

# From Gaussian measure to partial colorings and linear size sparsifiers

Thomas Rothvoss

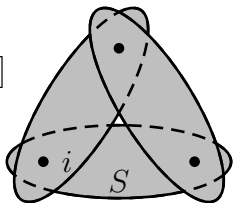
Based on [R. FOCS'14], [Reis, R. SODA'20],  
[Reis, R. Arxiv '20]



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WASHINGTON

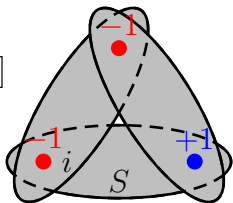
# Discrepancy theory

- ▶ Set system  $\mathcal{S} = \{S_1, \dots, S_m\}, S_i \subseteq [n]$



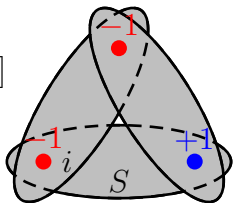
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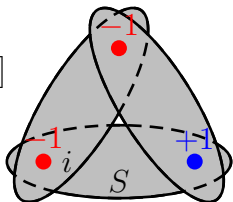
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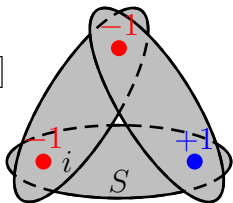
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## Known results:

- ▶  $n$  sets,  $n$  elements:  $\text{disc}(\mathcal{S}) = O(\sqrt{n})$  [Spencer '85]
- ▶ Every element in  $\leq t$  sets:  $\text{disc}(\mathcal{S}) < 2t$  [Beck & Fiala '81]

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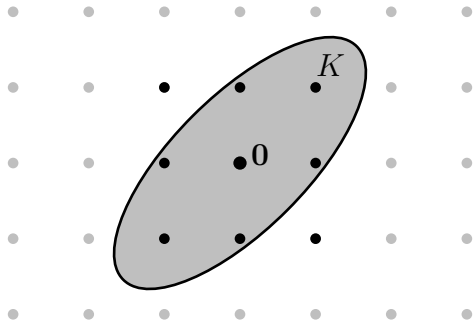
**Main method:** Find a **partial coloring**  $\chi : [n] \rightarrow \{0, \pm 1\}$

- ▶ low discrepancy  $\max_{S \in \mathcal{S}} |\chi(S)|$
- ▶  $|\text{supp}(\chi)| \geq \Omega(n)$

# Spencer/Gluskin/Giannopolous Thm

## Theorem (1980s)

Let  $K$  be symmetric convex set with  $\gamma_n(K) \geq e^{-\frac{1}{10}n}$ . Then  $\exists x \in K \cap \{-1, 0, 1\}^n$  with  $|\text{supp}(x)| \geq n/10$ .

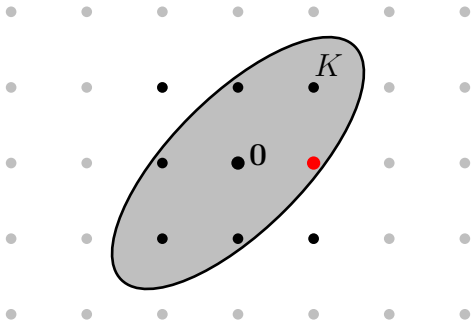


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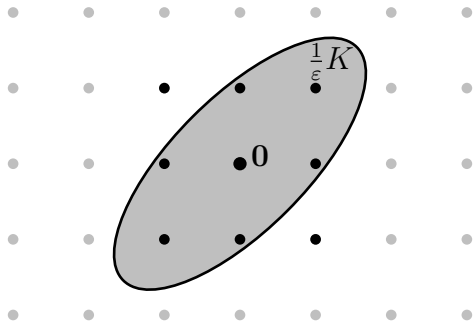
- ▶ **Gaussian measure:**  $\gamma_n(K) = \Pr[\text{gaussian} \in K]$
- ▶ Based on pigeonhole principle [non-algorithmic]



# Algorithmic Discrepancy

## Theorem

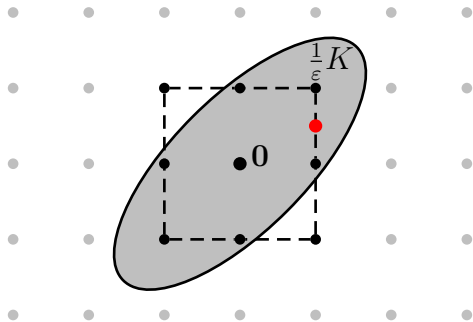
For any  $\alpha > 0$ , there are  $\varepsilon, \delta > 0$  so that: Let  $K$  be symmetric convex set with  $\gamma_n(K) \geq e^{-\alpha n}$ . Can find  $x \in \frac{1}{\varepsilon}K \cap [-1, 1]^n$  with  $|\{i : x_i \in \{-1, 1\}\}| \geq \delta n$  in **poly-time**.



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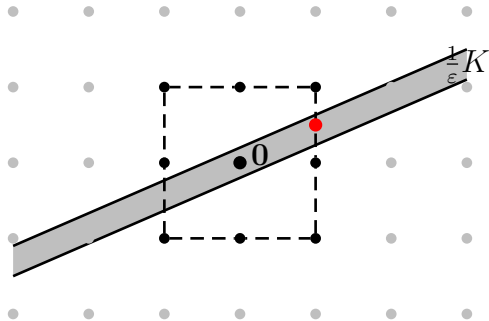
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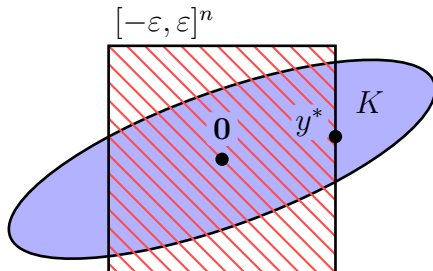


- ▶ Might not exist for  $x \in \{-1, 0, 1\}^n$

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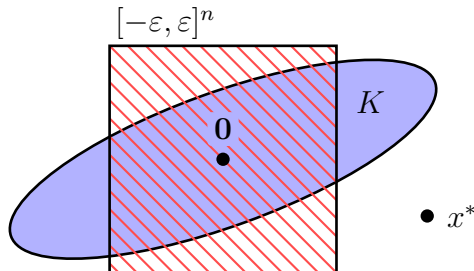
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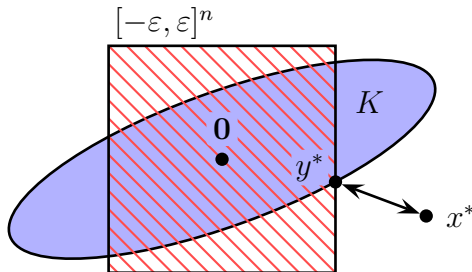
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- (1) take a random  $x^* \sim \gamma_n$
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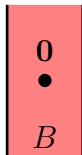
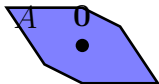


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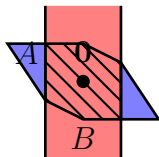
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- ▶ For **symmetric convex** sets  $A, B \subseteq \mathbb{R}^n$  one has  $\gamma_n(A \cap B) \geq \gamma_n(A) \cdot \gamma_n(B)$





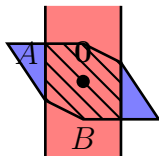
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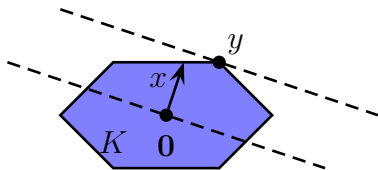


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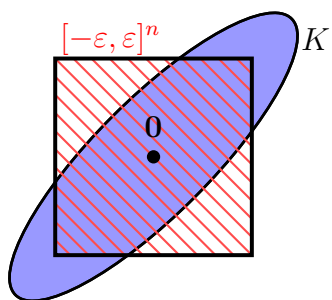


- ▶  $w(K) := \mathbb{E}_{x \sim S^{n-1}}[\max\{\langle x, y \rangle : y \in K\}]$



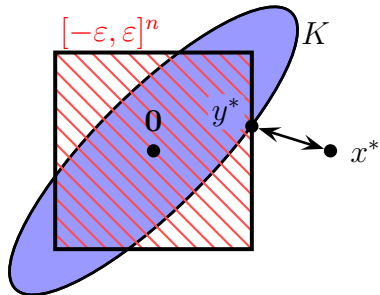
- ▶ **Urysohn:** Among convex bodies with same  $\gamma_n(K)$ ,  $\mathbf{0}$ -centered Euclidean ball minimizes  $w(K)$ .

