finalproject2

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Installing Packages:

```
library (tidyverse)
## Warning: package 'tidyverse' was built under R version 3.5.3
## -- Attaching packages ------ tidyverse 1.3.0 --
## v ggplot2 3.3.0
                   v purrr 0.3.3
## v tibble 3.0.0 v dplyr 0.8.5
## v tidyr 1.0.2 v stringr 1.4.0
## v readr 1.3.1
                   v forcats 0.5.0
## Warning: package 'ggplot2' was built under R version 3.5.3
## Warning: package 'tibble' was built under R version 3.5.3
## Warning: package 'tidyr' was built under R version 3.5.3
## Warning: package 'readr' was built under R version 3.5.3
## Warning: package 'purrr' was built under R version 3.5.3
## Warning: package 'dplyr' was built under R version 3.5.3
## Warning: package 'stringr' was built under R version 3.5.3
## Warning: package 'forcats' was built under R version 3.5.3
## -- Conflicts ------ tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag() masks stats::lag()
library (GGally)
## Warning: package 'GGally' was built under R version 3.5.3
## Attaching package: 'GGally'
## The following object is masked from 'package:dplyr':
##
    nasa
library (ggplot2)
library(scales)
## Warning: package 'scales' was built under R version 3.5.3
## Attaching package: 'scales'
```

```
## The following object is masked from 'package:purrr':
##
##
       discard
## The following object is masked from 'package:readr':
##
##
      col_factor
library (gridExtra)
## Warning: package 'gridExtra' was built under R version 3.5.3
## Attaching package: 'gridExtra'
## The following object is masked from 'package:dplyr':
##
##
      combine
library (grid)
library (randomForest)
## Warning: package 'randomForest' was built under R version 3.5.3
## randomForest 4.6-14
## Type rfNews() to see new features/changes/bug fixes.
##
## Attaching package: 'randomForest'
## The following object is masked from 'package:gridExtra':
##
##
      combine
## The following object is masked from 'package:dplyr':
##
      combine
##
## The following object is masked from 'package:ggplot2':
##
##
     margin
library(lmtest)
## Warning: package 'lmtest' was built under R version 3.5.3
## Loading required package: zoo
## Warning: package 'zoo' was built under R version 3.5.3
##
## Attaching package: 'zoo'
## The following objects are masked from 'package:base':
##
##
       as.Date, as.Date.numeric
```

```
Hotel <- read_csv("D:/UIUC/Spring2020/stat425/finalproject/stat425_fpdata.csv")</pre>
```

```
## Parsed with column specification:
## cols(
   hotel = col character(),
##
    is_canceled = col_double(),
   lead_time = col_double(),
##
   arrival_date_year = col_double(),
##
   arrival_date_month = col_character(),
##
##
   arrival date week number = col double(),
##
   arrival date day of month = col double(),
##
   stays_in_weekend_nights = col_double(),
##
   stays_in_week_nights = col_double(),
##
   adults = col_double(),
##
   children = col_double(),
##
   babies = col_double(),
##
   meal = col character(),
##
    market segment = col character(),
##
    reserved_room_type = col_character(),
##
    customer_type = col_character(),
   adr = col_double(),
##
    total_of_special_requests = col_double()
##
## )
```

city_hotels <- subset(Hotel, Hotel\$hotel == "City Hotel") #Subset just city hotels because im section two.</pre>

Creating seasons variable:

```
city_hotels$arrival_season = "" #init variable
i = 1 #index for rows
for(val in city_hotels$arrival_date_month) #increment through each row
{
    if(val == "January" | val == "February" | val == "December") { #conditional city_hotels$arrival_season[i] = "Winter" #change to season
} else if(val == "March" | val == "May" | val == "April") { city_hotels$arrival_season[i] = "Spring"
} else if(val == "June" | val == "July" | val == "August") { city_hotels$arrival_season[i] = "Summer"
} else { city_hotels$arrival_season[i] = "Fall"
}

i = i + 1 #incremenet index
}
```

```
head(city_hotels)
```

```
## # A tibble: 6 x 19
## hotel is_canceled lead_time arrival_date_ye~ arrival_date_mo~
## <chr> <dbl> <dbl> <dbl> <chr>
                       0
1
5
              0
                                        2015 August
2015 August
## 1 City~
## 2 City~
                 0
                                        2015 August
## 3 City~
                 0
                                        2015 August
## 4 City~
                          39
## 5 City~
                 0
                           3
                                        2015 September
                 0 82
## 6 City~
                                         2015 September
## # ... with 14 more variables: arrival date week number <dbl>,
## # arrival date day of month <dbl>, stays in weekend nights <dbl>,
## # stays_in_week_nights <dbl>, adults <dbl>, children <dbl>,
## # babies <dbl>, meal <chr>, market segment <chr>,
## # reserved_room_type <chr>, customer_type <chr>, adr <dbl>,
## # total_of_special_requests <dbl>, arrival_season <chr>
```

