

Math 151BH: Honors Applied Numerical Methods

Lecture 11–12: Finding leading eigenvalues

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Unnormalized power method

- Keep assuming $A \in \mathbb{R}^{n \times n}$ is symmetric.
- Suppose eigenvalues satisfy:

$$1 = \lambda_1 > |\lambda_2| \geq \dots \geq |\lambda_n| \geq 0 \quad (1)$$

- Corresponding eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$.

Consider the following algorithm:

1. Choose $\mathbf{x}^{(0)} \in \mathbb{R}^n$ at random.
2. For $k = 1, \dots, K$ do:
 - 2.1 $\mathbf{x}^{(k)} = A\mathbf{x}^{(k-1)}$.

Claim that $\mathbf{x}^{(k)} \rightarrow \mathbf{v}_1$.

Unnormalized power method

- The eigenvectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n$ are an (orthonormal) basis for \mathbb{R}^n .
- Write $\mathbf{x}^{(0)} = \alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \dots + \alpha_n \mathbf{v}_n$.
- Can compute:

$$\mathbf{x}^{(1)} = A\mathbf{x}^{(0)} = A(\alpha_1 \mathbf{v}_1 + \alpha_2 \mathbf{v}_2 + \dots + \alpha_n \mathbf{v}_n) \quad (2)$$

$$= \alpha_1 A\mathbf{v}_1 + \alpha_2 A\mathbf{v}_2 + \dots + \alpha_n A\mathbf{v}_n \quad (3)$$

$$= \alpha_1 \lambda_1 \mathbf{v}_1 + \alpha_2 \lambda_2 \mathbf{v}_2 + \dots + \alpha_n \lambda_n \mathbf{v}_n \quad (4)$$

$$\text{Similarly: } \mathbf{x}^{(k)} = \alpha_1 \lambda_1^k \mathbf{v}_1 + \alpha_2 \lambda_2^k \mathbf{v}_2 + \dots + \alpha_n \lambda_n^k \mathbf{v}_n \quad (5)$$

$$(6)$$

- By assumption $\lambda_1 = 1$ so $\lambda_1^k = 1$ for all k .
- By assumption $|\lambda_i| < 1$ for $i \geq 2$ so $\lambda_i^k \rightarrow 0$.
- **Conclusion:**

$$\lim_{k \rightarrow \infty} \mathbf{x}^{(k)} = \lim_{k \rightarrow \infty} (\alpha_1 \lambda_1^k \mathbf{v}_1 + \alpha_2 \lambda_2^k \mathbf{v}_2 + \dots + \alpha_n \lambda_n^k \mathbf{v}_n) = \alpha_1 \mathbf{v}_1 \quad (7)$$

Towards the normalized power method

Suppose that eigenvalues do not satisfy:

$$1 = \lambda_1 > |\lambda_2| \geq \dots \geq |\lambda_n| \geq 0. \quad (8)$$

Several things can go wrong:

1. If $\lambda_1 > 1$ then $\lim_{k \rightarrow \infty} \lambda_1^k = \infty$ so algorithm fails to converge.
2. If $\lambda_1 < 0$ then $\lambda_1^k = \begin{cases} \text{positive} & \text{if } k \text{ is even} \\ \text{negative} & \text{if } k \text{ is odd} \end{cases}$ so $\{\mathbf{x}^{(k)}\}_k$ will not converge.
3. What happens if A is not diagonalizable?

The Rayleigh Quotient

Assume that $A \in \mathbb{R}^{n \times n}$ is symmetric.

$$\text{The Rayleigh Quotient: } \lambda^R(\mathbf{x}) := \frac{\mathbf{x}^\top A \mathbf{x}}{\mathbf{x}^\top \mathbf{x}} \text{ for } \mathbf{x} \neq 0 \quad (9)$$

Some properties:

- If (λ, \mathbf{x}) is an eigenpair then $\lambda^R(\mathbf{x}) = \lambda$.
- $\min_{\mathbf{x}: \|\mathbf{x}\|_2=1} \lambda^R(\mathbf{x}) = \lambda_{\min}(A)$ and $\max_{\mathbf{x}: \|\mathbf{x}\|_2=1} \lambda^R(\mathbf{x}) = \lambda_{\max}(A)$.
- Rayleigh quotient is even: $\lambda^R(-\mathbf{x}) = \lambda^R(\mathbf{x})$
- $\lambda^R(\cdot)$ is continuous (away from $\mathbf{x} = 0$).