# Analysis



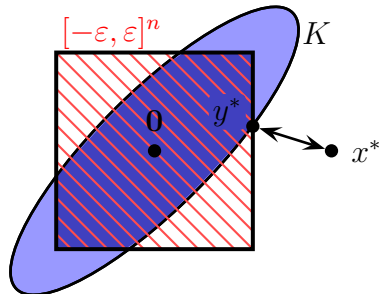
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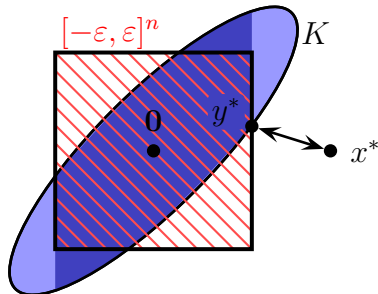


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$$\|y^* - x^*\|_2 = \min\{\|y - x^*\|_2 \mid y \in K \text{ and } |y_i| \leq \varepsilon \forall i\}$$

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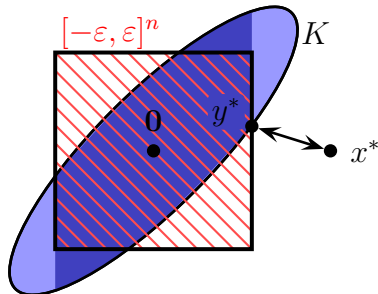
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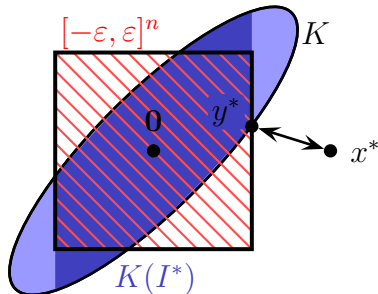
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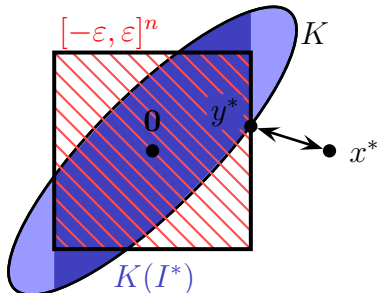
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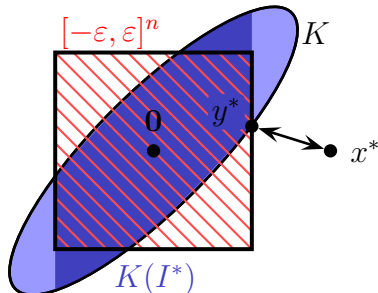
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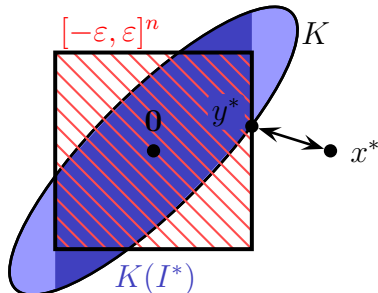
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- ▶ W.h.p.  $d(x^*, K(I^*)) \leq (1 - 10\varepsilon)\sqrt{n}$  (next slide!)
- ▶ Union bound over all  $|I| \leq \delta n$ :

$$\Pr \left[ \bigcup_{|I| \leq \delta n} d(x^*, K(I)) > (1 - 10\varepsilon)\sqrt{n} \right] \leq e^{-\Omega_\varepsilon(n)} \quad \square$$

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Let  $Q \subseteq \mathbb{R}^n$  be convex symmetric with  $\gamma_n(Q) \geq e^{-\alpha n}$ . Then

