HOTEL PRICE PREDICTION REGRESSION MODELS

A Course Project Report

University of Michigan

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4/12/2023

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Chapter 1 Introduction

1.1 Motivation

Japan is one of the most popular choices for traveling. For travelers, they are interested in the cost of traveling. Hostel cost accounts for a large portion of the traveling cost. Therefore, we want to build a prediction model to prediction the hostel price according to traveler's accommodation requirements.

In this study, we are interested in three popular sightseeing cities. They are Tokyo, Kyoto, and Osaka. We aim to build the hostel price prediction model for these three cities (As shown in Figure 1).

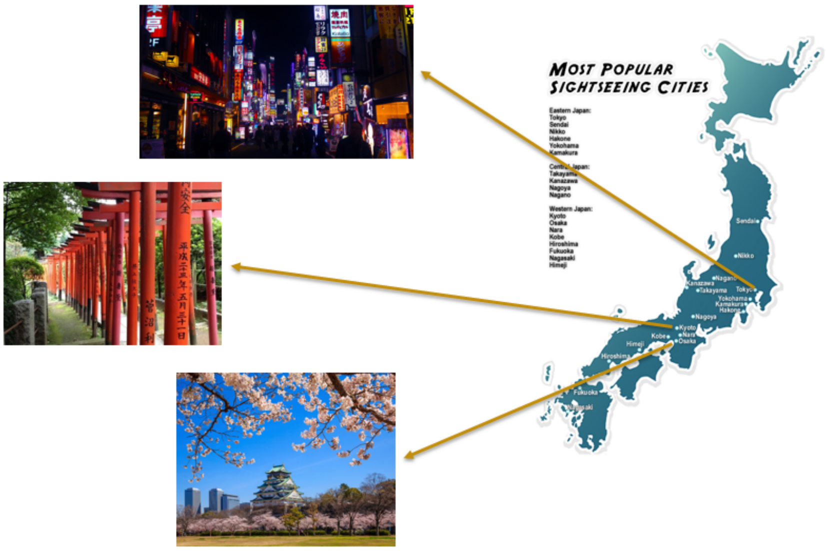


Figure 1

1.2 Data source

The dataset is from Kaggle [18].

Dataset

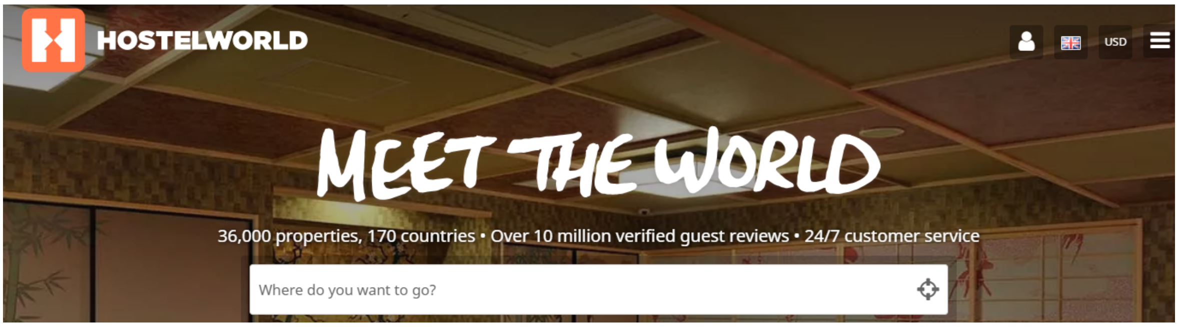
Japan Hostel Dataset

Data for 300+ Hostels in Japan by HostelWorld

Koki Ando • updated 5 months ago (Version 6)

Figure 2

This data is scraped from HostelWorld.com [19].



HOSTELWORLD
USD
MEET THE WORLD
36,000 properties, 170 countries • Over 10 million verified guest reviews • 24/7 customer service
Where do you want to go?

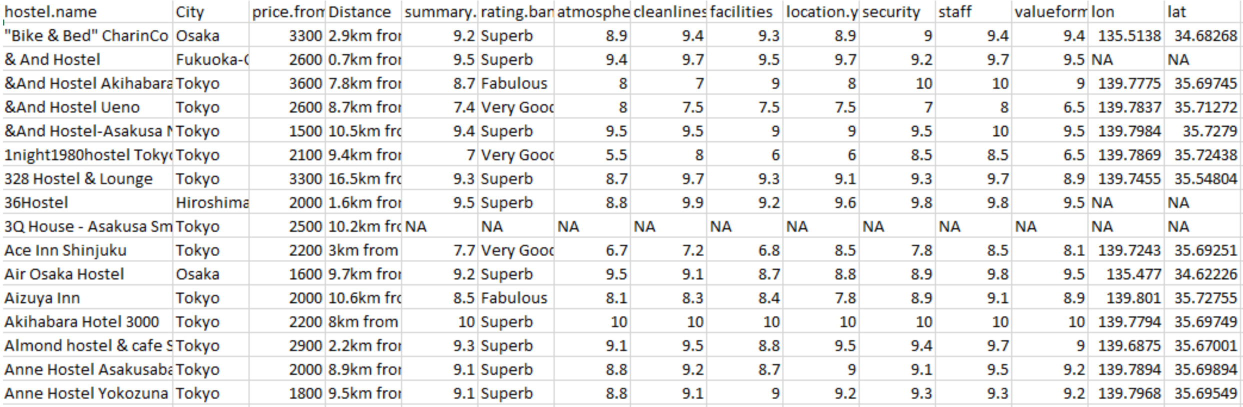
Figure 3

Chapter 2 Methods

2.1 Description of data

2.1.1 Overview of dataset

The original dataset is shown in Figure 4. The dataset contains 342 samples.



hostel.name	City	price.from	Distance	summary.	rating.ban	atmosphe	cleanlines	facilities	location.y	security	staff	valueform	lon	lat
"Bike & Bed" CharinCo	Osaka	3300	2.9km fror	9.2	Superb	8.9	9.4	9.3	8.9	9	9.4	9.4	135.5138	34.68268
& And Hostel	Fukuoka-(	2600	0.7km fror	9.5	Superb	9.4	9.7	9.5	9.7	9.2	9.7	9.5	NA	NA
&And Hostel Akihabara	Tokyo	3600	7.8km fror	8.7	Fabulous	8	7	9	8	10	10	9	139.7775	35.69745
&And Hostel Ueno	Tokyo	2600	8.7km fror	7.4	Very Gooc	8	7.5	7.5	7.5	7	8	6.5	139.7837	35.71272
&And Hostel-Asakusa N	Tokyo	1500	10.5km frc	9.4	Superb	9.5	9.5	9	9	9.5	10	9.5	139.7984	35.7279
1night1980hostel Tokyc	Tokyo	2100	9.4km fror	7	Very Gooc	5.5	8	6	6	8.5	8.5	6.5	139.7869	35.72438
328 Hostel & Lounge	Tokyo	3300	16.5km frc	9.3	Superb	8.7	9.7	9.3	9.1	9.3	9.7	8.9	139.7455	35.54804
36Hostel	Hiroshima	2000	1.6km fror	9.5	Superb	8.8	9.9	9.2	9.6	9.8	9.8	9.5	NA	NA
3Q House - Asakusa Sm	Tokyo	2500	10.2km frc	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Ace Inn Shinjuku	Tokyo	2200	3km from	7.7	Very Gooc	6.7	7.2	6.8	8.5	7.8	8.5	8.1	139.7243	35.69251
Air Osaka Hostel	Osaka	1600	9.7km fror	9.2	Superb	9.5	9.1	8.7	8.8	8.9	9.8	9.5	135.477	34.62226
Aizuya Inn	Tokyo	2000	10.6km frc	8.5	Fabulous	8.1	8.3	8.4	7.8	8.9	9.1	8.9	139.801	35.72755
Akihabara Hotel 3000	Tokyo	2200	8km from	10	Superb	10	10	10	10	10	10	10	139.7794	35.69749
Almond hostel & cafe S	Tokyo	2900	2.2km fror	9.3	Superb	9.1	9.5	8.8	9.5	9.4	9.7	9	139.6875	35.67001
Anne Hostel Asakusaba	Tokyo	2000	8.9km fror	9.1	Superb	8.8	9.2	8.7	9	9.1	9.5	9.2	139.7894	35.69894
Anne Hostel Yokozuna	Tokyo	1800	9.5km fror	9.1	Superb	8.8	9.1	9	9.2	9.3	9.3	9.2	139.7968	35.69549

Figure 4

The respond variable is hostel’s minimum price for 1-night stay.

The explanatory variables are show as below:

- Distance
- Atmosphere
- Cleanliness
- Facilities
- Location
- Security
- Staff
- 2 indicators (Tokyo, Osaka, Kyoto).

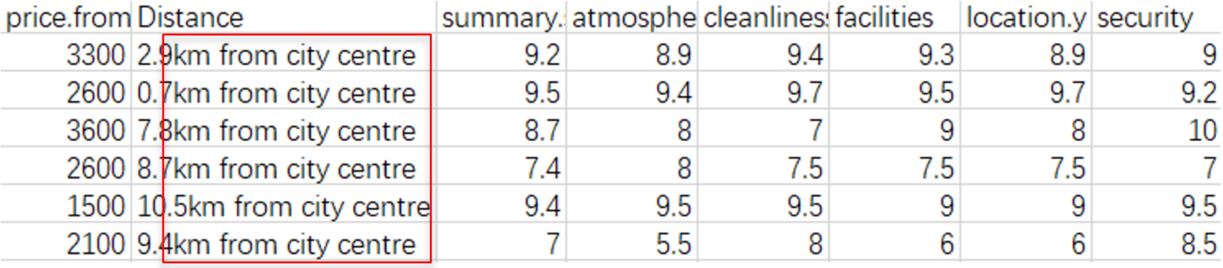
We divide these explanatory variables into three categories. The first category is the distance. The distance represents the distance between the hostel and the center of the city. The second category of the explanatory variable is the rating score from customers. The rating scores include atmosphere, cleanliness, facilities, location, security, staff. The last category of the explanatory variable is indicator. There are 2 indicators because we have three cities in the dataset (Tokyo, Osaka, Kyoto).

2.1.2 Data processing

After we got dataset, we used the following method to process the data:

- Delete useless characters:

An example of the useless characters are shown in Figure 5. In this case, we deleted characters in the red box.

