Final Project: Step III: Classification

Data Set - Zurich

AD699 A3 Data Mining (Spring 2024)

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Data Cleaning & Import

```
library(tidyverse)
# don't show scientific notation
options(scipen = 999)
```

```
── Attaching core tidyverse packages ──────────────────── tidyverse 2.0.0 ──
✔ dplyr     1.1.4     ✔ readr     2.1.5
✔ forcats   1.0.0     ✔ stringr   1.5.1
✔ ggplot2   3.4.4     ✔ tibble    3.2.1
✔ lubridate 1.9.3     ✔ tidyr     1.3.1
✔ purrr     1.0.2
── Conflicts ────────────────────────────────────────── tidyverse_conflicts() ──
✖ purrr::%||%()   masks base::%||%()
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors
```

```
#read data
zurich <- read_csv("zurich_listings_699.csv")
```

```
Rows: 2534 Columns: 75
── Column specification ────────────────────────────────────────────────
Delimiter: ","
chr (30): listing_url, last_scraped, source, name, description, neighborhood...
dbl (37): id, scrape_id, host_id, host_listings_count, host_total_listings_c...
lgl  (8): host_is_superhost, host_has_profile_pic, host_identity_verified, b...

ℹ Use `spec()` to retrieve the full column specification for this data.
ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
install.packages("naniar")
library(naniar)
```

```
Installing package into ‘/usr/local/lib/R/site-library’
(as ‘lib’ is unspecified)
```

```
# remove cols with no value at all
zurich1 <- zurich[,-c(7,36,38,50,69)]
colSums(is.na(zurich1))


test_cases <- complete.cases(zurich1)
l <- sum(test_cases)
percentage <- (l/nrow(zurich1))*100
cat("percentage  and l", percentage, l)
library(naniar)
missing_var <- miss_var_summary(zurich1)
print(missing_var)


# Review_score_value converted to factor and new variable is Review_value
zurich1$review_scores_value[is.na(zurich1$review_scores_value)] <- 0
summary(zurich1$review_scores_value)
bins= c(-Inf,0,4,5)
zurich1$review_value <- cut(zurich1$review_scores_value, breaks= bins, labels= c("No Reviews", "Poor Reviews","Good Reviews" ))
table(zurich1$review_value)

# Review_score_rating converted to factor and new variable is Review_rating
zurich1$review_scores_rating[is.na(zurich1$review_scores_rating)] <- 0
summary(zurich1$review_scores_rating)
bins= c(-Inf,0,4,5)
zurich1$review_rating <- cut(zurich1$review_scores_rating, breaks= bins, labels= c("No Reviews", "Poor Reviews","Good Reviews" ))
table(zurich1$review_rating)

# Review_score_rating converted to factor and new variable is Review_rating
zurich1$review_scores_accuracy[is.na(zurich1$review_scores_accuracy)] <- 0
summary(zurich1$review_scores_accuracy)
bins= c(-Inf,0,4,5)
zurich1$review_accuracy <- cut(zurich1$review_scores_accuracy, breaks= bins, labels= c("No Reviews", "Poor Reviews","Good Reviews" ))
table(zurich1$review_accuracy)

# Review_score_cleanliness  converted to factor and new variable is Review_cleanliness
zurich1$review_scores_cleanliness [is.na(zurich1$review_scores_cleanliness )] <- 0
summary(zurich1$review_scores_cleanliness )
bins= c(-Inf,0,4,5)
zurich1$review_cleanliness  <- cut(zurich1$review_scores_cleanliness , breaks= bins, labels= c("No Reviews", "Poor Reviews","Good Reviews" ))
table(zurich1$review_cleanliness )

# Review_score_checkin  converted to factor and new variable is Review_checkin
zurich1$review_scores_checkin [is.na(zurich1$review_scores_checkin )] <- 0
summary(zurich1$review_scores_checkin )
bins= c(-Inf,0,4,5)
zurich1$review_checkin  <- cut(zurich1$review_scores_checkin , breaks= bins, labels= c("No Reviews", "Poor Reviews","Good Reviews" ))
table(zurich1$review_checkin )

# Review_score_communication  converted to factor and new variable is Review_communication
zurich1$review_scores_communication [is.na(zurich1$review_scores_communication )] <- 0
summary(zurich1$review_scores_communication )
bins= c(-Inf,0,4,5)
zurich1$review_communication  <- cut(zurich1$review_scores_communication , breaks= bins, labels= c("No Reviews", "Poor Reviews","Good Reviews" ))
table(zurich1$review_communication )

# Review_score_location   converted to factor and new variable is Review_location
zurich1$review_scores_location  [is.na(zurich1$review_scores_location  )] <- 0
summary(zurich1$review_scores_location  )
bins= c(-Inf,0,4,5)
zurich1$review_location   <- cut(zurich1$review_scores_location  , breaks= bins, labels= c("No Reviews", "Poor Reviews","Good Reviews" ))
table(zurich1$review_location  )

# Removing redundant review scores

zurich1 <- zurich1[,-c(58,59,60,61,62,63,64)]
dim(zurich1)

# EXTRACTING PRICE & BATHS
zurich2 <- zurich1 %>%
  mutate(NumPrice=as.numeric(gsub("[$,]","",zurich1$price))) %>%
  mutate(baths=case_when(
    grepl("(half).*",  zurich1$bathrooms_text, ignore.case = TRUE) ~0.5,
    TRUE ~ as.numeric(gsub("[^0-9.]+","",zurich1$bathrooms_text))
  ))
head(zurich2$NumPrice)
colSums(is.na(zurich2))
zurich2$baths <- ifelse(is.na(zurich2$baths), 1,zurich2$baths) # imputing the last na value


#***To me removed later***
# Imputing missing price values
u_room_type<- unique(zurich2$room_type)
u_property_type <- unique(zurich2$property_type)
print(u_room_type)
print(u_property_type)

#***To me removed later***
test_u_property_type <- zurich2 %>% filter(property_type=="Casa particular")
test_u_room_type <- zurich2 %>% filter(room_type=="Hotel room")
test_u_beds <- unique(zurich2$beds)
```

```
table(test_u_beds)
summary(test_u_beds)
c<- mode(test_u_beds)
print(c)

#Imputing missing values in 'beds'
zurich2$beds <- ifelse(is.na(zurich2$beds) & zurich2$room_type == "Shared room", zurich2$accommodates,
                       ifelse(is.na(zurich2$beds) & zurich2$room_type %in% c("Private room", "Entire home/apt") & zurich2$accommodates %in% 1:2, 1,
                              ifelse(is.na(zurich2$beds) & zurich2$room_type %in% c("Private room", "Entire home/apt") & zurich2$accommodates %in% 3:8,
                                     zurich2$beds)))

colSums(is.na(zurich2))

# Creating new variabales guests per bath and bed
zurich_FE <- zurich2 %>% mutate(guestsPerBath= zurich2$accommodates/zurich2$baths) %>% mutate(guestsPerBed = zurich2$accommodates/zurich2$beds)
head(zurich_FE,2)

#***REDUNDANT STEP, REMOVE LATER****
zurich2_price_nonas<- zurich2 %>% filter(!is.na(NumPrice))
zurich2_price_nas<- zurich2 %>% filter(is.na(NumPrice))
zurich2_beds_nonas <- zurich2 %>% filter(is.na(beds))
price_imputing_mlr_model <- lm(NumPrice~neighbourhood_cleansed + neighbourhood_group_cleansed  + room_type +accommodates+beds, zurich2_price_nonas)
step_mlr <- step(price_imputing_mlr_model,  method= "backward")
summary(price_imputing_mlr_model)
impute_price_preds <- predict(price_imputing_mlr_model,zurich2_price_nas)
View(impute_price_preds)

# Impute Price
zurich_test <- zurich_FE %>% group_by(neighbourhood_group_cleansed,neighbourhood_cleansed, property_type,room_type, beds) %>% arrange(neighbourhood_gro

zurich_imputed <- zurich_test %>% mutate(NumPrice= ifelse(is.na(NumPrice), mean(NumPrice, na.rm= TRUE), NumPrice))
colSums(is.na(zurich_imputed))
# Removing redundant price and bathrooms_text as new variales NumPrice and baths are created
zurich_imputed <- zurich_imputed[,-c(35,38)]
```

