Hotels

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```
library(tidyverse)
library(infer)
library(leaps)
library(MASS)
```

```
hotel_bookings <- read.csv("~/R/DIIG/hotel_bookings.csv")
```

Data cleaning

First, I made some new variables and did some data cleaning:

New variable for total amount of nights stayed:

```
hotel_bookings <- hotel_bookings %>%
  mutate(total_nights = stays_in_week_nights + stays_in_weekend_nights)
```

Changing the month of arrival into chronologically-ordered levels:

```
hotel_bookings <- hotel_bookings %>%
  mutate(arrival_date_month = factor(arrival_date_month,
                                     levels = c("January", "February", "March", "April", "May",
                                                "June", "July", "August", "September",
                                                "October", "November", "December")))
```

I also changed the is_canceled variable from numeric to categorical, as 0 and 1 represent a booking being cancelled or not.

```
hotel_bookings$is_canceled <- as.factor(hotel_bookings$is_canceled)
```

I created a variable for the total number of guests during the duration of the stay:

```
hotel_bookings <- hotel_bookings %>%
  mutate(total_guests = adults + children + babies)
```

I also created a new variable for the season during the arrival at the hotel, assigning the months to season.

```
hotel_bookings <- hotel_bookings %>%
  mutate(arrival_season = case_when(arrival_date_month == "December" ~ "Winter",
                                    arrival_date_month == "January" ~ "Winter",
                                    arrival_date_month == "February" ~ "Winter",
                                    arrival_date_month == "September" ~ "Fall",
                                    arrival_date_month == "October" ~ "Fall",
                                    arrival_date_month == "November" ~ "Fall",
                                    arrival_date_month == "March" ~ "Spring",
                                    arrival_date_month == "April" ~ "Spring",
                                    arrival_date_month == "May" ~ "Spring",
                                    arrival_date_month == "June" ~ "Summer",
```

```
                                    arrival_date_month =="July" ~ "Summer",
                                    arrival_date_month =="August" ~ "Summer"))
```

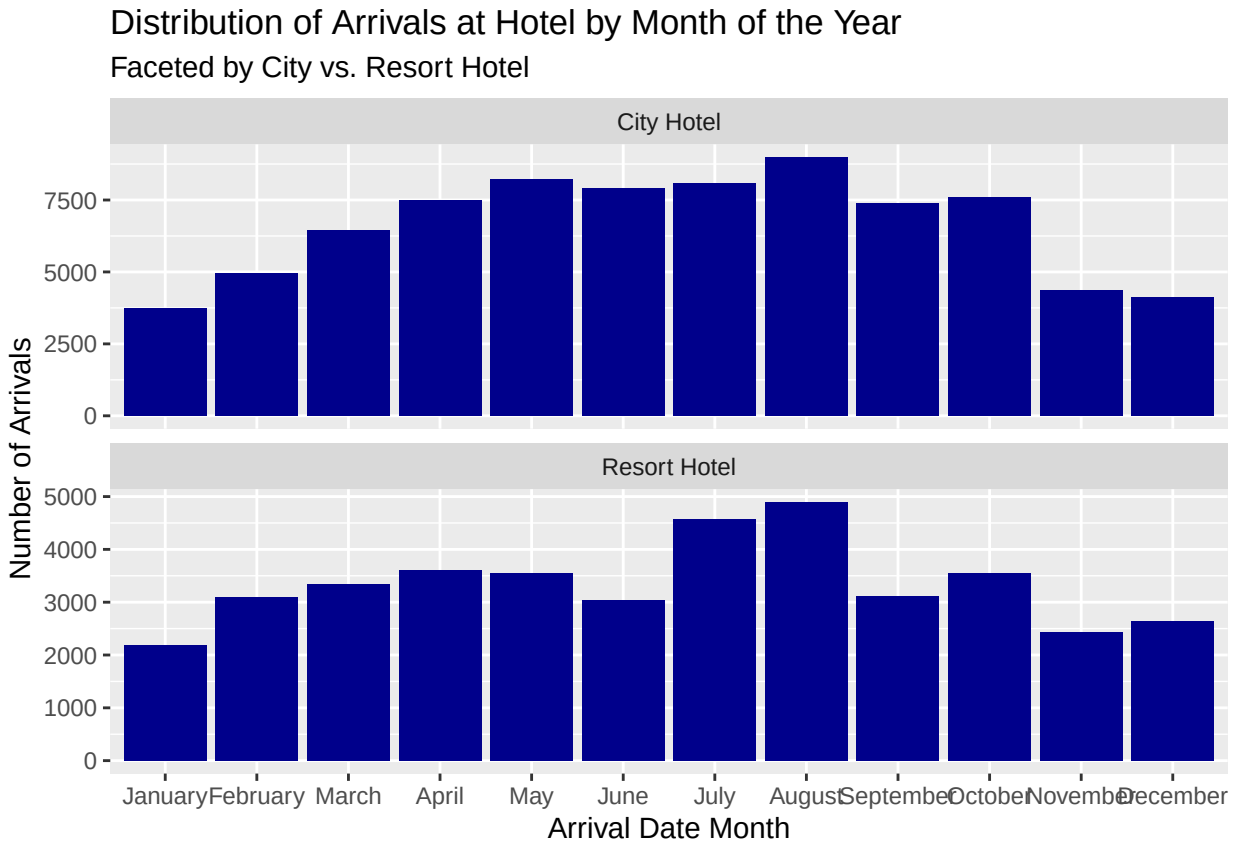
I also created another variable called "kids", which would classify whether or not the guests brought kids. Kids meant either bringing children or bringing babies–only when there were neither children nor babies would the guests be considered having "no kids".

