EXPLORATORY DATA ANALYSIS CSC 3220 - Real Estate Data

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Introduction

Our group, 5 little minds, have decided to look at real estate market data from 2012 to 2021 in order to predict future trends in the next 5 years. This data includes median list price for a given neighborhood in each state; median prices based upon housing unit categories, such as apartments, single-family housing, and condos; and year-to-year increases in sale prices of each unit.

Format the data

For the purposes of this assignment, were are turning off all warnings and centering each graph.

Import the necessary libraries

```
library("ggplot2")
library("DT")
library("pander")
library("corrplot")
library("zoo")
library("reshape")
library("scales")
```

Import the Data

We decided to use the data from this url from Kaggle for our dataset:

https://www.kaggle.com/datasets/thuynyle/redfin-housing-market-data?select=state_market_tracker.tsv000

```
state_market.df <- read.table("../data/state_market_tracker.tsv000", sep = '\t', header =
↪  TRUE)
```

Data Manipulation

Here, we have made R recognize the variables in the dataset that pertain to specific days, (i.e, 9/21/2022) as actual dates using the built-in as.Date function. We have also divided the median sale price and list price of homes in each neighborhood by 1000 in order to make the data more readable in subsequent graphs.

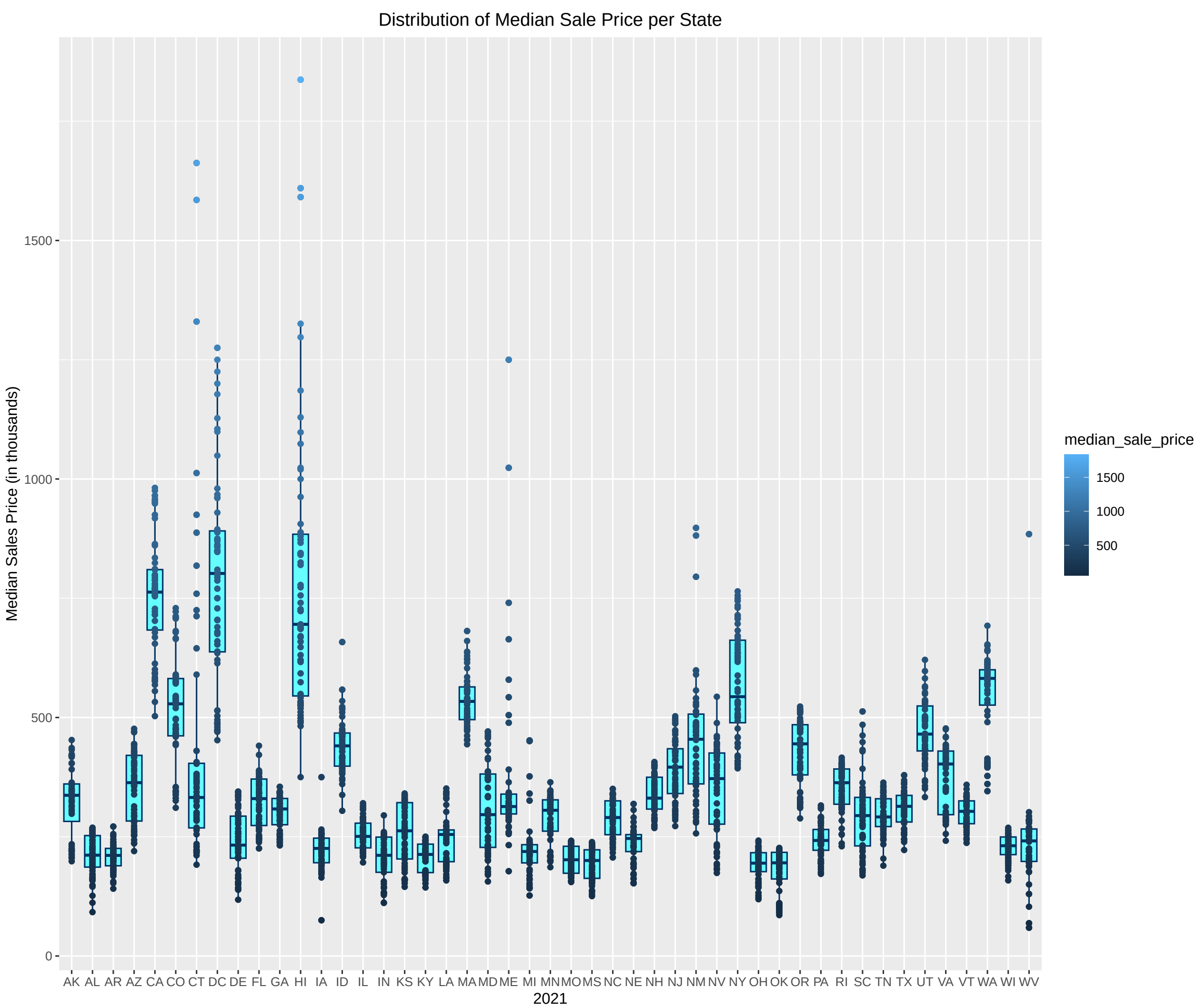
```
state_market.df$period_begin <- as.Date(state_market.df$period_begin)
state_market.df$period_end <- as.Date(state_market.df$period_end)
state_market.df$median_sale_price <- state_market.df$median_sale_price / 1000
state_market.df$median_list_price <- state_market.df$median_list_price / 1000
state_market.df$property_type[state_market.df$property_type == "Multi-Family (2-4 Unit)"]
↪  <- "Multi-Family"
```

