

Upper and Lower Bounds on the Quality of the PCA Bounding Boxes

Darko Dimitrov, Christian Knauer,
Klaus Kriegel, Günter Rote

Freie Universität Berlin

Known algorithms that solve bounding box problem

\mathbb{R}^2

- Minimum-area bounding rectangle [Tousaint '83]

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- Minimum-area bounding rectangle [Tousaint '83]
- Heuristics

AABB (Axis Aligned Bounding Boxes)

R-tree

Packed *R*-tree [Rousopoulos, Leifker '85]

R⁺-tree [Sellis, Rousopoulos, Faloutsos '87]

R^{*}-tree [Beckmann, Kriegel, Schneider, Seeger '90]

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$$O\left(n + \frac{1}{\epsilon^{4.5}}\right)$$

$$O\left(n \log n + \frac{n}{\epsilon^3}\right)$$

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AABB (Axis Aligned Bounding Boxes)

PCA-bounding box $O(n)$, $O(n \log n)$, $O(n^{\lfloor \frac{d}{2} \rfloor + 1})$

OBB-tree [Gottchalk, Lin, Manocha, '96]

BOXTREE [Barequet, Chazelle, Guibas, Mitchell, Tal '96]

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Principal Component Analysis

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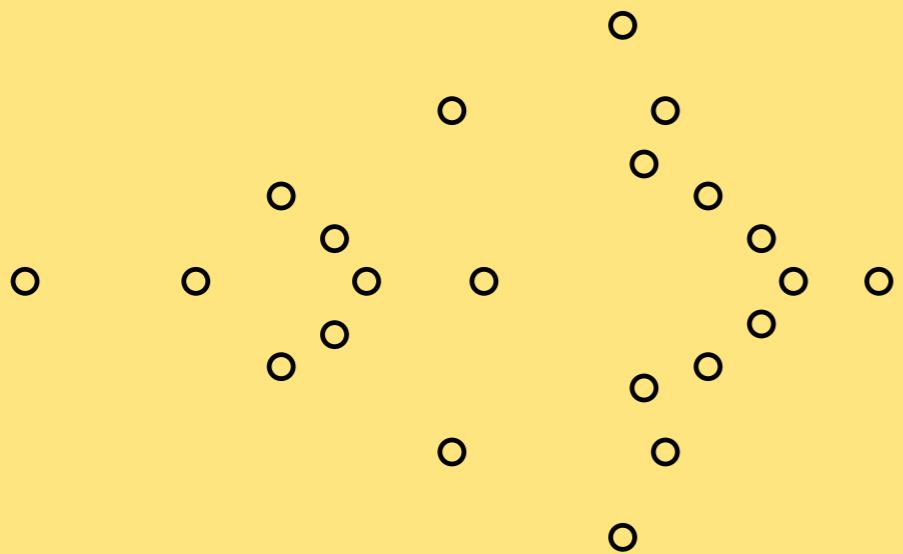
$$\text{var}(X, v) = \langle Cv, v \rangle, \quad C_{ij} = \frac{1}{m} \sum_{k=1}^m (x_{ik} - c_i)(x_{jk} - c_j).$$

PCA

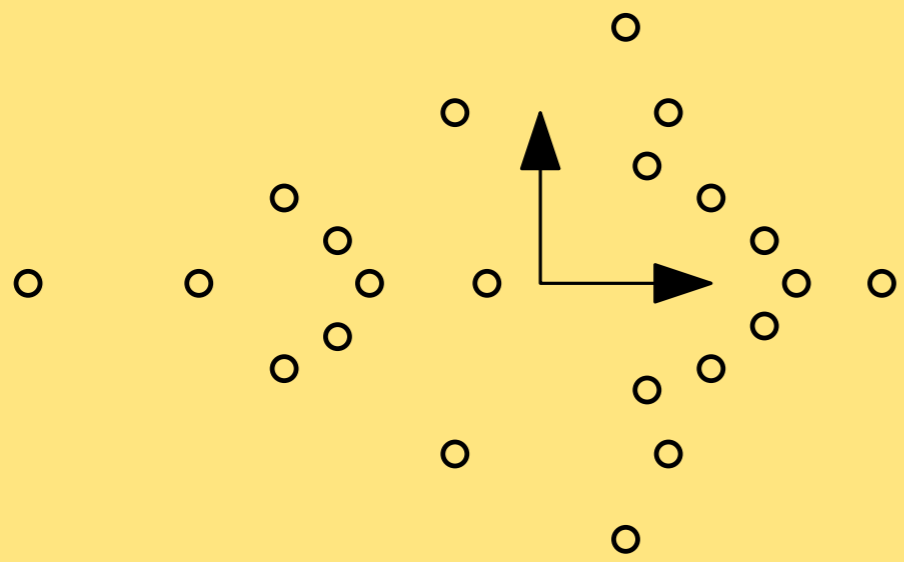
Lemma 1. For $1 \leq j \leq d$, let λ_j be the j -th largest eigenvalue of C and let v_j denote the unit eigenvector for λ_j . Let $B_j = \{v_1, v_2, \dots, v_j\}$, $sp(B_j)$ be the linear subspace spanned by B_j , and $sp(B_j)^\perp$ be the orthogonal complement of $sp(B_j)$. Then $\lambda_1 = \max\{var(X, v) : \text{unit vector } v \text{ in } \mathbb{R}^d\}$ and for any $2 \leq j \leq d$,

- i) $\lambda_j = \max\{var(X, v) : \text{unit vector } v \text{ in } sp(B_{j-1})^\perp\}$.
- ii) $\lambda_j = \min\{var(X, v) : \text{unit vector } v \text{ in } sp(B_j)\}$.
- iii) $var(X, B_j) \geq var(X, S)$ for any set S of j orthogonal unit vectors.

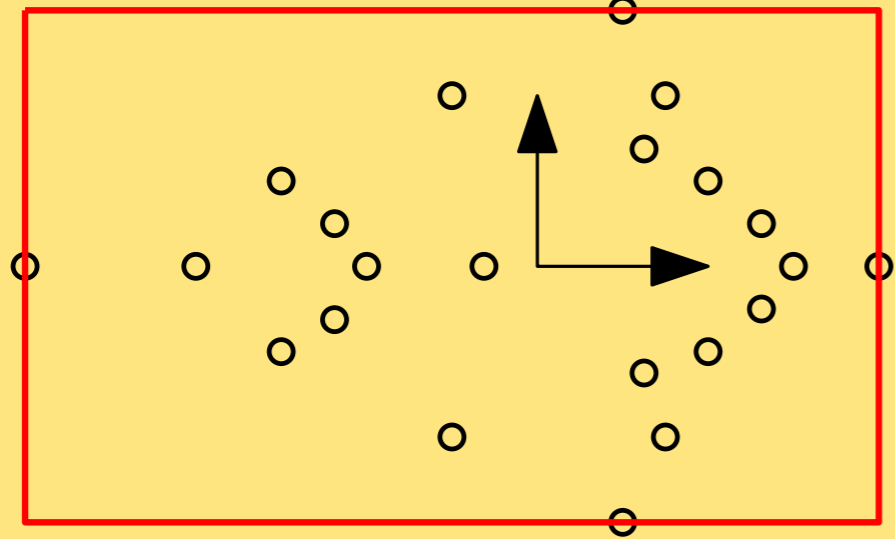
P



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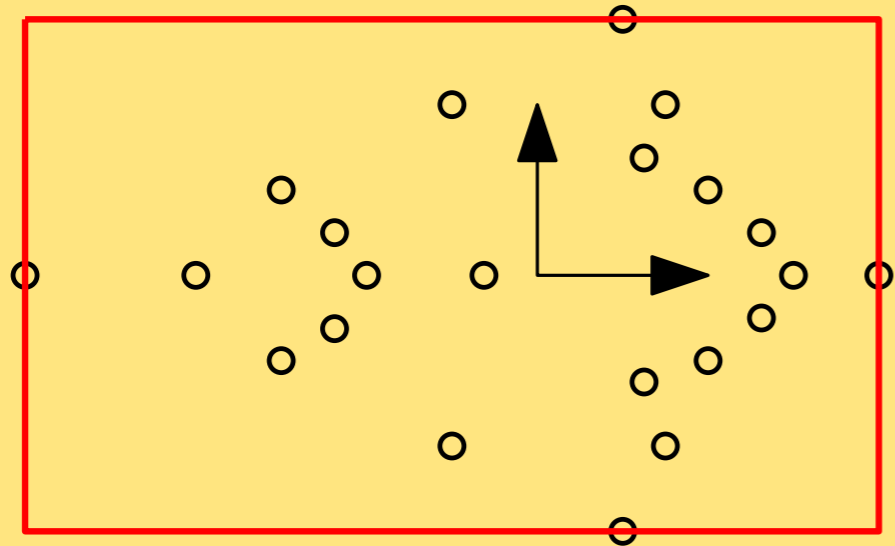