```
hotel_bookings <- hotel_bookings %>%
  mutate(kids = case_when(children > 0 & babies == 0 ~ "Have kids",
                          children == 0 & babies == 0 ~ "No kids",
                          babies > 0 & children == 0 ~ "Have kids"))
```

Visualizations

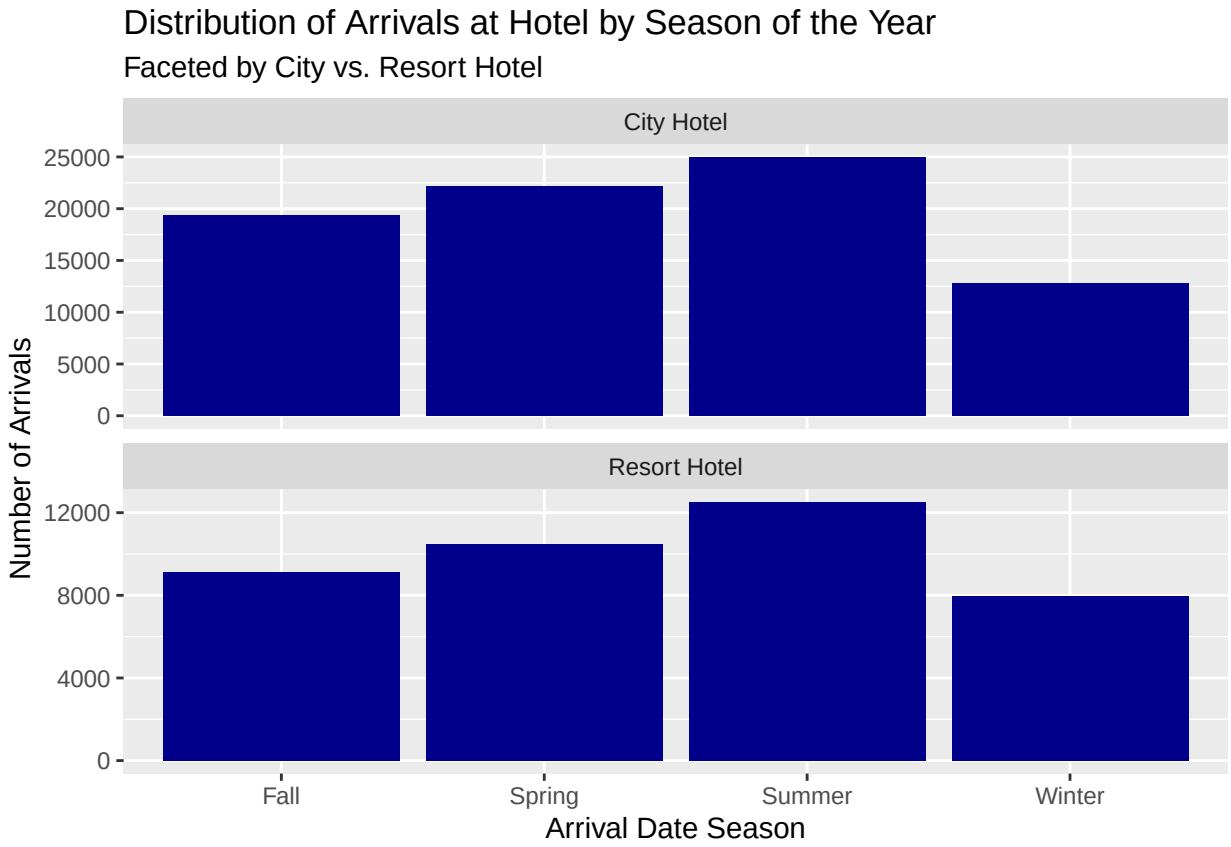
Next, I visualized the distribution of visits to the hotels based on month of the year, to find that there was an increase in volume of arrivals in the warmer months.

```
hotel_bookings %>%
  group_by(hotel, arrival_date_month) %>%
  ggplot(aes(x = arrival_date_month)) +
  geom_bar(fill = "darkblue") +
  facet_wrap(~ hotel,
             nrow = 2,
             scales = "free_y") +
  labs(title = "Distribution of Arrivals at Hotel by Month of the Year",
       subtitle = "Faceted by City vs. Resort Hotel",
       x = "Arrival Date Month",
       y = "Number of Arrivals")
```



Likewise, I visualized the distribution of arrivals at the hotels during the different seasons.

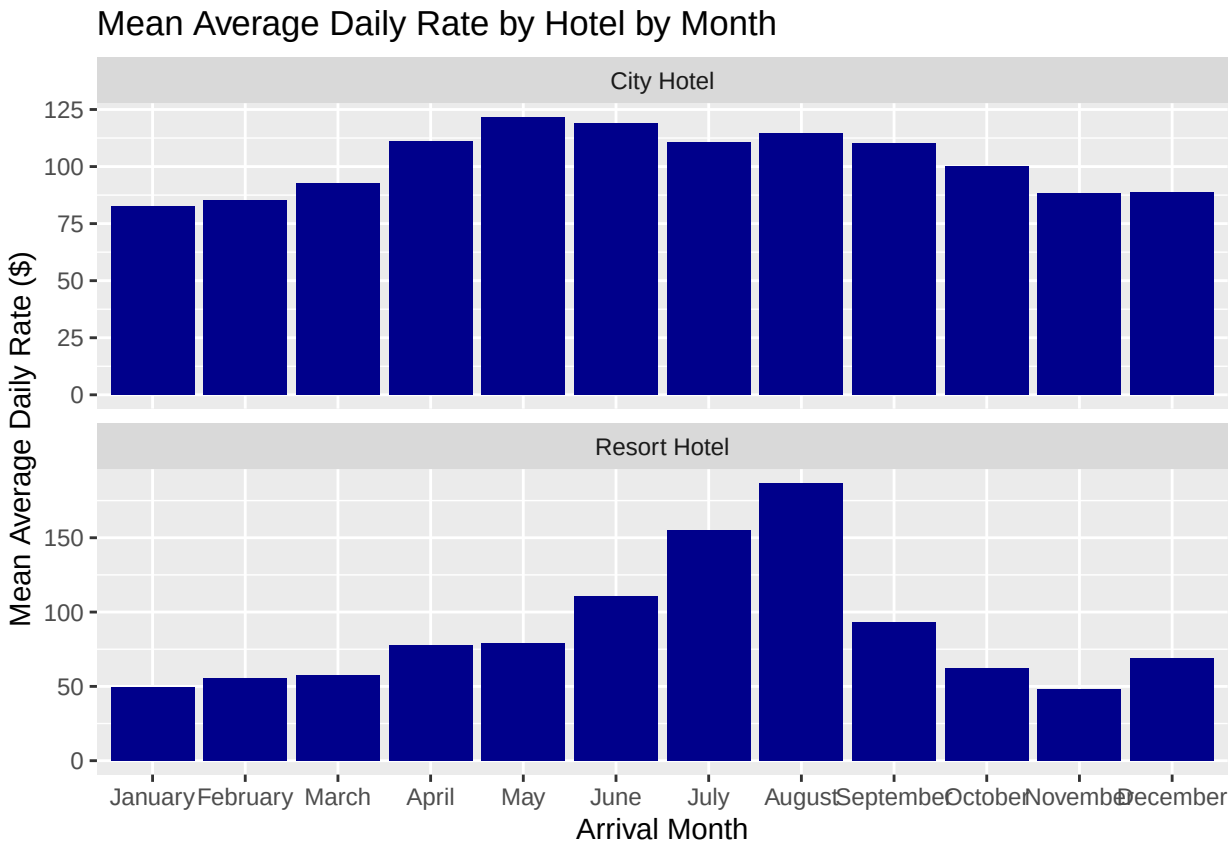
```
hotel_bookings %>%
  group_by(hotel, arrival_season) %>%
  ggplot(aes(x = arrival_season)) +
  geom_bar(fill = "darkblue") +
  facet_wrap(~ hotel,
             nrow = 2,
             scales = "free_y") +
  labs(title = "Distribution of Arrivals at Hotel by Season of the Year",
       subtitle = "Faceted by City vs. Resort Hotel",
       x = "Arrival Date Season",
       y = "Number of Arrivals")
```



Looking at average daily rate next, I visualized the distribution of average daily rate depending on the month of arrival at the hotels.