Out of the 48 variables in the dataset, these are the ones we will consider (the important variables) in our subsequent exploratory analysis:

- median sale price - **Median sale price the housing units of each of the 27,054 neighborhoods**
- median list price - **Median list price the housing units of each of the 27,054 neighborhoods**
- median sale price year-on-year - **Year-to-year percentage increase in median sale price of each neighborhood**
- median list price year-on-year - **Year-to-year percentage increase in median list price of each neighborbood**
- median sale ppsf - **Median sale price per-square-foot of each neighborhood**
- median list ppsf - **Median sale price per-square-foot of each neighborhood**
- median

Here, we created a boxplot graph for the median list price of the homes in each neighborhood in the dataset in the year 2021, with each boxplot representing each state. Hawaii and and Connecticut were had the highest number of outliers. Since there were more outliers above the boxplot than below it in both cases, we attributed these anomalies to the high cost of living in both states, Since Hawaii is a vacation destination and Connecticut is a New England state with a close proximity to New York City. We can also assume that the states that have a lower overall median sale price also have more consistent prices since boxplots such as Oklahoma and Ohio have a much lower variance and standard deviation than states with higher medians.

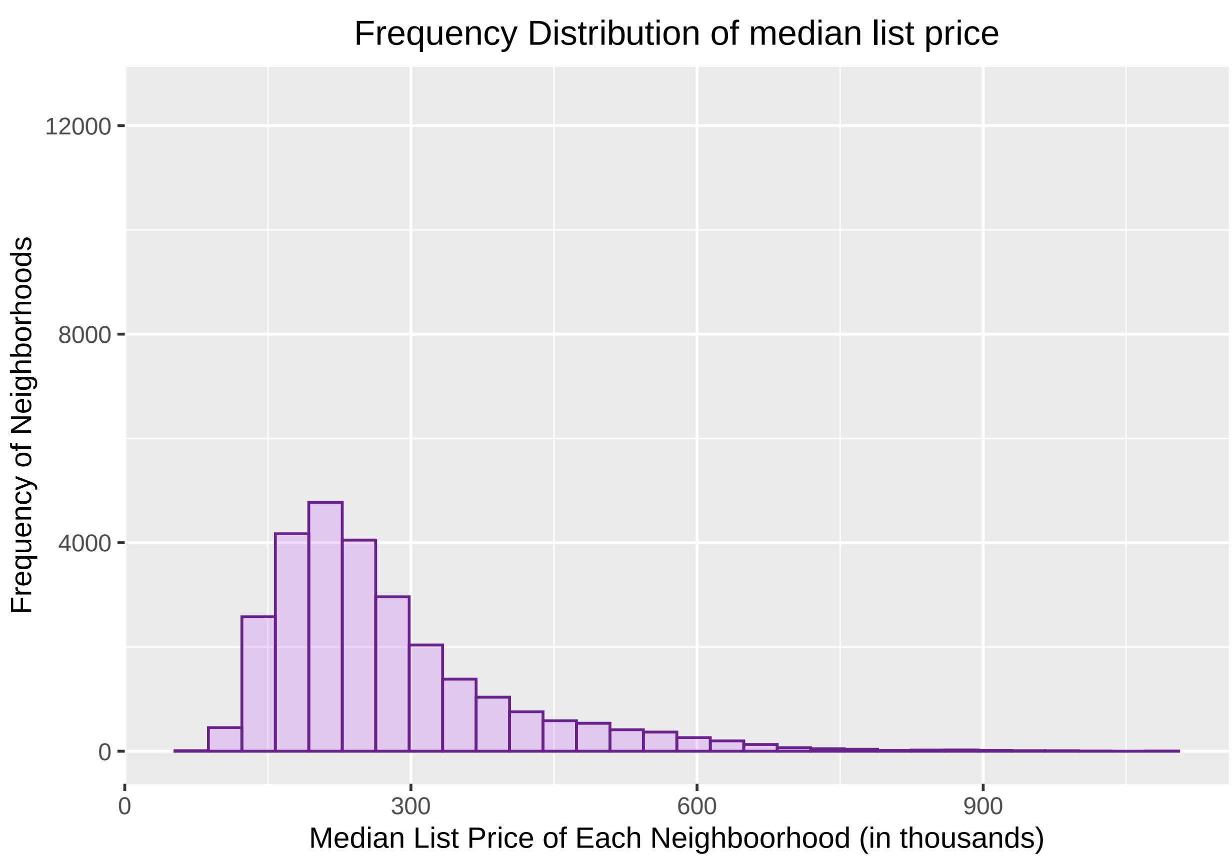
```
split_by_year <- split(state_market.df, format(state_market.df$period_begin, "%Y"))
ggplot(split_by_year[[length(split_by_year)]], aes(x = state_code, y = median_sale_price,
↪  color=median_sale_price)) +
  geom_boxplot(colour="#003366", fill="#66FFFF", alpha=5) +
  geom_point() +
  xlab("2021") +
  ylab("Median Sales Price (in thousands)") +
  ggtitle("Distribution of Median Sale Price per State") +
  theme(plot.title = element_text(hjust = 0.5))
```



