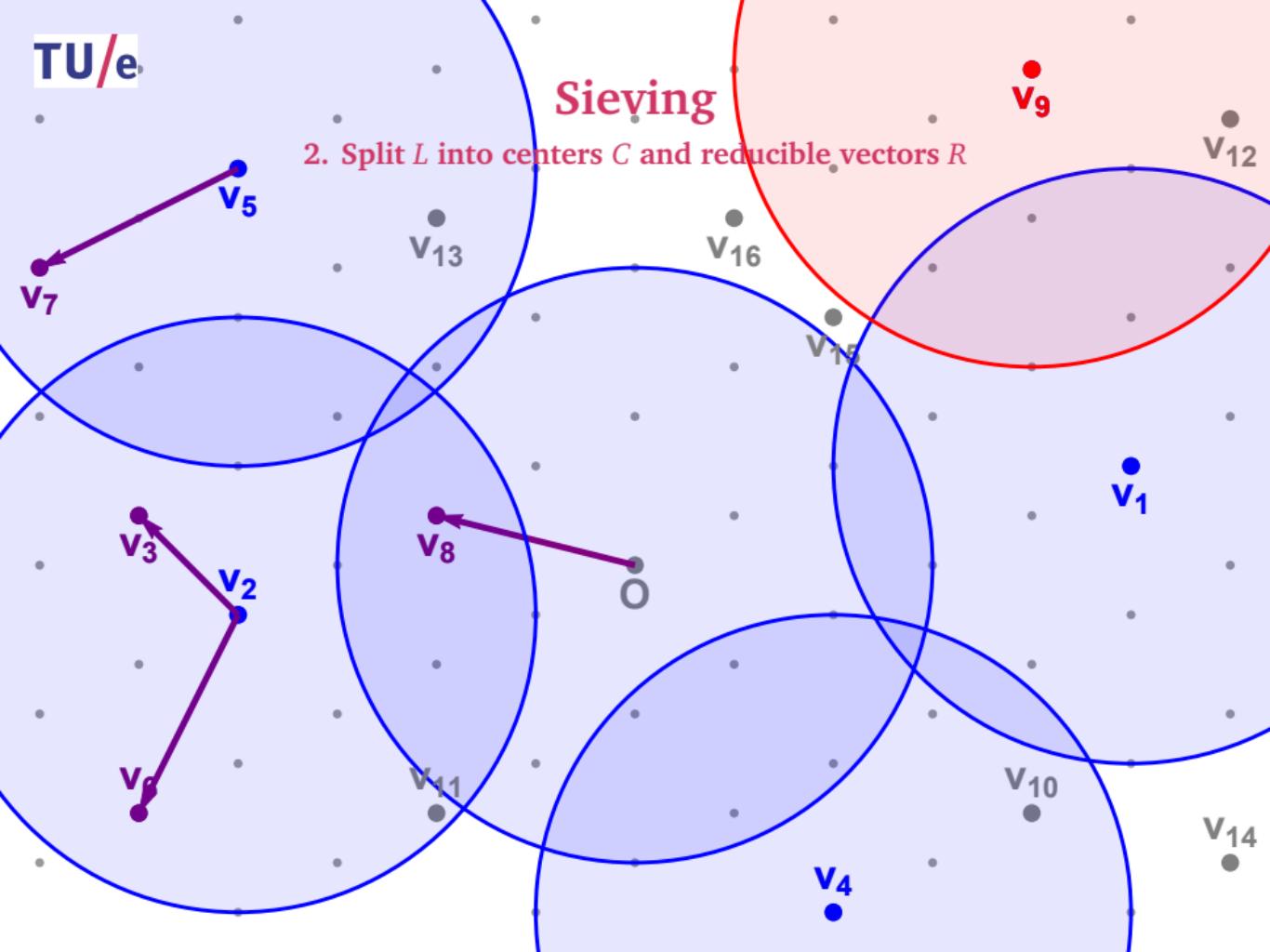
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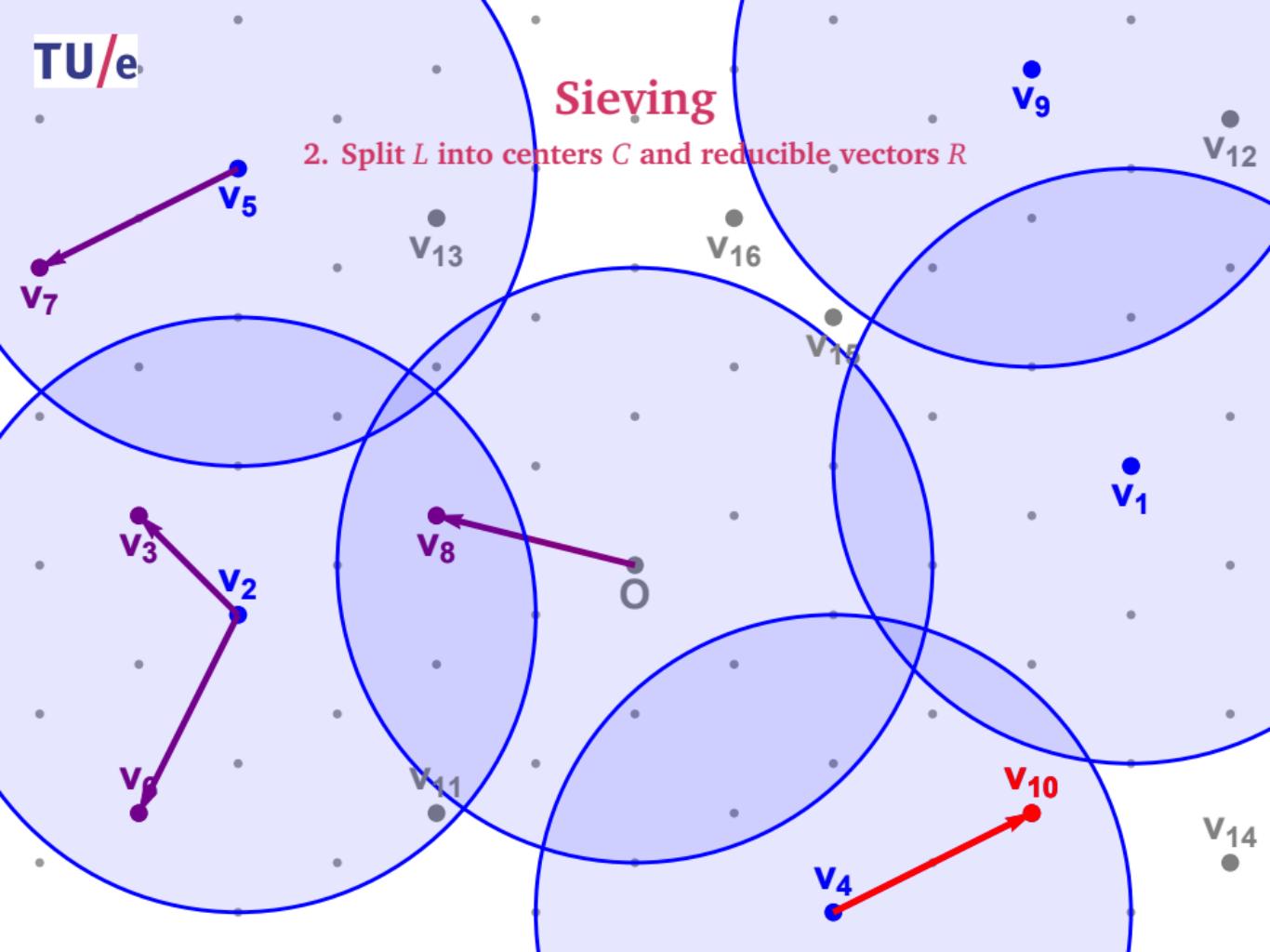
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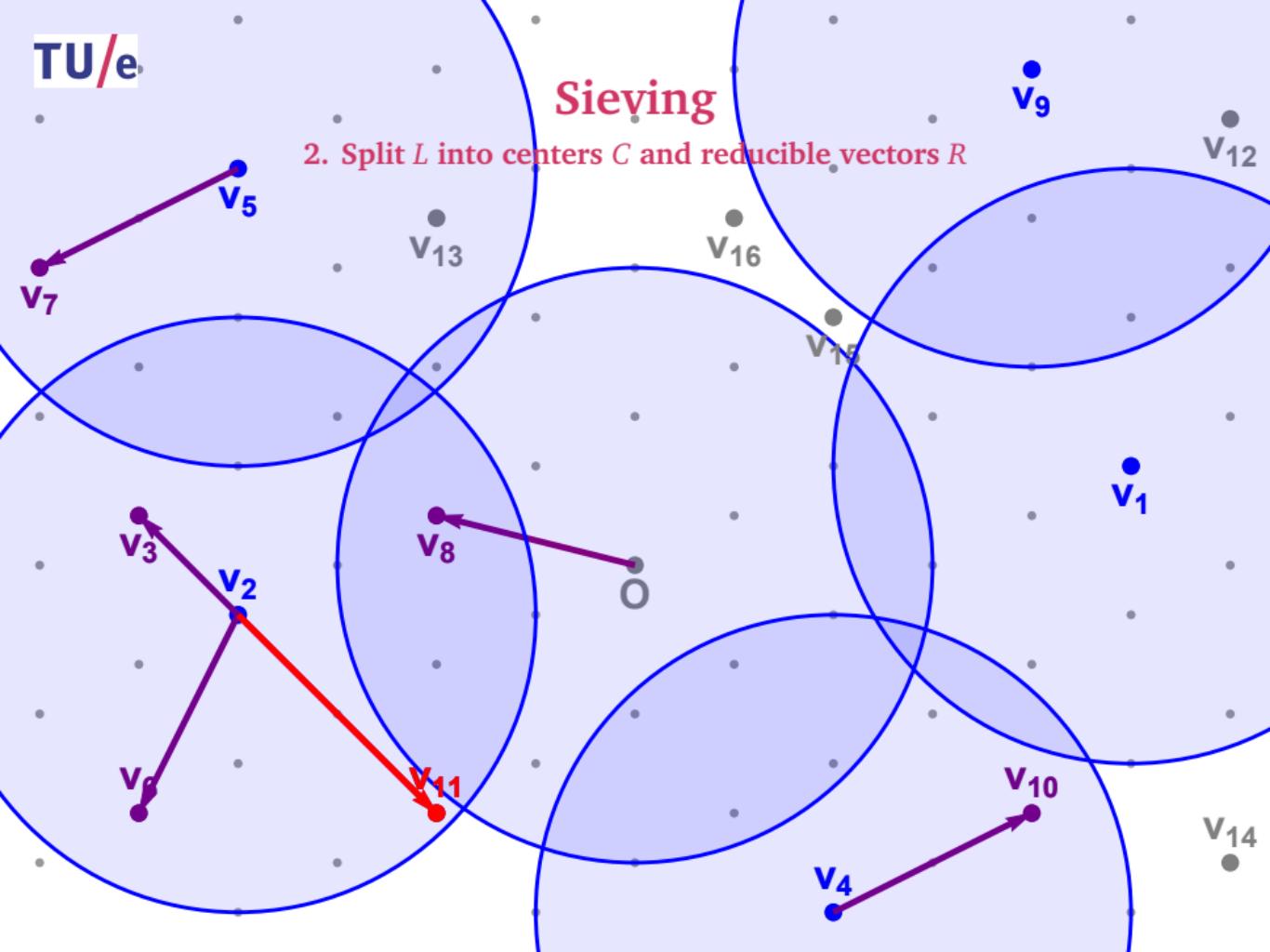
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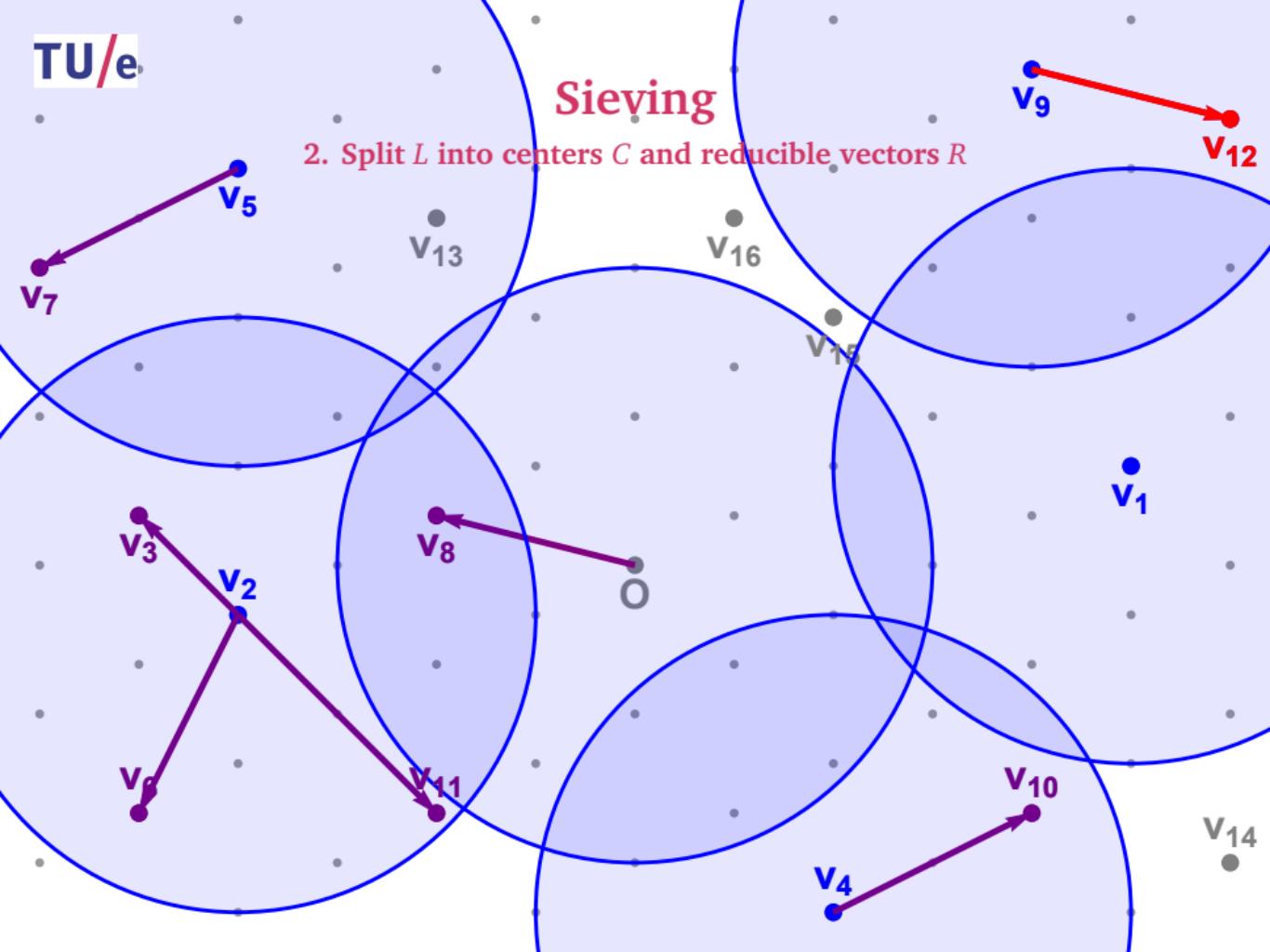
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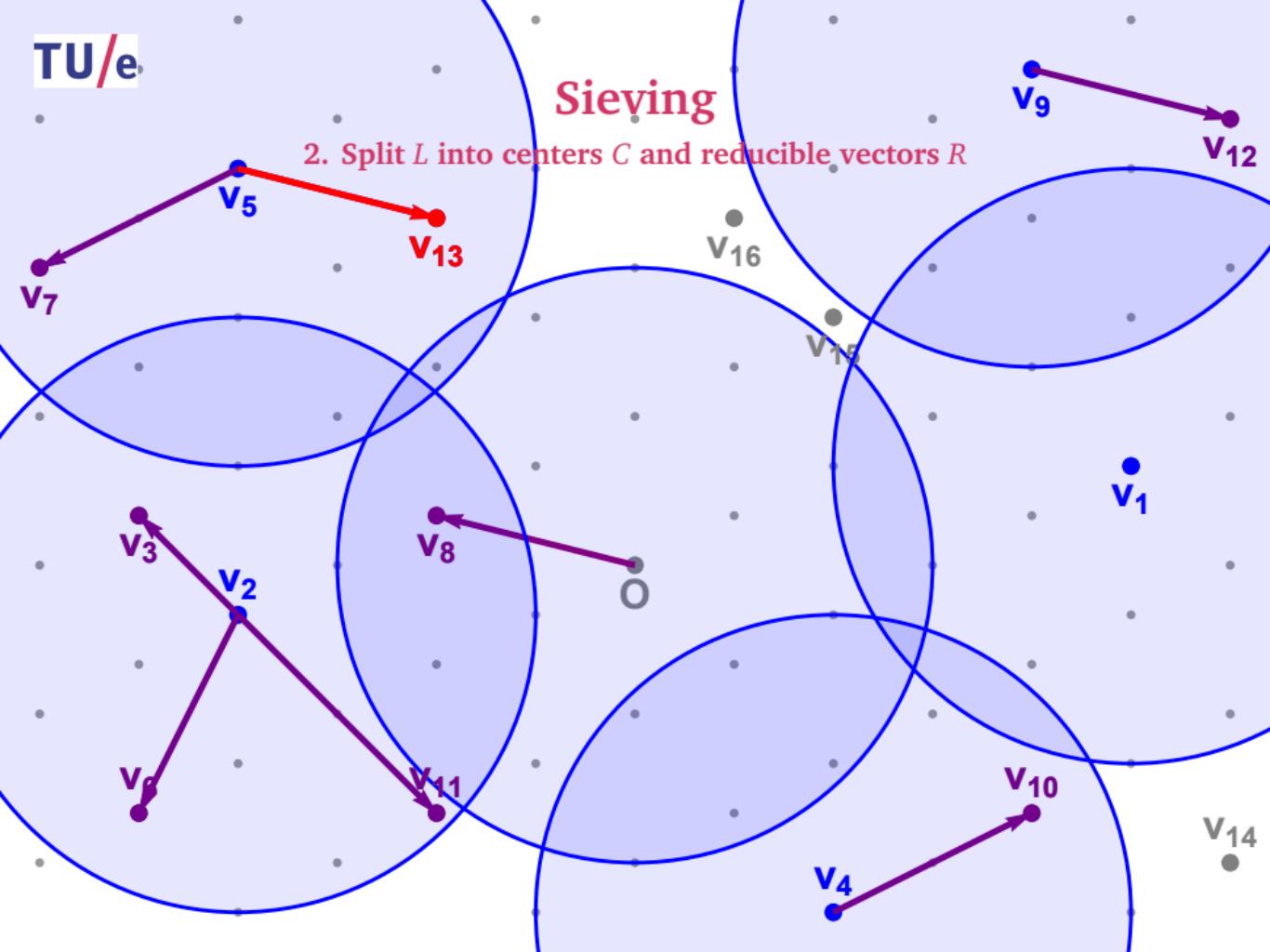
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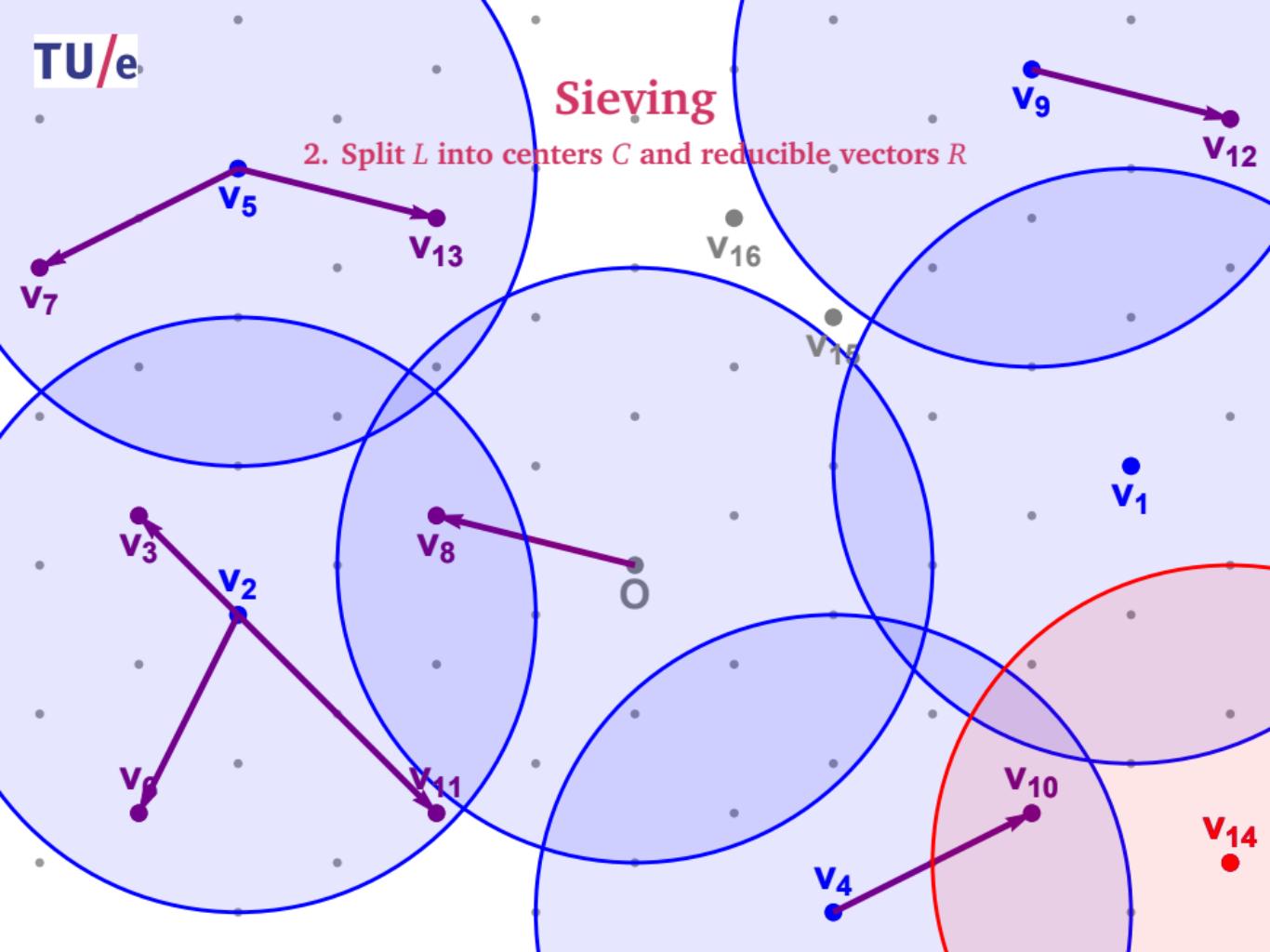
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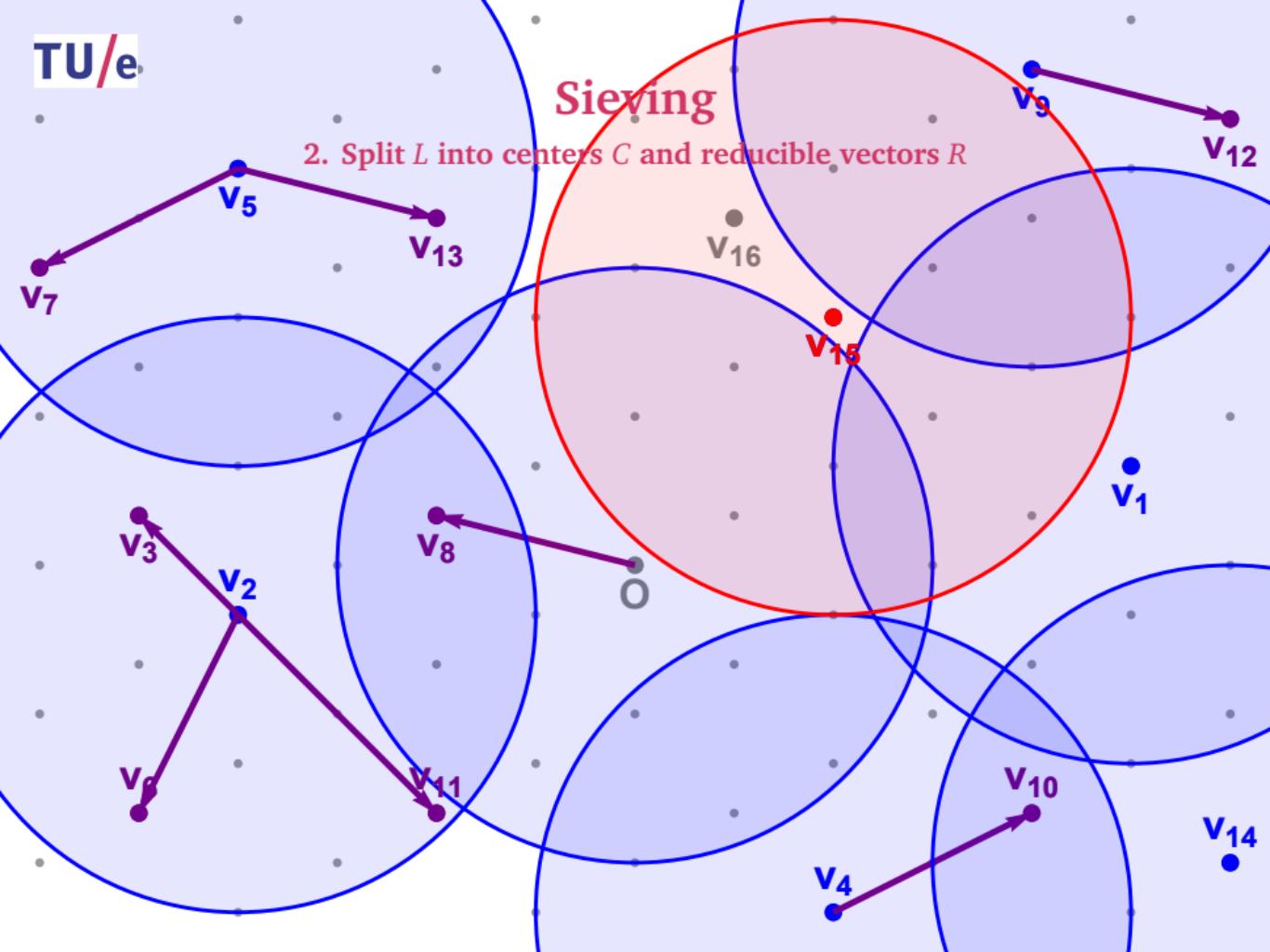
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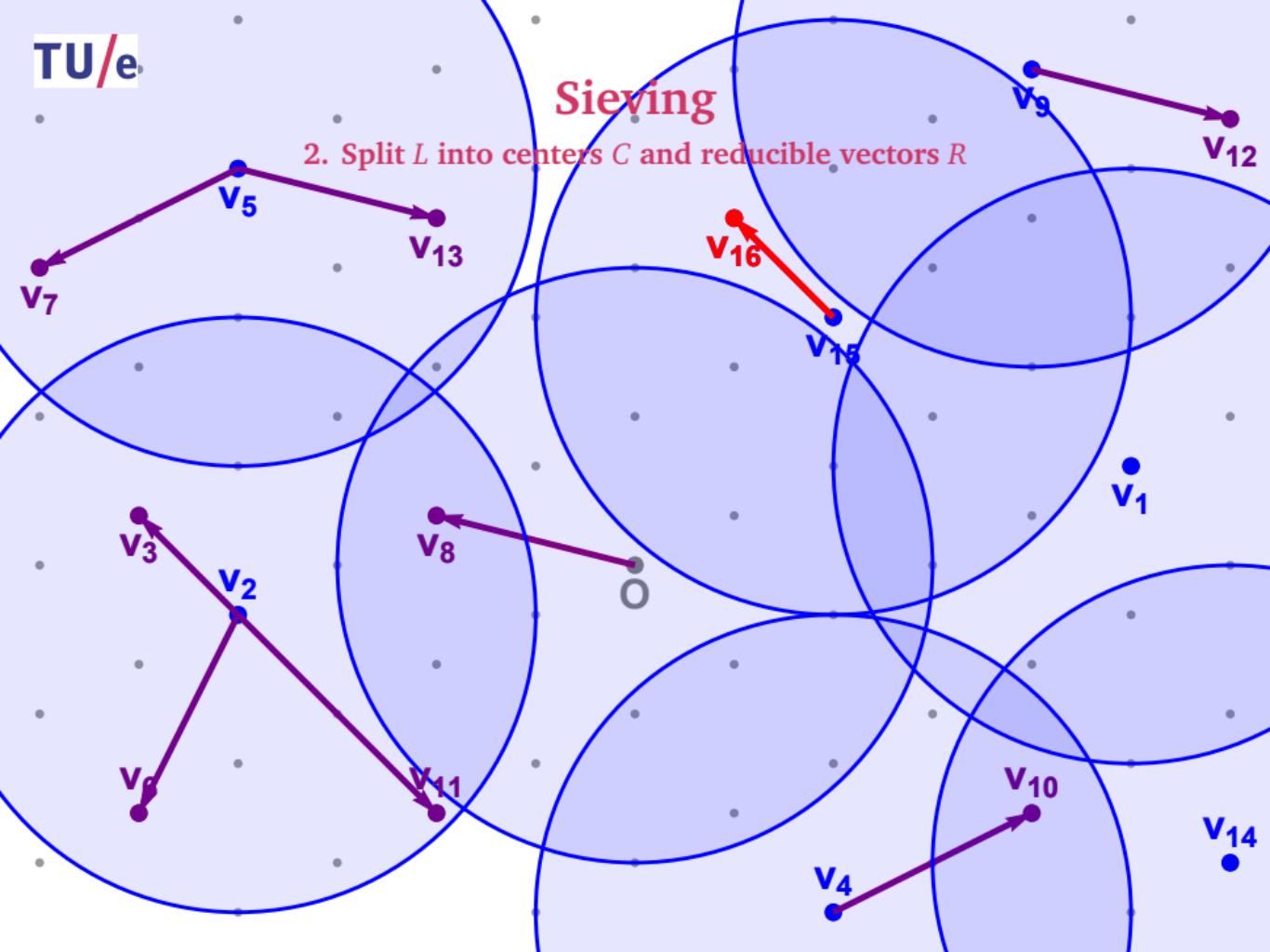
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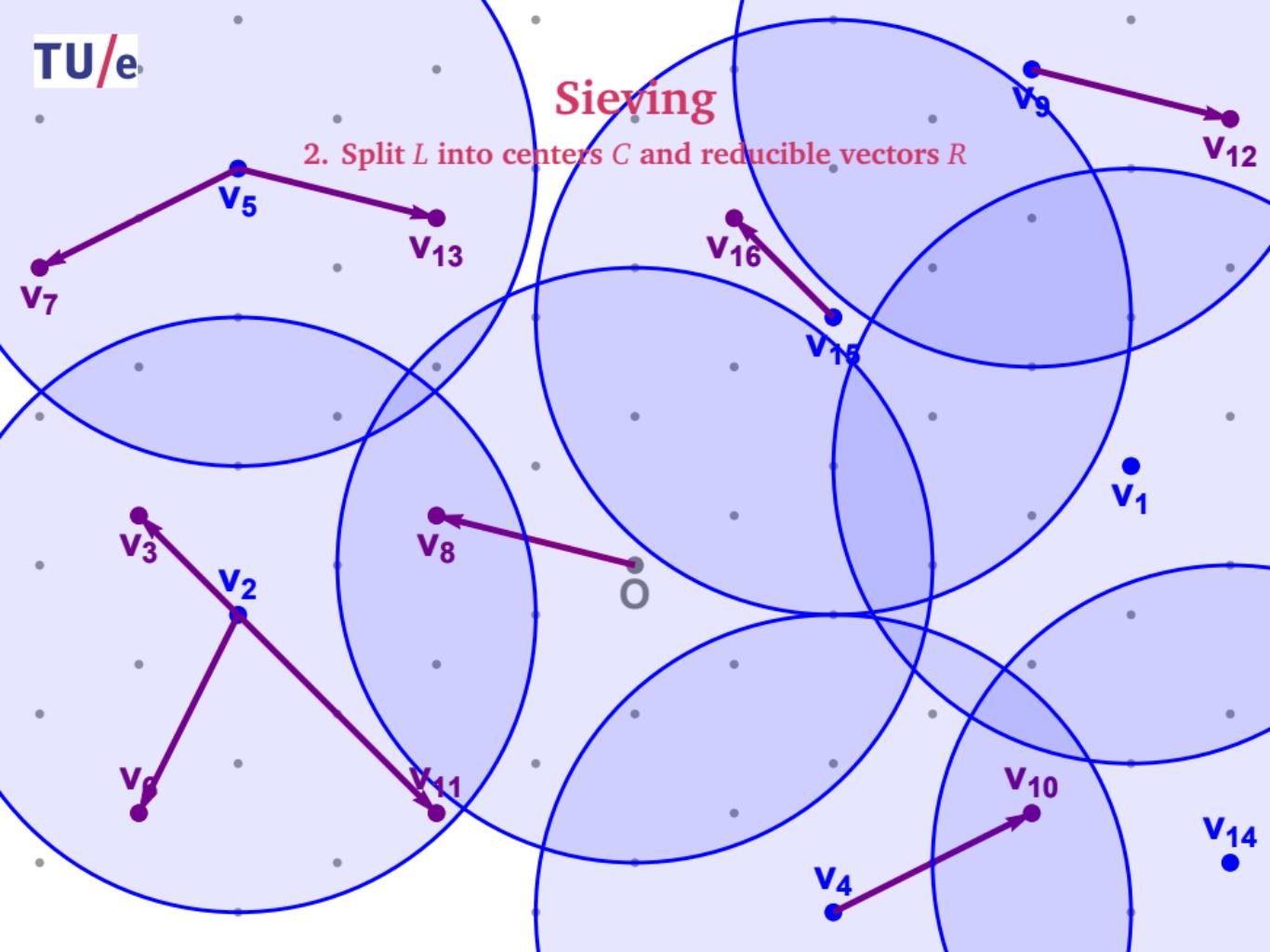
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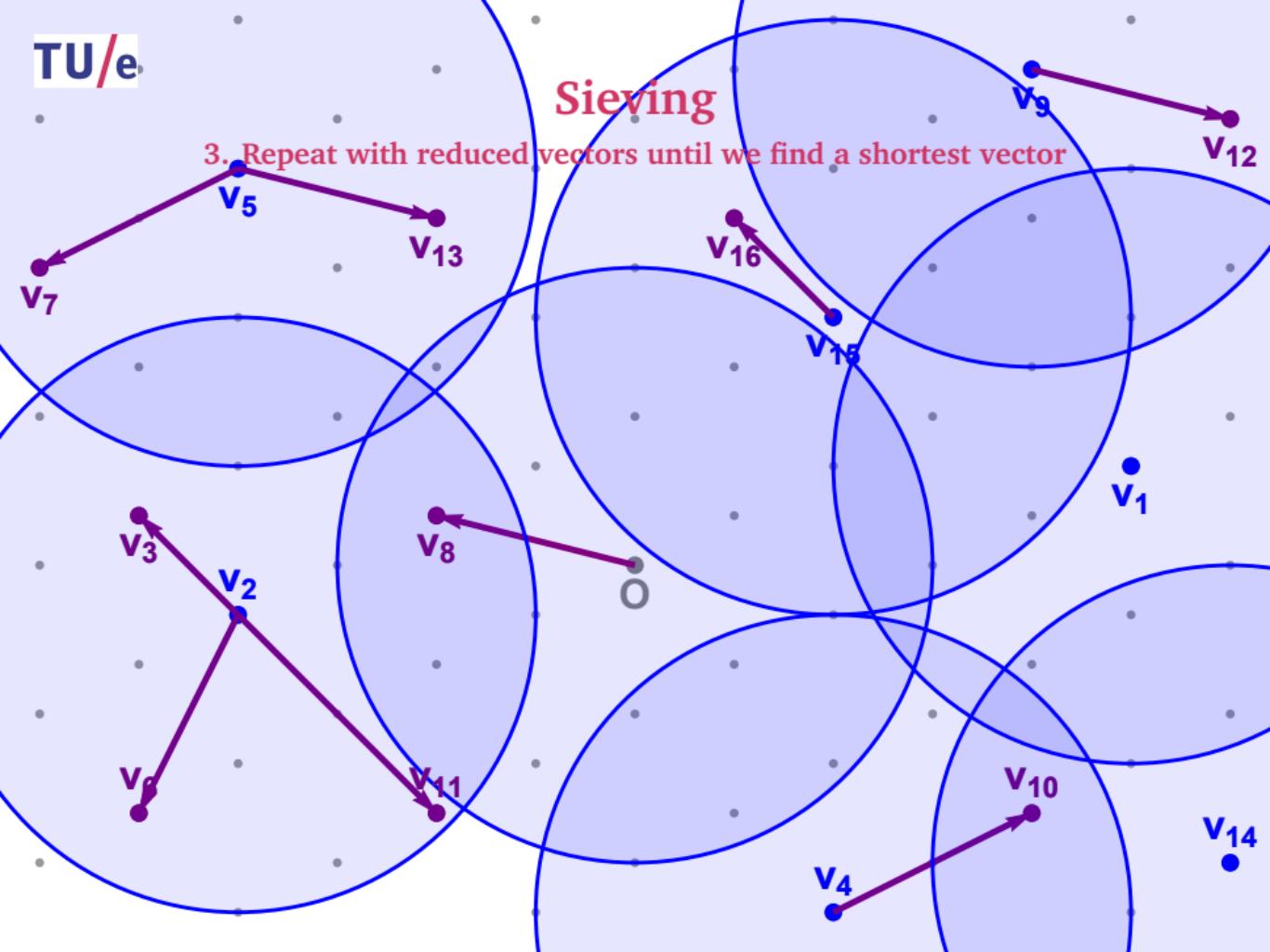
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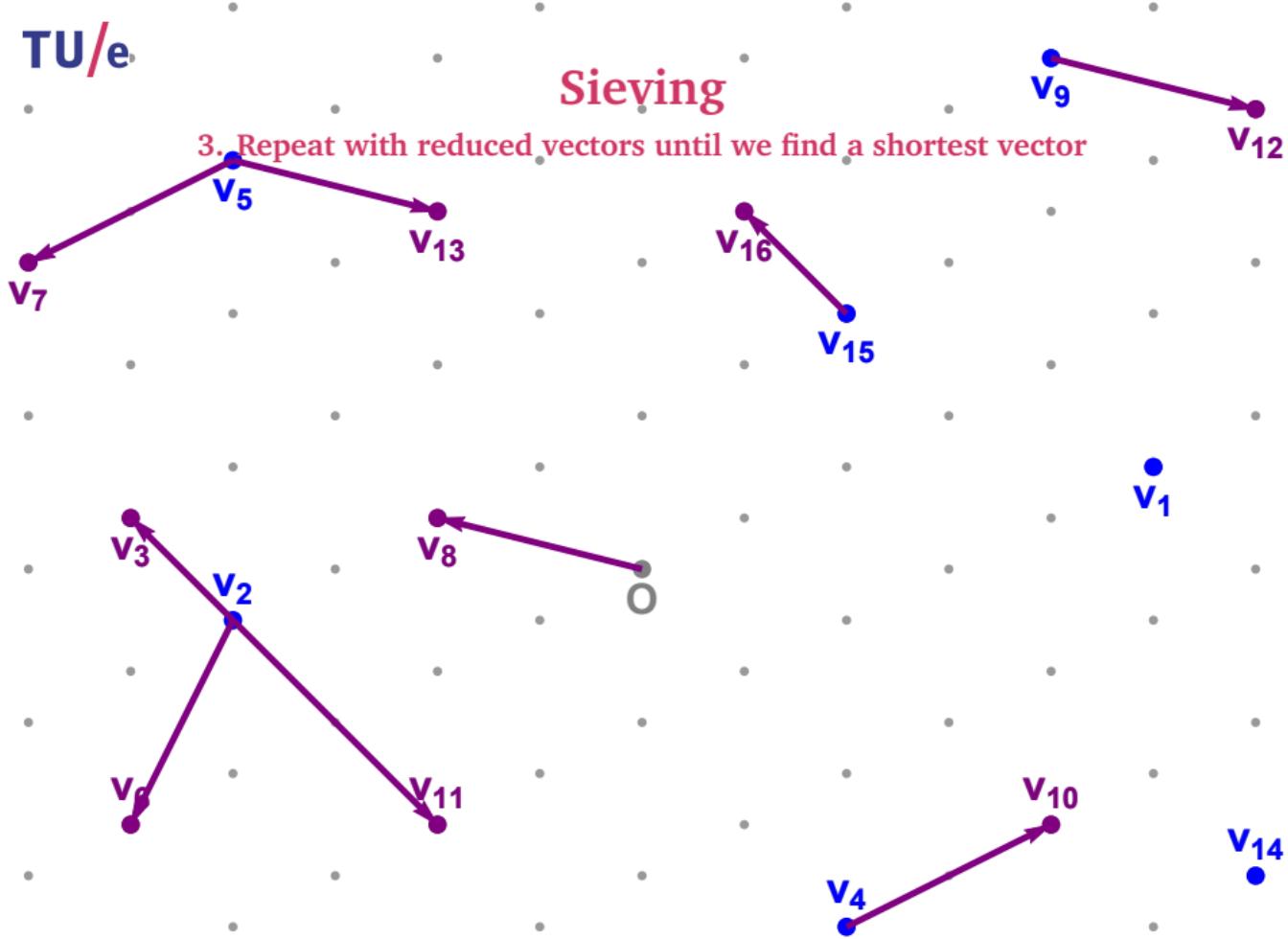
# Sieving

