

# 26: INFERENCE FOR SLR

Stat250 S25

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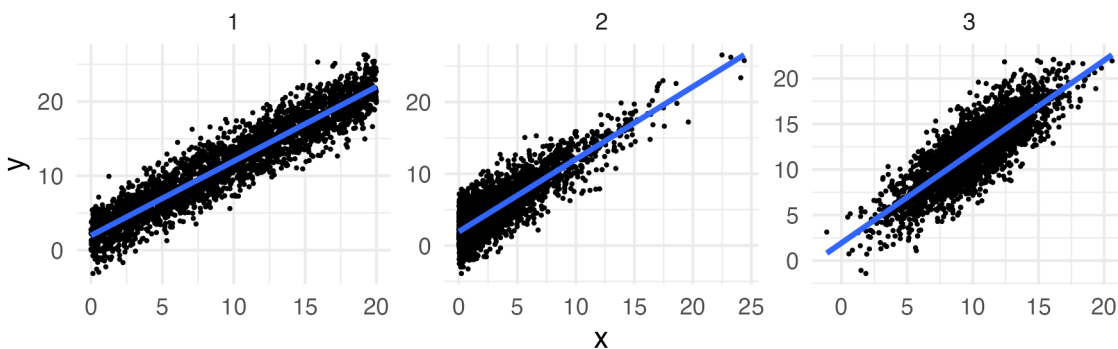
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## 1 SLR Model Recap

$$Y_i|x_i \sim N(\beta_0 + \beta_1 x_i, \sigma^2)$$

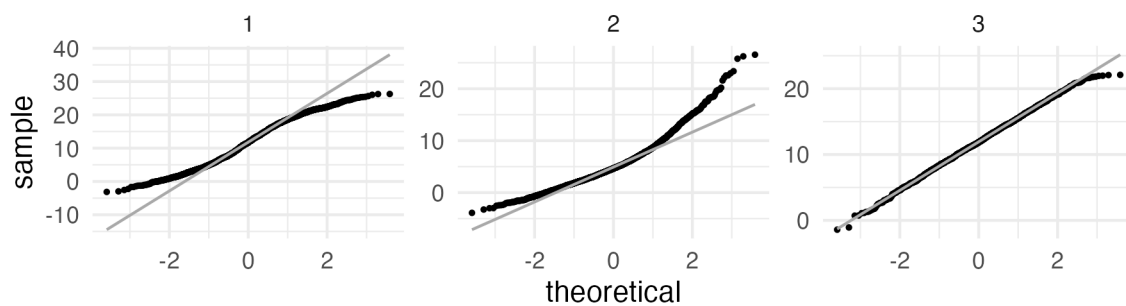
Key features:

All three of these data sets were generated from the SLR model:

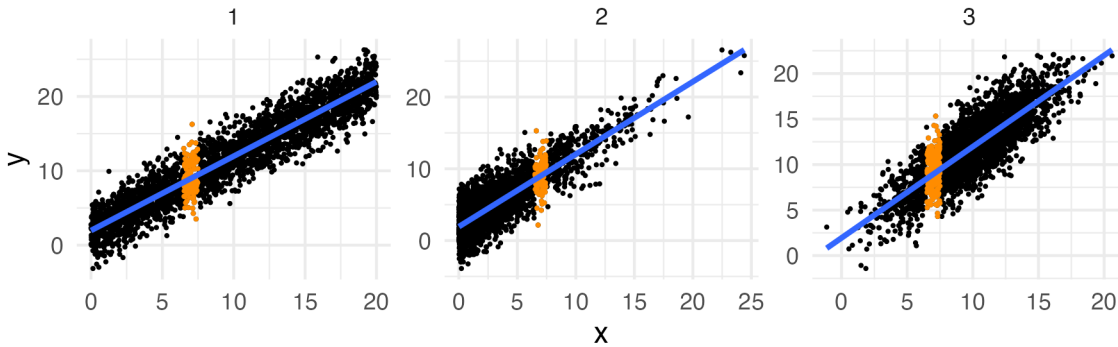


But only data 3 has (marginally) normally distributed responses:

Normal QQ plots of all Y's

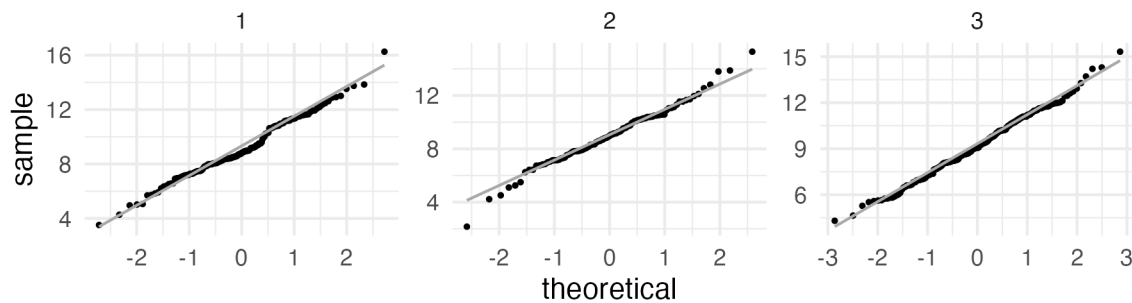


Let's look at the Y values for all cases with  $x \approx 7$ :



