STAT 151A Project

Predicting Housing Resale Prices in Singapore

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Introduction

In many developed nations across the world, the real estate sector is an area of valuable business prospects due to the high demand of good land. Within the real estate sector, residential homes are a commodity extremely sought after and utilized, but are also incredibly big investments. In the lens of a real estate investor and prospective homeowner, such an investment requires a myriad of factors to consider in order to determine the best returns. With this in mind, it would be worthwhile to explore statistical approaches to assist with it. In this project, we aim to understand the Singaporean housing market and its trends (if any) from the years 2017-2022, coincidentally also when the global pandemic, Covid-19 took place.

Problem Description

For the purpose of this report, we will attempt to formulate an effective prediction model for resale prices in the country of Singapore using the tools associated with linear modelling such as linear regression techniques, ridge and lasso regularization, and cross-validation. We will analyze how in general housing prices may have shifted based on state of housing (housing type, size, and town) and whether or not this time frame had a significant impact of resale prices. While we will keep in mind as researchers that the global pandemic had occurred within the time frame we are controlling, we will not be directly referencing Covid-19 as the reason for any of our findings.

Data

Our data collection process began with an open web research on the housing markets of Singapore. We landed on Kaggle, an open source hub of public data sets uploaded by public users, which can be used for data exploration, building predictive models, and general practice with real-world data. Specifically, our data from Kaggle was transcribed by a user from the Singapore Government Agency Website that studied Resale flat prices based on registration date from Jan-2017 onwards. Data was collected by the Housing and Development Board, commonly referred to as "HDB". It is a statutory board of the Ministry of National Development in Singapore and it seeks to provide support in homeownership and ease in rental processes for residents. Simultaneously as the HDB are providing aid, they are collecting data on what home are being bought, built, and sold for. As this government established board provides public housing for more than 80% of Singapore's population, this project will make the assumption that all data was collected as a random sample of Singapore's population and data quality is up to par with research standards.

EDA + Data Preprocessing

We will begin with Exploratory Data Analysis to understand the data that we are working with.

```r
#DATA
housing <- read_csv("Resale_Price_2017_2022.csv",show_col_types=FALSE)
```

1. Data Inspection

```r
# Checking for NA values in our data
na_counts <- colSums(is.na(housing))
any_na <- any(na_counts > 0)

cat("Datasets contains NA values : ",any_na)
```

```
## Datasets contains NA values :  FALSE
```

We have found that there are no null values in the dataset, and so it is clean for further analyses that will be conducted for this report.

```r
# Inspection
glimpse(housing)
```

```
## Rows: 134,168
## Columns: 11
## $ month               <chr> "2017-01", "2017-01", "2017-01", "2017-01", "2017-~
## $ town                <chr> "ANG MO KIO", "ANG MO KIO", "ANG MO KIO", "ANG MO ~
## $ flat_type           <chr> "2 ROOM", "3 ROOM", "3 ROOM", "3 ROOM", "3 ROOM", ~
## $ block               <chr> "406", "108", "602", "465", "601", "150", "447", "~
## $ street_name         <chr> "ANG MO KIO AVE 10", "ANG MO KIO AVE 4", "ANG MO K~
## $ storey_range        <chr> "10 TO 12", "01 TO 03", "01 TO 03", "04 TO 06", "0~
## $ floor_area_sqm      <dbl> 44, 67, 67, 68, 67, 68, 68, 67, 68, 67, 68, 67, 67~
## $ flat_model          <chr> "Improved", "New Generation", "New Generation", "N~
## $ lease_commence_date <dbl> 1979, 1978, 1980, 1980, 1980, 1981, 1979, 1976, 19~
## $ remaining_lease     <chr> "61 years 04 months", "60 years 07 months", "62 ye~
## $ resale_price        <dbl> 232000, 250000, 262000, 265000, 265000, 275000, 28~
```

Upon our first inspection of the data, we will be using the `resale_price` as the response variable since we are interested in predicting housing resale price.

```r
# Selecting the necessary columns for our analysis
# Modifying the time variable into a more easily usable data type
housing <- housing %>% dplyr::select(month,town,flat_type,floor_area_sqm,flat_model,
                                     remaining_lease,resale_price) %>%
            mutate(month = parse_date(month,format="%Y-%m"))
```

We also must note that for `town`, there are too many distinct values:

```r
cat("Distinct values for `town` :",length(unique(housing$town)))
```

```
## Distinct values for ‘town‘ : 26
```

