Dual Decomposition

http://bicmr.pku.edu.cn/~wenzw/opt-2017-fall.html

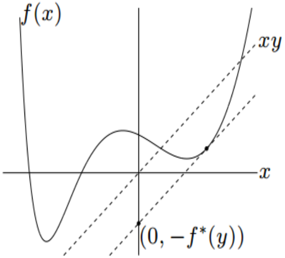
Acknowledgement: this slides is based on Prof. Lieven Vandenberghes lecture notes

Outline

Conjugate function

the **conjugate** of a function f is

$$f^*(y) = \sup_{x \in \mathbf{dom}\, f} (y^T x - f(x))$$



f^* is closed and convex even if f is not

Fenchel's s inequality

$$f(x) + f^*(y) \geq x^T y \quad \forall x, y$$

(extends inequality $x^T x/2 + y^T y/2 \geq x^T y$ to non-quadratic convex f)

The second conjugate

$$f^{**}(x) = \sup_{y \in \mathbf{dom}\, f^*} (x^T y - f^*(y))$$

- $f^{**}(x)$ is closed and convex
- from Fenchel's inequality $x^T y - f^*(y) \leq f(x)$ for all y and x):

  $$f^{**} \leq f(x) \quad \forall x$$

  equivalently, epi $f \subseteq$ epi f^{**} (for any f)
- if f is closed and convex, then

  $$f^{**}(x) = f(x) \quad \forall x$$

  equivalently, epi $f =$ epi f^{**} (if f is closed convex); proof on next page

Conjugates and subgradients

if f is closed and convex, then

$$y \in \partial f(x) \quad \Leftrightarrow \quad x \in \partial f^*(y) \quad \Leftrightarrow \quad x^T y = f(x) + f^*(y)$$

proof: if $y \in \partial f(x)$, then $f^*(y) = \sup_u (y^T u - f(u)) = y^T x - f(x)$

$$\begin{aligned} f^*(v) &= \sup_u (v^T u - f(u)) \\ &\geq v^T x - f(x) \\ &= x^T (v - y) - f(x) + y^T x \\ &= f^*(y) + x^T (v - y) \end{aligned} \tag{1}$$

for all v; therefore, x is a subgradient of f^* at y $(x \in \partial f^*(y))$
reverse implication $x \in \partial f^*(y) \Rightarrow y \in \partial f(x)$ follows from $f^{**} = f$

Moreau decomposition

$$prox_f(x) = \operatorname*{argmin}_u \left(f(u) + \frac{1}{2}\|u - x\|_2^2 \right)$$

$$x = \mathrm{prox}_f(x) + \mathrm{prox}_{f^*}(x) \qquad \forall x$$

- follows from properties of conjugates and subgradients:

$$\begin{aligned} u = prox_f(x) &\Longleftrightarrow x - u \in \partial f(u) \\ &\Longleftrightarrow u \in \partial f^*(x - u) \\ &\Longleftrightarrow x - u = prox_{f^*}(x) \end{aligned}$$

- generalizes decomposition by orthogonal projection on subspaces:

$$x = P_L(x) + P_{L^\perp}(x)$$

if L is a subspace, $L^\perp$ its orthogonal complement (this is Moreau decomposition with $f = I_L$, $f^* = I_{L^\perp}$)

Outline

Duality and conjugates

primal problem ($A \in \mathbb{R}^{m \times n}$, f and g convex)

$$\min \quad f(x) + g(Ax)$$

Lagrangian (after introducing new variable $y = Ax$)

$$f(x) + g(y) + z^T(Ax - y)$$

dual function

$$\inf_x (f(x) + z^T Ax) + \inf_y (g(y) - z^T y) = -f^*(-A^T z) - g^*(z)$$

dual problem

$$\max \quad -f^*(-A^T z) - g^*(z)$$

Examples

equality constraints: g is indicator for $\{b\}$

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & Ax = b \end{array} \qquad \begin{array}{ll} \max & -b^T z - f^*(-A^T z) \end{array}$$

