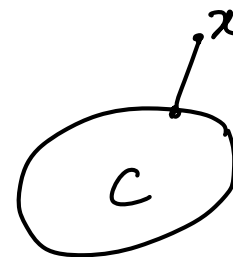


## 8. Geometric problems

- projection on a set
- extremal volume ellipsoids
- centering
- classification

## Projection on convex set



**projection** of point  $x$  on set  $C$  defined as

$$P_C(x) = \underline{\operatorname{argmin}_{z \in C} \|x - z\|_2}$$

*i.e.*, point in  $C$  closest to  $x$ . suppose  $C$  has form

$$C = \{ x \mid \underline{Ax = b}, \underline{f_i(x) \leq 0}, i = 1, \dots, m \}$$

$f_i : \mathbf{R}^n \rightarrow \mathbf{R}$  convex

$$\left[ \begin{array}{l} P_C(x) = \operatorname{argmin}_z \|x - z\|_2 \\ \text{subject to } \left\{ \begin{array}{l} Az = b \\ f_i(z) \leq 0, i = 1, \dots, m \end{array} \right. \end{array} \right.$$

computing  $P_C(x)$  is cvx opt problem

## Distance between convex sets

**distance** between sets  $\underline{C}, \underline{\tilde{C}}$  defined as

$$\text{dist}(C, \tilde{C}) = \min_{\underline{z \in C}, \underline{\tilde{z} \in \tilde{C}}} \|z - \tilde{z}\|_2$$

suppose  $C, \tilde{C}$  are convex, with form

$$C = \{ x \mid Ax = b, f_i(x) \leq 0, i = 1, \dots, m \}$$

$$\tilde{C} = \{ x \mid \tilde{A}x = \tilde{b}, \tilde{f}_i(x) \leq 0, i = 1, \dots, \tilde{m} \}$$

$f_i, \tilde{f}_i : \mathbf{R}^n \rightarrow \mathbf{R}$  convex

$\text{dist}(C, \tilde{C})$  is optimal value of cvx problem

$$\left[ \begin{array}{ll} \underset{\underline{z, \tilde{z}}}{\text{minimize}} & \|z - \tilde{z}\| \\ \text{subject to} & Az = b, \tilde{A}\tilde{z} = \tilde{b} \\ & f_i(z) \leq 0, i = 1, \dots, m \\ & \tilde{f}_i(\tilde{z}) \leq 0, i = 1, \dots, \tilde{m} \end{array} \right.$$

# Intersection & containment of polyhedra

## inequality description

$$\begin{aligned}\rightarrow \mathcal{P}_1 &= \{x \mid \underline{a_i^T x \leq b_i, i = 1, \dots, m} = \underline{\{x \mid Ax \preceq b\}} \\ \rightarrow \mathcal{P}_2 &= \{x \mid \underline{f_i^T x \leq g_i, i = 1, \dots, l} = \underline{\{x \mid Fx \preceq g\}}\end{aligned}$$

- $\mathcal{P}_1 \cap \mathcal{P}_2 = \emptyset$ ? solve feasibility problem

$$\underline{Ax \preceq b}, \quad \underline{Fx \preceq g}$$

- $\mathcal{P}_1 \subseteq \mathcal{P}_2$ ? for  $k = 1, \dots, l$ , check

$$\sup \{ \underline{f_k^T x} \mid \underbrace{Ax \preceq b} \} \stackrel{?}{\leq} \underline{g_k}, \quad \forall k$$

*i.e.*, solve LPs

$$\begin{array}{ll} \text{maximize} & \underline{f_k^T x} \stackrel{?}{\leq} g_k \\ \text{subject to} & \underline{Ax \preceq b} \end{array}$$

$$\rightarrow \mathcal{E} = \{Bu + d \mid \|u\|_2 \leq 1\} \quad \mathcal{E} = \{x \mid x^T P x + 2g^T x + r \leq 1\}$$

## Minimum volume ellipsoid around a set

**Löwner-John ellipsoid** of a set  $C$ : minimum volume ellipsoid  $\mathcal{E}$  s.t.  $C \subseteq \mathcal{E}$

- parametrize  $\mathcal{E}$  as  $\mathcal{E} = \{v \mid \|Av + b\|_2 \leq 1\}$ ; w.l.o.g. assume  $A \in \mathbf{S}_{++}^n$
- vol  $\mathcal{E}$  is proportional to  $\det A^{-1}$ ; to compute minimum volume ellipsoid,

$$\begin{cases} \text{minimize (over } A, b) & \log \det A^{-1} \\ \text{subject to} & \rightarrow \sup_{v \in C} \|\underline{A}v + \underline{b}\|_2 \leq 1 \end{cases}$$

convex, but evaluating the constraint can be hard (for general  $C$ )  
*(but can be infinite-dim — cannot solve)*



