Markov Chains and MCMC

CompSci 590.04
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Announcement

- First assignment has been posted
  - Please work on it in groups of 2 or 3
  - Involves accessing Twitter for information
  - Only allowed a restricted number of API calls to Twitter a day
  - So do not delay the assignment till the last minute.

- Due date: Friday Sep 11, 11:59 pm

Recap: Monte Carlo Method

- If U is a universe of items, and G is a subset satisfying some property, we want to estimate |G|
  - Either intractable or inefficient to count exactly

For i = 1 to N

- Choose u ε U, uniformly at random
- Check whether u ε G ?
- Let $X_i = 1$ if u ε G, $X_i = 0$ otherwise

Return $\hat{C} = |U| \cdot \frac{\sum_i X_i}{N}$

Variance: $|U| \frac{\mu(1-\mu)}{\sqrt{N}}, where\ \mu = \frac{|G|}{|U|}$

Recap: Monte Carlo Method

When is this method an FPRAS?

- |U| is known and easy to uniformly sample from U.
- Easy to check whether sample is in G
- |U|/|G| is small … (polynomial in the size of the input)

Theorem:

$$\forall\, 0 < \varepsilon < 1.5, 0 < \delta < 1, if\ N > \frac{|U|}{|G|} \cdot \frac{3}{\varepsilon^2} \cdot \ln \frac{2}{\delta}$$

$$then, P\left[(1-\varepsilon)|G| \le \hat{C} \le (1+\varepsilon)|G|\right] \ge 1-\delta$$

Recap: Importance Sampling

- In certain case |G| << |U|, hence the number of samples is not small.

- Suppose q(x) is the density of interest, sample from a different approximate density p(x)

$$\int f(x)q(x)dx = \int f(x)\left(\frac{q(x)}{p(x)}\right)p(x)dx$$

$$= E_{p(x)}\left[f(x)\frac{q(x)}{p(x)}\right]$$

$$Hence, \int f(x)q(x)dx \approx \frac{1}{N}\sum_{i=0}^{N} f(X_i)\frac{q(X_i)}{p(X_i)},$$

$$where\ X_i\ are\ sampled\ from\ p(x)$$

Today's Class

- Markov Chains
- Markov Chain Monte Carlo sampling
  - a.k.a. Metropolis-Hastings Method.
  - Standard technique for probabilistic inference in machine learning, when the probability distribution is hard to compute exactly

Markov Chains

- Consider a time varying random process which takes the value X_t at time t
  - Values of X_t are drawn from a finite (more generally countable) set of states Ω.

- $\{X_0 \ldots X_t \ldots X_n\}$ is a *Markov Chain* if the value of X_t ***only depends on*** X_{t-1}

Transition Probabilities

- $\Pr[X_{t+1} = s_j \mid X_t = s_i]$, denoted by P(i,j), is called the transition probability
  - Can be represented as a |Ω| x |Ω| matrix P.
  - P(i,j) is the probability that the chain moves from state i to state j

- Let $\pi_i(t) = \Pr[X_t = s_i]$ denote the probability of reaching state i at time t

$$
\begin{aligned}
\pi_j(t) &= \Pr[X_t = s_j] \\
&= \sum_i \Pr[X_t = s_j | X_{t-1} = s_i] \Pr[X_{t-1} = s_i] \\
&= \sum_i P(i,j) \cdot \Pr[X_{t-1} = s_i] = \sum_i P(i,j)\, \pi_i(t-1)
\end{aligned}
$$

Transition Probabilities

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  - Can be represented as a |Ω| x |Ω| matrix P.
  - P(i,j) is the probability that the chain moves from state i to state j

- If **π**(t) denotes the 1x|Ω| vector of probabilities of reaching all the states at time t,

$$\boldsymbol{\pi}(t) = \boldsymbol{\pi}(t-1)\boldsymbol{P}$$

Example

- Suppose Ω = {Rainy, Sunny, Cloudy}
- Tomorrow's weather only depends on today's weather.
  - Markov process

$\Pr[X_{t+1} = \text{Sunny} \mid X_t = \text{Rainy}] = 0.25$

$$\boldsymbol{P} = \begin{bmatrix} 0.5 & 0.25 & 0.25 \\ 0.5 & 0 & 0.5 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}$$

$\Pr[X_{t+1} = \text{Sunny} \mid X_t = \text{Sunny}] = 0$

No 2 consecutive days of sun (Seattle?)

