ISyE 6414 - HW 3

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1

From the scatter plot figure below, it does seem like a simple linear regression model is appropriate here

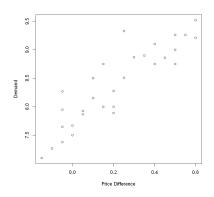


Figure 1: Scatter Plot (Price Difference vs. Demand)

2

I used R to create a linear regression model on the given data. The regression equation is

Demand = 2.665 * PriceDif + 7.814

From the summary of the model:

$$\hat{\beta_0} = 7.814$$

$$\hat{\beta_1} = 2.665$$

$$\hat{\sigma} = 0.3166$$

$$se(\hat{\beta_0}) = 0.0799$$

$$se(\hat{\beta_1}) = 0.2585$$

Figure 2: Linear Model Summary from R

3

$$\alpha = 0.05$$

 $n-2=28$
From the tables, $t_{0.025,28}=2.048$

Confidence interval for
$$\beta_1 = \left(\hat{\beta}_1 - \left(t_{\frac{\alpha}{2}, n-2} \sqrt{\frac{MSE}{S_{xx}}}\right), \hat{\beta}_1 + \left(t_{\frac{\alpha}{2}, n-2} \sqrt{\frac{MSE}{S_{xx}}}\right)\right)$$

$$= (\hat{\beta}_1 - t_{\frac{\alpha}{2}, n-2} se(\hat{\beta}_1), \hat{\beta}_1 + t_{\frac{\alpha}{2}, n-2} se(\hat{\beta}_1))$$

$$= (2.665 - 2.048 * 0.2585, 2.665 + 2.048 * 0.2585)$$

$$= \boxed{(2.136, 3.195)}$$

This means that we can state with 95% confidence, (or probability of 0.95) that the acual value of β_1 will lie within the interval (2.136, 3.195).

4

Let's say our null hypothesis is $H_0: \beta_1 = 0$ and our alternative hypothesis is $H_a: \beta_1 \neq 0$.

$$t - value = \frac{\hat{\beta}_1 - 0}{\sqrt{\hat{\sigma}^2 / S_{xx}}}$$

$$= \frac{\hat{\beta}_1 \sqrt{S_{xx}}}{\hat{\sigma}}$$

$$= \frac{2.665 * \sqrt{1.49967}}{0.3166}$$

$$= 10.30822$$

From the tables, the critical t value = $t_{\frac{alpha}{2},n-2} = t_{0.025,28} = 2.048$.

|t| = 10.308 which is very large compared to the critical t value. Thus, we can reject the null hypothesis. This means that β_1 is statistically significant.

By setting β_1 value (or slope of x) to 0, we are saying that the value of x does not play a role in determining the value of y. We were proven wrong by the hypothesis test, and hence, we now know that the predictor x is statistically significant.

5

From the model summary, the p value (Pr(>|t|)) of the intercept is < 2e - 16, which is very low. This implies that the intercept is statistically significant.

6

From the model summary, the p value (Pr(>|t|)) of β_1 is 4.88e-11, which is very low. Our p value is much smaller than all 3 values of alpha = 0.10, 0.05, 0.005. Hence, H_0 can be rejected. This suggests that y and x are strongly related, and we cannot disregard x's role while trying to estimate y.

7

Using R, we get that the point estimate is 8.0806 and the 95% confidence interval is [7.9479, 8.2133].

8

Using R, we get that the point prediction is 8.0806 and the 95% prediction interval is [7.4187, 8.7425].

The confidence interval half length is 0.1327 and the prediction interval half length is 0.6619. Yes, the prediction interval is wider than the confidence interval as we see from their half lengths.

9

Using R, we get that the point estimate is 8.4803 and the 95% confidence interval is [8.3604, 8.6003]. The half length of this interval is 0.1199.

No, the half length of this interval is not too similar to the half length of the confidence interval for PriceDif = 0.10. The half length of confidence interval for PriceDif = 0.25 is smaller than the half length of the confidence interval for PriceDif = 0.10 as 0.25 is closer to the mean of PriceDif (0.2133). As we move away from the mean, the interval becomes wider.

