## More Inference for Simple Linear Regression (Ch. 9.1)

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More Inference for Simple Linear Regression (Ch. 9.1)

Yifan Zhu

SLR: Inference for the Mean Response at some

for a new y at some x

#### Outline

SLR: Inference for the Mean Response at some *x* 

Prediction interval for a new y at some x

Simultaneous Confidence Intervals for  $\mu_{v|x}$ 

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Simultaneous Confidence Intervals for  $\mu_{_{Y}|_{X}}$ 

Recall our model:

constant

$$Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$$

 $\varepsilon_1, \dots, \varepsilon_n \sim \text{ iid } N(0, \sigma^2)$ 

Under the model, the true mean response at some observed covariate value  $\underline{x_i}$  is:

$$\xi(\gamma_i) = \mu_{y|x_i} = \beta_0 + \beta_1 x_i$$

Now, if some new covariate value x is within the range of the  $x_i$ 's, we can estimate the true mean response at this new x:

$$\widehat{\mu}_{y|x} = \underbrace{b_0 + b_1 x}_{\bullet}$$

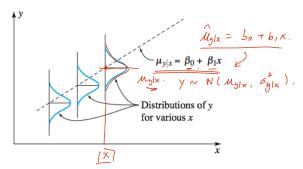
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▶ But how good is the estimate?



▶ That's why we do inference.

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Prediction interval for a new *y* at some *x* 

• Under the model  $\widehat{\mu}_{y|x}$  is normally distributed with:

$$E(\widehat{\mu}_{y|x}) = \mu_{y|x} = \beta_0 + \beta_1 x \rightarrow \text{ unbiased estimator}$$

$$Var(\widehat{\mu}_{y|x}) = \sigma^2 \left( \frac{1}{n} + \frac{(\cancel{\&} - \overline{x})^2}{\sum_i (x_i - \overline{x})^2} \right)$$

• We can construct a N(0,1) random variable by standardizing:

$$(\overline{Z} = \frac{\widehat{\mu}_{y|x} - \underline{\mu_{y|x}}}{\sqrt[n]{1}{n} \frac{(x-\overline{x})^2}{\sum_i (x_i - \overline{x})^2}} \sim \underline{N(0, 1)}$$

Peplacing 
$$\underline{\sigma}$$
 with  $\underline{s_{LF}} = \sqrt{\frac{1}{n-2} \sum_{i} (y_{i} - \widehat{y_{i}})^{2}}$ :

$$T = \frac{\widehat{\mu}_{y|x} - \mu_{y|x}}{\widehat{s_{LF}} \sqrt{\frac{1}{n} \frac{(x-\overline{x})^{2}}{\sum_{i} (x_{i}-\overline{x})^{2}}}} \sim \underline{t_{n-2}}$$

Set  $\underline{u_{y|x}}$ 

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▶ To test  $H_0: \mu_{y|x} = \#$ , we can use the test statistic:

$$T = \frac{\widehat{\mu}_{y|x} - \cancel{\text{#}}}{s_{LF}\sqrt{\frac{1}{n} + \frac{(x-\overline{x})^2}{\sum_i (x_i - \overline{x})^2}}} \underbrace{\frac{\mathcal{M}_{y|x}}{\mathcal{M}_{y|x}}}$$

which has a  $t_{n-2}$  distribution if  $\mathcal{H}_0$  is true and the model is correct.

A 2-sided  $1-\alpha$  confidence interval for  $(\mu_{y|x})$ s:

$$\left( \widehat{\mu}_{y|x} - t_{n-2, \ 1-\alpha/2} \cdot s_{LF} \sqrt{\frac{1}{n} + \frac{(x-\overline{x})^2}{\sum_i (x_i - \overline{x})^2}}, \ s_p^{1} (\widehat{\mathcal{M}}_{y|x}) \right)$$

$$\widehat{\mu}_{y|x} + t_{n-2, \ 1-\alpha/2} \cdot s_{LF} \sqrt{\frac{1}{n} + \frac{(x-\overline{x})^2}{\sum_i (x_i - \overline{x})^2}} \right)$$

and the one-sided intervals are analogous.