```
hotel_bookings %>%
  group_by(hotel, arrival_date_month) %>%
  summarise(meanadr = mean(adr)) %>%
  ggplot(aes(x = arrival_date_month, y = meanadr)) +
  geom_col(fill = "darkblue") +
  facet_wrap(~ hotel, nrow = 2, scales = "free_y") +
  labs(title = "Mean Average Daily Rate by Hotel by Month",
       x = "Arrival Month",
       y = "Mean Average Daily Rate ($)")
```

```
## `summarise()` regrouping output by 'hotel' (override with `.groups` argument)
```

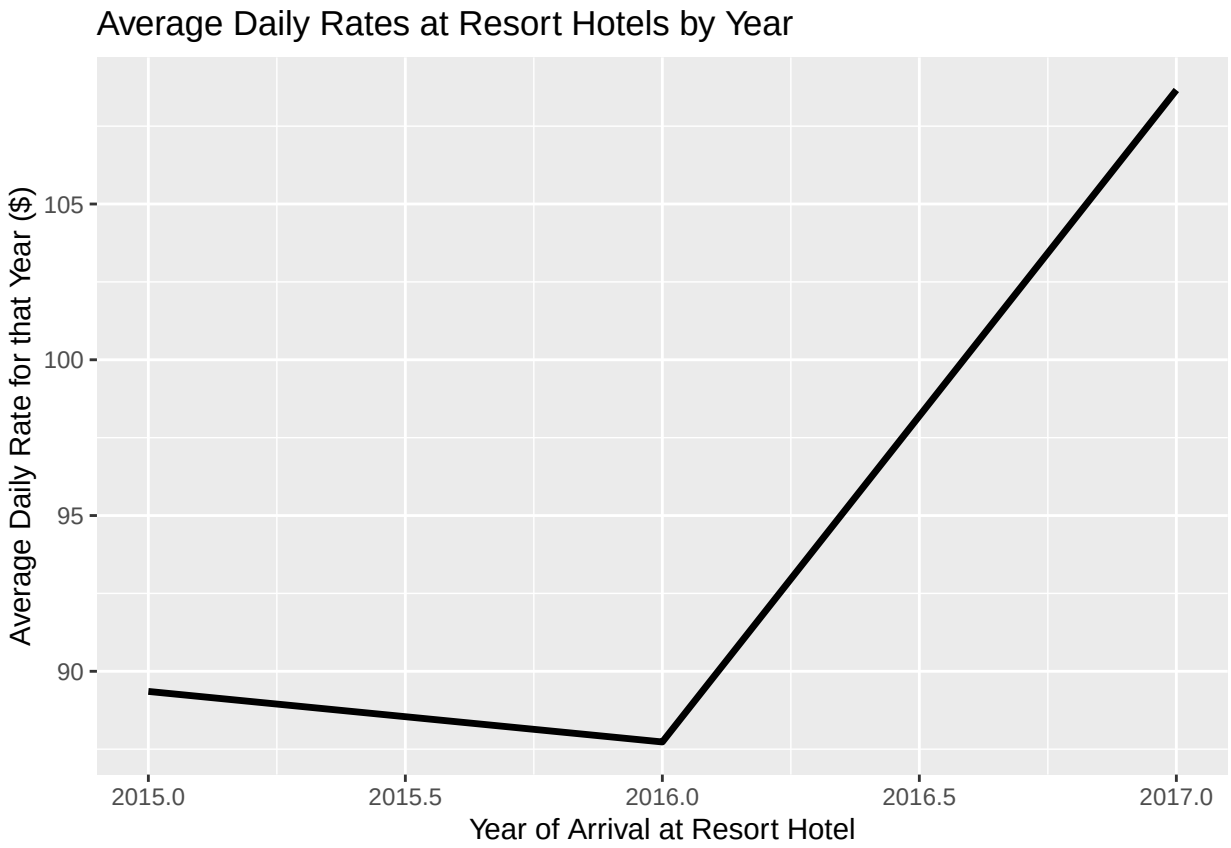


It seems that city hotels are pretty expensive year-round, whereas resort hotels are significantly cheaper in the colder months than in the warmer months.

I also want to see how the average daily rate at the hotels have changed over time.

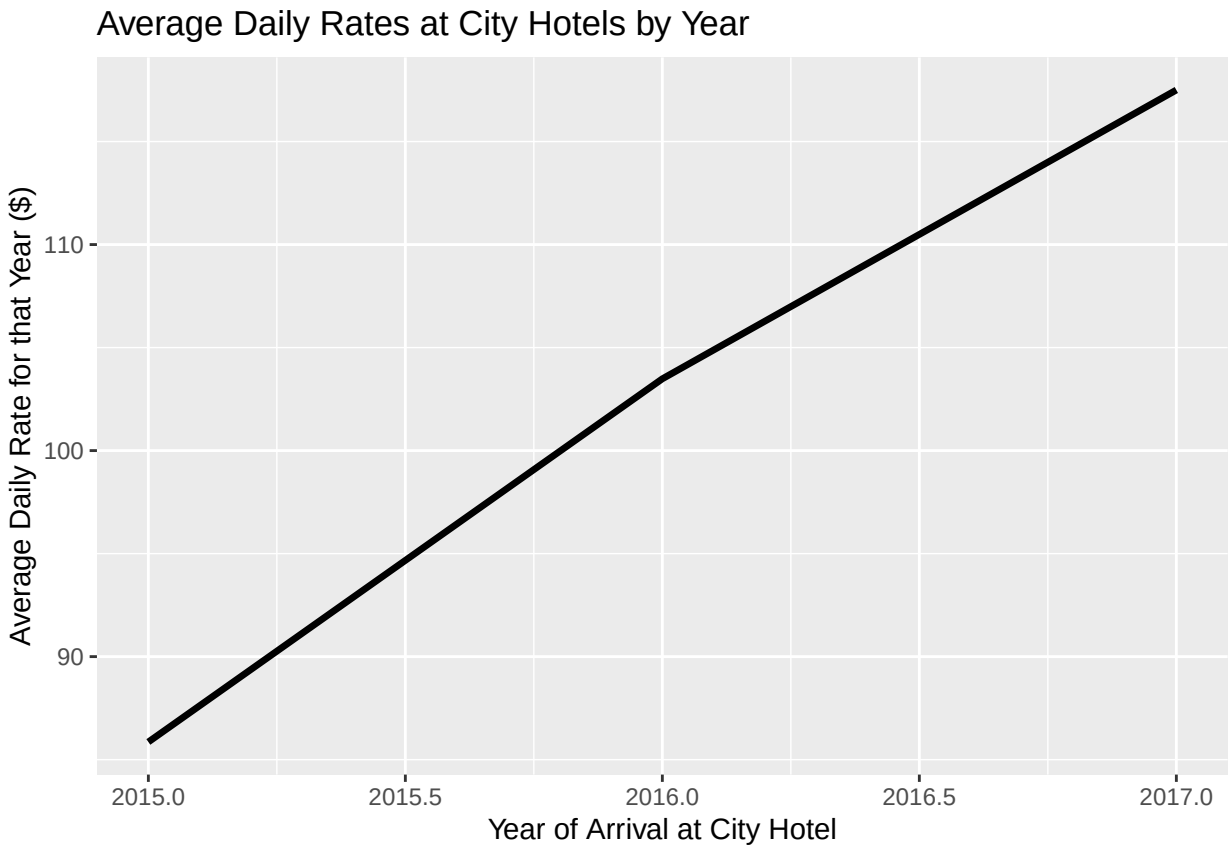
```
hotel_bookings %>%
  filter(hotel == "Resort Hotel") %>%
  group_by(arrival_date_year) %>%
  summarize(meanadryear = mean(adr)) %>%
  ggplot(mapping = aes(x = arrival_date_year, y = meanadryear)) +
  geom_line(size = 1.2) +
  labs(x = "Year of Arrival at Resort Hotel", y = "Average Daily Rate for that Year ($)",
       title = "Average Daily Rates at Resort Hotels by Year")
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

