

# **Matrix methods – Regular Markov chains**

**MATH 2740 – Mathematics of Data Science – Lecture 13**

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The University of Manitoba campuses are located on original lands of Anishinaabeg, Ininew, Anisininew, Dakota and Dene peoples, and on the National Homeland of the Red River Métis. We respect the Treaties that were made on these territories, we acknowledge the harms and mistakes of the past, and we dedicate ourselves to move forward in partnership with Indigenous communities in a spirit of Reconciliation and collaboration.

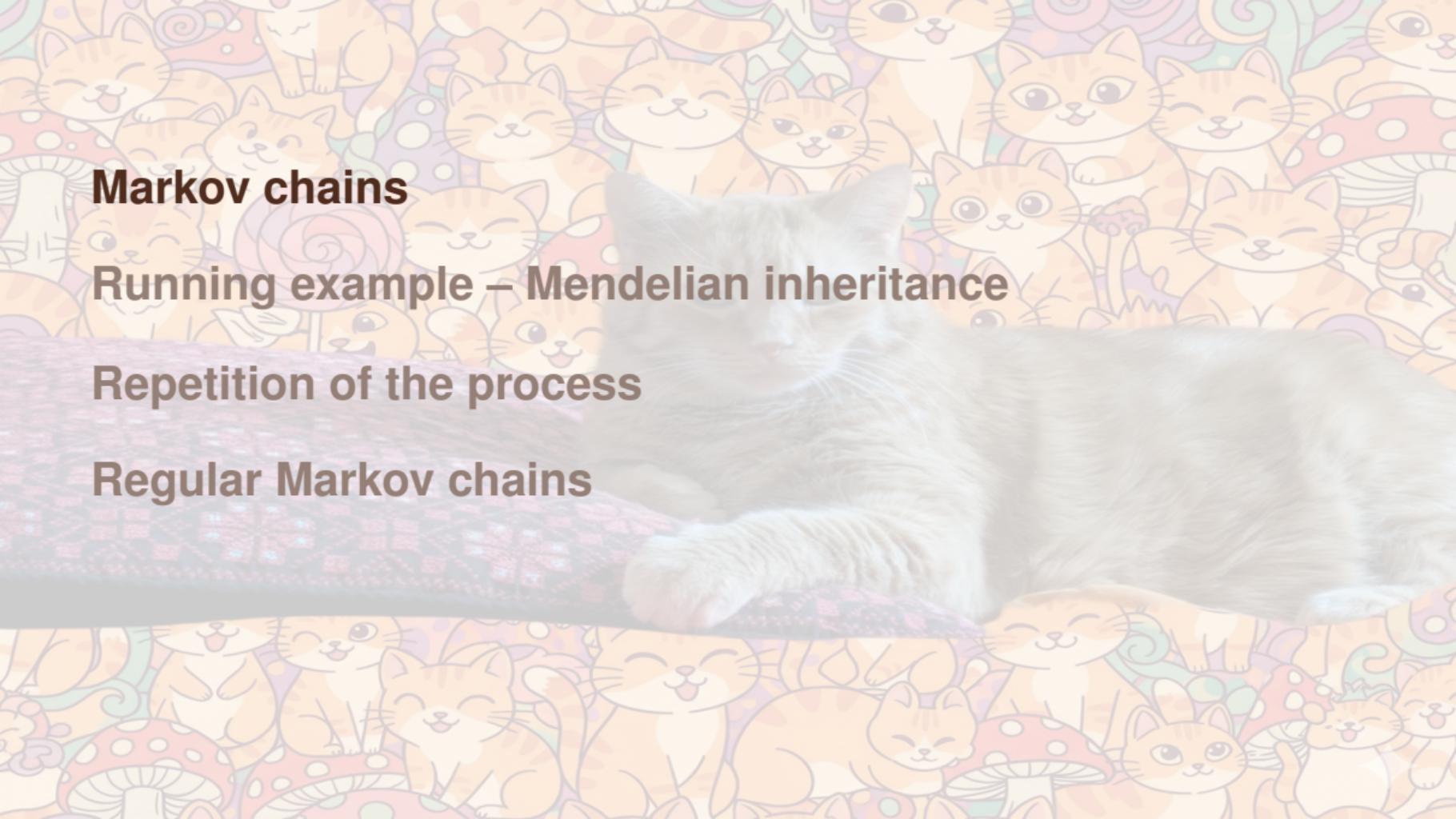
# Outline

Markov chains

Running example – Mendelian inheritance

Repetition of the process

Regular Markov chains



**Markov chains**

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## Markov chain

A Markov chain is a *stochastic process* in which the evolution through time depends only on the current state of the system (we say the process is *memoryless*)

Markov chains are an interesting combination of matrix theory and graph theory

They form the theoretical foundation for Hidden Markov processes or Markov Chain Monte Carlo (MCMC) methods, are used in ML

Conduct an experiment with a set of  $n$  possible outcomes

$$S = \{S_1, \dots, S_n\}$$

Experiment repeated  $t$  times (with  $t$  large, potentially infinite)