P



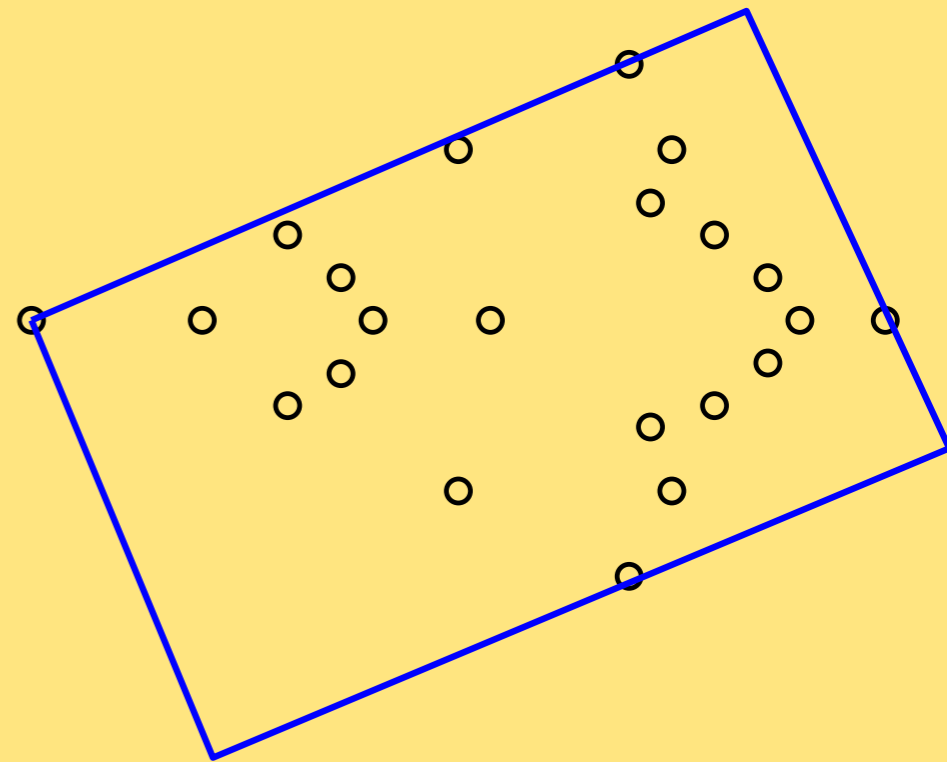
$BB_{pca}(P)$

P



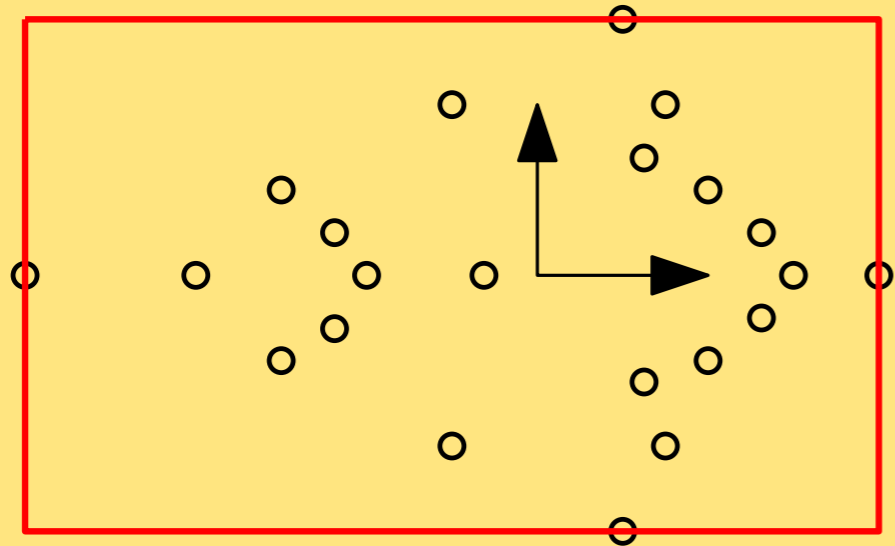
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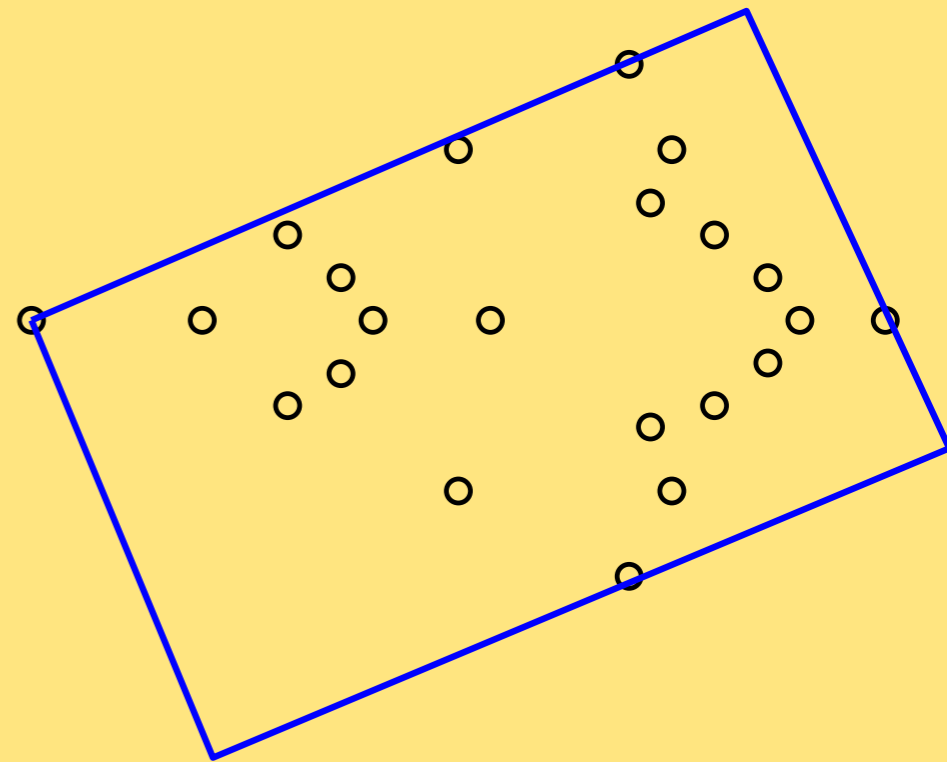
$BB_{opt}(P)$

P



$BB_{pca}(P)$

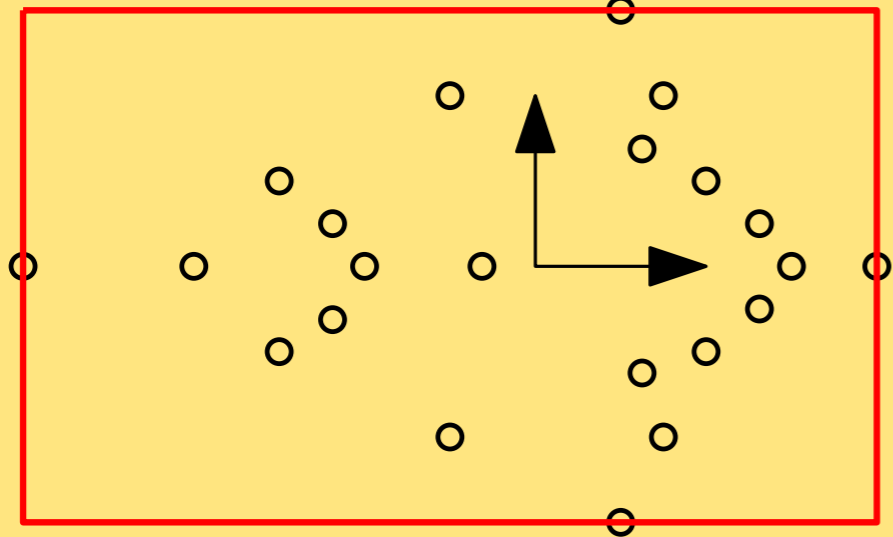
P



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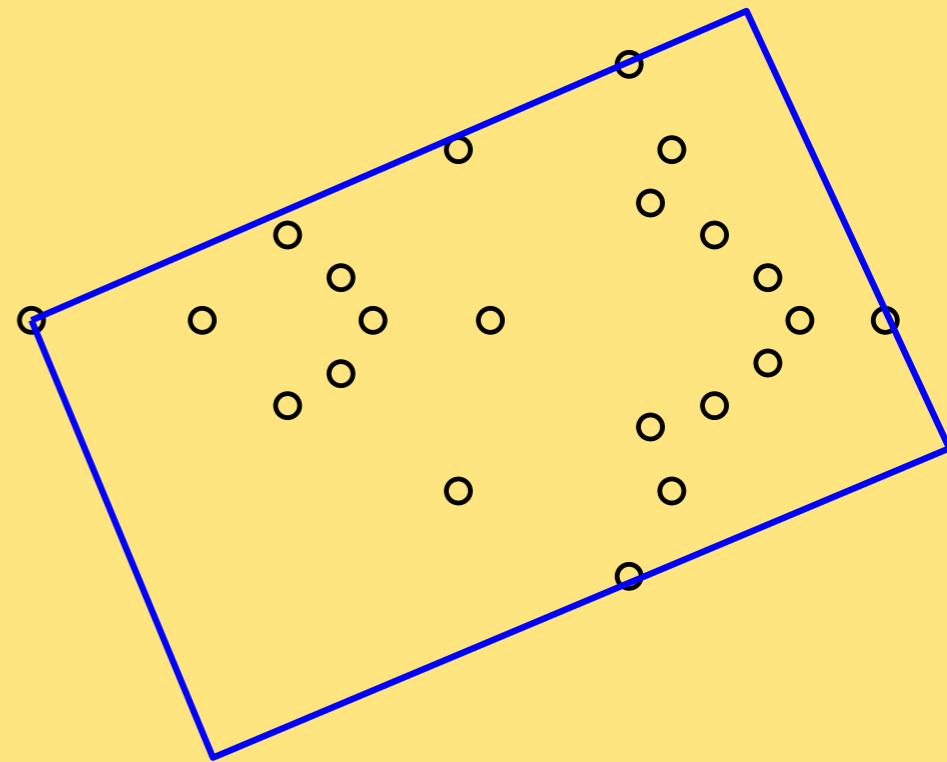
$$\lambda_d(P) = \frac{Vol(BB_{pca}(P))}{Vol(BB_{opt}(P))}$$

