4 Describing relationships between variables

This chapter provides methods that address a more involved problem of describing relationships between variables and require more computation. We start with relationships between two variables and move on to more.

4.1 Fitting a line by least squares

Goal:

We would like to use an equation to describe how a dependent (response) variable, y, changes in response to a change in one or more independent (experimental) variable(s), x.

4.1.1 Line review

Recall a linear equation of the form $y = mx + b$

In statistics, we use the notation $y = \beta_0 + \beta_1 x + \epsilon$ where we assume β_0 and β_1 are unknown parameters and ϵ is some error.

The goal is to find estimates b_0 and b_1 for the parameters.

Example 4.1 (Plastic hardness). Eight batches of plastic are made. From each batch one test item is molded and its hardness, y, is measured at time x. The following are the 8 measurements and times:

time	32	72	64	48	16	40	80	56
hardness	230	323	298	255	199	248	359	305

How do we find an equation for the line that best fits the data?

Definition 4.1. A *residual* is the vertical distance between the actual data point and a fitted line, $e = y - \hat{y}$.

The *principle of least squares* provides a method of choosing a “best” line to describe the data.

Definition 4.2. To apply the *principle of least squares* in the fitting of an equation for y to an n-point data set, values of the equation parameters are chosen to minimize

$$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where $y_1, y_2, \ldots, y_n$ are the observed responses and $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_n$ are corresponding responses predicted or fitted by the equation.

We want to choose b_0 and b_1 to minimize

$$\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 = \sum_{i=1}^{n}(y_i - b_0 - b_1 x_i)^2$$

Solving for b_0 and b_1, we get

$$b_0 = \overline{y} - b_1 \overline{x}$$

$$b_1 = \frac{\sum (x_i - \overline{x})(y_i - \overline{x})}{\sum (x_i - \overline{x})^2} = \frac{\sum x_i y_i - \frac{1}{n} \sum x_i \sum y_i}{\sum x_i^2 - \frac{1}{n} (\sum x_i)^2}$$

Example 4.2 (Plastic hardness, cont'd)**.** Compute the least squares line for the data in Example 4.1.

x	y	xy	x^2	y^2
32	230	7360	1024	52900
72	323	23256	5184	104329
64	298	19072	4096	88804
48	255	12240	2304	65025
16	199	3184	256	39601
40	248	9920	1600	61504
80	359	28720	6400	128881
56	305	17080	3136	93025

4.1.2 Interpreting slope and intercept

- Slope:

- Intercept

Interpreting the intercept is nonsense when

Example 4.3 (Plastic hardness, cont'd)**.** Interpret the coefficients in the plastic hardness example. Is the interpretation of the intercept reasonable?

When making predictions, don't *extrapolate*.

Definition 4.3. *Extrapolation* is when a value of x beyond the range of our actual observations is used to find a predicted value for y. We don't know the behavior of the line beyond our collected data.

Definition 4.4. *Interpolation* is when a value of x within the range of our observations is used to find a predicted value for y.

4.1.3 Correlation

Visually we can assess if a fitted line does a good job of fitting the data using a scatterplot. However, it is also helpful to have methods of quantifying the quality of that fit.

Definition 4.5. *Correlation* gives the strength and direction of the linear relationship between two variables.

