# Probability and Stochastic Processes II - Lecture 6e 

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## VI. 6 Continuous State Space Markov Chains

- here $T=\mathbb{N}_{0}$ and $\mathcal{S}$ with $\sigma$-algebra $\mathcal{C}$ (could be $\mathcal{S}=\mathbb{R}^{k}, \mathcal{C}=\mathcal{B}^{k}$ )

Definition VI. 11 A Markov kernel $P: \mathcal{S} \times \mathcal{C} \rightarrow[0,1]$ for a time homogeneous, Markov process with state space $\mathcal{S}$ and initial probability measure $v$ on $(\mathcal{S}, \mathcal{C})$ satisfies (i) $P(s, \cdot)$ is a probability measure on $\mathcal{C}$ for every $s \in \mathcal{S}$ and (ii) $P(\cdot, C):(\mathcal{S}, \mathcal{C}) \rightarrow\left(\mathbb{R}^{1}, \mathcal{B}^{1}\right)$ for every $C \in \mathcal{C}$.

- so $P(\cdot, C)$ is a random variable and $P(s, C)$ is interpreted as the conditional probability that the next state is in $C$ given that the current state is $s$
- note when $\mathcal{S} \subset \mathbb{Z}$, then $P(\cdot, C)$ is given by $P(i,\{j\})=p_{i j}$
- so the time homogeneous Markov process with state space $\mathcal{S}$ and Markov kernel $P$ is given by $\left\{X_{n}: n \in \mathbb{N}_{0}\right\}$ where $X_{0} \sim v$ and $X_{n} \mid X_{0}, \ldots, X_{n-1} \sim P\left(X_{n-1}, \cdot\right)$
- such Markov processes arise in many statistical problems where there is a (posterior) distribution on a continuous space we want to sample from but can only find a Markov chain Monte Carlo algorithm to do this approximately


## Example VI. 11

- $\left\{X_{n}: n \in \mathbb{N}_{0}\right\}$ is given by $X_{0}=0(v$ is degenerate a 0$)$ and $P(x, \cdot)=N(x / 2,1)$ so $X_{1} \sim N(0,1)$ and

$$
\begin{aligned}
P\left(X_{2} \leq x_{2}\right) & =\int_{-\infty}^{\infty} P\left(X_{2} \leq x_{2} \mid X_{1}\right)\left(x_{1}\right) P_{X_{1}}\left(d x_{1}\right) \\
& =\int_{-\infty}^{\infty} \Phi\left(\frac{x_{2}-x_{1} / 2}{1}\right) \varphi\left(x_{1}\right) d x_{1}
\end{aligned}
$$

but with $Z \sim N(0,1)$ independent of $X_{1}$, then
$X_{2}=Z+X_{1} / 2 \sim N(0,1+1 / 4)=N(0,5 / 4), X_{3}=Z+X_{2} / 2 \sim$
$N(0,1+5 / 16)=N(0,21 / 16)$, etc.

- note - as long as it is easy to generate from $v$ and $P(s, \cdot)$ for each $s$, then it is easy to simulate the process
- we need a generalization of the concept of irreducibility because in the continuous case $P(s,\{x\})=0$ for all $s, x$
- note

$$
\begin{aligned}
P^{(2)}(s, C) & =P\left(X_{2} \in C \mid X_{0}=s\right) \\
& =\int_{\mathcal{S}} P\left(X_{2} \in C \mid X_{0}=s, X_{1}=s^{\prime}\right) P\left(s, d s^{\prime}\right) \\
& =\int_{\mathcal{S}} P\left(X_{2} \in C \mid X_{1}=s^{\prime}\right) P\left(s, d s^{\prime}\right) \text { by MP } \\
& =\int_{\mathcal{S}} P\left(s^{\prime}, C\right) P\left(s, d s^{\prime}\right) \text { by TH }
\end{aligned}
$$

and $P^{(n)}$ is obtained similarly
Definition VI. 12 A MC with state space $\mathcal{S}$ is called $\phi$-irreducible, where $\phi$ is a measure on $\mathcal{C}$, if for all $s \in \mathcal{S}$, whenever $\phi(C)>0$ then $P^{(n)}(s, C)>0$ for some $n$.

- typically $\phi=$ volume measure and in the discrete case if $\phi=$ counting measure this is the same definition in that case

Proposition VI. 35 If there is $\delta>0$ s.t. $P(s, \cdot)$ has a positive density on $[s-\delta, s+\delta]$ for every $s \in \mathcal{S}=\mathbb{R}^{1}$, then the MC with this kernel is $\phi$-irreducible where $\phi$ is volume measure.