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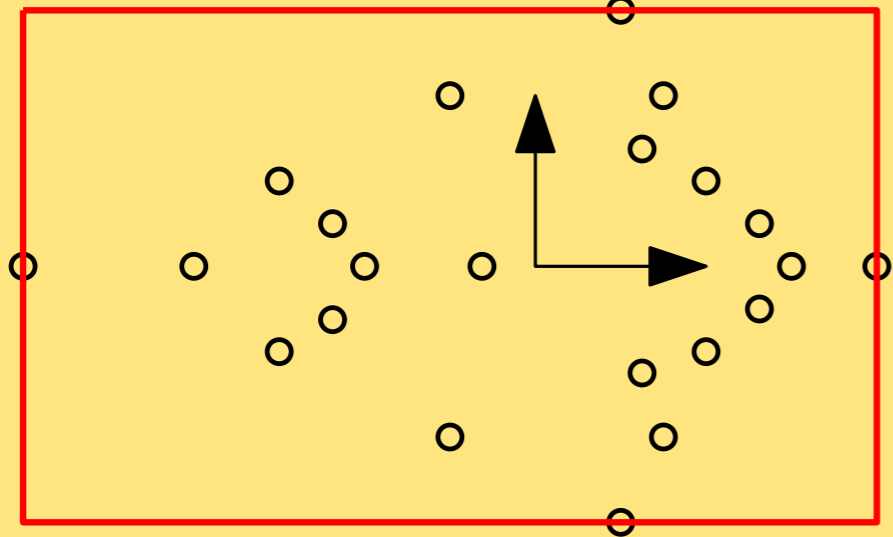


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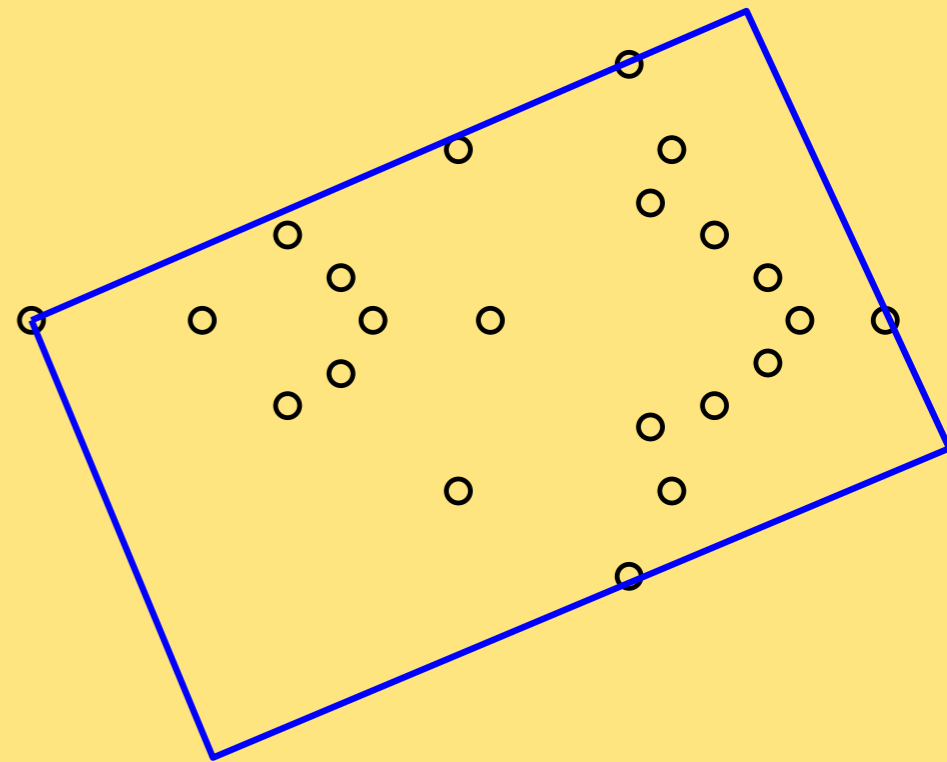
$$\lambda_d = \sup \{ \lambda_d(P) \mid P \subseteq \mathbb{R}^d, Vol(CH(P)) > 0 \}$$

P



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P



$BB_{opt}(P)$

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Lower bounds

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Proposition 1. $\lambda_{d,0} = \infty$ for any $d \geq 2$.