**finite set**  $C = \{\underline{x}_1, \dots, \underline{x}_m\}$ :



$$\begin{cases} \text{minimize (over } \underline{A}, \underline{b}) & \log \det A^{-1} \\ \text{subject to} & \|\underline{A}\underline{x}_i + \underline{b}\|_2 \leq 1, \quad i = 1, \dots, \underline{m} \end{cases}$$

also gives Löwner-John ellipsoid for polyhedron  $\text{conv}\{x_1, \dots, x_m\}$

# Maximum volume inscribed ellipsoid

maximum volume ellipsoid  $\mathcal{E}$  inside a convex set  $C \subseteq \mathbf{R}^n$

- parametrize  $\mathcal{E}$  as  $\mathcal{E} = \{Bu + d \mid \|u\|_2 \leq 1\}$ ; w.l.o.g. assume  $B \in \mathbf{S}_{++}^n$
- $\text{vol } \mathcal{E}$  is proportional to  $\det B$ ; can compute  $\mathcal{E}$  by solving

$$\rightarrow \begin{cases} \text{maximize} & \log \det B \\ \text{subject to} & \sup_{\|u\|_2 \leq 1} I_C(Bu + d) \leq 0 \end{cases}$$

$B, d$        $\nearrow$  convex       $\underbrace{\hspace{10em}}_{\text{h.h. in } B, d}$

(where  $I_C(x) = 0$  for  $x \in C$  and  $I_C(x) = \infty$  for  $x \notin C$ )

convex, but evaluating the constraint can be hard (for general  $C$ )



$$I_C(x) = \begin{cases} 0 & x \in C \\ +\infty & x \notin C \end{cases}$$

$\rightarrow$  polyhedron  $\{x \mid a_i^T x \leq b_i, i = 1, \dots, m\}$ :      • extends Chebyshev-center problem

$$\begin{cases} \text{maximize} & \log \det B \\ \text{subject to} & \|Ba_i\|_2 + a_i^T d \leq b_i, \quad i = 1, \dots, m \end{cases}$$

$B, d$

$$\begin{cases} \max & r \\ \text{c, r} & B(c, r) \subset P \end{cases}$$

(constraint follows from  $\sup_{\|u\|_2 \leq 1} a_i^T (Bu + d) = \|Ba_i\|_2 + a_i^T d$ )

$$\mathcal{H} = \{x \mid a^T x \leq b\}$$

variables:  $B, d$

$$Bu + d \in \mathcal{H} \quad \forall \quad \|u\|_2 \leq 1$$

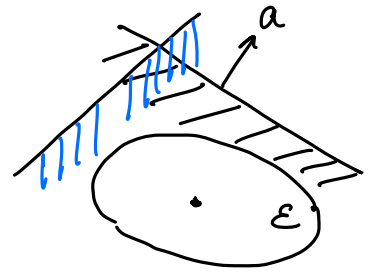
$$a^T (Bu + d) \leq b \quad \forall \quad \|u\|_2 \leq 1$$

$$\sup_{\|u\|_2 \leq 1} (B^T a)^T u + a^T d \leq b$$

$$(B^T a)^T u \leq \underbrace{\|B^T a\|_2}_{\leq 1} \underbrace{\|u\|_2}_{\leq 1} \quad (CS)$$

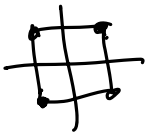
$$\|B^T a\|_2 \leq b - a^T d$$

SOC in  $(B, d)$



ellipsoidal fitting:

- statistics – ellipsoidal peeling  $\rightarrow$  remove outliers
- dynamical systems in state-space – reachable sets
- box/rectangle/polyhedron can have large representations:



$2n$  ineq.