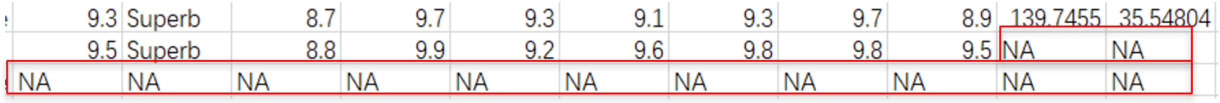


price.from	Distance	summary.	atmosphe	cleanlines	facilities	location.y	security
3300	2.9km from city centre	9.2	8.9	9.4	9.3	8.9	9
2600	0.7km from city centre	9.5	9.4	9.7	9.5	9.7	9.2
3600	7.8km from city centre	8.7	8	7	9	8	10
2600	8.7km from city centre	7.4	8	7.5	7.5	7.5	7
1500	10.5km from city centre	9.4	9.5	9.5	9	9	9.5
2100	9.4km from city centre	7	5.5	8	6	6	8.5

Figure 5

- Delete incomplete samples:

An example of incomplete sample in dataset is shown in Figure 6. We deleted all the samples that contain the incomplete data (in the red box).



9.3	Superb	8.7	9.7	9.3	9.1	9.3	9.7	8.9	139.7455	35.54804
9.5	Superb	8.8	9.9	9.2	9.6	9.8	9.8	9.5	NA	NA
NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Figure 6

- Standardization:

Since later we will introduce high-order terms in our prediction model. In order to reduce multi-collinearity issue, we use standardization to process the data.

2.2 Preliminary exploratory analyses

In this project, we first consider a first order linear model, which is composed of the first order terms of nine predictor variables. The first order model is presented as follows.

$$\text{Price} \sim \text{Distance} + \text{atmosphere} + \text{cleanliness} + \text{facilities} + \text{location} + \text{security} + \text{staff} + \mathrm{x}_1 + x_2$$

where x_1 and x_2 are two indicator variables to represent the three cities in the categorical variable. Based on this first order linear model, the residual plots can be given in *Figure 7*. It is quite obvious from the residual plots that the quadratic pattern exist for the first four predictor variables.

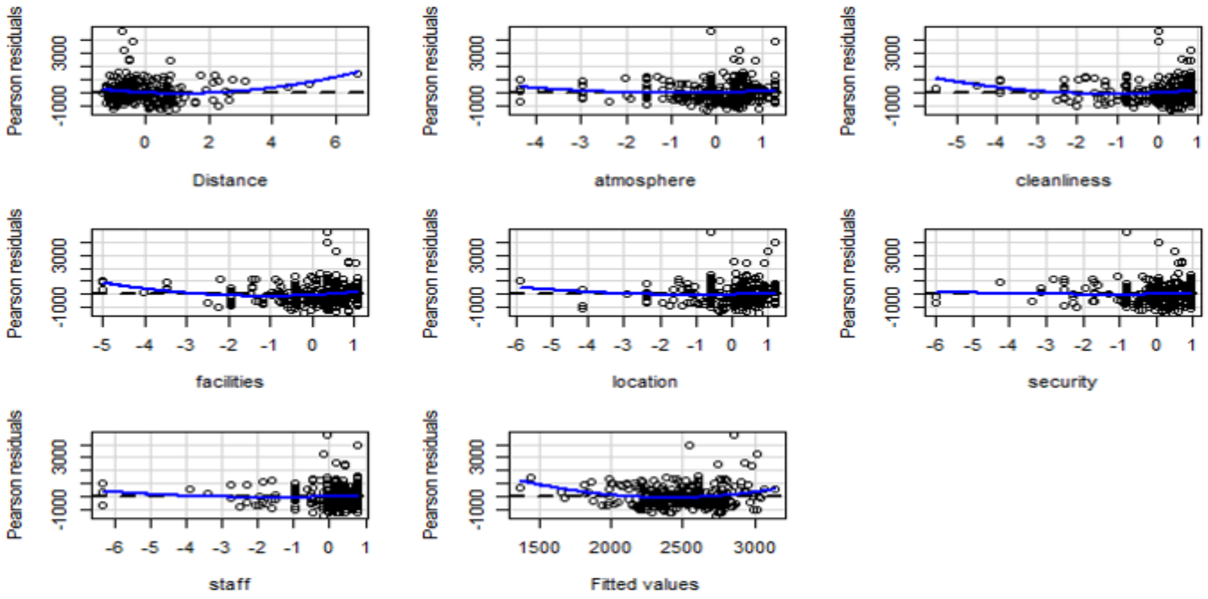


Figure 7. Residual plots for the first order linear regression model.

Since the quadratic pattern is clearly observed from the residual plots, it is necessary to check the sources which contributes to this quadratic pattern. First, we suspect that the quadratic pattern is created by the outlier data points out of the range of the data kernel. After the deletion of those outliers in the original data set, the residual plots are generated again, in which the quadratic pattern still exists. Therefore, it is straightforward to add the quadratic term of the first four predictor variables and raise the linear regression model to second order. The new regression formula is given by

$$\text{Price} \sim \text{Distance} + \text{Distance}^2 + \text{atmosphere} + \text{atmosphere}^2 + \text{cleanliness} + \text{cleanliness}^2 + \text{facilities} + \text{facilities}^2 + \text{location} + \text{security} + \text{staff} + \mathrm{x}_1 + x_2$$

2.3 Check model assumptions

Even though the second order linear regression model eliminate the quadratic patter in the scatter plot, this model still needs to be diagnosed to check the assumptions on the error terms. In the standard linear regression model, the error terms are assumed to be independently identically distributed with normal distribution $N(0, \sigma^2)$. From *Figure 7*, it is easily to see that the error terms do not have constant variance, since the distribution of the data points is not approximately symmetrical to the zero horizontal line.

Besides that, the probability plot and the Brown-Forsythe test are given in Figure 8 and *Figure 9*. It can be implied from these plots and arguments that the error terms are not normally distributed and the error terms do not have constant variance.

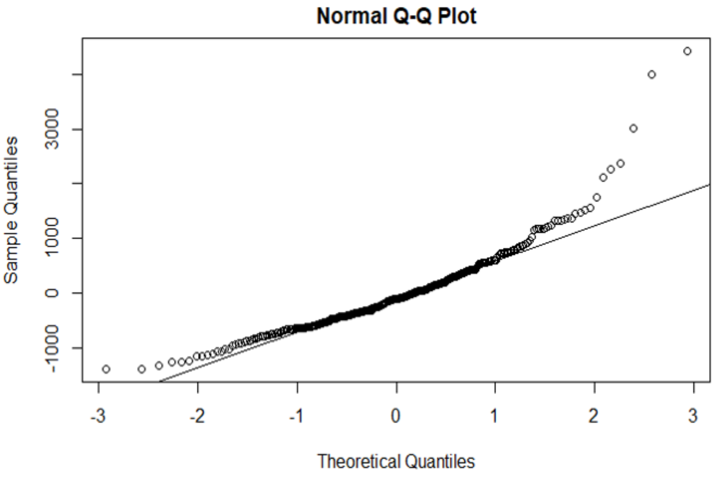
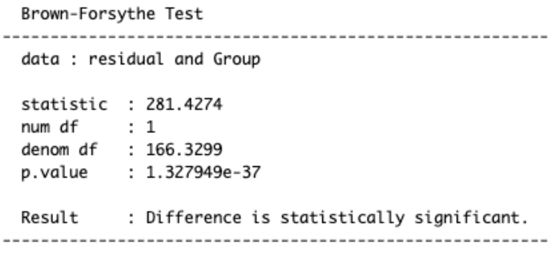


Figure 8. Probability plot for the second order model.



```
  Brown-Forsythe Test
---------------------------------------------------------
  data : residual and Group

  statistic  : 281.4274
  num df     : 1
  denom df   : 166.3299
  p.value    : 1.327949e-37

  Result     : Difference is statistically significant.
---------------------------------------------------------
```

Figure 9. Brown-Forsythe test for the second order model.

The diagnostic of the second order linear model shows that the necessity to take measures to remedy the non-normality and the non-constant variance issues caused by the error terms. Our first step is to apply the transformation techniques on the response variable Price, since the non-constancy of the variance may be resolved after the transformation. The Box-Cox transformation is adopted. Since $\lambda = 0$ is in the confidence interval in Figure 10, we choose to take log transform first to see the result.

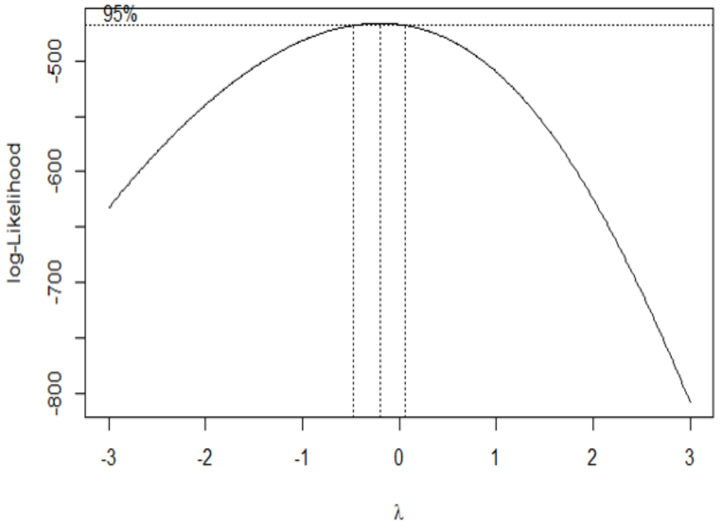


Figure 10. Box-Cox transformation.

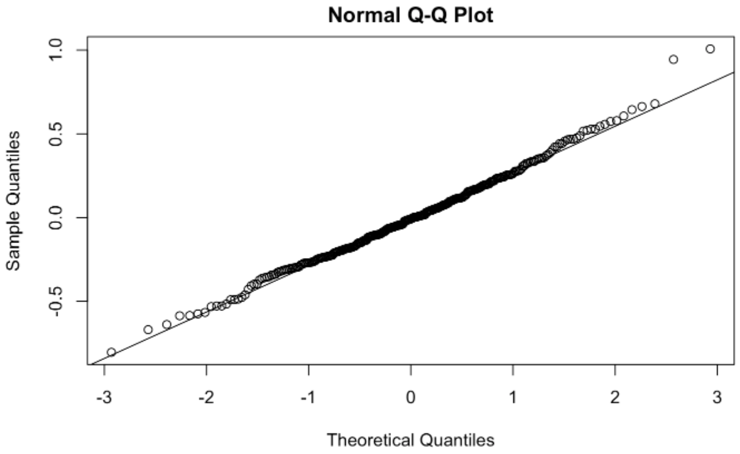


Figure 11. The probability for the transformed model.