3. Repeat with reduced vectors until we find a shortest vector



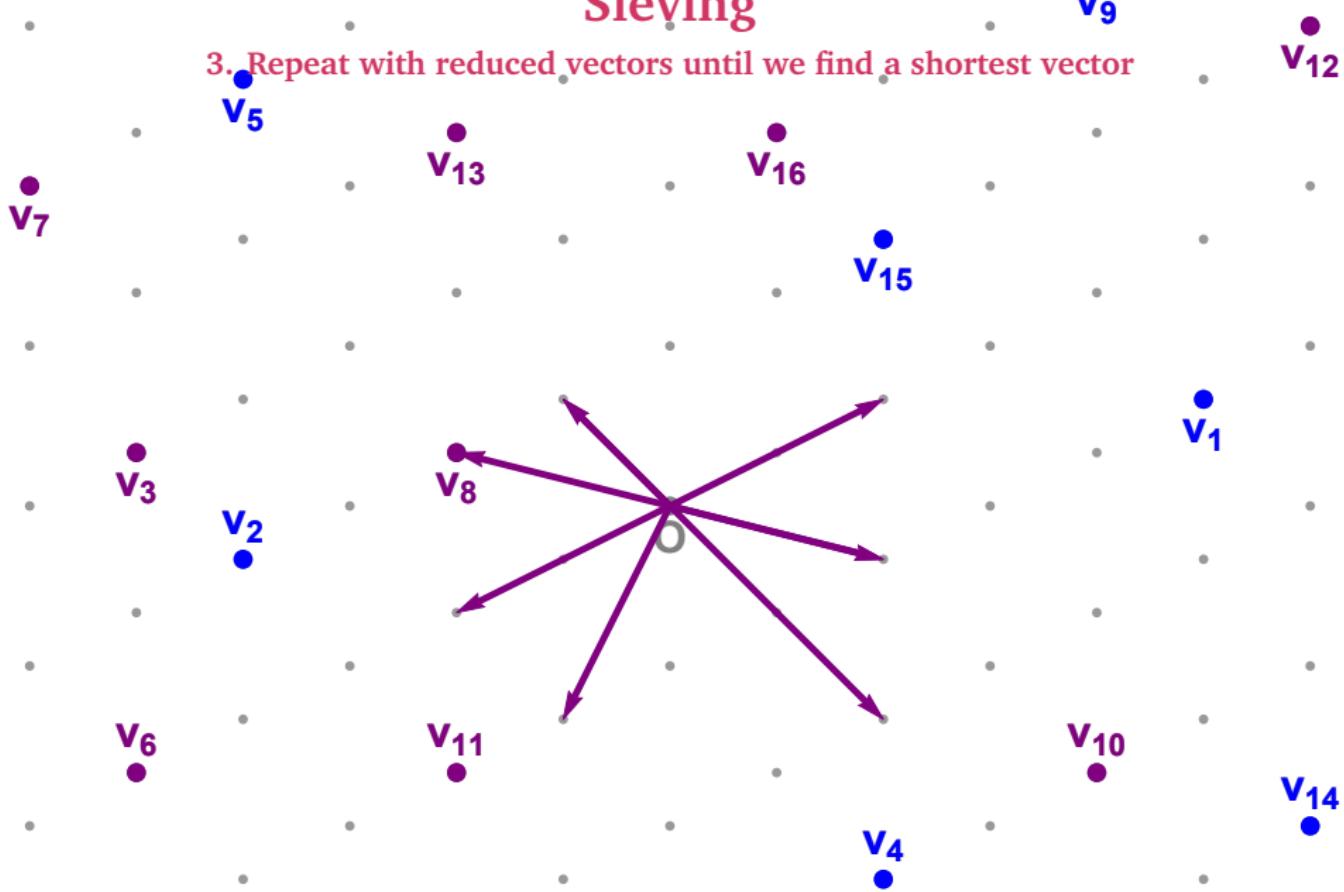
## Sieving

3. Repeat with reduced vectors until we find a shortest vector



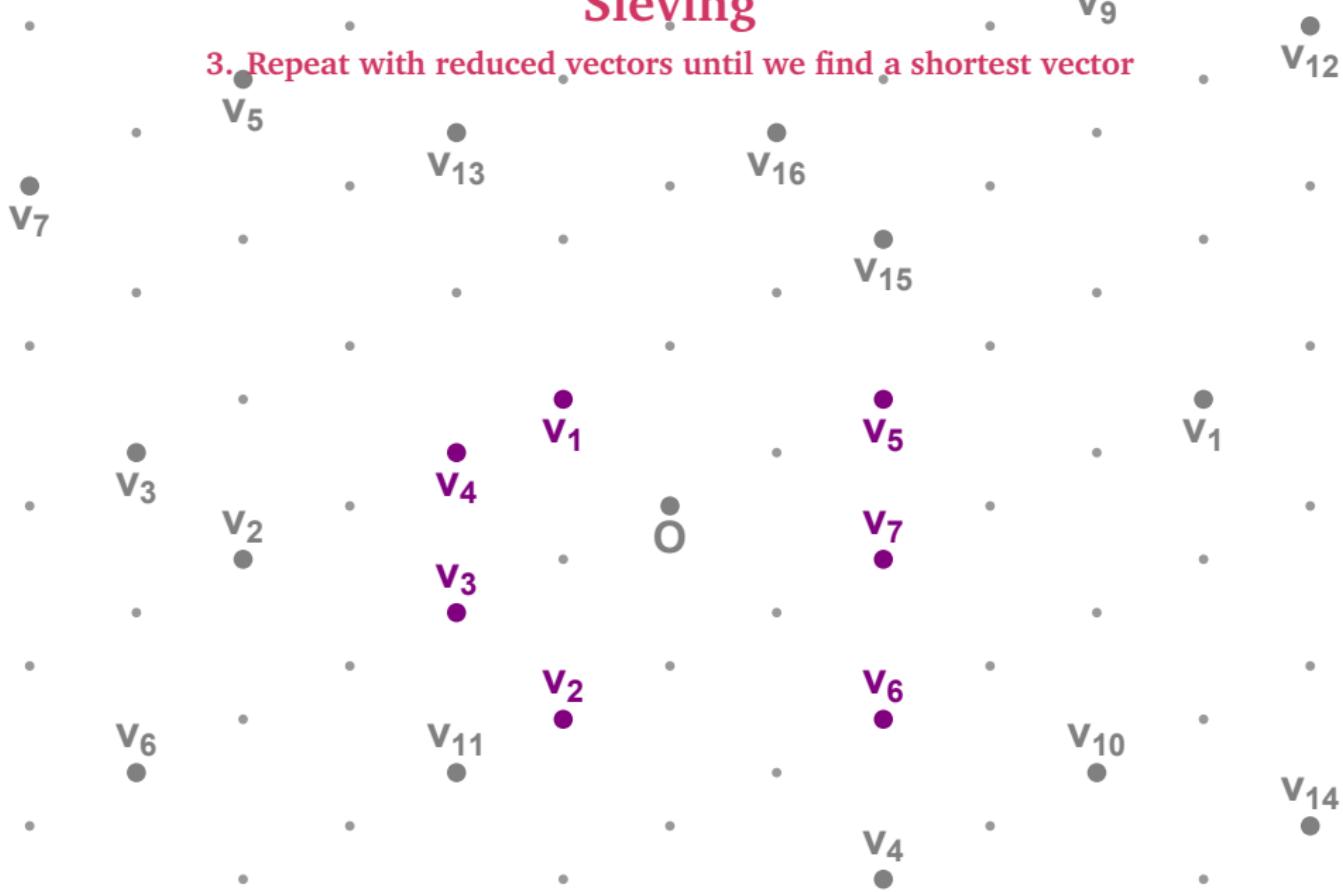
## Sieving

3. Repeat with reduced vectors until we find a shortest vector



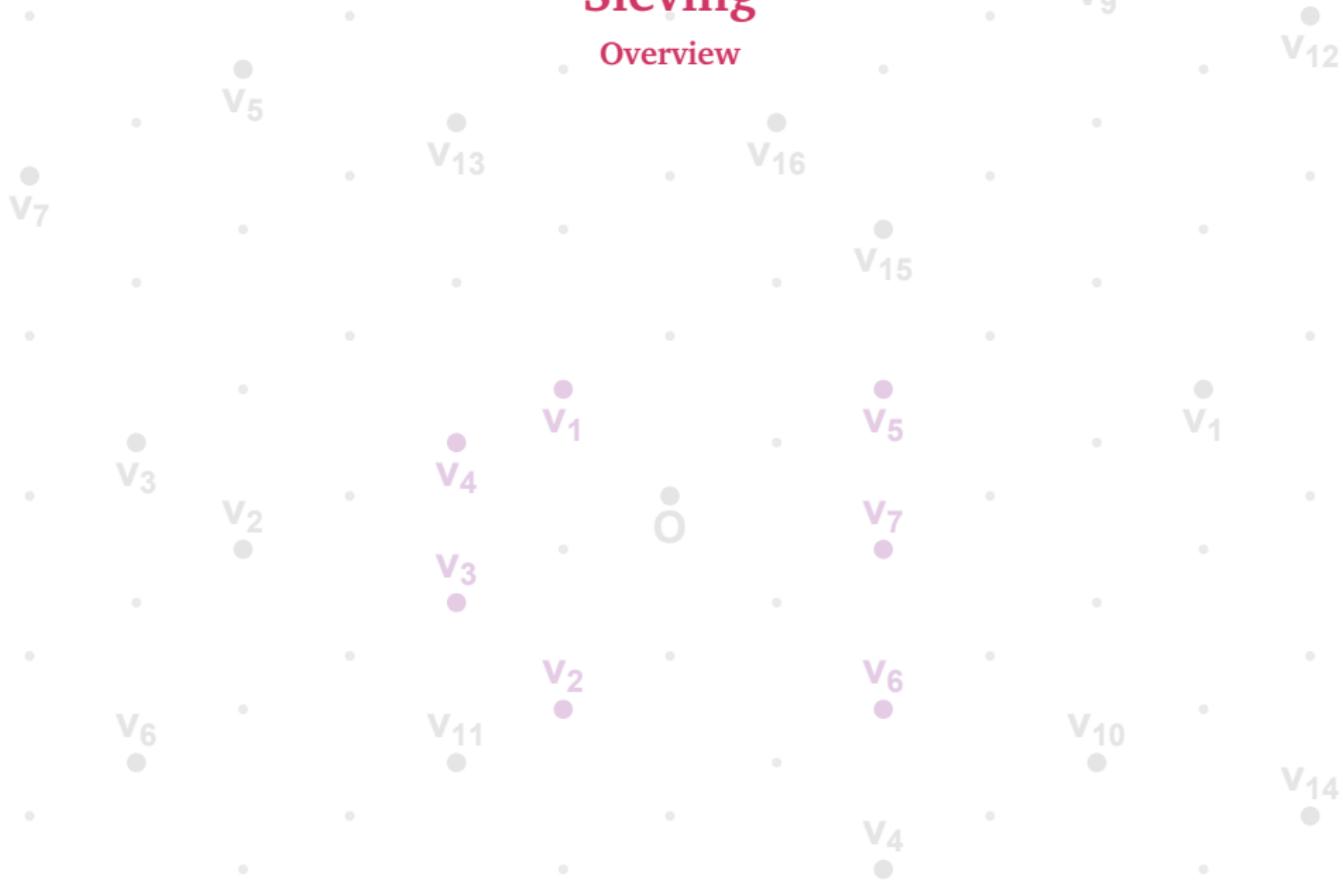
## Sieving

3. Repeat with reduced vectors until we find a shortest vector



# Sieving

## Overview



# Sieving

## Overview

Heuristic (Nguyen–Vidick, J. Math. Crypt. '08)

Sieving solves SVP in time  $(4/3)^{n+o(n)}$  and space  $(4/3)^{n/2+o(n)}$ .

v<sub>3</sub>

v<sub>2</sub>

v<sub>4</sub>

v<sub>3</sub>

v<sub>2</sub>

v<sub>6</sub>

v<sub>11</sub>

v<sub>7</sub>

v<sub>6</sub>

v<sub>4</sub>

v<sub>10</sub>

v<sub>14</sub>

v<sub>5</sub>

v<sub>13</sub>

v<sub>16</sub>

v<sub>9</sub>

v<sub>12</sub>

# Sieving

## Overview

Heuristic (Nguyen–Vidick, J. Math. Crypt. '08)

Sieving solves SVP in time  $(4/3)^{n+o(n)}$  and space  $(4/3)^{n/2+o(n)}$ .

