## **Exploratory Data Analysis**

Loading libraries

```
library(psych)
library(tidyverse)
## -- Attaching packages ----- tidyverse 1.
3.0 --
## v ggplot2 3.3.2
                    v purrr 0.3.4
## v tibble 3.0.4 v dplyr 1.0.2
## v tidyr 1.1.2 v stringr 1.4.0
## v readr 1.4.0 v forcats 0.5.0
## -- Conflicts -----
                                 ----- tidyverse conflict
s() --
## x ggplot2::%+%() masks psych::%+%()
## x ggplot2::alpha() masks psych::alpha()
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()
                    masks stats::lag()
library(mice)
##
## Attaching package: 'mice'
## The following object is masked from 'package:stats':
##
      filter
##
## The following objects are masked from 'package:base':
##
      cbind, rbind
##
library(ggplot2)
library(knitr)
library(pastecs)
##
## Attaching package: 'pastecs'
```

```
## The following objects are masked from 'package:dplyr':
##
## first, last
## The following object is masked from 'package:tidyr':
##
## extract
library(dplyr)
```

#### **Loading the data**

```
housing.dataset<-read.csv("C:/Users/asus/Desktop/melbourne_data.csv")</pre>
```

#### 1. Cleaning the Data

## Removing columns with too many missing values

```
housing.dataset %>%
select(-c(BuildingArea, YearBuilt)) -> housing.dataset
```

## Replacing Landsize values that are zero with NA and removing outliers

```
housing.dataset$Landsize[housing.dataset$Landsize == 0] <- NA
housing.dataset$Landsize[housing.dataset$Landsize>30000] <- NA
```

#### **Changing data types**

```
housing.dataset$Date<-as.Date(housing.dataset$Date,"%d/%m/%y")
housing.dataset$Distance<-as.numeric(housing.dataset$Distance)

## Warning: NAs introduced by coercion
housing.dataset$Propertycount<-as.numeric(housing.dataset$Propertycount)

## Warning: NAs introduced by coercion
```

## Removing all rows with either missing Price or Land size values

housing.dataset<-housing.dataset[!is.na(housing.dataset\$Price)&!is.na(housing.dataset\$Landsize),]

## Imputing missing values

```
tempData <- mice(housing.dataset, m=1, maxit=5, method='cart', seed=500)

##

## iter imp variable

## 1 1 Bathroom Car

## 2 1 Bathroom Car

## 3 1 Bathroom Car

## 4 1 Bathroom Car

## 5 1 Bathroom Car

## Warning: Number of logged events: 2</pre>
```

housing.dataset <- complete(tempData,1)</pre>

## 2 Statistical analysis

## **Summary of Numerical Variables**

```
Desc.stat<-stat.desc(housing.dataset[,c(4:9,11)],basic=FALSE,desc =TRUE)
options(scipen=100)
options(digits=0)
knitr::kable(Desc.stat,caption="Table 1: Summary statistics of Numerical Variables")</pre>
```

Table 1: Summary statistics of Numerical Variables

		Landsiz	Room	Bathroo	Ca	Distanc	Propertycou
	Price	e	S	m	r	e	nt
median	970000	553	3	2	2	11	6482
mean	1150714	590	3	2	2	12	7383
SE.mean	5214	6	0	0	0	0	35
CI.mean.0.9 5	10221	12	0	0	0	0	68
var	43573245742 8	620185	1	1	1	45	19399961
std.dev	660100	788	1	1	1	7	4405
coef.var	1	1	0	0	1	1	1
<pre>## [1] 16025 10 # nature of variables in the cleaned dataset str(housing.dataset[,-1])</pre>							
<pre>## 'data.frame': 16025 obs. of 10 variables: ## \$ Date</pre>							
	: int com : num : num nce : num	2 2 3 3 4 1 1 2 2 1 1 0 0 1 2 2.5 2.5 2 "Northern hern Metr	2 3 2 1 2 1 2 0 0 2 2.5 2.5 Metropopolita	1 2 2 2 2.5 2.5 2. olitan" "N n"	52. Iorth	5 2.5 2.5	

Our Cleaned dataset contains 10 variables and 16025 entries of Melbourne housing dataset. The data contained numerical, categorical, character and date types. The dataset contains the data collected from houses sold throughout the year 2020 across 8 districts in Melbourne, Australia. There is a sizable range between the 3rd quartile and the maximum value of most variable which leads us to believe our data is skewed by a few houses that vary from the others. The distribution is otherwise normal.

