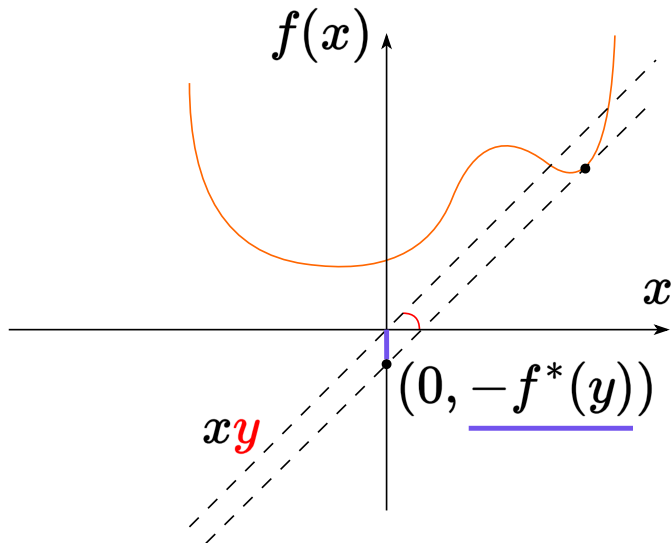


Introduction to dual methods

Daniil Merkulov

Optimization methods. MIPT

Definition

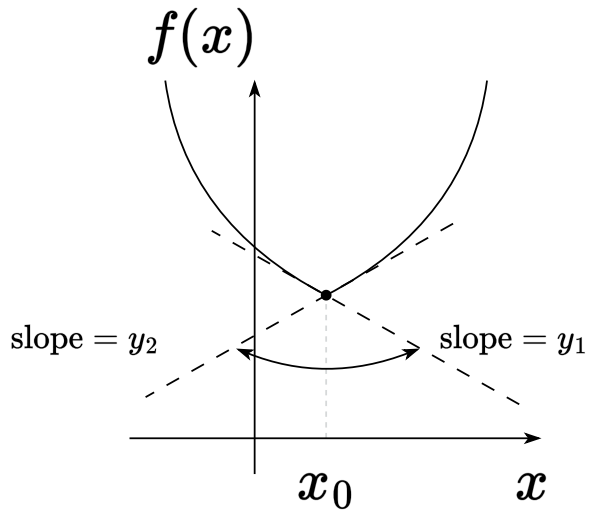


Recall that given $f : \mathbb{R}^n \rightarrow \mathbb{R}$, the function defined by

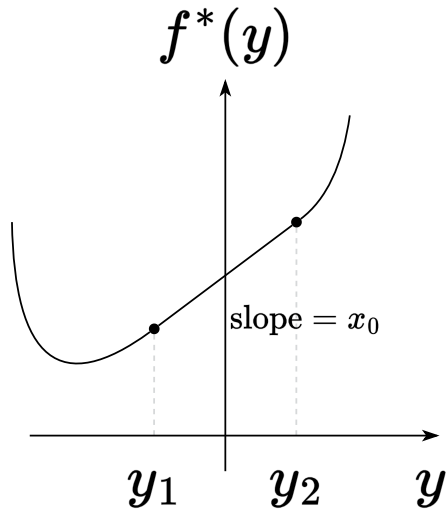
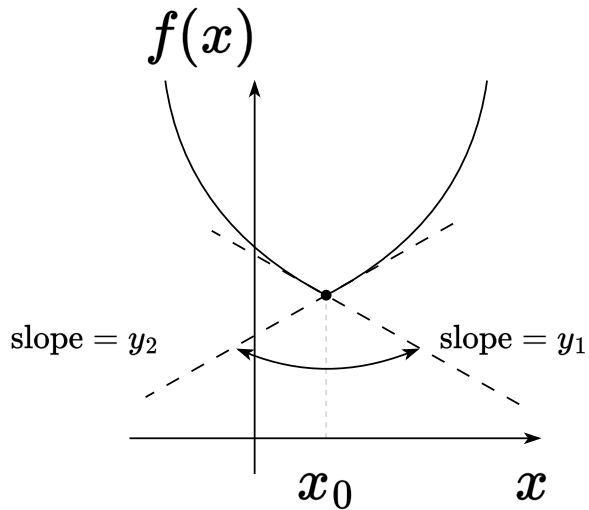
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is called its conjugate.

Geometrical intuition



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- If f is closed and convex, then $f^{**} = f$. Also,

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- If f is strictly convex, then

$$\nabla f^*(y) = \arg \min_z [f(z) - y^T z]$$

Conjugate function properties (proofs)

We will show that $x \in \partial f^*(y) \Leftrightarrow y \in \partial f(x)$, assuming that f is convex and closed.