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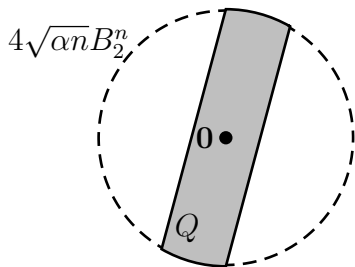
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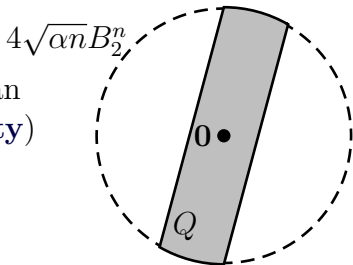
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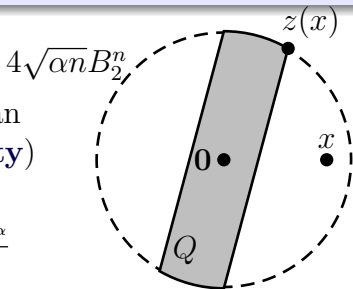
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- ▶  $z(x) := \operatorname{argmax}\{\langle z, x \rangle : z \in Q\}$
- ▶ Then  $\mathbb{E}_{x \sim \gamma_n} [\langle x, z(x) \rangle] \geq n \cdot \frac{e^{-2\alpha}}{4}$



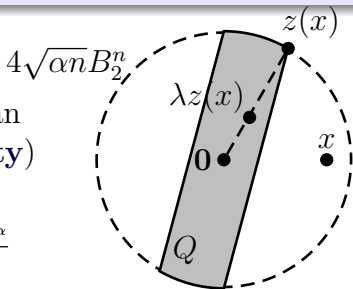
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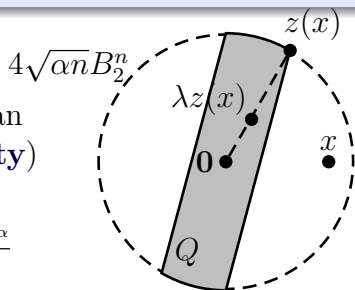
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PART II

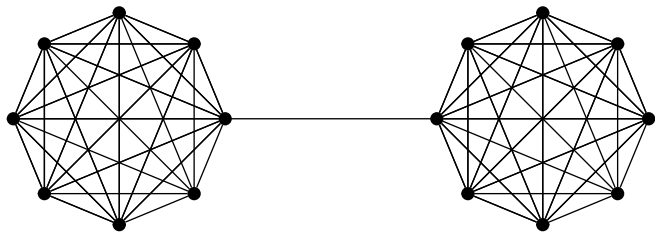
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LINEAR SIZE SPARSIFIERS IN  
GRAPHS

# Graph Sparsification

## Theorem (Batson-Spielman-Srivastava '08)

For any graph  $G = (V, E)$  one can find weights  $s(e) \geq 0$  in poly-time with  $|\text{supp}(s)| \leq O(n/\varepsilon^2)$  so that  $|\delta(U)| = (1 \pm \varepsilon) \cdot |s(\delta(U))|$  for every  $U \subseteq V$ .

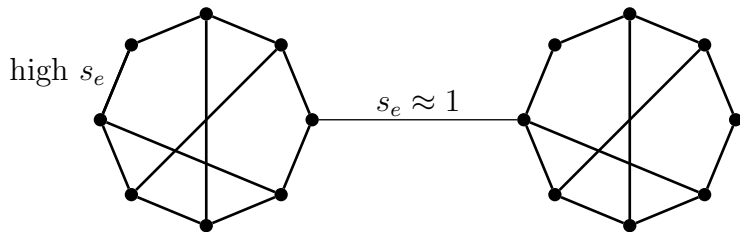


- ▶ Even stronger:  
Laplacian of weighted sparse graph  $\approx$  original Laplacian

# Graph Sparsification

## Theorem (Batson-Spielman-Srivastava '08)

For any graph  $G = (V, E)$  one can find weights  $s(e) \geq 0$  in poly-time with  $|\text{supp}(s)| \leq O(n/\varepsilon^2)$  so that  $|\delta(U)| = (1 \pm \varepsilon) \cdot |s(\delta(U))|$  for every  $U \subseteq V$ .



