

Time Series and Forecasting

Cross-correlation

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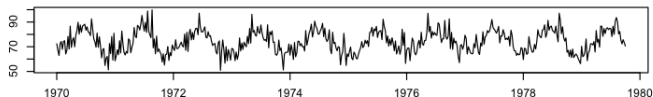
LMU, July 1 2022

Daily Pollution, Temperature and Cardiovascular Mortality in Los Angeles County

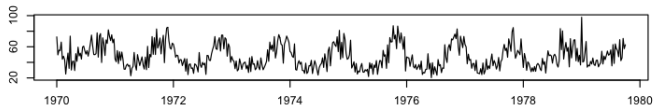
Cardiovascular Mortality



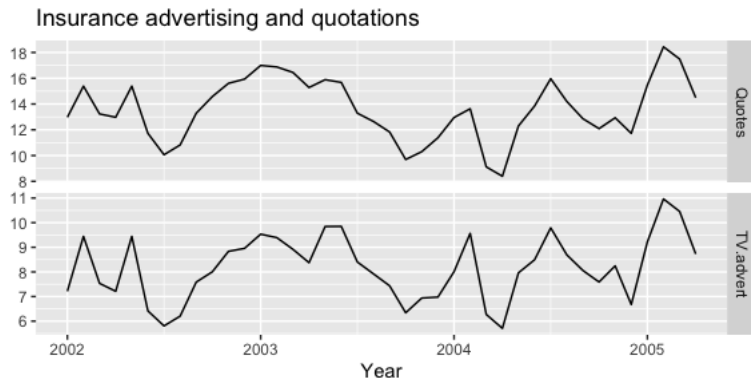
Temperature



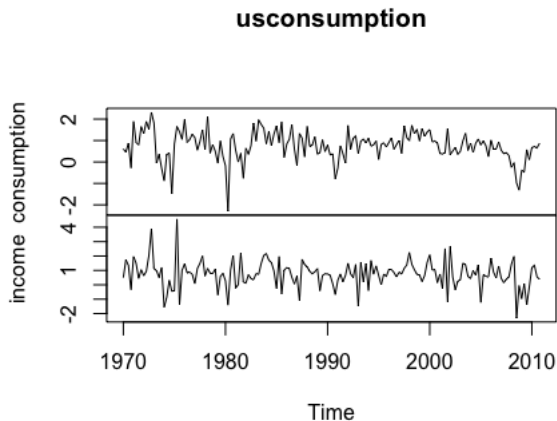
Particulates



TV advertising and insurance quotations



Percentage changes in quarterly personal consumption expenditure and personal disposable income for the US, 1970 to 2010.



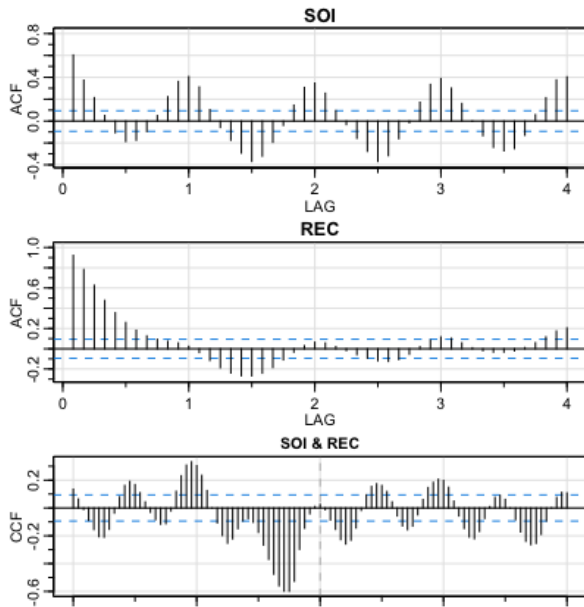
Sample Cross correlation

- $\hat{\rho}_{XY}(h) = \text{Corr}(X_{t+h}, Y_t) \quad h = 0, \pm 1, \pm 2, \dots$
- $\hat{\rho}_{XY}(h) = \hat{\rho}_{YX}(-h)$
- If X_t and Y_t are independent, then, for large sample sizes