- **Proof of \Leftarrow :** Suppose $y \in \partial f(x)$. Then $x \in M_y$, the set of maximizers of $y^T z - f(z)$ over z . But

$$f^*(y) = \max_z \{y^T z - f(z)\} \quad \text{and} \quad \partial f^*(y) = \text{cl}(\text{conv}(\bigcup_{z \in M_y} \{z\})).$$

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- **Proof of \Rightarrow :** From what we showed above, if $x \in \partial f^*(y)$, then $y \in \partial f^*(x)$, but $f^{**} = f$.

Clearly $y \in \partial f(x) \Leftrightarrow x \in \arg \min_z \{f(z) - y^T z\}$

Lastly, if f is strictly convex, then we know that $f(z) - y^T z$ has a unique minimizer over z , and this must be $\nabla f^*(y)$.

Dual (sub)gradient method

Even if we can't derive dual (conjugate) in closed form, we can still use dual-based gradient or subgradient methods.

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- Step sizes α_k , $k = 1, 2, 3, \dots$, are chosen in standard ways.

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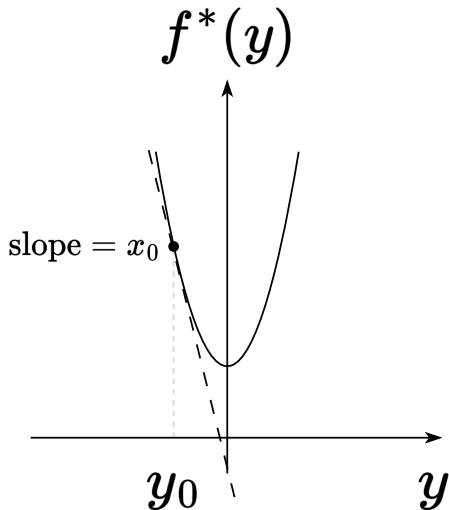
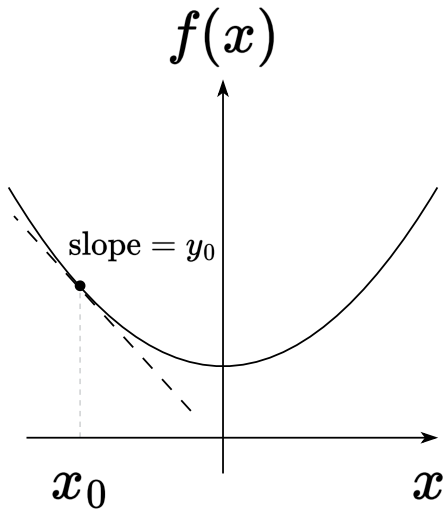
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- Proximal gradients and acceleration can be applied as they would usually.

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$$f(x_v) - u^T x_v \geq f(x_u) - u^T x_u + \frac{\mu}{2} \|x_u - x_v\|^2$$

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Adding these together, using the Cauchy-Schwarz inequality, and rearranging shows that

$$\|x_u - x_v\|^2 \leq \frac{1}{\mu} \|u - v\|^2$$

Slopes of f and f^*

Proof of “ \Leftarrow ”: for simplicity, call $g = f^*$ and $L = \frac{1}{\mu}$. As ∇g is Lipschitz with constant L , so is $g_x(z) = g(z) - \nabla g(x)^T z$, hence

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Let $u = \nabla f(x)$, $v = \nabla g(y)$; then $x \in \partial g^*(u)$, $y \in \partial g^*(v)$, and the above reads $(x - y)^T (u - v) \geq \frac{\|u - v\|^2}{L}$, implying the result.

Convergence guarantees

The following results hold from combining the last fact with what we already know about gradient descent:¹

- If f is strongly convex with parameter μ , then dual gradient ascent with constant step sizes $\alpha_k = \mu$ converges at sublinear rate $O(\frac{1}{\epsilon})$.

¹This is ignoring the role of A , and thus reflects the case when the singular values of A are all close to 1. To be more precise, the step sizes here should be: $\frac{\mu}{\sigma_{\max}(A)^2}$ (first case) and $\frac{2}{\frac{\sigma_{\max}(A)^2}{\mu} + \frac{\sigma_{\min}(A)^2}{L}}$ (second case).

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Note that this describes convergence in the dual. (Convergence in the primal requires more assumptions)

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$f \rightarrow \min_{x,y,z}$ Dual ascent

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Here $x = (x_1, \dots, x_B) \in \mathbb{R}^n$ divides into B blocks of variables, with each $x_i \in \mathbb{R}^{n_i}$. We can also partition A accordingly:

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where $(u)_+$ denotes the positive part of u , i.e., $(u_+)_i = \max\{0, u_i\}$, for $i = 1, \dots, m$.