(
$$\Omega_{\text{plx}} - t_{n-2, 1-d} \cdot \text{se}(\hat{\Omega}_{\text{plx}}), + \infty$$
)  $\in (\text{over } 1-\omega) \in (\text{over } 1-\omega)$ 

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#### Pressing pressures and specimen densities for a ceramic compound

A mixture of  $Al_2O_3$ , polyvinyl alcohol, and water was prepared, dried overnight, crushed, and sieved to obtain 100 mesh size grains. These were pressed into cylinders at pressures from 2,000 psi to 10,000 psi, and cylinder densities were calculated.

COVATIATE	
x (pressure in psi)	y (density in g/cc)
2000.00	2.49
2000.00	2.48
2000.00	2.47
4000.00	2.56
4000.00	2.57
4000.00	2.58
6000.00	2.65
6000.00	2.66
6000.00	2.65
8000.00	2.72
8000.00	2.77
8000.00	2.81
10000.00	2.86
10000.00	2.88
10000.00	2.86

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Prediction interval or a new y at some x

#### Example: ceramics

First, I'll make a 2-sided 95% confidence interval for the true mean density of the ceramics at 4000 psi.

$$\widehat{\mu}_{y|x} = 2.375 + 0.0000487(4000) = 2.5697g/cc$$

With  $t_{n-2, 1-\alpha/2} = t_{13,0.975} = 2.160$ , the margin of error in the confidence interval is:

$$t_{n-2, 1-\alpha/2} \underbrace{|\overline{s_{LF}}| \sqrt{\frac{1}{\overline{\omega}} + \frac{(\underline{x} - \overline{x})^2}{\sum_{i} (x_i - \overline{x})^2}}}_{= \underline{2.160(0.0199)} \sqrt{\frac{1}{15} + \frac{(4000 - 6000)^2}{1.2 \times 10^8}} = \underline{0.0136g/cc}$$

Hence, the 95% CI is:

$$\underbrace{(2.5697 - 0.0136, \ 2.5697 + 0.0136)}_{\mathcal{M}_{g/x} \text{ it month of error}} = \underbrace{(2.5561, \ 2.5833)}_{error}$$

► We're 95% confident that the true mean density of the ceramics at 4000 psi is between 2.5561 g/cc and 2.5833 g/cc.

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Prediction interval for a new *y* at some *x* 

#### Your turn: ceramics

- ► Calculate and interpret a 2-sided 95% confidence interval for the true mean density at 5000 psi, given:
  - $\widehat{\mu}_{V|x} = 2.375 + 0.0000487x$
  - ▶ The margin of error is  $t_{n-2,1-\alpha/2}s_{LF}\sqrt{\frac{1}{n}+\frac{(x-\overline{x})^2}{\sum_i(x_i-\overline{x})^2}}$
  - $\sum_{i} (x_i \overline{x})^2 = 1.2 \times 10^8$
  - ▶ n = 15,  $\bar{x} = 6000$ .
  - $s_{LF} = 0.0199$
  - $t_{13,0.975} = 2.16$
- ► Test  $H_0: \underline{\beta_0} = \underline{0}$  vs.  $\underline{H_a: \beta_0 \neq 0}$  at significance level  $\alpha = 0.05$  using the method of p-values.

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#### Answers: ceramics

► Make a 2-sided 95% confidence interval for the <u>true mean</u> density of the ceramics at 5000 psi:

$$\widehat{\mu}_{y|x} = \underbrace{2.375 + 0.0000487(5000)}_{b_{x} = 0.0000487(5000)} = \underbrace{2.6183g/cc}$$

With  $t_{n-2, 1-\alpha/2} = t_{\underline{13,0.975}} = 2.160$ , the margin of error in the confidence interval is:

$$t_{n-2, 1-\alpha/2} \cdot \underbrace{s_{LF}}_{n} \sqrt{\frac{1}{n} + \frac{(\cancel{x} - \cancel{x})^{2}}{\sum_{i} (x_{i} - \cancel{x})^{2}}}$$

$$= 2.160(\underline{0.0199}) \sqrt{\frac{1}{15} + \frac{(5000 - \underline{6000})^{2}}{\underline{1.2 \times 10^{8}}}} = \underline{0.0118g/cc}$$

Hence, the 95% CI is:

► We're 95% confident that the true mean density of the ceramics at 5000 psi is between 2.6065 g/cc and 2.6301 g/cc.