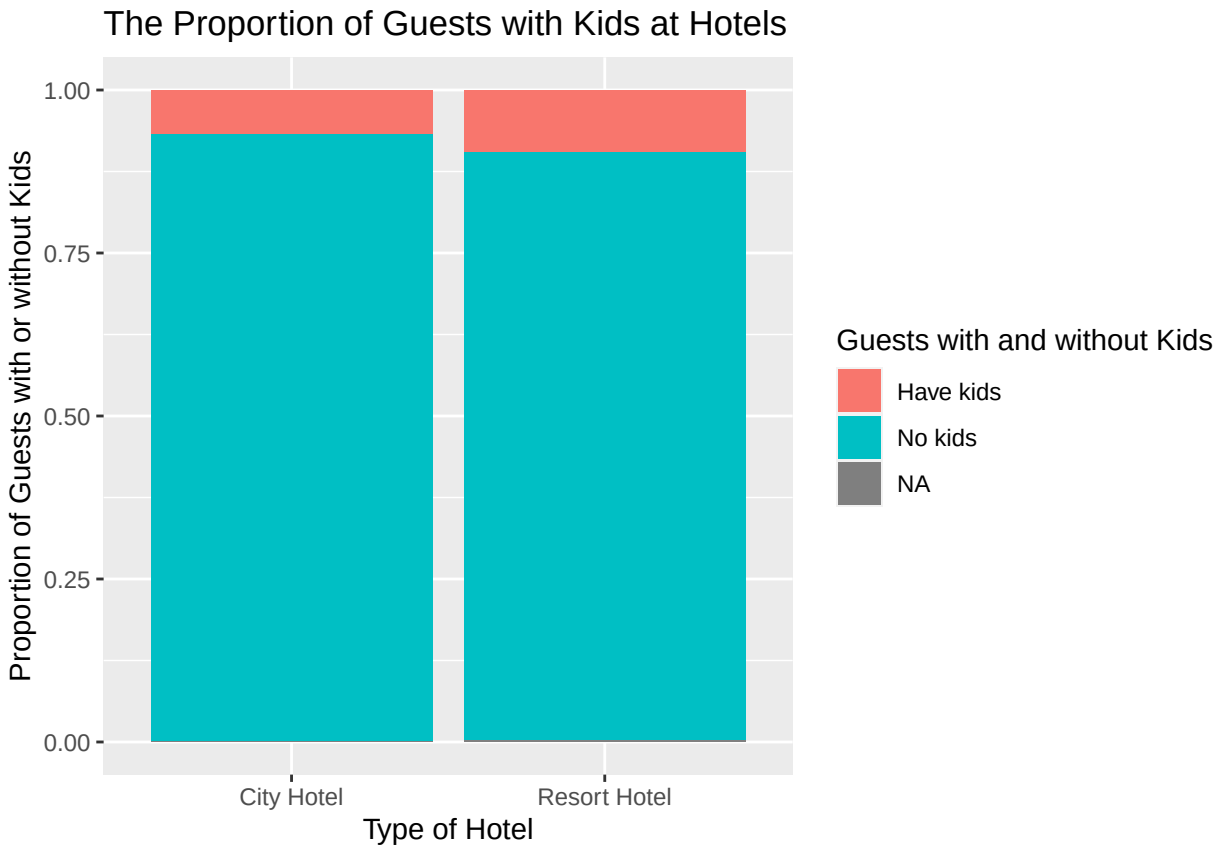



```
hotel_bookings %>%
  filter(hotel == "City Hotel") %>%
  group_by(arrival_date_year) %>%
  summarize(meanadryear = mean(adr)) %>%
  ggplot(mapping = aes(x = arrival_date_year, y = meanadryear)) +
  geom_line(size = 1.2) +
  labs(x = "Year of Arrival at City Hotel", y = "Average Daily Rate for that Year ($)",
       title = "Average Daily Rates at City Hotels by Year")
```