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Price Coordination Interpretation (Vandenberghe)

- **System Overview:** Consider a system with B units, where each unit independently chooses its decision variable x_i , which determines how to allocate its goods.
- **Resource Constraints:** These are limits on shared resources, represented by the rows of A . Each component of the dual variable u_j represents the price of resource j .

- **Dual Update Rule:**

$$u_j^{\text{new}} = (u_j - ts_j)_+, \quad j = 1, \dots, m$$

where $s = b - \sum_{i=1}^B A_i x_i$ represents the slacks.

- **Price Adjustments:**

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- **Decrease price** u_j if resource j is under-utilized ($s_j > 0$).
- **Never let prices get negative;** hence the use of the positive part notation $(\cdot)_+$.

Augmented Lagrangian method aka method of multipliers

Dual ascent disadvantage: convergence requires strong conditions. Augmented Lagrangian method transforms the primal problem:

$$\begin{aligned} \min_x \quad & f(x) + \frac{\rho}{2} \|Ax - b\|^2 \\ \text{s.t.} \quad & Ax = b \end{aligned}$$

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Dual gradient ascent: The iterative updates are given by:

$$\begin{aligned} x_k &= \arg \min_x \left[f(x) + (u_{k-1})^T Ax + \frac{\rho}{2} \|Ax - b\|^2 \right] \\ u_k &= u_{k-1} + \rho(Ax_k - b) \end{aligned}$$

Augmented Lagrangian method aka method of multipliers

Notice step size choice $\alpha_k = \rho$ in dual algorithm. Why?

Since x_k minimizes the function:

$$f(x) + (u_{k-1})^T Ax + \frac{\rho}{2} \|Ax - b\|^2$$

over x , we have the stationarity condition:

$$0 \in \partial f(x_k) + A^T (u_{k-1} + \rho(Ax_k - b))$$

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- **Advantage:** The augmented Lagrangian gives better convergence.
- **Disadvantage:** We lose decomposability! (Separability is ruined)

Alternating Direction Method of Multipliers (ADMM)

Alternating direction method of multipliers or ADMM aims for the best of both worlds. Consider the following optimization problem:

Minimize the function:

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where $\rho > 0$ is a parameter. The augmented Lagrangian for this problem is defined as:

$$L_\rho(x, z, u) = f(x) + g(z) + u^T (Ax + Bz - c) + \frac{\rho}{2} \|Ax + Bz - c\|^2$$

Alternating Direction Method of Multipliers (ADMM)

ADMM repeats the following steps, for $k = 1, 2, 3, \dots$:

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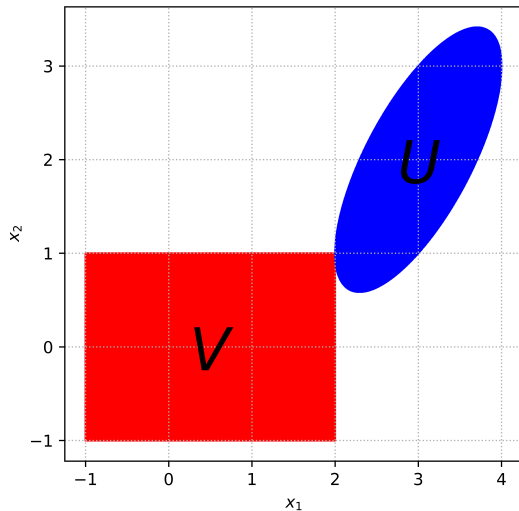
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Note: The usual method of multipliers would replace the first two steps by a joint minimization:

$$(x^{(k)}, z^{(k)}) = \arg \min_{x, z} L_\rho(x, z, u^{(k-1)})$$

Example: Alternating Projections



Consider finding a point in the intersection of convex sets $U, V \subseteq \mathbb{R}^n$:

$$\min_x I_U(x) + I_V(x)$$

To transform this problem into ADMM form, we express it as:

$$\min_{x,z} I_U(x) + I_V(z) \quad \text{subject to} \quad x - z = 0$$

Each ADMM cycle involves two projections:

$$x_k = \arg \min_x P_U(z_{k-1} - w_{k-1})$$

$$z_k = \arg \min_z P_V(x_k + w_{k-1})$$

$$w_k = w_{k-1} + x_k - z_k$$

Sources

- Ryan Tibshirani. Convex Optimization 10-725