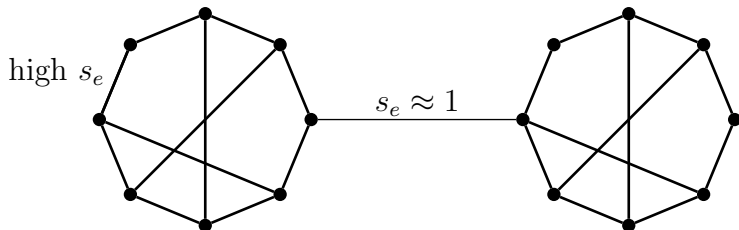
- ▶ Even stronger:  
Laplacian of weighted sparse graph  $\approx$  original Laplacian

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For vectors  $v_1, \dots, v_m \in \mathbb{R}^n$  with  $\sum_{i=1}^m v_i v_i^T = I_n$ , one can find weights  $s \in \mathbb{R}_{\geq 0}^m$  in poly-time with  $|\text{supp}(s)| \leq O(n/\varepsilon^2)$  so that

$$(1 - \varepsilon)I_n \preceq \sum_{i=1}^m s_i v_i v_i^T \preceq (1 + \varepsilon)I_n$$



# A new sparsification algorithm

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## Theorem

$O(\log m)$  iterations suffice and output is  $1 \pm O(\varepsilon)$  sparsifier w.h.p.

# How to find partial colorings

What do we know about the set

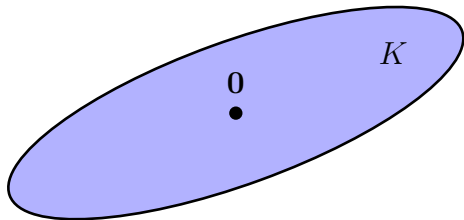
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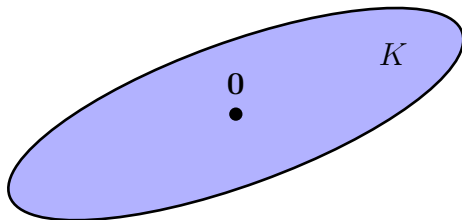


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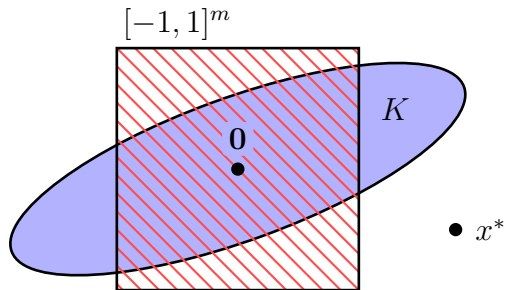


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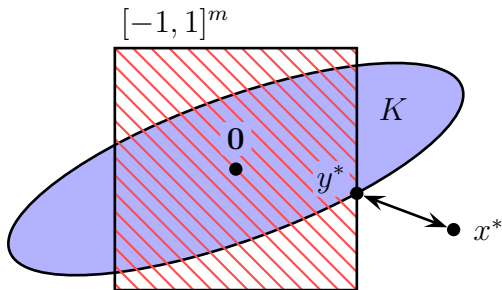


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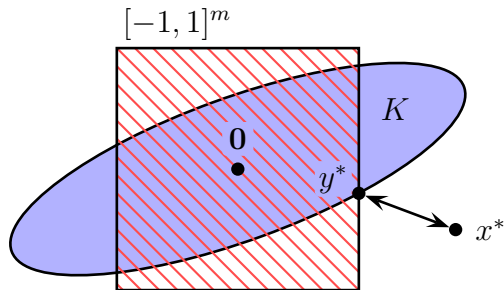


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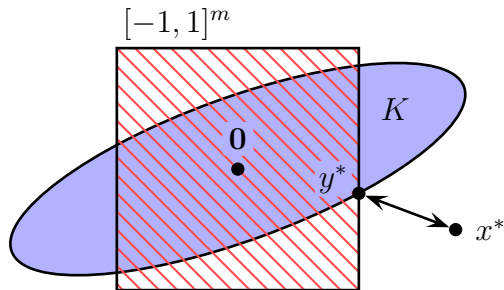