Creating total stays variable:

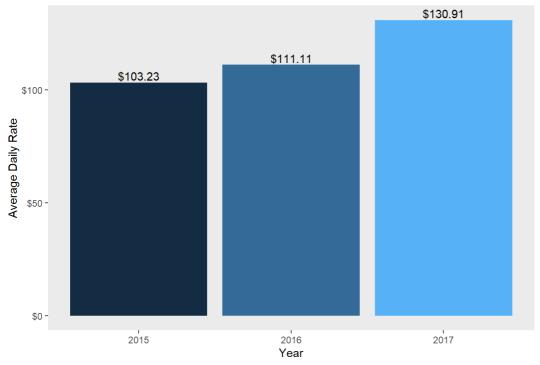
```
\verb|city_hotels$total_stays <- city_hotels$stays_in_weekend_nights + city_hotels$stays_in_week_nights \#|creating|| total stays variable||
```

Creating Bar Plots:

```
## Warning: funs() is soft deprecated as of dplyr 0.8.0
## Please use a list of either functions or lambdas:
##
\# \#
     # Simple named list:
##
    list(mean = mean, median = median)
##
    # Auto named with `tibble::lst()`:
##
##
    tibble::lst(mean, median)
##
##
    # Using lambdas
    list(~ mean(., trim = .2), ~ median(., na.rm = TRUE))
##
## This warning is displayed once per session.
```

```
ggplot(data = year_group, aes(x = arrival_date_year, y = adr, fill = arrival_date_year)) +
geom_bar(position = 'dodge', stat='identity') + #create bar plot
geom_text(aes(label= dollar(adr)), position=position_dodge(width=0.9), vjust=-0.25) + #add text to bar plo
t
    xlab("Year") + ylab("Average Daily Rate") + ggtitle("Average Daily Rate seperated by Year") + scale_y_cont
inuous(labels = scales::dollar) + theme(legend.position = "none", panel.grid = element_blank(), #add all t
itles and everything
    plot.title = element_text(hjust = 0.5),
    plot.subtitle = element_text(hjust = 0.5)) #ADD X, Y, TITLE LABELS AND ADJUST THEM
```

Average Daily Rate seperated by Year



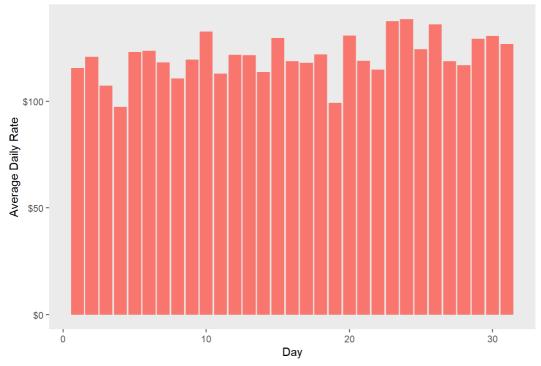
```
#plot for Average Daily Rate seperated by Season
season_group <- summarise_at(group_by(city_hotels, arrival_season), vars(adr), funs(mean(.,na.rm=FALSE)))

ggplot(data = season_group, aes(x = arrival_season, y = adr, fill = arrival_season)) +
    geom_bar(position = 'dodge', stat='identity') +
    geom_text(aes(label= dollar(adr)), position=position_dodge(width=0.9), vjust=-0.25) +
    xlab("Season") + ylab("Average Daily Rate") + ggtitle("Average Daily Rate seperated by Season") + scale_
    y_continuous(labels = scales::dollar) + theme(legend.position = "none", panel.grid = element_blank(),
        plot.title = element_text(hjust = 0.5),
        plot.subtitle = element_text(hjust = 0.5))</pre>
```