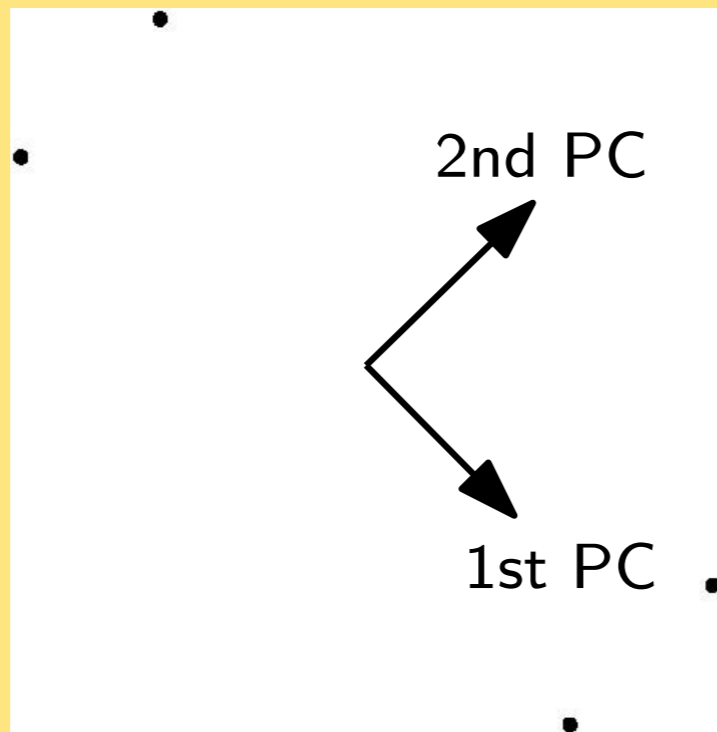
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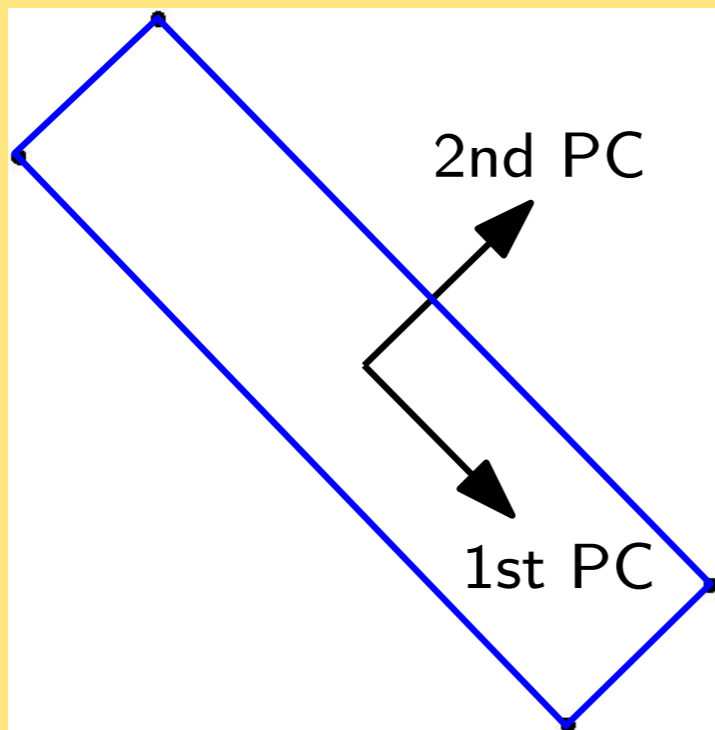
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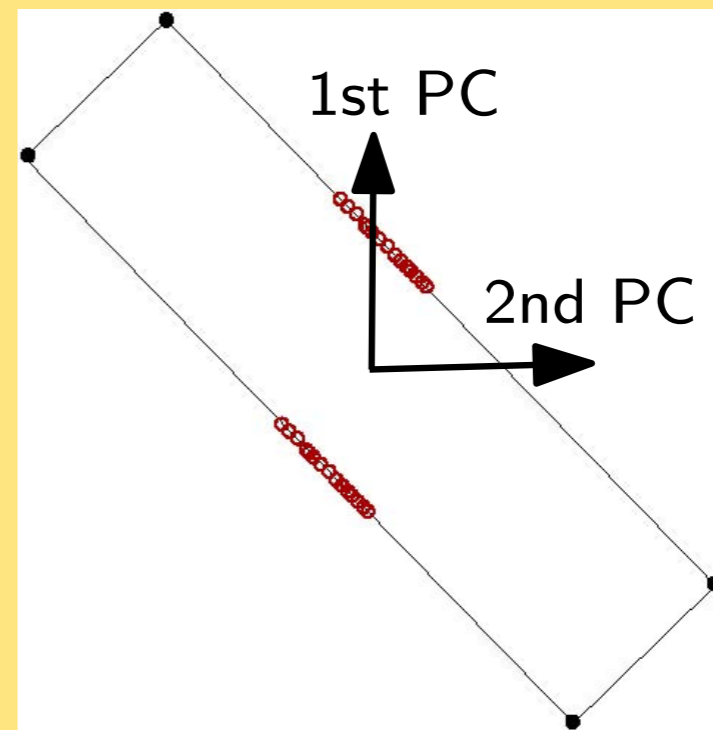
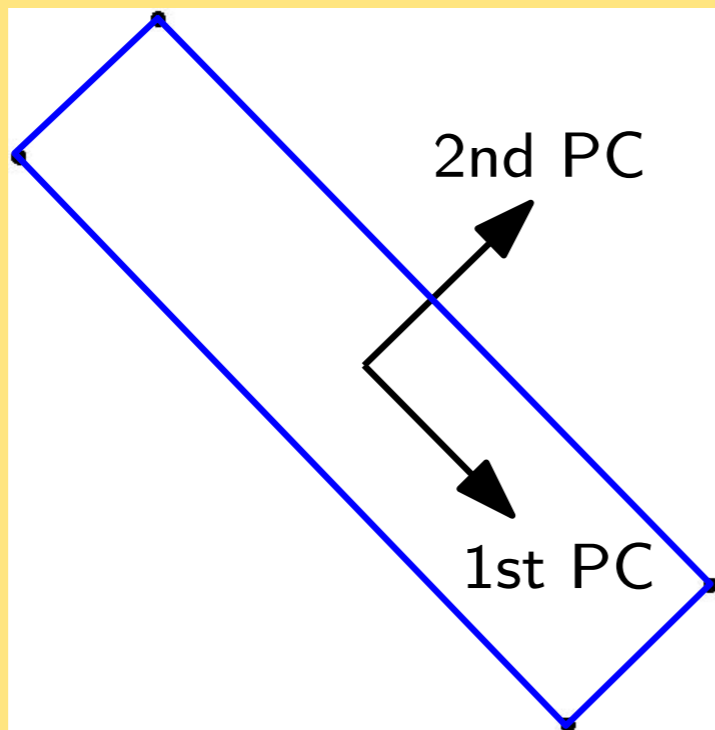
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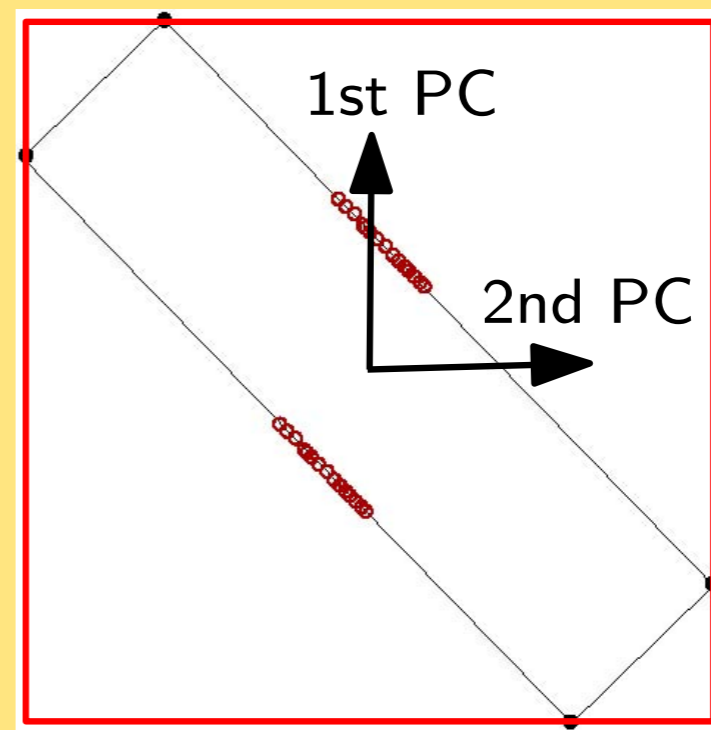
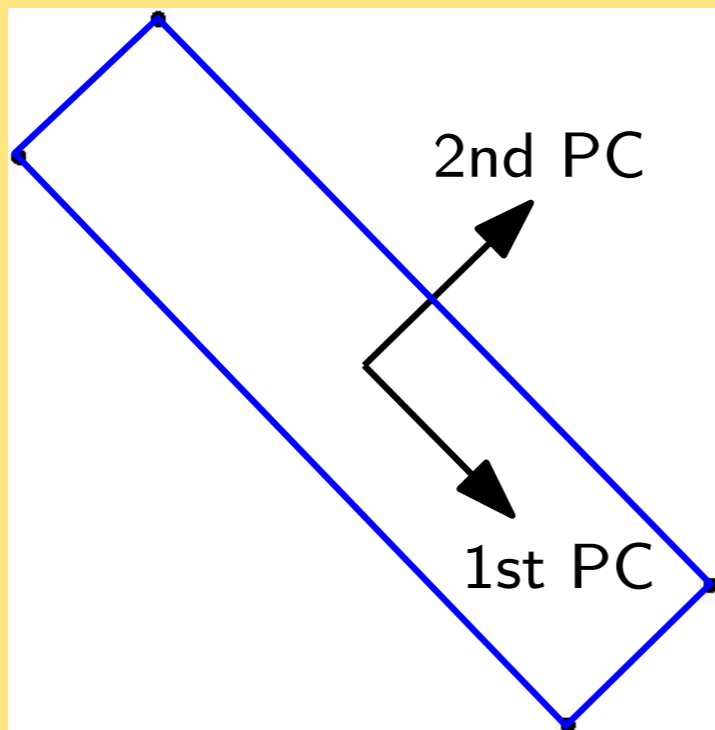
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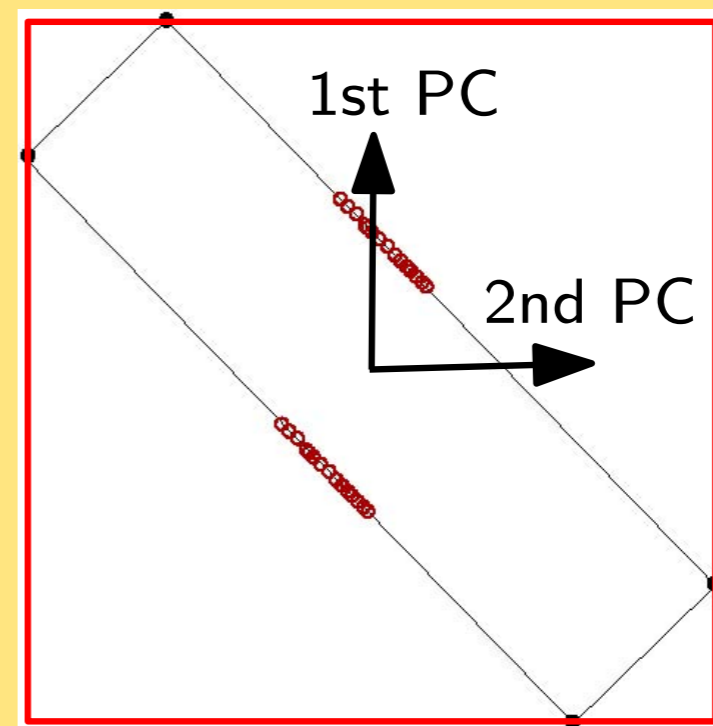
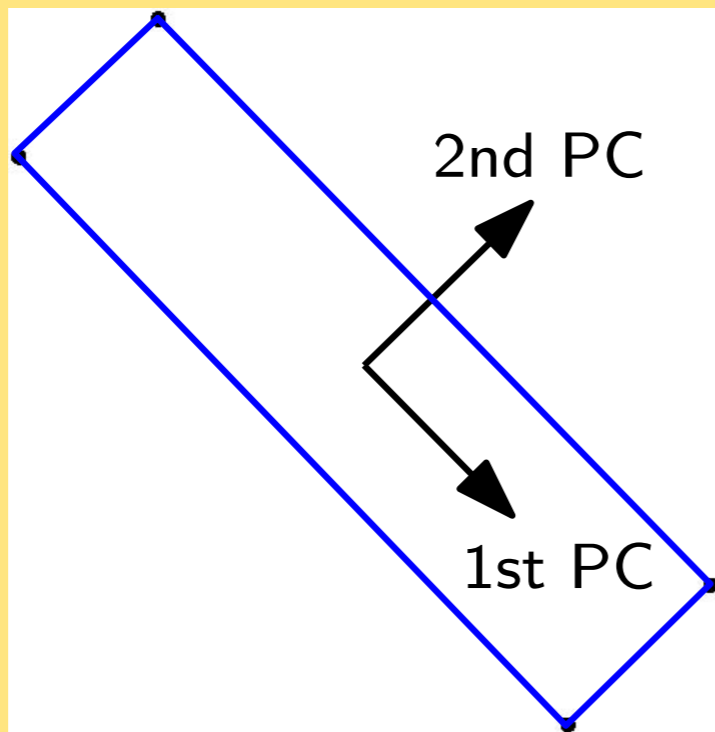
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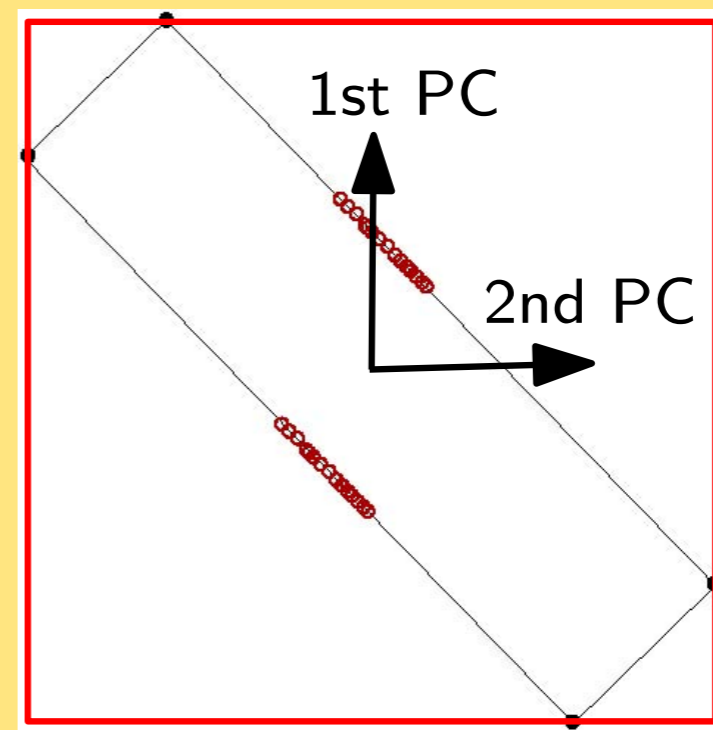
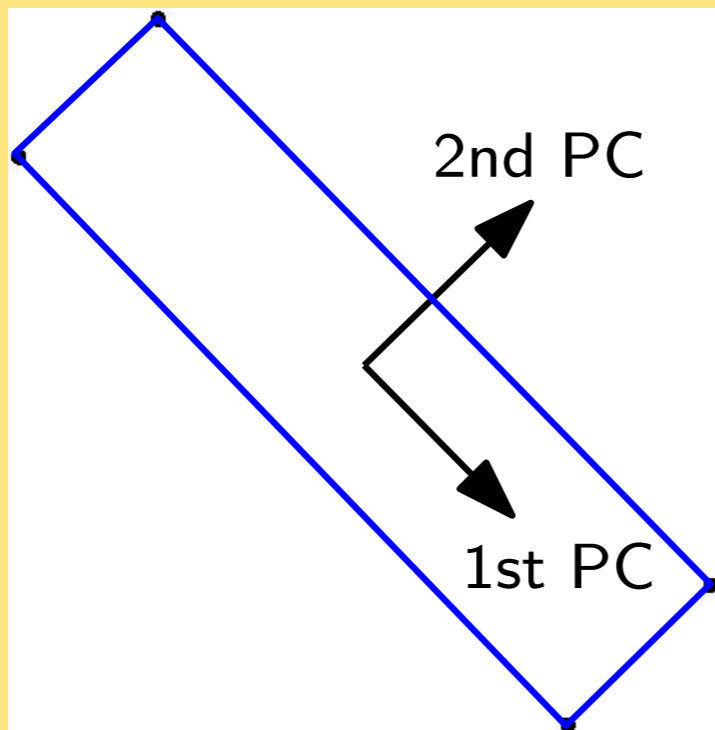
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$$\lambda_{d,d}, \quad \lambda_{d,d-1}$$

