NYC House Prediction for Harvard X Individual Project

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June 15 2020

Part 1 Executive Summary

1.1 Project Introduction

This project is to conduct data analysis and modeling on a dataset of real estate transaction deals within a year in New York property market. The dataset is orginally from New York City Department of Finance, https://www1.nyc.gov/site/finance/taxes/property-rolling-sales-data.page (https://www1.nyc.gov/site/finance/taxes/property-rolling-sales-data.page) . On their website, the Department of Finance's Rolling Sales files lists properties that sold in a twelve-month period from September 2016 to September 2017 in New York City for all tax classes. This dataset is a concatenated and slightly cleaned-up version provided in kaggle. The dataset contains both continuous and categorical data, including the sales prices, building locations, building types over 12 months periods.In this project, all variables have been analyzed and studied, and 4 data models have been introduced, studied and compared.

1.2 Project Goals

The objectives of this project is to build and compare with the models predicting property sales price in New York City, and find a better model suitable for real estate transaction price prediction.

Part 2 Method & Analysis

2.1 Dataset & Analysis Methods Summary

To smoothly carry forward this project, there will be 3 major steps:

*Step1: Download the dataset, explore the dataset and clean the data for further analysis.

*Step2: Split the cleaned dataset into training and testing datasets. Conduct exploratory data analysis (EDA) on training dataset, learn more about each variable and its distribution.

*Step3: Choose variables for data modeling, build data models on training dataset, and test the model on testing dataset. Root Mean Square Error (RMSE) will be used to analyze and compare the result of the models.

2.2 Data Analysis

2.2.1 Data Loading & Wrangling

NYC Housing Sales Dataset Loading

```
download.file("https://raw.github.com/morris4321/nyc_realestate_salesprice/master/nyc
-rolling-sales.csv", destfile = "/Users/elizabethli/nyc_property_salesprice_predictio
n/nyc-rolling-sales.csv")
setwd("/Users/elizabethli/nyc_property_salesprice_prediction")
nyc_property_original <- read_csv("nyc-rolling-sales.csv")
```

```
## Parsed with column specification:
## cols(
##   BOROUGH = col_double(),
##   NEIGHBORHOOD = col_character(),
##   BUILDING_CLASS_CATEGORY = col_character(),
##   TAX_CLASS_AT_PRESENT = col_character(),
##   EASE_MENT = col_logical(),
##   BUILDING_CLASS_AT_PRESENT = col_character(),
##   ADDRESS = col_character(),
##   APARTMENT_NUMBER = col_character(),
##   ZIP_CODE = col_double(),
##   RESIDENTIAL_UNITS = col_double(),
##   COMMERCIAL_UNITS = col_double(),
##   TOTAL_UNITS = col_double(),
##   LAND_SQUARE_FEET = col_character(),
##   GROSS_SQUARE_FEET = col_character(),
##   YEAR_BUILT = col_double(),
##   TAX_CLASS_AT_TIME_OF_SALE = col_double(),
##   BUILDING_CLASS_AT_TIME_OF_SALE = col_character(),
##   SALE_PRICE = col_character(),
##   SALE_DATE = col_character()
## )
```

```
nyc_property <- nyc_property_original
```

Dataset Glimpse

```
glimpse(nyc_property)
```

```
## Rows: 84,548
## Columns: 19
## $ BOROUGH                       <dbl> 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, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1,…
## $ NEIGHBORHOOD                  <chr> "ALPHABET CITY", "ALPHABET CITY", "ALPHABET
CITY", "ALPHABET CITY", "ALPHABET CITY", "ALPHABET CITY", "ALPHABET CITY", "ALPHABET
CITY", "ALPHABET CITY", "ALPH…
## $ BUILDING_CLASS_CATEGORY       <chr> "07 RENTALS - WALKUP APARTMENTS", "07 RENTA
LS - WALKUP APARTMENTS", "07 RENTALS - WALKUP APARTMENTS", "07 RENTALS - WALKUP APART
MENTS", "07 RENTALS - WALKUP A…
## $ TAX_CLASS_AT_PRESENT          <chr> "2A", "2", "2", "2B", "2A", "2", "2B", "2",
"2", "2", "2", "2B", "2", "2", "2", "2", "2", "2", "2", "2", "2C", "2", "2", "2", "2"
, "2", "2", "2C", "2C", "2", …
## $ EASE_MENT                     <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N
A, NA, NA, NA, NA, NA, NA, NA…
## $ BUILDING_CLASS_AT_PRESENT     <chr> "C2", "C7", "C7", "C4", "C2", "C4", "C4", "
C7", "D5", "D9", "D7", "D1", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C
```

```
6", "C6", "C6", "C6", "C6", "C…
## $ ADDRESS                       <chr> "153 AVENUE B", "234 EAST 4TH   STREET", "1
97 EAST 3RD   STREET", "154 EAST 7TH STREET", "301 EAST 10TH   STREET", "516 EAST 12T
H   STREET", "210 AVENUE B", "…
## $ APARTMENT_NUMBER              <chr> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N
A, NA, NA, NA, NA, NA, NA, NA…
## $ ZIP_CODE                      <dbl> 10009, 10009, 10009, 10009, 10009, 10009, 1
0009, 10009, 10009, 10009, 10009, 10009, 10009, 10009, 10009, 10009, 10009, 10009, 10
009, 10009, 10009, 10009, 1000…
## $ RESIDENTIAL_UNITS             <dbl> 5, 28, 16, 10, 6, 20, 8, 44, 15, 24, 30, 10
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 24, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…
## $ COMMERCIAL_UNITS              <dbl> 0, 3, 1, 0, 0, 0, 0, 2, 0, 0, 4, 0, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0,…
## $ TOTAL_UNITS                   <dbl> 5, 31, 17, 10, 6, 20, 8, 46, 15, 24, 34, 10
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 24, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…
## $ LAND_SQUARE_FEET              <chr> "1633", "4616", "2212", "2272", "2369", "25
81", "1750", "5163", "1534", "4489", "4295", "3717", "-", "-", "-", "-", "-", "-", "-
", "-", "-", "-", "4131", "-",…
## $ GROSS_SQUARE_FEET             <chr> "6440", "18690", "7803", "6794", "4615", "9
730", "4226", "21007", "9198", "18523", "21328", "12350", "-", "-", "-", "-", "-", "-
", "-", "-", "-", "-", "16776"…
## $ YEAR_BUILT                    <dbl> 1900, 1900, 1900, 1913, 1900, 1900, 1920, 1
900, 1920, 1920, 1910, 2009, 1920, 1920, 1920, 1920, 1920, 1925, 1920, 1920, 1900, 19
02, 1928, 1928, 1928, 1928, 19…
## $ TAX_CLASS_AT_TIME_OF_SALE     <dbl> 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2
, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
2, 2, 2, 2, 2, 2, 2, 2, 2, 2,…
## $ BUILDING_CLASS_AT_TIME_OF_SALE <chr> "C2", "C7", "C7", "C4", "C2", "C4", "C4", "
C7", "D5", "D9", "D7", "D1", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C
6", "C6", "C6", "C6", "C…
## $ SALE_PRICE                    <chr> "6625000", "-", "-", "3936272", "8000000",
"-", "3192840", "-", "-", "16232000", "-", "10350000", "1", "499000", "10", "529500",
"423000", "501000", "450000",…
## $ SALE_DATE                     <chr> "7/19/17 0:00", "12/14/16 0:00", "12/9/16 0
:00", "9/23/16 0:00", "11/17/16 0:00", "7/20/17 0:00", "9/23/16 0:00", "7/20/17 0:00"
, "6/20/17 0:00", "11/7/16 0:0…
```

BOROUGH: A digit code for the borough area. The codes are Manhattan (1), Bronx (2), Brooklyn (3), Queens (4), and Staten Island (5).

Data Type Transformation

```
# After have a glimpse of the data, the hour and minute part was removed from the sal
e date column because they are all zero.

nyc_property$SALE_DATE <- gsub( " .*$", "", nyc_property$SALE_DATE )

# Variable data type change

nyc_property$BOROUGH <- as.character(nyc_property$BOROUGH)
nyc_property$ZIP_CODE <- as.character(nyc_property$ZIP_CODE)
nyc_property$TAX_CLASS_AT_TIME_OF_SALE <- as.character(nyc_property$TAX_CLASS_AT_TIME
_OF_SALE)
nyc_property$SALE_PRICE <- as.numeric(nyc_property$SALE_PRICE)
```

```
## Warning: NAs introduced by coercion
```

```
nyc_property$LAND_SQUARE_FEET <- as.numeric(nyc_property$LAND_SQUARE_FEET)
```

```
## Warning: NAs introduced by coercion
```

```
nyc_property$GROSS_SQUARE_FEET <- as.numeric(nyc_property$GROSS_SQUARE_FEET)
```

```
## Warning: NAs introduced by coercion
```

```
nyc_property <- nyc_property%>%mutate_if(is.integer,as.numeric)

# Remove irrelavant variable
nyc_property$APARTMENT_NUMBER<- NULL
nyc_property$ADDRESS <- NULL # Location is represented by other more informative vara
ibles like BOROUGH, NEIGHBORHOOD and ZIPCODE
```

```
glimpse(nyc_property)
```

```
## Rows: 84,548
## Columns: 17
## $ BOROUGH                       <chr> "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", "1", "1", "1"…
## $ NEIGHBORHOOD                  <chr> "ALPHABET CITY", "ALPHABET CITY", "ALPHABET
CITY", "ALPHABET CITY", "ALPHABET CITY", "ALPHABET CITY", "ALPHABET CITY", "ALPHABET
CITY", "ALPHABET CITY", "ALPH…
## $ BUILDING_CLASS_CATEGORY       <chr> "07 RENTALS - WALKUP APARTMENTS", "07 RENTA
LS - WALKUP APARTMENTS", "07 RENTALS - WALKUP APARTMENTS", "07 RENTALS - WALKUP APART
MENTS", "07 RENTALS - WALKUP A…
## $ TAX_CLASS_AT_PRESENT          <chr> "2A", "2", "2", "2B", "2A", "2", "2B", "2",
```

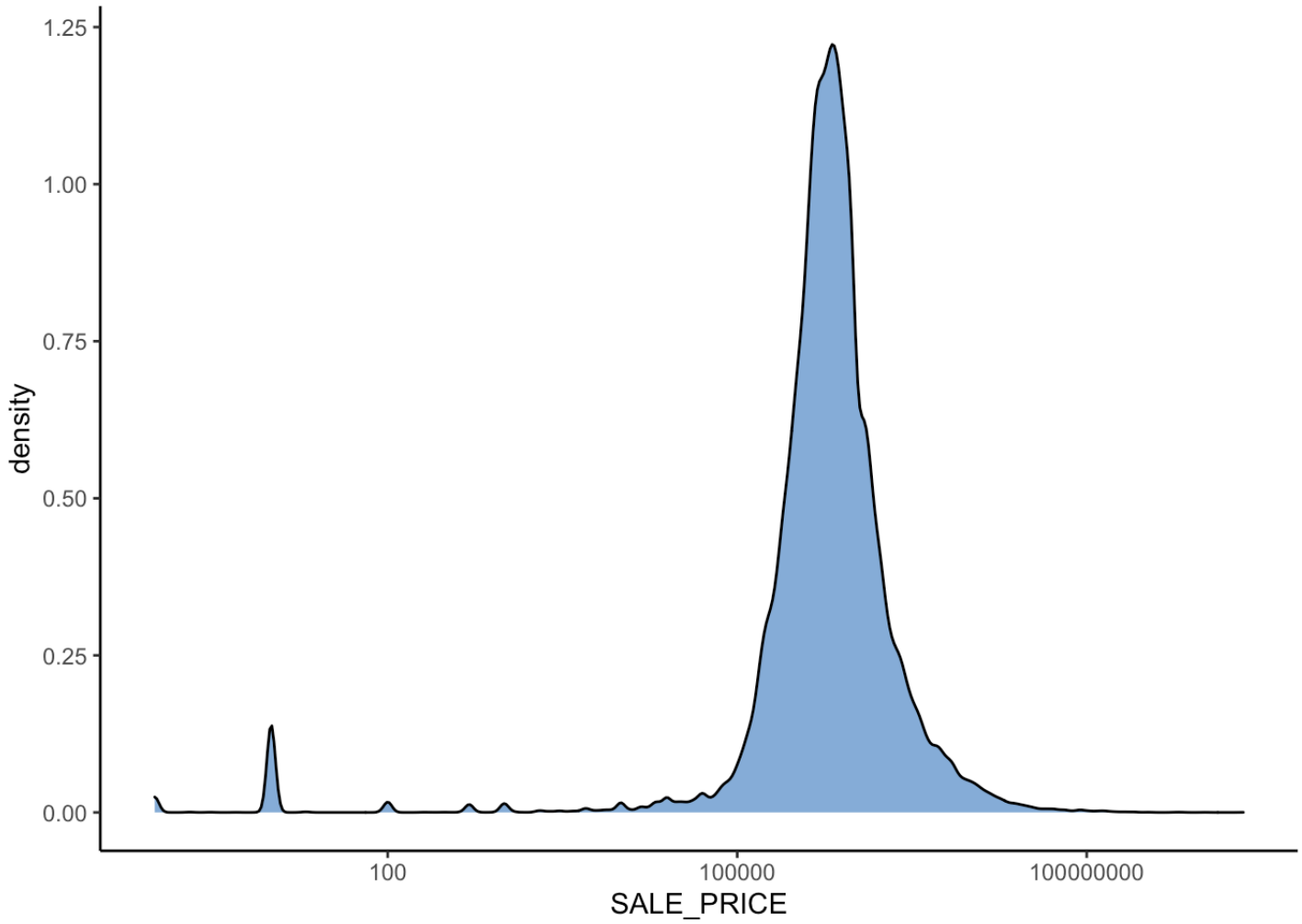
```
"2", "2", "2", "2B", "2", "2", "2", "2", "2", "2", "2", "2", "2C", "2", "2", "2", "2"
, "2", "2", "2C", "2C", "2", …
## $ EASE_MENT                      <lgl> NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA,
NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, N
A, NA, NA, NA, NA, NA, NA, NA…
## $ BUILDING_CLASS_AT_PRESENT      <chr> "C2", "C7", "C7", "C4", "C2", "C4", "C4", "
C7", "D5", "D9", "D7", "D1", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C
6", "C6", "C6", "C6", "C…
## $ ZIP_CODE                       <chr> "10009", "10009", "10009", "10009", "10009"
, "10009", "10009", "10009", "10009", "10009", "10009", "10009", "10009", "10009", "1
0009", "10009", "10009", "1000…
## $ RESIDENTIAL_UNITS              <dbl> 5, 28, 16, 10, 6, 20, 8, 44, 15, 24, 30, 10
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 24, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…
## $ COMMERCIAL_UNITS               <dbl> 0, 3, 1, 0, 0, 0, 0, 2, 0, 0, 4, 0, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0, 0, 0,…
## $ TOTAL_UNITS                    <dbl> 5, 31, 17, 10, 6, 20, 8, 46, 15, 24, 34, 10
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 24, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0
, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0…
## $ LAND_SQUARE_FEET               <dbl> 1633, 4616, 2212, 2272, 2369, 2581, 1750, 5
163, 1534, 4489, 4295, 3717, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 4131, NA, NA, NA
, NA, NA, NA, NA, NA, NA, NA, …
## $ GROSS_SQUARE_FEET              <dbl> 6440, 18690, 7803, 6794, 4615, 9730, 4226,
21007, 9198, 18523, 21328, 12350, NA, NA, NA, NA, NA, NA, NA, NA, NA, NA, 16776, NA,
NA, NA, NA, NA, NA, NA, NA, NA…
## $ YEAR_BUILT                     <dbl> 1900, 1900, 1900, 1913, 1900, 1900, 1920, 1
900, 1920, 1920, 1910, 2009, 1920, 1920, 1920, 1920, 1920, 1925, 1920, 1920, 1900, 19
02, 1928, 1928, 1928, 1928, 19…
## $ TAX_CLASS_AT_TIME_OF_SALE      <chr> "2", "2", "2", "2", "2", "2", "2", "2", "2"
, "2", "2", "2", "2", "2", "2", "2", "2", "2", "2", "2", "2", "2", "2", "2", "2", "2"
, "2", "2", "2", "2", "2", "2"…
## $ BUILDING_CLASS_AT_TIME_OF_SALE <chr> "C2", "C7", "C7", "C4", "C2", "C4", "C4", "
C7", "D5", "D9", "D7", "D1", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C6", "C
6", "C6", "C6", "C6", "C…
## $ SALE_PRICE                     <dbl> 6625000, NA, NA, 3936272, 8000000, NA, 3192
840, NA, NA, 16232000, NA, 10350000, 1, 499000, 10, 529500, 423000, 501000, 450000, 5
10000, NA, 350000, 11900000, 1…
## $ SALE_DATE                      <chr> "7/19/17", "12/14/16", "12/9/16", "9/23/16"
, "11/17/16", "7/20/17", "9/23/16", "7/20/17", "6/20/17", "11/7/16", "7/20/17", "10/1
7/16", "9/6/16", "3/10/17", "4…
```