2.4 Model building process

In previous study, we find transform Y can fix normality issue, but we still don’t have constant variance. Based on what we’ve learned, we choose to apply weighted regression to build a proper model.

2.4.1 Weighted linear regression

- Model predictor selection

Since the model selection method is majorly based on unweighted model, we choose to select predictors for this case. After that, we can use selected predictors for the weighted case.
We first consider model without interaction term. Since the predictor size is small, we can try both stepwise (based on PRESS, since we want to predict the hostel price) and best subset (based on AIC by default). It gives us:

$$\ln(Price) \sim Distance + clieanliness + staff + Distance^2 + facilities^2 + x1 + x2$$

Then we also want to model the different effect of predictors for different city, so we added 22 interaction terms and applied stepwise function (too many predictors for best subset) to find the predictors for the regression.

$$\ln(Price) \sim Distance + clieanliness + staff + Distance^2 + facilities^2 + x1 + x2 \\ + x2{:}Distance + x2{:}Distance^2$$

- Weight function selection

After selecting the predictors, one last thing we need to consider is how we model the weight function. For this purpose, we plot the residual vs. predictors to see the pattern of the residual.

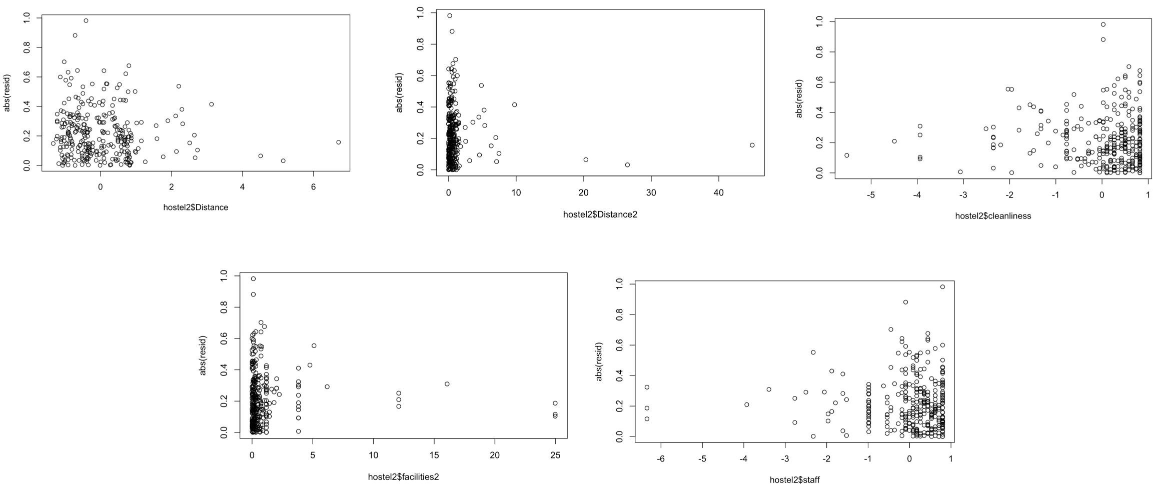


Figure 12 Residual vs. predictors

Base on the residual pattern, we choose to fit the standard deviation $\sigma_i = X_i\gamma$. The weight would be $\mathrm{w_i} = 1/\sigma_i$.

After selecting predictor as well as weight function, we can start building this weighted linear regression model.

2.4.2 Weighted ridge regression

In weighted ridge regression, we pick all the predictors as well as two interaction terms we selected in the previous terms to build our model.

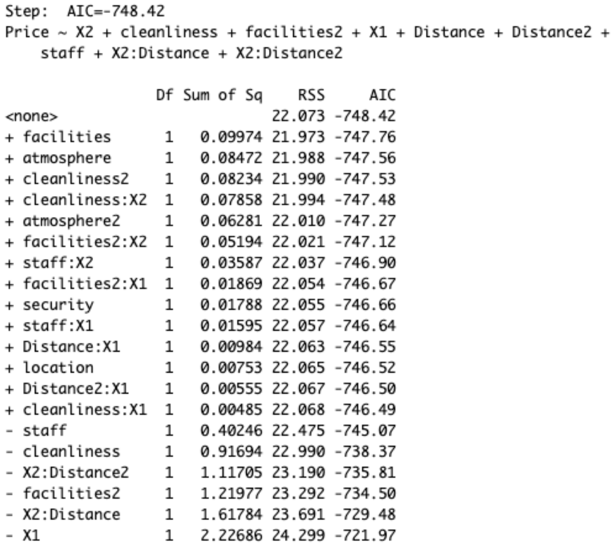
We use GCV to choose a suitable λ, and apply weighted ridge regression to build another model.

Chapter 3 Results

3.1 Weighted linear regression

3.1.1 Final model

In chapter 2, the way we select predictors is stepwise, which is mainly trying to find the smallest AIC model.



```
Step:  AIC=-748.42
Price ~ X2 + cleanliness + facilities2 + X1 + Distance + Distance2 +
    staff + X2:Distance + X2:Distance2

                 Df Sum of Sq    RSS     AIC
<none>                        22.073 -748.42
+ facilities      1   0.09974 21.973 -747.76
+ atmosphere      1   0.08472 21.988 -747.56
+ cleanliness2    1   0.08234 21.990 -747.53
+ cleanliness:X2  1   0.07858 21.994 -747.48
+ atmosphere2     1   0.06281 22.010 -747.27
+ facilities2:X2  1   0.05194 22.021 -747.12
+ staff:X2        1   0.03587 22.037 -746.90
+ facilities2:X1  1   0.01869 22.054 -746.67
+ security        1   0.01788 22.055 -746.66
+ staff:X1        1   0.01595 22.057 -746.64
+ Distance:X1     1   0.00984 22.063 -746.55
+ location        1   0.00753 22.065 -746.52
+ Distance2:X1    1   0.00555 22.067 -746.50
+ cleanliness:X1  1   0.00485 22.068 -746.49
- staff           1   0.40246 22.475 -745.07
- cleanliness     1   0.91694 22.990 -738.37
- X2:Distance2    1   1.11705 23.190 -735.81
- facilities2     1   1.21977 23.292 -734.50
- X2:Distance     1   1.61784 23.691 -729.48
- X1              1   2.22686 24.299 -721.97
```

Figure 13 Result of stepwise function

We've decided how to choose predictors and weight function, we can fit the model.

$$\ln(Price) \sim Distance + clieanliness + staff + Distance^2 + facilities^2 + x1 + x2 \\ + x2{:}\, Distance + x2{:}\, Distance^2$$

	Regression Model		Difference(%)
	Weighted	Unweighted	
(Intercept)	7.8891	7.8927	0.046
Distance	-0.1899	-0.1973	3.897
Distance2	0.0362	0.0375	3.591
cleanliness	0.0857	0.0824	3.851
facilities2	0.0299	0.0305	2.007
staff	0.0458	0.0507	10.699
X1TRUE	-0.2218	-0.2279	2.750
X2TRUE	-0.0835	-0.1171	40.240
Distance:X2TRUE	0.3801	0.3614	4.920
Distance2:X2TRUE	-0.0863	-0.0801	7.184

Figure 14 Comparison between weighted and unweighted model

We can see that the weighted regression has almost same coefficient as the unweighted one which also support that we can select predictors based on the unweighted linear regression model.

3.1.2 Simple analysis of the model

- Normality

Since we use different predictors as the initial model, we can recheck on our normality issue.

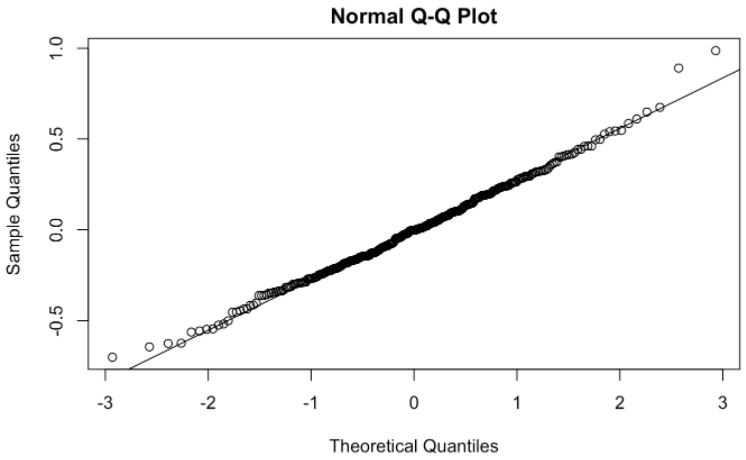


Figure 15 Q-Q plot for weighted linear regression

Besides, Shapiro-Wilk normality test also gives a p-value = 0.3665 which shows the residual is normal.

- Residual

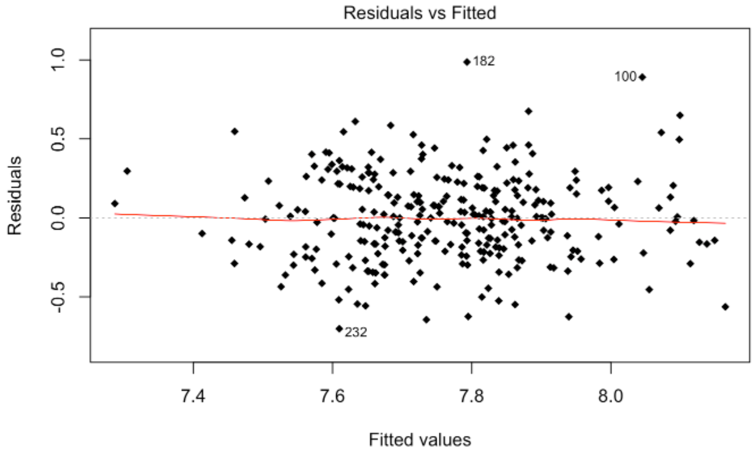


Figure 16 Residual vs. fitted values for weighted linear regression

We can see that the mean value of residual is fairly close to zero which is nice.

