Homework 4 - Data Wrangling in R

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Packages

```r
# 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()
```

1 - Data Quality Report

1 (a) - Read data

```r
# Read data
housingData <- read_csv('housingData.csv')
```

```
Rows: 1000 Columns: 74
-- Column specification --------------------------------------------------------
Delimiter: ","
chr (38): MSZoning, Alley, LotShape, LandContour, LotConfig, LandSlope, Neig...
dbl (36): Id, MSSubClass, LotFrontage, LotArea, OverallQual, OverallCond, Ye...

i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
# create three new variables
housingData <- housingData %>%
  dplyr::mutate(age              = YrSold - YearBuilt,
                ageSinceRemodel = YrSold - YearRemodAdd,
                ageofGarage      = YrSold - GarageYrBlt
                )
```

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]
}
```

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')
```

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
```

```
)

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

1 (i) - Pretty up data

Transform data to make it ready for output format

```
numericSummaryFinal <- numericSummary %>%
  pivot_longer("Id":"ageofGarage", names_to = "variable", values_to = "value") %>%
  pivot_wider(names_from = stat, values_from = value) %>%
  mutate(missing_pct = 100*missing/n,
         unique_pct = 100*unique/n) %>%
  select(variable, n, missing, missing_pct, unique, unique_pct, everything())
```

Show the output

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

variable	n	missing	missing_pct	unique	unique_pct	mean	min	Q1	median	Q3	max	sd
Id	1000	0	0.0	1000	100.0	500.500	1	251	500	750.2	1000	288.819
MSSubClass	1000	0	0.0	13	1.3	57.185	20	20	50	70.0	190	41.875
LotFrontage	1000	207	20.7	102	10.2	68.745	21	58	68	80.0	313	23.198
LotArea	1000	0	0.0	760	76.0	10424.881	1477	7500	9422	11423.5	215245	9940.619
OverallQual	1000	0	0.0	10	1.0	5.979	1	5	6	7.0	10	1.310
OverallCond	1000	0	0.0	8	0.8	5.638	2	5	5	6.0	9	1.114
YearBuilt	1000	0	0.0	108	10.8	1969.836	1875	1954	1971	1998.0	2009	29.119
YearRemodAdd	1000	0	0.0	61	6.1	1984.108	1950	1967	1992	2002.0	2010	20.116
MasVnrArea	1000	4	0.4	249	24.9	95.418	0	0	0	146.2	1600	177.318
BsmtFinSF1	1000	0	0.0	490	49.0	438.686	0	0	400	700.0	1880	405.837
BsmtFinSF2	1000	0	0.0	107	10.7	44.296	0	0	0	0.0	1127	150.493
BsmtUnfSF	1000	0	0.0	598	59.8	535.078	0	208	441	779.2	2153	417.944
TotalBsmtSF	1000	0	0.0	549	54.9	1018.060	0	793	962	1223.5	3206	403.641
X1stFlrSF	1000	0	0.0	581	58.1	1131.251	334	868	1060	1327.2	3228	350.862
X2ndFlrSF	1000	0	0.0	306	30.6	346.279	0	0	0	735.0	1872	426.395
LowQualFinSF	1000	0	0.0	15	1.5	4.991	0	0	0	0.0	528	45.295
GrLivArea	1000	0	0.0	664	66.4	1482.521	334	1111	1442	1735.0	4316	490.566
BsmtFullBath	1000	0	0.0	3	0.3	0.427	0	0	0	1.0	2	0.509
BsmtHalfBath	1000	0	0.0	2	0.2	0.059	0	0	0	0.0	1	0.236
FullBath	1000	0	0.0	4	0.4	1.529	0	1	2	2.0	3	0.531

