

# ADMM

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Optimization methods. MIPT

# 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.

Consider the problem:

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

## **i** Dual gradient ascent

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

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

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- **Bad:** require stringent assumptions (strong convexity of  $f$ ) to ensure convergence

# Augmented Lagrangian method aka method of multipliers

Augmented Lagrangian method transforms the primal problem to:

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- **Bad:** lose decomposability

# 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:

$$\min_{x,z} f(x) + g(z)$$

$$\text{s.t. } Ax + Bz = c$$



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

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

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

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

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

# Convergence

Assume (very little!)

- $f, g$  convex, closed, proper

then ADMM converges:

**i** If the functions  $f$  and  $g$  are convex and computationally friendly for  $\arg \min$ , then ADMM has the following convergence bound for any  $x \in \mathbb{R}^{d_x}$ ,  $y \in \mathbb{R}^{d_y}$ ,  $\lambda \in \mathbb{R}^n$ :

$$L_0 \left( \frac{1}{k} \sum_{i=1}^k x_i, \frac{1}{k} \sum_{i=1}^k y_i, \lambda \right) - L_0(x, y, \frac{1}{k} \sum_{i=1}^k \lambda_k) \leq \frac{1}{2k} \|z_0 - z\|_P^2,$$

where  $L_0$  is the Lagrangian without augmentation,  $P$  and the initial value of  $z^0$  are defined as :

$$P = \begin{pmatrix} \rho A^T A & 0 & -A^T \\ 0 & 0 & 0 \\ -A & 0 & \frac{1}{\rho} I \end{pmatrix} \quad z^0 = \begin{pmatrix} x^0 \\ y^0 \\ \lambda^0 \end{pmatrix}.$$



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- objective approaches optimal value:  $f(x_k) + g(z_k) \rightarrow p^*$

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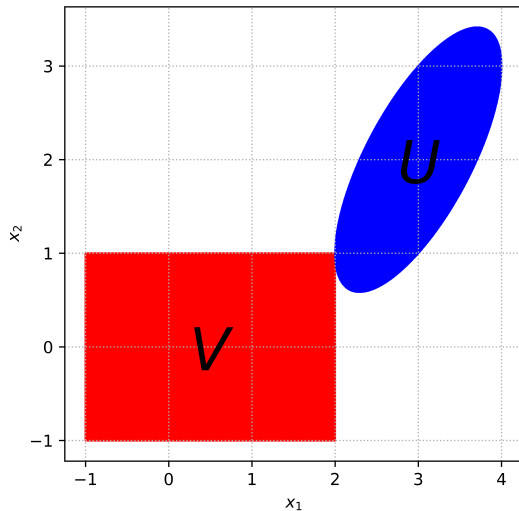
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Example:

## 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:

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

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

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

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- It is implemented in many solvers and is often used as a default method.
- The non-standard formulation of the problem itself, for which ADMM is invented, turns out to include many important special cases. “Unusual” variable  $y$  often plays the role of an auxiliary variable.
- Here the penalty is an additional modification to stabilize and accelerate convergence. It is not necessary to make  $\rho$  very large.

# Sources

- Alternating Direction Method of Multipliers by S.Boyd

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- Alternating Direction Method of Multipliers by S.Boyd
- Ryan Tibshirani. ConvAlternating Direction Method of Multipliers by S.Boydex Optimization 10-725