Outcome Variable Check - Sale Price

```
summary(nyc_property$SALE_PRICE,na.rm = TRUE)
```

```
##       Min.    1st Qu.     Median       Mean    3rd Qu.       Max.       NA's
##          0     225000     530000    1276456     950000 2210000000      14561
```

```
# Distribution plot on log scale
nyc_property%>%
  filter(SALE_PRICE> 0)%>%
  ggplot(aes(x =SALE_PRICE))+
  geom_density(fill = "#6699cc",alpha = 0.8)+
  theme_classic()+
  scale_x_log10()
```




```
quantile(nyc_property$SALE_PRICE,na.rm = TRUE,0.995)
```

```
##    99.5%
## 20309325
```

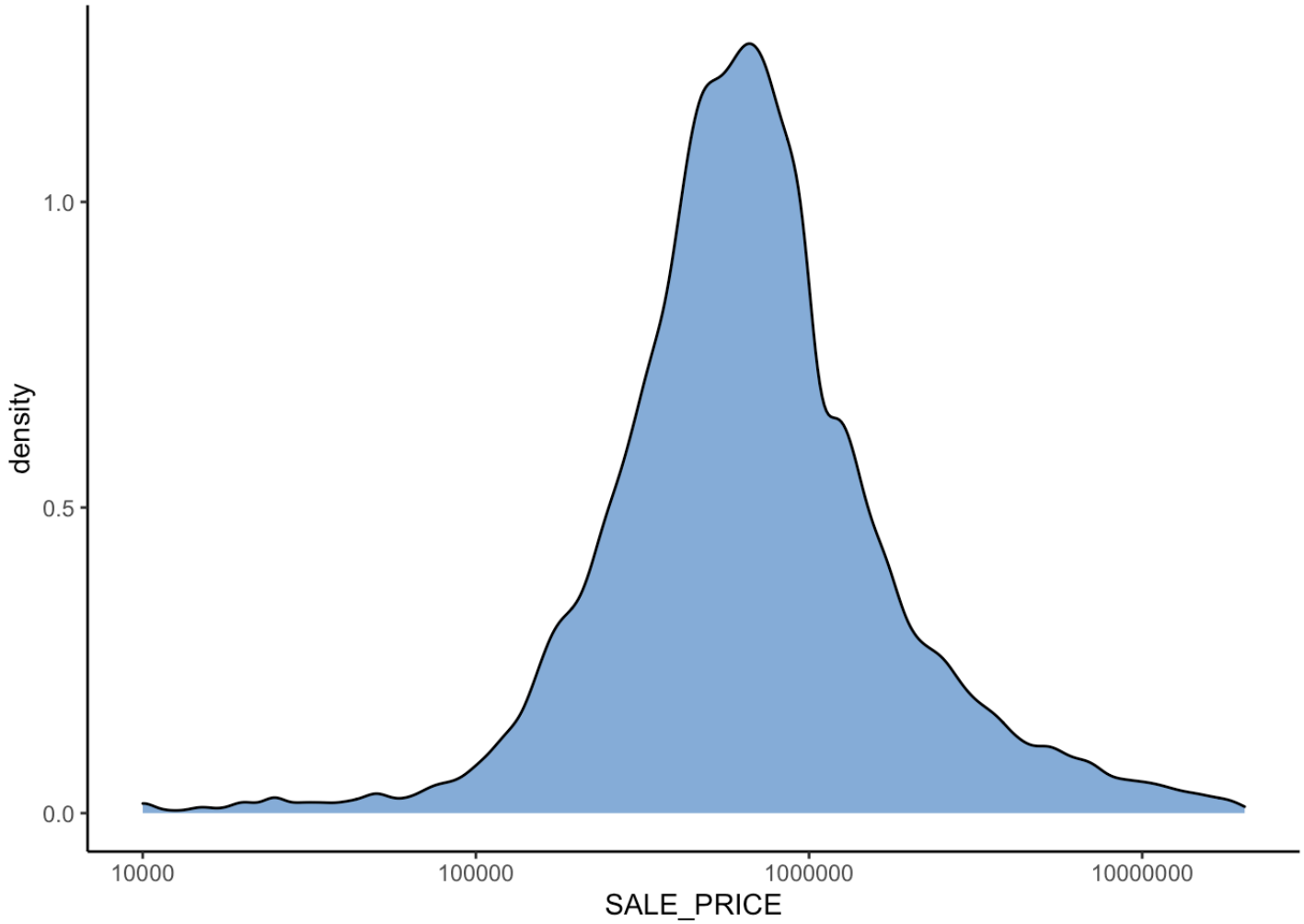
Those outlier high price properties are skycrapers,office building or a whole apartment building. While most of the extreme low property price(Many of those have a nonsensically small dollar amount: $0 most commonly. These sales are actually transfers of deeds between parties: for example, parents transferring ownership to their home to a child after moving out for retirement.

Records having sale price below than 10000 will be removed from the dataset because most of them are not fair market price. Only property with sale price within 99.5% quanitle(<= 20309325) will be used in later analysis so that the independent variable is more balanced. Also, records which do not have sales price will

also be removed from the dataset because sale price is the outcome variable of this project.

Data Cleaning - Remove Outliers Of Outcome Variables

```
# Remove outliers
nyc_property_subset <-
  nyc_property%>%
  filter(!is.na(SALE_PRICE) & SALE_PRICE>= 10000 & SALE_PRICE <= 20309325 )

# Distribution plot on log scale
nyc_property_subset%>%
  ggplot(aes(x=SALE_PRICE))+
  geom_density(fill = "#6699cc",alpha = 0.8)+
  theme_classic()+
  scale_x_log10()
```



Data Summary

Categorical Variables

```
nonNumeric_variable <- nyc_property_subset %>% select_if(negate(is.numeric))
records_have_value = sapply(nonNumeric_variable, function(x) sum(!is.na(x)))
populated = round(records_have_value/nrow(nyc_property_subset),2)
unique_values = sapply(nonNumeric_variable,n_distinct)
calculate_mode <- function(x) {
  uniqx <- unique(na.omit(x))
  uniqx[which.max(tabulate(match(x, uniqx)))]
}


most_common_values = sapply(nonNumeric_variable,calculate_mode)
dataSummaryNonnum <- data.frame(records_have_value,populated,unique_values,most_commo
n_values)
dataSummaryNonnum
```

	records_have_value <int>	populated <dbl>	unique_values <int>	most_c <chr>
BOROUGH	58115	1.00	5	4
NEIGHBORHOOD	58115	1.00	253	FLUSH
BUILDING_CLASS_CATEGORY	58115	1.00	45	01 ONE
TAX_CLASS_AT_PRESENT	57523	0.99	10	2
EASE_MENT	0	0.00	1	*NA*
BUILDING_CLASS_AT_PRESENT	57523	0.99	144	D4
ZIP_CODE	58115	1.00	182	10314
TAX_CLASS_AT_TIME_OF_SALE	58115	1.00	3	2
BUILDING_CLASS_AT_TIME_OF_SALE	58115	1.00	144	D4
SALE_DATE	58115	1.00	335	6/29/17

1-10 of 10 rows

The table above shows that EASE_MENT is a invalid column, and also suggests BUILDING_CLASS_AT_PRESENT and BUILDING_CLASS_AT_TIME_OF_SALE has the same number of unique value, therefore, we can check what is the relationship between the two variables.

Remove Invalid Column - EASE_MENT

```
nyc_property_subset$EASE_MENT <- NULL
nonNumeric_variable$EASE_MENT <- NULL
```

Check BUILDING_CLASS_AT_PRESENT and BUILDING_CLASS_AT_TIME_OF_SALE

```
# Check if the two variables have the same unique value
unique(nyc_property_subset$BUILDING_CLASS_AT_PRESENT)[!(unique(nyc_property_subset$BU
ILDING_CLASS_AT_PRESENT) %in% unique(nyc_property_subset$BUILDING_CLASS_AT_TIME_OF_SA
LE))]
```

```
## [1] NA
```

```
# Check if the two variables are the same in each record

length(which(nyc_property_subset$BUILDING_CLASS_AT_PRESENT!= nyc_property_subset$BUIL
DING_CLASS_AT_TIME_OF_SALE))
```

```
## [1] 121
```

Out of 58115 records, only 121 properties BUILDING_CLASS_AT_PRESENT is different from BUILDING_CLASS_AT_TIME_OF_SALE. Thus, we can create a new variable called BUILDING_CLASS_STATUS_CHANGE to demonstrate this status change instead of including both BUILDING_CLASS_AT_PRESENT and BUILDING_CLASS_AT_TIME_OF_SALE. I choose to keep BUILDING_CLASS_AT_TIME_OF_SALE because it is fully populated and can better represent the property status at time of sale.

Create BUILDING_CLASS_STATUS_CHANGE

```
nyc_property_subset$BUILDING_CLASS_STATUS_CHANGE <- "0"
nyc_property_subset$BUILDING_CLASS_STATUS_CHANGE[which(nyc_property_subset$BUILDING_C
LASS_AT_PRESENT!= nyc_property_subset$BUILDING_CLASS_AT_TIME_OF_SALE)] <- "1"
nyc_property_subset$BUILDING_CLASS_AT_PRESENT <- NULL
```

Fill Missing Values

```
# Set NA Value to mode value for modeling purpose

nyc_property_subset$TAX_CLASS_AT_PRESENT[is.na(nyc_property_subset$TAX_CLASS_AT_PRESE
NT)] <- "2"

nonNumeric_variable <- nyc_property_subset %>% select_if(negate(is.numeric))
records_have_value = sapply(nonNumeric_variable, function(x) sum(!is.na(x)))
populated = round(records_have_value/nrow(nyc_property_subset),2)
unique_values = sapply(nonNumeric_variable,n_distinct)
calculate_mode <- function(x) {
  uniqx <- unique(na.omit(x))
  uniqx[which.max(tabulate(match(x, uniqx)))]
}


most_common_values = sapply(nonNumeric_variable,calculate_mode)
dataSummaryNonnum <- data.frame(records_have_value,populated,unique_values,most_commo
n_values)
dataSummaryNonnum
```

	records_have_value <int>	populated <dbl>	unique_values <int>	most_c <chr>
BOROUGH	58115	1	5	4
NEIGHBORHOOD	58115	1	253	FLUSH
BUILDING_CLASS_CATEGORY	58115	1	45	01 ONE
TAX_CLASS_AT_PRESENT	58115	1	9	2
ZIP_CODE	58115	1	182	10314
TAX_CLASS_AT_TIME_OF_SALE	58115	1	3	2
BUILDING_CLASS_AT_TIME_OF_SALE	58115	1	144	D4
SALE_DATE	58115	1	335	6/29/17
BUILDING_CLASS_STATUS_CHANGE	58115	1	2	0

9 rows

Numeric Variables

```
numeric_variable <- nyc_property_subset %>% select_if(is.numeric)
records_have_value = sapply(numeric_variable, function(x) sum(!is.na(x)))
populated = round(records_have_value/nrow(nyc_property_subset),2)
number_of_zero_value = sapply(numeric_variable,function(x) sum(x == 0,na.rm = TRUE))
minvalues <- sapply(numeric_variable,function(x) {min(x,na.rm = TRUE)})
meanvalues <- round(sapply(numeric_variable,function(x) {mean(x,na.rm = TRUE)}),2)
maxvalues <- sapply(numeric_variable,function(x) {max(x,na.rm = TRUE)})

dataSummaryNum <- data.frame(records_have_value,populated,number_of_zero_value,minval
ues,meanvalues,maxvalues)
dataSummaryNum
```

	records_have_value <int>	populated <dbl>	number_of_zero_value <int>	minvalues <dbl>	me
RESIDENTIAL_UNITS	58115	1.00	18286	0	
COMMERCIAL_UNITS	58115	1.00	55559	0	
TOTAL_UNITS	58115	1.00	16458	0	
LAND_SQUARE_FEET	37204	0.64	8049	0	
GROSS_SQUARE_FEET	36692	0.63	8489	0	
YEAR_BUILT	58115	1.00	4117	0	
SALE_PRICE	58115	1.00	0	10000	11

