### Today

Lagrangian Dual. Already saw example! Convex Separator. Farkas Lemma.

#### Linear Program.

#### $\min cx, Ax \geq b$

 $\label{eq:constraint} \begin{array}{ll} \min & c \cdot x \\ \text{subject to } b_i - a_i \cdot x \leq 0, & i = 1, ..., m \end{array}$ 

#### Lagrangian (Dual):

 $L(\lambda, x) = cx + \sum_{i} \lambda_{i}(b_{i} - a_{i}x_{i}).$ or  $L(\lambda, x) = -(\sum_{j} x_{j}(a_{j}\lambda - c_{j})) + b\lambda.$ Best  $\lambda$ ? max  $b \cdot \lambda$  where  $a_{j}\lambda = c_{j}.$ max  $b\lambda, \lambda^{T}A = c, \lambda \ge 0$ 

Duals!

#### Lagrangian Dual.

Find *x*, subjet to  $f_i(x) \le 0, i = 1, ..., m.$ Remember calculus (constrained optimization.) Lagrangian:  $L(x, \lambda) = \sum_{i=1}^m \lambda_i f_i(x)$   $\lambda_i$  - Lagrangian multiplier for inequality *i*. For feasible solution *x*,  $L(x, \lambda)$  is (A) non-negative in expectation (B) positive for any  $\lambda$ . (C) non-positive for any valid  $\lambda$ . If  $\lambda$ , where  $L(x, \lambda)$  is positive for all *x* (A) there is no feasible *x*.

(B) there is no  $x, \lambda$  with  $L(x, \lambda) < 0$ .

## Linear Equations.

X1

Ax = bA is  $n \times n$  matrix... ...has a solution. If rows of A are linearly independent.  $y^T A \neq 0$  for any y ...or if b in subspace of A.  $x_3$ bad b bad b

 $X_2$ 

#### Lagrangian:constrained optimization.

 $\begin{array}{ll} \mbox{min} & f(x) \\ \mbox{subject to } f_i(x) \leq 0, & i = 1,...,m \end{array}$ 

Lagragian function: 
$$\begin{split} L(x,\lambda) &= f(x) + \sum_{i=1}^m \lambda_i f_i(x) \\ \text{If (primal) } x \text{ value } v \\ \text{ For all } \lambda \geq 0 \text{ with } L(x,\lambda) \leq v \\ \text{ Maximizing } \lambda \text{ only positive when } f_i(x) = 0. \end{split}$$

If there is  $\lambda$  with  $L(x,\lambda) \ge \alpha$  for all xFor optimum value of program is at least  $\alpha$ Primal problem:

*x*, that minimizes  $L(x, \lambda)$  over all  $\lambda > 0$ .

Dual problem:  $\lambda$ , that maximizes  $L(x,\lambda)$  over all x.

## Strong Duality.

Later. Actually. No. Now ...ish. Special Cases: min-max 2 person games and experts. Max weight matching and algorithm. Approximate: facility location primal dual. Today: Geometry!

#### Convex Body and point.

For a convex body *P* and a point *b*,  $b \in P$  or hyperplane separates P from b.

 $v, \alpha$ , where  $v \cdot x < \alpha$  and  $v \cdot b > \alpha$ .

point p where  $(x-p)^T(b-p) < 0$ 



# Generalization: exercise.

There is a separating hyperplane between any two convex bodies.

Let closest pair of points in two bodies define direction.

#### Proof.

For a convex body *P* and a point *b*,  $b \in A$  or hyperplane point *p* where  $(x-p)^{T}(b-p) < 0$ 



**Proof:** Choose *p* to be closest point to *b* in *P*. Done or  $\exists x \in P$  with  $(x-p)^T (b-p) \ge 0$ 







## More formally.



## Farkas 2

Farkas A: Solution for exactly one of: (1)  $Ax = b, x \ge 0$ (2)  $y^T A \ge 0, y^T b < 0.$ Farkas B: Solution for exactly one of: (1) Ax < b(2)  $y^T A = 0, y^T b < 0, y > 0.$ 

 $(x-p)^{T}(b-p) > 0$ 

Must be closer point on line to from *p* to *x*.

## Strong Duality

(From Goemans notes.)

Primal P  $z^* = \min c^T x$  Ax = b  $x \ge 0$ Dual D: $w^* = \max b^T y$  $A^T y \le c$ 

**Weak Duality:** x, y- feasible P, D:  $x^T c \ge b^T y$ .

$$x^{T}c - b^{T}y = x^{T}c - x^{T}A^{T}y$$
$$= x^{T}(c - A^{T}y)$$
$$\geq 0$$

**Strong duality** If P or D is feasible and bounded then  $z^* = w^*$ . Primal feasible, bounded, value  $z^*$ . **Claim:** Exists a solution to dual of value at least  $z^*$ .

 $\exists y, y^T A \leq c, b^T y \geq z^*.$ 

Want y.  
$$\begin{pmatrix} A^T \\ -b^T \end{pmatrix}$$
 y  $\leq \begin{pmatrix} c \\ -z^* \end{pmatrix}$ .

If none, then Farkas B says  $\exists x, \lambda \ge 0.$ 

$$(A \quad -b) \begin{pmatrix} x \\ \lambda \end{pmatrix} = 0$$

 $\begin{pmatrix} c^T & -z^* \end{pmatrix} \begin{pmatrix} x \\ \lambda \end{pmatrix} < 0$ 

 $\exists x, \lambda \text{ with } Ax - b\lambda = 0 \text{ and } c^t x - z^* \lambda < 0$ Case 1:  $\lambda > 0$ .  $A(\frac{x}{2}) = b$ ,  $c^T(\frac{x}{2}) < z^*$ . Better Primal!!

Case 2:  $\lambda = 0$ . Ax = 0,  $c^T x < 0$ . Feasible  $\tilde{x}$  for Primal. (a)  $\tilde{x} + \mu x \ge 0$  since  $\tilde{x}, x, \mu \ge 0$ . (b)  $A(\tilde{x} + \mu x) = A\tilde{x} + \mu Ax = b + \mu \cdot 0 = b$ . Feasible  $c^T(\tilde{x} + \mu x) = x^T \tilde{x} + \mu c^T x \rightarrow -\infty$  as  $\mu \rightarrow \infty$ Primal unbounded! See you on Thursday.