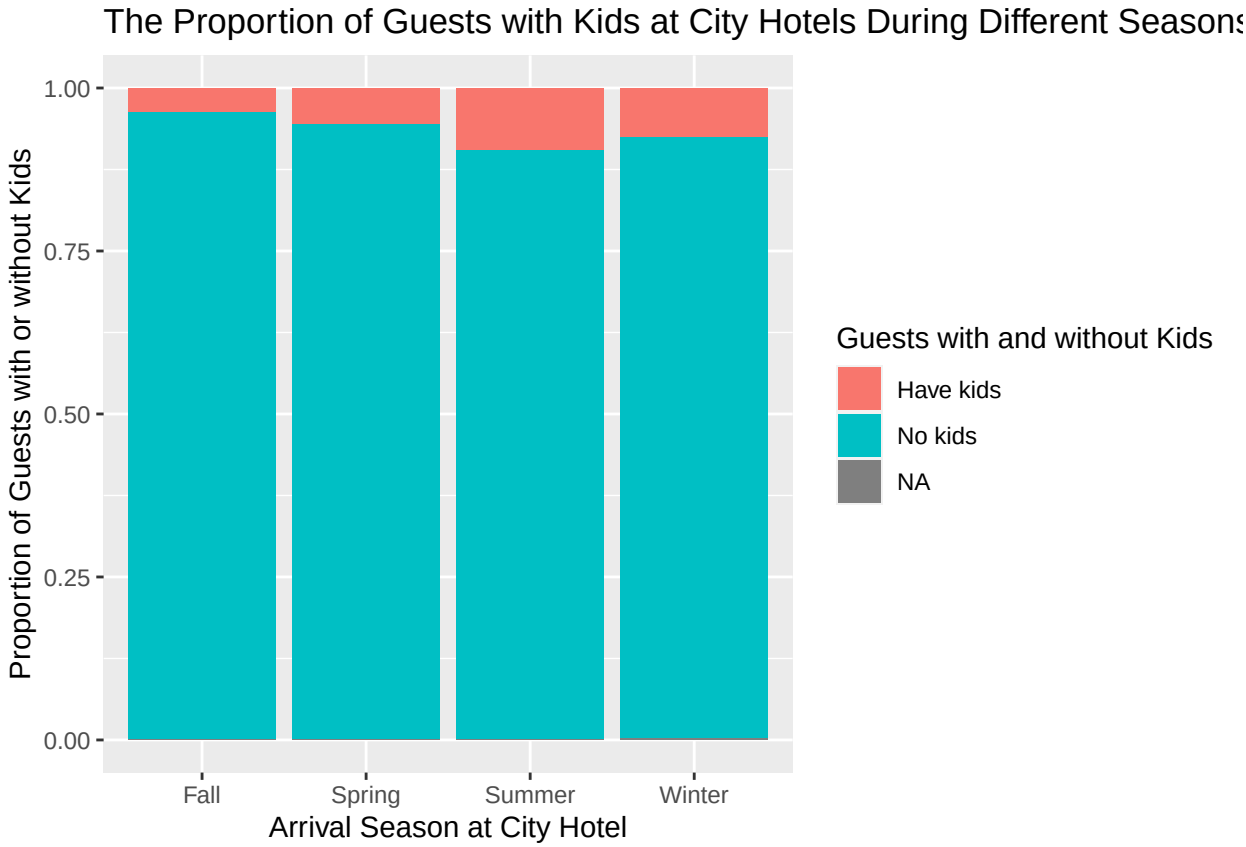
```
## `summarise()` ungrouping output (override with `.groups` argument)
```



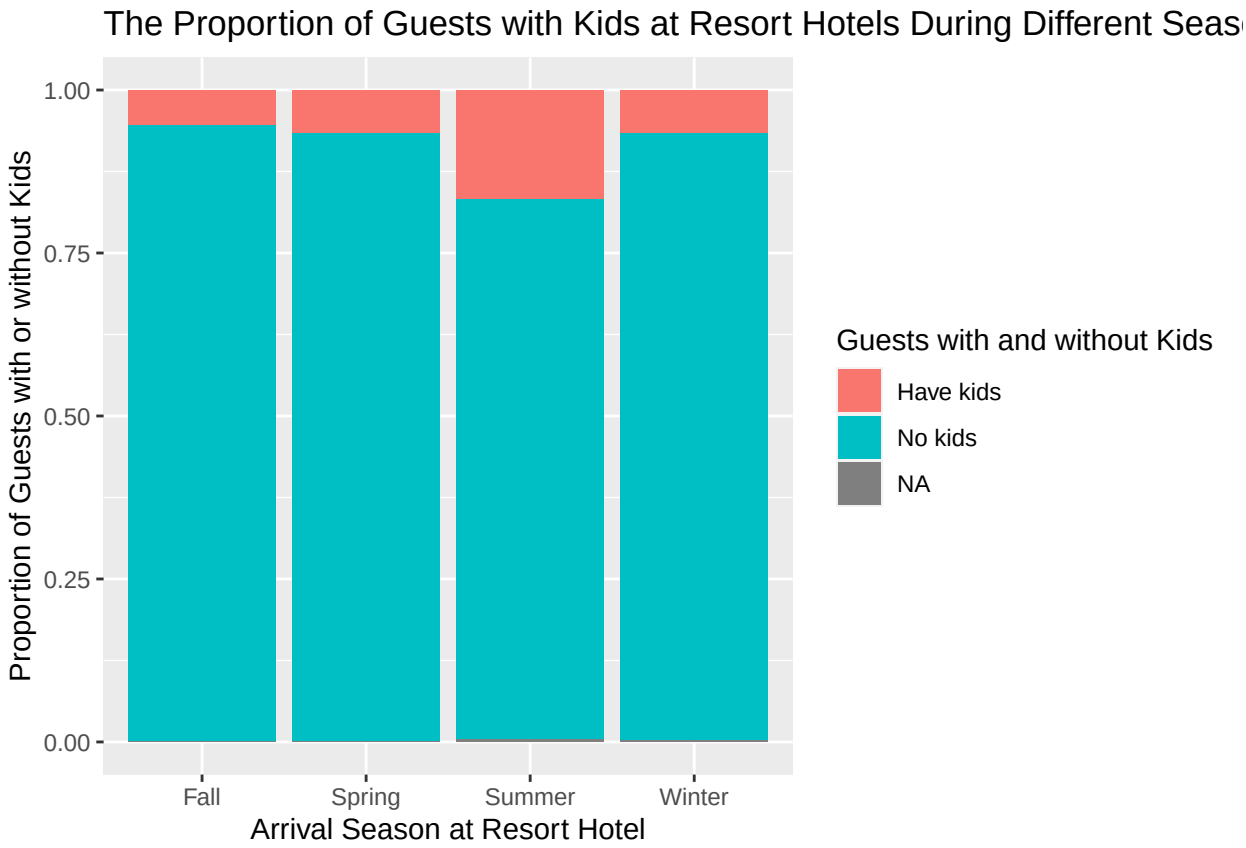

```
hotel_bookings %>%
  group_by(hotel) %>%
  ggplot(mapping = aes(x = hotel,
                       fill = kids)) +
  geom_bar(position = "fill") +
  labs(x = "Type of Hotel",
       y = "Proportion of Guests with or without Kids", fill = "Guests with and without Kids",
       title = "The Proportion of Guests with Kids at Hotels")
```




```
hotel_bookings %>%
  filter(hotel == "City Hotel") %>%
  group_by(arrival_season) %>%
  ggplot(mapping = aes(x = arrival_season,
                       fill = kids)) +
  geom_bar(position = "fill") +
  labs(x = "Arrival Season at City Hotel",
       y = "Proportion of Guests with or without Kids", fill = "Guests with and without Kids",
       title = "The Proportion of Guests with Kids at City Hotels During Different Seasons")
```




```
hotel_bookings %>%
  filter(hotel == "Resort Hotel") %>%
  group_by(arrival_season) %>%
  ggplot(mapping = aes(x = arrival_season,
                       fill = kids)) +
  geom_bar(position = "fill") +
  labs(x = "Arrival Season at Resort Hotel",
       y = "Proportion of Guests with or without Kids", fill = "Guests with and without Kids",
       title = "The Proportion of Guests with Kids at Resort Hotels During Different Seasons")
```



