

Volume Estimation

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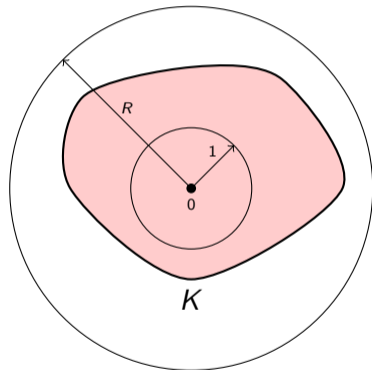
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Problem definitions

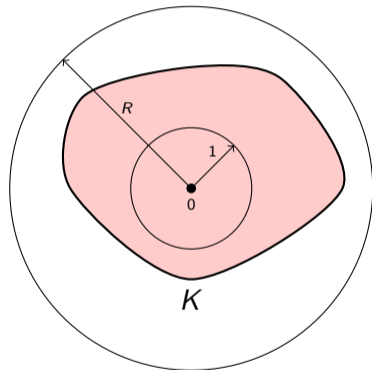
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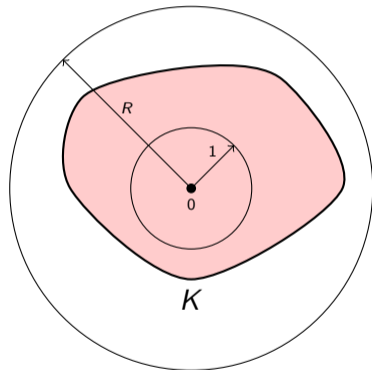
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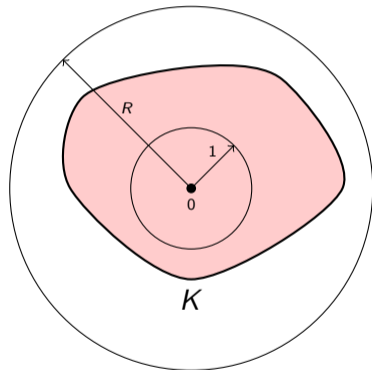
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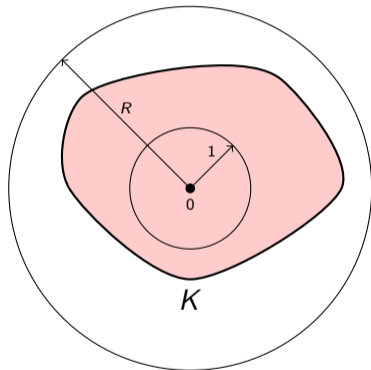
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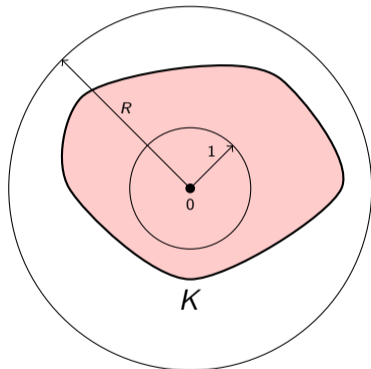
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5 **Computational models:**

- 1 Deterministic
- 2 Randomized (success prob. $\geq 2/3$)
- 3 Quantum ($O : |x\rangle |0\rangle \mapsto |x\rangle |x \in K\rangle$)



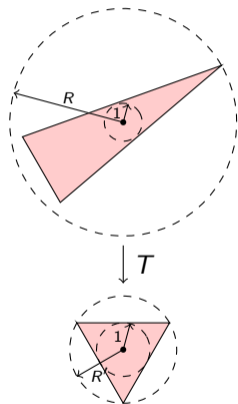
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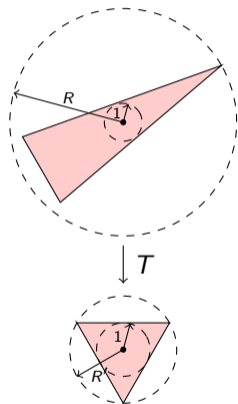
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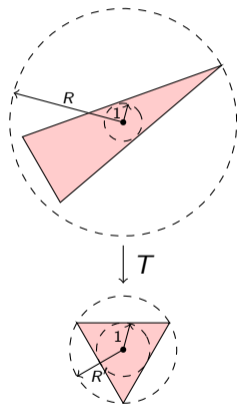
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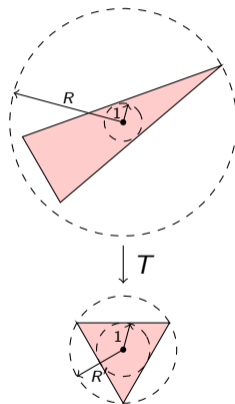
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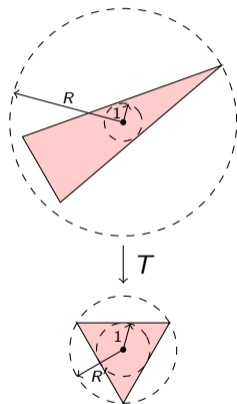
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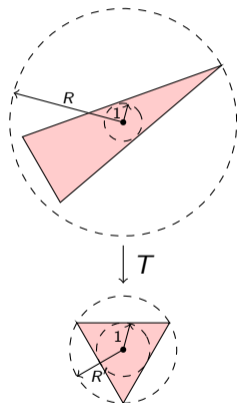
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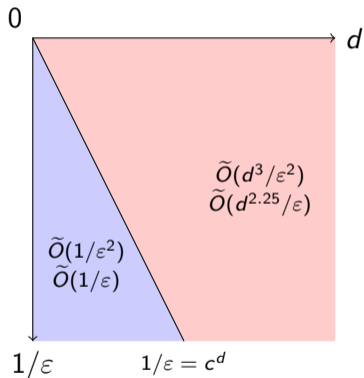
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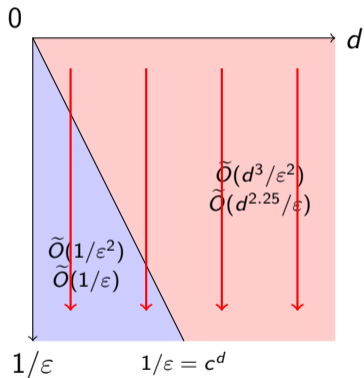
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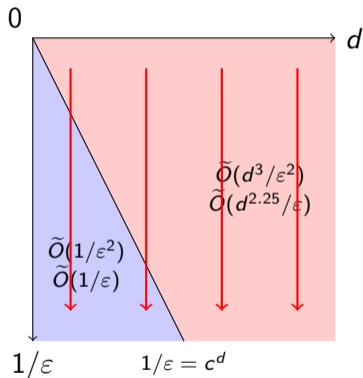
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- 4 *State of the art*:
 - 1 Randomized: $O(1/\varepsilon^2)$.
 - 2 Quantum: $O(1/\varepsilon)$.
 - 3 No lower bounds better than $\Omega(1)$.



