

Final Project

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Packages/Libraries & Setup

```
#Set cache for seed
knitr::opts_chunk$set(cache = T)
#Memory allocation for Java ~10gb and Garbage Collection
options(java.parameters = c("-XX:+UseConcMarkSweepGC", "-Xmx10000m"))
#Packages to load
pacman::p_load(
  ggplot2,
  tidyverse,
  data.table,
  R.utils,
  magrittr,
  dplyr,
  testthat,
  YARF,
  lubridate,
  missForest,
  parallel,
  doParallel,
  caret,
  glmnet
)

#Set CPU cores for YARF
num_of_cores = 8
set_YARF_num_cores(num_of_cores)
```

```
## YARF can now make use of 8 cores.
```

```
#Initialize rJava
library(rJava)
gc()
```

```
##           used (Mb) gc trigger (Mb) max used (Mb)
## Ncells 2560643 136.8   4437645 237.0 4437645 237.0
## Vcells 4280398  32.7   10146329  77.5 7143700  54.6
```

```
.jinit()
```

```
## [1] 0
```

The Data

```
#Set our file path & read in file
housingDataFilePath = "/home/peterjr/RepoCollections/MATH_342W_FinalProject/Datasets/housing_data_2016_1"
#Keep a unaltered "True" copy
housingDataTrue = data.table(fread(housingDataFilePath))

housingData = housingDataTrue

housingData
```

```
##                               HITId                               HITTypeId
## 1: 30ID399FXG7F26JWONXF0Y86J90FD4 36BILMLQB75QQNBTYKGYCZWDN8TVAU
## 2: 3MQY1YVHS3K2MF90MWR2LPQH7KJ2B0 36BILMLQB75QQNBTYKGYCZWDN8TVAU
## 3: 3DGDV62G7094Q9AA5193G9V600Y2PL 36BILMLQB75QQNBTYKGYCZWDN8TVAU
## 4: 3087LXLJ6MGL3MI2CB9KLRONPKRFOB 36BILMLQB75QQNBTYKGYCZWDN8TVAU
## 5: 3FULMHZ70UX88KSKHZ0ZSKY93XJ4MN 36BILMLQB75QQNBTYKGYCZWDN8TVAU
## ---
## 2226:                               <NA>                               <NA>
## 2227:                               <NA>                               <NA>
## 2228:                               <NA>                               <NA>
## 2229:                               <NA>                               <NA>
## 2230:                               <NA>                               <NA>
##
##                               Title
## 1: Find Information about Housing To Help a Student Project -- Very easy
## 2: Find Information about Housing To Help a Student Project -- Very easy
## 3: Find Information about Housing To Help a Student Project -- Very easy
## 4: Find Information about Housing To Help a Student Project -- Very easy
## 5: Find Information about Housing To Help a Student Project -- Very easy
## ---
## 2226:                               <NA>
## 2227:                               <NA>
## 2228:                               <NA>
## 2229:                               <NA>
## 2230:                               <NA>
##
##                               Description Keywords Reward
## 1: Go to a link and copy information into the HIT      NA $0.05
## 2: Go to a link and copy information into the HIT      NA $0.05
## 3: Go to a link and copy information into the HIT      NA $0.05
## 4: Go to a link and copy information into the HIT      NA $0.05
## 5: Go to a link and copy information into the HIT      NA $0.05
## ---
## 2226:                               <NA>      NA <NA>
## 2227:                               <NA>      NA <NA>
## 2228:                               <NA>      NA <NA>
## 2229:                               <NA>      NA <NA>
## 2230:                               <NA>      NA <NA>
##
##                               CreationTime MaxAssignments
## 1: Wed Feb 15 22:13:37 PST 2017      1
## 2: Wed Feb 15 22:13:37 PST 2017      1
## 3: Wed Feb 15 22:13:41 PST 2017      1
## 4: Wed Feb 15 22:13:33 PST 2017      1
## 5: Wed Feb 15 22:13:38 PST 2017      1
## ---
```

```

## 2226:                <NA>                NA
## 2227:                <NA>                NA
## 2228:                <NA>                NA
## 2229:                <NA>                NA
## 2230:                <NA>                NA
##
## RequesterAnnotation
## 1: BatchId:2689947;OriginalHitTemplateId:920937336;
## 2: BatchId:2689947;OriginalHitTemplateId:920937336;
## 3: BatchId:2689947;OriginalHitTemplateId:920937336;
## 4: BatchId:2689947;OriginalHitTemplateId:920937336;
## 5: BatchId:2689947;OriginalHitTemplateId:920937336;
## ---
## 2226:                <NA>
## 2227:                <NA>
## 2228:                <NA>
## 2229:                <NA>
## 2230:                <NA>
##
## AssignmentDurationInSeconds AutoApprovalDelayInSeconds
## 1:                900                60
## 2:                900                60
## 3:                900                60
## 4:                900                60
## 5:                900                60
## ---
## 2226:                NA                NA
## 2227:                NA                NA
## 2228:                NA                NA
## 2229:                NA                NA
## 2230:                NA                NA
##
## Expiration NumberOfSimilarHITs LifetimeInSeconds
## 1: Wed Feb 22 22:13:37 PST 2017                NA                NA
## 2: Wed Feb 22 22:13:37 PST 2017                NA                NA
## 3: Wed Feb 22 22:13:41 PST 2017                NA                NA
## 4: Wed Feb 22 22:13:33 PST 2017                NA                NA
## 5: Wed Feb 22 22:13:38 PST 2017                NA                NA
## ---
## 2226:                <NA>                NA                NA
## 2227:                <NA>                NA                NA
## 2228:                <NA>                NA                NA
## 2229:                <NA>                NA                NA
## 2230:                <NA>                NA                NA
##
## AssignmentId WorkerId AssignmentStatus
## 1: 32KTQ2V7RDFCSAWQOW1SXC5AZIC9MB A231MNJJDDF3LS                Approved
## 2: 35LDD5557A4W96FHSTSHNLJQAB7MKZ A394B5QVCVKU7A                Approved
## 3: 3FFJ6VRIL1080XIM3LK7C8X0F5U0I6 A231MNJJDDF3LS                Approved
## 4: 3S4AW7T80BIRPM8T7P4MGRF5DL74L7 AHXBZXWIZJSVG                Approved
## 5: 3JMSRU9HQIUCDTHGAZI5CMPYH7REVS A231MNJJDDF3LS                Approved
## ---
## 2226:                <NA>                <NA>                <NA>
## 2227:                <NA>                <NA>                <NA>
## 2228:                <NA>                <NA>                <NA>
## 2229:                <NA>                <NA>                <NA>
## 2230:                <NA>                <NA>                <NA>
##
## AcceptTime SubmitTime

```

```

##      1: Thu Feb 16 05:32:36 PST 2017 Thu Feb 16 05:35:37 PST 2017
##      2: Wed Feb 15 22:19:51 PST 2017 Wed Feb 15 22:21:52 PST 2017
##      3: Thu Feb 16 03:17:01 PST 2017 Thu Feb 16 03:19:01 PST 2017
##      4: Thu Feb 16 04:54:24 PST 2017 Thu Feb 16 04:57:04 PST 2017
##      5: Wed Feb 15 23:54:29 PST 2017 Wed Feb 15 23:56:45 PST 2017
##      ---
## 2226:                                <NA>                                <NA>
## 2227:                                <NA>                                <NA>
## 2228:                                <NA>                                <NA>
## 2229:                                <NA>                                <NA>
## 2230:                                <NA>                                <NA>
##      AutoApprovalTime      ApprovalTime RejectionTime
##      1: Thu Feb 16 05:36:37 PST 2017 2017-02-16 13:37:11 UTC      NA
##      2: Wed Feb 15 22:22:52 PST 2017 2017-02-16 06:23:11 UTC      NA
##      3: Thu Feb 16 03:20:01 PST 2017 2017-02-16 11:20:11 UTC      NA
##      4: Thu Feb 16 04:58:04 PST 2017 2017-02-16 12:58:11 UTC      NA
##      5: Wed Feb 15 23:57:45 PST 2017 2017-02-16 07:58:11 UTC      NA
##      ---
## 2226:                                <NA>                                <NA>      NA
## 2227:                                <NA>                                <NA>      NA
## 2228:                                <NA>                                <NA>      NA
## 2229:                                <NA>                                <NA>      NA
## 2230:                                <NA>                                <NA>      NA
##      RequesterFeedback WorkTimeInSeconds LifetimeApprovalRate
##      1:      NA      181      100% (187/187)
##      2:      NA      121      100% (8/8)
##      3:      NA      120      100% (187/187)
##      4:      NA      160      100% (115/115)
##      5:      NA      136      100% (187/187)
##      ---
## 2226:      NA      NA      <NA>
## 2227:      NA      NA      <NA>
## 2228:      NA      NA      <NA>
## 2229:      NA      NA      <NA>
## 2230:      NA      NA      <NA>
##      Last30DaysApprovalRate Last7DaysApprovalRate
##      1:      100% (187/187)      100% (187/187)
##      2:      100% (8/8)      100% (8/8)
##      3:      100% (187/187)      100% (187/187)
##      4:      100% (115/115)      100% (103/103)
##      5:      100% (187/187)      100% (187/187)
##      ---
## 2226:      <NA>      <NA>
## 2227:      <NA>      <NA>
## 2228:      <NA>      <NA>
## 2229:      <NA>      <NA>
## 2230:      <NA>      <NA>
##
##      1: http://www.mlsli.com/homes-for-sale/address-not-available-from-broker-Flushing-NY-11355-149238
##      2:      http://www.mlsli.com/homes-for-sale/30-11-Parsons-Blvd-Flushing-NY-11354-155242
##      3:      http://www.mlsli.com/homes-for-sale/102-14-Lewis-Ave-Corona-NY-11368-157084
##      4:      http://www.mlsli.com/homes-for-sale/144-48-Roosevelt-Ave-Flushing-NY-11354-155322
##      5:      http://www.mlsli.com/homes-for-sale/245-27-76th-Ave-Bellerose-NY-11426-161280
##      ---

```

```

## 2226:
## 2227:
## 2228:
## 2229:
## 2230:
##      approx_year_built cats_allowed common_charges community_district_num
##      1:      1955      no      $767      25
##      2:      1955      no      <NA>      25
##      3:      2004      no      $167      24
##      4:      2002      no      $275      25
##      5:      1949      yes     <NA>      26
##      ---
## 2226:      1987      no      $480      25
## 2227:      1983      yes     $956      25
## 2228:      2010      no      $250      24
## 2229:      2010      no      $250      24
## 2230:      1982      no      $792      25
##      coop_condo date_of_sale dining_room_type dogs_allowed fuel_type
##      1:      co-op  2/16/2016      combo      no      gas
##      2:      co-op  2/16/2016      formal      no      oil
##      3:      condo  2/17/2016      combo      no      <NA>
##      4:      condo  2/17/2016      combo      no      gas
##      5:      co-op  2/18/2016      combo      yes     gas
##      ---
## 2226:      condo      <NA>      combo      no      gas
## 2227:      condo      <NA>      formal      no      gas
## 2228:      condo      <NA>      formal      no      gas
## 2229:      condo      <NA>      formal      no      gas
## 2230:      condo      <NA>      formal      no      gas
##      full_address_or_zip_code garage_exists
##      1:      Flushing NY, 11355      <NA>
##      2: 30-11 Parsons Blvd, Flushing NY, 11354 ( Sold )      Share      <NA>
##      3:      102-14 Lewis Ave, Corona NY, 11368      <NA>
##      4:      144-48 Roosevelt Ave, Flushing NY, 11354      <NA>
##      5:      245-27 76th Ave, Bellerose NY, 11426      <NA>
##      ---
## 2226:      Not AvailableFlushing NY, 11355      <NA>
## 2227:      One Bay Club Dr, Bayside NY, 11360      yes
## 2228:      Ridgewood NY, 11385      <NA>
## 2229:      Ridgewood NY, 11385      <NA>
## 2230:      Two Bay Club Drive, Bayside NY, 11360      yes
##      kitchen_type maintenance_cost      model_type num_bedrooms
##      1:      eat in      <NA>      Mitchell Garden 3      2
##      2:      eat in      $604      Jr-4 Model      1
##      3:      efficiency      <NA>      Apt In Bldg      1
##      4:      eat in      <NA>      144-48 Roosevelt      3
##      5:      eat in      $660      C-1      2
##      ---
## 2226:      combo      <NA>      Colden Luxury Condo      2
## 2227:      eatin      <NA>      2 Br Deluxe      2
## 2228:      combo      <NA>      Modern      3
## 2229:      combo      <NA>      Condo      3
## 2230:      combo      <NA>      2 Bedroom      2
##      num_floors_in_building num_full_bathrooms num_half_bathrooms

```

```

##      1:              6              1              NA
##      2:              7              1              NA
##      3:              1              1              NA
##      4:             NA              2              NA
##      5:              2              1              NA
##    ---
## 2226:              7              1              NA
## 2227:             NA              2              NA
## 2228:             NA              2              NA
## 2229:              4              2              NA
## 2230:             NA              2              NA
##      num_total_rooms parking_charges pct_tax_deductibl sale_price sq_footage
##      1:              5             <NA>              NA $228,000          NA
##      2:              4             <NA>              NA $235,500          890
##      3:              3             <NA>              NA $137,550          550
##      4:              5             <NA>              NA $545,000          NA
##      5:              4             <NA>              39 $241,700          675
##    ---
## 2226:              4             <NA>              NA    <NA>          NA
## 2227:              5              $99              NA    <NA>          NA
## 2228:              6             <NA>              NA    <NA>          1500
## 2229:              6             <NA>              NA    <NA>          1600
## 2230:              5             <NA>              NA    <NA>          1134
##      total_taxes walk_score listing_price_to_nearest_1000
##      1:          <NA>          82             <NA>
##      2:          <NA>          89             <NA>
##      3:        $5,500          90             <NA>
##      4:        $2,260          94             <NA>
##      5:          <NA>          71             <NA>
##    ---
## 2226:        $3,588          97             $628
## 2227:        $5,100          82             $988
## 2228:         $250          96             $850
## 2229:         $250          96             $850
## 2230:        $3,785          82             $899
##
##      1:
##      2:
##      3:
##      4:
##      5:
##    ---
## 2226: http://www.mlsli.com/homes-for-sale/address-not-available-from-broker-Flushing-NY-11355-169427
## 2227:          http://www.mlsli.com/homes-for-sale/One-Bay-Club-Dr-Bayside-NY-11360-196274
## 2228: http://www.mlsli.com/homes-for-sale/address-not-available-from-broker-Ridgewood-NY-11385-92169
## 2229: http://www.mlsli.com/homes-for-sale/address-not-available-from-broker-Ridgewood-NY-11385-92101
## 2230:          http://www.mlsli.com/homes-for-sale/Two-Bay-Club-Drive-Bayside-NY-11360-140297

```

#Relevant columns begin at the column labeled (URL)

Initial Data Preparation I (Dropping Irrelevant Columns & Storing Possible Ones for Later Use)

```

#Dropping Mturk columns that are not relevant to our housing model
housingData[,c(1:27):=NULL]

#Save the urls in case they are needed
housingURLS = housingData[,.(URL)]

#Dropping URL from the data table
housingData[,URL:=NULL]
#Dropping other useless url column from data table (ALL NA's)
housingData[,url:=NULL]
#Dropping model_type because similar information is contained in other columns
housingData[,model_type:=NULL]

housingData