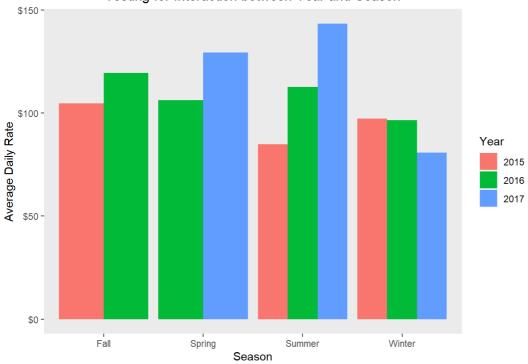
Average Daily Rate seperated by Season



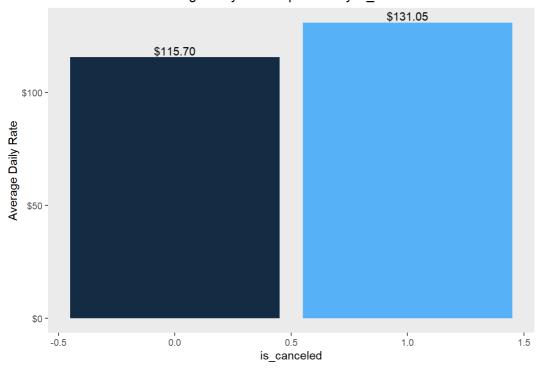
Average Daily Rate seperated by Arrival Date of Month



Testing for Interaction between Year and Season



Average Daily Rate seperated by is_canceled



```
#creating plot for meal group
meal_group <- summarise_at(group_by(city_hotels, meal), vars(adr), funs(mean(.,na.rm=FALSE)))

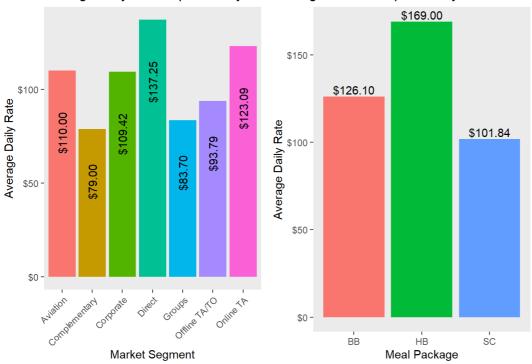
meal_package_plot <- ggplot(data = meal_group, aes(x = meal, y = adr, fill = meal)) +
    geom_bar(position = 'dodge', stat='identity') +
    geom_text(aes(label= dollar(adr)), position=position_dodge(width=0.9), vjust=-0.25) +
    xlab("Meal Package") + ylab("Average Daily Rate") + ggtitle("") + scale_y_continuous(labels = scales::do
    llar) + theme(legend.position = "none", panel.grid = element_blank(),
        plot.title = element_text(hjust = 0.5),
        plot.subtitle = element_text(hjust = 0.5))</pre>
```

```
#mcreating plot for market_group
market_group <- summarise_at(group_by(city_hotels, market_segment), vars(adr), funs(mean(.,na.rm=FALSE)))

market_segment_plot <- ggplot(data = market_group, aes(x = market_segment, y = adr, fill = market_segment))+
    geom_bar(position = 'dodge', stat='identity') +
    geom_text(aes(label= dollar(adr), angle = 90), hjust= 2) +
    xlab("Market Segment") + ylab("Average Daily Rate") + ggtitle("Average Daily Rate seperated by Market Segment and Seperated by Meal Plan") + scale_y_continuous(labels = scales::dollar) + theme(legend.position = "none", panel.grid = element_blank(),
    plot.title = element_text(hjust = 0),
    plot.subtitle = element_text(hjust = 0.5),
    axis.text.x = element_text(angle = 45, hjust = 1))</pre>
```

```
grid.arrange(meal_package_plot, market_segment_plot, layout_matrix = cbind(c(2,2), c(1,1))) #combining to sa
ve space
```