variable	n	missing	missing_pct	unique	unique_pct	mean	min	Q1	median	Q3	max	sd
HalfBath	1000	0	0.0	3	0.3	0.384	0	0	0	1.0	2	0.501
BedroomAbvGr	1000	0	0.0	7	0.7	2.865	0	2	3	3.0	6	0.791
KitchenAbvGr	1000	0	0.0	3	0.3	1.041	1	1	1	1.0	3	0.203
TotRmsAbvGrd	1000	0	0.0	11	1.1	6.410	2	5	6	7.0	12	1.562
Fireplaces	1000	0	0.0	4	0.4	0.618	0	0	1	1.0	3	0.642
GarageYrBlt	1000	53	5.3	94	9.4	1976.938	1906	1960	1977	1999.0	2009	23.592
GarageCars	1000	0	0.0	5	0.5	1.720	0	1	2	2.0	4	0.714
GarageArea	1000	0	0.0	353	35.3	458.329	0	319	470	572.0	1356	197.780
WoodDeckSF	1000	0	0.0	226	22.6	94.555	0	0	0	168.0	857	127.144
OpenPorchSF	1000	0	0.0	169	16.9	43.610	0	0	22	64.0	547	61.915
EncPorchSF	1000	0	0.0	122	12.2	40.641	0	0	0	0.0	508	82.139
PoolArea	1000	0	0.0	3	0.3	1.224	0	0	0	0.0	648	27.403
MiscVal	1000	0	0.0	14	1.4	27.210	0	0	0	0.0	3500	190.707
MoSold	1000	0	0.0	12	1.2	6.207	1	4	6	8.0	12	2.626
YrSold	1000	0	0.0	5	0.5	2007.919	2006	2007	2008	2009.0	2010	1.318
SalePrice	1000	0	0.0	477	47.7	174560.637	37300	130000	160000	205000.0	755000	69329.319
age	1000	0	0.0	115	11.5	38.083	1	10	37	55.0	135	29.109
ageSinceRemodel	1000	0	0.0	61	6.1	23.811	0	6	16	41.2	60	20.033
ageofGarage	1000	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

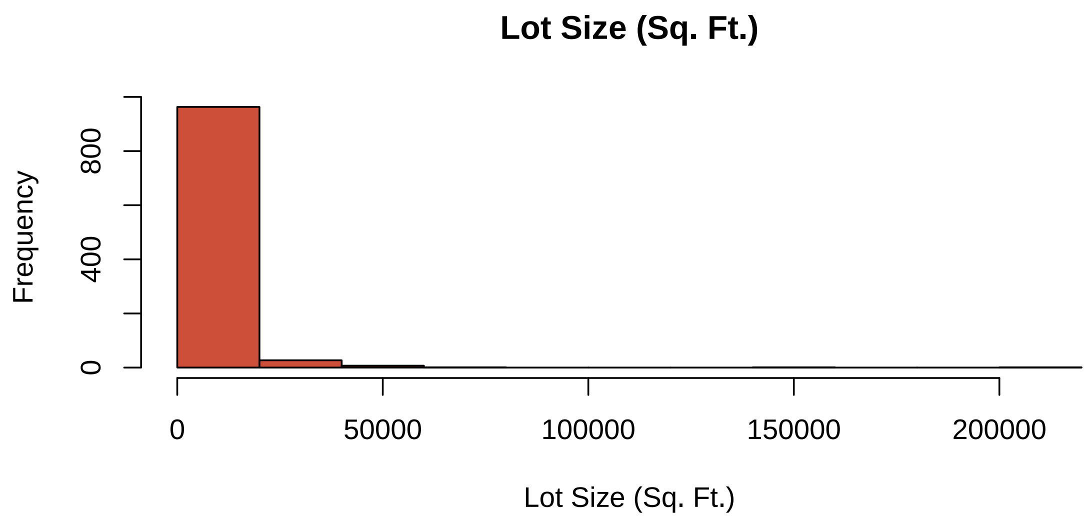
Function to Convert Skewed Data to Normally Distributed Vector

```
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'
```