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Prediction interval for a new *y* at some *x* 

#### Answers: ceramics

Now for the hypothesis test:

1. 
$$H_0: [\beta_0 = 0, H_a: \beta_0 \neq 0]$$
 Mg/x== - Bot fine = Bo.

 $\alpha = 0.05$ 

 $\beta_0$  is just  $\mu_{y|x=0}$ . The test statistic is:

$$T = \frac{b_0 - 0}{s_{LF}\sqrt{\frac{1}{n} + \frac{(0 - \bar{x})^2}{\sum_i (x_i - \bar{x})^2}}} = \frac{b_0}{s_{LF}\sqrt{\frac{1}{n} + \frac{\bar{x}^2}{\sum_i (x_i - \bar{x})^2}}}$$

- ►  $T \sim t_{n-2}$  assuming: n = 15.  $[t_{13}] \leftarrow reference$ 
  - $\vdash$   $H_0$  is true.
  - ▶ The model  $Y_i = \beta_0 + \beta_1 x_i + \varepsilon_i$  is correct, with  $\varepsilon_1, \ldots \varepsilon_n \sim \text{iid } N(0, \mathbb{I}).$

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#### Answers: ceramics

The observed test statistic:

$$b_0 = 2.375$$

$$t = \frac{2.375}{0.0199\sqrt{\frac{1}{15} + \frac{6000^2}{1.2 \times 10^8}}} = \underline{197.09}$$

$$p\text{-value} = P(|t_{13}| > \underline{197.09}) \ll 0.0001$$

- 5. With a p-value  $\ll 0.0001 < \alpha$ , we reject  $H_0$  and conclude  $H_a$ .
- 6. There is overwhelming evidence that the intercept of the "true" line is different from 0.

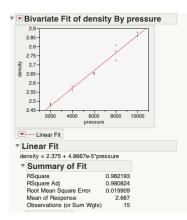
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Prediction interval for a new y at some x

### Ceramics: back to the JMP output



```
Lack Of Fit
Analysis of Variance
                   Sum of
 Source
                  Squares Mean Square
                                         F Ratio
 Model
              1 0.28421333
                               0.284213 717 0604
 Error
             13 0.00515267
                               0.000396 Prob > F
 C Total
             14 0.28936600
                                         <.0001*
▼ Parameter Estimates
            Estimate Std Error t Ratio Prob>ltl
 Term
 Intercept
               2.375 0.012055 197.01 <.0001*
           4.8667e-5 1.817e-6 26.78 <.0001*
 pressure
```

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Prediction interval for a new *y* at some *x* 

Ceramics: back to the JMP output

Ho: \$\beta, \times 0, H\_d: \beta, \delta 0

And the second second

- ► The observed test statistic *t* is under "t Ratio" for the intercept.
- "Prob> |t|" for the intercept is the p-value for the significance test you just did.
- "Estimate" for the intercept is  $b_0$ .
- "Std Error" for the intercept is:

$$\widehat{SD}(b_0) = s_{LF} \sqrt{\frac{1}{n} + \frac{\overline{x}^2}{\sum_{i} (x_i - \overline{x})^2}}$$

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### Be careful with Inference on $\beta_0$

- In this case and many others,  $\beta_0 = \mu_y$  is beyond the range of our data.
- Estimating beyond the range of our covariate values is called **extrapolation**, which is dangerous for linear regression.
- Only extrapolate when:
  - You know your process or system well, and can describe it with the right equations.
  - ► You estimate the parameters of the resulting model using *nonlinear* regression:
    - Fixample: special case of the Michaelis-Menten model for enzyme kinetics with reaction speed y and substrate concentration x:

      (A) Y

      15 a Lucys frue

substrate concentration x:  $Y_i = \underbrace{\begin{pmatrix} \theta_1 x_i \\ \theta_2 + x_i \end{pmatrix}}_{\text{is always free}} + \underbrace{\varepsilon_i}_{\text{for all } x}$ 

See Nonlinear Regression Analysis and Its Applications by Bates and Watts for more information on nonlinear regression.