Resort Hotels

For this data challenge, I'll mainly be focusing on Resort Hotels, so I filtered the "City Hotels" out of my dataset. Resort Hotels piqued my interests because of the vacation- and family-oriented aspect. Additionally, the huge disparity in amount of arrivals and cost of a resort hotel between cold weather months and warm weather months I think is worth investigating. Practically, that disparity makes sense because families tend to take resort-type vacations in the summer.

```
resort_bookings <- hotel_bookings %>%
  filter(hotel == "Resort Hotel")
```

Question: What influences the average daily rate at resort hotels?

I'll be looking at the number of adults, children, and babies, the arrival month, the total number of nights stayed, the meal plan, the number of special requests, and the number of purchased car parkings, because these variables are the most practical ones of the included variables when considering the price of a hotel during the booking stage. I'll build the model manually at first, and then use a stepwise backward and forward elimination to eliminate unnecessary predictors from the model. Afterwards, the model should follow the laws of Occam's Razor (the simplest model that explains the most).

```
resort_bookings %>%
  group_by(arrival_season) %>%
  summarise(meanadr = mean(adr))
```

```
## `summarise()` ungrouping output (override with `.groups` argument)
```

```
## # A tibble: 4 x 2
##   arrival_season meanadr
```

```
##   <chr>            <dbl>
## 1 Fall              69.0
## 2 Spring            71.7
## 3 Summer           157.
## 4 Winter            58.2
```

First, I need to figure out whether it is better to use month or season:

```
m_rate_month <- lm(adr ~ arrival_date_month,
                   data = resort_bookings)

glance(m_rate_month)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.566         0.566  40.5     4755.       0    11 -2.05e5 4.10e5 4.10e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
m_rate_season <- lm(adr ~ arrival_season,
                    data = resort_bookings)

glance(m_rate_season)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.464         0.464  45.0    11556.       0     3 -2.09e5 4.19e5 4.19e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

According to the r-squared values, arrival month explains more of the differences in average daily rate. Unfortunately, that means there will be twelve levels of that variable, rather than four levels.

I'll also need to figure out whether I want to use total number of guests or the individual number of adults, children, and babies.

```
m_rate_totalguests <- lm(adr ~ total_guests, data = resort_bookings)

glance(m_rate_totalguests)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.125         0.125  57.5     5709.       0     1 -2.19e5 4.38e5 4.38e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
m_rate_indguests <- lm(adr ~ adults + children + babies,
                       data = resort_bookings)

glance(m_rate_indguests)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.160         0.160  56.3     2536.       0     3 -2.18e5 4.37e5 4.37e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

Using the individual guests instead of the overall number of guests is better due to a slightly higher adjusted r-squared value.

Now, I'll start building the bigger model manually:

```
m_1 <- lm(adr ~ arrival_date_month + adults,
          data = resort_bookings)

glance(m_1)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.575         0.575  40.0     4520.       0    12 -2.05e5 4.09e5 4.09e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
tidy(m_1)
```

```
## # A tibble: 13 x 5
##    term                          estimate std.error statistic   p.value
##    <chr>                            <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                      35.5      0.982     36.1  9.07e-281
##  2 arrival_date_monthFebruary        4.50     1.12       4.03 5.67e-  5
##  3 arrival_date_monthMarch           7.37     1.10       6.70 2.16e- 11
##  4 arrival_date_monthApril          27.2      1.09      25.1  1.97e-137
##  5 arrival_date_monthMay            27.7      1.09      25.5  5.90e-142
##  6 arrival_date_monthJune           58.8      1.12      52.4  0.
##  7 arrival_date_monthJuly          103.       1.05      98.4  0.
##  8 arrival_date_monthAugust        134.       1.03     130.   0.
##  9 arrival_date_monthSeptember      41.2      1.12      36.8  1.39e-291
## 10 arrival_date_monthOctober        11.0      1.09      10.1  7.80e- 24
## 11 arrival_date_monthNovember       -1.56     1.18      -1.32 1.87e-  1
## 12 arrival_date_monthDecember       18.3      1.16      15.9  1.96e- 56
## 13 adults                            8.42     0.291     29.0  1.54e-182
```

Slight increase –> 0.575 in adj. r. squared with adults, without kids

```
m_2 <- lm(adr ~ arrival_date_month + adults + children,
          data = resort_bookings)

glance(m_2)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.629         0.629  37.4     5232.       0    13 -2.02e5 4.04e5 4.04e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
tidy(m_2)
```

```
## # A tibble: 14 x 5
##    term                          estimate std.error statistic   p.value
##    <chr>                            <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                      35.2      0.918     38.3   5.43e-316
##  2 arrival_date_monthFebruary        3.67     1.04       3.51  4.49e-  4
##  3 arrival_date_monthMarch           7.03     1.03       6.83  8.55e- 12
##  4 arrival_date_monthApril          26.2      1.01      25.9   3.66e-146
##  5 arrival_date_monthMay            26.7      1.02      26.3   5.20e-151
##  6 arrival_date_monthJune           56.0      1.05      53.3   0.
##  7 arrival_date_monthJuly           97.2      0.979     99.3   0.
```

```
##  8 arrival_date_monthAugust     128.        0.970   132.    0.
##  9 arrival_date_monthSeptember   41.0       1.05     39.2   0.
## 10 arrival_date_monthOctober     10.8       1.02     10.6   3.24e- 26
## 11 arrival_date_monthNovember    -0.873     1.10     -0.793 4.28e-  1
## 12 arrival_date_monthDecember    17.6       1.08     16.3   1.25e- 59
## 13 adults                         7.34      0.272    27.0   5.44e-159
## 14 children                      32.6       0.426    76.5   0.
```