PCA and reflective symmetry

Theorem 1. *Let P be a d -dimensional point set symmetric with respect to a hyperplane H . Then, a principal component of P is orthogonal to H .*

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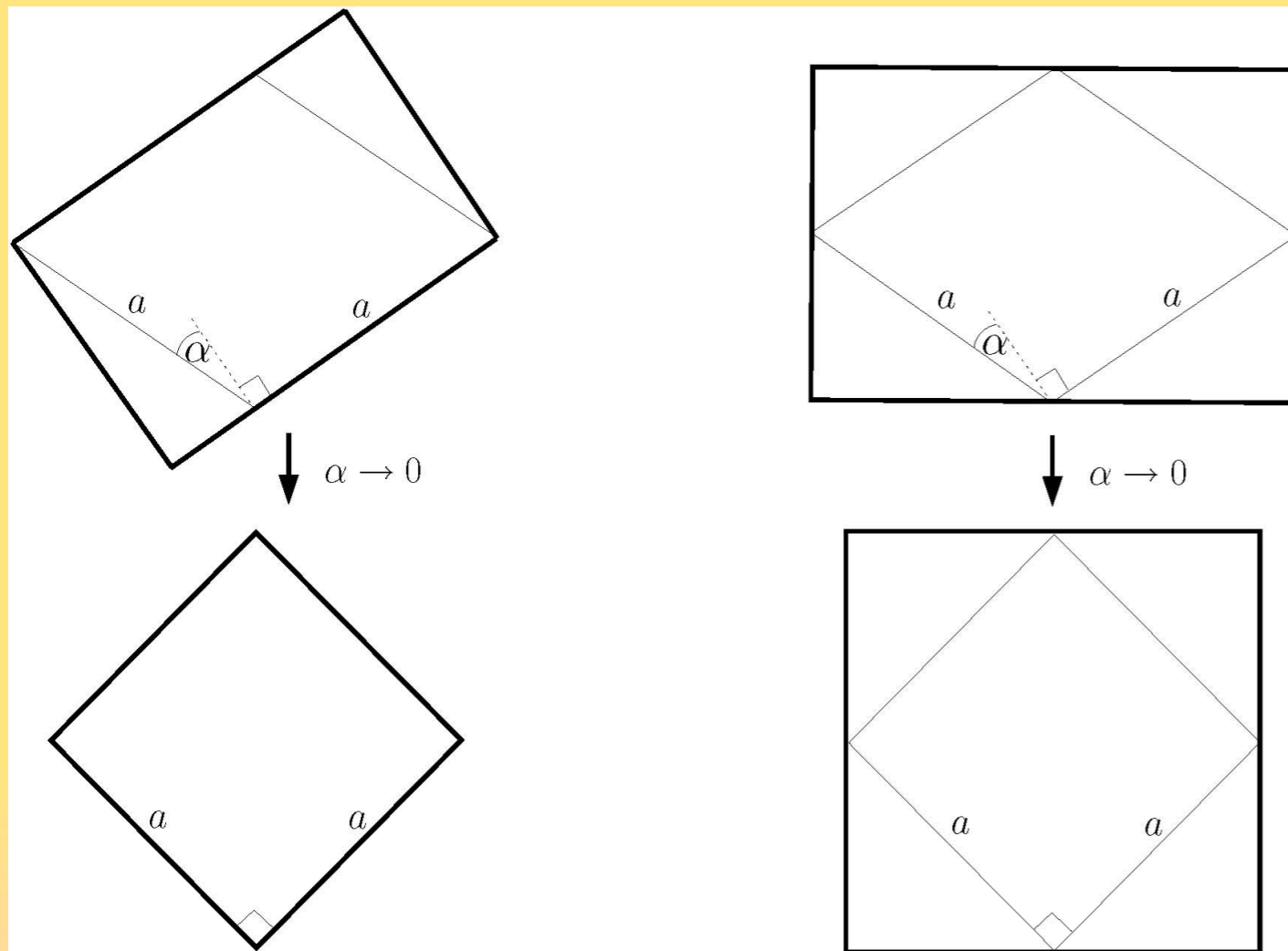
$$e = (1, 0, \dots, 0)$$

Lower bounds \mathbb{R}^2

Theorem 2. $\lambda_{2,1} \geq 2$ and $\lambda_{2,2} \geq 2$.

