

Combining lattice sieving algorithms with (quantum) nearest neighbor searching

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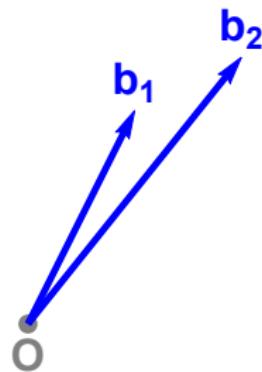
Lattices

What is a lattice?



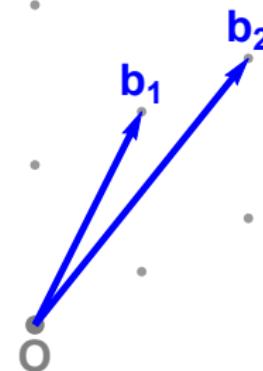
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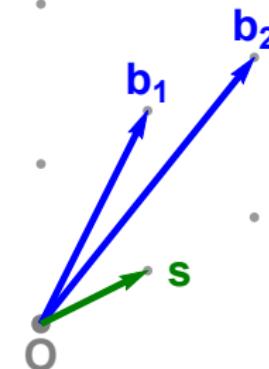
Lattices

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Lattices

Shortest Vector Problem (SVP)



Lattices

Exact SVP algorithms

	Algorithm	$\log_2(\text{Time})$	$\log_2(\text{Space})$
Provably SVP	Enumeration [Poh81, Kan83, ..., GNR10]	$\Omega(n \log n)$	$O(\log n)$
	AKS-sieve [AKS01, NV08, MV10, HPS11]	$3.398n$	$1.985n$
	ListSieve [MV10, MDB14]	$3.199n$	$1.327n$
	AKS-sieve-birthday [PS09, HPS11]	$2.648n$	$1.324n$
	ListSieve-birthday [PS09]	$2.465n$	$1.233n$
	Voronoi cell algorithm [MV10b]	$2.000n$	$1.000n$
SVP	Nguyen-Vidick sieve [NV08]	$0.415n$	$0.208n$
	GaussSieve [MV10, ..., IKMT14, BNvdP14]	$0.415n?$	$0.208n$
	Two-level sieve [WLTB11]	$0.384n$	$0.256n$
	Three-level sieve [ZPH13]	$0.3778n$	$0.283n$
Heuristic			

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	Overlattice sieving [BGJ14]	$0.3774n$	$0.293n$
	Hyperplane LSH [Laa15, MLB15]	$0.337n$	$0.208n$
	May and Ozerov's NNS method [BGJ15]	$0.311n$	$0.208n$
	Spherical LSH [LdW15]	$0.298n$	$0.208n$
	Cross-polytope LSH [BL15]	$0.298n$	$0.208n$
	Spherical filtering [BDGL15]	$0.293n$	$0.208n$