The list size comes from heuristic packing/saturation arguments,  
the time complexity is quadratic in the list size.

# Sieving

## Near neighbor techniques



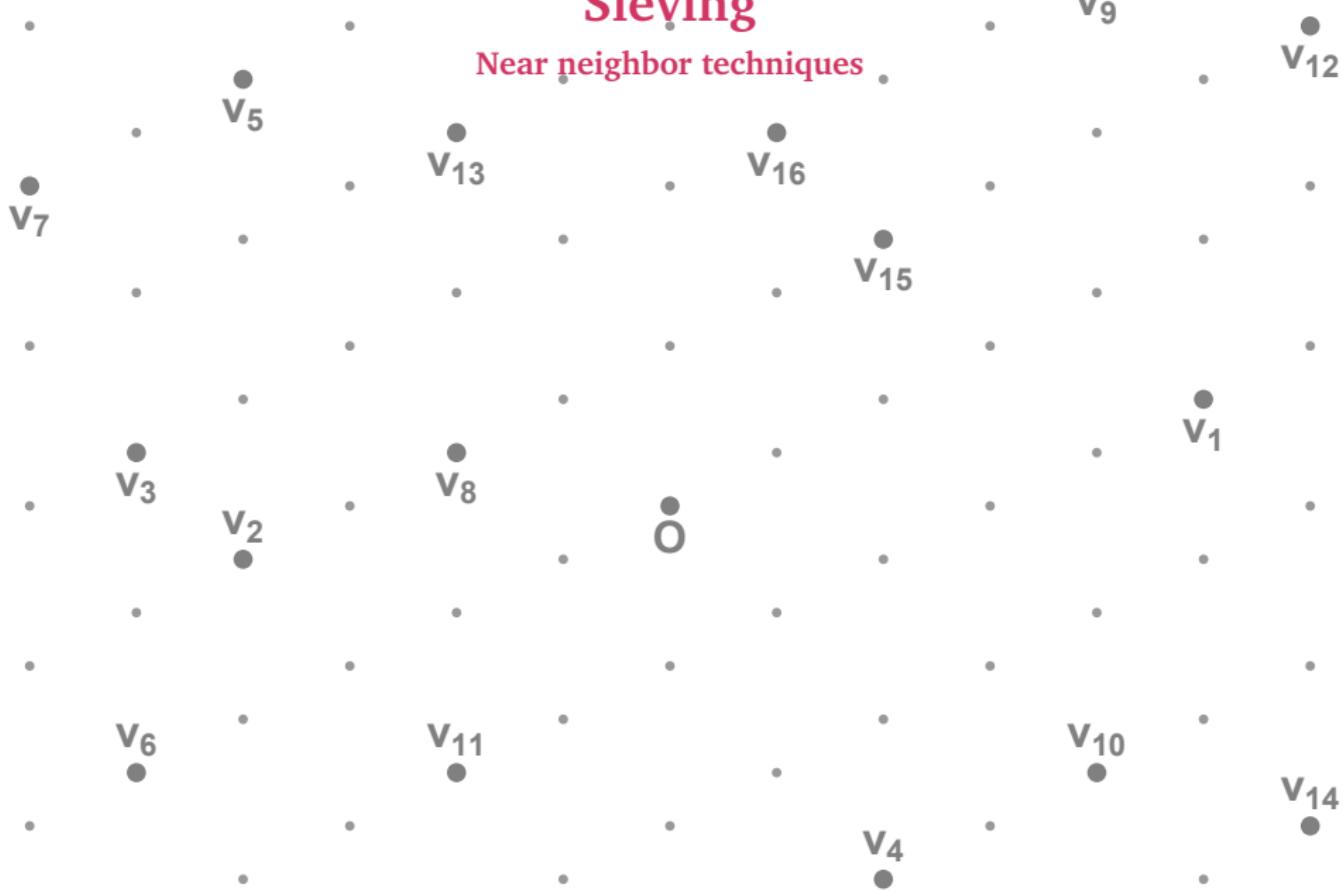
## Sieving

Near neighbor techniques



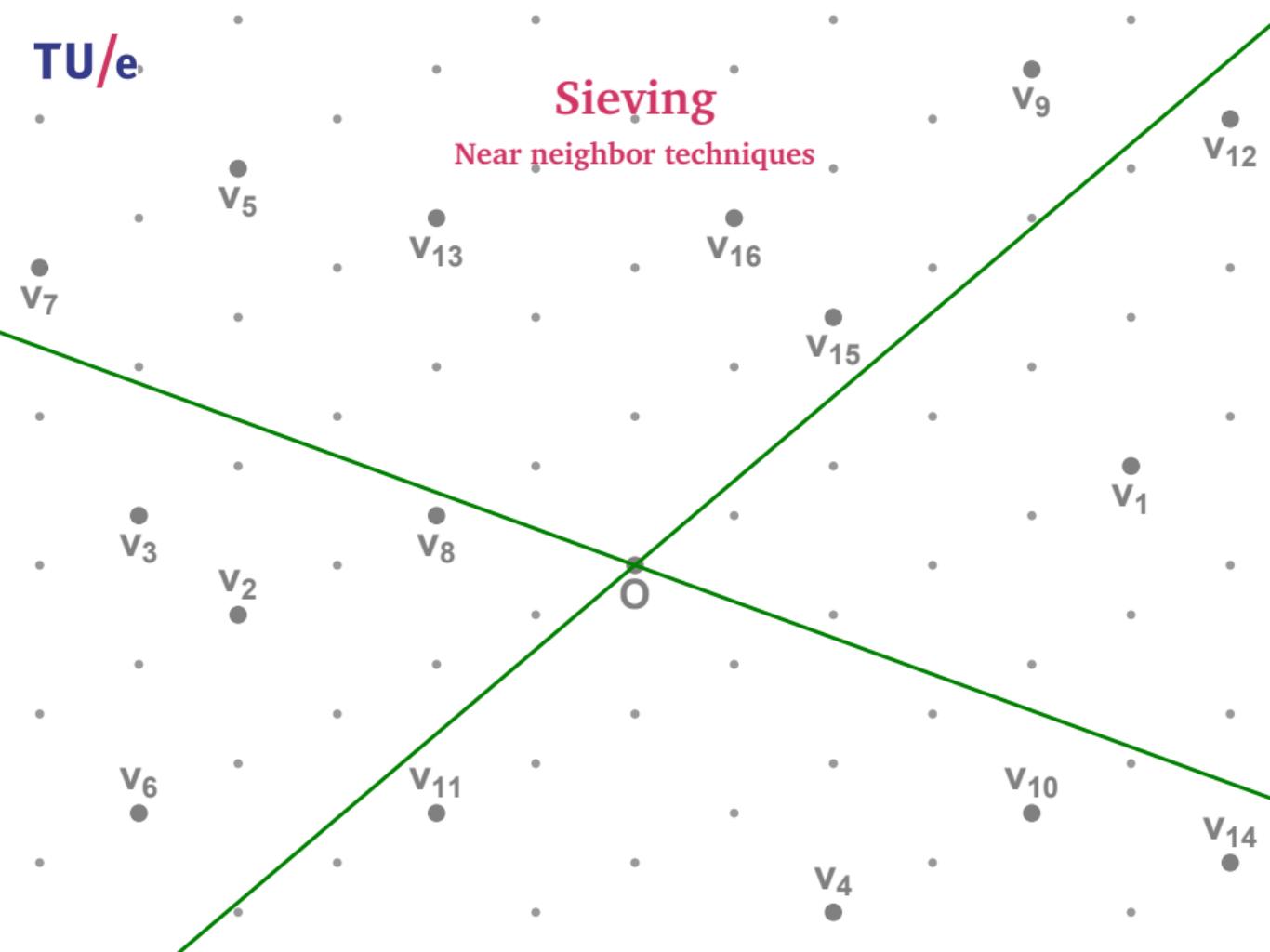
# Sieving

## Near neighbor techniques



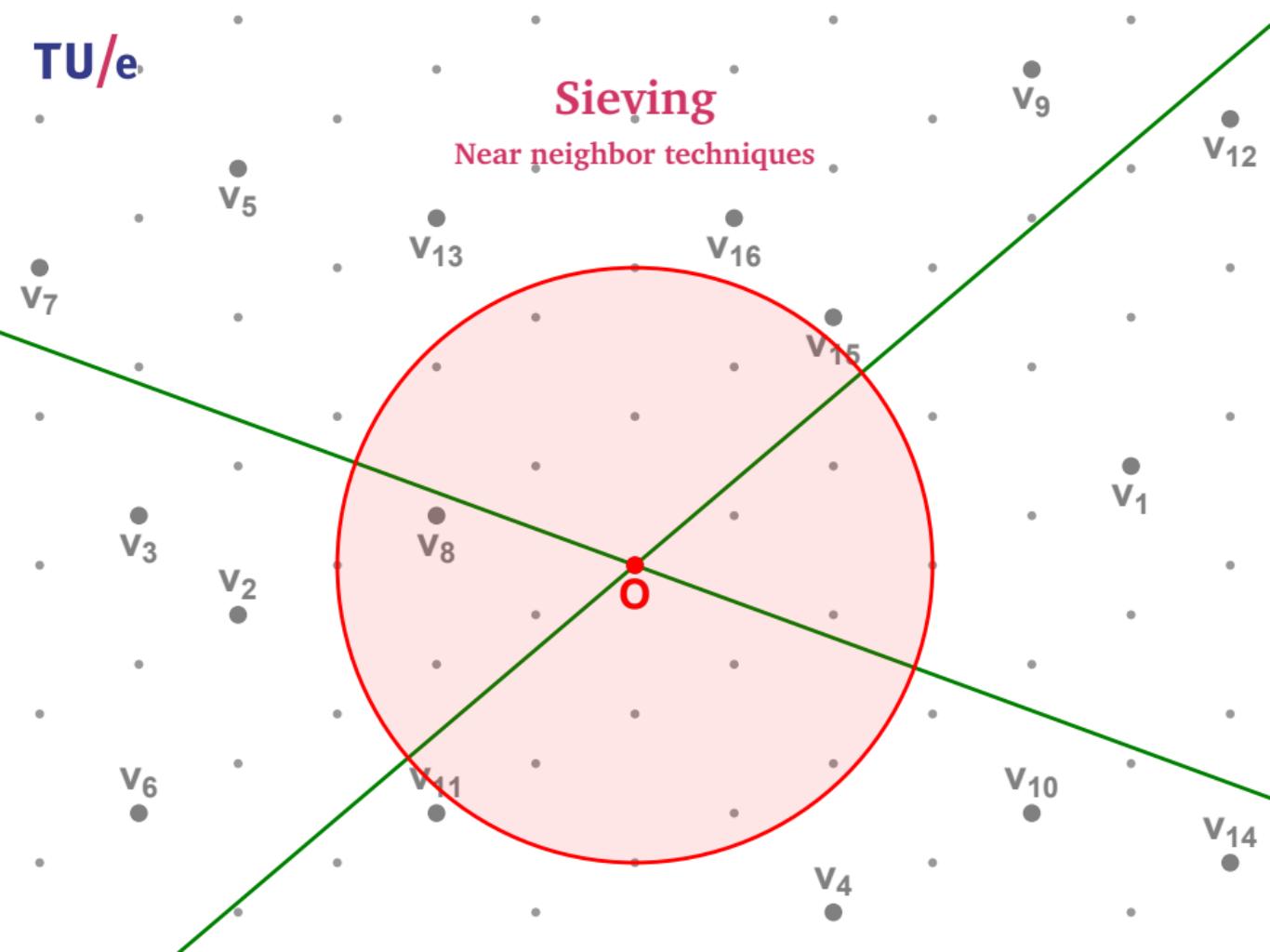
# Sieving

## Near neighbor techniques



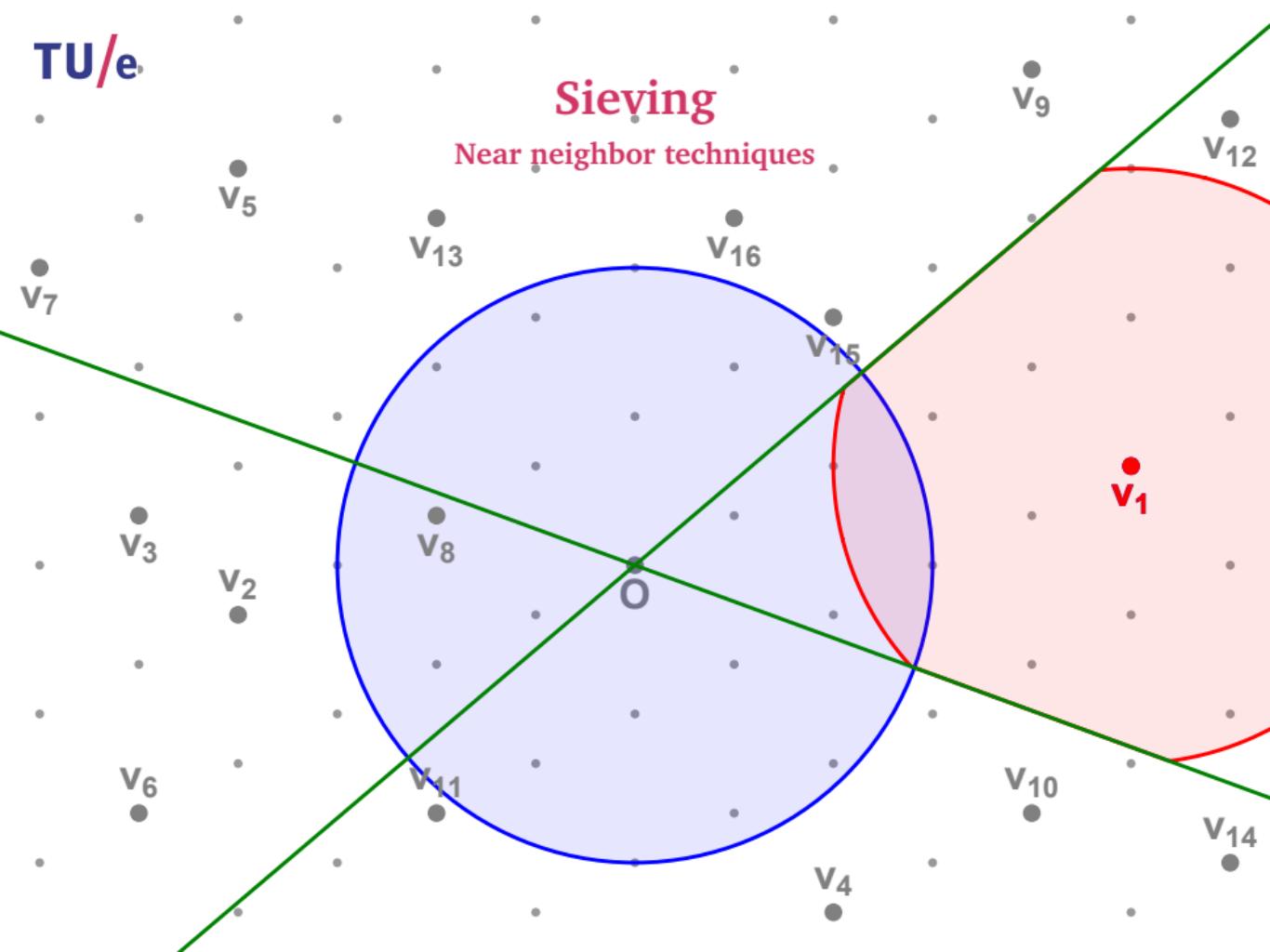
# Sieving

## Near neighbor techniques



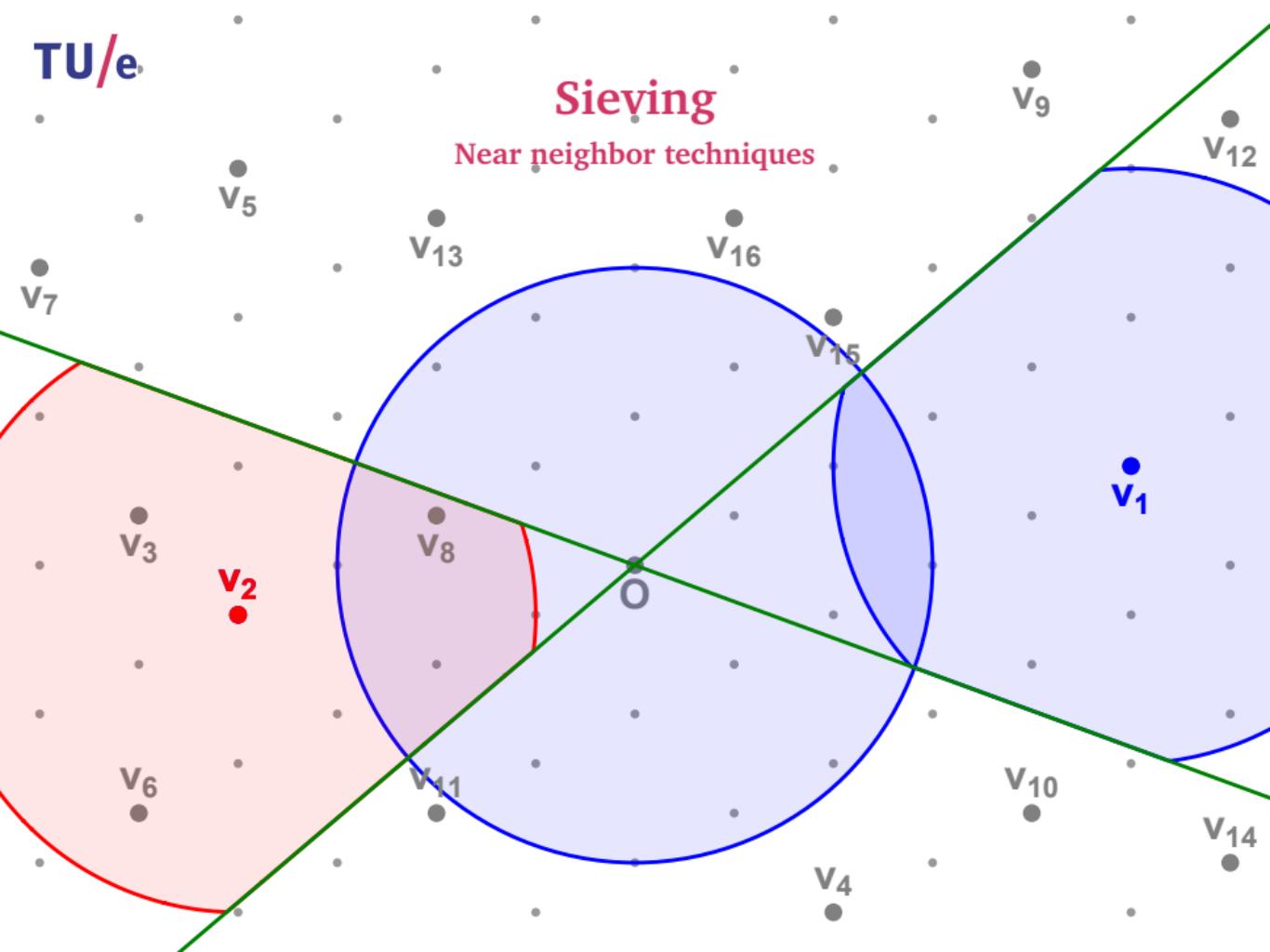
# Sieving

## Near neighbor techniques



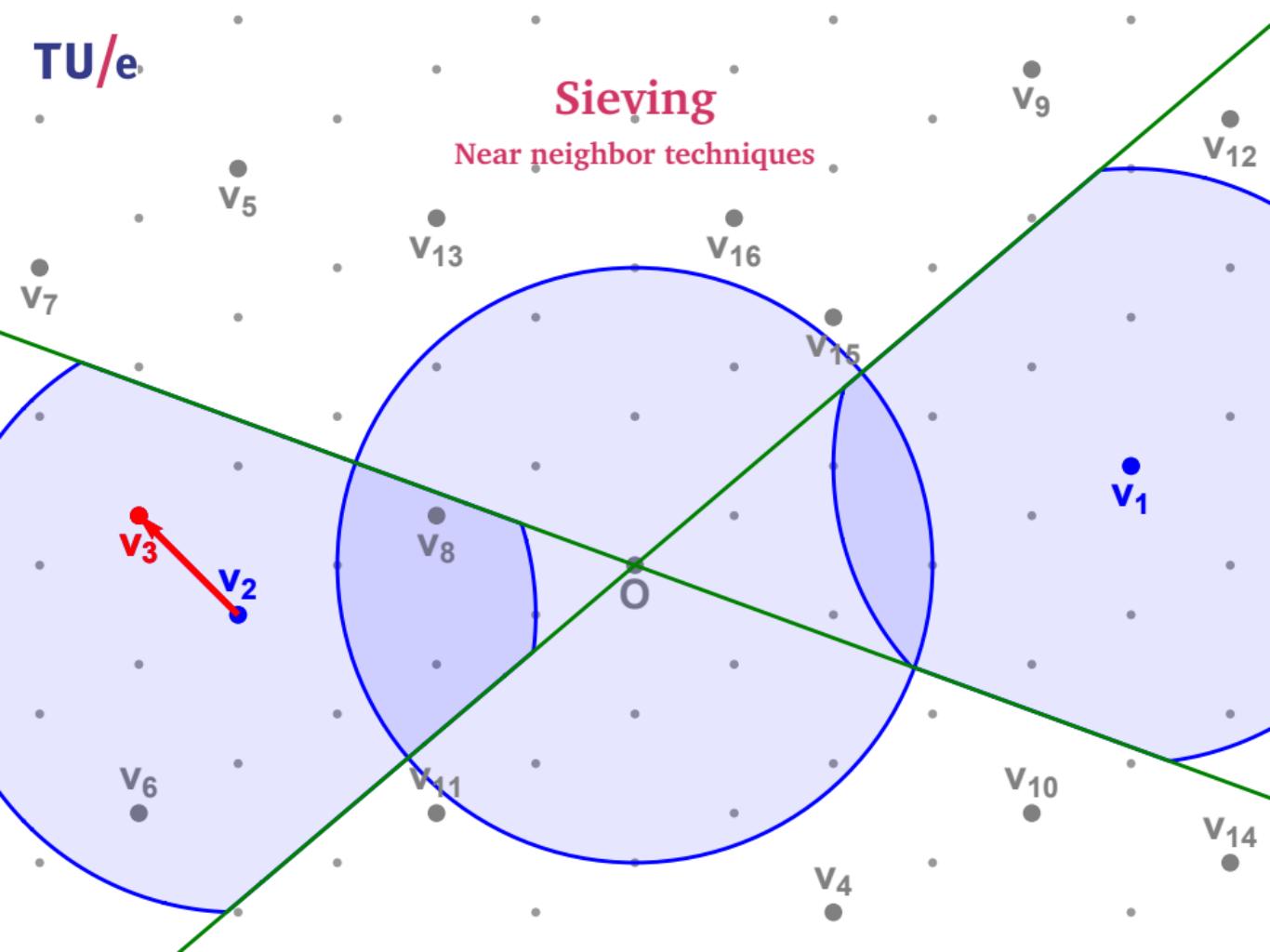
# Sieving

## Near neighbor techniques



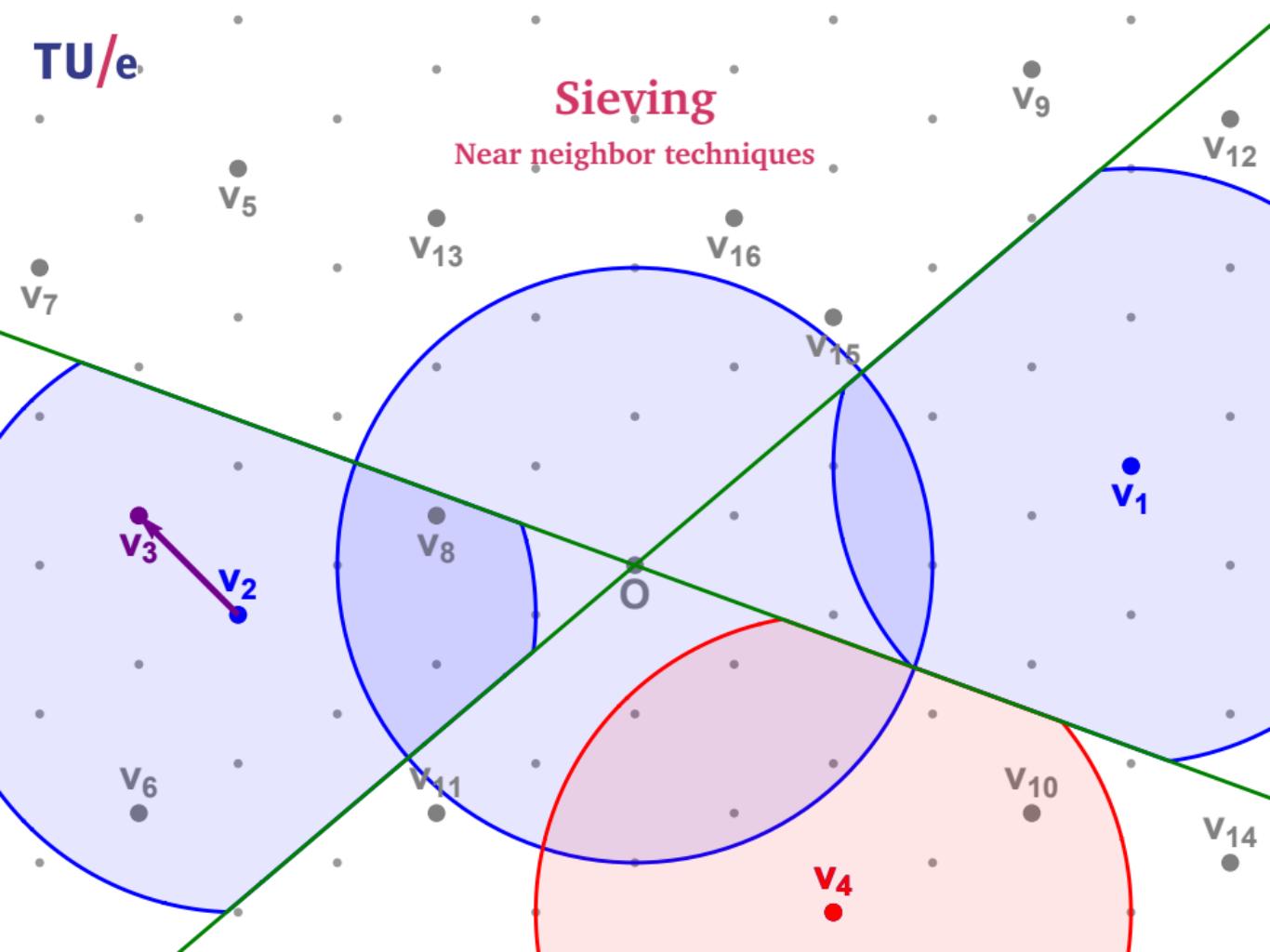
# Sieving

## Near neighbor techniques



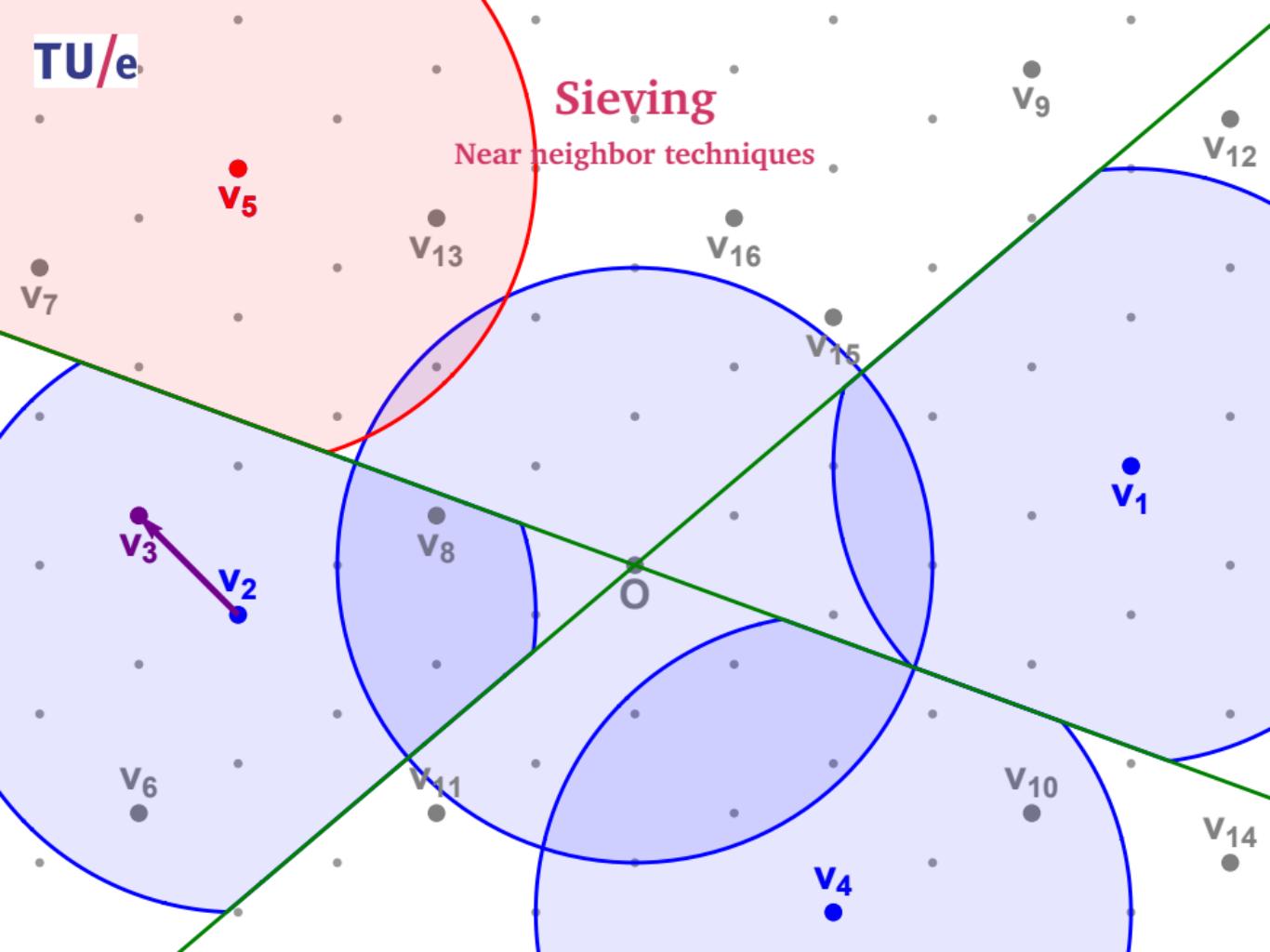
# Sieving

## Near neighbor techniques



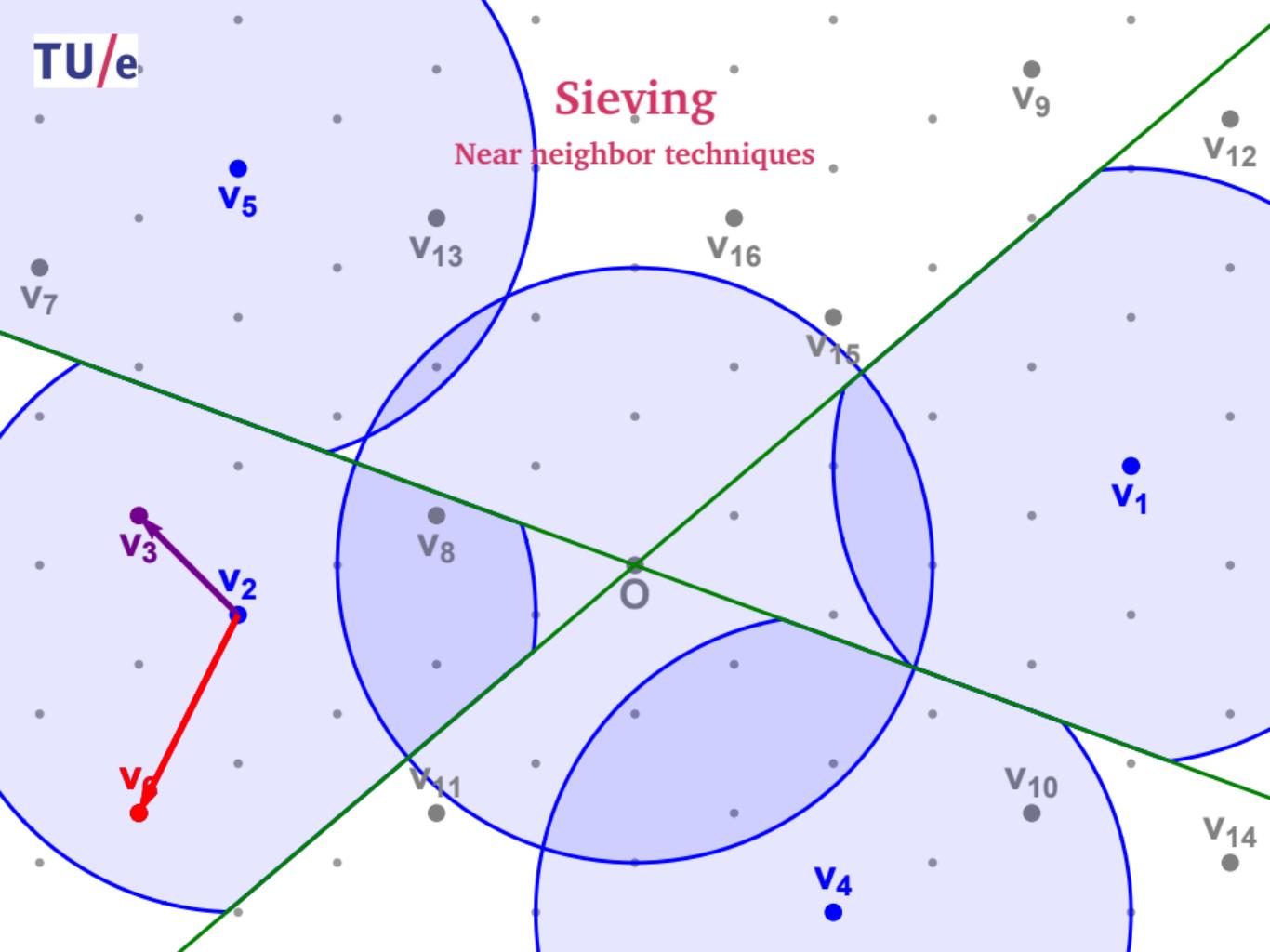
# Sieving

Near neighbor techniques



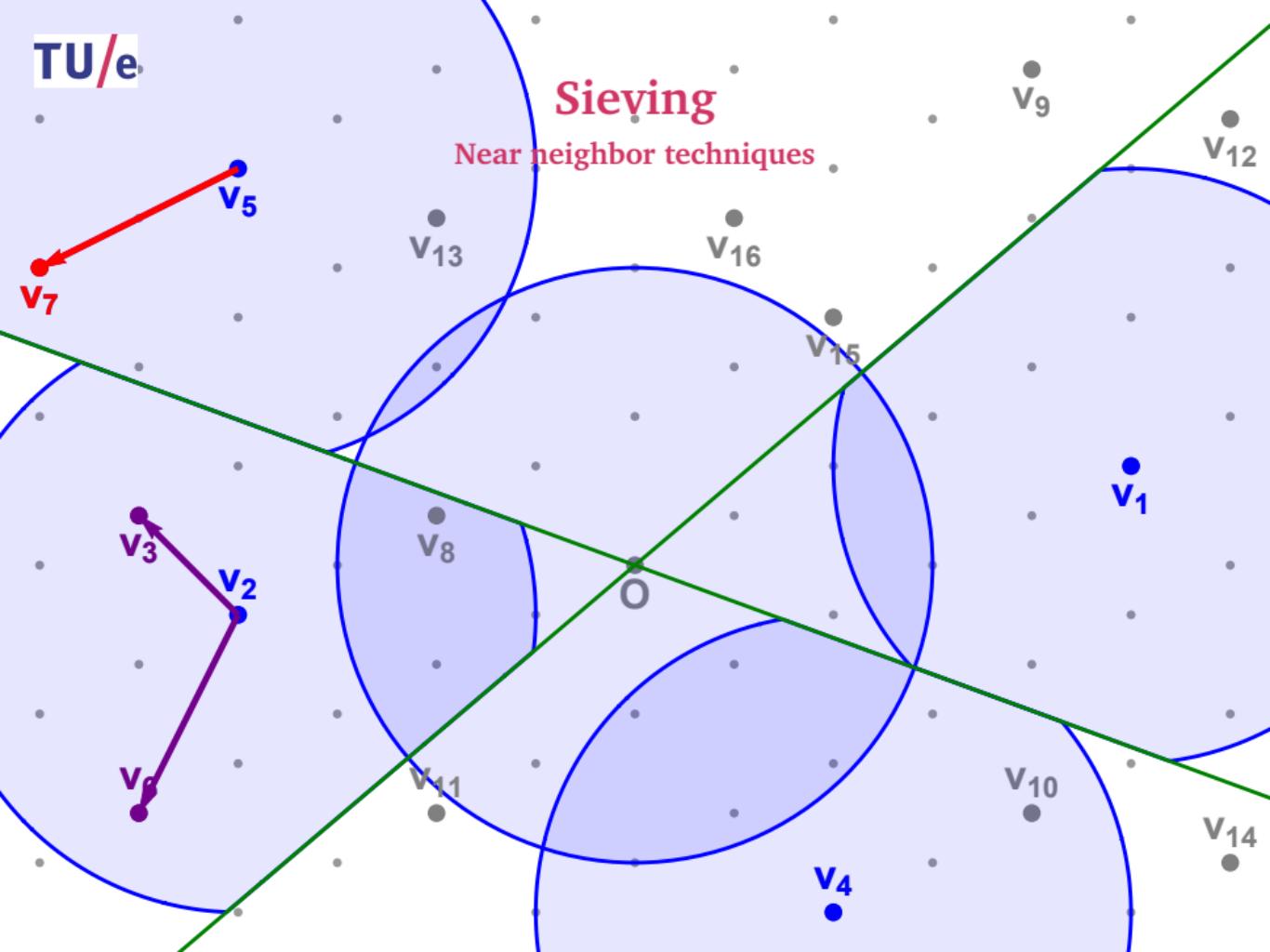
## Sieving

Near neighbor techniques



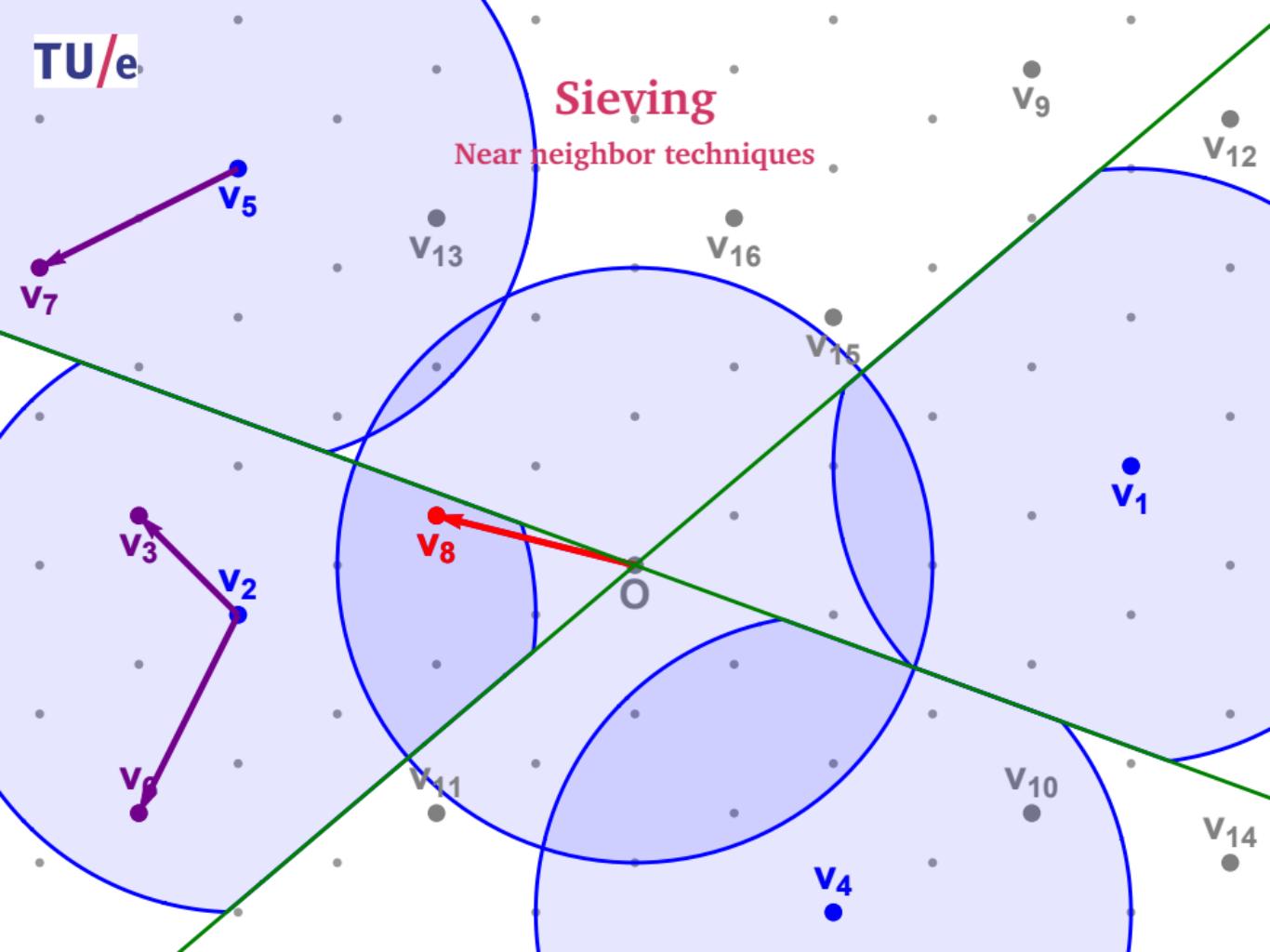
## Sieving

Near neighbor techniques



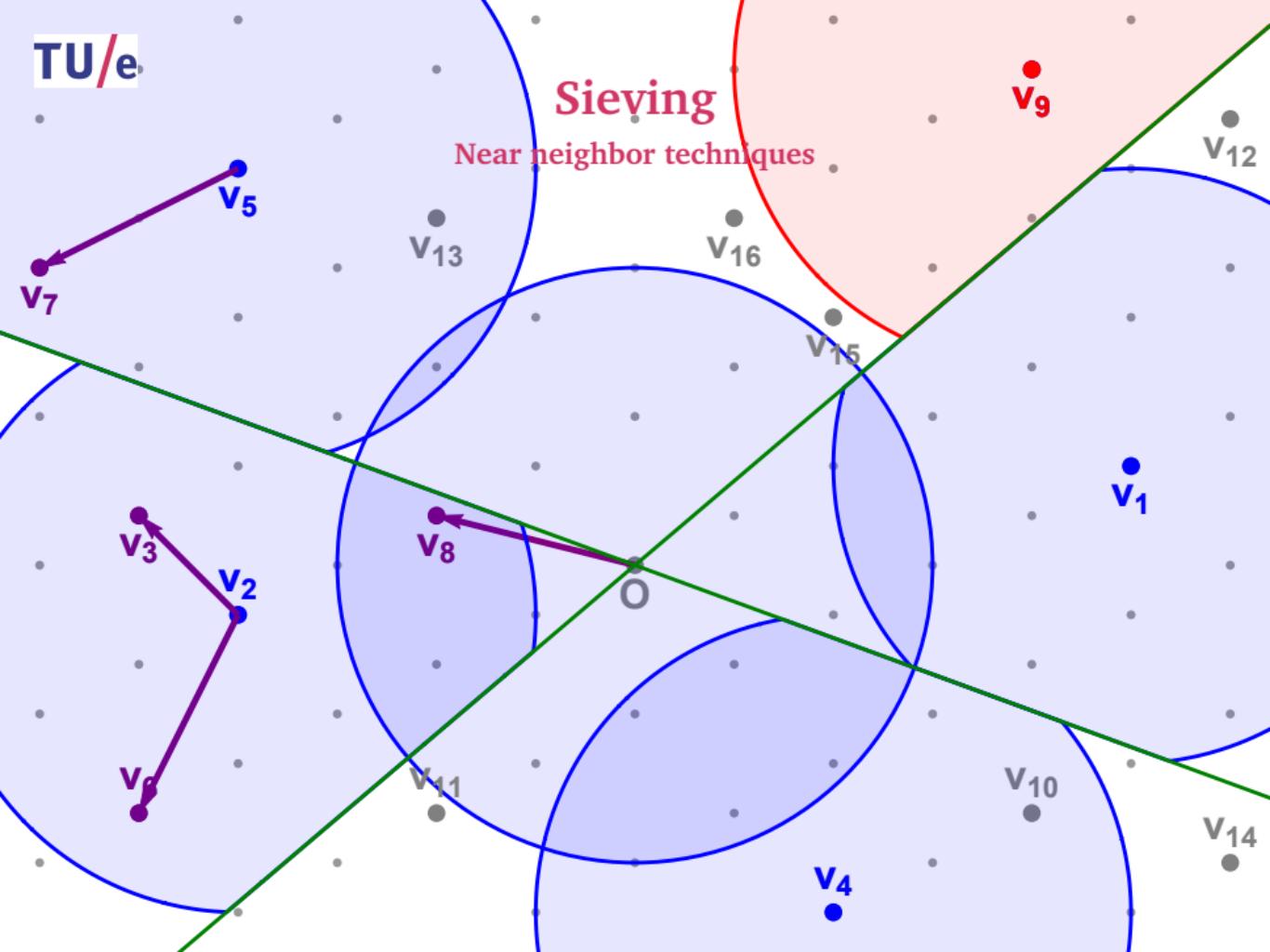
## Sieving

Near neighbor techniques



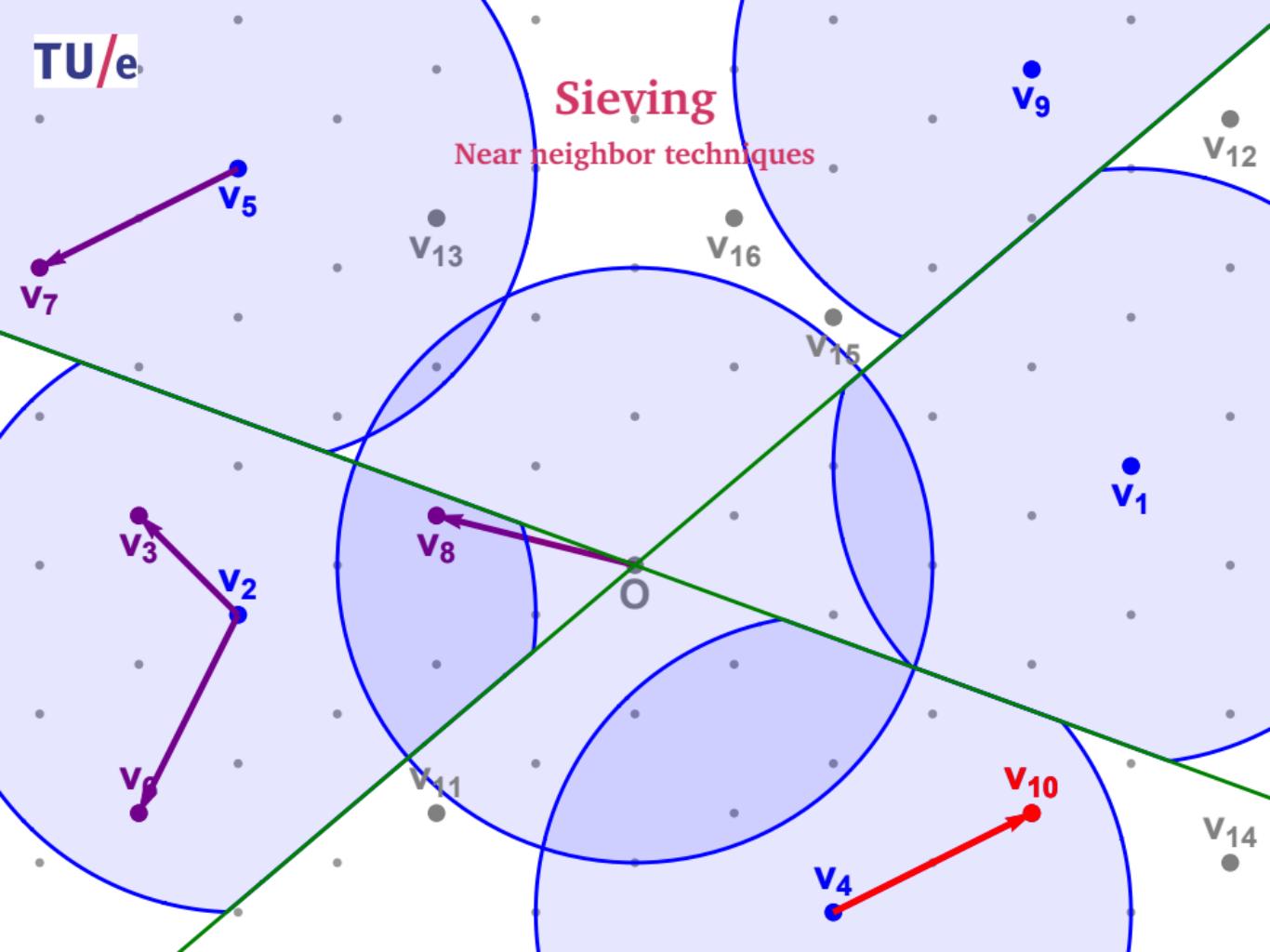
# Sieving

Near neighbor techniques



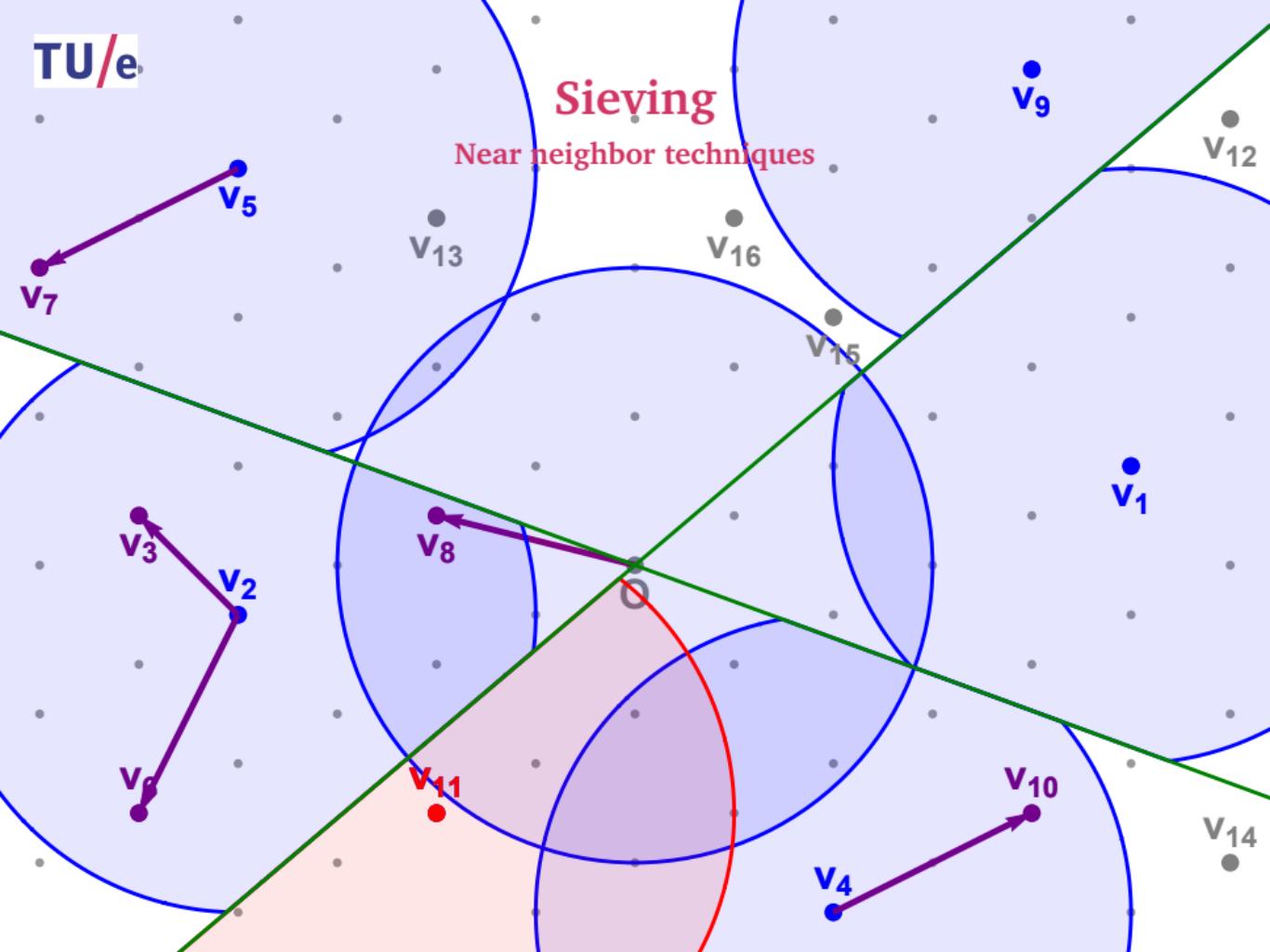
## Sieving

Near neighbor techniques



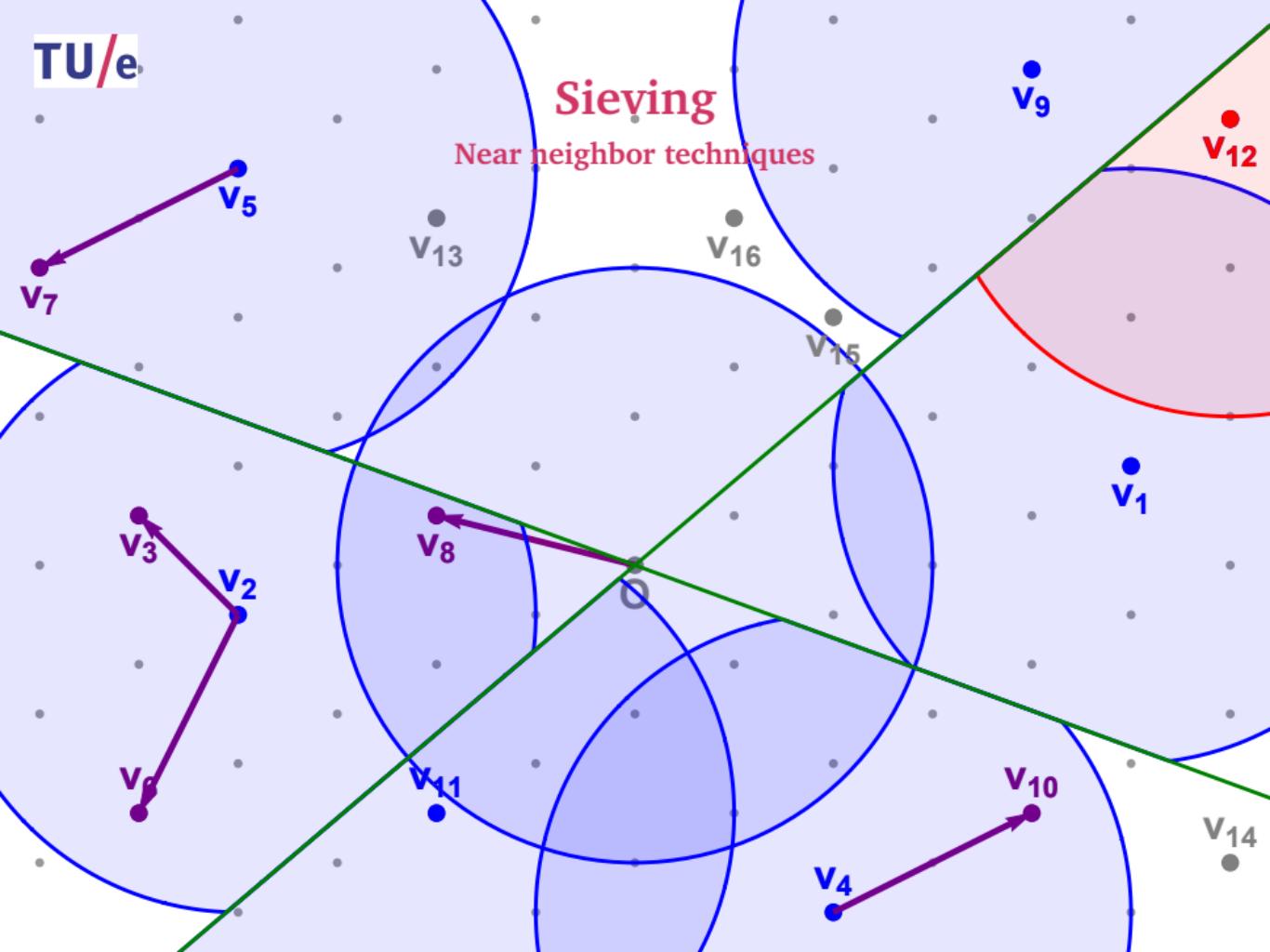
## Sieving

Near neighbor techniques



