

MODULE 9: DIAGONALIZATION AND PAGE RANK

Linear Algebra 3: Determinants and Eigenvalues

TOPIC 1: Diagonalization

Powers of Matrices

Motivation: It can be useful to take large powers of matrices, for example A^k , for large k .

But: multiplying $2 \times n$ matrices requires roughly n^3 computations. Is there a more efficient way to compute A^k ?

Diagonal Matrices

DEFINITION — Diagonal Matrices

↪ A matrix is diagonal if the only nonzero elements, if any, are on the main diagonal.

The following are all diagonal matrices.

$$\text{In. } \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}, \begin{pmatrix} 2 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 3 \end{pmatrix}$$

We will only be working with diagonal square matrices in the course.

Powers of Diagonal Matrices

If A is diagonal, then A^k is easy to compute. For example,

$$A = \begin{pmatrix} 3 & 0 \\ 0 & 5 \end{pmatrix}$$

$$A^2 = \begin{pmatrix} 3 & 0 \\ 0 & 5 \end{pmatrix} \begin{pmatrix} 3 & 0 \\ 0 & 5 \end{pmatrix} = \begin{pmatrix} 3^2 & 0 \\ 0 & 5^2 \end{pmatrix}$$

$$A^k = \begin{pmatrix} 3^k & 0 \\ 0 & 5^k \end{pmatrix}$$

But what if A is not diagonal?

Diagonalization

DEFINITION — Diagonalization

↪ Suppose $A \in \mathbb{R}^{n \times n}$. We say that A is diagonalizable if it is similar to a diagonal matrix, D . That is, we can write $A = PDP^{-1}$.

$$\text{Also note that } A = PDP^{-1} \text{ iff } A = (\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n) \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{pmatrix} (\vec{v}_1, \vec{v}_2, \dots, \vec{v}_n)^{-1}$$

$\vec{v}_1, \dots, \vec{v}_n$ are linearly independent eigenvectors, and $\lambda_1, \dots, \lambda_n$ are the corresponding eigenvalues (in order).

Proof: We construct $P = (\vec{v}_1 \ \vec{v}_2 \ \dots \ \vec{v}_n)$. Then

$$\begin{aligned} AP &= A(\vec{v}_1 \ \vec{v}_2 \ \dots \ \vec{v}_n) \\ &= (A\vec{v}_1 \ A\vec{v}_2 \ \dots \ A\vec{v}_n) \\ &= (\lambda_1 \vec{v}_1 \ \lambda_2 \vec{v}_2 \ \dots \ \lambda_n \vec{v}_n) \\ AP &= (\vec{v}_1 \ \vec{v}_2 \ \dots \ \vec{v}_n) \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_n \end{pmatrix} \\ &= PD \end{aligned}$$

Or, $A = PDP^{-1}$ - (QED)

Theorem: If A is diagonalizable $\Leftrightarrow A$ has n linearly independent vectors.

Note: \Leftrightarrow means if and only if (iff)

Example 1:

Diagonalize if possible. $\begin{pmatrix} 2 & 6 \\ 0 & -1 \end{pmatrix} = A$.

$$\lambda_1 = 2 : (A - 2I | 0) = \left(\begin{array}{cc|c} 0 & 6 & 0 \\ 0 & -3 & 0 \end{array} \right) \quad 6x_2 = 0 \Rightarrow x_2 = 0. \Rightarrow \vec{v}_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

$$\lambda_2 = -1 : (A + I | 0) = \left(\begin{array}{cc|c} 3 & 6 & 0 \\ 0 & 0 & 0 \end{array} \right) \quad 3x_1 + 6x_2 = 0 \Rightarrow \vec{v}_2 = \begin{pmatrix} 2 \\ -1 \end{pmatrix}$$

$$\begin{aligned} A &= PDP^{-1} \\ &= \begin{pmatrix} 1 & 2 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} 2 & 0 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} 1 & 2 \\ 0 & -1 \end{pmatrix} \end{aligned}$$

$$P^{-1} = \frac{1}{-1} \begin{pmatrix} 1 & -2 \\ 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 2 \\ 0 & -1 \end{pmatrix}.$$

Example 2:

Diagonalize if possible. $\begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} = A$.

$$\lambda = 1 : (A - I | 0) = \left(\begin{array}{cc|c} 0 & 1 & 0 \\ 0 & 0 & 0 \end{array} \right) \quad x_2 = 0. \Rightarrow \vec{v}_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}.$$

$\Rightarrow A$ is not diagonalizable.

Exercise:

Suppose matrix A is 2×2 and has the eigenvectors and eigenvalues below.

$$\lambda_1 = -1, \vec{v}_1 = \begin{pmatrix} 2 \\ 1 \end{pmatrix}; \quad \lambda_2 = 0, \vec{v}_2 = \begin{pmatrix} 1 \\ 3 \end{pmatrix}$$

If $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, what is a_{11} equal to?

$$P = \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix}, \quad P^{-1} = \frac{1}{2(3)-1(1)} \begin{pmatrix} 3 & -1 \\ -1 & 2 \end{pmatrix} = \begin{pmatrix} 3 & -1 \\ -1 & 2 \end{pmatrix}$$

$$D = \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix}$$

$$A = PDP^{-1}$$

$$= \begin{pmatrix} 2 & 1 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} 3 & -1 \\ -1 & 2 \end{pmatrix} = \begin{pmatrix} -2 & 0 \\ -1 & 0 \end{pmatrix} \begin{pmatrix} 3 & -1 \\ -1 & 2 \end{pmatrix}$$

$$A = \begin{pmatrix} -6 & 10 \\ -3 & 5 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}.$$

$$\therefore a_{11} = -6$$

Diagonalization Theorems

- Motivation:
- * how can we determine whether a given $n \times n$ matrix can be diagonalized?
 - * can we determine whether a square matrix can be diagonalized if we know:
 - ↳ the algebraic or geometric multiplicities of the eigenvalues? (we can)
 - ↳ whether the matrix is invertible? (we cannot)
 - * if a matrix has a repeated eigenvalue, how can we diagonalize the matrix?