2. Data Manipulation We will be converting the `remaining_lease` column that contains how long the lease is to be of unit months instead of the current year+month.

```
##Function to convert from years+ months to months
extract_months <- function(duration_str) {
    # Split into components
    components <- strsplit(duration_str, " ", perl = TRUE)[[1]]

    # Extract years and months (if available)
    years <- as.numeric(components[1])
    months <- ifelse(length(components) >= 3, as.numeric(components[length(components)-1]), 0)

    # Return total months
    return(years * 12 + months)
}

housing <- housing %>%
            rowwise() %>%
            mutate(remaining_lease_mth = extract_months(remaining_lease)) %>%
            dplyr::select(!remaining_lease)
```

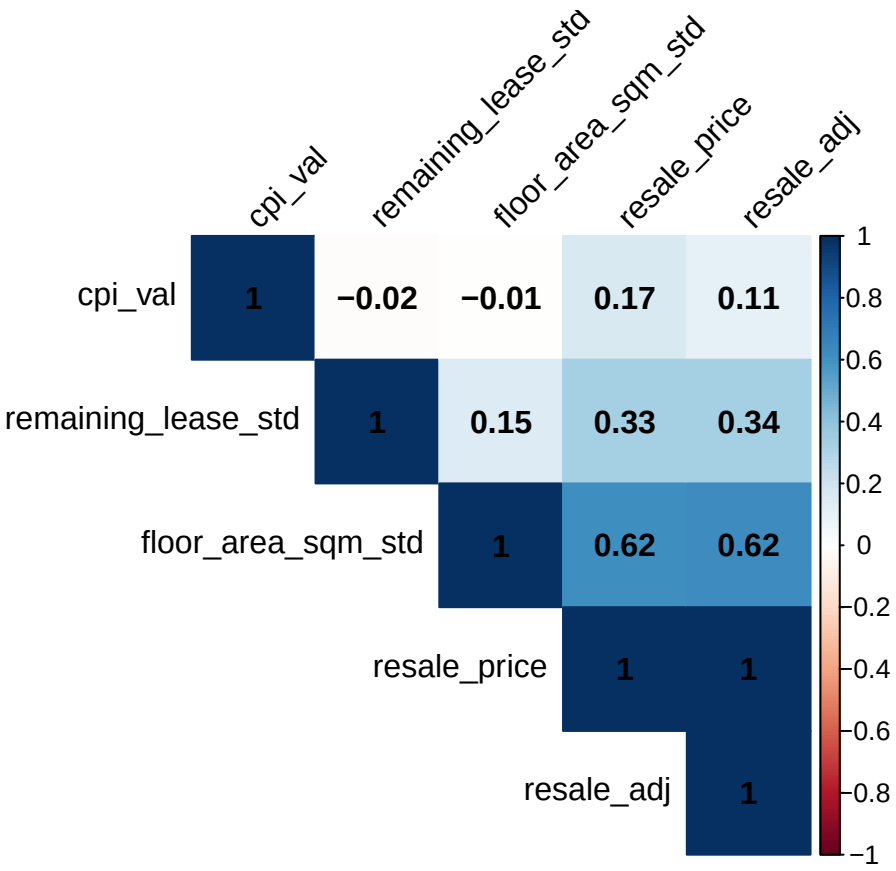
Next we would like to make adjustments for inflation using the Singaporean Consumer Price Index for "Housing and Utilities".

```
cpi <- readxl::read_xlsx("cpimar24.xlsx",sheet="T7",skip = 5) %>% as.data.frame()
cpi <- cpi %>%
          filter (Variables == "Housing & Utilities") %>%
          gather(MTH, Value, -Variables) %>%
          mutate(MTH = parse_date(MTH,format= "%Y %b")) %>%
          filter(year(MTH) >= 2017 & year(MTH) <= 2022) %>%
          select(!Variables) %>%
          mutate(Value = as.double(Value))

housing <- left_join(housing, cpi, by = c("month" = "MTH"))  %>%
            rename(cpi_val=Value) %>%
            mutate(resale_adj = (resale_price/cpi_val) *100)
```