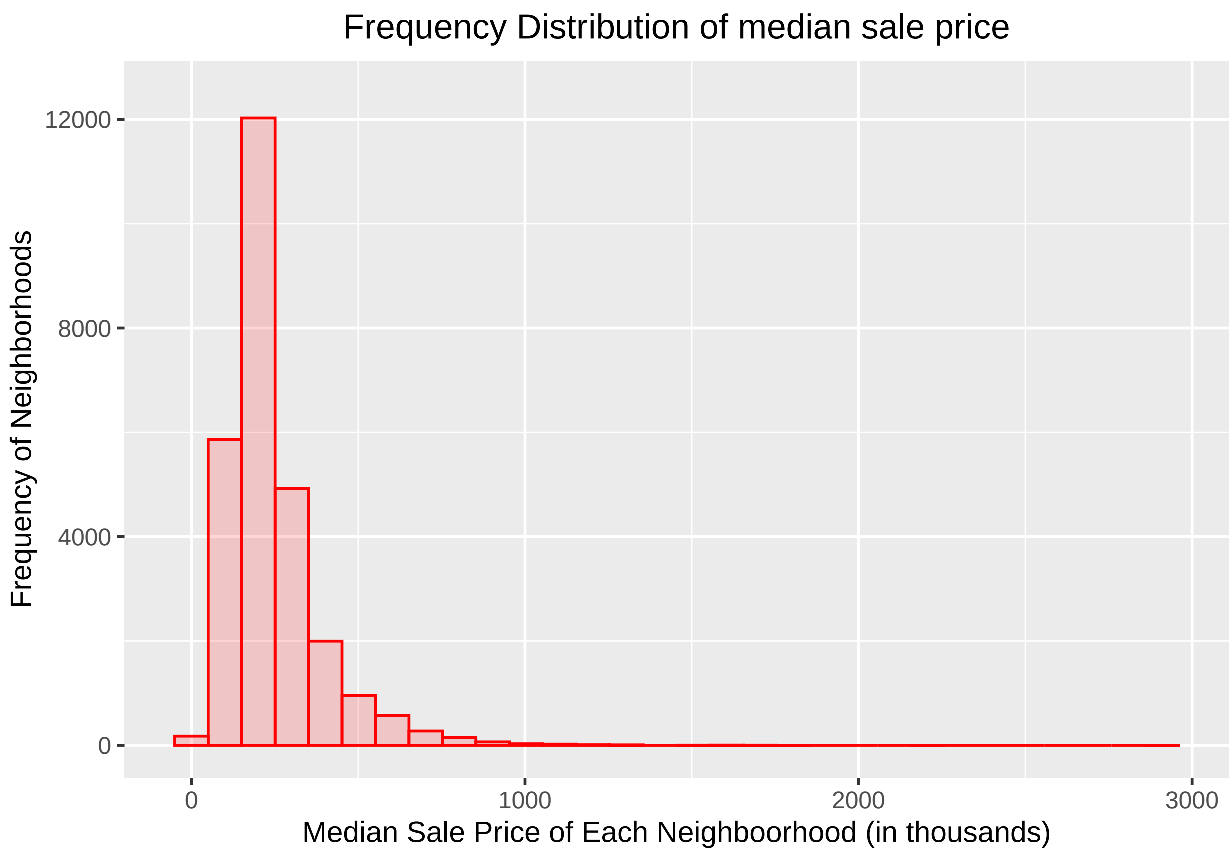
Interpreting the Data

We created 2 histograms. One is for the median list price of housing units in each of the 27,054 neighborhoods from 2012 to 2021. The other is the median sale price of over the same length of time. We noticed that both graphs are skewed to the right, so we can assume that there are more homes sold and listed above the overall median home price than below it in the U.S. We also noticed that there is much less variance in the sale price than in the list price, with the right skew in the list price being much less pronounced in the list price than the sale price. Therefore, we can assume that if the asking/list price is higher than the median, the seller receives less in the final sale price in most cases.

```
mean_years <- data.frame(state_market.df$period_begin,
↪  state_market.df$median_sale_price_yoy, state_market.df$state)

new_df <- subset.data.frame(state_market.df, select = c(state_code, median_list_price,
