

**Sequential linear-quadratic programming (SLQP)** is an [iterative method](#) for [nonlinear optimization problems](#) where [objective function](#) and constraints are twice [continuously differentiable](#). Similarly to [sequential quadratic programming](#) (SQP), SLQP proceeds by solving a sequence of optimization subproblems. The difference between the two approaches is that:

- in SQP, each subproblem is a [quadratic program](#), with a quadratic model of the objective subject to a linearization of the constraints
- in SLQP, two subproblems are solved at each step: a [linear program](#) (LP) used to determine an [active set](#), followed by an equality-constrained quadratic program (EQP) used to compute the total step

This decomposition makes SLQP suitable to large-scale optimization problems, for which efficient LP and EQP solvers are available, these problems being easier to scale than full-fledge quadratic programs.

## Algorithm basics

Consider a [nonlinear programming](#) problem of the form:

$$\begin{aligned} \min_x \quad & f(x) \\ \text{s.t.} \quad & b(x) \geq 0 \\ & c(x) = 0. \end{aligned}$$

The Lagrangian for this problem is<sup>[1]</sup>

$$\mathcal{L}(x, \lambda, \sigma) = f(x) - \lambda^T b(x) - \sigma^T c(x),$$

where  $\lambda$  and  $\sigma$  are [Lagrange multipliers](#).

### LP phase

In the LP phase of SLQP, the following linear program is solved:

$$\begin{aligned} \min_d \quad & f(x_k) + \nabla f(x_k)^T d \\ \text{s.t.} \quad & b(x_k) + \nabla b(x_k)^T d \geq 0 \\ & c(x_k) + \nabla c(x_k)^T d = 0. \end{aligned}$$

Let  $\mathcal{A}_k$  denote the *active set* at the optimum  $d_{\text{LP}}^*$  of this problem, that is to say, the set of constraints that are equal to zero at  $d_{\text{LP}}^*$ . Denote by  $b_{\mathcal{A}_k}$  and  $c_{\mathcal{A}_k}$  the sub-vectors of  $b$  and  $c$  corresponding to elements of  $\mathcal{A}_k$ .

## EQP phase

In the EQP phase of SLQP, the search direction  $\mathbf{d}_k$  of the step is obtained by solving the following quadratic program:

$$\begin{aligned} \min_{\mathbf{d}} \quad & f(\mathbf{x}_k) + \nabla f(\mathbf{x}_k)^T \mathbf{d} + \frac{1}{2} \mathbf{d}^T \nabla_{xx}^2 \mathcal{L}(\mathbf{x}_k, \lambda_k, \sigma_k) \mathbf{d} \\ \text{s. t.} \quad & b_{\mathcal{A}_k}(\mathbf{x}_k) + \nabla b_{\mathcal{A}_k}(\mathbf{x}_k)^T \mathbf{d} = 0 \\ & c_{\mathcal{A}_k}(\mathbf{x}_k) + \nabla c_{\mathcal{A}_k}(\mathbf{x}_k)^T \mathbf{d} = 0. \end{aligned}$$

Note that the term  $f(\mathbf{x}_k)$  in the objective functions above may be left out for the minimization problems, since it is constant.

## See also

- [Newton's method](#)
- [Secant method](#)
- [Sequential linear programming](#)
- [Sequential quadratic programming](#)

## Notes

1. Jorge Nocedal and Stephen J. Wright (2006). *Numerical Optimization* . Springer. ISBN 0-387-30303-0.

## References

- Jorge Nocedal and Stephen J. Wright (2006). *Numerical Optimization* . Springer. ISBN 0-387-30303-0.

---

**Last edited 7 months ago** by Graeme Bartlett

---