# Homework 4 - Data Wrangling in R

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## September 2022

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#### **Packages**

```
# Data Wrangling
library(tidyverse)

# Modeling
library(car)  # symbox
library(EnvStats) # boxcox function
library(mice)  # Predictive mean matching for missing values

# Aesthetics
library(cowplot) # multiple ggplots on one plot with plot_grid()
library(scales)
```

### 1 - Data Quality Report

#### 1 (a) - Read data

#### 1 (b) - Numeric Housing Tibble

- Create a tibble named housingNumeric which contains all of the numeric variables from the original data.
- use the dplyr::select command along with the is.numeric function to complete this task.

```
# Convert df to a tibble
housingNumeric <- as_tibble(housingData) %>%

# Only select numeric data
# note would usually use command select_if(is.numeric)
select(where(is.numeric))
```

#### 1 (c) - Factor Housing Tibble

• create a tibble named housingFactor which contains all of the character variables from the original data.

```
housingFactor <- as_tibble(housingData) %>%

# Change all character variables to factors

# Keep only the changed data. Implicitly keeping only factor (prev. char vars)

transmute_if(is.character, as.factor)
```

#### 1 (d) - Use Glimpse

```
# NOT RUN
# glimpse(housingNumeric)
# glimpse(housingFactor)
```

#### 1 (e) - Get Q1 and Q3

- create our own user-defined functions for extracting only first and 3rd quantile
- Explanation: Gets the quantiles of a vector using quantile function, but we use the [] brackets to retrieve the 2nd or 4th objects in the vector, which are Q1 and Q3

```
Q1 <- function(x,na.rm=TRUE) {
   quantile(x,na.rm=na.rm)[2]
}
Q3 <- function(x,na.rm=TRUE) {
   quantile(x,na.rm=na.rm)[4]
}</pre>
```

#### 1 (f) - Vectorized Summary Stats

- Function that will help apply several summary statistics to our data all at once
- Contains vector of functions with default to not evaluate if na

```
# Vector of functions
myNumericSummary <- function(x){
   c(length(x), n_distinct(x), sum(is.na(x)), mean(x, na.rm=TRUE),
   min(x,na.rm=TRUE), Q1(x,na.rm=TRUE), median(x,na.rm=TRUE), Q3(x,na.rm=TRUE),
   max(x,na.rm=TRUE), sd(x,na.rm=TRUE))
}

# Name of each functions within the vector
statNames <- c('n', 'unique', 'missing', 'mean', 'min', 'Q1', 'median', 'Q3', 'max', 'sd')</pre>
```

### 1 (g) - Apply Summary Stats

• Apply summary stats function with summarize function

```
numericSummary <- housingNumeric %>%

# Apply vector of functions using summarise
summarise( across( where(is.numeric), ~myNumericSummary(.x) ) )
```

#### 1 (h) - Add Stats Names

• Combine original data set and the names of each summary statistic

```
numericSummary <- cbind(
   stat=c("n","unique","missing","mean","min","Q1","median","Q3","max","sd"),
   numericSummary</pre>
```

```
# glimpse(numericSummary) # uncomment to see effects
```