↪  median_sale_price),  drop = FALSE)

print(
    ggplot(new_df, aes_string(x=new_df$median_list_price))
    + geom_histogram(
      colour="darkorchid4", fill="darkorchid1", position="identity", bins=30, alpha=0.2
    )
    + ggtitle(paste("Frequency Distribution of median list price", sep=""))
    + theme(plot.title=element_text(hjust = 0.5))
    + xlab("Median List Price of Each Neighboorhood (in thousands)")
    + ylab("Frequency of Neighborhoods")
    + ylim(0, 12500))
```

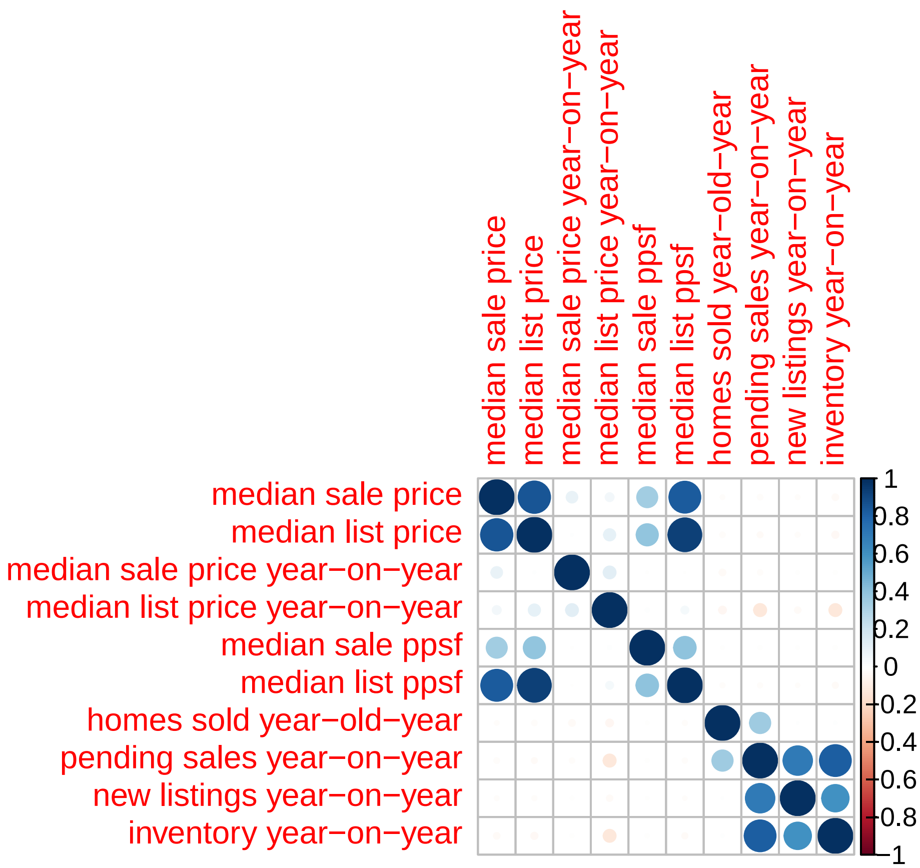


```
print(
    ggplot(new_df, aes_string(x=new_df$median_sale_price))
    + geom_histogram(
      colour="red", fill="firebrick1", position="identity", bins=30, alpha=0.2
    )
    + ggtitle(paste("Frequency Distribution of median sale price", sep=""))
    + theme(plot.title=element_text(hjust = 0.5))
    + xlab("Median Sale Price of Each Neighboorhood (in thousands)")
    + ylab("Frequency of Neighborhoods")
    + ylim(0, 12500))
```



