

⑧ Eigen values

$$A \in \mathbb{R}^{n \times n}$$

x is an eigenvector of A :

[eigenvectors unique?
No.

$$x \neq 0, \text{ there is a } \lambda \text{ so that } Ax = \lambda x$$

λ eigenvalue of A

[must A be square?
Yes.

$$\Leftrightarrow (A - \lambda I)x = 0 \text{ has a solution } x \neq 0$$

$$\Leftrightarrow N(A - \lambda I) \neq \{0\}$$

$$\begin{pmatrix} 1 & * & * & * & * \\ & \lambda & & & \\ & & 3 & & \\ & & & \lambda & \\ & & & & 4 \\ & & & & & \lambda \\ & & & & & & 7 \end{pmatrix}$$

For ∇ matrices, eigen values appear on the diagonal.

Because eigenvalues satisfy a polynomial equation of degree n , and because there is no formula to solve such equations, num. methods for eigenvalues must be approximate!

What matrix operations do to eigenvalues

Suppose $Ax = \lambda x$.

• "Scaling" $\beta A \rightsquigarrow (\beta A)x = \beta \lambda x$

• "Shift" $A - \sigma I \rightsquigarrow (A - \sigma I)x = Ax - \sigma x = (\lambda - \sigma)x$

• Power $A^k \rightsquigarrow A^k x = \lambda^k x$

• Inverse $A^{-1} \rightsquigarrow Ax = \lambda x \rightsquigarrow \frac{1}{\lambda}x = A^{-1}x$

• Similarity $T^{-1}AT \rightsquigarrow y := T^{-1}x$

$$\begin{aligned}(T^{-1}AT)y &= T^{-1}Ax \\ &= \lambda T^{-1}x \\ &= \lambda y\end{aligned}$$

\rightsquigarrow Similarity transforms preserve eigenvalues \triangle

Will also say: A, B are similar if there exists

a matrix T such that $B = T^{-1}AT$.

If A is similar to a diagonal matrix, it's called

Diagonalizable.

Let $X = (| | | |)$ be a matrix full of linearly independent eigenvectors. Then

$$AX = X \underbrace{\begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}}_{\mathbb{D}} \rightsquigarrow X^{-1}AX = \mathbb{D}.$$

So that would do it (= diagonalize a matrix).

algebraic multiplicity \geq geometric multiplicity

(multiplicity of λ as a root of the characteristic polynomial)

(# of lin. indep. eigenvectors corresponding to λ)

Defective matrix has eigenvalue with

$$AM > GM.$$

Defective matrices are not diagonalizable.

Diagonalizable matrices are not defective.

Tool: Schur form

Every matrix is orthogonally similar to an upper triangular matrix.

$$A = QUQ^T$$

If we knew how to compute this, why would it be helpful for knowing eigenvalues? *on the diagonal of U .*

Do we have the eigenvectors, too? *No, but easy to find.*

Finding eigenvectors from Schur form (for eigenvalue λ)

① Find x with $Ux = \lambda x \Leftrightarrow x \in N(U - \lambda I)$
 \rightarrow Nullspace finding, U is already upper tri.

② $y = Qx$ is an eigenvector of A :

$$Ay = QUQ^T Qx = \dots = \lambda y$$

Power iteration

A diagonalizable $n \times n$ - have x_1, \dots, x_n lin. indep. eigenvectors with $\lambda_1, \dots, \lambda_n$ eigenvalues

$$|\lambda_1| \geq |\lambda_2| \dots \geq |\lambda_n|$$

$$x = \alpha_1 x_1 + \dots + \alpha_n x_n$$

$$\begin{aligned} Ax &= \alpha_1 A x_1 + \dots + \alpha_n A x_n \\ &= \alpha_1 \lambda_1 x_1 + \dots + \alpha_n \lambda_n x_n \end{aligned}$$

$$A^{20,000} x = A \cdot A \cdot A \dots A x$$

$$= \alpha_1 \lambda_1^{20,000} x_1 + \dots + \alpha_n \lambda_n^{20,000} x_n$$

$$\frac{A^{20,000} x}{\lambda_1^{20,000}} = \alpha_1 x_1 + \alpha_2 \underbrace{\frac{\lambda_2^{20,000}}{\lambda_1^{20,000}}}_{\substack{|\cdot| \leq 1 \\ = \left(\frac{\lambda_2}{\lambda_1}\right)^{20k} \\ \ll 1!}} x_2 + \dots + \alpha_n \underbrace{\frac{\lambda_n^{20,000}}{\lambda_1^{20,000}}}_{\substack{\downarrow \\ \left(\frac{\lambda_n}{\lambda_1}\right)^{20k}}$$

Possible problems:

- starting vector has no component for λ_1 \leftarrow no problem because of rounding
- $\lambda_1 = \lambda_2$
- complex eigenvalues?

Demo: Power iteration and variants

Power it.

$$x_{k+1} = Ax_k$$

Normalized power it.

$$x_{k+1} = \frac{Ax_k}{\|Ax_k\|} \quad \leftarrow \text{fixes overflow issue}$$

Inverse iteration:

$$x_{k+1} = \frac{A^{-1}x_k}{\|A^{-1}x_k\|} \quad \leftarrow \text{finds eigenv. of smallest eigenvalue (by magnitude)}$$

Inverse iteration w/shift

$$x_{k+1} = \frac{(A - \sigma I)^{-1}x_k}{\|(A - \sigma I)^{-1}x_k\|} \quad \leftarrow \text{finds eigenvalues near } \sigma$$

Rayleigh quotient iteration: set σ to the Rayleigh quotient in inv. it. w/shift.