```

```

##      approx_year_built cats_allowed common_charges community_district_num
##  1:          1955         no          $767                25
##  2:          1955         no          <NA>                25
##  3:          2004         no          $167                24
##  4:          2002         no          $275                25
##  5:          1949        yes          <NA>                26
##  ---
## 2226:          1987         no          $480                25
## 2227:          1983        yes          $956                25
## 2228:          2010         no          $250                24
## 2229:          2010         no          $250                24
## 2230:          1982         no          $792                25
##      coop_condo date_of_sale dining_room_type dogs_allowed fuel_type
##  1:    co-op    2/16/2016          combo          no      gas
##  2:    co-op    2/16/2016          formal          no      oil
##  3:    condo    2/17/2016          combo          no    <NA>
##  4:    condo    2/17/2016          combo          no      gas
##  5:    co-op    2/18/2016          combo          yes      gas
##  ---
## 2226:    condo          <NA>          combo          no      gas
## 2227:    condo          <NA>          formal          no      gas
## 2228:    condo          <NA>          formal          no      gas
## 2229:    condo          <NA>          formal          no      gas
## 2230:    condo          <NA>          formal          no      gas
##      full_address_or_zip_code garage_exists
##  1:          Flushing NY, 11355          <NA>
##  2: 30-11 Parsons Blvd, Flushing NY, 11354 ( Sold )      Share          <NA>
##  3:          102-14 Lewis Ave, Corona NY, 11368          <NA>
##  4:          144-48 Roosevelt Ave, Flushing NY, 11354          <NA>
##  5:          245-27 76th Ave, Bellerose NY, 11426          <NA>
##  ---
## 2226:          Not AvailableFlushing NY, 11355          <NA>
## 2227:          One Bay Club Dr, Bayside NY, 11360          yes
## 2228:          Ridgewood NY, 11385          <NA>
## 2229:          Ridgewood NY, 11385          <NA>
## 2230:          Two Bay Club Drive, Bayside NY, 11360          yes
##      kitchen_type maintenance_cost num_bedrooms num_floors_in_building
##  1:      eat in          <NA>          2          6

```

```

##      2:      eat in      $604      1      7
##      3:    efficiency      <NA>      1      1
##      4:      eat in      <NA>      3      NA
##      5:      eat in      $660      2      2
##    ---
## 2226:      combo      <NA>      2      7
## 2227:      eatin      <NA>      2      NA
## 2228:      combo      <NA>      3      NA
## 2229:      combo      <NA>      3      4
## 2230:      combo      <NA>      2      NA
##      num_full_bathrooms num_half_bathrooms num_total_rooms parking_charges
##      1:              1              NA              5      <NA>
##      2:              1              NA              4      <NA>
##      3:              1              NA              3      <NA>
##      4:              2              NA              5      <NA>
##      5:              1              NA              4      <NA>
##    ---
## 2226:              1              NA              4      <NA>
## 2227:              2              NA              5      $99
## 2228:              2              NA              6      <NA>
## 2229:              2              NA              6      <NA>
## 2230:              2              NA              5      <NA>
##      pct_tax_deductibl sale_price sq_footage total_taxes walk_score
##      1:              NA $228,000      NA      <NA>      82
##      2:              NA $235,500      890      <NA>      89
##      3:              NA $137,550      550    $5,500      90
##      4:              NA $545,000      NA    $2,260      94
##      5:              39 $241,700      675      <NA>      71
##    ---
## 2226:              NA      <NA>      NA    $3,588      97
## 2227:              NA      <NA>      NA    $5,100      82
## 2228:              NA      <NA>    1500    $250      96
## 2229:              NA      <NA>    1600    $250      96
## 2230:              NA      <NA>    1134    $3,785      82
##      listing_price_to_nearest_1000
##      1:      <NA>
##      2:      <NA>
##      3:      <NA>
##      4:      <NA>
##      5:      <NA>
##    ---
## 2226:      $628
## 2227:      $988
## 2228:      $850
## 2229:      $850
## 2230:      $899

```

Initial Data Preparation II (Writing some notes about Columns)

```

#Getting the column names to write some notes about each column
names(housingData)

```

```

## [1] "approx_year_built"      "cats_allowed"

```



```
## [3] "common_charges"          "community_district_num"
## [5] "coop_condo"              "date_of_sale"
## [7] "dining_room_type"        "dogs_allowed"
## [9] "fuel_type"               "full_address_or_zip_code"
## [11] "garage_exists"           "kitchen_type"
## [13] "maintenance_cost"        "num_bedrooms"
## [15] "num_floors_in_building"  "num_full_bathrooms"
## [17] "num_half_bathrooms"      "num_total_rooms"
## [19] "parking_charges"         "pct_tax_deductibl"
## [21] "sale_price"              "sq_footage"
## [23] "total_taxes"             "walk_score"
## [25] "listing_price_to_nearest_1000"
```

```
#Getting some general information about the table
summary(housingData)
```

```
## approx_year_built cats_allowed common_charges community_district_num
## Min. :1893 Length:2230 Length:2230 Min. : 3.00
## 1st Qu.:1950 Class :character Class :character 1st Qu.:25.00
## Median :1958 Mode :character Mode :character Median :26.00
## Mean :1963 Mean :26.33
## 3rd Qu.:1970 3rd Qu.:28.00
## Max. :2017 Max. :32.00
## NA's :40 NA's :19
## coop_condo date_of_sale dining_room_type dogs_allowed
## Length:2230 Length:2230 Length:2230 Length:2230
## Class :character Class :character Class :character Class :character
## Mode :character Mode :character Mode :character Mode :character
##
##
##
## fuel_type full_address_or_zip_code garage_exists
## Length:2230 Length:2230 Length:2230
## Class :character Class :character Class :character
## Mode :character Mode :character Mode :character
##
##
##
## kitchen_type maintenance_cost num_bedrooms num_floors_in_building
## Length:2230 Length:2230 Min. :0.000 Min. : 1.000
## Class :character Class :character 1st Qu.:1.000 1st Qu.: 3.000
## Mode :character Mode :character Median :2.000 Median : 6.000
## Mean :1.653 Mean : 7.785
## 3rd Qu.:2.000 3rd Qu.: 7.000
## Max. :6.000 Max. :34.000
## NA's :115 NA's :650
## num_full_bathrooms num_half_bathrooms num_total_rooms parking_charges
## Min. :1.000 Min. :0.0000 Min. : 0.000 Length:2230
## 1st Qu.:1.000 1st Qu.:1.0000 1st Qu.: 3.000 Class :character
## Median :1.000 Median :1.0000 Median : 4.000 Mode :character
## Mean :1.231 Mean :0.9535 Mean : 4.139
## 3rd Qu.:1.000 3rd Qu.:1.0000 3rd Qu.: 5.000
```

```
## Max.      :3.000      Max.      :2.0000      Max.      :14.000
##          NA's      :2058      NA's      :2
## pct_tax_deductibl sale_price      sq_footage      total_taxes
## Min.      :20.0      Length:2230      Min.      : 100.0      Length:2230
## 1st Qu.:40.0      Class :character      1st Qu.: 743.0      Class :character
## Median :50.0      Mode  :character      Median : 881.0      Mode  :character
## Mean      :45.4      Mean      : 955.4
## 3rd Qu.:50.0      3rd Qu.:1100.0
## Max.      :75.0      Max.      :6215.0
## NA's      :1754      NA's      :1210
## walk_score      listing_price_to_nearest_1000
## Min.      : 7.00      Length:2230
## 1st Qu.:77.00      Class :character
## Median :89.00      Mode  :character
## Mean      :83.92
## 3rd Qu.:95.00
## Max.      :99.00
##
```

Column Name | Information | Notes to Self about column

“approx_year_built” | Integer representing the year the house was built | 40 NA’s

“cats_allowed” | Binary decision (0,1) are cats allowed in the home or not | Check for NA’s & Factor

“common_charges” | Some sort of charges in dollars (\$) | Remove the dollar symbol & Convert to integer & Check for NA’s

“community_district_num” | Integer representing the district number of community home is a part of | 19 NA’s

“coop_condo” | String representing “Co-op” or “Condo” | Lowercase everything | Check for levels & Factor

“date_of_sale” | String representing the date the home was sold |

“dining_room_type” | String representing “formal” or “combo” dining room type | Lowercase everything & Check for NA’s & Factor

“dogs_allowed” | Binary decision (0,1) are dogs allowed in the home or not | Factor this & Check for NA’s

“fuel_type” | String representing “gas”, “oil”, or “other” energy source for the home | Lowercase everything & Check for NA’s & factor

“full_address_or_zip_code” | String representing the address of the home |

“garage_exists” | String representing “Yes” if the home has a garage | Check for NA’s & Factor this & Missingness column

“kitchen_type” | String representing “Eat-In”, “Efficiency”, or “Combo” kitchen type | Lowercase everything & Factor this & Check for NA’s

“maintenance_cost” | Cost of maintenace for the home in dollars (\$) | Remove the dollar symbol & Convert to integer & Check for NA’s

“num_bedrooms” | Integer representing number of bedrooms present in the home | 115 NA’s

“num_floors_in_building” | Integer representing number of floors present in building containing home | 650 NA’s

“num_full_bathrooms” | Integer representing the number of full bathrooms present in the home | No NA’s

“num_half_bathrooms” | Integer representing the number of half bathrooms present in the home | 2058 NA’s

“num_total_rooms” | Integer representing the number of total rooms present in the home | 2 NA’s

“parking_charges” | Parking charges in dollars (\$) | Remove the dollar symbol & Convert to integer & Check for NA’s

“pct_tax_deductibl” | Integer representing percent of tax deduction | 1754 NA’s

“sale_price” | Sale price of the home in dollars (\$) | Remove the dollar symbol & Convert to integer & Check for NA’s

“sq_footage” | Integer representing the total square footage of the home | 1210 NA’s

“total_taxes” | Taxes on the home in dollars (\$) | Remove the dollar symbol & Convert to integer & Check for NA’s

“walk_score” | Integer representing a walking score for the home |

“listing_price_to_nearest_1000” | Listing price to the nearest 1000 for the home in dollars (\$) | Remove the dollar symbol & Convert to integer & Check for NA’s

Data Cleaning I (Symbol Removal & Establishing Column Types)

```
#First lets deal with the String columns that have $ symbols and convert to integer
```

```
#Extract dollar sign columns as subset to operate on
```

```
dollarSymbolSubset = housingData[,.(common_charges,maintenance_cost,parking_charges,sale_price,total_taxes,listing_price_to_nearest_1000)]
```

```
#Remove dollar signs based on pattern matching
```

```
dollarSymbolSubset[] = lapply(dollarSymbolSubset,gsub,pattern="$",fixed=TRUE,replacement="")
```

```
#Also Remove any commas that may appear for large values
```

```
dollarSymbolSubset[] = lapply(dollarSymbolSubset,gsub,pattern=",",fixed=TRUE,replacement="")
```

```
#Replace the columns in housing Data with the new dollarSymbolSubset
```

```
housingData[,c("common_charges","maintenance_cost","parking_charges","sale_price","total_taxes","listing_price_to_nearest_1000")] =  
  dollarSymbolSubset[,c("common_charges","maintenance_cost","parking_charges","sale_price","total_taxes","listing_price_to_nearest_1000")]
```

```
#Now we need to convert these columns in housing data to integer type
```

```
housingData[,c("common_charges","maintenance_cost","parking_charges","sale_price","total_taxes","listing_price_to_nearest_1000")] =  
  lapply(housingData[,c("common_charges","maintenance_cost","parking_charges","sale_price","total_taxes","listing_price_to_nearest_1000")],  
        as.integer)
```

```
#####
```

```
#Second lets deal with changing cats_allowed and dogs_allowed to factors
```

```
housingData[,sum(is.na(cats_allowed))] # No NA values for cats_allowed
```

```
## [1] 0
```

```
housingData[,sum(is.na(dogs_allowed))] # No NA values for dogs_allowed
```

```
## [1] 0
```

```
#Changing to factors for cats and dogs allowed  
unique(housingData[,cats_allowed]) # 3 "unique" values
```

```
## [1] "no" "yes" "y"
```

```
#Lets deal with the y instead of a yes  
housingData$cats_allowed[grepl("y", housingData$cats_allowed)] = "yes"  
length(unique(housingData[,cats_allowed])) # 2 unique values
```

```
## [1] 2
```

```
#Lets do the same for dogs  
unique(housingData[,dogs_allowed]) # 3 "unique" values"
```

```
## [1] "no" "yes" "yes89"
```

```
housingData$dogs_allowed[grepl("yes89", housingData$dogs_allowed)] = "yes"  
length(unique(housingData[,cats_allowed])) # 2 unique values
```

```
## [1] 2
```

```
#Factor them  
housingData[,c("cats_allowed", "dogs_allowed")] = lapply(housingData[,c("cats_allowed", "dogs_allowed")],  
levels(housingData$cats_allowed) #Check levels
```

```
## [1] "no" "yes"
```

```
levels(housingData$dogs_allowed) #Check levels
```

```
## [1] "no" "yes"
```

```
#####  
#Third lets deal with other String columns to be factored (track NA's for later)
```

```
housingData[,sum(is.na(coop_condo))] # No NA values for coop_condo
```

```
## [1] 0
```

```
length(unique(housingData[,coop_condo])) # 2 unique values
```

```
## [1] 2
```

```
#Factor it  
housingData[,coop_condo := factor(coop_condo)]  
levels(housingData$coop_condo)
```

```
## [1] "co-op" "condo"
```

```

housingData[,sum(is.na(dining_room_type))] # 448 NA values for dining_room_type

## [1] 448

length(unique(housingData[,dining_room_type])) # 6 unique values including NA

## [1] 6

length(which(housingData$dining_room_type == "none")) #none occurs 2 times

## [1] 2

length(which(housingData$dining_room_type == "dining area")) #dining area occurs 2 times

## [1] 2

#Lets deal with the issue of "dining area" as the room type and consider it as type other
housingData$dining_room_type[grepl("dining area", housingData$dining_room_type)] = "other"
housingData$dining_room_type[grepl("none", housingData$dining_room_type)] = "other"
length(unique(housingData[,dining_room_type])) # 4 unique values including NA

## [1] 4

housingData[,dining_room_type := factor(dining_room_type)]
levels(housingData$dining_room_type)

## [1] "combo" "formal" "other"

housingData[,sum(is.na(fuel_type))] # 112 NA values for dining_room_type

## [1] 112

length(unique(housingData[,fuel_type])) # 7 "unique" values including NA

## [1] 7

#Lets deal with the capitalization issues for fuel_type
housingData[,fuel_type := tolower(fuel_type)]
housingData$fuel_type[grepl("none", housingData$fuel_type)] = "other"
length(unique(housingData[,fuel_type])) # 5 unique values including NA

## [1] 5

housingData[,fuel_type := factor(fuel_type)]
levels(housingData$fuel_type)

## [1] "electric" "gas" "oil" "other"