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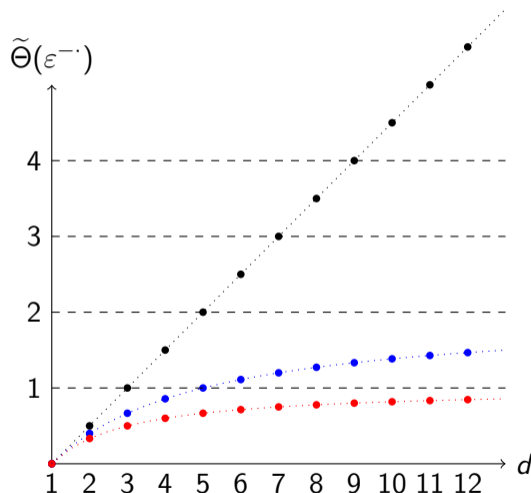
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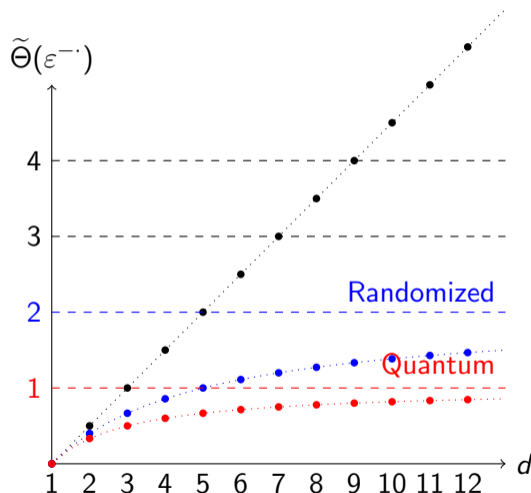
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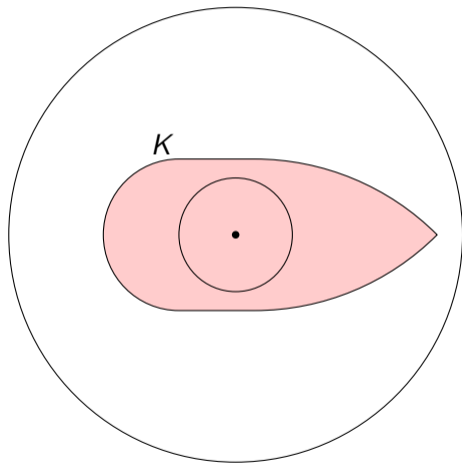
③ *Behavior of the exponent*:

- $\frac{d-1}{2} \rightarrow \infty$.
- $\frac{2(d-1)}{d+3} = 2 - O(\frac{1}{d}) \rightarrow 2$.
- $\frac{d-1}{d+1} = 1 - O(\frac{1}{d}) \rightarrow 1$.



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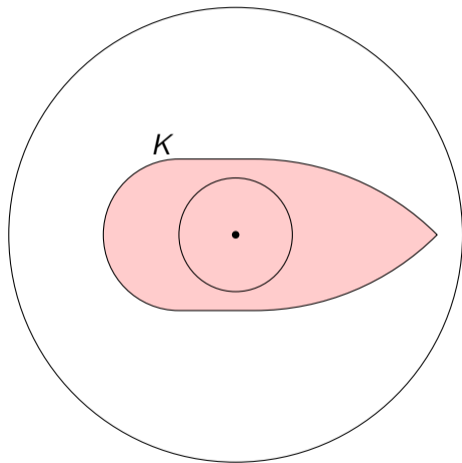


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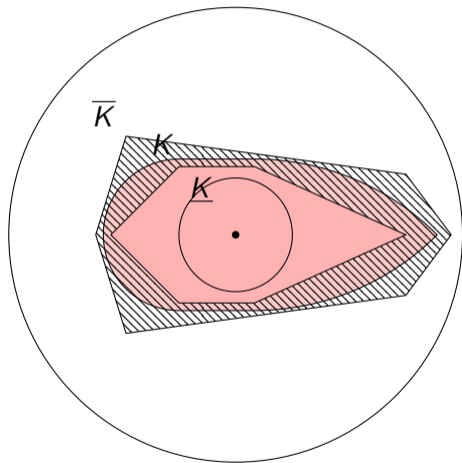