System has *no memory*: the next state depends only on the present state

Probability of  $S_i$  occurring on the next step given that  $S_j$  occurred on the last step:

$$p_{ij} = \mathbb{P}(S_i | S_j)$$

Suppose that  $S_i$  is the current state, then one of  $S_1, \dots, S_n$  must be the next state; so

$$p_{1i} + p_{2i} + \cdots + p_{ni} = 1, \quad 1 \leq i \leq n$$

(Some of the  $p_{ij}$  can be zero, all that is needed is that  $\sum_{j=1}^n p_{ij} = 1$  for all  $i$ )

## Definition 90

An experiment with finite number of possible outcomes  $S_1, \dots, S_n$  is repeated. The sequence of outcomes is a **Markov chain** if there is a set of  $n^2$  numbers  $\{p_{ij}\}$  such that the conditional probability of outcome  $S_i$  on any experiment given outcome  $S_j$  on the previous experiment is  $p_{ij}$ , i.e., for  $1 \leq i, j \leq n$ ,  $t = 1, \dots,$

$$p_{ij} = \mathbb{P}(S_i \text{ on experiment } t+1 \mid S_j \text{ on experiment } t)$$

Outcomes  $S_1, \dots, S_n$  are **states** and  $p_{ij}$  are **transition probabilities**.  $P = [p_{ij}]$  the **transition matrix**

The matrix

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ p_{21} & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rr} \end{pmatrix}$$

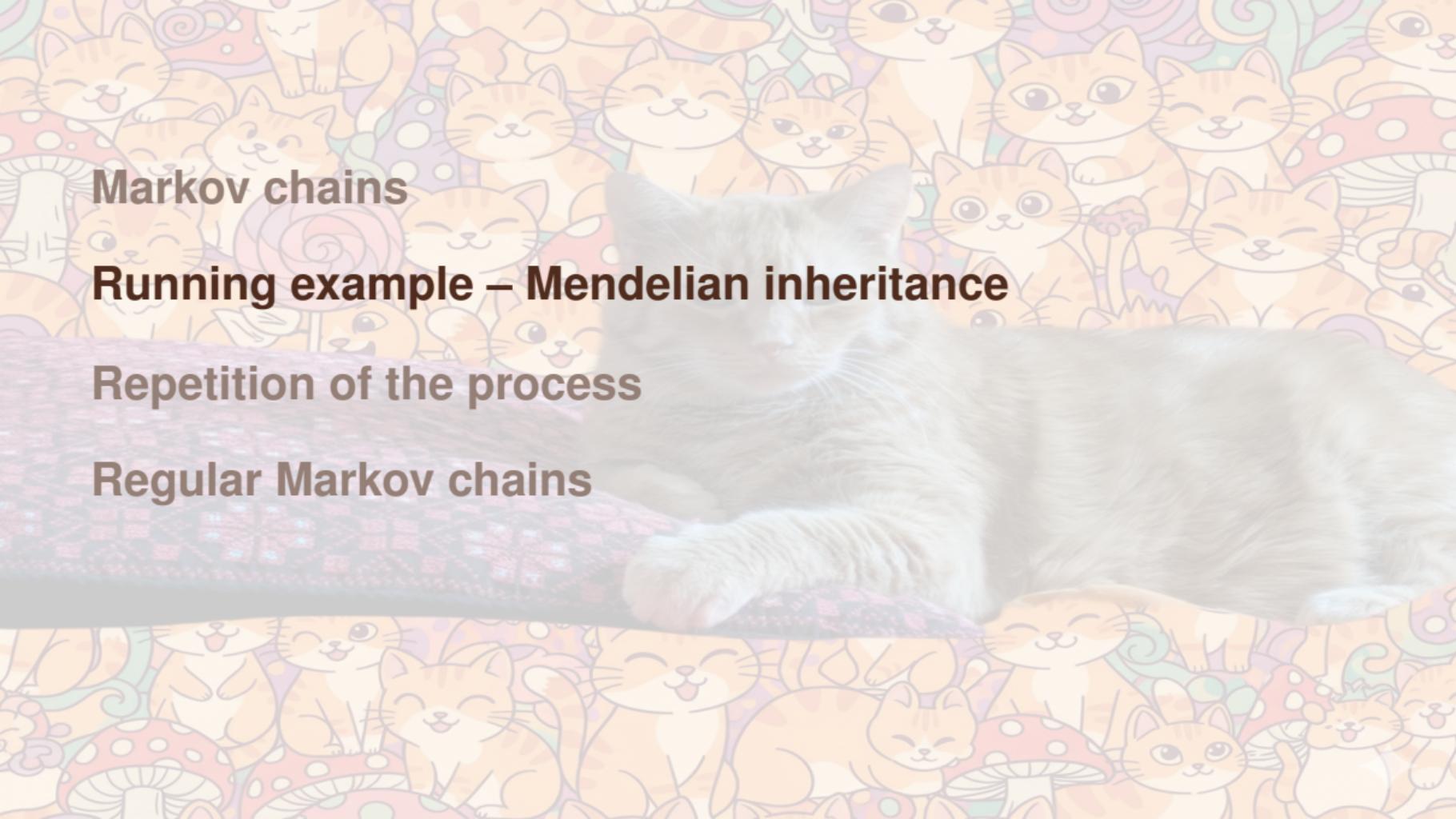
has

- ▶ nonnegative entries,  $p_{ij} \geq 0$
- ▶ entries less than 1,  $p_{ij} \leq 1$
- ▶ column sum 1, which we write