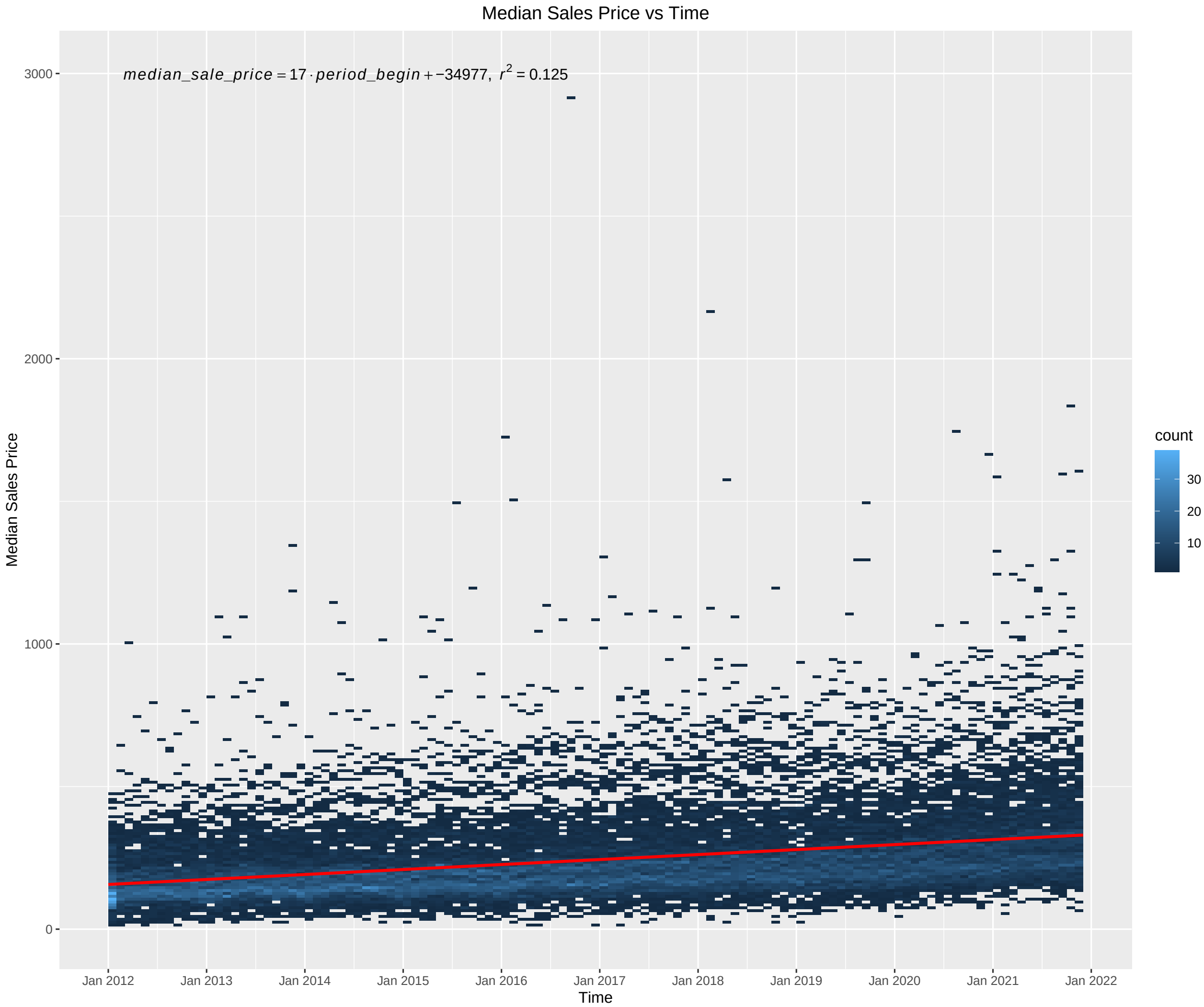
We created a correlation matrix with

```
cor.df <- subset.data.frame(state_market.df, select = c(median_sale_price,
↪   median_list_price, median_sale_price_yoy, median_list_price_yoy, median_ppsf,
↪   median_list_ppsf, homes_sold_yoy, pending_sales_yoy, new_listings_yoy,
↪   inventory_yoy),  drop = FALSE)

cor.table <- cor(cor.df, use="pairwise.complete.obs")

rownames(cor.table) <- c("median sale price", "median list price", "median sale price
↪   year-on-year", "median list price year-on-year", "median sale ppsf", "median list
↪   ppsf", "homes sold year-old-year", "pending sales year-on-year", "new listings
↪   year-on-year", "inventory year-on-year")

colnames(cor.table) <- c("median sale price", "median list price", "median sale price
↪   year-on-year", "median list price year-on-year", "median sale ppsf", "median list
↪   ppsf", "homes sold year-old-year", "pending sales year-on-year", "new listings
↪   year-on-year", "inventory year-on-year")

matrix <- corrplot(cor.table)

corrplot(cor.table)
```



