# **MCMC** Methods



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### Outline



#### Markov chain

• A **Markov chain** is a sequence of random variables X<sub>1</sub>, X<sub>2</sub>, X<sub>3</sub>, ... with the **Markov property**, namely that, given the present state, the future and past states are independent. Formally,

$$\begin{aligned} &\mathsf{Pr}(X_{n+1} = x | X_1 = x_1, X_2 = x_2, \dots, X_n = x_n) \\ &= \mathsf{Pr}(X_{n+1} = x | X_n = x_n). \end{aligned}$$

Example: hypothetical stock market

#### Hypothetical stock market example



#### Hypothetical stock market example

• The transition matrix for this example is

$$P = \begin{bmatrix} 0.9 & 0.075 & 0.025 \\ 0.15 & 0.8 & 0.05 \\ 0.25 & 0.25 & 0.5 \end{bmatrix}$$

• The distribution over states can be written as a stochastic row vector x with the relation x(n + 1) = x(n)P.

$$\begin{aligned} \mathbf{x}^{(n+3)} &= \mathbf{x}^{(n+2)} \mathbf{P} = \left( \mathbf{x}^{(n+1)} \mathbf{P} \right) \mathbf{P} = \mathbf{x}^{(n+1)} \mathbf{P}^2 = \left( \mathbf{x}^{(n)} \mathbf{P}^2 \right) \mathbf{P} \\ &= \mathbf{x}^{(n)} \mathbf{P}^3 = \begin{bmatrix} 0.3575 & 0.56825 & 0.07425 \end{bmatrix}. \end{aligned}$$

• Furthermore each column of

$$\lim_{N \to \infty} \mathbf{P}^{N} = \begin{bmatrix} 0.625 & 0.3125 & 0.0625 \\ 0.625 & 0.3125 & 0.0625 \\ 0.625 & 0.3125 & 0.0625 \end{bmatrix}$$

is the stationary distribution.

### Markov chain Monte Carlo (MCMC)

- Markov chain Monte Carlo: to simulate from a distribution π (for instance, the posterior distribution), it is actually sufficient to produce a Markov chain X<sub>t</sub> where t ∈ N whose stationary distribution is π
- If an algorithm that generates such a chain can be constructed, the ergodic theorem guarantees that, in almost all settings, the average

$$\frac{1}{T}\sum_{t=1}^{T}g(x_t)$$

converges to E(g(x)) no matter what the starting value is.

- Gibbs sampler is an MCMC algorithm.
- Metropolis-Hastings is an MCMC algorithm.

### **Diagnosing Convergence**

- We need a **stopping rule** to guarantee that the number of iterations is sufficient.
- Criteria
  - Convergence to the Stationary Distribution
  - Convergence of Averages
  - Convergence to iid Sampling

#### **Convergence in multiple chains**

- Many multiple-chain convergence diagnostics are quite elaborate.
- The performances of these parallel methods require a degree of a priori knowledge on the distribution in order to construct an initial distribution.
  - An initial distribution which is too concentrated around a local mode does not contribute significantly more than a single chain to the exploration
  - Moreover, slow algorithms, Gibbs sampling used in highly nonlinear setups, usually favor single chains.
- It is somewhat of an illusion to think we can control the flow of a Markov chain and assess its convergence behavior from a few realizations of this chain.

### **Monitoring Convergence of Distribution**

- A natural empirical approach to convergence control is to draw pictures of the output of simulated chains, in order to detect deviant or non-stationary behaviors. However, this plot is only useful for strong non-stationarities of the chain.
- Tests for non-stationary checking.
  - Autocorrelation functions.
- Another approach to convergence monitoring is to assess how much of the support of the target distribution has been explored by the chain via an evaluation of

$$\int_{A} f(x) dx \approx \sum_{t=1}^{T-1} (\theta(t+1) - \theta_{t}) f(\theta_{t})$$

when f(x) is a one-dimensional density, the above converges to 1.

### Monitoring Convergence of Average

- Graphical outputs can detect obvious problems of convergence of the empirical average.
- One may use cumulative sums (CUSUM), graphing the partial differences

$$D_T^* \sum_{t=1}^{i} (h(\theta_t) - \frac{1}{T} \sum_{t=1}^{T} h(\theta_t))$$

#### **Effective Sample Size**

• The standard approach to restore to the **effective sample size** which gives the size of an iid sample with the same variance as the current sample and thus indicates the loss in efficiency due to the use of a Markov chain. This value is computed as

$$\frac{\mathsf{T}}{1+2\sum_{t=1}^{\infty}\mathsf{Corr}(\mathsf{h}(\theta_0),\mathsf{h}(\theta_t))}$$

where the denominator is the measurement of efficiency (inefficiency factor)

### **Further Suggested Read**

*Monte Carlo Statistical Methods* Book by Christian P Robert and George Casella. (2004 edition)