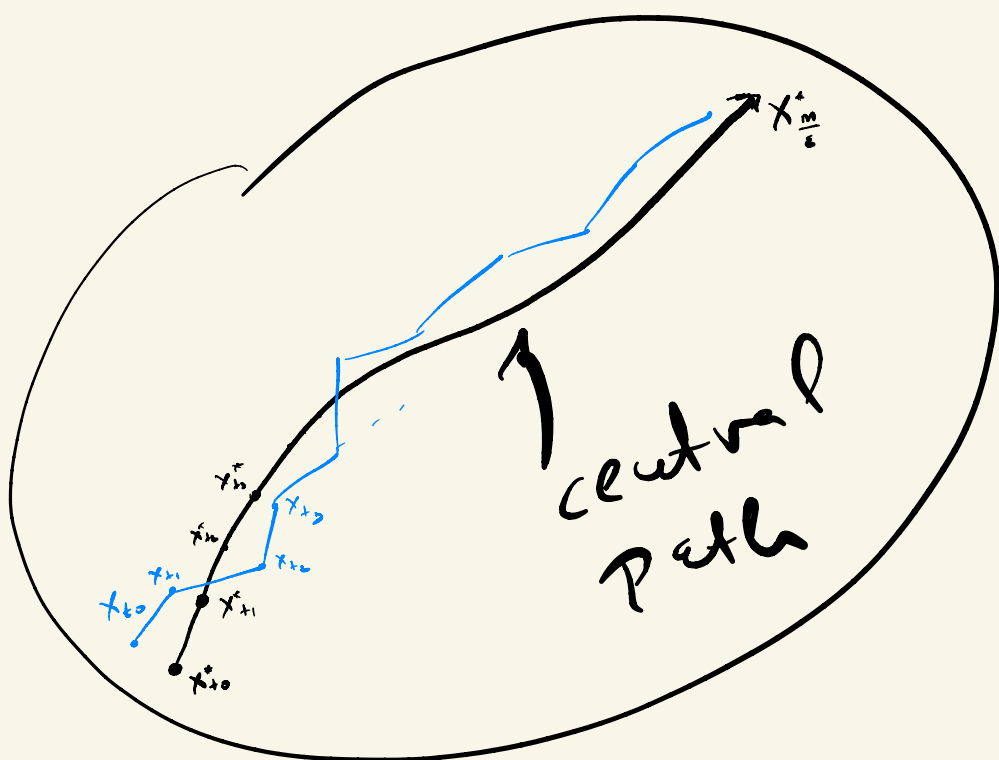


lecture 15

Self concordant Barriers

- Fast Recap of Interior point method
- what properties of the logarithmic Barrier function were crucial.
- self concordant functions
- self concordant Barriers
- properties.

- Recap of IPM



original LP

$$\min \langle c, x \rangle$$

$$\text{s.t. } Ax \geq b$$

$$x \in \mathbb{R}^n \quad A = \begin{pmatrix} -a_1^T \\ -a_2^T \\ \vdots \\ -a_m^T \end{pmatrix} \in \mathbb{R}^{m \times n}, \quad b \in \mathbb{R}^m$$



unconstrained problem

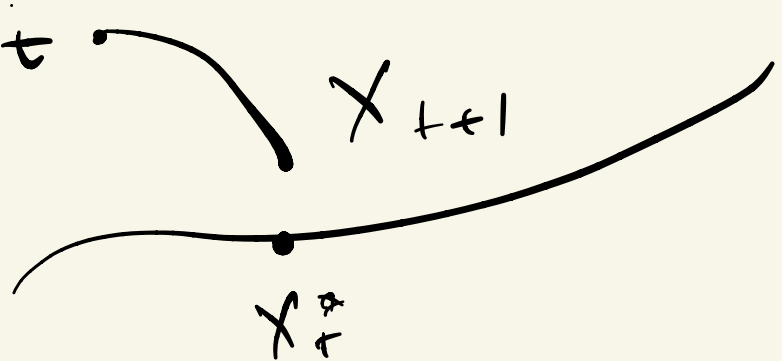
$$\min f_t(x) = t \langle c, x \rangle - \underbrace{\varphi(x)}$$

$$\sum_{i=1}^m \log(\langle a_i, x \rangle - b_i)$$

what properties were crucial?

