UNIVERSITY OF
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## Statistical Sciences

## DoSS Summer Bootcamp Probability Module 9

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## Recap

Learnt in last module:

- Convergence of functions of random variables
$\triangleright$ Slutsky's theorem
$\triangleright$ Continuous mapping theorem
- Laws of large numbers
- WLLN
$\triangleright$ SLLN
$\triangleright$ Glivenko-Cantelli theorem
- Central limit theorem


## Outline

- Markov Chain
- Markov Property
- Discrete-time Markov Chain
$\triangleright$ Transition probability
$\triangleright$ Chapman-Kolmogorov equation
- Continuous-time Markov Chain
$\triangleright$ Transition probability
$\triangleright$ Chapman-Kolmogorov equation
$\triangleright$ Generator matrix


## Markov chain

## Recall: <br> A sequence of random variables $\left\{X_{n}\right\}_{i=1}^{n}$ are used to describe outcomes of random experiments.

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## Examples:

- Daily weather in Toronto
- Daily Covid-19 cases in Canada


## Markov chain

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A sequence of random variables $\left\{X_{n}\right\}_{i=1}^{n}$ are used to describe outcomes of random experiments.

## Remark:

What if the random variables follow some time structure (happen subsequently)?

## Examples:

- Daily weather in Toronto
- Daily Covid-19 cases in Canada


## Difficulties:

- The possible values of $X_{i}$ 's can vary a lot
- The random structure of $X_{i}$ 's can be complicated


## Markov chain

Remark:
Consider a Markov chain to overcome the difficulties.

## Markov chain

A Markov chain is specified by three ingredients:

- A state space $\mathcal{S}$, any non-empty finite or countable set.
- Initial probabilities $\left\{\nu_{i}\right\}_{i \in \mathcal{S}}$ where $\nu_{i}$ is the probability of starting at $i$ (at time 0 ).
- Markov property:

$$
\mathbb{P}\left(X_{n+1}=j \mid X_{n}=i\right)=p_{i j}, \quad \forall i, j \in \mathcal{S},
$$

and $\left\{p_{i, j}\right\}_{i, j \in \mathcal{S}}$ are transition probabilities.

## Markov chain



Figure: Simplification by Markov chain

## Markov chain

## Remark:

The Markov chain we have introduced so far has discrete time index, and is called
Discrete-time Markov Chain (DTMC). But there is also Continuous-time Markov chain (CTMC), and is sometimes referred to as "Markov Process".

|  | Countable state space | Continuous state space |
| :---: | :---: | :---: |
| Discrete time | DTMC |  |
| Continuous time | CTMC | Continuous stochastic processes |

Table: Types of "Series with Markov Property"

## Discrete-time Markov chain

## Representation of DTMC:

- Transition graph


Figure: Example of the transition graph

## Discrete-time Markov chain

Representation of DTMC:

- Transition matrix

$$
P=\left[\begin{array}{lll}
p_{11} & p_{12} & p_{13} \\
p_{21} & p_{22} & p_{23} \\
p_{31} & p_{32} & p_{33}
\end{array}\right]
$$

Properties:

- $p_{i j} \geq 0, \quad i, j \in \mathcal{S}$
- $\sum_{j \in \mathcal{S}} p_{i j}=1, \quad i \in \mathcal{S}$


## Discrete-time Markov chain

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- $p_{i j} \geq 0, \quad i, j \in \mathcal{S}$
- $\sum_{j \in \mathcal{S}} p_{i j}=1, \quad i \in \mathcal{S}$

Remark:
We don't have $\sum_{i \in \mathcal{S}} p_{i j}=1, \quad j \in \mathcal{S}$.

## Discrete-time Markov chain

Computation of joint probability:

$$
\begin{aligned}
\mathbb{P}\left(X_{0}=i, X_{1}=j\right) & =\mathbb{P}\left(X_{0}=i\right) \cdot \mathbb{P}\left(X_{1}=j \mid X_{0}=i\right)=\nu_{i} \cdot p_{i j} \\
\mathbb{P}\left(X_{0}=i, X_{1}=j, X_{2}=k\right) & =\mathbb{P}\left(X_{0}=i, X_{1}=j\right) \cdot \mathbb{P}\left(X_{2}=k \mid X_{0}=i, X_{1}=j\right) \\
& =\mathbb{P}\left(X_{0}=i, X_{1}=j\right) \cdot \mathbb{P}\left(X_{2}=k \mid X_{1}=j\right) \quad \text { (Markov Property) } \\
& =\nu_{i} \cdot p_{i j} \cdot p_{j k}
\end{aligned}
$$

## Discrete-time Markov chain

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& =\nu_{i} \cdot p_{i j} \cdot p_{j k}
\end{aligned}
$$

## Remark:

From the transition graph: the joint probability is just specifying the path we are taking.