3. Standardizing Predictor Columns. Next, we standardize numeric columns to improve performance:

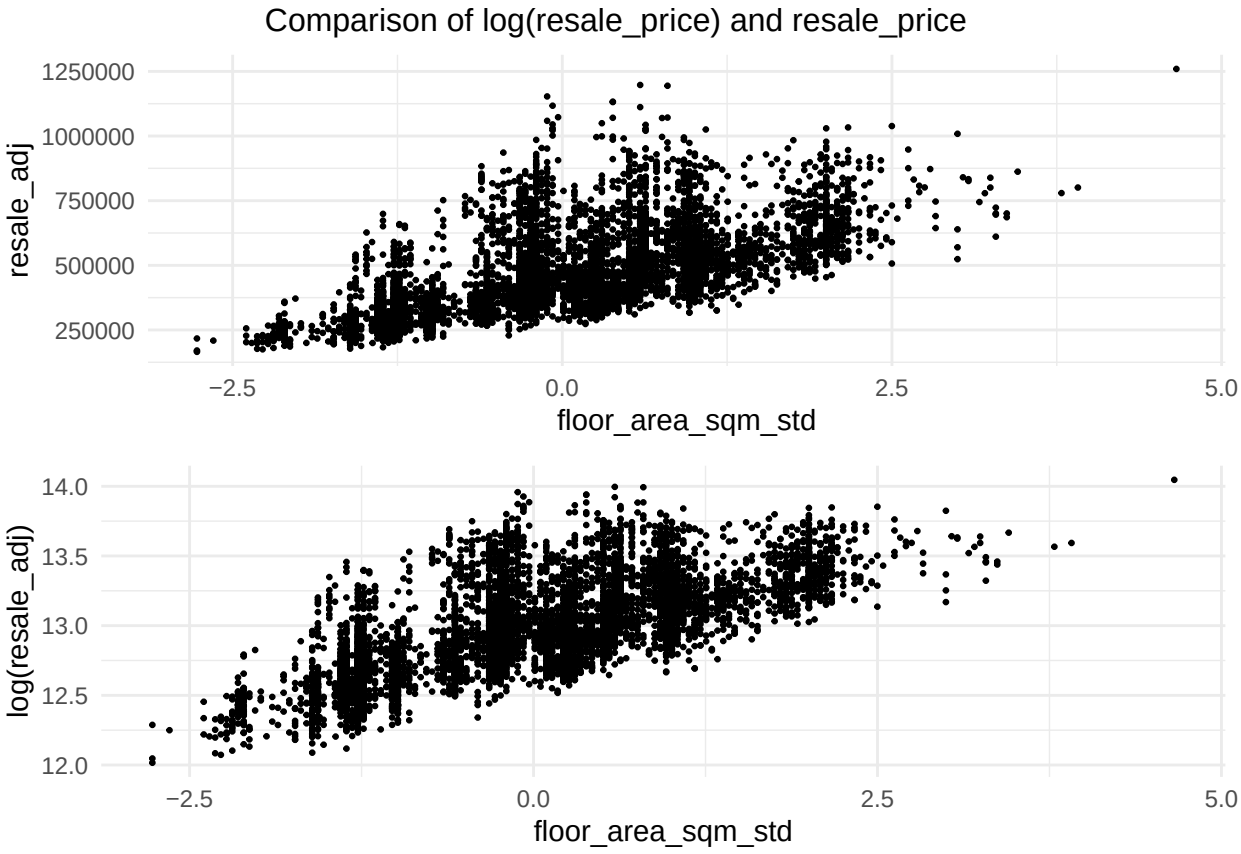
```
# Standardizing predictor columns
X <- housing %>% dplyr::select(floor_area_sqm,remaining_lease_mth) %>%
      scale() %>% as.data.frame()
colnames(X) <- c("floor_area_sqm_std","remaining_lease_std")

housing <- cbind(housing,X) %>%
  dplyr::select(!c(remaining_lease_mth,floor_area_sqm))
```

```
corr_mat<- cor(housing[sapply(housing, is.numeric)])
corrplot(corr_mat, method = "color", type = "upper", order ="hclust",
         tl.col = "black", tl.srt = 45,addCoef.col = "black")
```



4. Log Transform and Plots We do a sample of 7000 on the original dataset, to argue that the increase of a small amount of floor area(sqm) doesn't result it a linear amount of resale price being added, but instead some non-linear increase in the price. This is equivalent to adding to a log of the resale prices. So we conclude that it results in better prediction if we do a regression on the log(resale price).

```
id <- sample(nrow(housing),7000)
sample_housing <- housing[id,]

p1 <- ggplot(sample_housing) +
        geom_point(aes(x=floor_area_sqm_std, y=resale_adj),
                   size=0.5,position="identity") +
        theme_minimal()
p2 <- ggplot(sample_housing) +
        geom_point(aes(x=floor_area_sqm_std, y=log(resale_adj)),
                   size=0.5,position="identity") +
        theme_minimal()


grid.arrange(p1,p2,nrow=2,top="Comparison of log(resale_price) and resale_price")
```



5. Methods

To select the scope of our project, we select thirteen randomized towns and filter our data to the most popular housing models and house types for the selected towns in the country of Singapore.

```
set.seed(248)

randomTown <- sample(unique(housing$town), 13, replace=FALSE)

housing_dat <- housing %>%
  dplyr::filter(town %in% randomTown)

top_model <- names(sort(table(housing_dat$flat_model), decreasing = TRUE)[1])
top_type <- names(sort(table(housing_dat$flat_type), decreasing = TRUE)[1])
```

Of the thirteen towns, the top housing model is "Model A" and a house with "4 Rooms". Now that we know know the most populous buildings in the most populous towns, we will run our regression on the log adjusted resale prices that account for inflation.

```
housing_lm <- lm(log(resale_adj) ~ floor_area_sqm_std, data = housing_dat)

summary(housing_lm)
```