### 1 (i) - Pretty up data

#### Transform data to make it ready for output format

#### Show the output

```
library(knitr)
options(digits=3)
options(scipen=99)
numericSummaryFinal %>% kable()
```

variable r	n	missir	ngmissing_	_ <b>pnt</b> qu	eunique_	_protean	min	Q1	media	n Q3	max	$\operatorname{sd}$
Id 10	000	0	0.0	1000	100.0	500.500	1	251	500	750.2	1000	288.819
MSSubClass0	000	0	0.0	13	1.3	57.185	20	20	50	70.0	190	41.875
LotFrontag <b>&amp;</b> 0	000	207	20.7	102	10.2	68.745	21	58	68	80.0	313	23.198
LotArea 10	000	0	0.0	760	76.0	10424.88	3 <b>1</b> 477	7500	9422	11423.	521524	159940.619
OverallQual0	000	0	0.0	10	1.0	5.979	1	5	6	7.0	10	1.310
OverallCond0	000	0	0.0	8	0.8	5.638	2	5	5	6.0	9	1.114
YearBuilt 10	000	0	0.0	108	10.8	1969.836	61875	1954	1971	1998.0	2009	29.119
YearRemod 140	999	0	0.0	61	6.1	1984.108	81950	1967	1992	2002.0	2010	20.116
MasVnrArea0	000	4	0.4	249	24.9	95.418	0	0	0	146.2	1600	177.318
${\bf BsmtFinSF10}$	000	0	0.0	490	49.0	438.686	0	0	400	700.0	1880	405.837
${\bf BsmtFinSF20}$	000	0	0.0	107	10.7	44.296	0	0	0	0.0	1127	150.493
${\bf BsmtUnfSF10}$	000	0	0.0	598	59.8	535.078	0	208	441	779.2	2153	417.944
$TotalBsmtSI\!I\!O$	000	0	0.0	549	54.9	1018.060	0 (	793	962	1223.5	3206	403.641
X1stFlrSF 10	000	0	0.0	581	58.1	1131.251	1334	868	1060	1327.2	3228	350.862
X2ndFlrSF10	000	0	0.0	306	30.6	346.279	0	0	0	735.0	1872	426.395
LowQualFi <b>n</b> 8	<b>30</b> 00	0	0.0	15	1.5	4.991	0	0	0	0.0	528	45.295
$\operatorname{GrLivArea} 10$	000	0	0.0	664	66.4	1482.521	1334	1111	1442	1735.0	4316	490.566
BsmtFullBalt0	Ю0	0	0.0	3	0.3	0.427	0	0	0	1.0	2	0.509
BsmtHalfBat	<b>16</b> 0	0	0.0	2	0.2	0.059	0	0	0	0.0	1	0.236
FullBath 10	000	0	0.0	4	0.4	1.529	0	1	2	2.0	3	0.531

variable n		missing	missing_	_ <b>pnt</b> qu	eunique_	_prodean	min	Q1	media	n Q3	max	sd
HalfBath 100	00	0	0.0	3	0.3	0.384	0	0	0	1.0	2	0.501
BedroomAb 100	<b>O</b>	0	0.0	7	0.7	2.865	0	2	3	3.0	6	0.791
Kitchen Abvl GO	0	0	0.0	3	0.3	1.041	1	1	1	1.0	3	0.203
TotRmsAbv100	<b>16</b> 1	0	0.0	11	1.1	6.410	2	5	6	7.0	12	1.562
Fireplaces 100	00	0	0.0	4	0.4	0.618	0	0	1	1.0	3	0.642
GarageYrB <b>l</b> t00	00	53	5.3	94	9.4	1976.93	81906	1960	1977	1999.0	2009	23.592
GarageCars100	00	0	0.0	5	0.5	1.720	0	1	$^2$	2.0	4	0.714
GarageAreal00	00	0	0.0	353	35.3	458.329	0	319	470	572.0	1356	197.780
WoodDeck <b>SF</b> 0	00	0	0.0	226	22.6	94.555	0	0	0	168.0	857	127.144
OpenPorch <b>\$6</b> 0	00	0	0.0	169	16.9	43.610	0	0	22	64.0	547	61.915
EncPorchSIf00	00	0	0.0	122	12.2	40.641	0	0	0	0.0	508	82.139
PoolArea 100	00	0	0.0	3	0.3	1.224	0	0	0	0.0	648	27.403
MiscVal 100	00	0	0.0	14	1.4	27.210	0	0	0	0.0	3500	190.707
MoSold 100	00	0	0.0	12	1.2	6.207	1	4	6	8.0	12	2.626
YrSold 100	00	0	0.0	5	0.5	2007.91	92006	2007	2008	2009.0	2010	1.318
SalePrice 100	00	0	0.0	477	47.7	174560.	6 <b>89</b> 300	013000	016000	<b>2</b> 05000	.05500	069329.31
age 100	00	0	0.0	115	11.5	38.083	1	10	37	55.0	135	29.109
ageSinceRe <b>1100</b> 0	<b>(D</b> e	el 0	0.0	61	6.1	23.811	0	6	16	41.2	60	20.033
ageofGarag <b>&amp;</b> 00	00	53	5.3	97	9.7	30.973	0	9	30	48.0	102	23.563