linear inequality constraints: g is indicator for $\{y \mid y \preceq b\}$

$$\begin{array}{ll} \min & f(x) \\ \text{s.t.} & Ax \preceq b \end{array} \qquad \begin{array}{ll} \max & -b^T z - f^*(-A^T z) \\ \text{s.t.} & z \succeq 0 \end{array}$$

norm regularization: $g(y) = ||y - b||$

$$\begin{array}{ll} \min & f(x) + ||Ax - b|| \end{array} \qquad \begin{array}{ll} \max & -b^T z - f^*(-A^T z) \\ \text{s.t.} & ||z||_* \leq 1 \end{array}$$

Dual methods

apply first-order method to dual problem

$$\max \quad -f^*(-A^T z) - g^*(z)$$

reasons why dual problem may be easier for first-order method:

- dual problem is unconstrained or has simple constraints
- dual objective is differentiable or has a simple nondifferentiable term
- decomposition: exploit separable structure

Outline

(Sub-)gradients of conjugate function

assume $f : \mathbb{R}^n \to \mathbb{R}$ is closed and convex with conjugate

$$f^*(y) = \sup_x (y^T x - f(x))$$

subgradient

- f^* is subdifferentiable on (at least) **int dom** f^*
- maximizers in the definition of $f^*(y)$ are subgradients at y

$$y \in \partial f(x) \;\Leftrightarrow\; y^T x - f(x) = f^*(y) \;\Leftrightarrow\; x \in \partial f^*(y)$$

gradient: for strictly convex f , maximizer in definition is unique if it exists

$$\nabla f^*(y) = \operatorname*{argmax}_x (y^T x - f(x)) \quad \text{(if maximum is attained)}$$

Conjugate of strongly convex function

assume f is closed and strongly convex, with parameter $\mu > 0$

- f^* is defined for all y $(i.e.,$ dom $f^* = \mathbb{R}^n)$
- f^* is differentiable everywhere, with gradient

$$\nabla f^*(y) = \underset{x}{\text{argmax}}(y^T x - f(x))$$

- ∇f^* is Lipschitz continuous with constant $1/\mu$

$$||\nabla f^*(y) - \nabla f^*(y')||_2 \leq \frac{1}{\mu}||y - y'||_2 \quad \forall y, y'$$

proof: if f is strongly convex and closed

- $y^T x - f(x)$ has a unique maximizer x for every y
- x maximizes $y^T x - f(x)$ if and only if $y \in \partial f(x)$;

$$y \in \partial f(x) \Leftrightarrow x \in \partial f^*(y) = \{\nabla f^*(y)\}$$

  hence $\nabla f^*(y) = \operatorname{argmax}_x (y^T x - f(x))$
- from convexity of $f(x) - (\mu/2)x^T x$:

$$(y - y')^T (x - x') \geq \mu ||x - x'||_2^2 \text{ if } y \in \partial f(x), y' \in \partial f(x')$$

- this is co-coercivity of ∇f^* (which implies Lipschitz continuity)

$$(y - y')^T (\nabla f^*(y) - \nabla f^*(y')) \geq \mu ||\nabla f^*(y) - \nabla f^*(y')||_2^2$$

Outline

Equality constraints

$$\text{P:} \quad \begin{array}{ll} \min & f(x) \\ \text{s.t.} & Ax = b \end{array} \qquad \text{D:} \quad \min \quad f^*(-A^T z) + b^T z$$

dual gradient ascent (assuming **dom** $f^* = \mathbb{R}^n$):

$$\hat{x} = \underset{x}{\operatorname{argmin}}(f(x) + z^T A x), \quad z^+ = z + t(A\hat{x} - b)$$

