# Linear Regression

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3.1, 3.2, 3.5, 3.6, 3.11, 3.12, 3.13, 3.14

3.1 Describe the null hypotheses to which the p-values given in Table 3.4 correspond. Explain what conclusions you can draw based on these p-values. Your explanation should be phrased in terms of sales, TV, radio, and newspaper, rather than in terms of the coefficients of the linear model.

Answer

$$H0_1:\beta_1=0,\,H0_2:\beta_1=0,\,H0_3:\beta_1=0$$

TV and radio are significant and newspaper is not significant according to the p values, so we reject  $H0_1$  and  $H0_2$  and accept  $H0_3$ . In other wowrd, newspaper do not affect sales.

3.2 Carefully explain the differences between the KNN classifier and KNN regression methods.

#### Answer:

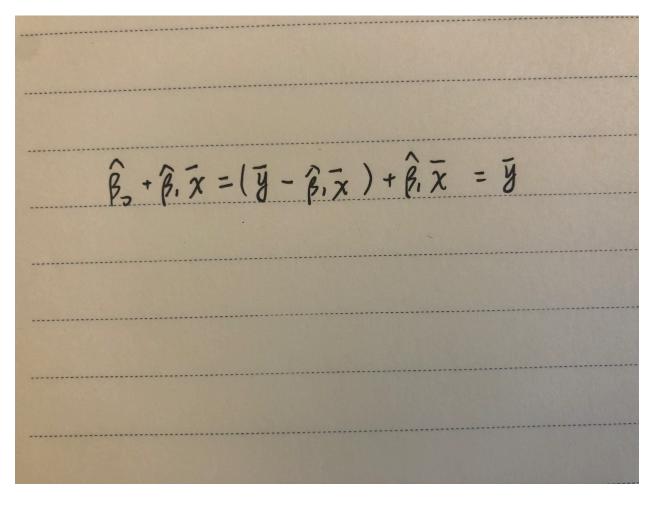
- 1) The KNN classifier: solve classification problems by identifying the neighborhood of  $x_0$  and then estimating the conditional probability  $P(Y=j|X=x_0)$  for class j as the fraction of points in the neighborhood whose response values equal j.
- 2) The KNN regression: solve regression problems by identifying the neighborhood of  $x_0$  and then estimating  $f(x_0)$  as the average of all the training responses in the neighborhood.

3.5

$$\frac{\hat{y}_{i}}{\hat{y}_{i}} = \chi_{i} \frac{\sum_{i=1}^{n} \chi_{i} y_{i}}{\sum_{i=1}^{n} \chi_{k}^{2}} = \frac{n}{2} \frac{\chi_{i} \chi_{j}}{\sum_{i=1}^{n} \chi_{k}^{2}} \frac{\chi_{i} \chi_{j}}{\chi_{k}^{2}}$$

$$\frac{\hat{y}_{i}}{\sum_{i=1}^{n} \chi_{k}^{2}} = \frac{n}{2} \frac{\chi_{i} \chi_{j}}{\chi_{k}^{2}} \frac{\chi_{j}}{\chi_{k}^{2}} \frac{\chi_{j}}{\chi_{k}^{2}} \frac{\chi_{j}}{\chi_{k}^{2}} \frac{\chi_{j}}{\chi_{k}^{2}} \frac{\chi_{j}}{\chi_{k}^{2}} \frac{\chi_{j}}{\chi_{k}^{2}} \frac{\chi_{k}^{2}}{\chi_{k}^{2}} \frac{\chi_{k}^{2}}{\chi$$

3.6 Using (3.4), argue that in the case of simple linear regression, the least squares line always passes through the point (xbar, ybar).



### 3.11

##

In this problem we will investigate the t-statistic for the null hypothesis H0: beta=0 in simple linear regression without an intercept. To begin, we generate a predictor x and a response y as follows.

```
set.seed(1)
x=rnorm(100)
y=2*x+rnorm (100)
fit1 <- lm(y ~x + 0)
summary(fit1)
a.
##
## Call:
## lm(formula = y \sim x + 0)
##
## Residuals:
##
       Min
                1Q Median
                                 ЗQ
                                        Max
## -1.9154 -0.6472 -0.1771 0.5056 2.3109
##
## Coefficients:
```

Estimate Std. Error t value Pr(>|t|)

```
## x 1.9939
                 0.1065 18.73 <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.9586 on 99 degrees of freedom
## Multiple R-squared: 0.7798, Adjusted R-squared: 0.7776
## F-statistic: 350.7 on 1 and 99 DF, p-value: < 2.2e-16
coefficient = 1.9939, standard error = 0.1065, t = 18.73, p-value = 2.2e-16 < 0.05, so we reject H0.
fit2 <- lm(x - y + 0)
summary(fit2)
b.
##
## Call:
## lm(formula = x ~ y + 0)
##
## Residuals:
##
      Min
               1Q Median
                               3Q
## -0.8699 -0.2368 0.1030 0.2858 0.8938
##
## Coefficients:
   Estimate Std. Error t value Pr(>|t|)
## y 0.39111 0.02089
                          18.73 <2e-16 ***
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.4246 on 99 degrees of freedom
## Multiple R-squared: 0.7798, Adjusted R-squared: 0.7776
## F-statistic: 350.7 on 1 and 99 DF, p-value: < 2.2e-16
```

**c.** We obtain the same value for the t-statistic and consequently the same value for the corresponding p-value.

coefficient = 0.39111, the standard error = 0.02089, t = 18.73, p-value = 2.2e-16 < 0.05, so we reject H0.

```
n <- length(x)
t <- sqrt(n - 1)*(x %*% y)/sqrt(sum(x^2) * sum(y^2) - (x %*% y)^2)
as.numeric(t)
d.</pre>
```

## [1] 18.72593

**e.** If we replace  $x_i$  by  $y_i$  in the formula for the t-statistic, the result would be the same.

```
fit3 <- lm(y ~ x)
summary(fit3)</pre>
```

f.

```
##
## Call:
## lm(formula = y \sim x)
##
## Residuals:
##
      Min
               1Q Median
                               3Q
                                      Max
## -1.8768 -0.6138 -0.1395 0.5394 2.3462
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -0.03769
                          0.09699 -0.389
                                             0.698
                          0.10773 18.556
               1.99894
                                            <2e-16 ***
## x
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.9628 on 98 degrees of freedom
## Multiple R-squared: 0.7784, Adjusted R-squared: 0.7762
## F-statistic: 344.3 on 1 and 98 DF, p-value: < 2.2e-16
fit4 <- lm(x ~ y)
summary(fit4)
##
## Call:
## lm(formula = x ~ y)
##
## Residuals:
##
                 1Q Median
## -0.90848 -0.28101 0.06274 0.24570 0.85736
## Coefficients:
              Estimate Std. Error t value Pr(>|t|)
                                             0.365
## (Intercept) 0.03880
                          0.04266
                                     0.91
## y
               0.38942
                          0.02099
                                    18.56
                                            <2e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.4249 on 98 degrees of freedom
## Multiple R-squared: 0.7784, Adjusted R-squared: 0.7762
## F-statistic: 344.3 on 1 and 98 DF, p-value: < 2.2e-16
```

#### 3.12 This problem involves simple linear regression without an intercept.

a.