## 1 (j) - Factor Data Report

# TODO

#### 2 - Transformation

### 2 (a) - Fixing Skewed Data

#### Function to Convert Skewed Data to Normally Distributed Vector

```
normalizeDist <- function(aVector) {

# Get the optimal lambda. Used later for converting to normal distribution
normLambda = boxcox(aVector, optimize = TRUE)$lambda

# Now convert vector to normal distribution, using the optimal lambda
normalizedVector <- (aVector ** normLambda - 1) / normLambda

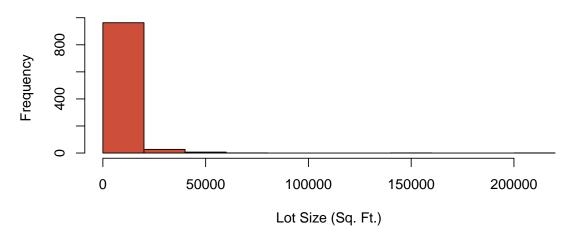
return(normalizedVector)
}

# Colors
goodCol = 'darkseagreen3'
badCol = 'tomato3'</pre>
```

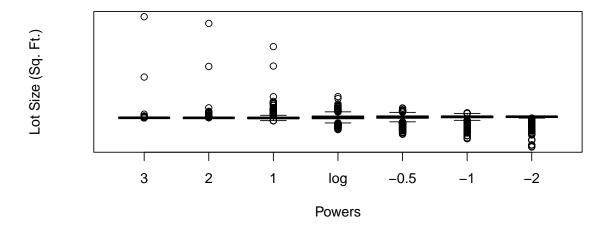
#### i. Fix LotArea in Housing Data Set

#### Lot area is highly skewed





```
# Look at the symbox to see where optimal may lie
symbox(housingData$LotArea, data=housingData, powers=c(3,2,1,0,-0.5,-1,-2),
    ylab = varTitle)
```



```
# Normalize the data and store in data
housingData <- housingData %>%
   mutate(normLotArea = normalizeDist(housingData$LotArea) )
```

#### See the normalized Lot Area variable

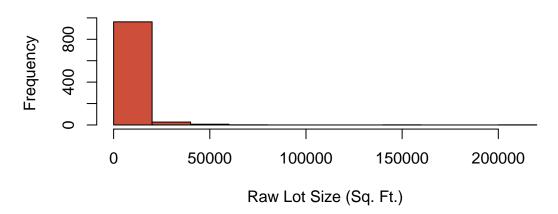
- You can see that the data is definitely more normal
- However, much of the data is near the median, which may or may not be fine, depending on the analysis

```
# Now see the results of the normalization
par(mfrow=c(2,1))

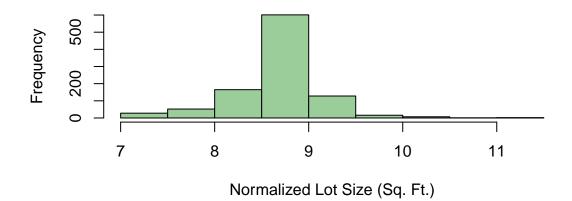
hist( housingData$LotArea,
    main = paste('Raw', varTitle), xlab = paste('Raw', varTitle),
    col = badCol )

hist( housingData$normLotArea,
    main = paste('Normalized', varTitle), xlab = paste('Normalized', varTitle),
    col = goodCol)
```

## Raw Lot Size (Sq. Ft.)



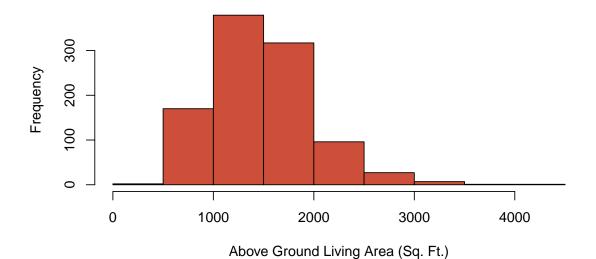
## Normalized Lot Size (Sq. Ft.)