- $\hat{x}$ is a subgradient of f^* at $-A^T z$ ($i.e., \hat{x} \in \partial f^*(-A^T z)$)
- $b - A\hat{x}$ is a subgradient of $f^*(-A^T z) + b^T z$ at z

It is of interest if calculation of $\hat{x}$ is inexpensive (for example, f is separable)

Dual decomposition

convex problem with separable objective

$$\begin{array}{ll} \min & f_1(x_1) + f_2(x_2) \\ \text{s.t.} & A_1x_1 + A_2x_2 \leq b \end{array}$$

constraint is *complicating or coupling* constraint

dual problem

$$\begin{array}{ll} \max & -f_1^*(-A_1^Tz) - f_2^*(-A_2^Tz) - b^Tz \\ \text{s.t.} & z \geq 0 \end{array}$$

can be solved by (sub-)gradient projection if $z \geq 0$ is the only constraint

Dual subgradient projection

subproblems: to calculate $f_j^*(-A_j^T z)$ and a (sub-) gradient for it,

$$\min_{x_j} \quad f_j(x_j) + z^T A_j x_j$$

optimal value is $f_j^*(-A_j^T z)$; minimizer $\hat{x}_j$ is in $\partial f_j^*(-A_j^T z)$
dual subgradient projection method

$$\begin{aligned} \hat{x}_j &= \operatorname*{argmin}_{x_j}(f_j(x_j) + z^T A_j x_j), \quad j = 1, 2 \\ z^+ &= (z + t(A_1\hat{x}_1 + A_2\hat{x}_2 - b))_+ \end{aligned}$$

- minimization problems over x_1, x_2 are independent
- z-update is projected subgradient step ($u_+ = \max\{u, 0\}$ elementwise)

Quadratic programming example

$$
\begin{array}{ll}
\min & \sum_{j=1}^{r}(x_j^T P_j x_j + q_j^T x_j) \\
\text{s.t.} & B_j x_j \preceq d_j, \quad j = 1, \ldots, r \\
& \sum_{j=1}^{p} A_j x_j \preceq b
\end{array}
$$

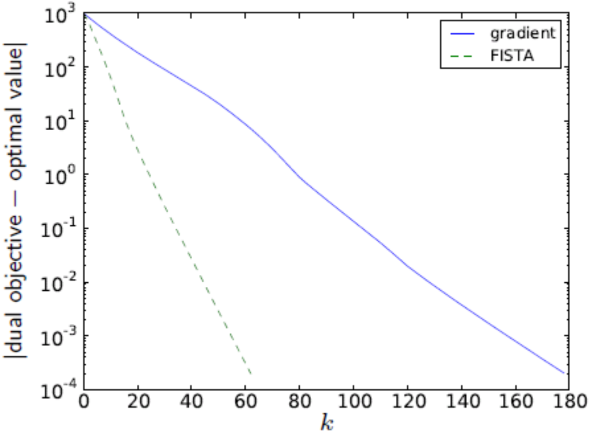
- $r = 10$, variables $x_j \in \mathbb{R}^{100}$, 10 coupling constraints ($A_j \in \mathbb{R}^{10\times 100}$)
- $P_j \succ 0$; implies dual function has Lipschitz continuous gradient

subproblems: each iteration requires solving 10 decoupled QPs

$$
\begin{array}{ll}
\min_{x_j} & x_j^T P_j x_j + (q_j + A_j^T z)^T x_j \\
\text{s.t.} & B_j x_j \preceq d_j
\end{array}
$$

gradient projection and fast gradient projection

- fixed step size (equal in the two methods)
- plot shows dual objective gap



Outline

Network utility maximization

network flows

- n flows, with fixed routes, in a network with m links
- variable $x_j \geq 0$ denotes the rate of flow j
- flow utility is $U_j : \mathbb{R} \to \mathbb{R}$, concave, increasing

capacity constraints

- traffic y_i on link i is sum of flows passing through it
- $y = Rx$, where R is the routing matrix

$$R_{ij} = \begin{cases} 1 & \text{flow } j \text{ passes over link } i \\ 0 & \text{otherwise} \end{cases}$$