```

```
housingData[,sum(is.na(kitchen_type))]# 16 NA values for dining_room_type
```

```
## [1] 16
```

```
length(unique(housingData[,kitchen_type])) # 14 "unique" values including NA
```

```
## [1] 14
```

```
#Lets deal with the upper case lower case kitchen type differences  
housingData[,kitchen_type:=tolower(kitchen_type)] # Lowercase everything to pattern match  
length(unique(housingData[,kitchen_type])) # 11 "unique" values including NA
```

```
## [1] 11
```

```
#Lets now deal with spaces creating more unique values  
housingData[,kitchen_type := lapply(kitchen_type,gsub,pattern="eat in",fixed=TRUE,replacement="eatin")]  
length(unique(housingData[,kitchen_type])) # 10 "unique" values including NA
```

```
## [1] 10
```

```
#Lets lets deal with the misspellings of efficiency kitchen  
housingData$kitchen_type[grepl("effic", housingData$kitchen_type)] = "efficiency"  
length(unique(housingData[,kitchen_type])) # 6 unique values including NA
```

```
## [1] 6
```

```
#Finally lets deal with 1955 and replace that with NA -> I am assuming here 1955 is wrong and not a typ  
housingData[, kitchen_type := sapply(kitchen_type, function(x) replace(x, which(x=="1955"), NA))]  
length(unique(housingData[,kitchen_type])) # t unique values including NA (no 1955 -> NA)
```

```
## [1] 5
```

```
housingData[,kitchen_type := factor(kitchen_type)]  
levels(housingData$kitchen_type)
```

```
## [1] "combo"      "eatin"      "efficiency" "none"
```

```
#####  
#Fourth lets deal with the Garage column (track NA's for later)
```

```
housingData[,sum(is.na(garage_exists))] # 1826 NA values for garage exists
```

```
## [1] 1826
```

```
length(unique(housingData[,garage_exists])) # 7 "unique" values
```

```
## [1] 7
```

```
#Lets deal with the capitalization and misspelling of yes
housingData[,garage_exists := tolower(garage_exists)]
housingData$garage_exists[grepl("y", housingData$garage_exists)] = "yes"
length(unique(housingData[,garage_exists])) # 5 unique values including NA
```

```
## [1] 5
```

```
#Lets treat underground and ug as yes
housingData$garage_exists[grepl("u", housingData$garage_exists)] = "yes"
length(unique(housingData[,garage_exists])) # 3 unique values including NA
```

```
## [1] 3
```

```
#Lets treat 1 as a yes
housingData$garage_exists[grepl("1", housingData$garage_exists)] = "yes"
length(unique(housingData[,garage_exists])) # 2 unique values including NA
```

```
## [1] 2
```

```
#Fill NA's in garage with No's -> Use 1s in missingness to indicate this later om.
housingData[, c("garage_exists")][is.na(housingData[, c("garage_exists")])] = "no"

housingData[,c("garage_exists")] = lapply(housingData[,c("garage_exists")], as.factor)
#setattr(housingData$garage_exists,"levels",c("no","yes"))
#housingData[,garage_exists := factor(garage_exists)]
levels(housingData$garage_exists)
```

```
## [1] "no" "yes"
```

```
#####
#Fifth lets take the date column treat is a an unordered factor

#In order to limit the total number of levels in Date, lets just grabs the months
#We sacrifice some granularity, but hopefully this generalize better

housingData$date_of_sale = format(as.Date(housingData$date_of_sale, format="%m/%d/%Y"), "%m")
housingData[,date_of_sale:= factor(date_of_sale,ordered=FALSE)]
length(unique(housingData[,date_of_sale])) #13 including NA which is what we want
```

```
## [1] 13
```

```
#Lets take a look at our data set now

ncol(housingData)
```

```
## [1] 25
```

```
summary(housingData)
```

```
## approx_year_built cats_allowed common_charges community_district_num
## Min. :1893 no :1402 Min. : 70.0 Min. : 3.00
## 1st Qu.:1950 yes: 828 1st Qu.: 280.0 1st Qu.:25.00
## Median :1958 Median : 390.0 Median :26.00
## Mean :1963 Mean : 441.8 Mean :26.33
## 3rd Qu.:1970 3rd Qu.: 551.5 3rd Qu.:28.00
## Max. :2017 Max. :2499.0 Max. :32.00
## NA's :40 NA's :1684 NA's :19
## coop_condo date_of_sale dining_room_type dogs_allowed fuel_type
## co-op:1661 12 : 58 combo :957 no :1684 electric: 62
## condo: 569 06 : 53 formal:620 yes: 546 gas :1348
## 01 : 50 other :205 oil : 664
## 11 : 47 NA's :448 other : 44
## 05 : 46 NA's : 112
## (Other): 274
## NA's :1702
## full_address_or_zip_code garage_exists kitchen_type maintenance_cost
## Length:2230 no :1826 combo :399 Min. : 155.0
## Class :character yes: 404 eatin :942 1st Qu.: 630.5
## Mode :character efficiency:849 Median : 767.0
## none : 23 Mean : 858.9
## NA's : 17 3rd Qu.: 985.5
## Max. :4659.0
## NA's :623
## num_bedrooms num_floors_in_building num_full_bathrooms num_half_bathrooms
## Min. :0.000 Min. : 1.000 Min. :1.000 Min. :0.0000
## 1st Qu.:1.000 1st Qu.: 3.000 1st Qu.:1.000 1st Qu.:1.0000
## Median :2.000 Median : 6.000 Median :1.000 Median :1.0000
## Mean :1.653 Mean : 7.785 Mean :1.231 Mean :0.9535
## 3rd Qu.:2.000 3rd Qu.: 7.000 3rd Qu.:1.000 3rd Qu.:1.0000
## Max. :6.000 Max. :34.000 Max. :3.000 Max. :2.0000
## NA's :115 NA's :650 NA's :2058
## num_total_rooms parking_charges pct_tax_deductibl sale_price
## Min. : 0.000 Min. : 6.0 Min. :20.0 Min. : 55000
## 1st Qu.: 3.000 1st Qu.: 60.0 1st Qu.:40.0 1st Qu.:171500
## Median : 4.000 Median : 99.0 Median :50.0 Median :259500
## Mean : 4.139 Mean :107.6 Mean :45.4 Mean :314957
## 3rd Qu.: 5.000 3rd Qu.:149.0 3rd Qu.:50.0 3rd Qu.:428875
## Max. :14.000 Max. :837.0 Max. :75.0 Max. :999999
## NA's :2 NA's :1671 NA's :1754 NA's :1702
## sq_footage total_taxes walk_score listing_price_to_nearest_1000
## Min. : 100.0 Min. : 11 Min. : 7.00 Min. : 65.0
## 1st Qu.: 743.0 1st Qu.: 281 1st Qu.:77.00 1st Qu.: 229.8
## Median : 881.0 Median :2411 Median :89.00 Median : 329.5
## Mean : 955.4 Mean :2226 Mean :83.92 Mean : 385.6
## 3rd Qu.:1100.0 3rd Qu.:3500 3rd Qu.:95.00 3rd Qu.: 525.0
## Max. :6215.0 Max. :9300 Max. :99.00 Max. :1000.0
## NA's :1210 NA's :1646 NA's :534
```

Data Manipulation I (Creating New Features)


```
#First lets just add up all the charges into a single column
```

```
#Assign new column totalCharges to be the row sum of the chargeCols ignoring NA's
```

```
housingData[, totalCharges := rowSums(.SD,na.rm=TRUE), .SDcols = c("common_charges","maintenance_cost",
```

```
##      approx_year_built cats_allowed common_charges community_district_num
##      1:              1955          no             767                  25
##      2:              1955          no              NA                  25
##      3:              2004          no             167                  24
##      4:              2002          no             275                  25
##      5:              1949         yes              NA                  26
##      ---
## 2226:              1987          no             480                  25
## 2227:              1983         yes             956                  25
## 2228:              2010          no             250                  24
## 2229:              2010          no             250                  24
## 2230:              1982          no             792                  25
##      coop_condo date_of_sale dining_room_type dogs_allowed fuel_type
##      1:      co-op           02          combo          no      gas
##      2:      co-op           02          formal          no      oil
##      3:      condo           02          combo          no    <NA>
##      4:      condo           02          combo          no      gas
##      5:      co-op           02          combo          yes      gas
##      ---
## 2226:      condo          <NA>          combo          no      gas
## 2227:      condo          <NA>          formal          no      gas
## 2228:      condo          <NA>          formal          no      gas
## 2229:      condo          <NA>          formal          no      gas
## 2230:      condo          <NA>          formal          no      gas
##      full_address_or_zip_code garage_exists
##      1:              Flushing NY, 11355          no
##      2: 30-11 Parsons Blvd, Flushing NY, 11354 ( Sold )      Share          no
##      3:              102-14 Lewis Ave, Corona NY, 11368          no
##      4:              144-48 Roosevelt Ave, Flushing NY, 11354          no
##      5:              245-27 76th Ave, Bellerose NY, 11426          no
##      ---
## 2226:              Not AvailableFlushing NY, 11355          no
## 2227:              One Bay Club Dr, Bayside NY, 11360          yes
## 2228:              Ridgewood NY, 11385          no
## 2229:              Ridgewood NY, 11385          no
## 2230:              Two Bay Club Drive, Bayside NY, 11360          yes
##      kitchen_type maintenance_cost num_bedrooms num_floors_in_building
##      1:      eatin              NA              2              6
##      2:      eatin             604              1              7
##      3:  efficiency              NA              1              1
##      4:      eatin              NA              3             NA
##      5:      eatin             660              2              2
##      ---
## 2226:      combo              NA              2              7
## 2227:      eatin              NA              2             NA
## 2228:      combo              NA              3             NA
## 2229:      combo              NA              3              4
## 2230:      combo              NA              2             NA
##      num_full_bathrooms num_half_bathrooms num_total_rooms parking_charges
```

```
##      1:      1      NA      5      NA
##      2:      1      NA      4      NA
##      3:      1      NA      3      NA
##      4:      2      NA      5      NA
##      5:      1      NA      4      NA
## ---
## 2226:      1      NA      4      NA
## 2227:      2      NA      5      99
## 2228:      2      NA      6      NA
## 2229:      2      NA      6      NA
## 2230:      2      NA      5      NA
##      pct_tax_deductibl sale_price sq_footage total_taxes walk_score
##      1:      NA      228000      NA      NA      82
##      2:      NA      235500      890      NA      89
##      3:      NA      137550      550      5500      90
##      4:      NA      545000      NA      2260      94
##      5:      39      241700      675      NA      71
## ---
## 2226:      NA      NA      NA      3588      97
## 2227:      NA      NA      NA      5100      82
## 2228:      NA      NA      1500      250      96
## 2229:      NA      NA      1600      250      96
## 2230:      NA      NA      1134      3785      82
##      listing_price_to_nearest_1000 totalCharges
##      1:      NA      767
##      2:      NA      604
##      3:      NA      5667
##      4:      NA      2535
##      5:      NA      660
## ---
## 2226:      628      4068
## 2227:      988      6155
## 2228:      850      500
## 2229:      850      500
## 2230:      899      4577
```

```
housingData[,sum(is.na(totalCharges))] # No NA's here which is good since
```

```
## [1] 0
```

```
#####
#Second lets extract the zip codes and assign them to their own column

#Lets use a regular expression to extract the zip code out of this field
housingData[,zip_code := substr(str_extract(full_address_or_zip_code,"[0-9]{5}"),1,5)]
housingData[,zip_code := as.numeric(zip_code)]
#We can now drop the full_address column since we wont need that
housingData[,full_address_or_zip_code := NULL]

#####
#Third lets add up full and half bathrooms
#Lets divide the half bathroom columns by 2 so that when we add them it is more granular
```

```
housingData[,num_half_bathrooms:=num_half_bathrooms/2]
#Assign a new column to represent the total number of bathrooms
housingData[,totalBathrooms :=rowSums(.SD,na.rm=TRUE), .SDcols = c("num_full_bathrooms","num_half_bathrooms")]
```

```
##      approx_year_built cats_allowed common_charges community_district_num
##  1:      1955          no          767                25
##  2:      1955          no           NA                25
##  3:      2004          no          167                24
##  4:      2002          no          275                25
##  5:      1949         yes           NA                26
##  ---
## 2226:      1987          no          480                25
## 2227:      1983         yes          956                25
## 2228:      2010          no          250                24
## 2229:      2010          no          250                24
## 2230:      1982          no          792                25
##      coop_condo date_of_sale dining_room_type dogs_allowed fuel_type
##  1:    co-op      02          combo          no      gas
##  2:    co-op      02          formal          no      oil
##  3:    condo      02          combo          no    <NA>
##  4:    condo      02          combo          no      gas
##  5:    co-op      02          combo          yes      gas
##  ---
## 2226:    condo    <NA>          combo          no      gas
## 2227:    condo    <NA>          formal          no      gas
## 2228:    condo    <NA>          formal          no      gas
## 2229:    condo    <NA>          formal          no      gas
## 2230:    condo    <NA>          formal          no      gas
##      garage_exists kitchen_type maintenance_cost num_bedrooms
##  1:      no      eatin              NA          2
##  2:      no      eatin             604          1
##  3:      no  efficiency              NA          1
##  4:      no      eatin              NA          3
##  5:      no      eatin             660          2
##  ---
## 2226:      no      combo              NA          2
## 2227:     yes      eatin              NA          2
## 2228:      no      combo              NA          3
## 2229:      no      combo              NA          3
## 2230:     yes      combo              NA          2
##      num_floors_in_building num_full_bathrooms num_half_bathrooms
##  1:              6              1              NA
##  2:              7              1              NA
##  3:              1              1              NA
##  4:             NA              2              NA
##  5:              2              1              NA
##  ---
## 2226:              7              1              NA
## 2227:             NA              2              NA
## 2228:             NA              2              NA
## 2229:              4              2              NA
## 2230:             NA              2              NA
##      num_total_rooms parking_charges pct_tax_deductibl sale_price sq_footage
```

```
##      1:      5      NA      NA      228000      NA
##      2:      4      NA      NA      235500      890
##      3:      3      NA      NA      137550      550
##      4:      5      NA      NA      545000      NA
##      5:      4      NA      39      241700      675
##      ---
## 2226:      4      NA      NA      NA      NA
## 2227:      5      99      NA      NA      NA
## 2228:      6      NA      NA      NA      1500
## 2229:      6      NA      NA      NA      1600
## 2230:      5      NA      NA      NA      1134
##      total_taxes walk_score listing_price_to_nearest_1000 totalCharges
##      1:      NA      82      NA      767
##      2:      NA      89      NA      604
##      3:      5500      90      NA      5667
##      4:      2260      94      NA      2535
##      5:      NA      71      NA      660
##      ---
## 2226:      3588      97      628      4068
## 2227:      5100      82      988      6155
## 2228:      250      96      850      500
## 2229:      250      96      850      500
## 2230:      3785      82      899      4577
##      zip_code totalBathrooms
##      1:      11355      1
##      2:      11354      1
##      3:      11368      1
##      4:      11354      2
##      5:      11426      1
##      ---
## 2226:      11355      1
## 2227:      11360      2
## 2228:      11385      2
## 2229:      11385      2
## 2230:      11360      2
```

```
#####
#Fourth lets bring in some extra data that shows median income by zipcode
queensIncomeDataFilePath = "/home/peterjr/RepoCollections/MATH_342W_FinalProject/Datasets/income_queens.csv"
queensIncomeData = data.table(read.csv(queensIncomeDataFilePath))

#Grab columns we want and remove the first row description of columns
queensIncomeData = queensIncomeData[-1,.(GEO_ID,S1901_C01_012E)]

#Change Data Type
queensIncomeData[,zip_code := as.numeric(GEO_ID)]

#Rename median income column
setnames(queensIncomeData, "S1901_C01_012E", "median_income")

queensIncomeData[,median_income := as.numeric(median_income)]
```

```
## Warning in eval(jsub, SDenv, parent.frame()): NAs introduced by coercion
```

```

#Drop the geo_id column
queensIncomeData[,GEO_ID := NULL]

#####
#Fifth lets join this to our housing data on the zipcode
#We are doing a left join because I want everything in housing preserved -> median income can be impute
housingData = left_join(housingData,queensIncomeData,by.x = "zip_code",by.y = "zip_code")

## Joining, by = "zip_code"

housingData[,sum(is.na(median_income))] # 64 NA values, not bad since most are getting filled, should b

## [1] 64

```

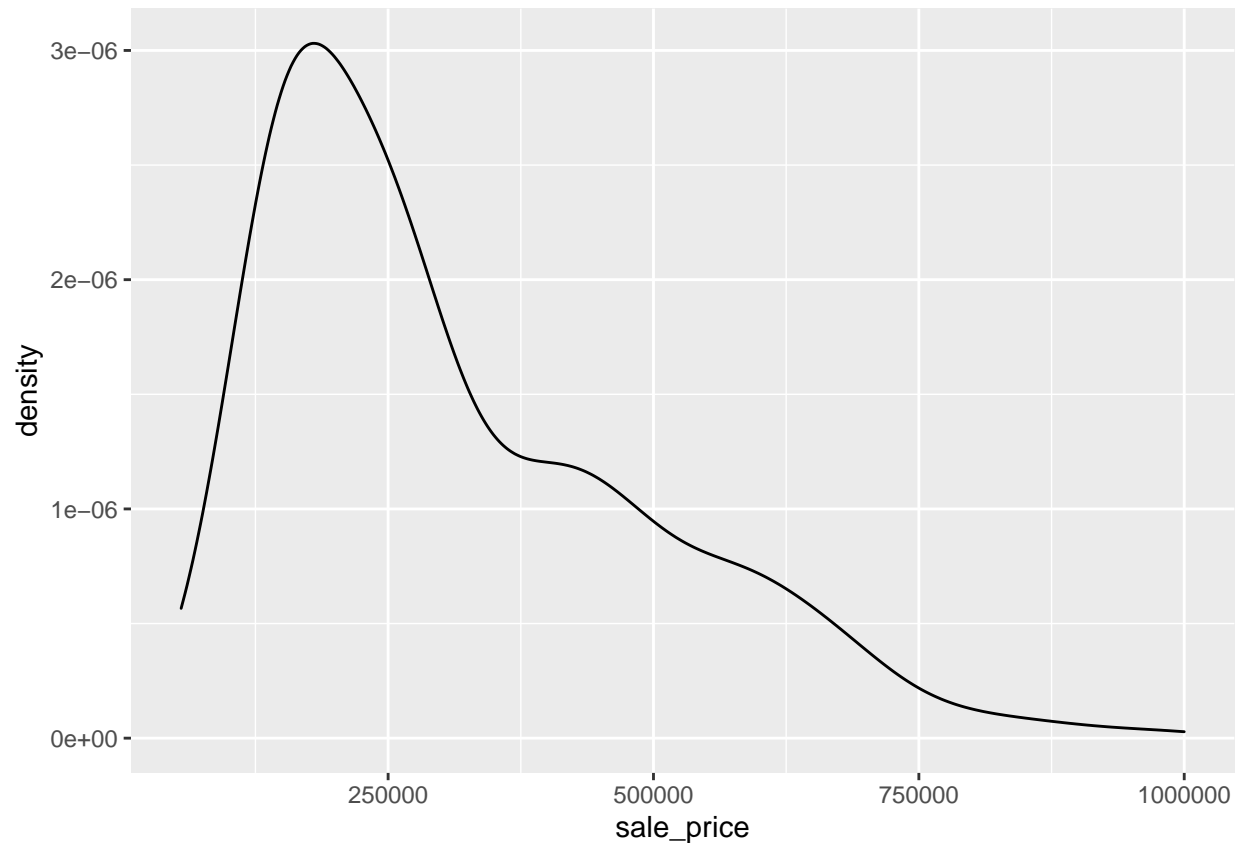
Initial Data Exploration I (Basic Visualization & Stats)

```

#####
#First lets take a look at sale_price. It is important we understand this since it is our response
sale_density = ggplot(housingData)+
  geom_density(aes(x=sale_price)) # From here we can see a concentration around ~ 225k
sale_density

## Warning: Removed 1702 rows containing non-finite values (stat_density).