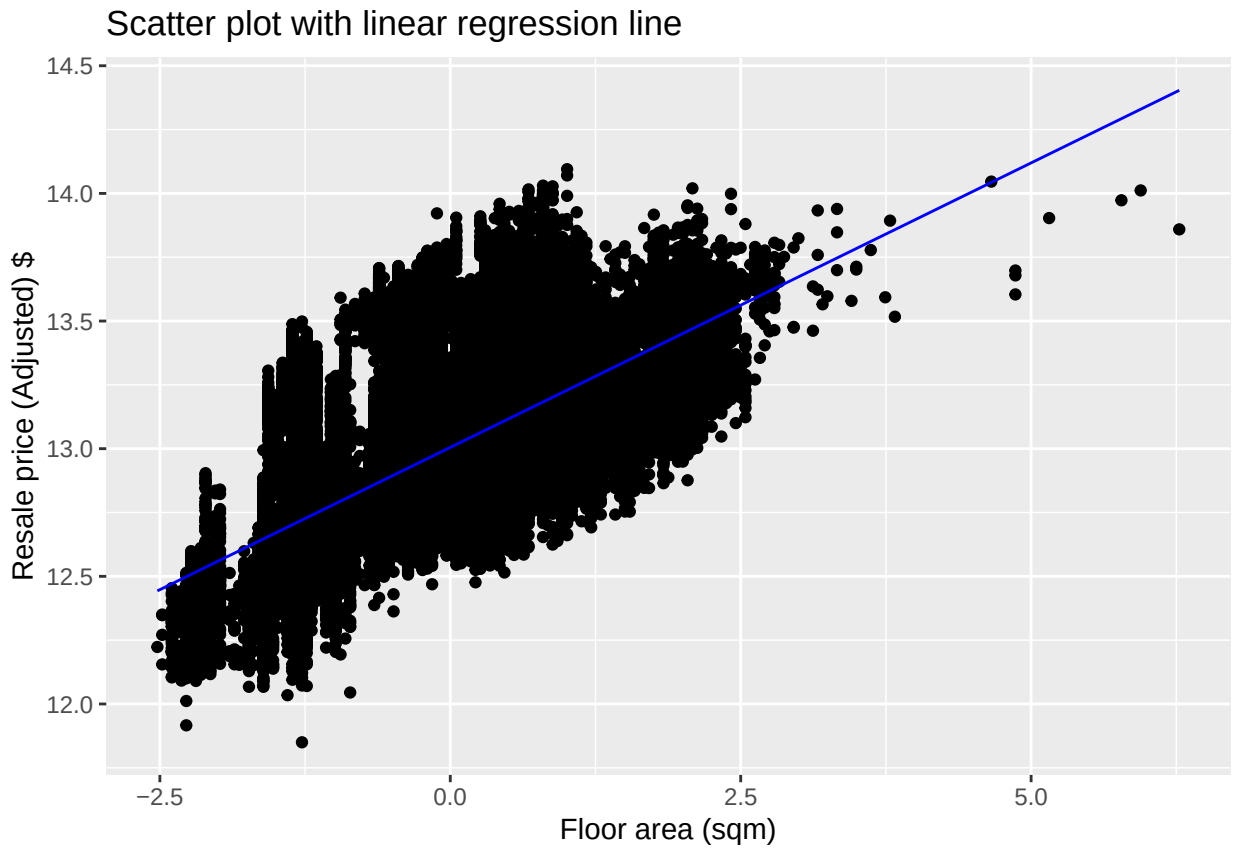
```
##
```

```
## Call:
## lm(formula = log(resale_adj) ~ floor_area_sqm_std, data = housing_dat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.87056 -0.18339 -0.03889  0.13898  0.94240
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)        13.004994   0.001049 12393.3   <2e-16 ***
## floor_area_sqm_std  0.222880   0.001043   213.8   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2582 on 60631 degrees of freedom
## Multiple R-squared:  0.4298, Adjusted R-squared:  0.4298
## F-statistic: 4.57e+04 on 1 and 60631 DF,  p-value: < 2.2e-16
```

```
housing_dat$predicted <- predict(housing_lm)
```

The summary statistics of our model give us an R^2 of 0.4562, and a model that claims a one unit increase in floor area square meter, the log adjusted resale price will increase by 0.244. Now to help us interpret, we will plot top visualize the linear regression model.