- link capacity constraint: $y \leq c$

Dual network utility maximization problem

$$\begin{array}{ll} \max & \sum_{j=1}^{n} U_j(x_j) \\ \text{s.t.} & Rx \leq c \end{array}$$

a convex problem; dual decomposition gives decentralized method

dual problem

$$\begin{array}{ll} \min & c^T z + \sum_{j=1}^{n} (-U_j)^*(r_j^T z) \\ \text{s.t.} & z \geq 0 \end{array}$$

- z_i is price (per unit flow) for using link i
- $r_j^T z$ is the sum of prices along route$j$ (r_j is jth column of R)

(Sub-)gradients of dual function

dual objective

$$\begin{aligned} f(x) &= c^T z + \sum_{j=1}^{n} (-U_j)^*(r_j^T z) \\ &= c^T z + \sum_{j=1}^{n} \sup_{x_j} (U_j(x_j) - (r_j^T z) x_j) \end{aligned}$$

subgradient

$$c - R\hat{x} \in \partial f(z) \ \text{ where } \ \hat{x}_j = \operatorname*{argmax}_{x_j} (U_j(x_j) - (r_j^T z) x_j)$$

- if U_j is strictly concave, this is a gradient
- $r_j^T z$ is the sum of link prices along route j
- $c - R\hat{x}$ is vector of link capacity margins for flow $\hat{x}$

Dual decomposition algorithm

given initial link price vector $z \geq 0$ ($e.g., z = 1$), repeat:

1. sum link prices along each route: calculate $\lambda_j = r_j^T z$ for $j = 1, \ldots, n$
2. optimize flows (separately) using flow prices

$$\hat{x}_j = \underset{x_j}{\operatorname{argmax}}(U_j(x_j) - \lambda_j x_j), \quad j = 1, \ldots, n$$

3. calculate link capacity margins $s = c - R\hat{x}$
4. update link prices using projected (sub-)gradient step with step t

$$z := (z - ts)_+$$

decentralized:

- to find $\lambda_j, \hat{x}$ source j only needs to know the prices on its route
- to update s_i, z_i , link i only needs to know the flows that pass through it

Outline

Single commodity network flow

network

- connected, directed graph with n links/arcs, m nodes
- node-arc incidence matrix $A \in \mathbb{R}^{m \times n}$ is

$$A_{ij} = \begin{cases} 1 & \text{arc } j \text{ enters node } i \\ -1 & \text{arc } j \text{ leaves node } i \\ 0 & \text{otherwise} \end{cases}$$

flow vector and external sources

- variable x_j denotes flow (traffic) on arc j
- b_i is external demand (or supply) of flow at node i (satisfies $\mathbf{1}^T b = 0$)
- flow conservation: $Ax = b$

Network flow optimization problem

$$\begin{array}{ll} \min & \phi(x) = \sum_{j=1}^{n} \phi_j(x_j) \\ \text{s.t.} & Ax = b \end{array}$$

- ϕ is a separable sum of convex functions
- dual decomposition yields decentralized solution method

dual problem (a_j is jth column of A)

$$\max \quad -b^T z - \sum_{j=1}^{n} \phi_j^*(-a_j^T z)$$

- dual variable z_i can be interpreted as potential at node i
- $y_j = -a_j^T z$ is the potential difference across arc j
  (potential at start node minus potential at end node)

(Sub-)gradients of dual function

negative dual objective

$$f(z) = b^T z + \sum_{j=1}^{n} \phi_j^*(-a_j^T z)$$

subgradient

$$b - A\hat{x} \in \partial f(z) \text{ where } \hat{x}_j = \operatorname{argmin}(\phi_j(x_j) + (a_j^T z)x_j)$$

