

LECTURE 12

CMPS 242 F17

OPTIMIZATION THEORY

LAGRANGIANS

DUALITY

HOW APPLIED TO SUPPORT VECTOR MACHINES

MORE ON KERNELS

NO CONSTRAINTS :

DIFFERENTIABLE

GIVEN A FUNCTION  $f$  DEFINED ON A DOMAIN  $\Omega \in \mathbb{R}^n$ .

MINIMIZE  $f(w)$   $w \in \Omega$

NECESSARY CONDITION FOR MINIMUM

$$\frac{\partial f(w)}{\partial w} = 0$$

$n \times 1$

SUFFICIENT CONDITION FOR MINIMUM

$$\frac{\partial f(w)}{\partial w} = 0 \quad \text{AND} \quad \frac{\partial^2 f(w)}{(\partial w)^2} \begin{matrix} \text{POSITIVE} \\ \text{SEMI-DEFINITE} \end{matrix}$$

$n \times n$

STRICT MIN. IF POSITIVE  
DEFINITE

A SYMMERIC POS. SEMI DEFINITE IF

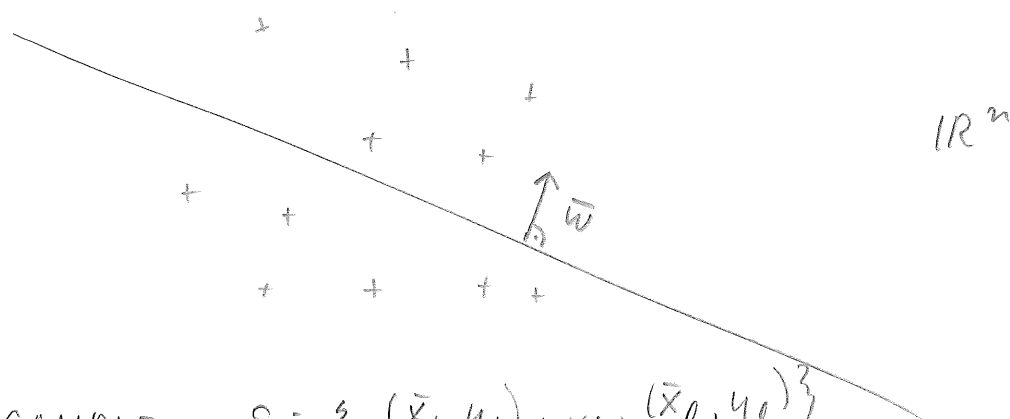
$n \times n$

1 - SYMMETRIC

2 -  $\forall$  UNIT VEC  $\bar{u}$   $\bar{u}^T A \bar{u} \geq 0$

OR 2' - ALL EIGENVALS  $\geq 0$

# EXAMPLE RIDGE REGRESSION (LEAST SQUARES)



SAMPLE  $S = \{(\bar{x}_1, y_1), \dots, (\bar{x}_l, y_l)\}$

$$f(w) = \underbrace{\frac{1}{\eta} \frac{1}{2} \|w - 0\|^2}_{\text{REGULARIZATION}} + \underbrace{\sum_{t=1}^l \frac{1}{2} (\bar{w} \cdot \bar{x}_t - y_t)^2}_{\text{LOSS}}$$

$\eta$  IS TRADE-OFF PARAMETER

REMARK:

- $\eta \rightarrow \infty$  NO REGULARIZATION  
ONLY THE LOSS MINIMIZED
  - NOISE-FREE CASE:  $\exists$  SOL. OF LOSS 0
    - $w \cdot x_t = y_t$  WHICH SOLUTION TO CHOOSE?
    - WHAT IF NO SOLUTION OF LOSS 0?
- CLAIM: IF  $\eta > 0$  THEN ALWAYS EXISTS  
UNIQUE SOLUTION