$$\sum_{i=1}^n p_{ij} = 1, \quad j = 1, \dots, n$$

or, using the notation  $\mathbb{1}^T = (1, \dots, 1)$ ,

$$\mathbb{1}^T P = \mathbb{1}^T$$



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## The “orange” gene

A cat's coat color is determined by many genes. The "orange" trait comes from a specific gene called the **orange locus**

It has two *alleles* (versions):

- ▶ **O** ⇒ Produces *phaeomelanin* (red/orange pigment)
- ▶ **o** ⇒ Produces *eumelanin* (black/brown pigment)

This gene is *sex-linked*. It is located on the **X chromosome**

- ▶ This changes the rules of inheritance!

# How sex-linked genes work

Because the gene is on the X chromosome, males and females inherit it differently

## Females have two X chromosomes (XX)

- ▶ They get two alleles for this gene (one from each parent)
- ▶ Possible genotypes:  $X^O X^O$ ,  $X^o X^o$ , or  $X^O X^o$

## Males have one X and one Y chromosome (XY)

- ▶ They get *only one* allele for this gene (always from the mother)
- ▶ Possible genotypes:  $X^O Y$  or  $X^o Y$

# Genotype vs. phenotype

## Males (simple):

- ▶  $X^OY \implies \text{orange cat}$
- ▶  $X^oY \implies \text{non-orange cat}$  (e.g., black)

## Females (the special case):

- ▶  $X^OX^O \implies \text{orange cat}$
- ▶  $X^oX^o \implies \text{non-orange cat}$  (e.g., black)
- ▶  $X^OX^o \implies \text{tortoiseshell cat}$

A “tortie” isn’t a simple hybrid. Both alleles ( $O$  and  $o$ ) are active in different patches of skin, creating the orange and black mottled pattern

## Example 1: Orange dad + black Mom

Let's cross an **orange male ( $X^O Y$ )** with a **black female ( $X^o X^o$ )**

		Father	
		$X^O$	$Y$
Mother	$X^o$	$X^O X^o$	$X^o Y$
	$X^o$	$X^O X^o$	$X^o Y$

**Results for their offspring:**

- ▶ All females ( $X^O X^o$ ) will be **tortoiseshell**
- ▶ All males ( $X^o Y$ ) will be **black** (non-orange)

## Example 2: black dad + tortoiseshell mom

Let's cross a **black male** ( $X^O Y$ ) with a **tortoiseshell female** ( $X^O X^o$ )

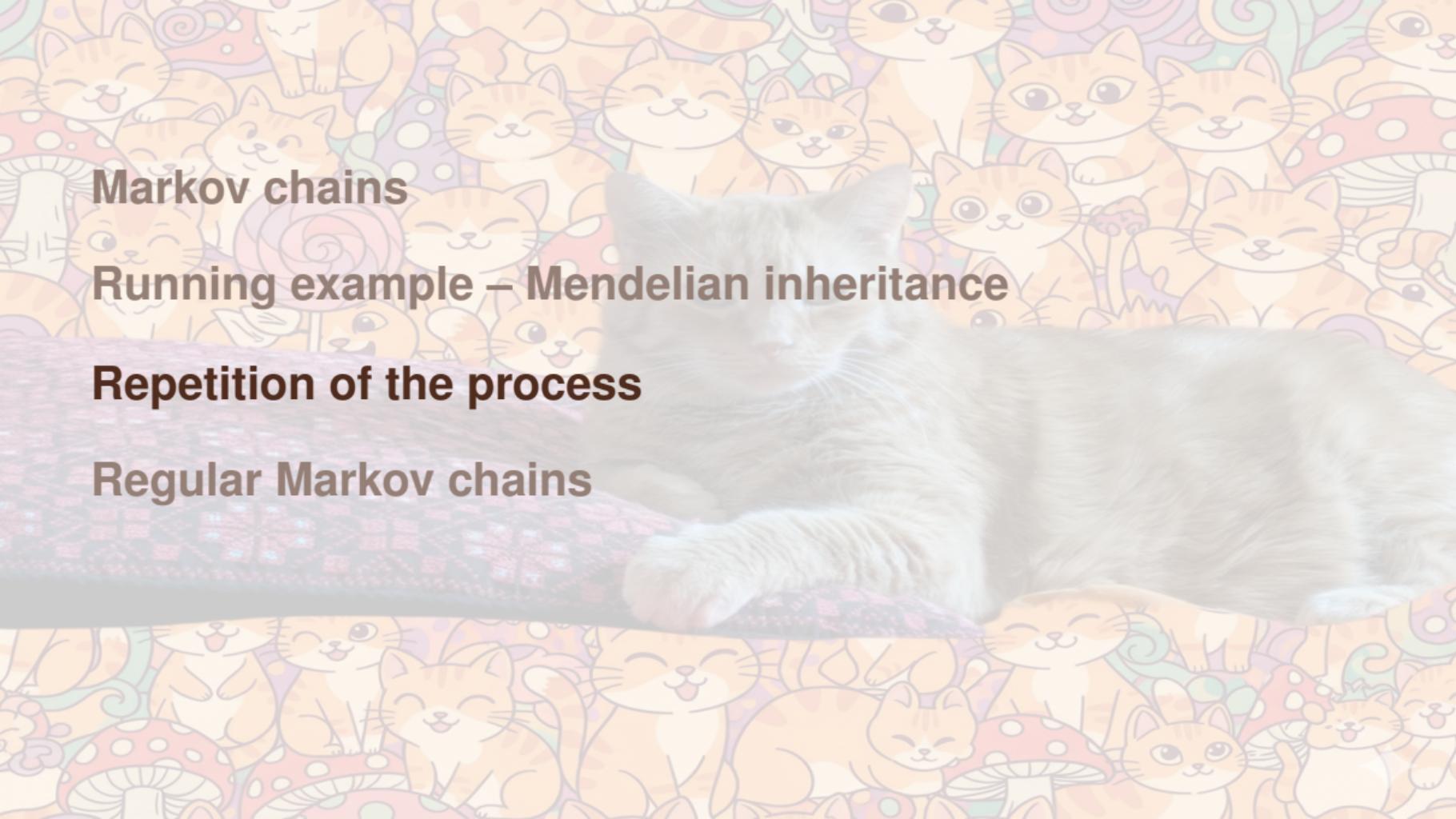
		Father		
		$X^O$	$Y$	
Mother	$X^O$	$X^O X^o$	$X^O Y$	
	$X^o$	$X^o X^o$	$X^o Y$	

