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WHAT STARTS HERE CHANGES THE WORLD

CHE384, From Data to Decisions: Measurement, Uncertainty, Analysis, and Modeling

Lecture 39

Autocorrelation in Time Series

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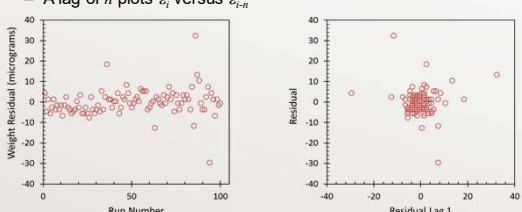
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Lag Plots

- A plot of ε_i versus ε_{i-1} (when residuals are ordered in time or other natural sequence) helps to discover correlations between a residual and its preceding residual
 - A lag of n plots ε_i versus ε_{i-n}

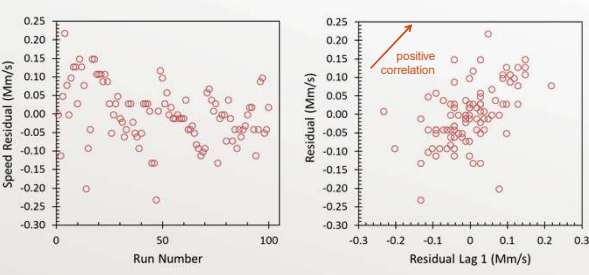


© Chris Mack, 2016 NBS measurements for a standard weight (Data Set 1) 2

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Lag Plots



Michelson speed of light measurements (Data Set 1)

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Modeling Autocorrelation

- The past is sometimes the best predictor of the future
- Consider the **first-order autoregressive model** AR(1):
 - $y_i = f(x_i) + \varepsilon_i$
 - $\varepsilon_i = \rho \varepsilon_{i-1} + u_i$, $u_i \sim N(0, \sigma^2)$ iid
 - ρ = autocorrelation parameter, $|\rho| < 1$
 - $\rho = 0$ means no autocorrelation
 - $\rho > 0$ means positive autocorrelation ("persistence")

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AR(1) Properties

- Properties of the error terms:
 - $E[\varepsilon_i] = 0$
 - $\text{var}[\varepsilon_i] = \sigma^2 / (1 - \rho^2)$
 - $\text{cov}[\varepsilon_i, \varepsilon_{i-1}] = \rho \sigma^2 / (1 - \rho^2) = \rho \text{var}[\varepsilon_i]$
 - $\text{cov}[\varepsilon_i, \varepsilon_{i-s}] = \rho^s \sigma^2 / (1 - \rho^2) = \rho^s \text{var}[\varepsilon_i]$, for $s > 0$
- Two questions:
 - Can we test for autocorrelation?
 - How can we estimate ρ ?

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Durbin-Watson Test

- We wish to perform a hypothesis test:
 - $H_0: \rho = 0$
 - $H_A: \rho > 0$ (negative autocorrelation is rare)
- Define the Durbin-Watson statistic

$$D = \frac{\sum_{i=2}^n (\varepsilon_i - \varepsilon_{i-1})^2}{\sum_{i=1}^n \varepsilon_i^2}$$

Based on the raw residuals
- If D is smaller than a critical value, we reject the null hypothesis

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Durbin-Watson Test

- We can't obtain an exact critical value for D. Instead, we define upper (d_U) and lower (d_L) critical values so that
 - $D > d_U$, can't reject H_0
 - $D < d_L$, conclude H_A
 - $d_L < D < d_U$, test is inconclusive
- Critical values are from
 - N.E. Savin and K.J. White, "The Durbin-Watson Test for Serial Correlation with Extreme Sample Sizes or Many Regressors," *Econometrica*, **45**, 1989-1996 (1977).

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Durbin-Watson Test

- This test only checks for autocorrelation with a lag of 1; longer lags may not be detected
- Note that $D \approx 2(1 - \hat{\rho})$
 - When $D \approx 2$ we have no autocorrelation
 - As $D \rightarrow 0$ we approach perfect autocorrelation
- While negative autocorrelation is rare, we can test for it
 - Test statistic is $4 - D$
 - Use the Durbin-Watson critical tables as before

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Consequences of Autocorrelation

- Regression coefficients remain unbiased but are no longer minimum variance estimates
- For positive autocorrelation, our MSE estimate of the residual variance will **underestimate** the true variance (sometimes seriously)
 - Estimated standard errors for regression coefficients will be too small
 - Statistical tests (such as F or t) on the model will not be appropriate

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How Do We Estimate ρ ?