NOTE: NON-HOMOGENEOUS HP IS  
HOMOGENEOUS HP IN ONE DIM. LARGER

$$w \cdot x + b = 0 \quad \text{IFF} \quad (w, b) \cdot (x, 1) = 0$$

FIND MINIMUM BY SETTING DERIV'S TO ZERO:

4

$$\frac{\partial f(w)}{\partial w_i} = \frac{1}{\eta} w_i + \sum_{t=1}^l x_{t,i} (w \cdot x_t - y_t)$$

$$\text{OR } \frac{\partial f(w)}{\partial w} = \frac{1}{\eta} w + \sum_{t=1}^l x_t (x_t^T w - y_t)$$

$$= \left( \frac{1}{\eta} I + \sum_{t=1}^l x_t x_t^T \right) w - \sum_{t=1}^l x_t y_t$$

$$\left. \frac{\partial f(w)}{\partial w} \right|_{w=w^*} = 0$$

$$w^* = \left( \frac{1}{\eta} I + \sum_{t=1}^l x_t x_t^T \right)^{-1} \sum_{t=1}^l x_t y_t$$

IN MATRIX NOTATION:

$$f(w) = \frac{1}{\eta} \frac{1}{2} \|w\|^2 + \frac{1}{2} \underbrace{\|X^T w - y\|^2}_{\text{RESIDUAL}}$$

$$X = \begin{array}{c} \text{-----} \\ \text{-----} \\ \text{-----} \\ \text{-----} \end{array} \rightarrow x_t$$

$l \times n$

$$\begin{aligned}
 \frac{\partial f(w)}{\partial w} &= \frac{1}{\eta} w + X^T (Xw - y) \\
 &= \frac{1}{\eta} w + X^T X w - X^T y \\
 &= \left( \frac{1}{\eta} I + X^T X \right) w - X^T y
 \end{aligned}$$

$$w^* = \left( \frac{1}{\eta} I + X^T X \right)^{-1} X^T y$$

$$\frac{\partial^2 f(w)}{(\partial w)^2} = \left( \frac{1}{\eta} I + X^T X \right)$$

STRICTLY POS. DEF. WHEN  $\eta > 0$  & FINITE

SO STRICT MIN. AT  $w^*$

$$\lim_{\eta \rightarrow \infty} \underbrace{\left( \frac{1}{\eta} I + X^T X \right)^{-1} X^T}_{\text{CONVERGES TO } X^+}$$

PSEUDO INVERSE

$w^* = X^+ y$  is SHORTEST SOLUTION

HESSIAN STRICTLY POS DEFINITE  
NOT NECESSARY CONDITION FOR STRICT MINIMA

$$f(x) = x^4$$

$$f'(x) = 4x^3$$

$$f''(x) = 12x^2$$



MINIMIZE A FUNCTION  $f$  SUBJECT TO  
EQUALITY CONSTRAINTS

GIVEN FUNCTIONS  $f, h_i$  ( $1 \leq i \leq m$ )  
DEFINED ON A DOMAIN  $\Omega \subseteq \mathbb{R}^n$

MINIMIZE  $f(w)$ ,  $w \in \Omega$   
SUBJECT TO:  $h_i(w) = 0$   $i = 1, \dots, m$

$f$  OBJECTIVE FUNCTION  
 $h_i$  CONSTRAINTS

LAGRANGIAN :

$$L(w, \beta) = f(w) + \sum_{i=1}^m \beta_i h_i(w)$$

$$= f(w) + \underbrace{\beta^T}_{1 \times m} \underbrace{h(w)}_{m \times 1}$$

$w$  PRIMAL VARIABLES

$\beta$  LAGRANGIAN OR DUAL VARS.  
(ONE PER CONSTRAINT)

## NECESSARY CONDITION

$w^*$  MIN OF  $f(w)$  SUBJECT TO = CONSTRAINTS

THEN 
$$\frac{\partial L(w^*, \beta^*)}{\partial w} = 0$$

$$\frac{\partial L(w^*, \beta^*)}{\partial \beta} = 0$$

"PRIMAL CONSTRAINTS"

