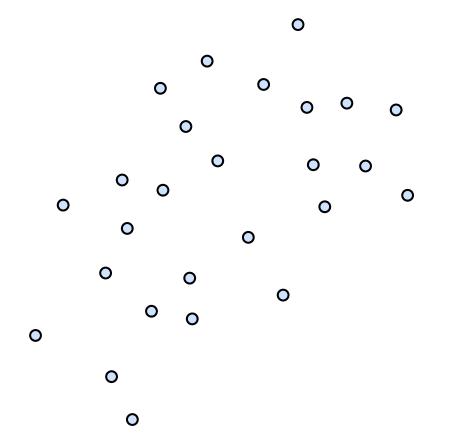
Geometric Approximation Algorithms

setting: Geometric optimization problem on a point set *P* **coreset:** Small subset $S \subset P$ that captures the structure of optimal solution

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geometric problem: smallest axis-aligned bounding box of $P \subset \mathbb{R}^d$

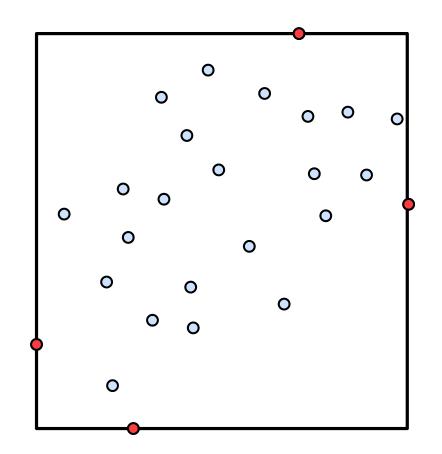


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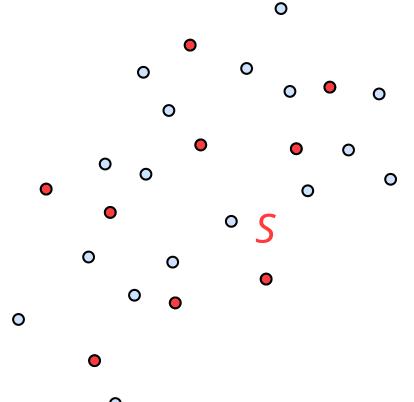
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S: points with minimum and maximum coordinate (for each coordinate)



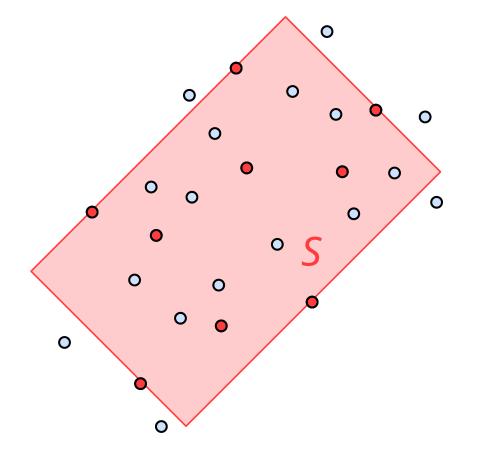
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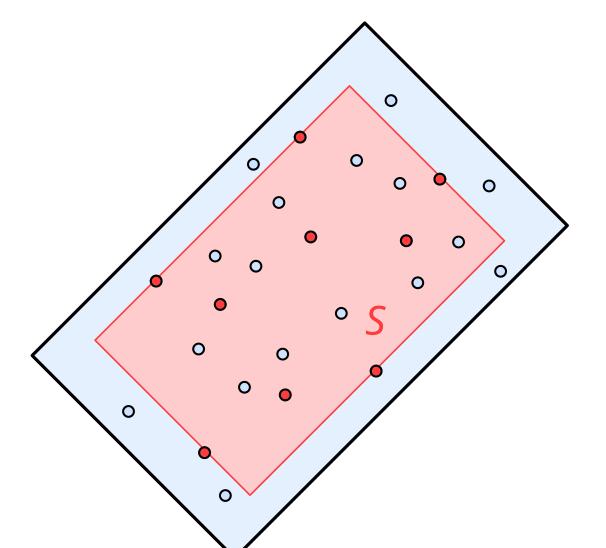
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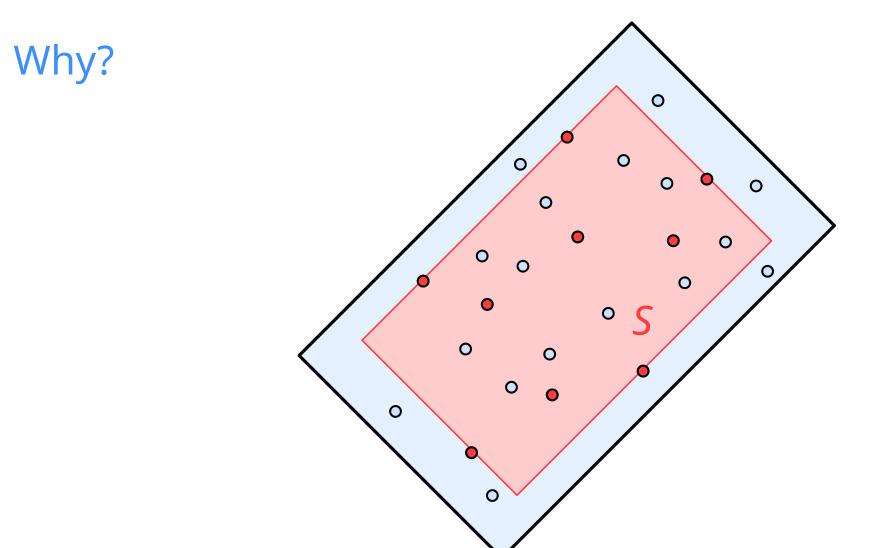
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slow (exact) algorithm + coreset = fast approximation algorithm

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exact algorithm: min-volume bounding box of $P \subset \mathbb{R}^3$ in $O(n^3)$ time.

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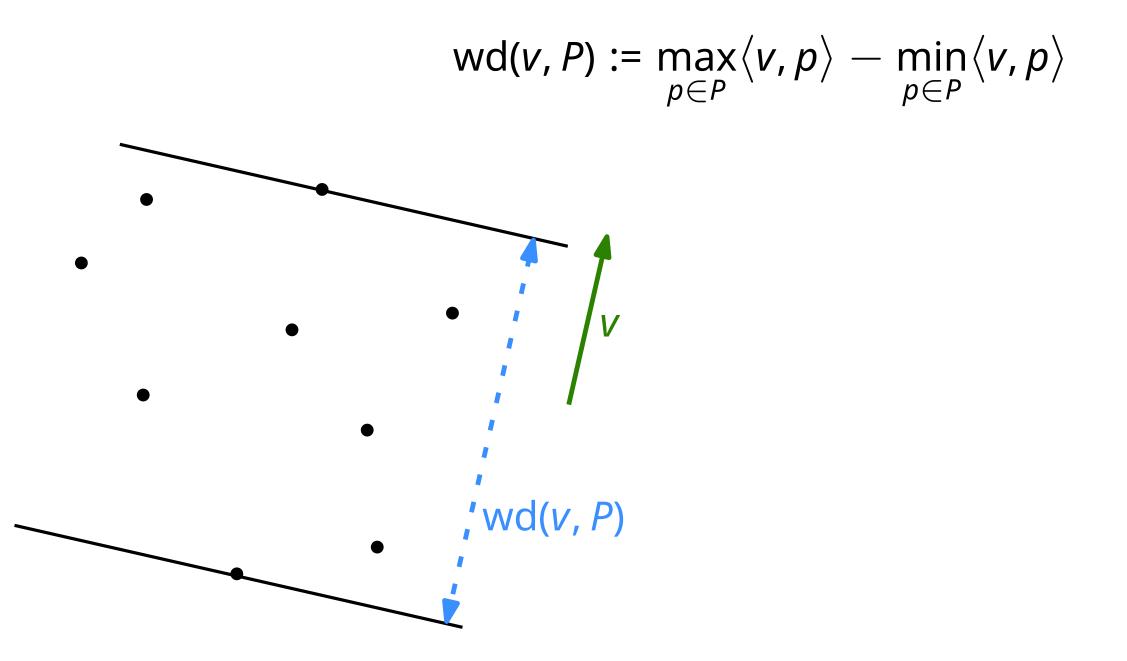
Overview

Coreset for directional width

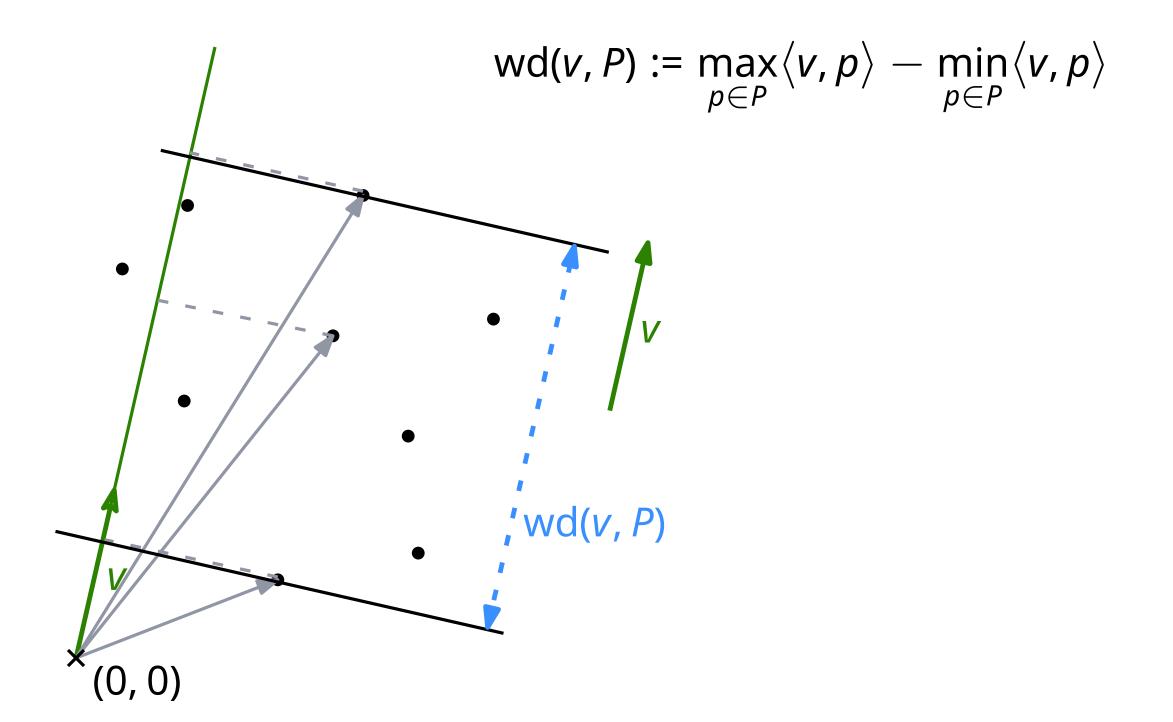
- definition
- applications
- construction algorithm