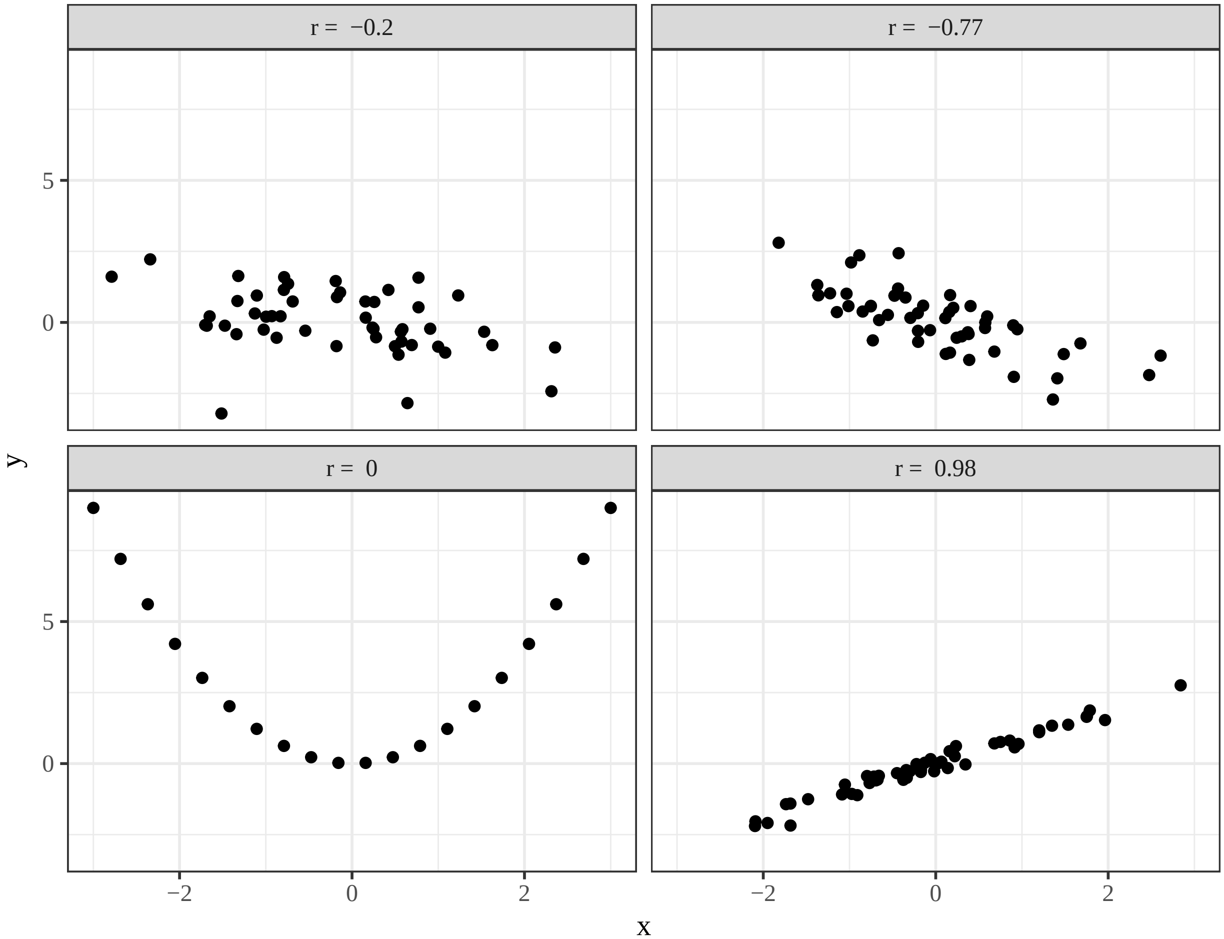
Definition 4.6. The *sample correlation* between x and y in a sample of n data points (x_i, y_i) is

$$r = \frac{\sum(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum(x_i - \overline{x})^2 \sum(y_i - \overline{y})^2}} = \frac{\sum x_i y_i - \frac{1}{n}\sum x_i \sum y_i}{\sqrt{\sum x_i^2 - \frac{1}{n}(\sum x_i)^2}\sqrt{\sum y_i^2 - \frac{1}{n}(\sum y_i)^2}}$$

Properties of the sample correlation:

- $-1 \leq r \leq 1$
- $r = -1$ or $r = 1$ if all points lie exactly on the fitted line
- The closer r is to 0, the weaker the linear relationship; the closer it is to 1 or -1, the stronger the linear relationship.
- Negative r indications negative linear relationship; Positive r indications positive linear relationship
- Interpretation always need 3 things
  1. Strength (strong, moderate, weak)
  2. Direction (positive or negative)
  3. Form (linear relationship or no linear relationship)

Note:



Example 4.4 (Plastic hardness, cont'd)**.** Compute and interpret the sample correlation for the plastic hardness example. Recall,

$$\sum x = 408, \sum y = 2217, \sum xy = 120832, \sum x^2 = 24000, \sum y^2 = 634069$$

4.1.4 Assessing models

When modeling, it's important to assess the (1) **validity** and (2) **usefulness** of your model.

