Time series

Kristian Wichmann

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1 Stochastic processes and time series

Definition 1.1. Let T be a set, called the index set, and (Ω, \mathcal{F}, P) be a probability space. Then a stochastic process is a set of random variables $\{X_t|t\in T\}$, i.e. \mathcal{F} -measurable functions $X_t:\Omega\to\mathbf{R}$.

Definition 1.2. For each $\omega \in \Omega^T$ we can define a function $x: T \to \mathbf{R}$ by:

$$x(t) = x_t = X_t(\omega(t)) \tag{1.1}$$

These are known as realizations or sample-paths of the stochastic process.

Definition 1.3. The distribution function for a stochastic process is a function $F: \mathbf{R}^T \to [0, 1]$ defined by:

$$F(x) = P(\forall \ t \in T : X_t \le x_t) \tag{1.2}$$

Here x may be any function $T \to \mathbf{R}$.

Definition 1.4. A stochastic process for which the index set $T \subseteq \mathbf{Z}$ is called a time series.

As long as there's no chance of confusion, we will use the term 'time series' interchangeably for the stochastic process itself, and any relevant realizations of it.

2 Simple random walk

Let the random variables Y_1, Y_2, Y_3, \dots be i.i.d. with the distribution:

$$P(Y_i = 1) = 1/2, \quad P(Y_i = -1) = 1/2$$
 (2.1)

Now let a time series be defined as:

$$X_0 = 0, \quad X_n = \sum_{i=1}^n Y_i$$
 (2.2)

This is known as the *simple random walk*.

2.1 Asymptotic behaviour

For each of the Y's we have:

$$E[Y_i] = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot (-1) = 0, \quad \text{var}[Y_i] = \frac{1}{2} \cdot 1^2 + \frac{1}{2} \cdot (-1)^2 = 1$$
 (2.3)

So, according to the central limit theorem, for large n, X_n will be approximately normally distributed:

$$X_n \sim N(0, n), \quad n \gg 1 \tag{2.4}$$

This means that the standard deviation for large n is \sqrt{n} .

3 Markov chains

A Markov chain is a time series, in which the conditional distribution of X_{n+1} given the realizations of X_0, X_1, \ldots, X_n only depends on the realization of X_n . Formally:

$$P(X_{n+1} = s | X_0 = x_0, X_1 = x_1, \dots, X_n = x_n) = P(X_{n+1} = s | X_n = x_n)$$
(3.1)

3.1 Markov chains with a finite number of states

In the case where each X only has a finite number of realizations n, the Markov chain can be conveniently specified in matrix form. Assume the realization of X_n is state i, then we might ask what to probability of X_{n+1} being realized as state j. This probability is called p_{ij} . These probabilities can be neatly organized in matrix form:

$$A = \begin{pmatrix} p_{11} & p_{21} & \cdots & p_{n1} \\ p_{12} & p_{22} & \cdots & p_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ p_{1n} & p_{2n} & \cdots & p_{nn} \end{pmatrix}$$
(3.2)

Since the n states exhaust the possibilities, each column must sum to 1:

$$\sum_{j=1}^{n} p_{ij} = 1, \quad i \in 1, 2, \dots n$$
(3.3)

4 Martingales