7 rows

The table above shows that there are missing values in LAND SQUARE FEET and GROSS SQUARE FEET, I will replace them with 0 as Unknown.

```
nyc_property_subset$LAND_SQUARE_FEET[is.na(nyc_property_subset$LAND_SQUARE_FEET)] <-
0

nyc_property_subset$GROSS_SQUARE_FEET[is.na(nyc_property_subset$GROSS_SQUARE_FEET)] <
- 0

nyc_property_subset$YEAR_BUILT[is.na(nyc_property_subset$YEAR_BUILT)] <- 0
```

2.2.2 Generate Training and Testing Datasets

Training/Testing Data Split

```
spec = c(train = .75, test = .25)

set.seed(1)

g = sample(cut(
  seq(nrow(nyc_property_subset)),
  nrow(nyc_property_subset)*cumsum(c(0,spec)),
  labels = names(spec)
))

res = split(nyc_property_subset, g)

Training <- res$train
Testing <- res$test
```

```
str(Training)
```

```
## tibble [43,586 × 16] (S3: tbl_df/tbl/data.frame)
##  $ BOROUGH                       : chr [1:43586] "1" "1" "1" "1" ...
##  $ NEIGHBORHOOD                  : chr [1:43586] "ALPHABET CITY" "ALPHABET CITY" "
ALPHABET CITY" "ALPHABET CITY" ...
##  $ BUILDING_CLASS_CATEGORY       : chr [1:43586] "07 RENTALS - WALKUP APARTMENTS"
"07 RENTALS - WALKUP APARTMENTS" "07 RENTALS - WALKUP APARTMENTS" "08 RENTALS - ELEVA
TOR APARTMENTS" ...
##  $ TAX_CLASS_AT_PRESENT          : chr [1:43586] "2A" "2B" "2A" "2" ...
##  $ ZIP_CODE                      : chr [1:43586] "10009" "10009" "10009" "10009" .
..
##  $ RESIDENTIAL_UNITS             : num [1:43586] 5 10 6 24 0 0 0 0 0 0 ...
##  $ COMMERCIAL_UNITS              : num [1:43586] 0 0 0 0 0 0 0 0 0 0 ...
##  $ TOTAL_UNITS                   : num [1:43586] 5 10 6 24 0 0 0 0 0 0 ...
##  $ LAND_SQUARE_FEET              : num [1:43586] 1633 2272 2369 4489 0 ...
##  $ GROSS_SQUARE_FEET             : num [1:43586] 6440 6794 4615 18523 0 ...
##  $ YEAR_BUILT                    : num [1:43586] 1900 1913 1900 1920 1920 ...
##  $ TAX_CLASS_AT_TIME_OF_SALE     : chr [1:43586] "2" "2" "2" "2" ...
##  $ BUILDING_CLASS_AT_TIME_OF_SALE: chr [1:43586] "C2" "C4" "C2" "D9" ...
##  $ SALE_PRICE                    : num [1:43586] 6625000 3936272 8000000 16232000
529500 ...
##  $ SALE_DATE                     : chr [1:43586] "7/19/17" "9/23/16" "11/17/16" "1
1/7/16" ...
##  $ BUILDING_CLASS_STATUS_CHANGE  : chr [1:43586] "0" "0" "0" "0" ...
```

```
nrow(Testing)
```

```
## [1] 14529
```

Training/Testing Data Level Check

```
# For variable levels that are in testing dataset and not in training dataset, I will
set it's value to mode

prepTest <- function(x)
  {
    for (i in unique(Testing[[x]]))
     {
      if(!(i%in% unique(Training[[x]])))
        {
          return(x)
      }
  }
}

uniqueTest <- unlist(lapply(colnames(nonNumeric_variable),prepTest))

Testing$NEIGHBORHOOD[!(Testing$NEIGHBORHOOD %in% unique(Training$NEIGHBORHOOD))] <- "
FLUSHING-NORTH"

Testing$BUILDING_CLASS_CATEGORY[!(Testing$BUILDING_CLASS_CATEGORY %in% unique(Trainin
g$BUILDING_CLASS_CATEGORY))] <- "01 ONE FAMILY DWELLINGS"

Testing$ZIP_CODE[!(Testing$ZIP_CODE %in% unique(Training$ZIP_CODE))] <- "10314"

Testing$BUILDING_CLASS_AT_TIME_OF_SALE[!(Testing$BUILDING_CLASS_AT_TIME_OF_SALE %in%
unique(Training$BUILDING_CLASS_AT_TIME_OF_SALE))] <- "D4"
```

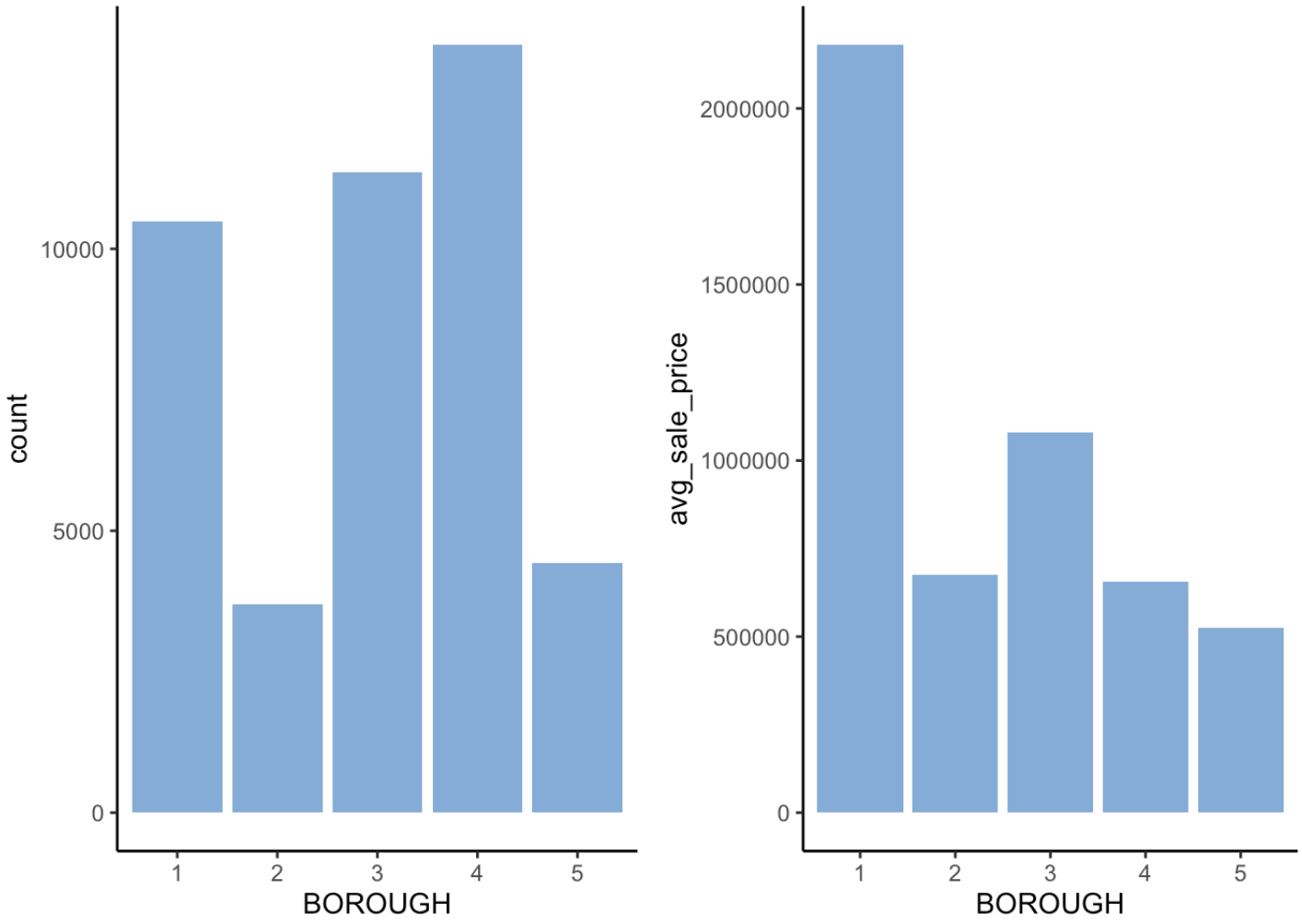
2.2.3 Exploratory Data Analysis (EDA) On Traning Dataset

Categorical Variable Distributions

Borough

Manhattan (1), Bronx (2), Brooklyn (3), Queens (4), Staten Island (5)

```
histPlot <- Training%>%
            filter(!is.na(BOROUGH))%>%
            group_by(BOROUGH)%>%
            ggplot(aes(x = BOROUGH))+
            geom_bar(stat = "count",fill = "#6699cc",alpha = 0.8)+
            theme_classic()

corrPlot <- Training%>%
            filter(!is.na(BOROUGH))%>%
            group_by(BOROUGH)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x = BOROUGH,y = avg_sale_price))+
            geom_bar(stat = "identity",fill = "#6699cc",alpha = 0.8)+
            theme_classic()



plot_grid(histPlot,corrPlot,nrow = 1)
```



The above plots shows that Borough 1,3 and 4 have the most of the sales, and location has an impact on the property sale price, borough 1 (Manhattan's average house price is way higher than other borough areas).

NEIGHBORHOOD

```
Training%>%
  group_by(NEIGHBORHOOD)%>%
  summarise(quantity = length(NEIGHBORHOOD),avg_sale_price = mean(SALE_PRICE))%>%
  arrange(desc(quantity))
```

NEIGHBORHOOD <chr>	quantity <int>	avg_sale_price <dbl>
FLUSHING-NORTH	1662	913703.9
UPPER EAST SIDE (59-79)	1073	2064445.1
UPPER EAST SIDE (79-96)	993	2250957.0
UPPER WEST SIDE (59-79)	794	2099253.6
MIDTOWN EAST	775	1537399.6
FOREST HILLS	660	514134.5
BAYSIDE	649	665426.9
BEDFORD STUYVESANT	646	1283527.2
JACKSON HEIGHTS	547	536293.1
EAST NEW YORK	502	588672.8

1-10 of 251 rows Previous **1** 2 3 4 5 6 … 26 Next

From above, we can learn that, the best selling neighborhoods (Top5) are Flushing-North, Upper East Side (59-79,79-96),Upper West Side (59-79), and Midtown East.

```
Training%>%
  group_by(NEIGHBORHOOD)%>%
  summarise(quantity = length(NEIGHBORHOOD),avg_sale_price = mean(SALE_PRICE))%>%
  arrange(desc(avg_sale_price))
```

NEIGHBORHOOD <chr>	quantity <int>	avg_sale_price <dbl>
EAST RIVER	1	11200000.0
CIVIC CENTER	210	5766352.6
BLOOMFIELD	2	5282500.0
LITTLE ITALY	20	5016468.8
SOHO	175	3734985.8
TRIBECA	404	3682138.1

FLATIRON	288	3593098.2
GREENWICH VILLAGE-WEST	330	3426342.2
FASHION	46	3229798.9
CHINATOWN	42	2831236.5

1-10 of 251 rows Previous **1** 2 3 4 5 6 … 26 Next

From above, we can learn that, the neighborhood which have highest average sales prices (Top5) are East River, Civic Center, Bloomfield, Little Italy and Soho.

BUILDING CLASS CATEGORY

```
Training%>%
  group_by(BUILDING_CLASS_CATEGORY)%>%
  summarise(quantity = length(BUILDING_CLASS_CATEGORY),avg_sale_price = mean(SALE_PRI
CE))%>%
  arrange(desc(quantity))
```

BUILDING_CLASS_CATEGORY <chr>	**quantity** <int>	**avg_sale_price** <dbl>
01 ONE FAMILY DWELLINGS	9506	655937.49
10 COOPS - ELEVATOR APARTMENTS	8625	778963.47
13 CONDOS - ELEVATOR APARTMENTS	7659	1910343.66
02 TWO FAMILY DWELLINGS	7404	805529.69
09 COOPS - WALKUP APARTMENTS	1882	481579.57
03 THREE FAMILY DWELLINGS	1714	990753.72
07 RENTALS - WALKUP APARTMENTS	1285	2932078.50
04 TAX CLASS 1 CONDOS	948	552670.03
17 CONDO COOPS	808	919448.00
15 CONDOS - 2-10 UNIT RESIDENTIAL	777	1523221.15