- Outliers and influential points

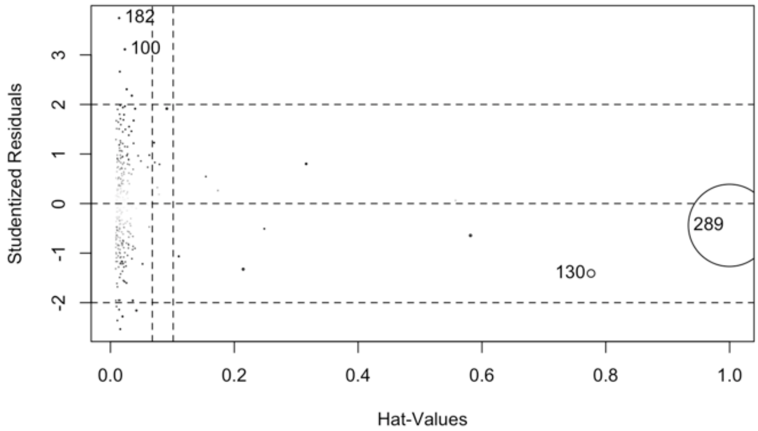


Figure 17 Influence plot of the weighted model

From the figure, we can see that no absolute value of studentized residual is larger than $qt\left(1-\frac{\alpha}{2}, n-1-p\right) = 3.81$ which means we don't have outliers in Y.

But we do have some outliers in X and some influential point which may effects the model selection step.

In order to check the influence of them, we exclude 289, 130 data, the initial residual plot still support us to include higher order terms and the result is similar.

3.2 Weighted ridge regression

In weighted ridge regression [4], we picked the following predictors:

- Distance, atmosphere, cleanliness, facilities, location, security, staff
- Distance^2 , atmosphere^2, cleanliness^2, facilities^2
- X1 + X2
- X2:Distance + X2:Distance

The lambda is chosen from 0 to 20 with step size 0.01.

We obtained the following output for the model selection.

- Modified HKB estimator is 6.976383
- Modified L-W estimator is 41.48205
- Smallest value of GCV at 4.41

As the prediction is needed for our work, we pick the best lambda 4.41 based on GCV.

Chapter 4 Discussion

4.1 Model comparison

5-fold cross validation is applied to compare the models. The details are shown in table 1.

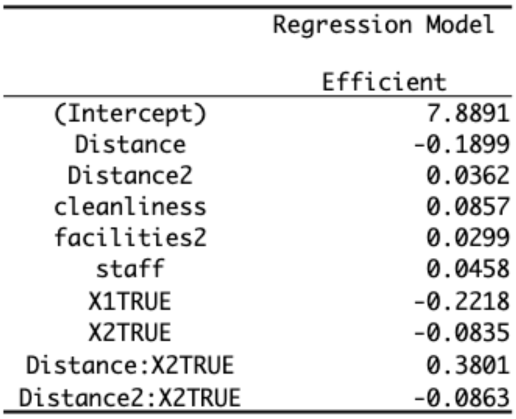
Table1. Results of cross validation for two models

Model	Mean Absolute Error
Weighted Linear Regression	0.22
Weighted Ridge Regression	0.25

As shown in the cross-validation table, MAE of weighted linear regression is close but slightly lower than that of the weighted ridge regression. Given that the weighted linear regression contains fewer predictors, we prefer the weighted linear regression to the weighted ridge regression.

4.2 Conclusion

The coefficients of the selected model are shown as below with the box-cox transformation formula $Y' = e^{Y}$.



```
                        Regression Model

                           Efficient
     (Intercept)                7.8891
       Distance                -0.1899
       Distance2                0.0362
      cleanliness               0.0857
      facilities2               0.0299
         staff                  0.0458
        X1TRUE                 -0.2218
        X2TRUE                 -0.0835
    Distance:X2TRUE             0.3801
   Distance2:X2TRUE            -0.0863
```

From the model coefficients, we could see different ratings have similar effects on three different cities. (cleanliness, facilities, staff, etc.) And distance has similar effect on Tokyo, Osaka, however, the influence of distance is different in Kyoto.

The first impression the coefficient of cleanliness suggests the negativity relationship of cleanliness and the response variable in the model which might be against the intuition. It indeed is positive related to the response variable after the backwards transformation of the response variable.

For influential points, we also tried remove the influential points, however, new influential points emerged, and the result of model selection remains same. In terms of this situation, we decided not to remove the influential points. Future research for regression analysis could resort to fractional calculus [1]-[3], which is a novel tool for extracting intermediate or transient behaviors of two consecutive integer-order regression models. The combination of fractional calculus has been found widely applied in engineering and technology domains [5]-[17].

Chapter 5 Reference

[1] F. Bu, Y. Cai, and Y. Yang, "Multiple object tracking based on faster-RCNN detector and KCF tracker," *Technical Report*, 2016. [Online]. Available: https://pdfs.semanticscholar.org

[2] E. Treadway, Y. Yang, and R. B. Gillespie, "Decomposing the performance of admittance and series elastic haptic rendering architectures," in *2017 IEEE World Haptics Conference (WHC)*, June 2017, pp. 346-351.

[3] Y. Yang and H. H. Zhang, "Stability study of LQR and pole-placement genetic algorithm synthesized input-output feedback linearization controllers for a rotary inverted pendulum system," *International Journal of Engineering Innovations and Research*, vol. 7, no. 1, pp. 62-68, 2018.

[4] P. W. Holland, Weighted Ridge Regression: Combining Ridge and Robust Regression Methods, the national bureau of economic research. DOI: 10.3386/w0011

[5] Y. Yang and H. H. Zhang, *Preliminary Tools of Fractional Calculus*, in *Fractional Calculus with its Applications in Engineering and Technology*, Cham: Springer International Publishing, 2019, pp. 3-42.

[6] Y. Yang and H. H. Zhang, *Fractional-Order Controller Design*, in *Fractional Calculus with its Applications in Engineering and Technology*, Cham: Springer International Publishing, 2019, pp. 43-65.

[7] Y. Yang and H. H. Zhang, *Control Applications in Engineering and Technology*, in *Fractional Calculus with its Applications in Engineering and Technology*, Cham: Springer International Publishing, 2019, pp. 67-89.

[8] Y. Yang, H. H. Zhang, and R. M. Voyles, "Rotary inverted pendulum system tracking and stability control based on input-output feedback linearization and PSO-optimized fractional order PID controller," in *Automatic Control, Mechatronics and Industrial Engineering*, CRC Press, 2019, pp. 79-84.

[9] Y. Yang, H. H. Zhang, W. Yu, and L. Tan, "Optimal design of discrete-time fractional-order PID controller for idle speed control of an IC engine," *International Journal of Powertrains*, vol. 9, nos. 1-2, pp. 79-97, 2020.

[10] Y. Yang, R. A. Nawrocki, R. M. Voyles, and H. H. Zhang, "Modeling of the electrical characteristics of an organic field effect transistor in presence of the bending effects," *Organic Electronics*, vol. 88, 106000, 2021.

[11] Y. Yang, "Electromechanical Characterization of Organic Field-Effect Transistors with Generalized Solid-State and Fractional Drift-Diffusion Models," Doctoral dissertation, Purdue University, 2021.

[12] Y. Yang, R. A. Nawrocki, R. M. Voyles, and H. H. Zhang, "A Fractional Drift Diffusion Model for Organic Semiconductor Devices," *Computers, Materials & Continua*, vol. 69, no. 1, 2021.

[13] Y. Yang, H. Bai, R. Nawrocki, R. Voyles, and H. Zhang, "Fractional drift-diffusion model of organic field effect transistors including effects of bending stress for smart materials," in *Smart Materials, Adaptive Structures and Intelligent Systems*, Vol. 85499, American Society of Mechanical Engineers, September 2021, p. V001T02A013.

[14] Y. Yang and H. H. Zhang, *Fractional Calculus with its Applications in Engineering and Technology*, Morgan & Claypool Publishers, 2019.

[15] Y. Yang and H. H. Zhang, "Optimal model reference adaptive fractional-order proportional integral derivative control of idle speed system under varying disturbances," *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 09596518241266670, 2024.

[16] Y. Yang, C. Bartolozzi, H. H. Zhang, and R. A. Nawrocki, "Neuromorphic electronics for robotic perception, navigation and control: A survey," *Engineering Applications of Artificial Intelligence*, vol. 126, 106838, 2023.

[17] Y. Yang, R. M. Voyles, H. H. Zhang, and R. A. Nawrocki, "Fractional-order spike-timing-dependent gradient descent for multi-layer spiking neural networks," *Neurocomputing*, vol. 611, 128662, 2025.

[18] https://www.kaggle.com/koki25ando/hostel-world-dataset/home

[19] https://www.hostelworld.com

Chapter 6 Appendix A: Code

— Appendix A should provide a complete, organized R program that generates all of the plots, diagnostics, models, and outputs referenced in the report. It should be sufficiently commented to make it easy to find relevant parts of the code.

~~~
```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = TRUE)
```
~~~

Read and rearrange the data

~~~
```{r, warning=FALSE}
library(stringr) # install stringr for number extraction

hostel <- read.csv('/Users/sgch/Desktop/STAT 512/Project/Hostel.csv', header=T)
~~~

~~~~
hostel <- subset(hostel, select = -c(1,2,6,7,14,15,16)) # remove old index column, and hostel name column
hostel <- na.omit(hostel) # remove rows that contain one or more NAs

# rapply(hostel, function(x) length(unique(x))) # number of unique values in each column
# table(hostel$City) # city count
hostel <- subset(hostel, City %in% c('Kyoto', 'Osaka', 'Tokyo') ) # get hostels from 'Kyoto', 'Osaka', 'Tokyo'
hostel$X1 <- hostel$City == "Osaka";
hostel$X2 <- hostel$City == "Kyoto";

# distance: extract distance from string and convert it from str type to int
# e.g. 5.9km from city centre -> 5.9
hostel[3] <- rapply(hostel[3], function(x) as.numeric( sub("km from city centre", "", x)) )

rownames(hostel) <- 1:nrow(hostel) # reindex
#hostel

colnames(hostel) <- c("City", "Price", "Distance", "atmosphere", "cleanliness", "facilities", "location", "security", "staff", "X1", "X2")
hostel <- hostel[,c("Price", "Distance", "atmosphere", "cleanliness", "facilities", "location", "security", "staff", "X1", "X2", "City")]
hostel <- subset(hostel, select = -c(11))