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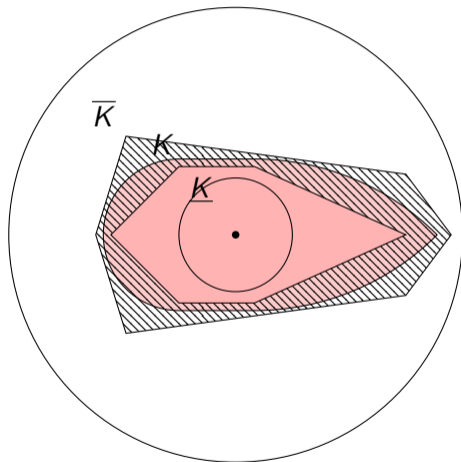
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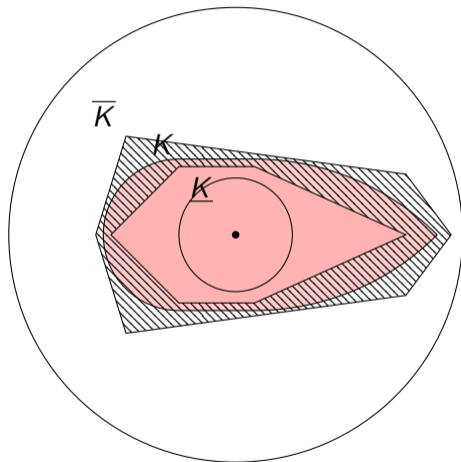
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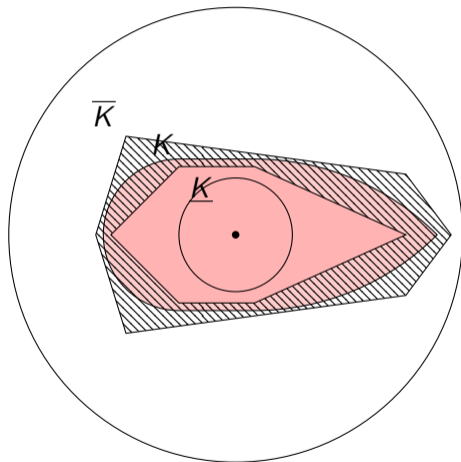
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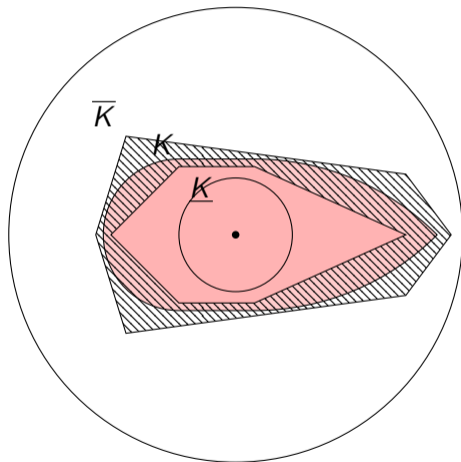
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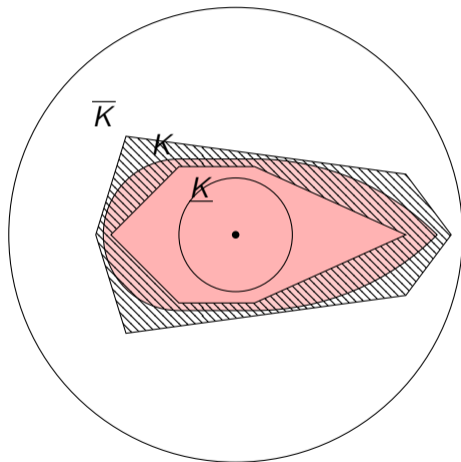
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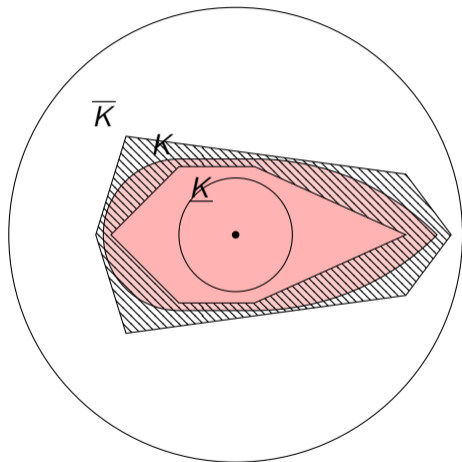
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4 Balance: Optimize δ .

\Rightarrow All complexities follow.



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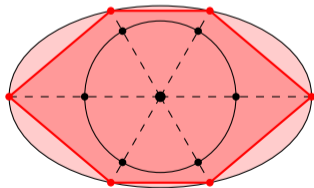
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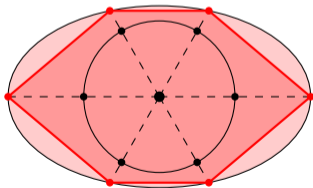


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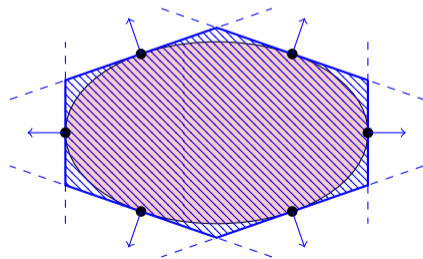
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- 2 Optimize over $x \mapsto v_j^T x$ over K .
- 3 \overline{K} is the intersection of the halfspaces.
- 4 Hard to bound volume difference.