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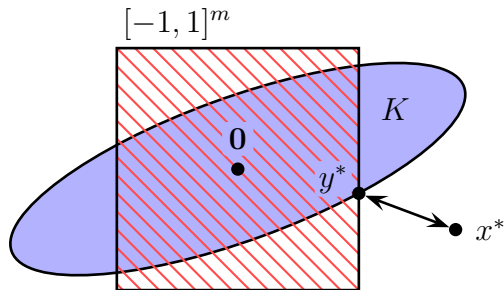


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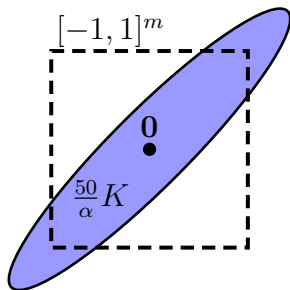


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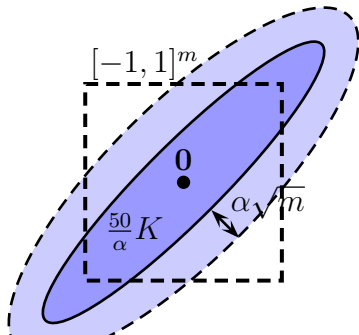


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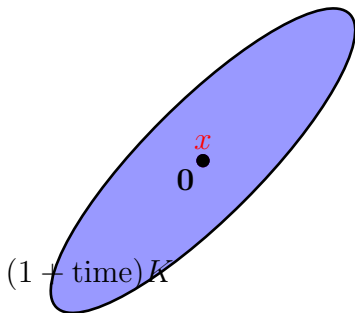
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## Corollary

$$w(K) \geq \Omega(\sqrt{m}).$$

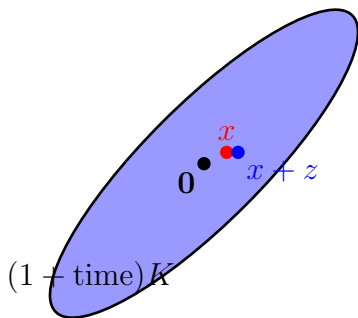
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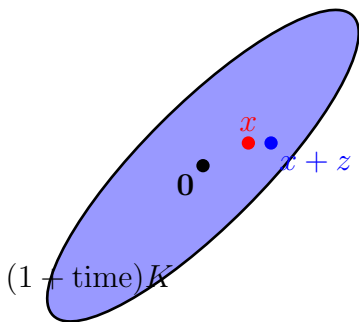
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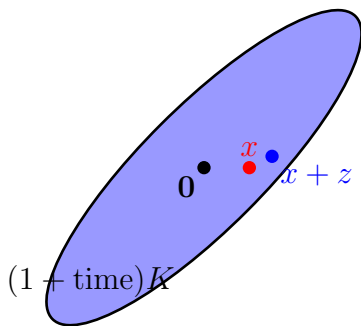
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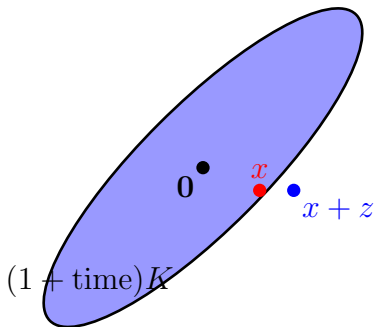
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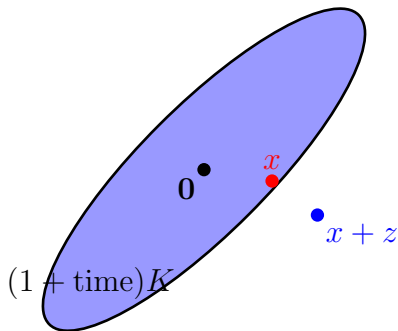
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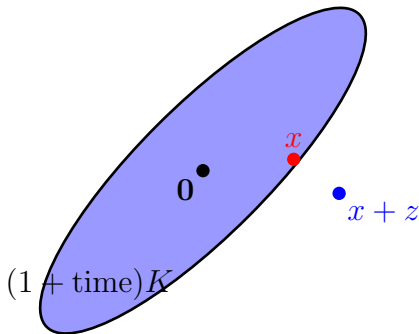
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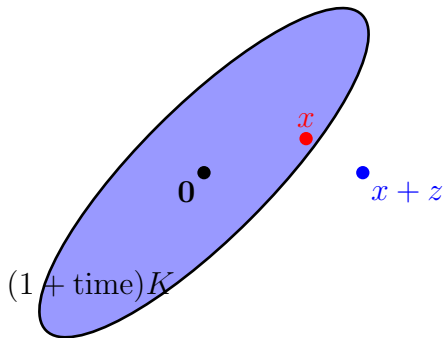
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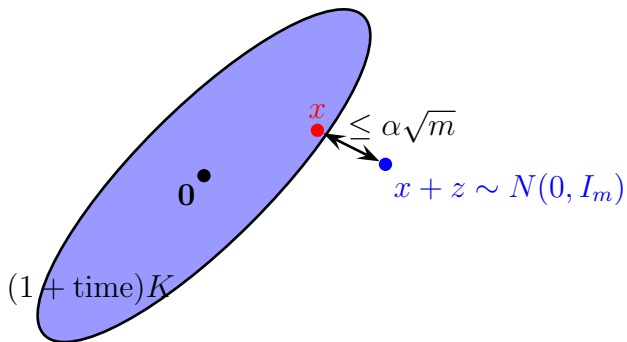
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## Main Lemma