Nguyen-Vidick sieve

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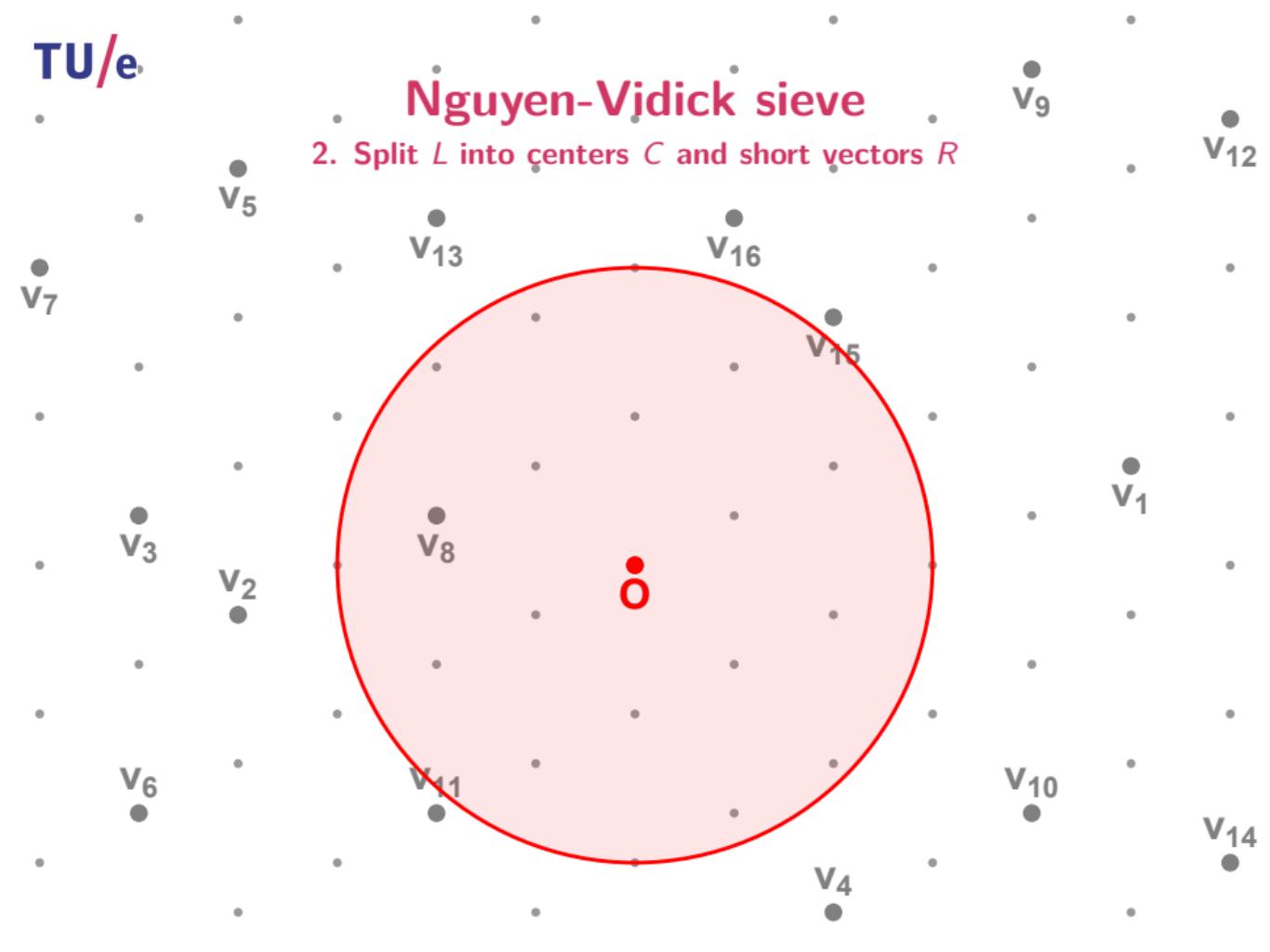
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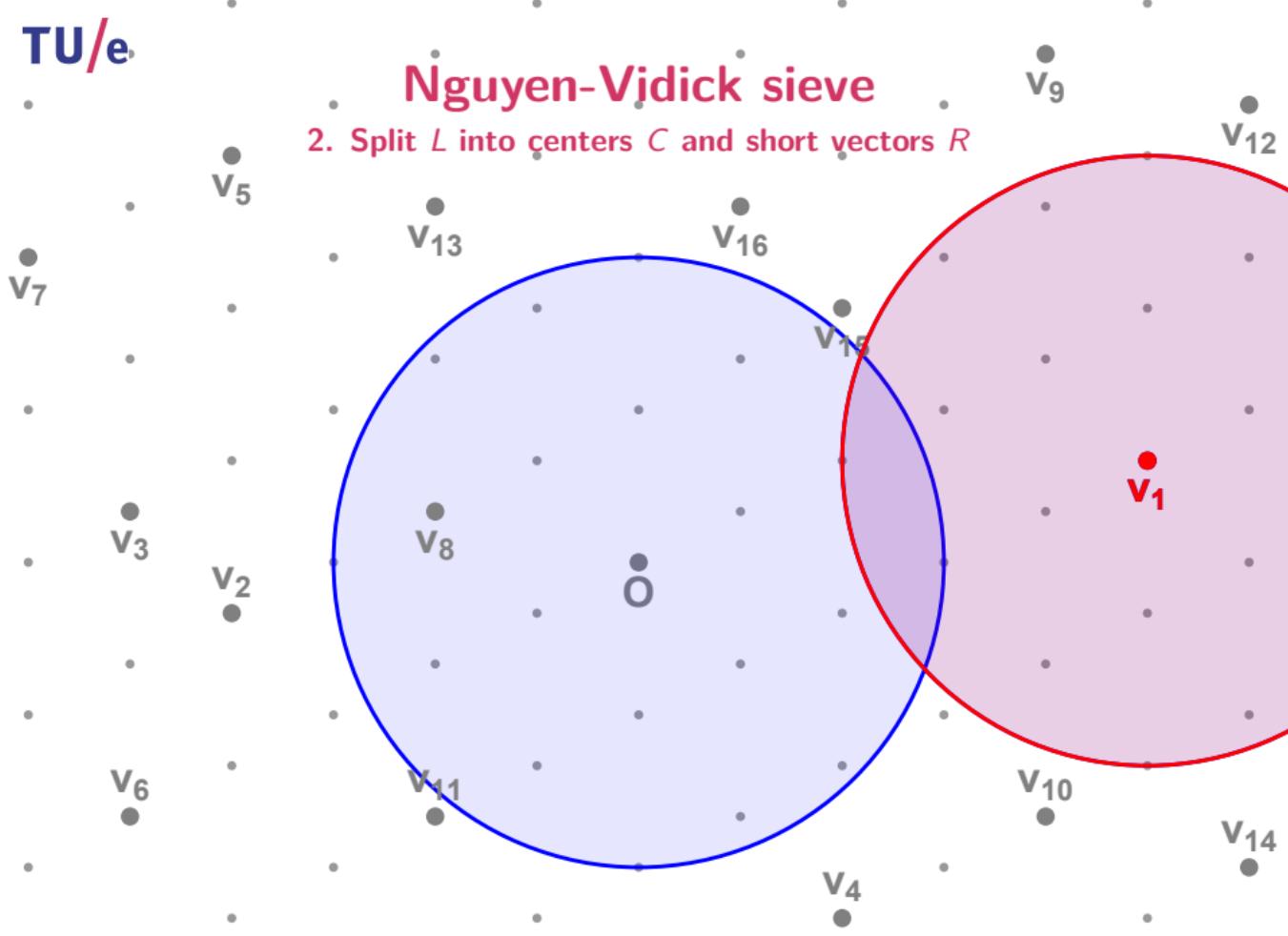
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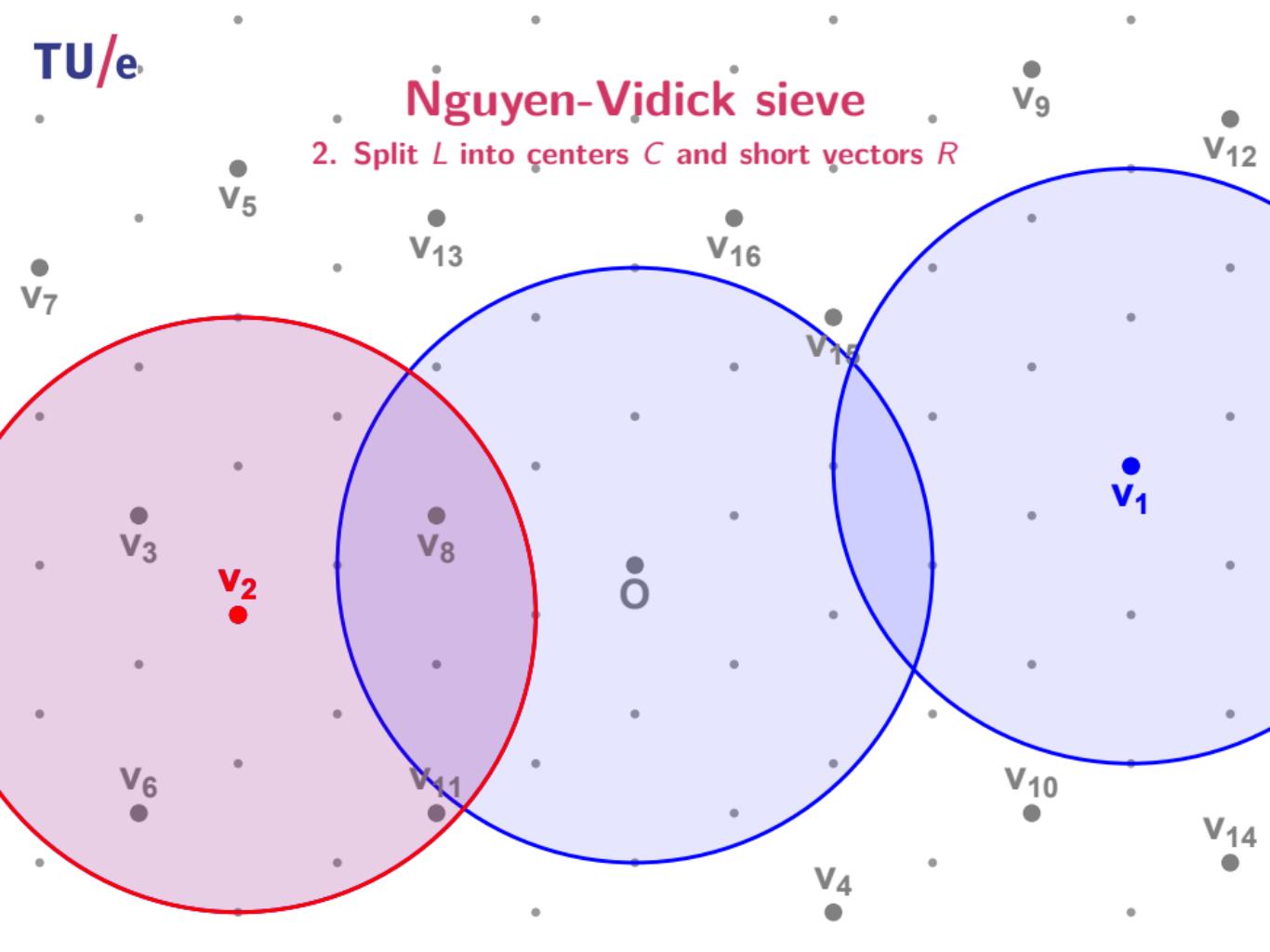
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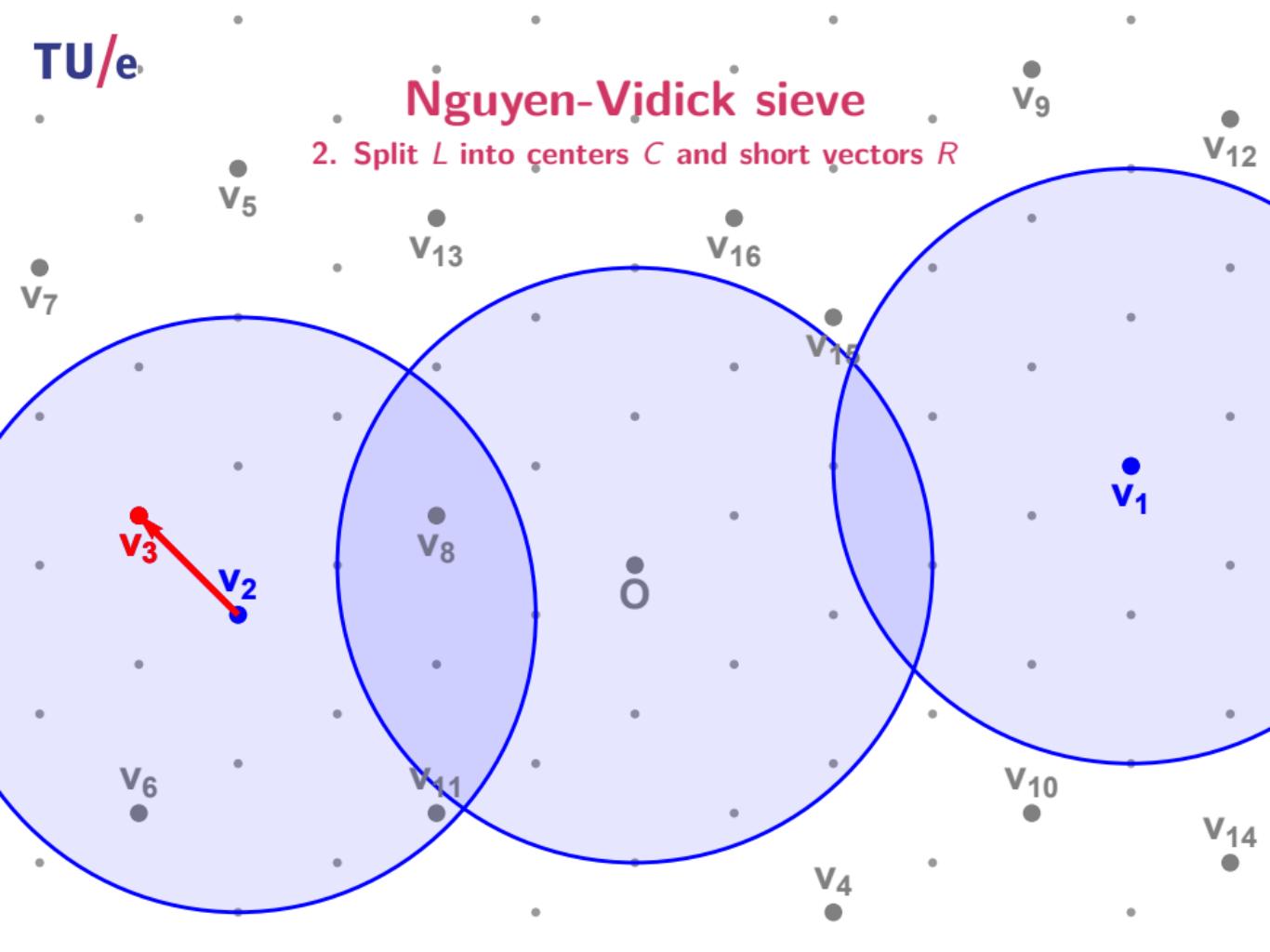
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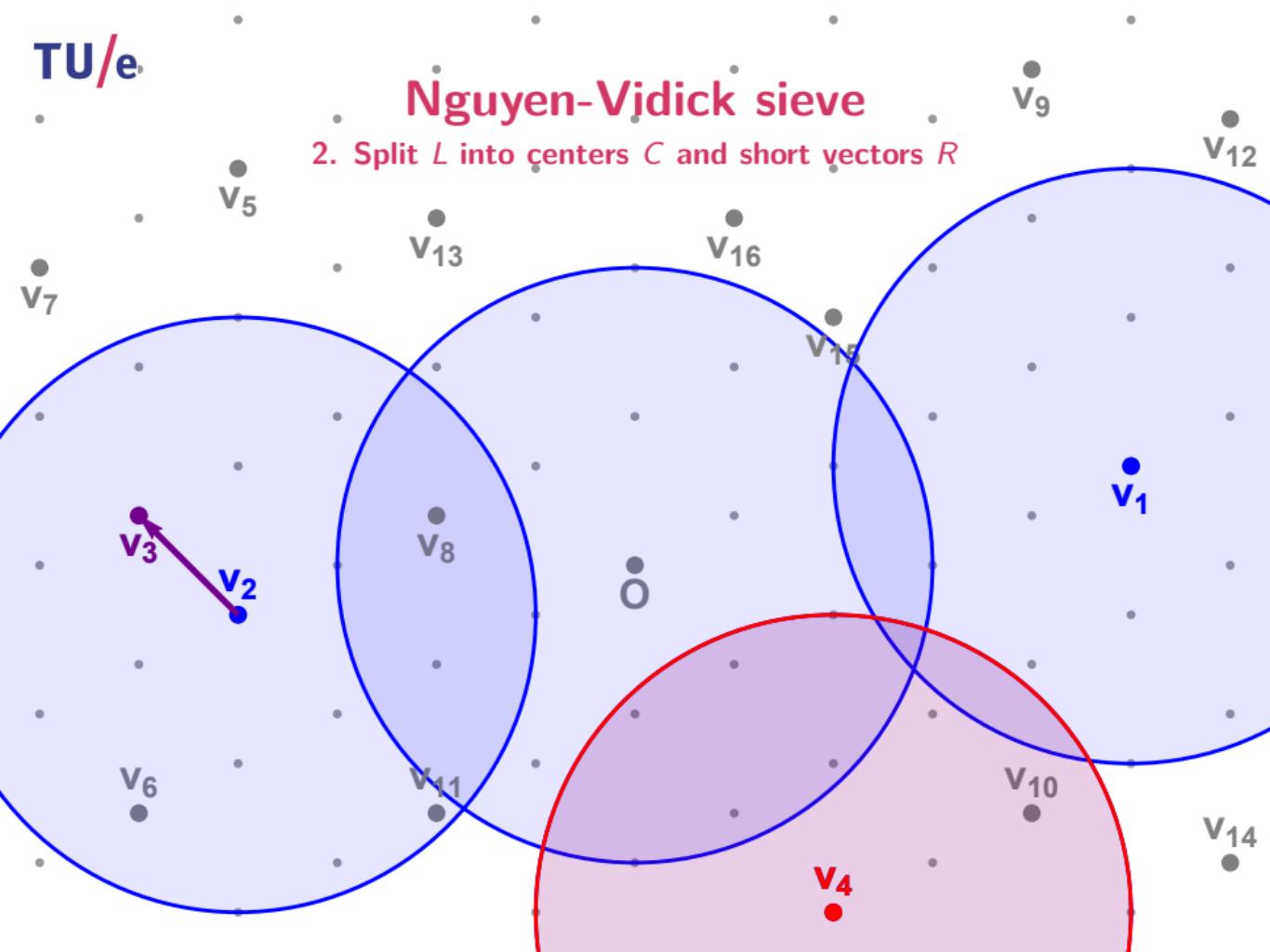
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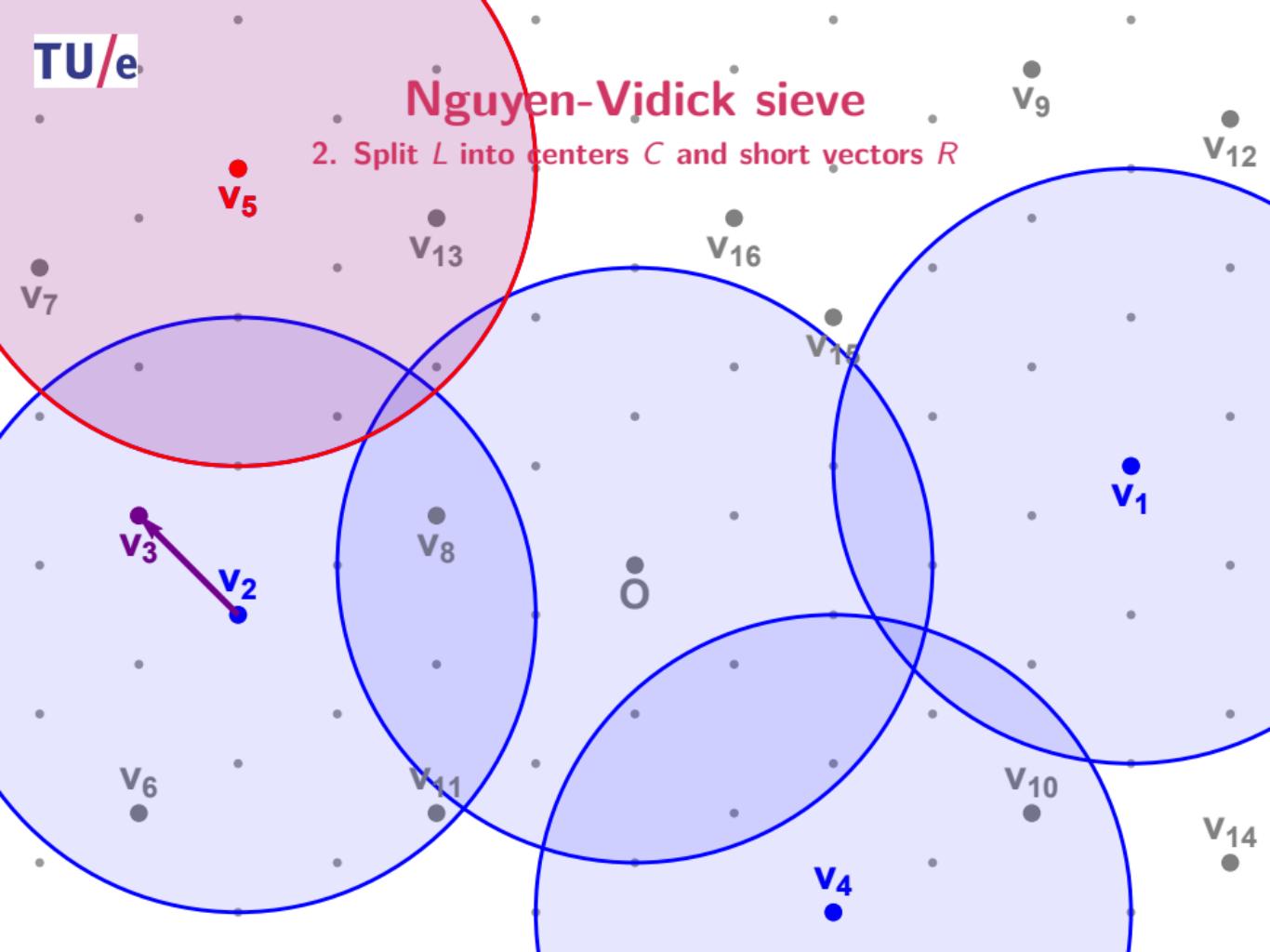
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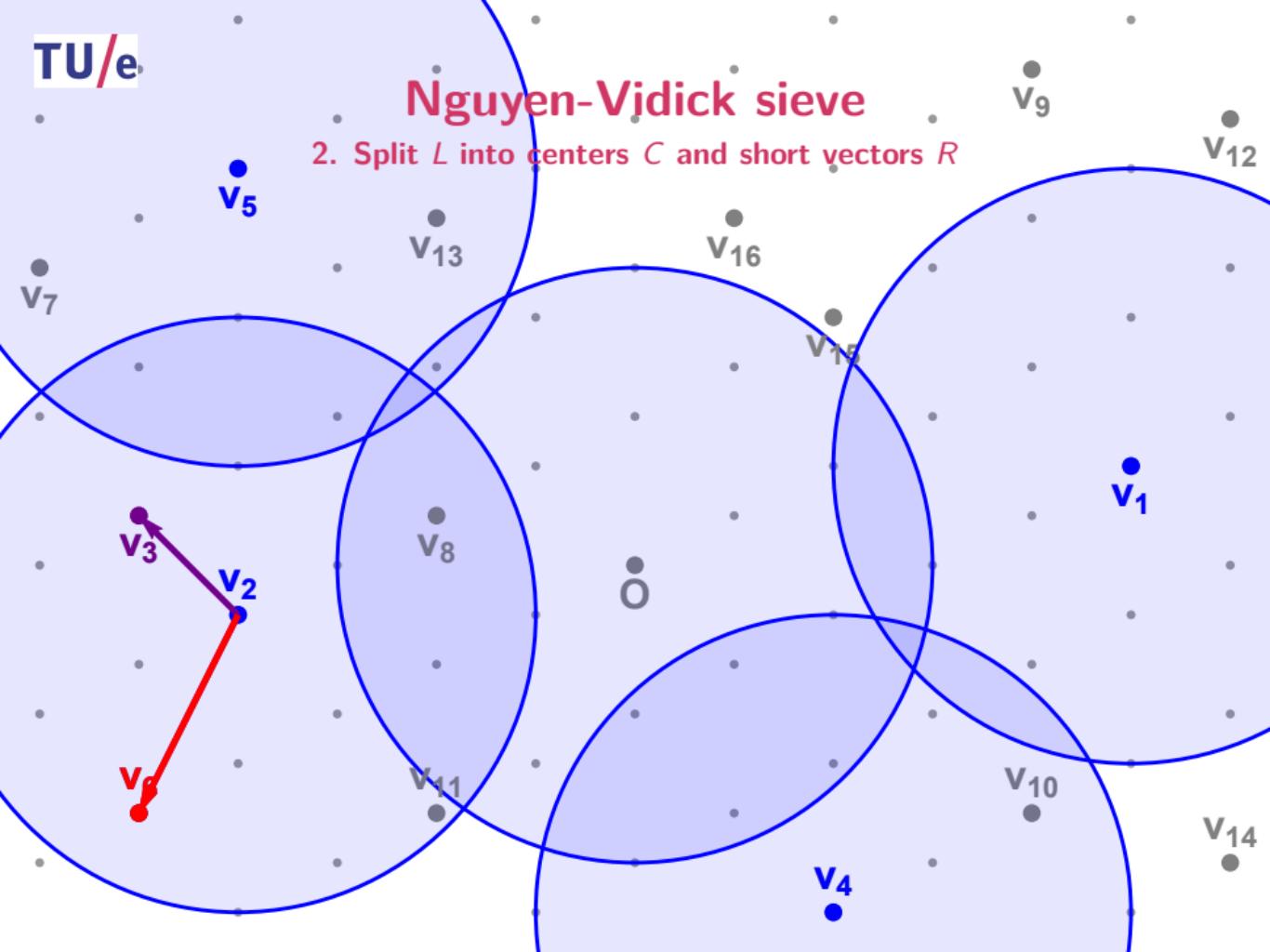
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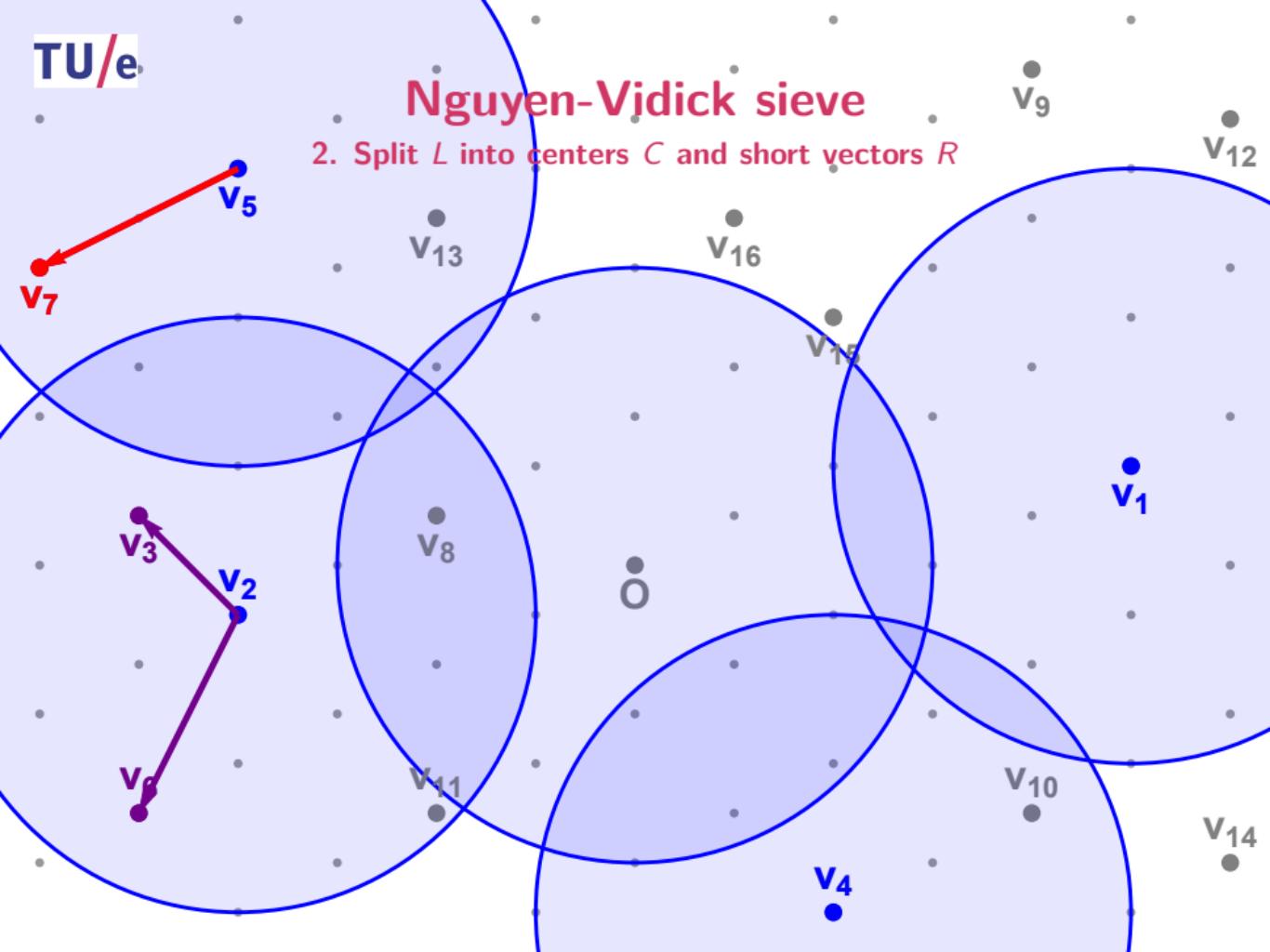
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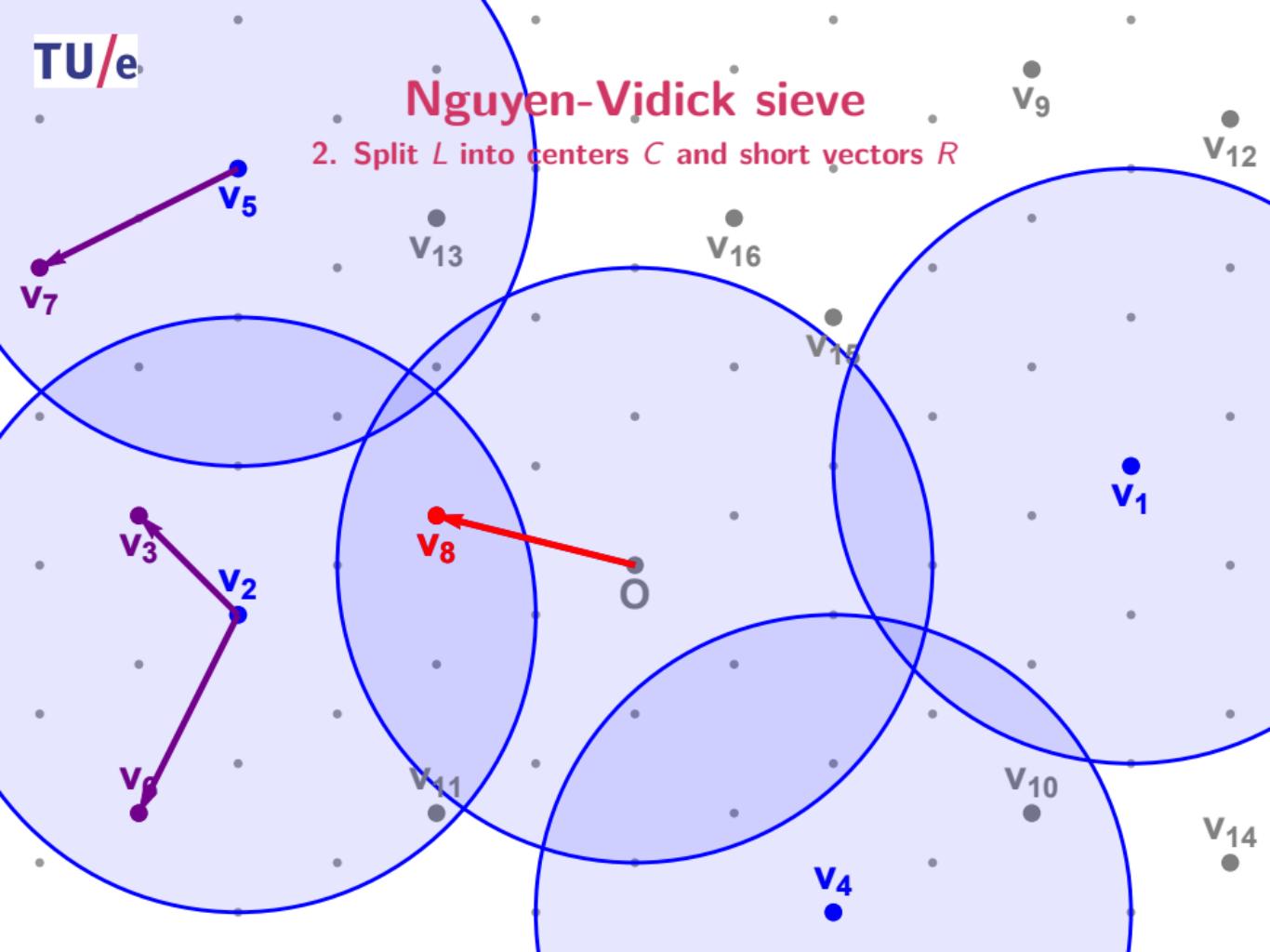
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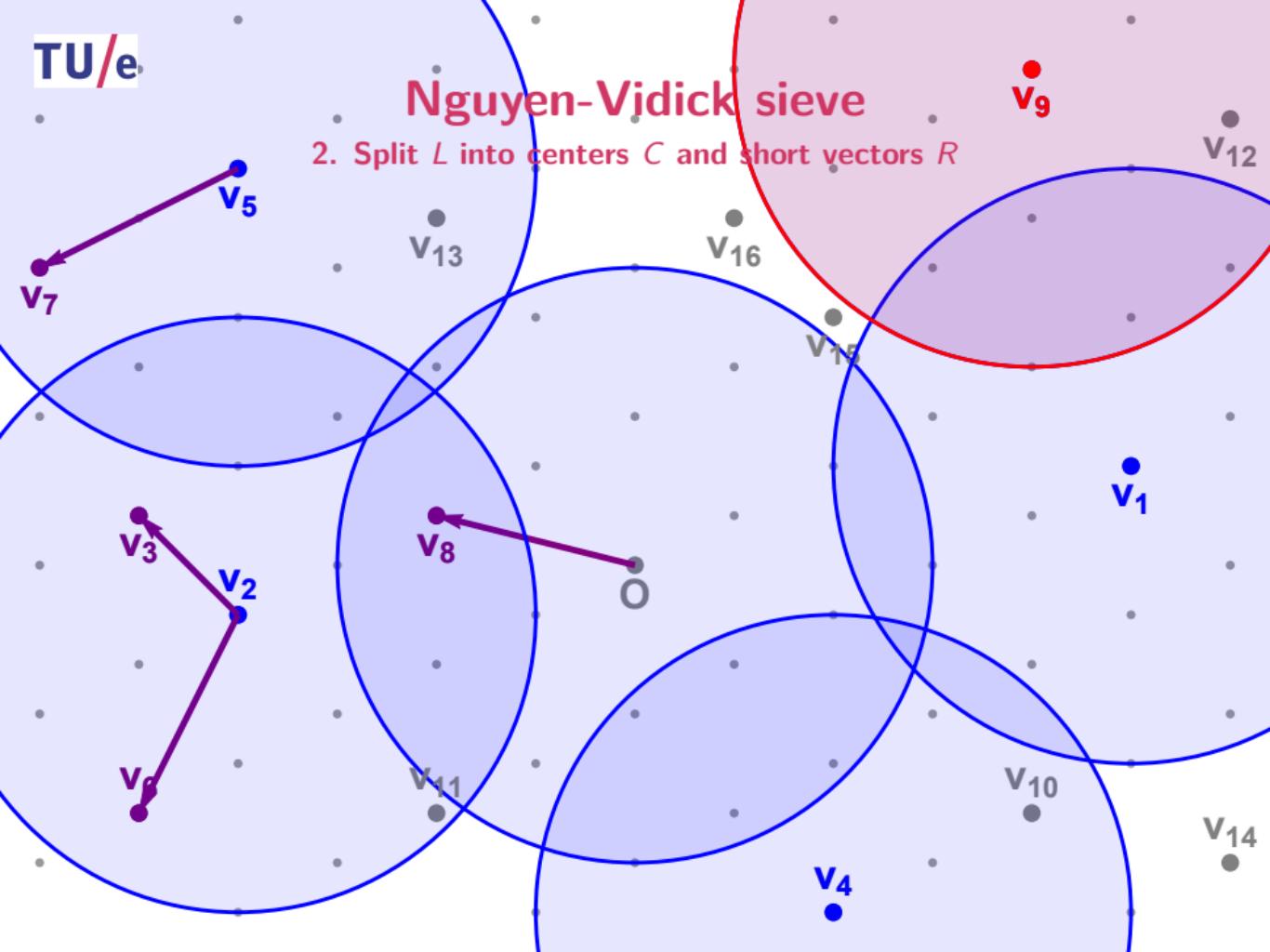
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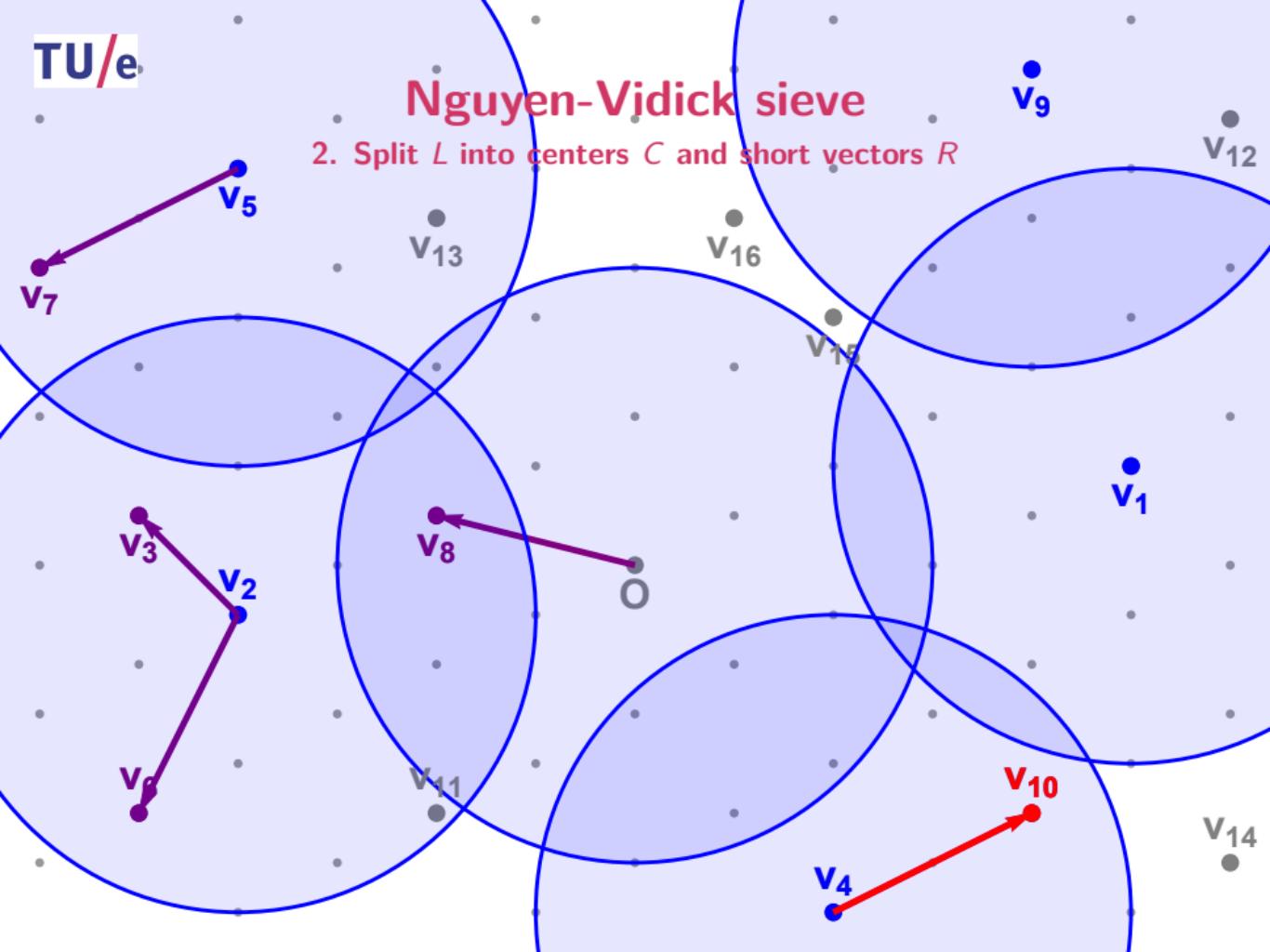
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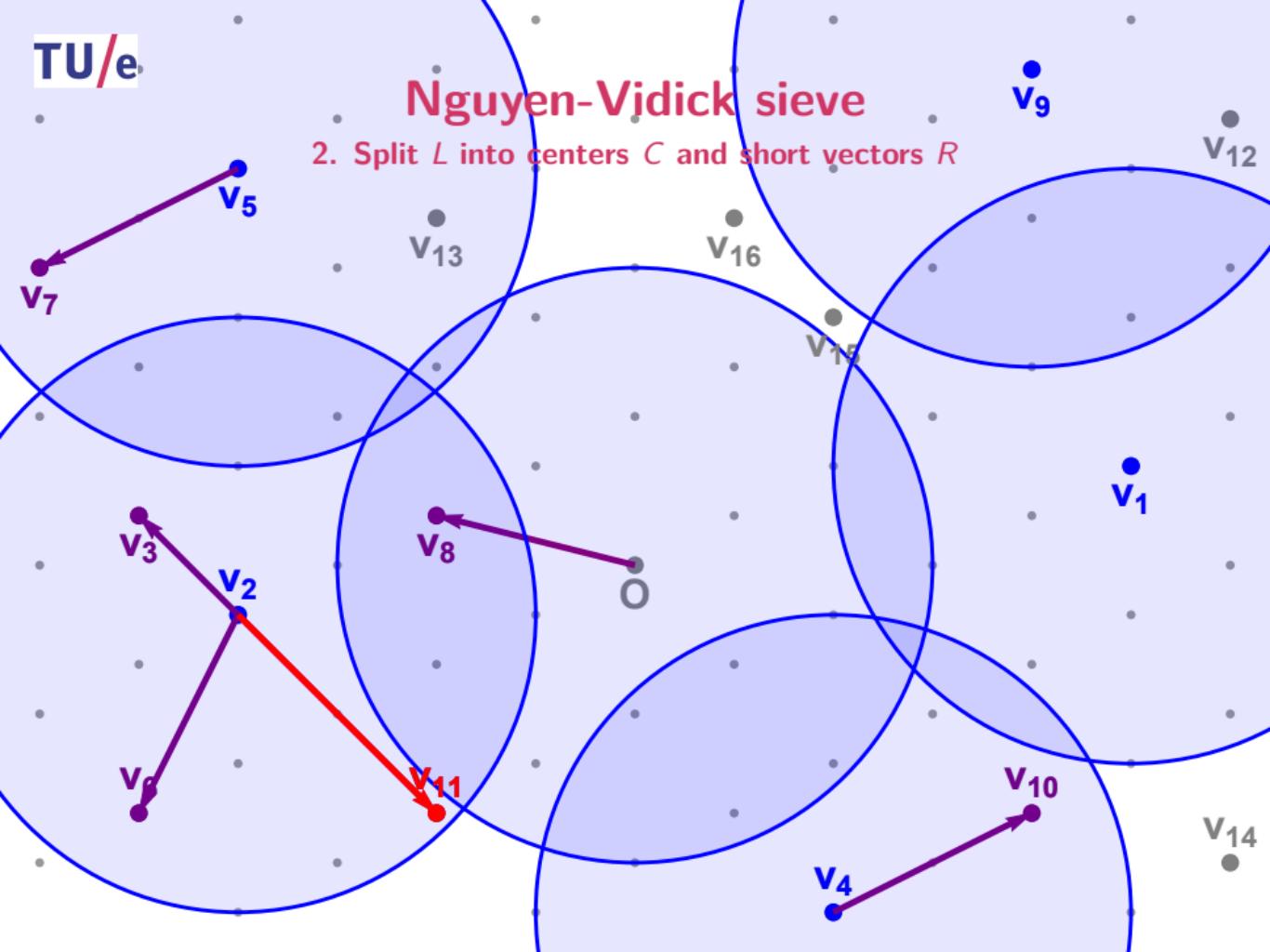
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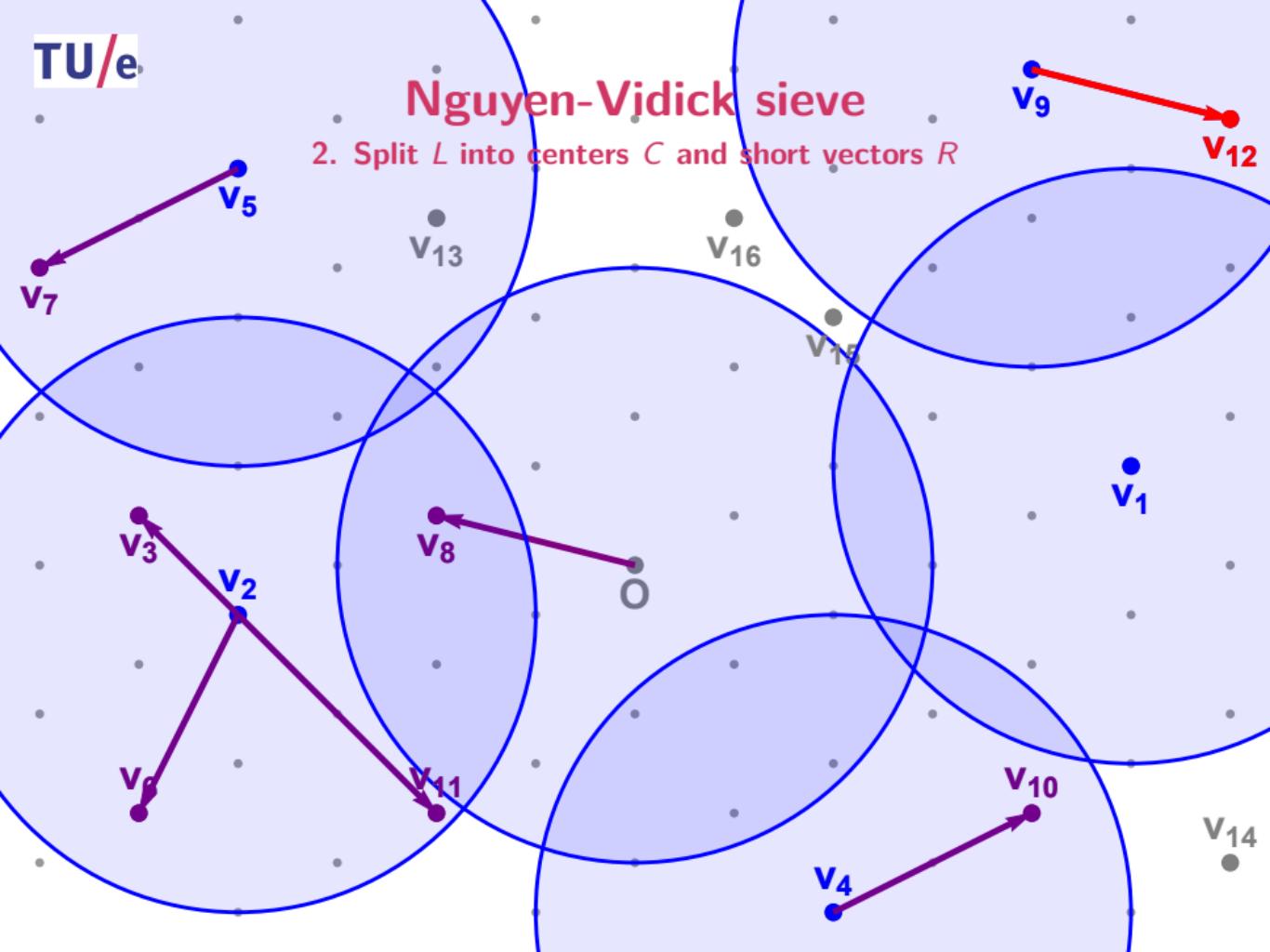
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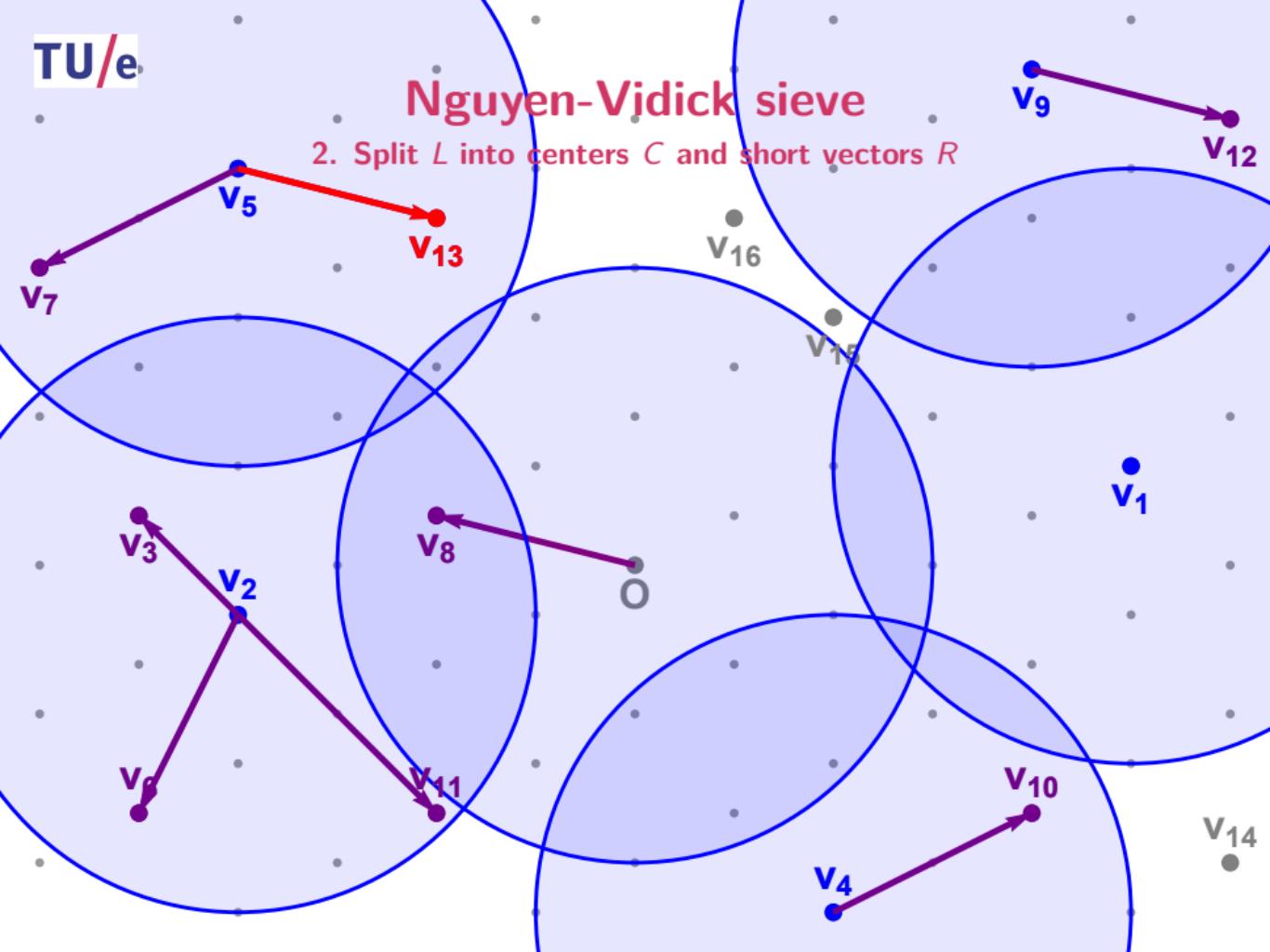
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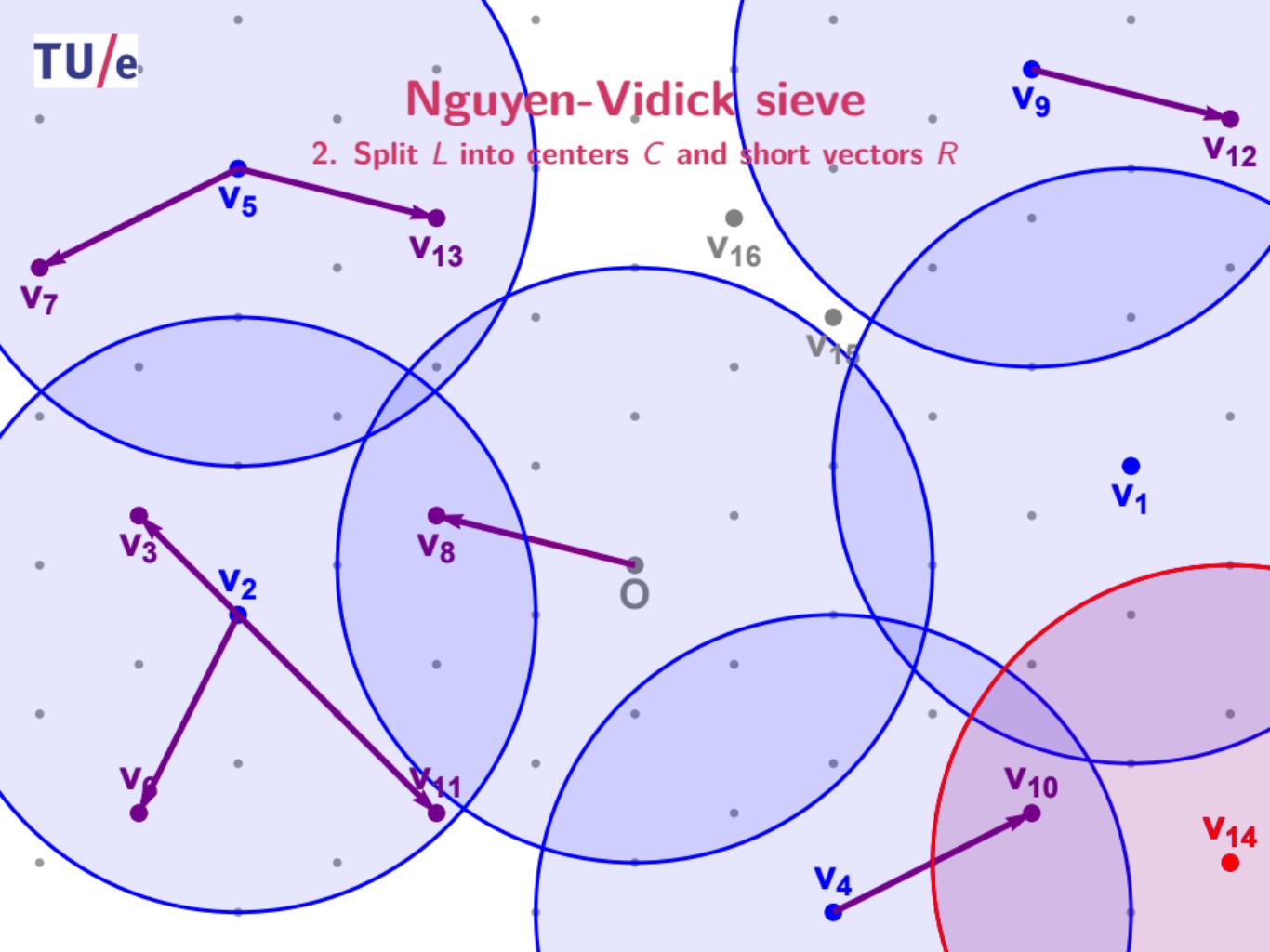
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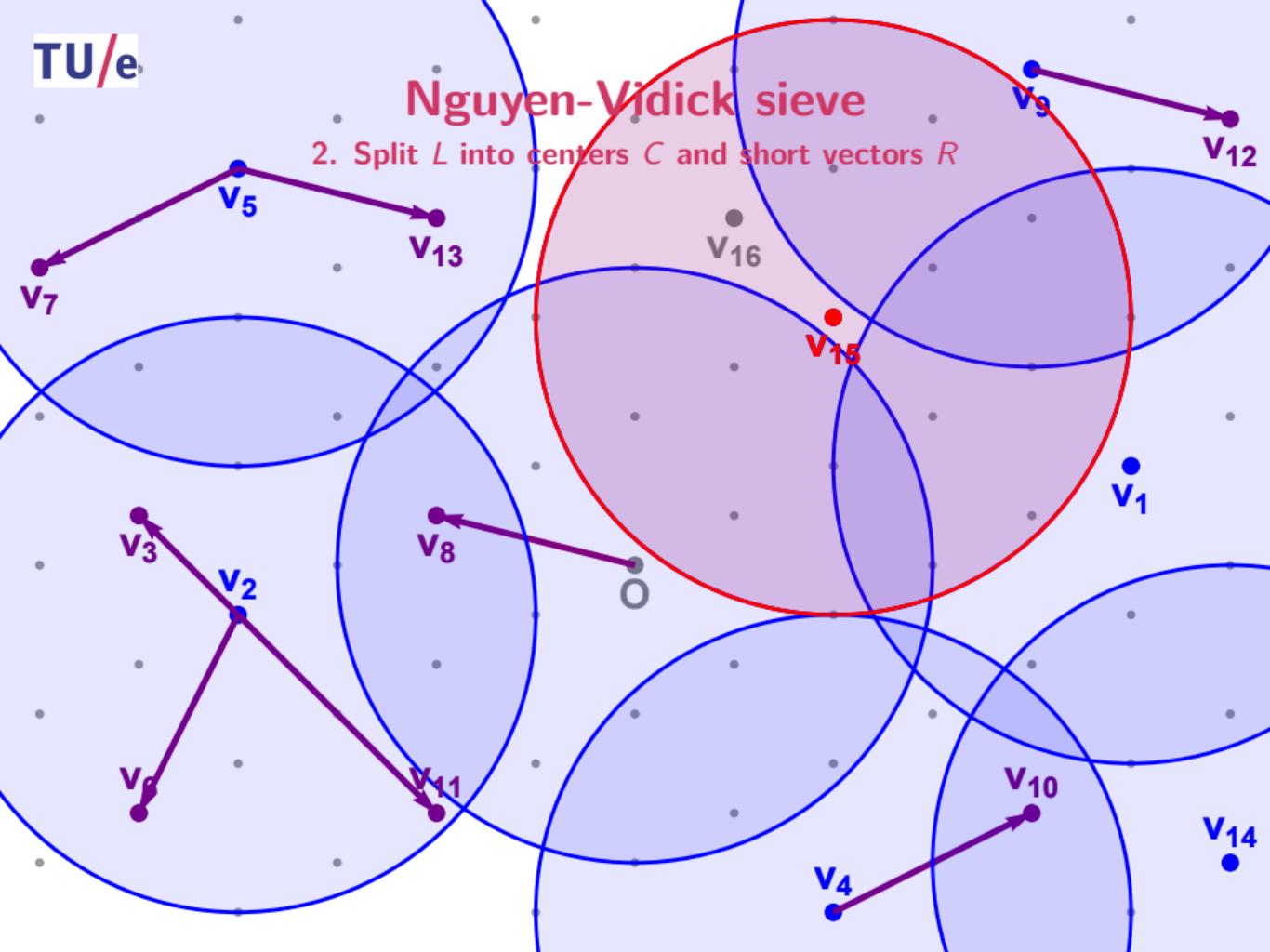
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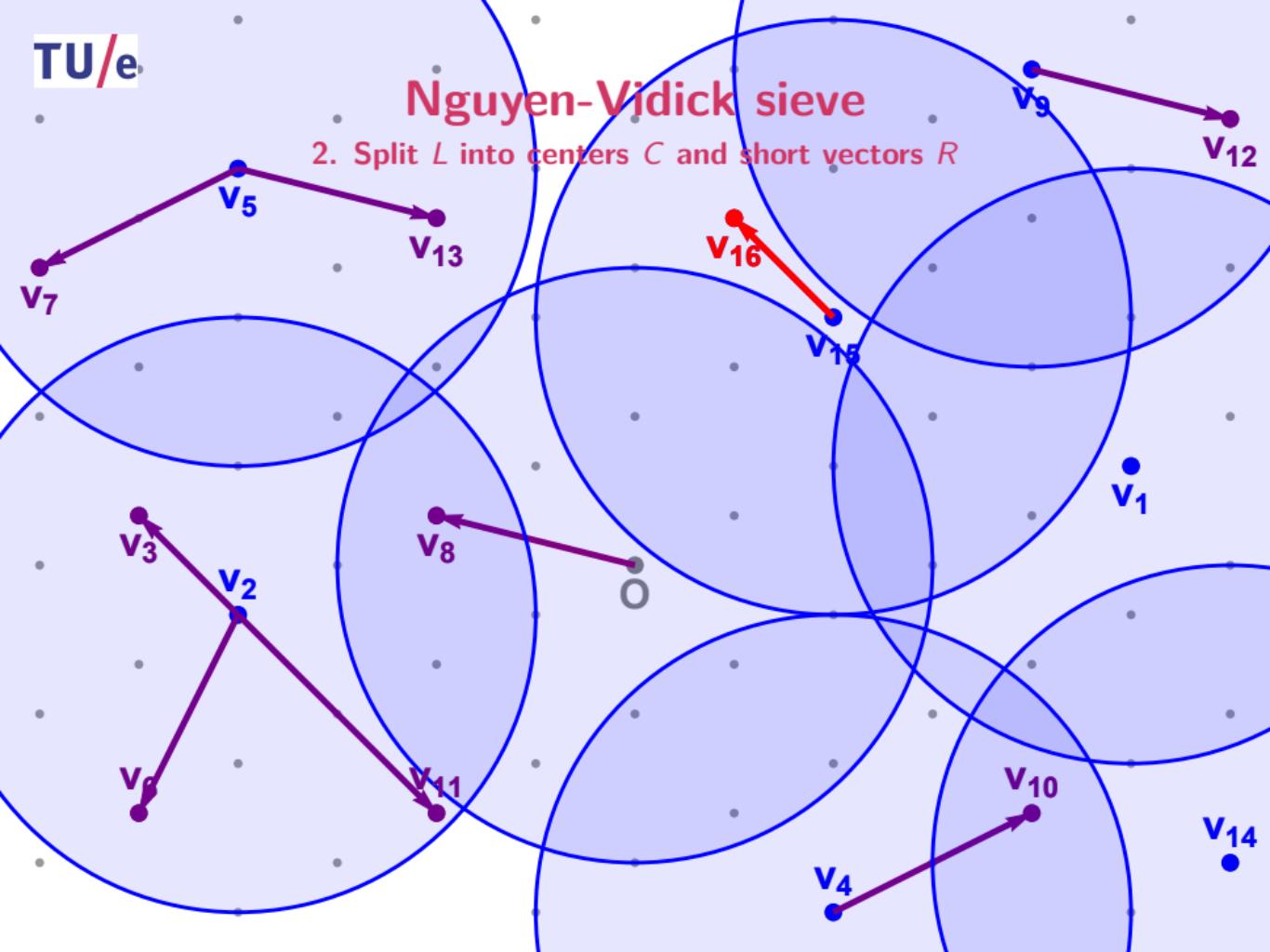
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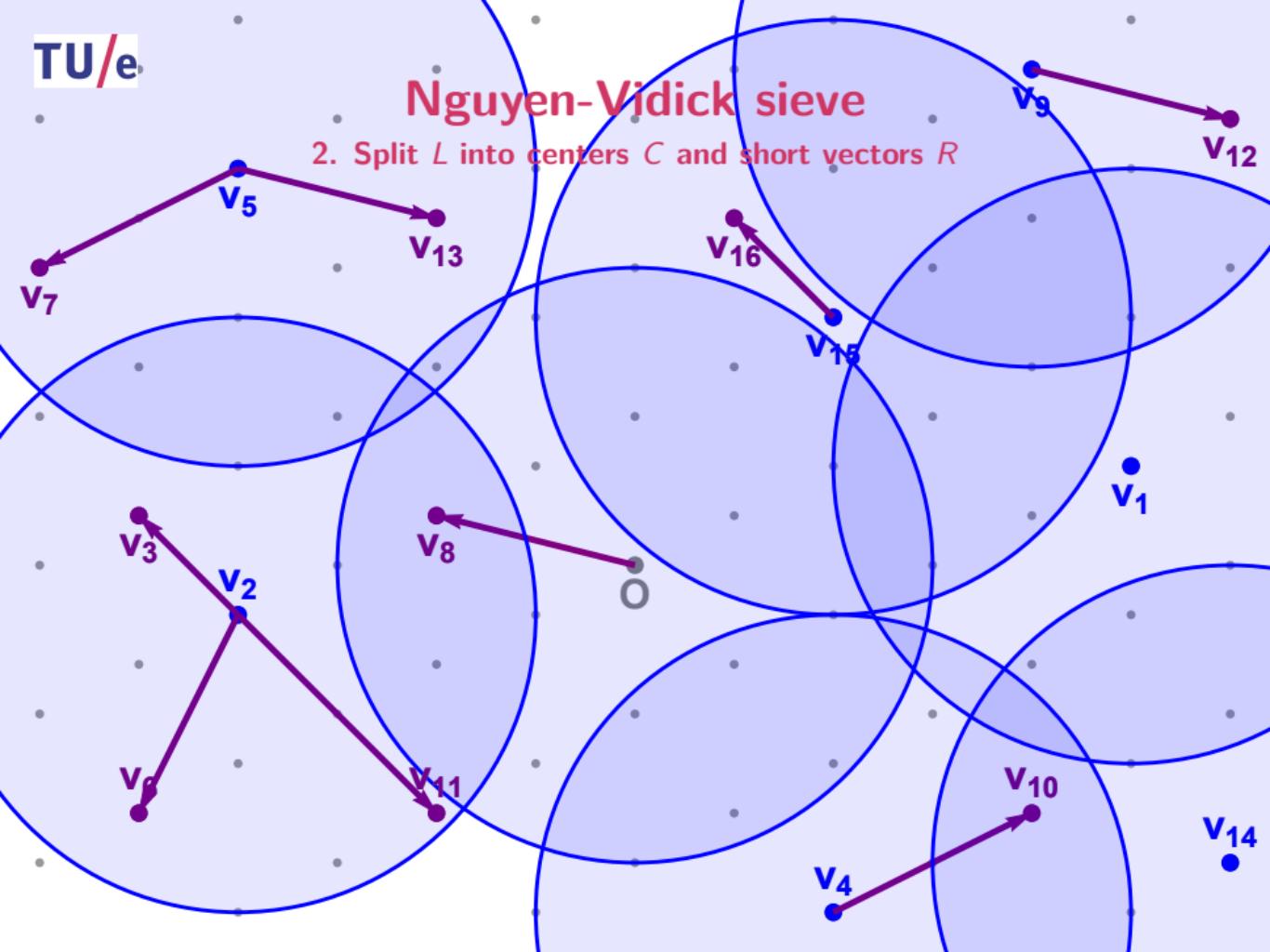
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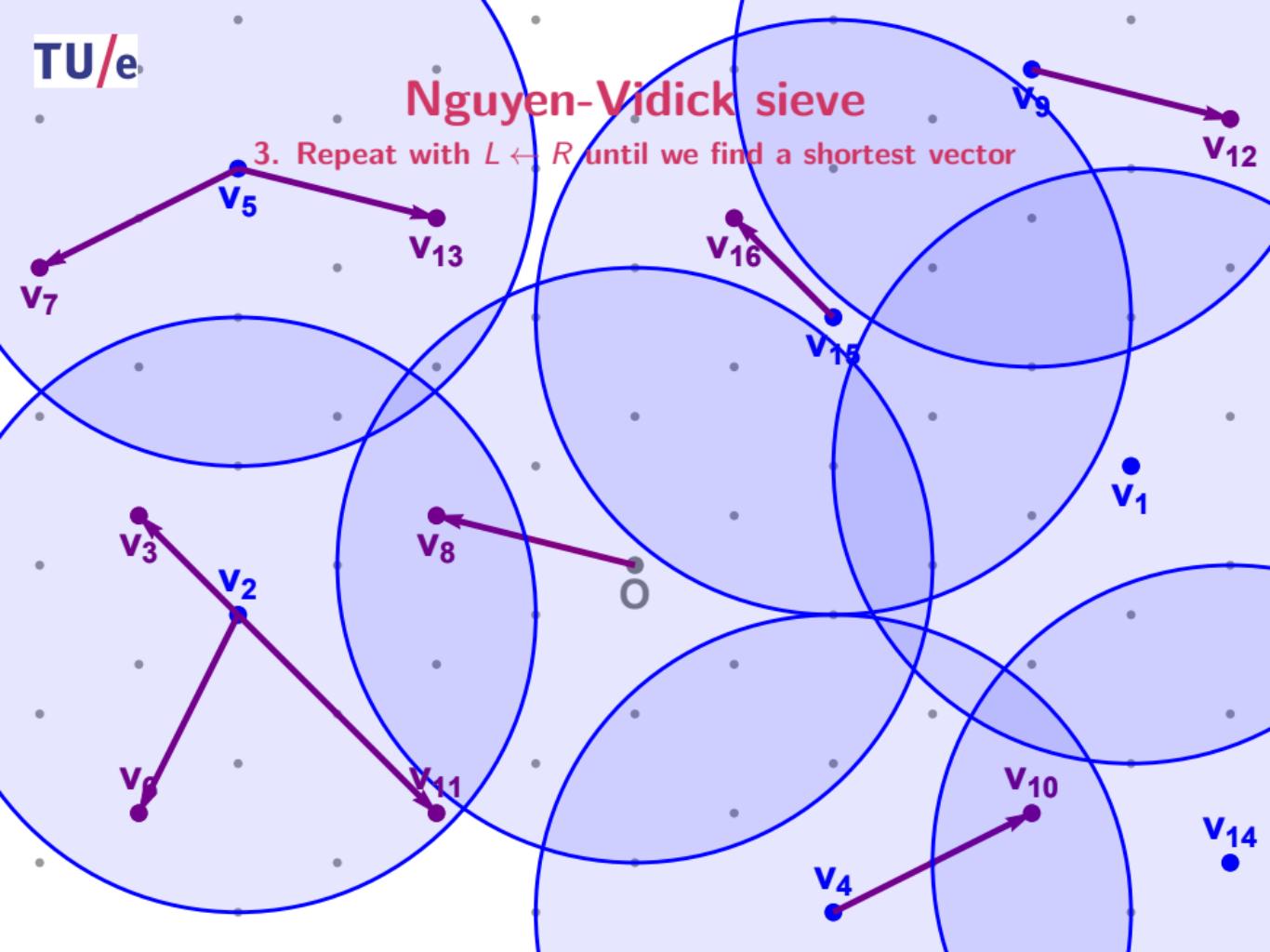
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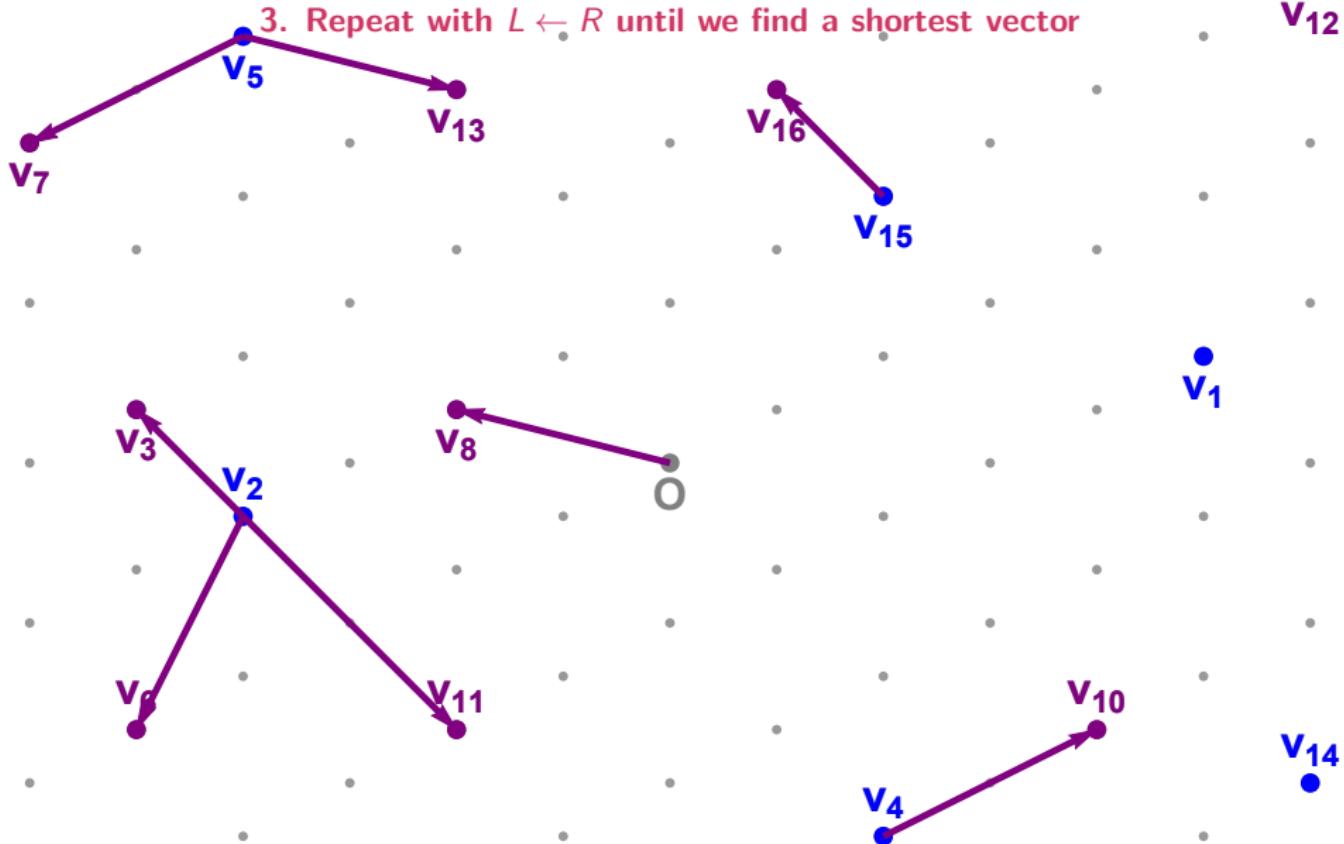
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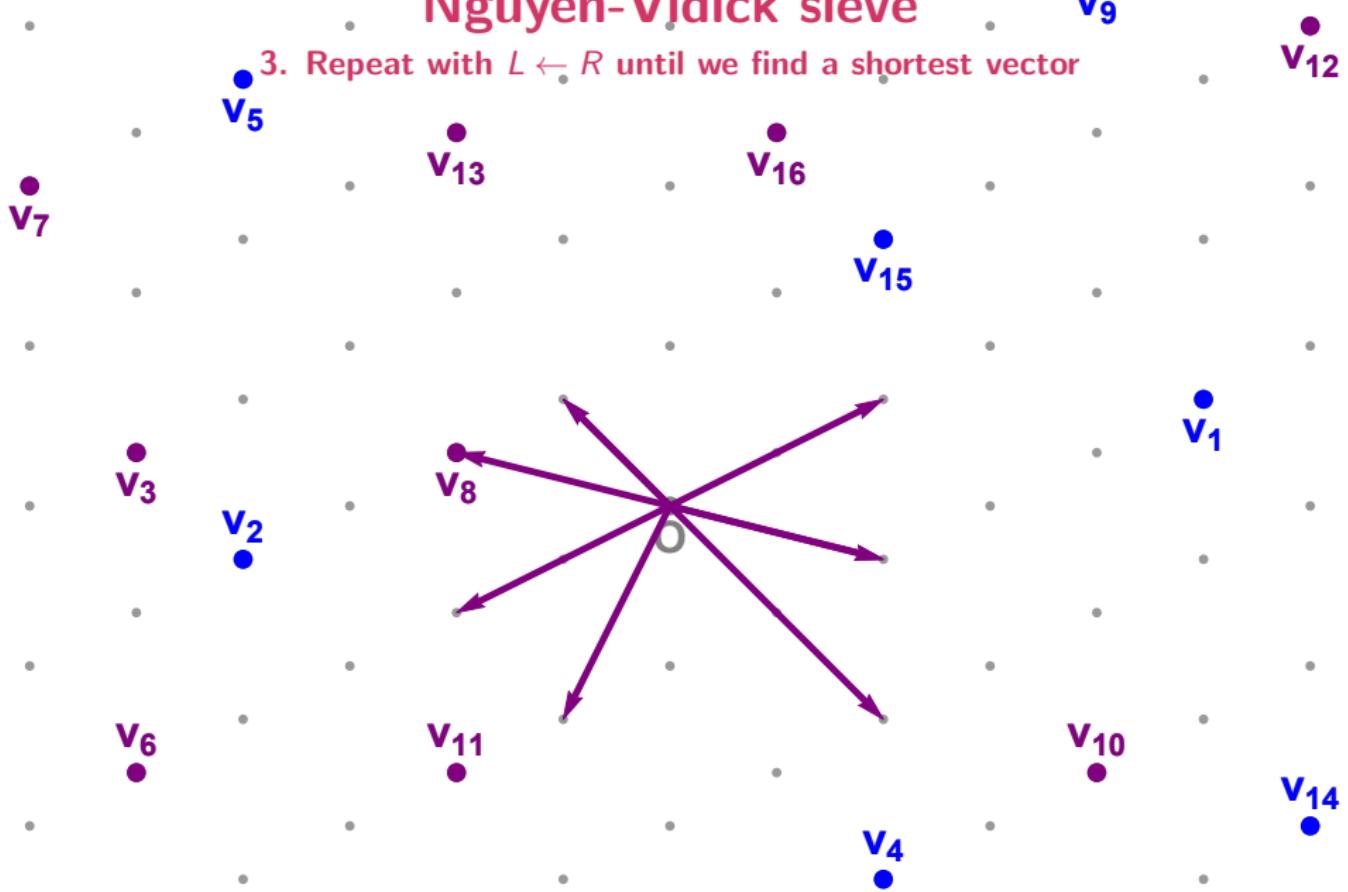
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Nguyen-Vidick sieve