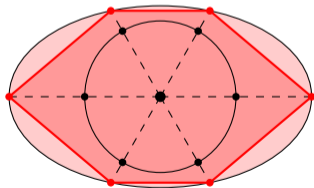


Techniques II – Convex set reconstruction attempts

Goal: Find $\underline{K} \subseteq K \subseteq \overline{K}$ s.t. $\text{Vol}(\overline{K} \setminus \underline{K}) \leq \delta$.

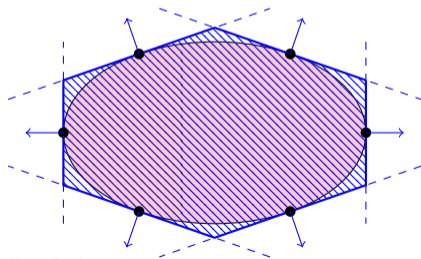
Failed attempt I:

- 1 Take v_1, \dots, v_n an η -net on $\partial B(0, 1)$.
- 2 Find the boundary points $r_j v_j \in \partial K$ with binary search.
- 3 $\underline{K} = \text{conv}(r_j v_j)$.
- 4 Hard to bound volume difference.



Failed attempt II:

- 1 Take v_1, \dots, v_n an η -net on $\partial B(0, 1)$.
- 2 Optimize over $x \mapsto v_j^T x$ over K .
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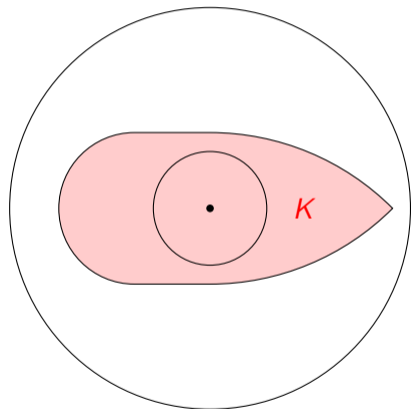


Successful attempt: “average” of the two.

Techniques III – Convex set reconstruction [Dud74]

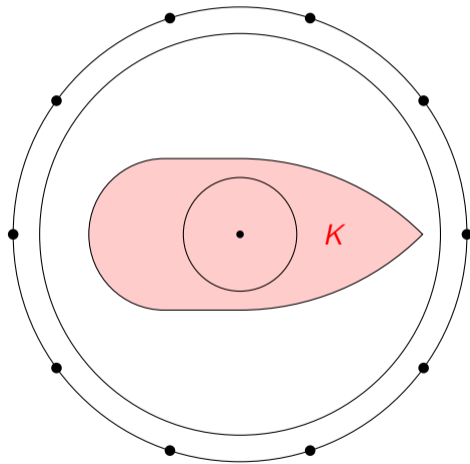
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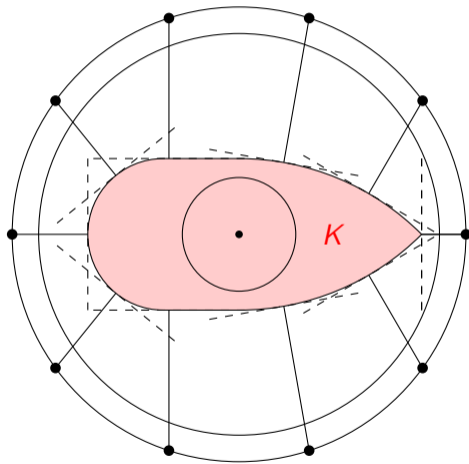
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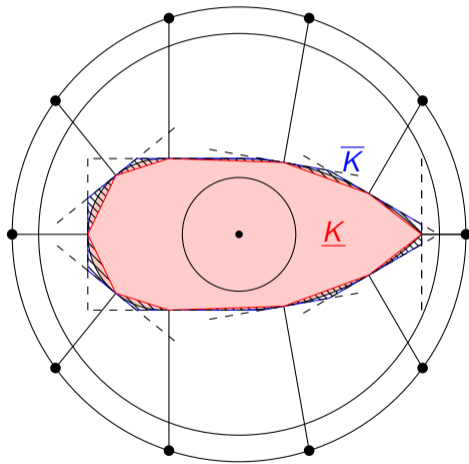
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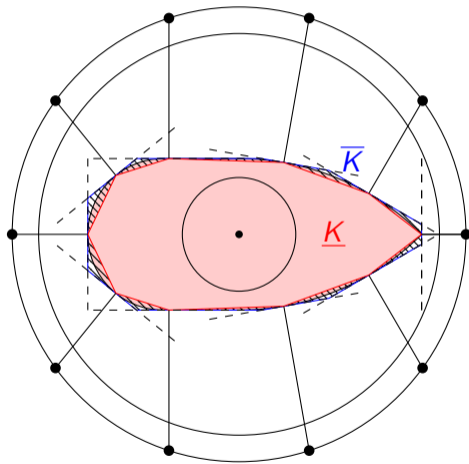
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 - 1 $\underline{K} \subseteq K + B(0, O(\eta^2))$
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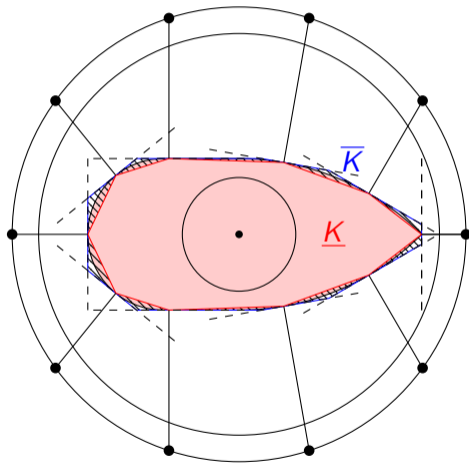
3 Let \underline{K} and \overline{K} be as before.

