

**Dual methods: Dual Gradient Ascent,
Augmented Lagrangian Method, ADMM**

Даня Меркулов

Методы Оптимизации в Машинном Обучении. ФКН ВШЭ

Introduction to dual methods

Why do we want to solve dual problems?

Primal problem

$$\begin{aligned} & f_0(x) \rightarrow \min_{x \in \mathbb{R}^n} \\ \text{s.t.} \quad & f_i(x) \leq 0, \quad i = 1, \dots, m \\ & h_i(x) = 0, \quad i = 1, \dots, p \end{aligned}$$

Dual problem

$$\begin{aligned} & g(\lambda, \nu) = \min_{x \in \mathcal{D}} L(x, \lambda, \nu) = \\ & \min_{x \in \mathcal{D}} \left(f_0(x) + \sum_{i=1}^m \lambda_i f_i(x) + \sum_{i=1}^p \nu_i h_i(x) \right) \rightarrow \max_{\lambda \in \mathbb{R}^m, \nu \in \mathbb{R}^p} \\ & \text{s.t. } \lambda \succeq 0 \end{aligned}$$

- **Shadow Prices.** In economics and resource allocation problems, dual variables can be interpreted as shadow prices, providing economic insights into resource utilization and constraints.

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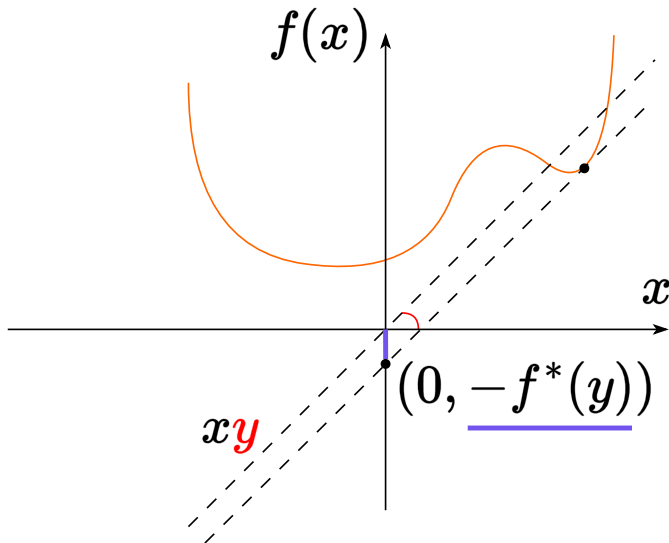
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- **Dual Problems Provide Bounds.** Dual problems often offer bounds on the optimal value of the primal problem. This can be useful for assessing the quality of approximate solutions.
- **Duality Gap.** The difference between the primal and dual solutions (duality gap) provides valuable information about the solution's optimality.

Conjugate functions

Conjugate functions



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

$$f^*(y) = \max_x [y^T x - f(x)]$$

is called its conjugate.