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Nguyen-Vidick sieve

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Nguyen-Vidick sieve

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- Space complexity: $(\sqrt{4/3})^n \approx 2^{0.208n+o(n)}$ vectors
 - ▶ Each center covers $(\sin \frac{\pi}{3})^{-n} = (\sqrt{3/4})^n$ of the space
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Nguyen-Vidick sieve

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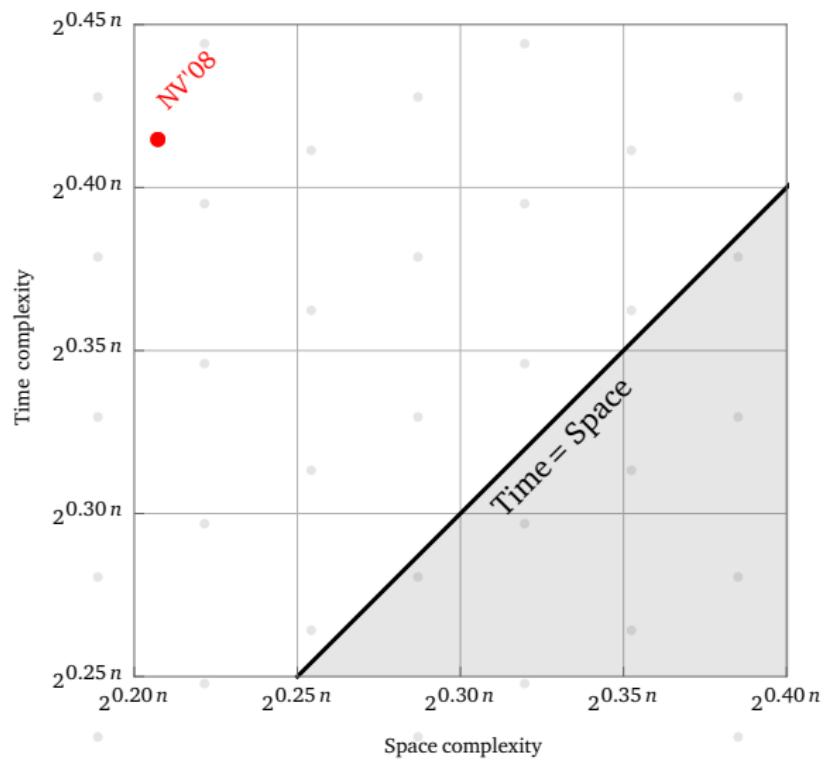
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Theorem (Nguyen and Vidick, J. Math. Crypt. '08)

The Nguyen-Vidick sieve heuristically solves SVP in time $2^{0.415n+o(n)}$ and space $2^{0.208n+o(n)}$.

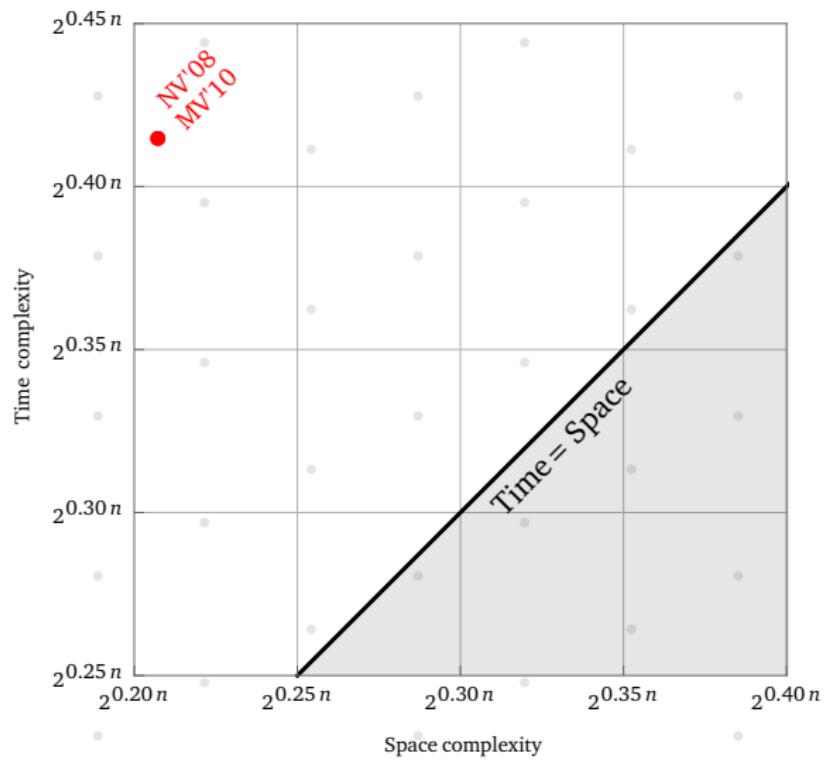
Nguyen-Vidick sieve

Space/time trade-off



GaussSieve

Space/time trade-off



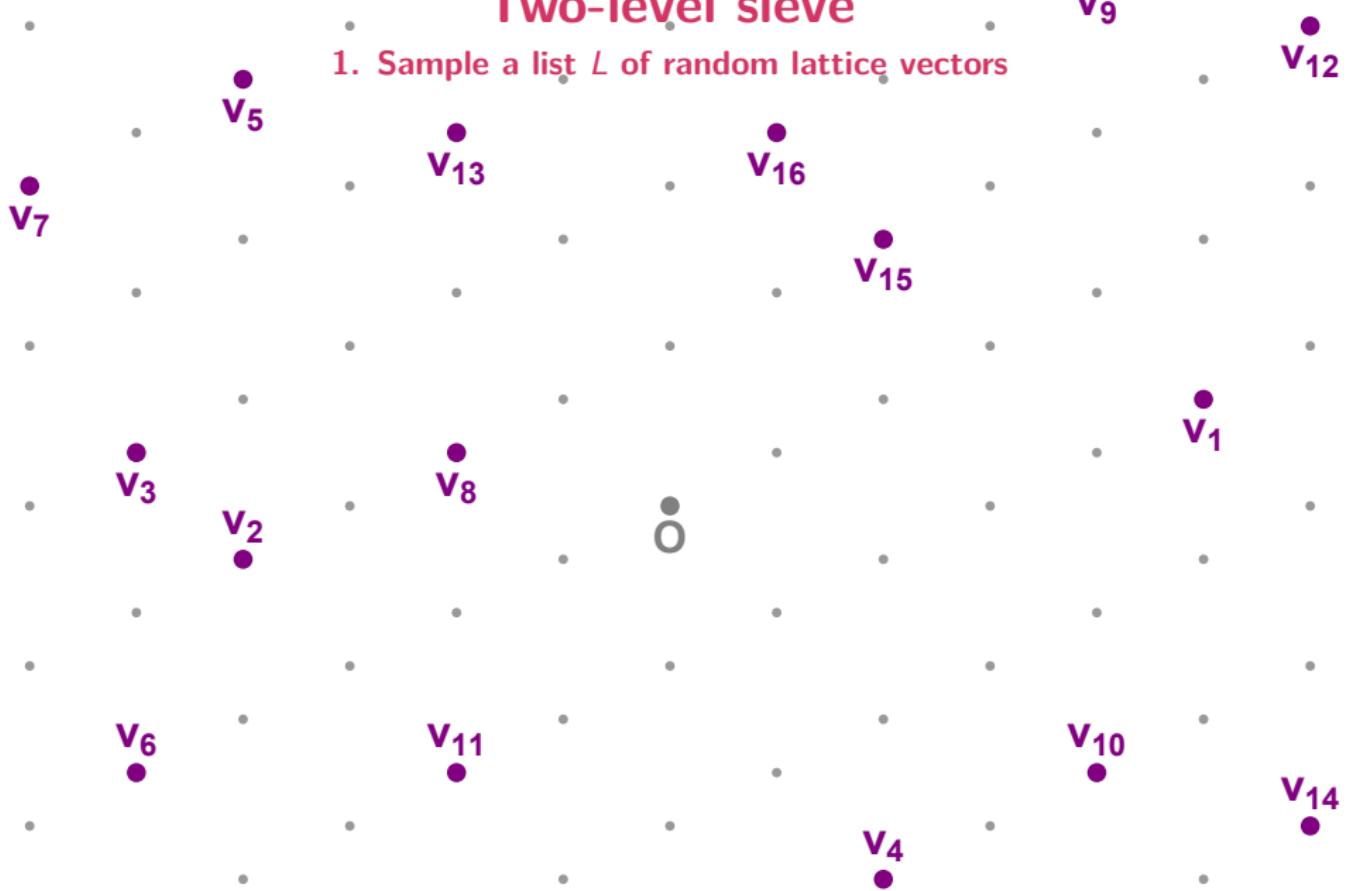
Two-level sieve

1. Sample a list L of random lattice vectors



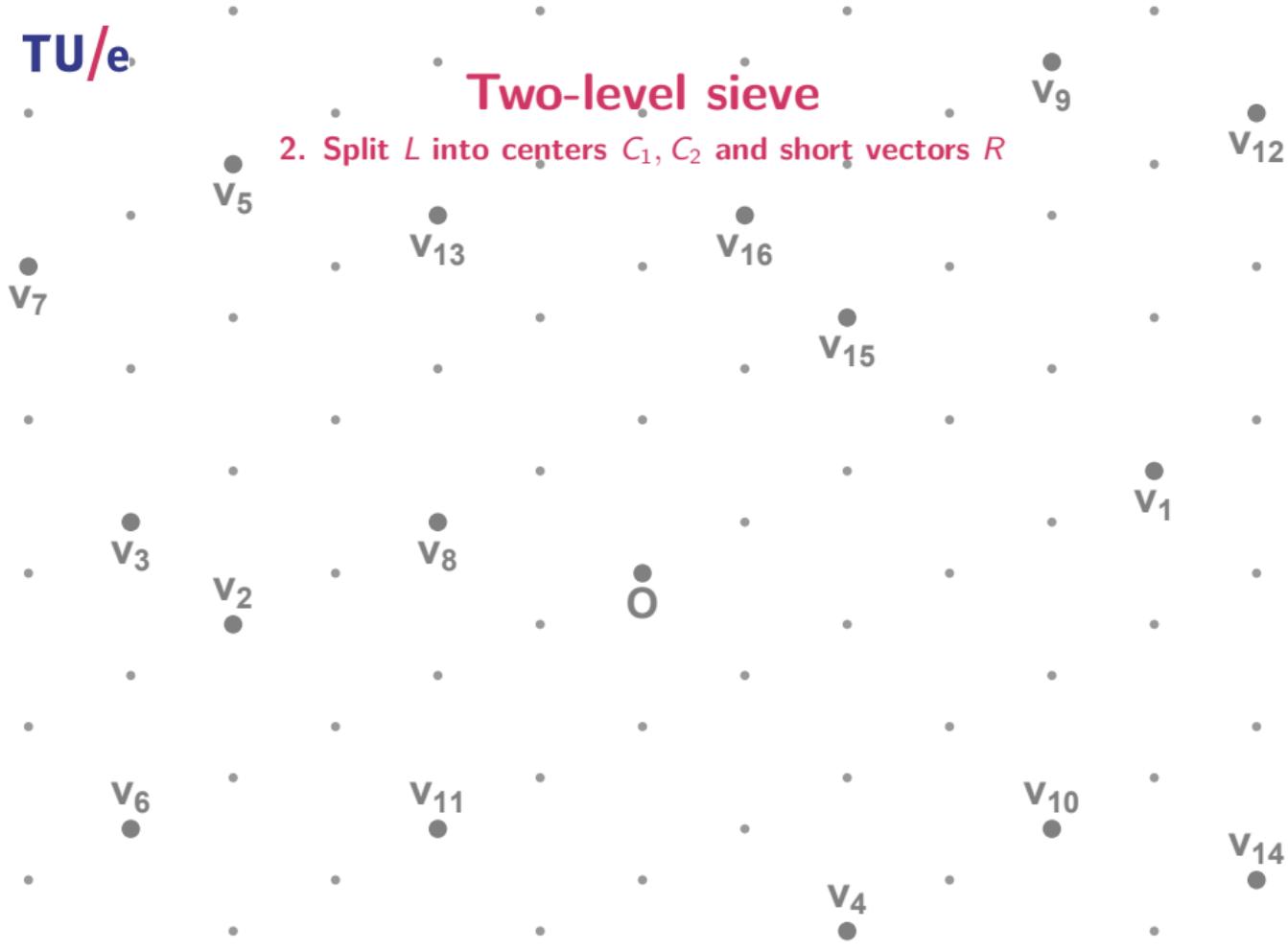
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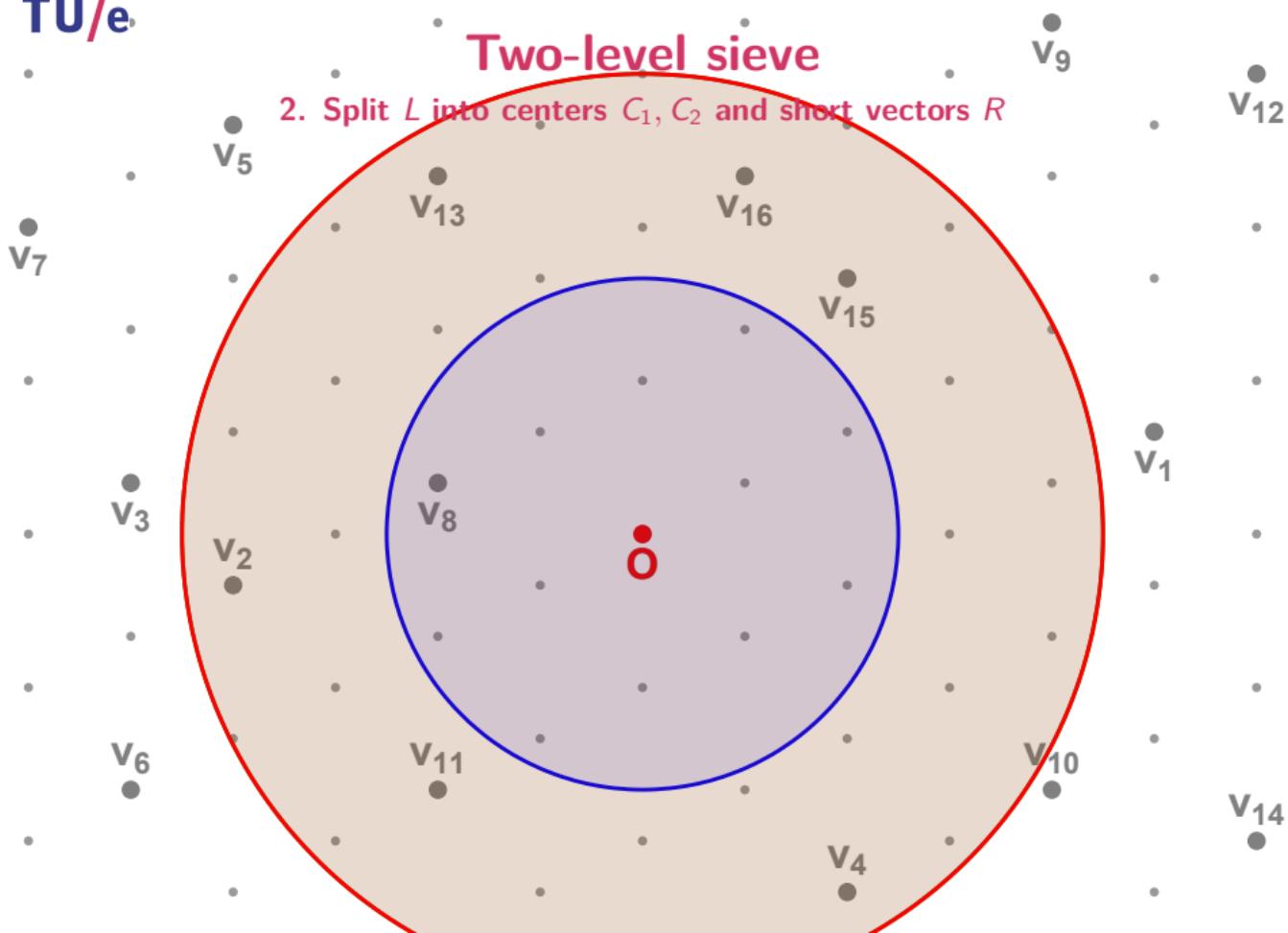
Two-level sieve

2. Split L into centers C_1, C_2 and short vectors R



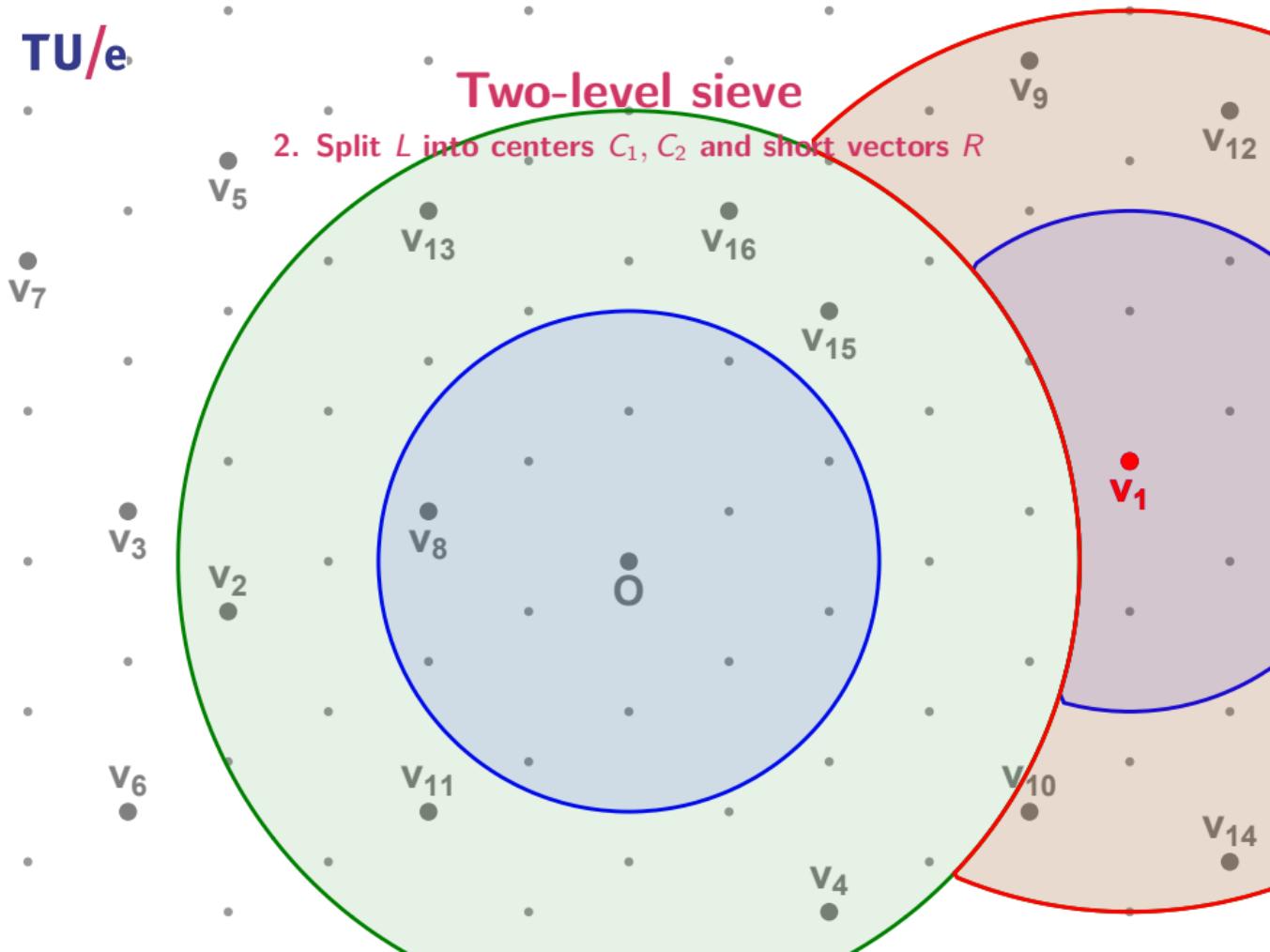
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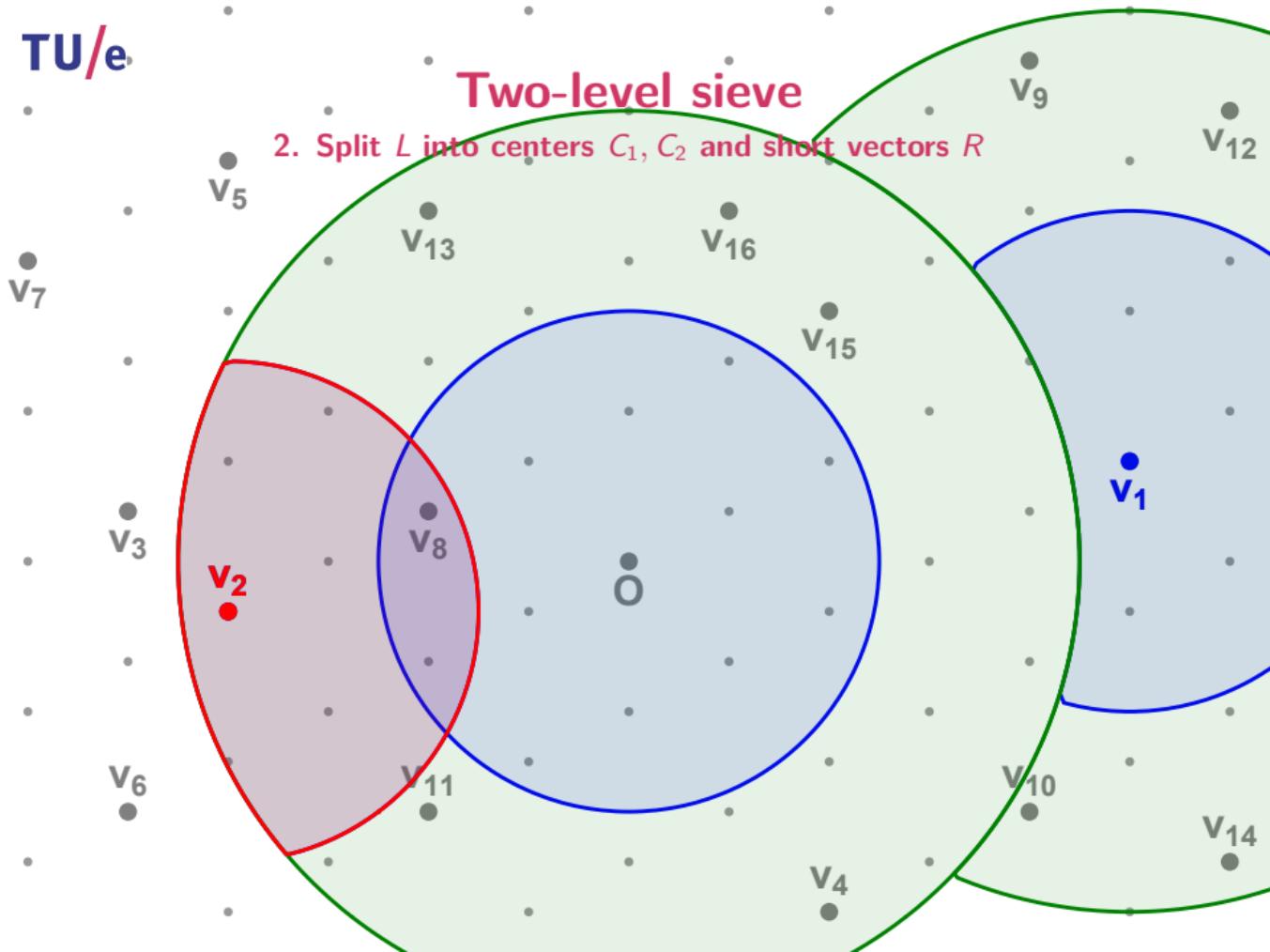
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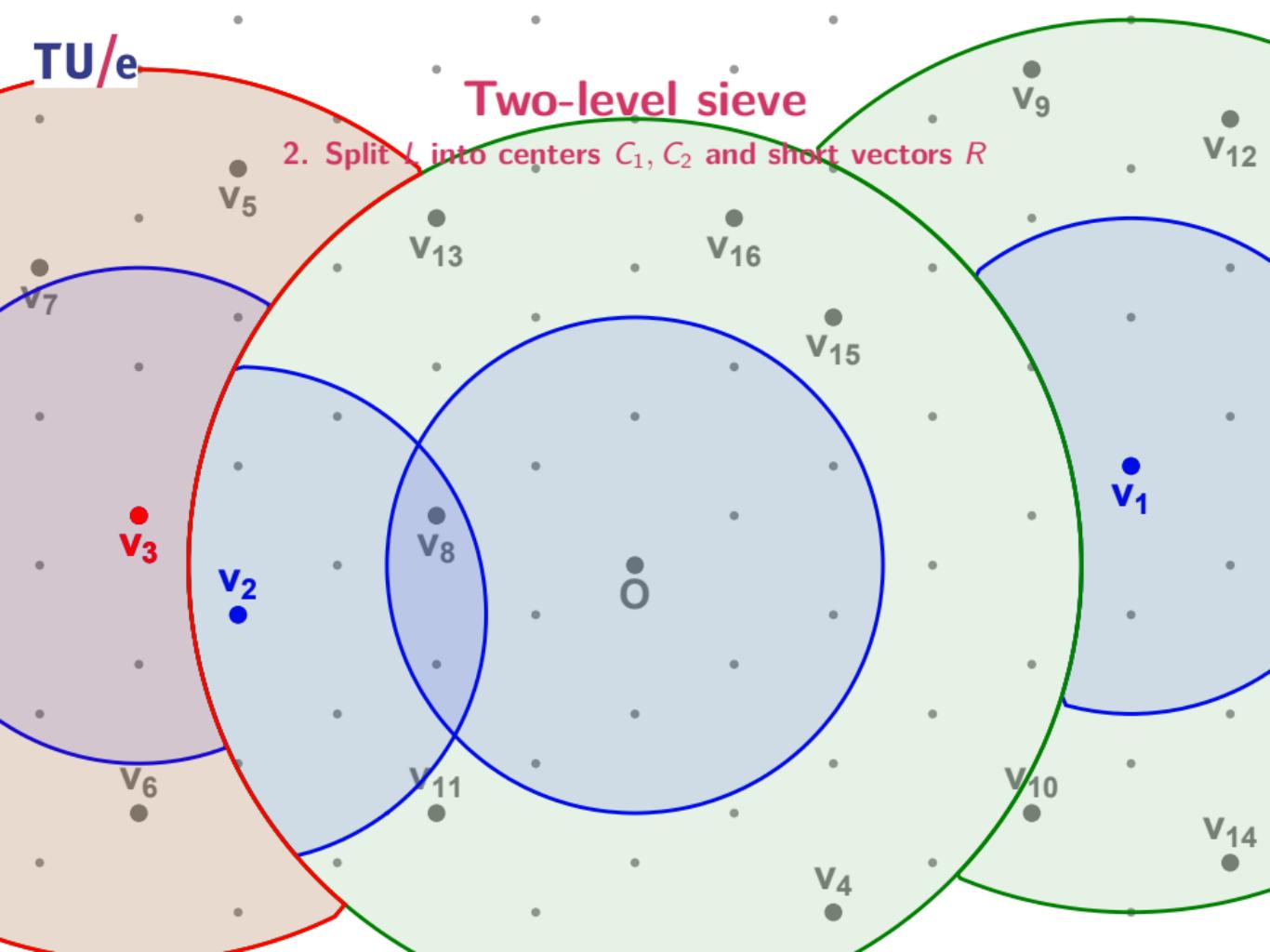
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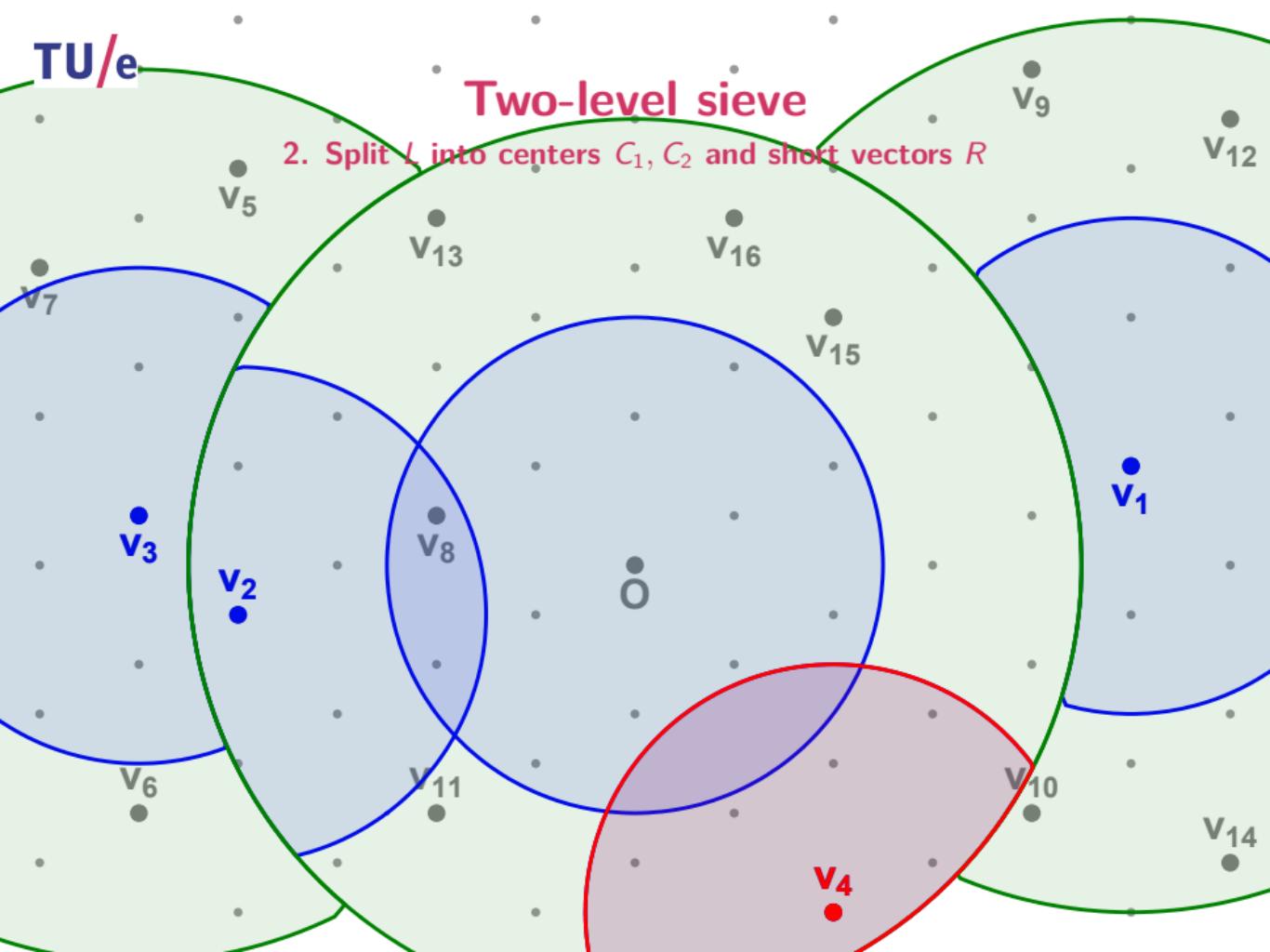
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2. Split \mathcal{V} into centers C_1, C_2 and short vectors R



