

1 Optimization Problem

Problem is

$$\min_{x \in X} f_0(x), \quad (1)$$

$$f_i(x) \leq 0, \quad (2)$$

for $i = 1, \dots, m$, where $X \subseteq \mathbb{R}^n$ is a box:

$$\{x \mid x_j^{\min} \leq x_j \leq x_j^{\max}\}. \quad (3)$$

2 Approximate Problem

Suppose k th iterate is $x^{(k)}$. Then, for $i = 0, \dots, m$, replace $f_i(x)$ with

$$g_i(x) = \nabla f_i(x_0) \cdot (x - x^{(k)}) + \frac{\rho_i^2}{2} \left| \frac{x - x^{(k)}}{\sigma} \right|^2. \quad (4)$$

And make a trust region T (actually its $T \cup X$)

$$T = \{x \mid |x_j - x_j^{(k)}| \leq \sigma_j\}. \quad (5)$$

So that the new problem is

$$\min_{x \in T} g_0(x), \quad (6)$$

$$g_i(x) \leq 0. \quad (7)$$

3 Overall Scheme

For the k th iteration:

1. Solve approximate problem to find candidate $x^{(k+1)}$
2. Check conservative: $g_i(x^{(k+1)}) < f_i(x^{(k+1)})$.
 - If no, throw away candidate, double ρ_i for each non-conservative g_i , and solve approximate problem again.
3. Halve ρ (take bigger steps) and update σ (decrease σ_i if x_i oscillating, increase if monotonic i.e. heading somewhere else).

4 Solving approximate problem

4.1 Evaluating dual function

Lagrangian relaxation,

$$L(x, y) = g_0(x) + \sum_{i=1}^m y_i g_i(x) \quad (8)$$

$$= \left(\nabla f_0(x_0) + \sum_{i=1}^m y_i \nabla f_i(x_0) \right) \cdot (x - x^{(k)}) + \frac{1}{2} \left(\rho_0 + \sum_{i=1}^m y_i \rho_i \right) \left| \frac{x - x^{(k)}}{\sigma} \right|^2 \quad (9)$$

$$= \sum_{j=1}^n \left(\left(\nabla f_0(x_0)_j + \sum_{i=1}^m y_i (\nabla f_i(x_0))_j \right) (x_j - x_j^{(k)}) + \frac{1}{2\sigma_j^2} \left(\rho_0 + \sum_{i=1}^m y_i \rho_i \right) (x_j - x_j^{(k)})^2 \right). \quad (10)$$

Define dual function,

$$g(y) = \min_{x \in T} L(x, y) \quad (11)$$

$$= \sum_{j=1}^n g_j(y), \quad (12)$$

where

$$g_j(y) = \min_{|\delta_j| \leq \sigma_j} \left(\left(\nabla f_0(x_0)_j + \sum_{i=1}^m y_i \nabla f_i(x_0)_j \right) \delta_j + \frac{1}{2\sigma_j} \left(\rho_0 + \sum_{i=1}^m y_i \rho_i \right) \delta_j^2 \right). \quad (13)$$

To evaluate, analytically minimize quadratic in $\delta_j = x_j - x_j^{(k)}$, snapping to bounds. Define

$$a_j = \frac{1}{2\sigma_j^2} \left(\rho_0 + \sum_{i=1}^m y_i \rho_i \right) = \frac{1}{2\sigma_j^2} u, \quad (14)$$

$$b_j = \nabla f_0(x_0)_j + \sum_{i=1}^m y_i \nabla f_i(x_0)_j = v_j, \quad (15)$$

so that

$$g_j(y) = \min_{|\delta_j| \leq \sigma_j} (a_j \delta_j^2 + b_j \delta_j) = \min_{|\delta_j| \leq \sigma_j} \left(\frac{u}{2\sigma_j^2} \delta_j^2 + v_j \delta_j \right). \quad (16)$$

Note that,

$$\frac{\partial a_j}{\partial y_i} = \frac{\rho_i}{2\sigma_j^2}, \quad (17)$$

$$\frac{\partial b_j}{\partial y_i} = \nabla f_i(x_0)_j. \quad (18)$$

If we snap to bounds, $g_j(y)$ should have gradient 0 (will have a kink, but oh well?). If we don't snap to bounds,

$$g_j(y) = \frac{b_j^2}{4a_j}, \quad (19)$$

$$\frac{\partial g_j}{\partial y_i} = \frac{b_j}{2a_j} \frac{\partial b_j}{\partial y_i} - \frac{b_j^2}{4a_j^2} \frac{\partial a_j}{\partial y_i} \quad (20)$$

$$= \frac{b_j}{2a_j} \nabla f_i(x_0)_j - \frac{b_j^2}{4a_j^2} \frac{\rho_i}{2\sigma_j^2} \quad (21)$$

$$= \delta_j \nabla f_i(x_0)_j - g_j(y) \frac{\rho_i}{2\sigma_j^2}. \quad (22)$$

And thus,

$$g(y) = -\frac{1}{4} \sum_{j=1}^n \frac{b_j^2}{a_j}, \quad (23)$$

$$\frac{\partial g}{\partial y_i} = \frac{1}{2} \sum_{j=1}^n \frac{b_j}{a_j} \nabla f_i(x_0)_j - \frac{\rho_i}{8} \sum_{j=1}^n \frac{b_j^2}{a_j^2 \sigma_j^2}. \quad (24)$$

We can first compute a_j and b_j for all j by Equation (14) and Equation (15), exploiting sparsity of the Jacobian column $\nabla f(x_0)_j$. We can then compute $g(y)$ directly, and $\frac{\partial g}{\partial y_i}$ for each i by exploiting sparsity of the Jacobian row $\nabla f_i(x_0)$.

4.2 Maximizing dual function

The dual problem is,

$$\max_{y \geq 0} g(y). \quad (25)$$

We can provide g and its gradient function recursively to CCSA, which will solve it for us.

5 Main Goals

- Support sparse Jacobians
- Support affine constraints
 - Does paper handle these? (First, find where paper handles box constraints.)
 - Maybe think of this as a more complicated X , rather than a simple f_i .