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Geometrical intuition

в $f(x)$

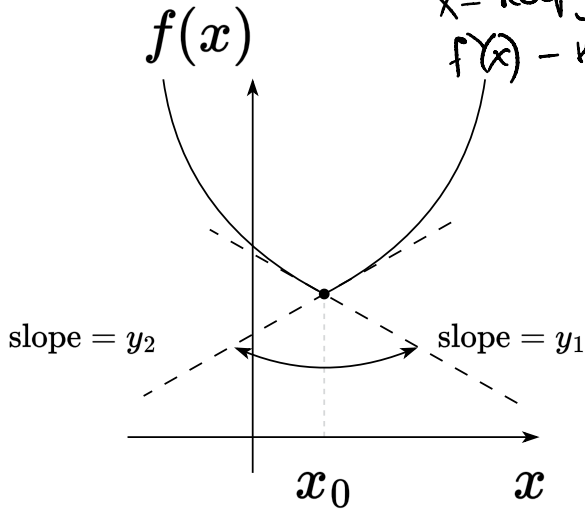
в $f^*(y)$

x - координата

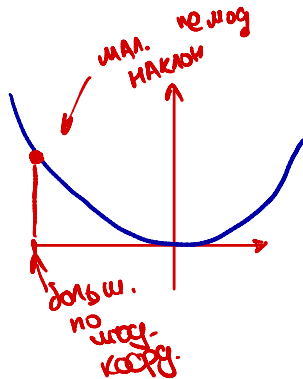
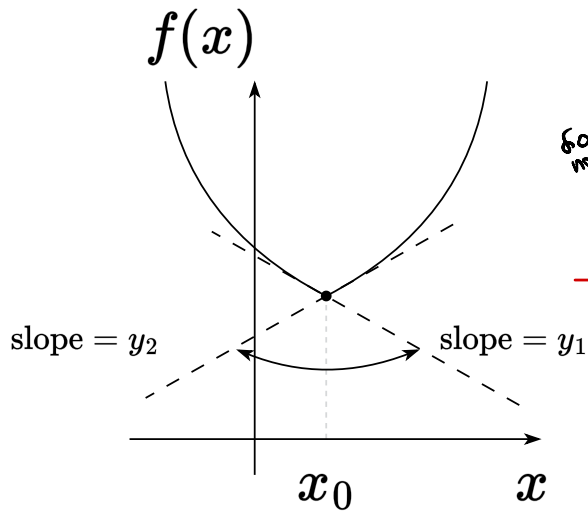
$f(x)$ - наклон

координата

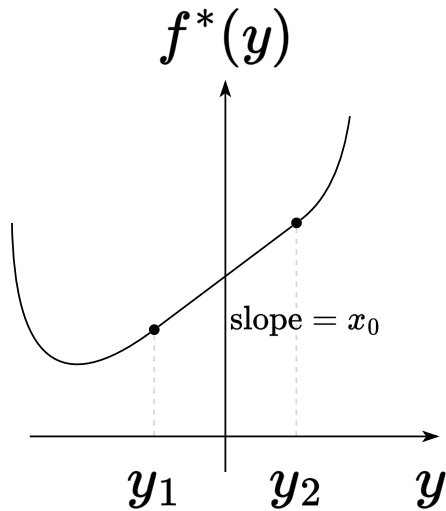
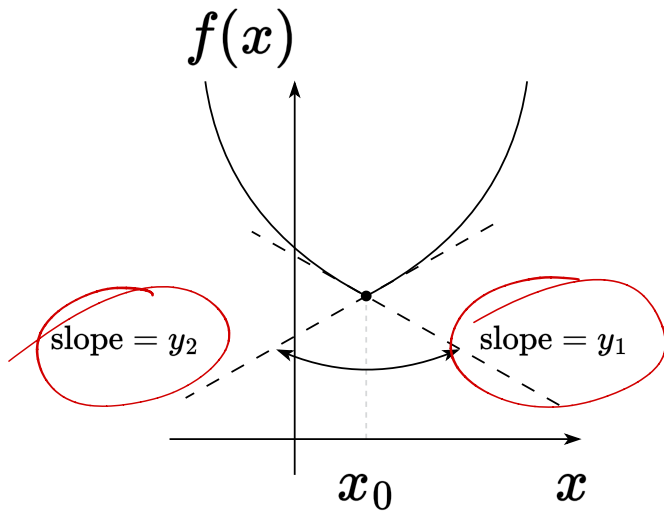
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- Conjugates appear frequently in dual programs, since

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$$\min -g(x) = -\max g(x)$$

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

$$x \in \partial f^*(y) \Leftrightarrow y \in \partial f(x) \Leftrightarrow x \in \arg \min_z [f(z) - y^T z]$$

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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)

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

координата
наклон
соед.
коэф.
соед.
наклон
вероят.

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

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

def.

Thus $x \in \partial f^*(y)$.

Teop.
DyS.-
Munrolet

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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 $f^{**} = f$.