Theorem: Distinct Eigenvalues and Diagonalizability

If A is $n \times n$ and has n distinct eigenvalues, then A is diagonalizable

Why does this theorem hold?

- ↳ For an $n \times n$ matrix to be diagonalizable it must have n linearly independent eigenvectors.
- ↳ Eigenvectors corresponding to distinct eigenvalues are independent.

Is it necessary for an $n \times n$ matrix to have n distinct eigenvalues for it to be diagonalizable?

↳ NO - The identity matrix is diagonalizable.

Diagonalization Example 1:

Give an example of a nonzero square matrix that is in RREF, is diagonalizable, and is singular.

Solution: Any matrix that has distinct eigenvalues can be diagonalized.

This matrix below can be diagonalized:

$$A = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$$

This matrix can be diagonalized:

$$A = PDP^{-1}, \quad P = P^{-1} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, \quad D = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}$$

Note: if we know that a matrix is not invertible, we cannot conclude that the matrix is not diagonalizable

How can we tell whether a matrix with repeated eigenvalues is diagonalizable?

Theorem: Diagonalizability

Suppose $\rightarrow A$ is any $n \times n$ real matrix

$\hookrightarrow A$ has distinct eigenvalues $\lambda_1, \dots, \lambda_k, k \leq n$

$\hookrightarrow a_i = \text{algebraic multiplicity of } \lambda_i$

$\hookrightarrow g_i = \text{dimension of } \lambda_i \text{ eigenspace, or the geometric multiplicity}$

Then

$\hookrightarrow A$ is diagonalizable $\Leftrightarrow \sum g_i = n \Leftrightarrow g_i = a_i \forall i$

$\hookrightarrow A$ is diagonalizable \Leftrightarrow the eigenvectors, λ eigenvalues, together form a basis for \mathbb{R}^n

Diagonalization Example 2:

True or False: If A is not invertible, then A is not diagonalizable.

False. If $A = \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$, then A is not invertible and can be diagonalized:

$$A = PDP^{-1} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Note \rightarrow some matrices that are not invertible can be diagonalized

\hookrightarrow some matrices that have a repeated eigenvalue can be diagonalized

Diagonalization Example 3:

For what value of k is $A = \begin{pmatrix} 1 & k \\ 0 & 1 \end{pmatrix}$ diagonalizable?

Case 1: $k=0$. Then $A = I_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$ and can be diagonalized:

$$A = PDP^{-1} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Case 2: $k \neq 0$. Then $A = \begin{pmatrix} 1 & k \\ 0 & 1 \end{pmatrix}$, and $\lambda=1$. Obtain eigenvectors:

$$(A - I | 0) = \begin{pmatrix} 0 & k & 0 \\ 0 & 0 & 0 \end{pmatrix} \Rightarrow \vec{v} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

A can only be diagonalized when $k=0$.

matrix invertibility does not tell if matrix is diagonalizable, have to look at multiplicities of the eigenvalues or whether the eigenvectors span all of our n

Note: Matrix A is invertible \wedge values of k .

Matrix A is diagonalizable \exists values of k .

The invertibility of a matrix does not tell us anything about whether the matrix is diagonalizable.

Diagonalization a Matrix with Repeated Eigenvalues

How can we diagonalize a matrix that has a repeated eigenvalue?

The only eigenvalues of A are $\lambda_1=1$ and $\lambda_2=\lambda_3=3$. If possible, construct P and D such that $AP=PD$.

$$A = \begin{pmatrix} 7 & 4 & 16 \\ 2 & 5 & 8 \\ -2 & -2 & -5 \end{pmatrix}$$

$\lambda_1 = 1$. Identifying corresponding eigenvectors:

$$A - \lambda_1 I = A - I = \begin{pmatrix} 6 & 4 & 16 \\ 2 & 4 & 8 \\ -2 & -2 & -6 \end{pmatrix} \xrightarrow{\frac{1}{2}R_1 \rightarrow R_1} \begin{pmatrix} 3 & 2 & 8 \\ 1 & 2 & 4 \\ 1 & 1 & 3 \end{pmatrix} \xrightarrow{R_2 - R_3 \rightarrow R_2} \begin{pmatrix} 3 & 2 & 8 \\ 0 & 1 & 1 \\ 1 & 1 & 3 \end{pmatrix} \xrightarrow{R_3 - R_2 \rightarrow R_3} \begin{pmatrix} 3 & 2 & 8 \\ 0 & 1 & 1 \\ 1 & 0 & 2 \end{pmatrix}$$

$$\xrightarrow{R_1 - 2R_2 - 3R_3 \rightarrow R_1} \begin{pmatrix} 0 & 0 & 0 \\ 0 & 1 & 1 \\ 1 & 0 & 2 \end{pmatrix} \xrightarrow{R_1 \leftrightarrow R_3} \begin{pmatrix} 1 & 0 & 2 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

$\chi_2 + \chi_3 = 0 \Rightarrow \chi_2 = -\chi_3$
 $\chi_1 = -2\chi_3 = 2\chi_2$

A vector in the null space of $A - \lambda_2 I$ is $\vec{v}_1 = \begin{pmatrix} 2 \\ 1 \\ -2 \end{pmatrix}$.

$\lambda_2 = 3$. $A - \lambda_2 I = A - 3I$

$$= \begin{pmatrix} 4 & 4 & 16 \\ 2 & 2 & 8 \\ -2 & -2 & -8 \end{pmatrix} \rightsquigarrow \begin{pmatrix} 1 & 1 & 4 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

$\chi_1 + \chi_2 + 4\chi_3 = 0$
Eigenvectors corresponding to $\lambda_2 = 3$ must satisfy this relation.

