Optimization: Summary

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\left. \begin{array}{l} \text{Optimization problem} \\ \text{Set of algorithms} \end{array} \right\} \rightarrow \text{most suited algorithm?}
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- Simplification of objective function and/or constraints
- ② Determination of most efficient available algorithm
- Oetermination of stopping criterion

Simplification of objective function or constraint

No systematic procedure.

Examples:

•
$$\min_{x \in \mathbb{R}^3} \exp(x_1^2 + x_1 x_2 + 2x_2^2 + x_3^2)$$

s.t. $(x_1 + x_2 + x_3)^2 \le 9$
 $\arctan(x_1 - x_2 x_3) \geqslant \frac{\pi}{4}$

can be recast as:

$$\min_{x \in \mathbb{R}^3} x_1^2 + x_1 x_2 + 2x_2^2 + x_3^2$$
s.t. $-3 \le x_1 + x_2 + x_3 \le 3$

 $x_1 - x_2 x_3 \geqslant 1$

Simplification of objective function/constraint (continued)

$$\bullet \min_{x} ||x||_1 = \min_{x} \sum_{i} |x_i| \quad \text{s.t. } Ax \leq b$$

can be recast as LP:

$$\min_{\alpha} \sum_{i} \alpha_{i} \quad \text{s.t.} \quad Ax \leq b$$

$$x \leq \alpha$$

$$-x \leq \alpha$$

• $\min_{x} ||x||_{\infty} = \min_{x} \max_{i} |x_{i}|$ s.t. $Ax \leq b$

can be recast as LP:

Also valid with positive weights added (see lecture notes)

Proof

(1)
$$\min_{x} \sum_{i} |x_{i}| = \min_{x} F_{1}(x) \quad \leftrightarrow \quad \min_{\alpha} \sum_{i} \alpha_{i} = \min_{\alpha} F_{2}(\alpha)$$
s.t. $Ax \leq b$ s.t. $Ax \leq b$
$$x, -x \leq \alpha$$

- First prove: feasible solution of $(1) \leftrightarrow$ feasible solution of (2)
- x^* : optimal solution of (1), define $\alpha^* = |x^*|$
- $\tilde{x}, \tilde{\alpha}$: optimal solution of (2)

$$\left\{ egin{array}{l} ilde{x} \leqslant ilde{lpha} \ - ilde{x} \leqslant ilde{lpha} \end{array} \right\} \;
ightarrow \; \left| ilde{x}
ight| \leqslant ilde{lpha} \;
ight|$$

Suppose $\tilde{\alpha}_j > |\tilde{x}_j|$ for some j

Set $\tilde{\alpha}_j = |\tilde{x}_j|$

 \Rightarrow still feasible, but lower value of $F_2 \Rightarrow$ impossible

$$\Rightarrow \tilde{lpha}_j = |\tilde{x}_j|$$
 for all j , so $\tilde{lpha} = |\tilde{x}|$

Proof (continued)

(1)
$$\min_{x} \sum_{i} |x_{i}| = \min_{x} F_{1}(x) \quad \leftrightarrow \quad \min_{\alpha} \sum_{i} \alpha_{i} = \min_{x} F_{2}(\alpha)$$
s.t. $Ax \leq b$ s.t. $Ax \leq b$

$$x, -x \leq \alpha$$

- x^*, α^* is feasible solution of problem (2) $\Rightarrow F_1(\tilde{x}) = F_2(\tilde{\alpha}) \leqslant F_2(\alpha^*) = F_1(x^*)$ $\Rightarrow \tilde{x}$ is also optimal solution of (1)
- \tilde{x} is feasible solution of problem (1) $\Rightarrow F_2(\alpha^*) = F_1(x^*) \leqslant F_1(\tilde{x}) = F_2(\tilde{\alpha})$ $\Rightarrow x^*, \alpha^*$ is also optimal solution of (2)

Examples

s.t.
$$|x_1 + x_2 - 2x_3 + x_4 + 9| \le 2$$

$$\min_{x} |x_1| + |x_2| + |x_3|$$

s.t.
$$x_1 + x_2 + x_3 \ge 3$$

 $x_1 - 2x_2 + 4x_3 \ge 1$

 \rightarrow is LP / can be recast as LP?

Selection of algorithm

- Linear objective + linear constraints: simplex (or interior-point, if >1000 variables or constraints)
- (Convex) quadratic objective + linear constraints: modified simplex (or interior-point)
- Convex objective + convex constraints: cutting-plane, ellipsoid, or interior-point
- Multiple local minima: multi-start local optimization, multi-run simulated annealing, or multi-run genetic algorithm
- Nonlinear non-convex problems
 - → use gradient and Hessian if possible! analytic/numerical computation

Selection of algorithm

- Nonlinear non-convex, unconstrained:
 - Levenberg-Marquardt or Newton
 - quasi-Newton algorithm
 - steepest descent
 - Powell's perpendicular method (or Nelder-Mead)
- Nonlinear non-convex constrained:
 - equality constraints:elimination, Lagrange method
 - ② linear inequality constraints: gradient projection or SQP
 - onlinear inequality constraints:
 SQP, or penalty or barrier function

Stopping criterion

- Simplex & modified simplex: finite number of steps
- Convex optimization algorithms:

$$|f(x^*) - f(x_k)| \le \varepsilon_f, \quad g(x_k) \le \varepsilon_g$$

 $||x^* - x_k||_2 \le \varepsilon_x$ (for ellipsoid)

- Unconstrained nonlinear optimization: $\|\nabla f(x_k)\|_2 \leqslant \varepsilon_{\nabla}$
- Constrained nonlinear optimization:

$$\| \nabla f(x_k) + \nabla g(x_k) \mu + \nabla h(x_k) \lambda \|_2 \leqslant \varepsilon_{\mathsf{KT},1}$$

$$| \mu^T g(x_k) | \leqslant \varepsilon_{\mathsf{KT},2}$$

$$\mu \geqslant -\varepsilon_{\mathsf{KT},3}$$

$$\| h(x_k) \|_2 \leqslant \varepsilon_{\mathsf{KT},4}$$

$$g(x_k) \leqslant \varepsilon_{\mathsf{KT},5}$$

Stopping criterion (continued)

 Simulated annealing, genetic algorithm, ...: maximum number of iterations

In general, it is recommended to always include this (provided maximum number is taken large enough)

• *Last* resort:

$$||x_{k+1}-x_k||_2 \leqslant \varepsilon_x, \quad |f(x_{k+1})-f(x_k)| \leqslant \varepsilon_f$$

Combinations

Examples

•
$$\max_{x \in \mathbb{R}^3} 4x_1 + 5x_2 - 6x_3$$

s.t.
$$\log |2x_1 + 7x_2 + 5x_3| \le 1$$

 $x_1, x_2, x_3 \ge 0.01$

•
$$\min_{x \in \mathbb{R}^3} \max \left(\cosh(x_1 + x_2 + x_3), (5x_1 - 6x_2 + 7x_3 + 6)^2 \right)$$

s.t.
$$||x||_2 \le 10$$

Remark:
$$\cosh x = \frac{e^x + e^{-x}}{2}$$

•
$$\max_{x \in \mathbb{R}^2} e^{-x_1^2 - x_2^2} (x_1^2 + x_1 x_2 + 6x_1)$$

$$\max_{x \in \mathbb{R}^3} \ \frac{x_1 x_2 x_3}{1 + x_1^6 + x_2^4 + x_3^2}$$

s.t.
$$x_1 + x_2 + x_3 = 1$$

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