

# Math 456: Mathematical Modeling

Thursday, March 29th, 2018

# Decomposition of Markov Chains

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## Last time

1. Counting visiting times.
2. The behavior of  $p^n(x, y)$  as  $n \rightarrow \infty$  when  $y$  is transient.
3. Convergence theorem for irreducible, aperiodic chains (statement only).

# Today

1. Examples of use of the convergence theorem.
2. Inequalities for hitting times
3. Decomposition of the state space into transient and closed+irreducible sets.

# Last time

## Convergence Theorem

Last time, we stated the following theorem

### Theorem

*Consider an irreducible, aperiodic chain, and let  $\pi(y)$  denote its stationary distribution.*

*Then, for any  $y \in S$ , we have*

$$\lim_{n \rightarrow \infty} p^n(x, y) = \pi(y) \quad \forall x \in S.$$

## Also last time...

We also proved that if  $y$  is transient, then for every  $x$ ,

$$\sum_{n=1}^{\infty} p^n(x, y) < \infty$$

and therefore

$$\lim_{n \rightarrow \infty} p^n(x, y) = 0$$

Thus, we have two ways of computing limits of  $p^n(x, y)$ , depending on the nature of  $y$ .

## Example

**Problem:** Consider the chain with transition matrix

$$p = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 2/3 & 0 & 1/3 & 0 \\ 1/8 & 1/4 & 5/8 & 0 & 0 \\ 0 & 1/6 & 0 & 5/6 & 0 \\ 1/3 & 0 & 1/3 & 0 & 1/3 \end{pmatrix}$$

and compute  $\lim_{n \rightarrow \infty} p^n(x, y)$  for every  $x$  and  $y$ .

## Example

**Solution:**

$$p = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 2/3 & 0 & 1/3 & 0 \\ 1/8 & 1/4 & 5/8 & 0 & 0 \\ 0 & 1/6 & 0 & 5/6 & 0 \\ 1/3 & 0 & 1/3 & 0 & 1/3 \end{pmatrix}$$

We note that  $p(1, y) = 0$  for all states  $y \neq 1$  and  $p(1, 1) = 1$ . It follows 1 is a **recurrent state**.



## Example

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We note that  $p(1, y) = 0$  for all states  $y \neq 1$  and  $p(1, 1) = 1$ . It follows 1 is a **recurrent state**.

Plus, since all the other states communicate with 1, it follows that  $\{2, 3, 4, 5\}$  are all **transient states**.

## Example

**Solution:**

$$p = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 2/3 & 0 & 1/3 & 0 \\ 1/8 & 1/4 & 5/8 & 0 & 0 \\ 0 & 1/6 & 0 & 5/6 & 0 \\ 1/3 & 0 & 1/3 & 0 & 1/3 \end{pmatrix}$$

Accordingly, if  $y = 2, 3, 4, 5$  then

$$\lim_{n \rightarrow \infty} p^n(x, y) = 0 \text{ for every } x$$

At the same time,

$$\lim_{n \rightarrow \infty} p^n(x, 1) = 0 \text{ for every } x$$

## Example

(Computing limits **using** the Convergence Theorem)

**Problem:** Consider the chain with transition matrix

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

and compute  $\lim_{n \rightarrow \infty} p^n(x, y)$  for every  $x$  and  $y$ .

## Example

**Solution:**

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

First, it is not difficult to see that every states communicates to each other, so the chain is **irreducible**.

## Example

**Solution:**

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

First, it is not difficult to see that every states communicates to each other, so the chain is **irreducible**.

Secondly, it is clear that  $p^3(1, 1) > 0$  and  $p^4(1, 1) > 0$ , so  $x = 1$  has period 1. Then, by irreducibility, all states have period 1.

## Example

**Solution:**

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

Since the chain is irreducible and aperiodic, the **convergence theorem** says that

$$\lim_{n \rightarrow \infty} P^n(x, y) = \pi(y) \quad \forall x, y.$$

Let us then find  $\pi(y)$  directly.

