CORRELATION FUNCTIONS

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CORRELATION FUNCTIONS

Dependencies

- A time series is *typically* analyzed with an assumption that observations have a potential relationship across time.
 - Ex: Weight
- Same approach can be taken with space as well as time.
 - Ex: Temperature

- Autocorrelation is the correlation between two sets of observations, from the same series, that are separated by k points in time.
- The autocorrelation function (ACF) is the function of all autocorrelations (between two **sets of observations** Y_t and Y_{t-k}) across time (for all values of k).

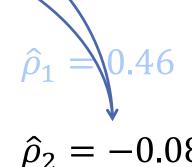
$$\rho_k = \operatorname{Corr}(Y_t, Y_{t-k})$$

t	Y_t	Y_{t-1}	Y_{t-2}
1	20	-	-
2	2	20	-
3	16	2	20
4	-3	16	2
5	-14	-3	16
6	-28	-14	-3
999	0	29	17
1000	-19	0	29

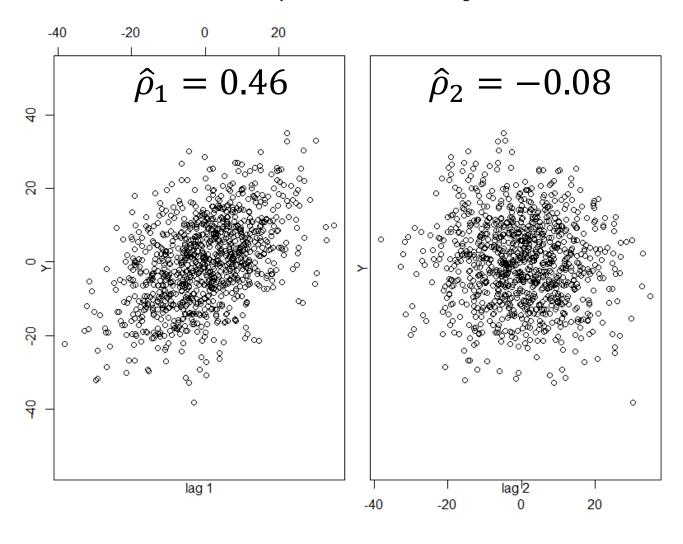
t	(Y_t)	Y_{t-1}	Y_{t-2}
1	20	•	
2	2	20	
3	16	2	20
4	-3	16	2
5	-14	-3	16
6	-28	-14	-3
999	0	29	17
1000	-19	0	29

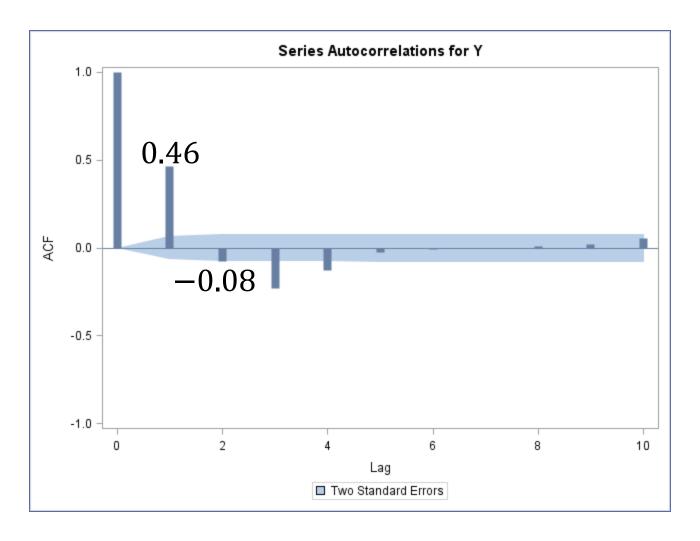
$$\hat{\rho}_1 = 0.46$$

(Y_t)	Y_{t-1}	(Y_{t-2})
20		
2	20	
16	2	20
-3	16	2
-14	-3	16
-28	-14	-3
0	29	17
-19	0	29
	2 16 -3 -14 -28 	2 20 16 2 -3 16 -14 -3 -28 -14 0 29



Scatterplots of Y with First 2 Lags





- Suppose that the first autocorrelation value (ACF(1)) is significant.
- This implies that two consecutive time points are related to each other.
 - March is related to April, April is related to May, etc.
 - Monday is related to Tuesday, Tuesday is related to Wednesday, etc.