#### Variable analysis

#### Bar chart of Regions and number of houses sold there

ggplot(housing.dataset,aes(y=Propertycount,x=Regionname,color=Regionname))+ge om\_bar(stat="identity")+theme\_classic()+labs(title="Figure1:A bar graph of Ho uses sold by region names")+theme(plot.title=element\_text(hjust=0.5))+theme(p lot.title=element text(size=20))+ylab("Houses sold")+xlab("Region names")

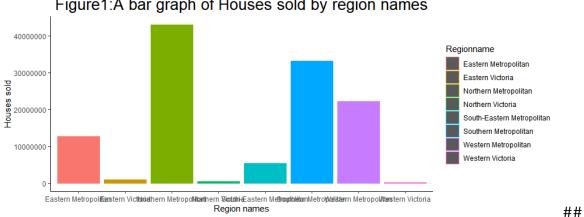


Figure 1: A bar graph of Houses sold by region names

Distribution of houses sold in the reviewed time period - histogram

ggplot(housing.dataset,aes(x=Date))+geom\_histogram(color="black",fill="red",b ins=8)+theme classic()+labs(title="Figure2:A histogram of Date hoses were sol d between January and december 2020")+theme(plot.title=element text(hjust=0.5 ))+theme(plot.title=element\_text(size=20))+ylab("Frequencies ")+xlab("Dates")

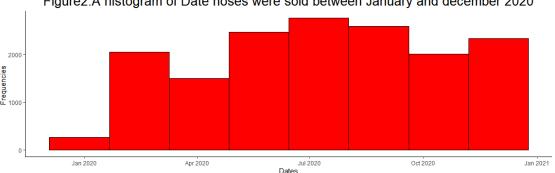
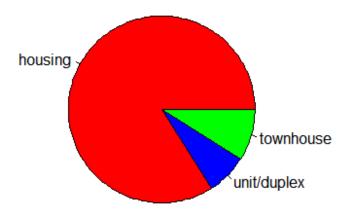


Figure 2: A histogram of Date hoses were sold between January and december 2020

## Piechart showing ratio of the different house types sold

```
#computing position of labels
pie(table(housing.dataset$Type), labels=c ("housing","unit/duplex","townhouse
"),radius=1,col=c("red","blue","green"),main="Figure3:A pie chart graph of Ho
uses sold by types")
```

Figure 3: A pie chart graph of Houses sold by types



# **Scatter plot of Landsize and number of rooms**

Figure 4: Relationship between Rooms and the Size of 12 10 8 Rooms 5 2 5000 10000 15000 20000 0 Size of land

## 3. Analysis of Price Variable

#### Histogram of price variable

ggplot(housing.dataset,aes(x=Propertycount))+geom\_histogram(color="black",fil l="pink",bins=8)+theme classic()+labs(title="Figure5: A histogram of Houses s old between January and december 2020")+theme(plot.title=element\_text(hjust=0 .5))+theme(plot.title=element\_text(size=20))+ylab("Frequencies ")+xlab("House s sold")

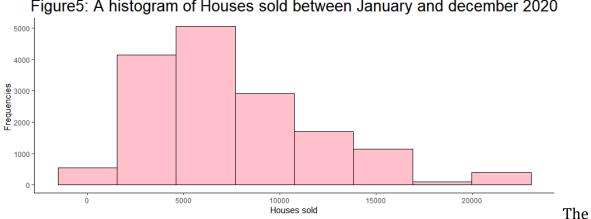


Figure 5: A histogram of Houses sold between January and december 2020

histogram is heavily skewed to the left and indicates that a vast majority of the houses were sold for below 3 million Australian dollars.