ДОКАЗАНО :
если
то
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нужно $f = g^*$
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 $x \in \partial g^{**}(y)$
 $g^{**} = g$
 $x \in \partial g(y)$

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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 ascent

Dual (sub)gradient method

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

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

Consider the problem:

$$\min_x f(x) \quad \text{subject to} \quad Ax = b$$

$$f: \mathbb{R}^n \rightarrow \mathbb{R}$$

$$f_1 = Ax - b = 0$$

$$1) L(x, \lambda) = f(x) + \lambda^T (Ax - b)$$

$$\begin{aligned} 2) \text{ Dual function } g(\lambda) &= \inf_{x \in \mathcal{D}} L(x, \lambda) = \\ &= \inf_{x \in \mathbb{R}^n} [f(x) + \lambda^T (Ax - b)] = \inf_{x \in \mathbb{R}^n} [f(x) + (A^T \lambda)^T x - b^T \lambda] = \\ &= \inf_{x \in \mathbb{R}^n} [f(x) - (-A^T \lambda)^T x] - b^T \lambda = -f^*(-A^T \lambda) - b^T \lambda \\ &\quad \downarrow \\ &\quad \text{max}_{\lambda} \end{aligned}$$

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$$\partial g(u) = A \partial f^*(-A^T u) - b$$

субградиент

$$u = \nabla$$

конъюгата :
дугам релшай

$$u_{k+1} = u_k + \alpha \cdot G$$

$$G \in \partial g(u_k)$$

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$x \in \partial f^*(-A^T u)$

Therefore, using what we know about conjugates

$$\partial g(u) = Ax - b$$

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Dual ascent method for maximizing dual objective:

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

i

$$x_k \in \arg \min_x [f(x) + (u_{k-1})^T Ax]$$

$$u_k = u_{k-1} + \alpha_k (Ax_k - b)$$

шаг
градиентного
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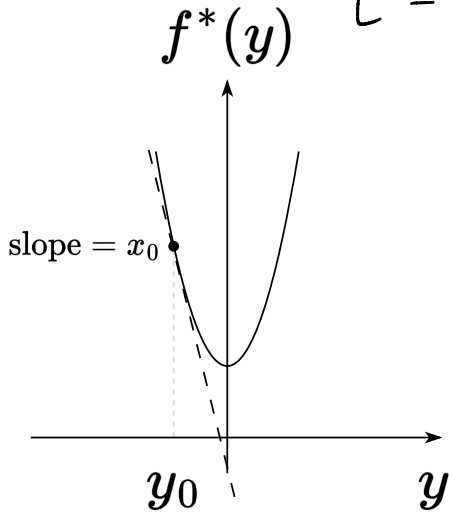
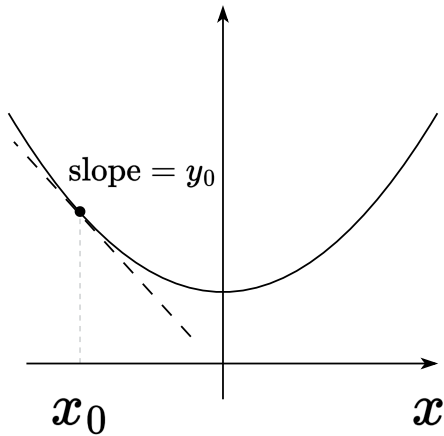
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- Step sizes α_k , $k = 1, 2, 3, \dots$, are chosen in standard ways.
- Proximal gradients and acceleration can be applied as they would usually.

