LP duality cheat sheet

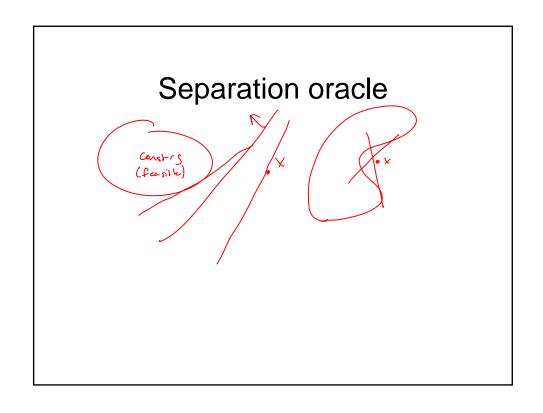
min
$$c'x + d'y$$
 s.t. max $p'v + g'w$ s.t.
 $Ax + By \ge p \leftarrow$ $A'v + E'w = c$
 $Ex + Fy = q \leftarrow$ $B'v + F'w \le d$
 $x \text{ free}, y \ge 0$ $v \ge 0, w \text{ free}$
 $A'v + E'w = c$
 $A'v + E'w = c$

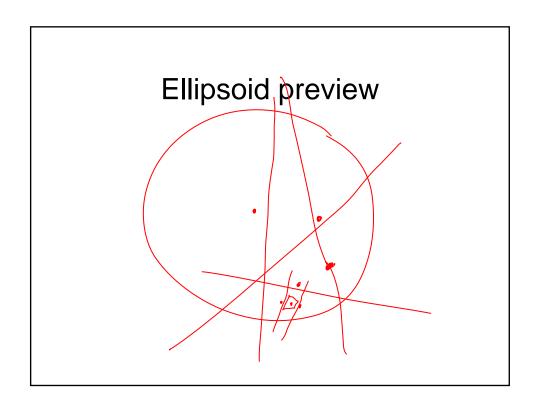
- Swap max/min <
- Swap RHS and objective Transpose constraint matrix +ve vars yield ≤, free vars yield =

Linear feasibility problem

min c'x s.t.
$$C^{T}x^{+} \in [L, U]$$
 $Ax + b \ge 0$
 $G = \frac{(L + U)}{2}$

find x s.t. $C^{T}x^{+} \in [L, U]$
 $Ax + b \ge 0$
 $C^{T}x^{+} \in [L, U]$
 $Ax + b \ge 0$
 $C^{T}x \in G$
 $C^{T}x^{+} \in [L, U]$
 $C^{T}x \in G$
 $C^$





Difficulties

- How do we get bounding sphere? | later
- How do we know when to stop?

V; & I aix + b; + m = 0 m>0, small

Bound region gets complicated
 —how do we find its center?

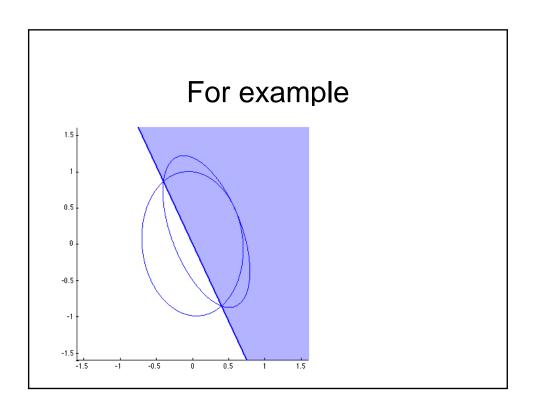
Bounding a partial ellipsoid

- General ellipsoid w/ center x_C, radius R:
- Halfspace: $p^Tx + q \le 0$
- Translate to origin, scale to be spherical

$$y = x = x = x$$

Bounding a partial sphere

- Rotate so hyperplane is axis-normal
- New center x_c:
- New shape A:



Ellipsoid algorithm

- Want to find x s.t. $Ax+b+\eta \ge 0$
- Pick R s.t. $||x^*|| \le R$
- $E_0 := \{ x \mid ||x|| \le R \}$
- Repeat:
 - $-x_t := center of E_t$
 - ask whether $Ax_t + b \ge 0$
 - yes: declare feasible!
 - no: get separating hyperplane
 - $E_{t+1} := bound(E_t \cap \{ x \mid p_t^T x \leq p_t^T x_t \})$
 - if vol(E_{t+1}) ≤ εvol(E_0): declare infeasible!

Getting bounds

- How big do L, U need to be?
- How big does R need to be?
- What should η be?
- How small does ε need to be?

Other algorithms

- Ellipsoid is polynomial, but slow
- Some other algorithms:
 - simplex: exponential in worst case, but often fast in practice
 - randomized simplex: polynomial [Kelner & Spielman, 2006]
 - interior point: polynomial
 - subgradient descent: weakly polynomial, but really simple, and fast for some purposes

What's a subgradient?

Subgradient descent for SVMs

- $\min_{s,w,b} ||w||^2 + C\sum_i s_i \text{ s.t.}$ $y_i(x_i^T w - b) \ge 1 - s_i$ $s_i \ge 0$
- Equivalently,

Subgradient in SVM

- $\min_{\mathbf{w}} L(\mathbf{w}) = ||\mathbf{w}||^2 + C\sum_{i} h(y_i x_i^T \mathbf{w})$
- Subgradient of h(z):
- Subgradient of L(w) wrt w: