

# Model diagnostics and remedies. II

Miaoyan Wang

Department of Statistics  
UW Madison

# Model Assumptions

- The relationship between the response variable  $Y$  and the explanatory variables  $X_1, X_2, \dots, X_{p-1}$  is

$$E(Y_i | \mathbf{X}_i) = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_{p-1} X_{i,p-1} \quad E(\varepsilon_i) = 0$$

- Equal variance:

$$\text{Var}(Y_i | \mathbf{X}_i) = \text{Var}(\varepsilon_i) = \sigma^2.$$

- Independence:

$$\text{Cov}(Y_i, Y_{i'} | \mathbf{X}_i, \mathbf{X}_{i'}) = \text{Cov}(\varepsilon_i, \varepsilon_{i'}) = 0 \quad \text{for } i \neq i'.$$

- Normal distribution:

$$Y_i | \mathbf{X}_i \sim N(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \dots + \beta_{p-1} X_{i,p-1}, \sigma^2) \quad \varepsilon_i \sim \text{i.i.d. } N(0, \sigma^2)$$

# Remedial Measures

Basic approaches: replace with a more complex model or transform so that the model is appropriate.

- Nonlinearity of regression function:
  - ▶ Transformation.
  - ▶ Polynomial regression, nonlinear regression.
- Nonequal error variance:
  - ▶ Transformation.
  - ▶ Weighted least squares.
- Nonindependence of error terms:
  - ▶ Models with correlated error terms (STAT 850).
- Nonnormality of error terms.
  - ▶ Transformation.
  - ▶ Nonparametric methods.
  - ▶ Generalized linear models (STAT 850).
- Presence of outliers:
  - ▶ Removal of outliers (with caution).
  - ▶ Detection. Robust estimation.

## Example: Surviving Bacteria

Data consist of number of surviving bacteria after exposure to X-rays for different periods of time.

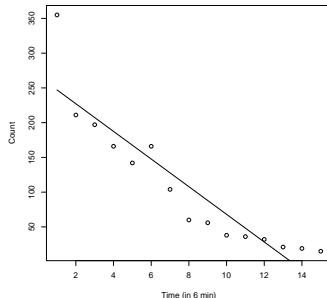
- Let  $t$  denote time (in number of 6-minute intervals)
- let  $n$  denote number of surviving bacteria after exposure to X-rays for  $t$  time.

$t$	1	2	3	4	5	6	7	8
$n$	355	211	197	166	142	166	104	60
$t$	9	10	11	12	13	14	15	
$n$	56	38	36	32	21	19	15	

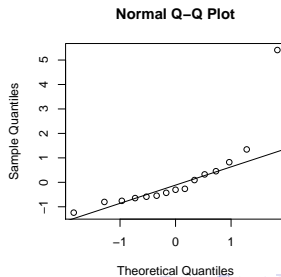
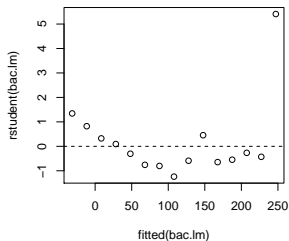
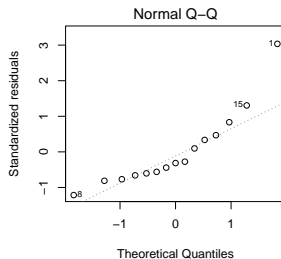
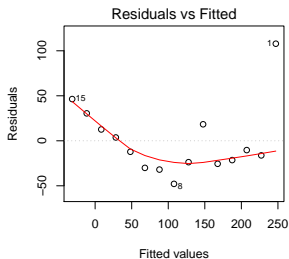
## Example: Surviving Bacteria

	Estimate	Std. Error	t value	$\Pr(\geq  t )$
(Intercept)	267.010	22.170	12.044	2.0e-08 ***
t	-19.893	2.438	-8.158	1.8e-06 ***

Residual standard error: 40.8 on 13 degrees of freedom  
Multiple R-squared: 0.8366, Adjusted R-squared: 0.824  
F-statistic: 66.56 on 1 and 13 DF, p-value: 1.804e-06



# Example: Surviving Bacteria



## Example: Surviving Bacteria

- Here there is a theoretical model:

$$n_t = n_0 e^{\beta t},$$

where

- ▶  $t$  is time,
  - ▶  $n_t$  is the number of bacteria at time  $t$ ,
  - ▶  $n_0$  is the number of bacteria at the start ( $t = 0$ ), and
  - ▶  $\beta$  is a decay rate with  $\beta < 0$ .
- Consider a log transformation:

$$\ln(n_t) = \ln(n_0) + \beta t = \alpha + \beta t,$$

by setting  $\alpha = \ln(n_0)$ .

That is, we log-transformed  $n_t$  and the result is a linear model.

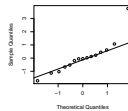
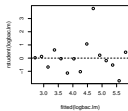
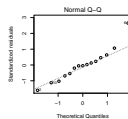
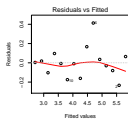
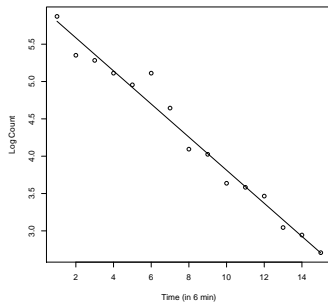
## Example: Surviving Bacteria

The transformed data are as follows.

$t$	1	2	3	4	5	6	7	8
$\ln(n)$	5.87	5.35	5.28	5.11	4.96	5.11	4.64	4.09
$t$	9	10	11	12	13	14	15	
$\ln(n)$	4.03	3.64	3.58	3.47	3.04	2.94	2.71	



# Example: Surviving Bacteria



## Example: Surviving Bacteria

	Estimate	Std. Error	t value	$Pr(>  t )$
(Intercept)	6.028695	0.088259	68.31	$< 2e-16$ ***
t	-0.221629	0.009707	-22.83	$7.1e-12$ ***

Residual standard error: 0.1624 on 13 degrees of freedom

Multiple R-squared: 0.9757, Adjusted R-squared: 0.9738

F-statistic: 521.3 on 1 and 13 DF, p-value:  $7.103e-12$

How to interpret  $\beta$  ? linear time trend in log count

How to interpret  $\alpha$  ? expected log count at the start

Inference for  $n_0$  is not straightforward.

$$\hat{n}_0 = e^{\hat{\alpha}} = 415.30 \quad \text{but} \quad E(\hat{n}_0) \neq n_0.$$

# Transformation: Remarks

- Ideally, theory should dictate what transformation to use.
- In practice, transformation is usually chosen empirically based on data analysis.
- Usually it is best to start with a simple transformation and experiment.
  - ▶ To meet the linearity assumption, transformation could be that of  $X$ , or  $Y$ , or both.
  - ▶ Common transformations are  $\log_{10}$ ,  $\ln$ ,  $\sqrt{\cdot}$ . Less common transformations are  $Y^2$ ,  $1/Y$ ,  $1/Y^2$ ,  $\arcsin \sqrt{Y}$ .
- Another advantage of transformation is to control unequal variance.

## Transformation: Remarks

- Consider a transformation ladder for  $Z = X$  or  $Y$ .

$\lambda$	$\dots$	$-2$	$-1$	$-0.5$	$0$	$0.5$	$1$	$2$	$\dots$
<hr/>									
$Z^\lambda$	$\dots$	$\frac{1}{Z^2}$	$\frac{1}{Z}$	$\frac{1}{\sqrt{Z}}$	$\log(Z)$	$\sqrt{Z}$	$Z$	$Z^2$	$\dots$

- Transforming  $Y$  can affect both linearity and equal variance, but transforming  $X$  can affect only linearity.
- Sometimes solving one problem can create another.

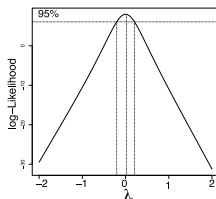
# Box-Cox Transformation

- **Box-Cox method** is a formal approach to selecting  $\lambda$  to transform  $Y$ .
- The idea is to consider

$$Y_i^\lambda = \beta_0 + \beta_1 X_i + \epsilon_i.$$

- Estimate  $\lambda$  (along with  $\beta_0, \beta_1, \sigma^2$ ) using ML.
- Choose an interpretable  $\hat{\lambda}$  within a 95% CI. In the surviving bacteria example, the Box-Cox method gives  $\hat{\lambda} = -0.0202$ .

Implication: \_\_\_\_\_



- R command: `boxcox(object, ...)` in the MASS library