# Standardize variables
for (i in 2:8){
  hostel[,i] = (hostel[,i]-mean(hostel[,i]))/sd(hostel[,i])
}
```
~~~~

Remove outliers and fit the model

Pre plot and check the issues

~~~~
```{r}
# plot(hostel)
# cor(hostel[,1:8])
hostel.mod <- lm(Price~., hostel)

summary(hostel.mod)
```
~~~~

Simply dignostic nonlinear, constant variance and normal variance issues.

~~~~
```{r}
# residual plot
library(car)
residualPlots(hostel.mod, smooth = FALSE)
```
```{r}
# Add higher order terms
hostel1.mod <-
lm(Price~Distance+I(Distance^2)+atmosphere+I(atmosphere^2)+cleanliness+I(cleanliness^2)+f
acilities+I(facilities^2)+location+security+staff+X1+X2,hostel)

summary(hostel1.mod)
```
```{r}
# resid = residuals(hostel1.mod)
#
# # Constant variance
# library(onewaytests)
# hostel$Group <- cut(hostel$Price,2)
# hostel$residual <- hostel1.mod$residuals
# bf.test(residual~Group, hostel)
#
# # Normality
# shapiro.test(resid)
# qqnorm(resid)
# qqline(resid)
```




```{r}
# Transform Y
library(MASS)
bcmle <- boxcox(hostel1.mod, lambda=seq(-3,3,by=0.01))
lambda <- bcmle$x[which.max(bcmle$y)]
hostel2 = hostel;
hostel2$Distance2 = hostel$Distance^2
hostel2$atmosphere2 = hostel$atmosphere^2
~~~~

~~~
hostel2$cleanliness2 = hostel$cleanliness^2
hostel2$facilities2 = hostel$facilities^2

hostel2$Price = hostel$Price^lambda;
hostel2.mod <-
lm(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2,hostel2);
summary(hostel2.mod)
lambda
```

```{r}
resid = residuals(hostel2.mod)

# Constant variance
library(onewaytests)
hostel2$Group <- cut(hostel2$Price,2)
hostel2$residual <- hostel2.mod$residuals
bf.test(residual~Group, hostel2)
hostel2 <- subset(hostel2, select = -c(15,16))
# Normality
shapiro.test(resid)
qqnorm(resid)
qqline(resid)
```

Model selection
Assume indicator only effect intercept
```{r}
library(stats)
step(lm(Price~1,data = hostel2), scope=~
Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2, method = "both")
```
```{r}
library(ALSM)
library(leaps)
BestSub(hostel2[,2:14], hostel2$Price, num = 1)
```
~~~

Based on the stepwise as well as PRESSp from bestsub method, we choose the model with 7 different parameters which includes 2 different indicators.

stepwise - Get a better model
BestSub - Get smallest PRESSp for prediction

Pay more attention to indicator terms
Add more terms to consider the effect of indicator

~~~
```{r}
step(lm(Price~1,data = hostel2), scope=~
Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X1*Distance+X1*Distance2+X1*atmosphere+X1*atmosphere2+X1*cleanliness+X1*cleanliness2+X1*facilities+X1*facilities2+X1*location+X1*security+X1*staff+X2*Distance+X2*Distance2+X2*atmosphere+X2*atmosphere2+X2*cleanliness+X2*cleanliness2+X2*facilities+X2*facilities2+X2*location+X2*security+X2*staff, method =
"both")

ori.mod=lm(formula = Price ~ X2 + cleanliness + facilities2 + X1 + Distance +
    Distance2 + facilities + staff + X2:Distance + X2:Distance2,
    data = hostel2)

```
~~~

Since we solve the normality issue, we can use weighted regression to deal with the unconstant variance issue.

~~~
```{r}
hostel3.mod <-
lm(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+X2*Distance2,hostel2);
summary(hostel3.mod)
resid = residuals(hostel3.mod)

wts1 <-
1/fitted(lm(abs(resid)~hostel2$Distance+hostel2$Distance2+hostel2$cleanliness+hostel2$facilities2+hostel2$staff+hostel2$X1+hostel2$X2+hostel2$X2*hostel2$Distance+hostel2$X2*hostel2$Distance2))^2
hostel.weight<-
lm(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+X2*Distance2, data = hostel2, weights = wts1)
summary(hostel.weight)
~~~

~~~
You can consider whether we can drop variable Staff?
** T value for weighted regression doesn't make sense.

Also we can analysis the multicolinearity issue based on VIF here, to show why we can drop other variables, they are trival or have linear relationship with other variables.


Influential point & Outliers
```{r}
alpha = 0.05
p = 9
n = 296
qt(1-alpha/2/n,n-1-p)
library(car)
influencePlot(hostel.weight)
plot(hostel.weight,pch = 18, col = "red", which = c(4))
plot(hostel.weight,pch = 18,which = c(1))
hostel.unweight<-lm(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+X2*Distance2, data = hostel2)
plot(hostel.unweight,pch = 18,which = c(1))
# axis(side=1,at=seq(0.195,0.235,0.005),lwd=3)
#plot(ori.mod)
~~~
No outliers in Y, some outliers in X. Can apply another window to cancel the influence of outerlier x.
```{r}
resid = residuals(hostel.weight)


# Normality
shapiro.test(resid)
qqnorm(resid)
qqline(resid)
```
```{r}
library(fmsb)
VIF(lm(staff~Distance+Distance2+cleanliness+facilities2+X2+X1+X2:Distance+X2:Distance2, data = hostel2))
```

Directly apply rigid regression (Ignore multicollinearity issue)

~~~
```{r}
library(MASS)
library(car)
library(leaps)
library(caret)
library(ggplot2)
library(lmridge)
# For prediction, chosse lambda
mod <- lmridge(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2,hostel2, lambda = seq(0,20,0.01))
resid = residuals(mod)

#mod1 = lm.ridge(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X1*Distance+X1*Distance2+X1*atmosphere+X1*atmosphere2+X1*cleanliness+X1*cleanliness2+X1*facilities+X1*facilities2+X1*location+X1*security+X1*staff+X2*Distance+X2*Distance2+X2*atmosphere+X2*atmosphere2+X2*cleanliness+X2*cleanliness2+X2*facilities+X2*facilities2+X2*location+X2*security+X2*staff,hostel2, lambda = seq(0,20,0.01), weights = wts2)
wts2 = 1/fitted(lm(abs(resid)~hostel2$Distance+hostel2$Distance2+hostel2$atmosphere+hostel2$atmosphere2+hostel2$cleanliness+hostel2$cleanliness2+hostel2$facilities+hostel2$facilities2+hostel2$location+hostel2$security+hostel2$staff+hostel2$X1+hostel2$X2+hostel2$X2:hostel2$Distance+hostel2$X2:hostel2$Distance2,data = hostel2))^2
mod1 <- lm.ridge(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2,hostel2, lambda = seq(0,20,0.01), weights = wts2)
plot(mod1)
select(mod1)
# mod2 <- lmridge(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2,data=as.data.frame(hostel2), k = seq(0,20,0.01), weights = wts2)
#
~~~

~~~~
# plot(mod2)
# vif(mod2)
summary(mod1)

# Can compare the result with rigid regression and selected model. I don't know how to plot and compare them.


train.control<-trainControl(method="cv", number=5)
set.seed(1)
step.model1<-
train(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+X2*Distance2, data=hostel2, method="leapBackward",
tuneGrid=data.frame(nvmax=15), trControl=train.control, weights=wts1)

step.model1$results



# mod2 <-
lm.ridge(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2,hostel2, lambda = 4.41, weights = wts2)
#
# mod2$coef

# residuals(mod2)

```



```{r}
# library('MXM')
# hostel2_m = data.matrix(hostel2)
# #hostel2_m = hostel2_m[1:270,]
# step.model2 = ridgereg.cv(hostel2_m[,1], hostel2_m, K = 10, lambda = seq(0, 10, by = 0.1))
# step.model2
set.seed(1)
~~~~

~~~~
step.model2<-
train(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2, data=hostel2, method="ridge", trControl=train.control, weights = wts2, tuneGrid=data.frame(lambda=4.41))

step.model2$results
```
~~~~

Chapter 7 Appendix B: Output

Read and rearrange the data

```r
library(stringr) # install stringr for number extraction

hostel <- read.csv('data/Hostel2.csv', header=T)
hostel <- subset(hostel, select = -c(1,2,6,7,14,15,16)) # remove old index column, and hostel name column
hostel <- na.omit(hostel) # remove rows that contain one or more NAs

# rapply(hostel, function(x) length(unique(x))) # number of unique values in each column
# table(hostel$City) # city count
hostel <- subset(hostel, City %in% c('Kyoto', 'Osaka', 'Tokyo') ) # get hostels from 'Kyoto', 'Osaka', 'Tokyo'
hostel$X1 <- hostel$City == "Osaka";
hostel$X2 <- hostel$City == "Kyoto";

# distance: extract distance from string and convert it from str type to int
# e.g. 5.9km from city centre -> 5.9
hostel[3] <- rapply(hostel[3], function(x) as.numeric( sub("km from city centre", "", x)) )

rownames(hostel) <- 1:nrow(hostel) # reindex
#hostel

colnames(hostel) <- c("City", "Price", "Distance", "atmosphere", "cleanliness", "facilities", "location", "security", "staff", "X1", "X2")
hostel <- hostel[,c("Price", "Distance", "atmosphere", "cleanliness", "facilities", "location", "security", "staff", "X1", "X2", "City")]
hostel <- subset(hostel, select = -c(11))
```

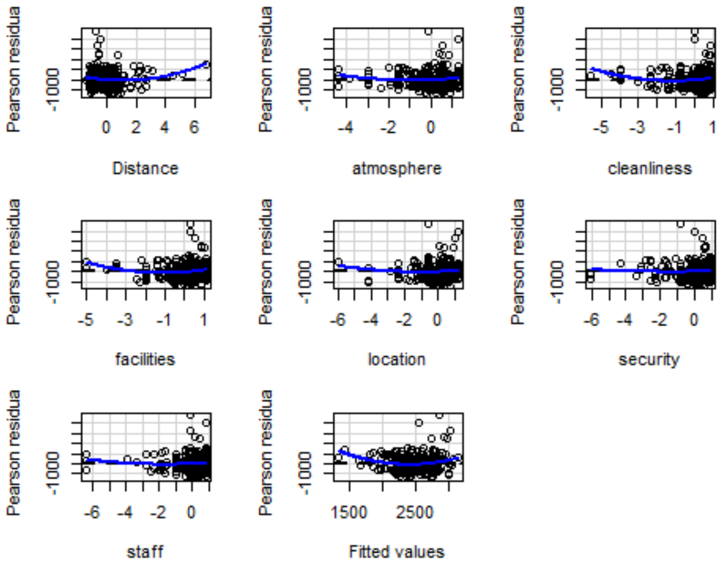
```
# Standardize variables
for (i in 2:8){
  hostel[,i] = (hostel[,i]-mean(hostel[,i]))/sd(hostel[,i])
}
```

Remove outliers and fit the model Pre plot and check the issues

```
# plot(hostel)
# cor(hostel[,1:8])
hostel.mod <- lm(Price~., hostel)

summary(hostel.mod)

## 
## Call:
## lm(formula = Price ~ ., data = hostel)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -1431.6  -570.2  -150.5   414.9  4748.5 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)  2791.66      78.79  35.430  < 2e-16 ***
## Distance     -166.17      58.08  -2.861  0.00453 ** 
## atmosphere     80.96      73.82   1.097  0.27370    
## cleanliness   165.82      87.36   1.898  0.05869 .  
## facilities   -110.32      99.62  -1.107  0.26906    
## location      -13.31      60.28  -0.221  0.82538    
## security       29.19      71.52   0.408  0.68347    
## staff          11.71      79.52   0.147  0.88307    
## X1TRUE       -383.79     115.60  -3.320  0.00102 ** 
## X2TRUE       -720.11     139.19  -5.174 4.33e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 811.9 on 286 degrees of freedom
## Multiple R-squared:  0.1122, Adjusted R-squared:  0.0843 
## F-statistic: 4.018 on 9 and 286 DF,  p-value: 7.414e-05
```

Simply dignostic nonlinear, constant variance and normal variance issues.

