UNIVERSITY OF
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## Statistical Sciences

# DoSS Summer Bootcamp Probability Module 10 

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## Recap

Learnt in last module:

- Markov Chain
$\triangleright$ 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


## Outline

- Poisson process
$\triangleright$ Poisson-Gamma relationship
$\triangleright$ Properties of Poisson Process
- Brownian motion
$\triangleright$ Properties of Brownian motion
$\triangleright$ Brownian motion with drift
$\triangleright$ Geometric Brownian motion


## Poisson process

Poisson process: an example of CTMC

## Poisson process

A Poisson process $\{N(t)\}_{t \geq 0}$ with intensity $\lambda>0$ is a collection of non-decreasing integer-valued random variables satisfying the properties that

- $N(0)=0$;

- Independent increments: $N(t)$ is independent of $N(t+s)-N(t)$;
- $N(t+s)-N(s) \sim \operatorname{Poisson}(\lambda t), \quad t \geq 0, s \geq 0$.


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Remark:

$$
s=0
$$

- Easy to verify the Markov property of Poisson process;
- $N(t) \sim \operatorname{Poisson}(\lambda t)$.


## Poisson process

## Examples:

- The number of customers arriving at a grocery store with intensity $\lambda=5$ customers per hour; $N(2) \sim \operatorname{Poisson}(10)$.
- The number of students coming to the TA session with intensity $\lambda=3$ students per hour;
- The number of births in Canada with intensity $\lambda=40$ per hour.


## Poisson process

## Examples:

- The number of customers arriving at a grocery store with intensity $\lambda=5$ customers per hour;
- The number of students coming to the TA session with intensity $\lambda=3$ students per hour;
- The number of births in Canada with intensity $\lambda=40$ per hour.

The probability that more than 60 babies are born between 9 to 11 AM in Canada:

$$
\begin{array}{cc}
N(t+2)-N(t) & N(2)-N(0) \\
\mathbb{P}(N(t+2)-N(t)>60) & \underset{\substack{N \\
t=9}}{\mathbb{P}(N(2)>60)}=1-\sum_{k=0}^{60} \frac{e^{-40 \cdot 2}(40 \cdot 2)^{k}}{k!} \\
\text { Poisson }(40 \times 2)
\end{array}
$$

Poisson process
$N(t+s)-N(t) \sim p_{0 i s s o n}(\lambda s) \geqslant 0$
Think about the waiting time for the event:


$$
N(t)=i
$$

$$
t:=N^{-1}(c)
$$

Inter-arrival time for Poisson process
Consider a Poisson process $\{N(t)\}_{t \geq 0}$ with intensity $\lambda$, and let $T_{1}$ be the time for the first event. Sequentially, let $T_{n}$ denote the time between the $(n-1)$-th and the $n$-th event. Then $\left\{T_{n}\right\}_{n \geq 1}$ are i.i.d. exponential random variables with parameter $\lambda$, egg.

$$
\mathbb{P}\left(T_{n} \leq t\right)=1-e^{-\lambda t}
$$



Proof:

$$
P\left(T_{1} \leq t\right)=P(N(t) \geqslant 1)
$$

$$
P\left(T_{1}>t\right)=P(N(t)=0)=\frac{(\lambda t)^{0}}{0!} e^{-\lambda t}=e^{-\lambda t}, t \geqslant 0 .
$$

$$
\begin{aligned}
P\left(T_{2}>t \mid \underline{T_{1}=s}\right) & =P(\underbrace{N(t+s)-N(s)=0} 1 \sim(s)=1) \\
& =P(\underbrace{N(t+s)-N(s)=0}) \\
& =P(\underbrace{N(t)=0)}=e^{-\lambda t} .
\end{aligned}
$$

Poisson process
Arrival time for Poisson process:


Poisson-Gamma relationship
Consider a Poisson process $\{N(t)\}_{t \geq 0}$ with intensity $\lambda$, then the total time until $n$ events is $\sum_{i=1}^{n} T_{i} \sim \Gamma(n, \lambda)$.

Proof:

$$
\begin{aligned}
& T_{i} . i r d \sim \operatorname{Exp}(\lambda) \\
& \longleftrightarrow \tau(1, \lambda) \\
& \sum_{i=1}^{n} \tau_{i} \sim \tau(n, \lambda)
\end{aligned}
$$



Poisson process
$N(s) \left\lvert\, N(t)=n \sim B\left(n, p=\frac{s}{t}\right)\right.$ for $s<t$
Consider a Poisson process $\{N(t)\}_{t \geq 0}$ with intensity $\lambda$, then for $s<t, N(s) N(t)-N(s)$

$$
\uparrow_{N(s)} \left\lvert\, \underline{N(t)}=n \sim B\left(n, p=\frac{s}{t}\right) .\right.
$$



Proof: $\quad P(N(s)=K / N(t)=n) \quad \longrightarrow \quad \rho m f$ at $k$.