χ_1 and χ_3 are free variables.
 $\Rightarrow \chi_1 = -\chi_2 - 4\chi_3$

Parametric vector form:

$$\vec{v} = \begin{pmatrix} \chi_1 \\ \chi_2 \\ \chi_3 \end{pmatrix} = \begin{pmatrix} -\chi_2 - 4\chi_3 \\ \chi_2 \\ \chi_3 \end{pmatrix} = \chi_2 \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix} + \chi_3 \begin{pmatrix} -4 \\ 0 \\ 1 \end{pmatrix}$$

$$\therefore P = (\vec{v}_1 \ \vec{v}_2 \ \vec{v}_3) = \begin{pmatrix} 2 & -1 & -4 \\ 1 & 1 & 0 \\ -2 & 0 & 1 \end{pmatrix}, \ D = \begin{pmatrix} \chi_1 & 0 & 0 \\ 0 & \chi_2 & 0 \\ 0 & 0 & \chi_3 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 3 & 0 \\ 0 & 0 & 3 \end{pmatrix}$$

Exercise: Are the following matrices diagonalizable?

???

$A = \begin{pmatrix} 7 & 1 \\ 0 & 5 \end{pmatrix}$ ✓. The eigenvalues of A can be determined by inspection, the eigenvalues are distinct, and eigenvectors corresponding to distinct eigenvalues are linearly independent, so we can form an invertible matrix P with the eigenvectors of A . So, A is diagonalizable.

$A = \begin{pmatrix} 7 & 1 \\ 0 & 7 \end{pmatrix}$ ✗. The eigenvalues of A can be determined by inspection, the eigenvalues are not distinct. An eigenvector we can find for this matrix is $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$, but we cannot

construct another eigenvector that will allow us to create an invertible matrix P , because the dimension of the eigenspace is only 1. So we cannot form an invertible matrix P . So A is not diagonalizable.

Matrix Powers

Motivation: suppose A is an $n \times n$ matrix. Recall that:

↳ in some applications we need to compute A^k for large k

↳ computing A^k directly could require many computations, especially if n is large and many of the elements in A are nonzero

Using the concept of similar matrices, we can obtain a more efficient approach.

Example: Matrix Powers

Suppose A is a 2×2 matrix whose eigenvalues and associated eigenvectors are as below.
Compute A^{100} .

$$\lambda_1 = -\frac{1}{2}, \vec{v}_1 = \begin{pmatrix} 2 \\ 1 \end{pmatrix}; \lambda_2 = \frac{1}{2}, \vec{v}_2 = \begin{pmatrix} 1 \\ -2 \end{pmatrix}$$

Because the eigenvalues of A are distinct, we can diagonalize A .

$$\begin{aligned} A &= PDP^{-1} \\ A^2 &= PDP^{-1}PDP^{-1} = PD^2P^{-1} \\ A^3 &= PDP^{-1}PDP^{-1}PDP^{-1} = PD^3P^{-1} \\ &\vdots \\ A^K &= PD^KP^{-1} \end{aligned}$$

$$\begin{aligned} (2 & 1)^{-1} = \frac{1}{-4-1} \begin{pmatrix} -2 & -1 \\ -1 & 2 \end{pmatrix} \\ &= \frac{1}{-5} \begin{pmatrix} -2 & 1 \\ -1 & 2 \end{pmatrix} = \frac{1}{5} \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} \end{aligned}$$

Thus, to compute A^{100} , we can instead compute $PD^{100}P^{-1}$.

Using these values, A^{100} becomes

$$\begin{aligned} A^{100} &= PD^{100}P^{-1} = \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} \begin{pmatrix} -1/2 & 0 \\ 0 & 1/2 \end{pmatrix}^{100} \begin{pmatrix} 1/5 & 2 & 1 \\ 1 & 1 & -2 \end{pmatrix} \\ &= \frac{1}{5} \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} \begin{pmatrix} 2^{-100} & 0 \\ 0 & 2^{-100} \end{pmatrix} \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} \\ &= \frac{1}{5(2^{100})} \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} = \frac{1}{5(2^{100})} \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} \begin{pmatrix} 2 & 1 \\ 1 & -2 \end{pmatrix} = \frac{1}{5(2^{100})} \begin{pmatrix} 5 & 0 \\ 0 & 5 \end{pmatrix} \\ &= \frac{1}{2^{100}} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \\ A^{100} &= 2^{-100} I_2 \end{aligned}$$

Exercise:

Suppose matrix A is 2×2 and has the following eigenvectors and eigenvalues:

$$\lambda_1 = -1, \vec{v}_1 = \begin{pmatrix} 2 \\ 1 \end{pmatrix}; \lambda_2 = 0, \vec{v}_2 = \begin{pmatrix} 5 \\ 3 \end{pmatrix}$$

Now suppose we want to compute A^{10} .

If $A^{10} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, what is a_{11} equal to?

$$\begin{aligned} A^{10} &= PD^{10}P^{-1}, P = \begin{pmatrix} 2 & 5 \\ 1 & 3 \end{pmatrix}, D = \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix} & P^{-1} \\ &= \begin{pmatrix} 2 & 5 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} -1 & 0 \\ 0 & 0 \end{pmatrix}^{10} \begin{pmatrix} 3 & -5 \\ -1 & 2 \end{pmatrix} &= \frac{1}{2(3)-5(1)} \begin{pmatrix} 3 & -5 \\ -1 & 2 \end{pmatrix} = \begin{pmatrix} 3 & -5 \\ -1 & 2 \end{pmatrix} \\ &= \begin{pmatrix} 2 & 5 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} 3 & -5 \\ -1 & 2 \end{pmatrix} &= \begin{pmatrix} 2 & 5 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} 3 & -5 \\ -1 & 2 \end{pmatrix} \\ &= \begin{pmatrix} 2 & 5 \\ 1 & 3 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} 6 & -10 \\ 3 & -5 \end{pmatrix} &= \begin{pmatrix} 6 & -10 \\ 3 & -5 \end{pmatrix} \therefore a_{11} = 6 \end{aligned}$$