Extra ingredient: Minimum volume bounding box

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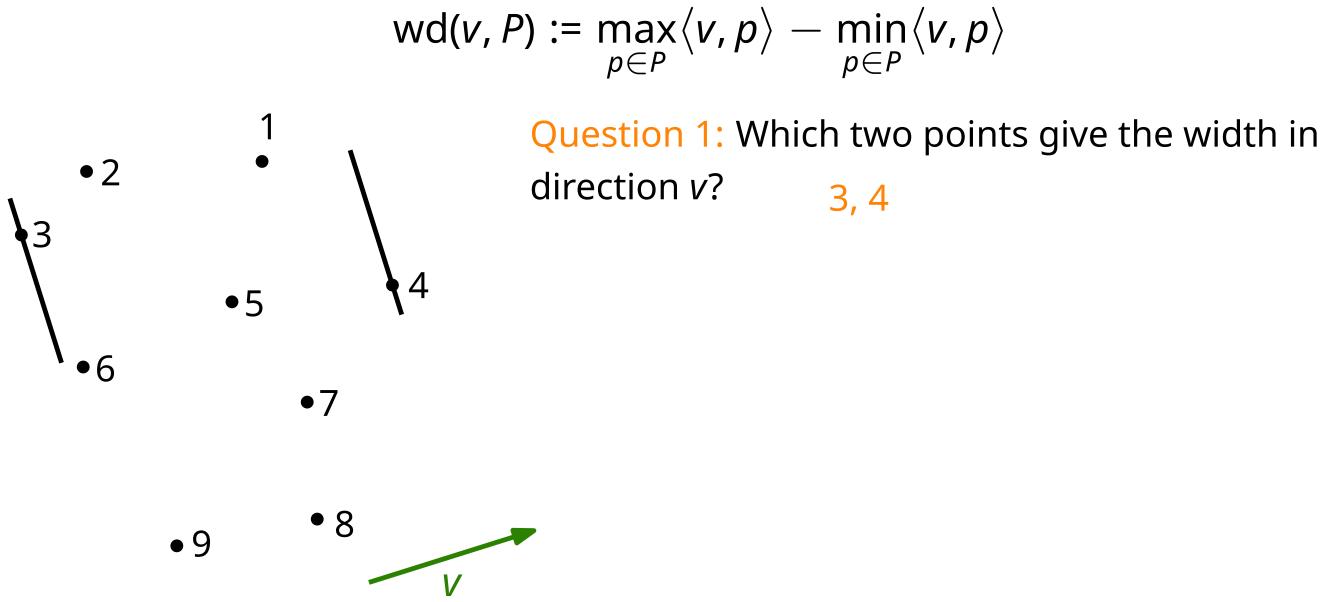


•3

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wd(v, P) := $\max_{p \in P} \langle v, p \rangle - \min_{p \in P} \langle v, p \rangle$ Question 1: Which two points give the width in •2 direction *v*? • 4 •5 •6 •7 • 8 •9

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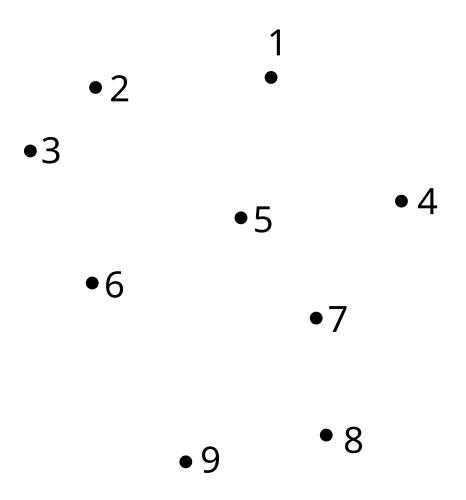


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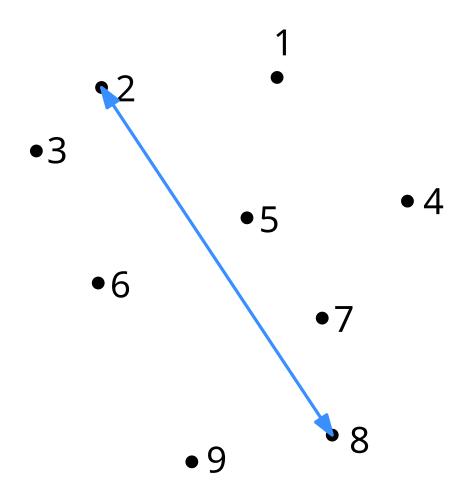


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The unit vector in direction from 2

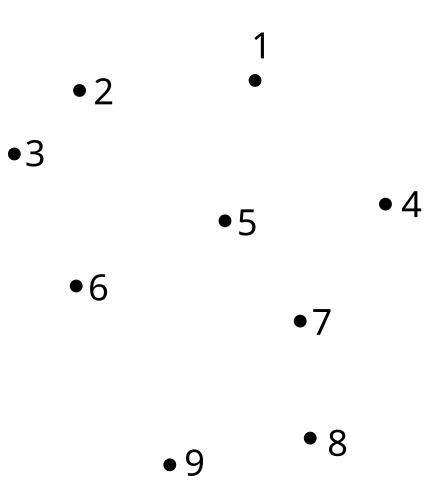
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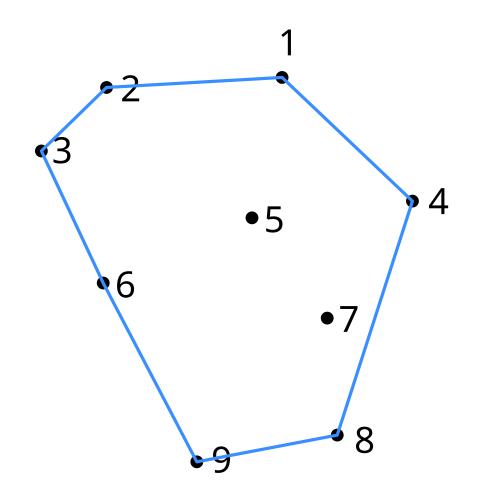
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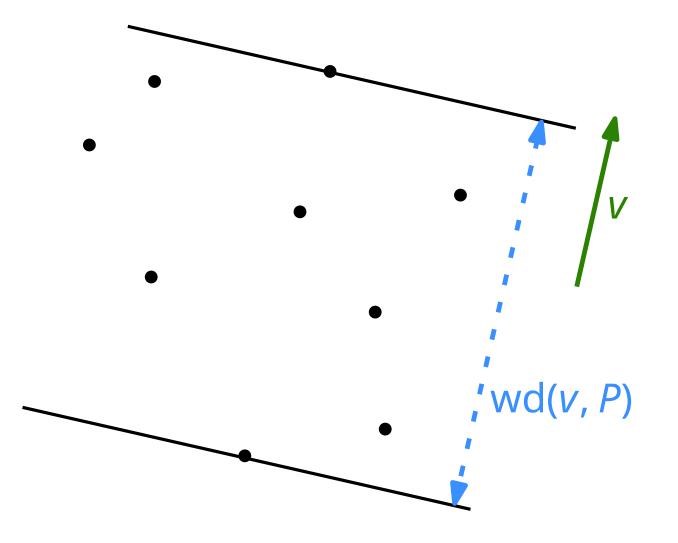
Question 3: Which are the only points of *P* relevant for computing directional width? Only points on convex hull (i.e. 1, 2, 3, 6, 9, 8, 4)



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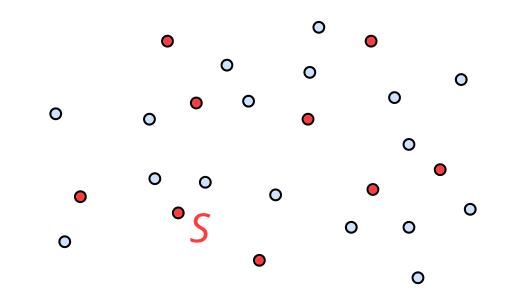


Properties:

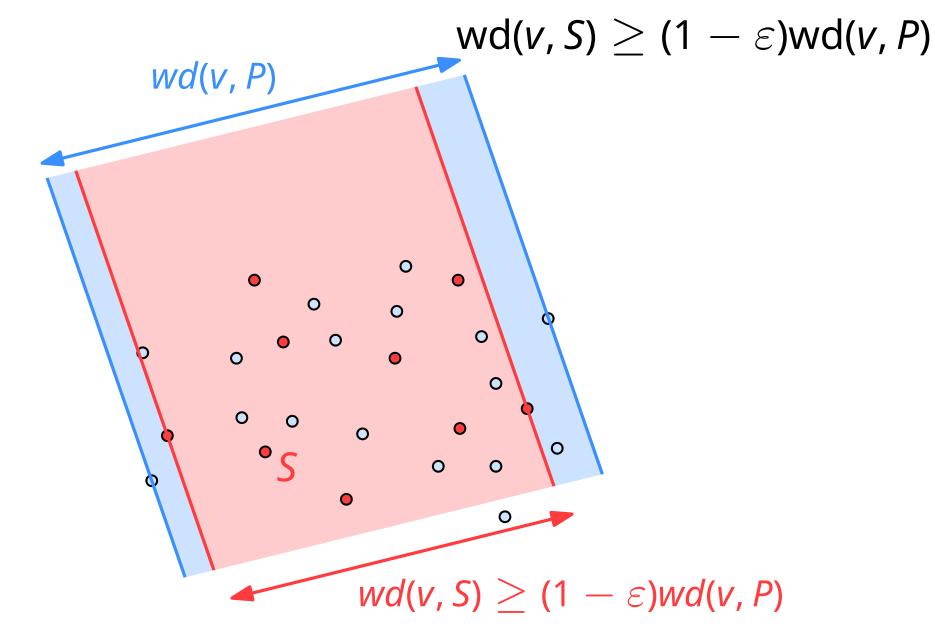
- translation invariant
- scales linearly
- wd(v, P) = wd(v, conv(P))
- monotone: if $Q \subset P$, then $wd(v, Q) \leq wd(v, P)$