$2^n$  vertices

norm balls are not flexible enough

ellipsoids: compact rep & flexible

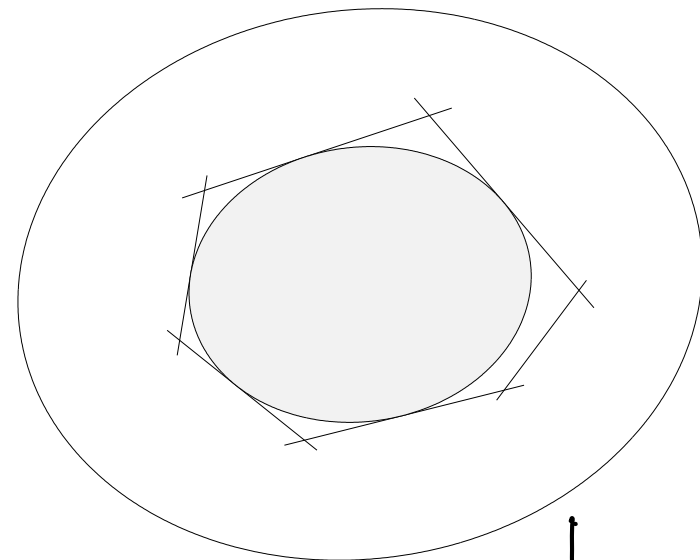
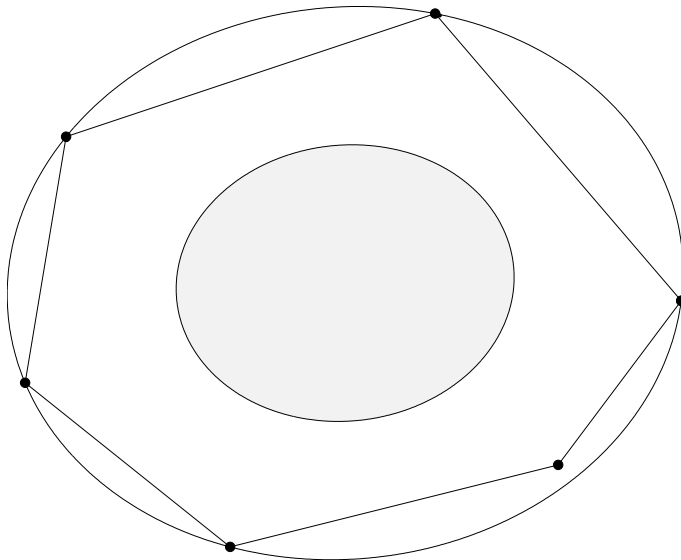
# Efficiency of ellipsoidal approximations

$C \subseteq \mathbf{R}^n$  convex, bounded, with nonempty interior

- Löwner-John ellipsoid, shrunk by a factor  $n$ , lies inside  $C$
- maximum volume inscribed ellipsoid, expanded by a factor  $n$ , covers  $C$

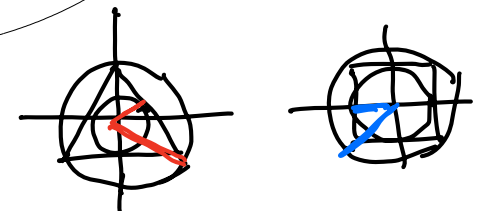
example (for two polyhedra in  $\mathbf{R}^2$ )

$n=2$



factor  $n$  can be improved to  $\sqrt{n}$  if  $C$  is symmetric

(sym. wrt a center)





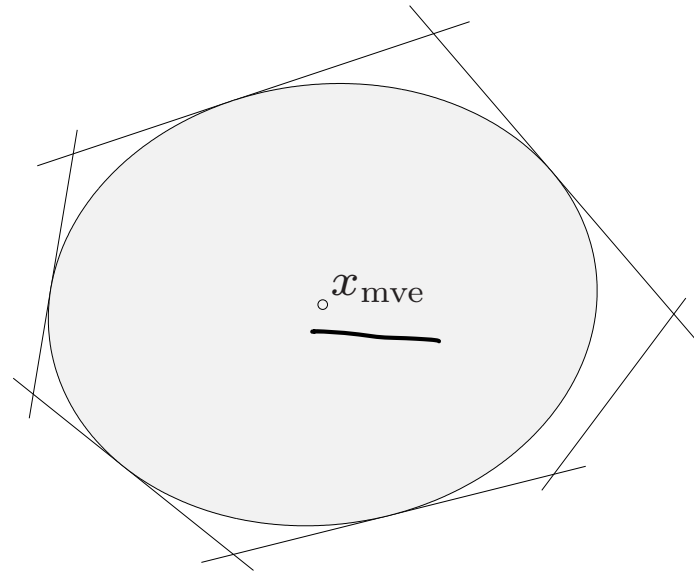
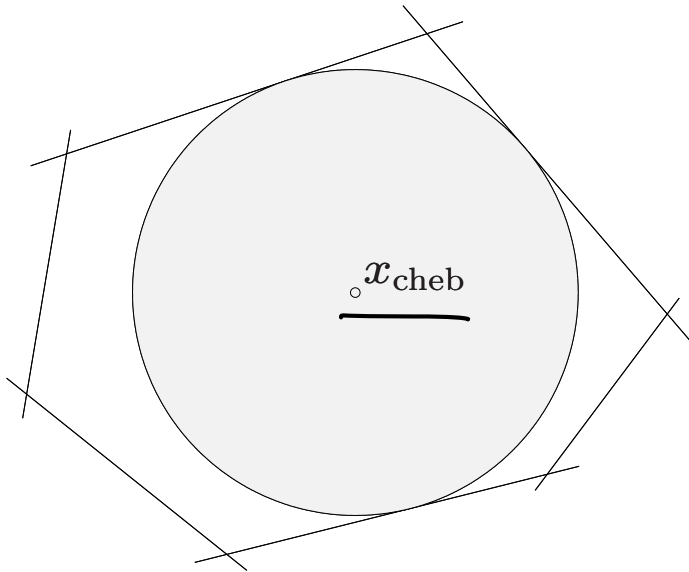
# Centering