id: 0 listing_url: 0 scrape_id: 0 last_scraped: 0 source: 0 name: 0 neighborhood_overview: 1334 picture_url: 0 host_id: 0 host_url: 0 host_name: 0 host_since: 0 host_location: 442 host_about: 992 host_response_time: 0 host_response_rate: 0 host_acceptance_rate: 0 host_is_superhost: 42 host_thumbnail_url: 0 host_picture_url: 0 host_neighbourhood: 2499 host_listings_count: 0 host_total_listings_count: 0 host_verifications: 0 host_has_profile_pic: 0 host_identity_verified: 0 neighbourhood: 1334 neighbourhood_cleansed: 0 neighbourhood_group_cleansed: 0 latitude: 0 longitude: 0 property_type: 0 room_type: 0 accommodates: 0 bathrooms_text: 2 beds: 44 amenities: 0 price: 0 minimum_nights: 0 maximum_nights: 0 minimum_minimum_nights: 0 maximum_minimum_nights: 0 minimum_maximum_nights: 0 maximum_maximum_nights: 0 minimum_nights_avg_ntm: 0 maximum_nights_avg_ntm: 0 has_availability: 0 availability_30: 0 availability_60: 0 availability_90: 0 availability_365: 0 calendar_last_scraped: 0 number_of_reviews: 0 number_of_reviews_ltm: 0 number_of_reviews_l30d: 0 first_review: 553 last_review: 553 review_scores_rating: 553 review_scores_accuracy: 561 review_scores_cleanliness: 561 review_scores_checkin: 561 review_scores_communication: 561 review_scores_location: 561 review_scores_value: 561 instant_bookable: 0 calculated_host_listings_count: 0 calculated_host_listings_count_entire_homes: 0 calculated_host_listings_count_private_rooms: 0 calculated_host_listings_count_shared_rooms: 0 reviews_per_month: 553

```
percentage  and l 0.394633 10# A tibble: 70 × 3
   variable                    n_miss pct_miss
   <chr>                        <int>    <num>
 1 host_neighbourhood            2499     98.6
 2 neighborhood_overview         1334     52.6
 3 neighbourhood                 1334     52.6
 4 host_about                     992     39.1
 5 review_scores_accuracy         561     22.1
 6 review_scores_cleanliness      561     22.1
 7 review_scores_checkin          561     22.1
 8 review_scores_communication    561     22.1
 9 review_scores_location         561     22.1
10 review_scores_value            561     22.1
# ℹ 60 more rows
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   3.880   4.610   3.608   4.840   5.000 

  No Reviews Poor Reviews Good Reviews 
         561          157         1816 
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   4.000   4.770   3.703   5.000   5.000 

  No Reviews Poor Reviews Good Reviews 
         561           98         1875 
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   4.000   4.820   3.731   5.000   5.000 

  No Reviews Poor Reviews Good Reviews 
         561           91         1882 
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   4.000   4.780   3.706   5.000   5.000 

  No Reviews Poor Reviews Good Reviews 
         561          104         1869 
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   4.250   4.880   3.773   5.000   5.000 

  No Reviews Poor Reviews Good Reviews 
         561           56         1917 
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   4.320   4.890   3.778   5.000   5.000 

  No Reviews Poor Reviews Good Reviews 
         561           55         1918 
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
  0.000   4.000   4.800   3.733   5.000   5.000 

  No Reviews Poor Reviews Good Reviews 
         561           79         1894 
```

