

Applications of Chatterjee's Correlation in MCMC

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Markov Chain Monte Carlo

Definition

A Markov chain is a discrete time stochastic process X_1, X_2, \dots such that the next state of the process depends solely on the present state, i.e.

$$\Pr(X_n | X_1, \dots, X_{n-1}) = \Pr(X_n | X_{n-1}).$$

- A Markov chain can be specified by two things
 - 1 The initial distribution, i.e. the marginal of X_1 .
 - 2 The transition probabilities, i.e. the conditional distribution of $X_{n+1} | X_n$



Markov chain Monte Carlo

Definition

A Markov chain is said to be **stationary** if the marginal of X_n is independent of n . This invariant distribution is called the stationary distribution.

Definition

A Markov chain is **ergodic** if the distribution of X_n converges to the invariant distribution.

Definition

A stationary Markov chain is **time-reversible** w.r.t. the stationary distribution if X_n and X_{n+1} are exchangeable.



Pearson's Correlation Coefficient

- Pearson's Correlation Coefficient measures the linear correlation between two sets of data.

Definition

Given random variables X, Y , Pearson Correlation ρ is defined as

$$\rho = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)} \cdot \sqrt{\text{Var}(Y)}}.$$

- Pearson Correlation is very powerful in detecting monotone relations and has a well developed asymptotic theory.



Problems with Pearson Correlation

- There are some problems with the Pearson Correlation.
- We would like the correlation to be close to its maximum value iff one variable is a function of the other. In Pearson's case, it is equal to ± 1 iff the variables are linearly dependent.
- We would also like the correlation to be 0 iff the variables are independent. If the variables are independent, Pearson correlation is indeed 0, but the converse is not always true.



Chatterjee's Correlation Coefficient

- In order to solve these problems, Chatterjee came up with a new measure of dependence in [Chatterjee, 2020]. It overcomes the above mentioned drawbacks, and has a computationally efficient consistent estimator.

Definition

Given random variables X, Y , where Y is not a constant, Chatterjee correlation ξ is defined as

$$\xi(X, Y) = \frac{\int \text{Var}(\mathbb{E}(1_{\{Y \geq t\}} | X)) d\mu(t)}{\int \text{Var}(1_{\{Y \geq t\}}) d\mu(t)}$$



Consistent Estimator of ξ

- Let $\{(X_i, Y_i)\}_{i=1}^n$ be i.i.d. pairs following the same distribution as (X, Y) . Rearrange the data as $(X_{(1)}, Y_{(1)}), \dots, (X_{(n)}, Y_{(n)})$ such that $X_{(1)} < \dots < X_{(n)}$. Let r_i be the rank of $Y_{(i)}$, i.e. the number of j such that $Y_{(j)} \leq Y_{(i)}$. Then the correlation coefficient ξ_n is defined to be

$$\xi_n(X, Y) := 1 - \frac{3 \sum_{i=1}^{n-1} |r_{i+1} - r_i|}{n^2 - 1}.$$

Theorem

If Y is not almost surely a constant, then as $n \rightarrow \infty$, $\xi_n(X, Y)$ converges almost surely to $\xi(X, Y)$.



Properties of ξ

- $\xi(X, Y) \in [0, 1]$
- $\xi(X, Y) = 0$ if and only if X and Y are independent.
- $\xi(X, Y) = 1$ if and only if at least one of X and Y is a measurable function of the other.
- ξ is not symmetric in X, Y . This is intentional and useful as we might want to study if Y is a measurable function of X , or X is a measurable function of Y . To get a symmetric coefficient, it suffices to consider $\max(\xi(X, Y), \xi(Y, X))$.
- ξ_n is based on ranks, and for the same reason, it can be computed in $O(n \log n)$.



Chatterjee's Autocorrelation Function

- We present a new autocorrelation function (ACF) using Chatterjee's correlation coefficient.

Definition

Let X_1, X_2, \dots be a stationary, time homogeneous Markov chain with stationary distribution π . We define the new lag- k ACF as follows

$$\gamma'_{k,n} := \xi(X_n, X_{n+k}).$$



$\gamma'_{k,n}$ is independent of n

Theorem

$\gamma_k = \text{Cov}(X_n, X_{n+k})$ is independent of n .

Theorem

$\gamma'_{k,n} = \xi(X_n, X_{n+k})$ is independent of n , where n and k are in \mathbb{N} .

- From now on, we'll denote $\gamma'_{k,n}$ by γ'_k



Theorem

$\xi(X_n, X_{n+k}) = \xi(X_{n+k}, X_n)$ for time reversal Markov chains for any $n, k \in \mathbb{N}$.



Convergence of γ'_k

Theorem

$\lim_{n \rightarrow \infty} \xi(X_1, X_n) = 0$ for an Ergodic Markov chain.



Proof of consistency of estimator

- Chatterjee presented the proof of consistency of the estimator in [Chatterjee, 2020], where the samples drawn from (X, Y) are i.i.d.
- In our case of stationary Markov chains, we have correlated but identically distributed draws.
- We aim to prove the consistency of the estimator for our case as well.



Proof of consistency of estimator

Theorem

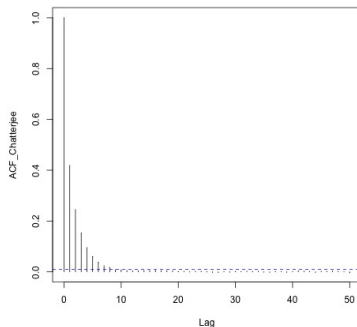
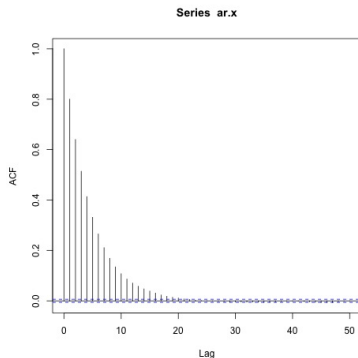
Let X_1, X_2, \dots be a stationary time-homogeneous Markov chain with stationary distribution μ . Then $\xi_n(X, Y)$ estimated using the draws from the Markov chain converge to $\xi(X, Y)$ as $n \rightarrow \infty$, where X, Y are any two time points in the chain.

- We presented some ideas and a pathway for proving it but could not complete it and is left as future work.



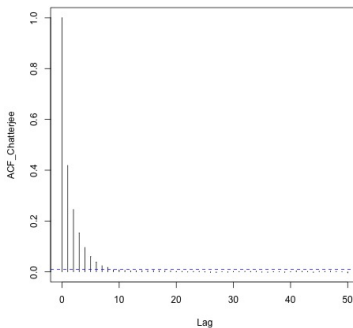
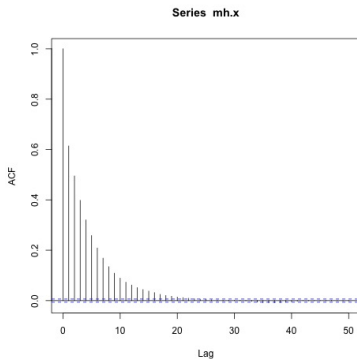
Simulations

- AR(1) process with $\rho = 0.8$.



Simulations

- Metropolis-Hastings algorithm with initial distribution as $\text{Exp}(0.01)$ and target distribution $\mathcal{N}(0, 1)$.



References I



Chatterjee, S. (2020).

A new coefficient of correlation.

