

# Stat 102

## Introduction to Business Statistics

### Class 7

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Wharton

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# Today's module

Topics to be covered in this module:

- Last time
- The residual definition
- RMSE ( $s_e$ )
- Various residual plots
- $R^2$  and the quality of fit
- The relationship between  $R^2$  and RMSE
- Summary
- Next time

Main points:

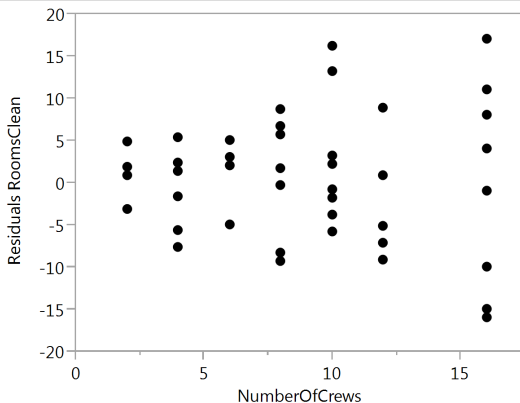
- Global and local approaches to prediction
- Line definition
- The least squares fit to data
- The residuals
- Interpreting the slope and intercept of a regression

# The residuals

- Every point has its own residual.
- It is the vertical distance from the point to the least squares line.
- Always look at a plot of the residuals,  $e$ , against  $x$ : the *residual plot*.
- The residuals should have no structure at all.
- They should look like a random swarm of points .

# The residual plot

**Bivariate Fit of Residuals RoomsClean By NumberOfCrews**



Not a disaster, but increasing variance is not ideal.

# Facts about the residuals

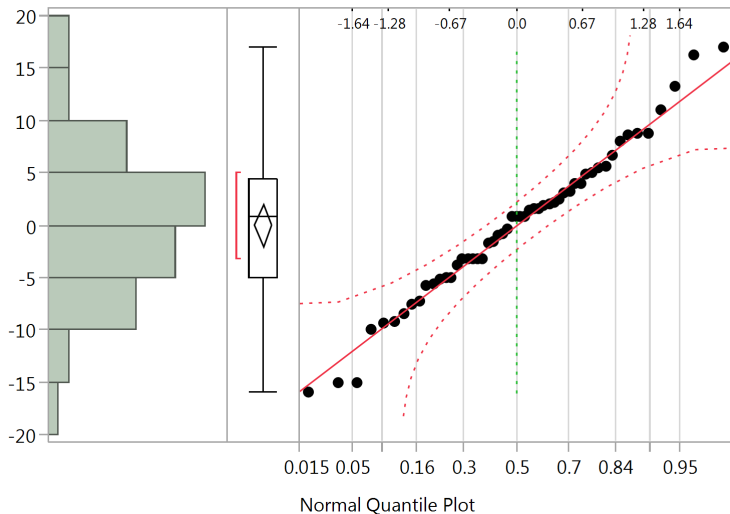
- There are two key numerical summaries of data. The mean and standard deviation.
  - ① Fact: the sample mean of the residuals is always exactly zero.
  - ② The sample standard deviation of the residuals:

$$s_e = \sqrt{\frac{e_1^2 + e_2^2 + \cdots + e_n^2}{n - 2}}.$$

- The  $(n - 2)$  in the denominator is there because we have estimated 2 parameters in the regression, the slope and intercept.
- $s_e$  is a measure of the variation in  $y$  that is not explained by knowing  $x$ . That is,  $s_e$  measures the unexplained variation in  $y$ .
- Low values of  $s_e$  are good, and if you are choosing between models with the same outcome variable, then prefer models with the lower  $s_e$ .
- $s_e$  is also known as **Root Mean Squared Error (RMSE)**.

# The residuals and the NQP

**Residuals RoomsClean**





# The numerical summaries of the residuals

## Summary Statistics

Mean	3.486e-15
Std Dev	7.2652969
Std Err Mean	0.9979653
Upper 95% Mea	2.0025638
Lower 95% Mean	-2.002564
N	53

Note that the sample mean is 0. It has to be as a by-product of the least squares methodology.

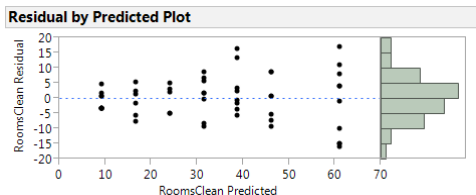
# JMPs residual plots

JMP produces 5 residual plots in simple regression:

- 1 Residuals against predicted
- 2 Actual by predicted
- 3 Residuals against row
- 4 Residuals against  $x$
- 5 Normal quantile plot of the residuals

# Plot #1

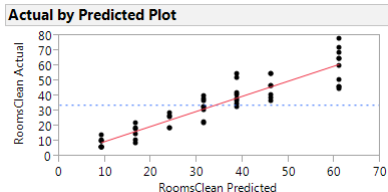
Plot:  $e_i$  v.  $\hat{y}_i$ .



- Hoping to see no structure.
- Useful in multiple regression, where  $\hat{y}$  can be thought of as a *blend* of all the  $x$ 's in the model.

## Plot #2

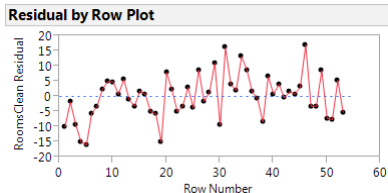
Plot:  $y_i$  v.  $\hat{y}_i$ .



- Hoping to see points tightly clustered about the 45° line.
- A way of visualizing  $R^2$  (works in multiple regression too).  $R^2$  is the square of the correlation in this plot.
- More sophisticated: a *calibration* plot. If you see systematic departures from the 45° line, then for some predicted values you are getting a biased estimate of  $E(y)$ , and you might want to fix this up.

## Plot #3

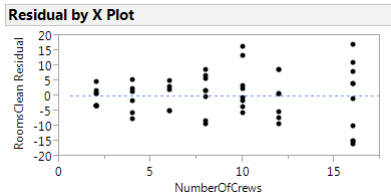
Plot:  $e_i$  v.  $i$  (the row number).



- Only useful is there is a concept of *adjacency* between rows. This will be true for time-series.
- Look for systematic structure, particularly a tracking in the residuals which may indicate a lack of independence between neighboring residuals.

## Plot #4

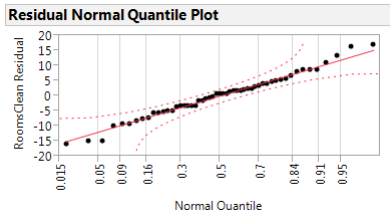
Plot:  $e_i$  v.  $x_i$ .



- The most *natural* residual plot.
- Equivalent in simple regression to plot #1.
- This is because  $\hat{y}$  is a linear transform of  $x$ :  $\hat{y}_i = b_0 + b_1 x_i$ .
- If  $b_1$  is negative then the orientation in the horizontal direction switches around between plots #1 and #4, but from the point of view of looking for *structure*, it is identical to #1.

## Plot #5

Plot: Normal Quantile Plot of the residuals.



- When we start checking assumptions, this is the one to assess normality of the error terms.

# $R^2$ and the quality of fit

- As the residuals are defined as  $e = y - \hat{y}$ , then so  $y = \hat{y} + e$ .
- The representation:

$$y = \hat{y} + e,$$

shows that the model splits the observed data  $y$  into two parts: a systematic part  $\hat{y}$ , and a random component  $e$ .

- This is the

$$\text{Data} = \text{Signal} + \text{Noise},$$

paradigm.



# Summarizing the fit

- Define  $R^2$  as  $(r)^2$ , that is the sample correlation squared.
- It is sometimes called the Coefficient of Determination, but  $R^2$  is more common.
- Interpretation: the proportion of variability in  $y$  explained by the regression model.
- Facts about  $R^2$ :
  - 1  $0 \leq R^2 \leq 1$ .
  - 2 An  $R^2$  of 1 means perfect linear association.
  - 3 An  $R^2$  of zero means no linear association.
  - 4  $R^2$  has no measurements units.
- All other things being equal, we prefer models with a higher  $R^2$ .

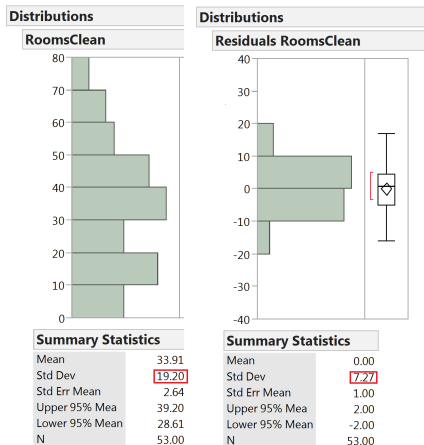
# Visualizing $R^2$

- Plot a histogram of  $y$  and measure its variance,  $s_y^2$ .
- Plot a histogram of the residuals ( $e$ ) and measure their variance  $s_e^2$ .
- Compare the two variances: if the variance of the residuals is small compared to the variance of the raw data  $y$ , then that is good, we have explained a lot of variation in  $y$  by using the model.
- In fact:

$$R^2 \approx 1 - \frac{s_e^2}{s_y^2}.$$

# Visualizing $R^2$

Look at the variation in the raw data and compare it to the variation in the residuals.



Notice that there is less variation in the residuals, 19.20 v. 7.27.

# Verifying the approximation

- The approximation to  $R^2$ :

$$1 - \frac{7.27^2}{19.20^2} = 0.86.$$

- The exact answer from JMP:

Summary of Fit	
RSquare	0.857
RSquare Adj	0.854
Root Mean Square Error	7.336
Mean of Response	33.906
Observations (or Sum Wgts)	53.000

- You don't ever have to use the approximation in practice, but it is helpful in understanding exactly what  $R^2$  is measuring.

# Things to think about when running regressions

- Think about lurking variables and be careful with your conclusions. Regression only identifies association and not causation.
- The association might be *spurious* because it may be driven by an omitted variable.
- Check that the association is approximately linear, otherwise the line doesn't make much sense.
- Inspect the residuals and hope to find no structure.

# Module summary

- 1 The residual definition
- 2 RMSE ( $s_e$ )
- 3 Various residual plots
- 4  $R^2$  and the quality of fit
- 5 The relationship between  $R^2$  and RMSE

# Next time

- Dealing with curvature