TOPIC 2: Complex Eigenvalues

Review of Complex Numbers

Set of imaginary (or complex) numbers, $\mathbb{C} = \{a+bi \mid a, b \in \mathbb{R}\}$, $i = \sqrt{-1}$

Addition and subtraction examples:

$$\begin{aligned}(2-3i) + (-1+i) &= (2-1) + (-3+1)i = 1-2i \\(2-3i)(-1+i) &= -2+2i+3i-3i^2 \\&= -2+5i+3 \\&= 1+5i\end{aligned}$$

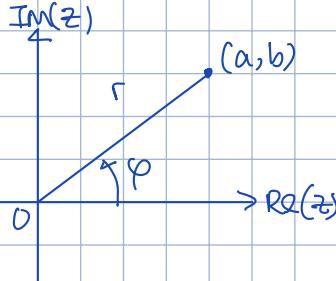
$i^2 = -1$

We can conjugate complex numbers: $\overline{a+bi} = a-bi$

The absolute value of a complex number: $|a+bi| = \sqrt{a^2+b^2}$

We can write complex numbers in polar form: $a+bi = r(\cos \varphi + i \sin \varphi)$, where:

$$r = |a+bi| \quad \tan \varphi = \frac{b}{a}$$



Complex Conjugate Properties:

If x and y are complex numbers, $\vec{v} \in \mathbb{C}^n$, it can be shown that:

$$*(\overline{x+y}) = \overline{x} + \overline{y}$$

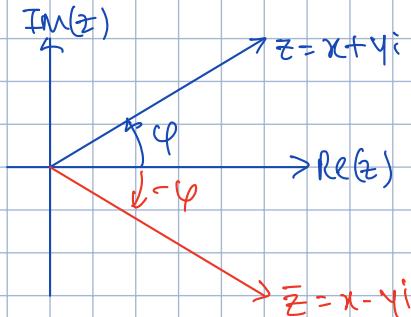
$$*\overline{A\vec{v}} = A\overline{\vec{v}}, \quad A \in \mathbb{R}^{n \times n}$$

$$*\operatorname{Im}(x\bar{y}) = 0$$

Example: (True or False) If x and y are complex numbers, then $(\overline{xy}) = (\bar{x}\bar{y})$ TRUE

$$\begin{aligned}\text{Let } x = a+bi, \quad y = c+di. \quad \overline{xy} &= \overline{(a+bi)(c+di)} \\&= \overline{(ac-bd) + i(ad+bc)} \\&= ac-bd - i(ad-bc) \\&= (a-bi)(c-di) = \bar{x}\bar{y} \quad (\text{QED}).\end{aligned}$$

Conjugation reflects points across the real axis.



Exercise: (True or False) If $k \in \mathbb{R}$ and $z \in \mathbb{C}$, then $\overline{kz} = k\bar{z}$. TRUE.

$$\begin{aligned} \text{Let } z = a+bi. \quad \overline{kz} &= \overline{k(a+bi)} = \overline{ak+bki} \\ &= ak - bki \\ &= k(a-bi) = k\bar{z} \quad (\text{QED}). \end{aligned}$$

Exercise: (True or False) If A is a real 2×2 matrix and \vec{v} is a vector with two complex entries, then $\overline{A\vec{v}} = A\vec{\bar{v}}$. TRUE.

If $x_1, x_2 \in \mathbb{C}$, then $\overline{x_1+x_2} = \overline{x_1} + \overline{x_2}$.

$$\begin{aligned} \text{If } x_1, x_2 \in \mathbb{C} \text{ and } a_{11}, a_{12} \in \mathbb{R}, \text{ then } \overline{a_{11}x_1 + a_{12}x_2} &= \overline{a_{11}x_1} + \overline{a_{12}x_2} \\ &= a_{11}\overline{x_1} + a_{12}\overline{x_2}. \end{aligned}$$

Suppose $A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}$, and $\vec{v} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$ is a vector with complex entries, then

$A\vec{v}$ is a vector with two entries.

$$A\vec{v} = \begin{pmatrix} a_{11}x_1 + a_{12}x_2 \\ a_{21}x_1 + a_{22}x_2 \end{pmatrix}$$

$$\overline{A\vec{v}} = \begin{pmatrix} \overline{a_{11}x_1 + a_{12}x_2} \\ \overline{a_{21}x_1 + a_{22}x_2} \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} \overline{x_1} \\ \overline{x_2} \end{pmatrix}$$

$$\overline{A\vec{v}} = A\vec{\bar{v}} \quad (\text{QED}) \star$$

Complex Numbers and Polynomials

Theorem: Fundamental Theorem of Algebra

Every polynomial of degree n has exactly n complex roots, counting multiplicity.

For example, $(x-2)^2$ is a 2nd order polynomial, it has two roots

$(x-2)^2(x-1)$ is a 3rd order polynomial, it has three roots

Theorem:

If $\lambda \in \mathbb{C}$ is a root of a real polynomial $p(x)$, then the conjugate $\bar{\lambda}$ is also a root of $p(x)$.