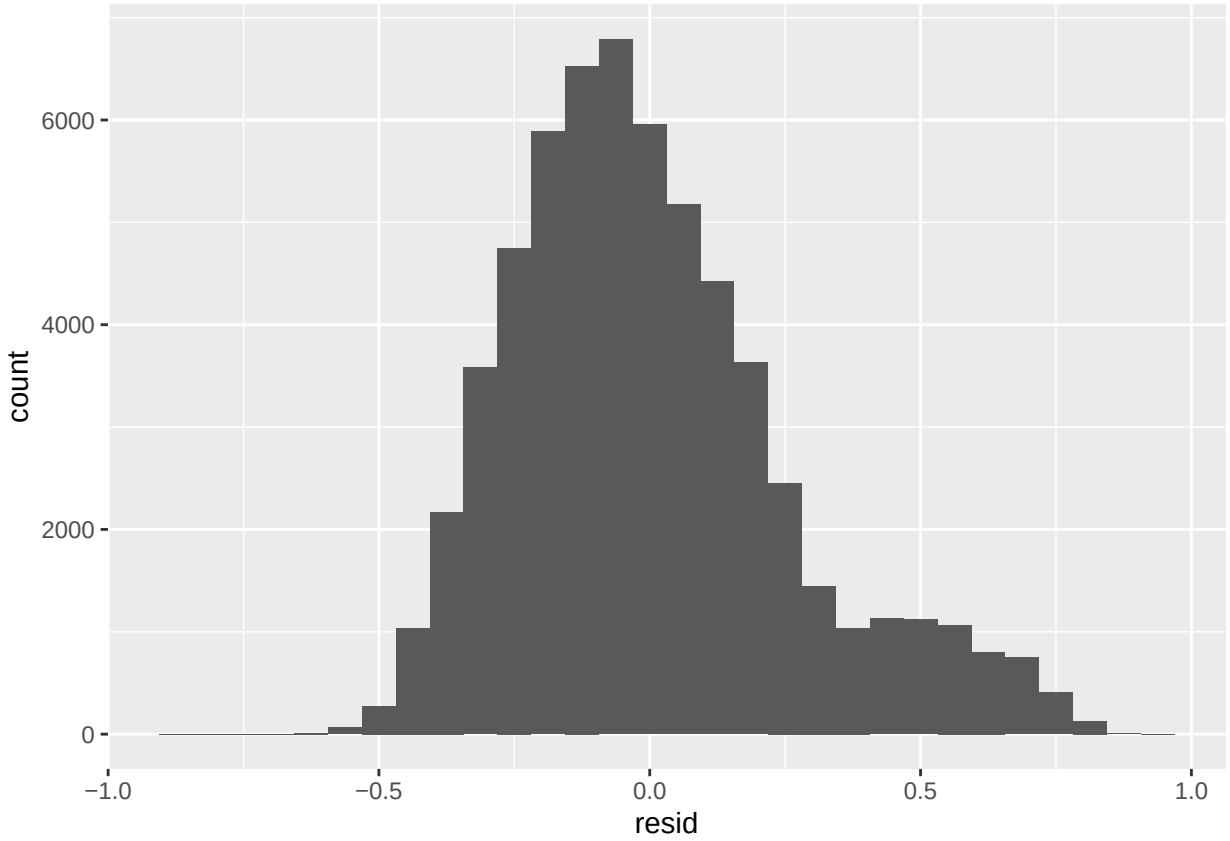
```
ggplot(data = housing_dat) +
  geom_point(aes(x = floor_area_sqm_std, y = log(resale_adj)),color="black") +
  geom_line(aes(x=floor_area_sqm_std,y = predicted), color = "blue") +
  labs(title = "Scatter plot with linear regression line",
       x = "Floor area (sqm)",
       y = "Resale price (Adjusted) $")
```



Next, we plot the residuals to ensure we can make assumptions on the normality of residuals.