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 - general concept: other objective functions f instead of directional width

(Exercise)

(Exercise)

Overview

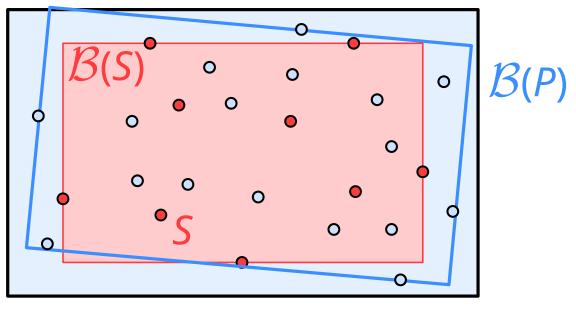
Coreset for directional width

- definition
- applications
- construction algorithm

Extra ingredient: Minimum volume bounding box

Given $\varepsilon > 0$, $P \subset \mathbb{R}^d$, let *S* be a δ -coreset of *P* for directional width ($\delta = \varepsilon/(8d)$). Let $\mathcal{B}(P)$ (resp. $\mathcal{B}(S)$) be the min volume bounding box of P (resp. S), and let B be $\mathcal{B}(S)$ scaled by (1 + 3 δ) around the center of $\mathcal{B}(S)$.

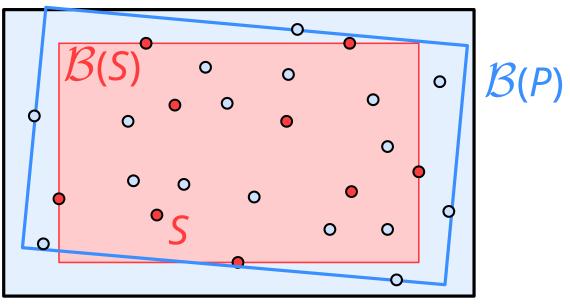
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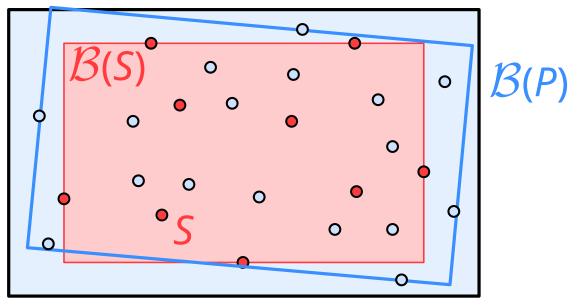


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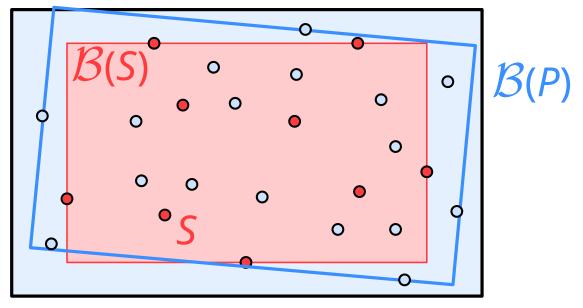
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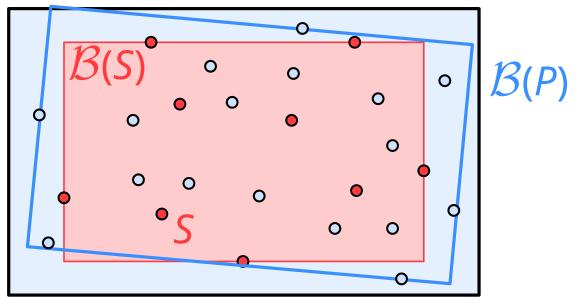
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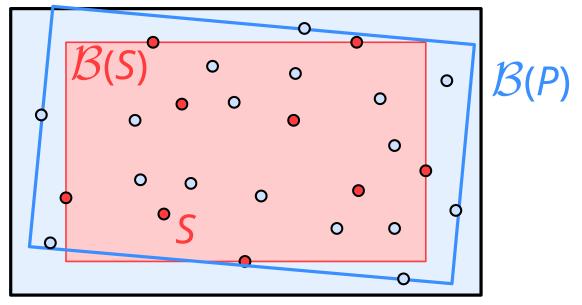
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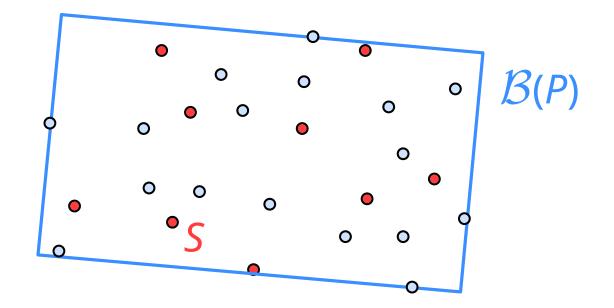
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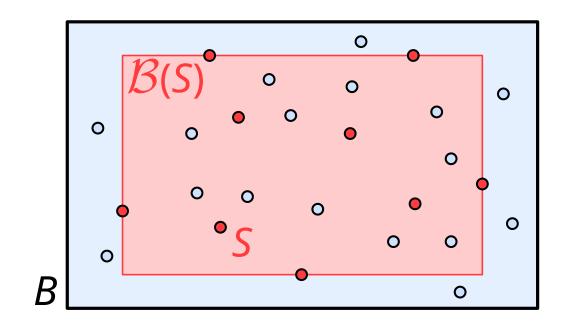
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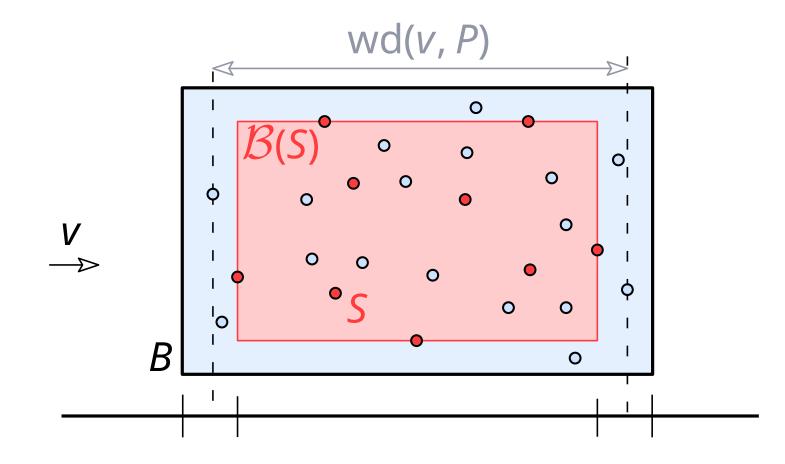
Still need: B contains P

