

# Math 415 - Lecture 31

Markov matrices and Google

**Textbook reading:** Chapter 5.3

**Suggested practice exercises:** Chapter 5.3: 8, 9, 12, 14, 10.

**Khan Academy video:** Finding Eigenvectors and Eigenspaces example

**Strang lecture:** Lecture 21: Eigenvalues and eigenvectors Lecture 24: Markov Matrices and Fourier Series.

## 1 Review

### 1.1 Properties of eigenvectors and eigenvalues

- If  $A\mathbf{x} = \lambda\mathbf{x}$  then  $\mathbf{x}$  is an **eigenvector** of  $A$  with **eigenvalue**  $\lambda$ . All eigenvectors (plus  $\mathbf{0}$ ) with eigenvalue  $\lambda$  form **eigenspace** of  $\lambda$ .
- $\lambda$  is an eigenvalue of  $A \iff \underbrace{\det(A - \lambda I)}_{\text{characteristic polynomial}} = 0$ . Why? Because  $A\mathbf{x} = \lambda\mathbf{x} \iff (A - \lambda I)\mathbf{x} = \mathbf{0}$ . By the way: this means that the eigenspace of  $\lambda$  is just  $\text{Nul}(A - \lambda I)$ .
- E.g. if  $A = \begin{bmatrix} 3 & 2 & 3 \\ 0 & 6 & 10 \\ 0 & 0 & 2 \end{bmatrix}$  then  $\det(A - \lambda I) = (3 - \lambda)(6 - \lambda)(2 - \lambda)$ .

*Example 1.* Find the eigenvalues of  $A$  as well as a basis for the corresponding eigenspaces, where

$$A = \begin{bmatrix} 2 & 0 & 0 \\ -1 & 3 & 1 \\ -1 & 1 & 3 \end{bmatrix}.$$

**Solution.**

- The characteristic polynomial is:

$$\begin{aligned} \det(A - \lambda I) &= \begin{vmatrix} 2 - \lambda & 0 & 0 \\ -1 & 3 - \lambda & 1 \\ -1 & 1 & 3 - \lambda \end{vmatrix} \\ &= (2 - \lambda) \begin{vmatrix} 3 - \lambda & 1 \\ 1 & 3 - \lambda \end{vmatrix} \\ &= (2 - \lambda)[(3 - \lambda)^2 - 1] \\ &= (2 - \lambda)(\lambda - 2)(\lambda - 4) \end{aligned}$$

- $A$  has eigenvalues 2, 2, 4  $\left( A = \begin{bmatrix} 2 & 0 & 0 \\ -1 & 3 & 1 \\ -1 & 1 & 3 \end{bmatrix} \right)$   
Since  $\lambda = 2$  is a double root, it has **(algebraic) multiplicity 2**.

- $\lambda_1 = 2$ :

$$(A - \lambda_1 I)\mathbf{x} = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 1 & 1 \\ -1 & 1 & 1 \end{bmatrix} \mathbf{x} = \mathbf{0}$$

Two independent solutions:  $\mathbf{x}_1 = \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}$ ,  $\mathbf{x}_2 = \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$

In other words, the eigenspace for  $\lambda_1 = 2$  is  $\text{span} \left\{ \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix} \right\}$ .

- $\lambda_2 = 4$ :  $\left( A = \begin{bmatrix} 2 & 0 & 0 \\ -1 & 3 & 1 \\ -1 & 1 & 3 \end{bmatrix} \right)$

$$(A - \lambda_2 I)\mathbf{x} = \begin{bmatrix} -2 & 0 & 0 \\ -1 & -1 & 1 \\ -1 & 1 & -1 \end{bmatrix} \mathbf{x} = \mathbf{0} \implies \mathbf{x}_3 = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$

- In summary,  $A$  has eigenvalues 2 and 4:

- eigenspace for  $\lambda_1 = 2$  has basis  $\begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ -1 \\ 1 \end{bmatrix}$ ,

- eigenspace for  $\lambda_2 = 4$  has basis  $\begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$

## 2 Markov matrices

**Definition 2.** An  $n \times n$  matrices  $A$  is **Markov matrix** if has non negative entries, and the entries in each column add to 1.

**Theorem 1.** Let  $A$  be a Markov matrix. Then

- (i) 1 is an eigenvalue of  $A$  and any other eigenvalue  $\lambda$  satisfies  $|\lambda| \leq 1$ .
- (ii) If  $A$  has only positive entries, then any other eigenvalue satisfies  $|\lambda| < 1$ .

*Example 3.* Let  $A$  be

$$\begin{bmatrix} .9 & .2 \\ .1 & .8 \end{bmatrix}.$$

Is  $A$  a Markov matrix?