- This relationship can be both in a positive and negative direction:
 - Positive High Mondays imply high Tuesdays
 - Negative High Mondays imply low Tuesdays
- This same relationship goes for all lags of the autocorrelation function.

- Partial autocorrelation is the correlation between two sets of observations, from the same series, that are separated by k points in time, after adjusting for all previous (1, 2, ..., k-1) autocorrelations.
- Partial autocorrelations are conditional correlations.
- The partial autocorrelation function (PACF) is the function of all partial autocorrelations (between two **sets of observations** Y_t and Y_{t-k}) across time (for all values of k).

$$\phi_k = \text{Corr}(Y_t, Y_{t-k} \mid Y_{t-1}, Y_{t-2}, \dots, Y_{t-k-1})$$

t	Y_t	Y_{t-1}	Y_{t-2}
1	20	-	-
2	2	20	-
3	16	2	20
4	-3	16	2
5	-14	-3	16
6	-28	-14	-3
999	0	29	17
1000	-19	0	29

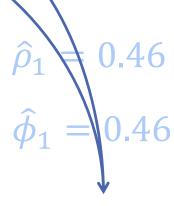
(Y_t)	(Y_{t-1})	Y_{t-2}
20	,	
2	20	
16	2	20
-3	16	2
-14	-3	16
-28	-14	-3
0	29	17
-19	0	29
	2 16 -3 -14 -28 	2 20 16 2 -3 16 -14 -3 -28 -14 0 29

$$\hat{\rho}_1 = 0.46$$

$$\hat{\phi}_1 = 0.46$$

No time points in between to influence results!

t	(Y_t)	Y_{t-1}	(Y_{t-2})
1	20		
2	2	20	-
3	16	2	20
4	-3	16	2
5	-14		16
6	-28	-14	-3
999	0	29	17
1000	-19		29
		4	



$$\hat{\rho}_2 = -0.08$$

$$\hat{\phi}_2 = -0.37$$

Must remove influence of time point in between!

 The partial autocorrelation for the kth lag is calculated from the following regression:

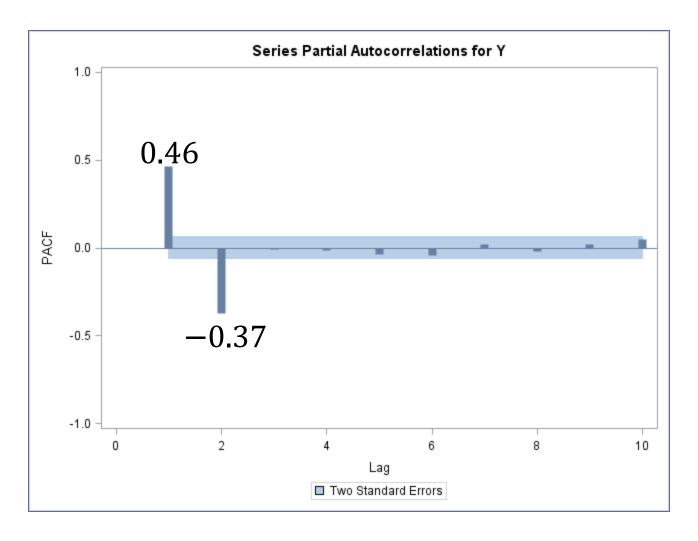
$$Y_{t} = \beta_{0} + \phi_{1}Y_{t-1} + \phi_{2}Y_{t-2} + \dots + \phi_{k}Y_{t-k} + e_{t}$$

 The partial autocorrelation for the kth lag is calculated from the following regression:

$$Y_t = \beta_0 + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_k Y_{t-k} + e_t$$

• For example, the 2nd partial autocorrelation (ϕ_2) is estimated from:

$$\hat{Y}_t = \hat{\beta}_0 + \hat{\phi}_1 Y_{t-1} + \hat{\phi}_2 Y_{t-2}$$



 The partial autocorrelation functions tries to measure the direct relationship between two sets of observations, without the influence of other sets of time in between.

Correlation Functions – R

```
acf1=Acf(Y, lag=10)$acf
pacf1=Pacf(Y, lag=10)$acf
index1=seq(1,length(pacf1))
all.dat=data.frame(cbind(acf1[2:11],pacf1,index1))
colnames(all.dat)=c("acf","pacf","index")
ggplot(all.dat,aes(x=factor(index),y=acf))+geom_col+labs
(x="Lags")
```

ACF for Y