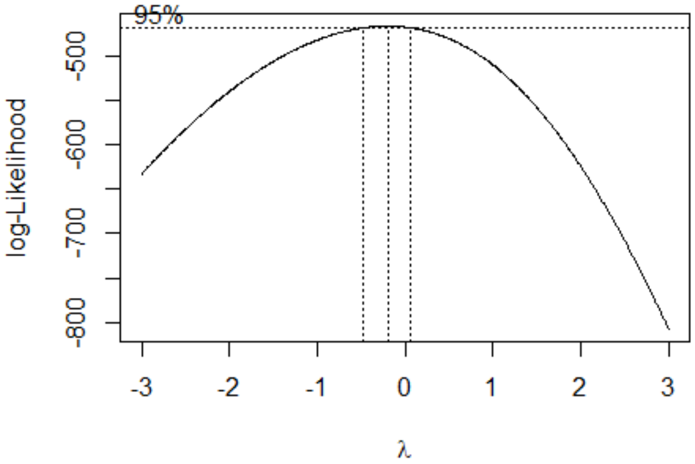
```
# residual plot
library(car)

## Loading required package: carData

residualPlots(hostel.mod, smooth = FALSE)
```



```
##            Test stat Pr(>|Test stat|)
## Distance      3.5601       0.0004343 ***
## atmosphere    1.6598       0.0980645 .
## cleanliness   2.6198       0.0092700 **
## facilities    3.1158       0.0020215 **
## location      1.1324       0.2584109
## security      0.4847       0.6282890
## staff         1.2545       0.2106899
## Tukey test    3.7478       0.0001784 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Add higher order terms
hostel1.mod <- lm(Price~Distance+I(Distance^2)+atmosphere+I(atmosphere^2)+cleanliness+I(cleanl
iness^2)+facilities+I(facilities^2)+location+security+staff+X1+X2,hostel)

summary(hostel1.mod)

##
## Call:
## lm(formula = Price ~ Distance + I(Distance^2) + atmosphere +
##     I(atmosphere^2) + cleanliness + I(cleanliness^2) + facilities +
##     I(facilities^2) + location + security + staff + X1 + X2,
##     data = hostel)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1386.7  -507.9  -113.9   370.0  4431.8
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)      2781.72      81.70  34.047  < 2e-16 ***
## Distance         -412.35      89.16  -4.625 5.72e-06 ***
## I(Distance^2)      73.60      21.98   3.348 0.000924 ***
## atmosphere         52.66      93.30   0.564 0.572906
## I(atmosphere^2)   -18.56      34.36  -0.540 0.589583
## cleanliness       258.04     122.34   2.109 0.035812 *
## I(cleanliness^2)   38.31      40.89   0.937 0.349645
## facilities         11.04     116.16   0.095 0.924355
## I(facilities^2)    59.13      33.50   1.765 0.078693 .
## location          -35.80      60.04  -0.596 0.551424
## security          -39.53      73.82  -0.536 0.592712
## staff              91.19      81.53   1.119 0.264300
## X1TRUE           -546.68     121.05  -4.516 9.26e-06 ***
## X2TRUE          -1070.62     161.56  -6.627 1.74e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 787.4 on 282 degrees of freedom
## Multiple R-squared:  0.1766, Adjusted R-squared:  0.1386
## F-statistic: 4.652 on 13 and 282 DF,  p-value: 2.884e-07
```

```
# resid = residuals(hostel1.mod)
#
# # Constant variance
# library(onewaytests)
# hostel$Group <- cut(hostel$Price,2)
# hostel$residual <- hostel1.mod$residuals
# bf.test(residual~Group, hostel)
#
# # Normality
# shapiro.test(resid)
# qqnorm(resid)
# qqline(resid)
# Transform Y
library(MASS)
bcmle <- boxcox(hostel1.mod, lambda=seq(-3,3,by=0.01))
```



```
lambda <- bcmle$x[which.max(bcmle$y)]
hostel2 = hostel;
hostel2$Distance2 = hostel$Distance^2
hostel2$atmosphere2 = hostel$atmosphere^2
hostel2$cleanliness2 = hostel$cleanliness^2
hostel2$facilities2 = hostel$facilities^2

hostel2$Price = hostel$Price^lambda;
hostel2.mod <- lm(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+fac
ilities+facilities2+location+security+staff+X1+X2,hostel2);
summary(hostel2.mod)

## 
## Call:
## lm(formula = Price ~ Distance + Distance2 + atmosphere + atmosphere2 + 
##     cleanliness + cleanliness2 + facilities + facilities2 + location + 
##     security + staff + X1 + X2, data = hostel2)
## 
## Residuals:
##       Min        1Q    Median        3Q       Max 
## -0.038959 -0.007798  0.000074  0.007945  0.036827 
## 
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept)   2.076e-01  1.262e-03 164.488  < 2e-16 ***
## Distance      5.849e-03  1.377e-03   4.246 2.95e-05 ***
## Distance2    -1.086e-03  3.396e-04  -3.197  0.00155 **
## atmosphere   -5.039e-04  1.441e-03  -0.350  0.72688
## atmosphere2   3.301e-04  5.308e-04   0.622  0.53459
## cleanliness  -4.634e-03  1.890e-03  -2.452  0.01481 *
## cleanliness2 -7.428e-04  6.317e-04  -1.176  0.24065
## facilities    2.155e-04  1.794e-03   0.120  0.90448
## facilities2  -1.009e-03  5.176e-04  -1.949  0.05226 .
## location      2.377e-04  9.275e-04   0.256  0.79791
## security      5.517e-05  1.140e-03   0.048  0.96145
## staff        -1.652e-03  1.259e-03  -1.311  0.19081
## X1TRUE        7.967e-03  1.870e-03   4.261 2.78e-05 ***
## X2TRUE        1.671e-02  2.496e-03   6.694 1.17e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01216 on 282 degrees of freedom
## Multiple R-squared:  0.1912, Adjusted R-squared:  0.1539
## F-statistic: 5.128 on 13 and 282 DF,  p-value: 3.5e-08
```

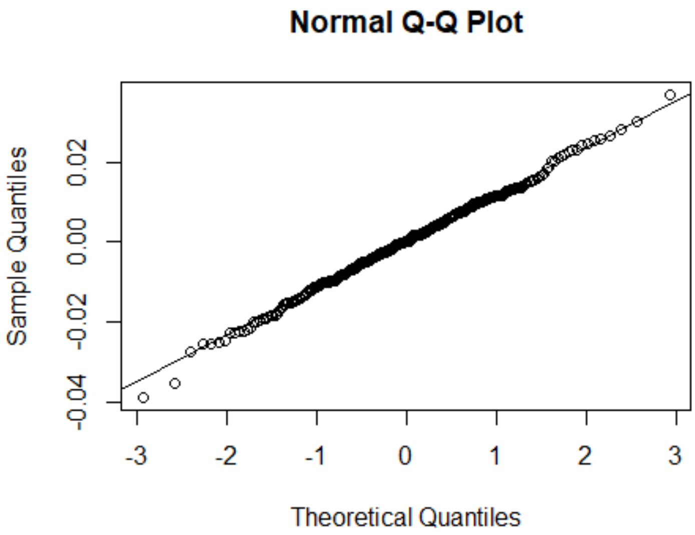
```
lambda
```

```
## [1] -0.2
```

```
resid = residuals(hostel2.mod)

# Constant variance
library(onewaytests)
hostel2$Group <- cut(hostel2$Price,2)
hostel2$residual <- hostel2.mod$residuals
bf.test(residual~Group, hostel2)
```

```
##
##   Brown-Forsythe Test
## ----------------------------------------------------------
##   data : residual and Group
##
##   statistic  : 368.1816
##   num df     : 1
##   denom df   : 293.0368
##   p.value    : 1.026002e-53
##
```

```
##   Result     : Difference is statistically significant.
## -----------------------------------------------------------

hostel2 <- subset(hostel2, select = -c(15,16))
# Normality
shapiro.test(resid)

##
##  Shapiro-Wilk normality test
##
## data:  resid
## W = 0.99755, p-value = 0.9393

qqnorm(resid)
qqline(resid)
```