FOR SOME VALUES  $\beta^*$  OF DUAL VARS

IF  $L(w, \beta^*)$  CONVEX IN  $w$  THEN  
ABOVE CONDITION ALSO SUFFICIENT

EXAMPLE: FIND LARGEST VOL. BOX WITH  
SURFACE AREA  $c$

MIN :  $-wuv$

SUBJ. TO :  $wu + uv + vw = c/2$

sol

$$L(u, v, w, \beta) = -wuv + \beta(wu + uv + vw - \frac{c}{2})$$

$$\frac{\partial L}{\partial w} = -uv + \beta(u+v) = 0$$

$$\frac{\partial L}{\partial u} = -vw + \beta(v+w) = 0$$

$$\frac{\partial L}{\partial v} = -wu + \beta(w+u) = 0$$

$$\frac{\partial L}{\partial \beta} = \underbrace{wu + uv + vw - \frac{c}{2}} = 0$$

PRIMAL CONSTRAINT

$$\text{ONLY ONE SOLUTION: } u^* = v^* = w^* = \sqrt{\frac{c}{6}}, \quad \beta^* = \frac{1}{2} \sqrt{\frac{c}{6}}$$

$\Rightarrow$  MAX VOL. IS CUBE

$$\text{CHECK: SURFACE AREA} = 6 \cdot \sqrt{\frac{c}{6}} \sqrt{\frac{c}{6}} = c$$

MAXIMUM ENTROPY DISTR.

$$\begin{aligned} & \text{MIN } \overbrace{\sum p_i \ln p_i}^{-H(p)} \\ & \text{SUBJ. TO: } \sum_i p_i = 1 \end{aligned}$$

$$\begin{aligned} H(p): & \quad \bigcirc \\ -H(p): & \quad \bigcirc \end{aligned}$$

$$L(\bar{p}, \beta) = \sum_i p_i \ln p_i + \beta (\sum_i p_i - 1)$$

$$\frac{\partial L}{\partial p_i} = \ln p_i + 1 + \beta = 0$$

$$p_i^* = e^{-1-\beta}$$

ALL  $p_i^*$  IDENTICAL

$$\text{CONSTRAINT: } \sum_i p_i^* = 1$$

$$\text{IMPLIES: } p_i^* = \frac{1}{n}, \quad \beta^* = 1 + \ln n$$

PLUG IN

$$\begin{aligned} \sum_i \frac{1}{n} \ln \frac{1}{n} &= -\sum_i \frac{1}{n} \ln n \\ &= -\ln n \end{aligned}$$



INEQUALITY CONSTRAINTS AS WELL

$$\left. \begin{array}{ll} \text{MINIMIZE} & f(w) \\ \text{SUBJECT TO} & g_i(w) \leq 0 \\ & h_i(w) = 0 \end{array} \right\} \begin{array}{ll} w \in \mathcal{R} & \\ 1 \leq i \leq k & \\ 1 \leq i \leq m & \end{array} \quad \text{PRIMAL}$$

LAGRANGIAN:

$$L(w, \underbrace{\alpha, \beta}_{\substack{\text{LAGRANGIAN VARS} \\ \text{OR DUAL VARS}}}) = f(w) + \underbrace{\alpha^T}_{\substack{\uparrow \\ k}} g(w) + \underbrace{\beta^T}_{\substack{\uparrow \\ m}} h(w)$$

PRIMAL VARS

LAGRANGIAN DUAL PROBLEM

$$\left. \begin{array}{ll} \text{MAXIMIZE :} & \theta(\alpha, \beta) \\ \text{SUBJECT TO} & \alpha \geq 0 \end{array} \right\} \text{DUAL}$$

WHERE  $\theta(\alpha, \beta) = \inf_{w \in \mathcal{R}} \underbrace{L(w, \overbrace{\alpha, \beta}^{\text{dual}})}_{\text{primal}}$

NOTE THAT  $\beta$  UNCONSTRAINED

PRIMAL:

$$\text{MIN } \sum p_i \ln p_i$$

$$\sum p_i = 1$$

WHAT IS THE DUAL?