Average Daily Rate seperated by Market Segment and Seperated by Meal Plan

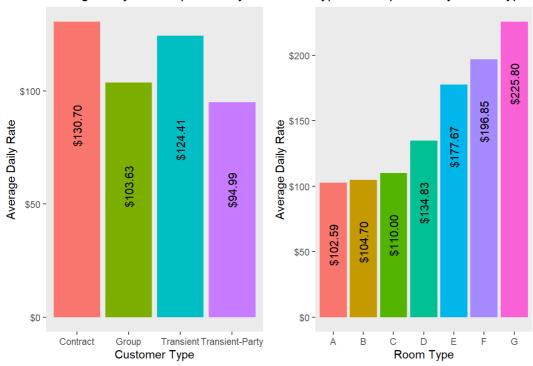


```
#creating customer group plot
customer_group <- summarise_at(group_by(city_hotels, customer_type), vars(adr), funs(mean(.,na.rm=FALSE)))

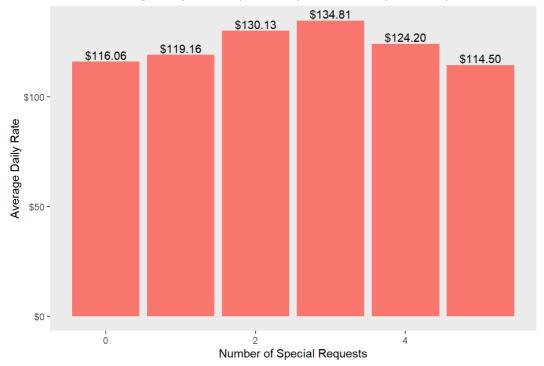
customer_group_plot <- ggplot(data = customer_group, aes(x = customer_type, y = adr, fill = customer_type))
+
    geom_bar(position = 'dodge', stat='identity') +
    geom_text(aes(label= dollar(adr), angle = 90), hjust = 3) +
    xlab("Customer Type") + ylab("Average Daily Rate") + ggtitle("Average Daily Rate seperated by Customer Typ
e and Seperated by Room Type") + scale_y_continuous(labels = scales::dollar) + theme(legend.position = "no
ne", panel.grid = element_blank(),
    plot.title = element_text(hjust = 0),
    plot.subtitle = element_text(hjust = 0.5))</pre>
```

```
#combining two plots to save space :(
grid.arrange(reserve_group_plot, customer_group_plot, layout_matrix = cbind(c(2,2), c(1,1)))
```

Average Daily Rate seperated by Customer Type and Seperated by Room Type



Average Daily Rate seperated by Number of Special Requests

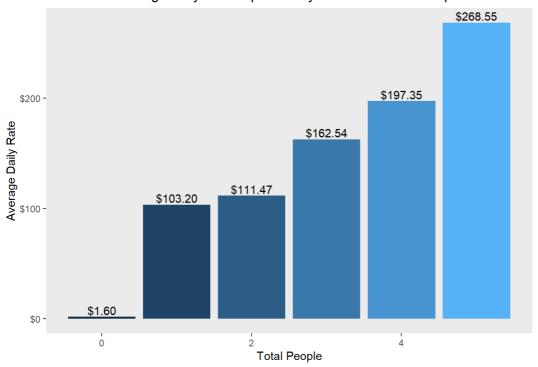


```
#looking at Average Daily Rate seperated by Number of Total People"
city_hotels$total_people <- city_hotels$adults + city_hotels$children

people_group <- summarise_at(group_by(city_hotels, total_people), vars(adr), funs(mean(.,na.rm=FALSE)))

ggplot(data = people_group, aes(x = total_people, y = adr, fill = total_people)) +
    geom_bar(position = 'dodge', stat='identity') +
    geom_text(aes(label= dollar(adr)), position=position_dodge(width=0.9), vjust=-0.25) +
    xlab("Total People") + ylab("Average Daily Rate") + ggtitle("Average Daily Rate seperated by Number of Tot
al People") + scale_y_continuous(labels = scales::dollar) + theme(legend.position = "none", panel.grid =
element_blank(),
    plot.title = element_text(hjust = 0.5),
    plot.subtitle = element_text(hjust = 0.5))</pre>
```