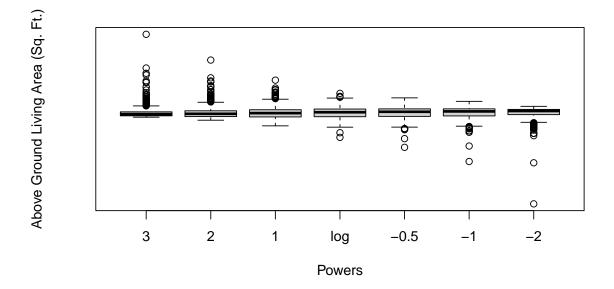
#### i. Fix GrLivArea in Housing Data Set

#### Above Ground Living Area is highly skewed

### Above Ground Living Area (Sq. Ft.)



```
# Look at the symbox to see where optimal may lie
symbox(housingData$GrLivArea, data=housingData, powers=c(3,2,1,0,-0.5,-1,-2),
    ylab = varTitle)
```

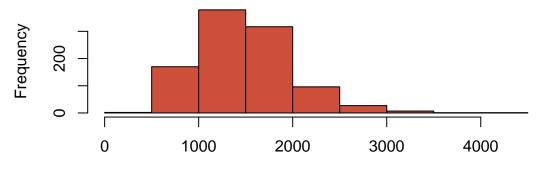


```
# Normalize the data and store in data
housingData <- housingData %>%
  mutate(normYearBuilt = normalizeDist(housingData$GrLivArea) )
```

#### See the normalized Lot Area variable

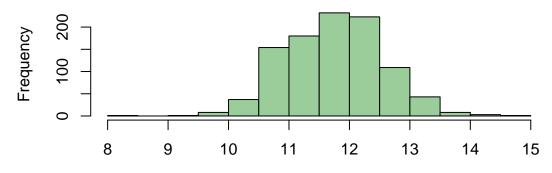
• You can see that the data is definitely more normal

## Raw Above Ground Living Area (Sq. Ft.)



Raw Above Ground Living Area (Sq. Ft.)

## Normalized Above Ground Living Area (Sq. Ft.)



Normalized Above Ground Living Area (Sq. Ft.)

#### 2 (b) - Impute Missing Values

#### Function to plot comparison of imputation methods

Highlights of function include:

- Histogram of actual data, with mean line on x-axis
- Histogram of imputed data, with mean line on x-axis
- Regression of actual and imputed data, spread across trival x-axis. Goal is to show variation in data

```
seeImputation <- function(df, df.meanInputed,</pre>
                        imputationMethod) {
 # Min/Max ranges so actual and imputed histograms align
 yMin = min(df.meanInputed$y)
 yMax = max(df.meanInputed$y)
 # Non Altered data -----
 meanVal = mean(df$y, na.rm=T) # mean of the non altered data
 # Create the plot
 p1 <- df %>%
   ggplot(aes(x = y)) +
   # Histogram
   geom_histogram(color = 'grey65', fill = 'grey95') +
   # The mean value line
   geom vline(xintercept = meanVal, color = 'tomato3') +
   # Text associated with mean value
   annotate("text",
            label = "Mean Value",
            x = meanVal, y = 100,
            size = 5, colour = "tomato3" ) +
   # Labels
   labs(title = 'Data with Missing Values',
            = 'Frequency',
```

```
xlim(yMin, yMax) + # min and max range of x axis (for equal comparison)
 theme_minimal() # Theme
# Imputed data -----
meanValImpute = mean(df.meanInputed$y, na.rm=T)
# Create the plot
p2 <- df.meanInputed %>%
 ggplot(aes(x = y)) +
 # Histogram
 geom_histogram(color = 'grey65', fill = 'grey95') +
 # The mean value line
 geom_vline(xintercept = meanVal, color = 'tomato3') +
 # Text associated with mean value
 annotate("text",
         label = "Mean Value",
         x = meanValImpute, y = 100,
         size = 5, colour = "tomato3" ) +
 # Labels
 labs(title = 'Data without Missing Values',
         subtitle = paste('Using', imputationMethod, 'Imputation Method'),
         y = 'Frequency',
         x = 'Linear feet of street connected to property') +
 xlim(yMin, yMax) + # min and max range of x axis (for equal comparison)
 theme_minimal() # Theme
p3 <- df.meanInputed %>% ggplot(aes(x=x, y=y, color=missing)) +
 # Add points
 geom_point(alpha = 0.5) +
```

```
# Colors, limits, labels, and themes
  scale_color_manual(values = c('grey80', badCol),
                     labels = c('Actuals', 'Imputed') ) +
  ylim(0, quantile(df.meanInputed$y, 0.99)) + # lower 99% of dist
  labs(title = 'Variation of Actuals vs. Imputed Data',
      X
               = 'X',
               = 'Lot Frontage',
       caption =paste0('\nUsing housing.csv data',
                       '\nOnly showing lower 99% of distribution for viewing')
       ) +
  theme_minimal() + theme(legend.position = 'bottom',
                          legend.title = element_blank())
# Combine the plots for the final returned output
combinedPlots <- plot_grid(p1, p2, p3,</pre>
                           ncol = 1, label_size = 12,
                           rel_heights = c(1, 1.1, 1.75))
return(combinedPlots)
```