Because of this theorem, if λ is an eigenvalue of real matrix A with eigenvector \vec{v} ,

then $\bar{\lambda}$ is an eigenvalue of A with eigenvector \vec{v} .

$$A\vec{v} = \lambda\vec{v}$$

$$A\vec{v} = \overline{\lambda}\vec{v}$$

$$A\vec{v} = \bar{\lambda}\vec{v}$$

Examples:

① If A is a 2×2 matrix and one of its eigenvectors is $\vec{v} = \begin{pmatrix} 1 \\ i \end{pmatrix}$, give another eigenvector of A

that is not a multiple of \vec{v} . $\vec{v} = \begin{pmatrix} 1 \\ -1 \end{pmatrix}$

② Four of the eigenvalues of a 7×7 matrix are $-2, 4+i, -4-i$, and i . What are the other eigenvalues? $\Rightarrow 4-i, -4+i, -i$

Exercises:

- (1) Suppose A is a 2×2 matrix and one of its eigenvectors is $\vec{v}_1 = \begin{pmatrix} 2 \\ 1+i \end{pmatrix}$. Which of the following vectors is also an eigenvector of A ?

$$\begin{pmatrix} 2 \\ 1-i \end{pmatrix} \checkmark \quad \because \text{conjugate of } \vec{v}_1$$

$$\begin{pmatrix} 4 \\ 2+2i \end{pmatrix} \checkmark \quad \because \text{multiple of } \vec{v}_1$$

- (2) Suppose A is a square matrix and $\lambda = 1+i$ is an eigenvalue of A . Which of the following would have to be an eigenvalue of A ?

$1-i$ ✓ \because If λ is an eigenvalue of A , then the conjugate of λ is also an eigenvalue of A .

i ✗ \because If λ is an eigenvalue of A , then the conjugate of λ is also an eigenvalue of A . Otherwise, we do not know enough about A to determine what its other eigenvalues could be.

Rotations, Dilations and Eigenvalues

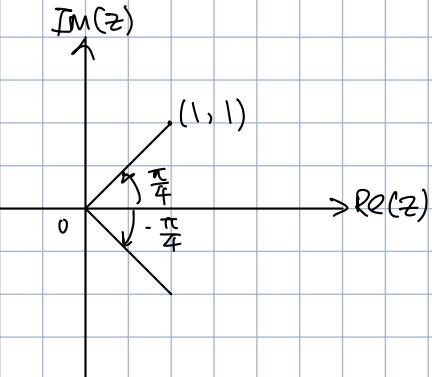
$$\varphi : \Phi^{\varphi}$$

The standard matrix for the transform that rotates vectors by $\varphi = \pi/4$ radians about the origin, and then scales (or dilates) vectors by $r = \sqrt{2}$, is

$$A = \begin{pmatrix} r & 0 \\ 0 & r \end{pmatrix} \begin{pmatrix} \cos \varphi & -\sin \varphi \\ \sin \varphi & \cos \varphi \end{pmatrix} = \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix}$$

What are the eigenvalues of A ? Express them in polar form.

$$\begin{aligned} 0 &= \det(A - \lambda I) = (1-\lambda)^2 + 1 = \lambda^2 - 2\lambda + 2 \\ \lambda &= \frac{2 \pm \sqrt{4-4(1)(2)}}{2} \\ &= 1 \pm \frac{1}{2}\sqrt{-4} = 1 \pm i \\ &= \sqrt{1^2+1^2} \left(\cos \frac{\pi}{4} \pm i \sin \frac{\pi}{4} \right) \\ &= r(\cos \varphi \pm i \sin \varphi) \end{aligned}$$



General Rotation-Dilation Case

The matrix in the previous example is an example of a rotation-dilation matrix.

A rotation-dilation matrix has the form:

$$C = \begin{pmatrix} a & -b \\ b & a \end{pmatrix}$$

Calculate the eigenvalues of C and express them in polar form.

$$0 = \det(C - \lambda I) = (a - \lambda)^2 + b^2 : \lambda^2 - 2a\lambda + (a^2 + b^2)$$

$$\lambda = \frac{2a \pm \sqrt{4a^2 - 4(a^2 + b^2)}}{2} = a \pm \frac{\sqrt{-4b^2}}{2}$$

$$= a \pm bi = r(\cos \varphi \pm i \sin \varphi) \text{ where } r^2 = a^2 + b^2, \tan \varphi = \frac{b}{a}.$$

Rotation-Dilation Matrices

DEFINITION — Rotation-Dilation Matrix

↳ A matrix of the form $C = \begin{pmatrix} a & -b \\ b & a \end{pmatrix}$ is a rotation-dilation matrix because it is the composition of a rotation by φ and dilation by r , where

$$r^2 = a^2 + b^2, \tan \varphi = \frac{b}{a}$$

Moreover, the eigenvalues of C are $\lambda = a \pm bi$.

Example: Determine the eigenvalues of $A = \begin{pmatrix} 2 & -3 \\ 3 & 2 \end{pmatrix}$

Because this is a rotation-dilation matrix, we do not need to determine the characteristic polynomial. The eigenvalues of this matrix are

$$\lambda = 2 \pm 3i$$

Exercise:

Suppose $T(\vec{x}) = A\vec{x}$ is a linear transform that maps vectors in \mathbb{R}^2 to vectors in \mathbb{R}^2 . Matrix A is, therefore, 2×2 . Suppose also that A is a rotation-dilation matrix, so T scales vectors in \mathbb{R}^2 by a factor of k , and rotates them by an angle θ . Assume $k \geq 0$, the rotation is counter-clockwise, and $0 \leq \theta \leq \pi$.

If the eigenvalues of A are $\lambda = \sqrt{2}(4 \pm 4i)$,

(a) what must k be equal to?

