

Lecture 14 - dual SVM

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today:
 • IPM
 • SVM dual

interior point method:

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & Ax=b \\ & x \geq 0 \end{array}$$

barrier method

$$\begin{array}{ll} \min & f(x) - t \log x \\ \text{s.t.} & Ax=b \end{array} \stackrel{\text{barrier function}}{=} g_t(x)$$

$\sum_i \log x_i$

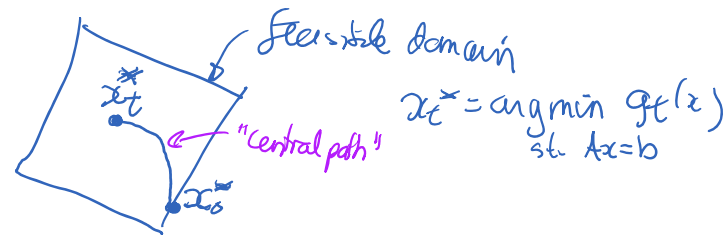
can transform

$$\begin{array}{ll} \tilde{A}z \leq \tilde{b} \\ \text{to} \\ Ax=b \\ x \geq 0 \end{array}$$

transform

$$\tilde{A}z + \tilde{s} = \tilde{b} \quad \tilde{s} \geq 0$$

$$\text{dom}(g_t(x)) = \{x : x > 0\}$$



interior point method: run Newton's method with warm start on $g_t(x)$ and decrease t with geometric schedule

Convergence: Newton's method take $\log(\log(1/\epsilon)) + \text{cst.}$ iterations to reach ϵ -accuracy

"self-concordant analysis"

IPM: # of ^{Newton} iterations is $\log(1/\epsilon)$, some constant overall convergence

$\hookrightarrow$ dimensionality

is appearing; but not condition of f
(vs. gradient method)

cost perturbation is $\approx O(d^3)$

review of Lagrangian duality

primal problem

$$p^* \triangleq \inf_x f(x) \quad \text{s.t. } h_i(x) \leq 0 \quad \forall i \in I$$

dual problem

$$d^* \triangleq \sup_{\alpha \geq 0} d(\alpha) \quad \text{Lagrangian dual fct.}$$

Saddle pt. perspective for
Lag. duality:

$$\inf_x f(x) \quad \text{s.t. } h_i(x) \leq 0 \quad \forall i \in I$$

$$p^* = \inf_x \sup_{\alpha \geq 0} \mathcal{L}(x, \alpha)$$

"weak duality"

$\rightarrow \sup_{\alpha \geq 0} \inf_x \mathcal{L}(x, \alpha) \triangleq d^*$

Fenchel conjugate of f

$$f^*(y) \triangleq \sup_x \langle y, x \rangle - f(x)$$

$x^* \text{ s.t. } \nabla f(x^*) = y$

Fenchel duality: $A: \mathbb{R}^d \rightarrow \mathbb{R}^p$

$$p^* = \inf_x f(x) + g(Ax)$$

$$d^* = \sup_y -f^*(A^T y) - g^*(y)$$

note: not unique.

$$\frac{\Delta \|w\|^2}{2} + \frac{1}{n} \sum_{i=1}^n H_i(w)$$

$\downarrow$
max $\frac{1}{n} \sum_{i=1}^n \langle g_i, w \rangle$

$$= \inf_x \left[\sup_{\alpha \geq 0} f(x) + \sum_i \alpha_i h_i(x) \right]$$

$\mathcal{L}(x, \alpha)$ "Lagrangian fct."

$$\text{because } g(x) \triangleq \sup_{\alpha \geq 0} \sum_i \alpha_i h_i(x) = \begin{cases} +\infty & \text{if } x \text{ is not feasible} \\ 0 & \text{o.w.} \end{cases}$$

$$= \delta_C(x) \quad \text{where } C \triangleq \{x \mid h_i(x) \leq 0 \forall i\}$$

$$\begin{aligned} & \sup_{\alpha \geq 0} \inf_x \mathcal{L}(x, \alpha) \triangleq d^* \\ & \quad \quad \quad \triangleq d(\alpha) \\ & \text{Lagrangian dual fct.} \end{aligned}$$

