

Programming Assignment Unit 3

September 19, 2025

1 Multiple Linear Regression Exercises

1.1 a) Calculate the parameter estimates (β_0 , β_1 , β_2 and β_3), in addition find the usual 95% confidence intervals for β_0 , β_1 , and β_2 .

```
[ ]: # Load the data
D <- data.frame(
  x1=c(0.58, 0.86, 0.29, 0.20, 0.56, 0.28, 0.08, 0.41, 0.22, 0.35,
       0.59, 0.22, 0.26, 0.12, 0.65, 0.70, 0.30, 0.70, 0.39, 0.72,
       0.45, 0.81, 0.04, 0.20, 0.95),
  x2=c(0.71, 0.13, 0.79, 0.20, 0.56, 0.92, 0.01, 0.60, 0.70, 0.73,
       0.13, 0.96, 0.27, 0.21, 0.88, 0.30, 0.15, 0.09, 0.17, 0.25,
       0.30, 0.32, 0.82, 0.98, 0.00),
  y=c(1.45, 1.93, 0.81, 0.61, 1.55, 0.95, 0.45, 1.14, 0.74, 0.98,
      1.41, 0.81, 0.89, 0.68, 1.39, 1.53, 0.91, 1.49, 1.38, 1.73,
      1.11, 1.68, 0.66, 0.69, 1.98)
)

fit_full <- lm(y ~ x1 + x2, data = D)
summary(fit_full)          # parameter estimates & tests
confint(fit_full, 0.95)    # 95% CIs
summary(fit_full)$sigma^2  #  $\sigma^2$  estimate
```

Call:

```
lm(formula = y ~ x1 + x2, data = D)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-0.15493	-0.07801	-0.02004	0.04999	0.30112

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.433547	0.065983	6.571	1.31e-06 ***
x1	1.652993	0.095245	17.355	2.53e-14 ***
x2	0.003945	0.074854	0.053	0.958

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

Residual standard error: 0.1127 on 22 degrees of freedom
 Multiple R-squared: 0.9399, Adjusted R-squared: 0.9344
 F-statistic: 172 on 2 and 22 DF, p-value: 3.699e-14

A matrix: 0 × 2 of type dbl 2.5 % 97.5 %
 0.0127052276665322

1.2 b) Reduce the model if appropriate ($\alpha = 0.05$)

```
[ ]: fit <- lm(y ~ x1, data = D)
      anova(fit_full, fit)      # confirms x2 not needed
      summary(fit)
```

		Res.Df	RSS	Df	Sum of Sq	F	Pr(>F)
		<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
A anova: 2 × 6	1	22	0.2795150	NA	NA	NA	NA
	2	23	0.2795503	-1	-3.528751e-05	0.002777401	0.9584457

Call:

