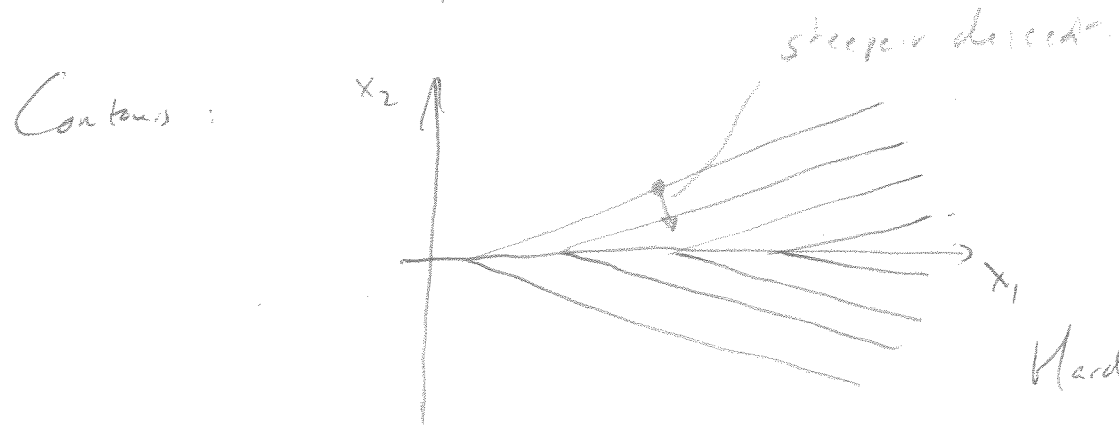


Nonsmooth Optimization

Gradient functions have discontinuities. Eg: l_1 -penalty function.

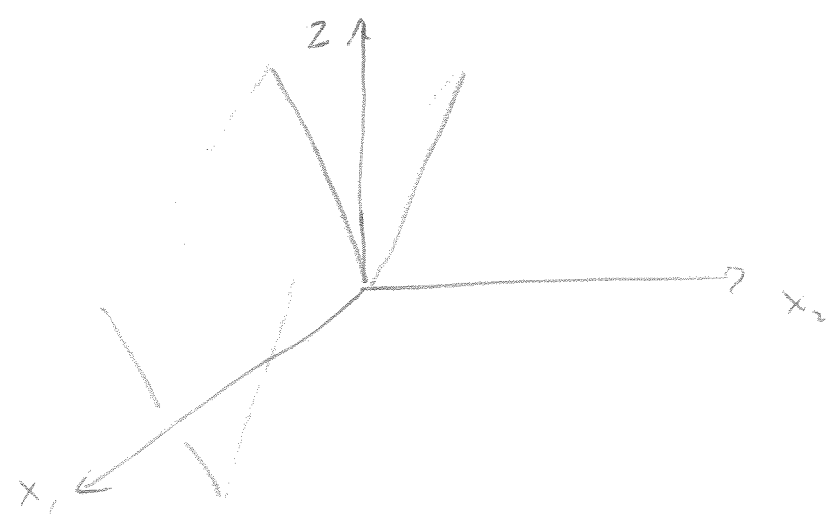
Eg:
$$\begin{aligned} \min \quad & -x_1 + 100|x_2| \\ \text{s.t.} \quad & 0 \leq x_1 \leq 10. \end{aligned}$$
Optimal soln: $x_1 = 10, x_2 = 0$.



Hard to choose good direction.
 Hard to ~~find~~ find good step length algebraically.

$$\nabla f = \begin{cases} \begin{bmatrix} -1 \\ +100 \end{bmatrix} & \text{if } x_2 > 0 \\ \begin{bmatrix} -1 \\ -100 \end{bmatrix} & \text{if } x_2 < 0 \end{cases}$$

Graph of function:



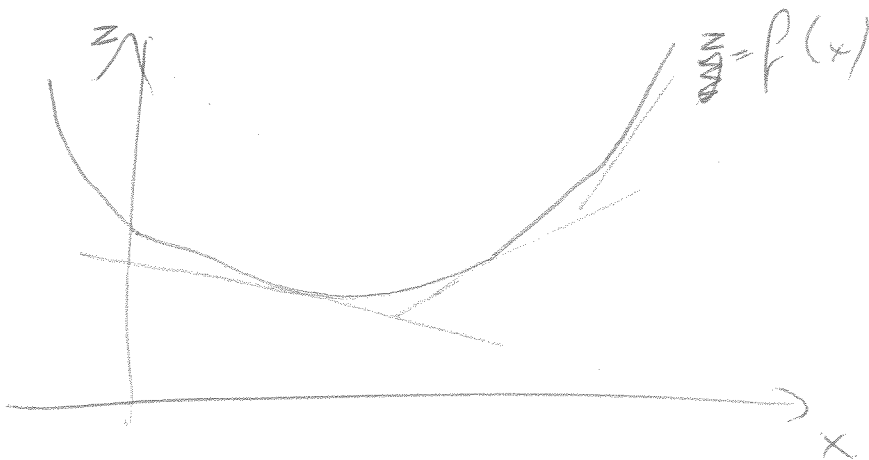
More involved example:

$$\begin{aligned} \max_{y, S} \quad & b^T y + \lambda \min(S) \\ \text{s.t.} \quad & A \Sigma A_i y_i + S = C \\ & A_i, C, S \text{ square symmetric matrices.} \\ & y \text{ vector} \end{aligned}$$

$$\begin{array}{ll} \text{min} & f(x) \\ \text{s.t.} & g_i(x) \leq 0 \quad i=1, \dots, n. \end{array} \quad (\text{NLP})$$

Assume functions are convex, ~~but~~ continuous, but may not be differentiable

Can approximate using LP:

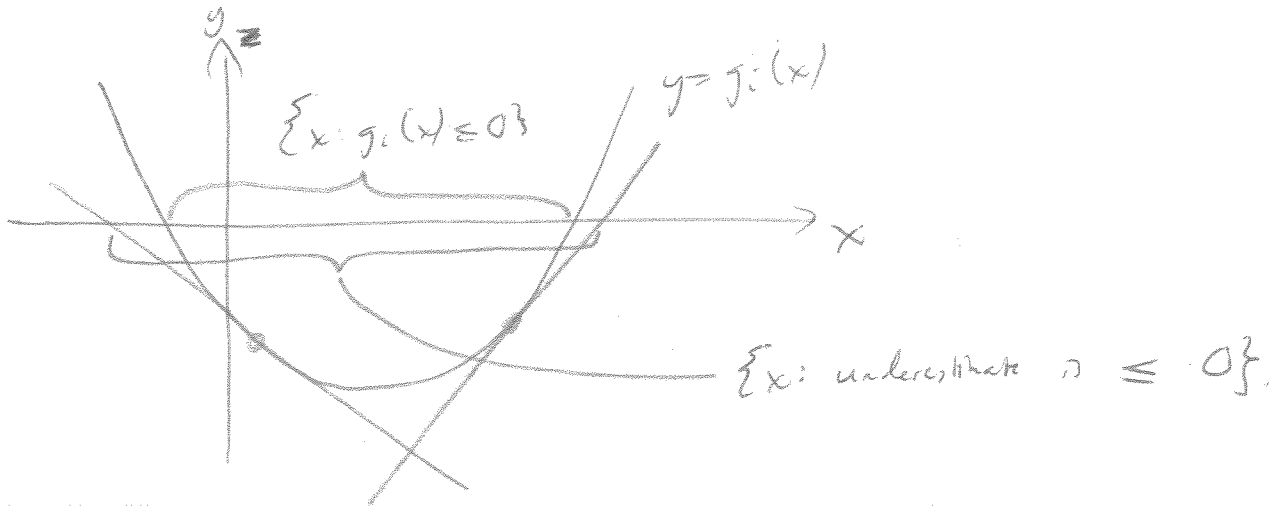


~~At a point \bar{x} :~~
Rewrite problem \rightarrow

$$\begin{array}{ll} \text{min} & z \\ \text{s.t.} & f(x) - z \leq 0 \\ & g_i(x) \leq 0 \quad i=1, \dots, n \end{array}$$

Approximate constraints from underneath: (as with Kelley's cutting plane algorithm)

$$\begin{array}{l} \text{At } \bar{x}: \\ g_i(x) \geq g_i(\bar{x}) + \xi^T(x - \bar{x}) \\ \text{if } \xi \text{ is a subgradient of } g_i \text{ at } \bar{x}. \end{array}$$



Can underestimate $f(x) - z$ similarly.