"weak duality"

note: $d(\alpha)$ always concave
even if $f(x)$ is not concave

$$= \delta_C(x) \quad \text{where } C \triangleq \{x : h_i(x) \leq 0 \forall i\}$$

KKT conditions: $\rightarrow$ necessary conditions for x^* & α^* to be primal & dual optimum
when f & h_i are differentiable fcts



- KKT conditions
- x^* primal feasible (i.e. $h_i(x^*) \leq 0 \forall i \in I$)
 - α^* dual feasible ($\alpha^* \geq 0$)
 - $\nabla f(x^*) + \sum_i \alpha_i^* \nabla h_i(x^*) = 0$ [i.e. (x^*, α^*) station. point of $\mathcal{L}(x, \alpha)$]
 - $\alpha_i^* h_i(x^*) = 0 \forall i$ complementary slackness

$\rightarrow$ if primal problem
is convex
(i.e. f & h_i 's)
are convex

and " Slater's condition "

$$\begin{aligned} & \exists x \text{ rel int}(\text{dom}(f)) \\ & \text{s.t. } h_i(x) < 0 \\ & \text{when } h_i \text{ is not affine} \end{aligned}$$

$\Rightarrow$ strong duality i.e. $p^* = d^*$

and KKT conditions are
sufficient!

(thus suppose get α^* which solves dual;

then get x^* through KKT
 $\Rightarrow x^*$ solves primal

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- $f(x) \geq d(\alpha) \quad \forall x \text{ if } \alpha \text{ feasible}$ $\lfloor g(x, \alpha) \leq f(x) \text{ when } \alpha \text{ is feasible and } x \text{ is ''}$
- $d(\alpha)$ is always concave in α
- $d(\alpha)$ is obtained through unconstrained opt.
- counter example for strong duality (see Boyd's book exercise 5.21)

$$\min f(x, y)$$

$$\text{s.t. } \frac{x^2}{y} \leq 0$$

where

$$f(x, y) = \begin{cases} x^2/y & y > 0 \\ +\infty & \text{o.w.} \end{cases}$$
- no unique "Lagrangian dual problem"

$\rightarrow$ depends how you write the primal problem

SVM struct dual problem

cons. primal $\min_{w, \xi} \frac{\lambda \|w\|^2}{2} + \frac{1}{n} \sum_{i=1}^n \xi_i$

s.t. $\frac{1}{n} \sum_{i=1}^n \xi_i \leq \frac{1}{n} \sum_{i=1}^n H_i(\tilde{y}_i; w) \quad \forall \tilde{y} \in \mathcal{Y}_i$

$H_i(\tilde{y}_i; w) = \xi_i(\tilde{y}_i) - w^T \phi(\tilde{y}_i)$

$$L(w, \xi; \alpha) = \frac{\lambda \|w\|^2}{2} + \frac{1}{n} \sum_{i=1}^n \xi_i + \frac{1}{n} \sum_{i=1}^n \alpha_i \xi_i \left[\xi_i(\tilde{y}_i) - w^T \phi(\tilde{y}_i) - \xi_i \right]$$

$h_{i, \tilde{y}}(w, \xi)$

$$\frac{\partial L}{\partial \xi_i} = 0 \Rightarrow \boxed{\sum_{\tilde{y} \in \mathcal{Y}_i} \alpha_i(\tilde{y}) = 1} \quad \text{re. } \alpha_i \in \Delta_{|\mathcal{Y}_i|}$$

$$\nabla_w L = 0 \Rightarrow \lambda w - \frac{1}{n} \sum_{i, \tilde{y}} \alpha_i(\tilde{y}) \psi_i(\tilde{y}) = 0$$

$$w(\alpha) \triangleq \frac{1}{\lambda n} \sum_{i=1}^n \left(\sum_{\tilde{y} \in \mathcal{Y}_i} \alpha_i(\tilde{y}) \psi_i(\tilde{y}) \right)$$