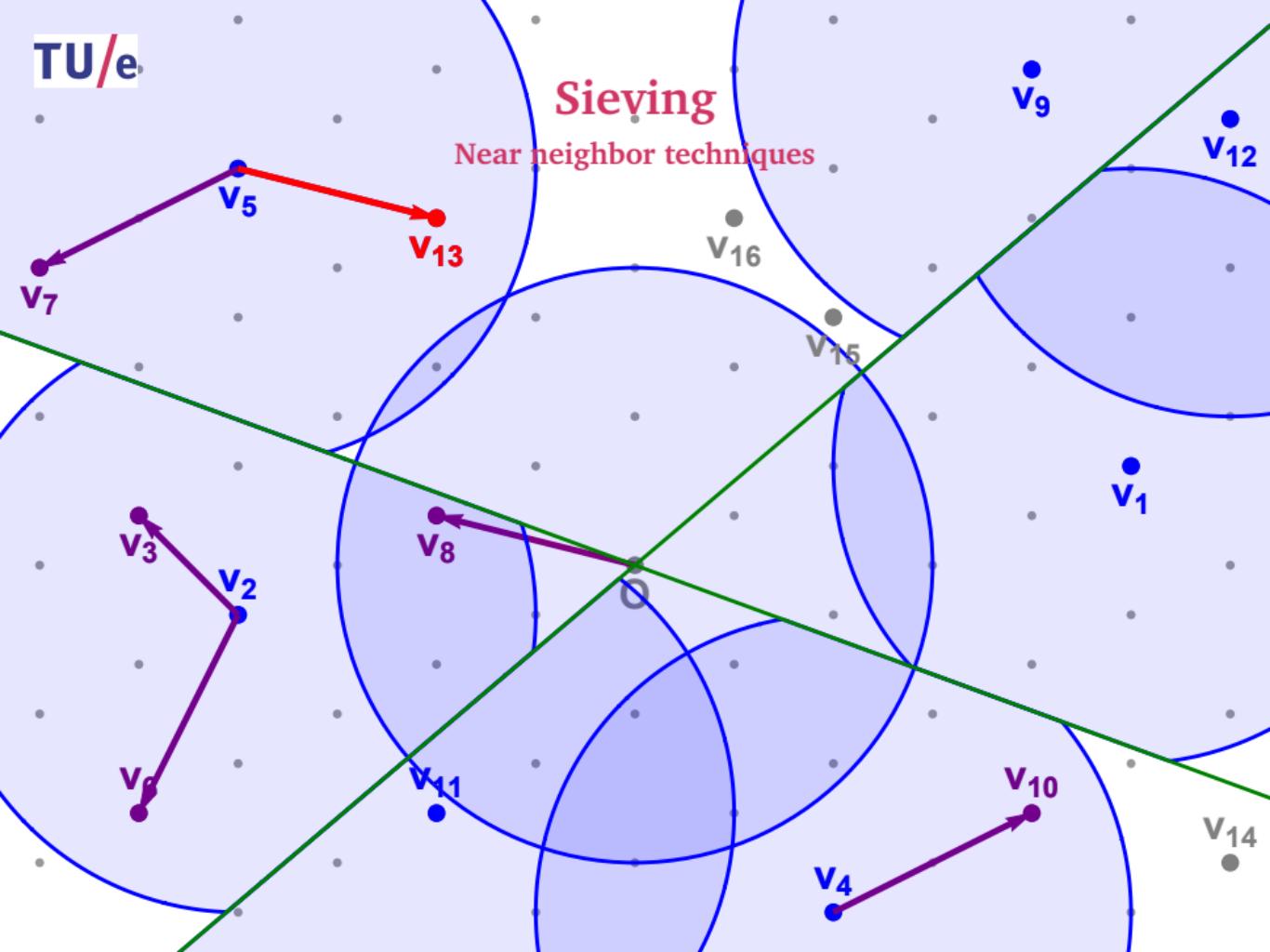
## Sieving

Near neighbor techniques



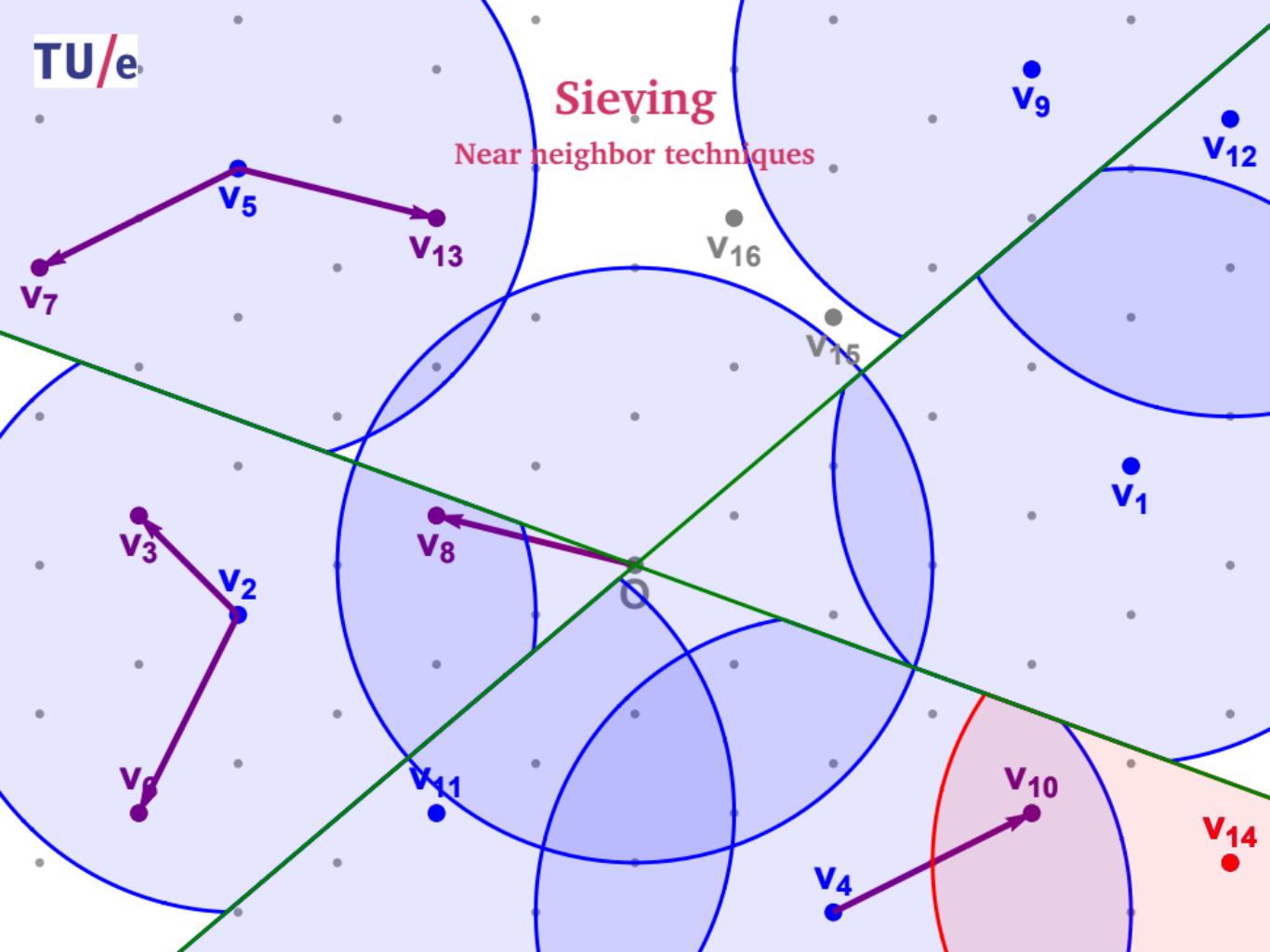
## Sieving

Near neighbor techniques



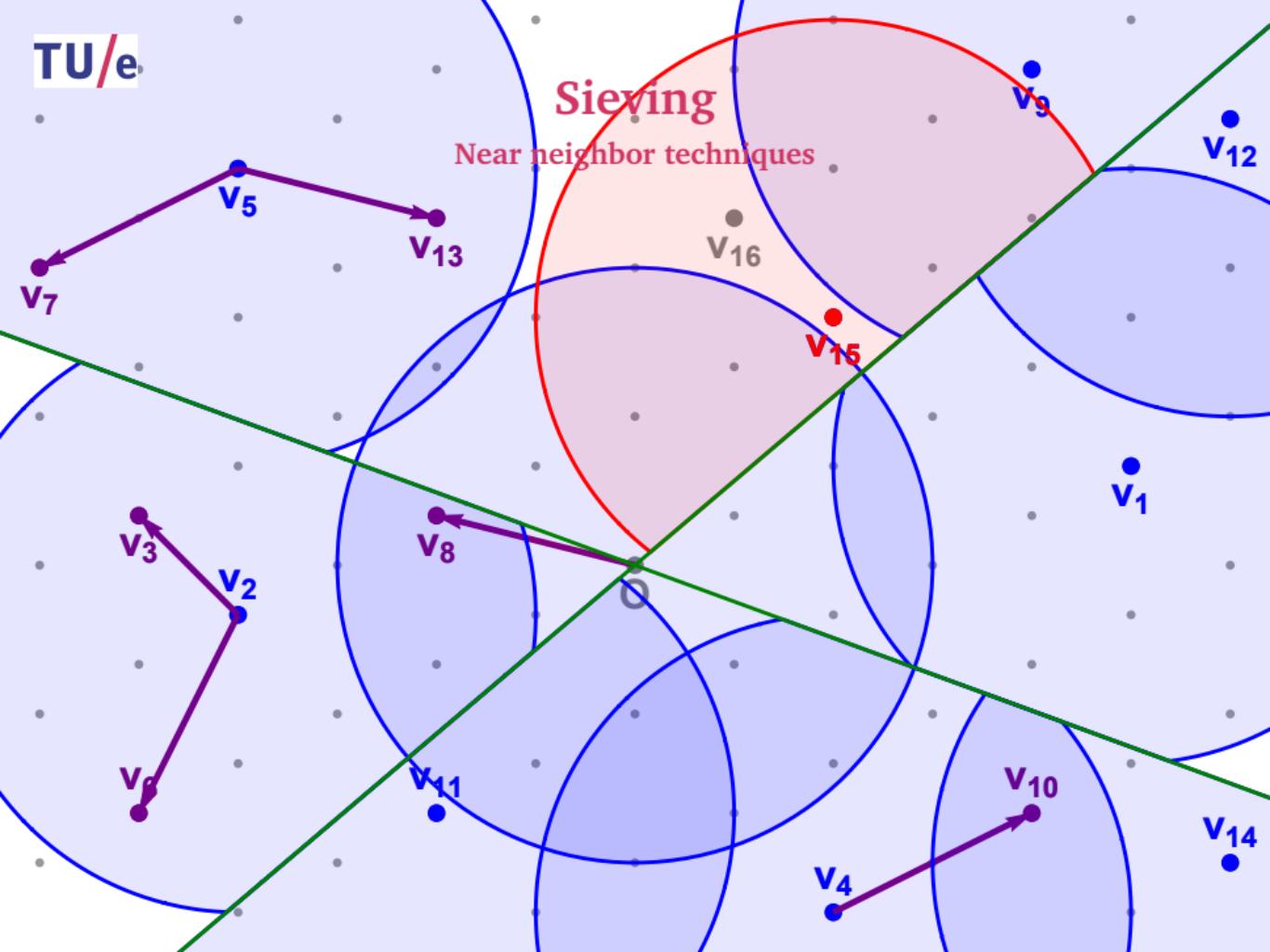
## Sieving

Near neighbor techniques



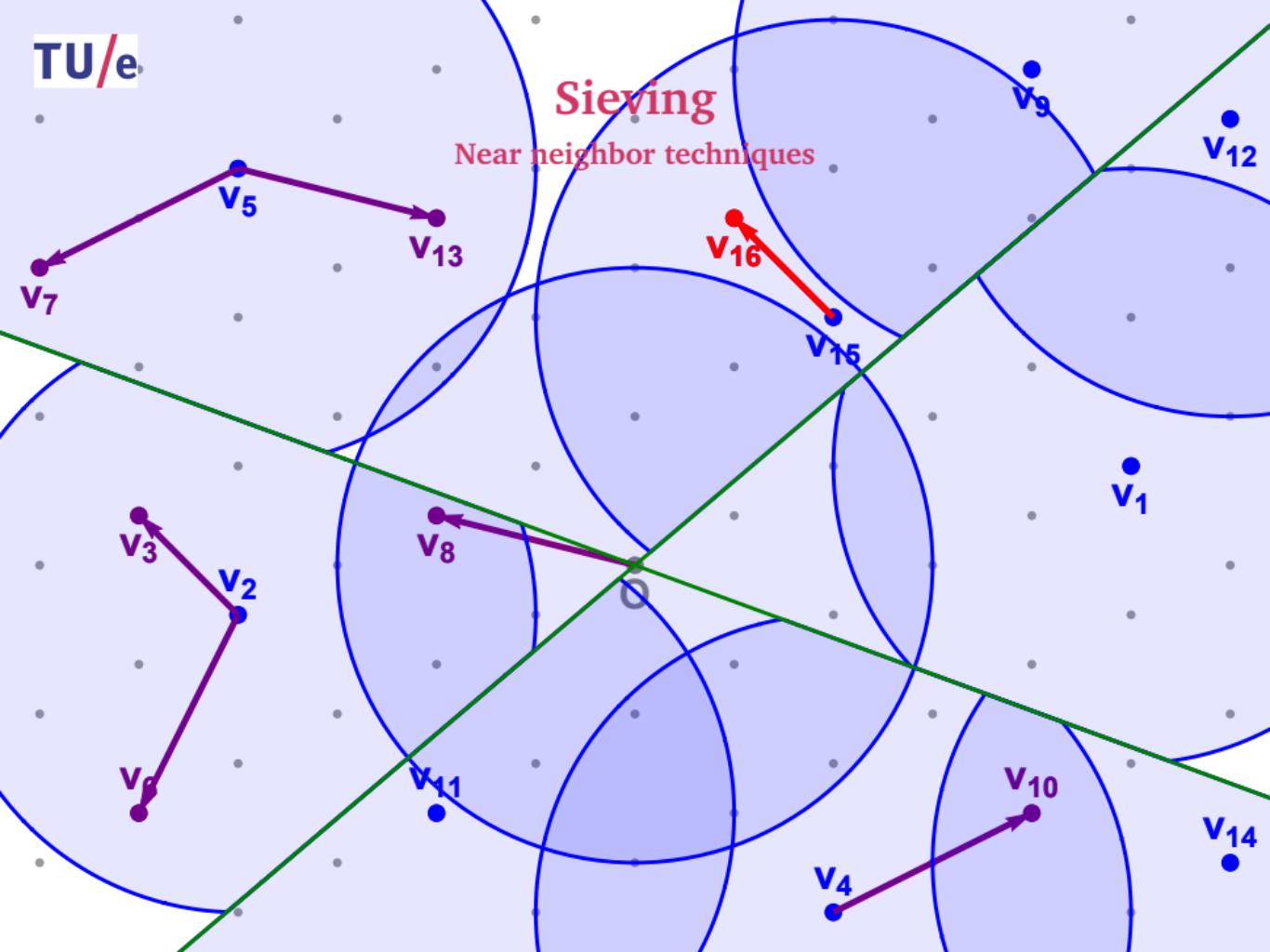
# Sieving

Near neighbor techniques



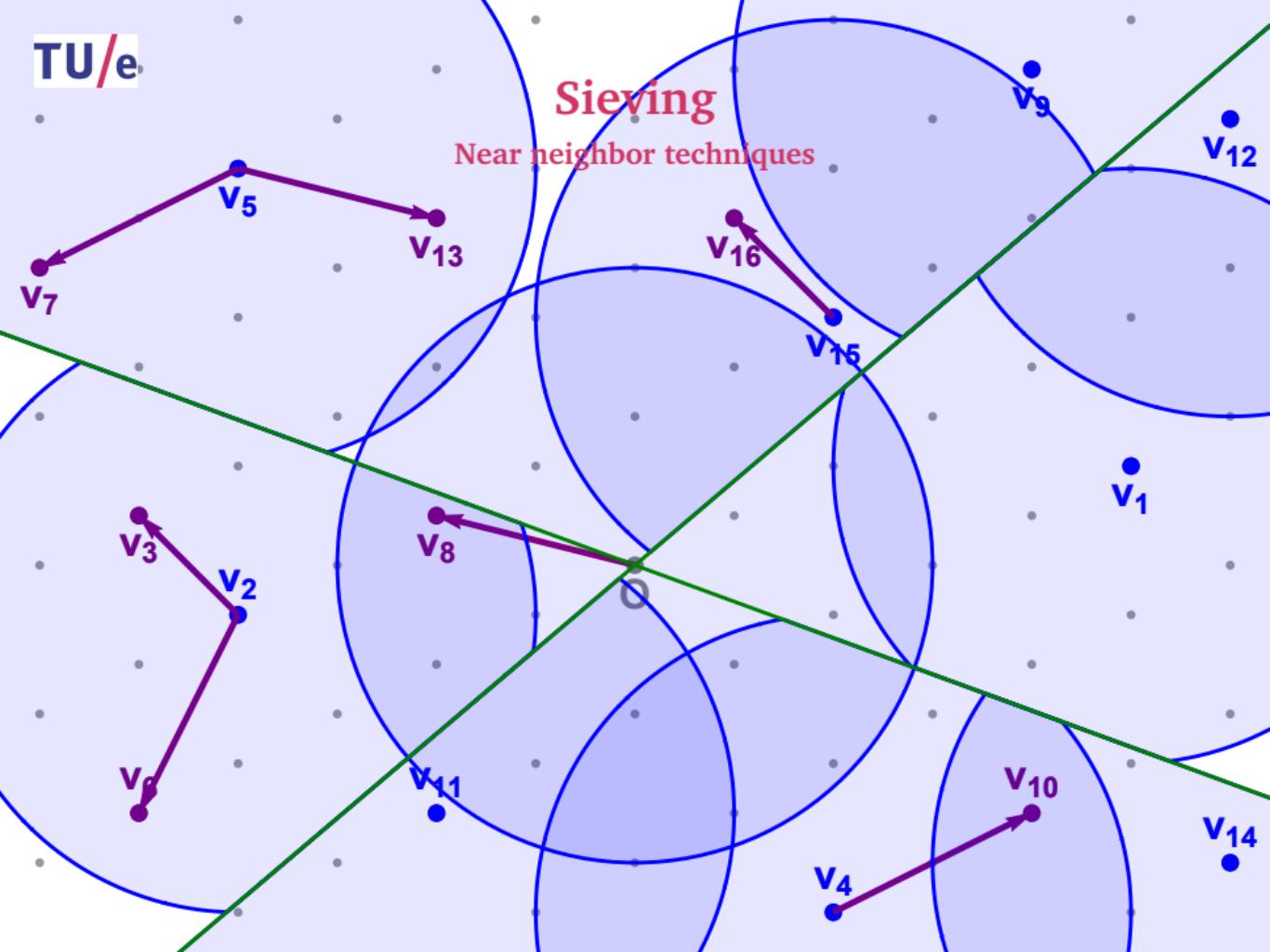
## Sieving

Near neighbor techniques



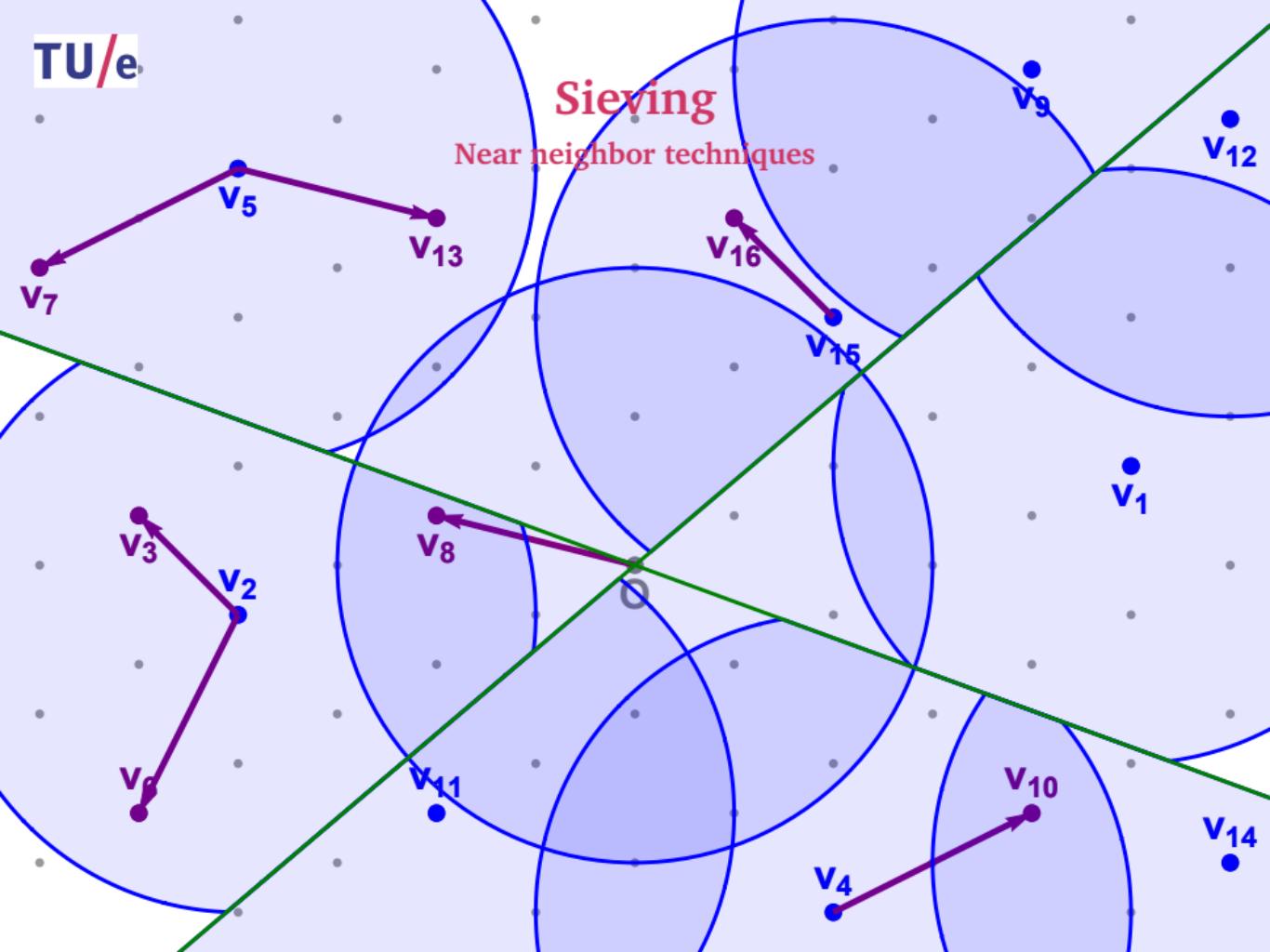
## Sieving

Near neighbor techniques



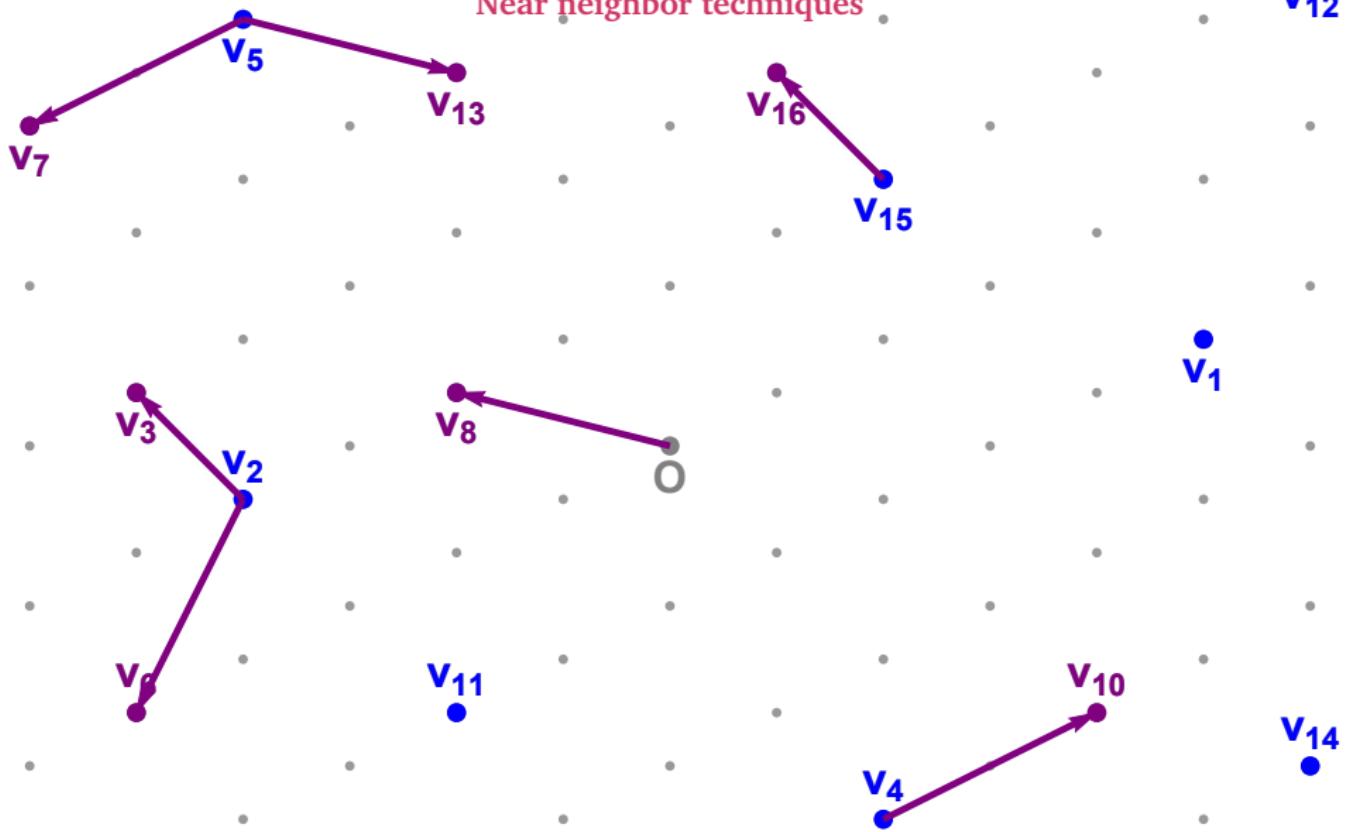
# Sieving

Near neighbor techniques



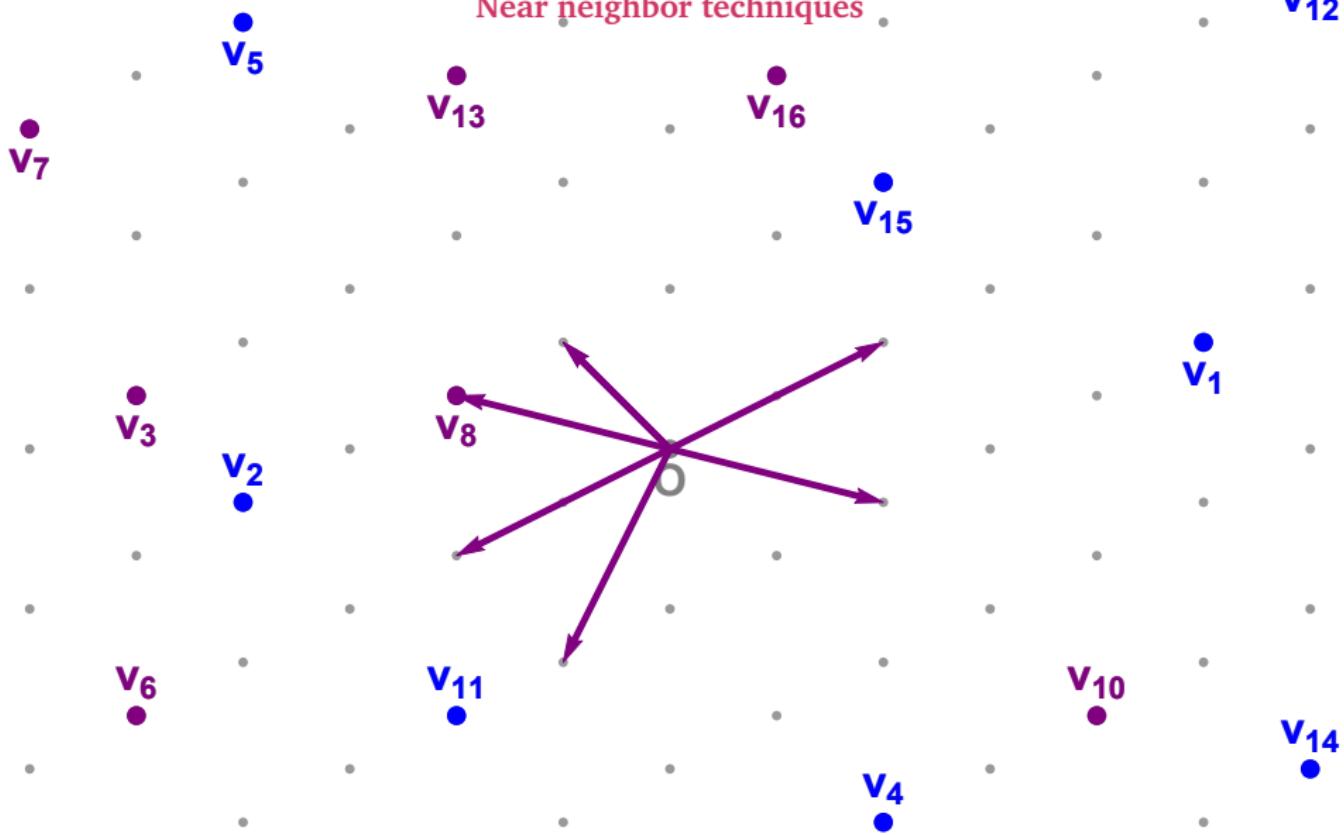
## Sieving

Near neighbor techniques



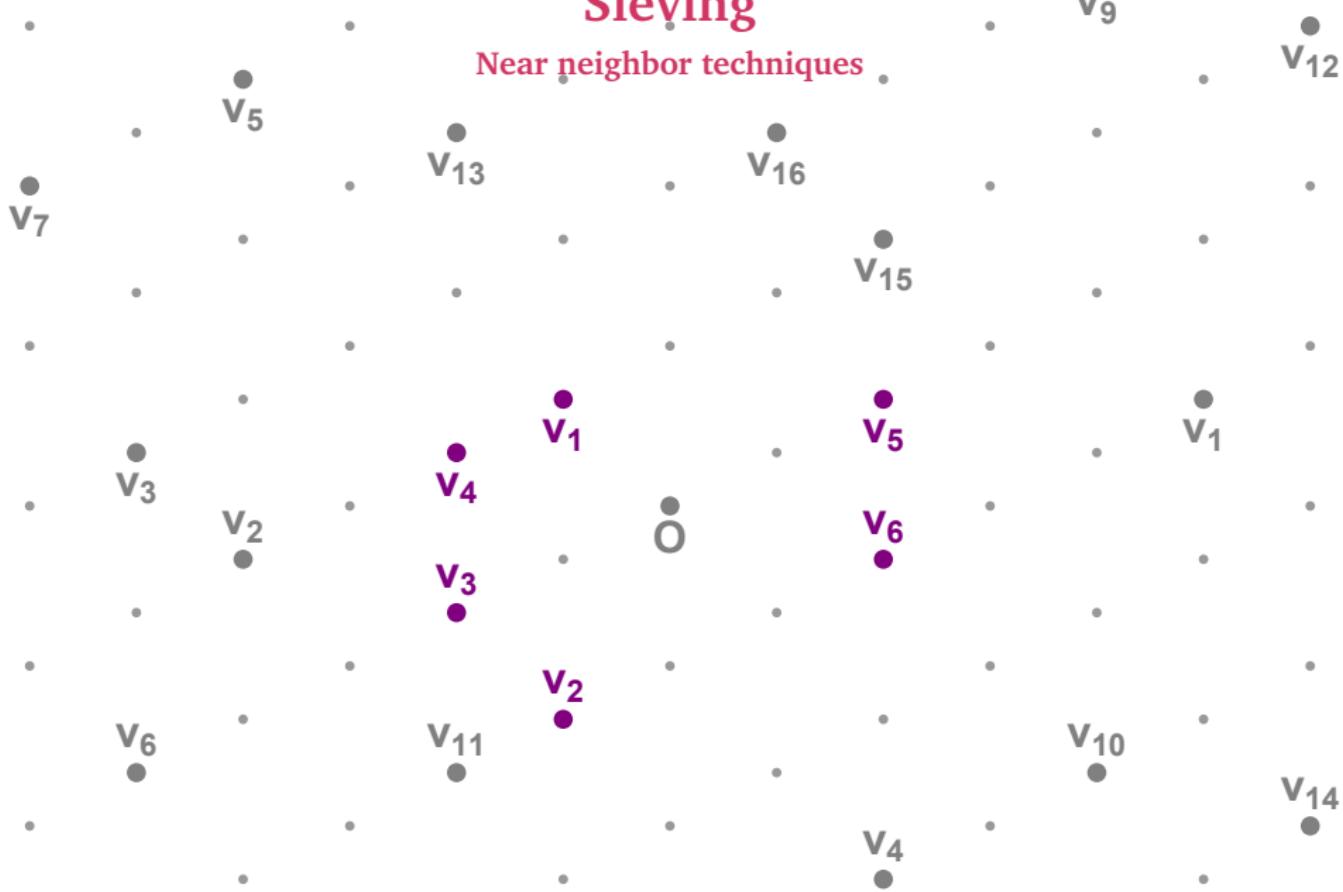
## Sieving

Near neighbor techniques



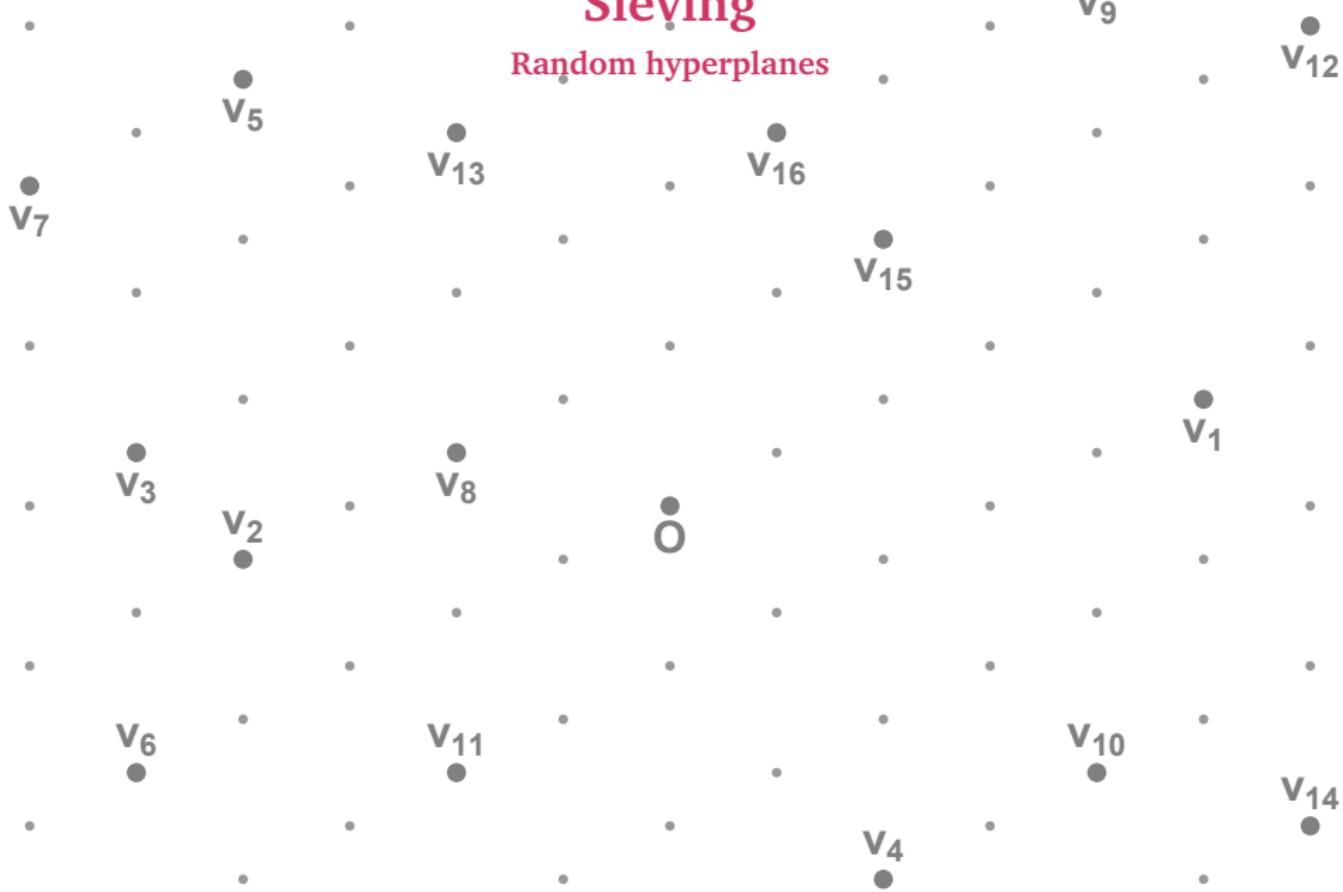
# Sieving

## Near neighbor techniques



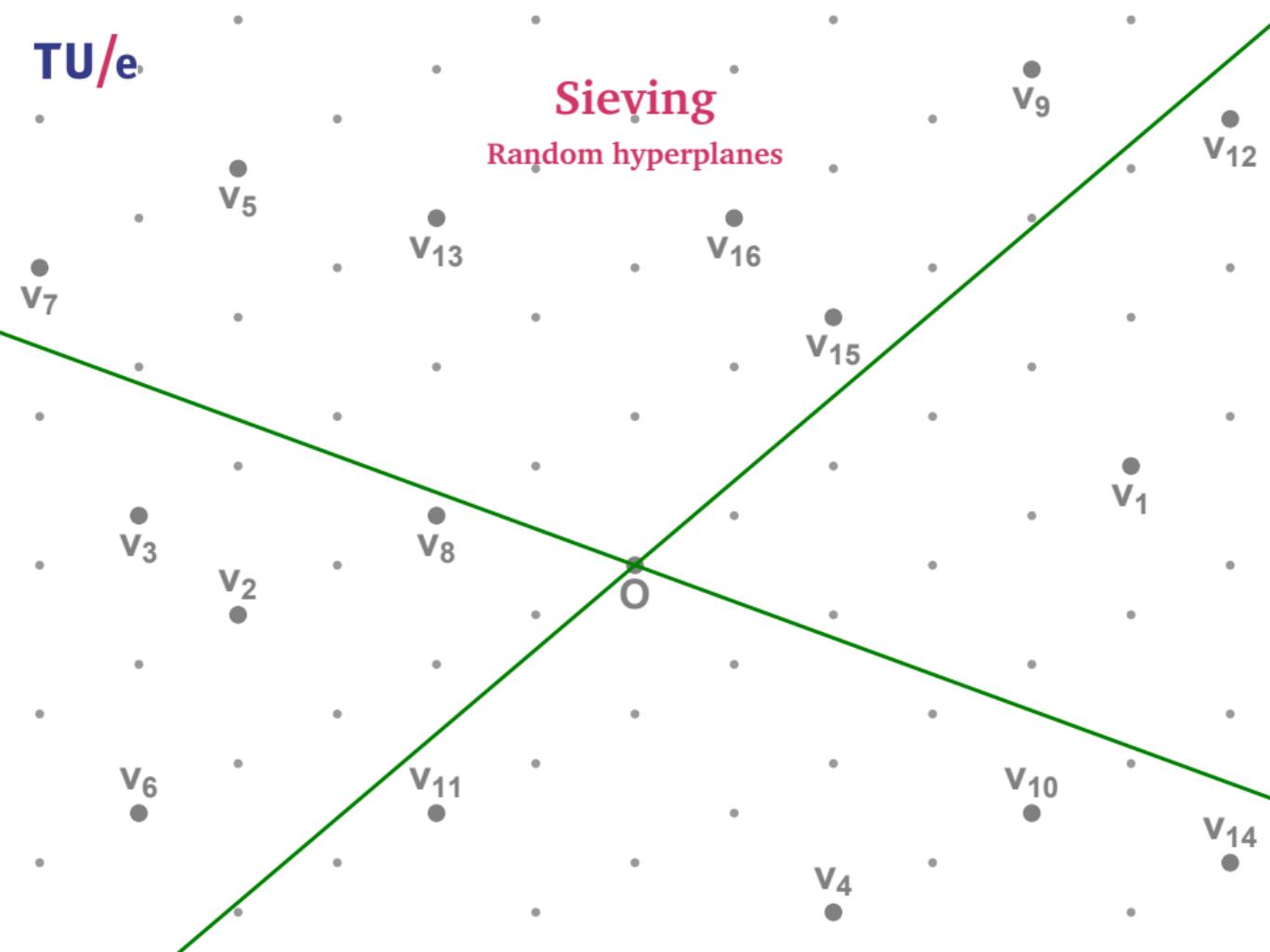
# Sieving

Random hyperplanes



# Sieving

Random hyperplanes



# Sieving

Random hypercones



# Sieving

Random hypercones



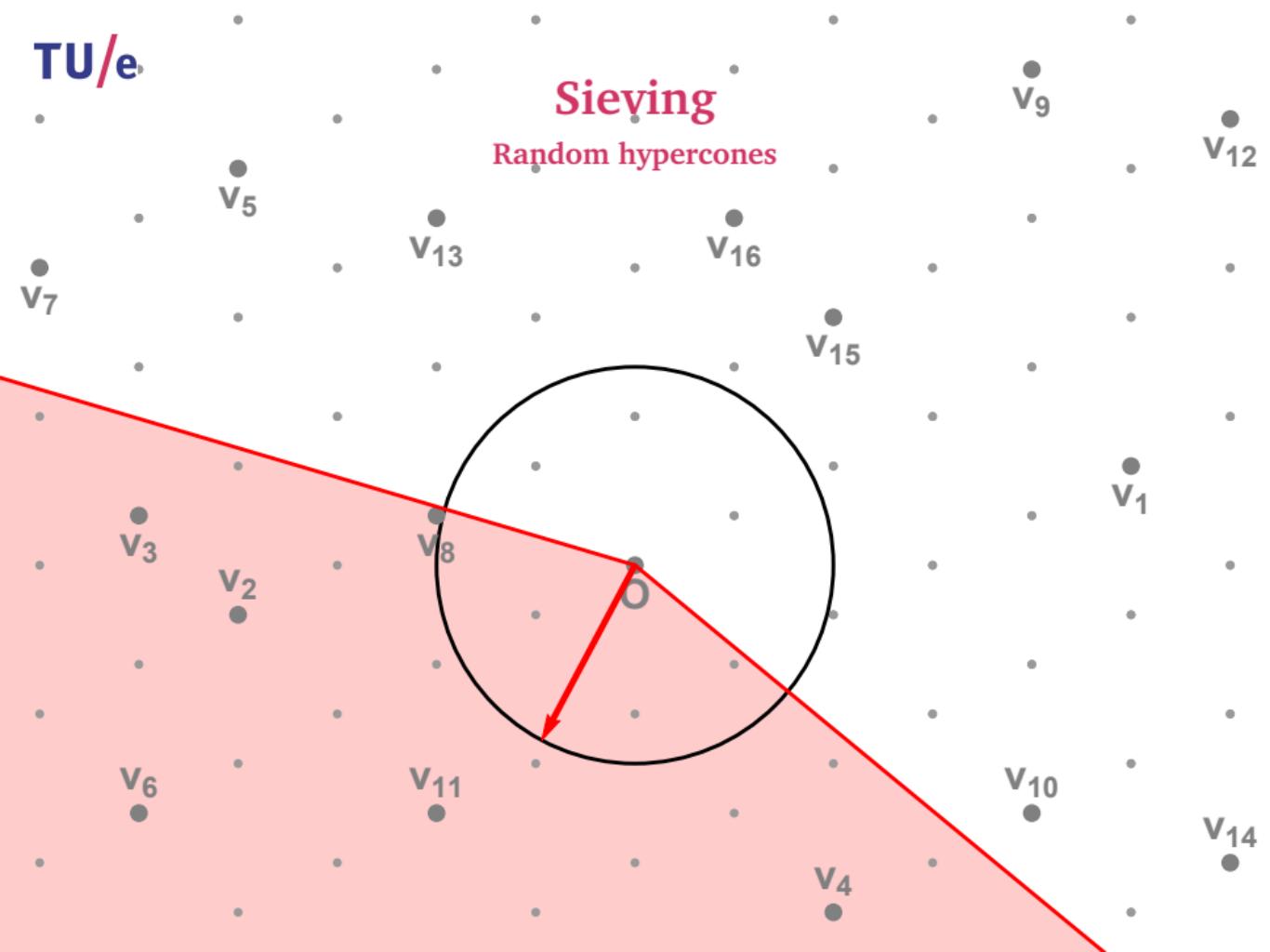
# Sieving

Random hypercones



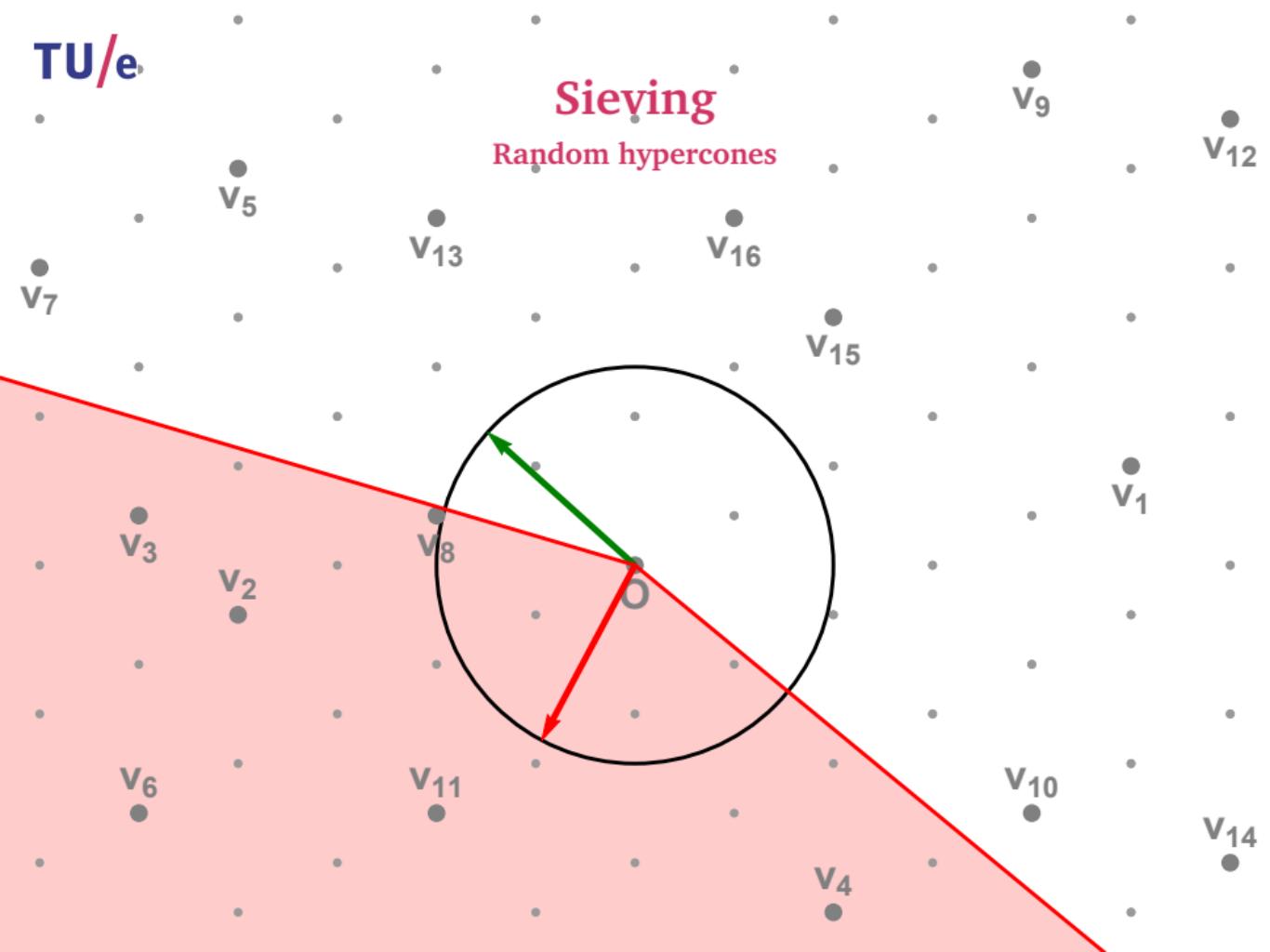
# Sieving

Random hypercones



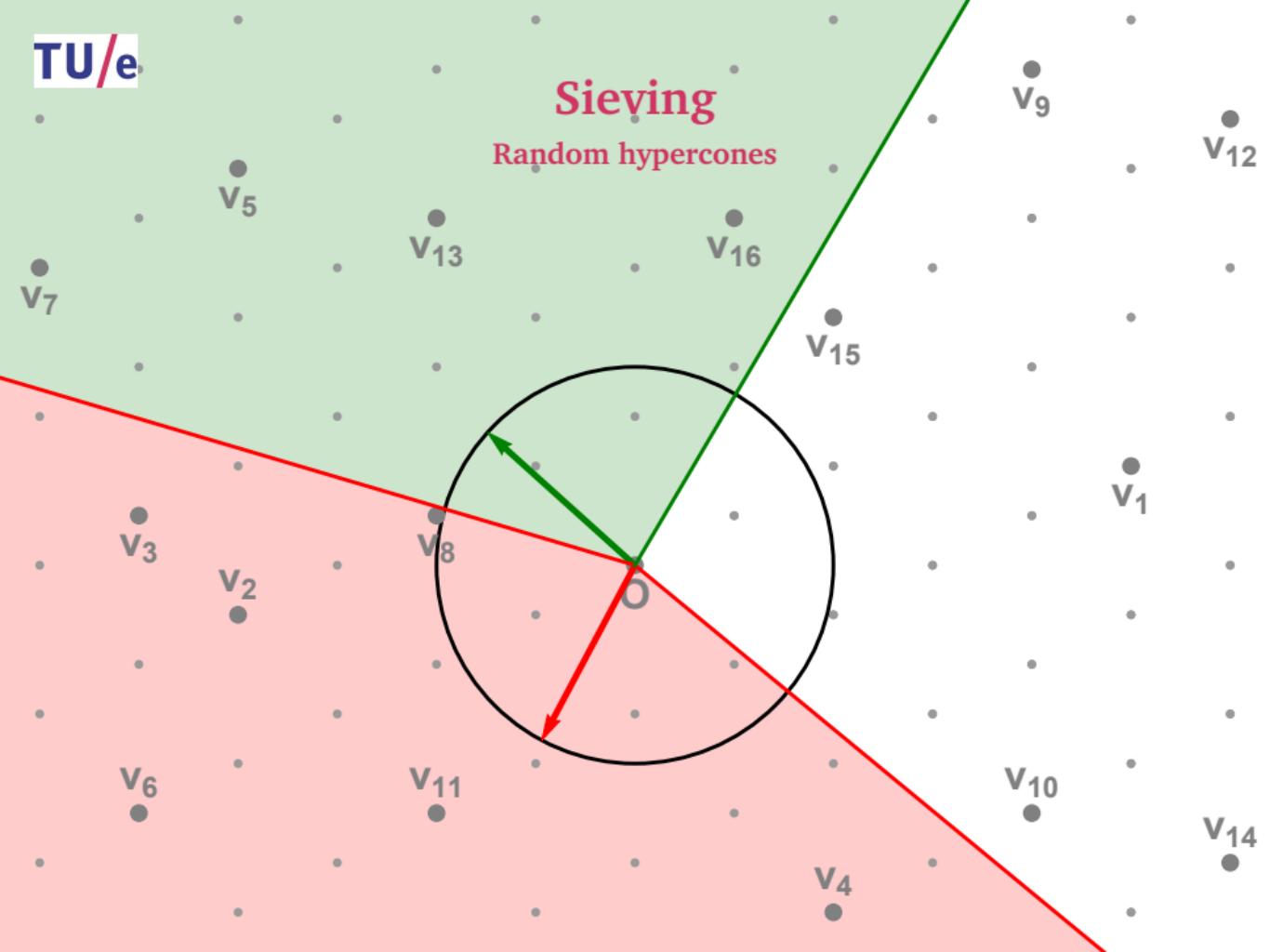
# Sieving

Random hypercones



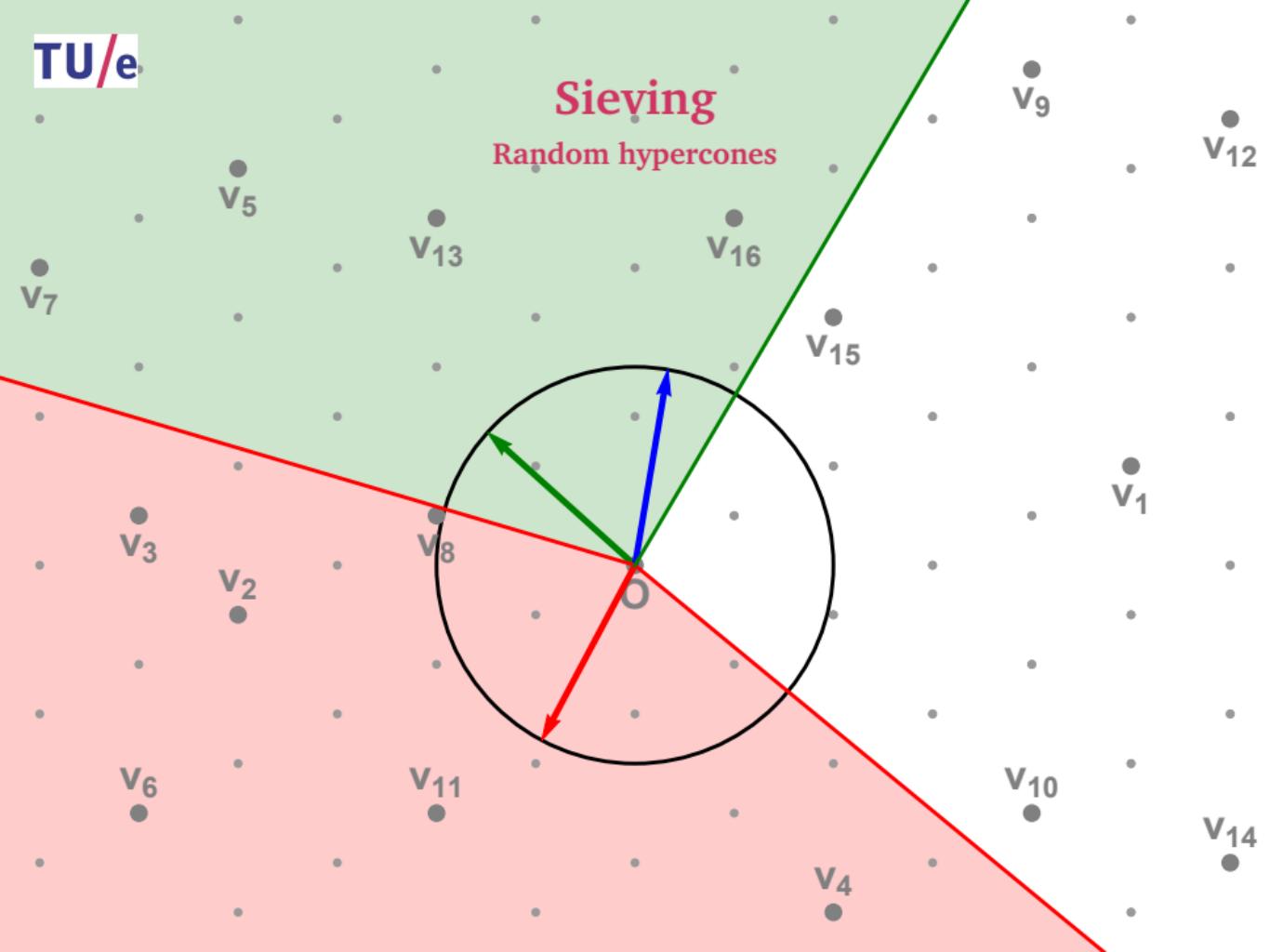
## Sieving

Random hypercones



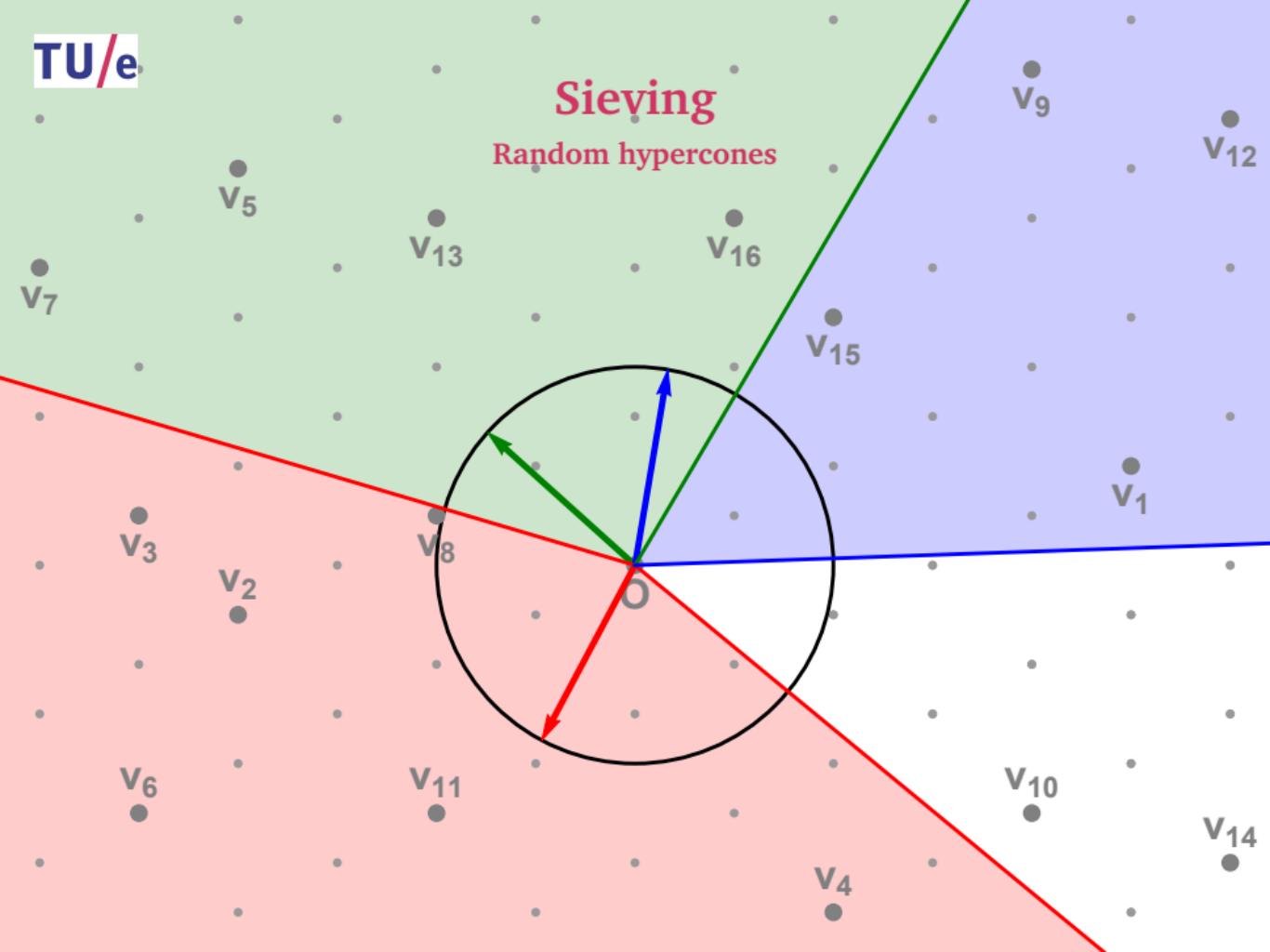
## Sieving

Random hypercones



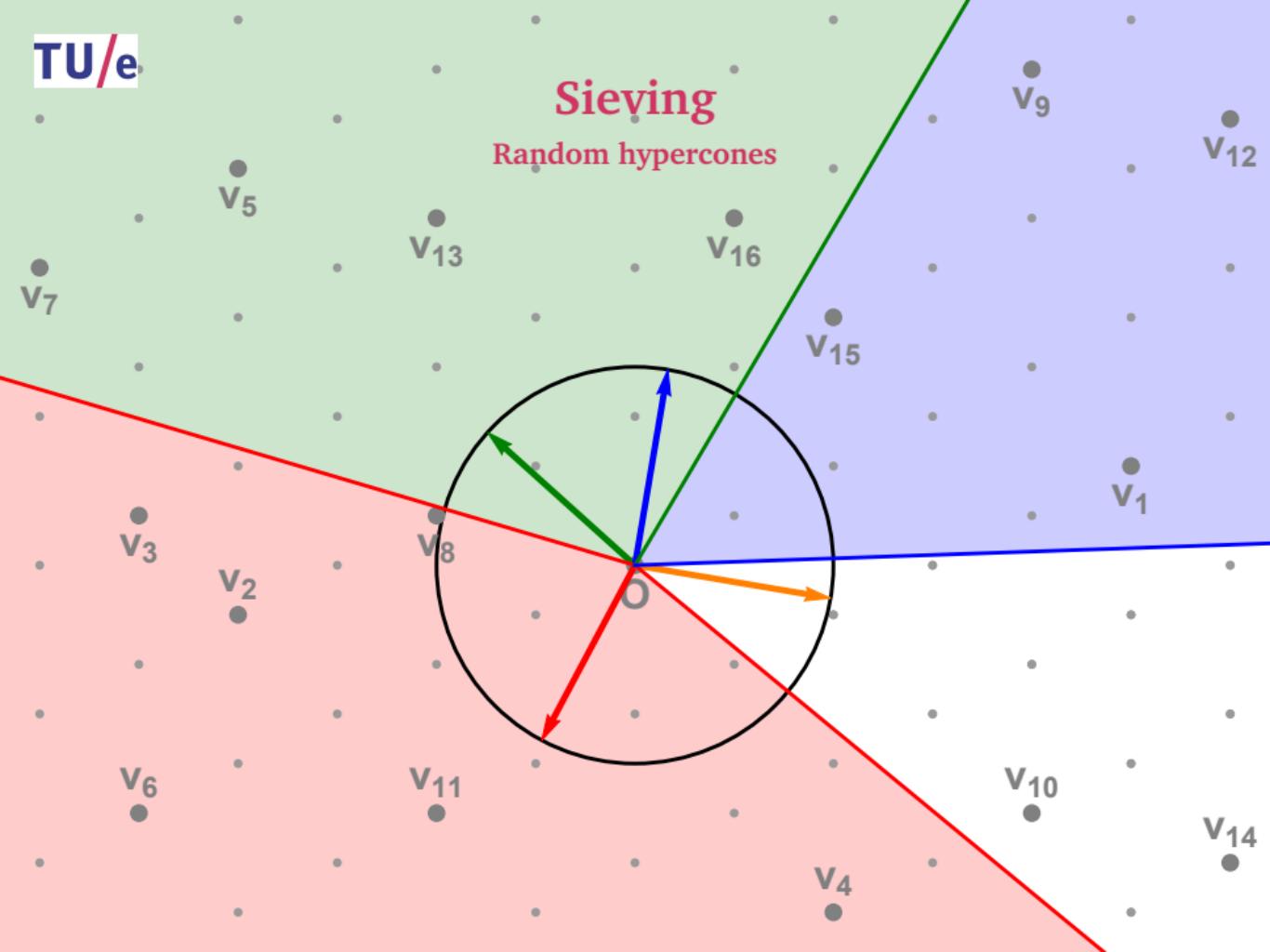