```



```
#####
#Second lets take a look at some basic statistics about sale_price
sd(housingData$sale_price,na.rm = TRUE)
```

```
## [1] 179526.6
```

```
median(housingData$sale_price,na.rm = TRUE)
```

```
## [1] 259500
```

```
mean(housingData$sale_price,na.rm = TRUE) # Mean higher than median makes sense with tail in graph above
```

```
## [1] 314956.6
```

```
min(housingData$sale_price,na.rm = TRUE)
```

```
## [1] 55000
```

```
max(housingData$sale_price,na.rm = TRUE)
```

```
## [1] 999999
```

```
#####
#Third lets look at some of the columns against sale_price
#I am looking at columns that I need will have the biggest influence on sale_price

bedrooms_sale = ggplot(housingData)+
  geom_point(aes(x=num_bedrooms, y=sale_price))# Looking at num_bedrooms VS sale_price

cats_sale = ggplot(housingData)+
  geom_point(aes(x=cats_allowed, y=sale_price)) # Looking at cats_allowed VS sale_price

dogs_sale = ggplot(housingData)+
  geom_point(aes(x=dogs_allowed, y=sale_price)) # Looking at dogs_allowed VS sale_price

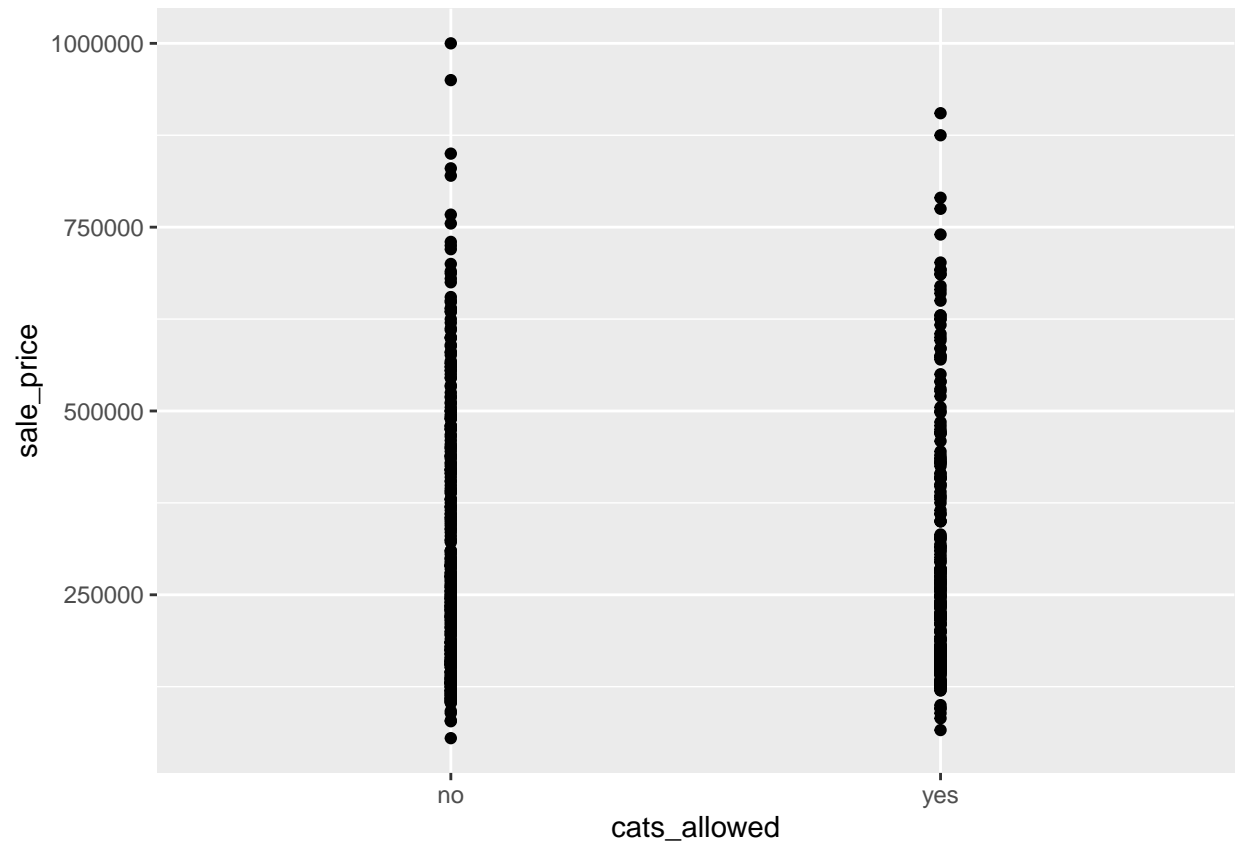
#This is a feature we created from num_full_bathrooms + (num_half_bathrooms)/2
bathrooms_sale = ggplot(housingData)+
  geom_point(aes(x=totalBathrooms, y=sale_price)) # Looking at totalBathrooms VS sale_price

#This is a feature we created by adding up all of the chargest columns
charges_sale = ggplot(housingData)+
  geom_point(aes(x=totalCharges, y=sale_price)) # Looking at totalCharges VS sale_price

walk_sale = ggplot(housingData)+
  geom_point(aes(x=walk_score, y=sale_price)) # Looking at walk_score VS sale_price

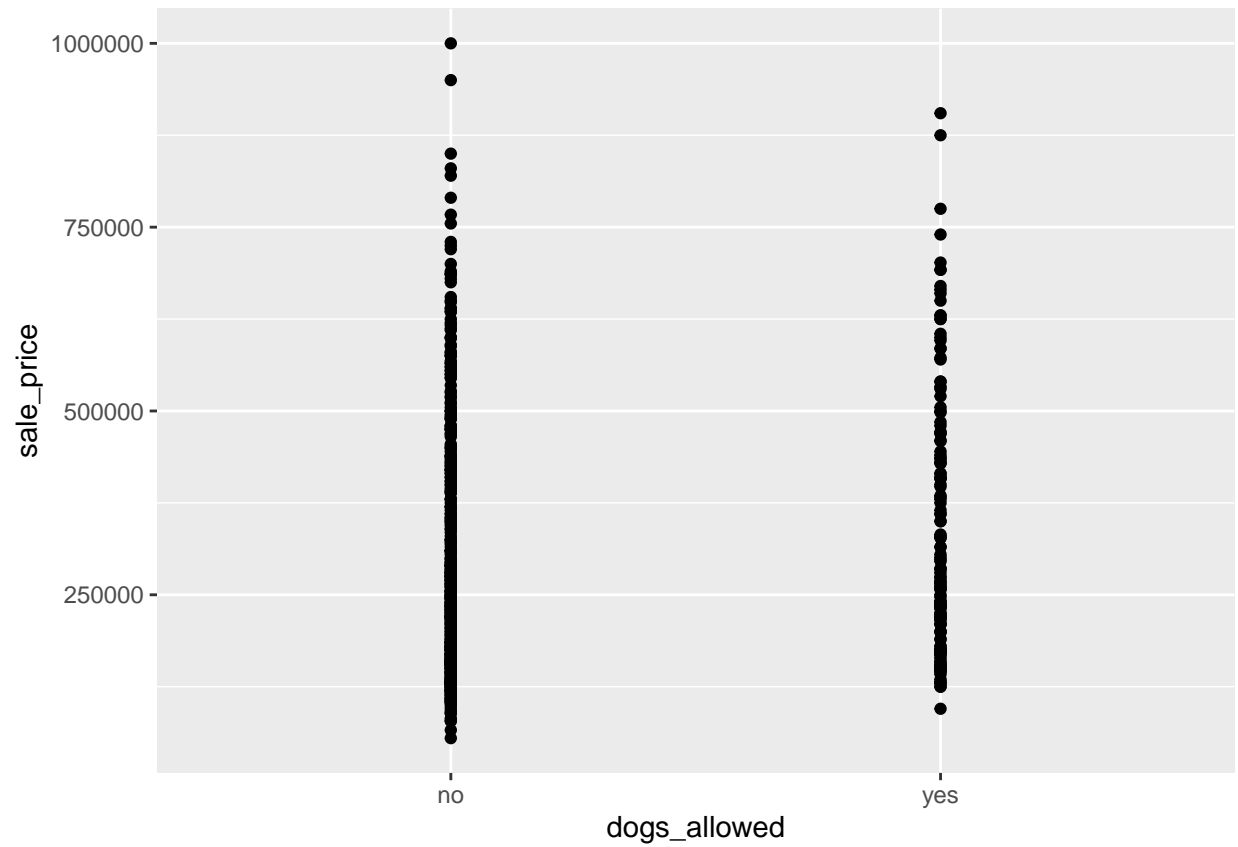
cats_sale
```

```
## Warning: Removed 1702 rows containing missing values (geom_point).
```



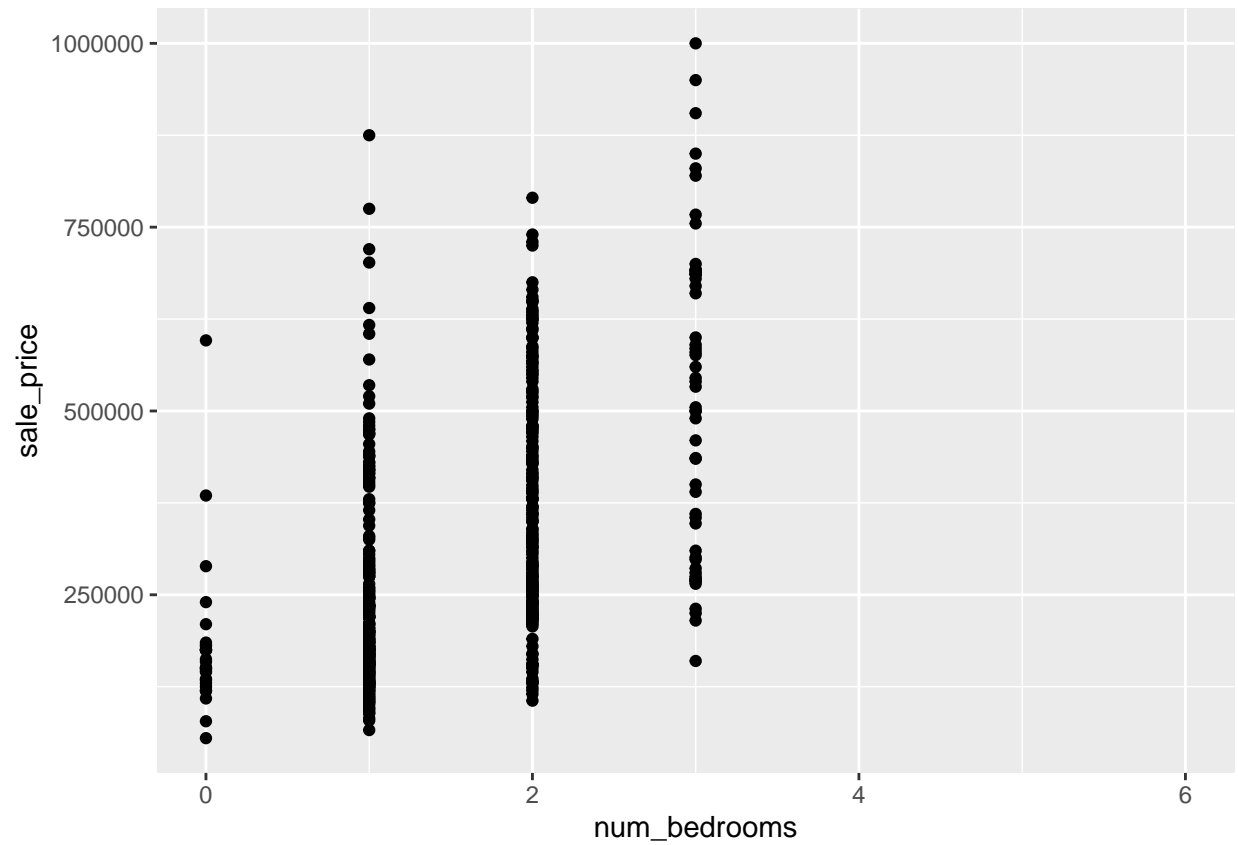
```
dogs_sale
```

```
## Warning: Removed 1702 rows containing missing values (geom_point).
```