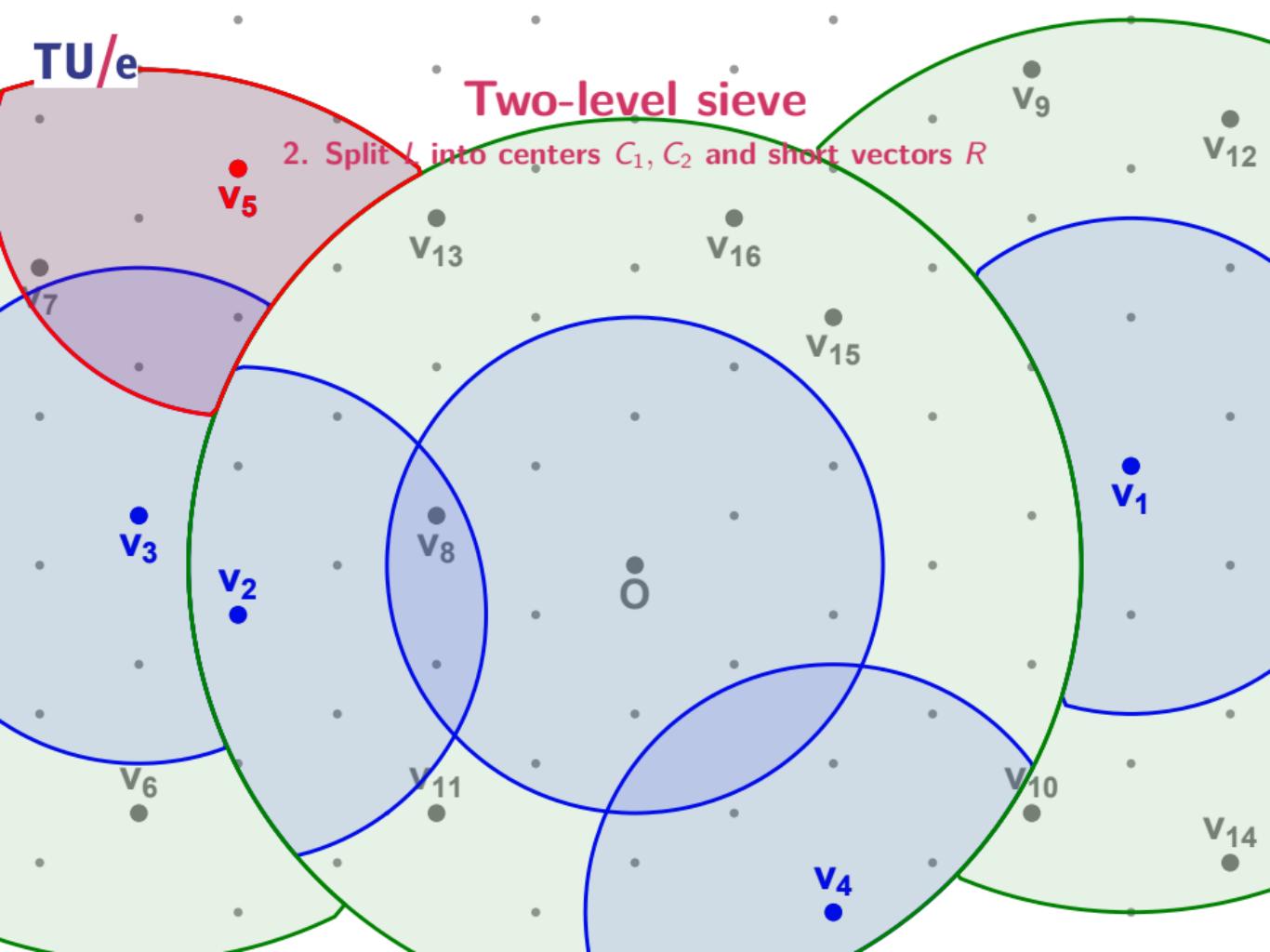
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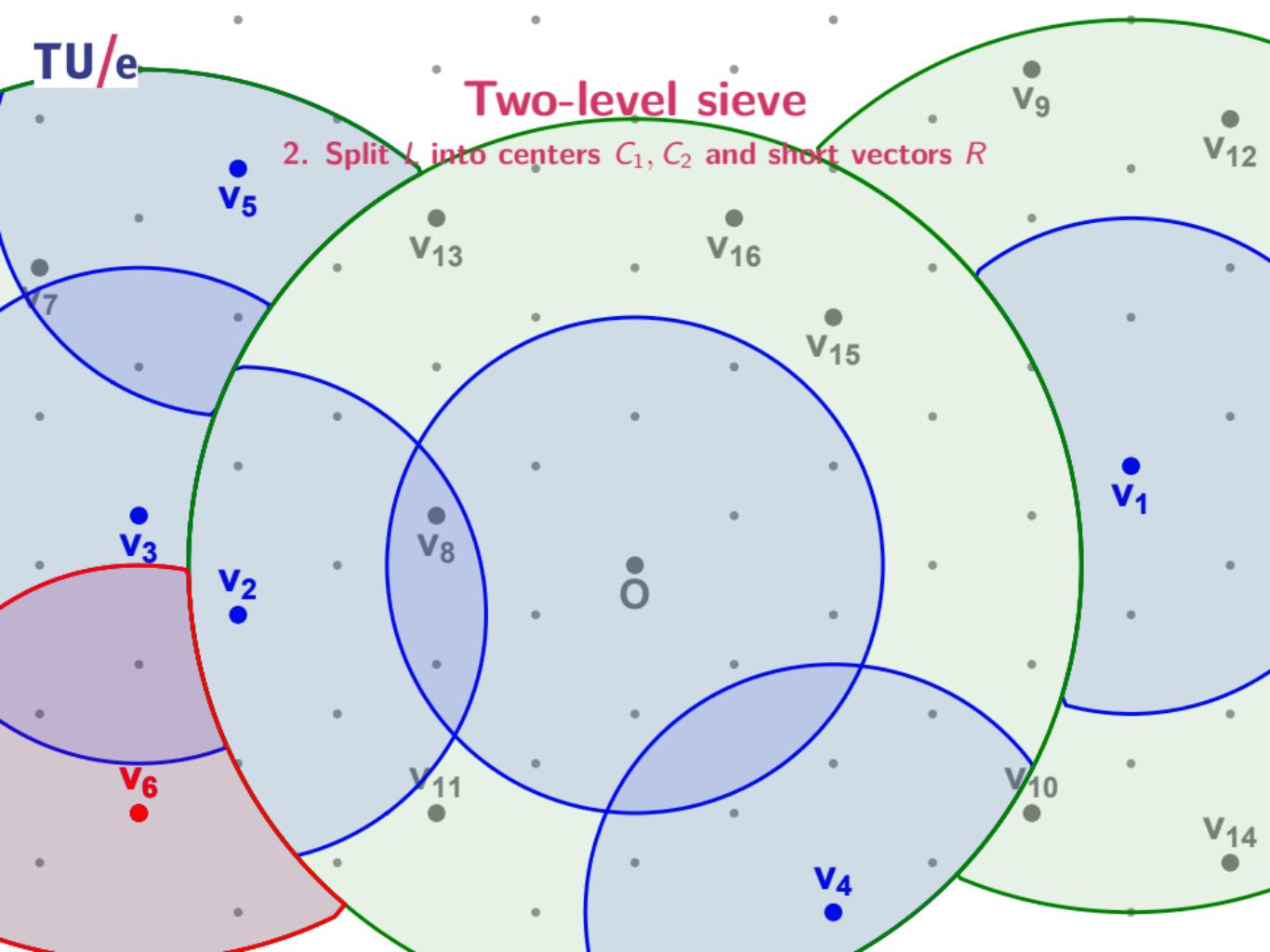
Two-level sieve

2. Split V into centers C_1, C_2 and short vectors R



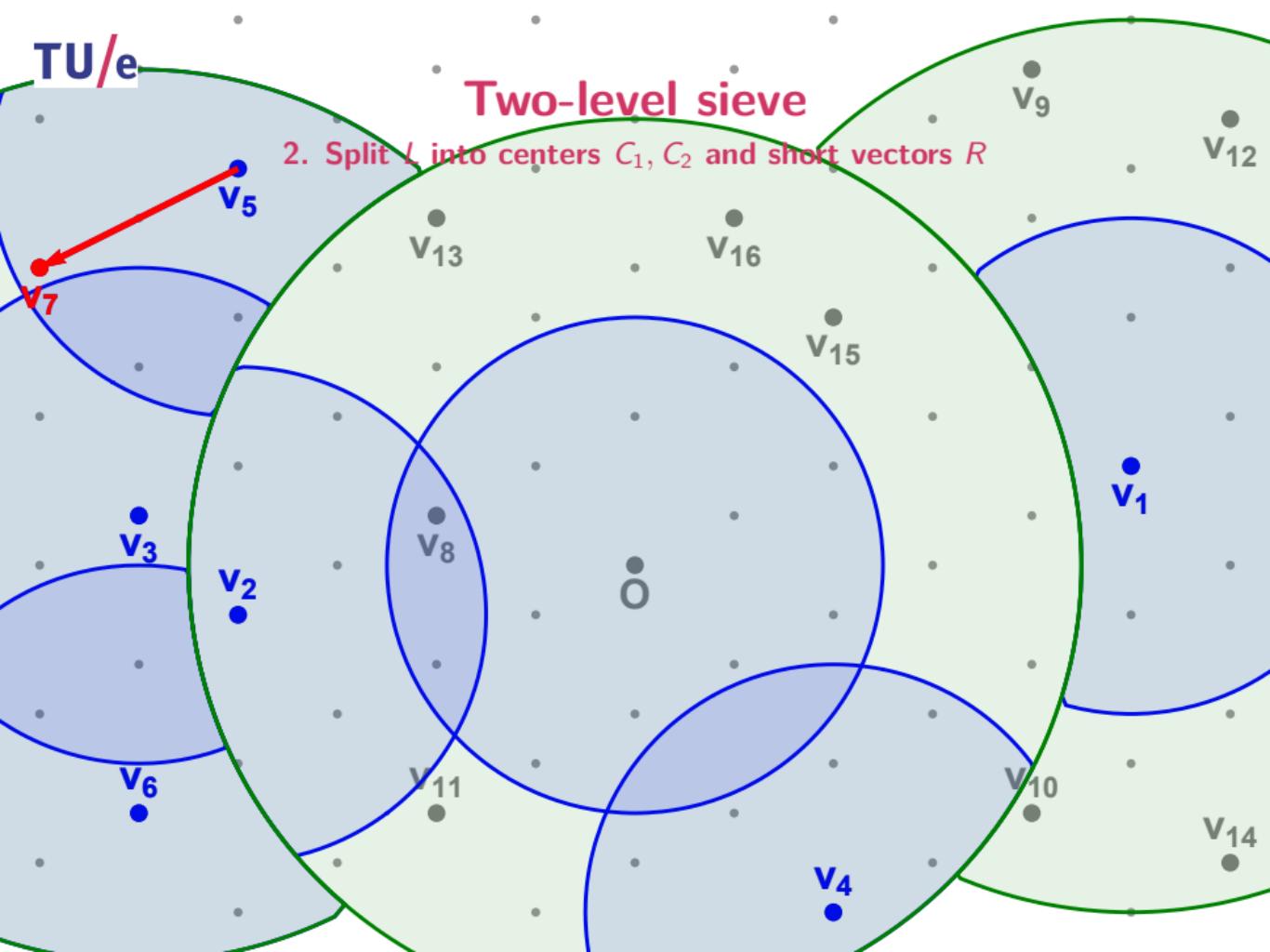
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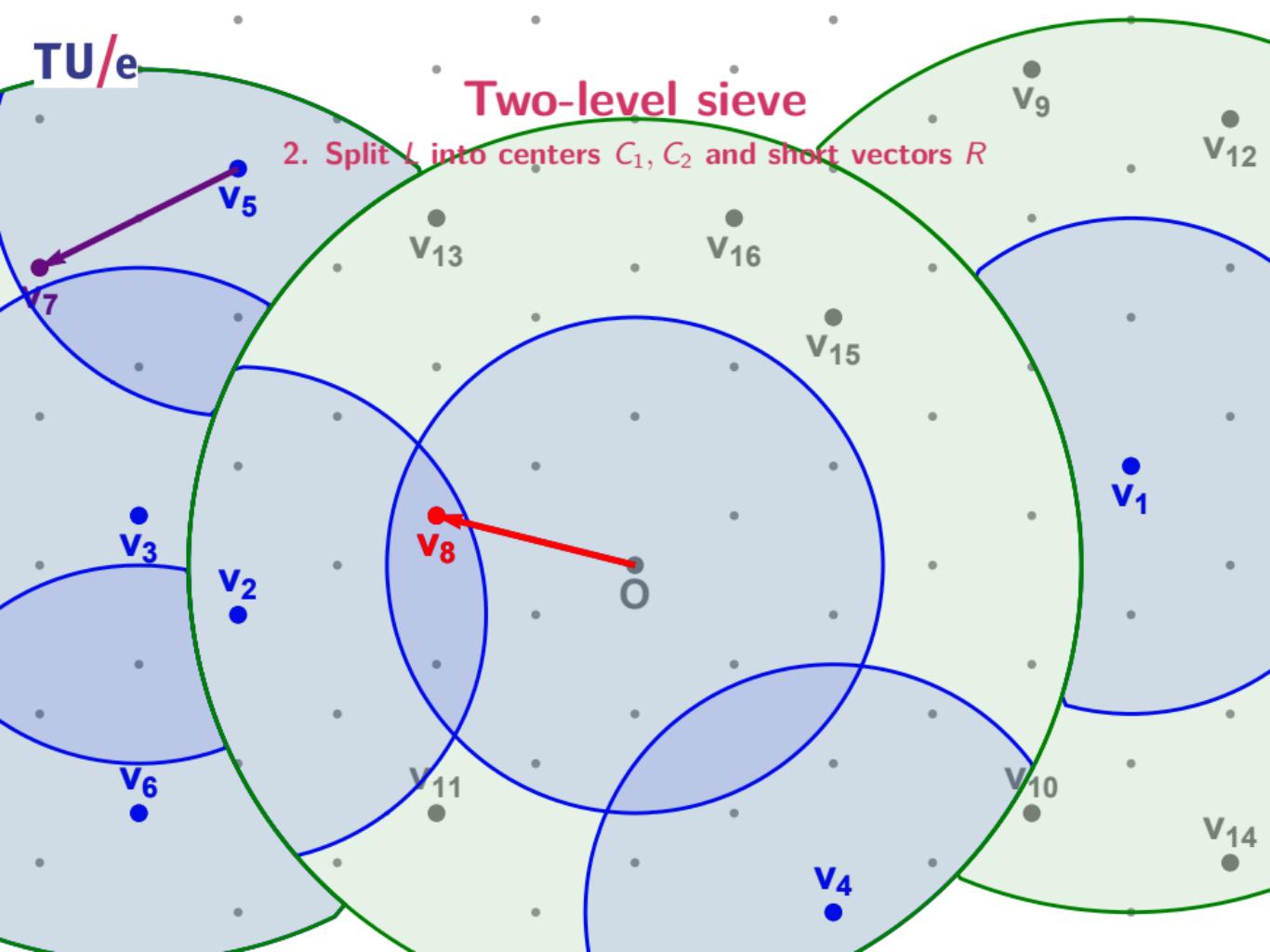
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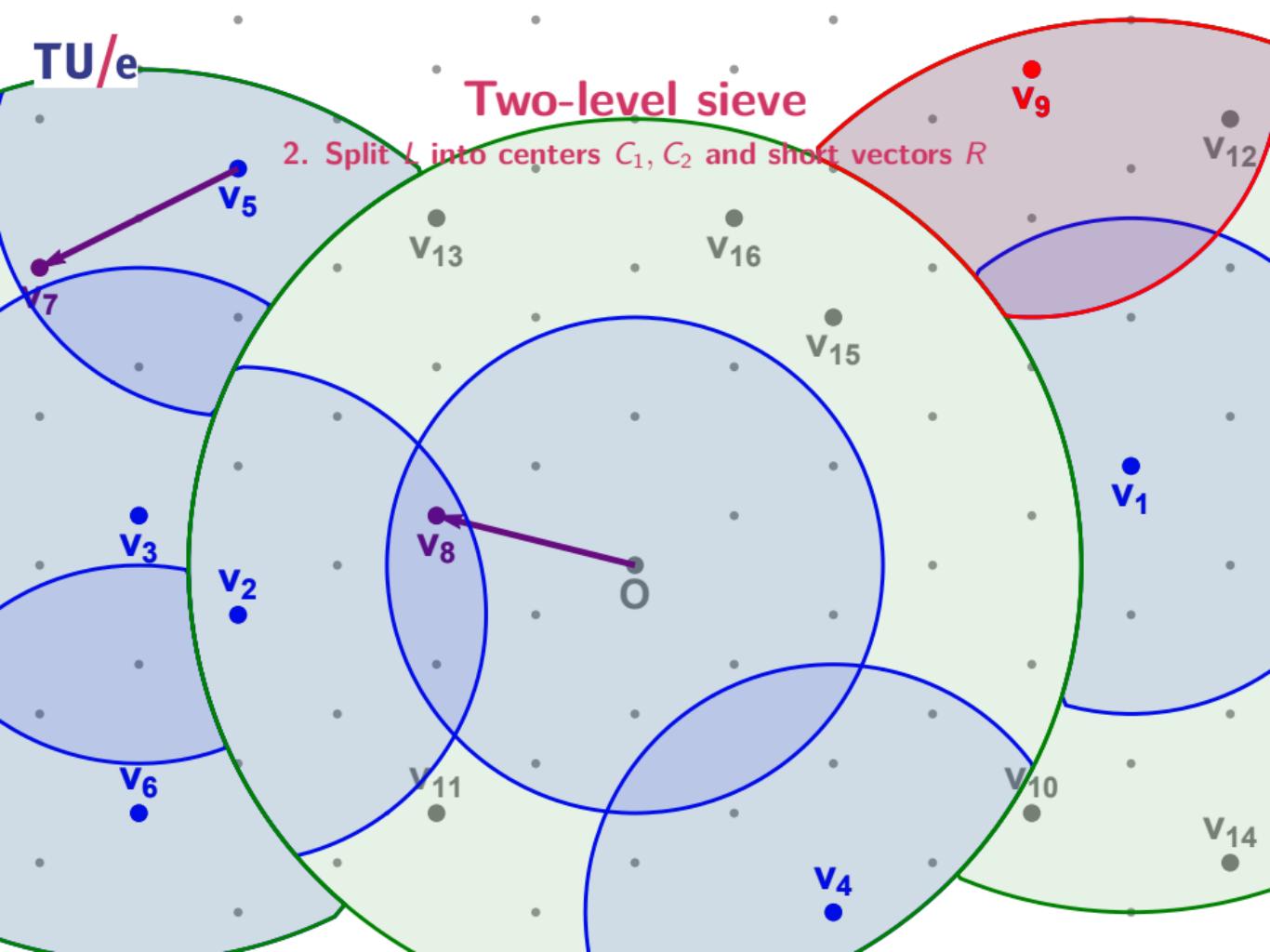
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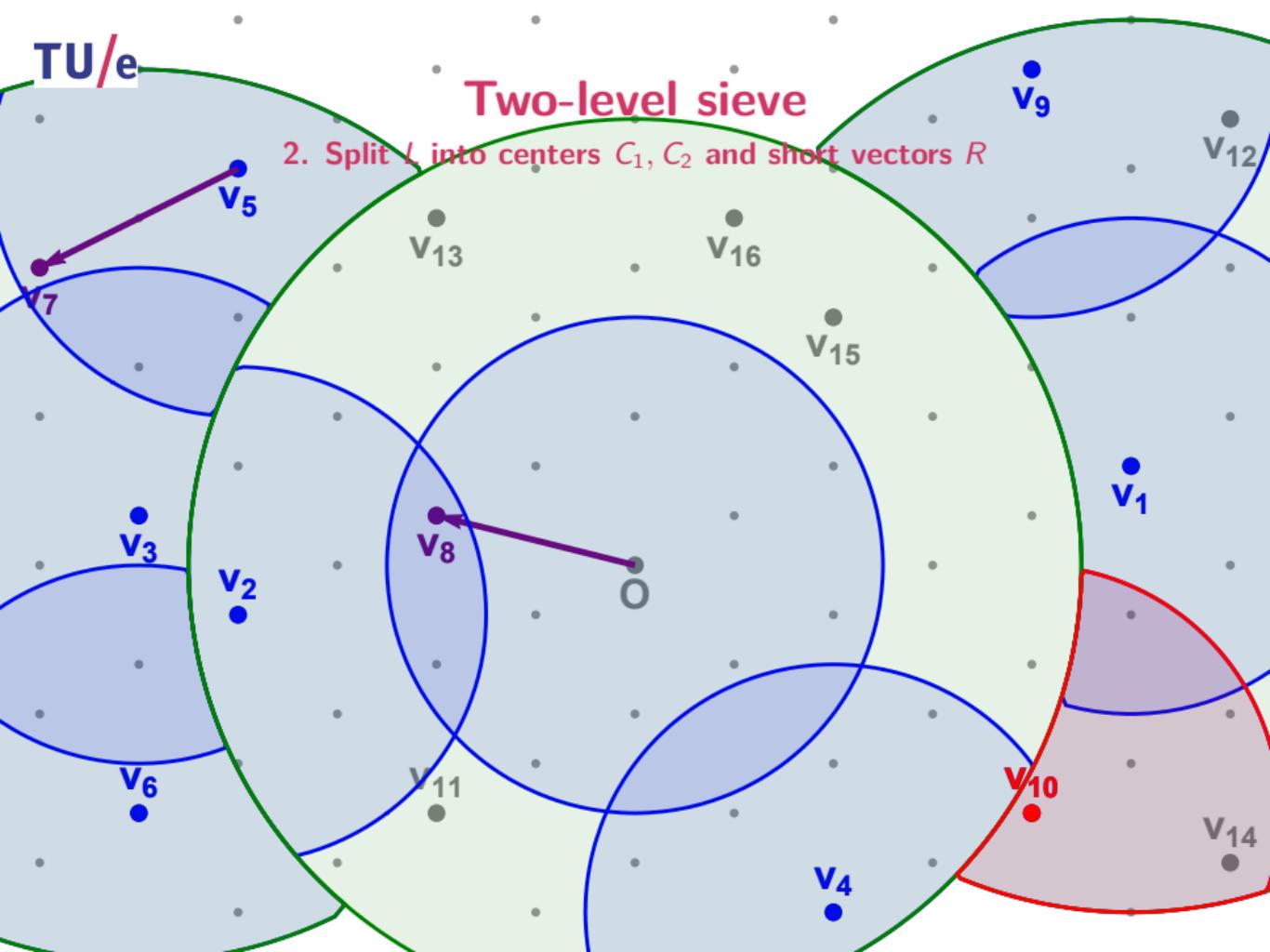
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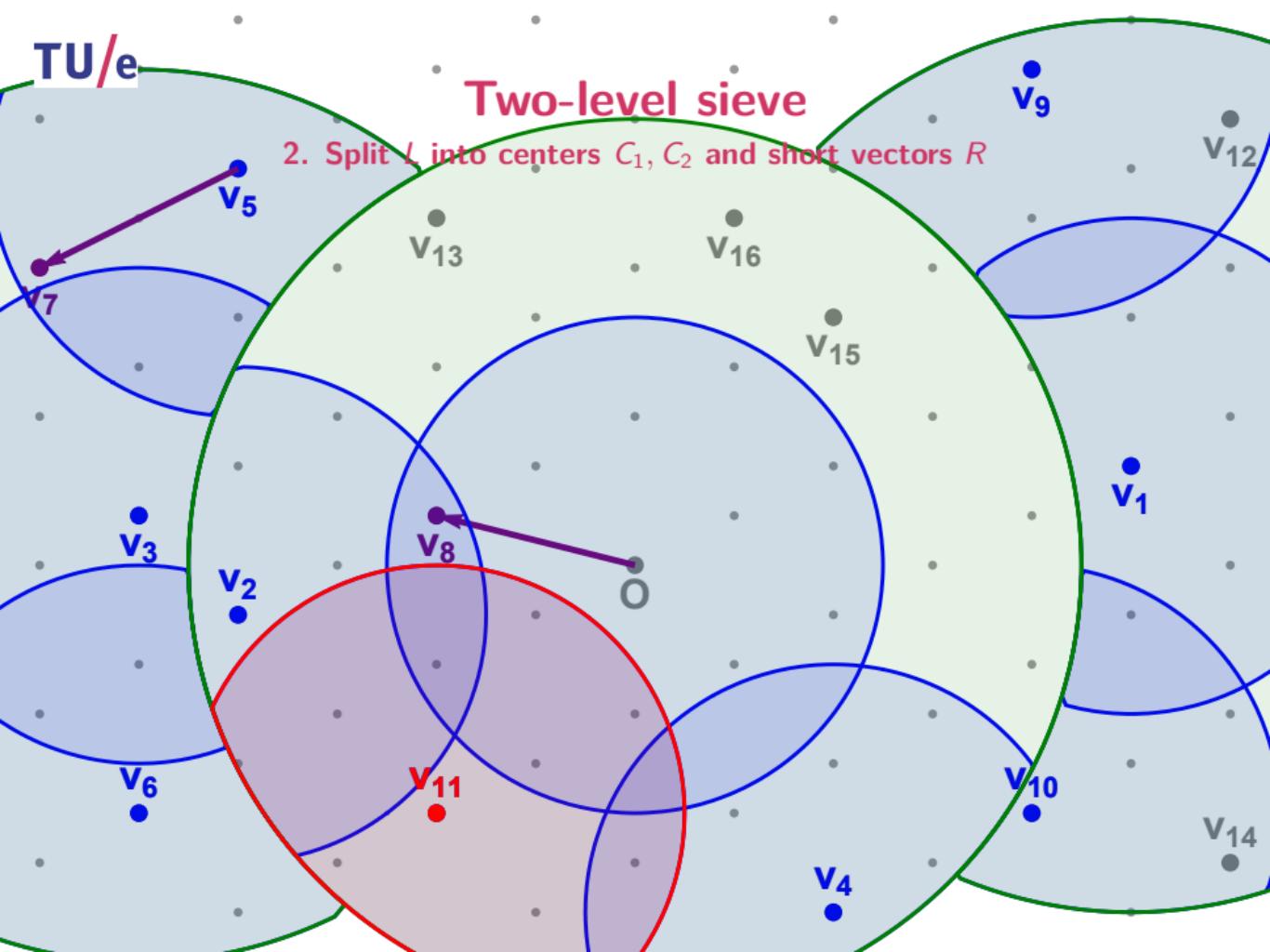
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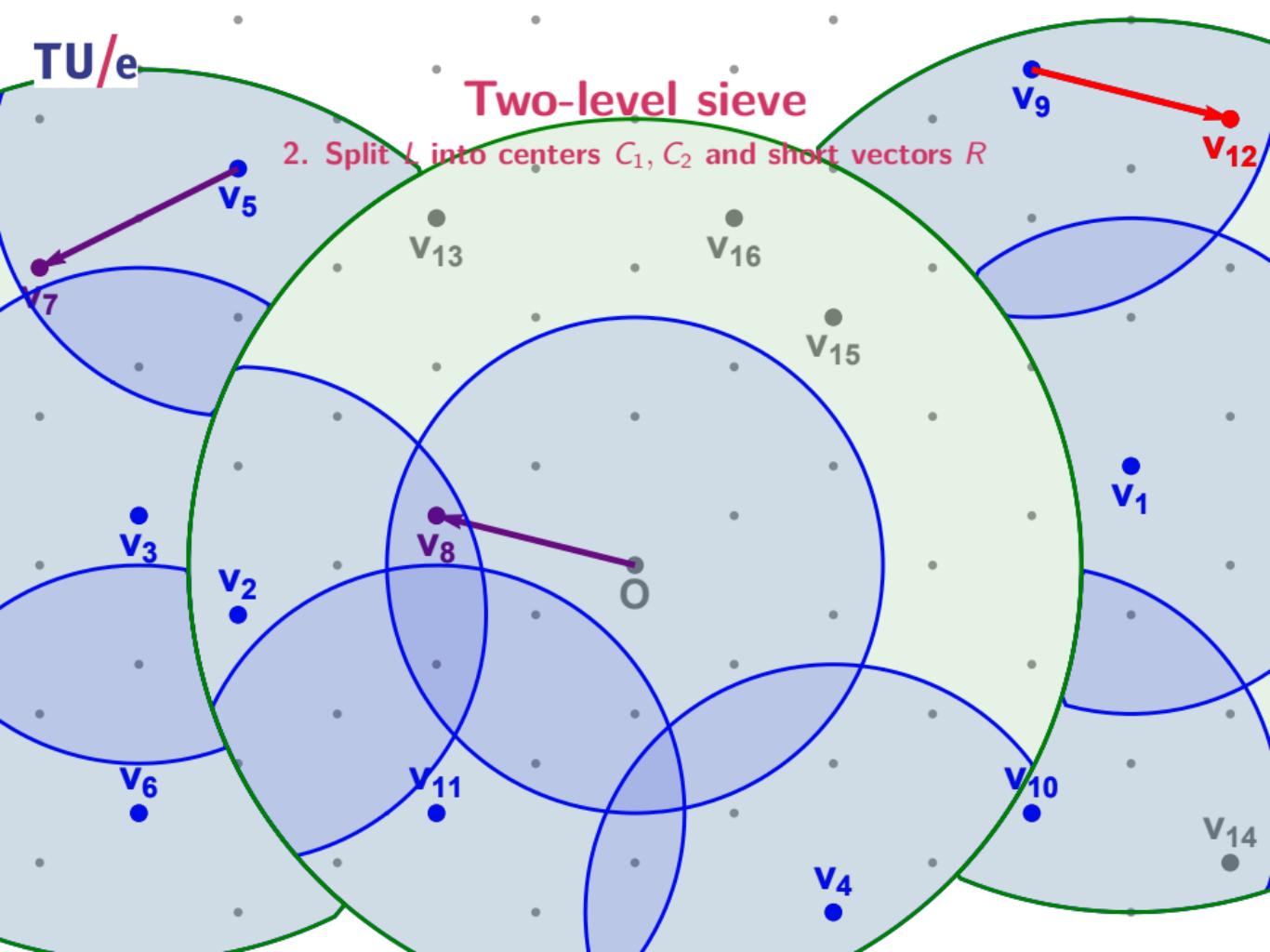
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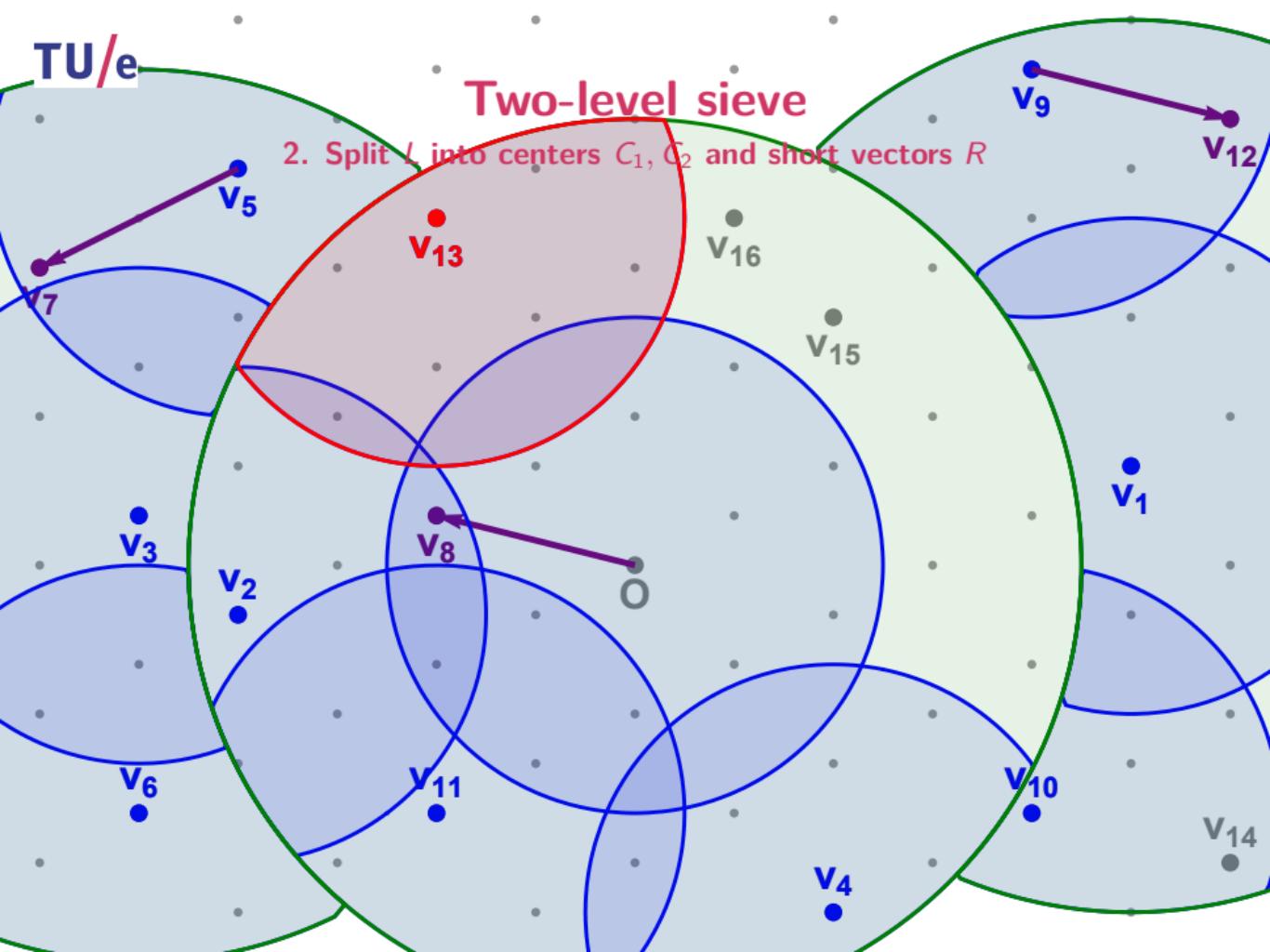
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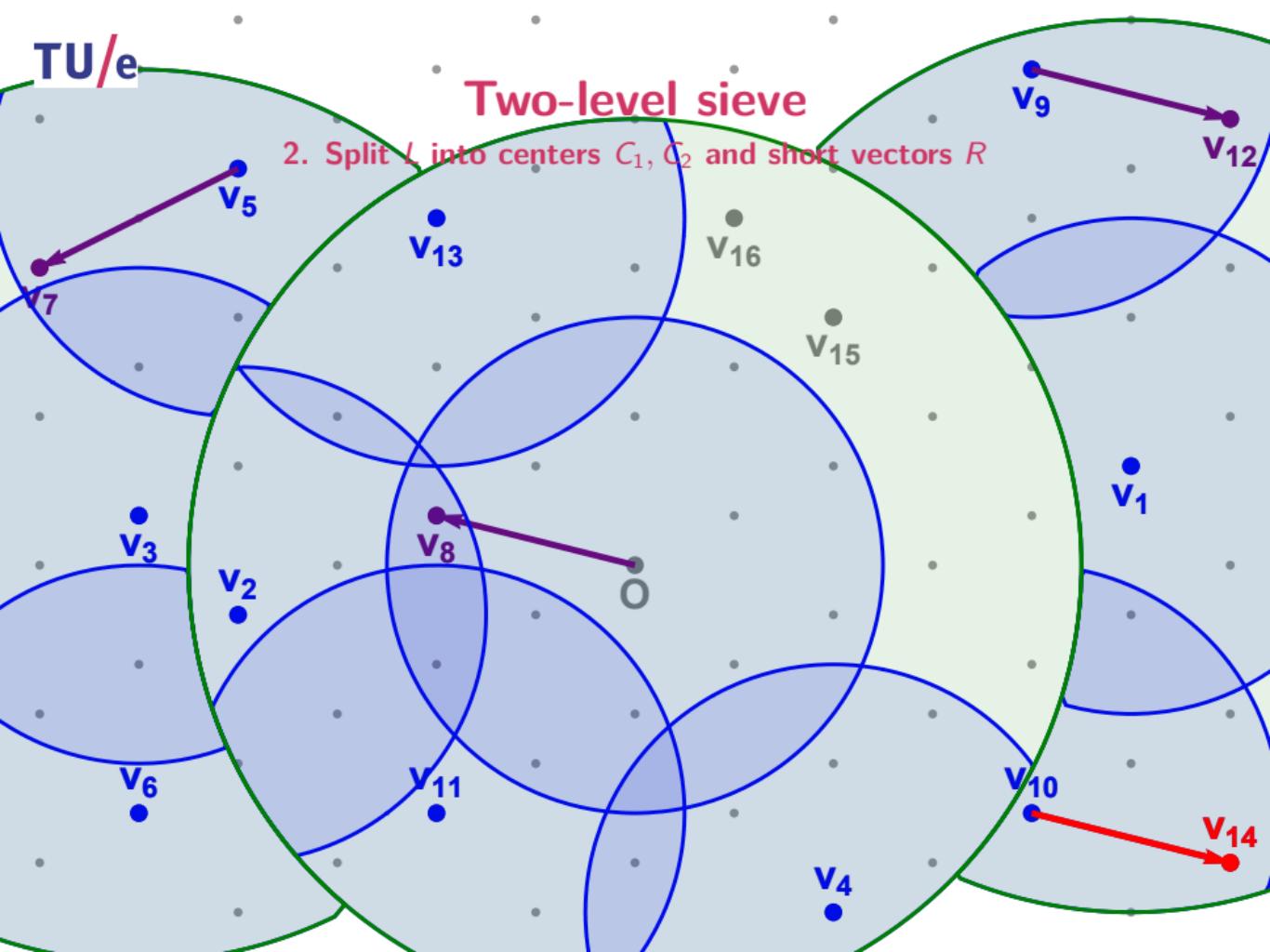
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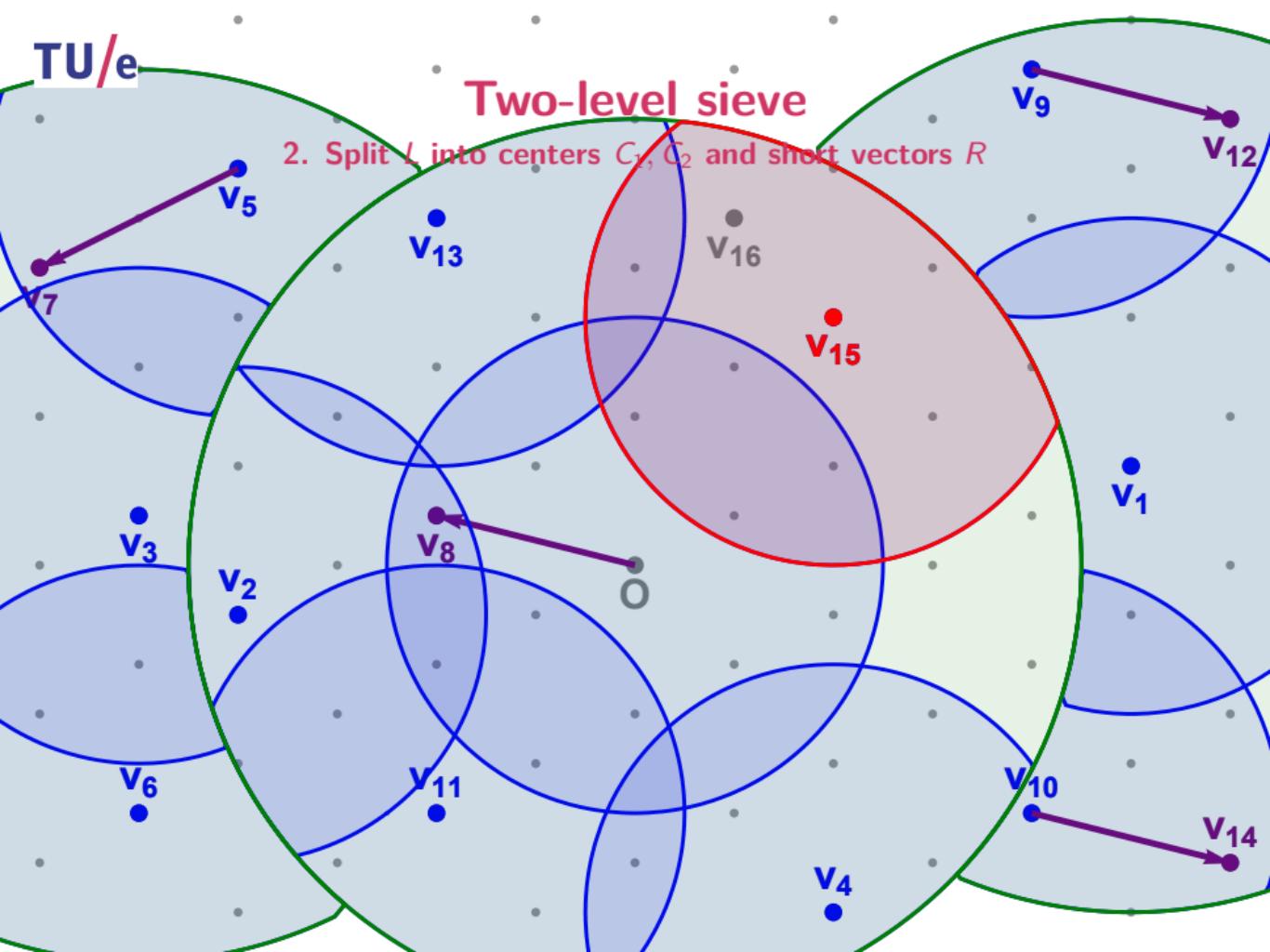
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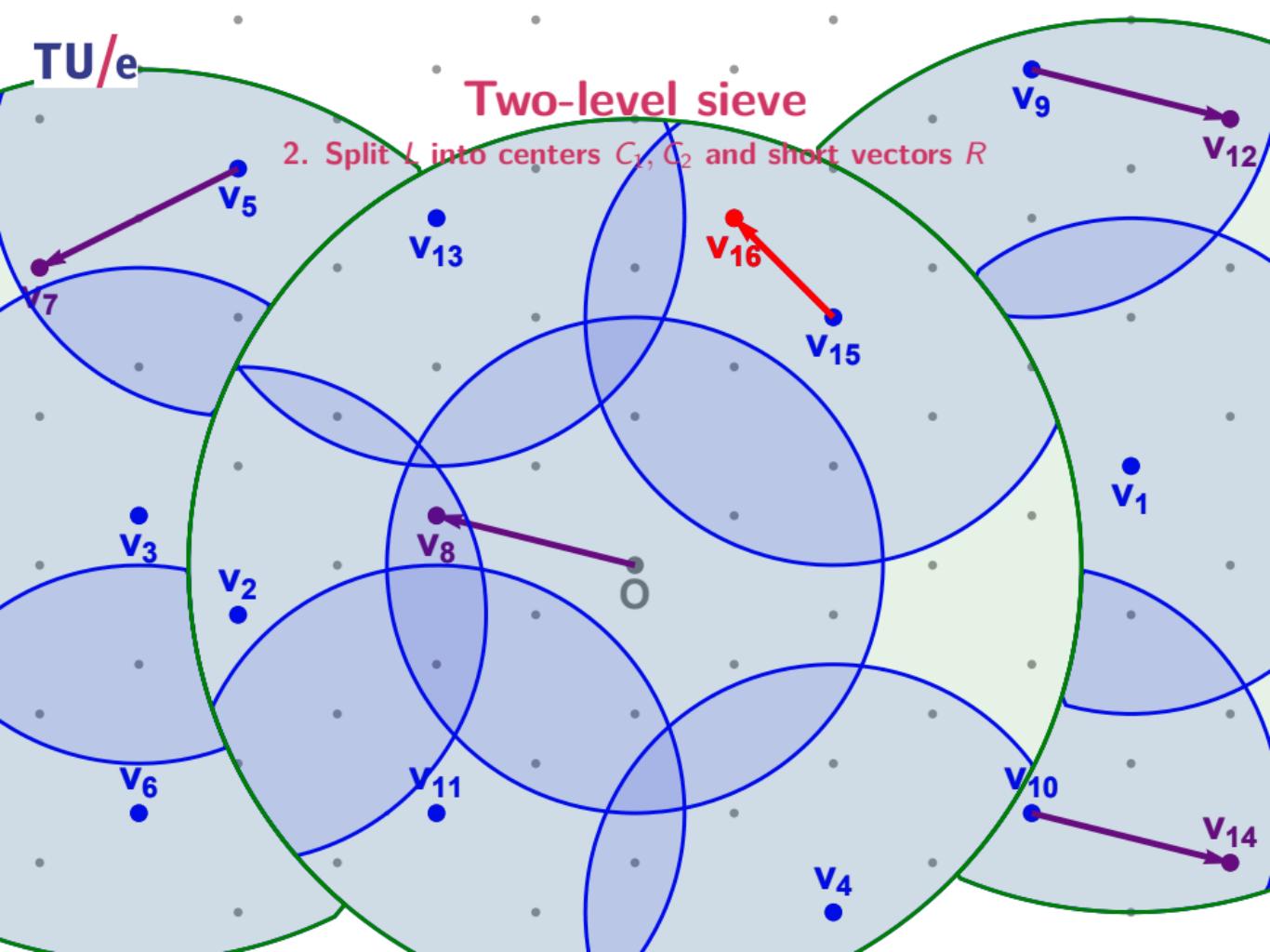
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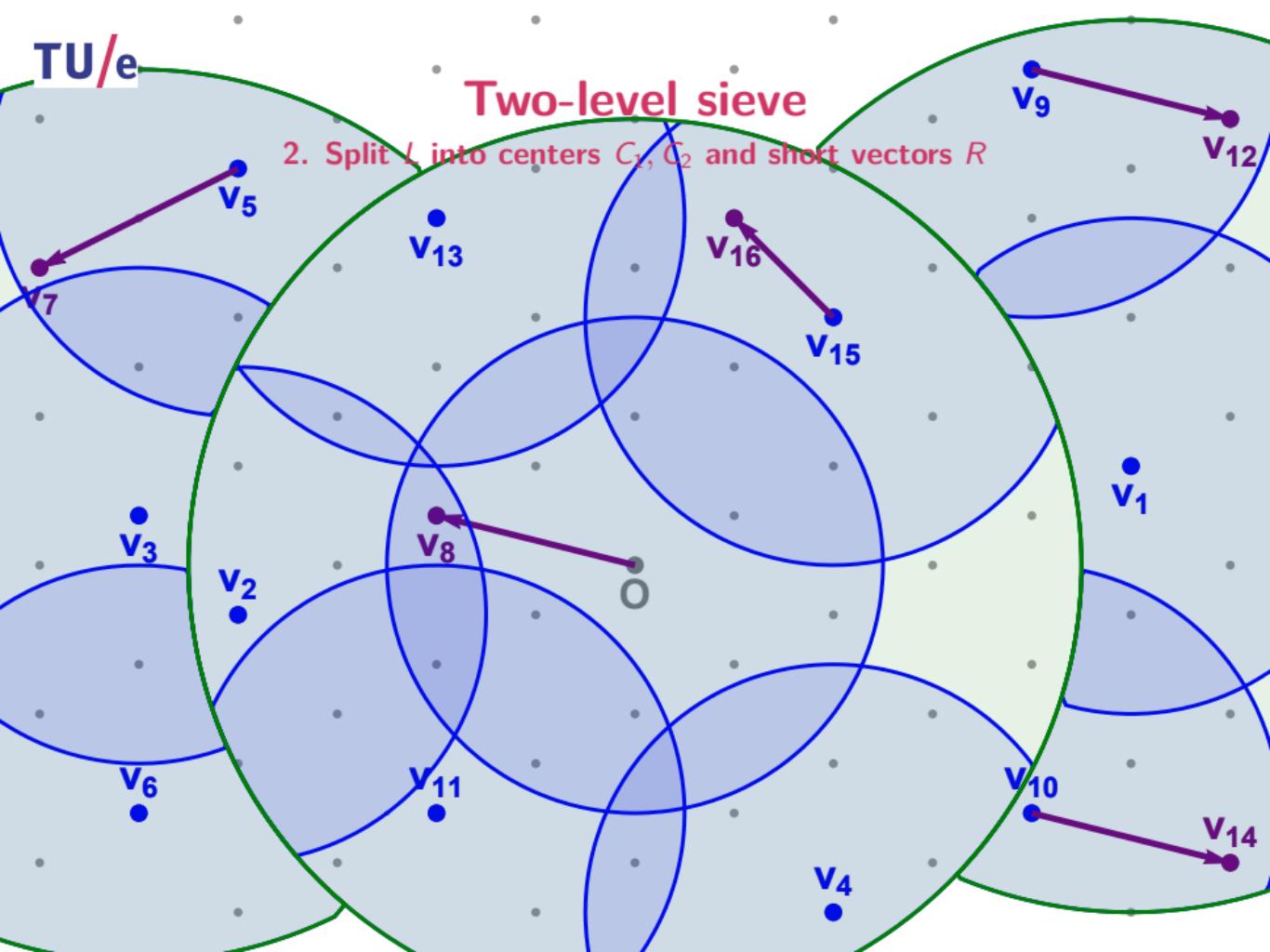
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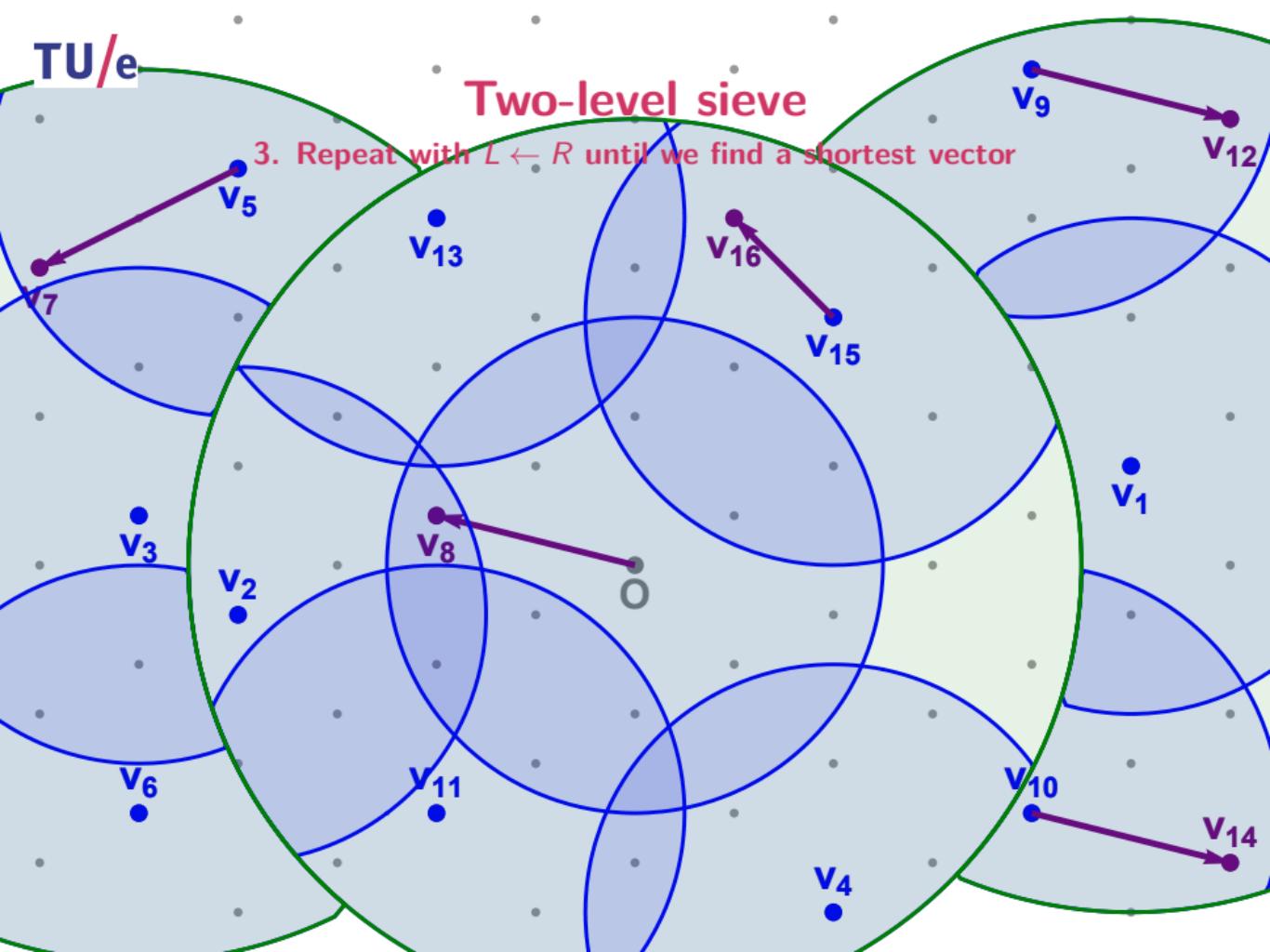
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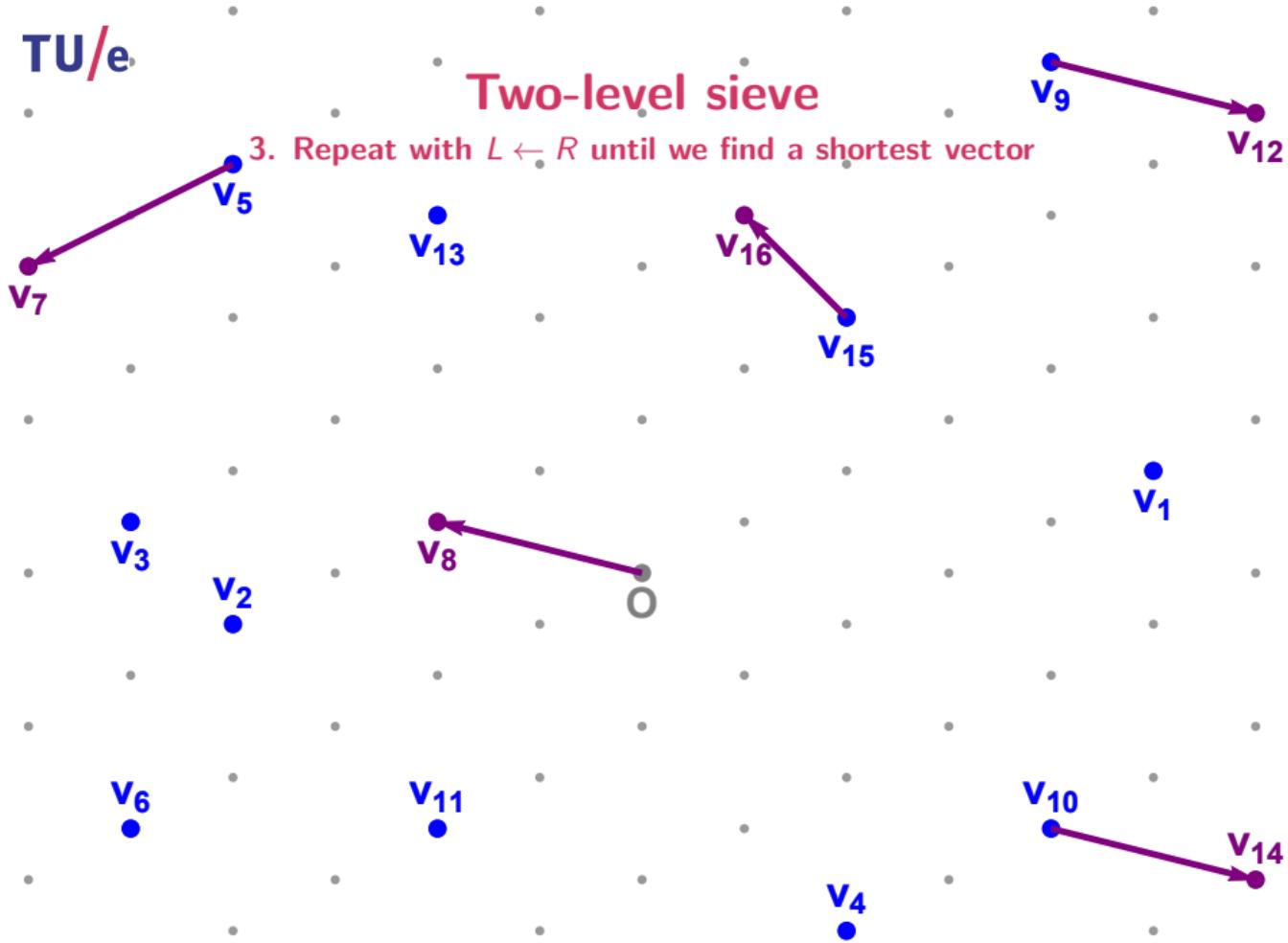
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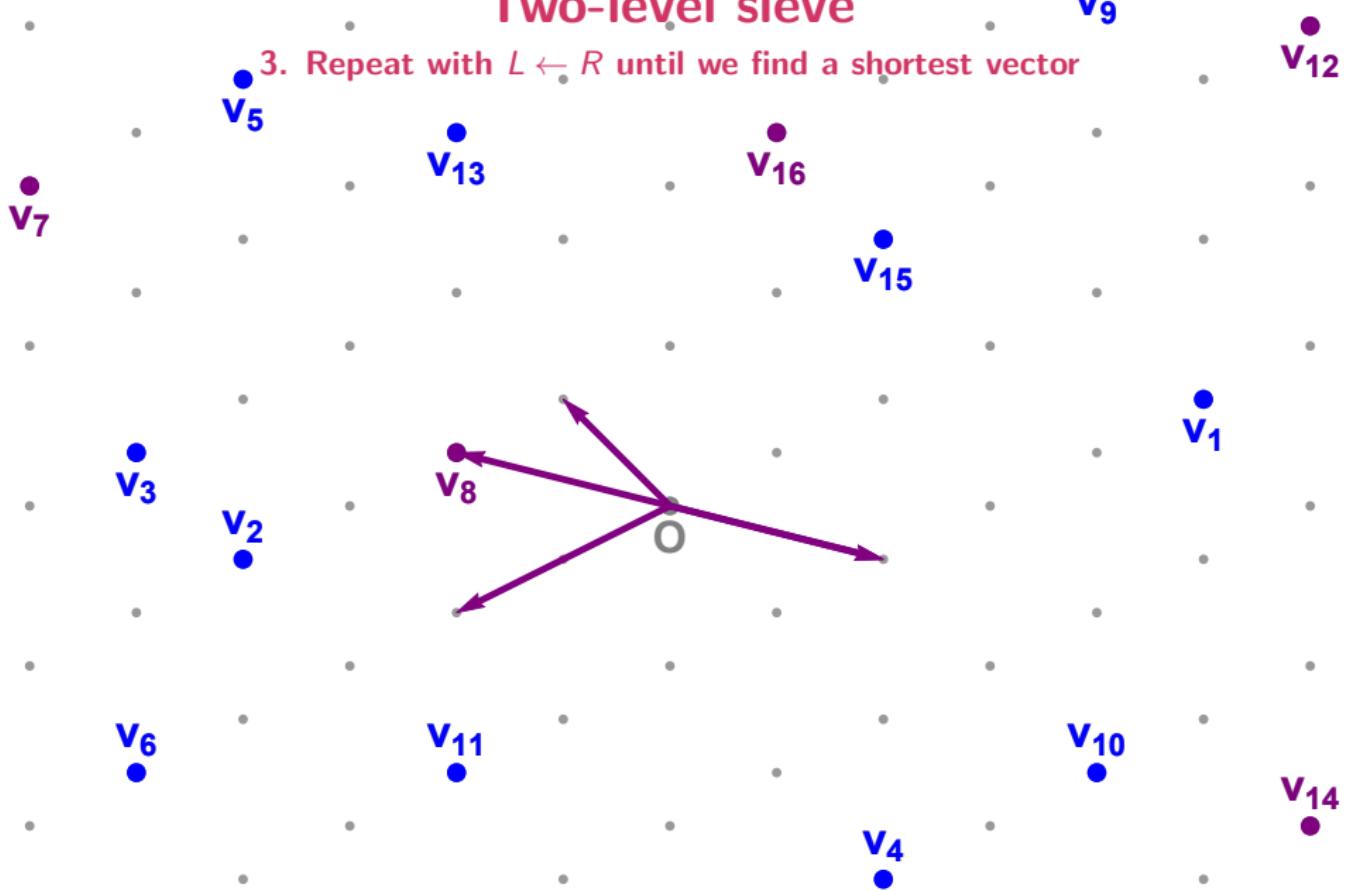
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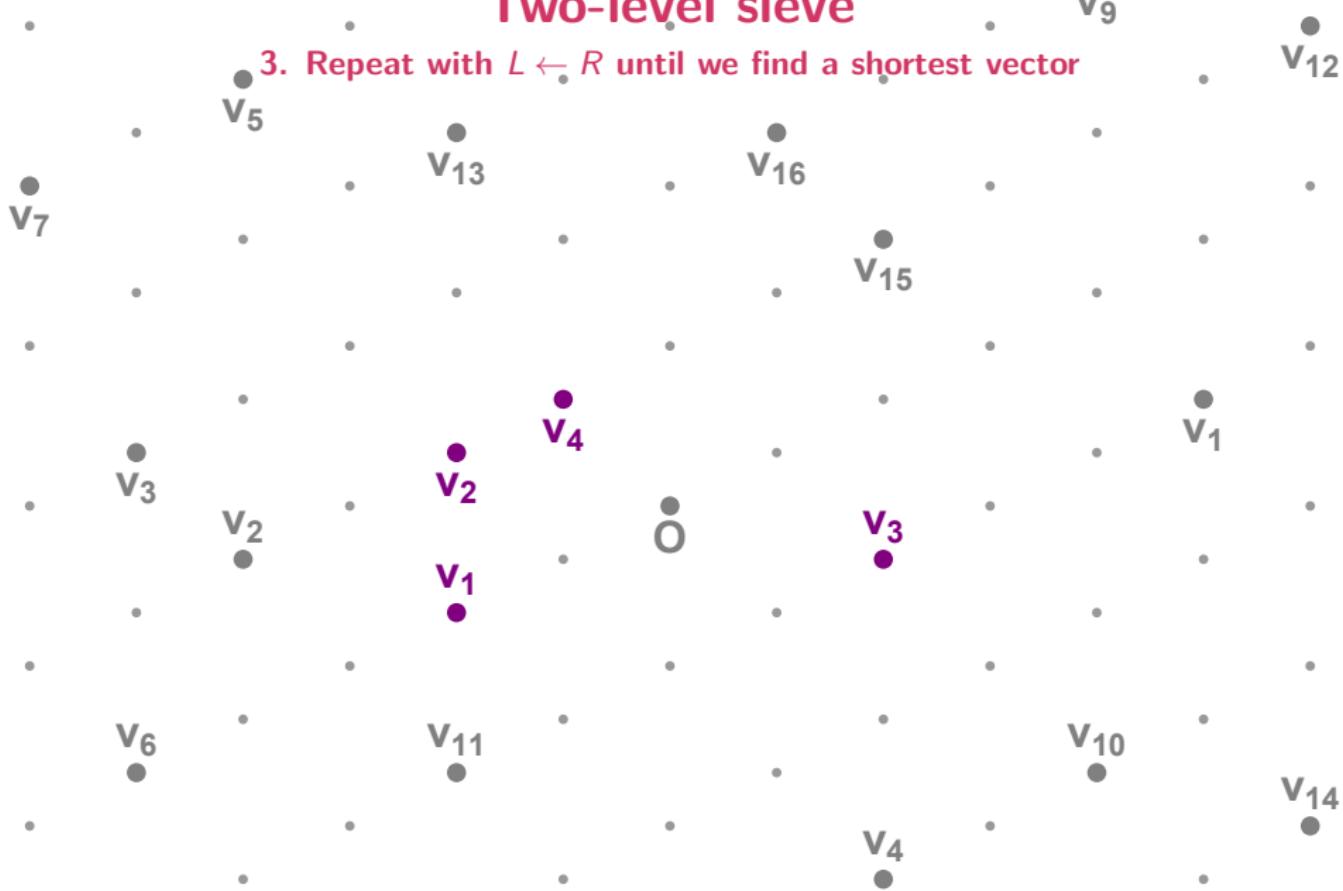
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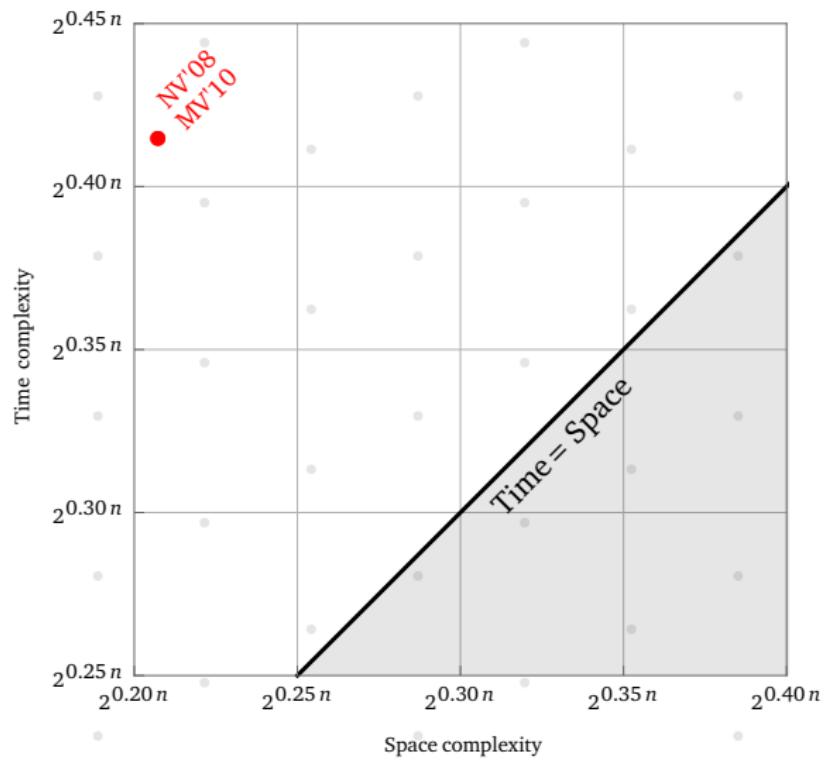
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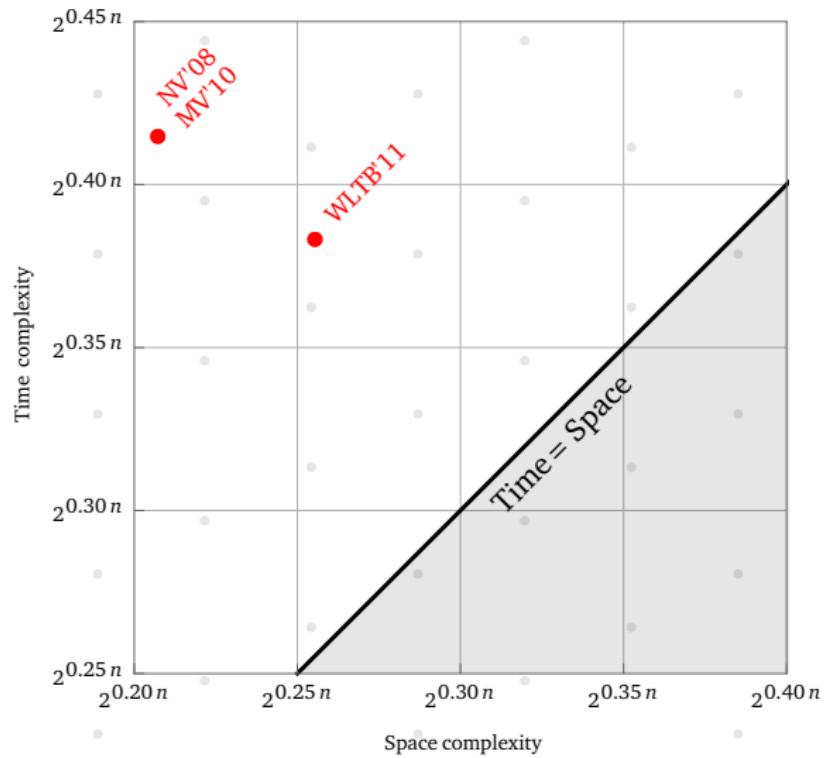
Two-level sieve