## Example

**Solution:**

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

Solving the eigenfunction problem defining the vector  $\pi$  yields

$$\pi^t = \left( \frac{3}{11}, \frac{3}{11}, \frac{2}{11}, \frac{3}{11} \right)$$

# Decomposition of the State Space

A different perspective on hitting times

Often computing the exact probabilities

$$\mathbb{P}_x[T_x = n], \quad n = 1, 2, \dots$$

is too difficult and not necessary.

What if for our purposes, it's enough to know  $\mathbb{P}_x[T_x = n]$  is not very large for some  $n$ ?

Inequalities are always easier to obtain than formulas (they give us less information), but is still useful information.



# Decomposition of the State Space

## Example

Consider a 3 state chain with transition matrix

$$p = \begin{pmatrix} 0.7 & 0.2 & 0.1 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.4 & 0.4 \end{pmatrix}$$

What can we say about, for instance

$$\mathbb{P}_3[T_3 > n]??$$

# Decomposition of the State Space

## Example

Consider a 3 state chain with transition matrix

$$p = \begin{pmatrix} 0.7 & 0.2 & 0.1 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.4 & 0.4 \end{pmatrix}$$

Observe that, no matter what  $x$  is, we always have

$$\mathbb{P}[X_{n+1} = 3 \mid X_n = x] \geq 0.1$$

Equivalently,

$$\mathbb{P}[X_{n+1} \neq 3 \mid X_n = x] \leq 0.9.$$

# Decomposition of the State Space

## Example

Consider a 3 state chain with transition matrix

$$p = \begin{pmatrix} 0.7 & 0.2 & 0.1 \\ 0.3 & 0.5 & 0.2 \\ 0.2 & 0.4 & 0.4 \end{pmatrix}$$

In this case, we can think of estimating a Bernoulli variable: “have we reached 3 yet  $y/n$ ?”. That is, we have the inequality

$$\mathbb{P}_x[X_n \neq 3, X_{n-1} \neq 3, \dots, X_1 \neq 3] \leq (0.9)^n.$$

Therefore,

$$\mathbb{P}_x[T_x > n] \leq (0.9)^n.$$

## Decomposition of the State Space

This last trick can be generalized:

Lemma (See Lemma 1.3 in Durrett)

*If there is a state  $y \in S$ , and  $\alpha \in (0, 1)$  and  $k_0 \in \mathbb{N}$  such that*

$$P_x[T_y \leq k_0] \geq \alpha \quad \forall x \in S,$$

*then for every  $n \in \mathbb{N}$ ,*

$$P_x[T_y > nk_0] \leq (1 - \alpha)^n.$$

# Decomposition of the State Space

The way to think about this lemma is:

*if regardless of the initial point you have some at least some chance of reaching the state  $y$  in at most  $k_0$  steps, then the chance that you have not reached  $y$  in  $n$  steps decreases exponentially with  $n$ .*

# Decomposition of the State Space

## Theorem

*If  $C \subset \mathcal{S}$  is closed and irreducible, then all of the states in  $C$  are recurrent.*

# Decomposition of the State Space

## Proof

**Recall** that if  $C$  is closed and irreducible and has  $N$  states, then

given  $x, y \in C$  there is  $k \leq N$  such that  $p^k(x, y) > 0$

# Decomposition of the State Space

## Proof

**In terms of  $T_x$**  this means there is a  $\delta > 0$  such that

$$P_x(T_x \leq N) \geq \delta \text{ for every } x \in C$$



## Decomposition of the State Space

### Proof

**In terms of  $T_x$**  this means there is a  $\delta > 0$  such that

$$P_x(T_x \leq N) \geq \delta \text{ for every } x \in C$$

(Say  $C = \{x_1, x_2, \dots, x_n\}$ , then take  $\delta = \min_{1 \leq i \leq n} P_{x_i}(T_{x_i} \leq N)$   
which must be  $> 0$ )

# Decomposition of the State Space

## Proof

Since  $P_x(T_x \leq N) \geq \delta$  for all  $x$ , the previous Lemma says that

$$P_x(T_x \geq kN) \leq (1 - \delta)^k$$

# Decomposition of the State Space

## Proof

Since  $P_x(T_x \leq N) \geq \delta$  for all  $x$ , the previous Lemma says that

$$P_x(T_x \geq kN) \leq (1 - \delta)^k$$

Since  $P_x(T_x = \infty) \leq P_x(T_x \geq kN)$  for every  $k$ , we conclude that

$$P_x(T_x = \infty) \leq (1 - \delta)^k$$

(for every  $k \geq 1$ )

