

Real-time convex optimization, with applications

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Convex optimization

- a convex optimization problem is of the form

$$\begin{aligned} & \text{minimize} && f(x) \\ & \text{subject to} && x \in \mathcal{C} \end{aligned}$$

where

- the cost function f is convex (graph of f curves upwards)
- the constraint set \mathcal{C} is convex (closed to averaging)
- includes linear and quadratic programming as special cases
- can solve convex optimization problems **extremely well**
 - on a generic processor with a generic method for problems of up to 10^5 variables
 - with specialized iterative methods on multiple processors for larger problems
- many applications: control, combinatorial optimization, signal processing, machine learning, finance, ...
- recent advances in convex optimization include
 - robust optimization methods to handle parameter variation
 - ℓ_1 -based heuristics for finding sparse solutions
 - parsers/solvers that make rapid prototyping easy
 - code generation for embedded optimization in real-time systems

Code generation

- say we have a quadratic program (QP), with variable $x \in \mathbf{R}^n$:

$$\begin{aligned} & \text{minimize} && x^T P x + q^T x \\ & \text{subject to} && G x \leq h, \quad A x = b \end{aligned}$$

- could *hand-write* a fast solver, but requires much time and is complicated
- instead, describe problem family in `cvxmod` (a Python package for convex optimization code generation):

```
A = matrix(...); b = matrix(...)
P = param('P', n, n, psd=True); q = param('q', n)
G = param('G', m, n); h = param('h', m)
x = optvar('x', n)
qpfam = problem(minimize(quadform(x, P) + tp(q)*x),
                [G*x <= h, A*x == b])
```

- generate a solver for the problem family `qpfam` with `qpfam.codegen()`
- output includes `qpfam/solver.c`, and various ancillary files.
- can solve an instance (in C) with


```
status = solve(params, vars, work);
```
- solve times are up to $1000\times$ faster than using off-the-shelf solver