Space/time trade-off



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Space/time trade-off



Three-level sieve

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

The one-level sieve runs in time $2^{0.4150n}$ and space $2^{0.2075n}$.

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The three-level sieve runs in time $2^{0.3778n}$ and space $2^{0.2833n}$.

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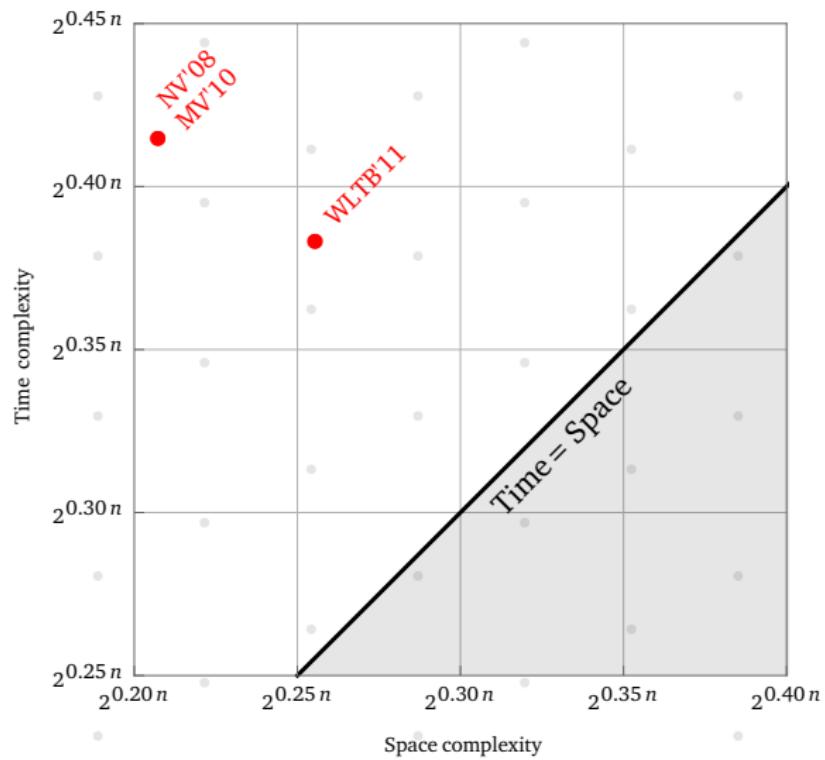
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Conjecture

The four-level sieve runs in time $2^{0.3774n}$ and space $2^{0.2925n}$, and higher-level sieves are not faster than this.