Significant increase in r-squared –> 0.629.

```
m_3 <- lm(adr ~ arrival_date_month + adults + children + babies,
          data = resort_bookings)

glance(m_3)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.630         0.629  37.4     4861.       0    14 -2.02e5 4.04e5 4.04e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
tidy(m_3)
```

```
## # A tibble: 15 x 5
##    term                        estimate std.error statistic   p.value
##    <chr>                          <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                   35.2       0.918    38.3   1.03e-315
##  2 arrival_date_monthFebruary     3.66      1.04      3.51  4.51e-  4
##  3 arrival_date_monthMarch        7.03      1.03      6.84  8.23e- 12
##  4 arrival_date_monthApril       26.2       1.01     25.9   2.92e-146
##  5 arrival_date_monthMay         26.7       1.02     26.2   1.36e-150
##  6 arrival_date_monthJune        55.9       1.05     53.2   0.
##  7 arrival_date_monthJuly        97.1       0.979    99.2   0.
##  8 arrival_date_monthAugust     128.        0.970   132.    0.
##  9 arrival_date_monthSeptember   41.0       1.05     39.2   0.
## 10 arrival_date_monthOctober     10.8       1.02     10.6   2.99e- 26
## 11 arrival_date_monthNovember    -0.880     1.10     -0.799 4.24e-  1
## 12 arrival_date_monthDecember    17.6       1.08     16.3   2.21e- 59
## 13 adults                         7.32      0.272    26.9   2.69e-158
## 14 children                      32.6       0.426    76.5   0.
## 15 babies                         6.22      1.57      3.95  7.70e-  5
```

Very insignificant increase in r-squared with babies.

```
m_4 <- lm(adr ~ arrival_date_month + adults + children + babies + meal,
          data = resort_bookings)

glance(m_4)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.655         0.655  36.1     4232.       0    18 -2.00e5 4.01e5 4.01e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
tidy(m_4)
```

```
## # A tibble: 19 x 5
```

```
##    term                          estimate std.error statistic   p.value
##    <chr>                            <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                     32.8       0.888    37.0   3.19e-294
##  2 arrival_date_monthFebruary       1.95      1.01      1.94  5.25e-  2
##  3 arrival_date_monthMarch          5.95      0.992     5.99  2.07e-  9
##  4 arrival_date_monthApril         23.4       0.980    23.9   5.38e-125
##  5 arrival_date_monthMay           26.1       0.983    26.5   6.87e-154
##  6 arrival_date_monthJune          55.1       1.01     54.3   0.
##  7 arrival_date_monthJuly          95.7       0.947   101.    0.
##  8 arrival_date_monthAugust       126.        0.940   134.    0.
##  9 arrival_date_monthSeptember     40.2       1.01     39.7   0.
## 10 arrival_date_monthOctober       11.0       0.983    11.2   6.93e- 29
## 11 arrival_date_monthNovember      -0.859     1.06     -0.808 4.19e-  1
## 12 arrival_date_monthDecember      14.5       1.05     13.9   1.57e- 43
## 13 adults                           6.51      0.263    24.8   2.48e-134
## 14 children                        32.8       0.411    79.7   0.
## 15 babies                           4.42      1.52      2.91  3.59e-  3
## 16 mealFB                          20.5       1.34     15.3   6.16e- 53
## 17 mealHB                          20.7       0.457    45.3   0.
## 18 mealSC                         -71.8       3.90    -18.4   1.89e- 75
## 19 mealUndefined                   26.9       1.09     24.6   8.59e-133
```

Tiny increase in r-squared with meal.

```
m_5 <- lm(adr ~ arrival_date_month + adults + children + babies + meal + total_nights,
          data = resort_bookings)

glance(m_5)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.659         0.659  35.9     4080.       0    19 -2.00e5 4.01e5 4.01e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
tidy(m_5)
```

```
## # A tibble: 20 x 5
##    term                          estimate std.error statistic   p.value
##    <chr>                            <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                     35.4       0.891    39.8    0.
##  2 arrival_date_monthFebruary       2.05      1.00      2.04   4.10e-  2
##  3 arrival_date_monthMarch          7.29      0.989     7.38   1.66e- 13
##  4 arrival_date_monthApril         24.4       0.976    25.1    2.00e-137
##  5 arrival_date_monthMay           27.6       0.980    28.1    2.50e-172
##  6 arrival_date_monthJune          57.9       1.02     56.9    0.
##  7 arrival_date_monthJuly          98.3       0.949   104.     0.
##  8 arrival_date_monthAugust       128.        0.941   136.     0.
##  9 arrival_date_monthSeptember     42.5       1.01     42.0    0.
## 10 arrival_date_monthOctober       12.1       0.979    12.4    5.03e- 35
## 11 arrival_date_monthNovember      -0.0759    1.06     -0.0718 9.43e-  1
## 12 arrival_date_monthDecember      14.7       1.04     14.1    2.87e- 45
## 13 adults                           6.88      0.262    26.3    8.27e-151
## 14 children                        32.8       0.409    80.2    0.
## 15 babies                           4.51      1.51      2.99   2.80e-  3
## 16 mealFB                          20.7       1.33     15.6    2.00e- 54
```

```
## 17 mealHB                       22.4       0.461    48.5    0.
## 18 mealSC                      -68.2       3.88    -17.6    6.87e- 69
## 19 mealUndefined                28.0       1.09     25.7    1.97e-144
## 20 total_nights                 -1.20      0.0557  -21.5    1.34e-101
```