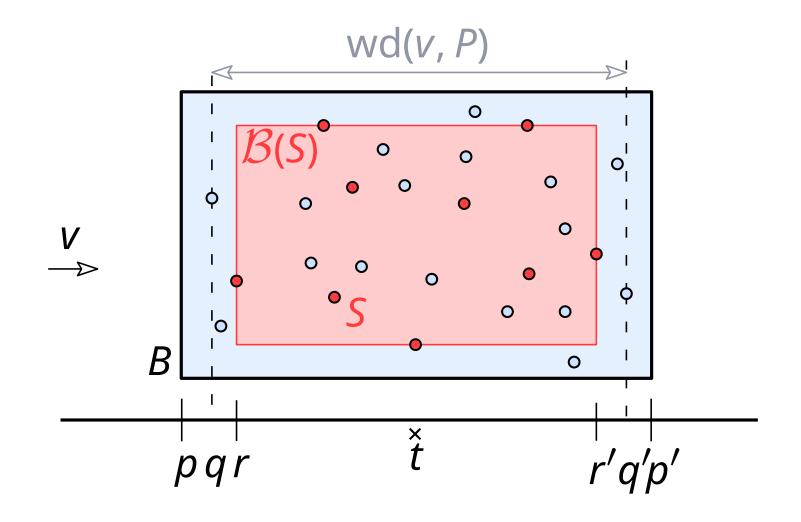


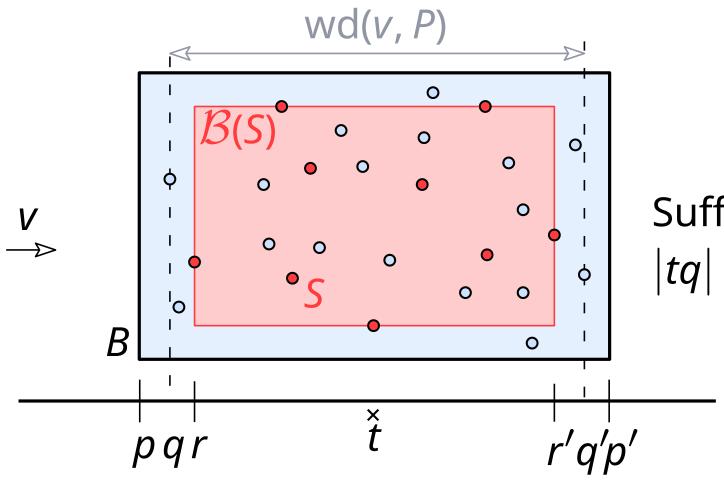
Proof: $P \subset B$



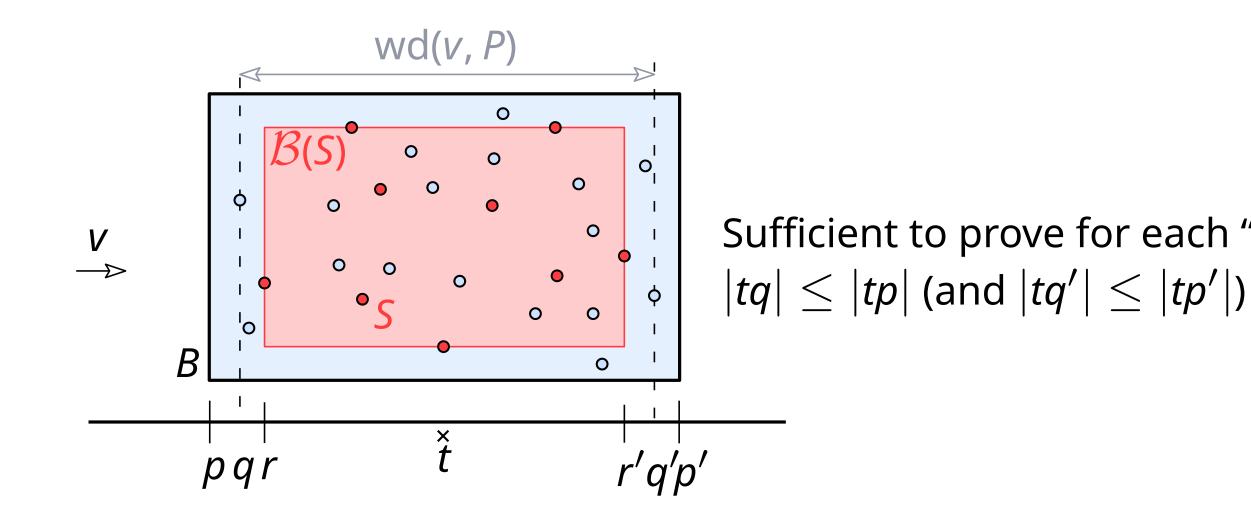




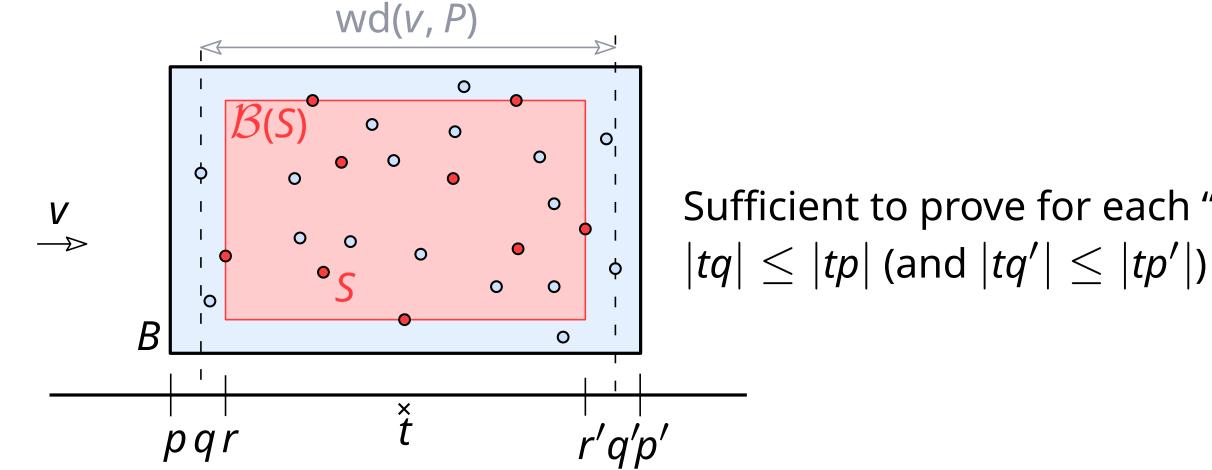




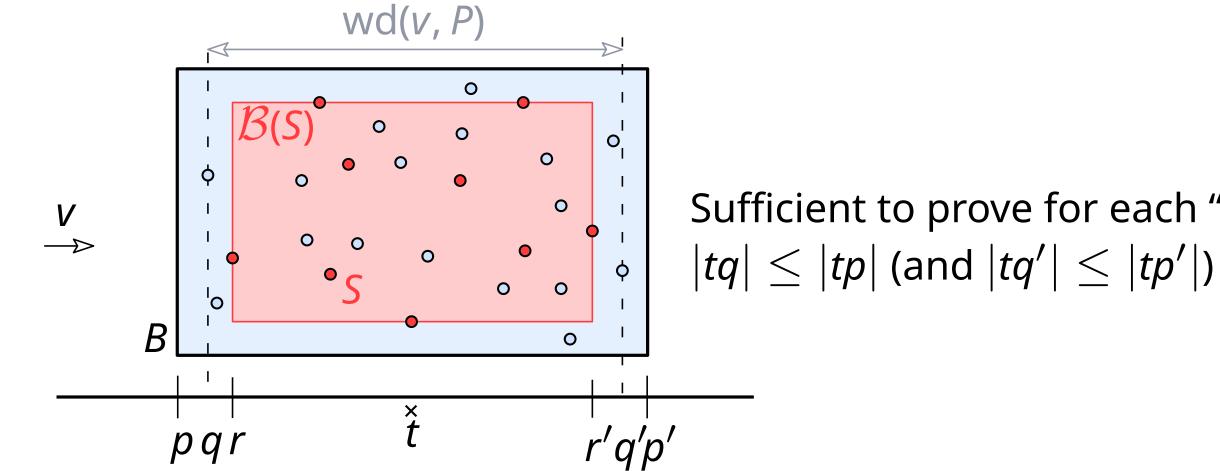
 $|tq| \leq |tp|$ (and $|tq'| \leq |tp'|$)



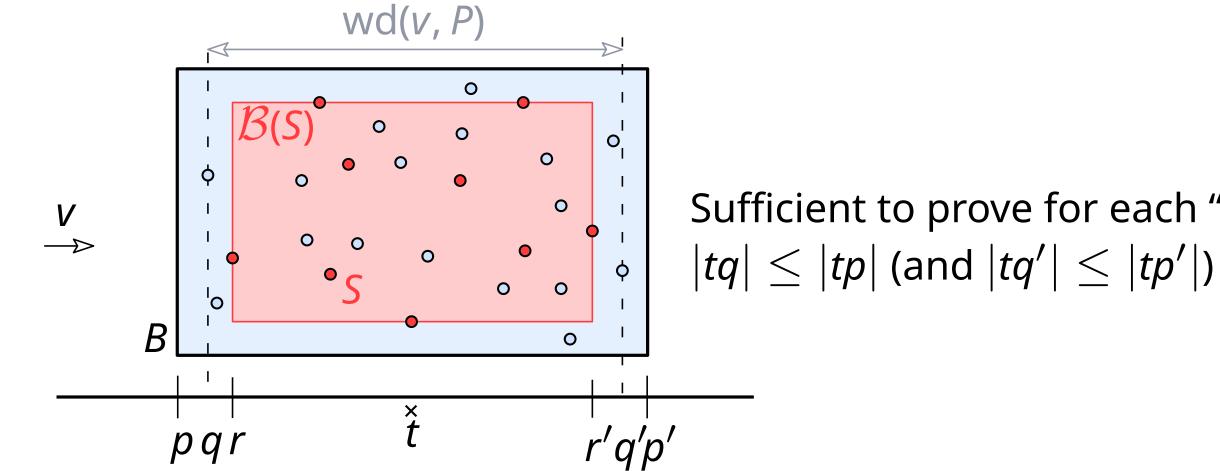
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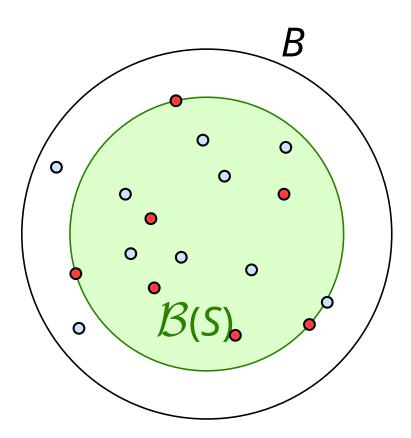


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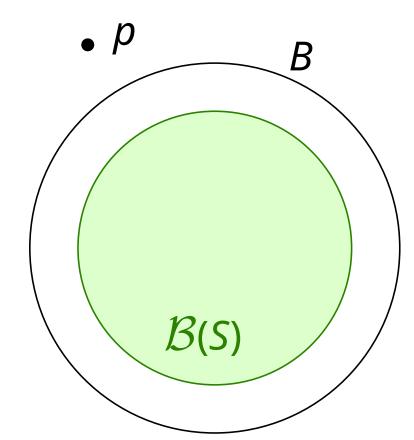
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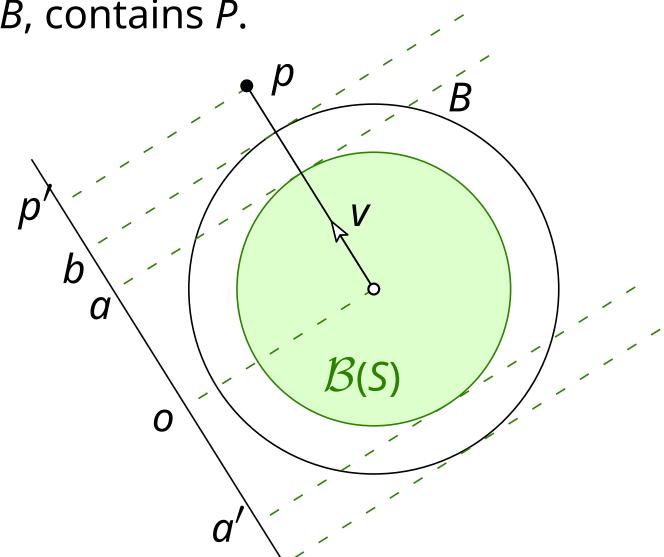
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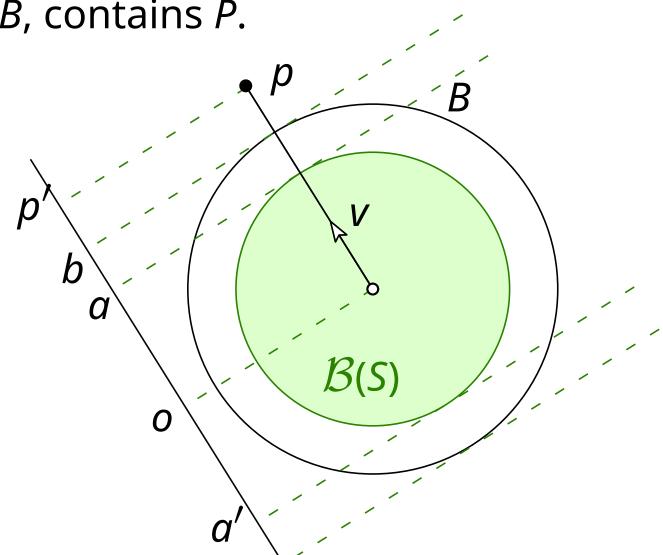


