



# Matrix Calculations: Eigenvalues, Eigenvectors, and Diagonalisation

A. Kissinger

Institute for Computing and Information Sciences  
Radboud University Nijmegen

Version: autumn 2017





## Last time

- Vectors look different in different bases, e.g. for:

$$\mathcal{B} = \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right\} \quad \mathcal{C} = \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \end{pmatrix} \right\}$$

- we have:

$$\begin{pmatrix} 1 \\ 0 \end{pmatrix}_S = \begin{pmatrix} \frac{1}{2} \\ \frac{1}{2} \end{pmatrix}_B = \begin{pmatrix} 2 \\ -1 \end{pmatrix}_C$$





## Last time

$$\mathcal{B} = \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ -1 \end{pmatrix} \right\} \quad \mathcal{C} = \left\{ \begin{pmatrix} 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 1 \\ 2 \end{pmatrix} \right\}$$

- We can transform bases using basis transformation matrices. Going to standard basis is easy (basis elements are columns):

$$\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}} = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \quad \mathbf{T}_{\mathcal{C} \Rightarrow \mathcal{S}} = \begin{pmatrix} 1 & 1 \\ 1 & 2 \end{pmatrix}$$

- ...coming back means **taking the inverse**:

$$\mathbf{T}_{\mathcal{S} \Rightarrow \mathcal{B}} = (\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}})^{-1} = \frac{1}{2} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}$$

$$\mathbf{T}_{\mathcal{S} \Rightarrow \mathcal{C}} = (\mathbf{T}_{\mathcal{C} \Rightarrow \mathcal{S}})^{-1} = \begin{pmatrix} 2 & -1 \\ -1 & 1 \end{pmatrix}$$



## Last time

- Converting from  $\mathcal{B}$  to  $\mathcal{C}$  is done by first converting to  $\mathcal{S}$  then to  $\mathcal{C}$ :

$$\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{C}} = \mathbf{T}_{\mathcal{S} \Rightarrow \mathcal{C}} \cdot \mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}}$$

- The **change of basis** of a vector is computed by applying the matrix. For example, changing from  $\mathcal{B}$  to  $\mathcal{C}$  is:

$$\mathbf{v}' = \mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{C}} \mathbf{v}$$

- The **change of basis** for a matrix is computed by surrounding it with basis-change matrices.
- Changing from a matrix  $\mathbf{A}$  in  $\mathcal{B}$  to a matrix  $\mathbf{A}'$  in  $\mathcal{C}$  is:

$$\mathbf{A}' = \mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{C}} \cdot \mathbf{A} \cdot \mathbf{T}_{\mathcal{C} \Rightarrow \mathcal{B}}$$

- (Memory aid: look at the **first** matrix on the right to see what basis transformation you are doing.)



# Outline

Eigenvalues and Eigenvectors

Applications

Diagonalisation and iteration





## Example: political swingers, part I

- We take an extremely crude view on politics and distinguish only **left** and **right** wing political supporters
- We study changes in political views, per year
- Suppose we observe, for each year:
  - 80% of lefties remain lefties and 20% become righties
  - 90% of righties remain righties, and 10% become lefties

### Questions ...

- start with a population  $L = 100, R = 150$ , and compute the number of lefties and righties after one year;
- similarly, after 2 years, and 3 years, ...
- We can represent these computations conveniently using matrix multiplication.



## Political swingers, part II

- So if we start with a population  $L = 100, R = 150$ , then after one year we have:
  - lefties:  $0.8 \cdot 100 + 0.1 \cdot 150 = 80 + 15 = 95$
  - righties:  $0.2 \cdot 100 + 0.9 \cdot 150 = 20 + 135 = 155$
- If  $\begin{pmatrix} L \\ R \end{pmatrix} = \begin{pmatrix} 100 \\ 150 \end{pmatrix}$ , then after **one year** we have:

$$P \cdot \begin{pmatrix} 100 \\ 150 \end{pmatrix} = \begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} \cdot \begin{pmatrix} 100 \\ 150 \end{pmatrix} = \begin{pmatrix} 95 \\ 155 \end{pmatrix}$$