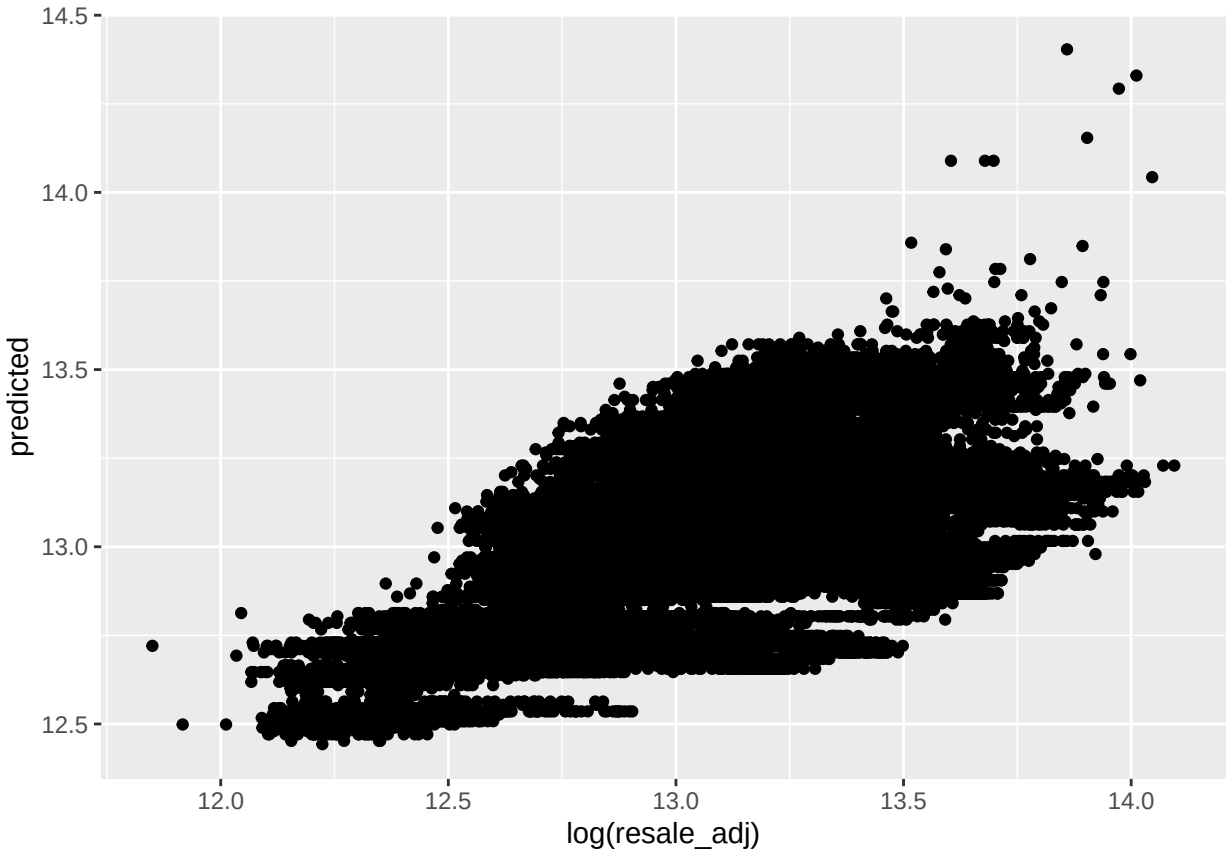
```
epsilon <- data.frame(resid=housing_lm$residuals,month=housing_dat$month)
ggplot(epsilon) +
  geom_histogram(aes(x=resid))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



They look normally distributed, so we may proceed with the comparison of resale and predicted values.

```
ggplot(housing_dat) +
  geom_point(aes(x=log(resale_adj),y=predicted))
```



Results and Discussion

After sub-setting the data into two categories (pre-covid and post-covid) and running our regression on both categories, we called the R function summary() to gather information on how our model was performing. In our pre-covid model, we achieved a R squared value of 0.9484. In our post-covid model, we achieved a R squared of 0.9462. There is only a slight difference between the two, which tells us. . . .

Limitations and Future Work

Reference ==========

All work prior to consultation:

Another thing to note for this dataset is that it contains a lot of categorical variables and the variables that we have chosen also fall under this characterization and so we must employ a technique that will be able to translate our categorical variables into numerical data for the purpose of our models.

1. One-hot-encoding From the above summary, we see that the `flat_type` is a categorical variable. Thus,we will be apply one hot encoding on it for the model to regress.

```
# housing <- housing %>%
#   mutate(
#     is_2_room = ifelse(flat_type == "2 ROOM", 1, 0),
#     is_3_room = ifelse(flat_type == "3 ROOM", 1, 0),
```

```
#     is_4_room = ifelse(flat_type == "4 ROOM", 1, 0),
#     is_5_room = ifelse(flat_type == "5 ROOM", 1, 0),
#     is_executive = ifelse(flat_type == "EXECUTIVE", 1, 0),
#     is_1_room = ifelse(flat_type == "1 ROOM", 1, 0),
#     is_multi_generation = ifelse(flat_type == "MULTI-GENERATION", 1, 0)
#   ) %>%
#   dplyr::select(!flat_type)
```

In order to remedy this in a way that will be better utilized for our model, we will categorize the different towns of Singapore into NSEW (North, South, East, West) regions, and further apply one-hot encoding as done above since it is a categorical variable.