$$\hat{\rho}_{xy}(h) \approx N(0, \frac{1}{n})$$

if at least one of the series is independent white noise

SOI and REC correlation analysis



Cross correlation and pre-whitening

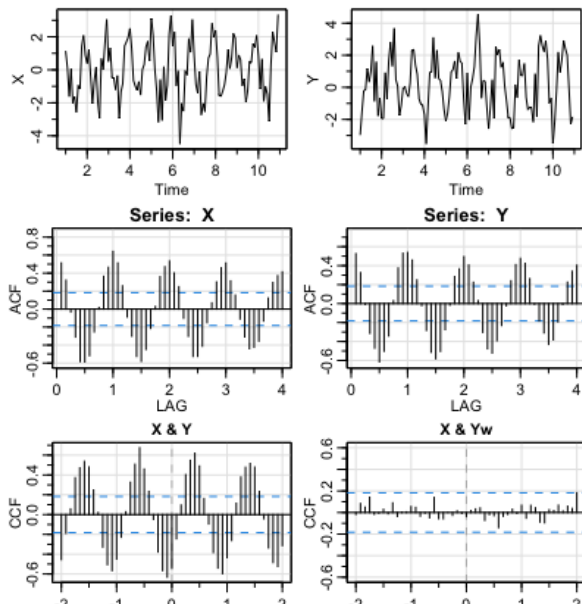
- To assess the significance of the cross correlations we need that (at least) one the series is white noise.
- Therefore we should pre-whiten a series prior to a cross-correlation analysis.
- Otherwise we may get spurious correlations.

Example of spurious correlations: 2 time series generated independently but showing high cross correlation.

$$x_t = 2 \cos(2\pi t \frac{1}{12}) + e_{t1}, \quad e_{t1} \sim N(0, 1)$$

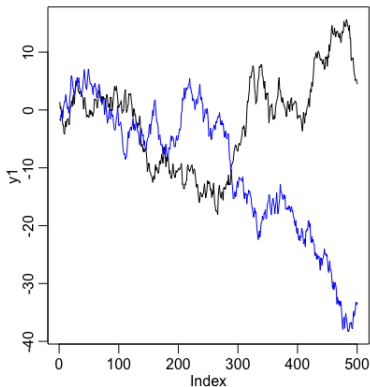
$$y_t = 2 \cos(2\pi(t + 5) \frac{1}{12}) + e_{t2}, \quad e_{t2} \sim N(0, 1)$$

Cross correlation and pre-whitening

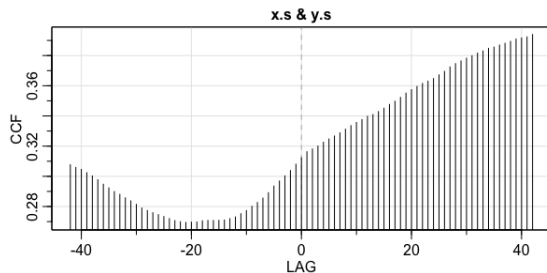


More on Spurious correlation

- A word of caution: spurious relationships arise also between trending time series
- Two independent random walks



High correlation



Significant linear relationship

```
> summary(sr.reg1)
```

```
Call:
lm(formula = y1 ~ y2)
```

```
Residuals:
```

Min	1Q	Median	3Q	Max
-12.6878	-5.3229	-0.0348	4.9765	13.1047

```
Coefficients:
```

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-6.01187	0.35794	-16.80	<2e-16 ***
y2	-0.44224	0.02312	-19.13	<2e-16 ***

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 6.107 on 498 degrees of freedom
```

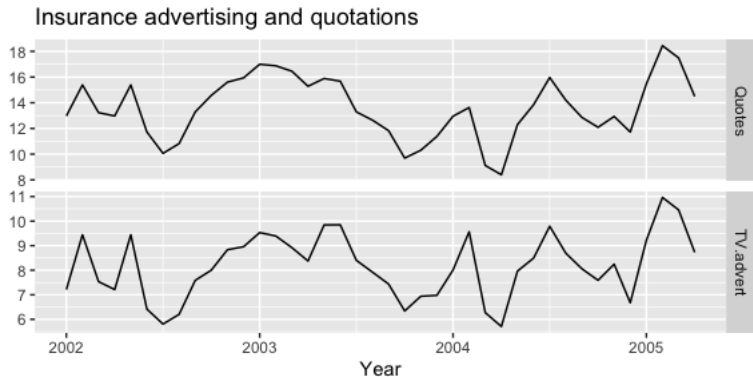
```
Multiple R-squared:  0.4235,    Adjusted R-squared:  0.4223
```