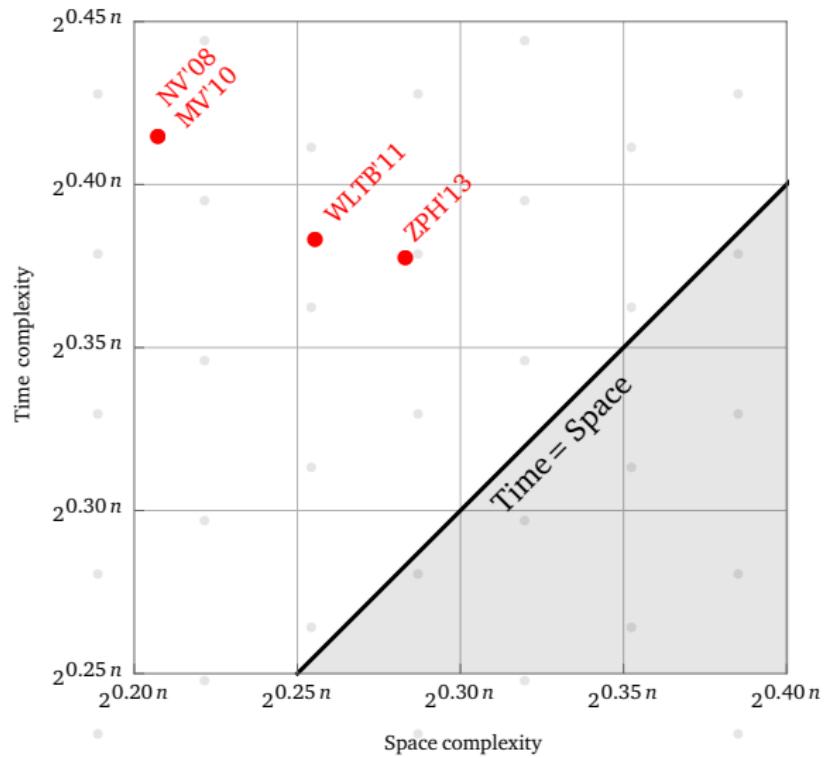
Three-level sieve

Space/time trade-off



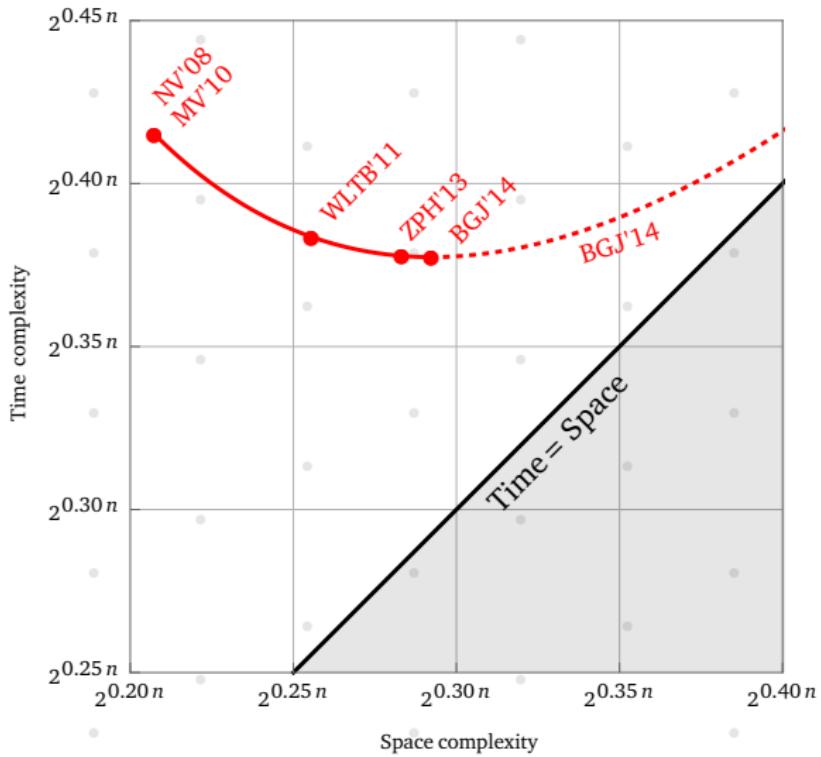
Three-level sieve

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Overlattice sieving

Space/time trade-off



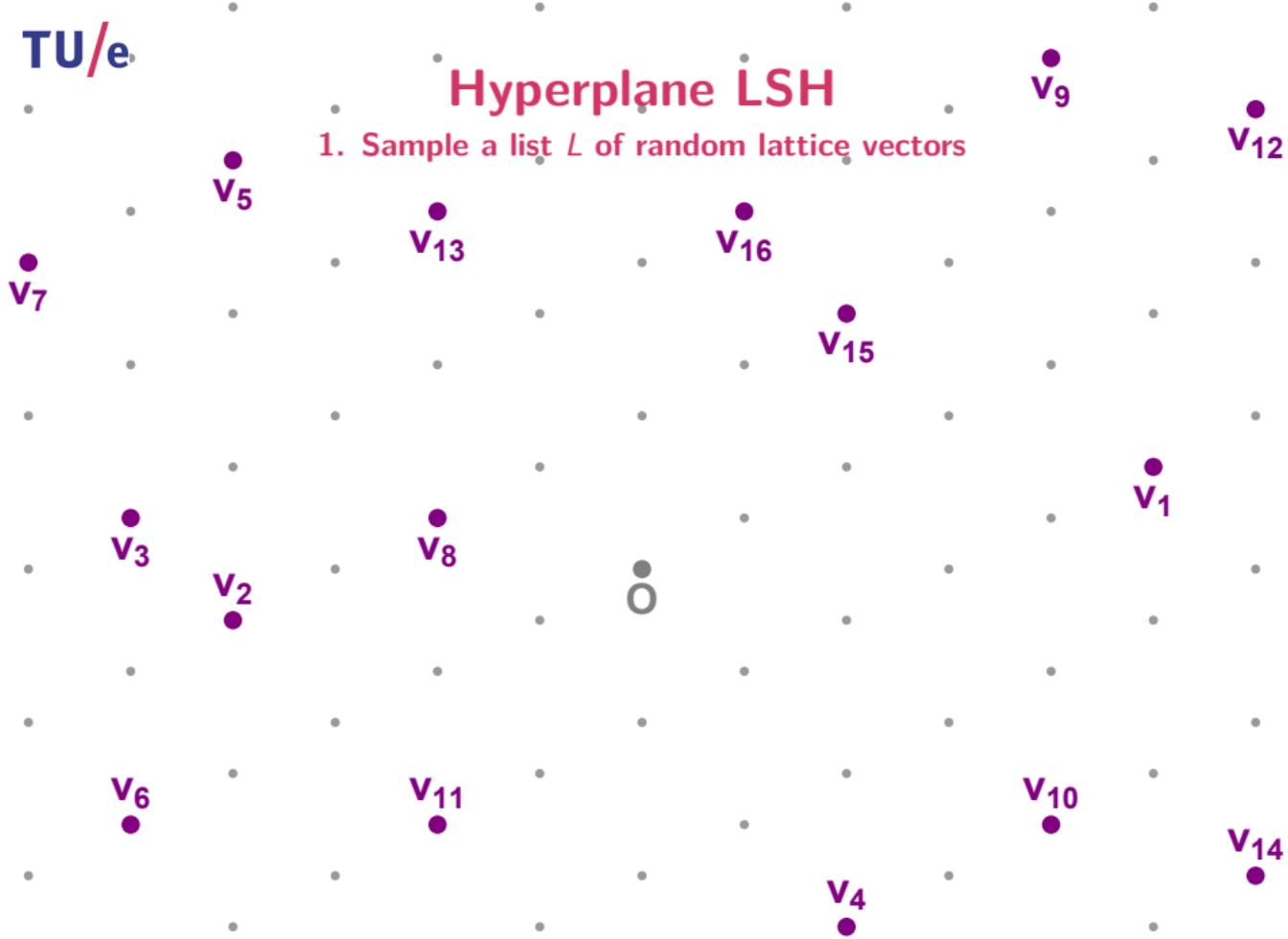
Hyperplane LSH

1. Sample a list L of random lattice vectors



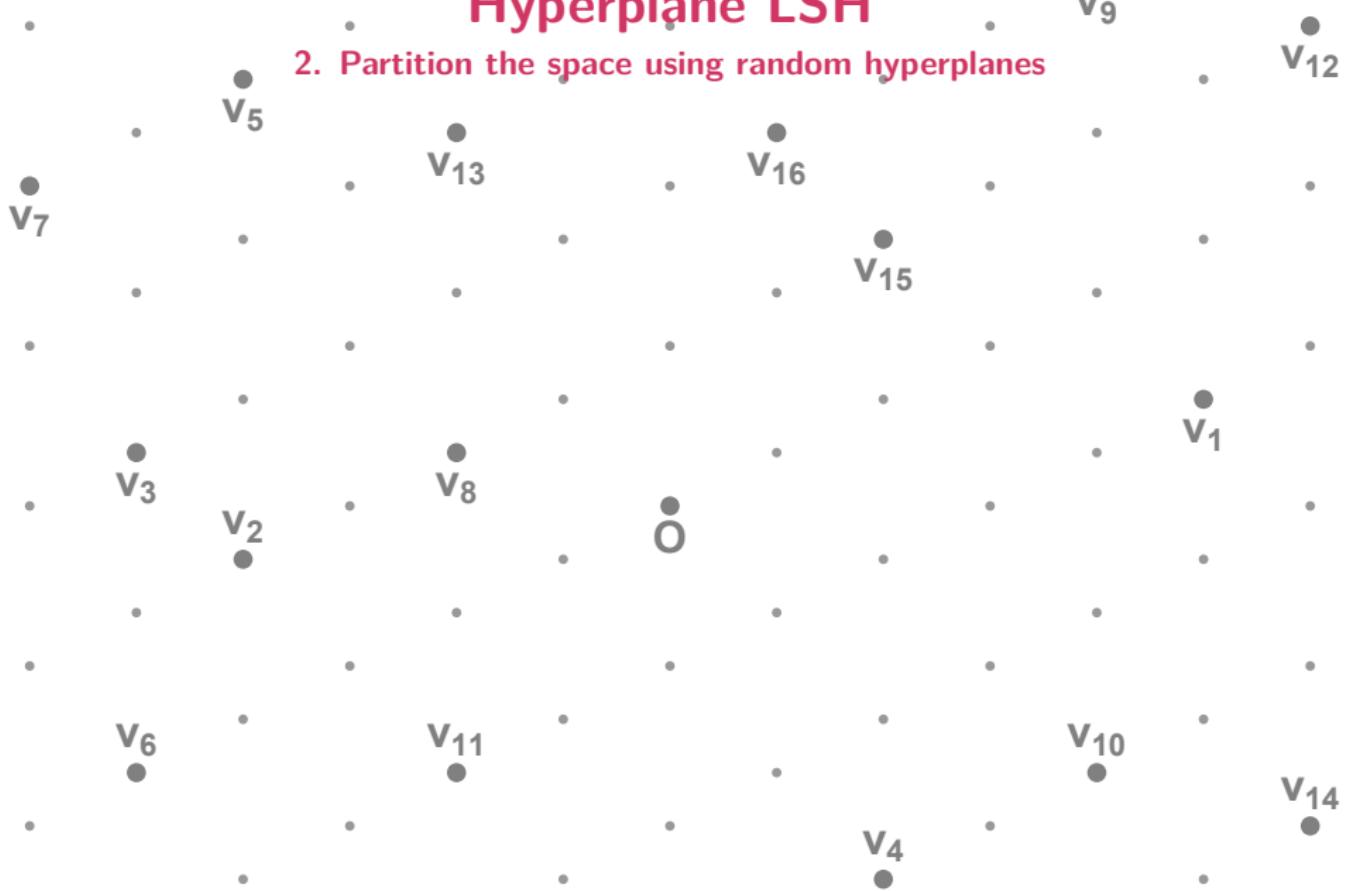
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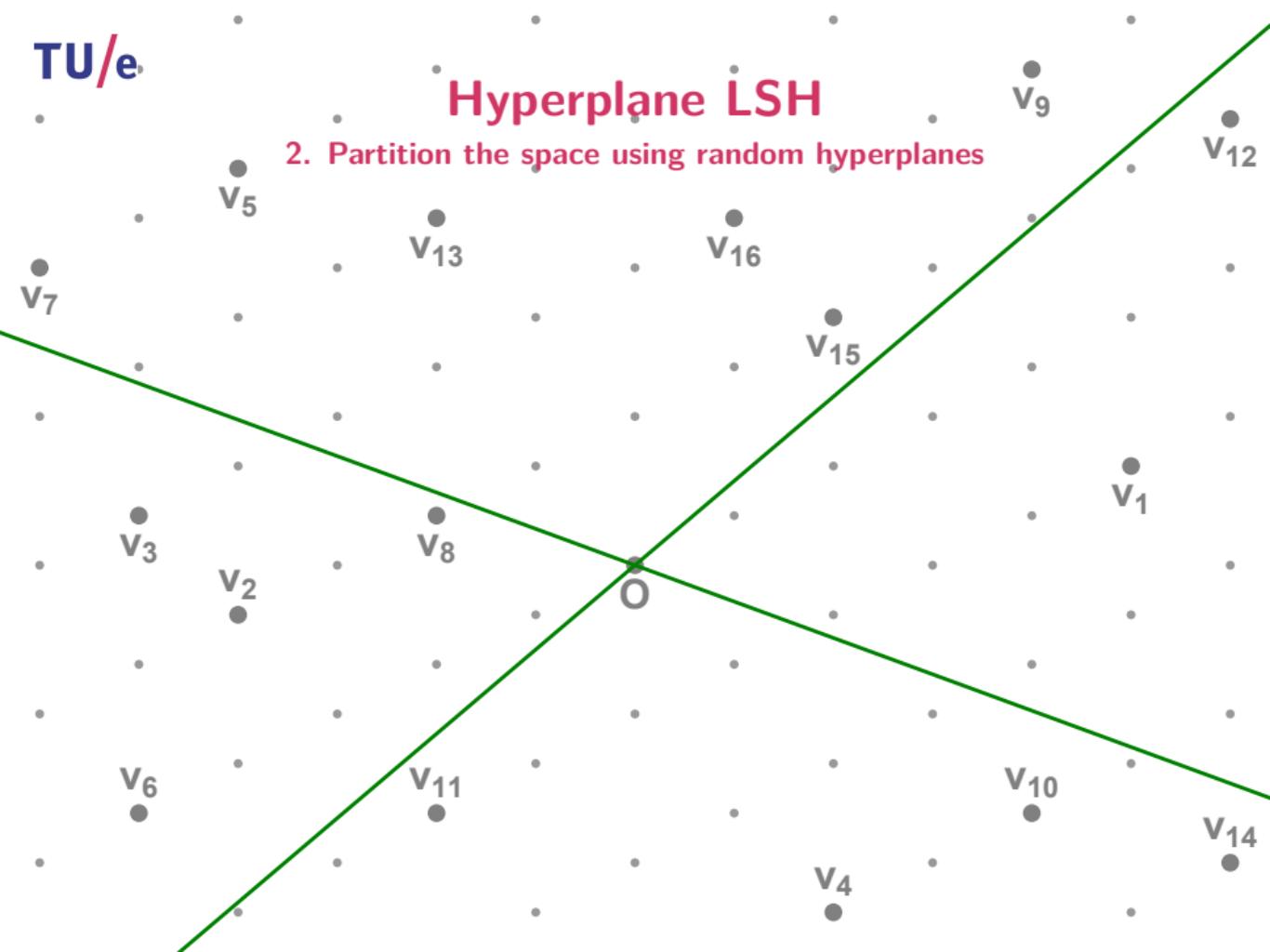
Hyperplane LSH

2. Partition the space using random hyperplanes



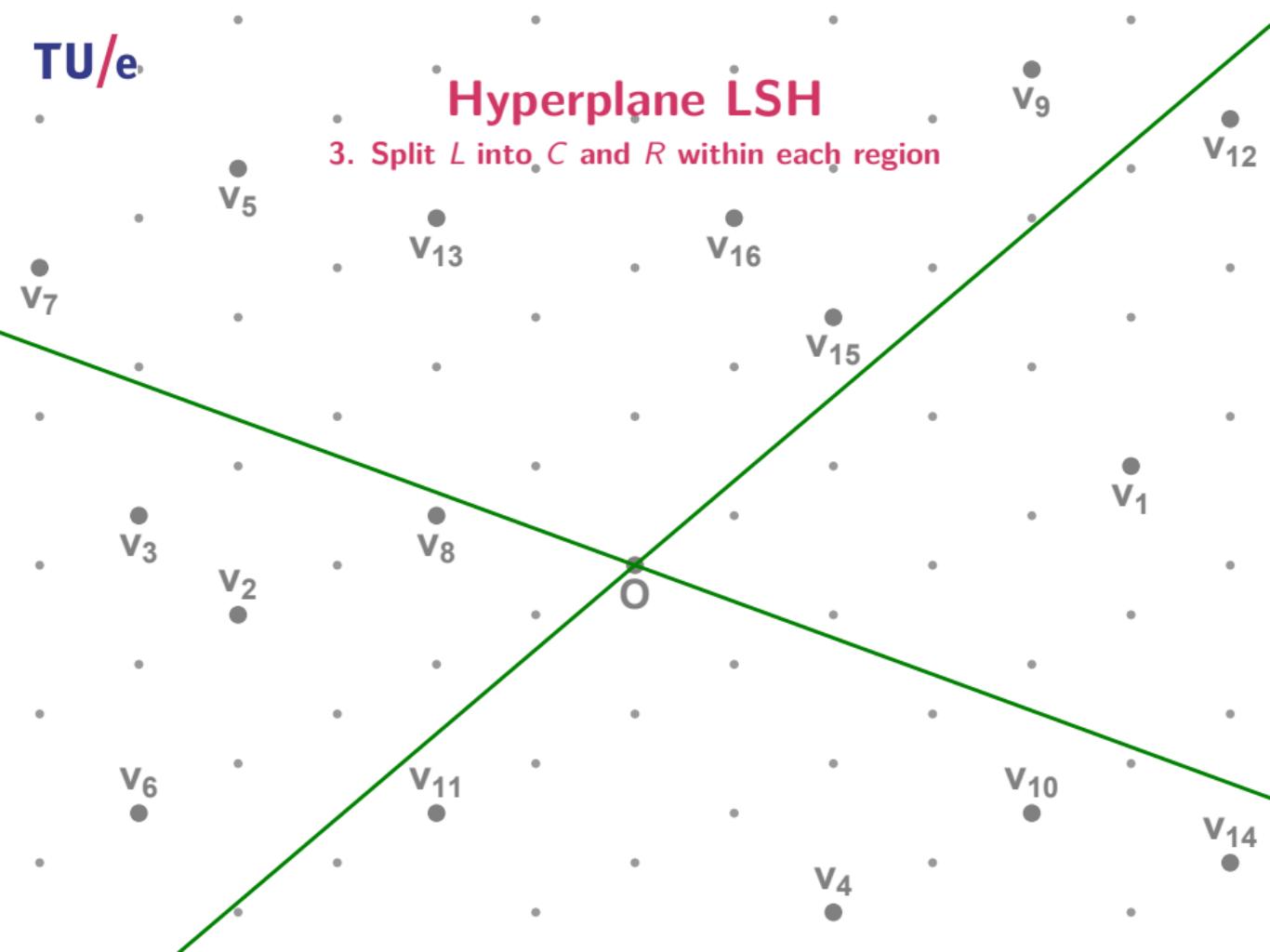
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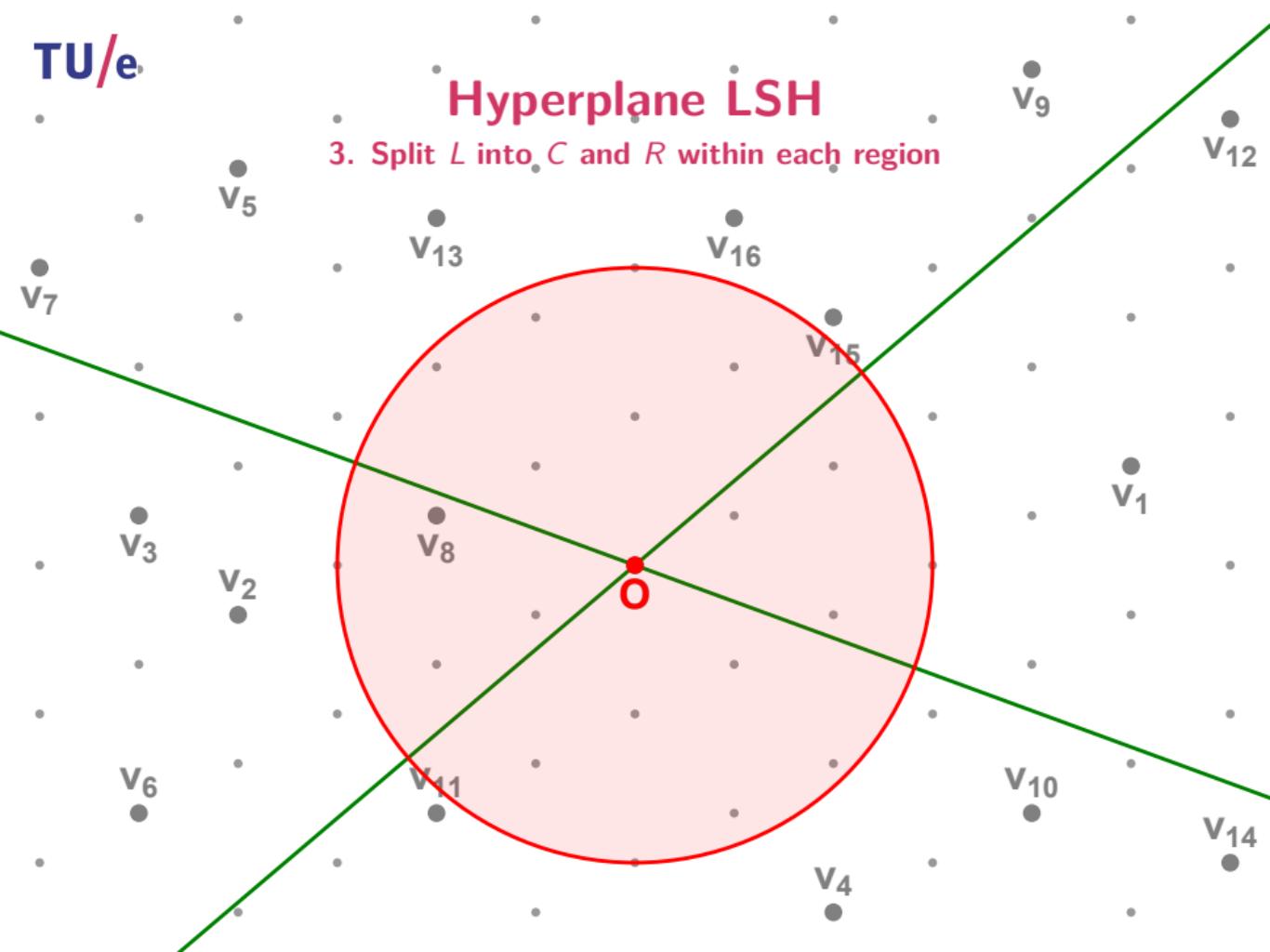
Hyperplane LSH