#### Create Reusable data set df

```
# How much is missing?
missing <- is.na(housingData$LotFrontage)
paste('There are', sum(missing), 'missing values')</pre>
```

#### [1] "There are 207 missing values"

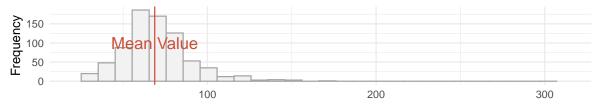
#### i Mean Value Imputation

```
# Create copy of the data with NAs
df.meanInputed <- df

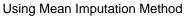
# Conduct Mean imputation
df.meanInputed[missing,"y"] <- mean(df.meanInputed$y, na.rm=T)

# Compare missing vs. non missing for given imputation method
seeImputation(df, df.meanInputed, imputationMethod = 'Mean')</pre>
```

### Data with Missing Values

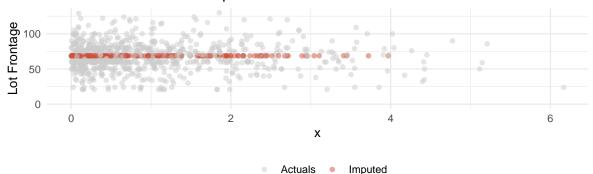


## Data without Missing Values





#### Variation of Actuals vs. Imputed Data



Using housing.csv data Only showing lower 99% of distribution for viewing

#### ii Regression with Error Imputation

- Output seems to capture appropriate variance of the actual data.
- It is clear that the mean does not change

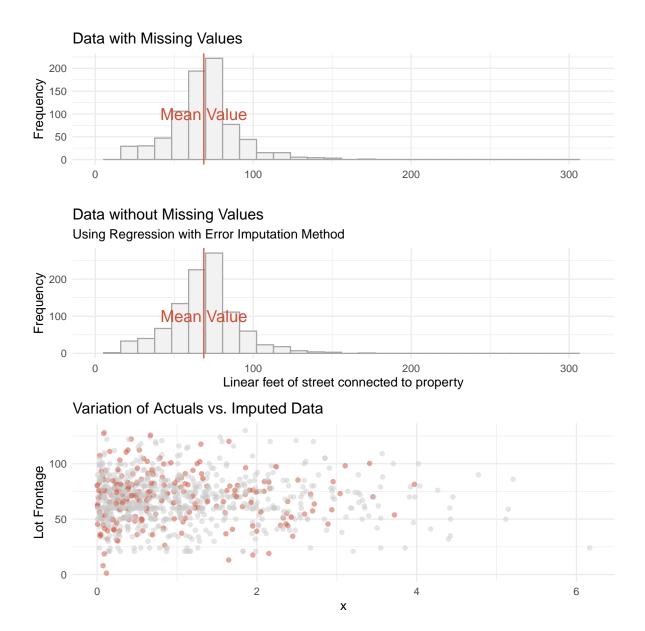
```
fit <- lm(y ~ x, data = df)  # fit a linear model to the data
f <- summary(fit)

c <- f[[4]] # extract the coefficients
se <- f[[6]] # extract the model standard error

# Regression with NO error
dfReg.imp <- df
dfReg.imp[missing,"y"]<- (c[1] + c[2] * dfReg.imp[missing,"x"])

# Imputation by Regression with error. Note se = standard error of model
df.regErrorImputed <- dfReg.imp %>%
    mutate(y = y + if_else(missing, rnorm(n(), 0, se), 0))

# Compare missing vs. non missing for given imputation method
seeImputation(df, df.regErrorImputed, imputationMethod = 'Regression with Error')
```