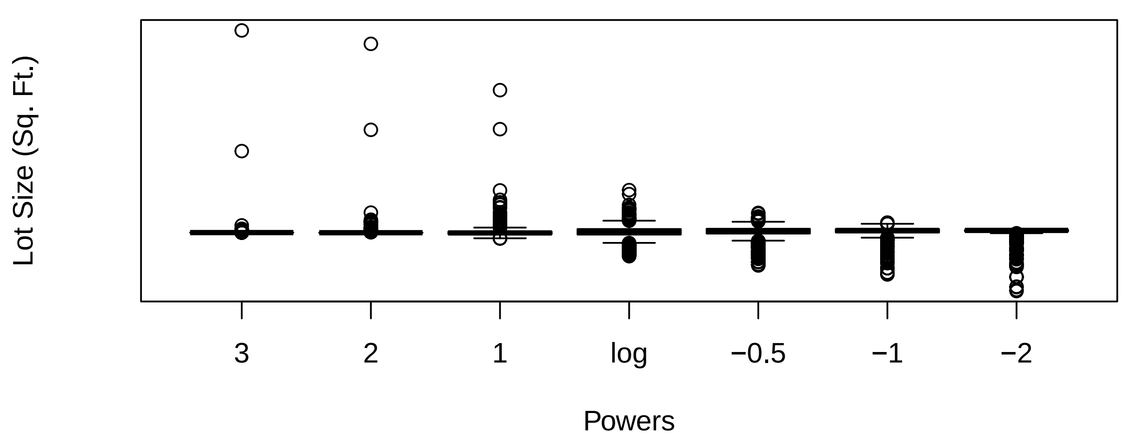
i. Fix `LotArea` in Housing Data Set

Lot area is highly skewed

```
varTitle = 'Lot Size (Sq. Ft.)'

# See that LotArea is highly skewed
hist(housingData$LotArea,
      main = varTitle, xlab = varTitle, col = badCol)
```




```r
# 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)
```