So get LP:

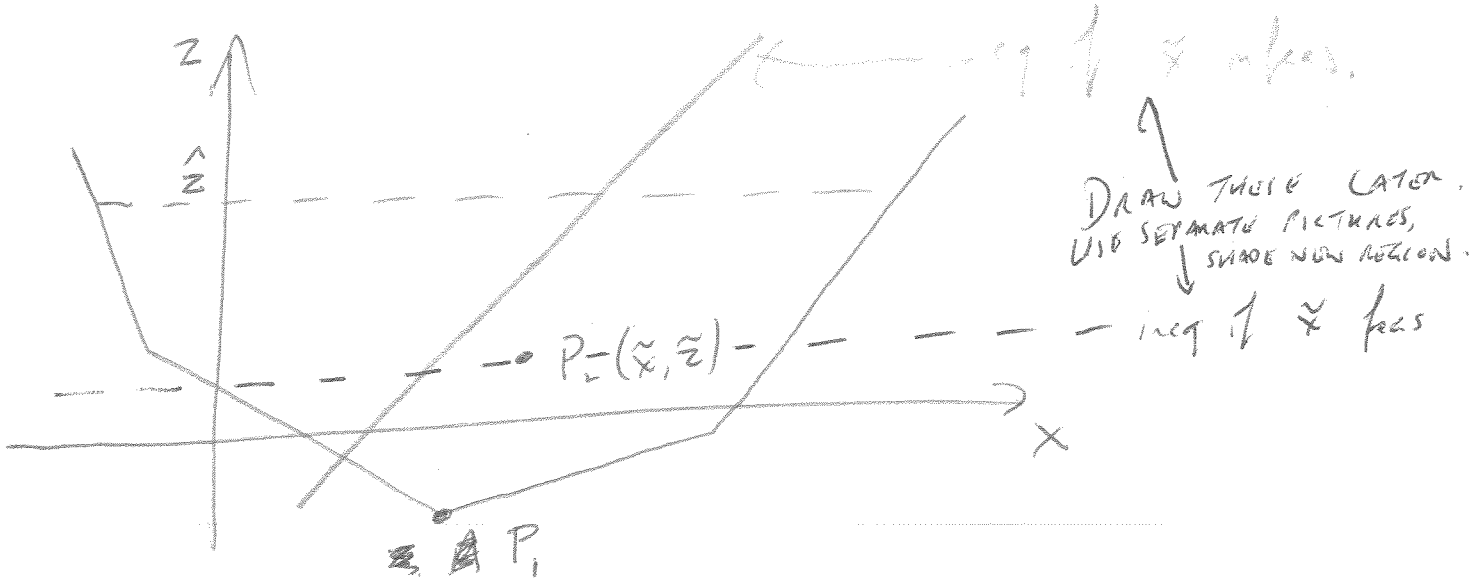
(LP) $\max z$ s.t. $Ax + hz \leq b$ for appropriate A, h, b ,
 ↑ generated from supporting
 relaxation of (NSP) inequalities.

Solve^(LP) using an algorithm for linear programming. Can use

Simplex, or an interior point method.

Note that any feasible point \hat{x} gives an upper bound $\hat{z} = f(\hat{x})$ on optimal value of (NSP).

If use an interior point method, best not to solve problem exactly:



If solve ~~exactly~~ (LP) exactly, get (P_1) . But hard to ~~start~~ restart an interior point method from an extreme point.
 So find analytic center (or a good point in the middle), P_2

Let P_2 be $\begin{pmatrix} \tilde{x} \\ \tilde{z} \end{pmatrix}$.