$$
=\frac{P(N(s)=k, N(t)=n)}{P(N(t)=n)}=\frac{P(N(s)=k, N(t)-N(s)=n-k)}{P(N(t)=n)}
$$

$$
=\frac{P(N(s)=k) P(N(t)-N(s)=n-k)}{P(N(t)=n)}=\frac{\left.\frac{(\lambda s)^{k}}{k!} e^{-\lambda s} \frac{(\lambda(t-s))^{n-k}}{(n-k)!} e^{-\lambda(t-)}\right)}{\frac{(\lambda t)^{n}}{n!} e^{-\lambda t}}
$$

## Poisson process

## Superposition

If $\left\{N_{1}(t)\right\}_{t \geq 0}$ and $\left\{N_{2}(t)\right\}_{t \geq 0}$ are independent Poisson processes with intensities $\lambda_{1}$ and $\lambda_{2}$, respectively, then $\left\{N(t):=N_{1}(t)+N_{2}(t)\right\}_{t \geq 0}$ is also a Poisson process with intensity $\lambda_{1}+\lambda_{2}$.

$$
\begin{aligned}
\text { Proof: } \quad N(0)=0 \quad & \\
& =(N(t+s)-N(t)
\end{aligned}
$$

- $N(t) \sim$ Poisson $(\lambda t) \quad \lambda=\lambda 1+\lambda_{2}$.

$$
\text { By } M G F \text {. }
$$

## Poisson process

## Thinning

Let $\{N(t)\}_{t \geq 0}$ be a Poisson process with intensity $\lambda$. Suppose each event is independently of type $i$ with probability $p_{i}$ for $i=1, \cdots, k$ with $\sum_{i=1}^{k} p_{i}=1$. If $N_{i}(t)$ is the number of events of type $i$ happen up to time $t$, then $\left\{N_{i}(t)\right\}$ is a Poisson process with rate $\lambda p_{i}$.

## Poisson process

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## Properties of Poisson process:

Let $\{N(t)\}_{t \geq 0}$ be a Poisson process with intensity $\lambda$, then

- $T_{1} \mid N(s)=1 \sim U[0, s]$;
- $N(s) \left\lvert\, N(t)=n \sim B\left(n, p=\frac{s}{t}\right)\right.$ for $s<t$;
- Superposition:
- Thinning.


## Brownian motion

Brownian motion: an example of process with continuous time and continuous state

## Brownian motion

Standard Brownian motion is a continuous-time process $\{B(t)\}_{t \geq 0}$ satisfying that

- $B(0)=0$;

$$
E q, r \geq[s, t]
$$

- Independent increments: for $0 \leq q<r \leq s<t, B(t)-B(s)$ and $B(r)-B(q)$ are independent random variables;
- $B(t+s)-B(s) \sim \mathcal{N}(0, t), s \geq 0, t>0$;
- $B(t)$ is almost surely continuous.



## Remark:

Easy to verify the Markov property.

## Brownian motion

Useful properties of Brownian motion:
Joint distribution regarding Brownian motion
For $0<t_{1}<\cdots<t_{n},\left(B\left(t_{1}\right), B\left(t_{2}\right), \cdots, B\left(t_{n}\right)\right)^{\top}$ follows a multivariate normal distribution.


$$
\begin{aligned}
& \sum_{i=1}^{n} c_{i} B\left(t_{i}\right)=b_{1} B\left(t_{1}\right)+\underbrace{\sum_{i=1}^{-1} b_{i+1}[\underbrace{B\left(t_{i+1}\right)}_{0}-B\left(t_{i}\right)}_{i=1}] \\
& b_{1}=c_{1}+c_{2} \cdots t_{3} \\
& b_{i+1}=\sum_{i+1}^{n} c_{i} .
\end{aligned}
$$

Brownian motion

$$
\operatorname{Cov}(B(s), B(t))=\min (t, s)
$$

For a standard Brownian motion $\left\{B(t)_{t \geq 0}\right\}$, the covariance satisfies

$$
\operatorname{Cov}(B(s), B(t))=\min (t, s)
$$

$$
\text { Proof: } \begin{aligned}
& \operatorname{Cov}(B(s), B(t)) \\
& =E(B(s) B(t))-[\underbrace{E(B(s)}_{0}) E(\underbrace{B(t)}_{0})] \underbrace{B(s)-B(t)}_{0} \\
= & E((B(s)-B(t)+B(t)) B(t)) \\
& =E[(B(s)-B(t)) B(t)]+E\left[B^{2}(t)\right] \rightarrow \operatorname{Var}(B(t)) \\
& =E[B(s)-B(t)] \cdot E(B(t))+t \\
& =t .
\end{aligned}
$$

## Brownian motion

## $\operatorname{Cov}(B(s), B(t))=\min (t, s)$

For a standard Brownian motion $\left\{B(t)_{t \geq 0}\right\}$, the covariance satisfies

$$
\operatorname{Cov}(B(s), B(t))=\min (t, s) .
$$

## Proof:

## Remark:

Useful technique: rearrange into independent parts

## Brownian motion

Note when

$$
\binom{X}{Y} \sim \mathcal{M V \mathcal { N }}\left(\binom{\mu_{1}}{\mu_{2}},\left[\begin{array}{cc}
\sigma_{1}^{2} & \rho \sigma_{1} \sigma_{2} \\
\rho \sigma_{1} \sigma_{2} & \sigma_{2}^{2}
\end{array}\right]\right)
$$

the conditional distribution satisfies

$$
X \left\lvert\, Y=y \sim \mathcal{N}\left(\underline{\mu_{1}+\rho \frac{\sigma_{1}}{\sigma_{2}}\left(y-\mu_{2}\right)}, \underline{\left(1-\rho^{2}\right) \sigma_{1}^{2}}\right)\right.
$$

