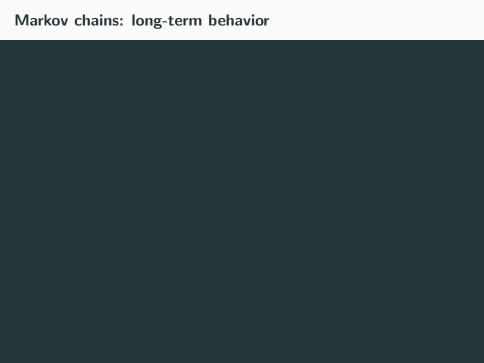
ORIE 4580/5580: Simulation Modeling and Analysis

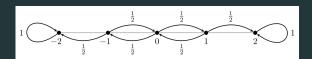
ORIE 5581: Monte Carlo Simulation

Unit 15: Markov chain Monte Carlo

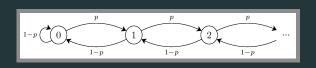
Sid Banerjee School of ORIE, Cornell University



Markov chains: absorbing chain

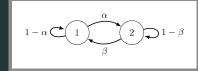


Markov chains: transient/recurrent chain

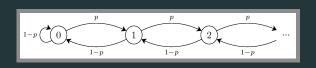


Markov chains: steady-state behavior

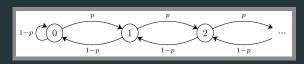
example:



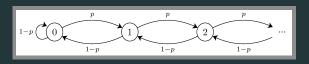
Markov chains: steady-state for infinite chains



Markov chains: reversibility



Markov chains: the ergodic theorem





the Metropolis algorithm

- target distribution P(x) = P(x)/Z
- proposal distribution(s) Q(x|y), with $Q(x|y) = Q(y|x) \forall x, y$

Metropolis sampling

- 1. choose initial Z_0
- 2. to obtain sample t, generate $Y_t \sim Q(\cdot|Z_{t-1})$
- 3. accept $Z_t = Y_y$ with probability $A(Y_t, Z_{t-1}) = \max \left\{ 1, \frac{\tilde{P}(Y_t)}{\tilde{P}(Z_{t-1})} \right\}$ else reject and set $Z_t = Z_{t-1}$

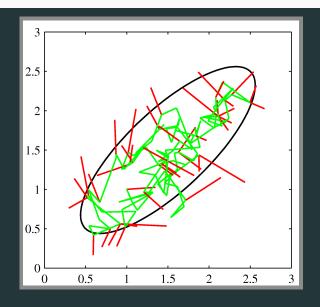
Metropolis-Hastings:example

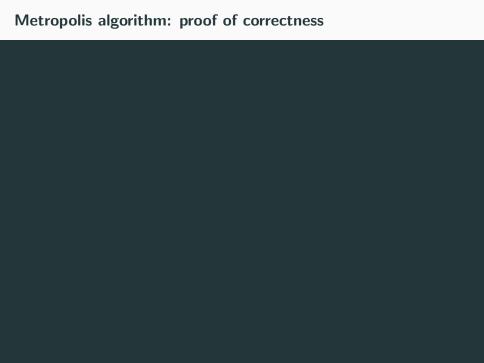
generate r.v. $X \in \{1, 2, \dots, n\}$ s.t. $\mathbb{P}[X = i] = 1/n$ for each $i \in [n]$

Metropolis-Hastings:example

generate r.v. $X \in \{1,2,\ldots,n\}$ s.t. $\mathbb{P}[X=i]=p_i$ for each $i \in [n]$

Metropolis for 2-d Gaussian





Metropolis-Hastings

- target distribution $P(x) = \widetilde{P}(x)/Z$
- proposal distribution(s) Q(x|y)

Metropolis-Hastings sampling

- 1. choose initial Z_0
- 2. to obtain sample t, generate $Y_t \sim Q(\cdot|Z_{t-1})$
- 3. accept $Z_t = Y_y$ with prob $A(Y_t, Z_{t-1}) = \max\left\{1, \frac{\tilde{P}(Y_t)Q(Z_{t-1}|Z_t)}{\tilde{P}(Z_{t-1})Q(Z_t|Z_{t-1})}\right\}$ else reject and set $Z_t = Z_{t-1}$

Gibbs sampling

- target distribution $P(x(1), x(2), \dots, x(n))$

Gibbs sampling

- 1. choose initial $X_0 = (X_0(1), X_0(2), \dots, X_0(n))$
- 2. to obtain sample t:

pick I_t uniformly at random

set
$$X_t(i) = X_{t-1}(i)$$
 for $i \neq I_t$

set
$$X_t(I_t) \sim P(\cdot|X_{t-1} \setminus X_{t-1}(I_t))$$

Gibbs sampling for 2-d Gaussian