① The Hessian is smooth. That property is needed for the Newton step to make sense

(i.e. $x_t \rightarrow x_{t+1}$ comp closer to x_t^*)



$$\forall x, y \text{ s.t. } \|x - y\|_{H^{-1}} \leq \delta \Rightarrow \langle \nabla \phi, y \rangle_{Hx} \leq \langle \nabla \phi, y \rangle$$

the barrier function gradient norm is bounded

② $\|\nabla \phi(x)\|_{H^{-1}} \leq b$

$$\Rightarrow \tilde{t} z_t + (1 - \frac{\delta}{\sqrt{b}})$$

$$\Rightarrow \tilde{O}\left(\frac{\sqrt{b}}{\delta}\right) \text{ iterations}$$

$$\Rightarrow c^T x_{w/\varepsilon}^* - c^T x^* < \varepsilon$$

(Not a lot about dP, was used)

self-concordant functions

Informal definition = a class of functions for which Newton's method work.

In the quadratic convergence close to the OPT proof of the Newton method we required

$$\|\nabla^2 f(x) - \nabla^2 f(y)\| \leq \mu \|x - y\|_2$$

which is not good for 2 reasons:

- ① It does not hold for functions that $\rightarrow \pm\infty$ in the boundary (barrier functions)
- ② It is not affine invariant

Definition

$f: \mathbb{R} \rightarrow \mathbb{R}$ is self-concordant if

$$|f'''(x)| \leq 2 f''(x)^{3/2} \leftarrow \begin{array}{l} \text{it permits to} \\ \rightarrow +\infty \text{ in the} \\ \text{boundary} \\ \text{but not too} \\ \text{fast.} \end{array}$$

Observations

- constant 2 is not important

$$\text{if } |f'''(x)| \leq K f''(x)^{3/2} \Rightarrow$$

$$\Rightarrow \tilde{f}(x) = \frac{K^2}{4} f(x) \text{ is self-concordant}$$

- affine invariant

$$g(y) = f(ay+b) = f(x)$$

$$g'''(y) = a^3 f'''(ay+b) = a^3 f'''(x)$$

$$g'(y) = a^2 f''(x) \quad |a^3 f'''(x)| \leq 2 (a^2 f''(x))^{3/2} = 2 \cdot a^3 f''(x)^{3/2}$$

Definition of self concordant function
in higher dimensions

(one dimension \longrightarrow higher dimension)

$f: \mathbb{R}^n \rightarrow \mathbb{R}$ is self concordant only
if $g(t) = f(x + tv)$ is self-concordant
for every x, v (in every line)

$$\Rightarrow \forall v, x \quad |\nabla^3 f(x)[v][v][v]| \leq 2 \left(v^T \nabla^2 f(x) v \right)^{3/2}$$

$$\sum_{i,j,k} \frac{\partial^3 f(x)}{\partial x_i \partial x_j \partial x_k} v_i v_j v_k$$

$$= 2 \|v\|^3 \nabla^2 f(x)$$

examples

$f(x) = -\log x$ self-concordant

$f(x) = -\sum_{i=1}^m \log(b_i - a_i^T x)$ self-concordant

$f(x) = -\log \det X \leftarrow$ self-concordant
 $X \in \mathcal{S}_{++}^n$

properties

If x, y are close
changing the quadratic
norm does not affect the
distance

$$\|y-x\|_{\nabla^2 f(x)} \ll 1 \quad \text{then also}$$

$$\|y-x\|_{\nabla^2 f(y)} \text{ is small}$$

proof

$$\varphi(t) = \frac{1}{\sqrt{v^T \nabla^2 f(x+tu) v}} = \frac{1}{\|u\|_{\nabla^2 f(x+tu)}}$$

$$|\varphi'(t)| = \left| -\frac{1}{2} \frac{\nabla^3 f(x+tu) [u][u][u]}{u^T \nabla^2 f(x+tu) u} \right| \leq 1$$

$x +$

take $u = y - x$. Then

$$\varphi(0) = \frac{1}{\|y-x\|_{\nabla^2 f(x)}} \quad \text{and} \quad \varphi(1) = \frac{1}{\|y-x\|_{\nabla^2 f(y)}}$$

$$\|y-x\|_{\nabla^2 f(x)} \ll 1 \Rightarrow \begin{cases} \varphi(0) > 1 \\ |\varphi'(t)| \leq 1 \end{cases} \quad \varphi(1) \geq \varphi(0) - 1$$

$$\|y-x\|_{\nabla^2 f(y)} \leq \frac{\|y-x\|_{\nabla^2 f(x)}}{1 - \|y-x\|_{\nabla^2 f(x)}}$$

Lemma

If $\|y - x\| \nabla^2 f(x) \leq 1$ then

$$(1 - \|y - x\| \nabla^2 f(x))^2 \nabla^2 f(x) \leq \nabla^2 f(y) \leq (1 + \|y - x\| \nabla^2 f(x))^2 \nabla^2 f(x)$$



a "smoothness" of the Hessian property

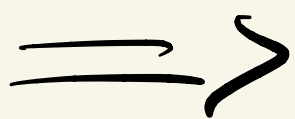
Let permits to prove quadratic convergence in a region around OPT of the Newton's method.

$$\textcircled{2} \quad \|\nabla f(x)\| (\nabla^2 f(x))^{-1} \leq b \quad \forall x$$

Definition

Let f be a self-concave function. We say it is b -self concave if

$$\sup_{u \in \mathbb{R}^n} [2 \langle \nabla f(x), u \rangle - u^T \nabla^2 f(x) u] \leq b$$



some intuition behind the definition.