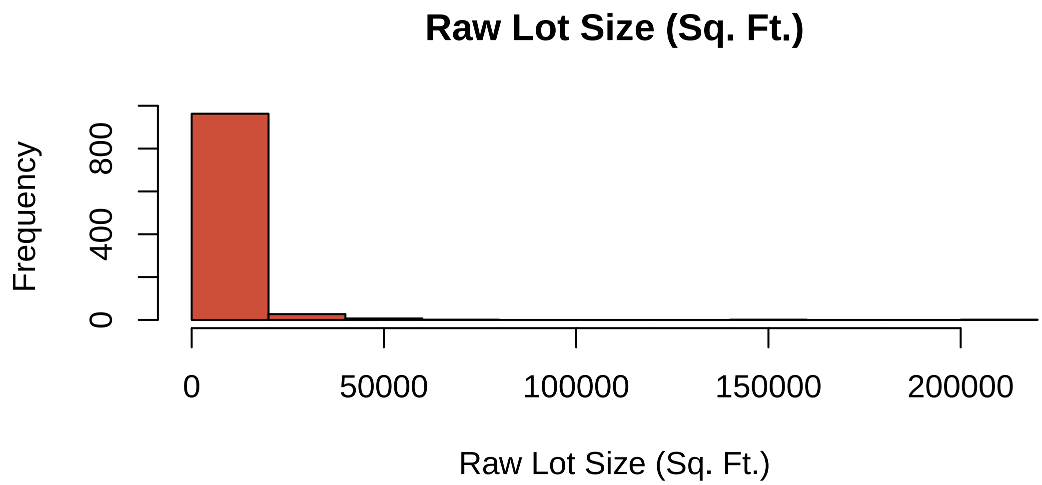


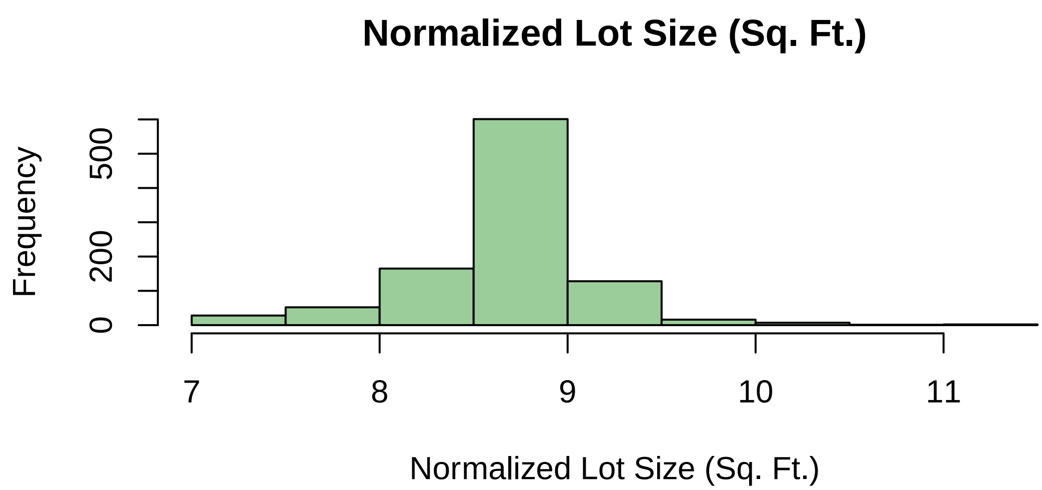
```
# Normalize the data and store in data
housingData <- housingData %>%
  mutate(normLotArea = normalizeDist(housingData$LotArea) )
```

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)
```

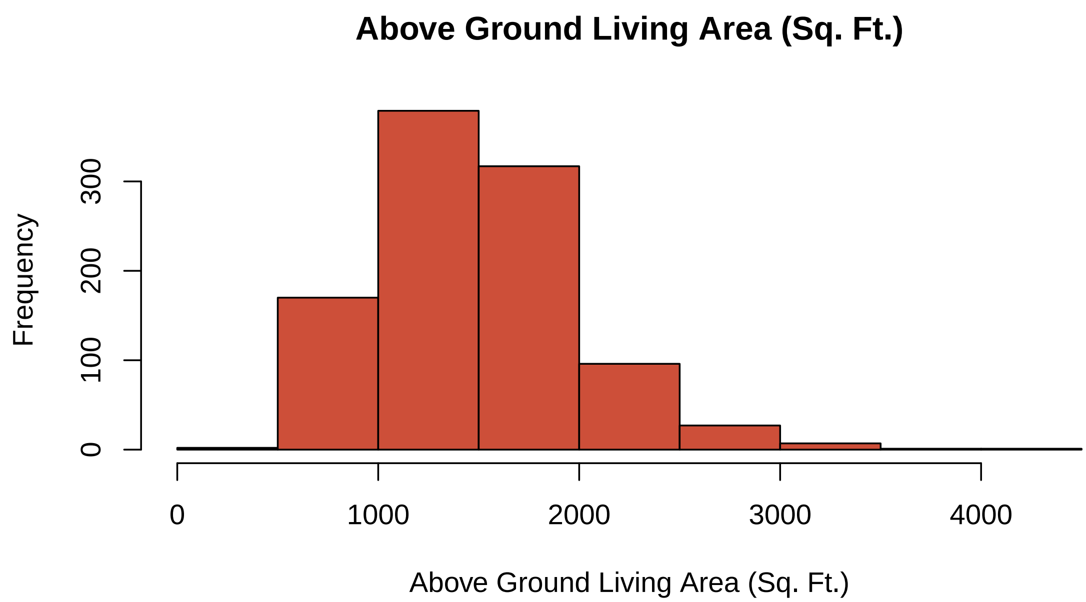