## Sieving

Random hypercones



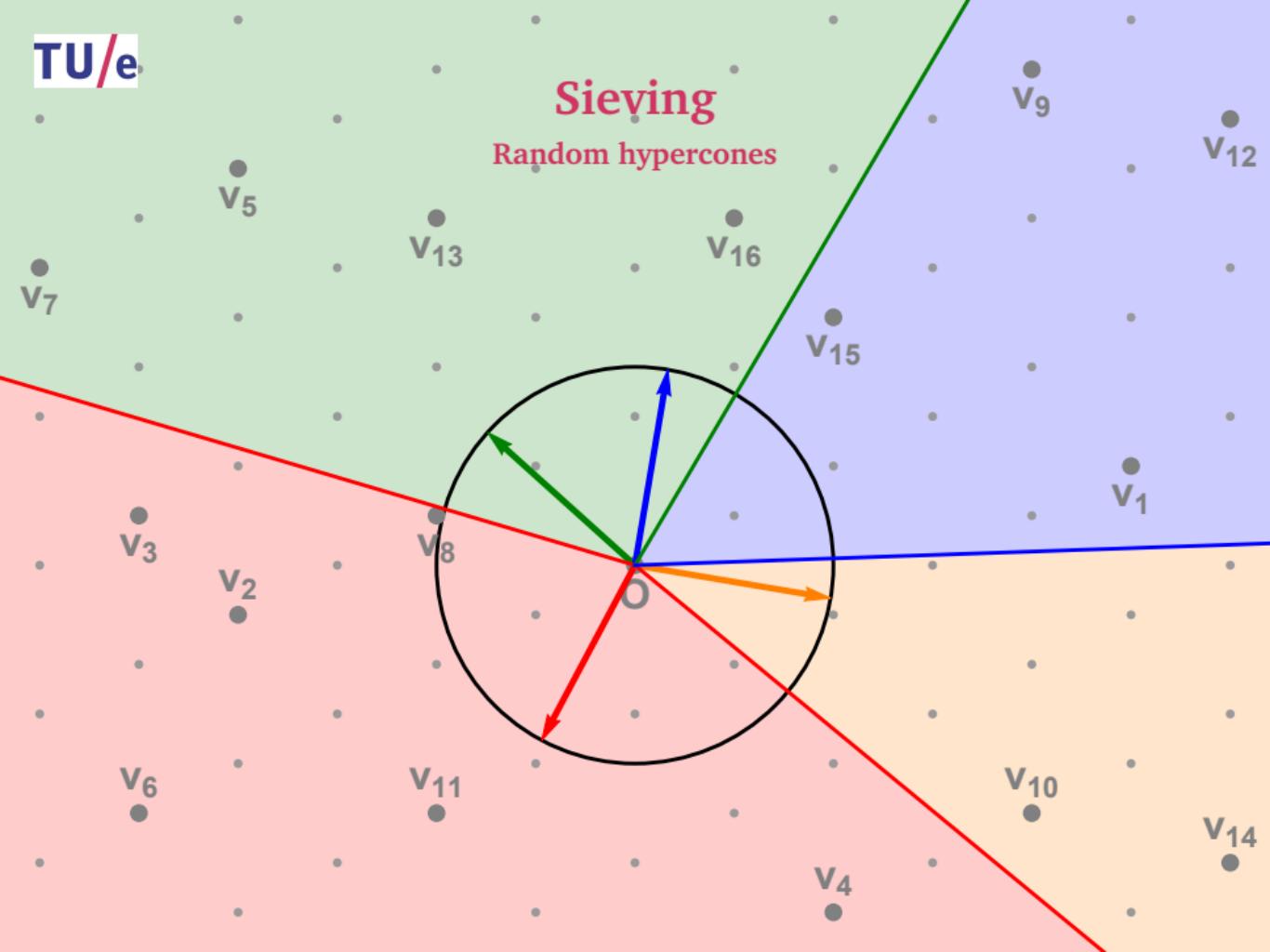
## Sieving

Random hypercones



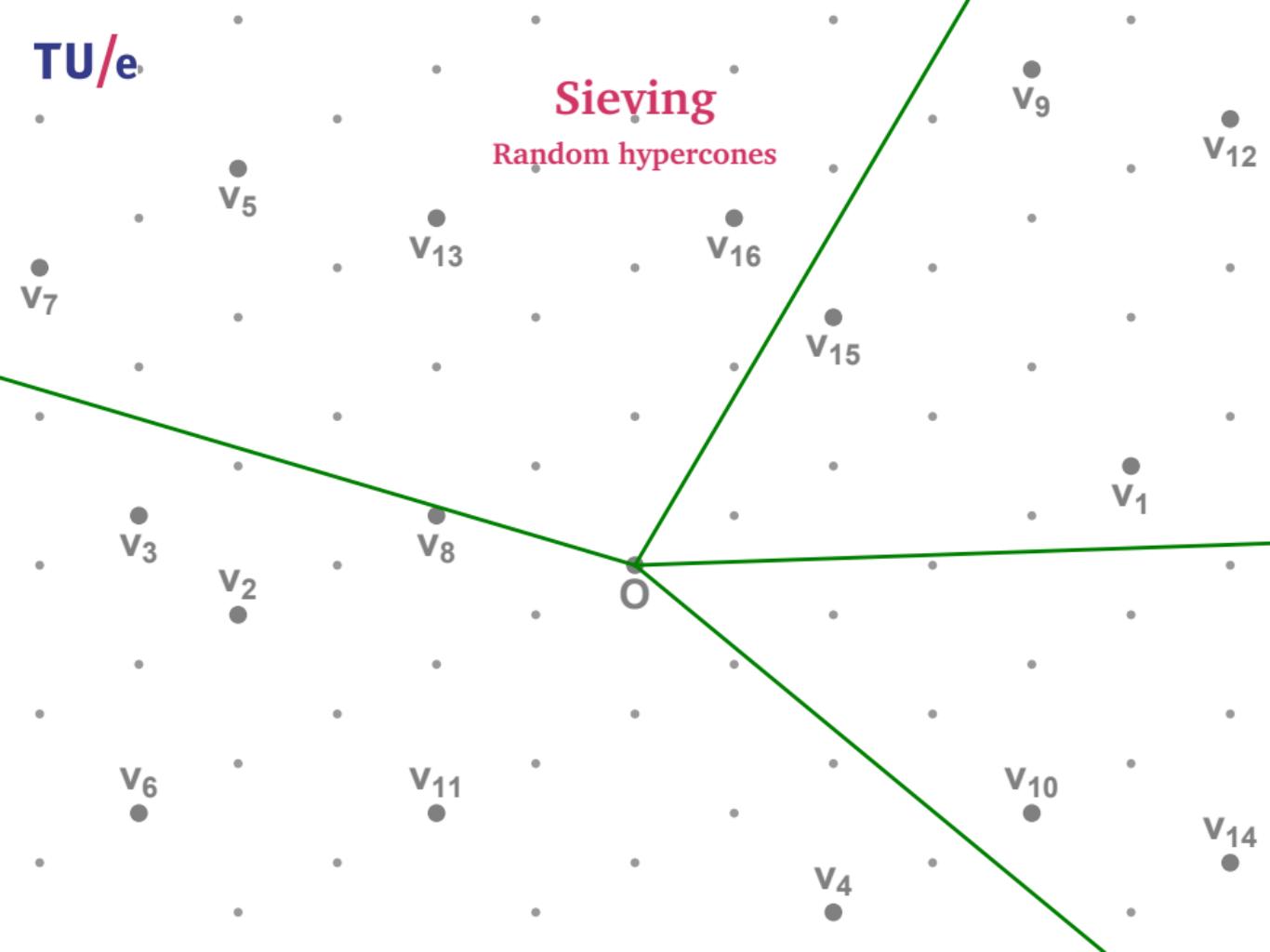
## Sieving

Random hypercones



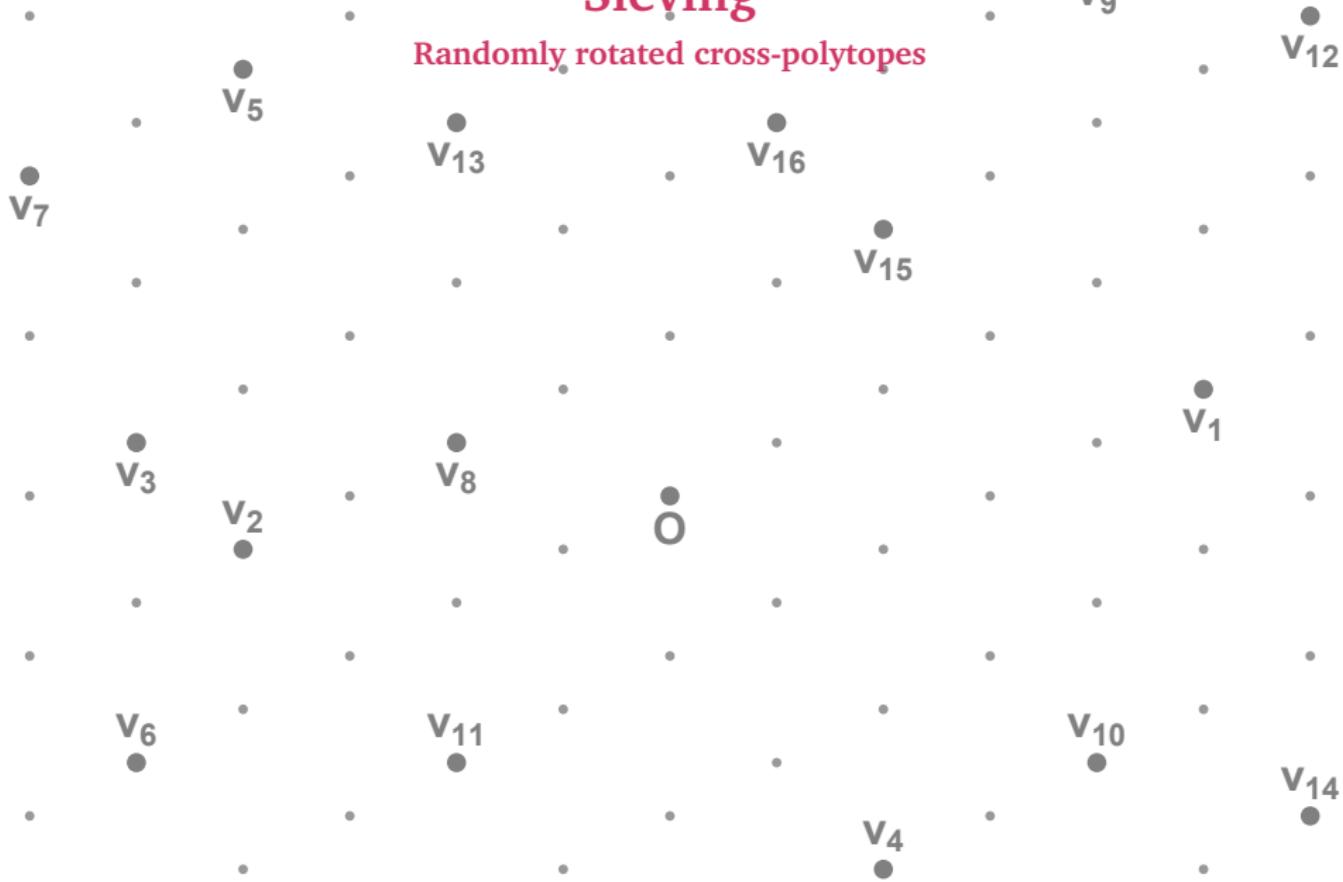
# Sieving

Random hypercones



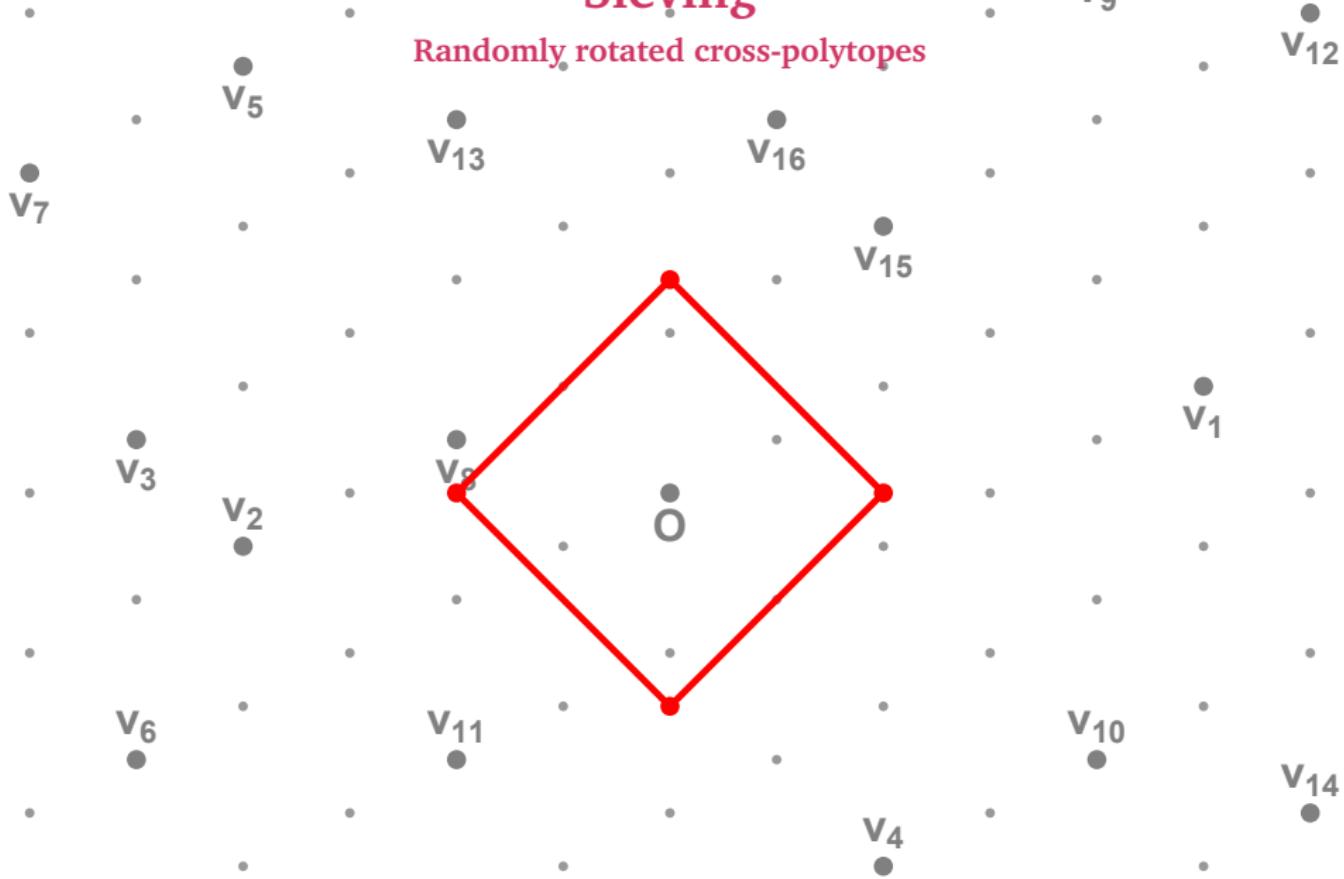
## Sieving

Randomly rotated cross-polytopes



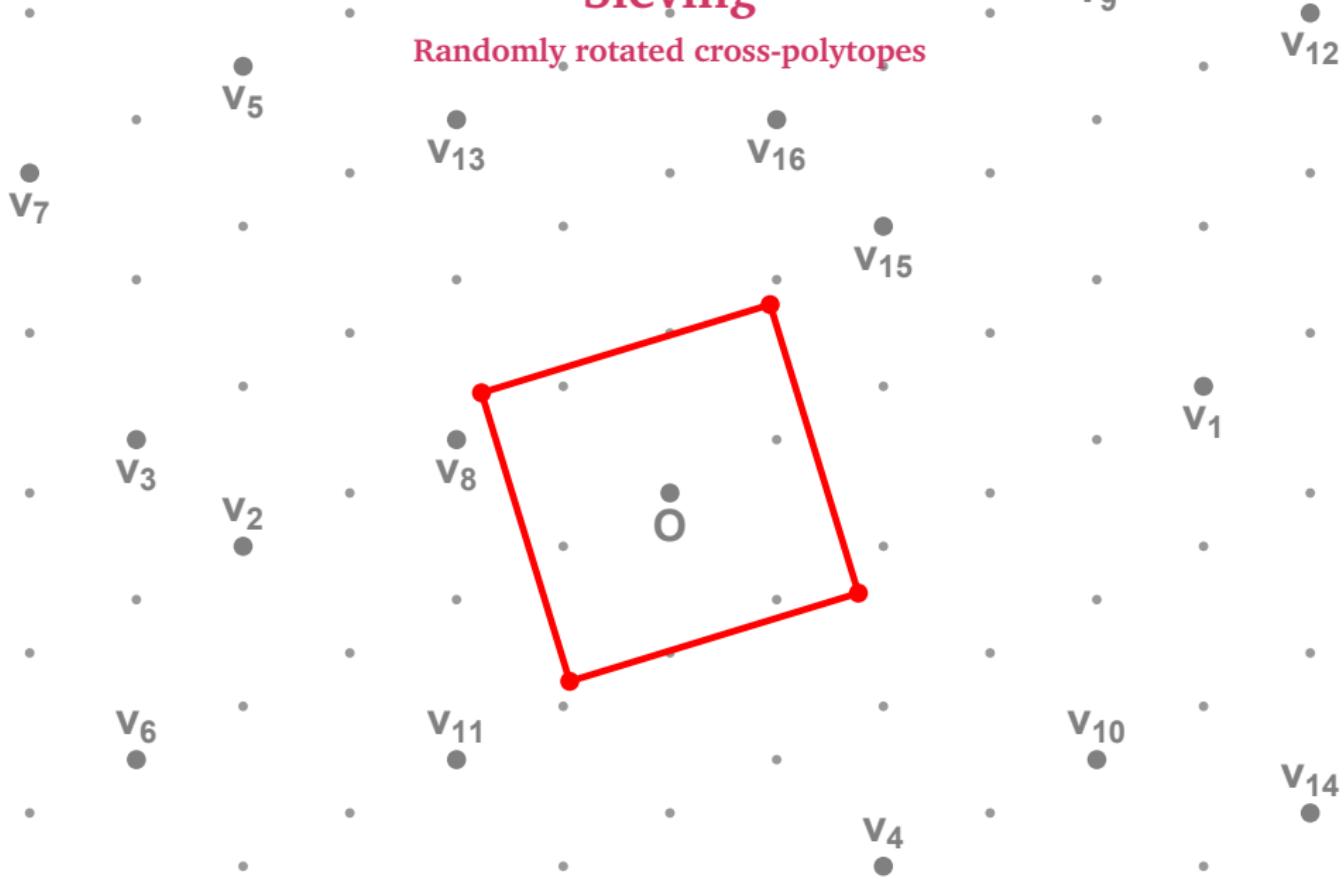
## Sieving

Randomly rotated cross-polytopes



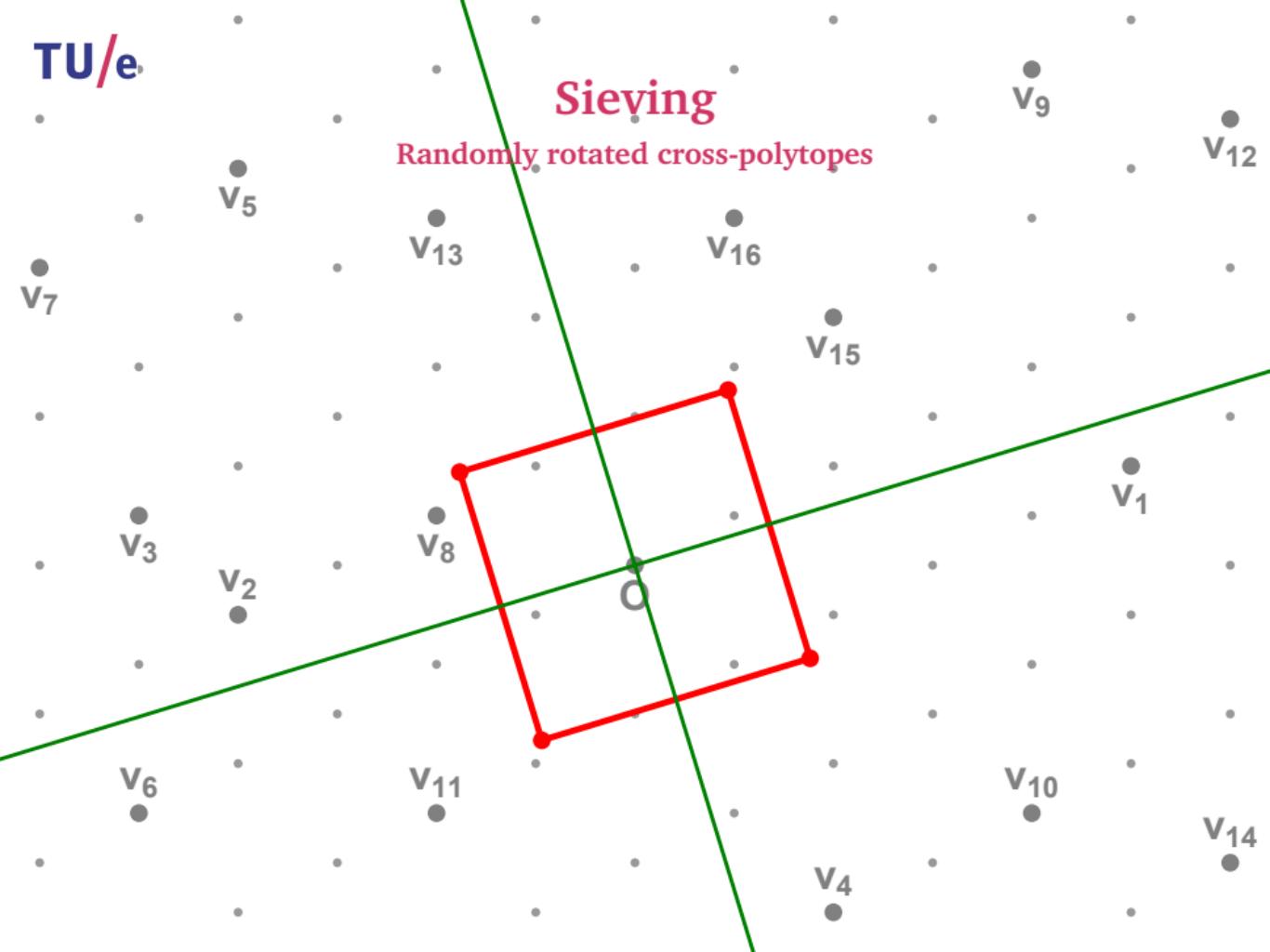
## Sieving

Randomly rotated cross-polytopes



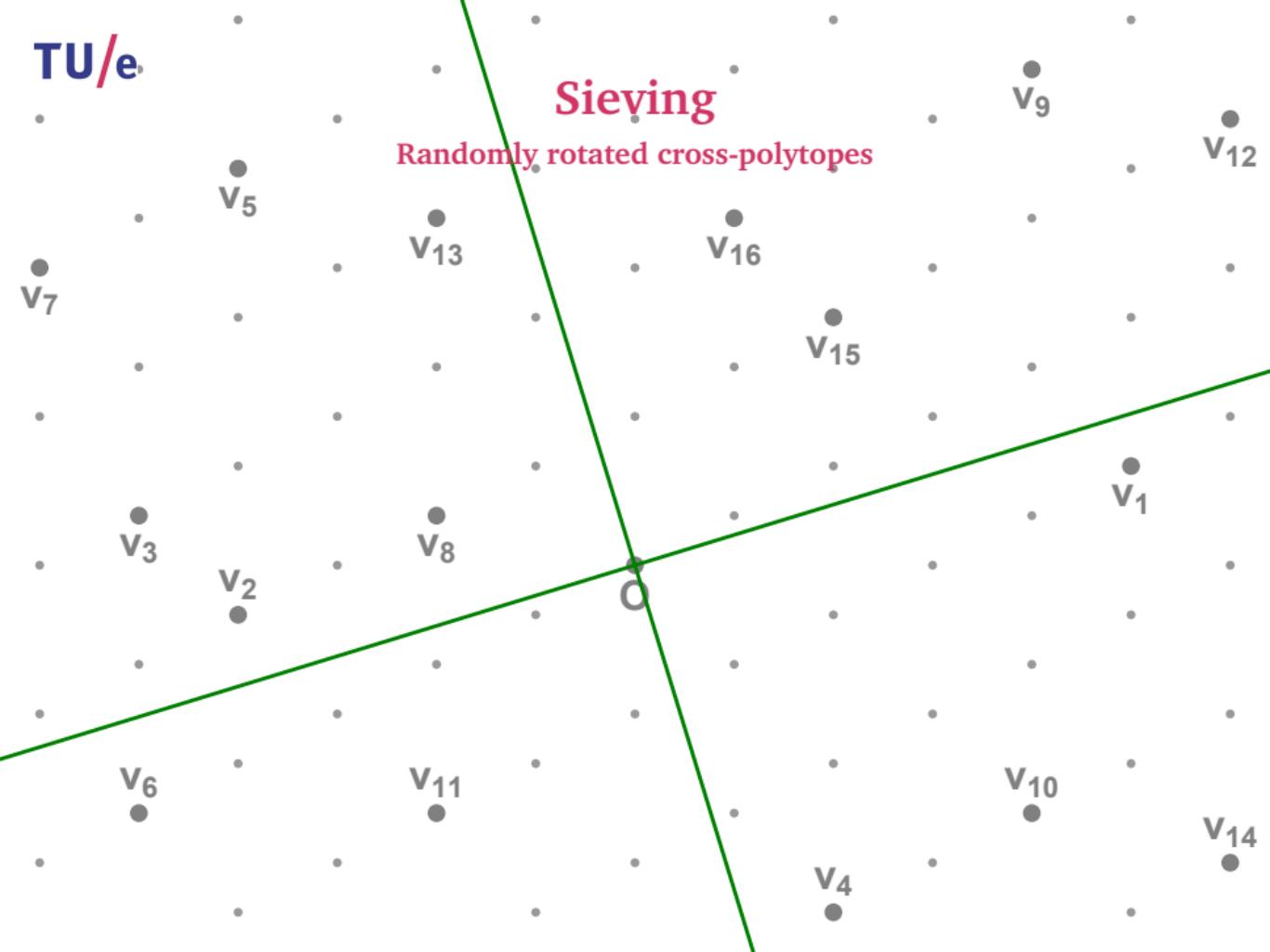
# Sieving

Randomly rotated cross-polytopes



## Sieving

Randomly rotated cross-polytopes



# Outline

- SVP algorithms

- Enumeration

- Sieving

- SVP hardness

- Theory

- Practice

- NIST submissions

- Conclusion

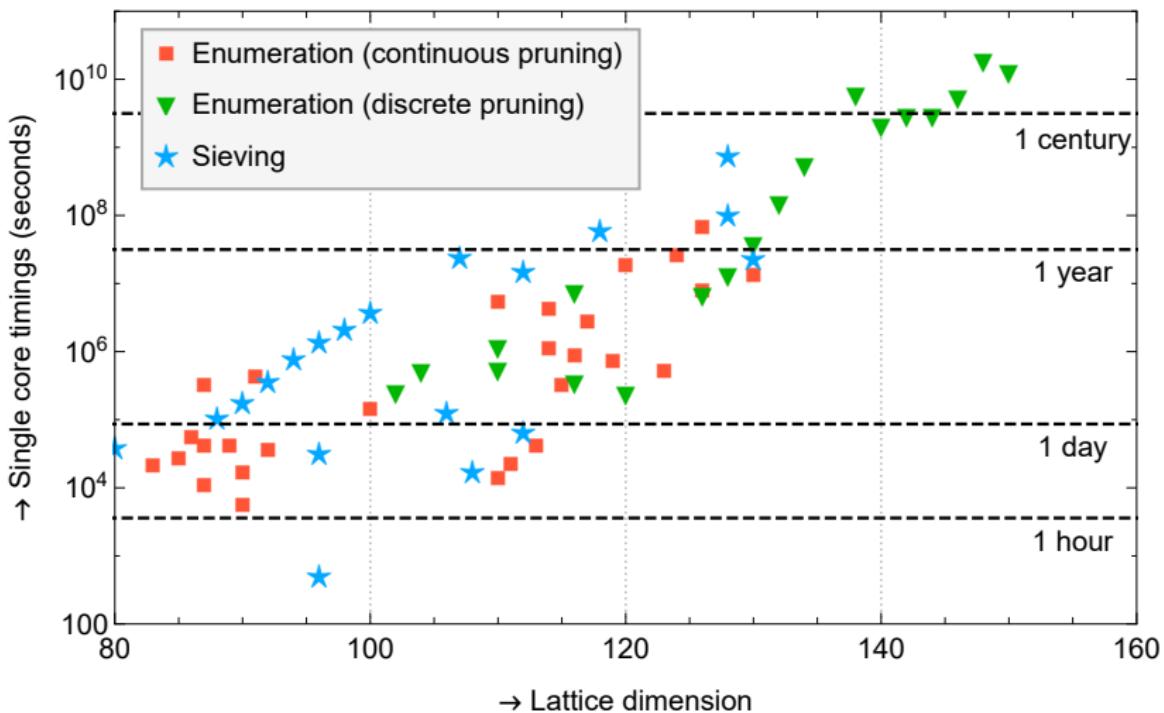
# SVP hardness

## Theory

	Algorithm	$\log_2(\text{Time})$	$\log_2(\text{Space})$
Proven SVP	Enumeration [Poh81, Kan83, ..., MW15, AN17]	$O(n \log n)$	$O(\log n)$
	AKS-sieve [AKS01, NV08, MV10, HPS11]	$3.398n$	$1.985n$
	ListSieve [MV10, MDB14]	$3.199n$	$1.327n$
	Birthday sieves [PS09, HPS11]	$2.465n$	$1.233n$
	Enumeration/DGS hybrid [CCL17]	$2.048n$	$0.500n$
	Voronoi cell algorithm [AEVZ02, MV10b]	$2.000n$	$1.000n$
	Quantum sieve [LMP13, LMP15]	$1.799n$	$1.286n$
	Quantum enum/DGS [CCL17]	$1.256n$	<b>0.500n</b>
