CVXPY Exercises

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1. Hello world. Solve the following optimization problem using CVXPY:

minimize
$$x^2 - 2\sqrt{y}$$

subject to $2 \ge e^x$
 $x + y = 5$,

where $x, y \in \mathbf{R}$ are variables.

Find the optimal values of x and y.

2. Non-negative least squares. We wish to recover a sparse, non-negative vector $x \in \mathbf{R}^n$ from measurements $y \in \mathbf{R}^m$. Our measurement model tells us that

$$y = Ax + v,$$

where $A \in \mathbf{R}^{n \times m}$ is a known matrix and $v \in \mathbf{R}^m$ is unknown measurement error. The entries of v are drawn IID from the distribution $\mathcal{N}(0, \sigma^2)$.

We can recover a good estimate of x by solving the optimization problem

minimize
$$||Ax - y||^2$$

subject to $x \ge 0$.

This problem is called non-negative least squares.

The file nnls.py defines n, m, A, x, and y. Use CVXPY to estimate x from y. First try standard regression, i.e., solve

minimize
$$||Ax - y||^2$$
.

Use the plotting code in nnls.py to compare the estimated x with the true x. Add the constraint $x \ge 0$ and see how it affects the estimate.

How many measurements n are needed for standard regression to find an accurate x? How about non-negative least squares?

3. Minimum fuel optimal control. We consider a vehicle moving along a 2D plane. The vehicle's state at time t is described by $x_t \in \mathbf{R}^4$, where $(x_{t,0}, x_{t,1})$ is the position of the vehicle in two dimensions and $(x_{t,0}, x_{t,1})$ is the vehicle velocity. At each time t a drive force $(u_{t,0}, u_{t,1})$ is applied to the vehicle.

The dynamics of the vehicle's motion is given by the the linear recurrence

$$x_{t+1} = Ax_t + Bu_t, \quad t = 0, \dots, N-1,$$

where $A \in \mathbf{R}^{4\times4}$ and $B \in \mathbf{R}^{4\times2}$ are given. We assume that the initial state is zero, *i.e.*, $x_0 = 0$.

The minimum fuel optimal control problem is to choose the drive force u_0, \ldots, u_{N-1} so as to minimize the total fuel consumed, which is given by

$$F = \sum_{t=0}^{N-1} f(u_t),$$

subject to the constraint that $x_N = x_{\text{des}}$, where N is the (given) time horizon, and $x_{\text{des}} \in \mathbf{R}^4$ is the (given) desired final or target state. The function $f: \mathbf{R}^2 \to \mathbf{R}$ is the fuel use map and gives the amount of fuel used as a function of the drive force.

We will use

$$f(a) = ||a||_2^2 + \gamma ||a||_1.$$

The file optimal_control.py defines N, A, B, and x_{des} . Use CVXPY to solve the minimum fuel optimal control problem for $\gamma \in \{0, 1, 10, 100\}$.

Use the plotting code in optimal_control.py to plot x and u for each γ .

4. Power grid single commodity flow. Recall the definition of a single commodity flow problem from the talk:

minimize
$$\sum_{i=1}^{n} \phi_i(f_i) + \sum_{j=1}^{p} \psi_j(s_j)$$
, subject to zero net flow at each node

where f_i is the flow on edge i, s_j is the external source/sink flow into node j, and ϕ_i, ψ_j are convex cost functions.

We will apply the single commodity flow framework to a power grid. Let nodes $\{1,\ldots,k\}$ be generators. The output at generator j is s_j . Each generator has the constraint $0 \le s_j \le U_j$ for some maximum output U_j and the cost function $\psi_j(s_j) = s_j^2$.

Nodes $\{k+1,\ldots,p\}$ are consumers. Each consumer j has a fixed load L_j , meaning $s_j=L_j$.

Each edge i has the constraint $|f_i| \leq c_i$ for some capacity c_i and the cost function $\phi_i(f_i) = f_i^2$. The edge flow cost represents power loss.

Explicitly, the power grid single commodity flow problem is

minimize
$$\sum_{i=1}^{n} f_i^2 + \sum_{j=1}^{k} s_j^2,$$
 subject to zero net flow at each node
$$0 \le s_j \le U_j, \quad j = 1, \dots, k$$

$$s_j = L_j, \quad j = k+1, \dots, p$$

$$|f_i| \le c_i, \quad i = 1, \dots, n.$$

The file $power_grid.py$ defines the power grid graph, the maximum generator outputs U, loads L, and edge capacities c. Complete the classes Generator, Generator, and Generator and Generator are them to solve the power grid single commodity flow problem.

Use the plotting code in power_grid.py to plot the edge flows in the solution.

5. Extra I've included the code for the total variation in-painting example from the talk in inpainting.py. Feel free to play around with it if you have time. Try changing PROB_PIXEL_LOST to increase or decrease the number of known pixels.