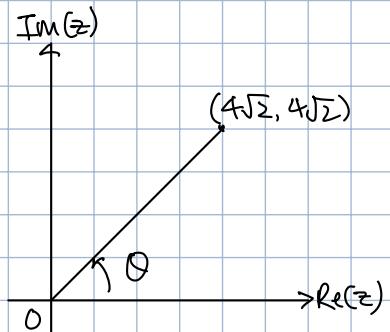
$$\text{Eigenvalues of } A, \lambda = \sqrt{2}(4 \pm 4i) = 4\sqrt{2} \pm 4\sqrt{2}i$$

$$r = k, a = b = 4\sqrt{2}$$

$$k^2 = (4\sqrt{2})^2 + (4\sqrt{2})^2 \\ = 64$$

$$k = \pm 8.$$

∴ Since $k \geq 0$, $k = 8$ *



(b) what must θ be equal to?

$$\tan \theta = \frac{4\sqrt{2}}{4\sqrt{2}} = 1 \Rightarrow \text{ref } \theta = \tan^{-1} 1 = \pi/4 \text{ rad.}$$

∴ Given $0 \leq \theta \leq \pi$, $\theta = \pi/4 \text{ rad.}$ *

The PCP⁻¹ Decomposition

Theorem:

If A is a real 2×2 matrix with eigenvalue $\lambda = a - bi$ (where $b \neq 0$) and associated eigenvector \vec{v} , then we may construct the decomposition

$$A = PCP^{-1}$$

→ Find proof from other sources.

where

$$P = (\operatorname{Re} \vec{v} \quad \operatorname{Im} \vec{v}) \text{ and } C = \begin{pmatrix} a & -b \\ b & a \end{pmatrix}$$

* C is referred to as a rotation-dilation matrix, because it is the composition of a rotation by φ and dilation by r .

* the $A = PCP^{-1}$ decomposition allows us to compute large powers of A efficiently.

Example: If possible, construct matrices P and C such that $AP = PC$. The eigenvalues of A are given.

$$A = \begin{pmatrix} 1 & -2 \\ 1 & 3 \end{pmatrix}, \lambda = 2 \pm i$$

$$(A - \lambda I | 0) = \left(\begin{array}{cc|c} 1-\lambda & 2 & 0 \\ 1 & 3-\lambda & 0 \end{array} \right) \quad (1-\lambda)x_1 - 2x_2 = 0.$$

$A - \lambda I$ has to
be singular,

so these rows
are expected to be
multiples of each other

$$\text{Eigenvector } \vec{v} = \begin{pmatrix} 2 \\ 1-\lambda \end{pmatrix}$$

$$= \begin{pmatrix} 2 \\ 1-(2-i) \end{pmatrix} \quad \therefore \text{choose } 2-i \text{ (either one is fine)}$$

$$= \begin{pmatrix} 2 \\ -1+i \end{pmatrix} = \begin{pmatrix} 2 \\ -1 \end{pmatrix} + i \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

$$\therefore P = (\operatorname{Re}(\vec{v}) \quad \operatorname{Im}(\vec{v})) = \begin{pmatrix} 2 & 0 \\ -1 & 1 \end{pmatrix}, C = \begin{pmatrix} a & -b \\ b & a \end{pmatrix} = \begin{pmatrix} 2 & -1 \\ 1 & 2 \end{pmatrix}$$

Exercise: Suppose A is the matrix below.

$$A = \begin{pmatrix} 2 & -1 \\ 1 & 2 \end{pmatrix}$$

Which of the following vectors are eigenvectors of A ?

$$\begin{pmatrix} i \\ -1 \end{pmatrix} \checkmark \quad \begin{pmatrix} i \\ 1 \end{pmatrix} \checkmark \quad \begin{pmatrix} -i \\ 1 \end{pmatrix} \checkmark$$

By inspection, A is a rotation-dilation matrix. $\Rightarrow \lambda = 2 \pm i$

$$(A - \lambda I | 0) = \left(\begin{array}{cc|c} 2-\lambda & -1 & 0 \\ \cdot & \cdot & \cdot \end{array} \right) \quad (2-\lambda)x_1 - x_2 = 0. \Rightarrow (2-\lambda)x_1 = x_2$$

$$\vec{v} = \begin{pmatrix} 1 \\ 2-\lambda \end{pmatrix}$$

$$= \begin{pmatrix} 1 \\ 2 - (2 \pm i) \end{pmatrix} = \begin{pmatrix} 1 \\ \mp i \end{pmatrix}$$

TOPIC 3: Google Page Rank

Example: Car Rental Company (from Module 3)

A car rental company has 3 rental locations, A, B and C. Cars can be returned at any location. The table below gives the pattern of rental and returns for a given week.

		rented from		
		A	B	C
returned to	A	0.8	0.1	0.2
	B	0.2	0.6	0.3
C	0	0.3	0.5	

There are 1000 cars at each location today. What happens to the distribution of cars after a long time?

Can use the transition matrix, P, to find the distribution of cars after 1 week.

$$\vec{x}_1 = P\vec{x}_0, \quad P = \frac{1}{10} \begin{pmatrix} 8 & 1 & 2 \\ 2 & 6 & 3 \\ 0 & 3 & 5 \end{pmatrix}$$

The distribution of cars after n weeks is

$$\vec{x}_n = P^n \vec{x}_0.$$

Because P is regular stochastic, \vec{x}_n tends to a steady-state, which we can find by solving

$$(P - I)\vec{q} = \vec{0} \quad (\text{defn})$$

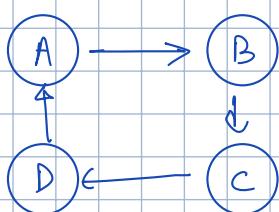
Recall: A stochastic matrix P is regular if there is some k such that P^k only contains strictly positive entries.

* We can determine whether a matrix, P, is regular stochastic by computing P^k for $k=2, 3, 4, \dots$. But sometimes we can see from inspection that a matrix will not be regular stochastic.