Results for their offspring (1/4 chance for each):

- ▶  $X^O X^o \Rightarrow$  **Tortoiseshell Female**
- ▶  $X^o X^o \Rightarrow$  **Black Female**
- ▶  $X^O Y \Rightarrow$  **Orange Male**
- ▶  $X^o Y \Rightarrow$  **Black Male**

## Fun fact: what about male tortoiseshells?

- ▶ As we saw, a male is  $XY$ . He can only get  $X^O$  or  $X^o$  from his mother, not both
- ▶ A male tortoiseshell is possible, but *extremely rare*
- ▶ It's a genetic anomaly where the cat has an extra X chromosome: **XXY**
- ▶ This genotype (e.g.,  $X^OX^oY$ ) allows the cat to be male ( $Y$ ) but also express both orange and non-orange alleles ( $X^OX^o$ ), just like a female



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## General case

$p_i(t)$ : probability that state  $S_i$  occurs on the  $t^{th}$  repetition of the experiment,  
 $1 \leq i \leq n$

Since one the states  $S_i$  must occur on the  $t^{th}$  repetition

$$p_1(t) + p_2(t) + \cdots + p_n(t) = 1$$

$p_i(t+1)$ : probability that state  $S_i$ ,  $1 \leq i \leq r$ , occurs on  $(t+1)^{th}$  repetition of the experiment

$n$  ways to be in state  $S_i$  at step  $t+1$ :

1. Step  $t$  is  $S_1$ . Probability of getting  $S_1$  on  $t^{th}$  step is  $p_1(t)$ , and probability of having  $S_i$  after  $S_1$  is  $p_{i1}$ . Therefore  $P(S_i|S_1) = p_{i1}p_1(t)$
2. We get  $S_2$  on step  $t$  and  $S_i$  on step  $(t+1)$ . Then  $P(S_i|S_2) = p_{i2}p_2(t)$
- ..
- n. Probability of occurrence of  $S_i$  at step  $t+1$  if  $S_n$  at step  $t$  is  
 $P(S_i|S_n) = p_{in}p_n(t)$

$$\begin{aligned}\implies p_i(t+1) &= P(S_i|S_1) + \cdots + P(S_i|S_n) \\ &= p_{i1}p_1(t) + \cdots + p_{in}p_n(t)\end{aligned}$$

Therefore,

$$p_1(t+1) = p_{11}p_1(t) + p_{12}p_2(t) + \cdots + p_{1n}p_n(t)$$

⋮

$$p_n(t+1) = p_{n1}p_1(t) + p_{n2}p_2(t) + \cdots + p_{nn}p_n(t)$$

In matrix form

$$p(t+1) = Pp(t), \quad n = 1, 2, 3, \dots$$

where  $p(t) = (p_1(t), p_2(t), \dots, p_n(t))^T$  is a probability vector and  $P = (p_{ij})$  is an  $n \times n$  transition matrix,

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ p_{21} & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rr} \end{pmatrix}$$