WE SHOWED ALREADY  
THAT  $p_i^* = \frac{1}{n}$

PLUGGING  $p^*$  INTO PRIMAL  
GIVES VALUE  $-\ln n$

$$L(\bar{p}, \beta) = \sum p_i \ln p_i + \beta (\sum p_i - 1)$$

$$\frac{\partial L}{\partial p_i} = \ln p_i + 1 + \beta = 0$$

$$p_i^* = e^{-1-\beta}$$

OPTIMAL PRIMAL

PLUG  
INTO LAGR.

$$L(p^*, \beta) = \sum_i e^{-1-\beta} (-1-\beta) + \beta (\sum_i e^{-1-\beta} - 1)$$

$$= -n e^{-1-\beta} - \beta$$

DUAL:

$$\text{MAX}_{\beta} \underbrace{-n e^{-1-\beta} - \beta}_{\Theta(\beta)}$$

↑  
UNCONST.

SOLVE DUAL FOR OPTIMUM  $\beta^*$

$$\frac{\partial \Theta(\beta)}{\partial \beta} = -n e^{-1-\beta} (-1) - 1 = 0$$

$$e^{-1-\beta^*} = \frac{1}{n}$$

$$-1-\beta^* = -\ln n$$

$$\beta^* = (\ln n) - 1$$

$$\begin{aligned} \Theta(\beta^*) &= -n e^{-(\ln n) - 1} - \ln n + 1 \\ &= -n \frac{1}{n} - \ln n + 1 \end{aligned}$$

SAME VALUE AS PRIMAL

## AN EXAMPLE WITH INEQUALITIES

$$\begin{array}{ll}
 \text{MINIMIZE} & \frac{1}{2} \underset{n \times n}{W^T Q W} - \underset{n}{k^T W} \\
 \text{SUBJECT TO} & \underset{m \times n}{X W} \leq \underset{m}{c}
 \end{array} \quad \left. \vphantom{\begin{array}{l} \text{MINIMIZE} \\ \text{SUBJECT TO} \end{array}} \right\} \text{PRIMAL}$$

$Q$  pos DEF.

$$L(w, \alpha) = \frac{1}{2} w^T Q w - k^T w + \alpha^T (Xw - c)$$

$$\frac{\partial L}{\partial w} = Qw - k + X^T \alpha = 0$$

$$w^* = Q^{-1} (k - X^T \alpha)$$

SUBSTITUTING INTO  $L$  GIVES

$$\frac{1}{2} (Q^{-1} (k - X^T \alpha))^T \cancel{Q} Q^{-1} (k - X^T \alpha) - k^T Q^{-1} (k - X^T \alpha)$$

$$- \alpha^T (X Q^{-1} (k - X^T \alpha) - c)$$

0  
0  
0

$$\begin{array}{ll}
 \text{MAX} & -\frac{1}{2} \alpha^T P \alpha - \alpha^T d - \frac{1}{2} k^T Q^{-1} k \\
 \text{SUBJECT TO} & \alpha \geq 0
 \end{array} \quad \left. \vphantom{\begin{array}{l} \text{MAX} \\ \text{SUBJECT TO} \end{array}} \right\} \text{DUAL}$$

SIMPLER  
CONSTRAINTS

$$\begin{aligned}
 \text{WHERE } P &= X Q^{-1} X \\
 d &= c - X Q^{-1} k
 \end{aligned}$$

WEAK DUALITY TH:

$w \in \mathcal{J}$  FEASIBLE SOL. TO PRIMAL

$(\alpha, \beta)$  " " DUAL

THEN  $f(w) \geq \theta(\alpha, \beta)$

$\uparrow$  MINIMIZED       $\uparrow$  MAXIMIZED  
 $f(w)$        $\theta(\alpha, \beta)$