To assess the validity of the model, we will look to the residuals. If the fitted equation is the good one, the residuals will be:

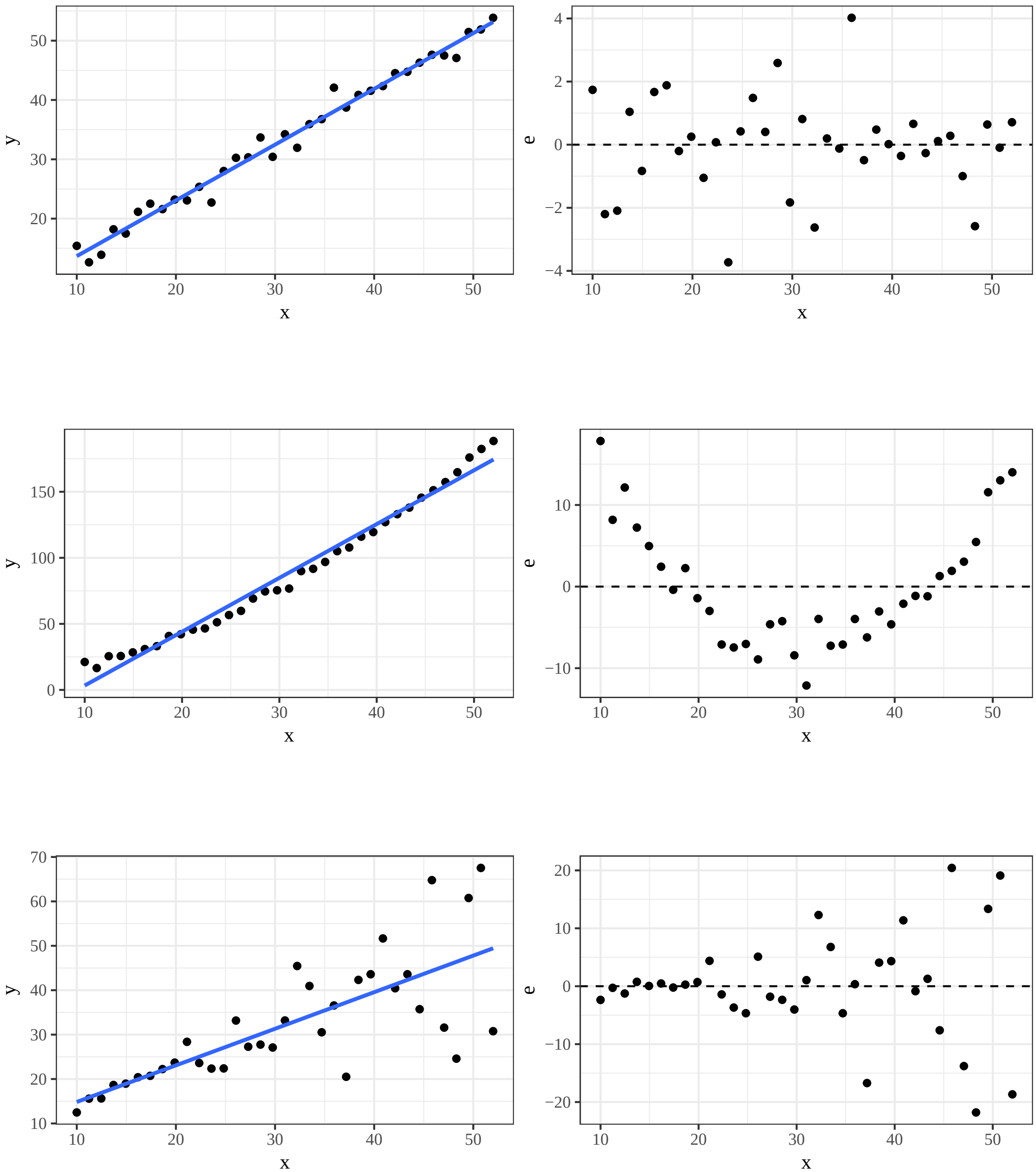
1.

2.

3.

To check if these three things hold, we will use two plotting methods.

Definition 4.7. A *residual plot* is a plot of the residuals, $e = y - \hat{y}$ vs. x (or $\hat{y}$ in the case of multiple regression, Section 4.2).


y
50
40
30
20
10
20
30
40
50
x
e
4
2
0
−2
−4
10
20
30
40
50
x
y
150
100
50
0
10
20
30
40
50
x
e
10
0
−10
10
20
30
40
50
x
y
70
60
50
40
30
20
10
10
20
30
40
50
x
e
20
10
0
−10
−20
10
20
30
40
50
x

To check if residuals have a Normal distribution,

To assess the usefulness of the model, we use R^2, the *coefficient of determination*.