```
# Function to categorize towns into NSEW regions
# categorize_town <- function(town) {
#   north <- c("ANG MO KIO", "SEMBAWANG", "SENGKANG", "WOODLANDS", "YISHUN","BISHAN")
#   south <- c("BUKIT MERAH", "BUKIT TIMAH", "CENTRAL AREA", "QUEENSTOWN")
#   east <- c("BEDOK", "MARINE PARADE", "PASIR RIS", "TAMPINES")
#   west <- c("BUKIT BATOK", "BUKIT PANJANG", "CHOA CHU KANG", "CLEMENTI", "JURONG EAST", "JURONG WEST"
#
#   if (town %in% north) {
#     return("North")
#   } else if (town %in% south) {
#     return("South")
#   } else if (town %in% east) {
#     return("East")
#   } else if (town %in% west) {
#     return("West")
#   } else {
#     return("Other")
#   }
# }
#
# # Add a new column for NSEW region
# housing <- housing %>%
#   rowwise() %>%
#   mutate(region = categorize_town(toupper(town))) %>%
#   mutate(
#     is_north = ifelse(region == "North", 1, 0),
#     is_south = ifelse(region == "South", 1, 0),
#     is_west = ifelse(region == "West", 1, 0),
#     is_east = ifelse(region == "East", 1, 0)
#   ) %>%
#   dplyr::select(!region)
```

Note that for one-hot encoding on the columns `region` and `flat_type` , we can just drop one of the columns as it can be identified by the rest of the columns, i.e `(is_north,is_south,is_west) = (0,0,0)`corresponds to the house being in the East Region.

```
# housing <- housing %>%
#         dplyr::select(!c(is_east,is_multi_generation))
```

In order to evaluate the most statistically significant housing metrics and reduce the number of predictors we have, we will use regularization. Beginning with Ridge Regularization:

```
# df <- housing %>% dplyr::select(!month)
#
# ori <- lm(log(resale_adj) ~ . + 0, data = df)
#
# yhat <- predict(ori)
#
# y <- log(df$resale_adj)
#
# MSE_ori <- mean((y-yhat)^2)
# cat("MSE from the linear model: ", MSE_ori)
#
# epsilon <- data.frame(resid=resid(ori),month=housing$month)
#
# residuals_means <- epsilon %>%
#   group_by(month) %>%
#   summarise(mean_residual = mean(resid))
#
# # Now you can plot the mean residuals against the months
# ggplot(residuals_means, aes(x = month, y = mean_residual)) +
#   geom_line() +
#   labs(x = "Month", y = "Mean Residuals", title = "Mean Residuals Over Time")
```

Ridge and Lasso

```
# # Set seed for reproducibility
# set.seed(123)
# # Create an index for splitting the data
# split <- createDataPartition(y = housing$resale_price, p = 0.8, list = FALSE)
# X <- dplyr::select(df,!resale_price)
# X_train <- X[split,]
# X_test <- as.matrix(X[-split,])
# y_train <- df$resale_price[split]
# y_test <- df$resale_price[-split]
# # Fit Ridge model
# ridge <- glmnet::glmnet(x = X_train, y = y_train, alpha = 0)
# yhat_ridge <- predict(ridge, newx = X_test)
# lambda_ridge <- ridge$lambda
# # Min MAE
# mae_ridge <- apply(abs(yhat_ridge - y_test),2,mean)
#
# #col mean for each lambda
# min_ridge <- which.min(mae_ridge) #index corresponding to min MAE
# min_lambda_ridge <- lambda_ridge[min_ridge]
# coef_min_ridge <- coef(ridge)[,min_ridge] #Corresponding indices of the non-zero coefs
# lagged_features <- as.numeric(which(coef_min_ridge != 0))
# print("Lagged features present in the MAE-optimal ridge model:")
#
# # Fit lasso model
# lasso <- glmnet::glmnet(x = X_train, y = y_train, alpha = 1)
# yhat_lasso <- predict(lasso, newx = X_test)
# lambda_lasso <- lasso$lambda # Min MAE
# mae_lasso <- apply(abs(yhat_lasso - y_test),2,mean)
# #col mean for each lambda
```

```
# min_lasso <- which.min(mae_lasso) #index corresponding to min MAE
# min_lambda_lasso <- lambda_lasso[min_lasso]
# coef_min_lasso <- as.data.frame(coef(lasso)[,min_lasso])
# #Corresponding indices of the non-zero coefs
# coef_min_lasso
```

F-test for feature selection

Using the F-test to understand the variability between the features in the data set, we want to select the features with most impact on our y variable.