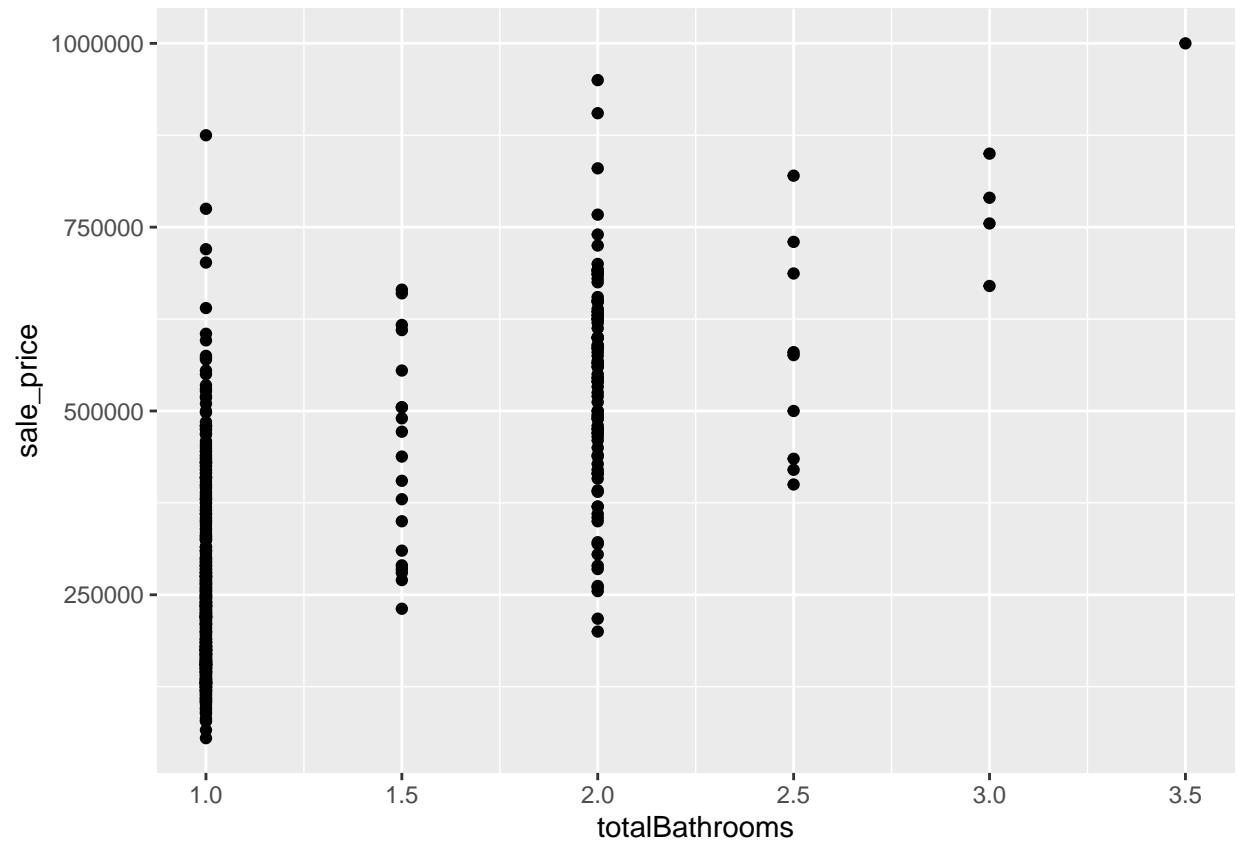
```
bedrooms_sale
```

```
## Warning: Removed 1702 rows containing missing values (geom_point).
```



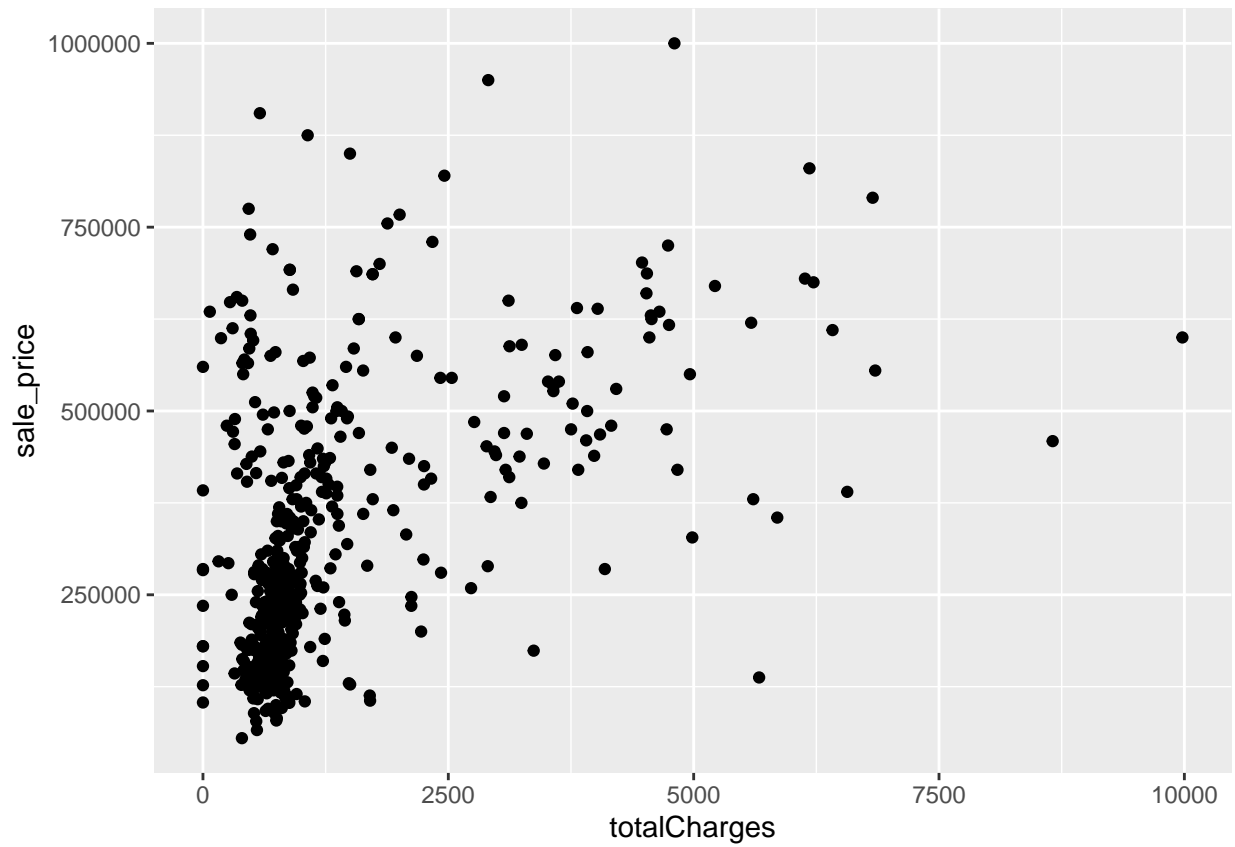
```
bathrooms_sale
```

```
## Warning: Removed 1702 rows containing missing values (geom_point).
```



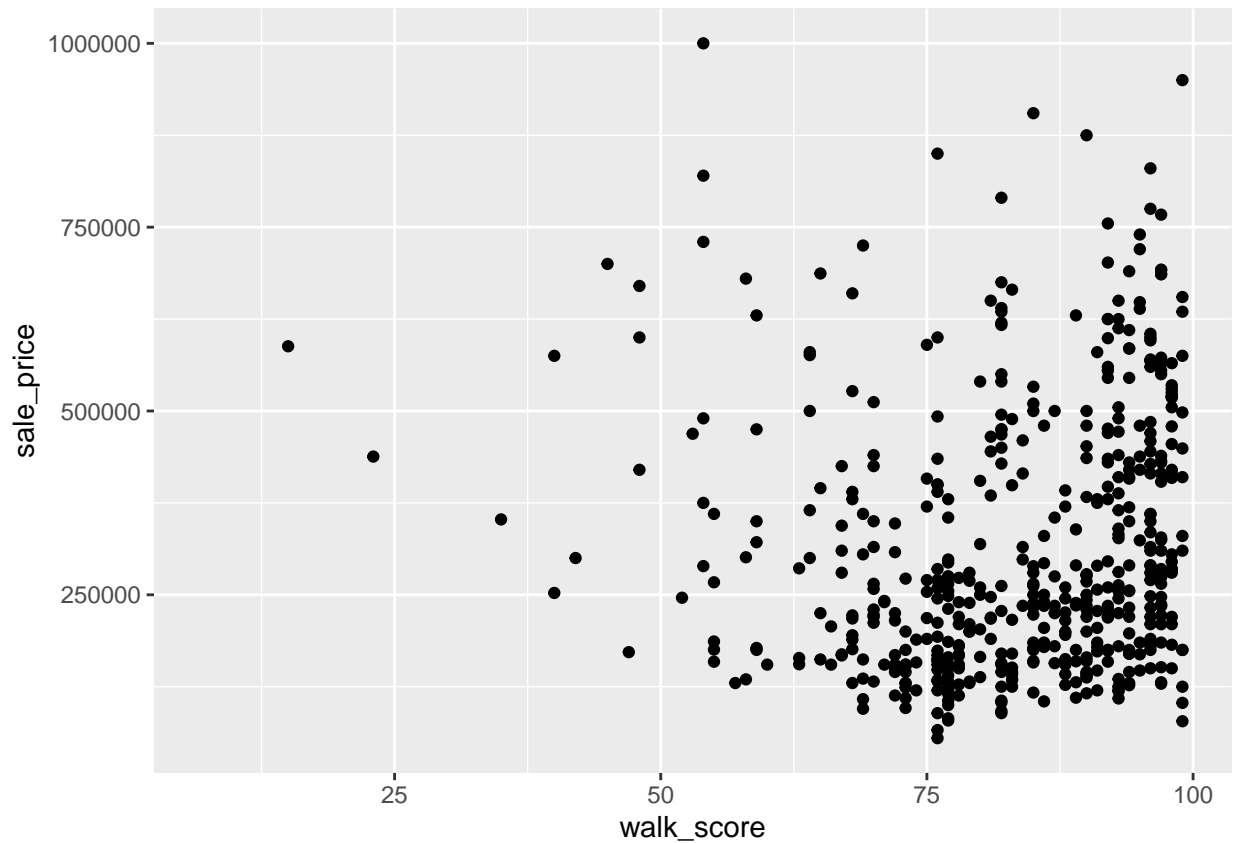
```
charges_sale
```

```
## Warning: Removed 1702 rows containing missing values (geom_point).
```



```
walk_sale
```

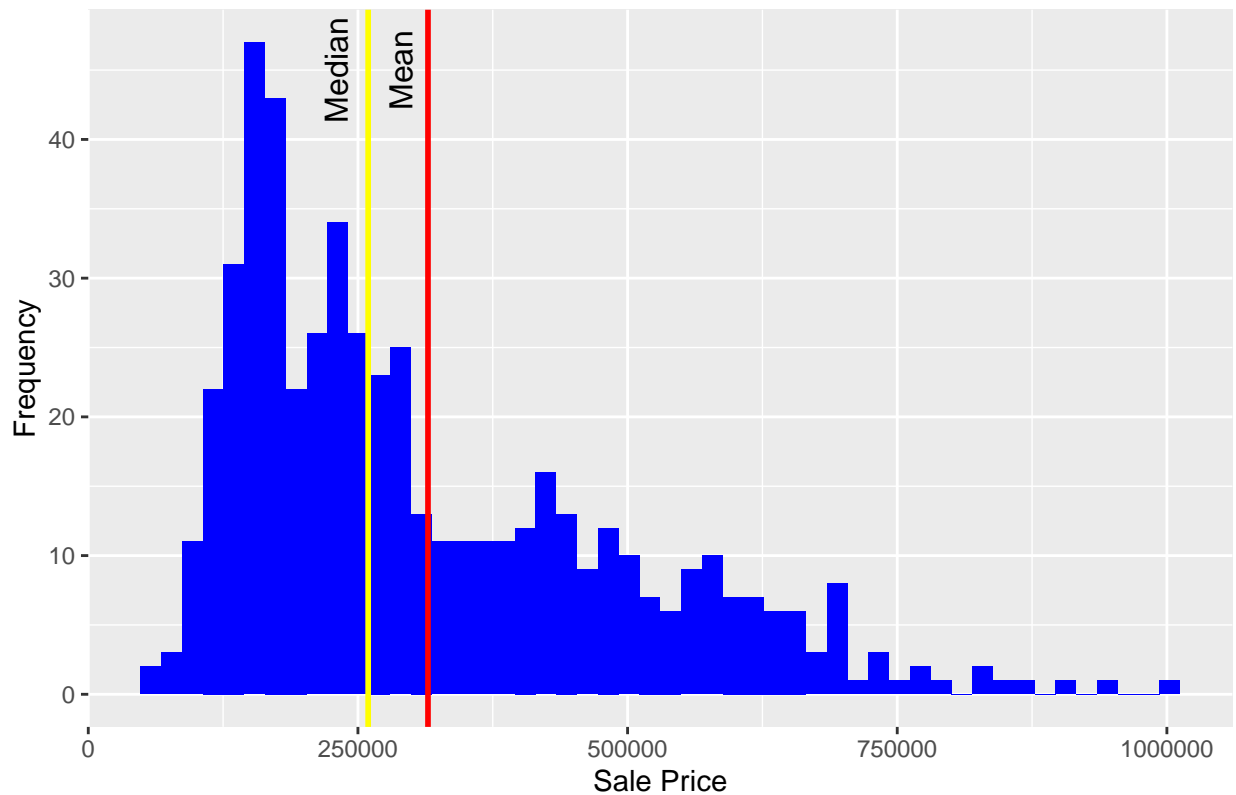
```
## Warning: Removed 1702 rows containing missing values (geom_point).
```



Initial Data Exploration II (Better visualizations)

```
ggplot(data=subset(housingData, !is.na(sale_price))) +
  aes(x = sale_price) +
  geom_histogram(bins = 50L, fill = "blue")+
  geom_vline(data = subset(housingData, !is.na(sale_price)), aes(xintercept = mean(sale_price)), color = "red")+
  annotate("text", x=290000, y=45, label=paste("Mean"),size=4.1,angle=90)+
  geom_vline(data = subset(housingData, !is.na(sale_price)), aes(xintercept = median(sale_price)), color = "green")+
  annotate("text", x=230000, y=45, label=paste("Median"),size=4.1,angle=90)+
  labs(x = "Sale Price", y = "Frequency")+
  ggtitle("Histogram of Sale Price")+
  theme(plot.title = element_text(hjust = 0.5))
```

Histogram of Sale Price



```
#Uncomment the following line if we want to save this picture to our notebook directory
#gsave("SalePriceHist.png",width=6, height=4,dpi=400)
```

Establishing a Missingness Table

```
#####
#First lets grab the columns that are of interest to us
housingData = housingData[,.(approx_year_built,cats_allowed,community_district_num,coop_condo,date_of_sale,
                             dogs_allowed,fuel_type,garage_exists,kitchen_type,num_bedrooms,num_floors,
                             sale_price,sq_footage,walk_score,totalCharges,zip_code,median_income)]

#####
#Second lets build up our missing table 0/1 where 1 indicates a NA value in the housingData

#Create a missing data table and fill with zeros
colNames = names(housingData)
missRows = nrow(housingData)
missCols = ncol(housingData)
missingData = setNames(data.table(matrix(0,nrow = missRows, ncol = missCols)), colNames)
setnames(missingData,1:ncol(missingData), paste0(names(missingData)[1:ncol(missingData)], '_miss'))
#Data Set with 1s indicating missing in housingData
missingData[is.na(housingData)] = 1

#Due to the nature of the construction of the missing table, all columns in housingData have a corresponding missingness column
#This may not be entirely accurate, since some of our columns in housingData have no NA's thus the *_mi
```

```

#Remove missing columns where the sum is 0. Implies housingData did not have any NAs.
checkZero= function(x){
  if(sum(x)==0){
    TRUE
  }
}

length(missingData[,apply(missingData, checkZero)]) # 7 columns with no missingness, we will drop the

## [1] 7

missingData = missingData[, colSums(missingData != 0) > 0, with = FALSE]

#Lets also drop missingness for sale_price. This will be made clear later, but since we plan on training,
#our missing will be all 1's aka a zero variance feature.
missingData = missingData[,!c("sale_price_miss")]

#Lets mark the indices where sale price is missing for reasons that will be made clear later
salePriceMissingIndices = which(is.na(housingData$sale_price))
salePriceFilledIndices = which(!is.na(housingData$sale_price))

```

Imputation Using The MissForest Algorithm

```

#####
#Lets impute our data set including sale price
imputeSet = housingData

#Setting up parallelization cluster
cluster = makePSOCKcluster(num_of_cores)
registerDoParallel(cluster)

#Initialize the missForest algorithm with 100 trees and parallelization
Ximp = missForest(imputeSet,verbose = TRUE, maxiter = 5, ntree = 100, parallelize = "variables")

## parallelizing over the variables of the input data matrix 'xmis'
## missForest iteration 1 in progress...done!
## estimated error(s): 0.3817819 0.1703643
## difference(s): 0.1066605 0.09372197
## time: 4.328 seconds
##
## missForest iteration 2 in progress...done!
## estimated error(s): 0.3830449 0.162378
## difference(s): 0.004361728 0.06008969
## time: 4.205 seconds
##
## missForest iteration 3 in progress...done!
## estimated error(s): 0.3696682 0.1637841
## difference(s): 0.001972756 0.04988789
## time: 4.446 seconds
##
## missForest iteration 4 in progress...done!
## estimated error(s): 0.3765333 0.1659532