If  $\Phi(x) \leq \frac{Dm^2\alpha^2}{10}$ , then there is  $X \preceq I_m$  with  $\text{Tr}[X] \geq (1 - \alpha^2)m$  so that  $y \sim N(0, X)$  one has  $\mathbb{E}[\Phi(x + \delta y)] \leq \Phi(x)$ .

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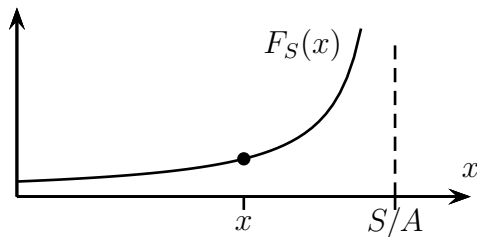
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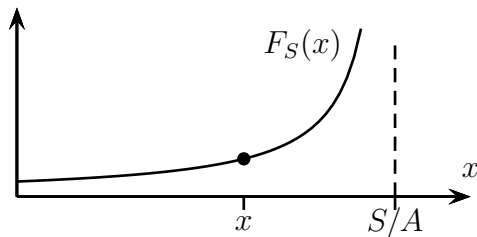
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# One-dimensional intuition



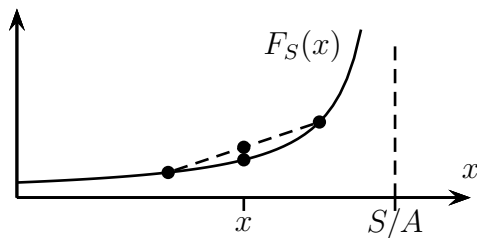
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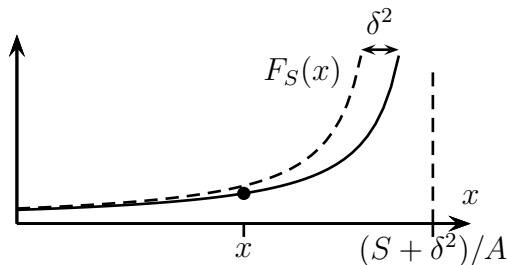


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- ▶ Shift gives

$$F_{S+\delta^2}(x) - F_S(x) \approx -\delta^2 F_S'(x) = -\delta^2 \frac{A}{(S - Ax)^2}$$

## One update step (2)

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- ▶ Pick Gaussian  $y$  orthogonal to  $x$  and any linear term in analysis

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# Open problems

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Thanks for your attention