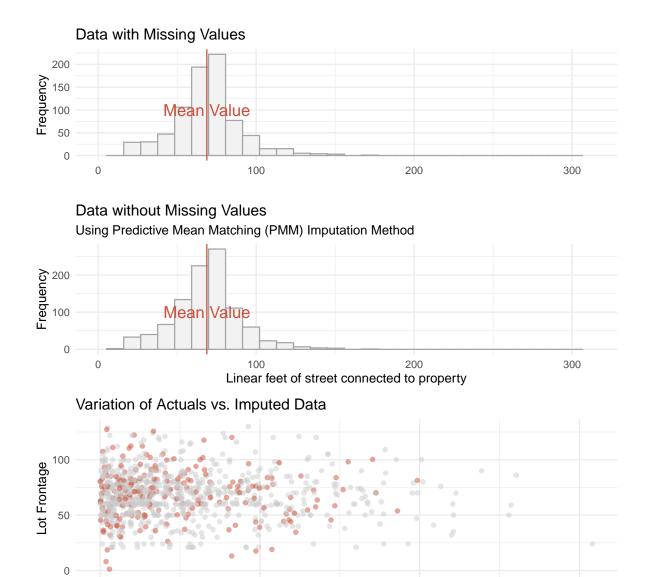
Using housing.csv data Only showing lower 99% of distribution for viewing

Imputed

Actuals

#### iii Predictive Mean Matching Imputation

- Output seems to capture appropriate variance of the actual data.
- It is clear that the mean does not change much, if at all.



Using housing.csv data Only showing lower 99% of distribution for viewing

4

Imputed

6

Х

Actuals

2

0

#### 2 (c) - Dummy Variable Manipulation

Collapse the factor levels in the Exterior1st down to only five levels – the first four levels should be the most frequent levels and all other levels should be collapsed into a single "Other" level.

#### Interpretation

- Now there are only 5 levels for the Exterior1st variable
- 4 most frequent left untouched, and the others grouped in Other

```
housingData <- housingData %>%

# lumps all levels except for the n most frequent
mutate(Exterior1st = fct_lump_n(Exterior1st, n=4))

# See that there are only 5 levels now
unique(housingData$Exterior1st)
```

[1] Other Wd Sdng VinylSd HdBoard MetalSd Levels: HdBoard MetalSd VinylSd Wd Sdng Other

```
length(unique(housingData$Exterior1st))
```

[1] 5

### 2 (d) - More fun with Factors

### i - Get average SalePrice for each Neighborhood using tidyverse

• Note sorted descending

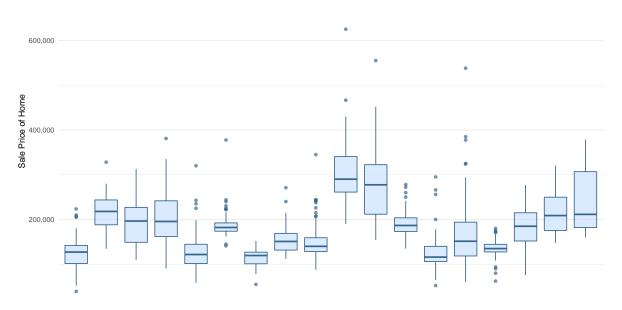
```
housingData %>%
  group_by(Neighborhood) %>%
  summarise(AvgSalePrice = mean(SalePrice)) %>%
  arrange(desc(AvgSalePrice)) %>% # sort descending on sale price
  kable() # output as a kable table
```

Neighborhood	AvgSalePrice
NoRidge	328794
NridgHt	283057
Timber	241940
ClearCr	218265
Somerst	211678
Crawfor	209766
CollgCr	194942
NWAmes	191823
Gilbert	189466
SawyerW	183971
other	170248
Mitchel	154788
NAmes	146669
Sawyer	134708
Edwards	128772
OldTown	126023
BrkSide	124844
IDOTRR	114319

#### ii - Boxplots of Avg. Sale Price by Neighborhood

Distribution of Sale Prices by Neighborhood

•



BrkSide ClearCr CollgCr Crawfor Edwards Gilbert IDOTRR Mitchel NAmes NoRidge NridgHt NWAmes OldTown other Sawyer SawyerW Somerst Timber Neighborhood

#### iii-iv - Boxplots Reordered by Descending Sale Price

Distribution of Sale Prices by Neighborhood Ordered Descending by Sale Price of Home

•