So

$$(p_1(t+1) \quad \cdots \quad p_n(t+1)) = (p_1(t) \quad \cdots \quad p_n(t)) \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1r} \\ p_{21} & p_{22} & \cdots & p_{2r} \\ \vdots & \vdots & \ddots & \vdots \\ p_{r1} & p_{r2} & \cdots & p_{rr} \end{pmatrix}$$

Easy to check that this gives the same expression as before

# Stochastic matrices

## Definition 91 (Stochastic matrix)

The nonnegative  $n \times n$  matrix  $M$  is **row-stochastic** (resp. **column-stochastic**) if  $\sum_{j=1}^n a_{ij} = 1$  for all  $i = 1, \dots, n$  (resp.  $\sum_{i=1}^n a_{ij} = 1$  for all  $j = 1, \dots, n$ )

We often say **stochastic** and let the context determine whether we mean row- or column-stochastic

If it is both row- and column-stochastic, the matrix is **doubly stochastic**

## Theorem 92

Let  $M \in \mathcal{M}_n$  be a stochastic matrix. Then all eigenvalues  $\lambda$  of  $M$  are such that  $|\lambda| \leq 1$ .

### Theorem 93

*Let  $M \in \mathcal{M}_n$  be a stochastic matrix.  $\lambda = 1$  is an eigenvalue of  $M$ . If  $M$  is row-stochastic, the eigenvalue 1 is associated to the column vector of ones (a right eigenvector of  $M$ ); if  $M$  is column-stochastic, the eigenvalue 1 is associated to the row vector of ones (a left eigenvector of  $M$ )*

## Proof of Theorem 93

Suppose  $M \in \mathcal{M}_n$  is row-stochastic. One way to write the requirement that each row sum equals 1 is as

$$M\mathbf{1} = \mathbf{1} \tag{1}$$

where  $\mathbf{1} = (1, \dots, 1) \in \mathbb{C}^n$  is a column vector

If  $M \in \mathcal{M}_n$ , then the eigenpair equation takes the form

$$M\mathbf{v} = \lambda\mathbf{v}, \quad \mathbf{v} \neq \mathbf{0}$$

So, in (1),  $\mathbf{v} = \mathbf{1}$  and  $\lambda = 1$

This works the same way for a column-stochastic matrix, except that here the relation is  $\mathbf{1}M = \mathbf{1}$  with  $\mathbf{1}$  a row vector and the (left)eigenpair relation is  $\mathbf{v}^T M = \lambda \mathbf{v}^T$  with  $\mathbf{v}^T$  a row vector

## Long time behaviour

Let  $p(0)$  be the initial distribution vector. Then

$$\begin{aligned} p(1) &= p(0)P \\ p(2) &= p(1)P \\ &= (p(0)P)P \\ &= p(0)P^2 \end{aligned}$$

Continuing, we get, for any  $t$ ,

$$p(t) = p(0)P^t$$

Therefore,

$$\lim_{t \rightarrow +\infty} p(t) = \lim_{t \rightarrow +\infty} p(0)P^t = p(0) \left( \lim_{t \rightarrow +\infty} P^t \right)$$