Sieving	Discrete Gaussian sampling [ADRS15, ADS15, AS18]	<b>1.000n</b>	$1.000n$
	The Nguyen–Vidick sieve [NV08]	$0.415n$	$0.208n$
	GaussSieve [MV10, ..., IKMT14, BNvdP16, YKCY17]	$0.415n$	$0.208n$
	Triple sieve [BLS16, HK17]	$0.396n$	$0.189n$
	Leveled sieving [WLTB11, ZPH13]	$0.3778n$	$0.283n$
	Overlattice sieve [BGJ14]	$0.3774n$	$0.293n$
	Quantum sieve [LMP13]	$0.312n$	$0.208n$
Sieving + NNS	Triple sieve with NNS [HK17, HKL18]	$0.359n$	<b>0.189n</b>
	Hyperplane LSH [Cha02, Laa15, ..., LM18, Duc18]	$0.337n$	$0.337n$
	Graph-based NNS [EPY99, DCL11, MPLK14, Laa18]	$0.327n$	$0.282n$
	Hypercube LSH [TT07, Laa17]	$0.322n$	$0.322n$
	May–Ozerov NNS [MO15, BGJ15]	$0.311n$	$0.311n$
	Spherical LSH [AINR14, LdW15]	$0.298n$	$0.298n$
	Cross-polytope LSH [TT07, AILRS15, BL16, KW17]	$0.298n$	$0.298n$
	Spherical LSF [BDGL16, MLB17, ALRW17, Chr17]	<b>0.293n</b>	$0.293n$
	Quantum NNS sieve [LMP15, Laa16]	<b>0.265n</b>	$0.265n$

## SVP hardness

## Practice



# SVP hardness

## NIST submissions

Title	S	E	O	Submitters
CRYSTALS-Dilithium	•			Lyubashevsky, Ducas, Kiltz, Lepoint, Schwabe, Seiler, Stehlé
CRYSTALS-Kyber	•			Schwabe, Avanzi, Bos, Ducas, Kiltz, Lepoint, Lyubashevsky, Schanck, ...
Ding Key Exchange	•			Ding, Takagi, Gao, Wang
DRS			•	Plantard, Sipasseuth, Dumondelle, Susilo
(R.)EMBLEM	•			Seo, Park, Lee, Kim, Lee
FALCON	•			Prest, Fouque, Hoffstein, Kirchner, Lyubashevsky, Pornin, Ricosset, ...