The Rayleigh quotient is an estimate of the eigenvalue for an approx. eigenvector x :

$$\frac{x \cdot Ax}{x \cdot x}$$

\leftarrow what if $Ax = \lambda x$ exactly?

lec 19

exam Tue

practice exam out tomorrow

hw4, hw3 solutions out today

outline

recap: inverse iteration

discuss quite

Q's: - diff btw normalized and un-normalized pwr it

- what is the point of pwr it if there is up. linalg?

- how come we can find the orig. eigval despite shift etc?

- how to get all eigvals?

[Downside of all these methods? One eigenvector at a time.

Idea: Just iterate multiple vectors at a time.

→ "Simultaneous iteration"

o [Why doesn't that work? → all vectors converge to the eigenvector for λ_1 (the largest by magnitude)

Idea: Keep them linearly independent. Even better: keep them orthogonal!

Orthogonal iteration

$$X_0 \in \mathbb{R}^{n \times p} \quad (p \leq n) \text{ arbitrary (ideally w/full rank)}$$

$$Q_1 R_1 = X_0$$

$$X_1 = A Q_1$$

$$Q_2 R_2 = X_1$$

$$X_2 = A Q_2$$

⋮

Suppose this "converges" so that $X_{k+1} \approx X_k$.

$$\leadsto Q_{k+1} R_{k+1} = X_k \approx X_{k+1}$$

$$\leadsto X_{k+1} = A Q_{k+1}$$

$$\leadsto Q_{k+1} R_{k+1} = A Q_{k+1}$$

$$\leadsto Q_{k+1} R_{k+1} Q_{k+1}^T = A \leftarrow [?] \quad \text{Schur form!}$$

"Professional" eigenvalue software uses the "QR algorithm" which is a variant of this.

<inclass-power-iteration>

lec 10

hw4 deadline next thurs
outline

Q's

Computing the SVD

Assume we know the SVD $A = U \Sigma V^T$

Then $A^T A = V \Sigma^T U^T U \Sigma V^T = \underbrace{V \Sigma^T \Sigma V^T}$

eigenvalues? $\sigma_1^2, \sigma_2^2, \dots, \sigma_n^2$
eigenvectors? v_1, v_2, \dots, v_n

Idea: To compute the SVD:

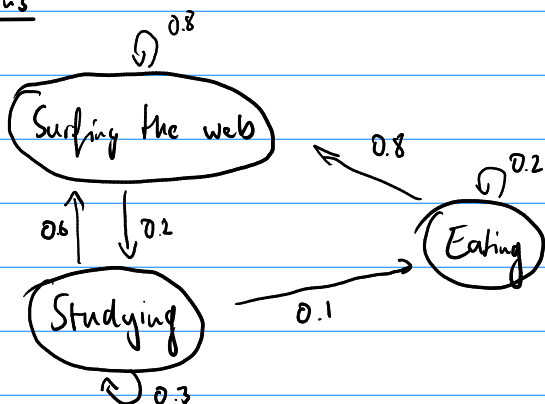
① compute the eigenvalues $\lambda_1, \dots, \lambda_n$ / eigenvectors of v_1, \dots, v_n of $A^T A$.
(e.g. using orthogonal iteration)

② set $V = \begin{pmatrix} | & & | \\ v_1 & \dots & v_n \\ | & & | \end{pmatrix}, \Sigma = \begin{pmatrix} \sqrt{\lambda_1} & & \\ & \dots & \\ & & \sqrt{\lambda_n} \end{pmatrix}$

③ Find U from $A = U \Sigma V^T$.

Demos: Computing the SVD

Markov chains



Important assumption: Only most recent state matters to determine the probabilities for the next state.
(“Markov assumption/property”)

Write transition probabilities into matrix:

$$A = \begin{matrix} & \begin{matrix} \text{surf} & \text{study} & \text{eat} \end{matrix} \\ \begin{matrix} \text{surf} \\ \text{study} \\ \text{eat} \end{matrix} & \begin{bmatrix} .8 & .6 & .8 \\ .2 & .3 & 0 \\ 0 & .1 & .2 \end{bmatrix} \end{matrix} \begin{matrix} \text{to state} \\ \\ \end{matrix} \quad \left[\text{Column sums} = 1. \text{ Why?} \right]$$

State transitions modeled by matrix vector product.

Vector entries: Probability of being in i -th state.

$$A \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} .8 \\ .2 \\ 0 \end{pmatrix} \begin{matrix} \text{surf} \\ \\ \end{matrix}$$

$$A \begin{pmatrix} .5 \\ .5 \\ 0 \end{pmatrix} = \begin{pmatrix} .4 + .3 \\ .1 + .15 \\ .05 \end{pmatrix}$$

If we observe all 50k UIUC students, what fraction of them are in each state?

Assume equilibrium: Previous state = next state.

$$\rightarrow Ax = \lambda x \quad \rightarrow \text{eigenvalue problem!}$$

Demo: Find equilibrium distribution using power iteration