Definition 4.8. The *coefficient of determination*, R^2, is the proportion of variation in the response that is explained by the model.

Total amount of variation in the response

$$Var(y) =$$

Sum of squares breakdown:

Properties of R^2:

- R^2 is used to assess the fit of other types of relationships as well (not just linear).
- Interpretation - fraction of raw variation in y accounted for by the fitted equation.
- $0 \leq R^2 \leq 1$
- The closer R^2 is to 1, the better the model.
- For SLR, $R^2 = (r)^2$

Example 4.5 (Plastic hardness, contd)**.** Compute and interpret R^2 for the example of the relationship between plastic hardness and time.

4.1.5 Precautions

Precautions about Simple Linear Regression (SLR)

- r only measures linear relationships
- R^2 and r can be drastically affected by a few unusual data points.

4.1.6 Using a computer

You can use JMP (or `R`) to fit a linear model. See BlackBoard for videos on fitting a model using JMP.

4.2 Fitting curves and surfaces by least squares

The basic ideas in Section 4.1 can be generalized to produce a powerful tool: **multiple linear regression**.

4.2.1 Polynomial regression

In the previous section, a straight line did a reasonable job of describing the relationship between time and plastic hardness. But what to do when there is not a linear relationship between variables?

Example 4.6 (Cylinders, pg. 132)**.** B. Roth studied the compressive strength of concrete-like fly ash cylinders. These were made using various amounts of ammonium phosphate as an additive.

ammonium.phosphate	strength	ammonium.phosphate	strength
0	1221	3	1609
0	1207	3	1627
0	1187	3	1642
1	1555	4	1451
1	1562	4	1472
1	1575	4	1465
2	1827	5	1321
2	1839	5	1289
2	1802	5	1292

Table 1: Additive concentrations and compressive strengths for fly ash cylinders.

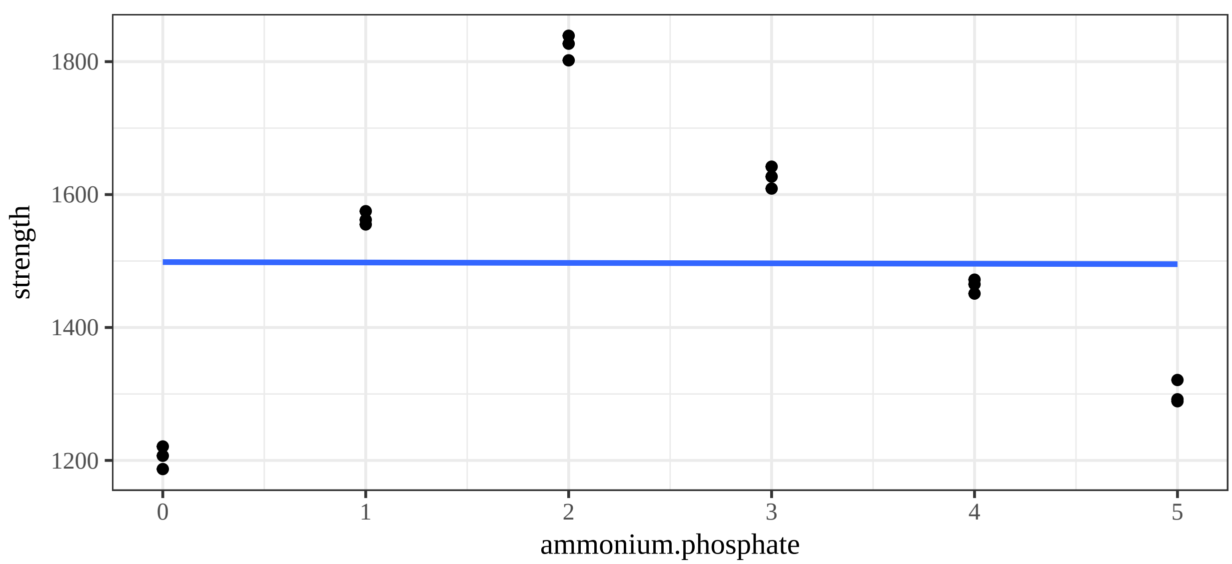


Figure 1: Scatterplot of compressive strength of concrete-like fly ash cylinders for various amounts of ammonium phosphate as an additive with a fitted line.