Slopes of f and f^*

μ - MAPO
 $f(x)$ L-MAPO

μ^* BEAUKO
 L^* - BEAUKO

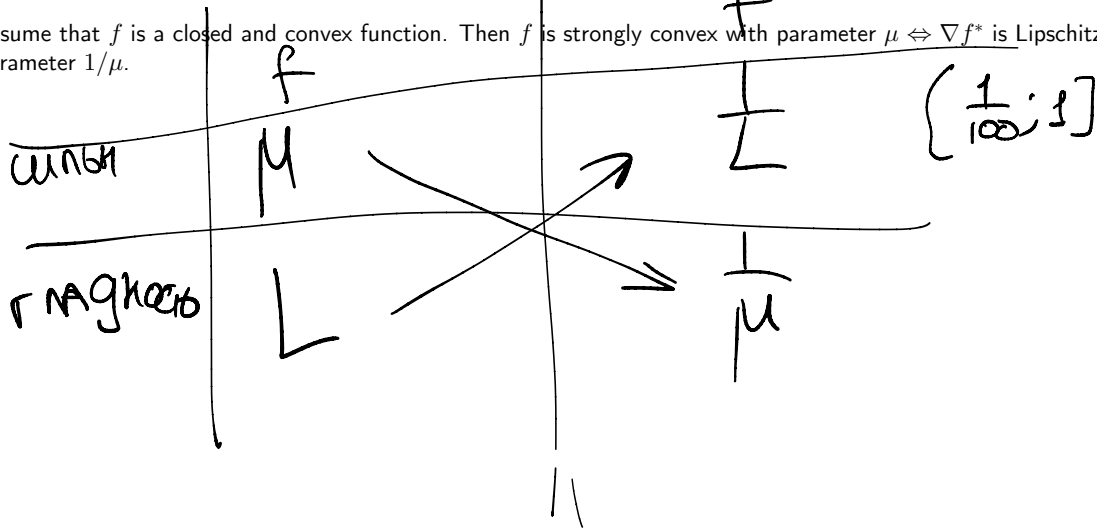


Slopes of f and f^*

$[1; \infty]$

f^*

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Hence, defining $x_u = \nabla f^*(u)$ and $x_v = \nabla f^*(v)$,

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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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Minimizing each side over z , and rearranging, gives

$$\frac{1}{2L}\|\nabla g(x) - \nabla g(y)\|^2 \leq g(y) - g(x) + \nabla g(x)^T(x - y)$$

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Exchanging roles of x , y , and adding together, gives

$$\frac{1}{L}\|\nabla g(x) - \nabla g(y)\|^2 \leq (\nabla g(x) - \nabla g(y))^T(x - y)$$

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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: (This 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).)

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

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- If f is strongly convex with parameter μ and ∇f is Lipschitz with parameter L , then dual gradient ascent with step sizes $\alpha_k = \frac{2}{\frac{1}{\mu} + \frac{1}{L}}$ converges at linear rate $O(\log(\frac{1}{\epsilon}))$.

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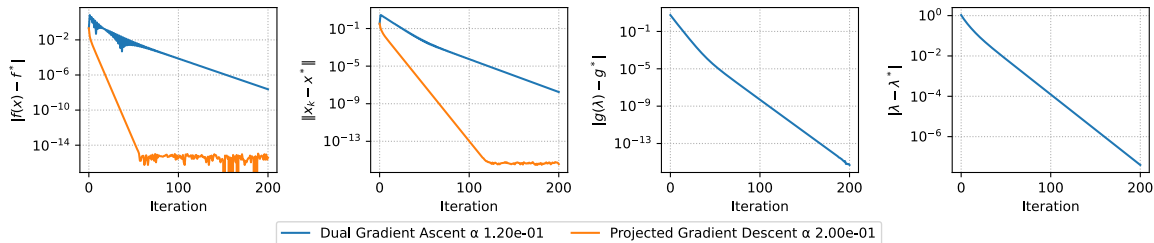
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- Note that this describes convergence in the dual. Convergence in the primal requires more assumptions

Example: equality constrained quadratic minimization.

$$f(x) = \frac{1}{2}x^T A x - b^T x \rightarrow \min_{x \in \mathbb{R}^n} \quad \text{subject to} \quad Cx = d, \quad A \in \mathbb{S}_+^n, C \in \mathbb{R}^{m \times n}, m < n.$$

Quadratic constrained optimization, $n=10, m=5, \mu=1, L=10$.