2534 · 70

100 · 60 · 200 · 79 · 500 · 145

id: 0 listing_url: 0 scrape_id: 0 last_scraped: 0 source: 0 name: 0 neighborhood_overview: 1334 picture_url: 0 host_id: 0 host_url: 0 host_name: 0 host_since: 0 host_location: 442 host_about: 992 host_response_time: 0 host_response_rate: 0 host_acceptance_rate: 0 host_is_superhost: 42 host_thumbnail_url: 0 host_picture_url: 0 host_neighbourhood: 2499 host_listings_count: 0 host_total_listings_count: 0 host_verifications: 0 host_has_profile_pic: 0 host_identity_verified: 0 neighbourhood: 1334 neighbourhood_cleansed: 0 neighbourhood_group_cleansed: 0 latitude: 0 longitude: 0 property_type: 0 room_type: 0 accommodates: 0 bathrooms_text: 2 beds: 44 amenities: 0 price: 0 minimum_nights: 0 maximum_nights: 0 minimum_minimum_nights: 0 maximum_minimum_nights: 0 minimum_maximum_nights: 0 maximum_maximum_nights: 0 minimum_nights_avg_ntm: 0 maximum_nights_avg_ntm: 0 has_availability: 0 availability_30: 0 availability_60: 0 availability_90: 0 availability_365: 0 calendar_last_scraped: 0 number_of_reviews: 0 number_of_reviews_ltm: 0 number_of_reviews_l30d: 0 first_review: 553 last_review: 553 instant_bookable: 0 calculated_host_listings_count: 0 calculated_host_listings_count_entire_homes: 0 calculated_host_listings_count_private_rooms: 0 calculated_host_listings_count_shared_rooms: 0 reviews_per_month: 553 review_value: 0 review_rating: 0 review_accuracy: 0 review_cleanliness: 0 review_checkin: 0 review_communication: 0 review_location: 0 NumPrice: 0 baths: 2

```
[1] "Entire home/apt" "Private room"    "Hotel room"      "Shared room"    
 [1] "Entire rental unit"                "Private room in rental unit"      
 [3] "Private room in home"              "Entire loft"                      
 [5] "Entire condo"                      "Entire home"                      
 [7] "Private room in castle"            "Private room in condo"            
 [9] "Private room in townhouse"         "Entire serviced apartment"        
[11] "Private room in hut"               "Private room in guesthouse"       
[13] "Private room in villa"             "Tiny home"                        
[15] "Room in boutique hotel"            "Private room in loft"             
[17] "Private room in bed and breakfast"  "Entire townhouse"                
[19] "Entire guest suite"                "Entire villa"                     
[21] "Shared room in hostel"             "Room in serviced apartment"       
[23] "Shared room in rental unit"        "Room in bed and breakfast"        
[25] "Room in hotel"                     "Entire guesthouse"                
[27] "Private room in serviced apartment" "Barn"                            
[29] "Private room in cabin"             "Private room"                     
[31] "Entire vacation home"              "Private room in chalet"           
[33] "Camper/RV"                         "Private room in casa particular"  
[35] "Casa particular"                   "Shared room in home"              
[37] "Shared room in hotel"             
test_u_beds
 1  2  3  4  5  6  7  8  9 10 18 32 
 1  1  1  1  1  1  1  1  1  1  1  1 
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
   1.00    3.75    6.50    8.75    9.25   32.00       1 
```

```
[1] "numeric"
```

id: 0 listing_url: 0 scrape_id: 0 last_scraped: 0 source: 0 name: 0 neighborhood_overview: 1334 picture_url: 0 host_id: 0 host_url: 0 host_name: 0 host_since: 0 host_location: 442 host_about: 992 host_response_time: 0 host_response_rate: 0 host_acceptance_rate: 0 host_is_superhost: 42 host_thumbnail_url: 0 host_picture_url: 0 host_neighbourhood: 2499 host_listings_count: 0 host_total_listings_count: 0 host_verifications: 0 host_has_profile_pic: 0 host_identity_verified: 0 neighbourhood: 1334 neighbourhood_cleansed: 0 neighbourhood_group_cleansed: 0 latitude: 0 longitude: 0 property_type: 0 room_type: 0 accommodates: 0 bathrooms_text: 2 beds: 0 amenities: 0 price: 0 minimum_nights: 0 maximum_nights: 0 minimum_minimum_nights: 0 maximum_minimum_nights: 0 minimum_maximum_nights: 0 maximum_maximum_nights: 0 minimum_nights_avg_ntm: 0 maximum_nights_avg_ntm: 0 has_availability: 0 availability_30: 0 availability_60: 0 availability_90: 0 availability_365: 0 calendar_last_scraped: 0 number_of_reviews: 0 number_of_reviews_ltm: 0 number_of_reviews_l30d: 0 first_review: 553 last_review: 553 instant_bookable: 0 calculated_host_listings_count: 0 calculated_host_listings_count_entire_homes: 0 calculated_host_listings_count_private_rooms: 0 calculated_host_listings_count_shared_rooms: 0 reviews_per_month: 553 review_value: 0 review_rating: 0 review_accuracy: 0 review_cleanliness: 0 review_checkin: 0 review_communication: 0 review_location: 0 NumPrice: 0 baths: 0