**Theorem 2.** Let  $A$  be an  $n \times n$ -Markov matrix with only positive entries and let  $\mathbf{z} = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix} \in \mathbb{R}^n$  such that  $z_1 + z_2 + \cdots + z_n = 1$ . Then

$$\mathbf{z}_\infty := \lim_{k \rightarrow \infty} A^k \mathbf{z} \text{ exists,}$$

and  $A\mathbf{z}_\infty = \mathbf{z}_\infty$ . In this case  $\mathbf{z}_\infty$  is often called the **steady state**.

*Proof.* For simplicity, assume that  $A$  has  $n$  different eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$ . Since  $A$  is a Markov matrix and has only positive entries, we can assume that  $\lambda_1 = 1$  and  $|\lambda_i| < 1$  for all  $i = 2, \dots, n$ . Let  $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n \in \mathbb{R}^n$  such that  $A\mathbf{v}_i = \lambda_i \mathbf{v}_i$ . Since eigenvectors to different eigenvalues are linear independent, the above eigenvectors form a basis of  $\mathbb{R}^n$ . Thus there are scalar  $c_1, \dots, c_n$  such that

$$\mathbf{z} = c_1 \mathbf{v}_1 + \cdots + c_n \mathbf{v}_n,$$

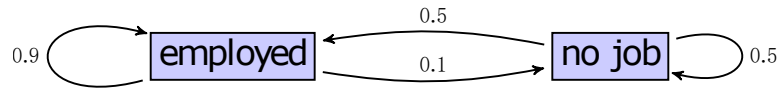
then

$$A^k \mathbf{z} = c_1 \lambda_1^k \mathbf{v}_1 + \cdots + c_n \lambda_n^k \mathbf{v}_n \rightarrow c_1 \mathbf{v}_1,$$

because  $|\lambda_i| < 1$  for each  $i = 2, \dots, n$ . (Exercise: Why is  $c_1 \neq 0$ ?) □

*Example 4.* Consider a fixed population of people with or without job. Suppose that each year, 50% of those unemployed find a job while 10% of those employed lose their job. What is the unemployment rate in the long term equilibrium?

**Solution.**



$x_t$ : proportion of population employed at time  $t$  (in years)

$y_t$ : proportion of population unemployed at time  $t$

$$\begin{bmatrix} x_{t+1} \\ y_{t+1} \end{bmatrix} = \begin{bmatrix} 0.9x_t + 0.5y_t \\ 0.1x_t + 0.5y_t \end{bmatrix} = \begin{bmatrix} 0.9 & 0.5 \\ 0.1 & 0.5 \end{bmatrix} \begin{bmatrix} x_t \\ y_t \end{bmatrix}$$

The matrix  $\begin{bmatrix} 0.9 & 0.5 \\ 0.1 & 0.5 \end{bmatrix}$  is a **Markov matrix**. Its columns add to 1 and it has no negative entries.

$\begin{bmatrix} x_\infty \\ y_\infty \end{bmatrix}$  is an equilibrium if  $\begin{bmatrix} x_\infty \\ y_\infty \end{bmatrix} = \begin{bmatrix} 0.9 & 0.5 \\ 0.1 & 0.5 \end{bmatrix} \begin{bmatrix} x_\infty \\ y_\infty \end{bmatrix}$ .

In other words,  $\begin{bmatrix} x_\infty \\ y_\infty \end{bmatrix}$  is an eigenvector with eigenvalue 1.

Eigenspace of  $\lambda = 1$ :  $\text{Nul} \left( \begin{bmatrix} -0.1 & 0.5 \\ 0.1 & -0.5 \end{bmatrix} \right) = \text{span} \left\{ \begin{bmatrix} 5 \\ 1 \end{bmatrix} \right\}$

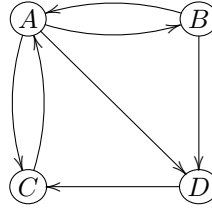
Since  $x_\infty + y_\infty = 1$ , we conclude that  $\begin{bmatrix} x_\infty \\ y_\infty \end{bmatrix} = \begin{bmatrix} 5/6 \\ 1/6 \end{bmatrix}$ .

Hence, the unemployment rate in the long term equilibrium is  $1/6$

### 3 Page rank (or: the 25000000000 \$ eigenvector)

Google's success is based on an algorithm to rank webpages, the **Page rank**, named after Google founder Larry Page. The idea is to determine how likely it is that a web user randomly gets to a given webpage. The webpages are ranked by these probabilities.

Suppose the internet consisted of the only four webpages  $A, B, C, D$  linked as in the following graph.



Imagine a surfer following these links at random. For the probability  $PR_n(A)$  that she is at  $A$  (after  $n$  steps), we need to think about how she could have reached  $A$ . We add:

- the probability that she was at  $B$  (at exactly one step before), and left for  $A$ , (that's  $PR_{n-1}(B) \cdot \frac{1}{2}$ )
- the probability that she was at  $C$ , and left for  $A$ ,
- the probability that she was at  $D$ , and left for  $A$ .

Hence:  $PR_n(A) = PR_{n-1}(B) \cdot \frac{1}{2} + PR_{n-1}(C) \cdot \frac{1}{3} + PR_{n-1}(D) \cdot \frac{0}{1}$ .