The normalized power method

1. Choose $\mathbf{x}^{(0)} \in \mathbb{R}^n$ at random with $\|\mathbf{x}^{(0)}\|_2 = 1$.
2. For $k = 1, \dots, K$ do:
 - 2.1 $\mathbf{y}^{(k)} = A\mathbf{x}^{(k-1)}$.
 - 2.2 $\mathbf{x}^{(k)} = \frac{1}{\|\mathbf{y}^{(k)}\|_2} \mathbf{y}^{(k)}$.
 - 2.3 $\lambda^{(k)} = \lambda^R(\mathbf{x}^{(k)})$.

Some remarks:

- Can use either $\mathbf{x}^{(k)}$ or $\mathbf{y}^{(k)}$ in the Rayleigh quotient.
- if $\mathbf{y}^{(k)} = 0$ terminate. Have found an eigenpair.

To show convergence:

1. First show **if** power method converges **then** limit point is an eigenpair.
2. Then show that¹ power method does converge and prove rate.

¹under some assumptions on the eigenvalues

Limit points are eigenpairs

For any $\alpha \in \mathbb{R}$ define:

$$\text{sign}(\alpha) = \begin{cases} +1 & \text{if } \alpha > 0 \\ -1 & \text{if } \alpha < 0 \\ 0 & \text{if } \alpha = 0 \end{cases} \quad (10)$$

Lemma

Suppose power method converges:

$$\lim_{k \rightarrow \infty} \lambda^{(k)} = \lambda \neq 0 \text{ and } \lim_{k \rightarrow \infty} (\text{sign}(\lambda))^k \mathbf{x}^{(k)} \rightarrow \mathbf{x} \quad (11)$$

Then $A\mathbf{x} = \lambda\mathbf{x}$.

Proof.

$$\begin{aligned} \lambda &= \lim_{k \rightarrow \infty} \lambda^{(k)} = \lim_{k \rightarrow \infty} \lambda^R(\mathbf{x}^{(k)}) \quad \text{by assumption} \\ &= \lim_{k \rightarrow \infty} \lambda^R(\text{sign}(\lambda)^k \mathbf{x}^{(k)}) \quad \text{Rayleigh quotient is even} \\ &= \lambda^R\left(\lim_{k \rightarrow \infty} \text{sign}(\lambda)^k \mathbf{x}^{(k)}\right) \quad \text{Rayleigh quotient is continuous} \\ &= \lambda^R(\mathbf{x}) \quad \text{by assumption.} \end{aligned}$$

Limit points are eigenpairs

Proof continued.

- Have established:

$$\lambda = \lim_{k \rightarrow \infty} \lambda^{(k)} = \lambda^R \left(\lim_{k \rightarrow \infty} \text{sign}(\lambda)^k \mathbf{x}^{(k)} \right) = \lambda^R(\mathbf{x}) \quad (12)$$

- Will now show: $A\mathbf{x} = \mu\mathbf{x}$ for some μ .
- Conclude that $\mu = \lambda^R(\mathbf{x}) = \lambda$ and so (\mathbf{x}, λ) is an eigenpair.
- (HW) Show that $\lim_{k \rightarrow \infty} \text{sign}(\lambda)^k \mathbf{y}^{(k+1)} = A\mathbf{x}$.
- (HW) Show that $\lim_{k \rightarrow \infty} \|\mathbf{y}^{(k)}\|_2 = \|A\mathbf{x}\|_2$.
- Conclude that:

$$A\mathbf{x} = \lim_{k \rightarrow \infty} \text{sign}(\lambda)^k \mathbf{y}^{(k+1)} \quad (13)$$

$$= \lim_{k \rightarrow \infty} \text{sign}(\lambda)^k \left[\|\mathbf{y}^{(k+1)}\|_2 \mathbf{x}^{(k+1)} \right] \quad \text{def. of } \mathbf{y}^{(k+1)} \quad (14)$$

$$= \text{sign}(\lambda) \lim_{k \rightarrow \infty} \left[\|\mathbf{y}^{(k+1)}\|_2 \right] \lim_{k \rightarrow \infty} \left[\text{sign}(\lambda)^{k+1} \mathbf{x}^{(k+1)} \right] \quad \text{limit of products} \quad (15)$$

$$= [\text{sign}(\lambda) \|A\mathbf{x}\|_2] \mathbf{x} := \alpha \mathbf{x} \quad (16)$$