We can create a bin plot to demonstrate that home sale prices tend to aggregate below a million, between 100 thousand to 300 thousand. We have fitted a best fit line to show that there is a positive increase in median sales price over time, however, with a r-squared value of 0.125, only 12.5% of this increase can be explained by time. This is understandable, since the value of a home includes many factors such as: location, land, size, time built, etc.

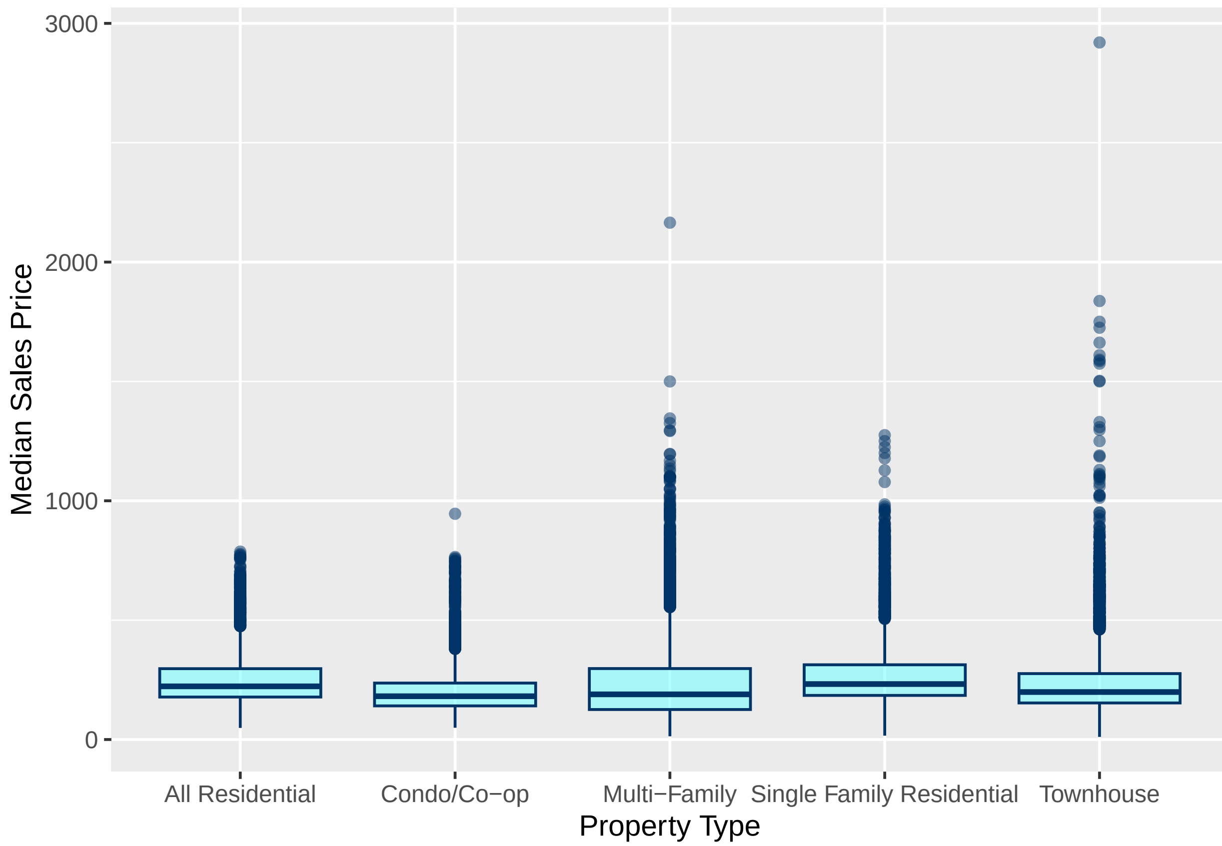
```r
lm_eqn <- function(df){
    m <- lm(median_sale_price ~ as.yearmon(period_begin), df);
    eq <- substitute(italic(median_sale_price) == b %.% italic(period_begin) +
↪   a*","~~italic(r)^2~"="~r2,
         list(a = format(unname(coef(m)[1]), digits = 2),
              b = format(unname(coef(m)[2]), digits = 2),
             r2 = format(summary(m)$r.squared, digits = 3)))
    as.character(as.expression(eq));
}

ggplot(state_market.df, aes(x = as.yearmon(period_begin), y = median_sale_price)) +
  geom_bin_2d(binwidth = c(1/12, 10)) +
  xlab("Time") +
  ylab("Median Sales Price") +
  ggtitle("Median Sales Price vs Time") +
  theme(plot.title = element_text(hjust = 0.5)) +
  scale_x_yearmon(n = 10) +
  geom_smooth(method = "lm", se = FALSE, color = "red") +
  annotate("text", x = as.numeric(as.yearmon("2014-06-01")), y = 3000, parse = TRUE,
   ↪  label = lm_eqn(state_market.df))
```



