

# IDS 702: MODULE 7.2

## STATIONARITY AND AUTOCORRELATION

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# STATIONARITY

- The most common time series models usually assume **stationarity**.
- **Stationarity** of a time series process means that the marginal distribution of any part of the series does not depend on time.
- Basically, the locations in time themselves does not matter in the marginal and joint distributions; however, the differences in locations, that is, the lags, do matter!
- Put a different way, a stationary time series is one whose properties do not depend on the particular time at which the series is observed.
- Examples of non stationary series:
  - Steadily increasing trend (like the melanoma example).
  - Known seasonal trends, like increase in sales before Christmas.
  - Break in trend due to some external event.

# STATIONARITY

- Denote the times series for the outcome by  $y_t$ .
- Stationarity  $\Rightarrow$ 
  - $\Pr(y_t)$  is the same for all  $t$ ,
  - $\Pr(y_t, y_{t+1})$  is the same for all  $t$ ,  
and so on...
- **Weak stationarity** requires that only marginal moments, that is, means, variances and covariances are the same.
- Stationarity  $\Rightarrow$  weak stationarity, but **the converse need not hold**.
- For a normal distribution, the mean and variance completely characterizes the distribution, so that stationarity and weak stationarity will be equivalent.
- Why does that matter?
- When dealing with linear models, what distribution do we assume??

# POPULAR STATIONARY MODELS

- We will mainly focus on two types of stationary time series models:
  - Autoregressive models (AR models)
    - Value of outcome at time  $t$  is correlated with value at previous times.
  - Moving average models (MA models)
    - Value of outcome at time  $t$  is correlated with value of prediction errors at previous times.
- Note: autoregressive moving average models (ARMA models)
  - Combination of AR and MA.
- There are many more types of time series models (see STA 642/942).

# AUTOCORRELATION

- **Autocorrelation** (serial correlation) measures the strength of the linear relationship between  $y_t$  and its lagged values.
- The lag  $k$  autocorrelation  $\rho_k$  measures the correlation in outcomes at time  $t$  and at time  $t - k$ , where  $k$  indicates how far back to go;  $k$  is called a lag.
- The sample lag  $k$  autocorrelation  $r_k$  can be calculated using

$$r_k = \frac{\sum_{t=k+1}^T (y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=1}^T (y_t - \bar{y})^2}.$$

# PARTIAL AUTOCORRELATION

- Autocorrelation  $\rho_k$  (and the sample version  $r_k$ ) between  $y_t$  and  $y_{t-k}$  will also include the linear relationships between  $y_t$  and each of  $y_{t-1}, y_{t-2}, \dots, y_{t-k+1}$ .
- As you will see, we will need to be able to assess the correlation between  $y_t$  and  $y_{t-k}$  without interference from the other lags.
- **Partial autocorrelation** lets us do just that.
- It is the autocorrelation between  $y_t$  and  $y_{t-k}$ , with all the linear relationships between  $y_t$  and each of  $y_{t-1}, y_{t-2}, \dots, y_{t-k+1}$  removed.
- In R, use `acf` to compute and plot autocorrelations and `pacf` to compute and plot partial autocorrelations.

# WHAT'S NEXT?

MOVE ON TO THE READINGS FOR THE NEXT MODULE!