## Discrete-time Markov chain

Computation of transition probability after $n$ transitions:
$n$-transition probability
$p_{i j}^{(n)}=\mathbb{P}\left(X_{n}=j \mid X_{0}=i\right)=\mathbb{P}\left(X_{m+n}=j \mid X_{m}=i\right)$ is the probability that the state after $n$ transitions is $j$ if the original state is $i$. As a special case, $p_{i j}^{(1)}=p_{i j}$.

## Discrete-time Markov chain

## Computation of transition probability after $n$ transitions:

## $n$-transition probability

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$$
\begin{aligned}
p_{i j}^{(2)}=\mathbf{P}\left(X_{2}=j \mid X_{0}=i\right) & =\sum_{k \in S} \mathbf{P}\left(X_{2}=j, X_{1}=k \mid X_{0}=i\right) \\
& =\sum_{k \in S} \mathbf{P}\left(X_{2}=j \mid X_{1}=k, X_{0}=i\right) \cdot \mathbf{P}\left(X_{1}=k \mid X_{0}=i\right) \\
& =\sum_{k \in S} \mathbf{P}\left(X_{2}=j \mid X_{1}=k\right) \cdot \mathbf{P}\left(X_{1}=k \mid X_{0}=i\right) \\
& =\sum_{k \in S} p_{i k} p_{k j}=\left(P^{2}\right)[i, j]
\end{aligned}
$$

## Discrete-time Markov chain

## Remark:

In general, we have

$$
p_{i j}^{(n)}=\left(P^{n}\right)[i, j]
$$

## Chapman-Kolmogorov equation / inequality

- $p_{i j}^{(m+n)}=\sum_{k \in \mathcal{S}} p_{i k}^{(m)} p_{k j}^{(n)}$ and $p_{i j}^{(m+s+n)}=\sum_{k \in \mathcal{S}} \sum_{l \in \mathcal{S}} p_{i k}^{(m)} p_{k l}^{(s)} p_{s j}^{(n)}$;
- $p_{i j}^{(m+n)} \geq p_{i k}^{(m)} p_{k j}^{(n)}$ and $p_{i j}^{(m+s+n)} \geq p_{i k}^{(m)} p_{k l}^{(s)} p_{s j}^{(n)}$ for any fixed state $k, l \in \mathcal{S}$.


## Proof:

## Discrete-time Markov chain

## Example:

Consider a Markov chain with $\mathcal{S}=1,2,3$, and $\nu=\left(\frac{1}{3}, \frac{2}{3}, 0\right)$, and

$$
P=\left[\begin{array}{lll}
p_{11} & p_{12} & p_{13} \\
p_{21} & p_{22} & p_{23} \\
p_{31} & p_{32} & p_{33}
\end{array}\right]
$$

- Compute $\mathbb{P}\left(X_{0}=2\right)$;
- Compute $\mathbb{P}\left(X_{0}=1, X_{1}=1, X_{2}=2\right)$;
- Compute $p_{12}^{(3)}$.


## Continuous-time Markov chain

Generalize the time index to be continuous:

## Continuous-time Markov chain

A Continuous-time Markov chain $\{X(t)\}_{t \geq 0}$ is specified by three ingredients:

- A state space $\mathcal{S}$, any non-empty finite or countable set.
- Initial probabilities $\left\{\nu_{i}\right\}_{i \in \mathcal{S}}$ where $\nu_{i}$ is the probability of starting at $t=0$.
- Markov property: $\forall i, j \in \mathcal{S}, s, t \geq 0$,

$$
\mathbb{P}(X(t+s)=j \mid X(s)=i, X(u)=x(u), 0 \leq u \leq s)=\mathbb{P}(X(t+s)=j \mid X(s)=i) .
$$

## Remark:

The process is called time-homogeneous when this probability does not depend on $s$. Throughout the module, we will assume this time-homogeneity as a default.

## Continuous-time Markov chain

## Remark:

For time-homogeneous CTMC, we can define transition probability

$$
p_{i j}^{(t)}=\mathbb{P}(X(s+t)=j \mid X(s)=i)=\mathbb{P}(X(t)=j \mid X(0)=i) .
$$

## Continuous-time Markov chain

## Remark:

For time-homogeneous CTMC, we can define transition probability

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p_{i j}^{(t)}=\mathbb{P}(X(s+t)=j \mid X(s)=i)=\mathbb{P}(X(t)=j \mid X(0)=i) .
$$

## Representation of CTMC:

- Transition graph after time $t$;
- Transition probability matrix:

$$
P^{(t)}=\left[\begin{array}{ccc}
p_{11}^{(t)} & p_{12}^{(t)} & \cdots \\
p_{21}^{(t)} & p_{22}^{(t)} & \cdots \\
\vdots & \vdots & \ddots
\end{array}\right]
$$