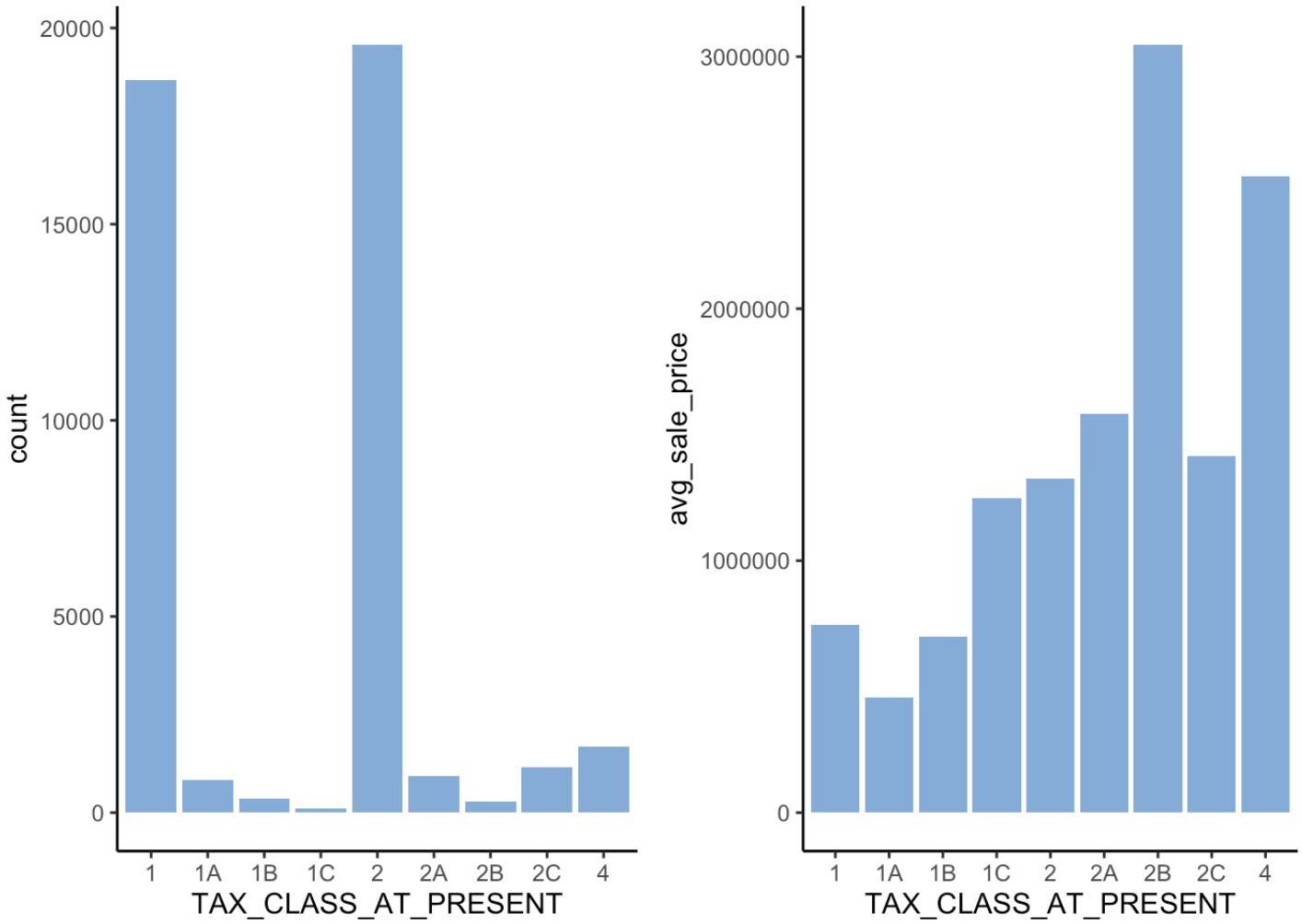
1-10 of 43 rows Previous **1** 2 3 4 5 Next

From above, we can learn that more common building classes sold in Borough are one family dwellings, Coops- Elevator Apartments, Condo - Elevator Apartment, and two family dwellings.

Tax Class At Present

Every property in the city is assigned to one of four tax classes (Classes 1, 2, 3, and 4),based on the use of the property.

```
histPlot <- Training%>%
            filter(!is.na(TAX_CLASS_AT_PRESENT))%>%
            group_by(TAX_CLASS_AT_PRESENT)%>%
            ggplot(aes(x = TAX_CLASS_AT_PRESENT))+
            geom_bar(stat = "count",fill = "#6699cc",alpha = 0.8)+
            theme_classic()

corrPlot <- Training%>%
            filter(!is.na(TAX_CLASS_AT_PRESENT))%>%
            group_by(TAX_CLASS_AT_PRESENT)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x = TAX_CLASS_AT_PRESENT,y = avg_sale_price))+
            geom_bar(stat = "identity",fill = "#6699cc",alpha = 0.8)+
            theme_classic()



plot_grid(histPlot,corrPlot,nrow = 1)
```



The majority of sold properties are in Class 1 and class 2. And the average sales price in Class 2B is the highest. The average sales price in Class 2B is the second highest.

Zip Code

```
Training%>%
  group_by(ZIP_CODE)%>%
  summarise(quantity = length(ZIP_CODE),avg_sale_price = mean(SALE_PRICE))%>%
  arrange(desc(quantity))
```

ZIP_CODE <chr>	quantity <int>	avg_sale_price <dbl>
11354	857	929676.1
10314	854	563299.1
11201	767	1846833.7
11375	688	519717.5
10011	637	2808479.5
10016	609	1464051.9
10312	604	526947.6
11235	602	656385.3
10023	590	1774946.6
10022	576	1987169.9

1-10 of 181 rows Previous **1** 2 3 4 5 6 … 19 Next

Among 181 zip codes in Borough NewYork,the top 5 selling zip code are 11354,10314,11201,11375 and 10011.

```
Training%>%
  group_by(ZIP_CODE)%>%
  summarise(quantity = length(ZIP_CODE),avg_sale_price = mean(SALE_PRICE))%>%
  arrange(desc(avg_sale_price))%>%head()
```

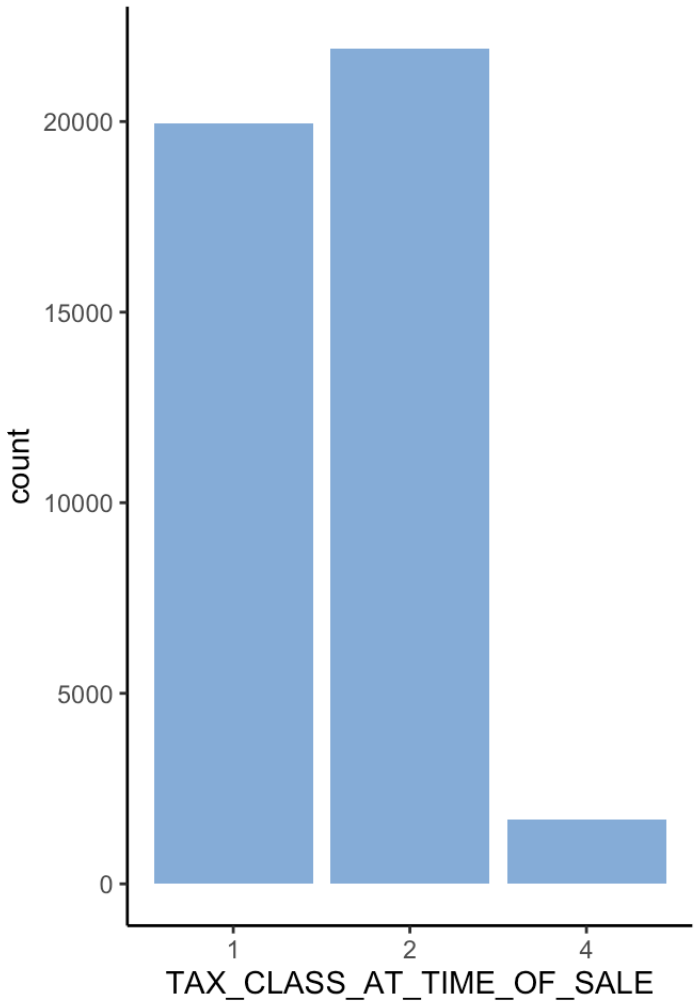
ZIP_CODE <chr>	quantity <int>	avg_sale_price <dbl>
10013	379	5314647
10007	207	4605301
10018	31	3314121
10069	84	3096248
10037	45	3055746
10006	121	2985595

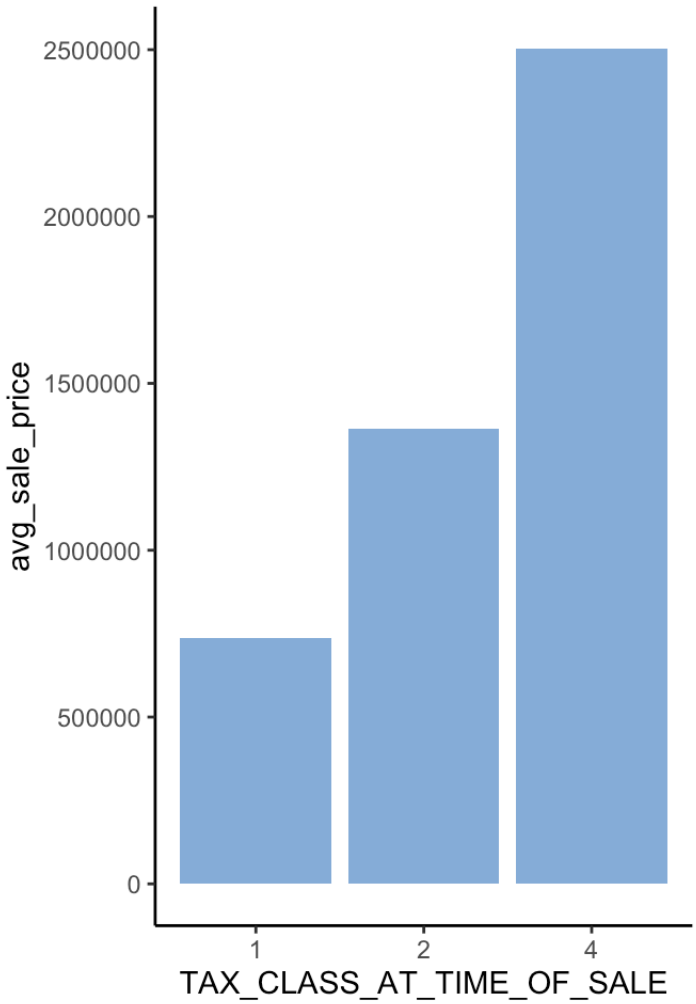
6 rows

Among 181 zip codes in Borough NewYork,the top 5 average sales price zip code are 10013,10007,10018,10069,10037. And the highest average sales price is $5314647.

Tax Class At Time Of Sale

```
histPlot <- Training%>%
            filter(!is.na(TAX_CLASS_AT_TIME_OF_SALE))%>%
            group_by(TAX_CLASS_AT_TIME_OF_SALE)%>%
            ggplot(aes(x = TAX_CLASS_AT_TIME_OF_SALE))+
            geom_bar(stat = "count",fill = "#6699cc",alpha = 0.8)+
            theme_classic()

corrPlot <- Training%>%
            filter(!is.na(TAX_CLASS_AT_TIME_OF_SALE))%>%
            group_by(TAX_CLASS_AT_TIME_OF_SALE)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x = TAX_CLASS_AT_TIME_OF_SALE,y = avg_sale_price))+
            geom_bar(stat = "identity",fill = "#6699cc",alpha = 0.8)+
            theme_classic()

plot_grid(histPlot,corrPlot,nrow = 1)
```





There are 4 different Tax Class At Time Of Sale value, but the Tax Class At Time Of Sale of three only has 4 record out of 84548 observations in the original dataset, and has been removed when deleting sale price outliers. Most tax class are class 1 and 2, however class 4 has the highest average sales price.

BUILDING CLASS AT TIME OF SALE

```
Training%>%
    group_by(BUILDING_CLASS_AT_TIME_OF_SALE)%>%
    summarise(quantity = length(BUILDING_CLASS_AT_TIME_OF_SALE),
              avg_sale_price =   mean(SALE_PRICE))%>%
    arrange(desc(quantity))
```

BUILDING_CLASS_AT_TIME_OF_SALE	quantity	avg_sale_price
<chr>	<int>	<dbl>
D4	8464	754882.44
R4	7659	1910343.66
A1	3545	631644.58
A5	3064	549379.92
B2	2402	694018.44

B1	2073	837929.12
B3	1902	778699.21
C6	1878	477884.85
C0	1714	990753.72
A2	1455	557772.27

Building Class D4, R4, A1, A5 and B2 are the building classes with the top sales.

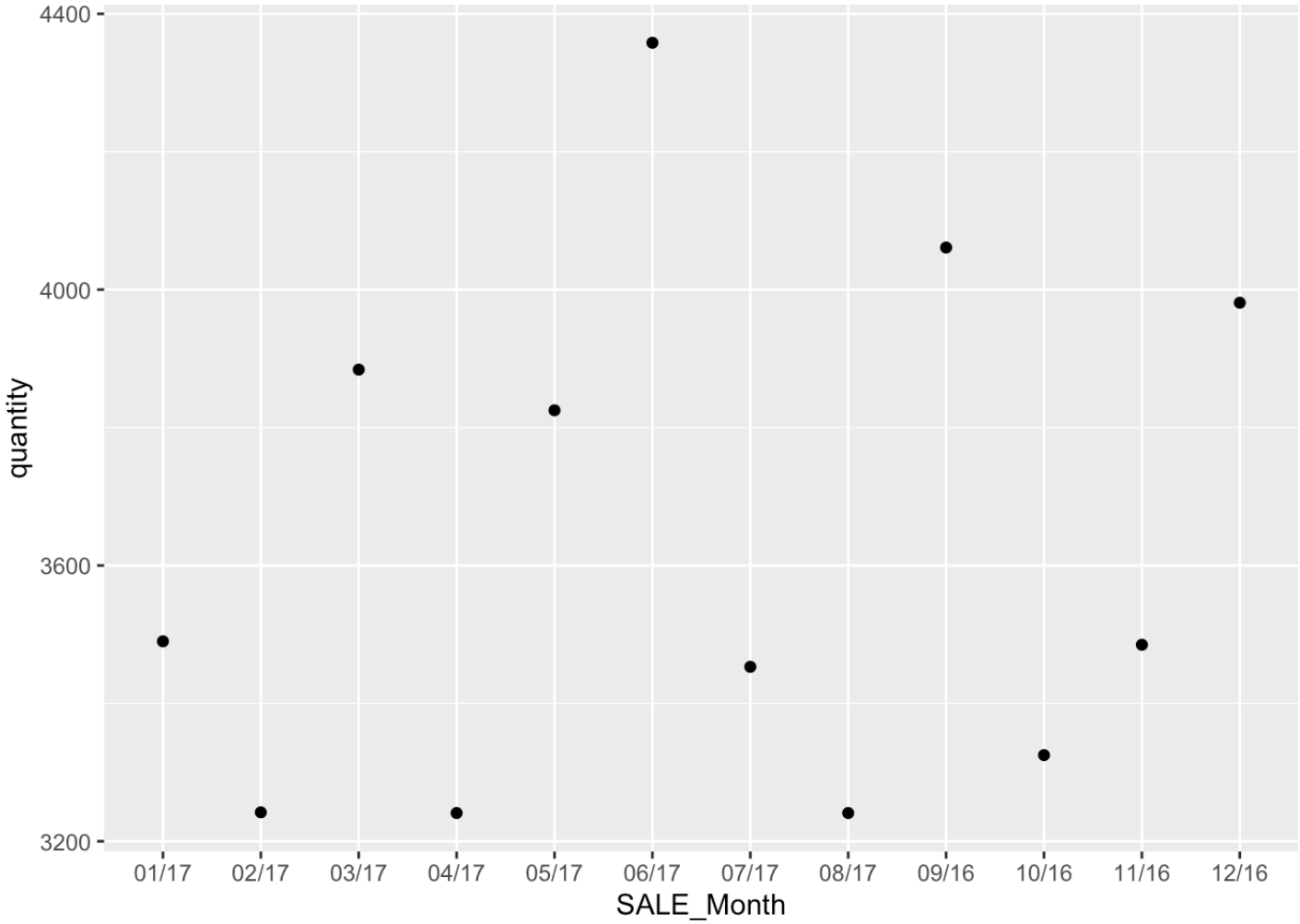
SALE Amount and Price across the time

```
Training$SALE_DATE <- as.Date(Training$SALE_DATE, format = "%m/%d/%y")
Training$SALE_YEAR <-  format(Training$SALE_DATE,"%y")
Training$SALE_Month <- format(Training$SALE_DATE,"%m/%y")
  Training%>%
    group_by(SALE_YEAR)%>%
    summarise(quantity = length(SALE_YEAR),avg_sale_price = mean(SALE_PRICE))%>%
    arrange(desc(quantity))
```

SALE_YEAR	quantity	avg_sale_price
<chr>	<int>	<dbl>
17	28734	1142520
16	14852	1078850

2 rows

```
  Training%>%
    group_by(SALE_Month)%>%
    summarise(quantity = length(SALE_Month),avg_sale_price = mean(SALE_PRICE))%>%as.d
ata.frame()%>%ggplot(aes(x=SALE_Month,y = quantity))+geom_point()
```



From above, we can learn that the last month of every quarter had the highest sales amounts, maybe because of the pressure of the sales target.