- If the Durbin-Watson test detects autocorrelated residuals, we have three common ways to estimate ρ :
 - Slope of residual lag plot (through the origin)
 - Correlation(e_i, e_{i-1}): $r = s_{xy}/(s_x s_y)$ (**preferred**)
 - Use $r' = \frac{\sum_{i=2}^n e_i e_{i-1}}{\sum_{i=1}^n e_i^2}$

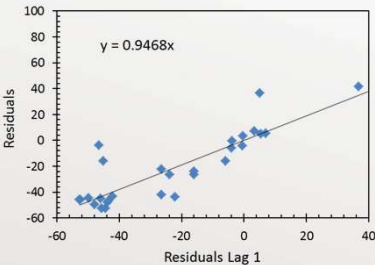
$$\text{slope} \approx r \left(1 + \frac{e_n^2 - e_1^2}{2SSE} \right), \quad r' \approx r \left(1 - \frac{e_n^2 + e_1^2}{2SSE} \right)$$

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Estimating the Autocorrelation Coefficient



Correlation of $e_i, e_{i-1} = 0.923$

$$\frac{\sum_{i=2}^n e_i e_{i-1}}{\sum_{i=1}^n e_i^2} = 0.846$$

Flow Meter Accumulated Liquid vs. Temperature (Data Set 2)

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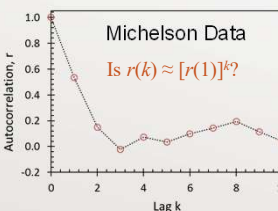
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Is AR(1) Appropriate?

Called the ACF, the autocorrelation function

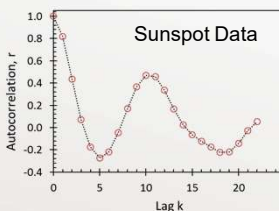
- Determine $r(k)$, r = correlation coefficient, k = lag



Michelson Data

Is $r(k) \approx [r(1)]^k$?

AR(1) is appropriate



Sunspot Data

AR(1) is not appropriate

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How to Fix Autocorrelated Residuals

- First, look for an improved model
 - Missing predictor variables often show up as autocorrelated residuals (especially if experiments are not randomized): an artificial time dependence
- If autocorrelation is a function of drift, aging, or other such behavior, then
 - Improve the measurement/experiment to remove the time/space/order dependence
 - Use an **autoregressive model** (last resort)

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First-Order Autoregressive Correction

- For a linear AR(1) model,
 - $y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$
 - $\varepsilon_i = \rho \varepsilon_{i-1} + u_i, u_i \sim N(0, \sigma^2)$ iid
- Define transformed variables
 - $y'_i = y_i - \rho y_{i-1}, \quad x'_i = x_i - \rho x_{i-1}$
 - $\beta'_0 = \beta_0(1 - \rho), \quad \beta'_1 = \beta_1$
- Then, the transformed regression model is
 - $y'_i = \beta'_0 + \beta'_1 x'_i + u_i$

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First-Order Autoregressive Correction

- Perform a standard (OLS) regression on the transformed data, then
 - $b_0 = b'_0 / (1 - r), \quad SE[b_0] = SE[b'_0] / (1 - r)$
 - $b_1 = b'_1, \quad SE[b_1] = SE[b'_1]$
 - $r =$ our estimate of ρ

The final model:

$$y_i = r y_{i-1} + (1 - r)b_0 + b_1(x_i - r x_{i-1}) + u_i$$

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More on Autoregressive Correction

- The Cochrane-Orcutt procedure: test the residuals after the autoregressive transformation and linear regression
 - Does the Durbin-Watson test show it is clear of autocorrelated residual behavior?
 - If not, iterate the whole procedure
- Alternate approaches
 - Just assume $\rho \approx 1$, see what happens
 - Find an MLE of ρ while fitting model (nonlinear regression)

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Lecture 39: What have we learned?

- What is an AR(1) model?
- What is the Durbin-Watson test and what can it tell you?
- How can we estimate the correlation parameter ρ of an AR(1) model?
- How can we correct for autocorrelation when doing a regression?

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