Example

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  - Markov process

$$\boldsymbol{P} = \begin{bmatrix} 0.5 & 0.25 & 0.25 \\ 0.5 & 0 & 0.5 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}$$

- Suppose today is Sunny. $\pi(0) = [0 \;\; 1 \;\; 0]$
- What is the weather 2 days from now?

$$\boldsymbol{\pi}(2) = \boldsymbol{\pi}(0)\boldsymbol{P}^2 = [0.375 \quad 0.25 \quad 0.375]$$

Example

- Suppose Ω = {Rainy, Sunny, Cloudy}
- Tomorrow's weather only depends on today's weather.
  - Markov process

$$\boldsymbol{P} = \begin{bmatrix} 0.5 & 0.25 & 0.25 \\ 0.5 & 0 & 0.5 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}$$

- Suppose today is Sunny. $\pi(0) = [0 \;\; 1 \;\; 0]$
- What is the weather 7 days from now?

$$\boldsymbol{\pi}(7) = \boldsymbol{\pi}(0)\boldsymbol{P}^7 = [0.4 \quad 0.2 \quad 0.4]$$

Example

- Suppose Ω = {Rainy, Sunny, Cloudy}
- Tomorrow's weather only depends on today's weather.
  - Markov process

$$P = \begin{bmatrix} 0.5 & 0.25 & 0.25 \\ 0.5 & 0 & 0.5 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}$$

- Suppose today is Rainy. $\pi(0) = [1 \;\; 0 \;\; 0]$
- What is the weather 2 days from now?

$$\pi(2) = \pi(0)P^2 = [0.4375 \quad 0.1875 \quad 0.375]$$

- Weather 7 days from now?

$$\pi(7) = \pi(0)P^7 = [0.4 \quad 0.2 \quad 0.4]$$

Example

$$\boldsymbol{P} = \begin{bmatrix} 0.5 & 0.25 & 0.25 \\ 0.5 & 0 & 0.5 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}$$

$$\pi(0) = [0 \;\; 1 \;\; 0] \qquad \boldsymbol{\pi}(7) = \boldsymbol{\pi}(0)\boldsymbol{P}^7 = [0.4 \quad 0.2 \quad 0.4]$$

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- After sufficient amount of time the expected weather distribution is independent of the starting value.
- Moreover, $\boldsymbol{\pi}(7) = \boldsymbol{\pi}(8) = \boldsymbol{\pi}(9) = \cdots = [0.4 \quad 0.2 \quad 0.4]$
- This is called the **stationary distribution.**

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Stationary Distribution

- **π** is called a *stationary distribution* of the Markov Chain if

$$\boldsymbol{\pi} = \boldsymbol{\pi} \boldsymbol{P}$$

- That is, once the stationary distribution is reached, every subsequent X_i is a sample from the distribution **π**

How to use Markov Chains:

- Suppose you want to sample from a set |Ω|, according to distribution π
- Construct a Markov Chain (**P**) such that π is the stationary distribution
- *Once stationary distribution is achieved,* we get samples from the correct distribution.

Conditions for a Stationary Distribution

A Markov chain is **ergodic** if it is:

- **Irreducible**: A state j can be reached from any state i in some finite number of steps.

$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0.5 \\ 0 & 0.25 & 0.75 \end{bmatrix}$$

Conditions for a Stationary Distribution

A Markov chain is **ergodic** if it is:

- **Irreducible**: A state j can be reached from any state i in some finite number of steps.

$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0.5 \\ 0 & 0.25 & 0.75 \end{bmatrix}$$

- **Aperiodic**: A chain is not forced into cycles of fixed length between certain states

$$P = \begin{bmatrix} 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 \end{bmatrix}$$

Conditions for a Stationary Distribution

A Markov chain is **ergodic** if it is:

- **Irreducible**: A state j can be reached from any state i in some finite number of steps.
- **Aperiodic**: A chain is not forced into cycles of fixed length between certain states

Theorem: For every ergodic Markov chain, there is a unique vector π such that for all initial probability vectors π(0),

$$\lim_{t\to\infty} \boldsymbol{\pi}(t) = \lim_{t\to\infty} \boldsymbol{\pi}(0)\boldsymbol{P}^t = \boldsymbol{\pi}$$

Sufficient Condition: Detailed Balance

- In a stationary walk, for any pair of states j, k, the Markov Chain is as likely to move from j to k as from k to j.

$$\pi_j P(j,k) = \pi_k P(k,j)$$

- Also called **reversibility condition**.

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Example: Random Walks

- Consider a graph G = (V,E), with weights on edges (w(e))

Random Walk:

- Start at some node u in the graph G(V,E)
- Move from node u to node v with probability proportional to w(u,v).