if this limit exists

## The matrix $P^t$

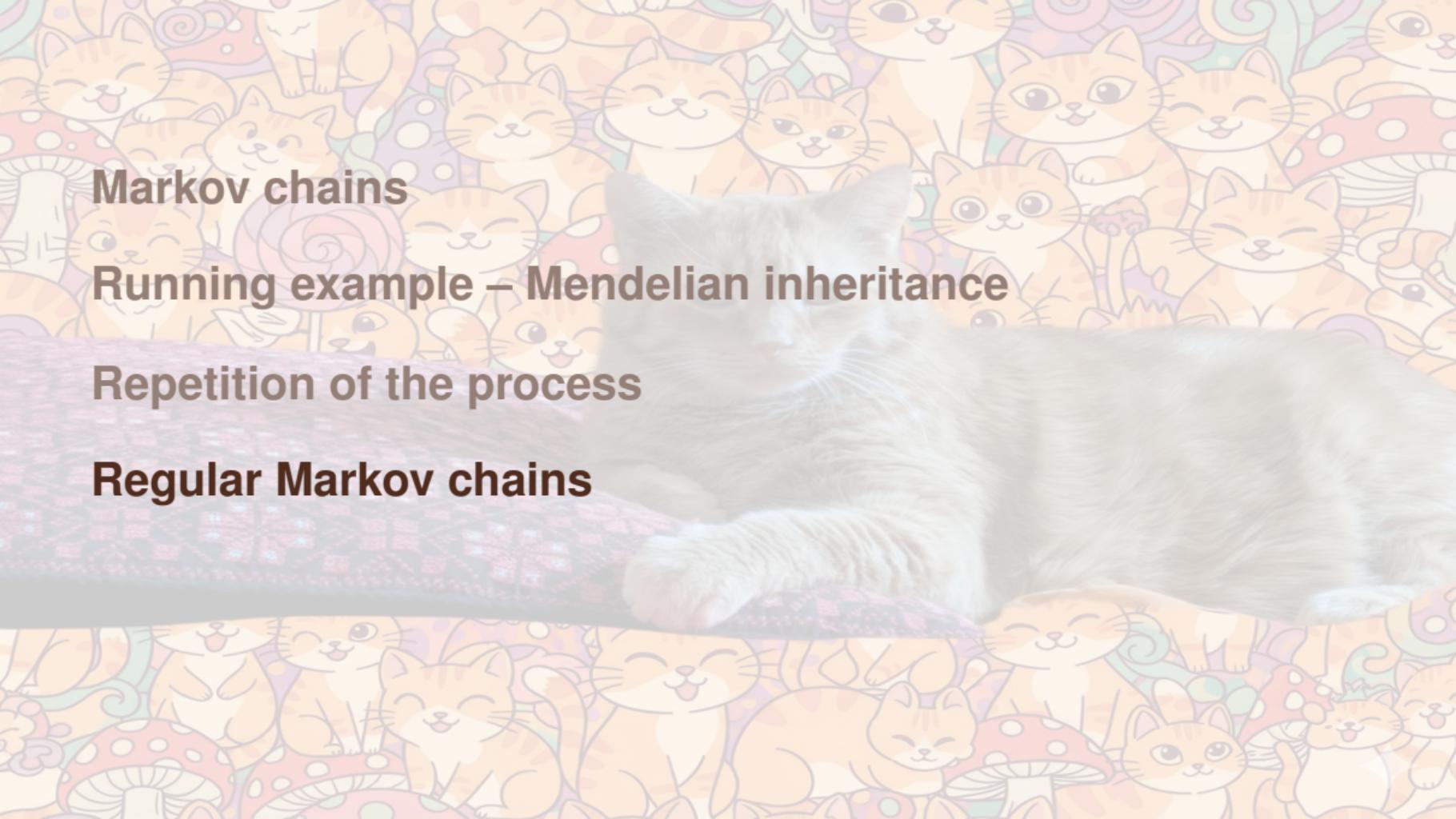
### Theorem 94

*If  $M, N$  are nonsingular stochastic matrices, then  $MN$  is a stochastic matrix*

### Corollary 95

*If  $M$  is a nonsingular stochastic matrix, then for any  $k \in \mathbb{N}$ ,  $M^k$  is a stochastic matrix*

So  $P^t$  is stochastic



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# Regular Markov chains

## Definition 96 (Regular Markov chain)

A **regular** Markov chain has  $P^k$  (entry-wise) positive for some integer  $k > 0$ , i.e.,  $P^k$  has only positive entries

## Definition 97 (Primitive matrix)

A nonnegative matrix  $M$  is **primitive** if, and only if, there is an integer  $k > 0$  such that  $M^k$  is positive.

## Theorem 98

*Markov chain regular  $\iff$  transition matrix  $P$  primitive*

## Matrices and graphs

Here and with absorbing chains, there is a lot to gain from using a bit of graph theory

Matrices and graphs are intimately linked

Some matrix problems are easier considered with graphs, some graph problems are easier with matrices

Note that I say *graph*, but in other contexts, people speak of *networks*

# What is a directed graph?

## Definition 99 (Digraph)

A **directed graph** (or **digraph**)  $G$  is a pair  $(V, A)$  where:

- ▶  $V$  is a finite set of elements called **vertices** or **nodes**
- ▶  $A \subseteq V \times V$  is a set of ordered pairs of vertices called **arcs** or **directed edges**

## Definition 100 (Arc)

An **arc**  $a = (u, v) \in A$  represents a connection **from** vertex  $u$  **to** vertex  $v$

- ▶  $u$  is the **tail** of the arc
- ▶  $v$  is the **head** of the arc

## In the context of Markov chains

- ▶ Vertices (nodes) represent the **states** of the system
- ▶ Arcs represent possible **transitions** between states
- ▶ The weights on the arcs represent the probability to make a given transition

## From matrix to graph

Given a transition matrix  $P = [p_{ij}]$ , define an induced digraph  $\mathcal{G} = (V, A)$  (often written  $\mathcal{G}(A)$ )

- ▶ Vertices  $V$  correspond to the states
- ▶ An arc  $(i, j)$  exists in  $A$  if and only if  $p_{ij} > 0$