some possible definitions of 'center' of a convex set  $C$ :

- center of largest inscribed ball ('Chebyshev center')

for polyhedron, can be computed via linear programming (see LP lecture)

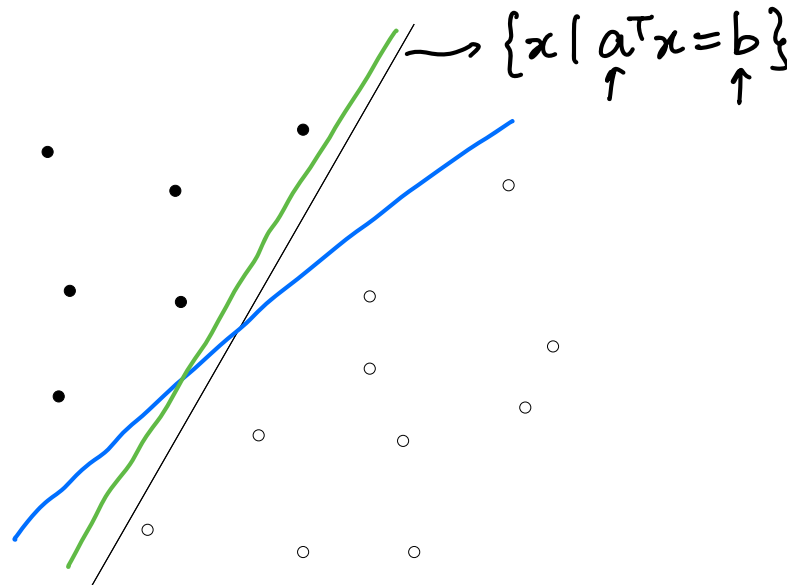
- center of maximum volume inscribed ellipsoid (page 8–3)



# Linear discrimination

separate two sets of points  $\{x_1, \dots, x_N\}$ ,  $\{y_1, \dots, y_M\}$  by a hyperplane:

$$\underline{a^T x_i + b} > 0, \quad i = 1, \dots, N, \quad \underline{a^T y_i + b} < \underline{0}, \quad i = 1, \dots, M$$



- training a classifier based on data
- use it to classify new data
- spam filter

homogeneous in  $a$ ,  $b$ , hence equivalent to

$$\longrightarrow \underline{a^T x_i + b} \geq \underline{1}, \quad i = 1, \dots, N, \quad \underline{a^T y_i + b} \leq \underline{-1}, \quad i = 1, \dots, M$$