3 *Approximation claims:* (next slide)

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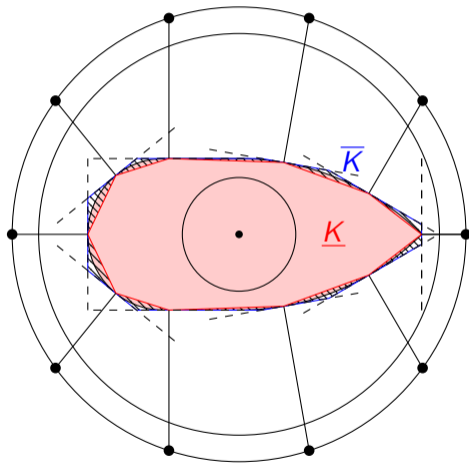
4 *Analysis sketch:*

- 1 $\text{Vol}(\overline{K} \setminus \underline{K}) = O(\eta^2) =: \delta$.



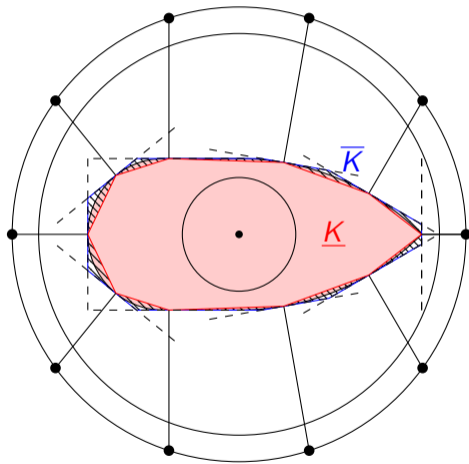
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 - 2 $O(\eta^{-(d-1)})$ points in the η -net.



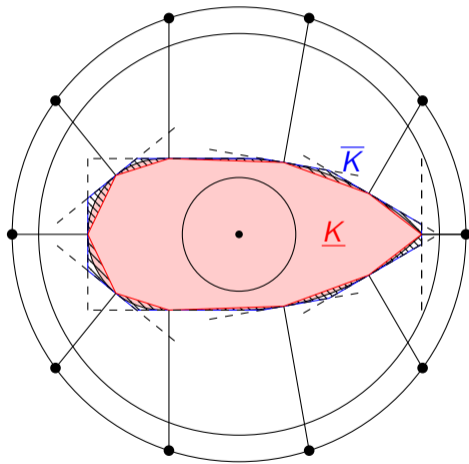
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(convex minimization problem)
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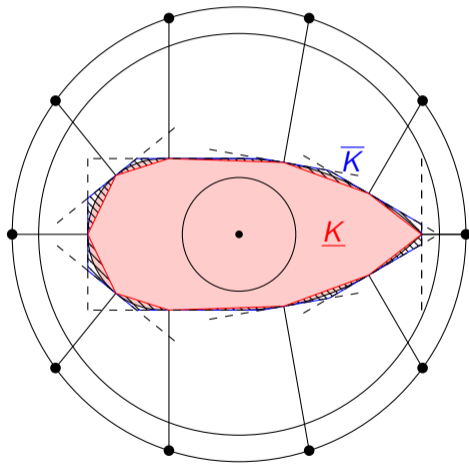
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- 5 **Remark:** Approximation errors.

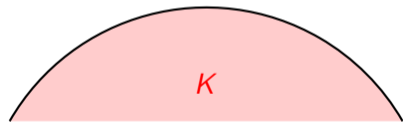


Techniques IV – Approximation proof

① *Goal:* $\bar{K} \subseteq K + B(0, O(\eta^2))$.