Average Daily Rate seperated by Number of Total People

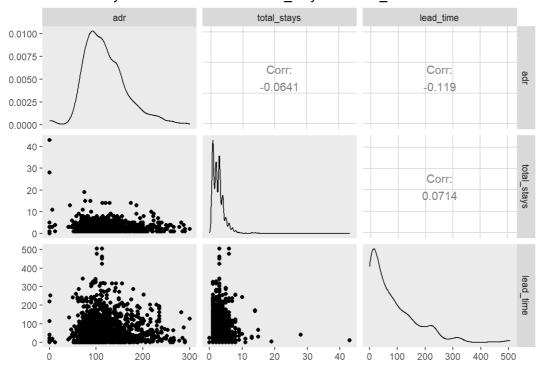


head(city hotels)

```
## # A tibble: 6 x 21
## hotel is canceled lead time arrival date ye~ arrival date mo~
## <chr> <dbl>
                       <dbl>
                                       <dbl> <chr>
## 1 City~
                                         2015 August
## 2 City~
                  0
                            1
                                          2015 August
## 3 City~
                  0
                            5
                                          2015 August
## 4 City~
                   0
                            39
                                          2015 August
## 5 City~
                   0
                            3
                                          2015 September
## 6 City~
                   0
                            82
                                          2015 September
## # ... with 16 more variables: arrival_date_week_number <dbl>,
      arrival_date_day_of_month <dbl>, stays_in_weekend_nights <dbl>,
      stays_in_week_nights <dbl>, adults <dbl>, children <dbl>,
## #
     babies <dbl>, meal <chr>, market_segment <chr>,
####
      reserved_room_type <chr>, customer_type <chr>, adr <dbl>,
      total_of_special_requests <dbl>, arrival_season <chr>,
## #
      total_stays <dbl>, total_people <dbl>
## #
```

Testing Numerical Variables:

Analysis between numerical total_stays and lead_time and ADR



#looking at total stays and lead time

Subsetting Dataset once more:

city_hotels_removed <- select(city_hotels, is_canceled, reserved_room_type, arrival_season, total_people, me al, market_segment, customer_type, arrival_date_year, adr) #subsetting data

Converting to factor variables:

```
city_hotels_removed$is_canceled = as.factor(city_hotels$is_canceled)
city_hotels_removed$reserved_room_type = as.factor(city_hotels$reserved_room_type)
city_hotels_removed$arrival_season = as.factor(city_hotels$arrival_season)
city_hotels_removed$total_people = as.factor(city_hotels$total_people)
city_hotels_removed$meal = as.factor(city_hotels$meal)
city_hotels_removed$market_segment = as.factor(city_hotels$market_segment)
city_hotels_removed$customer_type = as.factor(city_hotels$customer_type)
city_hotels_removed$arrival_date_year = as.factor(city_hotels$arrival_date_year)
#creating factor variables
```

head(city hotels removed)

```
## # A tibble: 6 x 9
##
  is_canceled reserved_room_t~ arrival_season total_people meal
            <fct>
                                      <fct>
  <fct>
                              <fct>
## 1 0
                                                       SC
              Α
## 2 0
             A
                              Summer
                                          2
                                                       SC
## 3 0
              A
                              Summer
                                           2
                                                       BB
## 4 0
                              Summer
                                                       ΗВ
              Α
                                           1
## 5 0
                                           2
                                                       ВВ
              Α
                              Fall
                              Fall
                                           2
              Α
## # ... with 4 more variables: market segment <fct>, customer type <fct>,
    arrival_date_year <fct>, adr <dbl>
```