Raw Lot Size (Sq. Ft.)
Frequency
0
400
800
0
50000
100000
150000
200000
Raw Lot Size (Sq. Ft.)


Normalized Lot Size (Sq. Ft.)
Frequency
0
200
500
7
8
9
10
11
Normalized Lot Size (Sq. Ft.)

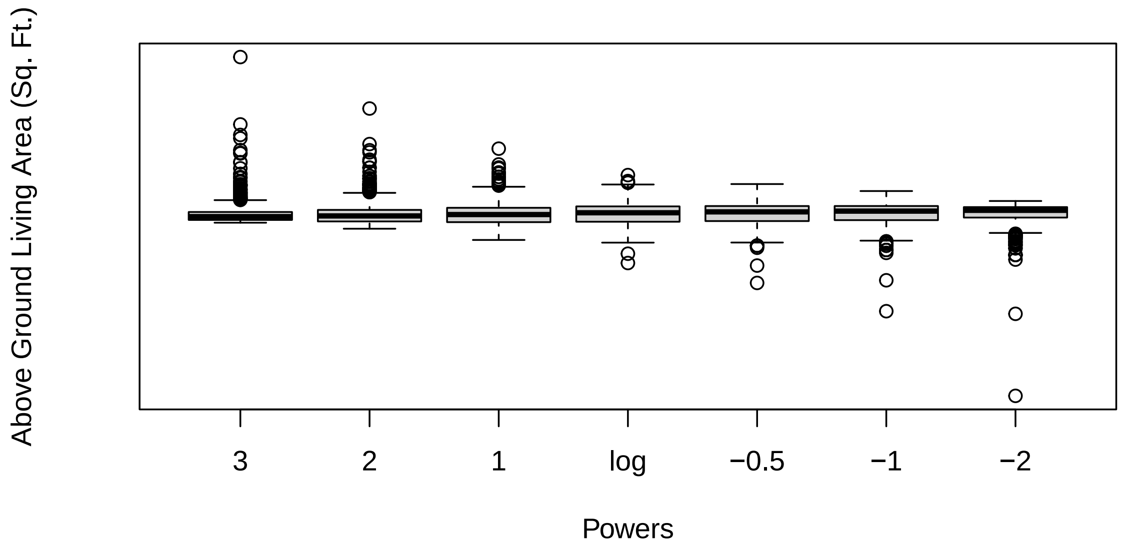
i. Fix `GrLivArea` in Housing Data Set

Above Ground Living Area is highly skewed

