A Very Short Survey of Solvers

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Review: Conic Programs

Most solvers work with the conic form of a problem:

$$\begin{array}{ll} \text{minimize} & c^T x\\ \text{subject to} & Fx + g \preceq_K 0\\ & Ax = b \end{array}$$

Modeling systems (e.g., Convex.jl) convert a problem to conic form by rewriting constraints f(x) ≤ t as conic inequalities

$$\begin{aligned} x^T P x + &\leq t \quad \Longleftrightarrow \| (P^{1/2} x, (t-1)/2) \|_2 \leq (t+1)/2 \\ \| X \|_2 \leq t \quad & \Longleftrightarrow \begin{bmatrix} tI & X \\ X^T & tI \end{bmatrix} \succeq 0 \end{aligned}$$

First-order methods: gradient descent and friends

• Gradient method with step size α_k (constant or from line search):

$$x^{(k+1)} = x^{(k)} - \alpha_k \nabla f(x^{(k)})$$

- Pros: inexpensive iterations
- Cons: often very slow convergence (can't get accurate solns); sensitive to scaling
- Extensions (proximal gradient, accelerated gradient) are faster

First-order algorithms

Decomposition methods implement these ideas.

Very popular method: Alternating Direction Method of Multipliers (ADMM)

- Advantages:
 - Works on huge problems; often can be parallelized/distributed
 - Often converges quickly to moderately accurate solution
- Disadvantages:
 - Very sensitive to problem scaling
 - Slow to get to high accuracy
- Examples: SCS, OSQP (QPs only), COSMO.j1

ADMM: split problem into easier problems

► Idea: min.
$$f(x) + g(x) \rightarrow \min f(x) + g(z)$$
 s.t. $x = z$

► Form the augmented Lagrangian (helps with smoothness & convergence)

$$L(x, z, \nu) = f(x) + g(z) + \nu^{T}(x - z) + (\rho/2) ||x - z||^{2}$$

► Iterate:

$$\begin{aligned} x^{(k+1)} &= \operatorname{argmin}_{x} L(x, z^{(k)}, \nu^{(k)}) \\ z^{(k+1)} &= \operatorname{argmin}_{z} L(x^{(k+1)}, z, \nu^{(k)}) \\ \nu^{(k+1)} &= \nu^{(k)} + (x^{(k+1)} - z^{(k+1)}) \end{aligned}$$

Decomposition and splitting methods

Second-order algorithms use Hessian information

- ▶ Use Hessian (or approximate Hessian) information to accelerate convergence
- Converge very quickly for unconstrained or linearly constrained smooth problems
- Common method: L-BFGS(-B) (approximates Hessian)
 - See Optim.jl and LBFGSB.jl
- ▶ Key parameter: line search (which controls the step size)

Second-order methods solve the optimality conditions

- In the unconstrained case, solve $\nabla f_0(x) = 0$.
- The Newton step Δx at current iterate x^(k) solves the system with ∇f₀ replaced by its first-order approximation around x^(k):

$$abla f_0(x^{(k)}) +
abla^2 f_0(x^{(k)}) \Delta x = 0.$$

Alternative interpretation: x + Δx minimizes the second order approximation to f₀ around x^(k):

$$\Delta x = \operatorname*{argmin}_{v} f_0(x^{(k)}) + \nabla f_0(x^{(k)})^T v + \frac{1}{2} v^T \nabla^2 f_0(x^{(k)}) v.$$

Second-oder algorithms

Interior point methods

Interior point methods deal with (smooth) conic programs by turning the inequality constraints into part of the objective function

min.
$$f_0(x) \rightarrow \min t f_0(x) - \sum_i \log(-f_i(x))$$

s.t. $f_i(x) \leq 0$

- ▶ Approximation improves as $t \to \infty$
- Different cones have different associated barrier functions
- Must start with feasible point
 - Enough to know a feasible point for each inequality individually
 - Primal-dual methods get around this & are more robust

Interior point methods

Interior point methods are very fast and accurate

- Often converge in <100 iterations (and good worst-case complexity)</p>
- Quadratic convergence to machine precision when close to the optimal (very different than first order methods!)
- Implementations: Hypatia.jl, ECOS, Mosek, Gurobi (QCQPs)
- ▶ Usually needed for poorly scaled problems (*e.g.*, many SDPs)

How to choose a solver?

- Choose an interior point method if you...
 - need a very accurate solution
 - have a poorly scaled problem
 - have a small to modest-sized problem
- Choose a first-order method if you...
 - have a very large problem (but if unconstrained, LBFGS works great)
 - don't need an accurate solution (common in machine learning)

https://jump.dev/JuMP.jl/stable/installation/#Supported-solvers

Conclusion