Very small in r-squared with total_nights. The coefficient for total_nights is negative, indicating that holding all other factors constant, for each additional night of the stay, we expect a slightly over $1 discount in the average daily rate. This decrease in average daily rate makes sense, because usually a longer stay warrants an additional stay discount.

```
m_6 <- lm(adr ~ arrival_date_month + adults + children + babies + meal + total_nights +
            total_of_special_requests,
          data = resort_bookings)

glance(m_6)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.665         0.665  35.6     3974.       0    20 -2.00e5 4.00e5 4.00e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
tidy(m_6)
```

```
## # A tibble: 21 x 5
##    term                        estimate std.error statistic   p.value
##    <chr>                          <dbl>     <dbl>     <dbl>     <dbl>
##  1 (Intercept)                    32.6      0.890     36.7  1.48e-289
##  2 arrival_date_monthFebruary      2.23     0.994      2.25 2.47e-  2
##  3 arrival_date_monthMarch         8.17     0.981      8.32 8.70e- 17
##  4 arrival_date_monthApril        25.1      0.968     25.9  1.17e-146
##  5 arrival_date_monthMay          28.1      0.972     28.9  2.02e-181
##  6 arrival_date_monthJune         57.7      1.01      57.2  0.
##  7 arrival_date_monthJuly         97.5      0.942    103.   0.
##  8 arrival_date_monthAugust      126.       0.935    135.   0.
##  9 arrival_date_monthSeptember    43.0      1.00      42.8  0.
## 10 arrival_date_monthOctober      12.9      0.972     13.3  2.43e- 40
## # ... with 11 more rows
```

Slightest increase in r-squared with number of special requests.

```
m_7 <- lm(adr ~ arrival_date_month + adults + children + babies + meal + total_nights +
            total_of_special_requests + required_car_parking_spaces,
          data = resort_bookings)

glance(m_7)
```

```
## # A tibble: 1 x 12
##   r.squared adj.r.squared sigma statistic p.value    df  logLik    AIC    BIC
##       <dbl>         <dbl> <dbl>     <dbl>   <dbl> <dbl>   <dbl>  <dbl>  <dbl>
## 1     0.673         0.672  35.2     3915.       0    21 -1.99e5 3.99e5 3.99e5
## # ... with 3 more variables: deviance <dbl>, df.residual <int>, nobs <int>
```

```
tidy(m_7)
```

```
## # A tibble: 22 x 5
##    term                        estimate std.error statistic   p.value
##    <chr>                          <dbl>     <dbl>     <dbl>     <dbl>
```

```
##  1 (Intercept)                   30.1      0.884     34.0  5.05e-250
##  2 arrival_date_monthFebruary     2.76     0.983      2.81 5.03e-  3
##  3 arrival_date_monthMarch        8.40     0.970      8.66 4.93e- 18
##  4 arrival_date_monthApril       25.3      0.957     26.4  1.94e-152
##  5 arrival_date_monthMay         28.3      0.961     29.4  3.11e-188
##  6 arrival_date_monthJune        57.6      0.997     57.7  0.
##  7 arrival_date_monthJuly        97.6      0.932    105.   0.
##  8 arrival_date_monthAugust     127.       0.925    137.   0.
##  9 arrival_date_monthSeptember   43.1      0.993     43.4  0.
## 10 arrival_date_monthOctober     13.0      0.961     13.6  9.40e- 42
## # ... with 12 more rows
```

Also a slight tiny increase in r-squared when car parking spaces are considered.

Because no coefficient in the model changes drastically when another is added, I can assume that there is not too much multicollinearity between the predictors and move forward without too much care for interaction variables.

I'm going to do backwards and forwards (both directions) elimination with multivariate regression to see which predictors most influences average daily rate. This stepwise elimination will remove excess variables from the model.

```
step.model <- stepAIC(m_7, direction = "both",
                      trace = FALSE)
summary(step.model)
```

```
##
## Call:
## lm(formula = adr ~ arrival_date_month + adults + children + meal +
##     total_nights + total_of_special_requests + required_car_parking_spaces,
##     data = resort_bookings)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -412.62  -17.20   -2.39   15.66  353.40
##
## Coefficients:
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                   30.09395    0.88428  34.032  < 2e-16 ***
## arrival_date_monthFebruary     2.75751    0.98323   2.805  0.00504 **
## arrival_date_monthMarch        8.39711    0.97009   8.656  < 2e-16 ***
## arrival_date_monthApril       25.27508    0.95693  26.413  < 2e-16 ***
## arrival_date_monthMay         28.26713    0.96121  29.408  < 2e-16 ***
## arrival_date_monthJune        57.56562    0.99735  57.719  < 2e-16 ***
## arrival_date_monthJuly        97.58704    0.93150 104.764  < 2e-16 ***
## arrival_date_monthAugust     126.87494    0.92480 137.191  < 2e-16 ***
## arrival_date_monthSeptember   43.09500    0.99266  43.414  < 2e-16 ***
## arrival_date_monthOctober     13.01692    0.96063  13.550  < 2e-16 ***
## arrival_date_monthNovember     0.21174    1.03691   0.204  0.83820
## arrival_date_monthDecember    14.50766    1.01936  14.232  < 2e-16 ***
## adults                         6.33478    0.25728  24.622  < 2e-16 ***
## children                      32.29981    0.40144  80.460  < 2e-16 ***
## mealFB                        24.39468    1.30634  18.674  < 2e-16 ***
## mealHB                        23.26121    0.45249  51.407  < 2e-16 ***
## mealSC                       -67.19850    3.80299 -17.670  < 2e-16 ***
## mealUndefined                 32.03642    1.07260  29.868  < 2e-16 ***
```

```
## total_nights                 -1.08184    0.05503 -19.660  < 2e-16 ***
## total_of_special_requests     5.35931    0.22206  24.135  < 2e-16 ***
## required_car_parking_spaces  15.32734    0.50688  30.239  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 35.17 on 40039 degrees of freedom
## Multiple R-squared:  0.6725, Adjusted R-squared:  0.6723
## F-statistic:  4111 on 20 and 40039 DF,  p-value: < 2.2e-16
```

The model kicked out babies, but kept all other predictors. The model has an adjusted r-squared of 0.6723, which is a pretty good r-squared value, signifying that approximately 67% of the variability in average daily rate at resort hotels can be explained by the model with the above predictors.

```
logit_mod2 <- glm(is_canceled ~ adults + children + babies + meal,
                  data = resort_bookings, family = "binomial", maxit = 100)

logit_mod2
```

```
##
## Call:  glm(formula = is_canceled ~ adults + children + babies + meal,
##     family = "binomial", data = resort_bookings, maxit = 100)
##
## Coefficients:
##   (Intercept)         adults       children         babies         mealFB
##      -1.85054        0.41463        0.32996       -0.64143        1.36302
##        mealHB         mealSC  mealUndefined
##       0.22745       -2.19245       -0.05317
##
## Degrees of Freedom: 40059 Total (i.e. Null);  40052 Residual
## Null Deviance:       47330
## Residual Deviance: 46310     AIC: 46330
```