Model selection Assume indicator only effect intercept

```
library(stats)
step(lm(Price~1,data = hostel2), scope=~ Distance+Distance2+atmosphere+atmosphere2+cleanliness
+cleanliness2+facilities+facilities2+location+security+staff+X1+X2, method = "both")

## Step:  AIC=-2606.14
## Price ~ X2 + cleanliness + facilities2 + X1 + Distance + Distance2 +
##     staff
##
##                 Df Sum of Sq      RSS     AIC
## <none>                         0.042079 -2606.1
## + cleanliness2  1 0.0001567 0.041922 -2605.2
## + atmosphere    1 0.0001260 0.041953 -2605.0
## + atmosphere2   1 0.0000520 0.042027 -2604.5
## + facilities    1 0.0000334 0.042045 -2604.4
## - staff         1 0.0005566 0.042635 -2604.2
## + security      1 0.0000072 0.042072 -2604.2
## + location      1 0.0000002 0.042079 -2604.1
## - Distance2     1 0.0015275 0.043606 -2597.6
## - cleanliness   1 0.0017399 0.043819 -2596.1
## - facilities2   1 0.0019927 0.044071 -2594.4
## - X1            1 0.0028132 0.044892 -2589.0
## - Distance      1 0.0028827 0.044961 -2588.5
## - X2            1 0.0067067 0.048785 -2564.4
```

```
##
## Call:
## lm(formula = Price ~ X2 + cleanliness + facilities2 + X1 + Distance +
##     Distance2 + staff, data = hostel2)
##
## Coefficients:
## (Intercept)       X2TRUE  cleanliness  facilities2       X1TRUE
##    0.207458     0.016511    -0.003590    -0.001231     0.007950
##    Distance    Distance2        staff
##    0.005660    -0.001068    -0.001880
```

```
library(ALSM)
```

```
## Loading required package: leaps
```

```
## Loading required package: SuppDists
```

```
library(leaps)
BestSub(hostel2[,2:14], hostel2$Price, num = 1)
```

```
##     p 1 2 3 4 5 6 7 8 9 A B C D       SSEp         r2     r2.adj        Cp
## 1   2 0 0 0 0 0 0 0 0 1 0 0 0 0 0.04982295 0.03425374 0.03096889 44.723945
## 2   3 0 0 1 0 0 0 0 0 1 0 0 0 0 0.04802296 0.06914407 0.06279010 34.558835
## 3   4 0 0 1 0 0 0 0 0 1 0 0 0 1 0.04642466 0.10012480 0.09087951 25.756873
## 4   5 0 0 1 0 0 0 0 1 1 0 0 0 1 0.04534102 0.12112964 0.10904895 20.433177
## 5   6 1 0 1 0 0 0 0 1 1 1 0 0 0 0.04416931 0.14384156 0.12908021 14.514278
## 6   7 1 0 1 0 0 0 0 1 1 1 0 0 1 0.04263535 0.17357503 0.15641742  6.147195
## 7   8 1 0 1 0 0 0 1 1 1 1 0 0 1 0.04207872 0.18436458 0.16454011  4.385234
## 8   9 1 0 1 0 0 0 1 1 1 1 0 1 1 0.04192203 0.18740174 0.16475092  5.326277
## 9  10 1 0 1 0 0 0 1 1 1 1 1 1 1 0.04175528 0.19063393 0.16516437  6.199318
## 10 11 1 1 1 0 0 0 1 1 1 1 1 1 1 0.04174123 0.19090633 0.16251708  8.104341
## 11 12 1 1 1 0 1 0 1 1 1 1 1 1 1 0.04172889 0.19114556 0.15981669 10.020931
## 12 13 1 1 1 1 1 0 1 1 1 1 1 1 1 0.04172614 0.19119888 0.15690342 12.002340
## 13 14 1 1 1 1 1 1 1 1 1 1 1 1 1 0.04172579 0.19120559 0.15392074 14.000000
##         AICp      SBCp     PRESSp
## 1  -2568.133 -2560.752 0.05052031
## 2  -2577.025 -2565.954 0.04905521
## 3  -2585.044 -2570.283 0.04750546
## 4  -2590.035 -2571.583 0.04667443
## 5  -2595.785 -2573.643 0.04604290
## 6  -2604.248 -2578.415 0.04442347
## 7  -2606.137 -2576.615 0.04428261
## 8  -2605.242 -2572.029 0.04489697
## 9  -2604.421 -2567.518 0.04476490
## 10 -2602.521 -2561.927 0.04515738
## 11 -2600.609 -2556.324 0.04560945
## 12 -2598.628 -2550.653 0.04598606
## 13 -2596.631 -2544.966 0.04631850
```

Based on the stepwise as well as PRESSp from bestsub method, we choose the model with 7 different parameters which includes 2 different indicators. stepwise - Get a better model BestSub - Get smallest PRESSp for prediction

Pay more attention to indicator terms Add more terms to consider the effect of indicator

```
step(lm(Price~1,data = hostel2), scope=~ Distance+Distance2+atmosphere+atmosphere2+cleanliness
+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X1*Distance+X1*Distance2+X
1*atmosphere+X1*atmosphere2+X1*cleanliness+X1*cleanliness2+X1*facilities+X1*facilities2+X1*lo
cation+X1*security+X1*staff+X2*Distance+X2*Distance2+X2*atmosphere+X2*atmosphere2+X2*cleanlin
ess+X2*cleanliness2+X2*facilities+X2*facilities2+X2*location+X2*security+X2*staff, method = "b
oth")
```

```
## Start:  AIC=-2559.82
## Step:  AIC=-2622.98
## Price ~ X2 + cleanliness + facilities2 + X1 + Distance + Distance2 +
##     staff + X2:Distance + X2:Distance2
##
##                 Df Sum of Sq      RSS     AIC
## <none>                       0.039217 -2623.0
## + facilities      1 0.0001836 0.039034 -2622.4
## + cleanliness:X2  1 0.0001666 0.039051 -2622.2
## + cleanliness2    1 0.0001599 0.039058 -2622.2
## + atmosphere      1 0.0001407 0.039077 -2622.1
## + atmosphere2     1 0.0001053 0.039112 -2621.8
## + facilities2:X2  1 0.0000908 0.039127 -2621.7
## + staff:X2        1 0.0000868 0.039131 -2621.6
## + security        1 0.0000459 0.039172 -2621.3
## + facilities2:X1  1 0.0000356 0.039182 -2621.2
## + staff:X1        1 0.0000320 0.039185 -2621.2
## + location        1 0.0000193 0.039198 -2621.1
## + Distance:X1     1 0.0000083 0.039209 -2621.0
## + Distance2:X1    1 0.0000068 0.039211 -2621.0
## + cleanliness:X1  1 0.0000044 0.039213 -2621.0
## - staff           1 0.0007577 0.039975 -2619.3
## - cleanliness     1 0.0016485 0.040866 -2612.8
## - X2:Distance2    1 0.0019758 0.041193 -2610.4
## - facilities2     1 0.0022344 0.041452 -2608.6
## - X2:Distance     1 0.0028603 0.042078 -2604.1
## - X1              1 0.0038828 0.043100 -2597.0
```

```
##
## Call:
## lm(formula = Price ~ X2 + cleanliness + facilities2 + X1 + Distance +
##     Distance2 + staff + X2:Distance + X2:Distance2, data = hostel2)
##
## Coefficients:
##      (Intercept)            X2TRUE       cleanliness       facilities2
##         0.206693          0.004911         -0.003495         -0.001306
##           X1TRUE          Distance         Distance2             staff
##         0.009519          0.008210         -0.001565         -0.002200
##  X2TRUE:Distance  X2TRUE:Distance2
##        -0.015195          0.003373
```

```
ori.mod=lm(formula = Price ~ X2 + cleanliness + facilities2 + X1 + Distance +
    Distance2 + facilities + staff + X2:Distance + X2:Distance2,
    data = hostel2)
```

Since we solve the normality issue, we can use weighted regression to deal with the unconstant variance issue.

```
hostel3.mod <- lm(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+X2*
Distance2,hostel2);
summary(hostel3.mod)
```

```
##
## Call:
## lm(formula = Price ~ Distance + Distance2 + cleanliness + facilities2 +
##     staff + X1 + X2 + X2 * Distance + X2 * Distance2, data = hostel2)
##
```

```
## Residuals:
##       Min        1Q    Median        3Q       Max 
## -0.037853 -0.007953 -0.000240  0.007738  0.032541 
## 
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)    
## (Intercept)       0.2066934  0.0011918 173.430  < 2e-16 ***
## Distance          0.0082096  0.0013582   6.044 4.67e-09 ***
## Distance2        -0.0015651  0.0003475  -4.503 9.75e-06 ***
## cleanliness      -0.0034954  0.0010081  -3.467 0.000606 ***
## facilities2      -0.0013059  0.0003235  -4.037 6.97e-05 ***
## staff            -0.0021999  0.0009359  -2.351 0.019419 *  
## X1TRUE            0.0095186  0.0017888   5.321 2.08e-07 ***
## X2TRUE            0.0049115  0.0035237   1.394 0.164452    
## Distance:X2TRUE  -0.0151950  0.0033270  -4.567 7.35e-06 ***
## Distance2:X2TRUE  0.0033726  0.0008885   3.796 0.000180 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Residual standard error: 0.01171 on 286 degrees of freedom
## Multiple R-squared:  0.2398, Adjusted R-squared:  0.2159 
## F-statistic: 10.03 on 9 and 286 DF,  p-value: 2.167e-13
```

```
resid = residuals(hostel3.mod)

wts1 <- 1/fitted(lm(abs(resid)~hostel2$Distance+hostel2$Distance2+hostel2$cleanliness+hostel2$facilities2+hostel2$staff+hostel2$X1+hostel2$X2+hostel2$X2*hostel2$Distance+hostel2$X2*hostel2$Distance2))^2
hostel.weight<-lm(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+X2*Distance2, data = hostel2, weights = wts1)
summary(hostel.weight)
```

```
## 
## Call:
## lm(formula = Price ~ Distance + Distance2 + cleanliness + facilities2 + 
##     staff + X1 + X2 + X2 * Distance + X2 * Distance2, data = hostel2, 
##     weights = wts1)
## 
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max 
## -4.2134 -0.8881 -0.0249  0.8474  3.3048 
## 
```

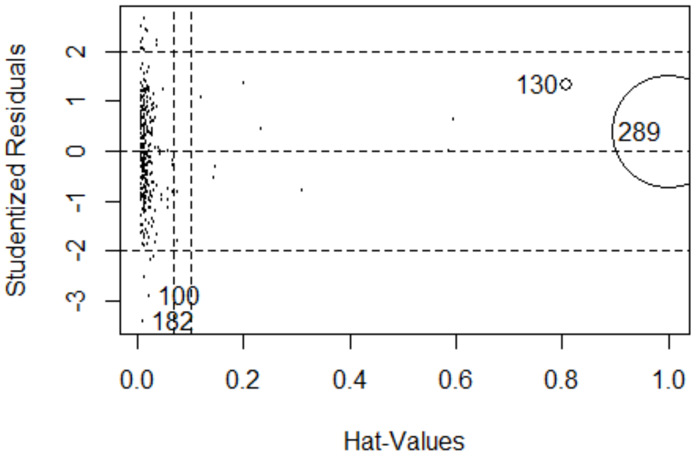
```
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)    
## (Intercept)        0.2067789  0.0011500 179.803  < 2e-16 ***
## Distance           0.0079569  0.0012951   6.144 2.69e-09 ***
## Distance2         -0.0014987  0.0003033  -4.941 1.33e-06 ***
## cleanliness       -0.0036837  0.0010287  -3.581 0.000402 ***
## facilities2       -0.0012715  0.0002867  -4.435 1.32e-05 ***
## staff             -0.0019466  0.0009023  -2.157 0.031815 *  
## X1TRUE             0.0093362  0.0017346   5.382 1.53e-07 ***
## X2TRUE             0.0034972  0.0027138   1.289 0.198547    
## Distance:X2TRUE   -0.0160599  0.0026425  -6.078 3.89e-09 ***
## Distance2:X2TRUE   0.0036200  0.0006059   5.975 6.83e-09 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.264 on 286 degrees of freedom
## Multiple R-squared:  0.3198, Adjusted R-squared:  0.2983 
## F-statistic: 14.94 on 9 and 286 DF,  p-value: < 2.2e-16
```

You can consider whether we can drop variable Staff? ** T value for weighted regression doesn't make sense.