id	listing_url	scrape_id	last_scraped	source	name	neighborhood_overview	
<dbl>	<chr>	<dbl>	<chr>	<chr>	<chr>	<chr>	
73282	https://www.airbnb.com/rooms/73282	20230900000000	9/24/2023	previous scrape	Rental unit in Zurich · ★4.78 · 1 bedroom · 1 bed · 1 bath	NA	https://a0.muscache.com/pictures/481072/a
178448	https://www.airbnb.com/rooms/178448	20230900000000	9/24/2023	city scrape	Rental unit in Zurich · ★4.89 · 1 bedroom · 1 bed · 1 bath	We live in one of the top locations of Zürich, the Hürrlimann Areal where the headquarter of Google Europe is located Its a 5 Minutes walk to Bahnhof Enge, 10 Minutes walk to the Bahnhofstrasse, 10 minutes to the lakeside.	https://a0.muscache.com/pictures/7d41e

```
Start:  AIC=28114.3
NumPrice ~ neighbourhood_cleansed + neighbourhood_group_cleansed +
    room_type + accommodates + beds


Step:  AIC=28114.3
NumPrice ~ neighbourhood_cleansed + room_type + accommodates +
    beds

                         Df Sum of Sq       RSS   AIC
- beds                    1     41110 161797520 28113
- room_type               3    302524 162058934 28113
<none>                                161756410 28114
- accommodates            1   4646657 166403067 28184
- neighbourhood_cleansed 33   9303394 171059804 28190

Step:  AIC=28112.94
NumPrice ~ neighbourhood_cleansed + room_type + accommodates

                         Df Sum of Sq       RSS   AIC
- room_type               3    312579 162110098 28112
<none>                                161797520 28113
- neighbourhood_cleansed 33   9275001 171072521 28188
- accommodates            1   9253726 171051245 28252

Step:  AIC=28111.83
NumPrice ~ neighbourhood_cleansed + accommodates

                         Df Sum of Sq       RSS   AIC
<none>                                162110098 28112
- neighbourhood_cleansed 33   9492079 171602177 28190
- accommodates            1  11507515 173617613 28284

Call:
lm(formula = NumPrice ~ neighbourhood_cleansed + neighbourhood_group_cleansed +
    room_type + accommodates + beds, data = zurich2_price_nonas)

Residuals:
   Min     1Q Median     3Q    Max
-573.7  -72.6  -23.9   21.6 9674.8

Coefficients: (11 not defined because of singularities)
                                           Estimate Std. Error t value
(Intercept)                                   5.653     35.765   0.158
neighbourhood_cleansedAlbisrieden            90.285     49.571   1.821
neighbourhood_cleansedAlt-Wiedikon           30.911     40.893   0.756
neighbourhood_cleansedAltstetten            126.216     39.393   3.204
neighbourhood_cleansedCity                  427.997     84.644   5.056
neighbourhood_cleansedEnge                  131.810     43.137   3.056
neighbourhood_cleansedEscher Wyss            60.251     49.134   1.226
neighbourhood_cleansedFluntern               50.544     53.600   0.943
neighbourhood_cleansedFriesenberg            51.972     50.166   1.036
neighbourhood_cleansedGewerbeschule          96.645     43.547   2.219
neighbourhood_cleansedHard                   13.666     43.517   0.314
neighbourhood_cleansedHirslanden             26.274     46.988   0.559
neighbourhood_cleansedHirzenbach             24.776     63.080   0.393
neighbourhood_cleansedHochschulen           113.185     60.605   1.868
neighbourhood_cleansedHöngg                   7.086     45.974   0.154
neighbourhood_cleansedHottingen              48.559     43.735   1.110
neighbourhood_cleansedLangstrasse            74.198     38.764   1.914
neighbourhood_cleansedLeimbach                8.821     84.046   0.105
neighbourhood_cleansedLindenhof             413.490     57.058   7.247
neighbourhood_cleansedMühlebach              48.673     44.451   1.095
neighbourhood_cleansedOberstrass             64.135     46.344   1.384
```

```
neighbourhood_cleansedOberstrass           64.135     46.344   1.384
neighbourhood_cleansedOerlikon             61.038     40.577   1.504
neighbourhood_cleansedRathaus             148.656     40.831   3.641
neighbourhood_cleansedSaatlen              27.006     96.286   0.280
neighbourhood_cleansedSchwamendingen-Mitte  11.034     76.191   0.145
neighbourhood_cleansedSeebach              21.178     45.165   0.469
neighbourhood_cleansedSeefeld             109.395     43.167   2.534
neighbourhood_cleansedSihlfeld             28.582     39.391   0.726
neighbourhood_cleansedUnterstrass          56.967     41.373   1.377
neighbourhood_cleansedWeinegg              47.235     48.440   0.975
neighbourhood_cleansedWerd                 60.659     49.097   1.235
neighbourhood_cleansedWipkingen            32.001     44.172   0.724
neighbourhood_cleansedWitikon               5.247     48.712   0.108
neighbourhood_cleansedWollishofen          43.536     43.341   1.004
neighbourhood_group_cleansedKreis 10           NA         NA      NA
neighbourhood_group_cleansedKreis 11           NA         NA      NA
neighbourhood_group_cleansedKreis 12           NA         NA      NA
neighbourhood_group_cleansedKreis 2            NA         NA      NA
neighbourhood_group_cleansedKreis 3            NA         NA      NA
neighbourhood_group_cleansedKreis 4            NA         NA      NA
neighbourhood_group_cleansedKreis 5            NA         NA      NA
neighbourhood_group_cleansedKreis 6            NA         NA      NA
neighbourhood_group_cleansedKreis 7            NA         NA      NA
neighbourhood_group_cleansedKreis 8            NA         NA      NA
neighbourhood_group_cleansedKreis 9            NA         NA      NA
room_typeHotel room                        72.489     88.464   0.819
room_typePrivate room                     -17.365     13.033  -1.332
room_typeShared room                      -88.161     58.266  -1.513
accommodates                               40.507      4.785   8.466
beds                                        4.605      5.783   0.796
                                                  Pr(>|t|)
(Intercept)                                       0.874427
neighbourhood_cleansedAlbisrieden                 0.068679 .
neighbourhood_cleansedAlt-Wiedikon                0.449776
neighbourhood_cleansedAltstetten                  0.001373 **
neighbourhood_cleansedCity               0.000000458191946 ***
neighbourhood_cleansedEnge                        0.002270 **
neighbourhood_cleansedEscher Wyss                 0.220218
neighbourhood_cleansedFluntern                    0.345784
neighbourhood_cleansedFriesenberg                 0.300310
neighbourhood_cleansedGewerbeschule               0.026554 *
neighbourhood_cleansedHard                        0.753526
neighbourhood_cleansedHirslanden                  0.576095
neighbourhood_cleansedHirzenbach                  0.694526
neighbourhood_cleansedHochschulen                 0.061935 .
neighbourhood_cleansedHöngg                       0.877522
neighbourhood_cleansedHottingen                   0.266972
neighbourhood_cleansedLangstrasse                 0.055719 .
neighbourhood_cleansedLeimbach                    0.916422
neighbourhood_cleansedLindenhof          0.000000000000566 ***
neighbourhood_cleansedMühlebach                   0.273635
neighbourhood_cleansedOberstrass                  0.166516
neighbourhood_cleansedOerlikon                    0.132644
neighbourhood_cleansedRathaus                     0.000277 ***
neighbourhood_cleansedSaatlen                     0.779133
neighbourhood_cleansedSchwamendingen-Mitte        0.884864
neighbourhood_cleansedSeebach                     0.639179
neighbourhood_cleansedSeefeld                     0.011330 *
neighbourhood_cleansedSihlfeld                    0.468155
neighbourhood_cleansedUnterstrass                 0.168667
neighbourhood_cleansedWeinegg                     0.329596
neighbourhood_cleansedWerd                        0.216762
neighbourhood_cleansedWipkingen                   0.468849
neighbourhood_cleansedWitikon                     0.914231
neighbourhood_cleansedWollishofen                 0.315240
neighbourhood_group_cleansedKreis 10                    NA
neighbourhood_group_cleansedKreis 11                    NA
neighbourhood_group_cleansedKreis 12                    NA
neighbourhood_group_cleansedKreis 2                     NA
neighbourhood_group_cleansedKreis 3                     NA
neighbourhood_group_cleansedKreis 4                     NA
neighbourhood_group_cleansedKreis 5                     NA
neighbourhood_group_cleansedKreis 6                     NA
neighbourhood_group_cleansedKreis 7                     NA
neighbourhood_group_cleansedKreis 8                     NA
neighbourhood_group_cleansedKreis 9                     NA
room_typeHotel room                               0.412626
room_typePrivate room                             0.182849
room_typeShared room                              0.130389
accommodates                          < 0.0000000000000002 ***
beds                                              0.425932
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 254.6 on 2495 degrees of freedom
Multiple R-squared:  0.121,	Adjusted R-squared:  0.1076 
F-statistic: 9.036 on 38 and 2495 DF,  p-value: < 0.00000000000000022
```