The Y values are (conditionally) normally distributed for with  $x \approx 7$

Normal QQ plots of all Y's



## 2 Inference for coefficients

Maximum Likelihood Estimators for SLR

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{x}$$

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(Y_i - \bar{Y})}{\sum (x_i - \bar{x})^2}$$

$$\hat{\sigma}^2 = \frac{\sum e_i^2}{n}$$

Properties of the MLE's for SLR:

1.  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are Normally-distributed random variables
2.  $\hat{\beta}_0$  and  $\hat{\beta}_1$  are unbiased estimators
3.  $V(\hat{\beta}_1) = \frac{\sigma^2}{\sum (x_i - \bar{x})^2}$

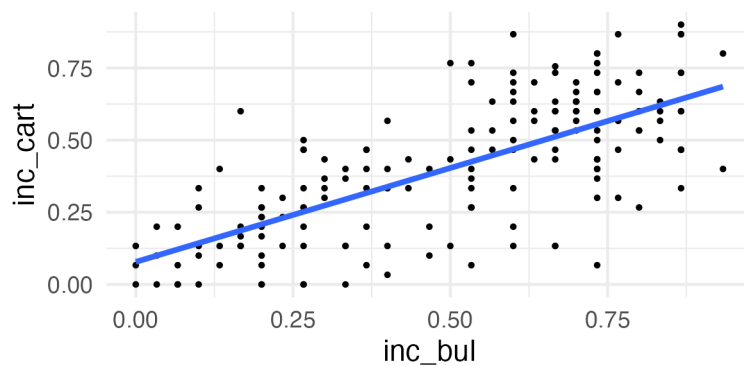
4.  $V(\hat{\beta}_0) = \sigma^2 \left[ \frac{1}{n} + \frac{\bar{x}^2}{\sum (x_i - \bar{x})^2} \right]$
5.  $\hat{\beta}_1, \bar{Y}$  and  $\hat{\sigma}^2$  are mutually independent
6.  $\frac{n\hat{\sigma}^2}{\sigma^2} \sim \chi_{n-2}^2$
7.  $s^2 = \frac{n}{n-2}\hat{\sigma}^2$  is an unbiased estimator for  $\sigma^2$

#### Test statistic for $\beta_1$

Let  $(x_1, Y_1), (x_2, Y_2), \dots, (x_n, Y_n)$  be a set of points satisfying  $E(Y|X = x) = \beta_0 + \beta_1 x$  and let  $S^2 = \frac{1}{n-2} \sum (Y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i))^2$ . Then,

$$T = \frac{\hat{\beta}_1 - \beta_1}{S / \sqrt{\sum (x_i - \bar{x})^2}}$$

**Example:** We are interested in the average *inconclusive rate* (how often the firearms examiner cannot come to a definitive conclusion) for bullets compared to cartridge cases. Some results from a study are included below:



```
cb_mod <- lm(inc_cart ~ inc_bul, data = firearms)
summary(cb_mod)
```

Call:

```
lm(formula = inc_cart ~ inc_bul, data = firearms)
```

Residuals:

|  | Min      | 1Q       | Median  | 3Q      | Max     |
|--|----------|----------|---------|---------|---------|
|  | -0.48856 | -0.11666 | 0.01347 | 0.10022 | 0.41347 |

Coefficients:

|             | Estimate | Std. Error | t value | Pr(> t )    |
|-------------|----------|------------|---------|-------------|
| (Intercept) | 0.07809  | 0.02811    | 2.778   | 0.00609 **  |
| inc_bul     | 0.65064  | 0.04972    | 13.087  | < 2e-16 *** |

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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1671 on 171 degrees of freedom

Multiple R-squared: 0.5004, Adjusted R-squared: 0.4975

F-statistic: 171.3 on 1 and 171 DF, p-value: < 2.2e-16

What is a 95% confidence interval for  $\beta_1$ ?

### 3 Inference for $\mu_{Y|x}$

**Example:** How do we find a confidence interval for the line?

## 4 Inference for new data points

**Example:** If we observe a new examiner who was inconclusive 75% of time on bullets, what would we predict for their inconclusive rate on cartridge cases?

```
predict(cb_mod, newdata = data.frame(inc_bul = .75))
>      1
> 0.5660712
predict(cb_mod, newdata = data.frame(inc_bul = .75), interval = "confidence")
>      fit      lwr      upr
> 1 0.5660712 0.5312891 0.6008534
predict(cb_mod, newdata = data.frame(inc_bul = .75), interval = "prediction")
>      fit      lwr      upr
> 1 0.5660712 0.2343576 0.8977849
```