- After **two years** we have:

$$P \cdot \begin{pmatrix} 95 \\ 155 \end{pmatrix} = \begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} \cdot \begin{pmatrix} 95 \\ 155 \end{pmatrix} = \begin{pmatrix} 91.5 \\ 158.5 \end{pmatrix}$$



## Political swingers, part IV

The situation after two years is obtained as:

$$\begin{aligned} P \cdot P \cdot \begin{pmatrix} L \\ R \end{pmatrix} &= \begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} \cdot \begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} \cdot \begin{pmatrix} L \\ R \end{pmatrix} \\ &\underbrace{\hspace{10em}}_{\text{do this multiplication first}} \\ &= \begin{pmatrix} 0.66 & 0.17 \\ 0.34 & 0.83 \end{pmatrix} \cdot \begin{pmatrix} L \\ R \end{pmatrix} \end{aligned}$$

The situation after  $n$  years is described by the  $n$ -fold iterated matrix:

$$P^n = \underbrace{P \cdot P \cdots P}_{n \text{ times}}$$

Etc. It looks like  $P^{100}$  (or worse,  $\lim_{n \rightarrow \infty} P^n$ ) is going to be a real pain to calculate. ...or is it?





# Diagonal matrices

- Multiplying lots of matrices together is hard ☹️
- But multiplying diagonal matrices is easy!

$$\begin{pmatrix} a & 0 & 0 & 0 \\ 0 & b & 0 & 0 \\ 0 & 0 & c & 0 \\ 0 & 0 & 0 & d \end{pmatrix} \cdot \begin{pmatrix} w & 0 & 0 & 0 \\ 0 & x & 0 & 0 \\ 0 & 0 & y & 0 \\ 0 & 0 & 0 & z \end{pmatrix} = \begin{pmatrix} aw & 0 & 0 & 0 \\ 0 & bx & 0 & 0 \\ 0 & 0 & cy & 0 \\ 0 & 0 & 0 & dz \end{pmatrix}$$

- **Strategy:** find a basis  $\mathcal{B}$  where our matrix  $\mathbf{P}$  is diagonal:

$$\begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix}_S \rightsquigarrow \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix}_{\mathcal{B}}$$

- So transform to  $\mathcal{B}$ , multiply, and (if we need to) transform back:

$$\begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix}_{\mathcal{B}}^{100} = \begin{pmatrix} 1^{100} & 0 \\ 0 & (0.7)^{100} \end{pmatrix}_{\mathcal{B}} \approx \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix}_{\mathcal{B}} \rightsquigarrow \frac{1}{3} \begin{pmatrix} 1 & 1 \\ 2 & 2 \end{pmatrix}_S$$



# Eigenvectors and eigenvalues

This magical basis  $\mathcal{B}$  consists of *eigenvectors* of a matrix.

## Definition

Assume an  $n \times n$  matrix  $\mathbf{A}$ .

An **eigenvector** for  $\mathbf{A}$  is a non-zero vector  $\mathbf{v} \neq 0$  for which there is an **eigenvalue**  $\lambda \in \mathbb{R}$  with:

$$\mathbf{A} \cdot \mathbf{v} = \lambda \cdot \mathbf{v}$$

## Example

$\begin{pmatrix} 1 \\ 2 \end{pmatrix}$  is an eigenvector for  $\mathbf{P} = \frac{1}{10} \begin{pmatrix} 8 & 1 \\ 2 & 9 \end{pmatrix}$  with eigenvalue  $\lambda = 1$ .




## Two basic results

### Lemma

*An eigenvector has at most one eigenvalue*

**Proof:** Assume  $\mathbf{A} \cdot \mathbf{v} = \lambda_1 \mathbf{v}$  and  $\mathbf{A} \cdot \mathbf{v} = \lambda_2 \mathbf{v}$ . Then:


$$0 = \mathbf{A} \cdot \mathbf{v} - \mathbf{A} \cdot \mathbf{v} = \lambda_1 \mathbf{v} - \lambda_2 \mathbf{v} = (\lambda_1 - \lambda_2) \mathbf{v}$$

Since  $\mathbf{v} \neq 0$  we must have  $\lambda_1 - \lambda_2 = 0$ , and thus  $\lambda_1 = \lambda_2$ . 