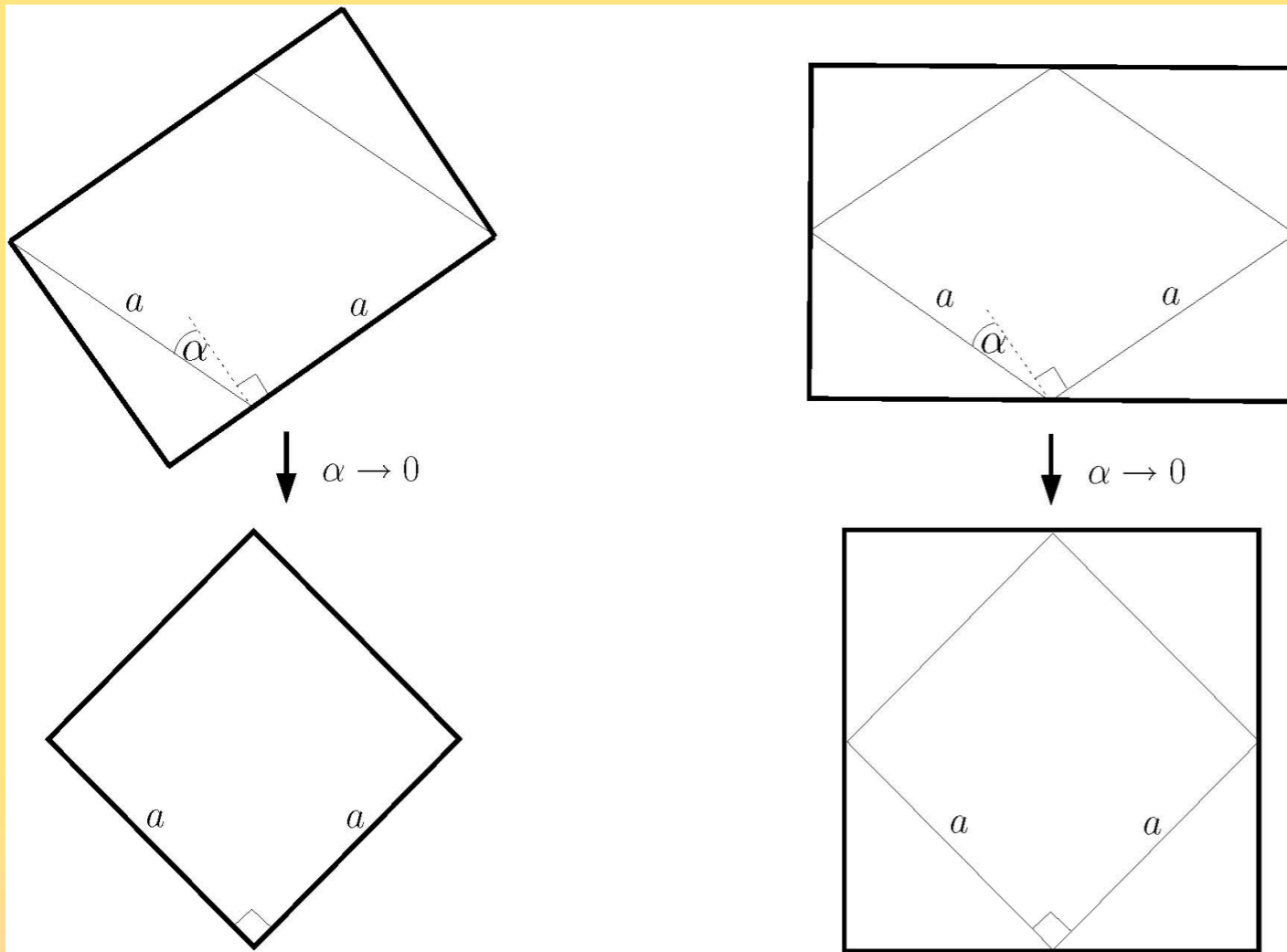
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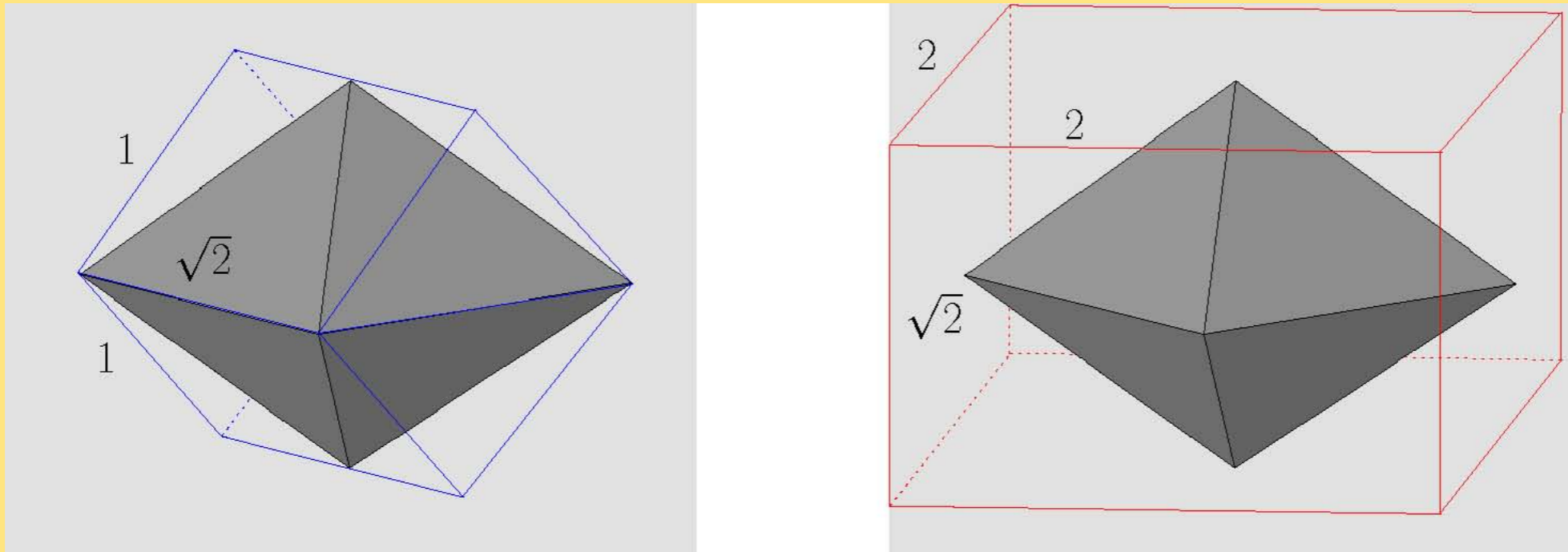
$$R_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

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Theorem 3. $\lambda_{3,2} \geq 4$ and $\lambda_{3,3} \geq 4$.

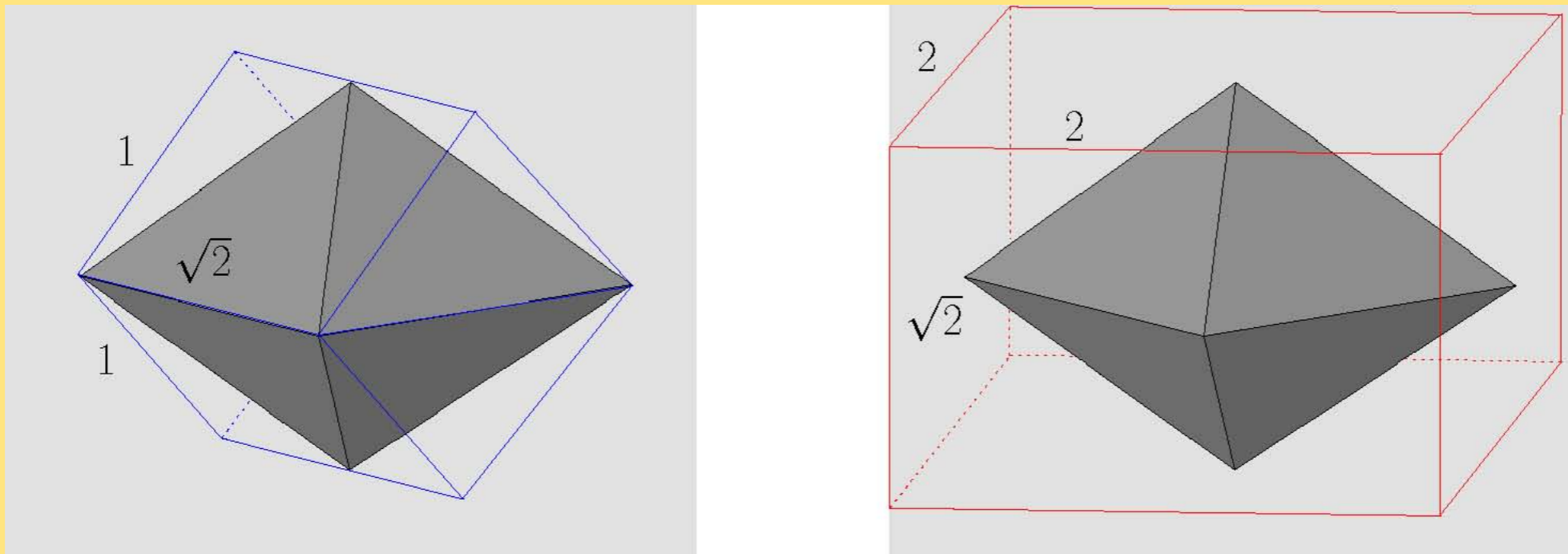
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$$R_3 = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 \\ \frac{1}{2} & \frac{1}{2} & -\frac{1}{\sqrt{2}} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

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$R_d(P_d)$ fits into unit cube $[-0.5, 0.5]^d$