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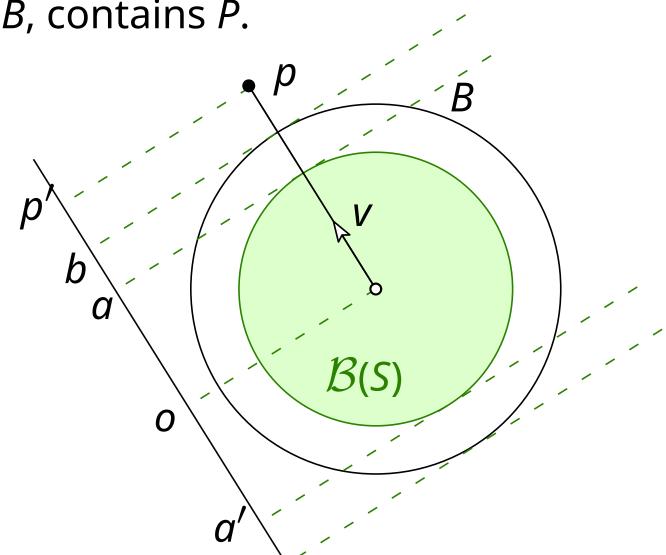
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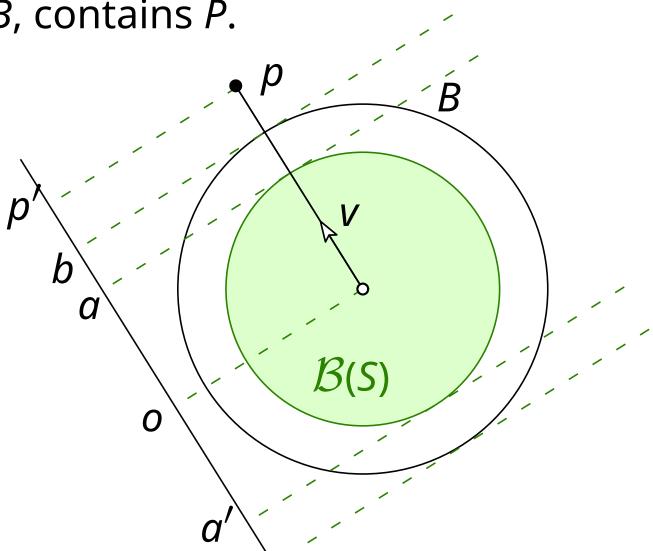
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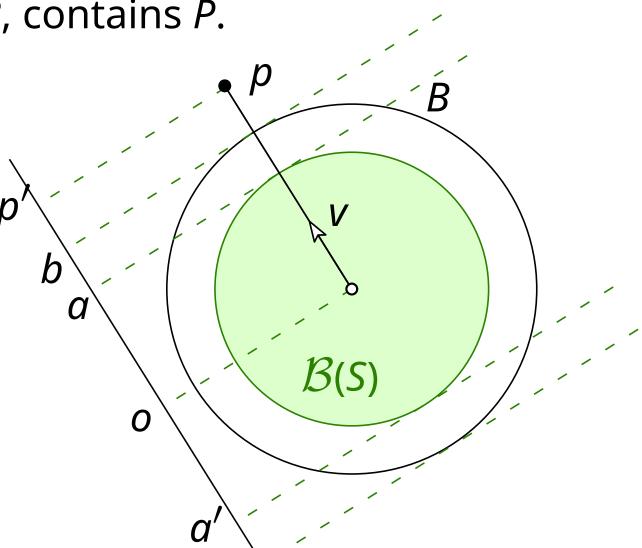
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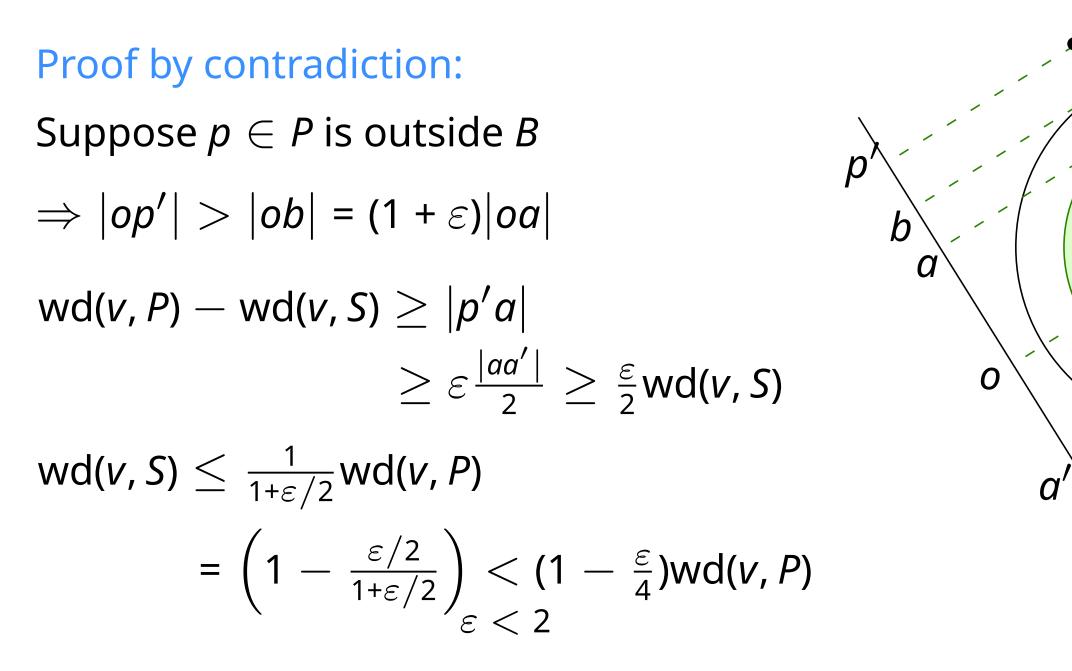


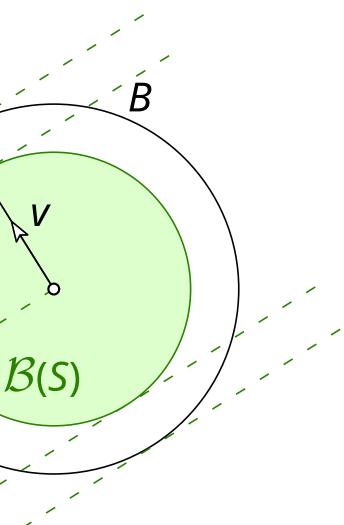
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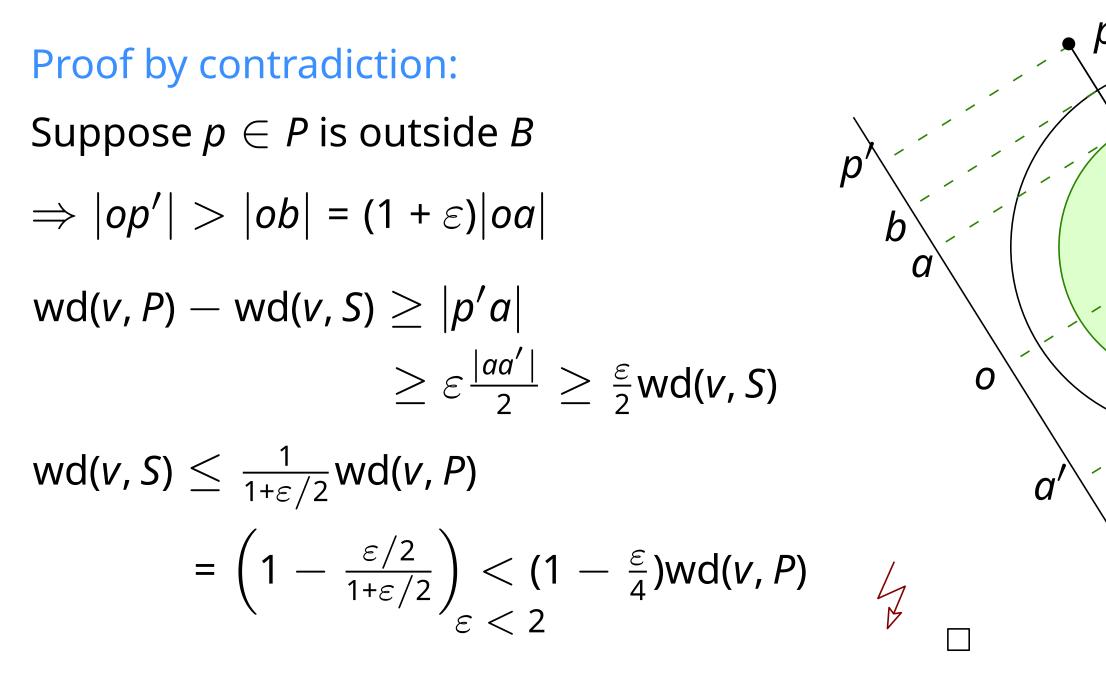