### Lemma

*If  $\mathbf{v}$  is an eigenvector, then so is  $a \cdot \mathbf{v}$ , for each  $a \neq 0$ .*

**Proof:** If  $\mathbf{A} \cdot \mathbf{v} = \lambda \mathbf{v}$ , then:

$$\begin{aligned} \mathbf{A} \cdot (a\mathbf{v}) &= a(\mathbf{A} \cdot \mathbf{v}) && \text{since matrix application is linear} \\ &= a(\lambda \mathbf{v}) = (a\lambda) \mathbf{v} = (\lambda a) \mathbf{v} = \lambda(a\mathbf{v}). \end{aligned}$$
 



## Finding eigenvectors and eigenvalues

- We seek a **eigenvector**  $\mathbf{v}$  and **eigenvalue**  $\lambda \in \mathbb{R}$  with  $\mathbf{A} \cdot \mathbf{v} = \lambda \mathbf{v}$
- That is:  $\lambda$  and  $\mathbf{v}$  ( $\mathbf{v} \neq 0$ ) such that  $(\mathbf{A} - \lambda \cdot \mathbf{I}) \cdot \mathbf{v} = 0$
- Thus, we seek  $\lambda$  for which the system of equations corresponding to the matrix  $\mathbf{A} - \lambda \cdot \mathbf{I}$  has a **non-zero** solution
- Hence we seek  $\lambda \in \mathbb{R}$  for which the matrix  $\mathbf{A} - \lambda \cdot \mathbf{I}$  does **not have  $n$  pivots** in its echelon form
- This means: we seek  $\lambda \in \mathbb{R}$  such that  $\mathbf{A} - \lambda \cdot \mathbf{I}$  is **not-invertible**
- So we need:  $\det(\mathbf{A} - \lambda \cdot \mathbf{I}) = 0$
- This can be seen as an equation, with  $\lambda$  as variable
- This  $\det(\mathbf{A} - \lambda \cdot \mathbf{I})$  is called the **characteristic polynomial** of the matrix  $\mathbf{A}$



# Eigenvalue example I

- **Task:** find eigenvalues of matrix  $\mathbf{A} = \begin{pmatrix} 1 & 5 \\ 3 & 3 \end{pmatrix}$
- $\mathbf{A} - \lambda \cdot \mathbf{I} = \begin{pmatrix} 1 & 5 \\ 3 & 3 \end{pmatrix} - \begin{pmatrix} \lambda & 0 \\ 0 & \lambda \end{pmatrix} = \begin{pmatrix} 1 - \lambda & 5 \\ 3 & 3 - \lambda \end{pmatrix}$
- Thus:

$$\begin{aligned} \det(\mathbf{A} - \lambda \cdot \mathbf{I}) = 0 &\iff \begin{vmatrix} 1 - \lambda & 5 \\ 3 & 3 - \lambda \end{vmatrix} = 0 \\ &\iff (1 - \lambda)(3 - \lambda) - 5 \cdot 3 = 0 \\ &\iff \lambda^2 - 4\lambda - 12 = 0 \\ &\iff (\lambda - 6)(\lambda + 2) = 0 \\ &\iff \lambda = 6 \text{ or } \lambda = -2. \end{aligned}$$



## Recall: quadratic formula

- Consider a **second-degree** (quadratic) equation

$$ax^2 + bx + c = 0 \quad (\text{for } a \neq 0)$$

- Its **solutions** are:

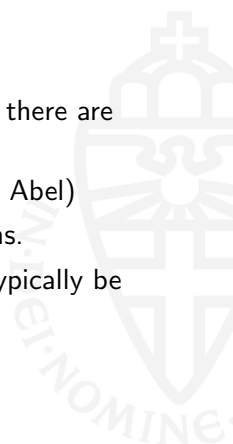
$$s_{1,2} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$$