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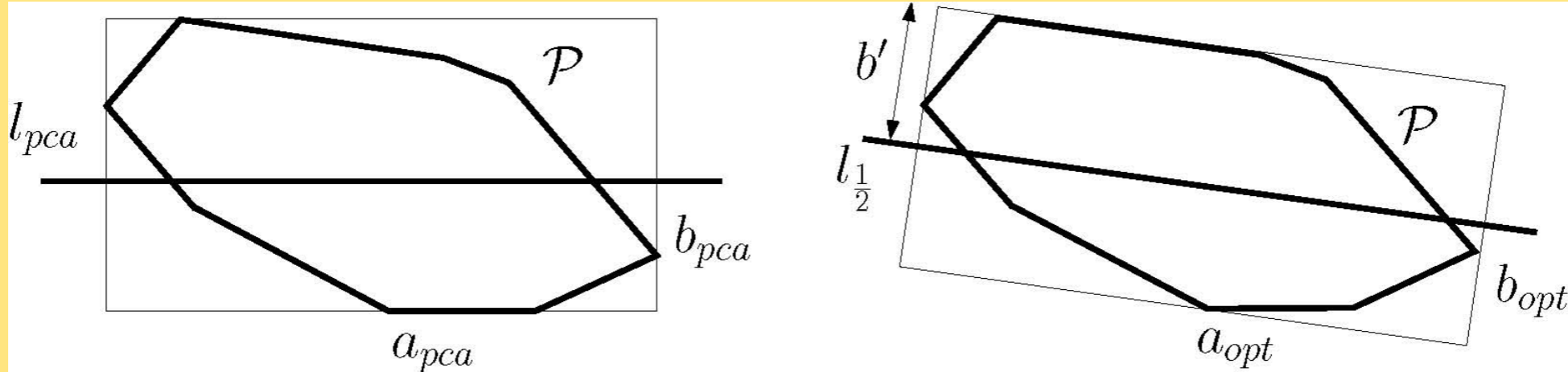
dimension	\mathbb{R}	\mathbb{R}^2	\mathbb{R}^3	\mathbb{R}^4	\mathbb{R}^5	\mathbb{R}^6	\mathbb{R}^7	\mathbb{R}^8	\mathbb{R}^9	\mathbb{R}^{10}
lower bound	1	2	4	16	16	32	64	4096	4096	8192

Upper bound \mathbb{R}^2

Theorem 5. $\lambda_{2,1} \leq 2.737.$

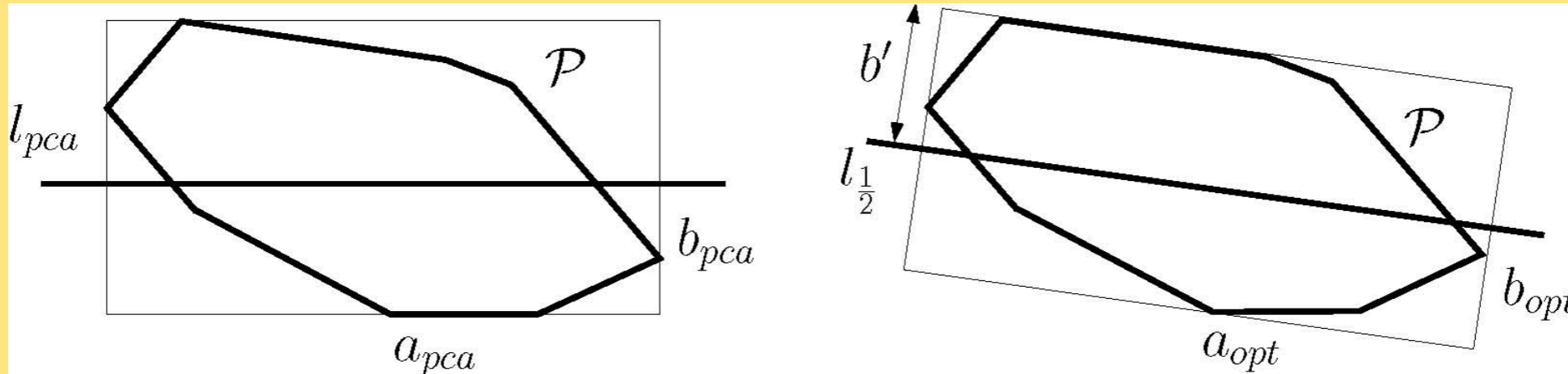
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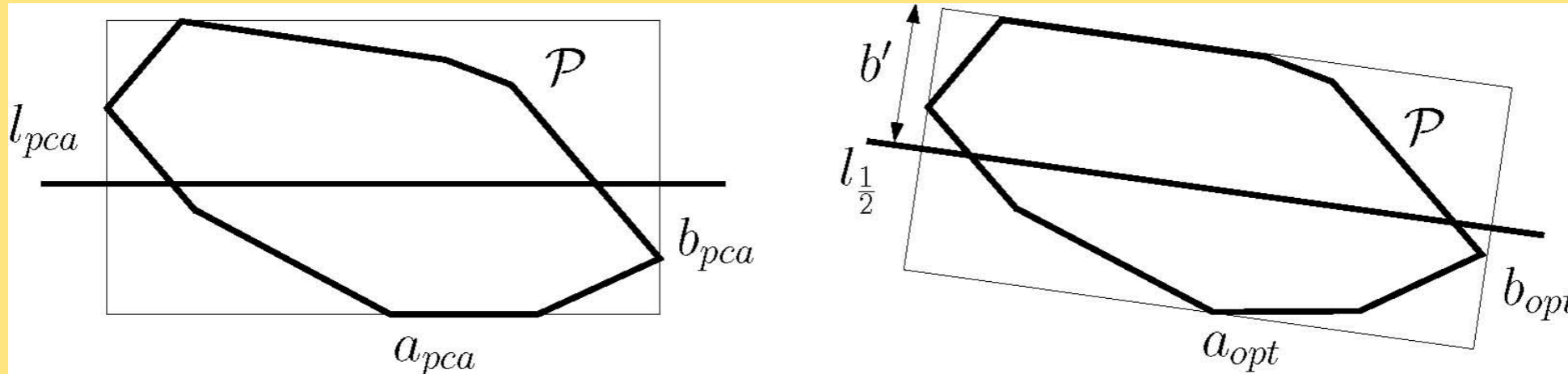


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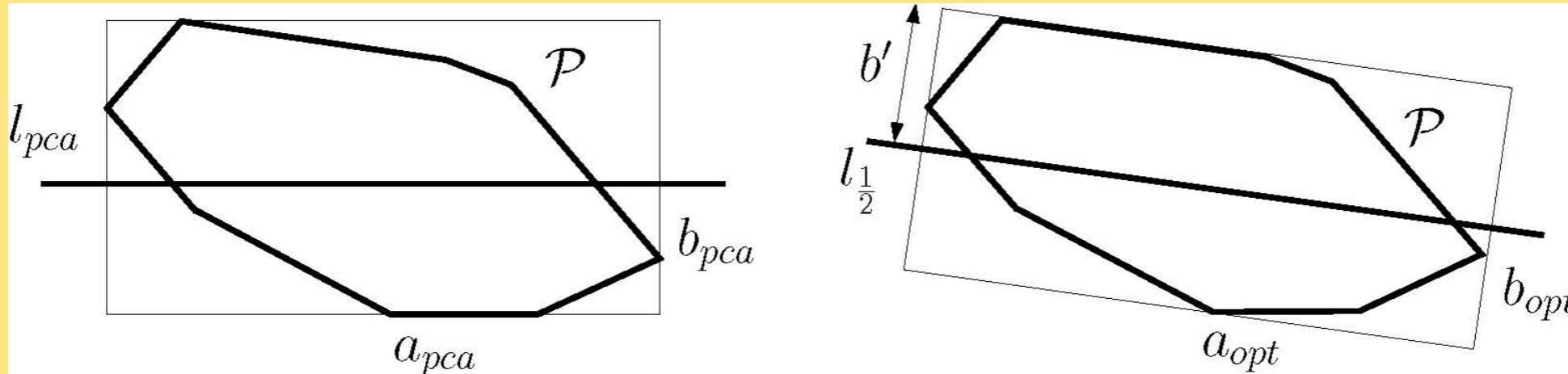
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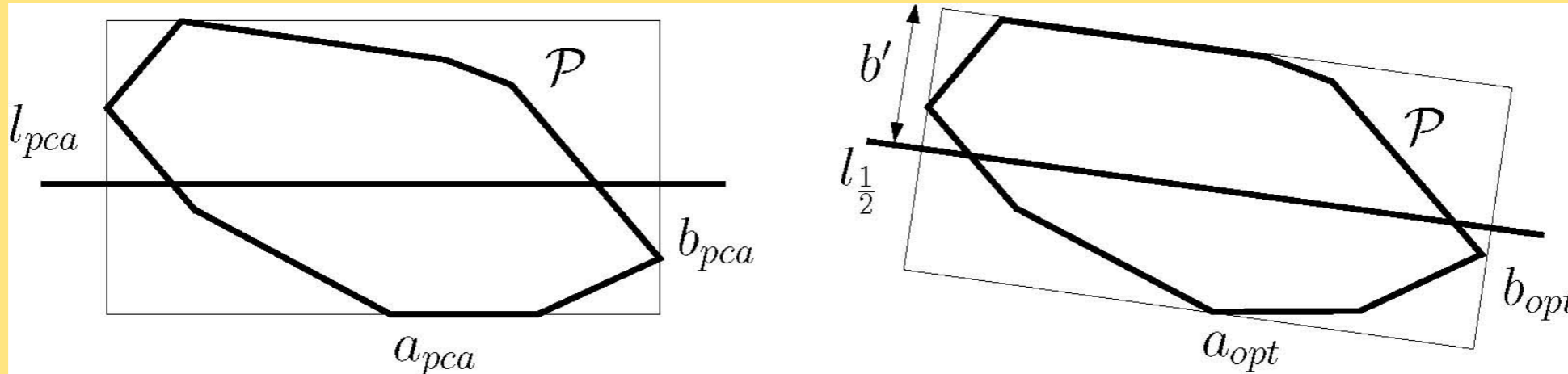
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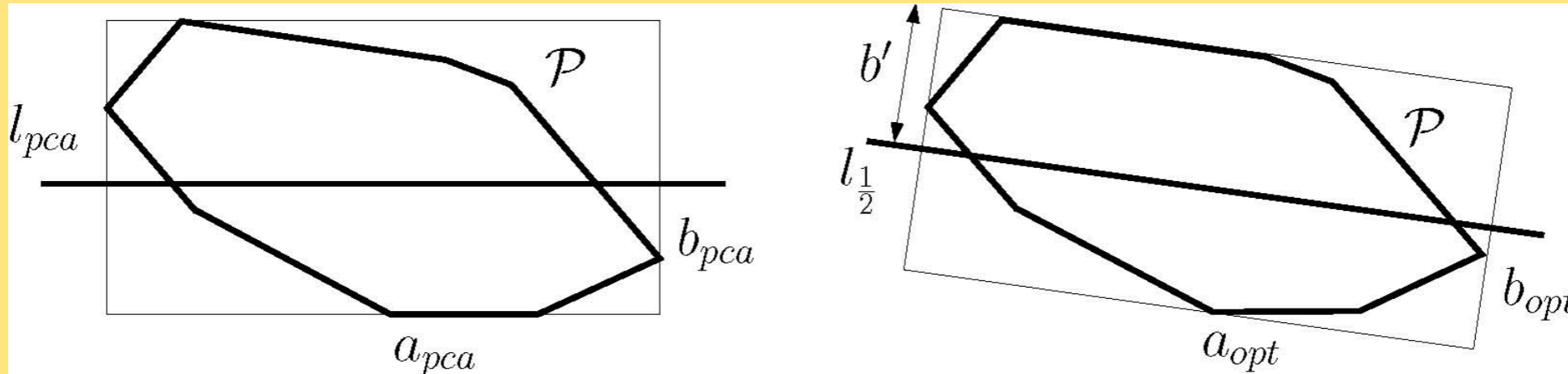
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Upper bound \mathbb{R}^2