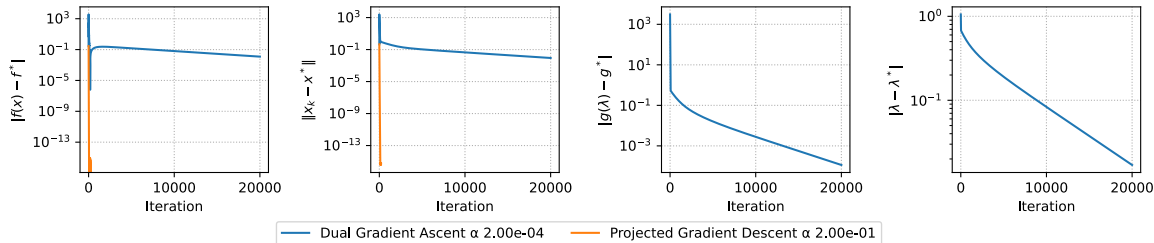


We need to find a minimum of a quadratic function in some linear subspace, defined by the solution of linear equation $Cx = d$. This is a conditional optimization problem, we start from strongly convex setting.

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Quadratic constrained optimization. $n=10$, $m=5$, $\mu=0.001$, $L=10$.



Situation is getting worse as soon as we loose strong convexity, the dual convergence will still be linear, but the rate is very low.

Dual decomposition

Consider

$$\min_x \sum_{i=1}^B f_i(x_i) \quad \text{subject to} \quad Ax = b$$

Dual decomposition

✓ npmlkas
3e90709

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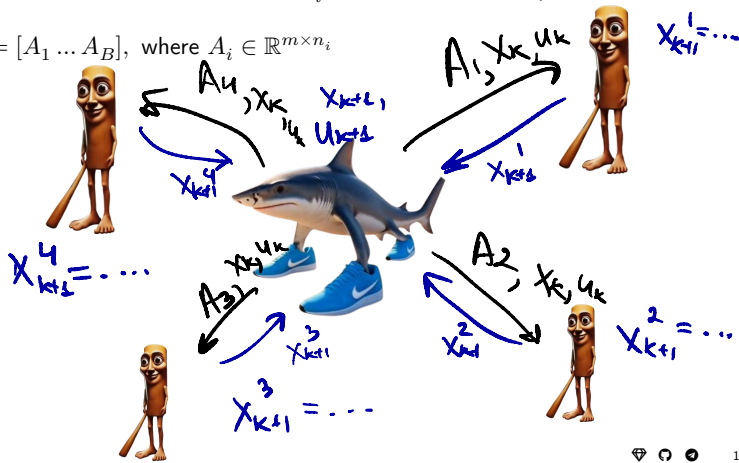
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gb. rp. noqre: au

$$x_{k+1} = \dots$$

$$u_{k+1} = u_k + \alpha \cdot G$$



Dual decomposition

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$$u^k = u^{k-1} + \alpha_k \left(\sum_{i=1}^B A_i x_i^k - b \right)$$

Can think of these steps as:

- **Broadcast:** Send u to each of the B processors, each optimizes in parallel to find x_i .
- **Gather:** Collect $A_i x_i$ from each processor, update the global dual variable u .

Inequality constraints

Consider the optimization problem:

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- The dual update step:

$$u^k = \left(u^{k-1} + \alpha_k \left(\sum_{i=1}^B A_i x_i^k - b \right) \right)_+$$

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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- **Never let prices get negative;** hence the use of the positive part notation $(\cdot)_+$.

Augmented Lagrangian method

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:

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

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

Since x_k minimizes the function:

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over x , we have the stationarity condition:

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

(Handwritten red arrow from u_k to $u_{k-1} + \rho(Ax_k - b)$)

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This represents the stationarity condition for the original primal problem; under mild conditions, $Ax_k - b \rightarrow 0$ as $k \rightarrow \infty$, so the KKT conditions are satisfied in the limit and x_k, u_k converge to the solutions.

