

# Lecture 3

## 1 Main Definitions

**Definition 1:** The mean function of a real-valued time series is the function

$$\mu_X : T \rightarrow \mathbb{R}$$

defined by:

$$\mu_X(t) \equiv E[X_t]$$

The mean function is one of the features of a time series model that allows us to understand how the marginal distributions of a time series changes over time.

**Definition 2:** Two random variables  $X, Y$  with a joint p.d.f.  $f(x, y)$  are independent if the joint p.d.f.  $f$  can be written as:

$$f(x, y) = f_1(x)f_2(y)$$

where  $f_1$  and  $f_2$  are two non-negative functions that integrate to one. Two random variables are said to be *dependent* if they are not independent.

Here are some properties of independent random variables:

**Claim:** For any sets  $A, B$

$$\mathbb{P}(X \in A \text{ and } Y \in B) = \mathbb{P}(X \in A)\mathbb{P}(Y \in B)$$

Proof:

$$\mathbb{P}(X \in A \text{ and } Y \in B) = \int_A \left( \int_B f(x, y) dy \right) dx$$

$$\begin{aligned}
&= \int_A \left( \int_B f_1(x) f_2(y) dy \right) dx \\
&= \int_A \left( \int_B f_2(y) dy \right) f_1(x) dx \\
&= \mathbb{P}(X \in A) \mathbb{P}(Y \in B).
\end{aligned}$$

This means that the product of any joint event, can be written as the product of the marginal events.

**Corollary:**  $\mathbb{P}(X \in A | Y \in B) = \mathbb{P}(X \in A)$

How do we know if two random variables are dependent? Well, based on the definition above this means that all we need to do is find a set  $A$  and a set  $B$  for which:

$$\mathbb{P}(X \in A | Y \in B) \neq \mathbb{P}(X \in A)$$

Computing conditional probabilities is difficult. But here is a trick we can use. Remember that for any two random variables  $X$  and  $Y$  the covariance is defined as:

$$\text{Cov}(X, Y) \equiv E[(X - \mu_x)(Y - \mu_y)]$$

**Claim:** If  $(X, Y)$  are independent then  $\text{Cov}(X, Y) = 0$ .

Proof: For any functions  $g, h$ :

$$\begin{aligned}
E[g(x)h(y)] &= \int_{\mathbb{R}} \left( \int_{\mathbb{R}} g(x)h(y)f(x, y)dx \right) dy \\
&= \int_{\mathbb{R}} \left( \int_{\mathbb{R}} g(x)h(y)f_1(x)f_2(y)dx \right) dy \\
&= \int_{\mathbb{R}} \left( \int_{\mathbb{R}} g(x)f_1(x)dx \right) h(y)f_2(y)dy \\
&= E[g(x)]E[h(y)]
\end{aligned}$$

Taking  $g(x) = x - \mu_x$  completes the proof, as  $E[x - \mu_x] = 0$ .

This means that in order to show that two random variables are not inde-

pendent, it suffices to find a non-zero covariance. Thus, the covariance can give us some superficial and preliminary glimpse into the dependence embedded in a time series model.

Let us compute the covariance function for the cosine model. Note that:

$$\begin{aligned}\gamma_X(r, s) &= \mathbb{E}[(X_r - \mu_X(r))(X_s - \mu_X(s))] \\ &= E[\varepsilon_r \varepsilon_s] \\ &= 0\end{aligned}$$

In general, zero covariance does not imply independence (remember this?). However, if the joint distribution is normal, then it does.

Complement these notes with Section 1.4 in the book.