

Announcements

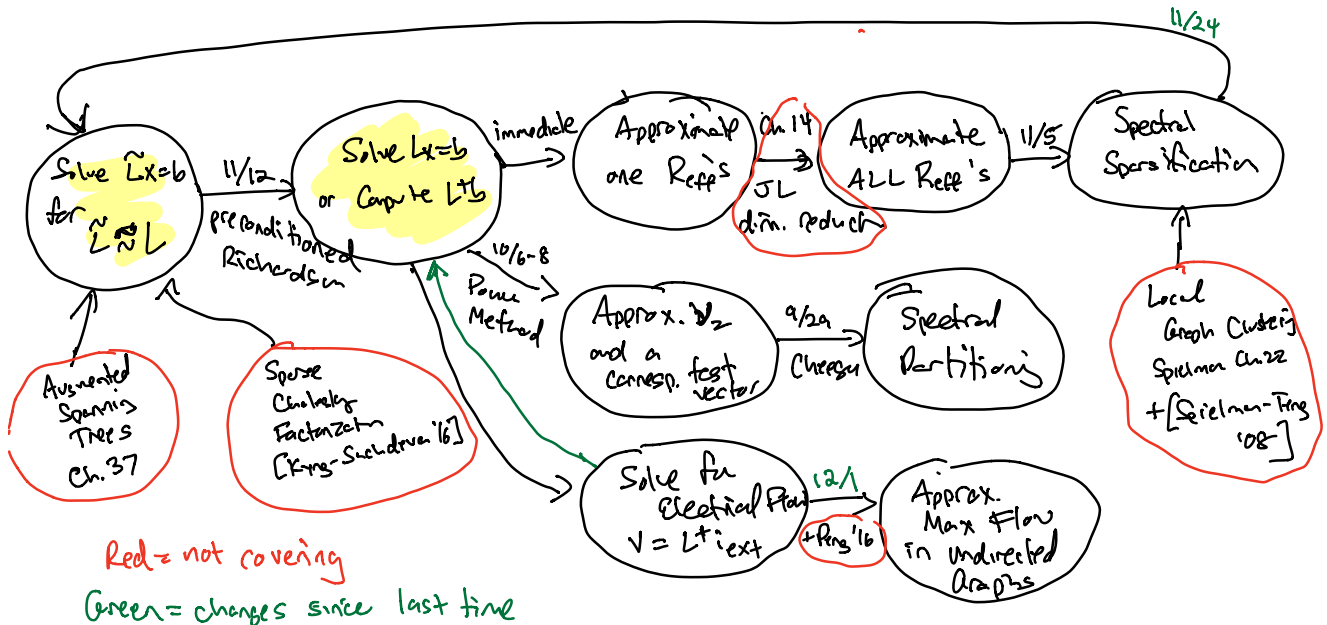
- start recording
- scribe: work w/other scribe to produce one set of notes
- My OH: Mon 12:30-1:30, Thu 9-10
- TR section/OH: Mon 2-3, Tue 8-9, Wed 5-6, Thu 5:30-6:30
- PS 4 posted. Project proposal due Sun 11/8, problems due TOE 11/17
- If Zoom goes down, check Piazza
- sync whiteboard → no class next week
- FOCS starting tomorrow! stay tuned for watch+discussion parties
we can reimburse the \$20 reg fee
- jamboard link in chat

Agenda

- Recap: Richardson iterations
- The A-norm
- Preconditioning

randomized
Reductions between nearly linear-time algorithms

time $O(m \cdot \text{poly} \log n)$ $m = \# \text{ edges w/ nonzero weights}$



Richardson Iterations

Goal: solve $Ax=b$ (e.s. A = a Laplacian or normalized Laplacian) restricted to v_1^\perp
without Gauss elimination (only applying A to vectors)

Algorithm: $x^{(0)} = \vec{0}$

$$x^{(k+1)} = (I - \alpha A)x^{(k)} + \alpha b$$

$$= x^{(k)} - \alpha(Ax^{(k)} - b)$$

when A is symmetric
gradient descent on
obj function

Analysis:

Solve $Ax=b$

$$f(x) = \frac{1}{2}x^T Ax - b^T x$$

Then $x^{(k+1)} - x = (I - \alpha A)(x^{(k)} - x)$

$$\Rightarrow x^{(k)} \rightarrow x \text{ if } \|I - \alpha A\| < 1$$

$$\|M\| = \max_{y \neq 0} \frac{\|My\|}{\|y\|}$$

$$\|x^{(k+1)} - x\| \leq \|I - \alpha A\|^{k+1} \cdot \|x\|$$

$t = O\left(\frac{\log(\frac{1}{\epsilon})}{1 - \|I - \alpha A\|}\right)$ iterations suffice to get $\|x^t - x\| \leq \epsilon \cdot \|x\|$

When A symmetric, $\|I - \alpha A\| = \max\{|1 - \alpha \lambda_1|, |1 - \alpha \lambda_n|\}$
 $\lambda_1 \leq \dots \leq \lambda_n$
 ϵ -values of A

Optimizing α : $(1 - \alpha \lambda_1) = -(1 - \alpha \lambda_n)$

$$\alpha = \frac{2}{\lambda_1 + \lambda_n} \quad \|I - \alpha A\| = \frac{\lambda_n - \lambda_1}{\lambda_1 + \lambda_n}$$

$$< 1 \text{ if } \lambda_1 > 0$$

iterations = $O\left(\left(1 + \frac{\lambda_n}{\lambda_1}\right) \cdot \log\left(\frac{1}{\epsilon}\right)\right)$ also measures numerical stability

$\kappa(A)$ "condition number"

Similarly $Ax^{(t+1)} - b = (I - \alpha A)(Ax^{(t)} - b)$
 "residual"

\Rightarrow Same # iterations gives $\|Ax^{(t)} - b\| \leq \epsilon \cdot \|b\|$.

Another view: $x^{(t)} = P_t(A)b$ for a polynomial P_t

Richardson: $P_t(A) = \alpha \cdot \sum_{j=0}^{t-1} (I - \alpha A)^j \xrightarrow{\text{as } t \rightarrow \infty} A^{-1}$

$(\alpha A)^{-1} = (I - (I - \alpha A))^{-1}$

$\forall x \quad \|P_t(A)(Ax) - x\| \leq \epsilon \cdot \|x\| \quad (1-x)^{-1} \dots$

Richardson: suffices to take degree $t = O\left(\frac{\lambda_n}{\lambda_1} \cdot \log\left(\frac{1}{\epsilon}\right)\right)$

Chebyshev: degree $O\left(\sqrt{\frac{\lambda_n}{\lambda_1}} \cdot \log\left(\frac{1}{\epsilon}\right)\right)$
 polys

Analysis of Richardson entirely in spectral norm:

$I - P_t(A)A = (I - \alpha A)(I - P_{t-1}(A)A)$

$\Rightarrow \|I - P_t(A)A\| \leq \|I - \alpha A\|^t$

$\forall x \quad \|x - P_t(A)b\| \leq \|I - \alpha A\|^t \cdot \|x\|$

NB: Holds for any submultiplicative matrix norm ($\|MN\| \leq \|M\| \cdot \|N\|$)

A-norm : $\|x\|_A = \sqrt{x^T A x}$ for $n \times n$ psd A
 for psd A

$\|M\|_A = \max_{x \neq 0} \frac{\|Mx\|_A}{\|x\|_A}$ for $n \times n$ M

$\|MN\|_A \leq \|M\|_A \cdot \|N\|_A$

Exercise for Breakouts : Fill in the missing matrices

1) $\|x\|_A = \|A^{1/2} x\|$

$\frac{\|Mx\|_A}{\|x\|_A} = \frac{\|A^{1/2} M A^{-1/2} (A^{1/2} x)\|}{\|A^{1/2} x\|}$