- These solutions **coincide** (ie.  $s_1 = s_2$ ) if  $b^2 - 4ac = 0$
- Real solutions **do not exist** if  $b^2 - 4ac < 0$   
(But “complex number” solutions do exist in this case.)
- [ Recall, if  $s_1$  and  $s_2$  are solutions of  $ax^2 + bx + c = 0$ , then we can write  $ax^2 + bx + c = a(x - s_1)(x - s_2)$  ]



## Higher degree polynomial equations

- For **third** and **fourth** degree polynomial equations there are (complicated) formulas for the solutions.
- For degree  $\geq 5$  no such formulas exist (proved by Abel)
- In those cases one can at most use approximations.
- In the examples in this course the solutions will typically be “obvious”.





## Eigenvalue example II

- **Task:** find eigenvalues of  $\mathbf{A} = \begin{pmatrix} 3 & -1 & -1 \\ -12 & 0 & 5 \\ 4 & -2 & -1 \end{pmatrix}$

- **Characteristic polynomial** is  $\begin{vmatrix} 3 - \lambda & -1 & -1 \\ -12 & -\lambda & 5 \\ 4 & -2 & -1 - \lambda \end{vmatrix}$

$$\begin{aligned} &= (3 - \lambda) \begin{vmatrix} -\lambda & 5 \\ -2 & -1 - \lambda \end{vmatrix} + 12 \begin{vmatrix} -1 & -1 \\ -2 & -1 - \lambda \end{vmatrix} + 4 \begin{vmatrix} -1 & -1 \\ -\lambda & 5 \end{vmatrix} \\ &= (3 - \lambda)(\lambda(1 + \lambda) + 10) + 12(1 + \lambda - 2) + 4(-5 - \lambda) \\ &= (3 - \lambda)(\lambda^2 + \lambda + 10) + 12(\lambda - 1) - 20 - 4\lambda \\ &= 3\lambda^2 + 3\lambda + 30 - \lambda^3 - \lambda^2 - 10\lambda + 12\lambda - 12 - 20 - 4\lambda \\ &= -\lambda^3 + 2\lambda^2 + \lambda - 2. \end{aligned}$$





## Eigenvalue example II (cntd)

- We need to **solve**  $-\lambda^3 + 2\lambda^2 + \lambda - 2 = 0$
- We try a few “obvious” values:  $\lambda = 1$  **YES!**
- Reduce from degree 3 to 2, by separating  $(\lambda - 1)$  in:

$$\begin{aligned} -\lambda^3 + 2\lambda^2 + \lambda - 2 &= (\lambda - 1)(a\lambda^2 + b\lambda + c) \\ &= a\lambda^3 + (b - a)\lambda^2 + (c - b)\lambda - c \end{aligned}$$

- This works for  $a = -1$ ,  $b = 1$ ,  $c = 2$
- Now we use quadratic equation for  $-\lambda^2 + \lambda + 2 = 0$
- Solutions:  $\lambda = \frac{-1 \pm \sqrt{1 + 4 \cdot 2}}{-2} = \frac{-1 \pm 3}{-2}$  giving  $\lambda = 2, -1$
- All three eigenvalues:  $\lambda = 1, \lambda = -1, \lambda = 2$



## Getting eigenvectors

- Once we have eigenvalues  $\lambda_i$  for a matrix  $\mathbf{A}$  we can find corresponding **eigenvectors**  $\mathbf{v}_i$ , with  $\mathbf{A} \cdot \mathbf{v}_i = \lambda_i \mathbf{v}_i$
- These  $\mathbf{v}_i$  appear as the solutions of  $(\mathbf{A} - \lambda_i \cdot \mathbf{I}) \cdot \mathbf{v} = 0$ 
  - We can make a convenient choice, using that scalar multiplications  $a \cdot \mathbf{v}_i$  are also a solution
- Once  $\lambda$  is known, getting  $\mathbf{v}$  is just a matter of solving this homogenous system:

$$(\mathbf{A} - \lambda \cdot \mathbf{I}) \cdot \mathbf{v} = 0$$



# Eigenvector example I

Recall the eigenvalues  $\lambda = -2, \lambda = 6$  for  $\mathbf{A} = \begin{pmatrix} 1 & 5 \\ 3 & 3 \end{pmatrix}$

