

$$w = u/\rho, \text{ i.e. } \rho w = u$$

$$\begin{aligned} & u^T Ax + \frac{\rho}{2} \|Ax - b\|_2^2 \\ & \frac{\rho}{2} \|Ax - b + w\|_2^2 \end{aligned} \left. \vphantom{\begin{aligned} & u^T Ax + \frac{\rho}{2} \|Ax - b\|_2^2 \\ & \frac{\rho}{2} \|Ax - b + w\|_2^2 \end{aligned}} \right\} \text{same terms involving } x$$

$$= \frac{\rho}{2} \|Ax - b\|_2^2 + \frac{\rho}{2} \|w\|_2^2$$

$$+ \underbrace{\rho w^T (Ax - b)}_{= u^T Ax}$$

$$u^+ = u + \rho(Ax - b)$$

$$w^+ = w + Ax - b.$$

$$x_1^+ = \underset{x_1}{\operatorname{argmin}} f_1(x_1) + \frac{\rho}{2} \|A_1 x_1 + A_2 x_2 - b + w\|_2^2$$

$$x_2^+ = \underset{x_2}{\operatorname{argmin}} f_2(x_2) + \frac{\rho}{2} \|A_1 x_1^+ + A_2 x_2 - b + w\|_2^2$$

$$w^+ = w + Ax - b.$$

$$\min \frac{1}{2} \|y - X\beta\|_2^2 + \lambda \|\alpha\|_1 \quad \text{s.t. } \alpha = D\beta$$

$$\begin{aligned} \beta^+ &= \underset{\beta}{\operatorname{argmin}} \frac{1}{2} \|y - X\beta\|_2^2 + \frac{\rho}{2} \|D\beta - \alpha + w\|_2^2 \\ &= \underset{\beta}{\operatorname{argmin}} \frac{1}{2} \|y - X\beta\|_2^2 + \frac{1}{2} \|(\alpha - w)\sqrt{\rho} - \sqrt{\rho} D\beta\|_2^2 \\ &= (X^T X + \rho D^T D)^{-1} (X^T y + \rho D^T (\alpha - w)) \end{aligned}$$

$$\alpha^+ = \underset{\alpha}{\operatorname{argmin}} \lambda \|\alpha\|_1 + \frac{\rho}{2} \|D\beta^+ - \alpha + w\|_2^2$$

$$= \underset{\alpha}{\operatorname{argmin}} \frac{1}{2} \|D\beta^+ - \alpha\|_2^2 + \frac{\lambda}{\rho} \|\alpha\|_1$$

$$= S_{\frac{\lambda}{\rho}}(D\beta^+ + w)$$

$$w^+ = w + D\beta^+ - \alpha^+$$

Implementation tip: factorize $X^T X + \rho D^T D$ once (eg. Cholesky), then use it for all β -updates.

$$\min \sum f_i(x_i) \quad \text{st.} \quad x_i = x, \quad i=1 \dots B \quad \begin{pmatrix} x_1 \\ \vdots \\ x_B \end{pmatrix} - \begin{pmatrix} x \\ \vdots \\ x \end{pmatrix} = 0$$

$$\mathcal{L}(x_1, \dots, x_B, x) = \sum_{i=1}^B f_i(x_i) + \frac{\rho}{2} \sum_{i=1}^B \|x_i - x + w_i\|_2^2$$

$$\frac{\rho}{2} \left\| \begin{pmatrix} x_1 \\ \vdots \\ x_B \end{pmatrix} - \begin{pmatrix} x \\ \vdots \\ x \end{pmatrix} + \begin{pmatrix} w_1 \\ \vdots \\ w_B \end{pmatrix} \right\|_2^2$$

$$\min \sum_{i=1}^B f_i(a_i^T x_i + b_i) + g(x)$$

$$\text{st.} \quad x_i = x$$

$$f(y) - f(x) = g(y) - g(x) + \sum (h_i(y_i) - h_i(x_i))$$

$$\geq \nabla g(x)^T (y - x) + \sum h_i(y_i) - h_i(x_i)$$

$$= \sum \left(\underbrace{\frac{\partial g}{\partial x_i}(x) (y_i - x_i)}_{\geq 0} + h_i(y_i) - h_i(x_i) \right)$$

Property : $g(x) + \sum h_i(x_i)$

look variable x_i alone, minimized at x

$\mathcal{L}_i(x_i) = g(x) + h_i(x_i)$ thought of only in terms of x_i

hence $0 \in \partial \mathcal{L}_i(x_i)$

$$0 \in \frac{\partial g}{\partial x_i} + \partial h_i(x_i)$$

$$-\frac{\partial g}{\partial x_i} \in \partial h_i(x_i)$$

$$\text{hence } h_i(y_i) \geq h_i(x_i) - \frac{\partial g}{\partial x_i} (y_i - x_i)$$