Also we can analysis the multicolinearity issue based on VIF here, to show why we can drop other variables, they are trival or have linear relationship with other variables.

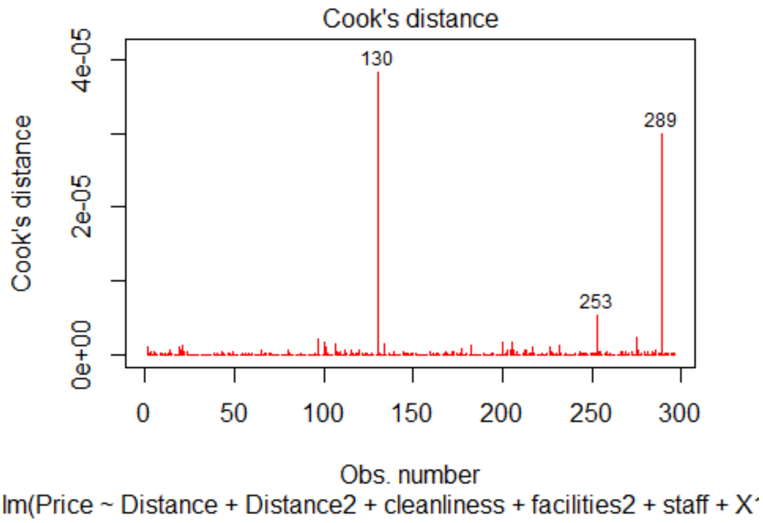
Influential point & Outliers

```
alpha = 0.05
p = 9
n = 296
qt(1-alpha/2/n,n-1-p)

## [1] 3.811871

library(car)
influencePlot(hostel.weight)
```

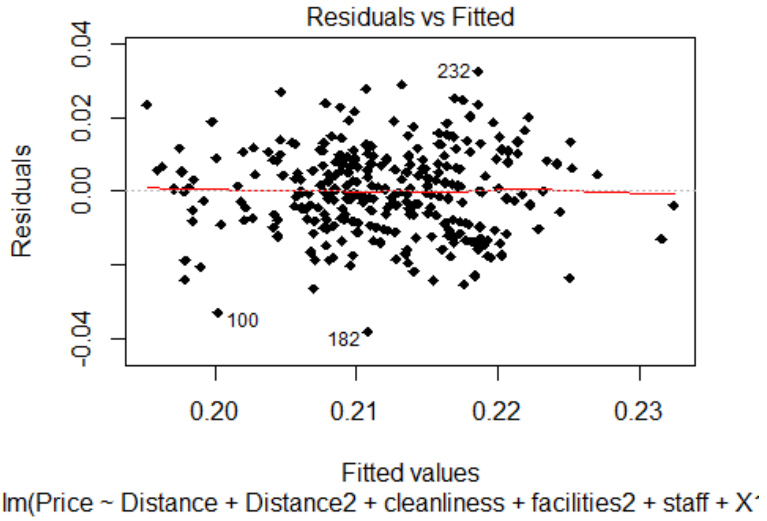


```
##       StudRes        Hat       CookD
## 100 -2.907301 0.02467940  0.02084470
## 130  1.325264 0.80773903  0.73593180
## 182 -3.418714 0.01416258  0.01618562
## 289  0.377428 0.99974425 55.85297206
```

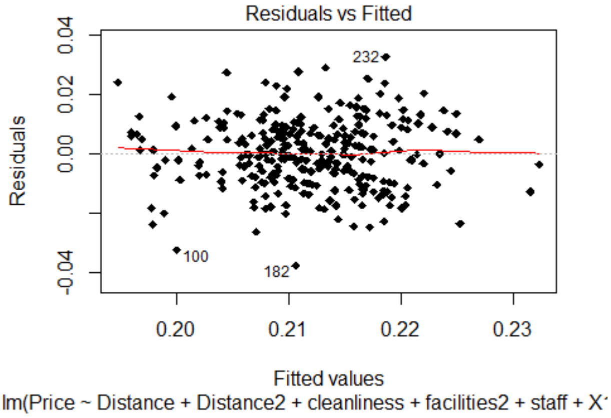
```
plot(hostel.weight,pch = 18, col = "red", which = c(4))
```



```
plot(hostel.weight,pch = 18,which = c(1))
```



```
hostel.unweight<-lm(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+
X2*Distance2, data = hostel2)
plot(hostel.unweight,pch = 18,which = c(1))
```

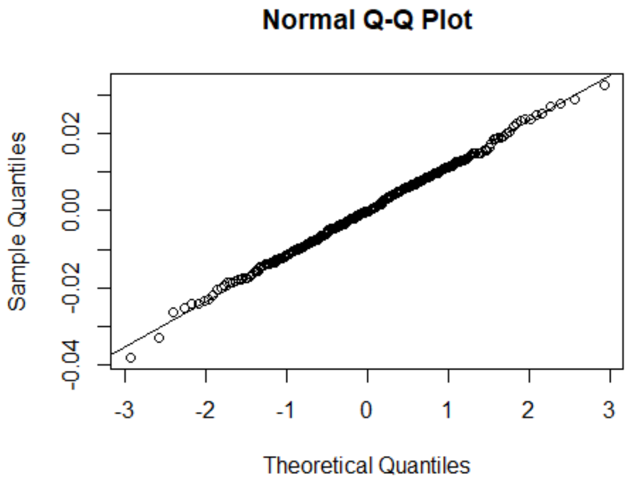


No outliers in Y, some outliers in X. Can apply another window to cancel the influence of outerlier x.

```
resid = residuals(hostel.weight)



# Normality
shapiro.test(resid)

##
##  Shapiro-Wilk normality test
##
```

```
## data:  resid
## W = 0.99826, p-value = 0.9907
```

```
qqnorm(resid)
qqline(resid)
```



```
library(fmsb)
VIF(lm(staff~Distance+Distance2+cleanliness+facilities2+X2+X1+X2:Distance+X2:Distance2, data = hostel2))
```

```
## [1] 1.884215
```

Directly apply rigid regression (Ignore multicollinearity issue)

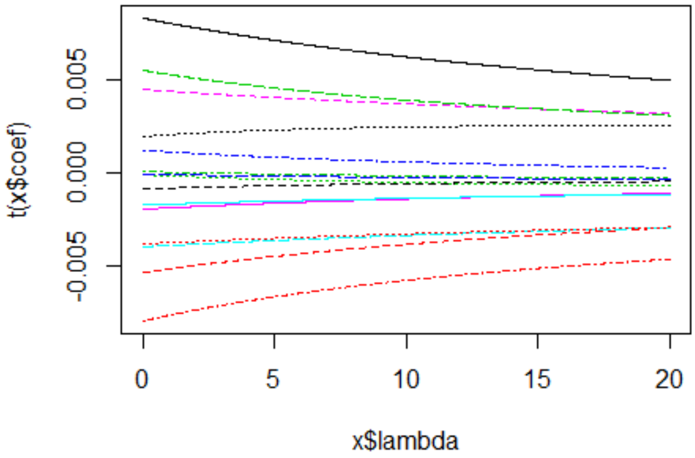
```
library(MASS)
library(car)
library(leaps)
library(caret)
```

```
## Loading required package: lattice

## 
## Attaching package: 'lattice'

## The following object is masked from 'package:ALSM':
## 
##     oneway

## Loading required package: ggplot2
```

```
library(ggplot2)
library(lmridge)
```

```
##
## Attaching package: 'lmridge'

## The following object is masked from 'package:car':
##
##     vif
```

```
# For prediction, chosse lambda
mod <- lmridge(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2,hostel2, lambda = seq(0,20,0.01))
resid = residuals(mod)

wts2 =  1/fitted(lm(abs(resid)~hostel2$Distance+hostel2$Distance2+hostel2$atmosphere+hostel2$atmosphere2+hostel2$cleanliness+hostel2$cleanliness2+hostel2$facilities+hostel2$facilities2+hostel2$location+hostel2$security+hostel2$staff+hostel2$X1+hostel2$X2+hostel2$X2:hostel2$Distance+hostel2$X2:hostel2$Distance2,data = hostel2))^2
mod1 <- lm.ridge(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+facilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2,hostel2, lambda = seq(0,20,0.01), weights = wts2)
plot(mod1)
```



```
select(mod1)

## modified HKB estimator is 6.976383
## modified L-W estimator is 41.48205
## smallest value of GCV  at 4.41

summary(mod1)
```

```
##        Length Class  Mode
## coef   30015  -none- numeric
## scales    15  -none- numeric
## Inter      1  -none- numeric
## lambda  2001  -none- numeric
## ym         1  -none- numeric
## xm        15  -none- numeric
## GCV     2001  -none- numeric
## kHKB       1  -none- numeric
## kLW        1  -none- numeric
```

```
train.control<-trainControl(method="cv", number=5)
set.seed(1)
step.model1<-train(Price~Distance+Distance2+cleanliness+facilities2+staff+X1+X2+X2*Distance+X
2*Distance2, data=hostel2, method="leapBackward",
tuneGrid=data.frame(nvmax=15), trControl=train.control, weights=wts1)

step.model1$results
```

```
##   nvmax      RMSE  Rsquared         MAE       RMSESD RsquaredSD
## 1    15 0.0119834 0.1895096 0.009611793 0.0004054488 0.08933626
##          MAESD
## 1 0.0004403936
```

```
set.seed(1)
step.model2<-train(Price~Distance+Distance2+atmosphere+atmosphere2+cleanliness+cleanliness2+f
acilities+facilities2+location+security+staff+X1+X2+X2*Distance+X2*Distance2, data=hostel2, me
thod="ridge", trControl=train.control, weights = wts2, tuneGrid=data.frame(lambda=4.41))

step.model2$results
```

```
##   lambda       RMSE   Rsquared        MAE       RMSESD RsquaredSD
## 1   4.41 0.01351856 0.05510238 0.01071577 0.0005667828 0.04291188
##          MAESD
## 1 0.0003764873
```