```
lm(formula = y ~ x1, data = D)
```

Residuals:

Min	1Q	Median	3Q	Max
-0.15633	-0.07633	-0.02145	0.05157	0.29994

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.43609	0.04399	9.913	9.02e-10 ***
x1	1.65121	0.08707	18.963	1.54e-15 ***

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

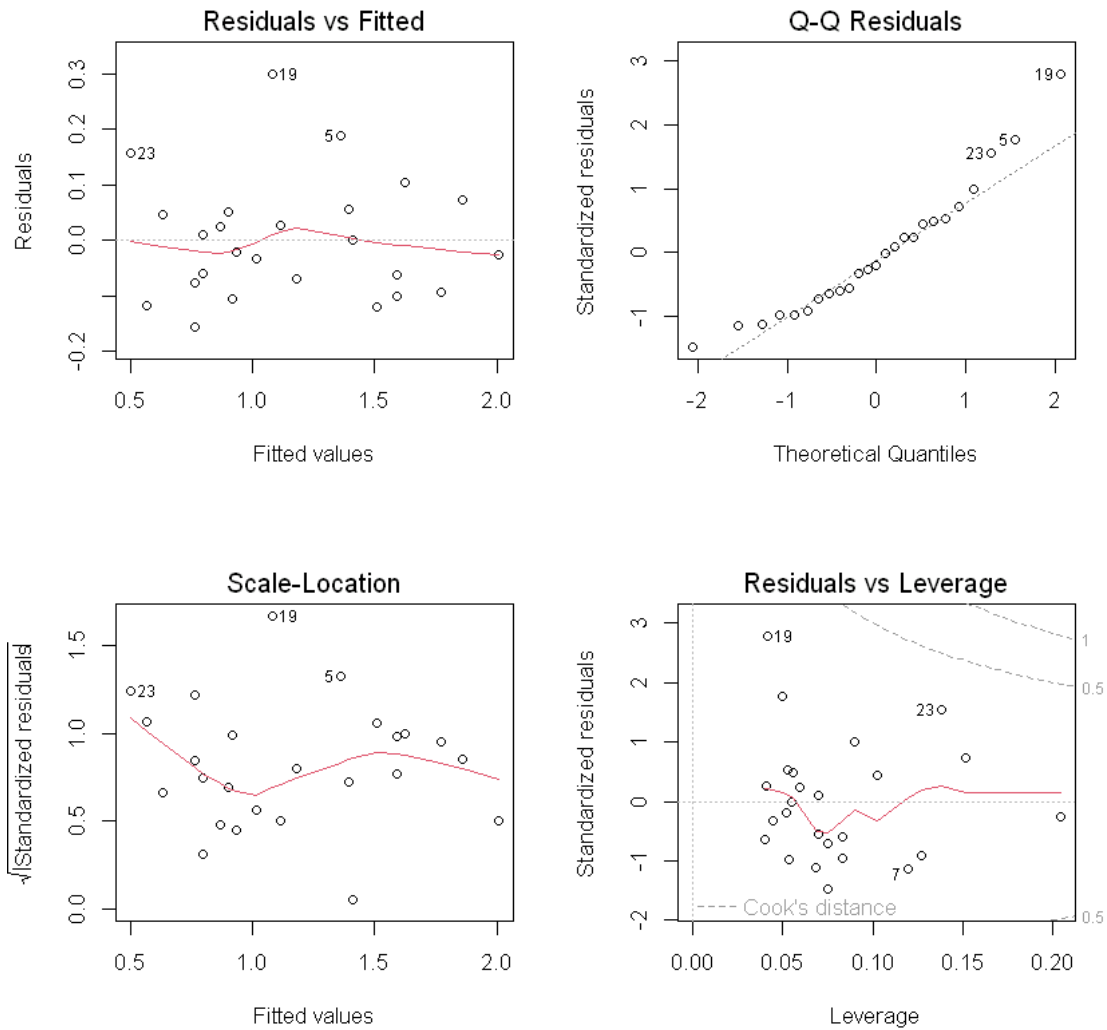
Residual standard error: 0.1102 on 23 degrees of freedom
 Multiple R-squared: 0.9399, Adjusted R-squared: 0.9373
 F-statistic: 359.6 on 1 and 23 DF, p-value: 1.538e-15

1.3 c) Residual analysis

```
[ ]: par(mfrow = c(2, 2))
      plot(fit)                # diagnostic plots
      shapiro.test(residuals(fit)) # normality check
```

Shapiro-Wilk normality test

