

$$f = f_1 + f_2$$

$$< \leq$$

$$\begin{aligned} &< \\ f(\alpha x + (1-\alpha)x) &= f_1(\cdot) + f_2(\cdot) \\ \equiv \end{aligned}$$

$$\text{sg. } \beta^+ = \beta - t \cdot g$$

$$g \in \partial f(\beta)$$

$O(1/\sqrt{k})$... any nonsmooth first-order method i.e.,

$$\beta^{(k)} \in \beta^{(0)} + \text{span}\{g^{(0)}, \dots, g^{(k-1)}\} \leftarrow$$

can't do better than $1/\sqrt{k}$

g.g.d. $O(1/k)$

Backtracking for g.d.

$$\text{while: } f(x - t \nabla f(x)) > f(x) - \frac{1}{2} t \cdot \|\nabla f(x)\|_2^2$$

update $t = \beta t$

Y_{ij} observed entries

$$\min_B \frac{1}{2} \sum_{i,j \in \Omega} (Y_{ij} - B_{ij})^2 + \lambda \|B\|_*$$

$$\|B\|_* = \sum_{i=1}^r \sigma_i(B)$$

cvx. surrogate
for $\text{rank}(B)$

$$B = U \Sigma V^T \quad \Sigma = \begin{pmatrix} \sigma_1 & & & \\ & \ddots & & \\ & & \sigma_r & \\ & & & 0 \dots 0 \end{pmatrix}$$

$\|B\|_*$ is to $\text{rank}(B)$

as

$\|B\|_1$ is to $\|B\|_0 \leftarrow \# \text{ of nzs in } B$

$$\min_B \frac{1}{2} \|P_\Omega(Y) - P_\Omega(B)\|_F^2 + \lambda \|B\|_*$$

$$[P_\Omega(B)]_{ij} = \begin{cases} B_{ij} & \text{if } i,j \in \Omega \\ 0 & \text{else} \end{cases}$$

$$\nabla g(B) = -(P_\Omega(Y) - P_\Omega(B))$$

Prox function:

$$\text{prox}(B) = \underset{Z}{\text{argmin}} \frac{1}{2} \|B - Z\|_F^2 + \lambda \|Z\|_*$$

let $B = U \Sigma V^T$, SVD of B
then

$$\text{prox}_t(B) = S_{\lambda t}(B) \quad \text{matrix-thresholding} \\ = \underline{U \Sigma_{\lambda t} V^T}$$

where $(\Sigma_{\lambda t})_{ii} = \max\{\Sigma_{ii} - \lambda t, 0\}$

egd.

$$B^+ = S_{\lambda t} \left(B + t(P_{\Omega}(Y) - P_{\Omega}(B)) \right)$$

$t=1$ gives convergent algorithm: because

∇g is 1-Lipschitz

$$\textcircled{B^+} = S_{\lambda t} \left(P_{\Omega}(Y) + B - P_{\Omega}(B) \right) \\ = S_{\lambda t} \left(P_{\Omega}(Y) + P_{\Omega^c}(B) \right)$$

Soft-impute

$$\text{prox}_t(x) = \underset{z}{\text{argmin}} \frac{1}{2t} \|x - z\|_2^2 + I_C(z) \\ = \underset{z \in C}{\text{argmin}} \|x - z\|_2 \\ = P_C(x)$$