```
F-statistic: 365.8 on 1 and 498 DF,  p-value: < 2.2e-16
```

Prediction via Cross-correlation

- Determining leading/lagging relations between stationary time series x_t , y_t is important for predicting y_t from x_t purposes
- If for some unknown l the model $y_t = Ax_{t-l} + e_t$ holds, then
 - ▶ $l > 0$ then x_t leads y_t
 - ▶ $l < 0$ x_t lags y_t

TV advertising and insurance quotations: which is the leading series?

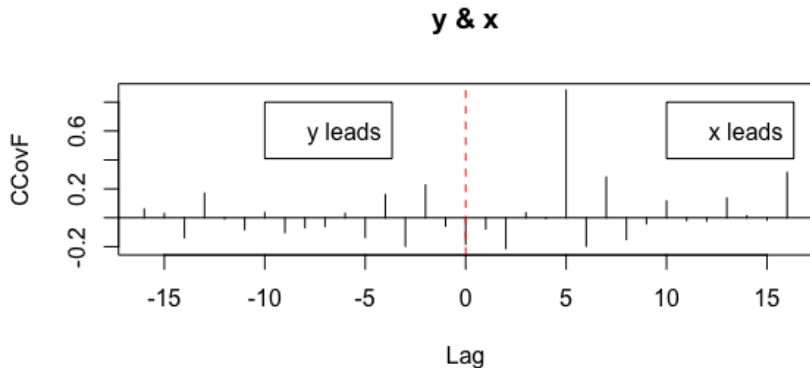


Prediction via Cross-correlation

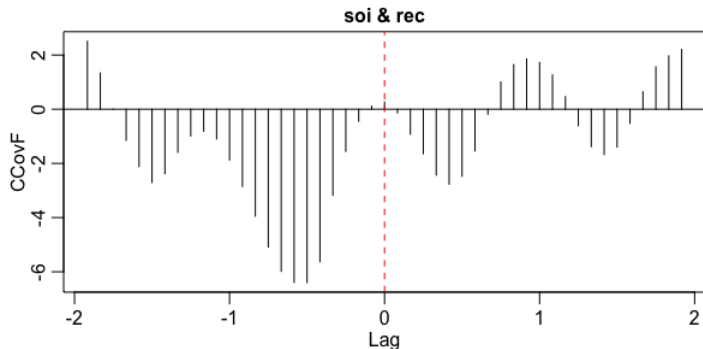
- $\gamma_{yx}(h) = A\gamma_x(h - l)$
- $\gamma_{yx}(h)$ will look like $\gamma_x(h - l)$
- Largest value of $\gamma_{yx}(h)$ is $\gamma_x(0)$ when $h = l$
- That is $\gamma_{yx}(h)$ has a peak at lag $h = l$
- Peak on positive lags h if x_t leads y_t
- Peak on negative lags if x_t lags y_t

Prediction via Cross-correlation

$$y_t = x_{t-5} + e_t$$

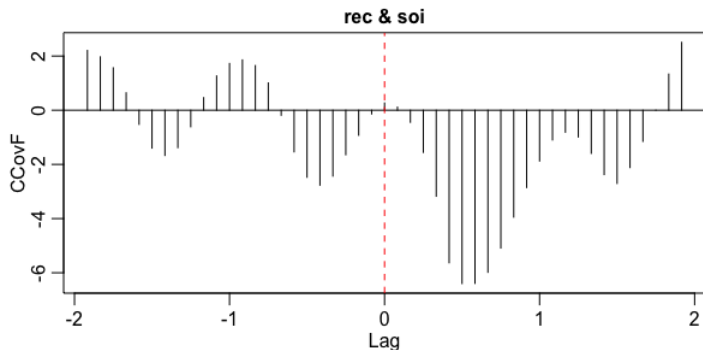


Prediction via Cross-correlation



This plot indicates a lag $l < 0$ around -6 (months) and so *soi* leads

Prediction via Cross-correlation



This plot indicates a lag $l > 0$ around 6 (months) and so *soi* leads

Measures of Dependence - bivariate context

If we have two time series X_t and Y_t we define

- Cross covariance function

$$\gamma_{XY}(s, t) = \text{cov}(X_s, Y_t) = E[(X_s - \mu_{X_s})(Y_t - \mu_{Y_t})] \quad (1)$$

- Cross Correlation function (CCF)

$$\rho_{XY}(s, t) = \frac{\gamma_{XY}(s, t)}{\sqrt{\gamma_X(t, t)\gamma_Y(s, s)}} \quad (2)$$

Jointly stationary time series

$\{X_t\}$ and $\{Y_t\}$ time series are jointly stationary if

- $\{X_t\}$ is stationary
- $\{Y_t\}$ is stationary
- The cross-correlation between $\{X_t\}$ and $\{Y_t\}$ depends only on the lag

Jointly stationary time series

Formaly

- $E(X_t) = \mu_X$
- $E(Y_t) = \mu_Y$
- $\gamma_X(h)$ ACF of X_t
- $\gamma_Y(h)$ ACF of Y_t
- **Cross covariance:**

$$\text{Cov}(X_s, Y_t) = E[(X_s - \mu_X)(Y_t - \mu_Y)] = \gamma_{XY}(s - t)$$

$$\gamma_{XY}(h) = \text{Cov}(X_{t+h}, Y_t) = E[(X_{t+h} - \mu_X)(Y_t - \mu_Y)]$$

- **Cross correlation, CCF:**

$$\rho_{XY}(h) = \frac{\gamma_{XY}(h)}{\sqrt{\gamma_X(0)\gamma_Y(0)}}$$

Properties of CCF

Note that

$$\gamma_{XY}(-h) = E[(X_{t-h} - \mu_X)(Y_t - \mu_Y)] = E[(Y_t - \mu_Y)(X_{t-h} - \mu_X)] = \gamma_{YX}(h)$$

- $\gamma_{XY}(h) = \gamma_{YX}(-h)$.
- $\rho_{XY}(h) = \rho_{YX}(-h)$.