## Continuous-time Markov chain

## Properties:

- $p_{i j}^{(t)} \geq 0, \quad i, j \in \mathcal{S}$
- $\sum_{j \in \mathcal{S}} p_{i j}^{(t)}=1, \quad i \in \mathcal{S}$
- $\mathbb{P}\left(X(0)=i_{0}, X\left(t_{1}\right)=i_{1}, \ldots, X\left(t_{n}\right)=i_{n}\right)=v_{i_{0}} p_{i_{0} i_{1}}^{\left(t_{1}\right)} \ldots p_{i_{n-1} i_{n}}^{\left(t_{n}-t_{n-1}\right)}$, for $0<t_{1}<\cdots<t_{n}$.


## Continuous-time Markov chain

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- $\mathbb{P}\left(X(0)=i_{0}, X\left(t_{1}\right)=i_{1}, \ldots, X\left(t_{n}\right)=i_{n}\right)=v_{i_{0}} p_{i_{0} i_{1}}^{\left(t_{1}\right)} \ldots p_{i_{n-1} i_{n}}^{\left(t_{n}-t_{n-1}\right)}$, for $0<t_{1}<\cdots<t_{n}$.


## Chapman-Kolmogorov Equation

For a Continuous-time Markov chain $\left\{X_{t}\right\}_{t \geq 0}$ with transition probability matrix $P^{(t)}$,

$$
P^{(s+t)}=P^{(s)} P^{(s)}
$$

## Proof:

## Continuous-time Markov chain

## Generator and generator matrix

Given a Markov process, its generator is

$$
g_{i j}=\lim _{t \rightarrow 0} \frac{p_{i j}^{(t)}-\delta_{i j}}{t}
$$

where $\delta_{i j}=p_{i j}^{(0)}=1$ if $i=j$, and 0 otherwise. The generator matrix is defined by

$$
G=\lim _{t \rightarrow 0} \frac{P^{(t)}-I}{t}
$$

## Properties:

- For $t$ small. $P^{(t)} \approx I+t G$;
- Row sums of $G$ is 0 .


## Continuous-time Markov chain

Continuous-time transition theorem
If a continuous-time markov chain has generator martix $G$, then for $t \geq 0$

$$
P^{(t)}=\exp (t G)=I+t G+\frac{t^{2} G^{2}}{2!}+\cdots
$$

Proof:

## Continuous-time Markov chain

## Remark:

Suppose the eigendecomposition of $G$ is $G=U D U^{-1}$, where $D$ is a diagonal matrix with diagonal entries $\left\{d_{1}, d_{2}, \cdots\right\}$, then

$$
P^{(t)}=U \exp (t D) U^{-1}
$$

## Continuous-time Markov chain

## Remark:

Suppose the eigendecomposition of $G$ is $G=U D U^{-1}$, where $D$ is a diagonal matrix with diagonal entries $\left\{d_{1}, d_{2}, \cdots\right\}$, then

$$
P^{(t)}=U \exp (t D) U^{-1}
$$

## Example:

Let

$$
P^{(t)}=\left[\begin{array}{cc}
1-3 t & 3 t \\
5 t & 1-5 t
\end{array}\right] .
$$

- Find G;
- Find the exact form of $P^{(t)}$.


## Problem Set

Problem 1: (Bernoulli Process) Let $0<p<1$, repeatedly flp a coin with head probability $p$. Let $X_{n}$ be the number of heads on the first $n$ flips.

- Verify that $\left\{X_{n}\right\}$ is a Markov chain, specify the state space, initial probability and transition probability;
- Draw a sketch of the transition graph;
- For $p=\frac{1}{4}$, compute $\mathbb{P}\left(X_{0}=0, X_{1}=1, X_{2}=1, X_{3}=2\right)$.

Problem 2: Suppose a fair six-sided die is repeatedly rolled at times $0,1, \cdots$ Let $X_{0}=0$, and for $n \geq 1$ let $X_{n}$ be the largest value that appears among all of the rolls up to time $n$.

- Verify that $\left\{X_{n}\right\}$ is a Markov chain, specify the state space, initial probability and transition probability;
- Compute two-step transitions $\left\{p_{35}^{(2)}\right\}$.


## Problem Set

Problem 3: Let $\{X(t)\}_{t \geq 0}$ be a continuous-time Markov chain on the state space $\mathcal{S}=\{1,2,3\}$, suppose that as $t \rightarrow 0$, the transition probabilities are given by

$$
P^{(t)}=\left(\begin{array}{ccc}
1-7 t & 7 t & 0 \\
0 & 1-3 t & 3 t \\
t & 2 t & 1-3 t
\end{array}\right)+o(t)
$$

Compute the generator matrix $G$.