```
# ANOVA - This is giving high RSE, meaning there is a lot of unexplained variability.
# anova_test <- aov(resale_price ~ is_1_room +
#                     is_2_room +
#                     is_3_room +
#                     is_4_room +
#                     is_5_room +
#                     is_executive +
#                     is_north +
#                     is_south +
#                     is_west +
#                     floor_area_sqm_std +
#                     remaining_lease_std, df)
#
#
# # F-test on each features with 2 levels
# is_1_room <- var.test(resale_price ~ is_1_room, df,
#          alternative = "two.sided")
# is_2_room <- var.test(resale_price ~ is_2_room, df,
#          alternative = "two.sided")
# is_3_room <- var.test(resale_price ~ is_3_room, df,
#          alternative = "two.sided")
# is_4_room <- var.test(resale_price ~ is_4_room, df,
#          alternative = "two.sided")
# is_5_room <- var.test(resale_price ~ is_5_room, df,
#          alternative = "two.sided")
# is_executive <- var.test(resale_price ~ is_executive, df,
#          alternative = "two.sided")
# is_north <- var.test(resale_price ~ is_north, df,
#          alternative = "two.sided")
# is_south <- var.test(resale_price ~ is_south, df,
#          alternative = "two.sided")
# is_west <- var.test(resale_price ~ is_west, df,
#          alternative = "two.sided")
#
# F_test_vals <- list(
#   is_1_room = is_1_room,
#   is_2_room = is_2_room,
#   is_3_room = is_3_room,
#   is_4_room = is_4_room,
#   is_5_room = is_5_room,
#   is_executive = is_executive,
#   is_north = is_north,
```

```
#   is_south = is_south,
#   is_west = is_west
# )
#
# # Extract p-values
# p_vals <- sapply(F_test_vals, function(result) {
#   result$p.value
# })
#
# # Check if any p-value is less than a significance level (e.g., 0.05)
# any(p_vals > 0.05)
# big_p <- which(p_vals>0.05)
#
# cat("Feature with p_value > 0.05: ", names(df)[big_p],"\n")
# cat("Corresponding p-value: ",p_vals[big_p])

# More than two levels, won't run with F-test.
#floor_area_sqm_std <- var.test(resale_price ~ floor_area_sqm_std, housing,
     #    alternative = "two.sided")
#remaining_lease_std <- var.test(resale_price ~ remaining_lease_std, housing,
     #    alternative = "two.sided")
```

In the Lasso model the feature "is_5_room" has a zero coefficient and this F-test confirms that we can drop this feature due to the p-value being higher than 0.05. So we will re-run the linear regression ommitting this feature.

```
# ori_no_5_rooms <- lm(log(resale_price) ~ is_2_room +
#                                          is_3_room +
#                                          is_4_room +
#                                          is_executive +
#                                          is_1_room +
#                                          is_north +
#                                          is_south +
#                                          is_west +
#                                          floor_area_sqm_std +
#                                          remaining_lease_std +
#                                          0, data = df)
#
# rsquared <- summary(ori_no_5_rooms)
# rsquared$r.squared
```

Regression Analysis on the Effects of COVID-19 on the Housing Market in Singapore

Now that we have performed ANOVA and F-test for feature selection and determined which variables to utilize in our model, we can move forward with further analyzing the effects of COVID-19 on the housing market in Singapore.

Subsetting our dataset

We will begin by filtering all dates before April 2020 as that was when the Singaporean government began enforcing preventive measures for the pandemic. This date was chosen based on the following information:

1. The first COVID-19 case in Singapore was confirmed on January 23, 2020.
2. COVID-19 clusters in the population were recorded in late March and early April 2020.
3. Singapore enacted the "COVID-19 Control Order" in April 3, 2020 and announced the "circuit breaker lockdown," which was a set of stringent preventive measures to curb the spread of COVID-19.

With all this information in mind, we believe that April 2020 would be the best date to choose as the boundary when subsetting our data into pre-COVID and COVID time periods.

```
# Subsetting our original dataset into the two time periods
pre_covid <- housing %>%
  filter(month < "2020-04-01")

covid <- housing %>%
  filter(month >= "2020-04-01")
```

Running Linear Regression on Both Periods

```
# Linear Regression on Pre-Covid Data
# pre_covid_lm <- lm(log(resale_price) ~ is_2_room +
#       is_3_room +
#       is_4_room +
#       is_executive +
#       is_1_room +
#       is_north +
#       is_south +
#       is_west +
#       floor_area_sqm_std +
#       remaining_lease_std +
#       0, data = pre_covid)
#
# # Linear Regression on Covid Period Data
# covid_lm <- lm(log(resale_price) ~ is_2_room +
#       is_3_room +
#       is_4_room +
#       is_executive +
#       is_1_room +
#       is_north +
#       is_south +
#       is_west +
#       floor_area_sqm_std +
#       remaining_lease_std +
#       0, data = covid)
#
# summary(pre_covid_lm)
# summary(covid_lm)
```

References

Resale flat prices based on registration date from Jan-2017 onwards. Data.gov.sg. https://beta.data.gov.sg/datasets/d_8b84c4ee58e3cfc0ece0d773c8ca6abc/view

Origin of data set for Singaporean homes. Kaggle.com. https://www.kaggle.com/code/ashydv/housing-price-prediction-linear-regression/notebook

Singaporean Consumer Price Index. https://www.singstat.gov.sg/whats-new/latest-news/cpi-highlights