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Prediction interval for a new *y* at some *x* 

Simultaneous Confidence Intervals for  $\mu_{_{V}|_{X}}$ 

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Simultaneous Confidence Intervals for  $\mu_{v|x}$ 

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Prediction interval for a new y at some x

### Prediction interval for a new y at some x

In one-sample inference: a. P.I. is for a new / the next door a point Know (a random variable) [P. I. is wider than C. I. due to more uncentainty

- ► The prediction interval in SLR is trying to capture the next response at a given value of predictor variable.

  • A 2-sided  $1-\alpha$  prediction interval for a new response y at
- some x is: me-sided: tn-2,1-a.

$$\widehat{\mu}_{y|x} - \underbrace{t_{n-2, \ 1-\alpha/2}}_{f} \cdot s_{LF} \sqrt{\underbrace{\frac{1}{n}}_{n} + \underbrace{\frac{(x-\overline{x})^{2}}{\sum_{i}(x_{i}-\overline{x})^{2}}}_{j}},$$

$$\widehat{\mu}_{y|x} + t_{n-2, \ 1-\alpha/2} \cdot s_{LF} \sqrt{\underbrace{\frac{1}{n}}_{n} + \underbrace{\frac{(x-\overline{x})^{2}}{\sum_{i}(x_{i}-\overline{x})^{2}}}_{j}}$$

$$\text{wider than } C.2... \text{ also the remove untainty}$$

and the one-sided intervals are analogous.

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Prediction interval for a new y at some x

Confidence

$$\widehat{\mu}_{y|x} = 2.375 + 0.0000487(4000) = 2.5697g/cc$$

With  $t_{n-2, 1-\alpha/2} = t_{13,0.975} = 2.160$ , the margin of error in the confidence interval is:

$$t_{n-2, 1-\alpha/2} \cdot s_{LF} \sqrt{1 + \frac{1}{n} + \frac{(x - \overline{x})^2}{\sum_i (x_i - \overline{x})^2}}$$

$$= 2.160(0.0199) \sqrt{1 + \frac{1}{15} + \frac{(4000 - 6000)^2}{1.2 \times 10^8}} = \underline{0.0451g/cc}$$

Hence, the 95% CI is:

$$(2.5697 - 0.0451, 2.5697 + 0.0451) = (2.5246, 2.6148)$$

▶ We're 95% confident that the next collected density of the ceramics at 4000 psi is between 2.5246 g/cc and 2.6148 g/cc.

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SLR: Inference for the Mean Response at some x

Prediction interval for a new *y* at some *x* 

#### Outline

SLR: Inference for the Mean Response at some >

Prediction interval for a new y at some x

Simultaneous Confidence Intervals for  $\mu_{y|x}$ 

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SLR: Inference for the Mean Response at some

or a new y at some x

#### Simultaneous confidence intervals

- Situations will arise when you'll want to do inference on  $\mu_{y|x=2000}, \mu_{y|x=4000}, \mu_{y|x=6000}, \ldots$ , all at once.
- When you compute several confidence intervals at once or do multiple tests at once, you need to account for the simultaneity.
- ▶ On average, for every 20 tests you do independently at  $\alpha = 0.05$ , we expect 1 of those tests to conclude  $H_a$  by chance alone.
  - ▶ Remember:  $\underline{\underline{\alpha}} = \underline{\underline{P}(\text{reject } H_0 \text{ assuming } H_0 \text{ is true})}.$

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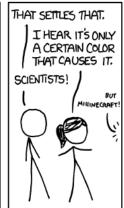
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for a new y at some x







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SLR: Inference for the Mean Response at some x

Prediction interval for a new y at some x

WE FOUND NO LINK BETWEEN PURPLE JELLY BEANS AND ACNE (P>0.05)



WE FOUND NO LINK BETWEEN BROWN JELLY BEANS AND ACNE (P > 0.05).