## Brownian motion

Note when

$$
\binom{X}{Y} \sim \mathcal{M} \mathcal{V} \mathcal{N}\left(\binom{\mu_{1}}{\mu_{2}},\left[\begin{array}{cc}
\sigma_{1}^{2} & \rho \sigma_{1} \sigma_{2} \\
\rho \sigma_{1} \sigma_{2} & \sigma_{2}^{2}
\end{array}\right]\right)
$$

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$$
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$$

Conditional distribution regarding Brownian motion
For $0<s<t$, we have

- $B(s) \left\lvert\, B(t)=a \sim \mathcal{N}\left(\frac{s}{t} a,\left(1-\frac{s}{t}\right) s\right)\right.$;
- $B(t) \mid B(s)=a \sim \mathcal{N}(a, t-s)$.

Brownian motion


Proof: $\left.\binom{B(s)}{B(t)} \sim N^{0}\left(\begin{array}{l}s \\ 0 \\ 0\end{array}\right),\left(\begin{array}{ll}s & s \\ s & t\end{array}\right)\right)$
$B(s) \left\lvert\, B(t)=a \sim N\left(\frac{s}{t} a,\left(1-\frac{s}{t}\right) s\right)\right.$.
$B(t) \mid B(s)=a \sim N(a, t-s)$.
$\{\underbrace{B(t)-B(s) \mid B(s)=a}_{B(s)=a}=B(t)-B(s) \sim N(0, t-s)$.

$$
\begin{aligned}
& B(s)=a \\
& B(t) \mid B(s)=a=\underbrace{B(s) \mid B(s)=a}+\underbrace{\sim(0, t-s)}
\end{aligned}
$$

## Brownian motion

## Brownian motion with drift

For $\mu \in \mathbb{R}$ and $\sigma>0$, the process defined by $\{D(t)=\mu t+\sigma B(t)\}$ is called the $\quad x=\sigma z+\mu$ Brownian motion with drift. $\mu$ is the drift parameter and $\sigma^{2}$ is the variance parameter.

## Remark:

- $D(0)=0$;
- $D(t) \sim \mathcal{N}\left(\mu t, \sigma^{2} t^{2}\right)$.


## Brownian motion

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For $\mu \in \mathbb{R}$ and $\sigma>0$, the process defined by $\{D(t)=\mu t+\sigma B(t)\}$ is called the Brownian motion with drift. $\mu$ is the drift parameter and $\sigma^{2}$ is the variance parameter.

## Remark:

- $D(0)=0$;
- $D(t) \sim \mathcal{N}\left(\mu t, \sigma^{2} t^{2}\right)$.


## Example:

Find the probability that Brownian motion with drift takes value between $\underline{1 \text { and } 2}$ at time $t=4$, when $\mu=0.6, \sigma^{2}=0.25$.

$$
\begin{aligned}
& P(\quad 1 \leq D(4) \leq 2) \\
= & P(1 \leq 2.4+0.5 B(4) \leq 2) \\
= & P(-1.4 \leq 0.5 B(4) \leq-0.4) .
\end{aligned}
$$

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$$
\Phi(-0.4)-\Phi(-1.4)
$$



## Brownian motion

## Geometric Brownian Motion

Let $\{D(t)=\mu t+\sigma B(t)\}$ be a Brownian motion with drift, the process
$\left\{G(t)=G(0) e^{D(t)}\right\}_{t \geq 0}$ is called Geometric Brownian motion, provided that $G(0)>0$.

Remark:
$\mathbb{E}(G(t))=G(0) e^{t\left(\mu+\frac{\sigma^{2}}{2}\right)}$.

## Problem Set

Problem 1: The Poisson process with intensity $\lambda$ is an example of CTMC.

- Find $P^{(t)}$;
- Compute the generator matrix $G$.

Problem 2: If $\{N(t)\}_{t \geq 0}$ is a Poisson process with $\lambda=3$, compute the probability $\mathbb{P}(N(2)=4, N(4)=8)$.

Problem 3: Suppose that undergraduate students and graduate students arrive for office hours according to a Poisson process with rate $\lambda_{1}=5$ and $\lambda_{2}=3$ respectively. What is the expected time until the first student arrives?

## Problem Set

Problem 4: Let $\{B(t)\}_{t \geq 0}$ be a standard Brownian motion. Show that the followings are Brownian motions.

- $\{Y(t)=B(t+\alpha)-B(\alpha)\}_{t \geq 0}$ for all $\alpha \geq 0$;
- $\left\{Y(t)=\alpha B\left(t / \alpha^{2}\right)\right\}_{t \geq 0}$ for all $\alpha \geq 0$.