```

```
##      difference(s): 0.001750518 0.0478139
##      time: 3.999 seconds
##
##      missForest iteration 5 in progress...done!
##      estimated error(s): 0.3655974 0.1635159
##      difference(s): 0.00163494 0.04557175
##      time: 4.36 seconds
```

```
#Stop the cluster
```

```
stopCluster(cluster)
registerDoSEQ()
```

```
#Get our final imputed Dataset and bind it to the missingness table
```

```
finalHousingData = cbind(Ximp$ximp,missingData)
```

```
finalHousingData
```

```
##      approx_year_built cats_allowed community_district_num coop_condo
##      1:      1955      no      25      co-op
##      2:      1955      no      25      co-op
##      3:      2004      no      24      condo
##      4:      2002      no      25      condo
##      5:      1949     yes      26      co-op
##      ---
## 2226:      1987      no      25      condo
## 2227:      1983     yes      25      condo
## 2228:      2010      no      24      condo
## 2229:      2010      no      24      condo
## 2230:      1982      no      25      condo
##      date_of_sale dining_room_type dogs_allowed fuel_type garage_exists
##      1:      02      combo      no      gas      no
##      2:      02      formal      no      oil      no
##      3:      02      combo      no      gas      no
##      4:      02      combo      no      gas      no
##      5:      02      combo     yes      gas      no
##      ---
## 2226:      10      combo      no      gas      no
## 2227:      02      formal      no      gas     yes
## 2228:      06      formal      no      gas      no
## 2229:      06      formal      no      gas      no
## 2230:      02      formal      no      gas     yes
##      kitchen_type num_bedrooms num_floors_in_building totalBathrooms
##      1:      eatin      2      6.00000      1
##      2:      eatin      1      7.00000      1
##      3: efficiency      1      1.00000      1
##      4:      eatin      3      5.15500      2
##      5:      eatin      2      2.00000      1
##      ---
## 2226:      combo      2      7.00000      1
## 2227:      eatin      2     15.75667      2
## 2228:      combo      3      4.13500      2
## 2229:      combo      3      4.00000      2
## 2230:      combo      2     14.25578      2
##      num_total_rooms sale_price sq_footage walk_score totalCharges zip_code
```


##	1:	5	228000.0	1012.0988	82	767	11355
##	2:	4	235500.0	890.0000	89	604	11354
##	3:	3	137550.0	550.0000	90	5667	11368
##	4:	5	545000.0	1018.4111	94	2535	11354
##	5:	4	241700.0	675.0000	71	660	11426
##	---						
##	2226:	4	471478.4	968.8313	97	4068	11355
##	2227:	5	610995.5	1225.8587	82	6155	11360
##	2228:	6	575402.7	1500.0000	96	500	11385
##	2229:	6	578105.3	1600.0000	96	500	11385
##	2230:	5	585690.5	1134.0000	82	4577	11360
##			median_income	approx_year_built_miss		community_district_num_miss	
##	1:		38451	0		0	
##	2:		43660	0		0	
##	3:		45980	0		0	
##	4:		43660	0		0	
##	5:		77487	0		0	
##	---						
##	2226:		38451	0		0	
##	2227:		82982	0		0	
##	2228:		60526	0		0	
##	2229:		60526	0		0	
##	2230:		82982	0		0	
##			date_of_sale_miss	dining_room_type_miss		fuel_type_miss	kitchen_type_miss
##	1:		0	0		0	0
##	2:		0	0		0	0
##	3:		0	0		1	0
##	4:		0	0		0	0
##	5:		0	0		0	0
##	---						
##	2226:		1	0		0	0
##	2227:		1	0		0	0
##	2228:		1	0		0	0
##	2229:		1	0		0	0
##	2230:		1	0		0	0
##			num_bedrooms_miss	num_floors_in_building_miss		num_total_rooms_miss	
##	1:		0	0		0	
##	2:		0	0		0	
##	3:		0	0		0	
##	4:		0	1		0	
##	5:		0	0		0	
##	---						
##	2226:		0	0		0	
##	2227:		0	1		0	
##	2228:		0	1		0	
##	2229:		0	0		0	
##	2230:		0	1		0	
##			sq_footage_miss	zip_code_miss		median_income_miss	
##	1:		1	0		0	
##	2:		0	0		0	
##	3:		0	0		0	
##	4:		1	0		0	
##	5:		0	0		0	
##	---						

```
## 2226:      1      0      0
## 2227:      1      0      0
## 2228:      0      0      0
## 2229:      0      0      0
## 2230:      0      0      0
```

```
Ximp$OOBError
```

```
##      NRMSE      PFC
## 0.3655974 0.1635159
```

Establishing Holdout Set I

*#Prior to any feature selection/modeling we want to establish a hold out set from our finalHousing Data
#We do this so that we can truly consider our hold out test set to be independent from any of the process*

```
holdout_K=5
holdout_prop = 1 / holdout_K
```

#Where sale price was NA prior to imputing ~ 75% of ALL data

```
salePriceNA_Data = finalHousingData[salePriceMissingIndices,]
```

*#This is crucial to note since our errors will be more honest albeit larger.
#If we test on imputed data we are essentially computing prediction error on a prediction rather than reality
#Most likely this will result in worse error, but it will generalize better in the real world.*

#Where sale price was not NA ~ 25% of ALL data

```
salePriceFilled_Data = finalHousingData[salePriceFilledIndices,]
```

#Training & Testing data (All Features)

```
finalHousingData_Train = salePriceNA_Data
finalHousingData_Test = salePriceFilled_Data
```

```
X_all_holdout = finalHousingData_Test[,!c("sale_price")]
y_all_holdout = finalHousingData_Test$sale_price
```

```
finalHousingData_Train
```

```
##      approx_year_built cats_allowed community_district_num coop_condo
## 1:      1983      no      25      condo
## 2:      1930      yes      28      co-op
## 3:      1912      no      28      co-op
## 4:      1953      yes      25      co-op
## 5:      1941      no      28      condo
## ---
## 1698:      1987      no      25      condo
## 1699:      1983      yes      25      condo
## 1700:      2010      no      24      condo
## 1701:      2010      no      24      condo
## 1702:      1982      no      25      condo
##      date_of_sale dining_room_type dogs_allowed fuel_type garage_exists
## 1:      08      combo      no      gas      yes
```

##	2:	12	other	yes	oil	no
##	3:	12	combo	no	electric	no
##	4:	01	combo	no	gas	no
##	5:	06	formal	no	gas	no
##	---					
##	1698:	10	combo	no	gas	no
##	1699:	02	formal	no	gas	yes
##	1700:	06	formal	no	gas	no
##	1701:	06	formal	no	gas	no
##	1702:	02	formal	no	gas	yes
##		kitchen_type	num_bedrooms	num_floors_in_building	totalBathrooms	
##	1:	eatin	2.00	14.518722	2	
##	2:	combo	1.00	3.000000	1	
##	3:	efficiency	0.85	5.000000	1	
##	4:	combo	3.00	8.972143	1	
##	5:	efficiency	4.00	6.000000	1	
##	---					
##	1698:	combo	2.00	7.000000	1	
##	1699:	eatin	2.00	15.756667	2	
##	1700:	combo	3.00	4.135000	2	
##	1701:	combo	3.00	4.000000	2	
##	1702:	combo	2.00	14.255778	2	
##		num_total_rooms	sale_price	sq_footage	walk_score	totalCharges
##	1:	6	620625.0	1250.0000	82	4955
##	2:	2	216285.0	450.0000	99	862
##	3:	2	207496.7	566.9533	99	738
##	4:	5	393730.0	1152.6725	49	1495
##	5:	7	488639.0	1524.0000	94	5776
##	---					
##	1698:	4	471478.4	968.8313	97	4068
##	1699:	5	610995.5	1225.8587	82	6155
##	1700:	6	575402.7	1500.0000	96	500
##	1701:	6	578105.3	1600.0000	96	500
##	1702:	5	585690.5	1134.0000	82	4577
##		median_income	approx_year_built_miss	community_district_num_miss		
##	1:	82982	0		0	
##	2:	72982	0		0	
##	3:	72982	0		0	
##	4:	74255	0		0	
##	5:	72982	0		0	
##	---					
##	1698:	38451	0		0	
##	1699:	82982	0		0	
##	1700:	60526	0		0	
##	1701:	60526	0		0	
##	1702:	82982	0		0	
##		date_of_sale_miss	dining_room_type_miss	fuel_type_miss	kitchen_type_miss	
##	1:	1	0	0	0	
##	2:	1	1	0	0	
##	3:	1	1	0	0	
##	4:	1	0	0	0	
##	5:	1	0	0	0	
##	---					
##	1698:	1	0	0	0	

```

## 1699:          1          0          0          0
## 1700:          1          0          0          0
## 1701:          1          0          0          0
## 1702:          1          0          0          0
##      num_bedrooms_miss num_floors_in_building_miss num_total_rooms_miss
## 1:          0          1          0
## 2:          0          0          0
## 3:          1          0          0
## 4:          0          1          0
## 5:          0          0          0
## ---
## 1698:          0          0          0
## 1699:          0          1          0
## 1700:          0          1          0
## 1701:          0          0          0
## 1702:          0          1          0
##      sq_footage_miss zip_code_miss median_income_miss
## 1:          0          0          0
## 2:          0          0          0
## 3:          1          0          0
## 4:          1          0          0
## 5:          0          0          0
## ---
## 1698:          1          0          0
## 1699:          1          0          0
## 1700:          0          0          0
## 1701:          0          0          0
## 1702:          0          0          0

```

finalHousingData_Test

```

##      approx_year_built cats_allowed community_district_num coop_condo
## 1:          1955          no          25      co-op
## 2:          1955          no          25      co-op
## 3:          2004          no          24      condo
## 4:          2002          no          25      condo
## 5:          1949          yes          26      co-op
## ---
## 524:          1950          no          28      co-op
## 525:          1947          no          28      co-op
## 526:          2010          no          24      condo
## 527:          2006          no          25      condo
## 528:          1958          no          30      co-op
##      date_of_sale dining_room_type dogs_allowed fuel_type garage_exists
## 1:          02          combo          no      gas          no
## 2:          02          formal          no      oil          no
## 3:          02          combo          no      gas          no
## 4:          02          combo          no      gas          no
## 5:          02          combo          yes      gas          no
## ---
## 524:          02          combo          no      gas          no
## 525:          02          formal          no      gas          no
## 526:          02          combo          no      gas          no
## 527:          02          combo          no  electric          no

```

## 528:	02	other	no	other	no	
##	kitchen_type	num_bedrooms	num_floors_in_building	totalBathrooms		
## 1:	eatin	2	6.000000	1.0		
## 2:	eatin	1	7.000000	1.0		
## 3:	efficiency	1	1.000000	1.0		
## 4:	eatin	3	5.155000	2.0		
## 5:	eatin	2	2.000000	1.0		
## ---						
## 524:	eatin	2	6.000000	1.0		
## 525:	combo	1	6.151667	1.0		
## 526:	eatin	2	4.000000	2.0		
## 527:	combo	2	5.950714	2.0		
## 528:	eatin	2	7.000000	1.5		
##	num_total_rooms	sale_price	sq_footage	walk_score	totalCharges	zip_code
## 1:	5	228000	1012.099	82	767	11355
## 2:	4	235500	890.000	89	604	11354
## 3:	3	137550	550.000	90	5667	11368
## 4:	5	545000	1018.411	94	2535	11354
## 5:	4	241700	675.000	71	660	11426
## ---						
## 524:	4	216000	889.805	83	850	11435
## 525:	5	232500	1000.000	94	680	11374
## 526:	5	428000	820.000	96	443	11368
## 527:	4	635000	1145.338	99	70	11355
## 528:	4	310000	972.426	96	659	11372
##	median_income	approx_year_built_miss	community_district_num_miss			
## 1:	38451	0	0			
## 2:	43660	0	0			
## 3:	45980	0	0			
## 4:	43660	0	0			
## 5:	77487	0	0			
## ---						
## 524:	55268	0	0			
## 525:	55550	0	0			
## 526:	45980	0	0			
## 527:	38451	0	0			
## 528:	52792	0	0			
##	date_of_sale_miss	dining_room_type_miss	fuel_type_miss	kitchen_type_miss		
## 1:	0	0	0	0		
## 2:	0	0	0	0		
## 3:	0	0	1	0		
## 4:	0	0	0	0		
## 5:	0	0	0	0		
## ---						
## 524:	0	1	0	0		
## 525:	0	0	0	0		
## 526:	0	0	0	0		
## 527:	0	0	0	0		
## 528:	0	0	0	0		
##	num_bedrooms_miss	num_floors_in_building_miss	num_total_rooms_miss			
## 1:	0	0	0			
## 2:	0	0	0			
## 3:	0	0	0			
## 4:	0	1	0			

```
## 5: 0 0 0
## ---
## 524: 0 0 0
## 525: 0 1 0
## 526: 0 0 0
## 527: 0 1 0
## 528: 0 0 0
## sq_footage_miss zip_code_miss median_income_miss
## 1: 1 0 0
## 2: 0 0 0
## 3: 0 0 0
## 4: 1 0 0
## 5: 0 0 0
## ---
## 524: 1 0 0
## 525: 0 0 0
## 526: 0 0 0
## 527: 1 0 0
## 528: 1 0 0
```

Feature Importance

```
#Setting up parallelization cluster
cluster = makePSOCKcluster(num_of_cores)
registerDoParallel(cluster)

#####
#Evaluating Feature Importance

# 5 fold cross validation repeated 2 times
control_selection = rfeControl(functions=rfFuncs, method="repeatedcv", number=5, repeats=2)

#We want to train it on the entire data just so we can see what subset of features are the best (exclud
trained_selection = rfe(data.matrix(finalHousingData_Train[,!c("sale_price")]),data.matrix(finalHousingData_Train[,!c("sale_price")]))

## Warning in rfout$mse/(var(y) * (n - 1)/n): Recycling array of length 1 in vector-array arithmetic is
## Use c() or as.vector() instead.
```

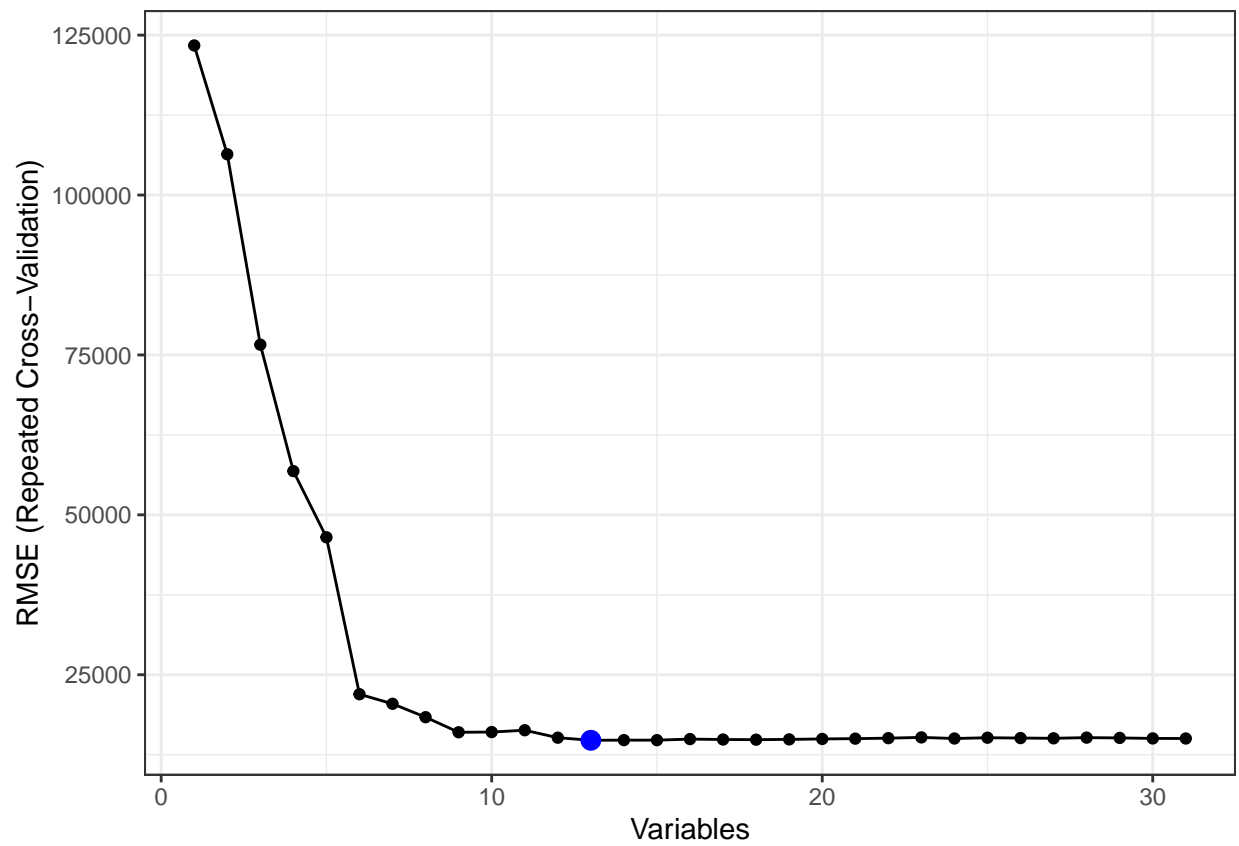
```
#Stop the cluster
stopCluster(cluster)
registerDoSEQ()

#Uncomment the following line to see a printout of the trained selection
#print(trained_selection)

predictors(trained_selection)
```