FrodoKEM	•			Naehrig, Alkim, Bos, Ducas, Easterbrook, LaMacchia, Longa, Mironov, ...
Giophantus	•			Akiyama, Goto, Okumura, Takagi, Nuida, Hanaoka, Shimizu, Ikematsu
HILA5	•			Saarinen
KCL	•			Zhao, Jin, Gong, Sui
KINDI	•			El Bansarkhani
LAC	•			Lu, Liu, Jia, Xue, He, Zhang
LIMA	•			Smart, Albrecht, Lindell, Orsini, Osheter, Paterson, Peer
Lizard	•			Cheon, Park, Lee, Kim, Song, Hong, Kim, Kim, Hong, Yun, Kim, Park, ...
LOTUS		•		Phong, Hayashi, Aono, Moriai
NewHope	•			Pöppelmann, Alkim, Avanzi, Bos, Ducas, De La Piedra, Schwabe, Stebila
NTRUEncrypt	◦	◦		Zhang, Chen, Hoffstein, Whyte
NTRU-HRSS-KEM	•			Schanck, Hülsing, Rijneveld, Schwabe
NTRU Prime		•		Bernstein, Chuengsatiansup, Lange, Van Vredendaal
Odd Manhattan		•		Plantard
pqNTRUSign	◦	◦		Zhang, Chen, Hoffstein, Whyte
qTESLA	•			Bindel, Akleylek, Alkim, Barreto, Buchmann, Eaton, Gutoski, Krämer, ...
Round2	•			Garcia-Morchon, Zhang, Bhattacharya, Rietman, Tolhuizen, Torre-Arce
SABER	•			D'Anvers, Karmakar, Roy, Vercauteren
Three Bears	•			Hamburg
Titanium	•			Steinfeld, Sakzad, Zhao
<b>Totals:</b>	<b>21</b>	<b>3</b>	<b>2</b>	<b>Total: 26 proposals with SVP hardness estimates</b>

\*Not included in the overview: Compact LWE, Mersenne, Ramstake, ...

# SVP hardness

NIST submissions

## Most common hardness estimates:

- Ignore space complexity, ignore  $o(n)$  in time complexity
- Classical sieving:  $2^{0.292n}$  time