```
data: residuals(fit)
W = 0.93532, p-value = 0.1154
```



1.4 d) Fitted line with 95% confidence & prediction intervals

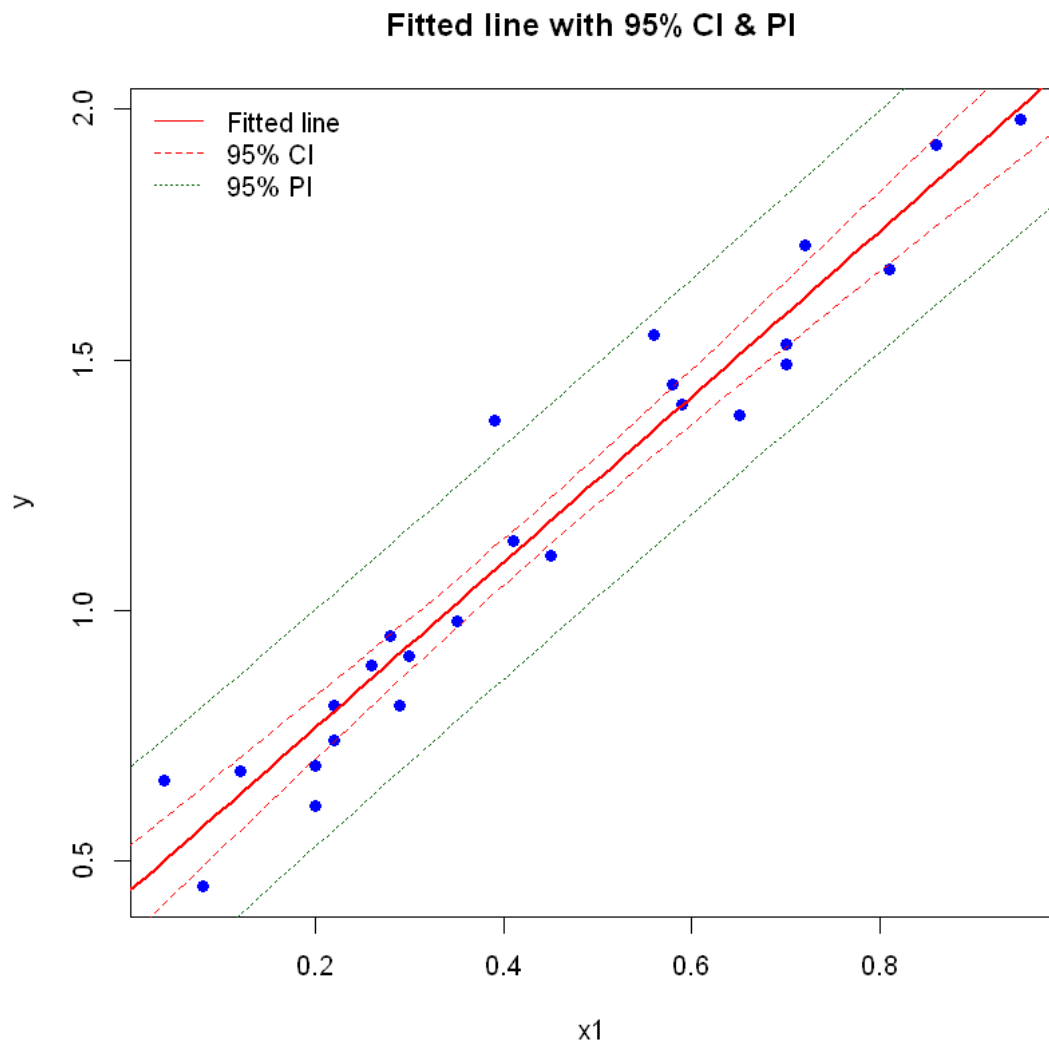
```
[ ]: new_x1 <- data.frame(x1 = seq(0, 1, length.out = 100))
ci <- predict(fit, new_x1, interval = "confidence")
pi <- predict(fit, new_x1, interval = "prediction")