WE. FOUND NO

LINK BETWEEN

BEANS AND ACNE

PINK JELLY

WE, FOUND NO LINK BETWEEN BUYE JEILY BEANS AND ACNE (P > 0.05)



WE FOUND NO LINK BETWEEN TEAL JELLY BEANS AND ACNE (P>0.05)



WE FOUND NO LINK BETWEEN SALMON JELLY BEANS AND ACNE



WE FOUND NO LINK BETWEEN RFD JELLY BEANS AND ACNE (P>0.05)



WE FOUND NO LINK BETWEEN TURQUOISE JELLY BEANS AND ACNE (P>0.05)



WE FOUND NO LINK BETWEEN MAGENTA JELLY BEANS AND ACNE (P>0.05)



WE FOUND NO LINK BETWEEN YELLOW JELLY BEANS AND ACNE.



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SLR: Inference for the Mean Response at some

Prediction interval

WE FOUND NO LINK BETWEEN GREY JELLY BEANS AND ACNE (P>0.05).



WE FOUND NO LINK BETWEEN TAN JELLY BEANS AND ACNE (P>0.05)



WE FOUND NO LINK BETWEEN CYAN JELLY BEANS AND ACNE (P > 0.05).



WE FOUND A LINK BETWEEN GREEN JELLY BEANS AND ACNE (P<0.05).



WE FOUND NO LINK BETWEEN MAUVE JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN BEIGE JELLY BEANS AND ACNE



WE FOUND NO LINK BETWEEN LICAC JELLY BEANS AND ACNE (P > 0.05).



WE FOUND NO LINK BETWEEN BLACK JELLY BEANS AND ACNE (P>0.05).



WE FOUND NO LINK BETWEEN PEACH JELLY BEANS AND ACNE (P>0.05).



WE FOUND NO LINK BETWEEN ORANGE JELLY BEANS AND ACNE (P>0.05)



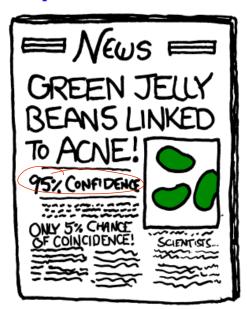
20 tests

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Prediction interval for a new *y* at



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SLR: Inference for the Mean Response at some x

Prediction interval for a new *y* at some *x* 

#### Simultaneous confidence interval

If we have k simutaneous tests, each with type I error  $\alpha$ , then the type I error for the simutaneous tests is

$$P(\text{at least one rejection in these } k \text{ tests}) > \alpha$$

If these tests are independent, the actual type I error is

$$P(\text{at least one rejection in these } k \text{ tests})$$

$$= 1 - P(\text{no rejection in these } k \text{ tests})$$

$$= 1 - \prod_{i=1}^{k} P(\text{fail to reject the } i\text{-th test}) = 1 - (1 - \alpha)^{k}$$

For k confidence intervals for  $\mu_1, \mu_2, \ldots, \mu_k$ , denote the corresponding random intervals  $l_1, l_2, \ldots, l_k$ . If the confidence level is  $1 - \alpha$ , then

$$P(\mu_i \in I_i) = 1 - \alpha, i = 1, 2, \dots, k$$

And the simutaneous confidence level would be when these events and  $P(\cdot) = (1-x)^n x^n x^n$ 

 $P(\mu_1 \in I_1 \text{ and } \mu_2 \in I_2 \text{ and } \cdots \mu_k \in I_k \text{ at the same time}) < 1 - \alpha$ 

To get the  $1-\alpha$  simutaneous confidence level, the simultaneous confidence intervals should be wider then individual confidence interval.