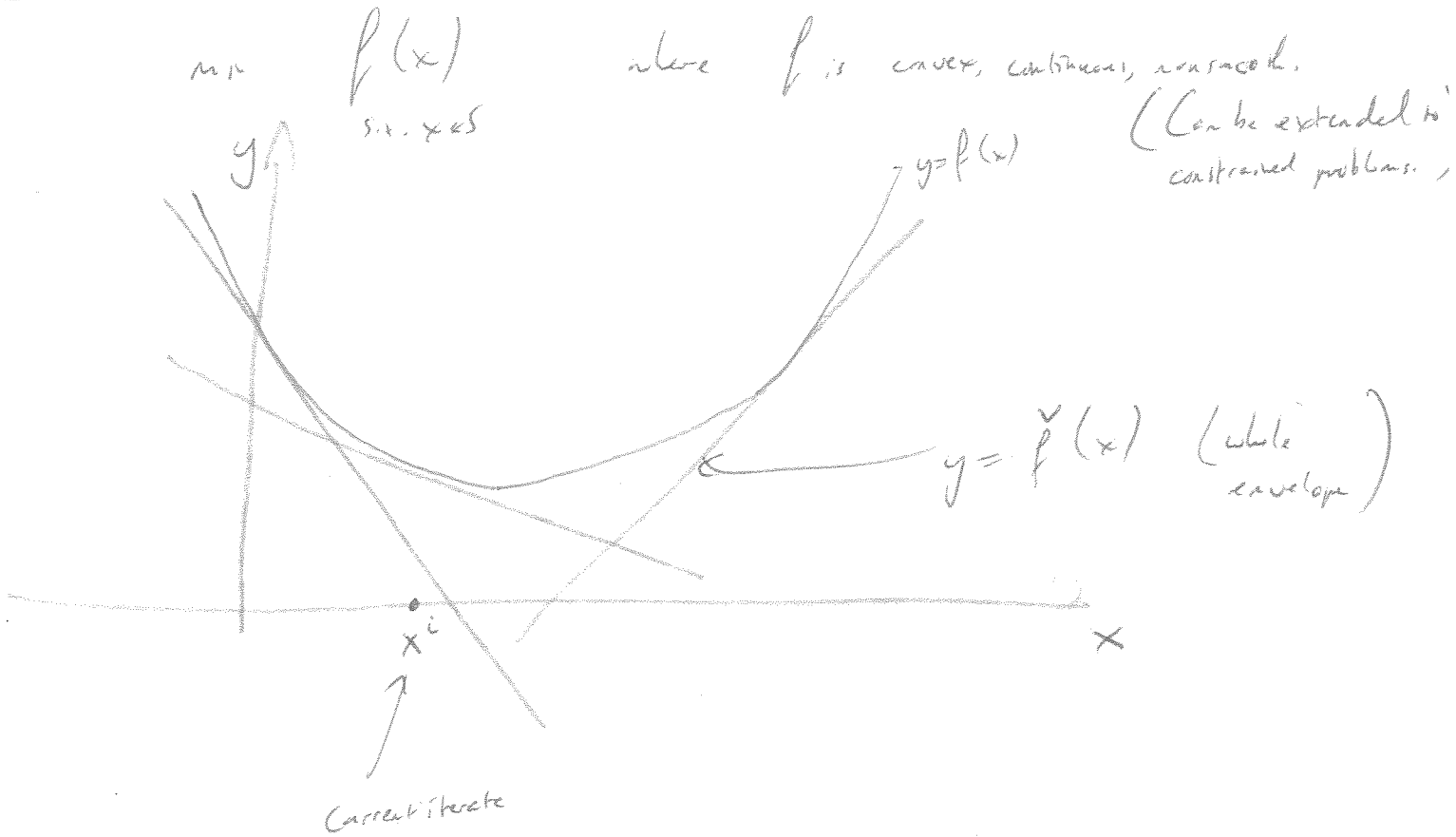
- if ~~\tilde{x} infeasible~~, add ϵ
- if \tilde{x} violates $g_i(x) \leq 0$, add supporting hyper for this constraint and resolve:
- if \tilde{x} feasible, all constraint $z \leq \tilde{z}$ and find new center

Algo finds a solution within ϵ of optimality in $O(n/\epsilon)$ iterations.

If also allow dropping of constraints, can get within ϵ of optimality in $O(n \ln(1/\epsilon))$ iterations.

Only need a handful of ~~more~~ iterations to find new center after adding a cut
 (add multiple cuts as nec.)