The definition, assuming that the hessian changes slowly and thus the second order approximation of $f(x+u)$ is good, bounds the increase of the function value if a full Newton step is taken.

observations

$$\nabla_u (2 \langle \nabla f(x), u \rangle - u^T \nabla^2 f(x) u) = 0$$

$$\Rightarrow 2 \nabla f(x) - 2 \nabla^2 f(x) \cdot u = 0$$

$$\Rightarrow u = (\nabla^2 f(x))^{-1} \nabla f(x)$$

$$\text{so } 2 \langle \nabla f(x), u \rangle - u^T \nabla^2 f(x) u \equiv$$

$$= \|\nabla f(x)\| (\nabla^2 f(x))^{-1}$$

$$\text{so } \|\nabla f(x)\| (\nabla^2 f(x))^{-1} \leq b$$

change u to λu and take
the gradient w.r.t λ

$$\nabla_{\lambda} (2\lambda \langle \nabla f(x), u \rangle - \lambda^2 u^T \nabla^2 f(x) u) = 0$$

$$\Rightarrow \langle \nabla f(x), u \rangle - \lambda u^T \nabla^2 f(x) u = 0 \Rightarrow$$

$$\Rightarrow \lambda = \frac{\langle \nabla f(x), u \rangle}{u^T \nabla^2 f(x) u}$$

plugging back λ we get

$$\nabla^2 f(x) \succeq \frac{1}{6} \nabla f(x) \nabla f(x)$$

$$\begin{aligned} \min f_0(x) & \quad \text{convex function} \\ \text{s.t. } x \in Q & \quad \text{convex set} \end{aligned}$$

$$\Rightarrow \min a \quad \text{s.t. } x \in Q' = Q \cap \{f_0(x) \leq a\}$$

we will focus
on linear
optimization
 $f_0(x) = \langle c, x \rangle$

when turning the
optimization
problem into
an unconstrained
one we introduce
an appropriate
barrier function
s.t. $\phi(x) \rightarrow +\infty$
when $f_0(x) \rightarrow a$

Theorem

$$\text{Let } f_+(x) = t \langle c, x \rangle + \phi(x)$$

ϕ -self concordant
barrier

$$\text{then } \langle c, x_t^* \rangle - \langle c, x^* \rangle \leq \frac{b}{t}$$

proof

x_t^* is optimal for $f_t(x)$ so

$$\nabla f_t(x_t^*) = 0 \Rightarrow t \cdot c + \nabla \phi(x) = 0 \Rightarrow$$

$$\Rightarrow \langle c, x_t^* - x^* \rangle = -\frac{1}{t} \langle \nabla \phi(x_t^*), x^* - x_t^* \rangle$$

It is enough to prove that

$$\langle \nabla \phi(x), y - x \rangle \leq b \quad \forall x, y$$

$$g(s) = \langle \nabla \phi(x + s(y-x)), y-x \rangle$$

$$g(0) \geq 0 \text{ (o.w.)} \quad \xrightarrow{\text{holds.}}$$

$$g'(s) = (y-x)^T \nabla^2 \phi(x + s(y-x)) (y-x) \geq$$

$$\geq \frac{1}{b} \langle \nabla \phi(x + s(y-x)), y-x \rangle^2 = \frac{1}{b} g^2(s)$$

$$g(0) > 0$$

$$g'(s) > \frac{1}{b} g^2(s)$$

If s close to 0 $g(s)$ is large
then it decreases super fast

$$\frac{g'(s)}{g^2(s)} > \frac{1}{b} \Rightarrow \int_{s=0}^1 \frac{g'(s)}{g^2(s)} ds > \frac{1}{b} \Rightarrow$$

$$\Rightarrow -\frac{1}{g(1)} + \frac{1}{g(0)} > \frac{1}{b} \Rightarrow$$

$$\Rightarrow g(0) < b$$

~~if~~

(If $g(1) < 0$
then we
would
be fine
since
 $g(0) < 0$)