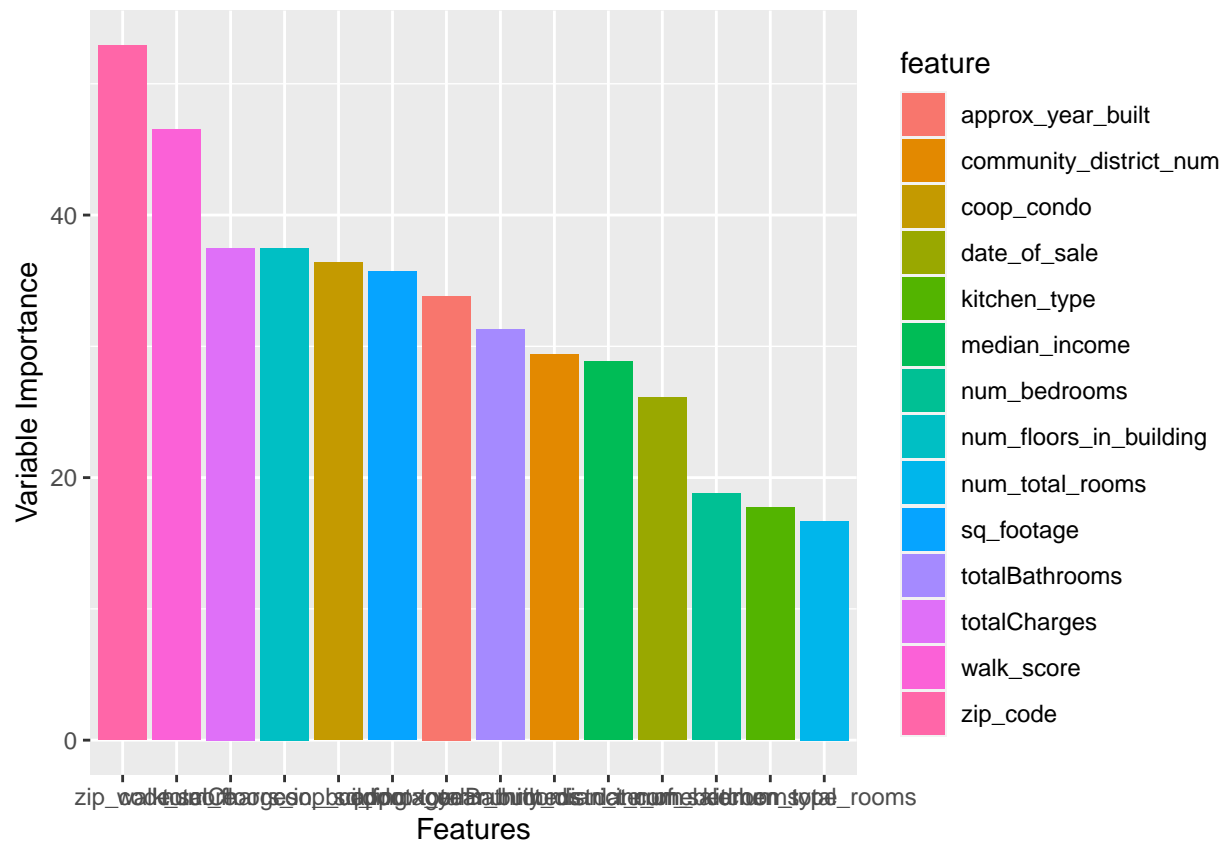
```
## [1] "zip_code" "walk_score" "totalCharges"
## [4] "num_floors_in_building" "coop_condo" "sq_footage"
## [7] "approx_year_built" "totalBathrooms" "community_district_num"
## [10] "median_income" "date_of_sale" "num_bedrooms"
## [13] "kitchen_type"
```

```
#Plot our RMSE by the number of variables
ggplot(data = trained_selection)+theme_bw()
```



```
feat_Importance = data.frame(feature = row.names(varImp(trained_selection)), importance = varImp(trained_selection))

ggplot(data = feat_Importance, aes(x=reorder(feature,-importance),y=importance ,fill = feature))+
  geom_bar(stat="identity")+
  labs(x = "Features", y = "Variable Importance")
```



Contending With Collinear Features

```
#Lets build a table consisting of only numeric values from finalHousingData
numericOnlyData2 = finalHousingData_Train[ , .SD, .SDcols = is.numeric]
ncol(numericOnlyData2) # total numeric columns
```

```
## [1] 24
```

```
#We expect at most p perfect collinearities in our p x p correlation matrix when i==j
#Greater than p columns indicates that there is perfect collinearity when i!=j
```

```
correlationMatrix2 = as.matrix(cor(numericOnlyData2))
```

```
## Warning in cor(numericOnlyData2): the standard deviation is zero
```

```
length(which(correlationMatrix2==1))
```

```
## [1] 24
```

Feature Selection (Using Results From Feature Importance & Collinearity Exploration)

```
#Here we implement feature selection based on the results provided from RFE and our test of perfect lin
#This was done in an effort to reduce the noise produced by irrelevant features in the hopes of reduci
```

```
#Let's get a list of our features ranked by importance from the previous cell
varImp(trained_selection)
```



```
##                                Overall
## zip_code                      52.92814
## walk_score                    46.52162
## totalCharges                  37.49589
## num_floors_in_building       37.48355
## coop_condo                   36.36705
## sq_footage                   35.72583
## approx_year_built            33.83540
## totalBathrooms               31.26524
## community_district_num       29.35821
## median_income                28.82297
## date_of_sale                 26.12452
## num_bedrooms                 18.80328
## kitchen_type                 17.74777
## num_total_rooms              16.70658
```

*#Thinking about this logically, it would be wise to retain sale_price_miss for the following reasons.
 #For starters, sale_price was imputed and so it would be wise to retain a marker indicating this
 #The sale price missing leads to there being no date of sale. No date of sale can just mean that is was
 #This is a judgement call here and we choose to retain sale_price_miss*

#Get the subset of features from the trained selection
 subsetF = c(predictors(trained_selection))

#Create a secondary finalHousingData table with only our selected features & response
 finalHousingDataImpFeat_Train = finalHousingData_Train[,..subsetF]

#Add back our sale price and sale price missingsince subsetF did not include sale_price as it was exclu
 finalHousingDataImpFeat_Train[,sale_price := finalHousingData_Train[,c("sale_price")]]

Establishing Holdout Set II

*#Since we are creating a secondary data set with only our selected features we want to use the same hol
 #We do this so that we can truly consider our hold out test set on the sub features to be independent f*

```
finalHousingDataImpFeat_Test = finalHousingData_Test[,..subsetF]
#Add back our sale price since subsetF did not include sale_price as it was excluded from feature impor
finalHousingDataImpFeat_Test[,sale_price := finalHousingData_Test[,c("sale_price")]] #This is our holdo
```

```
X_imp_holdout = finalHousingDataImpFeat_Test[,!c("sale_price")]
y_imp_holdout = finalHousingDataImpFeat_Test$sale_price
```

```
finalHousingDataImpFeat_Train
```

```
##      zip_code walk_score totalCharges num_floors_in_building coop_condo
## 1:    11360         82         4955          14.518722      condo
## 2:    11375         99          862           3.000000      co-op
## 3:    11375         99          738           5.000000      co-op
## 4:    11357         49         1495           8.972143      co-op
## 5:    11375         94         5776           6.000000      condo
## ---
## 1698:  11355         97         4068           7.000000      condo
## 1699:  11360         82         6155          15.756667      condo
```

```

## 1700:      11385      96      500      4.135000      condo
## 1701:      11385      96      500      4.000000      condo
## 1702:      11360      82      4577      14.255778      condo
##      sq_footage approx_year_built totalBathrooms community_district_num
## 1: 1250.0000      1983      2      25
## 2: 450.0000      1930      1      28
## 3: 566.9533      1912      1      28
## 4: 1152.6725      1953      1      25
## 5: 1524.0000      1941      1      28
## ---
## 1698: 968.8313      1987      1      25
## 1699: 1225.8587      1983      2      25
## 1700: 1500.0000      2010      2      24
## 1701: 1600.0000      2010      2      24
## 1702: 1134.0000      1982      2      25
##      median_income date_of_sale num_bedrooms kitchen_type sale_price
## 1:      82982      08      2.00      eatin 620625.0
## 2:      72982      12      1.00      combo 216285.0
## 3:      72982      12      0.85      efficiency 207496.7
## 4:      74255      01      3.00      combo 393730.0
## 5:      72982      06      4.00      efficiency 488639.0
## ---
## 1698:      38451      10      2.00      combo 471478.4
## 1699:      82982      02      2.00      eatin 610995.5
## 1700:      60526      06      3.00      combo 575402.7
## 1701:      60526      06      3.00      combo 578105.3
## 1702:      82982      02      2.00      combo 585690.5

```

```
finalHousingDataImpFeat_Test
```

```

##      zip_code walk_score totalCharges num_floors_in_building coop_condo
## 1: 11355      82      767      6.000000      co-op
## 2: 11354      89      604      7.000000      co-op
## 3: 11368      90      5667      1.000000      condo
## 4: 11354      94      2535      5.155000      condo
## 5: 11426      71      660      2.000000      co-op
## ---
## 524: 11435      83      850      6.000000      co-op
## 525: 11374      94      680      6.151667      co-op
## 526: 11368      96      443      4.000000      condo
## 527: 11355      99      70      5.950714      condo
## 528: 11372      96      659      7.000000      co-op
##      sq_footage approx_year_built totalBathrooms community_district_num
## 1: 1012.099      1955      1.0      25
## 2: 890.000      1955      1.0      25
## 3: 550.000      2004      1.0      24
## 4: 1018.411      2002      2.0      25
## 5: 675.000      1949      1.0      26
## ---
## 524: 889.805      1950      1.0      28
## 525: 1000.000      1947      1.0      28
## 526: 820.000      2010      2.0      24
## 527: 1145.338      2006      2.0      25
## 528: 972.426      1958      1.5      30

```

```
##      median_income date_of_sale num_bedrooms kitchen_type sale_price
##  1:          38451          02           2      eatin      228000
##  2:          43660          02           1      eatin      235500
##  3:          45980          02           1 efficiency      137550
##  4:          43660          02           3      eatin      545000
##  5:          77487          02           2      eatin      241700
##  ---
## 524:          55268          02           2      eatin      216000
## 525:          55550          02           1      combo      232500
## 526:          45980          02           2      eatin      428000
## 527:          38451          02           2      combo      635000
## 528:          52792          02           2      eatin      310000
```

Quick Check on our Full Feature Set and Important Feature Set

```
#Ensure the rows in both are the same...columns will obviously be different since *ImpFeat* contains le
setequal(dim(finalHousingData_Train)[1], dim(finalHousingDataImpFeat_Train)[1])
```

```
## [1] TRUE
```

```
setequal(dim(finalHousingData_Test)[1], dim(finalHousingDataImpFeat_Test)[1])
```

```
## [1] TRUE
```

Splitting Sets Into Train & Test

```
#Let's leave ~20% of our total data for testing
K=5
prop = 1 /K

#All Feature Set
#Training & Testing data (All Features)
trainIndices_all = sample(1 : nrow(finalHousingData_Train), round((1 - prop) * nrow(finalHousingData_Train)))
testIndices_all = setdiff(1 : nrow(finalHousingData_Train), trainIndices_all)

finalHousingData_subTrain = finalHousingData_Train[trainIndices_all,]
finalHousingData_subTest = finalHousingData_Train[testIndices_all,]
X_train_all= finalHousingData_subTrain[,!c("sale_price")]
y_train_all = finalHousingData_subTrain$sale_price

X_test_all = finalHousingData_subTest[,!c("sale_price")]
y_test_all = finalHousingData_subTest$sale_price

#####
#Important Feature Set
#Training & Testing data (Important Features)
trainIndices_imp = sample(1 : nrow(finalHousingDataImpFeat_Train), round((1 - prop) * nrow(finalHousingDataImpFeat_Train)))
testIndices_imp = setdiff(1 : nrow(finalHousingDataImpFeat_Train), trainIndices_imp)

finalHousingDataImpFeat_subTrain = finalHousingDataImpFeat_Train[trainIndices_imp,]
finalHousingDataImpFeat_subTest = finalHousingDataImpFeat_Train[testIndices_imp,]
X_train_imp= finalHousingDataImpFeat_subTrain[,!c("sale_price")]
```

```
y_train_imp = finalHousingDataImpFeat_subTrain$sale_price
```

```
X_test_imp = finalHousingDataImpFeat_subTest[,!c("sale_price")]
```

```
y_test_imp = finalHousingDataImpFeat_subTest$sale_price
```

Quick Check For Above Cell

```
setequal((dim(finalHousingData_subTrain)[1]+dim(finalHousingData_subTest)[1]), dim(finalHousingData_Tra
```

```
## [1] TRUE
```

```
setequal((dim(finalHousingDataImpFeat_subTrain)[1]+dim(finalHousingDataImpFeat_subTest)[1]), dim(finalH
```

```
## [1] TRUE
```

Linear Regression Model (Full Data Set)

```
#Lets run a traditional OLS with all of our features
```

```
lin_mod_all = lm(y_train_all~.,X_train_all,x = TRUE, y = TRUE)
```

```
#Test set performance
```

```
yHats_OLS_test_all = predict(lin_mod_all,X_test_all)
```

```
## Warning in predict.lm(lin_mod_all, X_test_all): prediction from a rank-deficient  
## fit may be misleading
```

```
oosRMSE_OLS_test_all = sqrt(sum((y_test_all-yHats_OLS_test_all)^2)/length(y_test_all))
```

```
#Hold out set performance
```

```
yHats_OLS_holdout_all = predict(lin_mod_all,X_all_holdout)
```

```
## Warning in predict.lm(lin_mod_all, X_all_holdout): prediction from a rank-  
## deficient fit may be misleading
```

```
oosRMSE_OLS_holdout_all = sqrt(sum((y_all_holdout-yHats_OLS_holdout_all)^2)/length(y_all_holdout))
```

```
oosRMSE_OLS_test_all
```

```
## [1] 49236.87
```

```
oosRMSE_OLS_holdout_all
```

```
## [1] 116163.6
```

```
#Notice we are being warned about a rank deficiency in our full feature data set. This is expected since  
#We should not trust the first value because of this
```

