

Notes

- ◆ In assignment 1, problem 2:
smoothness = number of times differentiable

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The Symmetric Eigenproblem

- ◆ Assume A is symmetric and real
- ◆ Find orthogonal matrix V and diagonal matrix D s.t. $AV=VD$
 - Diagonal entries of D are the eigenvalues, corresponding columns of V are the eigenvectors
- ◆ Also put: $A=VDV^T$ or $V^TAV=D$
- ◆ There are a few strategies
 - More if you only care about a few eigenpairs, not the complete set...
- ◆ Also: finding eigenvalues of an $n \times n$ matrix is equivalent to solving a degree n polynomial
 - No "analytic" solution in general for $n \geq 5$
 - Thus general algorithms are **iterative**

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The Jacobi Algorithm

- ◆ One of the oldest numerical methods, but still of interest
- ◆ Start with initial guess at V (e.g. $V=I$), set $A=V^TAV$
- ◆ For $k=1, 2, \dots$
 - If A is close enough to diagonal (Frobenius norm of off-diagonal tiny relative to A) stop
 - Find a Givens rotation Q that solves a 2×2 subproblem
 - Either zeroing max off-diagonal entry, or sweeping in order through matrix.
 - $V=VQ$, $A=Q^TAV$
- ◆ Typically $O(\log n)$ sweeps, $O(n^2)$ rotations each
- ◆ Quadratic convergence in the limit

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The Power Method

- ◆ Start with some random vector v , $\|v\|_2=1$
- ◆ Iterate $v=(Av)/\|Av\|$
- ◆ What happens? How fast?

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Shift and Invert (Rayleigh Iteration)

- ◆ Say we know the eigenvalue we want is approximately λ_k
- The matrix $(A-\lambda_k I)^{-1}$ has the same eigenvectors as A
- But the eigenvalues are $\mu = \frac{1}{\lambda - \lambda_k}$
- Use this in the power method instead
- Even better, update guess at eigenvalue each iteration:
$$\lambda_{k+1} = v_{k+1}^T A v_{k+1}$$
- Gives cubic convergence! (triples the number of significant digits each iteration when converging)

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Maximality and Orthogonality

- ◆ Unit eigenvectors v_1 of the maximum magnitude eigenvalue satisfy

$$\|Av_1\|_2 = \max_{\|u\|_2=1} \|Au\|_2$$

- ◆ Unit eigenvectors v_k of the k 'th eigenvalue satisfy

$$\|Av_k\|_2 = \max_{\substack{\|u\|_2=1 \\ u^T v_i=0, i < k}} \|Au\|_2$$

- ◆ Can pick them off one by one, or....

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Orthogonal iteration

- ◆ Solve for lots (or all) of eigenvectors simultaneously
- ◆ Start with initial guess V
- ◆ For $k=1, 2, \dots$
 - $Z=AV$
 - $VR=Z$ (QR decomposition: orthogonalize W)
- ◆ Easy, but slow
(linear convergence, nearby eigenvalues slow things down a lot)

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Rayleigh-Ritz

- ◆ Before going further with full problem, take a look at intermediate problem: find a subset of the eigenpairs
 - E.g. largest k , smallest k
- ◆ Orthogonal estimate V ($n \times k$) of eigenvectors
- ◆ Simple Rayleigh estimate of eigenvalues:
 - $\text{diag}(V^TAV)$
- ◆ Rayleigh-Ritz approach:
 - Solve $k \times k$ eigenproblem V^TAV
 - Use those eigenvalues (Ritz values) and the associated orthogonal combinations of columns of V
 - Note: another instance of “assume solution lies in span of a few basis vectors, solve reduced dimension problem”

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Solving the Full Problem

- ◆ Orthogonal iteration works, but it's slow
- ◆ First speed-up: make A tridiagonal
 - Sequence of symmetric Householder reflections
 - Then $Z=AV$ runs in $O(n^2)$ instead of $O(n^3)$
- ◆ Other ingredients:
 - Shifting: if we shift A by an exact eigenvalue, $A-\lambda I$, we get an exact eigenvector out of QR (improves on linear convergence)
 - Division: once an offdiagonal is almost zero, problem separates into decoupled blocks

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