plot(D$x1, D$y, pch = 19, col = "blue",
     xlab = "x1", ylab = "y",
```

```

main = "Fitted line with 95% CI & PI")
lines(new_x1$x1, ci[, "fit"], col = "red", lwd = 2)
lines(new_x1$x1, ci[, "lwr"], col = "red", lty = 2)
lines(new_x1$x1, ci[, "upr"], col = "red", lty = 2)
lines(new_x1$x1, pi[, "lwr"], col = "darkgreen", lty = 3)
lines(new_x1$x1, pi[, "upr"], col = "darkgreen", lty = 3)
legend("topleft",
      legend = c("Fitted line", "95% CI", "95% PI"),
      col = c("red", "red", "darkgreen"),
      lty = c(1, 2, 3), bty = "n")

```

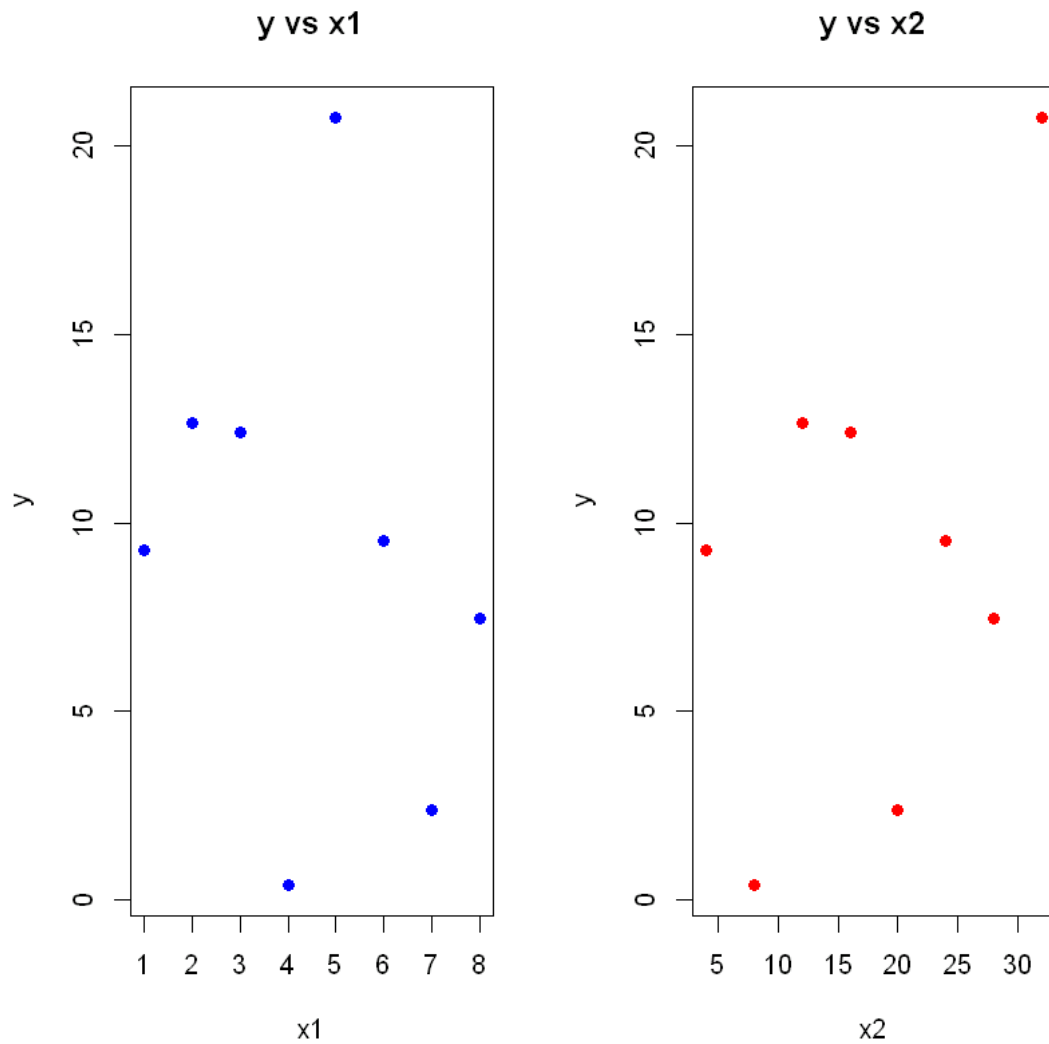


2 MLR simulation exercise