2) $\|x\|_A = \|Ax\|_{A^{-1}}$

3) $\|M\|_A = \|A^{1/2} M A^{-1/2}\|$

4) $\|I - ZA\|_A \leq \varepsilon \Leftrightarrow (1-\varepsilon)A^{-1} \preceq Z \preceq (1+\varepsilon)A^{-1}$
 for a symmetric Z

$A^{1/2} Z A^{1/2} \preceq \varepsilon A^{-1}$
 $\|A^{1/2} (I - ZA) A^{-1/2}\| \leq \varepsilon$

$-\varepsilon I \preceq \underbrace{A^{1/2} (I - ZA) A^{-1/2}}_I \preceq \varepsilon I$

Preconditioning Given $A (= L_G)$ ($B = Z^{-1}$ is the "preconditioner")

Find a matrix Z such that

(1) easy to apply Z

(2) condition number of \underline{ZA} is small.

\Rightarrow solve $Ax = b$ by applying an iterative method
to solve $\underline{(ZA)x = (Zb)}$

Example: preconditioned Richardson with $\alpha = 1$

$$\begin{aligned} x^{(t)} &= (I - ZA)x^{(t-1)} + Zb \\ &= P_t(ZA)Zb \end{aligned}$$

$$\|I - P_t(ZA) \cdot ZA\|_A \leq \|I - ZA\|_A^t \leq (1 - \delta)^t \leq \epsilon$$

$\delta = 1 - \epsilon / \|Zb\|$

$\delta = 1 - \epsilon$ in (3) above

for the largest value δ s.t. $\delta \cdot A^{-1} \preceq Z \preceq (2 - \delta) \cdot A^{-1}$

iterations to get w/in ϵ $\rightarrow O\left(\frac{1}{\delta}\right)$

$= O\left(\frac{1}{\delta} \cdot \log\left(\frac{1}{\epsilon}\right)\right)$

Up to scaling $B = Z^{-1}$, $\frac{1}{\delta} = O(K(A, B))$,

where $K(A, B) =$ smallest ratio $\frac{\beta}{\alpha}$ s.t. $\alpha A \preceq B \preceq \beta A$

$$= \frac{\lambda_{\max}(B^{-1}A)}{\lambda_{\min}(B^{-1}A)} = \frac{\lambda_{\max}(B^{-1/2}AB^{-1/2})}{\lambda_{\min}(B^{-1/2}AB^{-1/2})}$$

Goal: given G , construct Z s.t. $A = L_G$

(1) $L_G^+ \preceq Z \preceq c \cdot L_G^+$ for "small" c $Z L_G$

(2) Can apply Z in nearly linear time

\Rightarrow Can solve linear systems in L_n in time

$O(m \cdot \text{poly} \log n \cdot c \cdot \log 1/\epsilon)$

\uparrow can be \sqrt{c} using Chebyshev/CG

Subgraph preconditioners: $Z = L_H^+$ for ^{connected} subgraph H

Then (1) becomes $L_G^+ \preceq c \cdot L_H^+$

(2) true for trees

Prop: if H is a spanning tree of $G=(V,E)$, then $L_G \preceq c \cdot L_H$

for $c = \sum_{e=(a,b) \in E} \frac{1}{r_e} \cdot \sum_{f \in \text{path}_H(a,b)} r_f$ $r_e = \frac{1}{w_e}$

stretch of edge e wrt H

Proof, sketch $c = \lambda_{\max}(L_H^+ L_G) \leq \text{Tr}(L_H^+ L_G)$

$= \sum_{e=(a,b) \in E} w_e \cdot \text{Tr}(L_H^+ (\delta_a - \delta_b)(\delta_a - \delta_b)^T)$

$= \sum_{e=(a,b) \in E} \frac{1}{r_e} \cdot \text{Res}_H^+(a,b)$

Low-stretch Spanning trees: $c = \tilde{O}(m \cdot \log n - \log \log n)$

\Rightarrow Solve systems in L_G in time $\tilde{O}(m^{3/2})$

Next time (11/24): Construct Z with $c = \text{poly}(\log n)$
assuming spectral sparsification in near linear time.