□

Limit points are eigenpairs

- Thus power method is reasonable to apply.
- In practice, don't have $\text{sign}(\lambda)$. If $\lambda < 0$ observe limit cycle:

$$\lim_{k \rightarrow \infty} \mathbf{x}^{(2k)} = +\mathbf{x} \text{ and } \lim_{k \rightarrow \infty} \mathbf{x}^{(2k+1)} = -\mathbf{x} \quad (17)$$

Power method converges

- Assume that A is symmetric and that:

$$|\lambda_1| > |\lambda_2| \geq |\lambda_3| \geq \dots \geq |\lambda_n| \geq 0 \quad (18)$$

- Let $\mathbf{v}_1, \dots, \mathbf{v}_n$ be corresponding normalized eigenvectors and $Q = [\mathbf{v}_1 \ \dots \ \mathbf{v}_n]$.
- Write $A = Q\Lambda Q^\top$ with $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$.
- Observe that:

$$A^k = (Q\Lambda Q^\top)^k = \underbrace{(Q\Lambda Q^\top)(Q\Lambda Q^\top)\dots(Q\Lambda Q^\top)}_{k \text{ times}} \quad (19)$$

$$= Q\Lambda^k Q^\top \quad \text{where } \Lambda^k = \text{diag}(\lambda_1^k, \dots, \lambda_n^k) \quad (20)$$

Power method converges

- Recall that $\|\mathbf{x}^{(0)}\|_2 = 1$.
- Define auxiliary sequence as:
 1. $\mathbf{X}^{(0)} = \mathbf{x}^{(0)}$.
 2. $\mathbf{X}^{(k)} = A\mathbf{X}^{(k-1)}$.

Note that:

1. $\mathbf{X}^{(k)}$ will diverge if $|\lambda_1| > 1$!
 2. $\mathbf{X}^{(k)} = A^k \mathbf{x}^{(0)}$.
- (HW) Show that $\mathbf{x}^{(k)} = \|\mathbf{X}^{(k)}\|_2^{-1} \mathbf{X}^{(k)}$.

Power method converges

- Although $\mathbf{X}^{(k)}$ diverges $\lambda_1^{-k} \mathbf{X}^{(k)}$ will converge:

$$\lim_{k \rightarrow \infty} \lambda_1^{-k} \mathbf{X}^{(k)} = \lim_{k \rightarrow \infty} \lambda_1^{-k} \mathbf{A}^k \mathbf{x}^{(0)} \quad (21)$$

$$= \lim_{k \rightarrow \infty} \lambda_1^{-k} \left(\mathbf{Q} \mathbf{\Lambda} \mathbf{Q}^T \right)^k \mathbf{x}^{(0)} = \lim_{k \rightarrow \infty} \mathbf{Q} \lambda_1^{-k} \mathbf{\Lambda}^k \mathbf{Q}^T \mathbf{x}^{(0)} \quad (22)$$

$$= \lim_{k \rightarrow \infty} \mathbf{Q} \tilde{\mathbf{\Lambda}}^k \mathbf{Q}^T \mathbf{x}^{(0)} \text{ where } \tilde{\mathbf{\Lambda}} = \text{diag} \left(1, \lambda_2/\lambda_1, \dots, \lambda_n/\lambda_1 \right) \quad (23)$$

$$= \mathbf{Q} \left[\lim_{k \rightarrow \infty} \tilde{\mathbf{\Lambda}}^k \right] \mathbf{Q}^T \mathbf{x}^{(0)} \quad (24)$$

- Note that:

$$\lim_{k \rightarrow \infty} \tilde{\mathbf{\Lambda}}^k = \lim_{k \rightarrow \infty} \text{diag} \left(1, (\lambda_2/\lambda_1)^k, \dots, (\lambda_n/\lambda_1)^k \right) \quad (25)$$

$$= \text{diag} \left(1, \lim_{k \rightarrow \infty} (\lambda_2/\lambda_1)^k, \dots, \lim_{k \rightarrow \infty} (\lambda_n/\lambda_1)^k \right) \quad (26)$$

$$= \text{diag} (1, 0, \dots, 0) \text{ as } |\lambda_1| > |\lambda_i| \text{ for } i \neq 1 \quad (27)$$

$$=: \mathbf{E}_{11} \quad (28)$$

- Check that: $\mathbf{Q} \mathbf{E}_{11} \mathbf{Q}^T = \mathbf{v}_1 \mathbf{v}_1^T$.