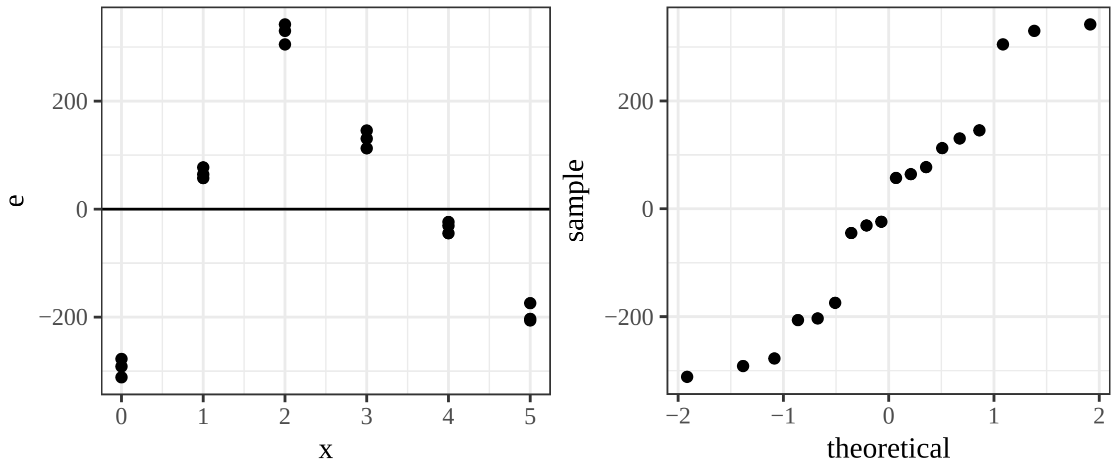


Figure 2: Residual plots for linear fit of cylinder compressive strength on amounts of ammonium phosphate.

A natural generalization of the linear equation

$$y \approx \beta_0 + \beta_1 x$$

is the **polynomial equation**

$$y \approx \beta_0 + \beta_1 x + \beta_2 x^2 + \cdots + \beta_{p-1} x^{p-1}.$$

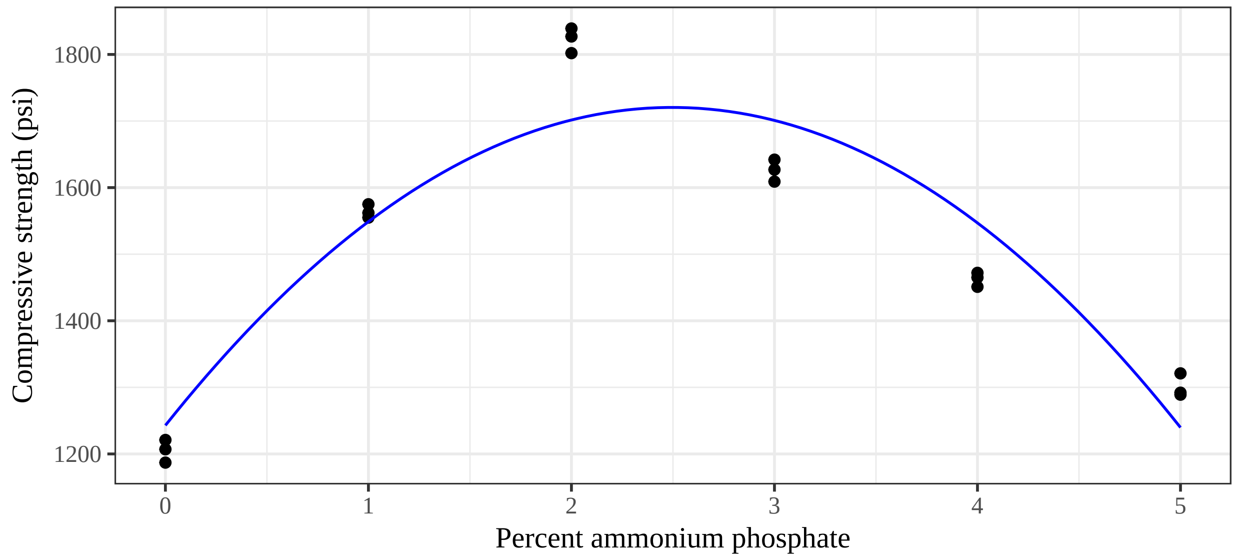
The p coefficients are again estimated using the *principle of least squares*, where the function