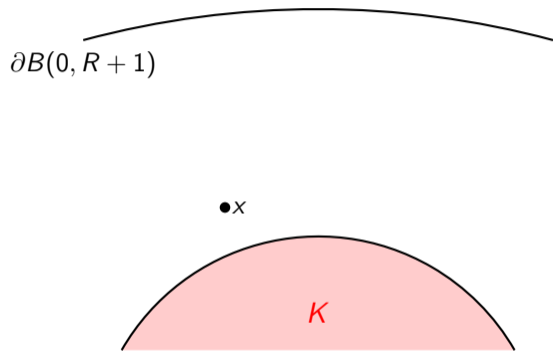
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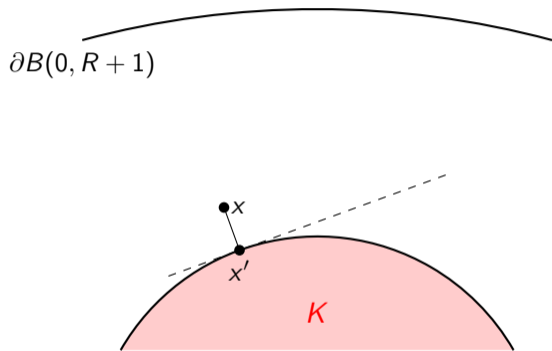
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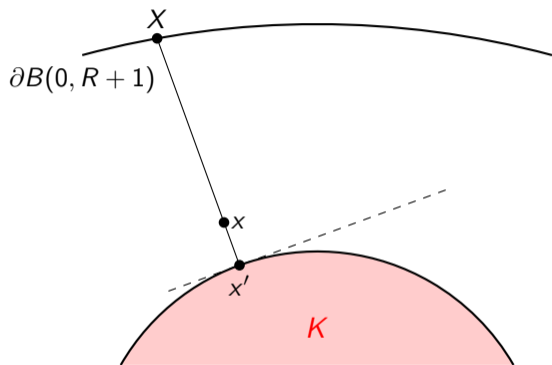
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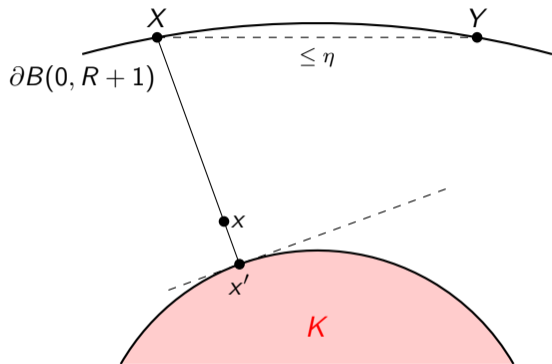
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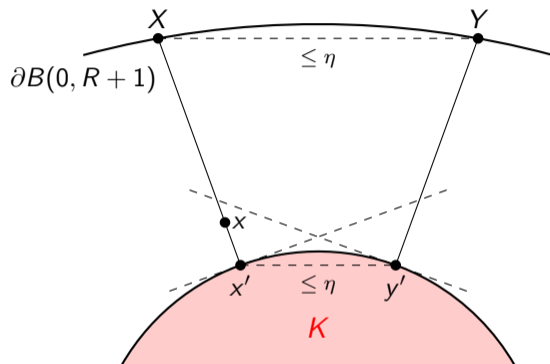
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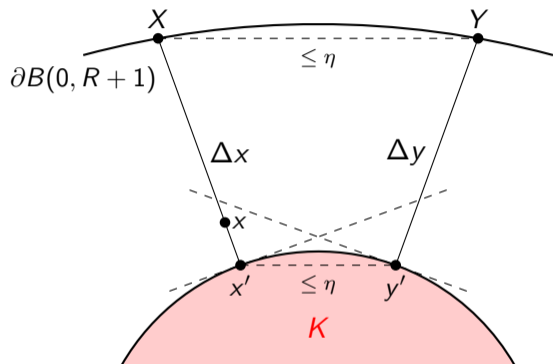
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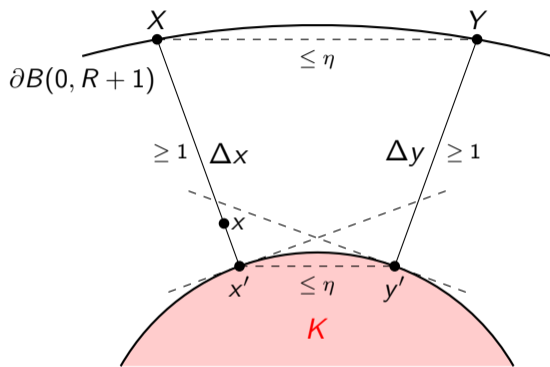
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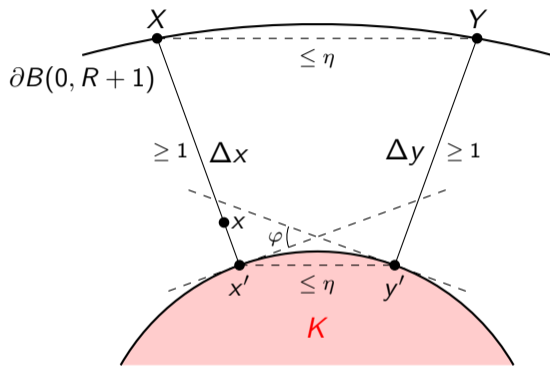
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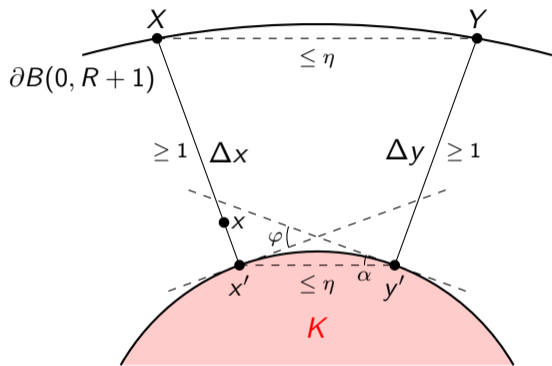
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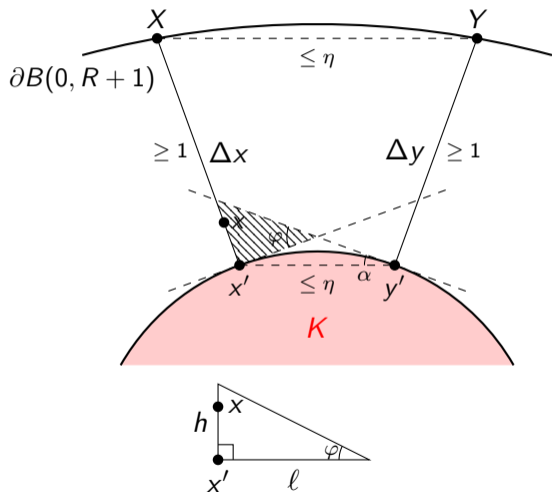
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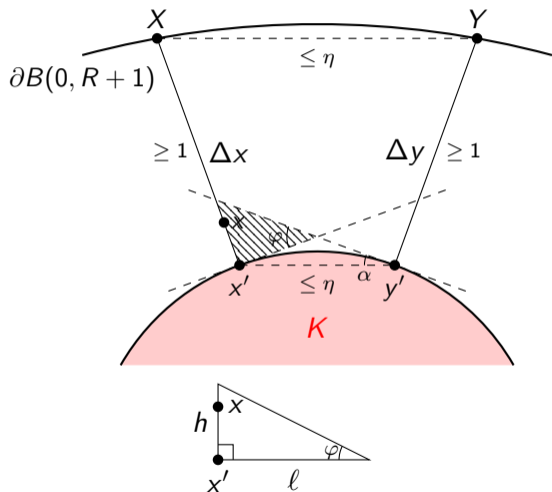