a set of linear inequalities in  $a$ ,  $b$

# Robust linear discrimination

(Euclidean) distance between hyperplanes

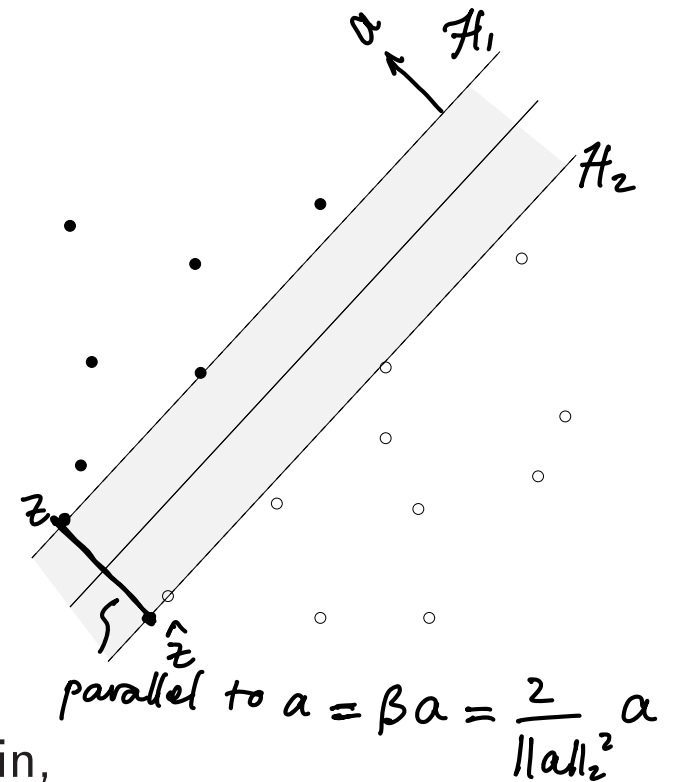
$$\mathcal{H}_1 = \{z \mid \underline{a}^T z + \underline{b} = 1\}$$

$$\mathcal{H}_2 = \{z \mid \underline{a}^T z + \underline{b} = -1\}$$

is  $\text{dist}(\mathcal{H}_1, \mathcal{H}_2) = 2/\|a\|_2$

$$\begin{array}{ll} z \in \mathcal{H}_1 & a^T z + b = 1 \\ \hat{z} \in \mathcal{H}_2 & a^T \hat{z} + b = -1 \end{array} \quad a^T (\underbrace{z - \hat{z}}_{\beta a}) = 2 \Rightarrow \beta = \frac{2}{a^T a} = \frac{2}{\|a\|_2^2}$$

to separate two sets of points by maximum margin,



$$\left[ \begin{array}{ll} \underset{a, b}{\text{minimize}} & (1/2) \|a\|_2^2 \\ \text{subject to} & a^T x_i + b \geq 1, \quad i = 1, \dots, N \\ & a^T \underline{y_i} + b \leq -1, \quad i = 1, \dots, M \end{array} \right. \quad (1)$$

(after squaring objective) a QP in  $a, b$

$$\begin{cases} \min. & \frac{1}{2} \|a\|_2 \\ a, b \\ \text{s.t.} & a^T x_i + b \geq 1 \quad i=1, \dots, N \quad \lambda_i \\ & a^T y_i + b \leq -1 \quad i=1, \dots, M \quad \mu_i \end{cases}$$

$$L(a, b, \lambda, \mu) = \frac{1}{2} \|a\|_2 + \sum_{i=1}^N \lambda_i (1 - \underline{a^T x_i} - \underline{b}) + \sum_{i=1}^M \mu_i (1 + \underline{a^T y_i} + \underline{b})$$

$$g(\lambda, \mu) = \inf_{a, b} L$$

$$\inf_b (-b \sum \lambda_i + b \sum \mu_i) = b (\sum \mu_i - \sum \lambda_i) = \begin{cases} 0 & , \sum \mu_i = \sum \lambda_i \quad (1^T \mu = 1^T \lambda) \\ -\infty & , \text{else} \end{cases}$$

$$\begin{aligned} \inf_a \left( \frac{1}{2} \|a\|_2 - \underbrace{a^T (\sum \lambda_i x_i - \sum \mu_i y_i)} \right) &= \inf_a \|a\|_2 \left( \frac{1}{2} - \left\| \sum_{i=1}^N \lambda_i x_i - \sum_{i=1}^M \mu_i y_i \right\| \right) \\ &= \begin{cases} 0 & , \left\| \sum \lambda_i x_i - \sum \mu_i y_i \right\| \leq \frac{1}{2} \\ -\infty & , \text{else} \end{cases} \end{aligned}$$

putting together:

$$\begin{cases} \min. & 1^T \lambda + 1^T \mu \\ \lambda, \mu \\ & 1^T \mu = 1^T \lambda, \quad \lambda \geq 0, \mu \geq 0 \\ & 2 \left\| \sum \lambda_i x_i - \sum \mu_i y_i \right\| \leq 1 \end{cases}$$

## Lagrange dual of maximum margin separation problem (1)

$$\begin{aligned}
 & \text{maximize} && \mathbf{1}^T \lambda + \mathbf{1}^T \mu \\
 & \text{subject to} && 2 \left\| \sum_{i=1}^N \lambda_i x_i - \sum_{i=1}^M \mu_i y_i \right\|_2 \leq 1 \\
 & && \mathbf{1}^T \lambda = \mathbf{1}^T \mu, \quad \lambda \succeq 0, \quad \mu \succeq 0
 \end{aligned} \tag{2}$$