3. Split L into C and R within each region



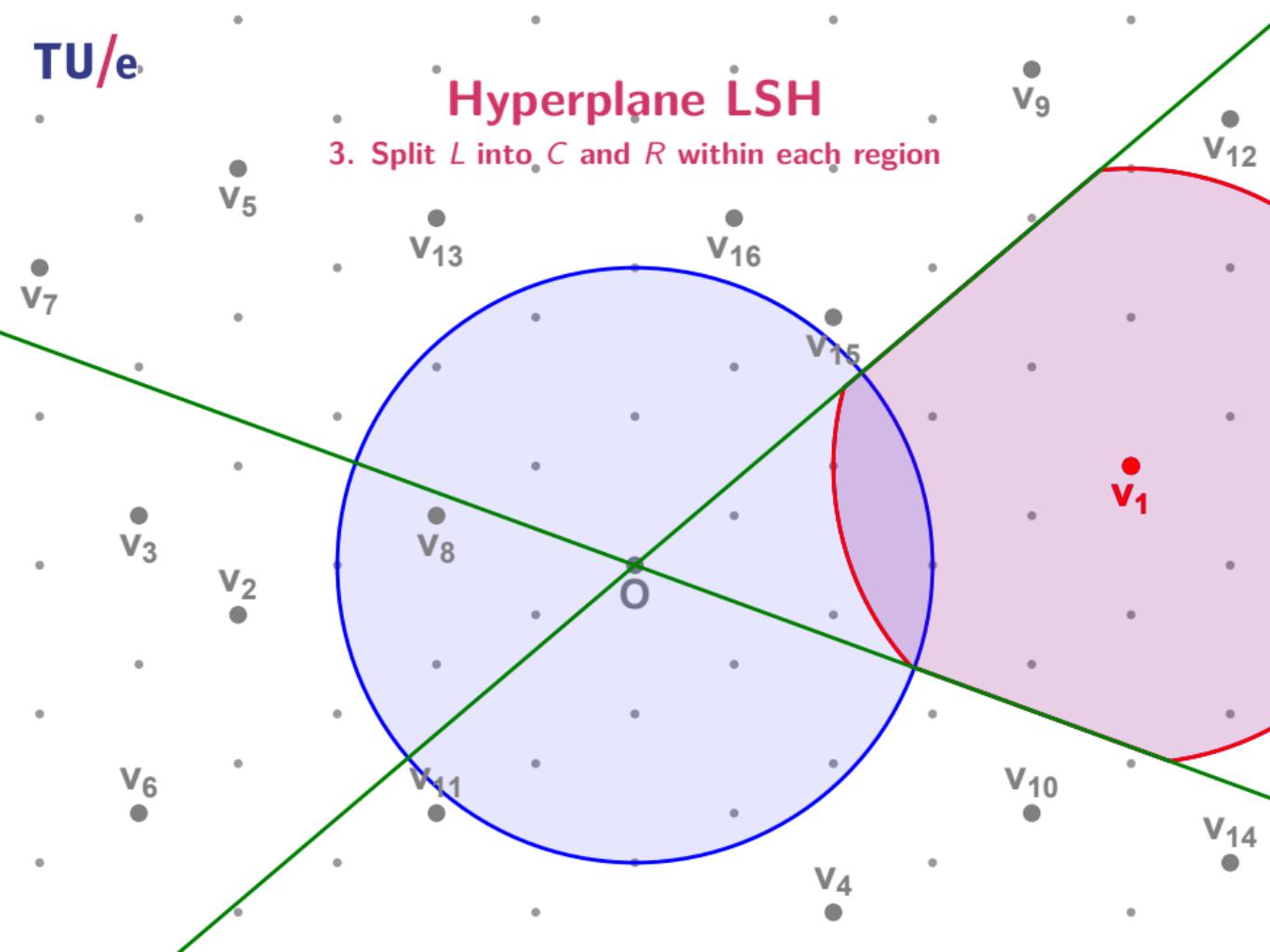
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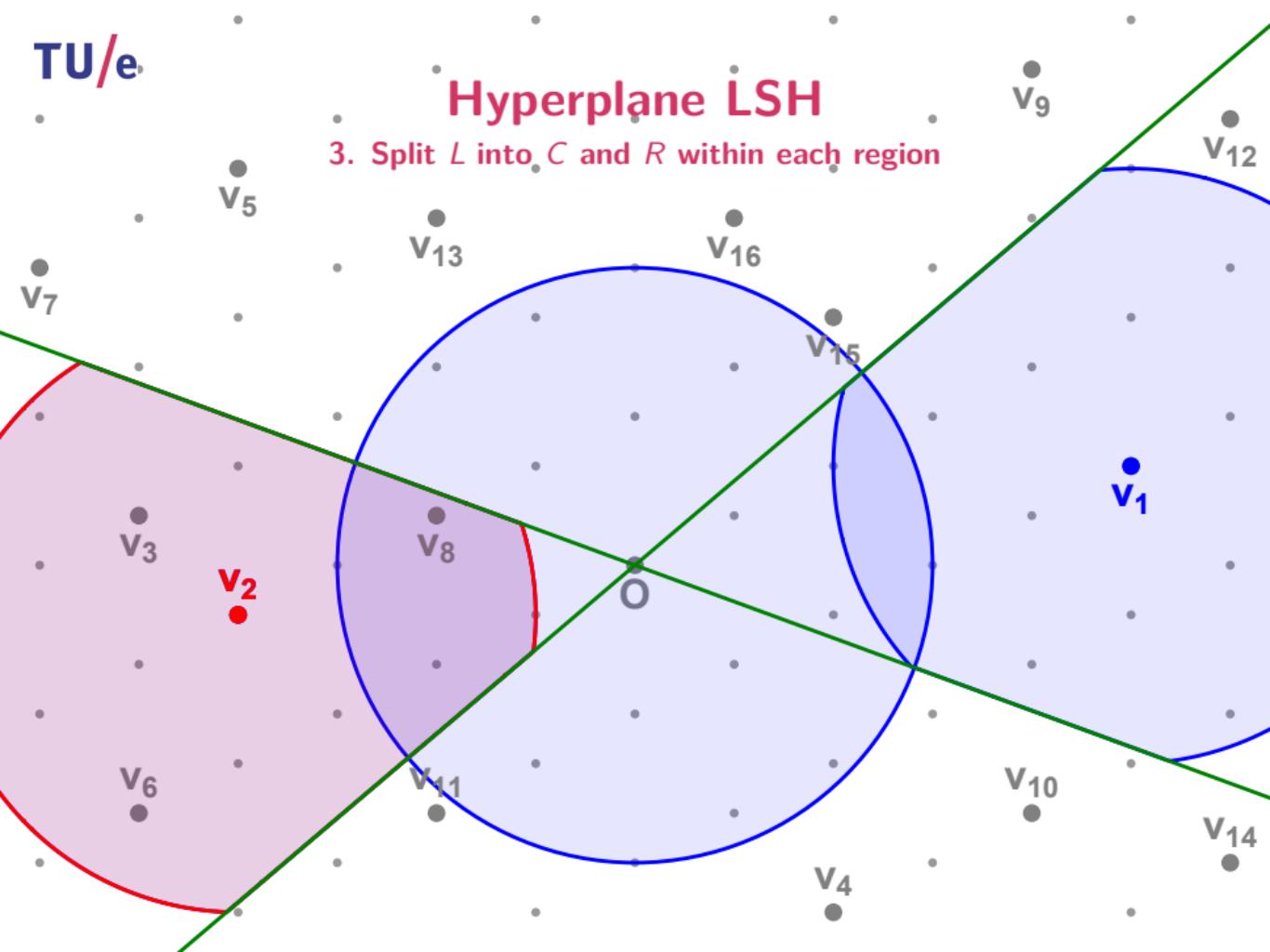
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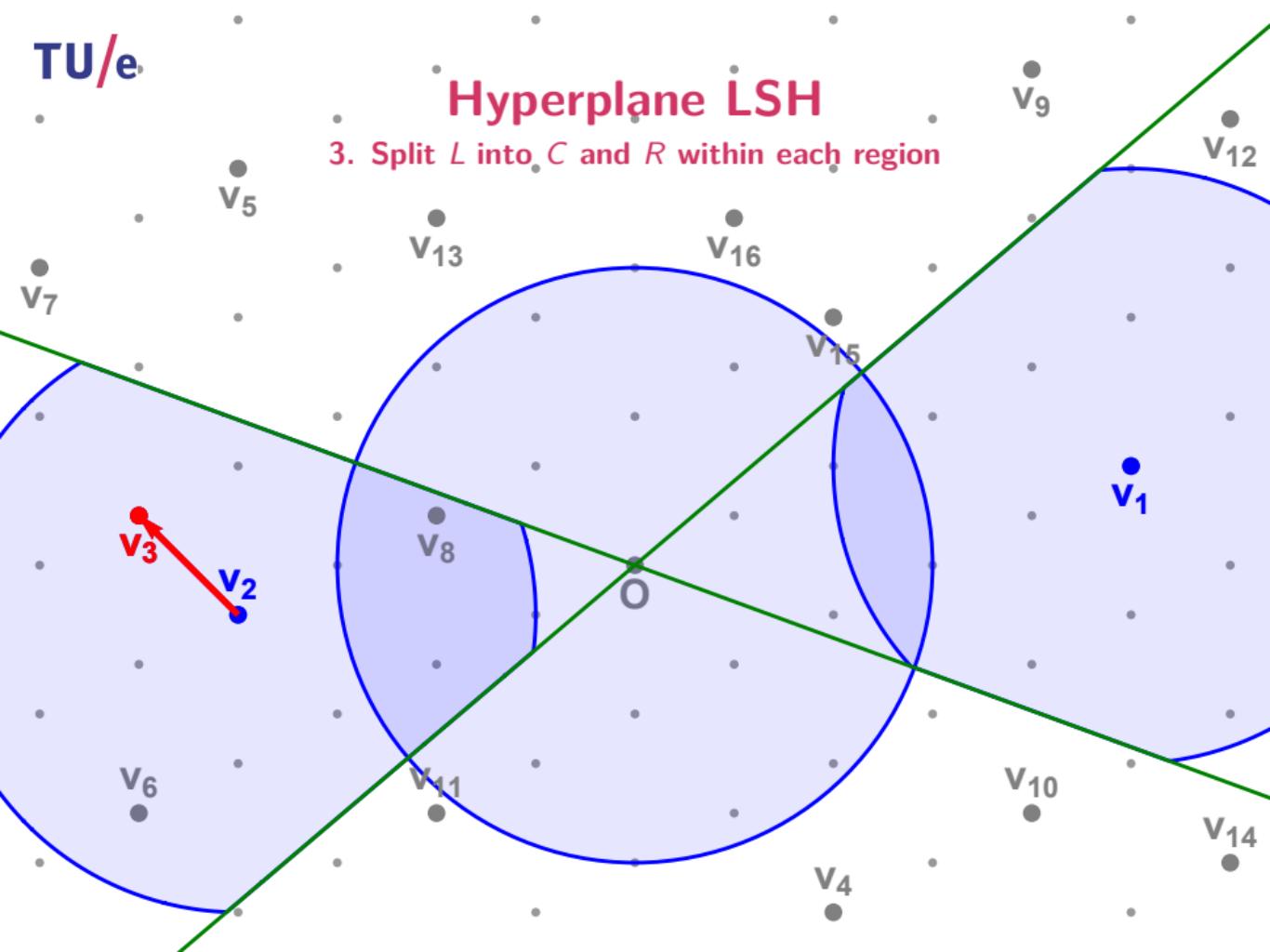
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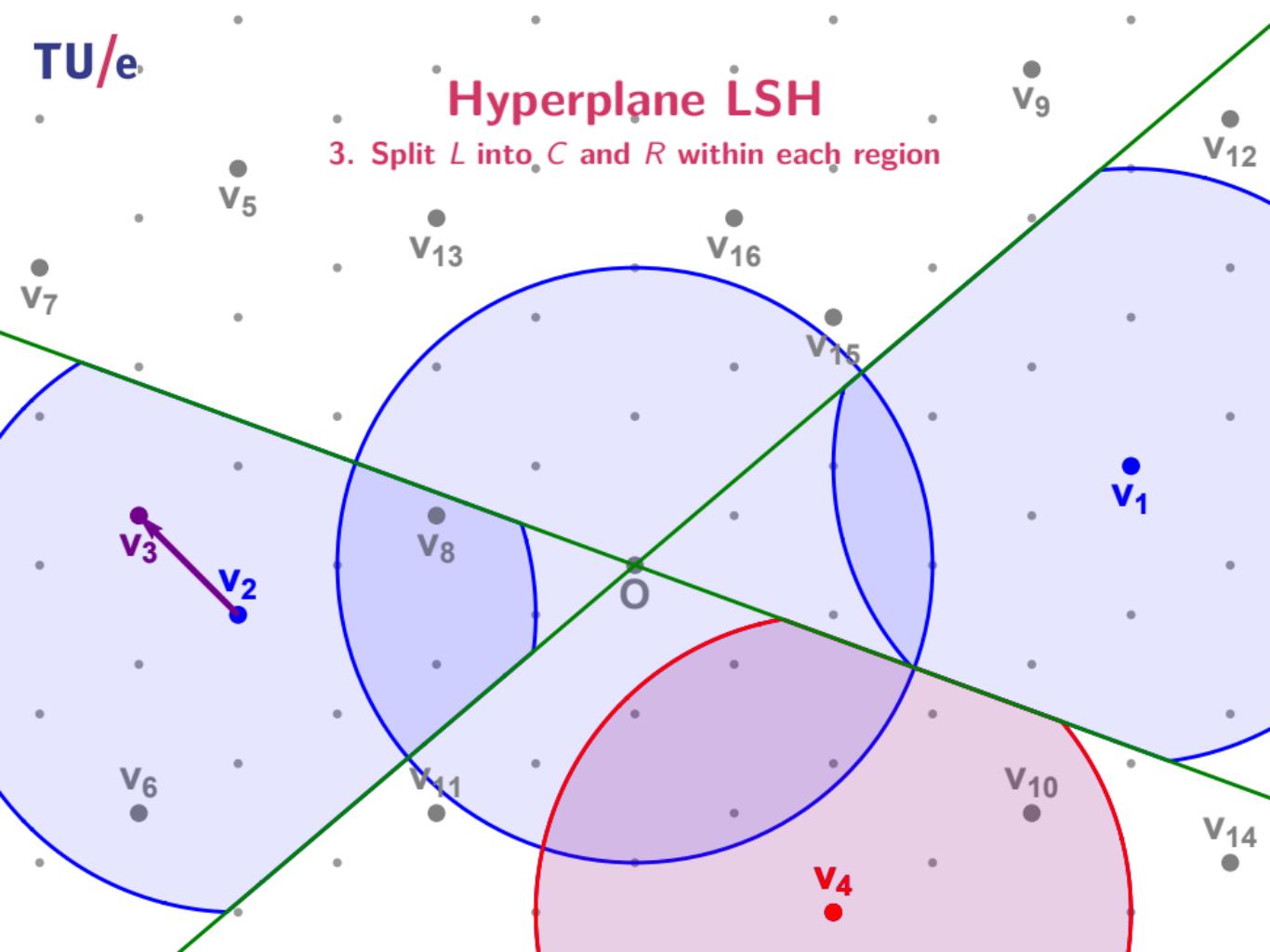
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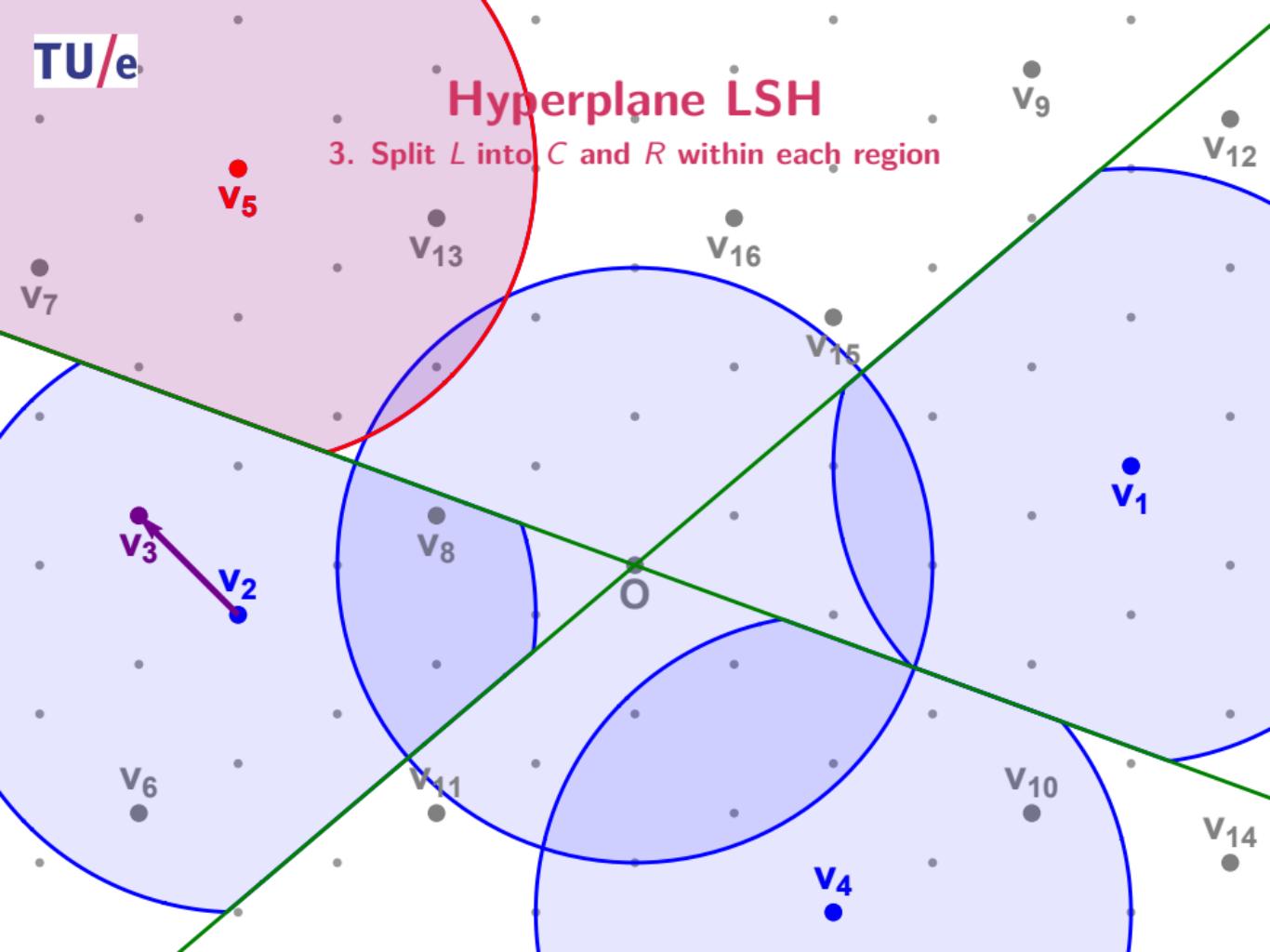
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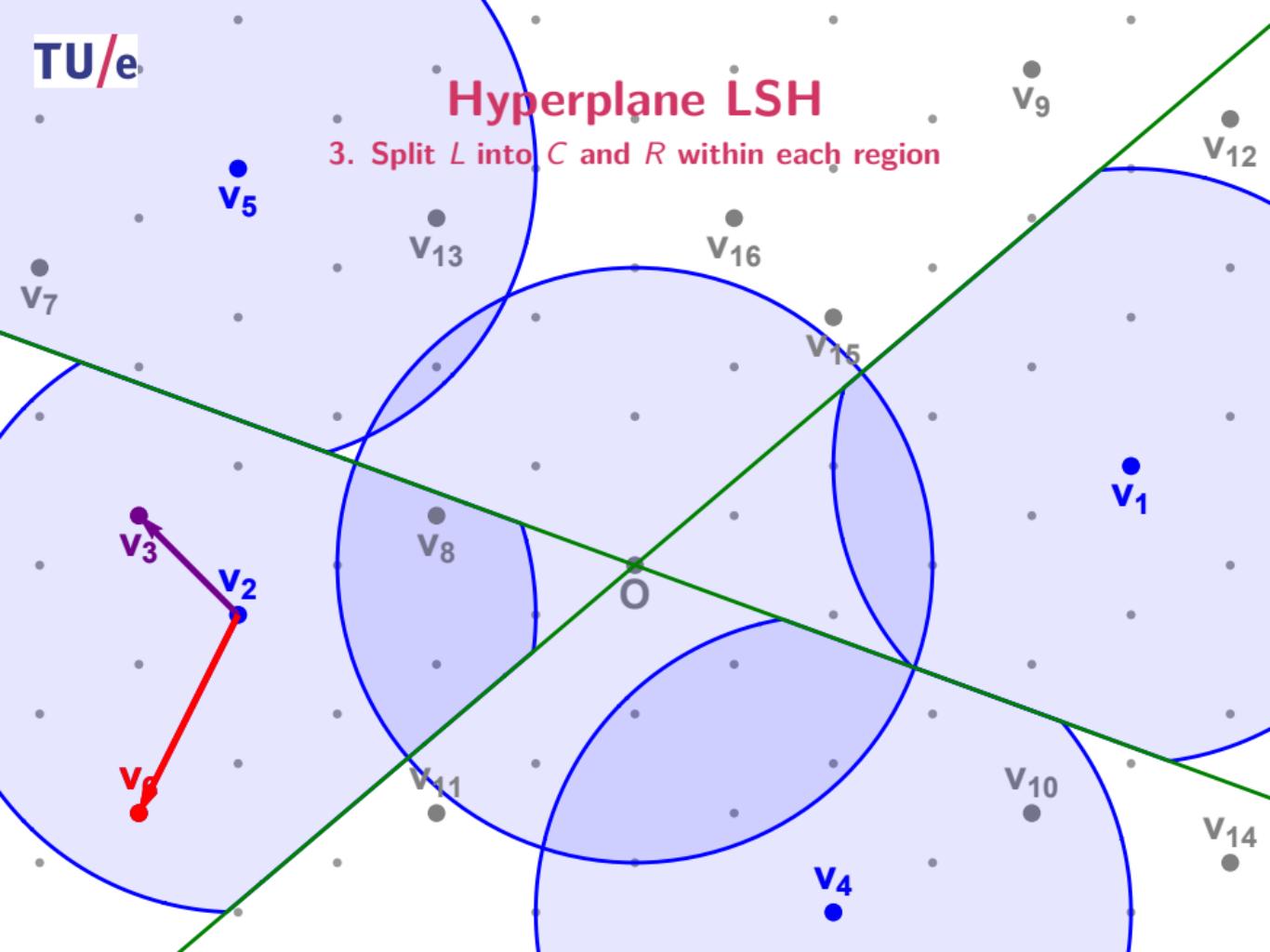
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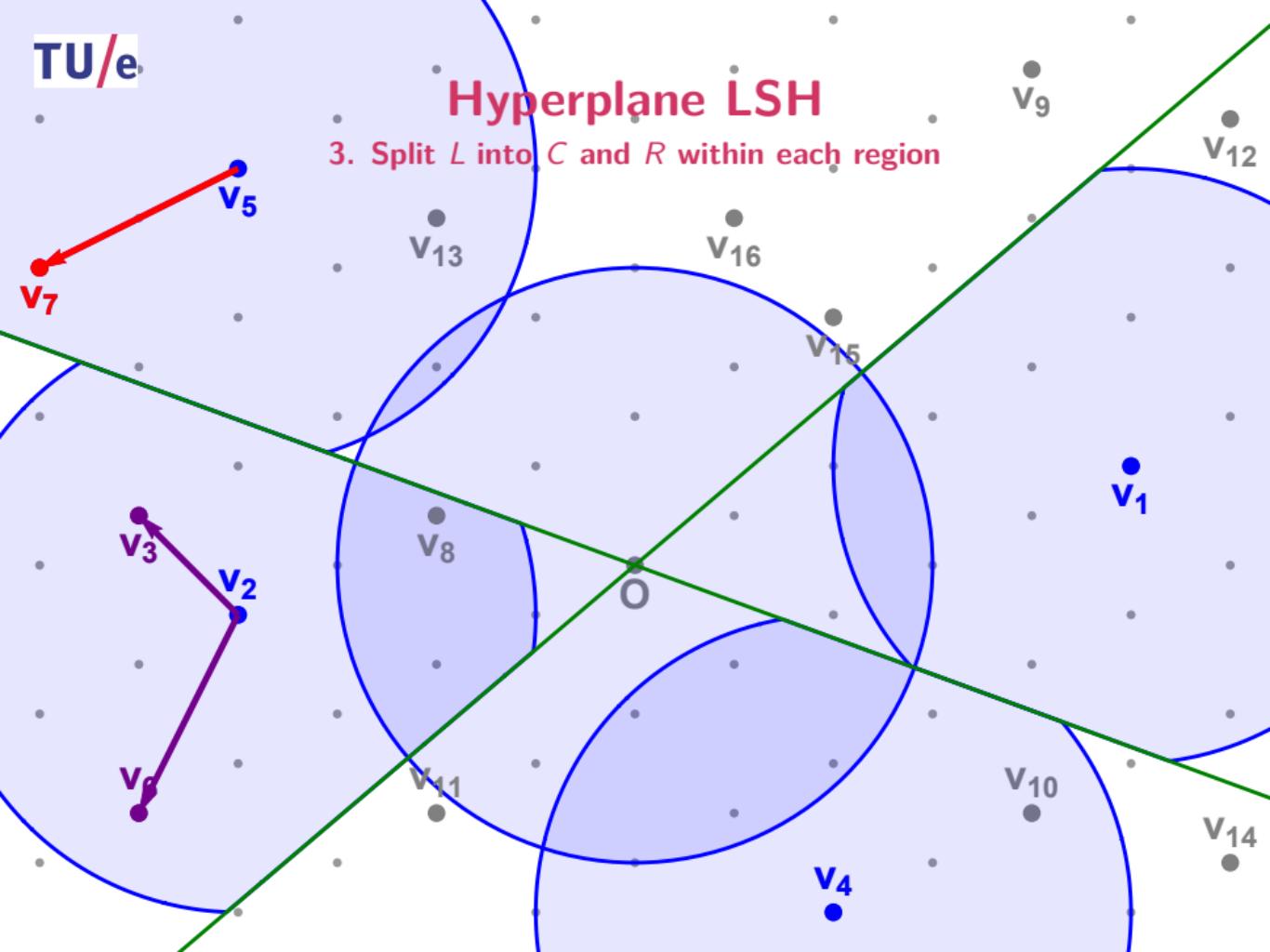
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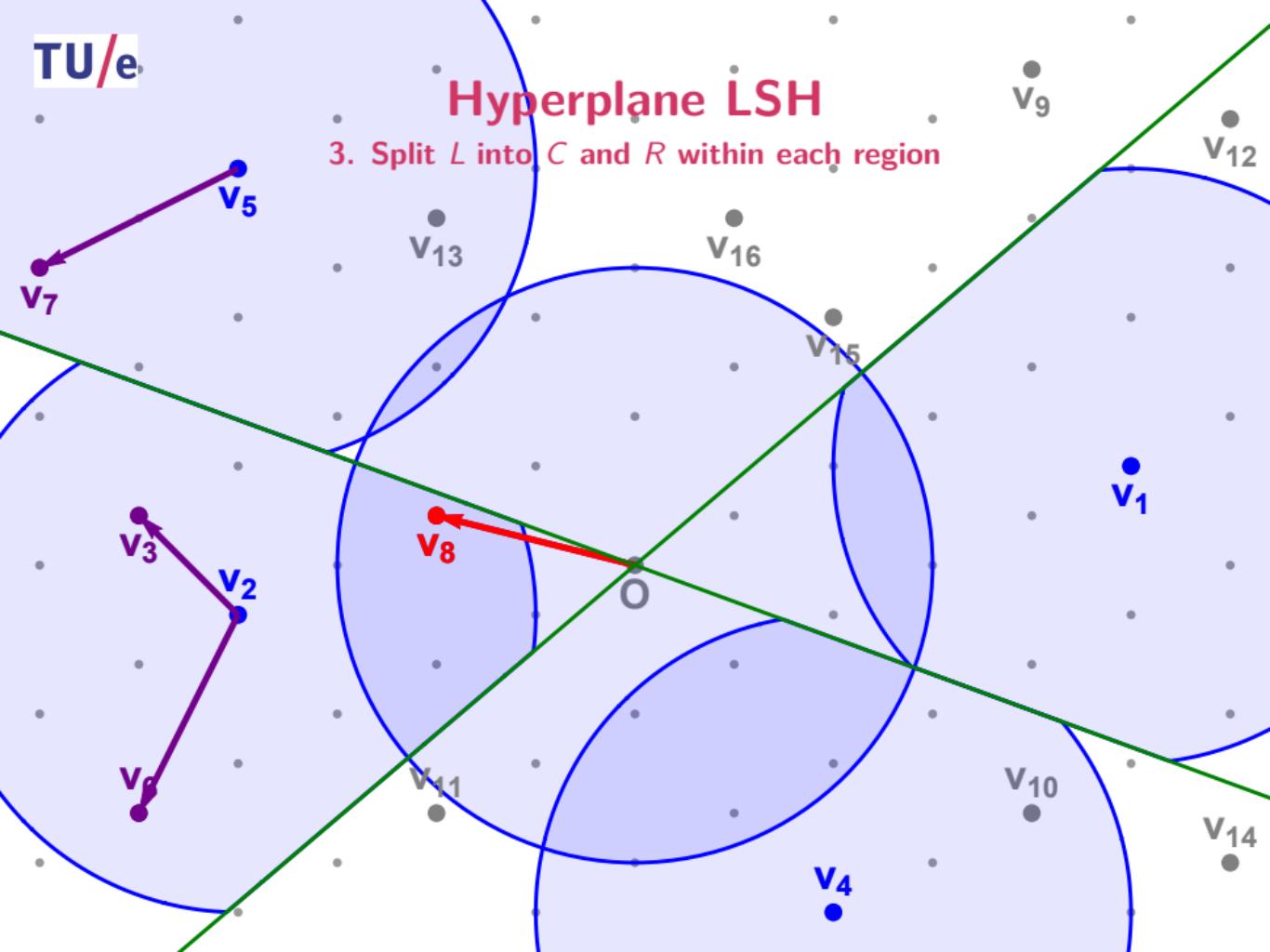
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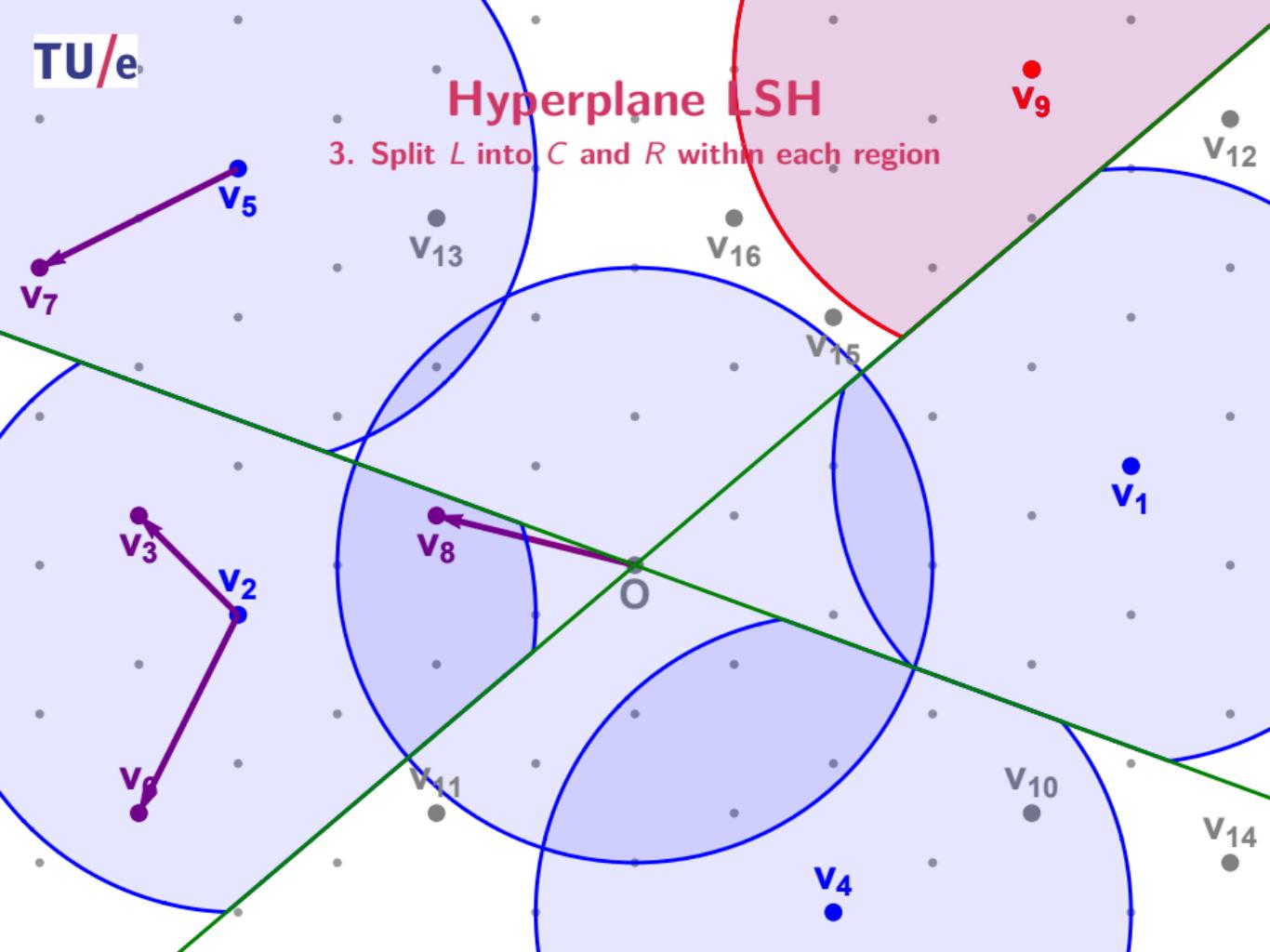
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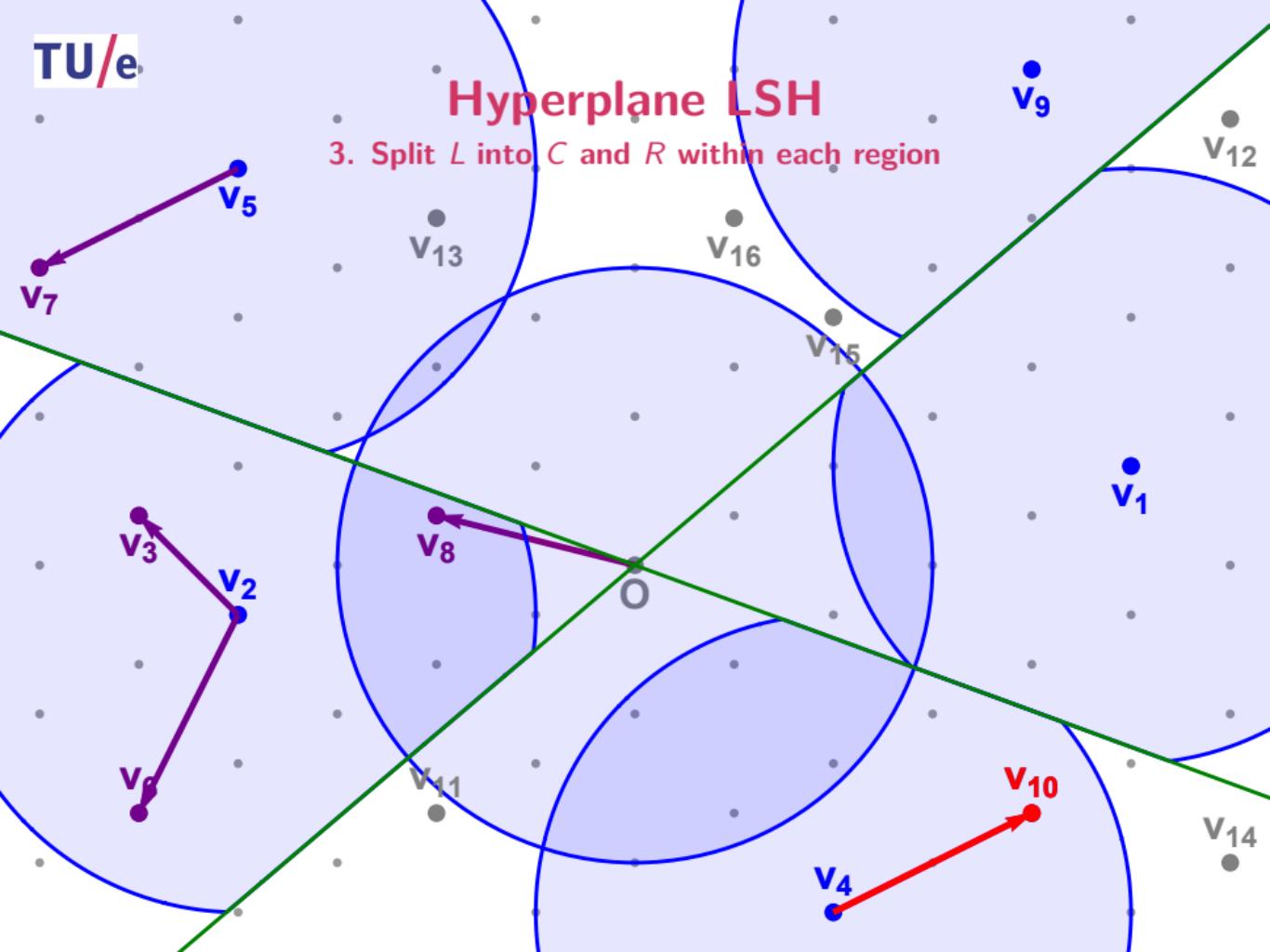
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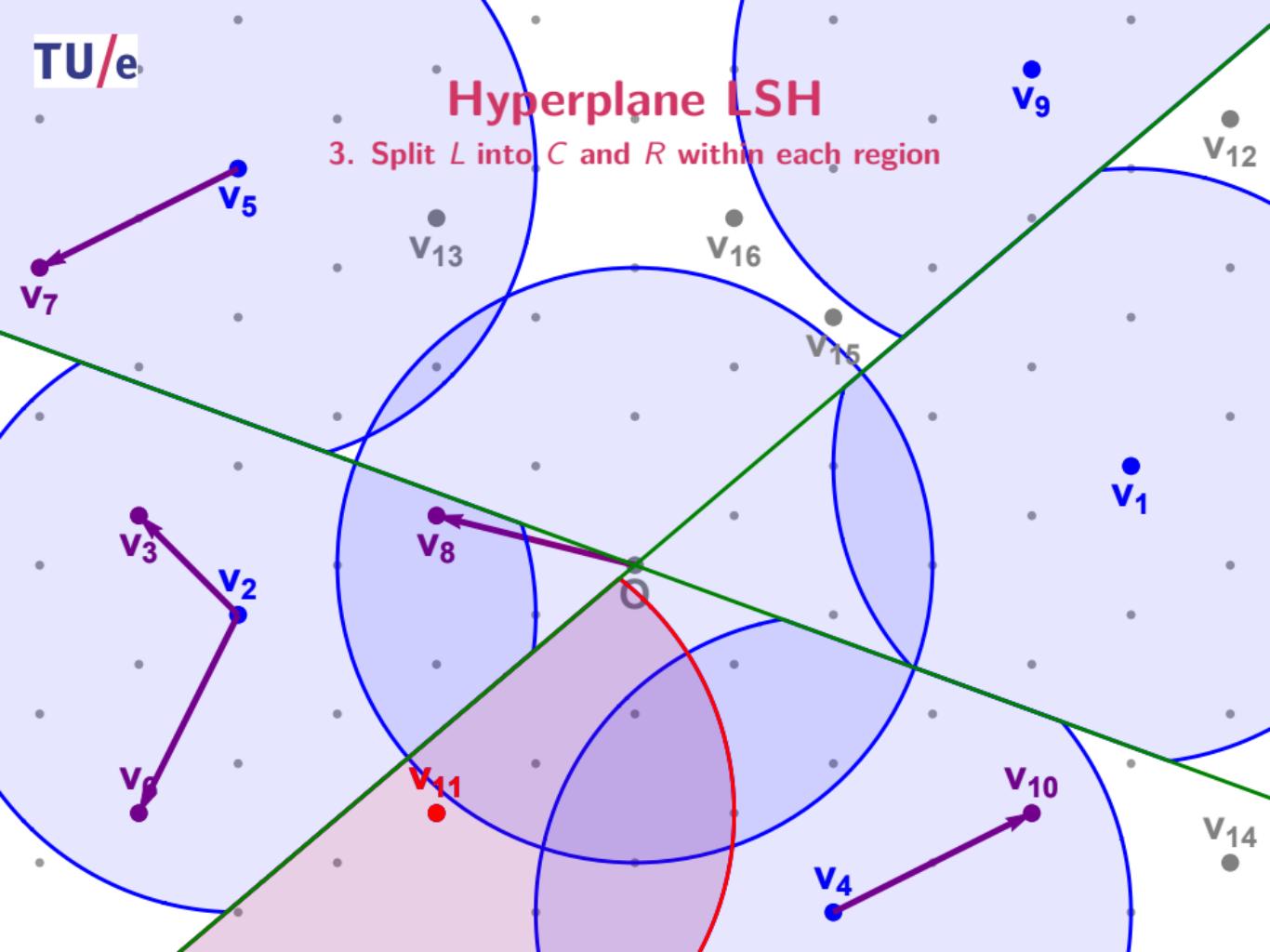
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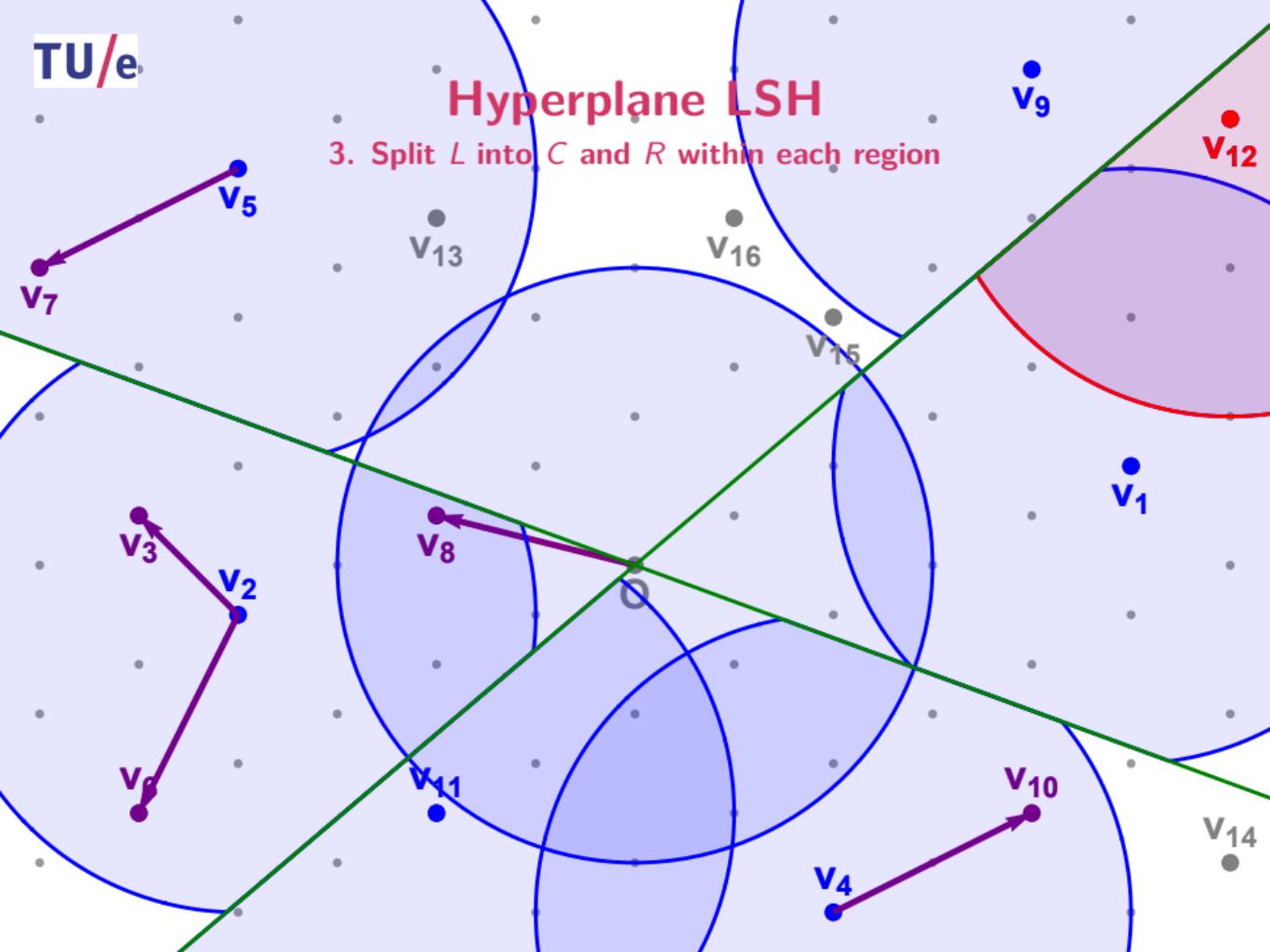
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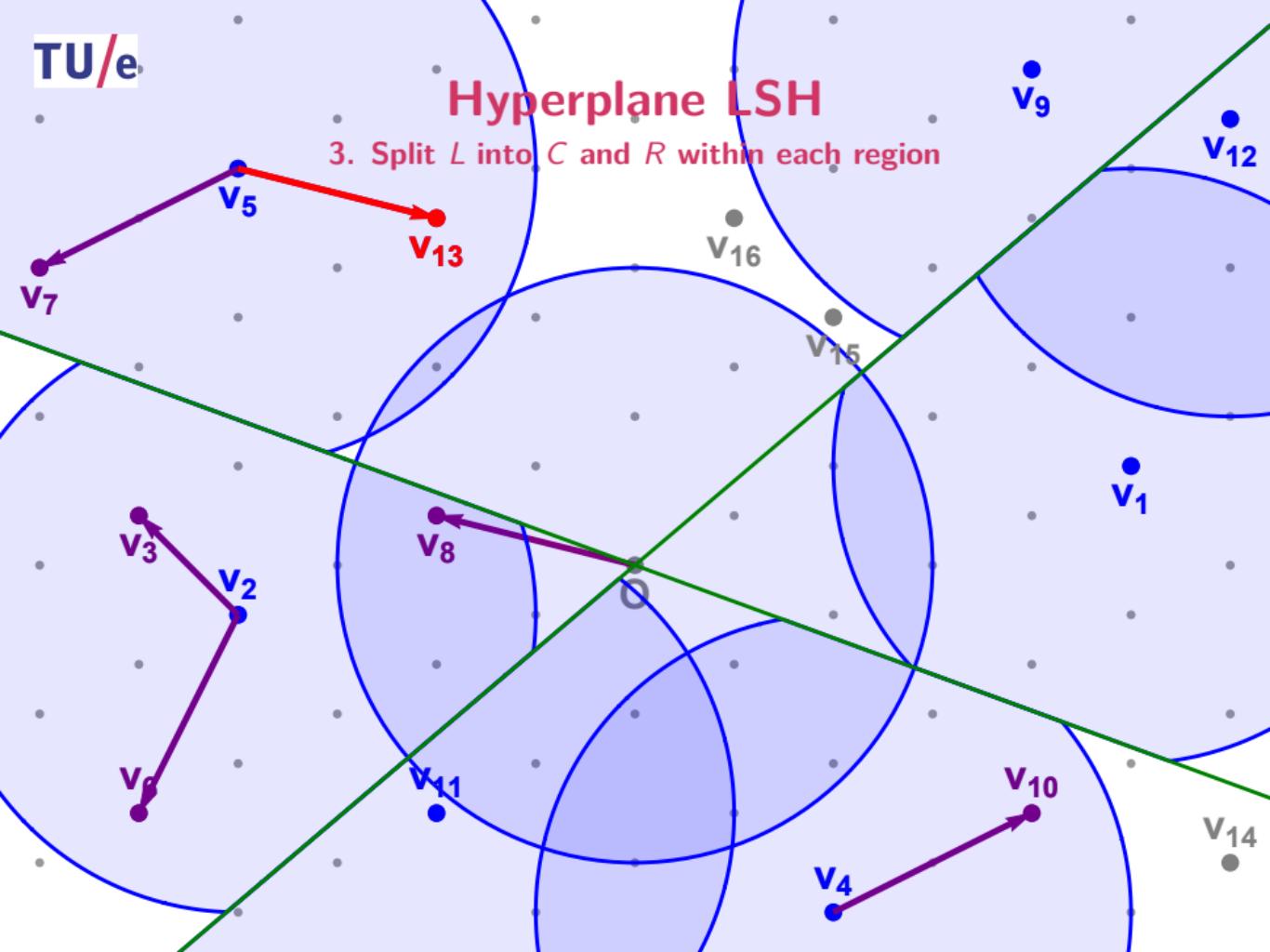
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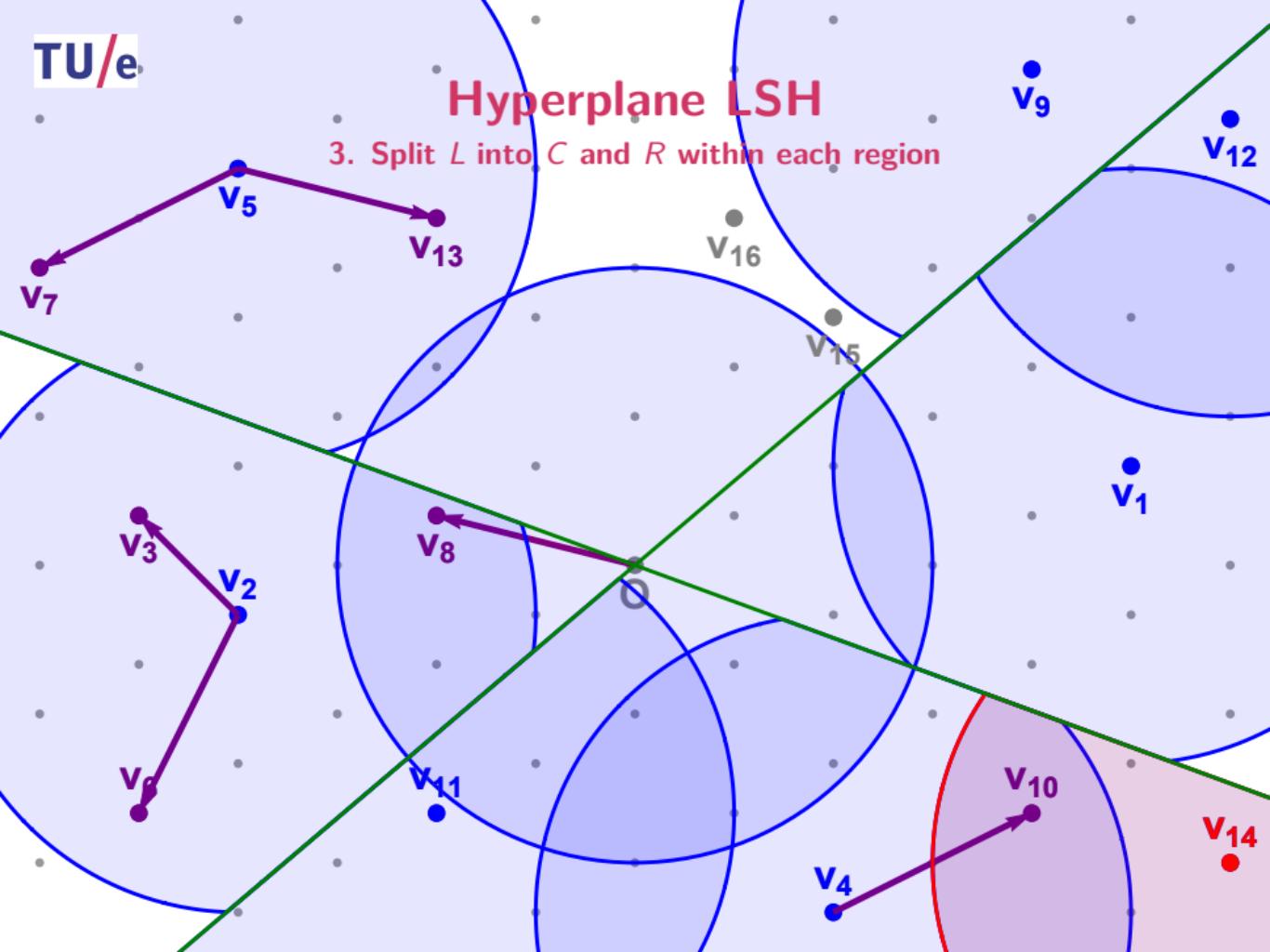
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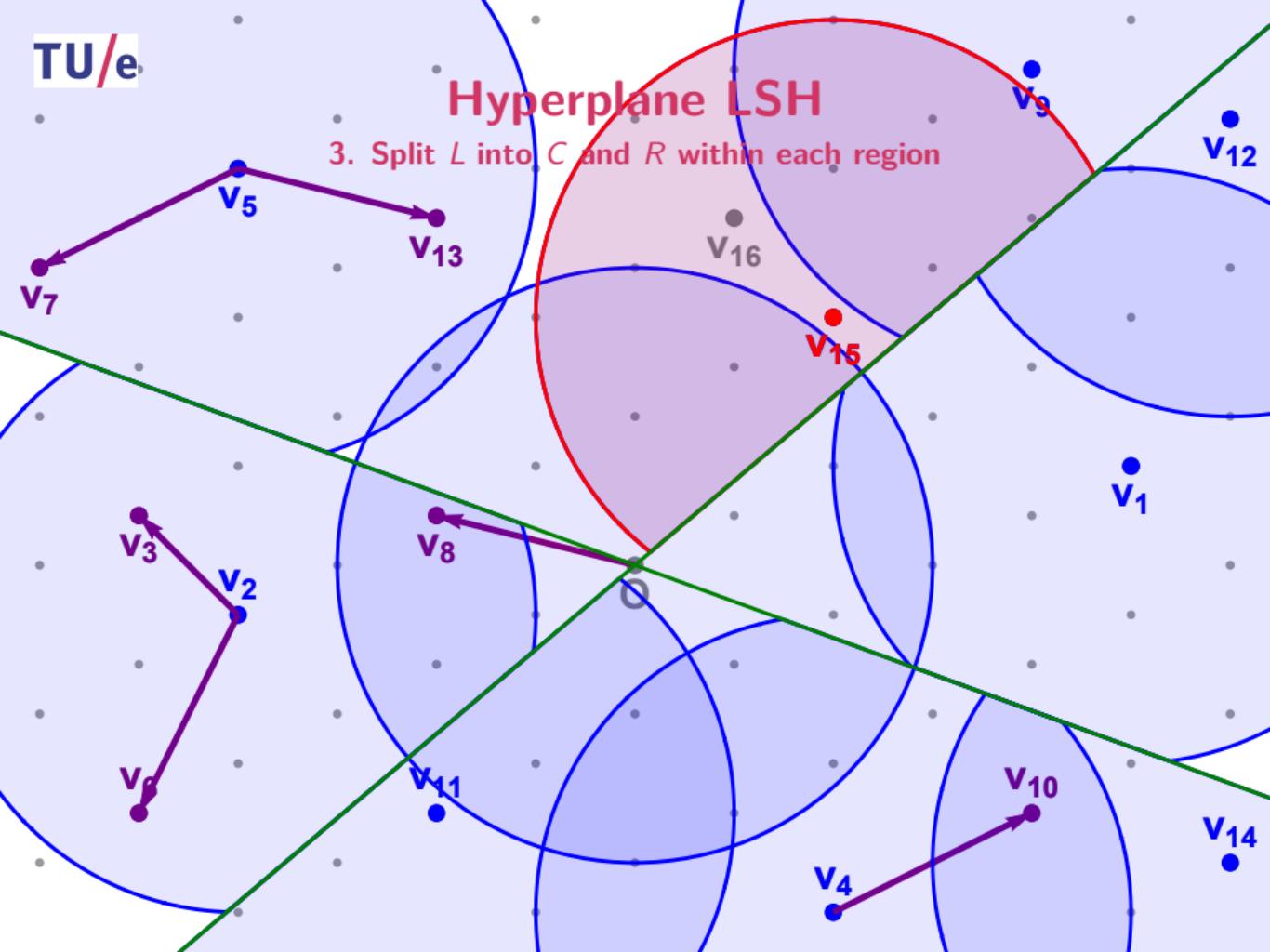
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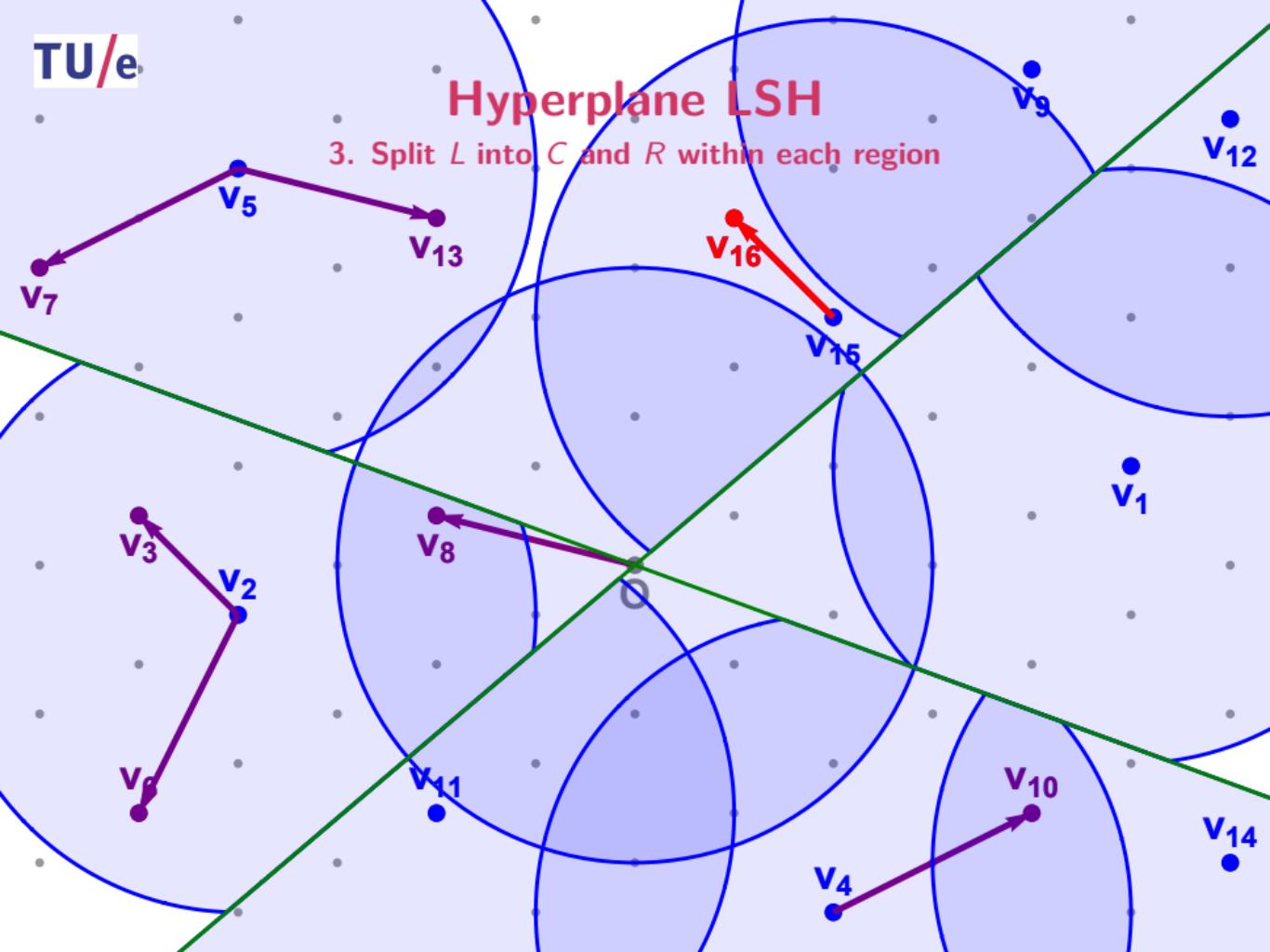
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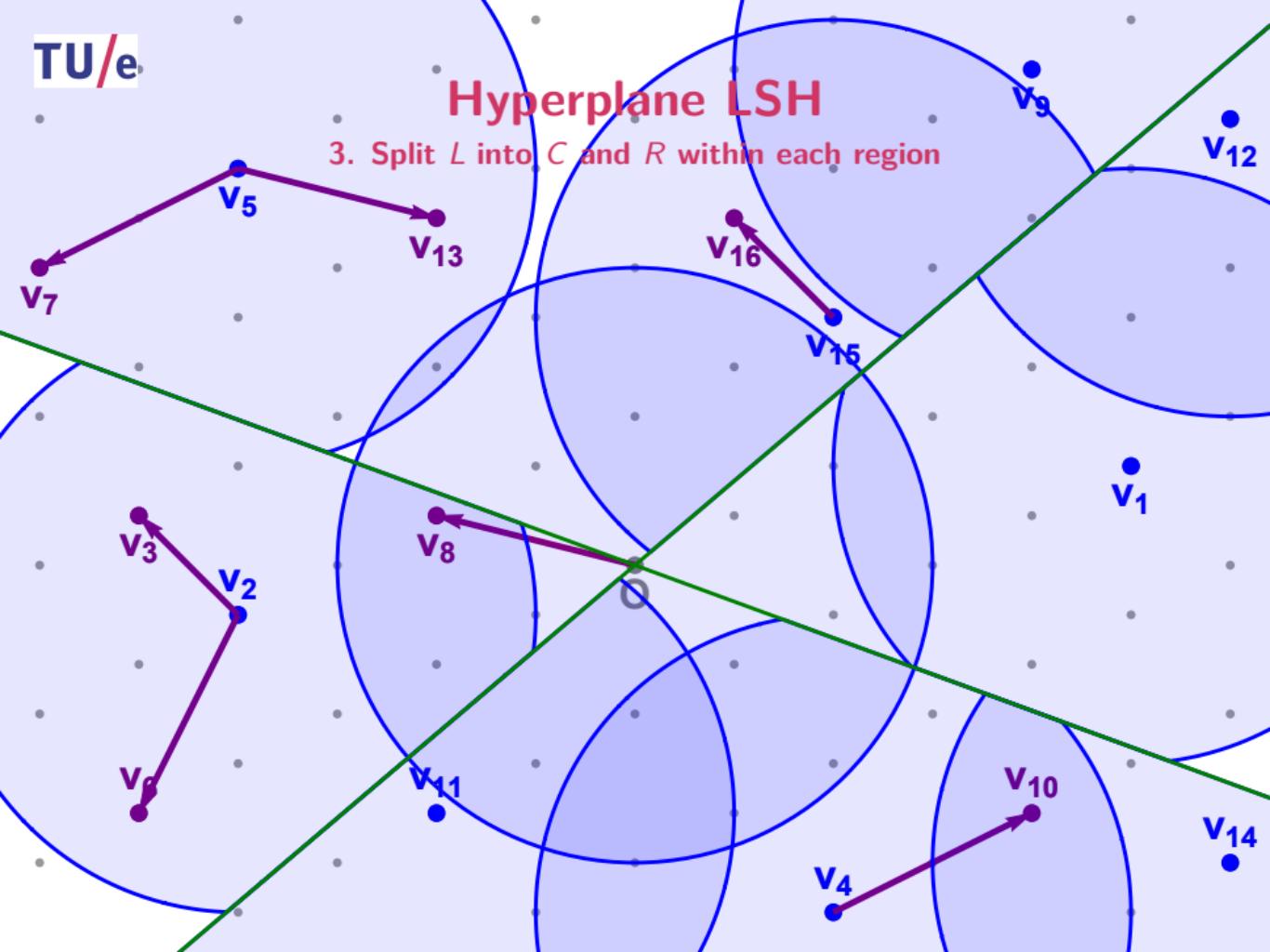
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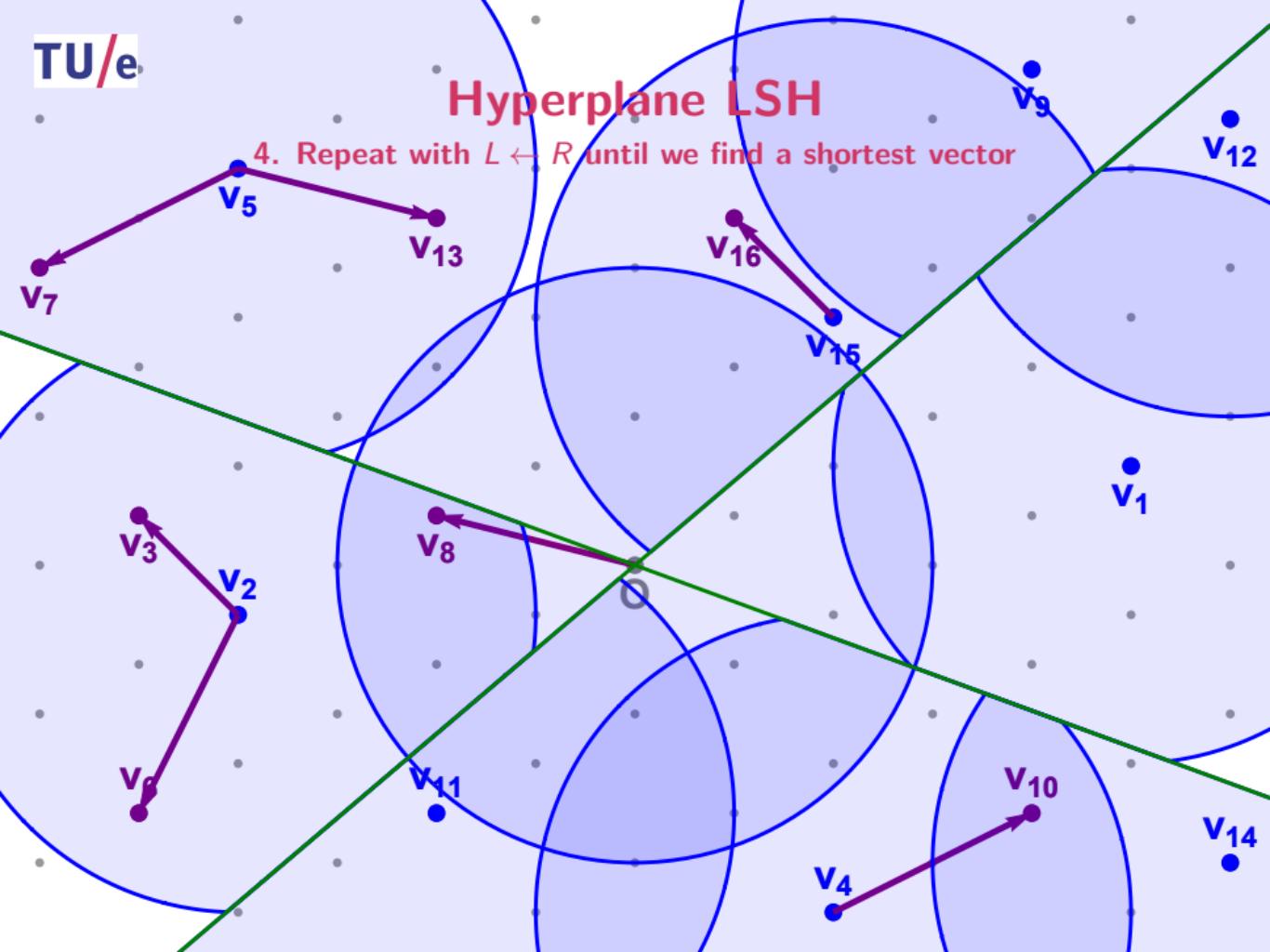
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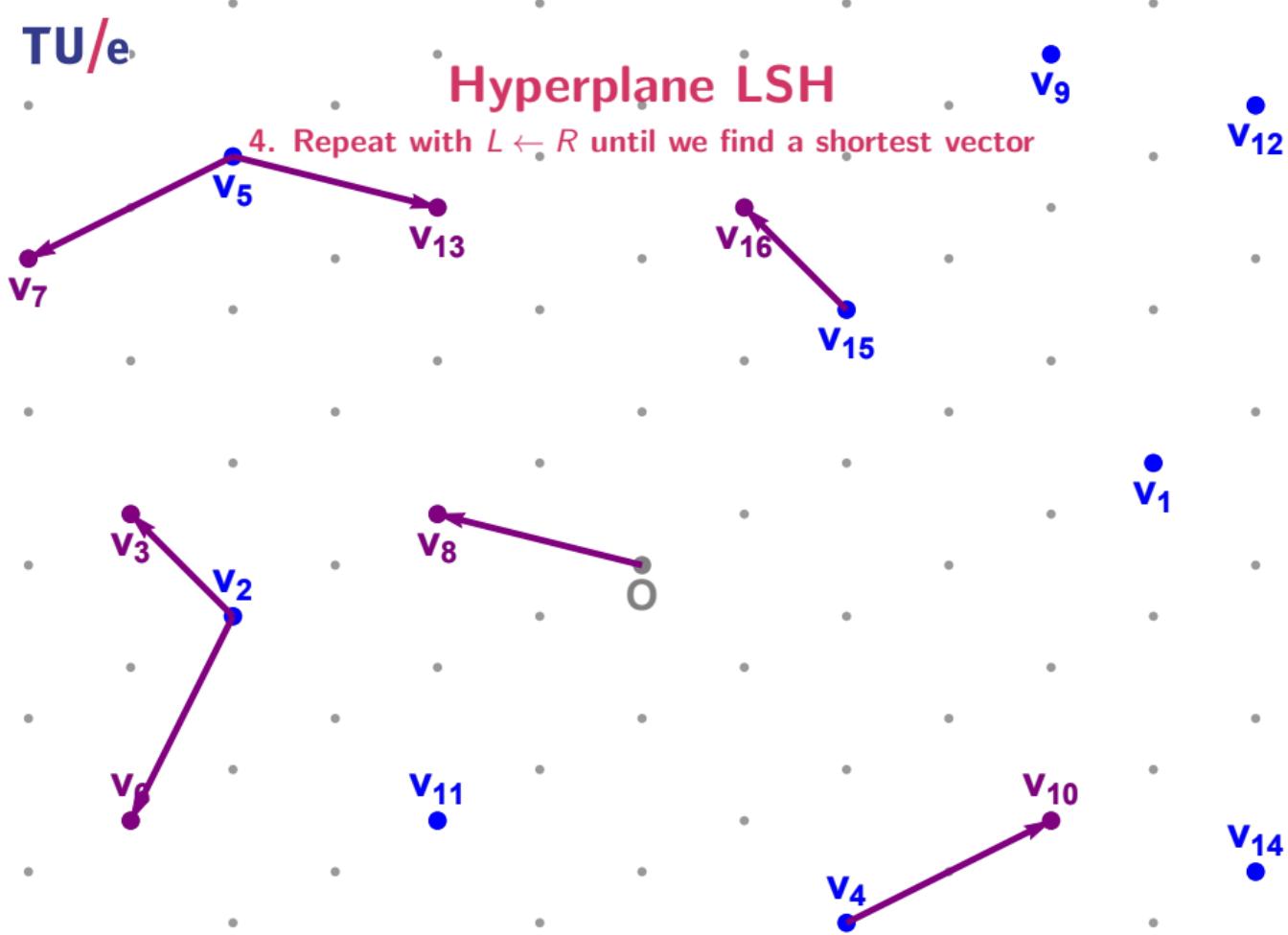
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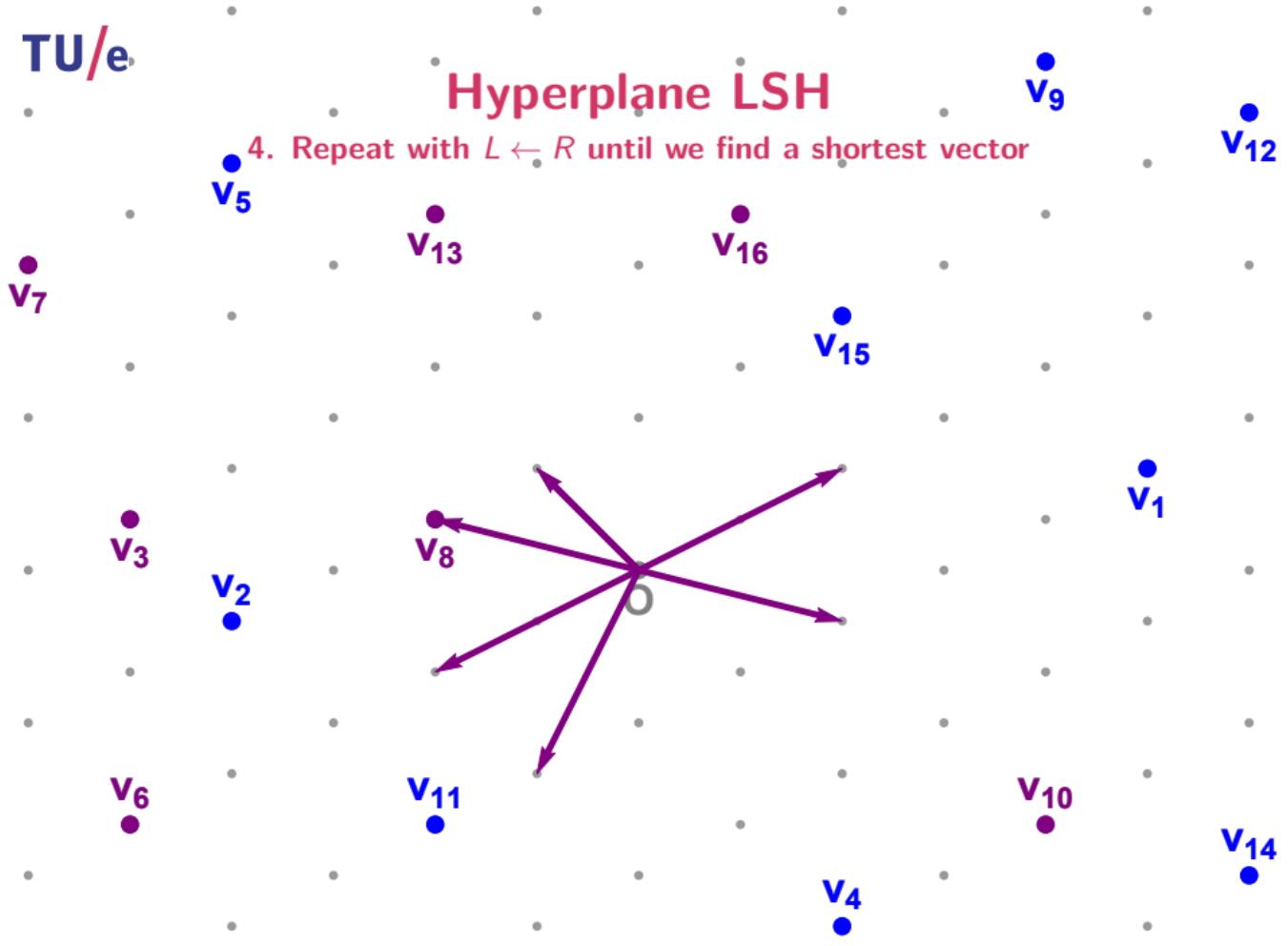
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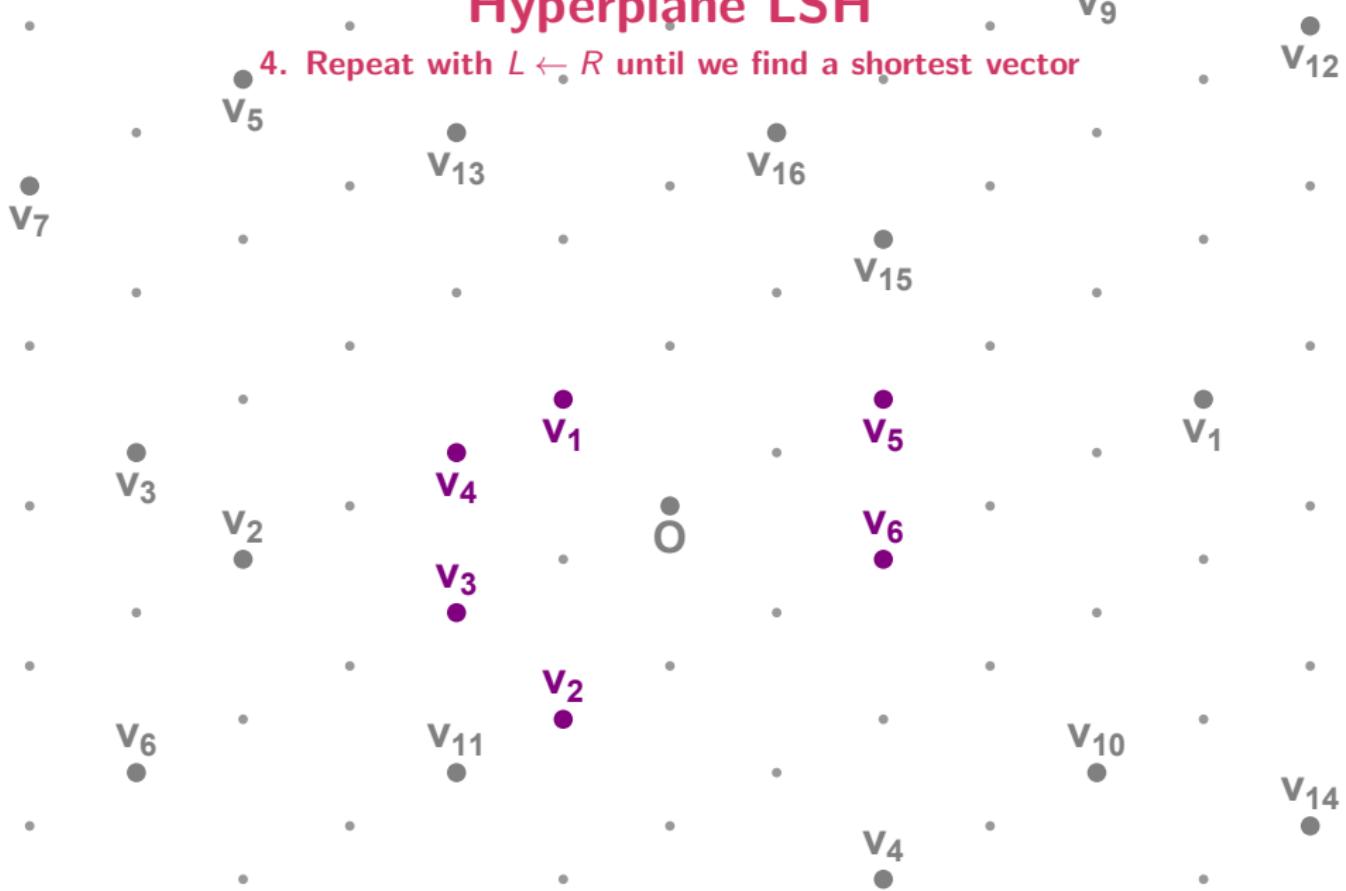
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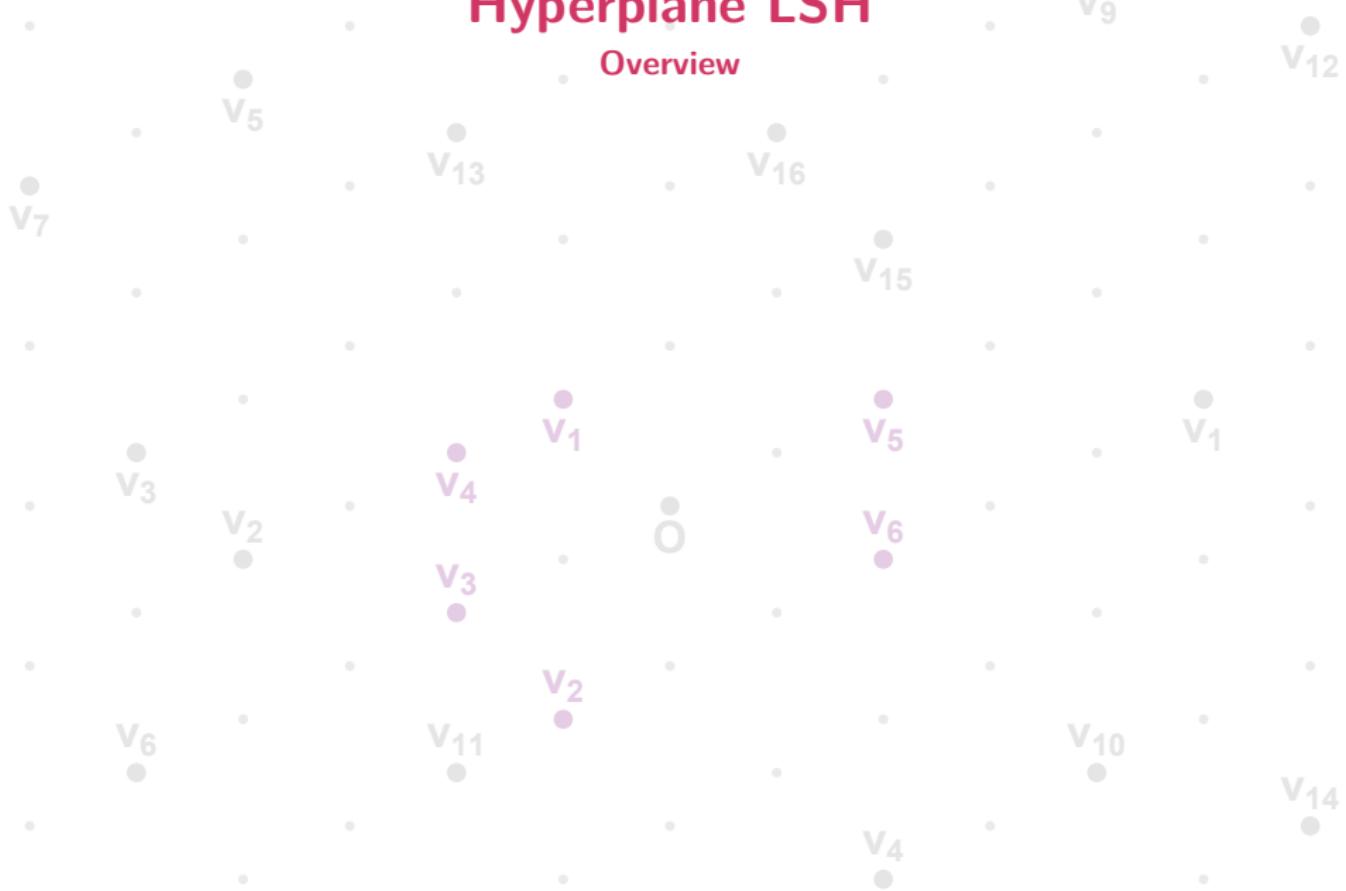
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Hyperplane LSH