```
[ ]: ## Load data
D <- data.frame(
  y = c(9.29,12.67,12.42,0.38,20.77,9.52,2.38,7.46),
  x1 = c(1,2,3,4,5,6,7,8),
  x2 = c(4,12,16,8,32,24,20,28)
)
```

2.1 a) Plots of y vs x1 and y vs x2

```
[ ]: par(mfrow = c(1, 2)) # two plots side by side
plot(D$x1, D$y, pch = 19, col = "blue",
      xlab = "x1", ylab = "y", main = "y vs x1")
plot(D$x2, D$y, pch = 19, col = "red",
      xlab = "x2", ylab = "y", main = "y vs x2")
par(mfrow = c(1, 1))
```



The plot of **y vs x1** shows no obvious upward or downward trend—the points are scattered. The plot of **y vs x2** is also diffuse. Neither predictor shows a clear linear relationship with y.

2.2 b) Fit the two simple linear models

```
[ ]: fit_x1 <- lm(y ~ x1, data = D)
      fit_x2 <- lm(y ~ x2, data = D)

      # Summaries with parameter estimates and p-values
      summary(fit_x1)
      summary(fit_x2)
```

```
# 95% confidence intervals for coefficients
confint(fit_x1, level = 0.95)
confint(fit_x2, level = 0.95)
```

Call:

```
lm(formula = y ~ x1, data = D)
```

Residuals:

Min	1Q	Median	3Q	Max
-9.2942	-3.0504	0.6933	1.8381	11.7217

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	12.1775	5.1984	2.343	0.0576 .
x1	-0.6258	1.0294	-0.608	0.5655

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

Residual standard error: 6.672 on 6 degrees of freedom

Multiple R-squared: 0.05802, Adjusted R-squared: -0.09897

F-statistic: 0.3696 on 1 and 6 DF, p-value: 0.5655

Call:

```
lm(formula = y ~ x2, data = D)
```

Residuals:

Min	1Q	Median	3Q	Max
-7.554	-5.104	1.036	4.212	7.397

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	4.2039	4.8069	0.875	0.415
x2	0.2865	0.2380	1.204	0.274

Residual standard error: 6.169 on 6 degrees of freedom

Multiple R-squared: 0.1946, Adjusted R-squared: 0.06035

F-statistic: 1.45 on 1 and 6 DF, p-value: 0.2739

		2.5 %	97.5 %
A matrix: 2 × 2 of type dbl	(Intercept)	-0.5426374	24.897637
	x1	-3.1447959	1.893129
		2.5 %	97.5 %
A matrix: 2 × 2 of type dbl	(Intercept)	-7.5580921	15.9659492
	x2	-0.2957889	0.8688246

Linear model with x1

Model: $y = \beta_0 + \beta_1 x_1 + \epsilon$

term	estimate	95% CI	p-value
Intercept	12.18	-0.54 , 24.90	0.058
x1 slope	-0.63	-3.14 , 1.89	0.566

- The slope is small and the confidence interval includes 0.
- $R^2 = 0.06$: x1 explains only about 6 % of the variation in y.

Linear model with x2

Model: $y = \beta_0 + \beta_2 x_2 + \epsilon$

term	estimate	95% CI	p-value
Intercept	4.20	-7.56 , 15.97	0.415
x2 slope	0.29	-0.30 , 0.87	0.274

- The slope is not significant; its confidence interval also spans 0.
- $R^2 = 0.19$: x2 explains about 19 % of the variation, still weak.

Interpretation

- Neither x1 nor x2 provides a statistically significant linear relationship with y at the 5 % level.
- Both models have wide confidence intervals and low R^2 values, so the data do not support using x1 or x2 alone to predict y.
- The visual scatterplots agree: there is no clear linear trend.

We can conclude that, with this small dataset, **neither x1 nor x2 is an effective predictor of y in a simple linear model.**