id: 0 listing_url: 0 scrape_id: 0 last_scraped: 0 source: 0 name: 0 neighborhood_overview: 1334 picture_url: 0 host_id: 0 host_url: 0 host_name: 0 host_since: 0 host_location: 442 host_about: 992 host_response_time: 0 host_response_rate: 0 host_acceptance_rate: 0 host_is_superhost: 42 host_thumbnail_url: 0 host_picture_url: 0 host_neighbourhood: 2499 host_listings_count: 0 host_total_listings_count: 0 host_verifications: 0 host_has_profile_pic: 0 host_identity_verified: 0 neighbourhood: 1334 neighbourhood_cleansed: 0 neighbourhood_group_cleansed: 0 latitude: 0 longitude: 0 property_type: 0 room_type: 0 accommodates: 0 bathrooms_text: 2 beds: 0 amenities: 0 price: 0 minimum_nights: 0 maximum_nights: 0 minimum_minimum_nights: 0 maximum_minimum_nights: 0 minimum_maximum_nights: 0 maximum_maximum_nights: 0 minimum_nights_avg_ntm: 0 maximum_nights_avg_ntm: 0 has_availability: 0 availability_30: 0 availability_60: 0 availability_90: 0 availability_365: 0 calendar_last_scraped: 0 number_of_reviews: 0 number_of_reviews_ltm: 0 number_of_reviews_l30d: 0 first_review: 553 last_review: 553 instant_bookable: 0 calculated_host_listings_count: 0 calculated_host_listings_count_entire_homes: 0 calculated_host_listings_count_private_rooms: 0 calculated_host_listings_count_shared_rooms: 0 reviews_per_month: 553 review_value: 0 review_rating: 0 review_accuracy: 0 review_cleanliness: 0 review_checkin: 0 review_communication: 0 review_location: 0 NumPrice: 0 baths: 0 guestsPerBath: 0 guestsPerBed: 0

```
head(zurich_imputed)
```

id	listing_url	scrape_id	last_scraped	source	name	neighborhood_overview	pi
<dbl>	<chr>	<dbl>	<chr>	<chr>	<chr>	<chr>	
49201447	https://www.airbnb.com/rooms/49201447	20230900000000	9/24/2023	city scrape	Loft in Zürich · ★5.0 · 1 bedroom · 1 bed · 1 bath	The loft is next to the luxury shopping street Bahnhofstrasse, the lake and beaches, top restaurants and bars, few minutes walking distance to all central cultural sightseeings, the old city, churches, museums etc. The only place with no street or tram in front of the Appartment overlooking the river and a beautiful marina with access to sunbathing platform and swimming / pure vacation feeling! Summer and winter! Restaurant with bio and organic fresh juices and food, coffee place, as well as gym in main floor or the same building.	https://a0.muscache.com/pictures/mis 49201447/original/e4e62822-c482-4 e081bd2
50101353	https://www.airbnb.com/rooms/50101353	20230900000000	9/24/2023	previous scrape	Loft in Zürich · ★5.0 · 2 bedrooms · 2 beds · 2 baths	Very central location, minutes from Bahnhofstrasse shopping areas, many bars and restaurants. A 5minute walk to the lake	https://a0.muscache.com/pictures c409-4c78-a8c2-be4c03
9785013	https://www.airbnb.com/rooms/9785013	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★4.57 · Studio · 2 beds · 1 bath	NA	https://a0.muscache.com/pictures/ 9e95-4f42-a5d8-93c572a
23324274	https://www.airbnb.com/rooms/23324274	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★5.0 · 1 bedroom · 2 beds · 1 bath	NA	https://a0.muscache.com/pictures/ 2414-42ec-a223-f56579a
23325594	https://www.airbnb.com/rooms/23325594	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★4.95 · 1 bedroom · 2 beds · 1 bath	NA	https://a0.muscache.com/pictures 597a-44fe-ac8d-33a49f
8370018	https://www.airbnb.com/rooms/8370018	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★4.81 · 2 bedrooms · 3 beds · 2 baths	NA	https://a0.muscache.com/pictures/mis 8370018/original/1d4716de-e5c1-4 436eed4a

Part I: KNN

Solution : A

Step - I: Dataset Handling

```
install.packages("caret")
install.packages("class")
library(caret)
library(class)
library(dplyr)
```

```
stalling package into ‘/usr/local/lib/R/site-library’
; ‘lib’ is unspecified)

so installing the dependencies ‘listenv’, ‘parallelly’, ‘future’, ‘globals’, ‘shape’, ‘future.apply’, ‘numDeriv’, ‘progressr’, ‘SQUAREM’, ‘diagram’,


stalling package into ‘/usr/local/lib/R/site-library’
; ‘lib’ is unspecified)

ading required package: lattice


taching package: ‘caret’


e following object is masked from ‘package:purrr’:

 lift
```

```
# Looking at the data set
head(zurich_imputed)
```

A data.frame: 6 × 74

host_url	host_name	⋯	review_checkin	review_communication	review_location	NumPrice	baths	guestsPerBath	guestsPerBed	Wifi	W
<chr>	<chr>	⋯	<fct>	<fct>	<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	
/users/show/12630015	Konstantin	⋯	Good Reviews	Good Reviews	Good Reviews	0.8155309	-0.4036603	2	2	1	
/users/show/13470694	Henry	⋯	Good Reviews	Good Reviews	Good Reviews	1.0863687	2.0640722	2	2	1	
/users/show/13570663	Christian Robert	⋯	Good Reviews	Good Reviews	Good Reviews	-0.2604000	-0.4036603	2	1	1	
om/users/show/475053	James	⋯	Good Reviews	Good Reviews	Good Reviews	2.2810230	-0.4036603	4	2	1	
om/users/show/475053	James	⋯	Good Reviews	Good Reviews	Good Reviews	2.2810230	-0.4036603	4	2	1	
om/users/show/475053	James	⋯	Good Reviews	Good Reviews	Good Reviews	4.2214088	2.0640722	3	2	1	

```
# Add a new column "index" with row numbers starting from 0
zurich_imputed$index <- seq_len(nrow(zurich_imputed)) - 1
# Reorder columns to make "index" the first column
zurich_imputed <- zurich_imputed[, c("index", setdiff(names(zurich_imputed), "index"))]
```

```
head(zurich_imputed)
```