Random walk is a Markov chain

- State space = V
- $P(u,v) = w(u,v) / \Sigma\, w(u,v')$ if $(u,v) \in E$
  $= 0$ if (u,v) is not in E

Example: Random Walk

Random walk is ergodic if:

- **Irreducible**: A state j can be reached from any state i in some finite number of steps.

  If G is connected.

$$P = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.5 & 0.5 \\ 0 & 0.25 & 0.75 \end{bmatrix}$$ ✗

- **Aperiodic**: A chain is not forced into cycles of fixed length between certain states

  If G is not bipartite

$$P = \begin{bmatrix} 0 & 0 & 0.5 & 0.5 \\ 0 & 0 & 0.5 & 0.5 \\ 0.5 & 0.5 & 0 & 0 \\ 0.5 & 0.5 & 0 & 0 \end{bmatrix}$$ ✗

Example: Random Walk

Uniform random walk:

- Suppose all weights on the graph are 1
- P(u,v) = 1/deg(u)   (or 0)

Theorem: If G is connected and not bipartite, then the stationary distribution of the random walk is

$$\pi_u = {}^{\deg(u)}/_{2|E|}$$

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Example: Random Walk

Symmetric random walk:

- Suppose P(u,v) = P(v,u)

Theorem: If G is connected and not bipartite, then the stationary distribution of the random walk is

$$\pi_u = {}^{1}/_{|V|}$$

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$$\pi = \pi P$$

- That is, once the stationary distribution is reached, every subsequent X_i is a sample from the distribution **π**

How to use Markov Chains:

- Suppose you want to sample from a set |Ω|, according to distribution π
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- *Once stationary distribution is achieved,* we get samples from the correct distribution.

Metropolis-Hastings Algorithm (MCMC)

- Suppose we want to sample from a complex distribution $f(x) = p(x) / K$, where K is unknown or hard to compute

- Example: Bayesian Inference

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Metropolis-Hastings Algorithm

- Start with any initial value x_0, such that $p(x_0) > 0$
- Using current value x_{t-1}, sample a new point according some **proposal distribution** $q(x_t \mid x_{t-1})$
- Compute $\alpha(x_t|x_{t-1}) = \min\left(1, \frac{p(x_t)}{p(x_{t-1})} \frac{q(x_{t-1}|x_t)}{q(x_t|x_{t-1})}\right)$
- With probability α accept the move to x_t,
  otherwise reject x_t

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Why does Metropolis-Hastings work?

- Metropolis-Hastings describes a Markov chain with transition probabilities:

$$P(x,y) = q(y|x) \min\left(1, \frac{p(y)}{p(x)} \frac{q(x|y)}{q(y|x)}\right)$$

- We want to show that f(x) = p(x)/K is the stationary distribution

- Recall sufficient condition for stationary distribution:

$$\pi_j P(j,k) = \pi_k P(k,j)$$

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Why does Metropolis-Hastings work?

- Metropolis-Hastings describes a Markov chain with transition probabilities:

$$P(x,y) = q(y|x)\ \min\left(1, \frac{p(y)}{p(x)}\frac{q(x|y)}{q(y|x)}\right)$$

- Sufficient to show: $p(x)P(x,y) = p(y)P(y,x)$

Proof: Case 1

$$P(x,y) = q(y\,|x)\ \min\left(1, \frac{p(y)}{p(x)} \frac{q(x|y)}{q(y|x)}\right)$$

- Suppose $p(y)q(x|y) = p(x)\, q(y|x)$

- Then, P(x,y) = q(y | x)

- Therefore
  P(x,y)p(x) = q(y | x) p(x) = p(y) q(x | y) = P(y,x) p(y)

Proof: Case 2

$$P(x,y) = q(y|x) \min\left(1, \frac{p(y)}{p(x)}\frac{q(x|y)}{q(y|x)}\right)$$

$$\textit{Suppose,} \quad p(y)q(x|y) > p(x)\,q(y|x)$$

$$\textit{Then,} \quad \alpha(y|x) = 1, \quad \alpha(x|y) = \frac{p(x)q(y|x)}{p(y)q(x|y)}$$

$$\begin{aligned} P(y,x)p(y) &= q(x|y)\alpha(x|y)p(y) \\ &= q(x|y)\frac{p(x)q(y|x)}{p(y)q(x|y)}p(y) = p(x)q(y|x) \\ &= p(x)q(y|x)\alpha(y|x) = p(x)P(x,y) \end{aligned}$$

- Proof of Case 3 is identical.

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When is stationary distribution reached?

- Next class …