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$$d^2(\mathcal{P}, l) = \int_{x \in \mathcal{P}} d^2(x, l) ds$$

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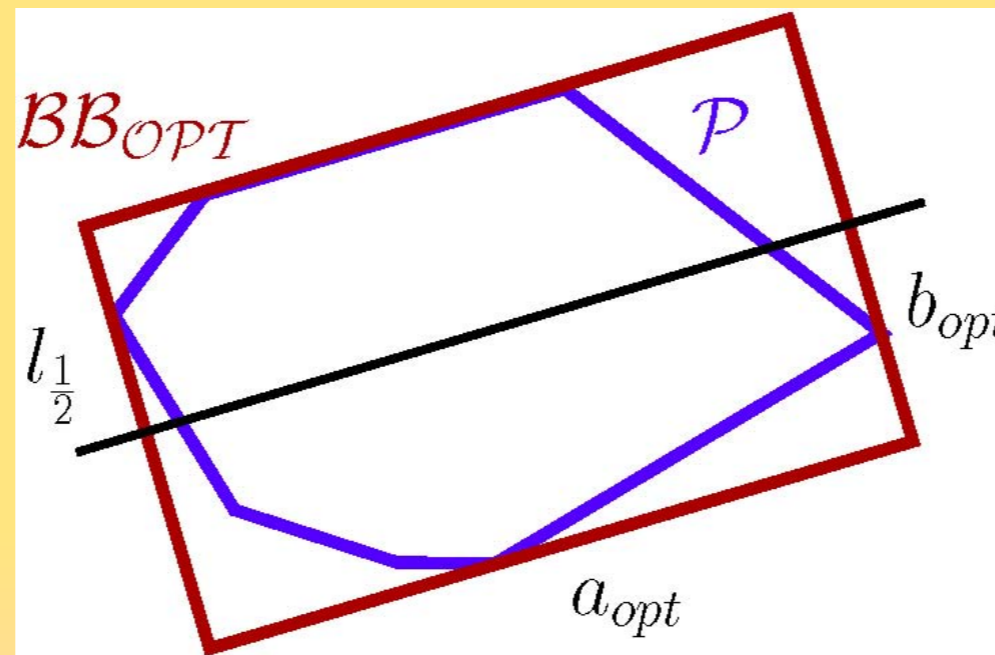
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Upper bound \mathbb{R}^2

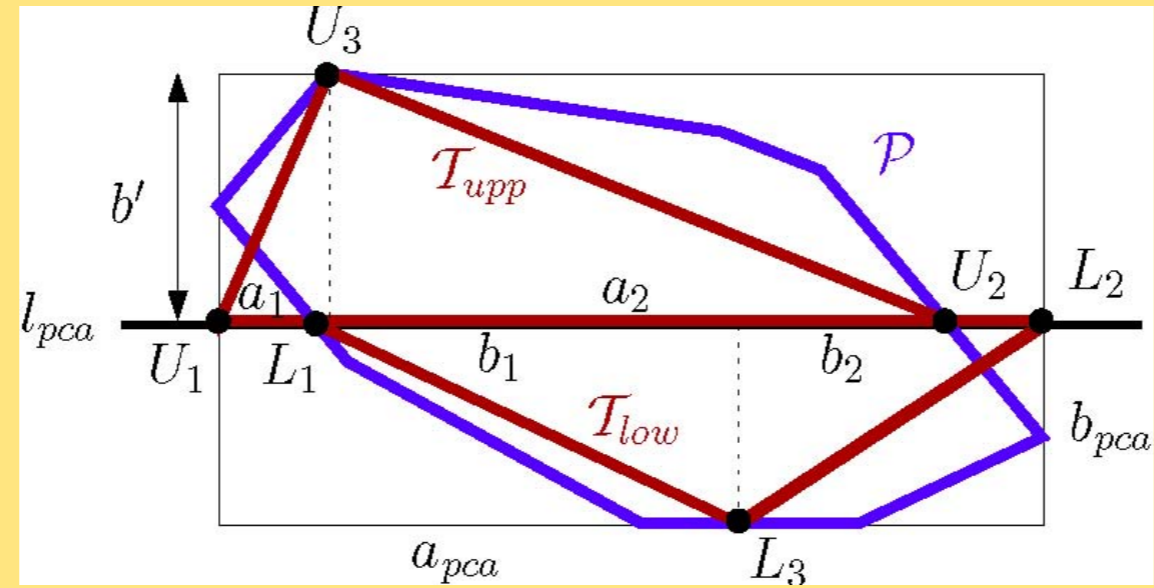
Lemma 4. $d^2(\mathcal{P}, l_{\frac{1}{2}}) \leq d^2(\mathcal{BB}_{OPT}, l_{\frac{1}{2}}) \quad \left(= \frac{b_{opt}^2 a_{opt}}{2} + \frac{b_{opt}^3}{6}\right)$

Upper bound \mathbb{R}^2

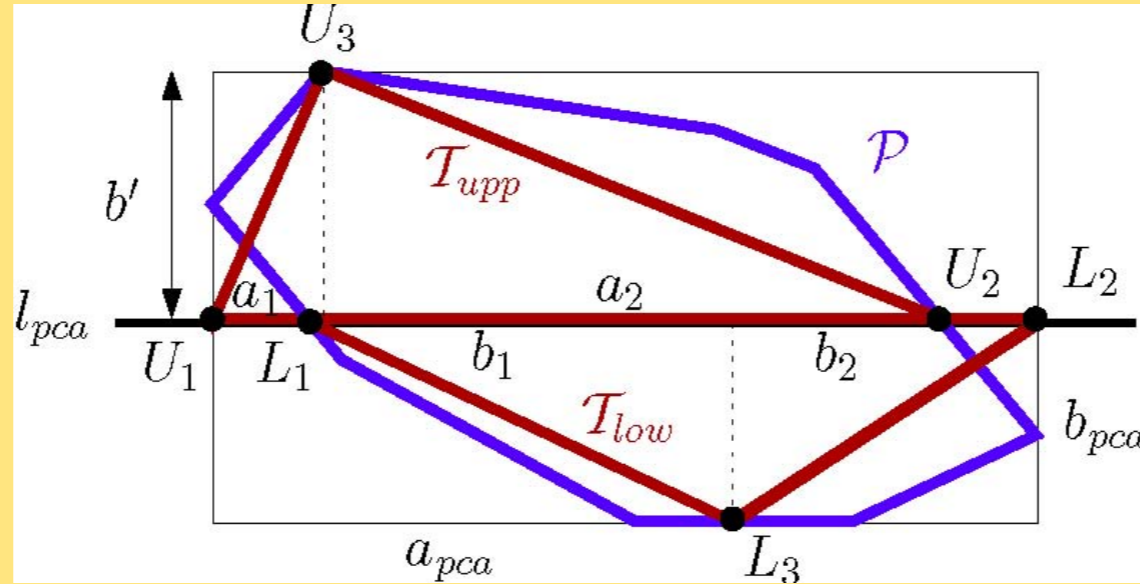
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Upper bound \mathbb{R}^2



Upper bound \mathbb{R}^2



Lemma 5.

$$\begin{aligned}
 d^2(\mathcal{P}, l_{pca}) &\geq d^2(\mathcal{T}_{upp}, l_{pca}) + d^2(\mathcal{T}_{low}, l_{pca}) \\
 &\geq \frac{b_{pca}^2}{12} \sqrt{a_{pca}^2 + 4b_{pca}^2}.
 \end{aligned}$$

Future work and open problems

- Improving the upper bound in \mathbb{R}^2
- Upper bound in \mathbb{R}^3
- Upper bounds for an approximation factor in arbitrary dimension

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