Determining Whether A Stochastic Matrix is Regular

Example:

By inspection, is the corresponding stochastic matrix regular? Is there a steady-state?



$$P = \begin{pmatrix} A & B & C & D \\ 0 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}, \quad \vec{x}_k = P\vec{x}_{k-1}$$

$$\vec{x}_0 = \frac{1}{4} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} = \vec{q}$$

Theorem: Regular Stochastic Matrices

If P is a regular $m \times m$ stochastic matrix with $m \geq 2$, then:

↳ for any initial probability vector $\vec{\pi}_0$, $\lim_{n \rightarrow \infty} P^n \vec{\pi}_0 = \vec{\pi}$

↳ P has a unique eigenvector, $\vec{\pi}$, which has eigenvalue $\lambda = 1$

↳ there is a stochastic matrix Π such that $\lim_{n \rightarrow \infty} P^n = \Pi$

↳ each column of Π is the same probability vector $\vec{\pi}$

↳ the eigenvalues of P satisfy $|\lambda| \leq 1$

Long Term Behavior

To investigate the long-term behavior of a system that has a regular stochastic matrix P , we could:

* compute the steady-state vector, $\vec{\pi}$, by solving $(P - I)\vec{\pi} = \vec{0}$

* compute $P^n \vec{\pi}_0$ for large n

* Compute P^n for large n , each column of the resulting matrix is the steady-state

Computing P^n for large n requires a computer. Students would not see much problems on exams, but they may appear on homework and other parts of the course.

Examples: Steady-State

① True or False: a steady-state vector for a stochastic matrix is an eigenvector

$$\text{True. } P\vec{\pi} = \vec{\pi}, \lambda = 1$$

② Give an example of a 2×2 stochastic matrix, A , that is in echelon form. A steady-state vector for the Markov chain $\vec{\pi}_{k+1} = A\vec{\pi}_k$ is $\vec{\pi} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$.

$$A = I = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}, A\vec{\pi} = \vec{\pi}.$$

Example: Convergence

If P is a regular stochastic matrix with steady state vector $\vec{r} = \frac{1}{6} \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}$ and $\vec{\pi}_0 = \frac{1}{10} \begin{pmatrix} 9 \\ 0 \\ 1 \end{pmatrix}$,

what does the sequence $\vec{\pi}_k = P^k \vec{\pi}_0$ converge to?

$$\vec{\pi}_k \rightarrow \vec{r} \text{ as } k \rightarrow \infty$$

Example: Long Term Behavior

Consider the Markov chain

$$\vec{x}_k = A\vec{x}_{k-1} = \begin{pmatrix} 0.8 & 0.2 \\ 0.2 & 0.8 \end{pmatrix} \vec{x}_{k-1}, k=1, 2, 3, \dots, \vec{x}_0 = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

The eigenvalues of A are 1 and 0.6. Analyze the long-term behavior of the system. In other words, determine what \vec{x}_k tends to as $k \rightarrow \infty$.

$$(A - I | 0) = \begin{pmatrix} -0.2 & 0.2 & 0 \\ 0.2 & -0.4 & 0 \end{pmatrix} \Rightarrow \vec{v} = \frac{1}{2} \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

$$\text{as } k \rightarrow \infty, \vec{x}_k \rightarrow \vec{v} = \frac{1}{2} \begin{pmatrix} 1 \\ 1 \end{pmatrix}.$$

Exercise:

Suppose P is a regular stochastic matrix with steady state vector

$$\vec{w} = \frac{1}{10} \begin{pmatrix} 4 \\ 2 \\ 4 \end{pmatrix}$$

and

$$\vec{x}_0 = \frac{1}{10} \begin{pmatrix} 3 \\ 3 \\ 4 \end{pmatrix}$$

As k goes to infinity, the sequence $\vec{x}_k = P^k \vec{x}_0$ converges to the vector below.

$$\vec{z} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

What is x_1 equal to?

P is regular stochastic, so the sequence will converge to the steady-state no matter what \vec{x}_0 happens to be (as long as \vec{x}_0 is a probability vector). $\therefore x_1 = 0.4$

Google PageRank

There are many search engines that we can use to find relevant information on the web.

* When searching for information on the Internet using any search engine, we can be presented with many search results

* For a search engine to give useful information to the user, it must quickly order search results in some way

* Essentially: how can the engine quickly decide which results appear at the top of the list?

Mathematical Model for Web Traffic

The PageRank algorithm is based on a mathematical model that assumes that we have:

* a collection of web pages that have links to each other

* users who are navigating the web

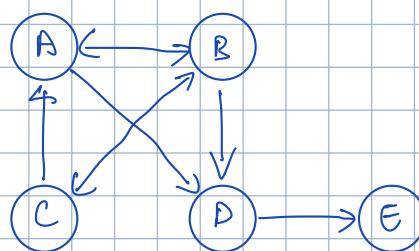
* a set of rules that govern how the users navigate the web

We impose assumptions about how the users navigate the web?

- (a) A user on a web page is equally likely to go to any page that their page links to.
- (b) If a user is on a page that does not link to other pages, the user stays at their page.
- (c) The distribution of users can be modeled using a Markov process, $\vec{r}_{k+1} = P \vec{r}_k$, where
 - * $\vec{r}_k \in \mathbb{R}^n$ is a probability vector, gives the proportion of users on each page at iteration k
 - * P is an $n \times n$ stochastic matrix — tells us how users transition from one iteration to the next
 - * n is the number of pages in the web

Example Web with Five Pages

A set of web pages link to each other according to the diagram below. Use the assumptions on the previous slide to construct a Markov chain that represents how users navigate the web.



