Monte Carlo Markov Chain methods

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Markov Chains

- Defined by transition probability $T_m(Z^m, Z^{m+1})$
- For time homogeneous chains T_m is same for all m.

Markov Chains (cont)

Stationary Distribution

A distribution p is stationary with respect to Markov chain defined by transition probability T if

$$p(z) = \sum_{z'} T(z', z)p(z')$$

Detailed Balance

Theorem

Given p, if we choose T such that detailed balance equation is satisfied then p will be stationary distribution for this T.

$$p(z)T(z,z') = p(z')T(z',z)$$

Proof.

$$\begin{aligned}\sum_{z'} p(z')T(z',z) &= \sum_{z'} p(z)T(z,z') && \text{by hypothesis} \\ &= p(z)\sum_{z'} T(z,z') \\ &= p(z)\end{aligned}$$

$\square$

Metropolis-Hastings Algorithm

- Generalizes Metropolis algorithm
- No need for proposal distribution to be symmetric
- Acceptance probability for proposal of z^* from z^τ

$$A(z^*|z^\tau) = \min\left(1, \frac{\tilde{p}(z^*)q(z^\tau|z^*)}{\tilde{p}(z^\tau)q(z^*|z^\tau)}\right)$$

  Where $\tilde{p}(z)$ is the unnormalized density at z and $q(z|z')$ is a proposal distribution at z'.
- Note that for symmetric q, this boils down to Metropolis algorithm
- Transition probability is given by

$$T(z^\tau, z^*) = q(z^*|z^\tau)A(z^*|z^\tau)$$

We will prove that our target distribution p (i.e. normalized version of $\tilde{p}$) is stationary distribution with respect to transition probability defined in last slide by proving that it satisfies detailed balance condition. (detailed balance $\implies$ stationary distribution)

Proof.

$$\begin{aligned}
p(z)T(z,z') &= p(z)q(z'|z)A(z'|z) \\
&= p(z)q(z'|z)\min\left(1, \frac{\tilde{p}(z')q(z|z')}{\tilde{p}(z)q(z'|z)}\right) \\
&= \min\left(p(z)q(z'|z), p(z)q(z'|z)\frac{\tilde{p}(z')q(z|z')}{\tilde{p}(z)q(z'|z)}\right) \\
&= \min\left(p(z)q(z'|z), p(z')q(z|z')\right) \\
&= \min\left(p(z')q(z|z'), p(z)q(z'|z)\right) \\
&= p(z')q(z|z')\min\left(1, \frac{p(z)q(z'|z)}{p(z')q(z|z')}\right) \\
&= p(z')q(z|z')\min\left(1, \frac{\tilde{p}(z)q(z'|z)}{\tilde{p}(z')q(z|z')}\right) \\
&= p(z')q(z|z')A(z|z') \\
&= p(z')T(z',z)
\end{aligned}$$

□

Gibbs Sampling

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Algorithm

- initialize $z_i \quad \forall i \in [1, 2, \dots, m]$
- for next step $\tau + 1$
  - $z_1^{\tau+1} \sim p(z_1|z_2^\tau, z_3^\tau, \dots, z_m^\tau)$
  - $z_2^{\tau+1} \sim p(z_2|z_1^{\tau+1}, z_3^\tau, \dots, z_m^\tau)$

    $\vdots$
  - $z_m^{\tau+1} \sim p(z_m|z_1^{\tau+1}, z_2^{\tau+1}, \dots, z_{m-1}^{\tau+1})$

First we will prove that this transitions leads to stationary distribution.

Proof.

$$\begin{aligned}
&\sum_{z'} p(z')T(z',z) \\
=&\sum_{z'_i}\sum_{z'_{-i}} T(z',z)p(z'_i|z'_{-i})p(z'_{-i}) \\
=&\sum_{z'_i} T(z',z)p(z'_i|z'_{-i})p(z'_{-i}) && \text{where } z'_{-i} = z_{-i} \\
=&p(z_{-i})\sum_{z'_i} p(z_i|z_{-i})p(z'_i|z_{-i}) \\
=&p(z_{-i})p(z_i|z_{-i})\sum_{z'_i} p(z'_i|z_{-i}) \\
=&p(z)
\end{aligned}$$

$\square$

Gibbs sampling as a special case of Metropolis-Hastings

Gibbs sampling is a special case of Metropolis-Hastings in which proposal distribution is univariate conditional and no proposals are rejected. Thus is more efficient than simple MH algorithm.

Proof.

Suppose we are at about to do kth update in this iteration. Our proposal distribution is $q(z^*|z) = p(z_k^*|z_{-k})$. Let's calculate ratio of MH algorithm.

$$\begin{aligned}
&\frac{p(z^*)q(z|z^*)}{p(z)q(z^*|z)} \\
=&\frac{p(z_k^*|z^*_{-k})p(z^*_{-k})p(z_k|z^*_{-k})}{p(z_k|z_{-k})p(z_{-k})p(z_k^*|z_{-k})} \\
=&1 \qquad\qquad \text{as} \quad z^*_{-k} = z_{-k}
\end{aligned}$$