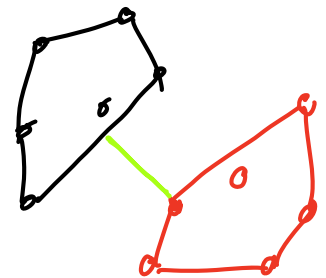
from duality, optimal value is inverse of maximum margin of separation

### interpretation

- change variables to  $\theta_i = \lambda_i / \mathbf{1}^T \lambda$ ,  $\gamma_i = \mu_i / \mathbf{1}^T \mu$ ,  $t = 1 / (\mathbf{1}^T \lambda + \mathbf{1}^T \mu) = \frac{1}{2(\mathbf{1}^T \lambda)}$
- invert objective to minimize  $1 / (\mathbf{1}^T \lambda + \mathbf{1}^T \mu) = t$

$$\left[ \begin{array}{ll} \text{minimize} & t \\ \text{subject to} & \left\| \sum_{i=1}^N \theta_i x_i - \sum_{i=1}^M \gamma_i y_i \right\|_2 \leq t \\ & \theta \succeq 0, \quad \mathbf{1}^T \theta = 1, \quad \gamma \succeq 0, \quad \mathbf{1}^T \gamma = 1 \end{array} \right.$$

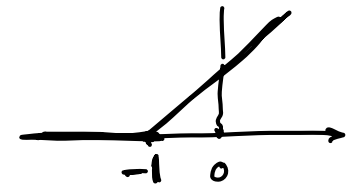
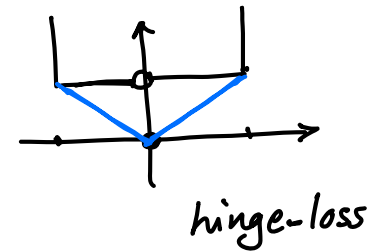
$t$  convex comb. of  $x_i$  convex comb. of  $y_i$



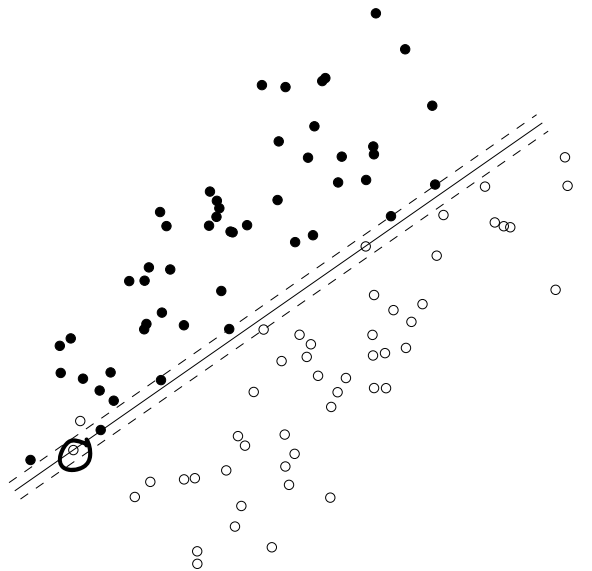
optimal value is distance between convex hulls

# Approximate linear separation of non-separable sets

$$\left[ \begin{array}{ll} \underset{a, b, u, v}{\text{minimize}} & \mathbf{1}^T u + \mathbf{1}^T v \\ \text{subject to} & a^T x_i + b \geq 1 - u_i, \quad i = 1, \dots, N \\ & a^T y_i + b \leq -1 + v_i, \quad i = 1, \dots, M \\ & \underline{u} \succeq 0, \quad \underline{v} \succeq 0 \end{array} \right.$$



- an LP in  $a, b, u, v$
- at optimum,  $\underline{u}_i = \max\{0, 1 - a^T x_i - b\}$ ,  $v_i = \max\{0, 1 + a^T y_i + b\}$
- can be interpreted as a heuristic for minimizing #misclassified points