```
varTitle = 'Above Ground Living Area (Sq. Ft.)'

# See that LotArea is highly skewed
hist(housingData$GrLivArea,
      main = varTitle, xlab = varTitle, col = badCol )
```




```
# 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)
```

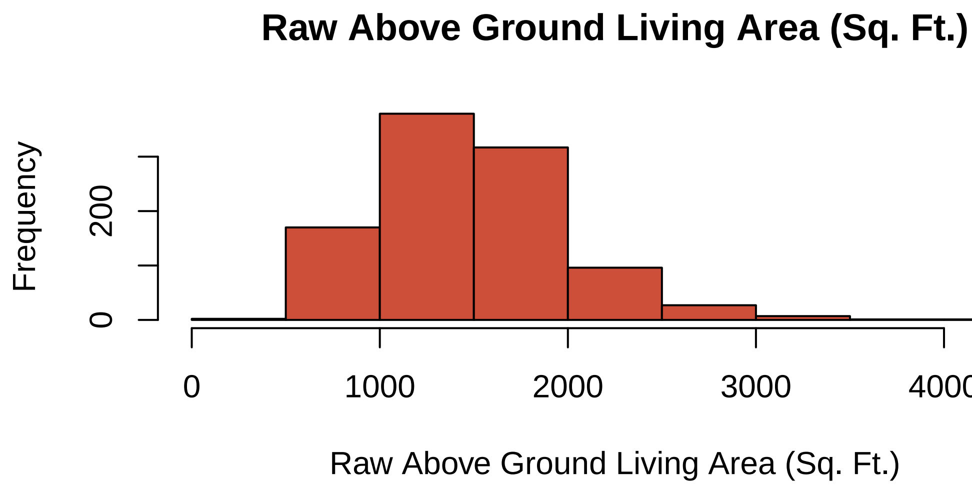


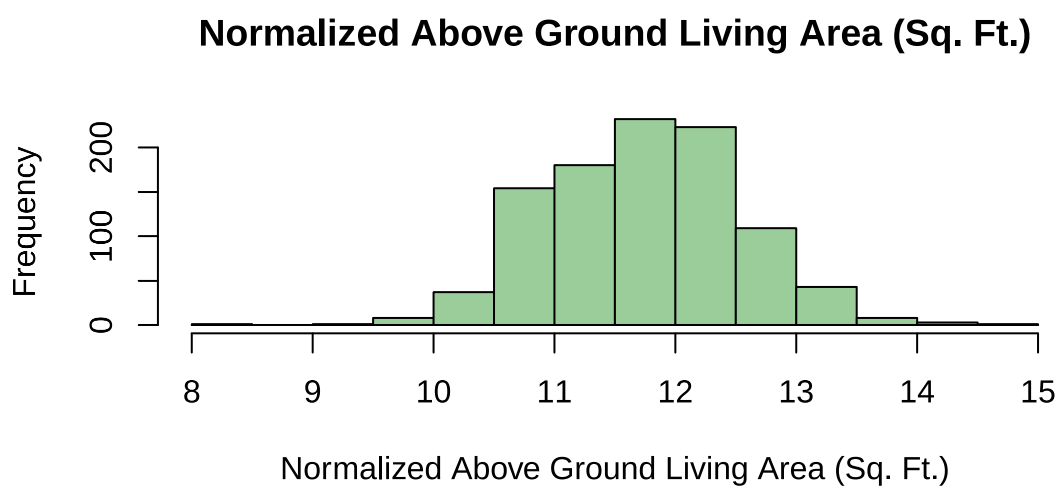