# Decomposition of the State Space

## Proof

Since  $P_x(T_x \leq N) \geq \delta$  for all  $x$ , the previous Lemma says that

$$P_x(T_x \geq kN) \leq (1 - \delta)^k$$

Since  $P_x(T_x = \infty) \leq P_x(T_x \geq kN)$  for every  $k$ , we conclude that

$$P_x(T_x = \infty) \leq (1 - \delta)^k \\ \text{(for every } k \geq 1)$$

This means that  $P_x(T_x = \infty) = 0$  and thus  $x$  is recurrent.

## Decomposition of the State Space

Now we know that closed, irreducible sets are an easy way to find recurrent states.

The following observation is good for detecting transient states.

### Proposition

If  $x, y$  are such that  $\rho_{xy} > 0$  and  $\rho_{yx} < 1$ , then  $x$  is transient.

## Decomposition of the State Space

Now we know that closed, irreducible sets are an easy way to find recurrent states.

The following observation is good for detecting transient states.

### Proposition

If  $x, y$  are such that  $\rho_{xy} > 0$  and  $\rho_{yx} < 1$ , then  $x$  is transient.

### Proof (sketch).

Heuristically, once  $y$  is reached, there is a non-zero probability of not reaching  $x$  ever again. Since it is possible to get from  $x$  to  $y$ , the probability of never returning to  $x$  is positive.  $\square$

# Decomposition of the State Space

An immediate consequence of the previous theorem is the following

## Corollary

*If  $x \mapsto y$  and  $x$  is recurrent, then  $y \mapsto x$*

## Decomposition of the State Space

With these observations in hand, we can now classify all states in a Markov chain, decomposing the underlying state space  $\mathcal{S}$

### Theorem

*For a Markov chain with finite state space  $S$ , we have the partition*

$$\mathcal{S} = T \cup C_1 \cup C_2 \cup \dots \cup C_m$$

*Where  $T$  is the set of transient states and each  $C_k$  ( $1 \leq k \leq m$ ) are closed and irreducible sets comprised of recurrent states.*



# Decomposition of the State Space

## Proof

Let  $C$  be the set of recurrent states, and  $T = \mathcal{S} \setminus C$  the transient states.

Observe that on  $C$ ,  $x \mapsto y$  becomes a recurrence relation!

Why?

Well, we need to show the following three things

1. If  $x \in C$  then  $x \mapsto x$ .
2. If  $x, y \in C$  then  $x \mapsto y$  if and only if  $y \mapsto x$ .
3. If  $x, y, z \in C$  and  $x \mapsto y, y \mapsto z$  then  $x \mapsto z$ .

## Decomposition of the State Space

### Proof (continued)

Since every  $x \in C$  is recurrent, it is immediate that  $x \mapsto x$ .

By the previous corollary, we have that if  $x$  is recurrent and  $x \mapsto y$ , then  $y \mapsto x$ . So if  $x, y \in C$  then  $x \mapsto y$  implies that  $y \mapsto x$  and vice versa.

Lastly, the third property is immediate by concatenating two appropriate paths of positive probability.

## Decomposition of the State Space

Proof (continued).

Since  $x \mapsto y$  is an equivalence relation, it defines equivalence classes

$$C_1, \dots, C_m$$

These subsets of  $C$  are disjoint from one another, and

$$C = C_1 \cup \dots \cup C_m$$

Then, it is clear that if  $x, y \in C_k$  then  $x \mapsto y$  and vice versa, and if  $x$  and  $y$  are in different  $C_k$ , then  $x$  does not communicate with  $y$ . This means each  $C_k$  is closed and irreducible, and



## Decomposition of the State Space

This theorem says that a Markov chain is made out of subsystems which are irreducible Markov Chains that do not communicate between one another (they are close), plus some spurious transient states.

Therefore, a great deal of questions about Markov chains only need to be treated for irreducible chains.