Creating simple model:

```
simple_model <- lm(adr ~ . , data = city_hotels_removed)
summary(simple_model) #fitting simple model, looking at summary</pre>
```

```
##
## lm(formula = adr ~ ., data = city_hotels_removed)
##
## Residuals:
## Min 1Q Median
                        3Q
                              Max
## -164.39 -16.12 -0.82 15.27 108.71
##
## Coefficients:
##
                          Estimate Std. Error t value Pr(>|t|)
                         17.443570 31.508732 0.554 0.5799
## (Intercept)
                          5.195600 1.670484 3.110 0.0019 **
## is canceled1
                      5.195600
-10.250066
## reserved_room_typeB
                                   5.302841 -1.933 0.0534 .
                        10.055988 28.025123
## reserved room typeC
                                            0.359
                                                  0.7198
                                            8.814 < 2e-16 ***
## reserved_room_typeD
                          17.629094
                                   2.000058
                         50.213001
                                    3.634015 13.818 < 2e-16 ***
## reserved_room_typeE
                         60.216543 4.960476 12.139 < 2e-16 ***
## reserved_room_typeF
                         96.488950 5.309933 18.171 < 2e-16 ***
## reserved_room_typeG
## arrival_seasonSpring
                       -11.333639 2.382911 -4.756 2.15e-06 ***
## arrival seasonSummer
                         -7.379294 2.372433 -3.110 0.0019 **
## arrival seasonWinter
                        -38.781802 2.741657 -14.145 < 2e-16 ***
## total_people1
                        105.031219 13.963074 7.522 8.97e-14 ***
## total_people2
                       106.687744 13.924728 7.662 3.17e-14 ***
                       133.965301 14.068555 9.522 < 2e-16 ***
## total_people3
## total_people4
## total_people5
                        131.698746 14.760775 8.922 < 2e-16 ***
                                           8.028 1.91e-15 ***
                        162.215765 20.207177
                                            6.183 7.98e-10 ***
## mealHB
                          32.179596
                                   5.204559
## mealSC
                          -8.957874
                                    1.911914 -4.685 3.03e-06 ***
## market_segmentComplementary -21.541852 39.798005 -0.541 0.5884
## market segmentOffline TA/TO -20.112166 27.600236 -0.729 0.4663
## customer_typeTransient-Party -14.520719 7.960738 -1.824 0.0683 .
## arrival_date_year2016 3.956157 3.291770 1.202 0.2296
## arrival date year2017
                         20.260854 3.655920 5.542 3.50e-08 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27.35 on 1589 degrees of freedom
## Multiple R-squared: 0.6401, Adjusted R-squared: 0.6337
## F-statistic: 100.9 on 28 and 1589 DF, p-value: < 2.2e-16
```

BIC of simple model:

```
BIC(simple_model) #BIC for simple model
```

```
## [1] 15490.89
```

ADD A TRAIN AND TEST SET FOR 3.2 AND 3.3

Subsetting data to remove marketsegment:

```
city_hotels_removed <- select(city_hotels_removed, is_canceled, reserved_room_type, arrival_season, total_pe
ople, meal, customer_type, arrival_date_year, adr) #cutting down dataset</pre>
```

Creating test and train sets:

```
# creating test and train datasets
## 75% of the sample size
smp_size <- floor(0.75 * nrow(city_hotels_removed))

## set the seed to make your partition reproducible
set.seed(123)
train_ind <- sample(seq_len(nrow(city_hotels_removed)), size = smp_size) #index

train <- city_hotels_removed[train_ind, ]
test <- city_hotels_removed[-train_ind, ]
#https://stackoverflow.com/questions/17200114/how-to-split-data-into-training-testing-sets-using-sample-func
tion</pre>
```