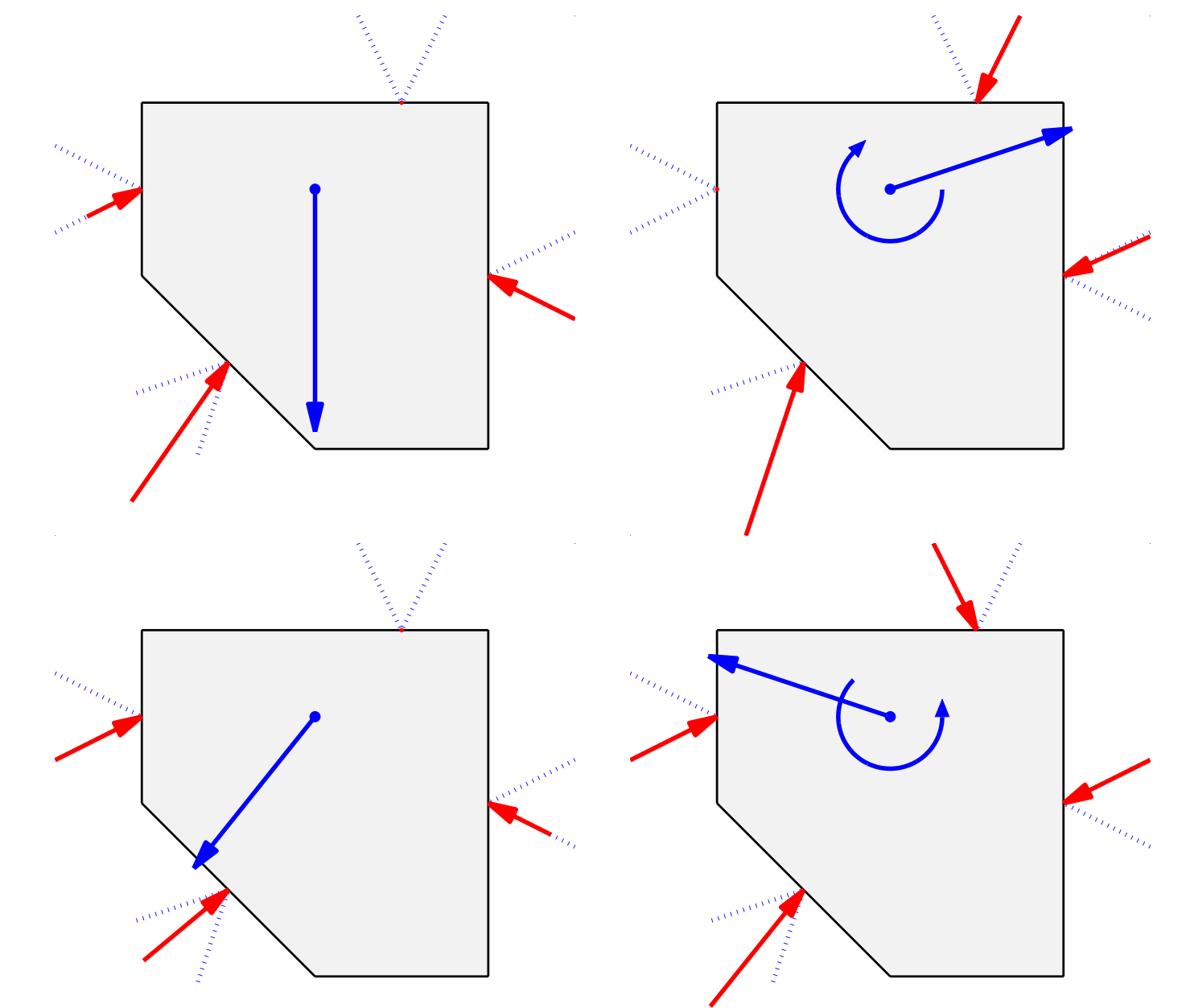
Example 1: Grasp force optimization

- choose K grasping forces on object to
 - resist external wrench
 - respect friction cone constraints
 - minimize maximum grasp force
- convex problem (second-order cone program):

$$\begin{aligned} & \text{minimize} && \max_i \|f^{(i)}\|_2 && \text{max contact force} \\ & \text{subject to} && \sum_i Q^{(i)} f^{(i)} = f^{\text{ext}} && \text{force equilibrium} \\ & && \sum_i p^{(i)} \times (Q^{(i)} f^{(i)}) = \tau^{\text{ext}} && \text{torque equilibrium} \\ & && \mu_i f_3^{(i)} \geq (f_1^{(i)2} + f_2^{(i)2})^{1/2} && \text{friction cone constraints} \end{aligned}$$

variables $f^{(i)} \in \mathbf{R}^3$, $i = 1, \dots, K$ (contact forces)

- can solve each instance in $60\mu s$



Example 2: Minimum energy processor speed scheduling

- processor adjusts its speed $s_t \in [s^{\min}, s^{\max}]$ in each of T time periods
- energy consumed in period t is $\phi(s_t)$; total energy is $E = \sum_{t=1}^T \phi(s_t)$
- n jobs
 - job i available at $t = A_i$; must finish by deadline $t = D_i$
 - job i requires total work $W_i \geq 0$
- $S_{ti} \geq 0$ is effective processor speed allocated to job i in period t

$$s_t = \sum_{i=1}^n S_{ti}, \quad \sum_{t=A_i}^{D_i} S_{ti} \geq W_i$$

- choose speeds s_t and allocations S_{ti} to minimize total energy E

- when ϕ is convex, can be formulated as convex problem

$$\begin{aligned} & \text{minimize} && E = \sum_{t=1}^T \phi(s_t) \\ & \text{subject to} && s^{\min} \leq s_t \leq s^{\max}, \quad t = 1, \dots, T \\ & && s_t = \sum_{i=1}^n S_{ti}, \quad t = 1, \dots, T \\ & && \sum_{t=A_i}^{D_i} S_{ti} \geq W_i, \quad i = 1, \dots, n \end{aligned}$$

- can solve each instance in $40\mu s$
- more sophisticated versions include
 - multiple processors
 - other constraints (thermal, speed slew rate, ...)
 - stochastic models for (future) data