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Techniques IV – Approximation proof

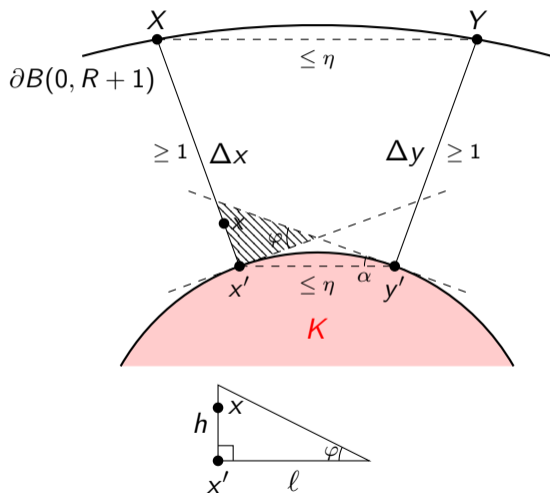
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Techniques IV – Approximation proof

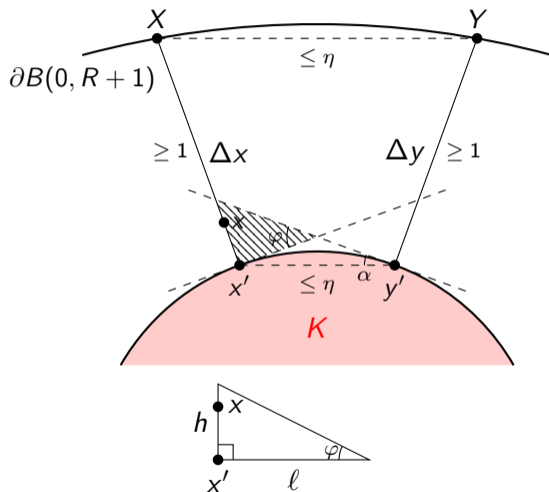
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Techniques V – Lower bounds

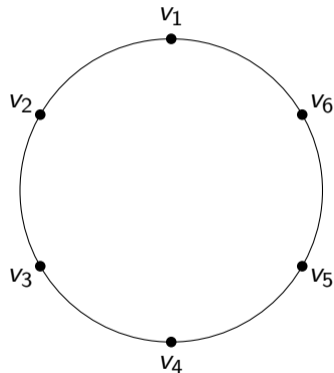
Techniques V – Lower bounds

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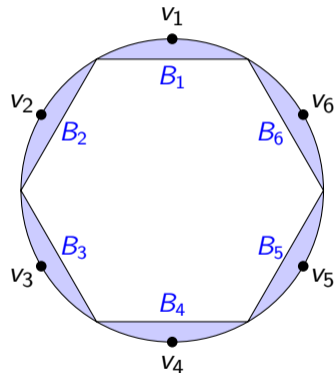
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Techniques V – Lower bounds

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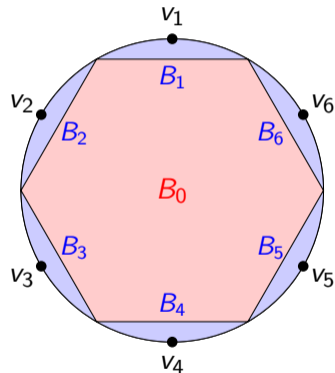
- 1 Let v_1, \dots, v_n be an η -net in $\partial B(0, R)$.
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 $\Rightarrow \text{Vol}(B_j) = \Theta(\eta^{d+1})$.



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- 3 For $x \in \{0, 1\}^n$, let $K_x = B_0 \cup \bigcup_{x_j=1}^n B_j$.
 $\Rightarrow \text{Vol}(K_x) = \text{Vol}(B_0) + |x| \text{Vol}(B_j)$.



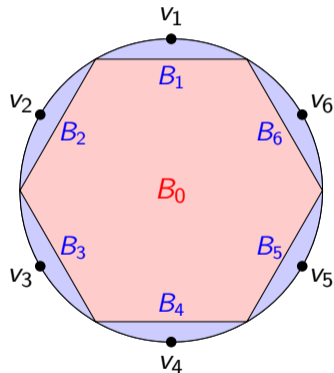
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2 Query complexities: ($k \in [1, n/4]$)

| Model | Recovery $ x \oplus \tilde{x} \leq k$ | Approx. counting $ x - \tilde{w} \leq k$ |
|---------------|---|--|
| Deterministic | $\Theta(n)$ | $\Theta(n)$ |
| Randomized | $\Theta(n)$ | $\Theta(\min(n, (n/k)^2))$ |
| Quantum | $\Theta(n)$ | $\Theta(n/k)$ |



Techniques V – Lower bounds

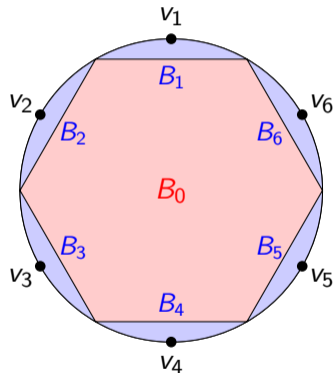
1 Bit string embedding:

- 1 Let v_1, \dots, v_n be an η -net in $\partial B(0, R)$.
 $\Rightarrow n = \Theta(\eta^{-(d-1)})$.
- 2 Let B_j be the spherical cap around v_j .
 $\Rightarrow \text{Vol}(B_j) = \Theta(\eta^{d+1})$.
- 3 For $x \in \{0, 1\}^n$, let $K_x = B_0 \cup \bigcup_{x_j=1}^n B_j$.
 $\Rightarrow \text{Vol}(K_x) = \text{Vol}(B_0) + |x| \text{Vol}(B_j)$.