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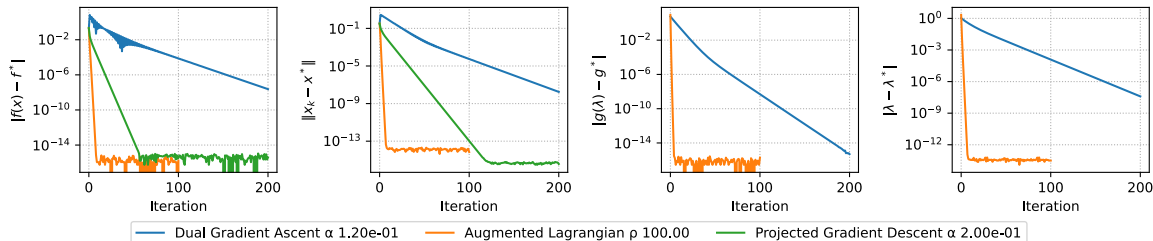
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- **Advantage:** The augmented Lagrangian gives better convergence.
- **Disadvantage:** We lose decomposability! (Separability is ruined)

Example: equality constrained quadratic minimization.

$$f(x) = \frac{1}{2}x^T Ax - b^T x \rightarrow \min_{x \in \mathbb{R}^n} \quad \text{subject to} \quad Cx = d, \quad A \in \mathbb{S}_+^n, C \in \mathbb{R}^{m \times n}, m < n.$$

Quadratic constrained optimization. $n=10, m=5, \mu=1, L=10$.

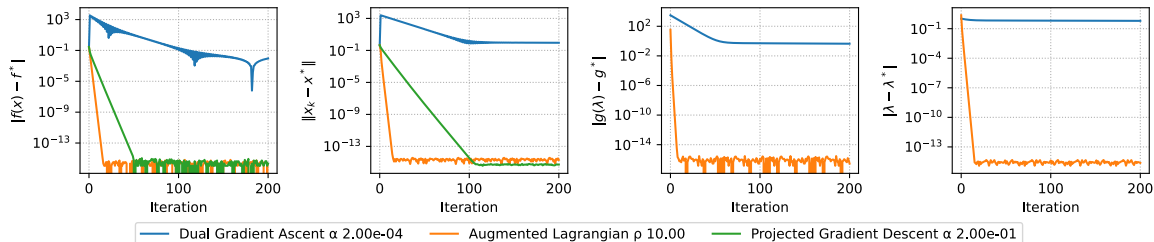


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Introduction to ADMM

Alternating Direction Method of Multipliers (ADMM)

$$f(x) + g(y)$$

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

Minimize the function:

$$\begin{aligned} \min_{x,z} \quad & f(x) + g(z) \\ \text{s.t.} \quad & Ax + Bz = c \end{aligned}$$

$$x = z$$

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$$I \cdot x - I z = 0$$

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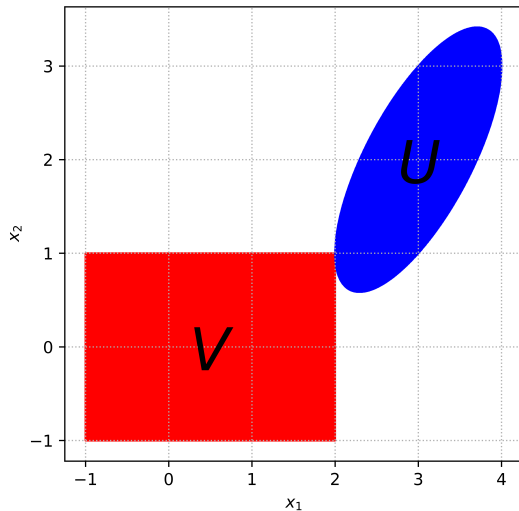
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Note: The usual method of multipliers would replace the first two steps by a joint minimization:

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

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

Boyd, ADMM