- A \rightarrow B or D (2 ways)
- B \rightarrow A, C or D (3 ways)
- C \rightarrow A or B (2 ways)
- D \rightarrow E (1 way)
- E \rightarrow \emptyset (assumed all users stay on that page)

$$\vec{r}_{k+1} = P \vec{r}_k, k=0,1,\dots$$

$$P = \begin{pmatrix} & A & B & C & D & E \\ A & 0 & \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ B & \frac{1}{2} & 0 & \frac{1}{2} & 0 & 0 \\ C & 0 & \frac{1}{3} & 0 & 0 & 0 \\ D & \frac{1}{2} & \frac{1}{3} & 0 & 0 & 0 \\ E & 0 & 0 & 0 & 1 & 1 \end{pmatrix}$$

↑
called a
transition
matrix

Transition Matrix, Importance and PageRank

- * The square matrix we constructed in the previous example is a transition matrix. It describes how users transition between pages in the web.
- * The steady-state vector, \vec{s} , for the Markov-chain, can characterize the long-term behavior of users in a given web.
- * The importance of a page in a web are the entries of \vec{s} .
- * The PageRank is the ranking assigned to each page based on its importance. The highest ranked page has PageRank 1, the second PageRank 2, and so on.
- * Two pages with same importance receive the same PageRank (some other method would be needed to resolve ties).

Exercise:

A web consists of exactly three pages, A, B, and C.

* page A only links to B

* page B has links to pages A and C.

* page C does not link to the other pages

The transition matrix for this web, P , has the form

$$P = \begin{pmatrix} 0 & 1/2 & C_1 \\ a & b & C_2 \\ 0 & 1/2 & C_3 \end{pmatrix}$$

$a=1, b=0.$
 $C_1=C_2=0, C_3=1.$

What are the values of a , b , C_1 , C_2 and C_3 ?

Remaining Questions

Our simple mathematical model has some limitations that must be addressed for it to be useful.

* Will our transition be regular stochastic?

* What can we do to build a model that will give us a regular stochastic matrix?

* What can we do to better handle the pages that do not link to other pages?

Adjustments Needed

Our mathematical model for Page Rank (PR) has two problems:

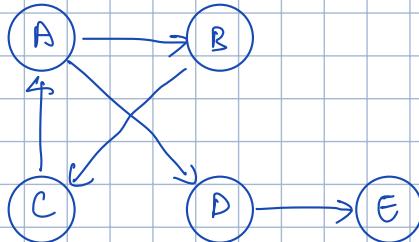
* the transition matrix is not regular: we do not have a unique steady-state

* pages that do not link to other pages can have the largest importance, or highest Page Rank

Adjustment 1: If a user reaches a page that does not link to other pages, the user will choose any page in the web, with equal probability, and move to that page.

↳ we will denote this modified transition matrix as P_{**} .

Example:



P and P_{**} are as follows:

$$P = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 \\ 1/2 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 1/2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 1 \end{pmatrix}, P_{**} = \begin{pmatrix} 0 & 0 & 1 & 0 & 1/5 \\ 1/2 & 0 & 0 & 0 & 1/5 \\ 0 & 1 & 0 & 0 & 1/5 \\ 1/2 & 0 & 0 & 0 & 1/5 \\ 0 & 0 & 0 & 1 & 1/5 \end{pmatrix}$$

Adjustment 2: A user at any page will navigate to any page among those that their page links to with equal probability p , and to any page in the web with equal probability $1-p$.

The transition matrix becomes

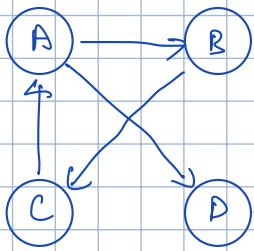
$$G = pP_{**} + (1-p)K.$$

All the elements of the $n \times n$ matrix K are equal to $\frac{1}{n}$.

Note: * p is referred to as the damping factor. Google is said to use $p = 0.85$.

* Adjustment 2 forces G to be regular stochastic when $0 < p \leq 1$.

Google Matrix Example



The Google matrix for this web, with $p = 0.85$ is
 $G = 0.85P_{**} + 0.15K$, where

$$P_{**} = \begin{pmatrix} 0 & 0 & 1 & 0 & \frac{1}{5} \\ \frac{1}{2} & 0 & 0 & 0 & \frac{1}{5} \\ 0 & 1 & 0 & 0 & \frac{1}{5} \\ \frac{1}{2} & 0 & 0 & 0 & \frac{1}{5} \\ 0 & 0 & 0 & 1 & \frac{1}{5} \end{pmatrix}, K = \frac{1}{3} \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{pmatrix}$$

Computing Page Rank

Because G is stochastic, for any initial probability vector \vec{x}_0 ,

$$\lim_{n \rightarrow \infty} G^n \vec{x}_0 = \vec{q}.$$

We can obtain steady-state evaluating $G^n \vec{x}_0$ for large n , by solving $G\vec{q} = \vec{q}$, or by evaluating $\vec{x}_n = G\vec{x}_{n-1}$ for large n .

Elements of the steady-state vector give the importance of each page in the web, which can be used to determine PageRank.

Largest element in steady-state vector corresponds to page with PageRank 1, second largest with PageRank 2, and so on.

Exercise:

A web consists of exactly three pages, A, B and C.

* page A only links to B.

* page B has links to pages A and C

* page C does not link to the other web pages

The transition matrix for this web, P , is

$$P = \begin{pmatrix} 0 & \frac{1}{2} & 0 \\ 1 & 0 & 0 \\ 0 & \frac{1}{2} & 1 \end{pmatrix}$$

After making adjustments 1 and 2, and using a damping factor of 0.85, we can construct the Google Matrix, G . The Google matrix has the following form-

$$G = pP_{**} + (1-p)K$$

$$G = 0.85P_{**} + 0.15K$$

What is every entry of matrix K equal to?

$$\frac{1}{n} = \frac{1}{3} -$$

Matrix P_{**} has the form below.

$$P_{**} = \begin{pmatrix} 0 & \frac{1}{2} & a \\ 1 & 0 & b \\ 0 & \frac{1}{2} & c \end{pmatrix}$$

Find a, b, and c.

$$a = b = c = \frac{1}{3}$$

With adjustment 2, a user will navigate to any page in the web. So every entry in the last column of the adjusted transition matrix will be equal to $\frac{1}{3}$.