$\lambda = -2$  gives matrix  $\mathbf{A} - \lambda \mathbf{I} = \begin{pmatrix} 1+2 & 5 \\ 3 & 3+2 \end{pmatrix} = \begin{pmatrix} 3 & 5 \\ 3 & 5 \end{pmatrix}$

- Corresponding system of equations  $\begin{cases} 3x + 5y = 0 \\ 3x + 5y = 0 \end{cases}$
- Solution choice  $x = -5, y = 3$ , so  $(-5, 3)$  is **eigenvector** (of matrix  $\mathbf{A}$  with eigenvalue  $\lambda = -2$ )
- Check:

$$\begin{pmatrix} 1 & 5 \\ 3 & 3 \end{pmatrix} \cdot \begin{pmatrix} -5 \\ 3 \end{pmatrix} = \begin{pmatrix} -5 + 15 \\ -15 + 9 \end{pmatrix} = \begin{pmatrix} 10 \\ -6 \end{pmatrix} = -2 \begin{pmatrix} -5 \\ 3 \end{pmatrix} \quad \checkmark$$



## Eigenvector example I (cntd)

$$\lambda = 6 \text{ gives matrix } \mathbf{A} - \lambda \mathbf{I} = \begin{pmatrix} 1-6 & 5 \\ 3 & 3-6 \end{pmatrix} = \begin{pmatrix} -5 & 5 \\ 3 & -3 \end{pmatrix}$$

- Corresponding system of equations  $\begin{cases} -5x + 5y = 0 \\ 3x - 3y = 0 \end{cases}$
- Solution choice  $x = 1, y = 1$ , so  $(1, 1)$  is **eigenvector**
- Check:

$$\begin{pmatrix} 1 & 5 \\ 3 & 3 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 1+5 \\ 3+3 \end{pmatrix} = \begin{pmatrix} 6 \\ 6 \end{pmatrix} = 6 \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$





# Diagonalisation theorem

## Theorem

Let  $\mathbf{A}$  be an  $n \times n$  matrix, represented wrt. the standard basis  $\mathcal{S}$ . Assume  $\mathbf{A}$  has  $n$  (pairwise) different eigenvalues  $\lambda_1, \dots, \lambda_n$ , with corresponding eigenvectors  $\mathcal{B} = \{v_1, \dots, v_n\}$ . **Then:**

- 1 These  $v_1, \dots, v_n$  are **linearly independent** (and thus a basis)
- 2 There is an invertible basis transformation matrix  $\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}}$  giving a **diagonalisation**:

$$\mathbf{A} = \mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}} \cdot \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & & 0 \\ 0 & & \ddots & 0 \\ 0 & \cdots & 0 & \lambda_n \end{pmatrix} \cdot \mathbf{T}_{\mathcal{S} \Rightarrow \mathcal{B}}$$

Thus, this diagonal matrix is the representation of  $\mathbf{A}$  wrt. the eigenvector basis  $\mathcal{B}$ .



# Multiple eigenvalues

- It may happen that a particular eigenvalue occurs multiple times for a matrix
  - eg. the characteristic polynomial of  $\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$  has  $\lambda = 1$  **twice** as a root.
  - for this  $\lambda = 1$  there are **two independent** eigenvectors, namely  $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$  and  $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$
- In general, if an eigenvalue  $\lambda$  occurs  $n$  times, then there are **at most  $n$**  independent eigenvectors for this  $\lambda$ 
  - linear combinations of eigenvectors with the *same* eigenvalue  $\lambda$  are also eigenvectors with eigenvalue  $\lambda$
  - they form a subspace of dimension  $n$ : the **eigenspace** of  $\lambda$ .
  - if  $\lambda$  are all distinct, eigenspaces are all 1-dimensional



# Diagonalising a matrix (study this slide!)

Putting it all together, we diagonalise a matrix  $\mathbf{A}$  as follows:

- 1 Compute each **eigenvalue**  $\lambda_1, \lambda_2, \dots, \lambda_n$  by solving the characteristic polynomial
- 2 For each eigenvalue, compute the **associated eigenvector**  $\mathbf{v}_i$  by solving the homogenous system  $\mathbf{A} - \lambda_i \mathbf{I} = \mathbf{0}$ .
- 3 Write down  $\mathbf{A}$  as the product of three matrices:

$$\mathbf{A} = \mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}} \cdot \mathbf{D} \cdot \mathbf{T}_{\mathcal{S} \Rightarrow \mathcal{B}}$$

where:

- $\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}}$  has the eigenvectors  $\mathbf{v}_1, \dots, \mathbf{v}_n$  (in order!) as its columns
- $\mathbf{D}$  has the eigenvalues (in the same order!) down its diagonal, and zeroes everywhere else
- $\mathbf{T}_{\mathcal{S} \Rightarrow \mathcal{B}}$  is the inverse of  $\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}}$ .



# Political swingers re-revisited, part I

- Recall the political transition matrix

$$\mathbf{P} = \begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} = \frac{1}{10} \begin{pmatrix} 8 & 1 \\ 2 & 9 \end{pmatrix}$$

- Eigenvalues  $\lambda$  are obtained via  $\det(\mathbf{P} - \lambda \mathbf{I}) = 0$ :

$$\left(\frac{8}{10} - \lambda\right)\left(\frac{9}{10} - \lambda\right) - \frac{1}{10} \cdot \frac{2}{10} = \lambda^2 - \frac{17}{10}\lambda + \frac{7}{10} = 0$$

- Solutions via quadratic equation

$$\begin{aligned} \frac{1}{2} \left( \frac{17}{10} \pm \sqrt{\left(\frac{17}{10}\right)^2 - \frac{28}{10}} \right) &= \frac{1}{2} \left( \frac{17}{10} \pm \sqrt{\frac{289}{100} - \frac{280}{100}} \right) \\ &= \frac{1}{2} \left( \frac{17}{10} \pm \sqrt{\frac{9}{100}} \right) \\ &= \frac{1}{2} \left( \frac{17}{10} \pm \frac{3}{10} \right) \end{aligned}$$

- Hence  $\lambda = \frac{1}{2} \cdot \frac{20}{10} = 1$  or  $\lambda = \frac{1}{2} \cdot \frac{14}{10} = \frac{7}{10} = 0.7$ .





## Political swingers re-revisited, part II

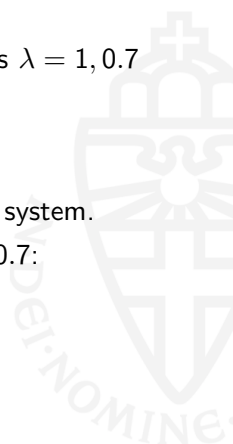
- Compute the eigenvectors by plugging eigenvalues  $\lambda = 1, 0.7$  into:

$$\begin{pmatrix} 0.8 - \lambda & 0.1 \\ 0.2 & 0.9 - \lambda \end{pmatrix} \cdot \begin{pmatrix} x \\ y \end{pmatrix} = \mathbf{0}$$

and find a solution to the resulting homogeneous system.

- That is, we need to solve this system, for  $\lambda = 1, 0.7$ :

$$\begin{cases} (0.8 - \lambda)x + 0.1y = 0 \\ 0.2x + (0.9 - \lambda)y = 0 \end{cases}$$





## Political swingers re-revisited, part II

$$\boxed{\lambda = 1} \text{ solve: } \begin{cases} -0.2x + 0.1y = 0 \\ 0.2x + -0.1y = 0 \end{cases} \text{ giving } (1, 2) \text{ as eigenvector}$$

- Indeed  $\begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ 2 \end{pmatrix} = \begin{pmatrix} 0.8 + 0.2 \\ 0.2 + 1.8 \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \end{pmatrix} = 1 \begin{pmatrix} 1 \\ 2 \end{pmatrix}$  ✓

$$\boxed{\lambda = 0.7} \text{ solve: } \begin{cases} 0.1x + 0.1y = 0 \\ 0.2x + 0.2y = 0 \end{cases} \text{ giving } (1, -1) \text{ as eigenvector}$$