$$S(b_0, \ldots, b_{p-1}) = \sum_{i=1}^{n} (y_i - \hat{y})^2 = \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x - \cdots - \beta_{p-1} x^{p-1})^2$$

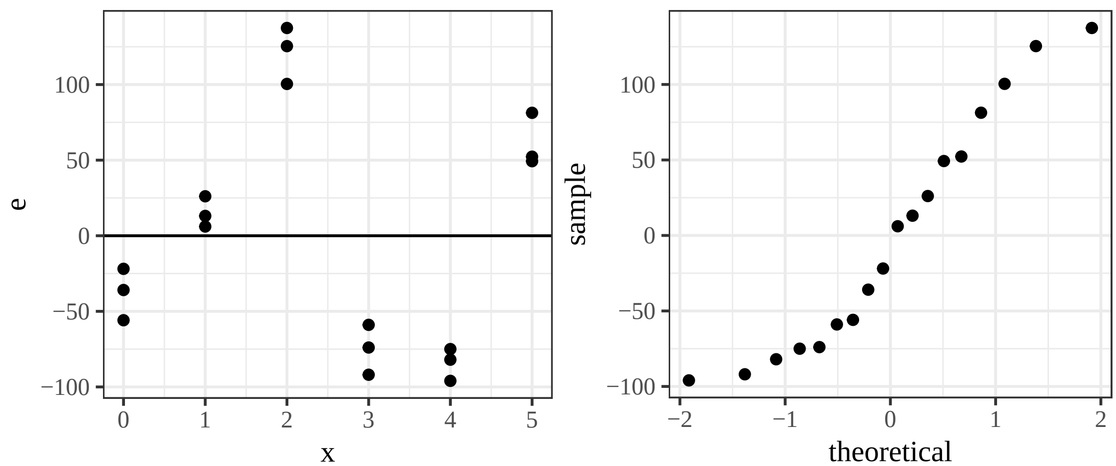
must be minimized to find the estimates $b_0, \ldots, b_{p-1}$.

Example 4.7 (Cylinders, cont'd)**.** The linear fit for the relationship between ammonium phosphate and compressive strength of cylinders was not great ($R^2 = 2.8147436 \times 10^{-5}$). We can fit a quadratic model.

```
Call:
lm(formula = strength ~ ammonium.phosphate + I(ammonium.phosphate^2),
    data = cylinders)

Residuals:
    Min      1Q  Median      3Q     Max
-95.983 -70.193  -7.895  51.548 137.419

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             1242.893     42.982  28.917 1.43e-14 ***
ammonium.phosphate       382.665     40.430   9.465 1.03e-07 ***
I(ammonium.phosphate^2)  -76.661      7.762  -9.877 5.88e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 82.14 on 15 degrees of freedom
Multiple R-squared:  0.8667,    Adjusted R-squared:  0.849
F-statistic: 48.78 on 2 and 15 DF,  p-value: 2.725e-07
```