Median Sales Price vs Time
median_sale_price = 17 · period_begin + −34977, r² = 0.125
3000
2000
1000
0
Median Sales Price
Jan 2012
Jan 2013
Jan 2014
Jan 2015
Jan 2016
Jan 2017
Jan 2018
Jan 2019
Jan 2020
Jan 2021
Jan 2022
Time
count
30
20
10

```r
ggplot(state_market.df, aes(x = property_type, y = median_sale_price)) +
  geom_boxplot(colour="#003366", fill="#66FFFF", alpha=1/2) +
  xlab("Property Type") +
  ylab("Median Sales Price")
```

Both townhouse and multi-family have extreme outliers in the median sales price.




```
## For our outlier tests, we will test if anything is above the 99th quantile. We can see
## that for the outliers for multi-family housing the state Hawaii has the most outliers. This
## gives us a good explanation in the reason for the outliers, since Hawaii is a small state
## in the middle of the Pacific serverely limiting the supply of land.
```

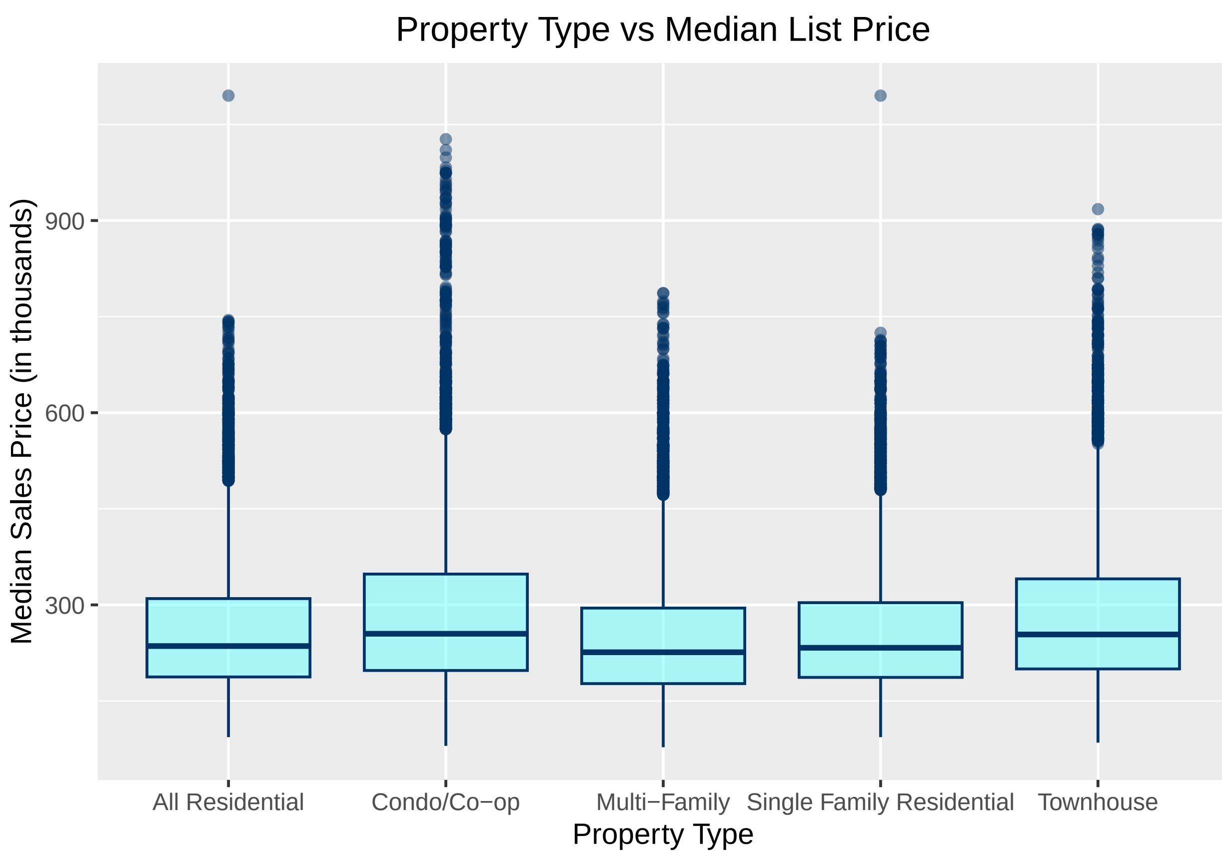
```
##
## California   Columbia     Hawaii New Mexico
##         11         11         30          3
```

```
## The same thing is repeated with townhouses, but Connecticut has almost as many as Hawaii
## now. There is a possibility that the reasoning behind this is the same as Hawaii with the
## limited supply of land, but it also could be that mostly everywhere in Connecticut is close
## to a town or city that sports many amenities.
```

```
##
##    Columbia Connecticut      Hawaii       Maine
##           9          19          20           2
```

```r
ggplot(state_market.df, aes(x = property_type, y = median_list_price)) +
  geom_boxplot(colour="#003366", fill="#66FFFF", alpha=1/2) +
  xlab("Property Type") +
  ylab("Median Sales Price (in thousands)") +
  ggtitle("Property Type vs Median List Price") +
  theme(plot.title = element_text(hjust = 0.5))
```