Overview



Hyperplane LSH

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- Two parameters to tune
 - ▶ $k = O(n)$: Number of hyperplanes, leading to 2^k regions
 - ▶ $t = 2^{O(n)}$: Number of different, independent “hash tables”

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 - ▶ Number of vectors: $2^{0.208n+o(n)}$
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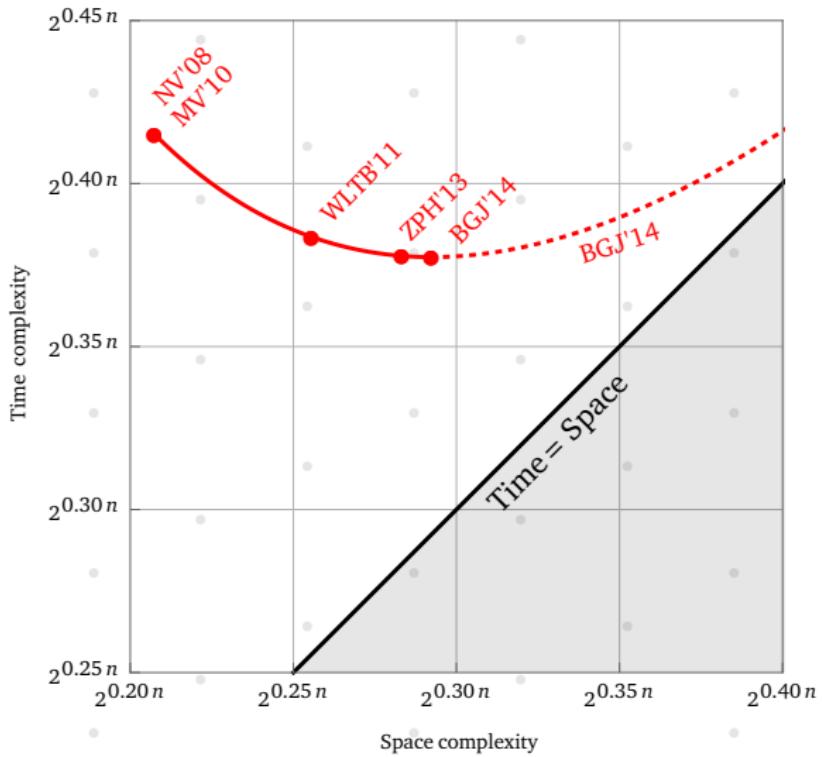
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Theorem

Sieving with hyperplane LSH heuristically solves SVP in time and space $2^{0.337n+o(n)}$.

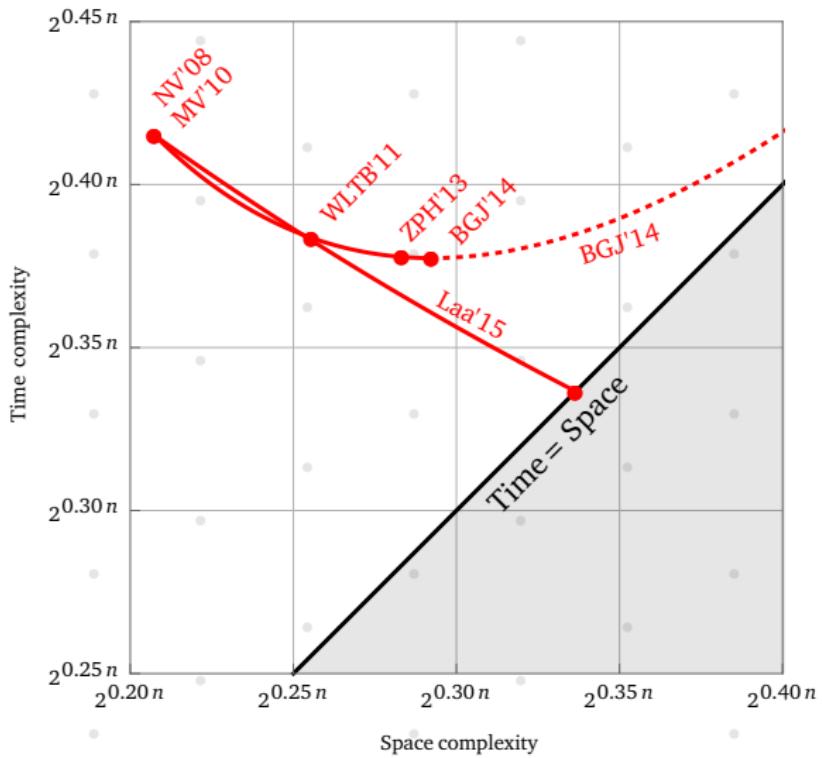
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Space/time trade-off



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NNS methods

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- [Laa15]: Hyperplane LSH

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- [BDGL15]: Spherical filtering

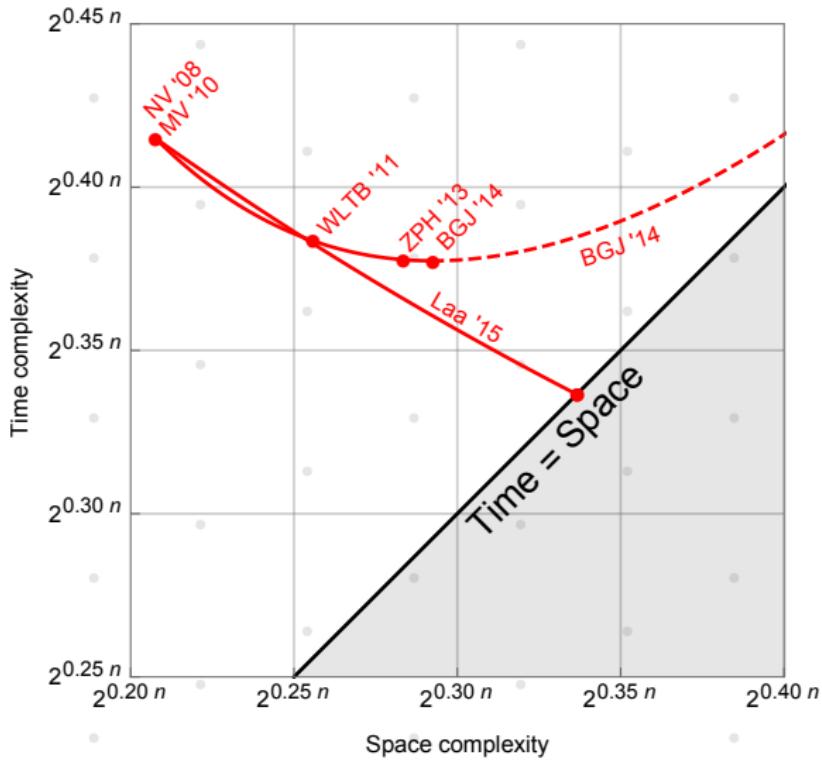
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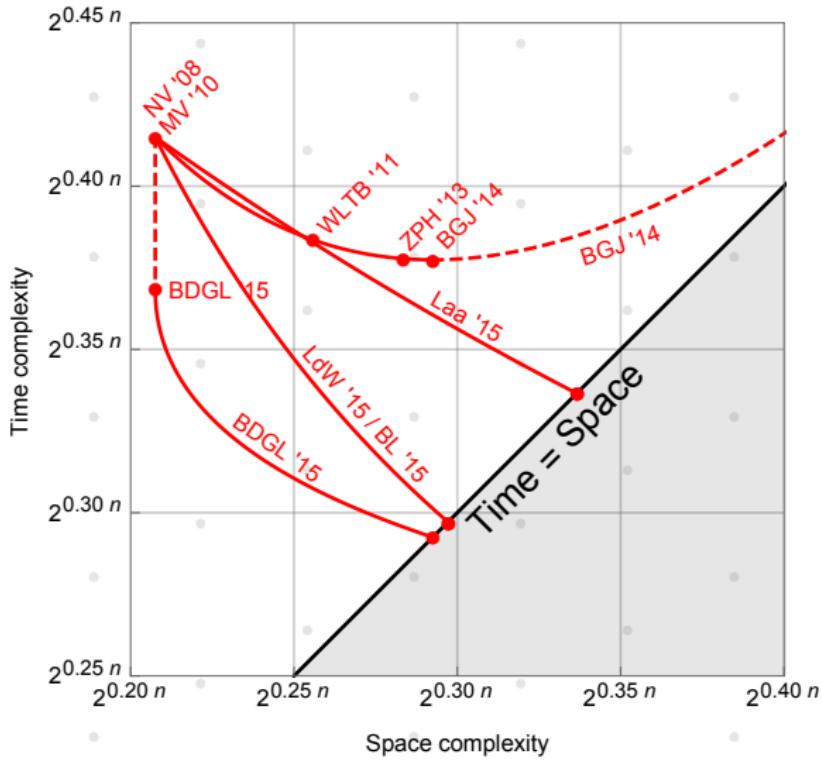
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Space/time trade-off



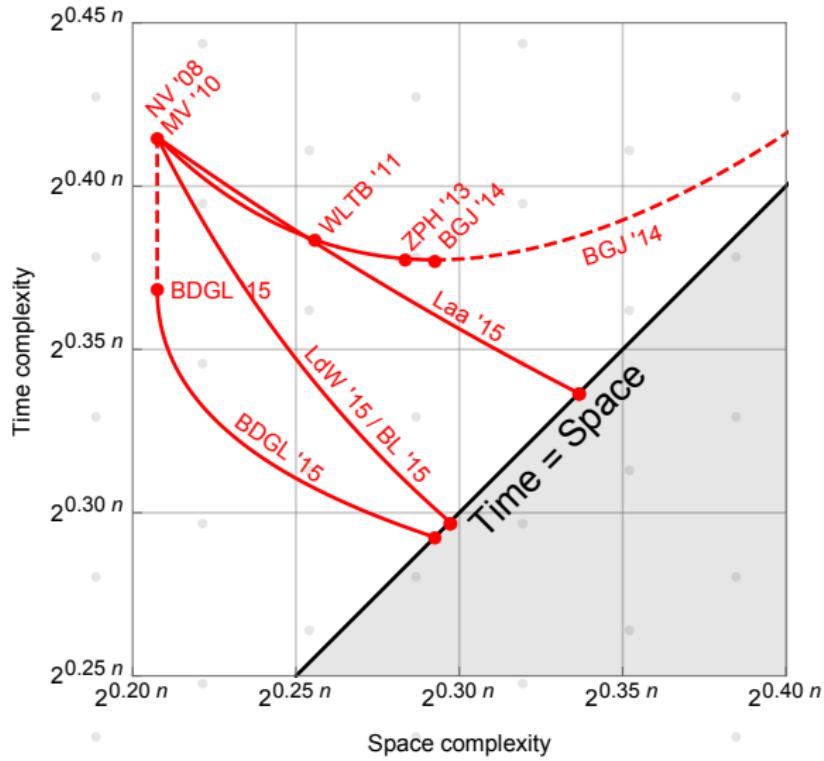
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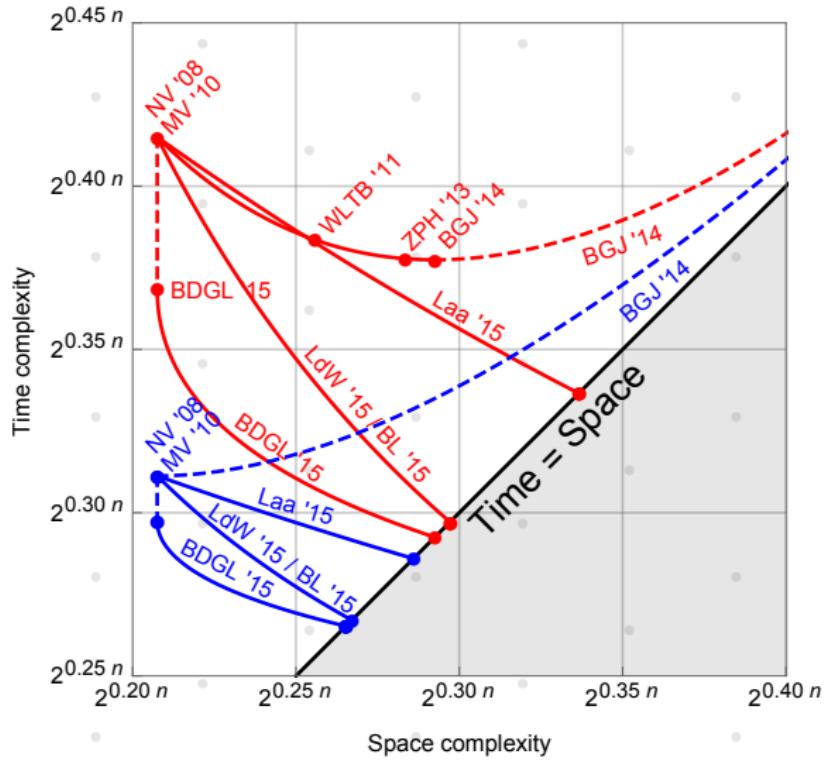
Quantum searching

Space/time trade-off



Quantum searching

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Questions?

[vdP'12]