Proof: Suppose $C \in \mathcal{B}^{1}$ and $\phi(C)>0$. Then $\exists m \in \mathbb{N}$ s.t. $\phi(C \cap[-m, m])>0$. Choose $n$ s.t. $s-n \delta<-m<m<s+n \delta$. Then since $P(s, \cdot)$ has positive density on $[s-\delta, s+\delta]$ this implies $P^{(n)}(s, \cdot)$ has positive density on $[s-n \delta, s+n \delta]>0$ (see * below). But $C \cap[-m, m] \subset[s-n \delta, s+n \delta]$ so

$$
P^{(n)}(s, C) \geq P^{(n)}(s, C \cap[-m, m])>0
$$

* if $P(s, \cdot)$ has positive density on $[s-\delta, s+\delta]$, then so does $P^{(2)}(s, \cdot)$ on $[s-2 \delta, s+2 \delta]$ since

$$
\begin{aligned}
& P^{(2)}(s,[s-2 \delta, s+2 \delta]) \\
= & \int_{-\infty}^{\infty} P(x,[s-2 \delta, s+2 \delta]) P(s, d x) \\
= & \int_{-\infty}^{\infty}\left(\int_{s-2 \delta}^{s+2 \delta} f(z \mid x) d z\right) P(s, d x) \\
\geq & \int_{s-\delta}^{s+\delta}\left(\int_{s-2 \delta}^{s+2 \delta} f(z \mid x) d z\right) f(x \mid s) d x>0
\end{aligned}
$$

since $f(z \mid x)>0$ for all $z \in[x-\delta, x+\delta]$ and this implies $\int_{s-2 \delta}^{s+2 \delta} f(z \mid x) d z>0$ whenever $[x-\delta, x+\delta] \subset[s-2 \delta, s+2 \delta]$ and this holds whenever $x \in[s-\delta, s+\delta]$ and note $f(x \mid s)>0$ there

Definition VI. 13 A MC with state space $\mathcal{S}$ has period $b$ if $\mathcal{S}$ can be decomposed into mutually disjoint subsets $\mathcal{S}=\mathcal{S}_{0} \cup \cdots \cup \mathcal{S}_{b-1}$ s.t. $P\left(s, S_{i}\right)=1$ whenever $s \in S_{i-1}$ and $i=[(i-1)+1] \bmod b$. If $b=1$, then the MC is said to be aperiodic.

Proposition VI. 36 If there is $\delta>0$ s.t. $P(s, \cdot)$ has a positive density on $[s-\delta, s+\delta]$ for every $s \in \mathcal{S}=\mathbb{R}^{1}$, then a $\phi$-irreducible MC, where $\phi$ is volume measure, is aperiodic.

Proof: Suppose $b$ is the period and let $s \in \mathcal{S}_{i}$ where $\operatorname{vol}\left(\mathcal{S}_{i}\right)>0$. Also, let $m \in \mathbb{N}$ be s.t. $\operatorname{vol}\left(\mathcal{S}_{i} \cap[-m, m]\right)>0$. Choose $n_{0}$ s.t. $s-n_{0} \delta<-m<m<s+n_{0} \delta$. Then $P(s, \cdot)$ has positive density on $[s-\delta, s+\delta]$ which implies $P^{(n)}(s, \cdot)$ has positive density on $[s-n \delta, s+n \delta]>0$ for every $n \geq n_{0}$ and in particular for $n=n_{0}$ and $n=n_{0}+1$. But if $b \geq 2$ it is not possible that $b \mid n_{0}$ and $b \mid n_{0}+1$ and so $b=1$. $\square$

Definition VI. 14 A MC with state space $\mathcal{S}$ has stationary distribution $\pi$ if $\Pi(C)=\int_{\mathcal{S}} P(s, C) \Pi(d s)$ for all $C \in \mathcal{C}$.

- as in the discrete case this implies that when $v=\pi$ then $X_{n} \sim \pi$ for all $n$
- also if $P(s, C)$ has density, $f(x \mid s)$ then $\pi$ is stationary when

$$
\pi(x)=\int_{\mathcal{S}} f(x \mid s) \pi(s) d s
$$

- if the Markov kernel $P(s, \cdot)$ has density $f(x \mid s)$ then it is reversible wrt $\pi$ whenever $f(x \mid s) \pi(s)=f(s \mid x) \pi(x)$ and then

$$
\int_{\mathcal{S}} f(x \mid s) \pi(s) d s=\int_{\mathcal{S}} f(s \mid x) \pi(x) d s=\pi(x)
$$

and so $\pi$ is stationary

Proposition VI. 37 If a MC is $\phi$-irreducible, aperiodic and has stationary distribution $\Pi$, then

$$
\lim _{n \rightarrow \infty} P\left(X_{n} \in C \mid X_{0}=s\right)=\Pi(C)
$$

for all $s \in \mathcal{S}$ excepting possibly a set having $\Pi$ measure 0 .
Proof: fact
Example VI. 11 (continued)