Power method converges

- So we observe that:

$$\lim_{k \rightarrow \infty} \lambda_1^{-k} \mathbf{X}^{(k)} = [\mathbf{v}_1 \mathbf{v}_1^T] \mathbf{x}^{(0)} = [\mathbf{v}_1^T \mathbf{x}^{(0)}] \mathbf{v}_1 \quad (29)$$

- We also have a convergence of norms:

$$\lim_{k \rightarrow \infty} |\lambda_1|^{-k} \|\mathbf{X}^{(k)}\|_2 = \lim_{k \rightarrow \infty} |\lambda_1^{-k}| \|\mathbf{X}^{(k)}\|_2 \quad (30)$$

$$= \lim_{k \rightarrow \infty} \|\lambda_1^{-k} \mathbf{X}^{(k)}\|_2 \quad (31)$$

$$= \left\| \lim_{k \rightarrow \infty} \lambda_1^{-k} \mathbf{X}^{(k)} \right\|_2 = \left\| [\mathbf{v}_1^T \mathbf{x}^{(0)}] \mathbf{v}_1 \right\|_2 \quad (32)$$

$$= \left| \mathbf{v}_1^T \mathbf{x}^{(0)} \right| \quad \text{as } \|\mathbf{v}_1\|_2 = 1 \quad (33)$$

Power method converges

- The final trick:

$$\begin{aligned}\lim_{k \rightarrow \infty} \text{sign}(\lambda_1)^k \mathbf{x}^{(k)} &= \lim_{k \rightarrow \infty} \frac{\text{sign}(\lambda_1)^k \mathbf{X}^{(k)}}{\|\mathbf{X}^{(k)}\|_2} \\ &= \lim_{k \rightarrow \infty} \frac{\text{sign}(\lambda_1)^k |\lambda_1|^{-k} \mathbf{X}^{(k)}}{|\lambda_1|^{-k} \|\mathbf{X}^{(k)}\|_2} \quad \text{multiplying top and bottom} \\ &= \lim_{k \rightarrow \infty} \frac{\lambda_1^{-k} \mathbf{X}^{(k)}}{|\lambda_1|^{-k} \|\mathbf{X}^{(k)}\|_2} \quad \text{as } \text{sign}(\alpha)|\alpha| = \alpha \\ &= \frac{\lim_{k \rightarrow \infty} \lambda_1^{-k} \mathbf{X}^{(k)}}{\lim_{k \rightarrow \infty} |\lambda_1|^{-k} \|\mathbf{X}^{(k)}\|_2} \quad \text{limit of quotient} \\ &= \frac{\begin{bmatrix} \mathbf{v}_1^\top \mathbf{x}^{(0)} \end{bmatrix} \mathbf{v}_1}{|\mathbf{v}_1^\top \mathbf{x}^{(0)}|} \quad \text{By earlier work} \\ &= \text{sign}(\mathbf{v}_1^\top \mathbf{x}^{(0)}) \mathbf{v}_1\end{aligned}$$

Power method converges: conclusion

Theorem

Suppose that:

1. A is symmetric.
2. $|\lambda_1| > |\lambda_2|$.
3. $\mathbf{v}_1^\top \mathbf{x}^{(0)} \neq 0$.

Let $\mathbf{x}^{(k)}, \lambda^{(k)}$ be the sequence generated by the power method. Then:

1. $\lim_{k \rightarrow \infty} \lambda^{(k)} = \lambda_1$.
2. $\lim_{k \rightarrow \infty} \mathbf{x}^{(k)} = \text{sign}(\mathbf{v}_1^\top \mathbf{x}^{(0)}) \mathbf{v}_1$.
3. $\left\| \text{sign}(\mathbf{v}_1^\top \mathbf{x}^{(0)}) \mathbf{v}_1 - \mathbf{x}^{(k)} \right\|_2 \leq C (|\lambda_2|/|\lambda_1|)^k$

- HW: Show the convergence to λ_1 .
- For rate of convergence, see textbook.
- Can remove assumption that A is symmetric; see textbook.