There's no obvious seasonal trend. We can delete it from the training set in later analysis.

```
Training$SALE_Month <- NULL
Training$SALE_YEAR <- NULL
Training$SALE_DATE <- NULL
Testing$SALE_DATE <- NULL
```

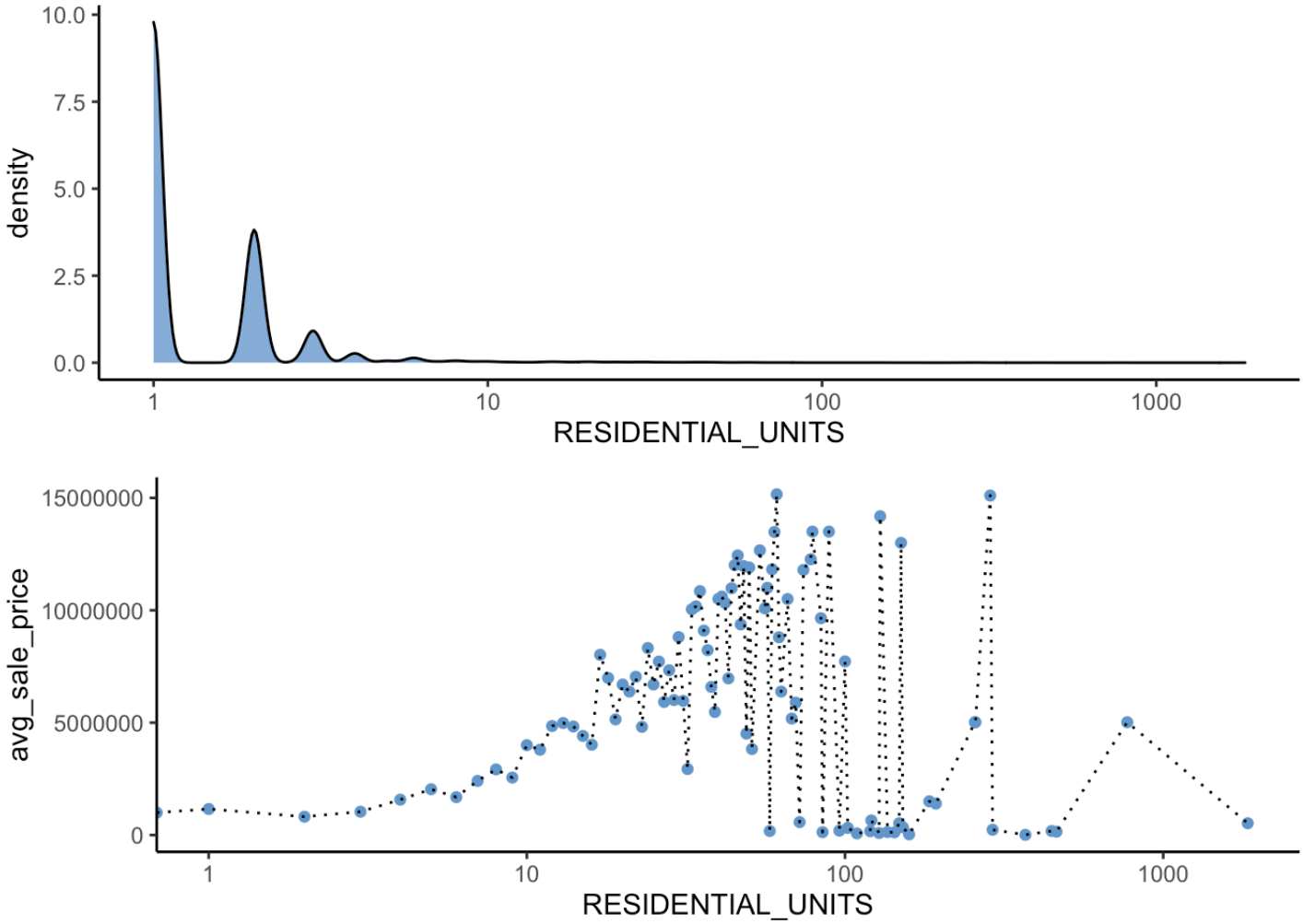
Numeric Variable Distributions

RESIDENTIAL UNITS

```
summary(Training$RESIDENTIAL_UNITS)
```

```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##    0.000    0.000    1.000    1.527    1.000 1844.000
```

```
histPlot <- Training%>%
            filter(!is.na(RESIDENTIAL_UNITS))%>%
            ggplot(aes(x=RESIDENTIAL_UNITS))+
            geom_density(fill = "#6699cc",alpha = 0.8)+
            theme_classic()+
            scale_x_log10()

corrPlot <- Training%>%
            group_by(RESIDENTIAL_UNITS)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x= RESIDENTIAL_UNITS, y = avg_sale_price ))+
            geom_point(color = "#6699cc")+
            geom_line(aes(group = 1),linetype = 'dotted')+
            theme_classic()+
            scale_x_log10()
plot_grid(histPlot,corrPlot,nrow = 2)
```



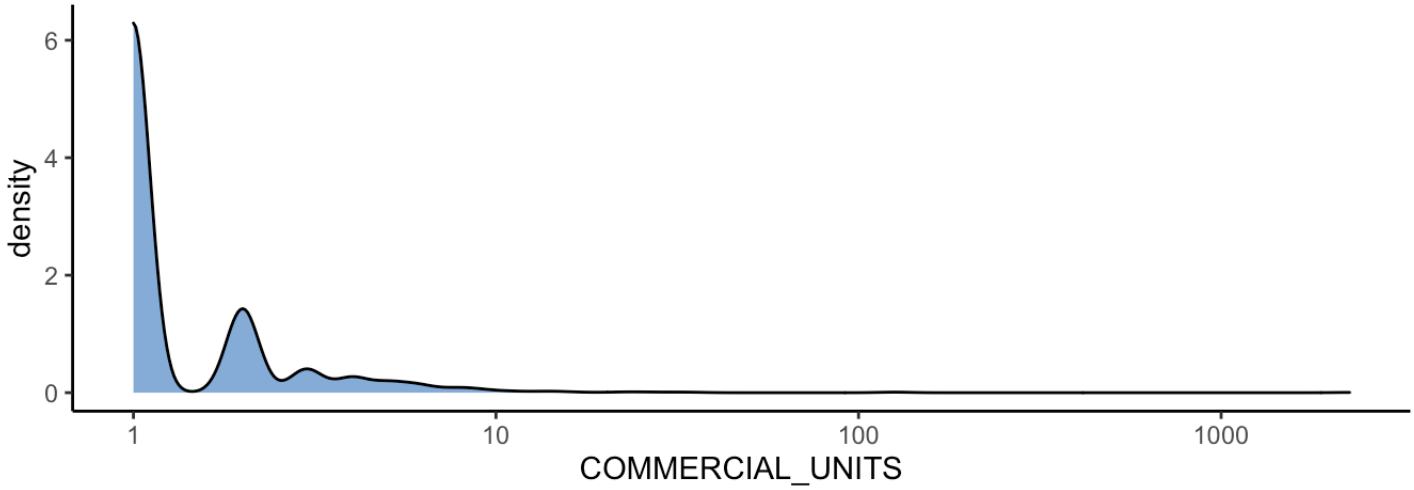
The plot above shows the residential units has a positive relationship with sale price when the number of units is lower than 100.

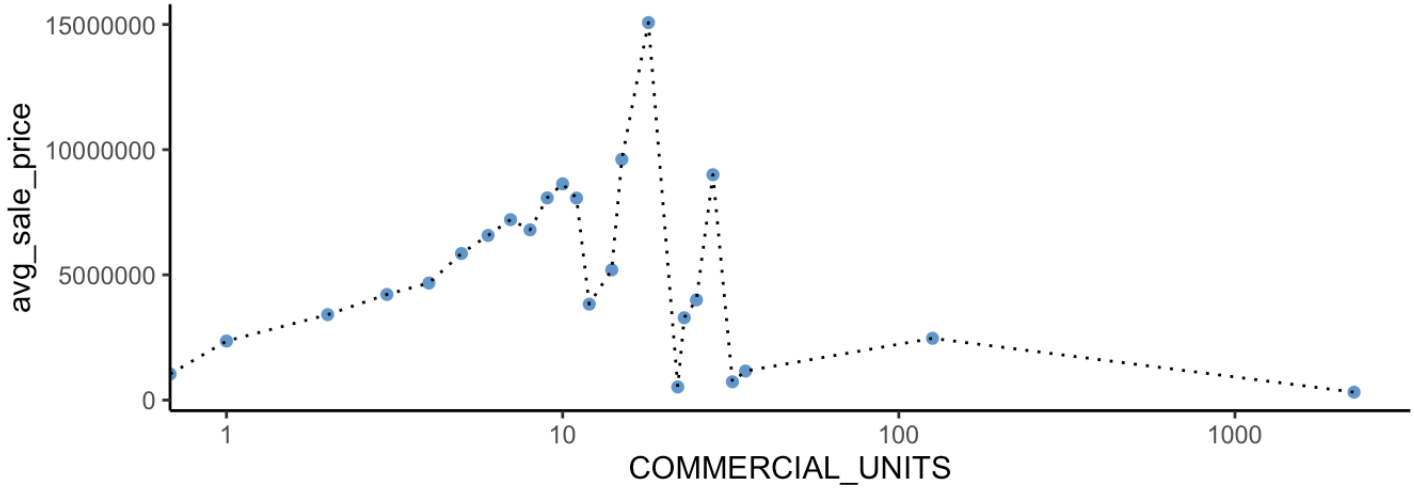
COMMERCIAL UNITS

```
summary(Training$COMMERCIAL_UNITS)
```

```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
##    0.0000    0.0000    0.0000    0.1323    0.0000 2261.0000
```

```
histPlot <- Training%>%
            filter(!is.na(COMMERCIAL_UNITS))%>%
            ggplot(aes(x=COMMERCIAL_UNITS))+
            geom_density(fill = "#6699cc",alpha = 0.8)+
            theme_classic()+
            scale_x_log10()

corrPlot <- Training%>%
            group_by(COMMERCIAL_UNITS)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x= COMMERCIAL_UNITS, y = avg_sale_price))+
            geom_point(color = "#6699cc")+
            geom_line(aes(group = 1),linetype = 'dotted')+
            theme_classic()+
            scale_x_log10()

plot_grid(histPlot,corrPlot,nrow = 2)
```





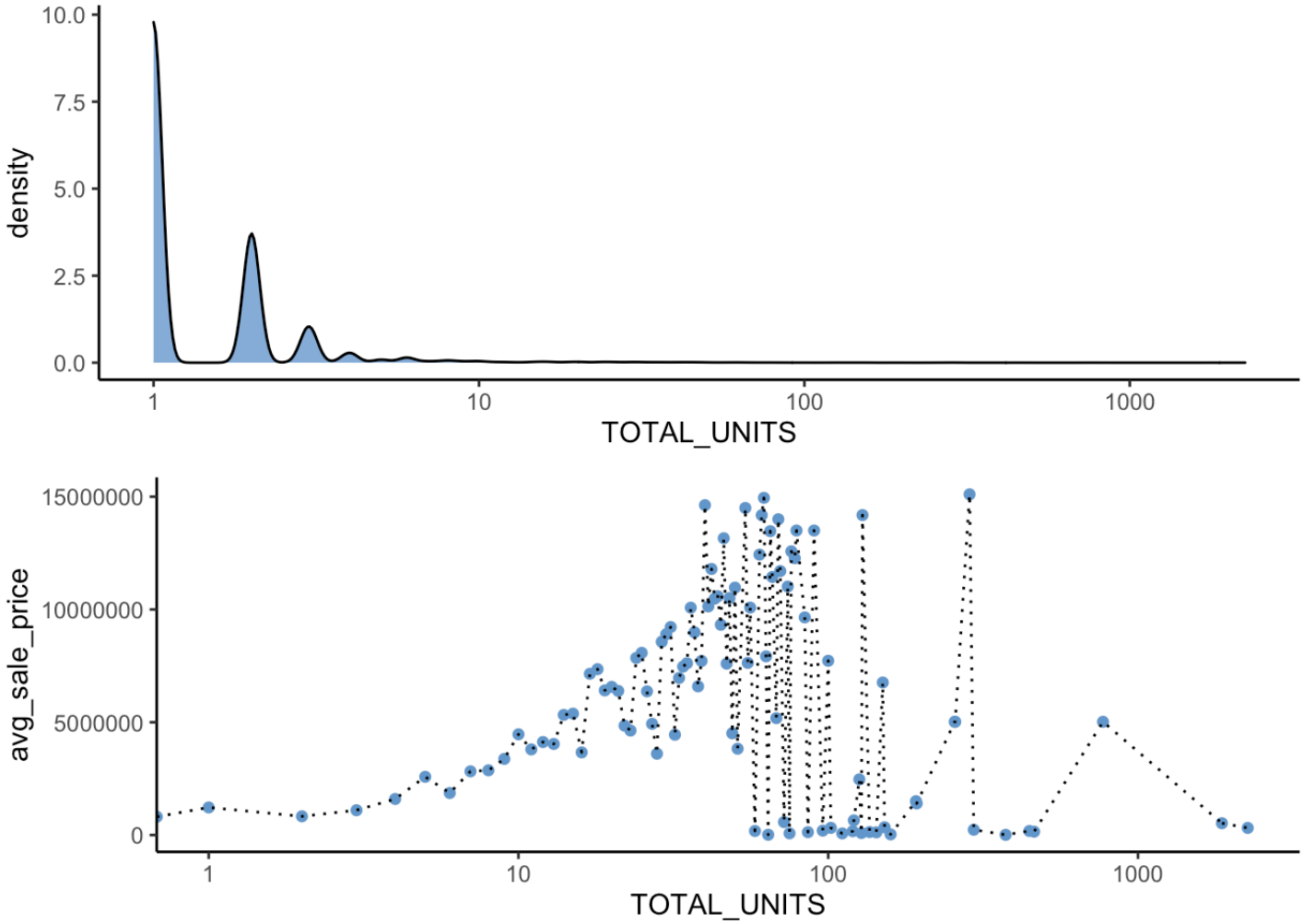
The plot above shows the majority of the commerical units is below 10, and it has a positive relationship when the number of units is lower than 10.