#### **Statistical analysis**

```
Mean=mean(housing.dataset$Price,na.rm=TRUE)
SD=sd(housing.dataset$Price,na.rm=TRUE)
Median=median(housing.dataset$Price,na.rm=TRUE)
Variance<-var(housing.dataset$Price,na.rm=TRUE)
Lower_Quartile<-quantile(housing.dataset$Price,0.25)
Upper_Quartile<-quantile(housing.dataset$Price,0.75)
Skew<-skew(housing.dataset$Price)
kurtosis<-kurtosi(housing.dataset$Price)
summ<-data.frame(Mean,SD,Median,Variance,Lower_Quartile,Upper_Quartile,Skew,kurtosis)
kable(summ,caption="Table 2: summary statistics of housing prices")</pre>
```

*Table 2: summary statistics of housing prices* 

			Media		Lower_Quar	Upper_Quar	Ske	kurtos
	Mean	SD	n	Variance	tile	tile	W	is
25	11507	6601	9700	435732457	711000	1400000	2	13
%	14	00	00	428				

#### **Group price by plot**

```
summary(housing.dataset$Price)

## Min. 1st Qu. Median Mean 3rd Qu. Max.
## 131000 711000 970000 1150714 1400000 11200000

housing.dataset$Range<-ifelse(housing.dataset$Price<970000,"Low",ifelse(housing.dataset$Price>=970000&housing.dataset$Price<=1400000,"Medium","High"))</pre>
```

## **Summary of price groups**

```
# summary table of prices by Range
library(dplyr)
Summm=housing.dataset%>%
group_by(Range)%>%
    summarise(Obs=n(), Mean=mean(Price,na.rm=TRUE),SD=sd(Price,na.rm=TRUE))
## `summarise()` ungrouping output (override with `.groups` argument)
kable(Summm,caption="Table 3: summary statistics of housing prices Price Leve ls")
```

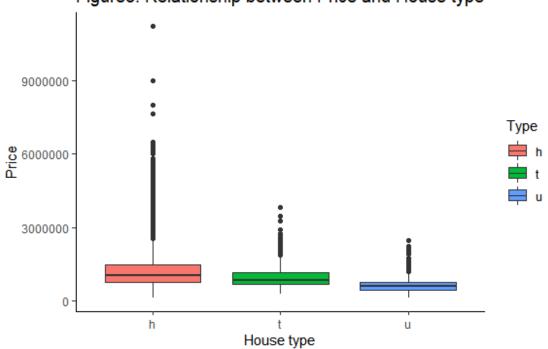
*Table 3: summary statistics of housing prices Price Levels* 

Range	Obs	Mean	SD
High	3948	2035399	712492
Low	7996	701839	161378
Medium	4081	1174350	128078

#### **Exploring prices for different types of houses**

```
housing.dataset %>%
  ggplot( aes(x=Type, y=Price, fill=Type)) +theme_classic()+
  geom_boxplot() +
  ggtitle("Figure6: Relationship between Price and House type") +
  xlab("House type")
```

Figure6: Relationship between Price and House type



Correletaion between price and other variables

```
i1<-sapply(housing.dataset,is.numeric)</pre>
y1<-"Price"
x1<-setdiff(names(housing.dataset)[i1],y1)</pre>
options(digits=5)
cor(housing.dataset[x1],housing.dataset[[y1]])
##
                       [,1]
## X
                  -0.039279
## Landsize
                   0.029802
## Rooms
                   0.386985
## Bathroom
                   0.405620
## Car
                   0.147890
## Distance
                  -0.309284
## Propertycount -0.038635
```

##

The variables that correlate most strongly with Price include number of Bathrooms, number of rooms and Distance. Distance has a negative correlation with price meaning the closer the house is to the Central Business District the more expensive it tends to be.

# **Listing frequency of house types**

```
table(housing.dataset$Type)
##
## h t u
## 13441 1164 1420
```

13,441 Houses 1,164 Townhouses 1420 Units/Duplexes

## **Scatterplots**

#### Relation between Price and Size of Land