- recall $f(x \mid s)$ is the $N(s / 2,1)$ density so $f(s \mid x)$ is the $N(x / 2,1)$ density
- so for reversibility we want

$$
\begin{aligned}
\exp \left(-(x-s / 2)^{2} / 2\right) \pi(s) & =\exp \left(-(x / 2-s)^{2} / 2\right) \pi(x) \text { or } \\
\frac{\pi(s)}{\pi(x)} & =\exp \left(-\frac{(x / 2-s)^{2}}{2}+\frac{(x-s / 2)^{2}}{2}\right) \\
& =\exp \left(\frac{3}{8}\left(x^{2}-s^{2}\right)\right)
\end{aligned}
$$

which is satisfied by $\pi=N(0,4 / 3)$

- also the chain satisfies Propositions VI. 35 and VI. 36 (normal densities are noitive evervahere) so Pron V/I 37 annliec


## Example VI. 12 Markov Chain Monte Carlo

- suppose we want to sample from a distribution $\pi$ and we can't find a good (e.g., rejection or inversion) algorithm to do this directly
- we try to create a MC, that can simulated from, s.t. $\pi$ is its unique stationary distribution so that $X_{n}$ is approximately distributed $\pi$ for large $n$
- let $q(s, \cdot)$ be a proposal density for each $s \in \mathcal{S}$ and suppose $q$ is symmetric, i.e., $q(s, x)=q(x, s)$
- define $P(s, \cdot)$ by

$$
\begin{aligned}
P(s, C \backslash\{s\}) & =\int_{C \backslash\{s\}} q(s, x) \min \left(1, \frac{\pi(x)}{\pi(s)}\right) d x \\
P(s,\{s\}) & =1-\int_{\mathcal{S}} q(s, x) \min \left(1, \frac{\pi(x)}{\pi(s)}\right) d x
\end{aligned}
$$

and note

$$
\int_{\mathcal{S}} q(s, x) \min \left(1, \frac{\pi(x)}{\pi(s)}\right) d x \leq \int_{\mathcal{S}} q(s, x) d x=1
$$

so $P(s,$.$) is a probability measure$

- the chain may stay at state $s$ with possibly positive probability
- this is known as the Metropolis algorithm

1. given $X_{n-1}=s$ generate $Y_{n} \sim q(s, \cdot)$ stat. ind. of $U_{n} \sim U(0,1)$
2. put

$$
X_{n}= \begin{cases}Y_{n} & \text { if } U_{n} \leq \pi\left(Y_{n}\right) / \pi\left(X_{n-1}\right) \\ X_{n-1} & \text { otherwise }\end{cases}
$$

- to see that this works

$$
\begin{aligned}
& P\left(X_{n} \in C \backslash\{s\} \mid X_{n-1}=s\right) \\
= & P\left(Y_{n} \in C \backslash\{s\}, U_{n} \leq \pi\left(Y_{n}\right) / \pi(s) \mid X_{n-1}=s\right) \\
= & \int_{C \backslash\{s\}} \int_{0}^{\min (1, \pi(x) / \pi(s))} q(s, x) d u d x \\
= & \int_{C \backslash\{s\}} q(s, x) \min (1, \pi(x) / \pi(s)) d u d x
\end{aligned}
$$

Proposition VI. 38 (Continuous MCMC Convergence) If $\pi(s)>0$ for every $s \in \mathcal{S}$ and there is $\delta>0$ s.t. $q(s, x)>0$ whenever $|x-s|<\delta$, then $X_{n} \xrightarrow{d} \pi$.

Proof: We have, for $s \neq x$

$$
\begin{aligned}
& \pi(s) q(s, x) \min (1, \pi(x) / \pi(s)) \\
= & \left\{\begin{array}{cl}
\pi(s) q(s, x) & \text { if } \pi(x) / \pi(s)>1 \\
\pi(x) q(s, x) & \text { if } \pi(x) / \pi(s) \leq 1
\end{array}\right. \\
= & \pi(x) q(x, s) \min (1, \pi(s) / \pi(x))
\end{aligned}
$$

and so the chain is reversible and $\pi$ is a stationary distribution for the chain. Also, $\pi(s) q(s, x) \min (1, \pi(x) / \pi(s))>0$ whenever $|x-s|<\delta$ and so $P(s, \cdot)$ has positive density when $|x-s|<\delta$ and so the chain is $\phi$-irreducible ( $\phi=$ volume) and aperiodic. The result then follows from Prop. VI. 37.

## Exercise VI.18 Text 4.7.11 <br> Exercise VI.19 Text 4.8.3