index	listing_url	scrape_id	last_scraped	source	name	neighborhood_overview	picture_
<dbl>	<chr>	<dbl>	<chr>	<chr>	<chr>	<chr>	<c
0	https://www.airbnb.com/rooms/49201447	20230900000000	9/24/2023	city scrape	Loft in Zürich · ★5.0 · 1 bedroom · 1 bed · 1 bath	The loft is next to the luxury shopping street Bahnhofstrasse, the lake and beaches, top restaurants and bars, few minutes walking distance to all central cultural sightseeings, the old city, churches, museums etc. The only place with no street or tram in front of the Appartment overlooking the river and a beautiful marina with access to sunbathing platform and swimming / pure vacation feeling! Summer and winter! Restaurant with bio and organic fresh juices and food, coffee place, as well as gym in main floor or the same building.	https://a0.muscache.com/pictures/miso/Hos 49201447/original/e4e62822-c482-4e39-9 e081bd2bb35f.
1	https://www.airbnb.com/rooms/50101353	20230900000000	9/24/2023	previous scrape	Loft in Zürich · ★5.0 · 2 bedrooms · 2 beds · 2 baths	Very central location, minutes from Bahnhofstrasse shopping areas, many bars and restaurants. A 5minute walk to the lake	https://a0.muscache.com/pictures/5a6bf c409-4c78-a8c2-be4c03b9fa0
2	https://www.airbnb.com/rooms/9785013	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★4.57 · Studio · 2 beds · 1 bath	NA	https://a0.muscache.com/pictures/01765 9e95-4f42-a5d8-93c572a4681
3	https://www.airbnb.com/rooms/23324274	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★5.0 · 1 bedroom · 2 beds · 1 bath	NA	https://a0.muscache.com/pictures/ad933 2414-42ec-a223-f56579a982a
4	https://www.airbnb.com/rooms/23325594	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★4.95 · 1 bedroom · 2 beds · 1 bath	NA	https://a0.muscache.com/pictures/ea9ff 597a-44fe-ac8d-33a49f4255f
5	https://www.airbnb.com/rooms/8370018	20230900000000	9/24/2023	city scrape	Rental unit in Zürich · ★4.81 · 2 bedrooms · 3 beds · 2 baths	NA	https://a0.muscache.com/pictures/miso/Hos 8370018/original/1d4716de-e5c1-45b9-b 436eed4aa250.

Step - II: T - Test

```
# Adding Wifi coloumn to the dataset
zurich_imputed <- zurich_imputed %>%
  mutate(Wifi = ifelse(grepl("wifi", tolower(amenities)), "Yes", "No"))
zurich_imputed$Wifi <- as.numeric(zurich_imputed$Wifi == "Yes")
```

💡 **Interpretation** 💡 -

We focused on Wifi availability as a key amenity. Reliable internet access is no longer a luxury for travelers; it's a fundamental expectation. When choosing a hotel, guests prioritize properties that offer strong and consistent Wifi to stay connected, informed, and entertained throughout their stay.

```
#Data Partitioning
set.seed(1131)
index <- createDataPartition(zurich_imputed$Wifi,  p =0.6, list=FALSE)

train <- zurich[index, ]
valid <- zurich[-index, ]
```

```
#Looking at the dimentions of the data
dim(train)
dim(valid)
```

```
1521 · 75
1013 · 75
```

```
# Use preProcess() from the caret package to normalize NumPrice, baths, and beds
# Use preProcess() from the caret package to normalize NumPrice, baths, and beds
norm_values <- preProcess(zurich_imputed [, c("baths", "beds", "NumPrice")], method = c("center", "scale"))
zurich_imputed[, c("baths", "beds", "NumPrice")] <- predict(norm_values, zurich_imputed[, c("baths", "beds", "NumPrice")])
```

```
# Filter data for listings with "Wifi"
with_Wifi <- zurich_imputed %>%
  filter(grepl("Wifi", amenities)) %>%
  select(NumPrice, beds, baths) %>%
  na.omit()
```

```
Adding missing grouping variables: `neighbourhood_group_cleansed`,
`neighbourhood_cleansed`, `property_type`, `room_type`
```

```
# Filter data for listings without "Wifi"
without_Wifi <- zurich_imputed %>%
  filter(!grepl("Wifi", amenities)) %>%
  select(NumPrice, beds, baths) %>%
  na.omit()
```

```
Adding missing grouping variables: `neighbourhood_group_cleansed`,
`neighbourhood_cleansed`, `property_type`, `room_type`
```

```
# Perform t- tests for NumPrice, beds & baths
t_test_Price <- t.test(with_Wifi$NumPrice, without_Wifi$NumPrice)
t_test_beds <- t.test(with_Wifi$beds, without_Wifi$beds)
t_test_baths <- t.test(with_Wifi$baths, without_Wifi$baths)
```

```
t_test_Price
```

```
        Welch Two Sample t-test

data:  with_Wifi$NumPrice and without_Wifi$NumPrice
t = 6.2774, df = 1070.9, p-value = 0.0000000004994
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.1397249 0.2667954
sample estimates:
  mean of x   mean of y
 0.02606928 -0.17719087
```

💡 **Interpretation** 💡 **-**

Price (NumPrice):

There is a statistically significant difference (p-value = 0.0000000004994) in the average price between listings with and without Wifi at the 95% confidence level. The confidence interval (0.1397 to 0.2668) indicates that listings with Wifi are likely `$0.14` to `$0.27` more expensive on average compared to listings without Wifi.

```
t_test_baths
```

```
        Welch Two Sample t-test

data:  with_Wifi$baths and without_Wifi$baths
t = 4.0564, df = 544.75, p-value = 0.00005713
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.09506352 0.27358479
sample estimates:
  mean of x   mean of y
 0.02364063 -0.16068353
```

💡 **Interpretation** 💡 **-**

Bathrooms (baths):

There is a statistically significant difference (p-value = 0.00005713) in the average number of bathrooms between listings with and without Wifi at the 95% confidence level. The confidence interval (0.0951 to 0.2736) suggests listings with Wifi tend to have 0.10 to 0.27 more bathrooms on average than listings without Wifi.

```
t_test_beds
```

```
        Welch Two Sample t-test

data:  with_Wifi$beds and without_Wifi$beds
t = 2.488, df = 523.71, p-value = 0.01316
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.02460134 0.20925056
sample estimates:
  mean of x   mean of y
 0.01499642 -0.10192953
```

💡 **Interpretation** 💡 **-**

Bedrooms (beds):

There is a statistically significant difference (p-value = 0.01316) in the average number of bedrooms between listings with and without Wifi at the 95% confidence level. The confidence interval (0.0246 to 0.2093) indicates listings with Wifi might have 0.02 to 0.21 more bedrooms on average compared to listings without Wifi.

💡 **Interpretation** 💡 **-**

Overall, these results suggest that listings with Wifi tend to be more expensive, have more bathrooms, and have slightly more bedrooms on average compared to listings without Wifi.