- Quantum sieving:  $2^{0.265n}$  time
- “Paranoid bound”:  $2^{0.208n}$  time
  - ▶ Note:  $2^{0.208n}$  is not a “lower bound” (Frodo, ...)
- Complexity of BKZ( $\beta$ )  $\geq$  Complexity of SVP( $\beta$ )

# Conclusion

## Summary

- Lattice-based crypto relies on hardness of finding short vectors
- State-of-the-art basis reduction: BKZ with fast SVP subroutine
- Enumeration for SVP:
  - ▶ Brute-force all combinations of basis vectors
  - ▶ Memory-efficient
  - ▶ Fast pruning heuristics
- Sieving for SVP:
  - ▶ Consider pairwise combinations of many lattice vectors
  - ▶ Large memory requirement
  - ▶ Practical near neighbor speed-ups
- Theory: Sieving superior in high dimensions
- Practice: Enumeration superior in low dimensions
- Hardness estimates: Commonly based on sieving

# Conclusion

## Open problems

### Challenges in provable SVP algorithms

- Sieving: Control distribution of lattice vectors
- DGS: Combine vectors more efficiently
- Obtain proven bounds for “random” lattices

### Challenges in heuristic SVP algorithms

- Enumeration: Find best pruning methods
- Sieving: Find best near neighbor techniques
- Effective time–memory trade-offs

### Challenges in SVP hardness estimation

- Analyze sieving in a more realistic memory model
- Lower bounds (SVP, sieving, enumeration, ...)
- Consensus on attack model/memory costs

Questions?