- Check:

$$\begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} \cdot \begin{pmatrix} 1 \\ -1 \end{pmatrix} = \begin{pmatrix} 0.8 - 0.1 \\ 0.2 - 0.9 \end{pmatrix} = \begin{pmatrix} 0.7 \\ -0.7 \end{pmatrix} = 0.7 \begin{pmatrix} 1 \\ -1 \end{pmatrix} \quad \checkmark$$



## Political swingers re-revisited, part III

- The eigenvalues 1 and 0.7 are **different**, and indeed the eigenvectors  $(1, 2)$  and  $(1, -1)$  are **independent**
- The coordinate-translation  $\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}}$  from the eigenvector basis  $\mathcal{B} = \{(1, 2), (1, -1)\}$  to the standard basis  $\mathcal{S} = \{(1, 0), (0, 1)\}$  consists of the eigenvectors:

$$\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}} = \begin{pmatrix} 1 & 1 \\ 2 & -1 \end{pmatrix}$$

- In the reverse direction:

$$\mathbf{T}_{\mathcal{S} \Rightarrow \mathcal{B}} = (\mathbf{T}_{\mathcal{B} \Rightarrow \mathcal{S}})^{-1} = \frac{1}{-1-2} \begin{pmatrix} -1 & -1 \\ -2 & 1 \end{pmatrix} = \frac{1}{3} \begin{pmatrix} 1 & 1 \\ 2 & -1 \end{pmatrix}$$



# Political swingers re-revisited, part IV

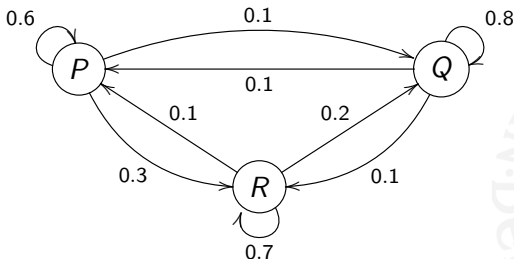
We explicitly check the **diagonalisation** equation:

$$\begin{aligned} T_{\mathcal{B} \Rightarrow \mathcal{S}} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix} \cdot T_{\mathcal{S} \Rightarrow \mathcal{B}} &= \begin{pmatrix} 1 & 1 \\ 2 & -1 \end{pmatrix} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix} \cdot \frac{1}{3} \begin{pmatrix} 1 & 1 \\ 2 & -1 \end{pmatrix} \\ &= \frac{1}{3} \begin{pmatrix} 1 & 0.7 \\ 2 & -0.7 \end{pmatrix} \cdot \begin{pmatrix} 1 & 1 \\ 2 & -1 \end{pmatrix} \\ &= \frac{1}{3} \begin{pmatrix} 2.4 & 0.3 \\ 0.6 & 2.7 \end{pmatrix} \\ &= \begin{pmatrix} 0.8 & 0.1 \\ 0.2 & 0.9 \end{pmatrix} \\ &= \mathbf{P}, \quad \text{the original political transition matrix!} \end{aligned}$$



# Applications: probabilistic transition systems

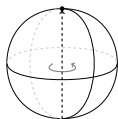
- In probabilistic transition systems (**Markov chains**)



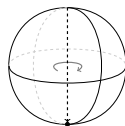
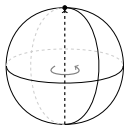
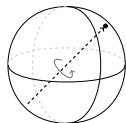
- Eigenvalues/vectors are used to make calculations more efficient, and elaborate long-term behaviour

# Applications: quantum mechanics/computation

- quantum **states** can be represented by vectors, and **measurements** by linear maps, e.g. rotations:



- eigenvalues represent **measurement outcomes** and eigenvectors represent **collapse of the quantum state**