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Prediction interval for a new y at some x

### Simultaneous confidence intervals for $\mu_{v|x}$

Let  $I_x$  be the random intervals for the simultaneous  $1-\alpha$  confidence intervals for  $\mu_{v|x}$ . Then we want

$$P(\mu_{y|x} \in I_x \text{ at the same time for all } x) = 1 - \alpha$$

The simultaneous confidence intervals for  $\mu_{y|x}$  are given by:

y: hefre. not simultaneous case:
$$\frac{b_0 + b_1 x}{b_0 + b_1 x} \pm \sqrt{\frac{2F_2(n-2)1-\alpha}{n}} s_{LF} \cdot \sqrt{\frac{1}{n} + \frac{(x-\overline{x})^2}{\sum_i (x_i - \overline{x})^2}}$$

$$5 \in (\mathcal{M}_{y|x})$$

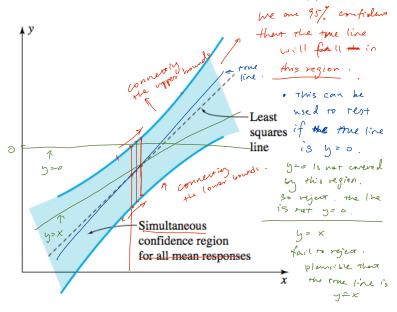
This formula accounts for the fact that we're computing k confidence intervals at the same time.

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## Simultaneous confidence intervals for $\mu_{y|x}$



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Prediction interval for a new *y* at some *x* 

#### Example: ceramics

- Given:
  - n = 15
  - $\bar{x} = 6000$
  - $\sum_{i} (x_i \overline{x})^2 = 1.2 \times 10^8$
  - $\hat{y} = 2.375 + 4.87 \times 10^{-5} x$ ,  $s_{IF} = 0.0199$ .
  - ► The simultaneous confidence interval formula is:

$$\underbrace{b_0 + b_1 x}_{f} \pm \underbrace{\sqrt{2F_{2,k,1-\alpha/2}}}_{f} s_{LF} \cdot \sqrt{\frac{1}{n} + \frac{(x-\overline{x})^2}{\sum_i (x_i - \overline{x})^2}}$$

▶ I will calculate simultaneous 95% confidence intervals for the mean responses  $\mu_{y|x}$  at x=2000, 4000, 6000, 8000, and 10000.

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Prediction interval for a new y at some x

#### Example: ceramics

Using  $F_{2,n-2|1-\alpha|} = F_{2,13,0.95} = 3.81$ , the intervals are of the form:

$$\underbrace{2.375 + 4.87 \times 10^{-5} \times \pm \sqrt{2 \cdot 3.81} \cdot 0.0199 \cdot \sqrt{\frac{1}{15} + \frac{(\cancel{x} - 6000)^2}{1.2 \times 10^8}}}_{= 2.375 + 4.87 \times 10^{-5} \times \pm 0.0549 \sqrt{0.066 + 8.33 \times 10^{-9} (x - 6000)^2}$$

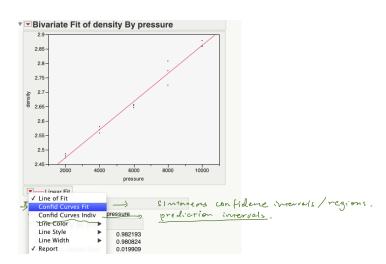
P		
(x, pressure	CI, compact form	CI
√ 2000	$2.4723 \pm 0.0246$	(2.4477, 2.4969)
4000	$2.5697 \pm 0.0174$	(2.5523, 2.5871)
6000	$2.6670 \pm 0.0142$	(2.6528, 2.6812)
8000	$2.7643 \pm 0.0174$	(2.7469, 2.7817)
10000	$2.8617 \pm 0.0246$	(2.8371, 2.8863)

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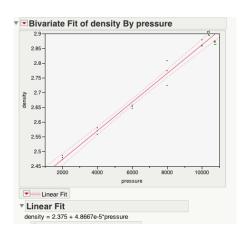