```
# Normalize the data and store in data
housingData <- housingData %>%
  mutate(normYearBuilt = normalizeDist(housingData$GrLivArea) )
```

See the normalized Lot Area variable

- You can see that the data is definitely more normal

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

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

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


Raw Above Ground Living Area (Sq. Ft.)
Frequency
0
200
0
1000
2000
3000
4000
Raw Above Ground Living Area (Sq. Ft.)


Normalized Above Ground Living Area (Sq. Ft.)
Frequency
0
100
200
8
9
10
11
12
13
14
15
Normalized Above Ground Living Area (Sq. Ft.)

2 (b) - Impute Missing Values

Function to plot comparison of imputation methods

```
seeImputation <- function(df, df.meanInputed,
                          imputationMethod) {

  # Equal tail 95% distributional ranges
  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',
         y     = 'Frequency',
         x     = '' ) +

    xlim(yMin, yMax) + # min and max range of x axis (for equal comparison)
    theme_minimal() # Theme


  # Imputed data -------------------------------------------------
```

```r
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

# Variation scatter -----------------------------------------------------------

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',
       y        = '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,
                             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')
```

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

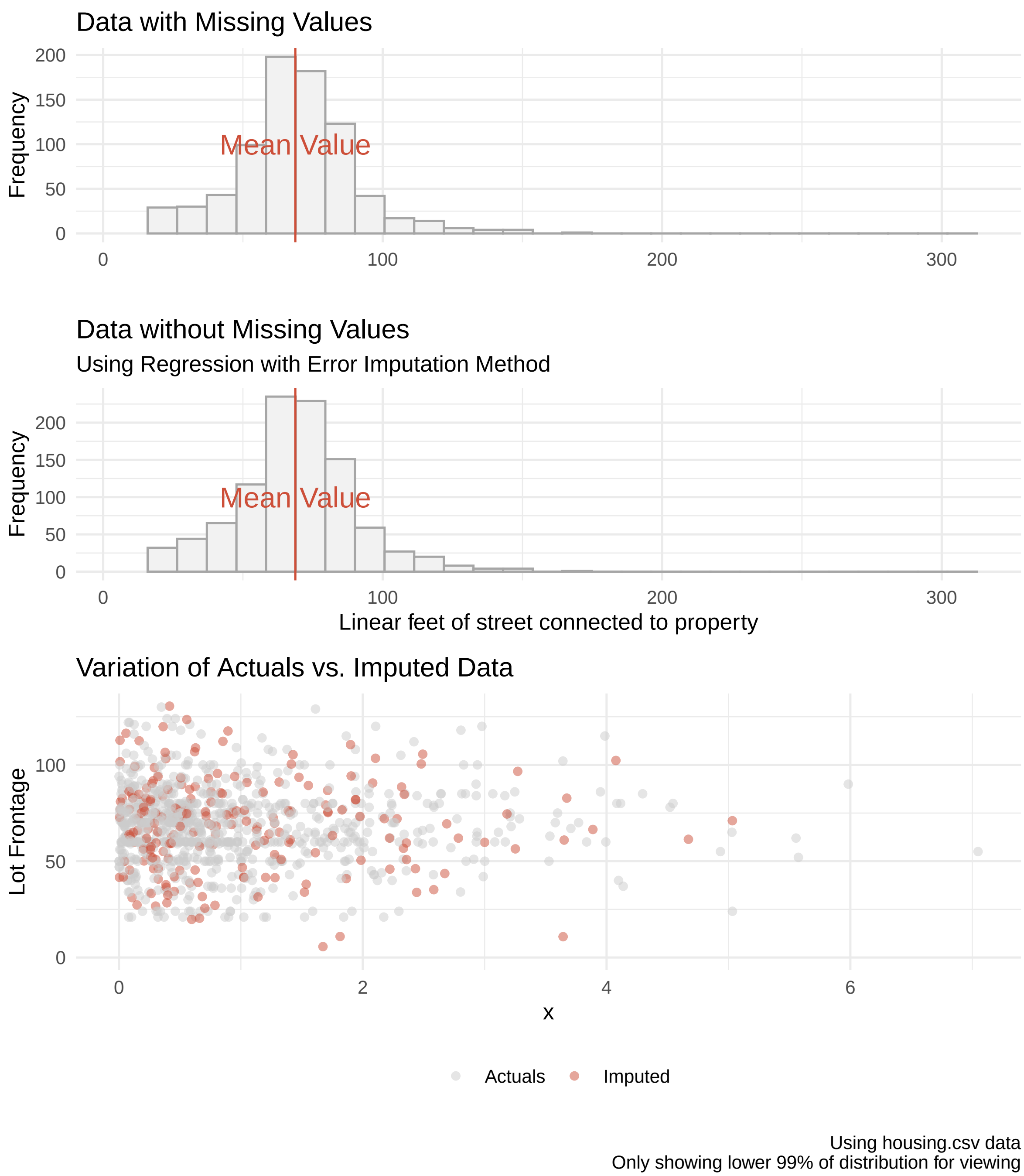
```
# Create a data frame to easily reference the lot frontage for other inputation
df <- data.frame(x = rexp(nrow(housingData)), # meaningless x to help show varation
                 y = housingData$LotFrontage,
                 missing = missing)
```

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')
```