All of the three t-test indicate statistically significant differences between listings with and without the **Wifi** amenity in terms of NUmPrice, no. of beds and no. of baths. Therefore, none of these variables should be dropped, as they all seem to have some level of influence on the presence of **Wifi** amenity.

Step - III: KNN

```
# Filter the data for the selected neighborhood
neighborhood <- "Hottingen"

data_test <- zurich_imputed %>%
  filter(neighbourhood_cleansed == "Hottingen") %>%
  select(baths, beds, NumPrice, amenities,Wifi) %>% # Select relevant numerical predictors and the outcome variable
  na.omit()  # Remove rows with missing values
```

```
Adding missing grouping variables: `neighbourhood_group_cleansed`,
`neighbourhood_cleansed`, `property_type`, `room_type`
```

```
head(data_test)
```

A grouped_df: 6 × 9

neighbourhood_group_cleansed	neighbourhood_cleansed	property_type	room_type	baths	beds	NumPrice	amenities	Wifi
<chr>	<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<chr>	<dbl>
Kreis 7	Hottingen	Entire condo	Entire home/apt	-0.4036603	-0.4869756	-0.40138404	[]	0
Kreis 7	Hottingen	Entire condo	Entire home/apt	2.0640722	0.3417660	-0.30863138	["Crib", "Books and reading material", "Conditioner", "Private backyard \u2013 Fully fenced", "Bed linens", "Dining table", "Hot water", "Babysitter recommendations", "Private outdoor kitchen", "Paid parking off premises", "Garden view", "First aid kit", "Kitchen", "Dishes and silverware", "Elevator", "Indoor fireplace: wood-burning", "Baby safety gates", "City skyline view", "Hangers", "Single level home", "Cleaning products", "Coffee maker", "BBQ grill", "Dishwasher", "Hair dryer", "Rice maker", "Essentials", "Body soap", "Heating", "Outdoor dining area", "Lockbox", "High chair", "Electric stove", "Free washer \u2013 In unit", "Wifi", "Free dryer \u2013 In unit", "Fire extinguisher", "Bluetooth sound system", "Baking sheet", "Cooking basics", "Dedicated workspace", "Changing table - always at the listing", "Baby bath - always at the listing", "Pack \u2019n play/Travel crib", "Blender", "Bidet", "HDTV with standard cable", "Refrigerator", "Hot water kettle", "Drying rack for clothing", "Freezer", "Outdoor furniture", "Shampoo", "Lake view", "Self check-in", "Table corner guards", "Toaster", "Room-darkening shades", "Children\u2019s dinnerware", "Children\u2019s books and toys", "Microwave", "Private patio or balcony", "Iron"]	1
Kreis 7	Hottingen	Entire condo	Entire home/apt	-0.4036603	0.3417660	0.27385535	["Books and reading material", "Fireplace guards", "Barbecue utensils", "Bed linens", "Dining table", "Hot water", "Fast wifi \u2013 430 Mbps", "Dishes and silverware", "First aid kit", "Kitchen", "Long term stays allowed", "Paid washer \u2013 In building", "Wine glasses", "Indoor fireplace: wood-burning", "Elevator", "Cleaning products", "BBQ grill", "Dishwasher", "Hair dryer", "Essentials", "Portable fans", "Body soap", "Heating", "Coffee maker: Nespresso", "Lockbox", "Oven", "Electric stove", "Baking sheet", "Cooking basics", "Coffee", "Dedicated workspace", "Blender", "Paid street parking off premises", "Refrigerator", "Hot water kettle", "Freezer", "Lake view", "Self check-in", "UE Boom Bluetooth sound system", "Toaster", "Room-darkening shades", "Microwave", "Paid dryer \u2013 In building", "Private patio or balcony"]	1
Kreis 7	Hottingen	Entire condo	Entire home/apt	-0.4036603	0.3417660	-0.07860477	["TV", "Wifi", "Kitchen", "Dedicated workspace", "Central heating", "Washer"]	1
Kreis 7	Hottingen	Entire rental unit	Entire home/apt	-0.4036603	-0.4869756	0.01414789	["Refrigerator", "Lockbox", "Heating", "Wifi", "Dryer", "Self check-in", "Hot water", "TV with standard cable", "Hair dryer", "Cooking basics", "Kitchen", "Dedicated workspace", "Washer", "Iron"]	1
							["Bed linens", "Luggage dropoff allowed", "Hot water", "Paid parking off premises", "Dishes and silverware", "First	

Kreis 7	Hottingen	Entire rental unit	Entire home/apt	-0.4036603	-0.4869756	-0.38283351	aid kit", "Kitchen", "Long term stays allowed", "Elevator", "Hangers", "Stove", "Single level home", "Smoke alarm", "Coffee maker", "Dishwasher", "Hair dryer", "Carbon monoxide alarm", "Essentials", "Heating", "Lockbox", "Oven", "Shower gel", "Wifi", "Fire extinguisher", "Baking sheet", "Cooking basics", "Patio or balcony", "Washer", "Bathtub", "Refrigerator", "Shampoo", "Self check-in", "Dryer", "Room-darkening shades", "Extra pillows and blankets", "Iron"]	1

```
# Split the data into training and testing sets
set.seed(1131)
train.rows<-sample(rownames(data_test),dim(data_test)[1]*0.6)
train.data<-data_test[train.rows,]
valid.rows<-setdiff(rownames(data_test),train.rows)
valid.data<-data_test[valid.rows,]
```

```
library(class)

# Use the selected value of k to make predictions on the testing set
knnFit <- knn(train = train.data[, c("baths", "beds", "NumPrice")],
              test = valid.data[, c("baths", "beds", "NumPrice")],
              cl = train.data$Wifi,  # Use Wifi from train.data for class labels
              k = 3)
```

```
# Print the predicted amenities
print(knnFit)
```

```
 [1] 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 0 1 1 1 1 1
Levels: 0 1
```

```
# Convert 'near' matrix into a simple vector
near_vector <- as.vector(attr(knnFit, "nn.index"))
```

```
# Subset rows using the simple vector
near_1 <- train.data[near_vector, c("baths", "beds", "NumPrice")]

# Print the subsetted data
print(near_1)
```

```
# A tibble: 0 × 3
# Groups:   beds [0]
# ℹ 3 variables: baths <dbl>, beds <dbl>, NumPrice <dbl>
```

```
# Load the necessary packages
install.packages("caret")
library(caret)
```