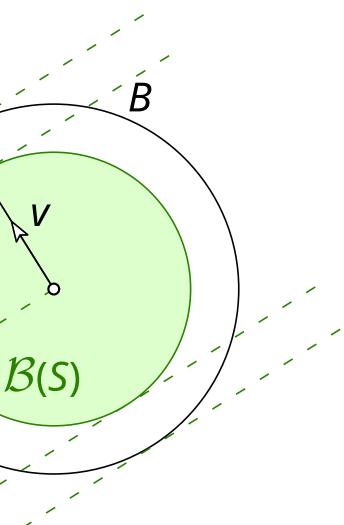
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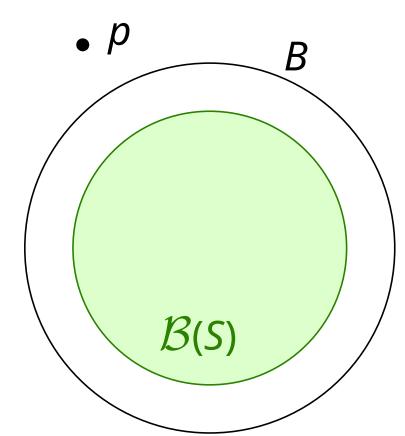




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Comparison to ε -samples:

 ε -sample:

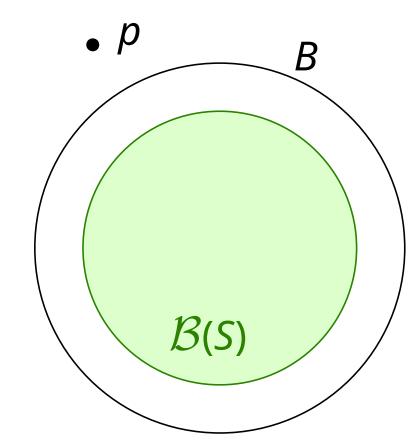


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Comparison to ε -samples:

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guarantees most points in $\mathcal{B}(S)$

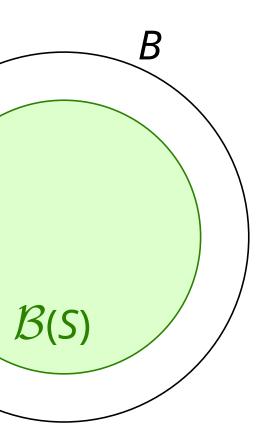


If S is an $\varepsilon/4$ -coreset of P for directional width, then the smallest enclosing ball of S, $\mathcal{B}(S)$, scaled by (1 + ε) around its center, B, contains P.

Comparison to ε -samples:

 ε -sample:

guarantees most points in $\mathcal{B}(S)$ combinatorial/statistical error

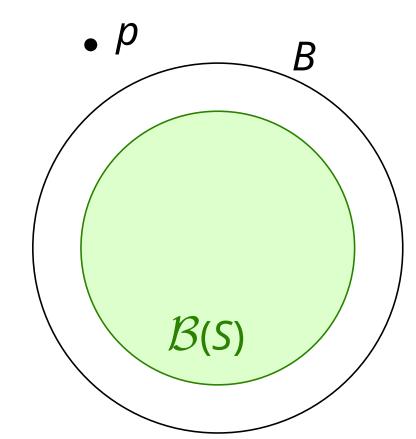


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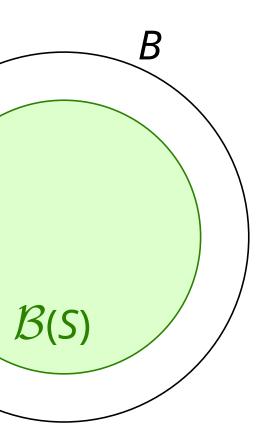


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Comparison to ε -samples:

 ε -sample: guarantees most points in $\mathcal{B}(S)$ combinatorial/statistical error does not guarantee $p \in B$

coreset: <u>geometric</u> error (bounded for all points)



• *p*

Overview

Coreset for directional width

- definition
- applications
- construction algorithm

Extra ingredient: Minimum volume bounding box <---

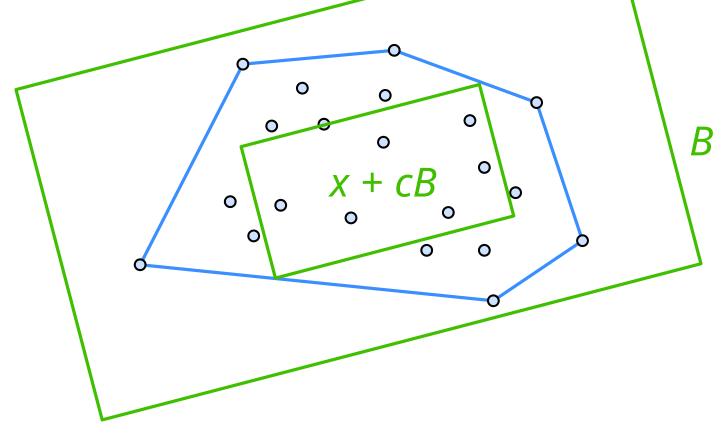
- - - -

Computing a tight (enough) bounding box

We can compute a bounding box B of P in $O(d^2n)$ time s.t.

(i) $Vol(B_{opt}(P)) \leq Vol(B) \leq 2^d d! Vol(B_{opt}(P))$

and (*ii*) there is a shift $x \in \mathbb{R}^d$ and c > 0 that depends only on d, s.t. $x + cB \subset \operatorname{conv}(P)$.



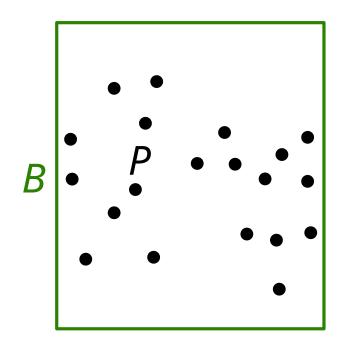
(without proof, for now)



Input: $P \subset \mathbb{R}^d$, $\varepsilon > 0$ (and bounding box *B* s.t. $c_d B \subset \text{conv}(P) \subset B$)

Output: an ε -coreset $S \subseteq P$ of size at most $|S| = O(1/\varepsilon^{d-1})$

Construction time: O(n) (also depends on *d* and ε).



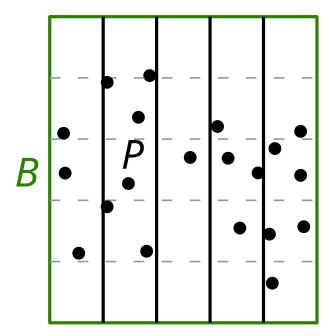
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Algorithm

1. Divide B into $M \times \cdots \times M$ grid cells with $M = \left\lceil \frac{2}{\varepsilon c_d} \right\rceil$



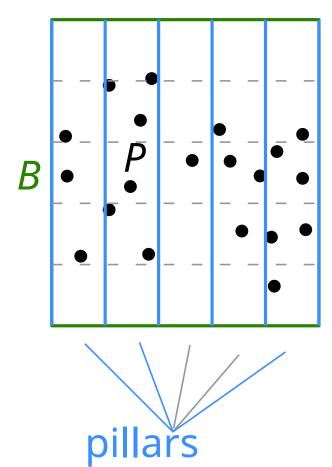


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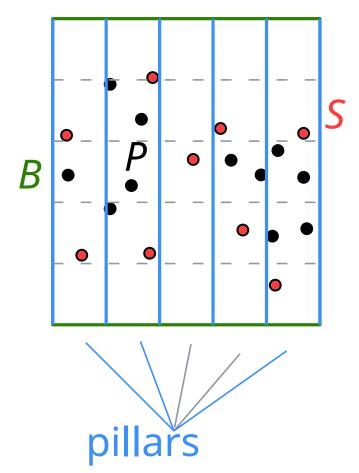
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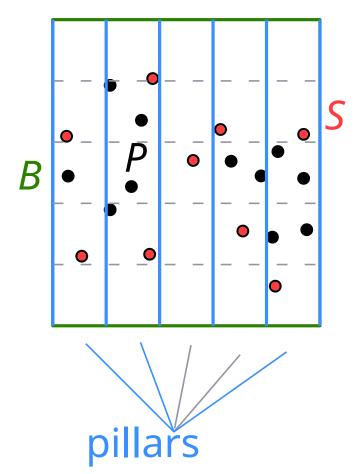
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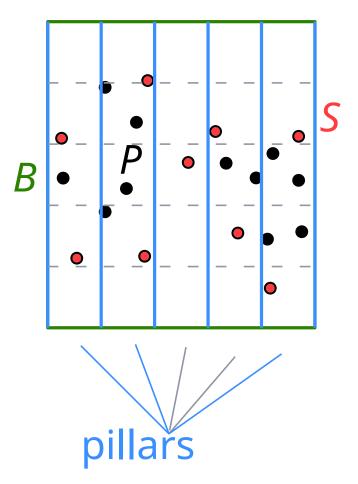
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 $|S| \leq 2M^{d-1} = O(1/\varepsilon^{d-1})$, still need: S is coreset

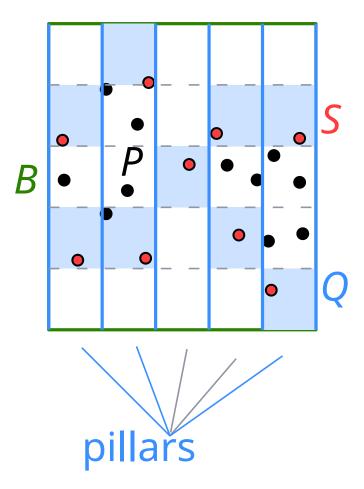


proof (*S* is coreset):



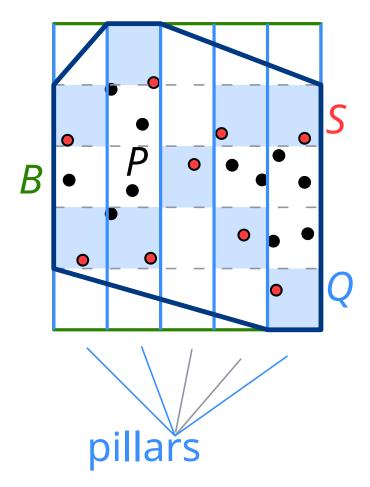
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Let *Q* = union of cells containg a point of *S*.