# Applications: data processing

- **Problem:** suppose we have a **HUGE** matrix, and we want to know approximately what it looks like
- **Solution:** diagonalise it using its basis  $\mathcal{B}$  of eigenvectors...then throw away (= set to zero) all the little eigenvalues:

$$\begin{pmatrix} \lambda_1 & 0 & \cdots & 0 & 0 \\ 0 & \lambda_2 & 0 & & 0 \\ \vdots & 0 & \lambda_3 & 0 & \vdots \\ 0 & & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \lambda_n \end{pmatrix}_{\mathcal{B}} \approx \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 & 0 \\ 0 & \lambda_2 & 0 & & 0 \\ \vdots & 0 & 0 & 0 & \vdots \\ 0 & & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & 0 \end{pmatrix}_{\mathcal{B}}$$

- If there are only a few **big**  $\lambda$ 's, and lots of **little**  $\lambda$ 's, we get almost the same matrix back
- A more sophisticated technique based on eigenvalues is called **principle component analysis** (very common in big data analytics and AI)



# Applications: data compression

- This technique can also be used for **lossy data compression**
- Since we can get (pretty much) the same matrix back by throwing away all but the highest couple of eigenvalues:

$$\begin{pmatrix} \lambda_1 & 0 & \cdots & 0 & 0 \\ 0 & \lambda_2 & & & 0 \\ \vdots & 0 & \lambda_3 & 0 & \vdots \\ 0 & & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \lambda_n \end{pmatrix}_B \approx \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 & 0 \\ 0 & \lambda_2 & 0 & & 0 \\ \vdots & 0 & 0 & 0 & \vdots \\ 0 & & 0 & \ddots & 0 \\ 0 & 0 & \cdots & 0 & 0 \end{pmatrix}_B$$

- ...then the resulting matrix only depends on the first couple of **eigenvectors**.
- Hence, we can **throw the rest away!**
- This can be used to **compress images** or **music**.





## Political swingers re-revisited, part V

Diagonalisation  $\mathbf{A} = \mathbf{T}_{B \Rightarrow S} \cdot \mathbf{D} \cdot \mathbf{T}_{S \Rightarrow B} = \mathbf{T} \cdot \mathbf{D} \cdot \mathbf{T}^{-1}$  used **iteration**, e.g.

- $\mathbf{P} = \mathbf{T} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix} \cdot \mathbf{T}^{-1}$

$$\mathbf{P}^2 = \mathbf{T} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix} \cdot \mathbf{T}^{-1} \cdot \mathbf{T} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix} \cdot \mathbf{T}^{-1}$$

$$= \mathbf{T} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0.7 \end{pmatrix} \cdot \mathbf{T}^{-1}$$

$$= \mathbf{T} \cdot \begin{pmatrix} 1^2 & 0 \\ 0 & (0.7)^2 \end{pmatrix} \cdot \mathbf{T}^{-1}$$

- $\mathbf{P}^n = \mathbf{T} \cdot \begin{pmatrix} (1)^n & 0 \\ 0 & (0.7)^n \end{pmatrix} \cdot \mathbf{T}^{-1}$

- $\lim_{n \rightarrow \infty} \mathbf{P}^n = \mathbf{T} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \cdot \mathbf{T}^{-1}$  since  $\lim_{n \rightarrow \infty} (0.7)^n = 0$

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



# Political swingers re-visited, part VI

- We now have a fairly easy way to compute  $\mathbf{P}^n \cdot \begin{pmatrix} 100 \\ 150 \end{pmatrix}$
- ...and we can see that in the limit it goes to:

$$\begin{aligned} \lim_{n \rightarrow \infty} \mathbf{P}^n \cdot \begin{pmatrix} 100 \\ 150 \end{pmatrix} &= \frac{1}{3} \begin{pmatrix} 1 & 1 \\ 2 & 2 \end{pmatrix} \cdot \begin{pmatrix} 100 \\ 150 \end{pmatrix} \\ &= \frac{1}{3} \begin{pmatrix} 250 \\ 500 \end{pmatrix} = \begin{pmatrix} 83\frac{1}{3} \\ 166\frac{2}{3} \end{pmatrix} \end{aligned}$$

(This was already suggested earlier, but now we can calculate it!)