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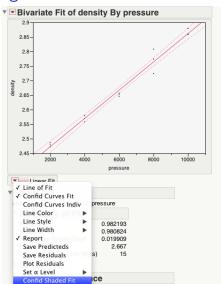


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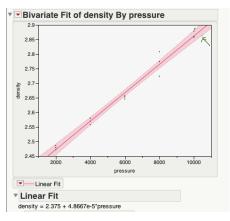


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SLR: Inference for the Mean Response at some

Prediction interval for a new *y* at some *x* 



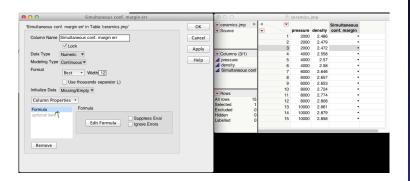
95% contidence region by defact.

More Inference for Simple Linear Regression (Ch. 9.1)

Yifan Zhu

SLR: Inference for the Mean Response at some x

Prediction interval for a new *y* at some *x* 



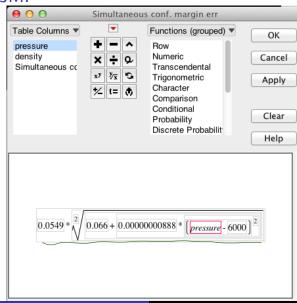
More Inference for Simple Linear Regression (Ch. 9.1)

Yifan Zhu

SLR: Inference for the Mean Response at some

Prediction interval for a new y at

Simultaneous Confidence Intervals for  $\mu_{_{V}|_{X}}$ 

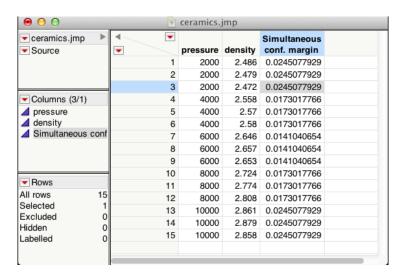


More Inference for Simple Linear Regression (Ch. 9.1)

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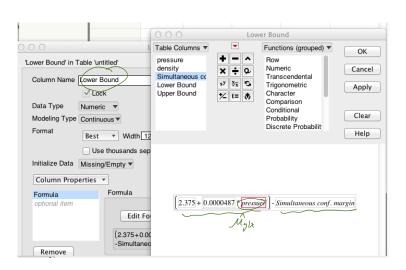


More Inference for Simple Linear Regression (Ch. 9.1)

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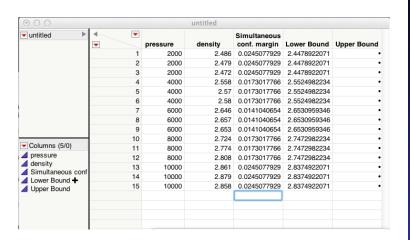


More Inference for Simple Linear Regression (Ch. 9.1)

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Prediction interval for a new *y* at some *x* 

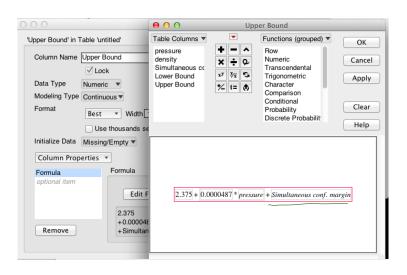


More Inference for Simple Linear Regression (Ch. 9.1)

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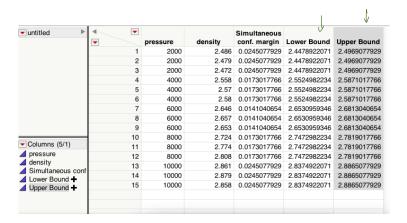


More Inference for Simple Linear Regression (Ch. 9.1)

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Prediction interval for a new *y* at some *x* 



More Inference for Simple Linear Regression (Ch. 9.1)

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Prediction interval for a new *y* at some *x*