R codes attached at the end

10

No-intercept model: $y = \beta_1 x + \epsilon$. To minimise $SSE = \sum_{i=1} n(y_i - \hat{y_i})^2$, we have to set $\frac{\partial}{\partial \beta_1}(SSE)$ to 0.

$$\frac{\partial}{\partial \beta_1} (SSE) = 0$$

$$\frac{\partial}{\partial \beta_1} \sum_{i=1}^n n(y_i - \hat{y}_i)^2 = 0$$

$$\frac{\partial}{\partial \beta_1} \sum_{i=1}^n n(y_i - \hat{\beta}_1 x)^2 = 0$$

$$\sum_{i=1}^n 2(y_i - \hat{\beta}_1 x_i)(-x_i) = 0$$

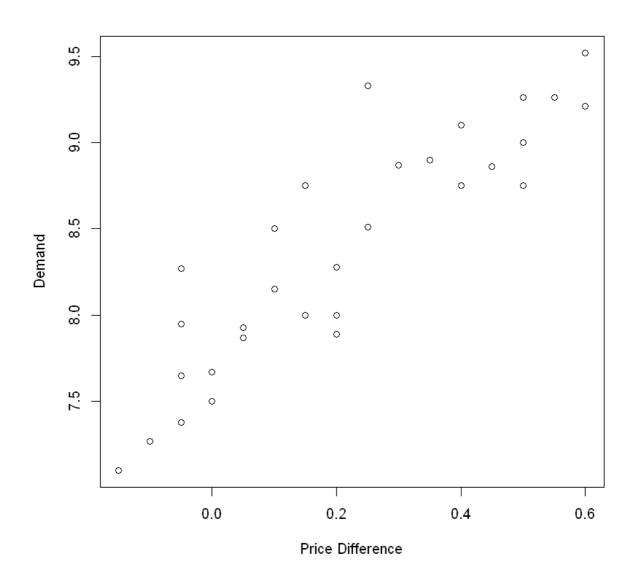
$$\sum_{i=1}^n (\hat{\beta}_1 x_i^2 - x_i y_i) = 0$$

$$\hat{\beta}_1 \sum_{i=1}^n (x_i^2) - \sum_{i=1}^n (x_i y_i) = 0$$

$$\implies \hat{\beta}_1 = \frac{\sum_{i=1}^n x_i y_i}{\sum_{i=1}^n nx_i^2}$$

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```
In [1]:
    data = read.csv('C:/Users/manvi/Documents/GT Acads/Fall 2022/Regression/HW3/6414_HW3
    Demand = data[,1]
    PriceDif = data[,2]
    plot(PriceDif, Demand, xlab = "Price Difference", ylab = "Demand")
```



```
In [2]:
         model = lm(Demand ~ PriceDif)
         summary(model)
        Call:
        lm(formula = Demand ~ PriceDif)
        Residuals:
                            Median
             Min
                       1Q
                                          3Q
                                                  Max
        -0.45713 -0.21121 -0.04898 0.14314 0.84961
        Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
        (Intercept) 7.81409
                                0.07988
                                          97.82 < 2e-16 ***
        PriceDif
                     2.66521
                                0.25850
                                          10.31 4.88e-11 ***
                        0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
        Signif. codes:
```

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```
Residual standard error: 0.3166 on 28 degrees of freedom
         Multiple R-squared: 0.7915,
                                         Adjusted R-squared: 0.7841
         F-statistic: 106.3 on 1 and 28 DF, p-value: 4.881e-11
In [20]:
          new = data.frame(PriceDif = 0.10)
          q7 = predict.lm(model, new, interval = "confidence", level = 0.95)
          q7
               fit
                      lwr
                              upr
         8.080609 7.947878 8.21334
In [21]:
          new = data.frame(PriceDif = 0.10)
          q8 = predict.lm(model, new, interval = "predict", level = 0.95)
          q8
              fit
                      lwr
                             upr
         8.080609 7.418719 8.7425
In [22]:
          new = data.frame(PriceDif = 0.25)
          q9 = predict.lm(model, new, interval = "confidence", level = 0.95)
          q9
              fit
                      lwr
                              upr
         8.480391 8.36042 8.600362
In [49]:
          q7hl = (q7[,'upr'] - q7[,'lwr']) /2
          q7h1
         0.132730642733149
In [50]:
          q8hl = (q8[,'upr'] - q8[,'lwr']) /2
          q8hl
         0.661890519414294
In [51]:
          q9hl = (q9[,'upr'] - q9[,'lwr']) /2
          q9h1
         0.119970889973496
In [48]:
          mean(PriceDif)
         0.2133333333333333
```