KKT condition

$$d(\alpha) = \frac{\lambda}{2} \|w(\alpha)\|^2 + \underbrace{\frac{1}{n} \sum_{i, \tilde{y}} \alpha_i(\tilde{y}) [l_i(\tilde{y}) - w(\alpha)^T \psi_i(\tilde{y})]}_{\langle b, \alpha \rangle}$$

$$d(\alpha) = \langle b, \alpha \rangle + \frac{\lambda}{2} \|w(\alpha)\|^2 - w(\alpha)^T \underbrace{\left[\frac{1}{n} \sum_{i, \tilde{y}} \alpha_i(\tilde{y}) \psi_i(\tilde{y}) \right]}_{=\lambda w(\alpha)}$$

$\dim(\alpha) = m$
 $b \in \mathbb{R}^m$

$A \in \mathbb{R}^{d \times m}$

$$d(\alpha) = \langle b, \alpha \rangle - \frac{\lambda}{2} \|w(\alpha)\|^2$$

dual problem:

$$\max_{\substack{\alpha_i \in \Delta_{|\mathcal{Y}_i|} \\ \text{decision}}} \frac{-\lambda \|w(\alpha)\|^2}{2} + \langle b, \alpha \rangle$$

$$w(\alpha) = A\alpha$$

$$A \triangleq \left[\dots \overset{i, \tilde{y} \text{ entry}}{\frac{\psi_i(\tilde{y})}{\lambda n}} \dots \right]$$

(exponentially many dual variables)

complementary slackness:

$$\alpha_i^*(\tilde{y}) > 0 \Rightarrow h_{i, \tilde{y}}(w^*, \xi^*) = 0$$

$$\text{ie } \xi_i^* = l_i(\tilde{y}) - w^T \mathcal{H}_i(\tilde{y}) = H_i(\tilde{y}, w)$$

by primal feasibility, $\xi_i^* \geq H_i(\tilde{y}, w) \forall \tilde{y} \in \mathcal{Y}_i$

thus $\xi_i^* = \max_{\tilde{y} \in \mathcal{Y}_i} H_i(\tilde{y}, w) = H_i(w)$

Support vectors are when $\alpha_i^* \tilde{y} > 0$ [and $\tilde{y} \neq y^{(i)}$ because $\mathcal{H}_i(y^{(i)}) = 0$]
[necessary condition $\tilde{y} \in \arg\max_{\tilde{y} \in \mathcal{Y}_i} H_i(\tilde{y}, w)$]

(*) sparse solution

primal-dual gap:

$$\text{gap}(\alpha) = p(w(\alpha), \xi(\alpha)) - d(\alpha) \geq 0$$

$$= \underbrace{p(w(\alpha), \xi(\alpha)) - p(w^*, \xi^*)}_{\text{primal suboptimality}} + \underbrace{p(w^*, \xi^*) - d(\alpha)}_{\text{dual suboptimality}}$$

certificate of suboptimality (*)

$$\rightarrow \frac{\lambda \|w\|^2}{2} + \frac{1}{n} \sum_{i=1}^n H_i(w) + \frac{\lambda}{2} \|w\|^2 - \frac{1}{n} \sum_{i=1}^n \alpha_i(\tilde{y}) l_i(\tilde{y})$$

$$= \frac{1}{n} \sum_{i=1}^n [H_i(w) - \sum_{\tilde{y}} \alpha_i(\tilde{y}) l_i(\tilde{y})] + \lambda \langle w, w(\alpha) \rangle$$

$$\text{gap}(\alpha) = \frac{1}{n} \sum_{i=1}^n \left[\underbrace{H_i(w)}_{\max_{\tilde{y}} H_i(\tilde{y}, w)} - \sum_{\tilde{y}} \alpha_i(\tilde{y}) \underbrace{H_i(\tilde{y}, w)}_{l_i(\tilde{y}) - w^T \mathcal{H}_i(\tilde{y})} \right]$$

$$\frac{1}{n} \sum_{i=1}^n \alpha_i(\tilde{y}) \mathcal{H}_i(\tilde{y})$$

use to get dual a bound on suboptimality of α

$$\left| \max_{\tilde{y}} f_i(\tilde{y}; w) - w^T y_i(\tilde{y}) \right|$$

a bound on suboptimality of σ
and primal " of $w(\sigma)$