- this is a gradient if the functions ϕ_j are strictly convex
- if ϕ_j is differentiable, $\phi_j'(\hat{x}_j) = -a_j^T z$

Dual decomposition network flow algorithm

given initial potential vector z, repeat

1. determine link flows from potential differences $y = -A^T z$

$$\hat{x}_j = \underset{x_j}{\operatorname{argmin}}(\phi_j(x_j) - y_j x_j), j = 1, \ldots, n$$

2. compute flow residual at each node: $s := b - A\hat{x}$
3. update node potentials using (sub-)gradient step with step size t

$$z := z - ts$$

decentralized

- flow is calculated from potential difference across arc
- node potential is updated from its own flow surplus

Electrical network interpretation

network flow optimality conditions (with differentiable ϕ_j)

$$Ax = b, \quad y + A^T z = 0, \quad y_j = \phi_j'(x_j), \; j = 1, \ldots, n$$

network with node incidence matrix A, nonlinear resistors in branches
Kirchhoff current law (KCL): $Ax = b$
x_j is the current flow in branch j; b_i is external current extracted at node i
Kirchhoff voltage law (KVL): $y + A^T z = 0$
z_j is node potential; $y_j = -a_j^T z$ is jth branch voltage
current-voltage characterics: $y_j = \phi_j'(x_j)$
for example, $\phi_j(x_j) = R_j x_j^2/2$ for linear resistor R_j
current and potentials in circuit are optimal flows and dual variables

Example: minimum queueing delay

flow cost function and conjugate ($c_j > 0$ are link capacities):

$$\phi_j(x_j) = \frac{x_j}{c_j - x_j}, \quad \phi_j^*(y_j) = \begin{cases} (\sqrt{c_j y_j} - 1)^2 & y_j > 1/c_j \\ 0 & y_j \leq 1/c_j \end{cases}$$

(with **dom** $\phi_j = [0, c_j)$)

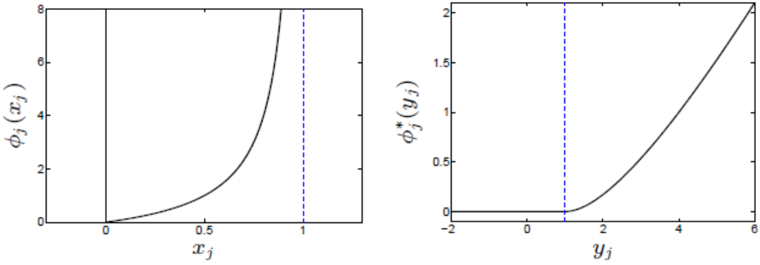
- ϕ_j is differentiable except at $x_j = 0$

$$\partial\phi_j(0) = (-\infty, 0], \quad \phi_j'(x_j) = \frac{c_j}{(c_j - x_j)^2} \quad (0 < x_j < c_j)$$

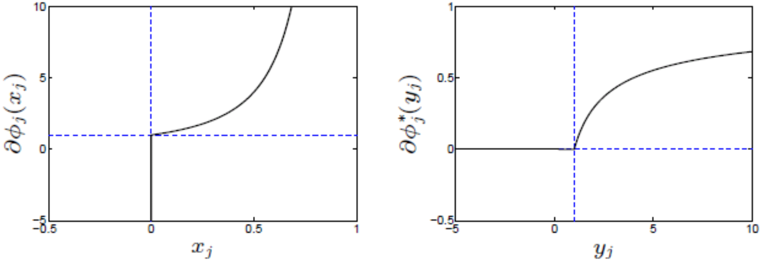
- ϕ_j^* is differentiable

$$\phi_j^{*\prime}(y_j) = \begin{cases} 0 & y_j \leq 1/c_j \\ c_j - \sqrt{c_j/y_j} & y_j > 1/c_j \end{cases}$$

flow cost function and conjugate ($c_j = 1$)



derivatives



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