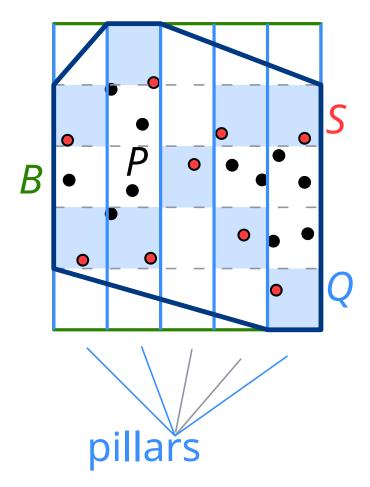


proof (S is coreset):

- Let *Q* = union of cells containg a point of *S*.
- $P \subset \operatorname{conv}(Q) \Rightarrow \operatorname{wd}(v, P) \leq \operatorname{wd}(v, \operatorname{conv}(Q))$ for all v

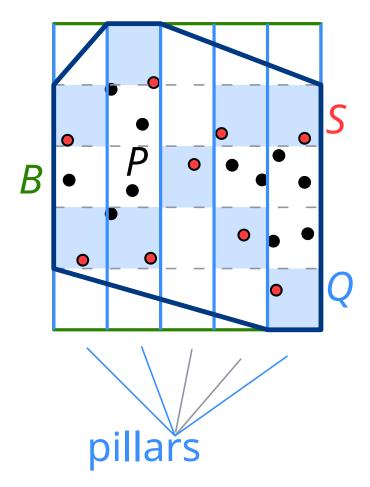


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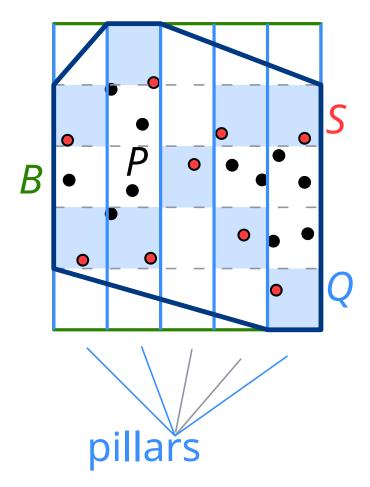
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$$wd(v, B/M) = \frac{wd(v,B)}{M} = \frac{wd(v,c_dB)}{c_dM}$$



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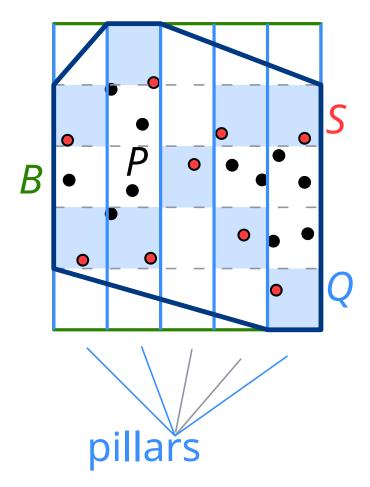
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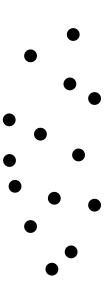
 \Rightarrow wd(v, P)(1 - 2 $\frac{\varepsilon}{2}$)wd(v, P) \leq wd(v, S)



Given $\varepsilon > 0$ and $P \subset \mathbb{R}^d$, we can compute an ε -coreset $S \subseteq P$ of size at most $|S| = O(1/\varepsilon^{(d-1)/2})$ in $O(n + 1/\varepsilon^{3(d-1)/2})$ time (where *d* is a fixed constant).

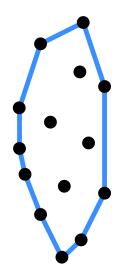
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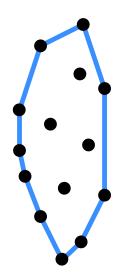
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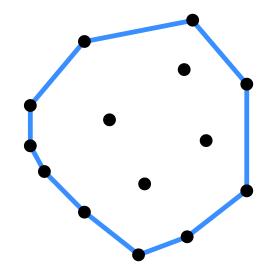
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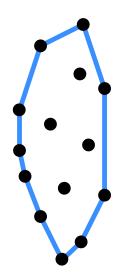
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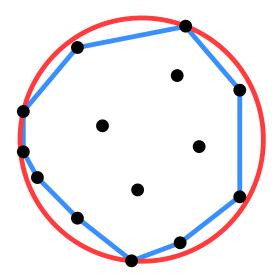




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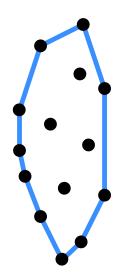
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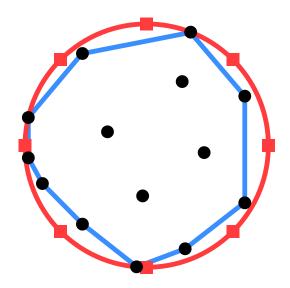




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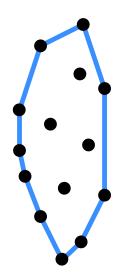
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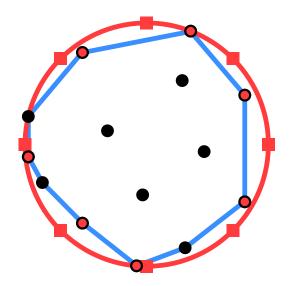




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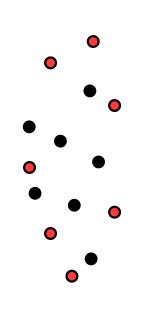
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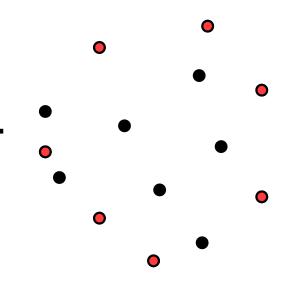




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Overview

Coreset for directional width

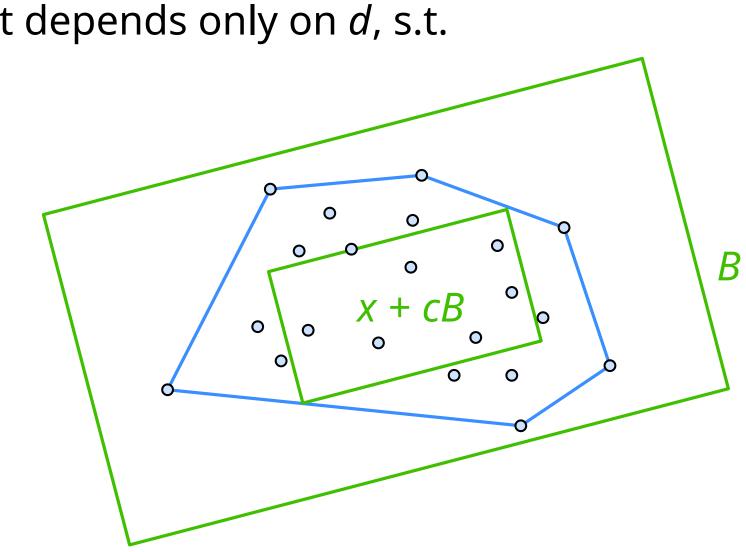
- definition
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Extra ingredient: Minimum volume bounding box <

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(i) $Vol(B_{opt}(P)) \leq Vol(B) \leq 2^d d! Vol(B_{opt}(P))$

and (*ii*) there is a shift $x \in \mathbb{R}^d$ and c > 0 that depends only on d, s.t. $x + cB \subset \operatorname{conv}(P)$.

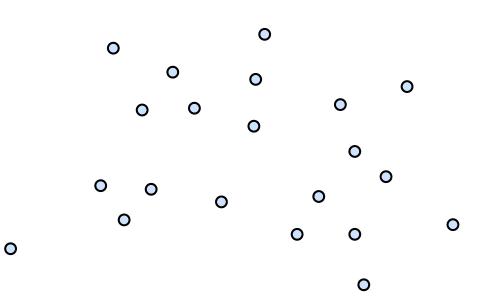


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1. Approximate diameter:





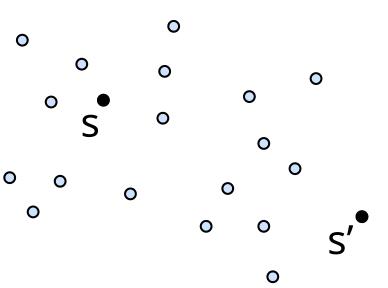
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1. Approximate diameter:
Let
$$s \in P$$
 arbitrary and let $s' \in P$ most distant form s .
If t, t' realize the diameter of P , then
diam(P) = $|tt'| \le |ts| + |st'| \le 2|ss'|$ °





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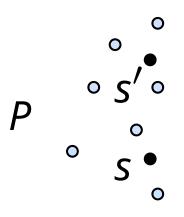
diam(P) =
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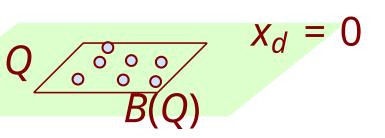
Wlog. ss' parallel to x_d axis. π := perpendicular projection to $x_d = 0$.