TOTAL UNITS

```
summary(Training$TOTAL_UNITS)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    1.00    1.67    2.00 2261.00
```

```
histPlot <- Training%>%
            filter(!is.na(TOTAL_UNITS))%>%
            ggplot(aes(x=TOTAL_UNITS))+
            geom_density(fill = "#6699cc",alpha = 0.8)+
            theme_classic()+
            scale_x_log10()

corrPlot <- Training%>%
            group_by(TOTAL_UNITS)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x= TOTAL_UNITS, y = avg_sale_price ))+
            geom_point(color = "#6699cc")+
            geom_line(aes(group = 1),linetype = 'dotted')+
            theme_classic()+
            scale_x_log10()
plot_grid(histPlot,corrPlot,nrow = 2)
```



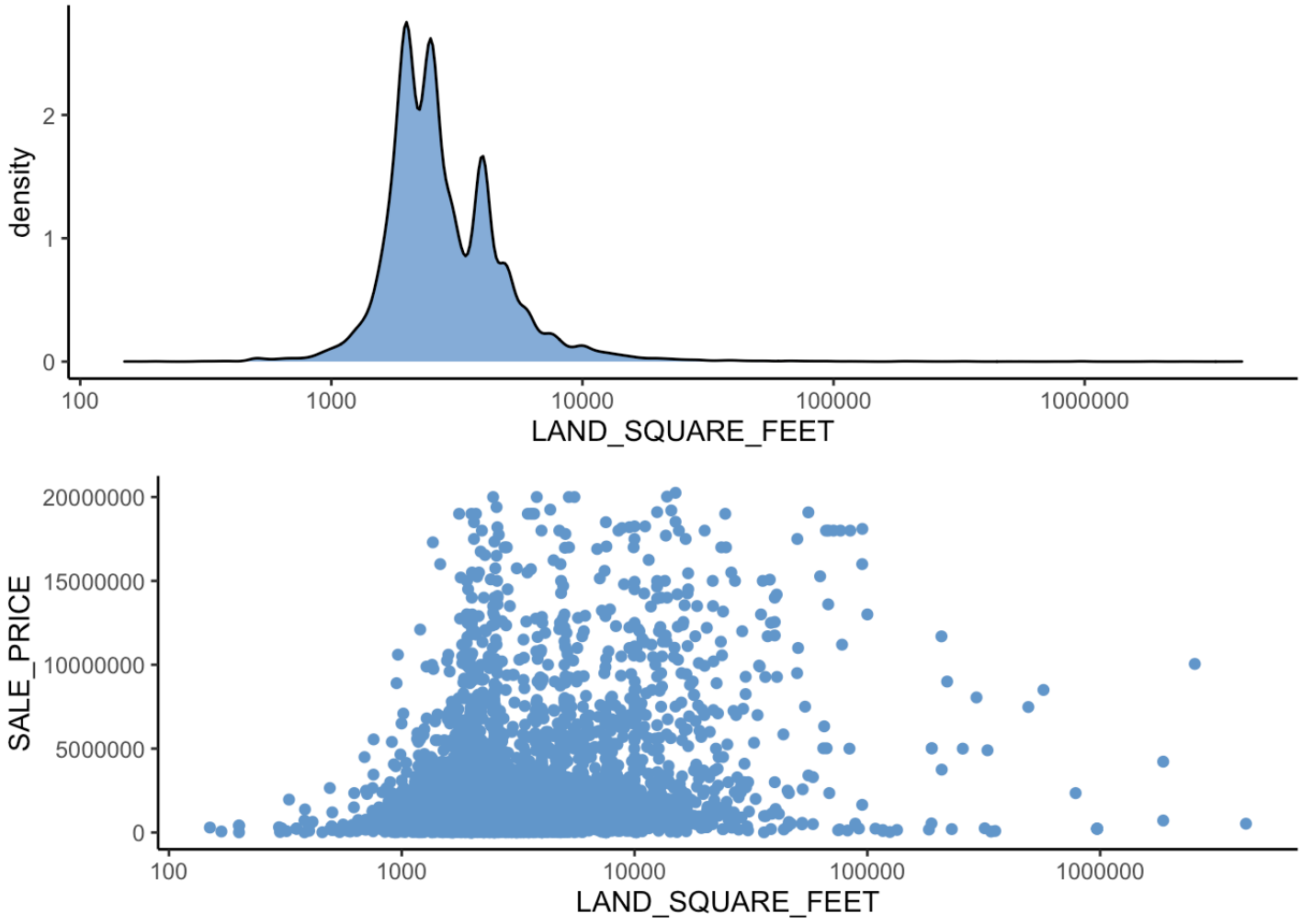
The plot above shows the total units has a positive relationship with sale price when the number of units is lower than 100. is lower than 100.

LAND SQUARE FEET

```
summary(Training$LAND_SQUARE_FEET)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0     500    2157    2500 4228300
```

```
histPlot <- Training%>%
            filter(LAND_SQUARE_FEET > 0)%>%
            ggplot(aes(x=LAND_SQUARE_FEET))+
            geom_density(fill = "#6699cc",alpha = 0.8)+
            theme_classic()+
            scale_x_log10()

corrPlot <- Training%>%
            filter(LAND_SQUARE_FEET > 0)%>%
            ggplot(aes(x= LAND_SQUARE_FEET, y = SALE_PRICE))+
            geom_point(color = "#6699cc")+
            theme_classic()+
            scale_x_log10()

plot_grid(histPlot,corrPlot,nrow = 2)
```



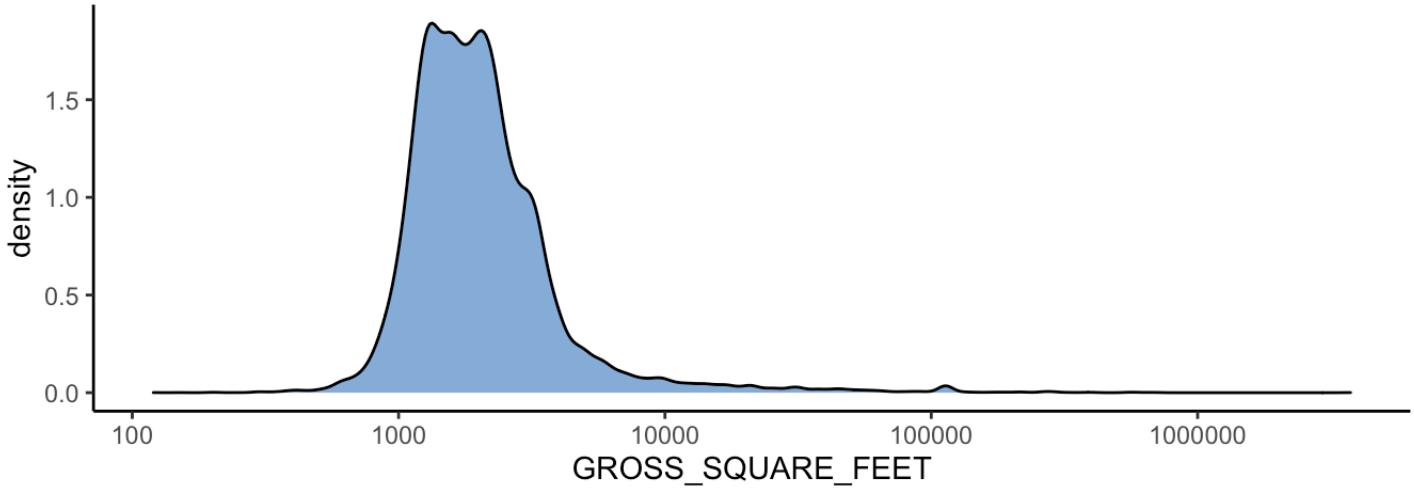
Most of houses have a land square feet between 1000 and 10000, and there is no clear correlation between land square feet and sale price.

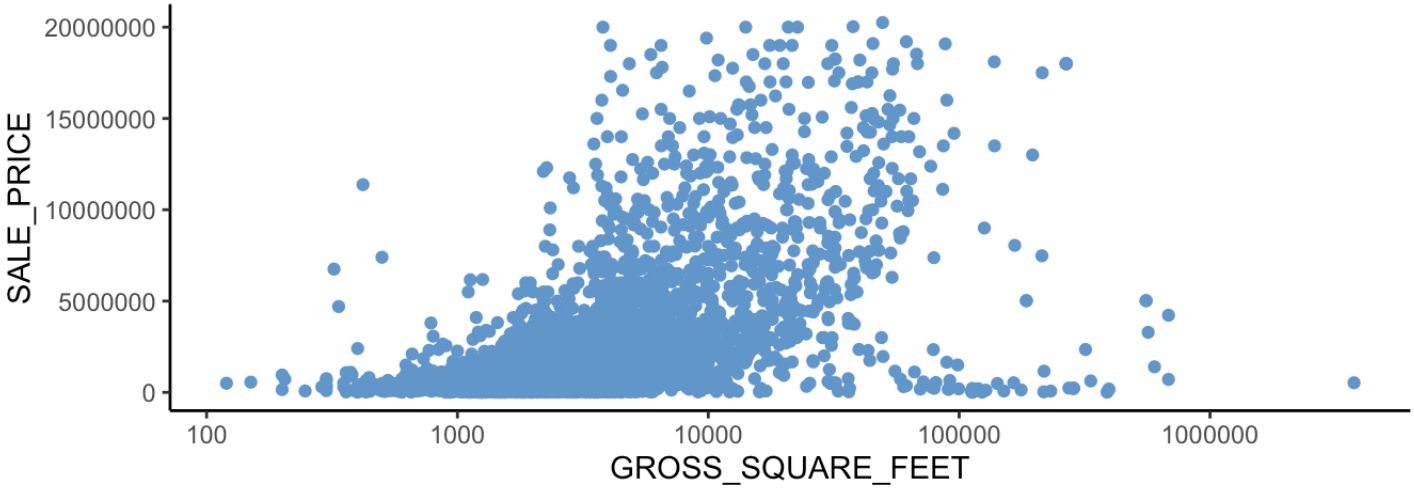
GROSS SQUARE FEET

```
summary(Training$GROSS_SQUARE_FEET,na.rm = TRUE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0       0       0    1806    1820 3750565
```

```
histPlot <- Training%>%
            filter(GROSS_SQUARE_FEET>0)%>%
            ggplot(aes(x=GROSS_SQUARE_FEET))+
            geom_density(fill = "#6699cc",alpha = 0.8)+
            theme_classic()+
            scale_x_log10()

corrPlot <- Training%>%
            filter(GROSS_SQUARE_FEET>0)%>%
            ggplot(aes(x= GROSS_SQUARE_FEET, y = SALE_PRICE))+
            geom_point(color = "#6699cc")+
            theme_classic()+
            scale_x_log10()

plot_grid(histPlot,corrPlot,nrow = 2)
```





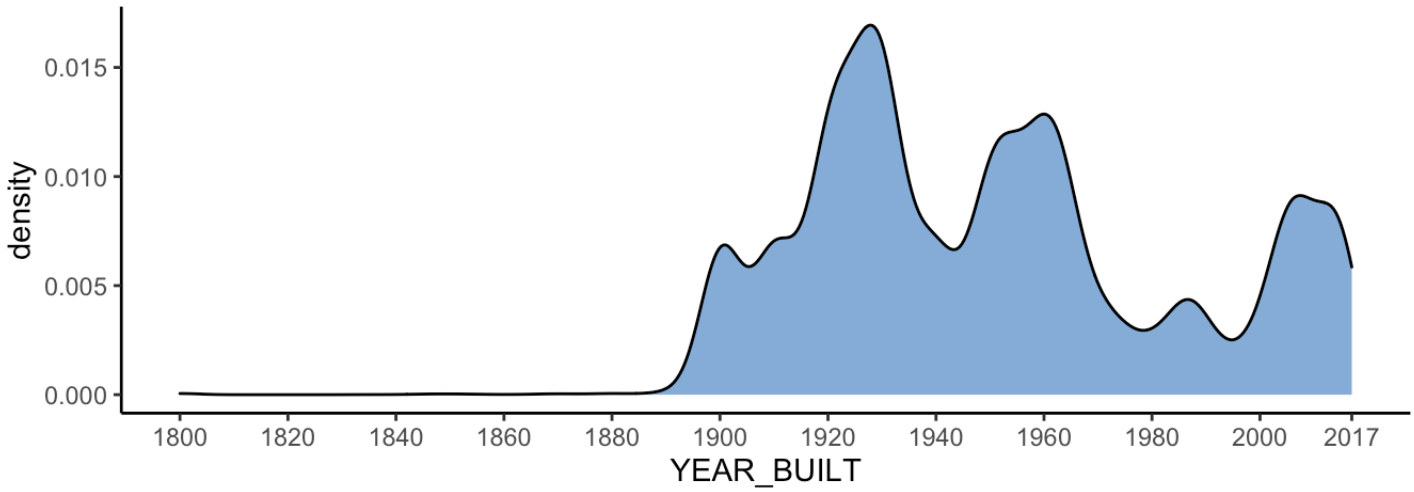
Most of houses have a land square feet between 1000 and 100000, and there is a slightly positive correlation between gross square feet and sale price.