Encode the probabilities at step  $n$  in a state vector with four entries.

$$\begin{bmatrix} PR_n(A) \\ PR_n(B) \\ PR_n(C) \\ PR_n(D) \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{2} & 1 & 0 \\ \frac{1}{3} & 0 & 0 & 0 \\ \frac{1}{3} & 0 & 0 & 1 \\ \frac{1}{3} & \frac{1}{2} & 0 & 0 \end{bmatrix} \begin{bmatrix} PR_{n-1}(A) \\ PR_{n-1}(B) \\ PR_{n-1}(C) \\ PR_{n-1}(D) \end{bmatrix}$$

**Definition 5.** The **PageRank vector** is the long-term equilibrium. It is an eigenvector of the Markov matrix with eigenvalue 1.

Let's call the Markov matrix with the probabilities  $T$ :

$$\bullet \quad T - 1I = \begin{bmatrix} -1 & \frac{1}{2} & 1 & 0 \\ \frac{1}{3} & -1 & 0 & 0 \\ \frac{1}{3} & 0 & -1 & 1 \\ \frac{1}{3} & \frac{1}{2} & 0 & -1 \end{bmatrix} \xrightarrow{\text{RREF}} \begin{bmatrix} 1 & 0 & 0 & -2 \\ 0 & 1 & 0 & -\frac{2}{3} \\ 0 & 0 & 1 & -\frac{1}{3} \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\Rightarrow \text{eigenspace of } \lambda = 1 \text{ is spanned by } \begin{bmatrix} 2 \\ 2 \\ 3 \\ 3 \\ 1 \end{bmatrix}.$$

- Now we need to make the entries add up to 1.

$$\begin{bmatrix} PR(A) \\ PR(B) \\ PR(C) \\ PR(D) \end{bmatrix} = \frac{3}{16} \begin{bmatrix} 2 \\ 2 \\ 3 \\ 3 \\ 1 \end{bmatrix} = \begin{bmatrix} 0.375 \\ 0.125 \\ 0.313 \\ 0.188 \end{bmatrix}.$$

This is the PageRank vector.

- The corresponding ranking of the webpages is  $A, C, D, B$ .

**Remark.** In practical situations the system might be too large for finding the eigenvalues by row operations.

- Google reports having met 60 trillion webpages. Google's search index is over 100,000,000 gigabytes. Number of Google's servers is secret: about 2,500,000 More than 1,000,000,000 websites (i.e. hostnames; about 75% not active)
- Thus we have a gigantic but very sparse matrix.

An alternative to row operations is the **power method** (see Theorem 2):

### Power method

If  $T$  is an (acyclic and irreducible) Markov matrix, then for any  $\mathbf{v}_0$  the vectors  $T^n \mathbf{v}_0$  converge to an eigenvector with eigenvalue 1

Here:

$$T = \begin{bmatrix} 0 & \frac{1}{2} & 1 & 0 \\ \frac{1}{3} & 0 & 0 & 0 \\ \frac{1}{3} & 0 & 0 & 1 \\ \frac{1}{3} & \frac{1}{2} & 0 & 0 \end{bmatrix}.$$

Start with an arbitrary state vector, hit it with powers of  $T$ .

$$\begin{pmatrix} PR(A) \\ PR(B) \\ PR(C) \\ PR(D) \end{pmatrix} = \begin{bmatrix} 0.375 \\ 0.125 \\ 0.313 \\ 0.188 \end{bmatrix}, T \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 0.375 \\ 0.083 \\ 0.333 \\ 0.208 \end{bmatrix}$$

. Note that the ranking of the webpages is already  $A, C, D, B$  if we stop here.

$$T \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 0.375 \\ 0.083 \\ 0.333 \\ 0.208 \end{bmatrix}, \quad T^2 \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 0.375 \\ 0.125 \\ 0.333 \\ 0.167 \end{bmatrix}, \quad T^3 \begin{bmatrix} 1/4 \\ 1/4 \\ 1/4 \\ 1/4 \end{bmatrix} = \begin{bmatrix} 0.396 \\ 0.125 \\ 0.292 \\ 0.188 \end{bmatrix}$$

**Remark.** • If all entries of  $T$  are positive (no zero entries!), then the power method is guaranteed to work.

- In the context of PageRank, we can make sure that this is the case by replacing  $T$  with

$$(1-p) \cdot \begin{bmatrix} 0 & \frac{1}{2} & 1 & 0 \\ \frac{1}{3} & 0 & 0 & 0 \\ \frac{1}{3} & 0 & 0 & 1 \\ \frac{1}{3} & \frac{1}{2} & 0 & 0 \end{bmatrix} + p \cdot \begin{bmatrix} \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \\ \frac{1}{4} & \frac{1}{4} & \frac{1}{4} & \frac{1}{4} \end{bmatrix}.$$

Just to make sure: still a Markov matrix, now with positive entries Google used to use  $p = 0.15$ .