ii Regression with Error Imputation

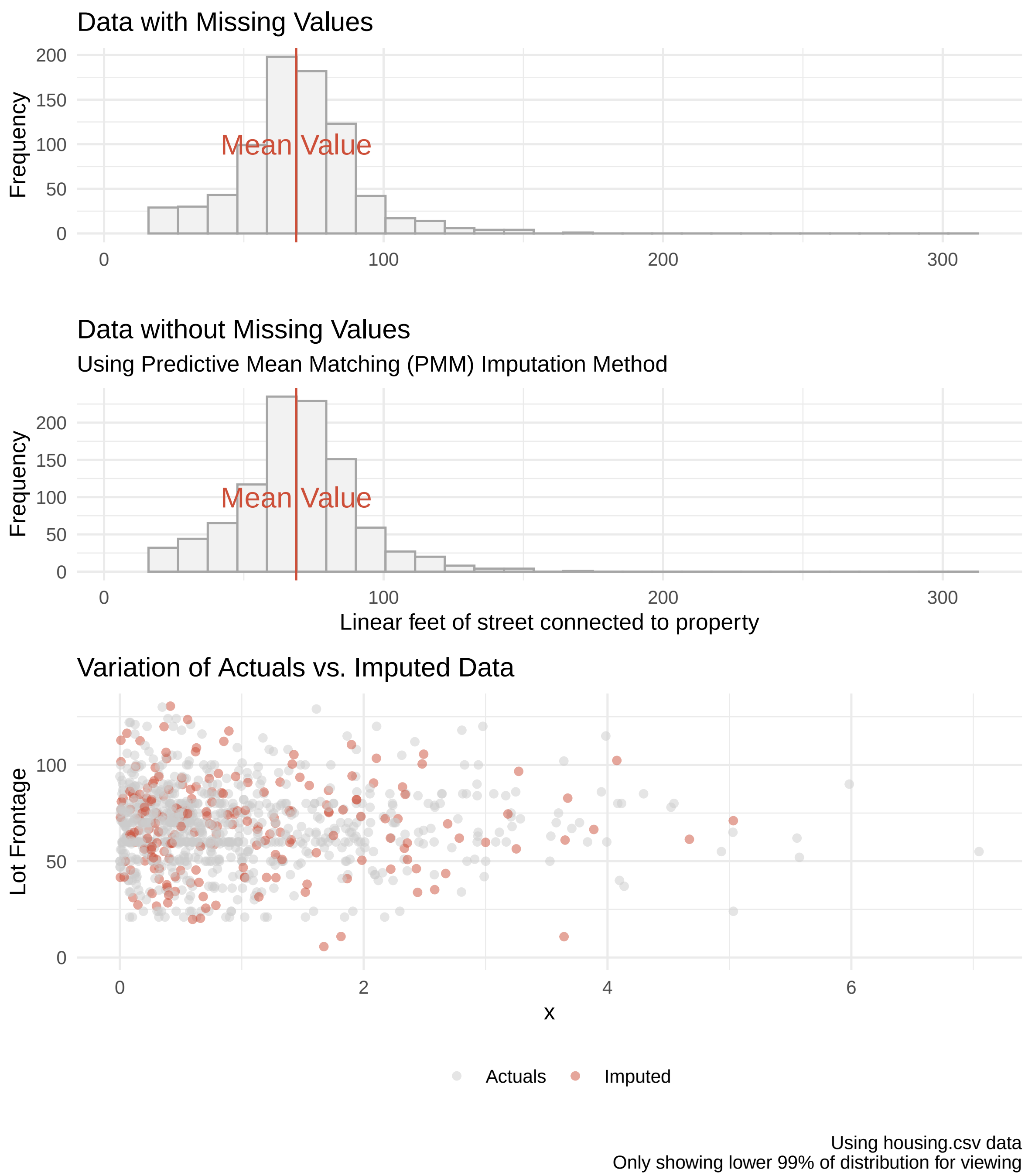
```r
fit <- lm(y ~ x, data = df)    # fit a linear model to the data
f   <- summary(fit)

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')
```


Data with Missing Values
Frequency
200
150
100
50
0
Mean Value
0
100
200
300
Data without Missing Values
Using Regression with Error Imputation Method
Frequency
200
150
100
50
0
Mean Value
0
100
200
300
Linear feet of street connected to property
Variation of Actuals vs. Imputed Data
Lot Frontage
100
50
0
0
2
4
6
x
Actuals
Imputed
Using housing.csv data
Only showing lower 99% of distribution for viewing

iii Predictive Mean Matching Imputation

- Output seems to capture appropriate variance of the actual data.

```
df.pmmImputed <- df # copy data with missingness

# imputation by PMM
df.pmmImputed[missing,"y"] <- mice.impute.pmm( df.pmmImputed$y,
                                              !df.pmmImputed$missing,
                                               df.pmmImputed$x)

# Compare missing vs. non missing for given imputation method
seeImputation(df, df.regErrorImputed,
              imputationMethod = 'Predictive Mean Matching (PMM)')
```


Data with Missing Values
Frequency
200
150
100
50
0
Mean Value
0
100
200
300
Data without Missing Values
Using Predictive Mean Matching (PMM) Imputation Method
Frequency
200
150
100
50
0
Mean Value
0
100
200
300
Linear feet of street connected to property
Variation of Actuals vs. Imputed Data
Lot Frontage
100
50
0
0
2
4
6
x
Actuals
Imputed
Using housing.csv data
Only showing lower 99% of distribution for viewing

2 (c)