S' 0 • • , S_o 0

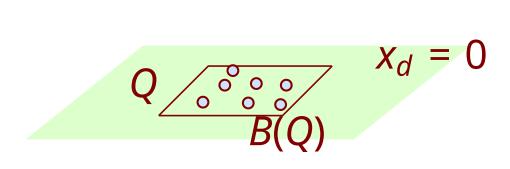
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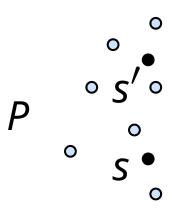
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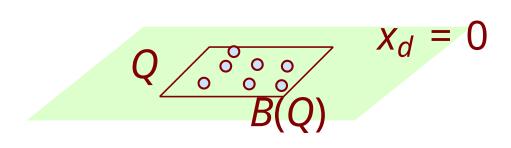
d = 1: return interval containing points

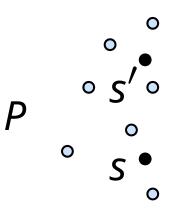




d = 1: return interval containing points

- *d* > 1:
- $Q := \pi(P)$ B(Q) := bounding box of Q (recursion)



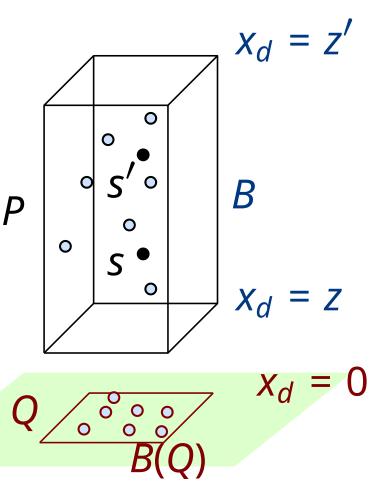


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[z, z']:= shortest interval on x_d axis covering projection of P $B := B(Q) \times [z, z']$



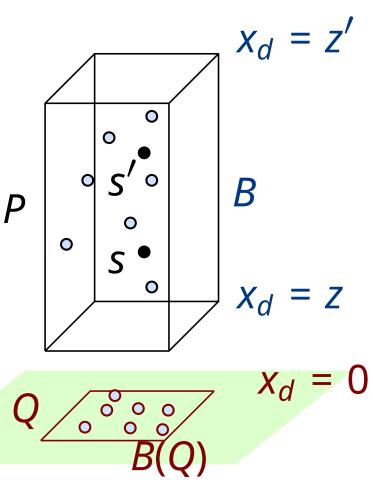
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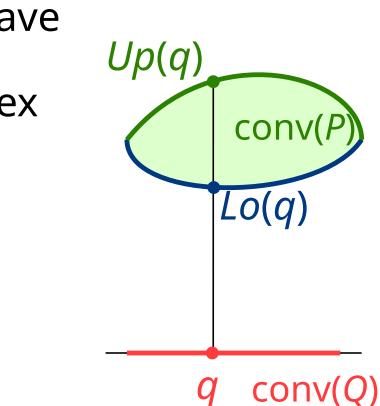
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Still need: $Vol_d(conv(P)) \ge Vol_d(B)/(2^d d!)$



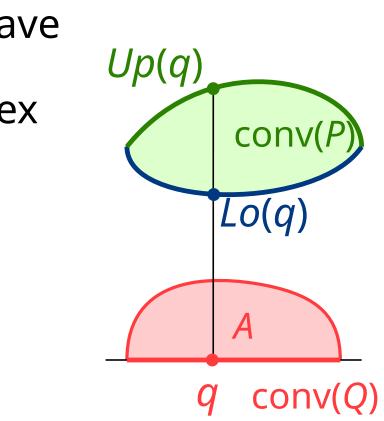
Upper hull conv[†](*P*) as function: $Up : \operatorname{conv}(Q) \to \mathbb{R}^d$ is concave Lower hull conv[↓](*P*) as function: $Lo : \operatorname{conv}(Q) \to \mathbb{R}^d$ is convex



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Up – *Lo* is concave

$$\Rightarrow A := \bigcup_{q \in \text{conv}(Q)} [0, Up(q) - Lo(q)] \text{ is convex}$$



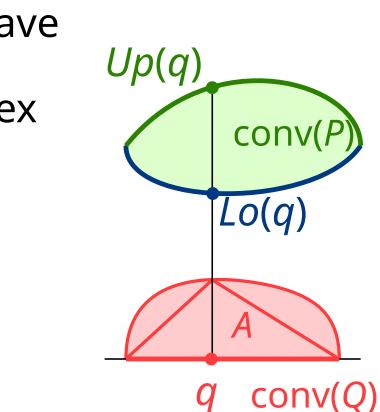
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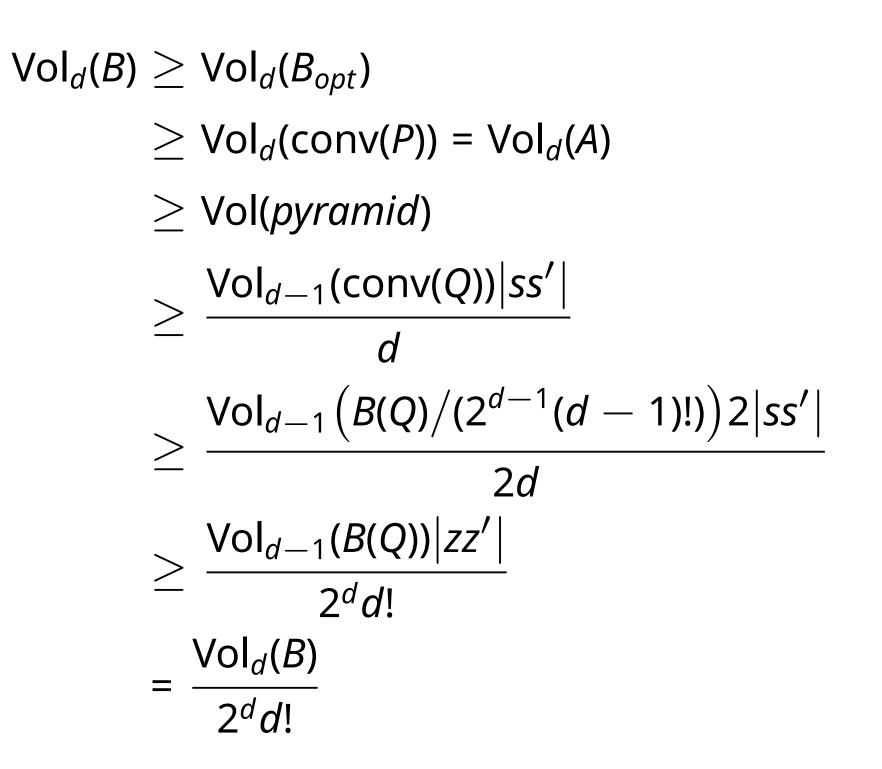
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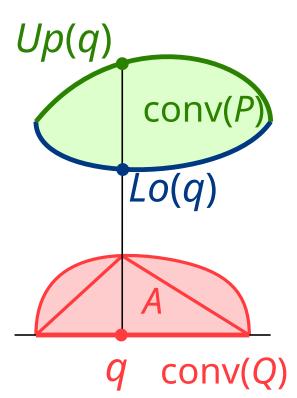
$$\Rightarrow A := \bigcup [0, Up(q) - Lo(q)] \text{ is convex}$$

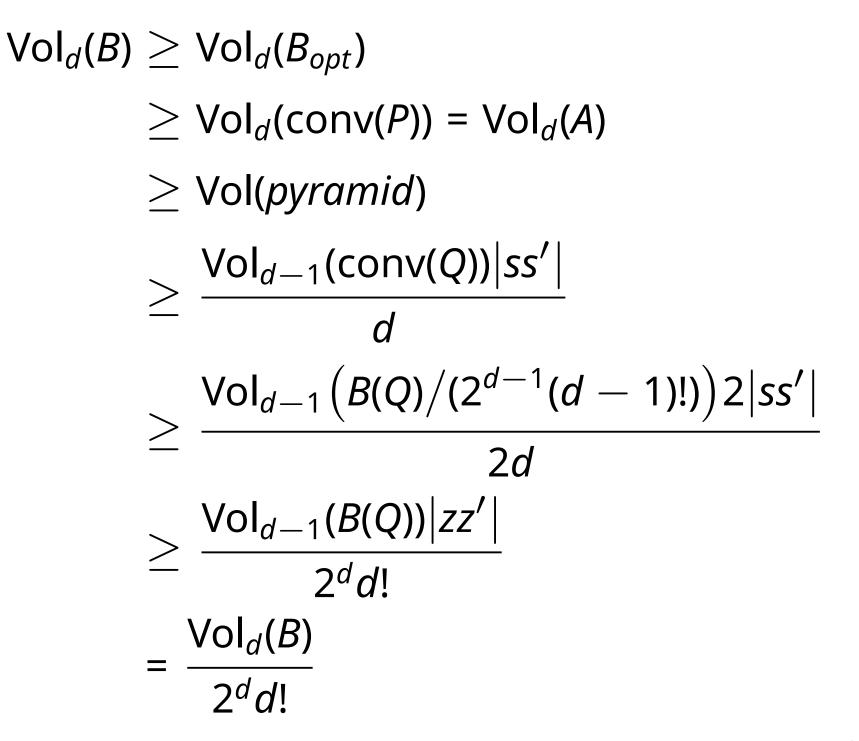
$$q \in \operatorname{conv}(Q)$$

At $\pi(s)$, height of *A* is at least |ss'|. *A* contains *pyramid* with base conv(*Q*) and pole length $\geq |ss'|$.

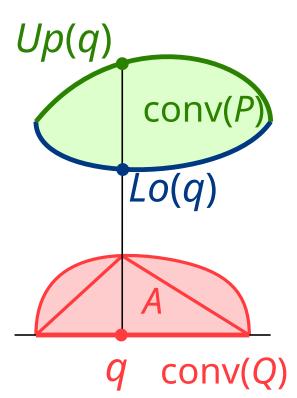








Running time: $T(n, d) = O(nd) + T(n, d - 1) = O(nd^2)$.



Summary

Coreset: small (sub-)set capturing the relevant geometry slow algorithm + coreset = fast approximation algorithm a coreset is constructed for specific geometric optimization problem

Coreset for directional width:

construction using grids (+ bounding box)

solves various other problems too: min-volume bounding box, min-enclosing ball, diameter, ...