Creating complex model:

```
complex_model <- lm(adr ~ . + arrival_season * arrival_date_year, data = train)
summary(complex_model) #fitting model and looking at summary</pre>
```

```
##
## Call:
## lm(formula = adr ~ . + arrival_season * arrival_date_year, data = train)
##
## Residuals:
                              3Q
##
   Min
               1Q Median
## -131.500 -15.119 -0.333 15.476 101.239
##
## Coefficients: (2 not defined because of singularities)
##
                                           Estimate Std. Error t value
                                            22.872 15.721 1.455
## (Intercept)
                                            3.935
                                                      1.920 2.050
## is_canceled1
                                                      5.954 -0.736
## reserved room typeB
                                            -4.384
                                            1.846 27.492 0.067
## reserved room typeC
                                                      2.319 8.997
                                            20.869
## reserved_room_typeD
## reserved room typeE
                                            52.990
                                                      4.068 13.026
                                            69.156
                                                      5.644 12.253
## reserved_room_typeF
                                           101.208
                                                      6.150 16.456
## reserved_room_typeG
                                            12.176
                                                       9.864 1.234
## arrival_seasonSpring
## arrival_seasonSummer
                                           -22.887
                                                     14.140 -1.619
                                                       8.898 -3.444
## arrival seasonWinter
                                           -30.643
                                                      14.102
## total_people1
                                            99.787
                                                               7.076
                                           100.577
## total people2
                                                      14.061
                                                               7.153
                                                      14.241 8.803
                                           125.362
## total_people3
## total_people4
                                                      15.107 7.935
                                           119.877
## total_people5
                                           159.145 22.018 7.228
## mealHB
                                            32.347
                                                      6.097 5.306
## mealSC
                                            -7.721
                                                      2.122 -3.639
## customer typeGroup
                                           -30.951 13.019 -2.377
                                                     7.611 -2.887
## customer_typeTransient
                                           -21.975
                                                       7.854 -4.509
                                           -35.415
## customer_typeTransient-Party
                                                      4.073 1.640
9.109 0.504
                                           6.680
## arrival_date_year2016
## arrival date year2017
                                             4.595
                                                      10.374 -2.122
## arrival_seasonSpring:arrival_date_year2016 -22.015
                                                      14.467 0.995
## arrival_seasonSummer:arrival_date_year2016 14.389
                                                      9.706 0.551
NA NA
                                            5.353
## arrival seasonWinter:arrival date year2016
## arrival_seasonSpring:arrival_date_year2017 NA
## arrival_seasonSummer:arrival_date_year2017 39.449 16.632 2.372
## arrival_seasonWinter:arrival_date_year2017
NA
                                                       NA NA
##
                                           Pr(>|t|)
                                           0.145973
## (Intercept)
## is canceled1
                                           0.040621 *
## reserved room typeB
                                          0.461657
                                          0.946476
## reserved_room_typeC
                                           < 2e-16 ***
## reserved_room_typeD
                                           < 2e-16 ***
## reserved room typeE
                                           < 2e-16 ***
## reserved room typeF
                                           < 2e-16 ***
## reserved room typeG
## arrival_seasonSpring
                                          0.217320
## arrival seasonSummer
                                          0.105807
                                          0.000594 ***
## arrival seasonWinter
                                          2.53e-12 ***
## total_people1
```

```
1.48e-12 ***
## total_people2
                                              < 2e-16 ***
## total_people3
                                             4.83e-15 ***
## total people4
## total people5
                                             8.76e-13 ***
## mealHB
                                             1.34e-07 ***
                                             0.000286 ***
## mealsc
                                            0.017597 *
## customer_typeGroup
                                            0.003958 **
## customer_typeTransient
                                             7.15e-06 ***
## customer_typeTransient-Party
## arrival date year2016
                                             0.101302
## arrival date year2017
## arrival_seasonSpring:arrival_date_year2016 0.034030 *
## arrival seasonSummer:arrival date year2016 0.320142
## arrival_seasonWinter:arrival_date_year2016 0.581408
## arrival_seasonSpring:arrival_date_year2017
NA
## arrival seasonSummer:arrival date year2017 0.017855 *
## arrival seasonWinter:arrival date year2017
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 27.37 on 1186 degrees of freedom
## Multiple R-squared: 0.647, Adjusted R-squared: 0.6392
## F-statistic: 83.6 on 26 and 1186 DF, p-value: < 2.2e-16
```

BIC of complex model:

```
BIC(complex_model) #BIC of MLR model
```

```
## [1] 11642.17
```

Predict using complex model:

```
#predict_df = data.frame(is_canceled = "0", arrival_season = "Winter", arrival_date_year = #"2016", meal = "
BB", reserved_room_type = "C", customer_type = "Transient", total_people #= "4")
mean(predict(complex_model, test)) #predicting the ADR from the MLR model using test data
```

```
## Warning in predict.lm(complex_model, test): prediction from a rank-
## deficient fit may be misleading
```

```
## [1] 118.9234
```

head(city_hotels_removed) #viewing dataset for convience

```
## # A tibble: 6 x 8
   is canceled reserved room t~ arrival season total people meal
   <fct> <fct>
                          <fct>
                                <fct>
## 1 0
            A
                          Summer
                                                 SC
            A
                                      2
## 2 0
                          Summer
                                                 SC
            A
                          Summer
## 3 0
                                      2.
                                                BB
## 4 0
            A
                                      1
                          Summer
                                                HB
## 5 0
            A
                                      2
                         Fall
                         Fall
            A
                                     2
## # ... with 3 more variables: customer_type <fct>, arrival_date_year <fct>,
## # adr <dbl>
```

Creating Random Forest:

```
rfModel = randomForest(adr ~ ., ntree = 2000, data = train, seed = 425)
rfModel #creating the RF
```

```
##
## Call:
## randomForest(formula = adr ~ ., data = train, ntree = 2000, seed = 425)
## Type of random forest: regression
## Number of trees: 2000
## No. of variables tried at each split: 2
##
## Mean of squared residuals: 748.6617
## % Var explained: 63.9
```