2 Query complexities: ($k \in [1, n/4]$)

| Model | Recovery $ x \oplus \tilde{x} \leq k$ | Approx. counting $ x - \tilde{w} \leq k$ |
|---------------|---|--|
| Deterministic | $\Theta(n)$ | $\Theta(n)$ |
| Randomized | $\Theta(n)$ | $\Theta(\min(n, (n/k)^2))$ |
| Quantum | $\Theta(n)$ | $\Theta(n/k)$ |

3 Plug in: $n = \Theta(\eta^{-(d-1)})$ and $k = \Theta(\varepsilon \eta^{-(d+1)})$.



Techniques V – Lower bounds

1 Bit string embedding:

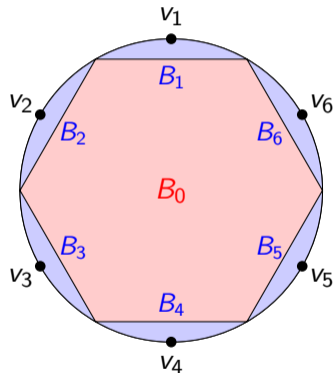
- 1 Let v_1, \dots, v_n be an η -net in $\partial B(0, R)$.
 $\Rightarrow n = \Theta(\eta^{-(d-1)})$.
- 2 Let B_j be the spherical cap around v_j .
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2 Query complexities: ($k \in [1, n/4]$)

| Model | Recovery | Approx. counting |
|---------------|-------------------------------|----------------------------|
| | $ x \oplus \tilde{x} \leq k$ | $ x - \tilde{w} \leq k$ |
| Deterministic | $\Theta(n)$ | $\Theta(n)$ |
| Randomized | $\Theta(n)$ | $\Theta(\min(n, (n/k)^2))$ |
| Quantum | $\Theta(n)$ | $\Theta(n/k)$ |

3 **Plug in:** $n = \Theta(\eta^{-(d-1)})$ and $k = \Theta(\varepsilon \eta^{-(d+1)})$.

4 **Balance:** Optimize $\eta \Rightarrow$ All bounds follow.



Summary & Outlook

Summary & Outlook

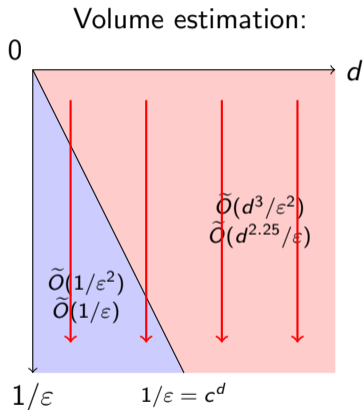
① *Our results:* (d fixed, $\varepsilon \downarrow 0$)

| Model | Reconstruction | Volume est. |
|---------------|--|---|
| Deterministic | $\tilde{\Theta}(\varepsilon^{-\frac{d-1}{2}})$ | $\tilde{\Theta}(\varepsilon^{-\frac{d-1}{2}})$ |
| Randomized | $\tilde{\Theta}(\varepsilon^{-\frac{d-1}{2}})$ | $\tilde{\Theta}(\varepsilon^{-\frac{2(d-1)}{d+3}})$ |
| Quantum | $\tilde{\Theta}(\varepsilon^{-\frac{d-1}{2}})$ | $\tilde{\Theta}(\varepsilon^{-\frac{d-1}{d+1}})$ |

Summary & Outlook

1 *Our results:* (d fixed, $\varepsilon \downarrow 0$)

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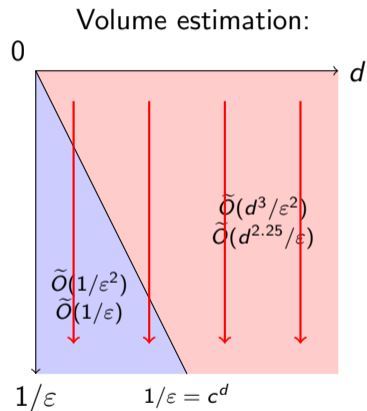
Summary & Outlook

- 1 *Our results:* (d fixed, $\varepsilon \downarrow 0$)

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- 2 *Follow-up questions:*

- 1 Limits in other directions.



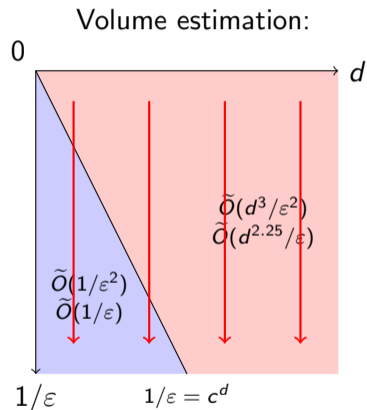
Summary & Outlook

- 1 *Our results:* (d fixed, $\varepsilon \downarrow 0$)

| Model | Reconstruction | Volume est. |
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| Deterministic | $\tilde{\Theta}(\varepsilon^{-\frac{d-1}{2}})$ | $\tilde{\Theta}(\varepsilon^{-\frac{d-1}{2}})$ |
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- 2 *Follow-up questions:*

- Limits in other directions.
- Quantum rounding.



Thanks for your attention!
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