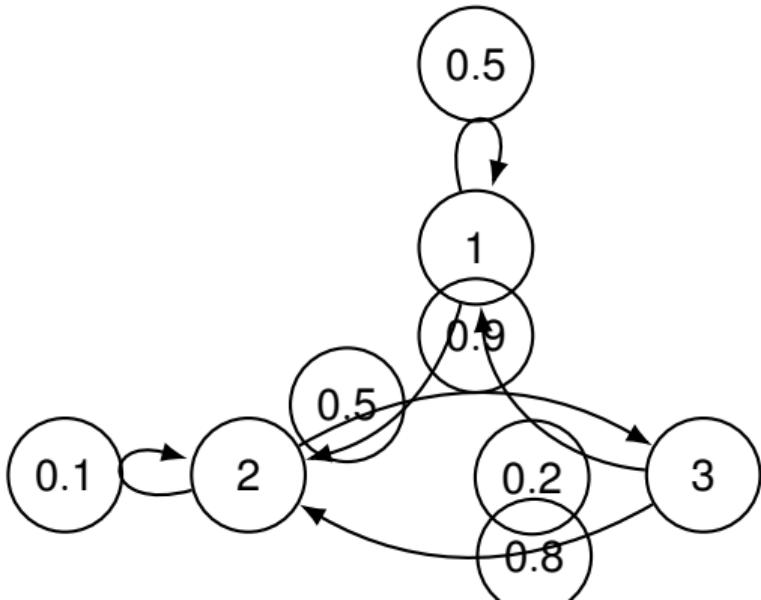
Let  $P$  be the transition matrix:

$$P = \begin{pmatrix} 0.5 & 0.5 & 0 \\ 0 & 0.1 & 0.9 \\ 0.2 & 0.8 & 0 \end{pmatrix}$$

### Arcs created:

- ▶  $p_{11} = 0.5 \Rightarrow (1, 1)$
- ▶  $p_{12} = 0.5 \Rightarrow (1, 2)$
- ▶  $p_{22} = 0.1 \Rightarrow (2, 2)$
- ▶  $p_{23} = 0.9 \Rightarrow (2, 3)$
- ▶  $p_{31} = 0.2 \Rightarrow (3, 1)$

### Induced transition graph:

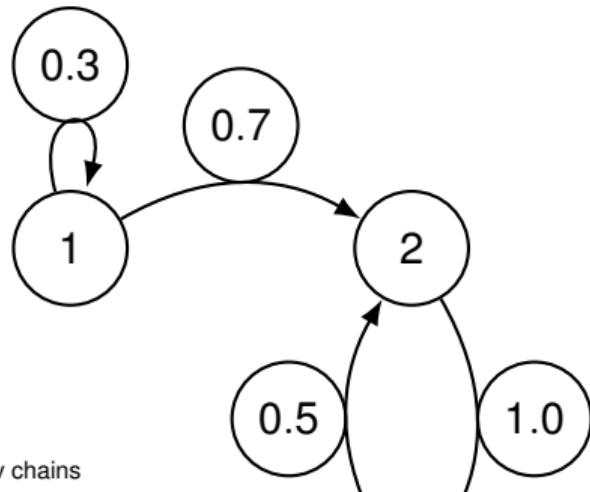


## Example: From graph to matrix

Conversely, a transition graph with  $n$  states and probabilities on its arcs defines an  $n \times n$  stochastic matrix  $P$ .

- ▶ The entry  $p_{ij}$  is the probability on the arc from state  $i$  to state  $j$ .
- ▶ If no arc  $(i, j)$  exists, then  $p_{ij} = 0$ .
- ▶ For the matrix to be stochastic, the sum of outgoing probabilities from each state must be 1.

A 4-state transition graph:



Induced transition matrix:

$$P = \begin{pmatrix} 0.3 & 0.7 & 0 & 0 \\ 0 & 0 & 1.0 & 0 \\ 0 & 0.5 & 0 & 0.5 \\ 0 & 0 & 0 & 1.0 \end{pmatrix}$$

Check row sums:

- ▶ Row 1:  $0.3 + 0.7 = 1$
- ▶ Row 2:  $1.0 = 1$
- ▶ Row 3:  $0.5 + 0.5 = 1$

### Definition 101 (Reducible/irreducible matrix)

A matrix  $M \in \mathcal{M}_n$  is **reducible** if there exists a permutation matrix  $P$  such that

$$P^T M P = \begin{pmatrix} P & Q \\ \mathbf{0} & R \end{pmatrix},$$

i.e.,  $M$  is similar to a block upper triangular matrix. The matrix  $M$  is **irreducible** if no such matrix exists

# Behaviour of a regular MC

## Theorem 102

If  $P$  is the transition matrix of a regular Markov chain, then

1. the powers  $P^t$  approach a stochastic matrix  $W$
2. each column of  $W$  is the same (column) vector  $w = (w_1, \dots, w_n)^T$
3. the components of  $w$  are positive

So if the Markov chain is regular

$$\lim_{t \rightarrow +\infty} p(t) = \lim_{t \rightarrow +\infty} P^t p(0) = Wp(0)$$

## Computing $W$

If  $p(t)$  converges, then  $p(t+1) = Pp(t)$  at the limit, so  $w = \lim_{t \rightarrow \infty} p(t)$  is a **fixed point** of the system. Write

$$w = Pw$$

and solve for  $w$ , i.e., find  $w$  as a (right) eigenvector corresponding to the eigenvalue 1

$w$  might have to be normalized (you want a probability vector). Check that the norm  $\|w\|_1$  defined by

$$\|w\|_1 = |w_1| + \cdots + |w_n| = w_1 + \cdots + w_n$$

(since  $w \geq 0$ ) is equal to one. If not, use

$$\tilde{w} = \frac{w}{\|w\|_1}$$

## Back to orange cats

Create a chain by tracking the 3 female genotypes:

- ▶  $S_1: X^O X^O$  (orange)
- ▶  $S_2: X^o X^o$  (black)
- ▶  $S_3: X^O X^o$  (tortoiseshell)

To make the chain regular, we mate our female with a male chosen randomly from a **fixed population** that is:

- ▶ 50% orange males ( $X^O Y$ )
- ▶ 50% black males ( $X^o Y$ )

## State 1: orange female ( $X^O X^O$ )

The mother is  $X^O X^O$ . We pick a father with 50/50 probability.