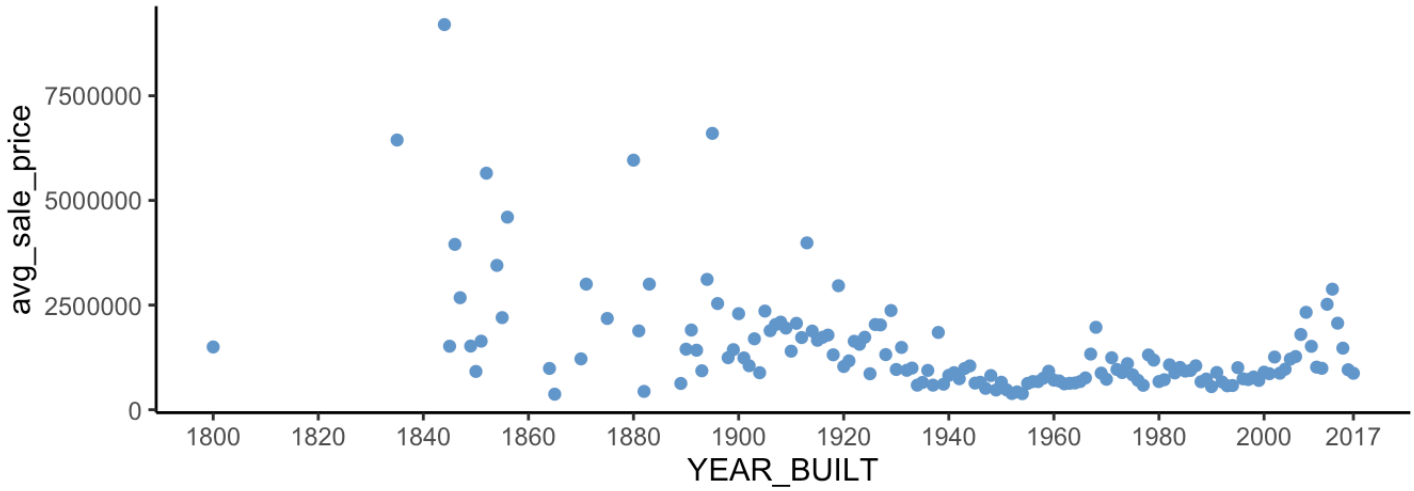
YEAR BUILT

```
summary(Training$YEAR_BUILT)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       0    1920    1940    1812    1966    2017
```

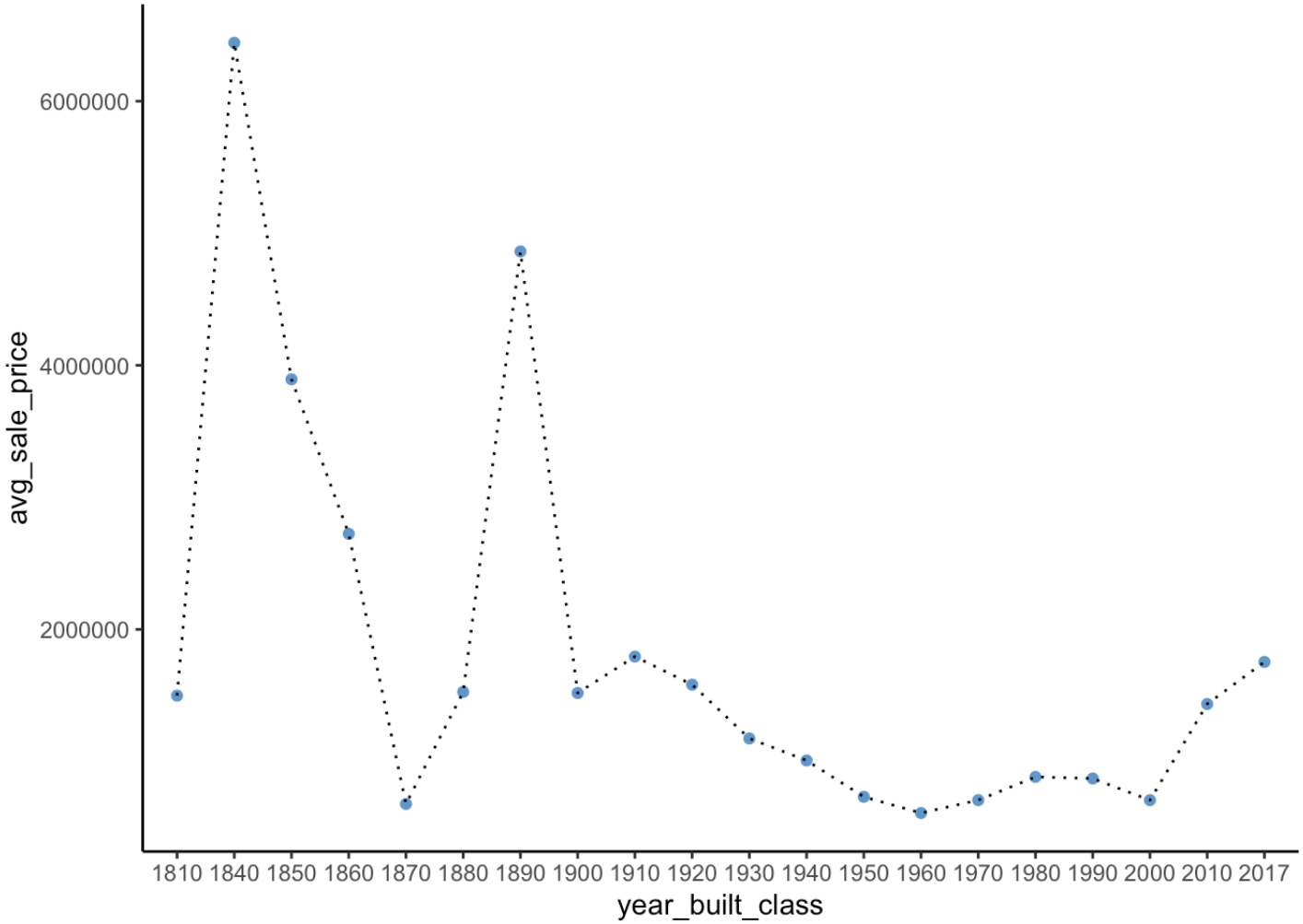
```
histPlot <- Training%>%
            filter(YEAR_BUILT >= 1800)%>%
            ggplot(aes(x=YEAR_BUILT))+
            geom_density(fill = "#6699cc",alpha = 0.8)+
            theme_classic()+
            scale_x_continuous(breaks=c(1800,1820,1840,1860,1880,1900,1920,1940,1960,
1980,2000,2017),
            labels=c("1800","1820","1840","1860","1880", "1900", "1920","1940","1960"
,"1980","2000","2017"))

corrPlot <- Training%>%
            filter(YEAR_BUILT >= 1800)%>%
            group_by(YEAR_BUILT)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x= YEAR_BUILT, y = avg_sale_price  ))+
            geom_point(color = "#6699cc")+
            theme_classic()+
            scale_x_continuous(breaks=c(1800,1820,1840,1860,1880,1900,1920,1940,1960,
1980,2000,2017),
            labels=c("1800","1820","1840","1860","1880", "1900", "1920","1940","1960"
,"1980","2000","2017"))

plot_grid(histPlot,corrPlot,nrow = 2)
```





From the plot above, we can see that most of sold properties are built after 1900. It is hard to see the trend clearly from the scatter plot above, therefore, let's create a new group for year built called year built class, each class include 10 years.

```
Training%>%
            mutate(year_built_class = cut(YEAR_BUILT,breaks = seq(1799,2020,10),
                                                  labels=c("1810","1820","1830","1840","1850
","1860","1870","1880","1890",
                                                                                  "1900","1910","1920","1930","1940
","1950","1960","1970","1980","1990",
                                                                                   "2000","2010","2017")))%>%
            filter(!is.na(year_built_class))%>%
            group_by(year_built_class)%>%
            summarise(avg_sale_price = mean(SALE_PRICE))%>%
            ggplot(aes(x= year_built_class, y = avg_sale_price  ))+
            geom_point(color = "#6699cc")+
            geom_line(aes(group = 1),linetype = 'dotted')+
            theme_classic()
```



From this plot above, we can see that the average house price has a down trend from 1810 to 1960, and start to increase after 1960.

2.2.4 Data Exploratory Analysis Summary

From above data exploratory analysis on the training set, we can get some insights as follows:

1. Among five areas of Borough: Manhattan (1), Bronx (2), Brooklyn (3), Queens (4), Staten Island (5), Manhattan, Brooklyn, and Queens are more popular, and sold more properties. The average sales price in Manhattan is much higher than other areas.
2. The top selling neighborhood in New York Borough are: Flushing-North, Upper East Side (59-79,79-96),Upper West Side (59-79), and Midtown East, and the top selling zip codes are 11354,10314,11201,11375 and 10011.
3. The most expensive neighborhoods are East River, Civic Center, Bloomfield, Little Italy and Soho. The most expensive zip codes are 10013,10007,10018,10069,10037. And the highest average sales price is around $531,4647.
4. The top selling property types/classes in Borough are one family dwellings, Coops- Elevator Apartments, Condo - Elevator Apartment, and two family dwellings.
5. The majority of sold properties are in Tax Class 1 and Tax class 2. And the average sales price in Tax Class 2B is the highest. The average sales price in TaxClass 4 is the second highest.

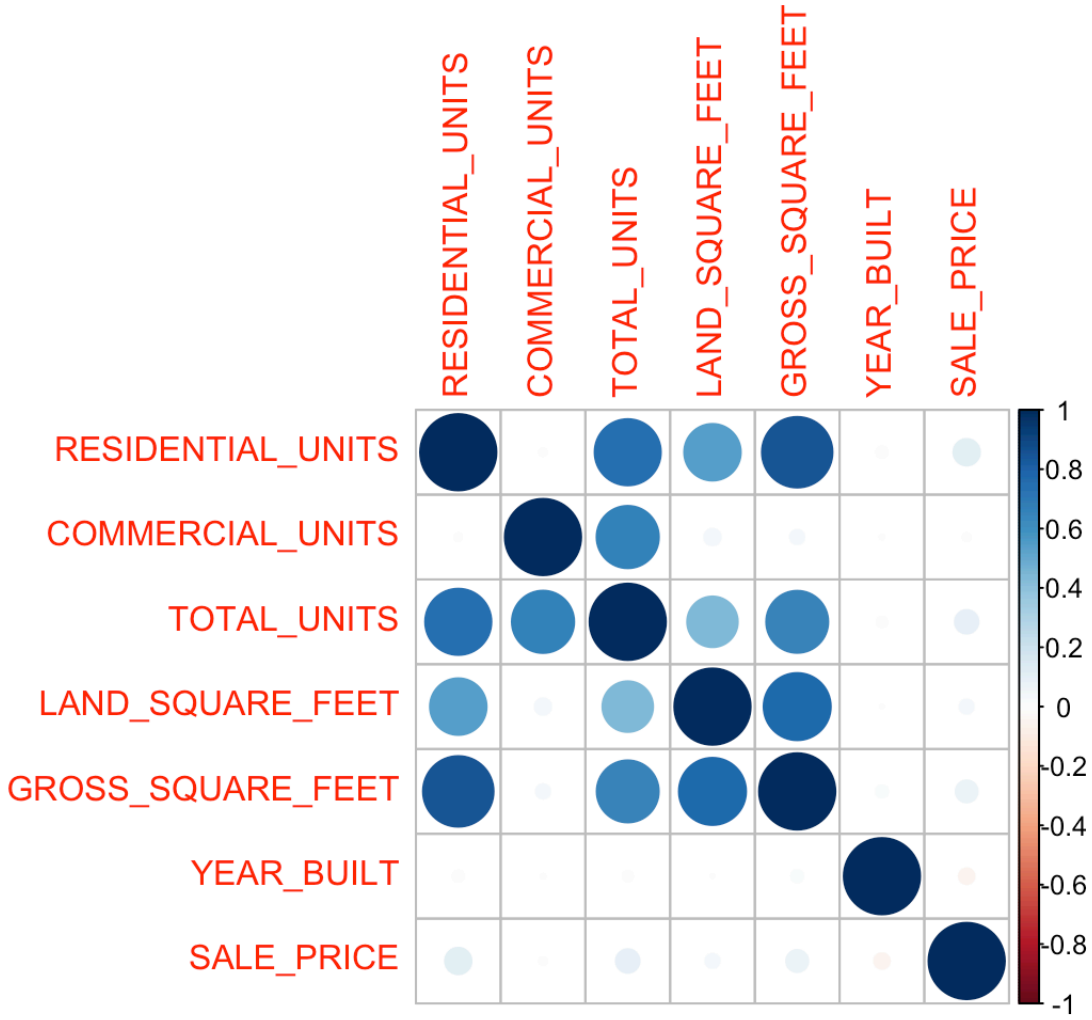
6. In the training dataset, the sales prices has a positive relationship with the following variables: the residential units when the number of units is lower than 100; the commercial units when the number of units is lower than 10; the total units when the number of units is lower than 100; and the sales prices has a slightly positive relationship correlation with gross square feet.There is no clear correlation between the sales price and the sales time and building ages.

2.3 Data Modeling

Correlation Check

Correlation Check on numerical variables

```
Training.cor <- cor(Training%>%select_if(is.numeric))
corrplot(Training.cor)
```



This plot shows the correlation among the variables. Since TOTAL_UNITS is the sum of both RESIDENTIAL_UNITS and COMMERCIAL_UNITS, I will use TOTAL_UNITS for later modeling. TOTAL_UNITS has a strong correlation with GROSS_SQUARE_FEET, therefore, it will not be included in the following linear model.