BUNDLE METHODS



Have upper bound: $\min f(x^j)$, $j=1, \dots, i$
 i.e., value of best point seen to date.

Have lower bound: min value of piecewise linear underestimator of f .

~~It can be very~~

this is a "bundle of information" provided by earlier iterates.

It can be very slow to move directly to the ~~set~~ minimizer of the underestimator.

So use "proximal" term, $\|x - x^i\|^2$, ~~where i~~

So:
$$\min z + \frac{1}{2} \mu \|x - x^i\|^2 \quad (Q^i)$$

s.t. $z \geq \text{underestimator function, } \check{f}(x).$

Then we don't move too far.

Let \bar{x} be the point that solves this quadratic problem (Qⁱ).

If $f(\bar{x})$ is too large compared to z (so \check{f} is not a good approximation to f),

REJECT the step, set $x^{i+1} = x^i$, update \check{f} with a constraint from \bar{x} and repeat

Else,

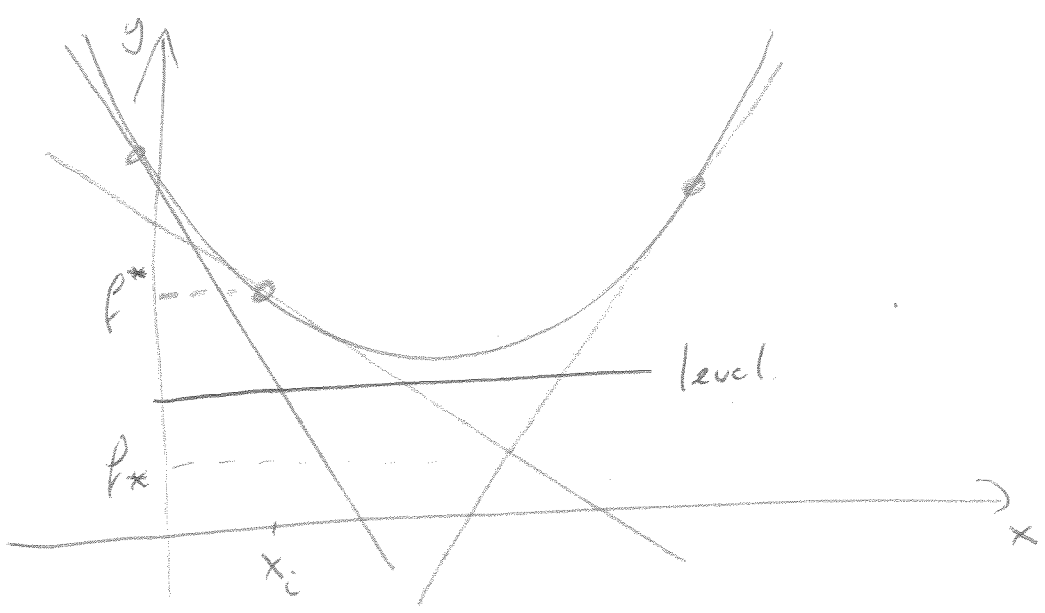
Set $x^{i+1} = \bar{x}$, update \check{f} with a constraint from \bar{x} , and repeat.

Repeat until upper and lower bounds are close enough.

Difficulty: hard to choose μ . Should probably be dynamically updated. Nonetheless, algorithm works well.

Reference:

proximal level bundle methods:



Optimal value is between f_x and f^* .

Look for proximal point with z -value $\leq \lambda f_x + (1-\lambda) f^*$ in the model, f .

So:
$$\min \frac{1}{2} \|x - x_i\|^2$$

s.t.
$$z \leq \lambda f_x + (1-\lambda) f^*$$

Note: $\lambda = 0$ or 1 get $x = x_i$ or $x = x^*$ respectively.

$z \geq \hat{f}$ underestimator of f , as a function in x .

$$z \geq f(x_i) - \frac{1}{2} L \|x - x_i\|^2$$

$$L = \frac{1}{\epsilon} \text{ or } \dots$$

Typically, get convergence in $O(\frac{K}{\epsilon})$ iterations, where $\epsilon =$ desired accuracy, $K =$ diameter of space or norm of largest Hessian, work well in practice.