Importance values of rf:

 ${\tt rfModel\$importance}\ \textit{\#importance}\ \textit{of}\ \textit{RF}\ \textit{model}\ \textit{variables}$

```
## is_canceled 25685.17
## reserved_room_type 736625.71
## arrival_season 172309.42
## total_people 450918.36
## meal 105655.29
## customer_type 77146.01
## arrival_date_year 128746.55
```

RMSE of RF:

```
mean(sqrt(rfModel$mse)) #rmse of RF model
```

```
## [1] 27.40389
```

Predict using RF:

```
predict_tree = predict(rfModel, data = test, predict.all = TRUE)
mean(predict_tree) #predict using RF
```

```
## [1] 120.5011
```

RMSE of MLR:

sqrt(sum(complex_model\$residuals^2)/nrow(city_hotels_removed)) #RMSE of MLR model

```
## [1] 23.42904
```

SD of ADR:

```
sd(test$adr)
```

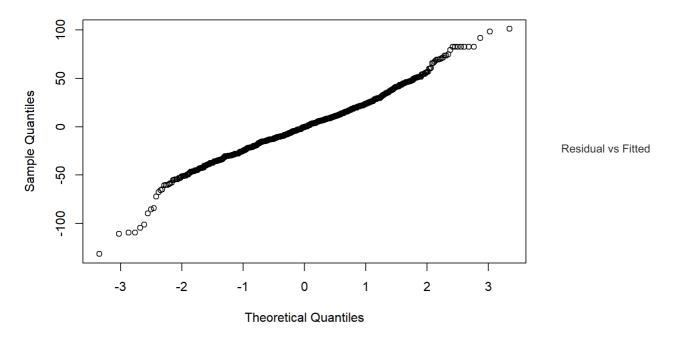
```
## [1] 44.01975
```

Model Diagnostics:

QQ plot

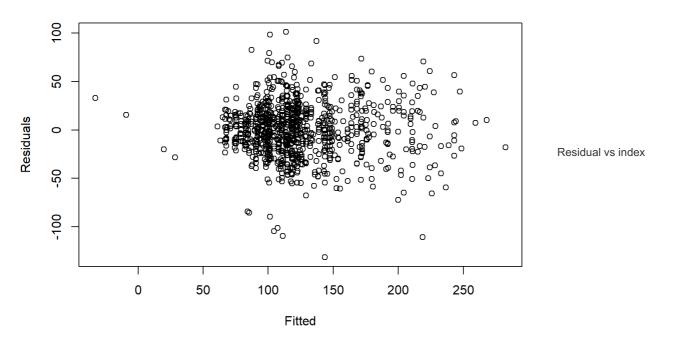
```
qqnorm(complex_model$residuals) #qq plot to test for normality
```

Normal Q-Q Plot



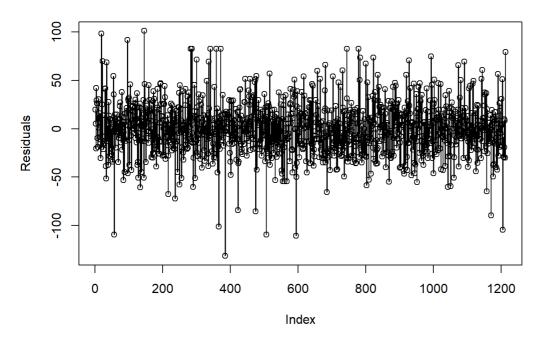
#plot for testing for constance variance assumption
plot(complex_model\$fitted.values, complex_model\$residuals, xlab = "Fitted", ylab = "Residuals", main = "Residuals vs Fitted")

Residuals vs Fitted



```
#plot to help test for correlated errors
len = 1:1213 #index
plot(len, complex_model$residuals, xlab = "Index", ylab = "Residuals", main = "Residuals vs Index")
lines(len, complex_model$residuals)
```

Residuals vs Index



durbin watson test

```
dwtest(complex_model) #correlated errors test
```

```
##
## Durbin-Watson test
##
## data: complex_model
## DW = 2.0429, p-value = 0.7605
## alternative hypothesis: true autocorrelation is greater than 0
```