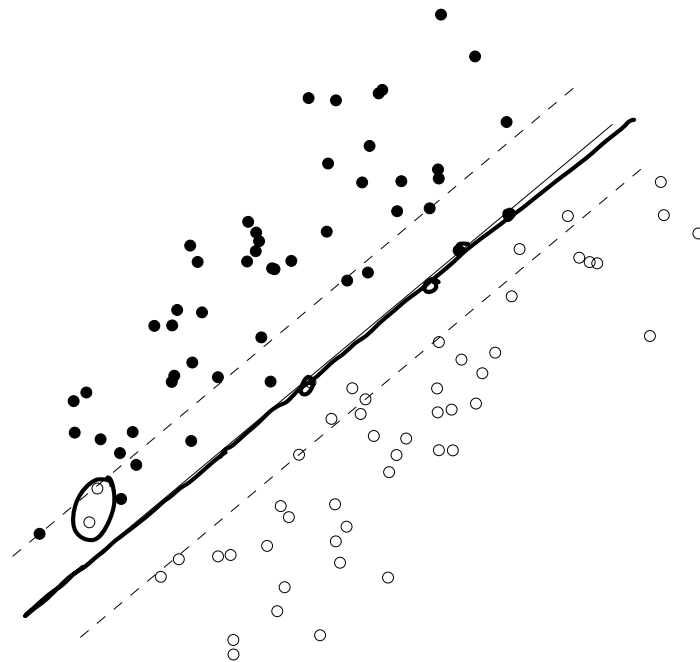


## Support vector classifier (SVM)

$$\left[ \begin{array}{ll} \underset{a, b, u, v}{\text{minimize}} & \|a\|_2 + \gamma(\mathbf{1}^T u + \mathbf{1}^T v) \\ \text{subject to} & a^T x_i + b \geq 1 - u_i, \quad i = 1, \dots, N \\ & a^T y_i + b \leq -1 + v_i, \quad i = 1, \dots, M \\ & u \succeq 0, \quad v \succeq 0 \end{array} \right.$$

produces point on trade-off curve between inverse of margin  $2/\|a\|_2$  and classification error, measured by total slack  $\mathbf{1}^T u + \mathbf{1}^T v$

same example as previous page,  
with  $\gamma = 0.1$ :



## Nonlinear discrimination

separate two sets of points by a nonlinear function:

$$f(x_i) > 0, \quad i = 1, \dots, N, \quad f(y_i) < 0, \quad i = 1, \dots, M$$

- choose a linearly parametrized family of functions

$$f(z) = \theta^T F(z)$$

*linear in  $\theta$*

$F = (F_1, \dots, F_k) : \mathbf{R}^n \rightarrow \mathbf{R}^k$  are basis functions

- solve a set of linear inequalities in  $\theta$ :

$$\theta^T F(\overset{\text{data}}{\tilde{x}_i}) \geq 1, \quad i = 1, \dots, N, \quad \theta^T F(y_i) \leq -1, \quad i = 1, \dots, M$$



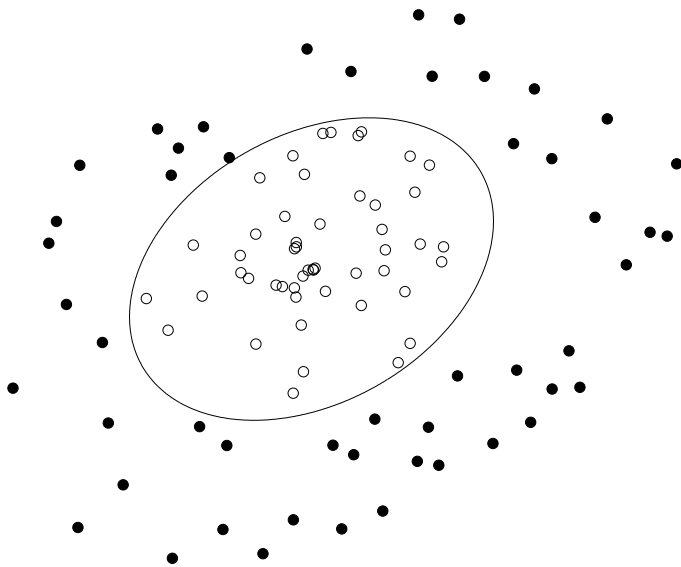
**quadratic discrimination:**  $f(z) = z^T P z + q^T z + r$   $(P, q, r)$

$$\underline{x_i^T P x_i + q^T x_i + r \geq 1}, \quad \underline{y_i^T P y_i + q^T y_i + r \leq -1}$$