### Case 1: Father is $X^O Y$

Mother	$X^O$	$Y$	
	$X^O$	$X^O X^O (S_1)$	Male
	$X^O$	$X^O X^O (S_1)$	Male

Daughters: 100%  $S_1$

### Case 2: Father is $X^O Y$

Mother	$X^O$	$Y$	
	$X^O$	$X^O X^o (S_3)$	Male
	$X^O$	$X^O X^o (S_3)$	Male

Daughters: 100%  $S_3$

### Transitions from $S_1$ :

- ▶  $\mathbb{P}(S_1 \rightarrow S_1) = 0.5 \times 1.0 = \mathbf{0.5}$
- ▶  $\mathbb{P}(S_1 \rightarrow S_2) = 0$
- ▶  $\mathbb{P}(S_1 \rightarrow S_3) = 0.5 \times 1.0 = \mathbf{0.5}$

## State 2: black female ( $X^oX^o$ )

The mother is  $X^oX^o$ . We pick a father with 50/50 probability.

### Case 1: Father is $X^oY$

Mother	$X^o$	$Y$	
	$X^o$	$X^oX^o (S_3)$	Male
	$X^o$	$X^oX^o (S_3)$	Male

Daughters: 100%  $S_3$

### Case 2: Father is $X^oY$

Mother	$X^o$	$Y$	
	$X^o$	$X^oX^o (S_2)$	Male
	$X^o$	$X^oX^o (S_2)$	Male

Daughters: 100%  $S_2$

### Transitions from $S_2$ :

- ▶  $\mathbb{P}(S_2 \rightarrow S_1) = 0$
- ▶  $\mathbb{P}(S_2 \rightarrow S_2) = 0.5 \times 1.0 = \mathbf{0.5}$
- ▶  $\mathbb{P}(S_2 \rightarrow S_3) = 0.5 \times 1.0 = \mathbf{0.5}$

## State 3: tortoiseshell female ( $X^O X^o$ )

The mother is  $X^O X^o$ . We pick a father with 50/50 probability.

### Case 1: Father is $X^O Y$

	$X^O$	$Y$	
Mother	$X^O$	$X^O X^O (S_1)$	Male
	$X^o$	$X^O X^o (S_3)$	Male

Daughters: 50%  $S_1$ , 50%  $S_3$

### Case 2: Father is $X^o Y$

	$X^O$	$Y$	
Mother	$X^O$	$X^O X^o (S_3)$	Male
	$X^o$	$X^o X^o (S_2)$	Male

Daughters: 50%  $S_2$ , 50%  $S_3$

### Transitions from $S_3$ :

- ▶  $\mathbb{P}(S_3 \rightarrow S_1) = 0.5 \times 0.5 = \mathbf{0.25}$
- ▶  $\mathbb{P}(S_3 \rightarrow S_2) = 0.5 \times 0.5 = \mathbf{0.25}$
- ▶  $\mathbb{P}(S_3 \rightarrow S_3) = (0.5 \times 0.5) + (0.5 \times 0.5) = \mathbf{0.5}$

## Summary of the 3-state chain

The transition matrix  $P$  for states  $\{S_1, S_2, S_3\}$  is:

$$P = \begin{pmatrix} 0.5 & 0 & 0.5 \\ 0 & 0.5 & 0.5 \\ 0.25 & 0.25 & 0.5 \end{pmatrix}$$

**Is this chain regular?**

- ▶ **Irreducible? Yes.** All states communicate.
  - ▶  $S_1 \rightarrow S_3 \rightarrow S_2$  (Path from  $S_1$  to  $S_2$ )
  - ▶  $S_2 \rightarrow S_3 \rightarrow S_1$  (Path from  $S_2$  to  $S_1$ )
  - ▶ All other paths are direct ( $S_1 \rightarrow S_3$ ,  $S_3 \rightarrow S_1$ , etc.)
- ▶ **Aperiodic? Yes.** All states have self-loops ( $p_{11}, p_{22}, p_{33} > 0$ ).

Since the chain is irreducible and aperiodic, it is **regular**.

Compute the left eigenvector associated to 1 (we know the right eigenvector associated to 1 is  $(1, \dots, 1)^T$ )

$$(w_1 \ w_2 \ w_3) \begin{pmatrix} 1/2 & 0 & 1/2 \\ 0 & 1/2 & 1/2 \\ 1/4 & 1/4 & 1/2 \end{pmatrix} = (w_1 \ w_2 \ w_3)$$