The extreme outliers are not as pronounced with the median list price.




```
## California leads the US in most outliers for all residential house prices while Columbia
## and Hawaii are not far behind. Hawaii has the same reasoning for the listing price as what
## was explained above. California's outliers can be explained by the housing markets
## predictions that a huge demand for housing will always be present in the state. Columbia has
## a low supply compared to the high demand in the housing market.
```

```
##
## California   Columbia     Hawaii      Maine
##         22         19         15          1
```

```
## New York leads the US in most outliers for condo/co-op house prices. New York will
## obviously lead in most outliers, since most people only live in condo's or cooperative
## housing in the state and the housing markets prediction of ever increasing demands of housing
## in places like New York City.
```

```
##
## California   New York       Utah
##          4         49          2
```

```
## California and Columbia leads the US in most outliers for single residential house prices.
## California is the same as described above. Columbia has a low supply compared to the high demand
## in the housing market.
```

```
##
## California   Columbia     Hawaii      Maine
##         19         23         14          1
```

Conclusion

Using the

```r
sample.df <- subset.data.frame(state_market.df, select = c(period_begin, state_code,
↪  property_type, median_sale_price, median_list_price, median_sale_price_yoy,
↪  median_list_price_yoy, median_ppsf, median_list_ppsf, homes_sold_yoy,
↪  pending_sales_yoy, new_listings_yoy, inventory_yoy),  drop = FALSE)

pander(head(sample.df))
```

Table 1: Table continues below

period_begin	state_code	property_type	median_sale_price
2019-10-01	OK	Multi-Family	162.2
2021-07-01	VT	All Residential	317.9
2016-08-01	NH	Condo/Co-op	200.1
2013-04-01	MS	All Residential	129.5
2019-12-01	MO	Condo/Co-op	152
2019-07-01	NM	All Residential	385.5

Table 2: Table continues below

median_list_price	median_sale_price_yoy	median_list_price_yoy
185	0.06697	0.005355
322.7	0.2048	0.07324
260.2	0.08944	0.09914
144.2	0.07135	0.05368
170.1	0.068	0.05685
390.8	0.08515	-0.05731

Table 3: Table continues below

median_ppsf	median_list_ppsf	homes_sold_yoy	pending_sales_yoy
77	107	-0.02326	0.175
177	183	-0.07414	0.1391
155	145	0.04545	0.0101
69	79	0.2043	0.1449
135	122	0.1264	NA
218	224	0.1007	-0.01429

new_listings_yoy	inventory_yoy
-0.1875	-0.2957
-0.0911	-0.27
-0.08157	-0.218
0.05665	0.2042
-0.09444	-0.2632
-0.1557	0.02579