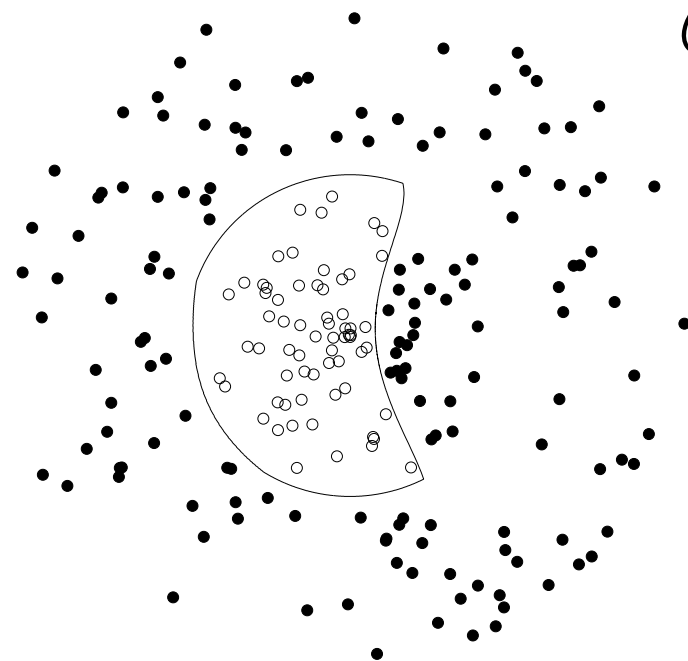
$y_i$ 's lie inside an ellipsoid

can add additional constraints (e.g.,  $P \preceq -I$  to separate by an ellipsoid)

**polynomial discrimination:**  $F(z)$  are all monomials up to a given degree



separation by ellipsoid



separation by 4th degree polynomial

(Kernel methods)

## Placement and facility location

(skipped)

- $N$  points with coordinates  $x_i \in \mathbf{R}^2$  (or  $\mathbf{R}^3$ )
- some positions  $x_i$  are given; the other  $x_i$ 's are variables
- for each pair of points, a cost function  $f_{ij}(x_i, x_j)$

### placement problem

$$\text{minimize } \sum_{i \neq j} f_{ij}(x_i, x_j)$$

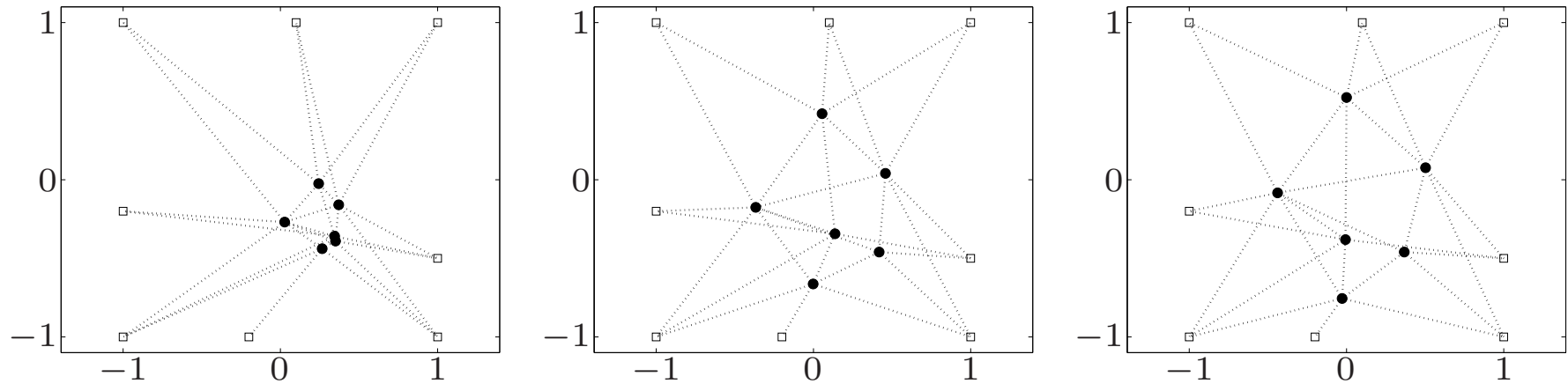
variables are positions of free points

### interpretations

- points represent plants or warehouses;  $f_{ij}$  is transportation cost between facilities  $i$  and  $j$
- points represent cells on an IC;  $f_{ij}$  represents wirelength

**example:** minimize  $\sum_{(i,j) \in \mathcal{A}} h(\|x_i - x_j\|_2)$ , with 6 free points, 27 links

optimal placement for  $h(z) = z$ ,  $h(z) = z^2$ ,  $h(z) = z^4$



histograms of connection lengths  $\|x_i - x_j\|_2$