Step - IV: Accuracy Test

```
# Initialize a data frame to store accuracy for different k values
accuracy.df <- data.frame(k = seq(1, 35, 1), accuracy = rep(0, 35))

# Compute kNN for different k values on the validation set
for (i in 1:35) {
  knn.pred <- knn(train.data[, c("baths", "beds", "NumPrice")],
                  valid.data[, c("baths", "beds", "NumPrice")],
                  cl = as.factor(train.data$Wifi), k = i)  # Convert class labels to factor
  accuracy.df[i, 2] <- confusionMatrix(knn.pred, as.factor(valid.data$Wifi))$overall["Accuracy"]
}

# Print accuracy dataframe
print(accuracy.df)
```

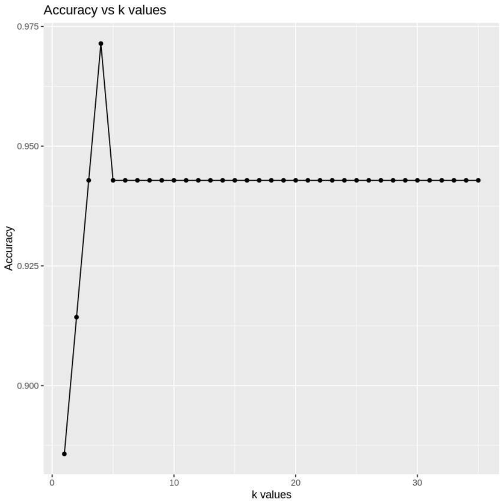
```
    k  accuracy
1   1 0.8857143
2   2 0.9142857
3   3 0.9428571
4   4 0.9714286
5   5 0.9428571
6   6 0.9428571
7   7 0.9428571
8   8 0.9428571
9   9 0.9428571
10 10 0.9428571
11 11 0.9428571
12 12 0.9428571
13 13 0.9428571
14 14 0.9428571
15 15 0.9428571
16 16 0.9428571
17 17 0.9428571
18 18 0.9428571
19 19 0.9428571
20 20 0.9428571
21 21 0.9428571
22 22 0.9428571
23 23 0.9428571
24 24 0.9428571
25 25 0.9428571
26 26 0.9428571
27 27 0.9428571
```

```
28 28 0.9428571
29 29 0.9428571
30 30 0.9428571
31 31 0.9428571
32 32 0.9428571
33 33 0.9428571
34 34 0.9428571
35 35 0.9428571
```

```
# Load the ggplot2 library
install.packages("ggplot2")
library(ggplot2)
```

```
Installing package into '/usr/local/lib/R/site-library'
(as 'lib' is unspecified)
```

```
# Plot accuracy vs. k values
ggplot(data = accuracy.df, aes(x = k, y = accuracy)) +
  geom_point() +
  geom_line() +
  labs(x = "k values", y = "Accuracy") +
  ggtitle("Accuracy vs k values")
```



Step - V: Optimal K Value

```
# Find the optimal k value
optimal_k <- accuracy.df$k[which.max(accuracy.df$accuracy)]
optimal_accuracy <- max(accuracy.df$accuracy)

# Print optimal k value and accuracy
cat("Optimal k value:", optimal_k, "\n")
cat("Optimal accuracy:", optimal_accuracy, "\n")
```

```
Optimal k value: 4
Optimal accuracy: 0.9714286
```

Step - VI: Confusion Matrix

```
# Build confusion matrix
confusionMatrix(table(predicted = knnFit, actual = valid.data$Wifi))
```

```
Confusion Matrix and Statistics

          actual
predicted  0  1
        0  1  1
        1  1 32

               Accuracy : 0.9429
                 95% CI : (0.8084, 0.993)
    No Information Rate : 0.9429
    P-Value [Acc > NIR] : 0.6768

                  Kappa : 0.4697

 Mcnemar's Test P-Value : 1.0000

            Sensitivity : 0.50000
            Specificity : 0.96970
         Pos Pred Value : 0.50000
         Neg Pred Value : 0.96970
             Prevalence : 0.05714
         Detection Rate : 0.02857
   Detection Prevalence : 0.05714
      Balanced Accuracy : 0.73485

       'Positive' Class : 0
```

💡 **Interpretation** 💡 -

- **Accuracy**: The overall accuracy of the model is 94.29%, indicating that it correctly predicted 94.29% of the instances in the validation set.
- **Sensitivity (True Positive Rate)**: The sensitivity, also known as the true positive rate, is 50%. This metric represents the proportion of actual positives (class 0, indicating presence of Wifi) that were correctly identified by the model.
- **Specificity (True Negative Rate)**: The specificity, or true negative rate, is 96.97%. This measures the proportion of actual negatives (class 1, indicating absence of Wifi) that were correctly identified by the model.
- **Positive Predictive Value (Precision)**: The positive predictive value, or precision, is 50%. This indicates the probability that instances predicted as having Wifi (class 0) actually have it.
- **Negative Predictive Value**: The negative predictive value is 96.97%, representing the probability that instances predicted as not having Wifi (class 1) actually don't have it.
- **Prevalence**: The prevalence of Wifi in the dataset is 5.71%, indicating the proportion of instances with Wifi.
- **Balanced Accuracy**: The balanced accuracy is 73.49%, calculated as the average of sensitivity and specificity. It provides a balanced assessment of the model's performance across both classes.

In summary, the model shows reasonably high accuracy and specificity but relatively low sensitivity, suggesting that it performs better at correctly identifying instances without Wifi than those with Wifi. This imbalance in performance could be due to the class distribution in the dataset or the model's inherent bias. Further tuning or exploration may be needed to improve sensitivity without compromising specificity.

Solution : B

💡 **Final Narative** 💡 -

In this analysis, the focus was on predicting the availability of Wifi as an amenity in rental listings in Zurich. The dataset contained information on various predictors such as the number of bathrooms, bedrooms, and the price of the listings. To prepare the data, I first created a binary variable for Wifi availability based on whether the term "wifi" was present in the amenities list. Then, I split the data into training and validation sets and normalized the numerical predictors. The kNN algorithm was chosen for its simplicity and effectiveness in handling classification tasks. To determine the optimal k-value, I utilized a loop to iterate through different values of k and evaluated the model's accuracy on the validation set for each k. The k-value that yielded the highest accuracy was selected as the optimal choice.

Upon evaluating the kNN model with the optimal k-value, it achieved an accuracy of 94.29% on the validation set, which suggests a good overall performance. However, a deeper analysis revealed that the model's sensitivity was relatively low at 50%, indicating a challenge in correctly identifying instances with Wifi. This imbalance in sensitivity and specificity might suggest potential areas for improvement in the model, such as exploring different feature selections or algorithmic approaches. Furthermore, comparing the model's performance against a naive Bayes algorithm, with the purpose of predicting the way consumers feel about the value that they recieve from the booking will help provide additional insights