Linear Regression Model (Sub Data Set)

```

#Lets run a traditional OLS with all of our features

lin_mod_imp = lm(y_train_imp~.,X_train_imp,x = TRUE, y = TRUE)

#Test set performance
yHats_OLS_test_imp = predict(lin_mod_imp,X_test_imp)

oosRMSE_OLS_test_imp = sqrt(sum((y_test_imp-yHats_OLS_test_imp)^2)/length(y_test_imp))

#Hold out set performance
yHats_OLS_holdout_imp = predict(lin_mod_imp,X_imp_holdout)

oosRMSE_OLS_holdout_imp = sqrt(sum((y_imp_holdout-yHats_OLS_holdout_imp)^2)/length(y_imp_holdout))

SSR_olsImp_Holdout = sum((y_imp_holdout - yHats_OLS_holdout_imp) ^ 2) ## residual sum of squares
SST_olsImp_Holdout = sum((y_imp_holdout - mean(y_imp_holdout)) ^ 2) ## total sum of squares
Rsqr_olsImp_Holdout = 1 - SSR_olsImp_Holdout/SST_olsImp_Holdout

lin_mod_imp$coefficients

```

```

##          (Intercept)          zip_code          walk_score
##      -8.802830e+05      1.161252e+00      1.020549e+03
##      totalCharges num_floors_in_building      coop_condocondo
##      1.879219e-01      6.152039e+03      1.292500e+05
##      sq_footage      approx_year_built      totalBathrooms
##      1.382113e+02      3.838950e+02      6.927525e+04
## community_district_num      median_income      date_of_sale02
##      8.987998e+02      2.854961e-01      -2.596055e+04
##      date_of_sale03      date_of_sale04      date_of_sale05
##      -2.279629e+04      -6.189772e+04      -3.282046e+04
##      date_of_sale06      date_of_sale07      date_of_sale08
##      -3.314503e+04      -2.199238e+04      4.304721e+02
##      date_of_sale09      date_of_sale10      date_of_sale11
##      -2.614294e+04      -1.044975e+04      -9.933625e+03
##      date_of_sale12      num_bedrooms      kitchen_typeeatin
##      -1.028978e+04      3.437368e+04      7.894143e+03
## kitchen_typeefficiency      kitchen_typenone
##      -1.861083e+04      1.084809e+04

```

```
oosRMSE_OLS_test_imp
```

```
## [1] 47812.54
```

```
oosRMSE_OLS_holdout_imp
```

```
## [1] 95162.5
```

```
Rsqr_olsImp_Holdout
```

```
## [1] 0.7184877
```

Cross Validated Linear Model (Full & Sub Data Set)

```
train_cv = trainControl(method = "cv", number = K)

#Create a model that is cross validated on the training portion of our all feature data
ols_all_cv = train(sale_price~., data=data.matrix(finalHousingData_subTrain),method="lm", trControl = t

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading

#Create a model that is cross validated on the training portion of our important feature data
ols_imp_cv = train(sale_price~., data=data.matrix(finalHousingDataImpFeat_subTrain),method="lm", trCont

#Predict for both models
yHats_OLS_all_cvTest = predict(ols_all_cv,data.matrix(X_test_all))

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading

yHats_OLS_imp_cvTest = predict(ols_imp_cv,data.matrix(X_test_imp))

#Test set performance
oosRMSE_OLS_all_cvTest = sqrt(sum((y_test_all-yHats_OLS_all_cvTest)^2)/length(y_test_all)) #Here there
oosRMSE_OLS_imp_cvTest = sqrt(sum((y_test_imp-yHats_OLS_imp_cvTest)^2)/length(y_test_imp)) #It is done

#Predict for both models
yHats_OLS_all_cvHoldout = predict(ols_all_cv,data.matrix(X_all_holdout))

## Warning in predict.lm(modelFit, newdata): prediction from a rank-deficient fit
## may be misleading

yHats_OLS_imp_cvHoldout = predict(ols_imp_cv,data.matrix(X_imp_holdout))

#Hold out set performance
oosRMSE_OLS_all_cvHoldout = sqrt(sum((y_all_holdout-yHats_OLS_all_cvHoldout)^2)/length(y_all_holdout))
oosRMSE_OLS_imp_cvHoldout = sqrt(sum((y_imp_holdout-yHats_OLS_imp_cvHoldout)^2)/length(y_imp_holdout))

SSR_olsImp_cvHoldout = sum((y_imp_holdout - yHats_OLS_imp_cvHoldout) ^ 2) ## residual sum of squares
SST_olsImp_cvHoldout = sum((y_imp_holdout - mean(y_imp_holdout)) ^ 2) ## total sum of squares
```

```
Rsq_olsImp_cvHoldout = 1 - SSR_olsImp_cvHoldout/SST_olsImp_cvHoldout
```

```
oosRMSE_OLS_all_cvTest
```

```
## [1] 52000.75
```

```
oosRMSE_OLS_all_cvHoldout
```

```
## [1] 125056.4
```

```
oosRMSE_OLS_imp_cvTest
```

```
## [1] 51348.13
```

```
oosRMSE_OLS_imp_cvHoldout
```

```
## [1] 96693.23
```

```
Rsq_olsImp_cvHoldout
```

```
## [1] 0.7093584
```

*#Notice we are being warned about a rank deficiency in our full feature data set. This is expected since
#We should not trust the first two values because of this*

Linear Regression Model Cross Validated Lasso (Full Dataset)

#This is mainly for fun to see how a cross validated Lasso Regression Model can tame the rank deficiency

```
lin_mod_lasso = cv.glmnet(data.matrix(X_train_all),y_train_all,nfolds=K,alpha = 1)  
opt_Lambda = lin_mod_lasso$lambda.min
```

#Test Performance

```
yHats_LassoTest = predict(lin_mod_lasso, data.matrix(X_test_all),s = opt_Lambda)
```

```
oosRMSE_Lasso_Test = sqrt(sum((y_test_all-yHats_LassoTest)^2)/length(y_test_all))
```

#Holdout Set Performance

```
yHats_LassoHoldout = predict(lin_mod_lasso, data.matrix(X_all_holdout),s = opt_Lambda)
```

```
oosRMSE_Lasso_Holdout = sqrt(sum((y_all_holdout-yHats_LassoHoldout)^2)/length(y_all_holdout))
```

```
SSR_lasso_cvHoldout = sum((y_imp_holdout - yHats_LassoHoldout) ^ 2) ## residual sum of squares
```

```
SST_lasso_cvHoldout = sum((y_imp_holdout - mean(y_imp_holdout)) ^ 2) ## total sum of squares
```

```
Rsq_lasso_cvHoldout = 1 - SSR_lasso_cvHoldout/SST_lasso_cvHoldout
```

```
oosRMSE_Lasso_Test
```

```
## [1] 53042.36
```

```
oosRMSE_Lasso_Holdout
```

```
## [1] 104030
```

```
Rsq_lasso_cvHoldout
```

```
## [1] 0.6635792
```

```
#At this point we will stop using the full feature data and stick with our important feature data set
```

Regression Tree Model (Important Feature Data Set)

```
#Lets fit a regression tree to our important feature set
```

```
regTree_mod = YARFCART(X_train_imp, y_train_imp, calculate_oob_error = FALSE)
```

```
## YARF initializing with a fixed 1 trees...
```

```
## YARF factors created...
```

```
## YARF after data preprocessed... 28 total features...
```

```
## Beginning YARF regression model construction...done.
```

```
#Test performance
```

```
yHats_RegTree_Test = predict(regTree_mod,X_test_imp)
```

```
oosRMSE_RegTree_Test = sqrt(sum((y_test_imp-yHats_RegTree_Test)^2)/length(y_test_imp))
```

```
#Holdout Set Performance
```

```
yHats_RegTree_Holdout = predict(regTree_mod,X_imp_holdout)
```

```
oosRMSE_RegTree_Holdout = sqrt(sum((y_imp_holdout-yHats_RegTree_Holdout)^2)/length(y_imp_holdout))
```

```
SSR_regTree_Holdout = sum((y_imp_holdout - yHats_RegTree_Holdout) ^ 2) ## residual sum of squares
```

```
SST_regTree_Holdout = sum((y_imp_holdout - mean(y_imp_holdout)) ^ 2) ## total sum of squares
```

```
Rsq_regTree_Holdout = 1 - SSR_regTree_Holdout/SST_regTree_Holdout
```

```
#Uncomment the following line to save an illustration of the tree
```

```
#illustrate_trees(regTree_mod, max_depth=5, open_file=TRUE)
```

```
oosRMSE_RegTree_Test
```

```
## [1] 20698.89
```

```
oosRMSE_RegTree_Holdout
```

```
## [1] 76429.7
```

```
Rsq_regTree_Holdout
```

```
## [1] 0.8184108
```

Random Forest Model (Important Feature Data Set)


```

#Lets fit a random Forest to our important feature set
rf_mod = YARF(X_train_imp, y_train_imp, calculate_oob_error = FALSE)

## YARF initializing with a fixed 500 trees...
## YARF factors created...
## YARF after data preprocessed... 28 total features...
## Beginning YARF regression model construction...done.

#Test performance
yHats_rf_Test = predict(rf_mod,X_test_imp)

oosRMSE_rf_Test = sqrt(sum((y_test_imp-yHats_rf_Test)^2)/length(y_test_imp))

#Holdout Set Performance
yHats_rf_Holdout = predict(rf_mod,X_imp_holdout)

oosRMSE_rf_Holdout = sqrt(sum((y_imp_holdout-yHats_rf_Holdout)^2)/length(y_imp_holdout))

SSR_rf_Holdout = sum((y_imp_holdout - yHats_rf_Holdout) ^ 2)  ## residual sum of squares
SST_rf_Holdout = sum((y_imp_holdout - mean(y_imp_holdout)) ^ 2)  ## total sum of squares
Rsqr_rf_Holdout = 1 - SSR_rf_Holdout/SST_rf_Holdout

oosRMSE_rf_Test

## [1] 13210.72

oosRMSE_rf_Holdout

## [1] 73465.9

Rsqr_rf_Holdout

## [1] 0.8322211

```

Bagged Random Forest Model (Important Feature Data Set)

```

#Lets fit a bagged random forest to our important feature set
rfBag_mod = YARFBAG(X_train_imp, y_train_imp, calculate_oob_error = TRUE)

## YARF initializing with a fixed 500 trees...
## YARF factors created...
## YARF after data preprocessed... 28 total features...
## Beginning YARF regression model construction...done.
## Calculating OOB error...done.

#Out of Bag Performance
oosRMSE_brfg_Bag = rfBag_mod$rmse_oob

#Holdout Set Performance
yHats_brfg_Holdout = predict(rfBag_mod,X_imp_holdout)

```

```

oosRMSE_brf_Holdout = sqrt(sum((y_imp_holdout-yHats_brf_Holdout)^2)/length(y_imp_holdout))

SSR_rfBag_Holdout = sum((y_imp_holdout - yHats_brf_Holdout) ^ 2) ## residual sum of squares
SST_rfBag_Holdout = sum((y_imp_holdout - mean(y_imp_holdout)) ^ 2) ## total sum of squares
Rsqr_rfBag_Holdout = 1 - SSR_rfBag_Holdout/SST_rfBag_Holdout

```

```
oosRMSE_brf_Bag
```

```
## [1] 19434.22
```

```
oosRMSE_brf_Holdout
```

```
## [1] 72718.72
```

```
Rsqr_rfBag_Holdout
```

```
## [1] 0.8356165
```

Bagged Random Forest Model Optimization (Hyper-Parameter Tuning)

```

#Hyper-Parameter Tuning
#Setting up parallelization cluster
cluster = makePSOCKcluster(num_of_cores)
registerDoParallel(cluster)

control_rf = trainControl(method='repeatedcv', number=K, repeats=2, search = 'random')

mtry = ncol(finalHousingDataImpFeat_subTrain) # Columns in our important feature set
nTree = 500
tuneGrid = expand.grid(.mtry=seq(1,mtry))

rf_optimized = train(sale_price~.,
                     data=data.matrix(finalHousingDataImpFeat_subTrain),
                     method='rf',
                     metric='RMSE',
                     tuneGrid=tuneGrid,
                     nTree = nTree,
                     trControl=control_rf
                     )

#Stop the cluster
stopCluster(cluster)
registerDoSEQ()

#Holdout Set Performance
yHats_bgf0pt_Holdout = predict(rf_optimized,data.matrix(X_imp_holdout))

oosRMSE_bgf0pt_Holdout = sqrt(sum((y_imp_holdout-yHats_bgf0pt_Holdout)^2)/length(y_imp_holdout))

SSR_bgf0pt_Holdout = sum((y_imp_holdout - yHats_bgf0pt_Holdout) ^ 2) ## residual sum of squares

```

```
SST_bgfOpt_Holdout = sum((y_imp_holdout - mean(y_imp_holdout)) ^ 2) ## total sum of squares
Rsq_bgfOpt_Holdout = 1 - SSR_bgfOpt_Holdout/SST_bgfOpt_Holdout

print(rf_optimized)
```

```
## Random Forest
##
## 1362 samples
## 13 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 2 times)
## Summary of sample sizes: 1089, 1091, 1089, 1089, 1090, 1088, ...
## Resampling results across tuning parameters:
##
## mtry RMSE Rsquared MAE
## 1 33450.78 0.9714715 26127.95
## 2 19905.75 0.9847797 14428.55
## 3 18109.15 0.9862737 12764.24
## 4 17816.12 0.9861786 12388.48
## 5 17768.79 0.9859781 12266.81
## 6 17979.31 0.9854403 12353.24
## 7 18178.53 0.9849586 12431.33
## 8 18467.35 0.9843565 12527.56
## 9 18914.51 0.9834826 12754.23
## 10 19217.54 0.9828363 12949.49
## 11 19686.39 0.9818814 13191.34
## 12 20358.54 0.9804927 13501.52
## 13 21066.04 0.9790198 13837.54
## 14 20948.49 0.9792665 13794.39
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 5.
```

```
oosRMSE_bgfOpt_Holdout
```

```
## [1] 70851.02
```

```
Rsq_bgfOpt_Holdout
```

```
## [1] 0.8439521
```

Final Shipped Model Trained On All Data

```
#Hyper-Parameter Tuning
#Setting up parallelization cluster
cluster = makePSOCKcluster(num_of_cores)
registerDoParallel(cluster)

#Lets combine the Train and Test Portion of our important feature data set into a single entity
finalHousingData_ImpFeat = rbind(finalHousingDataImpFeat_Train,finalHousingDataImpFeat_Test)
```

```

control_rf = trainControl(method='repeatedcv', number=K, repeats=2, search = 'random')

mtry = ncol(finalHousingData_ImpFeat) # Columns in our important feature set
nTree = 500
tuneGrid = expand.grid(.mtry=seq(1,mtry))

rf_optimizedFinal = train(sale_price~.,
                          data=data.matrix(finalHousingData_ImpFeat),
                          method='rf',
                          metric='RMSE',
                          tuneGrid=tuneGrid,
                          nTree = nTree,
                          trControl=control_rf
                          )

#Stop the cluster
stopCluster(cluster)
registerDoSEQ()

print(rf_optimizedFinal)

```

```

## Random Forest
##
## 2230 samples
## 13 predictor
##
## No pre-processing
## Resampling: Cross-Validated (5 fold, repeated 2 times)
## Summary of sample sizes: 1784, 1784, 1784, 1785, 1783, 1784, ...
## Resampling results across tuning parameters:
##
##  mtry  RMSE      Rsquared  MAE
##  1     44849.87  0.9369808  29319.55
##  2     34724.15  0.9516299  17739.55
##  3     33221.06  0.9544861  16407.39
##  4     32788.01  0.9553193  16234.95
##  5     32550.58  0.9557380  16187.83
##  6     32579.45  0.9554463  16356.35
##  7     32546.34  0.9554195  16450.45
##  8     32656.63  0.9550071  16644.05
##  9     32646.81  0.9549716  16820.57
## 10     32889.58  0.9541840  17060.57
## 11     33107.49  0.9535409  17376.83
## 12     33570.92  0.9521151  17850.41
## 13     34012.33  0.9507760  18332.96
## 14     34051.33  0.9506865  18348.73
##
## RMSE was used to select the optimal model using the smallest value.
## The final value used for the model was mtry = 7.

```