PROOF:

$$\theta(\alpha, \beta) = \inf_{\tilde{w} \in \mathcal{J}} L(\tilde{w}, \alpha, \beta)$$

$$\leq L(w, \alpha, \beta)$$

$$= f(w) + \underbrace{\alpha^T g(w)}_{\geq 0} + \underbrace{\beta^T h(w)}_{=0}$$

FEASIBILITY OF  $\alpha$

FEASIBILITY OF  $w$

$(\alpha)^*$   
 $\leq f(w)$

□

CONCLUSION:

VALUE OF DUAL UPPER BOUNDED  
BY VALUE OF PRIMAL

11

↓  
PUSH  
DOWN

$$\inf \{ f(w) : g(w) \leq 0, h(w) = 0 \}$$

VI

DUALITY GAP

$$\sup \{ \theta(\alpha, \beta) : \alpha \geq 0 \}$$

↑  
PUSH  
UP

WHEN THE GAP IS 0

THEN THIS GIVES FEASIBLE SOLUTIONS

$$\exists f(w^*) = \theta(\alpha^*, \beta^*), \text{ WHERE} \\ \alpha^* \geq 0 \quad g(w^*) \leq 0 \quad h(w^*) = 0$$

THEN  $w^*$  &  $(\alpha^*, \beta^*)$  SOLVE THE  
PRIMAL AND DUAL PROBLEM, RESP.

ALSO:

$$\alpha_i^* g_i(w^*) = 0 \text{ for } 1 \leq i \leq K$$

WHY? (\*) IS TIGHT IFF THE ABOVE HOLDS

FOR US THE CONSTRAINTS ARE ALWAYS AFFINE:

$$h_i(w) = (\bar{a}_i^T w - b_i = 0)$$

$$g_i(w) = (\bar{c}_i^T w - d_i \leq 0)$$

ALSO  $f$  ALWAYS CONVEX

STRONG DUALITY TH:

ASSUME  $f$  CONVEX

FOR A CONVEX DOMAIN  $\mathcal{R}$

$g_i, h_i$  AFFINE

THEN THE FOLLOWING OPTIM. PROBLEM

HAS DUALITY GAP 0

$$\min f(w) \quad w \in \mathcal{R}$$

$$\text{SUBJ. TO:} \quad \begin{array}{ll} g_i(w) \leq 0 & 1 \leq i \leq k \\ h_i(w) = 0 & 1 \leq i \leq m \end{array}$$

A TH. YOU SHOULD REMEMBER

MIN.  $f(w)$  FOR  $w \in \mathcal{J}$

SUBJ. TO:  $g_i(w) \leq 0 \quad 1 \leq i \leq k$

$h_i(w) = 0 \quad 1 \leq i \leq m$

$\mathcal{J}$  CONVEX,  $g_i, f_i$  AFFINE

NEC. & SUFF. CONDITIONS FOR  $w^*$  TO BE AN OPTIMUM ARE EXISTENCE OF  $\alpha^*, \beta^*$  S.T.

$$\frac{\partial L(w^*, \alpha^*, \beta^*)}{\partial w} = 0$$

$$h_i(w^*) = 0 \quad 1 \leq i \leq m$$

$$g_i(w^*) \leq 0 \quad 1 \leq i \leq k$$

$$\alpha_i^* g_i(w^*) = 0 \quad 1 \leq i \leq k$$

$$\alpha_i^* \geq 0$$

KARUSH-KUHN-TUCKER  
CONDITIONS

CONSTR.  $g_i(w^*) \leq 0$  ACTIVE IF  $g_i(w^*) = 0$   
INACTIVE  $< 0$

ACTIVE  $\Rightarrow \alpha_i^* \geq 0$

INACTIVE  $\Rightarrow \alpha_i^* = 0$