Combined with previous EDA on training dataset and correlation on continuous variables, I will choose the four variables for later modeling: 1) continous variable: TOTAL_UNITS,LAND_SQUARE_FEET; 2) categorical variable: ZIP_CODE, BUILDING_CLASS_AT_TIME_OF_SALE.

2.3.1 Linear Regression Model

Build Linear Model

```
myControl = trainControl(method = "cv", number = 5, verboseIter = TRUE)
model_lm = train(SALE_PRICE ~ TOTAL_UNITS + LAND_SQUARE_FEET,
              data = Training,
              method = "lm",
              trControl = myControl)
```

```
## + Fold1: intercept=TRUE
## - Fold1: intercept=TRUE
## + Fold2: intercept=TRUE
## - Fold2: intercept=TRUE
## + Fold3: intercept=TRUE
## - Fold3: intercept=TRUE
## + Fold4: intercept=TRUE
## - Fold4: intercept=TRUE
## + Fold5: intercept=TRUE
## - Fold5: intercept=TRUE
## Aggregating results
## Fitting final model on full training set
```

```
model_lm
```

```
## Linear Regression
##
## 43586 samples
##     2 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 34868, 34868, 34869, 34869, 34870
## Resampling results:
##
##   RMSE     Rsquared    MAE
##   1804994  0.01895318  898234.6
##
## Tuning parameter 'intercept' was held constant at a value of TRUE
```

Define RMSE function

```
RMSE <- function(true_price, predicted_price) {
  sqrt(mean((true_price-predicted_price)^2))
}
```

RMSE of Linear Model on Testing Dataset

```
pre_price_lm <- predict(model_lm,Testing)
RMSE_lm <- rmse(Testing$SALE_PRICE,pre_price_lm)
RMSE_lm
```

```
## [1] 1767925
```

2.3.2 Logical Regression Model

Build Logistic Regression Model

```
myControl = trainControl(method = "cv", number = 5, verboseIter = TRUE)
model_glm = train(SALE_PRICE ~ TOTAL_UNITS + LAND_SQUARE_FEET +factor(ZIP_CODE)+facto
r(BUILDING_CLASS_AT_TIME_OF_SALE),
               data = Training,
               method = "glm",
               trControl = myControl)
```

```
## + Fold1: parameter=none
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = ifelse(type == :
prediction from a rank-deficient fit may be misleading
```

```
## - Fold1: parameter=none
## + Fold2: parameter=none
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = ifelse(type == :
prediction from a rank-deficient fit may be misleading
```

```
## - Fold2: parameter=none
## + Fold3: parameter=none
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = ifelse(type == :
prediction from a rank-deficient fit may be misleading
```

```
## - Fold3: parameter=none
## + Fold4: parameter=none
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = ifelse(type == :
prediction from a rank-deficient fit may be misleading
```

```
## - Fold4: parameter=none
## + Fold5: parameter=none
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = ifelse(type == :
prediction from a rank-deficient fit may be misleading
```

```
## - Fold5: parameter=none
## Aggregating results
## Fitting final model on full training set
```

```
model_glm
```

```
## Generalized Linear Model
##
## 43586 samples
##     4 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold)
## Summary of sample sizes: 34869, 34869, 34869, 34869, 34868
## Resampling results:
##
##   RMSE     Rsquared   MAE
##   1415245  0.3812707  640009.9
```

RMSE of Logistic Model on Testing Dataset

```
pre_price_glm <- predict(model_glm,Testing)
RMSE_glm <- rmse(Testing$SALE_PRICE,pre_price_glm)
RMSE_glm
```

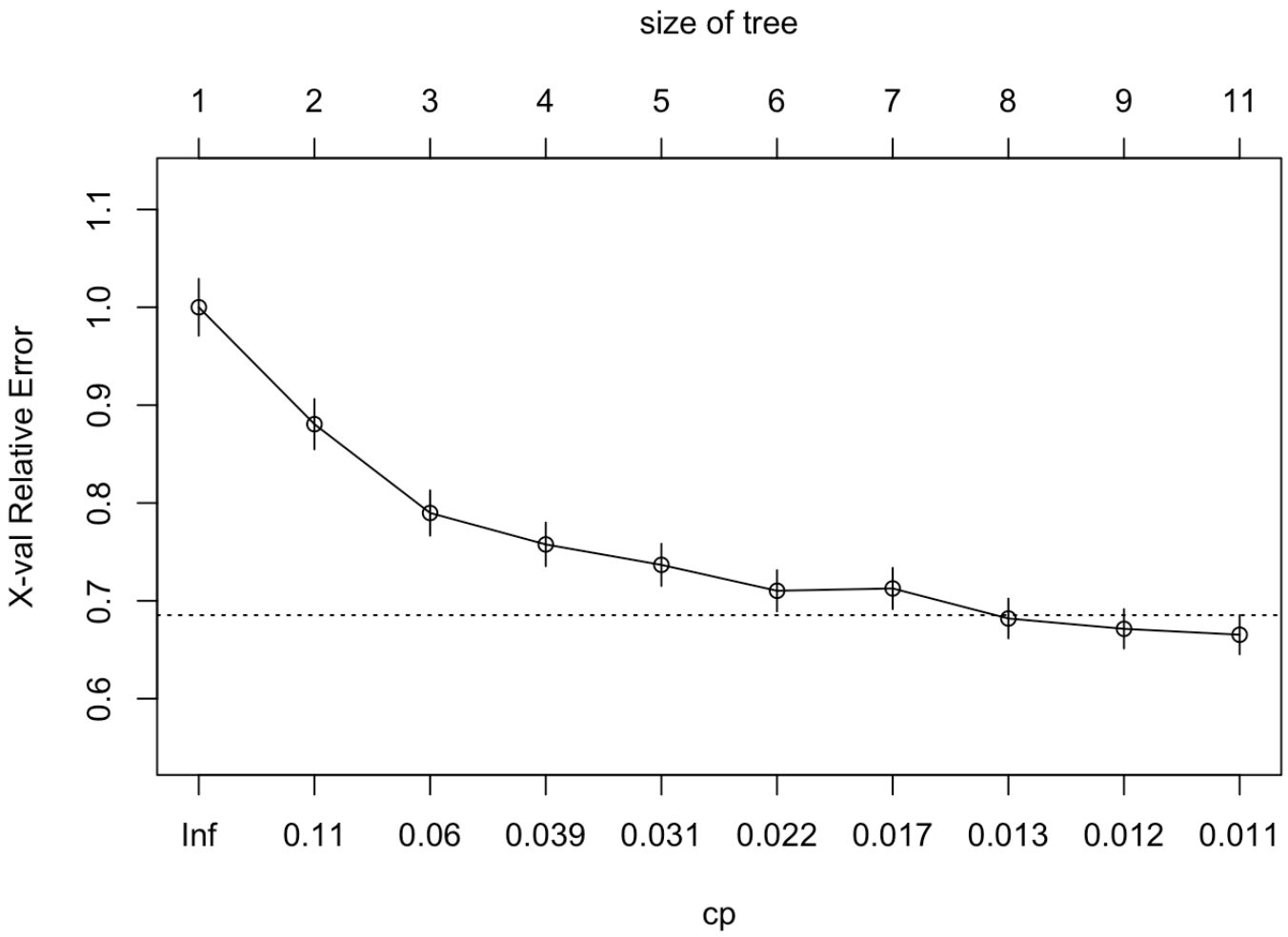
```
## [1] 1379589
```

2.3.3 Regression Tree Model

Build Regression Tree Model

```
library(rpart)
model_retree <- rpart(
  formula = SALE_PRICE ~ TOTAL_UNITS + LAND_SQUARE_FEET +factor(ZIP_CODE)+factor(BUIL
DING_CLASS_AT_TIME_OF_SALE),
  data    = Training,
  method  = "anova"
  )
```

```
plotcp(model_retree)
```




```
model_retree$cptable
```

```
##            CP nsplit rel error    xerror       xstd
## 1  0.13870850      0 1.0000000 1.0000301 0.02904990
## 2  0.09104143      1 0.8612915 0.8805367 0.02569371
## 3  0.03951908      2 0.7702501 0.7897786 0.02316341
## 4  0.03856828      3 0.7307310 0.7576469 0.02228199
## 5  0.02418470      4 0.6921627 0.7367390 0.02156037
## 6  0.02067328      5 0.6679780 0.7102544 0.02108251
## 7  0.01472913      6 0.6473047 0.7126215 0.02107560
## 8  0.01214174      7 0.6325756 0.6819344 0.02032067
## 9  0.01140170      8 0.6204339 0.6713546 0.02009545
## 10 0.01000000     10 0.5976305 0.6653207 0.02002852
```

Tuning

```
hyper_grid <- expand.grid(
  minsplit = seq(5, 20, 1),
  maxdepth = seq(8, 15, 1)
)

models <- list()

for (i in 1:nrow(hyper_grid)) {
  minsplit <- hyper_grid$minsplit[i]
  maxdepth <- hyper_grid$maxdepth[i]

  # train a model and store in the list
  models[[i]] <- rpart(
  formula = SALE_PRICE ~ TOTAL_UNITS + LAND_SQUARE_FEET +factor(ZIP_CODE)+factor(BUIL
DING_CLASS_AT_TIME_OF_SALE),
  data    = Training,
  method  = "anova",
    control = list(minsplit = minsplit, maxdepth = maxdepth)
    )
}
```

```
get_cp <- function(x) {
  min <- which.min(x$cptable[, "xerror"])
  cp <- x$cptable[min, "CP"]
}

get_min_error <- function(x) {
  min    <- which.min(x$cptable[, "xerror"])
  xerror <- x$cptable[min, "xerror"]
}

hyper_grid %>%
  mutate(
    cp    = purrr::map_dbl(models, get_cp),
    error = purrr::map_dbl(models, get_min_error)
    ) %>%
  arrange(error) %>%
  top_n(-5, wt = error)
```

minsplit <dbl>	maxdepth <dbl>	cp <dbl>	error <dbl>
19	14	0.01	0.6420466
15	13	0.01	0.6446688
16	15	0.01	0.6471475
20	12	0.01	0.6480415
14	12	0.01	0.6493184

5 rows

```
op_model_retree <- rpart(
  formula = SALE_PRICE ~ TOTAL_UNITS + LAND_SQUARE_FEET +factor(ZIP_CODE)+factor(BUIL
DING_CLASS_AT_TIME_OF_SALE),
  data    = Training,
  method  = "anova",
    control = list(minsplit = 19, maxdepth = 12, cp = 0.01)
    )
```

RMSE of Regression Tree Model on Testing Dataset

```
pre_price_retree <- predict(op_model_retree,Testing)
RMSE_retree <- rmse(Testing$SALE_PRICE,pre_price_retree)
RMSE_retree
```

```
## [1] 1449782
```

2.3.4 Model Ensemble

Ensemble Linear and Regression Tree

```
pre_price_em <- (pre_price_retree + pre_price_glm)/2
RMSE_em <- rmse(Testing$SALE_PRICE,pre_price_em)
RMSE_em
```

```
## [1] 1367118
```

Part 3 Model Results & Performance on Testing Dataset

```
modelname <-c("Linear","Logistic Regression","Regression Tree","Emsenble" )
rsme_result <- data.frame(model=modelname,rsme= c(RMSE_lm,RMSE_glm,RMSE_retree,RMSE_em))
print(rsme_result)
```

```
##                 model    rsme
## 1              Linear 1767925
## 2 Logistic Regression 1379589
## 3     Regression Tree 1449782
## 4            Emsenble 1367118
```

For all the models, we can know that the emsenble model of both Logistic Regression and Regression Tree, has the best result. And the RSME is 1367718.

Part 4 Conclusions

4.1 Lesson Learned

From this project, we can learn more about property market in New York City:

1. For real estate, the key factor is always location, location and location! As we can see from previous explorotary data analysis, the majorities of deals and highest average sales prices happened in Mahatton and Brooklyn, the hottest places in New York.
2. Most properties sold are residential properties. Only around 4% of transactions are commercial properties.Therefore, we can learn that, the residential market was very active during that period. There were strong needs for individual residential buyers instead of institutional commercial buyers.
3. The sales prices in this dataset are in a very big range,since the sales price is affected by its area, locations, ages, building type.

4. The RSME of the model is very large: $136,7118, which indicate to get a better result, more data and varialbes need be introduced for further analysis.

4.2 Limitation & Future Work

As mentioned previously, though all real property transactions have a big number, for this dataset the max sales price is 22 mission dollars, the RSME of $136,7118 is still too large. One of the reasons is, though the dataset originally contains 19 variables, most of them are highly correlated. For example,in fact, zip_code include all the information in area and neighborhood, building type contains the differences of tax classes. Gross Square feet is highly correlated with land square feet, because the zoning code is regulated by the government which set the rules of floor area ratio.

To build a better model to predict the sales prices, more variables and data for longer periods need to be introduced. For example, in the same zip code, with the same building type and similar scale of building, the prices can vary a lot, sometimes definitely over a million dollars. If the building is designed by a world known designer or represented by a super star, then its valuation is a lot higher than the average.

Glossary Of Terms

Borough: The name of the borough in which the property is located.

Zip Code: The property's postal code.

Residential Units: The number of residential units at the listed property.

Commercial Units: The number of commercial units at the listed property.

Total Units: The total number of units at the listed property.

** Land Square Feet:** The land area of the property listed in square feet.

** Gross Square Feet:** The total area of all the floors of a building as measured from the exterior surfaces of the outside walls of the building, including the land area and space within any building or structure on the property.

Tax class:

Class 1: Includes most residential property of up to three units (such as one-,two-, and three-family homes and small stores or offices with one or two attached apartments), vacant land that is zoned for residential use, and most condominiums that are not more than three stories.

Class 2: Includes all other property that is primarily residential, such as cooperatives and condominiums.

Class 3: Includes property with equipment owned by a gas, telephone or electric company.

Class 4: Includes all other properties not included in class 1,2, and 3, such as offices, factories, warehouses,garage buildings, etc.

Building Class at Time of Sale:

The Building Classification is used to describe a property's constructive use. The first position of the Building Class is a letter that is used to describe a general class of properties (for example "A" signifies one-family homes, "O" signifies office buildings. "R" signifies condominiums). The second position, a number, adds more specific information about the property's use or construction style (using our previous examples "A0" is a CapeCod style one family home, "O4" is a tower type office building and "R5" is a commercialcondominium unit). The term Building Class as used by the Department of Finance isinterchangeable with the term Building Code as used by the Department of Buildings.