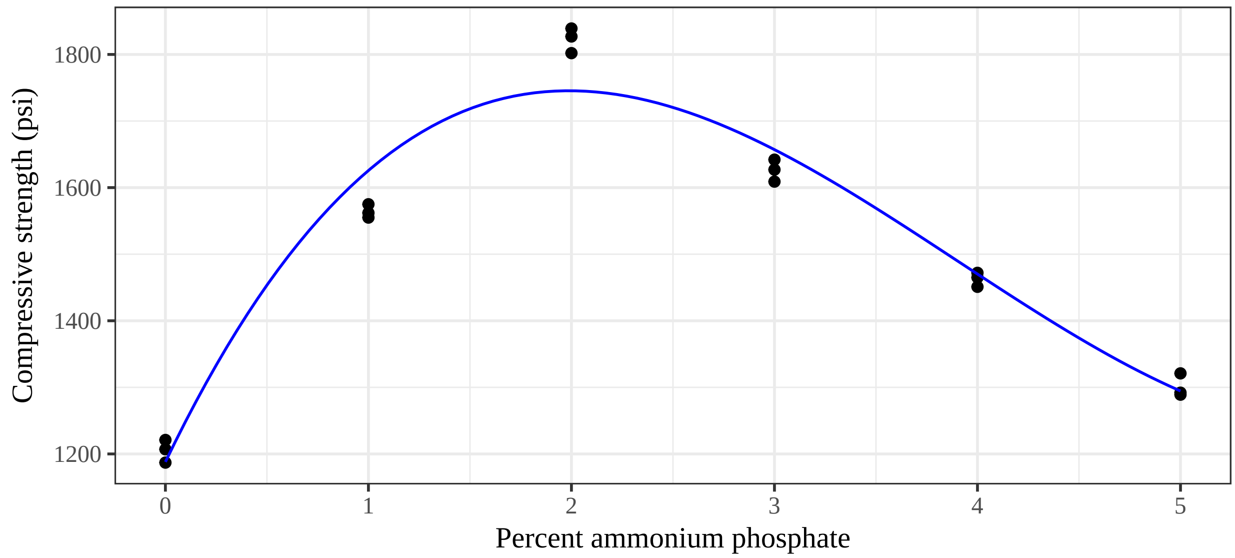
1800
1600
1400
1200
Compressive strength (psi)
0
1
2
3
4
5
Percent ammonium phosphate

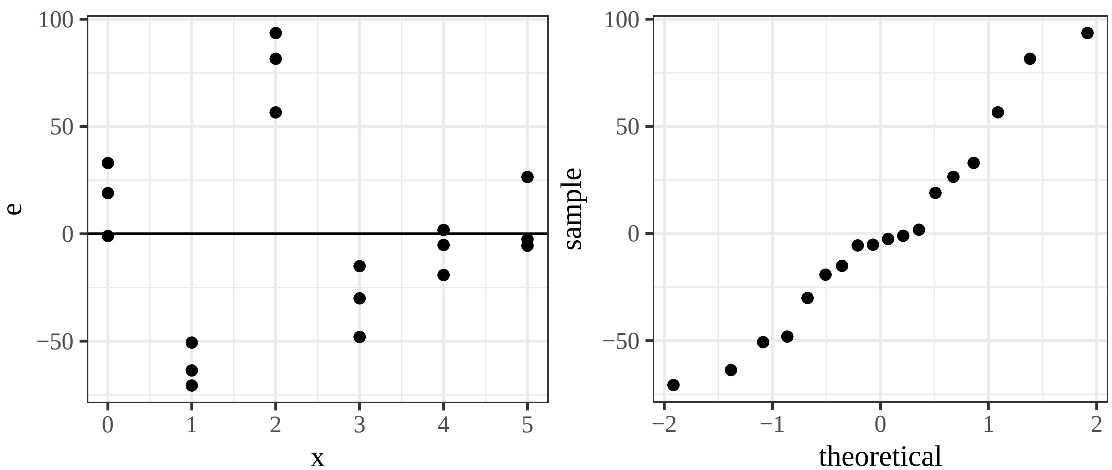


100
50
0
−50
−100
e
0
1
2
3
4
5
x
sample
−2
−1
theoretical

Example 4.8 (Cylinders, cont'd)**.** How about a cubic model.

```
Call:
lm(formula = strength ~ ammonium.phosphate + I(ammonium.phosphate^2) +
    I(ammonium.phosphate^3), data = cylinders)

Residuals:
    Min      1Q  Median      3Q     Max
-70.677 -27.353  -3.874  24.579  93.545

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             1188.050     28.786  41.272 5.03e-16 ***
ammonium.phosphate       633.113     55.913  11.323 1.96e-08 ***
I(ammonium.phosphate^2) -213.767     27.787  -7.693 2.15e-06 ***
I(ammonium.phosphate^3)   18.281      3.649   5.010 0.000191 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 50.88 on 14 degrees of freedom
Multiple R-squared:  0.9523,    Adjusted R-squared:  0.9421
F-statistic: 93.13 on 3 and 14 DF,  p-value: 1.733e-09
```





4.2.2 Multiple regression (surface fitting)